RETHINKING THE PRUNING CRITERIA FOR CONVOLUTIONAL NEURAL NETWORK

Anonymous authors
Paper under double-blind review

ABSTRACT

Channel pruning is a popular technique for compressing convolutional neural networks (CNNs), and various pruning criteria have been proposed to remove the redundant filters of CNNs. From our comprehensive experiments, we found some blind spots on pruning criteria: (1) Similarity: There are some strong similarities among several primary pruning criteria that are widely cited and compared. According to these criteria, the ranks of filters' *importance* in a convolutional layer are almost the same, resulting in similar pruned structures. (2) Applicability: For a large network (each convolutional layer has a large number of filters), some criteria can not distinguish the network redundancy well from their measured filters' *importance*. In this paper, we theoretically validate these two findings with our assumption that the well-trained convolutional filters in each layer approximately follow a Gaussian-alike distribution. This assumption is verified through systematic and extensive statistical tests.

1 INTRODUCTION

Pruning (LeCun et al., 1990; Hassibi & Stork, 1993; Han et al., 2015; He et al., 2019) a trained neural network is commonly seen in network compression. In particular, for neural networks with convolutional filters, channel pruning refers to the pruning of the filters in the convolutional layers. There are several critical factors for channel pruning. **Procedures**. One-shot method (Li et al., 2016): Train a network from scratch; Use a certain criterion to calculate filters' *importance*, and prune the filters which have small *importance*; After additional training, the pruned network can recover its accuracy to some extent. Iterative method (He et al., 2018; Frankle & Carbin, 2019): Unlike One-shot methods, they prune and fine-tune a network alternately. **Criteria**. The filters' *importance* can be definded by a given criterion. From different ideas, many types of pruning criteria have been proposed, such as Norm-based (Li et al., 2016), Activation-based (Hu et al., 2016; Luo & Wu, 2017), Importance-based (Molchanov et al., 2016; 2019a), BN-based (Liu et al., 2017b) and so on. **Strategy**. Layer-wise pruning: In each layer, we can sort and prune the filters, which have small *importance* measured by a given criterion. Global pruning: Different from layer-wise pruning, global pruning sort the filters from all the layers through their *importance* and prune them.

Table 1: The pruned filters' index ordered by the filters' *importance* from given pruning criteria, taking VGG16 (3^{rd} Conv) and ResNet18 (12^{th} Conv) as examples. The pruned filters' index (the ranks of filters' *importance*) are almost the same from different pruning criterion and it will lead to the similar pruned structures.

Criteria	Model	Pruned Filters' Index (Top 8)	Model	Pruned Filters' Index (Top 8)
ℓ_1	ResNet18	[111, 212, 33, 61, 68, 152, 171, 45]	VGG16	[102, 28, 9, 88, 66, 109, 86, 45]
ℓ_2	ResNet18	[111, 33, 212, 61, 171, 42, 243, 129]	VGG16	[102, 28, 88, 9, 109, 66, 86, 45]
$\mathbf{GM}$	ResNet18	[111, 212, 33, 61, 68, 45, 171, 42]	VGG16	[102, 28, 9, 88, 109, 66, 45, 86]
$\mathbf{Fermat}$	ResNet18	[111, 212, 33, 61, 45, 171, 42, 68]	VGG16	[102, 28, 88, 9, 109, 66, 45, 86]

As one of the simplest and most effective channel pruning criteria, ℓ_1 pruning (Li et al., 2016) is widely used in the industry. The core idea of this criterion is to sort the ℓ_1 norm of filters in one layer and then prune the filters, which have a small ℓ_1 norm. Similarly, there is ℓ_2 pruning (Frankle & Carbin, 2019; He et al., 2018). Through the study of the distribution of norm, He et al. (2019) demonstrates that these criteria should satisfy two conditions: (1) the variance of the norm of the filters cannot be too small; (2) the minimum norm of the filters should be small enough. Since these two conditions do not always hold, a new criterion considering the relative *importance* of the filters (ℓ_1 and ℓ_2 norm can be seen as one of algorithm which uses absolute *importance* of filters) is proposed (He et al., 2019). Since this criterion uses the Fermat point (*i.e.*, geometric median (Cohen et al., 2016)), we call this method $\mathbf{Fermat}$. However, due to the high calculation cost of Fermat point, He et al. (2019) relaxed it and then got another criterion $\mathbf{GM}$ method. Let $F_{ij} \in \mathbb{R}^{N_i \times k \times k}$ represents the j^{th} filter of the i^{th} convolutional layer, where N_i is the number of input channels for i^{th} layer and k denotes the kernel size of the convolutional filter. In i^{th} layer, there are N_{i+1} filters. The details of these criteria are shown in Table 2. $\mathbf{F}$ denotes the Fermat point of F_{ij} in Euclidean space. These four pruning criteria are called Norm-based pruning in this paper as they include norm in their design.

Table 2: Norm-based pruning criteria.

Criterion	Details of *importance*
ℓ_1 (Li et al., 2016)	$\|\|F_{ij}\|\|_1$
ℓ_2 (Frankle & Carbin, 2019)	$\|\|F_{ij}\|\|_2$
$\mathbf{Fermat}$ (He et al., 2019)	$\|\|\mathbf{F} - F_{ij}\|\|_2$
$\mathbf{GM}$ (He et al., 2019)	$\sum_{k=1}^{N_{i+1}} \|\|F_{ik} - F_{ij}\|\|_2$

In previous works (Luo et al., 2017; Han et al., 2015; Ding et al., 2019; Dong et al., 2017; Renda et al., 2020), including the criteria mentioned above, they usually focused on (a) How much the model was compressed; (b) How much performance was restored; (c) The inference efficiency of the pruned network and (d) The cost of finding the pruned network. However, there is little work to discuss two blind spots about the pruning criteria:

(1) Similarity: What are the actual differences among these previous pruning criteria? Using VGG16 and ResNet18 on ImageNet, we show the ranks of filters' *importance* under different criteria in Table 1. It is easy to find that they have almost the same sequence, leading to similar pruned structures. In this situation, the criteria used absolute *importance* of filters (ℓ_1,ℓ_2) and the criteria used relative *importance* of filters ($\mathbf{Fermat}$,$\mathbf{GM}$) may not be significantly different.

(2) Applicability: What is the Applicability of these pruning criteria to prune the CNNs? There is a toy example w.r.t. ℓ_2 criterion. If the ℓ_2 norm (regarded as *importance*) of the filters in one layer are 0.9, 0.8, 0.4 and 0.01, according to *smaller-norm-less-informative assumption* (Ye et al., 2018), it's easy to know that we should prune the last filter. However, if the norm are close, like 0.91, 0.92, 0.93, 0.92, it is hard to know which filter should be pruned even though the first one is the smallest. As shown in Fig. 1, taking Wide ResNet28-10 (WRN) as an example, this is a real and existing problem for pruning a network with the ℓ_2 criterion.

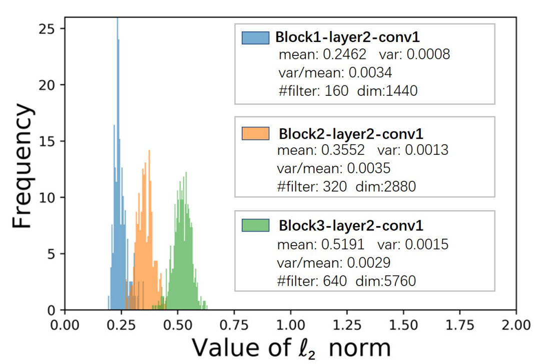


Figure 1: The distribution of ℓ_2 norm (WRN)

Some similar research methods and opinions on pruning criteria are mentioned in He et al. (2019) and Molchanov et al. (2019a). We make further analysis and observation of them in this paper. Since the criteria in Table 2 are widely cited and compared (Liu et al., 2020b; Li et al., 2020b; He et al., 2020; Liu et al., 2020a; Li et al., 2020a), therefore it's important to study them for the above two issues. In order to rigorously study them: First, we come up with an assumption about the distribution of the parameters of the convolutional filters, called *Convolution Weight Distribution Assumption* (CWDA), with systematic and comprehensive statistical tests (Appendix P) in Section 2. Next, in Section 3 and Section 4, we theoretically verify the problem about Similarity and Applicability for some Norm-based criteria in layer-wise pruning. Last but not least, in Section 5, we discuss more issues including: (1) the conditions for CWDA to be satisfied, (2) the Similarity and Applicability when we use other types of pruning criteria, (3) and another pruning strategy, the global pruning.

Contribution. **(1)** We propose and verify an assumption called CWDA, which reveals that the well-trained convolutional filters approximately follow a Gaussian-alike distribution.

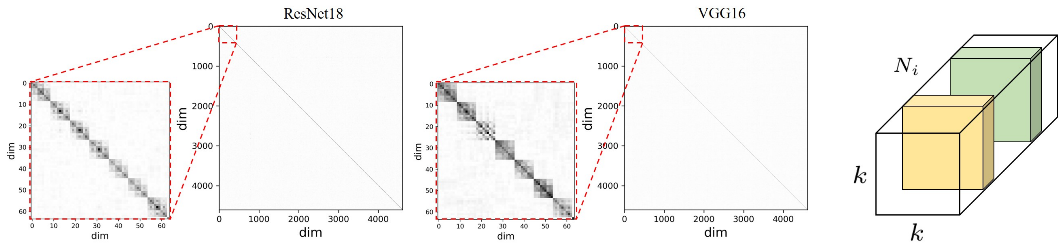


Figure 2: (a-d) Visualization of correlation matrix FF^T. More experiments on the different layers of other networks can be found in Appendix Q .(e) The structure of F_{ij}.

(2) We analyze the Applicability problem and Similarity from different types of pruning criteria. Under CWDA, we strictly validate these issues of Norm-based criteria in layer-wise pruning.

(3) Under CWDA, some Norm-based criteria using the global pruning strategy have the problem about the inconsistent magnitude of *importance* between different layers, which explains the phenomenon that they sometimes cut off the network. The estimations using CWDA almost coincides to the actual results obtained from the real network, which also demonstrates the effectiveness of the CWDA.

2 Weight Distribution-Assumption

In this section, to study the Similarity and the Applicability problem among the pruning criteria shown in Table 2, we propose and verify an assumption about the distribution of the parameters in convolutional filters.

(Convolution Weight Distribution Assumption) Let $F_{ij} \in \mathbb{R}^{N_i \times k \times k}$ be the j^{th} well-trained filter of the i^{th} convolutional layer. In i^{th} layer, $F_{ij}, j = 1, 2, ..., N_{i+1}$ are i.i.d and follow a Gaussian-alike distribution:

$$F_{ij} \sim \mathbf{N}(\mathbf{0}, c^2 \cdot \mathbf{\Sigma}_{\text{block}}), \tag{1}$$

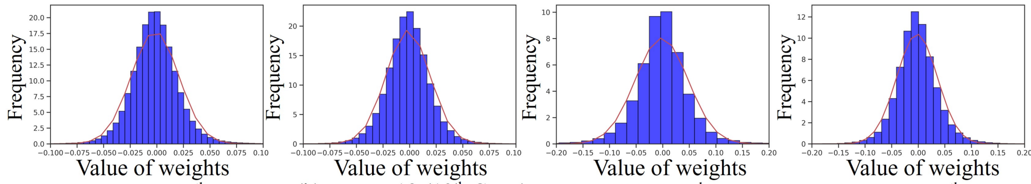
where c is a constant and $\mathbf{\Sigma}_{\text{block}} = \text{diag}(K_1, K_2, ..., K_{N_i})$ is a block diagonal matrix. The values of the off-diagonal elements are close to 0 and $K_l \in R^{k^2 \times k^2}, l = 1, 2, ..., N_i$.

This assumption is based on the observation shown in the Fig. 2. Let $F \in \mathbb{R}^{(N_i \times k \times k) \times N_{i+1}}$ denote all the parameters in i^{th} layer and we use the correlation matrix FF^T to estimate the shape of $\mathbf{\Sigma}_{\text{block}}$. Taking the last convolutional layers of ResNet18 and VGG16 trained ImageNet as an example, we find that FF^T is a block diagonal matrix. Specifically, each block is a $k^2 \times k^2$ matrix and the off-diagonal elements are close to 0. For j^{th} filter $F_{ij} \in \mathbb{R}^{N_i \times k \times k}$ in i^{th} layer as shown in Fig. 2(e), this phenomenon reveals that the parameters in the same channel of F_{ij} tend to be linearly correlated, and the parameters of any two different channels (yellow and green channels in Fig. 2(e)) in F_{ij} only have a low linear correlation. Since the kernel size k is a small constant (like 1 or 3) and $N_i \gg 1$, the length k^2 of each block is much smaller than the length $k^2 \cdot N_i$ of the covariance matrix in most convolutional layers. Therefore, the block diagonal matrix $\mathbf{\Sigma}_{\text{block}}$ can be regarded as a diagonal matrix, as shown in Fig. 2(b) and (d). For the convenience of analysis, we relax the assumption, *i.e.*, F_{ij} **approximately** follows a Gaussian-alike distribution[1]:

$$F_{ij} \sim \mathbf{N}(\mathbf{0}, c^2 \cdot \mathbf{I}_{N_i \times k \times k}), \tag{2}$$

where $\mathbf{I}_{N_i \times k \times k}$ is an identity matrix. The statistical tests in Section 2.1 and the estimation by CWDA in Fig. 10 show the reasonability of this relaxation. In the remaining sections, we use Eq.2 to represent CWDA unless otherwise specified. In Fig. 3, taking VGG16 and ResNet18 on ImageNet dataset as examples, we visualize the CWDA through the distribution of the convolutional filters.

[1]In Section 5, we make further discussion and analysis on the conditions for CWDA to be satisfied.



(a) ResNet18 (11th Conv) (b) ResNet18 (12th Conv) (c)VGG16 (3rd Conv) (d) VGG16 (4th Conv)

Figure 3: Visualization of the distribution of convolutional filters. The parameters of a convolutional filter approximately follow a Gaussian-alike distribution.

2.1 STATISTICAL TEST

In fact, CWDA is not easy to be verified. For example, for ResNet164 (On Cifar100), the number of filters in the first stage is only 16, which is too small to be used to estimate the statistics accurately. More other objective reasons are shown in Section 5.1. As these problems, we consider verifying three necessary conditions of CWDA: (1) Gaussian (*i.e.*, to verify whether F_{ij} approximately follows a Gaussian-alike distribution); (2) Standard Deviation (*i.e.*, to verify whether the standard deviation of each filter in any layers is close to a constant c); (3) Mean (*i.e.*, to verify whether the mean of F_{ij} is close to 0).

In Table 3, to illustrate that CWDA holds universally, we consider a variety of factors, such as network structure, optimizer, regularization[2], initialization, dataset, training strategy, and other tasks in computer vision (*e.g.*, semantic segmentation, detection, image matting and so on). The details of these statistical tests are shown in Appendix P.

Table 3: The experiments for having the comprehensive statistical tests on CWDA.

NETWORK STRUCTURE (P.1)	**OPTIMIZER** (P.2)	**REGULARIZATION** (P.3)
ResNet (He et al., 2016a) VGG (Simonyan & Zisserman, 2014) AlexNet (Krizhevsky, 2014) DenseNet (Huang et al., 2017) PreResNet (He et al., 2016b) WRN (Zagoruyko & Komodakis, 2016) ResNext (Xie et al., 2017)	SGD (Sutskever et al., 2013) ASGD (Polyak & Juditsky, 1992) Adam (Kingma & Ba, 2014) Adagrad (Duchi et al., 2011) Adamax (Kingma & Ba, 2014) Adadelta (Zeiler, 2012)	L1 norm L2 norm RReLu (Xu et al., 2015) Dropact (Liang et al., 2018) Autoaug (Cubuk et al., 2019) Cutout (DeVries & Taylor, 2017) Cutmix (Yun et al., 2019)
ATTENTION MECHANISM (P.4)	**INITIALIZATION** (P.5)	**DATASET** (P.6)
SENet (Hu et al., 2018) DIANet (Huang et al., 2019) SRMNet (Lee et al., 2019) CBAM (Woo et al., 2018) IEBN (Liang et al., 2019) SGENet (Li et al., 2019)	Kaiming-normal (He et al., 2015) Kaiming-uniform (He et al., 2015) Xavier-normal (Glorot & Bengio, 2010) Xavier-uniform (Glorot & Bengio, 2010) Orthogonal (Saxe et al., 2013)	CIFAR10 (Krizhevsky et al., 2009) CIFAR100 (Krizhevsky et al., 2009) ImageNet (Russakovsky et al., 2015) MNIST (LeCun et al., 1998)
SEGMENTATION (P.7)	**DETECTION** (P.7)	**BATCH NORMALIZATION** (P.8)
SegNet (Badrinarayanan et al., 2017) PSPNet (Zhao et al., 2017)	Faster RCNN (Ren et al., 2015)	VGG VGG-bn
PYTORCH PRETRAIN (P.9)	**MATTING** (P.7)	**LEARNING RATE** (P.10)
ResNet18/34/50 VGG11/16/19	Deep image matting (Xu et al., 2017) AlphaGAN matting (Lutz et al., 2018)	Schedule150-225 Schedule82-164
STYLE TRANSFER(P.7)	**GAN**(P.7)	Schedule60-120
Fast neural style (Johnson et al., 2016)	DCGAN (Radford et al., 2015)	Cos-lr (Loshchilov & Hutter, 2016)

3 SIMILARITY

In this section, we further verify the observation that the pruning criteria in Table 2 are highly similar from two perspectives. From an experimental point of view, we use more experiments about image classification to investigate the similarities. From a theoretical perspective, we rigorously show the similarities of the criteria in Table 2 in layer-wise pruning under CWDA.

[2] The statistical tests about the situation with or without weight decay can be found in Appendix O.

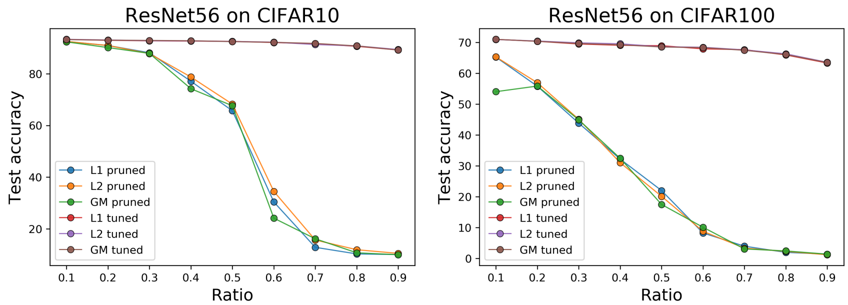


Figure 4: Test accuracy of the ResNet56 on CIFAR10/100 while using different pruning ratios. L1 pruned and L1 tuned denote the test accuracy of the ResNet56 after ℓ_1 pruning and fine-tuning, respectively. If pruning ratio is equal to 0.5, we prune 50% filters in all layers.

Empirical Analysis. (1) In Fig. 4, we show the test accuracy of the ResNet56 after pruning and fine-tuning under using different pruning ratios and datasets. The test accuracy curves of different pruning criteria at different stages are very close under different pruning ratios. This phenomenon implies that those pruned networks using different pruning criteria are very similar, and there are strong similarities among these pruning criteria. The experiments about other commonly used pruning ratio can be found in Appendix N. (2) In Fig. 5, we show the Spearman's rank correlation coefficient (Sp)[3] between different pruning criteria. The Sp in most convolutional layers are more than 0.9, which means the network structures are almost the same after pruning. Note that the Sp in transition layer (*i.e.*, the layer where the dimensions of the filter change, like the layer between stage 1 and stage 2 of ResNet164. The number of dimensions in stage 1 and stage 2 are 16 and 32 respectively.) are relatively small. It is interesting but will not greatly impact the structural similarity of the whole pruned network. The reason for this phenomenon may be that the layers in these areas are sensitive. The similar observations are shown in Fig. 2 in Ding et al. (2019), and Fig. 6 and Fig. 10 in Li et al. (2016).

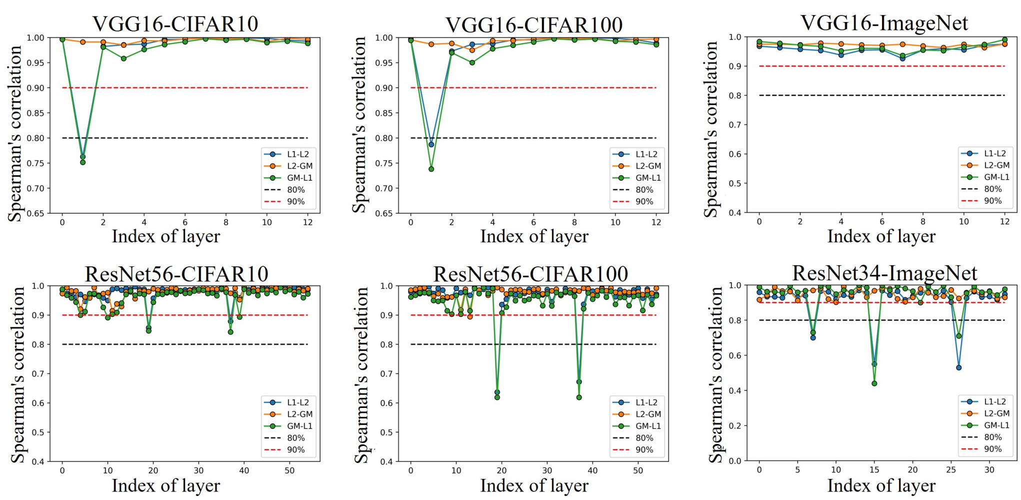


Figure 5: Spearman's rank correlation coefficient (Sp) between different pruning criteria on several networks and datasets (more experiments can be found in Appendix R).

Theoretical Analysis. After the verification by experiments, the similarities via using layer-wise pruning among the criteria in Table 2 are proved theoretically in this section. Let C_1 and C_2 be two pruning criteria to calculate the *importance* for all convolutional filters of one layer. If they

[3] Sp is a nonparametric measurement of ranking correlation, and it assesses how well the relationship between two variables can be described using a monotonic function, *i.e.*, filters ranking sequence in the same layer under two criteria in this paper.

can produce the similar ranks of *importance*, we define C_1 and C_2 are *approximately monotonic* to each other and use $C_1 \cong C_2$ to represent this relationship. In Section 3, we use the Sp to describe this relationship but it's hard to be analyzed theoretically. Therefore, we consider about a stronger condition. Let $\mathbf{X} = (x_1, x_2, ..., x_k)$ and $\mathbf{Y} = (y_1, y_2, ..., y_k)$ be two given sequences. we first normalize their magnitude, *i.e.*, let $\widehat{\mathbf{X}} = \mathbf{X}/\mathbb{E}(\mathbf{X})$ and $\widehat{\mathbf{Y}} = \mathbf{Y}/\mathbb{E}(\mathbf{Y})$. This operation does not change the ranking sequence of the elements of $\mathbf{X}$ and $\mathbf{Y}$, because $\mathbb{E}(\mathbf{X})$ and $\mathbb{E}(\mathbf{Y})$ are constants, *i.e.*, $\widehat{\mathbf{X}} \cong \widehat{\mathbf{Y}} \Leftrightarrow \mathbf{X} \cong \mathbf{Y}$. After that, if both $\mathbf{Var}(\widehat{\mathbf{X}}/\widehat{\mathbf{Y}})$ and $\mathbf{Var}(\widehat{\mathbf{Y}}/\widehat{\mathbf{X}})$ are small enough, then the Sp between $\mathbf{X}$ and $\mathbf{Y}$ is close to 1, where $\widehat{\mathbf{X}}/\widehat{\mathbf{Y}} = (\widehat{x_1}/\widehat{y_1}, .., \widehat{x_k}/\widehat{y_k})$. The reason is that in these situations, the ratio $\widehat{\mathbf{X}}/\widehat{\mathbf{Y}}$ and $\widehat{\mathbf{Y}}/\widehat{\mathbf{X}}$ will be close to two constants a, b. Note that, for any $1 \leq i \leq k$, $\widehat{x_i} \approx a \cdot \widehat{y_i}$ and $\widehat{y_i} \approx b \cdot \widehat{x_i}$. Then, $ab \approx 1$ and $a, b \neq 0$. Therefore, there exists an *approximately monotonic* mapping from $\widehat{y_i}$ to $\widehat{x_i}$ (linear function) and it makes the Sp between $\mathbf{X}$ and $\mathbf{Y}$ close to 1.

Theorem 1. *Let $X \sim N(\mathbf{0}, c^2 \cdot \mathbf{I}_n)$, and (C_1, C_2) is one of (ℓ_1, ℓ_2), $(\ell_1, \mathbf{Fermat})$ or $(\mathbf{Fermat}, \mathbf{GM})$, we have*

$$\max\left\{\mathbf{Var}_X\left(\frac{\widehat{C}_2(X)}{\widehat{C}_1(X)}\right), \mathbf{Var}_X\left(\frac{\widehat{C}_1(X)}{\widehat{C}_2(X)}\right)\right\} \lesssim B(n), \tag{3}$$

where $\widehat{C}_1(X)$ denotes $C_1(X)/\mathbb{E}(C_1(X))$ and $\widehat{C}_2(X)$ denotes $C_2(X)/\mathbb{E}(C_2(X))$. $B(n)$ denotes the upper bound of left-hand side and when n is large enough, $B(n) \to 0$.

Proof. (See Appendix G). ☐

For i^{th} convolutional layer of a neural network, since F_{ij}, $j = 1, 2, ...N_{i+1}$, meet CWDA and the dimensions of F_{ij} are generally large, we can obtain $\ell_1 \cong \ell_2$, $\ell_2 \cong \mathbf{Fermat}$ and $\mathbf{Fermat} \cong \mathbf{GM}$ according to Theorem 1. Therefore, we have $\ell_1 \cong \ell_2 \cong \mathbf{Fermat} \cong \mathbf{GM}$, which verifies the strong similarities among the criteria shown in Table 2.

4 APPLICABILITY

In this section, we analyze the Applicability problem of the Norm-based criteria when we use these criteria to prune a large network (each convolutional layer has a large number of filters). In Fig. 1, we can find that ℓ_2 can not distinguish the redundancy of Wide ResNet28-10 (regarded as a large network) well from their measured filters' *importance*, because their *importance* are very close (the distribution looks sharp). This problem is related to the variance of *importance*. He et al. (2019) argue that a *small norm deviation* (the values of variance of *importance* are small) makes it difficult to find an appropriate threshold to select filters to prune. However, even if the values of the variance are large, it may still have the Applicability problems. This is because the magnitude of these *importance* may be much greater than the values of the variance, where we can use the mean of *importance* to represent their magnitude. We believe that the following two situations may cause Applicability problem: for the filters F_i in i^{th} convolutional layer,

(1) If the mean $\mathbb{E}(F_i) = 0$ and the variance $\mathbf{Var}(F_i)$ is close to 0;

(2) If $\mathbb{E}(F_i) \neq 0$ and $\mathbf{Var}(F_i)/\mathbb{E}(F_i)$ is close to 0.

For a network with large number of convolutional filters, it's easy to know that the dimensions of the filters are also large enough. For ℓ_2 pruning, according to CWDA (the proof in Appendix L), we can obtain that the mean of $\ell_2(F_i)$ is $\sqrt{2}\sigma_i \cdot \Gamma(\frac{k_i+1}{2})/\Gamma(\frac{k_i}{2}) \neq 0$, where σ_i and k_i are the standard deviation and dimension of the parameters in i^{th} layer, respectively. And $\mathbf{Var}(F_i)/\mathbb{E}(F_i) \to 0$ when k_i is large enough. From these reasons, the *importance* measured by ℓ_2 norm tends to be identical, *i.e.*, it's hard to distinguish the network redundancy well in this situation. Moreover, from the proof in Appendix H, we know that the Fermat point $\mathbf{F}$ of F_i and the origin $\mathbf{0}$ approximately coincide. According to Table 2, $||\mathbf{F} - F_i||_2 \approx ||\mathbf{0} - F_i||_2 = ||F_i||_2$. Therefore, the *importance* of $\mathbf{Fermat}$ and ℓ_2 are almost equivalent when CWDA holds. Hence, a similar conclusion can be obtained for $\mathbf{Fermat}$ criterion. Intuitively, the ℓ_1 criterion should have the same Applicability problem as the ℓ_2 criterion. However, from the proof in Appendix L, the mean of $\ell_1(F_i)$ is $\sigma_i \cdot k\sqrt{\frac{2}{\pi}} \neq 0$, but

$\mathbf{Var}(F_i)/\mathbb{E}(F_i)$ tends to be a none-zero constant with respect to σ_i. In other words, ℓ_1 criterion does not necessarily have Applicability problems unless σ_i is small enough.

Except for the Norm-based criteria, we analyze another type pf pruning criteria called RePr (Prakash et al., 2019). This criterion considers the orthogonality among the filters in one layer. Based on the proof in Appendix L and the fact that the *importance* measured by ℓ_2 norm tend to be identical, we also know that this criterion cannot prune the network well when the number of filters is too large. Moreover, in Section 5.2, we study the Applicability problem for more different types of pruning criteria from a numerical perspective.

5 Discussion

5.1 Why CWDA sometimes does not hold?

CWDA may not always hold. As shown in Appendix P, a small number of convolutional filters may not pass the statistical tests. In this section, we try to analyze this phenomenon.

(1) **Need to be trained well enough**. The distribution of parameters can only be discussed when the network is trained well. If the network does not converge, it is easy to construct a scenario which does not satisfy CWDA, *e.g.*, in Fig. 16 (Appendix D), we train a network with uniform initialization. Although the distribution of parameters converges with the increase of epoch more and more to a normal distribution, when only a few epochs are trained, the distribution of parameters is closer to a uniform distribution. At this time, the distribution obviously does not satisfy CWDA. Moreover, if a network is not trained well, *e.g.*, its parameters converge to bad local minima, there may be many unforeseen circumstances causing CWDA to be unsatisfied. In order to eliminate these factors, the network should be trained when studying the parameter distribution.

(2) **The number of filters is insufficient.** In Appendix P, the layers that can not pass the statistical tests are almost those whose position is in the front of the network. A common feature of these layers is that they have a few filters, which may not estimate statistics well. In Fig. 5, due to the sensibility of layers, the Sp in the transition layer are relatively small. Taking the second convolutional layer (64 filters) in VGG16 on CIFAR10 as an example, we find that increasing the number of filters could alleviate this sensitivity. As shown in Fig. 6, we change the number of filters in this layer from 64 to 128 or 256. After that, the Sp increases significantly, and it suggests that enough number of filters are essential.

(3) **The dimensions of the filter are not large enough.** The dimension of a filter in the i^{th} layer is closely related to the number of filters in the $(i-1)^{\mathrm{th}}$ layer. To eliminate the influence from the number of the filters, we can consider the correlation matrix of each parameter in the filter. As the analysis in Section 2, only when the dimension of the convolutional filter is large enough will the matrix approximate a diagonal matrix. It may also be a reason why the layer in the front of the network usually can not pass the statistical test in Appendix P.

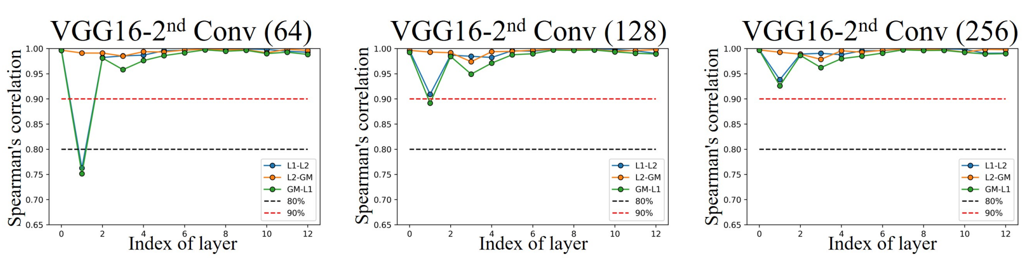


Figure 6: The Sp between different pruning criteria on VGG16 (CIFAR10). The number of filters in the second convolutional layers is changed from 64 to 256.

5.2 What about other pruning criteria?

In this section, we study the Similarity and Applicability problem in more types of pruning criteria through numerical experiments, such as Activation-based pruning (Hu et al., 2016; Luo & Wu, 2017), Importance-based pruning (Molchanov et al., 2016; 2019a) and BN-based pruning (Liu et al., 2017b).

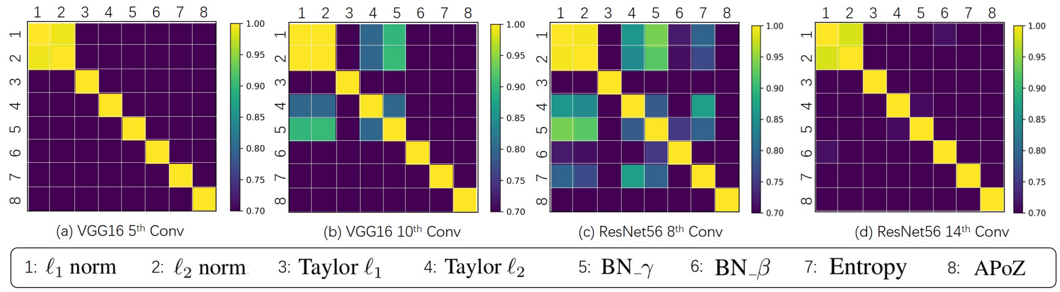


Figure 7: The Sp between different types of pruning criteria on VGG16 and ResNet56.

For each type, we choose two representative criteria and we call them: (1) Norm-based: ℓ_1 and ℓ_2; (2) Importance-based: Taylor ℓ_1 and Taylor ℓ_2 (Molchanov et al., 2016; 2019a;b); (3) BN-based: BN_γ[4] and BN_β (Liu et al., 2017b); (4) Activation-based: Entropy (Luo & Wu, 2017) and APoZ (Hu et al., 2016). The details of these criteria can be found in Appendix M.

The Similarity for different types of pruning criteria. In Fig. 7, we show the Sp between different types of pruning criteria, and only the Sp greater than 0.7 are shown because if Sp < 0.7, it means that there is no strong similarity between two criteria in the current layer. According to the Sp shown in Fig. 7, we can have the following observations: (1) As verified in Section 3, ℓ_1 and ℓ_2 maintain a strong similarity in each layer; (2) In the layers shown in Fig. 7(a) and Fig. 7(d), the Sp between most different pruning criteria are not large in these layers, which indicates that these methods have great differences in the redundancy measurement of convolution filters. This may lead to a phenomenon that one criterion considers a convolutional filter to be important, while another considers it redundant. We find a specific example which is shown in Appendix E; (3) Intuitively, the same type of criteria should be similar. However, it can be seen from Fig. 7(b) and Fig. 7(c) that the Sp between Taylor ℓ_1 and Taylor ℓ_2 is not large, but Taylor ℓ_2 has strong similarity with both two Norm-based criteria. Moreover, the Sp between BN_γ and each Norm-based criteria exceeds 0.9, but it is not large in other layers (Fig. 7(b) and Fig. 7(d)). These phenomena are worthy of further study.

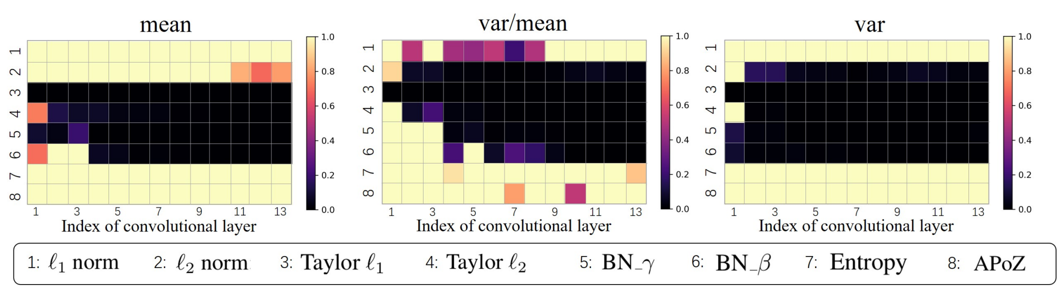


Figure 8: The visualization of Applicability problem for different types of criteria. (VGG16)

The Applicability for different types of pruning criteria. According to the analysis in Section 4, the Applicability problem depends on the mean and variance of the parameters. Fig. 8 shows the result of the *importance* measured by different pruning criteria on each layer of VGG16. VGG16 is a network whose width becomes larger gradually as the depth increases (from 64 to 512). For this reason, we can study the Applicability problem in generally wide (shallow layers) and sufficiently wide (deep layers) convolutional layers. First, we analyze the Norm-based criteria. The mean of both ℓ_1 and ℓ_2 are relatively large, but in most layers, the variance/mean of ℓ_2 is much smaller than that of ℓ_1, which means that the ℓ_2 pruning has Applicability problem, while the ℓ_1 does not. This is consistent with the conclusion in Section 4. Next, for the Activation-based criteria, the

[4]The empirical result for slimming training (Liu et al., 2017b) is shown in Appendix B.

mean and variance/mean are both large, which means that these two Activation-based criteria can distinguish the network redundancy well from their measured filters' *importance*. However, for the Importance-based and BN-based criteria, their mean and variance/mean are close to 0. According to the condition (1) shown in Section 4, these criteria have Applicability problem, especially in the deep layers.

5.3 What about global pruning?

Compared with layer-wise pruning, global pruning is more widely (Liu et al., 2018; Molchanov et al., 2016; Liu et al., 2017b) used in channel pruning.

Similarity while using global pruning. In Fig. 9, we show the similarity of different types of pruning criteria using global pruning on VGG16 and ResNet56. Comparing to the results from the layer-wise pruning shown in Fig. 7, we can find that the similarities of most pruning criteria are quite different in global pruning. In particular, for the results of ℓ_1 and ℓ_2 in Fig. 9(a), the similarity between ℓ_1 and ℓ_2 is not as strong as the one in the layer-wise case. We argue that this phenomenon may be due to the differences between the parameter distribution in different convolutional layers. More analysis can be found in Appendix A.

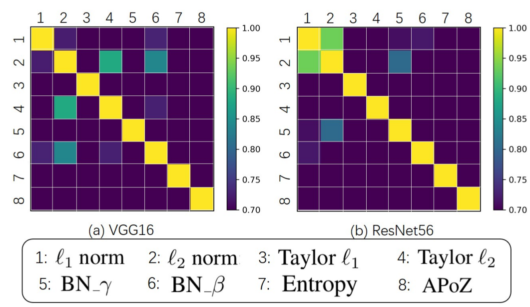


Figure 9: Similarity while using global pruning.

Applicability while using global pruning. In fact, for global pruning, Norm-based criteria are not prone to Applicability problems. From Section 4, we have the estimations for the magnitude of *importance* in i^{th} layer calculated by ℓ_1 and ℓ_2 as $\sigma_i \cdot k\sqrt{\frac{2}{\pi}}$ and $\sqrt{2}\sigma_i \cdot \Gamma(\frac{k_i+1}{2})/\Gamma(\frac{k_i}{2})$. Since σ_i and k_i are quite different, the variance of the *importance* is large in this situation. Fig. 10 shows this kind of difference of the magnitude on different convolutional layers.

Our estimation also explains a common problem in practical applications of global pruning: the network is easily pruned off. As shown in Fig. 10, we take ResNet56 as an example. Since the *importance* in first stage is much smaller than the *importance* in the deeper layer, global pruning will give priority to prune the convolutional filters of the first stage. To solve the problem of inconsistent magnitude, we suggest that some normalization methods should be implemented or a protection mechanism should be established, *e.g.*, a mechanism which can ensure that each layer has at least a certain number of convolutional filters that will not be pruned.

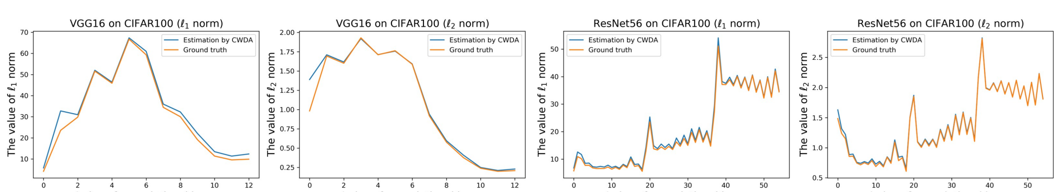


Figure 10: The magnitude of the *importance* measured by ℓ_1 and ℓ_2 criteria. The actual magnitude almost coincides with the estimation obtained by CWDA.

6 Conclusion

In this paper, we found two blind spots on pruning criteria: Similarity and Applicability. For Similarity, some primary pruning criteria can obtain very similar pruning results. For Applicability, some criteria can not distinguish the redundancy of the filters well when the number of filters is large enough. The comprehensive experiments validate these two findings, and our assumption is called CWDA. Under CWDA, these two blind spots are also discussed when using global pruning.

REFERENCES

Vijay Badrinarayanan, Alex Kendall, and Roberto Cipolla. Segnet: A deep convolutional encoder-decoder architecture for image segmentation. *IEEE transactions on pattern analysis and machine intelligence*, 39(12):2481–2495, 2017.

I Bellido and Emile Fiesler. Do backpropagation trained neural networks have normal weight distributions? In *International Conference on Artificial Neural Networks*, pp. 772–775. Springer, 1993.

Michael B Cohen, Yin Tat Lee, Gary Miller, Jakub Pachocki, and Aaron Sidford. Geometric median in nearly linear time. In *Proceedings of the forty-eighth annual ACM symposium on Theory of Computing*, pp. 9–21. ACM, 2016.

Gavin E Crooks. Survey of simple, continuous, univariate probability distributions. Technical report, Technical report, Lawrence Berkeley National Lab, 2013., 2012.

Ekin D Cubuk, Barret Zoph, Dandelion Mane, Vijay Vasudevan, and Quoc V Le. Autoaugment: Learning augmentation strategies from data. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 113–123, 2019.

Terrance DeVries and Graham W Taylor. Improved regularization of convolutional neural networks with cutout. *arXiv preprint arXiv:1708.04552*, 2017.

Xiaohan Ding, Xiangxin Zhou, Yuchen Guo, Jungong Han, Ji Liu, et al. Global sparse momentum sgd for pruning very deep neural networks. In *Advances in Neural Information Processing Systems*, pp. 6379–6391, 2019.

Xin Dong, Shangyu Chen, and Sinno Pan. Learning to prune deep neural networks via layer-wise optimal brain surgeon. In *Advances in Neural Information Processing Systems*, pp. 4857–4867, 2017.

John Duchi, Elad Hazan, and Yoram Singer. Adaptive subgradient methods for online learning and stochastic optimization. *Journal of machine learning research*, 12(Jul):2121–2159, 2011.

Bradley Efron. Student's t-test under symmetry conditions. *Journal of the American Statistical Association*, 64(328):1278–1302, 1969.

Jonathan Frankle and Michael Carbin. The lottery ticket hypothesis: Finding sparse, trainable neural networks. In *International Conference on Learning Representations*, 2019. URL `https://openreview.net/forum?id=rJl-b3RcF7`.

Xavier Glorot and Yoshua Bengio. Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, pp. 249–256, 2010.

Jinwook Go, Byungjoon Baek, and Chulhee Lee. Analyzing weight distribution of feedforward neural networks and efficient weight initialization. In *Joint IAPR International Workshops on Statistical Techniques in Pattern Recognition (SPR) and Structural and Syntactic Pattern Recognition (SSPR)*, pp. 840–849. Springer, 2004.

RL Graham. Applications of the fkg inequality and its relatives. In *Mathematical Programming The State of the Art*, pp. 115–131. Springer, 1983.

Song Han, Huizi Mao, and William J Dally. Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding. *arXiv preprint arXiv:1510.00149*, 2015.

Babak Hassibi and David G Stork. Second order derivatives for network pruning: Optimal brain surgeon. In *Advances in neural information processing systems*, pp. 164–171, 1993.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In *Proceedings of the IEEE international conference on computer vision*, pp. 1026–1034, 2015.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2016a.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Identity mappings in deep residual networks. In *European conference on computer vision*, pp. 630–645. Springer, 2016b.

Yang He, Guoliang Kang, Xuanyi Dong, Yanwei Fu, and Yi Yang. Soft filter pruning for accelerating deep convolutional neural networks. *arXiv preprint arXiv:1808.06866*, 2018.

Yang He, Ping Liu, Ziwei Wang, Zhilan Hu, and Yi Yang. Filter pruning via geometric median for deep convolutional neural networks acceleration. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 4340–4349, 2019.

Yang He, Yuhang Ding, Ping Liu, Linchao Zhu, Hanwang Zhang, and Yi Yang. Learning filter pruning criteria for deep convolutional neural networks acceleration. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 2009–2018, 2020.

Lars Hormander. *The analysis of partial differential operators*. Springer, 1983.

Hengyuan Hu, Rui Peng, Yu-Wing Tai, and Chi-Keung Tang. Network trimming: A data-driven neuron pruning approach towards efficient deep architectures. *arXiv preprint arXiv:1607.03250*, 2016.

Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 7132–7141, 2018.

Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4700–4708, 2017.

Zhongzhan Huang, Senwei Liang, Mingfu Liang, and Haizhao Yang. Dianet: Dense-and-implicit attention network. *arXiv preprint arXiv:1905.10671*, 2019.

Justin Johnson, Alexandre Alahi, and Li Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. In *European conference on computer vision*, pp. 694–711. Springer, 2016.

Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

Alex Krizhevsky. One weird trick for parallelizing convolutional neural networks. *arXiv preprint arXiv:1404.5997*, 2014.

Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

Yann LeCun, John S Denker, and Sara A Solla. Optimal brain damage. In *Advances in neural information processing systems*, pp. 598–605, 1990.

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

HyunJae Lee, Hyo-Eun Kim, and Hyeonseob Nam. Srm: A style-based recalibration module for convolutional neural networks. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 1854–1862, 2019.

Bailin Li, Bowen Wu, Jiang Su, Guangrun Wang, and Liang Lin. Eagleeye: Fast sub-net evaluation for efficient neural network pruning. *arXiv preprint arXiv:2007.02491*, 2020a.

Hao Li, Asim Kadav, Igor Durdanovic, Hanan Samet, and Hans Peter Graf. Pruning filters for efficient convnets. *arXiv preprint arXiv:1608.08710*, 2016.

Xiang Li, Xiaolin Hu, and Jian Yang. Spatial group-wise enhance: Improving semantic feature learning in convolutional networks. *arXiv preprint arXiv:1905.09646*, 2019.

Yawei Li, Shuhang Gu, Christoph Mayer, Luc Van Gool, and Radu Timofte. Group sparsity: The hinge between filter pruning and decomposition for network compression. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 8018–8027, 2020b.

Senwei Liang, Yuehaw Khoo, and Haizhao Yang. Drop-activation: Implicit parameter reduction and harmonic regularization. *arXiv preprint arXiv:1811.05850*, 2018.

Senwei Liang, Zhongzhan Huang, Mingfu Liang, and Haizhao Yang. Instance enhancement batch normalization: an adaptive regulator of batch noise. *arXiv preprint arXiv:1908.04008*, 2019.

Hubert W Lilliefors. On the kolmogorov-smirnov test for normality with mean and variance unknown. *Journal of the American statistical Association*, 62(318):399–402, 1967.

Yuchen Liu, David Wentzlaff, and SY Kung. Rethinking class-discrimination based cnn channel pruning. *arXiv preprint arXiv:2004.14492*, 2020a.

Zechun Liu, Xiangyu Zhang, Zhiqiang Shen, Zhe Li, Yichen Wei, Kwang-Ting Cheng, and Jian Sun. Joint multi-dimension pruning. *arXiv preprint arXiv:2005.08931*, 2020b.

Zhuang Liu, Jianguo Li, Zhiqiang Shen, Gao Huang, Shoumeng Yan, and Changshui Zhang. Learning efficient convolutional networks through network slimming. In *The IEEE International Conference on Computer Vision (ICCV)*, Oct 2017a.

Zhuang Liu, Jianguo Li, Zhiqiang Shen, Gao Huang, Shoumeng Yan, and Changshui Zhang. Learning efficient convolutional networks through network slimming. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 2736–2744, 2017b.

Zhuang Liu, Mingjie Sun, Tinghui Zhou, Gao Huang, and Trevor Darrell. Rethinking the value of network pruning. *arXiv preprint arXiv:1810.05270*, 2018.

Ilya Loshchilov and Frank Hutter. Sgdr: Stochastic gradient descent with warm restarts. *arXiv preprint arXiv:1608.03983*, 2016.

Jian-Hao Luo and Jianxin Wu. An entropy-based pruning method for cnn compression. *arXiv preprint arXiv:1706.05791*, 2017.

Jian-Hao Luo, Jianxin Wu, and Weiyao Lin. Thinet: A filter level pruning method for deep neural network compression. In *Proceedings of the IEEE international conference on computer vision*, pp. 5058–5066, 2017.

Sebastian Lutz, Konstantinos Amplianitis, and Aljosa Smolic. Alphagan: Generative adversarial networks for natural image matting. *arXiv preprint arXiv:1807.10088*, 2018.

Pavlo Molchanov, Stephen Tyree, Tero Karras, Timo Aila, and Jan Kautz. Pruning convolutional neural networks for resource efficient inference. *arXiv preprint arXiv:1611.06440*, 2016.

Pavlo Molchanov, Arun Mallya, Stephen Tyree, Iuri Frosio, and Jan Kautz. Importance estimation for neural network pruning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 11264–11272, 2019a.

Pavlo Molchanov, Arun Mallya, Stephen Tyree, Iuri Frosio, and Jan Kautz. Importance estimation for neural network pruning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2019b.

Radford M Neal. *BAYESIAN LEARNING FOR NEURAL NETWORKS*. PhD thesis, University of Toronto, 1995.

Rodrigo R Pescim, Clarice GB Demétrio, Gauss M Cordeiro, Edwin MM Ortega, and Mariana R Urbano. The beta generalized half-normal distribution. *Computational statistics & data analysis*, 54(4):945–957, 2010.

Boris T Polyak and Anatoli B Juditsky. Acceleration of stochastic approximation by averaging. *SIAM journal on control and optimization*, 30(4):838–855, 1992.

Aaditya Prakash, James Storer, Dinei Florencio, and Cha Zhang. Repr: Improved training of convolutional filters. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 10666–10675, 2019.

Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv preprint arXiv:1511.06434*, 2015.

Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems*, pp. 91–99, 2015.

Alex Renda, Jonathan Frankle, and Michael Carbin. Comparing fine-tuning and rewinding in neural network pruning. In *International Conference on Learning Representations*, 2020. URL `https://openreview.net/forum?id=S1gSj0NKvB`.

Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. *International journal of computer vision*, 115(3):211–252, 2015.

Andrew M Saxe, James L McClelland, and Surya Ganguli. Exact solutions to the nonlinear dynamics of learning in deep linear neural networks. *arXiv preprint arXiv:1312.6120*, 2013.

Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

Ilya Sutskever, James Martens, George Dahl, and Geoffrey Hinton. On the importance of initialization and momentum in deep learning. In *International conference on machine learning*, pp. 1139–1147, 2013.

Yuandong Tian, Tina Jiang, Qucheng Gong, and Ari Morcos. Luck matters: Understanding training dynamics of deep relu networks. *arXiv preprint arXiv:1905.13405*, 2019.

Sanghyun Woo, Jongchan Park, Joon-Young Lee, and In So Kweon. Cbam: Convolutional block attention module. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pp. 3–19, 2018.

Saining Xie, Ross Girshick, Piotr Dollár, Zhuowen Tu, and Kaiming He. Aggregated residual transformations for deep neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1492–1500, 2017.

Bing Xu, Naiyan Wang, Tianqi Chen, and Mu Li. Empirical evaluation of rectified activations in convolutional network. *arXiv preprint arXiv:1505.00853*, 2015.

Ning Xu, Brian Price, Scott Cohen, and Thomas Huang. Deep image matting. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2970–2979, 2017.

Jianbo Ye, Xin Lu, Zhe Lin, and James Z. Wang. Rethinking the smaller-norm-less-informative assumption in channel pruning of convolution layers. In *International Conference on Learning Representations*, 2018. URL `https://openreview.net/forum?id=HJ94fqApW`.

Sangdoo Yun, Dongyoon Han, Seong Joon Oh, Sanghyuk Chun, Junsuk Choe, and Youngjoon Yoo. Cutmix: Regularization strategy to train strong classifiers with localizable features. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 6023–6032, 2019.

Sergey Zagoruyko and Nikos Komodakis. Wide residual networks. *arXiv preprint arXiv:1605.07146*, 2016.

Matthew D Zeiler. Adadelta: an adaptive learning rate method. *arXiv preprint arXiv:1212.5701*, 2012.

Hengshuang Zhao, Jianping Shi, Xiaojuan Qi, Xiaogang Wang, and Jiaya Jia. Pyramid scene parsing network. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2881–2890, 2017.

A Additional study for CWDA

A.1 Is normal distribution necessary?

In this section, we use the random functions provided by NumPy[5] to generate data manually to study the influence of distribution on the similarity between Norm-based criteria. We use these distribution functions to generate 100 vectors with 50 dimensions each time. Each vector can be regarded as a convolutional filter with dimension 50.

As shown in the Table 4 (Left), we compare the Sp of these generated convolutional filters between ℓ_1, ℓ_2 and $\mathbf{GM}$ criteria. If Sp is greater than 0.9, we mark it as green. Otherwise, we mark it as red. Under these generated distribution, ℓ_1 and ℓ_2 can keep larger Sp in most cases, which indicates that they still maintain strong similarity for these distribution. But the similarity between $\mathbf{GM}$ and ℓ_1 (or ℓ_2) is relatively poor.

Table 4: The similarity when using different distribution.

Distribution	Mean	Std	ℓ_1-ℓ_2	$\mathbf{GM}$-ℓ_2	$\mathbf{GM}$-ℓ_1	Mean	Std	ℓ_1-ℓ_2	$\mathbf{GM}$-ℓ_2	$\mathbf{GM}$-ℓ_1
rand	0.50	0.29	0.94	0.31	0.03	**0.00**	0.29	0.96	0.97	0.95
randn	0.00	1.00	0.93	0.95	0.93	**0.00**	0.99	0.95	0.93	0.94
1+randn	1.00	1.00	0.95	0.63	0.51	**0.00**	1.00	0.95	0.96	0.95
beta(1,2)	0.33	0.24	0.94	0.44	0.21	**0.00**	0.23	0.96	0.97	0.96
beta(0.1,2)	0.04	0.11	0.92	0.96	0.95	**0.00**	0.12	0.95	0.97	0.98
beta(2,5)	0.28	0.15	0.96	0.70	0.49	**0.00**	0.15	0.91	0.94	0.95
chisquare(2)	2.02	2.03	0.92	0.91	0.73	**0.00**	2.01	0.97	0.95	0.94
gamma(2,0.5)	1.01	0.71	0.92	0.79	0.55	**0.00**	0.71	0.92	0.96	0.97
gamma(2,2)	3.93	2.76	0.94	0.86	0.69	**0.00**	2.73	0.91	0.96	0.96
beta(1,2)+beta(0.1,2)	0.37	0.26	0.81	0.67	0.31	**0.00**	0.26	0.81	0.91	0.96
beta(1,2)+beta(2,5)	0.61	0.27	0.93	0.44	0.17	**0.00**	0.27	0.93	0.94	0.94

If we use zero-mean normalization for the generated data X, *i.e.*, $X - \mathbb{E}X$, as shown in Table4 (Right), we also find that the Sp between these three criteria are greater than 0.9 for all distribution. This phenomenon may indicate that the normality in CWDA is not necessary for the similarity of criteria, but the zero mean is the key to the similarity.

Table 5: The similarity when using *mixed* distribution.

Distribution 1	Distribution 2	Use zero-mean?	Mean	Std	ℓ_1-ℓ_2	$\mathbf{GM}$-ℓ_2	$\mathbf{GM}$-ℓ_1
randn	randn×8		0.00	5.69	0.98	0.95	0.96
randn	rand		0.26	0.78	0.97	0.96	0.96
randn	rand	✓	0.00	0.78	0.99	0.98	0.98
randn	rand+5		2.72	2.87	0.99	-0.28	-0.24
randn	rand+5	✓	0.00	2.85	0.71	0.91	0.88
randn	log(rand)		-0.49	1.08	0.85	0.14	0.49
randn	log(rand)	✓	0.00	1.07	0.69	0.90	0.89
rand	log(rand)		-0.26	1.08	0.98	0.87	0.87
rand	log(rand)	✓	0.00	1.01	0.65	0.96	0.81

Next, we consider the *mixed* distribution, *i.e.*, as shown in Table 5, among the 100 vectors we generated, the first 50 vectors are generated by Distribution 1, and the last 50 vectors are generated by Distribution 2. There are several notable phenomena in Table 5:

(1) For the *mixed* distribution composed of two normal distribution with zero-mean but different variances, the three criteria can maintain strong similarity;

(2) In the *mixed* distribution, zero-mean normalization may not make the Sp between the three criteria stronger, which is inconsistent with the situation in Table 4.

(3) For ℓ_1 and ℓ_2, the Sp measured by the *mixed* distribution is lower than single distribution (Table 4) in general.

According to CWDA, the *mixed* distribution in phenomenon (1) actually corresponds to global pruning strategy. If CWDA holds, the distribution of parameters in different convolutional layers depends

[5] `https://docs.scipy.org/doc/numpy-1.13.0/reference/routines.random.html`

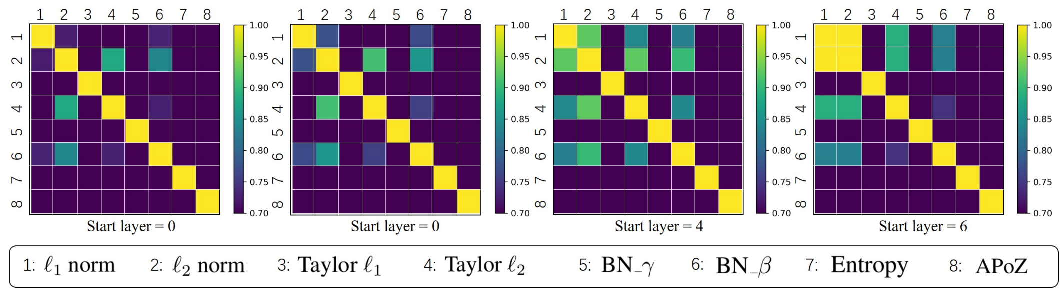


Figure 11: The similarity for different type of pruning criteria while using global pruning with different start layer.

on the variance of parameters in each layer, and these variances are generally different. Therefore, the global pruning strategy is actually to prune the convolutional filters that satisfy different Gaussian distribution. Unlike layer-wise pruning, these filters cannot be represented by a general random variable F, where $F \sim \mathbf{N}(\mathbf{0}, c^2 \cdot \mathbf{I}_{N_i \times k \times k})$. It needs to be described by a stochastic process, *i.e.*, $F_t \sim \mathbf{N}(\mathbf{0}, c^2 \cdot \mathbf{I}^{(t)}_{N_i \times k \times k})$.

According to the experiment of phenomenon (1) and CWDA, we expect that ℓ_1 and ℓ_2 should still maintain strong similarity while using the global pruning. However, as shown in Fig. 9, the Sp of ℓ_1 and ℓ_2 is not very large. This seems to contradict the experiment of phenomenon (1). In fact, however, according to the analysis in Section 9, CWDA may not hold in the first few layers of CNNs. So if these convolutional filters are also considered to be globally pruned in global pruning, then the similarity between ℓ_1 and ℓ_2 may be weakened, which is consistent with the experiment in Table 5.

To verify this statement, Fig. 11 shows the result of VGG16 via using global pruning strategy. The *Start layer* means the layer that we start to use for global pruning. For example, when *Start layer* is equal to 0, it is the general global pruning; When *Start layer* is equal to 5, the filters from the first five layers are not be considered to be pruned. In Fig. 11, we can see that, with the increase of *start layer*, the similarity between ℓ_1 and ℓ_2 becomes stronger and stronger. This shows that the similarity between ℓ_1 and ℓ_2 is not as strong as layer-wise in global pruning, which is mainly caused by the first few layers that do not satisfy CWDA.

Moreover, in phenomenon (2), global pruning is different from layer-wise pruning shown in Table 4. The zero-mean normalization may not make these pruning criteria similar. Therefore, global pruning is worthy of further studies, such as using the stochastic process to explore the similarity and the Applicability problem of different types of pruning criteria.

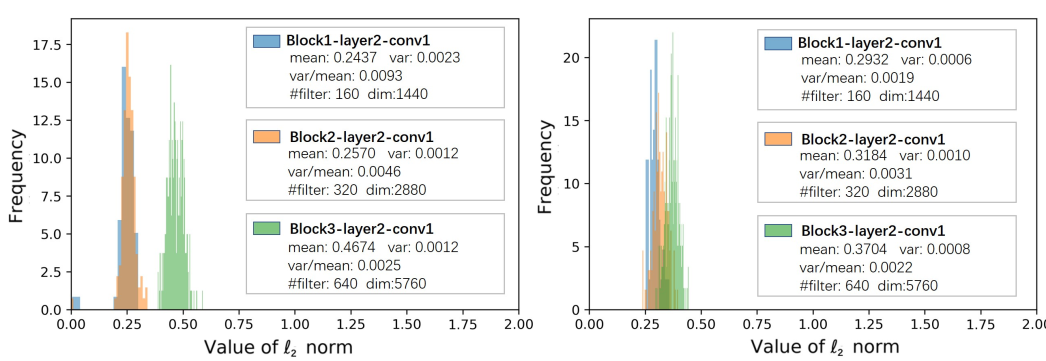


Figure 12: The distribution of ℓ_2 norm when the WRN is not trained well. Left: without data augmentation. Right: trained with uniform initialization and 6 epochs. Like the phenomenon in Fig. 1, ℓ_2 pruning still has Applicability problems when the network is not trained well.

B TRAINING THROUGH SLIMMING

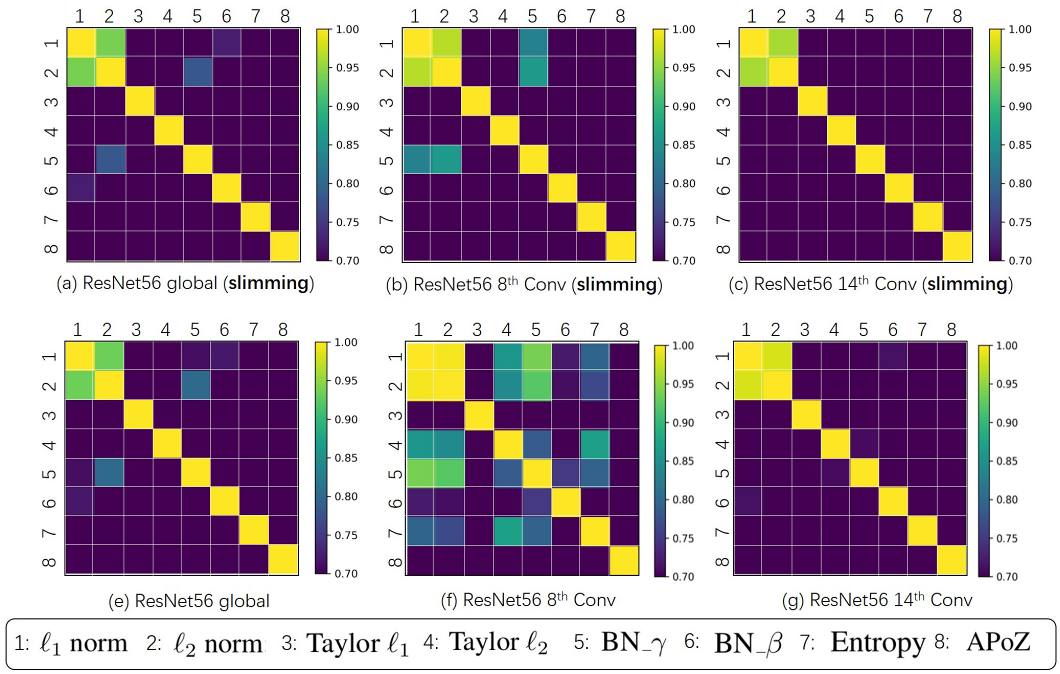
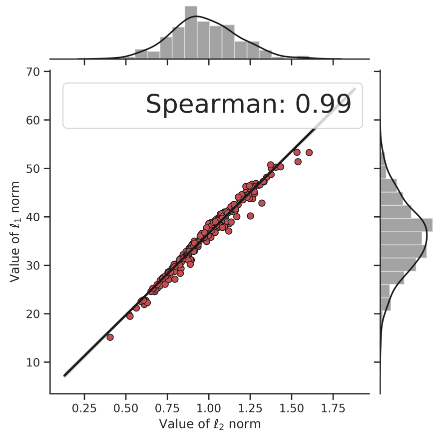


Figure 13: The Similarity for different criteria with/without slimming (Liu et al., 2017a).

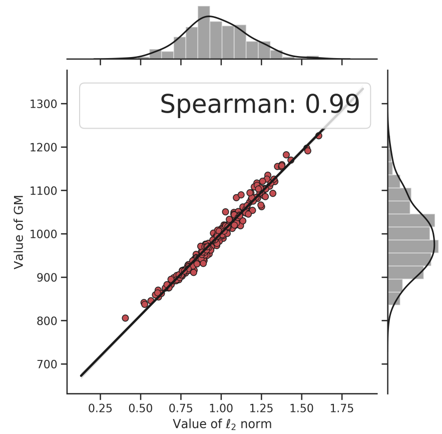
As a representative of the BN-based pruning method, slimming pruning(Liu et al., 2017a) can not be directly compared with the criteria mentioned in the paper because it adopts a special training method. Therefore, we use the training method in Liu et al. (2017a) to train another ResNet56 on cifar100. Then, the analysis of similarities between 8 different pruning criteria on such a model is shown in Fig. 13.

In this situation, the fifth criterion BN_γ is the method introduced in Liu et al. (2017a). From Fig. 13, there is no significant difference in the result of the similarity between ResNet56 obtained by slimming method and resnet56 trained in general.

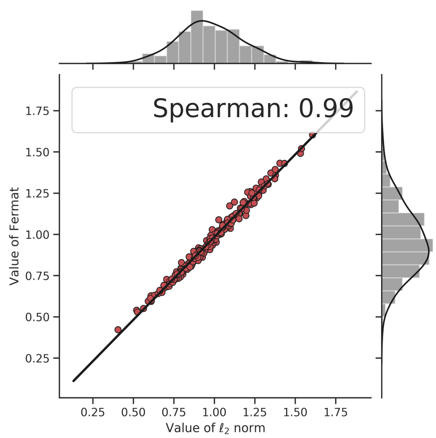
C THE RESULT OF SP



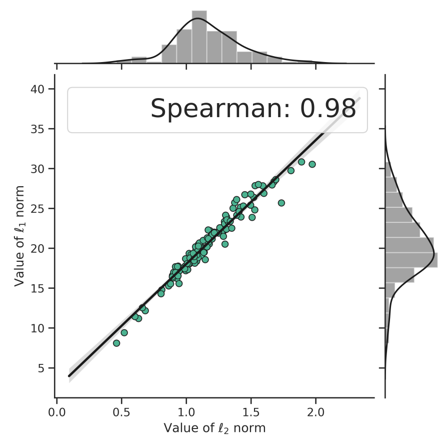
(a) Sp = 0.99



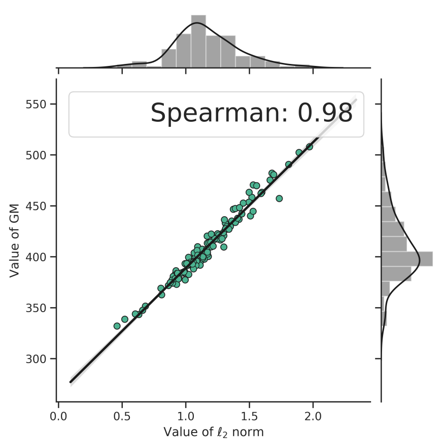
(b) Sp = 0.99



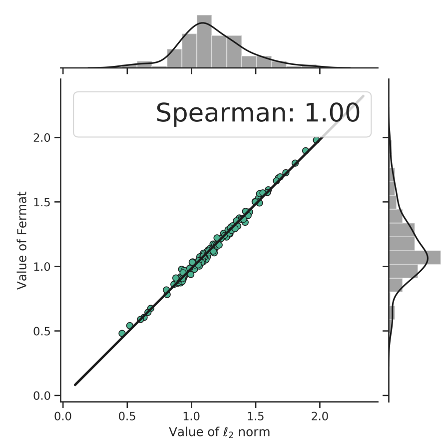
(c) Sp = 0.99



(d) Sp = 0.98



(e) Sp = 0.98



(f) Sp = 1.00

Figure 14: The Spearman's rank correlation coefficient (Sp) for different criteria. (a-c) are Sp between ℓ_1 and ℓ_2, $\mathbf{GM}$ and ℓ_2, $\mathbf{Fermat}$ and ℓ_2 from ResNet18 (12$^{\text{th}}$ Conv), respectively. The results of VGG16 (3$^{\text{rd}}$ Conv) are shown in (d-f). If the Sp of two pruning criteria is close to 1, then the sequence of their pruned filters may have strong similarity.

D OTHER RESULT

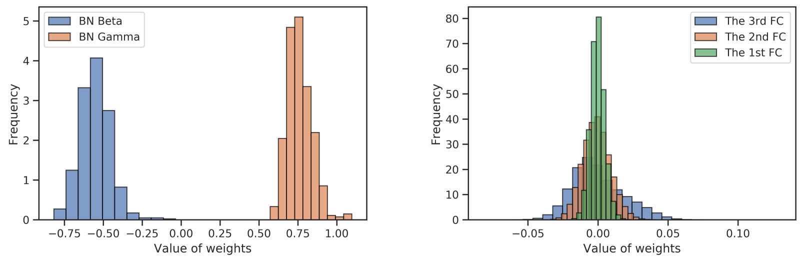


Figure 15: The distribution about other learnable parameters. (Left): The disrtibution about the learnable parameters of batch normalization. (Rihgt): The distribution of the parameters of fully-connected layers (FC). For FC, the Sp between the criteria in Table2 are greater than 0.9. More analysis can be found in Appendix A.

In Fig 15, we show the other learnable parameters (*i.e.* Batch normalization (BN) and fully connected neural network (FC)) in VGG16-BN. For BN, the distribution of its parameters does not satisfy CWDA, and similar results are shown in Liu et al. (2017a); Tian et al. (2019). Moreover, the learnable parameters of fully-connected layers also do not follow a Gaussian-alike distribution, which is consistent with the conclusion in previous work Bellido & Fiesler (1993); Neal (1995); Go et al. (2004).

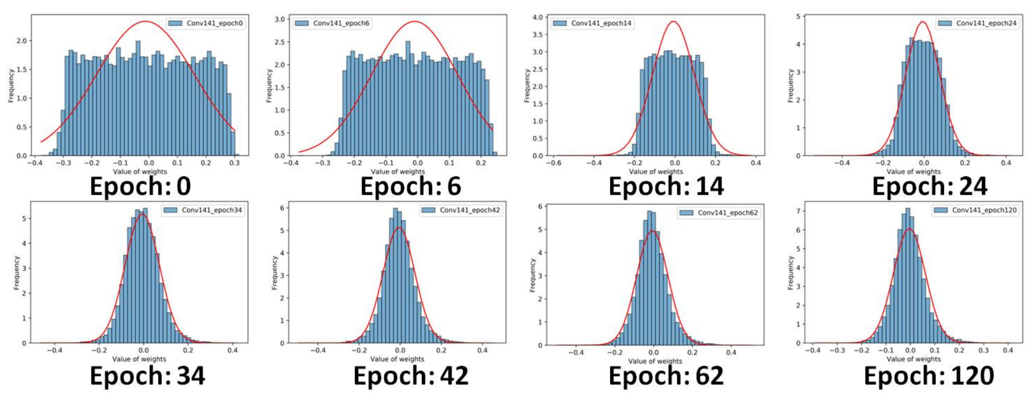


Figure 16: The distribution of the convolutional filter (141$^{\text{th}}$ Conv) with kaiming-uniform initialization for each epoch.

E AN INTERESTING CASE FOR *importance* MEASURED BY DIFFERENT CRITERIA

The following results are the index of pruned filters obtained by the filters' *importance* from different types of pruning criteria. We take VGG16 (2^{nd}) as an example. The 5^{th} filter in this layer is regarded as a redundant convolutional filter for APoZ criterion, but other criteria consider it to be almost the most important.

Taylor ℓ_1: [27, 36, 25, 11, 6, 23, 24, 16, 0, 57, 48, 53, 1, 61, 18, 55, 34, 15, 51, 58, 31, 3, 12, 21, 59, 30, 7, 38, 41, 50, 10, 33, 17, 46, 62, 13, 49, 43, 42, 47, 2, 32, 44, 20, 39, 52, 56, 40, 9, 26, 37, 22, 29, 54, 60, 8, 14, 45, 4, 63, 19, 35, 28, **5**]

Taylor ℓ_2: [23, 32, 36, 11, 62, 16, 30, 59, 10, 13, 2, 50, 38, 0, 46, 43, 21, 26, 15, 22, 7, 51, 39, 33, 14, 58, 9, 40, 57, 6, 61, 44, 20, 48, 3, 53, 41, 56, 17, 12, 18, 31, 4, 1, 25, 19, 63, 24, 54, 45, 52, 37, 55, 47, 34, 35, 8, 29, 42, 27, 49, 28, 60, **5**]

BN_β: [52, 46, 32, 21, 14, 29, 17, 0, 19, 36, 1, 51, 44, 40, 41, 60, 57, 27, 22, 53, 63, 8, 30, 26, 23, 58, 39, 18, 9, 47, 31, 35, 11, 37, 55, 45, 3, 61, 6, 4, 33, 25, 15, 48, 43, 28, 56, 2, 13, 16, 34, 20, 59, 10, 7, 24, 50, 62, 12, 49, 38, 42, **5**, 54]

APoZ: [**5**, 10, 38, 42, 62, 24, 13, 12, 7, 28, 59, 15, 23, 11, 16, 56, 34, 35, 57, 19, 2, 49, 43, 25, 6, 63, 61, 36, 9, 27, 33, 20, 48, 58, 55, 18, 51, 31, 1, 0, 53, 37, 26, 29, 47, 60, 8, 44, 41, 46, 21, 17, 14, 32, 52, 22, 39, 3, 40, 30, 4, 45, 50, 54]

F RELATED PROPOSITION

Proposition 1 (Amoroso distribution)**.** *The Amoroso distribution is a four parameter, continuous, univariate, unimodal probability density, with semi-infinite range (Crooks, 2012). And its probability density function is*

$$\mathbf{Amoroso}(X|a,\theta,\alpha,\beta) = \frac{1}{\Gamma(\alpha)}|\frac{\beta}{\theta}|(\frac{X-a}{\theta})^{\alpha\beta-1}\exp\left\{-(\frac{X-a}{\theta})^{\beta}\right\}, \tag{4}$$

for $x, a, \theta, \alpha, \beta \in \mathbb{R}, \alpha > 0$ and range $x \geq a$ if $\theta > 0$, $x \leq a$ if $\theta < 0$. The mean and variance of Amoroso distribution are

$$\mathbb{E}_{X\sim\mathbf{Amoroso}(X|a,\theta,\alpha,\beta)}X = a + \theta \cdot \frac{\Gamma(\alpha+\frac{1}{\beta})}{\Gamma(\alpha)}, \tag{5}$$

and

$$\mathbf{Var}_{X\sim\mathbf{Amoroso}(X|a,\theta,\alpha,\beta)}X = \theta^2\left[\frac{\Gamma(\alpha+\frac{2}{\beta})}{\Gamma(\alpha)} - \frac{\Gamma(\alpha+\frac{1}{\beta})^2}{\Gamma(\alpha)^2}\right]. \tag{6}$$

Proposition 2 (Half-normal distribution)**.** *Let random variable X follow a normal distribution $N(0,\sigma^2)$, then $Y = |X|$ follows a half-normal distribution (Pescim et al., 2010). Moreover, Y also follows $\mathbf{Amoroso}(x|0,\sqrt{2}\sigma,\frac{1}{2},2)$. By Eq. (5) and Eq. (6), the mean and variance of half-normal distribution are*

$$\mathbb{E}_{X\sim N(0,\sigma^2)}|X| = \sigma\sqrt{2/\pi}, \tag{7}$$

and

$$\mathbf{Var}_{X\sim N(0,\sigma^2)}|X| = \sigma^2\left(1-\frac{2}{\pi}\right). \tag{8}$$

Proposition 3 (Scaled Chi distribution)**.** *Let $X = (x_1, x_2, ...x_k)$ and $x_i, i = 1, ..., k$ are k independent, normally distributed random variables with mean 0 and standard deviation σ. The statistic $\ell_2(X) = \sqrt{\sum_{i=1}^{k} x_i^2}$ follows Scaled Chi distribution (Crooks, 2012). Moreover, $\ell_2(X)$ also follows $\mathbf{Amoroso}(x|0,\sqrt{2}\sigma,\frac{k}{2},2)$. By Eq. (5) and Eq. (6), the mean and variance of Scaled Chi distribution are*

$$\mathbb{E}_{X\sim N(\mathbf{0},\sigma^2\cdot\mathbf{I_k})}[\ell_2(X)]^j = 2^{j/2}\sigma^j \cdot \frac{\Gamma(\frac{k+j}{2})}{\Gamma(\frac{k}{2})}, \tag{9}$$

and

$$\mathbf{Var}_{X\sim N(\mathbf{0},\sigma^2\cdot\mathbf{I_k})}\ell_2(X) = 2\sigma^2\left[\frac{\Gamma(\frac{k}{2}+1)}{\Gamma(\frac{k}{2})} - \frac{\Gamma(\frac{k+1}{2})^2}{\Gamma(\frac{k}{2})^2}\right]. \tag{10}$$

G PROOF OF THEOREM 1

Theorem 1. Let $X \sim N(\mathbf{0}, c^2\cdot\mathbf{I}_n)$ and (C_1, C_2) is one of (ℓ_1, ℓ_2), $(\ell_1, \mathbf{Fermat})$ or $(\mathbf{Fermat}, \mathbf{GM})$, we have

$$\mathbf{max}\left\{\mathbf{Var}_X\left(\frac{\widehat{C}_2(X)}{\widehat{C}_1(X)}\right), \mathbf{Var}_X\left(\frac{\widehat{C}_1(X)}{\widehat{C}_2(X)}\right)\right\} \lesssim B(n). \tag{11}$$

where $\widehat{C}_1(X)$ denotes $C_1(X)/\mathbb{E}(C_1(X))$ and $\widehat{C}_2(X)$ denotes $C_2(X)/\mathbb{E}(C_2(X))$. $B(n)$ denotes the upper bound of left-hand side and when n is large enough, $B(n) \to 0$.

For i_{th} layer, we use v_j to represent F_{ij}, $j = 1, 2, ...N$. And v_j meets CWDA (*i.e.*, v_j are i.i.d and $v_j \sim N(0, c^2\cdot\mathbf{I})$). Actually, from the theoretical analysis in Section 3, the fact that two criteria C_1 and C_2 meet Eq.11 is equivalent to $C_1 \cong C_2$.

(1) For (ℓ_2, ℓ_1). In fact, $\ell_2 \cong \ell_1$ (their importance rankings are similar) is not trivial. Generally speaking, for convolutional filters, $\mathbf{dim}(v_j)$ is large enough. Since v_i satisfies CWDA, from Theorem 2, we know that the variance of ratio between $\widehat{\ell_1}$ and $\widehat{\ell_2}$ have a bound $O(\mathbf{dim}(v_j)^{-1})$, which means ℓ_2 and ℓ_1 are *appropriate monotonic*. Specific numerical validation is shown in Fig. 17 of Appendix H).

Theorem 2. *Let* $X \sim N(\mathbf{0}, c^2 \cdot \mathbf{I}_n)$, *we have*

$$\mathbf{max}\left\{\mathbf{Var}_X\left(\frac{\widehat{\ell_2}(X)}{\widehat{\ell_1}(X)}\right), \mathbf{Var}_X\left(\frac{\widehat{\ell_1}(X)}{\widehat{\ell_2}(X)}\right)\right\} \lesssim \frac{1}{n}. \tag{12}$$

where $\widehat{\ell_1}(X)$ *denotes* $\ell_1(X)/\mathbb{E}(\ell_1(X))$ *and* $\widehat{\ell_2}(X)$ *denotes* $\ell_2(X)/\mathbb{E}(\ell_2(X))$.

Proof. (See Appendix H). □

(2) For $(\ell_1, \mathbf{Fermat})$. Since v_i satisfies CWDA, from Theorem 3, we know that the Fermat point of v_i and the origin $\mathbf{0}$ approximately coincide. According to Table 2, $||\mathbf{Fermat} - v_i||_2 \approx ||\mathbf{0} - v_i||_2 = ||v_i||_2$. Therefore, from Theorem 2, the bound $B(n)$ for the (ℓ_1, $\mathbf{Fermat}$) is also $\frac{1}{n}$. Moreover, since CWDA, the centroid of v_i is $\mathbf{G} = \frac{1}{n}\sum_{i=1}^{N} v_i = \mathbf{0}$. Hence,

$$\mathbf{G} = \mathbf{0} \approx \mathbf{Fermat}. \tag{13}$$

Theorem 3. *Let random variable* $v_i \in \mathbb{R}^k$ *and they are i.i.d and follow normal distribution* $N(\mathbf{0}, \sigma\mathbf{I}_k)$. *For* $F \in \mathbb{R}^k$, *we have* $\mathbf{argmin}_F \left\{\mathbb{E}_{v_i \sim N(\mathbf{0},\sigma\mathbf{I}_k)} \sum_{i=1}^{n} ||F - v_i||_2\right\} = \mathbf{0}$.

Proof. (See Appendix I). □

(3) For $(\mathbf{GM}, \mathbf{Fermat})$. First, we show the following two theorems:

Theorem 4. *For* n *random variables* $a_i \in \mathbb{R}^k$ *follow* $N(\mathbf{0}, c^2 \cdot \mathbf{I}_k)$.*When* k *is large enough, we have such an estimation:*

$$\mathbf{Var}_{a_i}\frac{F_1(a_i)}{F_2(a_i)} \approx \frac{1}{2nk}, \quad \mathbf{Var}_{a_i}\frac{F_2(a_i)}{F_1(a_i)} \approx \frac{1}{2nk}, \tag{14}$$

where $F_1(a_i) = \sum_{i=1}^{n} ||a_i||_2/\mathbb{E}(\sum_{i=1}^{n} ||a_i||_2)$ *and* $F_2(a_i) = \sum_{i=1}^{n} ||a_i||_2^2/\mathbb{E}(\sum_{i=1}^{n} ||a_i||_2^2)$.

Proof. (See Appendix J). □

Theorem 5. *Let* $v_0, v_1, ..., v_k$ *be the* $k+1$ *vectors in* n *dimensional Euclidean space* $\mathbb{E}^n$. *For all* P *in* $\mathbb{E}^n$,

$$\sum_{i=0}^{k} ||P - v_i||_2^2 = \sum_{i=0}^{k} ||G - v_i||_2^2 + (k+1)||P - G||_2^2, \tag{15}$$

where G *is the centroid of* v_i, *will hold if it satisfies one of the following conditions:*

(1)if $k \geq n$ *and* $\mathbf{rank}(v_1 - v_0, v_2 - v_0, ..., v_k - v_0) = n$.

(2)if $k < n$ *and* $(v_1 - v_0, v_2 - v_0, ..., v_k - v_0)$ *are linearly independent.*

(3)if $v_i \sim N(\mathbf{0}, c^2 \cdot \mathbf{I}_n)$, *Eq.(15) holds with probability 1.*

Proof. (See Appendix K). □

Let $P \in \{v_1, v_2, ..., v_N\}$. Since $v_i \sim N(\mathbf{0}, c^2 \cdot \mathbf{I})$, we can obtain that $a_i = P - v_i \sim N(\mathbf{0}, 2c^2 \cdot \mathbf{I})$ if $P \neq v_i$. According to the analysis in Section 3 and Theorem 4, we have

$$\sum_{i=1}^{n} ||a_i||_2 \cong \sum_{i=1}^{n} ||a_i||_2^2, \tag{16}$$

Next, we can prove $(k+1)||P-F||_2^2$ (**Fermat**) and $\sum_{i=1}^{N}||P-v_i||_2$ (**GM**) are *approximately monotonic*, where $P \in \{v_1, v_2, ..., v_N\}$.

$$\begin{aligned}
(k+1)||P-F||_2^2 &\cong (k+1)||P-G||_2^2 && \text{Since Eq. (13)} \\
&= \sum_{i=1}^{N}||P-v_i||_2^2 - \sum_{i=1}^{N}||G-v_i||_2^2 && \text{Since Theorem 5} \\
&\cong \sum_{i=1}^{N}||P-v_i||_2 - \sum_{i=1}^{N}||G-v_i||_2^2 && \text{Since Eq. (16)} \\
&\cong \sum_{i=1}^{N}||P-v_i||_2 && (17)
\end{aligned}$$

The reason for the last equation is that $\sum_{i=1}^{N}||G-v_i||_2^2$ is a constant for given v_i.

H PROOF OF THEOREM 2

Proposition 4 (Stirling's formula). [6] *For big enough x and $x \in \mathbb{R}^+$, we have an approximation of Gamma function:*

$$\Gamma(x+1) \approx \sqrt{2\pi x}\left(\frac{x}{e}\right)^x. \tag{18}$$

Proposition 5 (FKG inequality). *If f and g are increasing functions on $\mathbb{R}^n$ (Graham, 1983), we have*

$$\mathbb{E}(f)\mathbb{E}(g) \leq \mathbb{E}(fg). \tag{19}$$

Say that a function on $\mathbb{R}^n$ is increasing if it is an increasing function in each of its arguments.(i.e., for fixed values of the other arguments).

Proposition 6. *Let $f(X,Y)$ is a two dimensional differentiable function. According to Taylor theorem (Hormander, 1983), we have*

$$f(X,Y) = f(\mathbb{E}(X),\mathbb{E}(Y)) + \sum_{cyc}(X-\mathbb{E}(X))\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y)) + Remainder1, \tag{20}$$

$$\begin{aligned}
f(X,Y) = f(\mathbb{E}(X),\mathbb{E}(Y)) + \sum_{cyc}(X-\mathbb{E}(X))\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y)) + \\
\frac{1}{2}\sum_{cyc}(X-\mathbb{E}(X))^T\frac{\partial^2}{\partial X^2}f(\mathbb{E}(X),\mathbb{E}(Y))(X-\mathbb{E}(X)) + Remainder2
\end{aligned} \tag{21}$$

Lemma 1. *Let X and Y are random variables. Then we have such an estimation*

$$\mathbf{Var}\left(\frac{X}{Y}\right) \approx \left(\frac{\mathbb{E}(X)}{\mathbb{E}(Y)}\right)^2\left(\frac{\mathbf{Var}X}{\mathbb{E}(X)^2} + \frac{\mathbf{Var}Y}{\mathbb{E}(Y)^2} - 2\frac{\mathbf{Cov}(X,Y)}{\mathbb{E}(X)\mathbb{E}(Y)}\right). \tag{22}$$

[6] `en.wikipedia.org/wiki/Stirling'sapproximation`

Proof. Let $f(X,Y) = X/Y$, according to the definition of variance, we have

$$
\begin{aligned}
\mathbf{Var} f(X,Y) &= \mathbb{E}[f(X,Y) - \mathbb{E}(f(X,Y))]^2 \\
&\approx \mathbb{E}[f(X,Y) - \mathbb{E}\left\{ f(\mathbb{E}(X),\mathbb{E}(Y)) + \sum_{cyc}(X-\mathbb{E}(X))\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y)) \right\}]^2 \\
&\qquad \text{from Eq. (20)} \\
&= \mathbb{E}[f(X,Y) - f(\mathbb{E}(X),\mathbb{E}(Y)) - \sum_{cyc}\mathbb{E}(X-\mathbb{E}(X))\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y))]^2 \\
&= \mathbb{E}[f(X,Y) - f(\mathbb{E}(X),\mathbb{E}(Y))]^2 \\
&\approx \mathbb{E}[\sum_{cyc}(X-\mathbb{E}(X))\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y))]^2 \qquad \text{from Eq. (20)} \\
&= 2\mathbf{Cov}(X,Y)\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y))\frac{\partial}{\partial Y}f(\mathbb{E}(X),\mathbb{E}(Y)) + \sum_{cyc}[\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y))]^2 \cdot \mathbf{Var}X \\
&= 2\mathbf{Cov}(X,Y)\cdot\frac{1}{\mathbb{E}(Y)}\cdot\left(-\frac{\mathbb{E}(X)}{(\mathbb{E}(Y))^2}\right) + \frac{1}{(\mathbb{E}(Y))^2}\cdot\mathbf{Var}X + \frac{(\mathbb{E}X)^2}{(\mathbb{E}Y)^4}\cdot\mathbf{Var}Y \\
&= \left(\frac{\mathbb{E}(X)}{\mathbb{E}(Y)}\right)^2\left(\frac{\mathbf{Var}X}{\mathbb{E}(X)^2} + \frac{\mathbf{Var}Y}{\mathbb{E}(Y)^2} - 2\frac{\mathbf{Cov}(X,Y)}{\mathbb{E}(X)\mathbb{E}(Y)}\right).
\end{aligned}
$$

□

Lemma 2. *For big enough x and $x \in \mathbb{R}^+$, we have*

$$
\lim_{x\to+\infty}\left[\frac{\Gamma(\frac{x+1}{2})}{\Gamma(\frac{x}{2})}\right]^2\cdot\frac{1}{x} = \frac{1}{2}. \tag{23}
$$

And

$$
\lim_{x\to+\infty}\frac{\Gamma(\frac{x}{2}+1)}{\Gamma(\frac{x}{2})} - \left[\frac{\Gamma(\frac{x+1}{2})}{\Gamma(\frac{x}{2})}\right]^2 = \frac{1}{4}. \tag{24}
$$

Proof.

$$
\begin{aligned}
\lim_{x\to+\infty}\left[\frac{\Gamma(\frac{x+1}{2})}{\Gamma(\frac{x}{2})}\right]^2\cdot\frac{1}{x} &\approx \lim_{x\to+\infty}\left(\frac{\sqrt{2\pi(\frac{x-1}{2})}\cdot(\frac{x-1}{2e})^{\frac{x-1}{2}}}{\sqrt{2\pi(\frac{x-2}{2})}\cdot(\frac{x-2}{2e})^{\frac{x-2}{2}}}\right)^2\cdot\frac{1}{x} \qquad \text{from Proposition. 4} \\
&= \lim_{x\to+\infty}\left(\frac{x-1}{x-2}\right)\cdot\frac{(\frac{x-1}{2e})^{x-2}}{(\frac{x-2}{2e})^{x-2}}\cdot\left(\frac{x-1}{2e}\right)\cdot\frac{1}{x} \\
&= \lim_{x\to+\infty}\left(1+\frac{1}{x-2}\right)^{x-2}\cdot\frac{x-1}{x-2}\cdot\frac{x-1}{2e}\cdot\frac{1}{x} \\
&= \frac{1}{2}
\end{aligned}
$$

on the other hand, we have

$$
\begin{aligned}
\lim_{x\to+\infty}\frac{\Gamma(\frac{x}{2}+1)}{\Gamma(\frac{x}{2})} - \left[\frac{\Gamma(\frac{x+1}{2})}{\Gamma(\frac{x}{2})}\right]^2 &= \lim_{x\to+\infty}\frac{x}{2} - \left(1+\frac{1}{x-2}\right)^{x-2}\cdot\frac{x-1}{x-2}\cdot\frac{x-1}{2e} \\
&= \lim_{x\to+\infty}\frac{x}{2e}\left(e-(1+\frac{1}{x})^x\right) \\
&= \frac{1}{2}\left(-\frac{\frac{1}{e}(-e)}{2}\right) \\
&= \frac{1}{4}
\end{aligned}
$$

$\square$

Theorem 2 Let $X \sim N(\mathbf{0}, c^2 \cdot \mathbf{I}_n)$, we have

$$\mathbf{max}\left\{\mathbf{Var}_X\left(\frac{\widehat{\ell}_2(X)}{\widehat{\ell}_1(X)}\right), \mathbf{Var}_X\left(\frac{\widehat{\ell}_1(X)}{\widehat{\ell}_2(X)}\right)\right\} \lesssim \frac{1}{n}.$$

where $\widehat{\ell}_1(X)$ denotes $\ell_1(X)/\mathbb{E}(\ell_1(X))$ and $\widehat{\ell}_2(X)$ denotes $\ell_2(X)/\mathbb{E}(\ell_2(X))$.

Proof. For the ratio $\widehat{\ell}_2(X)/\widehat{\ell}_1(X)$, we have

$$\begin{aligned}
\mathbf{Var}\left(\frac{\widehat{\ell}_2(X)}{\widehat{\ell}_1(X)}\right) &= \left(\frac{\mathbb{E}(\ell_1(X))}{\mathbb{E}(\ell_2(X))}\right)^2 \mathbf{Var}\left(\frac{\widehat{\ell}_2(X)}{\widehat{\ell}_1(X)}\right) \\
&\approx \left(\frac{\mathbb{E}(\ell_1(X))}{\mathbb{E}(\ell_2(X))}\right)^2 \left(\frac{\mathbb{E}(\ell_2(X))}{\mathbb{E}(\ell_1(X))}\right)^2 \left(\frac{\mathbf{Var}\ell_2(X)}{\mathbb{E}(\ell_2(X))^2} + \frac{\mathbf{Var}\ell_1(X)}{\mathbb{E}(\ell_1(X))^2} - 2\frac{\mathbf{Cov}(\ell_2(X), \ell_1(X))}{\mathbb{E}(\ell_2(X))\mathbb{E}(\ell_1(X))}\right) \\
&\qquad \text{from Lemma. 1} \\
&\leq \left(\frac{\mathbf{Var}\ell_2(X)}{\mathbb{E}(\ell_2(X))^2} + \frac{\mathbf{Var}\ell_1(X)}{\mathbb{E}(\ell_1(X))^2}\right). \qquad \text{from Proposition. 5}
\end{aligned}$$

similarly, we also have

$$\mathbf{Var}\left(\frac{\widehat{\ell}_1(X)}{\widehat{\ell}_2(X)}\right) \leq \left(\frac{\mathbf{Var}\ell_2(X)}{\mathbb{E}(\ell_2(X))^2} + \frac{\mathbf{Var}\ell_1(X)}{\mathbb{E}(\ell_1(X))^2}\right). \tag{25}$$

Therefore,

$$\begin{aligned}
\mathbf{max}\left\{\mathbf{Var}_X\left(\frac{\widehat{\ell}_2(X)}{\widehat{\ell}_1(X)}\right), \mathbf{Var}_X\left(\frac{\widehat{\ell}_1(X)}{\widehat{\ell}_2(X)}\right)\right\} &\leq \left(\frac{\mathbf{Var}\ell_2(X)}{\mathbb{E}(\ell_2(X))^2} + \frac{\mathbf{Var}\ell_1(X)}{\mathbb{E}(\ell_1(X))^2}\right) \\
&= \frac{2\sigma^2\left[\frac{\Gamma(\frac{n}{2}+1)}{\Gamma(\frac{n}{2})} - \frac{\Gamma(\frac{n+1}{2})^2}{\Gamma(\frac{n}{2})^2}\right]}{(\sqrt{2}\sigma \cdot \frac{\Gamma(\frac{n+1}{2})}{\Gamma(\frac{n}{2})})^2} + \frac{\sigma^2\left(1 - \frac{2}{\pi}\right)n}{(n \cdot \sigma\sqrt{2/\pi})^2} \\
&\qquad \text{from Proposition. 3 and 2} \\
&\approx \left(\frac{1}{2n} + (\frac{\pi}{2} - 1)\frac{1}{n}\right) \qquad \text{from Lemma 2} \\
&= \frac{\pi - 1}{2n}
\end{aligned}$$

$\square$

Because the approximation is widely used in the proof of Theorem 1, it is necessary to verify it numerically. As shown in Fig. 17, we use ResNet56 on Cifar100 and ResNet110 on Cifar10 respectively to verify Theorem 1. From Fig. 17, we find that the estimationn of Theorem 1 is reliable, *i.e.*, the estimation $O(\frac{1}{n})$ for $\mathbf{max}\left\{\mathbf{Var}_X\left(\frac{\widehat{\ell}_2(X)}{\widehat{\ell}_1(X)}\right), \mathbf{Var}_X\left(\frac{\widehat{\ell}_1(X)}{\widehat{\ell}_2(X)}\right)\right\}$ is appropriate.

I PROOF OF THEOREM 3

Proposition 7. *Let $L_p^{(\alpha)}(x)$ denotes generalized Laguerre function, and it have following properties:*

$$\frac{\partial^n}{\partial x^n} L_p^{(\alpha)} = (-1)^n L_{p-n}^{(\alpha+n)}(x), \tag{26}$$

and for $\alpha > 0$,

$$L_{-\frac{1}{2}}^{(\alpha)}(x) > 0. \tag{27}$$

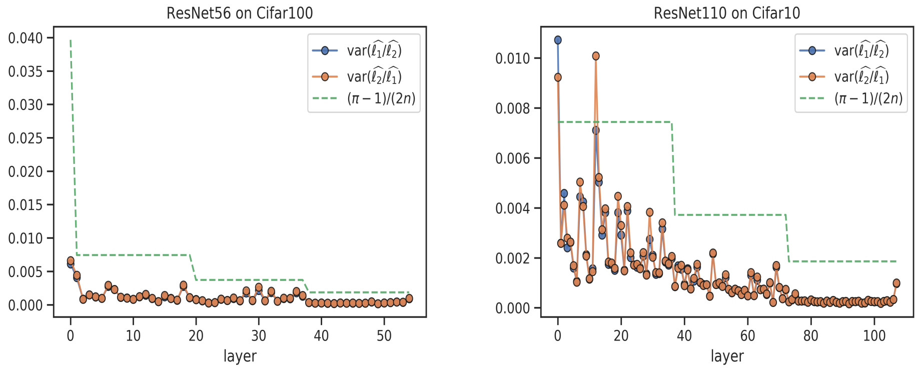


Figure 17: The approximation of **Theorem 2**: (Left) the example about ResNet56; (Right) the example about ResNet110.

Theorem 3. Let random variable $v_i \in \mathbb{R}^k$. They are i.i.d and follow normal distribution $N(\mathbf{0}, \sigma^2\mathbf{I}_k)$. For F in $\mathbb{R}^k$, we have

$$\mathbf{argmin}_F \left\{ \mathbb{E}_{v_i \sim N(\mathbf{0},\sigma^2\mathbf{I}_k)} \sum_{i=1}^{n} ||F - v_i||_2 \right\} = \mathbf{0}.$$

Proof. Let $w_i = F - v_i$ and we have $w_i \sim N(F, \sigma^2\mathbf{I}_k)$, then

$$\begin{aligned} \mathbb{E}_{v_i \sim N(\mathbf{0},\sigma^2\mathbf{I}_k)} \sum_{i=1}^{n} ||F - v_i||_2 &= \sum_{i=1}^{n} \mathbb{E}_{v_i \sim N(\mathbf{0},\sigma^2\mathbf{I}_k)} ||F - v_i||_2 \\ &= \sum_{i=1}^{n} \mathbb{E}_{w_i \sim N(F,\sigma^2\mathbf{I}_k)} ||w_i||_2 \\ &= n \cdot \sigma^2 \sqrt{\frac{\pi}{2}} \cdot L_{\frac{1}{2}}^{(\frac{k}{2}-1)} \left(-\frac{||F||_2^2}{2\sigma^2} \right) \end{aligned}$$

The reason for the last equation is that $||w_i||_2$ follows scaled noncentral chi distribution[7] when $w_i \sim N(F, \sigma^2\mathbf{I}_k)$. Let $T(x) = L_{\frac{1}{2}}^{(\frac{k}{2}-1)} \left(-\frac{x^2}{2\sigma^2} \right)$, we calculate the minimum of $T(x)$. From Eq. (26),

$$\frac{d}{dx} T(x) = \frac{x}{\sigma^2} \cdot L_{-\frac{1}{2}}^{(\frac{k}{2})} \left(-\frac{x^2}{2\sigma^2} \right). \tag{28}$$

Since Eq. (27), we find that $\frac{d}{dx}T(x) > 0$ when $x > 0$ and if $x \leq 0$, then $\frac{d}{dx}T(x) \leq 0$. It means that $T(x)$ gets the minimizer at $||F||_2 = 0$, *i.e.*, $F = \mathbf{0}$.

$\square$

J Proof of Theorem 4

Lemma 3. *For two random variables $X, Y \in \mathbb{R}^k$ follow $N(\mathbf{0}, c^2 \cdot \mathbf{I}_k)$ and they are i.i.d. When k is large enough, we have:*

$$\mathbb{E} \left(\frac{(||X||_2^2 - ||Y||_2^2)^2}{2||X||_2 \cdot ||Y||_2} \right) \approx 2c^2 + \frac{4c^2k + 1}{2k^2}, \tag{29}$$

and

$$\mathbf{Var} \left(\frac{(||X||_2^2 - ||Y||_2^2)^2}{2||X||_2 \cdot ||Y||_2} \right) \lesssim 8c^4 + \frac{16c^4k + c^2}{k^2}, \tag{30}$$

[7] Survey of simple,continuous,uniariate probability distribution and Wikipredia.

Proof. According to **Proposition 3** and **Lemma 2**, it is easy to know (similar method in Eq.(86)), when k is large enough, that

$$\mathbb{E}\left(2||X||_2 \cdot ||Y||_2\right) = 2c^2k, \quad \mathbf{Var}\left(2||X||_2 \cdot ||Y||_2\right) = c^2 + 4c^4k, \tag{31}$$

and

$$\mathbb{E}\left((||X||_2^2 - ||Y||_2^2)^2\right) = 4c^4k, \quad \mathbf{Var}\left((||X||_2^2 - ||Y||_2^2)^2\right) = 16c^8(2k^2 + 3k). \tag{32}$$

Since Lemma 1, we have an estimation

$$\begin{aligned}
\mathbf{Var}\left(\frac{(||X||_2^2 - ||Y||_2^2)^2}{2||X||_2 \cdot ||Y||_2}\right) &\leq \left(\frac{\mathbb{E}(||X||_2^2 - ||Y||_2^2)^2}{\mathbb{E}2||X||_2 \cdot ||Y||_2}\right)^2 \left(\frac{\mathbf{Var}(||X||_2^2 - ||Y||_2^2)^2}{\mathbb{E}(||X||_2^2 - ||Y||_2^2)^2} + \frac{\mathbf{Var}(2||X||_2 \cdot ||Y||_2)^2)}{\mathbb{E}(2||X||_2 \cdot ||Y||_2)^2}\right) \\
&\approx \left(\frac{4c^4k}{2c^2k}\right)^2 \cdot \left(\frac{c^2 + 4c^4k}{4c^4k} + \frac{16c^8(2k^2+3k)}{16c^8k^2}\right) \\
&\qquad \text{Since Eq.(31) and Eq.(32)} \\
&= 8c^4 + \frac{16c^4k + c^2}{k^2}.
\end{aligned}$$

From Eq.(21) and **Lemma 1**, we also can obtain an estimation of $\mathbb{E}(\mathbf{A}/\mathbf{B})$, where $\mathbf{A}$ and $\mathbf{B}$ are two random variables. *i.e.*,

$$\mathbb{E}\left(\frac{\mathbf{A}}{\mathbf{B}}\right) \approx \frac{\mathbb{E}\mathbf{A}}{\mathbb{E}\mathbf{B}} + \mathbf{Var}(\mathbf{B}) \cdot \frac{\mathbb{E}\mathbf{A}}{(\mathbb{E}\mathbf{B})^3}. \tag{33}$$

Therefore,

$$\begin{aligned}
\mathbb{E}\left(\frac{(||X||_2^2 - ||Y||_2^2)^2}{2||X||_2 \cdot ||Y||_2}\right) &\approx \frac{\mathbb{E}(||X||_2^2 - ||Y||_2^2)^2}{\mathbb{E}2||X||_2 \cdot ||Y||_2} + \mathbf{Var}(2||X||_2 \cdot ||Y||_2) \cdot \frac{\mathbb{E}(||X||_2^2 - ||Y||_2^2)^2}{(\mathbb{E}2||X||_2 \cdot ||Y||_2)^3} \\
&\qquad \text{Since Eq.(33)} \\
&\approx \frac{4c^4k}{2c^2k} + \frac{4c^4k}{8c^6k^3} \cdot (c^2 + 4c^4k) \qquad \text{Since Eq.(31) and Eq.(32)} \\
&= 2c^2 + \frac{4c^2k + 1}{2k^2}.
\end{aligned}$$

□

Note that, the approximation is widely used in the proof of Eq.(29) and Eq.(30). Hence, it is also necessary to verify it numerically. As shown in Fig. 18, the estimation is appropriate. According to **Lemma** 3, the mathematical expectation and variance of the ratio of $(||X||_2^2 - ||Y||_2^2)^2$ and $2||X||_2 \cdot ||Y||_2$ are both close to 0 when k is large enough and c is small enough. that is,

$$2(||X||_2 \cdot ||Y||_2) \gg (||X||_2^2 - ||Y||_2^2)^2. \tag{34}$$

By the way, the convolutional filters easily meet the condition that k is large enough.

Theorem 4. For n random variables $a_i \in \mathbb{R}^k$ follow $N(\mathbf{0}, c^2 \cdot \mathbf{I}_k)$.When k is large enough, we have such an estimation:

$$\mathbf{Var}_{a_i}\frac{F_1(a_i)}{F_2(a_i)} \approx \frac{1}{2nk}, \quad \mathbf{Var}_{a_i}\frac{F_2(a_i)}{F_1(a_i)} \approx \frac{1}{2nk}.$$

where $F_1(a_i) = \sum_{i=1}^n ||a_i||_2 / \mathbb{E}(\sum_{i=1}^n ||a_i||_2)$ and $F_2(a_i) = \sum_{i=1}^n ||a_i||_2^2 / \mathbb{E}(\sum_{i=1}^n ||a_i||_2^2)$.

Proof. Since Eq. (9) and Eq. (10), we have

$$\mathbf{Var}_{a_i}\frac{F_1(a_i)}{F_2(a_i)} = \left(\frac{nc^2k}{nc\sqrt{k}}\right)^2 \cdot \mathbf{Var}_{a_i}\left(\frac{\sum_{i=1}^n ||a_i||_2}{\sum_{i=1}^n ||a_i||_2^2}\right). \tag{35}$$

and

$$\mathbf{Var}_{a_i}\frac{F_2(a_i)}{F_1(a_i)} = \left(\frac{nc\sqrt{k}}{nc^2k}\right)^2 \cdot \mathbf{Var}_{a_i}\left(\frac{\sum_{i=1}^n ||a_i||_2^2}{\sum_{i=1}^n ||a_i||_2}\right). \tag{36}$$

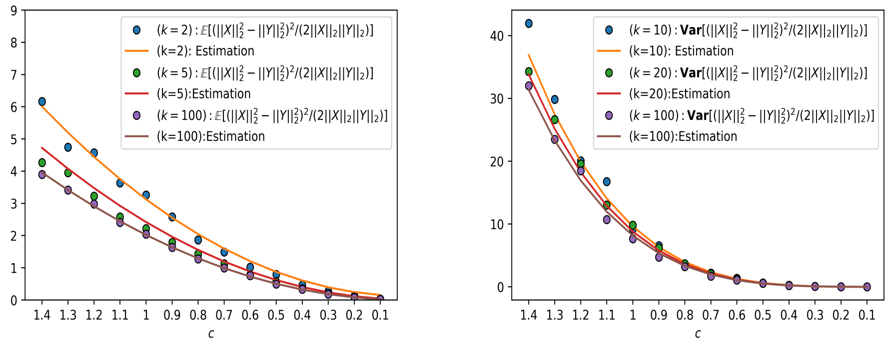


Figure 18: (Left) The numerical verification of Eq.(29) and (Right) The numerical verification of Eq.(30). X and Y follow $N(\mathbf{0}, c^2 \cdot I_k)$.

According to Lagrange's identity, we have

$$\begin{aligned}
\left(\sum_{i=1}^{n} ||a_i||_2^2\right)\left(\sum_{i=1}^{n} 1\right) &= \left(\sum_{i=1}^{n} ||a_i||_2\right)^2 + \sum_{1\le i<j\le n} (||a_i||_2^2 - ||a_j||_2^2)^2 \\
&= \sum_{i=1}^{n} ||a_i||_2^2 + \sum_{1\le i<j\le n} (||a_i||_2 \cdot ||a_j||_2) + 2\sum_{1\le i<j\le n} (||a_i||_2^2 - ||a_j||_2^2)^2 \\
&\approx \sum_{i=1}^{n} ||a_i||_2^2 + 2\sum_{1\le i<j\le n} (||a_i||_2 \cdot ||a_j||_2) \qquad \text{Since Eq. (34)} \\
&= \left(\sum_{i=1}^{n} ||a_i||_2\right)^2
\end{aligned}$$

so we have

$$\mathbf{Var}_{a_i\sim N(\mathbf{0},c^2\cdot\mathbf{I}_k)} \frac{\sum_{i=1}^{n} ||a_i||_2}{\sum_{i=1}^{n} ||a_i||_2^2} \approx \mathbf{Var}_{a_i\sim N(\mathbf{0},c^2\cdot\mathbf{I}_k)} \frac{n}{\sum_{i=1}^{n} ||a_i||_2} \tag{37}$$

By central limit theorem, we have $\sqrt{n}(\frac{1}{n}\sum_{i=1}^{n} ||a_i||_2 - \mu) \sim N(\mathbf{0}, \sigma^2)$. And let $g(x) = \frac{1}{x}$, we can use Delta method[8] to find the distribution of $g(\frac{1}{n}\sum_{i=1}^{n} ||a_i||_2)$:

$$\sqrt{n}\left(g(\frac{\sum_{i=1}^{n} ||a_i||_2}{n}) - g(\mu)\right) \sim N(0, \sigma^2 \cdot [g\prime(\mu)]^2) = N(0, \sigma^2 \cdot \frac{1}{\mu^4}). \tag{38}$$

where μ and σ^2 denote the mean and variance of $||a_i||_2$ respectively. From Eq. (37), we have

$$\begin{aligned}
\mathbf{Var}_{a_i\sim N(\mathbf{0},c^2\cdot\mathbf{I}_k)} \frac{\sum_{i=1}^{n} ||a_i||_2}{\sum_{i=1}^{n} ||a_i||_2^2} &\approx \mathbf{Var}_{a_i\sim N(\mathbf{0},c^2\cdot\mathbf{I}_k)} \frac{n}{\sum_{i=1}^{n} ||a_i||_2} \\
&= \sigma^2 \cdot \frac{1}{\mu^4 \cdot n} \qquad \text{Since Eq. (38)} \\
&= 2c^2\left[\frac{\Gamma(\frac{k}{2}+1)}{\Gamma(\frac{k}{2})} - \frac{\Gamma(\frac{k+1}{2})^2}{\Gamma(\frac{k}{2})^2}\right] \cdot \frac{1}{(\sqrt{2}c \cdot \frac{\Gamma(\frac{k+1}{2})}{\Gamma(\frac{k}{2})})^4 \cdot n} \\
&\qquad \text{Since Eq. (9) and Eq. (10)} \\
&= \frac{1}{2c^2 \cdot nk^2} \qquad \text{Since Lemma. 2}
\end{aligned}$$

[8] https://en.wikipedia.org/wiki/Delta_method

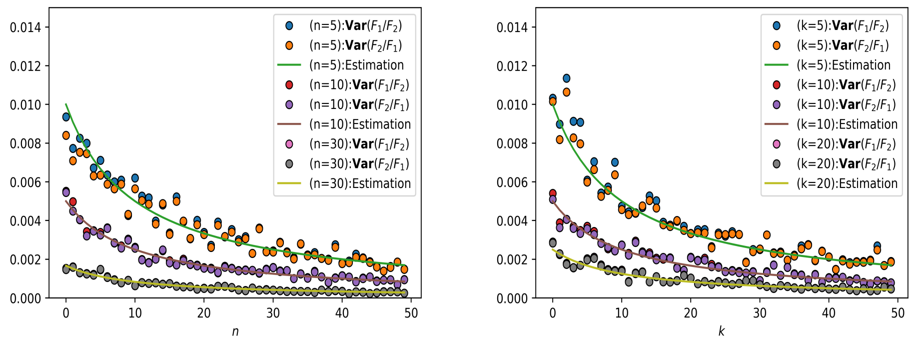


Figure 19: A numerical verification of **Theorem 4**, where $F_1 = \sum_{i=1}^n ||a_i||_2/\mathbb{E}(\sum_{i=1}^n ||a_i||_2)$ and $F_2 = \sum_{i=1}^n ||a_i||_2^2/\mathbb{E}(\sum_{i=1}^n ||a_i||_2^2)$. a_i follow $N(\mathbf{0}, 0.01^2 \cdot I_k)$.

Since Eq. (35), we have

$$\mathbf{Var}_{a_i} \frac{F_1(a_i)}{F_2(a_i)} = \left(\frac{nc^2k}{nc\sqrt{k}}\right)^2 \cdot \mathbf{Var}_{a_i} \left(\frac{\sum_{i=1}^n ||a_i||_2}{\sum_{i=1}^n ||a_i||_2^2}\right) \approx \frac{1}{2nk}. \tag{39}$$

Similar to Eq. (37),

$$\mathbf{Var}_{a_i \sim N(\mathbf{0}, c^2 \cdot \mathbf{I}_k)} \frac{\sum_{i=1}^n ||a_i||_2^2}{\sum_{i=1}^n ||a_i||_2} \approx \mathbf{Var}_{a_i \sim N(\mathbf{0}, c^2 \cdot \mathbf{I}_k)} \frac{\sum_{i=1}^n ||a_i||_2}{n} \tag{40}$$

$$\begin{aligned}
\mathbf{Var}_{a_i \sim N(\mathbf{0}, c^2 \cdot \mathbf{I}_k)} \frac{\sum_{i=1}^n ||a_i||_2^2}{\sum_{i=1}^n ||a_i||_2} &\approx \mathbf{Var}_{a_i \sim N(\mathbf{0}, c^2 \cdot \mathbf{I}_k)} \frac{\sum_{i=1}^n ||a_i||_2}{n} && \text{Similar to Eq. (37)} \\
&= \sigma^2 \cdot \frac{1}{n} && \text{Since central limit theorem} \\
&= 2c^2 \left[\frac{\Gamma(\frac{k}{2}+1)}{\Gamma(\frac{k}{2})} - \frac{\Gamma(\frac{k+1}{2})^2}{\Gamma(\frac{k}{2})^2}\right] \cdot \frac{1}{n} && \text{Since Eq. (10)} \\
&= \frac{c^2}{2n} && \text{Since Lemma. 2}
\end{aligned}$$

Since Eq. (36), we have

$$\mathbf{Var}_{a_i} \frac{F_2(a_i)}{F_1(a_i)} = \left(\frac{nc\sqrt{k}}{nc^2k}\right)^2 \cdot \mathbf{Var}_{a_i} \left(\frac{\sum_{i=1}^n ||a_i||_2^2}{\sum_{i=1}^n ||a_i||_2}\right) \approx \frac{1}{2nk}. \tag{41}$$

From Eq.(39) and Eq.(41), **Theorem 4** holds.

□

In Fig. 19, we also show a numerical verification of **Theorem 4**.

K Proof of Theorem 5

Proposition 8. *For a $n \times m$ random matrix $(a_{ij})_{n\times m}$, where $a_{ij} \sim N(0, \sigma^2)$. And Eq. (8) holds with probability 1.*

$$\mathbf{rank}((a_{ij})_{n\times m}) = \mathbf{min}(m, n). \tag{42}$$

Lemma 4. *Let $v_0, v_1, ..., v_k$ be the $k+1$ vectors in n dimensional Euclidean space V and $k \leq n$. If $\mathbf{rank}(v_1 - v_0, v_2 - v_0, ..., v_k - v_0) = n$, then $\forall x \in V$, $\exists \lambda_i (0 \leq i \leq k)$, s.t.*

$$x = \sum_{i=0}^{k} \lambda_i \cdot v_i, \tag{43}$$

and $\sum_{i=0}^{k} \lambda_i = 1$. We call $\lambda = (\lambda_0, \lambda_1, ..., \lambda_k)$ the generalized barycentric coordinate with respect to $(v_0, v_1, ..., v_k)$. (In general, barycentric coordinate is a concept in Polytope)

Proof. Note that v_i is the element of n dimensional linear space V and $\mathbf{rank}(v_1 - v_0, v_2 - v_0, ..., v_k - v_0) = n$. It means $(v_1 - v_0, v_2 - v_0, ..., v_k - v_0)$ form a set of basis in the linear space V. $\forall x \in V$, $x - v_0$ can be expressed linearly by them, *i.e.*,$\exists t_i (1 \leq i \leq k)$ s.t.

$$\begin{aligned} x &= v_0 + \sum_{i=1}^{k} t_i (v_i - v_0) \\ &= (1 - \sum_{i=1}^{k} t_i) v_0 + \sum_{i=1}^{k} t_i v_i. \end{aligned}$$

Let $\lambda_0 = (1 - \sum_{i=1}^{k} t_i)$ and $\lambda_i = t_i (1 \leq i \leq k)$, Lemma 4 holds. □

Lemma 5. *Let $v_0, v_1, ..., v_k$ be the $k+1$ vectors in n dimensional Euclidean space V. $\forall a, b \in V$, and the generalized barycentric coordinate of a, b with respect to $(v_0, v_1, ..., v_k)$ are $\lambda = (\lambda_0, \lambda_1, ..., \lambda_k)^T$ and $\mu = (\mu_0, \mu_1, ..., \mu_k)^T$,respectively. Then*

$$||a - b||_2^2 = (\lambda - \mu)^T D (\lambda - \mu), \tag{44}$$

where $D = (-\frac{1}{2} d_{ij})_{(k+1)\times(k+1)}$, and $d_{ij} = ||v_i - v_j||_2^2$.

Proof. Since Lemma 4, let $R = [v_0, v_1, ..., v_k]_{n \times (k+1)}$, and we have $a = R\lambda$ and $b = R\mu$. Moreover,

$$\begin{aligned} ||a - b||_2^2 &= (a - b)^T (a - b) && (45) \\ &= [R(\lambda - \mu)]^T [R(\lambda - \mu)] && (46) \\ &= (\lambda - \mu)^T R^T R (\lambda - \mu). && (47) \end{aligned}$$

Note that, for $D = (-\frac{1}{2} d_{ij})_{(k+1)\times(k+1)}$,

$$\begin{aligned} -\frac{1}{2} d_{ij} &= -\frac{1}{2} (v_i - v_j)^T (v_i - v_j) && (48) \\ &= v_i^T v_j - \frac{1}{2} (v_i^T v_i + v_j^T v_j). && (49) \end{aligned}$$

So we have $D = R^T R - \frac{1}{2} \left((v_i^T v_i + v_j^T v_j)_{(k+1)\times(k+1)} \right)$. It can be further simplified to $D = R^T R - \frac{1}{2} (V \alpha^T + \alpha V^T)$, where $V = (v_0^T v_0, ..., v_k^T v_k)^T$ and $\alpha = (1, ..., 1)^T$. So

$$\begin{aligned} ||a - b||_2^2 &= (\lambda - \mu)^T R^T R (\lambda - \mu) && (50) \\ &= (\lambda - \mu)^T (D + \frac{1}{2} (V \alpha^T + \alpha V^T)) (\lambda - \mu) && (51) \\ &= (\lambda - \mu)^T D (\lambda - \mu) + \frac{1}{2} (\lambda - \mu)^T (V \alpha^T + \alpha V^T) (\lambda - \mu), && (52) \end{aligned}$$

therefore, we only need to prove $(\lambda - \mu)^T (V \alpha^T + \alpha V^T)(\lambda - \mu) = 0$. From Lemma 4, we have $\alpha^T (\lambda - \mu) = (\lambda - \mu)^T \alpha = 0$ and the Lemma 5 holds.

□

Definition 1 (Ultra dimension)**.** *For a set U composed of vectors in a n dimensional linear space V, we define $\widehat{\mathbf{dim}}(U)$ as the Ultra dimension of U. The definition is that if U has k linearly independent vectors and there are no more, then $\widehat{\mathbf{dim}}(U) = k$.*

In fact, if U is a linear subspace in V, then the Ultra dimension and the dimensions of the linear subspace are equivalent. If U is a linear manifold, $U = \{x + v_0 | x \in W\}$, where v_0 and W are non-zero vectors and linear subspaces in V, respectively. And $\mathbf{dim}(W) = r$. Then

$$\widehat{\mathbf{dim}}(U) = \begin{cases} r, & v_0 \in W \\ r+1, & v_0 \notin W \end{cases} \tag{53}$$

In other words, $\widehat{\mathbf{dim}}(U) \geq \widehat{\mathbf{dim}}(W)$ always holds.

Lemma 6. *For arbitrary k $(1 \leq k \leq n-1)$, let $a_1, a_2, ..., a_k$ be k linearly independent vectors in n dimensional linear space V. Consider one $n-1$ dimensional linear subspace W in V and a non-zero vector v_0 in V. They form a linear manifold $P = \{v_0 + \alpha | \alpha \in W\}$. If $a_1, a_2, ..., a_k$ do not all belong to P, then there must exist $n-k$ vectors $p_1, p_2, ..., p_{n-k}$ from P, s.t $(a_1, a_2, ..., a_k, p_1, p_2, ..., p_{n-k})$ are a set of basis for the linear space V.*

Proof. we use mathematical induction. First, show that the Lemma 6 holds for $n - k = 1$. it means we need to find a vector $p_1 \in P$ s.t. $a_1, a_2, ..., a_k, p_1$ linearly independent. If p_1 does not exist, then $\forall p \in P$ would be linearly represented by $a_1, a_2, ..., a_k$. In other word,

$$P \subset L = \mathbf{span}(a_1, a_2, ..., a_k), \tag{54}$$

① For the linear manifold P, if $v_0 \in W$. This means that P is equal to the linear subspace W. Since Eq. (54), we have $W \subset L$ and $\widehat{\mathbf{dim}}(W) = \widehat{\mathbf{dim}}(L)$. Hence, $P = W = L$. However, $a_1, a_2, ..., a_k$ do not all belong to P, a contradiction.

② For the linear manifold P, if $v_0 \notin W$, then $\widehat{\mathbf{dim}}(P) = n$. Because $v_0 \notin W$, that is, v_0 cannot be represented by a set of basis of W. In other words, v_0 and a set of basis of W are linearly independent. However, the dimension of W is $n-1$, hence $\widehat{\mathbf{dim}}(P) = n$. From Eq. (54), we have $P \subset L$, so

$$n = \widehat{\mathbf{dim}}(P) \leq \widehat{\mathbf{dim}}(L) = k = n - 1, \tag{55}$$

a contradiction. Therefore, Lemma 6 holds for $n - k = 1$. Assume the induction hypothesis that Lemma 6 is true when $n - k = l$, where $1 \leq l$. when $n - k = l + 1$, *i.e.*, $k = n - (l + 1)$, we also can find a vector $p_1 \in P$ s.t. $a_1, a_2, ..., a_k, p_1$ linearly independent. Otherwise, $\forall p \in P$ would be linearly represented by $a_1, a_2, ..., a_k$. Similarly, we have Eq. (54). Note that, from Definition 1, $\widehat{\mathbf{dim}}(P) \geq n - 1$, hence

$$n - 1 \leq \widehat{\mathbf{dim}}(P) \leq \widehat{\mathbf{dim}}(L) = k = n - (l + 1). \tag{56}$$

a contradiction. At this time, we have $k + 1 = n - (l + 1) + 1 = n - l$ vectors $a_1, a_2, ..., a_k, p_1$ which are not all on P. Note that $n - (n - l) = l$, using the induction hypothesis, the Lemma 6 also holds for $n - k = l$. In summary, Lemma 6 holds.

□

Theorem 5. Let $v_0, v_1, ..., v_k$ be the $k + 1$ vectors in n dimensional Euclidean space $\mathbb{E}^n$. For all P in $\mathbb{E}^n$,

$$\sum_{i=0}^{k} ||P - v_i||_2^2 = \sum_{i=0}^{k} ||G - v_i||_2^2 + (k+1)||P - G||_2^2.$$

where G is the centroid of v_i, will hold if it satisfies one of the following conditions:

(1)if $k \geq n$ and $\mathbf{rank}(v_1 - v_0, v_2 - v_0, ..., v_k - v_0) = n$.

(2)if $k < n$ and $(v_1 - v_0, v_2 - v_0, ..., v_k - v_0)$ are linearly independent.

(3)if $v_i \sim N(\mathbf{0}, c \cdot \mathbf{I}_n)$, Eq.(15) holds with probability 1 where c is a constant.

Proof. **For Theorem 5 (1)**. From Lemma 4, $\forall P \in E^n$,$\exists \gamma = (\gamma_0, ..., \gamma_k)$, s.t. P can be represented by $\sum_{i=0}^k \gamma_i v_i$, where $\sum_{i=0}^k \gamma_i = 1$. In fact, for each v_i, it also can be respresented by $\sum_{j=0}^k \beta_{ij} v_i$, where $\sum_{i=0}^k \beta_{ij} = 1$. We just take $(\beta_{i0}, \beta_{i1}, ..., \beta_{ik})$ as one of the standard orthogonal basis $\epsilon_i = (0, 0, ..., 1_i, ...0)$. According to lemma 5,

$$||P - v_i||_2^2 = (\gamma - \epsilon_i)^T D(\gamma - \epsilon_i) \tag{57}$$
$$= \gamma^T D\gamma - 2\gamma^T D\epsilon_i + \epsilon_i^T D\epsilon_i \tag{58}$$
$$= \gamma^T D\gamma - 2\gamma^T D\epsilon_i. \tag{59}$$

The final equation is because the diagonal elements of the matrix are all 0. On the other hand, we have

$$||G - v_i||_2^2 = (\frac{1}{k+1}\sum_{i=0}^k \epsilon_i - \epsilon_i)^T D(\frac{1}{k+1}\sum_{i=0}^k \epsilon_i - \epsilon_i) \tag{60}$$
$$= \frac{1}{(k+1)^2}\alpha^T D\alpha - \frac{2}{k+1}\alpha^T D\epsilon_i + \epsilon_i^T D\epsilon_i \tag{61}$$
$$= \frac{1}{(k+1)^2}\alpha^T D\alpha - \frac{2}{k+1}\alpha^T D\epsilon_i, \tag{62}$$

where $\alpha = \sum_{i=0}^k \epsilon_i$, *i.e.*,$\alpha = (1, 1, ..., 1)$. Next, we consider $||P - G||_2^2$.

$$||P - G||_2^2 = (\gamma - \frac{1}{k+1}\alpha)^T D(\gamma - \frac{1}{k+1}\alpha) \tag{63}$$
$$= \gamma^T D\gamma + \frac{1}{(k+1)^2}\alpha^T D\alpha - \frac{2}{k+1}\gamma^T D\alpha. \tag{64}$$

In summary, we have

$$\sum_{i=0}^k ||P - v_i||_2^2 - ||G - v_i||_2^2 = (k+1)\gamma^T D\gamma - 2\gamma^T D\alpha + \frac{1}{k+1}\alpha^T D\alpha \tag{65}$$
$$= (k+1)||P - G||_2^2 \tag{66}$$

Therefore, Theorem 5 (1) holds.

For Theorem 5 (2). Next, we prove the case of $k < n$. Obviously, Lemma 4 does not hold. We consider about such a linear space $W_1 = \mathbf{span}(P - G)$, *i.e.*, a linear space expanded by $P - G$, and its orthogonal complement $W_1^\perp$ (in E^n). Since dimension formula from linear space, it is easy to konw that $\mathbf{dim}(W_1^\perp) = n - 1$.

Two linear manifolds T_1 and T_2 are constructed as follows,

$$T_1 = \{x + G | x \in W_1^\perp\} \tag{67}$$
$$T_2 = \{x + G - v_0 | x \in W_1^\perp\} \tag{68}$$

$\forall v_i \in T_1$, we have $(v_i - G)^T(P - G) = 0$, Furthermore,

$$||P - v_i||_2^2 = ||v_i - G||_2^2 + ||P - G||_2^2. \tag{69}$$

It is easy to know that $G - v_0$ is not 0. If $v_1 - v_0, ..., v_k - v_0$ are all belong to T_2, it means $v_1, .., v_k$ are all in T_1. Hence, we have Eq. (69). By summing both sides of Eq. (69) for i, it is obvious find that Theorem 5 (2) holds. If $v_1 - v_0, ..., v_k - v_0$ are not all belong to T_2, since Lemma 6, there are $n - k$ vectors $p_1 - v_0, p_2 - v_0, .., p_{n-k} - v_0$ from T_2 s.t. they and $v_1 - v_0, ..., v_k - v_0$ are linearly independent, where p_i obviously belongs to manifold T_1.

At the same time, we have $2G - p_i \in T_1$, we can also construct $n - k$ new vectors $2G - p_i - v_0 \in T_2$ and calculate the rank that

$$\mathbf{rank}(v_1 - v_0, ..., v_k - v_0, p_1 - v_0, ..., p_{n-k} - v_0, 2G - p_1 - v_0, ..., 2G - p_{n-k} - v_0)$$

$$= \mathbf{rank}(v_1 - v_0, ..., v_k - v_0, p_1 - v_0, ..., p_{n-k} - v_0, 2(G - v_0), ..., 2(G - v_0)) \tag{70}$$
$$= \mathbf{rank}(v_1 - v_0, ..., v_k - v_0, p_1 - v_0, ..., p_{n-k} - v_0, 0, ..., 0) \tag{71}$$
$$= n \tag{72}$$

The reason of the final equation is that $\sum_{i=1}^{k}(v_i - v_0) = (k+1)(G - v_0)$. Note that there are a total of $k + (n-k) + (n-k) = n + (n-k) \geq n$ vectors, meets the lemma 4 condition. For the convenience of description, we define

$$L_i^{(1)} = v_i, (0 \leq i \leq k), \tag{73}$$
$$L_i^{(2)} = p_i, (1 \leq i \leq n-k), \tag{74}$$
$$L_i^{(3)} = 2G - p_i, (1 \leq i \leq n-k). \tag{75}$$

And their centroid is

$$G' = \frac{1}{2n-k+1}\left(\sum_{i=0}^{k} v_i + \sum_{i=1}^{n-k}(L_i^{(2)} + L_i^{(3)})\right) \tag{76}$$
$$= \frac{1}{2n-k+1}((k+1)G + 2(n-k)G) \tag{77}$$
$$= G \tag{78}$$

That is, the newly added vector does not change the centroid of v_i. On the other hand, since both $L_i^{(2)}$ and $L_i^{(3)}$ are in the linear manifold T_1, and it meets the conditions of the Eq.(69). Similar to the derivation in the Theorem 5 (1), we have

$$(2n-k+1)||P-G||_2^2 = \sum_{t=L_i^{(1)},L_i^{(2)},L_i^{(3)}} \left(||P-t||_2^2 - ||G-t||_2^2\right) \tag{79}$$
$$= \sum_{i=0}^{k}\left(||P-v_i||_2^2 - ||G-v_i||_2^2\right) + \sum_{t=L_i^{(2)},L_i^{(3)}}\left(||P-t||_2^2 - ||G-t||_2^2\right) \tag{80}$$
$$= \sum_{i=0}^{k}\left(||P-v_i||_2^2 - ||G-v_i||_2^2\right) + 2(n-k)||P-G||_2^2 \tag{81}$$

The final equation is because both $L_i^{(2)}$ and $L_i^{(3)}$ are in the linear manifold T_1 and satisfy Eq. (69). To simplify Eq. (81), we obtain $\sum_{i=0}^{k}\left(||P-v_i||_2^2 - ||G-v_i||_2^2\right) = (k+1)||P-G||_2^2$. Therefore, Theorem 5 (2) holds.

For Theorem 5 (3). When $k \geq n$, from Proposition 8, we know that $\mathbf{rank}(v_1 - v_0, v_2 - v_0, ..., v_k - v_0)$ = n holds with probability 1. Hence, if we use the similar deduction from Theorem 5 (1), we can find that Theorem 5 (3) holds when $k \geq n$. On the other hand, when $k < n$, we can get the same result also according to Proposition 8. The reason is that $(v_1 - v_0, v_2 - v_0, ..., v_k - v_0)$ are linearly independent with probability 1.

□

L THE GEOMETRIC STRUCTURE OF CONVOLUTIONAL FILTERS.

Theorem 6. *Let $v_i \in \mathbb{R}^k$ and $v_i \sim N(\mathbf{0}, c^2 \cdot I_k)$. If $k \to \infty$ and $c \neq 0$, then*

(1) $||v_i||_2 \approx ||v_j||_2 \to \sqrt{2}c \cdot \frac{\Gamma((k+1)/2)}{\Gamma(k/2)}$,$1 \leq i < j \leq N$;

(2) $\mathbf{angle}(v_i, v_j) \to \frac{\pi}{2}$,$1 \leq i < j \leq N$;

(3) $||v_i - v_j||_2 \approx ||v_i - v_t||_2$,$1 \leq i < j < t \leq N$;

(4) $\mathbb{E}(||v_i||_1)/\mathbf{Var}(||v_i||_1) \to$ a non-zero constant.

Proof. First, since Chebyshev inequality, for $1 \leq i \leq N$ and a given M, we have

$$P\left\{|||v_i||_2 - \mathbb{E}(||v_i||_2)| \geq \sqrt{M\mathbf{Var}(||v_i||_2)}\right\} \leq \frac{1}{M}. \tag{82}$$

from Eq. (9), Eq. (10) and Lemma. (2), we can rewrite Eq. (82) when $k \to \infty$:

$$P\left\{||v_i||_2 \in \left[\sqrt{2}c \cdot \frac{\Gamma((k+1)/2)}{\Gamma(k/2)} - \sqrt{\frac{M}{2}}c, \sqrt{2}c \cdot \frac{\Gamma((k+1)/2)}{\Gamma(k/2)} + \sqrt{\frac{M}{2}}c\right]\right\} \geq 1 - \frac{1}{M}. \tag{83}$$

For a small enough $\epsilon > 0$, let $M = 1/\epsilon$. Note that $\sqrt{\frac{M}{2}}c = c/\sqrt{2\epsilon}$ is a constant. When $k \to \infty$, $\sqrt{2}c \cdot \frac{\Gamma((k+1)/2)}{\Gamma(k/2)} \gg \sqrt{\frac{M}{2}}c$. Hence, for any $i \in [1, N]$ and any small enough ϵ, we have

$$P\left\{||v_i||_2 \approx \sqrt{2}c \cdot \frac{\Gamma((k+1)/2)}{\Gamma(k/2)}\right\} \geq 1 - \epsilon. \tag{84}$$

So Theorem 6(1) holds.

Let $v_i = (v_{i1}, v_{i2}, ..., v_{ik})$ and $v_j = (v_{j1}, v_{j2}, ..., v_{jk})$. So $< v_i, v_j >= \sum_{p=1}^{k} v_{ip}v_{jp}$. Note that, v_i and v_j are independent, hence

$$\mathbb{E}(v_{ip}v_{jp}) = 0, \tag{85}$$

$$\mathbf{Var}(v_{ip}v_{jp}) = \mathbf{Var}(v_{ip})\mathbf{Var}(v_{jp}) + (\mathbb{E}(v_{ip}))^2\mathbf{Var}(v_{jp}) + (\mathbb{E}(v_{jp}))^2\mathbf{Var}(v_{ip}) = 1, \tag{86}$$

since central limit theorem, we have

$$\sqrt{k}\left(\frac{1}{k}\sum_{p=1}^{k} v_{ip}v_{jp} - 0\right) \sim N(0, 1), \tag{87}$$

According to Eq. (9), Lemma 2 and Eq. (87), when $k \to \infty$, we have

$$\frac{< v_i, v_j >}{||v_i||_2 \cdot ||v_j||_2} \to \frac{1}{\sqrt{k}} \cdot \frac{< v_i, v_j >}{\sqrt{k}} \sim N(0, \frac{1}{k}) \to N(0, 0). \tag{88}$$

So Theorem 6(2) holds. From Theorem 6(1) and Theorem 6(2), Theorem 6(3) can be proved through Pythagoras theorem.

For 6(4), from Proposition. 2, we have

$$\frac{\mathbb{E}(||v_i||_1)}{\mathbf{Var}(||v_i||_1)} = \frac{k \cdot c\sqrt{\frac{2}{\pi}}}{k \cdot c^2(1 - \frac{2}{\pi})} = \frac{\sqrt{\frac{2}{\pi}}}{c(1 - \frac{2}{\pi})} \tag{89}$$

$\square$

As shown in Fig. 21, Theorem 6 actually reveals the geometric structure formed by the parameters of the convolutional filters in CNNs. Specifically, from Theorem 6 (1), the convolutional filters v_i of each layer locate approximately on the surface of k dimensional sphere with $\mathbf{0}$ as the origin and $\sqrt{2}c \cdot \frac{\Gamma((k+1)/2)}{\Gamma(k/2)}$ as the radius. Then, from Theorem 6 (2), the vectors formed by any two different convolutional filters in the same layer are approximately orthogonal. As this result, for any three different filters v_1, v_2 and v_j, we can use Pythagoras theorem and Theorem 6 (1) to prove that they are equidistant,*i.e.*, $||v_1 - v_2||_2 \approx ||v_2 - v_3||_2 \approx ||v_3 - v_1||_2$. In fact, Fig. 20 provides another view of the geometric structure of convolutional filters. Since CWDA, $\mathbb{E}(v_i) = \mathbf{0}$. So the correlation matrix $\{(\mathbf{Cor}(v_i, v_j)\}_{N\times N} = c \cdot \{(v_i^T v_j\}_{N\times N}$, where c is a constant. That is to say, there is only one coefficient difference between correlation matrix and Gram matrix. Therefore, the diagonal elements of the matrix are $||v_i||_2^2$, and the off-diagonal elements are the dot product between the convolutional filters. This numerical visualization also verifies the conclusion of Theorem6.

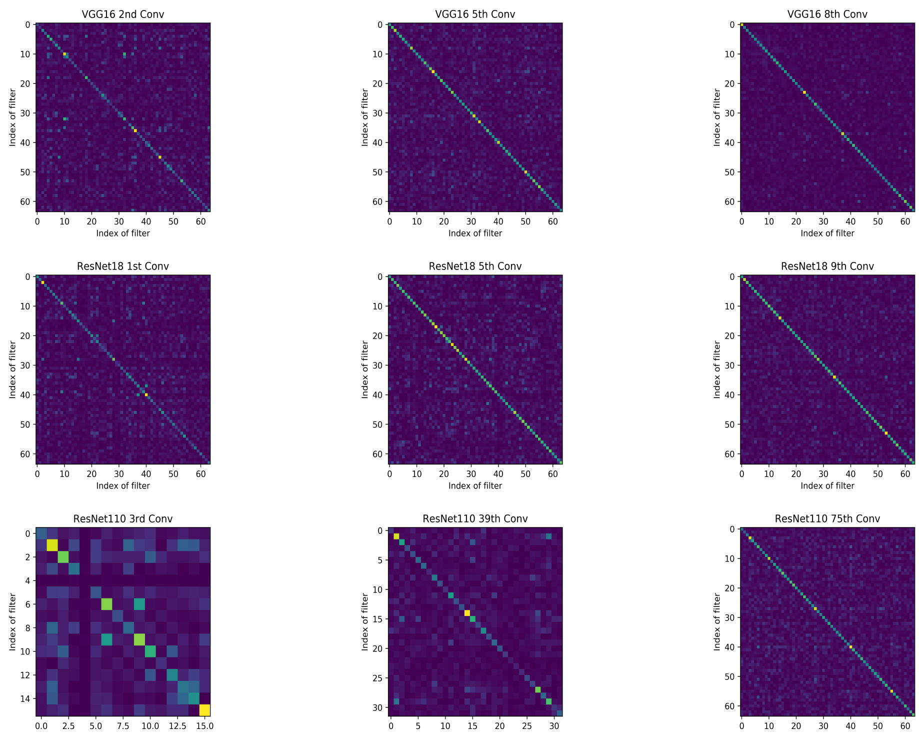


Figure 20: The correlation matrix of convolutional filters. For clarity, we use the first 64 filters in each layer to calculate the Gram matrix.

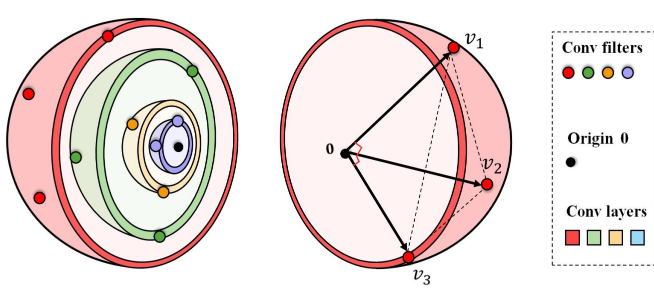


Figure 21: The geometric structure of convolutional filters when the network has large number of filters in each layer. for every pair of filters in one layer, (1) Their ℓ_2 norm are equivalent ($||v_1||_2 \approx ||v_2||_2 \approx ||v_3||_2$); (2) They are equidistant ($||v_1 - v_2||_2 \approx ||v_2 - v_3||_2 \approx ||v_3 - v_1||_2$); (3) and they are orthogonal ($v_1^T v_2 \approx v_2^T v_3 \approx v_3^T v_1 \approx 0$).

M THE DETAILS OF OTHER PRUNING CRITERIA

For notation, we denote i^{th} convolutional filter in layer l as F_i^l and the input feature maps in layer l as $\mathbf{I}^l \in \mathbb{R}^{N\times I^l\times H^l\times W^l}$, where N, I^l, H^l, W_l mean the train set size, number of channels, height and width respectively, $i = 1, 2, \cdots, \lambda_l$, and $l = 1, 2, \cdots, L$. The formulation of the filters' *importance* under each pruning criteria are illustrated as follows:

Norm-based criteria:

- ℓ_1-Norm Li et al. (2016): $||F_i^l||_1$;
- ℓ_2-Norm Frankle & Carbin (2019): $||F_i^l||_2$;

BN-based criteria Liu et al. (2017b):

- BN_γ: $|\gamma_i^l|$, where γ_i^l is the scaling factor in the Batch Normalization layer l;
- BN_β: $|\beta_i^l|$, where β_i^l is the shifting factor in the Batch Normalization layer l.

Activation-based criteria:

- APoZ Hu et al. (2016): $\frac{\sum_{p,q} \mathbb{1}\left((|\mathbf{I}^l * F_i^l|)_{p,q} > \sigma\right)}{N\times I^l\times H^l\times W^l}$, where we set $\sigma = 0.0001$ same as Luo & Wu (2017), and $\mathbb{1}(\cdot)$ is the indicator function, $*$ is convolution operator and $\mathbf{I}^l * F_i^l$ is the i-th output feature map;
- Entropy Luo & Wu (2017): we first prepare $\mathbf{G}_i^l = GAP(\mathbf{I}^l * F_i^l)$, where $\mathbf{G}_i^l \in \mathbb{R}^{N\times 1}$ and $GAP(\cdot)$ is the Global Average Pooling. Then, we estimate statistical distribution for $\mathbf{G}_i^l$ by dividing all elements in $\mathbf{G}_i^l$ into m bins. Let p_j is the probability of bin j, and the the *importance* score is $-\sum_{j=1}^m p_j \log p_j$.

First order Taylor based criteria Molchanov et al. (2016; 2019a;b):

- Taylor ℓ_1-Norm: $||\frac{\partial loss}{\partial F_i^l} \cdot F_i^l||_1$;
- Taylor ℓ_2-Norm: $||\frac{\partial loss}{\partial F_i^l} \cdot F_i^l||_2$;

The $loss$ is the Cross Entropy Loss on the split training set from the original training set.

N ADDITIONAL EXPERIMENTS ABOUT IMAGE CLASIFICATION

Table 6: The accuracy(%) of several networks and datasets using different pruning criteria.

		Experiment (1)			Experiment (2)			Experiment (3)		
		Trained	Pruned	Fine-tuned	Trained	Pruned	Fine-tuned	Trained	Pruned	Fine-tuned
CIFAR10 VGG16	ℓ_1	93.61	61.21	93.51	93.21	54.31	93.22	93.26	57.74	93.32
	ℓ_2	93.61	63.41	93.32	93.21	54.61	93.42	93.26	57.42	93.29
	GM	93.61	61.22	93.41	93.21	53.71	93.25	93.26	57.46	93.36
CIFAR100 VGG16	ℓ_1	72.67	25.91	71.50	72.99	20.43	71.36	72.56	24.01	71.07
	ℓ_2	72.67	27.07	71.28	72.99	22.31	71.12	72.56	24.45	70.92
	GM	72.67	26.37	71.27	72.99	21.67	71.26	72.56	24.26	70.78
ImageNet VGG16	ℓ_1	71.58	30.33	71.02	71.33	40.33	70.12	72.01	28.07	70.93
	ℓ_2	71.58	29.47	70.83	71.33	40.45	70.13	72.01	27.89	71.02
	GM	71.58	30.76	70.95	71.33	39.86	70.33	72.01	28.01	70.74
CIFAR10 ResNet56	ℓ_1	92.98	77.73	93.08	92.97	76.02	92.82	93.01	79.93	92.81
	ℓ_2	92.98	79.02	92.83	92.97	77.91	92.72	93.01	82.43	92.81
	GM	92.98	74.26	92.77	93.2	73.93	92.61	93.01	80.48	92.84
CIFAR100 ResNet56	ℓ_1	71.36	50.64	70.15	70.02	52.41	69.19	70.48	52.19	69.77
	ℓ_2	71.36	53.44	70.16	70.02	52.73	69.31	70.48	52.16	69.62
	GM	71.36	45.12	70.22	70.02	52.62	69.54	70.48	50.74	69.69
ImageNet ResNet34	ℓ_1	73.31	62.22	73.06	73.16	54.24	72.99	73.21	63.12	73.02
	ℓ_2	73.31	62.02	72.91	73.16	53.64	72.78	73.21	62.98	72.86
	GM	73.31	61.88	72.96	73.16	53.48	72.94	73.21	62.36	73.04

All the setting of these experiments are under can be found in `https://github.com/bearpaw/pytorch-classification`. Specifically, for pruning ratio:

VGG16 on CIFAR10, CIFAR100 and ImageNet:

`https://github.com/Eric-mingjie/rethinking-network-pruning/blob/master/cifar/l1-norm-pruning/vggprune.py#L84`

ResNet56 on CIFAR10 and CIFAR100:

`https://github.com/Eric-mingjie/rethinking-network-pruning/blob/master/cifar/l1-norm-pruning/res56prune.py#L94`

ResNet34 on ImageNet:

`https://github.com/Eric-mingjie/rethinking-network-pruning/blob/master/imagenet/l1-norm-pruning/prune.py#L138`

O ABOUT WEIGHT DECAY

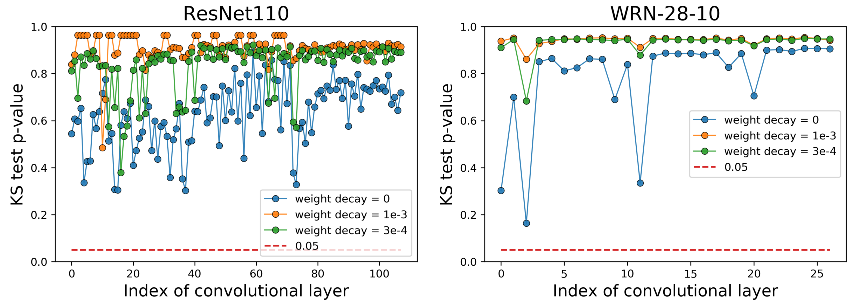


Figure 22: KS test (Lilliefors, 1967) while using different settings of weight decay.

We train the ResNet110 and WRN-28-10 on CIFAR100 with different weight decay (1e-3, 3e-4 and 0) and use KS test to verify whether the parameters of different layers follow a normal distribution. In Fig. 22, we can find

(1) When weight decay (wd) is non-zero, the normality is higher than that when weight decay is 0.

(2) If weight decay is 0, the p-value can still be much greater than 0.05, which means that the regularization of weight decay may not be the key reason for CWDA. The distribution of the parameters in these two networks (weight decay is 0) are shown in Fig. 24 and Fig. 23.

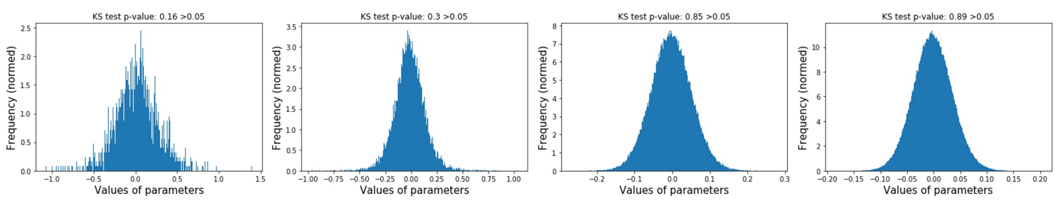


Figure 23: The distribution of parameters in different convolutional filters (WRN-28-10, wd = 0).

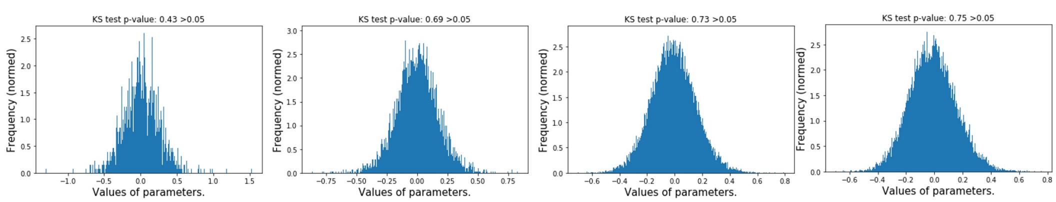


Figure 24: The distribution of parameters in different convolutional filters (ResNet110, wd = 0).

P STATISTICAL TEST

In this section, according to Table 3 and Section 2.1, we have a series of statistical tests for the necessary conditions of CWDA. let $F_{ij} \in \mathbb{R}^{N_i \times k \times k}$ represent the j^{th} filter of the i^{th} convolutional layer.

(1) **Gaussian** (*i.e.*, to verify whether F_{ij} approximatively follow a Gaussian-alike distribution.). In i^{th} layer, we use Kolmogorov–Smirnov (KS) test (Lilliefors, 1967) to check if all the weights in the same layer follow a normal distribution.

(2) **Standard Deviation** (*i.e.*, to verify whether the standard deviation of each filter in any layers tends to be a constant c.). Let σ_j denotes the standard deviation of all the weights of filter F_{ij} in i^{th} layer. We use Student's t test (Efron, 1969) to check if the variance of these σ_j is small enough. The null hypothesis H_0 and the alternative hypothesis H_1 are:

$$H_0 : \mathbf{Var}(\sigma_1, \sigma_2, .., \sigma_{N_i}) \leq \sigma_0^2, \qquad H_1 : \mathbf{Var}(\sigma_1, \sigma_2, .., \sigma_{N_i}) > \sigma_0^2.$$

where N_i denotes the number of the filters in i^{th} layer and σ_0 is a given real number which is small enough, like $\sigma_0^2 = 0.0001$.

(3) **Mean** (*i.e.*, to verify whether the mean of F_{ij} is 0.). Let the mean of all the weights in the same layer is μ. We use Student's t test (Efron, 1969) to check if μ is close to 0. First, we check the upper bound (Mean-Left) of μ, *i.e.*,

$$H_0 : \mu \leq \epsilon, \qquad H_1 : \mu > \epsilon.$$

where ϵ is a small constant, like $\epsilon = 0.01$. Next, we check the lower bound (Mean-Right) and the null hypothesis H_0 and the alternative hypothesis H_1 are:

$$H_0 : \mu \geq -\epsilon, \qquad H_1 : \mu < -\epsilon.$$

Of course, the p value for $H_0 : \mu \geq -\epsilon$ and $H_0 : \mu \leq \epsilon$ should be the same. There are several Notable points:

- In all the statistical tests, let the confidence level be 0.95, $\epsilon = 0.01$ and $\sigma_0^2 = 0.0001$.
- we use Green color to represent that the convolutional filters in one layer can pass the statistical test. Conversely, the Red color means that the filters can not pass the tests.
- In most layers, the convolutional filters can pass the statistical tests, except for a few layers which are in front of the network. This phenomenon is consistent with the analysis in Section 5.1 and it does not mean CWDA is not true.
- Most of the experiments are image classification, except for the tests in Appendix P.7.
- **p-value** and **c-value** denote p value and critical value (confidence level is 0.95), respectively. **t-value** is t values in Student's t test. If **p-value** is larger than **c-value** or **t-value** is smaller than **c-value**, we think this filter passes the tests.
- In fact, some of the experiments in Table 3 are repeated. These experiments are shown in following tables. The (*) means that ,for the sake of brevity, the repeat experiments are shown only once on the experiment with (*).

Table 7: The repeated experiments in Table 3.

(1)	**NETWORK STRUCTURE** (P.1) ResNet (*)	**OPTIMIZER** (P.2) SGD	**INITIALIZATION** (P.5) kaiming-normal
(2)	**NETWORK STRUCTURE** (P.1) WRN (*)	**REGULARIZATION** (P.3) L2 norm	
(3)	**BATCH NORMALIZATION** (P.8) VGG-bn (*)	**LEARNING RATE** (P.10) Schedule 150-225	

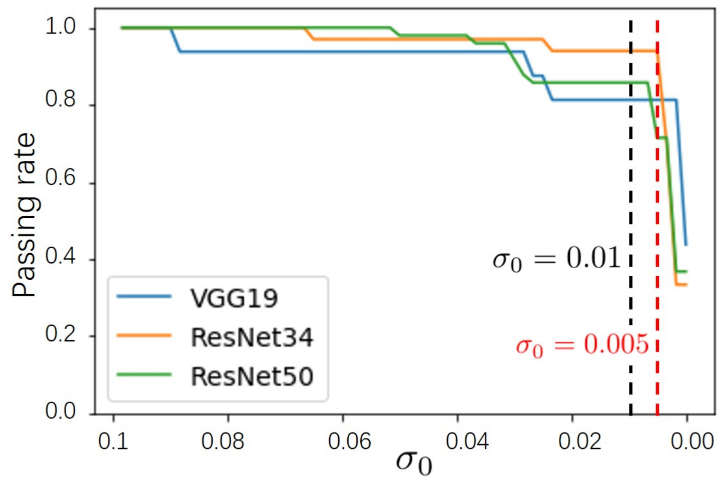


Figure 25: The passing rate of statistical test in Appendix P(2), where $0 < \sigma_0 \leq 0.1$ and passing rate is the ratio between the number of the filters passed the test and the number of total filters.

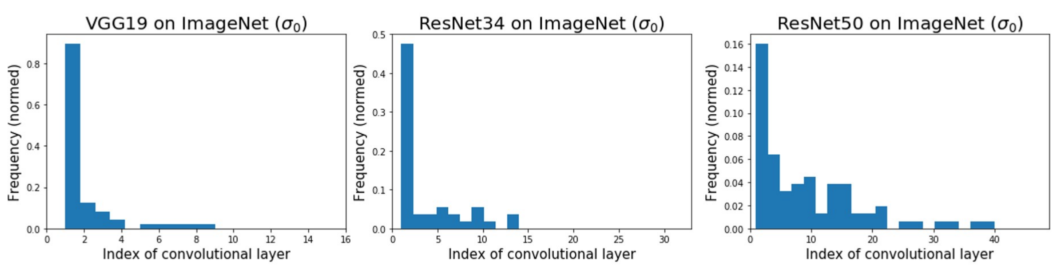


Figure 26: The filters that can not pass the statistical test in Appendix P(2). We record the convolutional filters that can not pass the statistical test under all settings of σ_0 in Fig. 25. It can be found that the filters that fail to pass the test are concentrated in the first few layers. This is consistent with the statement in Section 5.1.

P.1 NETWORK STRUCTURE

config: `https://github.com/bearpaw/pytorch-classification`.

Table 8: Cifar100 ResNet164

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	16	16	0.01	0.05	0.56	0.05	0.56	0.05	448.68	26.3
Conv2	16	144	0.04	0.05	0.68	0.05	0.68	0.05	114.12	26.3
Conv3	64	16	0.08	0.05	0.63	0.05	0.63	0.05	661.15	83.68
Conv4	16	64	0.44	0.05	0.63	0.05	0.63	0.05	17.16	26.3
Conv5	16	144	0.31	0.05	0.68	0.05	0.68	0.05	21.0	26.3
Conv6	64	16	0.36	0.05	0.63	0.05	0.63	0.05	112.55	83.68
Conv7	16	64	0.58	0.05	0.63	0.05	0.63	0.05	4.73	26.3
Conv8	16	144	0.35	0.05	0.68	0.05	0.68	0.05	11.9	26.3
Conv9	64	16	0.38	0.05	0.63	0.05	0.63	0.05	57.19	83.68
Conv10	16	64	0.69	0.05	0.63	0.05	0.63	0.05	2.61	26.3
Conv11	16	144	0.57	0.05	0.68	0.05	0.68	0.05	5.19	26.3
Conv12	64	16	0.52	0.05	0.63	0.05	0.63	0.05	41.82	83.68
Conv13	16	64	0.71	0.05	0.63	0.05	0.63	0.05	1.4	26.3
Conv14	16	144	0.62	0.05	0.68	0.05	0.68	0.05	2.9	26.3
Conv15	64	16	0.64	0.05	0.63	0.05	0.63	0.05	18.71	83.68
Conv16	16	64	0.83	0.05	0.63	0.05	0.63	0.05	1.35	26.3
Conv17	16	144	0.69	0.05	0.68	0.05	0.68	0.05	1.27	26.3
Conv18	64	16	0.84	0.05	0.63	0.05	0.63	0.05	9.65	83.68
Conv19	16	64	0.66	0.05	0.63	0.05	0.63	0.05	2.89	26.3
Conv20	16	144	0.7	0.05	0.68	0.05	0.68	0.05	0.77	26.3
Conv21	64	16	0.82	0.05	0.63	0.05	0.63	0.05	8.08	83.68
Conv22	16	64	0.81	0.05	0.63	0.05	0.63	0.05	1.8	26.3
Conv23	16	144	0.88	0.05	0.68	0.05	0.68	0.05	0.51	26.3
Conv24	64	16	0.86	0.05	0.63	0.05	0.63	0.05	4.45	83.68
Conv25	16	64	0.87	0.05	0.63	0.05	0.63	0.05	1.24	26.3
Conv26	16	144	0.84	0.05	0.68	0.05	0.68	0.05	0.68	26.3
Conv27	64	16	0.87	0.05	0.63	0.05	0.63	0.05	4.07	83.68
Conv28	16	64	0.47	0.05	0.63	0.05	0.63	0.05	4.45	26.3
Conv29	16	144	0.64	0.05	0.68	0.05	0.68	0.05	4.66	26.3
Conv30	64	16	0.8	0.05	0.63	0.05	0.63	0.05	12.15	83.68
Conv31	16	64	0.69	0.05	0.63	0.05	0.63	0.05	2.59	26.3
Conv32	16	144	0.84	0.05	0.68	0.05	0.68	0.05	1.03	26.3
Conv33	64	16	0.83	0.05	0.63	0.05	0.63	0.05	10.12	83.68
Conv34	16	64	0.52	0.05	0.63	0.05	0.63	0.05	6.17	26.3
Conv35	16	144	0.38	0.05	0.68	0.05	0.68	0.05	6.31	26.3
Conv36	64	16	0.67	0.05	0.63	0.05	0.63	0.05	12.34	83.68
Conv37	16	64	0.66	0.05	0.63	0.05	0.63	0.05	5.25	26.3
Conv38	16	144	0.69	0.05	0.68	0.05	0.68	0.05	2.07	26.3
Conv39	64	16	0.84	0.05	0.63	0.05	0.63	0.05	7.37	83.68
Conv40	16	64	0.63	0.05	0.63	0.05	0.63	0.05	6.93	26.3
Conv41	16	144	0.52	0.05	0.68	0.05	0.68	0.05	4.62	26.3
Conv42	64	16	0.69	0.05	0.63	0.05	0.63	0.05	18.53	83.68
Conv43	16	64	0.64	0.05	0.63	0.05	0.63	0.05	5.38	26.3
Conv44	16	144	0.6	0.05	0.68	0.05	0.68	0.05	2.7	26.3
Conv45	64	16	0.69	0.05	0.63	0.05	0.63	0.05	17.9	83.68
Conv46	16	64	0.82	0.05	0.63	0.05	0.63	0.05	2.32	26.3
Conv47	16	144	0.82	0.05	0.68	0.05	0.68	0.05	1.98	26.3
Conv48	64	16	0.82	0.05	0.63	0.05	0.63	0.05	9.34	83.68
Conv49	16	64	0.62	0.05	0.63	0.05	0.63	0.05	5.16	26.3

Conv50	16	144	0.39	0.05	0.68	0.05	0.68	0.05	6.45	26.3
Conv51	64	16	0.82	0.05	0.63	0.05	0.63	0.05	14.56	83.68
Conv52	16	64	0.54	0.05	0.63	0.05	0.63	0.05	6.05	26.3
Conv53	16	144	0.81	0.05	0.68	0.05	0.68	0.05	4.12	26.3
Conv54	64	16	0.67	0.05	0.63	0.05	0.63	0.05	15.76	83.68
Conv55	32	64	0.31	0.05	0.67	0.05	0.67	0.05	26.33	46.19
Conv56	32	288	0.56	0.05	0.83	0.05	0.83	0.05	6.36	46.19
Conv57	128	32	0.47	0.05	0.74	0.05	0.74	0.05	94.73	155.4
Conv58	32	128	0.56	0.05	0.74	0.05	0.74	0.05	7.21	46.19
Conv59	32	288	0.52	0.05	0.83	0.05	0.83	0.05	2.94	46.19
Conv60	128	32	0.63	0.05	0.74	0.05	0.74	0.05	27.0	155.4
Conv61	32	128	0.69	0.05	0.74	0.05	0.74	0.05	1.27	46.19
Conv62	32	288	0.84	0.05	0.83	0.05	0.83	0.05	1.94	46.19
Conv63	128	32	0.83	0.05	0.74	0.05	0.74	0.05	17.24	155.4
Conv64	32	128	0.31	0.05	0.74	0.05	0.74	0.05	7.84	46.19
Conv65	32	288	0.41	0.05	0.83	0.05	0.83	0.05	4.86	46.19
Conv66	128	32	0.81	0.05	0.74	0.05	0.74	0.05	33.53	155.4
Conv67	32	128	0.51	0.05	0.74	0.05	0.74	0.05	5.16	46.19
Conv68	32	288	0.83	0.05	0.83	0.05	0.83	0.05	2.86	46.19
Conv69	128	32	0.68	0.05	0.74	0.05	0.74	0.05	29.78	155.4
Conv70	32	128	0.83	0.05	0.74	0.05	0.74	0.05	1.27	46.19
Conv71	32	288	0.69	0.05	0.83	0.05	0.83	0.05	1.87	46.19
Conv72	128	32	0.84	0.05	0.74	0.05	0.74	0.05	9.81	155.4
Conv73	32	128	0.66	0.05	0.74	0.05	0.74	0.05	1.89	46.19
Conv74	32	288	0.83	0.05	0.83	0.05	0.83	0.05	1.06	46.19
Conv75	128	32	0.87	0.05	0.74	0.05	0.74	0.05	13.07	155.4
Conv76	32	128	0.83	0.05	0.74	0.05	0.74	0.05	1.93	46.19
Conv77	32	288	0.86	0.05	0.83	0.05	0.83	0.05	1.74	46.19
Conv78	128	32	0.86	0.05	0.74	0.05	0.74	0.05	12.89	155.4
Conv79	32	128	0.46	0.05	0.74	0.05	0.74	0.05	5.41	46.19
Conv80	32	288	0.84	0.05	0.83	0.05	0.83	0.05	1.63	46.19
Conv81	128	32	0.7	0.05	0.74	0.05	0.74	0.05	22.23	155.4
Conv82	32	128	0.57	0.05	0.74	0.05	0.74	0.05	4.95	46.19
Conv83	32	288	0.69	0.05	0.83	0.05	0.83	0.05	2.5	46.19
Conv84	128	32	0.8	0.05	0.74	0.05	0.74	0.05	24.7	155.4
Conv85	32	128	0.82	0.05	0.74	0.05	0.74	0.05	1.88	46.19
Conv86	32	288	0.81	0.05	0.83	0.05	0.83	0.05	1.88	46.19
Conv87	128	32	0.82	0.05	0.74	0.05	0.74	0.05	19.06	155.4
Conv88	32	128	0.8	0.05	0.74	0.05	0.74	0.05	2.68	46.19
Conv89	32	288	0.69	0.05	0.83	0.05	0.83	0.05	2.5	46.19
Conv90	128	32	0.69	0.05	0.74	0.05	0.74	0.05	15.94	155.4
Conv91	32	128	0.68	0.05	0.74	0.05	0.74	0.05	3.88	46.19
Conv92	32	288	0.82	0.05	0.83	0.05	0.83	0.05	2.55	46.19
Conv93	128	32	0.66	0.05	0.74	0.05	0.74	0.05	19.66	155.4
Conv94	32	128	0.52	0.05	0.74	0.05	0.74	0.05	6.16	46.19
Conv95	32	288	0.6	0.05	0.83	0.05	0.83	0.05	2.52	46.19
Conv96	128	32	0.81	0.05	0.74	0.05	0.74	0.05	22.61	155.4
Conv97	32	128	0.83	0.05	0.74	0.05	0.74	0.05	3.05	46.19
Conv98	32	288	0.62	0.05	0.83	0.05	0.83	0.05	2.4	46.19
Conv99	128	32	0.7	0.05	0.74	0.05	0.74	0.05	14.79	155.4
Conv100	32	128	0.32	0.05	0.74	0.05	0.74	0.05	6.89	46.19
Conv101	32	288	0.57	0.05	0.83	0.05	0.83	0.05	3.2	46.19
Conv102	128	32	0.65	0.05	0.74	0.05	0.74	0.05	20.08	155.4
Conv103	32	128	0.65	0.05	0.74	0.05	0.74	0.05	3.7	46.19
Conv104	32	288	0.66	0.05	0.83	0.05	0.83	0.05	1.77	46.19
Conv105	128	32	0.7	0.05	0.74	0.05	0.74	0.05	20.8	155.4
Conv106	32	128	0.55	0.05	0.74	0.05	0.74	0.05	5.14	46.19
Conv107	32	288	0.81	0.05	0.83	0.05	0.83	0.05	1.47	46.19
Conv108	128	32	0.55	0.05	0.74	0.05	0.74	0.05	21.77	155.4

Conv109	64	128	0.5	0.05	0.82	0.05	0.82	0.05	8.73	83.68
Conv110	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.37	83.68
Conv111	256	64	0.47	0.05	0.9	0.05	0.9	0.05	90.92	294.32
Conv112	64	256	0.67	0.05	0.9	0.05	0.9	0.05	2.2	83.68
Conv113	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.43	83.68
Conv114	256	64	0.66	0.05	0.9	0.05	0.9	0.05	26.24	294.32
Conv115	64	256	0.63	0.05	0.9	0.05	0.9	0.05	1.96	83.68
Conv116	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.45	83.68
Conv117	256	64	0.63	0.05	0.9	0.05	0.9	0.05	23.12	294.32
Conv118	64	256	0.81	0.05	0.9	0.05	0.9	0.05	1.66	83.68
Conv119	64	576	0.82	0.05	0.97	0.05	0.97	0.05	1.15	83.68
Conv120	256	64	0.8	0.05	0.9	0.05	0.9	0.05	18.65	294.32
Conv121	64	256	0.71	0.05	0.9	0.05	0.9	0.05	2.41	83.68
Conv122	64	576	0.85	0.05	0.97	0.05	0.97	0.05	1.07	83.68
Conv123	256	64	0.66	0.05	0.9	0.05	0.9	0.05	19.45	294.32
Conv124	64	256	0.81	0.05	0.9	0.05	0.9	0.05	1.33	83.68
Conv125	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.86	83.68
Conv126	256	64	0.81	0.05	0.9	0.05	0.9	0.05	17.83	294.32
Conv127	64	256	0.83	0.05	0.9	0.05	0.9	0.05	1.5	83.68
Conv128	64	576	0.86	0.05	0.97	0.05	0.97	0.05	1.33	83.68
Conv129	256	64	0.81	0.05	0.9	0.05	0.9	0.05	17.73	294.32
Conv130	64	256	0.83	0.05	0.9	0.05	0.9	0.05	1.45	83.68
Conv131	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.89	83.68
Conv132	256	64	0.68	0.05	0.9	0.05	0.9	0.05	18.82	294.32
Conv133	64	256	0.69	0.05	0.9	0.05	0.9	0.05	1.7	83.68
Conv134	64	576	0.83	0.05	0.97	0.05	0.97	0.05	1.05	83.68
Conv135	256	64	0.66	0.05	0.9	0.05	0.9	0.05	19.59	294.32
Conv136	64	256	0.84	0.05	0.9	0.05	0.9	0.05	1.48	83.68
Conv137	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.62	83.68
Conv138	256	64	0.67	0.05	0.9	0.05	0.9	0.05	17.88	294.32
Conv139	64	256	0.81	0.05	0.9	0.05	0.9	0.05	1.49	83.68
Conv140	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.59	83.68
Conv141	256	64	0.82	0.05	0.9	0.05	0.9	0.05	18.42	294.32
Conv142	64	256	0.67	0.05	0.9	0.05	0.9	0.05	1.39	83.68
Conv143	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.68	83.68
Conv144	256	64	0.8	0.05	0.9	0.05	0.9	0.05	19.86	294.32
Conv145	64	256	0.63	0.05	0.9	0.05	0.9	0.05	1.76	83.68
Conv146	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.77	83.68
Conv147	256	64	0.81	0.05	0.9	0.05	0.9	0.05	21.98	294.32
Conv148	64	256	0.65	0.05	0.9	0.05	0.9	0.05	1.51	83.68
Conv149	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.82	83.68
Conv150	256	64	0.65	0.05	0.9	0.05	0.9	0.05	24.23	294.32
Conv151	64	256	0.68	0.05	0.9	0.05	0.9	0.05	1.8	83.68
Conv152	64	576	0.83	0.05	0.97	0.05	0.97	0.05	1.09	83.68
Conv153	256	64	0.63	0.05	0.9	0.05	0.9	0.05	22.33	294.32
Conv154	64	256	0.69	0.05	0.9	0.05	0.9	0.05	1.2	83.68
Conv155	64	576	0.85	0.05	0.97	0.05	0.97	0.05	1.36	83.68
Conv156	256	64	0.53	0.05	0.9	0.05	0.9	0.05	31.15	294.32
Conv157	64	256	0.64	0.05	0.9	0.05	0.9	0.05	1.6	83.68
Conv158	64	576	0.82	0.05	0.97	0.05	0.97	0.05	1.08	83.68
Conv159	256	64	0.49	0.05	0.9	0.05	0.9	0.05	43.56	294.32
Conv160	64	256	0.5	0.05	0.9	0.05	0.9	0.05	1.94	83.68
Conv161	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.36	83.68
Conv162	256	64	0.36	0.05	0.9	0.05	0.9	0.05	137.02	294.32
Passing rate	-	-	98.77%		100.0%		100.0%		97.53%	

Table 9: Cifar100 VGG19

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	64	27	0.24	0.05	0.66	0.05	0.66	0.05	396.02	83.68
Conv2	64	576	0.51	0.05	0.97	0.05	0.97	0.05	1.73	83.68
Conv3	128	576	0.82	0.05	1.00	0.05	1.00	0.05	2.7	155.4
Conv4	128	1152	0.84	0.05	1.00	0.05	1.00	0.05	0.37	155.4
Conv5	256	1152	0.86	0.05	1.00	0.05	1.00	0.05	1.38	294.32
Conv6	256	2304	0.88	0.05	1.00	0.05	1.00	0.05	0.6	294.32
Conv7	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.38	294.32
Conv8	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.26	294.32
Conv9	512	2304	0.92	0.05	1.00	0.05	1.00	0.05	1.35	565.75
Conv10	512	4608	0.93	0.05	1.00	0.05	1.00	0.05	0.95	565.75
Conv11	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.21	565.75
Conv12	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.21	565.75
Conv13	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.19	565.75
Conv14	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.15	565.75
Conv15	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.11	565.75
Conv16	512	4608	0.93	0.05	1.00	0.05	1.00	0.05	0.37	565.75
Passing rate	-	-	100.00%		100.00%		100.00%		93.75%	

Table 10: Cifar100 AlexNet

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	64	363	0.51	0.05	0.94	0.05	0.94	0.05	54.46	83.68
Conv2	192	1600	0.39	0.05	1.00	0.05	1.00	0.05	44.19	225.33
Conv3	384	1728	0.66	0.05	1.00	0.05	1.00	0.05	6.62	430.69
Conv4	256	3456	0.87	0.05	1.00	0.05	1.00	0.05	1.40	294.32
Conv5	256	2304	0.85	0.05	1.00	0.05	1.00	0.05	8.74	294.32
Passing rate	-	-	100.00%		100.00%		100.00%		100.00%	

Table 11: Cifar100 DenseNet-bc-100-12

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	24	27	0.06	0.05	0.60	0.05	0.60	0.05	294.0	36.42
Conv2	48	24	0.64	0.05	0.63	0.05	0.63	0.05	21.13	65.17
Conv3	12	432	0.63	0.05	0.76	0.05	0.76	0.05	0.52	21.03
Conv4	48	36	0.63	0.05	0.66	0.05	0.66	0.05	4.04	65.17
Conv5	12	432	0.83	0.05	0.76	0.05	0.76	0.05	0.16	21.03
Conv6	48	48	0.54	0.05	0.68	0.05	0.68	0.05	12.54	65.17
Conv7	12	432	0.62	0.05	0.76	0.05	0.76	0.05	0.61	21.03
Conv8	48	60	0.64	0.05	0.70	0.05	0.70	0.05	3.88	65.17
Conv9	12	432	0.86	0.05	0.76	0.05	0.76	0.05	0.21	21.03
Conv10	48	72	0.67	0.05	0.72	0.05	0.72	0.05	2.61	65.17
Conv11	12	432	0.71	0.05	0.76	0.05	0.76	0.05	0.12	21.03
Conv12	48	84	0.62	0.05	0.74	0.05	0.74	0.05	3.88	65.17

Conv13	12	432	0.85	0.05	0.76	0.05	0.76	0.05	0.59	21.03
Conv14	48	96	0.82	0.05	0.75	0.05	0.75	0.05	1.89	65.17
Conv15	12	432	0.86	0.05	0.76	0.05	0.76	0.05	0.27	21.03
Conv16	48	108	0.70	0.05	0.76	0.05	0.76	0.05	3.75	65.17
Conv17	12	432	0.86	0.05	0.76	0.05	0.76	0.05	0.28	21.03
Conv18	48	120	0.85	0.05	0.78	0.05	0.78	0.05	2.31	65.17
Conv19	12	432	0.82	0.05	0.76	0.05	0.76	0.05	0.33	21.03
Conv20	48	132	0.59	0.05	0.79	0.05	0.79	0.05	2.91	65.17
Conv21	12	432	0.71	0.05	0.76	0.05	0.76	0.05	0.61	21.03
Conv22	48	144	0.66	0.05	0.80	0.05	0.80	0.05	3.15	65.17
Conv23	12	432	0.86	0.05	0.76	0.05	0.76	0.05	0.36	21.03
Conv24	48	156	0.64	0.05	0.81	0.05	0.81	0.05	1.35	65.17
Conv25	12	432	0.85	0.05	0.76	0.05	0.76	0.05	0.24	21.03
Conv26	48	168	0.70	0.05	0.82	0.05	0.82	0.05	1.15	65.17
Conv27	12	432	0.88	0.05	0.76	0.05	0.76	0.05	0.09	21.03
Conv28	48	180	0.60	0.05	0.82	0.05	0.82	0.05	1.84	65.17
Conv29	12	432	0.83	0.05	0.76	0.05	0.76	0.05	0.19	21.03
Conv30	48	192	0.69	0.05	0.83	0.05	0.83	0.05	2.52	65.17
Conv31	12	432	0.87	0.05	0.76	0.05	0.76	0.05	0.11	21.03
Conv32	48	204	0.61	0.05	0.84	0.05	0.84	0.05	1.71	65.17
Conv33	12	432	0.83	0.05	0.76	0.05	0.76	0.05	0.33	21.03
Conv34	108	216	0.29	0.05	0.94	0.05	0.94	0.05	5.21	133.26
Conv35	48	108	0.67	0.05	0.76	0.05	0.76	0.05	1.89	65.17
Conv36	12	432	0.70	0.05	0.76	0.05	0.76	0.05	0.41	21.03
Conv37	48	120	0.67	0.05	0.78	0.05	0.78	0.05	1.54	65.17
Conv38	12	432	0.84	0.05	0.76	0.05	0.76	0.05	0.13	21.03
Conv39	48	132	0.83	0.05	0.79	0.05	0.79	0.05	2.06	65.17
Conv40	12	432	0.82	0.05	0.76	0.05	0.76	0.05	0.67	21.03
Conv41	48	144	0.68	0.05	0.80	0.05	0.80	0.05	1.63	65.17
Conv42	12	432	0.81	0.05	0.76	0.05	0.76	0.05	0.29	21.03
Conv43	48	156	0.67	0.05	0.81	0.05	0.81	0.05	1.16	65.17
Conv44	12	432	0.85	0.05	0.76	0.05	0.76	0.05	0.13	21.03
Conv45	48	168	0.65	0.05	0.82	0.05	0.82	0.05	1.71	65.17
Conv46	12	432	0.69	0.05	0.76	0.05	0.76	0.05	0.35	21.03
Conv47	48	180	0.82	0.05	0.82	0.05	0.82	0.05	1.19	65.17
Conv48	12	432	0.83	0.05	0.76	0.05	0.76	0.05	0.14	21.03
Conv49	48	192	0.84	0.05	0.83	0.05	0.83	0.05	0.93	65.17
Conv50	12	432	0.67	0.05	0.76	0.05	0.76	0.05	0.36	21.03
Conv51	48	204	0.81	0.05	0.84	0.05	0.84	0.05	1.11	65.17
Conv52	12	432	0.81	0.05	0.76	0.05	0.76	0.05	0.25	21.03
Conv53	48	216	0.84	0.05	0.85	0.05	0.85	0.05	0.66	65.17
Conv54	12	432	0.83	0.05	0.76	0.05	0.76	0.05	0.2	21.03
Conv55	48	228	0.80	0.05	0.85	0.05	0.85	0.05	1.14	65.17
Conv56	12	432	0.65	0.05	0.76	0.05	0.76	0.05	0.37	21.03
Conv57	48	240	0.82	0.05	0.86	0.05	0.86	0.05	0.91	65.17
Conv58	12	432	0.83	0.05	0.76	0.05	0.76	0.05	0.25	21.03
Conv59	48	252	0.67	0.05	0.86	0.05	0.86	0.05	0.98	65.17
Conv60	12	432	0.66	0.05	0.76	0.05	0.76	0.05	0.41	21.03
Conv61	48	264	0.67	0.05	0.87	0.05	0.87	0.05	0.97	65.17
Conv62	12	432	0.83	0.05	0.76	0.05	0.76	0.05	0.24	21.03
Conv63	48	276	0.83	0.05	0.88	0.05	0.88	0.05	0.66	65.17
Conv64	12	432	0.85	0.05	0.76	0.05	0.76	0.05	0.13	21.03
Conv65	48	288	0.83	0.05	0.88	0.05	0.88	0.05	0.73	65.17
Conv66	12	432	0.67	0.05	0.76	0.05	0.76	0.05	0.15	21.03
Conv67	150	300	0.51	0.05	0.98	0.05	0.98	0.05	1.5	179.58
Conv68	48	150	0.66	0.05	0.80	0.05	0.80	0.05	0.93	65.17
Conv69	12	432	0.69	0.05	0.76	0.05	0.76	0.05	0.34	21.03
Conv70	48	162	0.63	0.05	0.81	0.05	0.81	0.05	1.04	65.17
Conv71	12	432	0.65	0.05	0.76	0.05	0.76	0.05	0.18	21.03

Conv72	48	174	0.84	0.05	0.82	0.05	0.82	0.05	0.71	65.17
Conv73	12	432	0.82	0.05	0.76	0.05	0.76	0.05	0.53	21.03
Conv74	48	186	0.80	0.05	0.83	0.05	0.83	0.05	0.74	65.17
Conv75	12	432	0.68	0.05	0.76	0.05	0.76	0.05	0.65	21.03
Conv76	48	198	0.33	0.05	0.84	0.05	0.84	0.05	0.9	65.17
Conv77	12	432	0.63	0.05	0.76	0.05	0.76	0.05	1.07	21.03
Conv78	48	210	0.82	0.05	0.84	0.05	0.84	0.05	0.77	65.17
Conv79	12	432	0.81	0.05	0.76	0.05	0.76	0.05	0.31	21.03
Conv80	48	222	0.71	0.05	0.85	0.05	0.85	0.05	0.48	65.17
Conv81	12	432	0.83	0.05	0.76	0.05	0.76	0.05	0.23	21.03
Conv82	48	234	0.82	0.05	0.86	0.05	0.86	0.05	0.79	65.17
Conv83	12	432	0.84	0.05	0.76	0.05	0.76	0.05	0.37	21.03
Conv84	48	246	0.82	0.05	0.86	0.05	0.86	0.05	1.21	65.17
Conv85	12	432	0.84	0.05	0.76	0.05	0.76	0.05	0.07	21.03
Conv86	48	258	0.84	0.05	0.87	0.05	0.87	0.05	0.85	65.17
Conv87	12	432	0.84	0.05	0.76	0.05	0.76	0.05	0.2	21.03
Conv88	48	270	0.80	0.05	0.87	0.05	0.87	0.05	0.88	65.17
Conv89	12	432	0.84	0.05	0.76	0.05	0.76	0.05	0.05	21.03
Conv90	48	282	0.82	0.05	0.88	0.05	0.88	0.05	0.88	65.17
Conv91	12	432	0.86	0.05	0.76	0.05	0.76	0.05	0.04	21.03
Conv92	48	294	0.83	0.05	0.88	0.05	0.88	0.05	0.75	65.17
Conv93	12	432	0.86	0.05	0.76	0.05	0.76	0.05	0.09	21.03
Conv94	48	306	0.81	0.05	0.89	0.05	0.89	0.05	0.79	65.17
Conv95	12	432	0.85	0.05	0.76	0.05	0.76	0.05	0.04	21.03
Conv96	48	318	0.64	0.05	0.89	0.05	0.89	0.05	0.87	65.17
Conv97	12	432	0.83	0.05	0.76	0.05	0.76	0.05	0.09	21.03
Conv98	48	330	0.82	0.05	0.90	0.05	0.90	0.05	0.94	65.17
Conv99	12	432	0.81	0.05	0.76	0.05	0.76	0.05	0.06	21.03
Passing rate	-	-	100.0%		100.0%		100.0%		98.99%	

Table 12: Cifar100 PreResNet110

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.05	0.05	0.58	0.05	0.58	0.05	96.78	26.3
Conv2	16	144	0.47	0.05	0.68	0.05	0.68	0.05	4.7	26.3
Conv3	16	144	0.64	0.05	0.68	0.05	0.68	0.05	3.3	26.3
Conv4	16	144	0.49	0.05	0.68	0.05	0.68	0.05	2.8	26.3
Conv5	16	144	0.58	0.05	0.68	0.05	0.68	0.05	4.53	26.3
Conv6	16	144	0.53	0.05	0.68	0.05	0.68	0.05	1.88	26.3
Conv7	16	144	0.59	0.05	0.68	0.05	0.68	0.05	1.29	26.3
Conv8	16	144	0.67	0.05	0.68	0.05	0.68	0.05	0.69	26.3
Conv9	16	144	0.70	0.05	0.68	0.05	0.68	0.05	1.2	26.3
Conv10	16	144	0.58	0.05	0.68	0.05	0.68	0.05	2.41	26.3
Conv11	16	144	0.62	0.05	0.68	0.05	0.68	0.05	1.5	26.3
Conv12	16	144	0.69	0.05	0.68	0.05	0.68	0.05	0.77	26.3
Conv13	16	144	0.62	0.05	0.68	0.05	0.68	0.05	2.18	26.3
Conv14	16	144	0.69	0.05	0.68	0.05	0.68	0.05	0.63	26.3
Conv15	16	144	0.67	0.05	0.68	0.05	0.68	0.05	1.66	26.3
Conv16	16	144	0.81	0.05	0.68	0.05	0.68	0.05	0.87	26.3
Conv17	16	144	0.67	0.05	0.68	0.05	0.68	0.05	1.22	26.3
Conv18	16	144	0.69	0.05	0.68	0.05	0.68	0.05	0.72	26.3
Conv19	16	144	0.82	0.05	0.68	0.05	0.68	0.05	1.29	26.3
Conv20	16	144	0.66	0.05	0.68	0.05	0.68	0.05	1.07	26.3
Conv21	16	144	0.83	0.05	0.68	0.05	0.68	0.05	1.64	26.3

Conv22	16	144	0.69	0.05	0.68	0.05	0.68	0.05	0.93	26.3
Conv23	16	144	0.70	0.05	0.68	0.05	0.68	0.05	1.76	26.3
Conv24	16	144	0.82	0.05	0.68	0.05	0.68	0.05	0.9	26.3
Conv25	16	144	0.83	0.05	0.68	0.05	0.68	0.05	1.51	26.3
Conv26	16	144	0.68	0.05	0.68	0.05	0.68	0.05	1.28	26.3
Conv27	16	144	0.81	0.05	0.68	0.05	0.68	0.05	2.35	26.3
Conv28	16	144	0.68	0.05	0.68	0.05	0.68	0.05	1.25	26.3
Conv29	16	144	0.80	0.05	0.68	0.05	0.68	0.05	2.06	26.3
Conv30	16	144	0.69	0.05	0.68	0.05	0.68	0.05	2.32	26.3
Conv31	16	144	0.85	0.05	0.68	0.05	0.68	0.05	0.81	26.3
Conv32	16	144	0.56	0.05	0.68	0.05	0.68	0.05	5.68	26.3
Conv33	16	144	0.49	0.05	0.68	0.05	0.68	0.05	9.37	26.3
Conv34	16	144	0.58	0.05	0.68	0.05	0.68	0.05	3.73	26.3
Conv35	16	144	0.83	0.05	0.68	0.05	0.68	0.05	0.76	26.3
Conv36	16	144	0.49	0.05	0.68	0.05	0.68	0.05	7.17	26.3
Conv37	16	144	0.55	0.05	0.68	0.05	0.68	0.05	4.83	26.3
Conv38	32	144	0.45	0.05	0.75	0.05	0.75	0.05	2.35	46.19
Conv39	32	288	0.54	0.05	0.83	0.05	0.83	0.05	1.89	46.19
Conv40	32	288	0.63	0.05	0.83	0.05	0.83	0.05	1.25	46.19
Conv41	32	288	0.69	0.05	0.83	0.05	0.83	0.05	0.91	46.19
Conv42	32	288	0.71	0.05	0.83	0.05	0.83	0.05	0.58	46.19
Conv43	32	288	0.83	0.05	0.83	0.05	0.83	0.05	0.45	46.19
Conv44	32	288	0.56	0.05	0.83	0.05	0.83	0.05	1.58	46.19
Conv45	32	288	0.67	0.05	0.83	0.05	0.83	0.05	0.74	46.19
Conv46	32	288	0.81	0.05	0.83	0.05	0.83	0.05	0.81	46.19
Conv47	32	288	0.70	0.05	0.83	0.05	0.83	0.05	0.59	46.19
Conv48	32	288	0.65	0.05	0.83	0.05	0.83	0.05	1.22	46.19
Conv49	32	288	0.80	0.05	0.83	0.05	0.83	0.05	0.34	46.19
Conv50	32	288	0.69	0.05	0.83	0.05	0.83	0.05	1.18	46.19
Conv51	32	288	0.83	0.05	0.83	0.05	0.83	0.05	0.74	46.19
Conv52	32	288	0.67	0.05	0.83	0.05	0.83	0.05	1.18	46.19
Conv53	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.36	46.19
Conv54	32	288	0.55	0.05	0.83	0.05	0.83	0.05	2.03	46.19
Conv55	32	288	0.82	0.05	0.83	0.05	0.83	0.05	0.88	46.19
Conv56	32	288	0.70	0.05	0.83	0.05	0.83	0.05	1.14	46.19
Conv57	32	288	0.83	0.05	0.83	0.05	0.83	0.05	0.42	46.19
Conv58	32	288	0.69	0.05	0.83	0.05	0.83	0.05	1.51	46.19
Conv59	32	288	0.82	0.05	0.83	0.05	0.83	0.05	0.57	46.19
Conv60	32	288	0.69	0.05	0.83	0.05	0.83	0.05	0.9	46.19
Conv61	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.43	46.19
Conv62	32	288	0.68	0.05	0.83	0.05	0.83	0.05	1.17	46.19
Conv63	32	288	0.82	0.05	0.83	0.05	0.83	0.05	0.61	46.19
Conv64	32	288	0.60	0.05	0.83	0.05	0.83	0.05	1.18	46.19
Conv65	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.6	46.19
Conv66	32	288	0.67	0.05	0.83	0.05	0.83	0.05	1.04	46.19
Conv67	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.41	46.19
Conv68	32	288	0.64	0.05	0.83	0.05	0.83	0.05	1.14	46.19
Conv69	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.58	46.19
Conv70	32	288	0.69	0.05	0.83	0.05	0.83	0.05	0.9	46.19
Conv71	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.48	46.19
Conv72	32	288	0.69	0.05	0.83	0.05	0.83	0.05	1.2	46.19
Conv73	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.38	46.19
Conv74	64	288	0.41	0.05	0.91	0.05	0.91	0.05	1.27	83.68
Conv75	64	576	0.50	0.05	0.97	0.05	0.97	0.05	1.01	83.68
Conv76	64	576	0.68	0.05	0.97	0.05	0.97	0.05	1.39	83.68
Conv77	64	576	0.80	0.05	0.97	0.05	0.97	0.05	0.96	83.68
Conv78	64	576	0.64	0.05	0.97	0.05	0.97	0.05	1.26	83.68
Conv79	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.99	83.68
Conv80	64	576	0.71	0.05	0.97	0.05	0.97	0.05	0.83	83.68

Conv81	64	576	0.82	0.05	0.97	0.05	0.97	0.05	0.74	83.68
Conv82	64	576	0.64	0.05	0.97	0.05	0.97	0.05	1.46	83.68
Conv83	64	576	0.71	0.05	0.97	0.05	0.97	0.05	0.75	83.68
Conv84	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.02	83.68
Conv85	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.64	83.68
Conv86	64	576	0.70	0.05	0.97	0.05	0.97	0.05	1.08	83.68
Conv87	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.44	83.68
Conv88	64	576	0.81	0.05	0.97	0.05	0.97	0.05	0.71	83.68
Conv89	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.53	83.68
Conv90	64	576	0.65	0.05	0.97	0.05	0.97	0.05	0.89	83.68
Conv91	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.39	83.68
Conv92	64	576	0.80	0.05	0.97	0.05	0.97	0.05	0.83	83.68
Conv93	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.4	83.68
Conv94	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.58	83.68
Conv95	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.38	83.68
Conv96	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.77	83.68
Conv97	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.37	83.68
Conv98	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.76	83.68
Conv99	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.35	83.68
Conv100	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.79	83.68
Conv101	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.42	83.68
Conv102	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.62	83.68
Conv103	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.42	83.68
Conv104	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.6	83.68
Conv105	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.55	83.68
Conv106	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.62	83.68
Conv107	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.6	83.68
Conv108	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.38	83.68
Conv109	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.47	83.68
Passing rate	-	-	100.0%		100.0%		100.0%		99.08%	

Table 13: Cifar100 WRN28-10

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	16	27	0.44	0.05	0.58	0.05	0.58	0.05	24.87	26.3
Conv2	160	144	0.92	0.05	0.94	0.05	0.94	0.05	5.96	190.52
Conv3	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.1	190.52
Conv4	160	16	0.67	0.05	0.69	0.05	0.69	0.05	35.0	190.52
Conv5	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.48	190.52
Conv6	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.12	190.52
Conv7	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.03	190.52
Conv8	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.23	190.52
Conv9	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.02	190.52
Conv10	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.39	190.52
Conv11	320	1440	0.95	0.05	1.00	0.05	1.00	0.05	1.13	362.72
Conv12	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.08	362.72
Conv13	320	160	0.88	0.05	0.99	0.05	0.99	0.05	2.81	362.72
Conv14	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.06	362.72
Conv15	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.06	362.72
Conv16	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.03	362.72
Conv17	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.12	362.72
Conv18	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.04	362.72
Conv19	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.3	362.72
Conv20	640	2880	0.94	0.05	1.00	0.05	1.00	0.05	2.18	699.96

Conv21	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.26	699.96
Conv22	640	320	0.91	0.05	1.00	0.05	1.00	0.05	1.91	699.96
Conv23	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.35	699.96
Conv24	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.24	699.96
Conv25	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.06	699.96
Conv26	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.36	699.96
Conv27	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.04	699.96
Conv28	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	1.23	699.96
Passing rate	-	-	100.0%		100.0%		100.0%		100.0%	

Table 14: Cifar100 ResNext-16x64d

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	27	0.70	0.05	0.66	0.05	0.66	0.05	32.22	83.68
Conv2	1024	64	0.91	0.05	0.99	0.05	0.99	0.05	1.51	1099.56
Conv3	1024	576	0.91	0.05	1.00	0.05	1.00	0.05	0.41	1099.56
Conv4	256	1024	0.93	0.05	1.00	0.05	1.00	0.05	0.12	294.32
Conv5	256	64	0.86	0.05	0.90	0.05	0.90	0.05	5.91	294.32
Conv6	1024	256	0.95	0.05	1.00	0.05	1.00	0.05	0.13	1099.56
Conv7	1024	576	0.95	0.05	1.00	0.05	1.00	0.05	0.04	1099.56
Conv8	256	1024	0.94	0.05	1.00	0.05	1.00	0.05	0.03	294.32
Conv9	1024	256	0.93	0.05	1.00	0.05	1.00	0.05	0.77	1099.56
Conv10	1024	576	0.93	0.05	1.00	0.05	1.00	0.05	0.46	1099.56
Conv11	256	1024	0.95	0.05	1.00	0.05	1.00	0.05	0.22	294.32
Conv12	2048	256	0.95	0.05	1.00	0.05	1.00	0.05	1.79	2154.4
Conv13	2048	1152	0.96	0.05	1.00	0.05	1.00	0.05	0.55	2154.4
Conv14	512	2048	0.94	0.05	1.00	0.05	1.00	0.05	0.6	565.75
Conv15	512	256	0.93	0.05	1.00	0.05	1.00	0.05	2.92	565.75
Conv16	2048	512	0.94	0.05	1.00	0.05	1.00	0.05	0.94	2154.4
Conv17	2048	1152	0.95	0.05	1.00	0.05	1.00	0.05	0.82	2154.4
Conv18	512	2048	0.94	0.05	1.00	0.05	1.00	0.05	0.4	565.75
Conv19	2048	512	0.93	0.05	1.00	0.05	1.00	0.05	1.55	2154.4
Conv20	2048	1152	0.95	0.05	1.00	0.05	1.00	0.05	0.95	2154.4
Conv21	512	2048	0.95	0.05	1.00	0.05	1.00	0.05	0.39	565.75
Conv22	4096	512	0.92	0.05	1.00	0.05	1.00	0.05	3.13	4246.0
Conv23	4096	2304	0.95	0.05	1.00	0.05	1.00	0.05	0.65	4246.0
Conv24	1024	4096	0.92	0.05	1.00	0.05	1.00	0.05	0.64	1099.56
Conv25	1024	512	0.94	0.05	1.00	0.05	1.00	0.05	2.9	1099.56
Conv26	4096	1024	0.88	0.05	1.00	0.05	1.00	0.05	1.72	4246.0
Conv27	4096	2304	0.94	0.05	1.00	0.05	1.00	0.05	1.54	4246.0
Conv28	1024	4096	0.94	0.05	1.00	0.05	1.00	0.05	0.24	1099.56
Conv29	4096	1024	0.95	0.05	1.00	0.05	1.00	0.05	2.25	4246.0
Conv30	4096	2304	0.96	0.05	1.00	0.05	1.00	0.05	1.03	4246.0
Conv31	1024	4096	0.94	0.05	1.00	0.05	1.00	0.05	0.22	1099.56
Passing rate	-	-	100.0%		100.0%		100.0%		100.0%	

P.2 OPTIMIZER

config:

`https://github.com/bearpaw/pytorch-classification`.

`https://pytorch.org/docs/master/optim.html#torch-optim`.

Table 15: Cifar100 ASGD-ResNet164

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	16	27	0.13	0.05	0.58	0.05	0.58	0.05	34.35	26.3
Conv2	16	16	0.33	0.05	0.56	0.05	0.56	0.05	9.29	26.3
Conv3	16	144	0.65	0.05	0.68	0.05	0.68	0.05	0.42	26.3
Conv4	64	16	0.58	0.05	0.63	0.05	0.63	0.05	13.54	83.68
Conv5	16	64	0.24	0.05	0.63	0.05	0.63	0.05	2.95	26.3
Conv6	16	144	0.68	0.05	0.68	0.05	0.68	0.05	0.21	26.3
Conv7	64	16	0.58	0.05	0.63	0.05	0.63	0.05	16.09	83.68
Conv8	16	64	0.29	0.05	0.63	0.05	0.63	0.05	4.05	26.3
Conv9	16	144	0.65	0.05	0.68	0.05	0.68	0.05	0.15	26.3
Conv10	64	16	0.60	0.05	0.63	0.05	0.63	0.05	15.79	83.68
Conv11	16	64	0.29	0.05	0.63	0.05	0.63	0.05	5.69	26.3
Conv12	16	144	0.70	0.05	0.68	0.05	0.68	0.05	0.28	26.3
Conv13	64	16	0.61	0.05	0.63	0.05	0.63	0.05	20.88	83.68
Conv14	16	64	0.29	0.05	0.63	0.05	0.63	0.05	8.67	26.3
Conv15	16	144	0.65	0.05	0.68	0.05	0.68	0.05	0.18	26.3
Conv16	64	16	0.60	0.05	0.63	0.05	0.63	0.05	17.85	83.68
Conv17	16	64	0.29	0.05	0.63	0.05	0.63	0.05	5.21	26.3
Conv18	16	144	0.65	0.05	0.68	0.05	0.68	0.05	0.23	26.3
Conv19	64	16	0.49	0.05	0.63	0.05	0.63	0.05	21.6	83.68
Conv20	16	64	0.24	0.05	0.63	0.05	0.63	0.05	2.93	26.3
Conv21	16	144	0.81	0.05	0.68	0.05	0.68	0.05	0.15	26.3
Conv22	64	16	0.58	0.05	0.63	0.05	0.63	0.05	15.96	83.68
Conv23	16	64	0.30	0.05	0.63	0.05	0.63	0.05	4.21	26.3
Conv24	16	144	0.71	0.05	0.68	0.05	0.68	0.05	0.22	26.3
Conv25	64	16	0.58	0.05	0.63	0.05	0.63	0.05	15.38	83.68
Conv26	16	64	0.29	0.05	0.63	0.05	0.63	0.05	5.46	26.3
Conv27	16	144	0.81	0.05	0.68	0.05	0.68	0.05	0.2	26.3
Conv28	64	16	0.60	0.05	0.63	0.05	0.63	0.05	17.53	83.68
Conv29	16	64	0.36	0.05	0.63	0.05	0.63	0.05	3.99	26.3
Conv30	16	144	0.70	0.05	0.68	0.05	0.68	0.05	0.25	26.3
Conv31	64	16	0.58	0.05	0.63	0.05	0.63	0.05	17.13	83.68
Conv32	16	64	0.24	0.05	0.63	0.05	0.63	0.05	10.61	26.3
Conv33	16	144	0.71	0.05	0.68	0.05	0.68	0.05	0.21	26.3
Conv34	64	16	0.63	0.05	0.63	0.05	0.63	0.05	21.96	83.68
Conv35	16	64	0.18	0.05	0.63	0.05	0.63	0.05	3.58	26.3
Conv36	16	144	0.68	0.05	0.68	0.05	0.68	0.05	0.33	26.3
Conv37	64	16	0.46	0.05	0.63	0.05	0.63	0.05	21.7	83.68
Conv38	16	64	0.28	0.05	0.63	0.05	0.63	0.05	5.06	26.3
Conv39	16	144	0.70	0.05	0.68	0.05	0.68	0.05	0.27	26.3
Conv40	64	16	0.60	0.05	0.63	0.05	0.63	0.05	23.91	83.68
Conv41	16	64	0.30	0.05	0.63	0.05	0.63	0.05	5.54	26.3
Conv42	16	144	0.81	0.05	0.68	0.05	0.68	0.05	0.27	26.3
Conv43	64	16	0.59	0.05	0.63	0.05	0.63	0.05	20.08	83.68
Conv44	16	64	0.24	0.05	0.63	0.05	0.63	0.05	2.2	26.3
Conv45	16	144	0.64	0.05	0.68	0.05	0.68	0.05	0.2	26.3
Conv46	64	16	0.57	0.05	0.63	0.05	0.63	0.05	15.52	83.68
Conv47	16	64	0.31	0.05	0.63	0.05	0.63	0.05	1.59	26.3
Conv48	16	144	0.67	0.05	0.68	0.05	0.68	0.05	0.23	26.3
Conv49	64	16	0.60	0.05	0.63	0.05	0.63	0.05	22.5	83.68
Conv50	16	64	0.27	0.05	0.63	0.05	0.63	0.05	4.37	26.3
Conv51	16	144	0.68	0.05	0.68	0.05	0.68	0.05	0.07	26.3
Conv52	64	16	0.61	0.05	0.63	0.05	0.63	0.05	20.81	83.68
Conv53	16	64	0.27	0.05	0.63	0.05	0.63	0.05	5.5	26.3

Conv54	16	144	0.67	0.05	0.68	0.05	0.68	0.05	0.36	26.3
Conv55	64	16	0.57	0.05	0.63	0.05	0.63	0.05	20.01	83.68
Conv56	32	64	0.48	0.05	0.67	0.05	0.67	0.05	4.04	46.19
Conv57	32	288	0.83	0.05	0.83	0.05	0.83	0.05	0.13	46.19
Conv58	128	32	0.66	0.05	0.74	0.05	0.74	0.05	10.05	155.4
Conv59	32	128	0.40	0.05	0.74	0.05	0.74	0.05	3.91	46.19
Conv60	32	288	0.82	0.05	0.83	0.05	0.83	0.05	0.2	46.19
Conv61	128	32	0.68	0.05	0.74	0.05	0.74	0.05	9.64	155.4
Conv62	32	128	0.31	0.05	0.74	0.05	0.74	0.05	2.19	46.19
Conv63	32	288	0.83	0.05	0.83	0.05	0.83	0.05	0.15	46.19
Conv64	128	32	0.66	0.05	0.74	0.05	0.74	0.05	10.3	155.4
Conv65	32	128	0.40	0.05	0.74	0.05	0.74	0.05	3.61	46.19
Conv66	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.12	46.19
Conv67	128	32	0.60	0.05	0.74	0.05	0.74	0.05	10.61	155.4
Conv68	32	128	0.37	0.05	0.74	0.05	0.74	0.05	1.97	46.19
Conv69	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.14	46.19
Conv70	128	32	0.70	0.05	0.74	0.05	0.74	0.05	9.04	155.4
Conv71	32	128	0.44	0.05	0.74	0.05	0.74	0.05	2.21	46.19
Conv72	32	288	0.81	0.05	0.83	0.05	0.83	0.05	0.19	46.19
Conv73	128	32	0.68	0.05	0.74	0.05	0.74	0.05	9.69	155.4
Conv74	32	128	0.40	0.05	0.74	0.05	0.74	0.05	1.31	46.19
Conv75	32	288	0.83	0.05	0.83	0.05	0.83	0.05	0.1	46.19
Conv76	128	32	0.68	0.05	0.74	0.05	0.74	0.05	9.75	155.4
Conv77	32	128	0.43	0.05	0.74	0.05	0.74	0.05	2.52	46.19
Conv78	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.17	46.19
Conv79	128	32	0.67	0.05	0.74	0.05	0.74	0.05	10.85	155.4
Conv80	32	128	0.38	0.05	0.74	0.05	0.74	0.05	2.17	46.19
Conv81	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.12	46.19
Conv82	128	32	0.68	0.05	0.74	0.05	0.74	0.05	9.48	155.4
Conv83	32	128	0.41	0.05	0.74	0.05	0.74	0.05	3.89	46.19
Conv84	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.16	46.19
Conv85	128	32	0.62	0.05	0.74	0.05	0.74	0.05	11.02	155.4
Conv86	32	128	0.39	0.05	0.74	0.05	0.74	0.05	2.04	46.19
Conv87	32	288	0.82	0.05	0.83	0.05	0.83	0.05	0.11	46.19
Conv88	128	32	0.66	0.05	0.74	0.05	0.74	0.05	10.19	155.4
Conv89	32	128	0.37	0.05	0.74	0.05	0.74	0.05	2.54	46.19
Conv90	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.09	46.19
Conv91	128	32	0.65	0.05	0.74	0.05	0.74	0.05	10.0	155.4
Conv92	32	128	0.40	0.05	0.74	0.05	0.74	0.05	2.28	46.19
Conv93	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.06	46.19
Conv94	128	32	0.69	0.05	0.74	0.05	0.74	0.05	10.16	155.4
Conv95	32	128	0.42	0.05	0.74	0.05	0.74	0.05	2.08	46.19
Conv96	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.11	46.19
Conv97	128	32	0.64	0.05	0.74	0.05	0.74	0.05	10.08	155.4
Conv98	32	128	0.33	0.05	0.74	0.05	0.74	0.05	2.23	46.19
Conv99	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.11	46.19
Conv100	128	32	0.66	0.05	0.74	0.05	0.74	0.05	10.11	155.4
Conv101	32	128	0.44	0.05	0.74	0.05	0.74	0.05	3.08	46.19
Conv102	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.09	46.19
Conv103	128	32	0.65	0.05	0.74	0.05	0.74	0.05	11.58	155.4
Conv104	32	128	0.38	0.05	0.74	0.05	0.74	0.05	3.37	46.19
Conv105	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.1	46.19
Conv106	128	32	0.68	0.05	0.74	0.05	0.74	0.05	11.59	155.4
Conv107	32	128	0.43	0.05	0.74	0.05	0.74	0.05	1.57	46.19
Conv108	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.11	46.19
Conv109	128	32	0.66	0.05	0.74	0.05	0.74	0.05	8.07	155.4
Conv110	64	128	0.56	0.05	0.82	0.05	0.82	0.05	3.13	83.68
Conv111	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.08	83.68
Conv112	256	64	0.84	0.05	0.90	0.05	0.90	0.05	4.87	294.32

Conv113	64	256	0.55	0.05	0.90	0.05	0.90	0.05	1.13	83.68
Conv114	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.07	83.68
Conv115	256	64	0.83	0.05	0.90	0.05	0.90	0.05	4.3	294.32
Conv116	64	256	0.52	0.05	0.90	0.05	0.90	0.05	1.52	83.68
Conv117	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.07	83.68
Conv118	256	64	0.69	0.05	0.90	0.05	0.90	0.05	4.38	294.32
Conv119	64	256	0.53	0.05	0.90	0.05	0.90	0.05	1.19	83.68
Conv120	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.06	83.68
Conv121	256	64	0.84	0.05	0.90	0.05	0.90	0.05	4.75	294.32
Conv122	64	256	0.52	0.05	0.90	0.05	0.90	0.05	1.08	83.68
Conv123	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.04	83.68
Conv124	256	64	0.84	0.05	0.90	0.05	0.90	0.05	4.98	294.32
Conv125	64	256	0.50	0.05	0.90	0.05	0.90	0.05	1.36	83.68
Conv126	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.06	83.68
Conv127	256	64	0.83	0.05	0.90	0.05	0.90	0.05	4.89	294.32
Conv128	64	256	0.47	0.05	0.90	0.05	0.90	0.05	1.42	83.68
Conv129	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.05	83.68
Conv130	256	64	0.82	0.05	0.90	0.05	0.90	0.05	5.59	294.32
Conv131	64	256	0.52	0.05	0.90	0.05	0.90	0.05	0.97	83.68
Conv132	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.06	83.68
Conv133	256	64	0.84	0.05	0.90	0.05	0.90	0.05	4.4	294.32
Conv134	64	256	0.52	0.05	0.90	0.05	0.90	0.05	0.84	83.68
Conv135	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.08	83.68
Conv136	256	64	0.82	0.05	0.90	0.05	0.90	0.05	5.17	294.32
Conv137	64	256	0.49	0.05	0.90	0.05	0.90	0.05	1.24	83.68
Conv138	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.05	83.68
Conv139	256	64	0.84	0.05	0.90	0.05	0.90	0.05	5.18	294.32
Conv140	64	256	0.52	0.05	0.90	0.05	0.90	0.05	1.94	83.68
Conv141	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.05	83.68
Conv142	256	64	0.81	0.05	0.90	0.05	0.90	0.05	5.9	294.32
Conv143	64	256	0.50	0.05	0.90	0.05	0.90	0.05	1.31	83.68
Conv144	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.06	83.68
Conv145	256	64	0.82	0.05	0.90	0.05	0.90	0.05	4.99	294.32
Conv146	64	256	0.53	0.05	0.90	0.05	0.90	0.05	1.05	83.68
Conv147	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.04	83.68
Conv148	256	64	0.83	0.05	0.90	0.05	0.90	0.05	4.7	294.32
Conv149	64	256	0.50	0.05	0.90	0.05	0.90	0.05	1.34	83.68
Conv150	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.05	83.68
Conv151	256	64	0.82	0.05	0.90	0.05	0.90	0.05	5.03	294.32
Conv152	64	256	0.51	0.05	0.90	0.05	0.90	0.05	1.36	83.68
Conv153	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.07	83.68
Conv154	256	64	0.81	0.05	0.90	0.05	0.90	0.05	5.44	294.32
Conv155	64	256	0.50	0.05	0.90	0.05	0.90	0.05	1.16	83.68
Conv156	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.06	83.68
Conv157	256	64	0.81	0.05	0.90	0.05	0.90	0.05	4.65	294.32
Conv158	64	256	0.47	0.05	0.90	0.05	0.90	0.05	1.52	83.68
Conv159	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.08	83.68
Conv160	256	64	0.82	0.05	0.90	0.05	0.90	0.05	5.66	294.32
Conv161	64	256	0.48	0.05	0.90	0.05	0.90	0.05	1.17	83.68
Conv162	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.05	83.68
Conv163	256	64	0.83	0.05	0.90	0.05	0.90	0.05	5.4	294.32
Passing rate	-	-	100.0%		100.0%		100.0%		99.39%	

Table 16: Cifar100 Adam-ResNet164

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	

			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	16	27	0.03	0.05	0.58	0.05	0.58	0.05	466.72	26.3
Conv2	16	16	0.12	0.05	0.56	0.05	0.56	0.05	222.95	26.3
Conv3	16	144	0.43	0.05	0.68	0.05	0.68	0.05	31.17	26.3
Conv4	64	16	0.35	0.05	0.63	0.05	0.63	0.05	103.14	83.68
Conv5	16	64	0.34	0.05	0.63	0.05	0.63	0.05	17.8	26.3
Conv6	16	144	0.52	0.05	0.68	0.05	0.68	0.05	5.97	26.3
Conv7	64	16	0.69	0.05	0.63	0.05	0.63	0.05	12.77	83.68
Conv8	16	64	0.33	0.05	0.63	0.05	0.63	0.05	31.39	26.3
Conv9	16	144	0.41	0.05	0.68	0.05	0.68	0.05	16.75	26.3
Conv10	64	16	0.66	0.05	0.63	0.05	0.63	0.05	26.55	83.68
Conv11	16	64	0.50	0.05	0.63	0.05	0.63	0.05	8.63	26.3
Conv12	16	144	0.61	0.05	0.68	0.05	0.68	0.05	3.88	26.3
Conv13	64	16	0.67	0.05	0.63	0.05	0.63	0.05	22.11	83.68
Conv14	16	64	0.66	0.05	0.63	0.05	0.63	0.05	5.01	26.3
Conv15	16	144	0.69	0.05	0.68	0.05	0.68	0.05	2.1	26.3
Conv16	64	16	0.87	0.05	0.63	0.05	0.63	0.05	5.14	83.68
Conv17	16	64	0.28	0.05	0.63	0.05	0.63	0.05	20.05	26.3
Conv18	16	144	0.17	0.05	0.68	0.05	0.68	0.05	7.17	26.3
Conv19	64	16	0.86	0.05	0.63	0.05	0.63	0.05	4.1	83.68
Conv20	16	64	0.57	0.05	0.63	0.05	0.63	0.05	17.79	26.3
Conv21	16	144	0.31	0.05	0.68	0.05	0.68	0.05	9.78	26.3
Conv22	64	16	0.91	0.05	0.63	0.05	0.63	0.05	3.07	83.68
Conv23	16	64	0.42	0.05	0.63	0.05	0.63	0.05	21.74	26.3
Conv24	16	144	0.31	0.05	0.68	0.05	0.68	0.05	10.79	26.3
Conv25	64	16	0.65	0.05	0.63	0.05	0.63	0.05	13.76	83.68
Conv26	16	64	0.34	0.05	0.63	0.05	0.63	0.05	14.28	26.3
Conv27	16	144	0.29	0.05	0.68	0.05	0.68	0.05	13.23	26.3
Conv28	64	16	0.54	0.05	0.63	0.05	0.63	0.05	31.67	83.68
Conv29	16	64	0.33	0.05	0.63	0.05	0.63	0.05	14.97	26.3
Conv30	16	144	0.50	0.05	0.68	0.05	0.68	0.05	5.76	26.3
Conv31	64	16	0.46	0.05	0.63	0.05	0.63	0.05	25.54	83.68
Conv32	16	64	0.39	0.05	0.63	0.05	0.63	0.05	14.78	26.3
Conv33	16	144	0.38	0.05	0.68	0.05	0.68	0.05	6.19	26.3
Conv34	64	16	0.84	0.05	0.63	0.05	0.63	0.05	9.25	83.68
Conv35	16	64	0.47	0.05	0.63	0.05	0.63	0.05	11.5	26.3
Conv36	16	144	0.42	0.05	0.68	0.05	0.68	0.05	13.26	26.3
Conv37	64	16	0.55	0.05	0.63	0.05	0.63	0.05	77.76	83.68
Conv38	16	64	0.46	0.05	0.63	0.05	0.63	0.05	20.83	26.3
Conv39	16	144	0.38	0.05	0.68	0.05	0.68	0.05	11.74	26.3
Conv40	64	16	0.68	0.05	0.63	0.05	0.63	0.05	35.12	83.68
Conv41	16	64	0.92	0.05	0.63	0.05	0.63	0.05	0.53	26.3
Conv42	16	144	0.94	0.05	0.68	0.05	0.68	0.05	0.15	26.3
Conv43	64	16	0.94	0.05	0.63	0.05	0.63	0.05	1.15	83.68
Conv44	16	64	0.42	0.05	0.63	0.05	0.63	0.05	20.83	26.3
Conv45	16	144	0.46	0.05	0.68	0.05	0.68	0.05	15.2	26.3
Conv46	64	16	0.45	0.05	0.63	0.05	0.63	0.05	50.71	83.68
Conv47	16	64	0.30	0.05	0.63	0.05	0.63	0.05	25.92	26.3
Conv48	16	144	0.43	0.05	0.68	0.05	0.68	0.05	15.15	26.3
Conv49	64	16	0.53	0.05	0.63	0.05	0.63	0.05	77.85	83.68
Conv50	16	64	0.34	0.05	0.63	0.05	0.63	0.05	23.91	26.3
Conv51	16	144	0.52	0.05	0.68	0.05	0.68	0.05	12.91	26.3
Conv52	64	16	0.45	0.05	0.63	0.05	0.63	0.05	74.94	83.68
Conv53	16	64	0.41	0.05	0.63	0.05	0.63	0.05	30.44	26.3
Conv54	16	144	0.41	0.05	0.68	0.05	0.68	0.05	21.99	26.3
Conv55	64	16	0.41	0.05	0.63	0.05	0.63	0.05	106.69	83.68
Conv56	32	64	0.13	0.05	0.67	0.05	0.67	0.05	167.36	46.19
Conv57	32	288	0.42	0.05	0.83	0.05	0.83	0.05	28.09	46.19

Conv58	128	32	0.17	0.05	0.74	0.05	0.74	0.05	320.85	155.4
Conv59	32	128	0.20	0.05	0.74	0.05	0.74	0.05	15.24	46.19
Conv60	32	288	0.23	0.05	0.83	0.05	0.83	0.05	10.97	46.19
Conv61	128	32	0.57	0.05	0.74	0.05	0.74	0.05	42.72	155.4
Conv62	32	128	0.22	0.05	0.74	0.05	0.74	0.05	15.01	46.19
Conv63	32	288	0.39	0.05	0.83	0.05	0.83	0.05	9.25	46.19
Conv64	128	32	0.63	0.05	0.74	0.05	0.74	0.05	40.35	155.4
Conv65	32	128	0.33	0.05	0.74	0.05	0.74	0.05	10.85	46.19
Conv66	32	288	0.64	0.05	0.83	0.05	0.83	0.05	4.2	46.19
Conv67	128	32	0.50	0.05	0.74	0.05	0.74	0.05	26.77	155.4
Conv68	32	128	0.15	0.05	0.74	0.05	0.74	0.05	22.12	46.19
Conv69	32	288	0.37	0.05	0.83	0.05	0.83	0.05	15.38	46.19
Conv70	128	32	0.49	0.05	0.74	0.05	0.74	0.05	69.31	155.4
Conv71	32	128	0.18	0.05	0.74	0.05	0.74	0.05	10.69	46.19
Conv72	32	288	0.26	0.05	0.83	0.05	0.83	0.05	6.71	46.19
Conv73	128	32	0.56	0.05	0.74	0.05	0.74	0.05	15.51	155.4
Conv74	32	128	0.38	0.05	0.74	0.05	0.74	0.05	23.08	46.19
Conv75	32	288	0.43	0.05	0.83	0.05	0.83	0.05	9.83	46.19
Conv76	128	32	0.49	0.05	0.74	0.05	0.74	0.05	29.79	155.4
Conv77	32	128	0.37	0.05	0.74	0.05	0.74	0.05	20.85	46.19
Conv78	32	288	0.43	0.05	0.83	0.05	0.83	0.05	7.53	46.19
Conv79	128	32	0.58	0.05	0.74	0.05	0.74	0.05	38.54	155.4
Conv80	32	128	0.26	0.05	0.74	0.05	0.74	0.05	18.75	46.19
Conv81	32	288	0.38	0.05	0.83	0.05	0.83	0.05	12.27	46.19
Conv82	128	32	0.62	0.05	0.74	0.05	0.74	0.05	32.84	155.4
Conv83	32	128	0.10	0.05	0.74	0.05	0.74	0.05	20.59	46.19
Conv84	32	288	0.31	0.05	0.83	0.05	0.83	0.05	16.6	46.19
Conv85	128	32	0.38	0.05	0.74	0.05	0.74	0.05	107.99	155.4
Conv86	32	128	0.44	0.05	0.74	0.05	0.74	0.05	18.28	46.19
Conv87	32	288	0.47	0.05	0.83	0.05	0.83	0.05	10.62	46.19
Conv88	128	32	0.62	0.05	0.74	0.05	0.74	0.05	35.83	155.4
Conv89	32	128	0.21	0.05	0.74	0.05	0.74	0.05	21.55	46.19
Conv90	32	288	0.57	0.05	0.83	0.05	0.83	0.05	7.98	46.19
Conv91	128	32	0.49	0.05	0.74	0.05	0.74	0.05	66.43	155.4
Conv92	32	128	0.43	0.05	0.74	0.05	0.74	0.05	17.04	46.19
Conv93	32	288	0.30	0.05	0.83	0.05	0.83	0.05	8.51	46.19
Conv94	128	32	0.58	0.05	0.74	0.05	0.74	0.05	43.25	155.4
Conv95	32	128	0.19	0.05	0.74	0.05	0.74	0.05	14.97	46.19
Conv96	32	288	0.29	0.05	0.83	0.05	0.83	0.05	9.6	46.19
Conv97	128	32	0.60	0.05	0.74	0.05	0.74	0.05	36.05	155.4
Conv98	32	128	0.35	0.05	0.74	0.05	0.74	0.05	7.96	46.19
Conv99	32	288	0.46	0.05	0.83	0.05	0.83	0.05	2.19	46.19
Conv100	128	32	0.81	0.05	0.74	0.05	0.74	0.05	11.53	155.4
Conv101	32	128	0.33	0.05	0.74	0.05	0.74	0.05	16.35	46.19
Conv102	32	288	0.34	0.05	0.83	0.05	0.83	0.05	9.13	46.19
Conv103	128	32	0.59	0.05	0.74	0.05	0.74	0.05	21.11	155.4
Conv104	32	128	0.39	0.05	0.74	0.05	0.74	0.05	20.91	46.19
Conv105	32	288	0.64	0.05	0.83	0.05	0.83	0.05	8.36	46.19
Conv106	128	32	0.54	0.05	0.74	0.05	0.74	0.05	44.06	155.4
Conv107	32	128	0.31	0.05	0.74	0.05	0.74	0.05	29.98	46.19
Conv108	32	288	0.45	0.05	0.83	0.05	0.83	0.05	15.03	46.19
Conv109	128	32	0.50	0.05	0.74	0.05	0.74	0.05	82.36	155.4
Conv110	64	128	0.14	0.05	0.82	0.05	0.82	0.05	197.08	83.68
Conv111	64	576	0.46	0.05	0.97	0.05	0.97	0.05	59.29	83.68
Conv112	256	64	0.16	0.05	0.90	0.05	0.90	0.05	594.89	294.32
Conv113	64	256	0.44	0.05	0.90	0.05	0.90	0.05	33.77	83.68
Conv114	64	576	0.32	0.05	0.97	0.05	0.97	0.05	26.61	83.68
Conv115	256	64	0.30	0.05	0.90	0.05	0.90	0.05	175.45	294.32
Conv116	64	256	0.38	0.05	0.90	0.05	0.90	0.05	24.35	83.68

Conv117	64	576	0.33	0.05	0.97	0.05	0.97	0.05	16.49	83.68
Conv118	256	64	0.51	0.05	0.90	0.05	0.90	0.05	123.0	294.32
Conv119	64	256	0.08	0.05	0.90	0.05	0.90	0.05	35.01	83.68
Conv120	64	576	0.34	0.05	0.97	0.05	0.97	0.05	24.5	83.68
Conv121	256	64	0.36	0.05	0.90	0.05	0.90	0.05	159.72	294.32
Conv122	64	256	0.42	0.05	0.90	0.05	0.90	0.05	21.93	83.68
Conv123	64	576	0.16	0.05	0.97	0.05	0.97	0.05	12.24	83.68
Conv124	256	64	0.54	0.05	0.90	0.05	0.90	0.05	86.27	294.32
Conv125	64	256	0.24	0.05	0.90	0.05	0.90	0.05	38.93	83.68
Conv126	64	576	0.44	0.05	0.97	0.05	0.97	0.05	17.46	83.68
Conv127	256	64	0.50	0.05	0.90	0.05	0.90	0.05	91.81	294.32
Conv128	64	256	0.32	0.05	0.90	0.05	0.90	0.05	29.94	83.68
Conv129	64	576	0.33	0.05	0.97	0.05	0.97	0.05	11.34	83.68
Conv130	256	64	0.58	0.05	0.90	0.05	0.90	0.05	76.05	294.32
Conv131	64	256	0.46	0.05	0.90	0.05	0.90	0.05	38.51	83.68
Conv132	64	576	0.42	0.05	0.97	0.05	0.97	0.05	13.99	83.68
Conv133	256	64	0.49	0.05	0.90	0.05	0.90	0.05	78.35	294.32
Conv134	64	256	0.28	0.05	0.90	0.05	0.90	0.05	55.05	83.68
Conv135	64	576	0.34	0.05	0.97	0.05	0.97	0.05	22.32	83.68
Conv136	256	64	0.40	0.05	0.90	0.05	0.90	0.05	127.27	294.32
Conv137	64	256	0.45	0.05	0.90	0.05	0.90	0.05	73.92	83.68
Conv138	64	576	0.39	0.05	0.97	0.05	0.97	0.05	20.65	83.68
Conv139	256	64	0.43	0.05	0.90	0.05	0.90	0.05	79.88	294.32
Conv140	64	256	0.46	0.05	0.90	0.05	0.90	0.05	57.87	83.68
Conv141	64	576	0.46	0.05	0.97	0.05	0.97	0.05	14.7	83.68
Conv142	256	64	0.49	0.05	0.90	0.05	0.90	0.05	62.55	294.32
Conv143	64	256	0.36	0.05	0.90	0.05	0.90	0.05	64.03	83.68
Conv144	64	576	0.51	0.05	0.97	0.05	0.97	0.05	17.48	83.68
Conv145	256	64	0.45	0.05	0.90	0.05	0.90	0.05	59.58	294.32
Conv146	64	256	0.36	0.05	0.90	0.05	0.90	0.05	106.22	83.68
Conv147	64	576	0.53	0.05	0.97	0.05	0.97	0.05	32.45	83.68
Conv148	256	64	0.39	0.05	0.90	0.05	0.90	0.05	110.05	294.32
Conv149	64	256	0.43	0.05	0.90	0.05	0.90	0.05	105.01	83.68
Conv150	64	576	0.43	0.05	0.97	0.05	0.97	0.05	30.32	83.68
Conv151	256	64	0.40	0.05	0.90	0.05	0.90	0.05	81.71	294.32
Conv152	64	256	0.34	0.05	0.90	0.05	0.90	0.05	113.29	83.68
Conv153	64	576	0.42	0.05	0.97	0.05	0.97	0.05	23.49	83.68
Conv154	256	64	0.37	0.05	0.90	0.05	0.90	0.05	75.03	294.32
Conv155	64	256	0.30	0.05	0.90	0.05	0.90	0.05	101.39	83.68
Conv156	64	576	0.63	0.05	0.97	0.05	0.97	0.05	15.84	83.68
Conv157	256	64	0.49	0.05	0.90	0.05	0.90	0.05	58.98	294.32
Conv158	64	256	0.23	0.05	0.90	0.05	0.90	0.05	84.02	83.68
Conv159	64	576	0.65	0.05	0.97	0.05	0.97	0.05	8.42	83.68
Conv160	256	64	0.54	0.05	0.90	0.05	0.90	0.05	33.29	294.32
Conv161	64	256	0.57	0.05	0.90	0.05	0.90	0.05	20.57	83.68
Conv162	64	576	0.82	0.05	0.97	0.05	0.97	0.05	1.41	83.68
Conv163	256	64	0.86	0.05	0.90	0.05	0.90	0.05	9.3	294.32
Passing rate	-	-	99.39%		100.0%		100.0%		90.18%	

Table 17: Cifar100 Adagrad-ResNet164

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	16	27	0.81	0.05	0.58	0.05	0.58	0.05	1.0	26.3
Conv2	16	16	0.29	0.05	0.56	0.05	0.56	0.05	27.5	26.3

Conv3	16	144	0.64	0.05	0.68	0.05	0.68	0.05	0.21	26.3
Conv4	64	16	0.58	0.05	0.63	0.05	0.63	0.05	26.43	83.68
Conv5	16	64	0.22	0.05	0.63	0.05	0.63	0.05	5.73	26.3
Conv6	16	144	0.69	0.05	0.68	0.05	0.68	0.05	0.31	26.3
Conv7	64	16	0.56	0.05	0.63	0.05	0.63	0.05	24.75	83.68
Conv8	16	64	0.26	0.05	0.63	0.05	0.63	0.05	2.68	26.3
Conv9	16	144	0.67	0.05	0.68	0.05	0.68	0.05	0.32	26.3
Conv10	64	16	0.57	0.05	0.63	0.05	0.63	0.05	23.47	83.68
Conv11	16	64	0.32	0.05	0.63	0.05	0.63	0.05	4.14	26.3
Conv12	16	144	0.68	0.05	0.68	0.05	0.68	0.05	0.16	26.3
Conv13	64	16	0.49	0.05	0.63	0.05	0.63	0.05	21.49	83.68
Conv14	16	64	0.25	0.05	0.63	0.05	0.63	0.05	7.46	26.3
Conv15	16	144	0.69	0.05	0.68	0.05	0.68	0.05	0.22	26.3
Conv16	64	16	0.56	0.05	0.63	0.05	0.63	0.05	22.21	83.68
Conv17	16	64	0.24	0.05	0.63	0.05	0.63	0.05	3.57	26.3
Conv18	16	144	0.68	0.05	0.68	0.05	0.68	0.05	0.36	26.3
Conv19	64	16	0.57	0.05	0.63	0.05	0.63	0.05	27.9	83.68
Conv20	16	64	0.22	0.05	0.63	0.05	0.63	0.05	3.02	26.3
Conv21	16	144	0.64	0.05	0.68	0.05	0.68	0.05	0.18	26.3
Conv22	64	16	0.57	0.05	0.63	0.05	0.63	0.05	18.51	83.68
Conv23	16	64	0.27	0.05	0.63	0.05	0.63	0.05	3.4	26.3
Conv24	16	144	0.71	0.05	0.68	0.05	0.68	0.05	0.24	26.3
Conv25	64	16	0.58	0.05	0.63	0.05	0.63	0.05	15.57	83.68
Conv26	16	64	0.30	0.05	0.63	0.05	0.63	0.05	3.65	26.3
Conv27	16	144	0.71	0.05	0.68	0.05	0.68	0.05	0.24	26.3
Conv28	64	16	0.51	0.05	0.63	0.05	0.63	0.05	20.17	83.68
Conv29	16	64	0.21	0.05	0.63	0.05	0.63	0.05	5.1	26.3
Conv30	16	144	0.69	0.05	0.68	0.05	0.68	0.05	0.23	26.3
Conv31	64	16	0.54	0.05	0.63	0.05	0.63	0.05	21.99	83.68
Conv32	16	64	0.30	0.05	0.63	0.05	0.63	0.05	5.37	26.3
Conv33	16	144	0.65	0.05	0.68	0.05	0.68	0.05	0.41	26.3
Conv34	64	16	0.49	0.05	0.63	0.05	0.63	0.05	22.39	83.68
Conv35	16	64	0.20	0.05	0.63	0.05	0.63	0.05	5.39	26.3
Conv36	16	144	0.63	0.05	0.68	0.05	0.68	0.05	0.15	26.3
Conv37	64	16	0.60	0.05	0.63	0.05	0.63	0.05	22.47	83.68
Conv38	16	64	0.33	0.05	0.63	0.05	0.63	0.05	2.65	26.3
Conv39	16	144	0.68	0.05	0.68	0.05	0.68	0.05	0.22	26.3
Conv40	64	16	0.56	0.05	0.63	0.05	0.63	0.05	15.34	83.68
Conv41	16	64	0.34	0.05	0.63	0.05	0.63	0.05	4.43	26.3
Conv42	16	144	0.69	0.05	0.68	0.05	0.68	0.05	0.28	26.3
Conv43	64	16	0.61	0.05	0.63	0.05	0.63	0.05	20.54	83.68
Conv44	16	64	0.34	0.05	0.63	0.05	0.63	0.05	5.02	26.3
Conv45	16	144	0.67	0.05	0.68	0.05	0.68	0.05	0.37	26.3
Conv46	64	16	0.63	0.05	0.63	0.05	0.63	0.05	19.02	83.68
Conv47	16	64	0.28	0.05	0.63	0.05	0.63	0.05	5.11	26.3
Conv48	16	144	0.68	0.05	0.68	0.05	0.68	0.05	0.29	26.3
Conv49	64	16	0.65	0.05	0.63	0.05	0.63	0.05	19.48	83.68
Conv50	16	64	0.36	0.05	0.63	0.05	0.63	0.05	3.04	26.3
Conv51	16	144	0.69	0.05	0.68	0.05	0.68	0.05	0.41	26.3
Conv52	64	16	0.64	0.05	0.63	0.05	0.63	0.05	21.89	83.68
Conv53	16	64	0.26	0.05	0.63	0.05	0.63	0.05	3.49	26.3
Conv54	16	144	0.70	0.05	0.68	0.05	0.68	0.05	0.07	26.3
Conv55	64	16	0.59	0.05	0.63	0.05	0.63	0.05	20.2	83.68
Conv56	32	64	0.47	0.05	0.67	0.05	0.67	0.05	3.86	46.19
Conv57	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.12	46.19
Conv58	128	32	0.65	0.05	0.74	0.05	0.74	0.05	10.75	155.4
Conv59	32	128	0.48	0.05	0.74	0.05	0.74	0.05	1.97	46.19
Conv60	32	288	0.82	0.05	0.83	0.05	0.83	0.05	0.14	46.19
Conv61	128	32	0.64	0.05	0.74	0.05	0.74	0.05	10.13	155.4

Conv62	32	128	0.48	0.05	0.74	0.05	0.74	0.05	2.12	46.19
Conv63	32	288	0.83	0.05	0.83	0.05	0.83	0.05	0.21	46.19
Conv64	128	32	0.67	0.05	0.74	0.05	0.74	0.05	9.34	155.4
Conv65	32	128	0.48	0.05	0.74	0.05	0.74	0.05	4.38	46.19
Conv66	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.23	46.19
Conv67	128	32	0.65	0.05	0.74	0.05	0.74	0.05	9.64	155.4
Conv68	32	128	0.43	0.05	0.74	0.05	0.74	0.05	4.33	46.19
Conv69	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.22	46.19
Conv70	128	32	0.68	0.05	0.74	0.05	0.74	0.05	9.63	155.4
Conv71	32	128	0.48	0.05	0.74	0.05	0.74	0.05	3.55	46.19
Conv72	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.19	46.19
Conv73	128	32	0.81	0.05	0.74	0.05	0.74	0.05	9.45	155.4
Conv74	32	128	0.44	0.05	0.74	0.05	0.74	0.05	5.7	46.19
Conv75	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.41	46.19
Conv76	128	32	0.69	0.05	0.74	0.05	0.74	0.05	10.14	155.4
Conv77	32	128	0.39	0.05	0.74	0.05	0.74	0.05	6.42	46.19
Conv78	32	288	0.83	0.05	0.83	0.05	0.83	0.05	0.25	46.19
Conv79	128	32	0.67	0.05	0.74	0.05	0.74	0.05	7.54	155.4
Conv80	32	128	0.52	0.05	0.74	0.05	0.74	0.05	3.95	46.19
Conv81	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.24	46.19
Conv82	128	32	0.70	0.05	0.74	0.05	0.74	0.05	8.76	155.4
Conv83	32	128	0.53	0.05	0.74	0.05	0.74	0.05	6.0	46.19
Conv84	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.33	46.19
Conv85	128	32	0.70	0.05	0.74	0.05	0.74	0.05	9.76	155.4
Conv86	32	128	0.51	0.05	0.74	0.05	0.74	0.05	3.95	46.19
Conv87	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.39	46.19
Conv88	128	32	0.81	0.05	0.74	0.05	0.74	0.05	10.14	155.4
Conv89	32	128	0.54	0.05	0.74	0.05	0.74	0.05	6.26	46.19
Conv90	32	288	0.86	0.05	0.83	0.05	0.83	0.05	0.62	46.19
Conv91	128	32	0.68	0.05	0.74	0.05	0.74	0.05	10.09	155.4
Conv92	32	128	0.48	0.05	0.74	0.05	0.74	0.05	3.63	46.19
Conv93	32	288	0.86	0.05	0.83	0.05	0.83	0.05	0.33	46.19
Conv94	128	32	0.71	0.05	0.74	0.05	0.74	0.05	9.94	155.4
Conv95	32	128	0.53	0.05	0.74	0.05	0.74	0.05	3.39	46.19
Conv96	32	288	0.87	0.05	0.83	0.05	0.83	0.05	0.4	46.19
Conv97	128	32	0.69	0.05	0.74	0.05	0.74	0.05	6.74	155.4
Conv98	32	128	0.52	0.05	0.74	0.05	0.74	0.05	7.89	46.19
Conv99	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.38	46.19
Conv100	128	32	0.82	0.05	0.74	0.05	0.74	0.05	9.47	155.4
Conv101	32	128	0.55	0.05	0.74	0.05	0.74	0.05	4.92	46.19
Conv102	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.37	46.19
Conv103	128	32	0.82	0.05	0.74	0.05	0.74	0.05	10.66	155.4
Conv104	32	128	0.49	0.05	0.74	0.05	0.74	0.05	4.22	46.19
Conv105	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.34	46.19
Conv106	128	32	0.81	0.05	0.74	0.05	0.74	0.05	9.11	155.4
Conv107	32	128	0.51	0.05	0.74	0.05	0.74	0.05	5.88	46.19
Conv108	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.42	46.19
Conv109	128	32	0.71	0.05	0.74	0.05	0.74	0.05	7.11	155.4
Conv110	64	128	0.55	0.05	0.82	0.05	0.82	0.05	3.26	83.68
Conv111	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.2	83.68
Conv112	256	64	0.83	0.05	0.90	0.05	0.90	0.05	5.43	294.32
Conv113	64	256	0.63	0.05	0.90	0.05	0.90	0.05	2.29	83.68
Conv114	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.23	83.68
Conv115	256	64	0.83	0.05	0.90	0.05	0.90	0.05	6.3	294.32
Conv116	64	256	0.62	0.05	0.90	0.05	0.90	0.05	2.39	83.68
Conv117	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.25	83.68
Conv118	256	64	0.86	0.05	0.90	0.05	0.90	0.05	6.52	294.32
Conv119	64	256	0.60	0.05	0.90	0.05	0.90	0.05	3.15	83.68
Conv120	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.28	83.68

Conv121	256	64	0.86	0.05	0.90	0.05	0.90	0.05	6.03	294.32
Conv122	64	256	0.61	0.05	0.90	0.05	0.90	0.05	4.13	83.68
Conv123	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.22	83.68
Conv124	256	64	0.85	0.05	0.90	0.05	0.90	0.05	5.46	294.32
Conv125	64	256	0.53	0.05	0.90	0.05	0.90	0.05	5.63	83.68
Conv126	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.21	83.68
Conv127	256	64	0.85	0.05	0.90	0.05	0.90	0.05	6.59	294.32
Conv128	64	256	0.63	0.05	0.90	0.05	0.90	0.05	4.57	83.68
Conv129	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.21	83.68
Conv130	256	64	0.85	0.05	0.90	0.05	0.90	0.05	5.21	294.32
Conv131	64	256	0.68	0.05	0.90	0.05	0.90	0.05	4.42	83.68
Conv132	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.21	83.68
Conv133	256	64	0.85	0.05	0.90	0.05	0.90	0.05	5.39	294.32
Conv134	64	256	0.65	0.05	0.90	0.05	0.90	0.05	6.82	83.68
Conv135	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.23	83.68
Conv136	256	64	0.85	0.05	0.90	0.05	0.90	0.05	6.57	294.32
Conv137	64	256	0.68	0.05	0.90	0.05	0.90	0.05	6.95	83.68
Conv138	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.22	83.68
Conv139	256	64	0.85	0.05	0.90	0.05	0.90	0.05	6.3	294.32
Conv140	64	256	0.62	0.05	0.90	0.05	0.90	0.05	4.99	83.68
Conv141	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.21	83.68
Conv142	256	64	0.86	0.05	0.90	0.05	0.90	0.05	4.94	294.32
Conv143	64	256	0.62	0.05	0.90	0.05	0.90	0.05	4.11	83.68
Conv144	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.27	83.68
Conv145	256	64	0.82	0.05	0.90	0.05	0.90	0.05	5.79	294.32
Conv146	64	256	0.62	0.05	0.90	0.05	0.90	0.05	4.72	83.68
Conv147	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.32	83.68
Conv148	256	64	0.85	0.05	0.90	0.05	0.90	0.05	4.91	294.32
Conv149	64	256	0.65	0.05	0.90	0.05	0.90	0.05	3.53	83.68
Conv150	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.21	83.68
Conv151	256	64	0.85	0.05	0.90	0.05	0.90	0.05	4.28	294.32
Conv152	64	256	0.65	0.05	0.90	0.05	0.90	0.05	4.26	83.68
Conv153	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.2	83.68
Conv154	256	64	0.86	0.05	0.90	0.05	0.90	0.05	3.77	294.32
Conv155	64	256	0.62	0.05	0.90	0.05	0.90	0.05	4.45	83.68
Conv156	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.12	83.68
Conv157	256	64	0.85	0.05	0.90	0.05	0.90	0.05	3.0	294.32
Conv158	64	256	0.66	0.05	0.90	0.05	0.90	0.05	5.59	83.68
Conv159	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.22	83.68
Conv160	256	64	0.85	0.05	0.90	0.05	0.90	0.05	3.12	294.32
Conv161	64	256	0.63	0.05	0.90	0.05	0.90	0.05	4.89	83.68
Conv162	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.17	83.68
Conv163	256	64	0.86	0.05	0.90	0.05	0.90	0.05	2.38	294.32
Passing rate	-	-	99.39%		100.0%		100.0%		99.39%	

Table 18: Cifar100 Adamax-ResNet164

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	16	27	0.13	0.05	0.58	0.05	0.58	0.05	68.0	26.3
Conv2	16	16	0.48	0.05	0.56	0.05	0.56	0.05	71.45	26.3
Conv3	16	144	0.66	0.05	0.68	0.05	0.68	0.05	11.09	26.3
Conv4	64	16	0.59	0.05	0.63	0.05	0.63	0.05	70.98	83.68
Conv5	16	64	0.55	0.05	0.63	0.05	0.63	0.05	20.74	26.3
Conv6	16	144	0.61	0.05	0.68	0.05	0.68	0.05	13.67	26.3

Conv7	64	16	0.63	0.05	0.63	0.05	0.63	0.05	78.55	83.68
Conv8	16	64	0.46	0.05	0.63	0.05	0.63	0.05	13.55	26.3
Conv9	16	144	0.69	0.05	0.68	0.05	0.68	0.05	7.71	26.3
Conv10	64	16	0.70	0.05	0.63	0.05	0.63	0.05	21.48	83.68
Conv11	16	64	0.66	0.05	0.63	0.05	0.63	0.05	4.16	26.3
Conv12	16	144	0.89	0.05	0.68	0.05	0.68	0.05	1.72	26.3
Conv13	64	16	0.88	0.05	0.63	0.05	0.63	0.05	7.36	83.68
Conv14	16	64	0.69	0.05	0.63	0.05	0.63	0.05	8.77	26.3
Conv15	16	144	0.67	0.05	0.68	0.05	0.68	0.05	2.77	26.3
Conv16	64	16	0.80	0.05	0.63	0.05	0.63	0.05	7.36	83.68
Conv17	16	64	0.70	0.05	0.63	0.05	0.63	0.05	6.74	26.3
Conv18	16	144	0.71	0.05	0.68	0.05	0.68	0.05	2.63	26.3
Conv19	64	16	0.82	0.05	0.63	0.05	0.63	0.05	11.07	83.68
Conv20	16	64	0.44	0.05	0.63	0.05	0.63	0.05	15.46	26.3
Conv21	16	144	0.51	0.05	0.68	0.05	0.68	0.05	7.75	26.3
Conv22	64	16	0.66	0.05	0.63	0.05	0.63	0.05	24.59	83.68
Conv23	16	64	0.54	0.05	0.63	0.05	0.63	0.05	16.27	26.3
Conv24	16	144	0.62	0.05	0.68	0.05	0.68	0.05	10.25	26.3
Conv25	64	16	0.71	0.05	0.63	0.05	0.63	0.05	44.15	83.68
Conv26	16	64	0.68	0.05	0.63	0.05	0.63	0.05	12.42	26.3
Conv27	16	144	0.64	0.05	0.68	0.05	0.68	0.05	4.52	26.3
Conv28	64	16	0.80	0.05	0.63	0.05	0.63	0.05	21.59	83.68
Conv29	16	64	0.54	0.05	0.63	0.05	0.63	0.05	19.57	26.3
Conv30	16	144	0.60	0.05	0.68	0.05	0.68	0.05	10.01	26.3
Conv31	64	16	0.63	0.05	0.63	0.05	0.63	0.05	50.96	83.68
Conv32	16	64	0.41	0.05	0.63	0.05	0.63	0.05	15.87	26.3
Conv33	16	144	0.58	0.05	0.68	0.05	0.68	0.05	6.75	26.3
Conv34	64	16	0.66	0.05	0.63	0.05	0.63	0.05	52.95	83.68
Conv35	16	64	0.59	0.05	0.63	0.05	0.63	0.05	10.96	26.3
Conv36	16	144	0.66	0.05	0.68	0.05	0.68	0.05	4.91	26.3
Conv37	64	16	0.65	0.05	0.63	0.05	0.63	0.05	21.71	83.68
Conv38	16	64	0.35	0.05	0.63	0.05	0.63	0.05	24.32	26.3
Conv39	16	144	0.50	0.05	0.68	0.05	0.68	0.05	8.62	26.3
Conv40	64	16	0.67	0.05	0.63	0.05	0.63	0.05	49.57	83.68
Conv41	16	64	0.61	0.05	0.63	0.05	0.63	0.05	16.45	26.3
Conv42	16	144	0.63	0.05	0.68	0.05	0.68	0.05	9.32	26.3
Conv43	64	16	0.68	0.05	0.63	0.05	0.63	0.05	38.26	83.68
Conv44	16	64	0.68	0.05	0.63	0.05	0.63	0.05	12.91	26.3
Conv45	16	144	0.65	0.05	0.68	0.05	0.68	0.05	8.54	26.3
Conv46	64	16	0.65	0.05	0.63	0.05	0.63	0.05	53.09	83.68
Conv47	16	64	0.55	0.05	0.63	0.05	0.63	0.05	16.67	26.3
Conv48	16	144	0.56	0.05	0.68	0.05	0.68	0.05	8.19	26.3
Conv49	64	16	0.66	0.05	0.63	0.05	0.63	0.05	39.79	83.68
Conv50	16	64	0.59	0.05	0.63	0.05	0.63	0.05	17.17	26.3
Conv51	16	144	0.61	0.05	0.68	0.05	0.68	0.05	10.77	26.3
Conv52	64	16	0.61	0.05	0.63	0.05	0.63	0.05	51.64	83.68
Conv53	16	64	0.37	0.05	0.63	0.05	0.63	0.05	24.49	26.3
Conv54	16	144	0.57	0.05	0.68	0.05	0.68	0.05	7.39	26.3
Conv55	64	16	0.62	0.05	0.63	0.05	0.63	0.05	45.71	83.68
Conv56	32	64	0.35	0.05	0.67	0.05	0.67	0.05	84.41	46.19
Conv57	32	288	0.56	0.05	0.83	0.05	0.83	0.05	19.39	46.19
Conv58	128	32	0.42	0.05	0.74	0.05	0.74	0.05	198.37	155.4
Conv59	32	128	0.43	0.05	0.74	0.05	0.74	0.05	16.2	46.19
Conv60	32	288	0.39	0.05	0.83	0.05	0.83	0.05	10.01	46.19
Conv61	128	32	0.62	0.05	0.74	0.05	0.74	0.05	49.07	155.4
Conv62	32	128	0.43	0.05	0.74	0.05	0.74	0.05	11.75	46.19
Conv63	32	288	0.55	0.05	0.83	0.05	0.83	0.05	6.82	46.19
Conv64	128	32	0.62	0.05	0.74	0.05	0.74	0.05	37.0	155.4
Conv65	32	128	0.54	0.05	0.74	0.05	0.74	0.05	8.23	46.19

Conv66	32	288	0.45	0.05	0.83	0.05	0.83	0.05	5.49	46.19
Conv67	128	32	0.69	0.05	0.74	0.05	0.74	0.05	34.13	155.4
Conv68	32	128	0.41	0.05	0.74	0.05	0.74	0.05	9.57	46.19
Conv69	32	288	0.49	0.05	0.83	0.05	0.83	0.05	6.21	46.19
Conv70	128	32	0.69	0.05	0.74	0.05	0.74	0.05	28.63	155.4
Conv71	32	128	0.38	0.05	0.74	0.05	0.74	0.05	12.89	46.19
Conv72	32	288	0.42	0.05	0.83	0.05	0.83	0.05	7.03	46.19
Conv73	128	32	0.59	0.05	0.74	0.05	0.74	0.05	34.59	155.4
Conv74	32	128	0.50	0.05	0.74	0.05	0.74	0.05	18.97	46.19
Conv75	32	288	0.68	0.05	0.83	0.05	0.83	0.05	8.88	46.19
Conv76	128	32	0.69	0.05	0.74	0.05	0.74	0.05	40.73	155.4
Conv77	32	128	0.57	0.05	0.74	0.05	0.74	0.05	12.85	46.19
Conv78	32	288	0.64	0.05	0.83	0.05	0.83	0.05	4.65	46.19
Conv79	128	32	0.82	0.05	0.74	0.05	0.74	0.05	23.62	155.4
Conv80	32	128	0.59	0.05	0.74	0.05	0.74	0.05	8.78	46.19
Conv81	32	288	0.61	0.05	0.83	0.05	0.83	0.05	3.45	46.19
Conv82	128	32	0.81	0.05	0.74	0.05	0.74	0.05	17.55	155.4
Conv83	32	128	0.55	0.05	0.74	0.05	0.74	0.05	16.4	46.19
Conv84	32	288	0.56	0.05	0.83	0.05	0.83	0.05	8.33	46.19
Conv85	128	32	0.66	0.05	0.74	0.05	0.74	0.05	38.5	155.4
Conv86	32	128	0.39	0.05	0.74	0.05	0.74	0.05	23.91	46.19
Conv87	32	288	0.56	0.05	0.83	0.05	0.83	0.05	12.35	46.19
Conv88	128	32	0.54	0.05	0.74	0.05	0.74	0.05	85.92	155.4
Conv89	32	128	0.56	0.05	0.74	0.05	0.74	0.05	20.14	46.19
Conv90	32	288	0.63	0.05	0.83	0.05	0.83	0.05	8.2	46.19
Conv91	128	32	0.69	0.05	0.74	0.05	0.74	0.05	47.23	155.4
Conv92	32	128	0.54	0.05	0.74	0.05	0.74	0.05	11.75	46.19
Conv93	32	288	0.58	0.05	0.83	0.05	0.83	0.05	5.63	46.19
Conv94	128	32	0.81	0.05	0.74	0.05	0.74	0.05	25.93	155.4
Conv95	32	128	0.61	0.05	0.74	0.05	0.74	0.05	16.71	46.19
Conv96	32	288	0.68	0.05	0.83	0.05	0.83	0.05	7.92	46.19
Conv97	128	32	0.69	0.05	0.74	0.05	0.74	0.05	37.55	155.4
Conv98	32	128	0.40	0.05	0.74	0.05	0.74	0.05	22.82	46.19
Conv99	32	288	0.80	0.05	0.83	0.05	0.83	0.05	6.79	46.19
Conv100	128	32	0.67	0.05	0.74	0.05	0.74	0.05	49.54	155.4
Conv101	32	128	0.62	0.05	0.74	0.05	0.74	0.05	19.77	46.19
Conv102	32	288	0.67	0.05	0.83	0.05	0.83	0.05	7.45	46.19
Conv103	128	32	0.62	0.05	0.74	0.05	0.74	0.05	56.52	155.4
Conv104	32	128	0.47	0.05	0.74	0.05	0.74	0.05	19.67	46.19
Conv105	32	288	0.59	0.05	0.83	0.05	0.83	0.05	11.28	46.19
Conv106	128	32	0.66	0.05	0.74	0.05	0.74	0.05	55.28	155.4
Conv107	32	128	0.53	0.05	0.74	0.05	0.74	0.05	20.02	46.19
Conv108	32	288	0.63	0.05	0.83	0.05	0.83	0.05	6.73	46.19
Conv109	128	32	0.67	0.05	0.74	0.05	0.74	0.05	38.49	155.4
Conv110	64	128	0.30	0.05	0.82	0.05	0.82	0.05	102.5	83.68
Conv111	64	576	0.51	0.05	0.97	0.05	0.97	0.05	20.27	83.68
Conv112	256	64	0.18	0.05	0.90	0.05	0.90	0.05	228.72	294.32
Conv113	64	256	0.63	0.05	0.90	0.05	0.90	0.05	19.19	83.68
Conv114	64	576	0.51	0.05	0.97	0.05	0.97	0.05	13.0	83.68
Conv115	256	64	0.59	0.05	0.90	0.05	0.90	0.05	59.58	294.32
Conv116	64	256	0.67	0.05	0.90	0.05	0.90	0.05	18.46	83.68
Conv117	64	576	0.47	0.05	0.97	0.05	0.97	0.05	11.64	83.68
Conv118	256	64	0.64	0.05	0.90	0.05	0.90	0.05	59.16	294.32
Conv119	64	256	0.65	0.05	0.90	0.05	0.90	0.05	18.95	83.68
Conv120	64	576	0.44	0.05	0.97	0.05	0.97	0.05	12.67	83.68
Conv121	256	64	0.63	0.05	0.90	0.05	0.90	0.05	47.73	294.32
Conv122	64	256	0.54	0.05	0.90	0.05	0.90	0.05	19.16	83.68
Conv123	64	576	0.63	0.05	0.97	0.05	0.97	0.05	10.26	83.68
Conv124	256	64	0.81	0.05	0.90	0.05	0.90	0.05	42.2	294.32

Conv125	64	256	0.59	0.05	0.90	0.05	0.90	0.05	24.01	83.68
Conv126	64	576	0.69	0.05	0.97	0.05	0.97	0.05	11.76	83.68
Conv127	256	64	0.65	0.05	0.90	0.05	0.90	0.05	39.33	294.32
Conv128	64	256	0.28	0.05	0.90	0.05	0.90	0.05	25.97	83.68
Conv129	64	576	0.60	0.05	0.97	0.05	0.97	0.05	13.68	83.68
Conv130	256	64	0.51	0.05	0.90	0.05	0.90	0.05	62.74	294.32
Conv131	64	256	0.18	0.05	0.90	0.05	0.90	0.05	37.84	83.68
Conv132	64	576	0.55	0.05	0.97	0.05	0.97	0.05	16.28	83.68
Conv133	256	64	0.43	0.05	0.90	0.05	0.90	0.05	98.19	294.32
Conv134	64	256	0.43	0.05	0.90	0.05	0.90	0.05	39.47	83.68
Conv135	64	576	0.47	0.05	0.97	0.05	0.97	0.05	13.86	83.68
Conv136	256	64	0.71	0.05	0.90	0.05	0.90	0.05	65.95	294.32
Conv137	64	256	0.64	0.05	0.90	0.05	0.90	0.05	44.63	83.68
Conv138	64	576	0.65	0.05	0.97	0.05	0.97	0.05	13.91	83.68
Conv139	256	64	0.53	0.05	0.90	0.05	0.90	0.05	70.45	294.32
Conv140	64	256	0.59	0.05	0.90	0.05	0.90	0.05	44.73	83.68
Conv141	64	576	0.68	0.05	0.97	0.05	0.97	0.05	11.5	83.68
Conv142	256	64	0.55	0.05	0.90	0.05	0.90	0.05	84.15	294.32
Conv143	64	256	0.52	0.05	0.90	0.05	0.90	0.05	45.81	83.68
Conv144	64	576	0.64	0.05	0.97	0.05	0.97	0.05	2.99	83.68
Conv145	256	64	0.58	0.05	0.90	0.05	0.90	0.05	80.95	294.32
Conv146	64	256	0.49	0.05	0.90	0.05	0.90	0.05	43.23	83.68
Conv147	64	576	0.67	0.05	0.97	0.05	0.97	0.05	11.54	83.68
Conv148	256	64	0.60	0.05	0.90	0.05	0.90	0.05	76.94	294.32
Conv149	64	256	0.53	0.05	0.90	0.05	0.90	0.05	30.26	83.68
Conv150	64	576	0.69	0.05	0.97	0.05	0.97	0.05	6.73	83.68
Conv151	256	64	0.48	0.05	0.90	0.05	0.90	0.05	81.75	294.32
Conv152	64	256	0.56	0.05	0.90	0.05	0.90	0.05	33.02	83.68
Conv153	64	576	0.81	0.05	0.97	0.05	0.97	0.05	8.73	83.68
Conv154	256	64	0.55	0.05	0.90	0.05	0.90	0.05	91.86	294.32
Conv155	64	256	0.59	0.05	0.90	0.05	0.90	0.05	29.47	83.68
Conv156	64	576	0.83	0.05	0.97	0.05	0.97	0.05	11.58	83.68
Conv157	256	64	0.60	0.05	0.90	0.05	0.90	0.05	76.05	294.32
Conv158	64	256	0.47	0.05	0.90	0.05	0.90	0.05	41.88	83.68
Conv159	64	576	0.82	0.05	0.97	0.05	0.97	0.05	15.7	83.68
Conv160	256	64	0.53	0.05	0.90	0.05	0.90	0.05	64.48	294.32
Conv161	64	256	0.51	0.05	0.90	0.05	0.90	0.05	68.02	83.68
Conv162	64	576	0.81	0.05	0.97	0.05	0.97	0.05	12.04	83.68
Conv163	256	64	0.61	0.05	0.90	0.05	0.90	0.05	51.41	294.32
Passing rate	-	-	100.0%		100.0%		100.0%		96.93%	

Table 19: Cifar100 Adadelta-ResNet164

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.11	0.05	0.58	0.05	0.58	0.05	8.49	26.3
Conv2	16	16	0.43	0.05	0.56	0.05	0.56	0.05	9.33	26.3
Conv3	16	144	0.56	0.05	0.68	0.05	0.68	0.05	4.11	26.3
Conv4	64	16	0.44	0.05	0.63	0.05	0.63	0.05	45.93	83.68
Conv5	16	64	0.53	0.05	0.63	0.05	0.63	0.05	3.17	26.3
Conv6	16	144	0.56	0.05	0.68	0.05	0.68	0.05	6.72	26.3
Conv7	64	16	0.64	0.05	0.63	0.05	0.63	0.05	23.93	83.68
Conv8	16	64	0.62	0.05	0.63	0.05	0.63	0.05	3.05	26.3
Conv9	16	144	0.67	0.05	0.68	0.05	0.68	0.05	2.49	26.3
Conv10	64	16	0.67	0.05	0.63	0.05	0.63	0.05	24.31	83.68

Conv11	16	64	0.44	0.05	0.63	0.05	0.63	0.05	8.09	26.3
Conv12	16	144	0.43	0.05	0.68	0.05	0.68	0.05	4.44	26.3
Conv13	64	16	0.59	0.05	0.63	0.05	0.63	0.05	26.43	83.68
Conv14	16	64	0.61	0.05	0.63	0.05	0.63	0.05	3.06	26.3
Conv15	16	144	0.54	0.05	0.68	0.05	0.68	0.05	2.9	26.3
Conv16	64	16	0.62	0.05	0.63	0.05	0.63	0.05	21.66	83.68
Conv17	16	64	0.63	0.05	0.63	0.05	0.63	0.05	2.38	26.3
Conv18	16	144	0.66	0.05	0.68	0.05	0.68	0.05	2.37	26.3
Conv19	64	16	0.62	0.05	0.63	0.05	0.63	0.05	22.61	83.68
Conv20	16	64	0.65	0.05	0.63	0.05	0.63	0.05	2.13	26.3
Conv21	16	144	0.81	0.05	0.68	0.05	0.68	0.05	1.53	26.3
Conv22	64	16	0.80	0.05	0.63	0.05	0.63	0.05	17.96	83.68
Conv23	16	64	0.62	0.05	0.63	0.05	0.63	0.05	3.82	26.3
Conv24	16	144	0.64	0.05	0.68	0.05	0.68	0.05	1.5	26.3
Conv25	64	16	0.70	0.05	0.63	0.05	0.63	0.05	13.74	83.68
Conv26	16	64	0.59	0.05	0.63	0.05	0.63	0.05	3.75	26.3
Conv27	16	144	0.62	0.05	0.68	0.05	0.68	0.05	1.67	26.3
Conv28	64	16	0.63	0.05	0.63	0.05	0.63	0.05	14.36	83.68
Conv29	16	64	0.67	0.05	0.63	0.05	0.63	0.05	1.62	26.3
Conv30	16	144	0.68	0.05	0.68	0.05	0.68	0.05	1.75	26.3
Conv31	64	16	0.80	0.05	0.63	0.05	0.63	0.05	11.87	83.68
Conv32	16	64	0.61	0.05	0.63	0.05	0.63	0.05	3.11	26.3
Conv33	16	144	0.69	0.05	0.68	0.05	0.68	0.05	1.36	26.3
Conv34	64	16	0.71	0.05	0.63	0.05	0.63	0.05	13.17	83.68
Conv35	16	64	0.80	0.05	0.63	0.05	0.63	0.05	1.92	26.3
Conv36	16	144	0.70	0.05	0.68	0.05	0.68	0.05	2.08	26.3
Conv37	64	16	0.70	0.05	0.63	0.05	0.63	0.05	12.17	83.68
Conv38	16	64	0.57	0.05	0.63	0.05	0.63	0.05	5.96	26.3
Conv39	16	144	0.67	0.05	0.68	0.05	0.68	0.05	1.45	26.3
Conv40	64	16	0.80	0.05	0.63	0.05	0.63	0.05	11.82	83.68
Conv41	16	64	0.46	0.05	0.63	0.05	0.63	0.05	5.85	26.3
Conv42	16	144	0.81	0.05	0.68	0.05	0.68	0.05	1.76	26.3
Conv43	64	16	0.67	0.05	0.63	0.05	0.63	0.05	13.14	83.68
Conv44	16	64	0.81	0.05	0.63	0.05	0.63	0.05	2.09	26.3
Conv45	16	144	0.82	0.05	0.68	0.05	0.68	0.05	1.25	26.3
Conv46	64	16	0.67	0.05	0.63	0.05	0.63	0.05	9.63	83.68
Conv47	16	64	0.70	0.05	0.63	0.05	0.63	0.05	3.38	26.3
Conv48	16	144	0.68	0.05	0.68	0.05	0.68	0.05	1.92	26.3
Conv49	64	16	0.81	0.05	0.63	0.05	0.63	0.05	12.43	83.68
Conv50	16	64	0.52	0.05	0.63	0.05	0.63	0.05	5.57	26.3
Conv51	16	144	0.62	0.05	0.68	0.05	0.68	0.05	2.08	26.3
Conv52	64	16	0.70	0.05	0.63	0.05	0.63	0.05	10.8	83.68
Conv53	16	64	0.62	0.05	0.63	0.05	0.63	0.05	4.59	26.3
Conv54	16	144	0.62	0.05	0.68	0.05	0.68	0.05	2.06	26.3
Conv55	64	16	0.80	0.05	0.63	0.05	0.63	0.05	10.21	83.68
Conv56	32	64	0.45	0.05	0.67	0.05	0.67	0.05	10.67	46.19
Conv57	32	288	0.65	0.05	0.83	0.05	0.83	0.05	1.79	46.19
Conv58	128	32	0.41	0.05	0.74	0.05	0.74	0.05	56.17	155.4
Conv59	32	128	0.81	0.05	0.74	0.05	0.74	0.05	2.03	46.19
Conv60	32	288	0.70	0.05	0.83	0.05	0.83	0.05	1.72	46.19
Conv61	128	32	0.62	0.05	0.74	0.05	0.74	0.05	19.79	155.4
Conv62	32	128	0.83	0.05	0.74	0.05	0.74	0.05	1.82	46.19
Conv63	32	288	0.80	0.05	0.83	0.05	0.83	0.05	1.2	46.19
Conv64	128	32	0.64	0.05	0.74	0.05	0.74	0.05	16.34	155.4
Conv65	32	128	0.58	0.05	0.74	0.05	0.74	0.05	2.33	46.19
Conv66	32	288	0.71	0.05	0.83	0.05	0.83	0.05	1.5	46.19
Conv67	128	32	0.61	0.05	0.74	0.05	0.74	0.05	12.64	155.4
Conv68	32	128	0.58	0.05	0.74	0.05	0.74	0.05	2.18	46.19
Conv69	32	288	0.70	0.05	0.83	0.05	0.83	0.05	2.15	46.19

Conv70	128	32	0.71	0.05	0.74	0.05	0.74	0.05	12.57	155.4
Conv71	32	128	0.68	0.05	0.74	0.05	0.74	0.05	2.74	46.19
Conv72	32	288	0.66	0.05	0.83	0.05	0.83	0.05	1.38	46.19
Conv73	128	32	0.67	0.05	0.74	0.05	0.74	0.05	12.65	155.4
Conv74	32	128	0.53	0.05	0.74	0.05	0.74	0.05	4.58	46.19
Conv75	32	288	0.68	0.05	0.83	0.05	0.83	0.05	1.19	46.19
Conv76	128	32	0.61	0.05	0.74	0.05	0.74	0.05	17.44	155.4
Conv77	32	128	0.67	0.05	0.74	0.05	0.74	0.05	1.33	46.19
Conv78	32	288	0.70	0.05	0.83	0.05	0.83	0.05	0.77	46.19
Conv79	128	32	0.68	0.05	0.74	0.05	0.74	0.05	14.49	155.4
Conv80	32	128	0.69	0.05	0.74	0.05	0.74	0.05	2.1	46.19
Conv81	32	288	0.83	0.05	0.83	0.05	0.83	0.05	1.19	46.19
Conv82	128	32	0.63	0.05	0.74	0.05	0.74	0.05	8.48	155.4
Conv83	32	128	0.83	0.05	0.74	0.05	0.74	0.05	1.89	46.19
Conv84	32	288	0.83	0.05	0.83	0.05	0.83	0.05	1.3	46.19
Conv85	128	32	0.81	0.05	0.74	0.05	0.74	0.05	10.26	155.4
Conv86	32	128	0.70	0.05	0.74	0.05	0.74	0.05	2.94	46.19
Conv87	32	288	0.83	0.05	0.83	0.05	0.83	0.05	0.79	46.19
Conv88	128	32	0.83	0.05	0.74	0.05	0.74	0.05	11.34	155.4
Conv89	32	128	0.82	0.05	0.74	0.05	0.74	0.05	3.05	46.19
Conv90	32	288	0.83	0.05	0.83	0.05	0.83	0.05	1.1	46.19
Conv91	128	32	0.84	0.05	0.74	0.05	0.74	0.05	10.63	155.4
Conv92	32	128	0.70	0.05	0.74	0.05	0.74	0.05	1.86	46.19
Conv93	32	288	0.81	0.05	0.83	0.05	0.83	0.05	0.7	46.19
Conv94	128	32	0.84	0.05	0.74	0.05	0.74	0.05	11.17	155.4
Conv95	32	128	0.81	0.05	0.74	0.05	0.74	0.05	2.22	46.19
Conv96	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.9	46.19
Conv97	128	32	0.69	0.05	0.74	0.05	0.74	0.05	10.03	155.4
Conv98	32	128	0.68	0.05	0.74	0.05	0.74	0.05	2.21	46.19
Conv99	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.6	46.19
Conv100	128	32	0.70	0.05	0.74	0.05	0.74	0.05	12.43	155.4
Conv101	32	128	0.68	0.05	0.74	0.05	0.74	0.05	4.78	46.19
Conv102	32	288	0.68	0.05	0.83	0.05	0.83	0.05	0.57	46.19
Conv103	128	32	0.81	0.05	0.74	0.05	0.74	0.05	11.88	155.4
Conv104	32	128	0.61	0.05	0.74	0.05	0.74	0.05	1.83	46.19
Conv105	32	288	0.87	0.05	0.83	0.05	0.83	0.05	1.61	46.19
Conv106	128	32	0.80	0.05	0.74	0.05	0.74	0.05	12.72	155.4
Conv107	32	128	0.60	0.05	0.74	0.05	0.74	0.05	1.77	46.19
Conv108	32	288	0.82	0.05	0.83	0.05	0.83	0.05	0.81	46.19
Conv109	128	32	0.82	0.05	0.74	0.05	0.74	0.05	11.31	155.4
Conv110	64	128	0.50	0.05	0.82	0.05	0.82	0.05	5.15	83.68
Conv111	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.7	83.68
Conv112	256	64	0.51	0.05	0.90	0.05	0.90	0.05	50.78	294.32
Conv113	64	256	0.64	0.05	0.90	0.05	0.90	0.05	3.01	83.68
Conv114	64	576	0.59	0.05	0.97	0.05	0.97	0.05	2.53	83.68
Conv115	256	64	0.60	0.05	0.90	0.05	0.90	0.05	26.61	294.32
Conv116	64	256	0.47	0.05	0.90	0.05	0.90	0.05	3.4	83.68
Conv117	64	576	0.67	0.05	0.97	0.05	0.97	0.05	1.73	83.68
Conv118	256	64	0.66	0.05	0.90	0.05	0.90	0.05	21.71	294.32
Conv119	64	256	0.81	0.05	0.90	0.05	0.90	0.05	2.6	83.68
Conv120	64	576	0.69	0.05	0.97	0.05	0.97	0.05	1.49	83.68
Conv121	256	64	0.57	0.05	0.90	0.05	0.90	0.05	21.92	294.32
Conv122	64	256	0.67	0.05	0.90	0.05	0.90	0.05	2.51	83.68
Conv123	64	576	0.81	0.05	0.97	0.05	0.97	0.05	0.8	83.68
Conv124	256	64	0.70	0.05	0.90	0.05	0.90	0.05	17.85	294.32
Conv125	64	256	0.63	0.05	0.90	0.05	0.90	0.05	2.41	83.68
Conv126	64	576	0.71	0.05	0.97	0.05	0.97	0.05	1.37	83.68
Conv127	256	64	0.65	0.05	0.90	0.05	0.90	0.05	22.35	294.32
Conv128	64	256	0.67	0.05	0.90	0.05	0.90	0.05	3.24	83.68

Conv129	64	576	0.70	0.05	0.97	0.05	0.97	0.05	1.04	83.68
Conv130	256	64	0.61	0.05	0.90	0.05	0.90	0.05	23.91	294.32
Conv131	64	256	0.68	0.05	0.90	0.05	0.90	0.05	2.08	83.68
Conv132	64	576	0.81	0.05	0.97	0.05	0.97	0.05	0.98	83.68
Conv133	256	64	0.80	0.05	0.90	0.05	0.90	0.05	19.13	294.32
Conv134	64	256	0.68	0.05	0.90	0.05	0.90	0.05	2.21	83.68
Conv135	64	576	0.81	0.05	0.97	0.05	0.97	0.05	0.9	83.68
Conv136	256	64	0.68	0.05	0.90	0.05	0.90	0.05	19.27	294.32
Conv137	64	256	0.68	0.05	0.90	0.05	0.90	0.05	2.7	83.68
Conv138	64	576	0.83	0.05	0.97	0.05	0.97	0.05	1.1	83.68
Conv139	256	64	0.69	0.05	0.90	0.05	0.90	0.05	22.22	294.32
Conv140	64	256	0.56	0.05	0.90	0.05	0.90	0.05	1.93	83.68
Conv141	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.87	83.68
Conv142	256	64	0.65	0.05	0.90	0.05	0.90	0.05	18.57	294.32
Conv143	64	256	0.67	0.05	0.90	0.05	0.90	0.05	2.23	83.68
Conv144	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.94	83.68
Conv145	256	64	0.63	0.05	0.90	0.05	0.90	0.05	21.58	294.32
Conv146	64	256	0.65	0.05	0.90	0.05	0.90	0.05	2.96	83.68
Conv147	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.1	83.68
Conv148	256	64	0.66	0.05	0.90	0.05	0.90	0.05	27.04	294.32
Conv149	64	256	0.61	0.05	0.90	0.05	0.90	0.05	3.3	83.68
Conv150	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.85	83.68
Conv151	256	64	0.67	0.05	0.90	0.05	0.90	0.05	23.12	294.32
Conv152	64	256	0.59	0.05	0.90	0.05	0.90	0.05	2.56	83.68
Conv153	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.68	83.68
Conv154	256	64	0.59	0.05	0.90	0.05	0.90	0.05	30.21	294.32
Conv155	64	256	0.62	0.05	0.90	0.05	0.90	0.05	2.84	83.68
Conv156	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.85	83.68
Conv157	256	64	0.65	0.05	0.90	0.05	0.90	0.05	32.78	294.32
Conv158	64	256	0.55	0.05	0.90	0.05	0.90	0.05	2.77	83.68
Conv159	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.88	83.68
Conv160	256	64	0.57	0.05	0.90	0.05	0.90	0.05	37.46	294.32
Conv161	64	256	0.54	0.05	0.90	0.05	0.90	0.05	3.55	83.68
Conv162	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.82	83.68
Conv163	256	64	0.56	0.05	0.90	0.05	0.90	0.05	48.35	294.32
Passing rate	-	-	100.0%		100.0%		100.0%		100.00%	

P.3 REGULARIZATION

config:

https://github.com/bearpaw/pytorch-classification.

https://github.com/LeungSamWai/Drop-Activation

https://github.com/uoguelph-mlrg/Cutout

https://github.com/clovaai/CutMix-PyTorch

https://github.com/DeepVoltaire/AutoAugment

Table 20: WRN28-10 Cifar100 ℓ_1

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.05	0.05	0.58	0.05	0.58	0.05	98.95	26.3
Conv2	160	144	0.69	0.05	0.94	0.05	0.94	0.05	8.19	190.52
Conv3	160	1440	0.93	0.05	1.00	0.05	1.00	0.05	0.31	190.52

Conv4	160	16	0.58	0.05	0.69	0.05	0.69	0.05	76.38	190.52
Conv5	160	1440	0.92	0.05	1.00	0.05	1.00	0.05	0.2	190.52
Conv6	160	1440	0.92	0.05	1.00	0.05	1.00	0.05	0.25	190.52
Conv7	160	1440	0.91	0.05	1.00	0.05	1.00	0.05	0.06	190.52
Conv8	160	1440	0.93	0.05	1.00	0.05	1.00	0.05	0.25	190.52
Conv9	160	1440	0.92	0.05	1.00	0.05	1.00	0.05	0.03	190.52
Conv10	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.95	190.52
Conv11	320	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.12	362.72
Conv12	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.19	362.72
Conv13	320	160	0.84	0.05	0.99	0.05	0.99	0.05	4.26	362.72
Conv14	320	2880	0.93	0.05	1.00	0.05	1.00	0.05	0.1	362.72
Conv15	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.16	362.72
Conv16	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.04	362.72
Conv17	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.26	362.72
Conv18	320	2880	0.93	0.05	1.00	0.05	1.00	0.05	0.06	362.72
Conv19	320	2880	0.93	0.05	1.00	0.05	1.00	0.05	0.52	362.72
Conv20	640	2880	0.93	0.05	1.00	0.05	1.00	0.05	0.05	699.96
Conv21	640	5760	0.93	0.05	1.00	0.05	1.00	0.05	0.64	699.96
Conv22	640	320	0.91	0.05	1.00	0.05	1.00	0.05	2.88	699.96
Conv23	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.1	699.96
Conv24	640	5760	0.93	0.05	1.00	0.05	1.00	0.05	0.49	699.96
Conv25	640	5760	0.93	0.05	1.00	0.05	1.00	0.05	0.05	699.96
Conv26	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.46	699.96
Conv27	640	5760	0.93	0.05	1.00	0.05	1.00	0.05	0.06	699.96
Conv28	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	2.74	699.96
Passing rate	-	-	100.0%		100.0%		100.0%		96.43%	

Table 21: WRN28-10 Cifar100 RReLU

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.43	0.05	0.58	0.05	0.58	0.05	40.44	26.3
Conv2	160	144	0.93	0.05	0.94	0.05	0.94	0.05	2.71	190.52
Conv3	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.12	190.52
Conv4	160	16	0.82	0.05	0.69	0.05	0.69	0.05	31.44	190.52
Conv5	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.06	190.52
Conv6	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.12	190.52
Conv7	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.02	190.52
Conv8	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.2	190.52
Conv9	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.02	190.52
Conv10	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.3	190.52
Conv11	320	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.09	362.72
Conv12	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.09	362.72
Conv13	320	160	0.90	0.05	0.99	0.05	0.99	0.05	2.73	362.72
Conv14	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.04	362.72
Conv15	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.07	362.72
Conv16	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.03	362.72
Conv17	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.14	362.72
Conv18	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.04	362.72
Conv19	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.31	362.72
Conv20	640	2880	0.93	0.05	1.00	0.05	1.00	0.05	0.05	699.96
Conv21	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.33	699.96
Conv22	640	320	0.93	0.05	1.00	0.05	1.00	0.05	1.54	699.96
Conv23	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.07	699.96
Conv24	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.28	699.96

Conv25	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.05	699.96
Conv26	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.35	699.96
Conv27	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.04	699.96
Conv28	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	1.23	699.96
Passing rate	-	-	100.0%		100.0%		100.0%		96.43%	

Table 22: WRN28-10 Cifar100 Dropact

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.54	0.05	0.58	0.05	0.58	0.05	19.13	26.3
Conv2	160	144	0.92	0.05	0.94	0.05	0.94	0.05	1.61	190.52
Conv3	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.11	190.52
Conv4	160	16	0.85	0.05	0.69	0.05	0.69	0.05	17.31	190.52
Conv5	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.06	190.52
Conv6	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.11	190.52
Conv7	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.01	190.52
Conv8	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.14	190.52
Conv9	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.02	190.52
Conv10	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.38	190.52
Conv11	320	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.06	362.72
Conv12	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.1	362.72
Conv13	320	160	0.90	0.05	0.99	0.05	0.99	0.05	0.92	362.72
Conv14	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.03	362.72
Conv15	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.08	362.72
Conv16	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.03	362.72
Conv17	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.08	362.72
Conv18	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.04	362.72
Conv19	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.23	362.72
Conv20	640	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.05	699.96
Conv21	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.61	699.96
Conv22	640	320	0.94	0.05	1.00	0.05	1.00	0.05	1.53	699.96
Conv23	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.06	699.96
Conv24	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.43	699.96
Conv25	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.05	699.96
Conv26	640	5760	0.96	0.05	1.00	0.05	1.00	0.05	0.28	699.96
Conv27	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.04	699.96
Conv28	640	5760	0.96	0.05	1.00	0.05	1.00	0.05	0.36	699.96
Passing rate	-	-	100.0%		100.0%		100.0%		100.0%	

Table 23: WRN28-10 Cifar100 Autoaugment

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.05	0.05	0.58	0.05	0.58	0.05	100.18	26.3
Conv2	160	144	0.69	0.05	0.94	0.05	0.94	0.05	8.3	190.52
Conv3	160	1440	0.93	0.05	1.00	0.05	1.00	0.05	0.31	190.52
Conv4	160	16	0.57	0.05	0.69	0.05	0.69	0.05	77.32	190.52
Conv5	160	1440	0.92	0.05	1.00	0.05	1.00	0.05	0.2	190.52
Conv6	160	1440	0.92	0.05	1.00	0.05	1.00	0.05	0.25	190.52
Conv7	160	1440	0.91	0.05	1.00	0.05	1.00	0.05	0.06	190.52

Conv8	160	1440	0.93	0.05	1.00	0.05	1.00	0.05	0.26	190.52
Conv9	160	1440	0.92	0.05	1.00	0.05	1.00	0.05	0.03	190.52
Conv10	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.97	190.52
Conv11	320	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.12	362.72
Conv12	320	2880	0.93	0.05	1.00	0.05	1.00	0.05	0.19	362.72
Conv13	320	160	0.84	0.05	0.99	0.05	0.99	0.05	4.31	362.72
Conv14	320	2880	0.93	0.05	1.00	0.05	1.00	0.05	0.1	362.72
Conv15	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.16	362.72
Conv16	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.04	362.72
Conv17	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.26	362.72
Conv18	320	2880	0.93	0.05	1.00	0.05	1.00	0.05	0.06	362.72
Conv19	320	2880	0.93	0.05	1.00	0.05	1.00	0.05	0.52	362.72
Conv20	640	2880	0.93	0.05	1.00	0.05	1.00	0.05	0.05	699.96
Conv21	640	5760	0.93	0.05	1.00	0.05	1.00	0.05	0.65	699.96
Conv22	640	320	0.91	0.05	1.00	0.05	1.00	0.05	2.92	699.96
Conv23	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.1	699.96
Conv24	640	5760	0.93	0.05	1.00	0.05	1.00	0.05	0.5	699.96
Conv25	640	5760	0.93	0.05	1.00	0.05	1.00	0.05	0.05	699.96
Conv26	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.47	699.96
Conv27	640	5760	0.93	0.05	1.00	0.05	1.00	0.05	0.06	699.96
Conv28	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	2.77	699.96
Passing rate	-	-	100.0%		100.0%		100.0%		96.43%	

Table 24: WRN28-10 Cifar100 Cutout

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.31	0.05	0.58	0.05	0.58	0.05	49.46	26.3
Conv2	160	144	0.88	0.05	0.94	0.05	0.94	0.05	5.66	190.52
Conv3	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.28	190.52
Conv4	160	16	0.81	0.05	0.69	0.05	0.69	0.05	42.43	190.52
Conv5	160	1440	0.93	0.05	1.00	0.05	1.00	0.05	0.18	190.52
Conv6	160	1440	0.93	0.05	1.00	0.05	1.00	0.05	0.23	190.52
Conv7	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.02	190.52
Conv8	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.22	190.52
Conv9	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.06	190.52
Conv10	160	1440	0.93	0.05	1.00	0.05	1.00	0.05	0.83	190.52
Conv11	320	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.1	362.72
Conv12	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.18	362.72
Conv13	320	160	0.89	0.05	0.99	0.05	0.99	0.05	1.71	362.72
Conv14	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.05	362.72
Conv15	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.12	362.72
Conv16	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.06	362.72
Conv17	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.16	362.72
Conv18	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.07	362.72
Conv19	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.4	362.72
Conv20	640	2880	0.93	0.05	1.00	0.05	1.00	0.05	0.05	699.96
Conv21	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.75	699.96
Conv22	640	320	0.93	0.05	1.00	0.05	1.00	0.05	2.01	699.96
Conv23	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.12	699.96
Conv24	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.54	699.96
Conv25	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.1	699.96
Conv26	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.55	699.96
Conv27	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.09	699.96
Conv28	640	5760	0.96	0.05	1.00	0.05	1.00	0.05	0.63	699.96

Passing rate	-	-	100.0%		100.0%		100.0%		96.43%	

Table 25: WRN28-10 Cifar100 Cutmix

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.54	0.05	0.58	0.05	0.58	0.05	21.26	26.3
Conv2	160	144	0.91	0.05	0.94	0.05	0.94	0.05	2.25	190.52
Conv3	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.16	190.52
Conv4	160	16	0.86	0.05	0.69	0.05	0.69	0.05	19.09	190.52
Conv5	160	1440	0.93	0.05	1.00	0.05	1.00	0.05	0.08	190.52
Conv6	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.14	190.52
Conv7	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.02	190.52
Conv8	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.14	190.52
Conv9	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.03	190.52
Conv10	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.29	190.52
Conv11	320	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.07	362.72
Conv12	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.12	362.72
Conv13	320	160	0.92	0.05	0.99	0.05	0.99	0.05	1.09	362.72
Conv14	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.04	362.72
Conv15	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.08	362.72
Conv16	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.04	362.72
Conv17	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.09	362.72
Conv18	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.05	362.72
Conv19	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.26	362.72
Conv20	640	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.05	699.96
Conv21	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.85	699.96
Conv22	640	320	0.94	0.05	1.00	0.05	1.00	0.05	1.8	699.96
Conv23	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.09	699.96
Conv24	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.51	699.96
Conv25	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.07	699.96
Conv26	640	5760	0.96	0.05	1.00	0.05	1.00	0.05	0.22	699.96
Conv27	640	5760	0.96	0.05	1.00	0.05	1.00	0.05	0.04	699.96
Conv28	640	5760	0.96	0.05	1.00	0.05	1.00	0.05	0.24	699.96
Passing rate	-	-	100.0%		100.0%		100.0%		100.0%	

P.4 ATTENTION MECHANISM

config:

`https://github.com/moskomule/senet.pytorch`

`https://github.com/gbup-group/DIANet`

`https://github.com/EvgenyKashin/SRMnet`

`https://github.com/luuuyi/CBAM.PyTorch`

`https://github.com/gbup-group/IEBN`

`https://github.com/implus/PytorchInsight`

Table 26: SENet (ResNet164) Cifar100

Layer	**Number**	**dim**	**Gaussian**	**Mean_Left**	**Mean_Right**	**Sigma**

			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.02	0.05	0.58	0.05	0.58	0.05	181.46	26.3
Conv2	16	16	0.54	0.05	0.56	0.05	0.56	0.05	6.12	26.3
Conv3	16	144	0.86	0.05	0.68	0.05	0.68	0.05	0.42	26.3
Conv4	64	16	0.87	0.05	0.63	0.05	0.63	0.05	11.54	83.68
Conv5	16	64	0.82	0.05	0.63	0.05	0.63	0.05	0.89	26.3
Conv6	16	144	0.89	0.05	0.68	0.05	0.68	0.05	0.37	26.3
Conv7	64	16	0.80	0.05	0.63	0.05	0.63	0.05	10.59	83.68
Conv8	16	64	0.67	0.05	0.63	0.05	0.63	0.05	1.54	26.3
Conv9	16	144	0.82	0.05	0.68	0.05	0.68	0.05	1.34	26.3
Conv10	64	16	0.64	0.05	0.63	0.05	0.63	0.05	11.73	83.68
Conv11	16	64	0.81	0.05	0.63	0.05	0.63	0.05	1.01	26.3
Conv12	16	144	0.84	0.05	0.68	0.05	0.68	0.05	1.63	26.3
Conv13	64	16	0.81	0.05	0.63	0.05	0.63	0.05	9.92	83.68
Conv14	16	64	0.43	0.05	0.63	0.05	0.63	0.05	3.99	26.3
Conv15	16	144	0.81	0.05	0.68	0.05	0.68	0.05	0.86	26.3
Conv16	64	16	0.81	0.05	0.63	0.05	0.63	0.05	11.13	83.68
Conv17	16	64	0.67	0.05	0.63	0.05	0.63	0.05	0.68	26.3
Conv18	16	144	0.84	0.05	0.68	0.05	0.68	0.05	0.61	26.3
Conv19	64	16	0.86	0.05	0.63	0.05	0.63	0.05	12.02	83.68
Conv20	16	64	0.87	0.05	0.63	0.05	0.63	0.05	0.65	26.3
Conv21	16	144	0.84	0.05	0.68	0.05	0.68	0.05	1.02	26.3
Conv22	64	16	0.85	0.05	0.63	0.05	0.63	0.05	7.73	83.68
Conv23	16	64	0.69	0.05	0.63	0.05	0.63	0.05	1.84	26.3
Conv24	16	144	0.89	0.05	0.68	0.05	0.68	0.05	1.07	26.3
Conv25	64	16	0.85	0.05	0.63	0.05	0.63	0.05	7.12	83.68
Conv26	16	64	0.69	0.05	0.63	0.05	0.63	0.05	1.85	26.3
Conv27	16	144	0.82	0.05	0.68	0.05	0.68	0.05	0.77	26.3
Conv28	64	16	0.86	0.05	0.63	0.05	0.63	0.05	14.12	83.68
Conv29	16	64	0.64	0.05	0.63	0.05	0.63	0.05	3.44	26.3
Conv30	16	144	0.81	0.05	0.68	0.05	0.68	0.05	0.81	26.3
Conv31	64	16	0.81	0.05	0.63	0.05	0.63	0.05	17.04	83.68
Conv32	16	64	0.68	0.05	0.63	0.05	0.63	0.05	2.15	26.3
Conv33	16	144	0.67	0.05	0.68	0.05	0.68	0.05	0.81	26.3
Conv34	64	16	0.71	0.05	0.63	0.05	0.63	0.05	23.95	83.68
Conv35	16	64	0.69	0.05	0.63	0.05	0.63	0.05	1.03	26.3
Conv36	16	144	0.89	0.05	0.68	0.05	0.68	0.05	0.1	26.3
Conv37	64	16	0.86	0.05	0.63	0.05	0.63	0.05	8.09	83.68
Conv38	16	64	0.68	0.05	0.63	0.05	0.63	0.05	3.55	26.3
Conv39	16	144	0.83	0.05	0.68	0.05	0.68	0.05	0.71	26.3
Conv40	64	16	0.84	0.05	0.63	0.05	0.63	0.05	11.45	83.68
Conv41	16	64	0.81	0.05	0.63	0.05	0.63	0.05	1.84	26.3
Conv42	16	144	0.82	0.05	0.68	0.05	0.68	0.05	1.1	26.3
Conv43	64	16	0.83	0.05	0.63	0.05	0.63	0.05	10.49	83.68
Conv44	16	64	0.81	0.05	0.63	0.05	0.63	0.05	2.3	26.3
Conv45	16	144	0.84	0.05	0.68	0.05	0.68	0.05	1.96	26.3
Conv46	64	16	0.46	0.05	0.63	0.05	0.63	0.05	18.47	83.68
Conv47	16	64	0.67	0.05	0.63	0.05	0.63	0.05	2.86	26.3
Conv48	16	144	0.82	0.05	0.68	0.05	0.68	0.05	0.84	26.3
Conv49	64	16	0.64	0.05	0.63	0.05	0.63	0.05	8.9	83.68
Conv50	16	64	0.82	0.05	0.63	0.05	0.63	0.05	3.4	26.3
Conv51	16	144	0.84	0.05	0.68	0.05	0.68	0.05	0.92	26.3
Conv52	64	16	0.71	0.05	0.63	0.05	0.63	0.05	14.29	83.68
Conv53	16	64	0.47	0.05	0.63	0.05	0.63	0.05	5.93	26.3
Conv54	16	144	0.86	0.05	0.68	0.05	0.68	0.05	0.92	26.3
Conv55	64	16	0.64	0.05	0.63	0.05	0.63	0.05	16.37	83.68
Conv56	32	64	0.51	0.05	0.67	0.05	0.67	0.05	3.25	46.19
Conv57	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.24	46.19

Conv58	128	32	0.80	0.05	0.74	0.05	0.74	0.05	14.02	155.4
Conv59	32	128	0.90	0.05	0.74	0.05	0.74	0.05	0.44	46.19
Conv60	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.37	46.19
Conv61	128	32	0.88	0.05	0.74	0.05	0.74	0.05	5.11	155.4
Conv62	32	128	0.85	0.05	0.74	0.05	0.74	0.05	0.72	46.19
Conv63	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.5	46.19
Conv64	128	32	0.85	0.05	0.74	0.05	0.74	0.05	5.3	155.4
Conv65	32	128	0.82	0.05	0.74	0.05	0.74	0.05	1.19	46.19
Conv66	32	288	0.81	0.05	0.83	0.05	0.83	0.05	1.05	46.19
Conv67	128	32	0.81	0.05	0.74	0.05	0.74	0.05	8.62	155.4
Conv68	32	128	0.87	0.05	0.74	0.05	0.74	0.05	0.41	46.19
Conv69	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.73	46.19
Conv70	128	32	0.85	0.05	0.74	0.05	0.74	0.05	5.21	155.4
Conv71	32	128	0.89	0.05	0.74	0.05	0.74	0.05	0.38	46.19
Conv72	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.5	46.19
Conv73	128	32	0.88	0.05	0.74	0.05	0.74	0.05	4.26	155.4
Conv74	32	128	0.83	0.05	0.74	0.05	0.74	0.05	0.85	46.19
Conv75	32	288	0.87	0.05	0.83	0.05	0.83	0.05	0.41	46.19
Conv76	128	32	0.68	0.05	0.74	0.05	0.74	0.05	6.07	155.4
Conv77	32	128	0.85	0.05	0.74	0.05	0.74	0.05	0.52	46.19
Conv78	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.44	46.19
Conv79	128	32	0.84	0.05	0.74	0.05	0.74	0.05	4.39	155.4
Conv80	32	128	0.82	0.05	0.74	0.05	0.74	0.05	0.83	46.19
Conv81	32	288	0.90	0.05	0.83	0.05	0.83	0.05	0.75	46.19
Conv82	128	32	0.88	0.05	0.74	0.05	0.74	0.05	5.93	155.4
Conv83	32	128	0.68	0.05	0.74	0.05	0.74	0.05	2.33	46.19
Conv84	32	288	0.87	0.05	0.83	0.05	0.83	0.05	0.57	46.19
Conv85	128	32	0.84	0.05	0.74	0.05	0.74	0.05	8.22	155.4
Conv86	32	128	0.82	0.05	0.74	0.05	0.74	0.05	1.0	46.19
Conv87	32	288	0.81	0.05	0.83	0.05	0.83	0.05	0.43	46.19
Conv88	128	32	0.89	0.05	0.74	0.05	0.74	0.05	5.04	155.4
Conv89	32	128	0.86	0.05	0.74	0.05	0.74	0.05	1.08	46.19
Conv90	32	288	0.91	0.05	0.83	0.05	0.83	0.05	0.34	46.19
Conv91	128	32	0.87	0.05	0.74	0.05	0.74	0.05	5.44	155.4
Conv92	32	128	0.86	0.05	0.74	0.05	0.74	0.05	0.93	46.19
Conv93	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.24	46.19
Conv94	128	32	0.86	0.05	0.74	0.05	0.74	0.05	5.26	155.4
Conv95	32	128	0.83	0.05	0.74	0.05	0.74	0.05	0.92	46.19
Conv96	32	288	0.90	0.05	0.83	0.05	0.83	0.05	0.19	46.19
Conv97	128	32	0.87	0.05	0.74	0.05	0.74	0.05	5.4	155.4
Conv98	32	128	0.87	0.05	0.74	0.05	0.74	0.05	0.92	46.19
Conv99	32	288	0.86	0.05	0.83	0.05	0.83	0.05	0.4	46.19
Conv100	128	32	0.88	0.05	0.74	0.05	0.74	0.05	5.19	155.4
Conv101	32	128	0.85	0.05	0.74	0.05	0.74	0.05	1.2	46.19
Conv102	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.37	46.19
Conv103	128	32	0.70	0.05	0.74	0.05	0.74	0.05	6.58	155.4
Conv104	32	128	0.85	0.05	0.74	0.05	0.74	0.05	1.03	46.19
Conv105	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.15	46.19
Conv106	128	32	0.87	0.05	0.74	0.05	0.74	0.05	6.01	155.4
Conv107	32	128	0.86	0.05	0.74	0.05	0.74	0.05	0.98	46.19
Conv108	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.19	46.19
Conv109	128	32	0.85	0.05	0.74	0.05	0.74	0.05	6.87	155.4
Conv110	64	128	0.61	0.05	0.82	0.05	0.82	0.05	2.17	83.68
Conv111	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.18	83.68
Conv112	256	64	0.83	0.05	0.90	0.05	0.90	0.05	12.64	294.32
Conv113	64	256	0.86	0.05	0.90	0.05	0.90	0.05	0.68	83.68
Conv114	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.32	83.68
Conv115	256	64	0.84	0.05	0.90	0.05	0.90	0.05	6.51	294.32
Conv116	64	256	0.70	0.05	0.90	0.05	0.90	0.05	0.67	83.68

Conv117	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.46	83.68
Conv118	256	64	0.86	0.05	0.90	0.05	0.90	0.05	7.04	294.32
Conv119	64	256	0.86	0.05	0.90	0.05	0.90	0.05	0.57	83.68
Conv120	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.35	83.68
Conv121	256	64	0.81	0.05	0.90	0.05	0.90	0.05	6.19	294.32
Conv122	64	256	0.82	0.05	0.90	0.05	0.90	0.05	0.36	83.68
Conv123	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.35	83.68
Conv124	256	64	0.86	0.05	0.90	0.05	0.90	0.05	6.66	294.32
Conv125	64	256	0.87	0.05	0.90	0.05	0.90	0.05	0.4	83.68
Conv126	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.29	83.68
Conv127	256	64	0.85	0.05	0.90	0.05	0.90	0.05	7.23	294.32
Conv128	64	256	0.86	0.05	0.90	0.05	0.90	0.05	0.47	83.68
Conv129	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.25	83.68
Conv130	256	64	0.86	0.05	0.90	0.05	0.90	0.05	6.13	294.32
Conv131	64	256	0.86	0.05	0.90	0.05	0.90	0.05	0.56	83.68
Conv132	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.3	83.68
Conv133	256	64	0.86	0.05	0.90	0.05	0.90	0.05	6.56	294.32
Conv134	64	256	0.85	0.05	0.90	0.05	0.90	0.05	0.54	83.68
Conv135	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.25	83.68
Conv136	256	64	0.86	0.05	0.90	0.05	0.90	0.05	6.57	294.32
Conv137	64	256	0.86	0.05	0.90	0.05	0.90	0.05	0.69	83.68
Conv138	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.2	83.68
Conv139	256	64	0.83	0.05	0.90	0.05	0.90	0.05	5.95	294.32
Conv140	64	256	0.84	0.05	0.90	0.05	0.90	0.05	0.4	83.68
Conv141	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.24	83.68
Conv142	256	64	0.83	0.05	0.90	0.05	0.90	0.05	6.64	294.32
Conv143	64	256	0.87	0.05	0.90	0.05	0.90	0.05	0.65	83.68
Conv144	64	576	0.91	0.05	0.97	0.05	0.97	0.05	0.19	83.68
Conv145	256	64	0.83	0.05	0.90	0.05	0.90	0.05	7.35	294.32
Conv146	64	256	0.69	0.05	0.90	0.05	0.90	0.05	0.66	83.68
Conv147	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.14	83.68
Conv148	256	64	0.84	0.05	0.90	0.05	0.90	0.05	7.95	294.32
Conv149	64	256	0.85	0.05	0.90	0.05	0.90	0.05	0.59	83.68
Conv150	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.18	83.68
Conv151	256	64	0.82	0.05	0.90	0.05	0.90	0.05	6.92	294.32
Conv152	64	256	0.82	0.05	0.90	0.05	0.90	0.05	0.42	83.68
Conv153	64	576	0.91	0.05	0.97	0.05	0.97	0.05	0.14	83.68
Conv154	256	64	0.85	0.05	0.90	0.05	0.90	0.05	7.74	294.32
Conv155	64	256	0.82	0.05	0.90	0.05	0.90	0.05	0.58	83.68
Conv156	64	576	0.91	0.05	0.97	0.05	0.97	0.05	0.16	83.68
Conv157	256	64	0.84	0.05	0.90	0.05	0.90	0.05	7.89	294.32
Conv158	64	256	0.84	0.05	0.90	0.05	0.90	0.05	0.47	83.68
Conv159	64	576	0.91	0.05	0.97	0.05	0.97	0.05	0.19	83.68
Conv160	256	64	0.85	0.05	0.90	0.05	0.90	0.05	8.11	294.32
Conv161	64	256	0.81	0.05	0.90	0.05	0.90	0.05	0.83	83.68
Conv162	64	576	0.91	0.05	0.97	0.05	0.97	0.05	0.15	83.68
Conv163	256	64	0.82	0.05	0.90	0.05	0.90	0.05	9.08	294.32
Passing rate	-	-	99.39%		100.0%		100.0%		99.39%	

Table 27: DIANet (ResNet164) Cifar100

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.02	0.05	0.58	0.05	0.58	0.05	218.97	26.3
Conv2	16	16	0.41	0.05	0.56	0.05	0.56	0.05	16.01	26.3

Conv3	16	144	0.54	0.05	0.68	0.05	0.68	0.05	2.13	26.3
Conv4	64	16	0.83	0.05	0.63	0.05	0.63	0.05	22.48	83.68
Conv5	16	64	0.82	0.05	0.63	0.05	0.63	0.05	1.21	26.3
Conv6	16	144	0.88	0.05	0.68	0.05	0.68	0.05	0.52	26.3
Conv7	64	16	0.83	0.05	0.63	0.05	0.63	0.05	10.96	83.68
Conv8	16	64	0.81	0.05	0.63	0.05	0.63	0.05	1.12	26.3
Conv9	16	144	0.88	0.05	0.68	0.05	0.68	0.05	0.65	26.3
Conv10	64	16	0.86	0.05	0.63	0.05	0.63	0.05	6.11	83.68
Conv11	16	64	0.84	0.05	0.63	0.05	0.63	0.05	1.32	26.3
Conv12	16	144	0.87	0.05	0.68	0.05	0.68	0.05	0.4	26.3
Conv13	64	16	0.86	0.05	0.63	0.05	0.63	0.05	10.91	83.68
Conv14	16	64	0.81	0.05	0.63	0.05	0.63	0.05	2.18	26.3
Conv15	16	144	0.69	0.05	0.68	0.05	0.68	0.05	1.12	26.3
Conv16	64	16	0.82	0.05	0.63	0.05	0.63	0.05	24.69	83.68
Conv17	16	64	0.83	0.05	0.63	0.05	0.63	0.05	0.87	26.3
Conv18	16	144	0.85	0.05	0.68	0.05	0.68	0.05	0.32	26.3
Conv19	64	16	0.85	0.05	0.63	0.05	0.63	0.05	10.98	83.68
Conv20	16	64	0.62	0.05	0.63	0.05	0.63	0.05	1.4	26.3
Conv21	16	144	0.89	0.05	0.68	0.05	0.68	0.05	0.41	26.3
Conv22	64	16	0.70	0.05	0.63	0.05	0.63	0.05	15.49	83.68
Conv23	16	64	0.84	0.05	0.63	0.05	0.63	0.05	1.03	26.3
Conv24	16	144	0.90	0.05	0.68	0.05	0.68	0.05	0.77	26.3
Conv25	64	16	0.83	0.05	0.63	0.05	0.63	0.05	10.43	83.68
Conv26	16	64	0.82	0.05	0.63	0.05	0.63	0.05	1.59	26.3
Conv27	16	144	0.86	0.05	0.68	0.05	0.68	0.05	0.47	26.3
Conv28	64	16	0.71	0.05	0.63	0.05	0.63	0.05	11.21	83.68
Conv29	16	64	0.65	0.05	0.63	0.05	0.63	0.05	2.22	26.3
Conv30	16	144	0.81	0.05	0.68	0.05	0.68	0.05	0.78	26.3
Conv31	64	16	0.86	0.05	0.63	0.05	0.63	0.05	9.33	83.68
Conv32	16	64	0.62	0.05	0.63	0.05	0.63	0.05	2.48	26.3
Conv33	16	144	0.85	0.05	0.68	0.05	0.68	0.05	1.23	26.3
Conv34	64	16	0.81	0.05	0.63	0.05	0.63	0.05	10.78	83.68
Conv35	16	64	0.59	0.05	0.63	0.05	0.63	0.05	3.47	26.3
Conv36	16	144	0.84	0.05	0.68	0.05	0.68	0.05	0.78	26.3
Conv37	64	16	0.83	0.05	0.63	0.05	0.63	0.05	17.75	83.68
Conv38	16	64	0.87	0.05	0.63	0.05	0.63	0.05	0.81	26.3
Conv39	16	144	0.85	0.05	0.68	0.05	0.68	0.05	0.57	26.3
Conv40	64	16	0.84	0.05	0.63	0.05	0.63	0.05	12.64	83.68
Conv41	16	64	0.67	0.05	0.63	0.05	0.63	0.05	1.94	26.3
Conv42	16	144	0.87	0.05	0.68	0.05	0.68	0.05	0.61	26.3
Conv43	64	16	0.69	0.05	0.63	0.05	0.63	0.05	10.1	83.68
Conv44	16	64	0.63	0.05	0.63	0.05	0.63	0.05	3.55	26.3
Conv45	16	144	0.70	0.05	0.68	0.05	0.68	0.05	1.23	26.3
Conv46	64	16	0.61	0.05	0.63	0.05	0.63	0.05	49.74	83.68
Conv47	16	64	0.88	0.05	0.63	0.05	0.63	0.05	1.3	26.3
Conv48	16	144	0.87	0.05	0.68	0.05	0.68	0.05	0.34	26.3
Conv49	64	16	0.85	0.05	0.63	0.05	0.63	0.05	7.77	83.68
Conv50	16	64	0.81	0.05	0.63	0.05	0.63	0.05	1.92	26.3
Conv51	16	144	0.87	0.05	0.68	0.05	0.68	0.05	0.67	26.3
Conv52	64	16	0.82	0.05	0.63	0.05	0.63	0.05	13.42	83.68
Conv53	16	64	0.69	0.05	0.63	0.05	0.63	0.05	3.6	26.3
Conv54	16	144	0.81	0.05	0.68	0.05	0.68	0.05	0.83	26.3
Conv55	64	16	0.70	0.05	0.63	0.05	0.63	0.05	24.26	83.68
Conv56	32	64	0.62	0.05	0.67	0.05	0.67	0.05	6.86	46.19
Conv57	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.39	46.19
Conv58	128	32	0.61	0.05	0.74	0.05	0.74	0.05	26.14	155.4
Conv59	32	128	0.87	0.05	0.74	0.05	0.74	0.05	0.65	46.19
Conv60	32	288	0.87	0.05	0.83	0.05	0.83	0.05	0.44	46.19
Conv61	128	32	0.85	0.05	0.74	0.05	0.74	0.05	10.89	155.4

Conv62	32	128	0.86	0.05	0.74	0.05	0.74	0.05	0.76	46.19
Conv63	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.62	46.19
Conv64	128	32	0.84	0.05	0.74	0.05	0.74	0.05	9.18	155.4
Conv65	32	128	0.87	0.05	0.74	0.05	0.74	0.05	0.53	46.19
Conv66	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.56	46.19
Conv67	128	32	0.84	0.05	0.74	0.05	0.74	0.05	6.94	155.4
Conv68	32	128	0.89	0.05	0.74	0.05	0.74	0.05	0.53	46.19
Conv69	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.45	46.19
Conv70	128	32	0.65	0.05	0.74	0.05	0.74	0.05	8.26	155.4
Conv71	32	128	0.88	0.05	0.74	0.05	0.74	0.05	0.62	46.19
Conv72	32	288	0.70	0.05	0.83	0.05	0.83	0.05	0.41	46.19
Conv73	128	32	0.83	0.05	0.74	0.05	0.74	0.05	6.53	155.4
Conv74	32	128	0.69	0.05	0.74	0.05	0.74	0.05	0.77	46.19
Conv75	32	288	0.91	0.05	0.83	0.05	0.83	0.05	0.27	46.19
Conv76	128	32	0.85	0.05	0.74	0.05	0.74	0.05	9.43	155.4
Conv77	32	128	0.68	0.05	0.74	0.05	0.74	0.05	1.07	46.19
Conv78	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.36	46.19
Conv79	128	32	0.84	0.05	0.74	0.05	0.74	0.05	10.11	155.4
Conv80	32	128	0.83	0.05	0.74	0.05	0.74	0.05	0.59	46.19
Conv81	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.29	46.19
Conv82	128	32	0.89	0.05	0.74	0.05	0.74	0.05	6.81	155.4
Conv83	32	128	0.82	0.05	0.74	0.05	0.74	0.05	1.28	46.19
Conv84	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.63	46.19
Conv85	128	32	0.84	0.05	0.74	0.05	0.74	0.05	12.87	155.4
Conv86	32	128	0.69	0.05	0.74	0.05	0.74	0.05	0.58	46.19
Conv87	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.28	46.19
Conv88	128	32	0.86	0.05	0.74	0.05	0.74	0.05	8.96	155.4
Conv89	32	128	0.84	0.05	0.74	0.05	0.74	0.05	1.59	46.19
Conv90	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.1	46.19
Conv91	128	32	0.87	0.05	0.74	0.05	0.74	0.05	9.08	155.4
Conv92	32	128	0.84	0.05	0.74	0.05	0.74	0.05	1.02	46.19
Conv93	32	288	0.90	0.05	0.83	0.05	0.83	0.05	0.09	46.19
Conv94	128	32	0.85	0.05	0.74	0.05	0.74	0.05	8.1	155.4
Conv95	32	128	0.85	0.05	0.74	0.05	0.74	0.05	0.96	46.19
Conv96	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.19	46.19
Conv97	128	32	0.84	0.05	0.74	0.05	0.74	0.05	8.75	155.4
Conv98	32	128	0.83	0.05	0.74	0.05	0.74	0.05	1.11	46.19
Conv99	32	288	0.90	0.05	0.83	0.05	0.83	0.05	0.22	46.19
Conv100	128	32	0.87	0.05	0.74	0.05	0.74	0.05	8.92	155.4
Conv101	32	128	0.85	0.05	0.74	0.05	0.74	0.05	1.12	46.19
Conv102	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.2	46.19
Conv103	128	32	0.86	0.05	0.74	0.05	0.74	0.05	8.21	155.4
Conv104	32	128	0.84	0.05	0.74	0.05	0.74	0.05	1.03	46.19
Conv105	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.31	46.19
Conv106	128	32	0.86	0.05	0.74	0.05	0.74	0.05	7.93	155.4
Conv107	32	128	0.70	0.05	0.74	0.05	0.74	0.05	1.65	46.19
Conv108	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.32	46.19
Conv109	128	32	0.86	0.05	0.74	0.05	0.74	0.05	8.7	155.4
Conv110	64	128	0.65	0.05	0.82	0.05	0.82	0.05	1.96	83.68
Conv111	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.18	83.68
Conv112	256	64	0.70	0.05	0.90	0.05	0.90	0.05	15.81	294.32
Conv113	64	256	0.60	0.05	0.90	0.05	0.90	0.05	0.85	83.68
Conv114	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.41	83.68
Conv115	256	64	0.82	0.05	0.90	0.05	0.90	0.05	6.26	294.32
Conv116	64	256	0.82	0.05	0.90	0.05	0.90	0.05	0.61	83.68
Conv117	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.31	83.68
Conv118	256	64	0.84	0.05	0.90	0.05	0.90	0.05	6.85	294.32
Conv119	64	256	0.69	0.05	0.90	0.05	0.90	0.05	0.54	83.68
Conv120	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.35	83.68

Conv121	256	64	0.82	0.05	0.90	0.05	0.90	0.05	6.53	294.32
Conv122	64	256	0.85	0.05	0.90	0.05	0.90	0.05	0.43	83.68
Conv123	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.39	83.68
Conv124	256	64	0.66	0.05	0.90	0.05	0.90	0.05	6.93	294.32
Conv125	64	256	0.67	0.05	0.90	0.05	0.90	0.05	0.6	83.68
Conv126	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.25	83.68
Conv127	256	64	0.71	0.05	0.90	0.05	0.90	0.05	8.9	294.32
Conv128	64	256	0.85	0.05	0.90	0.05	0.90	0.05	0.47	83.68
Conv129	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.18	83.68
Conv130	256	64	0.83	0.05	0.90	0.05	0.90	0.05	6.85	294.32
Conv131	64	256	0.86	0.05	0.90	0.05	0.90	0.05	0.47	83.68
Conv132	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.17	83.68
Conv133	256	64	0.86	0.05	0.90	0.05	0.90	0.05	5.22	294.32
Conv134	64	256	0.71	0.05	0.90	0.05	0.90	0.05	0.4	83.68
Conv135	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.22	83.68
Conv136	256	64	0.70	0.05	0.90	0.05	0.90	0.05	7.07	294.32
Conv137	64	256	0.84	0.05	0.90	0.05	0.90	0.05	0.39	83.68
Conv138	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.22	83.68
Conv139	256	64	0.85	0.05	0.90	0.05	0.90	0.05	5.24	294.32
Conv140	64	256	0.84	0.05	0.90	0.05	0.90	0.05	0.55	83.68
Conv141	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.21	83.68
Conv142	256	64	0.83	0.05	0.90	0.05	0.90	0.05	7.08	294.32
Conv143	64	256	0.84	0.05	0.90	0.05	0.90	0.05	0.36	83.68
Conv144	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.26	83.68
Conv145	256	64	0.82	0.05	0.90	0.05	0.90	0.05	8.28	294.32
Conv146	64	256	0.83	0.05	0.90	0.05	0.90	0.05	0.42	83.68
Conv147	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.27	83.68
Conv148	256	64	0.83	0.05	0.90	0.05	0.90	0.05	8.01	294.32
Conv149	64	256	0.69	0.05	0.90	0.05	0.90	0.05	0.68	83.68
Conv150	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.17	83.68
Conv151	256	64	0.82	0.05	0.90	0.05	0.90	0.05	7.8	294.32
Conv152	64	256	0.80	0.05	0.90	0.05	0.90	0.05	0.39	83.68
Conv153	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.11	83.68
Conv154	256	64	0.81	0.05	0.90	0.05	0.90	0.05	8.1	294.32
Conv155	64	256	0.80	0.05	0.90	0.05	0.90	0.05	0.55	83.68
Conv156	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.11	83.68
Conv157	256	64	0.82	0.05	0.90	0.05	0.90	0.05	8.92	294.32
Conv158	64	256	0.69	0.05	0.90	0.05	0.90	0.05	0.61	83.68
Conv159	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.1	83.68
Conv160	256	64	0.70	0.05	0.90	0.05	0.90	0.05	10.08	294.32
Conv161	64	256	0.82	0.05	0.90	0.05	0.90	0.05	0.44	83.68
Conv162	64	576	0.91	0.05	0.97	0.05	0.97	0.05	0.09	83.68
Conv163	256	64	0.81	0.05	0.90	0.05	0.90	0.05	11.0	294.32
Passing rate	-	-	99.39%		100.0%		100.0%		99.39%	

Table 28: SRMNet (ResNet164) Cifar100

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.00	0.05	0.58	0.05	0.58	0.05	1623.9	26.3
Conv2	16	16	0.35	0.05	0.56	0.05	0.56	0.05	33.36	26.3
Conv3	16	144	0.28	0.05	0.68	0.05	0.68	0.05	21.42	26.3
Conv4	64	16	0.31	0.05	0.63	0.05	0.63	0.05	156.52	83.68
Conv5	16	64	0.54	0.05	0.63	0.05	0.63	0.05	9.2	26.3
Conv6	16	144	0.43	0.05	0.68	0.05	0.68	0.05	17.06	26.3

Conv7	64	16	0.16	0.05	0.63	0.05	0.63	0.05	141.38	83.68
Conv8	16	64	0.71	0.05	0.63	0.05	0.63	0.05	1.14	26.3
Conv9	16	144	0.64	0.05	0.68	0.05	0.68	0.05	0.84	26.3
Conv10	64	16	0.68	0.05	0.63	0.05	0.63	0.05	26.28	83.68
Conv11	16	64	0.86	0.05	0.63	0.05	0.63	0.05	0.6	26.3
Conv12	16	144	0.82	0.05	0.68	0.05	0.68	0.05	1.66	26.3
Conv13	64	16	0.71	0.05	0.63	0.05	0.63	0.05	19.29	83.68
Conv14	16	64	0.68	0.05	0.63	0.05	0.63	0.05	1.02	26.3
Conv15	16	144	0.82	0.05	0.68	0.05	0.68	0.05	1.34	26.3
Conv16	64	16	0.85	0.05	0.63	0.05	0.63	0.05	6.93	83.68
Conv17	16	64	0.86	0.05	0.63	0.05	0.63	0.05	1.13	26.3
Conv18	16	144	0.87	0.05	0.68	0.05	0.68	0.05	0.33	26.3
Conv19	64	16	0.87	0.05	0.63	0.05	0.63	0.05	3.44	83.68
Conv20	16	64	0.82	0.05	0.63	0.05	0.63	0.05	1.76	26.3
Conv21	16	144	0.87	0.05	0.68	0.05	0.68	0.05	0.82	26.3
Conv22	64	16	0.86	0.05	0.63	0.05	0.63	0.05	5.63	83.68
Conv23	16	64	0.87	0.05	0.63	0.05	0.63	0.05	1.43	26.3
Conv24	16	144	0.88	0.05	0.68	0.05	0.68	0.05	0.71	26.3
Conv25	64	16	0.86	0.05	0.63	0.05	0.63	0.05	4.67	83.68
Conv26	16	64	0.63	0.05	0.63	0.05	0.63	0.05	2.74	26.3
Conv27	16	144	0.64	0.05	0.68	0.05	0.68	0.05	2.32	26.3
Conv28	64	16	0.84	0.05	0.63	0.05	0.63	0.05	7.18	83.68
Conv29	16	64	0.65	0.05	0.63	0.05	0.63	0.05	3.72	26.3
Conv30	16	144	0.52	0.05	0.68	0.05	0.68	0.05	2.86	26.3
Conv31	64	16	0.84	0.05	0.63	0.05	0.63	0.05	10.89	83.68
Conv32	16	64	0.85	0.05	0.63	0.05	0.63	0.05	2.79	26.3
Conv33	16	144	0.86	0.05	0.68	0.05	0.68	0.05	0.69	26.3
Conv34	64	16	0.86	0.05	0.63	0.05	0.63	0.05	8.82	83.68
Conv35	16	64	0.83	0.05	0.63	0.05	0.63	0.05	3.59	26.3
Conv36	16	144	0.81	0.05	0.68	0.05	0.68	0.05	1.62	26.3
Conv37	64	16	0.86	0.05	0.63	0.05	0.63	0.05	6.81	83.68
Conv38	16	64	0.71	0.05	0.63	0.05	0.63	0.05	2.18	26.3
Conv39	16	144	0.61	0.05	0.68	0.05	0.68	0.05	2.3	26.3
Conv40	64	16	0.84	0.05	0.63	0.05	0.63	0.05	8.24	83.68
Conv41	16	64	0.81	0.05	0.63	0.05	0.63	0.05	2.79	26.3
Conv42	16	144	0.63	0.05	0.68	0.05	0.68	0.05	3.23	26.3
Conv43	64	16	0.86	0.05	0.63	0.05	0.63	0.05	8.83	83.68
Conv44	16	64	0.62	0.05	0.63	0.05	0.63	0.05	5.95	26.3
Conv45	16	144	0.65	0.05	0.68	0.05	0.68	0.05	4.0	26.3
Conv46	64	16	0.80	0.05	0.63	0.05	0.63	0.05	13.79	83.68
Conv47	16	64	0.81	0.05	0.63	0.05	0.63	0.05	2.02	26.3
Conv48	16	144	0.85	0.05	0.68	0.05	0.68	0.05	1.49	26.3
Conv49	64	16	0.90	0.05	0.63	0.05	0.63	0.05	5.35	83.68
Conv50	16	64	0.69	0.05	0.63	0.05	0.63	0.05	10.35	26.3
Conv51	16	144	0.60	0.05	0.68	0.05	0.68	0.05	2.38	26.3
Conv52	64	16	0.66	0.05	0.63	0.05	0.63	0.05	27.58	83.68
Conv53	16	64	0.87	0.05	0.63	0.05	0.63	0.05	0.87	26.3
Conv54	16	144	0.89	0.05	0.68	0.05	0.68	0.05	1.13	26.3
Conv55	64	16	0.87	0.05	0.63	0.05	0.63	0.05	6.33	83.68
Conv56	32	64	0.32	0.05	0.67	0.05	0.67	0.05	20.91	46.19
Conv57	32	288	0.64	0.05	0.83	0.05	0.83	0.05	5.09	46.19
Conv58	128	32	0.39	0.05	0.74	0.05	0.74	0.05	86.43	155.4
Conv59	32	128	0.51	0.05	0.74	0.05	0.74	0.05	4.89	46.19
Conv60	32	288	0.46	0.05	0.83	0.05	0.83	0.05	4.81	46.19
Conv61	128	32	0.68	0.05	0.74	0.05	0.74	0.05	37.39	155.4
Conv62	32	128	0.54	0.05	0.74	0.05	0.74	0.05	5.83	46.19
Conv63	32	288	0.62	0.05	0.83	0.05	0.83	0.05	4.73	46.19
Conv64	128	32	0.65	0.05	0.74	0.05	0.74	0.05	25.68	155.4
Conv65	32	128	0.83	0.05	0.74	0.05	0.74	0.05	3.33	46.19

Conv66	32	288	0.84	0.05	0.83	0.05	0.83	0.05	2.21	46.19
Conv67	128	32	0.83	0.05	0.74	0.05	0.74	0.05	19.46	155.4
Conv68	32	128	0.60	0.05	0.74	0.05	0.74	0.05	3.71	46.19
Conv69	32	288	0.61	0.05	0.83	0.05	0.83	0.05	4.04	46.19
Conv70	128	32	0.71	0.05	0.74	0.05	0.74	0.05	28.1	155.4
Conv71	32	128	0.66	0.05	0.74	0.05	0.74	0.05	2.16	46.19
Conv72	32	288	0.66	0.05	0.83	0.05	0.83	0.05	2.64	46.19
Conv73	128	32	0.84	0.05	0.74	0.05	0.74	0.05	17.43	155.4
Conv74	32	128	0.82	0.05	0.74	0.05	0.74	0.05	1.55	46.19
Conv75	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.91	46.19
Conv76	128	32	0.71	0.05	0.74	0.05	0.74	0.05	24.07	155.4
Conv77	32	128	0.66	0.05	0.74	0.05	0.74	0.05	5.42	46.19
Conv78	32	288	0.70	0.05	0.83	0.05	0.83	0.05	2.84	46.19
Conv79	128	32	0.65	0.05	0.74	0.05	0.74	0.05	22.67	155.4
Conv80	32	128	0.61	0.05	0.74	0.05	0.74	0.05	9.26	46.19
Conv81	32	288	0.61	0.05	0.83	0.05	0.83	0.05	5.61	46.19
Conv82	128	32	0.61	0.05	0.74	0.05	0.74	0.05	28.81	155.4
Conv83	32	128	0.83	0.05	0.74	0.05	0.74	0.05	2.49	46.19
Conv84	32	288	0.81	0.05	0.83	0.05	0.83	0.05	2.07	46.19
Conv85	128	32	0.70	0.05	0.74	0.05	0.74	0.05	18.55	155.4
Conv86	32	128	0.67	0.05	0.74	0.05	0.74	0.05	4.81	46.19
Conv87	32	288	0.62	0.05	0.83	0.05	0.83	0.05	3.47	46.19
Conv88	128	32	0.82	0.05	0.74	0.05	0.74	0.05	14.21	155.4
Conv89	32	128	0.69	0.05	0.74	0.05	0.74	0.05	4.38	46.19
Conv90	32	288	0.84	0.05	0.83	0.05	0.83	0.05	2.32	46.19
Conv91	128	32	0.84	0.05	0.74	0.05	0.74	0.05	18.52	155.4
Conv92	32	128	0.60	0.05	0.74	0.05	0.74	0.05	4.86	46.19
Conv93	32	288	0.84	0.05	0.83	0.05	0.83	0.05	2.01	46.19
Conv94	128	32	0.85	0.05	0.74	0.05	0.74	0.05	21.5	155.4
Conv95	32	128	0.44	0.05	0.74	0.05	0.74	0.05	7.02	46.19
Conv96	32	288	0.61	0.05	0.83	0.05	0.83	0.05	3.26	46.19
Conv97	128	32	0.81	0.05	0.74	0.05	0.74	0.05	23.4	155.4
Conv98	32	128	0.84	0.05	0.74	0.05	0.74	0.05	2.63	46.19
Conv99	32	288	0.69	0.05	0.83	0.05	0.83	0.05	1.53	46.19
Conv100	128	32	0.68	0.05	0.74	0.05	0.74	0.05	22.25	155.4
Conv101	32	128	0.69	0.05	0.74	0.05	0.74	0.05	3.22	46.19
Conv102	32	288	0.85	0.05	0.83	0.05	0.83	0.05	1.5	46.19
Conv103	128	32	0.82	0.05	0.74	0.05	0.74	0.05	15.27	155.4
Conv104	32	128	0.83	0.05	0.74	0.05	0.74	0.05	3.01	46.19
Conv105	32	288	0.85	0.05	0.83	0.05	0.83	0.05	1.79	46.19
Conv106	128	32	0.70	0.05	0.74	0.05	0.74	0.05	21.86	155.4
Conv107	32	128	0.58	0.05	0.74	0.05	0.74	0.05	7.47	46.19
Conv108	32	288	0.81	0.05	0.83	0.05	0.83	0.05	1.14	46.19
Conv109	128	32	0.65	0.05	0.74	0.05	0.74	0.05	24.02	155.4
Conv110	64	128	0.42	0.05	0.82	0.05	0.82	0.05	10.69	83.68
Conv111	64	576	0.66	0.05	0.97	0.05	0.97	0.05	2.19	83.68
Conv112	256	64	0.53	0.05	0.90	0.05	0.90	0.05	80.96	294.32
Conv113	64	256	0.52	0.05	0.90	0.05	0.90	0.05	1.5	83.68
Conv114	64	576	0.83	0.05	0.97	0.05	0.97	0.05	1.43	83.68
Conv115	256	64	0.83	0.05	0.90	0.05	0.90	0.05	24.22	294.32
Conv116	64	256	0.82	0.05	0.90	0.05	0.90	0.05	1.18	83.68
Conv117	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.89	83.68
Conv118	256	64	0.87	0.05	0.90	0.05	0.90	0.05	12.44	294.32
Conv119	64	256	0.61	0.05	0.90	0.05	0.90	0.05	1.29	83.68
Conv120	64	576	0.62	0.05	0.97	0.05	0.97	0.05	1.29	83.68
Conv121	256	64	0.68	0.05	0.90	0.05	0.90	0.05	16.31	294.32
Conv122	64	256	0.71	0.05	0.90	0.05	0.90	0.05	1.4	83.68
Conv123	64	576	0.87	0.05	0.97	0.05	0.97	0.05	1.46	83.68
Conv124	256	64	0.86	0.05	0.90	0.05	0.90	0.05	13.1	294.32

Conv125	64	256	0.83	0.05	0.90	0.05	0.90	0.05	1.03	83.68
Conv126	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.67	83.68
Conv127	256	64	0.84	0.05	0.90	0.05	0.90	0.05	13.5	294.32
Conv128	64	256	0.71	0.05	0.90	0.05	0.90	0.05	1.42	83.68
Conv129	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.45	83.68
Conv130	256	64	0.82	0.05	0.90	0.05	0.90	0.05	17.02	294.32
Conv131	64	256	0.63	0.05	0.90	0.05	0.90	0.05	1.53	83.68
Conv132	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.62	83.68
Conv133	256	64	0.82	0.05	0.90	0.05	0.90	0.05	19.25	294.32
Conv134	64	256	0.71	0.05	0.90	0.05	0.90	0.05	1.2	83.68
Conv135	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.83	83.68
Conv136	256	64	0.85	0.05	0.90	0.05	0.90	0.05	18.2	294.32
Conv137	64	256	0.82	0.05	0.90	0.05	0.90	0.05	0.91	83.68
Conv138	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.59	83.68
Conv139	256	64	0.84	0.05	0.90	0.05	0.90	0.05	16.94	294.32
Conv140	64	256	0.65	0.05	0.90	0.05	0.90	0.05	1.14	83.68
Conv141	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.87	83.68
Conv142	256	64	0.64	0.05	0.90	0.05	0.90	0.05	17.78	294.32
Conv143	64	256	0.67	0.05	0.90	0.05	0.90	0.05	1.41	83.68
Conv144	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.78	83.68
Conv145	256	64	0.62	0.05	0.90	0.05	0.90	0.05	17.51	294.32
Conv146	64	256	0.52	0.05	0.90	0.05	0.90	0.05	1.45	83.68
Conv147	64	576	0.86	0.05	0.97	0.05	0.97	0.05	1.19	83.68
Conv148	256	64	0.67	0.05	0.90	0.05	0.90	0.05	24.19	294.32
Conv149	64	256	0.60	0.05	0.90	0.05	0.90	0.05	0.89	83.68
Conv150	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.97	83.68
Conv151	256	64	0.70	0.05	0.90	0.05	0.90	0.05	23.84	294.32
Conv152	64	256	0.49	0.05	0.90	0.05	0.90	0.05	1.09	83.68
Conv153	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.88	83.68
Conv154	256	64	0.65	0.05	0.90	0.05	0.90	0.05	25.16	294.32
Conv155	64	256	0.65	0.05	0.90	0.05	0.90	0.05	1.08	83.68
Conv156	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.74	83.68
Conv157	256	64	0.62	0.05	0.90	0.05	0.90	0.05	35.19	294.32
Conv158	64	256	0.53	0.05	0.90	0.05	0.90	0.05	1.14	83.68
Conv159	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.64	83.68
Conv160	256	64	0.52	0.05	0.90	0.05	0.90	0.05	57.16	294.32
Conv161	64	256	0.39	0.05	0.90	0.05	0.90	0.05	1.63	83.68
Conv162	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.53	83.68
Conv163	256	64	0.45	0.05	0.90	0.05	0.90	0.05	136.33	294.32
Passing rate	-	-	99.39%		100.0%		100.0%		97.55%	

Table 29: CBAM (ResNet164) Cifar100

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	16	27	0.02	0.05	0.58	0.05	0.58	0.05	197.16	26.3
Conv2	16	16	0.61	0.05	0.56	0.05	0.56	0.05	13.19	26.3
Conv3	16	144	0.82	0.05	0.68	0.05	0.68	0.05	2.7	26.3
Conv4	64	16	0.71	0.05	0.63	0.05	0.63	0.05	11.87	83.68
Conv5	16	64	0.89	0.05	0.63	0.05	0.63	0.05	0.5	26.3
Conv6	16	144	0.88	0.05	0.68	0.05	0.68	0.05	0.75	26.3
Conv7	64	16	0.88	0.05	0.63	0.05	0.63	0.05	3.67	83.68
Conv8	16	64	0.85	0.05	0.63	0.05	0.63	0.05	1.4	26.3
Conv9	16	144	0.83	0.05	0.68	0.05	0.68	0.05	1.35	26.3
Conv10	64	16	0.68	0.05	0.63	0.05	0.63	0.05	12.85	83.68

Conv11	16	64	0.84	0.05	0.63	0.05	0.63	0.05	1.46	26.3
Conv12	16	144	0.82	0.05	0.68	0.05	0.68	0.05	1.31	26.3
Conv13	64	16	0.71	0.05	0.63	0.05	0.63	0.05	8.4	83.68
Conv14	16	64	0.89	0.05	0.63	0.05	0.63	0.05	0.71	26.3
Conv15	16	144	0.91	0.05	0.68	0.05	0.68	0.05	0.28	26.3
Conv16	64	16	0.87	0.05	0.63	0.05	0.63	0.05	2.2	83.68
Conv17	16	64	0.84	0.05	0.63	0.05	0.63	0.05	1.68	26.3
Conv18	16	144	0.86	0.05	0.68	0.05	0.68	0.05	0.97	26.3
Conv19	64	16	0.89	0.05	0.63	0.05	0.63	0.05	5.12	83.68
Conv20	16	64	0.65	0.05	0.63	0.05	0.63	0.05	2.8	26.3
Conv21	16	144	0.54	0.05	0.68	0.05	0.68	0.05	1.76	26.3
Conv22	64	16	0.84	0.05	0.63	0.05	0.63	0.05	11.18	83.68
Conv23	16	64	0.82	0.05	0.63	0.05	0.63	0.05	2.65	26.3
Conv24	16	144	0.65	0.05	0.68	0.05	0.68	0.05	1.47	26.3
Conv25	64	16	0.86	0.05	0.63	0.05	0.63	0.05	5.79	83.68
Conv26	16	64	0.70	0.05	0.63	0.05	0.63	0.05	3.49	26.3
Conv27	16	144	0.86	0.05	0.68	0.05	0.68	0.05	0.96	26.3
Conv28	64	16	0.85	0.05	0.63	0.05	0.63	0.05	8.09	83.68
Conv29	16	64	0.91	0.05	0.63	0.05	0.63	0.05	1.29	26.3
Conv30	16	144	0.91	0.05	0.68	0.05	0.68	0.05	1.01	26.3
Conv31	64	16	0.92	0.05	0.63	0.05	0.63	0.05	1.54	83.68
Conv32	16	64	0.90	0.05	0.63	0.05	0.63	0.05	0.92	26.3
Conv33	16	144	0.91	0.05	0.68	0.05	0.68	0.05	0.4	26.3
Conv34	64	16	0.91	0.05	0.63	0.05	0.63	0.05	2.64	83.68
Conv35	16	64	0.88	0.05	0.63	0.05	0.63	0.05	1.48	26.3
Conv36	16	144	0.92	0.05	0.68	0.05	0.68	0.05	0.17	26.3
Conv37	64	16	0.91	0.05	0.63	0.05	0.63	0.05	4.65	83.68
Conv38	16	64	0.66	0.05	0.63	0.05	0.63	0.05	4.56	26.3
Conv39	16	144	0.67	0.05	0.68	0.05	0.68	0.05	5.55	26.3
Conv40	64	16	0.70	0.05	0.63	0.05	0.63	0.05	21.21	83.68
Conv41	16	64	0.87	0.05	0.63	0.05	0.63	0.05	0.91	26.3
Conv42	16	144	0.93	0.05	0.68	0.05	0.68	0.05	0.13	26.3
Conv43	64	16	0.91	0.05	0.63	0.05	0.63	0.05	2.14	83.68
Conv44	16	64	0.92	0.05	0.63	0.05	0.63	0.05	0.71	26.3
Conv45	16	144	0.93	0.05	0.68	0.05	0.68	0.05	0.33	26.3
Conv46	64	16	0.90	0.05	0.63	0.05	0.63	0.05	2.65	83.68
Conv47	16	64	0.69	0.05	0.63	0.05	0.63	0.05	3.17	26.3
Conv48	16	144	0.86	0.05	0.68	0.05	0.68	0.05	0.91	26.3
Conv49	64	16	0.87	0.05	0.63	0.05	0.63	0.05	6.35	83.68
Conv50	16	64	0.89	0.05	0.63	0.05	0.63	0.05	1.24	26.3
Conv51	16	144	0.89	0.05	0.68	0.05	0.68	0.05	1.15	26.3
Conv52	64	16	0.89	0.05	0.63	0.05	0.63	0.05	7.12	83.68
Conv53	16	64	0.53	0.05	0.63	0.05	0.63	0.05	5.77	26.3
Conv54	16	144	0.56	0.05	0.68	0.05	0.68	0.05	3.64	26.3
Conv55	64	16	0.84	0.05	0.63	0.05	0.63	0.05	17.53	83.68
Conv56	32	64	0.43	0.05	0.67	0.05	0.67	0.05	18.41	46.19
Conv57	32	288	0.54	0.05	0.83	0.05	0.83	0.05	10.34	46.19
Conv58	128	32	0.45	0.05	0.74	0.05	0.74	0.05	82.06	155.4
Conv59	32	128	0.55	0.05	0.74	0.05	0.74	0.05	6.51	46.19
Conv60	32	288	0.64	0.05	0.83	0.05	0.83	0.05	6.29	46.19
Conv61	128	32	0.67	0.05	0.74	0.05	0.74	0.05	50.8	155.4
Conv62	32	128	0.55	0.05	0.74	0.05	0.74	0.05	4.23	46.19
Conv63	32	288	0.48	0.05	0.83	0.05	0.83	0.05	4.17	46.19
Conv64	128	32	0.68	0.05	0.74	0.05	0.74	0.05	21.02	155.4
Conv65	32	128	0.70	0.05	0.74	0.05	0.74	0.05	1.86	46.19
Conv66	32	288	0.84	0.05	0.83	0.05	0.83	0.05	1.58	46.19
Conv67	128	32	0.67	0.05	0.74	0.05	0.74	0.05	25.18	155.4
Conv68	32	128	0.61	0.05	0.74	0.05	0.74	0.05	6.87	46.19
Conv69	32	288	0.70	0.05	0.83	0.05	0.83	0.05	2.08	46.19

Conv70	128	32	0.63	0.05	0.74	0.05	0.74	0.05	36.62	155.4
Conv71	32	128	0.62	0.05	0.74	0.05	0.74	0.05	2.77	46.19
Conv72	32	288	0.71	0.05	0.83	0.05	0.83	0.05	1.06	46.19
Conv73	128	32	0.82	0.05	0.74	0.05	0.74	0.05	12.76	155.4
Conv74	32	128	0.61	0.05	0.74	0.05	0.74	0.05	4.29	46.19
Conv75	32	288	0.70	0.05	0.83	0.05	0.83	0.05	2.75	46.19
Conv76	128	32	0.58	0.05	0.74	0.05	0.74	0.05	36.58	155.4
Conv77	32	128	0.81	0.05	0.74	0.05	0.74	0.05	1.8	46.19
Conv78	32	288	0.84	0.05	0.83	0.05	0.83	0.05	1.44	46.19
Conv79	128	32	0.83	0.05	0.74	0.05	0.74	0.05	22.78	155.4
Conv80	32	128	0.88	0.05	0.74	0.05	0.74	0.05	0.69	46.19
Conv81	32	288	0.86	0.05	0.83	0.05	0.83	0.05	0.39	46.19
Conv82	128	32	0.87	0.05	0.74	0.05	0.74	0.05	12.09	155.4
Conv83	32	128	0.85	0.05	0.74	0.05	0.74	0.05	2.09	46.19
Conv84	32	288	0.81	0.05	0.83	0.05	0.83	0.05	1.32	46.19
Conv85	128	32	0.84	0.05	0.74	0.05	0.74	0.05	11.39	155.4
Conv86	32	128	0.57	0.05	0.74	0.05	0.74	0.05	1.48	46.19
Conv87	32	288	0.86	0.05	0.83	0.05	0.83	0.05	0.5	46.19
Conv88	128	32	0.83	0.05	0.74	0.05	0.74	0.05	12.88	155.4
Conv89	32	128	0.57	0.05	0.74	0.05	0.74	0.05	2.43	46.19
Conv90	32	288	0.81	0.05	0.83	0.05	0.83	0.05	0.7	46.19
Conv91	128	32	0.81	0.05	0.74	0.05	0.74	0.05	12.91	155.4
Conv92	32	128	0.82	0.05	0.74	0.05	0.74	0.05	1.18	46.19
Conv93	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.58	46.19
Conv94	128	32	0.87	0.05	0.74	0.05	0.74	0.05	13.73	155.4
Conv95	32	128	0.86	0.05	0.74	0.05	0.74	0.05	0.97	46.19
Conv96	32	288	0.87	0.05	0.83	0.05	0.83	0.05	0.85	46.19
Conv97	128	32	0.70	0.05	0.74	0.05	0.74	0.05	14.06	155.4
Conv98	32	128	0.85	0.05	0.74	0.05	0.74	0.05	1.07	46.19
Conv99	32	288	0.82	0.05	0.83	0.05	0.83	0.05	0.67	46.19
Conv100	128	32	0.86	0.05	0.74	0.05	0.74	0.05	10.9	155.4
Conv101	32	128	0.65	0.05	0.74	0.05	0.74	0.05	3.05	46.19
Conv102	32	288	0.87	0.05	0.83	0.05	0.83	0.05	0.49	46.19
Conv103	128	32	0.82	0.05	0.74	0.05	0.74	0.05	14.8	155.4
Conv104	32	128	0.87	0.05	0.74	0.05	0.74	0.05	0.42	46.19
Conv105	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.88	46.19
Conv106	128	32	0.85	0.05	0.74	0.05	0.74	0.05	10.12	155.4
Conv107	32	128	0.81	0.05	0.74	0.05	0.74	0.05	1.94	46.19
Conv108	32	288	0.86	0.05	0.83	0.05	0.83	0.05	0.25	46.19
Conv109	128	32	0.85	0.05	0.74	0.05	0.74	0.05	17.64	155.4
Conv110	64	128	0.57	0.05	0.82	0.05	0.82	0.05	3.04	83.68
Conv111	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.62	83.68
Conv112	256	64	0.46	0.05	0.90	0.05	0.90	0.05	46.96	294.32
Conv113	64	256	0.70	0.05	0.90	0.05	0.90	0.05	0.81	83.68
Conv114	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.81	83.68
Conv115	256	64	0.60	0.05	0.90	0.05	0.90	0.05	13.34	294.32
Conv116	64	256	0.84	0.05	0.90	0.05	0.90	0.05	0.78	83.68
Conv117	64	576	0.81	0.05	0.97	0.05	0.97	0.05	0.53	83.68
Conv118	256	64	0.64	0.05	0.90	0.05	0.90	0.05	12.21	294.32
Conv119	64	256	0.65	0.05	0.90	0.05	0.90	0.05	1.11	83.68
Conv120	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.76	83.68
Conv121	256	64	0.81	0.05	0.90	0.05	0.90	0.05	10.67	294.32
Conv122	64	256	0.69	0.05	0.90	0.05	0.90	0.05	0.65	83.68
Conv123	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.43	83.68
Conv124	256	64	0.81	0.05	0.90	0.05	0.90	0.05	10.07	294.32
Conv125	64	256	0.81	0.05	0.90	0.05	0.90	0.05	0.76	83.68
Conv126	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.4	83.68
Conv127	256	64	0.84	0.05	0.90	0.05	0.90	0.05	10.13	294.32
Conv128	64	256	0.84	0.05	0.90	0.05	0.90	0.05	0.64	83.68

Conv129	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.32	83.68
Conv130	256	64	0.81	0.05	0.90	0.05	0.90	0.05	11.56	294.32
Conv131	64	256	0.81	0.05	0.90	0.05	0.90	0.05	0.75	83.68
Conv132	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.32	83.68
Conv133	256	64	0.58	0.05	0.90	0.05	0.90	0.05	13.42	294.32
Conv134	64	256	0.69	0.05	0.90	0.05	0.90	0.05	0.67	83.68
Conv135	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.27	83.68
Conv136	256	64	0.68	0.05	0.90	0.05	0.90	0.05	11.61	294.32
Conv137	64	256	0.65	0.05	0.90	0.05	0.90	0.05	0.65	83.68
Conv138	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.25	83.68
Conv139	256	64	0.65	0.05	0.90	0.05	0.90	0.05	12.04	294.32
Conv140	64	256	0.82	0.05	0.90	0.05	0.90	0.05	0.43	83.68
Conv141	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.39	83.68
Conv142	256	64	0.69	0.05	0.90	0.05	0.90	0.05	13.46	294.32
Conv143	64	256	0.81	0.05	0.90	0.05	0.90	0.05	0.51	83.68
Conv144	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.37	83.68
Conv145	256	64	0.62	0.05	0.90	0.05	0.90	0.05	14.42	294.32
Conv146	64	256	0.67	0.05	0.90	0.05	0.90	0.05	0.54	83.68
Conv147	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.34	83.68
Conv148	256	64	0.67	0.05	0.90	0.05	0.90	0.05	15.7	294.32
Conv149	64	256	0.60	0.05	0.90	0.05	0.90	0.05	0.52	83.68
Conv150	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.34	83.68
Conv151	256	64	0.69	0.05	0.90	0.05	0.90	0.05	18.04	294.32
Conv152	64	256	0.54	0.05	0.90	0.05	0.90	0.05	0.74	83.68
Conv153	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.27	83.68
Conv154	256	64	0.63	0.05	0.90	0.05	0.90	0.05	22.21	294.32
Conv155	64	256	0.63	0.05	0.90	0.05	0.90	0.05	0.82	83.68
Conv156	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.29	83.68
Conv157	256	64	0.63	0.05	0.90	0.05	0.90	0.05	23.29	294.32
Conv158	64	256	0.65	0.05	0.90	0.05	0.90	0.05	0.76	83.68
Conv159	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.27	83.68
Conv160	256	64	0.61	0.05	0.90	0.05	0.90	0.05	25.39	294.32
Conv161	64	256	0.63	0.05	0.90	0.05	0.90	0.05	0.84	83.68
Conv162	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.23	83.68
Conv163	256	64	0.57	0.05	0.90	0.05	0.90	0.05	37.17	294.32
Passing rate	-	-	99.39%		100.0%		100.0%		99.39%	

Table 30: IEBN (ResNet164) Cifar100

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	16	27	0.01	0.05	0.58	0.05	0.58	0.05	195.79	26.3
Conv2	16	16	0.54	0.05	0.56	0.05	0.56	0.05	4.71	26.3
Conv3	16	144	0.68	0.05	0.68	0.05	0.68	0.05	1.02	26.3
Conv4	64	16	0.81	0.05	0.63	0.05	0.63	0.05	15.02	83.68
Conv5	16	64	0.65	0.05	0.63	0.05	0.63	0.05	0.91	26.3
Conv6	16	144	0.85	0.05	0.68	0.05	0.68	0.05	0.77	26.3
Conv7	64	16	0.71	0.05	0.63	0.05	0.63	0.05	10.97	83.68
Conv8	16	64	0.51	0.05	0.63	0.05	0.63	0.05	2.16	26.3
Conv9	16	144	0.67	0.05	0.68	0.05	0.68	0.05	1.29	26.3
Conv10	64	16	0.82	0.05	0.63	0.05	0.63	0.05	13.51	83.68
Conv11	16	64	0.66	0.05	0.63	0.05	0.63	0.05	1.9	26.3
Conv12	16	144	0.80	0.05	0.68	0.05	0.68	0.05	0.85	26.3
Conv13	64	16	0.80	0.05	0.63	0.05	0.63	0.05	7.16	83.68
Conv14	16	64	0.69	0.05	0.63	0.05	0.63	0.05	2.7	26.3

Conv15	16	144	0.81	0.05	0.68	0.05	0.68	0.05	0.93	26.3
Conv16	64	16	0.83	0.05	0.63	0.05	0.63	0.05	14.86	83.68
Conv17	16	64	0.69	0.05	0.63	0.05	0.63	0.05	2.31	26.3
Conv18	16	144	0.66	0.05	0.68	0.05	0.68	0.05	1.09	26.3
Conv19	64	16	0.81	0.05	0.63	0.05	0.63	0.05	11.16	83.68
Conv20	16	64	0.82	0.05	0.63	0.05	0.63	0.05	1.1	26.3
Conv21	16	144	0.88	0.05	0.68	0.05	0.68	0.05	0.51	26.3
Conv22	64	16	0.85	0.05	0.63	0.05	0.63	0.05	8.11	83.68
Conv23	16	64	0.86	0.05	0.63	0.05	0.63	0.05	0.49	26.3
Conv24	16	144	0.87	0.05	0.68	0.05	0.68	0.05	1.0	26.3
Conv25	64	16	0.86	0.05	0.63	0.05	0.63	0.05	10.94	83.68
Conv26	16	64	0.71	0.05	0.63	0.05	0.63	0.05	1.04	26.3
Conv27	16	144	0.83	0.05	0.68	0.05	0.68	0.05	1.09	26.3
Conv28	64	16	0.68	0.05	0.63	0.05	0.63	0.05	15.37	83.68
Conv29	16	64	0.83	0.05	0.63	0.05	0.63	0.05	1.2	26.3
Conv30	16	144	0.87	0.05	0.68	0.05	0.68	0.05	0.58	26.3
Conv31	64	16	0.85	0.05	0.63	0.05	0.63	0.05	9.0	83.68
Conv32	16	64	0.70	0.05	0.63	0.05	0.63	0.05	1.73	26.3
Conv33	16	144	0.86	0.05	0.68	0.05	0.68	0.05	1.14	26.3
Conv34	64	16	0.82	0.05	0.63	0.05	0.63	0.05	9.77	83.68
Conv35	16	64	0.66	0.05	0.63	0.05	0.63	0.05	1.8	26.3
Conv36	16	144	0.84	0.05	0.68	0.05	0.68	0.05	0.69	26.3
Conv37	64	16	0.70	0.05	0.63	0.05	0.63	0.05	8.9	83.68
Conv38	16	64	0.59	0.05	0.63	0.05	0.63	0.05	2.08	26.3
Conv39	16	144	0.65	0.05	0.68	0.05	0.68	0.05	1.38	26.3
Conv40	64	16	0.81	0.05	0.63	0.05	0.63	0.05	10.24	83.68
Conv41	16	64	0.63	0.05	0.63	0.05	0.63	0.05	2.02	26.3
Conv42	16	144	0.84	0.05	0.68	0.05	0.68	0.05	0.9	26.3
Conv43	64	16	0.82	0.05	0.63	0.05	0.63	0.05	17.71	83.68
Conv44	16	64	0.81	0.05	0.63	0.05	0.63	0.05	2.86	26.3
Conv45	16	144	0.86	0.05	0.68	0.05	0.68	0.05	1.45	26.3
Conv46	64	16	0.64	0.05	0.63	0.05	0.63	0.05	19.59	83.68
Conv47	16	64	0.83	0.05	0.63	0.05	0.63	0.05	2.27	26.3
Conv48	16	144	0.85	0.05	0.68	0.05	0.68	0.05	0.56	26.3
Conv49	64	16	0.84	0.05	0.63	0.05	0.63	0.05	8.48	83.68
Conv50	16	64	0.63	0.05	0.63	0.05	0.63	0.05	3.11	26.3
Conv51	16	144	0.81	0.05	0.68	0.05	0.68	0.05	1.48	26.3
Conv52	64	16	0.71	0.05	0.63	0.05	0.63	0.05	17.95	83.68
Conv53	16	64	0.64	0.05	0.63	0.05	0.63	0.05	3.24	26.3
Conv54	16	144	0.87	0.05	0.68	0.05	0.68	0.05	1.26	26.3
Conv55	64	16	0.67	0.05	0.63	0.05	0.63	0.05	12.57	83.68
Conv56	32	64	0.49	0.05	0.67	0.05	0.67	0.05	5.98	46.19
Conv57	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.46	46.19
Conv58	128	32	0.68	0.05	0.74	0.05	0.74	0.05	22.72	155.4
Conv59	32	128	0.88	0.05	0.74	0.05	0.74	0.05	0.28	46.19
Conv60	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.44	46.19
Conv61	128	32	0.87	0.05	0.74	0.05	0.74	0.05	5.9	155.4
Conv62	32	128	0.86	0.05	0.74	0.05	0.74	0.05	0.89	46.19
Conv63	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.72	46.19
Conv64	128	32	0.87	0.05	0.74	0.05	0.74	0.05	5.71	155.4
Conv65	32	128	0.90	0.05	0.74	0.05	0.74	0.05	0.35	46.19
Conv66	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.43	46.19
Conv67	128	32	0.85	0.05	0.74	0.05	0.74	0.05	4.75	155.4
Conv68	32	128	0.85	0.05	0.74	0.05	0.74	0.05	0.67	46.19
Conv69	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.51	46.19
Conv70	128	32	0.88	0.05	0.74	0.05	0.74	0.05	5.8	155.4
Conv71	32	128	0.84	0.05	0.74	0.05	0.74	0.05	0.97	46.19
Conv72	32	288	0.90	0.05	0.83	0.05	0.83	0.05	0.69	46.19
Conv73	128	32	0.85	0.05	0.74	0.05	0.74	0.05	5.58	155.4

Conv74	32	128	0.88	0.05	0.74	0.05	0.74	0.05	0.67	46.19
Conv75	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.55	46.19
Conv76	128	32	0.89	0.05	0.74	0.05	0.74	0.05	4.63	155.4
Conv77	32	128	0.84	0.05	0.74	0.05	0.74	0.05	0.9	46.19
Conv78	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.24	46.19
Conv79	128	32	0.87	0.05	0.74	0.05	0.74	0.05	5.47	155.4
Conv80	32	128	0.87	0.05	0.74	0.05	0.74	0.05	0.71	46.19
Conv81	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.73	46.19
Conv82	128	32	0.88	0.05	0.74	0.05	0.74	0.05	5.61	155.4
Conv83	32	128	0.84	0.05	0.74	0.05	0.74	0.05	0.43	46.19
Conv84	32	288	0.91	0.05	0.83	0.05	0.83	0.05	0.35	46.19
Conv85	128	32	0.87	0.05	0.74	0.05	0.74	0.05	5.8	155.4
Conv86	32	128	0.84	0.05	0.74	0.05	0.74	0.05	1.03	46.19
Conv87	32	288	0.88	0.05	0.83	0.05	0.83	0.05	0.47	46.19
Conv88	128	32	0.88	0.05	0.74	0.05	0.74	0.05	5.64	155.4
Conv89	32	128	0.82	0.05	0.74	0.05	0.74	0.05	1.47	46.19
Conv90	32	288	0.89	0.05	0.83	0.05	0.83	0.05	0.33	46.19
Conv91	128	32	0.84	0.05	0.74	0.05	0.74	0.05	5.74	155.4
Conv92	32	128	0.87	0.05	0.74	0.05	0.74	0.05	0.8	46.19
Conv93	32	288	0.90	0.05	0.83	0.05	0.83	0.05	0.36	46.19
Conv94	128	32	0.88	0.05	0.74	0.05	0.74	0.05	5.16	155.4
Conv95	32	128	0.68	0.05	0.74	0.05	0.74	0.05	1.01	46.19
Conv96	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.38	46.19
Conv97	128	32	0.82	0.05	0.74	0.05	0.74	0.05	6.46	155.4
Conv98	32	128	0.85	0.05	0.74	0.05	0.74	0.05	0.95	46.19
Conv99	32	288	0.90	0.05	0.83	0.05	0.83	0.05	0.36	46.19
Conv100	128	32	0.84	0.05	0.74	0.05	0.74	0.05	5.54	155.4
Conv101	32	128	0.85	0.05	0.74	0.05	0.74	0.05	1.57	46.19
Conv102	32	288	0.87	0.05	0.83	0.05	0.83	0.05	0.2	46.19
Conv103	128	32	0.87	0.05	0.74	0.05	0.74	0.05	4.57	155.4
Conv104	32	128	0.86	0.05	0.74	0.05	0.74	0.05	0.65	46.19
Conv105	32	288	0.90	0.05	0.83	0.05	0.83	0.05	0.25	46.19
Conv106	128	32	0.86	0.05	0.74	0.05	0.74	0.05	5.92	155.4
Conv107	32	128	0.67	0.05	0.74	0.05	0.74	0.05	1.33	46.19
Conv108	32	288	0.84	0.05	0.83	0.05	0.83	0.05	0.3	46.19
Conv109	128	32	0.87	0.05	0.74	0.05	0.74	0.05	4.94	155.4
Conv110	64	128	0.67	0.05	0.82	0.05	0.82	0.05	2.21	83.68
Conv111	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.29	83.68
Conv112	256	64	0.64	0.05	0.90	0.05	0.90	0.05	12.03	294.32
Conv113	64	256	0.83	0.05	0.90	0.05	0.90	0.05	0.79	83.68
Conv114	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.37	83.68
Conv115	256	64	0.83	0.05	0.90	0.05	0.90	0.05	6.38	294.32
Conv116	64	256	0.86	0.05	0.90	0.05	0.90	0.05	0.44	83.68
Conv117	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.42	83.68
Conv118	256	64	0.81	0.05	0.90	0.05	0.90	0.05	6.49	294.32
Conv119	64	256	0.82	0.05	0.90	0.05	0.90	0.05	0.65	83.68
Conv120	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.51	83.68
Conv121	256	64	0.87	0.05	0.90	0.05	0.90	0.05	7.01	294.32
Conv122	64	256	0.83	0.05	0.90	0.05	0.90	0.05	0.63	83.68
Conv123	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.34	83.68
Conv124	256	64	0.85	0.05	0.90	0.05	0.90	0.05	7.76	294.32
Conv125	64	256	0.87	0.05	0.90	0.05	0.90	0.05	0.62	83.68
Conv126	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.28	83.68
Conv127	256	64	0.84	0.05	0.90	0.05	0.90	0.05	6.24	294.32
Conv128	64	256	0.84	0.05	0.90	0.05	0.90	0.05	0.67	83.68
Conv129	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.26	83.68
Conv130	256	64	0.84	0.05	0.90	0.05	0.90	0.05	6.71	294.32
Conv131	64	256	0.87	0.05	0.90	0.05	0.90	0.05	0.66	83.68
Conv132	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.23	83.68

Conv133	256	64	0.85	0.05	0.90	0.05	0.90	0.05	7.47	294.32
Conv134	64	256	0.85	0.05	0.90	0.05	0.90	0.05	0.47	83.68
Conv135	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.26	83.68
Conv136	256	64	0.87	0.05	0.90	0.05	0.90	0.05	6.6	294.32
Conv137	64	256	0.87	0.05	0.90	0.05	0.90	0.05	0.54	83.68
Conv138	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.22	83.68
Conv139	256	64	0.86	0.05	0.90	0.05	0.90	0.05	7.99	294.32
Conv140	64	256	0.83	0.05	0.90	0.05	0.90	0.05	0.63	83.68
Conv141	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.18	83.68
Conv142	256	64	0.84	0.05	0.90	0.05	0.90	0.05	8.04	294.32
Conv143	64	256	0.83	0.05	0.90	0.05	0.90	0.05	0.5	83.68
Conv144	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.21	83.68
Conv145	256	64	0.85	0.05	0.90	0.05	0.90	0.05	7.78	294.32
Conv146	64	256	0.83	0.05	0.90	0.05	0.90	0.05	0.43	83.68
Conv147	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.23	83.68
Conv148	256	64	0.85	0.05	0.90	0.05	0.90	0.05	7.64	294.32
Conv149	64	256	0.83	0.05	0.90	0.05	0.90	0.05	0.49	83.68
Conv150	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.24	83.68
Conv151	256	64	0.82	0.05	0.90	0.05	0.90	0.05	8.91	294.32
Conv152	64	256	0.83	0.05	0.90	0.05	0.90	0.05	0.75	83.68
Conv153	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.2	83.68
Conv154	256	64	0.83	0.05	0.90	0.05	0.90	0.05	8.11	294.32
Conv155	64	256	0.83	0.05	0.90	0.05	0.90	0.05	0.5	83.68
Conv156	64	576	0.91	0.05	0.97	0.05	0.97	0.05	0.18	83.68
Conv157	256	64	0.81	0.05	0.90	0.05	0.90	0.05	8.0	294.32
Conv158	64	256	0.83	0.05	0.90	0.05	0.90	0.05	0.63	83.68
Conv159	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.19	83.68
Conv160	256	64	0.82	0.05	0.90	0.05	0.90	0.05	7.69	294.32
Conv161	64	256	0.81	0.05	0.90	0.05	0.90	0.05	0.87	83.68
Conv162	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.17	83.68
Conv163	256	64	0.83	0.05	0.90	0.05	0.90	0.05	9.42	294.32
Passing rate	-	-	99.39%		100.0%		100.0%		99.39%	

Table 31: SGENet (ResNet164) Cifar100

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.00	0.05	0.58	0.05	0.58	0.05	289.86	26.3
Conv2	16	16	0.35	0.05	0.56	0.05	0.56	0.05	46.81	26.3
Conv3	16	144	0.29	0.05	0.68	0.05	0.68	0.05	25.84	26.3
Conv4	64	16	0.47	0.05	0.63	0.05	0.63	0.05	74.29	83.68
Conv5	16	64	0.84	0.05	0.63	0.05	0.63	0.05	1.15	26.3
Conv6	16	144	0.67	0.05	0.68	0.05	0.68	0.05	1.91	26.3
Conv7	64	16	0.48	0.05	0.63	0.05	0.63	0.05	23.94	83.68
Conv8	16	64	0.81	0.05	0.63	0.05	0.63	0.05	1.49	26.3
Conv9	16	144	0.81	0.05	0.68	0.05	0.68	0.05	2.24	26.3
Conv10	64	16	0.71	0.05	0.63	0.05	0.63	0.05	14.43	83.68
Conv11	16	64	0.88	0.05	0.63	0.05	0.63	0.05	0.9	26.3
Conv12	16	144	0.84	0.05	0.68	0.05	0.68	0.05	0.98	26.3
Conv13	64	16	0.84	0.05	0.63	0.05	0.63	0.05	6.21	83.68
Conv14	16	64	0.70	0.05	0.63	0.05	0.63	0.05	1.78	26.3
Conv15	16	144	0.62	0.05	0.68	0.05	0.68	0.05	2.58	26.3
Conv16	64	16	0.68	0.05	0.63	0.05	0.63	0.05	9.12	83.68
Conv17	16	64	0.69	0.05	0.63	0.05	0.63	0.05	2.25	26.3
Conv18	16	144	0.82	0.05	0.68	0.05	0.68	0.05	0.69	26.3

Conv19	64	16	0.85	0.05	0.63	0.05	0.63	0.05	6.68	83.68
Conv20	16	64	0.68	0.05	0.63	0.05	0.63	0.05	3.13	26.3
Conv21	16	144	0.81	0.05	0.68	0.05	0.68	0.05	1.92	26.3
Conv22	64	16	0.81	0.05	0.63	0.05	0.63	0.05	9.84	83.68
Conv23	16	64	0.88	0.05	0.63	0.05	0.63	0.05	0.99	26.3
Conv24	16	144	0.91	0.05	0.68	0.05	0.68	0.05	0.26	26.3
Conv25	64	16	0.91	0.05	0.63	0.05	0.63	0.05	2.74	83.68
Conv26	16	64	0.60	0.05	0.63	0.05	0.63	0.05	3.57	26.3
Conv27	16	144	0.85	0.05	0.68	0.05	0.68	0.05	1.47	26.3
Conv28	64	16	0.71	0.05	0.63	0.05	0.63	0.05	9.72	83.68
Conv29	16	64	0.58	0.05	0.63	0.05	0.63	0.05	3.86	26.3
Conv30	16	144	0.52	0.05	0.68	0.05	0.68	0.05	4.55	26.3
Conv31	64	16	0.62	0.05	0.63	0.05	0.63	0.05	9.97	83.68
Conv32	16	64	0.84	0.05	0.63	0.05	0.63	0.05	1.92	26.3
Conv33	16	144	0.86	0.05	0.68	0.05	0.68	0.05	0.87	26.3
Conv34	64	16	0.87	0.05	0.63	0.05	0.63	0.05	6.02	83.68
Conv35	16	64	0.84	0.05	0.63	0.05	0.63	0.05	1.97	26.3
Conv36	16	144	0.83	0.05	0.68	0.05	0.68	0.05	2.01	26.3
Conv37	64	16	0.86	0.05	0.63	0.05	0.63	0.05	3.83	83.68
Conv38	16	64	0.84	0.05	0.63	0.05	0.63	0.05	1.73	26.3
Conv39	16	144	0.83	0.05	0.68	0.05	0.68	0.05	1.99	26.3
Conv40	64	16	0.86	0.05	0.63	0.05	0.63	0.05	7.64	83.68
Conv41	16	64	0.90	0.05	0.63	0.05	0.63	0.05	1.03	26.3
Conv42	16	144	0.91	0.05	0.68	0.05	0.68	0.05	0.3	26.3
Conv43	64	16	0.89	0.05	0.63	0.05	0.63	0.05	3.45	83.68
Conv44	16	64	0.63	0.05	0.63	0.05	0.63	0.05	3.89	26.3
Conv45	16	144	0.61	0.05	0.68	0.05	0.68	0.05	3.72	26.3
Conv46	64	16	0.83	0.05	0.63	0.05	0.63	0.05	12.99	83.68
Conv47	16	64	0.49	0.05	0.63	0.05	0.63	0.05	4.34	26.3
Conv48	16	144	0.53	0.05	0.68	0.05	0.68	0.05	2.15	26.3
Conv49	64	16	0.84	0.05	0.63	0.05	0.63	0.05	10.73	83.68
Conv50	16	64	0.67	0.05	0.63	0.05	0.63	0.05	2.16	26.3
Conv51	16	144	0.83	0.05	0.68	0.05	0.68	0.05	2.72	26.3
Conv52	64	16	0.86	0.05	0.63	0.05	0.63	0.05	7.04	83.68
Conv53	16	64	0.82	0.05	0.63	0.05	0.63	0.05	4.5	26.3
Conv54	16	144	0.69	0.05	0.68	0.05	0.68	0.05	2.71	26.3
Conv55	64	16	0.81	0.05	0.63	0.05	0.63	0.05	14.14	83.68
Conv56	32	64	0.63	0.05	0.67	0.05	0.67	0.05	11.28	46.19
Conv57	32	288	0.65	0.05	0.83	0.05	0.83	0.05	5.96	46.19
Conv58	128	32	0.36	0.05	0.74	0.05	0.74	0.05	98.65	155.4
Conv59	32	128	0.54	0.05	0.74	0.05	0.74	0.05	5.87	46.19
Conv60	32	288	0.52	0.05	0.83	0.05	0.83	0.05	5.99	46.19
Conv61	128	32	0.64	0.05	0.74	0.05	0.74	0.05	40.2	155.4
Conv62	32	128	0.38	0.05	0.74	0.05	0.74	0.05	3.92	46.19
Conv63	32	288	0.53	0.05	0.83	0.05	0.83	0.05	3.51	46.19
Conv64	128	32	0.70	0.05	0.74	0.05	0.74	0.05	19.17	155.4
Conv65	32	128	0.67	0.05	0.74	0.05	0.74	0.05	1.91	46.19
Conv66	32	288	0.67	0.05	0.83	0.05	0.83	0.05	1.78	46.19
Conv67	128	32	0.82	0.05	0.74	0.05	0.74	0.05	18.69	155.4
Conv68	32	128	0.81	0.05	0.74	0.05	0.74	0.05	2.23	46.19
Conv69	32	288	0.66	0.05	0.83	0.05	0.83	0.05	2.37	46.19
Conv70	128	32	0.83	0.05	0.74	0.05	0.74	0.05	22.83	155.4
Conv71	32	128	0.31	0.05	0.74	0.05	0.74	0.05	7.17	46.19
Conv72	32	288	0.59	0.05	0.83	0.05	0.83	0.05	3.55	46.19
Conv73	128	32	0.53	0.05	0.74	0.05	0.74	0.05	28.29	155.4
Conv74	32	128	0.53	0.05	0.74	0.05	0.74	0.05	5.34	46.19
Conv75	32	288	0.64	0.05	0.83	0.05	0.83	0.05	3.14	46.19
Conv76	128	32	0.54	0.05	0.74	0.05	0.74	0.05	36.96	155.4
Conv77	32	128	0.84	0.05	0.74	0.05	0.74	0.05	2.0	46.19

Conv78	32	288	0.71	0.05	0.83	0.05	0.83	0.05	1.8	46.19
Conv79	128	32	0.85	0.05	0.74	0.05	0.74	0.05	15.94	155.4
Conv80	32	128	0.67	0.05	0.74	0.05	0.74	0.05	1.48	46.19
Conv81	32	288	0.85	0.05	0.83	0.05	0.83	0.05	1.17	46.19
Conv82	128	32	0.71	0.05	0.74	0.05	0.74	0.05	13.44	155.4
Conv83	32	128	0.84	0.05	0.74	0.05	0.74	0.05	1.66	46.19
Conv84	32	288	0.86	0.05	0.83	0.05	0.83	0.05	1.05	46.19
Conv85	128	32	0.84	0.05	0.74	0.05	0.74	0.05	10.81	155.4
Conv86	32	128	0.70	0.05	0.74	0.05	0.74	0.05	1.56	46.19
Conv87	32	288	0.68	0.05	0.83	0.05	0.83	0.05	0.98	46.19
Conv88	128	32	0.84	0.05	0.74	0.05	0.74	0.05	12.75	155.4
Conv89	32	128	0.82	0.05	0.74	0.05	0.74	0.05	2.06	46.19
Conv90	32	288	0.82	0.05	0.83	0.05	0.83	0.05	1.19	46.19
Conv91	128	32	0.84	0.05	0.74	0.05	0.74	0.05	10.13	155.4
Conv92	32	128	0.83	0.05	0.74	0.05	0.74	0.05	2.47	46.19
Conv93	32	288	0.84	0.05	0.83	0.05	0.83	0.05	1.3	46.19
Conv94	128	32	0.80	0.05	0.74	0.05	0.74	0.05	17.69	155.4
Conv95	32	128	0.87	0.05	0.74	0.05	0.74	0.05	1.15	46.19
Conv96	32	288	0.86	0.05	0.83	0.05	0.83	0.05	1.12	46.19
Conv97	128	32	0.84	0.05	0.74	0.05	0.74	0.05	11.38	155.4
Conv98	32	128	0.83	0.05	0.74	0.05	0.74	0.05	1.54	46.19
Conv99	32	288	0.86	0.05	0.83	0.05	0.83	0.05	1.13	46.19
Conv100	128	32	0.85	0.05	0.74	0.05	0.74	0.05	16.13	155.4
Conv101	32	128	0.59	0.05	0.74	0.05	0.74	0.05	2.81	46.19
Conv102	32	288	0.81	0.05	0.83	0.05	0.83	0.05	1.11	46.19
Conv103	128	32	0.83	0.05	0.74	0.05	0.74	0.05	11.62	155.4
Conv104	32	128	0.71	0.05	0.74	0.05	0.74	0.05	2.22	46.19
Conv105	32	288	0.85	0.05	0.83	0.05	0.83	0.05	1.28	46.19
Conv106	128	32	0.82	0.05	0.74	0.05	0.74	0.05	16.64	155.4
Conv107	32	128	0.68	0.05	0.74	0.05	0.74	0.05	2.62	46.19
Conv108	32	288	0.85	0.05	0.83	0.05	0.83	0.05	1.0	46.19
Conv109	128	32	0.62	0.05	0.74	0.05	0.74	0.05	18.47	155.4
Conv110	64	128	0.58	0.05	0.82	0.05	0.82	0.05	7.8	83.68
Conv111	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.22	83.68
Conv112	256	64	0.50	0.05	0.90	0.05	0.90	0.05	71.76	294.32
Conv113	64	256	0.84	0.05	0.90	0.05	0.90	0.05	0.75	83.68
Conv114	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.79	83.68
Conv115	256	64	0.70	0.05	0.90	0.05	0.90	0.05	15.19	294.32
Conv116	64	256	0.82	0.05	0.90	0.05	0.90	0.05	1.21	83.68
Conv117	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.8	83.68
Conv118	256	64	0.87	0.05	0.90	0.05	0.90	0.05	15.06	294.32
Conv119	64	256	0.62	0.05	0.90	0.05	0.90	0.05	1.12	83.68
Conv120	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.73	83.68
Conv121	256	64	0.82	0.05	0.90	0.05	0.90	0.05	13.67	294.32
Conv122	64	256	0.59	0.05	0.90	0.05	0.90	0.05	1.17	83.68
Conv123	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.86	83.68
Conv124	256	64	0.84	0.05	0.90	0.05	0.90	0.05	15.79	294.32
Conv125	64	256	0.84	0.05	0.90	0.05	0.90	0.05	1.12	83.68
Conv126	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.61	83.68
Conv127	256	64	0.84	0.05	0.90	0.05	0.90	0.05	10.56	294.32
Conv128	64	256	0.85	0.05	0.90	0.05	0.90	0.05	0.83	83.68
Conv129	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.64	83.68
Conv130	256	64	0.81	0.05	0.90	0.05	0.90	0.05	13.88	294.32
Conv131	64	256	0.85	0.05	0.90	0.05	0.90	0.05	1.07	83.68
Conv132	64	576	0.89	0.05	0.97	0.05	0.97	0.05	0.92	83.68
Conv133	256	64	0.85	0.05	0.90	0.05	0.90	0.05	12.13	294.32
Conv134	64	256	0.84	0.05	0.90	0.05	0.90	0.05	1.46	83.68
Conv135	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.8	83.68
Conv136	256	64	0.84	0.05	0.90	0.05	0.90	0.05	13.75	294.32

Conv137	64	256	0.83	0.05	0.90	0.05	0.90	0.05	0.95	83.68
Conv138	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.51	83.68
Conv139	256	64	0.84	0.05	0.90	0.05	0.90	0.05	13.21	294.32
Conv140	64	256	0.85	0.05	0.90	0.05	0.90	0.05	1.24	83.68
Conv141	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.75	83.68
Conv142	256	64	0.81	0.05	0.90	0.05	0.90	0.05	13.98	294.32
Conv143	64	256	0.81	0.05	0.90	0.05	0.90	0.05	0.93	83.68
Conv144	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.74	83.68
Conv145	256	64	0.83	0.05	0.90	0.05	0.90	0.05	15.25	294.32
Conv146	64	256	0.69	0.05	0.90	0.05	0.90	0.05	1.14	83.68
Conv147	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.67	83.68
Conv148	256	64	0.82	0.05	0.90	0.05	0.90	0.05	15.25	294.32
Conv149	64	256	0.81	0.05	0.90	0.05	0.90	0.05	0.89	83.68
Conv150	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.93	83.68
Conv151	256	64	0.71	0.05	0.90	0.05	0.90	0.05	18.2	294.32
Conv152	64	256	0.55	0.05	0.90	0.05	0.90	0.05	1.23	83.68
Conv153	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.97	83.68
Conv154	256	64	0.66	0.05	0.90	0.05	0.90	0.05	22.91	294.32
Conv155	64	256	0.60	0.05	0.90	0.05	0.90	0.05	1.26	83.68
Conv156	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.88	83.68
Conv157	256	64	0.62	0.05	0.90	0.05	0.90	0.05	23.61	294.32
Conv158	64	256	0.67	0.05	0.90	0.05	0.90	0.05	0.96	83.68
Conv159	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.91	83.68
Conv160	256	64	0.61	0.05	0.90	0.05	0.90	0.05	37.47	294.32
Conv161	64	256	0.54	0.05	0.90	0.05	0.90	0.05	1.39	83.68
Conv162	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.4	83.68
Conv163	256	64	0.37	0.05	0.90	0.05	0.90	0.05	133.74	294.32
Passing rate	-	-	99.39%		100.0%		100.0%		98.77%	

P.5 INITIALIZATION

config:

https://github.com/bearpaw/pytorch-classification.

https://pytorch.org/docs/master/nn.init.html#nn-init-doc.

Table 32: Cifar100 kaiming-uniform-ResNet164

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	16	27	0.00	0.05	0.58	0.05	0.58	0.05	425.97	26.3
Conv2	16	16	0.12	0.05	0.56	0.05	0.56	0.05	218.1	26.3
Conv3	16	144	0.01	0.05	0.68	0.05	0.68	0.05	168.11	26.3
Conv4	64	16	0.48	0.05	0.63	0.05	0.63	0.05	64.78	83.68
Conv5	16	64	0.20	0.05	0.63	0.05	0.63	0.05	38.28	26.3
Conv6	16	144	0.31	0.05	0.68	0.05	0.68	0.05	15.42	26.3
Conv7	64	16	0.56	0.05	0.63	0.05	0.63	0.05	41.67	83.68
Conv8	16	64	0.29	0.05	0.63	0.05	0.63	0.05	18.91	26.3
Conv9	16	144	0.48	0.05	0.68	0.05	0.68	0.05	9.02	26.3
Conv10	64	16	0.82	0.05	0.63	0.05	0.63	0.05	9.31	83.68
Conv11	16	64	0.42	0.05	0.63	0.05	0.63	0.05	9.62	26.3
Conv12	16	144	0.48	0.05	0.68	0.05	0.68	0.05	2.79	26.3
Conv13	64	16	0.69	0.05	0.63	0.05	0.63	0.05	13.65	83.68
Conv14	16	64	0.59	0.05	0.63	0.05	0.63	0.05	3.04	26.3
Conv15	16	144	0.65	0.05	0.68	0.05	0.68	0.05	2.18	26.3
Conv16	64	16	0.68	0.05	0.63	0.05	0.63	0.05	11.98	83.68

Conv17	16	64	0.67	0.05	0.63	0.05	0.63	0.05	1.2	26.3
Conv18	16	144	0.85	0.05	0.68	0.05	0.68	0.05	0.74	26.3
Conv19	64	16	0.86	0.05	0.63	0.05	0.63	0.05	7.27	83.68
Conv20	16	64	0.58	0.05	0.63	0.05	0.63	0.05	3.37	26.3
Conv21	16	144	0.50	0.05	0.68	0.05	0.68	0.05	3.47	26.3
Conv22	64	16	0.64	0.05	0.63	0.05	0.63	0.05	19.22	83.68
Conv23	16	64	0.60	0.05	0.63	0.05	0.63	0.05	1.89	26.3
Conv24	16	144	0.66	0.05	0.68	0.05	0.68	0.05	2.33	26.3
Conv25	64	16	0.67	0.05	0.63	0.05	0.63	0.05	10.58	83.68
Conv26	16	64	0.56	0.05	0.63	0.05	0.63	0.05	9.27	26.3
Conv27	16	144	0.32	0.05	0.68	0.05	0.68	0.05	6.39	26.3
Conv28	64	16	0.66	0.05	0.63	0.05	0.63	0.05	15.84	83.68
Conv29	16	64	0.81	0.05	0.63	0.05	0.63	0.05	3.21	26.3
Conv30	16	144	0.80	0.05	0.68	0.05	0.68	0.05	2.82	26.3
Conv31	64	16	0.83	0.05	0.63	0.05	0.63	0.05	12.09	83.68
Conv32	16	64	0.64	0.05	0.63	0.05	0.63	0.05	8.7	26.3
Conv33	16	144	0.63	0.05	0.68	0.05	0.68	0.05	3.56	26.3
Conv34	64	16	0.83	0.05	0.63	0.05	0.63	0.05	12.82	83.68
Conv35	16	64	0.38	0.05	0.63	0.05	0.63	0.05	21.3	26.3
Conv36	16	144	0.66	0.05	0.68	0.05	0.68	0.05	1.08	26.3
Conv37	64	16	0.81	0.05	0.63	0.05	0.63	0.05	13.25	83.68
Conv38	16	64	0.63	0.05	0.63	0.05	0.63	0.05	3.26	26.3
Conv39	16	144	0.82	0.05	0.68	0.05	0.68	0.05	3.46	26.3
Conv40	64	16	0.69	0.05	0.63	0.05	0.63	0.05	14.77	83.68
Conv41	16	64	0.71	0.05	0.63	0.05	0.63	0.05	2.69	26.3
Conv42	16	144	0.84	0.05	0.68	0.05	0.68	0.05	1.58	26.3
Conv43	64	16	0.88	0.05	0.63	0.05	0.63	0.05	10.16	83.68
Conv44	16	64	0.57	0.05	0.63	0.05	0.63	0.05	12.25	26.3
Conv45	16	144	0.80	0.05	0.68	0.05	0.68	0.05	2.95	26.3
Conv46	64	16	0.84	0.05	0.63	0.05	0.63	0.05	12.53	83.68
Conv47	16	64	0.81	0.05	0.63	0.05	0.63	0.05	3.93	26.3
Conv48	16	144	0.81	0.05	0.68	0.05	0.68	0.05	2.59	26.3
Conv49	64	16	0.82	0.05	0.63	0.05	0.63	0.05	8.55	83.68
Conv50	16	64	0.67	0.05	0.63	0.05	0.63	0.05	3.59	26.3
Conv51	16	144	0.70	0.05	0.68	0.05	0.68	0.05	2.53	26.3
Conv52	64	16	0.84	0.05	0.63	0.05	0.63	0.05	14.52	83.68
Conv53	16	64	0.63	0.05	0.63	0.05	0.63	0.05	2.31	26.3
Conv54	16	144	0.70	0.05	0.68	0.05	0.68	0.05	1.73	26.3
Conv55	64	16	0.87	0.05	0.63	0.05	0.63	0.05	10.24	83.68
Conv56	32	64	0.55	0.05	0.67	0.05	0.67	0.05	14.4	46.19
Conv57	32	288	0.55	0.05	0.83	0.05	0.83	0.05	6.19	46.19
Conv58	128	32	0.35	0.05	0.74	0.05	0.74	0.05	73.04	155.4
Conv59	32	128	0.61	0.05	0.74	0.05	0.74	0.05	4.02	46.19
Conv60	32	288	0.56	0.05	0.83	0.05	0.83	0.05	6.32	46.19
Conv61	128	32	0.64	0.05	0.74	0.05	0.74	0.05	34.02	155.4
Conv62	32	128	0.53	0.05	0.74	0.05	0.74	0.05	5.78	46.19
Conv63	32	288	0.59	0.05	0.83	0.05	0.83	0.05	5.53	46.19
Conv64	128	32	0.68	0.05	0.74	0.05	0.74	0.05	25.02	155.4
Conv65	32	128	0.83	0.05	0.74	0.05	0.74	0.05	3.52	46.19
Conv66	32	288	0.65	0.05	0.83	0.05	0.83	0.05	3.72	46.19
Conv67	128	32	0.66	0.05	0.74	0.05	0.74	0.05	17.98	155.4
Conv68	32	128	0.69	0.05	0.74	0.05	0.74	0.05	4.34	46.19
Conv69	32	288	0.69	0.05	0.83	0.05	0.83	0.05	3.5	46.19
Conv70	128	32	0.61	0.05	0.74	0.05	0.74	0.05	27.62	155.4
Conv71	32	128	0.81	0.05	0.74	0.05	0.74	0.05	2.84	46.19
Conv72	32	288	0.69	0.05	0.83	0.05	0.83	0.05	2.3	46.19
Conv73	128	32	0.69	0.05	0.74	0.05	0.74	0.05	20.52	155.4
Conv74	32	128	0.81	0.05	0.74	0.05	0.74	0.05	3.83	46.19
Conv75	32	288	0.83	0.05	0.83	0.05	0.83	0.05	2.45	46.19

Conv76	128	32	0.84	0.05	0.74	0.05	0.74	0.05	20.47	155.4
Conv77	32	128	0.66	0.05	0.74	0.05	0.74	0.05	9.06	46.19
Conv78	32	288	0.58	0.05	0.83	0.05	0.83	0.05	4.44	46.19
Conv79	128	32	0.60	0.05	0.74	0.05	0.74	0.05	32.04	155.4
Conv80	32	128	0.67	0.05	0.74	0.05	0.74	0.05	3.78	46.19
Conv81	32	288	0.64	0.05	0.83	0.05	0.83	0.05	2.57	46.19
Conv82	128	32	0.65	0.05	0.74	0.05	0.74	0.05	18.89	155.4
Conv83	32	128	0.55	0.05	0.74	0.05	0.74	0.05	9.07	46.19
Conv84	32	288	0.82	0.05	0.83	0.05	0.83	0.05	1.57	46.19
Conv85	128	32	0.70	0.05	0.74	0.05	0.74	0.05	20.75	155.4
Conv86	32	128	0.43	0.05	0.74	0.05	0.74	0.05	6.63	46.19
Conv87	32	288	0.66	0.05	0.83	0.05	0.83	0.05	3.08	46.19
Conv88	128	32	0.70	0.05	0.74	0.05	0.74	0.05	26.59	155.4
Conv89	32	128	0.67	0.05	0.74	0.05	0.74	0.05	3.37	46.19
Conv90	32	288	0.80	0.05	0.83	0.05	0.83	0.05	2.39	46.19
Conv91	128	32	0.68	0.05	0.74	0.05	0.74	0.05	13.65	155.4
Conv92	32	128	0.66	0.05	0.74	0.05	0.74	0.05	6.03	46.19
Conv93	32	288	0.58	0.05	0.83	0.05	0.83	0.05	2.37	46.19
Conv94	128	32	0.81	0.05	0.74	0.05	0.74	0.05	12.2	155.4
Conv95	32	128	0.82	0.05	0.74	0.05	0.74	0.05	3.9	46.19
Conv96	32	288	0.83	0.05	0.83	0.05	0.83	0.05	1.87	46.19
Conv97	128	32	0.80	0.05	0.74	0.05	0.74	0.05	18.32	155.4
Conv98	32	128	0.81	0.05	0.74	0.05	0.74	0.05	3.33	46.19
Conv99	32	288	0.69	0.05	0.83	0.05	0.83	0.05	2.19	46.19
Conv100	128	32	0.81	0.05	0.74	0.05	0.74	0.05	18.19	155.4
Conv101	32	128	0.83	0.05	0.74	0.05	0.74	0.05	2.32	46.19
Conv102	32	288	0.86	0.05	0.83	0.05	0.83	0.05	1.37	46.19
Conv103	128	32	0.69	0.05	0.74	0.05	0.74	0.05	16.8	155.4
Conv104	32	128	0.63	0.05	0.74	0.05	0.74	0.05	4.21	46.19
Conv105	32	288	0.84	0.05	0.83	0.05	0.83	0.05	2.49	46.19
Conv106	128	32	0.62	0.05	0.74	0.05	0.74	0.05	20.93	155.4
Conv107	32	128	0.67	0.05	0.74	0.05	0.74	0.05	2.95	46.19
Conv108	32	288	0.63	0.05	0.83	0.05	0.83	0.05	1.17	46.19
Conv109	128	32	0.65	0.05	0.74	0.05	0.74	0.05	16.5	155.4
Conv110	64	128	0.50	0.05	0.82	0.05	0.82	0.05	9.42	83.68
Conv111	64	576	0.70	0.05	0.97	0.05	0.97	0.05	2.0	83.68
Conv112	256	64	0.57	0.05	0.90	0.05	0.90	0.05	86.43	294.32
Conv113	64	256	0.59	0.05	0.90	0.05	0.90	0.05	2.79	83.68
Conv114	64	576	0.83	0.05	0.97	0.05	0.97	0.05	1.65	83.68
Conv115	256	64	0.68	0.05	0.90	0.05	0.90	0.05	17.79	294.32
Conv116	64	256	0.69	0.05	0.90	0.05	0.90	0.05	3.54	83.68
Conv117	64	576	0.81	0.05	0.97	0.05	0.97	0.05	2.4	83.68
Conv118	256	64	0.70	0.05	0.90	0.05	0.90	0.05	19.61	294.32
Conv119	64	256	0.83	0.05	0.90	0.05	0.90	0.05	2.09	83.68
Conv120	64	576	0.86	0.05	0.97	0.05	0.97	0.05	1.3	83.68
Conv121	256	64	0.82	0.05	0.90	0.05	0.90	0.05	17.89	294.32
Conv122	64	256	0.81	0.05	0.90	0.05	0.90	0.05	2.49	83.68
Conv123	64	576	0.64	0.05	0.97	0.05	0.97	0.05	1.33	83.68
Conv124	256	64	0.70	0.05	0.90	0.05	0.90	0.05	20.03	294.32
Conv125	64	256	0.83	0.05	0.90	0.05	0.90	0.05	2.66	83.68
Conv126	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.52	83.68
Conv127	256	64	0.63	0.05	0.90	0.05	0.90	0.05	22.08	294.32
Conv128	64	256	0.60	0.05	0.90	0.05	0.90	0.05	3.27	83.68
Conv129	64	576	0.64	0.05	0.97	0.05	0.97	0.05	2.41	83.68
Conv130	256	64	0.65	0.05	0.90	0.05	0.90	0.05	26.37	294.32
Conv131	64	256	0.81	0.05	0.90	0.05	0.90	0.05	2.14	83.68
Conv132	64	576	0.85	0.05	0.97	0.05	0.97	0.05	1.69	83.68
Conv133	256	64	0.71	0.05	0.90	0.05	0.90	0.05	16.51	294.32
Conv134	64	256	0.58	0.05	0.90	0.05	0.90	0.05	2.65	83.68

Conv135	64	576	0.84	0.05	0.97	0.05	0.97	0.05	2.34	83.68
Conv136	256	64	0.83	0.05	0.90	0.05	0.90	0.05	21.06	294.32
Conv137	64	256	0.81	0.05	0.90	0.05	0.90	0.05	2.17	83.68
Conv138	64	576	0.82	0.05	0.97	0.05	0.97	0.05	1.3	83.68
Conv139	256	64	0.66	0.05	0.90	0.05	0.90	0.05	23.37	294.32
Conv140	64	256	0.81	0.05	0.90	0.05	0.90	0.05	1.45	83.68
Conv141	64	576	0.85	0.05	0.97	0.05	0.97	0.05	1.02	83.68
Conv142	256	64	0.70	0.05	0.90	0.05	0.90	0.05	24.32	294.32
Conv143	64	256	0.68	0.05	0.90	0.05	0.90	0.05	2.39	83.68
Conv144	64	576	0.83	0.05	0.97	0.05	0.97	0.05	1.32	83.68
Conv145	256	64	0.81	0.05	0.90	0.05	0.90	0.05	26.7	294.32
Conv146	64	256	0.68	0.05	0.90	0.05	0.90	0.05	2.43	83.68
Conv147	64	576	0.82	0.05	0.97	0.05	0.97	0.05	1.31	83.68
Conv148	256	64	0.65	0.05	0.90	0.05	0.90	0.05	29.8	294.32
Conv149	64	256	0.62	0.05	0.90	0.05	0.90	0.05	2.1	83.68
Conv150	64	576	0.83	0.05	0.97	0.05	0.97	0.05	1.14	83.68
Conv151	256	64	0.62	0.05	0.90	0.05	0.90	0.05	35.97	294.32
Conv152	64	256	0.64	0.05	0.90	0.05	0.90	0.05	1.69	83.68
Conv153	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.07	83.68
Conv154	256	64	0.64	0.05	0.90	0.05	0.90	0.05	27.5	294.32
Conv155	64	256	0.59	0.05	0.90	0.05	0.90	0.05	2.52	83.68
Conv156	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.11	83.68
Conv157	256	64	0.59	0.05	0.90	0.05	0.90	0.05	32.33	294.32
Conv158	64	256	0.60	0.05	0.90	0.05	0.90	0.05	1.95	83.68
Conv159	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.16	83.68
Conv160	256	64	0.56	0.05	0.90	0.05	0.90	0.05	50.72	294.32
Conv161	64	256	0.41	0.05	0.90	0.05	0.90	0.05	2.61	83.68
Conv162	64	576	0.82	0.05	0.97	0.05	0.97	0.05	0.61	83.68
Conv163	256	64	0.33	0.05	0.90	0.05	0.90	0.05	194.0	294.32
Passing rate	-	-	98.77%		100.0%		100.0%		97.55%	

Table 33: Cifar100 Xavier-normal-ResNet164

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.00	0.05	0.58	0.05	0.42	0.05	4100.8	26.3
Conv2	16	16	0.07	0.05	0.56	0.05	0.56	0.05	263.78	26.3
Conv3	16	144	0.03	0.05	0.68	0.05	0.68	0.05	124.29	26.3
Conv4	64	16	0.24	0.05	0.63	0.05	0.63	0.05	218.9	83.68
Conv5	16	64	0.28	0.05	0.63	0.05	0.63	0.05	42.91	26.3
Conv6	16	144	0.25	0.05	0.68	0.05	0.68	0.05	29.6	26.3
Conv7	64	16	0.41	0.05	0.63	0.05	0.63	0.05	63.85	83.68
Conv8	16	64	0.38	0.05	0.63	0.05	0.63	0.05	10.79	26.3
Conv9	16	144	0.34	0.05	0.68	0.05	0.68	0.05	15.78	26.3
Conv10	64	16	0.59	0.05	0.63	0.05	0.63	0.05	40.51	83.68
Conv11	16	64	0.41	0.05	0.63	0.05	0.63	0.05	9.5	26.3
Conv12	16	144	0.43	0.05	0.68	0.05	0.68	0.05	8.63	26.3
Conv13	64	16	0.55	0.05	0.63	0.05	0.63	0.05	29.22	83.68
Conv14	16	64	0.47	0.05	0.63	0.05	0.63	0.05	3.81	26.3
Conv15	16	144	0.57	0.05	0.68	0.05	0.68	0.05	1.54	26.3
Conv16	64	16	0.80	0.05	0.63	0.05	0.63	0.05	13.88	83.68
Conv17	16	64	0.68	0.05	0.63	0.05	0.63	0.05	1.34	26.3
Conv18	16	144	0.83	0.05	0.68	0.05	0.68	0.05	1.23	26.3
Conv19	64	16	0.71	0.05	0.63	0.05	0.63	0.05	7.88	83.68
Conv20	16	64	0.70	0.05	0.63	0.05	0.63	0.05	0.98	26.3

Conv21	16	144	0.81	0.05	0.68	0.05	0.68	0.05	0.78	26.3
Conv22	64	16	0.83	0.05	0.63	0.05	0.63	0.05	7.01	83.68
Conv23	16	64	0.48	0.05	0.63	0.05	0.63	0.05	4.48	26.3
Conv24	16	144	0.53	0.05	0.68	0.05	0.68	0.05	2.56	26.3
Conv25	64	16	0.48	0.05	0.63	0.05	0.63	0.05	29.86	83.68
Conv26	16	64	0.84	0.05	0.63	0.05	0.63	0.05	0.63	26.3
Conv27	16	144	0.87	0.05	0.68	0.05	0.68	0.05	0.48	26.3
Conv28	64	16	0.92	0.05	0.63	0.05	0.63	0.05	2.04	83.68
Conv29	16	64	0.62	0.05	0.63	0.05	0.63	0.05	5.32	26.3
Conv30	16	144	0.53	0.05	0.68	0.05	0.68	0.05	3.17	26.3
Conv31	64	16	0.56	0.05	0.63	0.05	0.63	0.05	23.86	83.68
Conv32	16	64	0.61	0.05	0.63	0.05	0.63	0.05	4.21	26.3
Conv33	16	144	0.53	0.05	0.68	0.05	0.68	0.05	4.85	26.3
Conv34	64	16	0.65	0.05	0.63	0.05	0.63	0.05	12.41	83.68
Conv35	16	64	0.68	0.05	0.63	0.05	0.63	0.05	1.76	26.3
Conv36	16	144	0.89	0.05	0.68	0.05	0.68	0.05	0.46	26.3
Conv37	64	16	0.85	0.05	0.63	0.05	0.63	0.05	4.31	83.68
Conv38	16	64	0.40	0.05	0.63	0.05	0.63	0.05	10.81	26.3
Conv39	16	144	0.43	0.05	0.68	0.05	0.68	0.05	11.21	26.3
Conv40	64	16	0.66	0.05	0.63	0.05	0.63	0.05	21.52	83.68
Conv41	16	64	0.85	0.05	0.63	0.05	0.63	0.05	1.27	26.3
Conv42	16	144	0.89	0.05	0.68	0.05	0.68	0.05	0.7	26.3
Conv43	64	16	0.86	0.05	0.63	0.05	0.63	0.05	4.92	83.68
Conv44	16	64	0.80	0.05	0.63	0.05	0.63	0.05	3.44	26.3
Conv45	16	144	0.65	0.05	0.68	0.05	0.68	0.05	3.32	26.3
Conv46	64	16	0.67	0.05	0.63	0.05	0.63	0.05	20.05	83.68
Conv47	16	64	0.62	0.05	0.63	0.05	0.63	0.05	5.66	26.3
Conv48	16	144	0.67	0.05	0.68	0.05	0.68	0.05	4.6	26.3
Conv49	64	16	0.81	0.05	0.63	0.05	0.63	0.05	13.5	83.68
Conv50	16	64	0.55	0.05	0.63	0.05	0.63	0.05	6.88	26.3
Conv51	16	144	0.56	0.05	0.68	0.05	0.68	0.05	6.35	26.3
Conv52	64	16	0.59	0.05	0.63	0.05	0.63	0.05	26.53	83.68
Conv53	16	64	0.66	0.05	0.63	0.05	0.63	0.05	11.71	26.3
Conv54	16	144	0.56	0.05	0.68	0.05	0.68	0.05	5.5	26.3
Conv55	64	16	0.55	0.05	0.63	0.05	0.63	0.05	46.57	83.68
Conv56	32	64	0.33	0.05	0.67	0.05	0.67	0.05	32.25	46.19
Conv57	32	288	0.55	0.05	0.83	0.05	0.83	0.05	3.62	46.19
Conv58	128	32	0.42	0.05	0.74	0.05	0.74	0.05	78.52	155.4
Conv59	32	128	0.66	0.05	0.74	0.05	0.74	0.05	2.9	46.19
Conv60	32	288	0.53	0.05	0.83	0.05	0.83	0.05	4.46	46.19
Conv61	128	32	0.60	0.05	0.74	0.05	0.74	0.05	26.11	155.4
Conv62	32	128	0.57	0.05	0.74	0.05	0.74	0.05	6.41	46.19
Conv63	32	288	0.53	0.05	0.83	0.05	0.83	0.05	5.29	46.19
Conv64	128	32	0.67	0.05	0.74	0.05	0.74	0.05	40.74	155.4
Conv65	32	128	0.60	0.05	0.74	0.05	0.74	0.05	5.03	46.19
Conv66	32	288	0.60	0.05	0.83	0.05	0.83	0.05	4.94	46.19
Conv67	128	32	0.68	0.05	0.74	0.05	0.74	0.05	27.32	155.4
Conv68	32	128	0.85	0.05	0.74	0.05	0.74	0.05	2.84	46.19
Conv69	32	288	0.81	0.05	0.83	0.05	0.83	0.05	2.45	46.19
Conv70	128	32	0.82	0.05	0.74	0.05	0.74	0.05	17.34	155.4
Conv71	32	128	0.83	0.05	0.74	0.05	0.74	0.05	3.08	46.19
Conv72	32	288	0.66	0.05	0.83	0.05	0.83	0.05	2.93	46.19
Conv73	128	32	0.83	0.05	0.74	0.05	0.74	0.05	15.7	155.4
Conv74	32	128	0.63	0.05	0.74	0.05	0.74	0.05	3.95	46.19
Conv75	32	288	0.67	0.05	0.83	0.05	0.83	0.05	2.9	46.19
Conv76	128	32	0.63	0.05	0.74	0.05	0.74	0.05	21.4	155.4
Conv77	32	128	0.83	0.05	0.74	0.05	0.74	0.05	1.55	46.19
Conv78	32	288	0.63	0.05	0.83	0.05	0.83	0.05	1.41	46.19
Conv79	128	32	0.80	0.05	0.74	0.05	0.74	0.05	16.74	155.4

Conv80	32	128	0.84	0.05	0.74	0.05	0.74	0.05	1.6	46.19
Conv81	32	288	0.84	0.05	0.83	0.05	0.83	0.05	2.41	46.19
Conv82	128	32	0.84	0.05	0.74	0.05	0.74	0.05	12.17	155.4
Conv83	32	128	0.80	0.05	0.74	0.05	0.74	0.05	3.14	46.19
Conv84	32	288	0.83	0.05	0.83	0.05	0.83	0.05	1.82	46.19
Conv85	128	32	0.85	0.05	0.74	0.05	0.74	0.05	16.09	155.4
Conv86	32	128	0.46	0.05	0.74	0.05	0.74	0.05	7.45	46.19
Conv87	32	288	0.61	0.05	0.83	0.05	0.83	0.05	4.67	46.19
Conv88	128	32	0.82	0.05	0.74	0.05	0.74	0.05	26.75	155.4
Conv89	32	128	0.61	0.05	0.74	0.05	0.74	0.05	5.19	46.19
Conv90	32	288	0.68	0.05	0.83	0.05	0.83	0.05	3.7	46.19
Conv91	128	32	0.67	0.05	0.74	0.05	0.74	0.05	32.92	155.4
Conv92	32	128	0.86	0.05	0.74	0.05	0.74	0.05	2.79	46.19
Conv93	32	288	0.83	0.05	0.83	0.05	0.83	0.05	1.96	46.19
Conv94	128	32	0.81	0.05	0.74	0.05	0.74	0.05	16.14	155.4
Conv95	32	128	0.42	0.05	0.74	0.05	0.74	0.05	4.51	46.19
Conv96	32	288	0.68	0.05	0.83	0.05	0.83	0.05	2.83	46.19
Conv97	128	32	0.61	0.05	0.74	0.05	0.74	0.05	22.18	155.4
Conv98	32	128	0.80	0.05	0.74	0.05	0.74	0.05	1.75	46.19
Conv99	32	288	0.86	0.05	0.83	0.05	0.83	0.05	2.14	46.19
Conv100	128	32	0.88	0.05	0.74	0.05	0.74	0.05	14.54	155.4
Conv101	32	128	0.80	0.05	0.74	0.05	0.74	0.05	1.6	46.19
Conv102	32	288	0.85	0.05	0.83	0.05	0.83	0.05	1.48	46.19
Conv103	128	32	0.85	0.05	0.74	0.05	0.74	0.05	12.08	155.4
Conv104	32	128	0.82	0.05	0.74	0.05	0.74	0.05	4.97	46.19
Conv105	32	288	0.67	0.05	0.83	0.05	0.83	0.05	2.16	46.19
Conv106	128	32	0.59	0.05	0.74	0.05	0.74	0.05	22.44	155.4
Conv107	32	128	0.64	0.05	0.74	0.05	0.74	0.05	7.26	46.19
Conv108	32	288	0.65	0.05	0.83	0.05	0.83	0.05	1.05	46.19
Conv109	128	32	0.67	0.05	0.74	0.05	0.74	0.05	32.58	155.4
Conv110	64	128	0.49	0.05	0.82	0.05	0.82	0.05	6.7	83.68
Conv111	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.62	83.68
Conv112	256	64	0.47	0.05	0.90	0.05	0.90	0.05	76.58	294.32
Conv113	64	256	0.85	0.05	0.90	0.05	0.90	0.05	2.22	83.68
Conv114	64	576	0.70	0.05	0.97	0.05	0.97	0.05	1.93	83.68
Conv115	256	64	0.69	0.05	0.90	0.05	0.90	0.05	24.15	294.32
Conv116	64	256	0.80	0.05	0.90	0.05	0.90	0.05	2.17	83.68
Conv117	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.47	83.68
Conv118	256	64	0.70	0.05	0.90	0.05	0.90	0.05	23.34	294.32
Conv119	64	256	0.81	0.05	0.90	0.05	0.90	0.05	1.76	83.68
Conv120	64	576	0.85	0.05	0.97	0.05	0.97	0.05	1.17	83.68
Conv121	256	64	0.69	0.05	0.90	0.05	0.90	0.05	16.53	294.32
Conv122	64	256	0.70	0.05	0.90	0.05	0.90	0.05	1.66	83.68
Conv123	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.99	83.68
Conv124	256	64	0.80	0.05	0.90	0.05	0.90	0.05	15.94	294.32
Conv125	64	256	0.80	0.05	0.90	0.05	0.90	0.05	2.09	83.68
Conv126	64	576	0.71	0.05	0.97	0.05	0.97	0.05	1.94	83.68
Conv127	256	64	0.68	0.05	0.90	0.05	0.90	0.05	20.79	294.32
Conv128	64	256	0.70	0.05	0.90	0.05	0.90	0.05	1.87	83.68
Conv129	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.45	83.68
Conv130	256	64	0.68	0.05	0.90	0.05	0.90	0.05	17.26	294.32
Conv131	64	256	0.68	0.05	0.90	0.05	0.90	0.05	2.05	83.68
Conv132	64	576	0.82	0.05	0.97	0.05	0.97	0.05	1.15	83.68
Conv133	256	64	0.81	0.05	0.90	0.05	0.90	0.05	15.07	294.32
Conv134	64	256	0.61	0.05	0.90	0.05	0.90	0.05	2.3	83.68
Conv135	64	576	0.67	0.05	0.97	0.05	0.97	0.05	1.2	83.68
Conv136	256	64	0.65	0.05	0.90	0.05	0.90	0.05	17.54	294.32
Conv137	64	256	0.67	0.05	0.90	0.05	0.90	0.05	1.75	83.68
Conv138	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.06	83.68

Conv139	256	64	0.69	0.05	0.90	0.05	0.90	0.05	16.9	294.32
Conv140	64	256	0.66	0.05	0.90	0.05	0.90	0.05	1.9	83.68
Conv141	64	576	0.85	0.05	0.97	0.05	0.97	0.05	1.59	83.68
Conv142	256	64	0.81	0.05	0.90	0.05	0.90	0.05	18.95	294.32
Conv143	64	256	0.65	0.05	0.90	0.05	0.90	0.05	1.51	83.68
Conv144	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.07	83.68
Conv145	256	64	0.68	0.05	0.90	0.05	0.90	0.05	19.91	294.32
Conv146	64	256	0.69	0.05	0.90	0.05	0.90	0.05	1.26	83.68
Conv147	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.73	83.68
Conv148	256	64	0.62	0.05	0.90	0.05	0.90	0.05	23.67	294.32
Conv149	64	256	0.70	0.05	0.90	0.05	0.90	0.05	1.44	83.68
Conv150	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.26	83.68
Conv151	256	64	0.61	0.05	0.90	0.05	0.90	0.05	29.19	294.32
Conv152	64	256	0.65	0.05	0.90	0.05	0.90	0.05	1.48	83.68
Conv153	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.87	83.68
Conv154	256	64	0.57	0.05	0.90	0.05	0.90	0.05	29.35	294.32
Conv155	64	256	0.47	0.05	0.90	0.05	0.90	0.05	2.2	83.68
Conv156	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.07	83.68
Conv157	256	64	0.47	0.05	0.90	0.05	0.90	0.05	42.43	294.32
Conv158	64	256	0.61	0.05	0.90	0.05	0.90	0.05	2.28	83.68
Conv159	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.84	83.68
Conv160	256	64	0.49	0.05	0.90	0.05	0.90	0.05	39.92	294.32
Conv161	64	256	0.47	0.05	0.90	0.05	0.90	0.05	1.59	83.68
Conv162	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.97	83.68
Conv163	256	64	0.36	0.05	0.90	0.05	0.90	0.05	78.75	294.32
Passing rate	-	-	98.77%		100.0%		100.0%		96.32%	

Table 34: Cifar100 Xavier-uniform-ResNet164

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.00	0.05	0.58	0.05	0.42	0.05	5009.01	26.3
Conv2	16	16	0.02	0.05	0.56	0.05	0.56	0.05	453.3	26.3
Conv3	16	144	0.00	0.05	0.68	0.05	0.68	0.05	370.43	26.3
Conv4	64	16	0.20	0.05	0.63	0.05	0.63	0.05	303.06	83.68
Conv5	16	64	0.24	0.05	0.63	0.05	0.63	0.05	33.98	26.3
Conv6	16	144	0.06	0.05	0.68	0.05	0.68	0.05	61.45	26.3
Conv7	64	16	0.41	0.05	0.63	0.05	0.63	0.05	72.84	83.68
Conv8	16	64	0.42	0.05	0.63	0.05	0.63	0.05	8.9	26.3
Conv9	16	144	0.42	0.05	0.68	0.05	0.68	0.05	11.42	26.3
Conv10	64	16	0.47	0.05	0.63	0.05	0.63	0.05	46.89	83.68
Conv11	16	64	0.52	0.05	0.63	0.05	0.63	0.05	5.64	26.3
Conv12	16	144	0.53	0.05	0.68	0.05	0.68	0.05	6.54	26.3
Conv13	64	16	0.70	0.05	0.63	0.05	0.63	0.05	11.94	83.68
Conv14	16	64	0.59	0.05	0.63	0.05	0.63	0.05	4.51	26.3
Conv15	16	144	0.60	0.05	0.68	0.05	0.68	0.05	2.63	26.3
Conv16	64	16	0.67	0.05	0.63	0.05	0.63	0.05	13.71	83.68
Conv17	16	64	0.70	0.05	0.63	0.05	0.63	0.05	2.34	26.3
Conv18	16	144	0.68	0.05	0.68	0.05	0.68	0.05	1.4	26.3
Conv19	64	16	0.85	0.05	0.63	0.05	0.63	0.05	7.47	83.68
Conv20	16	64	0.52	0.05	0.63	0.05	0.63	0.05	6.4	26.3
Conv21	16	144	0.54	0.05	0.68	0.05	0.68	0.05	3.57	26.3
Conv22	64	16	0.63	0.05	0.63	0.05	0.63	0.05	22.62	83.68
Conv23	16	64	0.49	0.05	0.63	0.05	0.63	0.05	9.23	26.3
Conv24	16	144	0.47	0.05	0.68	0.05	0.68	0.05	3.77	26.3

Conv25	64	16	0.65	0.05	0.63	0.05	0.63	0.05	18.83	83.68
Conv26	16	64	0.52	0.05	0.63	0.05	0.63	0.05	3.82	26.3
Conv27	16	144	0.84	0.05	0.68	0.05	0.68	0.05	0.88	26.3
Conv28	64	16	0.82	0.05	0.63	0.05	0.63	0.05	9.15	83.68
Conv29	16	64	0.61	0.05	0.63	0.05	0.63	0.05	5.81	26.3
Conv30	16	144	0.56	0.05	0.68	0.05	0.68	0.05	3.08	26.3
Conv31	64	16	0.85	0.05	0.63	0.05	0.63	0.05	10.1	83.68
Conv32	16	64	0.52	0.05	0.63	0.05	0.63	0.05	8.13	26.3
Conv33	16	144	0.49	0.05	0.68	0.05	0.68	0.05	4.66	26.3
Conv34	64	16	0.63	0.05	0.63	0.05	0.63	0.05	14.52	83.68
Conv35	16	64	0.70	0.05	0.63	0.05	0.63	0.05	2.11	26.3
Conv36	16	144	0.86	0.05	0.68	0.05	0.68	0.05	1.17	26.3
Conv37	64	16	0.66	0.05	0.63	0.05	0.63	0.05	9.5	83.68
Conv38	16	64	0.59	0.05	0.63	0.05	0.63	0.05	7.3	26.3
Conv39	16	144	0.67	0.05	0.68	0.05	0.68	0.05	2.4	26.3
Conv40	64	16	0.80	0.05	0.63	0.05	0.63	0.05	9.38	83.68
Conv41	16	64	0.84	0.05	0.63	0.05	0.63	0.05	2.45	26.3
Conv42	16	144	0.85	0.05	0.68	0.05	0.68	0.05	2.08	26.3
Conv43	64	16	0.84	0.05	0.63	0.05	0.63	0.05	9.47	83.68
Conv44	16	64	0.38	0.05	0.63	0.05	0.63	0.05	15.34	26.3
Conv45	16	144	0.38	0.05	0.68	0.05	0.68	0.05	6.86	26.3
Conv46	64	16	0.66	0.05	0.63	0.05	0.63	0.05	20.76	83.68
Conv47	16	64	0.53	0.05	0.63	0.05	0.63	0.05	10.64	26.3
Conv48	16	144	0.67	0.05	0.68	0.05	0.68	0.05	3.99	26.3
Conv49	64	16	0.67	0.05	0.63	0.05	0.63	0.05	19.94	83.68
Conv50	16	64	0.50	0.05	0.63	0.05	0.63	0.05	12.16	26.3
Conv51	16	144	0.57	0.05	0.68	0.05	0.68	0.05	2.76	26.3
Conv52	64	16	0.66	0.05	0.63	0.05	0.63	0.05	21.25	83.68
Conv53	16	64	0.59	0.05	0.63	0.05	0.63	0.05	6.63	26.3
Conv54	16	144	0.81	0.05	0.68	0.05	0.68	0.05	2.3	26.3
Conv55	64	16	0.82	0.05	0.63	0.05	0.63	0.05	14.84	83.68
Conv56	32	64	0.52	0.05	0.67	0.05	0.67	0.05	15.63	46.19
Conv57	32	288	0.63	0.05	0.83	0.05	0.83	0.05	3.06	46.19
Conv58	128	32	0.52	0.05	0.74	0.05	0.74	0.05	52.26	155.4
Conv59	32	128	0.82	0.05	0.74	0.05	0.74	0.05	4.0	46.19
Conv60	32	288	0.61	0.05	0.83	0.05	0.83	0.05	4.98	46.19
Conv61	128	32	0.66	0.05	0.74	0.05	0.74	0.05	28.38	155.4
Conv62	32	128	0.68	0.05	0.74	0.05	0.74	0.05	3.28	46.19
Conv63	32	288	0.66	0.05	0.83	0.05	0.83	0.05	2.88	46.19
Conv64	128	32	0.82	0.05	0.74	0.05	0.74	0.05	13.36	155.4
Conv65	32	128	0.80	0.05	0.74	0.05	0.74	0.05	3.11	46.19
Conv66	32	288	0.70	0.05	0.83	0.05	0.83	0.05	1.08	46.19
Conv67	128	32	0.80	0.05	0.74	0.05	0.74	0.05	11.6	155.4
Conv68	32	128	0.86	0.05	0.74	0.05	0.74	0.05	1.2	46.19
Conv69	32	288	0.81	0.05	0.83	0.05	0.83	0.05	1.38	46.19
Conv70	128	32	0.85	0.05	0.74	0.05	0.74	0.05	13.39	155.4
Conv71	32	128	0.86	0.05	0.74	0.05	0.74	0.05	2.05	46.19
Conv72	32	288	0.82	0.05	0.83	0.05	0.83	0.05	2.02	46.19
Conv73	128	32	0.70	0.05	0.74	0.05	0.74	0.05	14.13	155.4
Conv74	32	128	0.87	0.05	0.74	0.05	0.74	0.05	1.56	46.19
Conv75	32	288	0.85	0.05	0.83	0.05	0.83	0.05	1.73	46.19
Conv76	128	32	0.83	0.05	0.74	0.05	0.74	0.05	12.27	155.4
Conv77	32	128	0.80	0.05	0.74	0.05	0.74	0.05	2.22	46.19
Conv78	32	288	0.63	0.05	0.83	0.05	0.83	0.05	2.79	46.19
Conv79	128	32	0.67	0.05	0.74	0.05	0.74	0.05	11.46	155.4
Conv80	32	128	0.50	0.05	0.74	0.05	0.74	0.05	5.83	46.19
Conv81	32	288	0.65	0.05	0.83	0.05	0.83	0.05	2.65	46.19
Conv82	128	32	0.83	0.05	0.74	0.05	0.74	0.05	18.09	155.4
Conv83	32	128	0.80	0.05	0.74	0.05	0.74	0.05	3.61	46.19

Conv84	32	288	0.87	0.05	0.83	0.05	0.83	0.05	1.97	46.19
Conv85	128	32	0.64	0.05	0.74	0.05	0.74	0.05	21.99	155.4
Conv86	32	128	0.87	0.05	0.74	0.05	0.74	0.05	2.38	46.19
Conv87	32	288	0.81	0.05	0.83	0.05	0.83	0.05	1.85	46.19
Conv88	128	32	0.87	0.05	0.74	0.05	0.74	0.05	14.13	155.4
Conv89	32	128	0.85	0.05	0.74	0.05	0.74	0.05	2.08	46.19
Conv90	32	288	0.87	0.05	0.83	0.05	0.83	0.05	1.11	46.19
Conv91	128	32	0.85	0.05	0.74	0.05	0.74	0.05	15.24	155.4
Conv92	32	128	0.83	0.05	0.74	0.05	0.74	0.05	2.64	46.19
Conv93	32	288	0.83	0.05	0.83	0.05	0.83	0.05	1.89	46.19
Conv94	128	32	0.83	0.05	0.74	0.05	0.74	0.05	15.49	155.4
Conv95	32	128	0.82	0.05	0.74	0.05	0.74	0.05	3.04	46.19
Conv96	32	288	0.84	0.05	0.83	0.05	0.83	0.05	1.86	46.19
Conv97	128	32	0.84	0.05	0.74	0.05	0.74	0.05	16.24	155.4
Conv98	32	128	0.55	0.05	0.74	0.05	0.74	0.05	6.03	46.19
Conv99	32	288	0.62	0.05	0.83	0.05	0.83	0.05	4.51	46.19
Conv100	128	32	0.59	0.05	0.74	0.05	0.74	0.05	24.42	155.4
Conv101	32	128	0.57	0.05	0.74	0.05	0.74	0.05	6.83	46.19
Conv102	32	288	0.70	0.05	0.83	0.05	0.83	0.05	2.47	46.19
Conv103	128	32	0.71	0.05	0.74	0.05	0.74	0.05	25.11	155.4
Conv104	32	128	0.83	0.05	0.74	0.05	0.74	0.05	2.85	46.19
Conv105	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.99	46.19
Conv106	128	32	0.81	0.05	0.74	0.05	0.74	0.05	16.7	155.4
Conv107	32	128	0.61	0.05	0.74	0.05	0.74	0.05	3.72	46.19
Conv108	32	288	0.85	0.05	0.83	0.05	0.83	0.05	1.75	46.19
Conv109	128	32	0.64	0.05	0.74	0.05	0.74	0.05	22.31	155.4
Conv110	64	128	0.55	0.05	0.82	0.05	0.82	0.05	9.69	83.68
Conv111	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.92	83.68
Conv112	256	64	0.52	0.05	0.90	0.05	0.90	0.05	70.08	294.32
Conv113	64	256	0.62	0.05	0.90	0.05	0.90	0.05	1.6	83.68
Conv114	64	576	0.84	0.05	0.97	0.05	0.97	0.05	2.01	83.68
Conv115	256	64	0.59	0.05	0.90	0.05	0.90	0.05	17.41	294.32
Conv116	64	256	0.81	0.05	0.90	0.05	0.90	0.05	1.63	83.68
Conv117	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.61	83.68
Conv118	256	64	0.66	0.05	0.90	0.05	0.90	0.05	12.81	294.32
Conv119	64	256	0.67	0.05	0.90	0.05	0.90	0.05	2.57	83.68
Conv120	64	576	0.68	0.05	0.97	0.05	0.97	0.05	2.84	83.68
Conv121	256	64	0.68	0.05	0.90	0.05	0.90	0.05	17.96	294.32
Conv122	64	256	0.70	0.05	0.90	0.05	0.90	0.05	2.2	83.68
Conv123	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.95	83.68
Conv124	256	64	0.69	0.05	0.90	0.05	0.90	0.05	19.88	294.32
Conv125	64	256	0.63	0.05	0.90	0.05	0.90	0.05	1.32	83.68
Conv126	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.81	83.68
Conv127	256	64	0.63	0.05	0.90	0.05	0.90	0.05	15.33	294.32
Conv128	64	256	0.59	0.05	0.90	0.05	0.90	0.05	2.0	83.68
Conv129	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.35	83.68
Conv130	256	64	0.67	0.05	0.90	0.05	0.90	0.05	14.09	294.32
Conv131	64	256	0.54	0.05	0.90	0.05	0.90	0.05	1.88	83.68
Conv132	64	576	0.85	0.05	0.97	0.05	0.97	0.05	1.32	83.68
Conv133	256	64	0.67	0.05	0.90	0.05	0.90	0.05	19.46	294.32
Conv134	64	256	0.63	0.05	0.90	0.05	0.90	0.05	1.51	83.68
Conv135	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.92	83.68
Conv136	256	64	0.65	0.05	0.90	0.05	0.90	0.05	18.41	294.32
Conv137	64	256	0.66	0.05	0.90	0.05	0.90	0.05	1.55	83.68
Conv138	64	576	0.85	0.05	0.97	0.05	0.97	0.05	1.18	83.68
Conv139	256	64	0.65	0.05	0.90	0.05	0.90	0.05	21.62	294.32
Conv140	64	256	0.80	0.05	0.90	0.05	0.90	0.05	1.64	83.68
Conv141	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.78	83.68
Conv142	256	64	0.63	0.05	0.90	0.05	0.90	0.05	23.34	294.32

Conv143	64	256	0.62	0.05	0.90	0.05	0.90	0.05	1.68	83.68
Conv144	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.95	83.68
Conv145	256	64	0.67	0.05	0.90	0.05	0.90	0.05	25.4	294.32
Conv146	64	256	0.69	0.05	0.90	0.05	0.90	0.05	1.81	83.68
Conv147	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.92	83.68
Conv148	256	64	0.52	0.05	0.90	0.05	0.90	0.05	30.63	294.32
Conv149	64	256	0.62	0.05	0.90	0.05	0.90	0.05	2.0	83.68
Conv150	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.84	83.68
Conv151	256	64	0.56	0.05	0.90	0.05	0.90	0.05	33.48	294.32
Conv152	64	256	0.63	0.05	0.90	0.05	0.90	0.05	1.26	83.68
Conv153	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.69	83.68
Conv154	256	64	0.51	0.05	0.90	0.05	0.90	0.05	37.11	294.32
Conv155	64	256	0.66	0.05	0.90	0.05	0.90	0.05	1.72	83.68
Conv156	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.65	83.68
Conv157	256	64	0.62	0.05	0.90	0.05	0.90	0.05	28.49	294.32
Conv158	64	256	0.58	0.05	0.90	0.05	0.90	0.05	1.7	83.68
Conv159	64	576	0.86	0.05	0.97	0.05	0.97	0.05	0.82	83.68
Conv160	256	64	0.57	0.05	0.90	0.05	0.90	0.05	42.43	294.32
Conv161	64	256	0.53	0.05	0.90	0.05	0.90	0.05	2.0	83.68
Conv162	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.51	83.68
Conv163	256	64	0.54	0.05	0.90	0.05	0.90	0.05	45.77	294.32
Passing rate	-	-	98.16%		100.0%		100.0%		96.32%	

Table 35: Cifar100 orthogonal-ResNet164

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	16	27	0.00	0.05	0.58	0.05	0.42	0.05	1011.26	26.3
Conv2	16	16	0.02	0.05	0.56	0.05	0.56	0.05	510.87	26.3
Conv3	16	144	0.05	0.05	0.68	0.05	0.68	0.05	91.21	26.3
Conv4	64	16	0.01	0.05	0.63	0.05	0.63	0.05	837.24	83.68
Conv5	16	64	0.02	0.05	0.63	0.05	0.63	0.05	132.43	26.3
Conv6	16	144	0.17	0.05	0.68	0.05	0.68	0.05	14.32	26.3
Conv7	64	16	0.19	0.05	0.63	0.05	0.63	0.05	213.05	83.68
Conv8	16	64	0.29	0.05	0.63	0.05	0.63	0.05	25.29	26.3
Conv9	16	144	0.37	0.05	0.68	0.05	0.68	0.05	11.98	26.3
Conv10	64	16	0.46	0.05	0.63	0.05	0.63	0.05	59.8	83.68
Conv11	16	64	0.40	0.05	0.63	0.05	0.63	0.05	8.49	26.3
Conv12	16	144	0.50	0.05	0.68	0.05	0.68	0.05	8.69	26.3
Conv13	64	16	0.31	0.05	0.63	0.05	0.63	0.05	59.75	83.68
Conv14	16	64	0.44	0.05	0.63	0.05	0.63	0.05	14.31	26.3
Conv15	16	144	0.67	0.05	0.68	0.05	0.68	0.05	1.84	26.3
Conv16	64	16	0.65	0.05	0.63	0.05	0.63	0.05	20.38	83.68
Conv17	16	64	0.59	0.05	0.63	0.05	0.63	0.05	2.67	26.3
Conv18	16	144	0.64	0.05	0.68	0.05	0.68	0.05	2.39	26.3
Conv19	64	16	0.65	0.05	0.63	0.05	0.63	0.05	11.96	83.68
Conv20	16	64	0.68	0.05	0.63	0.05	0.63	0.05	2.11	26.3
Conv21	16	144	0.84	0.05	0.68	0.05	0.68	0.05	0.51	26.3
Conv22	64	16	0.86	0.05	0.63	0.05	0.63	0.05	6.61	83.68
Conv23	16	64	0.68	0.05	0.63	0.05	0.63	0.05	2.92	26.3
Conv24	16	144	0.83	0.05	0.68	0.05	0.68	0.05	0.98	26.3
Conv25	64	16	0.80	0.05	0.63	0.05	0.63	0.05	7.3	83.68
Conv26	16	64	0.83	0.05	0.63	0.05	0.63	0.05	1.15	26.3
Conv27	16	144	0.82	0.05	0.68	0.05	0.68	0.05	0.61	26.3
Conv28	64	16	0.88	0.05	0.63	0.05	0.63	0.05	3.66	83.68

Conv29	16	64	0.83	0.05	0.63	0.05	0.63	0.05	1.14	26.3
Conv30	16	144	0.87	0.05	0.68	0.05	0.68	0.05	0.49	26.3
Conv31	64	16	0.88	0.05	0.63	0.05	0.63	0.05	4.51	83.68
Conv32	16	64	0.64	0.05	0.63	0.05	0.63	0.05	4.88	26.3
Conv33	16	144	0.40	0.05	0.68	0.05	0.68	0.05	4.29	26.3
Conv34	64	16	0.80	0.05	0.63	0.05	0.63	0.05	11.26	83.68
Conv35	16	64	0.66	0.05	0.63	0.05	0.63	0.05	2.42	26.3
Conv36	16	144	0.83	0.05	0.68	0.05	0.68	0.05	0.4	26.3
Conv37	64	16	0.88	0.05	0.63	0.05	0.63	0.05	2.93	83.68
Conv38	16	64	0.67	0.05	0.63	0.05	0.63	0.05	3.22	26.3
Conv39	16	144	0.88	0.05	0.68	0.05	0.68	0.05	0.64	26.3
Conv40	64	16	0.86	0.05	0.63	0.05	0.63	0.05	4.46	83.68
Conv41	16	64	0.67	0.05	0.63	0.05	0.63	0.05	4.24	26.3
Conv42	16	144	0.67	0.05	0.68	0.05	0.68	0.05	2.75	26.3
Conv43	64	16	0.63	0.05	0.63	0.05	0.63	0.05	11.6	83.68
Conv44	16	64	0.70	0.05	0.63	0.05	0.63	0.05	2.71	26.3
Conv45	16	144	0.85	0.05	0.68	0.05	0.68	0.05	0.51	26.3
Conv46	64	16	0.89	0.05	0.63	0.05	0.63	0.05	5.22	83.68
Conv47	16	64	0.55	0.05	0.63	0.05	0.63	0.05	7.37	26.3
Conv48	16	144	0.63	0.05	0.68	0.05	0.68	0.05	3.1	26.3
Conv49	64	16	0.82	0.05	0.63	0.05	0.63	0.05	14.35	83.68
Conv50	16	64	0.53	0.05	0.63	0.05	0.63	0.05	7.6	26.3
Conv51	16	144	0.63	0.05	0.68	0.05	0.68	0.05	4.49	26.3
Conv52	64	16	0.81	0.05	0.63	0.05	0.63	0.05	14.16	83.68
Conv53	16	64	0.70	0.05	0.63	0.05	0.63	0.05	5.13	26.3
Conv54	16	144	0.68	0.05	0.68	0.05	0.68	0.05	1.98	26.3
Conv55	64	16	0.69	0.05	0.63	0.05	0.63	0.05	10.12	83.68
Conv56	32	64	0.47	0.05	0.67	0.05	0.67	0.05	24.35	46.19
Conv57	32	288	0.53	0.05	0.83	0.05	0.83	0.05	7.11	46.19
Conv58	128	32	0.39	0.05	0.74	0.05	0.74	0.05	130.03	155.4
Conv59	32	128	0.64	0.05	0.74	0.05	0.74	0.05	4.38	46.19
Conv60	32	288	0.53	0.05	0.83	0.05	0.83	0.05	5.98	46.19
Conv61	128	32	0.66	0.05	0.74	0.05	0.74	0.05	46.94	155.4
Conv62	32	128	0.65	0.05	0.74	0.05	0.74	0.05	3.71	46.19
Conv63	32	288	0.68	0.05	0.83	0.05	0.83	0.05	1.96	46.19
Conv64	128	32	0.67	0.05	0.74	0.05	0.74	0.05	22.74	155.4
Conv65	32	128	0.68	0.05	0.74	0.05	0.74	0.05	4.41	46.19
Conv66	32	288	0.65	0.05	0.83	0.05	0.83	0.05	4.22	46.19
Conv67	128	32	0.57	0.05	0.74	0.05	0.74	0.05	31.38	155.4
Conv68	32	128	0.81	0.05	0.74	0.05	0.74	0.05	3.85	46.19
Conv69	32	288	0.60	0.05	0.83	0.05	0.83	0.05	3.02	46.19
Conv70	128	32	0.68	0.05	0.74	0.05	0.74	0.05	21.04	155.4
Conv71	32	128	0.44	0.05	0.74	0.05	0.74	0.05	14.29	46.19
Conv72	32	288	0.65	0.05	0.83	0.05	0.83	0.05	5.11	46.19
Conv73	128	32	0.51	0.05	0.74	0.05	0.74	0.05	58.28	155.4
Conv74	32	128	0.61	0.05	0.74	0.05	0.74	0.05	3.79	46.19
Conv75	32	288	0.84	0.05	0.83	0.05	0.83	0.05	3.0	46.19
Conv76	128	32	0.83	0.05	0.74	0.05	0.74	0.05	12.29	155.4
Conv77	32	128	0.85	0.05	0.74	0.05	0.74	0.05	2.66	46.19
Conv78	32	288	0.82	0.05	0.83	0.05	0.83	0.05	2.3	46.19
Conv79	128	32	0.85	0.05	0.74	0.05	0.74	0.05	13.49	155.4
Conv80	32	128	0.61	0.05	0.74	0.05	0.74	0.05	5.51	46.19
Conv81	32	288	0.84	0.05	0.83	0.05	0.83	0.05	2.35	46.19
Conv82	128	32	0.71	0.05	0.74	0.05	0.74	0.05	18.02	155.4
Conv83	32	128	0.58	0.05	0.74	0.05	0.74	0.05	5.69	46.19
Conv84	32	288	0.62	0.05	0.83	0.05	0.83	0.05	3.13	46.19
Conv85	128	32	0.70	0.05	0.74	0.05	0.74	0.05	26.25	155.4
Conv86	32	128	0.85	0.05	0.74	0.05	0.74	0.05	3.26	46.19
Conv87	32	288	0.86	0.05	0.83	0.05	0.83	0.05	1.88	46.19

Conv88	128	32	0.84	0.05	0.74	0.05	0.74	0.05	11.77	155.4
Conv89	32	128	0.81	0.05	0.74	0.05	0.74	0.05	3.42	46.19
Conv90	32	288	0.81	0.05	0.83	0.05	0.83	0.05	2.45	46.19
Conv91	128	32	0.81	0.05	0.74	0.05	0.74	0.05	16.74	155.4
Conv92	32	128	0.68	0.05	0.74	0.05	0.74	0.05	4.9	46.19
Conv93	32	288	0.68	0.05	0.83	0.05	0.83	0.05	1.94	46.19
Conv94	128	32	0.62	0.05	0.74	0.05	0.74	0.05	28.67	155.4
Conv95	32	128	0.39	0.05	0.74	0.05	0.74	0.05	7.35	46.19
Conv96	32	288	0.62	0.05	0.83	0.05	0.83	0.05	1.82	46.19
Conv97	128	32	0.67	0.05	0.74	0.05	0.74	0.05	29.33	155.4
Conv98	32	128	0.88	0.05	0.74	0.05	0.74	0.05	2.17	46.19
Conv99	32	288	0.88	0.05	0.83	0.05	0.83	0.05	1.18	46.19
Conv100	128	32	0.87	0.05	0.74	0.05	0.74	0.05	10.3	155.4
Conv101	32	128	0.71	0.05	0.74	0.05	0.74	0.05	5.73	46.19
Conv102	32	288	0.67	0.05	0.83	0.05	0.83	0.05	3.25	46.19
Conv103	128	32	0.68	0.05	0.74	0.05	0.74	0.05	24.74	155.4
Conv104	32	128	0.81	0.05	0.74	0.05	0.74	0.05	3.97	46.19
Conv105	32	288	0.68	0.05	0.83	0.05	0.83	0.05	2.33	46.19
Conv106	128	32	0.84	0.05	0.74	0.05	0.74	0.05	23.88	155.4
Conv107	32	128	0.66	0.05	0.74	0.05	0.74	0.05	2.85	46.19
Conv108	32	288	0.85	0.05	0.83	0.05	0.83	0.05	0.93	46.19
Conv109	128	32	0.86	0.05	0.74	0.05	0.74	0.05	17.92	155.4
Conv110	64	128	0.54	0.05	0.82	0.05	0.82	0.05	9.86	83.68
Conv111	64	576	0.69	0.05	0.97	0.05	0.97	0.05	3.44	83.68
Conv112	256	64	0.53	0.05	0.90	0.05	0.90	0.05	72.59	294.32
Conv113	64	256	0.81	0.05	0.90	0.05	0.90	0.05	2.17	83.68
Conv114	64	576	0.80	0.05	0.97	0.05	0.97	0.05	4.2	83.68
Conv115	256	64	0.60	0.05	0.90	0.05	0.90	0.05	27.87	294.32
Conv116	64	256	0.82	0.05	0.90	0.05	0.90	0.05	2.3	83.68
Conv117	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.58	83.68
Conv118	256	64	0.83	0.05	0.90	0.05	0.90	0.05	14.32	294.32
Conv119	64	256	0.82	0.05	0.90	0.05	0.90	0.05	2.93	83.68
Conv120	64	576	0.70	0.05	0.97	0.05	0.97	0.05	1.69	83.68
Conv121	256	64	0.80	0.05	0.90	0.05	0.90	0.05	12.83	294.32
Conv122	64	256	0.68	0.05	0.90	0.05	0.90	0.05	2.67	83.68
Conv123	64	576	0.65	0.05	0.97	0.05	0.97	0.05	2.46	83.68
Conv124	256	64	0.70	0.05	0.90	0.05	0.90	0.05	16.62	294.32
Conv125	64	256	0.70	0.05	0.90	0.05	0.90	0.05	2.21	83.68
Conv126	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.82	83.68
Conv127	256	64	0.67	0.05	0.90	0.05	0.90	0.05	17.12	294.32
Conv128	64	256	0.61	0.05	0.90	0.05	0.90	0.05	2.58	83.68
Conv129	64	576	0.70	0.05	0.97	0.05	0.97	0.05	1.92	83.68
Conv130	256	64	0.58	0.05	0.90	0.05	0.90	0.05	18.45	294.32
Conv131	64	256	0.63	0.05	0.90	0.05	0.90	0.05	2.37	83.68
Conv132	64	576	0.81	0.05	0.97	0.05	0.97	0.05	1.24	83.68
Conv133	256	64	0.70	0.05	0.90	0.05	0.90	0.05	21.78	294.32
Conv134	64	256	0.39	0.05	0.90	0.05	0.90	0.05	3.23	83.68
Conv135	64	576	0.71	0.05	0.97	0.05	0.97	0.05	1.68	83.68
Conv136	256	64	0.60	0.05	0.90	0.05	0.90	0.05	25.14	294.32
Conv137	64	256	0.59	0.05	0.90	0.05	0.90	0.05	1.62	83.68
Conv138	64	576	0.84	0.05	0.97	0.05	0.97	0.05	0.9	83.68
Conv139	256	64	0.58	0.05	0.90	0.05	0.90	0.05	23.89	294.32
Conv140	64	256	0.43	0.05	0.90	0.05	0.90	0.05	1.81	83.68
Conv141	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.01	83.68
Conv142	256	64	0.62	0.05	0.90	0.05	0.90	0.05	23.72	294.32
Conv143	64	256	0.61	0.05	0.90	0.05	0.90	0.05	1.68	83.68
Conv144	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.68	83.68
Conv145	256	64	0.62	0.05	0.90	0.05	0.90	0.05	26.18	294.32
Conv146	64	256	0.62	0.05	0.90	0.05	0.90	0.05	1.48	83.68

Conv147	64	576	0.83	0.05	0.97	0.05	0.97	0.05	0.64	83.68
Conv148	256	64	0.59	0.05	0.90	0.05	0.90	0.05	26.75	294.32
Conv149	64	256	0.66	0.05	0.90	0.05	0.90	0.05	1.97	83.68
Conv150	64	576	0.84	0.05	0.97	0.05	0.97	0.05	1.09	83.68
Conv151	256	64	0.59	0.05	0.90	0.05	0.90	0.05	27.51	294.32
Conv152	64	256	0.48	0.05	0.90	0.05	0.90	0.05	2.36	83.68
Conv153	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.58	83.68
Conv154	256	64	0.57	0.05	0.90	0.05	0.90	0.05	35.04	294.32
Conv155	64	256	0.58	0.05	0.90	0.05	0.90	0.05	1.68	83.68
Conv156	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.6	83.68
Conv157	256	64	0.53	0.05	0.90	0.05	0.90	0.05	34.74	294.32
Conv158	64	256	0.48	0.05	0.90	0.05	0.90	0.05	2.37	83.68
Conv159	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.8	83.68
Conv160	256	64	0.53	0.05	0.90	0.05	0.90	0.05	37.4	294.32
Conv161	64	256	0.47	0.05	0.90	0.05	0.90	0.05	1.81	83.68
Conv162	64	576	0.85	0.05	0.97	0.05	0.97	0.05	0.58	83.68
Conv163	256	64	0.49	0.05	0.90	0.05	0.90	0.05	36.85	294.32
Passing rate	-	-	97.55%		100.0%		100.0%		96.32%	

P.6 Dataset

config:

`https://github.com/bearpaw/pytorch-classification`.

Table 36: Cifar10 WRN28-10

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.46	0.05	0.58	0.05	0.58	0.05	27.8	26.3
Conv2	160	144	0.92	0.05	0.94	0.05	0.94	0.05	4.77	190.52
Conv3	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.09	190.52
Conv4	160	16	0.64	0.05	0.69	0.05	0.69	0.05	29.65	190.52
Conv5	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.5	190.52
Conv6	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.15	190.52
Conv7	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.05	190.52
Conv8	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.29	190.52
Conv9	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.08	190.52
Conv10	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.42	190.52
Conv11	320	1440	0.94	0.05	1.00	0.05	1.00	0.05	1.28	362.72
Conv12	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.09	362.72
Conv13	320	160	0.90	0.05	0.99	0.05	0.99	0.05	3.15	362.72
Conv14	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.12	362.72
Conv15	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.06	362.72
Conv16	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.03	362.72
Conv17	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.11	362.72
Conv18	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.04	362.72
Conv19	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.26	362.72
Conv20	640	2880	0.94	0.05	1.00	0.05	1.00	0.05	3.11	699.96
Conv21	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.21	699.96
Conv22	640	320	0.90	0.05	1.00	0.05	1.00	0.05	1.93	699.96
Conv23	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.91	699.96
Conv24	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.21	699.96
Conv25	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.16	699.96
Conv26	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.37	699.96
Conv27	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.05	699.96

Layer	Number	dim	Gaussian p-value	Gaussian c-value	Mean_Left p-value	Mean_Left c-value	Mean_Right p-value	Mean_Right c-value	Sigma t-value	Sigma c-value
Conv28	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	1.32	699.96
Passing rate	-	-	100.0%		100.0%		100.0%		96.43%	

Table 37: ImageNet WRN28-10

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.40	0.05	0.58	0.05	0.58	0.05	30.53	26.3
Conv2	160	144	0.91	0.05	0.94	0.05	0.94	0.05	6.08	190.52
Conv3	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.13	190.52
Conv4	160	16	0.68	0.05	0.69	0.05	0.69	0.05	25.89	190.52
Conv5	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.34	190.52
Conv6	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.19	190.52
Conv7	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.14	190.52
Conv8	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.28	190.52
Conv9	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.03	190.52
Conv10	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.36	190.52
Conv11	320	1440	0.95	0.05	1.00	0.05	1.00	0.05	1.54	362.72
Conv12	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.06	362.72
Conv13	320	160	0.89	0.05	0.99	0.05	0.99	0.05	3.39	362.72
Conv14	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.11	362.72
Conv15	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.06	362.72
Conv16	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.04	362.72
Conv17	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.11	362.72
Conv18	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.03	362.72
Conv19	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.5	362.72
Conv20	640	2880	0.94	0.05	1.00	0.05	1.00	0.05	3.36	699.96
Conv21	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.17	699.96
Conv22	640	320	0.90	0.05	1.00	0.05	1.00	0.05	1.98	699.96
Conv23	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.74	699.96
Conv24	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.2	699.96
Conv25	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.23	699.96
Conv26	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.36	699.96
Conv27	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.05	699.96
Conv28	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	1.3	699.96
Passing rate	-	-	100.0%		100.0%		100.0%		96.43%	

Table 38: MNIST WRN28-10

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	16	27	0.46	0.05	0.58	0.05	0.58	0.05	33.06	26.3
Conv2	160	144	0.92	0.05	0.94	0.05	0.94	0.05	5.57	190.52
Conv3	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.1	190.52
Conv4	160	16	0.64	0.05	0.69	0.05	0.69	0.05	30.62	190.52
Conv5	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.5	190.52
Conv6	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.13	190.52
Conv7	160	1440	0.94	0.05	1.00	0.05	1.00	0.05	0.1	190.52
Conv8	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.28	190.52
Conv9	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.02	190.52
Conv10	160	1440	0.95	0.05	1.00	0.05	1.00	0.05	0.43	190.52

Conv11	320	1440	0.94	0.05	1.00	0.05	1.00	0.05	1.56	362.72
Conv12	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.08	362.72
Conv13	320	160	0.90	0.05	0.99	0.05	0.99	0.05	3.91	362.72
Conv14	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.17	362.72
Conv15	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.06	362.72
Conv16	320	2880	0.94	0.05	1.00	0.05	1.00	0.05	0.03	362.72
Conv17	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.09	362.72
Conv18	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.03	362.72
Conv19	320	2880	0.95	0.05	1.00	0.05	1.00	0.05	0.5	362.72
Conv20	640	2880	0.94	0.05	1.00	0.05	1.00	0.05	2.85	699.96
Conv21	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.14	699.96
Conv22	640	320	0.89	0.05	1.00	0.05	1.00	0.05	2.34	699.96
Conv23	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	0.68	699.96
Conv24	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.23	699.96
Conv25	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.19	699.96
Conv26	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.44	699.96
Conv27	640	5760	0.95	0.05	1.00	0.05	1.00	0.05	0.05	699.96
Conv28	640	5760	0.94	0.05	1.00	0.05	1.00	0.05	1.5	699.96
Passing rate	-	-	100.0%		100.0%		100.0%		96.43%	

P.7 Other Tasks

P.7.1 Segmentation

config:

https://github.com/meetshah1995/pytorch-semse

https://github.com/speedinghzl/pytorch-segmentation-toolbox

Table 39: Cityscapes SegNet

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	27	0.86	0.05	0.66	0.05	0.66	0.05	20.77	83.68
Conv2	64	576	0.88	0.05	0.97	0.05	0.97	0.05	0.51	83.68
Conv3	128	576	0.84	0.05	1.00	0.05	1.00	0.05	0.8	155.4
Conv4	128	1152	0.92	0.05	1.00	0.05	1.00	0.05	0.42	155.4
Conv5	256	1152	0.91	0.05	1.00	0.05	1.00	0.05	1.05	294.32
Conv6	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.48	294.32
Conv7	256	2304	0.94	0.05	1.00	0.05	1.00	0.05	0.44	294.32
Conv8	512	2304	0.94	0.05	1.00	0.05	1.00	0.05	0.96	565.75
Conv9	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.39	565.75
Conv10	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.47	565.75
Conv11	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.48	565.75
Conv12	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.38	565.75
Conv13	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.45	565.75
Conv14	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.36	565.75
Conv15	512	4608	0.93	0.05	1.00	0.05	1.00	0.05	0.41	565.75
Conv16	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.26	565.75
Conv17	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.57	565.75
Conv18	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.32	565.75
Conv19	256	4608	0.93	0.05	1.00	0.05	1.00	0.05	0.14	294.32
Conv20	256	2304	0.95	0.05	1.00	0.05	1.00	0.05	0.42	294.32
Conv21	256	2304	0.95	0.05	1.00	0.05	1.00	0.05	0.28	294.32
Conv22	128	2304	0.94	0.05	1.00	0.05	1.00	0.05	0.17	155.4
Conv23	128	1152	0.91	0.05	1.00	0.05	1.00	0.05	0.29	155.4

Conv24	64	1152	0.93	0.05	1.00	0.05	1.00	0.05	0.15	83.68
Conv25	64	576	0.92	0.05	0.97	0.05	0.97	0.05	0.31	83.68
Conv26	19	576	0.87	0.05	0.85	0.05	0.85	0.05	0.9	30.14
Passing rate	-	-	100.0%		100.0%		100.0%		100.0%	

Table 40: Cityscapes PSPNet

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	64	27	0.38	0.05	0.66	0.05	0.66	0.05	286.98	83.68
Conv2	64	576	0.49	0.05	0.97	0.05	0.97	0.05	12.81	83.68
Conv3	128	576	0.70	0.05	1.00	0.05	1.00	0.05	1.47	155.4
Conv4	64	128	0.85	0.05	0.82	0.05	0.82	0.05	4.77	83.68
Conv5	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.95	83.68
Conv6	256	64	0.85	0.05	0.90	0.05	0.90	0.05	15.16	294.32
Conv7	256	128	0.60	0.05	0.96	0.05	0.96	0.05	17.95	294.32
Conv8	64	256	0.91	0.05	0.90	0.05	0.90	0.05	1.78	83.68
Conv9	64	576	0.87	0.05	0.97	0.05	0.97	0.05	0.25	83.68
Conv10	256	64	0.88	0.05	0.90	0.05	0.90	0.05	10.76	294.32
Conv11	64	256	0.91	0.05	0.90	0.05	0.90	0.05	2.01	83.68
Conv12	64	576	0.91	0.05	0.97	0.05	0.97	0.05	0.35	83.68
Conv13	256	64	0.89	0.05	0.90	0.05	0.90	0.05	10.08	294.32
Conv14	128	256	0.86	0.05	0.96	0.05	0.96	0.05	1.76	155.4
Conv15	128	1152	0.92	0.05	1.00	0.05	1.00	0.05	0.07	155.4
Conv16	512	128	0.87	0.05	0.99	0.05	0.99	0.05	21.04	565.75
Conv17	512	256	0.85	0.05	1.00	0.05	1.00	0.05	11.71	565.75
Conv18	128	512	0.91	0.05	0.99	0.05	0.99	0.05	0.45	155.4
Conv19	128	1152	0.89	0.05	1.00	0.05	1.00	0.05	1.22	155.4
Conv20	512	128	0.90	0.05	0.99	0.05	0.99	0.05	12.48	565.75
Conv21	128	512	0.93	0.05	0.99	0.05	0.99	0.05	0.22	155.4
Conv22	128	1152	0.90	0.05	1.00	0.05	1.00	0.05	0.17	155.4
Conv23	512	128	0.87	0.05	0.99	0.05	0.99	0.05	8.64	565.75
Conv24	128	512	0.91	0.05	0.99	0.05	0.99	0.05	0.12	155.4
Conv25	128	1152	0.92	0.05	1.00	0.05	1.00	0.05	0.11	155.4
Conv26	512	128	0.89	0.05	0.99	0.05	0.99	0.05	10.47	565.75
Conv27	256	512	0.87	0.05	1.00	0.05	1.00	0.05	0.65	294.32
Conv28	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.2	294.32
Conv29	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	16.07	1099.56
Conv30	1024	512	0.84	0.05	1.00	0.05	1.00	0.05	10.07	1099.56
Conv31	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.35	294.32
Conv32	256	2304	0.94	0.05	1.00	0.05	1.00	0.05	0.24	294.32
Conv33	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	7.69	1099.56
Conv34	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.26	294.32
Conv35	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.35	294.32
Conv36	1024	256	0.91	0.05	1.00	0.05	1.00	0.05	7.32	1099.56
Conv37	256	1024	0.86	0.05	1.00	0.05	1.00	0.05	0.3	294.32
Conv38	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.17	294.32
Conv39	1024	256	0.91	0.05	1.00	0.05	1.00	0.05	6.23	1099.56
Conv40	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.18	294.32
Conv41	256	2304	0.88	0.05	1.00	0.05	1.00	0.05	0.06	294.32
Conv42	1024	256	0.81	0.05	1.00	0.05	1.00	0.05	11.36	1099.56
Conv43	256	1024	0.92	0.05	1.00	0.05	1.00	0.05	0.15	294.32
Conv44	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.07	294.32
Conv45	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	7.5	1099.56
Conv46	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.17	294.32

Conv47	256	2304	0.94	0.05	1.00	0.05	1.00	0.05	0.1	294.32
Conv48	1024	256	0.92	0.05	1.00	0.05	1.00	0.05	5.1	1099.56
Conv49	256	1024	0.88	0.05	1.00	0.05	1.00	0.05	0.17	294.32
Conv50	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.09	294.32
Conv51	1024	256	0.88	0.05	1.00	0.05	1.00	0.05	7.45	1099.56
Conv52	256	1024	0.87	0.05	1.00	0.05	1.00	0.05	0.15	294.32
Conv53	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.13	294.32
Conv54	1024	256	0.88	0.05	1.00	0.05	1.00	0.05	3.5	1099.56
Conv55	256	1024	0.93	0.05	1.00	0.05	1.00	0.05	0.1	294.32
Conv56	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.11	294.32
Conv57	1024	256	0.93	0.05	1.00	0.05	1.00	0.05	3.86	1099.56
Conv58	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.18	294.32
Conv59	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.18	294.32
Conv60	1024	256	0.92	0.05	1.00	0.05	1.00	0.05	6.96	1099.56
Conv61	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.18	294.32
Conv62	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.16	294.32
Conv63	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	7.38	1099.56
Conv64	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.23	294.32
Conv65	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.12	294.32
Conv66	1024	256	0.92	0.05	1.00	0.05	1.00	0.05	5.27	1099.56
Conv67	256	1024	0.85	0.05	1.00	0.05	1.00	0.05	0.2	294.32
Conv68	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.18	294.32
Conv69	1024	256	0.90	0.05	1.00	0.05	1.00	0.05	4.64	1099.56
Conv70	256	1024	0.92	0.05	1.00	0.05	1.00	0.05	0.1	294.32
Conv71	256	2304	0.94	0.05	1.00	0.05	1.00	0.05	0.16	294.32
Conv72	1024	256	0.91	0.05	1.00	0.05	1.00	0.05	4.37	1099.56
Conv73	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.1	294.32
Conv74	256	2304	0.94	0.05	1.00	0.05	1.00	0.05	0.16	294.32
Conv75	1024	256	0.92	0.05	1.00	0.05	1.00	0.05	6.24	1099.56
Conv76	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.11	294.32
Conv77	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.15	294.32
Conv78	1024	256	0.92	0.05	1.00	0.05	1.00	0.05	3.44	1099.56
Conv79	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.1	294.32
Conv80	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.12	294.32
Conv81	1024	256	0.91	0.05	1.00	0.05	1.00	0.05	4.25	1099.56
Conv82	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.09	294.32
Conv83	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.15	294.32
Conv84	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	5.13	1099.56
Conv85	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.09	294.32
Conv86	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.17	294.32
Conv87	1024	256	0.88	0.05	1.00	0.05	1.00	0.05	4.76	1099.56
Conv88	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.09	294.32
Conv89	256	2304	0.89	0.05	1.00	0.05	1.00	0.05	0.09	294.32
Conv90	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	3.86	1099.56
Conv91	256	1024	0.92	0.05	1.00	0.05	1.00	0.05	0.07	294.32
Conv92	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.03	294.32
Conv93	1024	256	0.92	0.05	1.00	0.05	1.00	0.05	4.57	1099.56
Conv94	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.12	294.32
Conv95	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.07	294.32
Conv96	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	6.76	1099.56
Conv97	512	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.08	565.75
Conv98	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.02	565.75
Conv99	2048	512	0.89	0.05	1.00	0.05	1.00	0.05	1.67	2154.4
Conv100	2048	1024	0.69	0.05	1.00	0.05	1.00	0.05	1.49	2154.4
Conv101	512	2048	0.88	0.05	1.00	0.05	1.00	0.05	0.05	565.75
Conv102	512	4608	0.90	0.05	1.00	0.05	1.00	0.05	0.02	565.75
Conv103	2048	512	0.90	0.05	1.00	0.05	1.00	0.05	1.95	2154.4
Conv104	512	2048	0.85	0.05	1.00	0.05	1.00	0.05	0.07	565.75
Conv105	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.01	565.75

Conv106	2048	512	0.90	0.05	1.00	0.05	1.00	0.05	1.9	2154.4
Conv107	512	2048	0.96	0.05	1.00	0.05	1.00	0.05	0.01	565.75
Conv108	512	2048	0.96	0.05	1.00	0.05	1.00	0.05	0.0	565.75
Conv109	512	2048	0.96	0.05	1.00	0.05	1.00	0.05	0.0	565.75
Conv110	512	2048	0.96	0.05	1.00	0.05	1.00	0.05	0.0	565.75
Conv111	512	36864	0.95	0.05	1.00	0.05	1.00	0.05	0.0	565.75
Conv112	19	512	0.88	0.05	0.84	0.05	0.84	0.05	0.99	30.14
Conv113	512	9216	0.96	0.05	1.00	0.05	1.00	0.05	0.0	565.75
Conv114	19	512	0.87	0.05	0.84	0.05	0.84	0.05	1.06	30.14
Passing rate	-	-	100.0%		100.0%		100.0%		99.12%	

P.7.2 FASTER RCNN

config:

`https://github.com/jwyang/faster-rcnn.pytorch`

Table 41: COCO ResNet101 max epoch=6

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	64	0.57	0.05	0.74	0.05	0.74	0.05	23.34	83.68
Conv2	64	576	0.69	0.05	0.97	0.05	0.97	0.05	5.71	83.68
Conv3	256	64	0.80	0.05	0.90	0.05	0.90	0.05	28.22	294.32
Conv4	256	64	0.46	0.05	0.90	0.05	0.90	0.05	77.88	294.32
Conv5	64	256	0.86	0.05	0.90	0.05	0.90	0.05	3.87	83.68
Conv6	64	576	0.67	0.05	0.97	0.05	0.97	0.05	2.11	83.68
Conv7	256	64	0.85	0.05	0.90	0.05	0.90	0.05	22.48	294.32
Conv8	64	256	0.85	0.05	0.90	0.05	0.90	0.05	2.53	83.68
Conv9	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.13	83.68
Conv10	256	64	0.87	0.05	0.90	0.05	0.90	0.05	30.9	294.32
Conv11	128	256	0.62	0.05	0.96	0.05	0.96	0.05	3.99	155.4
Conv12	128	1152	0.83	0.05	1.00	0.05	1.00	0.05	2.08	155.4
Conv13	512	128	0.66	0.05	0.99	0.05	0.99	0.05	27.85	565.75
Conv14	512	256	0.55	0.05	1.00	0.05	1.00	0.05	18.51	565.75
Conv15	128	512	0.90	0.05	0.99	0.05	0.99	0.05	0.52	155.4
Conv16	128	1152	0.86	0.05	1.00	0.05	1.00	0.05	0.36	155.4
Conv17	512	128	0.67	0.05	0.99	0.05	0.99	0.05	15.55	565.75
Conv18	128	512	0.87	0.05	0.99	0.05	0.99	0.05	0.86	155.4
Conv19	128	1152	0.91	0.05	1.00	0.05	1.00	0.05	0.35	155.4
Conv20	512	128	0.71	0.05	0.99	0.05	0.99	0.05	16.78	565.75
Conv21	128	512	0.86	0.05	0.99	0.05	0.99	0.05	0.98	155.4
Conv22	128	1152	0.89	0.05	1.00	0.05	1.00	0.05	0.27	155.4
Conv23	512	128	0.83	0.05	0.99	0.05	0.99	0.05	27.72	565.75
Conv24	256	512	0.87	0.05	1.00	0.05	1.00	0.05	0.85	294.32
Conv25	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.49	294.32
Conv26	1024	256	0.86	0.05	1.00	0.05	1.00	0.05	12.09	1099.56
Conv27	1024	512	0.69	0.05	1.00	0.05	1.00	0.05	12.68	1099.56
Conv28	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.4	294.32
Conv29	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.63	294.32
Conv30	1024	256	0.86	0.05	1.00	0.05	1.00	0.05	6.72	1099.56
Conv31	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.27	294.32
Conv32	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.25	294.32
Conv33	1024	256	0.90	0.05	1.00	0.05	1.00	0.05	4.71	1099.56
Conv34	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.39	294.32
Conv35	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.16	294.32

Conv36	1024	256	0.87	0.05	1.00	0.05	1.00	0.05	9.99	1099.56
Conv37	256	1024	0.92	0.05	1.00	0.05	1.00	0.05	0.26	294.32
Conv38	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.2	294.32
Conv39	1024	256	0.88	0.05	1.00	0.05	1.00	0.05	4.41	1099.56
Conv40	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.23	294.32
Conv41	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.24	294.32
Conv42	1024	256	0.91	0.05	1.00	0.05	1.00	0.05	4.76	1099.56
Conv43	256	1024	0.85	0.05	1.00	0.05	1.00	0.05	0.33	294.32
Conv44	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.31	294.32
Conv45	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	7.7	1099.56
Conv46	256	1024	0.89	0.05	1.00	0.05	1.00	0.05	0.25	294.32
Conv47	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.27	294.32
Conv48	1024	256	0.86	0.05	1.00	0.05	1.00	0.05	13.24	1099.56
Conv49	256	1024	0.82	0.05	1.00	0.05	1.00	0.05	0.38	294.32
Conv50	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.21	294.32
Conv51	1024	256	0.90	0.05	1.00	0.05	1.00	0.05	4.57	1099.56
Conv52	256	1024	0.88	0.05	1.00	0.05	1.00	0.05	0.2	294.32
Conv53	256	2304	0.89	0.05	1.00	0.05	1.00	0.05	0.26	294.32
Conv54	1024	256	0.88	0.05	1.00	0.05	1.00	0.05	8.23	1099.56
Conv55	256	1024	0.89	0.05	1.00	0.05	1.00	0.05	0.28	294.32
Conv56	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.37	294.32
Conv57	1024	256	0.85	0.05	1.00	0.05	1.00	0.05	8.72	1099.56
Conv58	256	1024	0.88	0.05	1.00	0.05	1.00	0.05	0.28	294.32
Conv59	256	2304	0.89	0.05	1.00	0.05	1.00	0.05	0.24	294.32
Conv60	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	5.31	1099.56
Conv61	256	1024	0.89	0.05	1.00	0.05	1.00	0.05	0.25	294.32
Conv62	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.38	294.32
Conv63	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	5.22	1099.56
Conv64	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.21	294.32
Conv65	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.2	294.32
Conv66	1024	256	0.90	0.05	1.00	0.05	1.00	0.05	2.98	1099.56
Conv67	256	1024	0.92	0.05	1.00	0.05	1.00	0.05	0.26	294.32
Conv68	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.27	294.32
Conv69	1024	256	0.90	0.05	1.00	0.05	1.00	0.05	4.05	1099.56
Conv70	256	1024	0.87	0.05	1.00	0.05	1.00	0.05	0.28	294.32
Conv71	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.33	294.32
Conv72	1024	256	0.91	0.05	1.00	0.05	1.00	0.05	8.2	1099.56
Conv73	256	1024	0.85	0.05	1.00	0.05	1.00	0.05	0.31	294.32
Conv74	256	2304	0.88	0.05	1.00	0.05	1.00	0.05	0.19	294.32
Conv75	1024	256	0.88	0.05	1.00	0.05	1.00	0.05	5.23	1099.56
Conv76	256	1024	0.86	0.05	1.00	0.05	1.00	0.05	0.3	294.32
Conv77	256	2304	0.88	0.05	1.00	0.05	1.00	0.05	0.16	294.32
Conv78	1024	256	0.88	0.05	1.00	0.05	1.00	0.05	2.86	1099.56
Conv79	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.3	294.32
Conv80	256	2304	0.87	0.05	1.00	0.05	1.00	0.05	0.22	294.32
Conv81	1024	256	0.88	0.05	1.00	0.05	1.00	0.05	2.53	1099.56
Conv82	256	1024	0.89	0.05	1.00	0.05	1.00	0.05	0.2	294.32
Conv83	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.43	294.32
Conv84	1024	256	0.90	0.05	1.00	0.05	1.00	0.05	5.84	1099.56
Conv85	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.28	294.32
Conv86	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.35	294.32
Conv87	1024	256	0.85	0.05	1.00	0.05	1.00	0.05	3.08	1099.56
Conv88	256	1024	0.87	0.05	1.00	0.05	1.00	0.05	0.25	294.32
Conv89	256	2304	0.89	0.05	1.00	0.05	1.00	0.05	0.36	294.32
Conv90	1024	256	0.91	0.05	1.00	0.05	1.00	0.05	3.51	1099.56
Conv91	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.26	294.32
Conv92	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.19	294.32
Conv93	1024	256	0.90	0.05	1.00	0.05	1.00	0.05	3.62	1099.56
Conv94	512	1024	0.82	0.05	1.00	0.05	1.00	0.05	0.89	565.75

Conv95	512	4608	0.86	0.05	1.00	0.05	1.00	0.05	0.41	565.75
Conv96	2048	512	0.82	0.05	1.00	0.05	1.00	0.05	4.89	2154.4
Conv97	2048	1024	0.83	0.05	1.00	0.05	1.00	0.05	2.53	2154.4
Conv98	512	2048	0.83	0.05	1.00	0.05	1.00	0.05	0.28	565.75
Conv99	512	4608	0.91	0.05	1.00	0.05	1.00	0.05	0.26	565.75
Conv100	2048	512	0.88	0.05	1.00	0.05	1.00	0.05	4.5	2154.4
Conv101	512	2048	0.84	0.05	1.00	0.05	1.00	0.05	0.31	565.75
Conv102	512	4608	0.90	0.05	1.00	0.05	1.00	0.05	0.19	565.75
Conv103	2048	512	0.87	0.05	1.00	0.05	1.00	0.05	3.81	2154.4
Conv104	512	9216	0.93	0.05	1.00	0.05	1.00	0.05	0.06	565.75
Conv105	64	147	0.44	0.05	0.83	0.05	0.83	0.05	90.36	83.68
Passing rate	-	-	100.0%		100.0%		100.0%		99.05%	

Table 42: PASCAL VOC 2007 ResNet101 bz=24

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	64	0.57	0.05	0.74	0.05	0.74	0.05	23.34	83.68
Conv2	64	576	0.69	0.05	0.97	0.05	0.97	0.05	5.71	83.68
Conv3	256	64	0.80	0.05	0.90	0.05	0.90	0.05	28.22	294.32
Conv4	256	64	0.46	0.05	0.90	0.05	0.90	0.05	77.88	294.32
Conv5	64	256	0.86	0.05	0.90	0.05	0.90	0.05	3.87	83.68
Conv6	64	576	0.67	0.05	0.97	0.05	0.97	0.05	2.11	83.68
Conv7	256	64	0.85	0.05	0.90	0.05	0.90	0.05	22.48	294.32
Conv8	64	256	0.85	0.05	0.90	0.05	0.90	0.05	2.53	83.68
Conv9	64	576	0.90	0.05	0.97	0.05	0.97	0.05	0.13	83.68
Conv10	256	64	0.87	0.05	0.90	0.05	0.90	0.05	30.9	294.32
Conv11	128	256	0.55	0.05	0.96	0.05	0.96	0.05	4.34	155.4
Conv12	128	1152	0.68	0.05	1.00	0.05	1.00	0.05	2.69	155.4
Conv13	512	128	0.70	0.05	0.99	0.05	0.99	0.05	28.4	565.75
Conv14	512	256	0.56	0.05	1.00	0.05	1.00	0.05	14.13	565.75
Conv15	128	512	0.89	0.05	0.99	0.05	0.99	0.05	0.6	155.4
Conv16	128	1152	0.87	0.05	1.00	0.05	1.00	0.05	0.45	155.4
Conv17	512	128	0.65	0.05	0.99	0.05	0.99	0.05	17.14	565.75
Conv18	128	512	0.86	0.05	0.99	0.05	0.99	0.05	0.95	155.4
Conv19	128	1152	0.89	0.05	1.00	0.05	1.00	0.05	0.39	155.4
Conv20	512	128	0.81	0.05	0.99	0.05	0.99	0.05	16.68	565.75
Conv21	128	512	0.85	0.05	0.99	0.05	0.99	0.05	1.02	155.4
Conv22	128	1152	0.88	0.05	1.00	0.05	1.00	0.05	0.44	155.4
Conv23	512	128	0.84	0.05	0.99	0.05	0.99	0.05	27.01	565.75
Conv24	256	512	0.84	0.05	1.00	0.05	1.00	0.05	0.87	294.32
Conv25	256	2304	0.88	0.05	1.00	0.05	1.00	0.05	0.5	294.32
Conv26	1024	256	0.84	0.05	1.00	0.05	1.00	0.05	12.16	1099.56
Conv27	1024	512	0.67	0.05	1.00	0.05	1.00	0.05	15.39	1099.56
Conv28	256	1024	0.88	0.05	1.00	0.05	1.00	0.05	0.53	294.32
Conv29	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.7	294.32
Conv30	1024	256	0.86	0.05	1.00	0.05	1.00	0.05	8.23	1099.56
Conv31	256	1024	0.92	0.05	1.00	0.05	1.00	0.05	0.37	294.32
Conv32	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.31	294.32
Conv33	1024	256	0.90	0.05	1.00	0.05	1.00	0.05	5.96	1099.56
Conv34	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.44	294.32
Conv35	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.19	294.32
Conv36	1024	256	0.85	0.05	1.00	0.05	1.00	0.05	13.91	1099.56
Conv37	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.33	294.32
Conv38	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.22	294.32

Conv39	1024	256	0.88	0.05	1.00	0.05	1.00	0.05	4.78	1099.56
Conv40	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.23	294.32
Conv41	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.19	294.32
Conv42	1024	256	0.90	0.05	1.00	0.05	1.00	0.05	4.32	1099.56
Conv43	256	1024	0.86	0.05	1.00	0.05	1.00	0.05	0.37	294.32
Conv44	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.27	294.32
Conv45	1024	256	0.90	0.05	1.00	0.05	1.00	0.05	6.28	1099.56
Conv46	256	1024	0.89	0.05	1.00	0.05	1.00	0.05	0.33	294.32
Conv47	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.27	294.32
Conv48	1024	256	0.83	0.05	1.00	0.05	1.00	0.05	12.8	1099.56
Conv49	256	1024	0.81	0.05	1.00	0.05	1.00	0.05	0.42	294.32
Conv50	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.17	294.32
Conv51	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	5.84	1099.56
Conv52	256	1024	0.89	0.05	1.00	0.05	1.00	0.05	0.26	294.32
Conv53	256	2304	0.83	0.05	1.00	0.05	1.00	0.05	0.22	294.32
Conv54	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	7.67	1099.56
Conv55	256	1024	0.88	0.05	1.00	0.05	1.00	0.05	0.33	294.32
Conv56	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.3	294.32
Conv57	1024	256	0.87	0.05	1.00	0.05	1.00	0.05	7.21	1099.56
Conv58	256	1024	0.86	0.05	1.00	0.05	1.00	0.05	0.29	294.32
Conv59	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.16	294.32
Conv60	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	4.7	1099.56
Conv61	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.25	294.32
Conv62	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.26	294.32
Conv63	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	4.09	1099.56
Conv64	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.28	294.32
Conv65	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.16	294.32
Conv66	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	3.05	1099.56
Conv67	256	1024	0.91	0.05	1.00	0.05	1.00	0.05	0.22	294.32
Conv68	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.16	294.32
Conv69	1024	256	0.91	0.05	1.00	0.05	1.00	0.05	3.24	1099.56
Conv70	256	1024	0.86	0.05	1.00	0.05	1.00	0.05	0.21	294.32
Conv71	256	2304	0.93	0.05	1.00	0.05	1.00	0.05	0.17	294.32
Conv72	1024	256	0.87	0.05	1.00	0.05	1.00	0.05	7.3	1099.56
Conv73	256	1024	0.86	0.05	1.00	0.05	1.00	0.05	0.42	294.32
Conv74	256	2304	0.88	0.05	1.00	0.05	1.00	0.05	0.11	294.32
Conv75	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	6.51	1099.56
Conv76	256	1024	0.82	0.05	1.00	0.05	1.00	0.05	0.3	294.32
Conv77	256	2304	0.89	0.05	1.00	0.05	1.00	0.05	0.09	294.32
Conv78	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	3.63	1099.56
Conv79	256	1024	0.87	0.05	1.00	0.05	1.00	0.05	0.24	294.32
Conv80	256	2304	0.89	0.05	1.00	0.05	1.00	0.05	0.09	294.32
Conv81	1024	256	0.91	0.05	1.00	0.05	1.00	0.05	2.6	1099.56
Conv82	256	1024	0.89	0.05	1.00	0.05	1.00	0.05	0.17	294.32
Conv83	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.19	294.32
Conv84	1024	256	0.88	0.05	1.00	0.05	1.00	0.05	4.77	1099.56
Conv85	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.43	294.32
Conv86	256	2304	0.92	0.05	1.00	0.05	1.00	0.05	0.14	294.32
Conv87	1024	256	0.91	0.05	1.00	0.05	1.00	0.05	4.01	1099.56
Conv88	256	1024	0.88	0.05	1.00	0.05	1.00	0.05	0.22	294.32
Conv89	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.14	294.32
Conv90	1024	256	0.91	0.05	1.00	0.05	1.00	0.05	2.78	1099.56
Conv91	256	1024	0.90	0.05	1.00	0.05	1.00	0.05	0.34	294.32
Conv92	256	2304	0.87	0.05	1.00	0.05	1.00	0.05	0.1	294.32
Conv93	1024	256	0.89	0.05	1.00	0.05	1.00	0.05	2.44	1099.56
Conv94	512	1024	0.82	0.05	1.00	0.05	1.00	0.05	0.29	565.75
Conv95	512	4608	0.84	0.05	1.00	0.05	1.00	0.05	0.11	565.75
Conv96	2048	512	0.66	0.05	1.00	0.05	1.00	0.05	2.4	2154.4
Conv97	2048	1024	0.53	0.05	1.00	0.05	1.00	0.05	2.25	2154.4

Conv98	512	2048	0.81	0.05	1.00	0.05	1.00	0.05	0.12	565.75
Conv99	512	4608	0.89	0.05	1.00	0.05	1.00	0.05	0.07	565.75
Conv100	2048	512	0.85	0.05	1.00	0.05	1.00	0.05	2.43	2154.4
Conv101	512	2048	0.64	0.05	1.00	0.05	1.00	0.05	0.2	565.75
Conv102	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.04	565.75
Conv103	2048	512	0.90	0.05	1.00	0.05	1.00	0.05	2.01	2154.4
Conv104	512	9216	0.95	0.05	1.00	0.05	1.00	0.05	0.0	565.75
Conv105	64	147	0.44	0.05	0.83	0.05	0.83	0.05	90.36	83.68
Passing rate	-	-	100.0%		100.0%		100.0%		99.05%	

Table 43: Visual Genome VGG16

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	27	0.50	0.05	0.66	0.05	0.66	0.05	147.34	83.68
Conv2	64	576	0.85	0.05	0.97	0.05	0.97	0.05	3.2	83.68
Conv3	128	576	0.68	0.05	1.00	0.05	1.00	0.05	6.85	155.4
Conv4	128	1152	0.85	0.05	1.00	0.05	1.00	0.05	0.91	155.4
Conv5	256	1152	0.71	0.05	1.00	0.05	1.00	0.05	0.92	294.32
Conv6	256	2304	0.84	0.05	1.00	0.05	1.00	0.05	0.33	294.32
Conv7	256	2304	0.81	0.05	1.00	0.05	1.00	0.05	0.27	294.32
Conv8	512	2304	0.83	0.05	1.00	0.05	1.00	0.05	0.33	565.75
Conv9	512	4608	0.88	0.05	1.00	0.05	1.00	0.05	0.11	565.75
Conv10	512	4608	0.91	0.05	1.00	0.05	1.00	0.05	0.12	565.75
Conv11	512	4608	0.87	0.05	1.00	0.05	1.00	0.05	0.1	565.75
Conv12	512	4608	0.88	0.05	1.00	0.05	1.00	0.05	0.17	565.75
Conv13	512	4608	0.88	0.05	1.00	0.05	1.00	0.05	0.6	565.75
Conv14	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.06	565.75
Conv15	4096	25088	0.95	0.05	1.00	0.05	1.00	0.05	0.04	4246.0
Conv16	4096	4096	0.95	0.05	1.00	0.05	1.00	0.05	0.15	4246.0
Passing rate	-	-	100.0%		100.0%		100.0%		93.75%	

P.7.3 Image Matting

config:

`https://github.com/foamliu/Deep-Image-Matting-PyTorch`

`https://github.com/CDOTAD/AlphaGAN-Matting`

Table 44: AlphaGAN matting

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	36	0.10	0.05	0.68	0.05	0.68	0.05	446.15	83.68
Conv2	64	576	0.60	0.05	0.97	0.05	0.97	0.05	2.63	83.68
Conv3	128	576	0.63	0.05	1.00	0.05	1.00	0.05	24.49	155.4
Conv4	128	1152	0.70	0.05	1.00	0.05	1.00	0.05	2.71	155.4
Conv5	256	1152	0.53	0.05	1.00	0.05	1.00	0.05	5.23	294.32
Conv6	256	2304	0.85	0.05	1.00	0.05	1.00	0.05	0.81	294.32
Conv7	256	2304	0.66	0.05	1.00	0.05	1.00	0.05	0.35	294.32
Conv8	512	2304	0.67	0.05	1.00	0.05	1.00	0.05	0.78	565.75
Conv9	512	4608	0.84	0.05	1.00	0.05	1.00	0.05	0.81	565.75

Conv10	512	4608	0.87	0.05	1.00	0.05	1.00	0.05	0.87	565.75
Conv11	512	4608	0.70	0.05	1.00	0.05	1.00	0.05	0.22	565.75
Conv12	512	4608	0.81	0.05	1.00	0.05	1.00	0.05	0.18	565.75
Conv13	512	4608	0.87	0.05	1.00	0.05	1.00	0.05	0.45	565.75
Conv14	4096	25088	0.92	0.05	1.00	0.05	1.00	0.05	4.81	4246.0
Conv15	512	4096	0.94	0.05	1.00	0.05	1.00	0.05	0.04	565.75
Conv16	512	12800	0.93	0.05	1.00	0.05	1.00	0.05	0.09	565.75
Conv17	256	12800	0.80	0.05	1.00	0.05	1.00	0.05	0.41	294.32
Conv18	128	6400	0.70	0.05	1.00	0.05	1.00	0.05	0.87	155.4
Conv19	64	3200	0.58	0.05	1.00	0.05	1.00	0.05	0.87	83.68
Conv20	64	1600	0.46	0.05	1.00	0.05	1.00	0.05	2.43	83.68
Passing rate	-	-	100.0%		100.0%		100.0%		95.00%	

Table 45: Deep image matting

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	196	0.22	0.05	0.87	0.05	0.87	0.05	25.66	83.68
Conv2	64	64	0.29	0.05	0.74	0.05	0.74	0.05	24.7	83.68
Conv3	64	576	0.54	0.05	0.97	0.05	0.97	0.05	5.84	83.68
Conv4	256	64	0.53	0.05	0.90	0.05	0.90	0.05	46.45	294.32
Conv5	256	64	0.31	0.05	0.90	0.05	0.90	0.05	93.76	294.32
Conv6	64	256	0.65	0.05	0.90	0.05	0.90	0.05	5.86	83.68
Conv7	64	576	0.48	0.05	0.97	0.05	0.97	0.05	0.51	83.68
Conv8	256	64	0.49	0.05	0.90	0.05	0.90	0.05	19.67	294.32
Conv9	64	256	0.67	0.05	0.90	0.05	0.90	0.05	0.18	83.68
Conv10	64	576	0.81	0.05	0.97	0.05	0.97	0.05	0.1	83.68
Conv11	256	64	0.70	0.05	0.90	0.05	0.90	0.05	8.18	294.32
Conv12	128	256	0.60	0.05	0.96	0.05	0.96	0.05	1.46	155.4
Conv13	128	1152	0.67	0.05	1.00	0.05	1.00	0.05	0.16	155.4
Conv14	512	128	0.60	0.05	0.99	0.05	0.99	0.05	89.07	565.75
Conv15	512	256	0.27	0.05	1.00	0.05	1.00	0.05	83.22	565.75
Conv16	128	512	0.39	0.05	0.99	0.05	0.99	0.05	2.41	155.4
Conv17	128	1152	0.68	0.05	1.00	0.05	1.00	0.05	0.6	155.4
Conv18	512	128	0.67	0.05	0.99	0.05	0.99	0.05	17.33	565.75
Conv19	128	512	0.57	0.05	0.99	0.05	0.99	0.05	0.15	155.4
Conv20	128	1152	0.61	0.05	1.00	0.05	1.00	0.05	0.09	155.4
Conv21	512	128	0.52	0.05	0.99	0.05	0.99	0.05	3.61	565.75
Conv22	128	512	0.64	0.05	0.99	0.05	0.99	0.05	0.12	155.4
Conv23	128	1152	0.83	0.05	1.00	0.05	1.00	0.05	0.09	155.4
Conv24	512	128	0.69	0.05	0.99	0.05	0.99	0.05	4.59	565.75
Conv25	256	512	0.63	0.05	1.00	0.05	1.00	0.05	0.69	294.32
Conv26	256	2304	0.67	0.05	1.00	0.05	1.00	0.05	0.1	294.32
Conv27	1024	256	0.61	0.05	1.00	0.05	1.00	0.05	58.75	1099.56
Conv28	1024	512	0.56	0.05	1.00	0.05	1.00	0.05	52.35	1099.56
Conv29	256	1024	0.47	0.05	1.00	0.05	1.00	0.05	0.25	294.32
Conv30	256	2304	0.55	0.05	1.00	0.05	1.00	0.05	0.39	294.32
Conv31	1024	256	0.51	0.05	1.00	0.05	1.00	0.05	13.05	1099.56
Conv32	256	1024	0.57	0.05	1.00	0.05	1.00	0.05	0.14	294.32
Conv33	256	2304	0.80	0.05	1.00	0.05	1.00	0.05	0.14	294.32
Conv34	1024	256	0.66	0.05	1.00	0.05	1.00	0.05	6.25	1099.56
Conv35	256	1024	0.62	0.05	1.00	0.05	1.00	0.05	0.14	294.32
Conv36	256	2304	0.64	0.05	1.00	0.05	1.00	0.05	0.19	294.32
Conv37	1024	256	0.69	0.05	1.00	0.05	1.00	0.05	5.59	1099.56
Conv38	256	1024	0.67	0.05	1.00	0.05	1.00	0.05	0.54	294.32

Conv39	256	2304	0.69	0.05	1.00	0.05	1.00	0.05	0.68	294.32
Conv40	1024	256	0.67	0.05	1.00	0.05	1.00	0.05	5.87	1099.56
Conv41	256	1024	0.66	0.05	1.00	0.05	1.00	0.05	0.22	294.32
Conv42	256	2304	0.80	0.05	1.00	0.05	1.00	0.05	0.21	294.32
Conv43	1024	256	0.63	0.05	1.00	0.05	1.00	0.05	6.01	1099.56
Conv44	512	1024	0.69	0.05	1.00	0.05	1.00	0.05	0.51	565.75
Conv45	512	4608	0.64	0.05	1.00	0.05	1.00	0.05	0.28	565.75
Conv46	2048	512	0.57	0.05	1.00	0.05	1.00	0.05	4.17	2154.4
Conv47	2048	1024	0.38	0.05	1.00	0.05	1.00	0.05	2.83	2154.4
Conv48	512	2048	0.28	0.05	1.00	0.05	1.00	0.05	3.58	565.75
Conv49	512	4608	0.67	0.05	1.00	0.05	1.00	0.05	2.97	565.75
Conv50	2048	512	0.70	0.05	1.00	0.05	1.00	0.05	17.54	2154.4
Conv51	512	2048	0.55	0.05	1.00	0.05	1.00	0.05	6.14	565.75
Conv52	512	4608	0.64	0.05	1.00	0.05	1.00	0.05	3.58	565.75
Conv53	2048	512	0.61	0.05	1.00	0.05	1.00	0.05	24.98	2154.4
Conv54	1024	2048	0.84	0.05	1.00	0.05	1.00	0.05	0.92	1099.56
Conv55	1024	18432	0.66	0.05	1.00	0.05	1.00	0.05	3.88	1099.56
Conv56	1024	18432	0.65	0.05	1.00	0.05	1.00	0.05	3.91	1099.56
Conv57	1024	18432	0.68	0.05	1.00	0.05	1.00	0.05	2.13	1099.56
Conv58	1024	5120	0.63	0.05	1.00	0.05	1.00	0.05	14.47	1099.56
Conv59	1024	9216	0.24	0.05	1.00	0.05	1.00	0.05	48.34	1099.56
Conv60	1024	1024	0.63	0.05	1.00	0.05	1.00	0.05	18.39	1099.56
Conv61	1024	9216	0.55	0.05	1.00	0.05	1.00	0.05	59.85	1099.56
Conv62	1024	11520	0.58	0.05	1.00	0.05	1.00	0.05	5.42	1099.56
Conv63	512	9216	0.61	0.05	1.00	0.05	1.00	0.05	1.24	565.75
Conv64	256	4608	0.62	0.05	1.00	0.05	1.00	0.05	0.73	294.32
Conv65	64	2304	0.81	0.05	1.00	0.05	1.00	0.05	0.03	83.68
Conv66	16	64	0.50	0.05	0.63	0.05	0.63	0.05	5.7	26.3
Conv67	64	720	0.41	0.05	0.98	0.05	0.98	0.05	0.37	83.68
Conv68	64	3136	0.37	0.05	1.00	0.05	1.00	0.05	0.9	83.68
Conv69	64	576	0.39	0.05	0.97	0.05	0.97	0.05	6.03	83.68
Conv70	64	603	0.32	0.05	0.98	0.05	0.98	0.05	17.08	83.68
Conv71	64	576	0.23	0.05	0.97	0.05	0.97	0.05	46.48	83.68
Passing rate	-	-	100.0%		100.0%		100.0%		100.0%	

P.7.4 Style transfer

config:

`https://github.com/abhiskk/fast-neural-style`

Table 46: Fast neural style (candy)

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	32	243	0.14	0.05	0.81	0.05	0.81	0.05	9.84	46.19
Conv2	64	288	0.09	0.05	0.91	0.05	0.91	0.05	9.0	83.68
Conv3	128	576	0.13	0.05	1.00	0.05	1.00	0.05	8.91	155.4
Conv4	128	1152	0.02	0.05	1.00	0.05	1.00	0.05	23.03	155.4
Conv5	128	1152	0.10	0.05	1.00	0.05	1.00	0.05	2.99	155.4
Conv6	128	1152	0.11	0.05	1.00	0.05	1.00	0.05	1.76	155.4
Conv7	128	1152	0.06	0.05	1.00	0.05	1.00	0.05	3.21	155.4
Conv8	128	1152	0.13	0.05	1.00	0.05	1.00	0.05	19.79	155.4
Conv9	128	1152	0.04	0.05	1.00	0.05	1.00	0.05	4.09	155.4
Conv10	128	1152	0.24	0.05	1.00	0.05	1.00	0.05	1.11	155.4
Conv11	128	1152	0.05	0.05	1.00	0.05	1.00	0.05	3.34	155.4

Conv12	128	1152	0.15	0.05	1.00	0.05	1.00	0.05	1.49	155.4
Conv13	128	1152	0.25	0.05	1.00	0.05	1.00	0.05	2.38	155.4
Conv14	64	1152	0.30	0.05	1.00	0.05	1.00	0.05	0.93	83.68
Conv15	32	576	0.31	0.05	0.91	0.05	0.91	0.05	1.08	46.19
Passing rate	-	-	86.67%		100.0%		100.0%		100.0%	

Table 47: Fast neural style (mosaic)

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	32	243	0.18	0.05	0.81	0.05	0.81	0.05	1.44	46.19
Conv2	64	288	0.23	0.05	0.91	0.05	0.91	0.05	7.95	83.68
Conv3	128	576	0.21	0.05	1.00	0.05	1.00	0.05	27.77	155.4
Conv4	128	1152	0.18	0.05	1.00	0.05	1.00	0.05	7.1	155.4
Conv5	128	1152	0.04	0.05	1.00	0.05	1.00	0.05	2.78	155.4
Conv6	128	1152	0.30	0.05	1.00	0.05	1.00	0.05	11.29	155.4
Conv7	128	1152	0.13	0.05	1.00	0.05	1.00	0.05	3.61	155.4
Conv8	128	1152	0.19	0.05	1.00	0.05	1.00	0.05	1.48	155.4
Conv9	128	1152	0.12	0.05	1.00	0.05	1.00	0.05	2.61	155.4
Conv10	128	1152	0.28	0.05	1.00	0.05	1.00	0.05	1.44	155.4
Conv11	128	1152	0.23	0.05	1.00	0.05	1.00	0.05	2.27	155.4
Conv12	128	1152	0.22	0.05	1.00	0.05	1.00	0.05	8.63	155.4
Conv13	128	1152	0.26	0.05	1.00	0.05	1.00	0.05	2.33	155.4
Conv14	64	1152	0.38	0.05	1.00	0.05	1.00	0.05	1.12	83.68
Conv15	32	576	0.52	0.05	0.91	0.05	0.91	0.05	0.23	46.19
Passing rate	-	-	93.33%		100.0%		100.0%		100.0%	

Table 48: Fast neural style (starry night)

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	32	243	0.13	0.05	0.81	0.05	0.81	0.05	9.92	46.19
Conv2	64	288	0.14	0.05	0.91	0.05	0.91	0.05	19.39	83.68
Conv3	128	576	0.20	0.05	1.00	0.05	1.00	0.05	32.68	155.4
Conv4	128	1152	0.01	0.05	1.00	0.05	1.00	0.05	142.0	155.4
Conv5	128	1152	0.02	0.05	1.00	0.05	1.00	0.05	28.99	155.4
Conv6	128	1152	0.17	0.05	1.00	0.05	1.00	0.05	4.55	155.4
Conv7	128	1152	0.10	0.05	1.00	0.05	1.00	0.05	3.05	155.4
Conv8	128	1152	0.17	0.05	1.00	0.05	1.00	0.05	1.67	155.4
Conv9	128	1152	0.07	0.05	1.00	0.05	1.00	0.05	2.42	155.4
Conv10	128	1152	0.33	0.05	1.00	0.05	1.00	0.05	6.25	155.4
Conv11	128	1152	0.12	0.05	1.00	0.05	1.00	0.05	2.06	155.4
Conv12	128	1152	0.31	0.05	1.00	0.05	1.00	0.05	1.12	155.4
Conv13	128	1152	0.16	0.05	1.00	0.05	1.00	0.05	1.58	155.4
Conv14	64	1152	0.29	0.05	1.00	0.05	1.00	0.05	0.47	83.68
Conv15	32	576	0.44	0.05	0.91	0.05	0.91	0.05	0.71	46.19
Passing rate	-	-	86.67%		100.0%		100.0%		100.0%	

Table 49: Fast neural style (udnie)

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	32	243	0.22	0.05	0.81	0.05	0.81	0.05	9.61	46.19
Conv2	64	288	0.17	0.05	0.91	0.05	0.91	0.05	13.05	83.68
Conv3	128	576	0.19	0.05	1.00	0.05	1.00	0.05	10.46	155.4
Conv4	128	1152	0.06	0.05	1.00	0.05	1.00	0.05	20.22	155.4
Conv5	128	1152	0.14	0.05	1.00	0.05	1.00	0.05	4.46	155.4
Conv6	128	1152	0.14	0.05	1.00	0.05	1.00	0.05	3.17	155.4
Conv7	128	1152	0.02	0.05	1.00	0.05	1.00	0.05	5.85	155.4
Conv8	128	1152	0.17	0.05	1.00	0.05	1.00	0.05	18.5	155.4
Conv9	128	1152	0.00	0.05	1.00	0.05	1.00	0.05	18.88	155.4
Conv10	128	1152	0.02	0.05	1.00	0.05	1.00	0.05	3.59	155.4
Conv11	128	1152	0.00	0.05	1.00	0.05	1.00	0.05	10.35	155.4
Conv12	128	1152	0.02	0.05	1.00	0.05	1.00	0.05	3.33	155.4
Conv13	128	1152	0.21	0.05	1.00	0.05	1.00	0.05	3.99	155.4
Conv14	64	1152	0.25	0.05	1.00	0.05	1.00	0.05	2.52	83.68
Conv15	32	576	0.26	0.05	0.91	0.05	0.91	0.05	2.34	46.19
Passing rate	-	-	66.67%		100.0%		100.0%		100.0%	

P.7.5 GAN

config:

`https://github.com/csinva/gan-pretrained-pytorch`

Table 50: DCGAN MNIST

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	100	8192	0.70	0.05	1.00	0.05	1.00	0.05	1.88	124.34
Conv2	512	4096	0.69	0.05	1.00	0.05	1.00	0.05	0.8	565.75
Conv3	256	2048	0.64	0.05	1.00	0.05	1.00	0.05	0.92	294.32
Conv4	128	1024	0.50	0.05	1.00	0.05	1.00	0.05	3.88	155.4
Passing rate	-	-	100.0%		100.0%		100.0%		100.0%	

Table 51: DCGAN Cifar10

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	100	8192	0.65	0.05	1	0.05	1	0.05	1.48	124.34
Conv2	512	4096	0.48	0.05	1	0.05	1	0.05	3.56	565.75
Conv3	256	2048	0.32	0.05	1	0.05	1	0.05	10.52	294.32
Conv4	128	1024	0.44	0.05	1	0.05	1	0.05	9.06	155.4
Passing rate	-	-	100.0%		100.0%		100.0%		100.0%	

Table 52: DCGAN Cifar100

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	100	8192	0.53	0.05	1.00	0.05	1.00	0.05	2.13	124.34
Conv2	512	4096	0.33	0.05	1.00	0.05	1.00	0.05	4.32	565.75
Conv3	256	2048	0.48	0.05	1.00	0.05	1.00	0.05	8.49	294.32
Conv4	128	1024	0.27	0.05	1.00	0.05	1.00	0.05	15.21	155.4
Passing rate	-	-	100.0%		100.0%		100.0%		100.0%	

P.8 Batch Normalization

config:

https://github.com/bearpaw/pytorch-classification.

Table 53: Cifar10 VGG19

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	64	27	0.24	0.05	0.66	0.05	0.66	0.05	388.19	83.68
Conv2	64	576	0.62	0.05	0.97	0.05	0.97	0.05	1.55	83.68
Conv3	128	576	0.84	0.05	1.00	0.05	1.00	0.05	2.61	155.4
Conv4	128	1152	0.86	0.05	1.00	0.05	1.00	0.05	0.39	155.4
Conv5	256	1152	0.82	0.05	1.00	0.05	1.00	0.05	0.67	294.32
Conv6	256	2304	0.88	0.05	1.00	0.05	1.00	0.05	0.41	294.32
Conv7	256	2304	0.88	0.05	1.00	0.05	1.00	0.05	0.35	294.32
Conv8	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.21	294.32
Conv9	512	2304	0.92	0.05	1.00	0.05	1.00	0.05	1.23	565.75
Conv10	512	4608	0.91	0.05	1.00	0.05	1.00	0.05	1.08	565.75
Conv11	512	4608	0.93	0.05	1.00	0.05	1.00	0.05	0.32	565.75
Conv12	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.16	565.75
Conv13	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.17	565.75
Conv14	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.17	565.75
Conv15	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.12	565.75
Conv16	512	4608	0.93	0.05	1.00	0.05	1.00	0.05	0.25	565.75
Passing rate	-	-	100.0%		100.0%		100.0%		93.75%	

Table 54: Cifar10 VGG19-bn

Layer	Number	dim	Gaussian		Mean_Left		Mean_Right		Sigma	
			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	64	27	0.32	0.05	0.66	0.05	0.66	0.05	399.99	83.68
Conv2	64	576	0.53	0.05	0.97	0.05	0.97	0.05	1.69	83.68
Conv3	128	576	0.85	0.05	1.00	0.05	1.00	0.05	3.16	155.4
Conv4	128	1152	0.86	0.05	1.00	0.05	1.00	0.05	0.45	155.4
Conv5	256	1152	0.84	0.05	1.00	0.05	1.00	0.05	1.05	294.32
Conv6	256	2304	0.88	0.05	1.00	0.05	1.00	0.05	0.38	294.32
Conv7	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.45	294.32
Conv8	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.28	294.32
Conv9	512	2304	0.91	0.05	1.00	0.05	1.00	0.05	1.6	565.75
Conv10	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.91	565.75
Conv11	512	4608	0.92	0.05	1.00	0.05	1.00	0.05	0.22	565.75
Conv12	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.18	565.75

Conv13	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.29	565.75
Conv14	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.23	565.75
Conv15	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.13	565.75
Conv16	512	4608	0.93	0.05	1.00	0.05	1.00	0.05	0.32	565.75
Passing rate	-	-	100.0%		100.0%		100.0%		93.75%	

P.9 PYTORCH PRETRAIN

config: `http://pytorch.org/docs/master/torchvision/index.html`.

Table 55: Pytorch pre-trained VGG11

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	27	0.08	0.05	0.98	0.05	0.98	0.05	18556.94	83.68
Conv2	128	576	0.43	0.05	1.00	0.05	1.00	0.05	365.45	155.4
Conv3	256	1152	0.55	0.05	1.00	0.05	1.00	0.05	118.19	294.32
Conv4	256	2304	0.42	0.05	1.00	0.05	1.00	0.05	60.64	294.32
Conv5	512	2304	0.67	0.05	1.00	0.05	1.00	0.05	44.8	565.75
Conv6	512	4608	0.83	0.05	1.00	0.05	1.00	0.05	23.01	565.75
Conv7	512	4608	0.82	0.05	1.00	0.05	1.00	0.05	16.13	565.75
Conv8	512	4608	0.88	0.05	1.00	0.05	1.00	0.05	43.86	565.75
Passing rate	-	-	100.0%		100.0%		100.0%		75.0%	

Table 56: Pytorch pre-trained VGG16

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	27	0.20	0.05	0.98	0.05	0.98	0.05	8106.7	83.68
Conv2	64	576	0.59	0.05	1.00	0.05	1.00	0.05	134.8	83.68
Conv3	128	576	0.55	0.05	1.00	0.05	1.00	0.05	152.47	155.4
Conv4	128	1152	0.81	0.05	1.00	0.05	1.00	0.05	64.62	155.4
Conv5	256	1152	0.56	0.05	1.00	0.05	1.00	0.05	40.31	294.32
Conv6	256	2304	0.70	0.05	1.00	0.05	1.00	0.05	21.44	294.32
Conv7	256	2304	0.55	0.05	1.00	0.05	1.00	0.05	25.05	294.32
Conv8	512	2304	0.64	0.05	1.00	0.05	1.00	0.05	33.34	565.75
Conv9	512	4608	0.85	0.05	1.00	0.05	1.00	0.05	11.92	565.75
Conv10	512	4608	0.88	0.05	1.00	0.05	1.00	0.05	11.49	565.75
Conv11	512	4608	0.83	0.05	1.00	0.05	1.00	0.05	9.21	565.75
Conv12	512	4608	0.87	0.05	1.00	0.05	1.00	0.05	8.74	565.75
Conv13	512	4608	0.92	0.05	1.00	0.05	1.00	0.05	33.55	565.75
Passing rate	-	-	100.0%		100.0%		100.0%		84.62%	

Table 57: Pytorch pre-trained VGG19

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	

			p-value	c-value	p-value	c-value	p-value	c-value	t-value	c-value
Conv1	64	27	0.25	0.05	0.98	0.05	0.98	0.05	6679.05	83.68
Conv2	64	576	0.61	0.05	1.00	0.05	1.00	0.05	163.5	83.68
Conv3	128	576	0.58	0.05	1.00	0.05	1.00	0.05	132.27	155.4
Conv4	128	1152	0.58	0.05	1.00	0.05	1.00	0.05	52.71	155.4
Conv5	256	1152	0.51	0.05	1.00	0.05	1.00	0.05	36.91	294.32
Conv6	256	2304	0.66	0.05	1.00	0.05	1.00	0.05	19.93	294.32
Conv7	256	2304	0.85	0.05	1.00	0.05	1.00	0.05	14.54	294.32
Conv8	256	2304	0.64	0.05	1.00	0.05	1.00	0.05	20.24	294.32
Conv9	512	2304	0.64	0.05	1.00	0.05	1.00	0.05	26.91	565.75
Conv10	512	4608	0.86	0.05	1.00	0.05	1.00	0.05	10.7	565.75
Conv11	512	4608	0.89	0.05	1.00	0.05	1.00	0.05	8.98	565.75
Conv12	512	4608	0.89	0.05	1.00	0.05	1.00	0.05	7.87	565.75
Conv13	512	4608	0.87	0.05	1.00	0.05	1.00	0.05	7.51	565.75
Conv14	512	4608	0.90	0.05	1.00	0.05	1.00	0.05	9.71	565.75
Conv15	512	4608	0.92	0.05	1.00	0.05	1.00	0.05	7.61	565.75
Conv16	512	4608	0.90	0.05	1.00	0.05	1.00	0.05	22.02	565.75
Passing rate	-	-	100.0%		100.0%		100.0%		87.50%	

Table 58: Pytorch pre-trained ResNet18

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	147	0.31	0.05	1.00	0.05	1.00	0.05	3000.89	83.68
Conv2	64	576	0.42	0.05	1.00	0.05	1.00	0.05	90.98	83.68
Conv3	64	576	0.63	0.05	1.00	0.05	1.00	0.05	42.7	83.68
Conv4	64	576	0.52	0.05	1.00	0.05	1.00	0.05	82.51	83.68
Conv5	64	576	0.70	0.05	1.00	0.05	1.00	0.05	32.27	83.68
Conv6	128	576	0.82	0.05	1.00	0.05	1.00	0.05	14.37	155.4
Conv7	128	1152	0.67	0.05	1.00	0.05	1.00	0.05	35.48	155.4
Conv8	128	1152	0.66	0.05	1.00	0.05	1.00	0.05	15.09	155.4
Conv9	128	1152	0.81	0.05	1.00	0.05	1.00	0.05	34.26	155.4
Conv10	256	1152	0.70	0.05	1.00	0.05	1.00	0.05	11.25	294.32
Conv11	256	2304	0.82	0.05	1.00	0.05	1.00	0.05	10.09	294.32
Conv12	256	2304	0.84	0.05	1.00	0.05	1.00	0.05	12.4	294.32
Conv13	256	2304	0.82	0.05	1.00	0.05	1.00	0.05	42.29	294.32
Conv14	512	2304	0.70	0.05	1.00	0.05	1.00	0.05	4.8	565.75
Conv15	512	4608	0.81	0.05	1.00	0.05	1.00	0.05	8.93	565.75
Conv16	512	4608	0.86	0.05	1.00	0.05	1.00	0.05	3.92	565.75
Conv17	512	4608	0.85	0.05	1.00	0.05	1.00	0.05	1.47	565.75
Passing rate	-	-	100.0%		100.0%		100.0%		88.24%	

Table 59: Pytorch pre-trained ResNet34

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	147	0.35	0.05	1.00	0.05	1.00	0.05	3020.16	83.68
Conv2	64	576	0.54	0.05	1.00	0.05	1.00	0.05	76.24	83.68
Conv3	64	576	0.67	0.05	1.00	0.05	1.00	0.05	40.95	83.68

Conv4	64	576	0.67	0.05	1.00	0.05	1.00	0.05	26.53	83.68
Conv5	64	576	0.84	0.05	1.00	0.05	1.00	0.05	33.62	83.68
Conv6	64	576	0.84	0.05	1.00	0.05	1.00	0.05	14.46	83.68
Conv7	64	576	0.83	0.05	1.00	0.05	1.00	0.05	41.19	83.68
Conv8	128	576	0.83	0.05	1.00	0.05	1.00	0.05	13.86	155.4
Conv9	128	1152	0.81	0.05	1.00	0.05	1.00	0.05	86.4	155.4
Conv10	128	1152	0.66	0.05	1.00	0.05	1.00	0.05	20.55	155.4
Conv11	128	1152	0.85	0.05	1.00	0.05	1.00	0.05	36.72	155.4
Conv12	128	1152	0.54	0.05	1.00	0.05	1.00	0.05	9.64	155.4
Conv13	128	1152	0.84	0.05	1.00	0.05	1.00	0.05	18.48	155.4
Conv14	128	1152	0.69	0.05	1.00	0.05	1.00	0.05	11.52	155.4
Conv15	128	1152	0.85	0.05	1.00	0.05	1.00	0.05	39.51	155.4
Conv16	256	1152	0.83	0.05	1.00	0.05	1.00	0.05	9.06	294.32
Conv17	256	2304	0.81	0.05	1.00	0.05	1.00	0.05	13.99	294.32
Conv18	256	2304	0.81	0.05	1.00	0.05	1.00	0.05	15.44	294.32
Conv19	256	2304	0.64	0.05	1.00	0.05	1.00	0.05	17.56	294.32
Conv20	256	2304	0.68	0.05	1.00	0.05	1.00	0.05	7.88	294.32
Conv21	256	2304	0.69	0.05	1.00	0.05	1.00	0.05	29.32	294.32
Conv22	256	2304	0.87	0.05	1.00	0.05	1.00	0.05	7.87	294.32
Conv23	256	2304	0.87	0.05	1.00	0.05	1.00	0.05	45.76	294.32
Conv24	256	2304	0.86	0.05	1.00	0.05	1.00	0.05	6.93	294.32
Conv25	256	2304	0.84	0.05	1.00	0.05	1.00	0.05	36.02	294.32
Conv26	256	2304	0.89	0.05	1.00	0.05	1.00	0.05	6.78	294.32
Conv27	256	2304	0.89	0.05	1.00	0.05	1.00	0.05	22.54	294.32
Conv28	512	2304	0.83	0.05	1.00	0.05	1.00	0.05	2.31	565.75
Conv29	512	4608	0.86	0.05	1.00	0.05	1.00	0.05	2.42	565.75
Conv30	512	4608	0.85	0.05	1.00	0.05	1.00	0.05	4.27	565.75
Conv31	512	4608	0.86	0.05	1.00	0.05	1.00	0.05	6.3	565.75
Conv32	512	4608	0.88	0.05	1.00	0.05	1.00	0.05	1.64	565.75
Conv33	512	4608	0.87	0.05	1.00	0.05	1.00	0.05	1.24	565.75
Passing rate	-	-	100.0%		100.0%		100.0%		96.97%	

Table 60: Pytorch pre-trained ResNet50

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	**64**	**147**	0.43	0.05	1.00	0.05	1.00	0.05	1512.0	83.68
Conv2	**64**	**64**	0.47	0.05	1.00	0.05	1.00	0.05	512.72	83.68
Conv3	**64**	**576**	0.64	0.05	1.00	0.05	1.00	0.05	103.97	83.68
Conv4	**256**	**64**	0.69	0.05	1.00	0.05	1.00	0.05	786.24	294.32
Conv5	64	256	0.86	0.05	1.00	0.05	1.00	0.05	52.01	83.68
Conv6	64	576	0.60	0.05	1.00	0.05	1.00	0.05	31.52	83.68
Conv7	**256**	**64**	0.84	0.05	1.00	0.05	1.00	0.05	619.68	294.32
Conv8	64	256	0.89	0.05	1.00	0.05	1.00	0.05	14.19	83.68
Conv9	64	576	0.85	0.05	1.00	0.05	1.00	0.05	6.07	83.68
Conv10	**256**	**64**	0.85	0.05	1.00	0.05	1.00	0.05	789.85	294.32
Conv11	128	256	0.81	0.05	1.00	0.05	1.00	0.05	49.33	155.4
Conv12	128	1152	0.84	0.05	1.00	0.05	1.00	0.05	6.6	155.4
Conv13	**512**	**128**	0.70	0.05	1.00	0.05	1.00	0.05	1154.78	565.75
Conv14	128	512	0.86	0.05	1.00	0.05	1.00	0.05	20.26	155.4
Conv15	128	1152	0.84	0.05	1.00	0.05	1.00	0.05	59.31	155.4
Conv16	**512**	**128**	0.84	0.05	1.00	0.05	1.00	0.05	897.22	565.75
Conv17	128	512	0.87	0.05	1.00	0.05	1.00	0.05	14.87	155.4
Conv18	128	1152	0.86	0.05	1.00	0.05	1.00	0.05	10.56	155.4

Conv19	512	128	0.81	0.05	1.00	0.05	1.00	0.05	326.18	565.75
Conv20	128	512	0.85	0.05	1.00	0.05	1.00	0.05	5.57	155.4
Conv21	128	1152	0.88	0.05	1.00	0.05	1.00	0.05	7.15	155.4
Conv22	512	128	0.84	0.05	1.00	0.05	1.00	0.05	511.13	565.75
Conv23	256	512	0.82	0.05	1.00	0.05	1.00	0.05	32.44	294.32
Conv24	256	2304	0.89	0.05	1.00	0.05	1.00	0.05	8.35	294.32
Conv25	1024	256	0.83	0.05	1.00	0.05	1.00	0.05	608.91	1099.56
Conv26	256	1024	0.84	0.05	1.00	0.05	1.00	0.05	10.33	294.32
Conv27	256	2304	0.86	0.05	1.00	0.05	1.00	0.05	12.19	294.32
Conv28	1024	256	0.62	0.05	1.00	0.05	1.00	0.05	365.91	1099.56
Conv29	256	1024	0.85	0.05	1.00	0.05	1.00	0.05	6.6	294.32
Conv30	256	2304	0.89	0.05	1.00	0.05	1.00	0.05	7.69	294.32
Conv31	1024	256	0.81	0.05	1.00	0.05	1.00	0.05	306.61	1099.56
Conv32	256	1024	0.87	0.05	1.00	0.05	1.00	0.05	5.97	294.32
Conv33	256	2304	0.85	0.05	1.00	0.05	1.00	0.05	6.47	294.32
Conv34	1024	256	0.83	0.05	1.00	0.05	1.00	0.05	312.36	1099.56
Conv35	256	1024	0.85	0.05	1.00	0.05	1.00	0.05	5.81	294.32
Conv36	256	2304	0.89	0.05	1.00	0.05	1.00	0.05	5.38	294.32
Conv37	1024	256	0.83	0.05	1.00	0.05	1.00	0.05	330.13	1099.56
Conv38	256	1024	0.69	0.05	1.00	0.05	1.00	0.05	4.9	294.32
Conv39	256	2304	0.88	0.05	1.00	0.05	1.00	0.05	4.16	294.32
Conv40	1024	256	0.82	0.05	1.00	0.05	1.00	0.05	319.79	1099.56
Conv41	512	1024	0.82	0.05	1.00	0.05	1.00	0.05	6.42	565.75
Conv42	512	4608	0.69	0.05	1.00	0.05	1.00	0.05	1.38	565.75
Conv43	2048	512	0.81	0.05	1.00	0.05	1.00	0.05	97.84	2154.4
Conv44	512	2048	0.48	0.05	1.00	0.05	1.00	0.05	3.4	565.75
Conv45	512	4608	0.88	0.05	1.00	0.05	1.00	0.05	2.7	565.75
Conv46	2048	512	0.87	0.05	1.00	0.05	1.00	0.05	106.86	2154.4
Conv47	512	2048	0.65	0.05	1.00	0.05	1.00	0.05	4.34	565.75
Conv48	512	4608	0.92	0.05	1.00	0.05	1.00	0.05	0.65	565.75
Conv49	2048	512	0.85	0.05	1.00	0.05	1.00	0.05	139.29	2154.4
Passing rate	-	-	100.0%		100.0%		100.0%		83.67%	

P.10 LEARNING RATE

config:

`https://github.com/bearpaw/pytorch-classification`.

Table 61: Cifar10 VGG19 bn schedule(82-164)

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	27	0.22	0.05	0.66	0.05	0.66	0.05	313.52	83.68
Conv2	64	576	0.62	0.05	0.97	0.05	0.97	0.05	1.52	83.68
Conv3	128	576	0.82	0.05	1.00	0.05	1.00	0.05	1.88	155.4
Conv4	128	1152	0.89	0.05	1.00	0.05	1.00	0.05	0.31	155.4
Conv5	256	1152	0.88	0.05	1.00	0.05	1.00	0.05	0.5	294.32
Conv6	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.24	294.32
Conv7	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.22	294.32
Conv8	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.13	294.32
Conv9	512	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.6	565.75
Conv10	512	4608	0.92	0.05	1.00	0.05	1.00	0.05	0.4	565.75
Conv11	512	4608	0.89	0.05	1.00	0.05	1.00	0.05	0.53	565.75
Conv12	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.32	565.75

Conv13	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.19	565.75
Conv14	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.11	565.75
Conv15	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.08	565.75
Conv16	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.32	565.75
Passing rate	-	-	100.0%		100.0%		100.0%		93.75%	

Table 62: Cifar10 VGG19 bn schedule(60-120)

Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	27	0.23	0.05	0.66	0.05	0.66	0.05	292.85	83.68
Conv2	64	576	0.64	0.05	0.97	0.05	0.97	0.05	1.18	83.68
Conv3	128	576	0.85	0.05	1.00	0.05	1.00	0.05	2.03	155.4
Conv4	128	1152	0.88	0.05	1.00	0.05	1.00	0.05	0.34	155.4
Conv5	256	1152	0.85	0.05	1.00	0.05	1.00	0.05	0.54	294.32
Conv6	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.3	294.32
Conv7	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.23	294.32
Conv8	256	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.2	294.32
Conv9	512	2304	0.91	0.05	1.00	0.05	1.00	0.05	0.65	565.75
Conv10	512	4608	0.92	0.05	1.00	0.05	1.00	0.05	0.38	565.75
Conv11	512	4608	0.92	0.05	1.00	0.05	1.00	0.05	0.57	565.75
Conv12	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.34	565.75
Conv13	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.17	565.75
Conv14	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.11	565.75
Conv15	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.08	565.75
Conv16	512	4608	0.94	0.05	1.00	0.05	1.00	0.05	0.26	565.75
Passing rate	-	-	100.0%		100.0%		100.0%		93.75%	

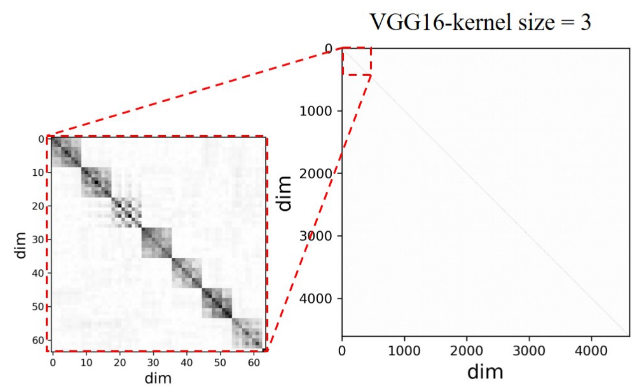
Table 63: Cifar10 VGG19 bn coslr

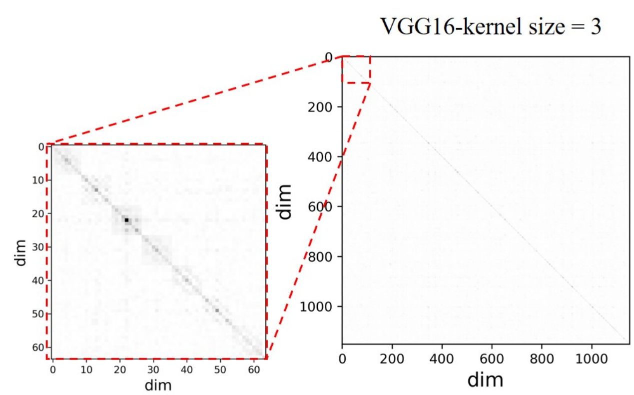
Layer	**Number**	**dim**	**Gaussian**		**Mean_Left**		**Mean_Right**		**Sigma**	
			p-value	**c-value**	**p-value**	**c-value**	**p-value**	**c-value**	**t-value**	**c-value**
Conv1	64	27	0.35	0.05	0.66	0.05	0.66	0.05	313.71	83.68
Conv2	64	576	0.65	0.05	0.97	0.05	0.97	0.05	1.31	83.68
Conv3	128	576	0.81	0.05	1.00	0.05	1.00	0.05	2.38	155.4
Conv4	128	1152	0.89	0.05	1.00	0.05	1.00	0.05	0.34	155.4
Conv5	256	1152	0.87	0.05	1.00	0.05	1.00	0.05	0.44	294.32
Conv6	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.3	294.32
Conv7	256	2304	0.90	0.05	1.00	0.05	1.00	0.05	0.22	294.32
Conv8	256	2304	0.85	0.05	1.00	0.05	1.00	0.05	0.1	294.32
Conv9	512	2304	0.89	0.05	1.00	0.05	1.00	0.05	0.74	565.75
Conv10	512	4608	0.91	0.05	1.00	0.05	1.00	0.05	0.34	565.75
Conv11	512	4608	0.92	0.05	1.00	0.05	1.00	0.05	0.54	565.75
Conv12	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.32	565.75
Conv13	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.2	565.75
Conv14	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.11	565.75
Conv15	512	4608	0.95	0.05	1.00	0.05	1.00	0.05	0.08	565.75
Conv16	512	4608	0.93	0.05	1.00	0.05	1.00	0.05	0.32	565.75
Passing rate	-	-	100.0%		100.0%		100.0%		93.75%	

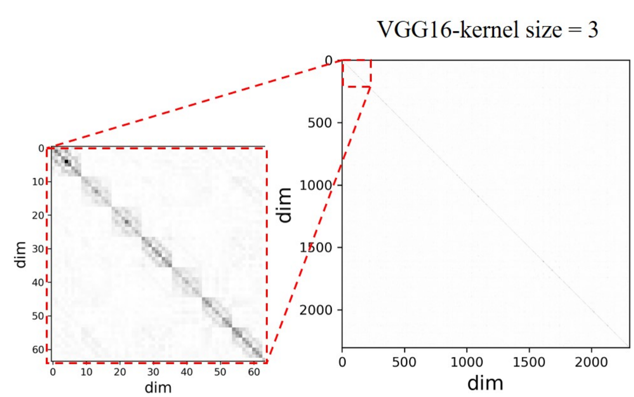
Q ADDITIONAL EXPERIMENTS FOR SECTION 2

In this section, we use more networks (Pytorch Pretrain Models[9] to verify the obersevations in Fig. 2 (a-d). We show the results of three layers for each network.

Q.1 VGG16

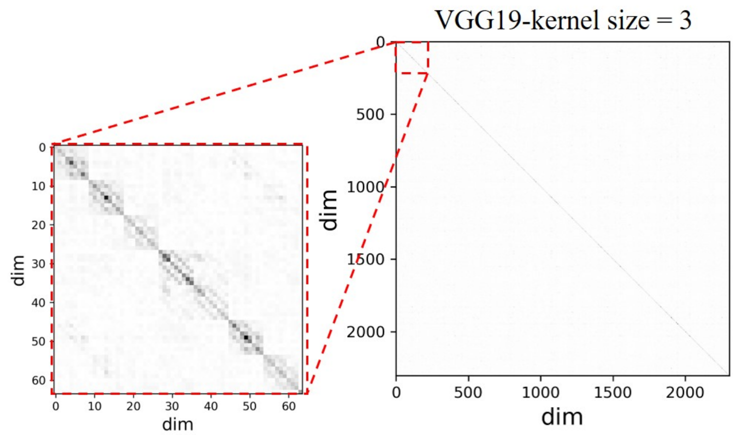


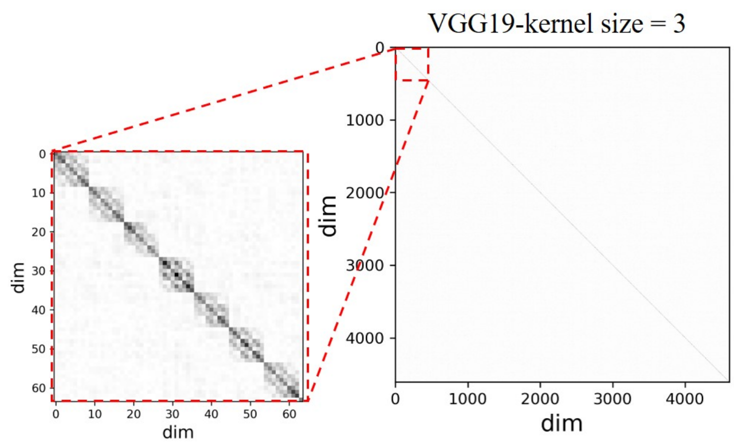


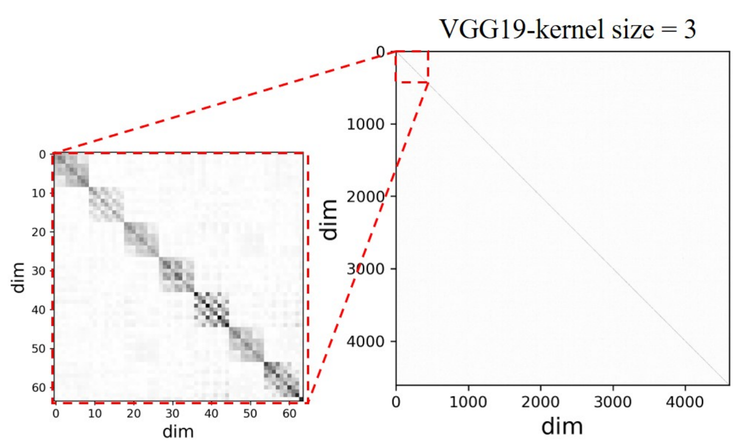


[9] https://pytorch.org/docs/stable/torchvision/models.html

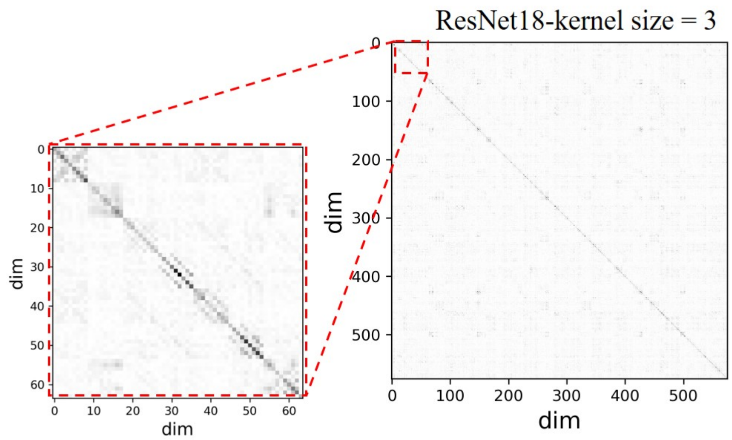
Q.2 VGG19

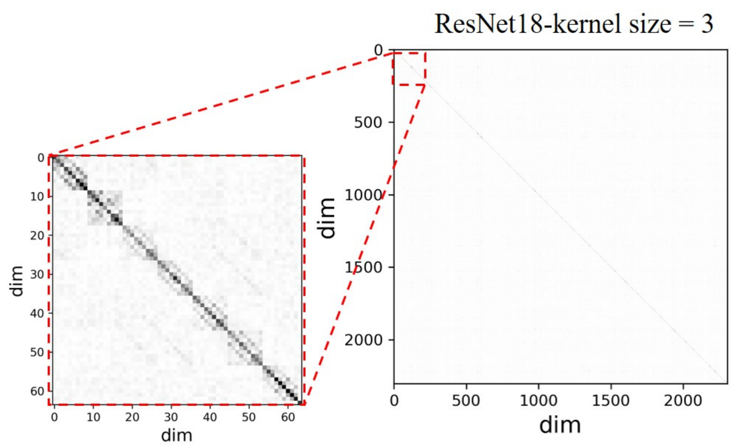

VGG19-kernel size = 3
dim
dim
dim
dim

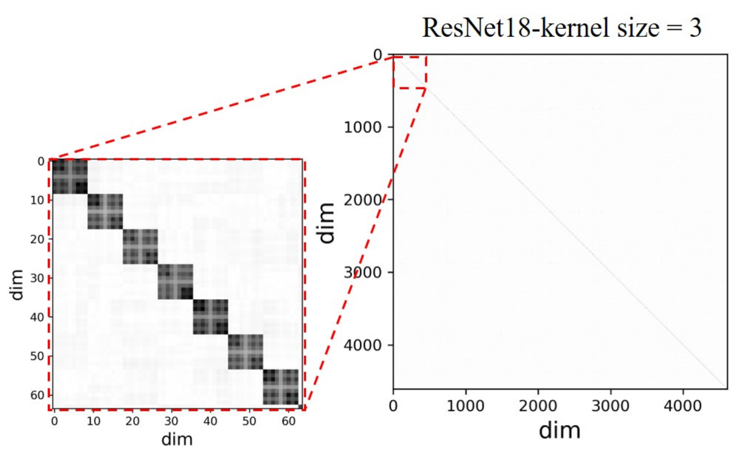

VGG19-kernel size = 3
dim
dim
dim
dim


VGG19-kernel size = 3
dim
dim
dim
dim

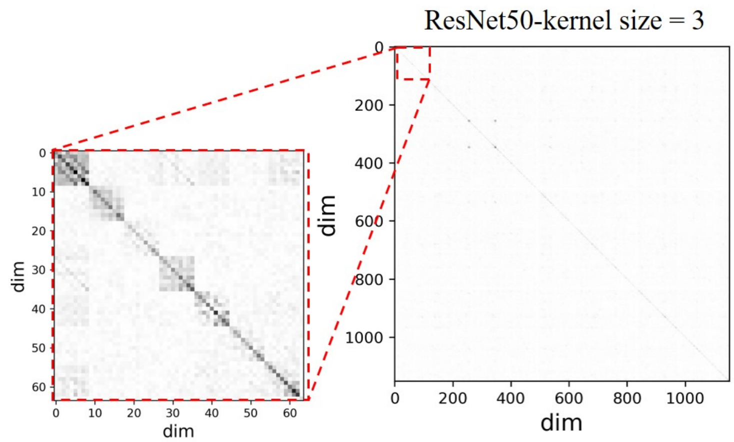
Q.3 ResNet18

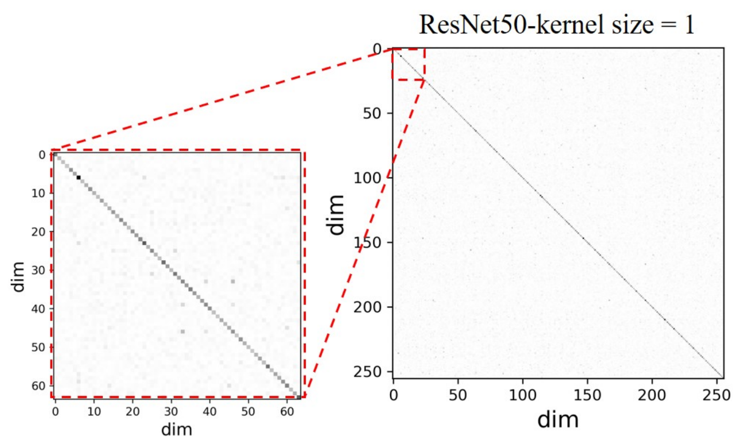

ResNet18-kernel size = 3
dim
dim
dim
dim

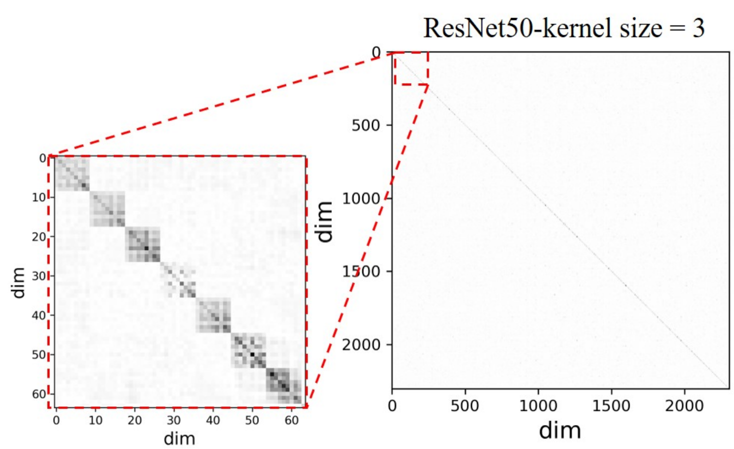

ResNet18-kernel size = 3
dim
dim
dim
dim


ResNet18-kernel size = 3
dim
dim
dim
dim

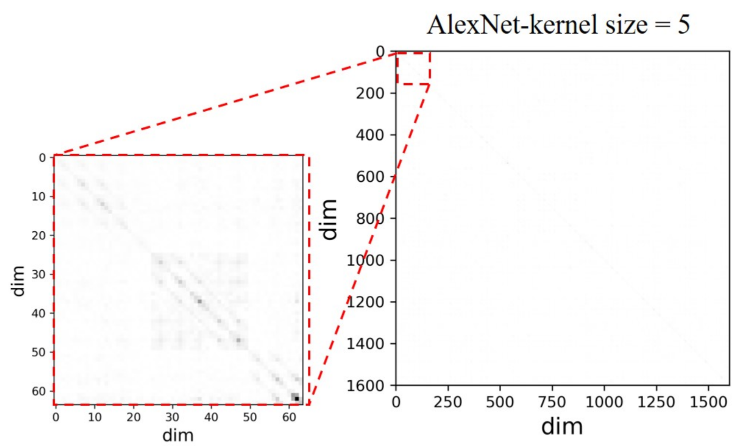
Q.4 RESNET50

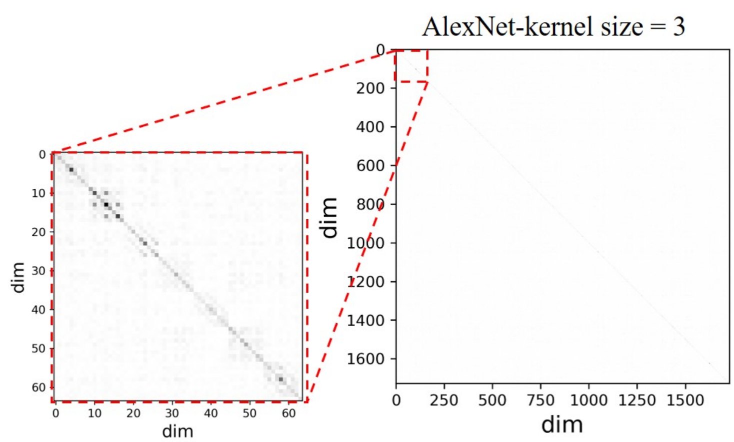

ResNet50-kernel size = 3
dim
dim
dim
dim

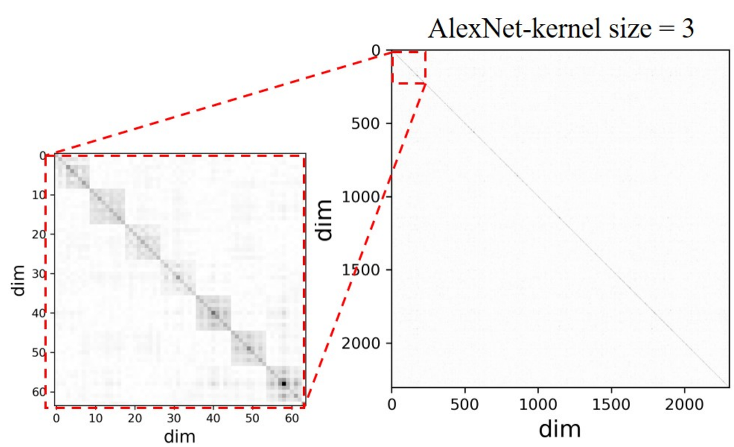

ResNet50-kernel size = 1
dim
dim
dim
dim


ResNet50-kernel size = 3
dim
dim
dim
dim

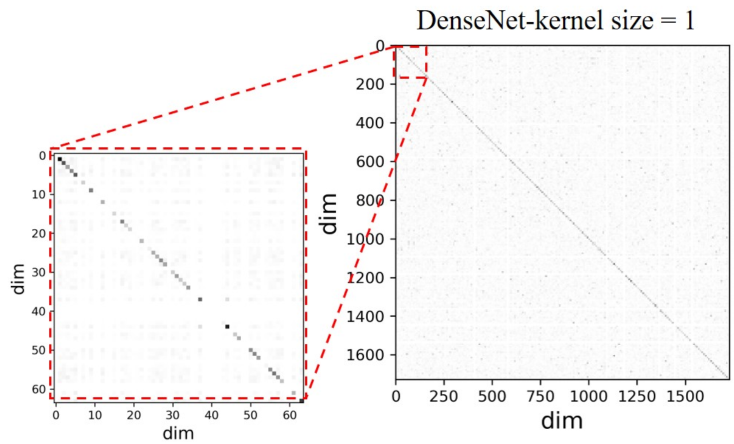
Q.5 AlexNet

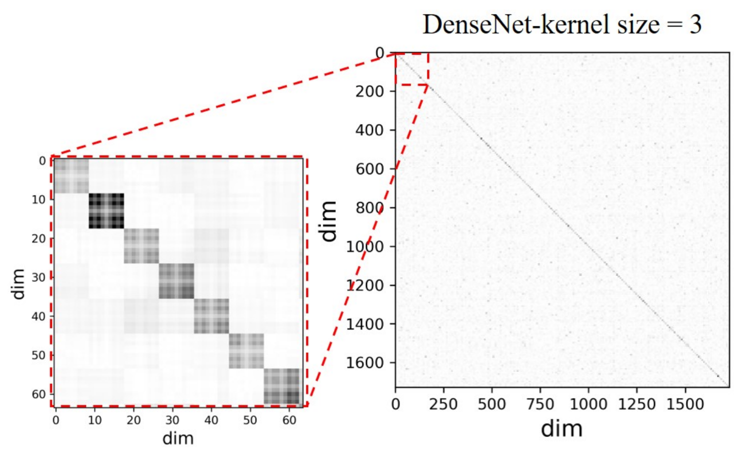

AlexNet-kernel size = 5
dim
dim
dim
dim

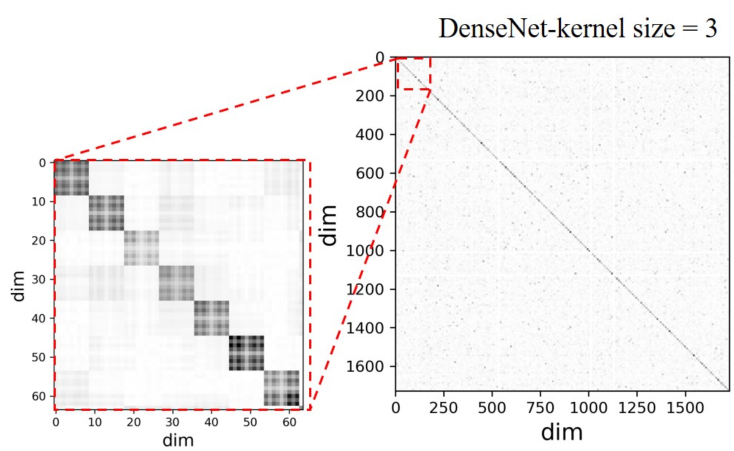

AlexNet-kernel size = 3
dim
dim
dim
dim


AlexNet-kernel size = 3
dim
dim
dim
dim

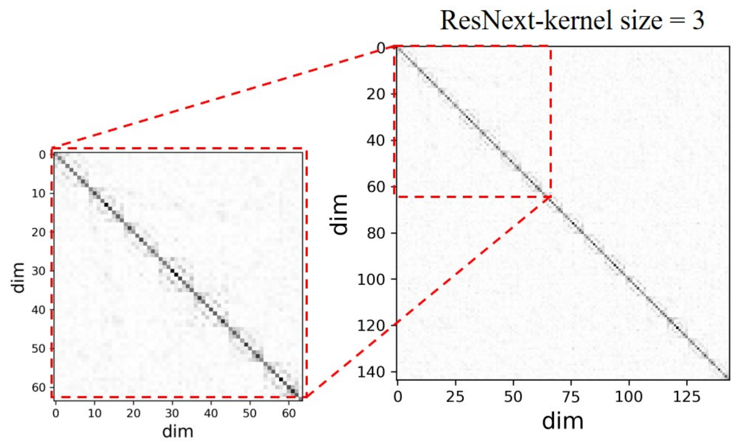
Q.6 DENSENET

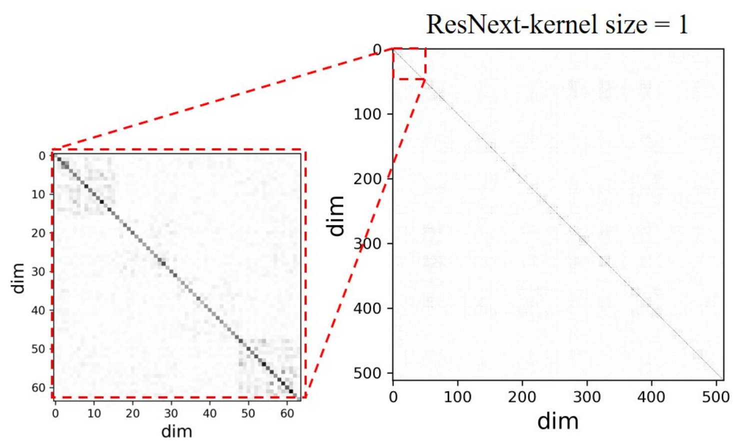

DenseNet-kernel size = 1
dim
dim
dim
dim

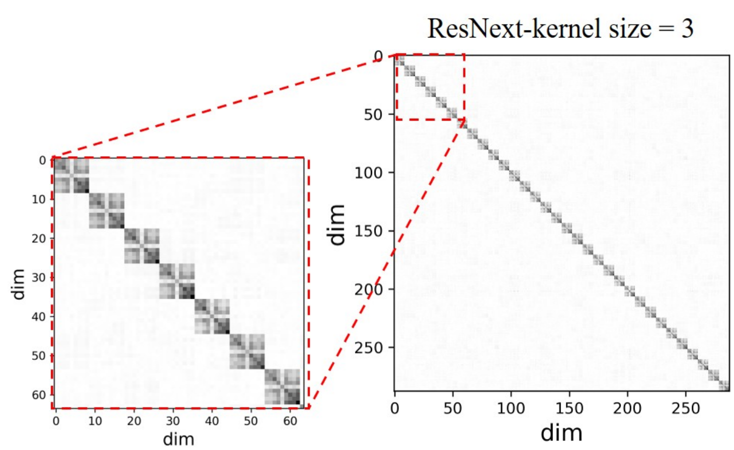

DenseNet-kernel size = 3
dim
dim
dim
dim


DenseNet-kernel size = 3
dim
dim
dim
dim

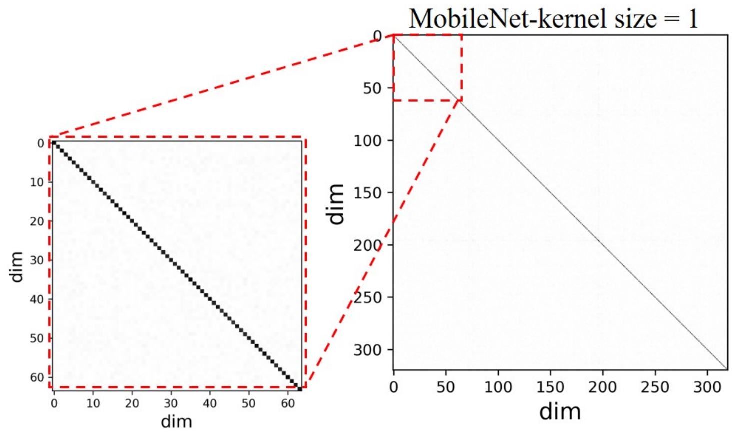
Q.7 RESNEXT

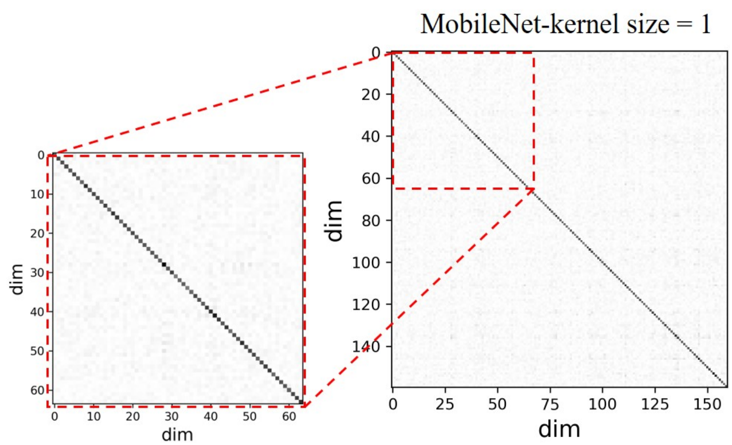

ResNext-kernel size = 3
dim
dim
dim
dim

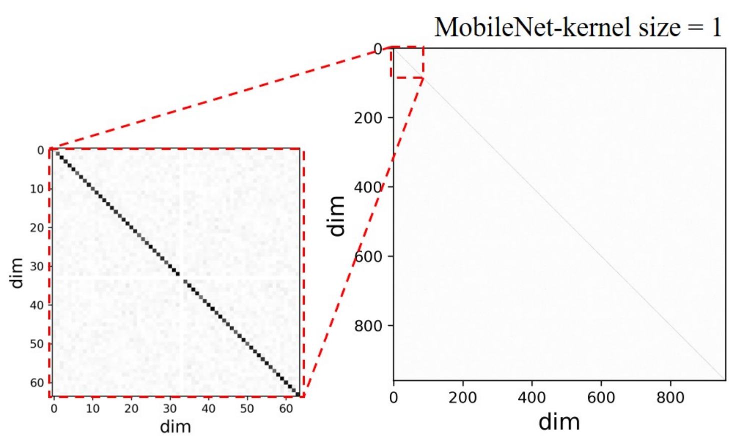

ResNext-kernel size = 1
dim
dim
dim
dim


ResNext-kernel size = 3
dim
dim
dim
dim

Q.8 MOBILENET







R Details of Experiments

Table 64: Implementation detail for Table 6.

Model	**Dataset**	**Batch size**	**Epoch**	**Optimizer**	**schedule**	**wd**	**gamma**
VGG16	CIFAR10	128	180	SGD(0.9)	82/164	1.00E-04	0.1
VGG16	CIFAR100	128	180	SGD(0.9)	82/164	1.00E-04	0.1
VGG16	ImageNet	256	120	SGD(0.9)	30/60/90	1.00E-04	0.1
ResNet56	CIFAR10	128	180	SGD(0.9)	82/164	1.00E-04	0.1
ResNet56	CIFAR100	128	180	SGD(0.9)	82/164	1.00E-04	0.1
ResNet34	ImageNet	256	120	SGD(0.9)	30/60/90	1.00E-04	0.1

Batch size	train batchsize
Epoch	number of total epochs to run
Optimizer	Optimizer
schedule	Decrease learning rate at these epochs
wd	weight decay
gamma	learning rate is multiplied by gamma on schedule

There are several additional experiments of Fig. 5 in following figures. They show the Spearman's rank correlation coefficient (Sp) among ℓ_1 pruning, ℓ_2 pruning and $\mathbf{GM}$ pruning for all the experiments in Table 3. These experiments further visualized the strong similarities of these pruning methods in different situations.

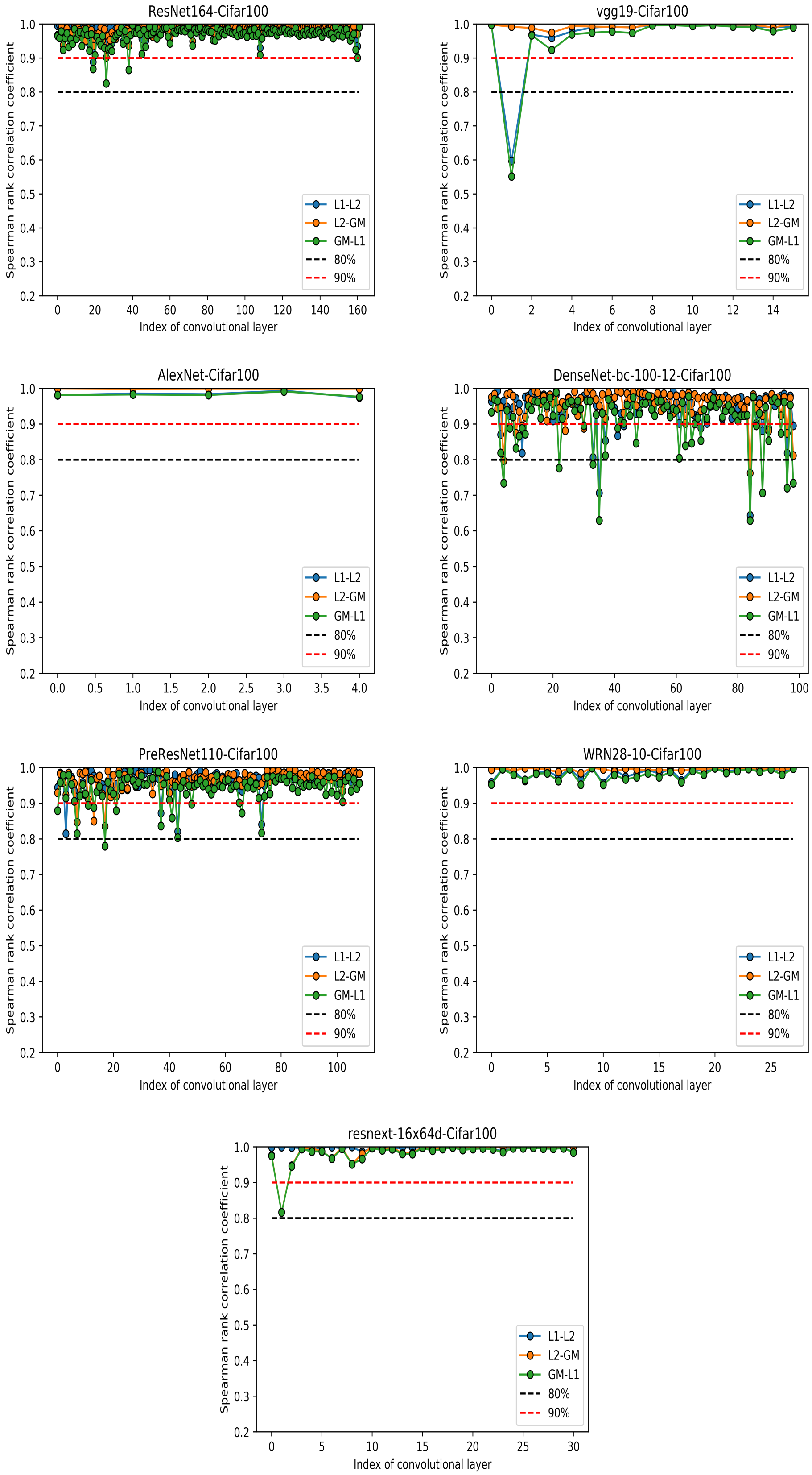


Figure 27: Network Structure

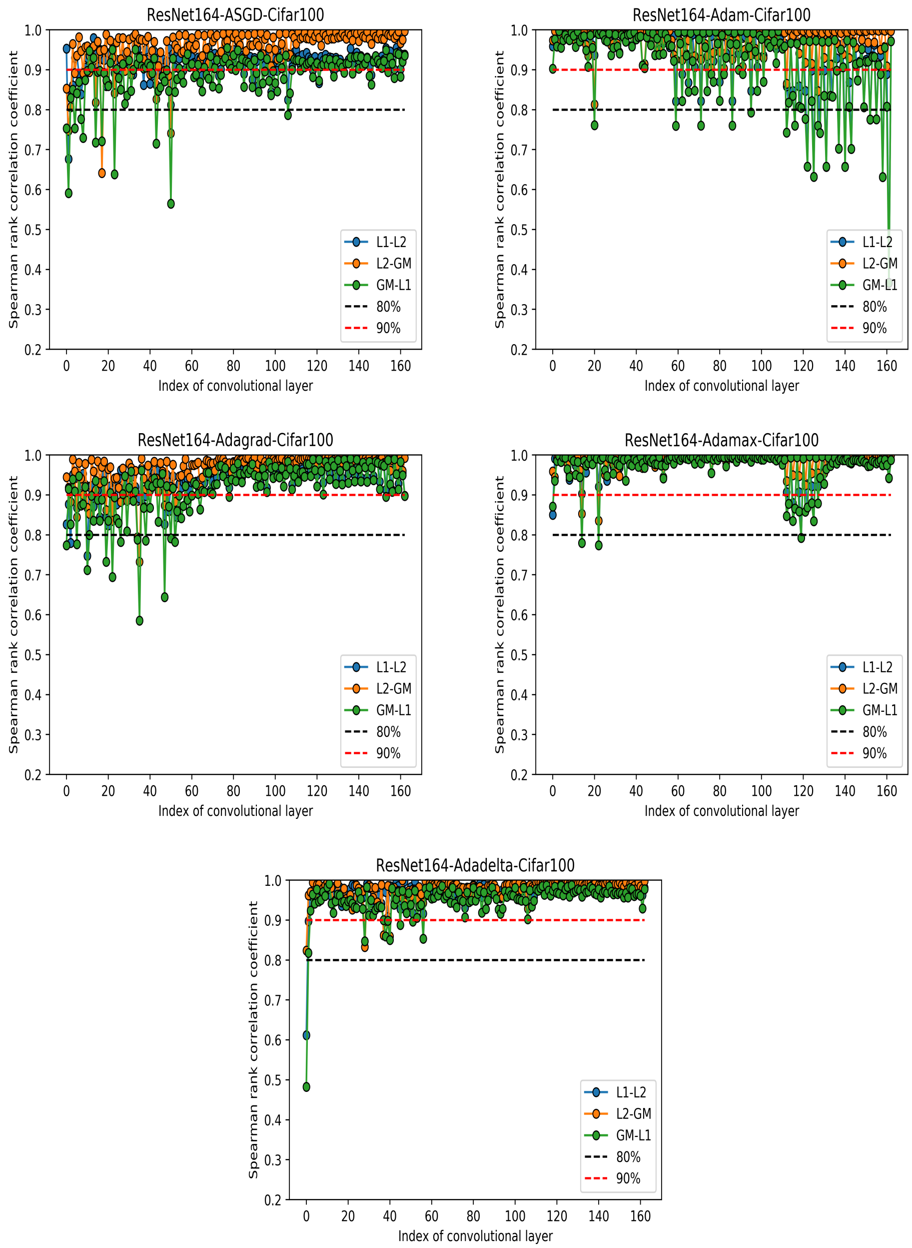


Figure 28: Optimizer

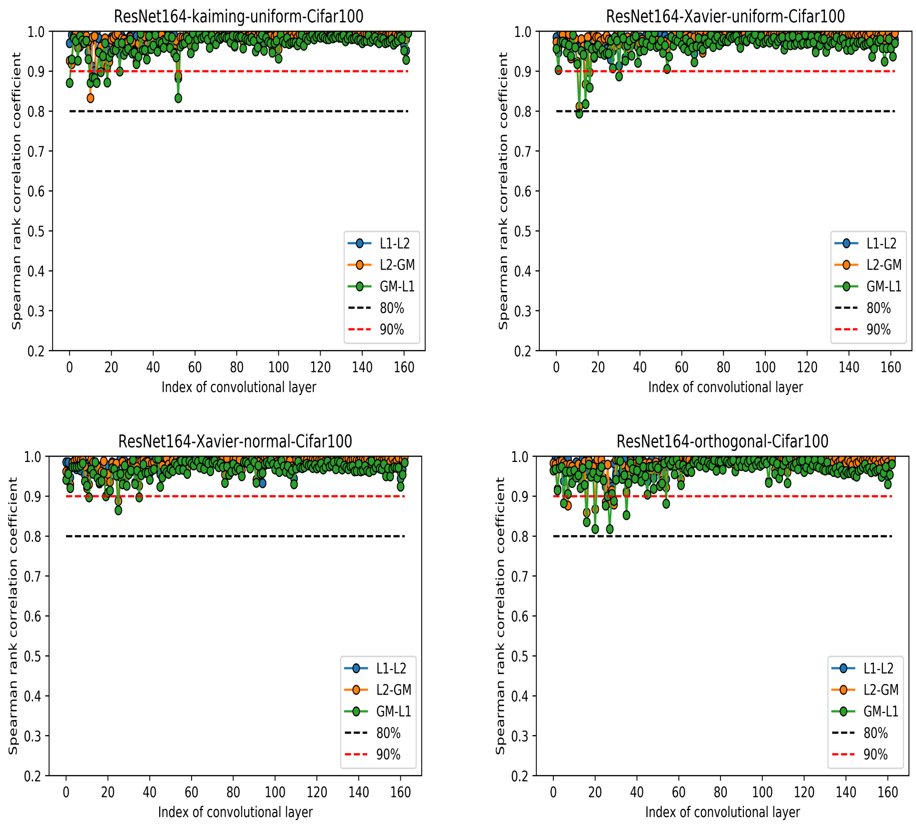


Figure 29: Initialization

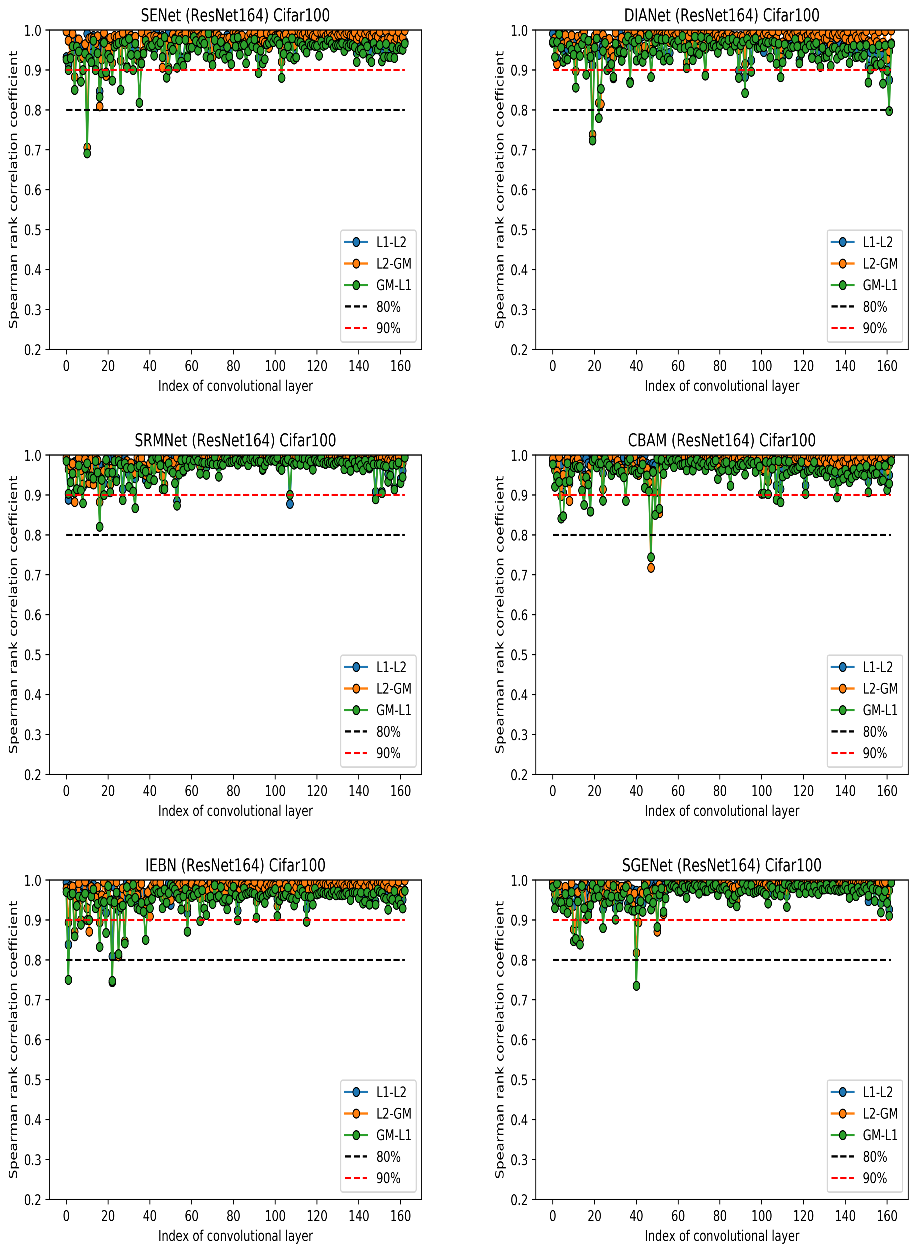


Figure 30: Attention mechanism

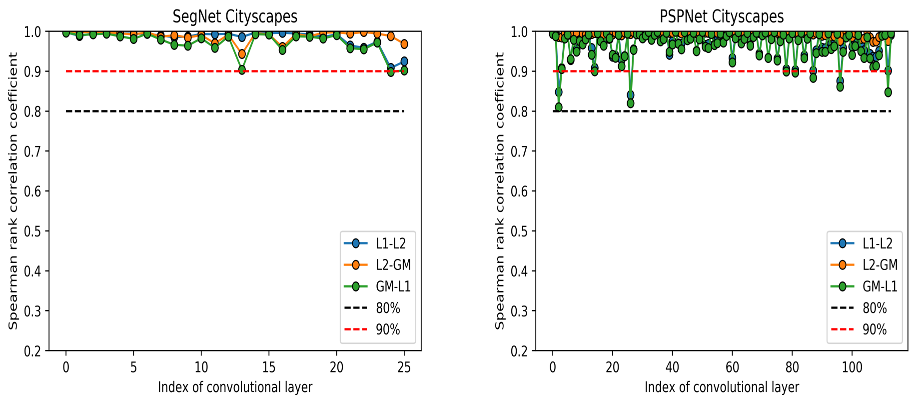


Figure 31: Other task: segmentation

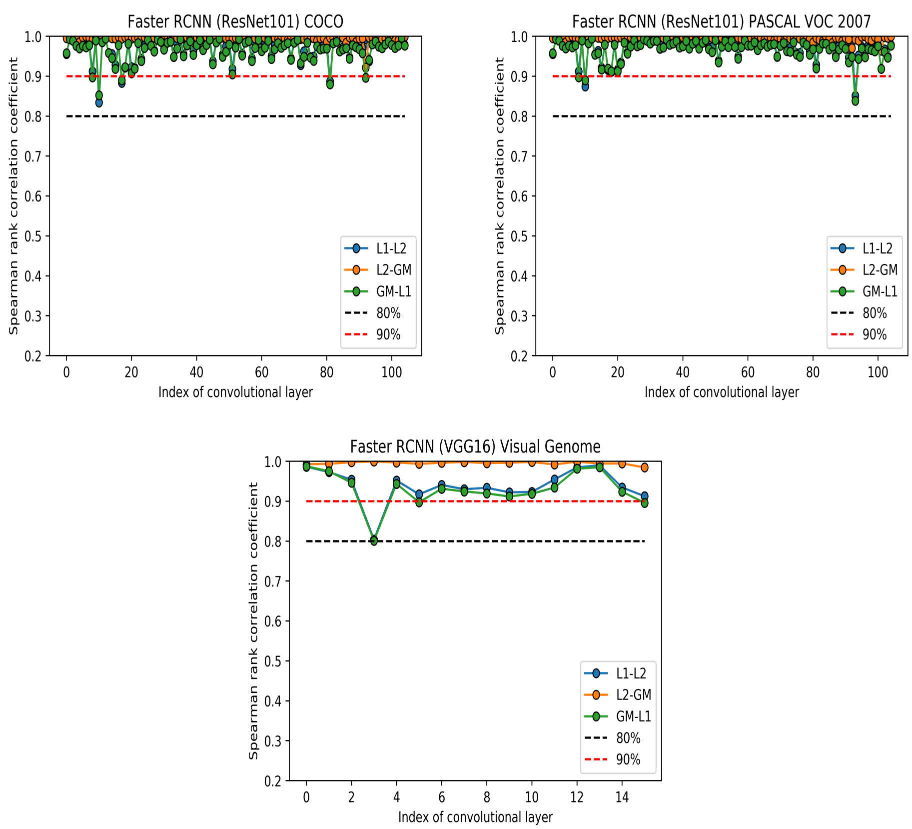


Figure 32: Other task: Faster RCNN

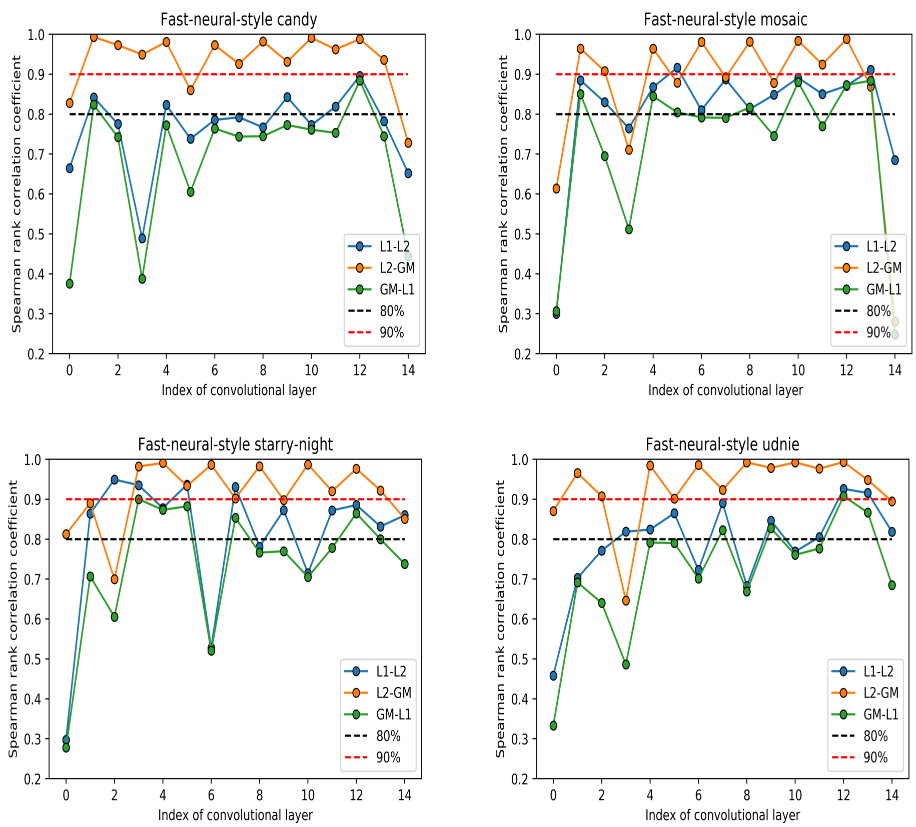


Figure 33: Other task: style transfer

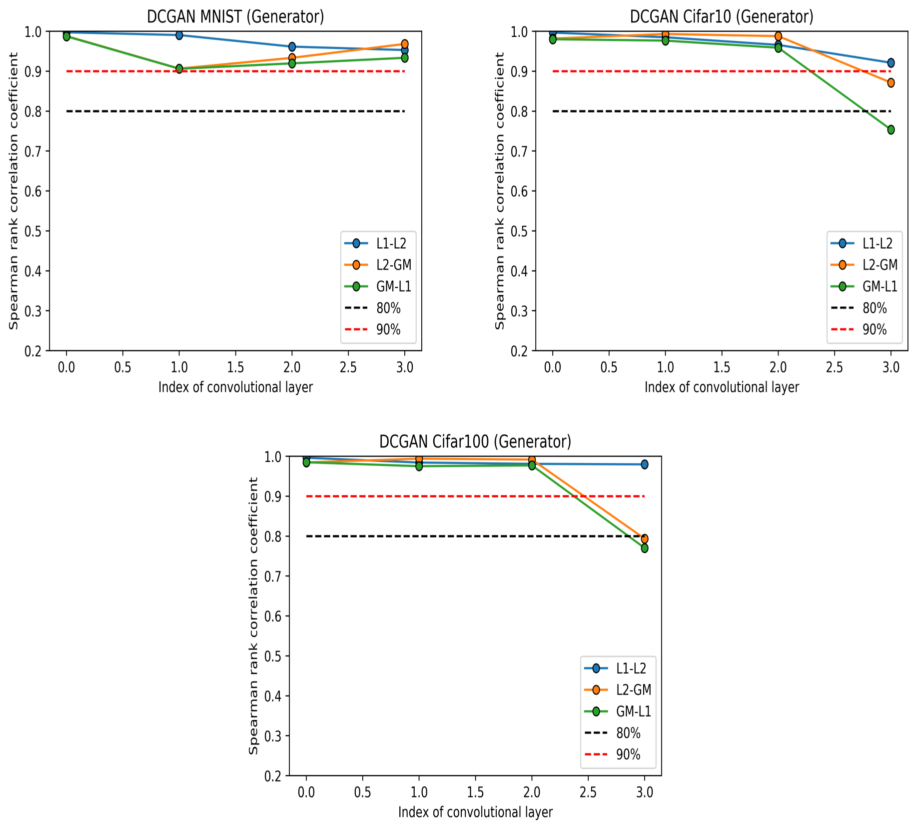


Figure 34: Other task: GAN

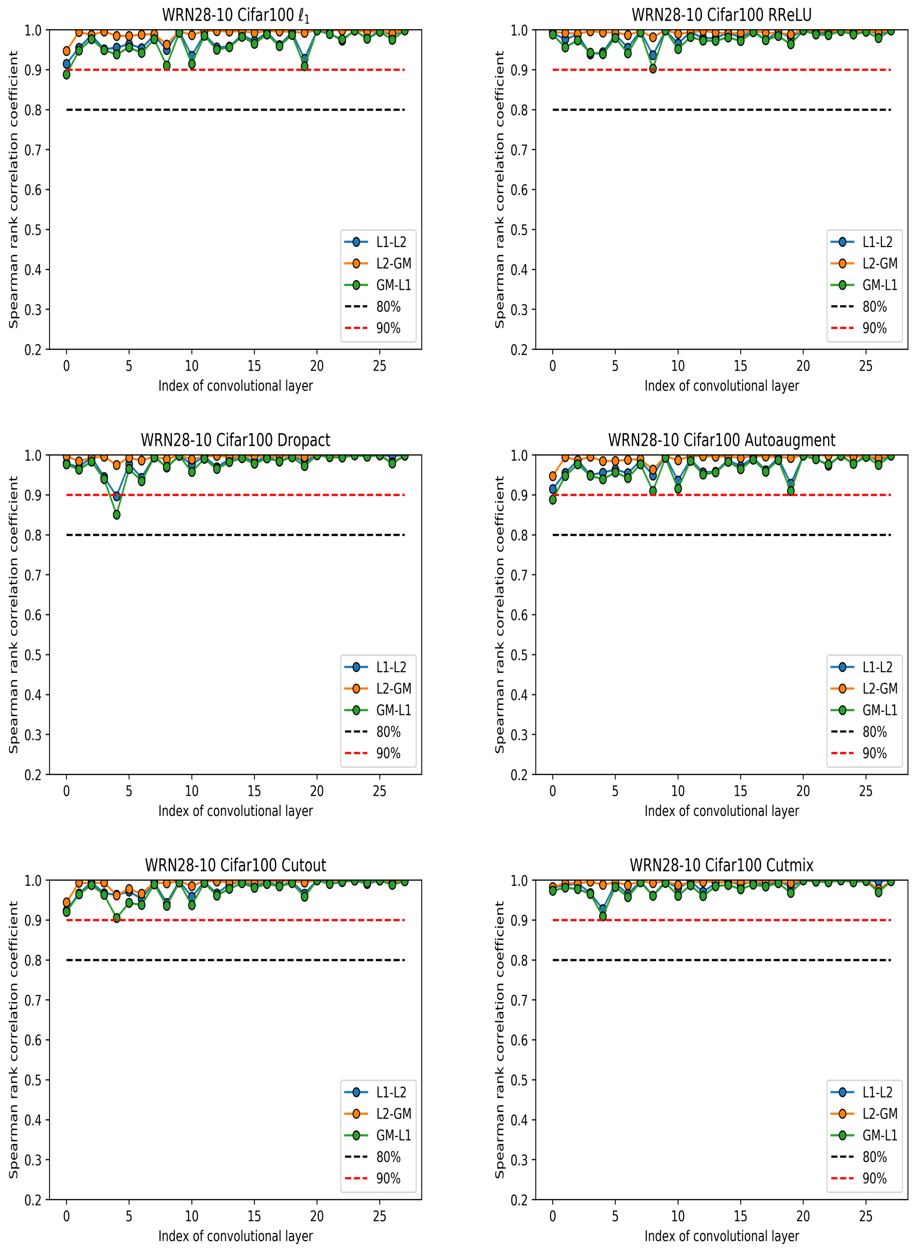


Figure 35: Other task: Regularization

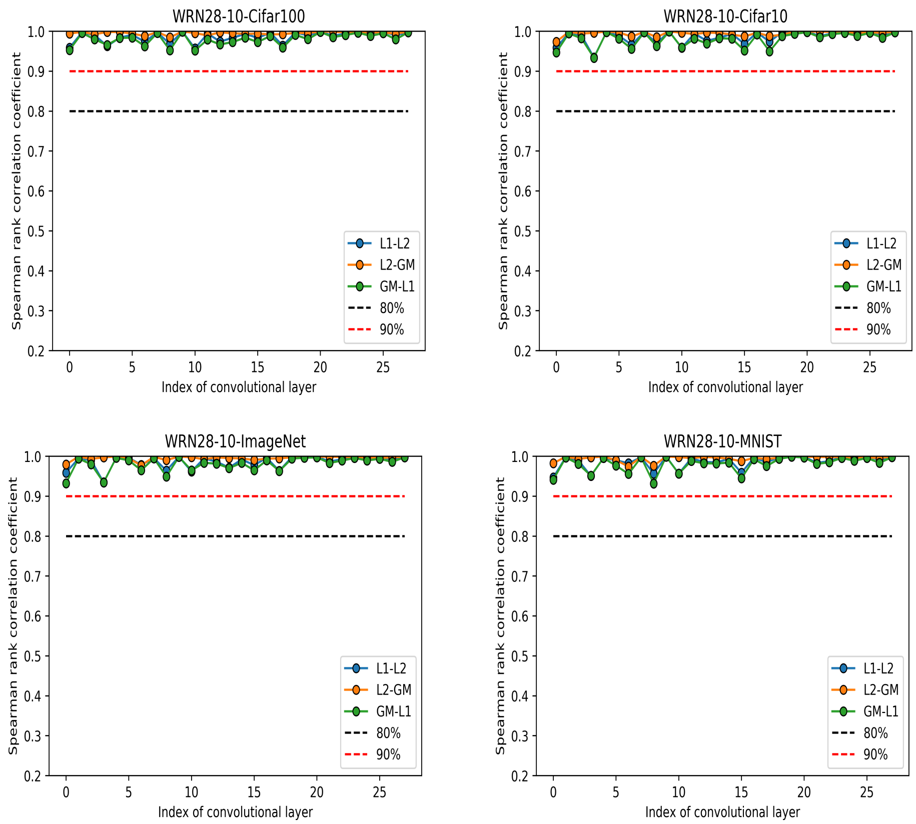


Figure 36: Dataset

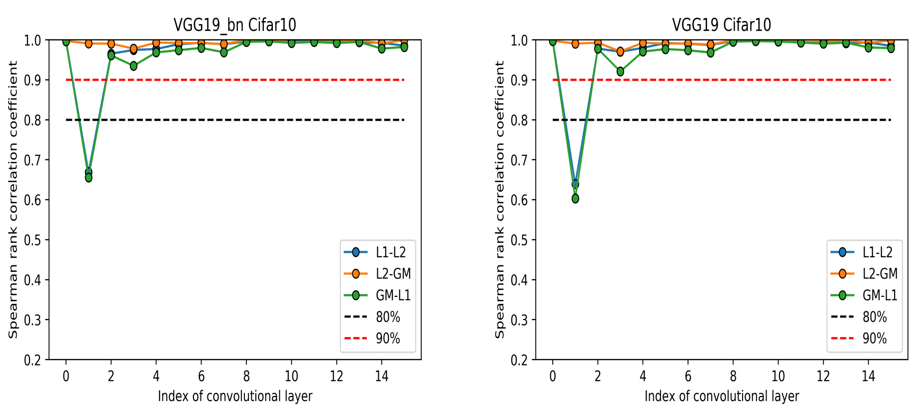


Figure 37: Batch normalization

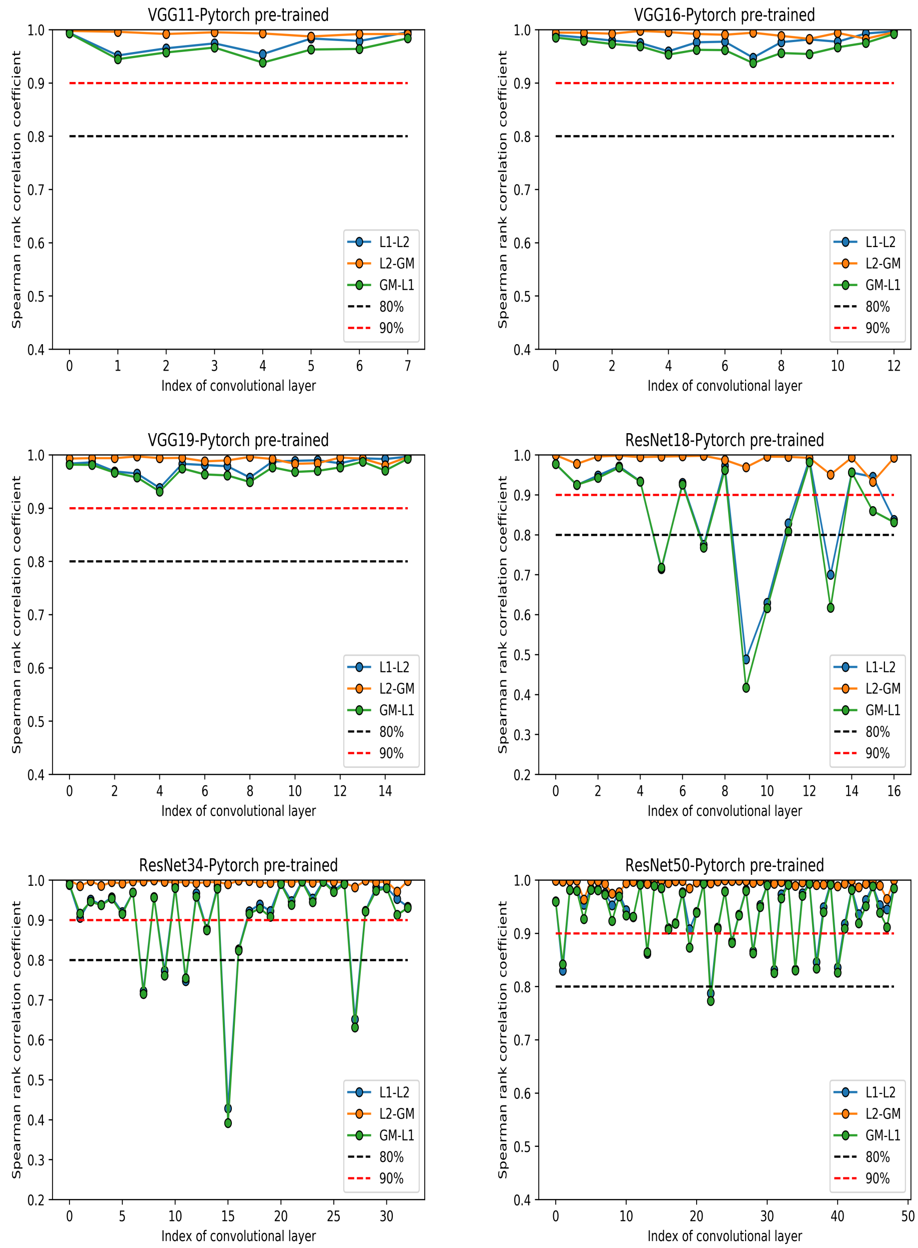


Figure 38: Pytorch pre-trained Model

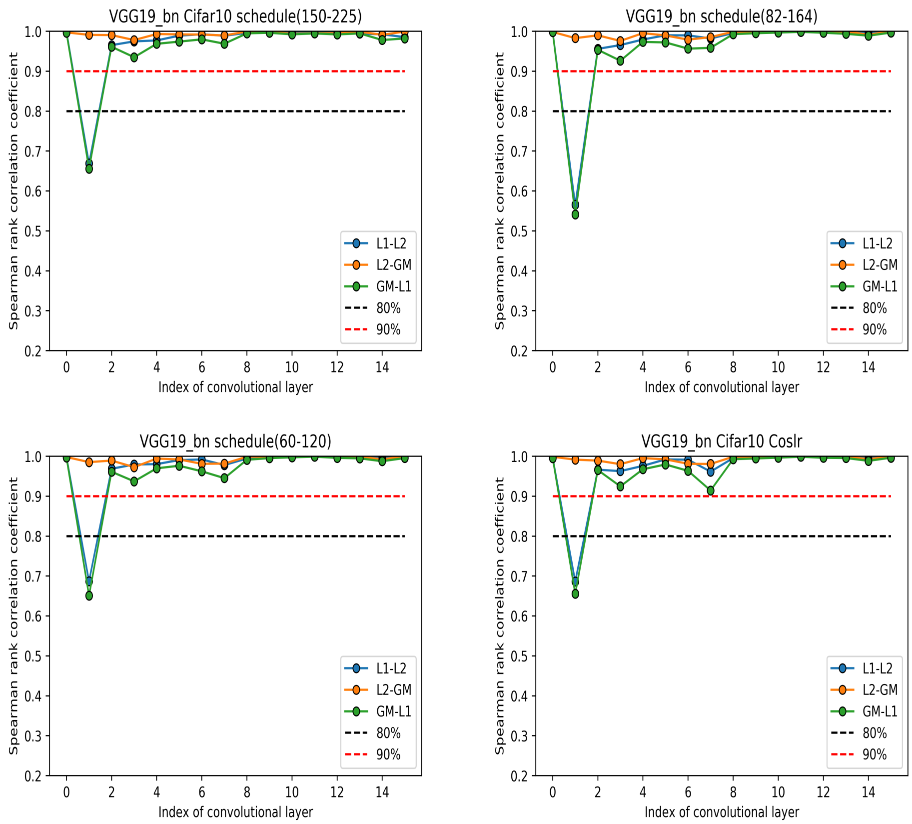


Figure 39: Learning rate