RETHINKING THE PRUNING CRITERIA FOR CONVOLUTIONAL NEURAL NETWORK

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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. The ranks of filters' *importance* in a convolutional layer according to these criteria are almost the same, resulting in similar pruned structures. (2) Applicability: For a large network (each convolutional layer has a large number of filters), these 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 (Han et al., 2015; Li et al., 2016; He et al., 2019) a trained neural network is commonly seen in network compression. In particular, for neural networks with convolutional filters, channel pruning (Liu et al., 2019; Ding et al., 2019a; Frankle & Carbin, 2019) refers to the pruning of the filters in the convolutional layers. Specifically, let $F_{i,j} \in \mathbb{R}^{N_i \times k \times k}$ represent 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. There are many pruning methods following three standard procedures, called one-shot pruning: (**Train**) Train a network from scratch; (**Prune**) Use a certain criterion to calculate filters' *importance*, and prune the filters which have small *importance*; (**Fine-tune**) After additional training, the pruned network can recover its accuracy to some extent. Similarly, there is iterative pruning (He et al., 2018; Frankle & Carbin, 2019; Renda et al., 2020), which uses **Prune** and **Fine-tune** alternately. In this paper, in order to focus on the pruning criteria, the relatively simple one-shot pruning (layer-wise) is used in all pruning experiments. 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 convolutional 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). These two pruning criteria are called *norm-based pruning* as they include norm in their design. Through the study of the distribution of norm, He et al. (2019) demonstrates that the *norm-based pruning* should satisfy two conditions: (1) the variance of the norm of the filters cannot be too small; (2) the minimum norm of

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]
GM	ResNet18	[111, 212, 33, 61, 68, 45, 171, 42]	VGG16	[102, 28, 9, 88, 109, 66, 45, 86]
Fermat	ResNet18	[111, 212, 33, 61, 45, 171, 42, 68]	VGG16	[102, 28, 88, 9, 109, 66, 45, 86]

the filters should be small enough. However, these two conditions do not always hold. Given this situation, a new criterion considering the relative *importance* of the filter (the *norm-based pruning* method 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 in Euclidean space (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. The details of these criteria are shown in Table 2. $\mathbf{F}$ denotes the Fermat point of F_{ij} in Euclidean space.

Table 2: Some channel 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 work (Liu et al., 2017; Han et al., 2015; Ding et al., 2019b; Aghasi et al., 2017; 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, etc. But, there is little work to discuss two blind spots about the pruning criteria as follow:

(1) Similarity: What are actually the differences among these previous pruning criteria? Using VGG16 and ResNet18 on ImageNet dataset, we show the ranks of filters' *importance* under different criteria in Table 1. It's easy to find that they have almost the same sequence which will lead to the 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's the applicability of these pruning criteria to prune the CNNs? There is a toy example. 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. But if the norm are similar, like 0.91, 0.92, 0.93, 0.92, it's 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 example, this's a real problem for pruning a network. This problem actually has been mentioned in He et al. (2019), and we will analyze it further 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 weights of the convolutional filters, called *Convolution Weight Distribution Assumption* (CWDA), with systematic and comprehensive statistical tests (about 80 pages in Appendix J) in Section 2. Next, in Section 3, under the CWDA, the similarities of these criteria is theoretically proved. At the same time, more experiments are provided to verify these similarities. The problem about the applicability of pruning criteria is discussed in Section 4. Last but not least, in Section 5, we discuss the conditions for CWDA to be satisfied.

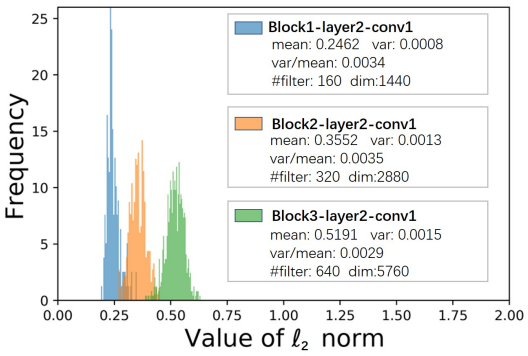


Figure 1: The distribution of ℓ_2 norm (WRN)

Contribution.

(1) We find the strong similarities among some primary pruning criteria for convolutional neural network, which are widely cited and compared.

(2) We propose a geometric structure of convolutional filters in weight space when the network exists too many filters. Using this structure, we prove that, for a large network (each convolutional layer has a large number of filters), these criteria can not distinguish the network redundancy well from their measured filters' *importance*.

(3) We propose and verify an assumption CWDA, which reveals that the well-trained convolutional filters approximately follow a Gaussian-alike distribution. The similaries of these criteria can be theoretically proved by CWDA and it also can be used to discuss the applicability of these pruning criteria.

2 WEIGHT DISTRIBUTION-ASSUMPTION

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

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

$$F_{ij} \sim \mathbf{N}(\mathbf{0}, c^2 \cdot \mathbf{I}_{N_i \times k \times k}), \tag{1}$$

where c is a constant and $\mathbf{I}_{N_i \times k \times k}$ is an identity matrix.

2.1 STATISTICAL TEST

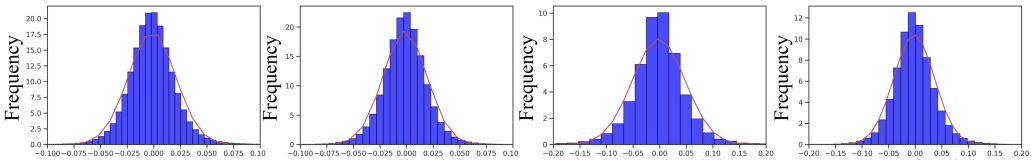
In fact, CWDA is not easy to be verified. For example, for ResNet164 (On Cifar100), the number of filters in the first stage is only 16, which is too small to be used to estimate statistics accurately. More other objective reasons are shown in Section 5.1 . In response to these problems, we consider to verify three **necessary conditions** of CWDA,

(1) **Gaussian**. (i.e., in order to verify if F_{ij} approximately 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 $N(0, c^2)$.

(2) **Standard Deviation**. (i.e., to verify if the standard deviation of each filter in any layers is close to 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.

(3) **Mean**. (i.e., to verify if 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 $\mu \leq \epsilon \cdot S$ and $\mu \geq -\epsilon \cdot S$, where ϵ is a small constant and S is sample variance.

In Table 3, we list a series of experiments to verify CWDA with different setting. Moreover, we show that the CWDA holds universally and the details of these statistical tests are shown in Appendix J. In Fig. 2, taking VGG16 and ResNet18 on ImageNet dataset as examples, we visualize the CWDA through the distribution of the convolutional filters.



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

Figure 2: Visualization of the distribution of convolutional filters. The parameters of a convolutional filter approximately follow a Gaussian-alike distribution.

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, in section 3.1, we used more experiments about image classification to investigate the similarities. From a theoretical perspective, in Section 3.2, we strictly prove the similarities of the criteria in Table 2 by CWDA.

[1](1) In Table 3, we perform a lot of experiments on various situations; (2) In Section 5, we make further discussion and analysis on the conditions for CWDA to be satisfied.

Table 3: The experiments for having the comprehensive statistical tests on CWDA. We show that the CWDA holds universally and the details of these statistical tests are shown in each description of the experiment in Appendix J.

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

3.1 EXPERIMENT

Using different networks, datasets, we provide additional image classification experiments, which are repeated three times for each criterion. Moreover, we examine the similarities among the criteria in Table 2 from two kinds of perspectives: **(1)** In Table 4, the classification accuracies (acc.) are similar to each other from different criteria in each group of experiments at the Pruned and Fine-tuned stage. This phenomenon implies to a certain extent that those pruned network from different pruning criteria are very similar and there are strong similarities among these pruning criteria. **(2)** In Fig. 3, we show the Spearman's rank correlation coefficient (Sp)[2] between different pruning criteria. The Sp in most convolutional layers is more than 0.9, which means the network structures after pruning are almost the same. Note that the Sp in transitional area (i.e., the layer where the dimensions of the filter change, as the layer between stage 1 and stage 2 of ResNet164. The number of channels in stage 1 and stage 2 are 16 and 32 respectively.) are relatively small. It's interesting but will not have a great impact on the structural similarity of the whole network pruned. The reason for this phenomenon may be that the layers in these areas are sensitive. The similar observations are shown in Figure.2 in Ding et al. (2019b) and Figure.6 and Figure.10 in Li et al. (2016).

3.2 THEORETICAL ANALYSIS

After the verification by experiments, the similarities among the pruning 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 can make 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. 3.1, 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 $\mathbf{Y} = (y_1, y_2, ..., y_k)$ are 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

[2]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.

Table 4: 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

that, if both $\mathbf{Var}(\widehat{\mathbf{X}}/\widehat{\mathbf{Y}})$ and $\mathbf{Var}(\widehat{\mathbf{Y}}/\widehat{\mathbf{X}})$ are small enough, then we have the Sp between $\mathbf{X}$ and $\mathbf{Y}$ is close to 1, where $\widehat{\mathbf{X}}/\widehat{\mathbf{Y}} = (\widehat{x_1}/\widehat{y_1}, .., \widehat{x_k}/\widehat{y_k})$. Because, 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 $\widehat{y_i} \approx b \cdot \widehat{x_i}$ and we have $ab \approx 1$ and $a, b \neq 0$. So there exists an *approximately monotonic* mapping from $\widehat{y_i}$ to $\widehat{x_i}$ and it makes the Sp between $\mathbf{X}$ and $\mathbf{Y}$ is close to 1. 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 $v_j \sim N(0, c^2 \cdot \mathbf{I})$).

(1) For $\ell_2 \cong \ell_1$. In fact, $\ell_2 \cong \ell_1$ (their ranks of *importance* are similar) is not trivial. Generally speaking, for CNNs, $\mathbf{dim}(v_j)$ is large enough. Since v_i satisfies CWDA, from Theorem 1, 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.10 of Appendix E).

Theorem 1. *Let $X \sim N(\mathbf{0}, c^2 \cdot \mathbf{I}_n)$, we have*

$$\mathbf{max}\left\{\mathbf{Var}_X\left(\frac{\widehat{\ell_2}(X)}{\widehat{\ell_1}(X)}\right), \mathbf{Var}_X\left(\frac{\widehat{\ell_1}(X)}{\widehat{\ell_2}(X)}\right)\right\} \lesssim \frac{1}{n}. \tag{2}$$

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 E). □

(2) For $\ell_2 \cong \mathbf{Fermat}$. Since v_i satisfies CWDA, from Theorem 2, 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, we have $\ell_2 \cong \mathbf{Fermat}$. Moreover, since CWDA, the centroid of v_i is $\mathbf{G} = \frac{1}{n}\sum_{i=1}^{N} v_i = \mathbf{0}$. Hence,

$$\mathbf{G} = \mathbf{0} \approx \mathbf{Fermat}. \tag{3}$$

Theorem 2. *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 F). □

(3) For $\mathbf{GM} \cong \mathbf{Fermat}$. First, two theorems are shown:

Theorem 3. *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:*

$$\mathbf{Var}_{a_i}\frac{F_1(a_i)}{F_2(a_i)} \approx \frac{1}{2nk}, \quad \mathbf{Var}_{a_i}\frac{F_2(a_i)}{F_1(a_i)} \approx \frac{1}{2nk}, \tag{4}$$

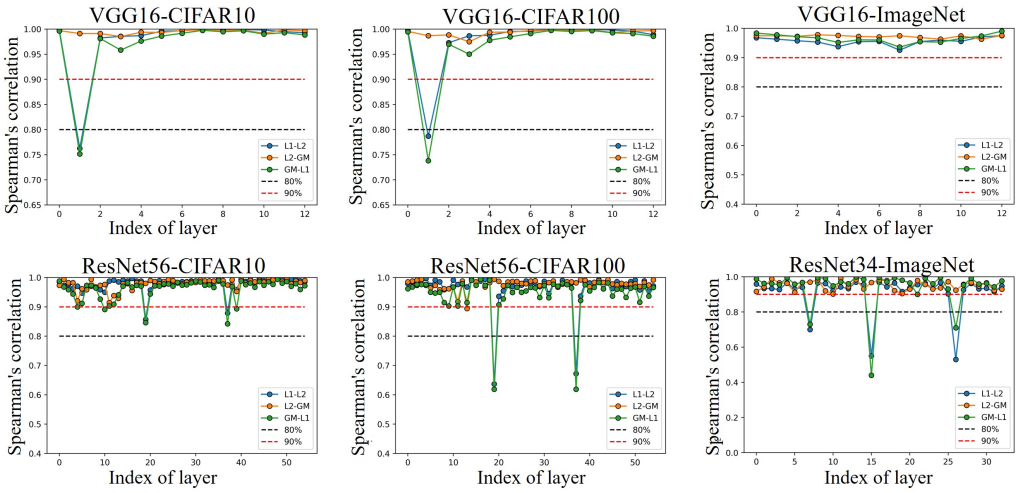


Figure 3: Spearman's rank correlation coefficient (Sp) between different pruning criteria on several networks and datasets (more experiments can be found in Appendix K). Each curve is the mean obtained by three experiments in Table 4.

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 G). □

Theorem 4. *Let* $v_0, v_1, ..., v_k$ *be the* $k+1$ *vectors in* n *dimensional Euclidean space* $\mathbb{E}^n$. *For all* P *in* $\mathbb{E}^n$,

$$\sum_{i=0}^{k} ||P - v_i||_2^2 = \sum_{i=0}^{k} ||G - v_i||_2^2 + (k+1)||P - G||_2^2, \tag{5}$$

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.(5) holds with probability 1.*

Proof. (See Appendix H). □

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 3.2 (1) and Theorem 3, we have

$$\sum_{i=1}^{n} ||a_i||_2 \cong \sum_{i=1}^{n} ||a_i||_2^2, \tag{6}$$

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 $P \in \{v_1, v_2, ..., v_N\}$.

$$\begin{aligned}
(k+1)||P - F||_2^2 &\cong (k+1)||P - G||_2^2 && \text{Since Eq. (3)} \\
&= \sum_{i=1}^{N} ||P - v_i||_2^2 - \sum_{i=1}^{N} ||G - v_i||_2^2 && \text{Since Theorem 4} \\
&\cong \sum_{i=1}^{N} ||P - v_i||_2 - \sum_{i=1}^{N} ||G - v_i||_2^2 && \text{Since Eq. (6)} \\
&\cong \sum_{i=1}^{N} ||P - v_i||_2 && (7)
\end{aligned}$$

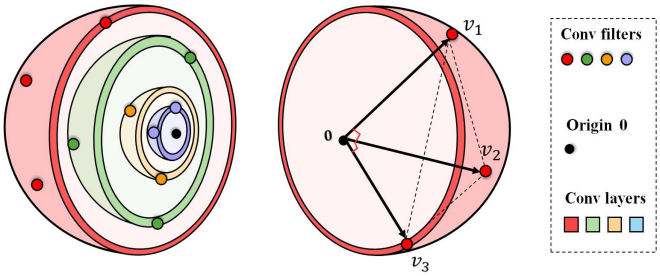


Figure 4: The geometric structure of convolutional filters when the network has large number of filters in each layer. for every pair of filters in one layer, (1) Their ℓ_2 norm are equivalent ($||v_1||_2 \approx ||v_2||_2 \approx ||v_3||_2$); (2) They are equidistant ($||v_1 - v_2||_2 \approx ||v_2 - v_3||_2 \approx ||v_3 - v_1||_2$); (3) and they are orthogonal ($v_1^T v_2 \approx v_2^T v_3 \approx v_3^T v_1 \approx 0$).

The reason for the last equation is that $\sum_{i=1}^{N} ||G - v_i||_2^2$ is a constant for given v_i. Therefore, from Section 3.2 (1) to Section 3.2 (3), we have $\ell_1 \cong \ell_2 \cong \textbf{Fermat} \cong \textbf{GM}$. ($\cong$ has transitive property) Hence, the similarities among these criteria are proved.

4 APPLICABILITY

In this section, we assume that CWDA holds. Let's consider about the pruning of the large networks (each convolutional layer has a large number of filters), which are the main objects of network pruning. Taking Wide ResNet28-10 as example (regarded as a large network), in Fig. 1, we can find that ℓ_2 can not distinguish the network redundancy well from their measured filters' *importance*, because their *importance* are very close (the distribution looks sharp). In order to solve this problem, He et al. (2019) comes up with **GM** but can it distinguish the redundancy of any large network well?

For a large network with large number of convolutional filters (It's easy to know that the dimensions of the filters are also large enough in this situation), from Theorem 5, the convolutional filters will form the geometric structure as shown in Fig. 4.

Theorem 5. *Let convolutional filters $v_i \in \mathbb{R}^k$ of one layer are i.i.d and $v_i \sim N(\mathbf{0}, c^2 \cdot I_k)$. If $k \to \infty$, 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) $\textbf{angle}(v_i, v_j) \to \frac{\pi}{2}$, $1 \leq i, j \leq N$;

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

Proof. (See Appendix I). □

Specifically, from Theorem 5 (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. Moreover, from Theorem 5 (2) and Theorem 5 (3), two vectors formed by any two convolutional filters in the same layer are approximately orthogonal and equidistant.

In fact, Fig. 7 in appendix B provides another view of the geometric structure of convolutional filters. Since CWDA, $\mathbb{E}(v_i) = \mathbf{0}$. So the covariance matrix $\{(\textbf{Cov}(v_i, v_j)\}_{N \times N} = c \cdot \{(v_i^T v_j\}_{N \times N}$, where c is a constant. That is to say, there is only one coefficient difference between covariance matrix and Gram matrix. Therefore, the diagonal elements of the matrix are $||v_i||_2^2$, and the non-diagonal elements are the dot product between the convolutional filters. Since Theorem 5 (1), with enough number of filters, the *importance* calculated by ℓ_2 norm tend to be identical, i.e., it's hard to distinguish the network redundancy well.

We can also use Theorem 5 to analyze other criteria. Due to Theorem 5 (3), for any given convolutional filter v_a and v_b in one layer, we have $\sum_{j=1}^{N} ||v_a - v_j||_2 \approx \sum_{j=1}^{N} ||v_b - v_j||_2$,which shows that the **GM** method also exist the same problem as ℓ_2.

Next, from the Eq. (3), the Fermat point coincides with the origin $\mathbf{0}$. From the analysis in Section 3.2 (2), Fermat and ℓ_2 are almost equivalent when the CWDA holds. Hence, a similar conclu-

sion can be obtained for **Fermat** method. In CVPR 2019 Oral, there is a pruning criterion using orthogonality among the filters in one layer, called RePr Prakash et al. (2019). Based on Theorem 5 (2) and Theorem 5 (1), we also know that this criterion can't prune the network well when the number of filters is too large. As the analysis above, for a large convolutional neural network, many criteria which are widely cited and compared can not distinguish the network redundancy well from their measured filters' *importance*.

5 Discussion

5.1 Why CWDA sometimes does not hold

CWDA may not be entirely correct. As shown in the statistical tests from Appendix J, a small number of convolutional filters can not pass the statistical test. In this section, we try to analyze this phenomenon.

(1) **Need to be trained well enough**. The distribution of weights can be discussed only when the network is trained well. If the network itself does not converge or its performance is too poor (Converges to a bad local minimal), the analysis about the distribution of weights is meaningless. For example, the model is too strong and causes severe overfitting, or the model is too weak to fit the data effectively.

(2) **The number of filters is insufficient.** In Appendix J, the layers that can not pass the statistical test are almost the layers that are in front of the network. A common feature of these layers is that they have very few numbers of filters, which are not enough to estimate statistics well. In Fig. 3, due to the sensibility of layers, a phenomenon that the Sp in transitional area are relatively small. Taking the second convolutional layer (64 filters) in VGG16 on CIFAR10 as example, we find that increasing the number of filters could alleviate this sensitivity. As shown in Fig. 5, we change the number of filters in this layer from 64 to 128 and 256. After that, the Sp increased significantly and it suggests that the enough number of filters are important.

(3) **The dimensions of the filter are not enough.** The dimension of filter in the i_{th} layer is closely related to the number of filters in the $(i-1)_{th}$ layer. To eliminate the factor about the number of the filters, we can check the covariance matrix of each layer of filters, i.e., $\{\mathbf{Cov}(v_i, v_j)\}_{N\times N}$. If CWDA holds, we can expect that these covariance matrices should approximatively be a diagonal matrix with the same diagonal elements. From the results in Fig. 7 in Appendix B, with the increase of dimensions (the dimensions of filters in these networks increase with the increase of depth), the covariance matrix is closer to a diagonal matrix with the same diagonal elements. This implies that the large enough dimensions of the filter is an important condition of CWDA.

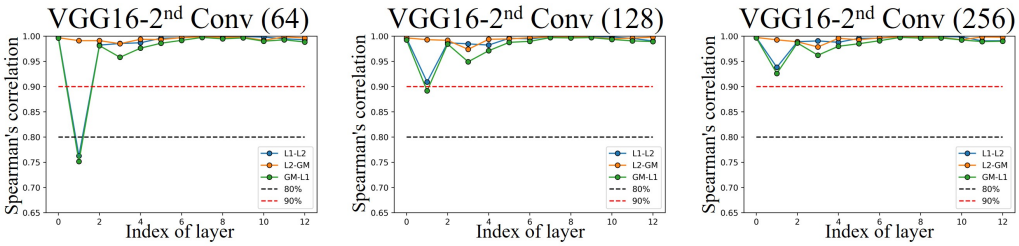


Figure 5: The Sp between different pruning criteria on VGG16 (CIFAR10). The number of filters in the second convolutional layers is changed from 64 to 256.

6 Conclusion

Two blind spots are found in this paper: some primary pruning criteria which are widely cited and compared can obtain very similar pruning results; Some of these criteria can not distinguish the *importance* of the filters well when the number of filters is large enough. These two findings are validated by a large number of experimenets and our theory.

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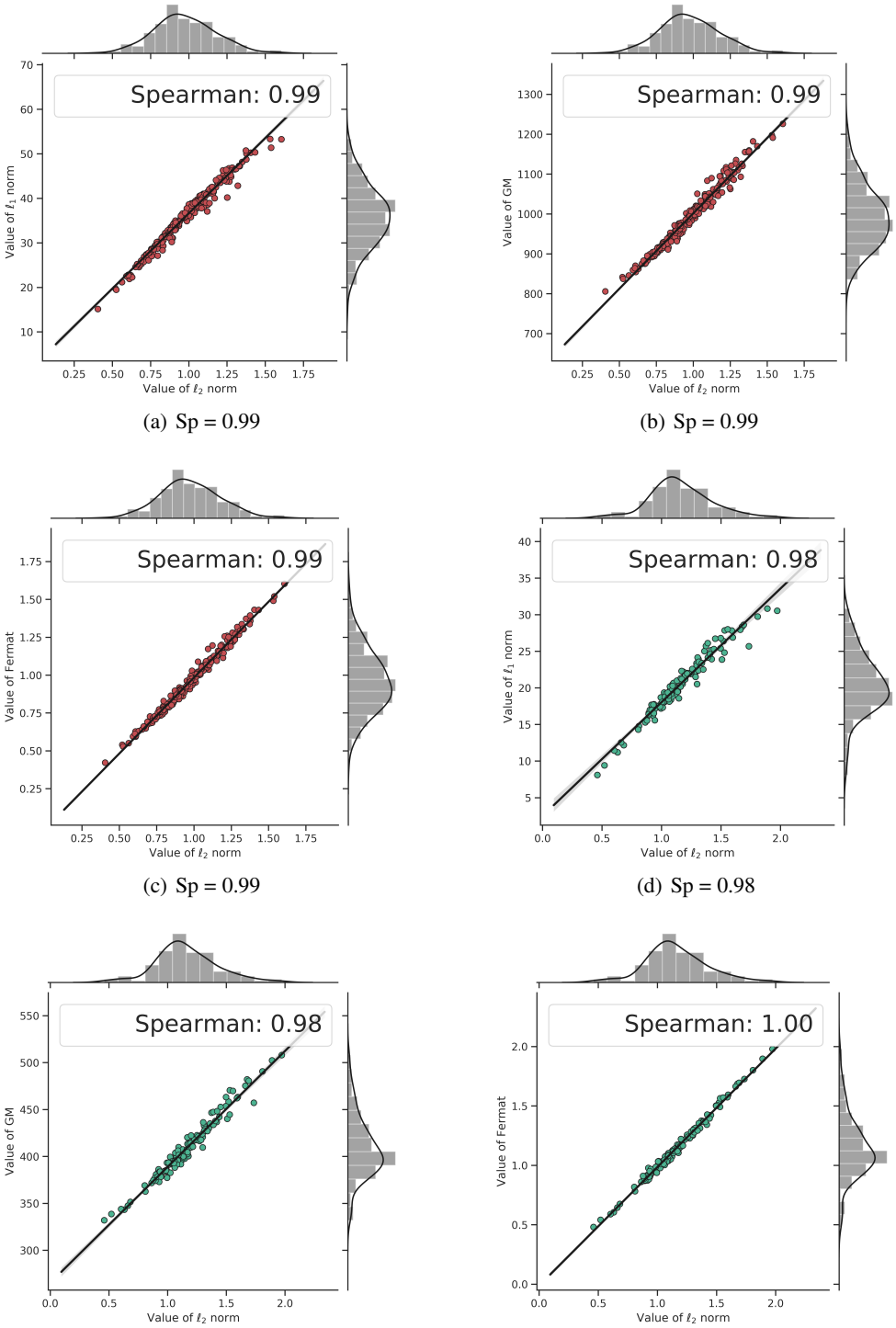
A THE RESULT OF SP



(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 6: 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_{th} Conv), respectively. The results of VGG16 (3_{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.

B DIAGONAL

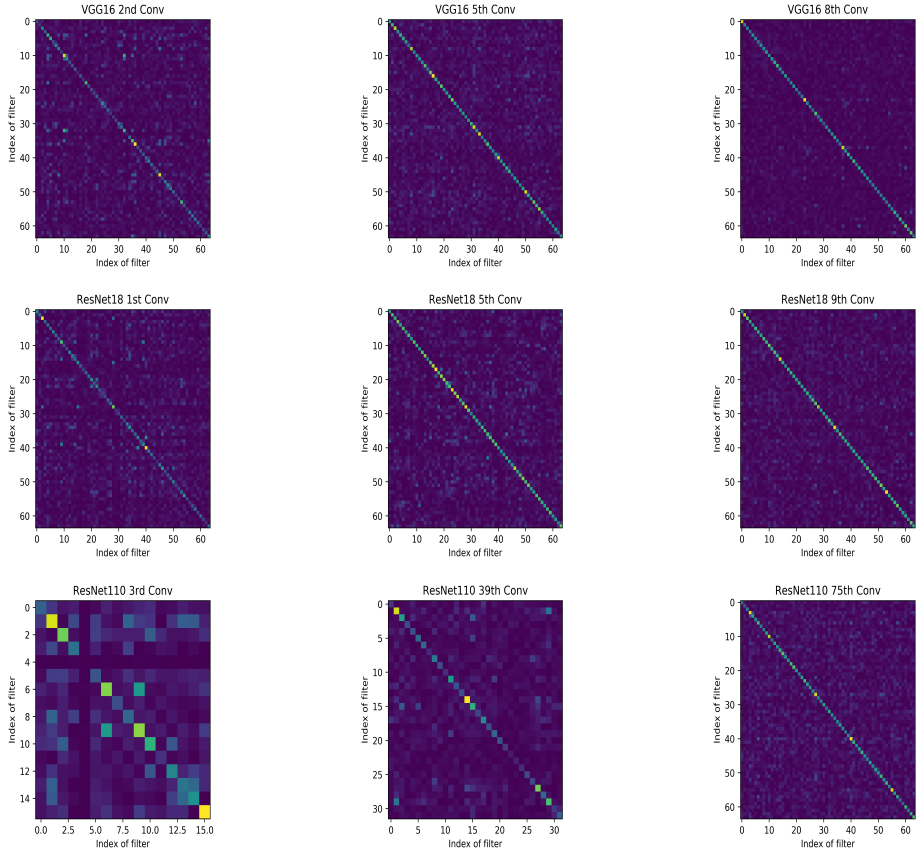


Figure 7: The covariance of convolutional filters. For clarity, we use the first 64 filters in each layer to calculate the covariance matrix.

C OTHER RESULT

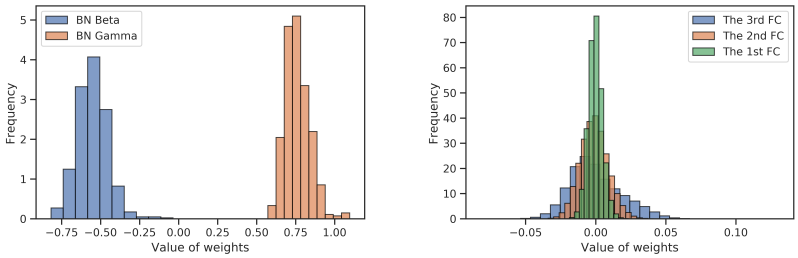


Figure 8: The distribution about other learnable parameters

In Fig 8, 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 weights does not satisfy CWDA and the similar results are shown in Liu et al. (2017); Tian et al. (2019). Moreover, the learnable parameters of fully connected network are also not follow a Gaussian-alike distribution, which is consistent with the conclusion in previous work Bellido & Fiesler (1993); Neal (1995); Go et al. (2004).

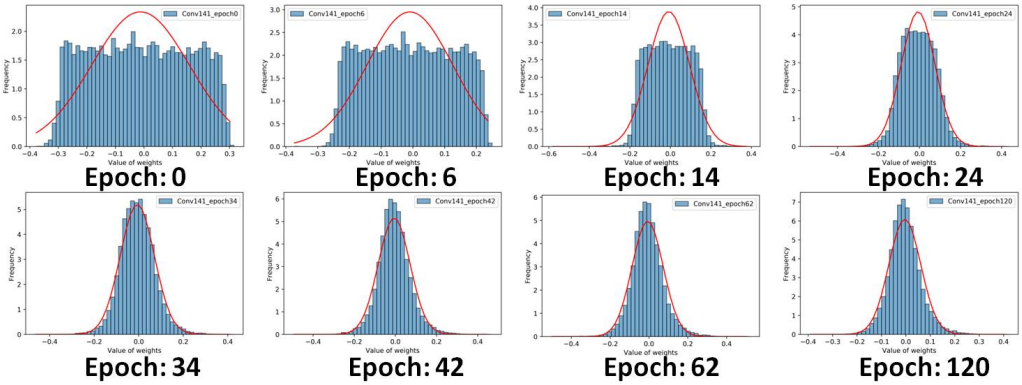


Figure 9: The distribution of the convolutional filter (141_{th} Conv) with kaiming-uniform initialization for each epoch.

D 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*

$$\mathbf{Amoroso}(X|a,\theta,\alpha,\beta) = \frac{1}{\Gamma(\alpha)}|\frac{\beta}{\theta}|(\frac{X-a}{\theta})^{\alpha\beta-1}\exp\left\{-(\frac{X-a}{\theta})^{\beta}\right\}, \tag{8}$$

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

$$\mathbb{E}_{X\sim\mathbf{Amoroso}(X|a,\theta,\alpha,\beta)}X = a + \theta \cdot \frac{\Gamma(\alpha+\frac{1}{\beta})}{\Gamma(\alpha)}, \tag{9}$$

and

$$\mathbf{Var}_{X\sim\mathbf{Amoroso}(X|a,\theta,\alpha,\beta)}X = \theta^2\left[\frac{\Gamma(\alpha+\frac{2}{\beta})}{\Gamma(\alpha)} - \frac{\Gamma(\alpha+\frac{1}{\beta})^2}{\Gamma(\alpha)^2}\right]. \tag{10}$$

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. (9) and Eq. (10), the mean and variance of half-normal distribution are*

$$\mathbb{E}_{X\sim N(0,\sigma^2)}|X| = \sigma\sqrt{2/\pi}, \tag{11}$$

and

$$\mathbf{Var}_{X\sim N(0,\sigma^2)}|X| = \sigma^2\left(1-\frac{2}{\pi}\right). \tag{12}$$

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. (9) and Eq. (10), the mean and variance of Scaled Chi distribution are*

$$\mathbb{E}_{X\sim N(\mathbf{0},\sigma^2\cdot\mathbf{I_k})}[\ell_2(X)]^j = 2^{j/2}\sigma^j \cdot \frac{\Gamma(\frac{k+j}{2})}{\Gamma(\frac{k}{2})}, \tag{13}$$

and

$$\mathbf{Var}_{X\sim N(\mathbf{0},\sigma^2\cdot\mathbf{I_k})}\ell_2(X) = 2\sigma^2\left[\frac{\Gamma(\frac{k}{2}+1)}{\Gamma(\frac{k}{2})} - \frac{\Gamma(\frac{k+1}{2})^2}{\Gamma(\frac{k}{2})^2}\right]. \tag{14}$$

E PROOF OF THEOREM 1

Proposition 4 (Stirling's formula)**.** [3] *For big enough x and $x \in \mathbb{R}^+$, we have an approximation of Gamma function:*

$$\Gamma(x+1) \approx \sqrt{2\pi x}\left(\frac{x}{e}\right)^x. \tag{15}$$

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

$$\mathbb{E}(f)\mathbb{E}(g) \leq \mathbb{E}(fg). \tag{16}$$

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).

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

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

$$f(X,Y) = f(\mathbb{E}(X),\mathbb{E}(Y)) + \sum_{cyc}(X-\mathbb{E}(X))\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y)) + Remainder1, \tag{17}$$

$$\begin{aligned} f(X,Y) = f(\mathbb{E}(X),\mathbb{E}(Y)) + \sum_{cyc}(X-\mathbb{E}(X))\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y)) + \\ \frac{1}{2}\sum_{cyc}(X-\mathbb{E}(X))^T\frac{\partial^2}{\partial X^2}f(\mathbb{E}(X),\mathbb{E}(Y))(X-\mathbb{E}(X)) + Remainder2 \end{aligned} \tag{18}$$

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

$$\mathbf{Var}\left(\frac{X}{Y}\right) \approx \left(\frac{\mathbb{E}(X)}{\mathbb{E}(Y)}\right)^2\left(\frac{\mathbf{Var}X}{\mathbb{E}(X)^2} + \frac{\mathbf{Var}Y}{\mathbb{E}(Y)^2} - 2\frac{\mathbf{Cov}(X,Y)}{\mathbb{E}(X)\mathbb{E}(Y)}\right). \tag{19}$$

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

$$\begin{aligned}
\mathbf{Var}f(X,Y) &= \mathbb{E}[f(X,Y) - \mathbb{E}(f(X,Y))]^2 \\
&\approx \mathbb{E}[f(X,Y) - \mathbb{E}\left\{f(\mathbb{E}(X),\mathbb{E}(Y)) + \sum_{cyc}(X-\mathbb{E}(X))\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y))\right\}]^2 \\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \text{from Eq. (17)} \\
&= \mathbb{E}[f(X,Y) - f(\mathbb{E}(X),\mathbb{E}(Y)) - \sum_{cyc}\mathbb{E}(X-\mathbb{E}(X))\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y))]^2 \\
&= \mathbb{E}[f(X,Y) - f(\mathbb{E}(X),\mathbb{E}(Y))]^2 \\
&\approx \mathbb{E}[\sum_{cyc}(X-\mathbb{E}(X))\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y))]^2 \qquad\qquad \text{from Eq. (17)} \\
&= 2\mathbf{Cov}(X,Y)\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y))\frac{\partial}{\partial Y}f(\mathbb{E}(X),\mathbb{E}(Y)) + \sum_{cyc}[\frac{\partial}{\partial X}f(\mathbb{E}(X),\mathbb{E}(Y))]^2\cdot\mathbf{Var}X \\
&= 2\mathbf{Cov}(X,Y)\cdot\frac{1}{\mathbb{E}(Y)}\cdot\left(-\frac{\mathbb{E}(X)}{(\mathbb{E}(Y))^2}\right) + \frac{1}{(\mathbb{E}(Y))^2}\cdot\mathbf{Var}X + \frac{(\mathbb{E}X)^2}{(\mathbb{E}Y)^4}\cdot\mathbf{Var}Y \\
&= \left(\frac{\mathbb{E}(X)}{\mathbb{E}(Y)}\right)^2\left(\frac{\mathbf{Var}X}{\mathbb{E}(X)^2} + \frac{\mathbf{Var}Y}{\mathbb{E}(Y)^2} - 2\frac{\mathbf{Cov}(X,Y)}{\mathbb{E}(X)\mathbb{E}(Y)}\right).
\end{aligned}$$

□

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

$$\lim_{x\to+\infty}\left[\frac{\Gamma(\frac{x+1}{2})}{\Gamma(\frac{x}{2})}\right]^2\cdot\frac{1}{x} = \frac{1}{2}. \tag{20}$$

And

$$\lim_{x\to+\infty}\frac{\Gamma(\frac{x}{2}+1)}{\Gamma(\frac{x}{2})} - \left[\frac{\Gamma(\frac{x+1}{2})}{\Gamma(\frac{x}{2})}\right]^2 = \frac{1}{4}. \tag{21}$$

Proof.

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

on the other hand, we have

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

□

Theorem 1 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

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

similarly, we also have

$$\mathbf{Var}\left(\frac{\widehat{\ell}_1(X)}{\widehat{\ell}_2(X)}\right)\le\left(\frac{\mathbf{Var}\ell_2(X)}{\mathbb{E}(\ell_2(X))^2}+\frac{\mathbf{Var}\ell_1(X)}{\mathbb{E}(\ell_1(X))^2}\right). \tag{22}$$

Therefore,

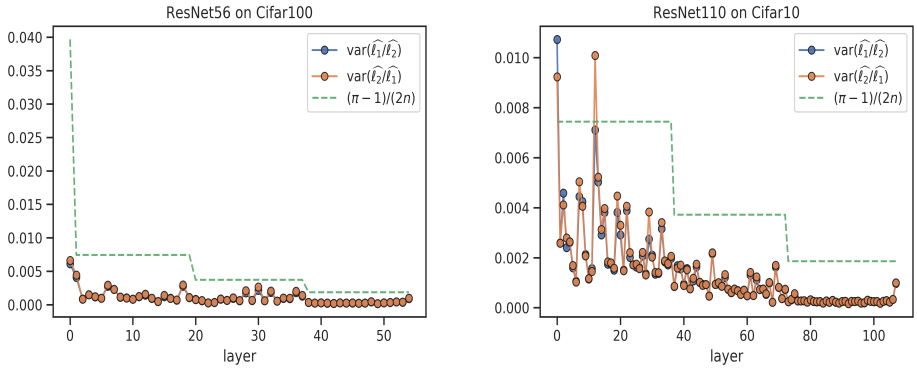


Figure 10: The approximation of **Theorem 1**: (Left) the example about ResNet56; (Right) the example about ResNet110.

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

□

Because the approximation is widely used in the proof of Theorem 1, it is necessary to verify it numerically. As shown in Fig. 10, we use ResNet56 on Cifar100 and ResNet110 on Cifar10 respectively to verify Theorem 1. From Fig. 10, 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.

F Proof of Theorem 2

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

$$\frac{\partial^n}{\partial x^n} L_p^{(\alpha)} = (-1)^n L_{p-n}^{(\alpha+n)}(x), \tag{23}$$

and for $\alpha > 0$,

$$L_{-\frac{1}{2}}^{(\alpha)}(x) > 0. \tag{24}$$

Theorem 2. 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[4] 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. (23),

$$\frac{d}{dx} T(x) = \frac{x}{\sigma^2} \cdot L_{-\frac{1}{2}}^{(\frac{k}{2})} \left(-\frac{x^2}{2\sigma^2} \right). \tag{25}$$

Since Eq. (24), 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., $F = \mathbf{0}$.

□

G PROOF OF THEOREM 3

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:*

$$\mathbb{E} \left(\frac{(||X||_2^2 - ||Y||_2^2)^2}{2||X||_2 \cdot ||Y||_2} \right) \approx 2c^2 + \frac{4c^2 k + 1}{2k^2}, \tag{26}$$

and

$$\mathbf{Var} \left(\frac{(||X||_2^2 - ||Y||_2^2)^2}{2||X||_2 \cdot ||Y||_2} \right) \lesssim 8c^4 + \frac{16c^4 k + c^2}{k^2}, \tag{27}$$

Proof. According to **Proposition 3** and **Lemma 2**, it is easy to know (similar method in Eq.(83)), when k is large enough, that

$$\mathbb{E} \left(2||X||_2 \cdot ||Y||_2 \right) = 2c^2 k, \quad \mathbf{Var} \left(2||X||_2 \cdot ||Y||_2 \right) = c^2 + 4c^4 k, \tag{28}$$

and

$$\mathbb{E} \left((||X||_2^2 - ||Y||_2^2)^2 \right) = 4c^4 k, \quad \mathbf{Var} \left((||X||_2^2 - ||Y||_2^2)^2 \right) = 16c^8 (2k^2 + 3k). \tag{29}$$

Since Lemma 1, we have an estimation

$$\begin{aligned}\mathbf{Var} \left(\frac{(||X||_2^2 - ||Y||_2^2)^2}{2||X||_2 \cdot ||Y||_2} \right) &\leq \left(\frac{\mathbb{E}(||X||_2^2 - ||Y||_2^2)^2}{\mathbb{E} 2||X||_2 \cdot ||Y||_2} \right)^2 \left(\frac{\mathbf{Var}(||X||_2^2 - ||Y||_2^2)^2}{\mathbb{E}(||X||_2^2 - ||Y||_2^2)^2} + \frac{\mathbf{Var}(2||X||_2 \cdot ||Y||_2)^2)}{\mathbb{E}(2||X||_2 \cdot ||Y||_2)^2} \right) \\ &\approx \left(\frac{4c^4 k}{2c^2 k} \right)^2 \cdot \left(\frac{c^2 + 4c^4 k}{4c^4 k} + \frac{16c^8 (2k^2 + 3k)}{16c^8 k^2} \right) \\ &\qquad \text{Since Eq.(28) and Eq.(29)} \\ &= 8c^4 + \frac{16c^4 k + c^2}{k^2}.\end{aligned}$$

From Eq.(18) 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.,

$$\mathbb{E} \left(\frac{\mathbf{A}}{\mathbf{B}} \right) \approx \frac{\mathbb{E}\mathbf{A}}{\mathbb{E}\mathbf{B}} + \mathbf{Var}(\mathbf{B}) \cdot \frac{\mathbb{E}\mathbf{A}}{(\mathbb{E}\mathbf{B})^3}. \tag{30}$$

[4] Survey of simple,continuous,uniariate probability distributions and Wikipredia.

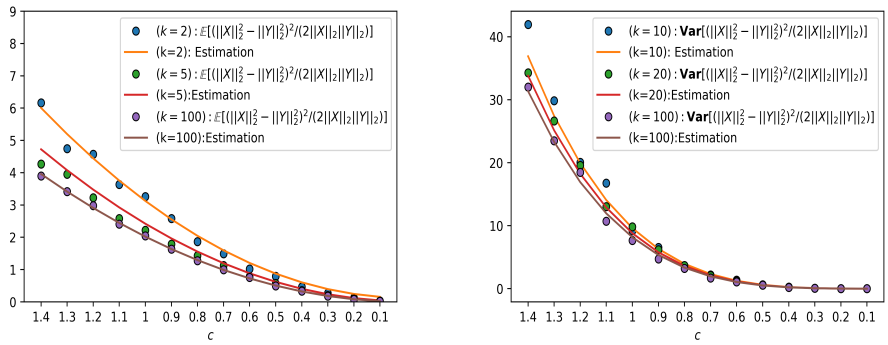


Figure 11: (Left) The numerical verification of Eq.(26) and (Right) The numerical verification of Eq.(27). X and Y follow $N(\mathbf{0}, c^2 \cdot I_k)$.

Therefore,

$$\mathbb{E}\left(\frac{(||X||_2^2 - ||Y||_2^2)^2}{2||X||_2 \cdot ||Y||_2}\right) \approx \frac{\mathbb{E}(||X||_2^2 - ||Y||_2^2)^2}{\mathbb{E}2||X||_2 \cdot ||Y||_2} + \mathbf{Var}(2||X||_2 \cdot ||Y||_2) \cdot \frac{\mathbb{E}(||X||_2^2 - ||Y||_2^2)^2}{(\mathbb{E}2||X||_2 \cdot ||Y||_2)^3} \quad \text{Since Eq.(30)}$$

$$\approx \frac{4c^4k}{2c^2k} + \frac{4c^4k}{8c^6k^3} \cdot (c^2 + 4c^4k) \quad \text{Since Eq.(28) and Eq.(29)}$$

$$= 2c^2 + \frac{4c^2k + 1}{2k^2}.$$

□

Note that, the approximation is widely used in the proof of Eq.(26) and Eq.(27). Hence, it is also necessary to verify it numerically. As shown in Fig. 11, 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,

$$2(||X||_2 \cdot ||Y||_2) \gg (||X||_2^2 - ||Y||_2^2)^2. \tag{31}$$

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

Theorem 3. 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. (13) and Eq. (14), we have

$$\mathbf{Var}_{a_i} \frac{F_1(a_i)}{F_2(a_i)} = \left(\frac{nc^2k}{nc\sqrt{k}}\right)^2 \cdot \mathbf{Var}_{a_i}\left(\frac{\sum_{i=1}^n ||a_i||_2}{\sum_{i=1}^n ||a_i||_2^2}\right). \tag{32}$$

and

$$\mathbf{Var}_{a_i} \frac{F_2(a_i)}{F_1(a_i)} = \left(\frac{nc\sqrt{k}}{nc^2k}\right)^2 \cdot \mathbf{Var}_{a_i}\left(\frac{\sum_{i=1}^n ||a_i||_2^2}{\sum_{i=1}^n ||a_i||_2}\right). \tag{33}$$

According to Lagrange's identity, we have

$$\begin{aligned}
\left(\sum_{i=1}^{n}||a_i||_2^2\right)\left(\sum_{i=1}^{n}1\right) &= \left(\sum_{i=1}^{n}||a_i||_2\right)^2 + \sum_{1\le i<j\le n}(||a_i||_2^2 - ||a_j||_2^2)^2 \\
&= \sum_{i=1}^{n}||a_i||_2^2 + \sum_{1\le i<j\le n}(||a_i||_2\cdot||a_j||_2) + 2\sum_{1\le i<j\le n}(||a_i||_2^2 - ||a_j||_2^2)^2 \\
&\approx \sum_{i=1}^{n}||a_i||_2^2 + 2\sum_{1\le i<j\le n}(||a_i||_2\cdot||a_j||_2) && \text{Since Eq. (31)} \\
&= \left(\sum_{i=1}^{n}||a_i||_2\right)^2
\end{aligned}$$

so we have

$$\mathbf{Var}_{a_i\sim N(\mathbf{0},c^2\cdot\mathbf{I}_k)}\frac{\sum_{i=1}^{n}||a_i||_2}{\sum_{i=1}^{n}||a_i||_2^2} \approx \mathbf{Var}_{a_i\sim N(\mathbf{0},c^2\cdot\mathbf{I}_k)}\frac{n}{\sum_{i=1}^{n}||a_i||_2} \tag{34}$$

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[5] to find the distribution of $g(\frac{1}{n}\sum_{i=1}^{n}||a_i||_2)$:

$$\sqrt{n}\left(g(\frac{\sum_{i=1}^{n}||a_i||_2}{n}) - g(\mu))\right) \sim N(0,\sigma^2\cdot[g\prime(\mu)]^2) = N(0,\sigma^2\cdot\frac{1}{\mu^4}). \tag{35}$$

where μ and σ^2 denote the mean and variance of $||a_i||_2$ respectively. From Eq. (34), we have

$$\begin{aligned}
\mathbf{Var}_{a_i\sim N(\mathbf{0},c^2\cdot\mathbf{I}_k)}\frac{\sum_{i=1}^{n}||a_i||_2}{\sum_{i=1}^{n}||a_i||_2^2} &\approx \mathbf{Var}_{a_i\sim N(\mathbf{0},c^2\cdot\mathbf{I}_k)}\frac{n}{\sum_{i=1}^{n}||a_i||_2} \\
&= \sigma^2\cdot\frac{1}{\mu^4\cdot n} && \text{Since Eq. (35)} \\
&= 2c^2\left[\frac{\Gamma(\frac{k}{2}+1)}{\Gamma(\frac{k}{2})} - \frac{\Gamma(\frac{k+1}{2})^2}{\Gamma(\frac{k}{2})^2}\right]\cdot\frac{1}{(\sqrt{2}c\cdot\frac{\Gamma(\frac{k+1}{2})}{\Gamma(\frac{k}{2})})^4\cdot n} \\
& && \text{Since Eq. (13) and Eq. (14)} \\
&= \frac{1}{2c^2\cdot nk^2} && \text{Since Lemma. 2}
\end{aligned}$$

Since Eq. (32), we have

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

Similar to Eq. (34),

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

$$\begin{aligned}
\mathbf{Var}_{a_i\sim N(\mathbf{0},c^2\cdot\mathbf{I}_k)}\frac{\sum_{i=1}^{n}||a_i||_2^2}{\sum_{i=1}^{n}||a_i||_2} &\approx \mathbf{Var}_{a_i\sim N(\mathbf{0},c^2\cdot\mathbf{I}_k)}\frac{\sum_{i=1}^{n}||a_i||_2}{n} && \text{Similar to Eq. (34)} \\
&= \sigma^2\cdot\frac{1}{n} && \text{Since central limit theorem} \\
&= 2c^2\left[\frac{\Gamma(\frac{k}{2}+1)}{\Gamma(\frac{k}{2})} - \frac{\Gamma(\frac{k+1}{2})^2}{\Gamma(\frac{k}{2})^2}\right]\cdot\frac{1}{n} && \text{Since Eq. (14)} \\
&= \frac{c^2}{2n} && \text{Since Lemma. 2}
\end{aligned}$$

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

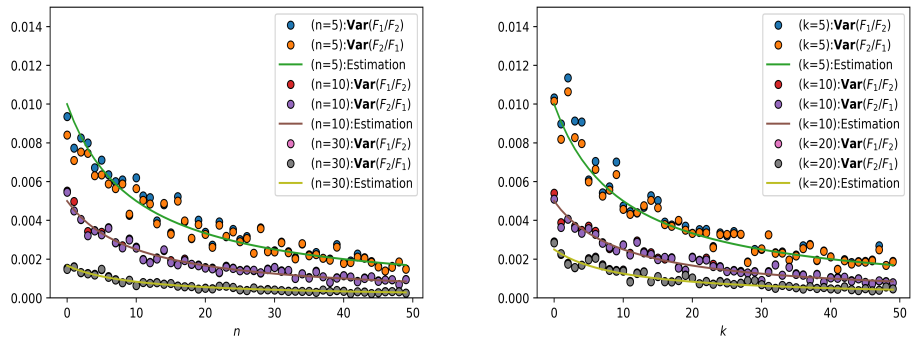


Figure 12: A numerical verification of **Theorem 3**, where $F_1 = \sum_{i=1}^{n} ||a_i||_2 / \mathbb{E}(\sum_{i=1}^{n} ||a_i||_2)$ and $F_2 = \sum_{i=1}^{n} ||a_i||_2^2 / \mathbb{E}(\sum_{i=1}^{n} ||a_i||_2^2)$. a_i follow $N(\mathbf{0}, 0.01^2 \cdot I_k)$.

Since Eq. (33), we have

$$\mathbf{Var}_{a_i} \frac{F_2(a_i)}{F_1(a_i)} = \left(\frac{nc\sqrt{k}}{nc^2 k} \right)^2 \cdot \mathbf{Var}_{a_i} \left(\frac{\sum_{i=1}^{n} ||a_i||_2^2}{\sum_{i=1}^{n} ||a_i||_2} \right) \approx \frac{1}{2nk}. \tag{38}$$

From Eq.(36) and Eq.(38), **Theorem 3** holds.

□

In Fig. 12, we also show a numerical verification of **Theorem 3**.

H Proof of Theorem 4

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.*

$$\mathbf{rank}((a_{ij})_{n \times m}) = \mathbf{min}(m, n). \tag{39}$$

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.*

$$x = \sum_{i=0}^{k} \lambda_i \cdot v_i, \tag{40}$$

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*

$$||a-b||_2^2 = (\lambda-\mu)^T D(\lambda-\mu), \tag{41}$$

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,

$$\begin{aligned} ||a-b||_2^2 &= (a-b)^T(a-b) && (42)\\ &= [R(\lambda-\mu)]^T[R(\lambda-\mu)] && (43)\\ &= (\lambda-\mu)^T R^T R(\lambda-\mu). && (44) \end{aligned}$$

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

$$\begin{aligned} -\frac{1}{2}d_{ij} &= -\frac{1}{2}(v_i - v_j)^T(v_i - v_j) && (45)\\ &= v_i^T v_j - \frac{1}{2}(v_i^T v_i + v_j^T v_j). && (46) \end{aligned}$$

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

$$\begin{aligned} ||a-b||_2^2 &= (\lambda-\mu)^T R^T R(\lambda-\mu) && (47)\\ &= (\lambda-\mu)^T(D + \frac{1}{2}(V\alpha^T + \alpha V^T))(\lambda-\mu) && (48)\\ &= (\lambda-\mu)^T D(\lambda-\mu) + \frac{1}{2}(\lambda-\mu)^T(V\alpha^T + \alpha V^T)(\lambda-\mu), && (49) \end{aligned}$$

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

$$\widehat{\mathbf{dim}}(U) = \begin{cases} r, & v_0 \in W \\ r+1, & v_0 \notin W \end{cases} \tag{50}$$

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,

$$P \subset L = \mathbf{span}(a_1, a_2, ..., a_k), \tag{51}$$

① For the linear manifold P, if $v_0 \in W$. This means that P is equal to the linear subspace W. Since Eq. (51), 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. (51), we have $P \subset L$, so

$$n = \widehat{\mathbf{dim}}(P) \leq \widehat{\mathbf{dim}}(L) = k = n-1, \tag{52}$$

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. (51). Note that, from Definition 1, $\widehat{\mathbf{dim}}(P) \geq n-1$, hence

$$n-1 \leq \widehat{\mathbf{dim}}(P) \leq \widehat{\mathbf{dim}}(L) = k = n-(l+1). \tag{53}$$

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 4. 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.(5) holds with probability 1 where c is a constant.

Proof. **For Theorem 4 (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,

$$||P - v_i||_2^2 = (\gamma - \epsilon_i)^T D(\gamma - \epsilon_i) \tag{54}$$

$$= \gamma^T D\gamma - 2\gamma^T D\epsilon_i + \epsilon_i^T D\epsilon_i \tag{55}$$

$$= \gamma^T D\gamma - 2\gamma^T D\epsilon_i. \tag{56}$$

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

$$||G - v_i||_2^2 = (\frac{1}{k+1}\sum_{i=0}^{k} \epsilon_i - \epsilon_i)^T D(\frac{1}{k+1}\sum_{i=0}^{k} \epsilon_i - \epsilon_i) \tag{57}$$

$$= \frac{1}{(k+1)^2}\alpha^T D\alpha - \frac{2}{k+1}\alpha^T D\epsilon_i + \epsilon_i^T D\epsilon_i \tag{58}$$

$$= \frac{1}{(k+1)^2}\alpha^T D\alpha - \frac{2}{k+1}\alpha^T D\epsilon_i, \tag{59}$$

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

$$||P - G||_2^2 = (\gamma - \frac{1}{k+1}\alpha)^T D(\gamma - \frac{1}{k+1}\alpha) \tag{60}$$

$$= \gamma^T D\gamma + \frac{1}{(k+1)^2}\alpha^T D\alpha - \frac{2}{k+1}\gamma^T D\alpha. \tag{61}$$

In summary, we have

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

$$= (k+1)||P - G||_2^2 \tag{63}$$

Therefore, Theorem 4 (1) holds.

For Theorem 4 (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,

$$T_1 = \{x + G | x \in W_1^{\perp}\} \tag{64}$$

$$T_2 = \{x + G - v_0 | x \in W_1^{\perp}\} \tag{65}$$

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

$$||P - v_i||_2^2 = ||v_i - G||_2^2 + ||P - G||_2^2. \tag{66}$$

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. (66). By summing both sides of Eq. (66) for i, it is obvious find that Theorem 4 (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

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

$$= \mathbf{rank}(v_1 - v_0, ..., v_k - v_0, p_1 - v_0, ..., p_{n-k} - v_0, 2(G - v_0), ..., 2(G - v_0)) \tag{67}$$

$$= \mathbf{rank}(v_1 - v_0, ..., v_k - v_0, p_1 - v_0, ..., p_{n-k} - v_0, 0, ..., 0) \tag{68}$$

$$= n \tag{69}$$

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

$$L_i^{(1)} = v_i, (0 \leq i \leq k), \tag{70}$$

$$L_i^{(2)} = p_i, (1 \leq i \leq n-k), \tag{71}$$

$$L_i^{(3)} = 2G - p_i, (1 \leq i \leq n-k). \tag{72}$$

And their centroid is

$$G' = \frac{1}{2n-k+1}\left(\sum_{i=0}^{k} v_i + \sum_{i=1}^{n-k}(L_i^{(2)} + L_i^{(3)})\right) \tag{73}$$

$$= \frac{1}{2n-k+1}((k+1)G + 2(n-k)G) \tag{74}$$

$$= G \tag{75}$$

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.(66). Similar to

the derivation in the Theorem 4 (1), we have

$$(2n-k+1)||P-G||_2^2 = \sum_{t=L_i^{(1)},L_i^{(2)},L_i^{(3)}} \left(||P-t||_2^2 - ||G-t||_2^2\right) \tag{76}$$

$$= \sum_{i=0}^{k} \left(||P-v_i||_2^2 - ||G-v_i||_2^2\right) + \sum_{t=L_i^{(2)},L_i^{(3)}} \left(||P-t||_2^2 - ||G-t||_2^2\right) \tag{77}$$

$$= \sum_{i=0}^{k} \left(||P-v_i||_2^2 - ||G-v_i||_2^2\right) + 2(n-k)||P-G||_2^2 \tag{78}$$

The final equation is because both $L_i^{(2)}$ and $L_i^{(3)}$ are in the linear manifold T_1 and satisfy Eq. (66). To simplify Eq. (78), 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 4 (2) holds.

For Theorem 4 (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 4 (1), we can find that Theorem 4 (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.

□

I PROOF OF THEOREM 5

Theorem 5. Let $v_i \in \mathbb{R}^k$ and $v_i \sim N(\mathbf{0}, c^2 \cdot I_k)$. If $k \to \infty$, 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) $||v_i - v_j||_2 \approx ||v_i - v_t||_2$,$1 \leq i,j,t \leq N$;

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

$$P\left\{|||v_i||_2 - \mathbb{E}(||v_i||_2)| \geq \sqrt{M\mathbf{Var}(||v_i||_2)}\right\} \leq \frac{1}{M}. \tag{79}$$

from Eq. (13), Eq. (14) and Lemma. (2), we can rewrite Eq. (79) when $k \to \infty$:

$$P\left\{||v_i||_2 \in \left[\sqrt{2}c \cdot \frac{\Gamma((k+1)/2)}{\Gamma(k/2)} - \sqrt{\frac{M}{2}}c, \sqrt{2}c \cdot \frac{\Gamma((k+1)/2)}{\Gamma(k/2)} + \sqrt{\frac{M}{2}}c\right]\right\} \geq 1 - \frac{1}{M}. \tag{80}$$

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

$$P\left\{||v_i||_2 \approx \sqrt{2}c \cdot \frac{\Gamma((k+1)/2)}{\Gamma(k/2)}\right\} \geq 1 - \epsilon. \tag{81}$$

So Theorem 5(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

$$\mathbb{E}(v_{ip}v_{jp}) = 0, \tag{82}$$

$$\mathbf{Var}(v_{ip}v_{jp}) = \mathbf{Var}(v_{ip})\mathbf{Var}(v_{jp}) + (\mathbb{E}(v_{ip}))^2\mathbf{Var}(v_{jp}) + (\mathbb{E}(v_{jp}))^2\mathbf{Var}(v_{ip}) = 1, \tag{83}$$

since central limit theorem, we have

$$\sqrt{k}\left(\frac{1}{k}\sum_{p=1}^{k} v_{ip}v_{jp} - 0\right) \sim N(0,1), \tag{84}$$

According to Eq. (13), Lemma 2 and Eq. (84), when $k \to \infty$, we have

$$\frac{< v_i, v_j >}{||v_i||_2 \cdot ||v_j||_2} \to \frac{1}{\sqrt{k}} \cdot \frac{< v_i, v_j >}{\sqrt{k}} \sim N(0, \frac{1}{k}) \to N(0,0). \tag{85}$$

So Theorem 5(2) holds. From Theorem 5(1) and Theorem 5(2), Theorem 5(3) can be proved through Pythagoras theorem. □

J 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 $F_{i,j} \in \mathbb{R}^{N_i \times k \times k}$ represent the j_{th} filter of the i_{th} convolutional layer.

(1) **Gaussian**. (i.e., in order to verify if 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 $N(0, c^2)$.

(2) **Standard Deviation**. (i.e., to verify if 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 if 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.,

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

where S is sample variance of all the weights in this layer (it is a small value actually as shown in Fig. 2(e) and (f)) and ϵ is a small constant, like $\epsilon = 0.05$. Next, we check the lower bound (Mean-Right) and the null hypothesis H_0 and the alternative hypothesis H_1 are:

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

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

- In all the statistical tests, let the confidence level be 0.95, $\epsilon = 0.02$ 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 J.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 Table. The (*) means that ,for the sake of brevity, the repeat experiments are shown only once on the experiment with (*).

Table 5: The repeated experiments in Table 3.

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

J.1 NETWORK STRUCTURE

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

Table 6: 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 7: 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 8: 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 9: 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 10: 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 11: 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 12: 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%	

J.2 OPTIMIZER

config:

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

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

Table 13: 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 14: 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 15: 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 16: 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 17: 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%	

J.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 18: 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 19: 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 20: 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 21: 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 22: 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 23: 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%	

J.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 24: 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 25: 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 26: 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 27: 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 28: 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 29: 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%	

J.5 INITIALIZATION

config:

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

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

Table 30: 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 31: 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 32: 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 33: 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%	

J.6 DATASET

config:

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

Table 34: 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

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 35: 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 36: 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%	

J.7 Other Tasks

J.7.1 Segmentation

config:

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

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

Table 37: 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 38: 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%	

J.7.2 FASTER RCNN

config:

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

Table 39: 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 40: 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 41: 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%	

J.7.3 IMAGE MATTING

config:

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

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

Table 42: 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 43: 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%	

J.7.4 STYLE TRANSFER

config:

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

Table 44: 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 45: 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 46: 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 47: 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%	

J.7.5 GAN

config:

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

Table 48: 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 49: 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 50: 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%	

J.8 BATCH NORMALIZATION

config:

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

Table 51: 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 52: 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%	

J.9 PYTORCH PRETRAIN

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

Table 53: 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 54: 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 55: 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 56: 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 57: 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 58: 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%	

J.10 LEARNING RATE

config:

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

Table 59: 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 60: 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 61: 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%	

K DETAILS OF EXPERIMENTS

Table 62: Implementation detail for Table 4.

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. 3 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.

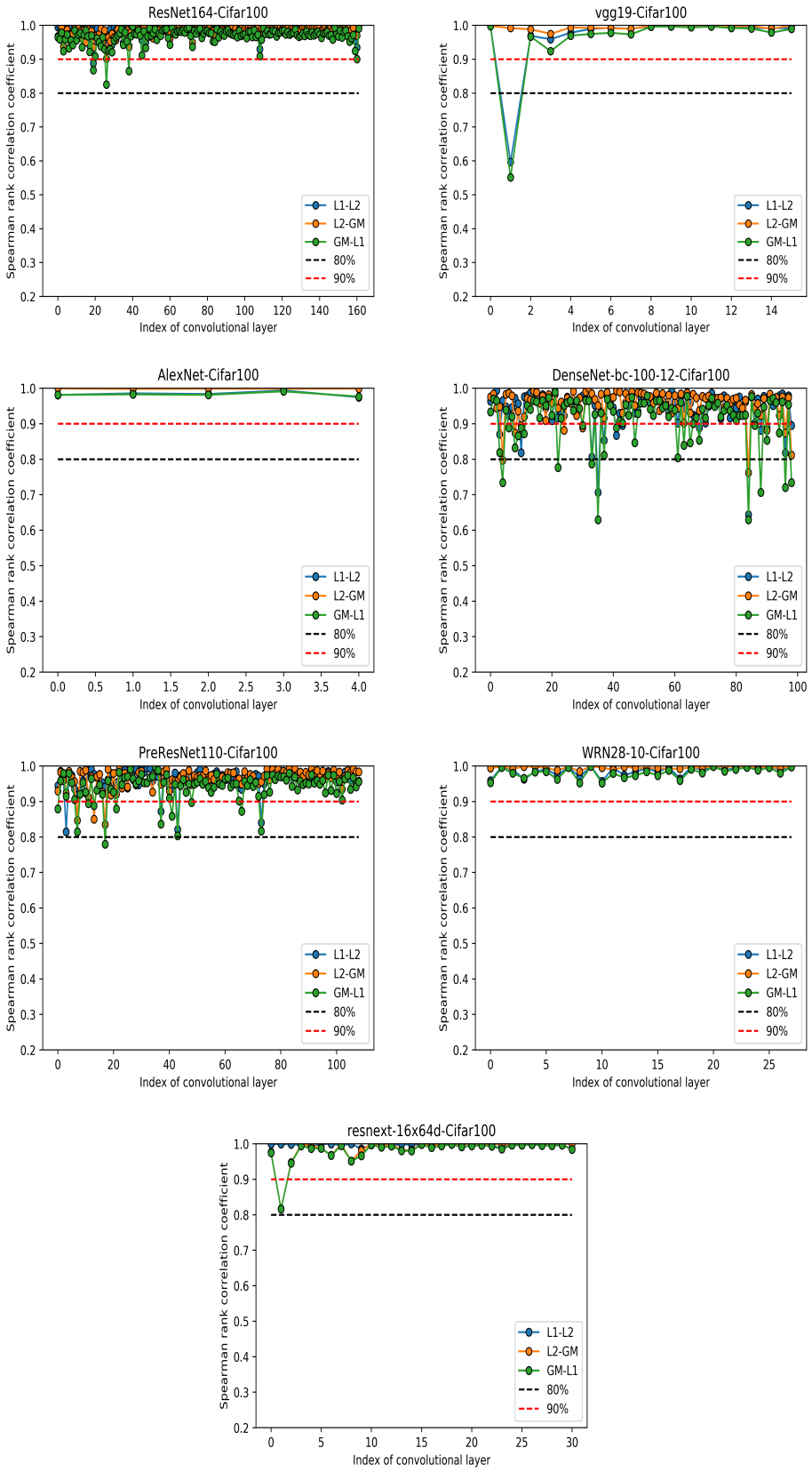


Figure 13: Network Structure

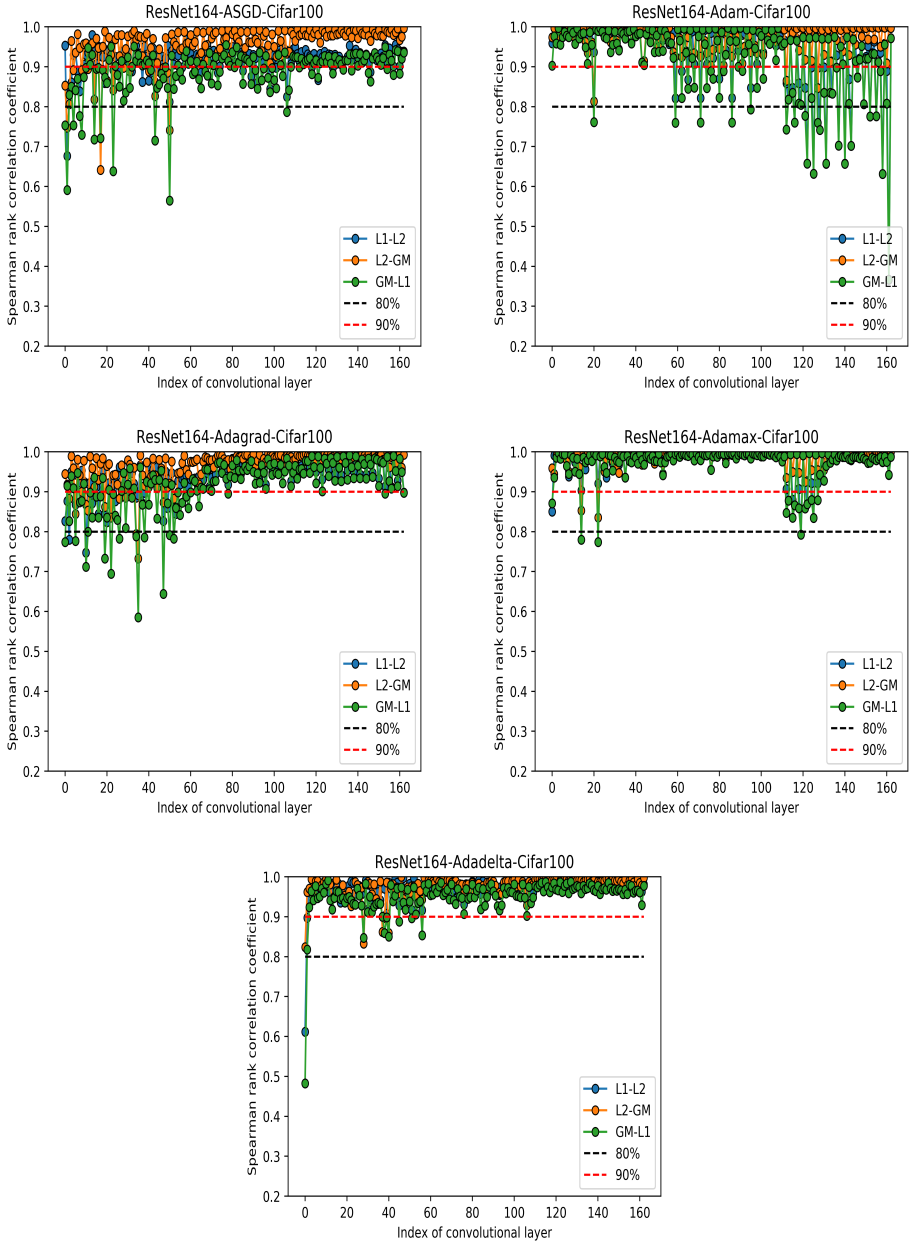


Figure 14: Optimizer

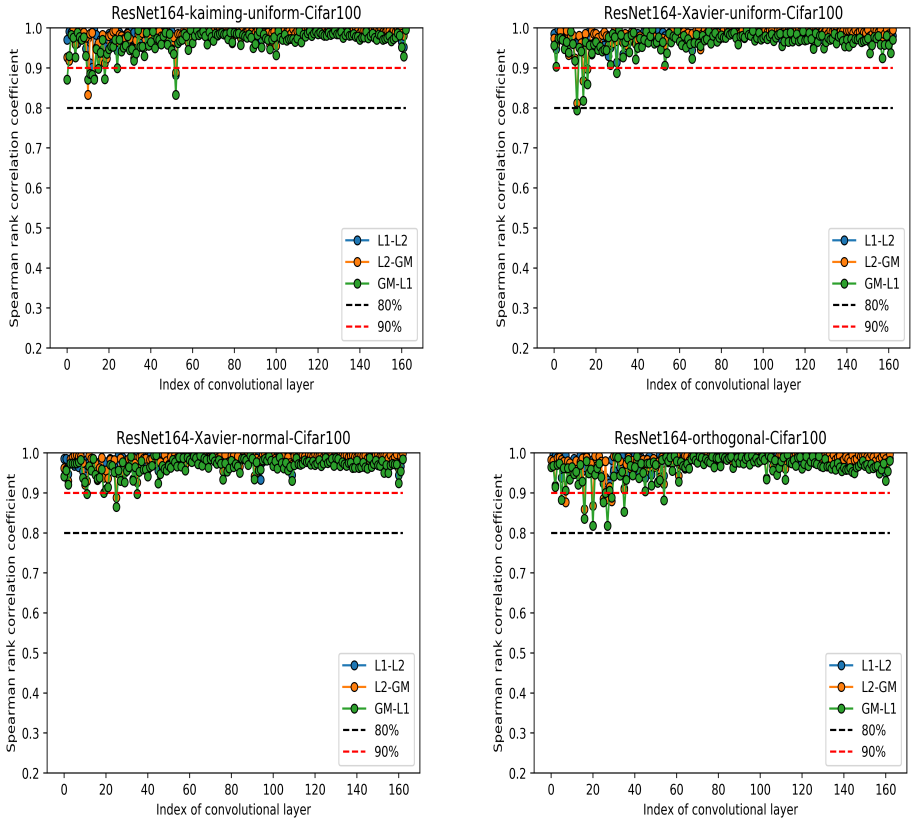


Figure 15: Initialization

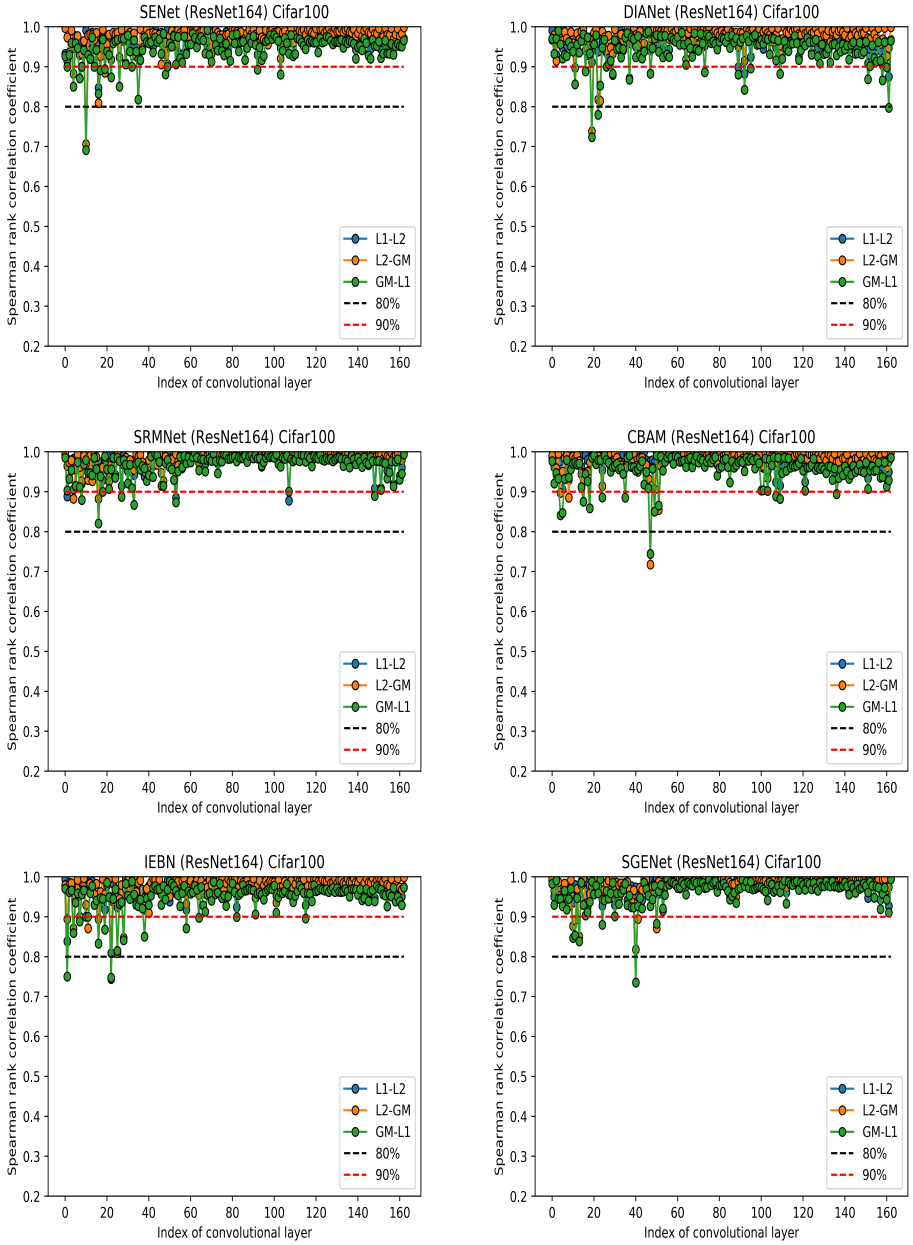


Figure 16: Attention mechanism

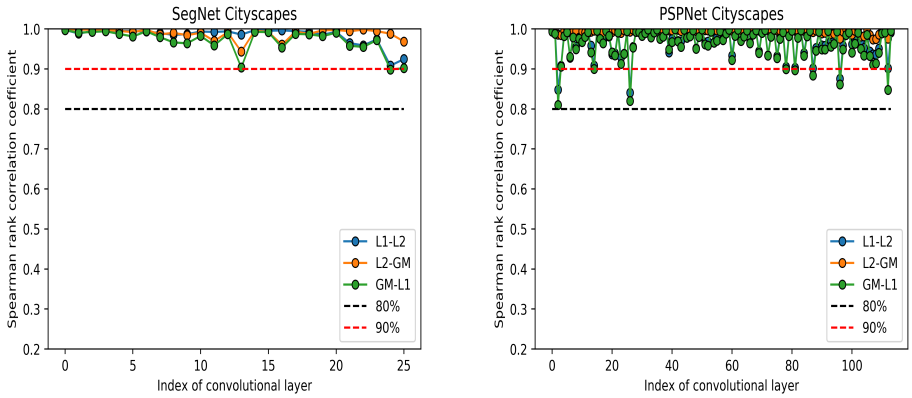


Figure 17: Other task: segmentation

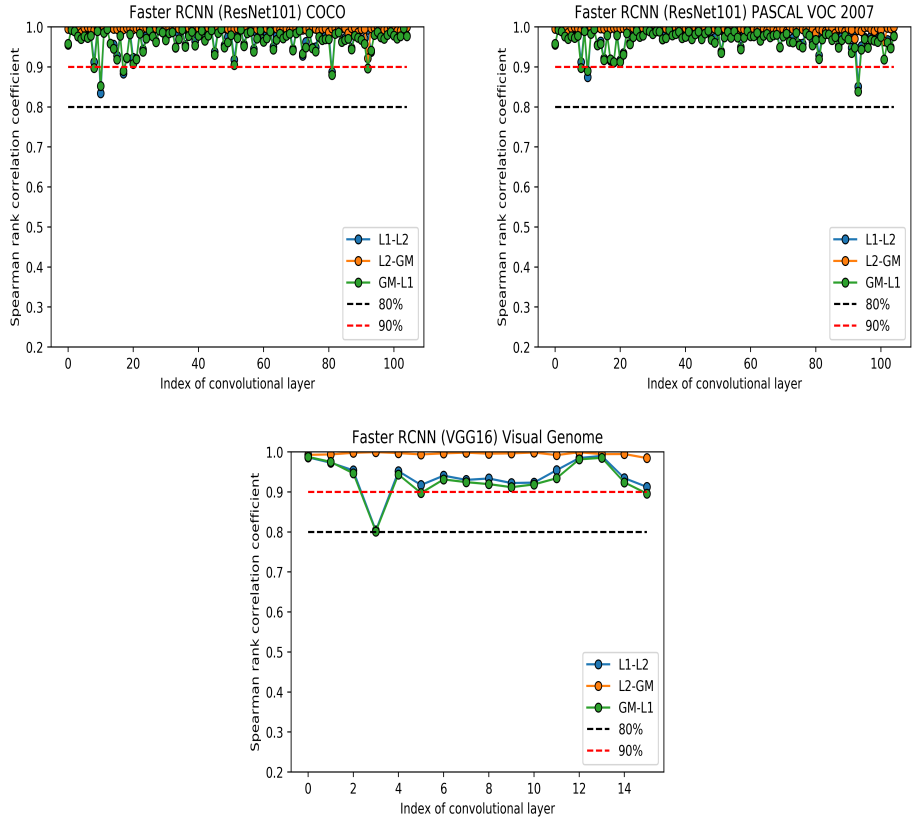


Figure 18: Other task: Faster RCNN

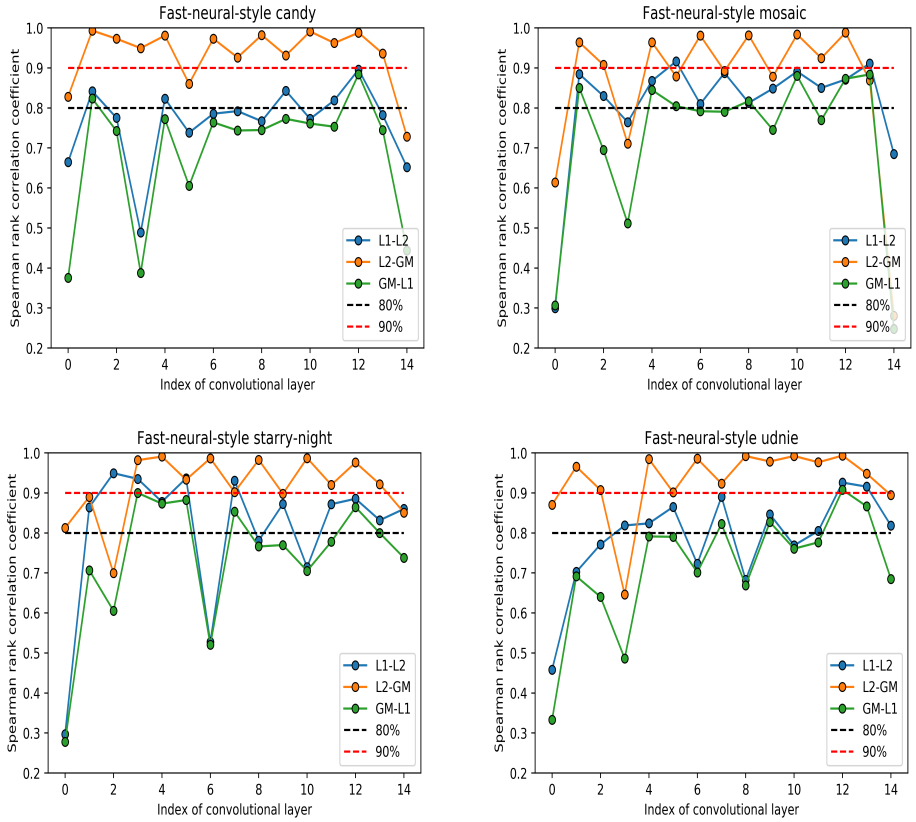


Figure 19: Other task: style transfer

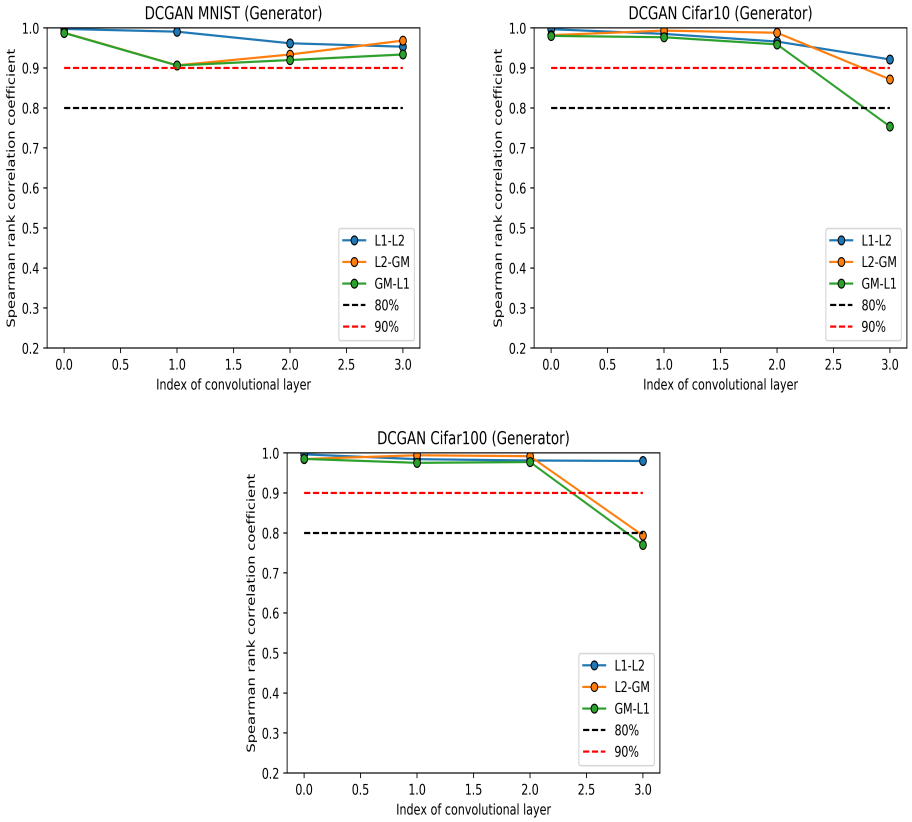


Figure 20: Other task: GAN

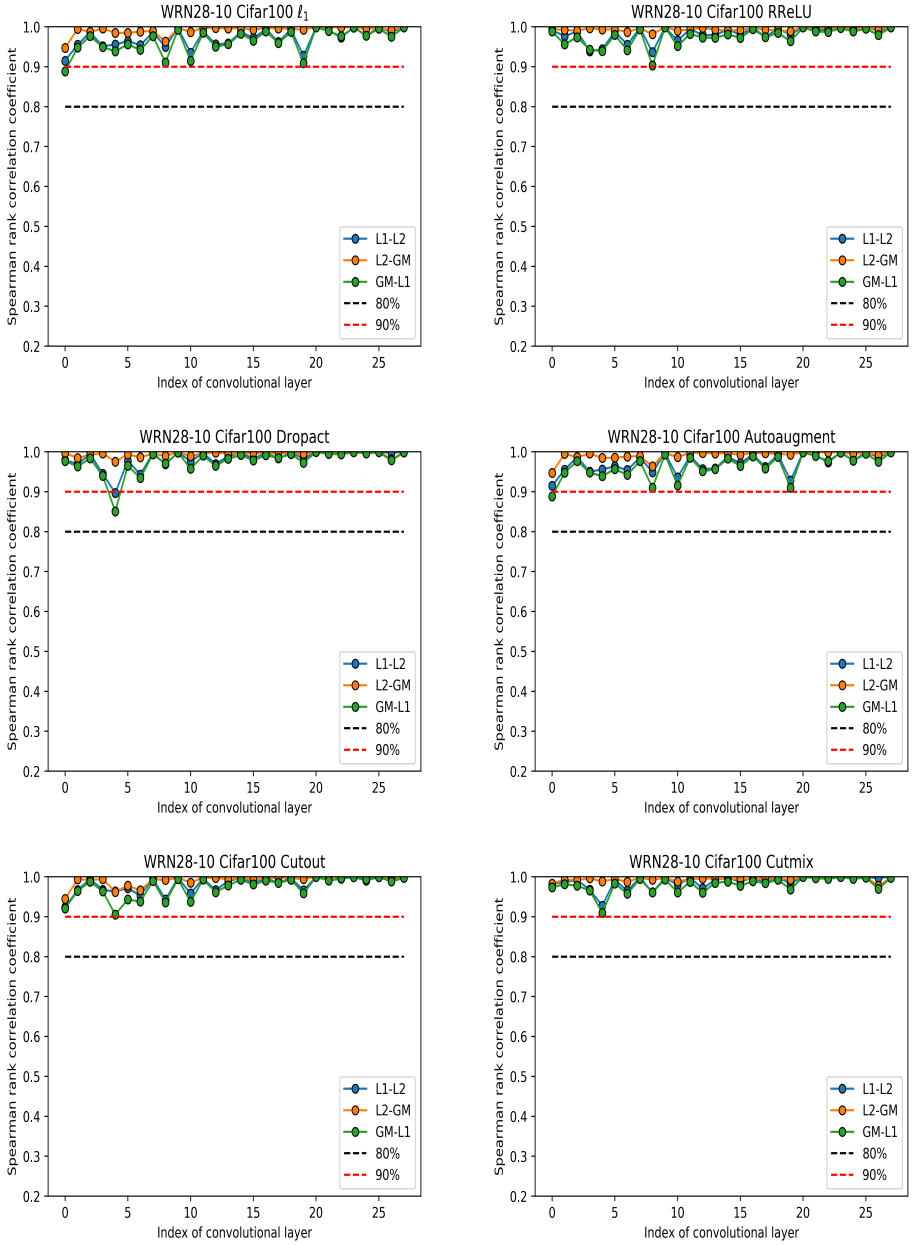


Figure 21: Other task: Regularization

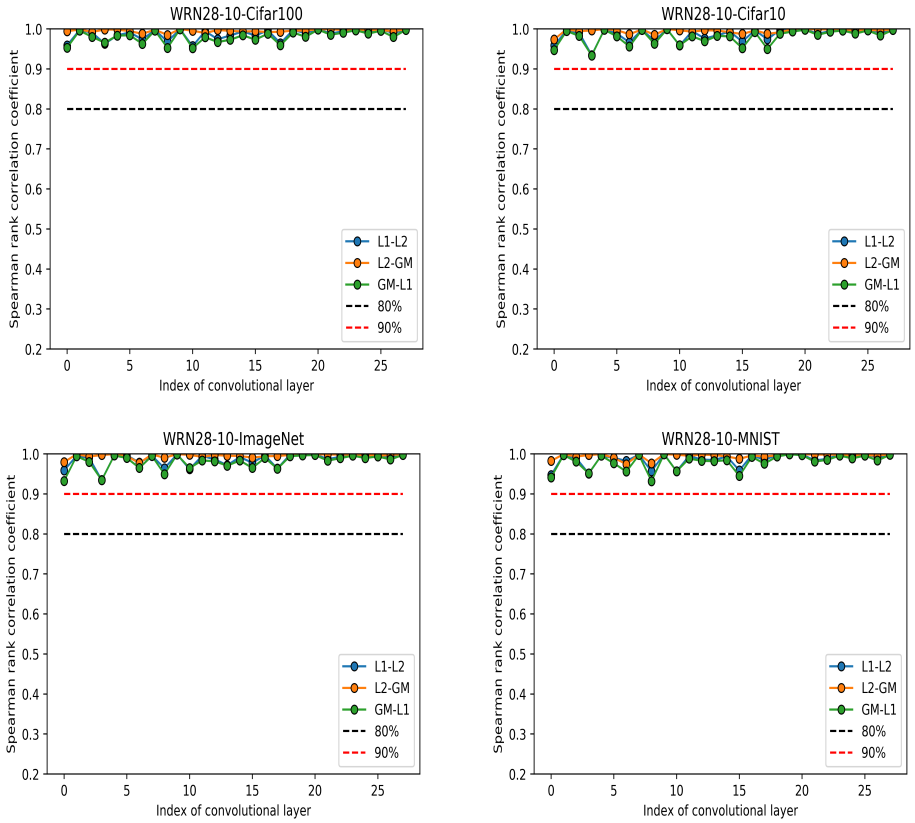


Figure 22: Dataset

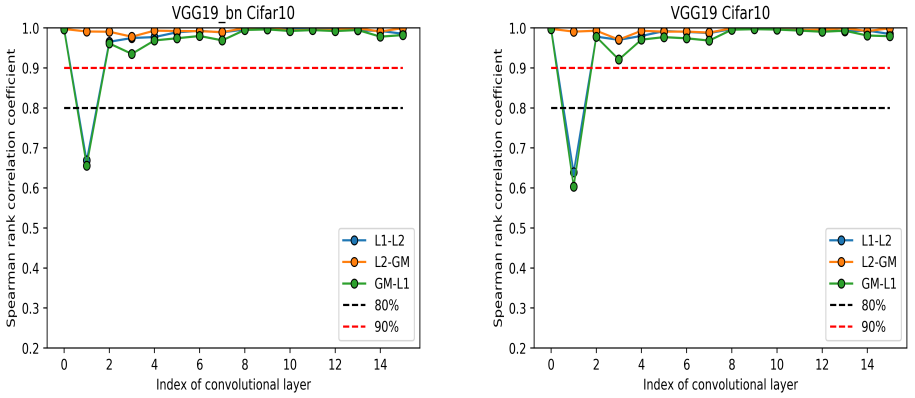


Figure 23: Batch normalization

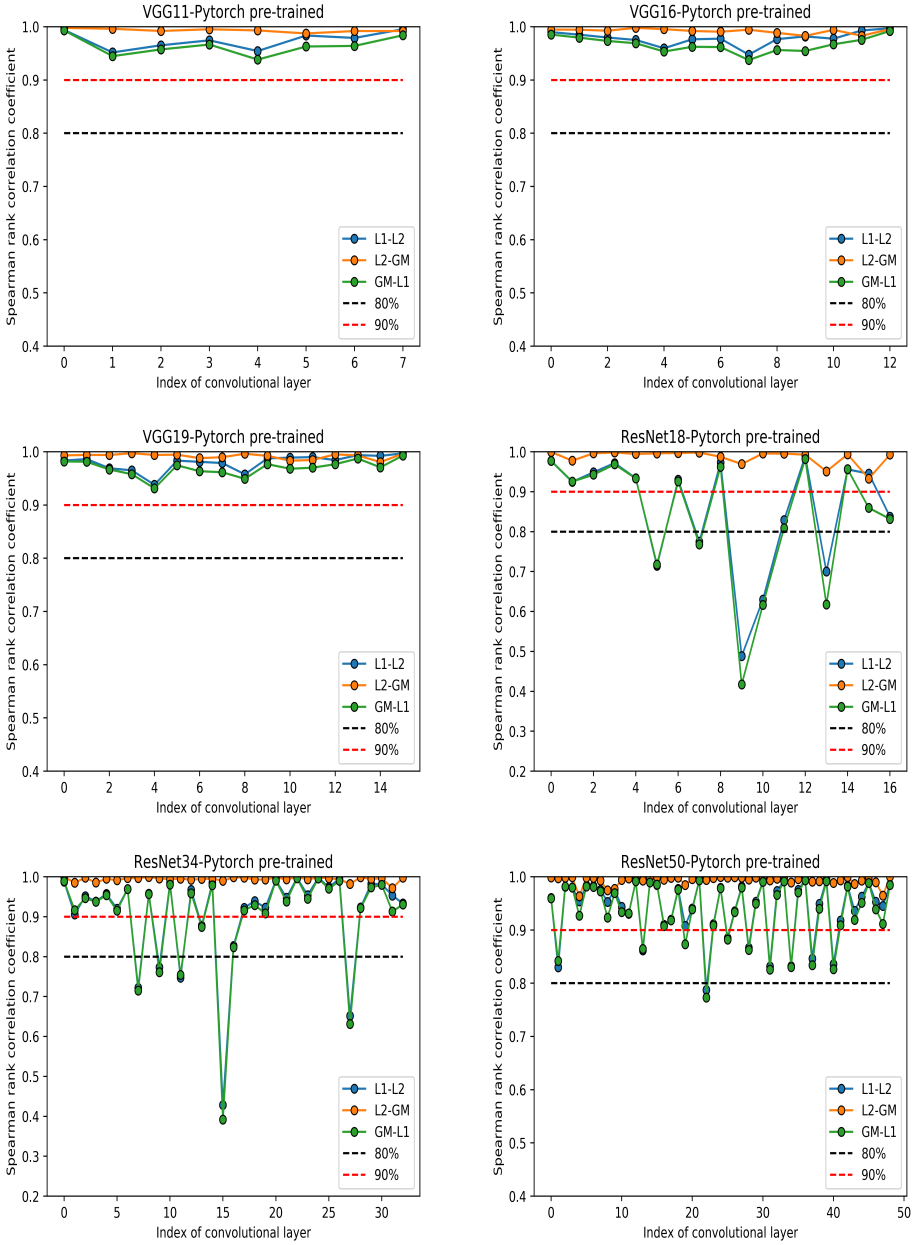


Figure 24: Pytorch pre-trained Model

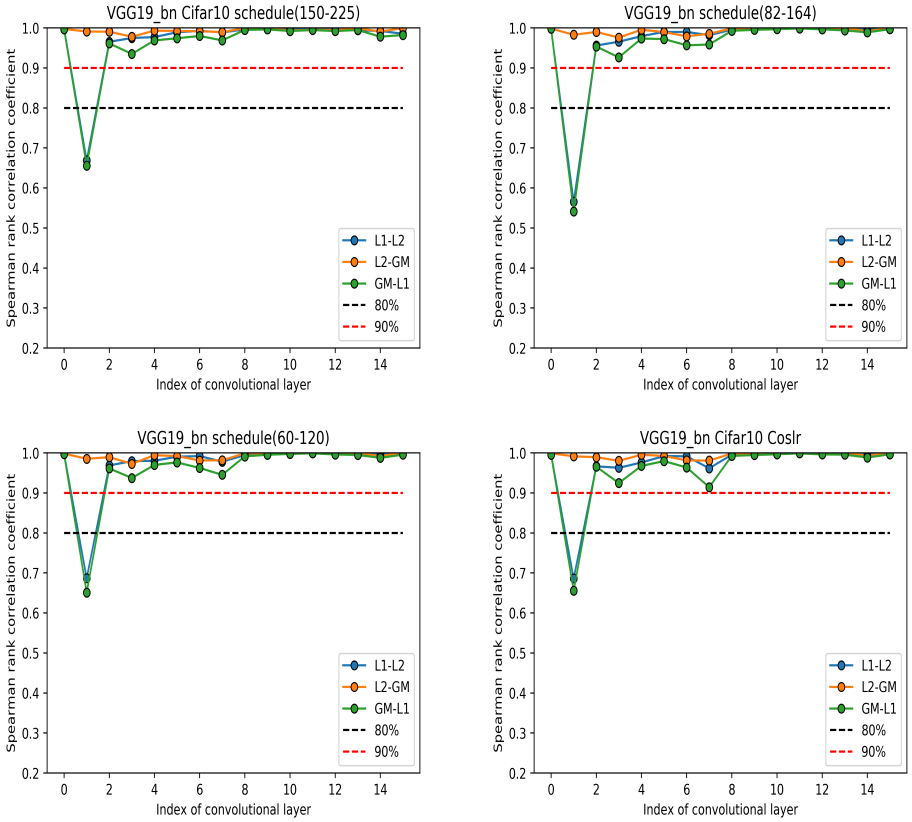


Figure 25: Learning rate