A comprehensive study on binary optimizer and its applicability

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Abstract

Binarized Neural Networks are paving a way towards the deployment of deep neural networks with less memory and computation. In this report, we present a detailed study on the paper titled "Latent Weights Do Not Exist: Rethinking Binarized Neural Network Optimization" by Helwegen et al. [2019] which proposes a new optimization method for training BNN called BOP. We first investigate the effect of using latent weights in BNN for analyzing prediction performance in terms of accuracy. Next, a comprehensive ablation study on hyperparameters is provided. Finally, we explore the usability of BNN in denoising autoencoders. Code for all our experiments are available at https://github.com/nancy-nayak/rethinking-bnn/

1 Introduction

In the era of Artificial Intelligence, deep learning methods are finding itself useful in a variety of tasks. This is not only limited to image or speech processing using supervised learning, game playing using reinforcement learning but to more complex tasks ranging from self driving car to smart personal assistants to autonomous drones helping with household work. The main challenge of using deep learning in computationally complex tasks is that it requires a big complex network which in turn requires huge memory to save its parameters and high computational power. These big networks are often trained with one or many power hungry GPUs. However, in order to enter a mass deployment of solutions, methods that can run low power devices are desirable. In order to satisfy the need of good performance of these networks but deployed with less resources in terms of memory and compute, Courbariaux et al. [2015] proposed Binaryconnect in which the learnt parameters are limited $+1$ or -1. Later Courbariaux et al. [2016] introduced binary neural networks (BNN) where activation also is a binarization function. The main problem of training BNN is that the gradient of binarization function is almost zero everywhere. This was mitigated by utilizing a special kind of function called straight through estimator (STE) Hinton [2012] . To train these neural networks with binary weights, a popular choice is to use Adam optimizer Kingma and Ba [2014]. During the training process, real weights are updated using one of the traditional optimizers during backpropagation and during the forward propagation, only a binarized version (sign) of these real weights (latent weights) are used for prediction and subsequent loss calculations.

In this paper (Helwegen et al. [2019]), the authors have developed an novel optimization method, Binary Optimizer (BOP), for training BNN. The main insight which underpins this development is the observation that latent weights are not necessary for gradient based optimization of BNNs. Instead of updating latent weights using one of the traditional optimizers, the authors proposed to use accumulated momentum to gradients inorder to flip between the binary weights possible for

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each parameter. They empirically demonstrate the performance of BOP on CIFAR10 and Imagenet datasets.

In this study, we explore the capabilities of the proposed optimizer for training BNNs through comprehensive ablation studies.

1.1 Outline of this study

In order to verify the claims presented in the paper and to assess the applicability of the proposed methods to tasks other than classification, we focus on the following questions in this report.

1. Does the use of latent weights instead of binary weights in BNN result in better performance?
2. The Binary Optimizer proposed in the paper has two hyper-parameters to tune. We provide a comprehensive ablation study of the impact of these two parameters in the context of both.
3. Most of the prior work in binary neural networks used batchnormalization at the output of each layer to stabilize training. We propose layernormalization as an alternative for batchnormalization and show that it can have slightly better performance for a proper choice of hyperparameters.
4. Most of the previous works in binary neural networks concentrate on classification tasks, possibly due to the reduced representative power of neural networks with binarized weights. We study the applicability of binary neural networks outside to classification tasks. We present initial results on using BNNs for denosing autoencoders.

2 How do Latent weights perform with respect to binary weights?

Previous works claimed that binary weight vector is an extremely quantized i.e. binarized version of the latent weights. Many of the previous works consider binary weights as an approximation of real latent weights. According to approximation viewpoint, using latent weights instead of binary weights along with binary activations should result in better accuracy than BNN. Authors of this paper (Helwegen et al. [2019]) claimed that using latent weights in BNN may not always result into higher accuracy. In this section, we study this claim with experiments conducted on multiple architectures with different datasets.

We consider the task of classification of images as the case for this study. Three neural network architectures are considered:

1. A fully connected dense neural network (referred as *FullyCon* here on).
2. Convolutional Neural Network based on popular LeNet architecture (referred as *LENET5* here on).
3. Convolutional Neural Network based in VGGNet architecture which is also considered by the authors (referred as *ConvNet*).

The architecture of each of the three networks are shown in Table 1, Table 2 and Table 3 respectively. For convolutional layers, the filter sizes of $(5, 5)$ and $(3, 3)$ are used for LENET5 and ConvNet respectively. The "Activation" mentioned in Table 1, Table 2 and Table 3 are the activation applied to the output of the corresponding layer. For all of the three cases, there is no binarization activation applied to the input layer. We provide the results on training these architectures in MNIST and CIFAR10 datasets till the training accuracy saturates.

Table 1: Architecture of *FullyCon*

Layer	No. of neurons	Batch normalization	Activation	Dropout rate
Dropout+DenseFC-binary	4096	Yes	Binary tanh	0.5
Dropout+DenseFC-binary	4096	Yes	Binary tanh	0.5
Dropout+DenseFC-binary	4096	Yes	Binary tanh	0.5
DenseFC-binary+L2SVM loss	10	Yes	None	-

Table 2: Architecture of *LENET5*

Layer	No. of filters/neurons	Batch normalization	Activation
Binary 2D Convolutional	20	Yes	Binary tanh
Binary 2D Convolutional + Maxpool	20	Yes	Binary tanh
Binary 2D Convolutional	50	Yes	Binary tanh
Binary 2D Convolutional + Maxpool	50	Yes	Binary tanh
Flatten	-	-	-
Binary DenseFC	500	Yes	Binary tanh
Binary DenseFC+Square hinge loss	10	Yes	None

Table 3: Architecture of *ConvNet*

Layer	No. of filters/neurons	Batch normalization	Activation
Binary 2D Convolutional	128	Yes	Binary tanh
Binary 2D Convolutional + Maxpool	128	Yes	Binary tanh
Binary 2D Convolutional	256	Yes	Binary tanh
Binary 2D Convolutional + Maxpool	256	Yes	Binary tanh
Binary 2D Convolutional	512	Yes	Binary tanh
Binary 2D Convolutional + Maxpool	512	Yes	Binary tanh
Flatten	-	-	-
Binary DenseFC	1024	Yes	Binary tanh
Binary DenseFC	1024	Yes	Binary tanh
Binary DenseFC+Square hinge loss	10	Yes	None

The results are provided for MNIST and CIFAR10 datasets are provided in Table 4) and Table 5 respectively. We trained the models by backpropagating losses due to binary weights during the training process. At the end of training, the accuracy of using binary weights and latent weights are reported.

Table 4: Effect of latent weights for MNIST

Binary NN with MNIST dataset	Fully Connected	LENET5
Training accuracy(%) at 500^{th} epoch	100.00	99.99
Test accuracy(%) with binary weights	98.35	99.20
Test accuracy(%) with latent weights	99.01	98.12

Table 5: Effect of latent weights for CIFAR10

Binary NN w/ CIFAR10 dataset	ConvNet	LENET5
Training accuracy(%) at 100^{th} epoch	100.00	85.16
Test accuracy(%) with binary weights	81.72	64.99
Test accuracy(%) with latent weights	50.52	54.62

We can observe from the experiment that, in general, latent weights when applied to BNN does not perform better than binary weights, verifying authors' claim. Hence, the alternate view point of seeing binary weights as approximation of real latent weights Courbariaux et al. [2015, 2016], Rastegari et al. [2016], Zhuang et al. [2019] is not necessarily true. Even though BNN is trained with latent weights, mostly (except MNIST) the BNN with latent weights achieves a lower accuracy than using binary weights.

3 Ablation studies on the effect of hyperparameters

In this section, we present results of the ablation studies on the effect of hyper parameters τ and γ. The paper Helwegen et al. [2019] considers a binary convolutional architecture called *BVGG* net as given in Simonyan and Zisserman [2014] inspired from the architecture of ConvNet in Courbariaux et al. [2016] we discussed before. The authors have shown that the main action which matters for BOP is flipping weights. The question boils down to the following: based on a sequence of gradients, whether to flip a weight or not. BOP should pay attention to the consistency and the strength (absolute value) of the gradient signals. In BOP the consistent signal is selected by looking at exponential moving average of gradients.

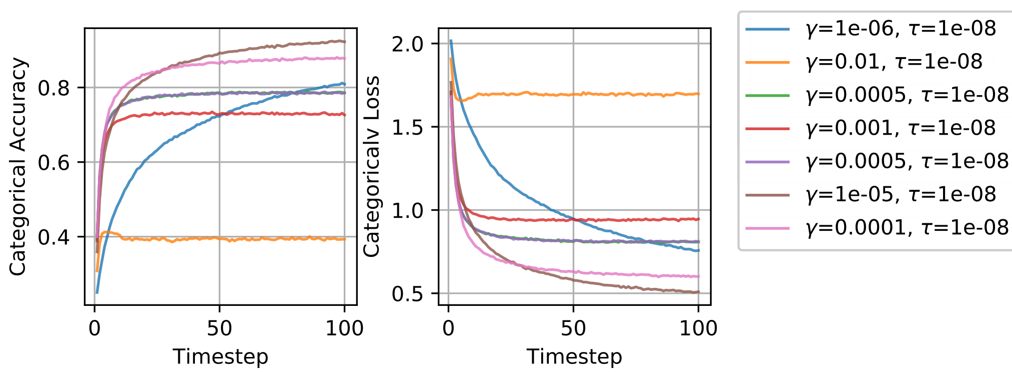
$$m_t = (1-\gamma)m_{t-1} + \gamma g_t = \gamma \sum_{r=0}^{t} (1-\gamma)^{(t-r)} g_r \tag{1}$$

where g_t is the gradient at time t, m_t is exponential moving average and γ is the adaptivity rate. The weight flip is determined by comparing the moving average with a threshold called τ:

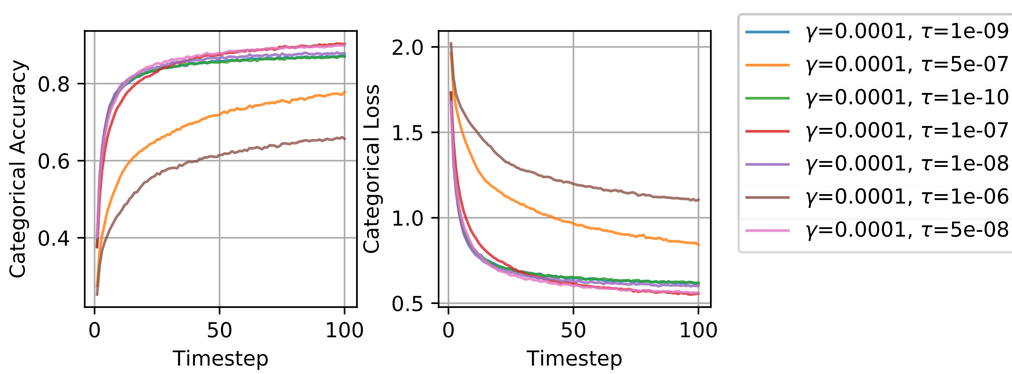
$$w_t^i = \begin{cases} -w_{t-1}^i & \text{if } |m_t^i| \geq \tau \text{ and } \mathrm{sign}(m_t^i) = \mathrm{sign}(m_{t-1}^i) \\ w_{t-1}^i & \text{otherwise} \end{cases} \tag{2}$$

The two hyper parameter for BOP are τ and γ. In this section we show the results of the experiments on BVGG net with BOP as optimization method and with CIFAR10 dataset. To use the dataset for training a binary network, in our work similar modifications are done to the dataset as Helwegen et al. [2019]. We use batch normalization to normalize the activations with a minibatch size of 64.

A non zero threshold γ avoids rapid flip of weights when the gradient reverses on a weight flip. One thing to note here is that high value of τ can result in never flipping of weights even though there is pressure from a consistent gradient signal. As given in the paper, a higher adaptivity rate γ gives more adaptive moving average which implies that if a new gradient signal pressurizes a weight to flip, it take lesser time steps to do so.



(a) Fixed τ



(b) Fixed γ

Figure 1: Ablation studies for τ and γ for Batch Normalization

Keeping τ same (10^{-8}) we see the effect of different γ in Fig (1a). From eq (1) it is clear that with the increase in the value of γ, m_t fluctuates more. A high $\gamma(= 0.01)$ gives very poor performance as high adaptivity rate makes weight to flip in less time steps if a gradient signal starts pressurizing it. Even though in the very beginning of the training, the accuracy trend is steep in case of $\gamma = 0.01$, within a short period of time the accuracy converges to 40%. A low $\gamma(= 10^{-6})$ provides stable training process but it takes long time to fully converge to final accuracy. From the plots we found for $\tau = 10^{-8}$, $\gamma = 10^{-5}$ performs best and converges to training accuracy 92.15%.

Fig (1b) gives training accuracy and loss for different threshold τ and a fixed $\gamma(= 0.0001)$. As explained in the paper, τ should be a non zero real number but not so big that the weight flipping is hindered. In our simulation result, networks with τ in the range of 10^{-8} perform nearly same.

4 Layer Normalization

Till date in most of the works in the line of BNN, batch normalization is used between consecutive non-linear layers in order to stabilize the training. The aim of batch normalization is to normalize the inputs with the global mean and variance but calculating mean and variance of activations for the whole dataset is very costly. So batch normalization is done in small batches and the estimated mean and variances vary from one minibatch to other. The main challenge of using batch normalization is limitation in batch size. If the batch size is very small the variance of the estimates would be very

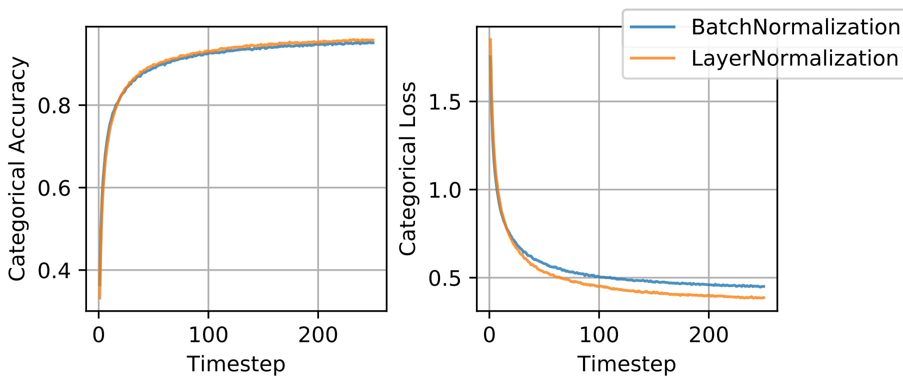


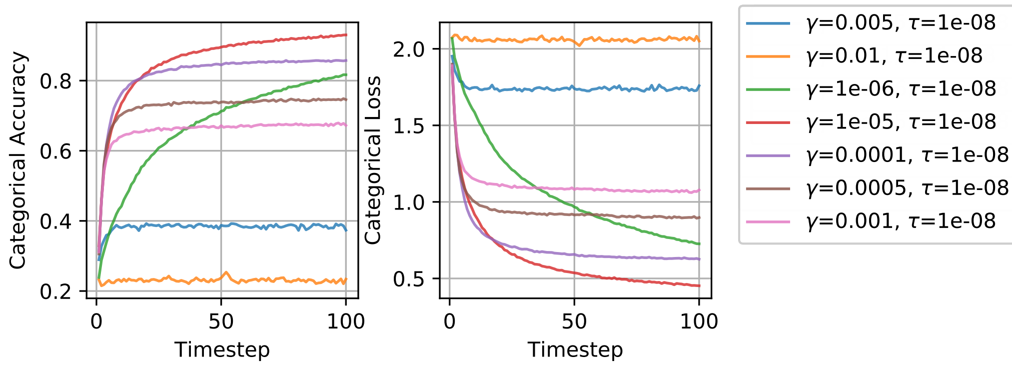
Figure 2: Comparison of BN and LN with $\tau = 10^{-8}$ and $\gamma = 10^{-5}$ in Binary VGG net with CIFAR10 dataset and BOP optimizer

high which makes it difficult to use batchnorm in online learning. Also in case of recurrent neural network, use of batchnorm is difficult as the layer statistics change at each timestep. In this section, we look into Layer Normalization as an alternative solution to avoid these problems Lei Ba et al. [2016].

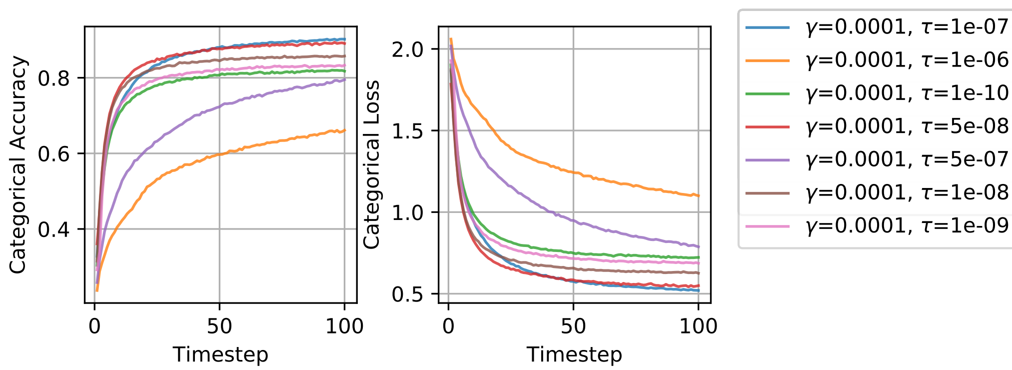
Layer Normalization works by normalizing across the activation (features) passed between two consecutive layers instead of over a mini batch. In LayerNorm, the statistics are calculated across each feature and are independent of other example. We propose to use Layer Normalization instead of batch normalization as an alternate way of stabilizing training. In Fig 2, we provide a comparison of training performances of layernorm and batchnorm for $\tau = 10^{-8}$ and $\gamma = 10^{-5}$. It is clear that layernorm performs slightly better than batchnorm for this choice of hyper parameter.

In Fig. 3, we provide a comprehensive ablation study for the effect of hyper parameters of BOP in conjuction with Layer Normalization. From Fig (3a), we can observe that for fixed $\tau(= 10^{-8})$ the performance of BVGG net is best for $\gamma = 10^{-5}$ and the explanation follows from the batchnorm ablation studies. Similarly, as shown in Fig (3b) for fixed γ, τ in the range of 10^{-8} has nearly same performance.

The above studies conclude that Layer Normalization can be used as a viable alternative to Batch Normalization in the case of training Binary Neural Networks. This can be especially useful in the cases where BNN has to be trained in an online fashion (as in the case of deep reinforcement learning) where acquiring a minibatch of sufficient size to alleviate the affect of noise variance in estimation is either costly or undesirable.



(a) Fixed τ



(b) Fixed γ

Figure 3: Ablation studies for γ and τ for Layer Normalization

5 Using BNNs Beyond Classification: Denoising binary Autoencoder

Most of the works on BNN till date focus on classification tasks as a benchmark for evaluating the performance of BNNs. In this section we explore the usage of BNNs in denoising auto encoder (AE), called Binary AE, referred as *BAE*. The architecture we consider for this experiment is given in Table 6. Convolution represents 2D convolution layer for AE and quantized 2D convolution layer for BAE. Kernel size of convolution and deconvolution layers is $(3, 3)$ and pool size of max pool layers is $(2, 2)$ for both AE and BAE. In this AE architecture first three layers make up the encoder and last three the decoder part. At the first layer of the encoder and decoder, real valued inputs are used. STE-sign function is used as activation on current layer inputs for BAE except for the last layer. The last layer is a deconvolution layer with tanh activation. Mean square loss is minimized with BOP and a metric

Table 6: Architecture for Denoising Binary Auto Encoder

Layer	No. of filters	Batch normalization	Activation on input
Convolution + Maxpool	32	Yes	-
Convolution + Maxpool	16	Yes	STE-sign
Convolution + Maxpool	8	Yes	STE-sign
Deconvolution + Upsampling2D	8	Yes	-
Deconvolution + Upsampling2D	16	Yes	STE-sign
Deconvolution + Upsampling2D	32	Yes	STE-sign
Deconvolution	3	Yes	tanh

called peak signal to noise ratio (PSNR) is calculated to see the performance of the network during training and testing.

$$PSNR = 10 * \log_{10}\left(\frac{max^2}{mse}\right) \tag{3}$$

where max is the maximum possible pixel value of the image and mse is the mean square error between original image and the image output from the network. For traditional AE, the architecture is exactly same except the each layer is trained on real weights with relu activation (instead of STE-sign in BAE) except for the last layer. As the architecture of AE is similar to binary AE except few changes, we do not repeat the architecture.

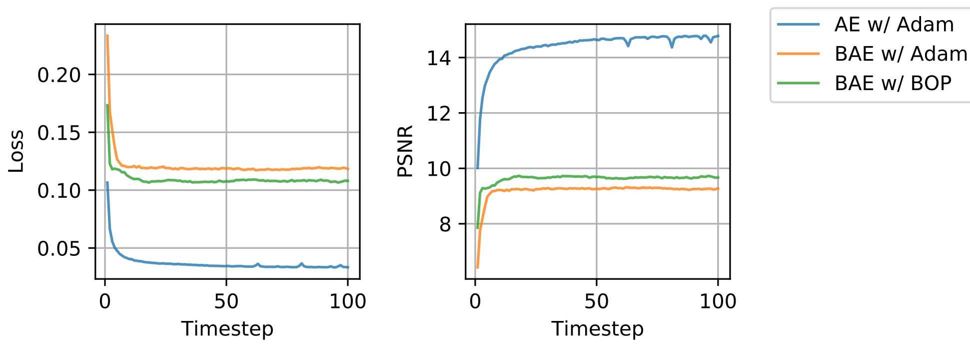


Figure 4: Training PSNR (dB); At the end of training, PSNR for AE: 14.76dB, BAE w/ Adam: 9.25dB and BAE w/ BOP: 9.66dB

In order to use CIFAR10 dataset for training, we scale the $(32, 32)$ images to $(-1, +1)$ say im_{org}. The shape of the images are referred as im_{shape}. Then a random normal $\mathcal{N}(0, 1)$ noise is added with a noise factor $f = 0.1$ and the results are clipped between $(-1, +1)$ again resulting in a noisy image referred as im_{noi}.

$$im_{noi} = \text{clip}\left((im_{org} + f * W), 0, 1\right) \qquad \text{where } W \sim \mathcal{N}(0, 1, im_{shape}) \tag{4}$$

We perform three sets of experiments, all using batch normalization to stabilize the training with a minibatch size of 64. The sets are as follows:

1. Traditional AE with Adam optimizer (with learning rate $lr = 10^{-3}$, $\beta_1 = 0.99$, $\beta_2 = 0.999$)
2. BAE with Adam optimizer with same hyper parameters
3. BAE with BOP optimizer ($\tau = 10^{-8}, \gamma = 10^{-5}$)

In Fig 4 the training loss and training PSNR is shown for all three cases. From the graphs we see that, BAE with BOP seems to be better than BAE with Adam for this task and the training converges faster. The test PSNRs of all three cases are as follows:

1. AE with Adam: 14.87 dB
2. Binary AE with Adam: 9.10 dB
3. Binary AE with BOP: 9.30 dB

However, the results are not impressive for both of the BAE cases. We plot 5 noisy samples of the CIFAR10 test dataset and the recovered images from the above three cases in Fig. 5. The reason behind degraded reconstructions for both of the BAE cases are: binary activations cannot pass enough information between the layers to develop a faithful reconstruction. Hence only a reduced finite set of information can be passed between intermediate layers of encoder and decoder. This could be the reason for not so good performance of BAE. We see a huge scope of improvement for BNN in case of BAE as well as other use cases.

6 Concluding Remarks

To summarize our work, we started with studying the effect of using latent weights on BNN. From our observations, it can be concluded that for most of the cases latent weights on BNN do not perform

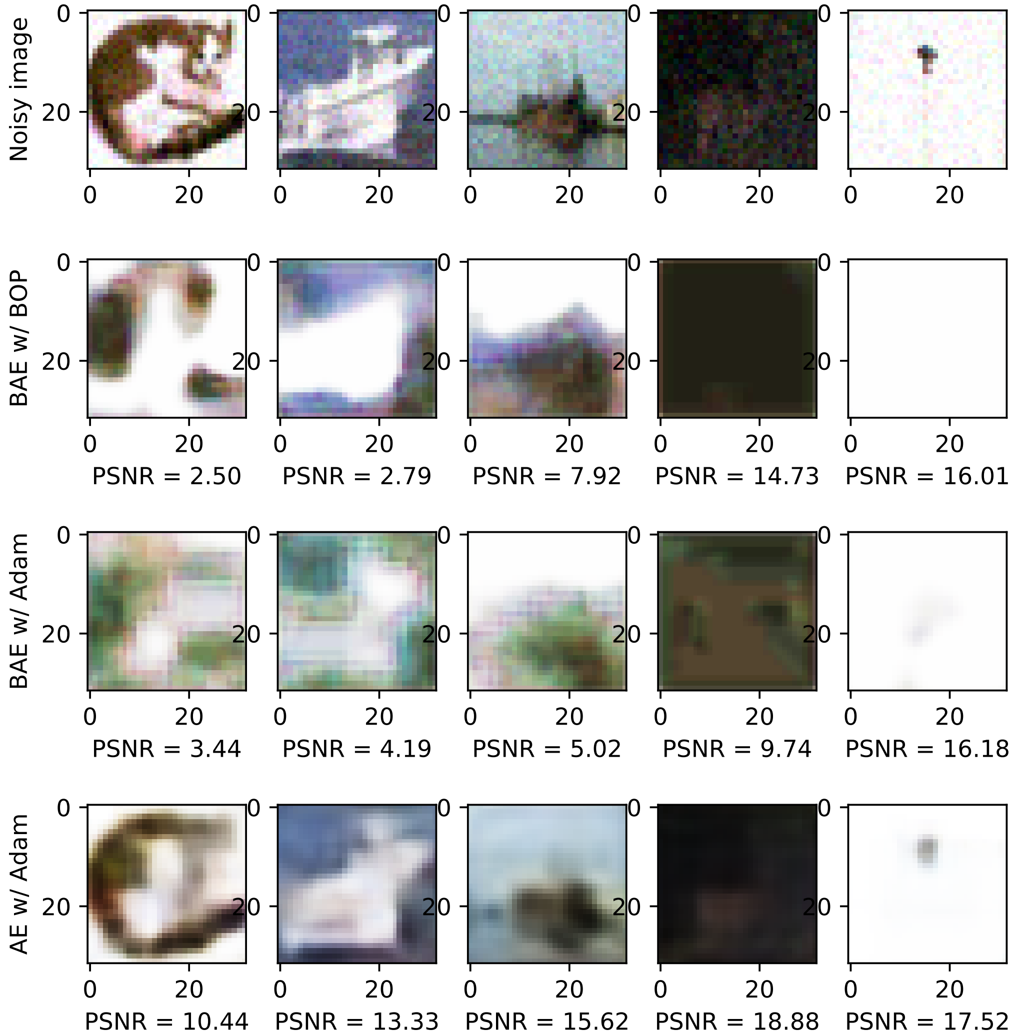


Figure 5: Comparison of recovered images by AE with Adam, BAE with Adam and BAE with BOP

better than binary weights. This conclusion aligns with the authors' claim that binary weight cannot be considered as an approximation of latent weights. We also present an ablation study for the choices of two hyper parameters τ and γ for BOP optimizer. Our comprehensive experimental analysis shows the effect of each of these hyper parameters in the optimization procedure. Next, while most of the works only considered batch normalization, we introduce Layer normalization as an alternative way of normalization and it shows impressive results. An ablation study on the effects of optimizer hyper parameters shows that LayerNorm can provide improved results in some cases. Finally to explore the applicability of BNN in other use cases, we consider Binary AutoEncoders (BAE). The performance of BOP for BAE is then compared with BAE with Adam and AE with Adam. Though a very preliminary results with BAE are shown in our report, BOP shows better PSNR than Adam when used for training binary neural networks.

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