Final Report

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Abstract: Overfitting is a serious problem when using deep neural networks with a large number of parameters. Large networks also take more time to train and test, making it less practical in the real world. To address this problem, Dropout is widely employed. By randomly removing units and its connections from the network, the technique significantly reduces co-adapting effects during training. In our report, we mainly investigate this technique using three datasets, MNIST, CIFAR10, and CIFAR100, and compare the result with related papers. The result suggests that Dropout leads to an increase of accuracy making predictions. Batch Normalization is another powerful technique in deep learning. However, combining Dropout and Batch Normalization together often result in a worse performance. We explore different strategies dealing with this problem. At the end, we further apply these strategies to GANs.

1. Paper Replication

1.1. Results on MNIST

The MNIST dataset consists of 28×28 pixel handwritten digit images, which are classified into 10 digit classes. We employ the same architecture in [1]. All networks use 0.8 as Dropout rate for input layers, and 0.5 for hidden layers respectively. The batch size we use is 200, and the number of training epochs is 1000. Table 1 compares the performance with [1]. The error rates we obtain are slightly larger than those in the paper. We think this may be due to the different batch size and number of epochs used in our report as opposed to [1]. However, the result still shows the effectiveness of Dropout. Without Dropout, the best error rate is 1.42% (ReLUs units, 3 layers). Adding Dropout and max-norm constraint reduces the error rate to 1.24%. Increasing the size of the network can further improve the performance. A network with 2 layers and 4096 units gets down to 1.1% error. We also try replacing ReLU with Maxout activation, and the error rate is a little bit higher (1.15%).

Table 1 MNIST

Method	Unit Type	Architecture	Error%	Error% in the paper
Standard NN	Logistic	2 layers, 800 units	1.58	1.6
Dropout NN	Logistic	3 layers, 1024 units	1.25	1.35
Dropout NN	ReLU	3 layers, 1024 units	1.42	1.25
Dropout NN + max-norm constraint	ReLU	3 layers, 2048 units	1.24	1.06
Dropout NN + max-norm constraint	ReLU	3 layers, 4096 units	1.17	1.04
Dropout NN + max-norm constraint	ReLU	2 layers, 4096 units	1.1	1.01
Dropout NN + max-norm constraint	Maxout	2 layers, (5*240) units	1.15	0.94

1.2. Results on CIFAR-10

The CIFAR-10 dataset consists of 50,000 training images and 10,000 test images. Each sample is 32 pixels by 32 pixels in the RGB color model drawn from 10 categories. The dataset comes in 6 batches, we choose 5 of them as training batches and the rest one as a test batch. Each of batch has around 1000 images per class.

We use three convolutional layers followed by max-pooling layers. Furthermore, we add two fully connected hidden layers followed three convolutional layers and all unit use rectified linear activation function. We apply Dropout with the probability of retaining the unit being p=0.5, 0.8 and 0.9 for different layers.

Table 2 shows the error rate obtained by different methods. The baseline is 25.7% using only convolutional nets and max pooling layers. Adding Dropout in fully-connected layers lead to 5.76% increase of accuracy. The error rate is further reduced to 18.54% by adding Dropout to all layers. Besides, we also use WRN and Densenet to test Dropout. The result further confirm that dropout can reduce overfitting in most cases.

Table 2 CIFAR-10

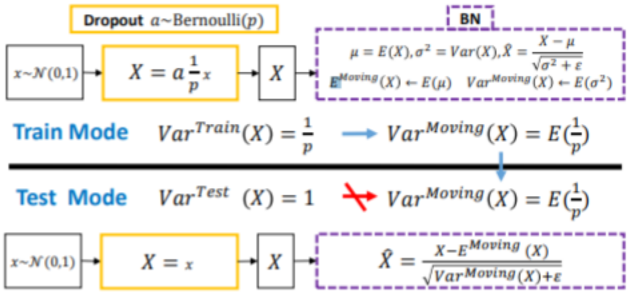
Method	Error%	Error% in the paper
Conv Net + max pooling	25.70	14.98
Conv Net + max pooling + Dropout in fully-connected layers	19.94	14.32
Conv Net + maxpooling + Dropout in all layers	18.54	12.61
DenseNet	10.18	-
DenseNet + Dropout (p=0.5)	10.04	-

WRN	8.73	-
WRN + Dropout (p=0.5)	8.36	-

2. Combine Dropout and Batch Normalization

Since the birth of Dropout, it has been proved to be significantly effective in preventing large networks from overfitting. As introduced in [5], Batch Normalization is another powerful technique introduced to speed up the architectures and improve the performance as regularizers. However, combining the above two techniques together often leads to a worse result.

[2] first answers the question in theoretical and statistical aspects. They discover that there exists mismatch of variance when the state changes from train to test, which could account for the disharmony between Dropout and Batch Normalization. As illustrated in Figure 1, Dropout would scale the variance by its retain ratio, yet Batch Normalization still maintains its variance. They name this scheme as “Variance Shift”.


Dropout $a \sim$ Bernoulli(p)
BN
$x \sim \mathcal{N}(0,1)$
$X = a\frac{1}{p}x$
X
$\mu = E(X), \sigma^2 = Var(X), \hat{X} = \frac{X-\mu}{\sqrt{\sigma^2+\epsilon}}$
$E^{Moving}(X) \leftarrow E(\mu) \quad Var^{Moving}(X) \leftarrow E(\sigma^2)$
Train Mode
$Var^{Train}(X) = \frac{1}{p}$
$Var^{Moving}(X) = E(\frac{1}{p})$
Test Mode
$Var^{Test}(X) = 1$
$Var^{Moving}(X) = E(\frac{1}{p})$
$X = x$
$\hat{X} = \frac{X - E^{Moving}(X)}{\sqrt{Var^{Moving}(X)+\epsilon}}$

2.1. Two strategies to avoid Variance Shift

Inspired by [2], we make an extension by applying two strategies to address the problem of “Variance Shift”.

2.1.1. Apply Dropout after all Batch Normalization layers (Strategy 1)

There would exists the Variance Shift in an architecture only if we have a Dropout layer before a Batch Normalization layer. Thus, one way to avoid the problem is to simply place dropout layers after all Batch Normalization layers. In the following sections, when using Strategy 1, we would only employ Dropout in fully-connected layers.

2.1.2. Modify the form of Dropout (Strategy 2)

Instead of completely removing the Variance Shift effect from our networks, we could also reduce the impact by modifying the form of Dropout. First, we would generate random variables from a uniform distribution that lies in $[-\beta, \beta]$, i.e., generate $r \;\; U(-\beta, \beta)$. Then, we would change each hidden activation to $X = x_i + x_i r_i$. By doing this, we add a layer that functions like Dropout but has a variance shift ratio, defined as the ratio of test variance to train variance, much closer to 1.0 in comparison with the traditional Dropout layer. We conduct experiments on MNIST, CIFAR-10 and CIFAR-100 using different values (0.1, 0.2, 0.3) for β.

2.2. Experimental results

2.2.1. MNIST

From Table 3, we can see that when combining Dropout and Batch Normalization together, the architecture performs worse on MNIST (Error% 0.89). To avoid the scaling on feature-map before every Batch Normalization layer, we only add Dropout on the fully connected layers after all Batch Normalization layers. Such an operation could bring 0.13% improvements on MNIST as opposed to only using Batch Normalization. We could also modify the formula of Dropout by adding a uniform distributed random variable $r \quad U(-\beta, \beta)$. This leads to 0.13~0.2% increase of accuracy.

Table 3 MNIST (Dropout + Batch Normalization)

Method (CNN)	Error%
Batch Normalization	0.85
Batch Normalization + Dropout(all,p=0.9,fc,p=0.5)	0.89
Dropout(all,p=0.9;fc,p=0.5)	0.75
Batch Normalization + Dropout(fc,p=0.5) + strategy1	0.72
Batch Normalization + Dropout(fc,p=0.5) + strategy2(beta=0.1)	0.73
Batch Normalization + Dropout(fc,p=0.5) + strategy2(beta=0.2)	0.64
Batch Normalization + Dropout(fc,p=0.5) + strategy2(beta=0.3)	0.72

2.2.2. CIFAR-10 and CIFAR-100

Besides CIFAR-10, we also use CIFAR-100 to test the two strategies. The CIFAR-100 dataset consists of 32×32 color images from 100 categories. The dataset contains train set and test set. We use the same architecture in 1.2.

First, we implement two strategies to CIFAR-10 dataset. As reported in table 4, when we add both Batch normalization and Dropout to all layers without strategies, we got error rate around 21.64%. Then, we implement the first strategy which applies Dropout after all BN layers, and we found that the error rate goes down to 16.42%. Furthermore, we change Dropout into a more variance-stable form based on strategy 2. The new form of Dropout achieves 4.64~5.18% increase of accuracy. In conclusion, improvements can be observed by using both strategies on Cifar10 set compared with the original results. Also, if we remove batch normalization and only apply strategy2 to Dropout, the error rate is around 19~20% which is close to the results from original methods without strategies.

Table 4 CIFAR-10 (Dropout + Batch Normalization)

Method (CNN)	Error%
No Dropout and Batch Normalization	25.70
Dropout (fc, p=0.5)	19.94
Batch Normalization	19.79
Dropout (fc,p=0.5) + strategy2 (beta=0.1)	19.70
Dropout (fc,p=0.5) + strategy2 (beta=0.2)	20.40
Dropout (fc,p=0.5) + strategy2 (beta=0.3)	19.76
Batch Normalization + Dropout (all, p=0.8)	21.64
Batch Normalization + Dropout (fc, p=0.5) + strategy1	16.42
Batch Normalization + Dropout (all, p=0.5) + strategy2 (beta=0.1)	17.00
Batch Normalization + Dropout (all, p=0.5) + strategy2 (beta=0.2)	16.79
Batch Normalization + Dropout (all, p=0.5) + strategy2 (beta=0.3)	16.46

Then we implement two strategies to CIFAR-100 dataset. From table 5, we can see that if we only add Dropout or batch normalization separately to the neural network, the accuracy rate is around 28~29%. Also, if we only add strategy2 with Dropout, no significant improvements are reported. Furthermore, when we apply Dropout and batch normalization together without strategies, the accuracy drops to around 20%. Thus, from the results above, strategies have led to a significant increase in accuracy. We use the first strategy which applies Dropout after all BN layers, and the accuracy goes up to 36.54% with Dropout equals 0.5 and 33.48% with Dropout equals 0.8. And for the second strategy, we add the uniform noise to each convolutional layer and the new structure achieves 3~6% increase of accuracy with different parameter values.

Table 5 CIFAR-100 (Dropout + Batch Normalization)

Method (CNN)	Accuracy%
No Dropout and Batch Normalization	20.12
Dropout (fc, p=0.5)	28.17
Batch Normalization	29.77
Dropout (fc,p=0.5) + strategy2 (beta=0.1)	30.23
Dropout (fc,p=0.5) + strategy2 (beta=0.2)	28.11
Dropout (fc,p=0.5) + strategy2 (beta=0.3)	25.47
Batch Normalization + Dropout (all, p=0.5)	20.38
Batch Normalization + Dropout (fc, p=0.5) + strategy1	36.54
Batch Normalization + Dropout (fc, p=0.8) + strategy1	33.48
Batch Normalization + Dropout (all, p=0.5) + strategy2 (beta=0.1)	33.46
Batch Normalization + Dropout (all, p=0.5) + strategy2 (beta=0.2)	36.04
Batch Normalization + Dropout (all, p=0.5) + strategy2 (beta=0.3)	33.16

Applying Dropout to GANs

Generative adversarial networks belong to one of the most popular machine learning algorithms developed in recent times. They belong to a set of algorithms named generative models. These algorithms belong to the field of unsupervised learning, a sub-set of ML which aims to study algorithms that learn the underlying structure of the given data, without specifying a target value. Generative models learn the intrinsic distribution function of the input data p(x) (or p(x,y) if there are multiple targets/classes in the dataset), allowing them to generate both synthetic inputs x and outputs/targets y' typically given some hidden parameters.

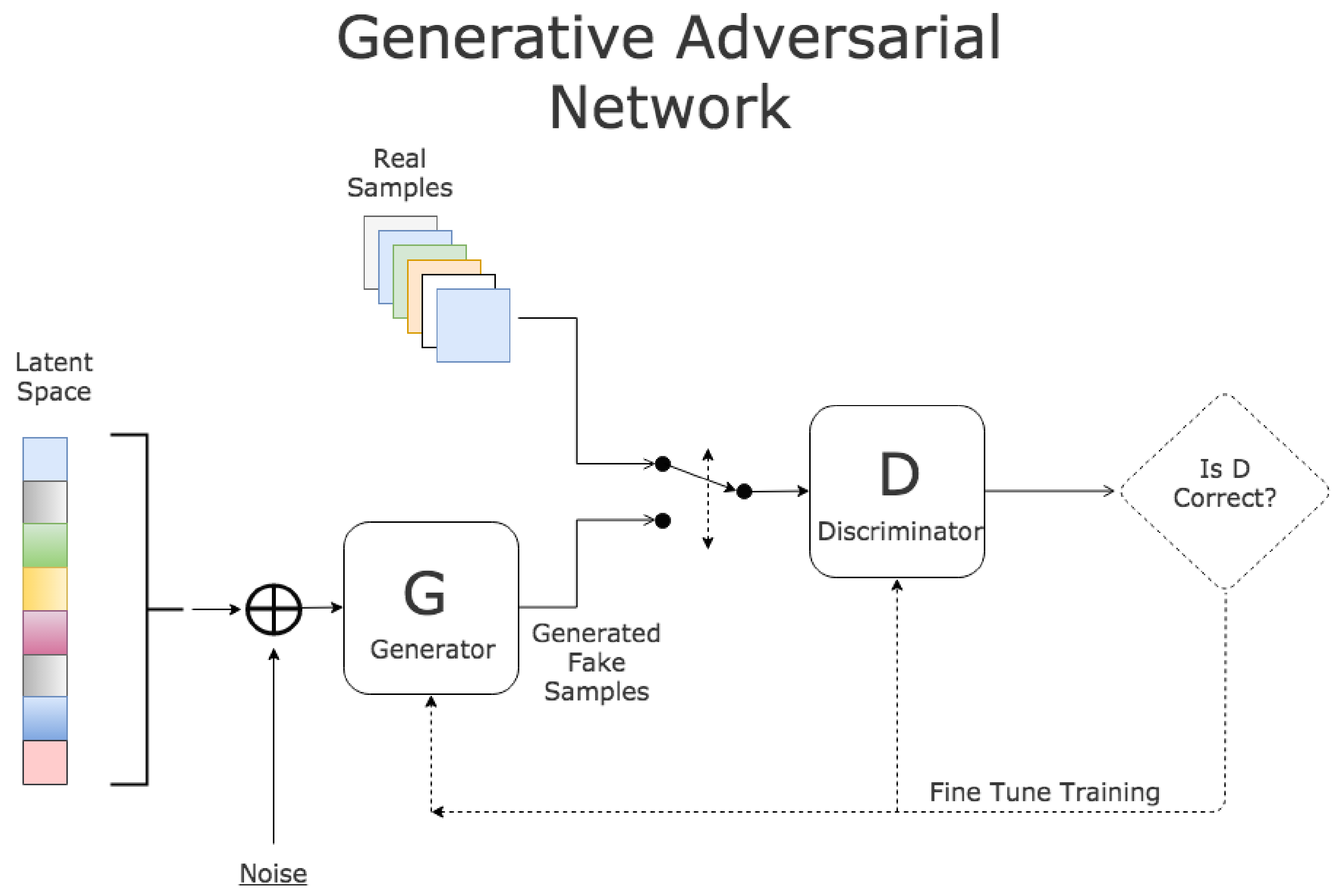
Generative adversarial networks

GANs they have proven to be really successful in modeling and generating high dimensional data, which is why they've become so popular. Nevertheless they are not the only types of Generative Models, others include Variational Autoencoders (VAEs) and pixelCNN/pixelRNN and real NVP. Each model has its own tradeoffs. Generative adversarial networks are a framework that integrates adverserial training in the generative modeling process.

Some of the most relevant GAN pros and cons for the are:

- They generate sharp and accurate images
- They are easy to train since no statistical interference is required and only back propogation is required to get the required gradients
- It is difficult to optimize GANs because of unstable training dynamics

the framework is composed of two models - one generator and one discriminator - that train together by playing a minimax game. The generator tries to fool the discriminator by producing random sample images and keeps learning to make the images as realistic as possible. The discriminator tries to differentiate between the real and fake samples generated by the generator. The discriminator gets better at distinguishing between the real and fake images over time.



Shortcomings of a traditional GAN framework

One of tha main problems of GANs is mode collapse where the generator is able to fool the discriminator by producing data only from connected components of the data manifold which leads to similar looking samples produced from a narrow scope of data. This leads to sub-optimal generator learning where the generator learns only a small segment of the actual distribution of the data. To counter this dropout was introduced and was proven to widely successful in countering the problem of overfitting. The idea behind using dropout is that neurons are not specifically dependent on certain other neurons to produce output.

In our case we try and test if we can use the dropout method with GAN and extend the concept by applying dropout in conjunction with two other methods viz. a viz. batch normalization and variance shift and test if we get better results.

MNIST dataset

The MNIST dataset is composed of 10 classes of handwritten digits varying from 0 to 9. It is visible that the quality and variation of the produced samples increase while using dropout rate values of 0.2 and 0.5 across all different sized discriminator sets. On the other hand, the quality of the produced numbers deteriorates considerably while using high dropout rates, i.e., 0.8 and 1, or no dropout rate at all. However, the quality gets slightly better when using more discriminators on such extreme end dropout rates, since Generator might still get enough feedback to be able to learn at the end of each batch.

Experimental Setup

We built a discriminator using 3 hidden layers and used tensorflow to setup the neural network. First we normalize the images between 1 and -1. We provide tanh as the activation function for the last layer of generator inputs. Although traditionally loss functions are defined as min(1 – log(D)), we use max(log(D)) as our loss function so as to counter the effects of vanishing gradients, early on. For the problem of batch normalization we construct different mini-batches for real and fake i.e. each mini batch either contains only real images or only generated images. To avoid sparse gradients we use leakyRelu as our activation function in hidden layers which is stable in both the discriminator and the generator. We use the ADAM optimizer for both the discriminator and generator. Adam uses first-order gradient-based optimization of stochastic objective functions, based on adaptive estimates of lower-order moments. We use adam because of its simplicity and computational efficiency. We set the learning rate equal to 0.002 and the beta_1 equal to 0.5 keeping all other parameters default. We keep the batch-size equal to 128 setting the number of epochs to 200.

Standard dropout results on the MNIST dataset

We observe that the quality and variation of images steadily improve for lower values of the dropout. We test for dropout rate values of 0.2 and 0.5 find much better values for the generative loss as compared to standard GAN algorithm implementation with no dropout. In the first figure (GAN with no dropout) we can see that the generative loss values are considerably higher. However using dropout values of 0.2 and 0.5 we see a high improvement in the values of generative loss although the discriminative loss tends to stay about the same. However as predicted the generative loss for higher values of dropout at 0.8 tends to deteriorate. We also observe much higher values of discriminative loss for higher values of dropout.

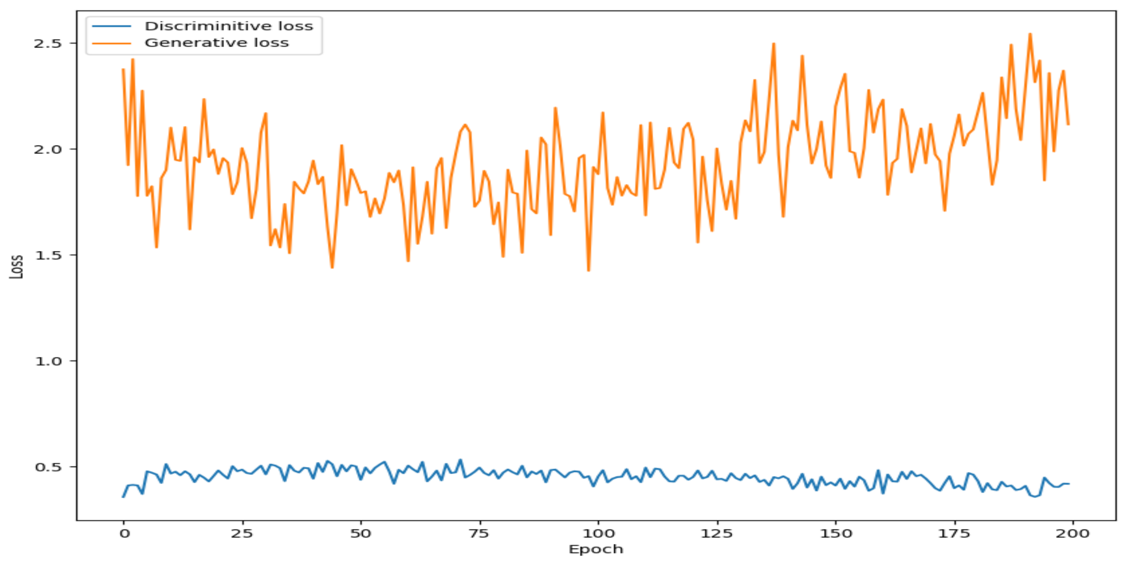

Discriminitive loss
Generative loss
2.5
2.0
1.5
1.0
0.5
Loss
0
25
50
75
100
125
150
175
200
Epoch

Fig: GAN without dropout

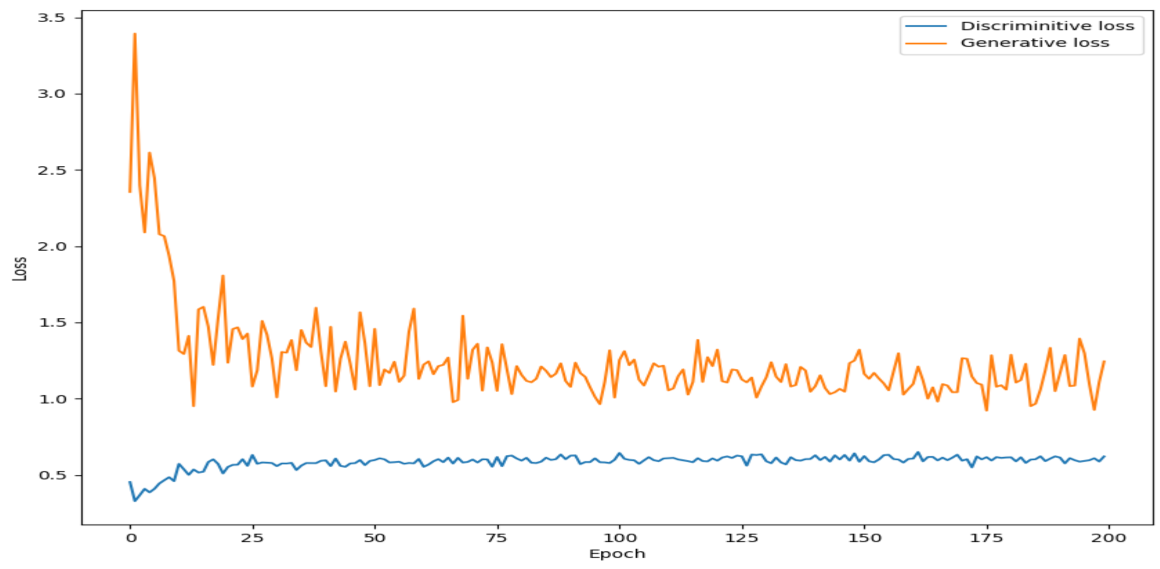


Fig: GAN with dropout 0.5

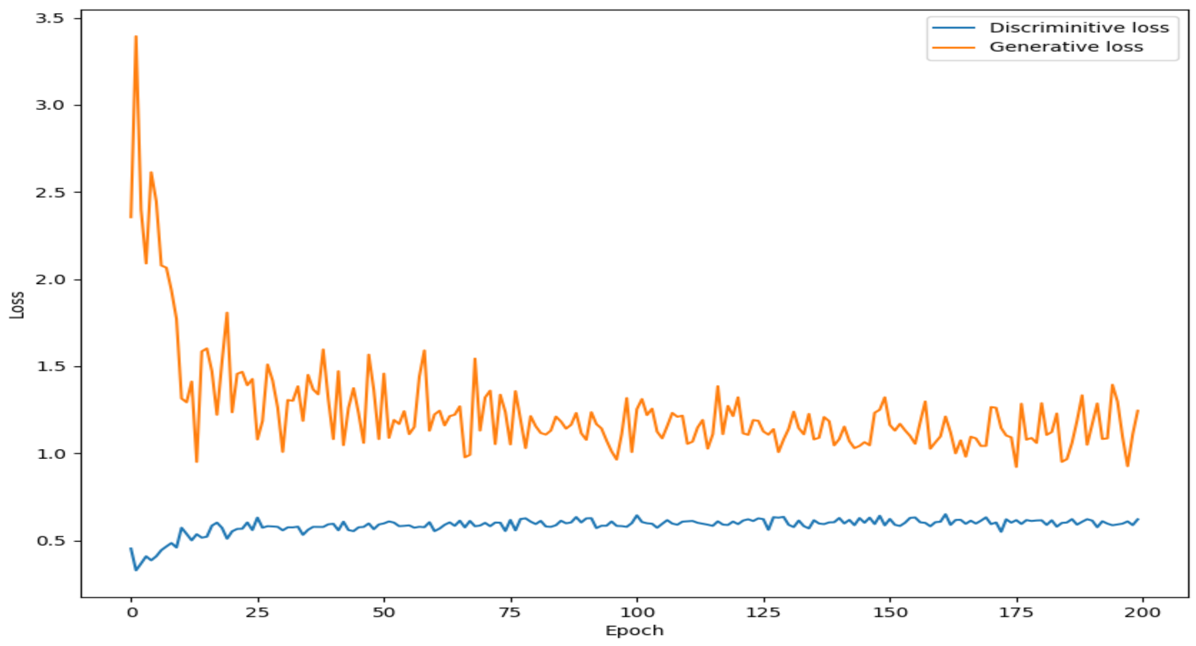


Fig: GAN with dropout 0.2

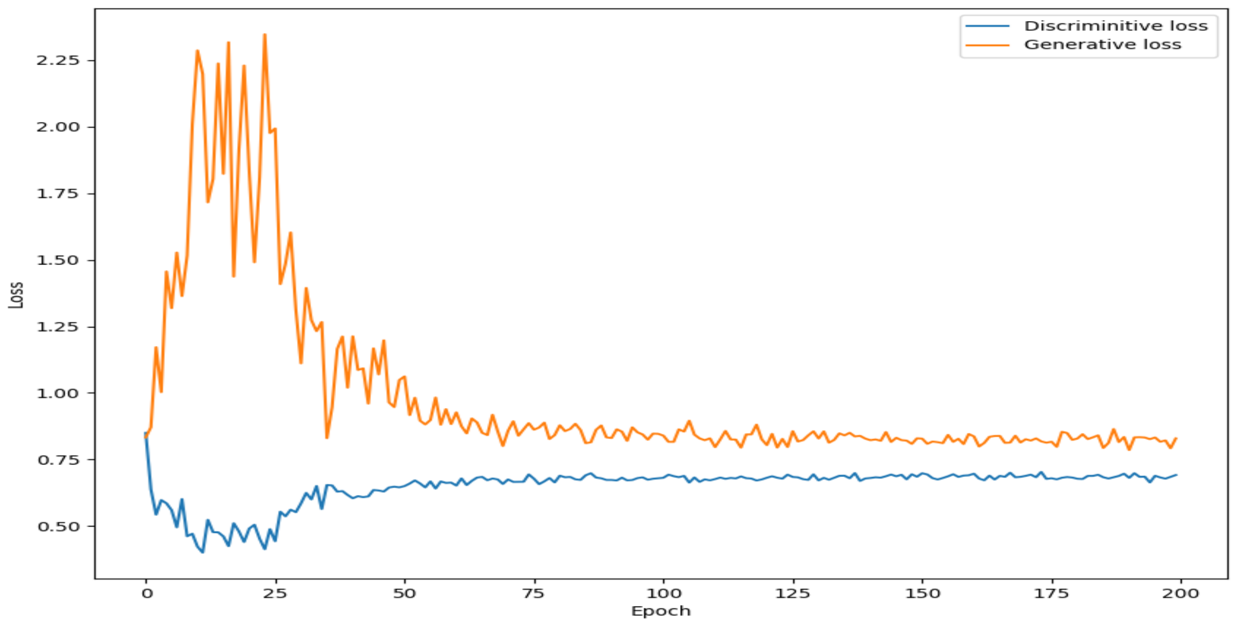


Fig: GAN with dropout 0.8

Adding Batch Normalization with dropout

We observe that if we apply batch-normalization with momentum 0.9 the generative loss increases for higher epochs although a sharp drop is seen between 25th and 50th epochs. He experiment was setup where batch-normalization was applied for the first two hidden layers along with dropout with dropout ratio 0.2. A dropout of 0.2 was also applied in the last hidden layer without batch-normalization. We also tested by lowering the momentum and increasing the dropout ratio and we observed the same results. As such we conclude that this strategy is not feasible.

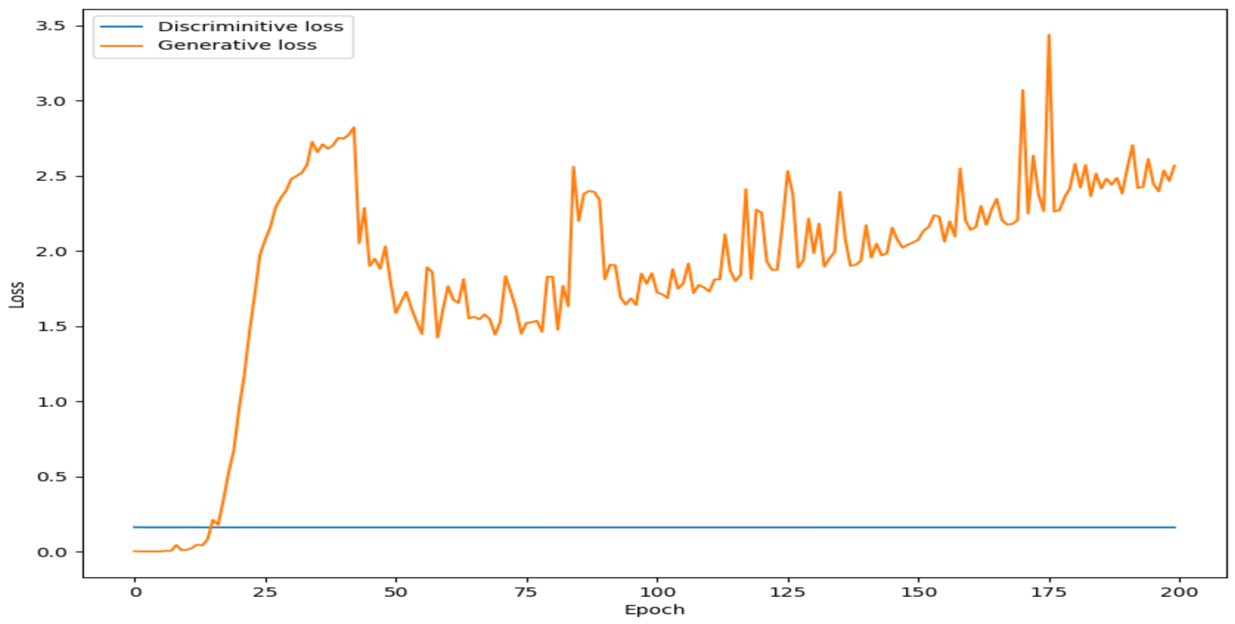


Fig: Batch normalization with dropout in the first two layers and only dropout in the third layer

In the second strategy, we apply batch-normalization to the first two layers without dropout and we apply a dropout with dropout ratio of 0.2 on the last layer. Here again, we see that there is sharp spike in the generative loss between epoch 1 and epoch 25 and although there is a sharp drop in generative loss close to epoch 75, we see a clear marked increase in the generative loss after 200 epochs. Although the values for discriminative loss look constant, there is in fact a slight variation in the values and we can refer to the appendix regarding the same. We can intuit the reason to be because of the variance shift occurring due to the fact that Dropout would shift the variance of the specific neural net whereas batch-normalization would try and maintain the variance which might lead to adverse results. As such both our strategies fail.

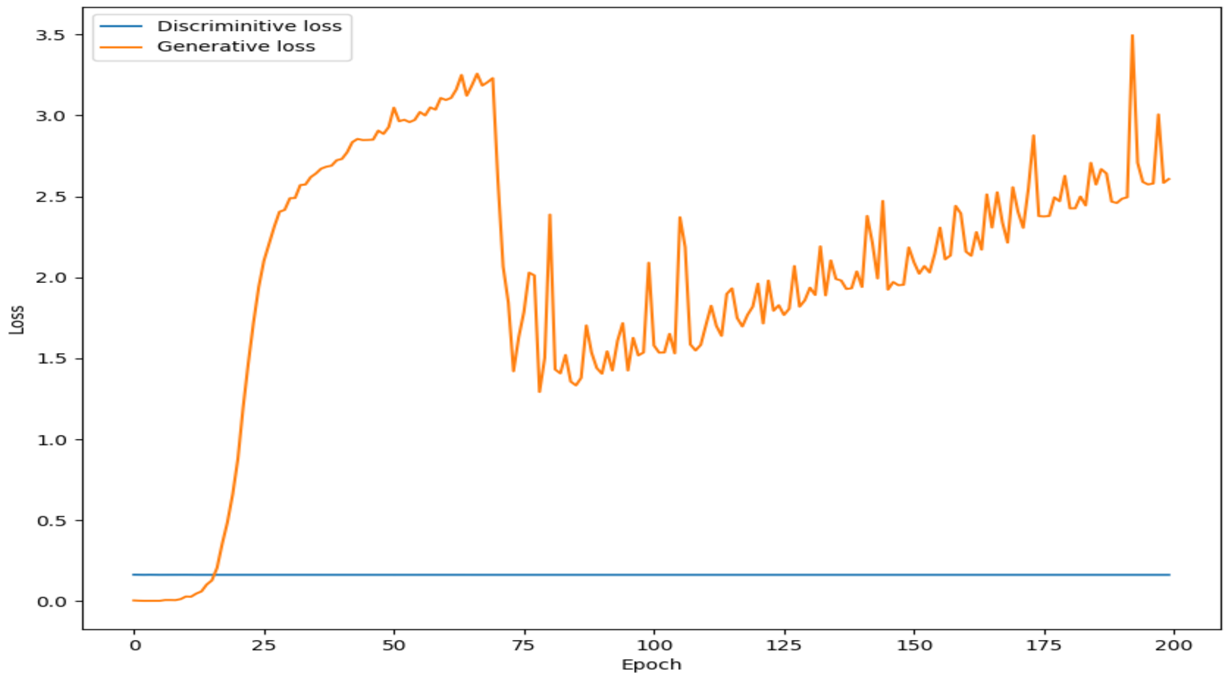


Fig: Batch normalization only in the first two layers and only dropout in the third layer

Adding random variables with dropout

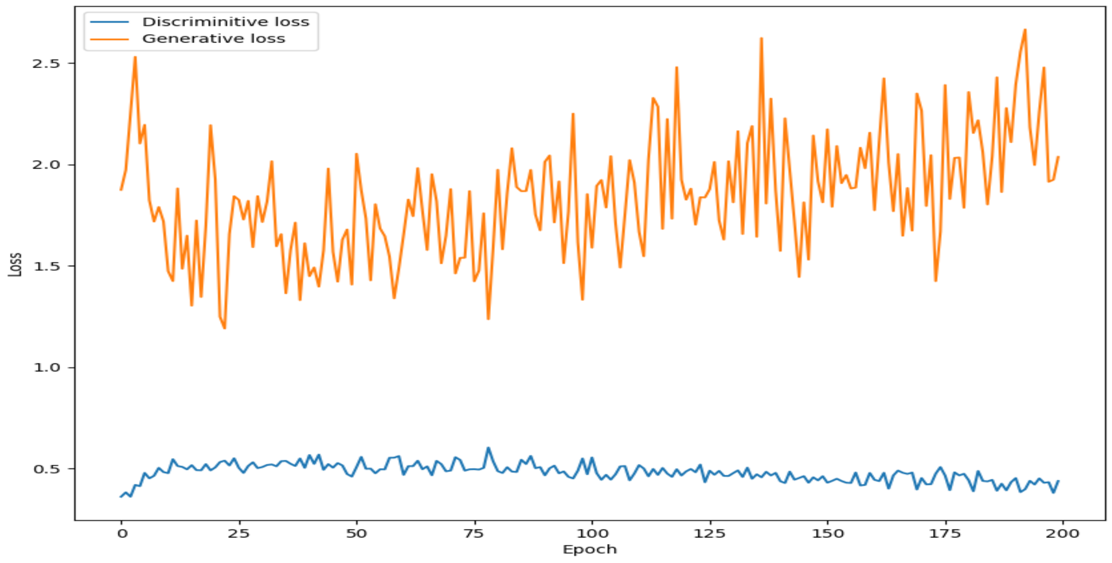


Fig: Strategy with random variable (U ~ (-0.1, 0.1) added to x added with dropout of 0.2 in the first two layers and only dropout of 0.2 on the third layer

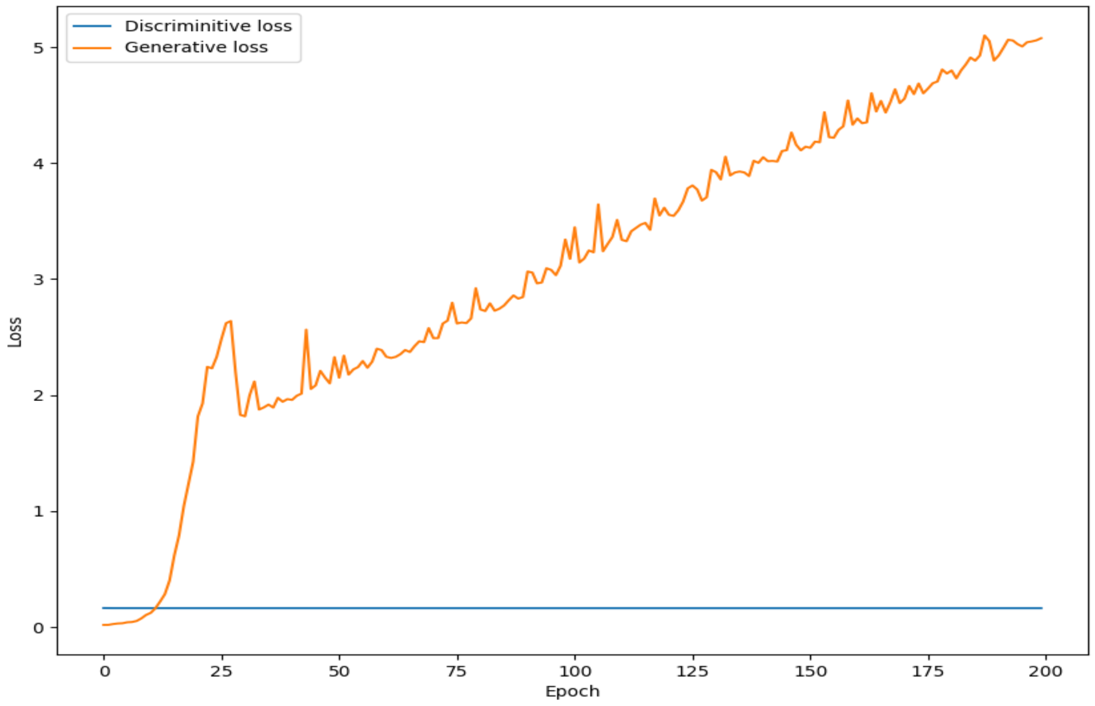


Fig: Strategy with only random variable in the first two layers and only dropout of 0.2 on the third layer

APPENDIX

Image1: Image after 200 epochs for no dropout strategy with d = 0.0

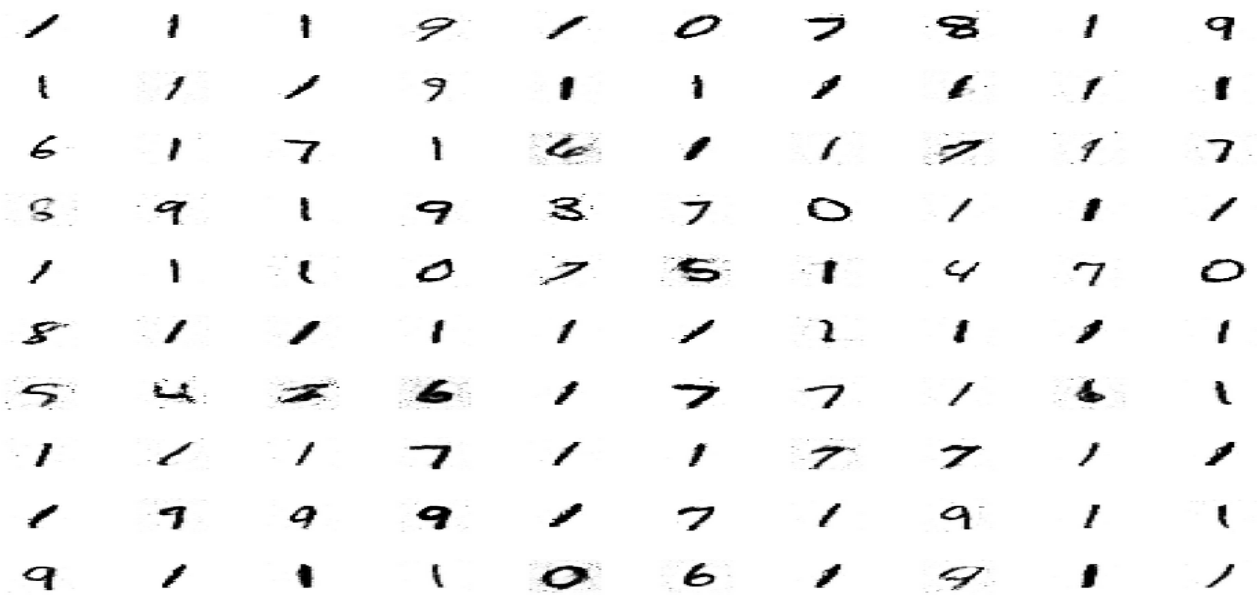


Image2: Image after 200 epochs for dropout strategy with d = 0.2

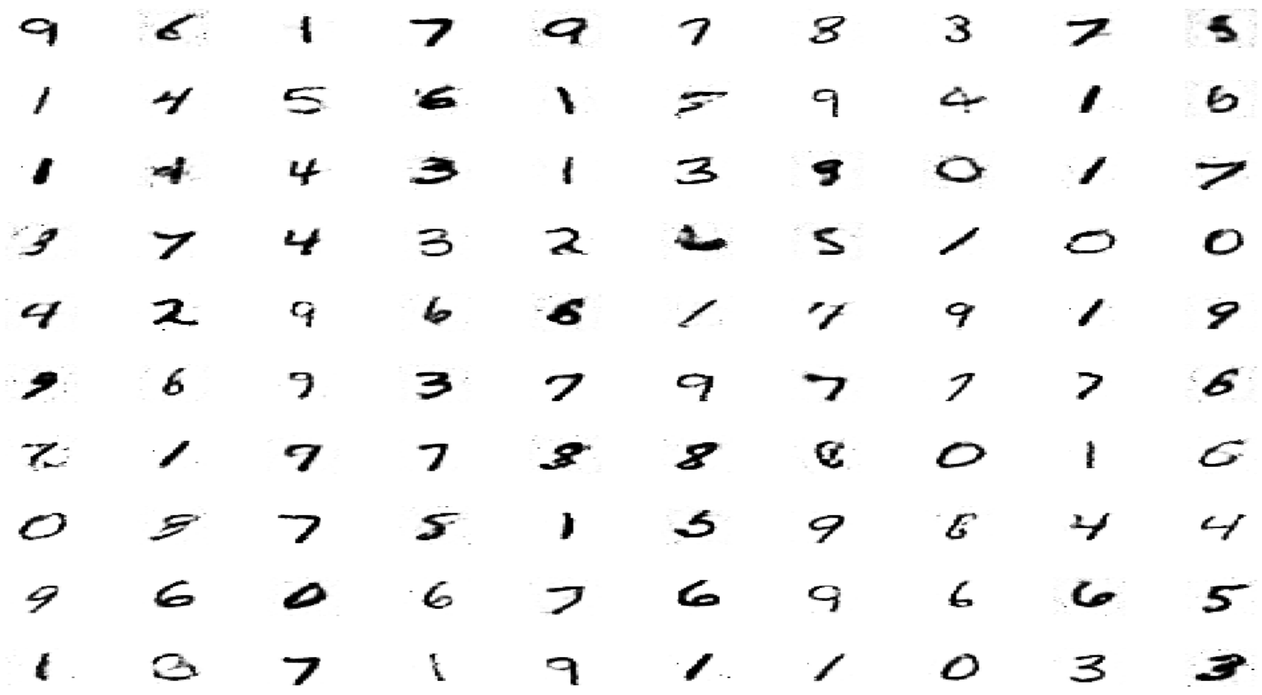


Image3: Image after 200 epochs for dropout strategy with d = 0.5

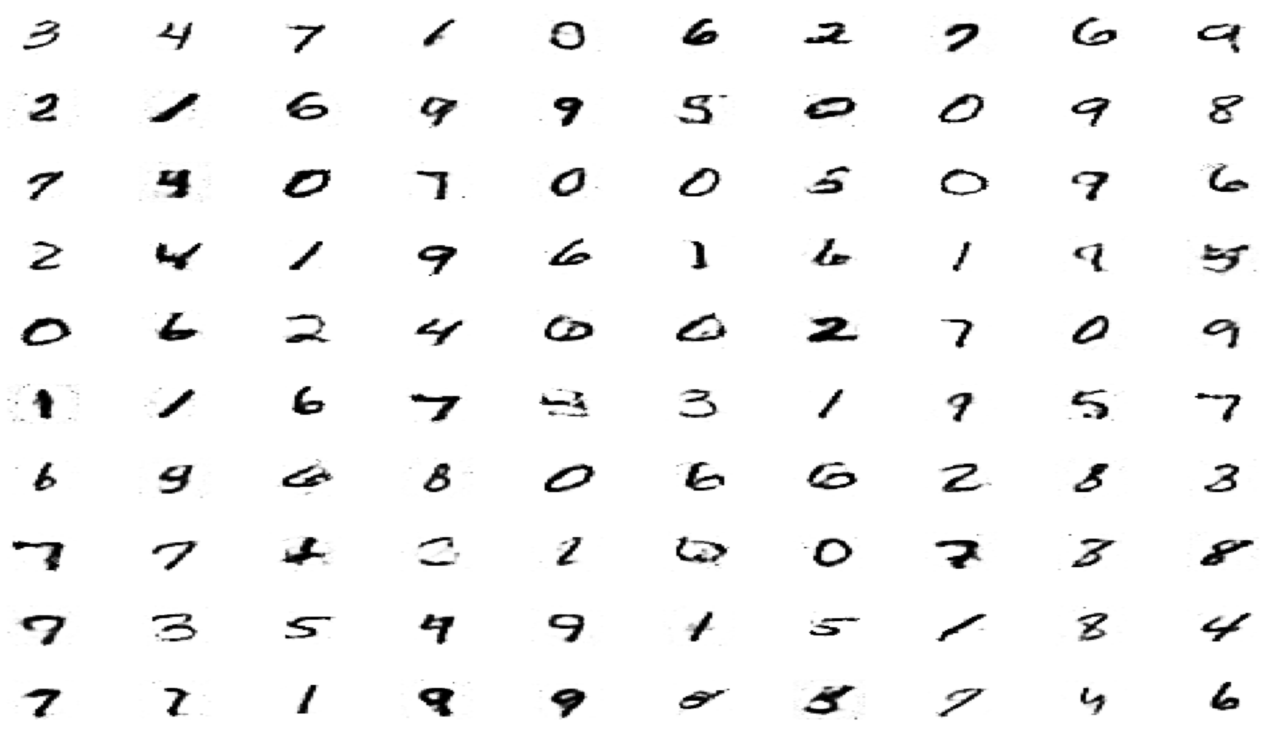


Image4: Image after 200 epochs for dropout strategy with d = 0.8

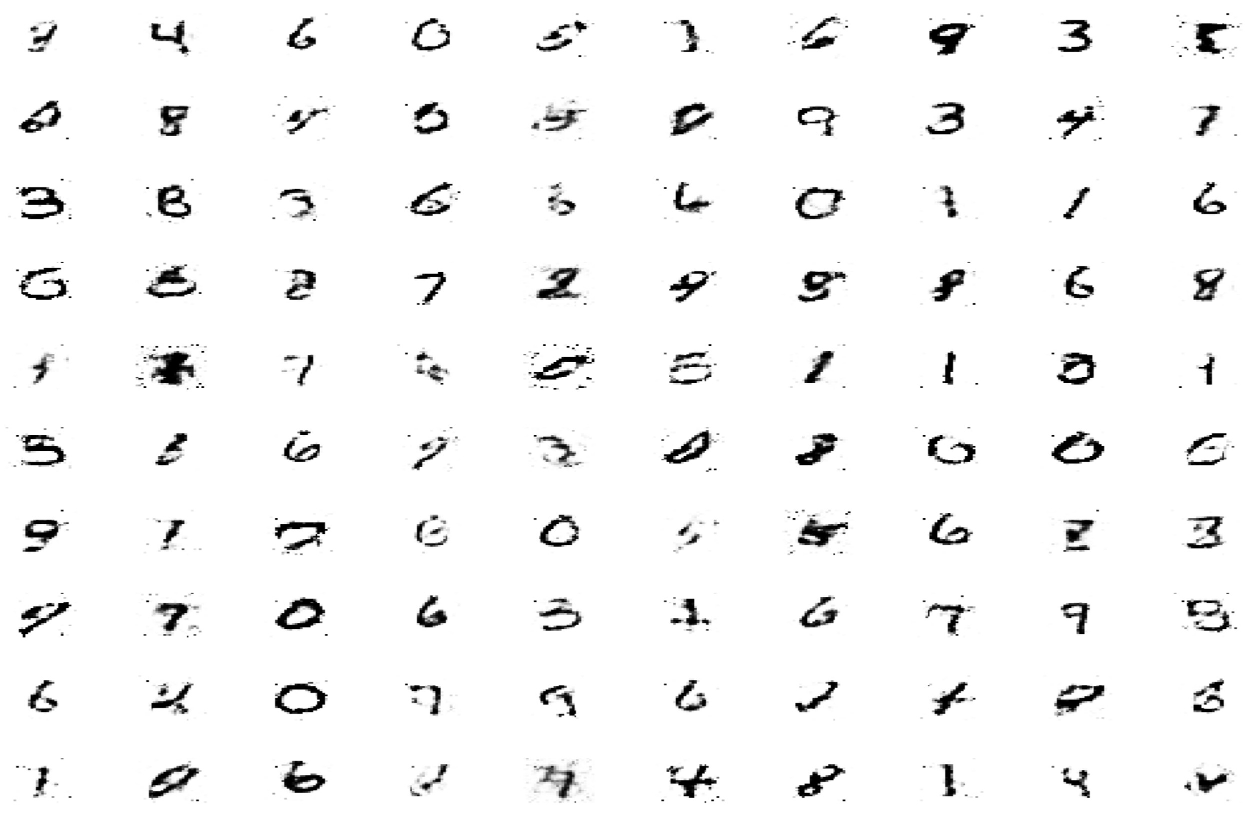


Image5: Image after 200 epochs for dropout + batch normalization strategy 1 with d = 0.2

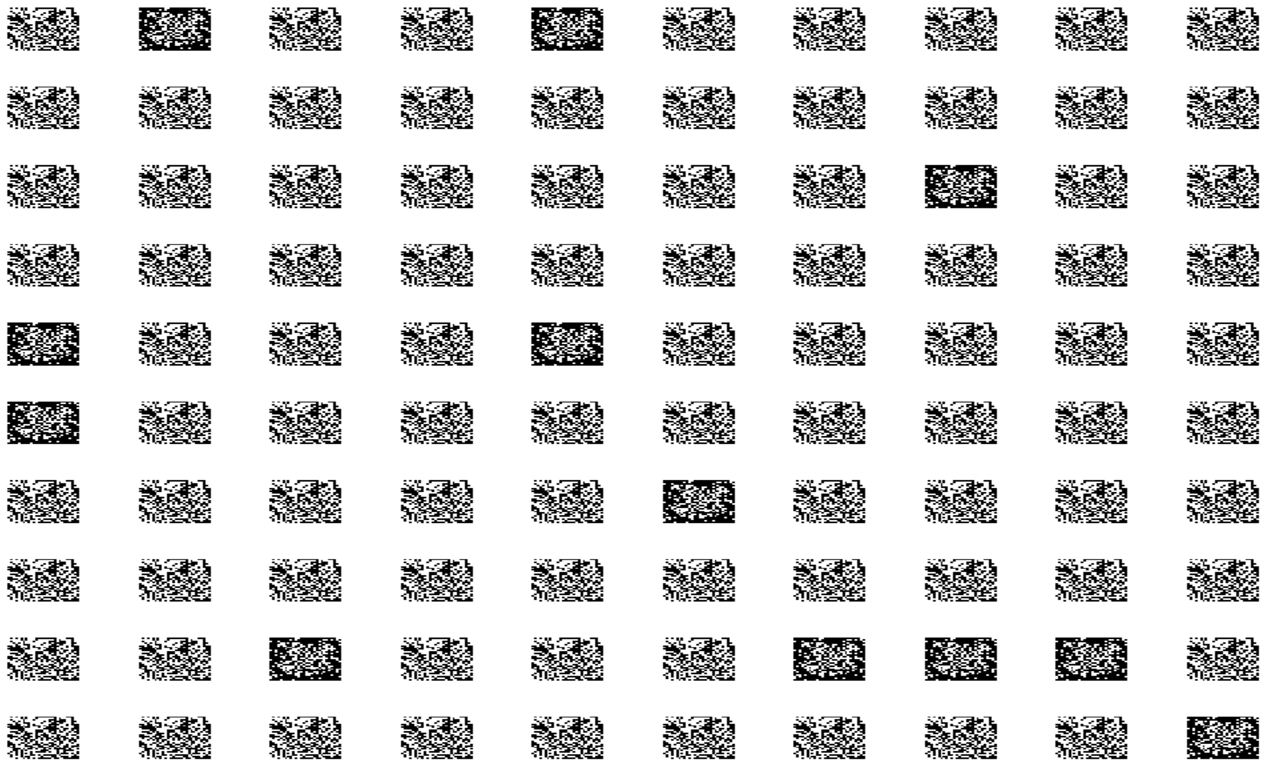


Image5: Image after 200 epochs for dropout + batch normalization strategy 1 with d = 0.2

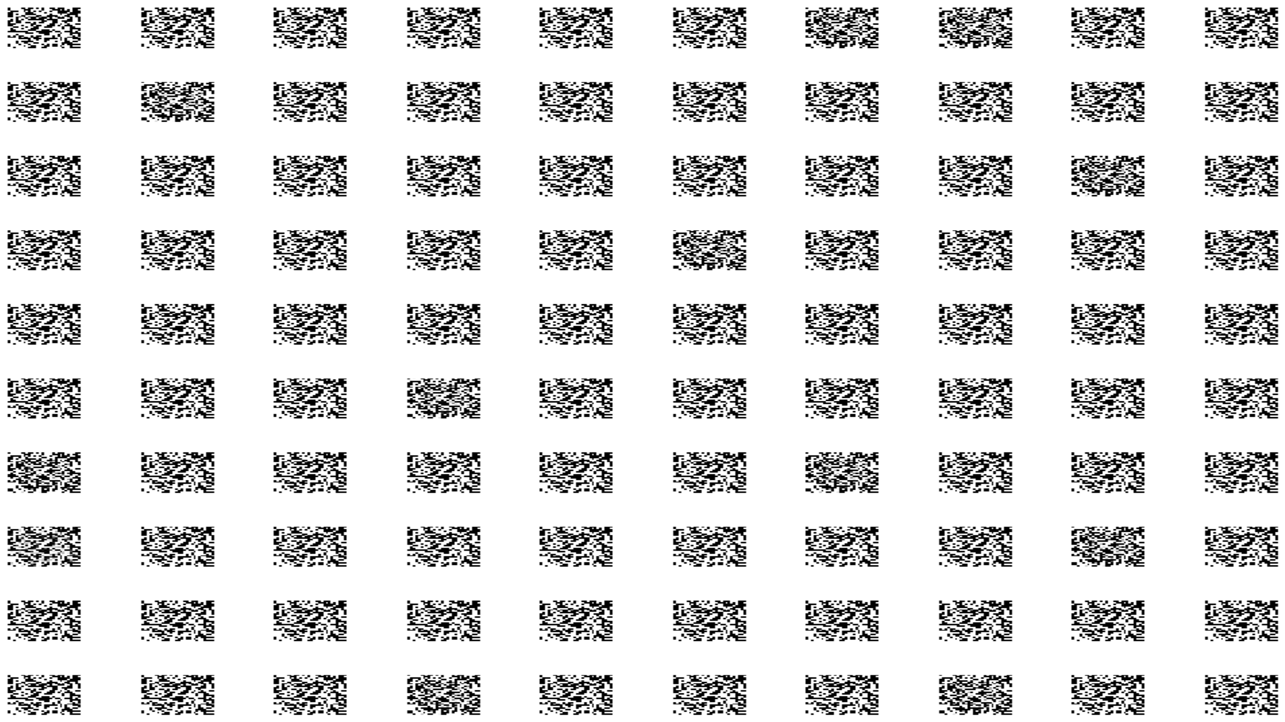


Image6: Image after 200 epochs for random variables + dropout strategy 1 with d = 0.2

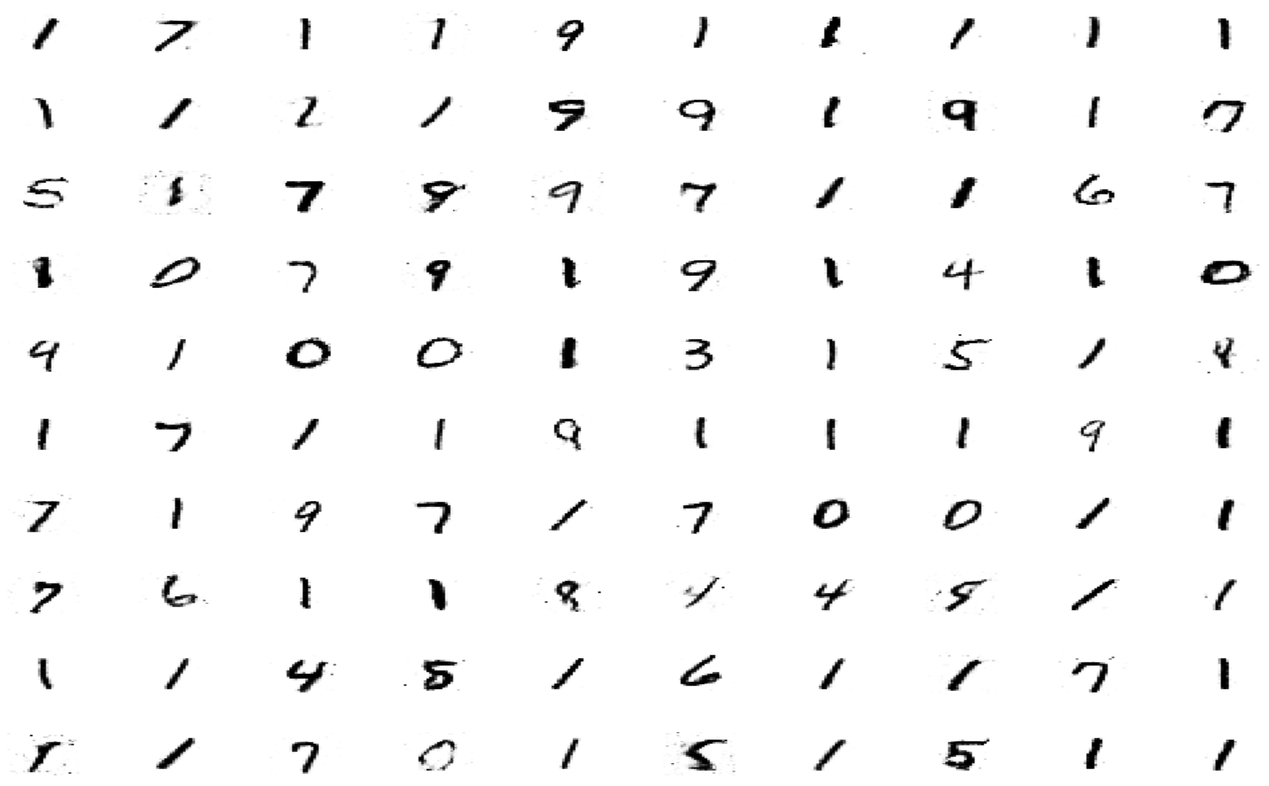
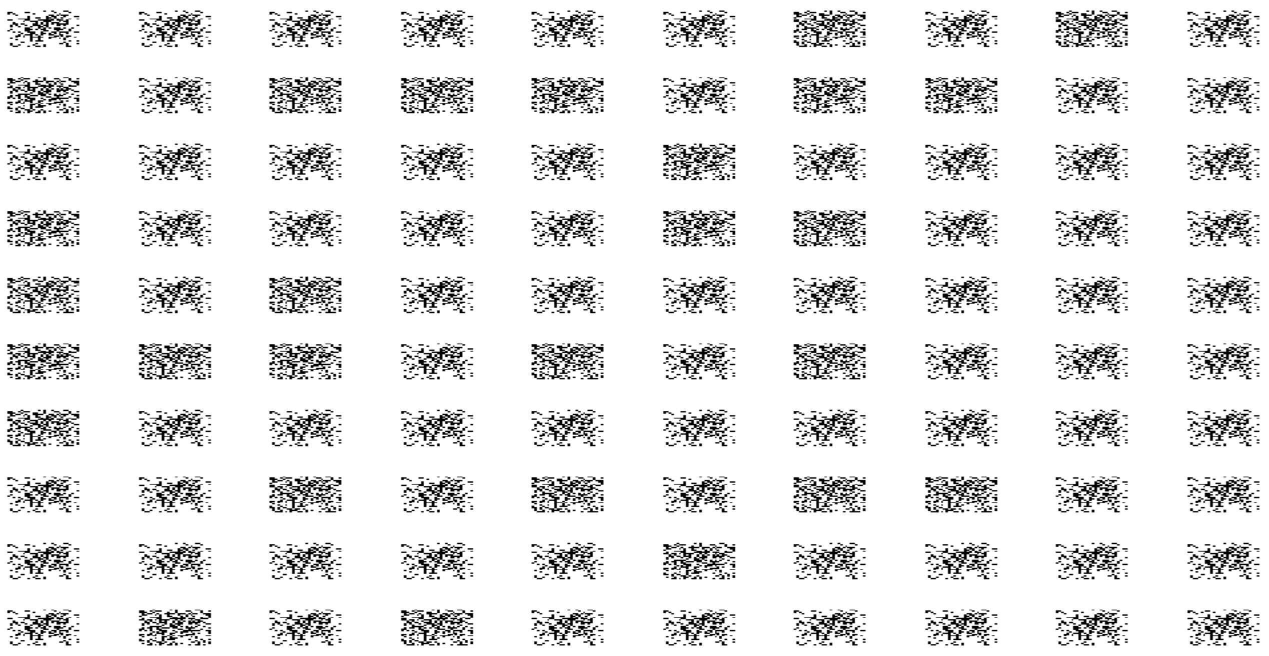


Image5: Image after 200 epochs for random variables + dropout strategy 2 with d = 0.2



PS. - All the loss tables can be found under the link

https://github.com/anuragdutt/Dropout_DL_TeamD/tree/master/src/dropout_gan

Reference

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