Contents

Hyper Parameter Tuning for Deep Neural Networks

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ABSTRACT

The popularity of deep neural networks has risen in the recent past. Though deep neural networks have an increased popularity there is a demand to improve their performance with the help of Hyper Parameter Tuning. The Hyper Parameter Tuning research study involves formulating a list of hyper parameters or a combination of hyperparameters that help improve the performance of the Neural Networks and describes various prospective hyper parameters to tune for these neural networks. The Neural Networks selected are namely Multi Layer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Restricted Boltzmann Machine (RBM), Generative Adversarial Network (GAN) and Autoencoders. Accuracy and Loss are taken as measure of performance. Accuracy is used as a measure for MLP, CNN , RNN and Loss or Reconstruction Cost is used as a measure for generative models - RBM, GAN and Autoencoders respectively. The table below indicates the highest accuracy achieved for each neural network with details of the dataset.

Highest Accuracy for Neural Network Types

Neural Network Type	Dataset Name	Train Accuracy	Test Accuracy
Multi Layer Perceptron	Iris Dataset	100%	97.72%
Convolutional Neural Network	CIFAR10 Dataset	56.25%	49.35%
Recurrent Neural Network	HASYV2 Dataset	100%	71.81%

The below table provides a list of Generative models with details of the dataset and lowest loss or cost achieved during Hyper Parameter Tuning

Generative Models

Neural Network Type	**Dataset Name**	**Loss/Cost**
Restricted Boltzmann Machine	MNIST	Reconstruction Cost -523.17
General Adversarial Networks	MNIST	Generator Loss 0.2892, Discriminator Loss 2.531
Autoencoder	MNIST	Train Loss 0.0999 Validation Loss 0.1006

INTRODUCTION

Hyper Parameters govern the algorithm irrespective of the data. Each algorithm has various hyper parameters that can be tuned that can improve the performance of the algorithm. There are various ways to perform hyper parameter tuning. One of the popular methods used is to tune one parameter and observe the effect on the performance of the algorithm. The second method used is to tune a combination of 2 parameters to observe its impact on the performance of the network. The third method involves selecting a list of parameters as a combination and observing its impact on the Neural Network. Method 1 and Method 2 have been used in the current research study. The various Neural Networks selected for hyper parameter tuning are as follows:

1. Multi Layered Perceptron (MLP)
2. Convolutional Neural Network (CNN)
3. Restricted Boltzmann Machine (RBM)
4. Generative Adversarial Neural Network (GAN)
5. Recurrent Neural Network (RNN)
6. Autoencoders

Below defined is the structure of the Neural Network used for hyper parameter tuning. The Hyper Parameter Tuning is done using Tensorflow, a library created by Google.

Structure and List of Hyper Parameters used for the Neural Networks

Multi Layered Perceptron (MLP)

The Multi Layered Perceptron (MLP) model used consists of 10 hidden layers. Gaussian Initialization was used to initialize the weights and bias of the network. It was first initialized with a learning rate of 0.01, activation function ReLU and using the Softmax Cross Entropy with Logits as the cost function. It traverses the gradient with gradient estimation Adam Optimizer.

Hyper Parameter List

Hyperparameter Name	Hyperparameter Values
Gradient Estimation	Adagrad, Adadelta, Stochastic Gradient Descent
Activation Functions	Tanh, ReLU6, Sigmoid, ReLU
Number of Epochs and Learning Rate	0.01 and 1000, 0.1 and 100

Convolutional Neural Network

This Neural Network consists 2 Convolutional Layers. Each Convolutional layer has an activation function Sigmoid and an Average Pooling layer. The 2 Convolutional layers are preceded by the flattened layer and the fully connected layer. The model is a LENET5 model. It uses the Softmax Cross Entropy cost function and Optimizer as Stochastic Gradient Descent. The model is initialized for 20000 epochs.

Hyper Parameter List

Hyperparameter Name	Hyperparameter Values
Number of Epochs	10000,15000,20000 (Might differ based on time to process the dataset)
Loss and Activation	Softmax Cross Entropy and Stochastic Gradient Descent, Hinge Loss and Tanh, Hing Loss and Sigmoid
Gradient Estimation	Stochastic Gradient Descent, Adam, Adadelta
Network Initialization	Xavier Glorot Initialization, Gaussian Initialization
Network Architecture	Average Pooling, Max Pooling

Recurrent Neural Network

The RNN-LSTM structure utilizes weights and bias with Gaussian initialization. The simplest form of an RNN known as the Static RNN Cell and Basic LSTM Cell is used. The RNN LSTM model uses a batch size of 128, learning rate selected is 0.001 and number of epochs is 800. The optimizer used to reduce the softmax cross entropy loss is the Adam Optimizer that is selected.

Hyperparameter Name	Hyperparameter Values
Number of Epochs	500,1000,2000
Batch Size	4,128,512
Number of Neurons	1,128,512
Learning Rate and Number of Neurons	0.1 and 512, 0.001 and 512, 0.001and 512
Activation	Tanh, ReLU, Softsign
Optimizers	RMSProp, Adagrad,Adam

Restricted Boltzmann Machine

The number of the visible units of the RBM equals to the number of the dimensions of the training data. Number of visible units selected 784 which is the total dimension of the input data. The number of hidden units are 200. The batch size selected is 128 and number of epochs is 100 for the first trial. This uses the Contrastive Divergence with K Gibbs Samples.

List of Hyper Parameters

Hyperparameter Name	Hyperparameter Values
Activation	ReLU, Sigmoid
Learning Rate	0.01,0.00001
Initialization	Xavier Initialization
Number of Hidden Layers	100,200,500
Regularization and Activation	L1 and Sigmoid

Generative Adversarial Network

This network uses the Xavier Initialization for weights and biases. The Generator and Discriminator use the ReLU activation function, with one hidden layer. It uses the solver Adam. The probability distribution is identified using the activation function sigmoid. The network is initialized with the 10000 epochs.

List of Hyper Parameters

Hyperparameter Name	Hyperparameter Values
Activation (Generator and Discriminator)	ReLU, Leaky ReLU
Optimizer and Learning Rate	Adam and 0.001, SGD and 0.001, SGD and 0.1

Autoencoders

This is a denoising Autoencoder. The autoencoder uses an activation of leaky ReLU. The encoder and decoder consist of a convolutional layer and uses the Sigmoid Activation with the Sigmoid Cross entropy cost function using the Adam Optimizer. It is initialized with a learning rate of 0.00001 noise factor of 0.5.

Hyperparameter Name	Hyperparameter Values
Activation of Output Layer	Sigmoid, ReLU
Loss	Hinge Loss, Sigmoid Cross Entropy Loss
Noise	0.5,0.3
Learning Rate	0.00001,0.01,0.1
Optimizer	Adam, RMSProp, Adadelta

It was observed that the Number of Epochs and Learning Rate was a significant parameter to tune in the MLP Neural Network. Number of Epochs, Network Initialization, Loss functions played a pivotal role in tuning the CNN Model. Number of Epochs, Batch Size and a combination of Learning Rate and Number of Neurons are significant hyper parameters to tune in the RNN LSTM model. The RBM Model was impacted most by the Network Initialization and Number of Epochs. The combination of the Gradient Estimation and Learning rate was an important parameter for the GAN and the Autoencoder.

The methods of implementation are described below

Methods

Evaluation Criteria

The accuracy or loss of the models that is generated when the model is first run is taken as a benchmark. If tuning the hyper parameter improves the existing bench mark or close to the bench mark then it is considered as a prospective parameter to tune for the respective model. If the model does not surpass the bench mark, then consider the parameter that is set initially.

Each algorithm is taken one at a time and the list of hyper parameters are applied to the algorithm. The MLP, CNN and RNN Neural Network performance is measured based on their accuracy, the performance of the RBM is measured based on the reconstruction cost, performance of the GAN and Autoencoder is measured on the basis of their respective losses. Each model is implemented in Python in a Jupyter Notebook using the Tensorflow Library. After initial running of the model as per the structure mentioned, each model is tuned for the selected hyper parameters.

Process of Hyper Parameter Tuning

1. **MLP**: The MLP Structure is set up as defined above using Python. After the initial set up and ensuring the model is running, each hyper parameter as per the list was selected and tuned. The test accuracy was noted for each hyper parameter tuned. The hyper parameters tuned were Gradient Estimation, Activation and a combination of Number of Epochs and Learning Rate.
2. **CNN**: The Dataset consisted of images, hence the dataset was first pre-processed and images are one hot encoded. The training for this dataset is time consuming hence, it is trained for only 10,000 epochs. Once the structure of the model is defined the CNN model is tuned for the enlisted hyper parameters. The accuracy is noted for each hyper parameter tuned. The Accuracy is compared to the bench mark model run in the initial stage.
3. **RNN**: The dataset must be pre-processed and converted to one hot encoded values. The RNN was then tested for the various Hyper Parameters enlisted.
4. **RBM**: To use RBM in Tensorflow a library names xRBM was used for the purpose. This library is installed in Python. The initial model is set up following which the model is trained for the enlisted hyper parameters
5. **GAN**: Since the GAN is used to generate images, the images must be pre-processed. After running the GAN with the initial model it is trained for the various enlisted hyper parameters.
6. **Autoencoders**: After initializing the model, the autoencoder is then tested on various hyper parameters enlisted in the above section.

The accuracy or loss for each hyper parameter tuned is compared to the initial accuracy or loss generated by the network after fine tuning the initial model that is set up. The detailed method of implementation can be found at **[21]**

Results

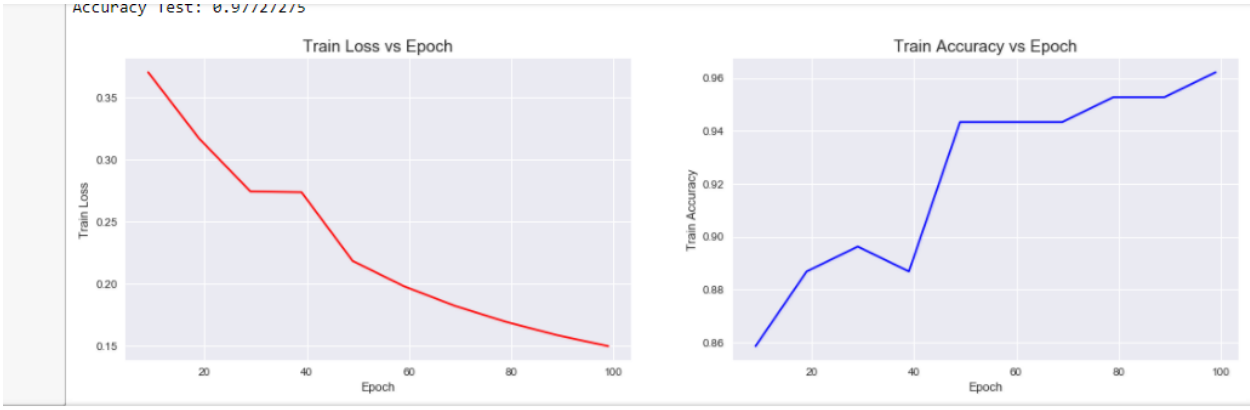
The objective of performing tuning for each Neural Network is to understand the hyper parameter values that can be used to improve the performance of the network and understand the prospective hyper parameters that can be tuned. The results of the best hyper parameters to tune for each of the neural networks is listed below.

Hyper Parameter Tuning Results for MLP Neural Network Results

Hyper Parameter Name	Hyper Parameter Value	Training Accuracy	Testing Accuracy
Gradient Estimation	Adam Adagrad	97.16% 96.22%	97.72% 97.72%
Activation Function	Sigmoid ReLu	98.11% 97.16%	100% 97.72%
Epoch and Learning Rate	100 and 0.1	99.05%	97.72%

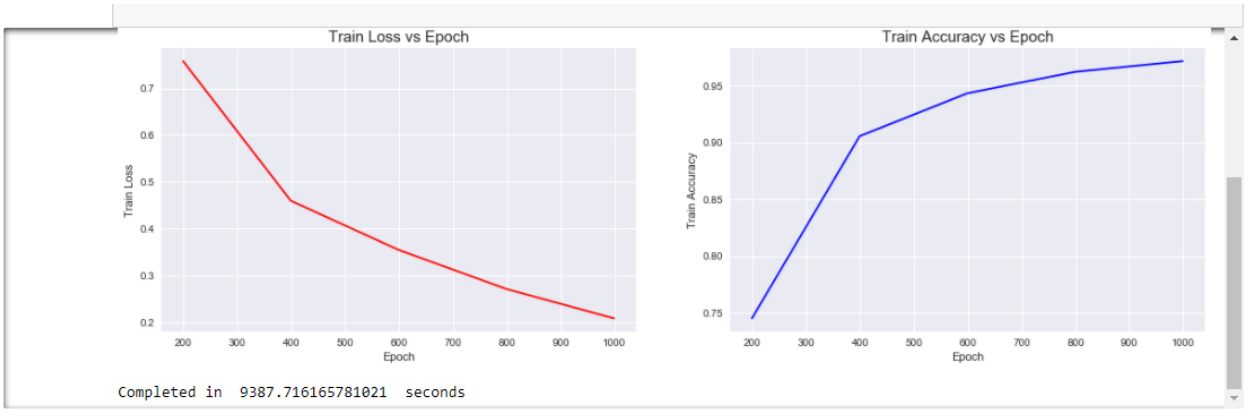
Graphical Representation of Results for the Multi-Layer Perceptron Neural Network

Gradient Estimation



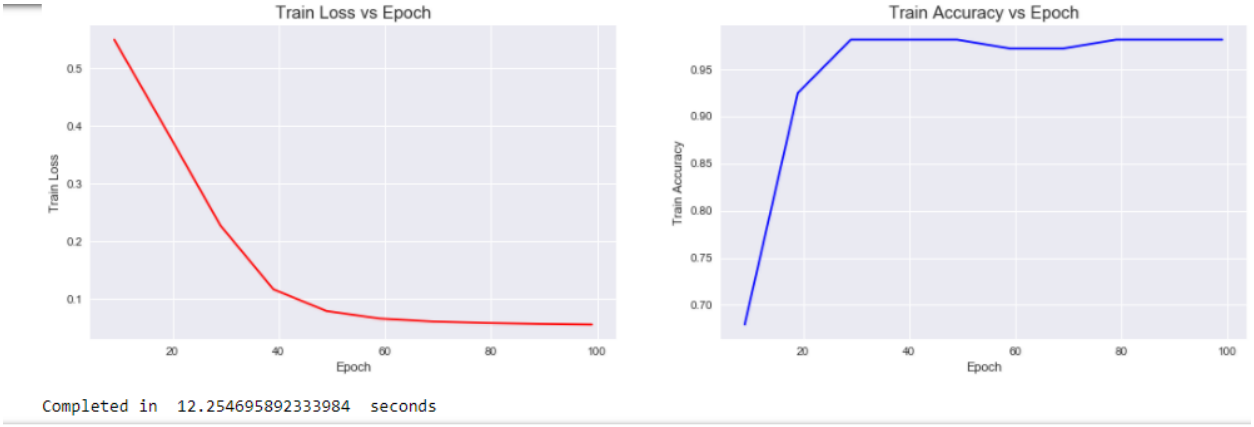
The above graph indicates accuracy and loss of the MLP Network with the tuned optimizer as Adagrad

Gradient Estimation - Adam



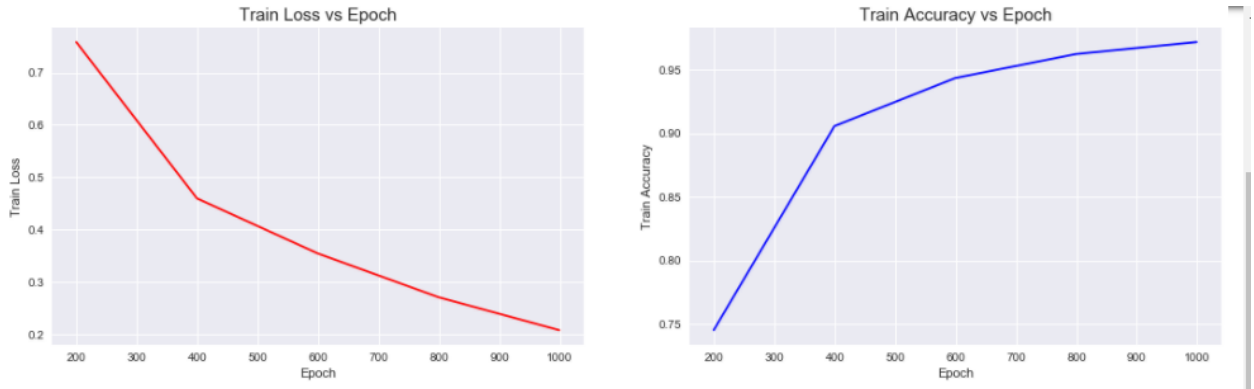
The above graph showcases the accuracy and loss for the initial model with 1000 epochs, learning rate of 0.01, activation function relu and gradient estimation Adam

Activation Function - Sigmoid



The above graph indicates the Loss and Accuracy for activation function Sigmoid for the MLP Neural Network

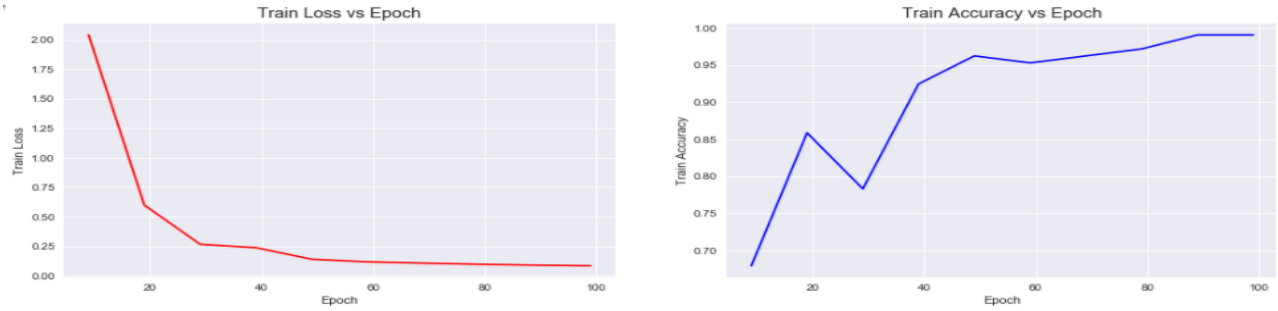
Activation Function - ReLU




```
Completed in  9387.716165781021  seconds
```

The above graph showcases the accuracy and loss for the initial model with 1000 epochs, learning rate of 0.01, activation function relu and gradient estimation Adam

Combination of Number of Epochs and Learning rate




```
Completed in  9.223546028137207  seconds
```

The above graph indicates the loss vs epochs and accuracy vs epochs for learning rate=0.1 and number of epochs =100

Hyper Parameter Tuning Results for Convolutional Neural Network Results

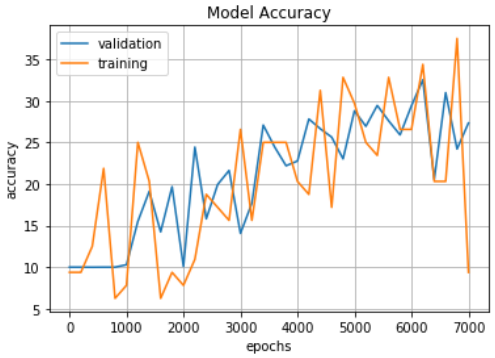
The CIFAR 10 Dataset has 10 classes of over 60000 images. Hence, training the algorithm takes extremely long. The Algorithm was first trained for 20 hours for 20000 epochs to reach a training and testing accuracy of 60.94% and 48.63% respectively. Hence, using a bench mark of 7000 epochs where the model reached an accuracy of 50% and 41.09% with stability was taken as the benchmark for hyper parameter tuning. Taking a consistent value of the 7000th epoch was 42.72% and 42.19%

Hyper Parameter Name	Hyper Parameter Value	Training Accuracy	Testing Accuracy
Loss and Activation Function	Softmax Cross Entropy and SGD Optimizer OR Hinge Loss and Tanh	42.19% OR 37.50%	42.72% OR 24.20%
Activation Function	Sigmoid	42.19%	42.72%
Network Initialization	Xavier Initialization and Gaussian Initialization	40.62% and 34.34%	42.19% and 39.52%
Number of Epochs (can be trained longer)	20000	60.94%	48.59%
Gradient Estimation	Stochastic Gradient Descent	42.19%	42.72%

Graphical Representation of Results for the Convolutional Neural Network Model

Loss and Activation

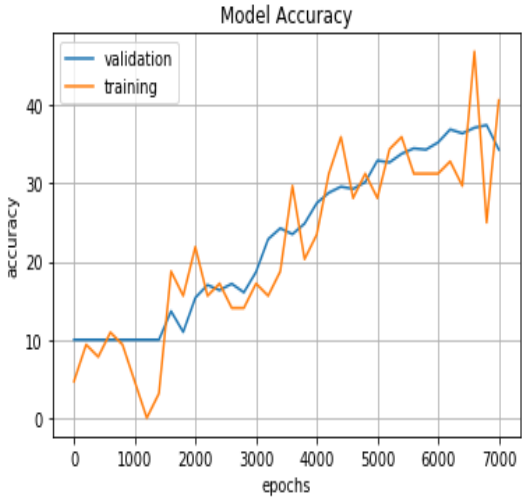
Loss (Hinge Loss) and Activation (Tanh)



The graph depicts the training and testing accuracy for a combination of hyper parameters - Hinge Loss and Activation Function for CNN

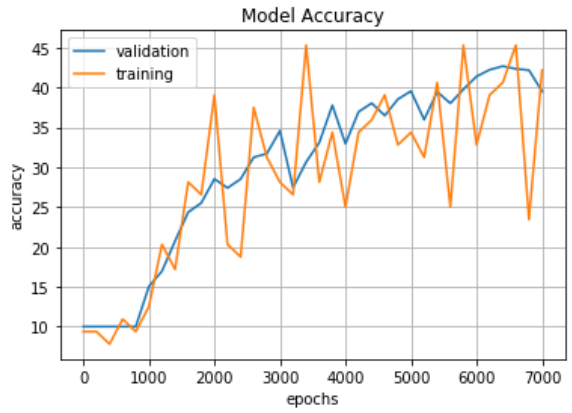
Network Initialization

Network Initialization (Xavier Glorott)



The graphs depicts training and testing accuracy for network initialization - Xavier Glorott for CNN

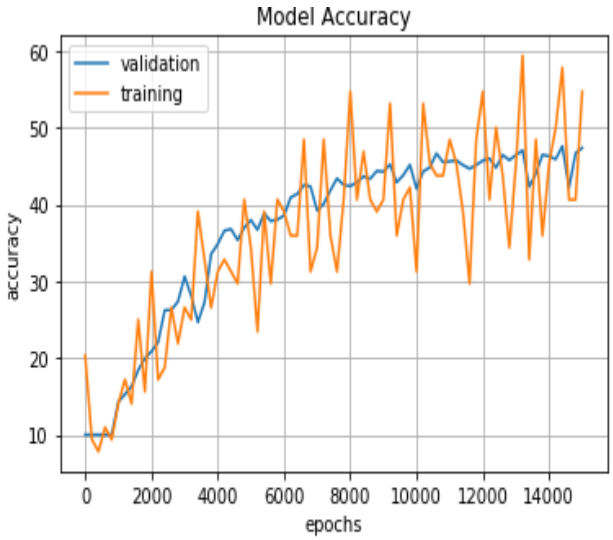
Network Initialization (Gaussian)



The graphs depicts training and testing accuracy for Hyper parameter Network Initialization - Gaussian for CNN

Number of Epochs

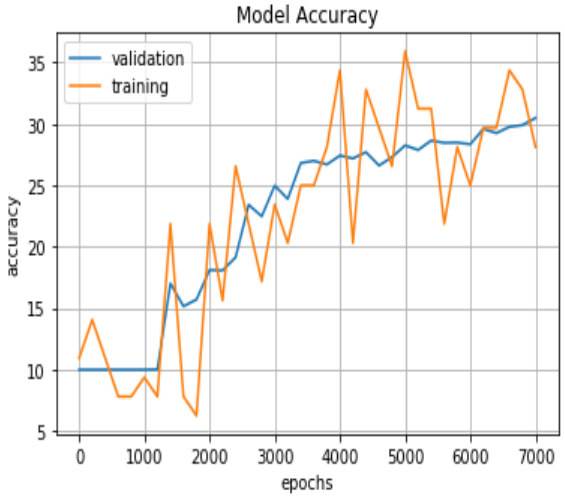
Number of Epochs



The above graph depicts the training and testing accuracy for 15000 epochs for CNN

Optimizer

Optimizer (Adagrad)



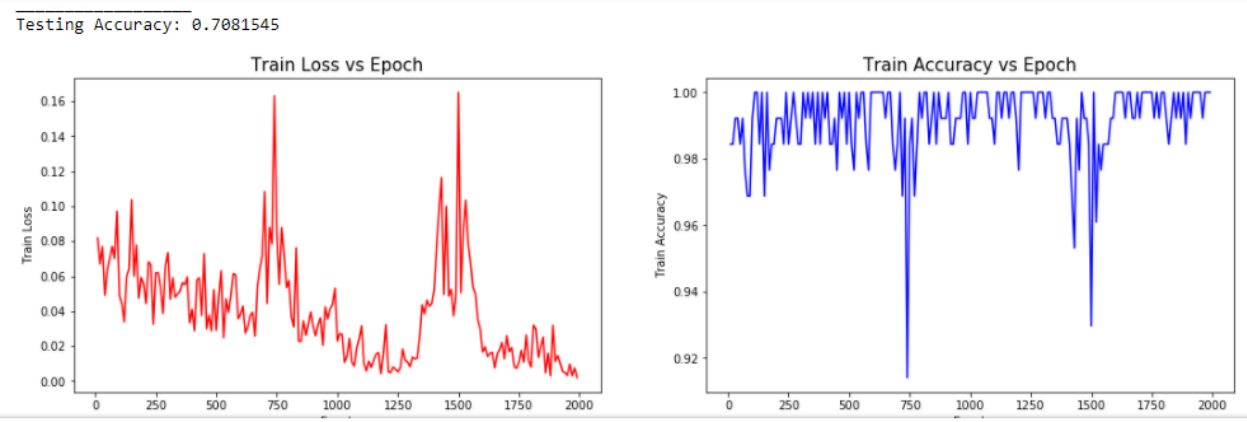
The graphs depicts training and testing accuracy for gradient estimation Adagrad for CNN

Hyper Parameter Tuning Results for Recurrent Neural Networks Neural Network Results

Hyperparameter Name	Hyperparameter Values	Training Accuracy	Testing Accuracy
Number of Epochs	2000	100%	70.81%
Batch Size	512	97.65%	68.52%
Number of Neurons	512	97.65%	71.81%
Learning Rate and Number of Neurons	0.001and 512	94.53%	68.59%
Activation	Tanh	92.96%	68.81%
Optimizers	Adam	94.53%	68.59%

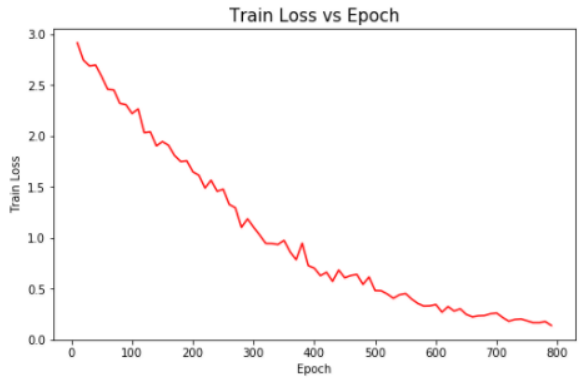
Graphical Representation of Results for the Recurrent Neural Network Model

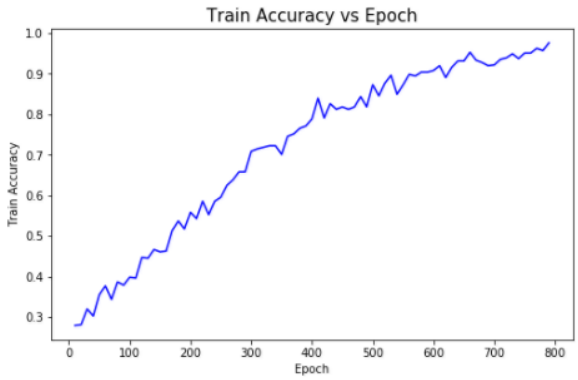
Number of Epochs



The last graphs will show us values of loss and accuracy for number of epochs as 2000 epcohs for RNN

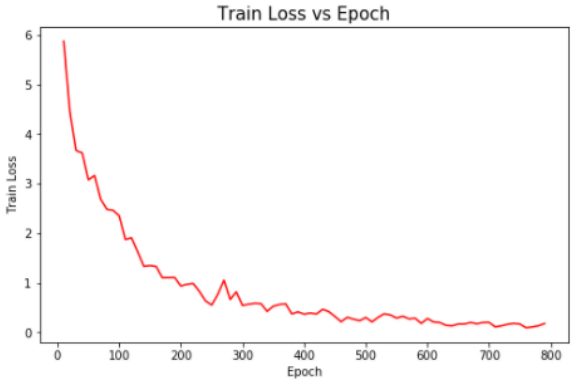
Batch Size





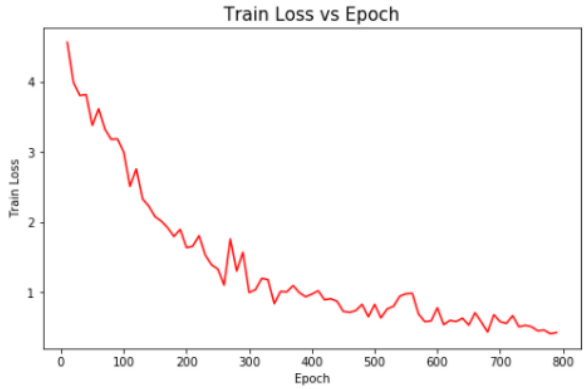
The last graph depicts training and testing accuracy for batch 512 for RNN-LSTM

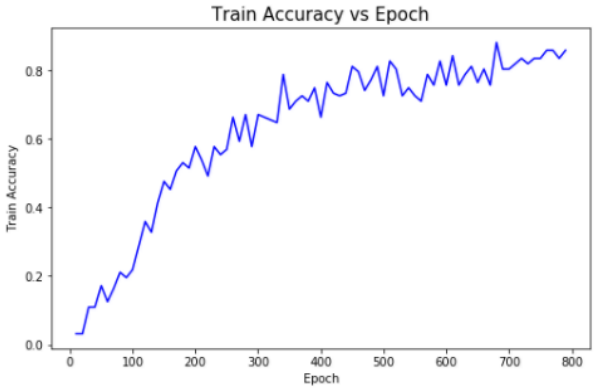
Number of Neurons



The graphs depicts training and testing accuracy for number of neurons=512 for RNN LSTM

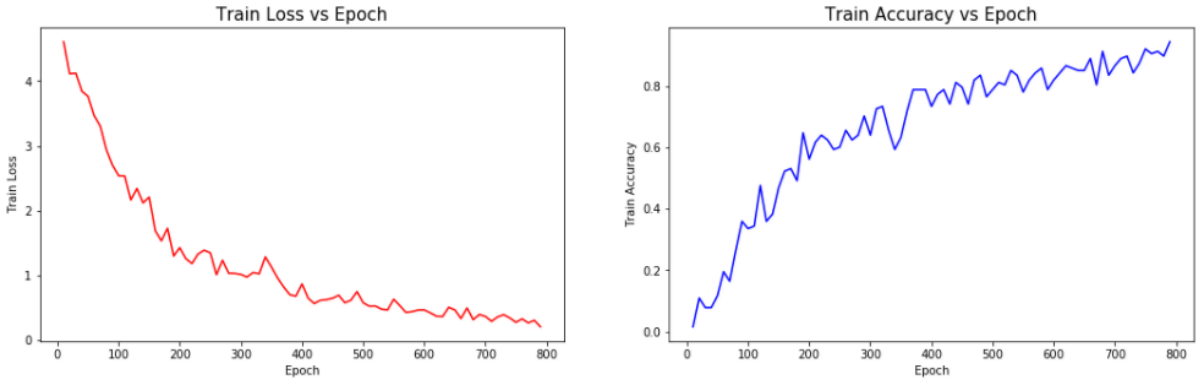
Learning Rate and Number of Neurons





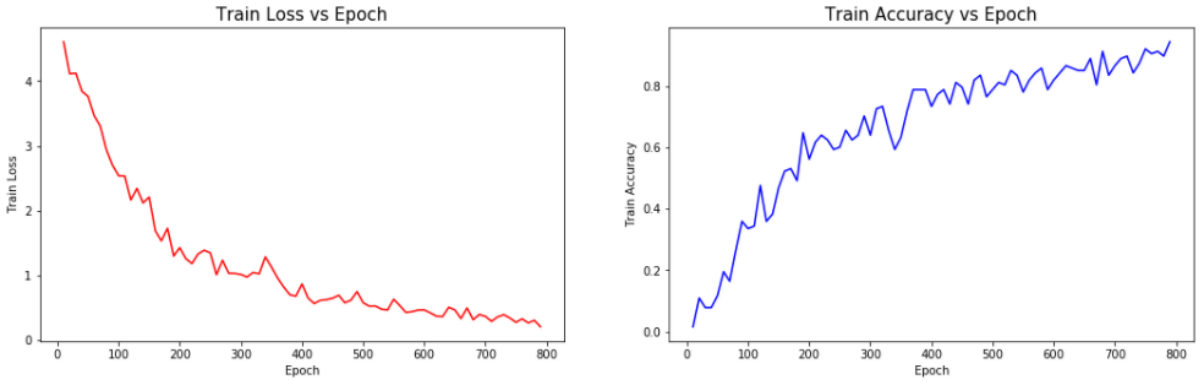
The graphs depicts training and testing accuracy for learning rate: 0.0001 and number of neurons : 512 for RNN LSTM

Gradient Estimation



The graph shows the loss and accuracy for the initial RNN LSTM model with learning rate selected as 0.001 and a batch size of 128, loss softmax_cross entropy loss optimizer Adam Optimizer and activation function Tanh

Activation



The graph shows the loss and accuracy for the initial RNN LSTM model with learning rate selected as 0.001 and a batch size of 128, loss softmax_cross entropy loss optimizer Adam Optimizer and activation function Tanh

Hyper Parameter Tuning Results for Restricted Boltzmann Machine Neural Network Results

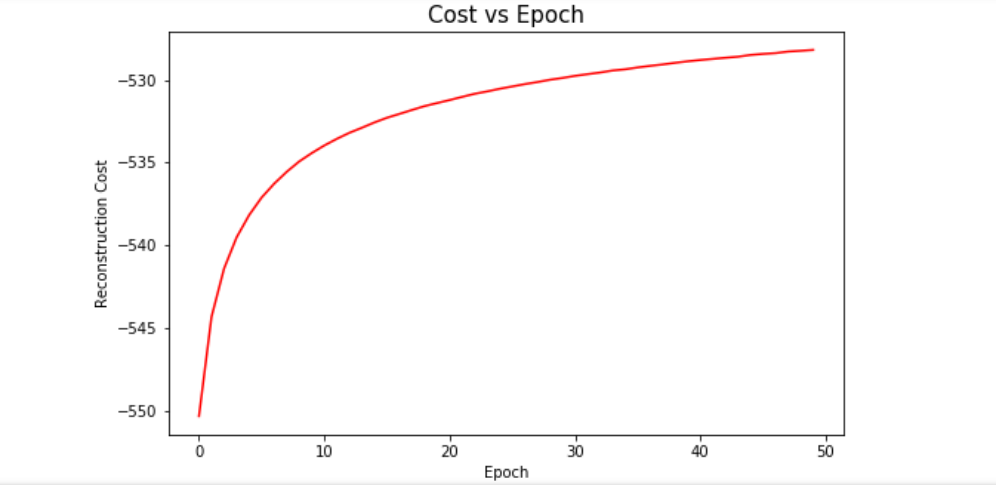
Since, generation of images takes a long time in RBM's I have restricted the training of the model to 50 epochs which has a loss of -525.82.

Hyperparameter Name	Hyperparameter Values	Reconstruction Cost
Activation	Sigmoid	-528.19
Learning Rate	0.01	-528.19
Initialization	Xavier Initialization	-527.42

Number of Hidden Layers	500	-523.227
Regularization	L1	-528.32

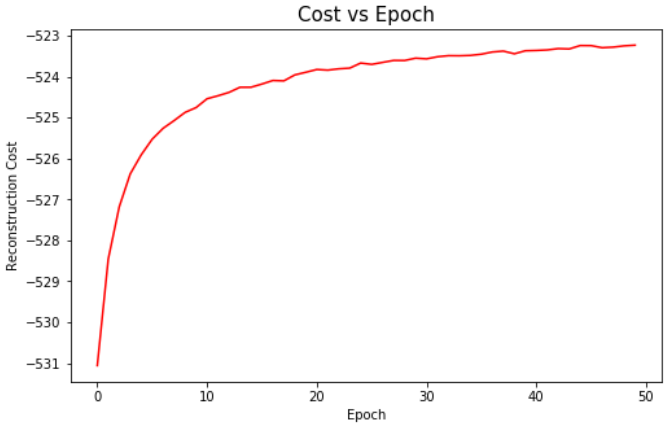
Graphical Representation of Results for the Recurrent Neural Network Model

Learning Rate



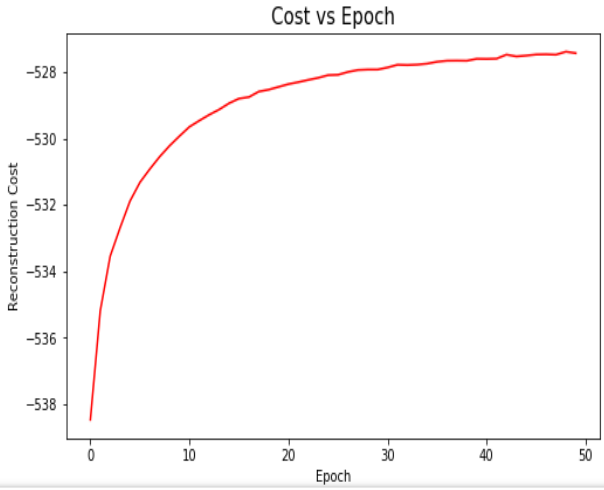
The graph depicts the reconstruction cost vs Epochs for learning rate:0.01 for RBM

Number of hidden layers



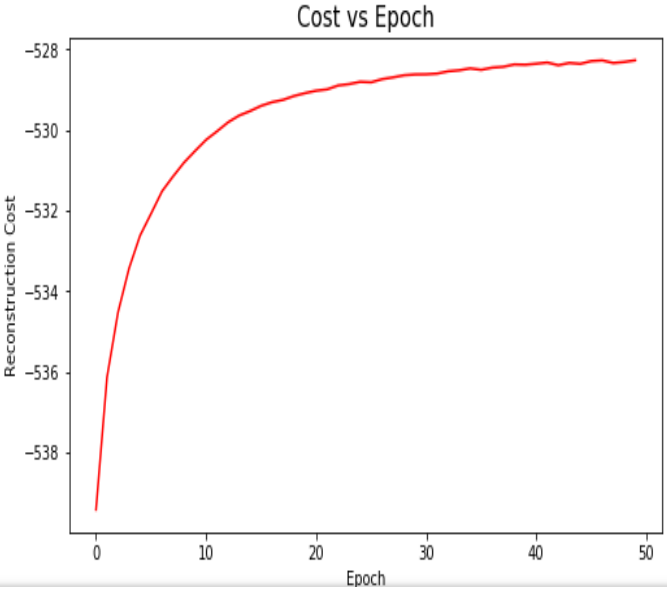
The graph shows resoctruction cost vs number of epochs for number of hidden layers : 500 for RBM

Network initialization



The above graphs indicates the reconstruction cost vs number of epochs for ntwork initialization : Xavier Glorett

Regularization



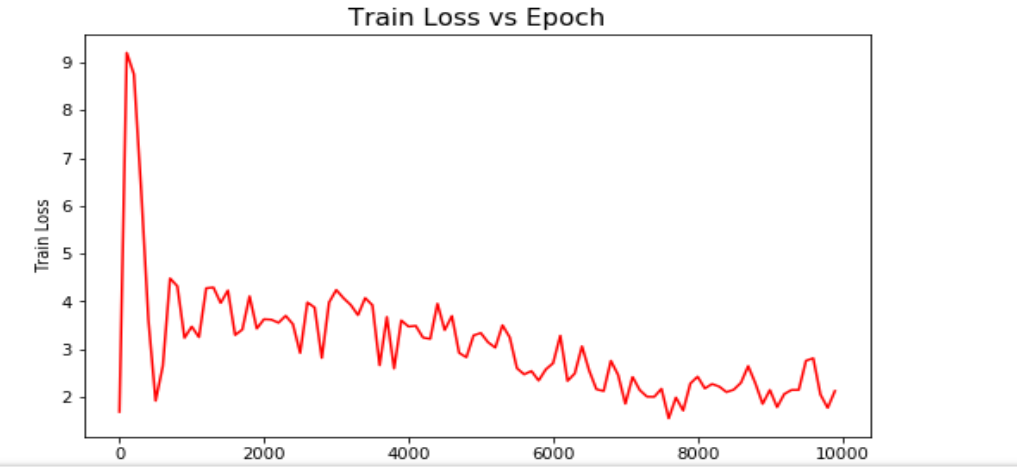
Hyper Parameter Tuning Results for Generative Adversarial Neural Network Results

Hyperparameter Name	Hyperparameter Values	Generator Loss	Discriminator Loss
Network Initialization	Xavier Initialization	0.4891	4.003
Activation (Generator and Discriminator)	ReLU	2.12	0.9232
Optimizer and Learning Rate	SGD and 0.1	0.3045	2.856

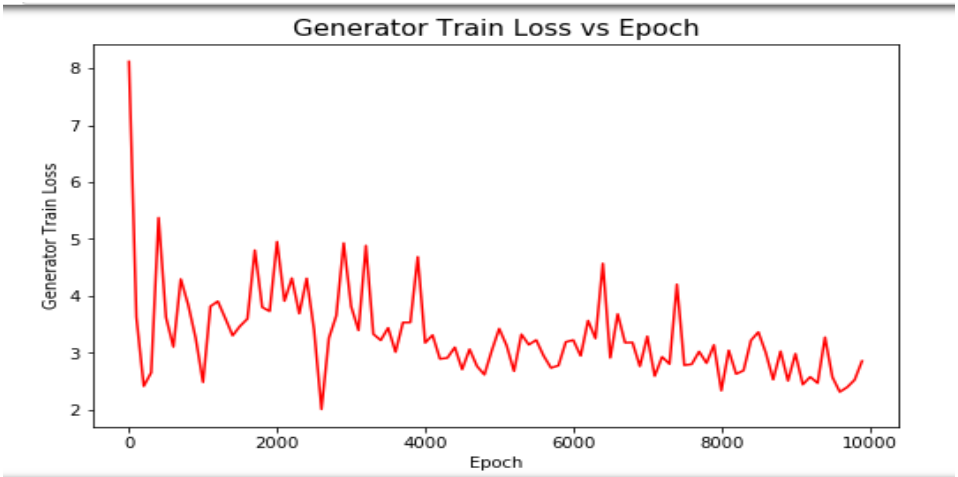
Graphical Representation of Results for the Generative Adversarial Neural Network Model

Activation Function

Generator-Loss

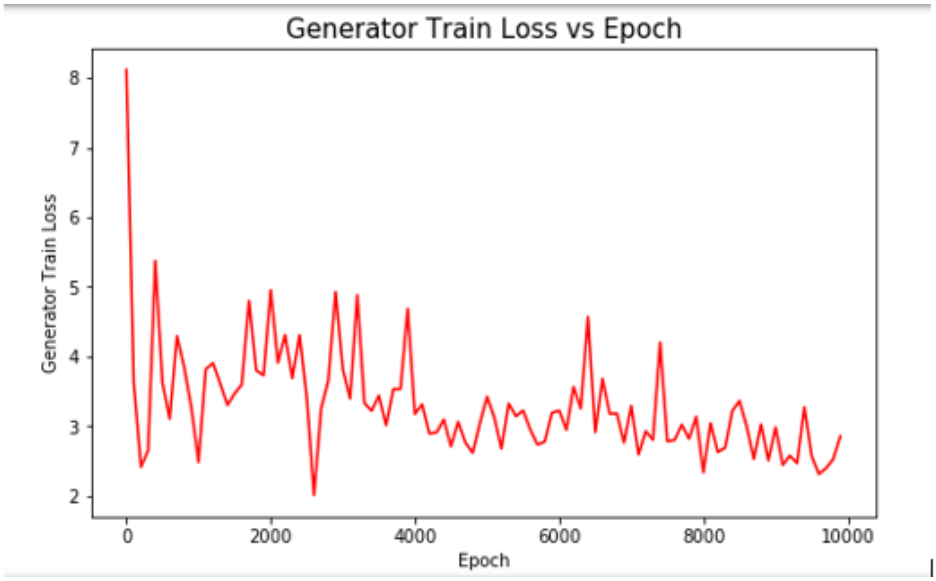


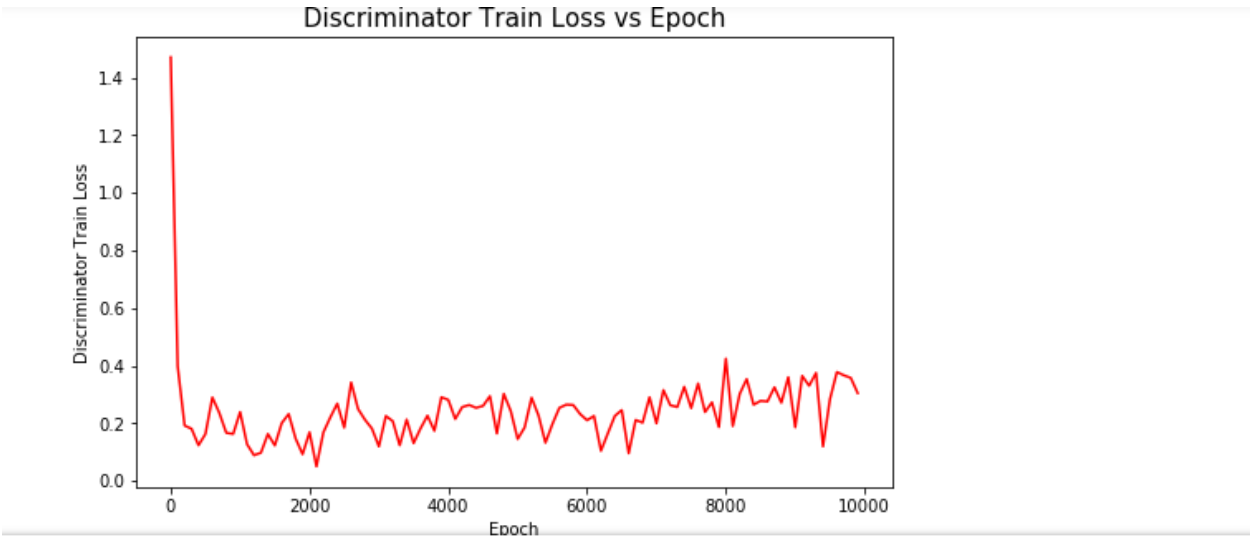
Discriminator-Loss



The above graphs depicts the Generator and Discriminator Loss for Activation Function ReLU

Optimizer and Learning rate





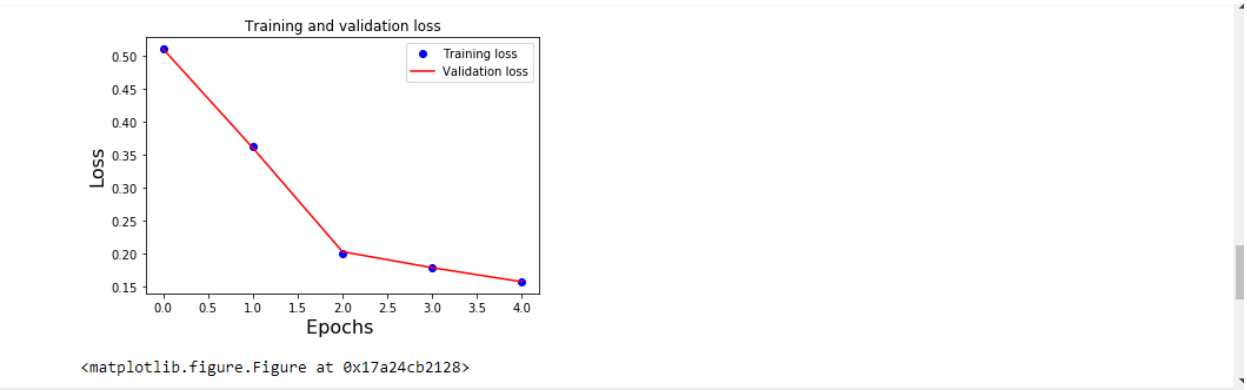
The above graph depicts the training loss and generator loss for Optimizer : SGD and learning rate:0.1

Hyper Parameter Tuning Results for Autoencoder

Hyperparameter Name	Hyperparameter Values	Training Loss	Validation Loss
Loss	Sigmoid Cross Entropy Loss	0.1575	0.1575
Noise	0.3	0.1256	0.1256
Learning Rate	0.01	0.0999	0.1006
Gradient Estimation	Adam	0.1575	0.1575

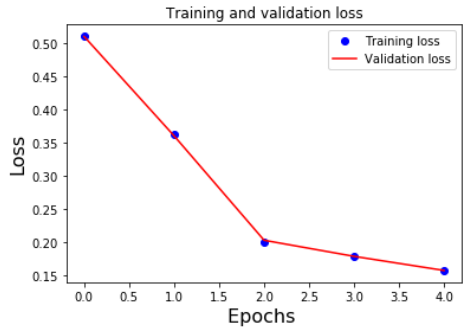
Graphical Representation of Results for the Recurrent Neural Network Model

Optimizer



The graph training and validation loss for a denoising autoencoder using activation : leaky relu, activation :Sigmoid Activation loss : Sigmoid Cross entropy cost function, using optimizer: Adam Optimizer, learning rate : 0.00001 and noise factor of 0.5.

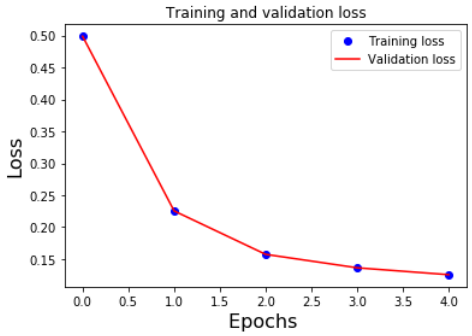
Loss




```
<matplotlib.figure.Figure at 0x17a24cb2128>
```

The graph training and validation loss for a denoising autoencoder using activation : leaky relu, activation :Sigmoid Activation loss : Sigmoid Cross entropy cost function, using optimizer: Adam Optimizer, learning rate : 0.00001 and noise factor of 0.5.

Noise



The above graph depicts the Number of Epochs vs Loss for noise factor=0.2

Learning rate

The above graphs shows the training and testing accuracy for autoencoder with learning rate : 0.01

Discussion

As mentioned in the methods the accuracy or loss of the models that is generated when the model is first run is taken as a benchmark. If tuning the hyper parameter improves the existing bench mark or close to the bench mark then it is considered as a prospective parameter to tune for the respective model. If the model does not surpass the bench mark, then I have considered the parameter that is present initially if present. Each of the model parameters are discussed below:

Multi-Layer Perceptron Neural Network

From the results the model performs the best with a gradient estimation of Adagrad or Adam. The activation function ReLu and Sigmoid provide the same accuracy. Hence, using either would be useful. In the case of the combination of learning rate and number of epochs it was observed that using a combination of 0.01 and 1000 or 0.1 and 100 resulted in the same accuracy. Hence, selecting 0.1 and 100 epochs was a better option with lesser computation. Increasing the learning rate causes the network to learn faster in lesser number of epochs. However, it is possible that in some Neural Networks the learning rate must be low for the network to perform better. In the MLP Model , increasing the learning rate improved performance.

Hence, though these parameter values worked the best and must be tried first to improve accuracy it would be best practice to tune these hyper parameters (enlisted in decreasing order of importance) to improve the accuracy of the MLP Model

1. Number of epoch and Learning rate
2. Activation
3. Gradient Estimation

Convolutional Neural Network

The CIFAR 10 Dataset has 10 classes of over 60000 images. Hence, training the algorithm takes extremely long. The Algorithm was first trained for 20 hours for 20000 epochs to reach a training and testing accuracy of 60.94% and 48.63% respectively. Hence, using a bench mark of 7000 epochs where the model reached an accuracy of 42.19% and 42.72% with stability was taken for hyper parameter tuning.

Though, it must be mentioned that the LENET5 model was not the best model as other CNN models with a different architecture performed better and took a comparatively lesser amount of time as referenced in [2]. The LENET5 Model was preferred as it was more conducive for hyper parameter tuning and a simple Tensorflow model implementation

Changing the activation for the CNN increases or decreases the accuracy. The activation function Sigmoid is the winner with the best accuracy. Training the model for greater number of epochs is preferred as the standard accuracy of CIFAR 10 can touch 80% or above if trained for a longer period. The CNN model works the best with a gradient estimation of Stochastic Gradient Descent. The combination of SGD and learning rate of 0.5 works best. But it is observed that the network would get lost in rise and fall of the Loss Scenario. This

is evident as the accuracy would vary from 45 to 50 % for over 5000 epochs with losses varying drastically. There was stabilization brought in with initializing the network with Xavier or Gaussian Initialization. Hence, network initialization plays a pivotal role in CNN.

Hence, even though activation -Sigmoid, Optimization – SGD, Number of Epochs and Cost function Hinge Loss worked the best, hyper parameters to tune (enlisted in decreasing order of importance) while improving the performance of a CNN are as follows

1. Network Initialization
2. Number of Epochs
3. Gradient Estimation
4. Cost Function
5. Activation
6. Combination of Loss and Activation Function

Recurrent Neural Network

The results for hyper parameter tuning of the RNN indicate that number of epochs as 2000, an increased batch size of 512, increasing number of neurons from 128 to 512 and the combined tuning of learning rate and number of neurons as 128 and 0.001 brought stability to the network. Though number of neurons as 512 provided greater accuracy, number of neurons as 128 and a learning rate of 0.01 brought stability to the network. This will ensure that the network plateaus well. Varying the gradient estimator Adam improved the performance as well. It was also observed during trials that a vanilla RNN provided poor performance without weight and bias initialization. Hence, presence of weights and bias plays an important role in tuning the RNN

Hence, though these values worked the best, list of prospective hyper parameters (enlisted in decreasing order of importance) to take into consideration while tuning the RNN – LSTM Model are as follows:

1. Number of Neurons
2. Number of Epochs
3. Activation Functions
4. Gradient Estimation
5. Batch Size
6. Learning Rate and Number of Neurons

Restricted Boltzmann Machine

Tuning the RBM indicates that reconstruction cost reduced by a unit of 5 with the increase in the number of Hidden Layer to 500. On the contrary decreasing the number of hidden layers increased the reconstruction cost. The neurons are the most important processing parts of the neural network. Regularization of L1 decreased the reconstruction cost slightly. Additionally, learning rate of 0.01 also improved the reconstruction cost

Hyper Parameters to take into account (in decreasing order of priority) while tuning the RBM are as follows:

1. Number of Hidden Layers
2. Network initialization
3. Learning Rate
4. Activation Functions
5. Regularization

Generative Adversarial Network

The performance of the GAN is said to be good when the generator loss increases and the discriminator loss decreases. This occurs as the discriminator finds the least difference between the generated image and actual image. The activation function ReLU provided a decreased discriminator loss in comparison to Leaky ReLU. Tuning the combination of optimizer and learning rate as Stochastic Gradient Descent and learning rate of 0.01 improved the performance of the GAN. Increasing the number of epochs will definitely also improve the performance further.

Hyper Parameters to take into consideration (In decreasing order of priority) while tuning a GAN are as follows

1. Learning Rate and Gradient Estimation
2. Network Initialization
3. Activation Function

Autoencoder

Tuning the Autoencoder depicts that the hyper parameter noise, loss function as Hinge Loss and Sigmoid Cross Entropy seem to work the best. The learning rate of 0.01 provided a very low loss 0.0999 and 0.1006 for the encoder and decoder respectively. Reducing the noise helped improving the loss as presumably the auto encoder can learn the image better.

Hence, the prospective hyper parameters to tune first while tuning an Autoencoder are as follows:

1. Learning Rate
2. Noise Factor
3. Optimizer
4. Cost Function
5. Gradient Estimation

The above methods implemented are manual methods of tuning which are time consuming but provide results that help understand the impact of each parameter on the performance of the network. There are libraries in Keras that implement grid search which provide the most optimal parameters automatically, the effect of each parameter on the performance cannot be identified in this case. Hence,

the manual search method helped to rank the hyper parameter based on their impact on the Neural Network.

For details on observation on each model refer to the link [21]

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