# **Deep Learning**

# **Assignment 3**

## **Classification Problem**

#### **Abstract**

To perform multi class classification on the dataset UCI car dataset and to evaluate against various optimizers and losses. Finally the best model is chosen and is regularized to get more optimized model if necessary.

## **Problem Statement**

The car dataset has 1728 instances and each instance has 6 attributes. These instances are classified against four classes based on the 6 attributes. The instances are words that are to be preprocessed and then classified. Finally various optimizers and losses are chose and the efficient model is chose. This one is then regularized if needed for a better model.

# **Proposed Solution**

The dataset is chose and is preprocessed. This step includes converting the data to numerical, splitting the data into test and train, splitting the training data further to validate and training, popping the labels out and finally encoding the label.

Then various loss functions are evaluated. They are

#### **Loss function used:**

Binary cross entropy – This loss builds up an entropy and measures the difference between the two probability distributions. It is mostly used in binary classification but since there are only 4 classes in this dataset, it is used here too.

Categorical cross entropy – This loss is similar to a cross entropy or a softmax function. It predicts the difference between the actual and predicted labels across all the instances.

Hinge loss – Hinge loss focuses more on the enforcement of distribution in classification. It determines a margin beside the dividing boundary in a classification and adds penalty to the elements that cross these margins. By this way it makes the classification better.

Squared hinge loss - This loss is similar to the hinge loss but squares the value obtained by the hinge loss. The aim of this loss is to smoothen the curve of the hinge loss.

KL divergence – Kullback – Leibler divergence also known as relative entropy is a ratio between the distributions given. It is a combination of both entropy and cross entropy. When the entropy of different instances are same, it is equal to cross entropy.

## **Optimizers used:**

Rmsprop – It is a gradient based optimization technique to optimize the neural network model. It decreased the gradient that increases to stop from exploding and increases the gradient that decreases to prevent from vanishing.

Sgd – At each iteration, this optimizer performs a parameter update. It finds the local minima and updates it to the parameters frequently to get the better results. One demerit of this optimizer is the frequent updates in the variance can cause a fluctuation in the loss function.

Adam – It is an alternative to sgd optimizer. It combines the properties of rmsprop and adagrad. It keeps the exponentially decaying average of the past gradients. One advantage of this optimizer is it converges faster and easily.

Adagrad – This optimizer is better than optimizers like rmsprop as it includes another hyper parameter in addition to the existing ones called the learning rate. Learning rate can be defined as the update or modification given to a parameter once there is a change in the gradients. This parameter makes a less update for a frequent parameter and a big update for a less frequent parameter.

# Regularization

Regularization includes certain methods followed to prevent the data from overfitting and under fitting once the correct loss functions and optimizers are determined.

The techniques used are:

Dropout – After each iteration the weight of the input or the parameter is decayed or decreased to prevent overfitting.

Batch Normalization – In this case the output of each layer of the neural network is normalized in batches to give a scalable input to the following layers.

Ensemble classifier – Finally multiple models are trained on parts of the data and all the models are combined to obtain an averaged accuracy of all the models. By this method many incompletely trained models are combined to form a completely trained model.

# **Evaluation metrics**

Rmsprop and binary\_crossentropy

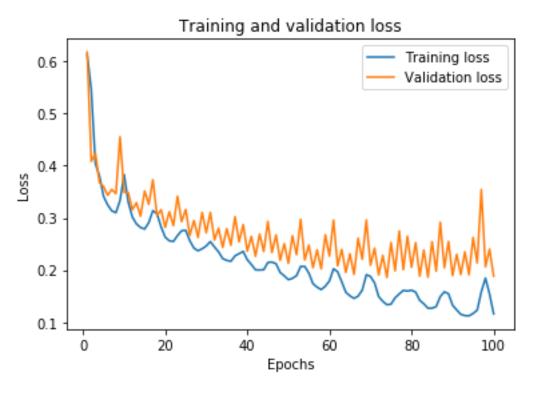
Hyper parameter change:

Layers = 4

Epoch = 100

Hidden units = 256

Epoch 96/100



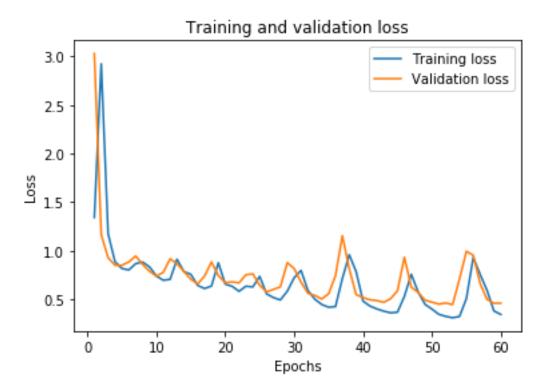
#### **Rmsprop and categorical cross entropy**

## Hyper parameter change

Layers = 5

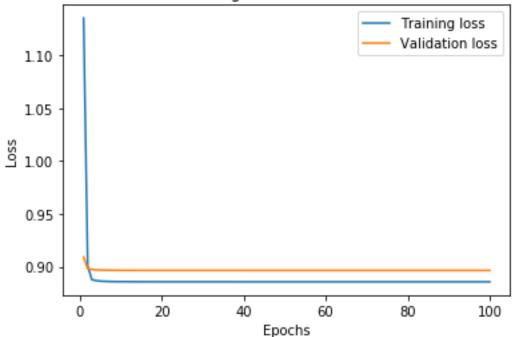
Epoch = 60

Hidden units = 512

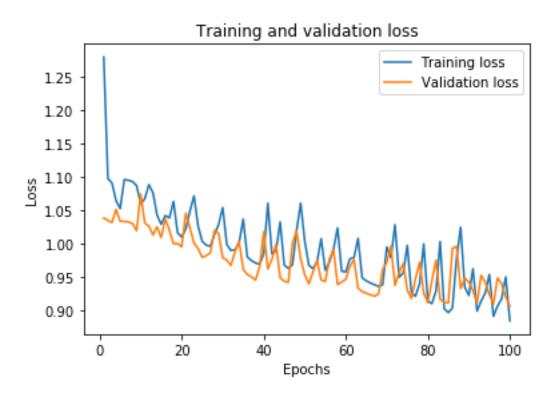


## **Rmsprop and hinge**

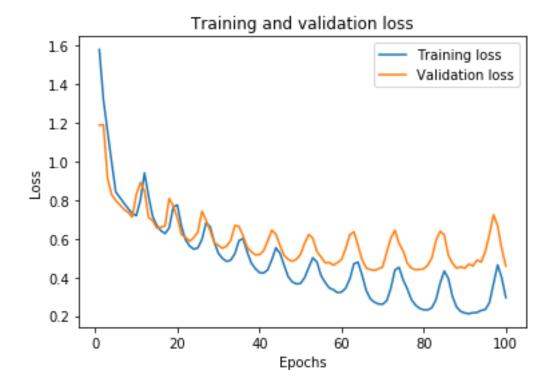
# Training and validation loss



# **Rmsprop and squared hinge**



## **Rmsprop and kl loss**

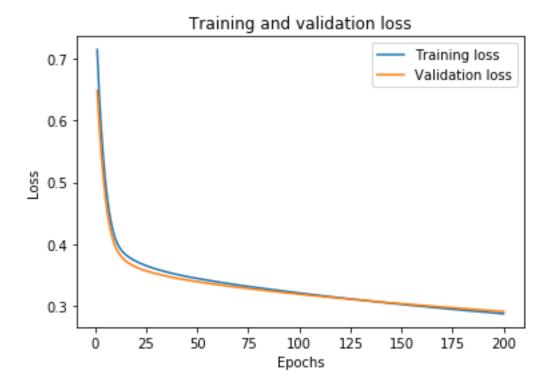


#### Sgd and binary cross entropy

# Hyper parameter change

Hidden units = 512

#### Epoch = 200



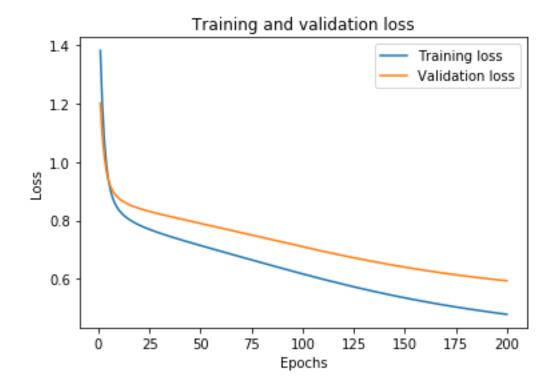
## Sgd and categorical cross entropy

# Hyper parameter change

5 layers

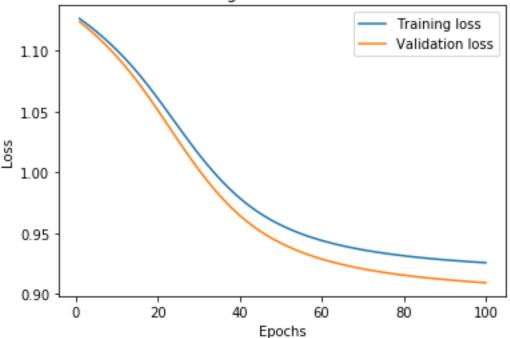
#### 512 hidden units

## 200 epoch



## Sgd and hinge



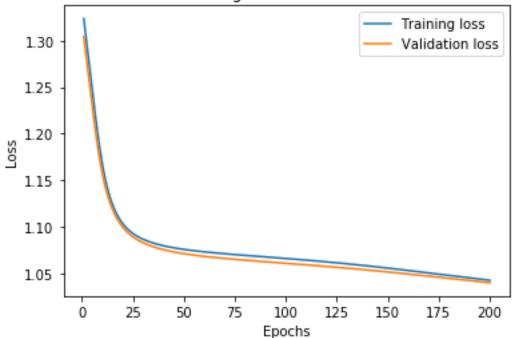


## Sgd and square hinge

#### Hyper parameter change

# Epoch 200





## Sgd and kl loss

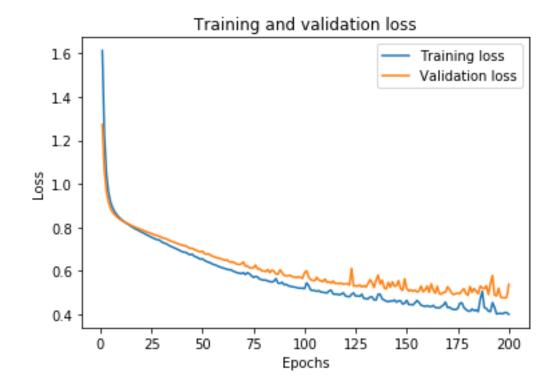
## Hyper parameter change

5 layers

512 hidden units

200 epoch

#### 128 batch size



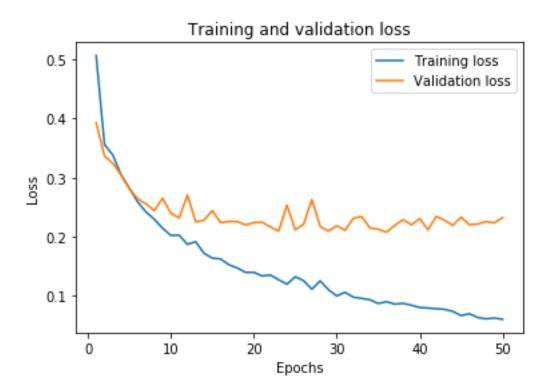
## Adam and binary cross entropy

#### Hyper parameter change

512 hidden units

50 epoch

## 128 batch size



## Adam and categorical cross entropy

## Hyper parameter change

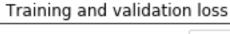
5 layers

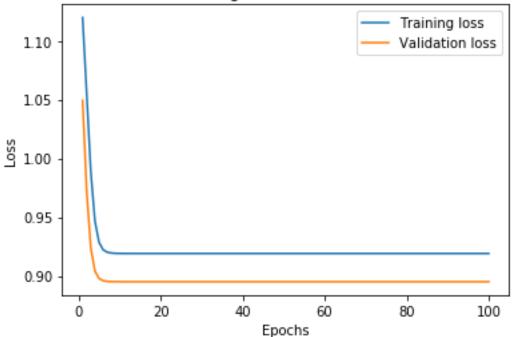
512 hidden units

## 70 epoch

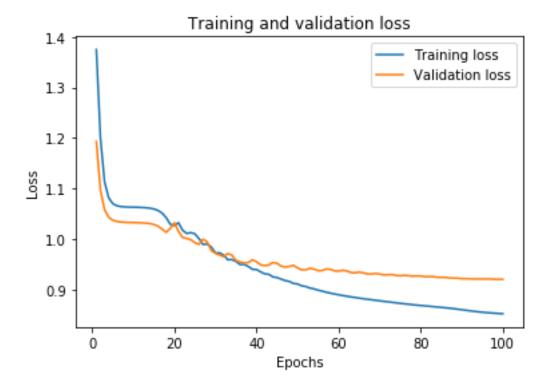


## Adam and hinge





## Adam and squared hinge



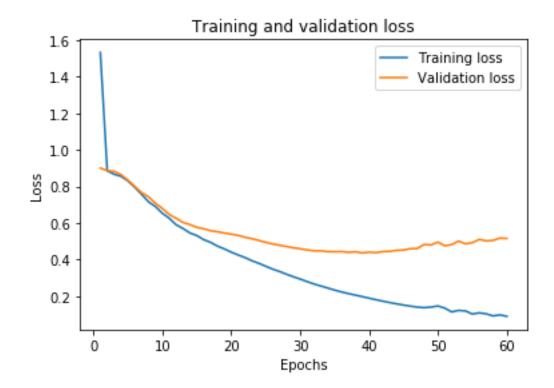
#### Adam and kl loss

## Hyper parameter change

3 layers

# 512 hidden units

#### 60 epochs

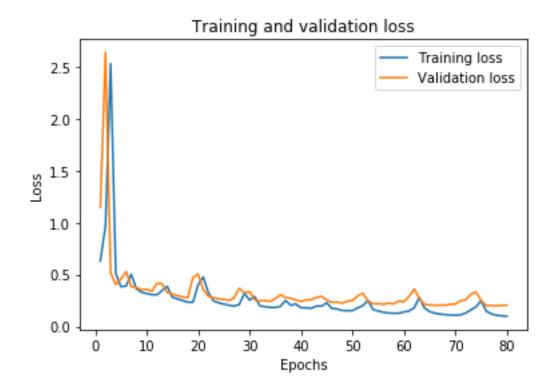


## Adagrad and binary cross entropy

## Hyper parameter change

# 5 layers

# 80 epoch

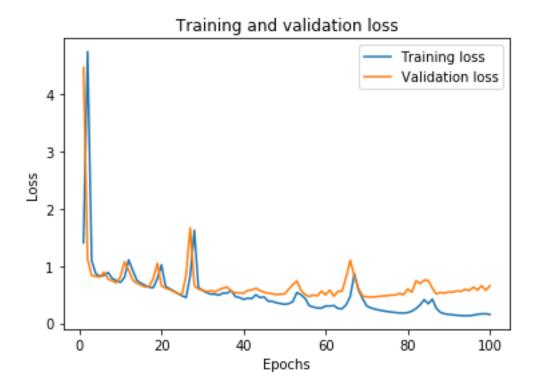


## Adagrad and categorical cross entropy

# Hyper parameter

# 5 layers

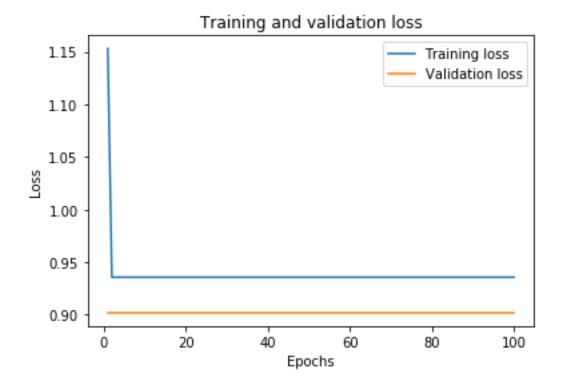
```
Epoch 96/100
ccuracy: 0.9667 - val loss: 0.6324 - val accuracy: 0.8220
Epoch 97/100
             ========= ] - Os 38us/step - loss: 0.1569 - a
210/210 [=======
ccuracy: 0.9286 - val loss: 0.5824 - val accuracy: 0.8160
Epoch 98/100
ccuracy: 0.9524 - val loss: 0.6572 - val accuracy: 0.8180
Epoch 99/100
ccuracy: 0.9286 - val loss: 0.5777 - val accuracy: 0.8030
Epoch 100/100
ccuracy: 0.9476 - val loss: 0.6535 - val accuracy: 0.8250
```



#### Adagrad and hinge

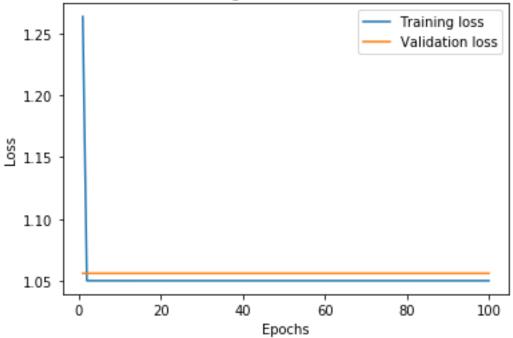
# Hyper parameter change

#### 512 hidden units



#### Adagrad and squared hinge

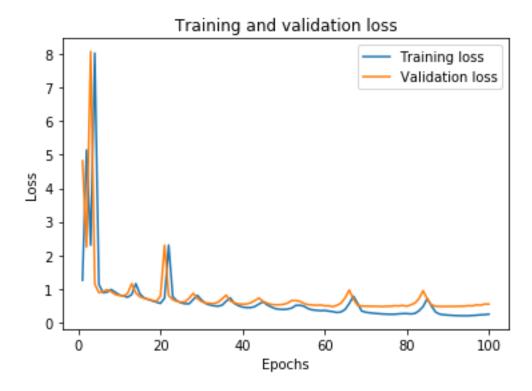




#### Adagrad and kl loss

#### Hyper parameter change

# 5 layers

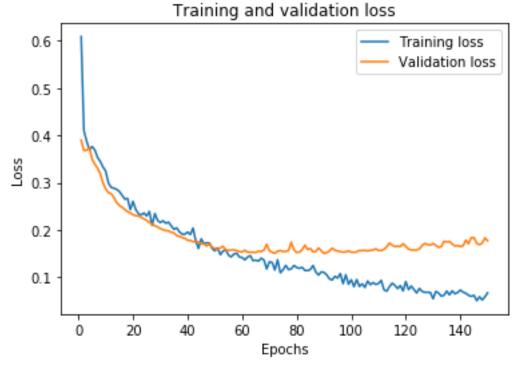


# **Applying Regularization**

The best combination of optimizer and loss found were adam and binary cross entropy with an accuracy of 91% (approx.).

A dropout of 0.5 was added to get a better model. Any other regularization such as batch normalization started decaying the accuracy of the model.

## Thus the final output is:



The model now is identified to converge faster and to give little better result than the previous one.

# Ensemble classifier:

For better optimization an ensemble model can be developed by combining the models

- 1. RMSprop and binary cross entropy
- 2. Adam and binary cross entropy
- 3. Adagrad and binary cross entropy

- =2.7195173811912537 / 3
- = 0.9065057937304179
- = 90 % (approx.)

It is found that the ensemble value is not as good as the regularized value. Thus an ensemble classifier is not required.

# **Implementation details**

Implemented using anaconda and jupyter.

The issues included

- 1. Large datasets took a longer time.
- 2. Time consumption due to evaluation against all optimizers and loss.
- 3. The code was ran on a CPU that consumed more time.
- 4. Not every model was saved because the models were misinterpreted by the jupyter kernel. Thus only the best model code is provided.
- 5. Since it was difficult to save multiple models ensemble classifiers were not implemented.

# **References:**

- 1. My own assignment 1 code
- 2. Code given by the professor