



University of Tehran

COLLEGE OF ENGINEERING

DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

NEURAL NETWORK & DEEP LEARNING

MINI PROJECT#2

SIAVASH SHAMS 810197644

Mohammad Heydari 810197494

UNDER SUPERVISION OF:

DR. AHMAD KALHOR

SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING
UNIVERSITY OF TEHRAN

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2 QUESTION #1: STOCK MARKET PREDICTION

2.1 Below we can see Google and Apple, day to day stock closing prices from 2010 to 2018.

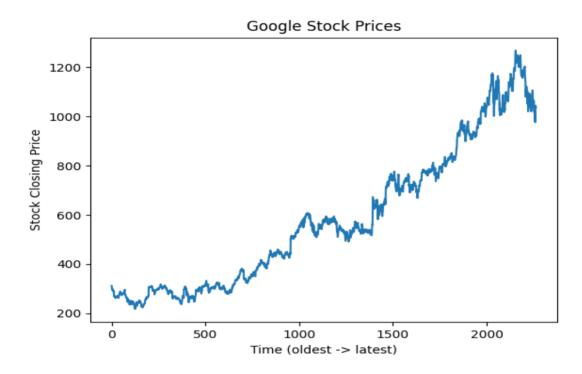


Figure 1. Representation of Google Stoch Prices

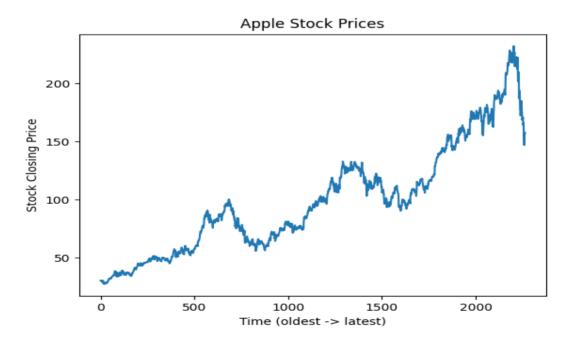


Figure 2. Representation of Apple Stoch Prices

• LSTM

Model: "sequential"			
Layer (type)	Output	Shape	 Param #
lstm (LSTM)	(None,	30, 64)	19712
lstm_1 (LSTM)	(None,	64)	33024
dense (Dense)	 (None, 	 2) 	 130 =======
Total params: 52,866 Trainable params: 52,866 Non-trainable params: 0			

Figure3. Model Architecture

We will train our model using Adam optimizer with 100 epochs.

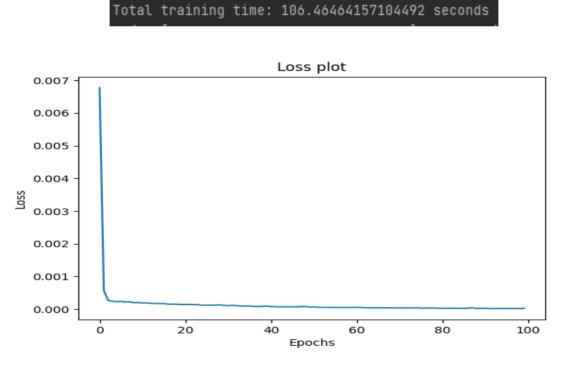


Figure4. Loss during the Epochs

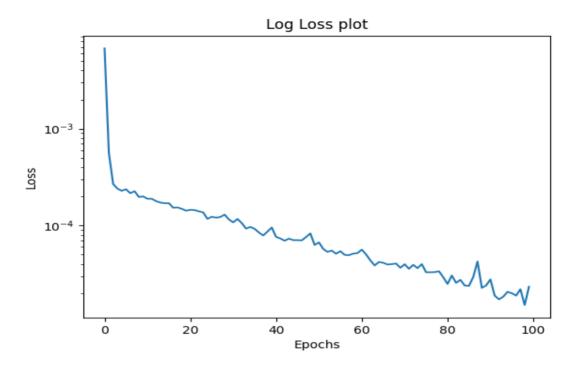


Figure 5. Log-Loss representation during the Epochs

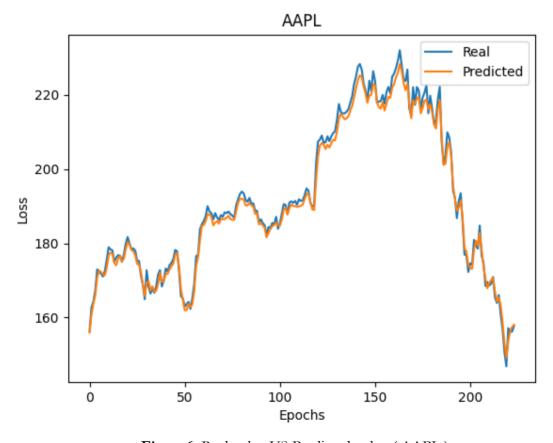


Figure 6. Real-value VS Predicted-value (AAPL)

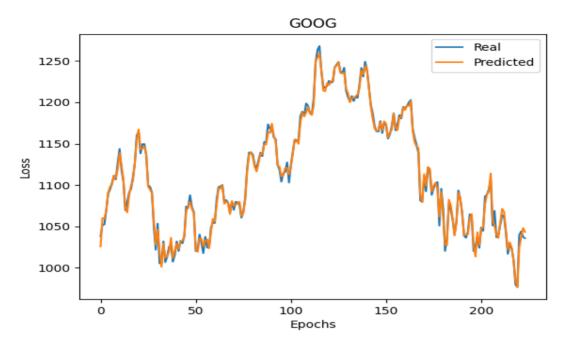


Figure 7. Real-value VS Predicted-value (GOOG)

• RNN

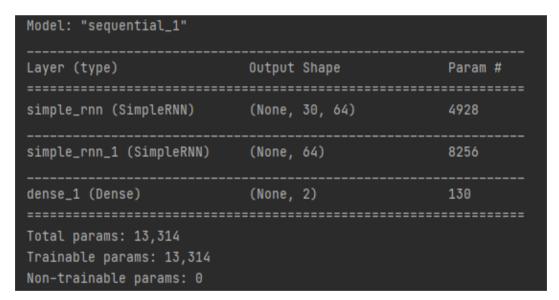


Figure8. Model Architecture

Total training time: 26.431206941604614 seconds

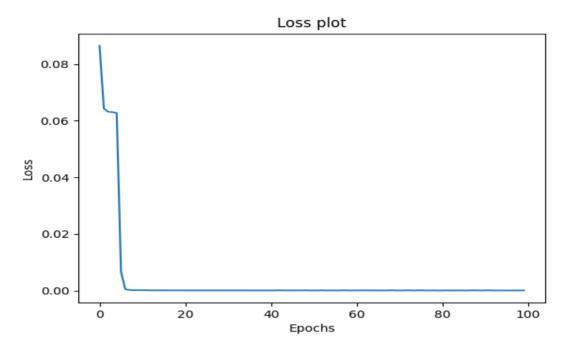


Figure 9. Loss representation during the Epochs

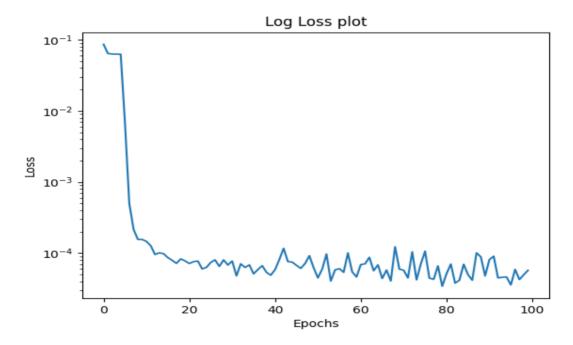


Figure 10. Loss-Loss representation during the Epochs

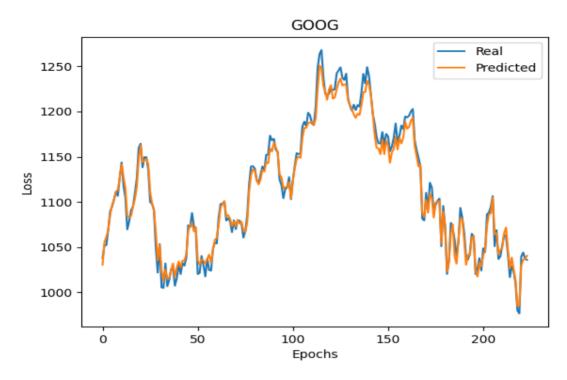


Figure 11. Real-value VS Predicted-value (GOOG)

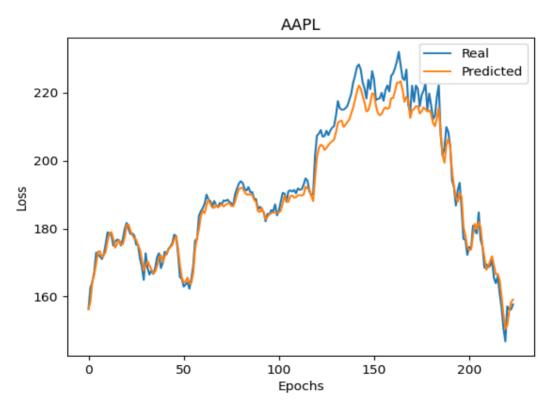
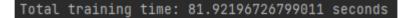


Figure 12. Real-value VS Predicted-value (AAPL)

• GRU

Model: "sequential_1"		
Layer (type)	Output Shape	 Param #
gru (GRU)	(None, 30, 64)	14976
gru_1 (GRU)	(None, 64)	24960
dense_1 (Dense) ====================================	 (None, 2) 	 130 ======

Figure 13. model architecture



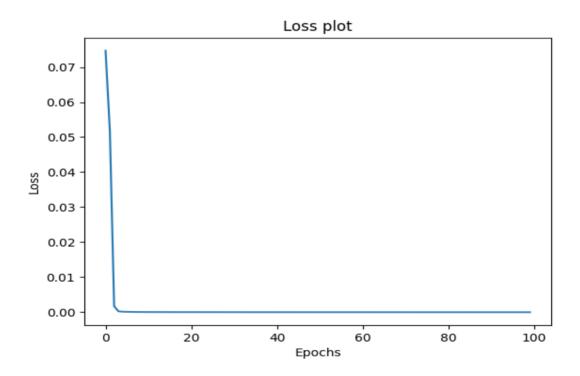


Figure 14. Loss representation during the Epochs

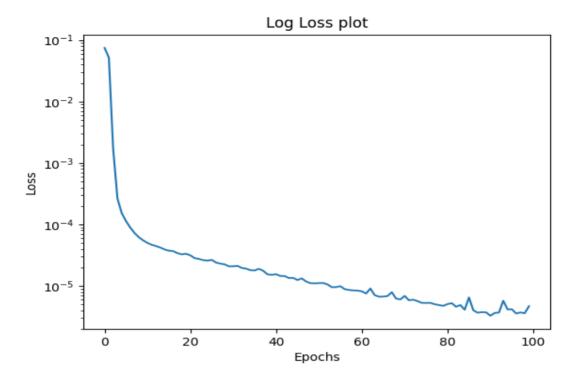
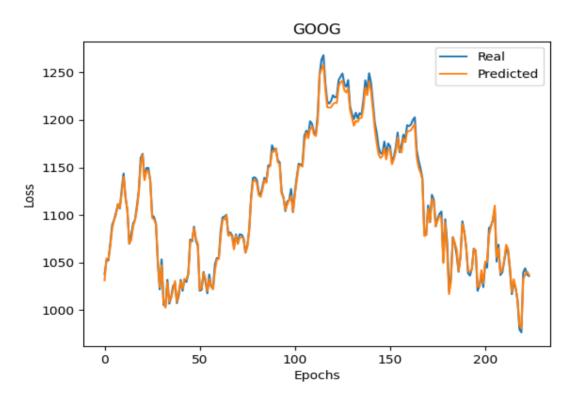


Figure 15. Log-Loss representation during the Epochs



 $\textbf{Figure 16.} \ \ \text{Real-value VS Predicted-value (GOOG)}$

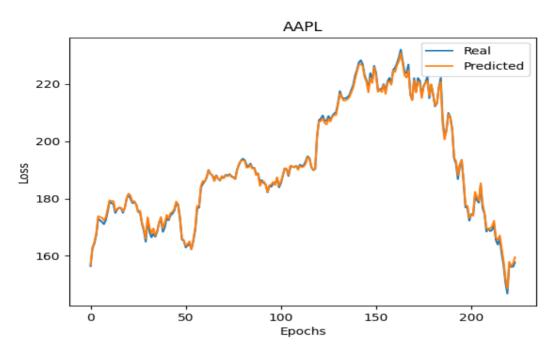


Figure 17. Real-value VS Predicted-value (AAPL)

By looking at the results we conclude that GRU outperforms the other two memory cells

Performance: GRU > LSTM > RNN

also training time is least for RNN and GRU comes second, and LSTM takes the longest. We can see that as the memory unit complexity (number of parameters) gets bigger, it requires more training time.

Training time: LSTM > GRU > RNN

2.2

• GRU + MAPE

Total training time: 145.55148577690125 seconds

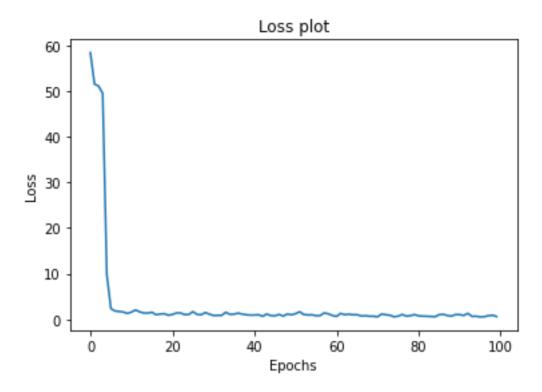


Figure 18. Loss representation during the Epochs

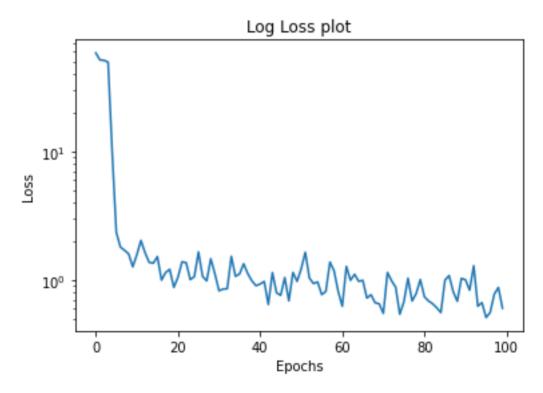


Figure 19. Log-Loss representation during the Epochs

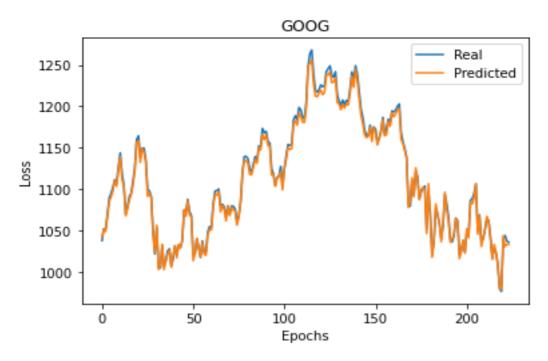


Figure 20. Real-value VS Predicted-value (GOOG)

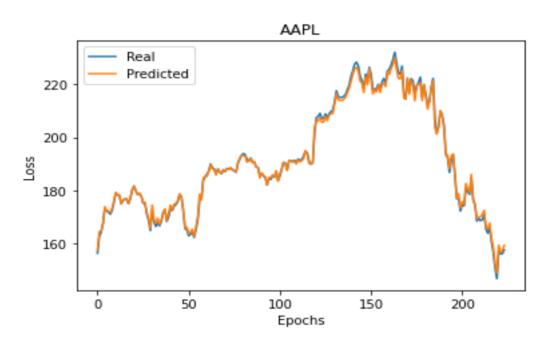


Figure 21. Real-value VS Predicted-value (AAPL)

• MAPE + RNN

Total training time: 60.38407301902771 seconds

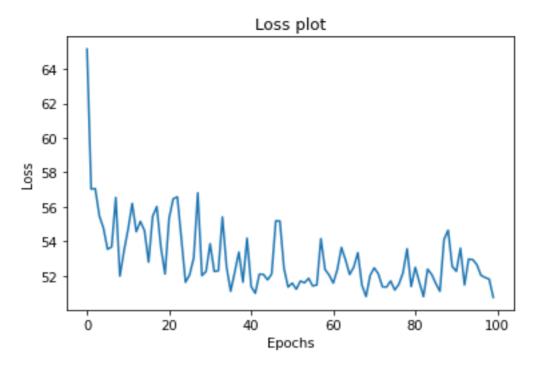


Figure 22. Loss representation during the Epochs

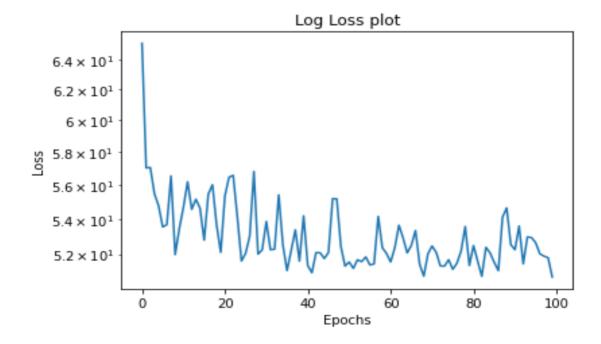


Figure 23. simple LSTM network to learn sequences of characters

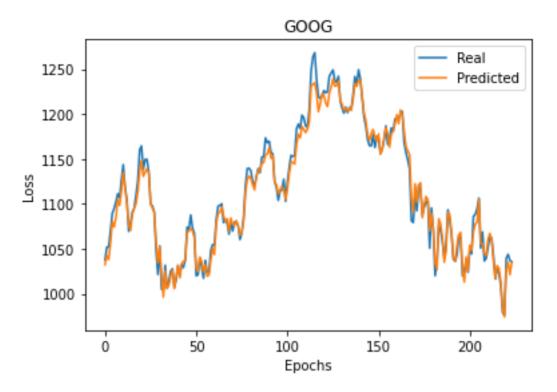


Figure 24. Real-value VS Predicted-value (GOOG)

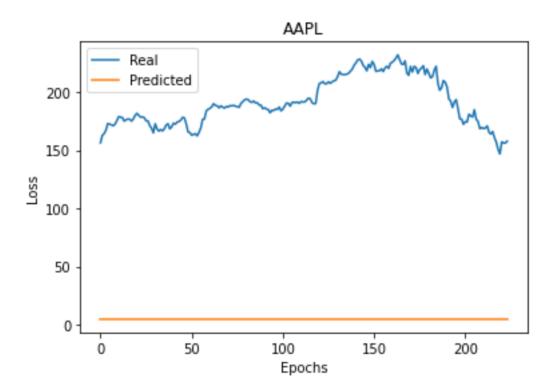


Figure25. Real-value VS Predicted-value (AAPL)

• MAPE + LSTM

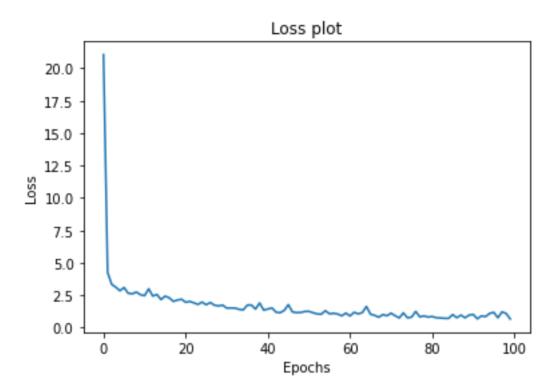


Figure 26. Loss representation during the Epochs

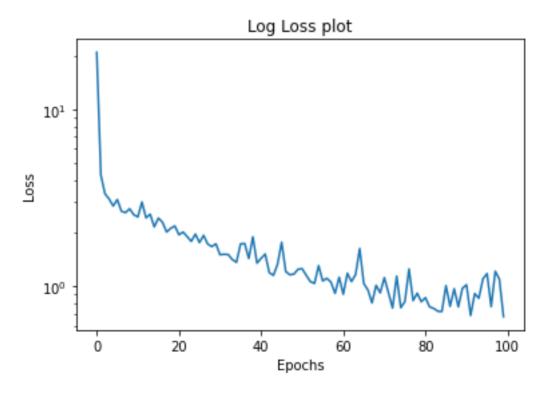


Figure 27. Log-Loss representation during the Epochs

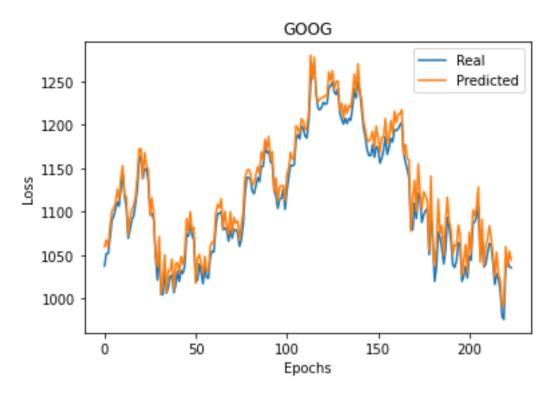


Figure 28. Real-value VS Predicted-value (GOOG)

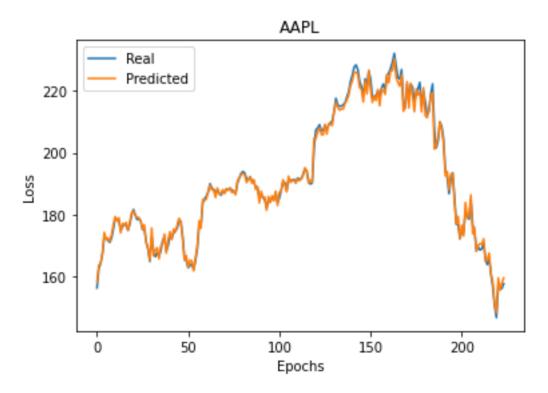


Figure29. Real-value VS Predicted-value (AAPL)

As we can see from the results, the MAPE loss function doesn't improve GRU and LSTM but reduces performance of RNN, as it has a constant gradient it suffers from vanishing gradient and thus the model is not trained well for RNN

2.3

Total training time: 149.08284449577332 seconds

• LSTM + Adagrad

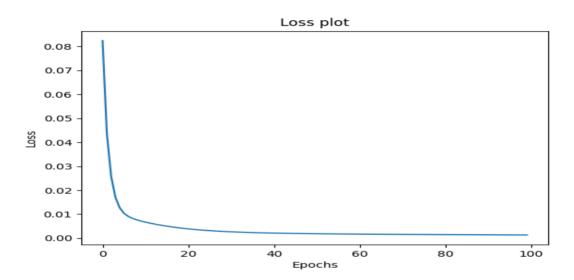


Figure 30. Loss representation during the Epochs

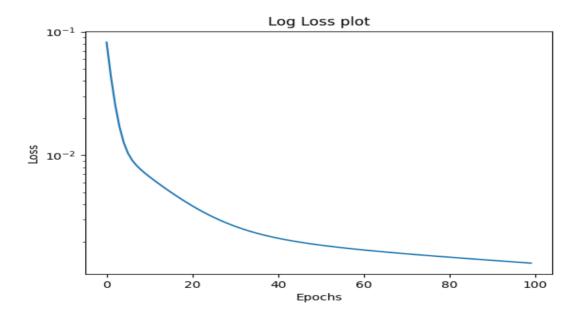


Figure 31. Log-Loss representation during the Epochs

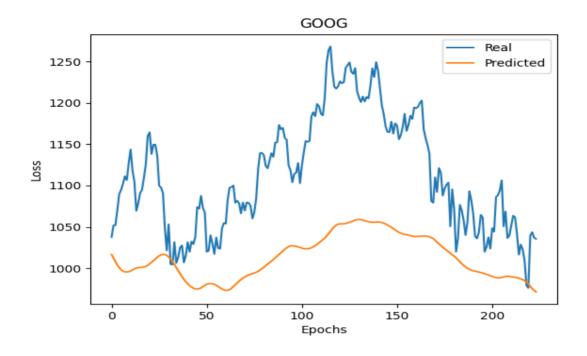


Figure 32. Real-value VS Predicted-value (GOOG)

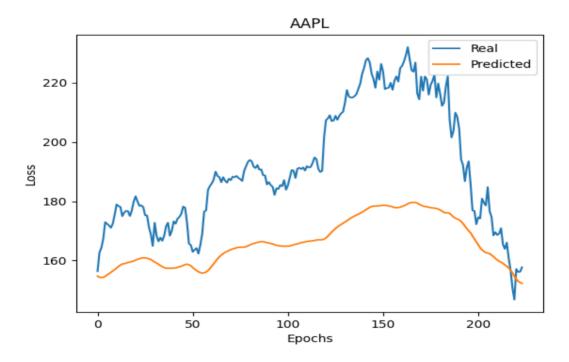


Figure 33. Real-value VS Predicted-value (AAPL)

• LSTM + RMSprop

Total training time: 205.3320653438568 seconds

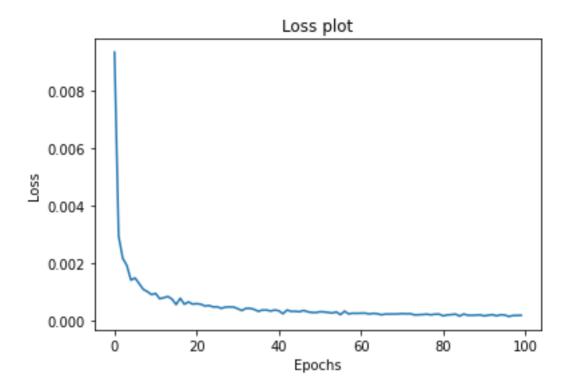


Figure 34. Loss representation during the Epochs

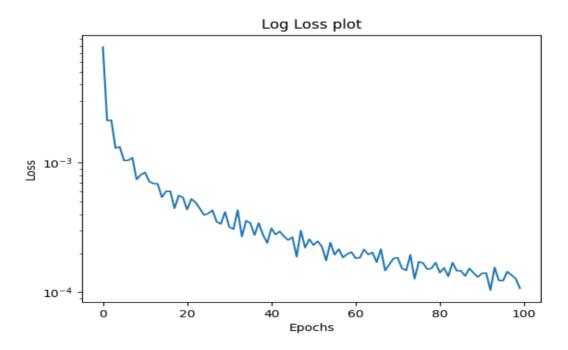


Figure 35. Log- Loss representation during the Epochs

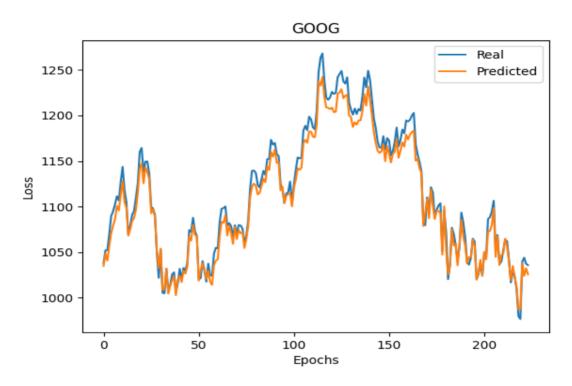


Figure 36. Real-value VS Predicted-value (GOOG)

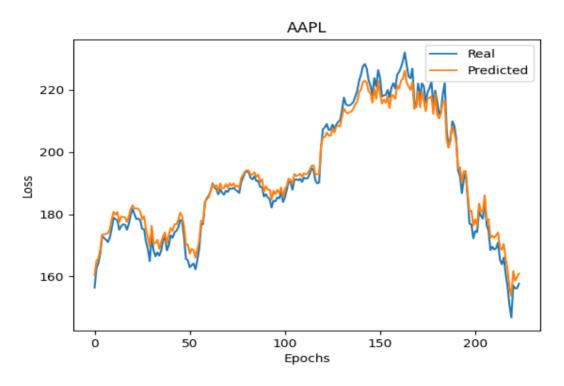


Figure 37. Real-value VS Predicted-value (AAPL)

• ADAgrad + RNN

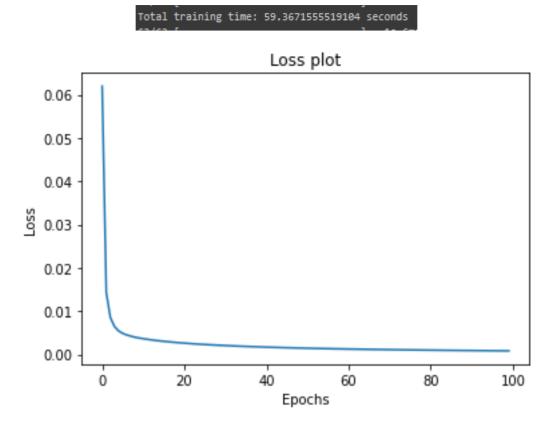


Figure 38. Loss representation during the Epochs

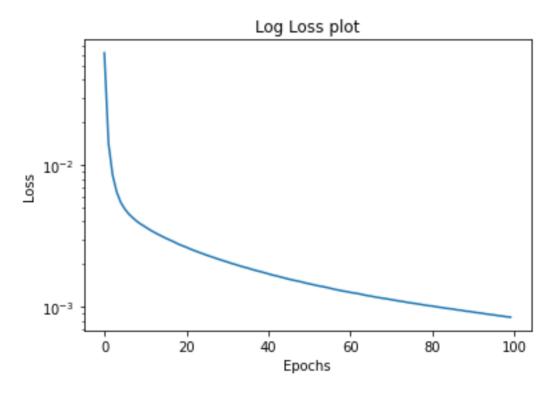


Figure 39. Log-Loss representation during the Epochs

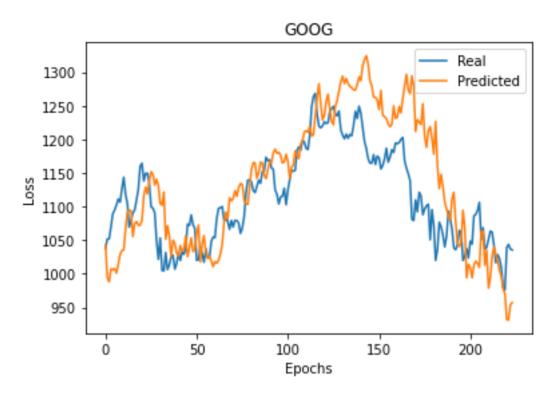


Figure 40. Real-value VS Predicted-value (GOOG)

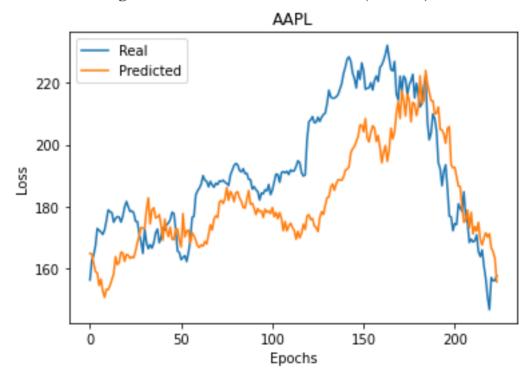


Figure 41. Real-value VS Predicted-value (AAPL)

• RMSprop +RNN

Total training time: 63.164148807525635 seconds

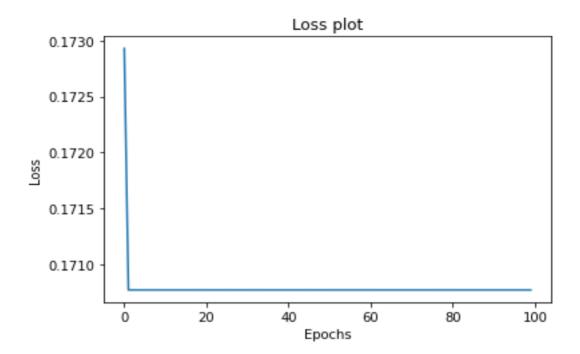


Figure 42. Loss representation during the Epochs

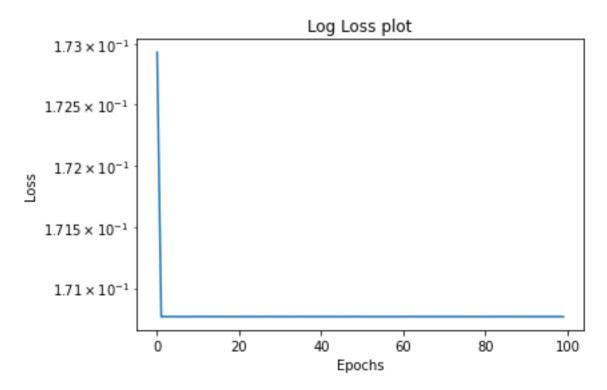


Figure 43. Log-Loss representation during the Epochs

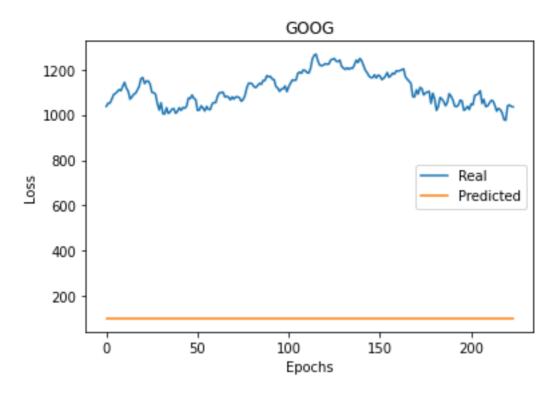


Figure 44. Real-value VS Predicted-value (GOOG)

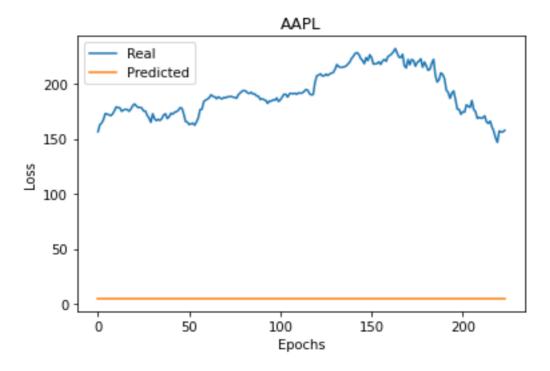


Figure 45. Real-value VS Predicted-value (AAPL)

• ADAgrad + GRU

Total training time: 137.29109835624695 seconds

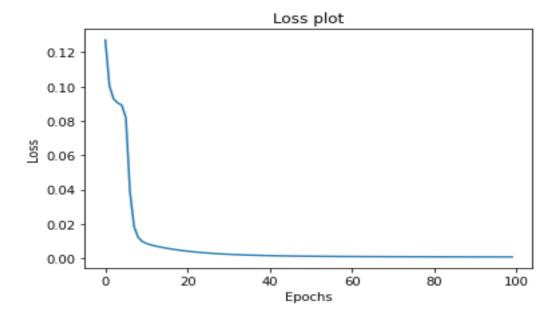


Figure 46. Loss representation during the Epochs

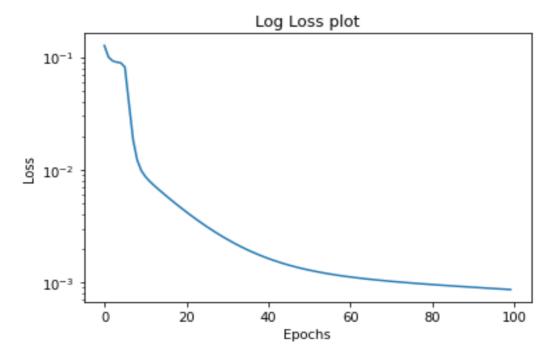


Figure 47. Log-Loss representation during the Epochs

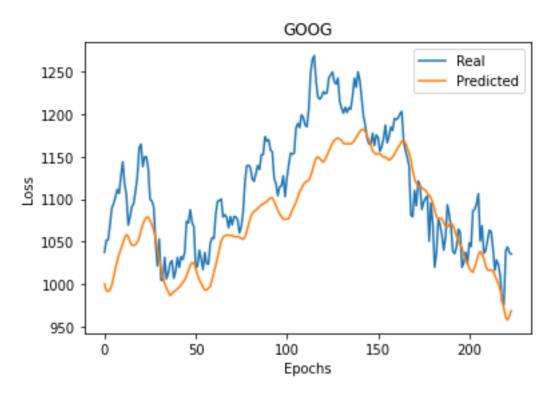
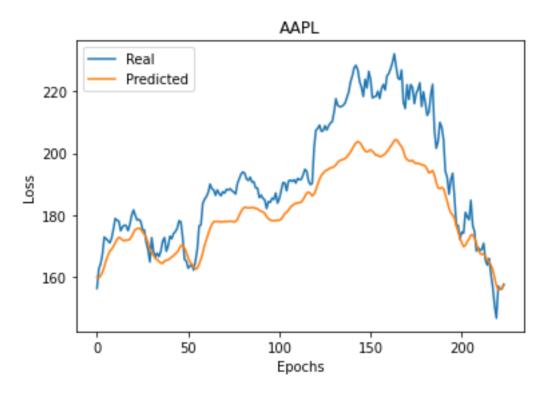


Figure 48. Real-value VS Predicted-value (GOOG)



 $\textbf{Figure 49.} \ \text{Real-value VS Predicted-value (AAPL)}$

• RMSprop + GRU

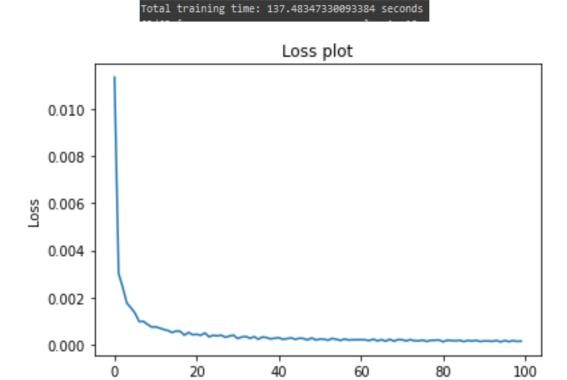


Figure 50. Loss representation during the Epochs

Epochs

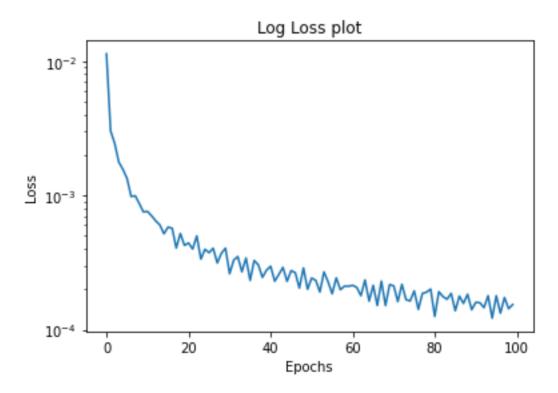


Figure 51. Log-Loss representation during the Epochs

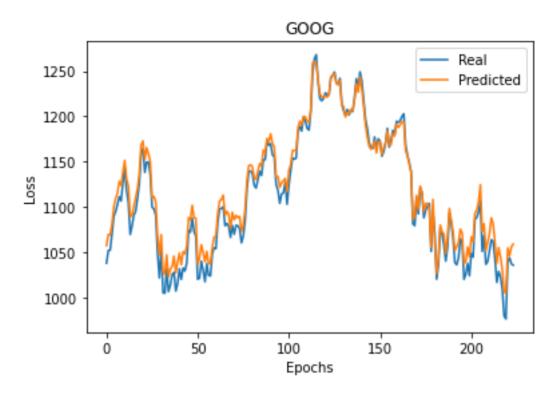
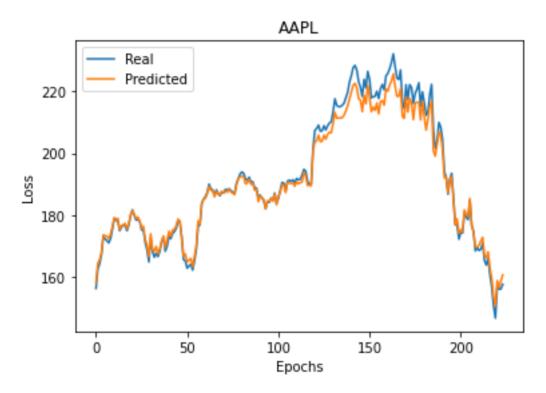


Figure 52. Real-value VS Predicted-value (GOOG)



 $\textbf{Figure 53.} \ \text{Real-value VS Predicted-value (AAPL)}$

As we can see from the results both ADAgrad and RMSprop optimizers get outperformed by Adam, because Adam uses both first and second moments and benefits from advantages of two other optimizers, so it is generally the best choice.

Also, Adam takes noticeably less time to train.

Table 2.1- Comparison between optimizers

Optimiser	Year	Learning Rate	Gradient
Momentum	1964		✓
AdaGrad	2011	✓	
RMSprop	2012	✓	
Adadelta	2012	✓	
Nesterov	2013		✓
Adam	2014	✓	✓
AdaMax	2015	✓	✓
Nadam	2015	✓	✓
AMSGrad	2018	✓	✓

2.4

• LSTM + 0.1 Dropout

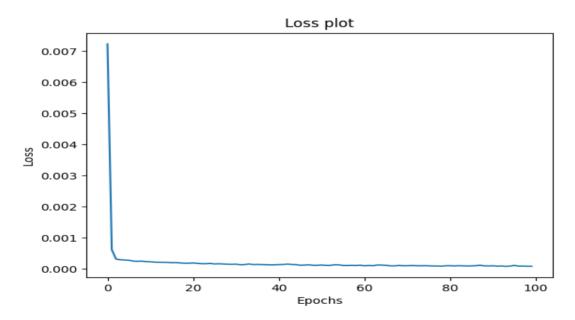


Figure 54. Loss representation during the Epochs

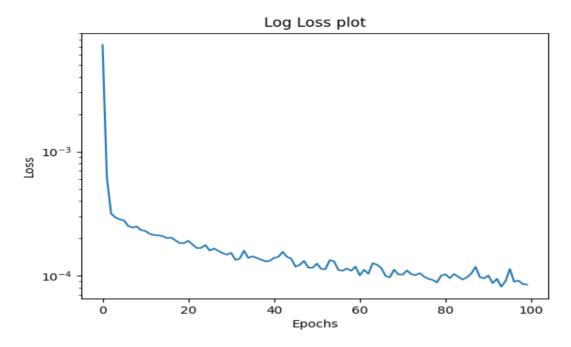


Figure 55. Log-Loss representation during the Epochs

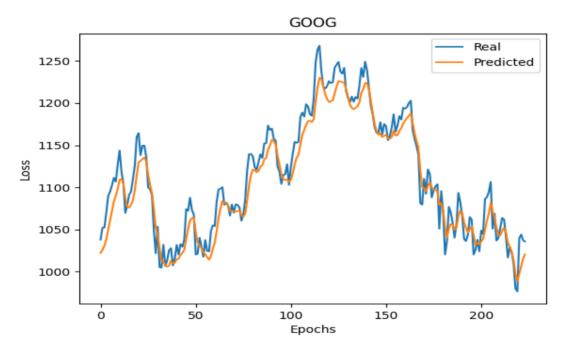


Figure 56. Real-value VS Predicted-value (GOOG)

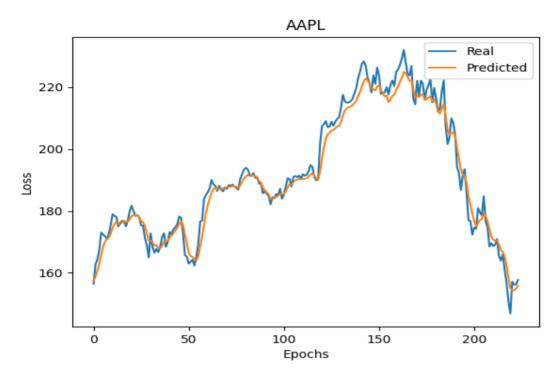


Figure 57. Real-value VS Predicted-value (AAPL)

• RNN + dropout 0.1

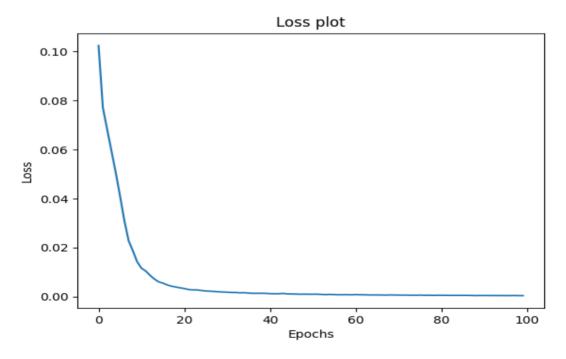


Figure 58. Loss representation during the Epochs

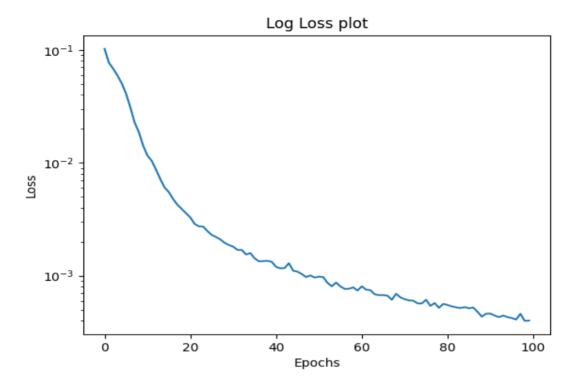


Figure 59. Log- Loss representation during the Epochs

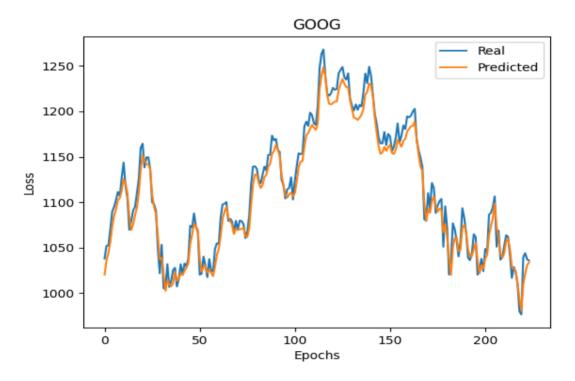


Figure 60. Real-value VS Predicted-value (GOOG)

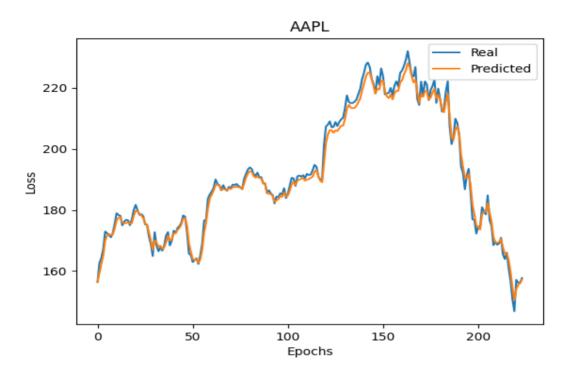


Figure 61. Real-value VS Predicted-value (AAPL)

• GRU + 0.1 dropout

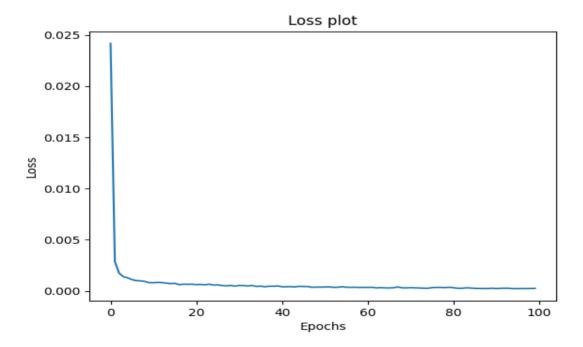


Figure 62. Loss representation during the Epochs

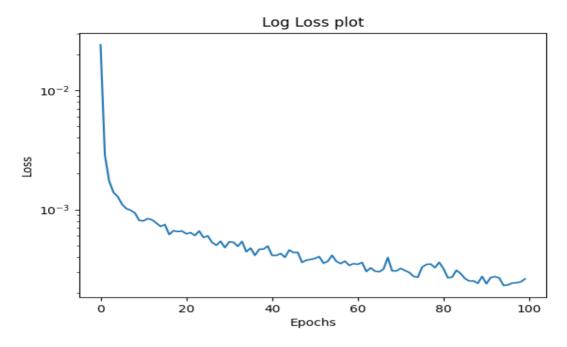


Figure 63. Log-Loss representation during the Epochs

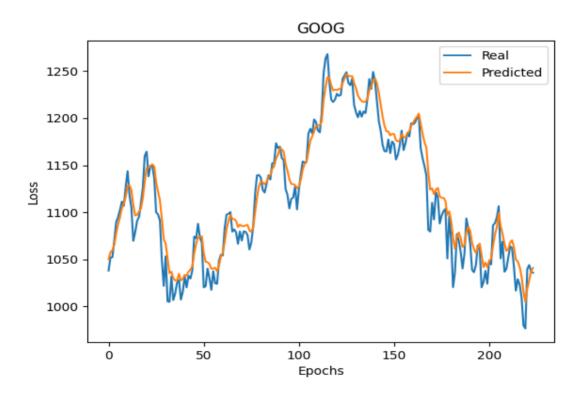


Figure64. Real-value VS Predicted-value (GOOG)

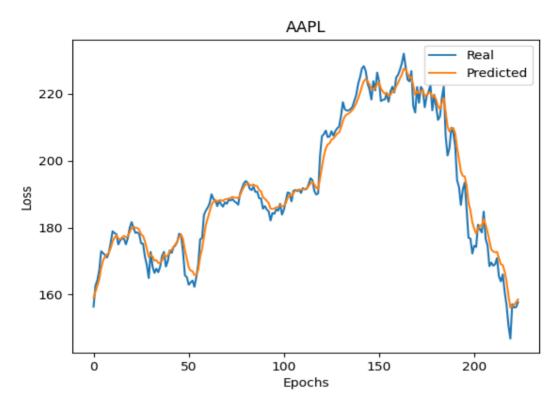


Figure65. Real-value VS Predicted-value (AAPL)

By comparing the results to part 2 we can see that adding dropout decreased performance of LSTM and GRU units but improved RNN unit.

Dropout is a regularization technique, and is most effective at preventing overfitting. However, there are several places when dropout can hurt performance.

- when the network is small relative to the dataset, regularization is usually unnecessary. If the model capacity is already low, lowering it further by adding regularization will hurt performance.
- when training time is limited. Usually, dropout hurts performance at the start of training, but results in the final "converged" error being lower. Therefore, if you don't plan to train until convergence, you may not want to use dropout.

3 QUESTION #2: TEXT GENERATION

In this part we intend to implement a Recurrent Neural Network which can be used to generate text.

First of all, it's so important to fit an appropriate model to our train-data which is the "HARRY POTTER AND THE GOBLET OF FIRE".

3.1

In this part we are going to analyse the loss and accuracy of model and investigate whether the model is an appropriate one or not.

In this section we will develop a simple LSTM network to learn sequences of characters from **HARRY POTTER AND THE GOBLET OF FIRE**. In the next section we will use this model to generate new sequences of characters.

Further you can see the architecture of model:

```
model = Sequential()
model.add(LSTM(256, input_shape=(100, 1), stateful=False, return_sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(256))
model.add(Dropout(0.2))
model.add(Dense(len(chars)))
model.add(Activation('softmax'))
```

Figure66. simple LSTM network to learn sequences of characters

Some notes about our model:

we define a single hidden LSTM layer with 256 memory units. The network uses dropout with a probability of 0.2. The output layer is a Dense layer using the softmax activation function to output a probability prediction for each of the 54 characters between 0 and 1.

The problem is really a single character classification problem with 54 classes and as such is defined as optimizing the log loss (cross entropy), here **using the ADAM** optimization algorithm for speed.

we have trained the model using the dataset and further you can find the results:

training process:

```
Total Characters: 1107542
Total Vocab: 54
Total Patterns: 1107442
Epoch 1/40
8652/8652 [============= ] - ETA: 0s - loss: 2.7356 - accuracy: 0.2304
Epoch 1: loss improved from inf to 2.73558, saving model to weights-improvement-01-2.7356.hdf5
8652/8652 [=========== ] - 133s 15ms/step - loss: 2.7356 - accuracy: 0.2304
Epoch 2/40
Epoch 2: loss improved from 2.73558 to 2.45016, saving model to weights-improvement-02-2.4502.hdf5
Epoch 3/40
Epoch 3: loss improved from 2.45016 to 2.28662, saving model to weights-improvement-03-2.2866.hdf5
Epoch 4/40
Epoch 5: loss improved from 2.18313 to 2.11050, saving model to weights-improvement-05-2.1105.hdf5
8652/8652 [=============== ] - 129s 15ms/step - loss: 2.1105 - accuracy: 0.3919
Epoch 6/40
Epoch 6: loss improved from 2.11050 to 2.05615, saving model to weights-improvement-06-2.0562.hdf5
8652/8652 [=============== ] - 129s 15ms/step - loss: 2.0562 - accuracy: 0.4070
Epoch 7: loss improved from 2.05615 to 2.01147, saving model to weights-improvement-07-2.0115.hdf5
8652/8652 [=========== ] - 129s 15ms/step - loss: 2.0115 - accuracy: 0.4189
Epoch 8/40
Epoch 8: loss improved from 2.01147 to 1.97620, saving model to weights-improvement-08-1.9762.hdf5
8652/8652 [=========== ] - 128s 15ms/step - loss: 1.9762 - accuracy: 0.4285
Epoch 9/40
Epoch 9: loss improved from 1.97620 to 1.94710, saving model to weights-improvement-09-1.9471.hdf5
8652/8652 [============= ] - 128s 15ms/step - loss: 1.9471 - accuracy: 0.4362
Epoch 10/40
Epoch 10: loss improved from 1.94710 to 1.92295, saving model to weights-improvement-10-1.9230.hdf5
Epoch 11: loss improved from 1.92295 to 1.90136, saving model to weights-improvement-11-1.9014.hdf5
8652/8652 [===========] - 128s 15ms/step - loss: 1.9014 - accuracy: 0.4482
Fnoch 12/40
Epoch 12: loss improved from 1.90136 to 1.88222, saving model to weights-improvement-12-1.8822.hdf5
8652/8652 [===========] - 128s 15ms/step - loss: 1.8822 - accuracy: 0.4531
Epoch 13/40
        Epoch 13: loss improved from 1.88222 to 1.86518, saving model to weights-improvement-13-1.8652.hdf5
8652/8652 [==
                   ======] - 128s 15ms/step - loss: 1.8652 - accuracy: 0.4578
Epoch 14/40
```

```
Epoch 15/40
Epoch 15: loss improved from 1.85031 to 1.83727, saving model to weights-improvement-15-1.8373.hdf5
8652/8652 [=========== ] - 128s 15ms/step - loss: 1.8373 - accuracy: 0.4655
Epoch 16/40
Epoch 16: loss improved from 1.83727 to 1.82468, saving model to weights-improvement-16-1.8247.hdf5
8652/8652 [=========== ] - 128s 15ms/step - loss: 1.8247 - accuracy: 0.4685
Epoch 17/40
Epoch 17: loss improved from 1.82468 to 1.81362, saving model to weights-improvement-17-1.8136.hdf5
8652/8652 [============ ] - 129s 15ms/step - loss: 1.8136 - accuracy: 0.4712
Fnoch 18/40
Epoch 18: loss improved from 1.81362 to 1.80392, saving model to weights-improvement-18-1.8039.hdf5
8652/8652 [=============== ] - 128s 15ms/step - loss: 1.8039 - accuracy: 0.4740
Fnoch 19/40
Epoch 19: loss improved from 1.80392 to 1.79467, saving model to weights-improvement-19-1.7947.hdf5
8652/8652 [=========== ] - 128s 15ms/step - loss: 1.7947 - accuracy: 0.4768
Fnoch 20/40
Epoch 20: loss improved from 1.79467 to 1.78615, saving model to weights-improvement-20-1.7861.hdf5
8652/8652 [========== - 128s 15ms/step - loss: 1.7861 - accuracy: 0.4788
Epoch 21/40
Epoch 21: loss improved from 1.78615 to 1.77785, saving model to weights-improvement-21-1.7779.hdf5
8652/8652 [=================== ] - 128s 15ms/step - loss: 1.7779 - accuracy: 0.4807
Epoch 22/40
Epoch 22: loss improved from 1.77785 to 1.76937, saving model to weights-improvement-22-1.7694.hdf5
Epoch 23/40
Epoch 23: loss improved from 1.76937 to 1.76254, saving model to weights-improvement-23-1.7625.hdf5
8652/8652 [============== ] - 128s 15ms/step - loss: 1.7625 - accuracy: 0.4842
Epoch 24/40
Epoch 24: loss improved from 1.76254 to 1.75562, saving model to weights-improvement-24-1.7556.hdf5
8652/8652 [=============== ] - 128s 15ms/step - loss: 1.7556 - accuracy: 0.4867
Epoch 25/40
Epoch 25: loss improved from 1.75562 to 1.74839, saving model to weights-improvement-25-1.7484.hdf5
8652/8652 [==================== ] - 128s 15ms/step - loss: 1.7484 - accuracy: 0.4891
Epoch 26/40
Epoch 26: loss improved from 1.74839 to 1.74327, saving model to weights-improvement-26-1.7433.hdf5
```

```
8652/8652 [============ ] - 128s 15ms/step - loss: 1.7433 - accuracy: 0.4896
Epoch 27/40
Epoch 27: loss improved from 1.74327 to 1.73799, saving model to weights-improvement-27-1.7380.hdf5
Epoch 28/40
8652/8652 [=============== ] - ETA: Os - loss: 1.7318 - accuracy: 0.4928
Epoch 28: loss improved from 1.73799 to 1.73181, saving model to weights-improvement-28-1.7318.hdf5
8652/8652 [============ - 129s 15ms/step - loss: 1.7318 - accuracy: 0.4928
Fnoch 29/40
Epoch 29: loss improved from 1.73181 to 1.72761, saving model to weights-improvement-29-1.7276.hdf5
8652/8652 [============ ] - 129s 15ms/step - loss: 1.7276 - accuracy: 0.4940
Fnoch 30/40
Epoch 30: loss improved from 1.72761 to 1.72201, saving model to weights-improvement-30-1.7220.hdf5
8652/8652 [============ ] - 129s 15ms/step - loss: 1.7220 - accuracy: 0.4951
Epoch 31/40
Epoch 31: loss improved from 1.72201 to 1.71603, saving model to weights-improvement-31-1.7160.hdf5
8652/8652 [============ ] - 129s 15ms/step - loss: 1.7160 - accuracy: 0.4973
Epoch 32/40
Epoch 33/40
Epoch 33: loss improved from 1.71308 to 1.70980, saving model to weights-improvement-33-1.7098.hdf5
8652/8652 [=========] - 129s 15ms/step - loss: 1.7098 - accuracy: 0.4989
Epoch 34/40
8652/8652 [=============== ] - ETA: 0s - loss: 1.7044 - accuracy: 0.5000
Epoch 34: loss improved from 1.70980 to 1.70438, saving model to weights-improvement-34-1.7044.hdf5
8652/8652 [=========== ] - 129s 15ms/step - loss: 1.7044 - accuracy: 0.5000
Epoch 35/40
Epoch 35: loss improved from 1.70438 to 1.70121, saving model to weights-improvement-35-1.7012.hdf5
Epoch 36: loss improved from 1.70121 to 1.69733, saving model to weights-improvement-36-1.6973.hdf5
Fnoch 37/40
Epoch 37: loss improved from 1.69733 to 1.69428, saving model to weights-improvement-37-1.6943.hdf5
8652/8652 [========== ] - 129s 15ms/step - loss: 1.6943 - accuracy: 0.5024
Epoch 38/40
Epoch 38: loss improved from 1.69428 to 1.68982, saving model to weights-improvement-38-1.6898.hdf5
8652/8652 [========== ] - 129s 15ms/step - loss: 1.6898 - accuracy: 0.5040
Epoch 39/40
Epoch 39: loss improved from 1.68982 to 1.68615, saving model to weights-improvement-39-1.6861.hdf5
8652/8652 [========== ] - 129s 15ms/step - loss: 1.6861 - accuracy: 0.5052
Epoch 40/40
8652/8652 [============] - ETA: 0s - loss: 1.6836 - accuracy: 0.5054
Epoch 40: loss improved from 1.68615 to 1.68356, saving model to weights-improvement-40-1.6836.hdf5
8652/8652 [=========== ] - 129s 15ms/step - loss: 1.6836 - accuracy: 0.5054
```

The Results:

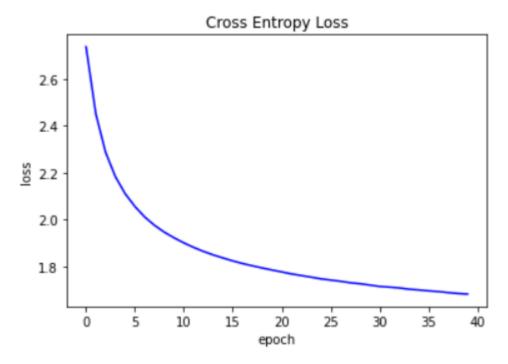


Figure 67. cross-entropy loss during the epochs

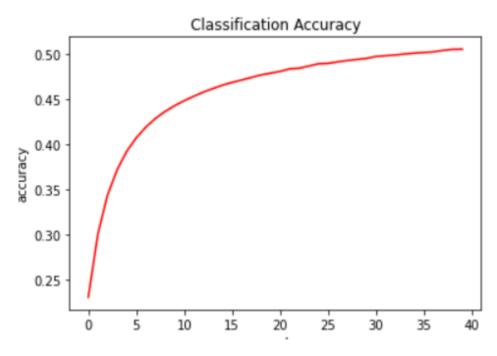


Figure 68. Classification accuracy during the epochs

TEXT PREDICTION RESULTS:

Here is some output from the stateless recurrent neural network that takes predicts characters one at a time, using a seed text of 100 characters (with some autocorrect applied):

SEED TEXT: behind them. at the same moment, bill, charlie, and percy emerged from the boys' tent, fully dress
PREDICTED TEXT: ed as though he was standing at him i was standing at the goblet of forest to the triwizard tourn
SEED TEXT: le divination this afternoon," harry groaned, looking down. divination was his least favorite subje
PREDICTED TEXT: CTT he was standing at the compartment and stared at him i was standing at the dark lord and he w

SEED TEXT: t because we know the dementors are standing guard at azkaban!" "the rest of us sleep less soundly i
PREDICTED TEXT: n the triwizard tournament i was standing at the goblet of forest to the triwizard tournament to
SEED TEXT: ccupied the carriages in front were already hurrying up the stone steps into the castle. harry, ron,
PREDICTED TEXT: and Hermione was standing at the compartment and stared at him i was standing at the goblet of fo
SEED TEXT: 've got more points on the second task," said cedric mulishly. "you stayed behind to get all the ho
PREDICTED TEXT: use of the triwizard tournament i was standing at the stands on the grounds he was standing at t

Figure 69. Text Prediction Results

Why pre-processing can improve the model performance?

- 1) we need to load the ASCII text for the book into memory and convert all of the characters to lowercase to reduce the vocabulary that the network must learn.
- 2) when that the book is loaded, we must prepare the data for modeling by the neural network. We cannot model the characters directly, instead we must convert the characters to integers. We can do this easily by first creating a set of all of the distinct characters in the book, then creating a map of each character to a unique integer.
- 3) Next, we need to **rescale the integers to the range 0-to-1** to make the patterns **easier to learn by the LSTM network** that uses the sigmoid activation function by default.
- 4) Finally, we need to convert the output patterns (single characters converted to integers) into a **one hot encoding**. This is so that we can configure the network to predict the probability of each of the 54 different characters in the vocabulary (an easier representation) rather than trying **to force it to predict precisely the next character**. Each y value is converted into a sparse vector with a length of 54, full of zeros except with a 1 in the column for the letter (integer) that the pattern represents.

In this section, we are going to use another loss-function in our optimizer and investigate is it a good deal or not.

A loss function is going to serve as a measurement of how far our current set of predictions are from the corresponding true values.

First-one: Mean-Squared-Error

Model-evaluation:

accuracy curve and loss curve during epochs have been attached:

```
Total Characters: 1107542
Total Vocab: 54
Total Patterns: 1107442
Epoch 1/20
8652/8652 [============== ] - ETA: 0s - loss: 0.0157 - accuracy: 0.2780
Epoch 1: loss improved from inf to 0.01575, saving model to weights-improvement-01-0.0157.hdf5
8652/8652 [================= ] - 288s 32ms/step - loss: 0.0157 - accuracy: 0.2780
Epoch 2/20
Epoch 2: loss improved from 0.01575 to 0.01371, saving model to weights-improvement-02-0.0137.hdf5
8652/8652 [=============== ] - 281s 33ms/step - loss: 0.0137 - accuracy: 0.3953
Epoch 3/20
Epoch 3: loss improved from 0.01371 to 0.01288, saving model to weights-improvement-03-0.0129.hdf5
8652/8652 [================ ] - 282s 33ms/step - loss: 0.0129 - accuracy: 0.4392
Epoch 4/20
Epoch 4: loss improved from 0.01288 to 0.01235, saving model to weights-improvement-04-0.0123.hdf5
8652/8652 [================ ] - 283s 33ms/step - loss: 0.0123 - accuracy: 0.4658
Epoch 5/20
Epoch 5: loss improved from 0.01235 to 0.01200, saving model to weights-improvement-05-0.0120.hdf5
8652/8652 [============== ] - 286s 33ms/step - loss: 0.0120 - accuracy: 0.4828
Epoch 6: loss improved from 0.01200 to 0.01174, saving model to weights-improvement-06-0.0117.hdf5
8652/8652 [=============== ] - 285s 33ms/step - loss: 0.0117 - accuracy: 0.4953
Epoch 7/20
Epoch 7: loss improved from 0.01174 to 0.01153, saving model to weights-improvement-07-0.0115.hdf5
```

```
Epoch 7: loss improved from 0.01174 to 0.01153, saving model to weights-improvement-07-0.0115.hdf5
8652/8652 [=========== ] - 285s 33ms/step - loss: 0.0115 - accuracy: 0.5057
Epoch 8/20
Epoch 8: loss improved from 0.01153 to 0.01135, saving model to weights-improvement-08-0.0114.hdf5
8652/8652 [============ ] - 284s 33ms/step - loss: 0.0114 - accuracy: 0.5142
Epoch 9: loss improved from 0.01135 to 0.01122, saving model to weights-improvement-09-0.0112.hdf5
Epoch 10: loss improved from 0.01122 to 0.01111, saving model to weights-improvement-10-0.0111.hdf5
8652/8652 [============== ] - 282s 33ms/step - loss: 0.0111 - accuracy: 0.5262
Epoch 11/20
Epoch 11: loss improved from 0.01111 to 0.01100, saving model to weights-improvement-11-0.0110.hdf5
8652/8652 [=========== ] - 282s 33ms/step - loss: 0.0110 - accuracy: 0.5318
Epoch 12/20
Epoch 12: loss improved from 0.01100 to 0.01092, saving model to weights-improvement-12-0.0109.hdf5
8652/8652 [============ ] - 282s 33ms/step - loss: 0.0109 - accuracy: 0.5354
Epoch 13/20
Epoch 13: loss improved from 0.01092 to 0.01083, saving model to weights-improvement-13-0.0108.hdf5
8652/8652 [============ ] - 282s 33ms/step - loss: 0.0108 - accuracy: 0.5391
Epoch 14/20
Epoch 14: loss improved from 0.01083 to 0.01076, saving model to weights-improvement-14-0.0108.hdf5
8652/8652 [=============== ] - 282s 33ms/step - loss: 0.0108 - accuracy: 0.5434
Epoch 15/20
Epoch 15: loss improved from 0.01076 to 0.01070, saving model to weights-improvement-15-0.0107.hdf5
Epoch 16: loss improved from 0.01070 to 0.01064, saving model to weights-improvement-16-0.0106.hdf5
Epoch 17/20
Epoch 17: loss improved from 0.01064 to 0.01059, saving model to weights-improvement-17-0.0106.hdf5
8652/8652 [================= ] - 283s 33ms/step - loss: 0.0106 - accuracy: 0.5513
Epoch 18/20
Epoch 18: loss improved from 0.01059 to 0.01054, saving model to weights-improvement-18-0.0105.hdf5
8652/8652 [================ ] - 282s 33ms/step - loss: 0.0105 - accuracy: 0.5538
Epoch 19/20
Epoch 19: loss improved from 0.01054 to 0.01050, saving model to weights-improvement-19-0.0105.hdf5
8652/8652 [============ ] - 282s 33ms/step - loss: 0.0105 - accuracy: 0.5556
Epoch 20/20
Epoch 20: loss improved from 0.01050 to 0.01045, saving model to weights-improvement-20-0.0105.hdf5
8652/8652 [============= ] - 284s 33ms/step - loss: 0.0105 - accuracy: 0.5579
```

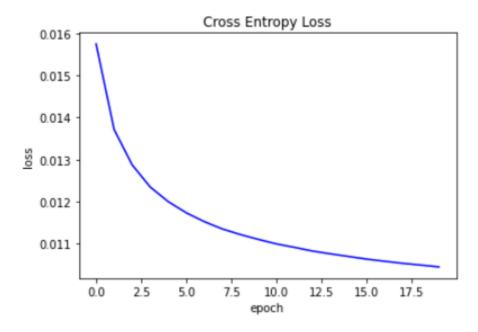


Figure 70. cross-entropy loss during the epochs

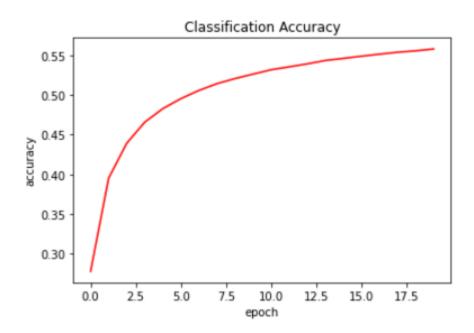


Figure 71. Classification accuracy during the epochs

Second-one: Mean-Absolute-Error

Model-evaluation:

accuracy curve and **loss curve** during epochs have been attached:

```
Total Characters: 1107542
Total Vocab: 54
Total Patterns: 1107442
Epoch 1/20
Epoch 1: loss improved from inf to 0.03047, saving model to weights-improvement-01-0.0305.hdf5
8652/8652 [=============== ] - 283s 32ms/step - loss: 0.0305 - accuracy: 0.1774
Epoch 2/20
Epoch 2: loss improved from 0.03047 to 0.03046, saving model to weights-improvement-02-0.0305.hdf5
8652/8652 [===========] - 275s 32ms/step - loss: 0.0305 - accuracy: 0.1774
Epoch 3/20
Epoch 3: loss did not improve from 0.03046
Epoch 4/20
Epoch 4: loss did not improve from 0.03046
8652/8652 [=========== ] - 275s 32ms/step - loss: 0.0305 - accuracy: 0.1774
Epoch 5: loss improved from 0.03046 to 0.03046, saving model to weights-improvement-05-0.0305.hdf5
8652/8652 [============ ] - 276s 32ms/step - loss: 0.0305 - accuracy: 0.1774
Epoch 6/20
Epoch 6: loss did not improve from 0.03046
Epoch 7/20
Epoch 7: loss did not improve from 0.03046
```

```
Fnoch 8/20
Epoch 8: loss did not improve from 0.03046
Epoch 9/20
Epoch 9: loss did not improve from 0.03046
Epoch 10/20
Epoch 10: loss did not improve from 0.03046
Epoch 11/20
Epoch 11: loss did not improve from 0.03046
Epoch 12/20
Epoch 12: loss did not improve from 0.03046
Epoch 13/20
Epoch 13: loss did not improve from 0.03046
Fnoch 14/20
Epoch 14: loss did not improve from 0.03046
Epoch 15/20
Epoch 15: loss did not improve from 0.03046
Epoch 15: loss did not improve from 0.03046
8652/8652 [================== ] - 276s 32ms/step - loss: 0.0305 - accuracy: 0.1774
Epoch 16/20
Epoch 16: loss did not improve from 0.03046
8652/8652 [============== ] - 276s 32ms/step - loss: 0.0305 - accuracy: 0.1774
Epoch 17/20
Epoch 17: loss did not improve from 0.03046
8652/8652 [=========== ] - 277s 32ms/step - loss: 0.0305 - accuracy: 0.1774
Epoch 18/20
8651/8652 [==========>.] - ETA: 0s - loss: 0.0305 - accuracy: 0.1774
Epoch 18: loss did not improve from 0.03046
8652/8652 [============ ] - 276s 32ms/step - loss: 0.0305 - accuracy: 0.1774
Epoch 19/20
Epoch 19: loss did not improve from 0.03046
8652/8652 [================ ] - 277s 32ms/step - loss: 0.0305 - accuracy: 0.1774
Enoch 20/20
Epoch 20: loss improved from 0.03046 to 0.03046, saving model to weights-improvement-20-0.0305.hdf5
8652/8652 [================= ] - 277s 32ms/step - loss: 0.0305 - accuracy: 0.1774
```

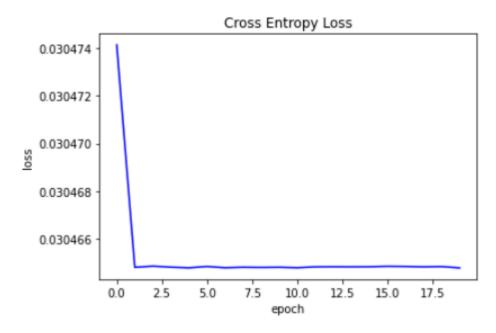


Figure 72. cross-entropy loss during the epochs

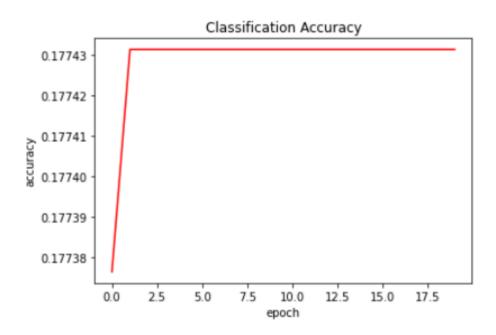


Figure 73. Classification accuracy during the epochs

As you can see the results of MSE in comparison with MAE is pretty much better and also the curves which are belongs to the MSE are most smooth in other words has a better convergence rate.

But in both cases, we are dealing with a lower performance in comparison to crossentropy loss which is highly better in all cases.

in this section we are going to change two of metrics and investigate whether the results tend to be better or not.

NUMBER OF EPOCHS # 20:

TRAINING PROCESS:

```
Total Characters: 1107542
Total Vocab: 54
Total Patterns: 1107442
Epoch 1/20
Epoch 1: loss improved from inf to 2.72788, saving model to weights-improvement-01-2.7279.hdf5
8652/8652 [========== ] - 131s 14ms/step - loss: 2.7279 - accuracy: 0.2329
Epoch 2: loss improved from 2.72788 to 2.44918, saving model to weights-improvement-02-2.4492.hdf5
8652/8652 [============ - 128s 15ms/step - loss: 2.4492 - accuracy: 0.3017
Epoch 3/20
8652/8652 [============= ] - ETA: 0s - loss: 2.2917 - accuracy: 0.3430
Epoch 3: loss improved from 2.44918 to 2.29173, saving model to weights-improvement-03-2.2917.hdf5
8652/8652 [============= ] - 129s 15ms/step - loss: 2.2917 - accuracy: 0.3430
Epoch 4: loss improved from 2.29173 to 2.19358, saving model to weights-improvement-04-2.1936.hdf5
Epoch 5/20
8652/8652 [============= ] - ETA: Os - loss: 2.1242 - accuracy: 0.3879
Epoch 5: loss improved from 2.19358 to 2.12422, saving model to weights-improvement-05-2.1242.hdf5
8652/8652 [============ ] - 129s 15ms/step - loss: 2.1242 - accuracy: 0.3879
Epoch 6/20
Epoch 6: loss improved from 2.12422 to 2.07192, saving model to weights-improvement-06-2.0719.hdf5
8652/8652 [============= ] - 129s 15ms/step - loss: 2.0719 - accuracy: 0.4021
Epoch 7/20
Epoch 7: loss improved from 2.07192 to 2.03000, saving model to weights-improvement-07-2.0300.hdf5
8652/8652 [==========] - 129s 15ms/step - loss: 2.0300 - accuracy: 0.4133
Epoch 8: loss improved from 2.03000 to 1.99621, saving model to weights-improvement-08-1.9962.hdf5
8652/8652 [=========== ] - 130s 15ms/step - loss: 1.9962 - accuracy: 0.4224
Epoch 9: loss improved from 1.99621 to 1.96713, saving model to weights-improvement-09-1.9671.hdf5
8652/8652 [============ ] - 129s 15ms/step - loss: 1.9671 - accuracy: 0.4308
Epoch 10/20
Epoch 10: loss improved from 1.96713 to 1.94198, saving model to weights-improvement-10-1.9420.hdf5
8652/8652 [=========== ] - 129s 15ms/step - loss: 1.9420 - accuracy: 0.4366
Epoch 11/20
8652/8652 [=========== ] - ETA: 0s - loss: 1.9213 - accuracy: 0.4425
Epoch 11: loss improved from 1.94198 to 1.92135, saving model to weights-improvement-11-1.9213.hdf5
Epoch 12/20
Epoch 12: loss improved from 1.92135 to 1.90170, saving model to weights-improvement-12-1.9017.hdf5
8652/8652 [============= ] - 129s 15ms/step - loss: 1.9017 - accuracy: 0.4478
```

```
Epoch 13/20
Epoch 13: loss improved from 1.90170 to 1.88533, saving model to weights-improvement-13-1.8853.hdf5
Epoch 14/20
Epoch 14: loss improved from 1.88533 to 1.86894, saving model to weights-improvement-14-1.8689.hdf5
Epoch 15/20
Epoch 15: loss improved from 1.86894 to 1.85545, saving model to weights-improvement-15-1.8554.hdf5
8652/8652 [============ ] - 129s 15ms/step - loss: 1.8554 - accuracy: 0.4602
Fnoch 16/20
Epoch 16: loss improved from 1.85545 to 1.84365, saving model to weights-improvement-16-1.8437.hdf5
Epoch 17/20
Epoch 17: loss improved from 1.84365 to 1.83267, saving model to weights-improvement-17-1.8327.hdf5
8652/8652 [================== ] - 129s 15ms/step - loss: 1.8327 - accuracy: 0.4658
Epoch 18/20
Epoch 18: loss improved from 1.83267 to 1.82119, saving model to weights-improvement-18-1.8212.hdf5
8652/8652 [=============== ] - 132s 15ms/step - loss: 1.8212 - accuracy: 0.4689
Epoch 19/20
Epoch 19: loss improved from 1.82119 to 1.81191, saving model to weights-improvement-19-1.8119.hdf5
8652/8652 [=========== ] - 131s 15ms/step - loss: 1.8119 - accuracy: 0.4709
Epoch 20: loss improved from 1.81191 to 1.80268, saving model to weights-improvement-20-1.8027.hdf5
8652/8652 [================= ] - 130s 15ms/step - loss: 1.8027 - accuracy: 0.4735
```

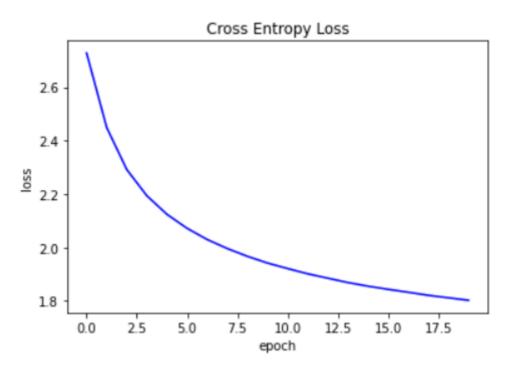


Figure 74. cross-entropy loss during the epochs

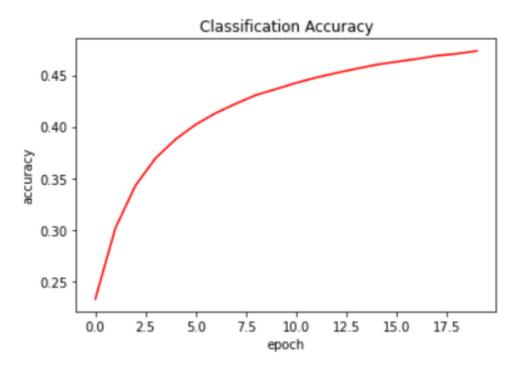


Figure 75. Classification accuracy during the epochs

BATCH-SIZE # 64:

TRAINING PROCESS:

```
Total Characters: 1107542
Total Vocab: 54
Total Patterns: 1107442
Epoch 1/20
Epoch 1: loss improved from inf to 2.35287, saving model to weights-improvement-01-2.3529.hdf5
Epoch 2/20
Epoch 2: loss improved from 2.35287 to 1.94207, saving model to weights-improvement-02-1.9421.hdf5
Epoch 3/20
Epoch 3: loss improved from 1.94207 to 1.80515, saving model to weights-improvement-03-1.8051.hdf5
Epoch 4/20
Epoch 4: loss improved from 1.80515 to 1.72237, saving model to weights-improvement-04-1.7224.hdf5
Epoch 5: loss improved from 1.72237 to 1.66774, saving model to weights-improvement-05-1.6677.hdf5
```

```
Epoch 6/20
Epoch 6: loss improved from 1.66774 to 1.62675, saving model to weights-improvement-06-1.6268.hdf5
Epoch 7/20
Epoch 7: loss improved from 1.62675 to 1.59461, saving model to weights-improvement-07-1.5946.hdf5
Epoch 8/20
Epoch 8: loss improved from 1.59461 to 1.56999, saving model to weights-improvement-08-1.5700.hdf5
Epoch 9/20
Epoch 9: loss improved from 1.56999 to 1.54780, saving model to weights-improvement-09-1.5478.hdf5
Fnoch 10/20
Epoch 10: loss improved from 1.54780 to 1.53057, saving model to weights-improvement-10-1.5306.hdf5
17302/17304 [============>.] - ETA: 0s - loss: 1.5161 - accuracy: 0.5497
Epoch 11: loss improved from 1.53057 to 1.51610, saving model to weights-improvement-11-1.5161.hdf5
Epoch 12/20
Epoch 12: loss improved from 1.51610 to 1.50351, saving model to weights-improvement-12-1.5035.hdf5
Epoch 13/20
Epoch 13: loss improved from 1.50351 to 1.49084, saving model to weights-improvement-13-1.4908.hdf5
17304/17304 [=============== ] - 340s 20ms/step - loss: 1.4908 - accuracy: 0.5556
Epoch 14: loss improved from 1.49084 to 1.48088, saving model to weights-improvement-14-1.4809.hdf5
Epoch 15/20
17304/17304 [============= ] - ETA: 0s - loss: 1.4706 - accuracy: 0.5614
Epoch 15: loss improved from 1.48088 to 1.47056, saving model to weights-improvement-15-1.4706.hdf5
17304/17304 [================= ] - 339s 20ms/step - loss: 1.4706 - accuracy: 0.5614
Epoch 16/20
Epoch 16: loss improved from 1.47056 to 1.46225, saving model to weights-improvement-16-1.4623.hdf5
Epoch 17/20
17304/17304 [============== ] - ETA: 0s - loss: 1.4553 - accuracy: 0.5649
Epoch 17: loss improved from 1.46225 to 1.45534, saving model to weights-improvement-17-1.4553.hdf5
17304/17304 [=============== ] - 340s 20ms/step - loss: 1.4553 - accuracy: 0.5649
Epoch 18/20
Epoch 19/20
Epoch 19: loss improved from 1.44757 to 1.44098, saving model to weights-improvement-19-1.4410.hdf5
17304/17304 [============== ] - 341s 20ms/step - loss: 1.4410 - accuracy: 0.5689
Epoch 20/20
Epoch 20: loss improved from 1.44098 to 1.43511, saving model to weights-improvement-20-1.4351.hdf5
17304/17304 [=============== ] - 341s 20ms/step - loss: 1.4351 - accuracy: 0.5698
```

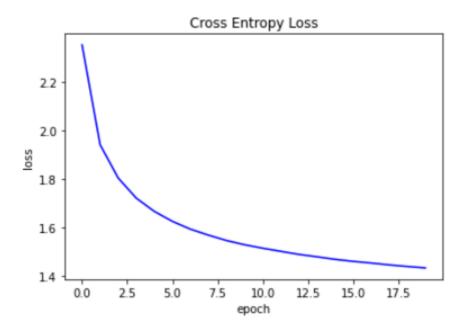


Figure 76. cross-entropy loss during the epochs

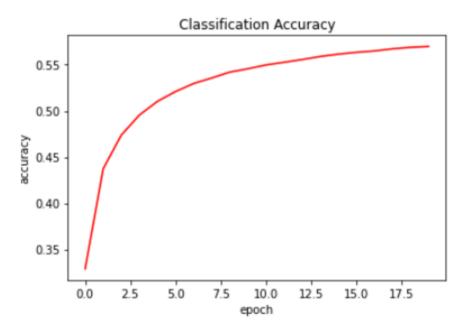


Figure 77. Classification accuracy during the epochs

As you can see the best parameters for fitting the model based on our dataset are:

Batch-size=128

Number-of-epochs: 100 (to have a really good text-generator)

PLEASE NOTE THAT THE WEIGHTS OF BEST TRY HAS BEEN ATTACHED IN RELATED DIRECTORY.

(WEIGHTS-IMPROVEMENT-97-1.2709.HDF5)

HOW MEMORY OF NEURAL NETS IN RNN CAN BE HELPFUL IN MODEL PERFORMANCE?

The main difference between the functioning of neural networks and the biological neural network is memory. While both the human brain and neural networks have the ability to read and write from the memory available, the brain can create/store the memory as well

Memory in neural networks is required to store input data, weight parameters and activations as an input propagates through the network. In training, activations from a forward pass must be retained until they can be used to calculate the error gradients in the backwards pass.

NNs effectively have an internal memory that allows the previous inputs to affect the subsequent predictions. It's much easier to predict the next word in a sentence with more accuracy, if you know what the previous words were.

All of above statements lead to have better performance when we are dealing with RNNs.

4 QUESTION3: CONTEXTUAL EMBEDDING + RNNS

4.1

- Remove entities like < > & which gets embedded in the original data.
- In the twitter datasets, there is also other information as retweet, Hashtag, Username and modified tweets. All of this is ignored and removed from the dataset.
- Replace digits with <number>
- Remove Punctuations
- Character normalization (toooooday -> today)
- Tweets shorter than a length are removed

4.2

We use pretrained Bert model and add LSTM and fully connected layers to it and fine tune the parameters as we do in transfer learning.

From figure? We can see that the length of tweets are shorter than 40 so we pad all the data to 40 maximum length.

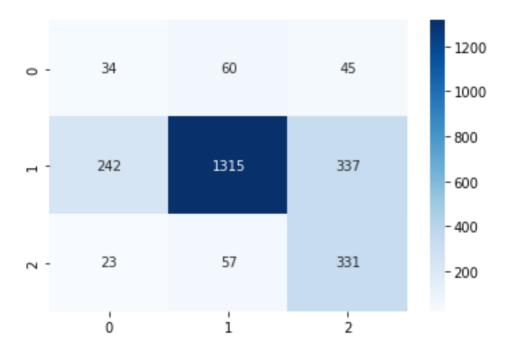


Figure 78. Confusion matrix

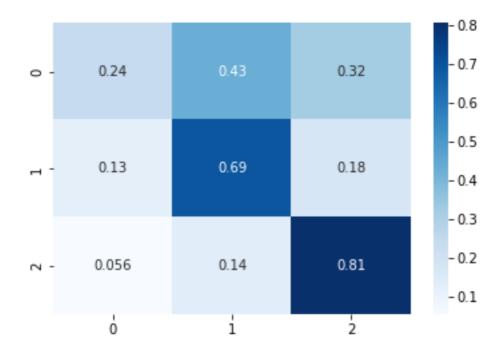


Figure 79. Normalized confusion matrix

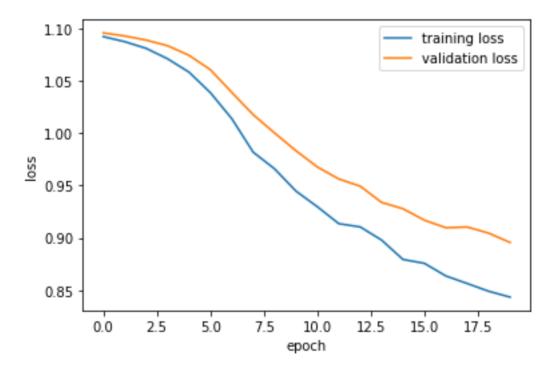


Figure 80. validation and train loss in each epoch

	precision	recall	f1-score	support
0	0.15	0.41	0.22	139
1	0.93	0.70	0.80	1894
2	0.51	0.79	0.62	411
accuracy			0.70	2444
macro avg	0.53	0.63	0.55	2444
weighted avg	0.81	0.70	0.73	2444

Figure81. evaluation metrics

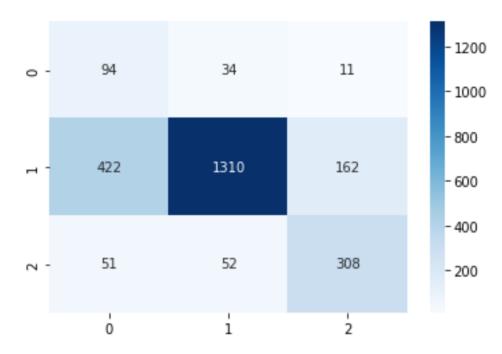


Figure82. confusion matrix

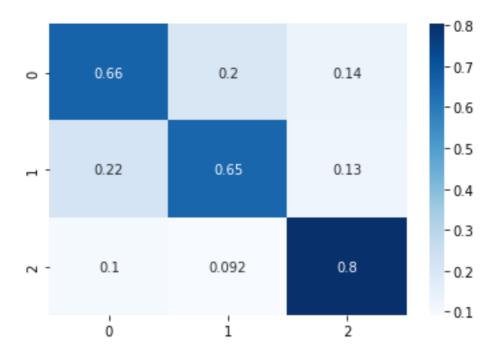


Figure83. Normalized confusion matrix

	precision	recall	f1-score	support
9	0.17	0.68	0.27	139
1	0.94	0.69	0.80	1894
2	0.64	0.75	0.69	411
accuracy			0.70	2444
macro avg	0.58	0.71	0.58	2444
weighted avg	0.84	0.70	0.75	2444

Figure84. evaluation metrics

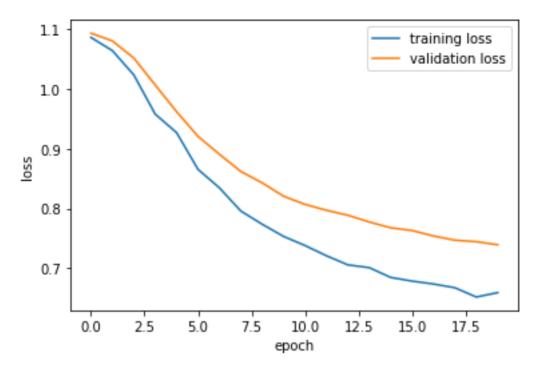


Figure 85. validation and train loss in each epoch

As we can see from the results the pretrained hatebert model has better performance on predicting hate tweets. Normal (class 2) and hate tweets (class 0) precision, recall and f1-score are higher in hatebert model because this model is re-trained by specific dataset that mostly contained hate comments.

So, models like Hatebert are generally trained to perform better at classifying of a particular subject for example hate or political comments.

4.5 (Bonus)

T5 is an encoder-decoder model pre-trained on a multi-task mixture of unsupervised and supervised tasks and for which each task is converted into a text-to-text format. T5 works well on a variety of tasks out-of-the-box by prepending a different prefix to the input corresponding to each task, e.g., for translation: *translate English to German:* ..., for summarization: *summarize:*

T5 uses relative scalar embeddings. Encoder input padding can be done on the left and on the right.

the differentiator that truly sets T5 apart from BERT-style models is that it does not output a label or a span of the input to the input sentence, but the output is a text string as well.

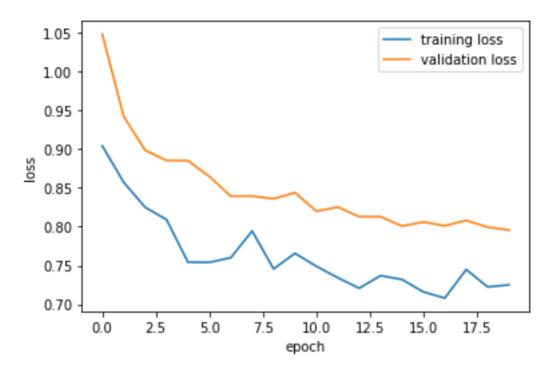


Figure86. validation and train loss in each epoch

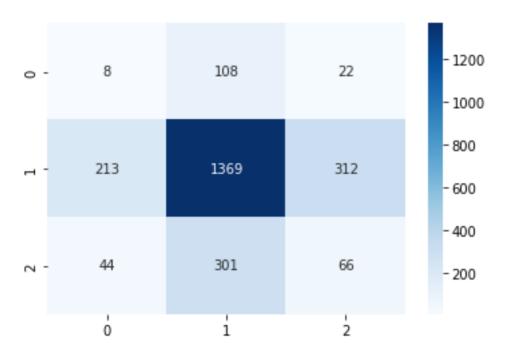


Figure87. confusion matrix

	precision	recall	f1-score	support
0 1 2	0.03 0.77 0.17	0.06 0.72 0.16	0.04 0.75 0.16	138 1894 411
accuracy macro avg	0.32	0.31	0.59 0.32	2443 2443
weighted avg	0.63	0.59	0.61	2443

Figure88. evaluation metrics