Consumer complaints classification

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1 Introduction

The objective is to implement deep learning frameworks to classify each complaint of the given corpus into one of five categories: credit reporting, debt collection, mortgages and loans, credit cards, and retail banking using text feature extraction and text classification techniques.
The data is collected from a federal U.S. agency (Consumer Financial Protection Bureau) that acts as a mediator when disputes arise between financial institutions and consumers. The data included customer complaints for one year, from March 2020 to March 2021.

2 Methods

The models were implemented on word vectors formed by the pre-defined TensorFlow embeddings. All models were compiled with Categorical cross-entropy loss, and Nestorov accelerated gradient descent(Nadam) optimizer. Early stopping was used to avoid overfitting the model on training data. The deep learning methods used in this project are:

Stacked Recurrent Neural Network (RNN): Multiple RNN layers are combined to form stacked RNNs, where the output from one layer is used as the input for the layer above it. In our project, we used 2 RNN layers having dimensions of 64 each. The final output of these RNN layers was passed through a feed-forward neural network with softmax activation to get classification probabilities for each class.[1]

Stacked Long Short Term Memory (LSTM): The stacked LSTM includes numerous LSTM layers, each of which has a number of memory cells. The model becomes deeper as a result of the stacked LSTM hidden layers, and better captures the features of sentences in each layer. 2 LSTM

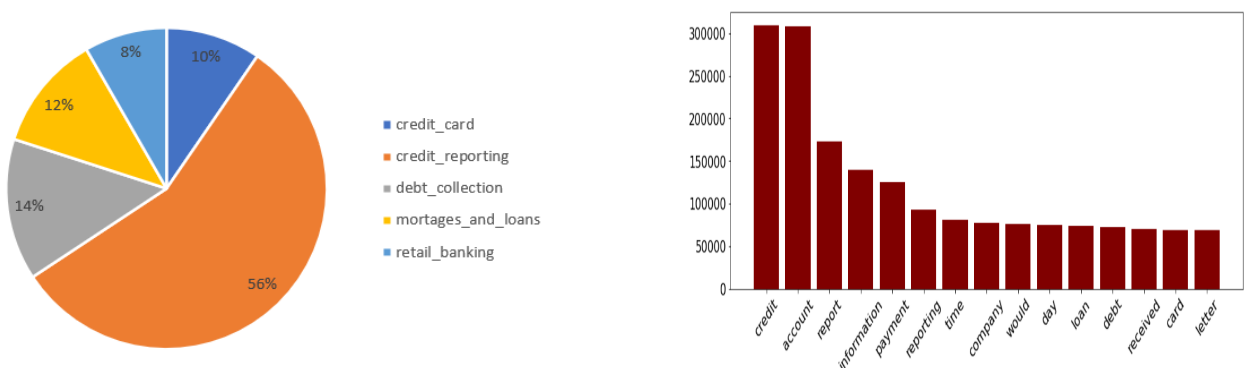

Figure 1: Distribution of categories of products and most frequent words

Table 1: Performance Metrics Of Different DL Models

Classifier	Accuracy	Loss
Stacked RNN	0.606	1.275
Stacked LSTM	0.880	0.381
Stacked FFNN	0.866	0.160
Transformer	0.860	0.471

layers with dimensions 256 and 128 were used in this project. The final layer was feed-forward to get classification output.[2]

Stacked Feed-Forward Neural Network (FFNN): It involves the combination of layers of feed-forward neural network. 2 layers with 16-dimensional size were used with the ReLU activation layer and then passed through the final feed-forward layer with softmax activation to get probabilities for each class.[3]

Transformer: The transformer is constructed from stacks of transformer blocks, which are multi-layer networks created by fusing feedforward networks, self-attention layers, residual connections and layer normalization.[4]

The above-mentioned models have been trained using the Tensorflow library with Python Programming Language.
https://github.com/shraddhaagarwal10/Consumer-complaints-classification/blob/main/NLP/phase2.ipynb

3 Evaluation Criteria

Categorical Accuracy and Categorical Cross Entropy Loss were the metrics used for evaluating the model.
Categorical Accuracy: For one-hot labels, categorical accuracy determines the proportion of predicted values that coincide with real values. Using argmax, we locate the index where the maximum value occurs. It is regarded as accurate if it is the same for both the predicted class and the true class. The number of accurately predicted records is then divided by the total number of records to determine categorical accuracy.[5]
Categorical Cross-Entropy Loss: For each class in the data, the average difference between the actual and predicted probability distributions is calculated as a score by cross-entropy. When the score is minimized, a cross-entropy value of 0 is obtained. [6]

4 Analysis of Results

It was observed that Stacked LSTM was the best-performing model and stacked RNN was the worst for this dataset. Also, the time taken by RNN was much higher than other models. Transformers and Feed-Forward Neural Networks gave significantly good results without taking a considerable amount of time. All these results are summarized in Table1.

5 Discussions and Conclusion

Since stacked LSTM has the highest accuracy of 0.88 on the validation set, it performs the best among the other implemented models. So, we predicted the class labels of consumer complaints of the test set using the Stacked LSTM model.
The project was completed in a team of two students. Both of them have trained two models each. Shraddha has trained the Stacked Feed-Forward Neural Network (FFNN) and Transformers. Anuradha has trained the Stacked Recurrent Neural Network (RNN) and Stacked Long-Short Term Memory (LSTM).

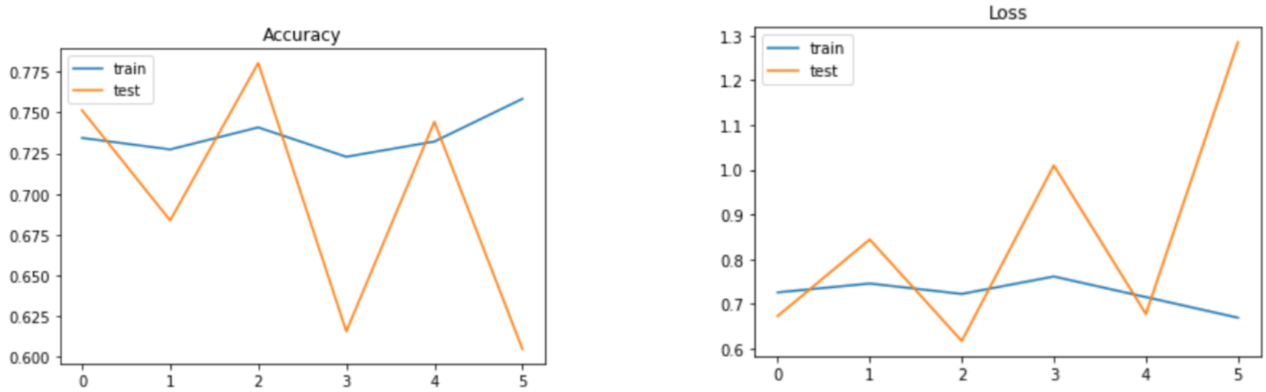

Figure 2: Plots for accuracy and loss for stacked RNN

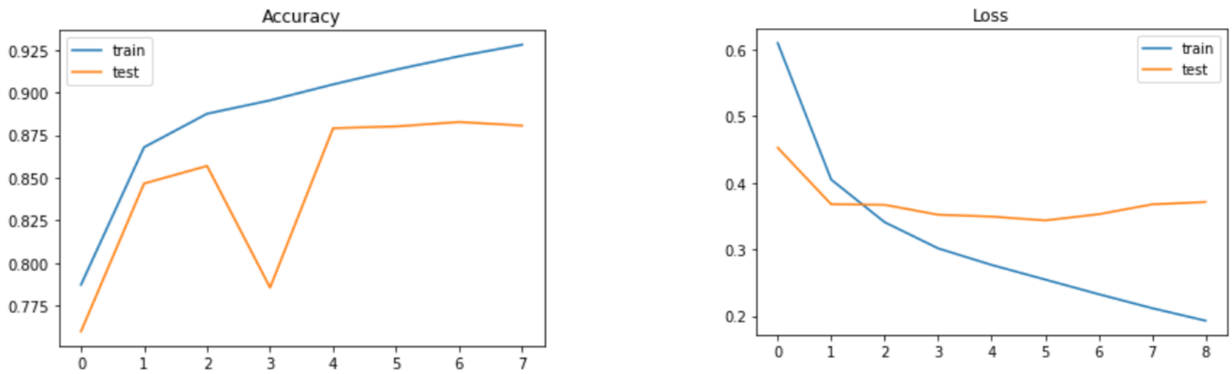

Figure 3: Plots for accuracy and loss for stacked LSTM

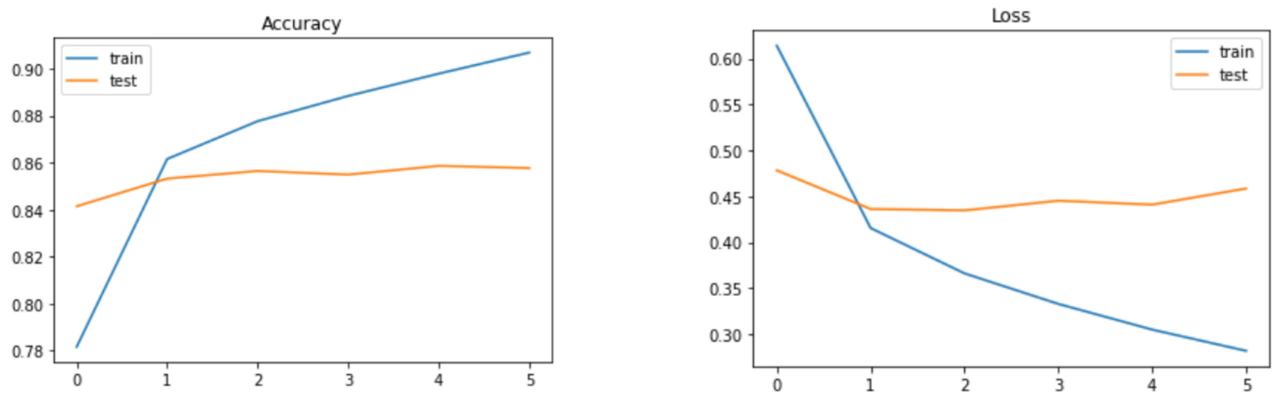

Figure 4: Plots for accuracy and loss for stacked FFNN

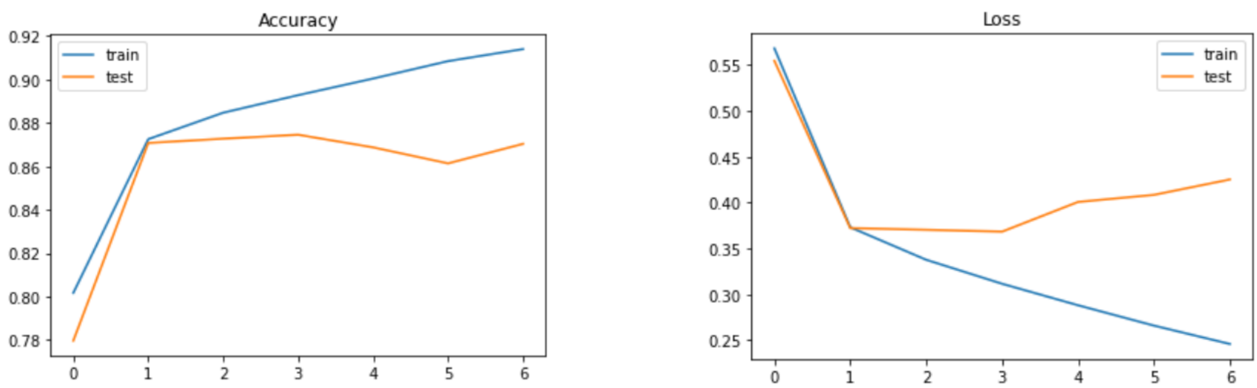

Figure 5: Plots for accuracy and loss for transformer

References

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