Exercises on Natural Language Processing with Recurrent Neural Networks

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Google Colab Link

1 RNN classifier implemented in Keras/TensorFlow

Develop a sentiment classifier for a kind of texts of your choice (e.g., tweets, product or movie reviews). Use an existing sentiment analysis dataset with at least two classes (e.g., positive/negative or positive/negative/neutral).2 The classes should be mutually exclusive, i.e., this is a single-label multi-class classification problem.

1.1 Introduction

Implementing classifiers to make a sentiment analysis on tweets/posts.

1.2 Dataset

For the purpose of the exercise we used the Twitter Sentiment Analysis Dataset. It contains tweets and the corresponding label (0 - negative, 1 - positive). In Figure (1) we can see how these tweets are distributed to each class for the entirety of the dataset. It is worth mentioning that this time we downloaded only the train dataset provided in Kaggle, due to the fact that the Google Colab, even with an enabled GPU, could not handle such a large dataset, especially after the TF-IDF vectorization using 5,000 features.

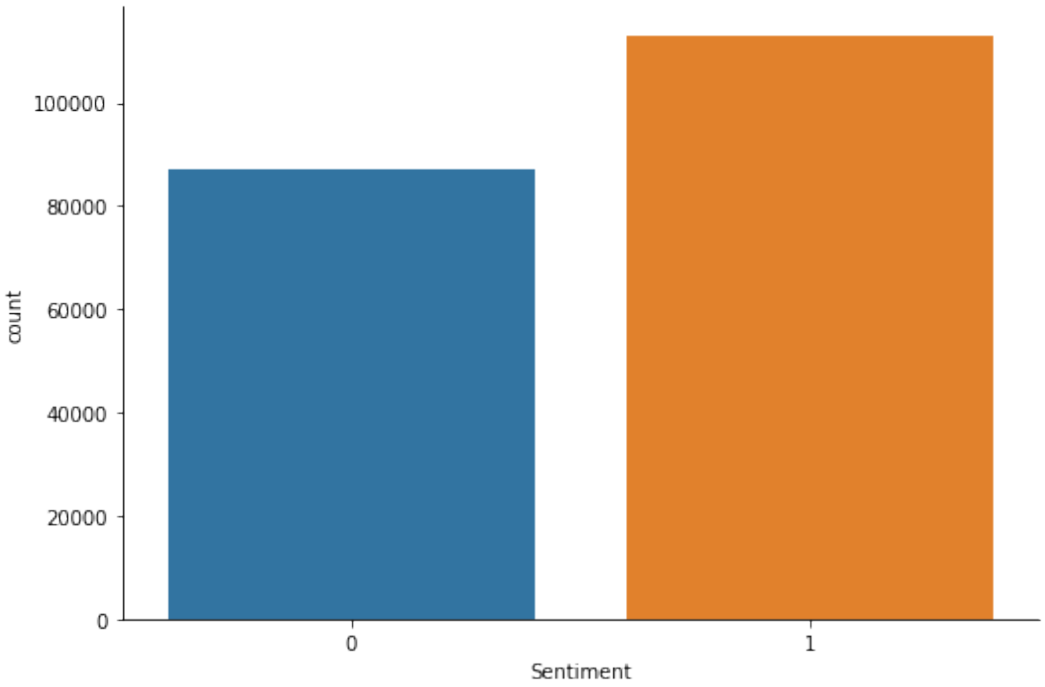


Figure 1: Class distribution for the whole dataset of twits.

1.3 Pre-Processing

Before proceeding with the development of the models, we had to do some data-prepossessing in order to clear the text of the twits and only keep words. The steps we followed may be found below:

1. Lower Case: using the `.lower()` method we converted the input string to the equivalent, only having lower case words. This ensures that there will be no differences in calculations due to differences in lower and capital letters.
2. Clean the text: using regular expressions we removed the following and kept only the words in each tweet.
   (a) underscores
   (b) twitter usernames
   (c) websites
   (d) non words
   (e) single characters

(f) numbers

(g) multiple whitespaces

3. Lemmatization: We split each tweet on whitspaces to get words and then we used the lematize methond from nltk to return the lemma of each word.

4. Finally, the words are put together and returned as a sentence.

In Table (1) we see some samples of the orginal tweets and the corresponding processed tweets.

Original text	Processed text
is so sad for my APL friend.....	is so sad for my apl friend
I missed the New Moon trailer...	missed the new moon trailer
omg its already 7:30 :O	omg it already
.. Omgaga. Im sooo im gunna CRy	omgaga im sooo im gunna cry
i think mi bf is cheating on me!!! T_T	think mi bf is cheating on me tt

Table 1: Sample tweets and the corresponding processed text

1.4 Train/Dev/Test split

In order to create our model we had to split the input into three parts. We set a seed for reproducibility purposes and shuffle the tweets.

1. Train: 70% of the input tweets were used to train the models.

2. Development: 30% of the train tweets were used for feature tuning and hyper-parameters tuning.

3. Test: 30% of the input tweets were used in order to test the performance of the model, using previously unseen data.

1.5 Features

In this exercise we choose to experiment with fasttext embeddings.

1.5.1 Fasttext embeddings

To load fasttext pre-trained embeddings more efficiently, we can read only once the embeddings file and save: A 2D np-array for the embedding vectors A dictionary that maps each word to the row index of its embedding on the 2D np-array

1.6 Model Training

For this part we chose to follow three main pillars in order to implement our analysis. We used the same dummy classifier and logistic regression models with the previous assignment and then we created various neural network models, starting from the single layer perceptron and then experimenting with more complicated models (e.g. adding layers, neurons and choosing different hyper-parameters) (this was for our previous assignments' implementations).

For the current one, we implemented the RNN framework with different characteristics (self attention, GRU etc etc)

Below is the model training applications followed in all the assignments:

Dummy Classifier - Logistic Regression - Single Layer Perceptron - Neural Networks - Recurrent Neural Networks

1.6.1 Dummy Neural Network

Firstly, we implement a Dummy Neural Network (NN) in order to get a "baseline" classification and we can have a first picture. This NN serves as a simple baseline to compare against other more complex NNs and this is exactly how we planned to use it in our assignment. In detail, a NN with 1 hidden layer and 1 neuron, i.e. a single layer perceptron which is a linear classifier. This is the simplest model we are going to examine. Finally we printed the test accuracy (see below).

Test accuracy: 73.35%

1.6.2 BOW Neural Network (from assignment 3)

BOW NN train accuracy: 77 %

BOW NN dev accuracy: 73 %

BOW NN test accuracy: 73 %

	precision	recall	f1-score	AUC
0	0.85	0.59	0.69	
1	0.74	0.92	0.82	
accuracy			0.77	0.753
macro avg	0.80	0.75	0.76	
weighted avg	0.79	0.77	0.77	

Table 2: Score table for the train set.

	precision	recall	f1-score	AUC
0	0.77	0.53	0.63	
1	0.71	0.88	0.79	
accuracy			0.73	0.705
macro avg	0.74	0.70	0.71	
weighted avg	0.74	0.73	0.72	

Table 3: Score table for the development set.

	precision	recall	f1-score	AUC
0	0.78	0.52	0.63	
1	0.71	0.88	0.78	
accuracy			0.73	0.704
macro avg	0.74	0.70	0.71	
weighted avg	0.74	0.73	0.72	

Table 4: Score table for the test set.

1.6.3 Recurrent Neural Networks

Firstly, we implemented a procedure in which the model requested, is created and trained. In our approach we created an empty sequential model, in which we added the layers needed (embedding layer, bidirectional GRU layer, dropout, MLP layer etc). We then wanted to check how the different architectures would impact the model's evaluation, keeping the inputs, the optimizer, the metrics and any hyper-parameters constant.

Loss Function
During the training of our models we used "binary cross-entropy" as loss function. It compares each of the predicted probabilities to actual class output which can be either 0 or 1. It then calculates the score that penalizes the probabilities based on

the distance from the expected value. That means how close or far from the actual value.

Optimizer
Furthermore, for optimization we chose the Adam optimizer, which is different to classical stochastic gradient descent. The latter maintains a single learning rate (termed alpha) for all weight updates and the learning rate does not change during training. However, in Adam optimizer a learning rate is maintained for each network weight (parameter) and separately adapted as learning unfolds. The method computes individual adaptive learning rates for different parameters from estimates of first and second moments of the gradients. Specifically, the algorithm calculates an exponential moving average of the gradient and the squared gradient, and the parameters beta1 and beta2 control the decay rates of these moving averages.

Metrics
A metric is a function that is used to judge the performance of our model. Metric functions are similar to loss functions, except that the results from evaluating a metric are not used when training the model. Taking into account the assignment instructions we monitored the following metrics during training: precision, recall, F1, precision-recall AUC scores.

Models' architectures
Finally, before proceeding with the models' specific architectures, i.e. the number of hidden layers and neurons per layer, we should mention that all our models are Sequential. Specifically we added an embedding layer, the bidirectional GRU layer with 0.33 variational (recurrent) dropout and the self attention layer. Also, the hidden MLP layer we choose is Dense, meaning that it is fully connected layer in which every output depends on every input. Regarding the activation functions, for the MLP hidden layer we used the rectified linear activation function or ReLU for short, which is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero.

1.7 Model architecture and results

For the model architecture diagram we decided to display the best model derived from our code. We will also display the metrics requested for this model as well. In fact we implemented two models, the BiLSTM & MLP model and the BiLSTM & Linear Self-Attention & MLP model. The latter had better performance so below you can find its architecture, learning curves during training and metrics for train, development and test data sets.

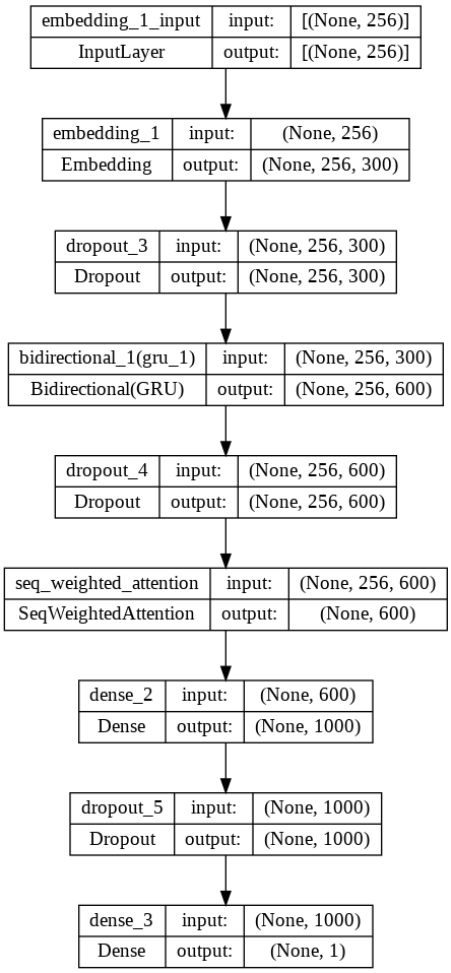


Figure 2: Best RNN architecture

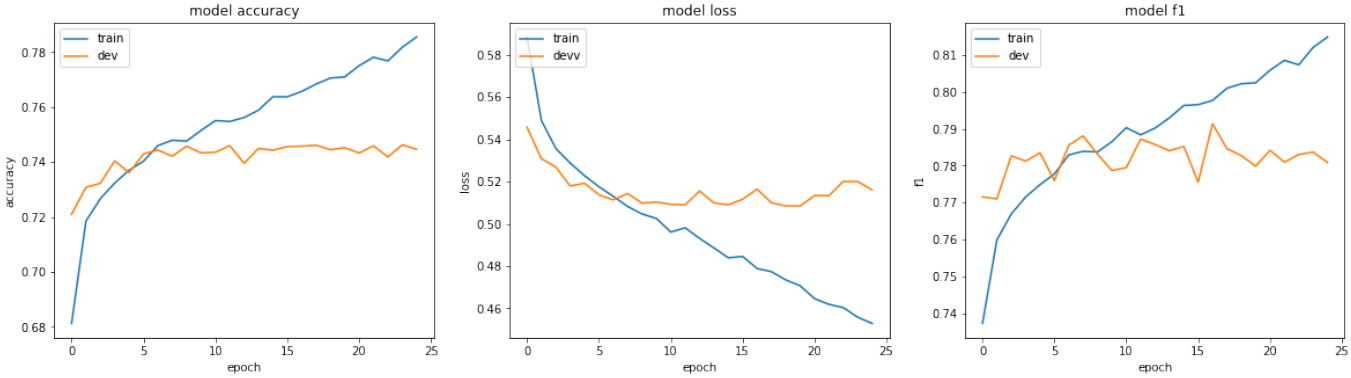
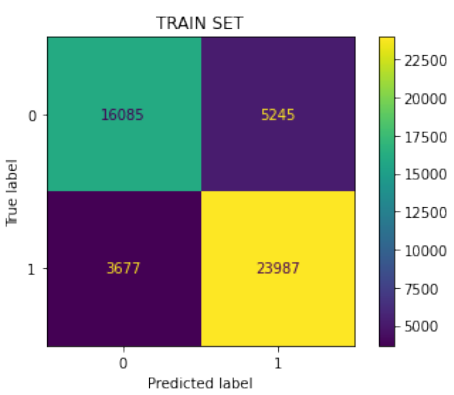
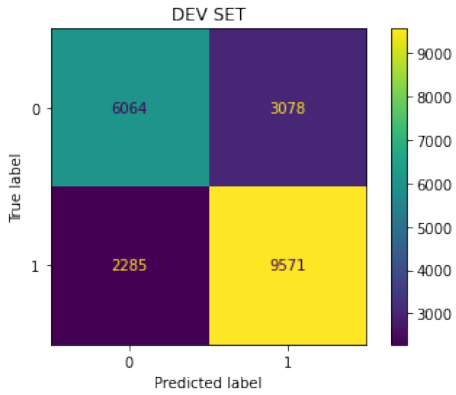


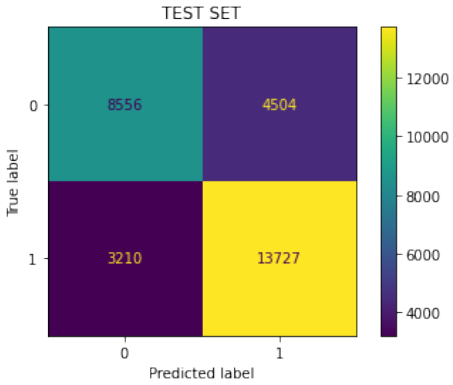
Figure 3: Best RNN Learning Curves



(a) TRAIN SET



(b) DEV SET



(c) TEST SET

Figure 4: Confusion Matrices for the best RNN model

Best RNN model evaluation metrics for test data set:

1. Binary Cross Entropy: 0.5158
2. Precision: 0.7532
3. Recall: 0.8106
4. F1: 0.7793
5. Accuracy: 0.7428

	precision	recall	f1-score	AUC
0	0.81	0.75	0.78	
1	0.82	0.87	0.84	
accuracy			0.82	0.8106
macro avg	0.82	0.81	0.81	
weighted avg	0.82	0.82	0.82	

Table 5: Score table for the train set.

	precision	recall	f1-score	AUC
0	0.73	0.66	0.69	
1	0.76	0.81	0.78	
accuracy			0.74	0.7353
macro avg	0.74	0.74	0.74	
weighted avg	0.74	0.74	0.74	

Table 6: Score table for the development set.

	precision	recall	f1-score	AUC
0	0.73	0.66	0.69	
1	0.75	0.81	0.78	
accuracy			0.74	0.7328
macro avg	0.74	0.73	0.73	
weighted avg	0.74	0.74	0.74	

Table 7: Score table for the test set.