Machine Learning Engineer Nanodegree Capstone

Natural Language Processing with Disaster Tweets

Project overview

Natural Language Processing is a complex field which is hypothesised to be part of AI-complete set of problems, implying that the difficulty of these computational problems is equivalent to that of solving the central artificial intelligence problem making computers as intelligent as people.[1]

Every year more and more data is produced and a great proportion of it corresponds to human generated unstructured texts, so the need to advance in the field of Natural Language processing is even more evident. It is important to notice that a lot of that data is generated in real time so the efficiency of text processing is also representing an important challenge.

This project focuses on the analysis of text generated messages in social media. In this particular case, we are going to analyse tweet messages generated in the Twitter social network with the aim to determine if a tweet has some content related to a natural disaster.

Problem statement

I have chosen this Kaggle competition because I don't have much experience with NLP projects and I wanted to get started into this field. This project seems like a good opportunity to start applying text processing techniques and get fluency.

From Kaggle[2] competition page:

Twitter has become an important communication channel in times of emergency.
The ubiquitousness of smartphones enables people to announce an emergency they're observing in real-time. Because of this, more agencies are interested in programatically monitoring Twitter (i.e. disaster relief organizations and news agencies).

But, it's not always clear whether a person's words are actually announcing a disaster.

[1] "Natural language processing - Wikipedia."
https://en.wikipedia.org/wiki/Natural_language_processing.
[2] https://www.kaggle.com/c/nlp-getting-started/overview

In this competition, you're challenged to build a machine learning model that predicts which Tweets are about real disasters and which one's aren't. You'll have access to a dataset of 10,000 tweets that were hand classified.

Metrics

In order to evaluate the performance of the model the metrics used are: accuracy, precision, recall and f1-score. These metrics will give us a good intuition about how well the model is classifying or misclassifying between disaster or non disaster. Additionally, I usedRMSprop as the optimizer inside the LSTM network.

Analysis

Data exploration

The datasets used are the included in Kaggle competition page. Three datasets are provided:

- train.csv
- test.csv
- sample_submission.csv

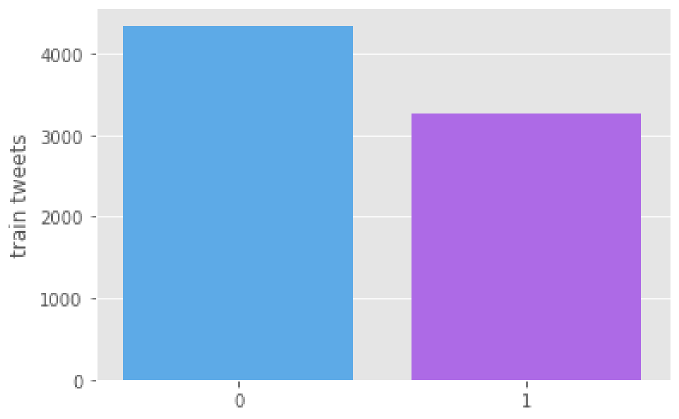
For the implementation in this capstone only train and test datasets will be used. Each of the samples of train and test datasets has the following information:

- **text**: The text of a tweet
- **keyword**: A keyword from that tweet (although this may be blank)
- **location**: The location the tweet was sent from (may also be blank)

After reading both train and test datasets some exploratory data analysis was made in order to get some insights from data. In next subsections the different data exploration steps will be detailed.

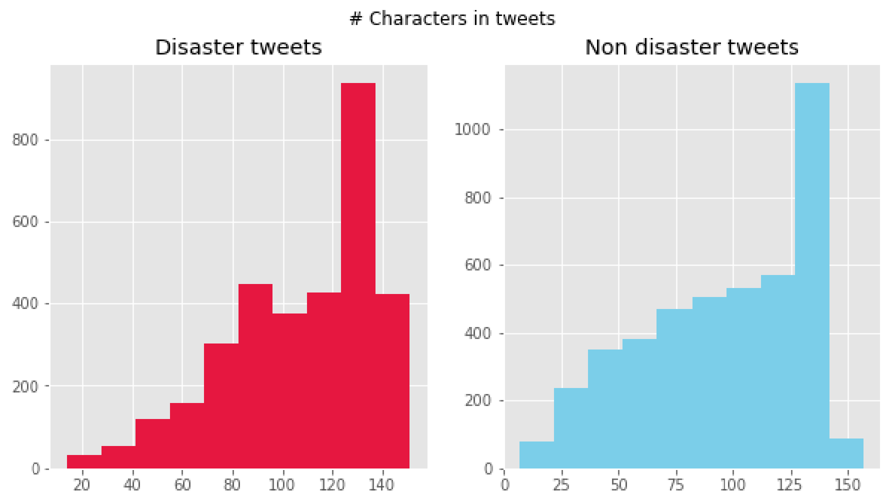
Checking class distribution

First, I analyzed the class distribution in the train dataset in order to know how many samples of each class there are. As we can see, there are more samples that represents non disaster tweets than disaster tweets but there is not a huge difference so we can consider that dataset is balanced.



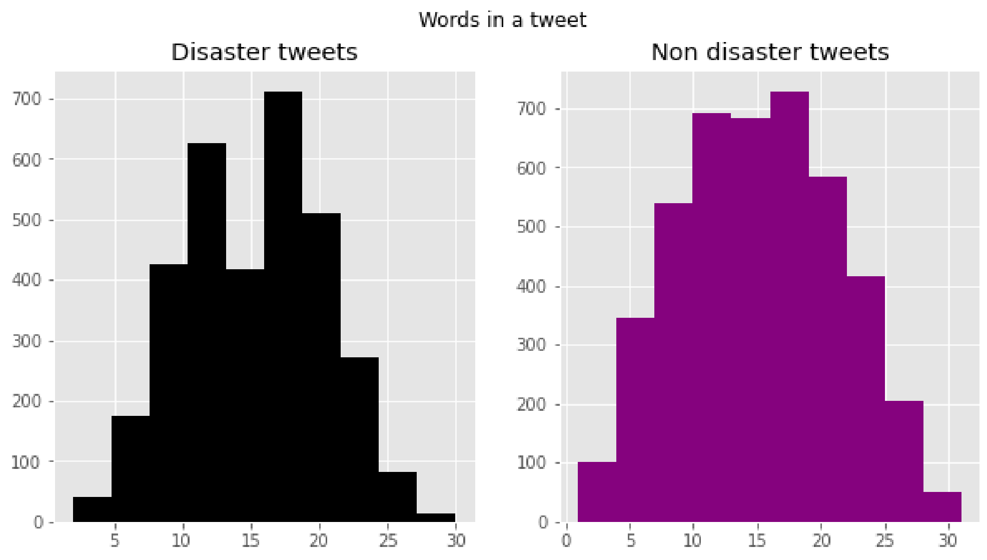
Get number of characters in tweets

Related to the analysis of the number of characters in tweets for both disaster tweets (class 1) and non disaster tweets (class 0) we can see that the distribution is more or less the same for both cases. Most of the tweets have between 120 and 140 characters.



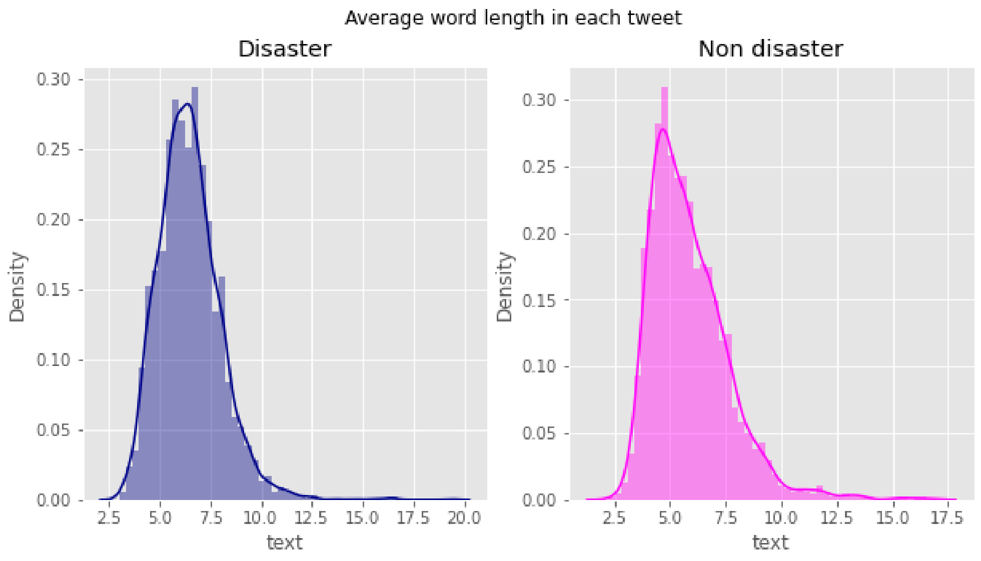
Get number of words in each tweet

Next, the same operation described in previous subsection was performed but for number of words instead of number of characters for both disaster and non disaster tweets.



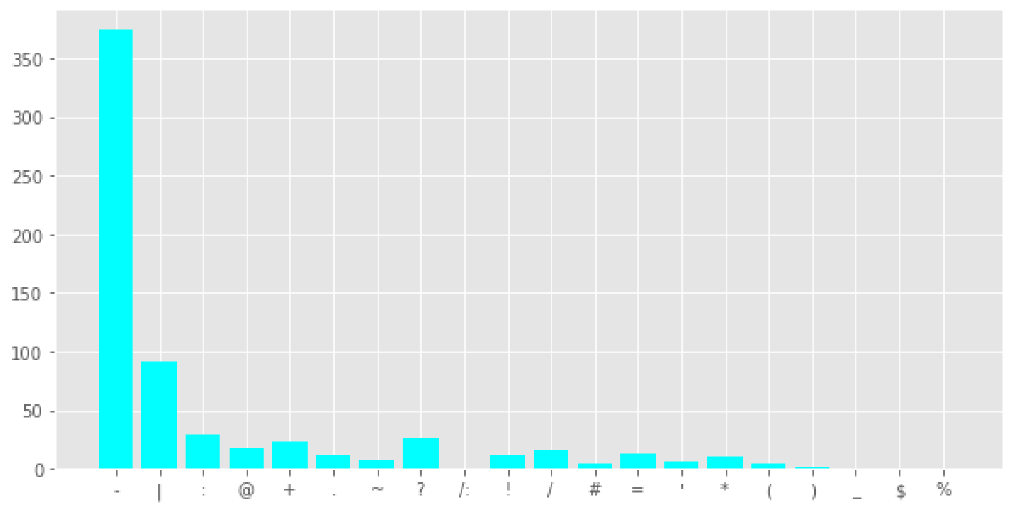
Calculate the average word length in each tweet

In order to do more focus I analyzed the average word length for each tweet. For both classes the distribution is very similar with average around 5.



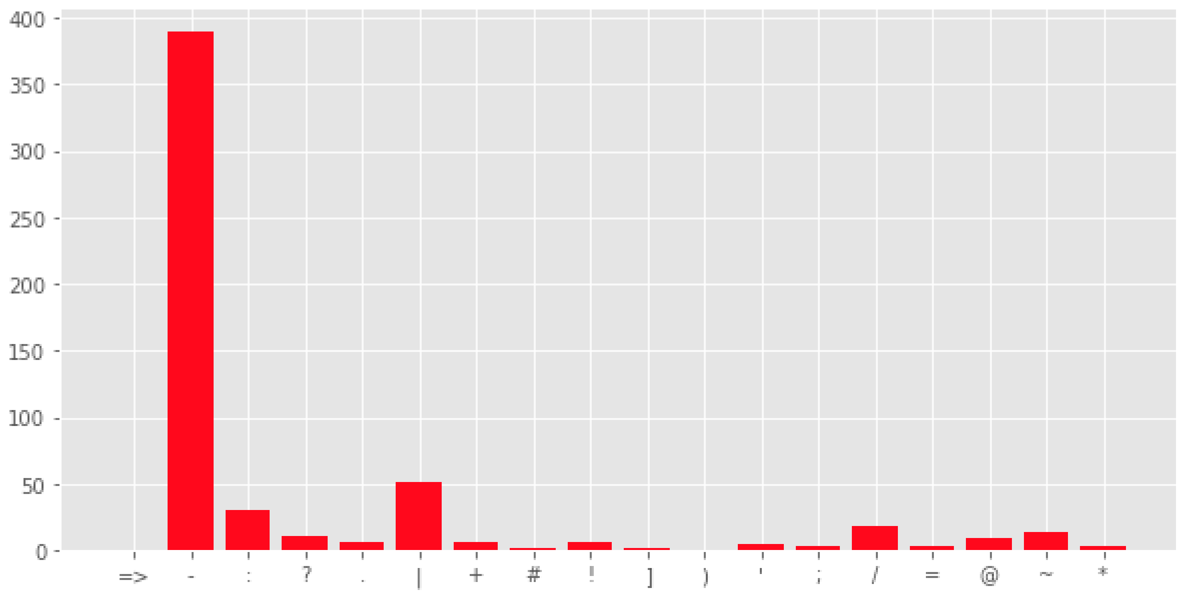
Analize punctuations marks in non-disaster class

With the objective of doing a good cleaning of the data, it is necessary to know how many punctuation marks there are and what they are. In the figure below we can see them to give us an idea in order to taking this punctuations marks into account when doing data cleaning.



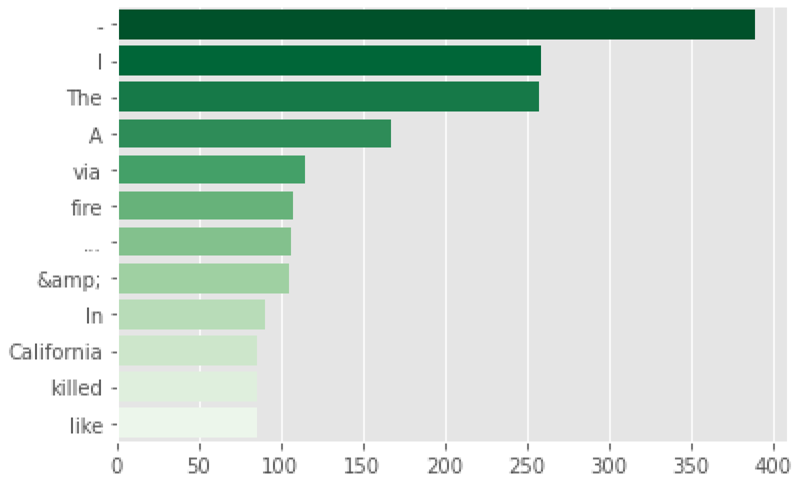
Analize punctuations marks in disaster class

With the same goal as described in the previous subsection, I perform the same punctuation mark analysis over disaster class (1).



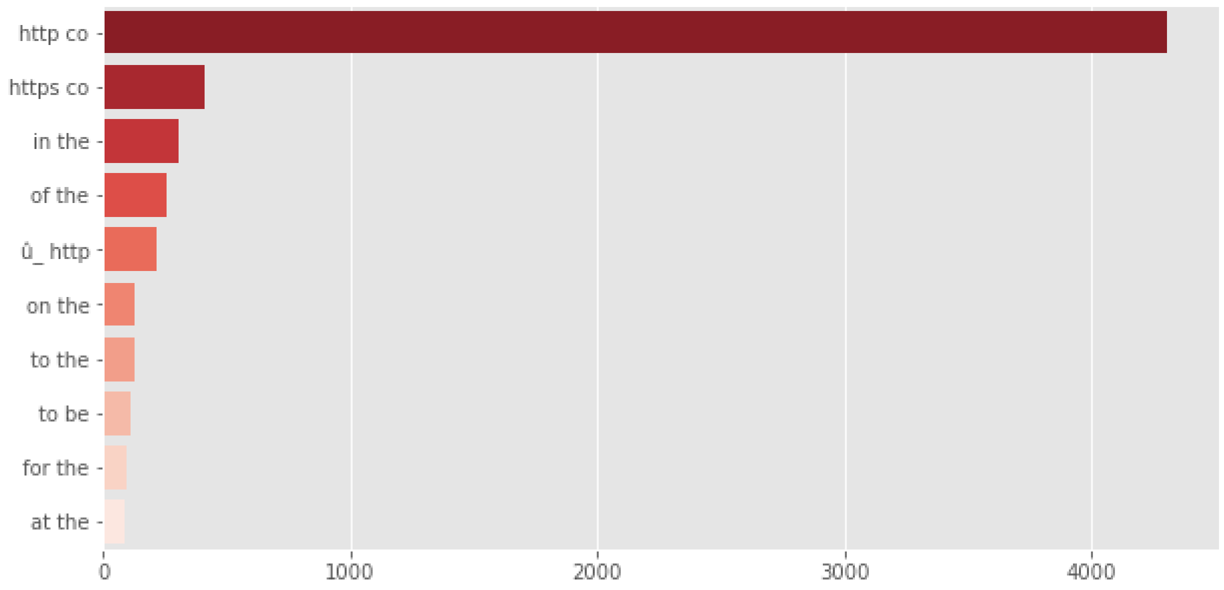
Get the most common words

In order to get more insights about data I studied what are the more common words present into the dataset. With this analysis I can notice that there are punctuation marks and stopwords at the top of this counting. This is important to take into account when doing data cleaning trying to remove this kind of character.



Bigram analysis

When performing the same operation as in the previous section but for bigrams (or combination of two words appearing together) I noticed that it is present some related to links and stopwords. Some this gave the clue that this kind of characters should also be removed when performing data cleaning.



Data cleaning

In base of the insight getting during data exploration I performed next data cleaning operations:

- Remove text in square brackets.
- Remove links.

- Remove punctuation marks.
- Remove words containing numbers.
- Remove emojis founded in text. Because of the text are tweets written in an informal way it could be possible the presence of emojis.

Algorithms and techniques

Once the data has been cleaned, it is necessary to perform preprocessing on it in order to prepare the data to execute the designed algorithm. For this project I applied two preprocessing operations described next: Tokenization and application of GloVe algorithm.

Tokenization

The first preprocessing step is performing a tokenization over the dataset in order to split the text into sentences of words. With this tokenization step we get the text into a format that is easier to convert to raw numbers, which can actually be used for the model later.

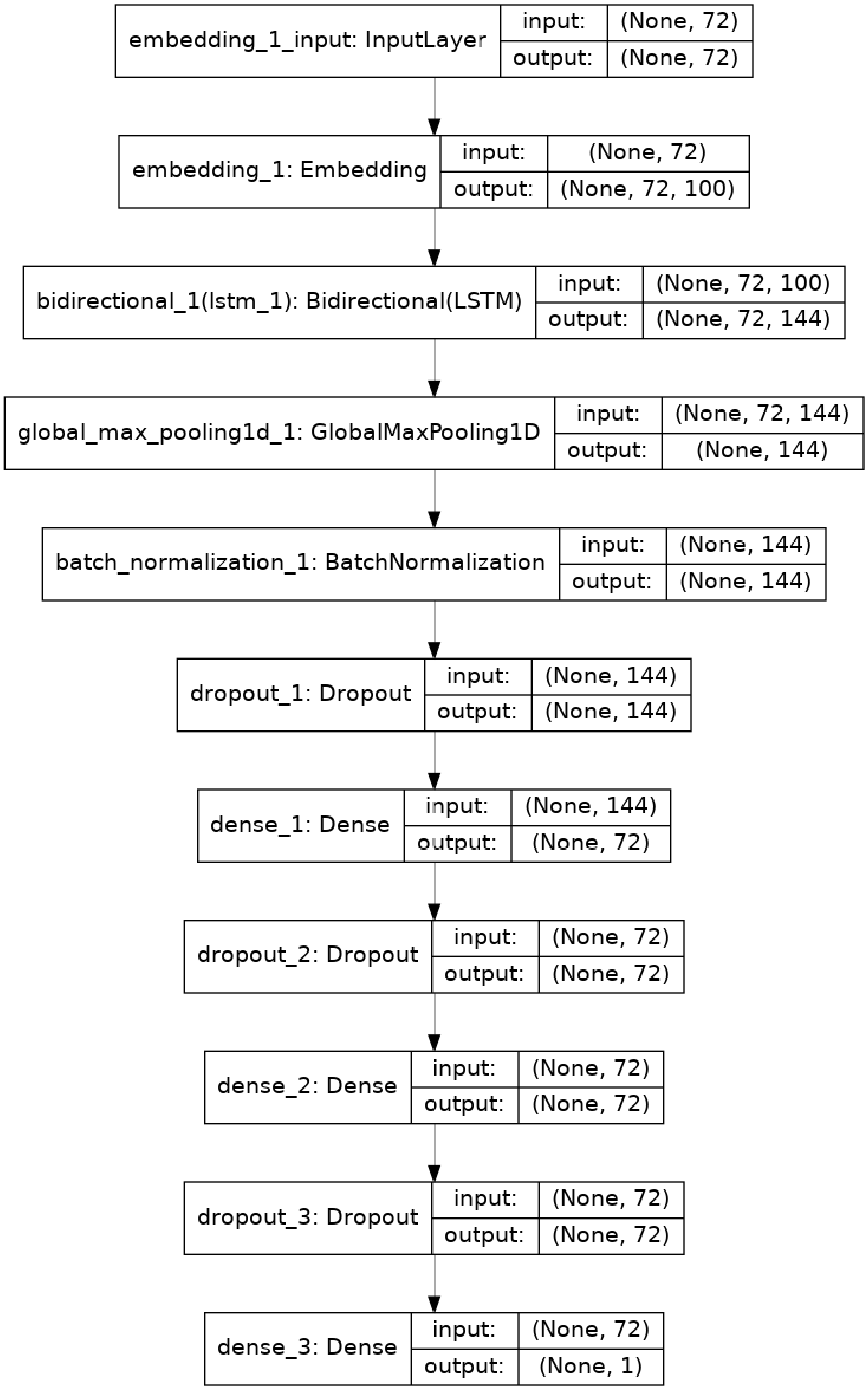
GloVe

Next to tokenization I apply another preprocessing step in which I execute the GloVe algorithm. GloVe (Global Vectors for Word Representation) in an unsupervised learning algorithm that let us obtain a vector representation for words. The performance of this algorithm focuses on finding words co-occurrences over the whole corpus and generates the embeddings relating the probabilities that two words appear together.

Model details implementation

For this project I have designed and trained a LSTM neural network using Keras library to define layers and Tensorflow as backend to build and execute the model. The topology of the neural network is presented in the figure below. The dimensionality of the inputs is calculated based on the dimension of the embedding matrix obtained when applying the GloVe algorithm.

The neural network starts with an Embeddings layer that holds the embedding vectors and its inner workings consist of a vector of indices that convert it to the corresponding vector. Next there is a LSTM layer setting to be bidirectional (this way form an acyclic graph where the cell memory from different time steps will be combined to produce the output prediction). Following, I applied a GlobalMaxPool layer to reduce dimensionality. In the next layer I applied BatchNormalization (it is a transformation that maintains the mean output close to 0 and the output standard deviation close to 1). In the rest of layers of the topology I applied a combination of Dropouts and Dense operations to prevent overfitting.Additionally, the chosen optimizer for the LSTM network is RMSprop.



embedding_1_input: InputLayer | input: (None, 72) | output: (None, 72)
embedding_1: Embedding | input: (None, 72) | output: (None, 72, 100)
bidirectional_1(lstm_1): Bidirectional(LSTM) | input: (None, 72, 100) | output: (None, 72, 144)
global_max_pooling1d_1: GlobalMaxPooling1D | input: (None, 72, 144) | output: (None, 144)
batch_normalization_1: BatchNormalization | input: (None, 144) | output: (None, 144)
dropout_1: Dropout | input: (None, 144) | output: (None, 144)
dense_1: Dense | input: (None, 144) | output: (None, 72)
dropout_2: Dropout | input: (None, 72) | output: (None, 72)
dense_2: Dense | input: (None, 72) | output: (None, 72)
dropout_3: Dropout | input: (None, 72) | output: (None, 72)
dense_3: Dense | input: (None, 72) | output: (None, 1)

Benchmark

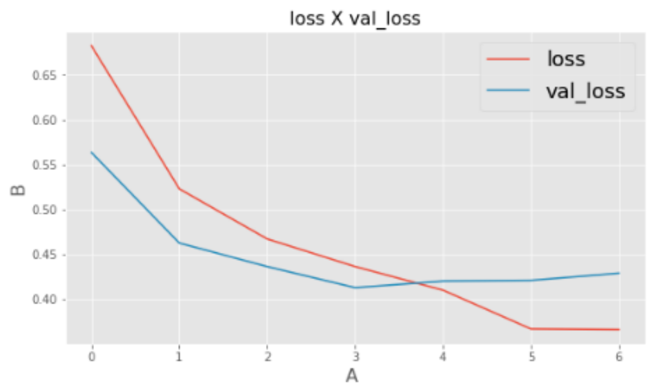
The execution of this project was made using a notebook created inside Sagemaker as we see during the Nanodegree. The selected kernel was *conda_tensorflow2_p36* because it has all the requirements needed to implement and execute this project.

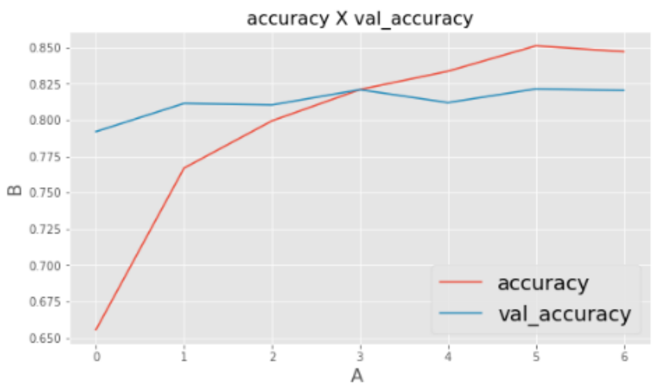
The model implemented will be trained using the train dataset and will be benchmarked against a test dataset evaluating the result using the metrics described in the next section.

Results

During training time I monitored the loss and accuracy during all steps. In the figure below we compare *loss* vs *val_loss* and the same for *accuracy* and *val_accuracy*. In tensorflow terms, *val_loss* is the value of the cost function for the cross-validation data and *loss* is the value obtained from the cost function for the training data. The same happens for *val_accuracy* and *accuracy*.

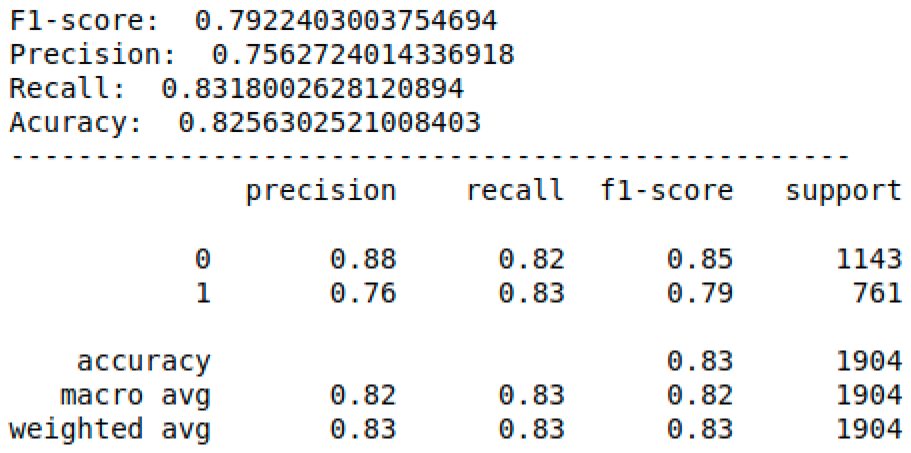
As we can see in the figure the results for both loss and accuracy respect to val_loss and val_accuracy do not diverged too much so we can say that the model does not have too much overfitting and it is performing very well with data with which it has not been trained.





Once the model is trained it is time to evaluate using the test dataset. The chosen metrics are accuracy, precision, recall and the relation between these two (F1-score) because they are very good metrics for supervised classification problems. In the case of precision and recall also give us a lot of information even if the dataset is unbalanced.

The results for all the chosen metrics are presented in the image below. As we can see for test data the accuracy obtained is 0.8256, so is really a high value. Also good values for precision, recall and F1-score are obtained. And, specifically we get a high value for recall that it is an interesting metric because it is a measure of comprehensiveness that is something important in this case so we need to distinguish real disasters.



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F1-score:  0.7922403003754694
Precision:  0.7562724014336918
Recall:  0.8318002628120894
Acuracy:  0.8256302521008403
--------------------------------------------------
              precision    recall  f1-score   support

           0       0.88      0.82      0.85      1143
           1       0.76      0.83      0.79       761

    accuracy                           0.83      1904
   macro avg       0.82      0.83      0.82      1904
weighted avg       0.83      0.83      0.83      1904
```