Capstone Project

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Quora Question Pairs

Definition

Project Overview

Quora is a place to gain and share knowledge. It is a platform to ask questions which are answered by the community itself. Being such a large community, related questions are often asked by members. Multiple questions with the same intent can cause seekers to spend more time finding the best answer to their question, and make writers feel they need to answer multiple versions of the same question. Quora values canonical questions because they provide a better experience to active seekers and writers, and offer more value to both groups in the long term. It is because of this reason Quora hosted the question pair challenge on Kaggle where they provided a train and test dataset consisting of similar and different question pairs. The expectation from the Kaggle community was to build state of the art models to predict whether the question pair is similar.

The dataset for the problem can be found in the competition page on kaggle but Quora has also released a updated dataset for the same problem (http://qim.ec.quoracdn.net/quora_duplicate_questions.tsv). This dataset is publicly available and we will use this to tackle the problem. The training dataset consists of question pairs and the target class for that pair (0 for non-duplicate pair and 1 for duplicate pair). It contains 404290 rows of data, of which 63% rows are non-duplicate pairs and 37% are duplicate pairs. Hence, we will divide the training set into two parts: train and test. We will use sklearn function train_test_split to do the splitting. We will use the train set to train and cross validate our model. We will measure the performance of our model using the test set.

Problem Statement

Predicting question pair similarity is a classification problem. It is a well-known problem in the field of Natural Language processing. We already have many state of the art models that attain high accuracy developed by the participants of the challenge on Kaggle. Before the challenge Quora was using Random Forest for classifying the question pairs. This problem can be approached in many ways and there are well known solutions based on boosting, others based on deep neural networks and many more.

We will use a deep neural network architecture for this problem. We will use keras which is a deep learning library in python. It provides us with many predefined functions to preprocess text e.g. Tokenizer() and text_to_sequences() etc. We start by removing the alphanumeric characters and converting short form of words to their full forms. We will use regular expressions for this purpose. Now we will convert our text to vectors using already available keras functions. Then we will feed the vectors to a neural network architecture for the classification task. We will use Embedding layers with pretrained weights, LSTM and Convolution 1D layers as the starting layers. The weights are calculated using embedding matrix created with the help tokenized words in the dataset and with the pretrained word embeddings model: stanfordNLP's GloVe: http://nlp.stanford.edu/data/glove.840B.300d.zip. These layers extract useful semantic information using the word vectors and their arrangement. On top of these layers we will use Dense Fully connected layers for our predictions. The final layer will give us the predicted probabilities which we will use to predict whether the question pairs are duplicate or not. We will then check the accuracy score to improve our model and parameters. The training, cross validation and testing will be done on different mutually exclusive subsets of the data and those will be prepared using python libraries such as numpy, pandas and scikit-learn. We will save our deep learning models using Keras Checkpoint functionality, that saves our model weights using h5py.

Metrics

We will use Accuracy and F1 Score as our evaluation metric for this problem. Since our data is a 37:63 percent split for duplicate : non-duplicate samples, which is not evenly distributed, hence, F1 score would be a better metric for our problem. F1 score is the harmonic mean of the precision (number of correct positive results divided by the number of all positive results) and recall (number of correct positive results divided by the number of positive results that should have been returned). Since F1 score is the harmonic mean and not a normal average hence we need better results for both precision and recall to get a better F1 score. For our problem, precision and recall both need equal importance since we neither can tend to predict non-duplicate question as duplicate nor can we predict duplicate questions as non-duplicate. If we only use accuracy as our metric, our predictor might easily fool us with a high accuracy by predicting the majority class (non-duplicate class) in more numbers.

We will use Accuracy to train our model but at the same time we will also use F1 score at the end of training iterations to check which models or architectures are better.

Analysis

Data Exploration

The dataset consists of 404290 rows and 6 columns. The column names are: 'id', 'qid1', 'qid2', 'question1', 'question2', 'is_duplicate'. 'id' is the index column, 'qid1' and 'qid2' give the question id's and finally 'question1' and 'question2' are the questions itself. 'is_duplicate' is the target column that we need to predict. Of the 404290 rows present in the dataset, 255027 rows are for non-duplicate questions and 149263 rows are for duplicate questions.

Question 1 column has an average of 10.9 words per row. And Question 2 has an average of 11.2 words per row.

Examples:

Question1	Question2	Is_duplicate
What is the story of Kohinoor (Koh-i-Noor) Diamond?	What would happen if the Indian government stole the Kohinoor (Koh-i-Noor) diamond back?	No

How can I be a good geologist?	What should I do to be a great geologist?	Yes

The dataset consists of diverse set of questions. Some questions only consist of 2 words while some consists of as long as 286 words. We do not need to do any kind of pre-processing before converting our questions to vectors. But after converting to vectors, we do have to add padding to the questions that contain less words than our sequence or vector length.

Exploratory Visualization

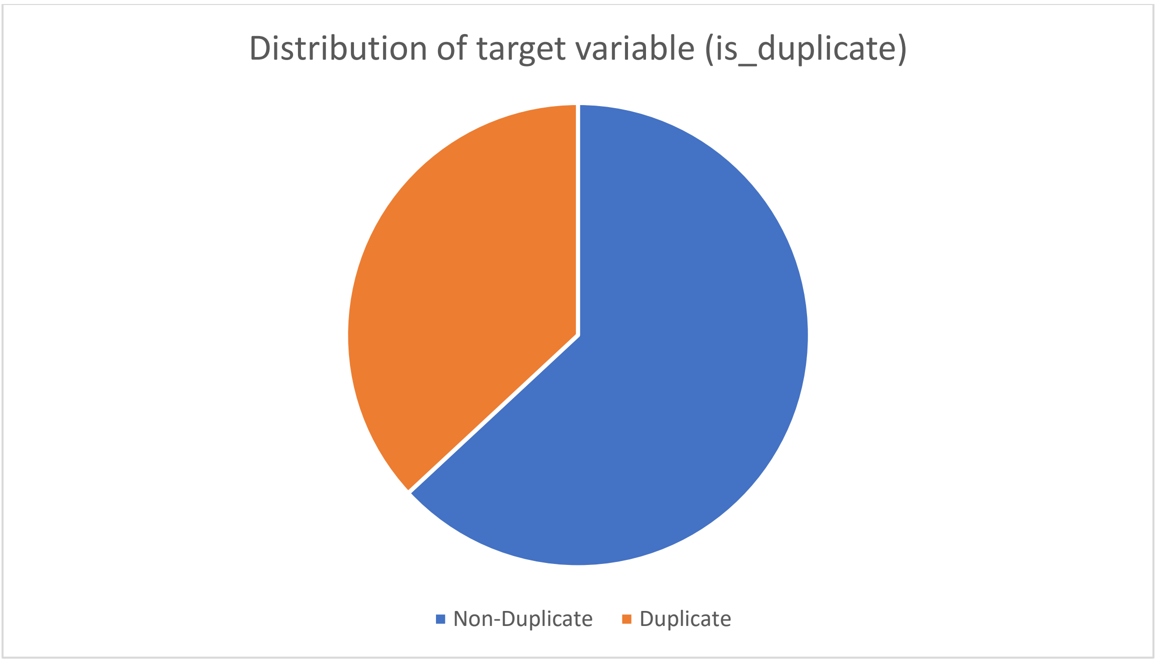


Fig-1

Fig-1 is a pie diagram showing the distribution of our train data. We can see from figure that we have around 63% non-duplicate question pairs and around 37% duplicate question pairs in our dataset.
Since we only got 2 classes and they are not completely balanced, hence our problem is a binary classification problem with imbalanced classes.

Algorithms and Techniques

We will use Keras and Tensorflow to train our neural network. Keras provides many high-level functions to pre-process our data and train our neural network with ease. For pre-processing we will use Regular Expressions. We will also use keras.Tokenizer() function to tokenize and convert out text data to vector sequences. We use Tokenizer() function since it is very easy to use. It automatically creates the bag of words along with the word indices after we fit() the text to the Tokenizer() function. After fitting we can easily convert our text to vectors using text_to_sequences() function.
Tokenizing means that we are assigning a number to every unique word present in our dataset. Now for converting a sentence to vector we simply replace each word in the sentence with the number assigned to the word.
After converting our text to vectors we will feed them to a neural network. We will use the Keras Functional Api to create our neural network architectures. The Functional Api of Keras is particularly

useful for multi input models (e.g. our model which will have question1 and question2 as inputs). The important Keras layers and terms that we use in our models are:

- **Embedding layer:** This layer turns positive integers (indexes) into dense vectors of fixed size. This layer can only be used as the first layer of a model. We will use this as our first layer. Using this layer we can initialize our models with pretrained weights that are publicly available on the internet (e.g. StanfordNLP's GloVe weights which we will use in our models).
- **TimeDistributed Layer:** This wrapper applies a layer to every temporal slice of an input. In other words, it applies a layer to all the time steps present in the data. We can use any layer with the Time Distributed wrapper. For our models, we will use TimeDistributed with Dense layers.
- **LSTM:** LSTM stands for Long Short Term memory and is a kind of Recurrent Neural Network. An LSTM is well-suited to classify, process and predict time series given time lags of unknown size and duration between important events. LSTM works by storing some information from the previously fed data and combining it with the newly fed data to give a combined output. We will use LSTM's since our data is sequential and some memory from previous words in the sequence might be helpful.
- **Conv1D:** This is a Convolution 1D layer. This layer creates a convolution kernel that is convolved with the layer input over a single spatial (or temporal) dimension to produce a tensor of outputs. A convolution is a small part of the whole sequence which is slided over the whole sequence in small steps(strides). The convolutions created by this layer are collectively called filters.
- **GlobalAveragePooling1D:** This layer is generally used with conv1D layers. It averages the convolutional filters created by the Conv1D layer and outputs one dimensional sequences.
- **Dense:** This layer is the regular densely connected Neural Network layer. We need to pass the number of nodes in the layer as argument.
- **Dropout:** This layer applies dropout to the input. Dropout consists in randomly setting a fraction rate of input units to 0 at each update during training time, which helps prevent overfitting.
- **BatchNormalization:** This layer normalize the activations of the previous layer at each batch, i.e. applies a transformation that maintains the mean activation close to 0 and the activation standard deviation close to 1.
- **Binary-Crossentropy:** It is a type of loss function used in binary classification problems. A loss function (or objective function, or optimization score function) is one of the two parameters required to compile a model.
- **ReLU:** Relu stands for Rectified Linear Unit and is a type of activation function. The activation function of a node defines the output of a node given an input or set of inputs. ReLU converts all inputs less than zero to zero.

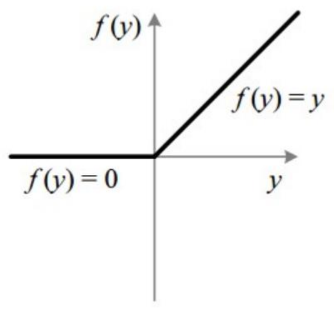


Fig-2(The ReLU function)

- **Sigmoid:** Sigmoid is also an activation that applies sigmoid function to its inputs. This function has the characteristic 'S'-shaped curve.

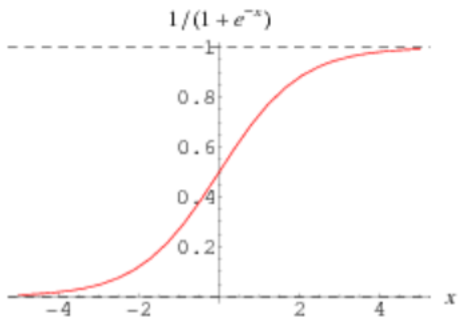


Fig-3(The Sigmoid function)

- **Adam:** Adam is a kind of optimization algorithm that is used commonly in neural networks. Adam is an extension of the Adagrad and Rmsprop algorithms. Adam results in faster convergence than normal Stochastic Gradient descent algorithm.

Benchmark

There are many state of the art models to tackle this problem. We would not be considering the models that were created using ensembles of many different models. Instead we will consider a single model as the benchmark that has been published on Medium: Implementing MaLSTM on Kaggle's Quora Question Pairs competition (https://medium.com/@eliorcohen/implementing-malstm-on-kaggles-quora-question-pairs-competition-8b31b0b16a07). This model scores around 82% accuracy on the validation set.

Methodology

Data Preprocessing

After importing the dataset as a data-frame, we remove symbols and punctuation marks from Question1 and Question2. For this we define a function clean_data() which takes some unprocessed input text and returns the processed text. The function removes punctuation marks such as: !,?,. etc. The function also fills up commonly used contractions such as: 'can't' gets replaced with 'can not', 'I'm' gets replaced with 'I am' etc. we take this preprocessing function from our Baseline model's implementation on github. (https://github.com/eliorc/Medium/blob/master/MaLSTM.ipynb)

After this step we call keras function Tokenizer() and fit it on our texts. This function lets us convert our text data to sequences using text_to_sequences(). We need to set the maximum length for our sequences. For this problem, we set the max length as 30. Also, there will be questions which do not have atleast 30 words, and hence they would have sequences of lesser length. For those questions we use the pad_sequences() function to fill the sequences with zeros and make their length 30.

Implementation

After pre-processing the data, we save the data-frame using pickle, so that we can directly use the pre-processed data.

We import the ‘glove.840B.300d.txt’ file downloaded from StanfordNLP website and save the data to a dictionary. The file consists of words represented by vectors of length 300.

We now take the complete set of words present in our dataset (collected using Tokenizer()) and assign glove vectors to each word thus creating a matrix (embedding_matrix). We will use this matrix to initialize our Embedding layer in Keras. We save this embedding_matrix using pickle so that we can directly reuse it later.

After this step, we start building our Keras model. At this step, I thought using Keras Sequential model would be a good option, but later realized that Keras 2.0 does not support the Merge of two Sequential models together. Hence, I used Keras Functional Api instead.

The first base model consists of two inputs: question1 sequence and question2 sequence and a single output that gives us the predicted class. The loss function used is ‘binary-crossentropy’ and optimizer is ‘adam’. Two call-backs are also used in the model. The first call-back is ‘Checkpoint’ which will save the model weights with the best accuracy during training. The second call-back used is ‘EarlyStopping’ which will stop the training process when validation loss does not decrease by 0.0001 in 20 iterations.

For cross-validation, I thought of creating separate datasets, but later found out that Keras model.fit() method already has an option to use out of bag validation data. Hence, I went forward with that and used 10% of the training data as validation. Also, shuffle option was set as True to curb overfitting.

During this process, the major difficulty faced was trying to get a lower train and validation loss during our training. If we see our Benchmark model, the train and validation losses hover in the ranges of 0.1 to 0.2. But for our base models as well as the final model, those hover around 0.3 to 0.5. All the models that we tried had the same issue. Even though our accuracy was more than the Baseline model (Baseline.ipynb Notebook), our confidence in the predictions was less.

Refinement

For the base model, we start with a Keras Embedding layer and its weights were initialized by the embedding_matrix that we created before. The number of nodes for this layer was 300 and its weights were non-trainable. We then add a TimeDistributed Dense layer on top of it having 300 nodes. The third layer used is a Lambda layer, which lets us add our own functions. For this layer, we sum our tensors along the column axis.

The above setup is used to create two models ‘q1’ and ‘q2’, which are for question1 and question2. We now add the outputs of both the models to create a third model ‘merged’. The output of ‘merged’ are then BatchNormalized and then fed to a Dense layer with 300 nodes. A Dropout of 0.2 is also added to layer. We then add another Dense layer with 300 nodes and a Dropout of 0.2.

All the Dense and TimeDistributed layers till this point were activated using ‘relu’. We now add our final Dense layer with a single node and this layer is activated using ‘sigmoid’.

We now compile our model using ‘binary-crossentropy’ as loss, ‘adam’ as optimizer, and ‘accuracy’ as the metric. We also define a Checkpoint call-back, which will save the model with the highest validation accuracy and a EarlyStopping call-back, which will monitor our validation loss and stop training if it does not improve by 0.0001 in 20 iterations.

We now start training our model using model.fit() on the training set and using a batch size of 500, we set the number of iterations as 100 and a validation split of 0.1 (10% of the testing data).

This model gets us upto 81.5% accuracy on the validation set and a F1 score of 0.86 on complete testing set and weights were saved as base 1.h5.

Now, for the second base model we increase our Dropouts to 0.3, and we use MAX instead of SUM in the Lambda layers. We increased the dropout because there were tell-tale signs of overfitting in the first base model (for the best iteration, train accuracy was 88.7 and validation accuracy was 81.5). The second model only worsened our predictions and the best iteration gave us a cross validation accuracy of 80.2% and a F1 score of 0.89 on complete testing set.

For the third model, we still use MAX in the Lambda layers but we decrease the dropout to 0.1. This time our predictions improved and the best iteration gave us 82.7% accuracy which is already higher than our benchmark. The F1 score on complete testing set was 0.94.

Now, let us dive into CNN architectures. Our first CNN model consists of an Embedding layer initialized by the GloVe weights and this layer is not trainable. We then use a Convolutional1D layer with 64 filters, kernel_size of 2 and strides of 1. We use padding as ‘same’. We also add a dropout of 0.2 to the Convolution layer.The convolutional layer is followed by GlobalAveragePooling layer that will output the average of our filters as a 1D tensor. This architecture is used for both question1 and question2 vectors.

We now concatenate the outputs of the above architectures for question1 and question2 and add a fully connected layer to it. The fully connected layer consists of two Dense layers, first layer with 128 hidden units and second layer with 64 hidden units. A dropout of 0.1 is added to both the layers. These two layers are followed by a Dense layer with single node. The convolutional layers and the Dense layers excluding the final layer were activated using ‘relu’ and the final layer had a ‘sigmoid’ activation.

We used the same process for training and saved the best weight to ‘base 4.h5’. This architecture could only give us 81.5% accuracy but overfitting was a lot less compared to the base 3 model. The F1 score on complete testing set was 0.85.

The final base model we will consider is with LSTM. Like before we start with an Embedding Layer initialized by GloVe weights. Now we add an LSTM layer with 30 nodes and set return_sequences to True so that the layer outputs all the sequences. This arrangement is done for both question1 and question2.

We now take the dot product of the outputs of the LSTM layers for question1 and question2, Flatten the resultant sequence and add two Dense layers on top of it. The Dense layers are accompanied by dropout of 0.1 and Batch Normalization. These dense layers are activated using ‘relu’. We now add the final Dense layer with 1 node and ‘sigmoid’ activation.

This model was also not sufficient to beat our benchmark.

So, we will use our third base model and refine it to get better results. This will be our final model. Our final solution is completely similar to Base 3 model only with minor changes that will be discussed in the Results section. This model gave us a final validation accuracy of 83.2% and an accuracy of 83.4% on the test set. The F1 score on the unseen test set was 0.77 which was also more than our Benchmark models score which was 0.75.

Results

Model Evaluation and Validation

The Final Model architecture is based upon Embedding layer initiated with GloVe Embedding weights, Time Distributed Dense layer, a lambda(max) layer and some fully connected dense layers. This model had 404,401 trainable parameters and the best accuracy was given in the 21’st iteration. The model weights are saved in ‘real_merge_2.h5’ file. Lets dive into the details and arrangement.

```
____________________________________________________________________________________________________
Layer (type)                           Output Shape       Param #          Connected to
==================================================================================================
==================
input_1 (InputLayer)                   (None, 30)         0
____________________________________________________________________________________________________
input_2 (InputLayer)                   (None, 30)         0
____________________________________________________________________________________________________
embedding_1 (Embedding)                (None, 30, 300)    26510400         input_1[0][0]
____________________________________________________________________________________________________
embedding_2 (Embedding)                (None, 30, 300)    26510400         input_2[0][0]
____________________________________________________________________________________________________
time_distributed_1 (TimeDistributed)   (None, 30, 300)    90300            embedding_1[0][0]
____________________________________________________________________________________________________
time_distributed_2 (TimeDistributed)   (None, 30, 300)    90300            embedding_2[0][0]
____________________________________________________________________________________________________
lambda_1 (Lambda)                      (None, 300)        0                time_distributed_1[0][0]
____________________________________________________________________________________________________
lambda_2 (Lambda)                      (None, 300)        0                time_distributed_2[0][0]
____________________________________________________________________________________________________
subtract_1 (Subtract)                  (None, 300)        0                lambda_1[0][0]
                                                                           lambda_2[0][0]
____________________________________________________________________________________________________
batch_normalization_1 (BatchNorm)      (None, 300)        1200             subtract_1[0][0]
____________________________________________________________________________________________________
dense_3 (Dense)                        (None, 200)        60200            batch_normalization_1[0][0]
```

```
________________________________________________________________________________
dropout_1 (Dropout)                      (None, 200)     0           dense_3[0][0]
________________________________________________________________________________
batch_normalization_2 (BatchNorm)        (None, 200)     800         dropout_1[0][0]
________________________________________________________________________________
dense_4 (Dense)                          (None, 200)     40200       batch_normalization_2[0][0]
________________________________________________________________________________
dropout_2 (Dropout)                      (None, 200)     0           dense_4[0][0]
________________________________________________________________________________
batch_normalization_3 (BatchNorm)        (None, 200)     800         dropout_2[0][0]
________________________________________________________________________________
dense_5 (Dense)                          (None, 200)     40200       batch_normalization_3[0][0]
________________________________________________________________________________
dropout_3 (Dropout)                      (None, 200)     0           dense_5[0][0]
________________________________________________________________________________
batch_normalization_4 (BatchNorm)        (None, 200)     800         dropout_3[0][0]
________________________________________________________________________________
dense_6 (Dense)                          (None, 200)     40200       batch_normalization_4[0][0]
________________________________________________________________________________
dropout_4 (Dropout)                      (None, 200)     0           dense_6[0][0]
________________________________________________________________________________
batch_normalization_5 (BatchNorm)        (None, 200)     800         dropout_4[0][0]
________________________________________________________________________________
dense_7 (Dense)                          (None, 200)     40200       batch_normalization_5[0][0]
________________________________________________________________________________
dropout_5 (Dropout)                      (None, 200)     0           dense_7[0][0]
________________________________________________________________________________
batch_normalization_6 (BatchNorm)        (None, 200)     800         dropout_5[0][0]
________________________________________________________________________________
dense_8 (Dense)                          (None, 1)       201         batch_normalization_6[0][0]
================================================================================
==================
Total params: 53,427,801
Trainable params: 404,401
Non-trainable params: 53,023,400
```

The inputs to the model are word sequences of length 30 each. We have two inputs to the model, question1 sequence and question2 sequence respectively. These two sequences are fed into two Embedding layers which are non-trainable. The Embedding layers are initialized with GloVe embedding weights that we saved in the embedding_matrix. The input dimension of the embedding layers were: (max integer index for our bag of words + 1). The output consisted of 300 dimensions since our pretrained weights were of length 300. The outputs of the two embedding layers are then connected to two TimeDistributed Dense layers with 300 nodes each. We use 'relu' activation on the TimeDistributed Dense layers. The outputs are now connected to a Lambda layer which in return outputs the maximum along the column axis. The lambda layer converts the 3 dimensional outputs from TimeDistributed layers to 2 dimensions.

The outputs for question2 layers are now subtracted from the outputs from question1 layers, which helps us generate a merged model. At this moment, the layer has 300 dimensions along with the batch dimension. we now add a BatchNormalize layer to the merged output. After this we add two Dense layers each with 'relu' activation, Dropout of 0.5 and outputs BatchNormalized. We then add three more Dense layers each with 'relu' activation, Dropout of 0.1 and outputs BatchNormalized. Finally, we add a Dense layer with single node and 'sigmoid' activation. We compile the model with 'binary-crossentropy' loss and 'adam' optimizer. After this we train the model on the training set for 50 iterations and save the model with the best accuracy using checkpoint. Our best iteration occurs at 21'st iteration and it gives a cross validation accuracy of 83.3% and F1 score of 0.77 on test set.

This model can be considered a robust one since it gives pretty good results on the completely unseen test set. This model consists of BatchNormalization layers and Dropout layers to tackle the overfitting problem. Also our Benchmark Model used LSTM's which took more time to train (approx. 90 secs per iteration and 81.5% accuracy in 30+ iterations). But our model took much less time to train and converge to the same point(19 secs per iteration and 83% accuracy in 21 iterations).

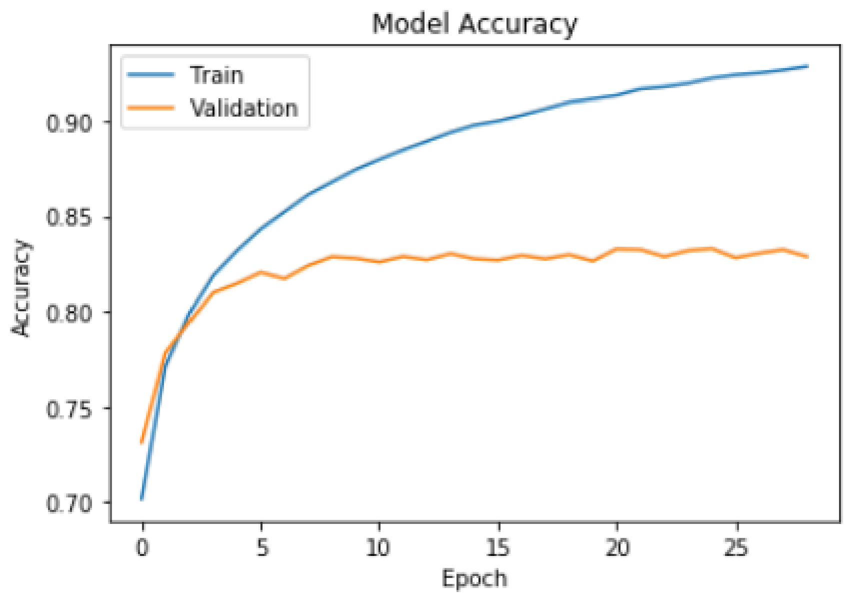
Justification

Considering the Accuracy of the model, we see that our final model gives about 1% more accuracy than the baseline model. Considering our baseline model already was a state of the art model, an increase of 1% accuracy is a valid improvement. We also checked the predictions on the completely unseen test set and our model gave an accuracy of 83.4%.

Considering the F1 score, we see that our model resulted in an F1 score of 0.77 in 21 iterations and the Benchmark model resulted in F1 score of 0.75 in 45 iterations. We definitely believe this is an improvement over the benchmark

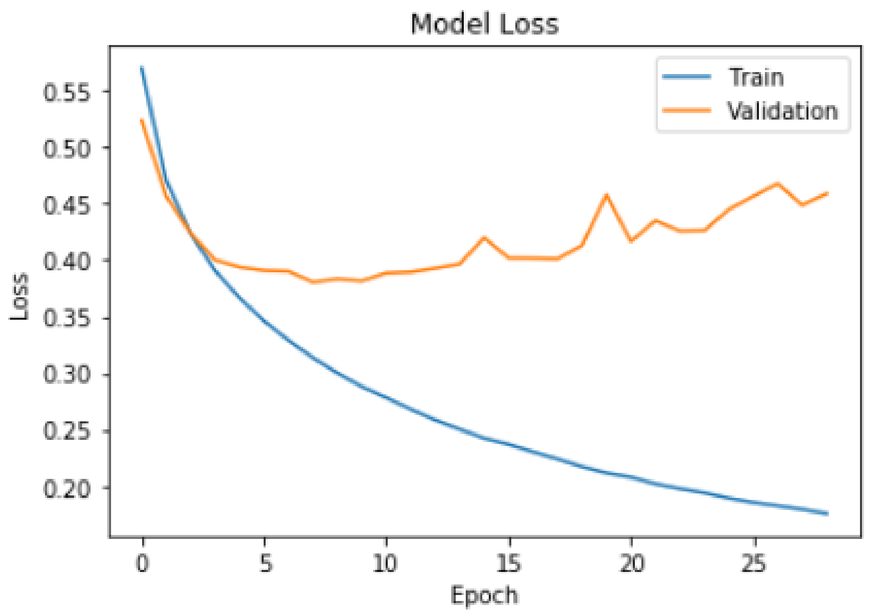
Conclusion

Free Form Visualization



The above figure shows the increase in accuracy for training and validation set. From this figure, we see that there is a steep increase in validation accuracy upto the 5th iteration, but after that there are only minor improvements in the accuracy. As the training iterations increase, the increase in validation accuracy tends to decrease and finally stops improving.

But it is not the case with training set accuracy. The accuracy on the training set continuously increase as the number of iterations increase.



The above figure shows the variation in training and validation loss during the training. From this figure, we see that training loss decreases as the training iterations increase. But validation loss decreases only upto a certain point (5th iteration) and after that starts increasing again. An increase in loss only means that we have started overfitting the model.

Reflection

I started this project with a bit of research on the different architectures that are available for the question similarity problem. There are a vast number of well documented architectures available to tackle this

kind of problem and that is where I learnt about TimeDistributed layers, Embedding layers, LSTM’s and 1D Convolutions. This helped me create some base models and validate the performance.
Using the performance of the base models, I could select a architecture type and build on it to create the final model. I tried different arrangements for the final layer, adding more Dense layers, adding Dropouts etc. And finally reached at a model that gave us the best accuracy.

Improvement

There is a lot of room for improvement in this model. Some of the major areas where it can be improved are:

- Now, the model is overfitting and we can add regularization or increase Dropout to tackle it.
- We can train our own embeddings using only the words in our dataset.
- We can stack many different models to get even more accuracy and minimize the loss.