Deep Learning Project - 3

Sentence pre-processing:

Stop words removal:

- Stop words (like the, a, an, is) are not important features for classification because these words are present in all the sentences. So, these words must be removed.
- I have used nltk pre-processing module to remove these words.

Lemmatization:

- Words present in the sentence are not in its root form. They are present in the sentence based on its tense or plural form. These words are unable recognize and hence unable to convert into vector by using embedding matrix.
- I have tried stemming and lemmatizer using porter Stemmer and Wordnet Lemmatizer of nltk library. In Stemming it truncates the words only (like leaves to leav, planning to plann), but Lemmatizer returns to its root form.
- I tried both these approaches in logistic regression and achieved accuracy of 62.85% in Porter Stemmer and 64.44% using Wordnet Lemmatizer. So, in Deep Learning I have used only Wordnet Lemmatizer.

Remove punctuation:

- Sentence contains punctuation characters (like: "!#$%&'()*+,-./:;?@[\]^_`{|}~)). Which must be removed because these punctuation characters along with words create problem in word to vector conversion using pretrained model in recognizing words.
- I have used RegexpTokenizer of nltk module which removes punctuation characters.

a) Logistic regression model:

- Target labels pre-processing:
  In this model I have simply converted labels into number zero, one and two, here zero for 'neutral', one for 'contradiction' and two for 'entailment'.
- Tf-idf features:
  - In this model pre-processed sentences are converted using Tfidfvectorizer of scikit learn library. These converted vectorized sentences are then joined using scipy sparse hstack function because these sentence one and two vectors are sparse vectors.
  - Now these sentences are in the form of TfIdf feature vector, along with target labels, which are directly used in LogisticRegression of scikit learn.
  - Sentences of testing these models are also transformed using same vectorizer which are used for training sentences to convert into tfidf feature vector.

	Accuracy
With Porter stemmer	62.85%
With Wordnet Lemmatizer	64.44%

  - TfIdf is not better feature for entailment because it gives less accuracy in test data as well as intuitively it does not perform well because words frequency features are not related to entailment.

b) Deep Learning Model:

Tokenization:

- Tokenizer is used to convert sentences into sequence of integers which allows to convert word into vector using embedding matrix in the embedding layer.
- Tokenizer assigns integer by turning each text into a sequence of integers (each integer being the index of a token in a dictionary) and then converts sentences into sequence of integer. So, both premise and hypothesis are tokenized using Tokenizer of tensorflow keras.

Padding:

- Each sentence in the dataset is not of same length. Now to pass the sentence into the layer one must make each sentence of same length because input layer can not be of variable size.
- Solution to this problem is to add zeros at the end of the sentences which are having less no of words based on the sentence of maximum length. So, for that padding function is used on tokenized sentence 1 and sentence 2.

Embedding Matrix:

- Tokenizer has assigned numbers to the words based on the words present in the whole corpus. Here these integers are not any features which can capture statistics of cooccurrence of words which can be related to its entailment.
- Now in order to capture these statistics and give more dimension so that model can learn in more dimension regarding sentence entailment, Word2Vec or GloVe can be used.
- Word2Vec captures local statistics but in this problem, we require global statistics because in entailment problem test set and validation set will not contain similar sentences. Hence, I have used GloVe of 300 dimensions pretrained model in Embedding matrix which will be used in Embedding layer.

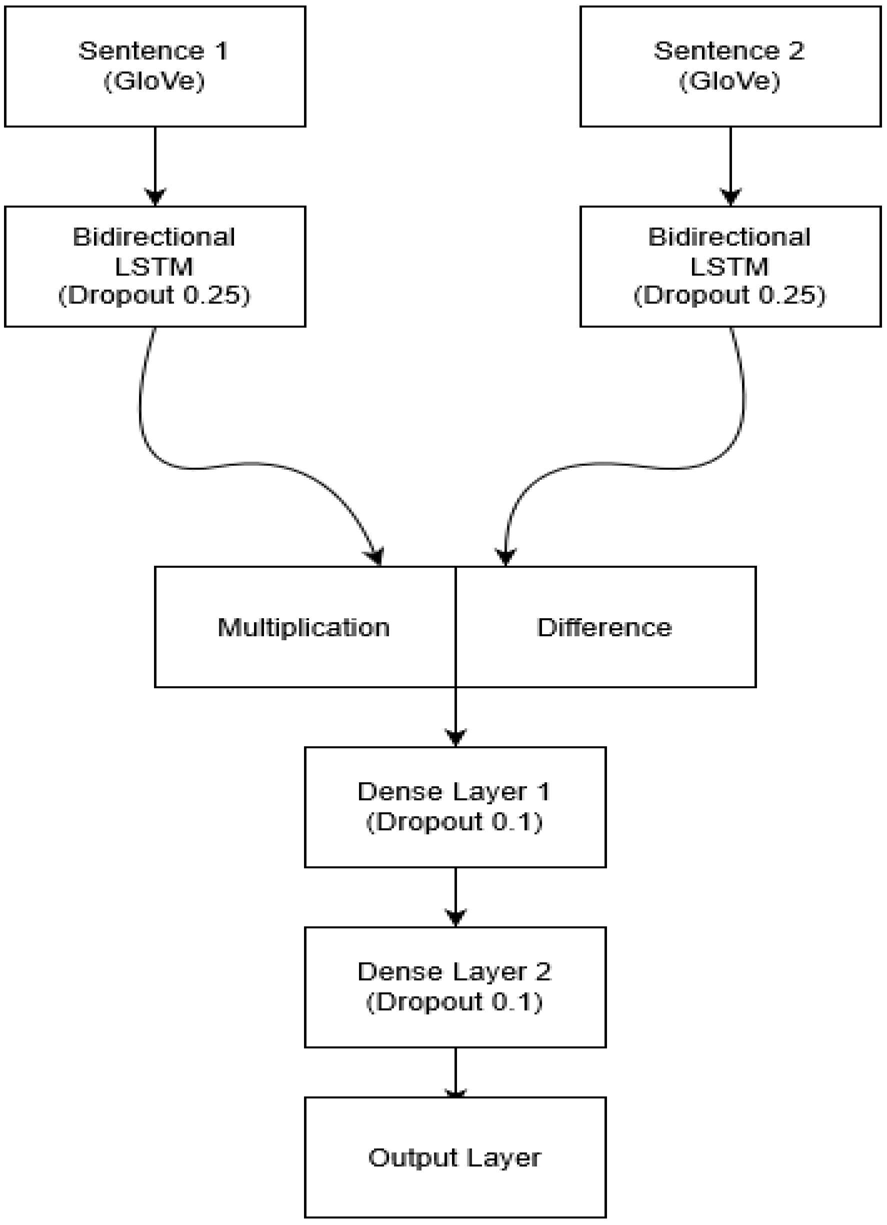
Masking:

- Zero padded sentences are directly passed to the model then model will train these zeros as features which is wrong. Masking layer can be used in this case, which will mask zeros as false and vector information as true which can be decoded by LSTM.

Target labels pre-processing:

- In this problem first I have used encoder and following which keras to categorical function which converts target labels into one hot vector. This one hot vector is used as target label.

Model:


Sentence 1 (GloVe)
Sentence 2 (GloVe)
Bidirectional LSTM (Dropout 0.25)
Bidirectional LSTM (Dropout 0.25)
Multiplication
Difference
Dense Layer 1 (Dropout 0.1)
Dense Layer 2 (Dropout 0.1)
Output Layer

- I have used Embedding layer to convert tokenizer output into Global Vector (GloVe) and difference and multiplication are calculated using lamda layer in create model.
- Activation function for both dense layers: ReLU
- Activation function for output layer: Softmax
- Loss function: categorical_crossentropy
- Optimizer: rmsprop
- Learning rate: 0.001

Hyper-parameter Tuning:

- No of layers:
  By varying no of dense layer change in accuracy are as shown in the table below. Here I have shown maximum accuracy by varying no of nodes in each layer and dropout.

No of dense layers	Maximum Accuracy (%)
Zero	77.81%
One	78.17%
Two	80.008%

- One dense layer accuracy:
  I have checked test accuracy by varying no of nodes in one dense layer. I have checked maximum 500 nodes because output of bidirectional LSTM is of 600 dimension2. I have shown output only for dropout of 0.2 because at 0.2 maximum accuracy achieved.

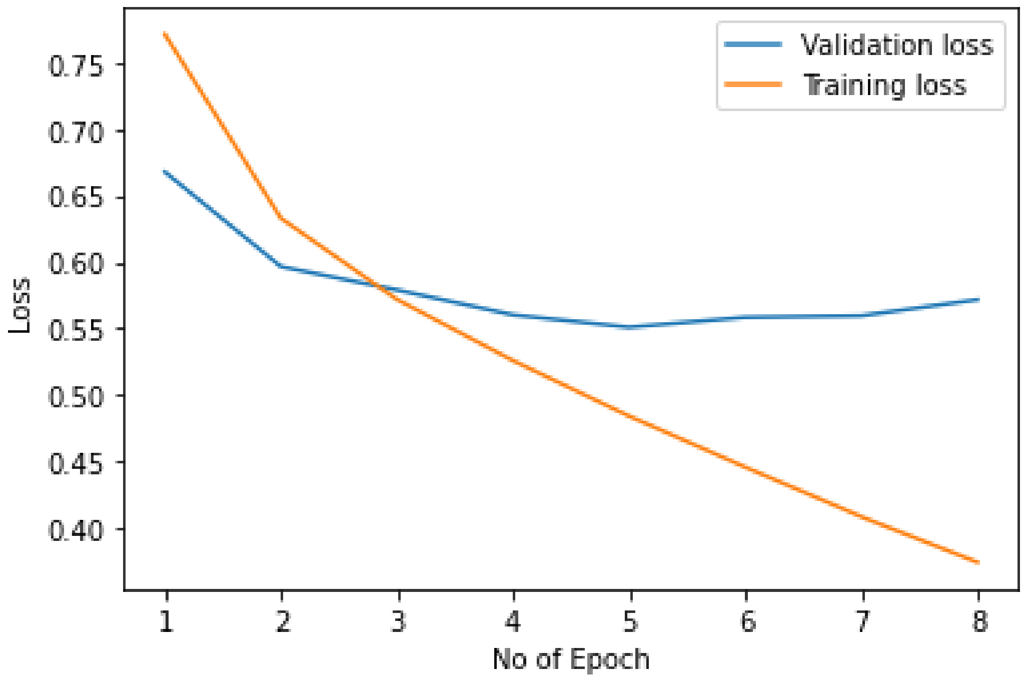
No of nodes	Dropout	Test Accuracy (%)
200	0.2	78.17
300	0.2	78.05
400	0.2	77.71
500	0.2	77.84

- Two dense layer accuracy:
  First, I have checked maximum accuracy by taking 50 no of nodes in second layer and varying no of nodes in first layer with dropout and after that I have fixed 400 nodes in dense layer 1 and dropout 0.1 and no of nodes in second layer increases which shows maximum accuracy at no of nodes 400.

No of nodes		Dropout (both layer)	Test Accuracy
Dense layer 1	Dense layer 2		
200	50	0.1	78.76%
200	50	0.2	78.83%
200	50	0.3	78.82%
300	50	0.1	78.84%
300	50	0.2	78.70%
300	50	0.3	78.79%
400	50	0.1	79.24%
400	50	0.2	78.86%
400	50	0.3	79.16%
500	50	0.1	78.75%
500	50	0.2	79.21%
500	50	0.3	78.92%
400	200	0.1	79.60%
400	400	0.1	80.008%

- I have used 300 units bidirectional LSTM and 0.25 dropout in both the bidirectional LSTM.

Training loss and validation loss vs no of epochs:



Note:

- I have used tensorflow 1.x for training deep learning model because tensorflow 2.x gives GPU error cuDNN Bad_Params but you can train deep learning model on cpu with tensorflow 2.x. If you want to train it on gpu then you must use tensorflow 1.x. Please check link below for the same error still have no solution:
  https://github.com/tensorflow/tensorflow/issues/33148

- I have uploaded my deep learning model on my google drive because of file size issue on github, which can be downloaded from the link given below:
  https://drive.google.com/open?id=1--tXMspAcO54UMZK-j8uzLal5jWQP0pv

- I have shown accuracy only for those sentences which are not having sentence label as '-'.