Capstone Project

Ashish Kumar Verma

11-April-2019

Title: Sentiment Analysis

Definition

Project Overview

Sentiment Analysis is contextual mining of text which identifies and extracts subjective information in source material, and helping a business to understand the social sentiment of their brand, product or service while monitoring online conversations.

It is the most common text classification tool that analyses an incoming message and tells Whether the underlying sentiment is positive or negative.
Sentiment analysis systems allows companies to make sense of this sea of unstructured text by automating business processes, getting actionable insights, and saving hours of manual data processing, in other words, by making teams more efficient.

Problem Statement

The objective of the task is to understand the underlying sentiment of the reviews and classify them as positive or negative.
Sentiment Analysis can be used as building block in several applications such as :
1.Computing customer satisfaction metrics :- One can get an idea of how happy customers are with your products from the ratio of positive to negative reviews about them.
2.Identifying detractors and promoters :- It can be used for customer service, by spotting dissatisfaction or problems with products.

The problem of automatically identifying underlying sentiment is difficult because of the near infinite number of permutations of words, positions, phrases and so on. It's a really hard problem. This is a well studied problem in Natural Language Processing and more recently an important demonstration of the capability of deep learning.

To Tackle this problem ,I have used three models :

1. Neural Bag Of Words + MLP Model
2. Embedding + 1D CNN Model .
3. N-Gram CNN Model (using multiple parallel convolutional neural networks)

Metrics

Accuracy Score -

Accuracy is the ratio of number of correct predictions on the total number of input samples.

$$Accuracy = \frac{Number\ of\ Correct\ predictions}{Total\ number\ of\ predictions\ made}$$

.

Analysis

Data Exploration

The [Movie Review Data] is a collection of movie reviews retrieved from the imdb.com website in the early 2000s by Bo Pang and Lillian Lee. The reviews were collected and made available as part of their research on natural language processing. The reviews were originally released in 2002, but an updated and cleaned up version was released in 2004, referred to as v2.0. The dataset is comprised of 1,000 positive and 1,000 negative movie reviews drawn from an archive of the rec.arts.movies.reviews newsgroup hosted at IMDB.

Data Files:

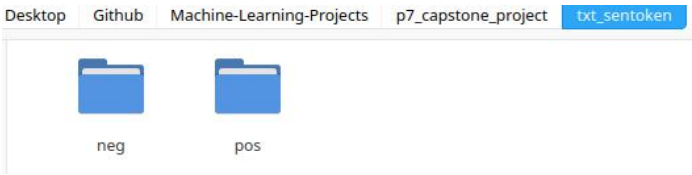
Dataset have a directory called **txt sentoken** with two subdirectories containing the text **neg** and **pos** for negative and positive reviews. Reviews are stored one per file with a naming convention from **cv000** to **cv999** for each of neg and pos.

Total Positive Files =1000

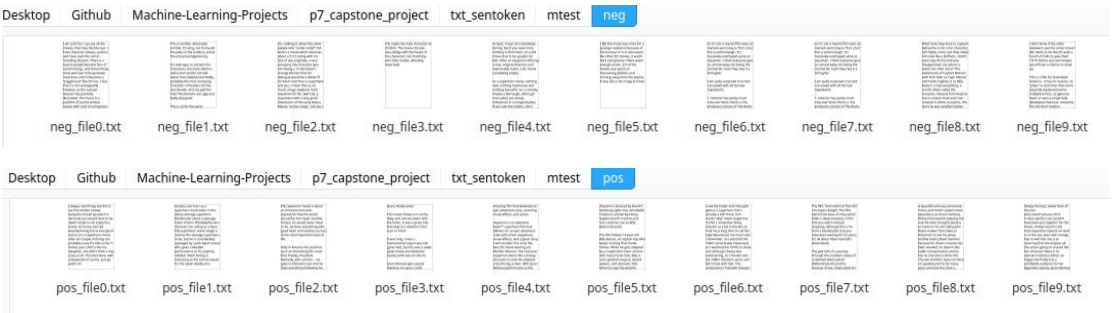
Total Negative Files =1000

Train Files From each folder contains file from **cv000 to cv999.**

Test Files From each folder contains file from **cv899 to cv999**



I have scrapped 10 positive as well as 10 negative reviews of movies from IMDB.com and kept them in "mtest" folder for testing model on unseen data.



Each text file contains a negative or positive review of a movie.

Exploratory Visualization.

Snap of the text files as present on the local disk.

I have divided the dataset into 90-10 % ratio. I have used 900 files from both neg(negative) as well as pos(positive) folder for training the model and rest 100 files from both folder for testing accuracy of the model.

I have explained this process in detail in data preprocessing section.

Algorithms And Techniques

For this problem, I will basically use 3 different techniques:

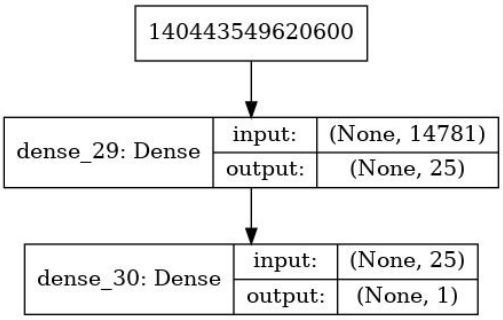
Benchmark Models.

Neural Bag Of Words + MLP Model

In this model, I have used Neural Bag of Words(used Keras Tokenizer)and then used simple Multilayer Perceptron Model to predict sentiment of encoded reviews.

I have used a Sequential Model with an input layer ,single hidden layer with 25 neurons and rectified linear activation function .Output layer has a single neuron with a sigmoid activation function.
I have used “Adam” optimizer with binary cross entropy loss function .

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_11 (Dense)             (None, 25)                369550
_________________________________________________________________
dense_12 (Dense)             (None, 1)                 26
=================================================================
Total params: 369,576
Trainable params: 369,576
Non-trainable params: 0
```




```
# define the model
def define_model(n_words):
    # define network
    model = Sequential()
    model.add(Dense(25, input_shape=(n_words,), activation='relu'))
    model.add(Dense(1, activation='sigmoid'))
    # compile network
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    # summarize defined model
    model.summary()
    plot_model(model, to_file='model.png', show_shapes=True)
    return model
```

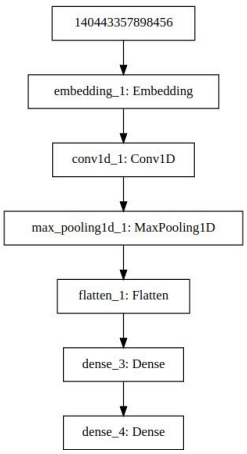
```
#fit network
model=define_model(n_words)
model.fit(Xtrain, ytrain, epochs=10, verbose=1)
```

Embedding + 1D CNN Model .

In this Model,First I have encoded the movie reviews to a squence of integers and then used the model as described including Embedding layer. (CNN) as they have proven to be successful at document classification problems. I have used CNN layer with kernel size of 8 with “relu” activation function, followed by a pooling layer which reduces the output of the CNN layer by half. Next, the 2D output from the CNN layer is flattened to one long 2D vector to represent the features extracted by the CNN. The back-end of the model is a standard Multilayer Perceptron layers to interpret the CNN features. The output layer is a sigmoid activation function to output a value between 0 and 1.I have used “Adam” optimizer with binary cross entropy loss function .

Layer (type)	Output Shape	Param #
embedding_5 (Embedding)	(None, 1244, 100)	1478100
conv1d_5 (Conv1D)	(None, 1237, 32)	25632
max_pooling1d_5 (MaxPooling1	(None, 618, 32)	0
flatten_5 (Flatten)	(None, 19776)	0
dense_13 (Dense)	(None, 10)	197770
dense_14 (Dense)	(None, 1)	11

Total params: 1,701,513
Trainable params: 1,701,513
Non-trainable params: 0

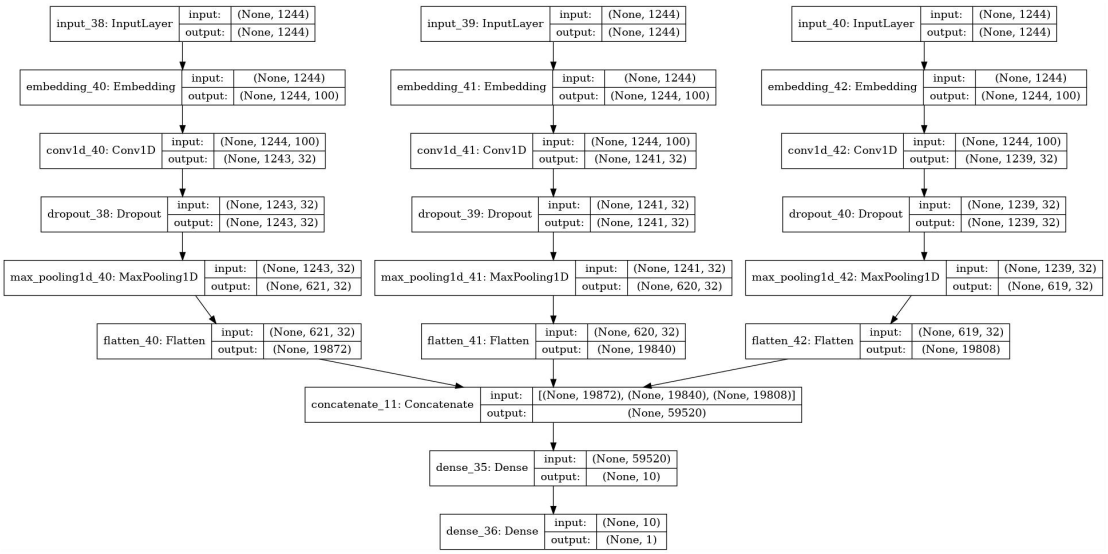


```
def define_embed_cnn_model(vocab_size, max_length):
    model = Sequential()
    model.add(Embedding(vocab_size, 100, input_length=max_length))
    model.add(Conv1D(filters=32, kernel_size=8, activation='relu'))
    model.add(MaxPooling1D(pool_size=2))
    model.add(Flatten())
    model.add(Dense(10, activation='relu'))
    model.add(Dense(1, activation='sigmoid'))
    # compile network
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

#     filepath="weights.best.hdf5"
#     checkpoint = ModelCheckpoint(filepath, monitor= 'val_acc' , verbose=1, save_best_on
e,
#     mode= max )
#     callbacks_list = [checkpoint]
    # summarize defined model
    model.summary()
    plot_model(model, to_file='cnn_model.png', show_shapes=True)
#     return model,callbacks_list
    return model
```

N-Gram CNN Model

In this model I have developed a multichannel CNN . I have choose to work also with this model as this allows the document to be processed at different n-grams (groups of words) at a time. Each channel consist of an embedding layer as input,followed by a 1D CNN layer,dropout Layer to prevent overfitting,pooling layer and then a prediction output layer .

I have used “Adam” optimizer with binary cross entropy loss function .



```python
def define_ncnn_model(length, vocab_size):
    # channel 1
    inputs1 = Input(shape=(length,))
    embedding1 = Embedding(vocab_size, 100)(inputs1)
    conv1 = Conv1D(filters=32, kernel_size=2, activation='relu')(embedding1)
    drop1 = Dropout(0.5)(conv1)
    pool1 = MaxPooling1D(pool_size=2)(drop1)
    flat1 = Flatten()(pool1)
    # channel 2
    inputs2 = Input(shape=(length,))
    embedding2 = Embedding(vocab_size, 100)(inputs2)
    conv2 = Conv1D(filters=32, kernel_size=4, activation='relu')(embedding2)
    drop2 = Dropout(0.5)(conv2)
    pool2 = MaxPooling1D(pool_size=2)(drop2)
    flat2 = Flatten()(pool2)
    # channel 3
    inputs3 = Input(shape=(length,))
    embedding3 = Embedding(vocab_size, 100)(inputs3)
    conv3 = Conv1D(filters=32, kernel_size=6, activation='relu')(embedding3)
    drop3 = Dropout(0.5)(conv3)
    pool3 = MaxPooling1D(pool_size=2)(drop3)
    flat3 = Flatten()(pool3)
#     # channel 3
#     inputs4 = Input(shape=(length,))
#     embedding4 = Embedding(vocab_size, 100)(inputs4)
#     conv4 = Conv1D(filters=32, kernel_size=8, activation='relu')(embedding4)
#     drop4 = Dropout(0.5)(conv4)
#     pool4 = MaxPooling1D(pool_size=2)(drop4)
#     flat4 = Flatten()(pool4)
    # merge
    merged = concatenate([flat1, flat2, flat3])
    # interpretation
    dense1 = Dense(10, activation='relu')(merged)
    outputs = Dense(1, activation='sigmoid')(dense1)
    model = Model(inputs=[inputs1, inputs2, inputs3], outputs=outputs)
    # compile
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    # summarize
    model.summary()
    plot_model(model, show_shapes=True, to_file='ncnn_model.png')
    return model
```

```python
ncnn_model= define_ncnn_model(length, vocab_size)
```

Methodology

Data Preprocessing.

Looking at the text in the files of the dataset .We need to preprocess it inorder to make it work with our model to successfully give sentiment analysis of the reviews.

My data preprocessing Steps:

1. Data Cleaning
2. Developing a vocabulary.

Data Cleaning

Splitting token into white space. (Tokenization)
Removing all punctuation from words.
Removing all words that are not purely comprised of alphabetical characters.
Removing all words that are known stop words.
Removing all words that have a length <= 1 character.

```
def clean_document(document,m_type="mlp"):
    document=document.lower()
    #split the review into tokens by white space
    tokens=document.split()
    # regex for char filtering
    re_punc = re.compile('[%s]' % re.escape(string.punctuation))
    # remove punctuation from each word
    tokens = [re_punc.sub('', w) for w in tokens]
    # removetokens which are not alphabetis
    if m_type=="mlp":
        tokens = [word for word in tokens if word.isalpha()]
        # remove stop words
        ##  A stop word is a commonly used word (such as "the", "a", "an", "in")
        stop_words = set(stopwords.words('english'))
        tokens = [w for w in tokens if not w in stop_words]
        # remove out short tokens
        tokens = [word for word in tokens if len(word) > 1]

    return tokens
```

```
filename="txt_sentoken/pos/cv001_18431.txt"
text=load_document(filename)
tokens=clean_document(text)
print(tokens)
```

```
['every', 'movie', 'comes', 'along', 'suspect', 'studio', 'every', 'indication', 'stinker', 'ever
ybodys', 'surprise', 'perhaps', 'even', 'studio', 'film', 'becomes', 'critical', 'darling', 'mt
v', 'films', 'election', 'high', 'school', 'comedy', 'starring', 'matthew', 'broderick', 'reese',
'witherspoon', 'current', 'example', 'anybody', 'know', 'film', 'existed', 'week', 'opened', 'plo
t', 'deceptively', 'simple', 'george', 'washington', 'carver', 'high', 'school', 'student', 'elec
tions', 'tracy', 'flick', 'reese', 'witherspoon', 'overachiever', 'hand', 'raised', 'nearly', 'ev
ery', 'question', 'way', 'way', 'high', 'mr', 'matthew', 'broderick', 'sick', 'megalomaniac', 'st
udent', 'encourages', 'paul', 'popularbutslow', 'jock', 'run', 'pauls', 'nihilistic', 'sister',
```

....

Which on passing a text file returns a list of tokens which is further executed on these two lines

```
tokens=[w for w in tokens if w in vocab]
line=' '.join(tokens)
```

Line obtained is encoded (on the basis of the model requirement) and further passed to model for analysis.

Example -

Review: [Give me a break. Top 200 movie of all time? Not even close. The bad guy in the movie was one of the worst characters I ever seen. It just was not a very good flick. It tried to build up the love between Peter Parker and the girl and then all of a sudden, he just cant be with her? Please. This movie will become a cult movie and will get good rating because people will be afraid to speak the truth, which was, this movie wasnt very good.However, I feel that the sequel might be better because they dont have to build up the character so much..]

After **Datacleaning** ,

[give break top movie time even close bad guy movie one worst characters ever seen good flick tried build love peter parker girl sudden cant please movie become cult movie get good rating people afraid speak tru th movie wasnt feel sequel might better dont build character much]

Then this line is passed to the model.

Developing a Vocabulary :

Developing of a Vocabulary is also needed when working with predictive model of text, inorder to reduce the size as more words will have larger representation of documents.Therefore it is important to constrain the words to only those believed to be predictive.

```
vocab = Counter()

def develop_vocab():
    global vocab
#     vocab= Counter()
    process_documents('txt_sentoken/neg', vocab)
    process_documents('txt_sentoken/pos', vocab)


    min_occur = 5

    tokens = [k for k,c in vocab.items() if c >= min_occur]
    save_list(tokens,"vocab.txt")

develop_vocab()
```

```
#print Length of the Vocabulary
print("Total Length Of The Vocabulary %s" %len(vocab))
```

```
Total Length Of The Vocabulary 46557
```

```
# 50 Most Common Words
print(vocab.most_common(50))
```

```
[('film', 8860), ('one', 5521), ('movie', 5440), ('like', 3553), ('even', 2555), ('good', 2320),
('time', 2283), ('story', 2118), ('films', 2102), ('would', 2042), ('much', 2024), ('also', 196
5), ('characters', 1947), ('get', 1921), ('character', 1906), ('two', 1825), ('first', 1768), ('s
ee', 1730), ('well', 1694), ('way', 1668), ('make', 1590), ('really', 1563), ('little', 1491),
('life', 1472), ('plot', 1451), ('people', 1420), ('movies', 1416), ('could', 1395), ('bad', 137
4), ('scene', 1373), ('never', 1364), ('best', 1301), ('new', 1277), ('many', 1268), ('doesnt', 1
267), ('man', 1266), ('scenes', 1265), ('dont', 1210), ('know', 1207), ('hes', 1150), ('great', 1
141), ('another', 1111), ('love', 1089), ('action', 1078), ('go', 1075), ('us', 1065), ('directo
r', 1056), ('something', 1048), ('end', 1047), ('still', 1038)]
```

After extracting all the words in the Counter Class and saving it in a file.We have t otal number of words 14803.

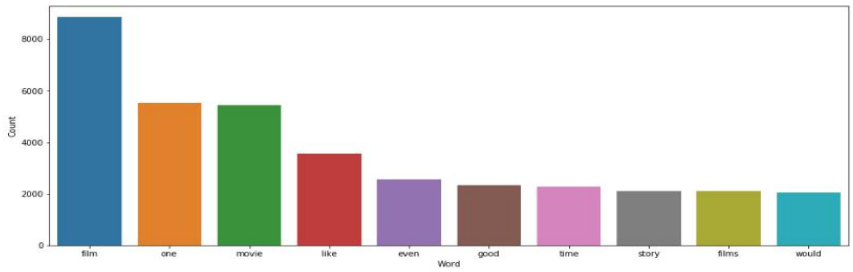
```
#Load The Vocabulary from Vocab.txt File.

vocab_data=load_document("vocab.txt")
vocab_data=vocab_data.split()
vocab=set(vocab_data)
print("Number of Words in Vocab.txt is %s" %len(vocab))
```

```
Number of Words in Vocab.txt is 14803
```

Top Ten Most Common Words

```
vocabmcdf=pd.DataFrame(data=vocab.most_common(10),columns=['Word','Count'])
plt.figure(figsize=(16,6))
sns.barplot(x='Word',y="Count",data=vocabmcdf)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbb5760b198>
```



Implementation

As stated earlier , I have created 3 models with dataset splitted in the ratio 90/10 % ratio.After that as explained in the Data Preprocessing section,performed operation on the raw reviews and then encoded(using tokenizer api of keras) the processed reviews and trained all the models with the same .

Neural Bag Of Words + MLP Model

```
#fit network
model=define_model(n_words)
model.fit(Xtrain, ytrain, epochs=10, verbose=1)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_11 (Dense)             (None, 25)                369550
_________________________________________________________________
dense_12 (Dense)             (None, 1)                 26
=================================================================
Total params: 369,576
Trainable params: 369,576
Non-trainable params: 0
```

Embedding + 1D CNN Model .

```
embed_cnn_model.fit(cnn_Xtrain, ytrain, epochs=10, verbose=1)

# history=embed_cnn_model.fit(cnn_Xtrain, ytrain,validation_split=0.20 ,epochs=10, verbose=0,bat
ch_size=100,callbacks=callb)
```

N-Gram CNN Model

```
ncnn_model.fit( [ncnn_Xtrain,ncnn_Xtrain,ncnn_Xtrain,ncnn_Xtrain] , ytrain, epochs=7, batch_size
=16)
```

Refinement.

I experimented with my model quite a bit.I decreased the number of words in vocabulary.txt which resulted in better performance in **Embedding + 1D CNN Model** as well as **N-Gram CNN Model.**

I tried for different no of epochs, larges no of epochs led to worse performance for the **N-Gram CNN Model.** as well

as **Embedding + 1D CNN Model .**

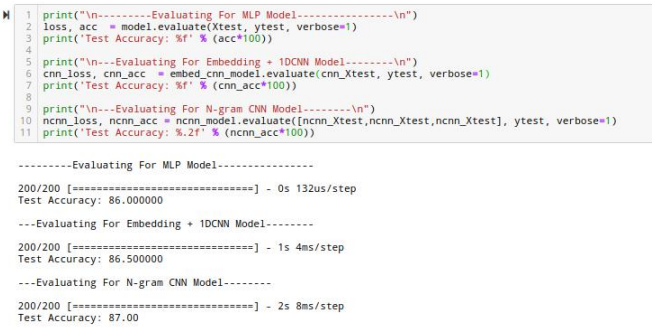
In N-Gram CNN Model , I experimented with different no of channels such as 2,3,4,5,6 with different kernel size for 1D CNN configuration but I got better results in the configuration as reported above.

Results

Model Evaluation and Validation.

As stated in the previous section,I experimented with my model by increasing/decreasing its epochs as well as changing no of channels in N-gram model,changing optimizers,including dropouts ,pooling layer in my model. In each model I got a slightly better result than the previous one.

Justification



```
print("\n---------Evaluating For MLP Model----------------\n")
loss, acc  = model.evaluate(Xtest, ytest, verbose=1)
print('Test Accuracy: %f' % (acc*100))

print("\n---Evaluating For Embedding + 1DCNN Model--------\n")
cnn_loss, cnn_acc  = embed_cnn_model.evaluate(cnn_Xtest, ytest, verbose=1)
print('Test Accuracy: %f' % (cnn_acc*100))

print("\n---Evaluating For N-gram CNN Model--------\n")
ncnn_loss, ncnn_acc = ncnn_model.evaluate([ncnn_Xtest,ncnn_Xtest,ncnn_Xtest], ytest, verbose=1)
print('Test Accuracy: %.2f' % (ncnn_acc*100))
```

```
---------Evaluating For MLP Model----------------

200/200 [==============================] - 0s 132us/step
Test Accuracy: 86.000000

---Evaluating For Embedding + 1DCNN Model--------

200/200 [==============================] - 1s 4ms/step
Test Accuracy: 86.500000

---Evaluating For N-gram CNN Model--------

200/200 [==============================] - 2s 8ms/step
Test Accuracy: 87.00
```

Due to stochastic nature of neural networks ,results kept varying in accuracy with a difference of 0.5-3.0 for each model ,but most time the later model was better from the earlier one.

But confidence of sentiment analysis kept getting better in each subsequent model.

Conclusion

Free Form Visualization

Analysis for Positive File.

	FILE_NAME	MLP		CNN		NCNN	
		SENTIMENT	PERCENT	SENTIMENT	PERCENT	SENTIMENT	PERCENT
0	pos_file0.txt	NEGATIVE	68.4756	NEGATIVE	60.1269	NEGATIVE	71.4369
1	pos_file1.txt	POSITIVE	63.4451	POSITIVE	89.2659	POSITIVE	57.2307
2	pos_file2.txt	POSITIVE	79.4919	POSITIVE	99.9031	POSITIVE	93.8895
3	pos_file3.txt	POSITIVE	63.6199	POSITIVE	84.136	NEGATIVE	62.6304
4	pos_file4.txt	POSITIVE	71.7437	POSITIVE	100	POSITIVE	99.9602
5	pos_file5.txt	POSITIVE	58.3309	POSITIVE	99.9953	POSITIVE	95.0724
6	pos_file6.txt	NEGATIVE	57.8446	NEGATIVE	86.5762	NEGATIVE	62.8652
7	pos_file7.txt	POSITIVE	66.0336	POSITIVE	99.6336	POSITIVE	95.6444
8	pos_file8.txt	POSITIVE	64.7007	POSITIVE	98.1397	POSITIVE	93.685
9	pos_file9.txt	POSITIVE	51.4868	POSITIVE	57.1966	POSITIVE	56.7932

Analysis for Negative File.

	FILE_NAME	MLP		CNN		NCNN	
		SENTIMENT	PERCENT	SENTIMENT	PERCENT	SENTIMENT	PERCENT
0	neg_file0.txt	NEGATIVE	69.1851	NEGATIVE	99.9608	NEGATIVE	97.4781
1	neg_file1.txt	NEGATIVE	85.5158	NEGATIVE	97.6648	NEGATIVE	96.1784
2	neg_file2.txt	NEGATIVE	79.9565	NEGATIVE	96.6374	NEGATIVE	90.2806
3	neg_file3.txt	NEGATIVE	84.9834	NEGATIVE	64.9796	NEGATIVE	70.162
4	neg_file4.txt	NEGATIVE	81.3019	NEGATIVE	99.5586	NEGATIVE	98.9984
5	neg_file5.txt	NEGATIVE	63.7474	NEGATIVE	59.4952	NEGATIVE	68.2308
6	neg_file6.txt	NEGATIVE	71.4874	NEGATIVE	95.7333	NEGATIVE	81.5003
7	neg_file7.txt	NEGATIVE	71.4874	NEGATIVE	95.7333	NEGATIVE	81.5003
8	neg_file8.txt	NEGATIVE	57.9819	NEGATIVE	57.1348	NEGATIVE	59.736
9	neg_file9.txt	NEGATIVE	67.6197	NEGATIVE	96.9229	NEGATIVE	86.7453

* Confidence % is lower in N-gram Cnn model as it has been trained on text containing approx 1000 or more words and is expecting more or atleast 1000 words.

Reflection

The following steps were taken to complete this process:

1 .Downloaded Dataset From the source.

2. Performed Development of Vocabulary.

3. Performed Data Cleaning.

4. Splitted Dataset into Train set and Test set.

5. Designed Model Architecture .

6. Evaluated.

This was the first time I dealt with predictive text analysis problem.I have learned a lot of new concepts from this project such Tokenization, Embedding Layers ,Multichannel Models as well steps involved in Data Cleaning Process .Most challenging part of the project was finding out the architecture of the N-Gram CNN model as well tunning hyperparameters.

Improvement

There are few ways in which I think more accuracy can be achieved on this accuracy :

1. Exploring better Data Cleaning procedure.
2. Exploring tuning CNN Hyperparameters.
3. Deeper Network
4. Longer Test Reviews.
5. Using Pre-Trained Embedding .such as Word2Vec or Glove.
6. Using Recurrent Neural Network.