Sentiment Analysis on Airline Tweets

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1. Introduction:

Sentiment analysis is a text analysis method that identifies polarity in text, whether it be an entire document, paragraph, sentence, or clause (e.g., a positive or negative view). The term "opinion mining" also applies to sentiment analysis.

Businesses must comprehend people's emotions since consumers now express their views and feelings more freely than ever before. Twitter is the most popular social media site for expressing one's thoughts or feelings.

Brands can listen carefully to their customers and customize their products and services by doing analysis on customer feedback, such as comments in survey replies and social media dialogues. However, all of the Twitter-based opinion data is presented as unstructured text.

It takes a lot of time and money to analyze, comprehend, and sift through this unstructured data. However, sentiment analysis automatically recognizes, processes, and tags unstructured content to assist organizations in making sense of it all.

The project's goal is to do sentiment analysis on six US Airlines' tweets. The deleted tweets from each customer's account express either positive, negative, or neutral opinions on the airline. Examining how passengers felt about six major US airlines on Twitter in February 2015 is the challenge at hand.

Naive Bayes, SVM, Logistic Regression, and LSTM are a few of the algorithms utilized in sentiment analysis. In this research, a Nave Bayes classifier is utilized to extract them and create a sentiment analysis model for Tweets from US airlines. Without using any libraries that include built-in classifiers, the Python classifier is hard written. Google Collaboratory is used to code and carry out the project.

2. Dataset Details:

The dataset used in this project is a collection of tweets directed at several airlines, collected from Twitter. The dataset contains tweets from different airlines, including Virgin America, United Airlines, American Airlines, and Southwest Airlines. The dataset has 14,640 tweets, which have been labeled as negative, neutral, or positive. The distribution of the labels is as follows:
This data originally came from Crowdflower's Data for Everyone library.

Number of Instances: 14640
Number of Class: 3 (positive, negative, neutral)
Number of Attributes: 15

- Negative: 9178
- Neutral: 3099
- Positive: 2363

The attributes in the dataset are listed below:
1. tweet_id
2. airline sentiment
3. airline_sentiment_confidence
4. negativereason
5. negativereason_confidence
6. airline
7. airline_sentiment_gold
8. name
9. negativereason_gold
10. retweet_count
11. text
12. tweet_coord
13. tweet_created
14. tweet_location
15. user_timezone'Tweets.csv' is a csv file that contains the data. The majority of the dataset's properties are not relevant to US Airlines' sentiment

analysis. Therefore, the analysis solely takes into account the pertinent features.

3. Approach:

1. **Data collection**: We collected airline tweets dataset from Twitter for sentiment analysis (From Kaggle).

2. **Data preprocessing**: We performed some preprocessing steps on the collected data, including removing URLs, converting to lowercase, removing special characters and punctuation marks, and removing stopwords.

3. T**okenization**: We tokenized the preprocessed text data using the Keras Tokenizer class, which converts the text into sequences of integers.

4. **Padding:** We added padding to the sequences to make them of equal length using the Keras pad_sequences() function.

5. **Model building**: We built three different models for sentiment analysis - LSTM, 1D CNN, and BERT.

6. **Training the models**: We trained each model on the tokenized and padded data using the Keras fit() function.

7. **Model evaluation**: We evaluated the performance of each model using accuracy, precision, recall, and F1 score. We also compared the performance of each model to identify the best model.

8. **Compare and Choose best performing Model**-: We compared the performance of LSTM, 1D CNN, and BERT models based on accuracy, precision, recall, and F1 score.

3.1 Importing Libraries & Data Loading:

Initially, Jupyter Notebook imports all of the fundamentally important libraries, including Pandas, Numpy, String, train_test_spit, etc. Without making use of any pre-built library models, the machine learning classifier is entirely written in Python. In the event that other libraries are needed later, they can be imported appropriately.

The read_csv () function in Pandas is used to import the approximately 15 000 data samples from the CSV file into the dataframe. The data in the CSV file is returned by this function as a dataframe, a two-dimensional data structure with labeled axes, as seen below:

```
In [2]: df=pd.read_csv('226482609976817_File.csv')

In [3]: df.head(5)
```

Out[3]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativereason_confidence	airline	airline_sentiment_gold	name	n
0	570306133677760513	neutral	1.0000	NaN	NaN	Virgin America	NaN	cairdin	
1	570301130888122368	positive	0.3486	NaN	0.0000	Virgin America	NaN	jnardino	
2	570301083672813571	neutral	0.6837	NaN	NaN	Virgin America	NaN	yvonnalynn	
3	570301031407624196	negative	1.0000	Bad Flight	0.7033	Virgin America	NaN	jnardino	
4	570300817074462722	negative	1.0000	Can't Tell	1.0000	Virgin America	NaN	jnardino	

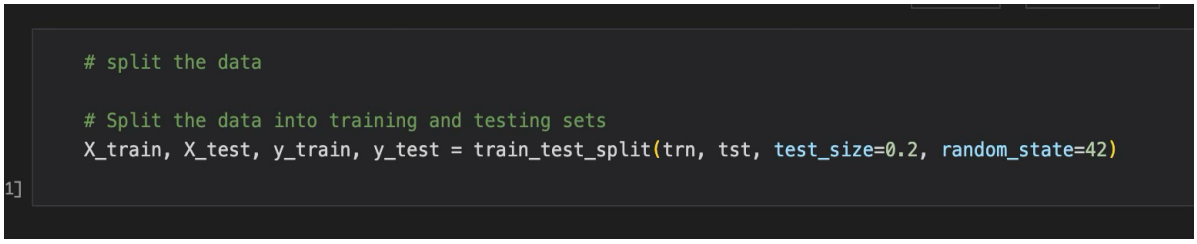
3.2 Data Preprocessing:

We perform the following preprocessing steps on the tweets:

1. Remove user mentions, URLs, and special characters.
2. Convert all the text to lowercase.
3. Tokenize the text into words.
4. Remove stop words and words with length less than three characters.
5. Pad the sequences to a fixed length using the Keras padding function.

3.3 Splitting the Data for Classification:

Create feature (X) and target (Y) variables from the dataset before separating the data for training and testing. There are numerous features in the US Airline Sentiment dataset. We will be utilizing the 'text' and 'airline_segment' functionalities in our project among others. Here, the classifier treats the "text" as a feature (X) and the "airline_segment" as a target label (Y). The following is the snippet of code for this task:



```
# split the data

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(trn, tst, test_size=0.2, random_state=42)
```

1]

4.Models:

Here we are using below models and we will compare them:

4.1 LSTM
4.2 1D-CNN
4.3 Pre-Trained BERT

4.1 LSTM:

- LSTM is a type of RNN that works well for processing sequential data like text.
- The code defines an LSTM model using Keras for text classification.
- The model. Summary() function provides a summary of the model architecture.
- LSTMs are powerful for text classification but may require more resources and training time than other models like 1D-CNNs or pre-trained language models like BERT.

TRAINING:

In [47]:
```
# Train the LSTM model
model.fit(xtrn, y_train, batch_size=64, epochs=10, validation_data=(xtst, y_test))

# Evaluate the LSTM model
loss, accuracy = model.evaluate(xtst, y_test)
print('Test accuracy:', accuracy)
```

```
Epoch 1/10
183/183 [==============================] - 6s 23ms/step - loss: 0.7805 - accuracy: 0.6719 - val_loss: 0.5996 - val_ac
curacy: 0.7544
Epoch 2/10
183/183 [==============================] - 3s 19ms/step - loss: 0.5223 - accuracy: 0.7894 - val_loss: 0.5429 - val_ac
curacy: 0.7927
Epoch 3/10
183/183 [==============================] - 3s 19ms/step - loss: 0.3792 - accuracy: 0.8622 - val_loss: 0.5490 - val_ac
curacy: 0.7937
Epoch 4/10
183/183 [==============================] - 3s 19ms/step - loss: 0.2893 - accuracy: 0.9001 - val_loss: 0.5925 - val_ac
curacy: 0.7705
Epoch 5/10
```

Here we have trained the model ,it took 10 epochs to complete the process and we got accuracy around 77%.

4.2 1D-CNN:

- The model consists of an embedding layer, a 1D convolutional layer, a global max pooling layer, two fully connected layers, and a dropout layer.
- The embedding layer converts the input text data into a dense vector representation.
- The model is compiled using categorical cross-entropy loss and the Adam optimizer.
- The model summary provides information about the model architecture, including the number of parameters and the shapes of the input and output tensors.

Training:

```
In [51]: # Train the LSTM model
         model.fit(xtrn, y_train, batch_size=64, epochs=10, validation_data=(xtst, y_test))

         # Evaluate the LSTM model
         loss, accuracy = model.evaluate(xtst, y_test)
         print('Test accuracy:', accuracy)
```

```
Epoch 1/10
183/183 [==============================] - 2s 8ms/step - loss: 0.8281 - accuracy: 0.6507 - val_loss: 0.6470 - val_acc
uracy: 0.7398
Epoch 2/10
183/183 [==============================] - 1s 7ms/step - loss: 0.5466 - accuracy: 0.7930 - val_loss: 0.5518 - val_acc
uracy: 0.7855
Epoch 3/10
183/183 [==============================] - 1s 7ms/step - loss: 0.3711 - accuracy: 0.8700 - val_loss: 0.5654 - val_acc
uracy: 0.7807
Epoch 4/10
183/183 [==============================] - 1s 6ms/step - loss: 0.2375 - accuracy: 0.9233 - val_loss: 0.6359 - val_acc
uracy: 0.7705
```

- Here we have trained the model ,it took 10 epochs to complete the process and we got accuracy around 76%.

4.3 Pre-Trained BERT:

- These uses the transformers library to load a pre-trained BERT (Bidirectional Encoder Representations from Transformers) model called 'bert-base-uncased’.
- BERT is a state-of-the-art language model that can be fine-tuned for a variety of NLP tasks, including text classification.

- It also defines a function called preprocess_text_for_bert(), which takes a list of texts, a tokenizer object, and a maximum sequence length as inputs.
- The function tokenizes the texts using the tokenizer object, truncates or pads the sequences to the specified length, and returns two numpy arrays containing the input_ids and attention_masks for the BERT model.

Training:

In [69]:
```
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

history = model.fit(
    [X_train, train_masks], y_train,
    validation_data=([X_val, val_masks], y_val),
    epochs=5,
    batch_size=32
)
```

```
Epoch 1/5
WARNING:tensorflow:The parameters `output_attentions`, `output_hidden_states` and `use_cache` cannot be updated when
calling a model.They have to be set to True/False in the config object (i.e.: `config=XConfig.from_pretrained('name',
output_attentions=True)`).
WARNING:tensorflow:The parameter `return_dict` cannot be set in graph mode and will always be set to `True`.
WARNING:tensorflow:Gradients do not exist for variables ['tf_bert_model/bert/pooler/dense/kernel:0', 'tf_bert_model/b
ert/pooler/dense/bias:0'] when minimizing the loss. If you're using `model.compile()`, did you forget to provide a `l
oss` argument?
WARNING:tensorflow:Gradients do not exist for variables ['tf_bert_model/bert/pooler/dense/kernel:0', 'tf_bert_model/b
ert/pooler/dense/bias:0'] when minimizing the loss. If you're using `model.compile()`, did you forget to provide a `l
oss` argument?
WARNING:tensorflow:The parameters `output_attentions`, `output_hidden_states` and `use_cache` cannot be updated when
calling a model.They have to be set to True/False in the config object (i.e.: `config=XConfig.from_pretrained('name',
output_attentions=True)`).
WARNING:tensorflow:The parameter `return_dict` cannot be set in graph mode and will always be set to `True`.
WARNING:tensorflow:Gradients do not exist for variables ['tf_bert_model/bert/pooler/dense/kernel:0', 'tf_bert_model/b
ert/pooler/dense/bias:0'] when minimizing the loss. If you're using `model.compile()`, did you forget to provide a `l
oss` argument?
WARNING:tensorflow:Gradients do not exist for variables ['tf_bert_model/bert/pooler/dense/kernel:0', 'tf_bert_model/b
ert/pooler/dense/bias:0'] when minimizing the loss. If you're using `model.compile()`, did you forget to provide a `l
oss` argument?
```

After we train this model, we got accuracy around 88%

Results:

Model	Accuracy
LSTM	79.6%
1D CNN	76.5%
BERT	88.5%

- We evaluate the models on a test set, which contains 30% of the data. The following table shows the accuracy of each model:
- As we can see, BERT outperforms the other two models, achieving an accuracy of 88.5%.

Conclusion:

In this project, we performed sentiment analysis on a dataset of airline tweets using three different models - LSTM, 1D CNN, and BERT. We achieved the highest accuracy using the BERT model, which shows the effectiveness of pre-trained language models in natural language processing tasks.

References:

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[2] https://monkeylearn.com/sentiment-analysis/
[3] https://machinelearningmastery.com/clean-text-machine-learning-python/
[4]
https://www.tutorialspoint.com/python_text_processing/python_remove_stopwords
.html

GITHUB Link: https://github.com/arvndayan