In this machine learning project, we build a binary text classifier to classify the sentiment behind the text. We use the various NLP preprocessing techniques to clean the data and utilize the LSTM layers to build the text classifier.

Python Sentiment Analysis Dataset

The dataset contains more than 14000 tweets data samples classified into 3 types: positive, negative, neutral

Please download the dataset for python sentiment analysis project: **Project Dataset**

Tools and Libraries used

- Python – 3.x
- Pandas – 1.2.4
- Matplotlib – 3.3.4
- TensorFlow – 2.4.1

To install the above modules into your local machine, run the following command in your command line.

```
pip install pandas matplotlib tensorflow
```

Download Sentiment Analysis Python Code

Please download the source code of python sentiment analysis project: **Sentiment Analysis Project Code**

Sentiment Analysis with Python

To build a machine learning model to accurately classify whether customers are saying positive or negative

Steps to build Sentiment Analysis Text Classifier in Python

1. Data Preprocessing

As we are dealing with the text data, we need to preprocess it using word embeddings.

Let's see what our data looks like.

```
import pandas as pd
df =
pd.read_csv("./DesktopDataFlair/Sentiment
-Analysis/Tweets.csv")
```

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativereason_confidence	airline	airline_sentiment_gold	name
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

We only need the text and sentiment column.

```
review_df =
df[['text','airline_sentiment']]

print(review_df.shape)
review_df.head(5)
```

```
(14640, 2)
```

Out[4]:

	text	airline_sentiment
0	@VirginAmerica What @dhepburn said.	neutral
1	@VirginAmerica plus you've added commercials t...	positive
2	@VirginAmerica I didn't today... Must mean I n...	neutral
3	@VirginAmerica it's really aggressive to blast...	negative
4	@VirginAmerica and it's a really big bad thing...	negative

There are more than 14,000 data samples in the sentiment analysis dataset.

Let's check the column names.

```
df.columns
```

```
Out[23]: Index(['tweet_id', 'airline_sentiment', 'airline_sentiment_confidence',
                'negativereason', 'negativereason_confidence', 'airline',
                'airline_sentiment_gold', 'name', 'negativereason_gold',
                'retweet_count', 'text', 'tweet_coord', 'tweet_created',
                'tweet_location', 'user_timezone'],
               dtype='object')
```

We don't really need neutral reviews in our dataset for this binary classification problem. So, drop those rows from the dataset.

```
review_df =
review_df[review_df['airline_sentiment']
!= 'neutral']

print(review_df.shape)
review_df.head(5)
```

```
(11541, 2)
```

Out[22]:

	text	airline_sentiment
1	@VirginAmerica plus you've added commercials t...	positive
3	@VirginAmerica it's really aggressive to blast...	negative
4	@VirginAmerica and it's a really big bad thing...	negative
5	@VirginAmerica seriously would pay $30 a figh...	negative
6	@VirginAmerica yes, nearly every time I fly VX...	positive

Check the values of the airline_sentiment column.

```
review_df["airline_sentiment"].value_coun
ts()
```

```
In [21]: tweet_df["airline_sentiment"].value_counts()
Out[21]: negative    9178
         positive    2363
         Name: airline_sentiment, dtype: int64
```

The labels for this dataset are categorical. Machines understand only numeric data. So, convert the categorical values to numeric using the factorize() method. This returns an array of numeric values and an Index of categories.

```
sentiment_label =
review_df.airline_sentiment.factorize()
sentiment_label
```

```
In [6]: sentiment_label = tweet_df.airline_sentiment.factorize()
        sentiment_label
Out[6]: (array([0, 1, 1, ..., 0, 1, 1], dtype=int64),
         Index(['positive', 'negative'], dtype='object'))
```

If you observe, the 0 here represents positive sentiment and the 1 represents negative sentiment.

Now, the major part in python sentiment analysis. We should transform our text data into something that our machine learning model understands. Basically, we

need to convert the text into an array of vector embeddings. Word embeddings are a beautiful way of representing the relationship between the words in the text.

To do this, we first give each of the unique words a unique number and then replace that word with the number assigned.

First, retrieve all the text data from the dataset.

```
tweet = review_df.text.values
```

Now, before proceeding ahead in python sentiment analysis project let's tokenize all the words in the text with the help of Tokenizer. In tokenization, we break down all the words/sentences of a text into small parts called tokens.

```
from tensorflow.keras.preprocessing.text
import Tokenizer

tokenizer = Tokenizer(num_words=5000)

tokenizer.fit_on_texts(tweet)
```

The fit_on_texts() method creates an association between the words and the assigned numbers. This association is stored in the form of a dictionary in the tokenizer.word_index attribute.

Now, replace the words with their assigned numbers using the text_to_sequence() method.

```
encoded_docs =
tokenizer.texts_to_sequences(tweet)
```

Each of the sentences in the dataset is not of equal length. Use padding to pad the sentences to have equal length.

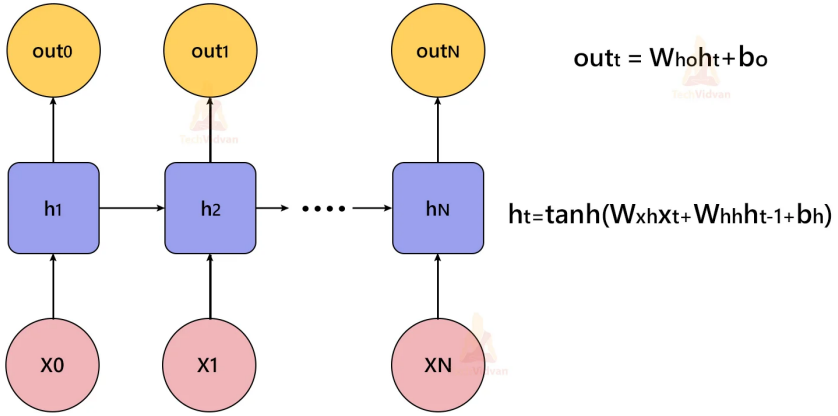
```
from
tensorflow.keras.preprocessing.sequence
import pad_sequences

padded_sequence =
pad_sequences(encoded_docs, maxlen=200)
```

2. Build the Text Classifier

For sentiment analysis project, we use LSTM layers in the machine learning model. The architecture of our model consists of an embedding layer, an LSTM layer, and a Dense layer at the end. To avoid overfitting, we introduced the Dropout mechanism in-between the LSTM layers.

LSTM stands for Long Short Term Memory Networks. It is a variant of Recurrent Neural Networks. Recurrent Neural Networks are usually used with sequential data such as text and audio. Usually, while computing an embedding matrix, the meaning of every word and its calculations (which are called hidden states) are stored. If the reference of a word, let's say a word is used after 100 words in a text, then all these calculations RNNs cannot store in its memory. That's why RNNs are not capable of learning these long-term dependencies.

LSTMs on the other hand work well with such text. LSTM networks work well with time-series data.



Dropout is one of the regularization techniques. It is used to avoid overfitting. In the dropout mechanism, we drop some neurons randomly. The layer takes an argument, a number between 0 and 1 that represents the probability to drop the neurons. This creates a robust model avoiding overfitting.

```
from tensorflow.keras.models import
Sequential
from tensorflow.keras.layers import
LSTM,Dense, Dropout, SpatialDropout1D
from tensorflow.keras.layers import
Embedding


embedding_vector_length = 32
model = Sequential()
model.add(Embedding(vocab_size,
embedding_vector_length,
```

```
input_length=200))
model.add(SpatialDropout1D(0.25))
model.add(LSTM(50, dropout=0.5,
recurrent_dropout=0.5))
model.add(Dropout(0.2))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy',
optimizer='adam', metrics=['accuracy'])

print(model.summary())
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 200, 32)           423488
_________________________________________________________________
spatial_dropout1d (SpatialDr (None, 200, 32)           0
_________________________________________________________________
lstm (LSTM)                  (None, 50)                16600
_________________________________________________________________
dropout (Dropout)            (None, 50)                0
_________________________________________________________________
dense (Dense)                (None, 1)                 51
=================================================================
Total params: 440,139
Trainable params: 440,139
Non-trainable params: 0
_________________________________________________________________
None
```

3. Train the sentiment analysis model

Train the sentiment analysis model for 5 epochs on the whole dataset with a batch size of 32 and a validation split of 20%.

```
history =
model.fit(padded_sequence,sentiment_label
[0],validation_split=0.2, epochs=5,
batch_size=32)
```

The output while training looks like below:

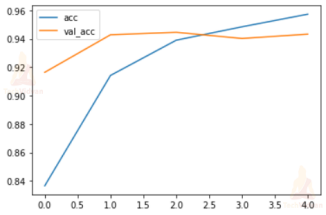
```
Epoch 1/5
289/289 [==============================] - 471s 2s/step - loss: 0.4916 - accuracy: 0.7980 - val_loss: 0.2133 - val_accuracy: 0.
9164
Epoch 2/5
289/289 [==============================] - 457s 2s/step - loss: 0.2282 - accuracy: 0.9118 - val_loss: 0.1624 - val_accuracy: 0.
9428
Epoch 3/5
289/289 [==============================] - 423s 1s/step - loss: 0.1755 - accuracy: 0.9340 - val_loss: 0.1667 - val_accuracy: 0.
9446
Epoch 4/5
289/289 [==============================] - 420s 1s/step - loss: 0.1292 - accuracy: 0.9519 - val_loss: 0.1678 - val_accuracy: 0.
9402
Epoch 5/5
289/289 [==============================] - 420s 1s/step - loss: 0.1117 - accuracy: 0.9600 - val_loss: 0.1818 - val_accuracy: 0.
9433
```

The python sentiment analysis model obtained 96% accuracy on the training set and 94.33% accuracy on the test set.

Let's plot these metrics using the matplotlib.

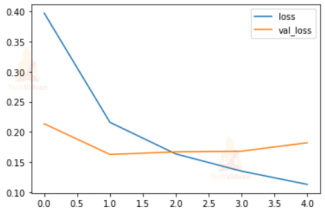
```
import matplotlib.pyplot as plt

plt.plot(history.history['accuracy'],
label='acc')
plt.plot(history.history['val_accuracy'],
label='val_acc')
plt.legend()
plt.show()

plt.savefig("Accuracy plot.jpg")
```

Output:




```
plt.plot(history.history['loss'],
label='loss')
plt.plot(history.history['val_loss'],
label='val_loss')

plt.legend()
plt.show()

plt.savefig("Loss plt.jpg")
```

Output:



Let's execute sentiment analysis model

Define a function that takes a text as input and outputs its prediction label.

```
def predict_sentiment(text):
    tw =
tokenizer.texts_to_sequences([text])
    tw = pad_sequences(tw,maxlen=200)
    prediction =
int(model.predict(tw).round().item())
    print("Predicted label: ",
sentiment_label[1][prediction])


test_sentence1 = "I enjoyed my journey on
this flight."
predict_sentiment(test_sentence1)

test_sentence2 = "This is the worst
flight experience of my life!"
predict_sentiment(test_sentence2)
```

Python Sentiment Analysis Output

```
In [19]: test_sentence1 = "I enjoyed my journey on this flight."
         predict_sentiment(test_sentence1)

         test_sentence2 = "This is the worst flight experience of my life!"
         predict_sentiment(test_sentence2)

         Predicted label:  positive
         Predicted label:  negative
```

Summary

We have successfully developed python sentiment analysis model. In this machine learning project, we