In [101]:

```
import pandas as pd
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, c
all drive.mount("/content/drive", force_remount=True).
```

In [102]:

```
path = "/content/drive/MyDrive/Tweets.csv"
df = pd.read_csv(path)
df.head()
```

Out[102]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativereas
0	5.703060e+17	neutral	1.0000	NaN	
1	5.703010e+17	positive	0.3486	NaN	
2	5.703010e+17	neutral	0.6837	NaN	
3	5.703010e+17	negative	1.0000	Bad Flight	
4	5.703010e+17	negative	1.0000	Can't Tell	

Only text and sentiment columns are required

In [103]:

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

print(imp_df.shape)
imp_df.head()
```

```
(14640, 2)
```

Out[103]:

	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

In [104]:

```
df.columns
```

Out[104]:

```
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')
```

Neutral values are not required as we are doing binary classification

In [105]:

```
imp_df = imp_df[imp_df['airline_sentiment'] != 'neutral']
print(imp_df.shape)
imp_df.head()
```

```
(11541, 2)
```

Out[105]:

	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 fligh...	negative
6	@VirginAmerica yes, nearly every time I fly VX...	positive

In [106]:

```
imp_df["airline_sentiment"].value_counts()
```

Out[106]:

```
negative    9178
positive    2363
Name: airline_sentiment, dtype: int64
```

Dealing with categorical values and converting them into numeric

In [107]:

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

Out[107]:

```
(array([0, 1, 1, ..., 0, 1, 1]),
 Index(['positive', 'negative'], dtype='object'))
```

In [108]:

```
# positive: 0, negative: 1
tweet = imp_df.text.values
```

Creating small tokens of words from sentences

In [109]:

```
from tensorflow.keras.preprocessing.text import Tokenizer
tokenizer = Tokenizer(num_words=5000)
tokenizer.fit_on_texts(tweet)
```

After binding the words with their assigned numbers, we replace the words with their assigned numbers

In [110]:

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

Padding the sentences to make them of equal length

In [111]:

```
from tensorflow.keras.preprocessing.sequence import pad_sequences
padded_sequence = pad_sequences(encoded_docs, maxlen=200)
```

Regularisation to avoid overfitting

In [112]:

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

In [113]:

```
embedding_vector_length = 32
vocab_size = len(tokenizer.word_index) + 1
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_12"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_9 (Embedding)     (None, 200, 32)           423488    
                                                                 
 spatial_dropout1d_9 (Spatia  (None, 200, 32)          0         
 lDropout1D)                                                     
                                                                 
 lstm_9 (LSTM)               (None, 50)                16600     
                                                                 
 dropout_9 (Dropout)         (None, 50)                0         
                                                                 
 dense_9 (Dense)             (None, 1)                 51        
                                                                 
=================================================================
Total params: 440,139
Trainable params: 440,139
Non-trainable params: 0
_________________________________________________________________
None
```

Training the model

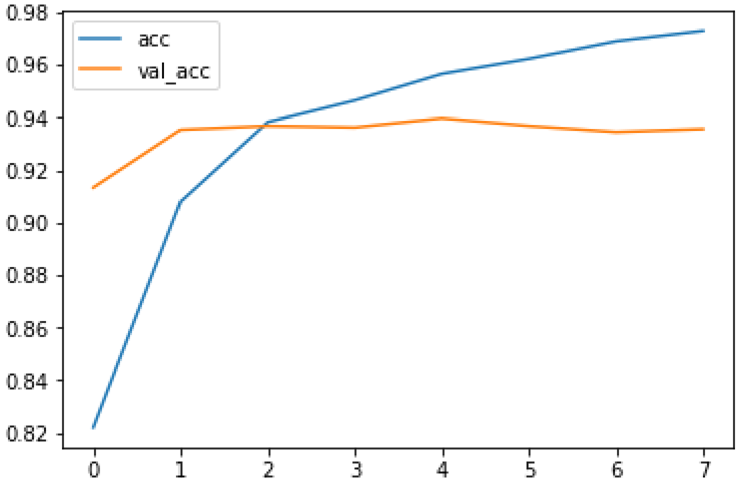
In [114]:

```
history = model.fit(padded_sequence,sentiment_label[0],validation_split=0.3, epochs=8,
batch_size=32)
```

```
Epoch 1/8
253/253 [==============================] - 40s 149ms/step - loss: 0.4267 -
accuracy: 0.8221 - val_loss: 0.2209 - val_accuracy: 0.9134
Epoch 2/8
253/253 [==============================] - 37s 148ms/step - loss: 0.2344 -
accuracy: 0.9080 - val_loss: 0.1709 - val_accuracy: 0.9353
Epoch 3/8
253/253 [==============================] - 37s 148ms/step - loss: 0.1722 -
accuracy: 0.9382 - val_loss: 0.1679 - val_accuracy: 0.9368
Epoch 4/8
253/253 [==============================] - 39s 152ms/step - loss: 0.1387 -
accuracy: 0.9465 - val_loss: 0.1778 - val_accuracy: 0.9362
Epoch 5/8
253/253 [==============================] - 38s 149ms/step - loss: 0.1177 -
accuracy: 0.9565 - val_loss: 0.1869 - val_accuracy: 0.9396
Epoch 6/8
253/253 [==============================] - 38s 150ms/step - loss: 0.0986 -
accuracy: 0.9622 - val_loss: 0.1993 - val_accuracy: 0.9368
Epoch 7/8
253/253 [==============================] - 37s 148ms/step - loss: 0.0854 -
accuracy: 0.9689 - val_loss: 0.2007 - val_accuracy: 0.9344
Epoch 8/8
253/253 [==============================] - 38s 149ms/step - loss: 0.0735 -
accuracy: 0.9729 - val_loss: 0.2439 - val_accuracy: 0.9356
```

In [115]:

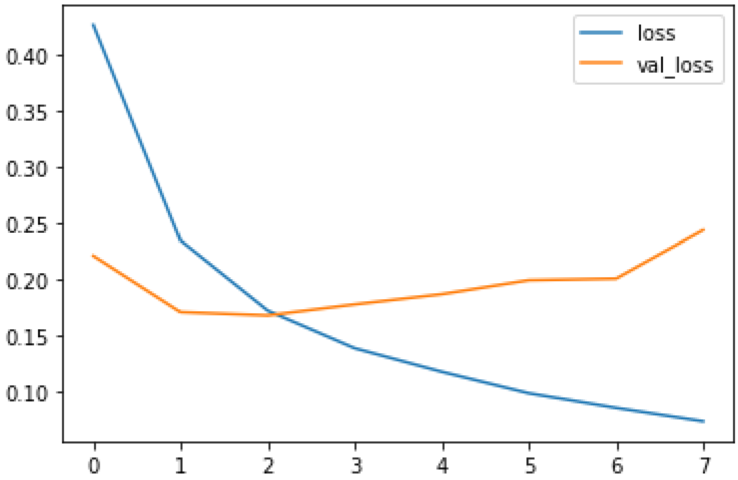
```
import matplotlib.pyplot as plt
plt.plot(history.history['accuracy'], label='acc')
plt.plot(history.history['val_accuracy'], label='val_acc')
plt.legend()
plt.show()
plt.savefig("Accuracy Plot.jpg")
```



```
<Figure size 432x288 with 0 Axes>
```

In [116]:

```
plt.plot(history.history['loss'], label='loss')
plt.plot(history.history['val_loss'], label='val_loss')
plt.legend()
plt.show()
plt.savefig("Loss Plot.jpg")
```



```
<Figure size 432x288 with 0 Axes>
```

Predicting the sentiment of sentences

In [119]:

```
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 love going to theme parks and fun fairs."
print("Sentence 1: ", test_sentence1)
predict_sentiment(test_sentence1)
test_sentence2 = "Traffic noise makes me frustrated and angry."
print("Sentence 2: ", test_sentence2)
predict_sentiment(test_sentence2)
```

```
Sentence 1:  I love going to theme parks and fun fairs.
Predicted Label:  positive
Sentence 2:  Traffic noise makes me frustrated and angry.
Predicted Label:  negative
```