14_Amazon_Food_Reviews_LSTM

April 14, 2019

In [1]:
```
# data frame related packages
import pandas as pd
import numpy as np
from datetime import datetime

# database related packages
import sqlite3

# package for converting words to count values
from sklearn.feature_extraction.text import CountVectorizer


# import LSTM related packages
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout
from keras.layers.embeddings import Embedding
from keras.callbacks import ModelCheckpoint # for checkpoint of model

# package for zero padding
from keras.preprocessing import sequence

# fix random seed for reproducibility
np.random.seed(7)

# visualization related packages
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()

# model evaluation related packages
from sklearn.metrics import precision_recall_fscore_support
from sklearn.metrics import confusion_matrix
```

```
/home/amd_3/anaconda3/lib/python3.6/site-packages/h5py/__init__.py:36: FutureWarning: Conversion
  from ._conv import register_converters as _register_converters
```

```
Using TensorFlow backend.
```

1 Data Fetching and Preprocessing

```
In [2]: db_path = '/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/final.sqlite'
        # declare vocabulary size
        vocab_size = 9999

In [3]: def get_number_format_data(db_path, vocab_size):

            """
            This function convert the data into a format which is suitable for LSTM training.
            All rows will be converted into a list of numbers
            """

            # create a connection object
            con = sqlite3.connect(db_path)

            # read from database
            df_db = pd.read_sql_query('SELECT Time, CleanedText, Label from Reviews', con)

            # combine all texts into a bigger text
            temp = str()
            for rev_txt in df_db['CleanedText']:
                temp += rev_txt + ' '

            # get BoW represntation to get count of each word
            bow_obj = CountVectorizer()
            count_info = bow_obj.fit_transform([temp])

            # get the word and its count in list of tuples form
            word_count_list = list(zip(bow_obj.get_feature_names(), count_info.toarray()[0]))

            # sort the data in descending order of count
            sorted_word_cnt_list = sorted(word_count_list, reverse=True, key=lambda x: x[1])[0:v

            # assign rank to each word
            word_rank_list = [(val[0], index + 1) for index, val in enumerate(sorted_word_cnt_li

            # create a dictionary where key = word and value = rank.
            rank_dict = dict(word_rank_list)


            # declare a list to save number format review for all reviews
            all_review_num_list = list()
```

```python
        # process each review one by one
        for rev_txt in df_db['CleanedText']:

            # get a list of words
            rev_txt_list = rev_txt.split()

            # declare a list for number format
            num_list = list()

            # get rank representation for each word
            for word in rev_txt_list:
                try:
                    num_list.append(rank_dict[word])
                except:
                    pass

            # update the list
            all_review_num_list.append(num_list)

        # create the final data frame for LSTM model
        df = pd.DataFrame({'Features': all_review_num_list,
                           'Label': df_db['Label'], 'Time': df_db['Time']})
        # align the columns of data frame
        df = df[['Time', 'Features', 'Label']]

        # remove all zero lenght reviews
        df = df[df['Features'].apply(len) > 0 ]

        return df
```

In [4]:
```python
start_ts = datetime.now()
final_df = get_number_format_data(db_path, vocab_size)
end_ts = datetime.now()
print('Total time', end_ts - start_ts)
```

```
Total time 0:00:18.003695
```

In [5]:
```python
final_df.head()
```

Out[5]:

	Time	Features	Label
0	939340800	[30, 1076, 17, 362, 2383, 3193, 1111, 1188, 53...	1
1	940809600	[530, 137, 652, 937, 6302, 46, 303, 968, 1131,...	1
2	944092800	[4339, 36, 1975, 1203, 334, 166, 1776, 447, 46...	1
3	944438400	[1550, 3808, 2599, 184, 2531, 5705, 8127, 5801...	1
4	946857600	[4339, 166, 1414, 1203, 5705, 5373, 4339, 10, ...	1

In [6]:
```python
def get_train_test_split(final_df):
    """
```

```
        This function split the data into train and test. It balances the train data.
        """

        # consider first 237800 points for generating train sample and remaining for  test s
        # within 237800 points we have 35000 - ve samples and others are +ve, from this set
        # can take a sample of 35000 +ve, so we will have a balanced data set having 35K +ve
        # points which is apt for training the model

        # partiton the data for train, test data set generation
        final_df_train = final_df[0:237800]
        final_df_test = final_df[237800:]

        # partition the data frame to positive and negative
        final_df_positive = final_df_train[final_df_train['Label'] == 1]
        final_df_negative = final_df_train[final_df_train['Label'] == 0]

        # since positive sample is dominating we select 30K samples randomly from the positi
        #  take whole negative samples
        final_df_positive = final_df_positive.sample(n=35000)

        # form train sample set
        final_train_df = final_df_positive.append(final_df_negative)
        final_train_df = final_train_df.sample(frac=1.0)
        final_train_df = final_train_df.reset_index(drop=True)

        # sample 30K points for testing
        final_test_df = final_df_test.sample(n=30000)
        final_test_df = final_test_df.reset_index(drop=True)

        print('Final train df statistics:\n', final_train_df['Label'].value_counts())
        print('\n\nFinal test df statistics:\n', final_test_df['Label'].value_counts())

        return (final_train_df, final_test_df,)
```

In [7]:
```
final_train_df, final_test_df = get_train_test_split(final_df)
```

```
Final train df statistics:
 1    35000
0    34997
Name: Label, dtype: int64


Final test df statistics:
 1    24675
0     5325
Name: Label, dtype: int64
```

In [8]:
```
final_test_df.head()
```

```
Out[8]:          Time                                           Features  Label
        0  1344816000  [137, 553, 591, 693, 7, 258, 599, 431, 1832, 8...      1
        1  1325980800  [8, 85, 1627, 2060, 357, 1286, 8522, 45, 120, ...      1
        2  1337126400  [383, 19, 532, 39, 141, 95, 1828, 51, 539, 405...      1
        3  1349740800  [4374, 2102, 15, 3997, 2171, 130, 159, 15, 193...      1
        4  1347408000  [72, 919, 1, 35, 13, 2551, 3565, 51, 744, 101,...      1
```

```
In [9]: # get train dataset
        y_train = final_train_df['Label']
        X_train = final_train_df['Features'].values
        # get test dataset
        y_test = final_test_df['Label']
        X_test = final_test_df['Features'].values
```

```
In [10]: max_seq_length = 900
         X_train = sequence.pad_sequences(X_train, maxlen=max_seq_length)
         X_test = sequence.pad_sequences(X_test, maxlen=max_seq_length)

         print(X_train.shape)
         print(X_train[1])
```

```
(69997, 900)
[   0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
```

```
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    1  154 3507  692   68
  504 1340   16   41  313   68 1340  329 1340  675   20   29  675  983
    2  534  130   41  225 6266  572    1  189   20  109  240   18   37
  602   41   51  252]
```

2 UTIL functions

```
In [11]: def plot_loss_curve(train_metric_list, val_metric_list):
             """
             This function plots the loss curve
             """
```

```
        # get x-label list
        epcoh_list = range(1, len(train_metric_list) + 1 )

        # get train_accuracy data
        train_acc_list = [ item[0] for item in train_metric_list]

        # get validation accuracy data
        val_acc_list = [ item[0] for item in val_metric_list]

        # plot both train, validation curve
        plt.plot(epcoh_list, train_acc_list, label='Train Loss', color='r')
        plt.plot(epcoh_list, val_acc_list, label='Validation Loss', color='b')
        plt.xlabel('Training Epoch')
        plt.ylabel('Cross Entropy Error')
        plt.title('Training Loss Vs Validation Loss')
        plt.legend()
        plt.show()
```

```
In [12]: def plot_accuracy_curve(train_metric_list, val_metric_list):
             """
             This is a helper function for plotting accuracy
             """

             # get x-label list
             epcoh_list = range(1, len(train_metric_list) + 1 )

             # get train_accuracy data
             train_acc_list = [ item[1] for item in train_metric_list]

             # get validation accuracy data
             val_acc_list = [ item[1] for item in val_metric_list]

             # plot both train, validation curve
             plt.plot(epcoh_list, train_acc_list, label='Train Accuracy', color='r')
             plt.plot(epcoh_list, val_acc_list, label='Validation Accuracy', color='b')
             plt.xlabel('Training Epoch')
             plt.ylabel('Accuracy')
             plt.title('Training Accuracy Vs Validation Accuracy')
             plt.legend()
             plt.show()
```

```
In [13]: def get_confusion_matrix(actual_list, predicted_list, cm_title):
             """
             This function plots confusion matrix for test data set
             """

             conf_matrix = confusion_matrix(actual_list, predicted_list)
```

```
            col_names = ['Negative', 'Positive']
            conf_df = pd.DataFrame(conf_matrix,columns=col_names)
            conf_df.index = col_names

            plt.figure(figsize = (5,5))

            plt.title(cm_title)
            sns.set(font_scale=1.4)#for label size
            sns.heatmap(conf_df, annot=True, annot_kws={"size": 16}, fmt='g')

            plt.show()
```

3 MODEL

```
In [14]: vocabulary_size = 10000
         max_input_length = 900
```

3.1 A) Single layered LSTM Architecture

```
In [15]: def single_layer_lstm(h_params, vocabulary_size, max_input_length):
             """
             A function which builds single layered LSTM
             """

             # define the embedding length
             embedding_vecor_length = 32

             # set the number of LSTM units for each layer
             drop_rate = h_params[0]
             num_hidden_units_1 = h_params[1]

             # declare the model
             model = Sequential()

             # add layers to the model
             model.add(Embedding(vocabulary_size, embedding_vecor_length, input_length=max_input
             model.add(LSTM(num_hidden_units_1))
             model.add(Dropout(drop_rate))
             model.add(Dense(1, activation='sigmoid'))

             print(model.summary())

             return model
```

3.2 B) Multilayered LSTM Architecture

```
In [16]: def multi_layer_lstm(h_params, vocabulary_size, max_input_length):
```

```
    """
    A function which builds multi layered (2-layers) LSTM
    """

    # define the embedding length
    embedding_vecor_length = 32

    # set the number of LSTM units for each layer
    drop_rate = h_params[0]
    num_hidden_units_1 = h_params[1]
    num_hidden_units_2 = h_params[2]


    # declare the model
    model = Sequential()

    # add layers to the model
    model.add(Embedding(vocabulary_size, embedding_vecor_length, input_length=max_input
    model.add(LSTM(num_hidden_units_1, return_sequences=True))
    model.add(LSTM(num_hidden_units_2))
    model.add(Dropout(drop_rate)) # dropout layer for reducing overfit
    model.add(Dense(1, activation='sigmoid'))

    print(model.summary())

    return model
```

3.3 UTIL function to train models

```
In [17]: def train_and_evaluate_model(model, model_file_path, num_epochs, X_train, y_train, X_te
    """
    This function train a given model and evaluate its performance on test data set
    """

    # set the loss function, optimizer and evaluation metric
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

    # monitor the performace of model on  every epoch
    checkpoint = ModelCheckpoint(model_file_path, monitor='val_loss', verbose=1,
                                 save_best_only=True, mode='auto')
    callbacks_list = [checkpoint]


    # Train the model
    hist_obj = model.fit(X_train, y_train, nb_epoch=num_epochs, batch_size=128, validat
                         callbacks=callbacks_list)
    hist_obj = hist_obj.history
```

```python
# load weights from the saved model
model.load_weights(model_file_path)

# Compile model (required to make predictions)
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
print('Restored best model weights from saved file')

train_metric_list = list(zip(hist_obj['loss'], hist_obj['acc']))
validation_metric_list = list(zip(hist_obj['val_loss'], hist_obj['val_acc']))

# plot the performace
plot_loss_curve(train_metric_list, validation_metric_list)
plot_accuracy_curve(train_metric_list, validation_metric_list)

# get the loss and accuracy on test data
scores = model.evaluate(X_test, y_test, verbose=0)
scores[1] *= 100
print('Test loss:%f, Test Accuracy:%f'%tuple(scores))

# predict the test data points class
predicted = model.predict_classes(X_test)

# compute precision, recall, fscore and class support values
all_metrics = precision_recall_fscore_support(y_test, predicted.flatten())

# create a data frame having records of all the above metrics
all_metrics_df = pd.DataFrame(list(all_metrics), columns=['Negative', 'Positive'])
all_metrics_df.index = ['Precision', 'Recall', 'Fscore', 'Support']

fscores = all_metrics[2]
fscores *=  100

# display the confusion matrix
cm_title = 'LSTM Confusion Matrix'
get_confusion_matrix(y_test, predicted, cm_title)

print(all_metrics_df.head())

# return all the required test metrics, to save in a table
test_metrics = scores + list(fscores)

# round all results upto four decimal places
test_metrics = [ '%.4f' % item for item in test_metrics]

return test_metrics
```

3.4 Train and Evaluate each model

3.4.1 a) Single layered architecture 1

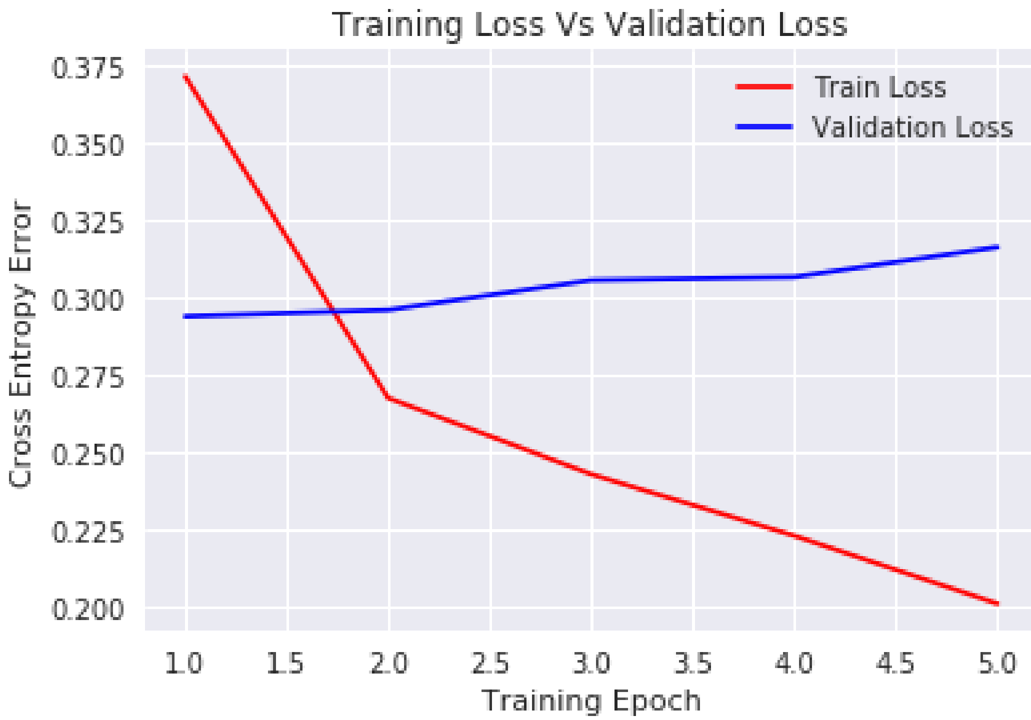
```
In [18]: # crete model object
         h_params_s_a1 = (0.10, 80,)
         model_obj = single_layer_lstm(h_params_s_a1, vocabulary_size, max_input_length)

         # checkpoint
         num_epochs = 5
         model_file_path = 'single_a1_weights.best.hdf5'
         # train and evaluate the model
         test_metrics_s_a1 = train_and_evaluate_model(model_obj, model_file_path, num_epochs, X_
                                                      X_test, y_test)
```

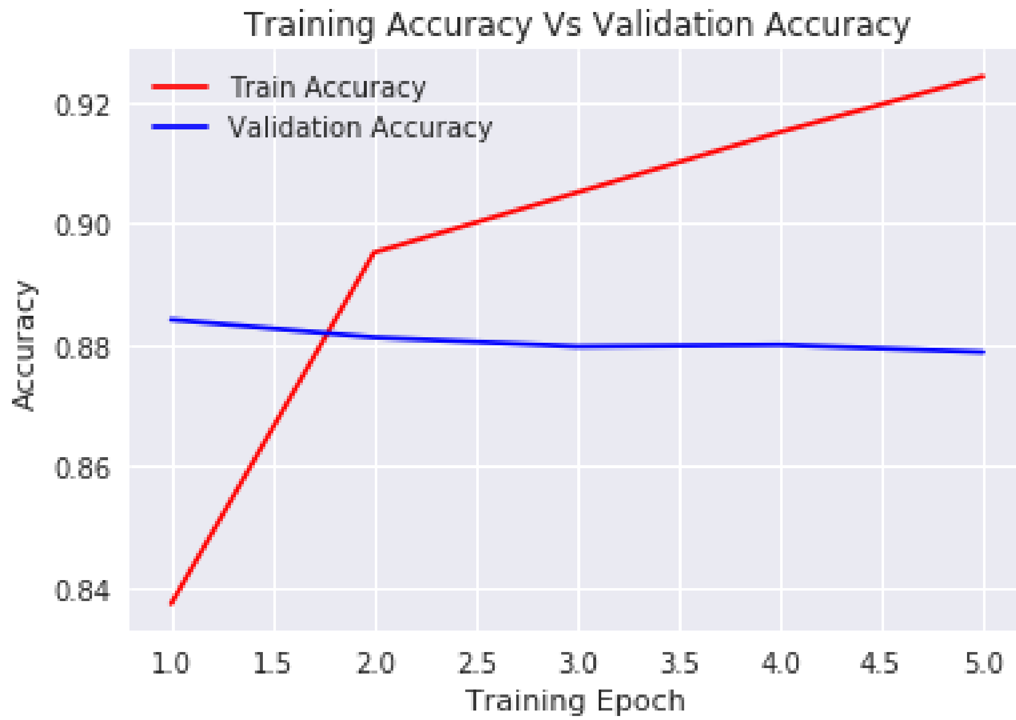
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 900, 32)           320000
_________________________________________________________________
lstm_1 (LSTM)                (None, 80)                36160
_________________________________________________________________
dropout_1 (Dropout)          (None, 80)                0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 81
=================================================================
Total params: 356,241
Trainable params: 356,241
Non-trainable params: 0
_________________________________________________________________
None
```

```
/home/amd_3/anaconda3/lib/python3.6/site-packages/keras/models.py:939: UserWarning: The `nb_epoc
  warnings.warn('The `nb_epoch` argument in `fit` '
```

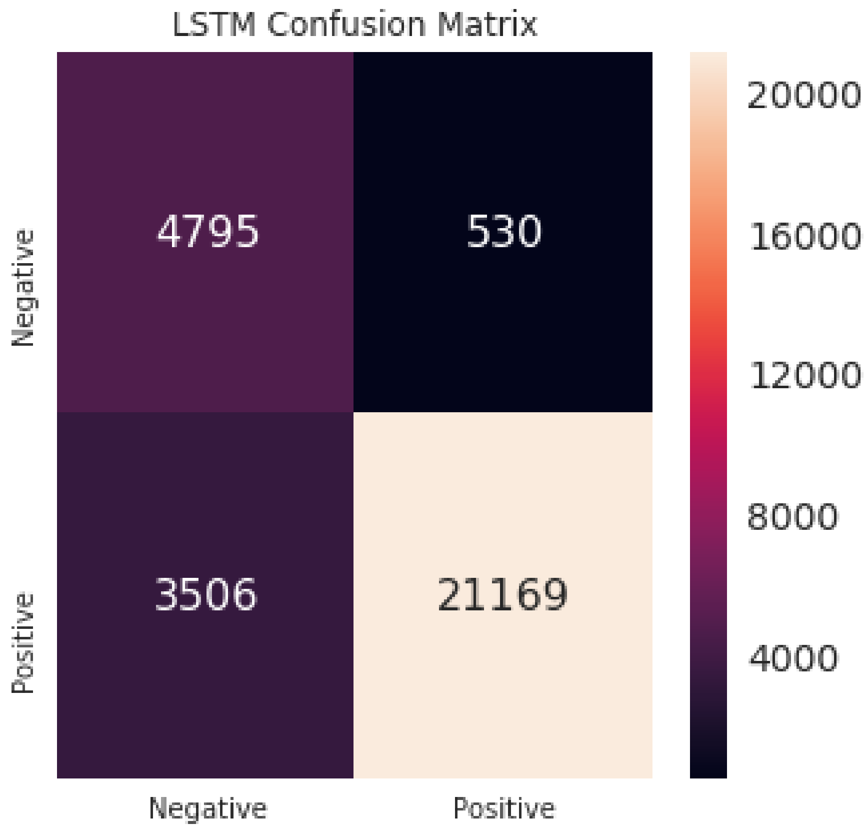
```
Train on 55997 samples, validate on 14000 samples
Epoch 1/5
55936/55997 [============================>.] - ETA: 0s - loss: 0.3714 - acc: 0.8373Epoch 00001:
55997/55997 [==============================] - 762s 14ms/step - loss: 0.3713 - acc: 0.8373 - val
Epoch 2/5
55936/55997 [============================>.] - ETA: 0s - loss: 0.2676 - acc: 0.8951Epoch 00002:
55997/55997 [==============================] - 788s 14ms/step - loss: 0.2675 - acc: 0.8952 - val
Epoch 3/5
55936/55997 [============================>.] - ETA: 0s - loss: 0.2429 - acc: 0.9051Epoch 00003:
55997/55997 [==============================] - 791s 14ms/step - loss: 0.2430 - acc: 0.9051 - val
Epoch 4/5
55936/55997 [============================>.] - ETA: 0s - loss: 0.2231 - acc: 0.9151Epoch 00004:
```

```
55997/55997 [==============================] - 817s 15ms/step - loss: 0.2231 - acc: 0.9150 - val
Epoch 5/5
55936/55997 [============================>.] - ETA: 0s - loss: 0.2012 - acc: 0.9241Epoch 00005:
55997/55997 [==============================] - 857s 15ms/step - loss: 0.2011 - acc: 0.9242 - val
Restored best model weights from saved file
```






```
Test loss:0.324790, Test Accuracy:86.546667
```




```
             Negative      Positive
Precision    0.577641      0.975575
Recall       0.900469      0.857913
Fscore       0.703802      0.912968
Support   5325.000000  24675.000000
```

3.4.2 b) Single layered architecture 2

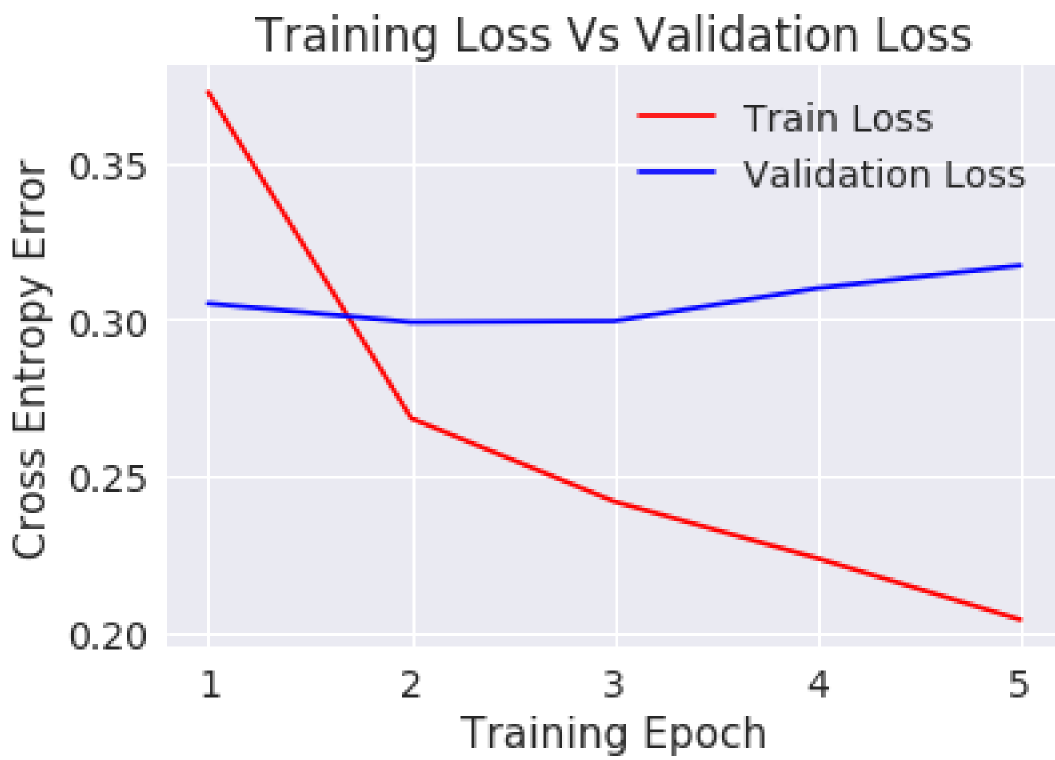
```
In [19]: # crete model object
         h_params_s_a2 = (0.15, 100,)
         model_obj = single_layer_lstm(h_params_s_a2, vocabulary_size, max_input_length)

         # checkpoint
         num_epochs = 5
         model_file_path = 'single_a2_weights.best.hdf5'
         # train and evaluate the model
         test_metrics_s_a2 = train_and_evaluate_model(model_obj, model_file_path, num_epochs, X_
                                                      X_test, y_test)
```

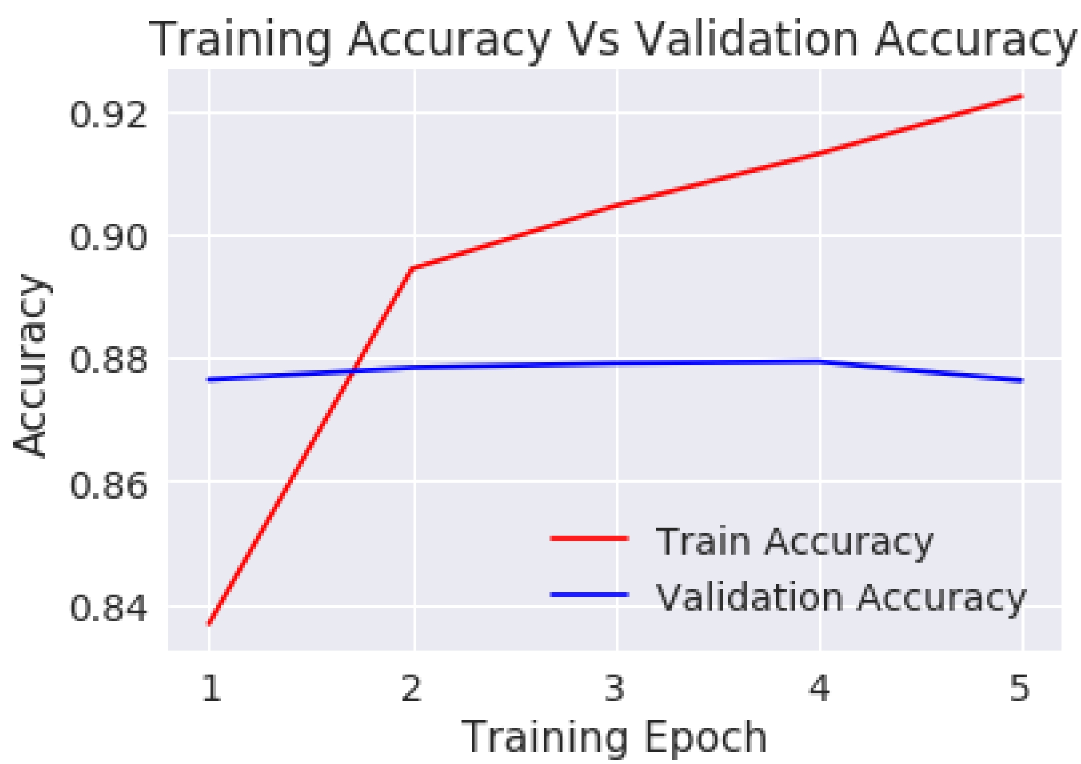
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
```

```
=================================================================
embedding_2 (Embedding)      (None, 900, 32)          320000
_________________________________________________________________
lstm_2 (LSTM)                (None, 100)              53200
_________________________________________________________________
dropout_2 (Dropout)          (None, 100)              0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                101
=================================================================
Total params: 373,301
Trainable params: 373,301
Non-trainable params: 0
_________________________________________________________________
None
```

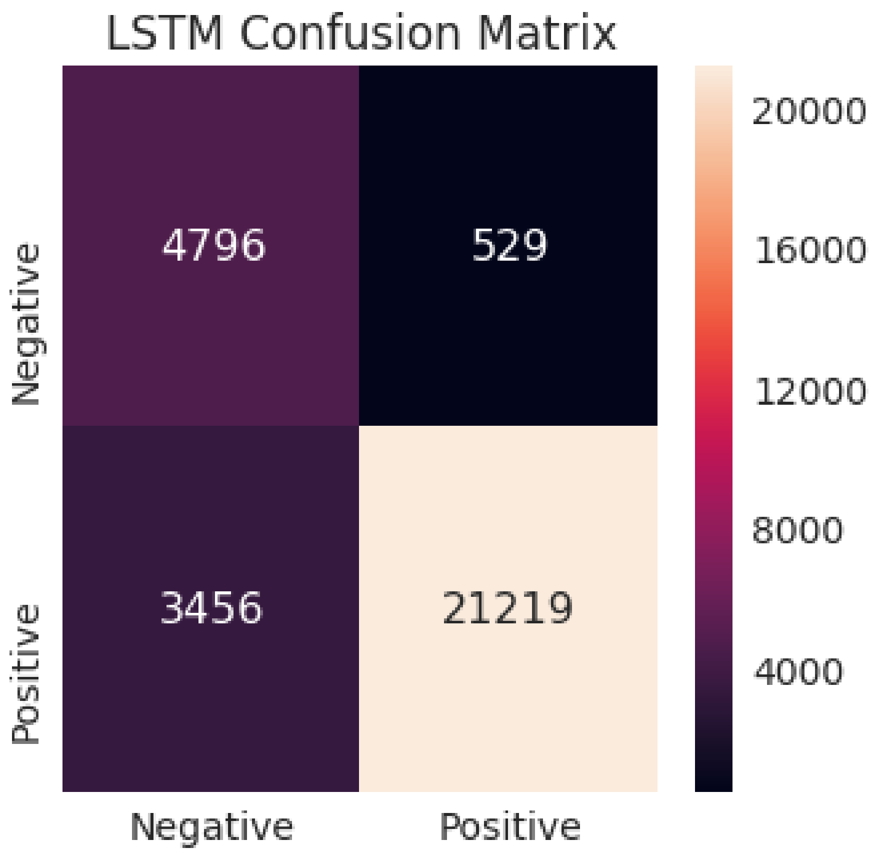
```
/home/amd_3/anaconda3/lib/python3.6/site-packages/keras/models.py:939: UserWarning: The `nb_epoc
  warnings.warn('The `nb_epoch` argument in `fit` '
```

```
Train on 55997 samples, validate on 14000 samples
Epoch 1/5
55936/55997 [============================>.] - ETA: 1s - loss: 0.3726 - acc: 0.8368Epoch 00001:
55997/55997 [==============================] - 1036s 18ms/step - loss: 0.3725 - acc: 0.8368 - va
Epoch 2/5
55936/55997 [============================>.] - ETA: 0s - loss: 0.2684 - acc: 0.8943Epoch 00002:
55997/55997 [==============================] - 955s 17ms/step - loss: 0.2684 - acc: 0.8943 - val
Epoch 3/5
55936/55997 [============================>.] - ETA: 0s - loss: 0.2418 - acc: 0.9046Epoch 00003:
55997/55997 [==============================] - 949s 17ms/step - loss: 0.2419 - acc: 0.9045 - val
Epoch 4/5
55936/55997 [============================>.] - ETA: 0s - loss: 0.2238 - acc: 0.9129Epoch 00004:
55997/55997 [==============================] - 958s 17ms/step - loss: 0.2238 - acc: 0.9129 - val
Epoch 5/5
55936/55997 [============================>.] - ETA: 0s - loss: 0.2040 - acc: 0.9223Epoch 00005:
55997/55997 [==============================] - 950s 17ms/step - loss: 0.2042 - acc: 0.9223 - val
Restored best model weights from saved file
```


Training Loss Vs Validation Loss
Train Loss
Validation Loss
Cross Entropy Error
0.35
0.30
0.25
0.20
1
2
3
4
5
Training Epoch


Training Accuracy Vs Validation Accuracy
0.92
0.90
0.88
0.86
0.84
Accuracy
Train Accuracy
Validation Accuracy
1
2
3
4
5
Training Epoch

```
Test loss:0.313953, Test Accuracy:86.716667
```




```
              Negative       Positive
Precision     0.581192       0.975676
Recall        0.900657       0.859939
Fscore        0.706489       0.914159
Support    5325.000000   24675.000000
```

3.4.3 c) Multi layered architecture 1

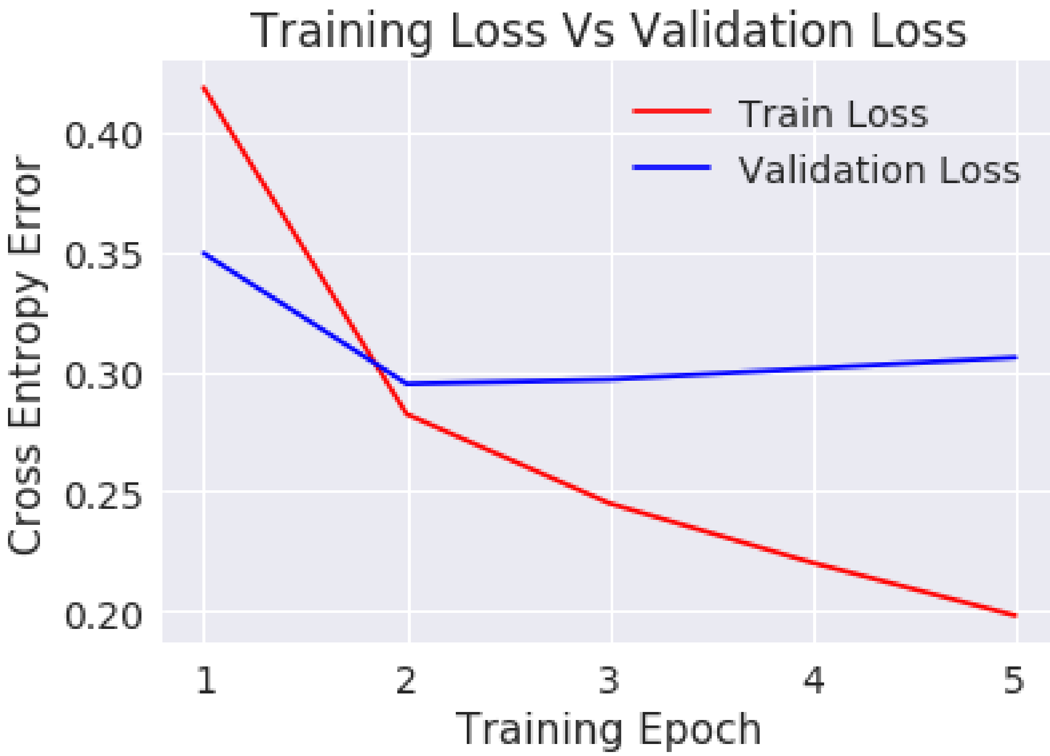
In [20]:
```
# crete model object
h_params_m_a1 = (0.10, 64, 20)
model_obj = multi_layer_lstm(h_params_m_a1, vocabulary_size, max_input_length)

# checkpoint
```

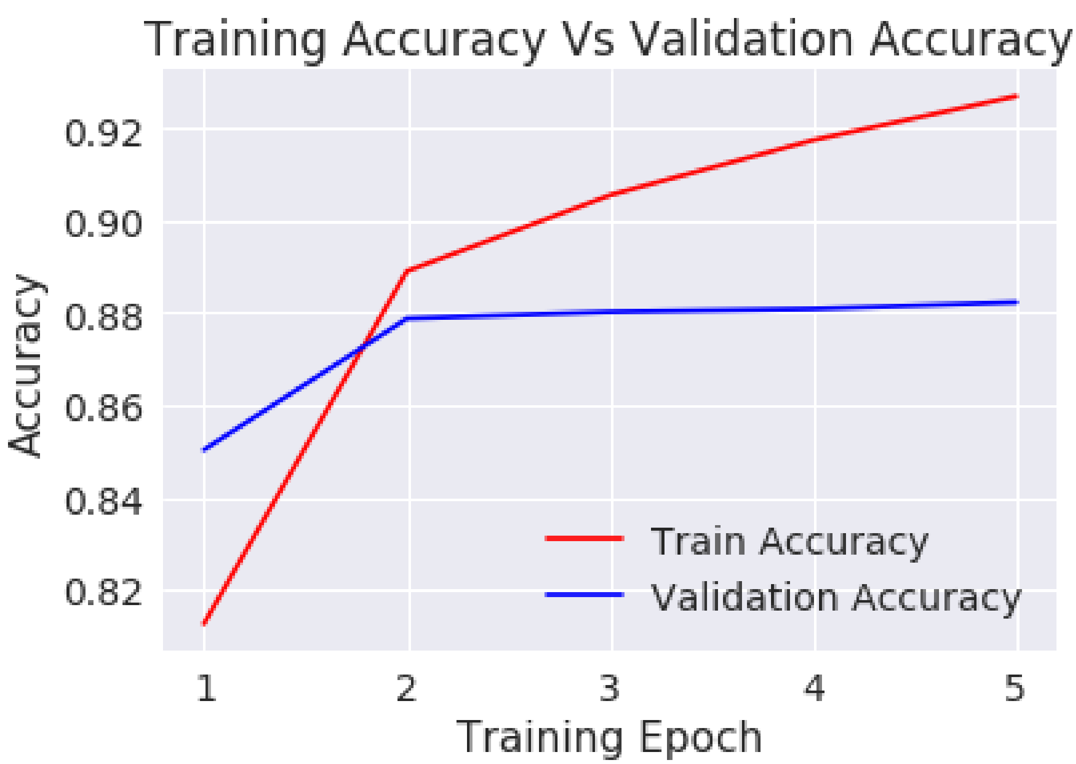
```python
num_epochs = 5
model_file_path = 'multi_a1_weights.best.hdf5'
# train and evaluate the model
test_metrics_m_a1 = train_and_evaluate_model(model_obj, model_file_path, num_epochs, X_
                                             X_test, y_test)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_3 (Embedding)      (None, 900, 32)           320000
_________________________________________________________________
lstm_3 (LSTM)                (None, 900, 64)           24832
_________________________________________________________________
lstm_4 (LSTM)                (None, 20)                6800
_________________________________________________________________
dropout_3 (Dropout)          (None, 20)                0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 21
=================================================================
Total params: 351,653
Trainable params: 351,653
Non-trainable params: 0
_________________________________________________________________
None
```

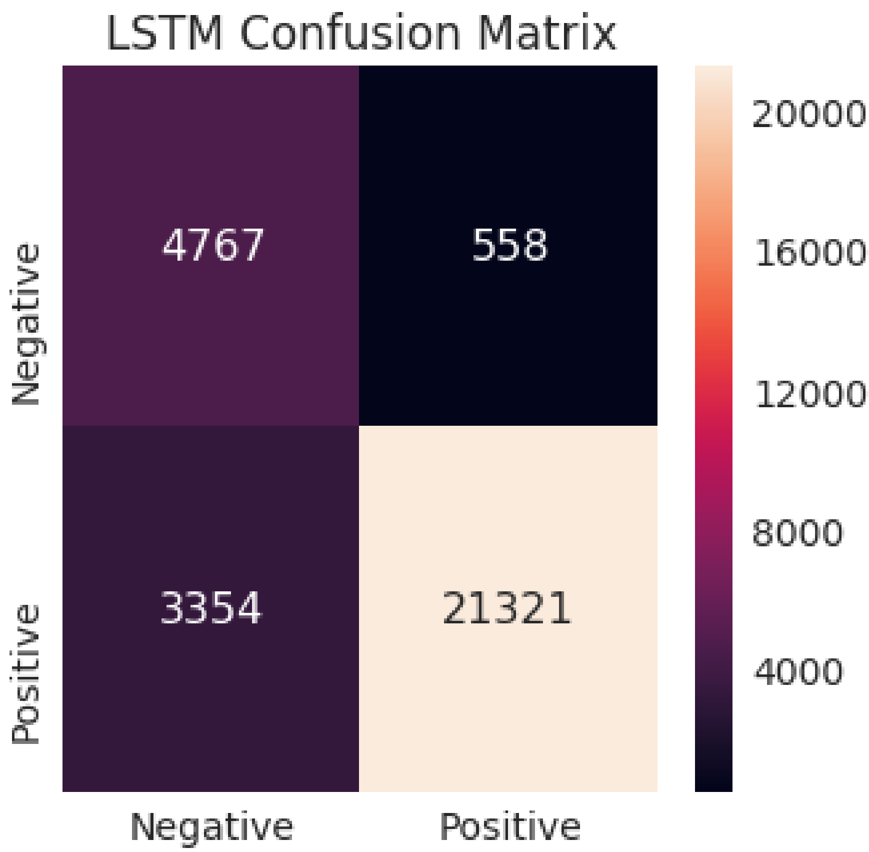
```
/home/amd_3/anaconda3/lib/python3.6/site-packages/keras/models.py:939: UserWarning: The `nb_epoc
  warnings.warn('The `nb_epoch` argument in `fit` '
```

```
Train on 55997 samples, validate on 14000 samples
Epoch 1/5
55936/55997 [============================>.] - ETA: 0s - loss: 0.4186 - acc: 0.8126Epoch 00001:
55997/55997 [==============================] - 924s 16ms/step - loss: 0.4185 - acc: 0.8126 - val
Epoch 2/5
55936/55997 [============================>.] - ETA: 0s - loss: 0.2822 - acc: 0.8891Epoch 00002:
55997/55997 [==============================] - 913s 16ms/step - loss: 0.2824 - acc: 0.8891 - val
Epoch 3/5
55936/55997 [============================>.] - ETA: 0s - loss: 0.2451 - acc: 0.9055Epoch 00003:
55997/55997 [==============================] - 955s 17ms/step - loss: 0.2451 - acc: 0.9055 - val
Epoch 4/5
55936/55997 [============================>.] - ETA: 1s - loss: 0.2203 - acc: 0.9174Epoch 00004:
55997/55997 [==============================] - 991s 18ms/step - loss: 0.2203 - acc: 0.9175 - val
Epoch 5/5
55936/55997 [============================>.] - ETA: 1s - loss: 0.1984 - acc: 0.9269Epoch 00005:
55997/55997 [==============================] - 1085s 19ms/step - loss: 0.1982 - acc: 0.9270 - va
Restored best model weights from saved file
```


Training Loss Vs Validation Loss
Train Loss
Validation Loss
Cross Entropy Error
0.40
0.35
0.30
0.25
0.20
1
2
3
4
5
Training Epoch


Training Accuracy Vs Validation Accuracy
Accuracy
0.92
0.90
0.88
0.86
0.84
0.82
Train Accuracy
Validation Accuracy
1
2
3
4
5
Training Epoch

```
Test loss:0.310434, Test Accuracy:86.960000
```




```
                Negative       Positive
Precision       0.586997       0.974496
Recall          0.895211       0.864073
Fscore          0.709058       0.915969
Support      5325.000000   24675.000000
```

3.4.4 d) Multi layered architecture 2

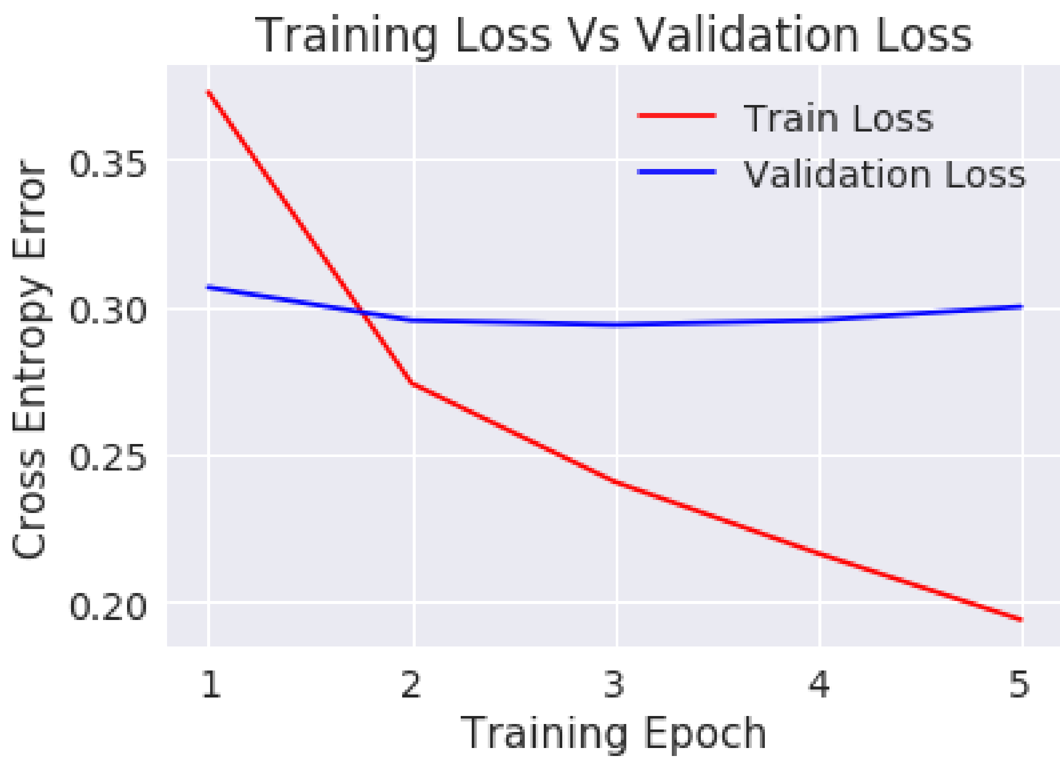
In [21]:
```
# crete model object
h_params_m_a2 = (0.15, 100, 32)
model_obj = multi_layer_lstm(h_params_m_a2, vocabulary_size, max_input_length)

# checkpoint
```

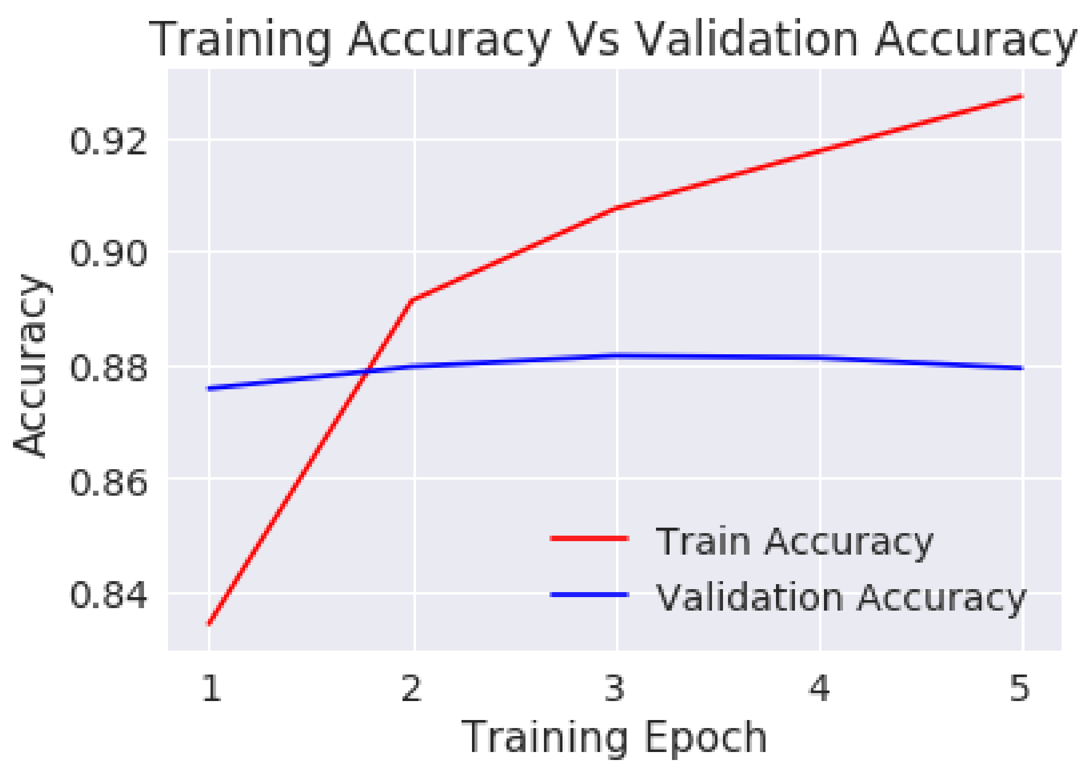
```python
num_epochs = 5
model_file_path = 'multi_a2_weights.best.hdf5'
# train and evaluate the model
test_metrics_m_a2 = train_and_evaluate_model(model_obj, model_file_path, num_epochs, X_
                                             X_test, y_test)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_4 (Embedding)      (None, 900, 32)           320000
_________________________________________________________________
lstm_5 (LSTM)                (None, 900, 100)          53200
_________________________________________________________________
lstm_6 (LSTM)                (None, 32)                17024
_________________________________________________________________
dropout_4 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 33
=================================================================
Total params: 390,257
Trainable params: 390,257
Non-trainable params: 0
_________________________________________________________________
None
```

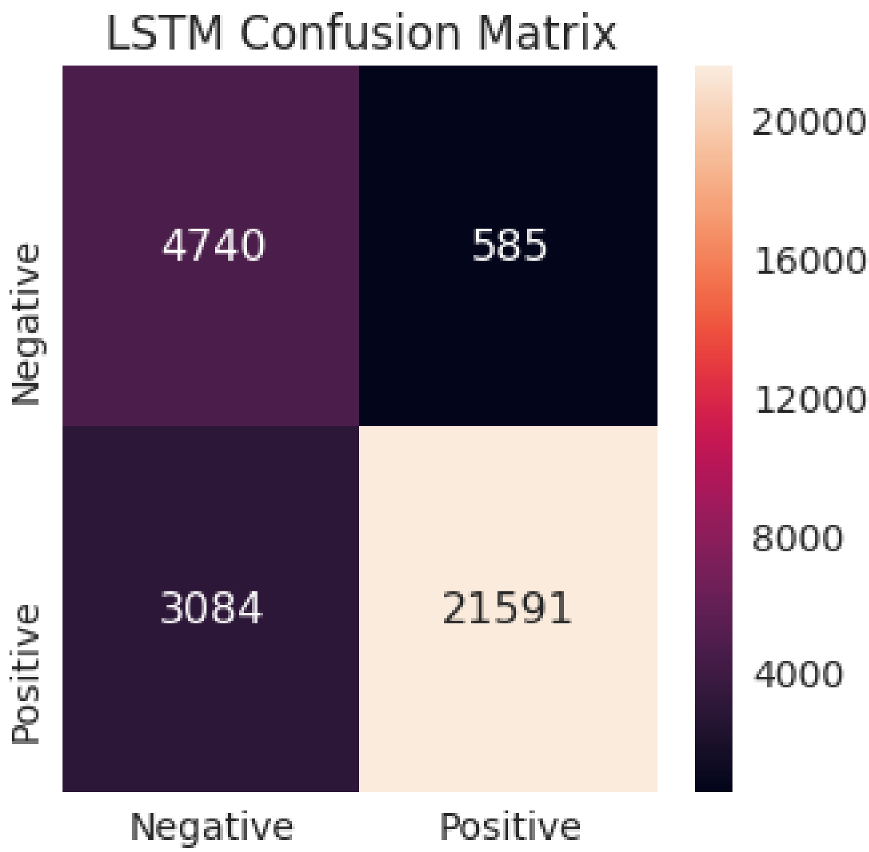
```
/home/amd_3/anaconda3/lib/python3.6/site-packages/keras/models.py:939: UserWarning: The `nb_epoc
  warnings.warn('The `nb_epoch` argument in `fit` '
```

```
Train on 55997 samples, validate on 14000 samples
Epoch 1/5
55936/55997 [============================>.] - ETA: 1s - loss: 0.3729 - acc: 0.8342Epoch 00001:
55997/55997 [==============================] - 1753s 31ms/step - loss: 0.3728 - acc: 0.8343 - va
Epoch 2/5
55936/55997 [============================>.] - ETA: 1s - loss: 0.2743 - acc: 0.8912Epoch 00002:
55997/55997 [==============================] - 1824s 33ms/step - loss: 0.2742 - acc: 0.8912 - va
Epoch 3/5
55936/55997 [============================>.] - ETA: 1s - loss: 0.2410 - acc: 0.9073Epoch 00003:
55997/55997 [==============================] - 1646s 29ms/step - loss: 0.2409 - acc: 0.9074 - va
Epoch 4/5
55936/55997 [============================>.] - ETA: 1s - loss: 0.2166 - acc: 0.9175Epoch 00004:
55997/55997 [==============================] - 1557s 28ms/step - loss: 0.2166 - acc: 0.9175 - va
Epoch 5/5
55936/55997 [============================>.] - ETA: 1s - loss: 0.1942 - acc: 0.9272Epoch 00005:
55997/55997 [==============================] - 1643s 29ms/step - loss: 0.1941 - acc: 0.9272 - va
Restored best model weights from saved file
```


Training Loss Vs Validation Loss
Train Loss
Validation Loss
Cross Entropy Error
0.35
0.30
0.25
0.20
1
2
3
4
5
Training Epoch


Training Accuracy Vs Validation Accuracy
0.92
0.90
0.88
0.86
0.84
Accuracy
Train Accuracy
Validation Accuracy
1
2
3
4
5
Training Epoch

```
Test loss:0.292912, Test Accuracy:87.770000
```



	Negative	Positive
Precision	0.605828	0.973620
Recall	0.890141	0.875015
Fscore	0.720967	0.921688
Support	5325.000000	24675.000000

4 Observations

From the loss curve, Single layered model tend to overfit after epcoh 2

From the loss curve, Multi layered model tend to overfit after epcoh 3

For both single layered, multilayered version models the positive class fscore is close to 90 % where as for -ve class it is close to 69%

Since precision is low for -ve class, most of the data points the model predicts as -ve are actually not negative.

Since dropout value did not help well to reduce overfit, early stopping method can be tried.

5 Procedure Summary

Fetch reviews from the data base and prepare the dataset in a sequence of number format which is suitable for keras LSTM model training

Design different LSTM models having different architectures (single layer, multiple layer, different dropout rate, different number of cells etc.)

Train & Evaluate the model on the prepared dataset.

6 Results Summary

```
In [22]: from prettytable import PrettyTable
```

```
In [23]: ptable = PrettyTable()
         ptable.title = 'Comparison of LSTM Models'
         ptable.field_names = ['Model', 'Loss', 'Accuracy', 'F1-Score (-ve)', 'F1-Score (+ve)']
```

```
In [24]: ptable.add_row(['1-Layer - ' + str(h_params_s_a1)] + test_metrics_s_a1)
         ptable.add_row(['1-Layer - ' + str(h_params_s_a2)] + test_metrics_s_a2)
         ptable.add_row(['2-Layer - ' + str(h_params_m_a1)] + test_metrics_m_a1)
         ptable.add_row(['2-Layer - ' + str(h_params_m_a2)] + test_metrics_m_a2)
```

```
In [25]: print(ptable)
```

```
+-------------------------------------------------------------------------------------+
|                              Comparison of LSTM Models                              |
+---------------------------+--------+----------+----------------+----------------+
|           Model           |  Loss  | Accuracy | F1-Score (-ve) | F1-Score (+ve) |
+---------------------------+--------+----------+----------------+----------------+
|     1-Layer - (0.1, 80)   | 0.3248 | 86.5467  |    70.3802     |    91.2968     |
|    1-Layer - (0.15, 100)  | 0.3140 | 86.7167  |    70.6489     |    91.4159     |
|   2-Layer - (0.1, 64, 20) | 0.3104 | 86.9600  |    70.9058     |    91.5969     |
| 2-Layer - (0.15, 100, 32) | 0.2929 | 87.7700  |    72.0967     |    92.1688     |
+---------------------------+--------+----------+----------------+----------------+
```

7 Conclusion

All models performed well on +ve class with above 91% f-score

The best F-score for negative class is 72.09% and +ve class is 92.16% model: (2-Layer - (0.15, 100, 32))

More feature engineering methods can be tried to improve the negative class performance