Recurrent Neural Networks (RNN)

In [0]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os

#Importing keras
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers.embeddings import Embedding
from keras.preprocessing import sequence
from keras.layers import Dropout
np.random.seed(7)
```

In [119]:
```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 data p
# you can change the number to any other number based on your computing power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LI
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 """,

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a neg
def partition(x):
    if x < 3:
        return 0
    return 1

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (525814, 10)
```

Out[119]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominat
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	

[1] Text Preprocessing

[1.1] Data Cleaning: Deduplication

In [120]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[120]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomir
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	

In [0]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplac
```

In [122]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"},
final.shape
```

Out[122]:
```
(364173, 10)
```

In [123]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[123]:
```
69.25890143662969
```

In [124]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[124]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomir
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	

In [0]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [126]:
```
#Before starting the next phase of preprocessing lets see the number of entries l
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
(364171, 10)
```

Out[126]:
```
1    307061
0     57110
Name: Score, dtype: int64
```

[1.2] Stemming, stop-word removal and Lemmatization.

In [0]:
```
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [0]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st st

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'our
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', '
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itsel
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because'
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'th
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all'
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than',
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "di
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma',
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn'
            'won', "won't", 'wouldn', "wouldn't"])
```

In [129]:
```
from bs4 import BeautifulSoup
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in s
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████| 364171/364171 [02:26<00:00, 2491.20it/s]
```

In [0]:
```
final['CleanedText']=preprocessed_reviews
```

[2] Data Preparation

In [191]:
```
#Sorting data according to Time in ascending order for Time Based Splitting
data = final.sort_values('Time', axis=0, ascending=True, inplace=False, kind='qui
data.head(3)
```

Out[191]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDe
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	

In [0]:
```
X = data['CleanedText'].values
y = data['Score']
```

In [173]:
```
#Vocabulary
count_vect = CountVectorizer()
count_vect.fit(X)

vocabulary = count_vect.get_feature_names()
print('Words in the Vocabulary : ',len(vocabulary))
```

```
Words in the Vocabulary :  116756
```

In [0]:
```
#Creating dictionary
corpus = dict()
ind = 0
for sent in X:
  for word in sent.split():
    corpus.setdefault(word,[])
    corpus[word].append(ind)
    ind += 1

#Frequency for each word of vocabulary
freq = []
for w in vocabulary:
  freq.append(len(corpus[w]))
```

In [0]:
```
#Frequencies in decreasing order
inc_index =np.argsort(np.array(freq))[::-1]

#Allocating ranks
word_rank = dict()
rank = 1
for i in inc_index:
  word_rank[vocabulary[i]] = rank
  rank +=1
```

In [0]:
```
data = []
for sent in X:
  row = []
  for word in sent.split():
    if(len(word)>1):
      row.append(word_rank[word])
  data.append(row)

#Splitting the data
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(data, y, test_size=0.3, rando
```

[3] Recurrent Neural Networks(RNN) with one LSTM layer

In [177]:
```
#padding input sequences
max_review_length = 100
X_train = sequence.pad_sequences(X_train, maxlen=max_review_length)
X_test = sequence.pad_sequences(X_test, maxlen=max_review_length)

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

```
(254919, 100)
[    0     0     0     0     0     0     0     0     0     0     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
     0     0    43    36    21    17   425   281   272   141     4   308
   304    89  4220   134  1306  1380   137     8   166    80   272   179
  1380    21    68   141  6207   182   276    66    96   285    56   396
  3271    85   406   304   727   134     2  4097 12684   436     1  4220
   132   304  8709   973     2  4513  3051   212  1773   123   336    16
   302  1380   272   179]
```

In [0]:
```
import matplotlib.pyplot as plt
import numpy as np
import time
# https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
# https://stackoverflow.com/a/14434334
# this function is used to update the plots for each epoch and error
def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
    plt.legend()
    plt.grid(True)
    fig.canvas.draw()
```

In [179]:
```
vocab_size = len(vocabulary)
embedding_vecor_length = 32
epochs = 10

model = Sequential()
model.add(Embedding(vocab_size+1, embedding_vecor_length, input_length=max_review
model.add(Dropout(0.2))
model.add(LSTM(100))
model.add(Dropout(0.2))
model.add(Dense(1, activation='sigmoid'))

print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_12 (Embedding)     (None, 100, 32)           3736224
_________________________________________________________________
dropout_23 (Dropout)         (None, 100, 32)           0
_________________________________________________________________
lstm_12 (LSTM)               (None, 100)               53200
_________________________________________________________________
dropout_24 (Dropout)         (None, 100)               0
_________________________________________________________________
dense_12 (Dense)             (None, 1)                 101
=================================================================
Total params: 3,789,525
Trainable params: 3,789,525
Non-trainable params: 0
_________________________________________________________________
None
```

In [180]:
```
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

#Fitting the data to the model
history = model.fit(X_train, Y_train, nb_epoch=epochs, batch_size=512 ,verbose=1,
```

```
Train on 254919 samples, validate on 109252 samples
Epoch 1/10
254919/254919 [==============================] - 541s 2ms/step - loss: 0.2359 -
acc: 0.9087 - val_loss: 0.1891 - val_acc: 0.9255
Epoch 2/10
254919/254919 [==============================] - 537s 2ms/step - loss: 0.1622 -
acc: 0.9378 - val_loss: 0.1807 - val_acc: 0.9287
Epoch 3/10
254919/254919 [==============================] - 536s 2ms/step - loss: 0.1410 -
acc: 0.9464 - val_loss: 0.1814 - val_acc: 0.9291
Epoch 4/10
254919/254919 [==============================] - 539s 2ms/step - loss: 0.1259 -
acc: 0.9529 - val_loss: 0.1874 - val_acc: 0.9269
Epoch 5/10
254919/254919 [==============================] - 540s 2ms/step - loss: 0.1130 -
acc: 0.9583 - val_loss: 0.1964 - val_acc: 0.9287
Epoch 6/10
254919/254919 [==============================] - 540s 2ms/step - loss: 0.1015 -
acc: 0.9627 - val_loss: 0.1993 - val_acc: 0.9280
Epoch 7/10
254919/254919 [==============================] - 536s 2ms/step - loss: 0.0927 -
acc: 0.9665 - val_loss: 0.2065 - val_acc: 0.9274
Epoch 8/10
254919/254919 [==============================] - 536s 2ms/step - loss: 0.0833 -
acc: 0.9701 - val_loss: 0.2318 - val_acc: 0.9259
Epoch 9/10
254919/254919 [==============================] - 534s 2ms/step - loss: 0.0754 -
acc: 0.9731 - val_loss: 0.2337 - val_acc: 0.9283
Epoch 10/10
254919/254919 [==============================] - 533s 2ms/step - loss: 0.0674 -
acc: 0.9760 - val_loss: 0.2540 - val_acc: 0.9280
```

In [182]:
```
score = model.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('binary_crossentropy')

# list of epoch numbers
x = list(range(1,epochs+1))

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Test score: 0.2540366640108507
Test accuracy: 0.9279921649031597
```

[4] Recurrent Neural Networks(RNN) with two LSTM layer

In [183]:
```
vocab_size = len(vocabulary)
embedding_vecor_length = 32
epochs = 10

model = Sequential()
model.add(Embedding(vocab_size+1, embedding_vecor_length, input_length=max_review_
model.add(LSTM(100,return_sequences=True, dropout=0.4, recurrent_dropout=0.4))
model.add(LSTM(100, dropout=0.4, recurrent_dropout=0.4))
model.add(Dense(1, activation='sigmoid'))

print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_13 (Embedding)     (None, 100, 32)           3736224
_________________________________________________________________
lstm_13 (LSTM)               (None, 100, 100)          53200
_________________________________________________________________
lstm_14 (LSTM)               (None, 100)               80400
_________________________________________________________________
dense_13 (Dense)             (None, 1)                 101
=================================================================
Total params: 3,869,925
Trainable params: 3,869,925
Non-trainable params: 0
_________________________________________________________________
None
```

In [184]:
```
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

#Fitting the data to the model
history = model.fit(X_train, Y_train, nb_epoch=epochs, batch_size=512 ,verbose=1,
```

```
Train on 254919 samples, validate on 109252 samples
Epoch 1/10
254919/254919 [==============================] - 1289s 5ms/step - loss: 0.2451
- acc: 0.9058 - val_loss: 0.1861 - val_acc: 0.9269
Epoch 2/10
254919/254919 [==============================] - 1282s 5ms/step - loss: 0.1711
- acc: 0.9345 - val_loss: 0.1842 - val_acc: 0.9296
Epoch 3/10
254919/254919 [==============================] - 1281s 5ms/step - loss: 0.1529
- acc: 0.9419 - val_loss: 0.1833 - val_acc: 0.9304
Epoch 4/10
254919/254919 [==============================] - 1282s 5ms/step - loss: 0.1393
- acc: 0.9475 - val_loss: 0.1784 - val_acc: 0.9307
Epoch 5/10
254919/254919 [==============================] - 1280s 5ms/step - loss: 0.1285
- acc: 0.9521 - val_loss: 0.1844 - val_acc: 0.9281
Epoch 6/10
254919/254919 [==============================] - 1279s 5ms/step - loss: 0.1187
- acc: 0.9560 - val_loss: 0.1837 - val_acc: 0.9321
Epoch 7/10
254919/254919 [==============================] - 1281s 5ms/step - loss: 0.1090
- acc: 0.9599 - val_loss: 0.1860 - val_acc: 0.9341
Epoch 8/10
254919/254919 [==============================] - 1279s 5ms/step - loss: 0.1005
- acc: 0.9636 - val_loss: 0.1916 - val_acc: 0.9340
Epoch 9/10
254919/254919 [==============================] - 1278s 5ms/step - loss: 0.0929
- acc: 0.9665 - val_loss: 0.1903 - val_acc: 0.9330
Epoch 10/10
254919/254919 [==============================] - 1282s 5ms/step - loss: 0.0868
- acc: 0.9688 - val_loss: 0.2011 - val_acc: 0.9343
```

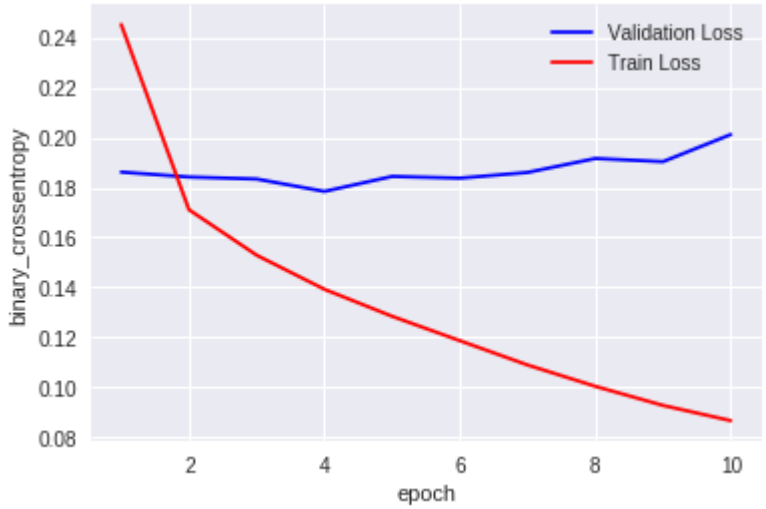
In [186]:
```
score = model.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('binary_crossentropy')

# list of epoch numbers
x = list(range(1,epochs+1))


vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Test score: 0.20112270053751743
Test accuracy: 0.9342529198550141
```



In [188]:
```
from prettytable import PrettyTable
x = PrettyTable()

x.field_names = ["RNN_MODEL", "TRAIN_ACCURACY", "TEST_ACCURACY"]
x.add_row(["LSTM", 0.976, 0.928])
x.add_row(["LSTM(2-hidden layers)", 0.968, 0.934])

print('\t\tRNN WITH DIFFERNET ARCHITECTURES')
print(x)
```

```
                RNN WITH DIFFERNET ARCHITECTURES
+----------------------+----------------+---------------+
|       RNN_MODEL      | TRAIN_ACCURACY | TEST_ACCURACY |
+----------------------+----------------+---------------+
|          LSTM        |     0.976      |     0.928     |
| LSTM(2-hidden layers) |     0.968      |     0.934     |
+----------------------+----------------+---------------+
```

Conclusion

1. After including more than one LSTM layers the test accuracy has increased
2. Both the models are overfit