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

import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
import pickle

from tqdm import tqdm
import os
```

In [9]:

```
# Credits: https://machinelearningmastery.com/sequence-classification-l
stm-recurrent-neural-networks-python-keras/
# LSTM for sequence classification in the IMDB dataset
import numpy
from keras.datasets import imdb
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
# fix random seed for reproducibility
numpy.random.seed(7)
```

```
Using TensorFlow backend.
```

In [10]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?
client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleuser
content.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%3Aoob&scope=emai
l%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2
Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2
Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Faut
h%2Fpeopleapi.readonly&response_type=code

Enter your authorization code:
··········
Mounted at /content/drive
```

In [0]:
```
!cp "/content/drive/My Drive/database.sqlite" "database.sqlite"
```

In [12]:
```
from bs4 import BeautifulSoup
con = sqlite3.connect('database.sqlite')

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

# Give reviews with Score>3 a positive rating(1), and reviews with a sc
ore<3 a negative rating(0).
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)

#Sorting data according to ProductId in ascending order
```

```
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')

#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
print(final.shape)

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

final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)

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



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
```

```python
 # 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 stopwords)
    preprocessed_reviews.append(sentance.strip())
```

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

```
  0%|          | 0/364171 [00:00<?, ?it/s]
```

```
(364173, 10)
(364171, 10)
```

```
100%|██████████| 364171/364171 [02:32<00:00, 2382.16it/s]
```

In [0]:

```python
from bs4 import BeautifulSoup
con = sqlite3.connect('database.sqlite')

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

# Give reviews with Score>3 a positive rating(1), and reviews with a sc
ore<3 a negative rating(0).
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)

#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=Tr
ue, inplace=False, kind='quicksort', na_position='last')

#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time"
,"Text"}, keep='first', inplace=False)
print(final.shape)

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

final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
#Before starting the next phase of preprocessing lets see the number of
 entries left
print(final.shape)

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



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)
```

```python
    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


 # 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 stopwords)
    preprocessed_reviews.append(sentance.strip())
```

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

```
  0%|          | 0/364171 [00:00<?, ?it/s]
```

```
(364173, 10)
(364171, 10)
```

```
100%|██████████| 364171/364171 [02:31<00:00, 2405.69it/s]
```

In [14]:

```python
from sklearn.model_selection import train_test_split

preprocessed_reviews=preprocessed_reviews[:100000]
score=final['Score'][:100000]
X_train, X_test, y_train, y_test = train_test_split(preprocessed_review
s, score, test_size=0.33, random_state=42)

print("X_train shape :: ",len(X_train))
print("X_test shape  :: ",len(X_test))
```

```
print("X_test shape  :: ",y_train.shape)
print("X_test shape  :: ",y_test.shape)
```

```
X_train shape ::  67000
X_test shape  ::  33000
X_test shape  ::  (67000,)
X_test shape  ::  (33000,)
```

In [15]:

```
from collections import Counter

words=[i for review in X_train for i in review.split()]
frequency_words=Counter(words)
#frequency_words.sort()

import operator

sorted_x = sorted(frequency_words.items(), key=operator.itemgetter(1))
sorted_x.reverse()
print(len(sorted_x))

desc_words=[i[0] for i in sorted_x]
```

```
64483
```

In [0]:

```
desc_words=desc_words[:20000]
```

In [17]:

```
print(type(desc_words))
print(len(desc_words))

X_train_sentence_in_num=[]
list_text=X_train
for j in tqdm(range(len(list_text))):
  sentence_in_vec=[]
  for i in list_text[j].split():
    if(i in desc_words):
      val=(desc_words.index(i))+1
      sentence_in_vec.append(val)
    else:
```

```
      sentence_in_vec.append(0)
  #if(i in desc_words):
  X_train_sentence_in_num.append(sentence_in_vec)
```

```
  0%|          | 20/67000 [00:00<06:21, 175.79it/s]
```

```
<class 'list'>
20000
```

```
100%|██████████| 67000/67000 [04:44<00:00, 235.13it/s]
```

In [18]:

```
print(type(desc_words))
print(len(desc_words))

X_test_sentence_in_num=[]
list_text=X_test
for j in tqdm(range(len(list_text))):
  sentence_in_vec=[]
  for i in list_text[j].split():
    if(i in desc_words):
      val=(desc_words.index(i))+1
      sentence_in_vec.append(val)
    else:
      sentence_in_vec.append(0)
  #if(i in desc_words):
  X_test_sentence_in_num.append(sentence_in_vec)
```

```
  0%|          | 29/33000 [00:00<02:00, 272.88it/s]
```

```
<class 'list'>
20000
```

```
100%|██████████| 33000/33000 [02:25<00:00, 226.59it/s]
```

In [19]:

```
print(len(X_train_sentence_in_num))
print(len(X_test_sentence_in_num))
```

```
67000
33000
```

In [20]:
```
# truncate and/or pad input sequences
max_review_length = 600
X_train = sequence.pad_sequences(X_train_sentence_in_num, maxlen=max_re
view_length)
X_test = sequence.pad_sequences(X_test_sentence_in_num, maxlen=max_revi
ew_length)

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

```
(67000, 600)
```

In [0]:
```

```

Model 1

- LStm(100)

In [26]:
```
# create the model
top_words=20000
embedding_vecor_length = 32
model = Sequential()
model.add(Embedding(top_words, embedding_vecor_length, input_length=max
_review_length))
model.add(LSTM(100))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['a
ccuracy'])
print(model.summary())
#Refer: https://datascience.stackexchange.com/questions/10615/number-of
-parameters-in-an-lstm-model
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 600, 32)           640000
_________________________________________________________________
```

```
lstm_2 (LSTM)                (None, 100)               53200
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 101
=================================================================
Total params: 693,301
Trainable params: 693,301
Non-trainable params: 0
_________________________________________________________________
None
```

In [28]:

```python
history =  model.fit(X_train, y_train, nb_epoch=10, batch_size=512  , validation_split=0.2)
# Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
```

```
Train on 53600 samples, validate on 13400 samples
Epoch 1/10
53600/53600 [==============================] - 140s 3ms/step - loss: 0.3632 - acc: 0.8602 - val_loss: 0.3487 - val_acc: 0.8575
Epoch 2/10
53600/53600 [==============================] - 140s 3ms/step - loss: 0.2612 - acc: 0.8862 - val_loss: 0.2530 - val_acc: 0.8933
Epoch 3/10
53600/53600 [==============================] - 141s 3ms/step - loss: 0.1962 - acc: 0.9202 - val_loss: 0.2380 - val_acc: 0.9010
Epoch 4/10
53600/53600 [==============================] - 140s 3ms/step - loss: 0.1543 - acc: 0.9392 - val_loss: 0.2210 - val_acc: 0.9169
Epoch 5/10
53600/53600 [==============================] - 141s 3ms/step - loss: 0.1247 - acc: 0.9539 - val_loss: 0.2290 - val_acc: 0.9070
Epoch 6/10
53600/53600 [==============================] - 140s 3ms/step - loss: 0.1062 - acc: 0.9623 - val_loss: 0.2324 - val_acc: 0.9167
Epoch 7/10
53600/53600 [==============================] - 140s 3ms/step - loss: 0.0894 - acc: 0.9704 - val_loss: 0.2614 - val_acc: 0.9181
Epoch 8/10
```

```
53600/53600 [==============================] - 141s 3ms/step - loss: 0.
0793 - acc: 0.9733 - val_loss: 0.2686 - val_acc: 0.9141
Epoch 9/10
53600/53600 [==============================] - 140s 3ms/step - loss: 0.
0693 - acc: 0.9780 - val_loss: 0.3110 - val_acc: 0.9119
Epoch 10/10
53600/53600 [==============================] - 141s 3ms/step - loss: 0.
0614 - acc: 0.9808 - val_loss: 0.3119 - val_acc: 0.9119
Accuracy: 91.25%
```

In [29]:

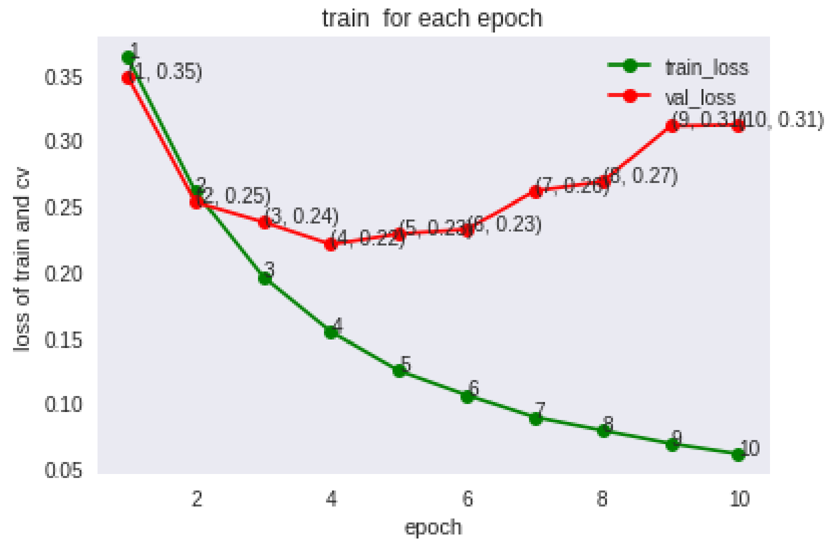
```
history.history.keys()
print(history.history['val_loss'])
print(history.history['val_acc'])
print(history.history['loss'])
print(history.history['acc'])
scores
print("loss : %.2f%%" % (scores[0]*100))
print("Accuracy: %.2f%%" % (scores[1]*100))
```

```
[0.3487152955603244, 0.2530329608917236, 0.23802739037506615, 0.2209604
5949565832, 0.22897370456759608, 0.23242721106579053, 0.261413915975769
96, 0.26855400616553293, 0.31095292189228, 0.3119151732725884]
[0.8574626866383339, 0.8932835821963069, 0.9010447761549879, 0.91694029
86498021, 0.90701492519521, 0.9167164177325234, 0.9181343281802846, 0.9
14104477434016, 0.9119402983295384, 0.9119402983295384]
[0.36324422638807724, 0.2611873199334785, 0.19617704807822384, 0.154318
69440559132, 0.1247030643918621, 0.10623054945646827, 0.089440458399146
36, 0.07929462131724428, 0.06928426061548404, 0.06139028950858472]
[0.8602238805614301, 0.8862499998932454, 0.9201865670930094, 0.93917910
44420271, 0.9538992538736827, 0.9623320896589934, 0.9704104478323637,
0.9733395520608816, 0.9779664178392781, 0.9808395523099757]
loss : 29.46%
Accuracy: 91.25%
```

In [36]:

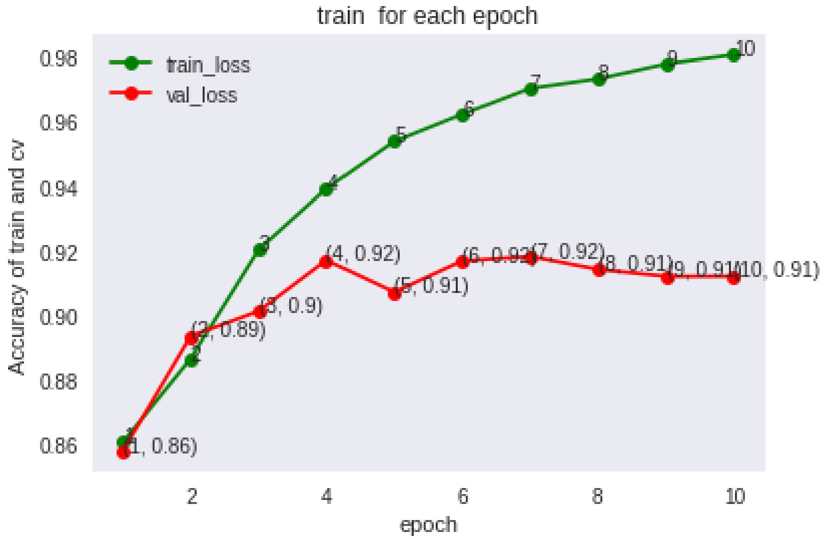
```
val_loss=[0.3487152955603244, 0.2530329608917236, 0.23802739037506615,
0.22096045949565832, 0.22897370456759608, 0.23242721106579053, 0.261413
91597576996, 0.26855400616553293, 0.31095292189228, 0.3119151732725884]
val_acc=[0.8574626866383339, 0.8932835821963069, 0.9010447761549879, 0.
9169402986498021, 0.90701492519521, 0.9167164177325234, 0.9181343281802
```

```
846, 0.914104477434016, 0.9119402983295384, 0.9119402983295384]
train_loss=[0.36324422638807724, 0.2611873199334785, 0.1961770480782238
4, 0.15431869440559132, 0.1247030643918621, 0.10623054945646827, 0.0894
4045839914636, 0.07929462131724428, 0.06928426061548404, 0.061390289508
58472]
train_acc=[0.8602238805614301, 0.8862499998932454, 0.9201865670930094,
0.9391791044420271, 0.9538992538736827, 0.9623320896589934, 0.970410447
8323637, 0.9733395520608816, 0.9779664178392781, 0.9808395523099757]




epoch=list(range(1,11))

fig, ax = plt.subplots()
ax.plot(epoch, train_loss,c='g',marker='o',label="train_loss")

for i, txt in enumerate(epoch):
    ax.annotate(txt, (epoch[i], train_loss[i]))
ax.plot(epoch, val_loss,c='r',marker='o',label="val_loss")

for i, txt in enumerate(epoch):
    ax.annotate((txt,np.round(val_loss[i],2)) , (epoch[i], val_loss[i
]))

plt.title("train  for each epoch")
plt.xlabel("epoch")
plt.ylabel("loss of train and cv")
plt.legend()
plt.grid()
plt.show()
```



In [37]:

```
fig, ax1 = plt.subplots()
ax1.plot(epoch, train_acc,c='g',marker='o',label="train_loss")

for i, txt in enumerate(epoch):
    ax1.annotate(txt, (epoch[i], train_acc[i]))

ax1.plot(epoch, val_acc,c='r',marker='o',label="val_loss")

for i, txt in enumerate(epoch):
    ax1.annotate((txt,np.round(val_acc[i],2)) , (epoch[i], val_acc[i]))

plt.title("train  for each epoch")
plt.xlabel("epoch")
plt.ylabel("Accuracy of train and cv")
plt.legend()
plt.grid()
plt.show()
```



Model

- LSTM(100) - epoch(10)

In [0]:
```
history = model.fit(X_train, y_train, nb_epoch=10, batch_size=1024 , va
lidation_split=0.2 )
# Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
```

```
Train on 53600 samples, validate on 13400 samples
Epoch 1/10
53600/53600 [==============================] - 144s 3ms/step - loss: 0.
2627 - acc: 0.8937 - val_loss: 0.3246 - val_acc: 0.8707
Epoch 2/10
53600/53600 [==============================] - 88s 2ms/step - loss: 0.2
392 - acc: 0.8929 - val_loss: 0.2279 - val_acc: 0.9029
Epoch 3/10
53600/53600 [==============================] - 88s 2ms/step - loss: 0.1
849 - acc: 0.9227 - val_loss: 0.2050 - val_acc: 0.9119
```

```
Epoch 4/10
53600/53600 [==============================] - 88s 2ms/step - loss: 0.1
653 - acc: 0.9334 - val_loss: 0.2055 - val_acc: 0.9152
Epoch 5/10
53600/53600 [==============================] - 141s 3ms/step - loss: 0.
1502 - acc: 0.9400 - val_loss: 0.2128 - val_acc: 0.9160
Epoch 6/10
53600/53600 [==============================] - 128s 2ms/step - loss: 0.
1376 - acc: 0.9452 - val_loss: 0.2159 - val_acc: 0.9137
Epoch 7/10
53600/53600 [==============================] - 151s 3ms/step - loss: 0.
1243 - acc: 0.9509 - val_loss: 0.2011 - val_acc: 0.9240
Epoch 8/10
53600/53600 [==============================] - 88s 2ms/step - loss: 0.1
059 - acc: 0.9589 - val_loss: 0.1975 - val_acc: 0.9220
Epoch 9/10
53600/53600 [==============================] - 88s 2ms/step - loss: 0.0
948 - acc: 0.9643 - val_loss: 0.2022 - val_acc: 0.9204
Epoch 10/10
53600/53600 [==============================] - 88s 2ms/step - loss: 0.0
851 - acc: 0.9687 - val_loss: 0.2150 - val_acc: 0.9230
Accuracy: 91.48%
```

In [0]:

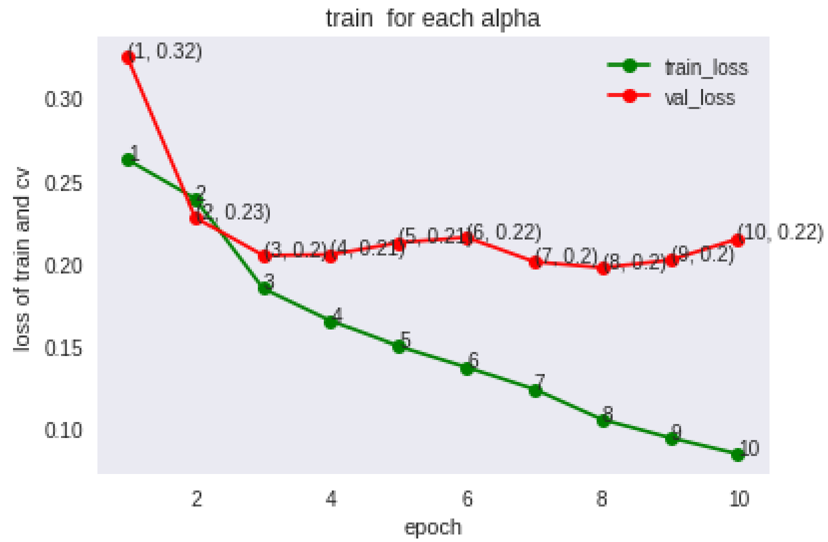
```
history.history.keys()
print(history.history['val_loss'])
print(history.history['val_acc'])
print(history.history['loss'])
print(history.history['loss'])
scores
print("loss : %.2f%%" % (scores[0]*100))
print("Accuracy: %.2f%%" % (scores[1]*100))
```

```
[0.32455565870697817, 0.22791154921944462, 0.20499946213480252, 0.20551
191191175092, 0.21275373498895275, 0.21594194265443886, 0.2011096647515
226, 0.1975470318901005, 0.20219409488919957, 0.21503558000966685]
[0.8707462687278862, 0.9029104477967789, 0.9119402985430476, 0.91522388
07037695, 0.9159701492181465, 0.9137313433191669, 0.9240298505683443,
0.92201492519521, 0.9204477610872752, 0.9229850747692051]
[0.26267628030990486, 0.23915745393553778, 0.18494821048494595, 0.16534
```

```
929706979154, 0.15015576346596676, 0.13758256768112753, 0.1242568447696
6288, 0.1059092135749646, 0.09482933028420405, 0.08510983836295]
[0.26267628030990486, 0.23915745393553778, 0.18494821048494595, 0.16534
929706979154, 0.15015576346596676, 0.13758256768112753, 0.1242568447696
6288, 0.1059092135749646, 0.09482933028420405, 0.08510983836295]
loss : 25.09%
Accuracy: 91.48%
```

plot bewteen loss(train and val) and Epochs

In [5]:
```
val_loss=[0.32455565870697817, 0.22791154921944462, 0.20499946213480252
, 0.20551191191175092, 0.21275373498895275, 0.21594194265443886, 0.2011
096647515226, 0.1975470318901005, 0.20219409488919957, 0.21503558000966
685]
train_loss=[0.26267628030990486, 0.23915745393553778, 0.184948210484945
95, 0.16534929706979154, 0.15015576346596676, 0.13758256768112753, 0.12
425684476966288, 0.1059092135749646, 0.09482933028420405, 0.08510983836
295]

epoch=list(range(1,11))

fig, ax = plt.subplots()
ax.plot(epoch, train_loss,c='g',marker='o',label="train_loss")

for i, txt in enumerate(epoch):
    ax.annotate(txt, (epoch[i], train_loss[i]))
ax.plot(epoch, val_loss,c='r',marker='o',label="val_loss")

for i, txt in enumerate(epoch):
    ax.annotate((txt,np.round(val_loss[i],2)) , (epoch[i], val_loss[i
]))

plt.title("train  for each alpha")
plt.xlabel("epoch")
plt.ylabel("loss of train and cv")
plt.legend()
plt.grid()
plt.show()
```



Model

- LSTM(100) - epoch(20) -BatchSize(1024)

In [38]:
```
history_epoch20 = model.fit(X_train, y_train, nb_epoch=20, batch_size=1
024 , validation_split=0.2 )
# Final evaluation of the model
scores_epoch20 = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores_epoch20[1]*100))
```

```
Train on 53600 samples, validate on 13400 samples
Epoch 1/20
53600/53600 [==============================] - 87s 2ms/step - loss: 0.0
467 - acc: 0.9872 - val_loss: 0.3305 - val_acc: 0.9124
Epoch 2/20
53600/53600 [==============================] - 87s 2ms/step - loss: 0.0
409 - acc: 0.9892 - val_loss: 0.3414 - val_acc: 0.9101
Epoch 3/20
53600/53600 [==============================] - 87s 2ms/step - loss: 0.0
```

```
367 - acc: 0.9909 - val_loss: 0.3864 - val_acc: 0.9069
Epoch 4/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
335 - acc: 0.9918 - val_loss: 0.3909 - val_acc: 0.9078
Epoch 5/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
295 - acc: 0.9929 - val_loss: 0.3869 - val_acc: 0.9062
Epoch 6/20
53600/53600 [==============================] - 87s 2ms/step - loss: 0.0
329 - acc: 0.9918 - val_loss: 0.3894 - val_acc: 0.9057
Epoch 7/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
277 - acc: 0.9932 - val_loss: 0.4083 - val_acc: 0.9056
Epoch 8/20
53600/53600 [==============================] - 87s 2ms/step - loss: 0.0
281 - acc: 0.9926 - val_loss: 0.4102 - val_acc: 0.9036
Epoch 9/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
253 - acc: 0.9939 - val_loss: 0.4282 - val_acc: 0.9058
Epoch 10/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
260 - acc: 0.9933 - val_loss: 0.4689 - val_acc: 0.9041
Epoch 11/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
226 - acc: 0.9948 - val_loss: 0.4459 - val_acc: 0.9035
Epoch 12/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
210 - acc: 0.9954 - val_loss: 0.4344 - val_acc: 0.9020
Epoch 13/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
204 - acc: 0.9955 - val_loss: 0.5145 - val_acc: 0.9033
Epoch 14/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
216 - acc: 0.9949 - val_loss: 0.4836 - val_acc: 0.9036
Epoch 15/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
179 - acc: 0.9962 - val_loss: 0.4968 - val_acc: 0.9036
Epoch 16/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
```

```
187 - acc: 0.9954 - val_loss: 0.4772 - val_acc: 0.9046
Epoch 17/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
157 - acc: 0.9968 - val_loss: 0.5305 - val_acc: 0.9028
Epoch 18/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
164 - acc: 0.9966 - val_loss: 0.5136 - val_acc: 0.9024
Epoch 19/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
141 - acc: 0.9973 - val_loss: 0.5355 - val_acc: 0.9032
Epoch 20/20
53600/53600 [==============================] - 86s 2ms/step - loss: 0.0
129 - acc: 0.9977 - val_loss: 0.5206 - val_acc: 0.9026
Accuracy: 90.33%
```

In [42]:

```
history_epoch20.history.keys()
print(history_epoch20.history['val_loss'])
print(history_epoch20.history['val_acc'])
print(history_epoch20.history['loss'])
print(history_epoch20.history['acc'])
scores
print("loss : %.2f%%" % (scores[0]*100))
print("Accuracy: %.2f%%" % (scores[1]*100))
```

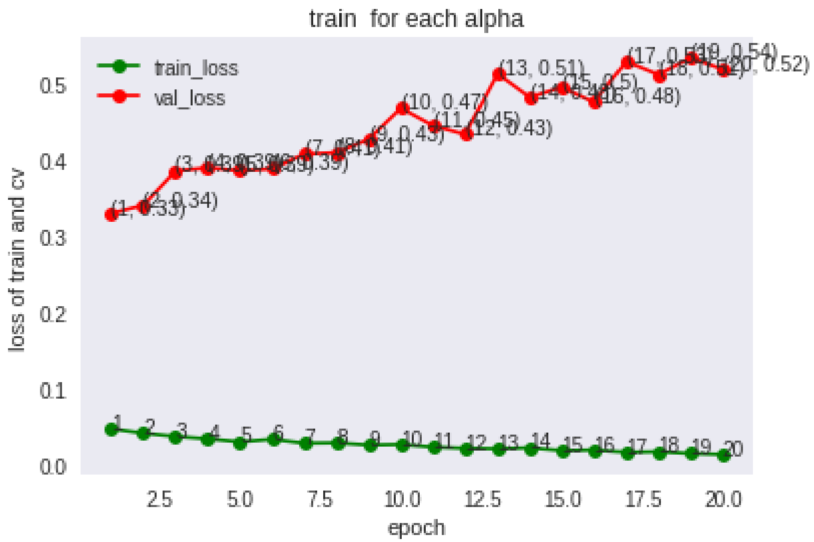
```
[0.33054351805751003, 0.3413731307414041, 0.3864407458056265, 0.3909177
0511064955, 0.38685415706527765, 0.38943654278321055, 0.408266270178467
5, 0.41016663710572826, 0.42824954108515784, 0.4689083670324354, 0.4459
3090909630506, 0.4343883624984257, 0.5145191513780337, 0.48358026371073
365, 0.49675003299072606, 0.47715033251847794, 0.5304994242048975, 0.51
36028800615624, 0.5354603843368702, 0.5206351370597954]
[0.9123880595235683, 0.9100746266877473, 0.9068656714638668, 0.90776119
38519264, 0.9061940297439917, 0.9057462685499619, 0.9055970147474488,
0.9035820894454842, 0.9058208954156335, 0.904104477434016, 0.9035074625
798126, 0.9020149253375495, 0.9032835819827977, 0.9035820894454842, 0.9
035820895878237, 0.904552238841555, 0.9028358208599375, 0.9023880597370
774, 0.9032089552594654, 0.902611940405262]
[0.04667290706910304, 0.04088750344381403, 0.036674711704254154, 0.0334
6883856316111, 0.02946827065588823, 0.03291236470550744, 0.027687280696
27463, 0.028130231784350836, 0.025270247439395137, 0.02603105122418101,
```

```
0.022641155493737602, 0.020952905507674858, 0.020392574357119O7, 0.0215
93344244383163, 0.017943981433037055, 0.018727007913889725, 0.015746384
194926983, 0.016387049886328515, 0.014108134739434541, 0.01288634411462
4297]
[0.9871828357141409, 0.9892164178036932, 0.9908582088128844, 0.99175373
13432836, 0.9929291044420271, 0.9917910448117042, 0.9931716416487053,
0.9926492538380979, 0.993936567199764, 0.9933022386280458, 0.9947574626
865672, 0.9953917908668518, 0.9954850746268656, 0.9948507462686568, 0.9
961567162399861, 0.9954477610161055, 0.9968283582089552, 0.996623134328
3583, 0.9972574626865671, 0.9977425371355085]
loss : 29.46%
Accuracy: 91.25%
```

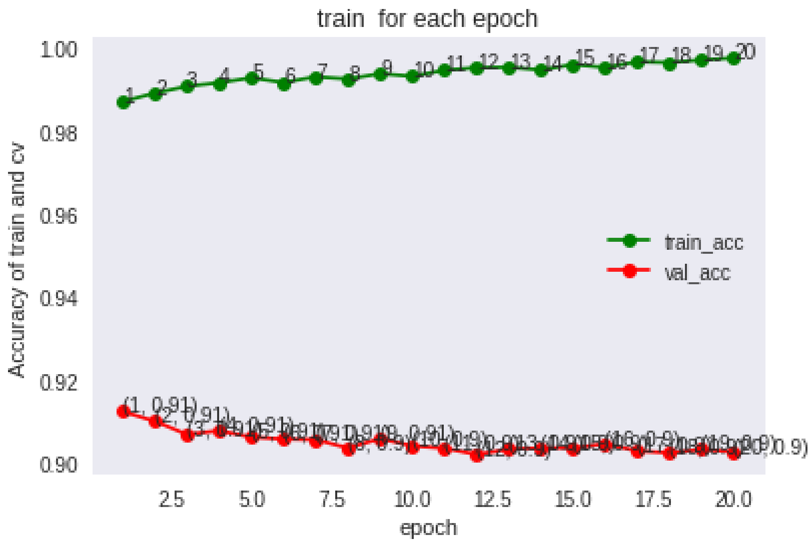
In [44]:

```
val_loss=[0.330543518057510O3, 0.3413731307414041, 0.3864407458056265,
0.39091770511064955, 0.38685415706527765, 0.38943654278321055, 0.408266
2701784675, 0.41016663710572826, 0.42824954108515784, 0.468908367032435
4, 0.44593090909630506, 0.4343883624984257, 0.5145191513780337, 0.48358
026371073365, 0.49675003299072606, 0.47715033251847794, 0.5304994242048
975, 0.5136028800615624, 0.5354603843368702, 0.5206351370597954]
val_acc=[0.9123880595235683, 0.9100746266877473, 0.9068656714638668, 0.
9077611938519264, 0.9061940297439917, 0.9057462685499619, 0.90559701474
74488, 0.9035820894454842, 0.9058208954156335, 0.904104477434016, 0.903
5074625798126, 0.9020149253375495, 0.9032835819827977, 0.90358208944548
42, 0.9035820895878237, 0.904552238841555, 0.9028358208599375, 0.902388
0597370774, 0.9032089552594654, 0.902611940405262]
train_loss=[0.04667290706910304, 0.04088750344381403, 0.036674711704254
154, 0.03346883856316111, 0.02946827065588823, 0.03291236470550744, 0.0
2768728069627463, 0.028130231784350836, 0.025270247439395137, 0.0260310
5122418101, 0.022641155493737602, 0.020952905507674858, 0.0203925743571
1907, 0.021593344244383163, 0.017943981433037055, 0.018727007913889725,
 0.015746384194926983, 0.016387049886328515, 0.014108134739434541, 0.01
2886344114624297]
train_acc=[0.9871828357141409, 0.9892164178036932, 0.9908582088128844,
0.9917537313432836, 0.9929291044420271, 0.9917910448117042, 0.993171641
6487053, 0.9926492538380979, 0.993936567199764, 0.9933022386280458, 0.9
947574626865672, 0.9953917908668518, 0.9954850746268656, 0.994850746268
6568, 0.9961567162399861, 0.9954477610161055, 0.9968283582089552, 0.996
```

```
6231343283583, 0.9972574626865671, 0.9977425371355085]

epoch=list(range(1,21))

fig, ax = plt.subplots()
ax.plot(epoch, train_loss,c='g',marker='o',label="train_loss")

for i, txt in enumerate(epoch):
    ax.annotate(txt, (epoch[i], train_loss[i]))
ax.plot(epoch, val_loss,c='r',marker='o',label="val_loss")

for i, txt in enumerate(epoch):
    ax.annotate((txt,np.round(val_loss[i],2)) , (epoch[i], val_loss[i
]))

plt.title("train  for each alpha")
plt.xlabel("epoch")
plt.ylabel("loss of train and cv")
plt.legend()
plt.grid()
plt.show()
```



In [46]:
```
fig, ax1 = plt.subplots()
ax1.plot(epoch, train_acc,c='g',marker='o',label="train_acc")

for i, txt in enumerate(epoch):
    ax1.annotate(txt, (epoch[i], train_acc[i]))

ax1.plot(epoch, val_acc,c='r',marker='o',label="val_acc")

for i, txt in enumerate(epoch):
    ax1.annotate((txt,np.round(val_acc[i],2)) , (epoch[i], val_acc[i]))

plt.title("train  for each epoch")
plt.xlabel("epoch")
plt.ylabel("Accuracy of train and cv")
plt.legend()
plt.grid()
plt.show()
```



Model

- LSTM(32)

- LSTM(32)
- epoch(20) -BatchSize(1024)

In [0]:
```
# create the model
top_words=20000
embedding_vecor_length = 32

model = Sequential()
model.add(Embedding(top_words, embedding_vecor_length, input_length=max_review_length))
model.add(LSTM(32, return_sequences=True))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
print(model.summary())
#Refer: https://datascience.stackexchange.com/questions/10615/number-of-parameters-in-an-lstm-model
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding_2 (Embedding)      (None, 600, 32)           640000    
_________________________________________________________________
lstm_2 (LSTM)                (None, 600, 32)           8320      
_________________________________________________________________
lstm_3 (LSTM)                (None, 32)                8320      
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 33        
=================================================================
Total params: 656,673
Trainable params: 656,673
Non-trainable params: 0
_________________________________________________________________
None
```

In [0]:
```
history_epoch10_LSTM2 = model.fit(X_train, y_train, nb_epoch=10, batch_size=1024 , validation_split=0.2 )
```

```
# Final evaluation of the model
scores_epoch20 = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores_epoch10_LSTM2[1]*100))
```

```
Train on 53600 samples, validate on 13400 samples
Epoch 1/10
53600/53600 [==============================] - 151s 3ms/step - loss: 0.
4855 - acc: 0.8418 - val_loss: 0.3974 - val_acc: 0.8520
Epoch 2/10
53600/53600 [==============================] - 150s 3ms/step - loss: 0.
3296 - acc: 0.8654 - val_loss: 0.2994 - val_acc: 0.8717
Epoch 3/10
53600/53600 [==============================] - 150s 3ms/step - loss: 0.
2358 - acc: 0.9032 - val_loss: 0.2549 - val_acc: 0.8956
Epoch 4/10
53600/53600 [==============================] - 206s 4ms/step - loss: 0.
1907 - acc: 0.9254 - val_loss: 0.2436 - val_acc: 0.8992
Epoch 5/10
53600/53600 [==============================] - 198s 4ms/step - loss: 0.
1570 - acc: 0.9394 - val_loss: 0.2295 - val_acc: 0.9130
Epoch 6/10
53600/53600 [==============================] - 155s 3ms/step - loss: 0.
1288 - acc: 0.9530 - val_loss: 0.2374 - val_acc: 0.9142
Epoch 7/10
53600/53600 [==============================] - 154s 3ms/step - loss: 0.
1102 - acc: 0.9619 - val_loss: 0.2416 - val_acc: 0.9142
Epoch 8/10
53600/53600 [==============================] - 158s 3ms/step - loss: 0.
0958 - acc: 0.9688 - val_loss: 0.2605 - val_acc: 0.9107
Epoch 9/10
53600/53600 [==============================] - 150s 3ms/step - loss: 0.
0838 - acc: 0.9742 - val_loss: 0.2739 - val_acc: 0.9124
Epoch 10/10
53600/53600 [==============================] - 151s 3ms/step - loss: 0.
0753 - acc: 0.9769 - val_loss: 0.2979 - val_acc: 0.9081

-----------------------------------------------------------------------
----
NameError                                 Traceback (most recent call l
ast)
```

```
<ipython-input-26-4f6f23914563> in <module>()
      2 # Final evaluation of the model
      3 scores_epoch20 = model.evaluate(X_test, y_test, verbose=0)
----> 4 print("Accuracy: %.2f%%" % (scores_epoch10_LSTM2[1]*100))

NameError: name 'scores_epoch10_LSTM2' is not defined
```

In [0]:

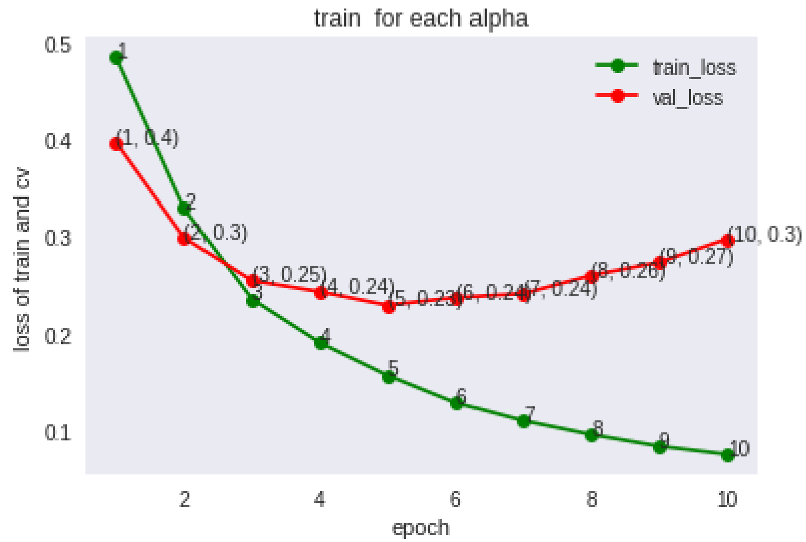
```
scores_epoch10_LSTM2=scores_epoch20
print("Accuracy: %.2f%%" % (scores_epoch20[1]*100))
history_epoch10_LSTM2


history_epoch10_LSTM2.history.keys()
print(history_epoch10_LSTM2.history['val_loss'])
print(history_epoch10_LSTM2.history['val_acc'])
print(history_epoch10_LSTM2.history['loss'])
print(history_epoch10_LSTM2.history['loss'])
scores
print("loss : %.2f%%" % (scores_epoch10_LSTM2[0]*100))
print("Accuracy: %.2f%%" % (scores_epoch10_LSTM2[1]*100))
```

```
Accuracy: 91.01%
[0.3974162083241477, 0.29942880187461623, 0.25494988042027206, 0.243599
962965766, 0.22954293419620883, 0.2374324997592328, 0.2416116583792131
4, 0.2604869239365877, 0.27393566471427233, 0.2978505916292988]
[0.8520149253019647, 0.8717164180883721, 0.8955970148186185, 0.89917910
44420271, 0.9129850746980354, 0.9141791046199514, 0.9141791042996876,
0.9107462684787921, 0.9123880595235683, 0.908059701314613]
[0.48547945456718333, 0.3295929052758573, 0.2358010243301961, 0.1907428
3160380462, 0.15698250969844077, 0.1288127305970263, 0.1101923648145661
4, 0.0958224734486039, 0.08378641776629349, 0.07534008701123408]
[0.48547945456718333, 0.3295929052758573, 0.2358010243301961, 0.1907428
3160380462, 0.15698250969844077, 0.1288127305970263, 0.1101923648145661
4, 0.0958224734486039, 0.08378641776629349, 0.07534008701123408]
loss : 28.42%
Accuracy: 91.01%
```

In [8]:

```
val_loss=[0.3974162083241477, 0.29942880187461623, 0.25494988042027206,
 0.243599962965766, 0.22954293419620883, 0.2374324997592328, 0.24161165
```

```
837921314, 0.2604869239365877, 0.27393566471427233, 0.2978505916292988]
train_loss=[0.48547945456718333, 0.3295929052758573, 0.2358010243301961
, 0.19074283160380462, 0.15698250969844077, 0.1288127305970263, 0.11019
236481456614, 0.0958224734486039, 0.08378641776629349, 0.07534008701123
408]



epoch=list(range(1,11))

fig, ax = plt.subplots()
ax.plot(epoch, train_loss,c='g',marker='o',label="train_loss")

for i, txt in enumerate(epoch):
    ax.annotate(txt, (epoch[i], train_loss[i]))
ax.plot(epoch, val_loss,c='r',marker='o',label="val_loss")

for i, txt in enumerate(epoch):
    ax.annotate((txt,np.round(val_loss[i],2)) , (epoch[i], val_loss[i
]))

plt.title("train  for each alpha")
plt.xlabel("epoch")
plt.ylabel("loss of train and cv")
plt.legend()
plt.grid()
plt.show()
```



Pretty Table

In [47]:
```python
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["No_Of_Layers", 'LSTM_Units' , 'Epoch', 'Batch_Size' ,
 "Test_acc"]

x.add_row(["1", 100 , 10   , 512  , '91.25%' ])
x.add_row(["1", 100 , 10  , 1024 , '91.48%' ])
x.add_row(["1", 100 , 20 , 1024 , '90.58%' ])
x.add_row(["2", [32,32] , 10 , 1024  , '91.01%' ])



print(x)
```

```
+--------------+------------+-------+------------+----------+
| No_Of_Layers | LSTM_Units | Epoch | Batch_Size | Test_acc |
```

1	100	10	512	91.25%
1	100	10	1024	91.48%
1	100	20	1024	90.58%
2	[32, 32]	10	1024	91.01%

Summary ::

- LSTM -100 , Epoch -10 , Batch-Size -512
  - from 1 to 4 epochs val_loss decrease and from 4 to 9 Epochs val_loss increaing and from 9 to 10 Epochs val_loss got stable
- LSTM -100 , Epoch -10 , Batch-Size -1024
  - from 1 to 3 epochs val_loss decrease linearlly and from 3 to 10 Epoch loss got stable
- LSTM -100 , Epoch -20 , Batch-Size -1024
  - val_loss for epoch 1 to 13 incresing linearly and then from 13 to 16 decresing and then agin from 16 to 20 val_loss increaisng
- LSTM -32 ,LSTM -32 , Epoch -10 , Batch-Size - 1024
  - from epoch 1 to 5 loss decreased linreally and from epochs 5 to 10 loss tending to increas