EMOTION PREDICTION IN CONVERSATIONS:

APPROACH :

- We will create a very basic first model first and then improve it using different other features. We will also see how deep neural networks can be used and end this post with some ideas about ensembling in general.

This covers:

- TFIDF
- BOW
- logistic regression
- naive bayes
- svm
- xgboost
- grid search
- word vectors
- LSTM
- Customised Ensembling

Research PAPER: https://arxiv.org/pdf/1810.02508.pdf

DATASET : MELD : https://affective-meld.github.io/

Metric Used: MULTI CLASS LOG LOSS

In [1]:

```
cd drive/My\ Drive/MELD
```

```
/content/drive/My Drive/MELD
```

LOAD DEPENDENCIES

In [2]:

```
import nltk
nltk.download('stopwords')

import pandas as pd
import seaborn as sns
import numpy as np
import xgboost as xgb
from tqdm import tqdm
from sklearn.svm import SVC
from keras.models import Sequential
from keras.layers.recurrent import LSTM, GRU
from keras.layers.core import Dense, Activation, Dropout
from keras.layers.embeddings import Embedding
from keras.layers.normalization import BatchNormalization
from keras.utils import np_utils
from sklearn import preprocessing, decomposition, model_selection, metrics, pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.decomposition import TruncatedSVD
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from keras.layers import GlobalMaxPooling1D, Conv1D, MaxPooling1D, Flatten, Bidirectional, SpatialD
ropout1D
from keras.preprocessing import sequence, text
from keras.callbacks import EarlyStopping
from nltk import word_tokenize
```

```
from nltk.corpus import stopwords
stop_words = stopwords.words('english')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning:
pandas.util.testing is deprecated. Use the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
Using TensorFlow backend.
```

LOAD DATA

In [3]:

```
train = pd.read_csv('train_sent_emo.csv')
cv = pd.read_csv('dev_sent_emo.csv')
test = pd.read_csv('test_sent_emo.csv')
```

EXPLORATORY DATA ANALYSIS

In [4]:

```
train.shape, cv.shape , test.shape
```

Out[4]:

```
((9989, 11), (1109, 11), (2610, 11))
```

In [5]:

```
train.columns
```

Out[5]:

```
Index(['Sr No.', 'Utterance', 'Speaker', 'Emotion', 'Sentiment', 'Dialogue_ID',
       'Utterance_ID', 'Season', 'Episode', 'StartTime', 'EndTime'],
      dtype='object')
```

In [6]:

```
cv.columns
```

Out[6]:

```
Index(['Sr No.', 'Utterance', 'Speaker', 'Emotion', 'Sentiment', 'Dialogue_ID',
       'Utterance_ID', 'Season', 'Episode', 'StartTime', 'EndTime'],
      dtype='object')
```

In [7]:

```
test.columns
```

Out[7]:

```
Index(['Sr No.', 'Utterance', 'Speaker', 'Emotion', 'Sentiment', 'Dialogue_ID',
       'Utterance_ID', 'Season', 'Episode', 'StartTime', 'EndTime'],
      dtype='object')
```

In [8]:

```
train.head()
```

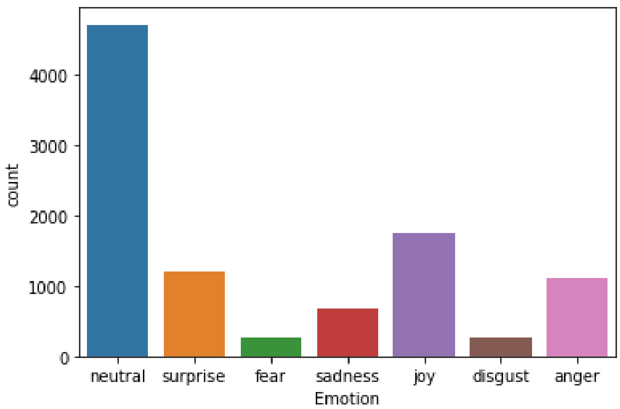
Out[8]:

	Sr No.	Utterance	Speaker	Emotion	Sentiment	Dialogue_ID	Utterance_ID	Season	Episode	StartTime	EndTime
0	1	also I was the point person on my companys tr...	Chandler	neutral	neutral	0	0	8	21	00:16:16,059	00:16:21,731
1	2	You mustve had your hands full.	The Interviewer	neutral	neutral	0	1	8	21	00:16:21,940	00:16:23,442
2	3	That I did. That I did.	Chandler	neutral	neutral	0	2	8	21	00:16:23,442	00:16:26,389
3	4	So lets talk a little bit about your duties.	The Interviewer	neutral	neutral	0	3	8	21	00:16:26,820	00:16:29,572
4	5	My duties? All right.	Chandler	surprise	positive	0	4	8	21	00:16:34,452	00:16:40,917

In [9]:

```
#Imbalanced Data
ax = sns.countplot(x=train['Emotion'], data=train)
print(train['Emotion'].value_counts())
```

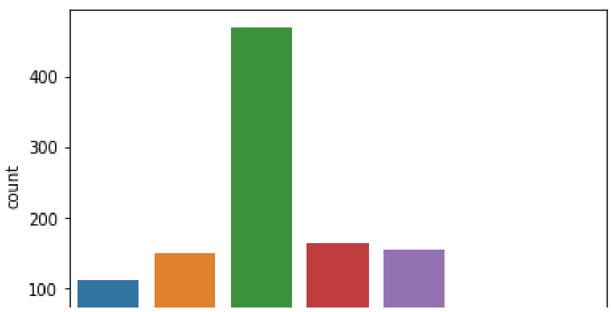
```
neutral     4710
joy         1743
surprise    1205
anger       1109
sadness      683
disgust      271
fear         268
Name: Emotion, dtype: int64
```

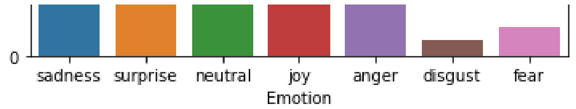


In [10]:

```
#Imbalanced Data
ax = sns.countplot(x=cv['Emotion'], data=cv)
print(cv['Emotion'].value_counts())
```

```
neutral     470
joy         163
anger       153
surprise    150
sadness     111
fear         40
disgust      22
Name: Emotion, dtype: int64
```

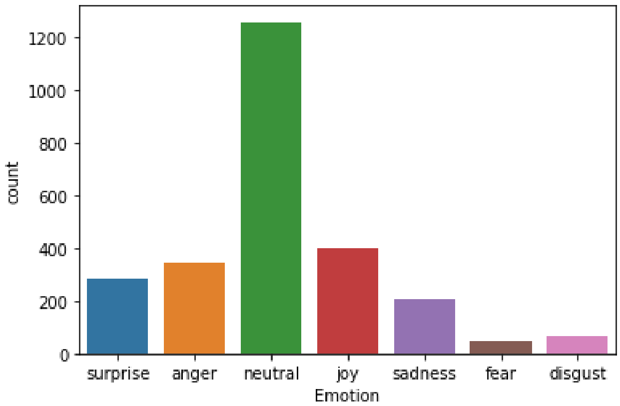




In [11]:

```
#Imbalanced Data
ax = sns.countplot(x=test['Emotion'], data=test)
print(test['Emotion'].value_counts())
```

```
neutral     1256
joy          402
anger        345
surprise     281
sadness      208
disgust       68
fear          50
Name: Emotion, dtype: int64
```



Observation :

1. Neutral emotion is dominating in CV ,Test set and Train set

In [12]:

```
train.info() #No nulls
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9989 entries, 0 to 9988
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   Sr No.        9989 non-null   int64 
 1   Utterance     9989 non-null   object
 2   Speaker       9989 non-null   object
 3   Emotion       9989 non-null   object
 4   Sentiment     9989 non-null   object
 5   Dialogue_ID   9989 non-null   int64 
 6   Utterance_ID  9989 non-null   int64 
 7   Season        9989 non-null   int64 
 8   Episode       9989 non-null   int64 
 9   StartTime     9989 non-null   object
 10  EndTime       9989 non-null   object
dtypes: int64(5), object(6)
memory usage: 858.6+ KB
```

In [13]:

```
cv.info()  #No nulls
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1109 entries, 0 to 1108
```

```
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   Sr No.        1109 non-null   int64 
 1   Utterance     1109 non-null   object
 2   Speaker       1109 non-null   object
 3   Emotion       1109 non-null   object
 4   Sentiment     1109 non-null   object
 5   Dialogue_ID   1109 non-null   int64 
 6   Utterance_ID  1109 non-null   int64 
 7   Season        1109 non-null   int64 
 8   Episode       1109 non-null   int64 
 9   StartTime     1109 non-null   object
 10  EndTime       1109 non-null   object
dtypes: int64(5), object(6)
memory usage: 95.4+ KB
```

In [14]:

```
test.info()  #No nulls
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2610 entries, 0 to 2609
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   Sr No.        2610 non-null   int64 
 1   Utterance     2610 non-null   object
 2   Speaker       2610 non-null   object
 3   Emotion       2610 non-null   object
 4   Sentiment     2610 non-null   object
 5   Dialogue_ID   2610 non-null   int64 
 6   Utterance_ID  2610 non-null   int64 
 7   Season        2610 non-null   int64 
 8   Episode       2610 non-null   int64 
 9   StartTime     2610 non-null   object
 10  EndTime       2610 non-null   object
dtypes: int64(5), object(6)
memory usage: 224.4+ KB
```

Splits

In [15]:

```
X_train , y_train = train[['Utterance']] , train[['Emotion']]
X_cv , y_cv = cv[['Utterance']] , cv[['Emotion']]
X_test , y_test = test[['Utterance']] , test[['Emotion']]
```

Defining Multi Class LogLoss

In [16]:

```
def multiclass_logloss(actual, predicted, eps=1e-15):
    """Multi class version of Logarithmic Loss metric.
    :param actual: Array containing the actual target classes
    :param predicted: Matrix with class predictions, one probability per class
    """
    # Convert 'actual' to a binary array if it's not already:
    if len(actual.shape) == 1:
        actual2 = np.zeros((actual.shape[0], predicted.shape[1]))
        for i, val in enumerate(actual):
            actual2[i, val] = 1
        actual = actual2

    clip = np.clip(predicted, eps, 1 - eps)
    rows = actual.shape[0]
    vsota = np.sum(actual * np.log(clip))
    return -1.0 / rows * vsota
```

Define a scorer to be used in Grid Search

In [17]:

```
mll_scorer = metrics.make_scorer(multiclass_logloss, greater_is_better=False, needs_proba=True)
```

Using LabelEncoder to vectorise labels

In [18]:

```
lbl_enc = preprocessing.LabelEncoder()
y_train_enc = lbl_enc.fit_transform(y_train.Emotion.values)
y_cv_enc = lbl_enc.transform(y_cv.Emotion.values)
y_test_enc = lbl_enc.transform(y_test.Emotion.values)
```

In [149]:

```
y_train.Emotion.values[1:200]
```

Out[149]:

```
array(['neutral', 'neutral', 'neutral', 'surprise', 'neutral', 'neutral',
       'neutral', 'neutral', 'neutral', 'fear', 'neutral', 'surprise',
       'neutral', 'surprise', 'sadness', 'surprise', 'fear', 'neutral',
       'neutral', 'neutral', 'neutral', 'neutral', 'joy', 'sadness',
       'surprise', 'neutral', 'disgust', 'sadness', 'neutral', 'neutral',
       'joy', 'neutral', 'joy', 'surprise', 'surprise', 'surprise',
       'neutral', 'neutral', 'neutral', 'surprise', 'sadness', 'neutral',
       'surprise', 'joy', 'surprise', 'neutral', 'neutral', 'neutral',
       'neutral', 'neutral', 'joy', 'joy', 'joy', 'sadness', 'neutral',
       'neutral', 'neutral', 'neutral', 'neutral', 'neutral', 'surprise',
       'joy', 'surprise', 'joy', 'neutral', 'neutral', 'anger', 'joy',
       'neutral', 'surprise', 'anger', 'anger', 'anger', 'neutral',
       'neutral', 'sadness', 'sadness', 'sadness', 'surprise', 'anger',
       'anger', 'anger', 'anger', 'neutral', 'anger', 'neutral',
       'neutral', 'neutral', 'neutral', 'joy', 'neutral', 'joy',
       'neutral', 'neutral', 'neutral', 'joy', 'neutral', 'neutral',
       'neutral', 'neutral', 'neutral', 'joy', 'neutral', 'neutral',
       'disgust', 'anger', 'anger', 'anger', 'anger', 'anger', 'anger',
       'neutral', 'neutral', 'anger', 'neutral', 'joy', 'neutral',
       'neutral', 'joy', 'joy', 'joy', 'joy', 'neutral', 'joy', 'disgust',
       'surprise', 'disgust', 'neutral', 'fear', 'neutral', 'surprise',
       'fear', 'disgust', 'anger', 'joy', 'neutral', 'surprise',
       'neutral', 'neutral', 'neutral', 'neutral', 'surprise', 'neutral',
       'neutral', 'anger', 'neutral', 'neutral', 'sadness', 'surprise',
       'sadness', 'anger', 'sadness', 'neutral', 'sadness', 'neutral',
       'neutral', 'neutral', 'neutral', 'neutral', 'joy', 'anger',
       'anger', 'anger', 'neutral', 'anger', 'joy', 'joy', 'joy', 'joy',
       'disgust', 'surprise', 'neutral', 'neutral', 'anger', 'joy',
       'neutral', 'neutral', 'fear', 'neutral', 'fear', 'joy', 'joy',
       'joy', 'joy', 'neutral', 'neutral', 'neutral', 'joy', 'neutral',
       'joy', 'fear', 'neutral', 'sadness', 'surprise', 'fear', 'neutral',
       'neutral', 'neutral', 'joy'], dtype=object)
```

In [148]:

```
y_train_enc[1:200]
```

Out[148]:

```
array([4, 4, 4, 6, 4, 4, 4, 4, 4, 2, 4, 6, 4, 6, 5, 6, 2, 4, 4, 4, 4, 4,
       3, 5, 6, 4, 1, 5, 4, 4, 3, 4, 3, 6, 6, 6, 4, 4, 4, 6, 5, 4, 6, 3,
       6, 4, 4, 4, 4, 4, 3, 3, 3, 5, 4, 4, 4, 4, 4, 4, 6, 3, 6, 3, 4, 4,
       0, 3, 4, 6, 0, 0, 0, 4, 4, 5, 5, 5, 6, 0, 0, 0, 0, 4, 0, 4, 4, 4,
       4, 3, 4, 3, 4, 4, 4, 3, 4, 4, 4, 4, 4, 3, 4, 4, 1, 0, 0, 0, 0, 0,
       0, 4, 4, 0, 4, 3, 4, 4, 3, 3, 3, 3, 4, 3, 1, 6, 1, 4, 2, 4, 6, 2,
       1, 0, 3, 4, 6, 4, 4, 4, 4, 6, 4, 4, 0, 4, 4, 5, 6, 5, 0, 5, 4, 5,
       4, 4, 4, 4, 4, 3, 0, 0, 0, 4, 0, 3, 3, 3, 3, 1, 6, 4, 4, 0, 3, 4,
       4, 2, 4, 2, 3, 3, 3, 3, 4, 4, 4, 3, 4, 3, 2, 4, 5, 6, 2, 4, 4, 4,
       3])
```

Data Preprocesing

In [19]:

```
import re

### Dataset Preprocessing training set
from nltk.stem.porter import PorterStemmer
ps = PorterStemmer()
train_corpus = []
for i in range(0, len(X_train)):
    review = re.sub('[^a-zA-Z]', ' ', X_train['Utterance'][i])
    review = review.lower()
    review = review.split()

    review = [ps.stem(word) for word in review if not word in stopwords.words('english')]
    review = ' '.join(review)
    train_corpus.append(review)
```

In [20]:

```
import re

### Dataset Preprocessing cv set
from nltk.stem.porter import PorterStemmer
ps = PorterStemmer()
cv_corpus = []
for i in range(0, len(X_cv)):
    review = re.sub('[^a-zA-Z]', ' ', X_cv['Utterance'][i])
    review = review.lower()
    review = review.split()

    review = [ps.stem(word) for word in review if not word in stopwords.words('english')]
    review = ' '.join(review)
    cv_corpus.append(review)
```

In [21]:

```
import re

### Dataset Preprocessing test set
from nltk.stem.porter import PorterStemmer
ps = PorterStemmer()
test_corpus = []
for i in range(0, len(X_test)):
    review = re.sub('[^a-zA-Z]', ' ', X_test['Utterance'][i])
    review = review.lower()
    review = review.split()

    review = [ps.stem(word) for word in review if not word in stopwords.words('english')]
    review = ' '.join(review)
    test_corpus.append(review)
```

In [90]:

```
X_train['clean_utterance'] = train_corpus
X_train.drop('Utterance',axis=1,inplace=True)
```

In [90]:

```
X_cv['clean_utterance'] = cv_corpus
X_cv.drop('Utterance',axis=1,inplace=True)
```

In [90]:

```
X_test['clean_utterance'] = test_corpus
X_test.drop('Utterance',axis=1,inplace=True)
```

MODELLING

MODEL 1: TFIDF + LR

In [119]:

```
tfv = TfidfVectorizer(min_df=3,  max_features=None,
            strip_accents='unicode', analyzer='word',token_pattern=r'\w{1,}',
            ngram_range=(1, 3), use_idf=1,smooth_idf=1,sublinear_tf=1,
            stop_words = 'english')

# Fitting TF-IDF to both training and test sets (semi-supervised learning)
tfv.fit(list(X_train['clean_utterance']) + list(X_cv['clean_utterance']) +
list(X_test['clean_utterance']))
X_train_tfv =  tfv.transform(X_train['clean_utterance'])
X_valid_tfv = tfv.transform(X_cv['clean_utterance'])
X_test_tfv = tfv.transform(X_test['clean_utterance'])
```

In [120]:

```
X_train_tfv.shape,X_valid_tfv.shape,X_test_tfv.shape
```

Out[120]:

```
((9989, 3179), (1109, 3179), (2610, 3179))
```

In [121]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_auc_score


alpha = [10 ** x for x in range(-6, 3)]


# initialize Our first RandomForestRegressor model...
regr2 = LogisticRegression()

# declare parameters for hyperparameter tuning
parameters = {'C':alpha}

# Perform cross validation
clf = GridSearchCV(regr2,
                    param_grid = parameters,
                    scoring=mll_scorer,
                    n_jobs = -1,
                    verbose = 10, refit=True, cv=2)
result = clf.fit(X_train_tfv, y_train_enc)

# Summarize results
print("Best: %f using %s" % (result.best_score_, result.best_params_))
means = result.cv_results_['mean_test_score']
stds = result.cv_results_['std_test_score']
params = result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f 1(%f) with: %r" % (mean, stdev, param))
```

```
Fitting 2 folds for each of 9 candidates, totalling 18 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done   1 tasks      | elapsed:    2.0s
[Parallel(n_jobs=-1)]: Done   4 tasks      | elapsed:    2.6s
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    3.2s
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:    4.9s
[Parallel(n_jobs=-1)]: Done  18 out of  18 | elapsed:    7.1s finished
```

```
Best: -1.417605 using {'C': 1}
-1.536665 1(0.000177) with: {'C': 1e-06}
-1.536648 1(0.000177) with: {'C': 1e-05}
```

```
-1.536648 1(0.000177) with: {'C': 1e-05}
-1.536480 1(0.000177) with: {'C': 0.0001}
-1.534834 1(0.000178) with: {'C': 0.001}
-1.520896 1(0.000221) with: {'C': 0.01}
-1.463340 1(0.000332) with: {'C': 0.1}
-1.417605 1(0.004722) with: {'C': 1}
-1.622374 1(0.001400) with: {'C': 10}
-2.300202 1(0.032847) with: {'C': 100}
```

In [122]:

```
lr = LogisticRegression(C = 1)
lr.fit(X_train_tfv, y_train_enc)
```

Out[122]:

```
LogisticRegression(C=1, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

Train,Test and CV loss

In [77]:

```
predictions = lr.predict_proba(X_train_tfv)
print ("logloss: %0.3f " % multiclass_logloss(y_train_enc, predictions))
```

```
logloss: 1.129
```

In [75]:

```
predictions = lr.predict_proba(X_valid_tfv)
print ("logloss: %0.3f " % multiclass_logloss(y_cv_enc, predictions))
```

```
logloss: 1.477
```

In [76]:

```
predictions = lr.predict_proba(X_test_tfv)
print ("logloss: %0.3f " % multiclass_logloss(y_test_enc, predictions))
```

```
logloss: 1.372
```

MODEL 2:BOW + LR

In [85]:

```
ctv = CountVectorizer(analyzer='word',token_pattern=r'\w{1,}',
            ngram_range=(1, 3), stop_words = 'english')

# Fitting Count Vectorizer to both training and test sets (semi-supervised learning)
ctv.fit(list(X_train['clean_utterance']) + list(X_cv['clean_utterance']) +
list(X_test['clean_utterance']))
X_train_ctv =  ctv.transform(X_train['clean_utterance'])
X_valid_ctv = ctv.transform(X_cv['clean_utterance'])
X_test_ctv = ctv.transform(X_test['clean_utterance'])
```

In [79]:

```
X_train_ctv.shape,X_valid_ctv.shape,X_test_ctv.shape
```

Out[79]:

```
((9989, 51082), (1109, 51082), (2610, 51082))
```

In [80]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_auc_score


alpha = [10 ** x for x in range(-6, 3)]


# initialize Our first RandomForestRegressor model...
regr2 = LogisticRegression()

# declare parameters for hyperparameter tuning
parameters = {'C':alpha}

# Perform cross validation
clf = GridSearchCV(regr2,
                    param_grid = parameters,
                    scoring=mll_scorer,
                    n_jobs = -1,
                    verbose = 10, refit=True, cv=2)
result = clf.fit(X_train_ctv, y_train_enc)

# Summarize results
print("Best: %f using %s" % (result.best_score_, result.best_params_))
means = result.cv_results_['mean_test_score']
stds = result.cv_results_['std_test_score']
params = result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f 1(%f) with: %r" % (mean, stdev, param))
```

```
Fitting 2 folds for each of 9 candidates, totalling 18 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done   1 tasks      | elapsed:    6.5s
[Parallel(n_jobs=-1)]: Done   4 tasks      | elapsed:   12.7s
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:   15.9s
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:   29.6s
[Parallel(n_jobs=-1)]: Done  18 out of  18 | elapsed:   48.0s finished
```

```
Best: -1.427496 using {'C': 0.1}
-1.536658 1(0.000176) with: {'C': 1e-06}
-1.536569 1(0.000177) with: {'C': 1e-05}
-1.535706 1(0.000178) with: {'C': 0.0001}
-1.528054 1(0.000209) with: {'C': 0.001}
-1.489068 1(0.000305) with: {'C': 0.01}
-1.427496 1(0.001608) with: {'C': 0.1}
-1.460494 1(0.008207) with: {'C': 1}
-1.784036 1(0.024584) with: {'C': 10}
-2.629078 1(0.109224) with: {'C': 100}
```

In [81]:

```
lr = LogisticRegression(C = 0.1)
lr.fit(X_train_ctv, y_train_enc)
```

Out[81]:

```
LogisticRegression(C=0.1, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [82]:

```
predictions = lr.predict_proba(X_train_ctv)
print ("logloss: %0.3f " % multiclass_logloss(y_train_enc, predictions))
```

```
logloss: 1.115
```

In [83]:

```
predictions = lr.predict_proba(X_valid_ctv)
print ("logloss: %0.3f " % multiclass_logloss(y_cv_enc, predictions))
```

```
logloss: 1.501
```

In [84]:

```
predictions = lr.predict_proba(X_test_ctv)
print ("logloss: %0.3f " % multiclass_logloss(y_test_enc, predictions))
```

```
logloss: 1.394
```

since MODEL 1 was better so we will move forward with TFIDF

MODEL 3 : Word Vectors

In [29]:

```
# stronging variables into pickle files python: http://www.jessicayung.com/how-to-use-pickle-to-sa
ve-and-load-variables-in-python/
# make sure you have the glove_vectors file
import pickle
with open('glove_vectors', 'rb') as f:
    model = pickle.load(f)
    glove_words =  set(model.keys())
```

In [30]:

```
# average Word2Vec
# compute average word2vec for each review.
avg_w2v_vectors_train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_train['clean_utterance']): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors_train.append(vector)

print(len(avg_w2v_vectors_train))
print(len(avg_w2v_vectors_train[0]))
```

```
100%|██████████| 9989/9989 [00:00<00:00, 70173.54it/s]
```

```
9989
300
```

In [31]:

```
# average Word2Vec
# compute average word2vec for each review.
avg_w2v_vectors_cv = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_cv['clean_utterance']): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
```

```
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors_cv.append(vector)

print(len(avg_w2v_vectors_cv))
print(len(avg_w2v_vectors_cv[0]))
```

```
100%|██████████| 1109/1109 [00:00<00:00, 50739.39it/s]
```

```
1109
300
```

In [32]:

```
# average Word2Vec
# compute average word2vec for each review.
avg_w2v_vectors_test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_test['clean_utterance']): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors_test.append(vector)

print(len(avg_w2v_vectors_test))
print(len(avg_w2v_vectors_test[0]))
```

```
100%|██████████| 2610/2610 [00:00<00:00, 59699.37it/s]
```

```
2610
300
```

In [33]:

```
xtrain_glove = np.array(avg_w2v_vectors_train)
xvalid_glove = np.array(avg_w2v_vectors_cv)
xtest_glove = np.array(avg_w2v_vectors_test)
```

In [42]:

```
import xgboost as xgb

# Fitting a simple xgboost on glove features
clf = xgb.XGBClassifier(max_depth=7, n_estimators=200, colsample_bytree=0.8,
                        subsample=0.8, nthread=10, learning_rate=0.1, silent=False)
clf.fit(xtrain_glove, y_train_enc)
predictions = clf.predict_proba(xvalid_glove)


print ("Valid logloss: %0.3f " % multiclass_logloss(y_cv_enc, predictions))
```

```
Valid logloss: 1.726
```

MODEL 4 : Truncated SVD + SVM

In [28]:

```
# Apply SVD, I chose 120 components. 120-200 components are good enough for SVM model.
svd = decomposition.TruncatedSVD(n_components=120)
svd.fit(X_train_tfv)
```

```
svd.fit(X_train_tfv)
X_train_svd = svd.transform(X_train_tfv)
X_valid_svd = svd.transform(X_valid_tfv)
X_test_svd = svd.transform(X_test_tfv)

# Scale the data obtained from SVD. Renaming variable to reuse without scaling.
scl = preprocessing.StandardScaler()
scl.fit(X_train_svd)
X_train_svd_scl = scl.transform(X_train_svd)
X_valid_svd_scl = scl.transform(X_valid_svd)
X_test_svd_scl = scl.transform(X_test_svd)
```

In [29]:

```
X_train_svd_scl.shape,X_valid_svd_scl.shape,X_test_svd_scl.shape
```

Out[29]:

```
((9989, 120), (1109, 120), (2610, 120))
```

In [30]:

```
from sklearn.linear_model import SGDClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.calibration import CalibratedClassifierCV

# initialize Our first RandomForestRegressor model...
svm = SVC(C=1)
regr2 = CalibratedClassifierCV(svm)
# declare parameters for hyperparameter tuning
regr2.fit(X_train_svd_scl, y_train_enc)
```

Out[30]:

```
CalibratedClassifierCV(base_estimator=SVC(C=1, break_ties=False, cache_size=200,
                                          class_weight=None, coef0=0.0,
                                          decision_function_shape='ovr',
                                          degree=3, gamma='scale', kernel='rbf',
                                          max_iter=-1, probability=False,
                                          random_state=None, shrinking=True,
                                          tol=0.001, verbose=False),
                       cv=None, method='sigmoid')
```

In [31]:

```
predictions = regr2.predict_proba(X_train_svd_scl)
print ("logloss: %0.3f " % multiclass_logloss(y_train_enc, predictions))
```

```
logloss: 1.356
```

In [32]:

```
predictions = regr2.predict_proba(X_valid_svd_scl)
print ("logloss: %0.3f " % multiclass_logloss(y_cv_enc, predictions))
```

```
logloss: 1.556
```

In [33]:

```
predictions = regr2.predict_proba(X_test_svd_scl)
print ("logloss: %0.3f " % multiclass_logloss(y_test_enc, predictions))
```

```
logloss: 1.456
```

MODEL 5 : MLP

In [45]:

```
# scale the data before any neural net:
scl = preprocessing.StandardScaler()
xtrain_glove_scl = scl.fit_transform(xtrain_glove)
xvalid_glove_scl = scl.transform(xvalid_glove)
xtest_glove_scl = scl.transform(xtest_glove)
```

In [46]:

```
y_train_enc_nn = np_utils.to_categorical(y_train_enc)
y_cv_enc_nn = np_utils.to_categorical(y_cv_enc)
y_test_enc_nn = np_utils.to_categorical(y_test_enc)
```

In [68]:

```
model = Sequential()

model.add(Dense(128, input_dim=300, activation='relu'))
model.add(Dropout(0.2))
model.add(BatchNormalization())

model.add(Dense(256, activation='relu'))
model.add(Dropout(0.3))
model.add(BatchNormalization())

model.add(Dense(256, activation='relu'))
model.add(Dropout(0.3))
model.add(BatchNormalization())

model.add(Dense(128, activation='relu'))
model.add(Dropout(0.3))
model.add(BatchNormalization())

model.add(Dense(7))
model.add(Activation('softmax'))

# compile the model
model.compile(loss='categorical_crossentropy', optimizer='adam')
```

In [69]:

```
model.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_17 (Dense)             (None, 128)               38528
_________________________________________________________________
dropout_12 (Dropout)         (None, 128)               0
_________________________________________________________________
batch_normalization_12 (Batc (None, 128)               512
_________________________________________________________________
dense_18 (Dense)             (None, 256)               33024
_________________________________________________________________
dropout_13 (Dropout)         (None, 256)               0
_________________________________________________________________
batch_normalization_13 (Batc (None, 256)               1024
_________________________________________________________________
dense_19 (Dense)             (None, 256)               65792
_________________________________________________________________
dropout_14 (Dropout)         (None, 256)               0
_________________________________________________________________
batch_normalization_14 (Batc (None, 256)               1024
_________________________________________________________________
dense_20 (Dense)             (None, 128)               32896
_________________________________________________________________
dropout_15 (Dropout)         (None, 128)               0
_________________________________________________________________
batch_normalization_15 (Batc (None, 128)               512
_________________________________________________________________
dense_21 (Dense)             (None, 7)                 903
_________________________________________________________________
activation_6 (Activation)    (None, 7)                 0
```

```
activation_6 (Activation)    (None, 7)                 0
=================================================================
Total params: 174,215
Trainable params: 172,679
Non-trainable params: 1,536
_________________________________________________________________
```

In [70]:

```python
y_cv_enc.shape
```

Out[70]:

```
(1109,)
```

In [71]:

```python
history = model.fit(xtrain_glove_scl, y=y_train_enc_nn, batch_size=64,
          epochs=10, verbose=1,
          validation_data=(xvalid_glove_scl, y_cv_enc_nn))
```

```
Train on 9989 samples, validate on 1109 samples
Epoch 1/10
9989/9989 [==============================] - 3s 262us/step - loss: 2.0361 - val_loss: 1.5816
Epoch 2/10
9989/9989 [==============================] - 2s 188us/step - loss: 1.6298 - val_loss: 1.5613
Epoch 3/10
9989/9989 [==============================] - 2s 186us/step - loss: 1.5424 - val_loss: 1.5323
Epoch 4/10
9989/9989 [==============================] - 2s 179us/step - loss: 1.4867 - val_loss: 1.5060
Epoch 5/10
9989/9989 [==============================] - 2s 181us/step - loss: 1.4608 - val_loss: 1.5041
Epoch 6/10
9989/9989 [==============================] - 2s 183us/step - loss: 1.4384 - val_loss: 1.4926
Epoch 7/10
9989/9989 [==============================] - 2s 180us/step - loss: 1.4248 - val_loss: 1.5016
Epoch 8/10
9989/9989 [==============================] - 2s 180us/step - loss: 1.4079 - val_loss: 1.4954
Epoch 9/10
9989/9989 [==============================] - 2s 182us/step - loss: 1.4059 - val_loss: 1.4948
Epoch 10/10
9989/9989 [==============================] - 2s 176us/step - loss: 1.3914 - val_loss: 1.4963
```

In [76]:

```python
# using keras tokenizer here
token = text.Tokenizer(num_words=None)
max_len = 70
a =list(X_train['clean_utterance']) + list(X_cv['clean_utterance']) +
list(X_test['clean_utterance'])
token.fit_on_texts(a)
xtrain_seq = token.texts_to_sequences(X_train['clean_utterance'])
xvalid_seq = token.texts_to_sequences(X_cv['clean_utterance'])
xtest_seq = token.texts_to_sequences(X_test['clean_utterance'])

# zero pad the sequences
xtrain_pad = sequence.pad_sequences(xtrain_seq, maxlen=max_len)
xvalid_pad = sequence.pad_sequences(xvalid_seq, maxlen=max_len)
xtest_pad = sequence.pad_sequences(xtest_seq, maxlen=max_len)

word_index = token.word_index
```

In [77]:

```python
# create an embedding matrix for the words we have in the dataset
embedding_matrix = np.zeros((len(word_index) + 1, 300))
for word, i in tqdm(word_index.items()):
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

```
100%|██████████| 4709/4709 [00:00<00:00, 1526114.78it/s]
```

MODEL 6 : LSTM

In [81]:

```
# A simple LSTM with glove embeddings and two dense layers
model = Sequential()
model.add(Embedding(len(word_index) + 1,
                     300,
                     weights=[embedding_matrix],
                     input_length=max_len,
                     trainable=False))
model.add(SpatialDropout1D(0.3))
model.add(LSTM(300, dropout=0.3, recurrent_dropout=0.3))

model.add(Dense(1024, activation='relu'))
model.add(Dropout(0.8))

model.add(Dense(1024, activation='relu'))
model.add(Dropout(0.8))

model.add(Dense(7))
model.add(Activation('softmax'))
model.compile(loss='categorical_crossentropy', optimizer='adam')

# Fit the model with early stopping callback
earlystop = EarlyStopping(monitor='val_loss', min_delta=0, patience=3, verbose=0, mode='auto')

history=model.fit(xtrain_pad, y=y_train_enc_nn, batch_size=512, epochs=200, verbose=1,
validation_data=(xvalid_pad, y_cv_enc_nn), callbacks=[earlystop])
```

```
Train on 9989 samples, validate on 1109 samples
Epoch 1/200
9989/9989 [==============================] - 7s 658us/step - loss: 1.9394 - val_loss: 1.9347
Epoch 2/200
9989/9989 [==============================] - 6s 584us/step - loss: 1.9256 - val_loss: 1.9239
Epoch 3/200
9989/9989 [==============================] - 6s 593us/step - loss: 1.9122 - val_loss: 1.9134
Epoch 4/200
9989/9989 [==============================] - 6s 573us/step - loss: 1.8992 - val_loss: 1.9032
Epoch 5/200
9989/9989 [==============================] - 6s 587us/step - loss: 1.8867 - val_loss: 1.8934
Epoch 6/200
9989/9989 [==============================] - 6s 585us/step - loss: 1.8744 - val_loss: 1.8839
Epoch 7/200
9989/9989 [==============================] - 6s 591us/step - loss: 1.8627 - val_loss: 1.8746
Epoch 8/200
9989/9989 [==============================] - 6s 589us/step - loss: 1.8512 - val_loss: 1.8656
Epoch 9/200
9989/9989 [==============================] - 6s 593us/step - loss: 1.8400 - val_loss: 1.8569
Epoch 10/200
9989/9989 [==============================] - 6s 582us/step - loss: 1.8292 - val_loss: 1.8485
Epoch 11/200
9989/9989 [==============================] - 6s 586us/step - loss: 1.8188 - val_loss: 1.8402
Epoch 12/200
9989/9989 [==============================] - 6s 586us/step - loss: 1.8085 - val_loss: 1.8323
Epoch 13/200
9989/9989 [==============================] - 6s 590us/step - loss: 1.7987 - val_loss: 1.8245
Epoch 14/200
9989/9989 [==============================] - 6s 590us/step - loss: 1.7890 - val_loss: 1.8169
Epoch 15/200
9989/9989 [==============================] - 6s 577us/step - loss: 1.7797 - val_loss: 1.8095
Epoch 16/200
9989/9989 [==============================] - 6s 582us/step - loss: 1.7707 - val_loss: 1.8024
Epoch 17/200
9989/9989 [==============================] - 6s 584us/step - loss: 1.7618 - val_loss: 1.7954
Epoch 18/200
9989/9989 [==============================] - 6s 588us/step - loss: 1.7533 - val_loss: 1.7886
Epoch 19/200
9989/9989 [==============================] - 6s 587us/step - loss: 1.7450 - val_loss: 1.7820
Epoch 20/200
9989/9989 [==============================] - 6s 592us/step - loss: 1.7370 - val_loss: 1.7758
Epoch 21/200
9989/9989 [==============================] - 6s 581us/step - loss: 1.7292 - val_loss: 1.7697
```

```
9989/9989 [==============================] - 6s 581us/step - loss: 1.7292 - val_loss: 1.7697
Epoch 22/200
9989/9989 [==============================] - 6s 588us/step - loss: 1.7216 - val_loss: 1.7640
Epoch 23/200
9989/9989 [==============================] - 6s 570us/step - loss: 1.7144 - val_loss: 1.7582
Epoch 24/200
9989/9989 [==============================] - 6s 574us/step - loss: 1.7073 - val_loss: 1.7528
Epoch 25/200
9989/9989 [==============================] - 6s 579us/step - loss: 1.7005 - val_loss: 1.7476
Epoch 26/200
9989/9989 [==============================] - 6s 577us/step - loss: 1.6939 - val_loss: 1.7426
Epoch 27/200
9989/9989 [==============================] - 6s 563us/step - loss: 1.6875 - val_loss: 1.7376
Epoch 28/200
9989/9989 [==============================] - 6s 603us/step - loss: 1.6813 - val_loss: 1.7330
Epoch 29/200
9989/9989 [==============================] - 6s 585us/step - loss: 1.6755 - val_loss: 1.7285
Epoch 30/200
9989/9989 [==============================] - 6s 611us/step - loss: 1.6698 - val_loss: 1.7242
Epoch 31/200
9989/9989 [==============================] - 6s 583us/step - loss: 1.6643 - val_loss: 1.7202
Epoch 32/200
9989/9989 [==============================] - 6s 578us/step - loss: 1.6590 - val_loss: 1.7162
Epoch 33/200
9989/9989 [==============================] - 6s 571us/step - loss: 1.6539 - val_loss: 1.7124
Epoch 34/200
9989/9989 [==============================] - 6s 585us/step - loss: 1.6490 - val_loss: 1.7088
Epoch 35/200
9989/9989 [==============================] - 6s 598us/step - loss: 1.6443 - val_loss: 1.7053
Epoch 36/200
9989/9989 [==============================] - 6s 579us/step - loss: 1.6398 - val_loss: 1.7021
Epoch 37/200
9989/9989 [==============================] - 6s 572us/step - loss: 1.6355 - val_loss: 1.6989
Epoch 38/200
9989/9989 [==============================] - 6s 579us/step - loss: 1.6313 - val_loss: 1.6959
Epoch 39/200
9989/9989 [==============================] - 6s 568us/step - loss: 1.6273 - val_loss: 1.6931
Epoch 40/200
9989/9989 [==============================] - 6s 596us/step - loss: 1.6235 - val_loss: 1.6903
Epoch 41/200
9989/9989 [==============================] - 6s 585us/step - loss: 1.6198 - val_loss: 1.6878
Epoch 42/200
9989/9989 [==============================] - 6s 595us/step - loss: 1.6163 - val_loss: 1.6853
Epoch 43/200
9989/9989 [==============================] - 6s 577us/step - loss: 1.6129 - val_loss: 1.6829
Epoch 44/200
9989/9989 [==============================] - 6s 572us/step - loss: 1.6097 - val_loss: 1.6808
Epoch 45/200
9989/9989 [==============================] - 6s 587us/step - loss: 1.6065 - val_loss: 1.6786
Epoch 46/200
9989/9989 [==============================] - 6s 589us/step - loss: 1.6036 - val_loss: 1.6765
Epoch 47/200
9989/9989 [==============================] - 6s 588us/step - loss: 1.6007 - val_loss: 1.6746
Epoch 48/200
9989/9989 [==============================] - 6s 604us/step - loss: 1.5980 - val_loss: 1.6728
Epoch 49/200
9989/9989 [==============================] - 6s 586us/step - loss: 1.5954 - val_loss: 1.6710
Epoch 50/200
9989/9989 [==============================] - 6s 572us/step - loss: 1.5929 - val_loss: 1.6694
Epoch 51/200
9989/9989 [==============================] - 6s 585us/step - loss: 1.5904 - val_loss: 1.6678
Epoch 52/200
9989/9989 [==============================] - 6s 584us/step - loss: 1.5882 - val_loss: 1.6664
Epoch 53/200
9989/9989 [==============================] - 6s 596us/step - loss: 1.5860 - val_loss: 1.6648
Epoch 54/200
9989/9989 [==============================] - 6s 568us/step - loss: 1.5839 - val_loss: 1.6636
Epoch 55/200
9989/9989 [==============================] - 6s 596us/step - loss: 1.5819 - val_loss: 1.6624
Epoch 56/200
9989/9989 [==============================] - 6s 589us/step - loss: 1.5799 - val_loss: 1.6611
Epoch 57/200
9989/9989 [==============================] - 6s 588us/step - loss: 1.5781 - val_loss: 1.6599
Epoch 58/200
9989/9989 [==============================] - 6s 596us/step - loss: 1.5763 - val_loss: 1.6588
Epoch 59/200
9989/9989 [==============================] - 6s 579us/step - loss: 1.5746 - val_loss: 1.6579
Epoch 60/200
```

```
Epoch 60/200
9989/9989 [==============================] - 6s 582us/step - loss: 1.5730 - val_loss: 1.6568
Epoch 61/200
9989/9989 [==============================] - 6s 584us/step - loss: 1.5715 - val_loss: 1.6558
Epoch 62/200
9989/9989 [==============================] - 6s 591us/step - loss: 1.5700 - val_loss: 1.6550
Epoch 63/200
9989/9989 [==============================] - 6s 584us/step - loss: 1.5686 - val_loss: 1.6540
Epoch 64/200
9989/9989 [==============================] - 6s 590us/step - loss: 1.5673 - val_loss: 1.6532
Epoch 65/200
9989/9989 [==============================] - 6s 635us/step - loss: 1.5660 - val_loss: 1.6525
Epoch 66/200
9989/9989 [==============================] - 6s 633us/step - loss: 1.5647 - val_loss: 1.6517
Epoch 67/200
9989/9989 [==============================] - 6s 613us/step - loss: 1.5636 - val_loss: 1.6511
Epoch 68/200
9989/9989 [==============================] - 6s 608us/step - loss: 1.5624 - val_loss: 1.6504
Epoch 69/200
9989/9989 [==============================] - 6s 610us/step - loss: 1.5613 - val_loss: 1.6497
Epoch 70/200
9989/9989 [==============================] - 6s 631us/step - loss: 1.5603 - val_loss: 1.6492
Epoch 71/200
9989/9989 [==============================] - 6s 621us/step - loss: 1.5593 - val_loss: 1.6486
Epoch 72/200
9989/9989 [==============================] - 6s 641us/step - loss: 1.5584 - val_loss: 1.6480
Epoch 73/200
9989/9989 [==============================] - 6s 620us/step - loss: 1.5574 - val_loss: 1.6475
Epoch 74/200
9989/9989 [==============================] - 6s 624us/step - loss: 1.5566 - val_loss: 1.6470
Epoch 75/200
9989/9989 [==============================] - 6s 617us/step - loss: 1.5557 - val_loss: 1.6466
Epoch 76/200
9989/9989 [==============================] - 6s 629us/step - loss: 1.5550 - val_loss: 1.6461
Epoch 77/200
9989/9989 [==============================] - 6s 609us/step - loss: 1.5542 - val_loss: 1.6458
Epoch 78/200
9989/9989 [==============================] - 6s 616us/step - loss: 1.5534 - val_loss: 1.6452
Epoch 79/200
9989/9989 [==============================] - 6s 603us/step - loss: 1.5527 - val_loss: 1.6448
Epoch 80/200
9989/9989 [==============================] - 6s 634us/step - loss: 1.5521 - val_loss: 1.6445
Epoch 81/200
9989/9989 [==============================] - 6s 612us/step - loss: 1.5514 - val_loss: 1.6441
Epoch 82/200
9989/9989 [==============================] - 6s 596us/step - loss: 1.5508 - val_loss: 1.6436
Epoch 83/200
9989/9989 [==============================] - 6s 596us/step - loss: 1.5502 - val_loss: 1.6433
Epoch 84/200
9989/9989 [==============================] - 6s 581us/step - loss: 1.5496 - val_loss: 1.6430
Epoch 85/200
9989/9989 [==============================] - 6s 575us/step - loss: 1.5491 - val_loss: 1.6427
Epoch 86/200
9989/9989 [==============================] - 6s 617us/step - loss: 1.5486 - val_loss: 1.6424
Epoch 87/200
9989/9989 [==============================] - 6s 619us/step - loss: 1.5481 - val_loss: 1.6422
Epoch 88/200
9989/9989 [==============================] - 6s 612us/step - loss: 1.5476 - val_loss: 1.6420
Epoch 89/200
9989/9989 [==============================] - 6s 605us/step - loss: 1.5471 - val_loss: 1.6418
Epoch 90/200
9989/9989 [==============================] - 6s 613us/step - loss: 1.5467 - val_loss: 1.6414
Epoch 91/200
9989/9989 [==============================] - 6s 594us/step - loss: 1.5463 - val_loss: 1.6412
Epoch 92/200
9989/9989 [==============================] - 6s 597us/step - loss: 1.5459 - val_loss: 1.6410
Epoch 93/200
9989/9989 [==============================] - 6s 576us/step - loss: 1.5455 - val_loss: 1.6407
Epoch 94/200
9989/9989 [==============================] - 6s 591us/step - loss: 1.5451 - val_loss: 1.6406
Epoch 95/200
9989/9989 [==============================] - 6s 582us/step - loss: 1.5447 - val_loss: 1.6403
Epoch 96/200
9989/9989 [==============================] - 6s 596us/step - loss: 1.5444 - val_loss: 1.6402
Epoch 97/200
9989/9989 [==============================] - 6s 584us/step - loss: 1.5441 - val_loss: 1.6399
Epoch 98/200
```

```
9989/9989 [==============================] - 6s 582us/step - loss: 1.5437 - val_loss: 1.6398
Epoch 99/200
9989/9989 [==============================] - 6s 573us/step - loss: 1.5434 - val_loss: 1.6397
Epoch 100/200
9989/9989 [==============================] - 6s 583us/step - loss: 1.5431 - val_loss: 1.6395
Epoch 101/200
9989/9989 [==============================] - 6s 585us/step - loss: 1.5429 - val_loss: 1.6394
Epoch 102/200
9989/9989 [==============================] - 6s 587us/step - loss: 1.5426 - val_loss: 1.6391
Epoch 103/200
9989/9989 [==============================] - 6s 579us/step - loss: 1.5423 - val_loss: 1.6389
Epoch 104/200
9989/9989 [==============================] - 6s 602us/step - loss: 1.5421 - val_loss: 1.6387
Epoch 105/200
9989/9989 [==============================] - 6s 602us/step - loss: 1.5418 - val_loss: 1.6386
Epoch 106/200
9989/9989 [==============================] - 6s 603us/step - loss: 1.5416 - val_loss: 1.6385
Epoch 107/200
9989/9989 [==============================] - 6s 608us/step - loss: 1.5414 - val_loss: 1.6383
Epoch 108/200
9989/9989 [==============================] - 6s 593us/step - loss: 1.5412 - val_loss: 1.6383
Epoch 109/200
9989/9989 [==============================] - 6s 587us/step - loss: 1.5410 - val_loss: 1.6382
Epoch 110/200
9989/9989 [==============================] - 6s 604us/step - loss: 1.5408 - val_loss: 1.6380
Epoch 111/200
9989/9989 [==============================] - 6s 578us/step - loss: 1.5406 - val_loss: 1.6379
Epoch 112/200
9989/9989 [==============================] - 6s 586us/step - loss: 1.5404 - val_loss: 1.6378
Epoch 113/200
9989/9989 [==============================] - 6s 584us/step - loss: 1.5403 - val_loss: 1.6377
Epoch 114/200
9989/9989 [==============================] - 6s 596us/step - loss: 1.5401 - val_loss: 1.6375
Epoch 115/200
9989/9989 [==============================] - 6s 595us/step - loss: 1.5399 - val_loss: 1.6374
Epoch 116/200
9989/9989 [==============================] - 6s 604us/step - loss: 1.5398 - val_loss: 1.6373
Epoch 117/200
9989/9989 [==============================] - 6s 579us/step - loss: 1.5397 - val_loss: 1.6373
Epoch 118/200
9989/9989 [==============================] - 6s 600us/step - loss: 1.5395 - val_loss: 1.6373
Epoch 119/200
9989/9989 [==============================] - 6s 582us/step - loss: 1.5394 - val_loss: 1.6371
Epoch 120/200
9989/9989 [==============================] - 6s 577us/step - loss: 1.5393 - val_loss: 1.6371
Epoch 121/200
9989/9989 [==============================] - 6s 592us/step - loss: 1.5392 - val_loss: 1.6370
Epoch 122/200
9989/9989 [==============================] - 6s 592us/step - loss: 1.5390 - val_loss: 1.6368
Epoch 123/200
9989/9989 [==============================] - 6s 594us/step - loss: 1.5389 - val_loss: 1.6367
Epoch 124/200
9989/9989 [==============================] - 6s 592us/step - loss: 1.5388 - val_loss: 1.6367
Epoch 125/200
9989/9989 [==============================] - 6s 596us/step - loss: 1.5387 - val_loss: 1.6367
Epoch 126/200
9989/9989 [==============================] - 6s 583us/step - loss: 1.5386 - val_loss: 1.6366
Epoch 127/200
9989/9989 [==============================] - 6s 584us/step - loss: 1.5385 - val_loss: 1.6365
Epoch 128/200
9989/9989 [==============================] - 6s 600us/step - loss: 1.5384 - val_loss: 1.6364
Epoch 129/200
9989/9989 [==============================] - 6s 601us/step - loss: 1.5383 - val_loss: 1.6365
Epoch 130/200
9989/9989 [==============================] - 6s 599us/step - loss: 1.5382 - val_loss: 1.6363
Epoch 131/200
9989/9989 [==============================] - 6s 591us/step - loss: 1.5382 - val_loss: 1.6364
Epoch 132/200
9989/9989 [==============================] - 6s 602us/step - loss: 1.5381 - val_loss: 1.6363
Epoch 133/200
9989/9989 [==============================] - 6s 595us/step - loss: 1.5380 - val_loss: 1.6361
Epoch 134/200
9989/9989 [==============================] - 6s 601us/step - loss: 1.5380 - val_loss: 1.6361
Epoch 135/200
9989/9989 [==============================] - 6s 599us/step - loss: 1.5379 - val_loss: 1.6361
Epoch 136/200
9989/9989 [==============================] - 6s 571us/step - loss: 1.5378 - val_loss: 1.6360
```

```
Epoch 137/200
9989/9989 [==============================] - 6s 595us/step - loss: 1.5378 - val_loss: 1.6360
Epoch 138/200
9989/9989 [==============================] - 6s 587us/step - loss: 1.5377 - val_loss: 1.6360
Epoch 139/200
9989/9989 [==============================] - 6s 595us/step - loss: 1.5377 - val_loss: 1.6359
Epoch 140/200
9989/9989 [==============================] - 6s 597us/step - loss: 1.5376 - val_loss: 1.6357
Epoch 141/200
9989/9989 [==============================] - 6s 584us/step - loss: 1.5376 - val_loss: 1.6357
Epoch 142/200
9989/9989 [==============================] - 6s 590us/step - loss: 1.5375 - val_loss: 1.6357
Epoch 143/200
9989/9989 [==============================] - 6s 597us/step - loss: 1.5375 - val_loss: 1.6358
Epoch 144/200
9989/9989 [==============================] - 6s 590us/step - loss: 1.5374 - val_loss: 1.6356
Epoch 145/200
9989/9989 [==============================] - 6s 581us/step - loss: 1.5374 - val_loss: 1.6357
Epoch 146/200
9989/9989 [==============================] - 6s 586us/step - loss: 1.5374 - val_loss: 1.6356
Epoch 147/200
9989/9989 [==============================] - 6s 585us/step - loss: 1.5373 - val_loss: 1.6355
Epoch 148/200
9989/9989 [==============================] - 6s 576us/step - loss: 1.5373 - val_loss: 1.6355
Epoch 149/200
9989/9989 [==============================] - 6s 578us/step - loss: 1.5373 - val_loss: 1.6355
Epoch 150/200
9989/9989 [==============================] - 6s 577us/step - loss: 1.5372 - val_loss: 1.6355
Epoch 151/200
9989/9989 [==============================] - 6s 599us/step - loss: 1.5372 - val_loss: 1.6354
Epoch 152/200
9989/9989 [==============================] - 6s 595us/step - loss: 1.5372 - val_loss: 1.6355
Epoch 153/200
9989/9989 [==============================] - 6s 588us/step - loss: 1.5371 - val_loss: 1.6354
Epoch 154/200
9989/9989 [==============================] - 6s 587us/step - loss: 1.5371 - val_loss: 1.6355
```

We would obviouslt get better results with LSTM but we need more epochs

MODEL 7 : Bi -LSTM

One question could be: why do i use so much dropout? Well, fit the model with no or little dropout and you will that it starts to overfit :)

Let's see if Bi-directional LSTM can give us better results. Its a piece of cake to do it with Keras :)

In [82]:

```python
# A simple bidirectional LSTM with glove embeddings and two dense layers
model = Sequential()
model.add(Embedding(len(word_index) + 1,
                     300,
                     weights=[embedding_matrix],
                     input_length=max_len,
                     trainable=False))
model.add(SpatialDropout1D(0.3))
model.add(Bidirectional(LSTM(300, dropout=0.3, recurrent_dropout=0.3)))

model.add(Dense(1024, activation='relu'))
model.add(Dropout(0.8))

model.add(Dense(1024, activation='relu'))
model.add(Dropout(0.8))

model.add(Dense(7))
model.add(Activation('softmax'))
model.compile(loss='categorical_crossentropy', optimizer='adam')

# Fit the model with early stopping callback
earlystop = EarlyStopping(monitor='val_loss', min_delta=0, patience=3, verbose=0, mode='auto')

history=model.fit(xtrain_pad, y=y_train_enc_nn, batch_size=512, epochs=200, verbose=1,
validation_data=(xvalid_pad, y_cv_enc_nn), callbacks=[earlystop])
```

```
Train on 9989 samples, validate on 1109 samples
Epoch 1/200
9989/9989 [==============================] - 13s 1ms/step - loss: 1.9397 - val_loss: 1.9351
Epoch 2/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.9259 - val_loss: 1.9240
Epoch 3/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.9122 - val_loss: 1.9135
Epoch 4/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.8991 - val_loss: 1.9033
Epoch 5/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.8864 - val_loss: 1.8934
Epoch 6/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.8742 - val_loss: 1.8838
Epoch 7/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.8623 - val_loss: 1.8745
Epoch 8/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.8508 - val_loss: 1.8655
Epoch 9/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.8396 - val_loss: 1.8567
Epoch 10/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.8288 - val_loss: 1.8482
Epoch 11/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.8183 - val_loss: 1.8401
Epoch 12/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.8081 - val_loss: 1.8320
Epoch 13/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.7982 - val_loss: 1.8242
Epoch 14/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.7886 - val_loss: 1.8166
Epoch 15/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.7792 - val_loss: 1.8092
Epoch 16/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.7701 - val_loss: 1.8021
Epoch 17/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.7613 - val_loss: 1.7951
Epoch 18/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.7528 - val_loss: 1.7885
Epoch 19/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.7445 - val_loss: 1.7819
Epoch 20/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.7365 - val_loss: 1.7757
Epoch 21/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.7287 - val_loss: 1.7696
Epoch 22/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.7212 - val_loss: 1.7637
Epoch 23/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.7139 - val_loss: 1.7582
Epoch 24/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.7069 - val_loss: 1.7527
Epoch 25/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.7001 - val_loss: 1.7475
Epoch 26/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6936 - val_loss: 1.7425
Epoch 27/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6873 - val_loss: 1.7376
Epoch 28/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6811 - val_loss: 1.7329
Epoch 29/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6752 - val_loss: 1.7285
Epoch 30/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6695 - val_loss: 1.7243
Epoch 31/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6641 - val_loss: 1.7201
Epoch 32/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6588 - val_loss: 1.7161
Epoch 33/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.6537 - val_loss: 1.7124
Epoch 34/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6488 - val_loss: 1.7088
Epoch 35/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6442 - val_loss: 1.7054
Epoch 36/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6397 - val_loss: 1.7021
Epoch 37/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6353 - val_loss: 1.6990
Epoch 38/200
```

```
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6312 - val_loss: 1.6960
Epoch 39/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6272 - val_loss: 1.6932
Epoch 40/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6234 - val_loss: 1.6905
Epoch 41/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6197 - val_loss: 1.6879
Epoch 42/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.6162 - val_loss: 1.6854
Epoch 43/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6128 - val_loss: 1.6831
Epoch 44/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6096 - val_loss: 1.6808
Epoch 45/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6065 - val_loss: 1.6786
Epoch 46/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6035 - val_loss: 1.6767
Epoch 47/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.6007 - val_loss: 1.6747
Epoch 48/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5979 - val_loss: 1.6729
Epoch 49/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5954 - val_loss: 1.6712
Epoch 50/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5928 - val_loss: 1.6695
Epoch 51/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5904 - val_loss: 1.6679
Epoch 52/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5882 - val_loss: 1.6663
Epoch 53/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5860 - val_loss: 1.6650
Epoch 54/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5839 - val_loss: 1.6637
Epoch 55/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5819 - val_loss: 1.6623
Epoch 56/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5799 - val_loss: 1.6611
Epoch 57/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5781 - val_loss: 1.6599
Epoch 58/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5763 - val_loss: 1.6588
Epoch 59/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5746 - val_loss: 1.6578
Epoch 60/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5730 - val_loss: 1.6567
Epoch 61/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5715 - val_loss: 1.6558
Epoch 62/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5700 - val_loss: 1.6549
Epoch 63/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5686 - val_loss: 1.6541
Epoch 64/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5673 - val_loss: 1.6533
Epoch 65/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5660 - val_loss: 1.6525
Epoch 66/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5647 - val_loss: 1.6519
Epoch 67/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5636 - val_loss: 1.6511
Epoch 68/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5624 - val_loss: 1.6505
Epoch 69/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5614 - val_loss: 1.6499
Epoch 70/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5603 - val_loss: 1.6492
Epoch 71/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5593 - val_loss: 1.6486
Epoch 72/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5584 - val_loss: 1.6481
Epoch 73/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5575 - val_loss: 1.6475
Epoch 74/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5566 - val_loss: 1.6471
Epoch 75/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5558 - val_loss: 1.6466
Epoch 76/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5549 - val_loss: 1.6460
Epoch 77/200
```

```
Epoch 77/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5542 - val_loss: 1.6457
Epoch 78/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5535 - val_loss: 1.6453
Epoch 79/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5527 - val_loss: 1.6449
Epoch 80/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5521 - val_loss: 1.6445
Epoch 81/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5514 - val_loss: 1.6441
Epoch 82/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5508 - val_loss: 1.6437
Epoch 83/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5502 - val_loss: 1.6434
Epoch 84/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5496 - val_loss: 1.6431
Epoch 85/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5491 - val_loss: 1.6428
Epoch 86/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5486 - val_loss: 1.6425
Epoch 87/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5481 - val_loss: 1.6422
Epoch 88/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5476 - val_loss: 1.6420
Epoch 89/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5471 - val_loss: 1.6417
Epoch 90/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5467 - val_loss: 1.6415
Epoch 91/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5462 - val_loss: 1.6412
Epoch 92/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5458 - val_loss: 1.6410
Epoch 93/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5454 - val_loss: 1.6408
Epoch 94/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5451 - val_loss: 1.6406
Epoch 95/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5447 - val_loss: 1.6403
Epoch 96/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5444 - val_loss: 1.6402
Epoch 97/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5441 - val_loss: 1.6398
Epoch 98/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5437 - val_loss: 1.6396
Epoch 99/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5434 - val_loss: 1.6395
Epoch 100/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5431 - val_loss: 1.6392
Epoch 101/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5428 - val_loss: 1.6391
Epoch 102/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5426 - val_loss: 1.6390
Epoch 103/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5423 - val_loss: 1.6388
Epoch 104/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5421 - val_loss: 1.6387
Epoch 105/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5418 - val_loss: 1.6386
Epoch 106/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5416 - val_loss: 1.6385
Epoch 107/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5414 - val_loss: 1.6383
Epoch 108/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5412 - val_loss: 1.6384
Epoch 109/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5410 - val_loss: 1.6381
Epoch 110/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5408 - val_loss: 1.6380
Epoch 111/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5406 - val_loss: 1.6379
Epoch 112/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5404 - val_loss: 1.6378
Epoch 113/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5403 - val_loss: 1.6377
Epoch 114/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5401 - val_loss: 1.6376
Epoch 115/200
```

```
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5399 - val_loss: 1.6374
Epoch 116/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5398 - val_loss: 1.6374
Epoch 117/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5397 - val_loss: 1.6373
Epoch 118/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5395 - val_loss: 1.6372
Epoch 119/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5394 - val_loss: 1.6371
Epoch 120/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5392 - val_loss: 1.6370
Epoch 121/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5391 - val_loss: 1.6370
Epoch 122/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5390 - val_loss: 1.6369
Epoch 123/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5389 - val_loss: 1.6368
Epoch 124/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5388 - val_loss: 1.6366
Epoch 125/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5387 - val_loss: 1.6366
Epoch 126/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5386 - val_loss: 1.6366
Epoch 127/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5385 - val_loss: 1.6366
Epoch 128/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5384 - val_loss: 1.6365
Epoch 129/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5383 - val_loss: 1.6364
Epoch 130/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5382 - val_loss: 1.6363
Epoch 131/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5382 - val_loss: 1.6363
Epoch 132/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5381 - val_loss: 1.6363
Epoch 133/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5380 - val_loss: 1.6361
Epoch 134/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5379 - val_loss: 1.6362
Epoch 135/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5379 - val_loss: 1.6361
Epoch 136/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5378 - val_loss: 1.6360
Epoch 137/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5378 - val_loss: 1.6360
Epoch 138/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5377 - val_loss: 1.6360
Epoch 139/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5377 - val_loss: 1.6359
Epoch 140/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5376 - val_loss: 1.6358
Epoch 141/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5376 - val_loss: 1.6359
Epoch 142/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5375 - val_loss: 1.6358
Epoch 143/200
9989/9989 [==============================] - 12s 1ms/step - loss: 1.5375 - val_loss: 1.6358
Epoch 144/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5374 - val_loss: 1.6357
Epoch 145/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5374 - val_loss: 1.6356
Epoch 146/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5374 - val_loss: 1.6357
Epoch 147/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5373 - val_loss: 1.6357
Epoch 148/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5373 - val_loss: 1.6356
Epoch 149/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5373 - val_loss: 1.6356
Epoch 150/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5372 - val_loss: 1.6355
Epoch 151/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5372 - val_loss: 1.6354
Epoch 152/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5372 - val_loss: 1.6354
Epoch 153/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5371 - val_loss: 1.6354
```

```
Epoch 154/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5371 - val_loss: 1.6355
Epoch 155/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5371 - val_loss: 1.6355
Epoch 156/200
9989/9989 [==============================] - 11s 1ms/step - loss: 1.5371 - val_loss: 1.6355
```

MODEL 8 : Trying customised Ensembling

In [83]:

```
# this is the main ensembling class. how to use it is in the next cell!
import numpy as np
from sklearn.metrics import roc_auc_score
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import StratifiedKFold, KFold
import pandas as pd
import os
import sys
import logging

logging.basicConfig(
    level=logging.DEBUG,
    format="[%(asctime)s] %(levelname)s %(message)s",
    datefmt="%H:%M:%S", stream=sys.stdout)
logger = logging.getLogger(__name__)


class Ensembler(object):
    def __init__(self, model_dict, num_folds=3, task_type='classification', optimize=roc_auc_score,
                 lower_is_better=False, save_path=None):
        """
        Ensembler init function
        :param model_dict: model dictionary, see README for its format
        :param num_folds: the number of folds for ensembling
        :param task_type: classification or regression
        :param optimize: the function to optimize for, e.g. AUC, logloss, etc. Must have two argum
ents y_test and y_pred
        :param lower_is_better: is lower value of optimization function better or higher
        :param save_path: path to which model pickles will be dumped to along with generated
predictions, or None
        """

        self.model_dict = model_dict
        self.levels = len(self.model_dict)
        self.num_folds = num_folds
        self.task_type = task_type
        self.optimize = optimize
        self.lower_is_better = lower_is_better
        self.save_path = save_path

        self.training_data = None
        self.test_data = None
        self.y = None
        self.lbl_enc = None
        self.y_enc = None
        self.train_prediction_dict = None
        self.test_prediction_dict = None
        self.num_classes = None

    def fit(self, training_data, y, lentrain):
        """
        :param training_data: training data in tabular format
        :param y: binary, multi-class or regression
        :return: chain of models to be used in prediction
        """

        self.training_data = training_data
        self.y = y

        if self.task_type == 'classification':
            self.num_classes = len(np.unique(self.y))
            logger.info("Found %d classes", self.num_classes)
            self.lbl_enc = LabelEncoder()
            self.y_enc = self.lbl_enc.fit_transform(self.y)
```

```
            self.y_enc = self.lbl_enc.fit_transform(self.y)
            kf = StratifiedKFold(n_splits=self.num_folds)
            train_prediction_shape = (lentrain, self.num_classes)
        else:
            self.num_classes = -1
            self.y_enc = self.y
            kf = KFold(n_splits=self.num_folds)
            train_prediction_shape = (lentrain, 1)

        self.train_prediction_dict = {}
        for level in range(self.levels):
            self.train_prediction_dict[level] = np.zeros((train_prediction_shape[0],
                                                          train_prediction_shape[1] * len(self.mode
dict[level])))

        for level in range(self.levels):

            if level == 0:
                temp_train = self.training_data
            else:
                temp_train = self.train_prediction_dict[level - 1]

            for model_num, model in enumerate(self.model_dict[level]):
                validation_scores = []
                foldnum = 1
                for train_index, valid_index in kf.split(self.train_prediction_dict[0], self.y_enc)
:
                    logger.info("Training Level %d Fold # %d. Model # %d", level, foldnum,
model_num)

                    if level != 0:
                        l_training_data = temp_train[train_index]
                        l_validation_data = temp_train[valid_index]
                        model.fit(l_training_data, self.y_enc[train_index])
                    else:
                        l0_training_data = temp_train[0][model_num]
                        if type(l0_training_data) == list:
                            l_training_data = [x[train_index] for x in l0_training_data]
                            l_validation_data = [x[valid_index] for x in l0_training_data]
                        else:
                            l_training_data = l0_training_data[train_index]
                            l_validation_data = l0_training_data[valid_index]
                        model.fit(l_training_data, self.y_enc[train_index])

                    logger.info("Predicting Level %d. Fold # %d. Model # %d", level, foldnum, model
num)

                    if self.task_type == 'classification':
                        temp_train_predictions = model.predict_proba(l_validation_data)
                        self.train_prediction_dict[level][valid_index,
                        (model_num * self.num_classes):(model_num * self.num_classes) +
                                                       self.num_classes] = temp_train_predictions

                    else:
                        temp_train_predictions = model.predict(l_validation_data)
                        self.train_prediction_dict[level][valid_index, model_num] = temp_train_pred
ctions
                    validation_score = self.optimize(self.y_enc[valid_index],
temp_train_predictions)
                    validation_scores.append(validation_score)
                    logger.info("Level %d. Fold # %d. Model # %d. Validation Score = %f", level, fo
dnum, model_num,
                                validation_score)
                    foldnum += 1
                avg_score = np.mean(validation_scores)
                std_score = np.std(validation_scores)
                logger.info("Level %d. Model # %d. Mean Score = %f. Std Dev = %f", level, model_num
,
                            avg_score, std_score)

            logger.info("Saving predictions for level # %d", level)
            train_predictions_df = pd.DataFrame(self.train_prediction_dict[level])
            train_predictions_df.to_csv(os.path.join(self.save_path, "train_predictions_level_" + s
tr(level) + ".csv"),
                                        index=False, header=None)

        return self.train_prediction_dict
```

```python
    def predict(self, test_data, lentest):
        self.test_data = test_data
        if self.task_type == 'classification':
            test_prediction_shape = (lentest, self.num_classes)
        else:
            test_prediction_shape = (lentest, 1)

        self.test_prediction_dict = {}
        for level in range(self.levels):
            self.test_prediction_dict[level] = np.zeros((test_prediction_shape[0],
                                                          test_prediction_shape[1] * len(self.model_
ct[level])))
        self.test_data = test_data
        for level in range(self.levels):
            if level == 0:
                temp_train = self.training_data
                temp_test = self.test_data
            else:
                temp_train = self.train_prediction_dict[level - 1]
                temp_test = self.test_prediction_dict[level - 1]

            for model_num, model in enumerate(self.model_dict[level]):

                logger.info("Training Fulldata Level %d. Model # %d", level, model_num)
                if level == 0:
                    model.fit(temp_train[0][model_num], self.y_enc)
                else:
                    model.fit(temp_train, self.y_enc)

                logger.info("Predicting Test Level %d. Model # %d", level, model_num)

                if self.task_type == 'classification':
                    if level == 0:
                        temp_test_predictions = model.predict_proba(temp_test[0][model_num])
                    else:
                        temp_test_predictions = model.predict_proba(temp_test)
                    self.test_prediction_dict[level][:, (model_num * self.num_classes): (model_num
* self.num_classes) +

self.num_classes] = temp_test_predictions

                else:
                    if level == 0:
                        temp_test_predictions = model.predict(temp_test[0][model_num])
                    else:
                        temp_test_predictions = model.predict(temp_test)
                    self.test_prediction_dict[level][:, model_num] = temp_test_predictions

            test_predictions_df = pd.DataFrame(self.test_prediction_dict[level])
            test_predictions_df.to_csv(os.path.join(self.save_path, "test_predictions_level_" + str
(level) + ".csv"),
                                       index=False, header=None)

        return self.test_prediction_dict
```

In [87]:

```python
import warnings
warnings.filterwarnings("ignore")
# specify the data to be used for every level of ensembling:
train_data_dict = {0: [X_train_tfv, X_train_ctv, X_train_tfv, X_train_ctv], 1: [xtrain_glove]}
test_data_dict = {0: [X_valid_tfv, X_valid_ctv, X_valid_tfv, X_valid_ctv], 1: [xvalid_glove]}

model_dict = {0: [LogisticRegression(), LogisticRegression(), MultinomialNB(alpha=0.1), Multinomial
NB()],

              1: [xgb.XGBClassifier(silent=True, n_estimators=120, max_depth=7)]}

ens = Ensembler(model_dict=model_dict, num_folds=3, task_type='classification',
                optimize=multiclass_logloss, lower_is_better=True, save_path='')

ens.fit(train_data_dict, y_train_enc, lentrain=xtrain_glove.shape[0])
preds = ens.predict(test_data_dict, lentest=xvalid_glove.shape[0])
```

```
[10:31:55] INFO Found 7 classes
```

```
[10:31:55] INFO Training Level 0 Fold # 1. Model # 0
[10:31:57] INFO Predicting Level 0. Fold # 1. Model # 0
[10:31:57] INFO Level 0. Fold # 1. Model # 0. Validation Score = 1.425598
[10:31:57] INFO Training Level 0 Fold # 2. Model # 0
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning:
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
[10:31:58] INFO Predicting Level 0. Fold # 2. Model # 0
[10:31:58] INFO Level 0. Fold # 2. Model # 0. Validation Score = 1.402926
[10:31:58] INFO Training Level 0 Fold # 3. Model # 0
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning:
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
[10:31:59] INFO Predicting Level 0. Fold # 3. Model # 0
[10:31:59] INFO Level 0. Fold # 3. Model # 0. Validation Score = 1.408808
[10:31:59] INFO Level 0. Model # 0. Mean Score = 1.412444. Std Dev = 0.009607
[10:31:59] INFO Training Level 0 Fold # 1. Model # 1
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning:
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
[10:32:07] INFO Predicting Level 0. Fold # 1. Model # 1
[10:32:07] INFO Level 0. Fold # 1. Model # 1. Validation Score = 1.475822
[10:32:07] INFO Training Level 0 Fold # 2. Model # 1
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning:
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
[10:32:14] INFO Predicting Level 0. Fold # 2. Model # 1
[10:32:15] INFO Level 0. Fold # 2. Model # 1. Validation Score = 1.444641
[10:32:15] INFO Training Level 0 Fold # 3. Model # 1
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning:
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
[10:32:21] INFO Predicting Level 0. Fold # 3. Model # 1
[10:32:22] INFO Level 0. Fold # 3. Model # 1. Validation Score = 1.463754
[10:32:22] INFO Level 0. Model # 1. Mean Score = 1.461406. Std Dev = 0.012837
[10:32:22] INFO Training Level 0 Fold # 1. Model # 2
[10:32:22] INFO Predicting Level 0. Fold # 1. Model # 2
[10:32:22] INFO Level 0. Fold # 1. Model # 2. Validation Score = 1.547975
[10:32:22] INFO Training Level 0 Fold # 2. Model # 2
[10:32:22] INFO Predicting Level 0. Fold # 2. Model # 2
[10:32:22] INFO Level 0. Fold # 2. Model # 2. Validation Score = 1.500929
[10:32:22] INFO Training Level 0 Fold # 3. Model # 2
[10:32:22] INFO Predicting Level 0. Fold # 3. Model # 2
[10:32:22] INFO Level 0. Fold # 3. Model # 2. Validation Score = 1.521596
[10:32:22] INFO Level 0. Model # 2. Mean Score = 1.523500. Std Dev = 0.019254
[10:32:22] INFO Training Level 0 Fold # 1. Model # 3
[10:32:22] INFO Predicting Level 0. Fold # 1. Model # 3
[10:32:22] INFO Level 0. Fold # 1. Model # 3. Validation Score = 2.029555
[10:32:22] INFO Training Level 0 Fold # 2. Model # 3
[10:32:22] INFO Predicting Level 0. Fold # 2. Model # 3
[10:32:22] INFO Level 0. Fold # 2. Model # 3. Validation Score = 1.981980
[10:32:22] INFO Training Level 0 Fold # 3. Model # 3
[10:32:22] INFO Predicting Level 0. Fold # 3. Model # 3
[10:32:22] INFO Level 0. Fold # 3. Model # 3. Validation Score = 1.957865
[10:32:22] INFO Level 0. Model # 3. Mean Score = 1.989800. Std Dev = 0.029785
[10:32:22] INFO Saving predictions for level # 0
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning:
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
[10:32:22] INFO Training Level 1 Fold # 1. Model # 0
[10:32:46] INFO Predicting Level 1. Fold # 1. Model # 0
[10:32:46] INFO Level 1. Fold # 1. Model # 0. Validation Score = 1.496972
[10:32:46] INFO Training Level 1 Fold # 2. Model # 0
[10:33:10] INFO Predicting Level 1. Fold # 2. Model # 0
[10:33:10] INFO Level 1. Fold # 2. Model # 0. Validation Score = 1.462039
[10:33:10] INFO Training Level 1 Fold # 3. Model # 0
[10:33:35] INFO Predicting Level 1. Fold # 3. Model # 0
[10:33:35] INFO Level 1. Fold # 3. Model # 0. Validation Score = 1.476698
[10:33:35] INFO Level 1. Model # 0. Mean Score = 1.478570. Std Dev = 0.014322
[10:33:35] INFO Saving predictions for level # 1
[10:33:35] INFO Training Fulldata Level 0. Model # 0
[10:33:37] INFO Predicting Test Level 0. Model # 0
[10:33:37] INFO Training Fulldata Level 0. Model # 1
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning:
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
[10:33:44] INFO Predicting Test Level 0. Model # 1
[10:33:44] INFO Training Fulldata Level 0. Model # 2
[10:33:44] INFO Predicting Test Level 0. Model # 2
[10:33:44] INFO Training Fulldata Level 0. Model # 3
[10:33:44] INFO Predicting Test Level 0. Model # 3
[10:33:45] INFO Training Fulldata Level 1. Model # 0
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning:
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
```

```
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
[10:34:21] INFO Predicting Test Level 1. Model # 0
```

In [88]:

```
# check error:
multiclass_logloss(y_cv_enc, preds[1])
```

Out[88]:

```
1.5316193489752536
```

In [91]:

```
# Also check train error
preds = ens.predict(train_data_dict, lentest=xtrain_glove.shape[0])
multiclass_logloss(y_train_enc, preds[1])
```

```
[10:52:30] INFO Training Fulldata Level 0. Model # 0
[10:52:31] INFO Predicting Test Level 0. Model # 0
[10:52:31] INFO Training Fulldata Level 0. Model # 1
[10:52:39] INFO Predicting Test Level 0. Model # 1
[10:52:39] INFO Training Fulldata Level 0. Model # 2
[10:52:39] INFO Predicting Test Level 0. Model # 2
[10:52:39] INFO Training Fulldata Level 0. Model # 3
[10:52:39] INFO Predicting Test Level 0. Model # 3
[10:52:40] INFO Training Fulldata Level 1. Model # 0
[10:53:14] INFO Predicting Test Level 1. Model # 0
```

Out[91]:

```
1.0485667689038733
```

INFERENCE MODELLING:

In [94]:

```
from sklearn.externals import joblib

# Save the model as a pickle in a file
joblib.dump(ens, 'custom_ensembler.pkl')
joblib.dump(model, 'lstm.pkl')
joblib.dump(lr, 'lr2.pkl')
joblib.dump(tfv, 'tfidf.pkl')
```

Utility Functions:

In [95]:

```
import re

### Dataset Preprocessing
from nltk.stem.porter import PorterStemmer
def preprocessor(sentence):
  ps = PorterStemmer()

  review = re.sub('[^a-zA-Z]', ' ', sentence)
  review = review.lower()
  review = review.split()

  review = [ps.stem(word) for word in review if not word in stopwords.words('english')]
  review = ' '.join(review)
  return review
```

In [151]:

```
def mapper(ans):
  for i in ans:
    if ans==0:
      return 'Anger'
    elif ans==1:
      return 'Disgust'
    elif ans==2:
      return 'Fear'
    elif ans==3:
      return 'Joy'
    elif ans==4:
      return 'Neutral'
    elif ans==5:
      return 'Sadness'
    elif ans==6:
      return 'Surprise'
```

In [152]:

```
from sklearn.externals import joblib
def predictor(sentence):
  lst = []
  my_model = joblib.load('lr2.pkl')
  tfv = joblib.load('tfidf.pkl')

  sent = preprocessor(sentence)

  lst.append(sent)
  sent_tfv = tfv.transform(lst)
  ans = my_model.predict(sent_tfv)
  mapped_ans = mapper(ans)
  return mapped_ans
```

Let's Predict

In [153]:

```
ans = predictor('I hate you from bottom of my heart')
print(ans)
```

```
Anger
```

In [154]:

```
ans = predictor('Oh Wow what a beautiful place')
print(ans)
```

```
Joy
```

In [158]:

```
ans = predictor('I am really sorry , i am feeling reaaly very sad')
print(ans)
```

```
Sadness
```

CONCLUSION:

1. The results of Infernece model are okay'ish since we used Logistic Regression + TFIDF which performed awesome.
2. We see that ensembling improves the score by a great extent!
3. LSTM can win this with higher number of epochs or altering the learnng rate.

In [ ]:

```

```