Assignment

1. Try out models (Logistic regression, Linear-SVM) with simple TF-IDF vectors instead of TD_IDF weighted word2Vec.
2. Hyperparameter tune XgBoost using RandomSearch to reduce the log-loss.

1. Try out models (Logistic regression, Linear-SVM) with simple TF-IDF vectors instead of TD_IDF weighted word2Vec.

3.6 Featurizing text data with tfidf

In [62]:

```
import warnings
warnings.filterwarnings("ignore")

import pandas as pd
import matplotlib.pyplot as plt
import re
import time
import warnings
import numpy as np
from nltk.corpus import stopwords
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
warnings.filterwarnings("ignore")
import sys
import os
from tqdm import tqdm
from collections import Counter, defaultdict
from scipy.sparse import hstack
from sklearn.manifold import TSNE
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics.classification import accuracy_score, log_
loss
from sklearn.feature_extraction.text import TfidfVectorizer
from collections import Counter
from scipy.sparse import hstack
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC
from sklearn.model_selection import StratifiedKFold
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
import math
from sklearn.metrics import normalized_mutual_info_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
```

```
from sklearn.linear_model import SGDClassifier
from mlxtend.classifier import StackingClassifier
from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_recall_curve, auc, roc_cu
rve
import spacy
from lightgbm import LGBMClassifier
```

In [2]:
```
# avoid decoding problems
df = pd.read_csv("train.csv")

# encode questions to unicode
# https://stackoverflow.com/a/6812069
# ----------------- python 2 ---------------------
# df['question1'] = df['question1'].apply(lambda x: unicode(str
(x),"utf-8"))
# df['question2'] = df['question2'].apply(lambda x: unicode(str
(x),"utf-8"))
# ----------------- python 3 ---------------------
df['question1'] = df['question1'].apply(lambda x: str(x))
df['question2'] = df['question2'].apply(lambda x: str(x))
```

In [3]:
```
#prepro_features_train.csv (Simple Preprocessing Feartures)
#nlp_features_train.csv (NLP Features)
if os.path.isfile('nlp_features_train.csv'):
    dfnlp = pd.read_csv("nlp_features_train.csv",encoding='lati
n-1')
else:
    print("download nlp_features_train.csv from drive or run pr
evious notebook")

if os.path.isfile('df_fe_without_preprocessing_train.csv'):
    dfppro = pd.read_csv("df_fe_without_preprocessing_train.cs
v",encoding='latin-1')
else:
    print("download df_fe_without_preprocessing_train.csv from
 drive or run previous notebook")
```

In [4]:
```
df1 = dfnlp
df2 = dfppro.drop(['qid1','qid2','question1','question2','is_du
plicate'],axis=1)

# mregin df1 and df2

data=pd.merge(df1,df2,how='inner',on='id',)
y_true=data["is_duplicate"]
data=data.drop("is_duplicate",axis=1)
```

Random train test split(70:30)

Doing it before vectorising Question1 and Question2 to avoid data leakage

Taking only 100K of total datapoints because of computational strain

In [5]:
```
X_train,X_test, y_train, y_test = train_test_split(data, y_true
, stratify=y_true,test_size=0.3)
```

In [6]:
```
print("Number of data points in train data :",X_train.shape)
print("Number of data points in test data :",X_test.shape)
```

```
Number of data points in train data : (283003, 31)
Number of data points in test data : (121287, 31)
```

```
In [7]: print("-"*10, "Distribution of output variable in train data",
        "-"*10)
        train_distr = Counter(y_train)
        train_len = len(y_train)
        print("Class 0: ",int(train_distr[0])/train_len,"Class 1: ", in
        t(train_distr[1])/train_len)
        print("-"*10, "Distribution of output variable in test data",
        "-"*10)
        test_distr = Counter(y_test)
        test_len = len(y_test)
        print("Class 0: ",int(test_distr[1])/test_len, "Class 1: ",int(
        test_distr[1])/test_len)
```

```
---------- Distribution of output variable in train data
----------
Class 0:  0.6308025003268517 Class 1:  0.369197499673148
35
---------- Distribution of output variable in test data
----------
Class 0:  0.3691986775169639 Class 1:  0.369198677516963
9
```

TfIDF of Question1 and Question2

Doing this after the split to avoid data leakage

```
In [8]: from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.feature_extraction.text import CountVectorizer
        # merge texts
        train_questions = (X_train['question1']) + (X_train['question2'
        ])
        train_questions =train_questions.apply(lambda x: str(x))

        test_questions = (X_test['question1']) + (X_test['question2'])
        test_questions=test_questions.apply(lambda x: str(x))

        tfidf = TfidfVectorizer(lowercase=False,)
        train_tfidf_questions=tfidf.fit_transform(train_questions)
        test_tfidf_questions=tfidf.transform(test_questions)
```

```
In [9]: train_final_features = hstack((train_tfidf_questions,X_train.dr
        op(['id','qid1','qid2','question1','question2'],axis=1)))
        test_final_features = hstack((test_tfidf_questions,X_test.drop
        (['id','qid1','qid2','question1','question2'],axis=1)))
```

```
In [10]: train_final_features.shape,test_final_features.shape
```

```
((283003, 73906), (121287, 73906))
```

Machine learning models

```
In [63]: # This function plots the confusion matrices given y_i, y_i_ha
```

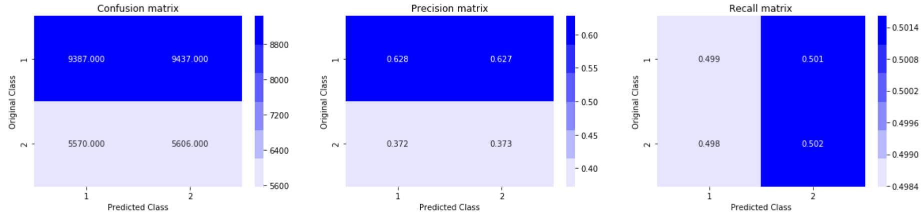
```
t.
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)

    A =(((C.T)/(C.sum(axis=1))).T)

    B =(C/C.sum(axis=0))

    plt.figure(figsize=(20,4))

    labels = [1,2]
    # representing A in heatmap format
    cmap=sns.light_palette("blue")
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabel
s=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")

    plt.subplot(1, 3, 2)
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabel
s=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Precision matrix")

    plt.subplot(1, 3, 3)
    # representing B in heatmap format
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabel
s=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")

    plt.show()
```

4.4 Building a random model (Finding worst-case log-loss)

In [27]:

```
# we need to generate 9 numbers and the sum of numbers should b
e 1
# one solution is to genarate 9 numbers and divide each of the
 numbers by their sum
# ref: https://stackoverflow.com/a/18662466/4084039
# we create a output array that has exactly same size as the CV
data
predicted_y = np.zeros((test_len,2))
for i in range(test_len):
    rand_probs = np.random.rand(1,2)
    predicted_y[i] = ((rand_probs/sum(sum(rand_probs)))[0])
print("Log loss on Test Data using Random Model",log_loss(y_tes
t, predicted_y, eps=1e-15))

predicted_y =np.argmax(predicted_y, axis=1)
plot_confusion_matrix(y_test, predicted_y)
```

```
Log loss on Test Data using Random Model 0.8861836643485
206
```

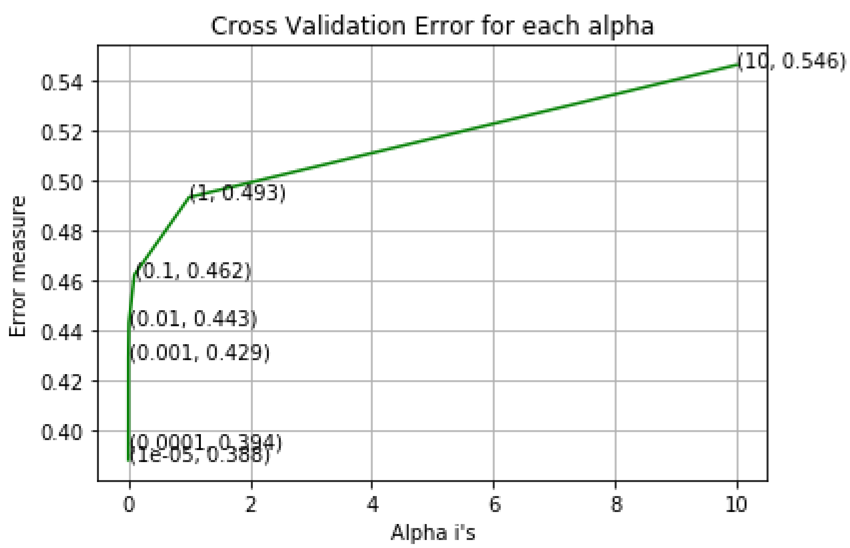


4.4 Logistic Regression with hyperparameter tuning

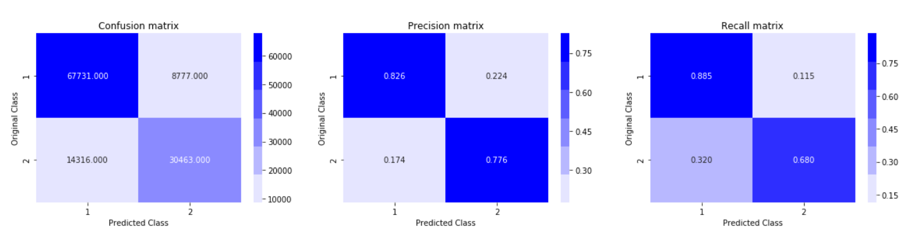
In [36]:

```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.


log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l2', loss='log', random_state=42)
    clf.fit(train_final_features, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_final_features, y_train)
    predict_y = sig_clf.predict_proba(test_final_features)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))

fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log_error_array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss='log', random_state=42)
clf.fit(train_final_features, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(train_final_features, y_train)

predict_y = sig_clf.predict_proba(train_final_features)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(test_final_features)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

```
For values of alpha =  1e-05 The log loss is: 0.38840477
731593986
For values of alpha =  0.0001 The log loss is: 0.3936099
3477465694
For values of alpha =  0.001 The log loss is: 0.42912329
650555026
For values of alpha =  0.01 The log loss is: 0.443291317
54336976
For values of alpha =  0.1 The log loss is: 0.4623789885
9229515
For values of alpha =  1 The log loss is: 0.493426792920
5486
For values of alpha =  10 The log loss is: 0.54634331858
0212
```




```
For values of best alpha =  1e-05 The train log loss is:
0.38513688366523374
For values of best alpha =  1e-05 The test log loss is:
0.38840477731593986
Total number of data points : 121287
```



4.5 Linear SVM with hyperparameter tuning

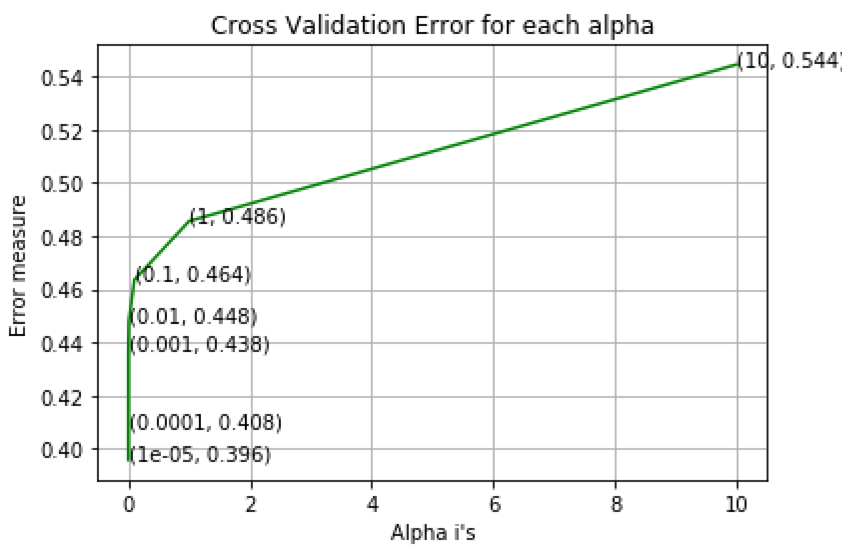
In [ ]:

In [37]:
```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD cl
assifier.
```

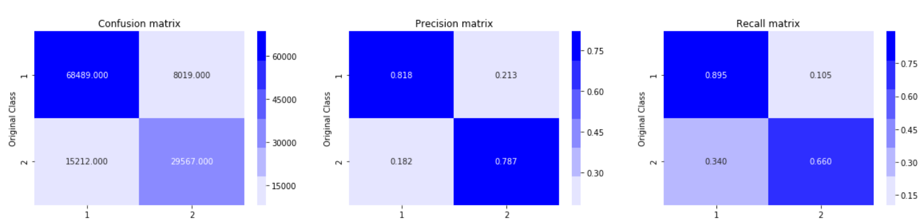
```
# read more about SGDClassifier() at http://scikit-learn.org/st
able/modules/generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1_ra
tio=0.15, fit_intercept=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=
None, learning_rate='optimal', eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=No
ne)

# some of methods
# fit(X, y[, coef_init, intercept_init, …])     Fit linear mode
l with Stochastic Gradient Descent.
# predict(X)    Predict class labels for samples in X.

#------------------------------
# video link:
#------------------------------


log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l2', loss='hinge', ra
ndom_state=42)
    clf.fit(train_final_features, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_final_features, y_train)
    predict_y = sig_clf.predict_proba(test_final_features)
    log_error_array.append(log_loss(y_test, predict_y, labels=c
lf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_l
oss(y_test, predict_y, labels=clf.classes_, eps=1e-15))

fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log_error_array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error
_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss
='hinge', random_state=42)
clf.fit(train_final_features, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(train_final_features, y_train)

predict_y = sig_clf.predict_proba(train_final_features)
print('For values of best alpha = ', alpha[best_alpha], "The tr
ain log loss is:",log_loss(y_train, predict_y, labels=clf.class
es_, eps=1e-15))
predict_y = sig_clf.predict_proba(test_final_features)
print('For values of best alpha = ', alpha[best_alpha], "The te
st log loss is:",log_loss(y_test, predict_y, labels=clf.classes
_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
```

```
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

```
For values of alpha =  1e-05 The log loss is: 0.39591530
572376715
For values of alpha =  0.0001 The log loss is: 0.4084412
6641409034
For values of alpha =  0.001 The log loss is: 0.43754415
094079085
For values of alpha =  0.01 The log loss is: 0.448087479
99311643
For values of alpha =  0.1 The log loss is: 0.4635168350
686396
For values of alpha =  1 The log loss is: 0.485616729095
75904
For values of alpha =  10 The log loss is: 0.54448017615
76894
```




```
For values of best alpha =  1e-05 The train log loss i
s: 0.39301733371888375
For values of best alpha =  1e-05 The test log loss i
s: 0.39591530572376715
Total number of data points : 121287
```



2. Hyperparameter tune XgBoost using RandomSearch to reduce the log-loss.

4.6 LGBM (*altenative of XGBoost*)

```
In [54]: from lightgbm import LGBMClassifier

param={'num_leaves': [25,30,40,50,60], 'learning_rate': [0.1,0.2,0.3], 'n_estimators': [50,75,100,150,200]}

lgbm = LGBMClassifier( boosting_type='gbdt', class_weight='balanced', objective='binary', n_jobs=1)
rscv=RandomizedSearchCV(estimator=lgbm, param_distributions=param, scoring='neg_log_loss', n_jobs=-2, return_train_score=True,)
rscv.fit(train_final_features,y_train)

result=pd.DataFrame({"param":rscv.cv_results_["params"], "train_log_loss":(-rscv.cv_results_["mean_train_score"]),"cv_log_los":(-rscv.cv_results_["mean_test_score"])})
result
```

	param	train_log_loss	cv_log_los
0	{'num_leaves': 40, 'n_estimators': 50, 'learni...	0.306635	0.330089
1	{'num_leaves': 60, 'n_estimators': 150, 'learn...	0.285764	0.316318
2	{'num_leaves': 60, 'n_estimators': 100, 'learn...	0.302621	0.323599
3	{'num_leaves': 25, 'n_estimators': 75, 'learni...	0.319722	0.332139
4	{'num_leaves': 50, 'n_estimators': 100, 'learn...	0.264356	0.314788
5	{'num_leaves': 60, 'n_estimators': 75, 'learni...	0.314702	0.330281
6	{'num_leaves': 40, 'n_estimators': 200, 'learn...	0.292058	0.318372
7	{'num_leaves': 30, 'n_estimators': 75, 'learni...	0.313913	0.329016
8	{'num_leaves': 40, 'n_estimators': 50, 'learni...	0.343494	0.349954
9	{'num_leaves': 25, 'n_estimators': 150, 'learn...	0.283210	0.323187

```
In [65]: # Best Scores
print("best score on traing dataset:", -(rscv.best_score_))
print("best hyperparameter:",rscv.best_params_)

y_train_pred=rscv.predict_proba(train_final_features)
predict_y=rscv.predict_proba(test_final_features)
print("\nThe train log loss is:",log_loss(y_train, y_train_pred,))
print("The test log loss is:",log_loss(y_test, predict_y, ))
```

```
best score on traing dataset: 0.31478816906978896
best hyperparameter: {'num_leaves': 50, 'n_estimators':
100, 'learning_rate': 0.3}

The train log loss is: 0.27728475542021147
The test log loss is: 0.3139864359999996
```

```
In [66]: # Best Hyperparameter Confusion matrix
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

```
Total number of data points : 121287
```