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[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import re
import time
import warnings
import sqlite3
from sqlalchemy import create_engine # database connection
import csv
import os
warnings.filterwarnings("ignore")
import datetime as dt
import numpy as np
from nltk.corpus import stopwords
from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
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_curve
```

```
C:\Users\user\Anaconda3\lib\site-packages\sklearn\externals\six.py:31:
DeprecationWarning: The module is deprecated in version 0.21 and will be removed
in version 0.23 since we've dropped support for Python 2.7. Please rely on the
official version of six (https://pypi.org/project/six/).
  "(https://pypi.org/project/six/).", DeprecationWarning)
```

4. Machine Learning Models

4.1 Reading data from file

[2]:
```
X_train = pd.read_csv('final_features_tfidf_train.csv')
X_test = pd.read_csv('final_features_tfidf_test.csv')
```

[3]:
```
y_train = pd.read_csv('final_features_tfidf_train_label.csv',header=None)
y_test = pd.read_csv('final_features_tfidf_test_label.csv',header=None)
y_train = y_train[1]
y_train = y_train.values.reshape((y_train.shape[0],1))
print(y_train.shape)
y_test = y_test[1]
y_test = y_test.values.reshape((y_test.shape[0],1))
print(y_test.shape)
```

```
(140000, 1)
(60000, 1)
```

[4]:
```
X_train.drop(['Unnamed: 0', 'id','is_duplicate'], axis=1, inplace=True)
X_test.drop(['Unnamed: 0', 'id','is_duplicate'], axis=1, inplace=True)
```

[5]:
```
X_train.head()
```

[5]:
```
   0_x  1_x  2_x  3_x  4_x  5_x  6_x  7_x  8_x  9_x  ...  freq_qid2  q1len  \
0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...          2     40
1  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...          1     50
2  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...         12     37
3  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...          2     60
4  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...          1     59

   q2len  q1_n_words  q2_n_words  word_Common  word_Total  word_share  \
0     33           9           7          6.0        16.0    0.375000
```

```
1     35         9         8         6.0        16.0     0.375000
2     48         7         9         4.0        16.0     0.250000
3     39        10         8         1.0        18.0     0.055556
4    114        12        21         4.0        30.0     0.133333

   freq_q1+q2  freq_q1-q2
0           4           0
1           3           1
2          35          11
3           4           0
4           6           4

[5 rows x 2026 columns]
```

4.2 Converting strings to numerics

[6]:
```python
# after we read from sql table each entry was read it as a string
# we convert all the features into numaric before we apply any model
cols = list(X_train.columns)
for i in cols:
    X_train[i] = X_train[i].apply(pd.to_numeric)
    #print(i)
```

[7]:
```python
# after we read from sql table each entry was read it as a string
# we convert all the features into numaric before we apply any model
cols = list(X_test.columns)
for i in cols:
    X_test[i] = X_test[i].apply(pd.to_numeric)
    #print(i)
```

4.3 Generic method for plotting confusion matrix

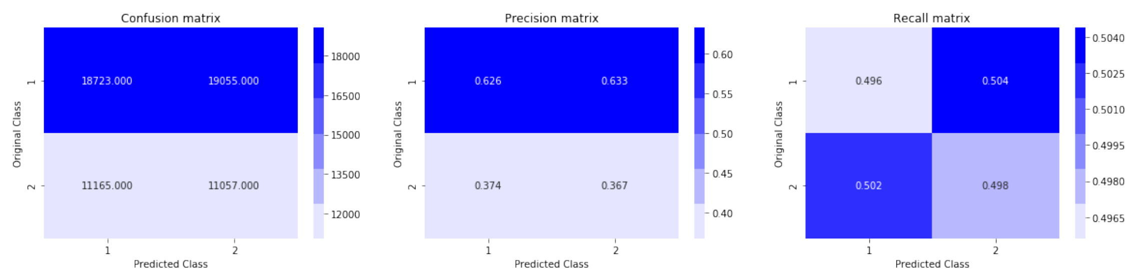
[8]:
```python
# This function plots the confusion matrices given y_i, y_i_hat.
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i␣
 ↪are predicted class j

    A =(((C.T)/(C.sum(axis=1))).T)
    #divid each element of the confusion matrix with the sum of elements in␣
 ↪that column

    # C = [[1, 2],
    #      [3, 4]]
    # C.T = [[1, 3],
    #        [2, 4]]
    # C.sum(axis = 1)  axis=0 corresonds to columns and axis=1 corresponds to␣
 ↪rows in two diamensional array
    # C.sum(axix =1) = [[3, 7]]
    # ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
```

```
    #                            [2/3, 4/7]]

    # ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
    #                            [3/7, 4/7]]
    # sum of row elements = 1

    B =(C/C.sum(axis=0))
    #divid each element of the confusion matrix with the sum of elements in␣
↪that row
    # C = [[1, 2],
    #     [3, 4]]
    # C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to␣
↪rows in two diamensional array
    # C.sum(axix =0) = [[4, 6]]
    # (C/C.sum(axis=0)) = [[1/4, 2/6],
    #                      [3/4, 4/6]]
    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", xticklabels=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", xticklabels=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", xticklabels=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)

[9]:
```
# we need to generate 9 numbers and the sum of numbers should be 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
test_len = y_test.shape[0]
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_test, 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 0.8946451543795837
```



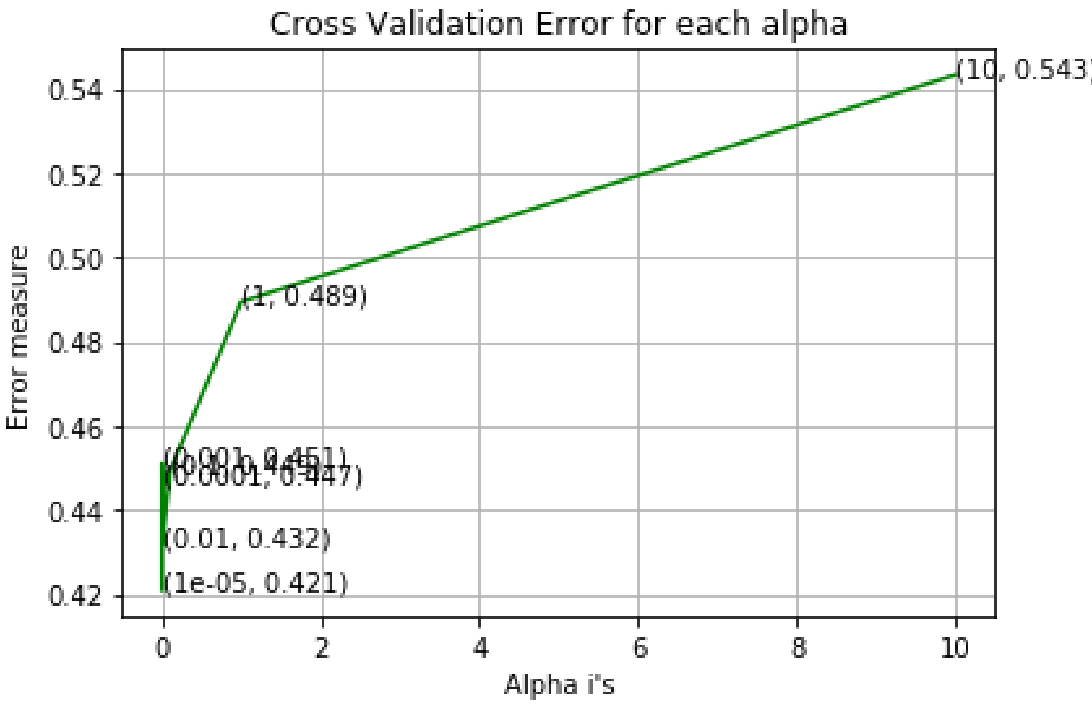
4.4 Logistic Regression with hyperparameter tuning

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

# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/
↪generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss=hinge, penalty=l2, alpha=0.0001, l1_ratio=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=None)

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

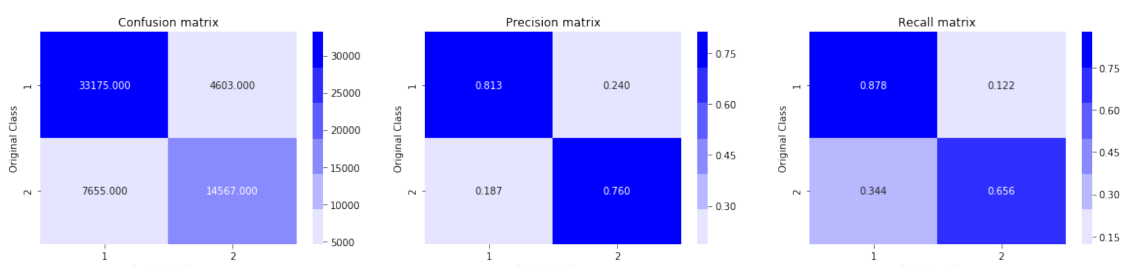
```
#-------------------------------
# video link:
#------------------------------


log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l2', loss='log', random_state=42)
    clf.fit(X_train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X_train, y_train)
    predict_y = sig_clf.predict_proba(X_test)
    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(X_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train, y_train)

predict_y = sig_clf.predict_proba(X_train)
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(X_test)
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: 0.42107034776101715
For values of alpha =  0.0001 The log loss is: 0.4467932754269884
```

```
For values of alpha =  0.001 The log loss is: 0.45105223648176035
For values of alpha =  0.01 The log loss is: 0.4320378625142579
For values of alpha =  0.1 The log loss is: 0.4492084241860258
For values of alpha =  1 The log loss is: 0.4894598746560532
For values of alpha =  10 The log loss is: 0.5432669264172524
```




```
For values of best alpha =  1e-05 The train log loss is: 0.41918545363002374
For values of best alpha =  1e-05 The test log loss is: 0.42107034776101715
Total number of data points : 60000
```



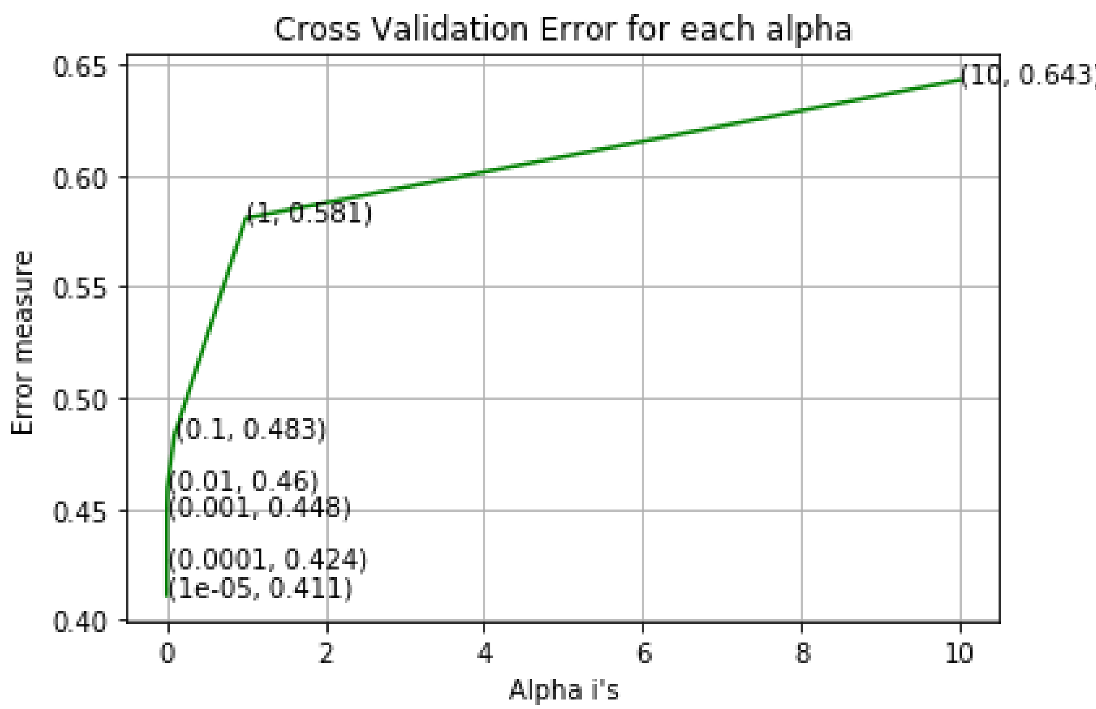
4.5 Linear SVM with hyperparameter tuning

[11]:
```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.
```

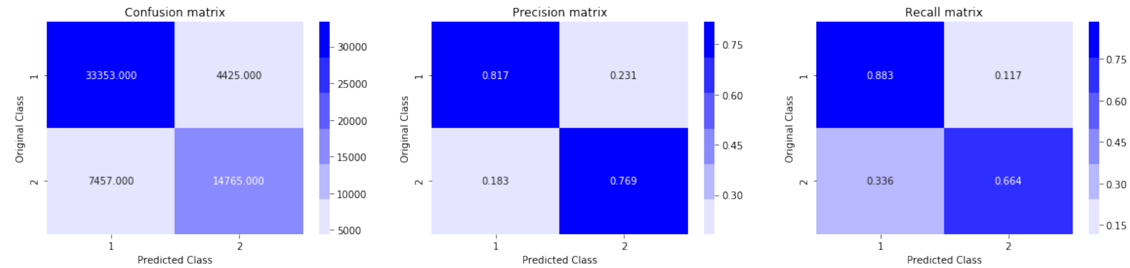
```
# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/
↪generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss=hinge, penalty=l2, alpha=0.0001, l1_ratio=0.15,␣
↪fit_intercept=True, max_iter=None, tol=None,
# 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=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, ])        Fit linear model 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='l1', loss='hinge', random_state=42)
    clf.fit(X_train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X_train, y_train)
    predict_y = sig_clf.predict_proba(X_test)
    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='l1', loss='hinge',␣
↪random_state=42)
```

```
clf.fit(X_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train, y_train)

predict_y = sig_clf.predict_proba(X_train)
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(X_test)
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: 0.4111543493357448
For values of alpha =  0.0001 The log loss is: 0.424165337237207
For values of alpha =  0.001 The log loss is: 0.4475273946489084
For values of alpha =  0.01 The log loss is: 0.459505556906909
For values of alpha =  0.1 The log loss is: 0.48317805572479033
For values of alpha =  1 The log loss is: 0.5807274815927826
For values of alpha =  10 The log loss is: 0.6428145505812121
```




```
For values of best alpha =  1e-05 The train log loss is: 0.4072066344844586
For values of best alpha =  1e-05 The test log loss is: 0.4111543493357448
Total number of data points : 60000
```



4.6 XGBoost

4.6.1 Reading data from file

[12]:
```
X_train = pd.read_csv('final_features_w2v_train.csv')
X_test = pd.read_csv('final_features_w2v_test.csv')
```

[13]:
```
y_train = pd.read_csv('final_features_tfidf_train_label.csv',header=None)
y_test = pd.read_csv('final_features_tfidf_test_label.csv',header=None)
y_train = y_train[1]
y_train = y_train.values.reshape((y_train.shape[0],1))
print(y_train.shape)
y_test = y_test[1]
y_test = y_test.values.reshape((y_test.shape[0],1))
print(y_test.shape)
```

```
(140000, 1)
(60000, 1)
```

[14]:
```
X_train.drop(['Unnamed: 0', 'id','is_duplicate'], axis=1, inplace=True)
X_test.drop(['Unnamed: 0', 'id','is_duplicate'], axis=1, inplace=True)
```

[15]:
```
X_train.head()
```

[15]:
```
         0_x        1_x         2_x         3_x        4_x        5_x  \
0   2.439142  18.114910  -12.255746  104.130825 -19.363592  -2.205739
1 -15.773163  36.496838    8.192818   47.599665  37.109427  62.937893
2 -12.001888  88.561495   54.594788    1.760126 -36.467282  33.917674
3 -18.628788  74.915513  115.482397   50.463298 -12.816265 -43.315368
4  -2.920037  64.090752    9.972080  105.365901  35.781809  31.707977

          6_x         7_x        8_x        9_x  ...  freq_qid2  q1len  q2len  \
0  -13.635292   -3.182549  30.811532  -4.650403  ...          2     40     33
1  -38.917103  -61.323661   5.005070 -25.191947  ...          1     50     35
2  -59.055783  -20.182544  43.250478 -36.022031  ...         12     37     48
3 -102.989147 -104.574963  46.028487 -52.984333  ...          2     60     39
4  -89.826797  -13.955268  27.267864  18.659436  ...          1     59    114

   q1_n_words  q2_n_words  word_Common  word_Total  word_share  freq_q1+q2  \
0           9           7          6.0        16.0    0.375000           4
```

```
1           9           8         6.0       16.0    0.375000          3
2           7           9         4.0       16.0    0.250000         35
3          10           8         1.0       18.0    0.055556          4
4          12          21         4.0       30.0    0.133333          6

   freq_q1-q2
0           0
1           1
2          11
3           0
4           4

[5 rows x 794 columns]
```

4.6.2 Converting strings to numerics

[16]:
```
# after we read from sql table each entry was read it as a string
# we convert all the features into numaric before we apply any model
cols = list(X_train.columns)
for i in cols:
    X_train[i] = X_train[i].apply(pd.to_numeric)
    #print(i)
```

[17]:
```
# after we read from sql table each entry was read it as a string
# we convert all the features into numaric before we apply any model
cols = list(X_test.columns)
for i in cols:
    X_test[i] = X_test[i].apply(pd.to_numeric)
    #print(i)
```

[18]:
```
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBClassifier
params = {
        'min_child_weight': [1, 5, 10],
        'gamma': [0.5, 1, 1.5, 2, 5],
        'subsample': [0.6, 0.8, 1.0],
        'colsample_bytree': [0.6, 0.8, 1.0],
        'max_depth': [3, 4, 5],
        'eta':[0.02,0.01,0.1]
        }



xgb = XGBClassifier(learning_rate=0.02, n_estimators=400, objective='binary:
 ↪logistic',
                    silent=True, early_stopping_rounds=20)
```

[19]:
```
folds = 3
param_comb = 10
skf = StratifiedKFold(n_splits=folds, shuffle = True, random_state = 1001)
```

```
random_search = RandomizedSearchCV(xgb, param_distributions=params,␣
 ↪n_iter=param_comb, scoring='neg_log_loss', n_jobs=4, cv=skf.split(X_train,␣
 ↪y_train), verbose=3, random_state=1001 )
history = random_search.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  30 out of  30 | elapsed: 220.1min finished
```

[20]:
```
random_search.best_params_
```

[20]:
```
{'subsample': 0.6,
 'min_child_weight': 1,
 'max_depth': 5,
 'gamma': 2,
 'eta': 0.02,
 'colsample_bytree': 1.0}
```

[21]:
```
import xgboost as xgb
params = {}
params['objective'] = 'binary:logistic'
params['eval_metric'] = 'logloss'
params['eta'] = 0.02
params['max_depth'] = 5
params['booster'] = 'gbtree'
params['gama'] = 2
params['max_depth'] = 5
params['min_child_weight'] = 1
params['subsample'] = 0.6
params['colsample_bytree'] = 1

d_train = xgb.DMatrix(X_train, label=y_train)
d_test = xgb.DMatrix(X_test, label=y_test)

watchlist = [(d_train, 'train'), (d_test, 'valid')]

bst = xgb.train(params, d_train, 400, watchlist, early_stopping_rounds=20,␣
 ↪verbose_eval=10)

xgdmat = xgb.DMatrix(X_train,y_train)
predict_y = bst.predict(d_test)
print("The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_,␣
 ↪eps=1e-15))
```

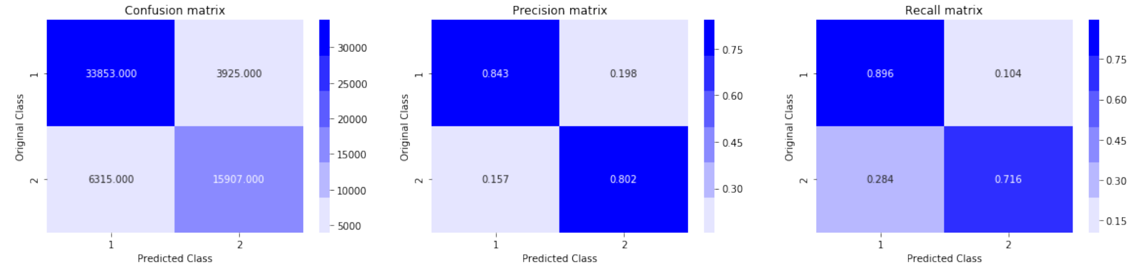
```
[0]	train-logloss:0.683686	valid-logloss:0.684189
Multiple eval metrics have been passed: 'valid-logloss' will be used for early
stopping.
```

```
Will train until valid-logloss hasn't improved in 20 rounds.
[10]	train-logloss:0.610007	valid-logloss:0.610489
[20]	train-logloss:0.556155	valid-logloss:0.557228
[30]	train-logloss:0.515604	valid-logloss:0.516966
[40]	train-logloss:0.484679	valid-logloss:0.486367
[50]	train-logloss:0.460706	valid-logloss:0.462706
[60]	train-logloss:0.44181	valid-logloss:0.44415
[70]	train-logloss:0.426772	valid-logloss:0.429376
[80]	train-logloss:0.41461	valid-logloss:0.417434
[90]	train-logloss:0.404625	valid-logloss:0.407675
[100]	train-logloss:0.396265	valid-logloss:0.399621
[110]	train-logloss:0.389444	valid-logloss:0.393158
[120]	train-logloss:0.383771	valid-logloss:0.387708
[130]	train-logloss:0.378983	valid-logloss:0.383192
[140]	train-logloss:0.374681	valid-logloss:0.379133
[150]	train-logloss:0.370981	valid-logloss:0.375716
[160]	train-logloss:0.367785	valid-logloss:0.372786
[170]	train-logloss:0.364977	valid-logloss:0.370218
[180]	train-logloss:0.362547	valid-logloss:0.368006
[190]	train-logloss:0.360328	valid-logloss:0.366092
[200]	train-logloss:0.358146	valid-logloss:0.364216
[210]	train-logloss:0.356406	valid-logloss:0.36272
[220]	train-logloss:0.354673	valid-logloss:0.36121
[230]	train-logloss:0.353141	valid-logloss:0.360046
[240]	train-logloss:0.351529	valid-logloss:0.358695
[250]	train-logloss:0.349967	valid-logloss:0.357449
[260]	train-logloss:0.348429	valid-logloss:0.356223
[270]	train-logloss:0.346931	valid-logloss:0.35514
[280]	train-logloss:0.345593	valid-logloss:0.354215
[290]	train-logloss:0.344015	valid-logloss:0.352978
[300]	train-logloss:0.342692	valid-logloss:0.351988
[310]	train-logloss:0.341379	valid-logloss:0.351134
[320]	train-logloss:0.340107	valid-logloss:0.350297
[330]	train-logloss:0.338866	valid-logloss:0.349517
[340]	train-logloss:0.337701	valid-logloss:0.348788
[350]	train-logloss:0.336542	valid-logloss:0.348085
[360]	train-logloss:0.335393	valid-logloss:0.347365
[370]	train-logloss:0.33424	valid-logloss:0.346627
[380]	train-logloss:0.333213	valid-logloss:0.346047
[390]	train-logloss:0.332199	valid-logloss:0.345358
[399]	train-logloss:0.33119	valid-logloss:0.34472
The test log loss is: 0.34471666093470993
```

[22]:

```
predicted_y =np.array(predict_y>0.5,dtype=int)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

Total number of data points : 60000



[24]:
```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Vectorizer", "Model","train log loss", "test log loss",␣
 ↪"train vs test precision", "train vs test recall"]
x.add_row(["TFIDF", "Linear Regression" , 0.4191, 0.429, "0.813 - 0.760","0.878␣
 ↪- 0.656"])
x.add_row(["TFIDF", "SVM" , 0.4072, 0.4111, "0.817 - 0.769","0.883 - 0.664"])
x.add_row(["TFIDFAvergeW2V", "XGBoost" , 0.3311, 0.3447, "0.843 - 0.802","0.896␣
 ↪- 0.716"])
x.border=True
print(x)
```

```
+----------------+-------------------+----------------+---------------+---------
----------------+----------------------+
|   Vectorizer   |       Model       | train log loss | test log loss | train vs
test precision | train vs test recall |
+----------------+-------------------+----------------+---------------+---------
----------------+----------------------+
|     TFIDF      | Linear Regression |     0.4191     |     0.429     |
0.813 - 0.760      |    0.878 - 0.656     |
|     TFIDF      |        SVM        |     0.4072     |     0.4111    |
0.817 - 0.769      |    0.883 - 0.664     |
| TFIDFAvergeW2V |      XGBoost      |     0.3311     |     0.3447    |
0.843 - 0.802      |    0.896 - 0.716     |
+----------------+-------------------+----------------+---------------+---------
----------------+----------------------+
```

Clearly XGBoost Model is the best model as it has minimum train and test log loss and precission and recall are better than other two models