## 3.6 Featurizing text data with tfidf weighted word-vectors

```
In [4]:
        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
        import pandas as pd
        import numpy as np
        from tqdm import tqdm
```

```
In [2]: !pip install -U -q PyDrive
        from pydrive.auth import GoogleAuth
        from pydrive.drive import GoogleDrive
        from google.colab import auth
        from oauth2client.client import GoogleCredentials
        # Authenticate and create the PyDrive client.
        auth.authenticate user()
        gauth = GoogleAuth()
        gauth.credentials = GoogleCredentials.get application default()
        drive = GoogleDrive(gauth)
        id1='1gTfCTD3fz-3NJnfYLm59nZFN3WC3fzfD'
        downloaded1 = drive.CreateFile({'id': id1})
        downloaded1.GetContentFile('df fe without preprocessing train.csv')
        id2='1JncN1Fyt-ND yZXOzqEfcRsYMTKqtu7Q'
        downloaded1 = drive.CreateFile({'id': id2})
        downloaded1.GetContentFile('nlp features train.csv')
        id3='10QDGTSI5PEV9e7CTpfzsXRpUwRIsJA-J'
        downloaded1 = drive.CreateFile({'id': id3})
        downloaded1.GetContentFile('train.csv')
```

```
| 993kB 45.3MB/s eta 0:00:01 Building wheel for PyDrive (setup.py) ... done
```

```
In [ ]: # avoid decoding problems
        df = pd.read csv("train.csv")
        from sklearn.model selection import train test split
        # merge texts
        df train,df test=train test split(df,test size=0.2)
        # 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 train['question1'] = df train['question1'].apply(lambda x: str(x))
        df train['question2'] = df train['question2'].apply(lambda x: str(x))
        df test['question1'] = df test['question1'].apply(lambda x: str(x))
        df test['question2'] = df test['question2'].apply(lambda x: str(x))
In [4]: | df.head(2)
Out[4]:
            id qid1 qid2
                                                   question1
                                                                                        question2 is_duplicate
                      What is the step by step guide to invest in sh...
                                                                                                         n
         0 0
                                                               What is the step by step guide to invest in sh...
                      4 What is the story of Kohinoor (Koh-i-Noor) Dia... What would happen if the Indian government sto...
         1 1
                 3
                                                                                                         0
In [ ]: from sklearn.feature extraction.text import TfidfVectorizer
        from sklearn.feature extraction.text import CountVectorizer
        # merge texts
        questions = list(df train['question1']) + list(df train['question2'])
        tfidf = TfidfVectorizer(lowercase=False, )
        tfidf.fit transform(questions)
        # dict key:word and value:tf-idf score
        word2tfidf = dict(zip(tfidf.get feature names(), tfidf.idf ))
```

- After we find TF-IDF scores, we convert each question to a weighted average of word2vec vectors by these scores.
- here we use a pre-trained GLOVE model which comes free with "Spacy". <a href="https://spacy.io/usage/vectors-similarity">https://spacy.io/usage/vectors-similarity</a> (<a href="https://spacy.io/usage/vectors-similarity">https://spacy.io/usage/vectors-similarity</a>)

• It is trained on Wikipedia and therefore, it is stronger in terms of word semantics.

In [6]: # en\_vectors\_web\_lg, which includes over 1 million unique vectors.

nlp = spacy.load('en core web sm')

```
vecs1 = []
        # https://github.com/noamraph/tqdm
        # tgdm is used to print the progress bar
        for qu1 in tqdm(list(df train['question1'])):
            doc1 = nlp(qu1)
            # 96 is the number of dimensions of vectors
            mean vec1 = np.zeros([len(doc1), len(doc1[0].vector)])
            for word1 in doc1:
                # word2vec
                vec1 = word1.vector
                # fetch df score
                try:
                    tfidf = word2tfidf[str(word1)] * (qu1.count(str(word1))/len(qu1.split()))
                except:
                    tfidf = 0
                # compute final vec
                mean vec1 += vec1 * tfidf
            mean vec1 = mean vec1.mean(axis=0)
            vecs1.append(mean_vec1)
        df train['q1 feats_m'] = list(vecs1)
              323432/323432 [43:06<00:00, 125.03it/s]
        df_train.to_csv('mid1.csv')
In [ ]:
        df test.to csv('test.csv')
```

```
In [11]: vecs2 = []
         from tqdm import tqdm
         for qu2 in tqdm(list(df_train['question2'])):
             doc2 = nlp(qu2)
             mean vec2 = np.zeros([len(doc2), len(doc2[0].vector)])
             for word2 in doc2:
                 # word2vec
                 vec2 = word2.vector
                 # fetch df score
                 try:
                     tfidf = word2tfidf[str(word2)] * (qu2.count(str(word2))/len(qu2.split()))
                 except:
                     #print word
                     tfidf = 0
                 # compute final vec
                 #print(tfidf)
                 mean vec2 += vec2 * tfidf
             mean_vec2 = mean_vec2.mean(axis=0)
             vecs2.append(mean vec2)
         df train['q2 feats m'] = list(vecs2)
```

100%| 323432/323432 [41:04<00:00, 131.24it/s]

```
In [12]: #Test Features Questions1 and Questions2
         # en_vectors_web_lg, which includes over 1 million unique vectors.
         nlp = spacy.load('en core web sm')
         vecs1 = []
         # https://github.com/noamraph/tqdm
         # tadm is used to print the progress bar
         for qu1 in tqdm(list(df_test['question1'])):
             doc1 = nlp(qu1)
             # 384 is the number of dimensions of vectors
             mean vec1 = np.zeros([len(doc1), len(doc1[0].vector)])
             for word1 in doc1:
                 # word2vec
                 vec1 = word1.vector
                 # fetch df score
                 try:
                     tfidf = word2tfidf[str(word1)] * (qu1.count(str(word1))/len(qu1.split()))
                 except:
                    tfidf = 0
                 # compute final vec
                 mean vec1 += vec1 * tfidf
             mean vec1 = mean vec1.mean(axis=0)
             vecs1.append(mean vec1)
         df test['q1 feats m'] = list(vecs1)
         vecs2 = []
         for qu2 in tqdm(list(df test['question2'])):
             doc2 = nlp(qu2)
             mean vec2 = np.zeros([len(doc2), len(doc2[0].vector)])
             for word2 in doc2:
                 # word2vec
                 vec2 = word2.vector
                 # fetch df score
                 try:
                    tfidf = word2tfidf[str(word2)] * (qu2.count(str(word2))/len(qu2.split()))
                 except:
                     #print word
                    tfidf = 0
                 # compute final vec
```

```
mean_vec2 += vec2 * tfidf
mean_vec2 = mean_vec2.mean(axis=0)
vecs2.append(mean_vec2)
df_test['q2_feats_m'] = list(vecs2)
```

100%| 80858/808 100%| 80858/808

80858/80858 [10:44<00:00, 125.52it/s] 80858/80858 [10:07<00:00, 133.04it/s]

### In [13]: df\_train.head(2)

#### Out[13]:

:		id qid1 qid2 question1		question2	is_duplicate	q1_feats_m	q2_feats_m		
	287851	287851	408683	408684	What are some examples of terrestrial animals?	What are terrestrial animals? What are example	1	[9.50959499180317, -2.984976351261139, -11.809	[4.78945130109787, -5.7303591668605804, -9.730
	172952	172952	266924	266925	Why is ASEAN one of the most peaceful and pros	Why and how did Lebanon become the most peacef	0	[0.6344003081321716, -1.813245631987229, -12.8	[-7.4249771372415125, -6.347789332270622, -11

```
In []: #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='latin-1')
    else:
        print("download nlp_features_train.csv from drive or run previous notebook")

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

#### 

# Out[55]:

•		id	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_eq	first_word_eq	abs_len_diff	mean_len	token_set_ratio
	0	0	0	0.999980	0.833319	0.999983	0.999983	0.916659	0.785709	0.0	1.0	2.0	13.0	100
	1	1	0	0.799984	0.399996	0.749981	0.599988	0.699993	0.466664	0.0	1.0	5.0	12.5	86
	2	2	0	0.399992	0.333328	0.399992	0.249997	0.399996	0.285712	0.0	1.0	4.0	12.0	6(
	3	3	0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	2.0	12.0	36
	4	4	0	0.399992	0.199998	0.999950	0.666644	0.571420	0.307690	0.0	1.0	6.0	10.0	67
	4													•

## In [ ]: # data before preprocessing df2.head()

### Out[56]:

	id	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_Common	word_Total	word_share	freq_q1+q2	freq_q1-q2
0	0	1	1	66	57	14	12	10.0	23.0	0.434783	2	0
1	1	4	1	51	88	8	13	4.0	20.0	0.200000	5	3
2	2	1	1	73	59	14	10	4.0	24.0	0.166667	2	0
3	3	1	1	50	65	11	9	0.0	19.0	0.000000	2	0
4	4	3	1	76	39	13	7	2.0	20.0	0.100000	4	2

```
In [16]:
           # Questions 1 tfidf weighted word2vec
           df3 q1 train.head()
Out[16]:
                          0
                                    1
                                               2
                                                          3
                                                                    4
                                                                              5
                                                                                        6
                                                                                                   7
                                                                                                             8
                                                                                                                       9
                                                                                                                                10
                                                                                                                                          11
            287851 9.509595 -2.984976
                                       -11.809498
                                                   -9.398076
                                                              3.067511 8.801890
                                                                                18.589524 13.412171 -8.947324
                                                                                                                3.094738
                                                                                                                          1.691513
                                                                                                                                    8.095941
                                                                                                                                               -6.30305
            172952 0.634400 -1.813246 -12.816122 -12.080643
                                                              5.457196 6.322567
                                                                                 15.836552
                                                                                           13.633682
                                                                                                      0.312183
                                                                                                                8.396769
                                                                                                                           0.150165
                                                                                                                                    7.360641
                                                                                                                                               -5.96279
            247768 4.431505 -4.361650 -14.430818 -18.104730 -2.806155
                                                                       6.768903
                                                                                  9.910724
                                                                                            4.264563
                                                                                                     -0.473978
                                                                                                                10.360899
                                                                                                                          -4.802288
                                                                                                                                    -1.079249
                                                                                                                                              -19.05542
             97009 8.108846 -5.319327
                                        -6.192122 -12.733797 -1.011927 4.555990
                                                                                 10.343346
                                                                                                     -1.492674
                                                                                            8.802996
                                                                                                                6.124089
                                                                                                                         -2.084184
                                                                                                                                    3.179069
                                                                                                                                               -8.06257
            223297 3.949012 -6.848152
                                        -4.856686 -11.317435 -9.334562 1.511885
                                                                                 7.551820
                                                                                          10.383319
                                                                                                      0.304397
                                                                                                                9.664529 -6.060358
                                                                                                                                    3.826666 -12.00161
           5 rows × 96 columns
           df3 q1 test.head()
In [17]:
Out[17]:
                           0
                                      1
                                                 2
                                                            3
                                                                                 5
                                                                                                                 8
                                                                                                                                    10
                                                                                                                                               11
                                                                                            6
                                                                                                      7
                                                                                                                           9
            157561 25.026054 -12.854203
                                          -9.678908 -11.264161 -10.215891
                                                                          -2.118202 31.566062
                                                                                               5.966860
                                                                                                          -6.212604
                                                                                                                   12.947480
                                                                                                                              -4.721270
                                                                                                                                         -6.075376
                                                                                                                                                    -8.
             55473
                    3.153236
                               -9.807701
                                          -4.287981
                                                    -10.497754
                                                                -5.162055
                                                                          -4.743260
                                                                                     8.219638
                                                                                               2.725274
                                                                                                          0.194639
                                                                                                                     8.444565
                                                                                                                              -8.259800
                                                                                                                                          8.336918
                                                                                                                                                  -18.
                   26.724261
                              -34.266608
                                         -16.617415 -27.571456
                                                                -6.003354
                                                                          5.019149
                                                                                    37.134820
                                                                                              13.056351
                                                                                                         -15.587229
                                                                                                                    10.477277
                                                                                                                               2.765593
                                                                                                                                        -14.594760
                                                                                                                                                    -7.
             58292
                               -5.579635
                                                     -6.650882
                                                                                     4.982583
                                                                                                                     6.909354
            124205
                    5.418724
                                          -5.298835
                                                                -0.867129
                                                                          2.277497
                                                                                              14.247606
                                                                                                          -7.309681
                                                                                                                              -3.446842
                                                                                                                                         -7.683994
                                                                                                                                                    -5.
                               -4.670748
            211135 -0.915871
                                          -7.094173
                                                     -7.577088
                                                                -2.944890
                                                                          4.100913 15.464195
                                                                                               8.516277
                                                                                                          3.587404
                                                                                                                     1.071980
                                                                                                                               2.100014
                                                                                                                                          5.814831
                                                                                                                                                    -8.
           5 rows × 96 columns
 In [ ]:
           print("Number of features in nlp dataframe :", df1.shape[1])
           print("Number of features in preprocessed dataframe :", df2.shape[1])
           print("Number of features in question1 w2v dataframe :", df3 q1.shape[1])
           print("Number of features in question2 w2v dataframe :", df3 q2.shape[1])
           print("Number of features in final dataframe :", df1.shape[1]+df2.shape[1]+df3 q1.shape[1]+df3 q2.shape[1])
```

```
In []: # storing the final features to csv file
if not os.path.isfile('final_features.csv'):
    df3_q1_train['id']=df_train['id']
    df3_q2_train['id']=df_train['id']

    df3_q1_test['id']=df_test['id']
    df3_q2_test['id']=df_test['id']

    df1 = df1.merge(df2, on='id',how='inner')

    df2_train = df3_q1_train.merge(df3_q2_train, on='id',how='inner')
    df2_test = df3_q1_test.merge(df3_q2_test, on='id',how='inner')

    result_train = df1.merge(df2_train, on='id',how='inner')

    result_train.to_csv('final_features_train.csv')
    result_test.to_csv('final_features_test.csv')
In [19]: result_test.shape,result_train.shape
```

### **XGBoost on TFIDF Weighted W2V on Questions**

Out[19]: ((80858, 220), (323432, 220))

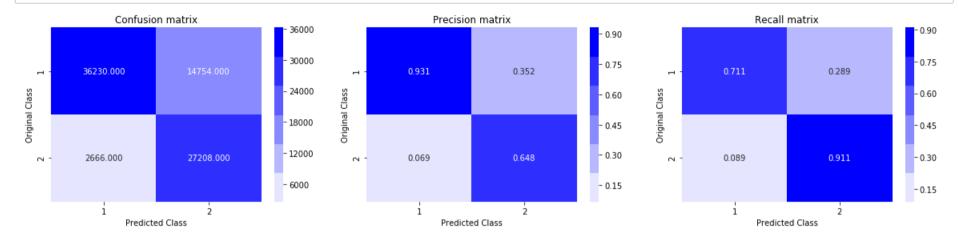
```
!wget --header="Host: doc-00-58-docs.googleusercontent.com" --header="User-Agent: Mozilla/5.0 (Windows NT 10.0; Win64; x6
In [1]:
        --2019-08-13 19:14:42-- https://doc-00-58-docs.googleusercontent.com/docs/securesc/qgbh6kjdsd98f3gihp270udf3ooq8huc/72
        \tt qp0q01ae1bdm21j1lpmu1i3u8nh8fa/1565719200000/15923203954827925545/15923203954827925545/1NE360hqn27kUkhKpra\ P2f3-tXsYl9x
        G?e=download (https://doc-00-58-docs.googleusercontent.com/docs/securesc/qgbh6kjdsd98f3gihp270udf3ooq8huc/72qp0q01ae1bd
        m21illpmu1i3u8nh8fa/1565719200000/15923203954827925545/15923203954827925545/1NE360hgn27kUkhKpra P2f3-tXsYl9xG?e=downloa
        d)
        Resolving doc-00-58-docs.googleusercontent.com (doc-00-58-docs.googleusercontent.com)... 74.125.197.132, 2607:f8b0:400
        e:c03::84
        Connecting to doc-00-58-docs.googleusercontent.com (doc-00-58-docs.googleusercontent.com)|74.125.197.132|:443... connec
        ted.
        HTTP request sent, awaiting response... 200 OK
        Length: unspecified [text/csv]
        Saving to: 'final features train.csv'
        final features trai
                                       <=>
                                                          1.16G
                                                                  160MB/s
                                                                             in 8.9s
        2019-08-13 19:14:51 (133 MB/s) - 'final features train.csv' saved [1244544516]
```

```
!wget --header="Host: doc-08-58-docs.googleusercontent.com" --header="User-Agent: Mozilla/5.0 (Windows NT 10.0; Win64; x6
In [2]:
        --2019-08-13 19:15:20-- https://doc-08-58-docs.googleusercontent.com/docs/securesc/qgbh6kjdsd98f3gihp270udf3ooq8huc/3f
        4htdnq5pk7ck92fiukbahq2efnmbdj/1565719200000/15923203954827925545/15923203954827925545/11kPWHuyFUvomF-vwmkkIiKXryZNfXJI
        Y?e=download (https://doc-08-58-docs.googleusercontent.com/docs/securesc/qgbh6kjdsd98f3gihp270udf3ooq8huc/3f4htdnq5pk7c
        k92fiukbahg2efnmbdj/1565719200000/15923203954827925545/15923203954827925545/11kPWHuyFUvomF-vwmkkIiKXryZNfXJIY?e=downloa
        d)
        Resolving doc-08-58-docs.googleusercontent.com (doc-08-58-docs.googleusercontent.com)... 74.125.197.132, 2607:f8b0:400
        e:c03::84
        Connecting to doc-08-58-docs.googleusercontent.com (doc-08-58-docs.googleusercontent.com)|74.125.197.132|:443... connec
        ted.
        HTTP request sent, awaiting response... 200 OK
        Length: unspecified [text/csv]
        Saving to: 'final features test.csv'
        final features test
                                             <=>
                                                      1 296.67M
                                                                 103MB/s
                                                                            in 2.9s
        2019-08-13 19:15:23 (103 MB/s) - 'final features test.csv' saved [311078704]
        result train=pd.read csv('final features train.csv')
In [5]:
        result test=pd.read csv('final features test.csv')
In [ ]:
```

```
In [6]:
        import xgboost as xgb
        from sklearn.model selection import RandomizedSearchCV
        y train=result train['is duplicate']
        v test=result test['is duplicate']
        X tr=result train.drop(['is duplicate'],axis=1)
        X te=result test.drop(['is duplicate'],axis=1)
        x cfl=xgb.XGBClassifier()
        prams = {
             'learning rate':[0.01,0.1,0.2],
              'n estimators':[100,500,1000],
             'max depth':[3,5,8],
             'colsample bytree':[0.1,0.5,1],
             'subsample': [0.1,0.5,1]
        random cfl1=RandomizedSearchCV(x cfl,param distributions=prams,scoring='neg log loss',cv=2,verbose=1,n jobs=-1)
        random cfl1.fit(X tr,y train)
        Fitting 2 folds for each of 10 candidates, totalling 20 fits
        [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
        [Parallel(n jobs=-1)]: Done 20 out of 20 | elapsed: 104.6min finished
Out[6]: RandomizedSearchCV(cv=2, error score='raise-deprecating',
                            estimator=XGBClassifier(base score=0.5, booster='gbtree',
                                                    colsample bylevel=1,
                                                    colsample_bynode=1,
                                                    colsample bytree=1, gamma=0,
                                                    learning rate=0.1, max delta step=0,
                                                    max depth=3, min child weight=1,
                                                    missing=None, n estimators=100,
                                                    n jobs=1, nthread=None,
                                                    objective='binary:logistic',
                                                    random state=0, reg alpha=0,
                                                    reg lambda=1, scale pos weight=1,
                                                    seed=None, silent=None, subsample=1,
                                                    verbosity=1),
                            iid='warn', n iter=10, n jobs=-1,
                            param distributions={'colsample bytree': [0.1, 0.5, 1],
```

```
'learning rate': [0.01, 0.1, 0.2],
                                                  'max depth': [3, 5, 8],
                                                  'n estimators': [100, 500, 1000],
                                                  'subsample': [0.1, 0.5, 1]},
                             pre dispatch='2*n jobs', random state=None, refit=True,
                             return train score=False, scoring='neg log loss', verbose=1)
         import shutil
 In [ ]:
         import os
         source = os.listdir("/content")
         destination = "/content/drive/My Drive"
         for files in source:
             if files.endswith(".csv"):
                  shutil.copy(files,destination)
In [7]: print (random cfl1.best params )
         {'subsample': 0.1, 'n estimators': 500, 'colsample bytree': 0.1, 'max depth': 5, 'learning rate': 0.01}
In [8]: from sklearn.calibration import CalibratedClassifierCV
         cfl=xgb.XGBClassifier(n estimators=500,subsample=0.1,learning rate=0.01,colsample bytree=0.1,max depth=5)
         cfl.fit(X tr,y train)
         c cfl=CalibratedClassifierCV(x cfl,method='sigmoid')
         c cfl.fit(X tr,y train)
         predict y = c cfl.predict proba(X tr)
In [11]:
         print ('train loss', log loss(y train, predict y))
         predict y = c cfl.predict proba(X te)
         print ('test loss', log loss(y test, predict y))
         train loss 0.39909822481038637
         test loss 0.40790524897003333
```

In [14]: #y\_test = list(map(int, y\_test.values))
 from sklearn.metrics import confusion\_matrix
 import seaborn as sns
 predicted\_y =np.array(predict\_y>0.5,dtype=int)
 plot\_confusion\_matrix(y\_test, predicted\_y[:,1])



```
In [10]: # This function plots the confusion matrices given y i, y i hat.
          from sklearn.metrics import log loss
          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 i
              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, 41]
              # C.T = [[1, 3],
                     [2, 4]1
              # 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))) = \lceil \lceil 1/3, 3/7 \rceil
                                           [2/3, 4/711]
              \# ((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)) = \lceil \lceil 1/4, 2/6 \rceil,
                                     [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")
```

### Conclusion

So the Train Logloss is 0.39909822481038637 and the Test Logloss 0.40790524897003333

```
In [ ]:
```