```
In [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 import sparse
from scipy.sparse import hstack
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC
from sklearn.cross_validation 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 RandomizedSearchCV



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
import pickle
```

```
C:\Users\ashwin\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning: This module was deprecated in v
ersion 0.18 in favor of the model_selection module into which all the refactored classes and functions are moved. Also note tha
t the interface of the new CV iterators are different from that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
C:\Users\ashwin\Anaconda3\lib\site-packages\sklearn\ensemble\weight_boosting.py:29: DeprecationWarning: numpy.core.umath_tests
is an internal NumPy module and should not be imported. It will be removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
```

# 4. Machine Learning Models

## 4.1 Reading data from file and storing into sql table

```
In [6]: X_train= sparse.load_npz('train_tfidf.npz')        #Loading the sparse matrix
X_cv= sparse.load_npz('cv_tfidf.npz')
X_test= sparse.load_npz('test_tfidf.npz')
```

```
In [5]: y_train= pd.read_pickle('y_train')                            #Loading the true labels
y_cv= pd.read_pickle('y_cv')
y_test= pd.read_pickle('y_test')
```

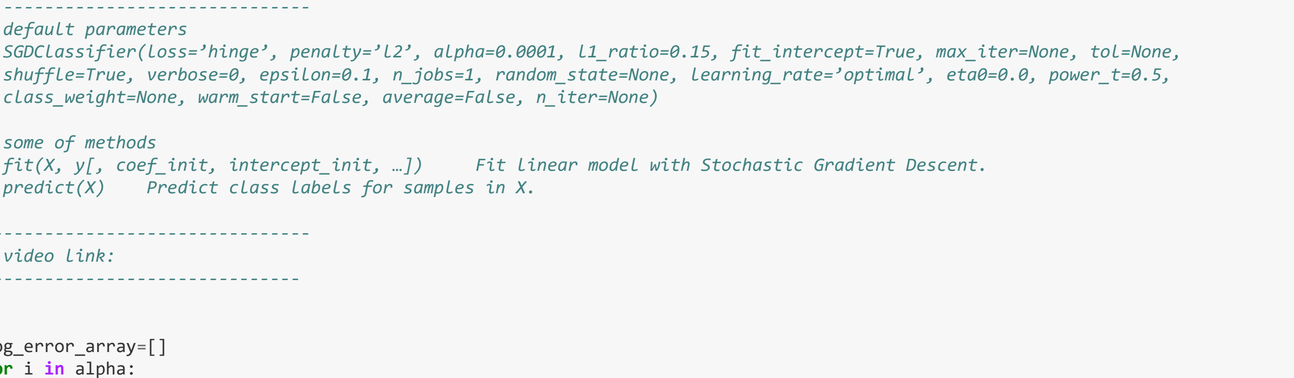
```
In [7]: # This function plots the confusion matrices given y_i, y_i_hat.
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i are predicted class j

    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()
```

```
In [9]: test_len= len(y_test)
```

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

```
In [11]: # 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
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)
```

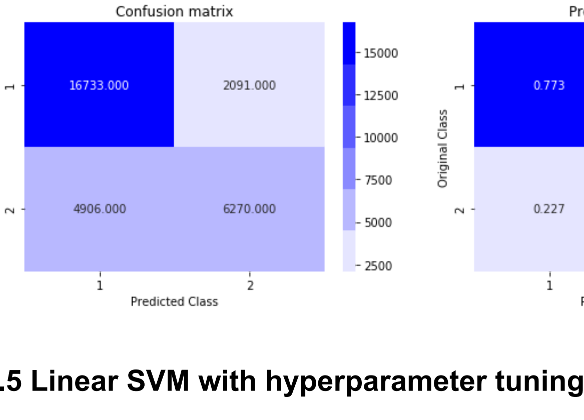
```
Log loss on Test Data using Random Model 0.890406332722044
```



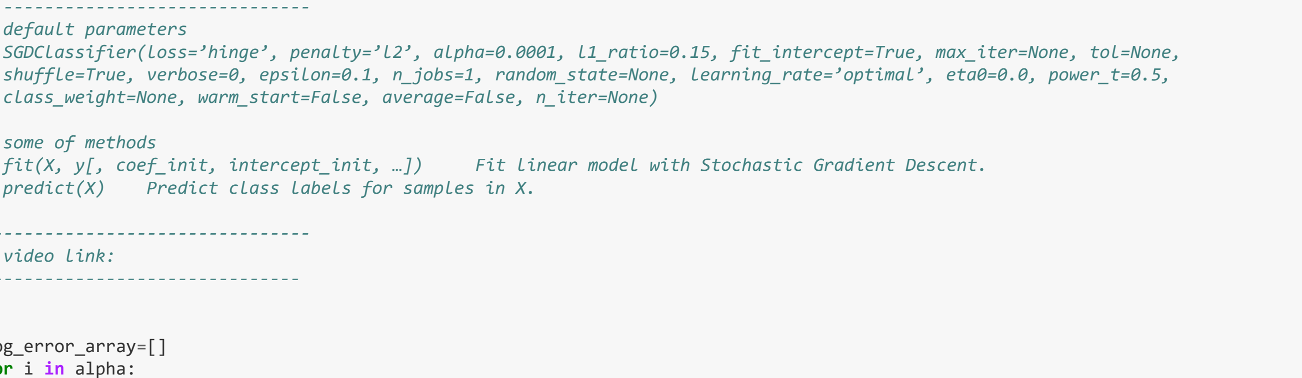

## 4.4 Logistic Regression with hyperparameter tuning

```
In [12]: 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_cv)
    log_error_array.append(log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_cv, 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: 0.4628248156566899
For values of alpha =  0.0001 The log loss is: 0.4635490310781471
For values of alpha =  0.001 The log loss is: 0.45758041043745834
For values of alpha =  0.01 The log loss is: 0.4583540479557229
For values of alpha =  0.1 The log loss is: 0.4596301339062383
For values of alpha =  1 The log loss is: 0.4938739275495117
For values of alpha =  10 The log loss is: 0.5503894811020347
```



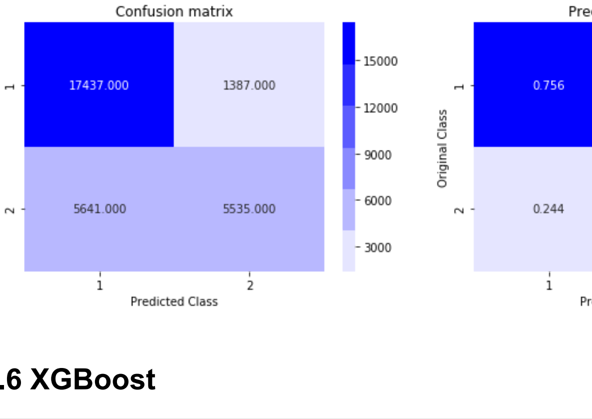

```
For values of best alpha =  0.001 The train log loss is: 0.4631925973121764
For values of best alpha =  0.001 The test log loss is: 0.4624834859878377
Total number of data points : 30000
```



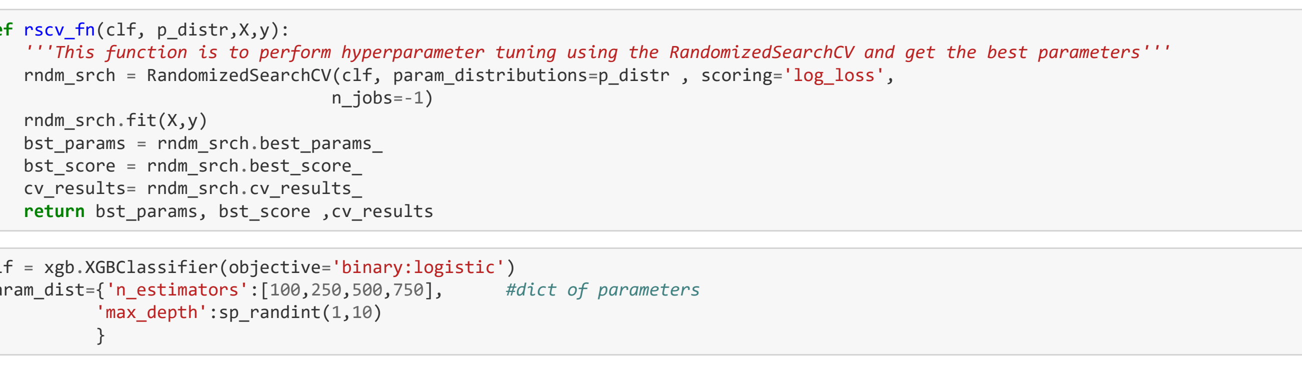

## 4.5 Linear SVM with hyperparameter tuning

```
In [13]: 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_cv)
    log_error_array.append(log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_cv, 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: 0.4639310789526797
For values of alpha =  0.0001 The log loss is: 0.484553792700581
For values of alpha =  0.001 The log loss is: 0.49158210905297833
For values of alpha =  0.01 The log loss is: 0.4926120880835452
For values of alpha =  0.1 The log loss is: 0.5042605207323733
For values of alpha =  1 The log loss is: 0.5875819873698122
For values of alpha =  10 The log loss is: 0.6285632427194632
```




```
For values of best alpha =  1e-05 The train log loss is: 0.4726584890371186
For values of best alpha =  1e-05 The test log loss is: 0.46888247083234114
Total number of data points : 30000
```




## 4.6 XGBoost

```
In [14]: import xgboost as xgb
from scipy.stats import randint as sp_randint
```

```
In [15]: def rscv_fn(clf, p_distr,X,y):
    '''This function is to perform hyperparameter tuning using the RandomizedSearchCV and get the best parameters'''
    rndm_srch = RandomizedSearchCV(clf, param_distributions=p_distr , scoring='log_loss',
                                   n_jobs=-1)
    rndm_srch.fit(X,y)
    bst_params = rndm_srch.best_params_
    bst_score = rndm_srch.best_score_
    cv_results= rndm_srch.cv_results_
    return bst_params, bst_score ,cv_results
```

```
In [16]: clf = xgb.XGBClassifier(objective='binary:logistic')
param_dist={'n_estimators':[100,250,500,750],      #dict of parameters
           'max_depth':sp_randint(1,10)
          }
```

```
In [17]: warnings.filterwarnings('ignore')
bst_params, bst_score ,cv_results = rscv_fn(clf, param_dist , X_train, y_train)
```

```
In [18]: print(bst_params)
print('Hyper-tuned model score :')
print(bst_score)
```

```
{'max_depth': 7, 'n_estimators': 500}
Hyper-tuned model score :
-0.32576959904005676
```

```
In [19]: clf=xgb.XGBClassifier(max_depth=7, n_estimators=500 , objective='binary:logistic',n_jobs=-1)

clf.fit(X_train , y_train)
predict_test= clf.predict_proba(X_test)
```

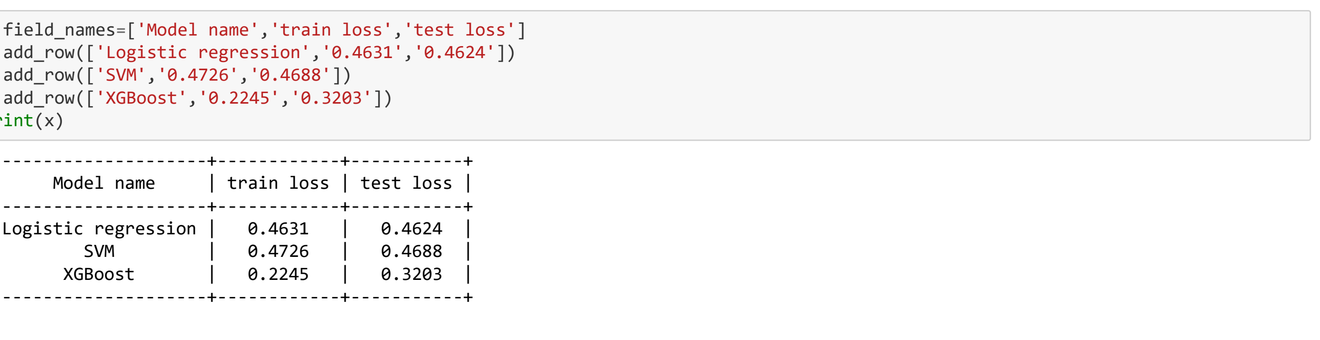
```
In [24]: predict_train = clf.predict_proba(X_train)
```

```
In [26]: print("log loss on the test data is :",log_loss(y_test,predict_test, labels=clf.classes_))
print("log loss on the train data is :",log_loss(y_train,predict_train, labels=clf.classes_))
```

```
log loss on the test data is : 0.3203122402669013
log loss on the train data is : 0.22454529825749367
```

```
In [21]: predicted_y=np.argmax(predict_test,axis=1)

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

```
Total number of data points : 30000
```




# Conclusion

```
In [22]: from prettytable import PrettyTable
```

```
In [23]: x= PrettyTable()
```

```
In [27]: x.field_names=['Model name','train loss','test loss']
x.add_row(['Logistic regression','0.4631','0.4624'])
x.add_row(['SVM','0.4726','0.4688'])
x.add_row(['XGBoost','0.2245','0.3203'])
print(x)
```

```
+---------------------+------------+-----------+
|      Model name     | train loss | test loss |
+---------------------+------------+-----------+
| Logistic regression |   0.4631   |   0.4624  |
|         SVM         |   0.4726   |   0.4688  |
|       XGBoost       |   0.2245   |   0.3203  |
+---------------------+------------+-----------+
```

**Steps followed in the case study**

- **Data analysis** : 1) We loaded the data and checked for the duplicates, unique questions ,null values .
- **Basic Feature Extraction** : 2) We performed the basic feature extraction with features: freq_qid1, freq_qid2 ,q1_len ,q2_len , q1_n_words ,q2_n_words ,word_common ,word_Total ,word_share,freq_q1+freq_q2 ,freq_q1-freq_q2 .
- **EDA on basic features** : 3) We plotted violin plots , contour plots and distribution plots with the basic features and pointed the best features.
- **Advanced feature extraction** : 4) We performed the advanced feature extraction using the features: cwc_min ,cwc_max, ctc_min, ctc_max, csc_min, csc_max , last_word_eq, first_word_eq ,abs_len_diff ,mean_len ,fuzz_ratio ,fuzz_partial_ratio ,token_sort_ratio ,token_set_ratio , longest_substr_ratio .
- **EDA on advanced features** : 5)We plotted the violin plots,contour plots and distributon plots with these advanced features and pointed the best features.
- **Data splitting** :6) We split the data into train cv and test after h_stacking the basic , advanced features with the original dataframe. We took 100,000 points and performed random splitting.
- **Vectorization** : 7) As our questions are still in the english form so we need to convert them to vectors using the TFIDF vectorizer , by training the tfidf on the train data and fitting the tfidf model on the cv and test data.
- **Models** : 8) We build models like Logistic regression , linear SVM and XGBoost and interpretted the results using log_loss as the performance metric.
- **Conclusion** : 9) We concluded the results using a prettytable .