NAIVE BAYES ON DONORS CHOOSE DATASET

1.1 Loading Data

In [ ]:

```
import pandas
data = pandas.read_csv(r'C:\Users\NADEEM\Downloads\preprocessed_data.csv', nrows=50000)
data.head(2)
```

Out[ ]:

	school_state	teacher_prefix	project_grade_category	teacher_number_of_previously_posted_projects	project_is_approved	cl
0	ca	mrs	grades_prek_2	53	1	
1	ut	ms	grades_3_5	4	1	

In [ ]:

```
y = data['project_is_approved'].values
X = data.drop(['project_is_approved'], axis=1)
X.head(1)
```

Out[ ]:

	school_state	teacher_prefix	project_grade_category	teacher_number_of_previously_posted_projects	clean_categories	clear
0	ca	mrs	grades_prek_2	53	math_science	a he

1.2 Splitting data into Train and cross validation(or test): Stratified Sampling

In [ ]:

```
# train test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, stratify=y)
 # stratify ensures the same ratio of class label in these three set
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33, strati
fy=y_train)
```

1.3 Make Data Model Ready: encoding essay, and project_title

In [ ]:

```
from sklearn.feature_extraction.text import CountVectorizer

print(X_train.shape, y_train.shape)
print(X_cv.shape, y_cv.shape)
print(X_test.shape, y_test.shape)

print("="*100)


vectorizer1 = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=5000) # ngram_ra
nge : we want no. of words of length 1-4
vectorizer1.fit(X_train['essay'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_essay_bow = vectorizer1.transform(X_train['essay'].values)
X_cv_essay_bow = vectorizer1.transform(X_cv['essay'].values)
X_test_essay_bow = vectorizer1.transform(X_test['essay'].values)

print("After vectorizations")
print(X_train_essay_bow.shape, y_train.shape)
print(X_cv_essay_bow.shape, y_cv.shape)
print(X_test_essay_bow.shape, y_test.shape)
print("="*100)
```

```
(22445, 8) (22445,)
(11055, 8) (11055,)
(16500, 8) (16500,)
====================================================================================================
After vectorizations
(22445, 5000) (22445,)
(11055, 5000) (11055,)
(16500, 5000) (16500,)
====================================================================================================
```

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer01 = TfidfVectorizer(min_df=10)
vectorizer01.fit(X_train['essay'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_essay_tfidf = vectorizer01.transform(X_train['essay'].values)
X_cv_essay_tfidf = vectorizer01.transform(X_cv['essay'].values)
X_test_essay_tfidf = vectorizer01.transform(X_test['essay'].values)

print(X_train_essay_tfidf.shape, y_train.shape)
print(X_cv_essay_tfidf.shape, y_cv.shape)
print(X_test_essay_tfidf.shape, y_test.shape)
print("="*100)
```

```
(22445, 8802) (22445,)
(11055, 8802) (11055,)
(16500, 8802) (16500,)
====================================================================================================
```

1.4 Make Data Model Ready: encoding numerical, categorical features

Encoding Categorical Features: Teacher Prefix

In [ ]:

```
vectorizer2 = CountVectorizer()
vectorizer2.fit(X_train['teacher_prefix'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
```

```
X_train_teacher_ohe = vectorizer2.transform(X_train['teacher_prefix'].values)
X_cv_teacher_ohe = vectorizer2.transform(X_cv['teacher_prefix'].values)
X_test_teacher_ohe = vectorizer2.transform(X_test['teacher_prefix'].values)

print("After vectorizations")
print(X_train_teacher_ohe.shape, y_train.shape)
print(X_cv_teacher_ohe.shape, y_cv.shape)
print(X_test_teacher_ohe.shape, y_test.shape)
print(vectorizer2.get_feature_names())
print("="*100)
```

```
After vectorizations
(22445, 5) (22445,)
(11055, 5) (11055,)
(16500, 5) (16500,)
['dr', 'mr', 'mrs', 'ms', 'teacher']
========================================================================================
============
```

Encoding Categorical Features: Project Grade Category

In [ ]:

```
vectorizer3 = CountVectorizer()
vectorizer3.fit(X_train['project_grade_category'].values) # fit has to happen only on tra
in data

# we use the fitted CountVectorizer to convert the text to vector
X_train_grade_ohe = vectorizer3.transform(X_train['project_grade_category'].values)
X_cv_grade_ohe = vectorizer3.transform(X_cv['project_grade_category'].values)
X_test_grade_ohe = vectorizer3.transform(X_test['project_grade_category'].values)

print("After vectorizations")
print(X_train_grade_ohe.shape, y_train.shape)
print(X_cv_grade_ohe.shape, y_cv.shape)
print(X_test_grade_ohe.shape, y_test.shape)
print(vectorizer3.get_feature_names())
print("="*100)
```

```
After vectorizations
(22445, 4) (22445,)
(11055, 4) (11055,)
(16500, 4) (16500,)
['grades_3_5', 'grades_6_8', 'grades_9_12', 'grades_prek_2']
========================================================================================
============
```

Encoding Categorical Features: School State

In [ ]:

```
vectorizer4 = CountVectorizer()
vectorizer4.fit(X_train['school_state'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_state_ohe = vectorizer4.transform(X_train['school_state'].values)
X_cv_state_ohe = vectorizer4.transform(X_cv['school_state'].values)
X_test_state_ohe = vectorizer4.transform(X_test['school_state'].values)

print("After vectorizations")
print(X_train_state_ohe.shape, y_train.shape)
print(X_cv_state_ohe.shape, y_cv.shape)
print(X_test_state_ohe.shape, y_test.shape)
print(vectorizer4.get_feature_names())
print("="*100)
```

```
After vectorizations
(22445, 51) (22445,)
(11055, 51) (11055,)
(16500, 51) (16500,)
```

(16500, 51) (16500,)
['ak', 'al', 'ar', 'az', 'ca', 'co', 'ct', 'dc', 'de', 'fl', 'ga', 'hi', 'ia', 'id', 'il'
, 'in', 'ks', 'ky', 'la', 'ma', 'md', 'me', 'mi', 'mn', 'mo', 'ms', 'mt', 'nc', 'nd', 'ne
', 'nh', 'nj', 'nm', 'nv', 'ny', 'oh', 'ok', 'or', 'pa', 'ri', 'sc', 'sd', 'tn', 'tx', 'u
t', 'va', 'vt', 'wa', 'wi', 'wv', 'wy']
==
===========

Encoding Categorical Features: Clean Categories

In [ ]:

```
vectorizer5 = CountVectorizer()
vectorizer5.fit(X_train['clean_categories'].values) # fit has to happen only on train dat
a

# we use the fitted CountVectorizer to convert the text to vector
X_train_clean_ohe = vectorizer5.transform(X_train['clean_categories'].values)
X_cv_clean_ohe = vectorizer5.transform(X_cv['clean_categories'].values)
X_test_clean_ohe = vectorizer5.transform(X_test['clean_categories'].values)

print("After vectorizations")
print(X_train_clean_ohe.shape, y_train.shape)
print(X_cv_clean_ohe.shape, y_cv.shape)
print(X_test_clean_ohe.shape, y_test.shape)
print(vectorizer5.get_feature_names())
print("="*100)
```

```
After vectorizations
(22445, 9) (22445,)
(11055, 9) (11055,)
(16500, 9) (16500,)
['appliedlearning', 'care_hunger', 'health_sports', 'history_civics', 'literacy_language'
, 'math_science', 'music_arts', 'specialneeds', 'warmth']
==========================================================================================
===========
```

Encoding Categorical Features: Clean Subcategories

In [ ]:

```
vectorizer6 = CountVectorizer()
vectorizer6.fit(X_train['clean_subcategories'].values) # fit has to happen only on train
data

# we use the fitted CountVectorizer to convert the text to vector
X_train_clean_sub_ohe = vectorizer6.transform(X_train['clean_subcategories'].values)
X_cv_clean_sub_ohe = vectorizer6.transform(X_cv['clean_subcategories'].values)
X_test_clean_sub_ohe = vectorizer6.transform(X_test['clean_subcategories'].values)

print("After vectorizations")
print(X_train_clean_sub_ohe.shape, y_train.shape)
print(X_cv_clean_sub_ohe.shape, y_cv.shape)
print(X_test_clean_sub_ohe.shape, y_test.shape)
print(vectorizer6.get_feature_names())
print("="*100)
```

```
After vectorizations
(22445, 30) (22445,)
(11055, 30) (11055,)
(16500, 30) (16500,)
['appliedsciences', 'care_hunger', 'charactereducation', 'civics_government', 'college_ca
reerprep', 'communityservice', 'earlydevelopment', 'economics', 'environmentalscience', '
esl', 'extracurricular', 'financialliteracy', 'foreignlanguages', 'gym_fitness', 'health_
lifescience', 'health_wellness', 'history_geography', 'literacy', 'literature_writing', '
mathematics', 'music', 'nutritioneducation', 'other', 'parentinvolvement', 'performingart
s', 'socialsciences', 'specialneeds', 'teamsports', 'visualarts', 'warmth']
==========================================================================================
===========
```

Encoding Categorical Features: Price

In [ ]:

```
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
# normalizer.fit(X_train['price'].values)
# this will rise an error Expected 2D array, got 1D array instead:
# array=[105.22 215.96  96.01 ... 368.98  80.53 709.67].
# Reshape your data either using
# array.reshape(-1, 1) if your data has a single feature
# array.reshape(1, -1)  if it contains a single sample.
normalizer.fit(X_train['price'].values.reshape(-1,1))

X_train_price_norm = normalizer.transform(X_train['price'].values.reshape(-1,1))
X_cv_price_norm = normalizer.transform(X_cv['price'].values.reshape(-1,1))
X_test_price_norm = normalizer.transform(X_test['price'].values.reshape(-1,1))



print("After vectorizations")
print(X_train_price_norm.shape, y_train.shape)
print(X_cv_price_norm.shape, y_cv.shape)
print(X_test_price_norm.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
==========================================================================================
==========
```

Encoding Categorical Features: No. of Teacher who previously posted projects

In [ ]:

```
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
# normalizer.fit(X_train['price'].values)
# this will rise an error Expected 2D array, got 1D array instead:
# array=[105.22 215.96  96.01 ... 368.98  80.53 709.67].
# Reshape your data either using
# array.reshape(-1, 1) if your data has a single feature
# array.reshape(1, -1)  if it contains a single sample.
normalizer.fit(X_train['teacher_number_of_previously_posted_projects'].values.reshape(-1
,1))

X_train_previous_project_norm = normalizer.transform(X_train['teacher_number_of_previousl
y_posted_projects'].values.reshape(-1,1))
X_cv_previous_project_norm = normalizer.transform(X_cv['teacher_number_of_previously_post
ed_projects'].values.reshape(-1,1))
X_test_previous_project_norm = normalizer.transform(X_test['teacher_number_of_previously_
posted_projects'].values.reshape(-1,1))



print("After vectorizations")
print(X_train_previous_project_norm.shape, y_train.shape)
print(X_cv_previous_project_norm.shape, y_cv.shape)
print(X_test_previous_project_norm.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
==========================================================================================
==========
```

1.5 Appling NB on different kind of featurization as mentioned in the instructions

Apply NB on different kind of featurization as mentioned in the instructions
For Every model that you work on make sure you do the step 2 and step 3 of instrucations

Concatinating all the features

In [ ]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
Set1_tr = hstack((X_train_essay_bow, X_train_teacher_ohe, X_train_grade_ohe, X_train_state_ohe, X_train_clean_ohe, X_train_clean_sub_ohe, X_train_price_norm, X_train_previous_project_norm)).tocsr()
Set1_cr = hstack((X_cv_essay_bow, X_cv_teacher_ohe, X_cv_grade_ohe, X_cv_state_ohe, X_cv_clean_ohe, X_cv_clean_sub_ohe, X_cv_price_norm, X_cv_previous_project_norm)).tocsr()
Set1_te = hstack((X_test_essay_bow, X_test_teacher_ohe, X_test_grade_ohe, X_test_state_ohe, X_test_clean_ohe, X_test_clean_sub_ohe, X_test_price_norm, X_test_previous_project_norm)).tocsr()

print("Final Data matrix")
print(Set1_tr.shape, y_train.shape)
print(Set1_cr.shape, y_cv.shape)
print(Set1_te.shape, y_test.shape)
print("="*100)
```

```
Final Data matrix
(22445, 5101) (22445,)
(11055, 5101) (11055,)
(16500, 5101) (16500,)
====================================================================================================
```

In [ ]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
Set2_tr = hstack((X_train_essay_tfidf, X_train_teacher_ohe, X_train_grade_ohe, X_train_state_ohe, X_train_clean_ohe, X_train_clean_sub_ohe, X_train_price_norm, X_train_previous_project_norm)).tocsr()
Set2_cr = hstack((X_cv_essay_tfidf, X_cv_teacher_ohe, X_cv_grade_ohe, X_cv_state_ohe, X_cv_clean_ohe, X_cv_clean_sub_ohe, X_cv_price_norm, X_cv_previous_project_norm)).tocsr()
Set2_te = hstack((X_test_essay_tfidf, X_test_teacher_ohe, X_test_grade_ohe, X_test_state_ohe, X_test_clean_ohe, X_test_clean_sub_ohe, X_test_price_norm, X_test_previous_project_norm)).tocsr()

print("Final Data matrix")
print(Set1_tr.shape, y_train.shape)
print(Set1_cr.shape, y_cv.shape)
print(Set1_te.shape, y_test.shape)
print("="*100)
```

```
Final Data matrix
(22445, 5101) (22445,)
(11055, 5101) (11055,)
(16500, 5101) (16500,)
====================================================================================================
```

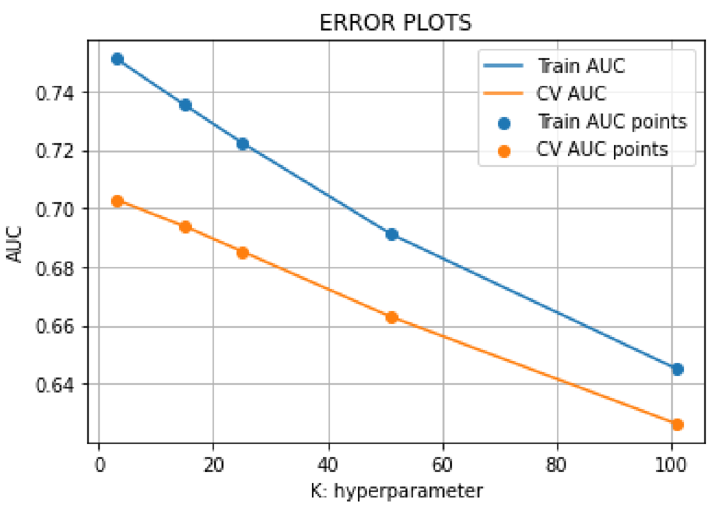
2. Applying Naive Bayes on BOW, SET 1

HYPER PARAMETER TUNING (SET 1)

In [ ]:

```
import matplotlib.pyplot as plt
from tqdm import tqdm
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
"""
y_true : array, shape = [n_samples] or [n_samples, n_classes]
True binary labels or binary label indicators.

y_score : array, shape = [n_samples] or [n_samples, n_classes]
Target scores, can either be probability estimates of the positive class, confidence valu
es, or non-thresholded measure of
decisions (as returned by "decision_function" on some classifiers).
For binary y_true, y_score is supposed to be the score of the class with greater label.

"""

train_auc = []
cv_auc = []
K = [3, 15, 25, 51, 101]
for i in tqdm(K):
    neigh =  MultinomialNB(alpha=i,class_prior=[0.5,0.5])
    # n_jobs=-1  means we want to use all the course of the cpu to run the code faster
    neigh.fit(Set1_tr, y_train)

    y_train_pred = neigh.predict_proba(Set1_tr)[:,1]
    y_cv_pred = neigh.predict_proba(Set1_cr)[:,1]

    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of
the positive class
    # not the predicted outputs
    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))

plt.plot(K, train_auc, label='Train AUC')
plt.plot(K, cv_auc, label='CV AUC')

plt.scatter(K, train_auc, label='Train AUC points')
plt.scatter(K, cv_auc, label='CV AUC points')

plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

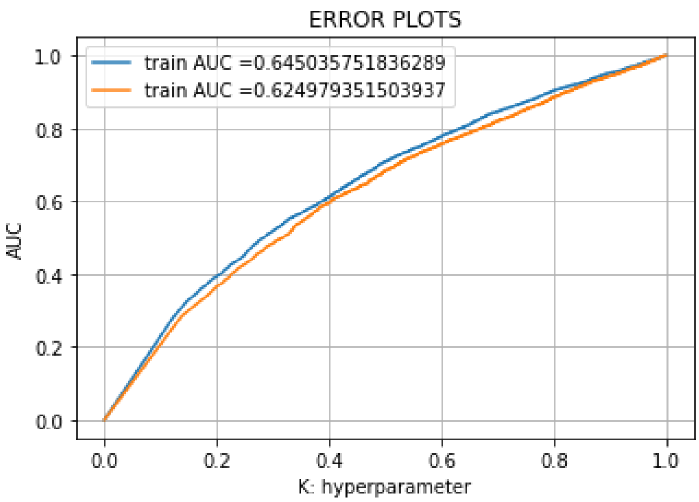
```
100%|██████████████████████████████████████████████████
| 5/5 [00:00<00:00,  8.23it/s]
```



In [ ]:

```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklear
```

```
n.metrics.roc_curve
from sklearn.metrics import roc_curve, auc

best_k = 101
neigh =  MultinomialNB(alpha=best_k,class_prior=[0.5,0.5])
neigh.fit(Set1_tr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the
positive class
# not the predicted outputs

y_train_pred = neigh.predict_proba(Set1_tr)[:,1]
y_test_pred = neigh.predict_proba(Set1_te)[:,1]

train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

Set1_train_auc = str(auc(train_fpr, train_tpr))
Set1_test_auc = str(auc(test_fpr, test_tpr))

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="train AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



In [ ]:

```
# we are writing our own function for predict, with defined thresould
# we will pick a threshold that will give the least fpr
def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for threshold", np.round
(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

In [ ]:

```
import numpy as np
print("="*100)
from sklearn.metrics import confusion_matrix
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

```
============================================================================================
===========
the maximum value of tpr*(1-fpr) 0.3786042359156359 for threshold 1.0
Train confusion matrix
[[ 2200  1395]
 [ 7188 11662]]
Test confusion matrix
[[1490 1152]
 [5433 8425]]
```

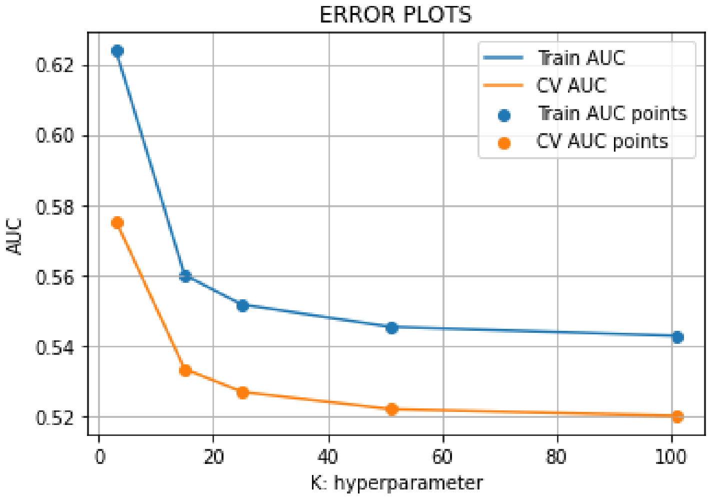
Applying Naive Bayes on BOW, SET 2

HYPERPARAMETER TUNING SET 2

In [ ]:

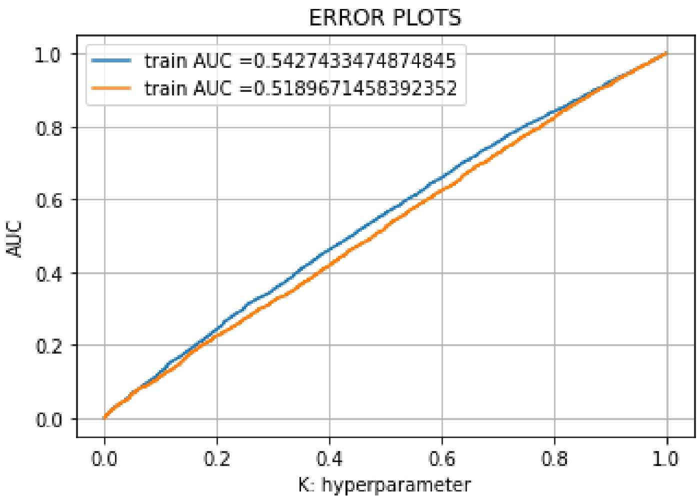
```
import matplotlib.pyplot as plt
from tqdm import tqdm
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
"""
y_true : array, shape = [n_samples] or [n_samples, n_classes]
True binary labels or binary label indicators.

y_score : array, shape = [n_samples] or [n_samples, n_classes]
Target scores, can either be probability estimates of the positive class, confidence valu
es, or non-thresholded measure of
decisions (as returned by "decision_function" on some classifiers).
For binary y_true, y_score is supposed to be the score of the class with greater label.

"""

train_auc = []
cv_auc = []
K = [3, 15, 25, 51, 101]
for i in tqdm(K):
    neigh =  MultinomialNB(alpha=i,class_prior=[0.5,0.5])
    # n_jobs=-1  means we want to use all the course of the cpu to run the code faster
    neigh.fit(Set2_tr, y_train)

    y_train_pred = neigh.predict_proba(Set2_tr)[:,1]
    y_cv_pred = neigh.predict_proba(Set2_cr)[:,1]

    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of
the positive class
    # not the predicted outputs
    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))

plt.plot(K, train_auc, label='Train AUC')
plt.plot(K, cv_auc, label='CV AUC')

plt.scatter(K, train_auc, label='Train AUC points')
plt.scatter(K, cv_auc, label='CV AUC points')

plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

```
100%|
| 5/5 [00:00<00:00,  8.99it/s]
```



In [ ]:

```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklear
n.metrics.roc_curve
from sklearn.metrics import roc_curve, auc

best_k = 101
neigh =  MultinomialNB(alpha=best_k,class_prior=[0.5,0.5])
neigh.fit(Set2_tr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the
positive class
# not the predicted outputs

y_train_pred = neigh.predict_proba(Set2_tr)[:,1]
y_test_pred = neigh.predict_proba(Set2_te)[:,1]

train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

Set2_train_auc = str(auc(train_fpr, train_tpr))
Set2_test_auc = str(auc(test_fpr, test_tpr))

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="train AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



In [ ]:

```
# we are writing our own function for predict, with defined thresould
# we will pick a threshold that will give the least fpr
def find_best_threshold(threshould, fpr, tpr):
```

```
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for threshold", np.round
(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

In [ ]:

```
import numpy as np
print("="*100)
from sklearn.metrics import confusion_matrix
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

```
====================================================================================================
the maximum value of tpr*(1-fpr) 0.2729891575021305 for threshold 1.0
Train confusion matrix
[[ 1751  1844]
 [ 8285 10565]]
Test confusion matrix
[[1266 1376]
 [6142 7716]]
```

Top 10 important features of positive class from SET 1

In [ ]:

```
best_k = 101
nb_alp = MultinomialNB(alpha =best_k ,class_prior=[0.5,0.5])
nb_alp.fit(Set1_tr, y_train)
```

Out[ ]:

```
MultinomialNB(alpha=101, class_prior=[0.5, 0.5])
```

In [ ]:

```
neg_class_prob_sorted = nb_alp.feature_log_prob_[0, :].argsort()
pos_class_prob_sorted = nb_alp.feature_log_prob_[1, :].argsort()
```

In [ ]:

```
# https://stackoverflow.com/questions/14131615/possible-to-append-multiple-lists-at-once-
python
from itertools import chain
Stacked_Feature_list = list(chain(vectorizer1.get_feature_names(),vectorizer2.get_feature
_names(),vectorizer3.get_feature_names(),\
                                  vectorizer4.get_feature_names(),vectorizer5.get_featur
e_names(),vectorizer6.get_feature_names()))
```

In [ ]:

```
import numpy as np
print("The words with higest importance in Postive class is")
print(np.take(Stacked_Feature_list,pos_class_prob_sorted[0:10]))
print("*"*20)
print("The words with higest importance in Negative class is")
```

```
print(np.take(Stacked_Feature_list, neg_class_prob_sorted[0:10]))
```

```
The words with higest importance in Postive class is
['dr' 'warmth' 'care_hunger' 'warmth' 'care_hunger' 'wy' 'vt' 'nd'
 'financialliteracy' 'economics']
********************
The words with higest importance in Negative class is
['warmth' 'care_hunger' 'wy' 'warmth' 'care_hunger' 'dr' 'nd' 'ri'
 'economics' 'vt']
```

3. Summary

In [ ]:

```
from prettytable import PrettyTable
#If you get a ModuleNotFoundError error , install prettytable using: pip3 install prettyt
able

x = PrettyTable()
x.field_names = ["Vectorizer", "Model", "Hyper Parameter", "Train AUC", "TEST AUC"]


x.add_row(["BOW", "Naive Bayes", best_k , Set1_train_auc , Set1_test_auc])
x.add_row([" ", " ", " ", " "," "])
x.add_row(["TFIDF", "Naive Bayes", best_k , Set2_train_auc , Set2_test_auc])

print(x)
```

```
+------------+-------------+-----------------+--------------------+--------------------
+
| Vectorizer |    Model    | Hyper Parameter |     Train AUC      |      TEST AUC      |
+------------+-------------+-----------------+--------------------+--------------------
+
|    BOW     | Naive Bayes |       101       | 0.645035751836289  | 0.624979351503937  |
|            |             |                 |                    |
|
|   TFIDF    | Naive Bayes |       101       | 0.5427433474874845 | 0.5189671458392352 |
+------------+-------------+-----------------+--------------------+--------------------
+
```