NaiveBayse on Donors choose

April 23, 2021

[2]:
```
import pandas as pd
import numpy as np
import nltk
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import Normalizer
import re
from scipy.sparse import hstack
import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
import pickle
from tqdm import tqdm
import os
from collections import Counter
```

[3]:
```
data = pd.read_csv("preprocessed_data.csv", nrows=50000)
data.head(1)
```

[3]:
```
  school_state teacher_prefix project_grade_category  \
0           ca            mrs          grades_prek_2

   teacher_number_of_previously_posted_projects  project_is_approved  \
0                                            53                    1

  clean_categories                  clean_subcategories  \
0     math_science  appliedsciences health_lifescience

                                               essay   price  \
0  i fortunate enough use fairy tale stem kits cl…  725.05
```

```
                           project_title
0  educational support english learners home
```

[4]:
```python
y = data["project_is_approved"].values
x = data.drop(["project_is_approved"], axis=1)

x.head(1)
```

[4]:
```
  school_state teacher_prefix project_grade_category  \
0           ca            mrs          grades_prek_2

   teacher_number_of_previously_posted_projects clean_categories  \
0                                            53     math_science

                clean_subcategories  \
0  appliedsciences health_lifescience

                                              essay   price  \
0  i fortunate enough use fairy tale stem kits cl…  725.05

                           project_title
0  educational support english learners home
```

1 Splitting train, CV and test

[5]:
```python
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33,␣
↪stratify=y)
x_train, x_cv, y_train, y_cv = train_test_split(x_train, y_train, test_size=0.
↪33, stratify=y_train)

print(x_train.shape)
print(x_cv.shape)
print(x_test.shape)
```

```
(22445, 9)
(11055, 9)
(16500, 9)
```

2 Vectorizing price

[6]:
```python
# Vectorizing price

normalizer_price = Normalizer()
normalizer_price.fit(x_train['price'].values.reshape(-1, 1))
```

```
x_train_price_norm = normalizer_price.transform(x_train['price'].values.
 ↪reshape(-1, 1))
x_cv_price_norm = normalizer_price.transform(x_cv['price'].values.reshape(-1,␣
 ↪1))
x_test_price_norm = normalizer_price.transform(x_test['price'].values.
 ↪reshape(-1, 1))

print(x_train_price_norm.shape)
print(x_cv_price_norm.shape)
print(x_test_price_norm.shape)
```

```
(22445, 1)
(11055, 1)
(16500, 1)
```

3 Vectorizing teacher_number_of_previously_posted_projects

[7]:
```
# Vectorizing teacher_number_of_previously_posted_projects



normalizer_teacher_number_of_previously_posted_projects = Normalizer()

normalizer_teacher_number_of_previously_posted_projects.
 ↪fit(x_train['teacher_number_of_previously_posted_projects'].values.
 ↪reshape(-1, 1))

x_train_pre_posted_norm =␣
 ↪normalizer_teacher_number_of_previously_posted_projects.transform(
    x_train['teacher_number_of_previously_posted_projects'].values.reshape(-1,␣
 ↪1))
x_cv_pre_posted_norm = normalizer_teacher_number_of_previously_posted_projects.
 ↪transform(x_cv['teacher_number_of_previously_posted_projects'].values.
 ↪reshape(-1, 1))
x_test_pre_posted_norm =␣
 ↪normalizer_teacher_number_of_previously_posted_projects.transform(
    x_test['teacher_number_of_previously_posted_projects'].values.reshape(-1,␣
 ↪1))

print(x_train_pre_posted_norm.shape)
print(x_cv_pre_posted_norm.shape)
print(x_test_pre_posted_norm.shape)
```

```
(22445, 1)
(11055, 1)
(16500, 1)
```

4 Vectorizing essay (BOW, TF_IDF)

Essay

[8]:
```
# https://www.kaggle.com/nafisur/sentiment-analysis-for-beginner

# Vectorizing essay (BOW, TF_IDF)

countVectorizer_essay = CountVectorizer(min_df=10, max_features=5000)
tfidfVectorizer_essay = TfidfVectorizer(min_df=10, max_features=5000)

countVectorizer_essay.fit(x_train['essay'].values)
tfidfVectorizer_essay.fit(x_train['essay'].values)

x_train_essay_bow = countVectorizer_essay.transform(x_train['essay'].values)
x_cv_essay_bow = countVectorizer_essay.transform(x_cv['essay'].values)
x_test_essay_bow = countVectorizer_essay.transform(x_test['essay'].values)

x_train_essay_tfidf = tfidfVectorizer_essay.transform(x_train['essay'].values)
x_cv_essay_tfidf = tfidfVectorizer_essay.transform(x_cv['essay'].values)
x_test_essay_tfidf = tfidfVectorizer_essay.transform(x_test['essay'].values)

print(x_train_essay_bow.shape)
print(x_cv_essay_bow.shape)
print(x_test_essay_bow.shape)

print("=" * 50)
print("TFIDF Encoded")

print(x_train_essay_tfidf.shape)
print(x_cv_essay_tfidf.shape)
print(x_test_essay_tfidf.shape)
```

```
(22445, 5000)
(11055, 5000)
(16500, 5000)
==================================================
TFIDF Encoded
(22445, 5000)
(11055, 5000)
(16500, 5000)
```

5 Vectorizing project_title ((BOW, TF_IDF))

Project Title

```
[9]: # Vectorizing project_title ((BOW, TF_IDF))

countVectorizer_project_title = CountVectorizer(min_df=10, max_features=5000)
tfidfVectorizer_project_title = TfidfVectorizer(min_df=10, max_features=5000)

countVectorizer_project_title.fit(x_train['project_title'].astype('U').values)
tfidfVectorizer_project_title.fit(x_train['project_title'].astype('U').values)

x_train_project_title_bow = countVectorizer_project_title.
 ↪transform(x_train['project_title'].astype('U').values)
x_cv_project_title_bow = countVectorizer_project_title.
 ↪transform(x_cv['project_title'].astype('U').values)
x_test_project_title_bow = countVectorizer_project_title.
 ↪transform(x_test['project_title'].astype('U').values)

x_train_project_title_tfidf = tfidfVectorizer_project_title.
 ↪transform(x_train['project_title'].astype('U').values)
x_cv_project_title_tfidf = tfidfVectorizer_project_title.
 ↪transform(x_cv['project_title'].astype('U').values)
x_test_project_title_tfidf = tfidfVectorizer_project_title.
 ↪transform(x_test['project_title'].astype('U').values)

print(x_train_project_title_bow.shape)
print(x_cv_project_title_bow.shape)
print(x_test_project_title_bow.shape)

print("=" * 50)
print("TFIDF Encoded")

print(x_train_project_title_tfidf.shape)
print(x_cv_project_title_tfidf.shape)
print(x_test_project_title_tfidf.shape)
```

```
(22445, 1153)
(11055, 1153)
(16500, 1153)
==================================================
TFIDF Encoded
(22445, 1153)
(11055, 1153)
(16500, 1153)
```

6 Vectorizing school_state

[10]:
```
# Vectorizing school_state

countVectorizer_school_state = CountVectorizer()

countVectorizer_school_state.fit(x_train['school_state'].values)

x_train_school_state_ohe = countVectorizer_school_state.
 ↪transform(x_train['school_state'].values)
x_cv_school_state_ohe = countVectorizer_school_state.
 ↪transform(x_cv['school_state'].values)
x_test_school_state_ohe = countVectorizer_school_state.
 ↪transform(x_test['school_state'].values)

print(x_train_school_state_ohe.shape, y_train.shape)
print(x_cv_school_state_ohe.shape, y_cv.shape)
print(x_test_school_state_ohe.shape, y_test.shape)
```

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

[11]:
```
# Vectorizing teacher_prefix
```

[12]:
```
# Vectorizing teacher_prefix


countVectorizer_teacher_prefix = CountVectorizer()

countVectorizer_teacher_prefix.fit(x_train['teacher_prefix'].values)

x_train_teacher_prefix_ohe = countVectorizer_teacher_prefix.
 ↪transform(x_train['teacher_prefix'].values)
x_cv_teacher_prefix_ohe = countVectorizer_teacher_prefix.
 ↪transform(x_cv['teacher_prefix'].values)
x_test_teacher_prefix_ohe = countVectorizer_teacher_prefix.
 ↪transform(x_test['teacher_prefix'].values)

print(x_train_teacher_prefix_ohe.shape)
print(x_cv_teacher_prefix_ohe.shape)
print(x_test_teacher_prefix_ohe.shape)
```

```
(22445, 5)
(11055, 5)
(16500, 5)
```

[13]:
```
# Vectorizing project_grade_category
```

[14]:
```
# Vectorizing project_grade_category

countVectorizer_project_grade_category = CountVectorizer()

countVectorizer_project_grade_category.fit(x_train['project_grade_category'].
↪values)

x_train_project_grade_category_ohe = countVectorizer_project_grade_category.
↪transform(x_train['project_grade_category'].values)
x_cv_project_grade_category_ohe = countVectorizer_project_grade_category.
↪transform(x_cv['project_grade_category'].values)
x_test_project_grade_category_ohe = countVectorizer_project_grade_category.
↪transform(x_test['project_grade_category'].values)

print(x_train_project_grade_category_ohe.shape)
print(x_cv_project_grade_category_ohe.shape)
print(x_test_project_grade_category_ohe.shape)
```

```
(22445, 4)
(11055, 4)
(16500, 4)
```

[15]:
```
# Vectorizing clean_categories
```

[16]:
```
# Vectorizing clean_categories

countVectorizer_clean_categories = CountVectorizer()

countVectorizer_clean_categories.fit(x_train['clean_categories'].values)

x_train_category_ohe = countVectorizer_clean_categories.
↪transform(x_train['clean_categories'].values)
x_cv_category_ohe = countVectorizer_clean_categories.
↪transform(x_cv['clean_categories'].values)
x_test_category_ohe = countVectorizer_clean_categories.
↪transform(x_test['clean_categories'].values)

print(x_train_category_ohe.shape)
print(x_cv_category_ohe.shape)
print(x_test_category_ohe.shape)
```

```
(22445, 9)
(11055, 9)
(16500, 9)
```

[17]:
```
# Vectorizing clean_subcategories
```

[18]:
```
# Vectorizing clean_subcategories

countVectorizer_clean_subcategories = CountVectorizer()

countVectorizer_clean_subcategories.fit(x_train['clean_subcategories'].values)

x_train_clean_subcategories_ohe = countVectorizer_clean_subcategories.
↪transform(x_train['clean_subcategories'].values)
x_cv_clean_subcategories_ohe = countVectorizer_clean_subcategories.
↪transform(x_cv['clean_subcategories'].values)
x_test_clean_subcategories_ohe = countVectorizer_clean_subcategories.
↪transform(x_test['clean_subcategories'].values)

print(x_train_clean_subcategories_ohe.shape)
print(x_cv_clean_subcategories_ohe.shape)
print(x_test_clean_subcategories_ohe.shape)
```

```
(22445, 30)
(11055, 30)
(16500, 30)
```

7 Create Sparse matrix set 1 (title, essay with BOW representation)

[19]:
```
# Concatinating all the features   (BOW Vectorization)

x_tr_set_1 = hstack((x_train_price_norm,
                     x_train_clean_subcategories_ohe,
                     x_train_category_ohe,
                     x_train_project_grade_category_ohe,
                     x_train_essay_bow,
                     x_train_teacher_prefix_ohe,
                     x_train_project_title_bow)).tocsr()

x_cv_set_1 = hstack((x_cv_price_norm,
                     x_cv_clean_subcategories_ohe,
                     x_cv_category_ohe,
                     x_cv_project_grade_category_ohe,
                     x_cv_essay_bow,
                     x_cv_teacher_prefix_ohe,
                     x_cv_project_title_bow)).tocsr()

x_te_set_1 = hstack((x_test_price_norm,
                     x_test_clean_subcategories_ohe,
```

```
                    x_test_category_ohe,
                    x_test_project_grade_category_ohe,
                    x_test_essay_bow,
                    x_test_teacher_prefix_ohe,
                    x_test_project_title_bow)).tocsr()

print(x_tr_set_1.shape)
print(x_cv_set_1.shape)
print(x_te_set_1.shape)
```

```
(22445, 6202)
(11055, 6202)
(16500, 6202)
```

8 Create Sparse matrix set 2 (title, essay with TF-IDF representation)

[20]:
```
# Concatinating all the features (TF_IDF vectorization)

x_tr_set_2 = hstack((x_train_price_norm,
                    x_train_clean_subcategories_ohe,
                    x_train_category_ohe,
                    x_train_project_grade_category_ohe,
                    x_train_essay_tfidf,
                    x_train_teacher_prefix_ohe,
                    x_train_project_title_tfidf)).tocsr()

x_cv_set_2 = hstack((x_cv_price_norm,
                    x_cv_clean_subcategories_ohe,
                    x_cv_category_ohe,
                    x_cv_project_grade_category_ohe,
                    x_cv_essay_tfidf,
                    x_cv_teacher_prefix_ohe,
                    x_cv_project_title_tfidf)).tocsr()

x_te_set_2 = hstack((x_test_price_norm,
                    x_test_clean_subcategories_ohe,
                    x_test_category_ohe,
                    x_test_project_grade_category_ohe,
                    x_test_essay_tfidf,
                    x_test_teacher_prefix_ohe,
                    x_test_project_title_tfidf)).tocsr()

print(x_tr_set_2.shape)
print(x_cv_set_2.shape)
print(x_te_set_2.shape)
```

```
(22445, 6202)
(11055, 6202)
(16500, 6202)
```

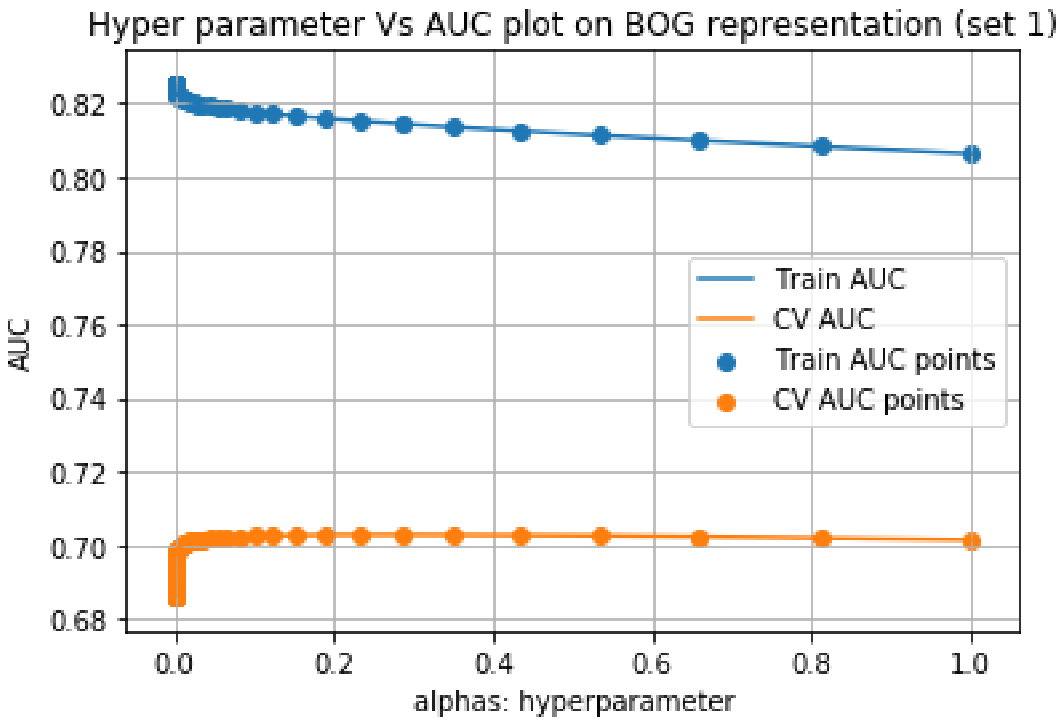
9 Batch Predict

[21]:
```python
# Batch Predict

def batch_predict(clf, data):
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability␣
 ↪estimates of the positive class
    # not the predicted outputs

    y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0] % 1000
    # consider you X_tr shape is 49041, then your tr_loop will be 49041 -␣
 ↪49041%1000 = 49000
    # in this for loop we will iterate unti the last 1000 multiplier
    for i in range(0, tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i + 1000])[:, 1])
    # we will be predicting for the last data points
    if data.shape[0] % 1000 != 0:
        y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:, 1])

    return y_data_pred
```

10 Hyper Parameter tunning on set_1(BOW) , gridsearchCV

[23]:
```python
# GridSearchCV on SET_1

# https://www.featureranking.com/tutorials/machine-learning-tutorials/
 ↪sk-part-3-cross-validation-and-hyperparameter-tuning/

from sklearn.model_selection import GridSearchCV
from scipy.stats import randint as sp_randint
from sklearn.model_selection import RandomizedSearchCV

nb = MultinomialNB()
# alphas = [0.00001, 0.0001, 0.001 ,0.01, 0.1, 0.25, 0.5, 0.8, 1]
# p_grid_NB = {'alpha': alphas, 'fit_prior': [False]}
p_grid_NB = {'alpha': np.logspace(0,-9, num=100)}

gridSearchCv_1 = GridSearchCV(estimator=nb, param_grid=p_grid_NB, cv=10,␣
 ↪scoring='roc_auc', return_train_score=True)
gridSearchCv_1.fit(x_tr_set_1, y_train)
```

```python
results = pd.DataFrame.from_dict(gridSearchCv_1.cv_results_)

train_auc = results['mean_train_score']
train_auc_std = results['std_train_score']
cv_auc = results['mean_test_score']
cv_auc_std = results['std_test_score']


plt.plot(p_grid_NB["alpha"], train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
# plt.gca().fill_between(K, train_auc - train_auc_std,train_auc +␣
 ↪train_auc_std,alpha=0.2,color='darkblue')

plt.plot(p_grid_NB["alpha"], cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
# plt.gca().fill_between(K, cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.
 ↪2,color='darkorange')

plt.scatter(p_grid_NB["alpha"], train_auc, label='Train AUC points')
plt.scatter(p_grid_NB["alpha"], cv_auc, label='CV AUC points')

plt.legend()
plt.xlabel("alphas: hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot on BOG representation (set 1)")
plt.grid()
plt.show()

results.head()
```



[23]:

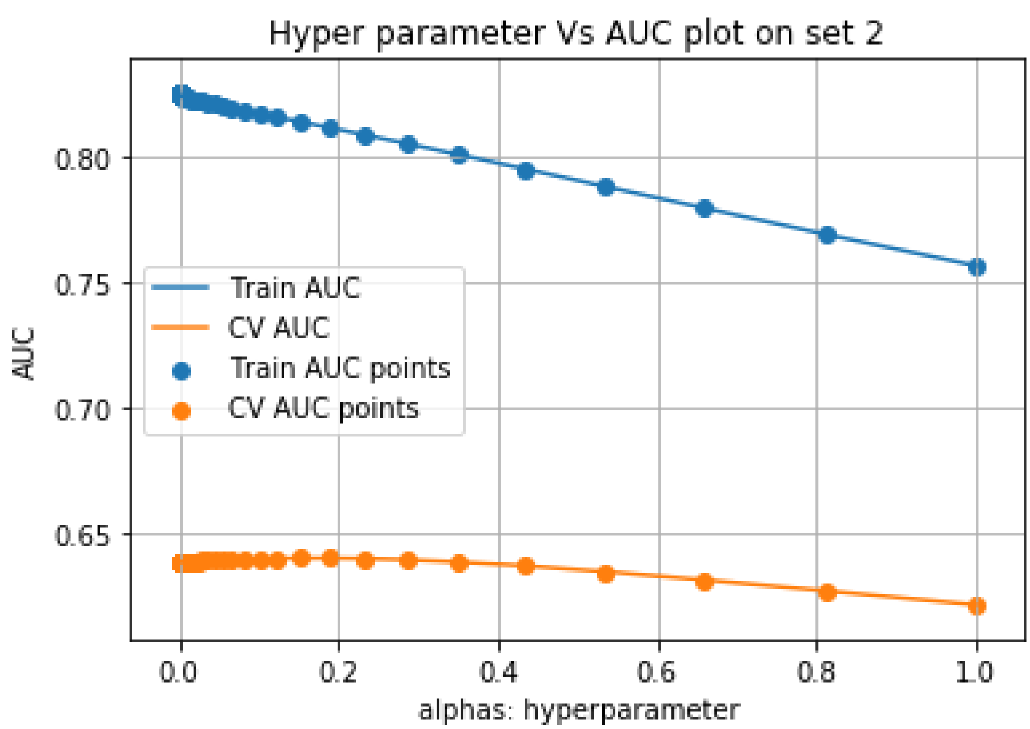
```
   mean_fit_time  std_fit_time  mean_score_time  std_score_time param_alpha  \
0       0.051913      0.003019         0.006188        0.001626           1
1       0.051157      0.001457         0.005704        0.000453    0.811131
2       0.050562      0.000828         0.005468        0.000521    0.657933
3       0.054224      0.004584         0.005579        0.000610     0.53367
4       0.050887      0.001219         0.005696        0.000638    0.432876

                          params  split0_test_score  split1_test_score  \
0                 {'alpha': 1.0}           0.689620           0.704801
1  {'alpha': 0.8111308307896871}           0.689999           0.705576
2   {'alpha': 0.657933224657568}           0.690317           0.706360
3   {'alpha': 0.533669923120631}           0.690439           0.706938
4 {'alpha': 0.43287612810830584}           0.690559           0.707174

   split2_test_score  split3_test_score  …  split2_train_score  \
0           0.708421           0.717427  …            0.804511
1           0.709125           0.718202  …            0.806446
2           0.709562           0.718889  …            0.808069
3           0.709859           0.719327  …            0.809471
4           0.710119           0.719643  …            0.810681

   split3_train_score  split4_train_score  split5_train_score  \
0            0.804775            0.807282            0.806769
```

```
1             0.806710            0.809141            0.808673
2             0.808348            0.810707            0.810302
3             0.809768            0.812061            0.811693
4             0.810996            0.813219            0.812885

   split6_train_score  split7_train_score  split8_train_score  \
0            0.803273            0.806603            0.808024
1            0.805137            0.808521            0.809865
2            0.806727            0.810143            0.811448
3            0.808083            0.811539            0.812780
4            0.809240            0.812719            0.813943

   split9_train_score  mean_train_score  std_train_score
0            0.808780          0.806464         0.001651
1            0.810745          0.808370         0.001656
2            0.812428          0.809988         0.001664
3            0.813860          0.811374         0.001667
4            0.815093          0.812567         0.001672

[5 rows x 31 columns]
```

11 Hyperparameter tunning in set_2 (TF-IDF) using GridsearchCV

[25]:
```
# GridSearchCV on set2

# https://www.featureranking.com/tutorials/machine-learning-tutorials/
↪sk-part-3-cross-validation-and-hyperparameter-tuning/

from sklearn.model_selection import GridSearchCV
from scipy.stats import randint as sp_randint
from sklearn.model_selection import RandomizedSearchCV

nb = MultinomialNB()

# alphas = [0.00001, 0.0001, 0.001 ,0.01, 0.1, 0.25, 0.5, 0.8, 1]
# p_grid_NB = {'alpha': alphas}
p_grid_NB = {'alpha': np.logspace(0,-9, num=100)}

gridSearchCv_2 = GridSearchCV(estimator=nb, param_grid=p_grid_NB, cv=10,␣
↪scoring='roc_auc', return_train_score=True)
gridSearchCv_2.fit(x_tr_set_2, y_train)

results = pd.DataFrame.from_dict(gridSearchCv_2.cv_results_)

train_auc = results['mean_train_score']
```

```
train_auc_std = results['std_train_score']
cv_auc = results['mean_test_score']
cv_auc_std = results['std_test_score']

plt.plot(p_grid_NB["alpha"], train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
# plt.gca().fill_between(K, train_auc - train_auc_std,train_auc +␣
↪train_auc_std,alpha=0.2,color='darkblue')

plt.plot(p_grid_NB["alpha"], cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
# plt.gca().fill_between(K, cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.
↪2,color='darkorange')

plt.scatter(p_grid_NB["alpha"], train_auc, label='Train AUC points')
plt.scatter(p_grid_NB["alpha"], cv_auc, label='CV AUC points')

plt.legend()
plt.xlabel("alphas: hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot on set 2")
plt.grid()
plt.show()

results.head()
```

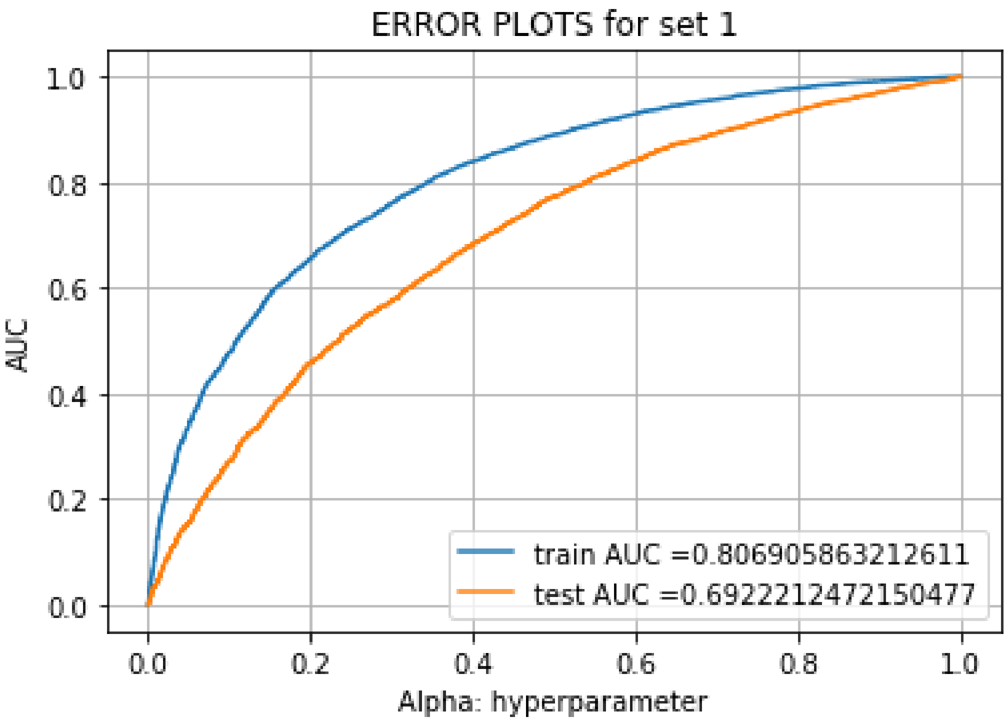


```
[25]:    mean_fit_time  std_fit_time  mean_score_time  std_score_time param_alpha  \
      0       0.054457      0.003009         0.006066        0.001030           1
      1       0.054934      0.004201         0.006193        0.000756    0.811131
      2       0.051608      0.001688         0.005697        0.000460    0.657933
      3       0.052406      0.002501         0.006200        0.001468     0.53367
      4       0.051954      0.002183         0.005601        0.000662    0.432876

                                   params  split0_test_score  split1_test_score  \
      0                   {'alpha': 1.0}           0.601320           0.617418
      1  {'alpha': 0.8111308307896871}           0.605790           0.624436
      2   {'alpha': 0.657933224657568}           0.608985           0.629973
      3   {'alpha': 0.533669923120631}           0.611892           0.634257
      4 {'alpha': 0.43287612810830584}           0.613532           0.638121

         split2_test_score  split3_test_score  …  split2_train_score  \
      0           0.633280           0.625531  …            0.754919
      1           0.638946           0.631745  …            0.767585
      2           0.643439           0.636627  …            0.778226
      3           0.647100           0.641096  …            0.786943
      4           0.649552           0.644418  …            0.794006

         split3_train_score  split4_train_score  split5_train_score  \
      0            0.754150            0.759655            0.756160
      1            0.766543            0.772117            0.768775
      2            0.776896            0.782474            0.779320
      3            0.785391            0.790937            0.788016
      4            0.792266            0.797749            0.795075

         split6_train_score  split7_train_score  split8_train_score  \
      0            0.754858            0.755781            0.756834
      1            0.767232            0.768364            0.769320
      2            0.777590            0.778913            0.779773
      3            0.786115            0.787574            0.788359
      4            0.793023            0.794596            0.795306

         split9_train_score  mean_train_score  std_train_score
      0            0.757885          0.756347         0.001639
      1            0.770882          0.768910         0.001674
      2            0.781759          0.779424         0.001700
      3            0.790654          0.788052         0.001721
      4            0.797839          0.795044         0.001732

      [5 rows x 31 columns]
```

12 Testing alpha value on test data (set_1 BOW representation)

[32]:
```
# For set_1 data - Naive bayes on test data

from sklearn.metrics import roc_auc_score, auc

best_alpha_set1 = gridSearchCv_1.best_params_["alpha"]

print("Best Param set 1 : {}".format(gridSearchCv_1.best_params_))

nb = MultinomialNB(alpha=best_alpha_set1)
nb.fit(x_tr_set_1, y_train)

y_train_pred_1 = batch_predict(nb, x_tr_set_1)
y_test_pred_1 = batch_predict(nb, x_te_set_1)


train_fpr_1, train_tpr_1, tr_thresholds_1 = roc_curve(y_train, y_train_pred_1)
test_fpr_1, test_tpr_1, te_thresholds_1 = roc_curve(y_test, y_test_pred_1)

auc_score_1 = auc(test_fpr_1, test_tpr_1)

print(auc_score_1)

plt.plot(train_fpr_1, train_tpr_1, label="train AUC =" + str(auc(train_fpr_1,␣
 ↪train_tpr_1)))
plt.plot(test_fpr_1, test_tpr_1, label="test AUC =" + str(auc(test_fpr_1,␣
 ↪test_tpr_1)))
plt.legend()
plt.xlabel("Alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS for set 1")
plt.grid()
plt.show()
```

```
Best Param set 1 : {'alpha': 0.23101297000831597}
0.6922212472150477
```

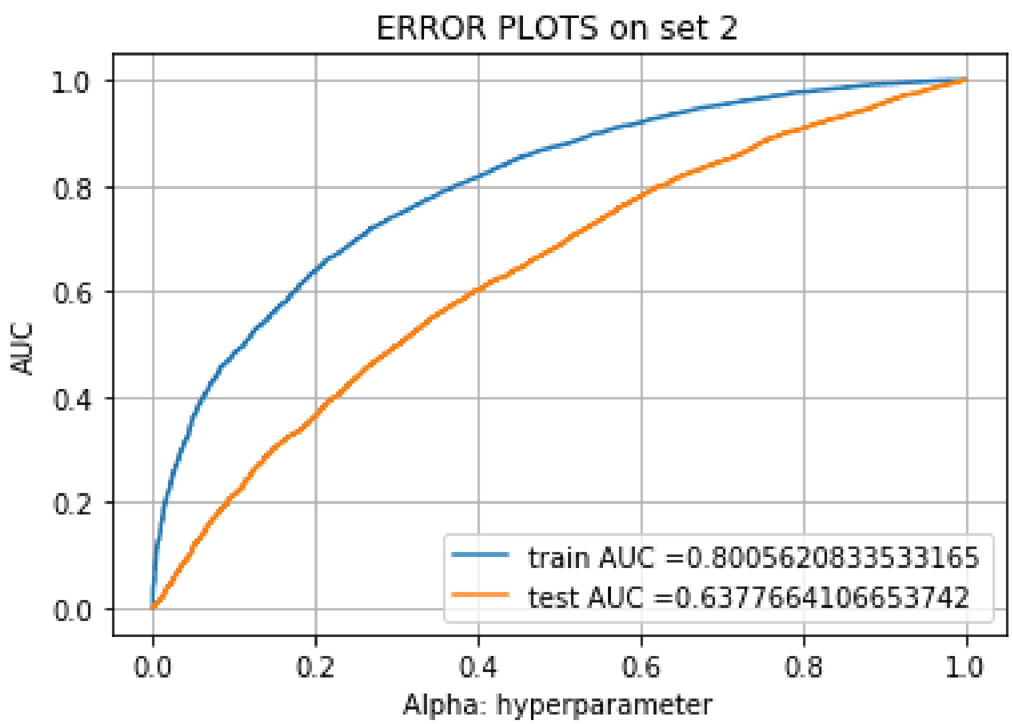


13 Testing alpha value on test data (set_2 TF_IDFrepresentation)

[33]:
```
# For set_2 data - Naive bayes on test data

from sklearn.metrics import roc_auc_score, auc


print("Best param SET 2 : {}".format(gridSearchCv_2.best_params_))
best_alpha_set2 = gridSearchCv_2.best_params_["alpha"]

nb = MultinomialNB(alpha=best_alpha_set1)
nb.fit(x_tr_set_2, y_train)


y_train_pred_2 = batch_predict(nb, x_tr_set_2)
y_test_pred_2 = batch_predict(nb, x_te_set_2)

train_fpr_2, train_tpr_2, tr_thresholds_2 = roc_curve(y_train, y_train_pred_2)
test_fpr_2, test_tpr_2, te_thresholds_2 = roc_curve(y_test, y_test_pred_2)

auc_score_2 = auc(test_fpr_2, test_tpr_2)
```

```
print(auc_score_2)

plt.plot(train_fpr_2, train_tpr_2, label="train AUC =" + str(auc(train_fpr_2,␣
↪train_tpr_2)))
plt.plot(test_fpr_2, test_tpr_2, label="test AUC =" + str(auc(test_fpr_2,␣
↪test_tpr_2)))
plt.legend()
plt.xlabel("Alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS on set 2")
plt.grid()
plt.show()
```

```
Best param SET 2 : {'alpha': 0.1873817422860384}
0.6377664106653742
```



14 Confusion matrix set_1

[28]:
```
# Confusion matrix for set_1

# 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


from sklearn.metrics import confusion_matrix

best_t = find_best_threshold(tr_thresholds_1, train_fpr_1, train_tpr_1)

print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred_1, best_t)))
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred_1, best_t)))
```

```
the maximum value of tpr*(1-fpr) 0.5353876995384836 for threshold 0.86
Train confusion matrix
[[ 2713   882]
 [ 5477 13373]]
Test confusion matrix
[[1564 1078]
 [4305 9553]]
```

15 Confusion matrix set_2

[29]:

```
# Confusion matrix for  set_2

# 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


from sklearn.metrics import confusion_matrix

best_t = find_best_threshold(tr_thresholds_2, train_fpr_2, train_tpr_2)

print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred_2, best_t)))
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred_2, best_t)))
```

```
the maximum value of tpr*(1-fpr) 0.5260657485529194 for threshold 0.84
Train confusion matrix
[[ 2629   966]
 [ 5290 13560]]
Test confusion matrix
[[1330 1312]
 [4388 9470]]
```

16 Get top features of set_1

[30]:
```
# Get top features of set_1



nb_bow = MultinomialNB(alpha=best_alpha_set1, class_prior=[0.5, 0.5],␣
↪fit_prior=True)
nb_bow.fit(x_tr_set_1, y_train)


feature_names_set_1 = []

for word in countVectorizer_clean_subcategories.get_feature_names():
    feature_names_set_1.append(word)
```

```
for word in countVectorizer_clean_categories.get_feature_names():
    feature_names_set_1.append(word)

for word in countVectorizer_project_grade_category.get_feature_names():
    feature_names_set_1.append(word)

for word in countVectorizer_essay.get_feature_names():
    feature_names_set_1.append(word)

for word in countVectorizer_teacher_prefix.get_feature_names():
        feature_names_set_1.append(word)

for word in countVectorizer_project_title.get_feature_names():
    feature_names_set_1.append(word)


# https://www.geeksforgeeks.org/python-reverse-a-numpy-array/
pos_class_prob_sorted = nb_bow.feature_log_prob_[1].argsort()[::-1]

# https://stackoverflow.com/questions/50526898/
 ↪how-to-get-feature-importance-in-naive-bayes
print(np.take(feature_names_set_1, pos_class_prob_sorted[:20]))
```

```
['studied' 'schoolers' 'myriad' 'classrooms' 'learns' 'theater' 'notch'
 'thier' 'learned' 'helped' 'appliedsciences' 'map' 'narrative' 'readings'
 'workbooks' 'weaknesses' 'needed' 'used' 'days' 'about']
```

17 Representing result of vectorizer, model, Hyper parameter, AUC

[31]:
```
# Representing result of vectorizer, model, Hyper parameter, AUC

# https://stackoverflow.com/questions/36423259/
 ↪how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists

import prettytable

x = prettytable.PrettyTable(["vectorizer", "model", "Hyper parameter", "AUC"])
x.add_row(["BOW","NB",best_alpha_set1,round(auc_score_1, 4)])
x.add_row(["TF_IDF", "NB", best_alpha_set2, round(auc_score_2,4)])

print(x)
```

```
+------------+-------+--------------------+--------+
| vectorizer | model |   Hyper parameter  |  AUC   |
```

```
+------------+-------+--------------------+--------+
|    BOW     |   NB  | 0.23101297000831597 | 0.6922 |
|   TF_IDF   |   NB  |  0.1873817422860384 | 0.6378 |
+------------+-------+--------------------+--------+
```

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```