Naive Bayes

```
In [0]:
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import pickle
```

In [102]:

```
from google.colab import drive
drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

In [103]:

```
! ls '/content/drive/My Drive/Applied AI/Datasets/New Donors/'
```

glove_vectors Preprocessed_inc_others.csv train_data.csv
PreProcessed.csv resources.csv

Importing data

In [104]:

```
data = pd.read_csv('/content/drive/My Drive/Applied AI/Datasets/New
Donors/Preprocessed_inc_others.csv')
data.head()
```

Out[104]:

Unnamed: school_state teacher_prefix project_grade_category teacher_number_of_previously_posted_projects project_is_approved

0	0	са	mrs	grades_prek_2	53	1
1	1	ut	ms	grades_3_5	4	1
2	2	ca	mrs	grades_prek_2	10	1
3	3	ga	mrs	grades_prek_2	2	1

```
grades_3_5
          Unnamed:
                                  school_state teacher_prefix project_grade_category teacher_number_of_previously_posted_projects project_is_approved
 In [105]:
 data.describe()
Out[105]:
                       Unnamed: 0 teacher_number_of_previously_posted_projects project_is_approved
                                                                                                                                                                                                                           price
                                                                                                                                                                                                                                                      quantity sentiment_sco
   count 109248.000000
                                                                                                                                                                                                        109248.000000
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                    54623.500000
   mean
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                                                                                                                                                                                  0.848583
                                                                                                                                                                                                               298.119343
                                                                                                                                                                                                                                                   16.965610
                                                                                                                                                                                                                                                                                           0.2100
        std
                    31537.325441
                                                                                                                                  27.777154
                                                                                                                                                                                  0.358456
                                                                                                                                                                                                               367.498030
                                                                                                                                                                                                                                                   26.182942
                                                                                                                                                                                                                                                                                           0.0835
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                              0.000000
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                    81935.250000
                                                                                                                                    9.000000
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      75%
                109247.000000
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                                                                                                                                                                                                                                                 930.000000
                                                                                                                                                                                                                                                                                           0.6633
      max
4
                                                                                                                                                                                                                                                                                                  Þ
 In [106]:
 y = data['project is approved'].values
 X = data.drop(['project is approved'], axis=1)
 X.head(1)
Out[106]:
         Unnamed:
                                  school_state teacher_prefix project_grade_category teacher_number_of_previously_posted_projects clean_categories clean_catego
   0
                            O
                                                       ca
                                                                                       mrs
                                                                                                                     grades_prek_2
                                                                                                                                                                                                                                                   53
                                                                                                                                                                                                                                                                     math_science
 In [0]:
 y = y.reshape(-1,1)
 In [108]:
 print(X.shape)
 print(y.shape)
 (109248, 14)
 (109248, 1)
Splitting the data
 In [0]:
 from sklearn.model selection import train test split
 data_train, data_test, label_train, label_test = train_test_split(X, y, test_size=0.33, stratify=y,
 random state=42)
```

Tn [1101:

```
print(data_train.shape)
print(data test.shape)
print(label train.shape)
print(label_test.shape)
(73196, 14)
(36052, 14)
(73196, 1)
(36052, 1)
In [0]:
X train = data train
X test = data test
y_train = label_train
y_test = label_test
In [112]:
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
(73196, 14)
(36052, 14)
(73196, 1)
(36052, 1)
1. Vectorizing all the features
1.1 School State
In [0]:
from sklearn.feature_extraction.text import CountVectorizer
vectorizer 1 = CountVectorizer(list(X train['school state'].values), lowercase=False, binary=True)
In [0]:
X train Sstate = vectorizer 1.fit transform(X train['school state'].values)
X_test_Sstate = vectorizer_1.transform(X_test['school_state'].values)
In [115]:
print(X train Sstate.shape)
print(X test Sstate.shape)
(73196, 51)
(36052, 51)
1.2 Clean_Categories
In [116]:
X train.head(1)
Out[116]:
```

school_state teacher_prefix project_grade_category teacher_number_of_previously_posted_projects clean_categories

in the con-

Unnamed:

```
Unnamed:
               school_state teacher_prefix project_grade_category teacher_number_of_previously_posted_projects clean_categories
                                                                                             literacy_language
76564
         76564
                                             grades_prek_2
                                                                                          13
                                 mrs
                                                                                                math science
In [0]:
vectorizer 2 = CountVectorizer(list(X_train['clean_categories'].values),lowercase=False,
binary=True)
In [0]:
X train cat = vectorizer 2.fit transform(X train['clean categories'].values)
X_test_cat = vectorizer_2.transform(X_test['clean_categories'].values)
In [119]:
print(X_train_cat.shape)
print(X test cat.shape)
(73196, 9)
(36052, 9)
1.3 Clean sub categories
In [0]:
vectorizer 3 = CountVectorizer(list(X train['clean subcategories'].values), lowercase=False,
binary=True)
In [0]:
X_train_subcat = vectorizer_3.fit_transform(X_train['clean_subcategories'].values)
X test subcat = vectorizer 3.transform(X test['clean subcategories'].values)
In [122]:
print(X train subcat.shape)
print(X test subcat.shape)
(73196, 30)
(36052, 30)
1.4 Project Grade Category
In [0]:
vectorizer 4 = CountVectorizer(list(X train['project grade category'].values), lowercase=False,
binary=True)
In [0]:
X_train_grade = vectorizer_4.fit_transform(X_train['project_grade_category'].values)
X test grade = vectorizer 4.transform(X test['project grade category'].values)
In [125]:
print(X train grade.shape)
print(X test grade.shape)
(73196, 4)
```

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1.5 Teacher Prefix

172106 14066

```
In [0]:
vectorizer_5 = CountVectorizer(list(X_train['teacher_prefix'].values), lowercase=False,
binary=True)
In [0]:
X_train_prefix = vectorizer_5.fit_transform(X_train['teacher_prefix'].values)
X_test_prefix = vectorizer_5.transform(X_test['teacher_prefix'].values)
In [128]:
print(X train prefix.shape)
print(X test prefix.shape)
(73196, 5)
(36052, 5)
1.6 Essay
1.6.1 BOW
In [0]:
vectorizer 6 = CountVectorizer(list(X train['essay'].values), min df=10)
In [0]:
#We are considering the words which atleast in atleat 10 documents
X train essay bow = vectorizer 6.fit transform(X train['essay'].values)
X_test_essay_bow = vectorizer_6.transform(X_test['essay'].values)
In [131]:
print(X train essay bow.shape)
print(X_test_essay_bow.shape)
(73196, 14266)
(36052, 14266)
1.6.2 TFIDF
In [0]:
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer 7 = TfidfVectorizer(list(X train['essay'].values), min df=10)
In [0]:
X train essay tfidf = vectorizer 7.fit transform(X train['essay'].values)
X_test_essay_tfidf = vectorizer_7.transform(X_test['essay'].values)
In [134]:
print(X train essay tfidf.shape)
print(X_test_essay_tfidf.shape)
```

```
(/3190, 14200)
(36052, 14266)
```

1.7 PROJECT TITLE

1.7.1 BOW

```
In [0]:
```

```
vectorizer_8 = CountVectorizer(list(X_train['title'].values), min_df=10)
```

In [0]:

```
X_train_title_bow = vectorizer_8.fit_transform(X_train['title'].values)
X test title bow = vectorizer 8.transform(X test['title'].values)
```

In [137]:

```
print(X train title bow.shape)
print(X test title bow.shape)
(73196, 2617)
(36052, 2617)
```

1.7.2 TFIDF

In [0]:

```
vectorizer 9 = TfidfVectorizer(list(X train['title'].values), min df=10)
```

In [0]:

```
X train title tfidf = vectorizer 9.fit transform(X train['title'].values)
X_test_title_tfidf = vectorizer_9.transform(X_test['title'].values)
```

In [140]:

```
print(X_train_title_tfidf.shape)
print(X_test_title_tfidf.shape)
(73196, 2617)
(36052, 2617)
```

1.8 Price

Note:

• Since the Naive Bayes will not process with negative values and we can't standardize it

In [0]:

```
X_train_price = X_train['price'].values.reshape(-1,1)
X_test_price = X_test['price'].values.reshape(-1,1)
```

In [142]:

```
print(X_train_price.shape)
print(X test price.shape)
```

```
(73196, 1)
```

(36052.1)

()))) , , ,

1.9 Previously posted projects

```
In [0]:
```

```
X_train_previous = X_train['teacher_number_of_previously_posted_projects'].values.reshape(-1,1)
X_test_previous = X_test['teacher_number_of_previously_posted_projects'].values.reshape(-1,1)
```

```
In [144]:
```

```
print(X_train_previous.shape)
print(X_test_previous.shape)

(73196, 1)
(36052, 1)
```

2. SET-1

2.1 Merge all the features

In [43]:

```
print(X train Sstate.shape)
print(X train cat.shape)
print(X_train_subcat.shape)
print(X train grade.shape)
print(X_train_prefix.shape)
print(X_train_essay_bow.shape)
print(X_train_essay_tfidf.shape)
print(X train title bow.shape)
print(X train title tfidf.shape)
print(X train price.shape)
print(X_train_previous.shape)
print('='*50)
print(X_test_Sstate.shape)
print(X test cat.shape)
print(X test subcat.shape)
print(X_test_grade.shape)
print(X_test_prefix.shape)
print(X_test_essay_bow.shape)
print(X_test_essay_tfidf.shape)
print(X test title bow.shape)
print(X test title tfidf.shape)
print(X_test_price.shape)
print(X_test_previous.shape)
(73196, 51)
(73196, 9)
(73196, 30)
(73196, 4)
(73196, 5)
(73196, 14266)
(73196, 14266)
(73196, 2617)
(73196, 2617)
(73196, 1)
(73196, 1)
______
(36052, 51)
(36052, 9)
(36052, 30)
(36052, 4)
(36052, 5)
(36052, 14266)
(36052, 14266)
(36052, 2617)
(36052, 2617)
(36052, 1)
```

```
(36052, 1)
In [0]:
from scipy.sparse import hstack
X train 1 = hstack((X train Sstate, X train cat, X train subcat, X train grade, X train prefix, X t
rain essay bow, X train title bow, X train previous, X train price)).tocsr()
X test 1 = hstack((X test Sstate, X test cat, X test subcat, X test grade, X test prefix, X test es
say_bow, X_test_title_bow, X_test_previous, X_test_price)).tocsr()
In [57]:
print(X train 1.shape)
print(X test 1.shape)
(73196, 16984)
(36052, 16984)
2.2 Grid Search CV
In [0]:
from sklearn.naive_bayes import MultinomialNB
classifier 1 = MultinomialNB()
In [0]:
from sklearn.model selection import GridSearchCV
parameters = [
                   gridsearch_1 = GridSearchCV(classifier_1, parameters, scoring='roc_auc', cv=10, n_jobs=-1, return_t
rain score=True)
In [60]:
print(X train 1.shape)
print(y_train.shape)
(73196, 16984)
(73196, 1)
In [61]:
gridsearch_1 = gridsearch_1.fit(X_train_1, y_train)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWarning: A c
olumn-vector y was passed when a 1d array was expected. Please change the shape of y to
(n samples, ), for example using ravel().
 y = column_or_1d(y, warn=True)
```

```
In [62]:
```

```
import warnings
warnings.filterwarnings('ignore')
results = pd.DataFrame.from_dict(gridsearch_1.cv_results_)
results.head()
```

Out[62]:

mean_fit_time std_fit_time mean_score_time std_score_time param_alpha params split0_test_score split1_test_score split2_test_

1	mean_fit_time 0.123135	std_fit_time 0.004729	mean_score_time 0.012991	std_score_time 0.000809	param_alpha 0.001	Params 0.001}	split0_test_score 0.650303	split1_test_score 0.656382	split2_test 0.€
2	0.118874	0.005027	0.013573	0.001144	0.01	{'alpha': 0.01}	0.650659	0.656824	0.6
3	0.113551	0.004523	0.012937	0.000709	0.1	{'alpha': 0.1}	0.650738	0.656396	0.6
4	0.111400	0.001876	0.015732	0.003122	1	{'alpha': 1}	0.651656	0.657538	0.6
4									Þ

In [63]:

```
best_alpha_1 = gridsearch_1.best_params_['alpha']
print('best_alhpa:', best_alpha_1)
```

best_alhpa: 10

Summary:

- It shows that the best alpha = 10

2.3 AUC vs Hyperparameter

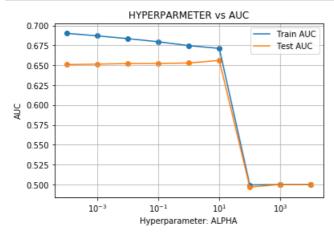
In [0]:

```
train_auc_1 = results['mean_train_score']
test_auc_1 = results['mean_test_score']
alpha_1 = results['param_alpha']
```

In [65]:

```
plt.plot(alpha_1, train_auc_1, label='Train AUC')
plt.plot(alpha_1, test_auc_1, label='Test AUC')
plt.scatter(alpha_1, train_auc_1)
plt.scatter(alpha_1, test_auc_1)

plt.title('HYPERPARMETER vs AUC')
plt.xlabel('Hyperparameter: ALPHA')
plt.ylabel('AUC')
plt.ylabel('AUC')
plt.xscale('log')
plt.legend()
plt.grid()
plt.show()
```

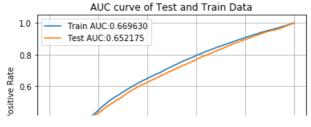


2.4 Modelling with alpha = 10

In [66]:

classifier_withAlpha_1 = MultinomialNB(alpha=10)

```
classifier withAlpha 1.fit(X train 1, y train)
Out[66]:
MultinomialNB(alpha=10, class_prior=None, fit_prior=True)
2.5 Cross Validation
In [0]:
from sklearn.model selection import cross val score
cv 1 = cross val score(estimator=classifier withAlpha 1, X=X train 1, y=y train,cv=10,
scoring='roc auc')
In [165]:
best_auc_1 = cv_1.mean()
print('Best AUC:%4f' %best_auc_1)
Best AUC: 0.656119
2.6 AUC curve for Train and Test
In [0]:
def batch predict(clf, data):
   y data pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    for i in range(0,tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
    if data.shape[0]%1000 != 0:
        y data pred.extend(clf.predict proba(data[tr loop:])[:,1])
    return y_data_pred
In [0]:
y train pred 1 = batch predict(classifier withAlpha 1, X train 1)
y_test_pred_1 = batch_predict(classifier withAlpha 1, X test 1)
In [0]:
from sklearn.metrics import roc curve, auc
train_fpr_1, train_tpr_1, train_thresh_1 = roc_curve(y_train, y_train_pred_1)
test_fpr_1, test_tpr_1, test_thresh_1 = roc_curve(y_test, y_test_pred_1)
In [72]:
plt.plot(train_fpr_1, train_tpr_1, label='Train AUC:%4f'%auc(train_fpr_1, train_tpr_1))
plt.plot(test fpr 1, test tpr 1, label='Test AUC:%4f'%auc(test fpr 1, test tpr 1))
plt.title('AUC curve of Test and Train Data')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.grid()
plt.show()
```



2.7 Confusion Matrix

In [0]:

```
def find_best_threshold(fpr, tpr, threhsold):
    t = threhsold[np.argmax(tpr*(1-fpr))]
    print('The maximum tpr*(1-fpr) is:', max(tpr*(1-fpr)), 'for threshold', (np.round(t,3)))
    return t
```

In [74]:

```
best_t = find_best_threshold(train_fpr_1, train_tpr_1, train_thresh_1)
```

The maximum tpr*(1-fpr) is: 0.3970900910561266 for threshold 1.0

In [0]:

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

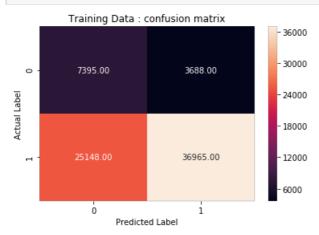
    return predictions
```

In [0]:

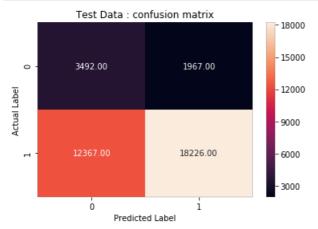
```
from sklearn.metrics import confusion_matrix
cm_train_1 = confusion_matrix(y_train, predict_with_threshold(y_train_pred_1, best_t))
cm_test_1 = confusion_matrix(y_test, predict_with_threshold(y_test_pred_1, best_t))
```

In [77]:

```
sns.heatmap(cm_train_1, annot=True, fmt='.2f')
plt.title('Training Data : confusion matrix')
plt.xlabel('Predicted Label')
plt.ylabel('Actual Label')
plt.show()
```



```
sns.heatmap(cm_test_1, annot=True, fmt='.2f')
plt.title('Test Data : confusion matrix')
plt.xlabel('Predicted Label')
plt.ylabel('Actual Label')
plt.show()
```



2. 8 Top 20 Features

In [0]:

In [80]:

```
len(features_list)
```

Out[80]:

16984

In [0]:

```
#For postive class , we get the indices
sorted_prob_class1_ind = classifier_withAlpha_1.feature_log_prob_[1,:].argsort()
#For Negative Class
sorted_prob_class0_ind = classifier_withAlpha_1.feature_log_prob_[0,:].argsort()
```

In [82]:

In [0]:

12371])

```
#https://www.geeksforgeeks.org/python-get-last-n-elements-from-given-list/
#since argsort gives it in ascending order we need the last 20 eleemnts
Most_important_word_for_1 = []
Most_important_word_for_0 = []
```

```
| most_Tumborrant_mora_tor_n = []
for i in (sorted_prob_class1_ind[-20:-1]):
    Most_important_word_for_1.append(features_list[i])
for j in (sorted_prob_class0_ind[-20:-1]):
    Most important word for 0.append(features list[j])
In [84]:
print('Top 20 words in Postive Class')
print(Most important word for 1)
print('='*50)
print('Top 20 words in Negative class')
print(Most important word for 0)
Top 20 words in Postive Class
['love', 'use', 'reading', 'work', 'need', 'we', 'nannan', 'many', 'help', 'learn', 'not', 'they', 'the', 'classroom', 'learning', 'my', 'school', 'students',
'teacher_number_of_previously_posted_projects']
Top 20 words in Negative class
['reading', 'love', 'come', 'work', 'need', 'we', 'many', 'nannan', 'the', 'help', 'they', 'learn', 'not', 'classroom', 'my', 'learning', 'school',
'teacher number of previously posted projects', 'students']
3. Set 2
3.1 Merge all the features
In [0]:
from scipy.sparse import hstack
X_train_2 = hstack((X_train_Sstate, X_train_cat, X_train_subcat, X_train_grade, X_train_prefix, X t
rain_essay_tfidf, X_train_title_tfidf, X_train_previous, X_train_price)).tocsr()
X test 2 = hstack((X test Sstate, X test cat, X test subcat, X test grade, X test prefix, X test es
say_tfidf, X_test_title_tfidf, X_test_previous, X_test_price)).tocsr()
In [146]:
print(X train 2.shape)
print(X_test_2.shape)
(73196, 16984)
(36052, 16984)
3.2 Grid Search
In [0]:
classifier 2 = MultinomialNB()
In [0]:
parameters = [
                     gridsearch 2 = GridSearchCV(estimator=classifier_2, param_grid=parameters, scoring='roc_auc',
n jobs=-1, cv=10, return train score=True)
In [0]:
```

gridsearch 2 = gridsearch 2.fit(X train 2, y train)

In [91]:

```
results = pd.DataFrame.from_dict(gridsearch_2.cv_results_)
results = results.sort_values(['param_alpha'])
results.head()
```

Out[91]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	params	split0_test_score	split1_test_score	split2_test_
0	0.122821	0.004070	0.013092	0.000593	0.0001	{'alpha': 0.0001}	0.613831	0.622304	0.6
1	0.127190	0.004452	0.013374	0.000319	0.001	{'alpha': 0.001}	0.614316	0.622410	0.6
2	0.123700	0.005153	0.013480	0.000411	0.01	{'alpha': 0.01}	0.614795	0.622272	0.6
3	0.129093	0.011464	0.013330	0.000664	0.1	{'alpha': 0.1}	0.615036	0.621804	0.6
4	0.122390	0.002708	0.014902	0.002513	1	{'alpha': 1}	0.614182	0.620320	0.6
4]						Þ

In [92]:

```
best_alpha_2 = gridsearch_2.best_params_['alpha']
print('best_alpha:', best_alpha_2)
```

best alhpa: 0.01

Summary:

- It shows that the best alpha could be 0.01

3.3 Plotting AUC vs Hyperparameter

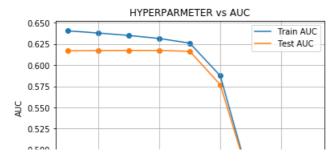
In [0]:

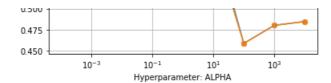
```
train_auc_2 = results['mean_train_score']
test_auc_2 = results['mean_test_score']
alpha_2 = results['param_alpha']
```

In [96]:

```
plt.plot(alpha_2, train_auc_2, label='Train AUC')
plt.plot(alpha_2, test_auc_2, label='Test AUC')
plt.scatter(alpha_2, train_auc_2)
plt.scatter(alpha_2, test_auc_2)

plt.title('HYPERPARMETER vs AUC')
plt.xlabel('Hyperparameter: ALPHA')
plt.ylabel('AUC')
plt.xscale('log')
plt.legend()
plt.grid()
plt.show()
```





Summary

- Here also it shows that the AUC is high when alpha = 1

3.4 Modelling with Parameters

```
In [147]:
```

```
classifier_withAlpha_2 = MultinomialNB(alpha=best_alpha_2)
classifier_withAlpha_2.fit(X_train_2, y_train)
```

Out[147]:

MultinomialNB(alpha=0.01, class_prior=None, fit_prior=True)

3.5 Cross Validation

```
In [0]:
```

```
from sklearn.model_selection import cross_val_score
cv_2 = cross_val_score(estimator=classifier_withAlpha_2, X=X_train_2, y=y_train,cv=10,
scoring='roc_auc')
```

```
In [149]:
```

```
best_auc_2 = cv_2.mean()
print('Best AUC:%4f' %best_auc_2)
```

Best AUC:0.617436

3.6 Plotting ROC curve

```
In [0]:
```

```
def batch_predict(clf, data):
    y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    for i in range(0,tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
    if data.shape[0]%1000 != 0:
        y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])
    return y_data_pred
```

```
In [0]:
```

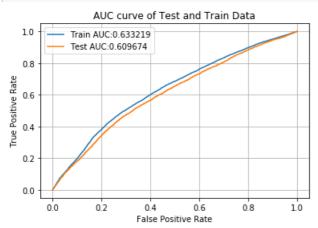
```
y_train_pred_2 = batch_predict(classifier_withAlpha_2, X_train_2)
y_test_pred_2 = batch_predict(classifier_withAlpha_2, X_test_2)
```

In [0]:

```
from sklearn.metrics import roc_curve, auc
train_fpr_2, train_tpr_2, train_thresh_2 = roc_curve(y_train, y_train_pred_2)
test_fpr_2, test_tpr_2, test_thresh_2 = roc_curve(y_test, y_test_pred_2)
```

```
plt.plot(train_fpr_2, train_tpr_2, label='Train AUC:%4f'%auc(train_fpr_2, train_tpr_2))
plt.plot(test_fpr_2, test_tpr_2, label='Test AUC:%4f'%auc(test_fpr_2, test_tpr_2))

plt.title('AUC curve of Test and Train Data')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.grid()
plt.show()
```



3.7 Confusion Matrix

```
In [154]:
```

```
def find_best_threshold(fpr, tpr, threhsold):
    t = threhsold[np.argmax(tpr*(1-fpr))]
    print('The maximum tpr*(1-fpr) is:', max(tpr*(1-fpr)), 'for threshold', (np.round(t,3)))
    return t

best_t = find_best_threshold(train_fpr_2, train_tpr_2, train_thresh_2)
```

The maximum tpr*(1-fpr) is: 0.3606844925473015 for threshold 0.685

In [0]:

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

    return predictions
```

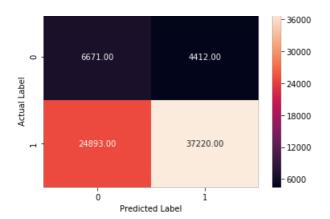
In [0]:

```
from sklearn.metrics import confusion_matrix
cm_train_2 = confusion_matrix(y_train, predict_with_threshold(y_train_pred_2, best_t))
cm_test_2 = confusion_matrix(y_test, predict_with_threshold(y_test_pred_2, best_t))
```

In [157]:

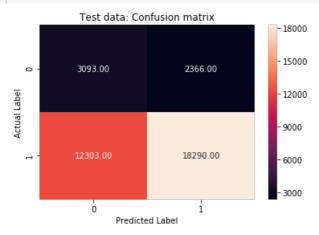
```
sns.heatmap(cm_train_2, annot=True, fmt='.2f')
plt.title('Training Data : confusion matrix')
plt.xlabel('Predicted Label')
plt.ylabel('Actual Label')
plt.show()
```

Training Data: confusion matrix



In [158]:

```
sns.heatmap(cm_test_2, annot=True, fmt='.2f')
plt.title('Test data: Confusion matrix')
plt.xlabel('Predicted Label')
plt.ylabel('Actual Label')
plt.show()
```



3.8 Top 20 Features

In [0]:

In [0]:

```
#For postive class , we get the indices
sorted_prob_class1_ind_2 = classifier_withAlpha_2.feature_log_prob_[1,:].argsort()
#For Negative Class
sorted_prob_class0_ind_2 = classifier_withAlpha_2.feature_log_prob_[0,:].argsort()
```

In [0]:

```
#https://www.geeksforgeeks.org/python-get-last-n-elements-from-given-list/
#since argsort gives it in ascending order we need the last 20 eleemnts
Most_important_word_for_postive_2 = []
Most_important_word_for_neagtive_2 = []
for i in (sorted prob class1 ind 2[-20:-1]):
```

```
Most_important_word_for_postive_2.append(features_list[i])
for j in (sorted prob class0 ind 2[-20:-1]):
   Most important word for neagtive 2.append(features list[j])
```

In [162]:

```
print('Top 20 words in Postive Class')
print(Most important word for 1)
print('='*50)
print('Top 20 words in Negative class')
print(Most_important_word_for_0)
Top 20 words in Postive Class
['love', 'use', 'reading', 'work', 'need', 'we', 'nannan', 'many', 'help', 'learn', 'not', 'they', 'the', 'classroom', 'learning', 'my', 'school', 'students',
'teacher number_of_previously_posted_projects']
______
Top 20 words in Negative class
['reading', 'love', 'come', 'work', 'need', 'we', 'many', 'nannan', 'the', 'help', 'they', 'learn', 'not', 'classroom', 'my', 'learning', 'school',
'teacher_number_of_previously_posted_projects', 'students']
```

Summary

In [168]:

```
#http://zetcode.com/python/prettytable/
from prettytable import PrettyTable
x = PrettyTable()
x.field names = ['Vectorizer', 'Model', 'Alpha', 'AUC']
x.add row(['BOW', 'Naive Bayes', str(best alpha 1), str('%4f'%best auc 1)])
x.add_row(['TFIDF', 'Naive Bayes', str(best_alpha_2), str('%4f'%best_auc_2)])
print(x)
```

Vectorizer	Model 	Alpha	++ AUC +
BOW TFIDF +	Naive Bayes Naive Bayes +	0.01	0.617436

Note: That's the end of the code