IEE 520

Stat Learning for Data Mining

Final Project

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Introduction:

This project has an objective to fit a classification model for the given training data and to predict the outcomes ('y') on the Test data which is also provided.

Dimensions of the dataset provided:

Sr.No.	Data	Rows (Samples)	Columns (Attributes)
1	Training	2500	68
2	Test	1647	68

Initial Observations on dataset:

i) No missing values (NaN), infinity value found in the dataset.
ii) Y has 2 possible class values -1 or 1.
iii) The number row in the beginning is to be dropped while processing the data.
iv) Test data contains 'y' head but has no values hence, it is dropped while preprocessing.
v) Dataset contains numeric and categorical values.
vi) Unbalanced frequency of class values.

Software used: Jupyter Notebook

Preprocessing:

1) Reading the both the datasets into the notebook, using the pandas 'pd.read_csv'.
2) Dropping the redundant columns by '.drop'and checking the dimension by shape function.

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In [1]:
```
import pandas as pd
data = pd.read_csv('Traindata.csv')
```

In [2]:
```
X=data.iloc[:,0:68]
y=data.iloc[:,67]
```

In [3]:
```
X=X.drop('Row',axis=1)
```

In [4]:
```
X.shape
```

Out[4]:
```
(2500, 67)
```

In [5]:
```
y.shape
```

Out[5]:
```
(2500,)
```

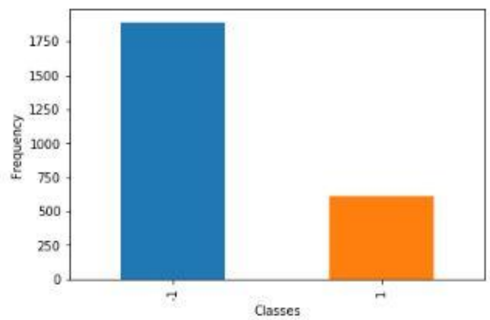
In [6]:
```
testdata = pd.read_csv('Testdata.csv')
TestX = testdata.iloc[:,0:68]
TestX = TestX.drop('Row',axis=1)
TestX = TestX.drop('y',axis=1)
```

3) If there are any missing or infinity values, replace with mean value.
4) Showing the y value count using the plot and values counts.

```
In [7]: import numpy as np
        X.fillna(np.mean(X), inplace = True)
```

```
In [8]: import matplotlib.pyplot as plt

        ax=y.value_counts().plot(kind='bar')
        ax.set_ylabel('Frequency')
        ax.set_xlabel('Classes')
        plt.show()
```




```
In [9]: y.value_counts()

Out[9]: -1    1891
         1     609
        Name: y, dtype: int64
```

5) An important aspect for preprocessing for fitting the models is converting categorical variables into numerical values by using label encoders. This converts categorical variables into dummy variables with binary values.

```
In [11]: Cat=list(X.select_dtypes(include=['object']))
         print(Cat)

         ['x5', 'x13', 'x64', 'x65']
```

```
In [12]: from sklearn.preprocessing import OneHotEncoder
         from sklearn.preprocessing import LabelEncoder
         for i in Cat:
             LE = LabelEncoder()
             label = pd.DataFrame(X[i]).apply(LE.fit_transform)
             encoder = OneHotEncoder()
             encoder.fit(label)
             ohl = encoder.transform(label).toarray()
             X = X.join(pd.DataFrame(ohl),lsuffix='_left',rsuffix='_right')
             X = X.drop(i,axis=1)
             label_test = pd.DataFrame(TestX[i]).apply(LE.transform)
             ohl_test = encoder.transform(label_test).toarray()
             TestX = TestX.join(pd.DataFrame(ohl_test),lsuffix='_left',rsuffix='_right')
             TestX = TestX.drop(i,axis=1)
```

```
In [13]: X.head()
         X_new = X
         y=X_new['y']
         #X_new=X_new.drop('y',axis=1)
```

```
In [14]: X_new.shape

Out[14]: (2500, 79)
```

6) Splitting the original data into train and test data in the ratio 80:20.

```
In [15]: from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split(X_new, y, test_size=0.20, random_state=42)

In [16]: X_train.y.value_counts()

Out[16]: -1    1516
          1     484
         Name: y, dtype: int64
```

7) Upsampling the data as there was imbalance in the frequency of the class values.

```
In [17]: from sklearn.utils import resample
         minclass = resample(X_train[X_train.y==1], replace = True, n_samples= 1032, random_state = 123)
         X_train_new = pd.concat([X_train,minclass])

In [18]: X_train_new.y.value_counts()

Out[18]:  1    1516
         -1    1516
         Name: y, dtype: int64

In [19]: X_train_new.shape

Out[19]: (3032, 79)
```

8) Dropping the resampled y variable from the X data.

```
In [20]: y_train = X_train_new['y']
         X_train_new=X_train_new.drop('y',axis=1)
         X_train = X_train_new
         X_test=X_test.drop('y',axis=1)
```

9) Using Normalization to the dataset by using Minmax scaler

```
In [23]: from sklearn.preprocessing import MinMaxScaler
         scale = MinMaxScaler()
         X_train = scale.fit(X_train_new).transform(X_train_new)
         X_test = scale.transform(X_test)
         TestX = scale.transform(TestX)

In [24]: X_train.shape

Out[24]: (3032, 78)

In [25]: X_new=X_new.drop('y',axis=1)
         X_new = scale.transform(X_new)

In [26]: X_new.shape

Out[26]: (2500, 78)
```

Fitting the models:

Following types of classifiers were tried and best accuracy out of all obtained models tried for those respective types is mentioned as follows:

1) Decision Trees
2) Random Forest
3) Boosting (Adaboost)
4) Support Vector Machines (SVM)

I have used Grid Search CV for tuning the best parameters for each model type.

1) Decision Trees

As some of the attributes are categorical, I tried using Decision trees for this dataset for classification. Altering the max_depth, min_samples_split and random parameters attribute of sklearn.DecisionTreesClassifier in grid search CV (cross validation)

```
In [52]: from sklearn.model_selection import GridSearchCV
         from sklearn.metrics import confusion_matrix
         parameters = {'max_depth':[5,10,50,100],'min_samples_split':[2,3,5]}
         cross = GridSearchCV(DT, parameters, cv=5)
         cross.fit(X_train, y_train)
         yhat = cross.predict(X_test)
         print (" Accuracy")
         print (metrics.accuracy_score(y_test, yhat))
         print (metrics.classification_report(y_test, yhat))
         print (confusion_matrix(y_test, yhat))
```

the best obtained accuracy was obtained on the following parameters.

```
In [30]: cross.best_estimator_

Out[30]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=50,
                     max_features=None, max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, presort=False, random_state=123,
                     splitter='best')
```

The accuracy and confusion matrix are as follows corresponding to above parameters:

```
 Accuracy
0.798
             precision    recall  f1-score   support

         -1       0.85      0.89      0.87       375
          1       0.61      0.54      0.57       125

avg / total       0.79      0.80      0.79       500

[[332  43]
 [ 58  67]]
```

2) Random Forests

As the accuracy obtained is lower, I tried to fit random forests model because it is ensemble of different Decision trees model and it's not a weak learner like decision trees. Also, RF is good in prediction.

Random Forest

```
In [31]: from sklearn import metrics
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.metrics import confusion_matrix
         RF=RandomForestClassifier()

         RF.fit(X_train,y_train)



         yhat = RF.predict(X_test)
         print ("Training Accuracy")
         print (metrics.accuracy_score(y_test, yhat))
         print (metrics.classification_report(y_test, yhat))
         print (confusion_matrix(y_test, yhat))
```

```
C:\Users\User\Anaconda3\lib\site-packages\sklearn\ensemble\weight_
an internal NumPy module and should not be imported. It will be re
  from numpy.core.umath_tests import inner1d
```

```
Training Accuracy
0.8
             precision    recall  f1-score   support

         -1       0.84      0.91      0.87       375
          1       0.63      0.48      0.55       125

avg / total       0.79      0.80      0.79       500

[[340  35]
 [ 65  60]]
```

However, this accuracy can be improved by using Grid Search CV.

```
In [33]: from sklearn.model_selection import GridSearchCV
         parameters = {'n_estimators':[10,50,300,500],'max_features':['auto','sqrt','log2'],'oob_score':['False'],'n_jobs':[1]}
         cross1 = GridSearchCV(RF, parameters, cv=5)
         cross1.fit(X_train, y_train)
         yhat = cross1.predict(X_test)
         print (" Accuracy")
         print (metrics.accuracy_score(y_test, yhat))
         print (metrics.classification_report(y_test, yhat))
         print (confusion_matrix(y_test, yhat))
```

Best parameters obtained in this grid search:

```
In [34]: print(cross1.best_estimator_)

         RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=None, max_features='sqrt', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=50, n_jobs=1,
                     oob_score='False', random_state=None, verbose=0,
                     warm_start=False)
```

Accuracy and confusion matrix corresponding to this model,

```
 Accuracy
0.836
             precision    recall  f1-score   support

         -1       0.87      0.92      0.89       375
          1       0.71      0.58      0.64       125

avg / total       0.83      0.84      0.83       500

[[345  30]
 [ 52  73]]
```

3) Boosting with Adaboost classifier
   I tried using boosting model taking Random Forest Model as the base estimator, to check if the accuracy further increases. But it was not the case and the balanced error rate that was obtained by changing different parameters was higher.

   Code:

Adaboost Classifier

```
In [53]: from sklearn.ensemble import AdaBoostClassifier
         from sklearn.metrics import confusion_matrix
         AB=AdaBoostClassifier(RF)
         AB.fit(X_train,y_train)

         yhat = AB.predict(X_test)
         print ("Training Accuracy")
         print (metrics.accuracy_score(y_test, yhat))
         print (metrics.classification_report(y_test, yhat))
         print (confusion_matrix(y_test, yhat))
```

```
Training Accuracy
0.804
             precision    recall  f1-score   support

         -1       0.81      0.97      0.88       375
          1       0.78      0.30      0.44       125

avg / total       0.80      0.80      0.77       500

[[364  11]
 [ 87  38]]
```

Running GridSearch CV on adaboost by changing different parameters. I have had tried different values for tuning but, have shown only important ones that caused significant change to the accuracy of the model.

```
In [57]: from sklearn.model_selection import GridSearchCV
         parameters = {'n_estimators':[10,50,300],'learning_rate':[1]}
         cross2 = GridSearchCV(AB, parameters, cv=5)
         cross2.fit(X_train, y_train)
         yhat = cross2.predict(X_test)
         print (" Accuracy")
         print (metrics.accuracy_score(y_test, yhat))
         print (metrics.classification_report(y_test, yhat))
         print (confusion_matrix(y_test, yhat))

          Accuracy
         0.81
                      precision    recall  f1-score   support

                  -1       0.81      0.98      0.89       375
                   1       0.81      0.31      0.45       125

         avg / total       0.81      0.81      0.78       500

         [[366   9]
          [ 86  39]]
```

```
In [58]: print(cross2.best_estimator_)

         AdaBoostClassifier(algorithm='SAMME.R',
                   base_estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=None, max_features='auto', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
                     oob_score=False, random_state=None, verbose=0,
                     warm_start=False),
                   learning_rate=1, n_estimators=300, random_state=None)
```

4) Support Vector Machines
   Finally, I wanted to check if the accuracy and balanced error rate change if I consider modeling based on Euclidean distance parameter into consideration. Taking kernel as rbf.

SVM

```
In [59]: from sklearn.svm import SVC
         from sklearn.metrics import confusion_matrix
         SVM=SVC()
         SVM.fit(X_train,y_train)

         yhat = SVM.predict(X_test)
         print ("Training Accuracy")
         print (metrics.accuracy_score(y_test, yhat))
         print (metrics.classification_report(y_test, yhat))
         print (confusion_matrix(y_test, yhat))

         Training Accuracy
         0.722
                      precision    recall  f1-score   support

                  -1       0.95      0.67      0.78       375
                   1       0.47      0.89      0.61       125

         avg / total       0.83      0.72      0.74       500

         [[250 125]
          [ 14 111]]
```

```
In [60]: from sklearn.model_selection import GridSearchCV
         parameters = {'C':[50,500,1000],'gamma':[0.001,0.01],'kernel':['rbf'],'class_weight':['balanced'],'probability':[True]}
         cross3 = GridSearchCV(SVM, parameters, cv=5)
         cross3.fit(X_train, y_train)
         yhat = cross3.predict(X_test)
         print (" Accuracy")
         print (metrics.accuracy_score(y_test, yhat))
         print (metrics.classification_report(y_test, yhat))
         print (confusion_matrix(y_test, yhat))
```

Changing the parameter that provide best results in accuracy in the grid search cv. Following parameters are obtained:

```
In [61]: print(cross3.best_estimator_)

SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.01, kernel='rbf',
  max_iter=-1, probability=True, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

Corresponding accuracy and confusion matrix are shown:

```
 Accuracy
0.75
             precision    recall  f1-score   support

         -1       0.84      0.82      0.83       375
          1       0.50      0.54      0.52       125

avg / total       0.76      0.75      0.75       500

[[308  67]
 [ 58  67]]
```

Selection of Final Model

Sr.No.	Model type	Accuracy	Grid search accuracy	Balanced Error Rate
1)	Decision Trees	0.798	0.798	0.2893
2)	Random Forests	0.8	0.836	0.248
3)	Adaboost (with RF)	0.804	0.81	0.356
4)	SVM	0.784	0.75	0.321

The best model of all the types considering accuracy and balanced error rate as the judging parameters is Random Forest model.

Eventhough, Adaboost has similar accuracy, it's balanced error rate is higher corresponding to the random forests model.

Final Model Parameters:

```
#Selected Model
S_M= RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='sqrt', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=50, n_jobs=1,
            oob_score='False', random_state=None, verbose=0,
            warm_start=False)

S_M.fit(X_new,y)
```

Setting bootstrap = 'True' indicates that bootstrap samples are taken, criterion = 'gini' considers gini impurity for information gain, n_estimators: number of decision trees are taken as 50, no_jobs = 1 indicates no job is running in parallel to predict and fit.

This model is then fitted to the whole training data and obtained predictions on the given Test data.

```
In [36]: yhat = S_M.predict(TestX)
         yhat

Out[36]: array([-1, -1, -1, ..., -1, -1, -1], dtype=int64)

In [44]: import numpy as np
         import pandas as pd
         row_num = np.linspace(1,1647,1647)
         test_y = pd.DataFrame(row_num)
         test_y['yhat'] = yhat
         test_y.to_csv('testRF.csv',header=None, index = False)
```

The predictions were saved to excel file 'testRF.csv' which is renamed to the required format.