Machine Learning DA3

November 9, 2018

Shushil Kumar Ravishankar
16BCE1259

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        %matplotlib inline
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import accuracy_score,recall_score,precision_score,roc_curve,roc_a
        from sklearn.preprocessing import LabelEncoder
        from sklearn.cross_validation import cross_val_score
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/sklearn/cross_val
  "This module will be removed in 0.20.", DeprecationWarning)
```

```
In [2]: data=pd.read_csv('clean_bmart.csv',sep=',')
        data.head()
```

```
Out[2]:    Unnamed: 0 Item_Identifier  Item_Weight Item_Fat_Content  Item_Visibility  \
        0           0           FDA15         9.30          Low Fat         0.016047
        1           1           DRC01         5.92          Regular         0.019278
        2           2           FDN15        17.50          Low Fat         0.016760
        3           3           FDX07        19.20          Regular         0.000000
        4           4           NCD19         8.93          Low Fat         0.000000

                       Item_Type  Item_MRP Outlet_Identifier  \
        0                  Dairy  249.8092            OUT049
        1            Soft Drinks   48.2692            OUT018
        2                   Meat  141.6180            OUT049
        3  Fruits and Vegetables  182.0950            OUT010
        4              Household   53.8614            OUT013

           Outlet_Establishment_Year Outlet_Size Outlet_Location_Type  \
        0                       1999      Medium               Tier 1
        1                       2009      Medium               Tier 3
        2                       1999      Medium               Tier 1
        3                       1998      Medium               Tier 3
```

```
   4                       1987        High              Tier 3

            Outlet_Type  Item_Outlet_Sales
   0  Supermarket Type1          3735.1380
   1  Supermarket Type2           443.4228
   2  Supermarket Type1          2097.2700
   3      Grocery Store           732.3800
   4  Supermarket Type1           994.7052
```

```
In [3]: X=data.loc[(data['Outlet_Location_Type']=='Tier 1')|(data['Outlet_Location_Type']=='Ti
        x=X.values[:,:]
        y=X.values[:,10]
        ley=LabelEncoder()
        ley.fit(y)
        y=ley.transform(y)
        for i in [1,3,5,7,9,11]:
            en=LabelEncoder()
            en.fit(X.values[:,i])
            x[:,i]=en.transform(x[:,i])

        x=x[:,[1,2,3,4,5,6,7,8,9,11,12]]
        X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3,random_state=0)
        print(y)
        print(x)
        print(data.columns.values[[4,8,10]])
```

```
[0 0 1 ... 1 1 0]
[[156 9.3 0 ... 0 1 3735.138]
 [659 17.5 0 ... 0 1 2097.27]
 [438 16.2 1 ... 0 1 1076.5986]
 ...
 [890 8.38 1 ... 0 1 549.285]
 [1348 10.6 0 ... 1 1 1193.1136]
 [50 14.8 0 ... 1 1 765.67]]
['Item_Visibility' 'Outlet_Establishment_Year' 'Outlet_Location_Type']
```

```
In [4]: from sklearn.neural_network import MLPClassifier
```

```
In [5]: mlp=MLPClassifier(hidden_layer_sizes=(5),max_iter=1000,random_state=0)
```

```
In [6]: mlp.fit(X_train,y_train)
```

```
Out[6]: MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.9,
               beta_2=0.999, early_stopping=False, epsilon=1e-08,
               hidden_layer_sizes=5, learning_rate='constant',
               learning_rate_init=0.001, max_iter=1000, momentum=0.9,
               nesterovs_momentum=True, power_t=0.5, random_state=0, shuffle=True,
               solver='adam', tol=0.0001, validation_fraction=0.1, verbose=False,
               warm_start=False)
```

```
In [7]: predictions=mlp.predict(X_test)
```

```
In [8]: print(" 0's in y_test:",(y_test==0).sum())
        print(" 1's in y_test:",(y_test==1).sum())
```

```
 0's in y_test: 730
 1's in y_test: 822
```

The number of transactions of each class are almost same i.e. the dataset is unbiased and doesn't require techniques like over-sampling or under-sampling to be applied before training a model. A dumb model cannot get a high accuracy score in this dataset by just predicting the class with highest frequency.

```
In [9]: y_test.shape[0]
```

```
Out[9]: 1552
```

```
In [10]: print("null accuracy:",max(((y_test==0).sum())/y_test.shape[0],((y_test==1).sum())/y_
```

```
null accuracy: 52.9639175257732
```

This is the Null accuracy of the dataset i.e. it is the accuracy that a model can achieve while just predicting the majority class of this dataset.

```
In [11]: from sklearn.metrics import classification_report,confusion_matrix
         confusion = confusion_matrix(y_test, predictions)
         print(confusion)
         #[row, column]
         TP = confusion[1, 1]
         TN = confusion[0, 0]
         FP = confusion[0, 1]
         FN = confusion[1, 0]
```

```
[[650  80]
 [218 604]]
```

604 transactions are correctly classified as '1'.
650 transactions are correctly classified as '0'.
80 transactions are wrongly classified as '1'.
218 transactions are wrongly classified as '0'.

```
In [12]: print((TP + TN) / float(TP + TN + FP + FN))
         print(accuracy_score(y_test, predictions))
```

```
0.8079896907216495
0.8079896907216495
```

The Accuracy score of the model is high enough to show that there is actual learning taking place here and the model isn't just predicting the majority class.

```
In [13]: classification_error = (FP + FN) / float(TP + TN + FP + FN)

         print(classification_error)
         print(1 - accuracy_score(y_test, predictions))
```

```
0.19201030927835053
0.1920103092783505
```

```
In [14]: sensitivity = TP / float(FN + TP)

         print(sensitivity)
         print(recall_score(y_test, predictions))
```

```
0.7347931873479319
0.7347931873479319
```

```
In [15]: specificity = TN / (TN + FP)

         print(specificity)
```

```
0.8904109589041096
```

```
In [16]: false_positive_rate = FP / float(TN + FP)

         print(false_positive_rate)
         print(1 - specificity)
```

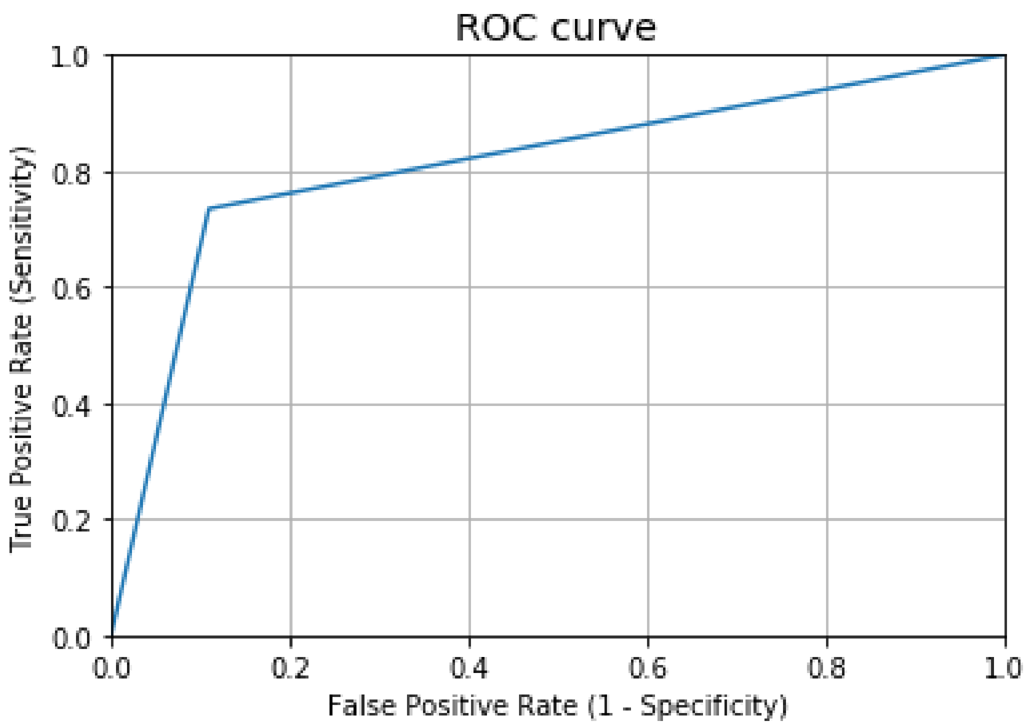
```
0.1095890410958904
0.1095890410958904
```

```
In [17]: precision = TP / float(TP + FP)

         print(precision)
         print(precision_score(y_test, predictions))
```

```
0.8830409356725146
0.8830409356725146
```

The above model has a good sensitivity i.e. it very oftenly predicts '1' for transaction with value '1' instead as '0'.
The model has a very good specificity i.e. it mostly predicts a transaction with value '0' as '0' instrad of '1' in other words, it has a low False Positive Rate but has a high False Negative Rate, which means that the model has higher probability of wrongly classifying a transaction with value '1' as '0' than predicting a transaction with value '0' as '1'.
The model is highly precise i.e. of the 1's predicticted by the model, most of them are actually 1.

```
In [18]: fpr, tpr, thresholds = roc_curve(y_test, predictions)

         plt.plot(fpr, tpr)
         plt.xlim([0.0, 1.0])
         plt.ylim([0.0, 1.0])
         plt.rcParams['font.size'] = 12
         plt.title('ROC curve')
         plt.xlabel('False Positive Rate (1 - Specificity)')
         plt.ylabel('True Positive Rate (Sensitivity)')
         plt.grid(True)
```




```
In [19]: print(roc_auc_score(y_test, predictions))
```

```
0.8126020731260207
```

AUC ROC indicates how well the probabilities from the positive classes are separated from the negative classes.

The area under the ROC curve is high. It indicates that the distributions of positives and negatives are well separated for the model. It means that the model is very well able to differentiate between the two classes, indicating it to be good model.

```
In [20]: cross_val_score(mlp, x, y, cv=10, scoring='roc_auc').mean()

Out[20]: 0.9374891828808163
```

In the basic approach, called k-fold CV, the training set is split into k smaller sets (other approaches are described below, but generally follow the same principles). The following procedure is followed for each of the k "folds":

1) A model is trained using k-1 of the folds as training data;

2) the resulting model is validated on the remaining part of the data (i.e., it is used as a test set to compute a performance measure such as accuracy).

The performance measure reported by k-fold cross-validation is then the average of the values computed in the loop. This approach can be computationally expensive, but is very useful when the number of samples are very less.

Here we use Area Under the ROC as the scoring parameter and cv=10 i.e. we divide the testset in 10 parts, use 9 for training and the remaining 1 as validation-set and then the area under the ROC is measured. This process is repeated 10 times with each part being validation-set 1 time.

The high Cross validation score indicates that the given model has a very good performance