COMP 219 Coursework 1

Yifan Xu

Student Number : 201377026

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Step 1. Loading data

1. Import some libraries

```
#Numpy
import numpy as np

#Datafram operations
import pandas as pd

#Data visualization
from matplotlib import pyplot as plt
import seaborn as sns

#Common Model Helpers
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler

#Models
from sklearn.neighbors import KNeighborsClassifier #KNN
```

2. Import dataset

```
train_df = pd.read_csv('train.csv')
test_df = pd.read_csv('test.csv')
data = train_df.append(test_df)# The entire data = train + test
```

3. Feature Engineering

- Calculate the missing data and drop some columns

```
#Calculate the missing data
data = data.fillna(np.nan)
data.isnull().sum()
```

```
Age             263
Cabin          1014
Embarked          2
Fare              1
Name              0
Parch             0
PassengerId       0
Pclass            0
Sex               0
SibSp             0
Survived        418
Ticket            0
dtype: int64
```

let's drop some columns which don't have many missing values

```
drop_elements = ['Name', 'PassengerId', 'SibSp', 'Parch', 'Ticket', 'Cabin',
                 'Embarked']
train_df.drop(drop_elements, axis = 1, inplace = True)
test_df.drop(drop_elements, axis = 1, inplace = True)
```

- Processing fare, age, title, family size, sex features

Step 2.Training

Step 2.1 Code for training

1. Feature scaling

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(train_df.drop('Survived', axis =1))
```

```
StandardScaler(copy=True, with_mean=True, with_std=True)
```

```
scaled = scaler.transform(train_df.drop('Survived', axis =1))
```

```
df_scaled = pd.DataFrame(scaled, columns = train_df.columns.drop('Survived'))
```

```
X = df_scaled
y = train_df['Survived']
X_test = test_df.copy()
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
```

Step 2.2 Successful training

2. Using KNN Model

```
knn = KNeighborsClassifier(n_neighbors=2)
knn.fit(X, y)
```

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=2, p=2,
           weights='uniform')
```

```
y_pred = knn.predict(X_test)
```

Step 3. Model Evaluation

Step 3.1 Explain your experimental design

1. Using confusion matrix

   Directly using sklearn and calculate the TP, TN, FP, TN

```
#Accuracy, classification_report, confusion_matrix
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
confusion = confusion_matrix(y_test, y_pred)
TP = confusion[1, 1]
TN = confusion[0, 0]
FP = confusion[0, 1]
FN = confusion[1, 0]
print ("TP:", TP)
print ("TN:", TN)
print ("FP:", FP)
print ("FN:", FN)
```

2. Classification Accuracy

```
print ((TP+TN) / float(TP+TN+FN+FP))
accuracy = accuracy_score(y_test,y_pred)
```

- **True positives (TP):** These are cases in which we predicted yes , and the actual is also positive.
- **True negatives (TN):** We predicted no, and the actual is also negative.
- **False positives (FP):** We predicted yes, but the actual is negative(Also known as a "Type I error.")
- **False negatives (FN):** We predicted no, but the actual is positive. (Also known as a "Type II error.")

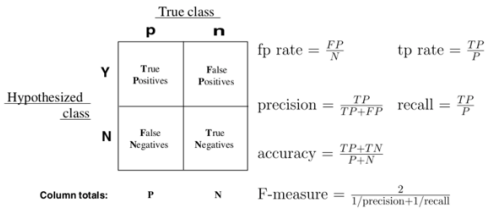


Fig. 1. Confusion matrix and common performance metrics calculated from it.

3. Classification Error

```
print ((FP+FN) / float(TP+TN+FN+FP))
error = 1-accuracy_score(y_test, y_pred)
```

4. Using ROC curve

X– axis: the True Positive-rate ; Y-axis: the False Positive Rate; Threshold = 0.5

In the result we can see that over 80% of cases, the model scores higher on positive samples than on negative samples

```
from sklearn import metrics
def plot_roc_curve(fpr, tpr, label= None):
    threshold = 0.5
    plt.figure(figsize = (12,5))
    plt.plot(fpr, tpr, label = label)
    plt.axis([0, 1, 0, 1])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.show()
```

Step 3.2 Document your evaluation results

1.Confusion matrix result

```
[[106   4]
 [ 27  42]]
```

The left graph is the basic concept of accuracy rate and confusion matrix, the right graph is the result of confusion matrix:

- There are 106 cases that predicted true and actual true,
- There are 4 cases that predicted yes but actual false
- There are 27 cases that predicted false but actual true
- There are 42 cases that predicted false and actual false

2.Accuracy and error results

```
print(confusion)
print("Accuracy: "+ str(accuracy))
print("Error: "+ str(error))
print(classification_report(y_test, y_pred))
```

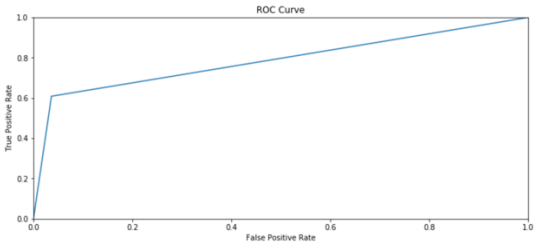
```
[[106   4]
 [ 27  42]]
Accuracy: 0.8268156424581006
Error: 0.17318435754189943
             precision    recall  f1-score   support

          0       0.80      0.96      0.87       110
          1       0.91      0.61      0.73        69

avg / total       0.84      0.83      0.82       179
```

3.ROC curve result

```
fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred)
plot_roc_curve(fpr, tpr)
plt.show()
print("AUC Score:\n",metrics.roc_auc_score(y_test, y_pred))
```




```
AUC Score:
 0.7861660079051384
```

Extra

Train new models via KNN

```
from sklearn.neighbors import KNeighborsClassifier
clf=KNeighborsClassifier(n_neighbors=5)
clf.fit(X, y)

from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score

k_range = range(1,50)
k_scores = []
for k in k_range:
    knn=KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X, y, cv = 4, scoring='accuracy')
    print("k = " + str(k) + ", score = " + str(scores) + ", mean = " +  str(scores.mean())+"\n"+"Accuracy: "+str(accura
          +", AUC Score:",metrics.roc_auc_score(y_test, y_pred))
    k_scores.append(scores.mean())
```

```
k = 1, score = [0.69196429 0.73542601 0.6981982  0.71621622], mean = 0.7104511772743275
Accuracy: 0.8268156424581006, AUC Score: 0.7861660079051384
k = 2, score = [0.74107143 0.80269058 0.79279279 0.8018018 ], mean = 0.7845891515314161
Accuracy: 0.8268156424581006, AUC Score: 0.7861660079051384
k = 3, score = [0.78571429 0.81165919 0.75225225 0.76126126], mean = 0.7777217480132278
Accuracy: 0.8268156424581006, AUC Score: 0.7861660079051384
k = 4, score = [0.77678571 0.8206278  0.78828829 0.8018018 ], mean = 0.796875901766597
Accuracy: 0.8268156424581006, AUC Score: 0.7861660079051384
k = 5, score = [0.79017857 0.8206278  0.82432432 0.82882883], mean = 0.815989881818077
Accuracy: 0.8268156424581006, AUC Score: 0.7861660079051384
k = 6, score = [0.79910714 0.8206278  0.78828829 0.81531532], mean = 0.8058346372878323
Accuracy: 0.8268156424581006, AUC Score: 0.7861660079051384
k = 7, score = [0.76785714 0.81165919 0.8018018  0.81981982], mean = 0.8002844893259692
Accuracy: 0.8268156424581006, AUC Score: 0.7861660079051384
k = 8, score = [0.76339286 0.81165919 0.79279279 0.81531532], mean = 0.7957900395190193
Accuracy: 0.8268156424581006, AUC Score: 0.7861660079051384
k = 9, score = [0.77232143 0.80717489 0.80630631 0.83333333], mean = 0.8047839890258612
Accuracy: 0.8268156424581006, AUC Score: 0.7861660079051384
k = 10, score = [0.78125    0.81165919 0.78828829 0.84234234], mean = 0.8058849558639357
Accuracy: 0.8268156424581006, AUC Score: 0.7861660079051384
```

Model Compare

```
plt.plot(k_range, k_scores)
plt.xlabel('K for KNN')
plt.ylabel('Cross Validation Accuracy')
plt.show()
```