Bank_MT18052

October 22, 2019

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline
        import warnings
        warnings.filterwarnings('ignore')
```

```
In [2]: bank = pd.read_csv('./data/bank-marketing/bank-additional-full.csv', sep = ';')
        #Converting dependent variable categorical to dummy
        labels = pd.get_dummies(bank['y'], columns = ['y'], prefix = ['y'], drop_first = True)
        bank.head()
```

```
Out[2]:    age        job  marital    education  default housing loan    contact  \
        0   56  housemaid  married     basic.4y       no      no   no  telephone
        1   57   services  married  high.school  unknown      no   no  telephone
        2   37   services  married  high.school       no     yes   no  telephone
        3   40     admin.  married     basic.6y       no      no   no  telephone
        4   56   services  married  high.school       no      no  yes  telephone

          month day_of_week  ...  campaign  pdays  previous     poutcome emp.var.rate  \
        0   may         mon  ...         1    999         0  nonexistent          1.1
        1   may         mon  ...         1    999         0  nonexistent          1.1
        2   may         mon  ...         1    999         0  nonexistent          1.1
        3   may         mon  ...         1    999         0  nonexistent          1.1
        4   may         mon  ...         1    999         0  nonexistent          1.1

           cons.price.idx  cons.conf.idx  euribor3m  nr.employed   y
        0          93.994          -36.4      4.857       5191.0  no
        1          93.994          -36.4      4.857       5191.0  no
        2          93.994          -36.4      4.857       5191.0  no
        3          93.994          -36.4      4.857       5191.0  no
        4          93.994          -36.4      4.857       5191.0  no

        [5 rows x 21 columns]
```

```
In [3]: # bank.columns
```

```
In [4]: bank = bank.drop(['y'],axis=1)
```

In [5]:
```
data_client = bank.iloc[: , 0:7]
data_client.head()
```

Out[5]:

	age	job	marital	education	default	housing	loan
0	56	housemaid	married	basic.4y	no	no	no
1	57	services	married	high.school	unknown	no	no
2	37	services	married	high.school	no	yes	no
3	40	admin.	married	basic.6y	no	no	no
4	56	services	married	high.school	no	no	yes

In [6]:
```
from sklearn.preprocessing import LabelEncoder
labelencoder_X = LabelEncoder()
for i in ['job','marital','default','education','housing','loan']:
    data_client[i]      = labelencoder_X.fit_transform(data_client[i])
```

In [49]:
```
def age(dataframe,i):
    dataframe.loc[dataframe[i] <= 32, i] = 1
    dataframe.loc[(dataframe[i] > 32) & (dataframe[i] <= 47), i] = 2
    dataframe.loc[(dataframe[i] > 47) & (dataframe[i] <= 70), i] = 3
    dataframe.loc[(dataframe[i] > 70) & (dataframe[i] <= 98), i] = 4

    return dataframe

age(data_client,'age');
```

In [8]:
```
data_client.head()
```

Out[8]:

	age	job	marital	education	default	housing	loan
0	3	3	1	0	0	0	0
1	3	7	1	3	1	0	0
2	2	7	1	3	0	2	0
3	2	0	1	1	0	0	0
4	3	7	1	3	0	0	2

1 Related with the last contact of the current campaign

In [10]:
```
# Slicing DataFrame to treat separately, make things more easy
data_bank_related = bank.iloc[: , 7:11]
data_bank_related.head()
```

Out[10]:

	contact	month	day_of_week	duration
0	telephone	may	mon	261
1	telephone	may	mon	149
2	telephone	may	mon	226
3	telephone	may	mon	151
4	telephone	may	mon	307

2 Contact, Month, Day of Week treatment

In [11]:
```
# Label encoder order is alphabetical
from sklearn.preprocessing import LabelEncoder
labelencoder_X = LabelEncoder()
for i in ['contact','month','day_of_week']:
    data_bank_related[i]     = labelencoder_X.fit_transform(data_bank_related[i])
```

In [12]:
```
data_bank_related.head()
```

Out[12]:

	contact	month	day_of_week	duration
0	1	6	1	261
1	1	6	1	149
2	1	6	1	226
3	1	6	1	151
4	1	6	1	307

In [50]:
```
def duration(data,col):
    data.loc[data[col] <= 102, col] = 1
    data.loc[(data[col] > 102) & (data[col] <= 180)  , col]    = 2
    data.loc[(data[col] > 180) & (data[col] <= 319)  , col]   = 3
    data.loc[(data[col] > 319) & (data[col] <= 644.5), col] = 4
    data.loc[data[col]  > 644.5, col] = 5
    return data
duration(data_bank_related,'duration');
```

In [14]:
```
data_bank_related.head()
```

Out[14]:

	contact	month	day_of_week	duration
0	1	6	1	3
1	1	6	1	2
2	1	6	1	3
3	1	6	1	2
4	1	6	1	3

3 Social and economic context attributes

In [15]:
```
data_bank_se = bank.loc[: , ['emp.var.rate', 'cons.price.idx', 'cons.conf.idx', 'euri
data_bank_se.head()
```

Out[15]:

	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
0	1.1	93.994	-36.4	4.857	5191.0
1	1.1	93.994	-36.4	4.857	5191.0
2	1.1	93.994	-36.4	4.857	5191.0
3	1.1	93.994	-36.4	4.857	5191.0
4	1.1	93.994	-36.4	4.857	5191.0

4 Other attributes

```
In [16]: data_bank_o = bank.loc[: , ['campaign', 'pdays','previous', 'poutcome']]
         data_bank_o.head()
```

```
Out[16]:    campaign  pdays  previous     poutcome
         0         1    999         0  nonexistent
         1         1    999         0  nonexistent
         2         1    999         0  nonexistent
         3         1    999         0  nonexistent
         4         1    999         0  nonexistent
```

```
In [17]: data_bank_o['poutcome'].unique()
```

```
Out[17]: array(['nonexistent', 'failure', 'success'], dtype=object)
```

```
In [18]: data_bank_o['poutcome'].replace(['nonexistent', 'failure', 'success'], [1,2,3], inpla
```

5 Model

```
In [19]: data_bank_final= pd.concat([data_client, data_bank_related, data_bank_se, data_bank_o]
         data_bank_final = data_bank_final[['age', 'job', 'marital', 'education', 'default', 'h
                                  'contact', 'month', 'day_of_week', 'duration', 'emp.var.rate', 'c
                                  'cons.conf.idx', 'euribor3m', 'nr.employed', 'campaign', 'pdays'
         data_bank_final.shape
```

```
Out[19]: (41188, 20)
```

```
In [20]: from sklearn.metrics import classification_report
         def reports(truelab,predlabels):
             print(confusion_matrix(truelab, predlabels))
             print("Accuracy ",round(accuracy_score(truelab, predlabels),2)*100)

             print (classification_report(y_pred=predlabels,y_true=truelab))
             return ( round(accuracy_score(truelab, predlabels),2)*100)
```

```
In [21]: from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split(data_bank_final, labels, test_size

         from sklearn.model_selection import KFold
         from sklearn.model_selection import cross_val_score
         from sklearn.metrics import confusion_matrix, accuracy_score
         k_fold = KFold(n_splits=10, shuffle=True, random_state=0)
```

```
In [22]: X_train.head()
```

```
Out[22]:        age  job  marital  education  default  housing  loan  contact  month  \
         7271     2    9        1          2        1        0     2        1      6
         13284    1    3        2          3        0        0     0        0      3
```

```
11580    3    1         1          2          1          0     0         1      4
31835    2    6         1          5          0          2     0         0      6
19551    3    4         1          6          0          2     0         0      1

       day_of_week  duration  emp.var.rate  cons.price.idx  cons.conf.idx  \
7271             2         2           1.1          93.994          -36.4
13284            4         5           1.4          93.918          -42.7
11580            0         1           1.4          94.465          -41.8
31835            2         2          -1.8          92.893          -46.2
19551            2         1           1.4          93.444          -36.1

       euribor3m  nr.employed  campaign  pdays  previous  poutcome
7271       4.860       5191.0         4    999         0         1
13284      4.962       5228.1         1    999         0         1
11580      4.959       5228.1        10    999         0         1
31835      1.327       5099.1         2    999         0         1
19551      4.968       5228.1         1    999         0         1
```

In [ ]:

In [23]:
```python
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
```

6 Logistic Regression

In [24]:
```python
from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
logpred = logmodel.predict(X_test)

LOGCV = reports(y_test,logpred)
```

```
[[10708   270]
 [  884   495]]
Accuracy  91.0
              precision    recall  f1-score   support

           0       0.92      0.98      0.95     10978
           1       0.65      0.36      0.46      1379

    accuracy                           0.91     12357
   macro avg       0.79      0.67      0.71     12357
weighted avg       0.89      0.91      0.89     12357
```

7 KNN

```
In [25]: from sklearn.neighbors import KNeighborsClassifier
         knn = KNeighborsClassifier(n_neighbors=22)
         knn.fit(X_train, y_train)
         knnpred = knn.predict(X_test)
         KNNCV = reports(y_test,knnpred)
```

```
[[10793   185]
 [ 1023   356]]
Accuracy  90.0
              precision    recall  f1-score   support

           0       0.91      0.98      0.95     10978
           1       0.66      0.26      0.37      1379

    accuracy                           0.90     12357
   macro avg       0.79      0.62      0.66     12357
weighted avg       0.88      0.90      0.88     12357
```

8 Random Forest

```
In [26]: from sklearn.ensemble import RandomForestClassifier
         rfc = RandomForestClassifier(n_estimators = 200)#criterion = entopy,gini
         rfc.fit(X_train, y_train)
         rfcpred = rfc.predict(X_test)

         RFCCV = reports(y_test,rfcpred)
```

```
[[10543   435]
 [  721   658]]
Accuracy  91.0
              precision    recall  f1-score   support

           0       0.94      0.96      0.95     10978
           1       0.60      0.48      0.53      1379

    accuracy                           0.91     12357
   macro avg       0.77      0.72      0.74     12357
weighted avg       0.90      0.91      0.90     12357
```

9 GNB

```
In [27]: from sklearn.naive_bayes import GaussianNB
         gaussiannb= GaussianNB()
         gaussiannb.fit(X_train, y_train)
         gaussiannbpred = gaussiannb.predict(X_test)
         probs = gaussiannb.predict(X_test)

         GAUSIAN = reports(y_test,gaussiannbpred)
```

```
[[9688 1290]
 [ 616  763]]
Accuracy  85.0
              precision    recall  f1-score   support

           0       0.94      0.88      0.91     10978
           1       0.37      0.55      0.44      1379

    accuracy                           0.85     12357
   macro avg       0.66      0.72      0.68     12357
weighted avg       0.88      0.85      0.86     12357
```

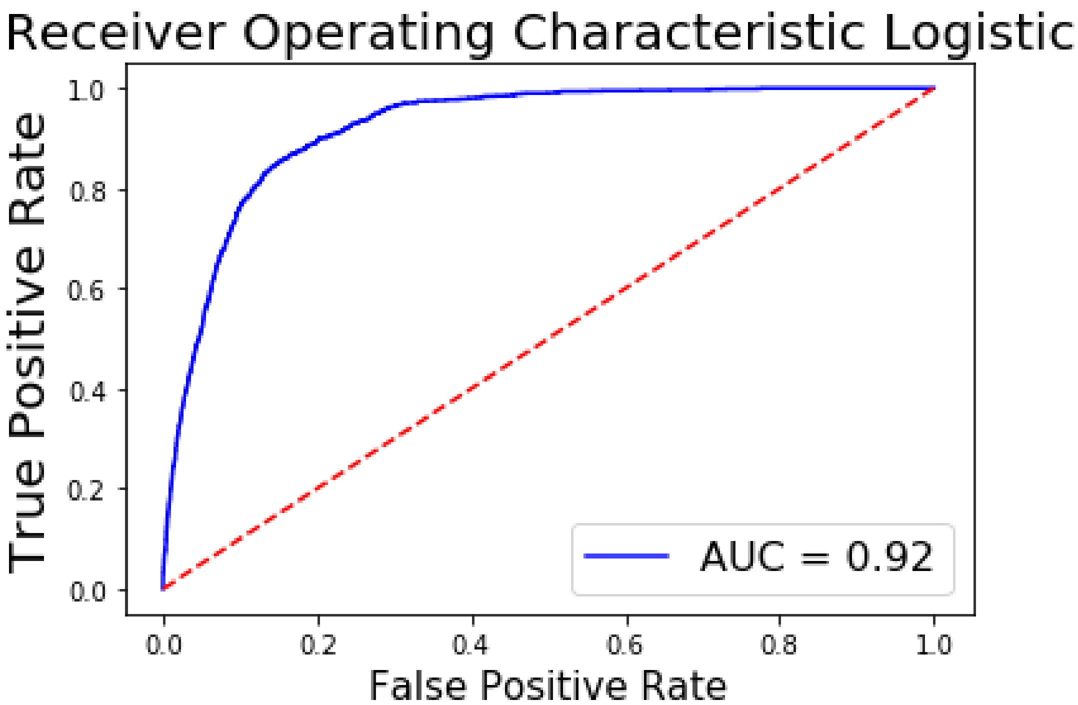
```
In [28]: models = pd.DataFrame({
                         'Models': ['Random Forest Classifier','K-Near Neighbors', 'Logistic Mo
                         'Score':  [RFCCV,  KNNCV, LOGCV, GAUSIAN]})

         models.sort_values(by='Score', ascending=False)
```

```
Out[28]:                      Models  Score
         0  Random Forest Classifier   91.0
         2            Logistic Model   91.0
         1          K-Near Neighbors   90.0
         3               Gausian NB   85.0
```

```
In [30]: from sklearn import metrics
```

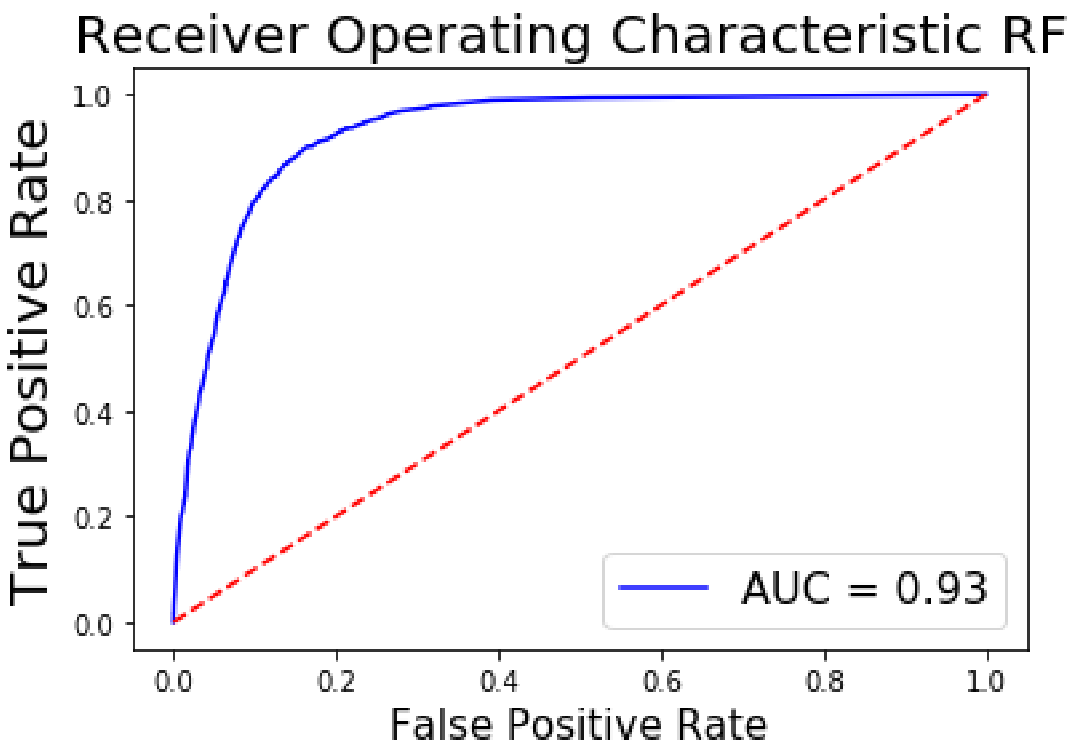
```
In [31]: #LOGMODEL
         probs = logmodel.predict_proba(X_test)
         preds = probs[:,1]
         fprlog, tprlog, thresholdlog = metrics.roc_curve(y_test, preds)
         roc_auclog = metrics.auc(fprlog, tprlog)

         plt.plot(fprlog, tprlog, 'b', label = 'AUC = %0.2f' % roc_auclog)
         plt.plot([0, 1], [0, 1],'r--')
         plt.title('Receiver Operating Characteristic Logistic ',fontsize=20)
         plt.ylabel('True Positive Rate',fontsize=20)
         plt.xlabel('False Positive Rate',fontsize=15)
         plt.legend(loc = 'lower right', prop={'size': 16})
```

Out[31]: <matplotlib.legend.Legend at 0x7fb502d5d390>

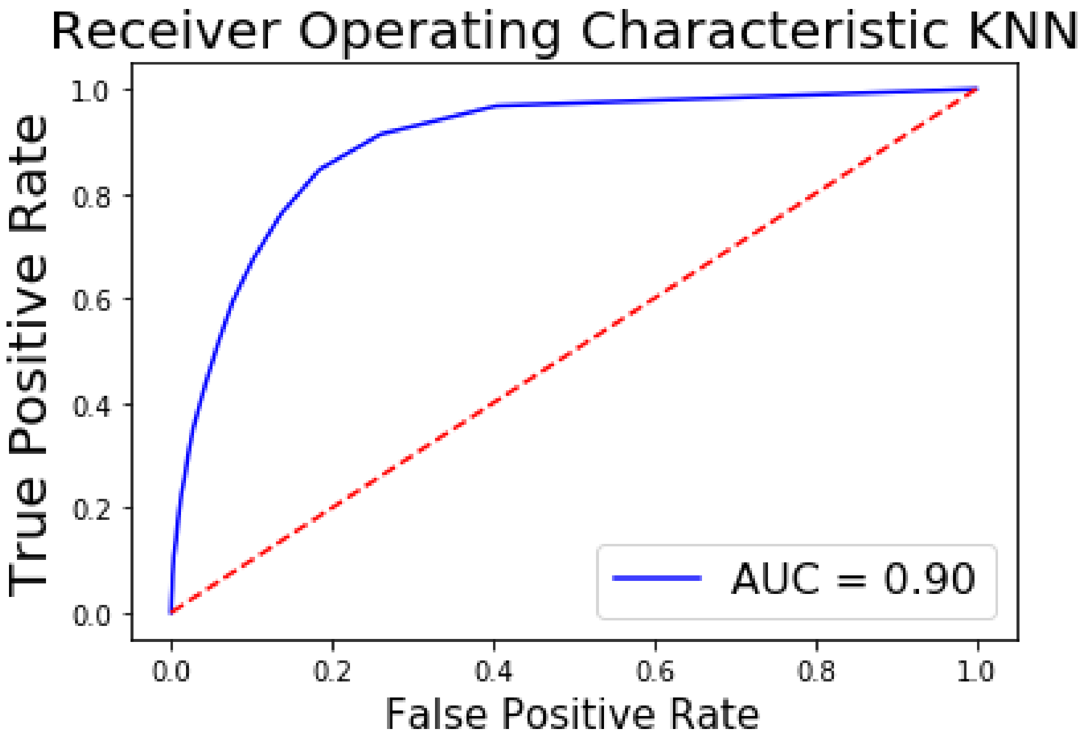



```
In [32]: #RANDOM FOREST --------------------
         probs = rfc.predict_proba(X_test)
         preds = probs[:,1]
         fprrfc, tprrfc, thresholdrfc = metrics.roc_curve(y_test, preds)
         roc_aucrfc = metrics.auc(fprrfc, tprrfc)

         plt.plot(fprrfc, tprrfc, 'b', label = 'AUC = %0.2f' % roc_aucrfc)
         plt.plot([0, 1], [0, 1],'r--')
         plt.title('Receiver Operating Characteristic RF ',fontsize=20)
         plt.ylabel('True Positive Rate',fontsize=20)
         plt.xlabel('False Positive Rate',fontsize=15)
         plt.legend(loc = 'lower right', prop={'size': 16})
```

Out[32]: <matplotlib.legend.Legend at 0x7fb502ce35c0>

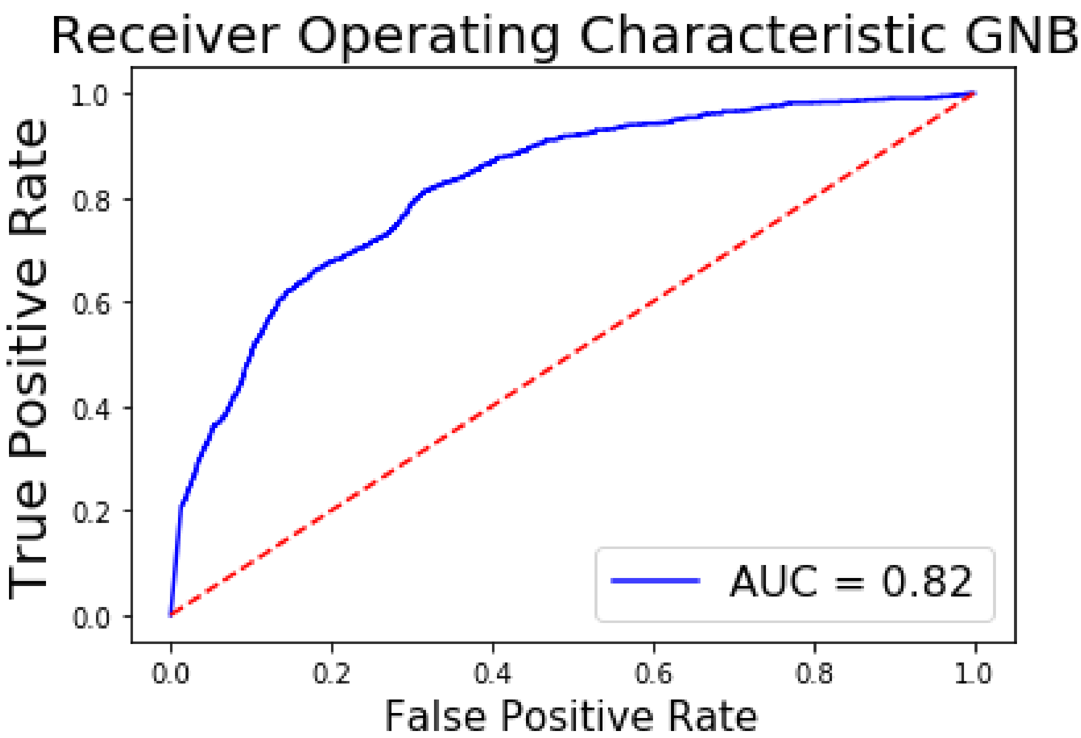



```
In [33]: #KNN----------------------
         probs = knn.predict_proba(X_test)
         preds = probs[:,1]
         fprknn, tprknn, thresholdknn = metrics.roc_curve(y_test, preds)
         roc_aucknn = metrics.auc(fprknn, tprknn)

         plt.plot(fprknn, tprknn, 'b', label = 'AUC = %0.2f' % roc_aucknn)
         plt.plot([0, 1], [0, 1],'r--')
         plt.title('Receiver Operating Characteristic KNN ',fontsize=20)
         plt.ylabel('True Positive Rate',fontsize=20)
         plt.xlabel('False Positive Rate',fontsize=15)
         plt.legend(loc = 'lower right', prop={'size': 16})

Out[33]: <matplotlib.legend.Legend at 0x7fb502c5ae80>
```

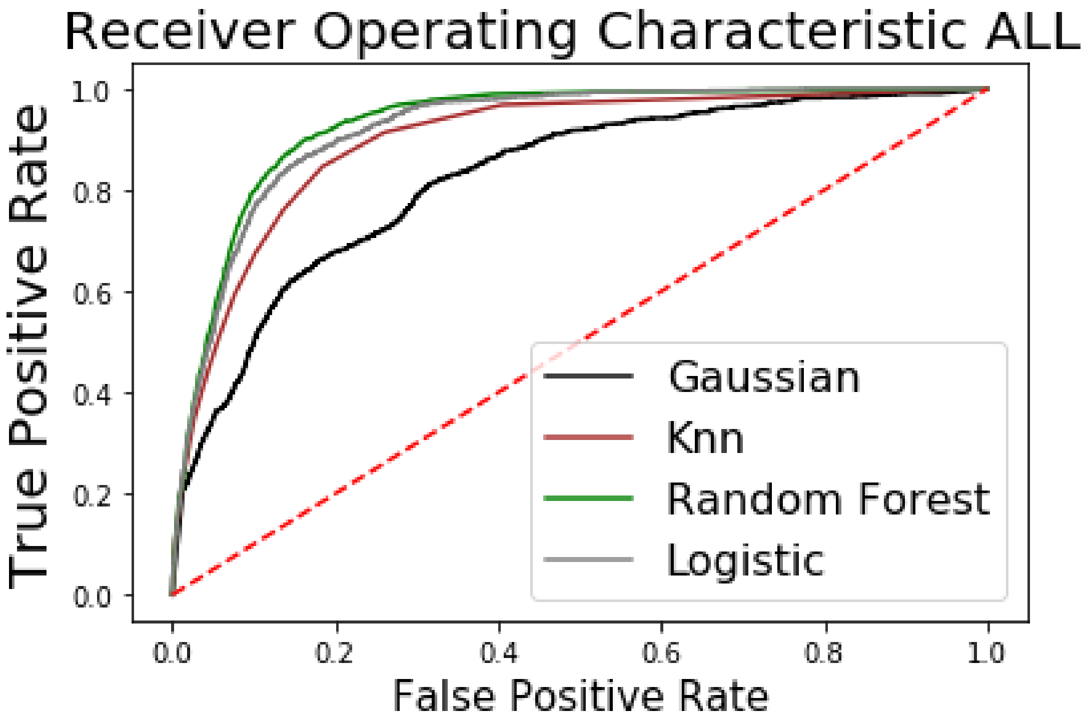



```
In [34]: probs = gaussiannb.predict_proba(X_test)
         preds = probs[:,1]
         fprgau, tprgau, thresholdgau = metrics.roc_curve(y_test, preds)
         roc_aucgau = metrics.auc(fprgau, tprgau)

         plt.plot(fprgau, tprgau, 'b', label = 'AUC = %0.2f' % roc_aucgau)
         plt.plot([0, 1], [0, 1],'r--')
         plt.title('Receiver Operating Characteristic GNB ',fontsize=20)
         plt.ylabel('True Positive Rate',fontsize=20)
         plt.xlabel('False Positive Rate',fontsize=15)
         plt.legend(loc = 'lower right', prop={'size': 16})
```

```
Out[34]: <matplotlib.legend.Legend at 0x7fb502c2feb8>
```




```
In [35]: #ALL PLOTS -----------------------------------
         plt.plot(fprgau, tprgau, 'b', label = 'Gaussian', color='black')
         plt.plot(fprknn, tprknn, 'b', label = 'Knn', color='brown')
         plt.plot(fprrfc, tprrfc, 'b', label = 'Random Forest', color='green')
         plt.plot(fprlog, tprlog, 'b', label = 'Logistic', color='grey')
         plt.plot([0, 1], [0, 1],'r--')
         plt.title('Receiver Operating Characteristic ALL ',fontsize=20)
         plt.ylabel('True Positive Rate',fontsize=20)
         plt.xlabel('False Positive Rate',fontsize=15)
         plt.legend(loc = 'lower right', prop={'size': 16})

         plt.subplots_adjust(wspace=0.2)
         plt.tight_layout()
```



10 Data Balancing

In [37]:
```
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
ros = RandomOverSampler(random_state=42)
X_train, y_train = ros.fit_resample(X_train, y_train)
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
# rus = RandomUnderSampler(random_state=42)
# X_resampled_u, y_resampled_u = rus.fit_resample(X_train, y_train)
```

11 Logistic Regression

In [38]:
```
from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
logpred = logmodel.predict(X_test)

LOGCV = reports(y_test,logpred)
```

```
[[9344 1634]
 [ 195 1184]]
Accuracy  85.0
              precision    recall  f1-score   support

           0       0.98      0.85      0.91     10978
           1       0.42      0.86      0.56      1379

    accuracy                           0.85     12357
   macro avg       0.70      0.85      0.74     12357
weighted avg       0.92      0.85      0.87     12357
```

12 KNN

```
In [39]: from sklearn.neighbors import KNeighborsClassifier
         knn = KNeighborsClassifier(n_neighbors=22)
         knn.fit(X_train, y_train)
         knnpred = knn.predict(X_test)
         KNNCV = reports(y_test,knnpred)
```

```
[[9018 1960]
 [ 279 1100]]
Accuracy  82.0
              precision    recall  f1-score   support

           0       0.97      0.82      0.89     10978
           1       0.36      0.80      0.50      1379

    accuracy                           0.82     12357
   macro avg       0.66      0.81      0.69     12357
weighted avg       0.90      0.82      0.85     12357
```

13 Random Forest

```
In [40]: from sklearn.ensemble import RandomForestClassifier
         rfc = RandomForestClassifier(n_estimators = 200)#criterion = entopy,gini
         rfc.fit(X_train, y_train)
         rfcpred = rfc.predict(X_test)

         RFCCV = reports(y_test,rfcpred)
```

```
[[10336   642]
 [  563   816]]
```

```
Accuracy  90.0
              precision    recall  f1-score   support

           0       0.95      0.94      0.94     10978
           1       0.56      0.59      0.58      1379

    accuracy                           0.90     12357
   macro avg       0.75      0.77      0.76     12357
weighted avg       0.90      0.90      0.90     12357
```

14 GNB

```
In [41]: from sklearn.naive_bayes import GaussianNB
         gaussiannb= GaussianNB()
         gaussiannb.fit(X_train, y_train)
         gaussiannbpred = gaussiannb.predict(X_test)
         probs = gaussiannb.predict(X_test)

         GAUSIAN = reports(y_test,gaussiannbpred)
```

```
[[9028 1950]
 [ 475  904]]
Accuracy  80.0
              precision    recall  f1-score   support

           0       0.95      0.82      0.88     10978
           1       0.32      0.66      0.43      1379

    accuracy                           0.80     12357
   macro avg       0.63      0.74      0.65     12357
weighted avg       0.88      0.80      0.83     12357
```

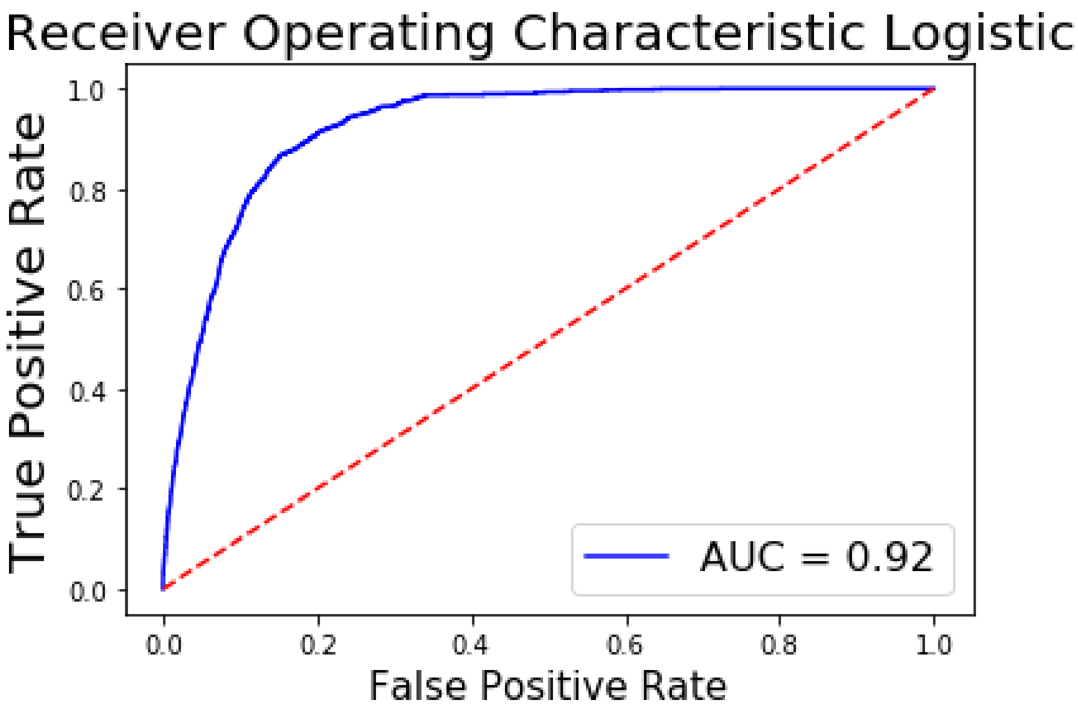
```
In [42]: models = pd.DataFrame({
                         'Models': ['Random Forest Classifier','K-Near Neighbors', 'Logistic Mo
                         'Score':  [RFCCV,  KNNCV, LOGCV, GAUSIAN]})

         models.sort_values(by='Score', ascending=False)
```

```
Out[42]:                    Models  Score
         0  Random Forest Classifier   90.0
         2            Logistic Model   85.0
         1          K-Near Neighbors   82.0
         3               Gausian NB   80.0
```

```
In [43]: from sklearn import metrics
```

In [44]:
```
#LOGMODEL
probs = logmodel.predict_proba(X_test)
preds = probs[:,1]
fprlog, tprlog, thresholdlog = metrics.roc_curve(y_test, preds)
roc_auclog = metrics.auc(fprlog, tprlog)

plt.plot(fprlog, tprlog, 'b', label = 'AUC = %0.2f' % roc_auclog)
plt.plot([0, 1], [0, 1],'r--')
plt.title('Receiver Operating Characteristic Logistic ',fontsize=20)
plt.ylabel('True Positive Rate',fontsize=20)
plt.xlabel('False Positive Rate',fontsize=15)
plt.legend(loc = 'lower right', prop={'size': 16})
```

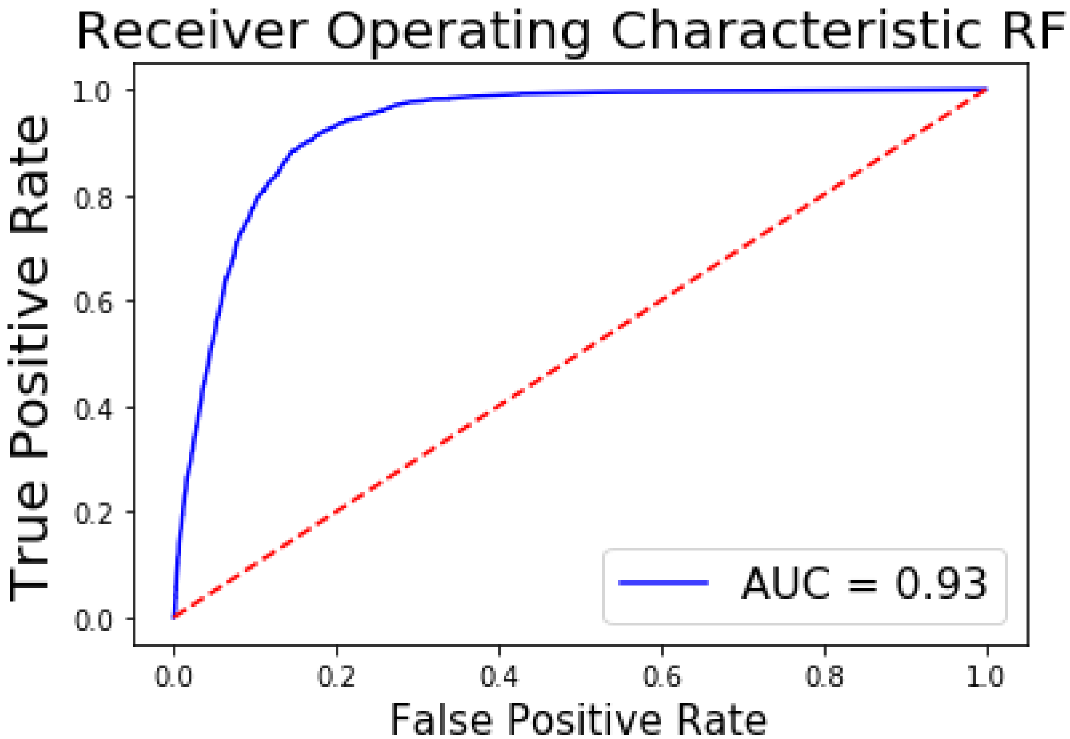
Out[44]: <matplotlib.legend.Legend at 0x7fb501564278>



In [45]:
```
#RANDOM FOREST --------------------
probs = rfc.predict_proba(X_test)
preds = probs[:,1]
fprrfc, tprrfc, thresholdrfc = metrics.roc_curve(y_test, preds)
roc_aucrfc = metrics.auc(fprrfc, tprrfc)

plt.plot(fprrfc, tprrfc, 'b', label = 'AUC = %0.2f' % roc_aucrfc)
plt.plot([0, 1], [0, 1],'r--')
plt.title('Receiver Operating Characteristic RF ',fontsize=20)
```

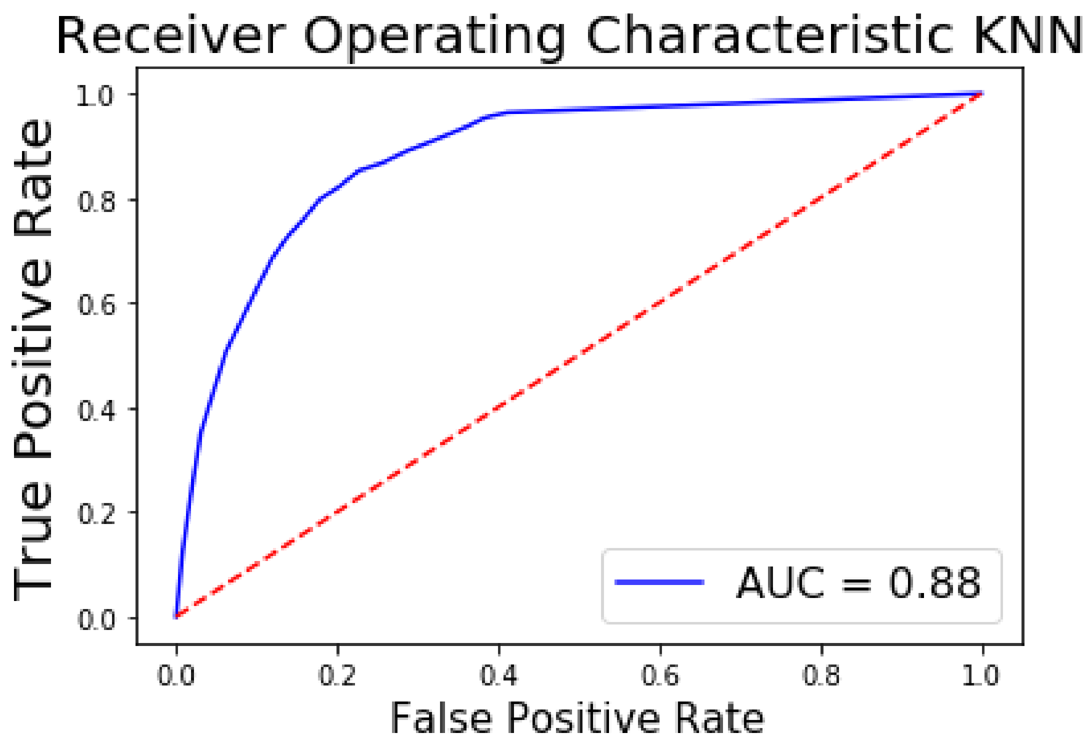
```
plt.ylabel('True Positive Rate',fontsize=20)
plt.xlabel('False Positive Rate',fontsize=15)
plt.legend(loc = 'lower right', prop={'size': 16})
```

Out[45]: <matplotlib.legend.Legend at 0x7fb50153fe48>

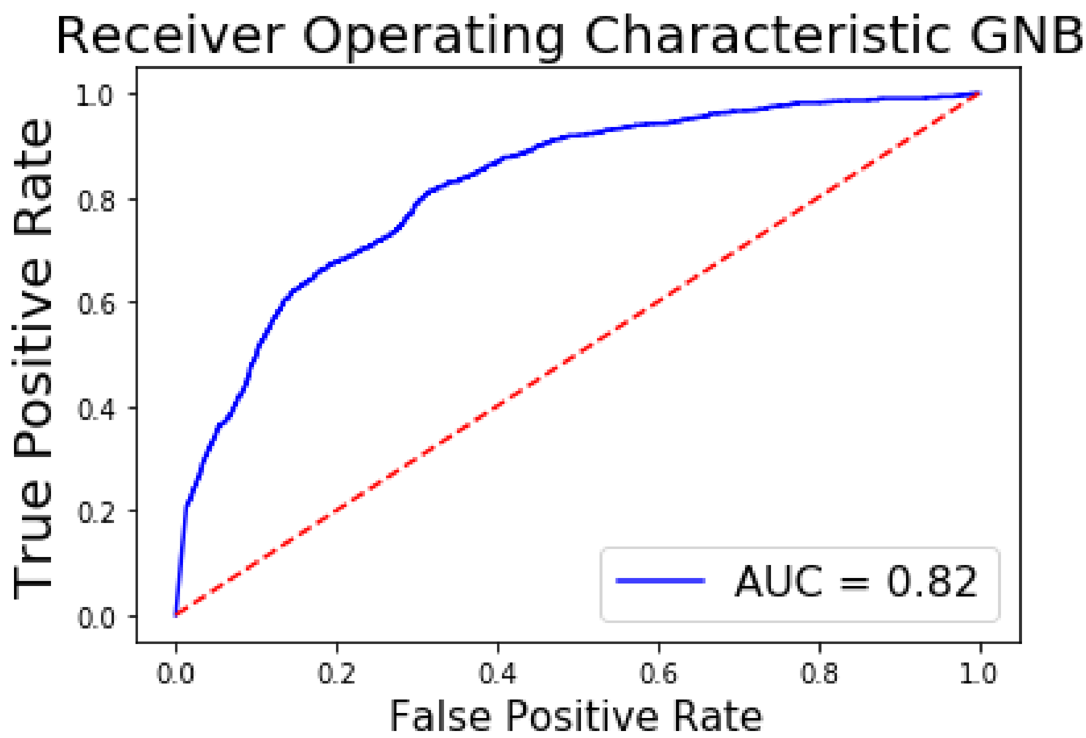


In [46]:
```
#KNN----------------------
probs = knn.predict_proba(X_test)
preds = probs[:,1]
fprknn, tprknn, thresholdknn = metrics.roc_curve(y_test, preds)
roc_aucknn = metrics.auc(fprknn, tprknn)

plt.plot(fprknn, tprknn, 'b', label = 'AUC = %0.2f' % roc_aucknn)
plt.plot([0, 1], [0, 1],'r--')
plt.title('Receiver Operating Characteristic KNN ',fontsize=20)
plt.ylabel('True Positive Rate',fontsize=20)
plt.xlabel('False Positive Rate',fontsize=15)
plt.legend(loc = 'lower right', prop={'size': 16})
```

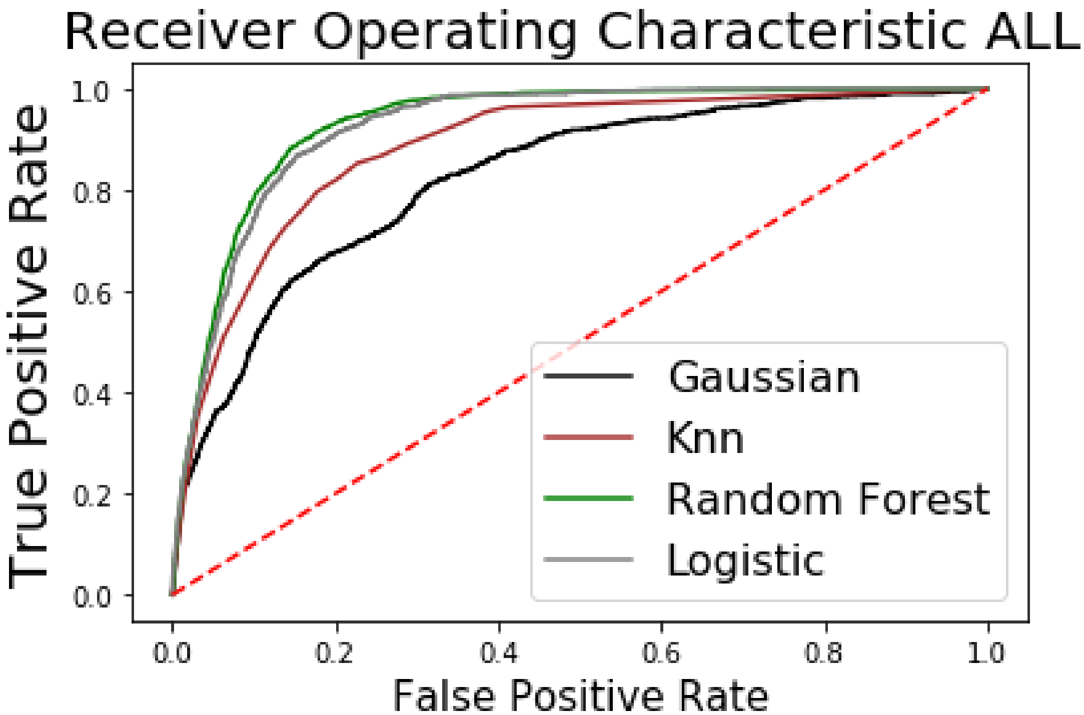
Out[46]: <matplotlib.legend.Legend at 0x7fb5014a6a20>




```
In [47]: probs = gaussiannb.predict_proba(X_test)
         preds = probs[:,1]
         fprgau, tprgau, thresholdgau = metrics.roc_curve(y_test, preds)
         roc_aucgau = metrics.auc(fprgau, tprgau)

         plt.plot(fprgau, tprgau, 'b', label = 'AUC = %0.2f' % roc_aucgau)
         plt.plot([0, 1], [0, 1],'r--')
         plt.title('Receiver Operating Characteristic GNB ',fontsize=20)
         plt.ylabel('True Positive Rate',fontsize=20)
         plt.xlabel('False Positive Rate',fontsize=15)
         plt.legend(loc = 'lower right', prop={'size': 16})

Out[47]: <matplotlib.legend.Legend at 0x7fb50148f6a0>
```



In [48]:
```
#ALL PLOTS ----------------------------------
plt.plot(fprgau, tprgau, 'b', label = 'Gaussian', color='black')
plt.plot(fprknn, tprknn, 'b', label = 'Knn', color='brown')
plt.plot(fprrfc, tprrfc, 'b', label = 'Random Forest', color='green')
plt.plot(fprlog, tprlog, 'b', label = 'Logistic', color='grey')
plt.plot([0, 1], [0, 1],'r--')
plt.title('Receiver Operating Characteristic ALL ',fontsize=20)
plt.ylabel('True Positive Rate',fontsize=20)
plt.xlabel('False Positive Rate',fontsize=15)
plt.legend(loc = 'lower right', prop={'size': 16})

plt.subplots_adjust(wspace=0.2)
plt.tight_layout()
```



For Data balancin random oversampling is used results show increase in recall of positive class

```
In [ ]:
```