Bank_

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	month	day_of_week	...	campaign	pdays	previous	poutcome	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	y
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	...	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	...	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
2	37	services	married	high.school	no	yes	no	telephone	may	mon	...	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	...	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
4	56	services	married	high.school	no	no	yes	telephone	may	mon	...	1	999	0	nonexistent	1.1	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()
        data_client['job']      = labelencoder_X.fit_transform(data_client['job'])
        data_client['marital']  = labelencoder_X.fit_transform(data_client['marital'])
        data_client['education']= labelencoder_X.fit_transform(data_client['education'])
        data_client['default']  = labelencoder_X.fit_transform(data_client['default'])
        data_client['housing']  = labelencoder_X.fit_transform(data_client['housing'])
        data_client['loan']     = labelencoder_X.fit_transform(data_client['loan'])
```

```
In [7]: def age(dataframe):
            dataframe.loc[dataframe['age'] <= 32, 'age'] = 1
            dataframe.loc[(dataframe['age'] > 32) & (dataframe['age'] <= 47), 'age'] = 2
            dataframe.loc[(dataframe['age'] > 47) & (dataframe['age'] <= 70), 'age'] = 3
            dataframe.loc[(dataframe['age'] > 70) & (dataframe['age'] <= 98), 'age'] = 4

            return dataframe

        age(data_client);
```

```
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()
         data_bank_related['contact']     = labelencoder_X.fit_transform(data_bank_related['co
         data_bank_related['month']       = labelencoder_X.fit_transform(data_bank_related['mo
         data_bank_related['day_of_week'] = labelencoder_X.fit_transform(data_bank_related['da
```

```
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 [13]: def duration(data):

             data.loc[data['duration'] <= 102, 'duration'] = 1
             data.loc[(data['duration'] > 102) & (data['duration'] <= 180)  , 'duration']    =
             data.loc[(data['duration'] > 180) & (data['duration'] <= 319)  , 'duration']   = 3
             data.loc[(data['duration'] > 319) & (data['duration'] <= 644.5), 'duration'] = 4
             data.loc[data['duration']  > 644.5, 'duration'] = 5

             return data
         duration(data_bank_related);
```

```
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', 'euril
         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', '
                      'contact', 'month', 'day_of_week', 'duration', 'emp.var.rate', '
                      '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]:
```
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]:
```
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 M
                        'Score':  [RFCCV,  KNNCV, LOGCV, GAUSIAN]})

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

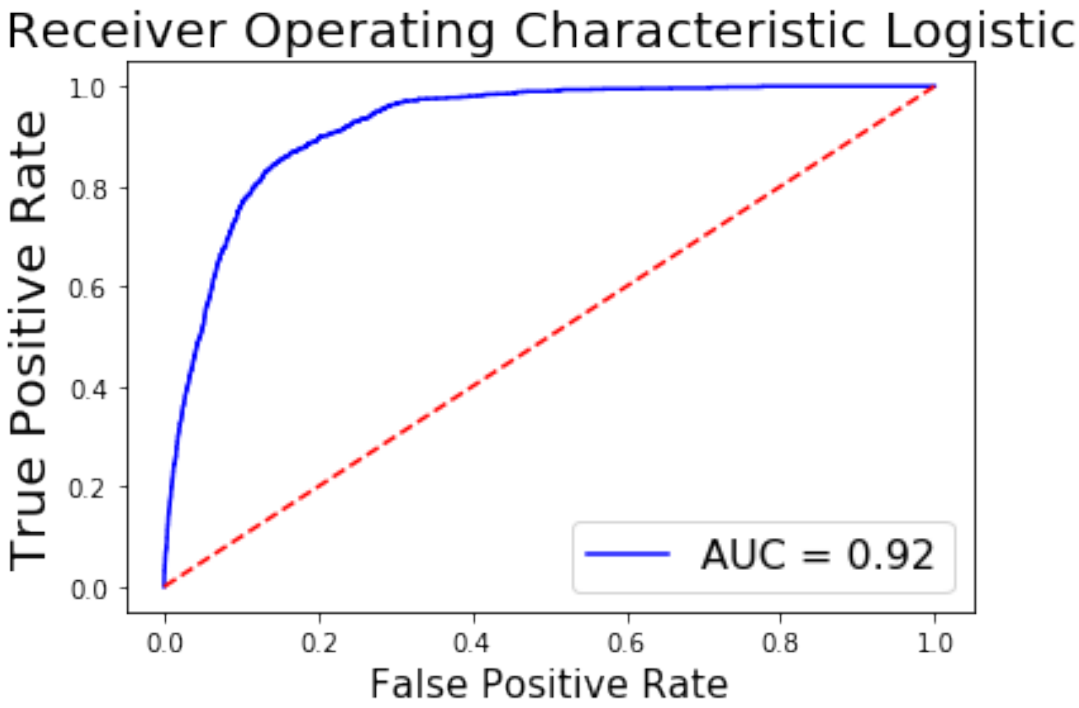
Out[28]:

	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
```

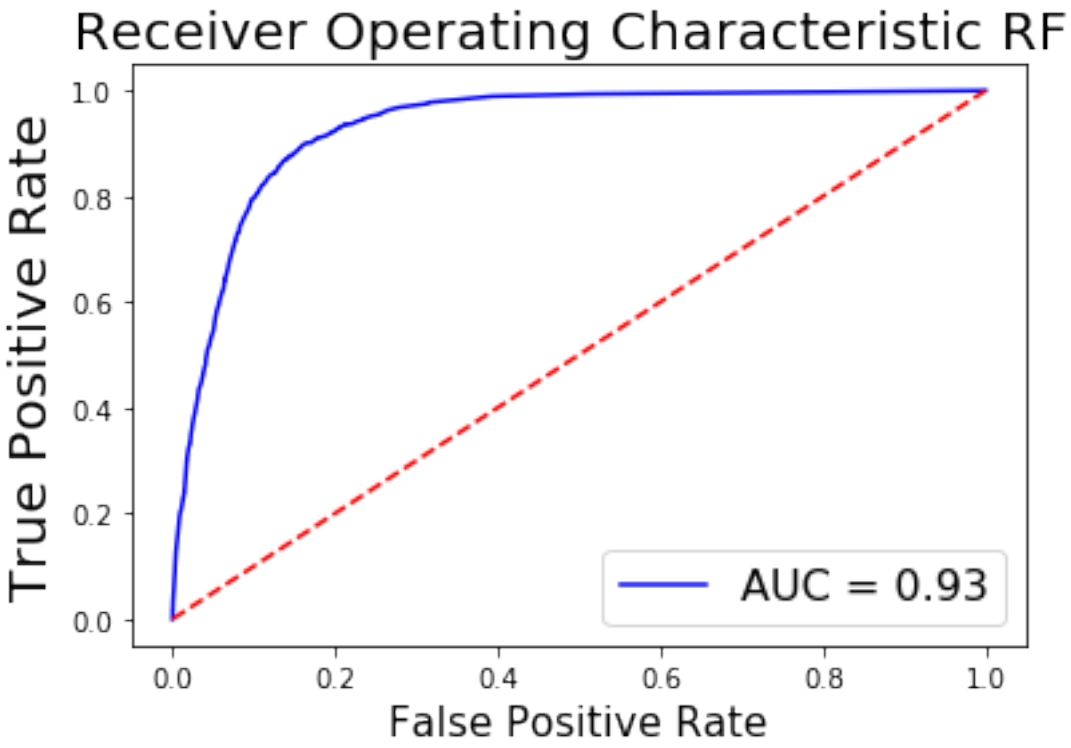
In [31]:
```
#LOGMODEL
probs = logmodel.predict_proba(X_test)
preds = probs[:,1]
fprlog, tprlog, thresholdlog = metrics.roc_curve(y_test, preds)
roc_auclog = metrics.auc(fprlog, tprlog)

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>



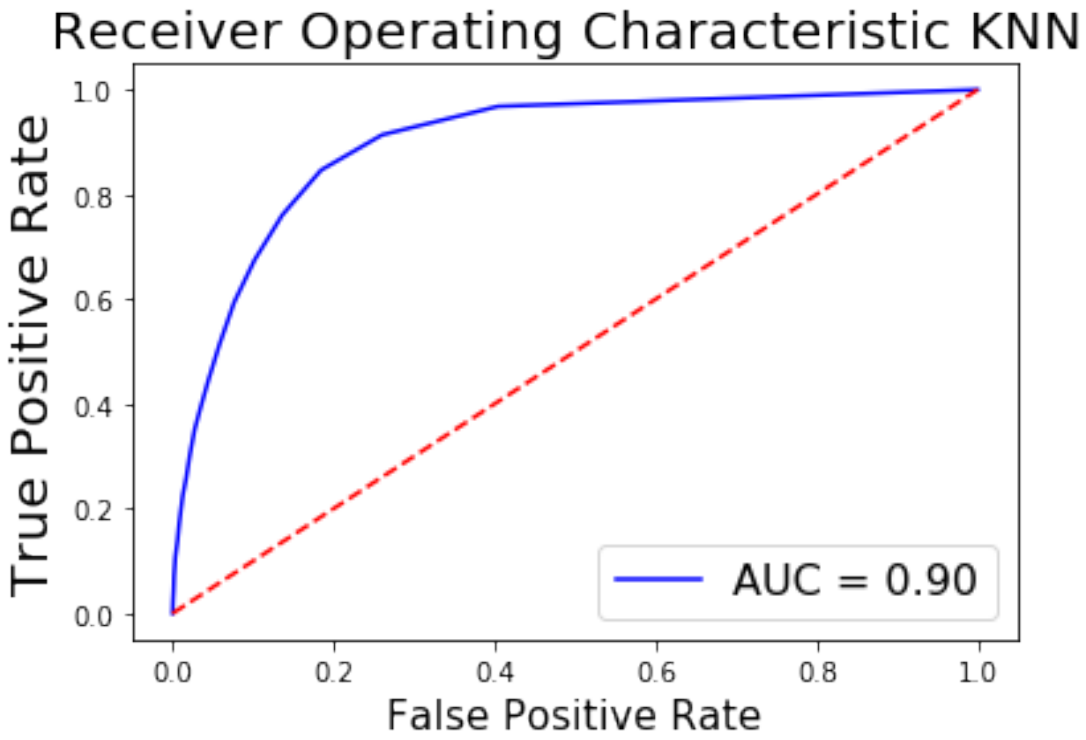
In [32]:
```
#RANDOM FOREST --------------------
probs = rfc.predict_proba(X_test)
preds = probs[:,1]
fprrfc, tprrfc, thresholdrfc = metrics.roc_curve(y_test, preds)
roc_aucrfc = metrics.auc(fprrfc, tprrfc)

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>



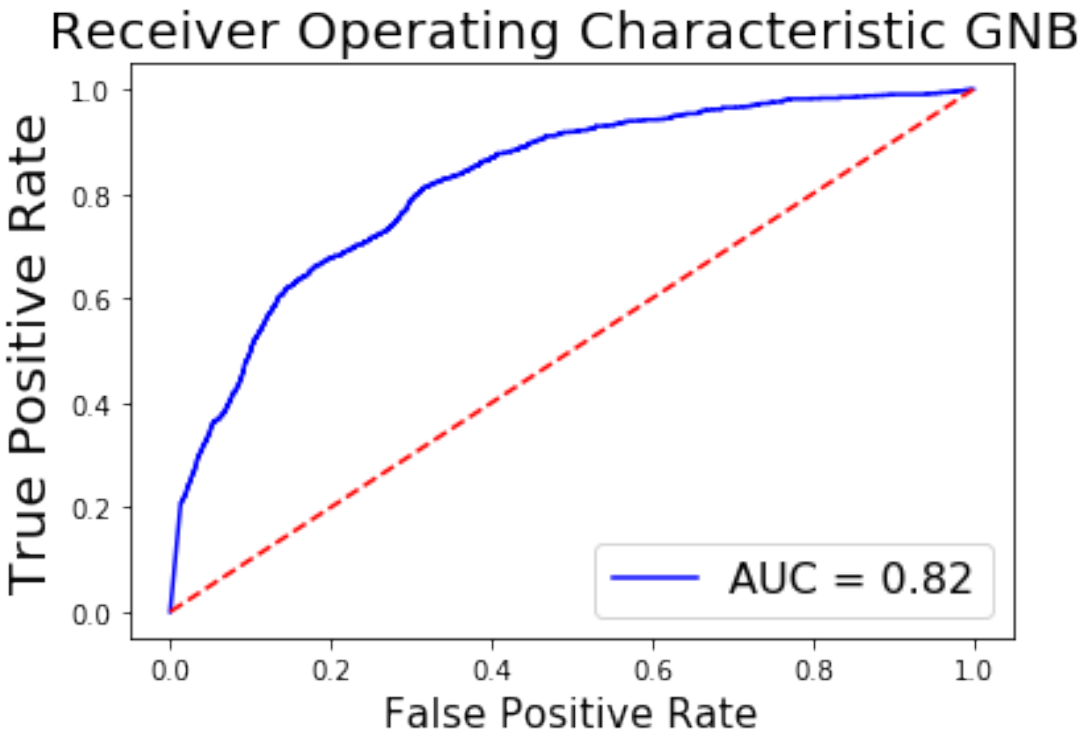
In [33]:
```
#KNN----------------------
probs = knn.predict_proba(X_test)
preds = probs[:,1]
fprknn, tprknn, thresholdknn = metrics.roc_curve(y_test, preds)
roc_aucknn = metrics.auc(fprknn, tprknn)

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>
```

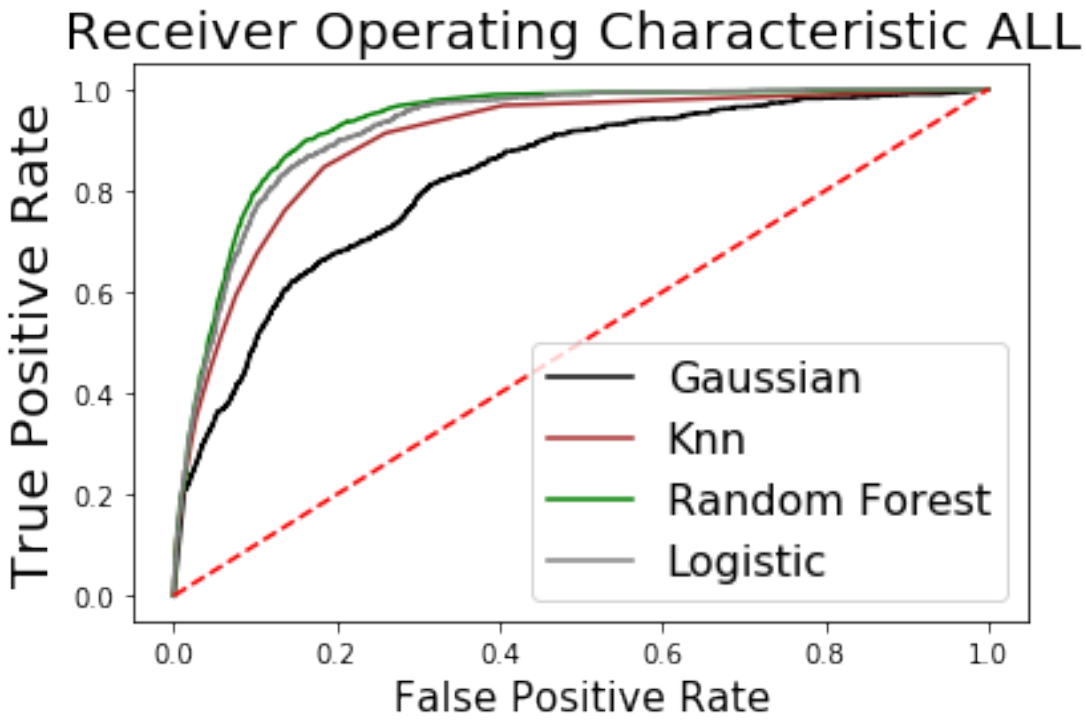


In [34]:
```
probs = gaussiannb.predict_proba(X_test)
preds = probs[:,1]
fprgau, tprgau, thresholdgau = metrics.roc_curve(y_test, preds)
roc_aucgau = metrics.auc(fprgau, tprgau)

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
```

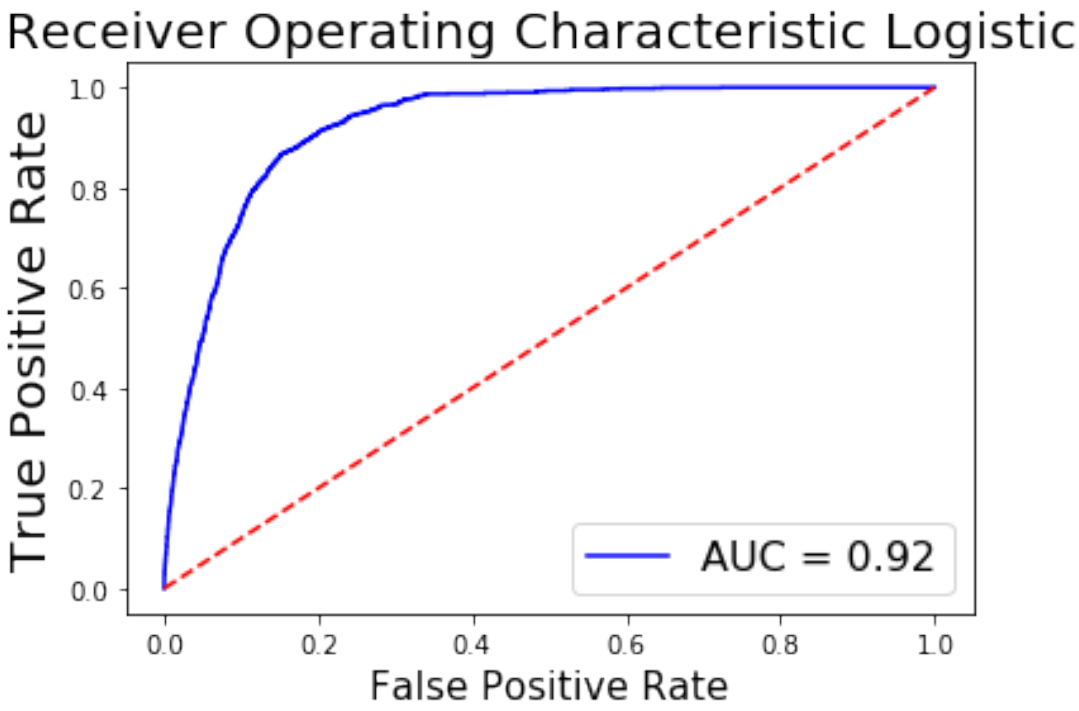
```
In [42]: models = pd.DataFrame({
                        'Models': ['Random Forest Classifier','K-Near Neighbors', 'Logistic Mo
                        'Score':  [RFCCV,  KNNCV, LOGCV, GAUSIAN]})

         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})
```

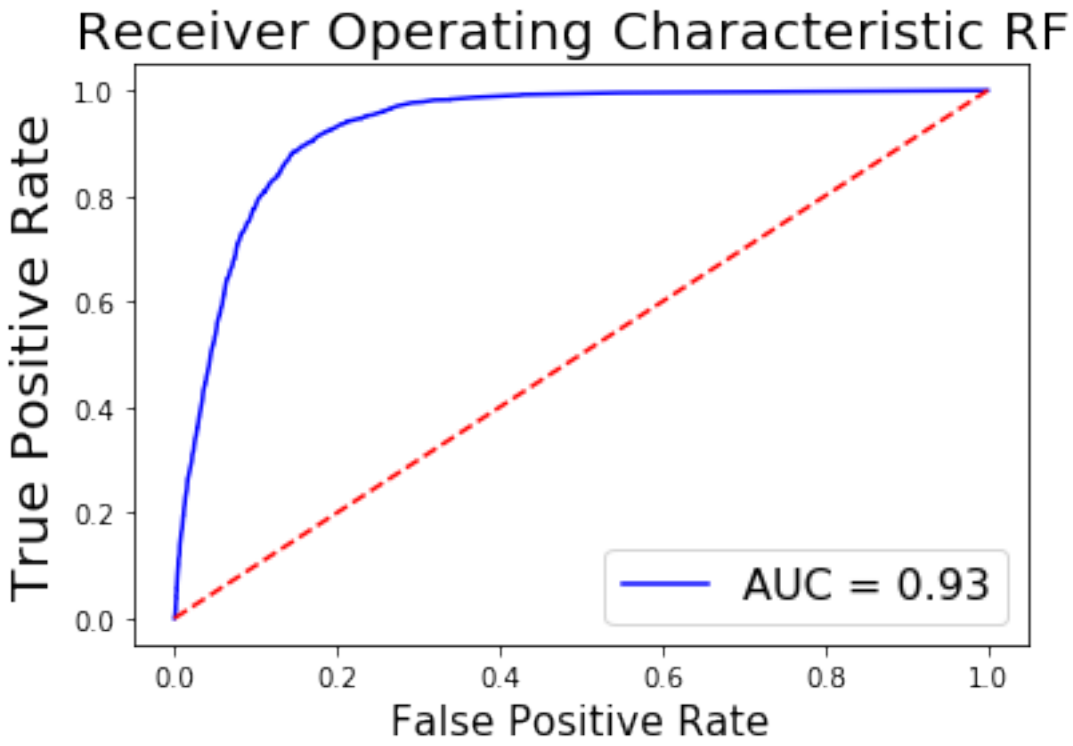
Out[44]: <matplotlib.legend.Legend at 0x7fb501564278>



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)
```

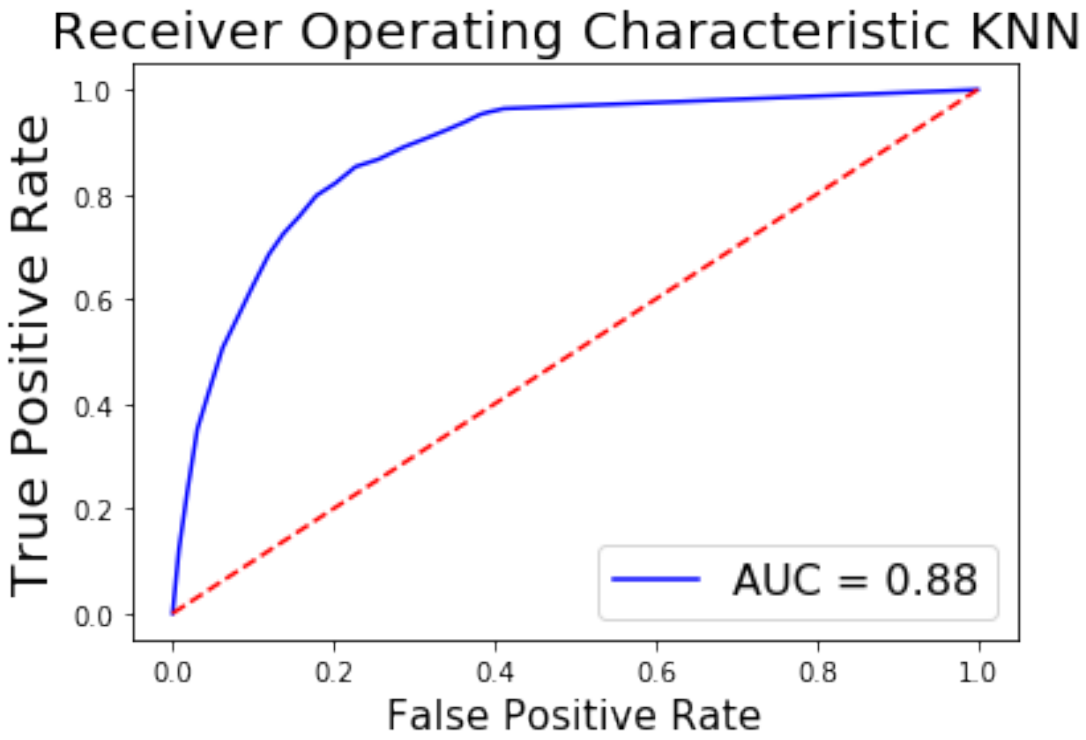
```
plt.ylabel('True Positive Rate',fontsize=20)
plt.xlabel('False Positive Rate',fontsize=15)
plt.legend(loc = 'lower right', prop={'size': 16})
```

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

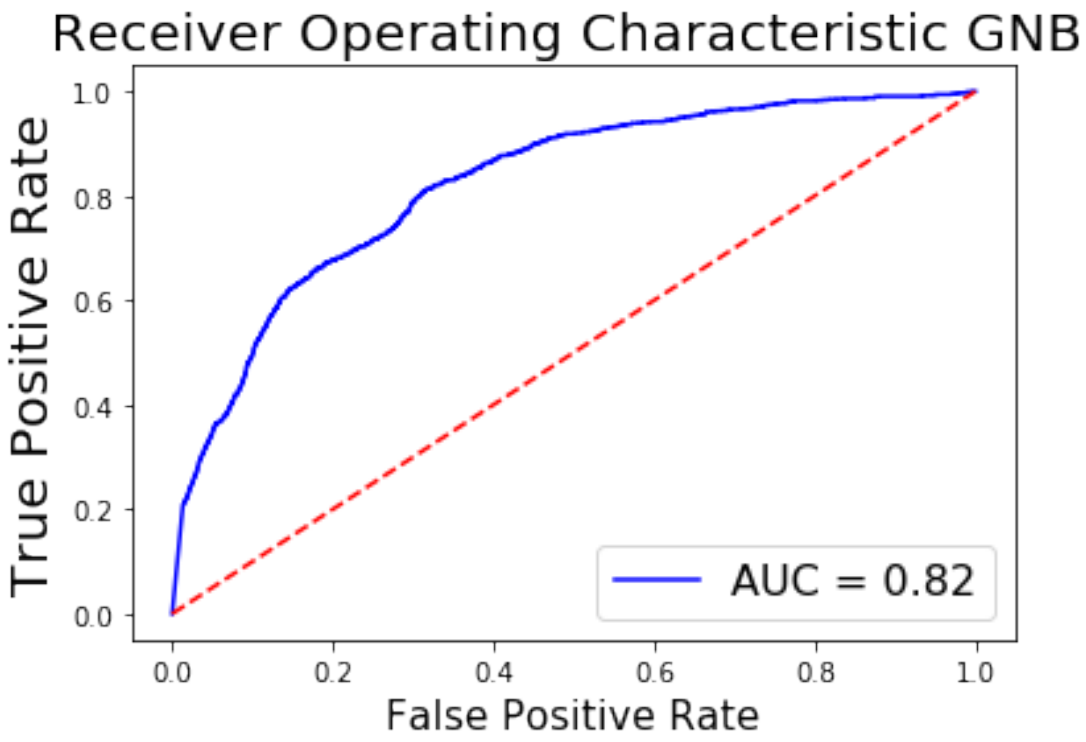


In [46]:
```
#KNN----------------------
probs = knn.predict_proba(X_test)
preds = probs[:,1]
fprknn, tprknn, thresholdknn = metrics.roc_curve(y_test, preds)
roc_aucknn = metrics.auc(fprknn, tprknn)

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})
```

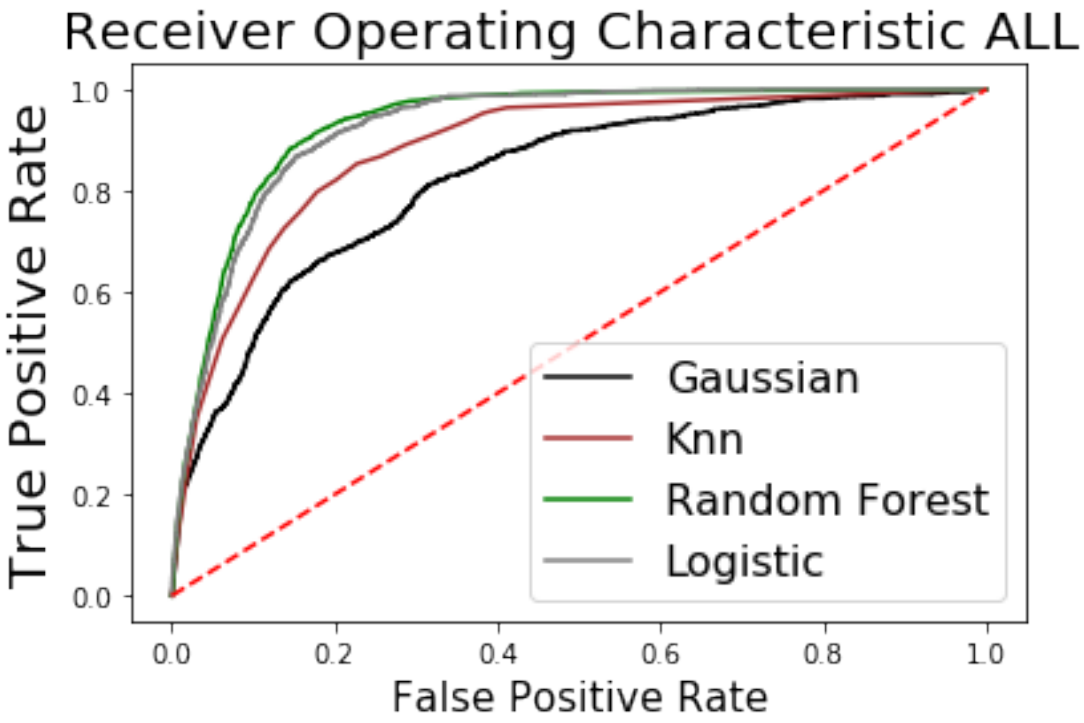
Out[46]: <matplotlib.legend.Legend at 0x7fb5014a6a20>




```
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()
```


Receiver Operating Characteristic ALL
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Gaussian
Knn
Random Forest
Logistic

In [ ]: