ROC Curves

This notebook demonstrates the code for comparing ROC (Receiver Operating Characteristic) scores across different classifier models.

In [1]:
```
#import the right libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB, BernoulliNB, MultinomialNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis, QuadraticDiscriminantAnalysis
from sklearn.metrics import f1_score, confusion_matrix, classification_report, accuracy_score, log_loss, roc_au
from sklearn.model_selection import cross_val_predict, cross_val_score, learning_curve, GridSearchCV, Randomize
from sklearn.metrics import classification_report, accuracy_score, precision_recall_fscore_support
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler, Normalizer, LabelEncoder, RobustScaler, MinMaxScaler
from sklearn.svm import SVC, LinearSVC, NuSVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer, KNNImputer
from sklearn import metrics
plt.rcParams["figure.figsize"] = (9,9)
```

In [2]:
```
#this option just allwos us to see every column in the notebook
pd.set_option('display.max_columns', None)

#pd.get_option("display.max_columns")
```

In [3]:
```
#pull in the dataset and turn into a DataFrame
bank_main_df = pd.read_csv('./Dataset_1_Bank Marketing/bank_marketing.csv',delimiter=';')
bank_main_df
```

Out[3]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous
0	58.0	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0
1	44.0	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0
2	33.0	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0
3	47.0	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0
4	33.0	unknown	single	unknown	no	1	no	no	NaN	5	may	198	1	-1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	51.0	technician	married	tertiary	no	825	no	no	cellular	17	nov	977	3	-1	0
45207	71.0	retired	divorced	primary	no	1729	no	no	cellular	17	nov	456	2	-1	0
45208	72.0	retired	married	secondary	no	5715	no	no	cellular	17	nov	1127	5	184	3
45209	57.0	blue-collar	married	secondary	no	668	no	no	telephone	17	nov	508	4	-1	0
45210	37.0	entrepreneur	married	secondary	no	2971	no	no	cellular	17	nov	361	2	188	11

45211 rows × 17 columns

In [4]:
```
bank_main_df.describe()
```

Out[4]:

	age	balance	day	duration	campaign	pdays	previous
count	43872.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.924781	1362.272058	15.806419	258.163080	2.763841	40.197828	0.580323
std	10.610835	3044.765829	8.322476	257.527812	3.098021	100.128746	2.303441
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000	0.000000
25%	33.000000	72.000000	8.000000	103.000000	1.000000	-1.000000	0.000000
50%	39.000000	448.000000	16.000000	180.000000	2.000000	-1.000000	0.000000
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.000000	0.000000
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.000000	275.000000

In [5]:
```
#creating a field that determines whether or not the customer was ever previously contacted
bank_main_df['prior_contact'] = [ 0 if bank_main_df['pdays'][i] == -1 else 1 for i in range(len(bank_main_df))]

#replacing the yes/no categorical values with 1/0 binary digits
bank_main_df['deposit'] = [0 if (bank_main_df['deposit'][i] == 'yes') else 1 for i in range(len(bank_main_df))

#convert the "day" field to a categorical variable
bank_main_df['day'] = pd.Categorical(bank_main_df['day'])

#dropping pdays and previous, because the important information is captured in prior_contact
bank_main_df.drop(columns=['pdays','previous','job','marital','education','default','housing','loan','contact',
```

In [6]:
```
#because we have so many cateogrical variables, we should one-hot encode them (i.e. create dummy categorical va
#we also use drop_first=True to reduce the redundant column count
bank_main_df = pd.get_dummies(bank_main_df, drop_first=False)

# bank_main_df
```

In [7]:
```
#note that only the "age" category has null values

# pd.isnull(bank_main_df).sum()
```

Imputing the missing values in "Age" variable

- **Iterative Imputer:** Multivariate imputer that estimates each feature from all the others. A strategy for imputing missing values by modeling each feature with missing values as a function of other features in a round-robin fashion.

https://scikit-learn.org/stable/modules/generated/sklearn.impute.IterativeImputer.html

In [8]:
```
# Use multivariate imputer that estimates and imputes null values based on all the others.

imp = IterativeImputer(max_iter=10, verbose=0) # values passed are defaults, but added them because they seem i
imp.fit(bank_main_df)
imputed_df = imp.transform(bank_main_df)
imputed_df = pd.DataFrame(imputed_df, columns=bank_main_df.columns)
```

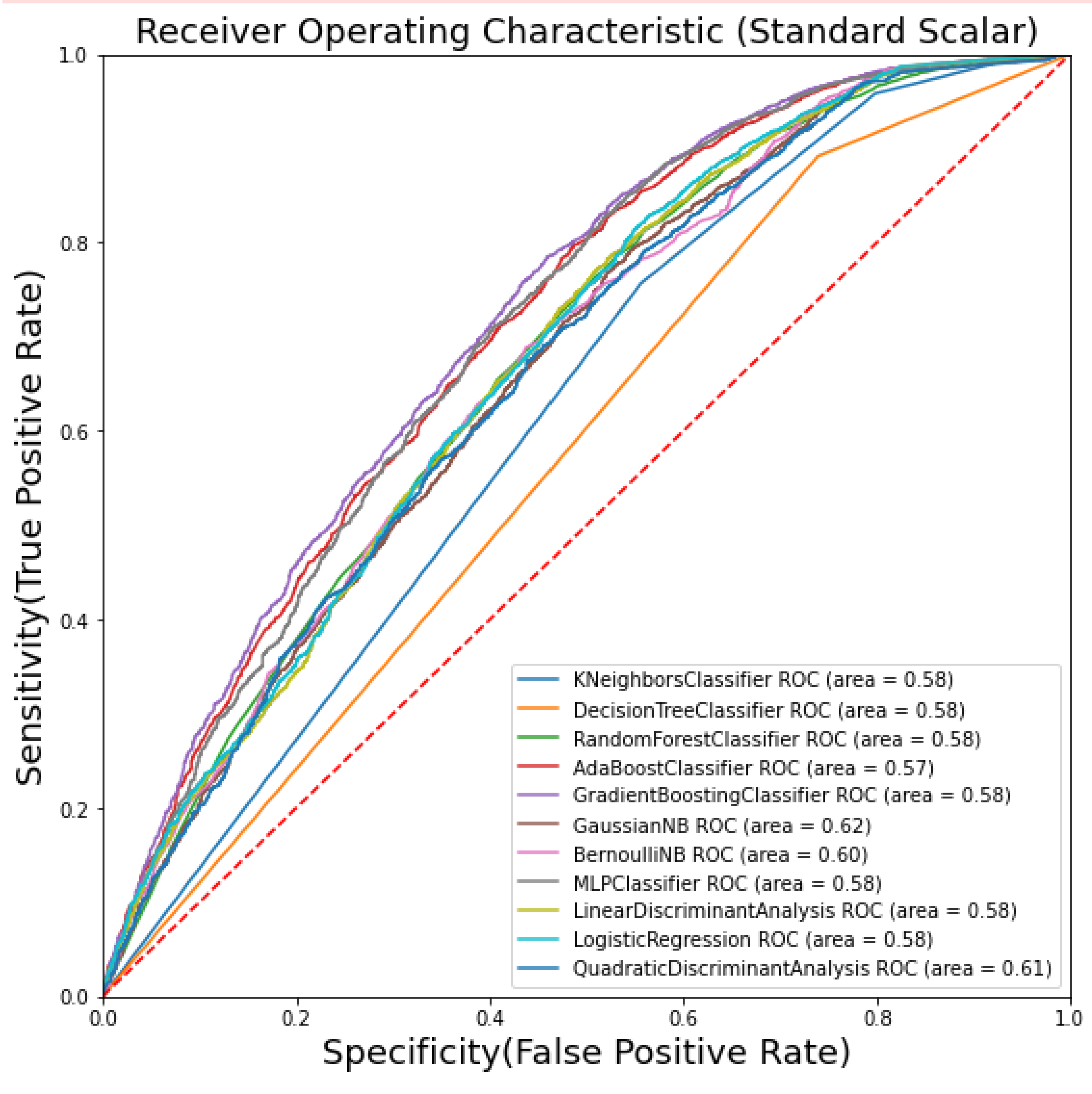
Scaling the data (Standard, MinMax, Robust)

In [9]:
```
# StandardScaler, MinMaxScaler, RobustScaler
#scaler = RobustScaler()
#scaler = MinMaxScaler()
#scaler = StandardScaler()

X = imputed_df.drop(columns='deposit')
y = imputed_df['deposit']

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3, shuffle=True)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

R-Forest Feature Importance

In [10]:
```
# Add the models to the list that you want to view on the ROC plot
models = [
{
    'label': 'KNeighborsClassifier',
    'model': KNeighborsClassifier(3),
},
{
    'label': 'DecisionTreeClassifier',
    'model': DecisionTreeClassifier(),
},
    {
    'label': 'RandomForestClassifier',
    'model': RandomForestClassifier(),
},
    {
    'label': 'AdaBoostClassifier',
    'model': AdaBoostClassifier(),
},
    {
    'label': 'GradientBoostingClassifier',
    'model': GradientBoostingClassifier(),
},
    {
    'label': 'GaussianNB',
    'model': GaussianNB(),
},
    {
    'label': 'BernoulliNB',
    'model': BernoulliNB(),
},
    {
    'label': 'MLPClassifier',
    'model': MLPClassifier(),
},
    {
    'label': 'LinearDiscriminantAnalysis',
    'model': LinearDiscriminantAnalysis(),
},
    {
    'label': 'LogisticRegression',
    'model': LogisticRegression(),
},
    {
    'label': 'QuadraticDiscriminantAnalysis',
    'model': QuadraticDiscriminantAnalysis(),
}
]

# Below for loop iterates through your models list
for m in models:
    model = m['model'] # select the model
    model.fit(X_train, y_train) # train the model
    y_pred=model.predict(X_test) # predict the test data
# Compute False postive rate, and True positive rate
    fpr, tpr, thresholds = metrics.roc_curve(y_test, model.predict_proba(X_test)[:,1])
# Calculate Area under the curve to display on the plot
    auc = metrics.roc_auc_score(y_test,model.predict(X_test))
# Now, plot the computed values
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (m['label'], auc))
# Custom settings for the plot
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('Specificity(False Positive Rate)', fontsize=18)
plt.ylabel('Sensitivity(True Positive Rate)', fontsize=18)
plt.title('Receiver Operating Characteristic (Standard Scalar)', fontsize=18)
plt.legend(loc="lower right")
plt.show()   # Display
```

```
C:\Users\reagins\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kfra8p0\LocalCache\local-pac
kages\Python310\site-packages\sklearn\discriminant_analysis.py:878: UserWarning: Variables are collinear
  warnings.warn("Variables are collinear")
```



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