ML-Credit-Card-Defaulter-Prediction

May 2, 2023

[ ]:
```
import os
import sys
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report,␣
↪accuracy_score, ConfusionMatrixDisplay
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score

import warnings
warnings.filterwarnings("ignore")
```

0.0.1 Setting up Dataset for EDA

`Default_Fin.csv` This is a synthetic dataset created using actual data from a financial institution. The data has been modified to remove identifiable features and the numbers transformed to ensure they do not link to original source (financial institution).

This is intended to be used for academic purposes for beginners who want to practice financial analytics from a simple financial dataset

In this dataset. Following are the columns present: - `index`: This is the serial number or unique identifier of the loan taker - `Employed`: This is a Boolean 1= employed 0= unemployed - `Bank Balance`: Bank Balance of the loan taker - `Annul Salary`: Annual salary of the loan taker - `Defaulted?`: This is a Boolean 1 = defaulted(means, created issue in loan payment) 0 = not defaulted

[ ]:
```
df = pd.read_csv('Default_Fin.csv')
df
```

```
[ ]:       Index  Employed  Bank Balance  Annual Salary  Defaulted?
     0         1         1       8754.36      532339.56           0
     1         2         0       9806.16      145273.56           0
     2         3         1      12882.60      381205.68           0
     3         4         1       6351.00      428453.88           0
     4         5         1       9427.92      461562.00           0
     …         …         …             …              …           …
     9995   9996         1       8538.72      635908.56           0
     9996   9997         1       9095.52      235928.64           0
     9997   9998         1      10144.92      703633.92           0
     9998   9999         1      18828.12      440029.32           0
     9999  10000         0       2411.04      202355.40           0

     [10000 rows x 5 columns]
```

0.0.2 Preparing Dataset

```
[ ]: df.head(6)
```

```
[ ]:    Index  Employed  Bank Balance  Annual Salary  Defaulted?
     0      1         1       8754.36      532339.56           0
     1      2         0       9806.16      145273.56           0
     2      3         1      12882.60      381205.68           0
     3      4         1       6351.00      428453.88           0
     4      5         1       9427.92      461562.00           0
     5      6         0      11035.08       89898.72           0
```

```
[ ]: df.columns
```

```
[ ]: Index(['Index', 'Employed', 'Bank Balance', 'Annual Salary', 'Defaulted?'],
     dtype='object')
```

```
[ ]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Index          10000 non-null  int64
 1   Employed       10000 non-null  int64
 2   Bank Balance   10000 non-null  float64
 3   Annual Salary  10000 non-null  float64
 4   Defaulted?     10000 non-null  int64
dtypes: float64(2), int64(3)
memory usage: 390.8 KB
```

Checking for missing data :

```
[ ]: # Missing Value
     df.isnull().sum()
```

```
[ ]: Index             0
     Employed          0
     Bank Balance      0
     Annual Salary     0
     Defaulted?        0
     dtype: int64
```

There are no missing values.

Checking for Duplicate Rows

```
[ ]: df.duplicated().sum()
```

```
[ ]: 0
```

0.0.3 Exploratory Data Analysis

```
[ ]: f_desc = round(df.describe().T, 2)
     f_desc
```

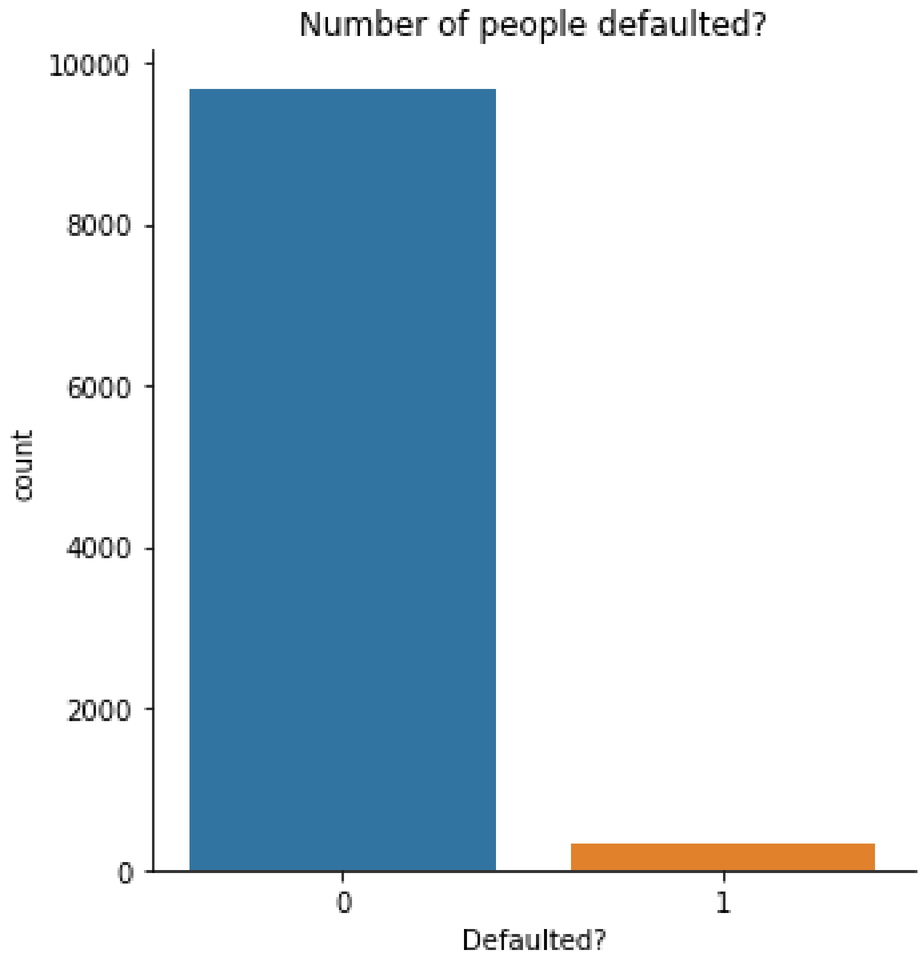
```
[ ]:
                  count       mean        std      min        25%        50%  \
Index           10000.0    5000.50    2886.90     1.00    2500.75    5000.50
Employed        10000.0       0.71       0.46     0.00       0.00       1.00
Bank Balance    10000.0   10024.50    5804.58     0.00    5780.79    9883.62
Annual Salary   10000.0  402203.78  160039.67  9263.64  256085.52  414631.74
Defaulted?      10000.0       0.03       0.18     0.00       0.00       0.00

                      75%        max
Index             7500.25   10000.00
Employed             1.00       1.00
Bank Balance     13995.66   31851.84
Annual Salary   525692.76  882650.76
Defaulted?           0.00       1.00
```

```
[ ]: # Target Class
     table = df['Defaulted?'].value_counts().reset_index()
     table.columns = ['Status', 'Number']
     table['Status'] = table['Status'].map({1 :'Defaulted', 0 :'Not defaulted'})
     print(table)
```

```
          Status  Number
0  Not defaulted    9667
1      Defaulted     333
```

[ ]:
```
# Target Class
sns.catplot(x = 'Defaulted?', kind='count', data = df)
plt.title('Number of people defaulted?')
```

[ ]: Text(0.5, 1.0, 'Number of people defaulted?')

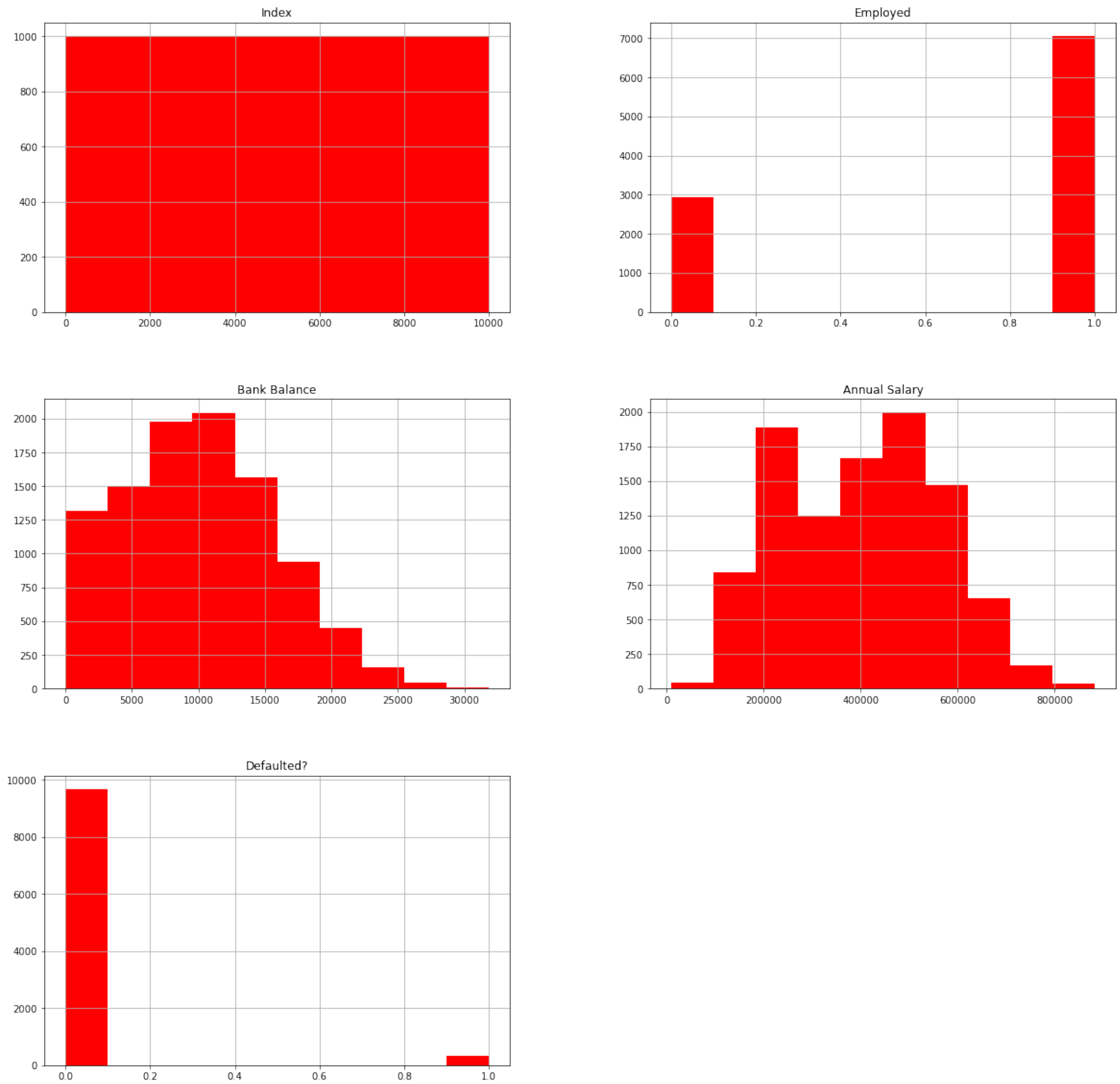


[ ]:
```
# 19020 data points with 4 features and 1 label column
df.shape
```

[ ]: (10000, 5)

Histogram Distribution Plot

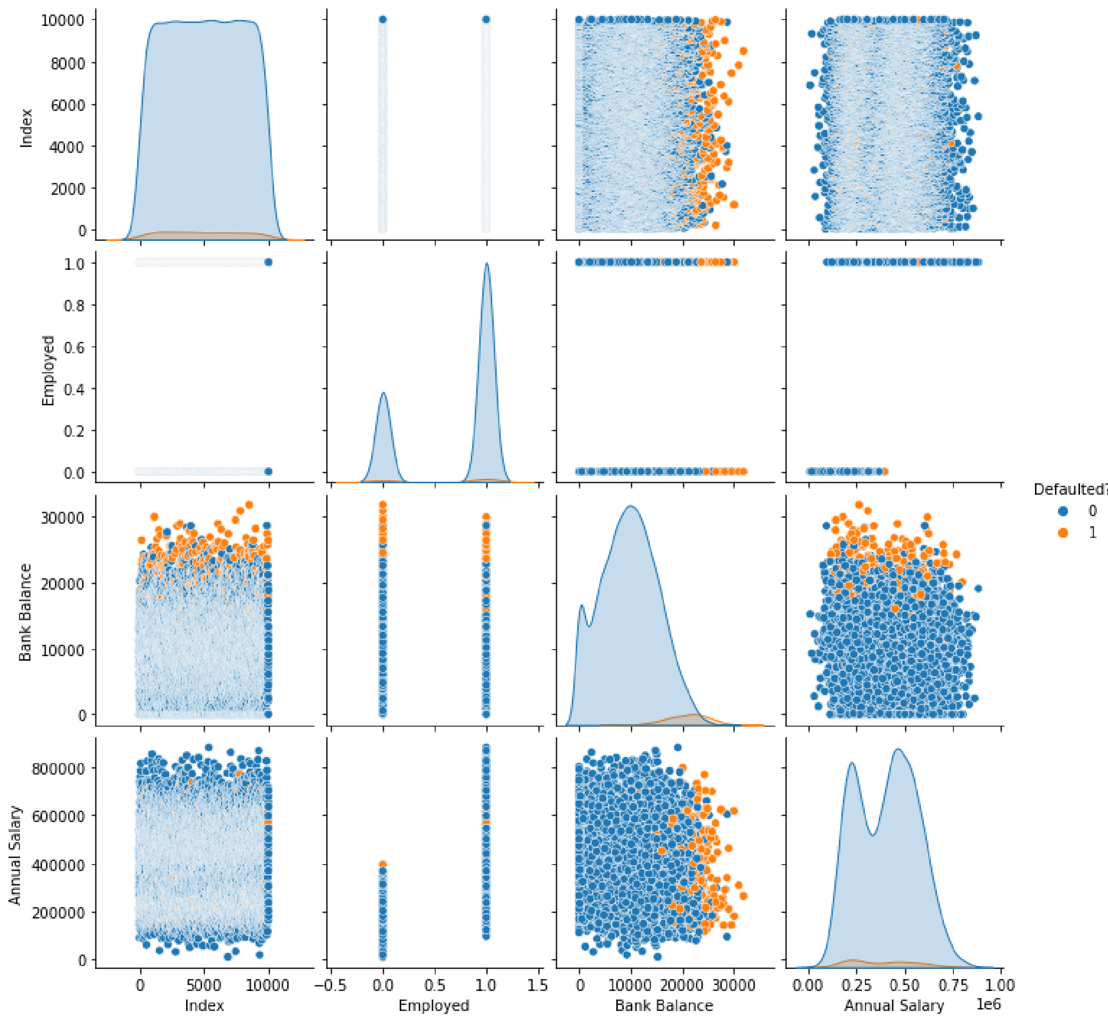
[ ]:
```
df.hist(figsize=(20,20), color='red')
plt.show()
```



Pair Plot

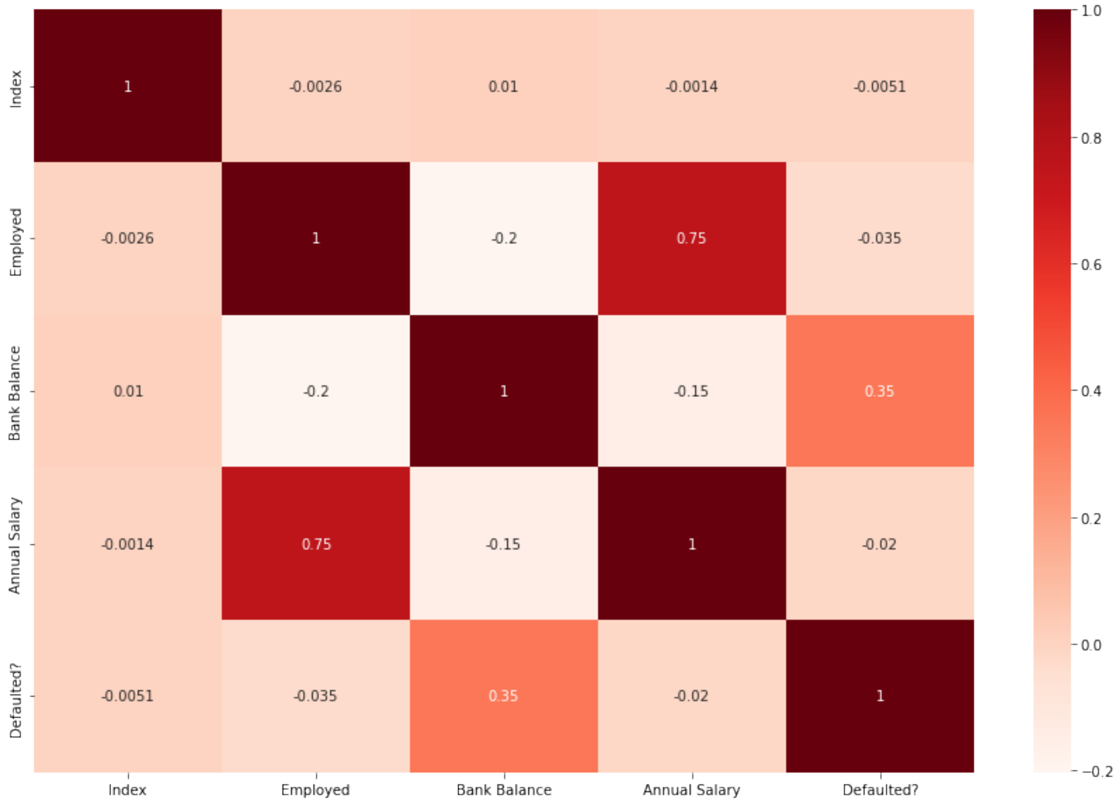
[ ]:
```
sns.pairplot(df, diag_kind='kde', hue = 'Defaulted?')
```

[ ]: <seaborn.axisgrid.PairGrid at 0x7fb32c897400>



Correlation Plot

[ ]:
```
#Using Pearson Correlation
plt.figure(figsize=(15,10))
corr = df.corr()

sns.heatmap(corr, annot=True, cmap=plt.cm.Reds)
plt.show()
```



Correlation Map

0.0.4 Split Data into different Training and Test Dataset (75% Training Data / 25% Test or validation Data)

[ ]:
```
X = df.drop(columns='Defaulted?')
y = df['Defaulted?']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25)
print("Shape of X_train: ",X_train.shape)
print("Shape of X_test: ", X_test.shape)
print("Shape of y_train: ",y_train.shape)
print("Shape of y_test",y_test.shape)
```

```
Shape of X_train:  (7500, 4)
Shape of X_test:  (2500, 4)
Shape of y_train:  (7500,)
Shape of y_test (2500,)
```

Feature Scaling

[ ]:
```
scaler = StandardScaler()
```

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

0.0.5 Upsampling by SMOTE

In the EDA part, we know that defaulted cases only take about 3% of the samples.

This imbalanced dataset may cause problem for classification models when they try to minimize the cost function.

So we introduce SMOTE upsampling method to rebablance the dataset.

[ ]:
```
X_train.shape, X_test.shape
```

[ ]: ((7500, 4), (2500, 4))

[ ]:
```
y_train.value_counts()
```

[ ]:
```
0    7255
1     245
Name: Defaulted?, dtype: int64
```

[ ]:
```
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=6)
X_train, y_train = sm.fit_resample(X_train, y_train)
```

[ ]:
```
X_train.shape, y_train.shape
```

[ ]: ((14510, 4), (14510,))

[ ]:
```
y_train.value_counts()
```

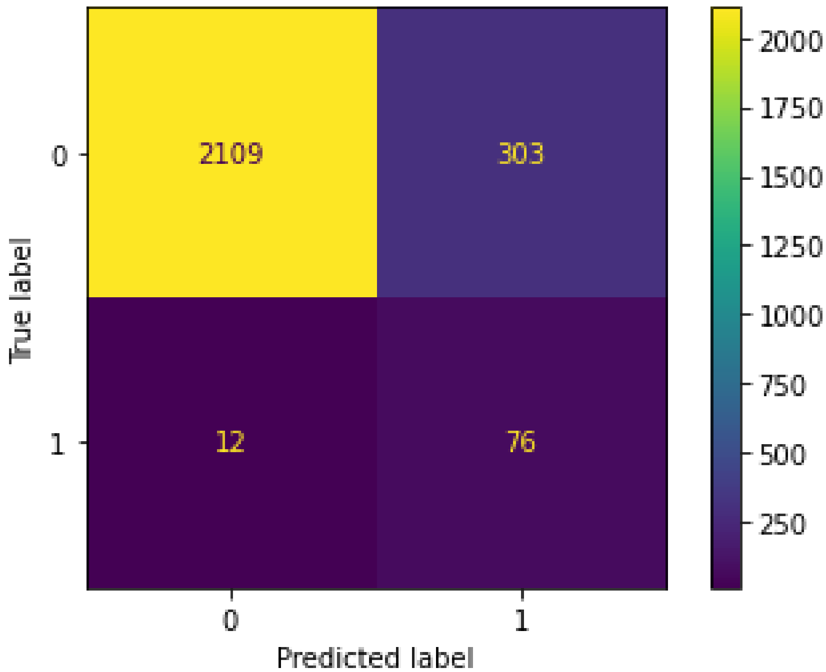
[ ]:
```
0    7255
1    7255
Name: Defaulted?, dtype: int64
```

0.0.6 Logistic Regression

[ ]:
```
lr_model = LogisticRegression(solver='saga',random_state=6)
lr_model.fit(X_train, y_train)

cv_lr = cross_val_score(estimator=lr_model, X=X_train, y =y_train.ravel(),␣
 ↪cv=10)
print("Cross Validation Score for Naive Bayes Model: ", cv_lr.mean())

lr_accuracy_train = accuracy_score(y_train, lr_model.predict(X_train))
print(f"Accuracy with Training data: {lr_accuracy_train}")
```

```
lr_y_pred = lr_model.predict(X_test)
lr_accuracy_test = accuracy_score(y_test, lr_y_pred)
print(f"Accuracy with test data: {lr_accuracy_test}")


print("Confusion Matrix for Naive Bayes Model: ")
cm_lr = confusion_matrix(y_test, lr_y_pred)
print(cm_lr)
print("Classification Report for Naive Bayes model: ")
print(classification_report(y_test, lr_y_pred))

disp = ConfusionMatrixDisplay(confusion_matrix=cm_lr, display_labels=lr_model.
 ↪classes_)
disp.plot()

tp_lr = cm_lr[0,0]
fp_lr = cm_lr[0,1]
tn_lr = cm_lr[1,1]
fn_lr = cm_lr[1,0]
```

```
Cross Validation Score for Naive Bayes Model:  0.8866988283942108
Accuracy with Training data: 0.8867677463818057
Accuracy with test data: 0.874
Confusion Matrix for Naive Bayes Model:
[[2109  303]
 [  12   76]]
Classification Report for Naive Bayes model:
              precision    recall  f1-score   support

           0       0.99      0.87      0.93      2412
           1       0.20      0.86      0.33        88

    accuracy                           0.87      2500
   macro avg       0.60      0.87      0.63      2500
weighted avg       0.97      0.87      0.91      2500
```

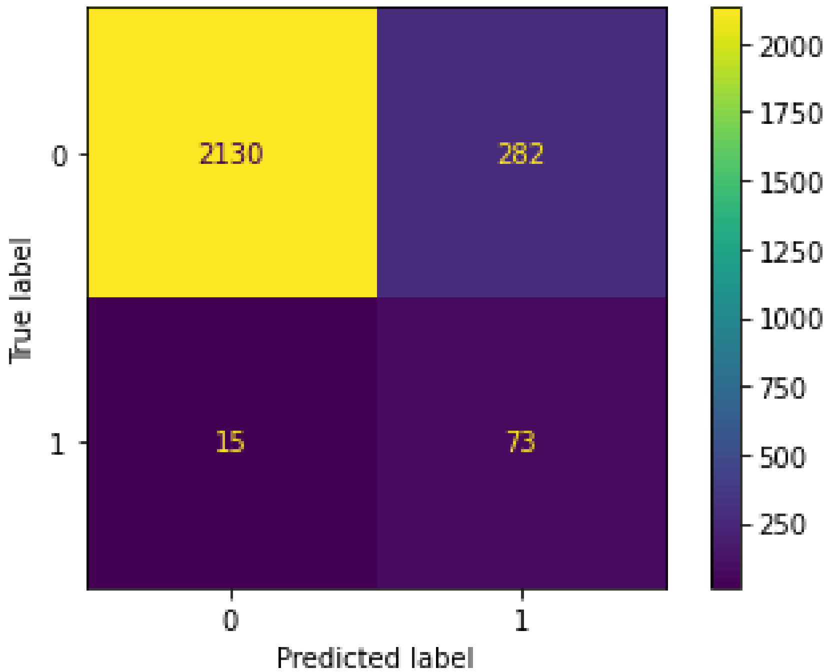


0.0.7 Random Forest Classifier model

[ ]:
```
rf_model = RandomForestClassifier(
    n_estimators=500,
    max_depth=6,
    random_state=6,
    )

rf_model.fit(X_train, y_train)


cv_rf = cross_val_score(estimator=rf_model, X=X_train, y=y_train.ravel(), cv=10)
print("Cross Validation Score for RandomForest Classifier Model: ", cv_rf.
 ↪mean())

rf_accuracy_train = accuracy_score(y_train, rf_model.predict(X_train))
print(f"Accuracy with Training data: {rf_accuracy_train}")

rf_y_pred = rf_model.predict(X_test)
rf_accuracy_test = accuracy_score(y_test, rf_y_pred)
print(f"Accuracy with test data: {rf_accuracy_test}")


print("Confusion Matrix for RandomForest Classifier Model: ")
```

```
cm_rf = confusion_matrix(y_test, rf_y_pred)
print(cm_rf)
print("Classification Report for RandomForest Classifier model: ")
print(classification_report(y_test, rf_y_pred))

disp = ConfusionMatrixDisplay(confusion_matrix=cm_rf, display_labels=rf_model.
 ↪classes_)
disp.plot()

tp_rf = cm_rf[0,0]
fp_rf = cm_rf[0,1]
tn_rf = cm_rf[1,1]
fn_rf = cm_rf[1,0]
```

```
Cross Validation Score for RandomForest Classifier Model:  0.8995175740868367
Accuracy with Training data: 0.906685044796692
Accuracy with test data: 0.8812
Confusion Matrix for RandomForest Classifier Model:
[[2130  282]
 [  15   73]]
Classification Report for RandomForest Classifier model:
              precision    recall  f1-score   support

           0       0.99      0.88      0.93      2412
           1       0.21      0.83      0.33        88

    accuracy                           0.88      2500
   macro avg       0.60      0.86      0.63      2500
weighted avg       0.97      0.88      0.91      2500
```

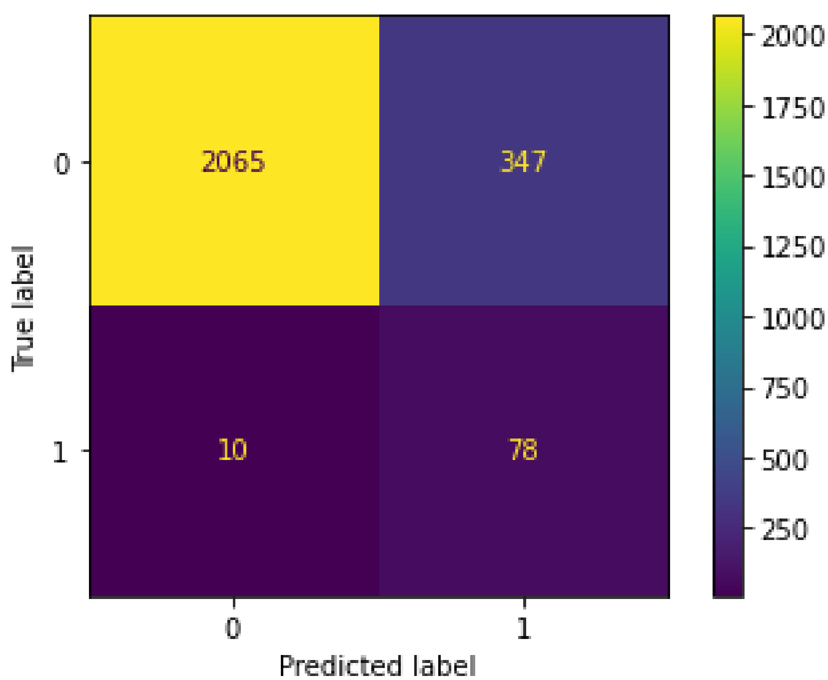


0.0.8 Naive Bayes Model

[ ]:
```
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)

cv_nb = cross_val_score(estimator=nb_model, X=X_train, y =y_train.ravel(),␣
 ↪cv=10)
print("Cross Validation Score for Naive Bayes Model: ", cv_nb.mean())

nb_accuracy_train = accuracy_score(y_train, nb_model.predict(X_train))
print(f"Accuracy with Training data: {nb_accuracy_train}")

nb_y_pred = nb_model.predict(X_test)
nb_accuracy_test = accuracy_score(y_test, nb_y_pred)
print(f"Accuracy with test data: {nb_accuracy_test}")


print("Confusion Matrix for Naive Bayes Model: ")
cm_nb = confusion_matrix(y_test, nb_y_pred)
print(cm_nb)
print("Classification Report for Naive Bayes model: ")
print(classification_report(y_test, nb_y_pred))
```

```
disp = ConfusionMatrixDisplay(confusion_matrix=cm_nb, display_labels=nb_model.
 ↪classes_)
disp.plot()

tp_nb = cm_nb[0,0]
fp_nb = cm_nb[0,1]
tn_nb = cm_nb[1,1]
fn_nb = cm_nb[1,0]
```

```
Cross Validation Score for Naive Bayes Model:  0.8787732598208133
Accuracy with Training data: 0.879117849758787
Accuracy with test data: 0.8572
Confusion Matrix for Naive Bayes Model:
[[2065  347]
 [  10   78]]
Classification Report for Naive Bayes model:
              precision    recall  f1-score   support

           0       1.00      0.86      0.92      2412
           1       0.18      0.89      0.30        88

    accuracy                           0.86      2500
   macro avg       0.59      0.87      0.61      2500
weighted avg       0.97      0.86      0.90      2500
```



Measuring The Error and Comparing Metrics

[ ]:
```
models = [
    ('Logistic Regression', tp_lr, fp_lr, tn_lr, fn_lr, lr_accuracy_train,␣
 ↪lr_accuracy_test, cv_lr.mean()),
    ('Naive Bayes', tp_nb, fp_nb, tn_nb, fn_nb, nb_accuracy_train,␣
 ↪nb_accuracy_test, cv_nb.mean()),
    ('Random Forest', tp_rf, fp_rf, tn_rf, fn_rf, rf_accuracy_train,␣
 ↪rf_accuracy_test, cv_rf.mean(),)
]
predict = pd.DataFrame(data = models, columns=['Model', 'True Positive', 'False␣
 ↪Positive', 'True Negative',
                                               'False Negative',␣
 ↪'Accuracy(training)', 'Accuracy(test)',
                                               'Cross-Validation'])

predict.T
```

[ ]:

	0	1	2
Model	Logistic Regression	Naive Bayes	Random Forest
True Positive	2109	2065	2130
False Positive	303	347	282
True Negative	76	78	73
False Negative	12	10	15
Accuracy(training)	0.886768	0.879118	0.906685
Accuracy(test)	0.874	0.8572	0.8812
Cross-Validation	0.886699	0.878773	0.899518

[ ]:
```

```

Using GridSearchCV to Propose optimal values for the depth and number of trees in the random forest

[ ]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import StratifiedKFold
param_grid = {
    "n_estimators": [500, 600, 1000],
    "max_depth": [6, 8],
}

rf_model = RandomForestClassifier(
    random_state=6,
    )

kfold = StratifiedKFold(n_splits=10, shuffle=True, random_state=6)

grid_search = GridSearchCV(rf_model, param_grid, n_jobs=-1, cv=kfold)
new_rf_model = grid_search.fit(X_train, y_train)
```

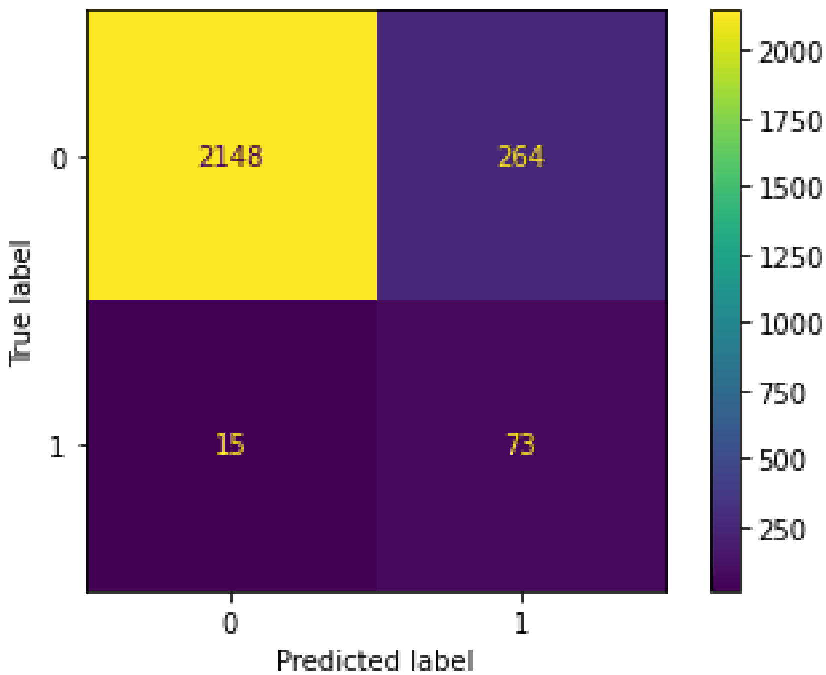
[ ]:
```
best_rf_results = new_rf_model.best_params_
print(best_rf_results)
```

```
{'max_depth': 8, 'n_estimators': 300}
```

[ ]:
```
new_rf_model = RandomForestClassifier(
    n_estimators=best_rf_results["n_estimators"],
    max_depth=best_rf_results["max_depth"],
    random_state=6,
    )

new_rf_model.fit(X_train, y_train)


new_cv_rf = cross_val_score(estimator=new_rf_model, X=X_train, y =y_train.
 ↪ravel(), cv=10)
print("Cross Validation Score for RandomForest Classifier Model: ", new_cv_rf.
 ↪mean())

new_rf_accuracy_train = accuracy_score(y_train, new_rf_model.predict(X_train))
print(f"Accuracy with Training data: {new_rf_accuracy_train}")

new_rf_y_pred = new_rf_model.predict(X_test)
new_rf_accuracy_test = accuracy_score(y_test, new_rf_y_pred)
print(f"Accuracy with test data: {new_rf_accuracy_test}")


print("Confusion Matrix for RandomForest Classifier Model: ")
new_cm_rf = confusion_matrix(y_test, new_rf_y_pred)
print(cm_rf)
print("Classification Report for RandomForest Classifier model: ")
print(classification_report(y_test, new_rf_y_pred))

disp = ConfusionMatrixDisplay(confusion_matrix=new_cm_rf,␣
 ↪display_labels=new_rf_model.classes_)
disp.plot()


new_tp_rf = new_cm_rf[0,0]
new_fp_rf = new_cm_rf[0,1]
new_tn_rf = new_cm_rf[1,1]
new_fn_rf = new_cm_rf[1,0]
```

```
Cross Validation Score for RandomForest Classifier Model:  0.9168849069607168
Accuracy with Training data: 0.9286009648518263
Accuracy with test data: 0.8884
Confusion Matrix for RandomForest Classifier Model:
```

```
[[2130  282]
 [  15   73]]
Classification Report for RandomForest Classifier model:
              precision    recall  f1-score   support

           0       0.99      0.89      0.94      2412
           1       0.22      0.83      0.34        88

    accuracy                           0.89      2500
   macro avg       0.60      0.86      0.64      2500
weighted avg       0.97      0.89      0.92      2500
```



[ ]:
```
models = [
    ('Logistic Regression', tp_lr, fp_lr, tn_lr, fn_lr, lr_accuracy_train,␣
 ↪lr_accuracy_test, cv_lr.mean()),
    ('Naive Bayes', tp_nb, fp_nb, tn_nb, fn_nb, nb_accuracy_train,␣
 ↪nb_accuracy_test, cv_nb.mean()),
    ('Random Forest (Before Improvement)', tp_rf, fp_rf, tn_rf, fn_rf,␣
 ↪rf_accuracy_train, rf_accuracy_test, cv_rf.mean()),
    ('Random Forest (After Improvement)', new_tp_rf, new_fp_rf, new_tn_rf,␣
 ↪new_fn_rf, new_rf_accuracy_train, new_rf_accuracy_test, new_cv_rf.mean()),

]
```

```
predict = pd.DataFrame(data = models, columns=['Model', 'True Positive', 'False␣
↪Positive', 'True Negative',
                                             'False Negative',␣
↪'Accuracy(training)', 'Accuracy(test)',
                                             'Cross-Validation'])

predict.T
```

[ ]:

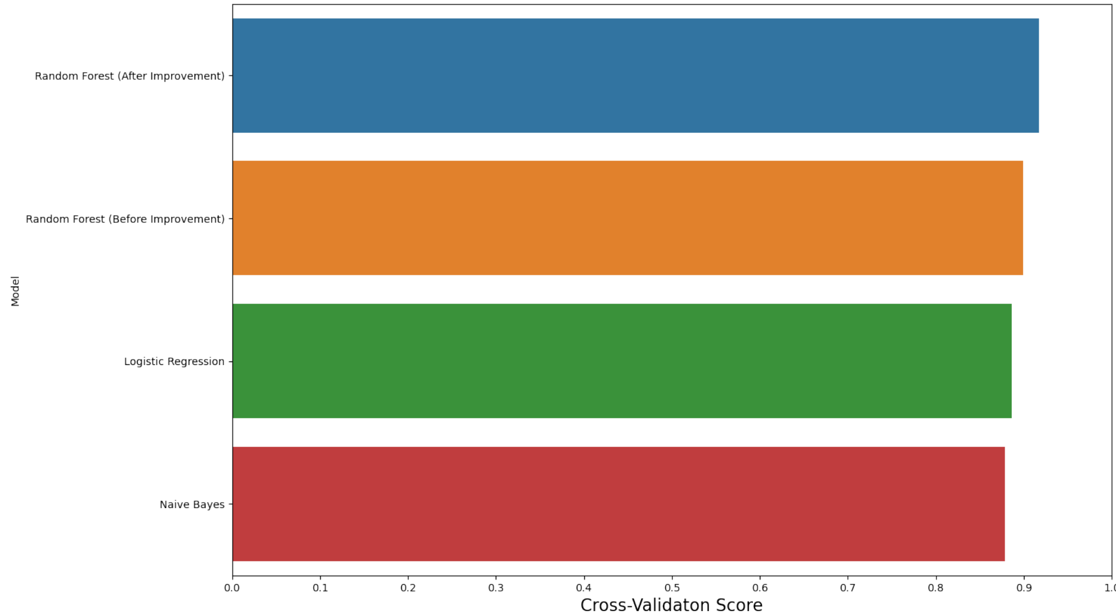
```
                                      0            1  \
Model                Logistic Regression  Naive Bayes
True Positive                       2109         2065
False Positive                       303          347
True Negative                         76           78
False Negative                        12           10
Accuracy(training)              0.886768     0.879118
Accuracy(test)                     0.874       0.8572
Cross-Validation                0.886699     0.878773

                                                2  \
Model                Random Forest (Before Improvement)
True Positive                                  2130
False Positive                                  282
True Negative                                    73
False Negative                                   15
Accuracy(training)                         0.906685
Accuracy(test)                               0.8812
Cross-Validation                           0.899518

                                               3
Model                Random Forest (After Improvement)
True Positive                                 2148
False Positive                                 264
True Negative                                   73
False Negative                                  15
Accuracy(training)                        0.928601
Accuracy(test)                              0.8884
Cross-Validation                          0.916885
```

0.0.9 Visualizing Models Performance

[ ]:

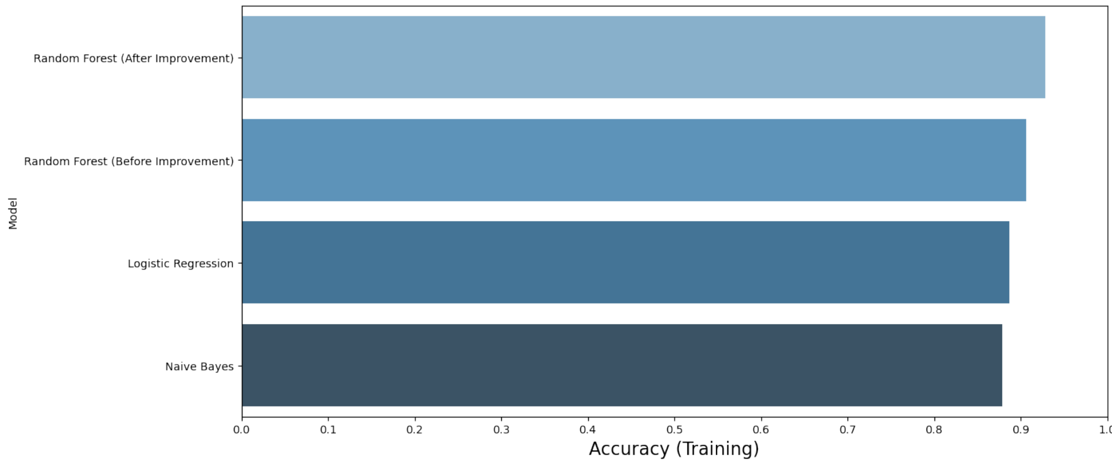
```
f, axe = plt.subplots(1,1, figsize=(15,10),dpi=100)

predict.sort_values(by=['Cross-Validation'], ascending=False, inplace=True)

sns.barplot(x='Cross-Validation', y='Model', data = predict, ax = axe)
#axes[0].set(xlabel='Region', ylabel='Charges')
axe.set_xlabel('Cross-Validaton Score', size=16)
```

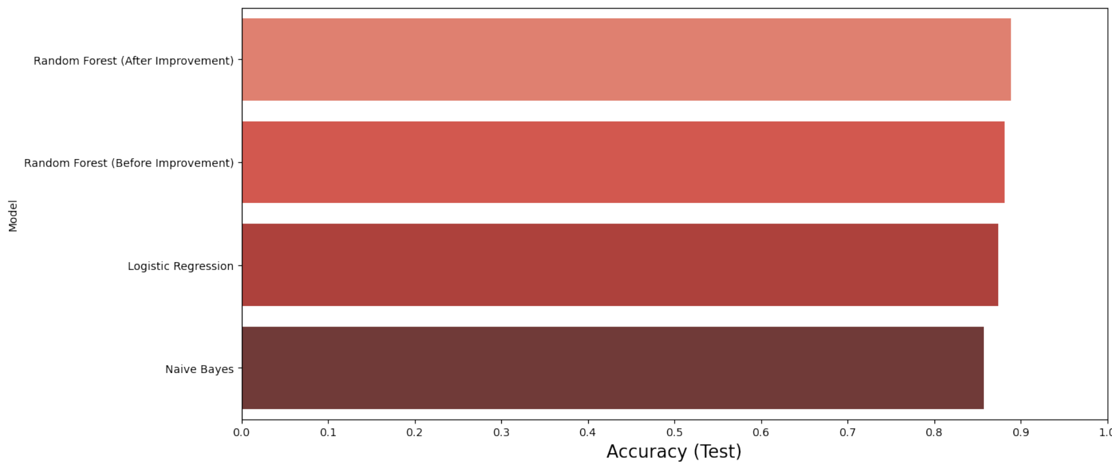
```
axe.set_ylabel('Model')
axe.set_xlim(0,1.0)
axe.set_xticks(np.arange(0, 1.1, 0.1))
plt.show()
```



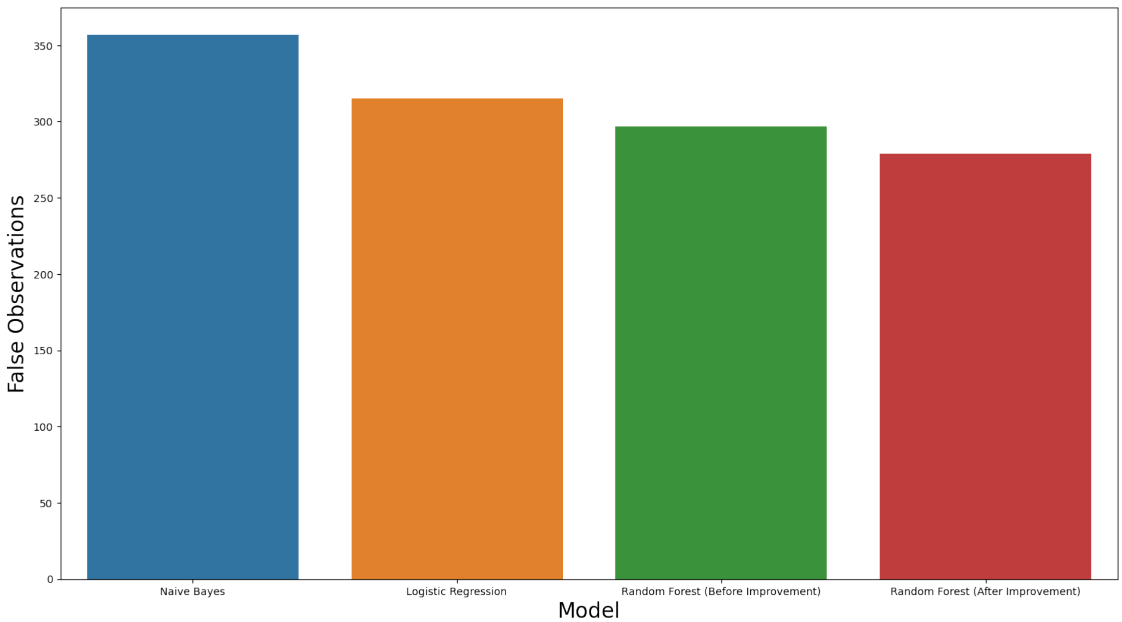
[ ]:
```
f, axes = plt.subplots(2,1, figsize=(14,15),dpi=100)

predict.sort_values(by=['Accuracy(training)'], ascending=False, inplace=True)

sns.barplot(x='Accuracy(training)', y='Model', data = predict,␣
↪palette='Blues_d', ax = axes[0])
#axes[0].set(xlabel='Region', ylabel='Charges')
axes[0].set_xlabel('Accuracy (Training)', size=16)
axes[0].set_ylabel('Model')
axes[0].set_xlim(0,1.0)
axes[0].set_xticks(np.arange(0, 1.1, 0.1))

predict.sort_values(by=['Accuracy(test)'], ascending=False, inplace=True)

sns.barplot(x='Accuracy(test)', y='Model', data = predict, palette='Reds_d', ax␣
↪= axes[1])
#axes[0].set(xlabel='Region', ylabel='Charges')
axes[1].set_xlabel('Accuracy (Test)', size=16)
axes[1].set_ylabel('Model')
axes[1].set_xlim(0,1.0)
axes[1].set_xticks(np.arange(0, 1.1, 0.1))
```

```
plt.show()
```





[ ]:
```
predict.sort_values(by=(['Accuracy(test)']), ascending=True, inplace=True)

f, axe = plt.subplots(1,1, figsize=(18,10), dpi=100)
sns.barplot(x = predict['Model'], y=predict['False Positive'] + predict['False␣
↪Negative'], ax = axe)
axe.set_xlabel('Model', size=20)
axe.set_ylabel('False Observations', size=20)

plt.show()
```



False Observations
350
300
250
200
150
100
50
0
Naive Bayes
Logistic Regression
Random Forest (Before Improvement)
Random Forest (After Improvement)
Model

[ ]: