

```

RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
RowNumber      10000 non-null int64
CustomerId     10000 non-null int64
Surname        10000 non-null object
CreditScore    10000 non-null int64
Geography      10000 non-null object
Gender         10000 non-null object
Age            10000 non-null int64
Tenure         10000 non-null int64
Balance        10000 non-null float64
NumOfProducts 10000 non-null int64
HasCrCard      10000 non-null int64
IsActiveMember 10000 non-null int64
EstimatedSalary 10000 non-null float64
Exited         10000 non-null int64
dtypes: float64(2), int64(9), object(3)

```

	CreditScore	Gender	...	IsActiveMember	EstimatedSalary
count	10000.000000	10000.000000	...	10000.000000	10000.000000
mean	650.528800	0.545700	...	0.515100	100090.239881
std	96.653299	0.497932	...	0.499797	57510.492818
min	350.000000	0.000000	...	0.000000	11.580000
25%	584.000000	0.000000	...	0.000000	51002.110000
50%	652.000000	1.000000	...	1.000000	100193.915000
75%	718.000000	1.000000	...	1.000000	149388.247500
max	850.000000	1.000000	...	1.000000	199992.480000

R code:

```
data.info()
```

We have 10,000 customer/entries in the dataset with information in above variables.

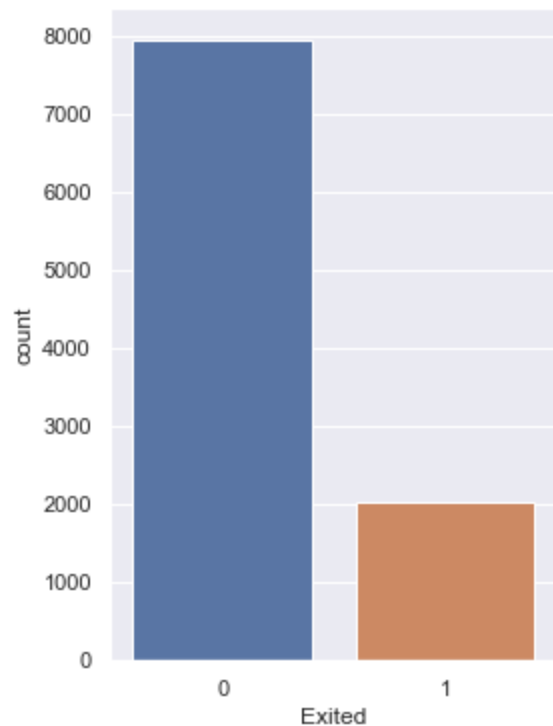
R code:

```

data.drop(['RowNumber', 'CustomerId', 'Surname', 'Geography'], axis=1, inplace=True)
data.Gender = [1 if each == 'Male' else 0 for each in data.Gender]

```

We do not need RowNumber, CustomerId, Surname, Geography so we drop those variables. We also change Gender data types from object to integer (binary in this case)



	CreditScore	Gender	Age	...	HasCrCard	IsActiveMember	EstimatedSalary
0	0.538	0.0	0.324324	...	1.0	1.0	0.506735
1	0.516	0.0	0.310811	...	0.0	1.0	0.562709
2	0.304	0.0	0.324324	...	1.0	0.0	0.569654
3	0.698	0.0	0.283784	...	0.0	0.0	0.469120
4	1.000	0.0	0.337838	...	1.0	1.0	0.395400

We use the bar plot to graph the information of exited customer which is about 20% compared to the total customer. We also scale variables by using this function

$$(x_data - \text{np.min}(x_data)) / (\text{np.max}(x_data) - \text{np.min}(x_data))$$

R code:

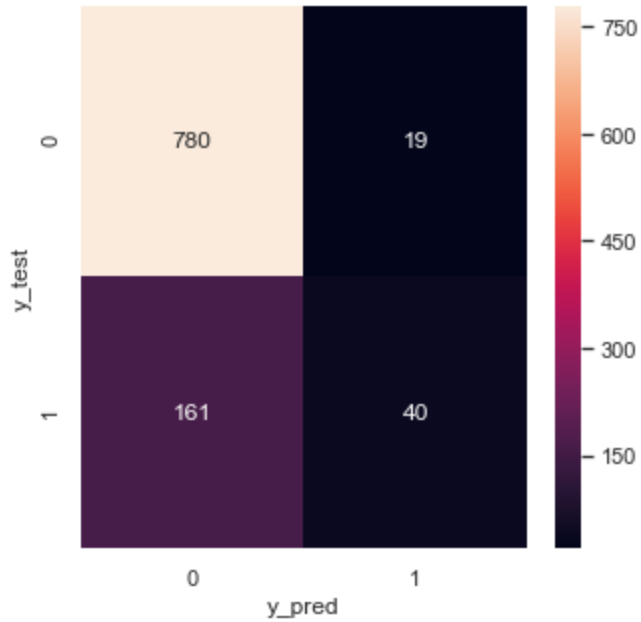
```
plt.figure(figsize=[4,6])
sns.set(style='darkgrid')
ax = sns.countplot(x='Exited', data=data)
print(data.loc[:, 'Exited'].value_counts())

y = data.Exited.values
x_data = data.drop(['Exited'], axis=1)
print(x_data.describe())
x = (x_data - np.min(x_data)) / (np.max(x_data) - np.min(x_data))
print(x.head())
```

PREDICTIVE

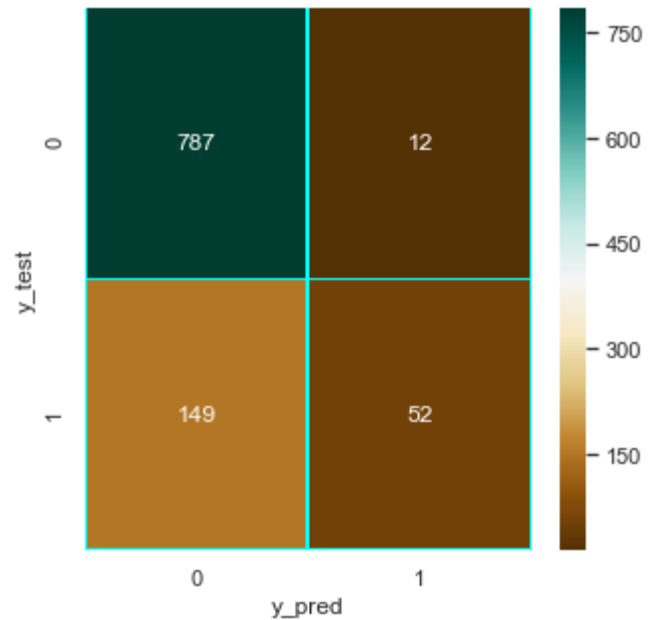
We compare the accuracy of many methods such as: Logistic Regression, KNN, SVM, Decision Tree, Random Forest by using Confusion Matrix.

Logistic Regression Classification Confusion Matrix



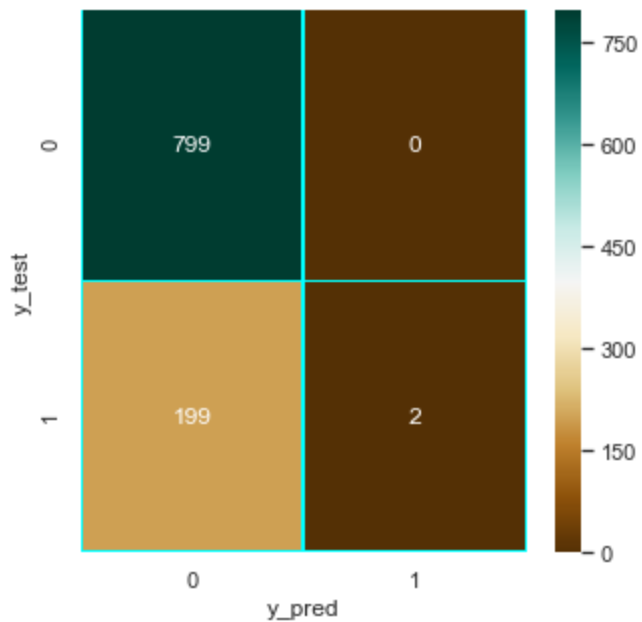
0.82

KNN Classification Confusion Matrix

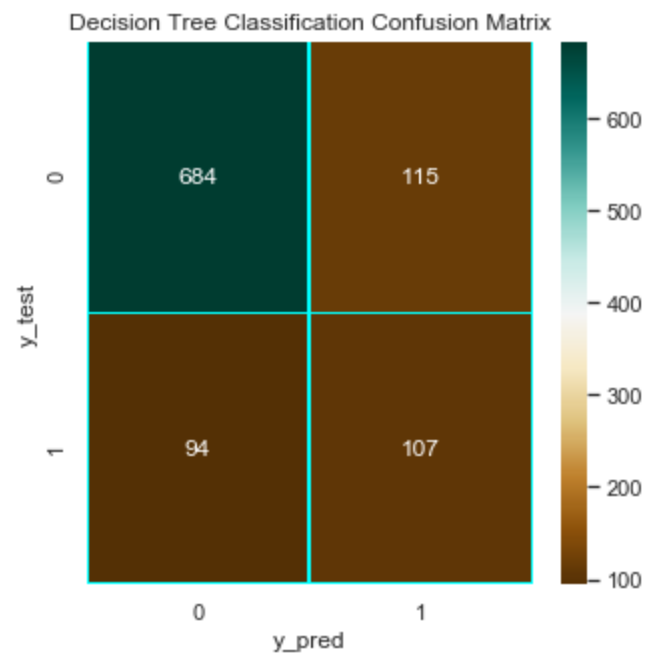


0.839

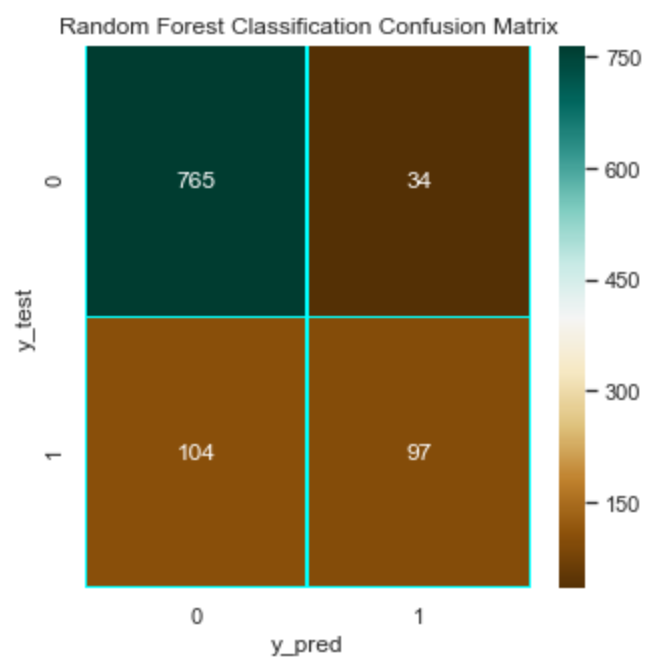
SVM Classification Confusion Matrix



0.801



0.791



0.862

The Random Forest method has the highest accuracy while the Decision Tree method has the lowest one.

R code:

```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.10, random_state=7)

print('x_train shape: ', x_train.shape)
print('y_train shape: ', y_train.shape)
print('x_test shape: ', x_test.shape)
print('y_test shape: ', y_test.shape)

from sklearn.linear_model import LogisticRegression

# Defining the model
lr = LogisticRegression()

# Training the model:
lr.fit(x_train, y_train)

# Predicting target values by using x_test and our model:
y_pred0 = lr.predict(x_test)

# Confusion matrix for visualization of our prediction accuracy:
from sklearn.metrics import confusion_matrix

# Creating the confusion matrix:
lr_cm = confusion_matrix(y_test, y_pred0)

#Visualization:
f, ax = plt.subplots(figsize=(5,5))
sns.heatmap(lr_cm, annot=True, fmt='.0f')
plt.title('Logistic Regression Classification Confusion Matrix')
plt.xlabel('y_pred')
plt.ylabel('y_test')
plt.show()

score_lr = lr.score(x_test, y_test)
print(score_lr)
```