a0201746_YuShing_Lui

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0.0.1 Machine Learning CIS4035-N-FJ1-2020

0.0.2 YU SHING LUI

0.0.3 a0201746@tees.ac.uk

1 Data Analysis on Predicting Churn for Bank Customers

Data Source: https://www.kaggle.com/shrutimechlearn/churn-modelling

[3]:
```
#Mathematical operations
import numpy as np

#Data manipulation
import pandas as pd

#Data visulaization
import matplotlib.pyplot as plt
import seaborn as sns

#Scaling, for standardizatiom
from sklearn. preprocessing import StandardScaler, MinMaxScaler

#Splitting data libraries and finding the best parameters
from sklearn.model_selection import train_test_split, GridSearchCV

#Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier

#Finding accuracy score, confusion matrix
from sklearn.metrics import accuracy_score, confusion_matrix,␣
↪plot_confusion_matrix

#Logistic Regression for calssification
from sklearn.linear_model import LogisticRegression

#Evaluate a model
from sklearn.metrics import classification_report

#Gradient Boosting
```

```python
from sklearn.ensemble import GradientBoostingClassifier
```

[4]:
```python
#Loading the dataset

dataset = pd.read_csv('churn_for_bank_customers.csv')

df = pd.DataFrame(dataset)
```

[5]:
```python
#Showing how many rows and columns in the dataset

df.shape
```

[5]: (10000, 14)

There are 10,000 rows and 14 columns

[6]:
```python
#Showing the first five rows of data

df.head()
```

[6]:
```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age  \
0          1    15634602  Hargrave          619    France  Female   42
1          2    15647311      Hill          608     Spain  Female   41
2          3    15619304      Onio          502    France  Female   42
3          4    15701354      Boni          699    France  Female   39
4          5    15737888  Mitchell          850     Spain  Female   43

   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1
1       1   83807.86              1          0               1
2       8  159660.80              3          1               0
3       1       0.00              2          0               0
4       2  125510.82              1          1               1

   EstimatedSalary  Exited
0        101348.88       1
1        112542.58       0
2        113931.57       1
3         93826.63       0
4         79084.10       0
```

Features for the dataset

RowNumber — the row number

CustomerId — unique number for the customer in the bank

Surname — the surname of a customer

CreditScore — how many credit score for the customer

Geography — the customer's location

Gender — Male or Female for the customer

Age - how old for the customer

Tenure — number of years for the customer using for the bank

Balance - how much money the customer has in the bank

NumOfProducts - the number of products the customer has in the bank

HasCrCard - does the customer has credit card or not

IsActiveMember - is it the active user in the bank

EstimatedSalary - how much the customer earns

Exited - the customer left the bank or not

[8]:
```
#Looking for the type of each attributes

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  int64
 11  IsActiveMember   10000 non-null  int64
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64
```

```
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

[9]:

```
#Checking any missing data in the dataset

df.isna().sum()
```

[9]:

```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

[10]:

```
#Exploratory dataset

round(df.describe(),2)
```

[10]:

```
       RowNumber   CustomerId  CreditScore       Age    Tenure    Balance  \
count   10000.00     10000.00     10000.00  10000.00  10000.00   10000.00
mean     5000.50  15690940.57       650.53     38.92      5.01   76485.89
std      2886.90     71936.19        96.65     10.49      2.89   62397.41
min         1.00  15565701.00       350.00     18.00      0.00       0.00
25%      2500.75  15628528.25       584.00     32.00      3.00       0.00
50%      5000.50  15690738.00       652.00     37.00      5.00   97198.54
75%      7500.25  15753233.75       718.00     44.00      7.00  127644.24
max     10000.00  15815690.00       850.00     92.00     10.00  250898.09

       NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary   Exited
count       10000.00   10000.00        10000.00         10000.00  10000.0
mean            1.53       0.71            0.52        100090.24      0.2
std             0.58       0.46            0.50         57510.49      0.4
min             1.00       0.00            0.00            11.58      0.0
25%             1.00       0.00            0.00         51002.11      0.0
50%             1.00       1.00            1.00        100193.92      0.0
75%             2.00       1.00            1.00        149388.25      0.0
max             4.00       1.00            1.00        199992.48      1.0
```

Understading the descriptive statistics from the dataset

CreditScore: the range of credit score is from 350 to 850

Age: the range of customer's age is from 18 to 92

Tenure: average a customer uses the bank over 5 years

NumOfProducts: overall most of customers has over one product in the bank

IsActiveMember: average over 50% of customers are still activating an account

Exited: around 20% customers exited a bank

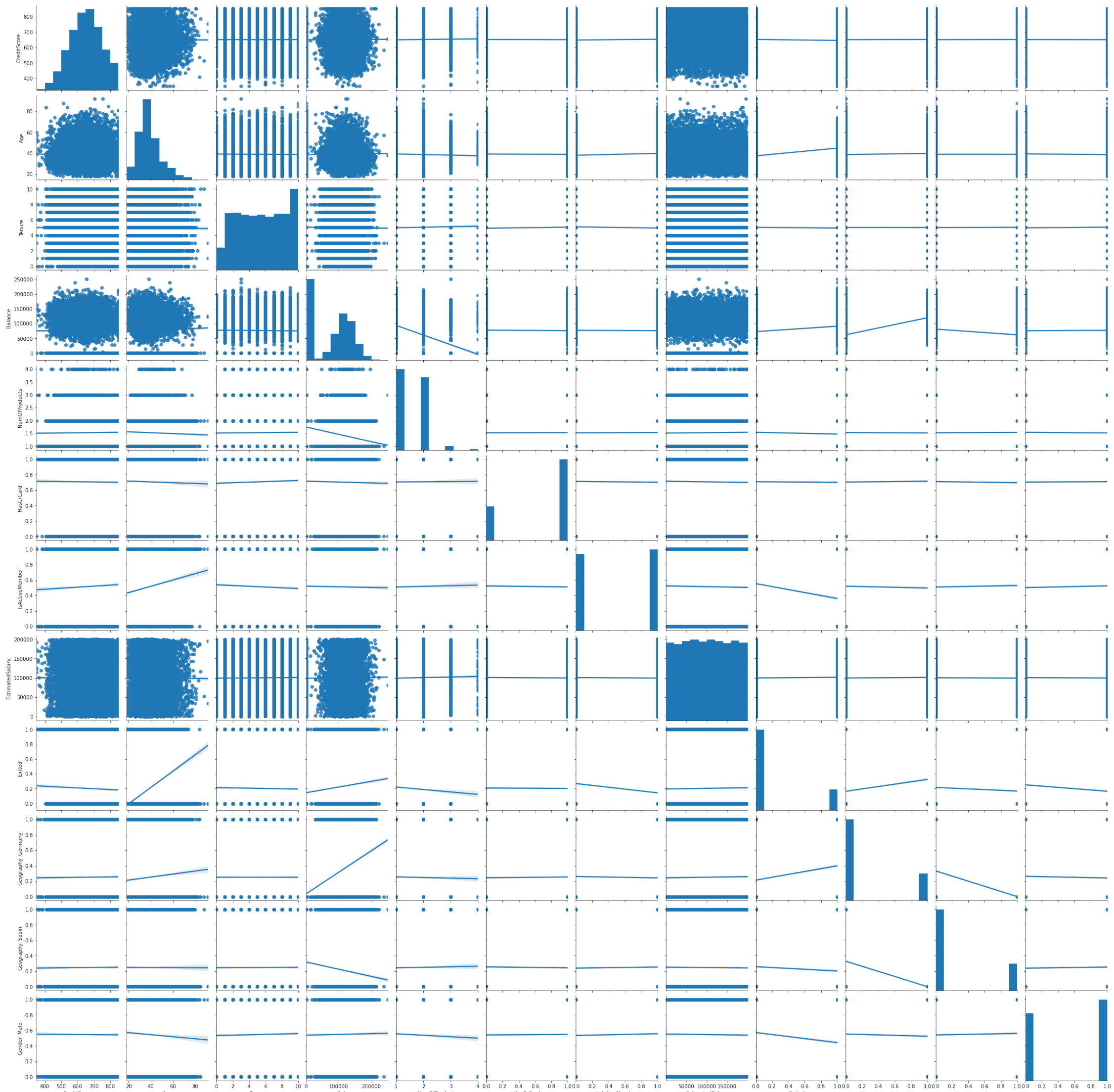
[12]:
```
#Drop those three columns as it is not necessary for analysing the dataset

df_edit=df.drop(['RowNumber','CustomerId','Surname'], axis=1)
```

[13]:
```
# Changing categorical values to numerical and avoiding dummy variable

df_edit_final = pd.get_dummies(df_edit, drop_first=True)

df_edit_final.head()
```

[13]:
```
   CreditScore  Age  Tenure    Balance  NumOfProducts  HasCrCard  \
0          619   42       2       0.00              1          1
1          608   41       1   83807.86              1          0
2          502   42       8  159660.80              3          1
3          699   39       1       0.00              2          0
4          850   43       2  125510.82              1          1

   IsActiveMember  EstimatedSalary  Exited  Geography_Germany  \
0               1        101348.88       1                  0
1               1        112542.58       0                  0
2               0        113931.57       1                  0
3               0         93826.63       0                  0
4               1         79084.10       0                  0

   Geography_Spain  Gender_Male
0                0            0
1                1            0
2                0            0
3                0            0
4                1            0
```

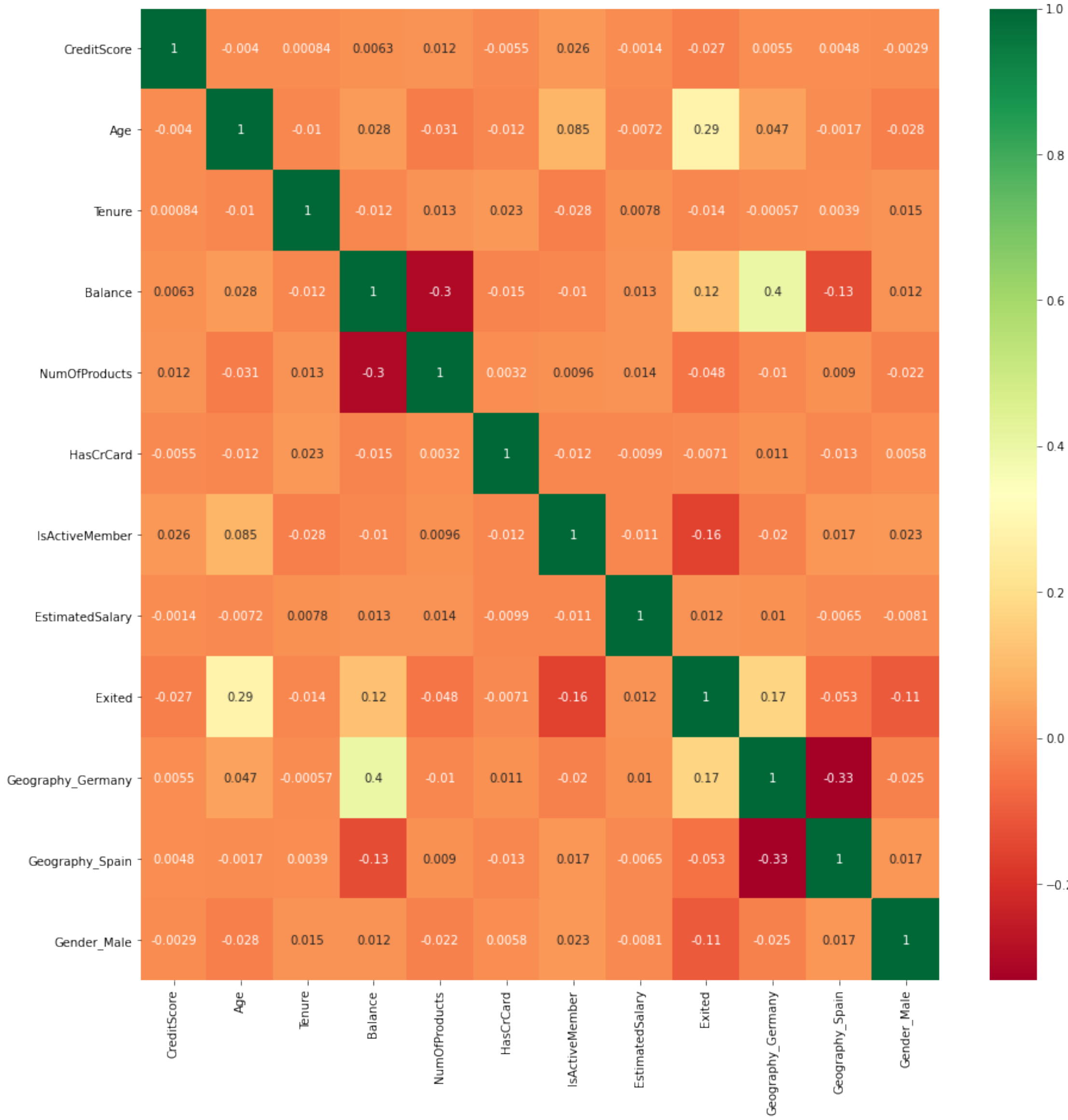
[14]:
```
# finding the relationsip about the features

sns.pairplot(df_edit_final, kind='reg')
```

[14]: <seaborn.axisgrid.PairGrid at 0x7f9c1e6afe80>



[15]:
```python
#Finding the correlations cross with the features

df_corr = df_edit_final.corr()
features = df_corr.index
plt.figure(figsize=(15,15))
sns.heatmap(df_edit_final[features].corr(), annot=True, cmap='RdYlGn')
```

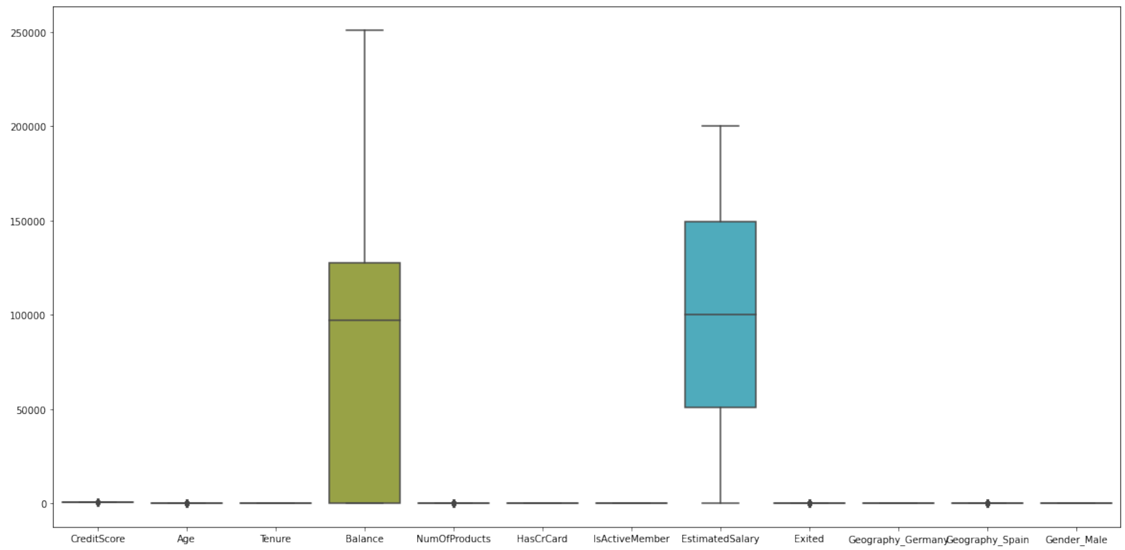
[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9c257f5df0>



According to the heatmap, the attributes of 'age', 'location' and 'balance' will affect by the attribute of 'exited'

[16]:
```python
# Using boxplot to show the dataframe

ax = plt.subplots(figsize=(20,10))
sns.boxplot(data=df_edit_final)
```

[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9c086363d0>



Balance and EstimatedSalary column's range are much hihger than the others, normalization is necessary

[17]:
```
#Dividing the dataset

X = df_edit_final.drop(['Exited'], axis=1)
y = df_edit_final['Exited']
```

Scaling the dataset

[18]:
```
# MinMaxScaler for min-max normalization

minMaxScaler = MinMaxScaler().fit(X)
X_processed = minMaxScaler.transform(X)

df_processed = pd.DataFrame(X_processed, columns=X.columns)
df_processed
```

[18]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	\
0	0.538	0.324324	0.2	0.000000	0.000000	1.0	
1	0.516	0.310811	0.1	0.334031	0.000000	0.0	
2	0.304	0.324324	0.8	0.636357	0.666667	1.0	
3	0.698	0.283784	0.1	0.000000	0.333333	0.0	
4	1.000	0.337838	0.2	0.500246	0.000000	1.0	
…	…	…	…	…	…	…	
9995	0.842	0.283784	0.5	0.000000	0.333333	1.0	
9996	0.332	0.229730	1.0	0.228657	0.000000	1.0	
9997	0.718	0.243243	0.7	0.000000	0.000000	0.0	
9998	0.844	0.324324	0.3	0.299226	0.333333	1.0	

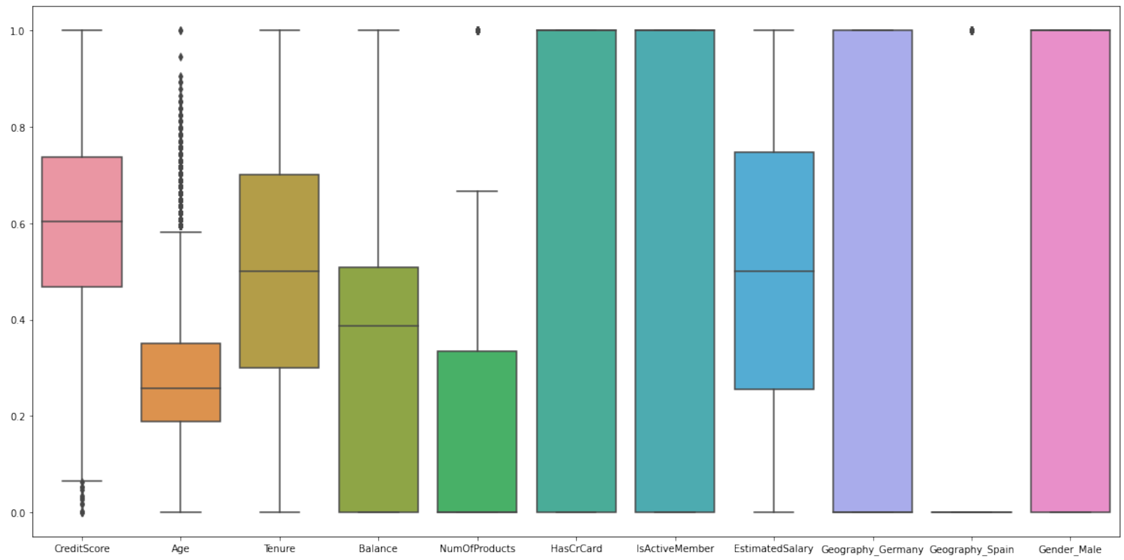
```
9999        0.884  0.135135     0.4  0.518708       0.000000        1.0

      IsActiveMember  EstimatedSalary  Geography_Germany  Geography_Spain  \
0                1.0         0.506735                0.0              0.0
1                1.0         0.562709                0.0              1.0
2                0.0         0.569654                0.0              0.0
3                0.0         0.469120                0.0              0.0
4                1.0         0.395400                0.0              1.0
…                  …              …                 …               …
9995             0.0         0.481341                0.0              0.0
9996             1.0         0.508490                0.0              0.0
9997             1.0         0.210390                0.0              0.0
9998             0.0         0.464429                1.0              0.0
9999             0.0         0.190914                0.0              0.0

      Gender_Male
0             0.0
1             0.0
2             0.0
3             0.0
4             0.0
…               …
9995          1.0
9996          1.0
9997          0.0
9998          1.0
9999          0.0

[10000 rows x 11 columns]
```

[19]:

```
# Showing the boxplot after min-max normalization

ax = plt.subplots(figsize=(20,10))
sns.boxplot(data=df_processed)
```

[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9c08b3bbb0>
```



All columns are the same range

[20]:
```
#Separating the dataset to training and testing data

X_train, X_test, y_train, y_test = train_test_split(X_processed, y, test_size=0.
↪2, random_state = 0)

X_train.shape
X_test.shape
```

X_train.shape #(8000,11)

X_test.shape #(2000,11)

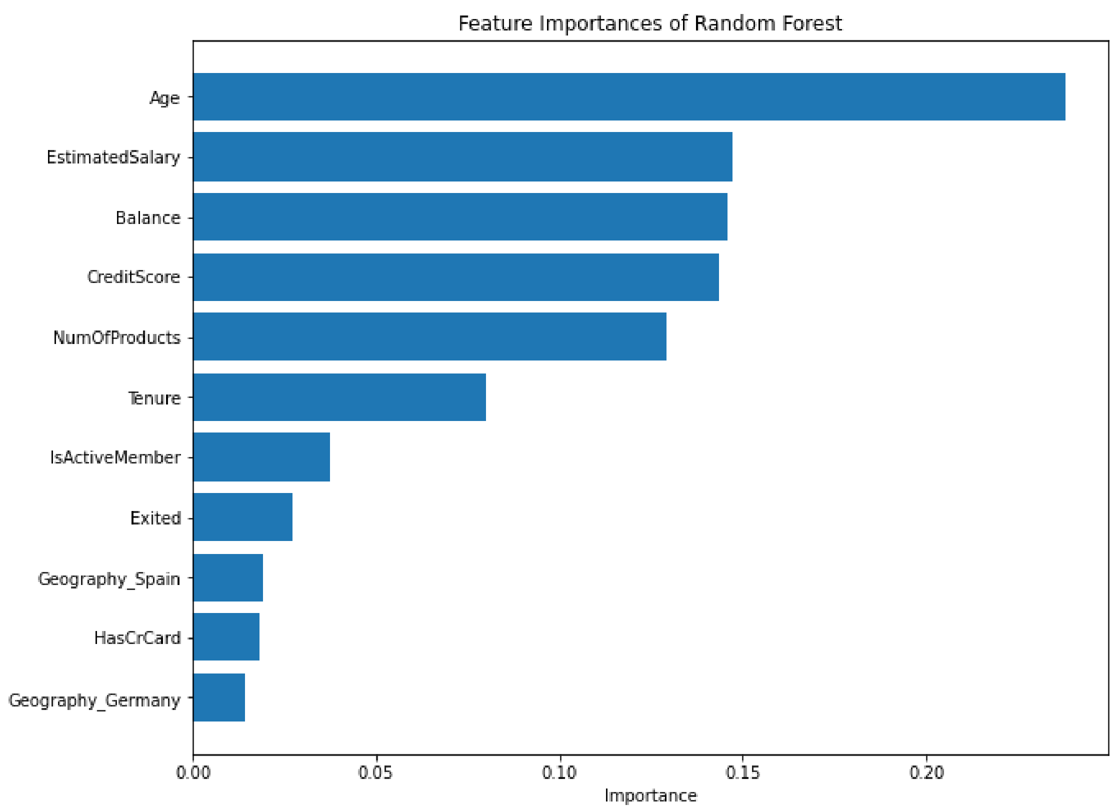
For the first prediction, let's use the Random Forest Classifier searching for the best parameters using the GridSearchCV function:

[21]:
```
# Using Random Forest Classifier

parameters = {'criterion': ['gini', 'entropy'], 'n_estimators': [50, 100, 300,␣
↪500]}

rfc = RandomForestClassifier()

search_rfc = GridSearchCV(rfc, parameters, cv = 5).fit(X_train, y_train)
```

[22]:
```
# Showing the best parameters

search_rfc.best_params_
```

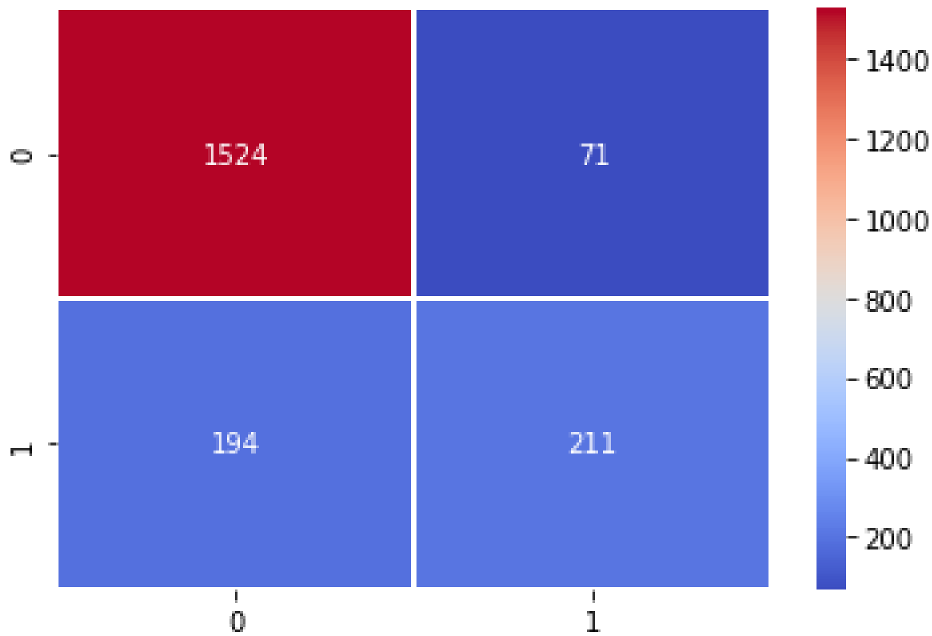
[22]: {'criterion': 'gini', 'n_estimators': 500}

[23]:
```
# Summarizing RandomForestClassifier calculated permutation feature importance

model_rfc = RandomForestClassifier(**search_rfc.best_params_).fit(X_train,␣
↪y_train)

importances = model_rfc.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize = (10, 8))
plt.title('Feature Importances of Random Forest')
plt.barh(range(len(indices)), importances[indices], align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Importance')
plt.show()
```



[24]:
```
# Showing confusion matrix heatmap

y_pred = model_rfc.predict(X_test)
cm_rfc=confusion_matrix(y_test,y_pred)
```

```
sns.heatmap(cm_rfc,cmap='coolwarm',annot=True,linewidth=1,fmt='d')
plt.show()
```



[25]:

```
# Finding the accuracy score

print(classification_report(y_test,y_pred))
print('The accuracy score is: ',accuracy_score(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.89      0.96      0.92      1595
           1       0.75      0.52      0.61       405

    accuracy                           0.87      2000
   macro avg       0.82      0.74      0.77      2000
weighted avg       0.86      0.87      0.86      2000

The accuracy score is:  0.8675
```

[26]:

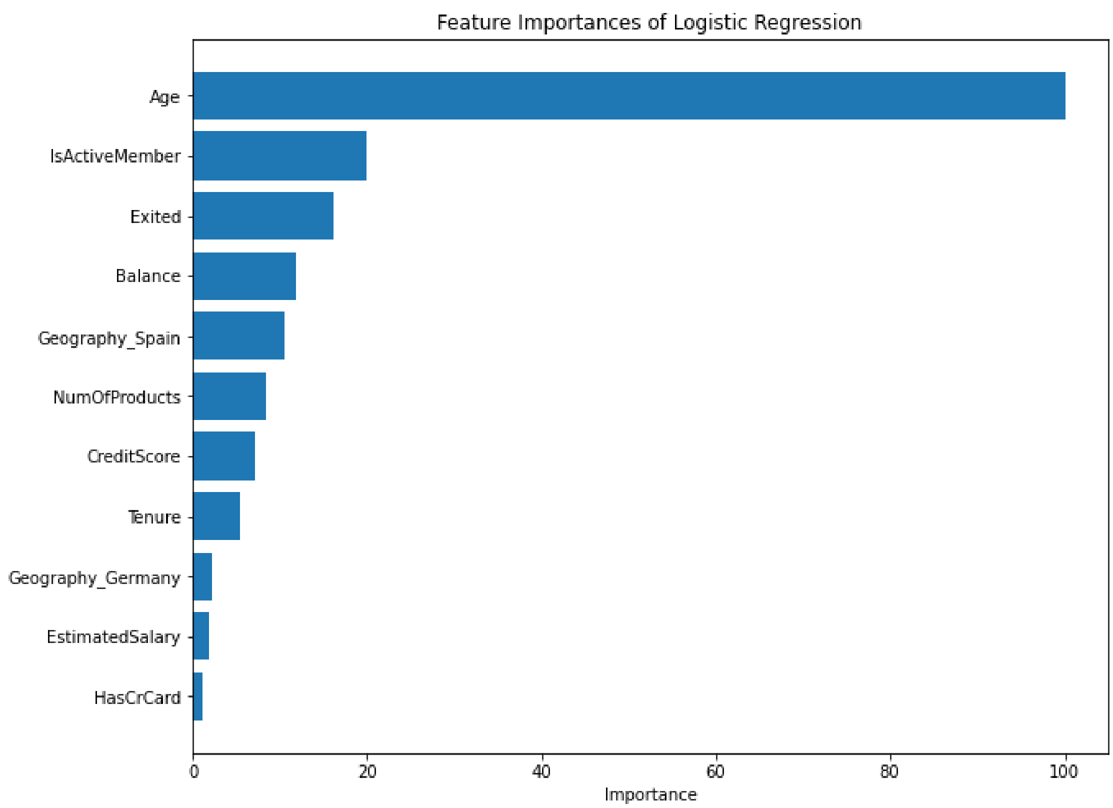
```
# Using Logistic Regression

parameters = {'C': [0.01, 0.1, 1, 10], 'solver': ['newton-cg', 'lbfgs',␣
↪'liblinear', 'sag', 'saga'], 'max_iter': range(50,150)}

lr = LogisticRegression()
```

```
search_lr = GridSearchCV(lr, parameters, cv = 5).fit(X_train, y_train)
```

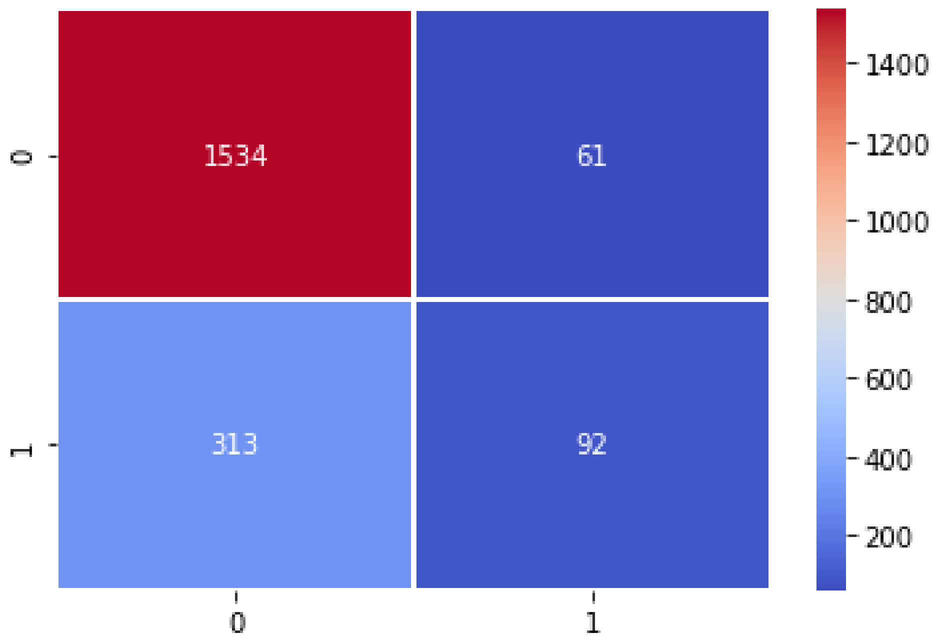
[27]:
```
# Showing the best parameters

search_lr.best_params_
```

[27]: {'C': 1, 'max_iter': 50, 'solver': 'newton-cg'}

[28]:
```
# Summarizing Logistic Regression calculated permutation feature importance

model_lr = LogisticRegression(**search_lr.best_params_).fit(X_train, y_train)

importances = abs(model_lr.coef_[0])
importances = 100.0 * (importances / importances.max())
indices = np.argsort(importances)

plt.figure(figsize = (10, 8))
plt.title('Feature Importances of Logistic Regression')
plt.barh(range(len(indices)), importances[indices], align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Importance')
plt.show()
```



[29]:
```python
# Showing confusion matrix heatmap

y_pred = model_lr.predict(X_test)
cm_lr=confusion_matrix(y_test,y_pred)
sns.heatmap(cm_lr,cmap='coolwarm',annot=True,linewidth=1,fmt='d')
plt.show()
```



[30]:
```python
# Finding the accuracy score

print(classification_report(y_test,y_pred))
print('The accuracy score is: ',accuracy_score(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.83      0.96      0.89      1595
           1       0.60      0.23      0.33       405

    accuracy                           0.81      2000
   macro avg       0.72      0.59      0.61      2000
weighted avg       0.78      0.81      0.78      2000

The accuracy score is:  0.813
```

[31]:
```
# Using Gradient Boosting Classifier

parameters = {'max_depth': [2, 3, 4, 6, 10, 15], 'n_estimators': [50, 100, 300,␣
↪500]}

gbc = GradientBoostingClassifier()

search_gbc = GridSearchCV(gbc, parameters, cv = 5, n_jobs = 10, verbose = 1).
↪fit(X_train, y_train)
```

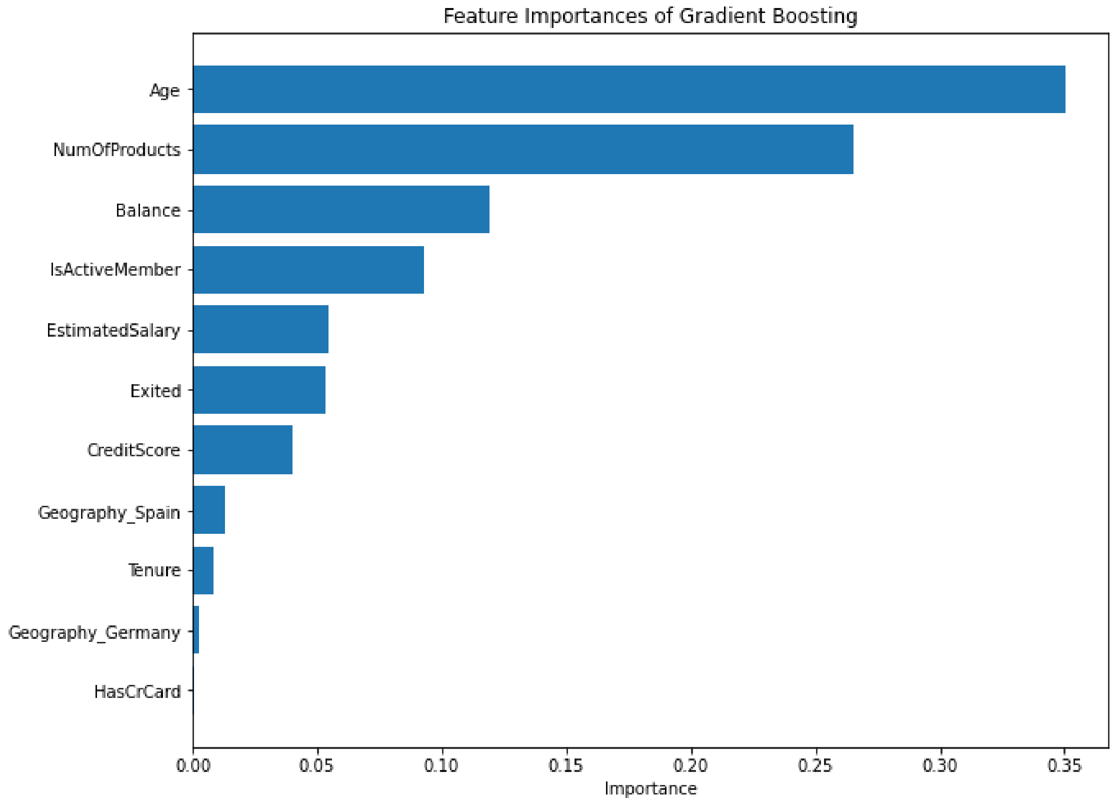
```
Fitting 5 folds for each of 24 candidates, totalling 120 fits
```

```
[Parallel(n_jobs=10)]: Using backend LokyBackend with 10 concurrent workers.
[Parallel(n_jobs=10)]: Done  30 tasks      | elapsed:   34.1s
[Parallel(n_jobs=10)]: Done 120 out of 120 | elapsed:  9.4min finished
```

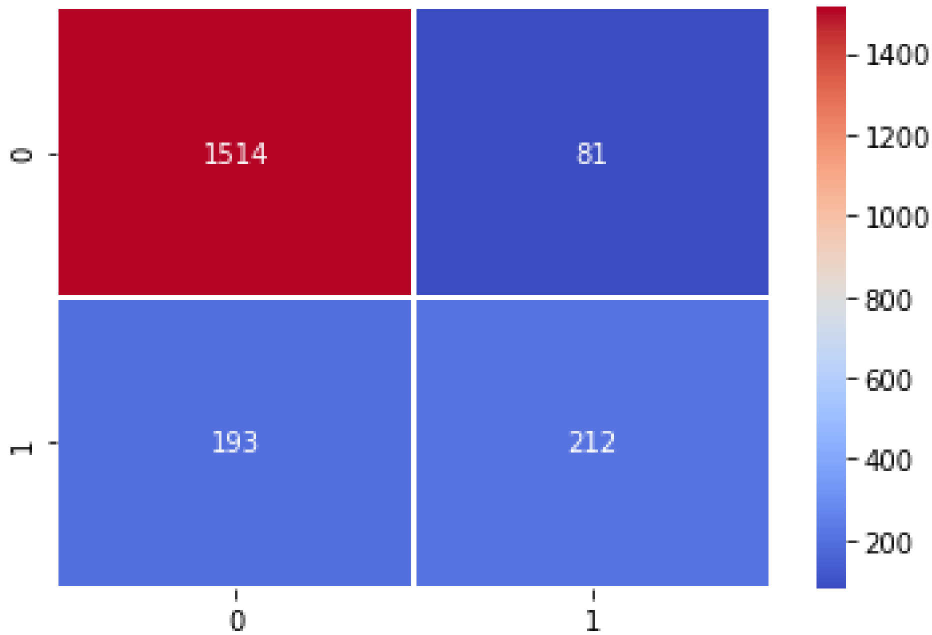
[32]:
```
# Showing the best parameters

search_gbc.best_params_
```

[32]:
```
{'max_depth': 3, 'n_estimators': 300}
```

[33]:
```
# Summarizing GradientBoostingClassifier calculated permutation feature␣
↪importance

model_gbc = GradientBoostingClassifier(**search_gbc.best_params_).fit(X_train,␣
↪y_train)

importances = model_gbc.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize = (10, 8))
plt.title('Feature Importances of Gradient Boosting')
plt.barh(range(len(indices)), importances[indices], align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Importance')
plt.show()
```



[34]:
```
# Showing confusion matrix heatmap

y_pred = model_gbc.predict(X_test)
cm_gbc=confusion_matrix(y_test,y_pred)
sns.heatmap(cm_gbc,cmap='coolwarm',annot=True,linewidth=1,fmt='d')
plt.show()
```



[35]:
```
# Finding the accuracy score

print(classification_report(y_test,y_pred))
print('The accuracy score is: ',accuracy_score(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.89      0.95      0.92      1595
           1       0.72      0.52      0.61       405

    accuracy                           0.86      2000
   macro avg       0.81      0.74      0.76      2000
weighted avg       0.85      0.86      0.85      2000

The accuracy score is:  0.863
```

1.0.1 Summary the accuracy score of those model

Random Forest accuracy score is: 0.868

Logistic Regression accuracy score is: 0.813

Gradient Boosting accuracy score is: 0.863

Looking into the accuracy score for those algorithms are pretty good. Even logistic regression is the lowest accuracy score, it has 81.3%. The accuracy score of random

forest and gradient boosting are very closed that are 86.75% and 86.3%. So random forest is slightly better than gradient boosting.