Bank Customer Churn Prediction

In this project, I use supervised learning models to identify customers who are likely to churn in the
factors that influence user retention. [Dataset information](#).

Contents

Part 0. oad packages, load data

```
#import neccessary libraries
import numpy as np
import pandas as pd
import sklearn as sl
import sklearn.preprocessing as preprocessing
from sklearn.model_selection import train_test_split
import seaborn as sns
import matplotlib.pyplot as plt
pd.set_option('display.float_format', lambda x: '%.3f' % x)
pd.set_option('display.max_columns',None)
pd.set_option('display.max_rows',None)
pd.set_option('max_colwidth',100)
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarnin
  import pandas.util.testing as tm
```

```
from google.colab import files
uploaded = files.upload()
```

Choose Files bank.data.csv

- **bank.data.csv**(application/vnd.ms-excel) - 684858 bytes, last modified: 3/12/2020 - 100% done

```
Saving bank.data.csv to bank.data.csv
```

```
churn_df=pd.read_table('bank.data.csv',header=0,sep=',',lineterminator='\n')
print(churn_df.head())
print ("Num of rows: " + str(churn_df.shape[0])) # row count
print ("Num of columns: " + str(churn_df.shape[1])) # col count
```

```
   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      0.000              1          1               1
1       1  83807.860              1          0               1
2       8 159660.800              3          1               0
3       1      0.000              2          0               0
4       2 125510.820              1          1               1

   EstimatedSalary  Exited\r
0       101348.880         1
1       112542.580         0
2       113931.570         1
3        93826.630         0
4        79084.100         0
Num of rows: 10000
Num of columns: 14
```

Part 1. Exploratory Analysis and Data Visualization

1.1 Exclude erroneous data

```
if churn_df.set_index('CustomerId').index.duplicated().sum()==0:
  print('No duplicated index.')
```

```
No duplicated index.
```

1.2: Understand the Raw Dataset

```
# check data info
churn_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
```

```
# check the unique values for each column
churn_df.nunique()
```

```
RowNumber          10000
CustomerId         10000
Surname             2932
CreditScore          460
Geography              3
Gender                 2
Age                   70
Tenure                11
Balance             6382
NumOfProducts          4
HasCrCard              2
IsActiveMember         2
EstimatedSalary     9999
Exited\r               2
dtype: int64
```

```
# Get target variable
y = churn_df['Exited\r']
```

```
# check the propotion of y = 1
print(y.sum() / y.shape * 100)
```

```
[20.37]
```

1.3: Understand numerical features

1.3.1 Overview

```
# check missing values
churn_df.isnull().sum()
```

```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
```

```
churn_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
          10000 non-null  int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

```
print(churn_df.drop(columns=['CustomerId','RowNumber'],axis=1).describe(percentiles=[0.1,0
```

```
       CreditScore        Age    Tenure    Balance  NumOfProducts  HasCrCard  \
count    10000.000 10000.000 10000.000  10000.000      10000.000  10000.000
mean       650.529    38.922     5.013  76485.889          1.530      0.706
std         96.653    10.488     2.892  62397.405          0.582      0.456
min        350.000    18.000     0.000      0.000          1.000      0.000
10%        521.000    27.000     1.000      0.000          1.000      0.000
25%        584.000    32.000     3.000      0.000          1.000      0.000
50%        652.000    37.000     5.000  97198.540          1.000      1.000
75%        718.000    44.000     7.000 127644.240          2.000      1.000
95%        812.000    60.000     9.000 162711.669          2.000      1.000
max        850.000    92.000    10.000 250898.090          4.000      1.000

       IsActiveMember  EstimatedSalary  Exited\r
count       10000.000        10000.000 10000.000
mean            0.515       100090.240     0.204
std             0.500        57510.493     0.403
min             0.000           11.580     0.000
10%             0.000        20273.580     0.000
25%             0.000        51002.110     0.000
50%             1.000       100193.915     0.000
75%             1.000       149388.247     0.000
95%             1.000       190155.375     1.000
max             1.000       199992.480     1.000
```

```
(churn_df==0).sum(axis=0)/churn_df.shape[0]
```

```
RowNumber         0.000
CustomerId        0.000
Surname           0.000
CreditScore       0.000
Geography         0.000
Gender            0.000
Age               0.000
Tenure            0.041
Balance           0.362
NumOfProducts     0.000
HasCrCard         0.294
IsActiveMember    0.485
EstimatedSalary   0.000
Exited\r          0.796
```

```
# understand Numerical feature
# discrete/continuous
# 'CreditScore', 'Age', 'Tenure', 'NumberOfProducts'
# 'Balance', 'EstimatedSalary'
churn_df[['CreditScore', 'Age', 'Tenure', 'NumOfProducts','Balance', 'EstimatedSalary']].d
```

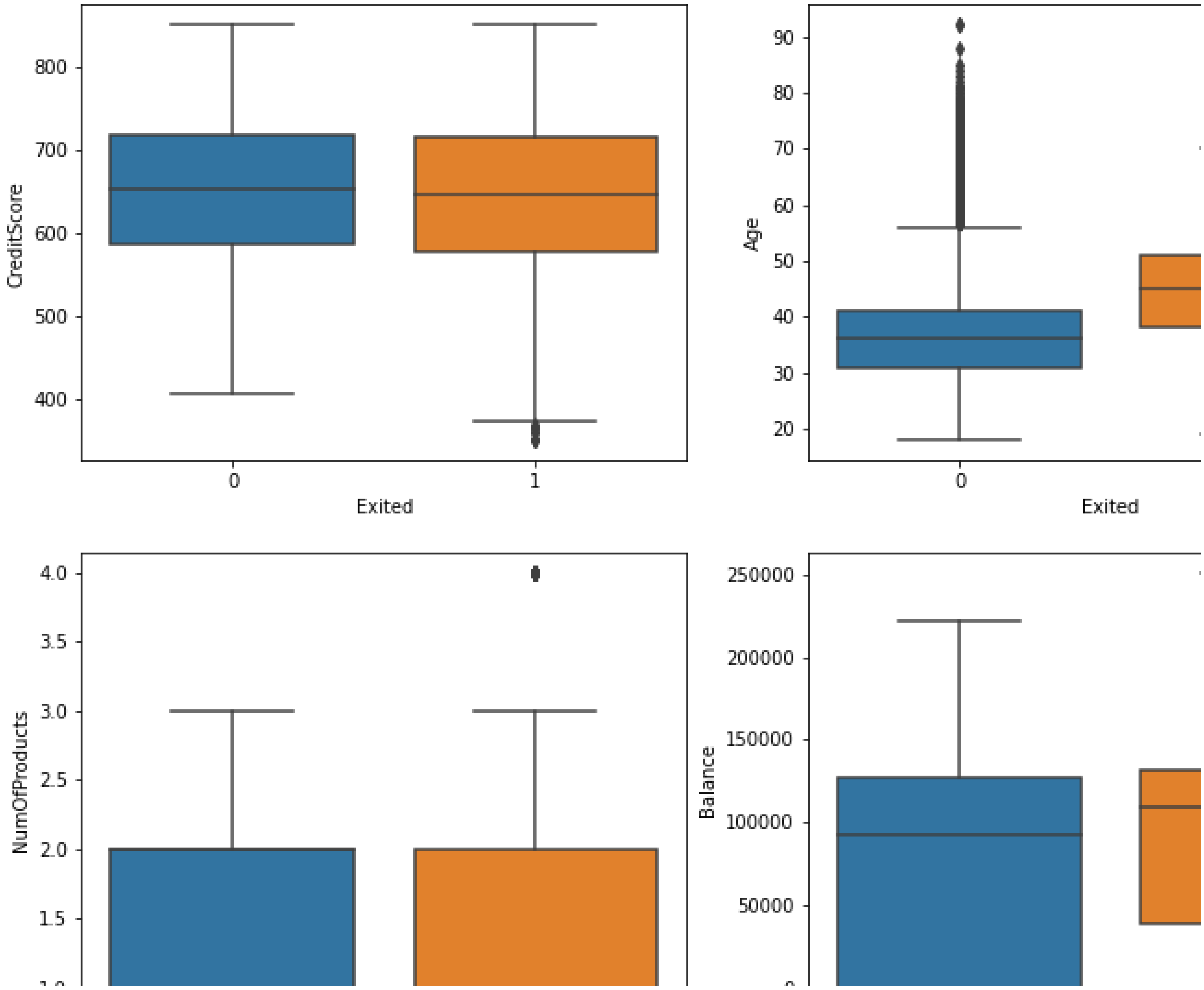
	CreditScore	Age	Tenure	NumOfProducts	Balance	EstimatedSalary
count	10000.000	10000.000	10000.000	10000.000	10000.000	10000.000
mean	650.529	38.922	5.013	1.530	76485.889	100090.240
std	96.653	10.488	2.892	0.582	62397.405	57510.493
min	350.000	18.000	0.000	1.000	0.000	11.580
25%	584.000	32.000	3.000	1.000	0.000	51002.110
50%	652.000	37.000	5.000	1.000	97198.540	100193.915
75%	718.000	44.000	7.000	2.000	127644.240	149388.247
max	850.000	92.000	10.000	4.000	250898.090	199992.480

```
# Rename columns
churn_df.rename(columns={'Exited\r':'Exited'},inplace=True)
```

1.3.2 'Exited' feature

```
# boxplot for numerical feature
_,axss = plt.subplots(2,3, figsize=[20,10])
sns.boxplot(x='Exited', y ='CreditScore', data=churn_df, ax=axss[0][0])
sns.boxplot(x='Exited', y ='Age', data=churn_df, ax=axss[0][1])
sns.boxplot(x='Exited', y ='Tenure', data=churn_df, ax=axss[0][2])
sns.boxplot(x='Exited', y ='NumOfProducts', data=churn_df, ax=axss[1][0])
sns.boxplot(x='Exited', y ='Balance', data=churn_df, ax=axss[1][1])
sns.boxplot(x='Exited', y ='EstimatedSalary', data=churn_df, ax=axss[1][2])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb7fc7c0208>
```



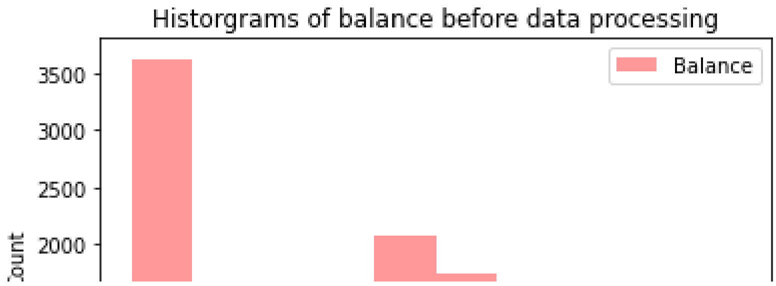
insights:

Senior people are more likely to churn.

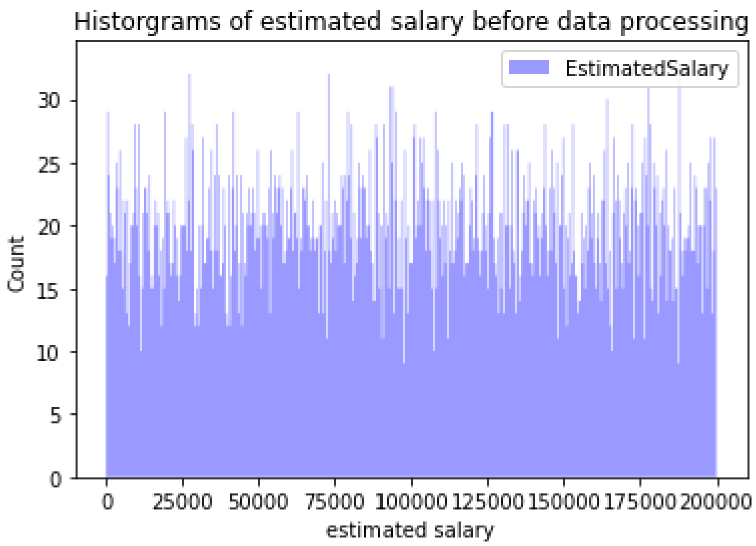
People have more banlance are more likely to churn.

1.3.3 Distribution of 'Balance' and 'Estimated Salary'

```
plt.hist(churn_df['Balance'], bins = 10, alpha = 0.4, color='r', histtype='stepfilled', la
plt.legend(loc ='upper right')
plt.title('Historgrams of balance before data processing')
plt.xlabel('blance')
plt.ylabel('Count')
plt.show()
```




```
plt.hist(churn_df['EstimatedSalary'], bins = 500, alpha = 0.4, color='b', histtype='stepfi
plt.legend(loc ='upper right')
plt.title('Historgrams of estimated salary before data processing')
plt.xlabel('estimated salary')
plt.ylabel('Count')
plt.show()
```



1.2.3 Correlation among numerical features

```
corr_score = churn_df[['CreditScore', 'Age', 'Tenure', 'NumOfProducts','Balance', 'Estimat

# show heapmap of correlations
sns.heatmap(corr_score,cmap="YlGnBu")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb7fc08edd8>
```

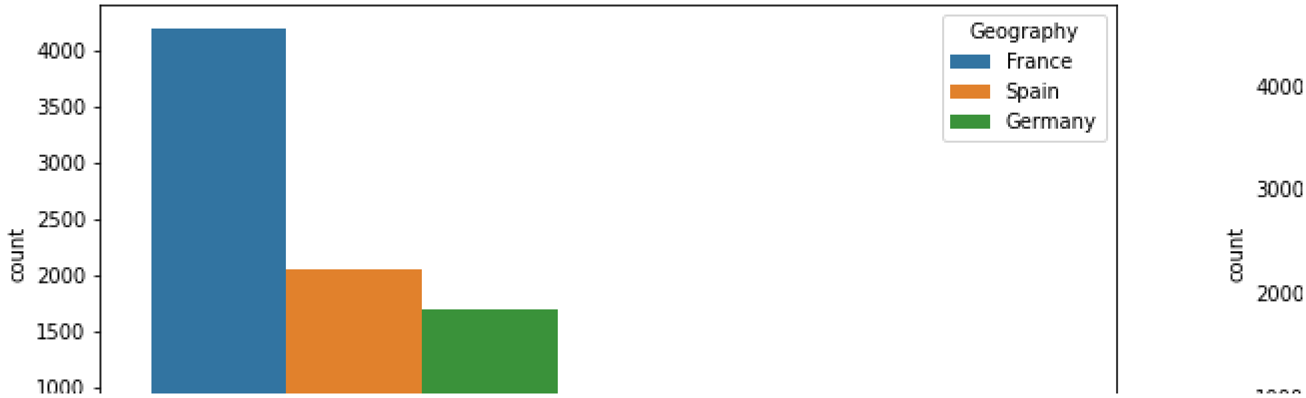

```
# check the actual values of correlations
corr_score
```

	CreditScore	Age	Tenure	NumOfProducts	Balance	EstimatedSalary
CreditScore	1.000	-0.004	0.001	0.012	0.006	-0.001
Age	-0.004	1.000	-0.010	-0.031	0.028	-0.007
Tenure	0.001	-0.010	1.000	0.013	-0.012	0.008
NumOfProducts	0.012	-0.031	0.013	1.000	-0.304	0.014
Balance	0.006	0.028	-0.012	-0.304	1.000	0.013
EstimatedSalary	-0.001	-0.007	0.008	0.014	0.013	1.000

1.4 Understand Categorical Features

```
# understand categorical feature
# 'Geography', 'Gender'
# 'HasCrCard', 'IsActiveMember'
_,axss = plt.subplots(2,2, figsize=[20,10])
sns.countplot(x='Exited', hue='Geography', data=churn_df, ax=axss[0][0])
sns.countplot(x='Exited', hue='Gender', data=churn_df, ax=axss[0][1])
sns.countplot(x='Exited', hue='HasCrCard', data=churn_df, ax=axss[1][0])
sns.countplot(x='Exited', hue='IsActiveMember', data=churn_df, ax=axss[1][1])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb7f9726940>



Insights:

Female are more likely to churn.

Less active members are more likely to churn.

Part 2: Feature Preprocessing

feature encoding, feature scaling

After very basic Exploratory Data Analysis, we have to do some data cleaning and data preprocess we need to encode the categorical feature Second, we need to impute the missing value for both r need to scale out feature,which can be better for our models' performance

Read more for handling categorical feature, and there is an awesome package for encoding.

```
# ordinal encoding
churn_df['Gender'] = churn_df['Gender'] == 'Female'


# one hot encoding
churn_df = pd.get_dummies(churn_df, columns=['Geography'], drop_first=True)


churn_df.head(10)
```

	RowNumber	CustomerId	Surname	CreditScore	Gender	Age	Tenure	Balance	NumO
0	1	15634602	Hargrave	619	True	42	2	0.000	
1	2	15647311	Hill	608	True	41	1	83807.860	

```
# Get feature space by dropping useless feature
to_drop = ['RowNumber','CustomerId','Surname','Exited']
X = churn_df.drop(to_drop, axis=1)
```

```
X.head()
```

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMe
0	619	True	42	2	0.000	1	1	
1	608	True	41	1	83807.860	1	0	
2	502	True	42	8	159660.800	3	1	
3	699	True	39	1	0.000	2	0	
4	850	True	43	2	125510.820	1	1	

Part 3: Model Training and Result Evaluation

3.1 Feature scaling

The impact of different scaling methods on the model performance is small. In the following mode
scaling (sc) data is used.

```
# Scale the data, using standardization
# standardization (x-mean)/std
# normalization (x-x_min)/(x_max-x_min) ->[0,1]

# 1. speed up gradient descent
# 2. same scale
# 3. algorithm requirments

# for example, use training data to train the standardscaler to get mean and std
# apply mean and std to both training and testing data.
# fit_transform does the training and applying, transform only does applying.
# Because we can't use any info from test, and we need to do the same modification
# to testing data as well as training data

# https://scikit-learn.org/stable/auto_examples/preprocessing/plot_all_scaling.html#sphx-g
# https://scikit-learn.org/stable/modules/preprocessing.html


# min-max example: (x-x_min)/(x_max-x_min)
```

```
# min-max example: (x-x_min)/(x_max-x_min)
# [1,2,3,4,5,6] -> fit(min:1, max:6) (scalar.min = 1, scalar.max = 6) -> transform [(1-1)/
# scalar.fit(train) -> min:1, max:100
# scalar.transform(apply to x) -> apply min:1, max:100 to X_train
# scalar.transform -> apply min:1, max:100 to X_test

# scalar.fit -> mean:1, std:100
# scalar.transform -> apply mean:1, std:100 to X_train
# scalar.transform -> apply mean:1, std:100 to X_test

from sklearn.preprocessing import StandardScaler
scale_lst = ['CreditScore','Age','Tenure','NumOfProducts','Balance','EstimatedSalary']
scaler = StandardScaler()
scaler.fit(X[scale_lst])
X[scale_lst] = scaler.transform(X[scale_lst])

X.head()
```

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMeml
0	-0.326	True	0.294	-1.042	-1.226	-0.912	1	
1	-0.440	True	0.198	-1.388	0.117	-0.912	0	
2	-1.537	True	0.294	1.033	1.333	2.527	1	
3	0.502	True	0.007	-1.388	-1.226	0.808	0	
4	2.064	True	0.389	-1.042	0.786	-0.912	1	

3.2 Split the data

```
# Splite data into training and testing
from sklearn import model_selection

# Reserve 20% for testing
X_train, X_test, y_train, y_test = model_selection.train_test_split(X, y, test_size=0.25,

print('training data has ' + str(X_train.shape[0]) + ' observation with ' + str(X_train.sh
print('test data has ' + str(X_test.shape[0]) + ' observation with ' + str(X_test.shape[1]
```

```
training data has 7500 observation with 11 features
test data has 2500 observation with 11 features
```

3.3: Model Training and Selection

```
# build models
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn import svm

# Logistic Regression
```

```
# Logistic Regression
classifier_logistic = LogisticRegression()

# K Nearest Neighbors
classifier_KNN = KNeighborsClassifier()

# Random Forest
classifier_RF = RandomForestClassifier()

#SVM
classifier_SVM = svm.SVC()


# Train the model
#classifier_logistic.fit(X_train, y_train)


# Prediction of test data
#classifier_logistic.predict(X_test)


# Accuracy of test data
#classifier_logistic.score(X_test, y_test)


# Use 5-fold Cross Validation to get the accuracy for different models
model_names = ['Logistic Regression','KNN','Random Forest','SVM']
model_list = [classifier_logistic, classifier_KNN, classifier_RF, classifier_SVM]
count = 0

for classifier in model_list:
  if count<=len(model_list):
    cv_score = model_selection.cross_val_score(classifier, X_train, y_train, cv=5)
    print(cv_score)
    print('Model accuracy of ' + model_names[count] + ' is ' + str(cv_score.mean()))
    count += 1
```

```
[0.81       0.81466667 0.802      0.818      0.81266667]
Model accuracy of Logistic Regression is 0.8114666666666667
[0.852      0.83333333 0.846      0.85133333 0.848     ]
Model accuracy of KNN is 0.8461333333333334
[0.86133333 0.868      0.86333333 0.86533333 0.862     ]
Model accuracy of Random Forest is 0.8640000000000001
[0.86       0.86266667 0.85133333 0.85866667 0.85666667]
Model accuracy of SVM is 0.8578666666666667
```

3.4 Use Grid Search to Find Optimal Hyperparameters

```
from sklearn.model_selection import GridSearchCV

# helper function for printing out grid search results
def print_grid_search_metrics(gs):
    print ("Best score: " + str(gs.best_score_))
    print ("Best parameters set:")
    best_parameters = gs.best_params_
    for param_name in sorted(parameters.keys()):
```

```
    for param_name in sorted(parameters.keys()):
        print(param_name + ':' + str(best_parameters[param_name]))
```

3.4.1 Find Optimal Hyperparameters - LogisticRegression

```
# Possible hyperparamter options for Logistic Regression Regularization
# Penalty is choosed from L1 or L2
# C is the lambda value(weight) for L1 and L2

# ('l1', 1) ('l1', 5) ('l1', 10) ('l2', 1) ('l2', 5) ('l2', 10)
parameters = {
    'penalty':('l1', 'l2'),
    'C':(0.01, 0.1, 1, 5, 10)
}
Grid_LR = GridSearchCV(LogisticRegression(solver='liblinear'),parameters, cv=5)
Grid_LR.fit(X_train, y_train)
```

```
GridSearchCV(cv=5, error_score=nan,
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='auto',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='liblinear',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'C': (0.01, 0.1, 1, 5, 10), 'penalty': ('l1', 'l2')},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

```
# the best hyperparameter combination
print_grid_search_metrics(Grid_LR)
```

```
Best score: 0.8134666666666666
Best parameters set:
C:0.1
penalty:l1
```

```
# best model
best_LR_model = Grid_LR.best_estimator_
```

3.4.2 Find Optimal Hyperparameters: KNN

```
# Possible hyperparamter options for KNN
# Choose k
parameters = {
    'n_neighbors':[1,3,5,7,9]
}
Grid_KNN = GridSearchCV(KNeighborsClassifier(),parameters, cv=5)
Grid_KNN.fit(X_train, y_train)
```

```
GridSearchCV(cv=5, error_score=nan,
             estimator=KNeighborsClassifier(algorithm='auto', leaf_size=30,
                                            metric='minkowski',
                                            metric_params=None, n_jobs=None,
                                            n_neighbors=5, p=2,
                                            weights='uniform'),
             iid='deprecated', n_jobs=None,
             param_grid={'n_neighbors': [1, 3, 5, 7, 9]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

```
# best k
print_grid_search_metrics(Grid_KNN)
```

```
Best score: 0.8492000000000001
Best parameters set:
n_neighbors:9
```

```
best_KNN_model = Grid_KNN.best_estimator_
```

3.4.3 Find Optimal Hyperparameters: Random Forest

```
# Possible hyperparamter options for Random Forest
# Choose the number of trees
parameters = {
    'n_estimators' : [40,60,80]
}
Grid_RF = GridSearchCV(RandomForestClassifier(),parameters, cv=5)
Grid_RF.fit(X_train, y_train)
```

```
GridSearchCV(cv=5, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                              class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators=100, n_jobs=None,
                                              oob_score=False,
                                              random_state=None, verbose=0,
                                              warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'n_estimators': [40, 60, 80]}, pre_dispatch='2*n_jobs',
             refit=True, return_train_score=False, scoring=None, verbose=0)
```

```
# best number of tress
print_grid_search_metrics(Grid_RF)
```

```
Best score: 0.8614666666666666
Best parameters set:
```

```
# best random forest
best_RF_model = Grid_RF.best_estimator_
```

3.4.4 Find Optimal Hyperparameters: Support Vector Machines

```
# Possible hyperparamter options for SVM
# Choose kernal
parameters = {'kernel': ['rbf'], 'gamma': [1e-3, 1e-4],
                     'C': [1, 10, 100, 1000]}
Grid_SVM = GridSearchCV(svm.SVC(),parameters, cv=5)
Grid_SVM.fit(X_train, y_train)
```

```
GridSearchCV(cv=5, error_score=nan,
             estimator=SVC(C=1.0, break_ties=False, cache_size=200,
                           class_weight=None, coef0=0.0,
                           decision_function_shape='ovr', degree=3,
                           gamma='scale', kernel='rbf', max_iter=-1,
                           probability=False, random_state=None, shrinking=True,
                           tol=0.001, verbose=False),
             iid='deprecated', n_jobs=None,
             param_grid={'C': [1, 10, 100, 1000], 'gamma': [0.001, 0.0001],
                         'kernel': ['rbf']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

```
# best gmma and C
print_grid_search_metrics(Grid_SVM)
```

```
Best score: 0.8512000000000001
Best parameters set:
C:1000
gamma:0.001
kernel:rbf
```

```
# best SVM model
best_SVM_model = Grid_SVM.best_estimator_
```

3.5 Model Evaluation

class of interest as positive

TP: correctly labeled real churn

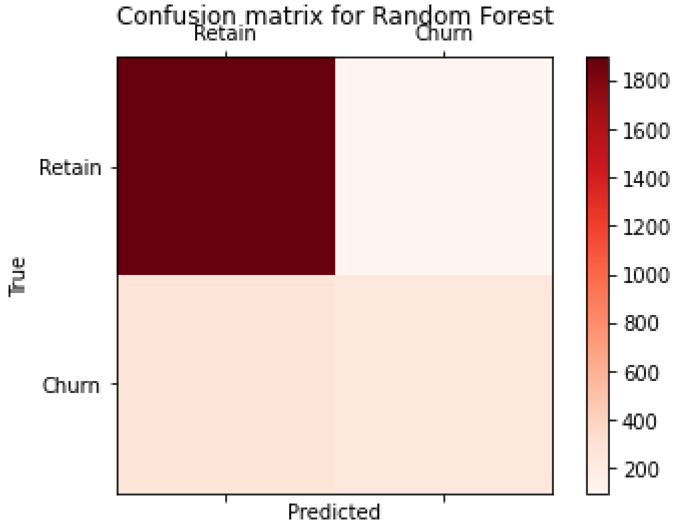
Precision(PPV, positive predictive value): tp / (tp + fp); Total number of true predictive churn divide
High Precision means low fp, not many return users were predicted as churn users.

Recall(sensitivity, hit rate, true positive rate): tp / (tp + fn) Predict most postive or churn user corre
users were predicted as return users.

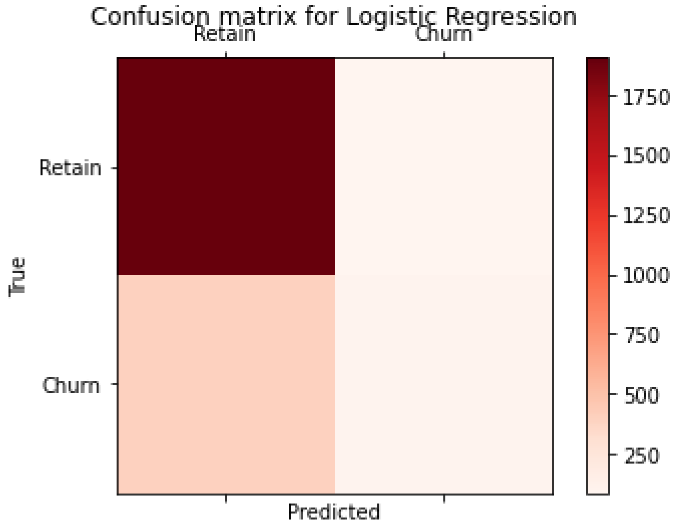
3.5.1 Model Evaluation - Confusion Matrix (Precision, Recall, Accuracy)

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score

# calculate accuracy, precision and recall, [[tn, fp],[]]
def cal_evaluation(classifier, cm):
    tn = cm[0][0]
    fp = cm[0][1]
    fn = cm[1][0]
    tp = cm[1][1]
    accuracy  = (tp + tn) / (tp + fp + fn + tn + 0.0)
    precision = tp / (tp + fp + 0.0)
    recall = tp / (tp + fn + 0.0)
    print (classifier)
    print ("Accuracy is: " + str(accuracy))
    print ("precision is: " + str(precision))
    print ("recall is: " + str(recall))

# print out confusion matrices
def draw_confusion_matrices(confusion_matricies):
    class_names = ['Retain','Churn']
    for cm in confusion_matrices:
        classifier, cm = cm[0], cm[1]
        cal_evaluation(classifier, cm)
        fig = plt.figure()
        ax = fig.add_subplot(111)
        cax = ax.matshow(cm, interpolation='nearest',cmap=plt.get_cmap('Reds'))
        plt.title('Confusion matrix for ' + classifier)
        fig.colorbar(cax)
        ax.set_xticklabels([''] + class_names)
        ax.set_yticklabels([''] + class_names)
        plt.xlabel('Predicted')
        plt.ylabel('True')
        plt.show()


#confusion_matrix(y_test,best_RF_model.predict(X_test))


# Confusion matrix, accuracy, precison and recall for random forest and logistic regressio
confusion_matrices = [
    ("Random Forest", confusion_matrix(y_test,best_RF_model.predict(X_test))),
    ("Logistic Regression", confusion_matrix(y_test,best_LR_model.predict(X_test))),
    ("K nearest neighbor", confusion_matrix(y_test, best_KNN_model.predict(X_test))),
    ('Support Vector Moachines', confusion_matrix(y_test, best_SVM_model.predict(X_test)))
]

draw_confusion_matrices(confusion_matrices)
```

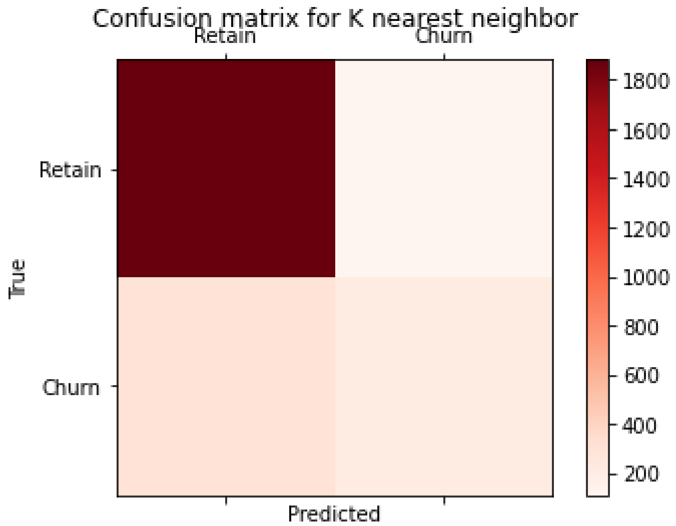
```
Random Forest
Accuracy is: 0.8536
precision is: 0.7109144542772862
recall is: 0.47347740667976423
```




```
Logistic Regression
Accuracy is: 0.8044
precision is: 0.5515463917525774
recall is: 0.21021611001964635
```

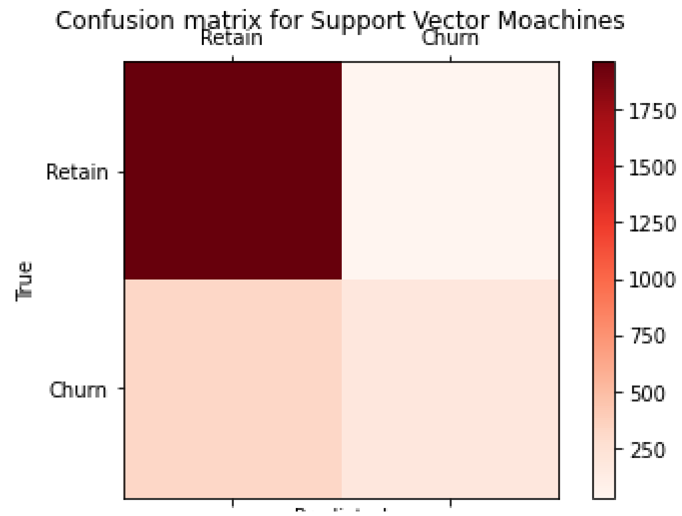



```
K nearest neighbor
Accuracy is: 0.838
precision is: 0.6614906832298136
recall is: 0.41846758349705304
```




```
Support Vector Moachines
```

```
Accuracy is: 0.8576
precision is: 0.8558139534883721
recall is: 0.3614931237721022
```

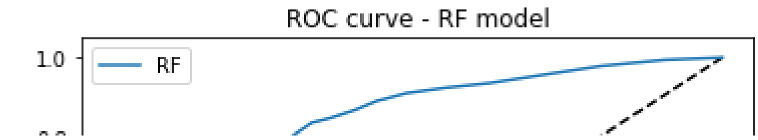


Random Forest has the best performance

3.5.2 Model Evaluation - ROC & AUC

ROC of RF Model

```
from sklearn.metrics import roc_curve
from sklearn import metrics

# Use predict_proba to get the probability results of Random Forest
y_pred_rf = best_RF_model.predict_proba(X_test)[:, 1]
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_pred_rf)


# ROC curve of Random Forest result
plt.figure(1)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr_rf, tpr_rf, label='RF')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('ROC curve - RF model')
plt.legend(loc='best')
plt.show()
```



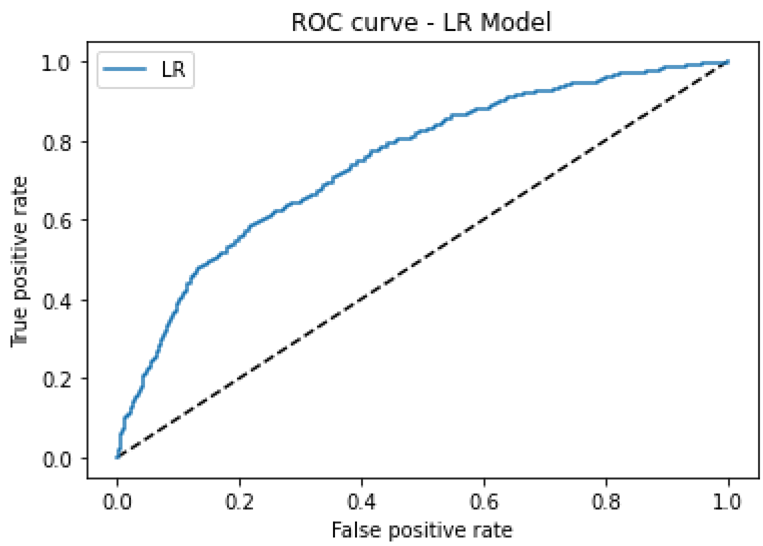

```
from sklearn import metrics

# AUC score
metrics.auc(fpr_rf,tpr_rf)
```

```
0.8424501612857072
```

ROC of LR Model

False positive rate

```
# Use predict_proba to get the probability results of Logistic Regression
y_pred_lr = best_LR_model.predict_proba(X_test)[:, 1]
fpr_lr, tpr_lr, thres = roc_curve(y_test, y_pred_lr)


# ROC Curve
plt.figure(1)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr_lr, tpr_lr, label='LR')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('ROC curve - LR Model')
plt.legend(loc='best')
plt.show()
```



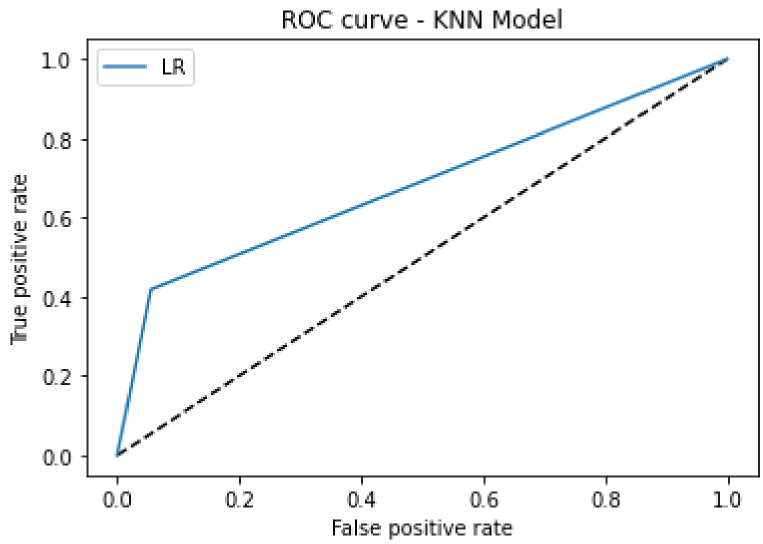

```
# AUC score
metrics.auc(fpr_lr,tpr_lr)
```

```
0.745923453181754
```

ROC of KNN Model

```
y_pred_knn = best_KNN_model.predict(X_test)
```

```
y_pred_knn = best_KNN_model.predict(X_test)
fpr_knn, tpr_knn, thres = roc_curve(y_test, y_pred_knn)


# ROC Curve
plt.figure(1)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr_knn, tpr_knn, label='LR')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('ROC curve - KNN Model')
plt.legend(loc='best')
plt.show()
```

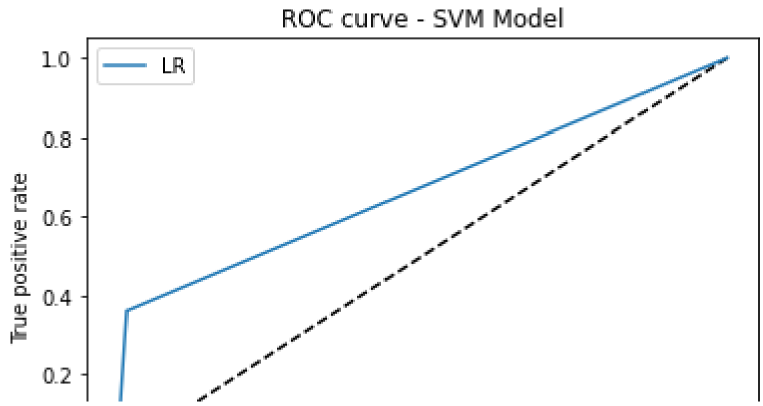



```
metrics.auc(fpr_knn, tpr_knn)
```

```
0.6818606124416455
```

ROC of SVM Model

```
y_pred_svm = best_SVM_model.predict(X_test)
fpr_svm, tpr_svm, thres = roc_curve(y_test, y_pred_svm)


# ROC Curve
plt.figure(1)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr_svm, tpr_svm, label='LR')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('ROC curve - SVM Model')
plt.legend(loc='best')
plt.show()
```




```
metrics.auc(fpr_svm, tpr_svm)
```

```
0.67296152923914
```

Part 4: Feature Importance

4.1 Logistic Regression Model - Feature Selection Discussion

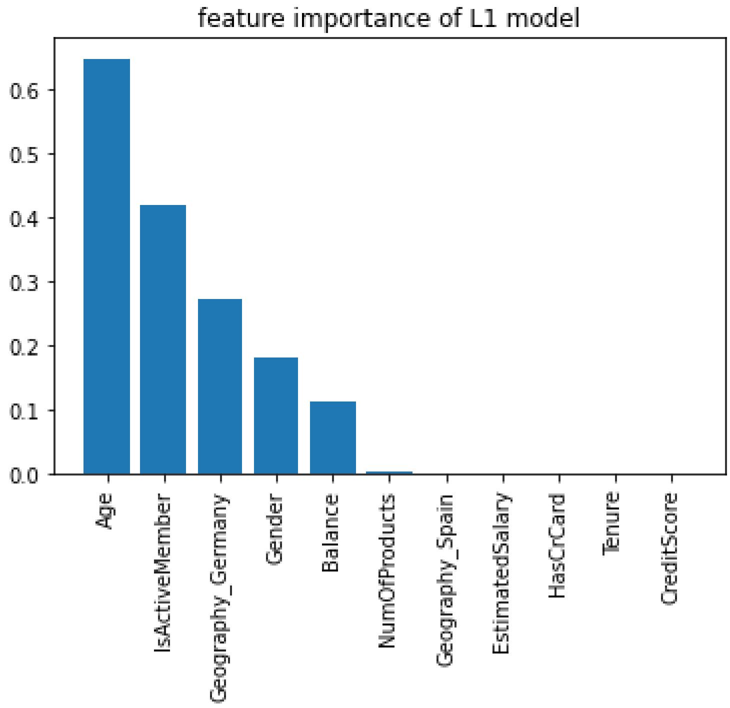
The corelated features that we are interested in

```
# add L1 regularization to logistic regression
# check the coef for feature selection
scaler = StandardScaler()
X_l1 = scaler.fit_transform(X)
LRmodel_l1 = LogisticRegression(penalty="l1", C = 0.01, solver='liblinear')
LRmodel_l1.fit(X_l1, y)

indices = np.argsort(abs(LRmodel_l1.coef_[0]))[::-1]

print ("Logistic Regression (L1) Coefficients")
for ind in range(X.shape[1]):
  print ("{0} : {1}".format(X.columns[indices[ind]],round(LRmodel_l1.coef_[0][indices[ind]
```

```
Logistic Regression (L1) Coefficients
Age : 0.6469
IsActiveMember : -0.419
Geography_Germany : 0.2719
Gender : 0.1802
Balance : 0.1133
NumOfProducts : -0.0029
Geography_Spain : 0.0
EstimatedSalary : 0.0
HasCrCard : 0.0
Tenure : 0.0
CreditScore : 0.0
```

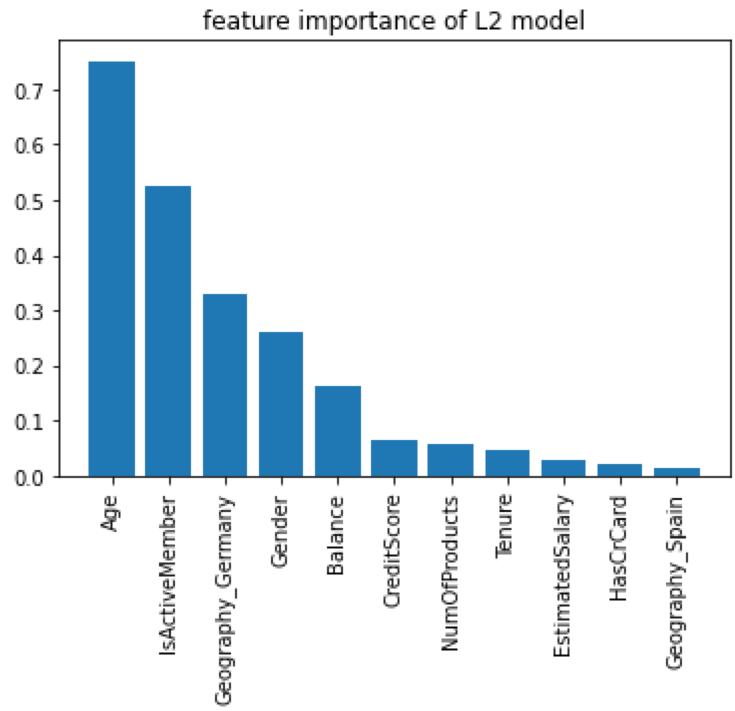
```
feature_name = X_train.columns.values
importances_l1 = abs(LRmodel_l1.coef_[0])
plt.figure(1)
```

```
plt.figure(1)
axes = plt.gca()
plt.bar(feature_name[indices], importances_l1[indices])
plt.title('feature importance of L1 model')
plt.xticks(rotation=90)
#axes.set_ylim([-0.2,0.5])
plt.show()
```




```
# add L2 regularization to logistic regression
# check the coef for feature selection
np.random.seed()
scaler = StandardScaler()
X_l2 = scaler.fit_transform(X)
LRmodel_l2 = LogisticRegression(penalty="l2", C = 0.1, solver='liblinear', random_state=42
LRmodel_l2.fit(X_l2, y)
LRmodel_l2.coef_[0]

indices = np.argsort(abs(LRmodel_l2.coef_[0]))[::-1]

print ("Logistic Regression (L2) Coefficients")
for ind in range(X.shape[1]):
  print ("{0} : {1}".format(X.columns[indices[ind]],round(LRmodel_l2.coef_[0][indices[ind]
```

```
feature_name = X_train.columns.values
plt.figure(1)
importances_l2 = abs(LRmodel_l2.coef_[0])
axes = plt.gca()
plt.bar(feature_name[indices], importances_l2[indices])
plt.title('feature importance of L2 model')
plt.xticks(rotation=90)
plt.show()
```



4.2 Random Forest Model - Feature Importance Discussion

```
# check feature importance of random forest for feature selection
forest = RandomForestClassifier()
forest.fit(X, y)

importances = forest.feature_importances_

indices = np.argsort(importances)[::-1]

# Print the feature ranking
print("Feature importance ranking by Random Forest Model:")
for ind in range(X.shape[1]):
  print ("{0} : {1}".format(X.columns[indices[ind]],round(importances[indices[ind]], 4)))
```

```
Feature importance ranking by Random Forest Model:
Age : 0.2381
EstimatedSalary : 0.1458
CreditScore : 0.1449
```

```
feature_name = X_train.columns.values
plt.figure(1)
plt.bar(feature_name[indices], importances[indices])
plt.title('feature importance of Random Forest model')
plt.xticks(rotation=90)
plt.show()
```