Assignment -2

Python Programming

Assignment Date	26 September 2022
Student Name	PIRUTHIVIRAJ R
Student Roll Number	913319104038
Maximum Marks	2 Marks

Question-1:

DOWNLOAD THE DATA SET

The given data set

Question-2:

LOAD THE DATA SET

Solution :

```
import numpy as np
import pandas as pd
kd=pd.read_csv("/content/Churn_Modelling.csv")
kd.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiv
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	

Question-3:

Perform below visualization

- **Univariate analysis**
- **Bivariate analysis**
- **Multivariate analysis**

Solution :

UNIVARIATE ANALYSIS

```
#Calculate Summary Statistics

import numpy as np
import pandas as pd
kd=pd.read_csv("/content/Churn_Modelling.csv")
print("mean",kd ['EstimatedSalary'].mean())
print("median",kd ['EstimatedSalary'].median())
print("mode",kd ['EstimatedSalary'].mode())
```

```
#Calculate Summary Statistics
print("mean",df['EstimatedSalary'].mean())
print("median",df['EstimatedSalary'].median())
print("mode",df['EstimatedSalary'].mode())
```

```
mean 100090.239881
median 100193.915
mode 0    24924.92
dtype: float64
```

```
#frequency
kd['Age'].value_counts()
```



```
#frequency
kd['Age'].value_counts()
```

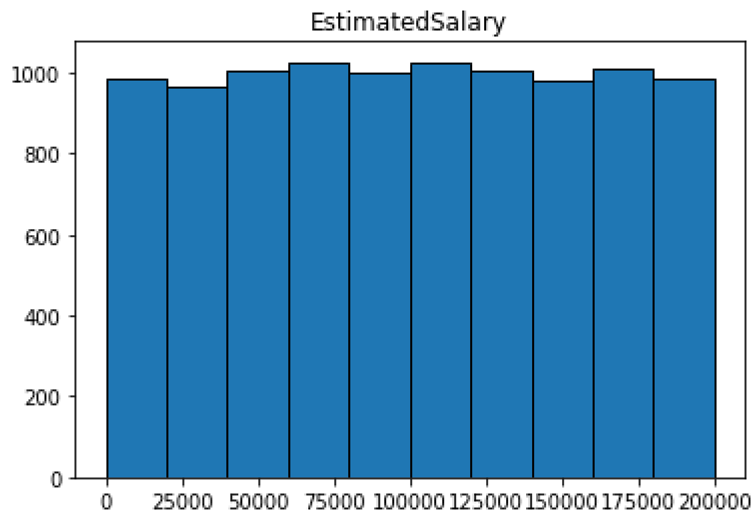


```
37    478
38    477
35    474
36    456
34    447
     ...
92      2
82      1
88      1
85      1
83      1
Name: Age, Length: 70, dtype: int64
```

```
#create charts
kd.hist(column='EstimatedSalary', grid=False, edgecolor='black')
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f271186fed0>]],
dtype=object)
```

```
#create charts
kd.hist(column='EstimatedSalary', grid=False, edgecolor='black')
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f6b11167f90>]],
      dtype=object)
```

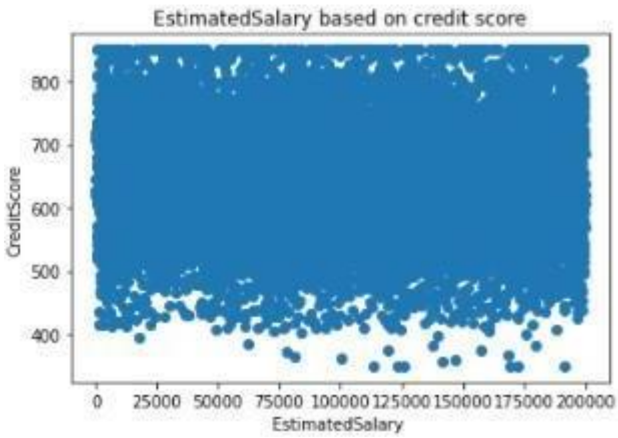


BIVARIATE ANALYSIS

Scatter plot

```
import matplotlib.pyplot as plt
dataset=pd.read_csv("/content/Churn_Modelling.csv")
plt.scatter(kd.EstimatedSalary, kd.CreditScore)
plt.title('EstimatedSalary based on credit score')

plt.xlabel('EstimatedSalary ')
plt.ylabel('CreditScore')
```



Corelation coeficient

```
kd.corr()
```

```
kd.corr()
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance
RowNumber	1.000000	0.004202	0.005840	0.000783	-0.006495	-0.009067
CustomerId	0.004202	1.000000	0.005308	0.009497	-0.014883	-0.012419
CreditScore	0.005840	0.005308	1.000000	-0.003965	0.000842	0.006268
Age	0.000783	0.009497	-0.003965	1.000000	-0.009997	0.028308
Tenure	-0.006495	-0.014883	0.000842	-0.009997	1.000000	-0.012254
Balance	-0.009067	-0.012419	0.006268	0.028308	-0.012254	1.000000
NumOfProducts	0.007246	0.016972	0.012238	-0.030680	0.013444	-0.304180
HasCrCard	0.000599	-0.014025	-0.005458	-0.011721	0.022583	-0.014858
IsActiveMember	0.012044	0.001665	0.025651	0.085472	-0.028362	-0.010084
EstimatedSalary	-0.005988	0.015271	-0.001384	-0.007201	0.007784	0.012797

#Simple linear regression

```
import statsmodels.api as sm
y = kd['EstimatedSalary']
x = kd['CreditScore']
```

```
x = sm.add_constant(x)
model = sm.OLS(y, x).fit()
print(model.summary())
```

```
Dep. Variable:          EstimatedSalary   R-squared:                       0.000
Model:                              OLS   Adj. R-squared:                 -0.000
Method:                   Least Squares   F-statistic:                   0.01916
Date:                  Sat, 08 Oct 2022   Prob (F-statistic):              0.890
Time:                          09:22:48   Log-Likelihood:          -1.2379e+05
No. Observations:                 10000   AIC:                       2.476e+05
Df Residuals:                      9998   BIC:                       2.476e+05
Df Model:                             1
Covariance Type:              nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        1.006e+05   3913.640     25.712      0.000      9.3e+04    1.08e+05
CreditScore    -0.8237      5.951     -0.138      0.890      -12.488     10.841
===============================================================================
Omnibus:                       7392.705   Durbin-Watson:                   2.010
Prob(Omnibus):                    0.000   Jarque-Bera (JB):              581.607
Skew:                             0.002   Prob(JB):                    5.08e-127
Kurtosis:                         1.819   Cond. No.                     4.48e+03
==============================================================================
```

MULTIVARIATE ANALYSIS

```
ax = kd.plot(figsize=(20,15)) ax.legend(loc='center
left', bbox_to_anchor=(1, 0.5));
```

Question-4:

Perform descriptive statistics on the dataset

Solution

```
kd.describe()
```

```
df.describe()
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818	
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000	

```
kd.describe(include=['object'])
```

	Surname	Geography	Gender
count	10000	10000	10000
unique	2932	3	2
top	Smith	France	Male
freq	32	5014	5457

Question-5 :

Handle the missing values

Solution

kd.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
```

```
missing_values=kd.isnull().sum()
print(missing_values[missing_values>0]/len(kd)*100)
missing_values
```

```
Series([], dtype: float64)
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
```

Question-6

Find out the outliers

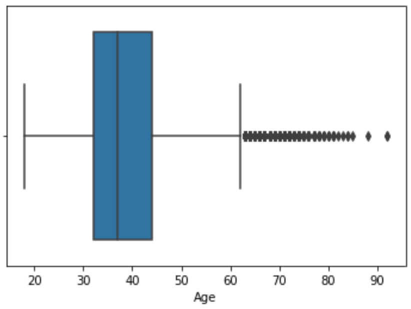
Solution

AGE OUTLIER

```
import seaborn as sns
sns.boxplot(kd['Age'])
```

```
import seaborn as sns
sns.boxplot(kd['Age'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the o
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f6b035efb90>
```

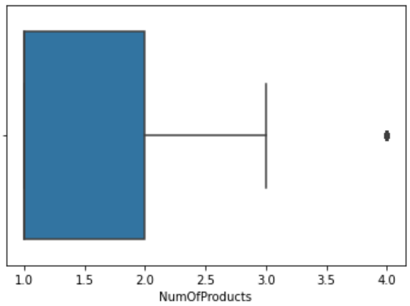


NUMOFPRODUCTS OUTLIER

sns.boxplot(kd['NumOfProducts'])

```
sns.boxplot(kd['NumOfProducts'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f6b035679d0>
```

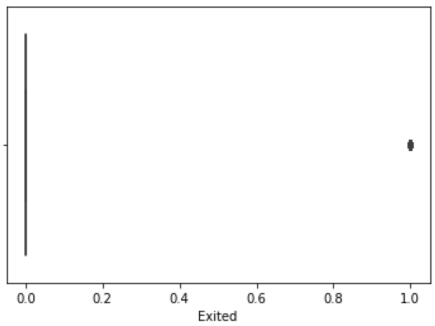


EXITED OUTLIER

sns.boxplot(kd['Exited'])

```
sns.boxplot(kd['Exited'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f6b03553310>
```



DETECTION OF FHE OUTLIER

a=np.where(kd['Age']>60)

print("OUTLIERS OF Age\n",a)

```
OUTLIERS OF AGE
 (array([  42,   44,   58,   85,  104,  158,  181,  230,  234,  243,  252,
         276,  310,  364,  371,  385,  387,  399,  416,  484,  538,  559,
         561,  567,  602,  612,  617,  630,  658,  678,  696,  736,  766,
         769,  807,  811,  823,  859,  884,  888,  921,  928,  948,  952,
         957,  963,  969,  997, 1009, 1039, 1040, 1055, 1114, 1118, 1192,
        1205, 1234, 1235, 1246, 1252, 1278, 1285, 1328, 1342, 1387, 1407,
        1410, 1433, 1439, 1457, 1519, 1543, 1588, 1607, 1614, 1642, 1790,
        1810, 1858, 1866, 1901, 1904, 1907, 1933, 1981, 1996, 2002, 2012,
        2039, 2053, 2078, 2094, 2103, 2108, 2154, 2159, 2164, 2244, 2261,
        2274, 2298, 2301, 2433, 2438, 2458, 2459, 2519, 2520, 2533, 2541,
        2553, 2599, 2615, 2659, 2670, 2713, 2717, 2760, 2772, 2777, 2778,
        2781, 2791, 2855, 2877, 2901, 2908, 2925, 2926, 3008, 3033, 3054,
        3110, 3142, 3166, 3192, 3203, 3229, 3305, 3308, 3311, 3314, 3317,
        3346, 3366, 3368, 3378, 3382, 3384, 3387, 3396, 3403, 3434, 3462,
        3497, 3499, 3527, 3531, 3541, 3549, 3559, 3563, 3573, 3575, 3593,
        3602, 3641, 3646, 3647, 3651, 3690, 3691, 3702, 3719, 3728, 3733,
        3761, 3774, 3813, 3826, 3880, 3881, 3888, 3909, 3910, 3927, 3940,
        3947, 3980, 3994, 4010, 4025, 4048, 4051, 4095, 4142, 4147, 4157,
        4162, 4170, 4241, 4244, 4256, 4273, 4280, 4297, 4313, 4318, 4335,
        4360, 4366, 4378, 4387, 4396, 4435, 4438, 4463, 4490, 4491, 4501,
        4506, 4559, 4563, 4590, 4595, 4644, 4678, 4698, 4747, 4751, 4801,
        4815, 4832, 4849, 4931, 4947, 4966, 4992, 5000, 5020, 5033, 5038,
        5068, 5132, 5136, 5148, 5159, 5197, 5223, 5225, 5235, 5255, 5299,
        5313, 5368, 5377, 5405, 5439, 5457, 5490, 5508, 5514, 5520, 5576,
        5577, 5581, 5639, 5651, 5655, 5660, 5664, 5671, 5683, 5698, 5742,
        5777, 5783, 5817, 5825, 5840, 5867, 5907, 5957, 5996, 6046, 6116,
        6152, 6166, 6167, 6171, 6173, 6212, 6230, 6278, 6289, 6315, 6357,
        6366, 6373, 6375, 6410, 6443, 6515, 6530, 6532, 6581, 6612, 6626,
        6706, 6709, 6715, 6721, 6759, 6763, 6812, 6899, 6970, 6997, 7008,
```

DETECTION OF NUMOFPRODUCTS OUTLIER

b=np.where(kd['NumOfProducts']>3) print("OUTLIERS OF NUMOFPRODUCTS\n",b)

```
OUTLIERS OF NUMOFPRODUCTS
 (array([   7,   70, 1254, 1469, 1488, 1701, 1876, 2124, 2196, 2285, 2462,
        2499, 2509, 2541, 2614, 2617, 2872, 3152, 3365, 3841, 4013, 4014,
        4166, 4260, 4403, 4511, 4516, 4606, 4654, 4748, 4822, 5010, 5137,
        5235, 5386, 5700, 5904, 6150, 6172, 6279, 6750, 6875, 7257, 7457,
        7567, 7698, 7724, 7729, 8041, 8590, 8683, 8850, 8923, 9215, 9255,
        9323, 9370, 9411, 9540, 9565]),)
```

DETECTION OF EXITED OUTLIER

c=np.where(FH['Exited']>0)
print("OUTLIERS OF Exited\n",c)

```
c=np.where(kd['Exited']>0)
print("OUTLIERS OF Exited\n",c)
```

```
OUTLIERS OF Exited
 (array([   0,    2,    5, ..., 9991, 9997, 9998]),)
```

Question-7:
Check the categorical columns and perform encoding

Solution :

location=pd.get_dummies(km['Geography'])
from sklearn.preprocessing import LabelEncoder
from collections import Counter as count
le=LabelEncoder()
count(km['Geography'])
kd['Geography']=le.fit_transform(kd['Geography'])
count(dataset['Geography'])

```
from sklearn.preprocessing import LabelEncoder
from collections import Counter as count
count(kd['Geography'])
df['Geography']=le.fit_transform(kd['Geography'])
count(kd['Geography'])
```

```
Counter({0: 5014, 2: 2477, 1: 2509})
```

Count(kd['Surname'])
dataset'Surname']=le.fit_transform(dataset['Surname'])
count(kd['Surname'])

```
Counter({1115: 1,
         1177: 17,
         2040: 8,
         289: 14,
         1822: 20,
         537: 22,
         177: 4,
         2000: 2,
         1146: 18,
         1081: 19,
         195: 1,
         83: 6,
         1369: 5,
         515: 16,
         2389: 29,
         1021: 1,
         2307: 1,
         1154: 16,
         1872: 1,
         1108: 12,
         1736: 19,
         697: 13,
         991: 2,
         1862: 1,
         2880: 14,
         1642: 24,
         2897: 20,
         1908: 6,
         1772: 2,
         1609: 11,
         133: 5,
         2007: 4,
```

kd['Gender']=kd['Gender'].replace(['Male','Female'],[0,1]) kd

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	1115	619	0	1	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	1177	608	2	1	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	2040	502	0	1	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	289	699	0	1	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	1822	850	2	1	43	2	125510.82	1	1	1	79084.10	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	9996	15606229	1999	771	0	0	39	5	0.00	2	1	0	96270.64	0
9996	9997	15569892	1336	516	0	0	35	10	57369.61	1	1	1	101699.77	0
9997	9998	15584532	1570	709	0	1	36	7	0.00	1	0	1	42085.58	1
9998	9999	15682355	2345	772	1	0	42	3	75075.31	2	1	0	92888.52	1
9999	10000	15628319	2751	792	0	1	28	4	130142.79	1	1	0	38190.78	0

10000 rows × 14 columns

Question-8

Split the data into dependent and independent variables

Solution :

Independent

```
FH['Gender']=FH['Gender'].replace(['Male','Female'],[0,1])
x=FH.iloc[:,2:]
print("\nindependent variable\n",x)
```

```
independent variable
       Surname  CreditScore  Geography  Gender  Age  Tenure    Balance  \
0        1115          619          0       1   42       2       0.00
1        1177          608          2       1   41       1   83807.86
2        2040          502          0       1   42       8  159660.80
3         289          699          0       1   39       1       0.00
4        1822          850          2       1   43       2  125510.82
...       ...          ...        ...     ...  ...     ...        ...
9995     1999          771          0       0   39       5       0.00
9996     1336          516          0       0   35      10   57369.61
9997     1570          709          0       1   36       7       0.00
9998     2345          772          1       0   42       3   75075.31
9999     2751          792          0       1   28       4  130142.79

      NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary  Exited
0                 1          1               1        101348.88       1
1                 1          0               1        112542.58       0
2                 3          1               0        113931.57       1
3                 2          0               0         93826.63       0
4                 1          1               1         79084.10       0
...             ...        ...             ...              ...     ...
9995              2          1               0         96270.64       0
9996              1          1               1        101699.77       0
9997              1          0               1         42085.58       1
9998              2          1               0         92888.52       1
9999              1          1               0         38190.78       0

[10000 rows x 12 columns]
```

Dependent

```
y=kd.iloc[:,0:2] print("dependent
variables\n",y)
```

```
dependent variables
      RowNumber  CustomerId
0             1    15634602
1             2    15647311
2             3    15619304
3             4    15701354
4             5    15737888
...         ...         ...
9995       9996    15606229
9996       9997    15569892
9997       9998    15584532
9998       9999    15682355
9999      10000    15628319

[10000 rows x 2 columns]
```

Question-9:

Scale the independent variables

Solution :

Xtrain

```
from sklearn.preprocessing import MinMaxScaler
nm=MinMaxScaler()
n_xtrain=nm.fit_transform(X_train)
n_xtrain
```

```
array([[0.33879222, 0.974     , 1.        , ..., 1.        , 0.25485714,
        0.        ],
       [0.57795974, 1.        , 1.        , ..., 1.        , 0.51955874,
        0.        ],
       [0.97065848, 0.636     , 1.        , ..., 0.        , 0.53233635,
        1.        ],
       ...,
       [0.40361651, 0.55     , 1.        , ..., 1.        , 0.67404984,
        0.        ],
       [0.21050836, 0.324    , 0.5       , ..., 0.        , 0.07409993,
        0.        ],
       [0.5663596 , 0.356    , 0.5       , ..., 1.        , 0.00475092,
        0.        ]])
```

Xtest

```
n_X_test=nm.fit_transform(X_test)
n_X_test
```

```
array([[0.61659269, 0.352     , 0.5       , ..., 0.        , 0.66189298,
        0.        ],
       [0.28303175, 0.496     , 0.        , ..., 1.        , 0.37133981,
        0.        ],
       [0.95800615, 0.384     , 0.        , ..., 1.        , 0.10631272,
        0.        ],
       ...,
       [0.76681461, 0.874     , 0.        , ..., 1.        , 0.31051302,
        0.        ],
       [0.8477296 , 0.74      , 1.        , ..., 0.        , 0.68981209,
        0.        ],
       [0.94093547, 0.384     , 0.        , ..., 0.        , 0.62636535,
        0.        ]])
```

Question-10:

Split the data into training and testing

Solution :

Xtrain

```
from sklearn.model_selection import train_test_split
x=km.iloc[:,2:]
y=km.iloc[:,0:2]
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=11)
X_train
```

	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
1264	993	837	2	0	31	9	104678.62	1	0	1	50972.60	0
5376	1694	850	2	0	38	1	146343.98	1	0	1	103902.11	0
2037	2845	668	2	1	24	7	173962.32	1	0	0	106457.11	1
6485	1016	640	1	0	26	5	90402.77	1	1	1	3298.65	0
1600	1037	517	0	0	28	2	115062.61	1	1	0	179056.23	0
...	...	...	...	...	...	...	...	...	...	...	...	...
1293	1067	641	0	0	30	2	87505.47	2	0	1	7278.57	0
4023	2611	535	0	0	38	8	85982.07	1	1	0	9238.35	0
7259	1183	625	2	0	32	7	106957.28	1	1	1	134794.02	0
5200	617	512	1	0	42	9	93955.83	2	1	0	14828.54	0
3775	1660	528	1	0	22	5	93547.23	2	0	1	961.57	0

7000 rows × 12 columns

X_test

	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
3104	1808	526	1	0	31	5	145537.21	1	1	0	132404.64	0
6353	831	598	0	0	35	8	114212.60	1	1	1	74322.85	0
8689	2808	542	0	0	67	10	129431.36	1	0	1	21343.74	0
5857	909	594	0	1	56	7	0.00	1	1	0	26215.85	1
6011	2113	520	1	1	45	1	123086.39	1	1	1	41042.40	1
...	...	...	...	...	...	...	...	...	...	...	...	...
8125	2496	629	1	1	38	9	123948.85	1	1	0	76053.07	0
8444	839	792	0	1	70	3	0.00	2	1	1	172240.27	0
2167	2248	787	0	0	33	1	126588.81	2	0	1	62163.53	0
8043	2485	720	2	0	31	4	141356.47	1	0	0	137985.69	0
4917	2758	542	0	0	32	7	107871.72	1	1	0	125302.64	0

3000 rows × 12 columns

y_train

	RowNumber	CustomerId
1264	1265	15732199
5376	5377	15602500
2037	2038	15678146
6485	6486	15635197
1600	1601	15748718
...	...	...
1293	1294	15687752
4023	4024	15629187
7259	7260	15718921
5200	5201	15641298
3775	3776	15709004

7000 rows × 2 columns

y_test

	RowNumber	CustomerId
3104	3105	15654230
6353	6354	15676353
8689	8690	15684769
5857	5858	15813659
6011	6012	15783007
...	...	...
8125	8126	15666982
8444	8445	15793641
2167	2168	15780846
8043	8044	15616525
4917	4918	15681991

3000 rows × 2 columns