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Domain: AI

Project Tittle: Emerging Methods For Early Detection Of Forest Fires

ASSIGNMENT NO.: 2

Importing Necessary Libraries

import pandas as pd import numpy as np import matplotlib.pyplot as pltimport seaborn as sns from sklearn.compose import ColumnTransformer

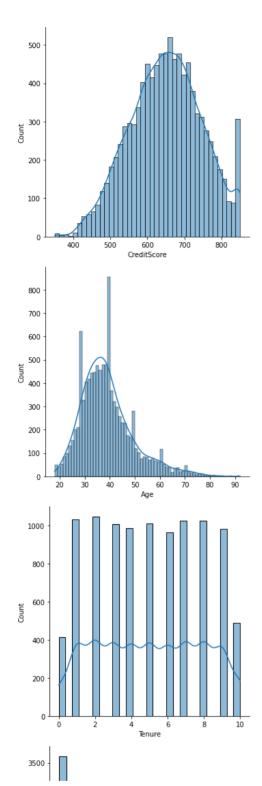
 $from \ sklearn.preprocessing \ import \ One Hot Encoder \ from \ sklearn.preprocessing \ import \ Standard Scaler$

2. Load the dataset

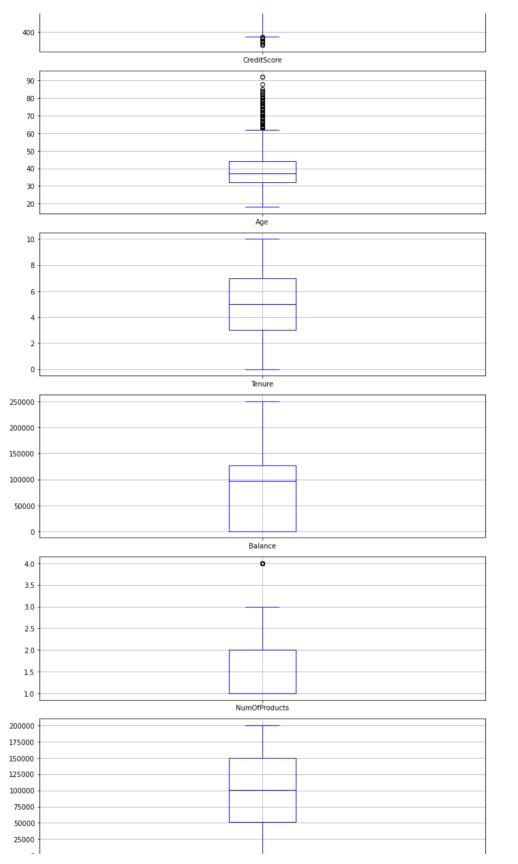
data = pd.read_csv('<u>/content/Churn_Modelling.csv</u>')

3. Perform Below Visualizations. UNIVARIATE ANALYSIS

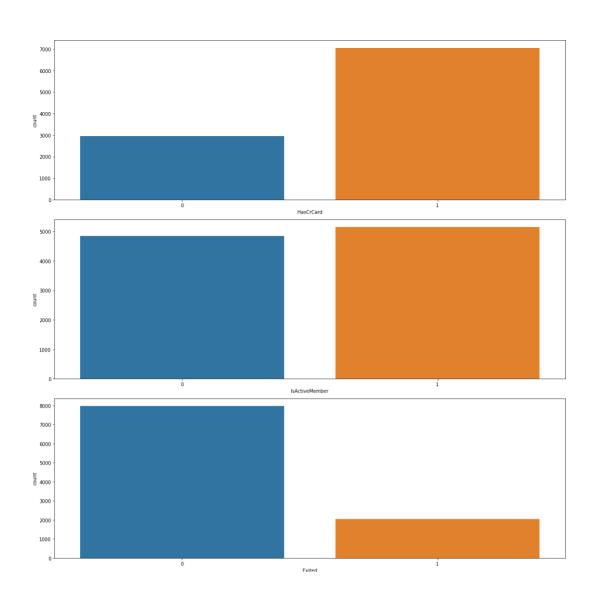
С→



 $\label{eq:controller} $$ l=['CreditScore','Age','Tenure','Balance','NumOfProducts','EstimatedSalary']$ fig, (ax1, ax2, ax3, ax4, ax5, ax6) = plt.subplots(nrows=6, ncols=1, figsize=(10,20))$ data.boxplot(column=[[[0]],grid='False',color='blue',ax=ax1)$ data.boxplot(column=[[12]],grid='False',color='blue',ax = ax2)$ data.boxplot(column=[[2]],grid='False',color='blue',ax = ax3)$ data.boxplot(column=[[3]],grid='False',color='blue',ax = ax4)$ data.boxplot(column=[[4]],grid='False',color='blue',ax = ax5)$ data.boxplot(column=[[5]],grid='False',color='blue',ax = ax6) plt.tight_layout() $$$

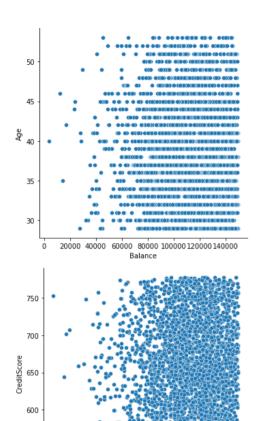


import warnings
warnings.filterwarnings("ignore")
fig, (ax1, ax2, ax3) = plt.subplots(nrows=3, ncols=1, figsize=(16,16))
sns.countplot(data.HasCrCard,ax=ax1)
sns.countplot(data.IsActiveMember,ax=ax2)
sns.countplot(data.Exited,ax=ax3)
plt.tight_layout()



BI - VARIATE ANALYSIS

$$\label{eq:continuous} \begin{split} &\text{for i in range(len(l)-1):} \\ &\text{for j in range(i+1,len(l)):} \\ &\text{sns.relplot(x = l[i],y = l[j],data = data)} \end{split}$$



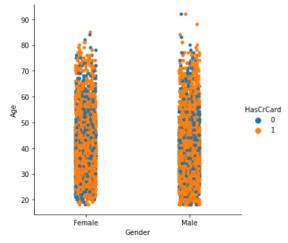
MULTI - VARIATE ANALYSIS

550

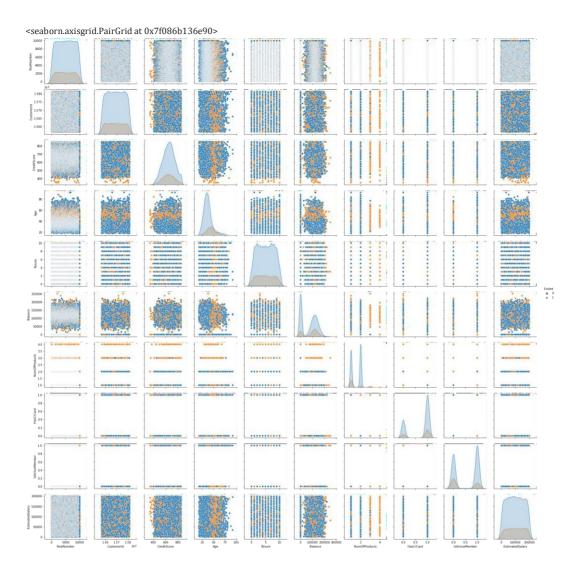
20000 40000 60000 80000 100000120000140000 Balance

sns.catplot(x='Gender', y='Age', hue='HasCrCard', data=data)

<seaborn.axisgrid.FacetGrid at 0x7f086b124bd0>



sns.pairplot(data = data,hue='Exited')



4. Perform descriptive statistics on the dataset

data.head()

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

data.describe()

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000

data.dtypes

RowNumber int64 CustomerId int64 object Surname CreditScore int64 Geography object Gender object Age int64 Tenure int64 Balance float64 NumOfProducts int64 Has Cr Cardint64 IsActiveMember int64 EstimatedSalary float64 Exited int64

dtype: object

data.skew()

RowNumber	0.000000
CustomerId	0.001149
CreditScore	-0.071607
Age	1.011320
Tenure	0.010991
Balance	-0.141109
NumOfProducts	0.745568
HasCrCard	-0.901812
IsActiveMember	-0.060437
EstimatedSalary	0.002085
Exited dtype: float64	1.471611

5. Handle the Missing values.

data.isnull().any()

RowNumber False CustomerId False Surname False CreditScore False Geography False False Gender Age False Tenure False Balance False NumOfProducts False False HasCrCard IsActiveMember False EstimatedSalary False Exited False

dtype: bool

6. Find the outliers and replace the outliers

data['CreditScore'].describe()

10000.000000 count 650.528800 mean 96.653299 std min 350.000000 25% 584.000000 50% 652.000000 718.000000 75% 850.000000 max

Name: CreditScore, dtype: float64

data['Age'].describe()

count	10000.000000
mean	38.921800
std	10.487806
min	18.000000
25%	32.000000
50%	37.000000
75%	44.000000
max	92.000000

Name: Age, dtype: float64

data['Balance'].describe()

 count
 10000.00000

 mean
 76485.889288

 std
 62397.405202

 min
 0.000000

 25%
 0.000000

 50%
 97198.540000

 75%
 127644.240000

 max
 250898.090000

Name: Balance, dtype: float64

l=['Balance','Age','CreditScore']for i in l:

 $percentile_least = data[i].quantile(0.1)percentile90 =$

data[i].quantile(0.9)

data = data[(data[i]<percentile90)& (data[i]>percentile_least)]data['CreditScore'].describe()

 count
 3354.000000

 mean
 651.885808

 std
 66.341508

 min
 522.000000

 25%
 601.000000

 75%
 705.000000

 max
 777.000000

Name: CreditScore, dtype: float64

data['Age'].describe()

count 3354.000000 38.594812 mean 6.171482 std 29.000000 min 34.000000 25% 38.000000 50% 75% 43.000000 max 53.000000 Name: Age, dtype: float64

data['Balance'].describe()

count 3354.000000 mean 111127.251270 23930.791436 std 3768.690000 min 25% 96579.825000 113904.805000 50% 129621.14000075% 149238.970000 max

Name: Balance, dtype: float64

7. Check for Categorical columns and perform encoding.

from sklearn.preprocessing import LabelEncoder encoder=LabelEncoder() for i in data:

if data[i].dtype=='object':

data[i]=encoder.fit_transform(data[i])data.head()

	RowNuml	ber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure		Balance NumOfProduc
1		2	15647311	645	61	08	2	0	41	1	83807.86
5		6	15574012	302	64	45	2	1	44	8	113755.78
40	-		A E 712 713		1 <i>E</i>	OO	73	4	***		
8. Split	the data i	nto	dependent a	nd indepe	ndent varia	bles.					
26 data.shape(3 14) x = data.iloc[data.iloc[:,13	[:,:13]y =	7	15736816	1605	75	56	1	1	36	2	136815.64
1 5 10 15 26 Name	0 1 0 0 0 0 e: Exited, dt	ype:	înt64								

x.head()

	RowNumbe r	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProdu c
1	2	15647311	645	608	2	0	41	1	83807.86	
5	6	15574012	302	645	2	1	44	8	113755.78	
10	11	15767821	109	528	0	1	31	6	102016.72	
15	16	15643966	561	616	1	1	45	3	143129.41	
26	27	15736816	1605	756	1	1	36	2	136815.64	

9. Scale the independent variables

 $from \ sklearn.preprocessing \ import \ Standard Scalersc = Standard Scaler() \\ x = sc.fit_transform(x)$

10. Split the data into training and testing

 $from \ sklearn.model_selection \ import \ train_test_split \\ x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2, random_state=0)x_train.shape$

(2683, 13)

y_train.shape

(2683,)

x_test.shape

(671, 13)

y_test.shape

(671,)