Personal Loan prediction

- Introduction
- Data Set
- Project Overview
- Projett Motivation
- Gatgering Data
- Exploratory Data Analysis
- Modelling
- Conclusion

Introduction

Your client is a banking service provider in the US.They are experiencing issues related to customers personal loan prediction.

In this project we are going to predict which customer will take personal loan.
we will use classification algorithms to differentiate people with buy loan vs the who will not.

Data Set

- The files contains data of 5000 customers.The data include customer demographic information(age , income etc.) , customer relationship with bank and customers response on campaign on personal loan.

Attribute Information

- **CCAvg** : Avg speding on credit cards per month
- **Education Level** : 1:UG , 2:Graduate , 3:Advance/Professional
- **Mortgage** :Value of house mortgage if any

Project Objective

Client is interested in understanding the leading indicatior for interested customers for personal loan.This will enable them to take pre-emptive action such offering better plans to encouraging them to take personal loan.

Importing Libraries

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import plotly.express as px
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
print('Libraries imported')
```

```
Libraries imported
```

Gathering Data

In [2]:
```
bank_df = pd.read_csv('Bank_Personal_Loan_Modelling.csv')
df = bank_df.copy()
```

Data Shape

In [3]:
```
print('Shape of data{}'.format(df.shape))
print("Number of rows:{}".format(df.shape[0]))
print("Number of rows:{}".format(df.shape[1]))
```

```
Shape of data(5000, 14)
Number of rows:5000
Number of rows:14
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   ID                  5000 non-null   int64  
 1   Age                 5000 non-null   int64  
 2   Experience          5000 non-null   int64  
 3   Income              5000 non-null   int64  
 4   ZIP Code            5000 non-null   int64  
 5   Family              5000 non-null   int64  
 6   CCAvg               5000 non-null   float64
 7   Education           5000 non-null   int64  
 8   Mortgage            5000 non-null   int64  
 9   Securities Account  5000 non-null   int64  
 10  CD Account          5000 non-null   int64  
 11  Online              5000 non-null   int64  
 12  CreditCard          5000 non-null   int64  
 13  Personal Loan       5000 non-null   int64  
dtypes: float64(1), int64(13)
memory usage: 547.0 KB
```

you can see we don't have any categoricals columns.

Observation:

There are 13 features and 5000 entires, all non-null. all features are numerical features, and of them, Education , Mortagage , Securities Account , CD Account , Online ,Credit Card , Personal Loan is a numerical categorical feature.

Missings And duplicates values

In [5]:
```
print(df.isna().sum().sort_values(ascending = False))
print('duplicate values in  df are' ,df.duplicated().sum() )
print('duplicates dropped')
```

```
ID                    0
Age                   0
Experience            0
Income                0
ZIP Code              0
Family                0
CCAvg                 0
Education             0
Mortgage              0
Securities Account    0
CD Account            0
Online                0
CreditCard            0
Personal Loan         0
dtype: int64
duplicate values in  df are 0
duplicates dropped
```

There is not any missings values and also not any duplicaltes values.

Missing Data - Initial Intuition

Here, we don't have any missing data. General Thumb Rules:

- For features with less missing values- can use regression to predict the missing values or fill with the mean of the values present, depending on the feature.
- For features with very high number of missing values- it is better to drop those columns as they give very less insight on analysis. As there's no thumb rule on what criteria do we delete the columns with high number of missing values, but generally you can delete the columns, if you have more than 30-40% of missing values.

In [6]:
```
df.describe()
```

Out[6]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAv
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.00000
mean	2500.500000	45.338400	20.104600	73.774200	93152.503000	2.396400	1.93793
std	1443.520003	11.463166	11.467954	46.033729	2121.852197	1.147663	1.74765
min	1.000000	23.000000	-3.000000	8.000000	9307.000000	1.000000	0.00000
25%	1250.750000	35.000000	10.000000	39.000000	91911.000000	1.000000	0.70000
50%	2500.500000	45.000000	20.000000	64.000000	93437.000000	2.000000	1.50000
75%	3750.250000	55.000000	30.000000	98.000000	94608.000000	3.000000	2.50000
max	5000.000000	67.000000	43.000000	224.000000	96651.000000	4.000000	10.00000

In [7]:
```
df.columns
```

Out[7]:
```
Index(['ID', 'Age', 'Experience', 'Income', 'ZIP Code', 'Family', 'CCAvg',
       'Education', 'Mortgage', 'Securities Account', 'CD Account', 'Online',
       'CreditCard', 'Personal Loan'],
      dtype='object')
```

Dropping Unnecessary columns 'ID' and 'ZIP Code'

In [8]:
```
df.drop(columns = ['ID' , 'ZIP Code'] ,  axis = 1 , inplace =True)
```

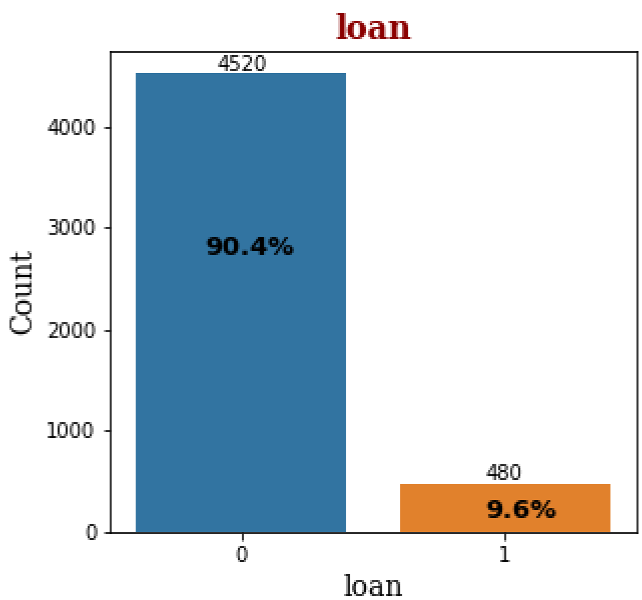
Target Varaible is :Personal Loan

In [9]:
```
#create counts of df for plotting categorical variables
loan = np.unique(df['Personal Loan'], return_counts=True)
print('loan = {}\n'.format(loan))
```

```
loan = (array([0, 1], dtype=int64), array([4520,  480], dtype=int64))
```

In [10]:
```
# create fontdicts for formatting figure text
axtitle_dict = {'family': 'serif','color':  'darkred','weight': 'bold','size': 16
axlab_dict = {'family': 'serif', 'color': 'black','size': 14}
```

In [11]:
```
# Display a frequency distribution for Personal Loan.
fig = plt.figure(figsize=[16,15]);
ax1 = fig.add_subplot(3, 3, 2);
sns.barplot(x=list(loan[0]), y=list(loan[1]), ax=ax1 );
ax1.text(0.2, 2800, '{}%' .format(str(round(loan[1][0]/sum(loan[1])*100,1))), ha=
ax1.text(1.2, 200, '{}%' .format(str(round(loan[1][1]/sum(loan[1])*100,1))), ha='
ax1.set_title('loan', fontdict=axtitle_dict);
ax1.set_xlabel('loan', fontdict=axlab_dict);
ax1.set_ylabel('Count', fontdict=axlab_dict);
ax1.bar_label(ax1.containers[0])
plt.show()
```



Data is Highly Imblanaced.majority of the data are class 0.Imblanaced ratio is **90:10**.out of 5000 data 4520 is for not opting personal loan and 480 is for personal loan.

Filtering Numericals and Categoricals columns:

In [12]:
```
categ_columns = []
for col in df.columns:
    if df[col].nunique()<=5:
        if col!='Personal Loan':
            categ_columns.append(col)
print('categ numericals columns are {}'.format(categ_columns))
```

```
categ numericals columns are ['Family', 'Education', 'Securities Account', 'CD Account', 'Online', 'CreditCard']
```

In [13]:
```
Num_cols = [col for col in df.columns if col not in categ_columns]
print('numericals columns are {}'.format(Num_cols))
Num_cols.pop() #Removing Personal Loan
Num_cols
```

```
numericals columns are ['Age', 'Experience', 'Income', 'CCAvg', 'Mortgage', 'Pe
rsonal Loan']
```

Out[13]:
```
['Age', 'Experience', 'Income', 'CCAvg', 'Mortgage']
```

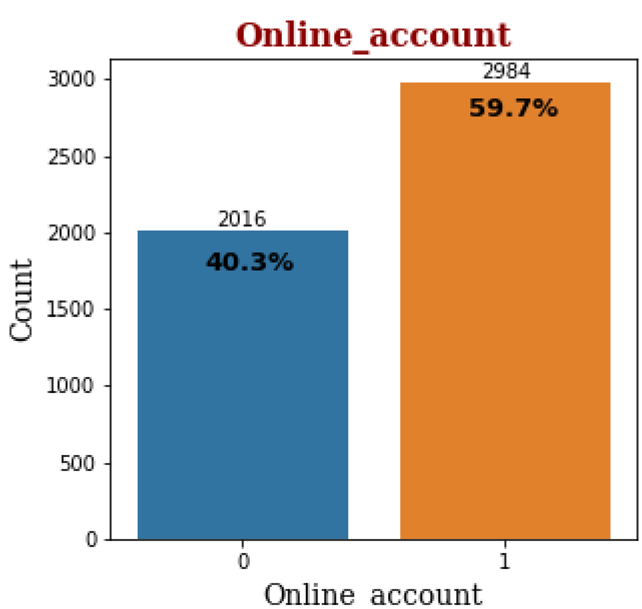
EDA

In [14]:
```
#create counts of df for plotting categorical variables
Online_account = np.unique(df['Online'], return_counts=True)
print('Online_account = {}\n'.format(Online_account))
```

```
Online_account = (array([0, 1], dtype=int64), array([2016, 2984], dtype=int64))
```

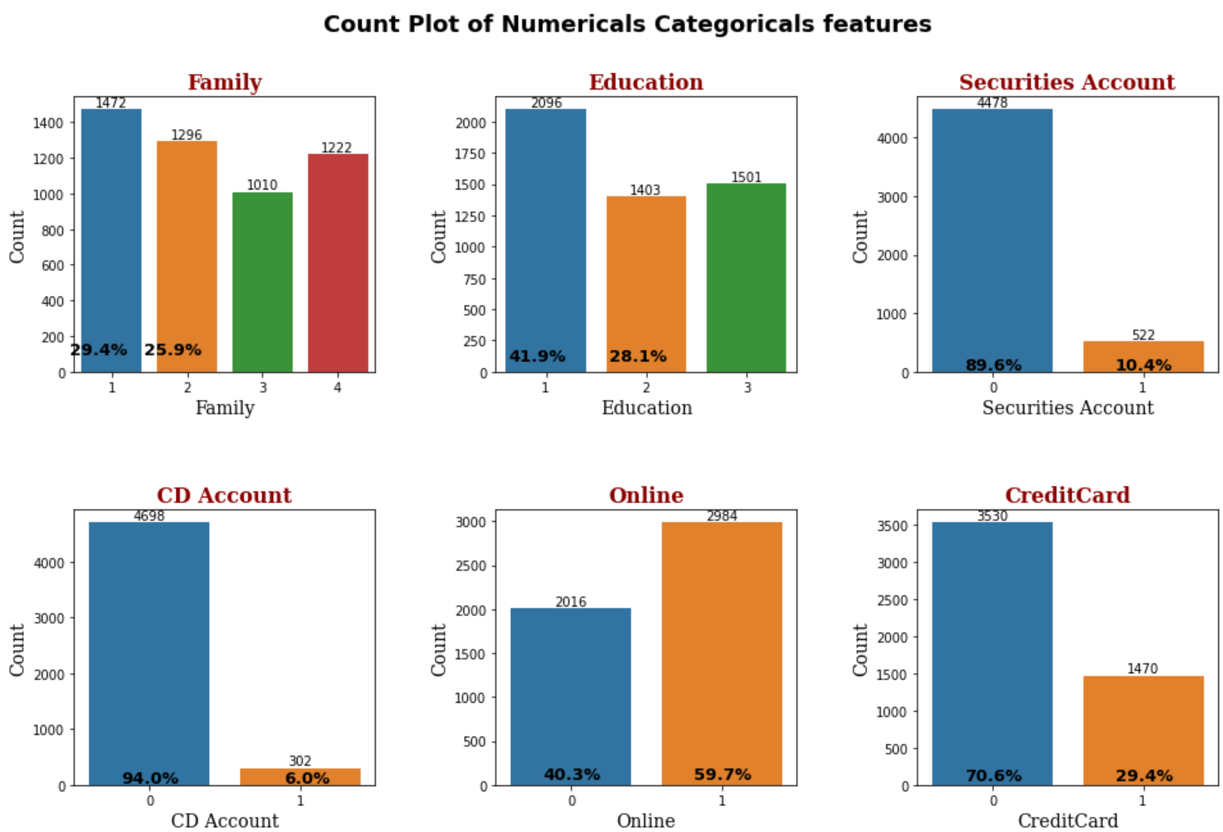
This plot is for one columns.we can use for loop to plot subplots.

In [15]:
```
fig = plt.figure(figsize=[16,15]);
ax1 = fig.add_subplot(3, 3, 2);
sns.barplot(x=list(Online_account[0]), y=list(Online_account[1]), ax=ax1 );
#below two lines of codes of codes are for showing percentage values in bargraph
ax1.text(0.2, 1800, '{}%' .format(str(round(Online_account[1][0]/sum(Online_accou
ax1.text(1.2, 2800, '{}%' .format(str(round(Online_account[1][1]/sum(Online_accou
ax1.set_title('Online_account', fontdict=axtitle_dict);
ax1.set_xlabel('Online_account', fontdict=axlab_dict);
ax1.set_ylabel('Count', fontdict=axlab_dict);
ax1.bar_label(ax1.containers[0])
plt.show()
```



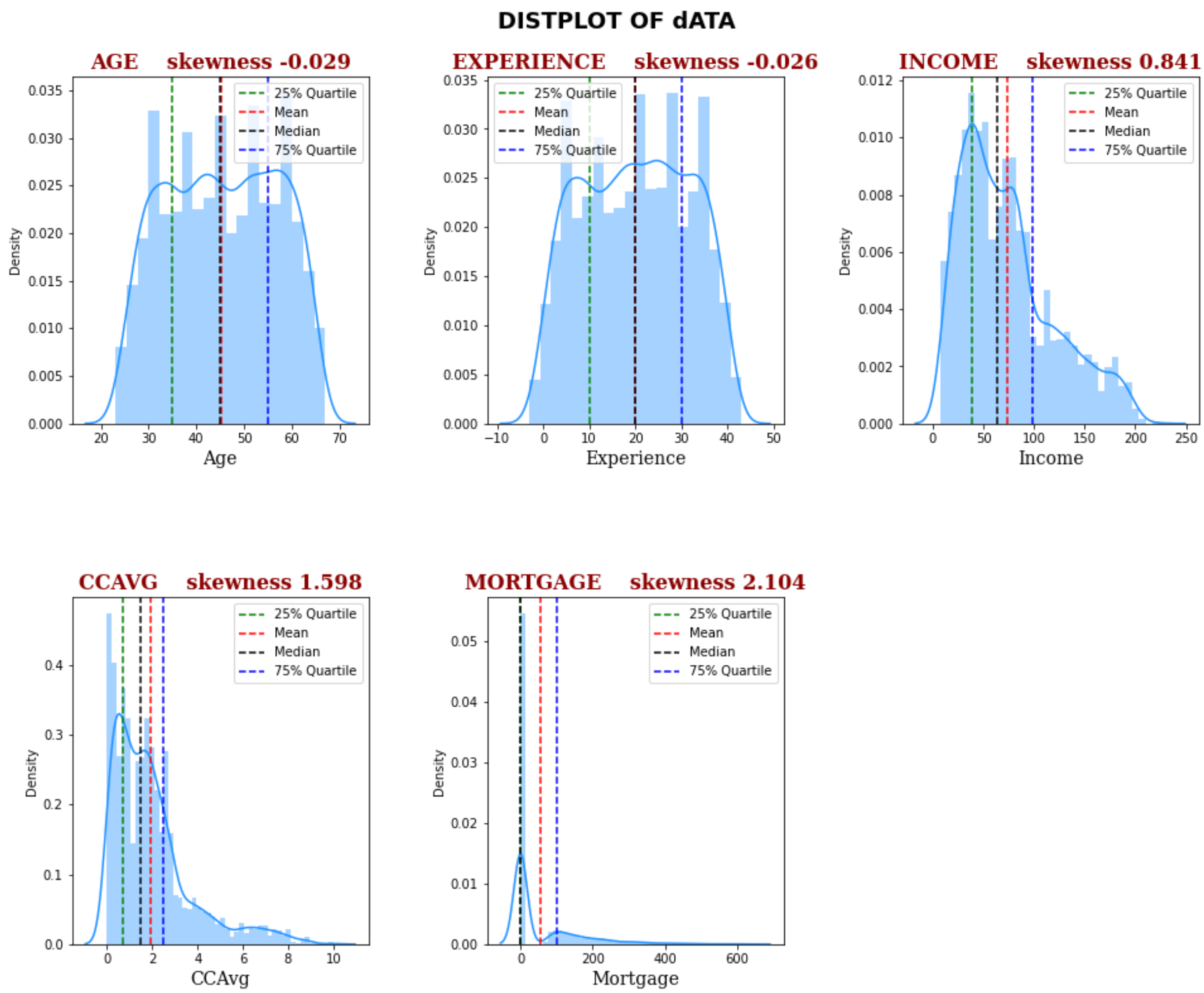
Unvariate Analysis

In [16]:
```
fig = plt.figure(figsize=[16,15])
fig.suptitle('Count Plot of Numericals Categoricals features', fontsize=18, fontw
fig.subplots_adjust(top=0.92);
fig.subplots_adjust(hspace=0.5, wspace=0.4);
for i , columns in enumerate(categ_columns):
    input = np.unique(df[columns] , return_counts = True)
    col= 'input'
    ax1 = fig.add_subplot(3, 3, i+1);
    ax1 = sns.barplot(x=list(eval(f'{col}[0]')), y=list(eval(f'{col}[1]')))
    #The below two lines of codes are used for percentage values.
    ax1.text(0.2, 120, '{}%' .format(str(round(eval(f'{col}[1][0]')/sum(eval(f'{c
    ax1.text(1.2, 120, '{}%' .format(str(round(eval(f'{col}[1][1]')/sum(eval(f'{c
    ax1.set_title(f'{columns}', fontdict=axtitle_dict)
    ax1.set_xlabel(f'{columns}', fontdict=axlab_dict)
    ax1.set_ylabel('Count', fontdict=axlab_dict)
    ax1.bar_label(ax1.containers[0])
#for showing percentage top of the bar we can increase 120
```



Distplot

In [17]:
```
#create figure with 3 x 3 grid of subplots
fig = plt.figure(figsize=[16,12])
fig.suptitle('DISTPLOT OF dATA', fontsize=18, fontweight='bold')
fig.subplots_adjust(top=0.92);
fig.subplots_adjust(hspace=0.5, wspace=0.4);
for i ,col in enumerate(Num_cols):
    ax = fig.add_subplot(2, 3, i+1)
    ax = sns.distplot(df[col],  color='dodgerblue')
    ax.axvline(df[col].quantile(q=0.25),color='green',linestyle='--',label='25% Q
    ax.axvline(df[col].mean(),color='red',linestyle='--',label='Mean')
    ax.axvline(df[col].median(),color='black',linestyle='--',label='Median')
    ax.axvline(df[col].quantile(q=0.75),color='blue',linestyle='--',label='75% Qu
    # ax.text('skewness: {}' .format(str(round(df[col].skew(),3))), ha='right', v
    ax.set_xlabel(f'{col}', fontdict=axlab_dict)
    ax.set_title(f'{col.upper()}    skewness {round(df[col].skew(),3)}', fontdict
    ax.legend(fontsize=10)
```



In [18]:
```
colours = ['forestgreen','dodgerblue','goldenrod', 'coral' , 'silver' , 'gold' ,
```

Outliers Detection

In [19]:
```
# Check of outliers by applying the IQR method checking if values are way outside
# numerical_features = ["tenure", "MonthlyCharges", "TotalCharges"]
df_num = df[Num_cols]
df_num.describe()

Q1 = df_num.quantile(0.25)
Q3 = df_num.quantile(0.75)
IQR = Q3 - Q1
IQR
((df_num < (Q1 - 1.5 * IQR)) | (df_num > (Q3 + 1.5 * IQR))).any()
```

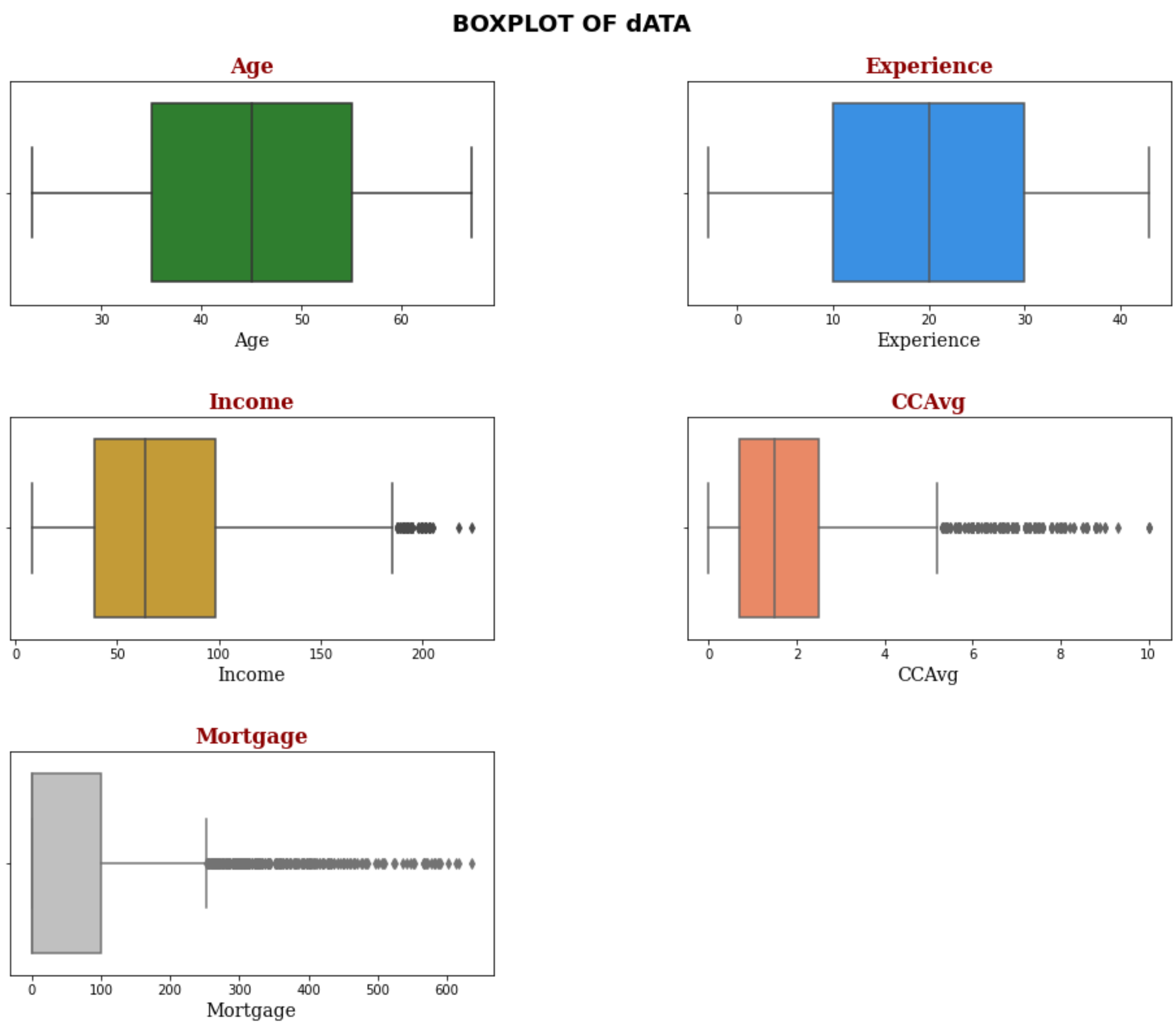
Out[19]:
```
Age            False
Experience     False
Income          True
CCAvg           True
Mortgage        True
dtype: bool
```

Income , CCAvg , Mortgage have outliers.

Visualization of outliers using box plot

In [20]:
```
#create figure with 3 x 3 grid of subplots
fig = plt.figure(figsize=[16,12])
fig.suptitle('BOXPLOT OF dATA', fontsize=18, fontweight='bold')
fig.subplots_adjust(top=0.92);
fig.subplots_adjust(hspace=0.5, wspace=0.4);
for i ,col in enumerate(Num_cols):
    ax1 = fig.add_subplot(3, 2, i+1);
    ax1 = sns.boxplot(data = df, x=col ,  color= colours[i]);

    ax1.set_title(f'{col}', fontdict=axtitle_dict)
    ax1.set_xlabel(f'{col}', fontdict=axlab_dict)
```



Outliers Detection

In [21]:
```
# Finding the IQR For Budget columns
dict = {}
for col in ['Income' , 'CCAvg' , 'Mortgage']:
    percentile25 = df[col].quantile(0.25)
    percentile75 = df[col].quantile(0.75)
    IQR  = percentile75 - percentile25
    upper_limit = percentile75 + 1.5 * IQR
    lower_limit = percentile25 - 1.5 * IQR
    dict['upper_limit'+ '_' + col] = upper_limit
    dict['lower_limit'+ '_' + col] = lower_limit
```

In Above code cell i just created a dictionary to keep upper_limit and lower_limit of Income , CCAvg , Mortgage...

In [22]:
```
dict
```

Out[22]:
```
{'upper_limit_Income': 186.5,
 'lower_limit_Income': -49.5,
 'upper_limit_CCAvg': 5.2,
 'lower_limit_CCAvg': -2.0,
 'upper_limit_Mortgage': 252.5,
 'lower_limit_Mortgage': -151.5}
```

In [23]:
```
for col in ['Income' , 'CCAvg' , 'Mortgage']:
    print('There are total {} Customers data which {} are less than lower limit.'
    print('There are total {} Customers data which {} are more than upper limit.'
```

```
There are total 0 Customers data which Income are less than lower limit.
There are total 96 Customers data which Income are more than upper limit.
There are total 0 Customers data which CCAvg are less than lower limit.
There are total 324 Customers data which CCAvg are more than upper limit.
There are total 0 Customers data which Mortgage are less than lower limit.
There are total 291 Customers data which Mortgage are more than upper limit.
```

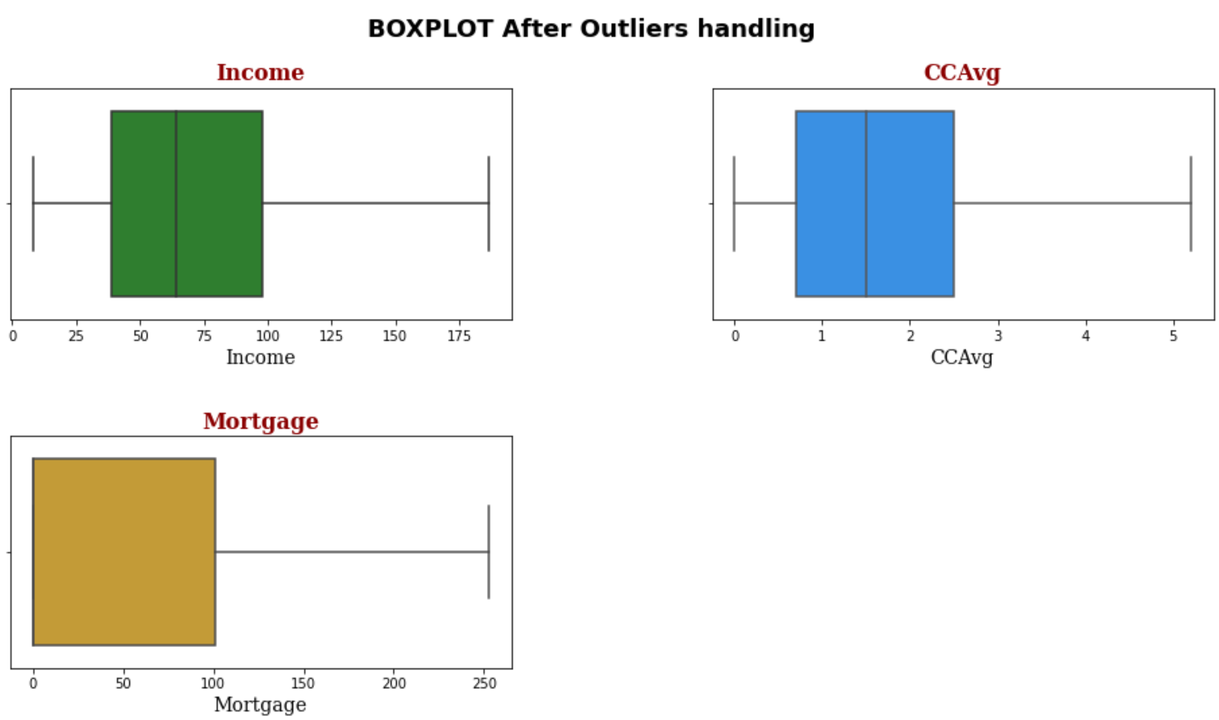
Capping Income , CCAvg and Mortgage with upper limit and lower limit.

In [24]:
```
for col in ['Income' , 'CCAvg' , 'Mortgage']:
    df[col] = np.where(
        df[col] > dict['upper_limit_' + col],
        dict['upper_limit_' + col],
        np.where(
            df[col] < dict['lower_limit_' + col],
            dict['lower_limit_' + col],
            df[col]
        )
    )
```

After Outliers treatment

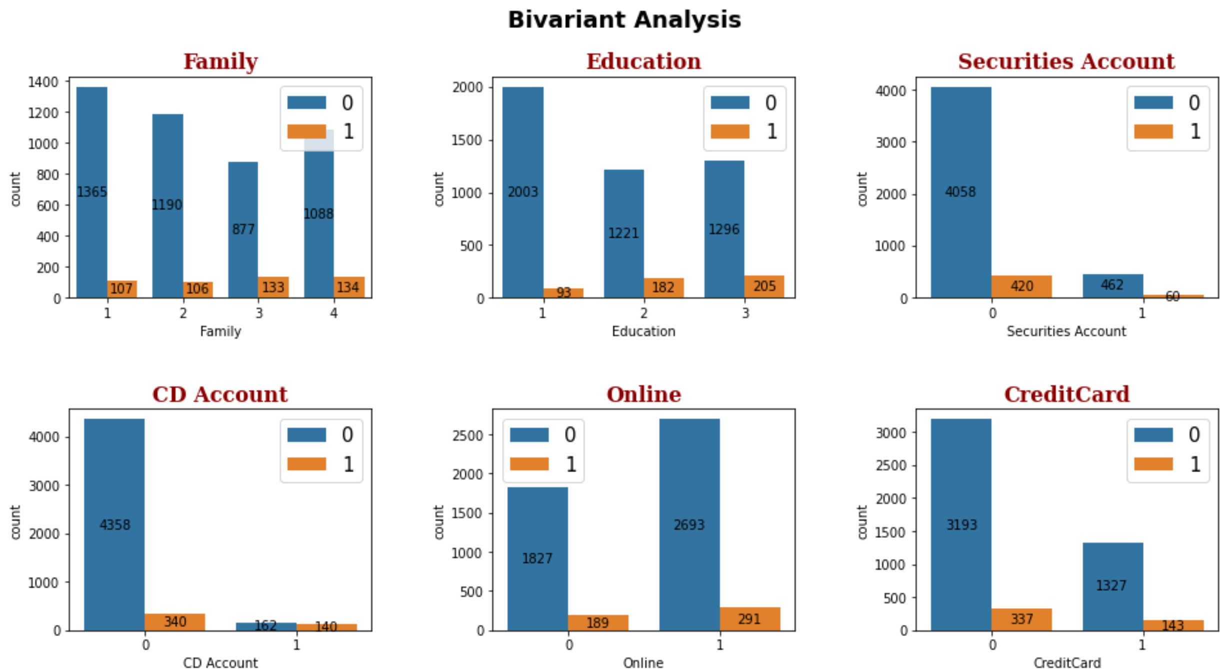
In [25]:
```
#create figure with 3 x 3 grid of subplots
fig = plt.figure(figsize=[16,12])
fig.suptitle('BOXPLOT After Outliers handling', fontsize=18, fontweight='bold')
fig.subplots_adjust(top=0.92);
fig.subplots_adjust(hspace=0.5, wspace=0.4);
for i ,col in enumerate( ['Income' , 'CCAvg' , 'Mortgage']):
    ax1 = fig.add_subplot(3, 2, i+1);
    ax1 = sns.boxplot(data = df, x=col ,  color= colours[i]);

    ax1.set_title(f'{col}', fontdict=axtitle_dict)
    ax1.set_xlabel(f'{col}', fontdict=axlab_dict)
```



Bivariate analysis

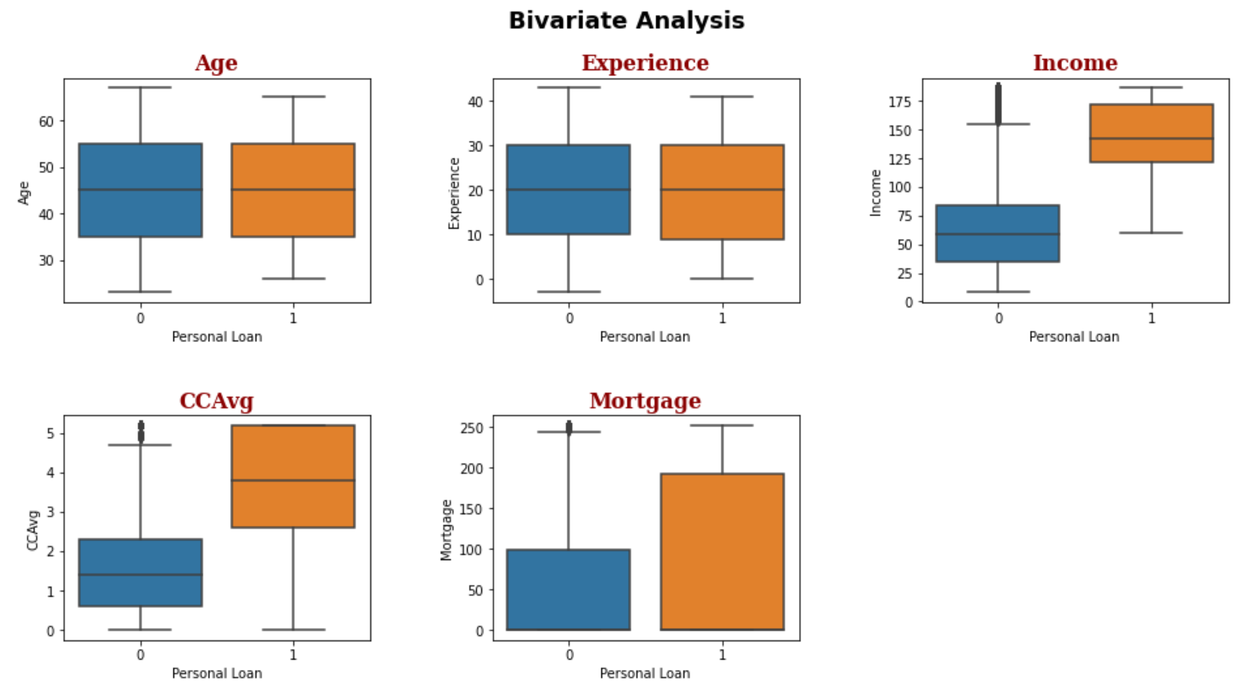
In [26]:
```
#create figure with 3 x 3 grid of subplots
fig = plt.figure(figsize=[16,12])
fig.suptitle('Bivariant Analysis', fontsize=18, fontweight='bold')
fig.subplots_adjust(top=0.92);
fig.subplots_adjust(hspace=0.5, wspace=0.4);
for i ,col in enumerate(categ_columns):
    a = fig.add_subplot(3, 3, i+1)
    a=sns.countplot(x = df[col] , ax=a , hue = df['Personal Loan'] )
    a.set_title(col , fontdict=axtitle_dict)
    a.bar_label(a.containers[0] , label_type='center')
    a.bar_label(a.containers[1] , label_type='center')
    a.legend(fontsize=15)
```



Plot Insights:

- Highly educated customers seem to much interested in personal loan than lower educated customers.
- Customers without securites account seem to more interseted than not securities account customers in personal loan.
- Customers with CD Account have higher probablity to take personal loan.in bar graph you can clearly see out of 163 cd account customers 140 is taken personal loan.
- Customers with Online internet banking are more intersted than non online customers in personal loan.
- Customers without Credit Card have much higher chance to take personal loan.

In [27]:
```
#create figure with 3 x 3 grid of subplots
fig = plt.figure(figsize=[16,12])
fig.suptitle('Bivariate Analysis', fontsize=18, fontweight='bold')
fig.subplots_adjust(top=0.92);
fig.subplots_adjust(hspace=0.5, wspace=0.4);
for i ,col in enumerate(Num_cols):
    a = fig.add_subplot(3, 3, i+1)
    a=sns.boxplot(x = 'Personal Loan' , y =col , ax=a  , data = df )
    a.set_title(col , fontdict=axtitle_dict)
```

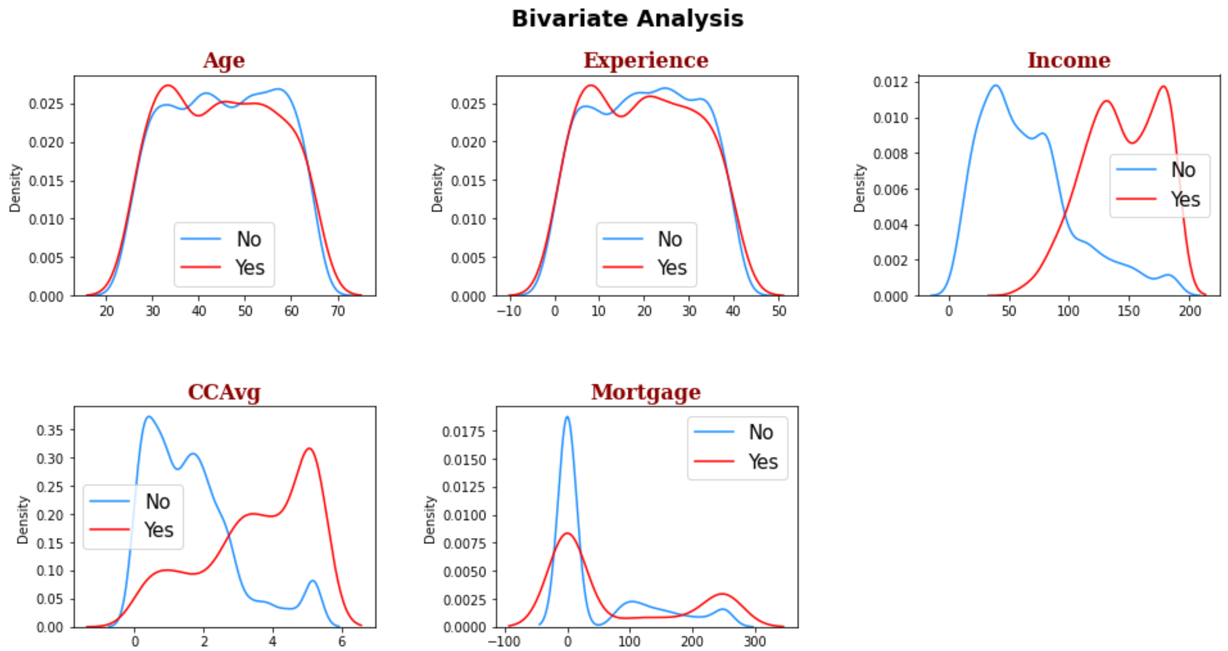


Plot Insights:

- Customers with personal loan Have Much higher Income with a median of 145 USD compared to a median of customers not opting for personal loan of median 55 USD.
- Customers who opted for personal loan have higher credit card avg spending with median 4 USD.
- Customers who opted for personal loan have slightly higher mortgate.
- Age and Experience doesn't have much effect on personal loan.

In [28]:
```
fig = plt.figure(figsize=[16,12])
fig.suptitle('Bivariate Analysis', fontsize=18, fontweight='bold')
fig.subplots_adjust(top=0.92);
fig.subplots_adjust(hspace=0.5, wspace=0.4);
for i ,col in enumerate(Num_cols):
    a = fig.add_subplot(3, 3, i+1)

    sns.distplot(x =df[df['Personal Loan']==0][col],  color='dodgerblue' , ax=a ,
    sns.distplot(x =df[df['Personal Loan']==1][col],  color='red' , ax=a , hist =
    a.set_title(col , fontdict=axtitle_dict)
    labels = ['No' , 'Yes']
    a.legend( labels  , fontsize = 15)
```



Creating Dummies for Categ columns

In [29]:
```
dum_df = pd.get_dummies(df , columns = categ_columns)
dum_df.head()
```

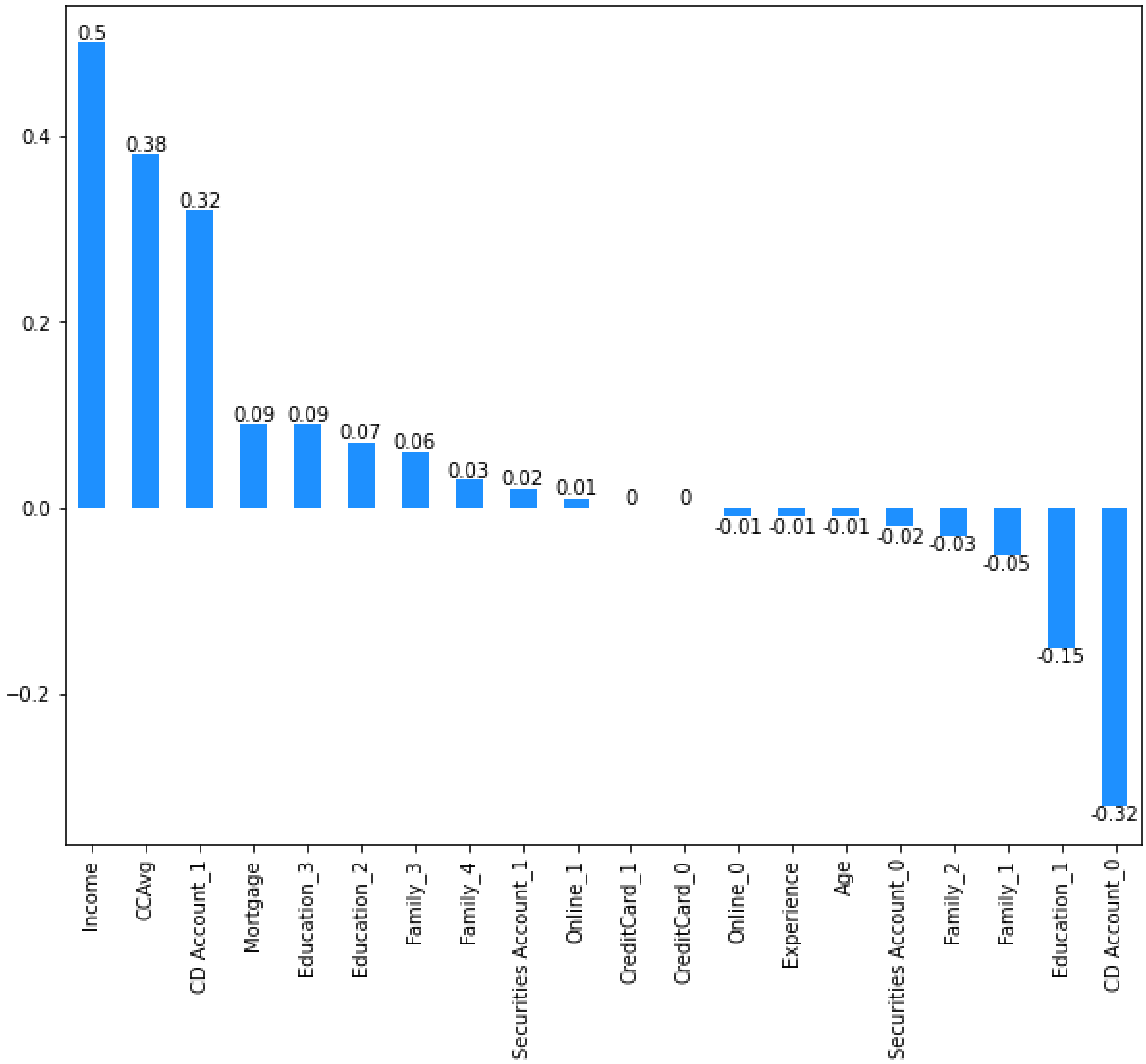
Out[29]:

	Age	Experience	Income	CCAvg	Mortgage	Personal Loan	Family_1	Family_2	Family_3	Family_4
0	25	1	49.0	1.6	0.0	0	0	0	0	1
1	45	19	34.0	1.5	0.0	0	0	0	1	0
2	39	15	11.0	1.0	0.0	0	1	0	0	0
3	35	9	100.0	2.7	0.0	0	1	0	0	0
4	35	8	45.0	1.0	0.0	0	0	0	0	1

5 rows × 21 columns

Correlation Analysis

In [30]:
```
ax = round(dum_df.corr()['Personal Loan'].sort_values(ascending = False)[1:] ,2 )
ax.bar_label(ax.containers[0])
plt.show()
```



Derived Insight:

HIGH Possibility to take personal loan seen in case of **Higher Income**, **High Credit Cards Spending**, and **Customers with CD Account**,

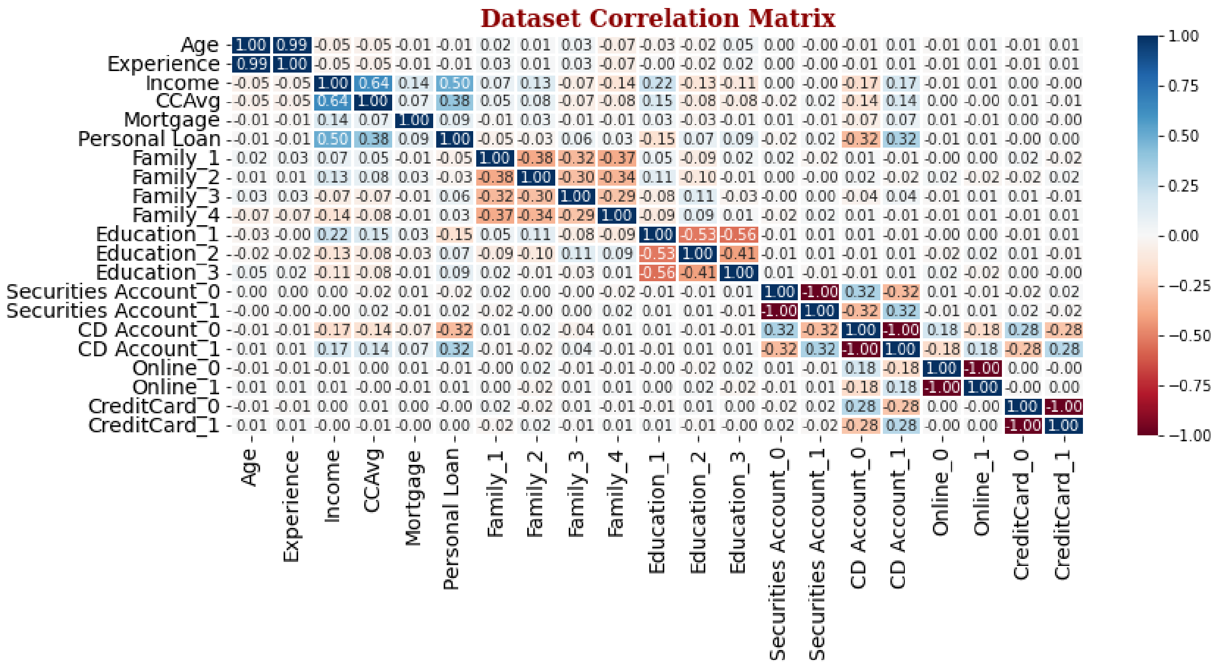
HIGH Possibility to take personal loan is seen in case of **Without CD Account**, **Lower Eduction** and **With One Family Members**

Factors like **Credit Cards Availability**, **Availability of Online Internet Banking** have alomost **NO** impact on personal loan.

This is also evident from the **Heatmap** below

Heatmap

In [31]:
```
# plot correlation matrix heatmap
fig, ax = plt.subplots(figsize=[13,5])
sns.heatmap(dum_df.corr(), ax=ax,  annot=True, linewidths=0.05, fmt= '.2f',cmap='
ax.tick_params(axis='both', which='major', labelsize=14)
ax.set_title('Dataset Correlation Matrix', fontdict=axtitle_dict)
fig.show()
```



Modelling

In [32]:
```
X = dum_df.drop('Personal Loan' , 1 )
y = dum_df['Personal Loan']
```

In [33]:
```
from sklearn.model_selection import train_test_split
X_train , X_test , y_train , y_test = train_test_split(X , y  ,test_size = 0.33 ,
```

In [34]:
```
X_train.shape , y_train.shape , X_test.shape , y_test.shape
```

Out[34]:
```
((3350, 20), (3350,), (1650, 20), (1650,))
```

In [35]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn import metrics
from sklearn.metrics import recall_score , classification_report , confusion_matr
from sklearn.metrics import precision_recall_curve , auc ,f1_score , plot_confusi
from sklearn.tree import DecisionTreeClassifier
```

The models used include:

- K Nearest Neighbors - fast, simple and instance-based
- Logistic Regression - fast and linear model
- Random Forest - slower but accurate ensemble model based on decision trees
- Support Vector Machines - slower but accurate model used here in the non-linear form-

In [36]:
```
model_list = []
accuracy_list = []
recall_list = []
precision_list = []
f1_score_list= []
```

In [37]:
```
def Model_features(X_train , y_train , X_test , y_test , y_pred , classifier  , m
#     fig ,ax = plt.subplots(figsize = (7,6))
    accuracy , precision , recall , f1_s = round(accuracy_score(y_test , y_pred)
    print(f'Accuracy Score is :{accuracy}')
    print(f'Precision Score is :{precision}')
    print(f'Recall Score is :{recall}')
    print(f'f1  Score is :{f1_s}')
    model_list.append(model_name)
    accuracy_list.append(accuracy)
    recall_list.append(recall)
    precision_list.append(precision)
    f1_score_list.append(f1_s)

#     print(f'f1  Score is :{round(specificity_score(y_test , y_pred) , 3)}')
    print(metrics.classification_report(y_test, y_pred))
```

Features Importanaces

In [38]:
```
# Define a function that plots the feature weights for a classifier.
def feature_weights(X_df, classifier, classifier_name):
    weights = round(pd.Series(classifier.coef_[0], index=X_df.columns.values).sor

    top_weights_selected = weights[:5]
    plt.figure(figsize=(7,6))
    plt.tick_params(labelsize=10)#plt.xlabel(fontsize=10)
    plt.title(f'{classifier_name} - Top 5 Features')
    ax = top_weights_selected.plot(kind="bar")
    ax.bar_label(ax.containers[0])

    return print("")
```

In [39]:
```
def confusion_matrix_plot(X_test , y_test , classifier ,classifier_name):
    ax = plot_confusion_matrix(classifier, X_test, y_test, display_labels=["No Pe
```

Logistic Regression

In [40]:
```
model_lr= LogisticRegression(random_state=0)
model_lr.fit(X_train, y_train)
y_pred = model_lr.predict(X_test)
model_lr.score(X_test , y_test)
```

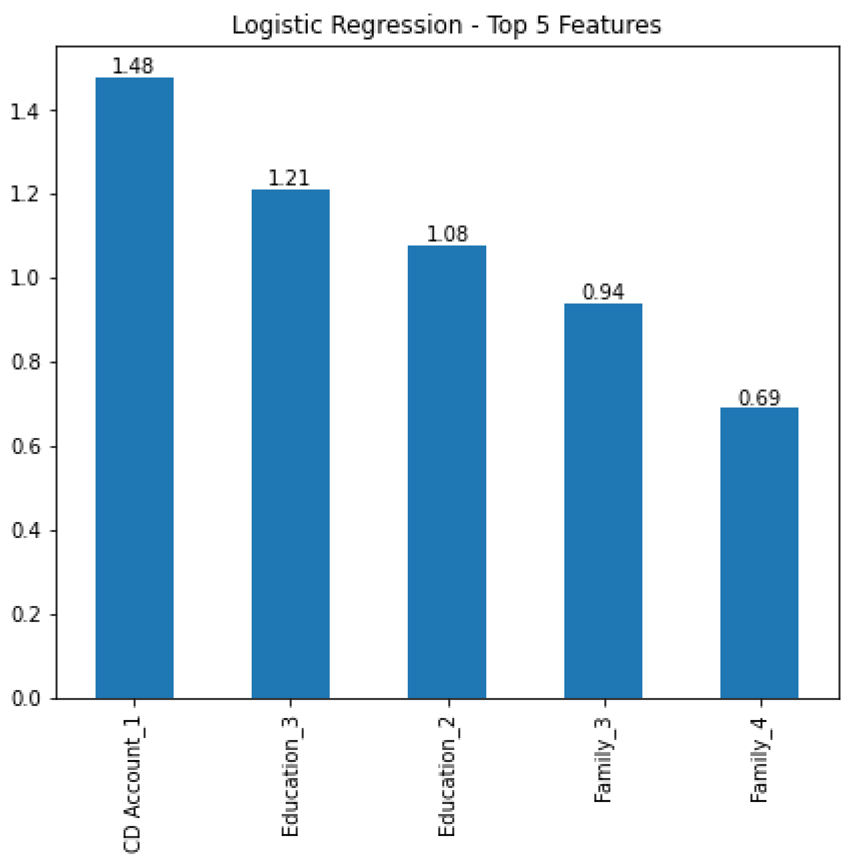
Out[40]: 0.9660606060606061

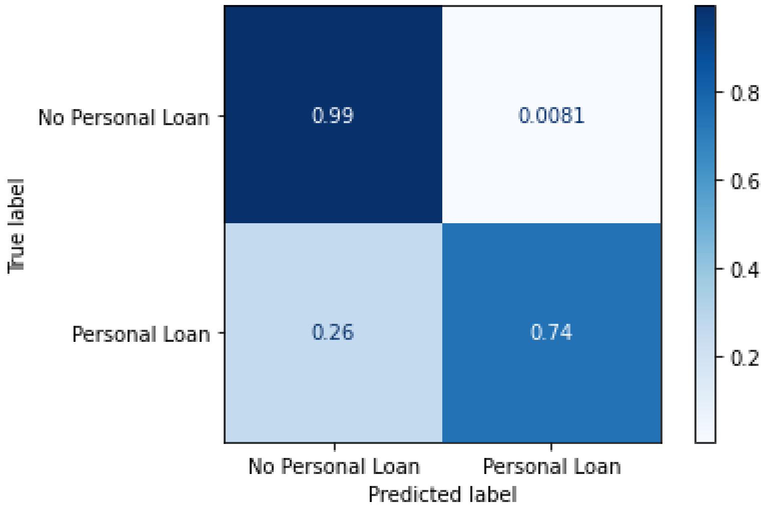
In [41]:
```
Model_features(X_train , y_train , X_test , y_test  , y_pred , model_lr , "Logist
feature_weights(X_train , model_lr , "Logistic Regression")
confusion_matrix_plot(X_test , y_test , model_lr , "Logistic Regression")
```

```
Accuracy Score is :0.966
Precision Score is :0.966
Recall Score is :0.741
f1  Score is :0.818
              precision    recall  f1-score   support

           0       0.97      0.99      0.98      1480
           1       0.91      0.74      0.82       170

    accuracy                           0.97      1650
   macro avg       0.94      0.87      0.90      1650
weighted avg       0.96      0.97      0.96      1650
```





KNN Classifier

In [42]:
```
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
knn.score(X_test , y_test)
```

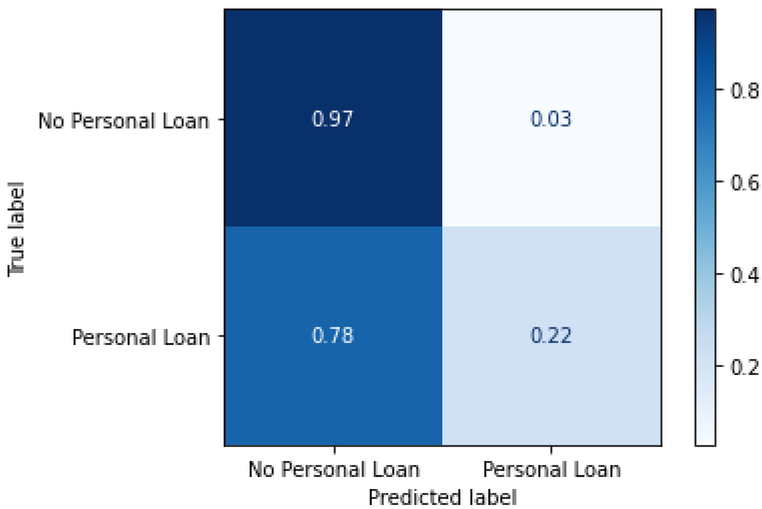
Out[42]:
```
0.8927272727272727
```

In [43]:
```
Model_features(X_train , y_train , X_test , y_test  , y_pred , knn , "Knn Classi
confusion_matrix_plot(X_test , y_test , knn , "Knn Classifier")
```

```
Accuracy Score is :0.893
Precision Score is :0.893
Recall Score is :0.218
f1  Score is :0.295
              precision    recall  f1-score   support

           0       0.92      0.97      0.94      1480
           1       0.46      0.22      0.29       170

    accuracy                           0.89      1650
   macro avg       0.69      0.59      0.62      1650
weighted avg       0.87      0.89      0.88      1650
```



Knn is giving good result for majority call 0 but for class 1 logistic regression is better than this.

Random Forest Classifier

In [44]:
```
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
rf.score(X_test , y_test)
```

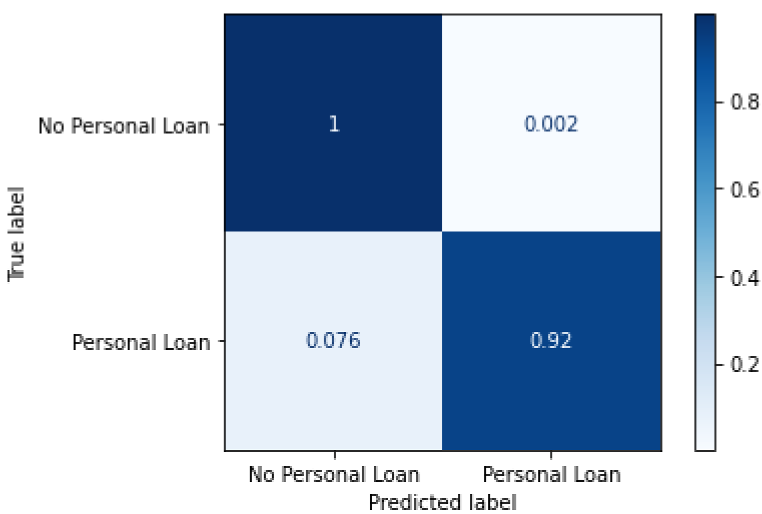
Out[44]: 0.9903030303030304

In [45]:
```
Model_features(X_train , y_train , X_test , y_test  , y_pred , rf , "Random Fores
confusion_matrix_plot(X_test , y_test , rf , "Random Forest Classifier")
```

```
Accuracy Score is :0.99
Precision Score is :0.99
Recall Score is :0.924
f1  Score is :0.952
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      1480
           1       0.98      0.92      0.95       170

    accuracy                           0.99      1650
   macro avg       0.99      0.96      0.97      1650
weighted avg       0.99      0.99      0.99      1650
```



Support Vector Machine

In [46]:
```
svm = SVC(kernel='rbf', probability=True)
svm.fit(X_train,y_train)

# Make predictions (classes and probabilities) with the trained model on the test
y_pred = svm.predict(X_test)
svm.score(X_test , y_test)
```

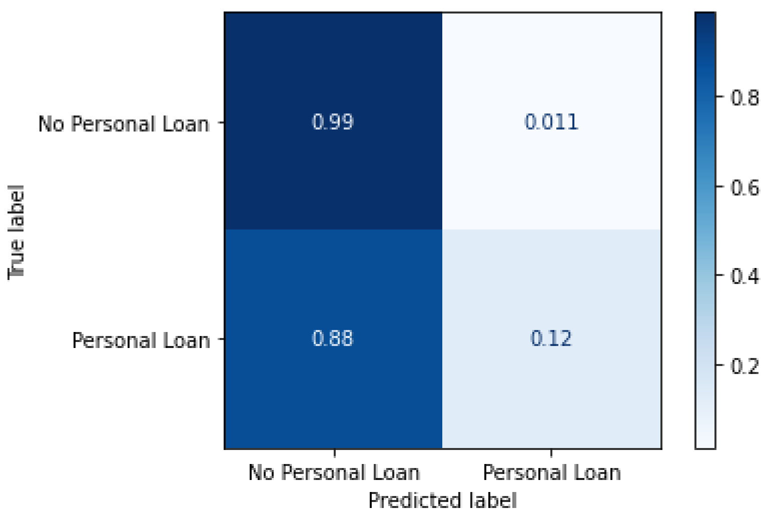
Out[46]: 0.9

In [47]:
```
Model_features(X_train , y_train , X_test , y_test  , y_pred , svm , "Support Vec
confusion_matrix_plot(X_test , y_test , svm , "Support Vector Machine")
```

```
Accuracy Score is :0.9
Precision Score is :0.9
Recall Score is :0.124
f1  Score is :0.203
              precision    recall  f1-score   support

           0       0.91      0.99      0.95      1480
           1       0.57      0.12      0.20       170

    accuracy                           0.90      1650
   macro avg       0.74      0.56      0.57      1650
weighted avg       0.87      0.90      0.87      1650
```



DecisionTreeClassifier

In [48]:
```
dtc = DecisionTreeClassifier()
dtc.fit(X_train, y_train)
y_pred = dtc.predict(X_test)
dtc.score(X_test , y_test)
```

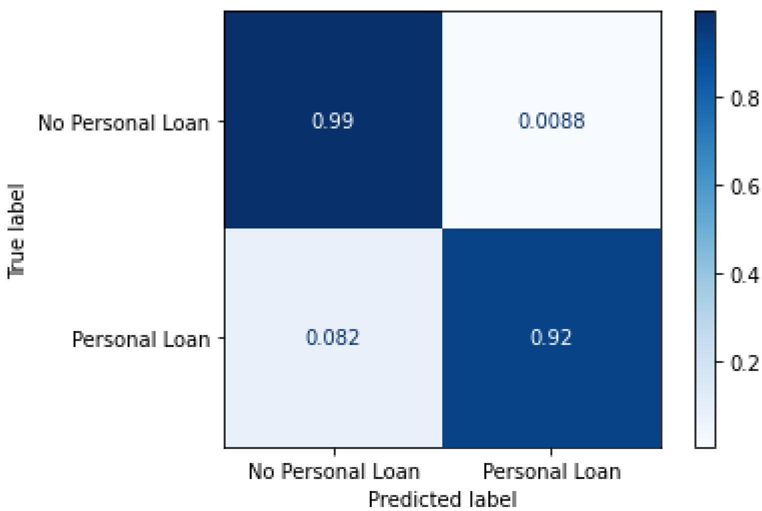
Out[48]: 0.9836363636363636

In [49]:
```
Model_features(X_train , y_train , X_test , y_test  , y_pred , dtc , "Decision Tr
confusion_matrix_plot(X_test , y_test , dtc , "Decision Tree Classifier")
```

```
Accuracy Score is :0.984
Precision Score is :0.984
Recall Score is :0.918
f1  Score is :0.92
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1480
           1       0.92      0.92      0.92       170

    accuracy                           0.98      1650
   macro avg       0.96      0.95      0.96      1650
weighted avg       0.98      0.98      0.98      1650
```



In [50]:
```
dict = {'Model':model_list, 'Accuracy':accuracy_list , 'Precision':precision_list
model_df = pd.DataFrame(dict).sort_values(ascending = False , by = 'Accuracy')
model_df
```

Out[50]:

	Model	Accuracy	Precision	f1_score	Recall
2	Random Forest Classifier	0.990	0.990	0.952	0.924
4	Decision Tree Classifier	0.984	0.984	0.920	0.918
0	Logistic Reegression	0.966	0.966	0.818	0.741
3	Support Vector Machine	0.900	0.900	0.203	0.124
1	Knn Classifier	0.893	0.893	0.295	0.218

In [ ]: