Capstone Project

Project proposal to predict credit card approval:

A bank's credit card department is one of the top adopters of data science. A top focus for the bank has always been acquiring new credit card customers. Giving out credit cards without doing proper research or evaluating applicants' creditworthiness is quite risky. The credit card department has been using a data-driven system for credit assessment called Credit Scoring for many years, and the model is known as an application scorecard. A credit card application's cutoff value is determined using the application scorecard, which also aids in estimating the applicant's level of risk. This decision is made based on strategic priority at a given time.

Customers must fill out a form, either physically or online, to apply for a credit card. The application data is used to evaluate the applicant's creditworthiness. The decision is made using the application data in addition to the Credit Bureau Score, such as the FICO Score in the US or the CIBIL Score in India, and other internal information on the applicants. Additionally, the banks are rapidly taking a lot of outside data into account to enhance the caliber of credit judgements.

Credit card score are generally built on historical data, the predictive models built upon these data are subjected to economic fluctuations. Hence, it is very important to tune with latest data and build resilient models. At present, with the development of machine learning algorithms. More predictive methods such as Boosting, Random Forest, and Support Vector Machines have been introduced into credit card scoring.

Build a machine learning model to predict if an applicant is 'good' or 'bad' client, different from other tasks, the definition of 'good' or 'bad' is not given. Also, unbalance data problem is a big problem in this task.

Machine Learning Development LifeCycle (MLDLC)

- Data Preprocessing
- Exploratory Data Analysis (EDA)
- Handling Missing Values & Outliers
- Feature Engineering & Feature Transformation
- Model Traning & Model Selection
- Testing & Optimizing

DATA IMPORTING

```
# Importing required libaries

import numpy as np
import pandas as pd

# Visualization libaraires
import matplotlib.pyplot as plt
import seaborn as sns

# ignore warning
import warnings
warnings.filterwarnings("ignore")
```

```
# importing dataset

credit = pd.read_csv('Credit_card.csv')

credit.head()
```

	Ind_ID	GENDER	Car_Owner	Propert_Owner	CHILDREN	Annual_income	Type_Income	EDU
0	5008827	M	Y	Y	0	180000.0	Pensioner	edu
1	5009744	F	Y	N	0	315000.0	Commercial associate	edu
2	5009746	F	Y	N	0	315000.0	Commercial associate	edu
3	5009749	F	Y	N	0	NaN	Commercial associate	edu

```
credit.shape
```

```
(1548, 18)
```

```
#  importing one more dataset
```

```
credit_label = pd.read_csv('Credit_card_label.csv')
```

```
credit_label.head()
```

	Ind_ID	label
0	5008827	1
1	5009744	1
2	5009746	1
3	5009749	1
4	5009752	1

```
credit_label.sample(5)
```

	Ind_ID	label
1100	5024726	0
980	5111172	0
949	5096604	0
517	5089896	0
1308	5090310	0

Label:

- 0 is application approved
- 1 is application rejected

```
credit_label.shape
```

```
(1548, 2)
```

```
# merging both the datasets
```

```
df = credit.merge(credit_label , how ='inner', on='Ind_ID')
```

```
df.head()
```

	Ind_ID	GENDER	Car_Owner	Propert_Owner	CHILDREN	Annual_income	Type_Income	EDU(
0	5008827	M	Y	Y	0	180000.0	Pensioner	edu
1	5009744	F	Y	N	0	315000.0	Commercial associate	edu
2	5009746	F	Y	N	0	315000.0	Commercial associate	edu
3	5009749	F	Y	N	0	NaN	Commercial associate	edu
4	5009752	F	Y	N	0	315000.0	Commercial associate	edu

```
df.shape
```

```
(1548, 19)
```

DATA PREPROCESSING

```
# checking for duplicate values

df.duplicated().sum()
```

```
0
```

```
# checking all the columns

df.columns
```

```
Index(['Ind_ID', 'GENDER', 'Car_Owner', 'Propert_Owner', 'CHILDREN',
       'Annual_income', 'Type_Income', 'EDUCATION', 'Marital_status',
       'Housing_type', 'Birthday_count', 'Employed_days', 'Mobile_phone',
       'Work_Phone', 'Phone', 'EMAIL_ID', 'Type_Occupation', 'Family_Members',
       'label'],
      dtype='object')
```

```
# Renaming the Columns

df.rename(columns={'GENDER':'Gender','Propert_Owner':'Property_owner','CHILDREN':'Children',
                   'Type_Income':'Income_type','EDUCATION':'Education','EMAIL_ID':'Email_ID',
                   'Type_Occupation':'Occupation_type'}, inplace=True)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1548 entries, 0 to 1547
Data columns (total 19 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Ind_ID           1548 non-null   int64  
 1   Gender           1541 non-null   object 
 2   Car_Owner        1548 non-null   object 
 3   Property_owner   1548 non-null   object 
 4   Children         1548 non-null   int64  
 5   Annual_income    1525 non-null   float64
 6   Income_type      1548 non-null   object 
 7   Education        1548 non-null   object 
 8   Marital_status   1548 non-null   object 
 9   Housing_type     1548 non-null   object 
 10  Birthday_count   1526 non-null   float64
 11  Employed_days    1548 non-null   int64  
 12  Mobile_phone     1548 non-null   int64  
 13  Work_Phone       1548 non-null   int64  
 14  Phone            1548 non-null   int64  
 15  Email_ID         1548 non-null   int64  
```

```
 16  Occupation_type  1060 non-null   object
 17  Family_Members   1548 non-null   int64
 18  label            1548 non-null   int64
dtypes: float64(2), int64(9), object(8)
memory usage: 241.9+ KB
```

```
# checking for missing values

df.isnull().sum()
```

```
Ind_ID              0
Gender              7
Car_Owner           0
Property_owner      0
Children            0
Annual_income      23
Income_type         0
Education           0
Marital_status      0
Housing_type        0
Birthday_count     22
Employed_days       0
Mobile_phone        0
Work_Phone          0
Phone               0
Email_ID            0
Occupation_type   488
Family_Members      0
label               0
dtype: int64
```

We have missing values in the below features:

- Gender
- Annual_income
- Occupation_type
- Birthday_count

Birthday_count: Use backward count from current day (0), -1 means yesterday.

Employed_days: Start date of employment. Use backward count from current day (0). Positive value means, individual is currently unemployed.

```
# Creating new column by dividing the birthday_count with 365, by which we get age in years

df['Age_in_years'] = np.abs((df['Birthday_count'])/365)

df['Age_in_years'].sample(5)
```

```
1214    60.627397
1012    37.991781
1358    44.602740
33      43.704110
748     44.104110
Name: Age_in_years, dtype: float64
```

```
# Check if there are any employed_days > 0

df[df['Employed_days']>0].shape
```

```
(261, 20)
```

There are 261 records which have employed days in positive (so they are not working)

```
# Creating new column which gives experience in years by dividing employed_days with 365
```

```
df['Experience_years']= np.abs(df['Employed_days'])/365
```

```
df['Experience_years'].sample(5)
```

```
1215    9.147945
32      6.558904
486     6.345205
624     3.627397
914     0.263014
Name: Experience_years, dtype: float64
```

```
df1 = df.loc[df["Experience_years"] >=1000 ]
print(df1)
```

```
       Ind_ID Gender Car_Owner Property_owner  Children  Annual_income  \
0     5008827      M         Y              Y         0       180000.0
7     5009894      F         N              N         0       180000.0
26    5024916      F         N              Y         0       112500.0
27    5024917      F         N              Y         0            NaN
31    5029311      F         N              Y         0       112500.0
...       ...    ...       ...            ...       ...            ...
1509  5024077      F         Y              Y         0       157500.0
1511  5053535      F         N              Y         0       216000.0
1514  5051097      F         N              N         0        69750.0
1525  5023719      F         Y              Y         0       175500.0
1531  5048642      F         N              N         0       157500.0

     Income_type                      Education       Marital_status  \
0      Pensioner               Higher education              Married
7      Pensioner  Secondary / secondary special              Married
26     Pensioner  Secondary / secondary special              Married
27     Pensioner  Secondary / secondary special              Married
31     Pensioner  Secondary / secondary special              Married
...          ...                            ...                  ...
1509   Pensioner  Secondary / secondary special                Widow
1511   Pensioner               Higher education  Single / not married
1514   Pensioner  Secondary / secondary special                Widow
1525   Pensioner               Higher education              Married
1531   Pensioner  Secondary / secondary special            Separated

            Housing_type  ...  Employed_days  Mobile_phone  Work_Phone  \
0      House / apartment  ...         365243             1           0
7      House / apartment  ...         365243             1           0
26     House / apartment  ...         365243             1           0
27     House / apartment  ...         365243             1           0
31     House / apartment  ...         365243             1           0
...                  ...  ...            ...           ...         ...
1509   House / apartment  ...         365243             1           0
1511   House / apartment  ...         365243             1           0
1514  Municipal apartment  ...         365243             1           0
1525   House / apartment  ...         365243             1           0
1531   House / apartment  ...         365243             1           0

      Phone  Email_ID  Occupation_type Family_Members  label  Age_in_years  \
0         0         0              NaN              2      1     51.430137
7         0         0              NaN              2      1     60.641096
26        1         0              NaN              2      1     59.813699
27        1         0              NaN              2      1     59.813699
31        1         1              NaN              2      1     59.934247
...     ...       ...              ...            ...    ...           ...
1509      0         0              NaN              1      0     55.978082
1511      0         0              NaN              1      0     55.857534
1514      1         0              NaN              1      0     60.235616
1525      1         0              NaN              2      0     60.484932
1531      0         0              NaN              1      0     65.884932

      Experience_years
0          1000.665753
```

```
7          1000.665753
26         1000.665753
27         1000.665753
31         1000.665753
```

```
df.shape
```

```
(1548, 21)
```

```
df = df.drop(index=[row for row in df.index if 1000 <= df.loc[row, 'Experience_years']])
```

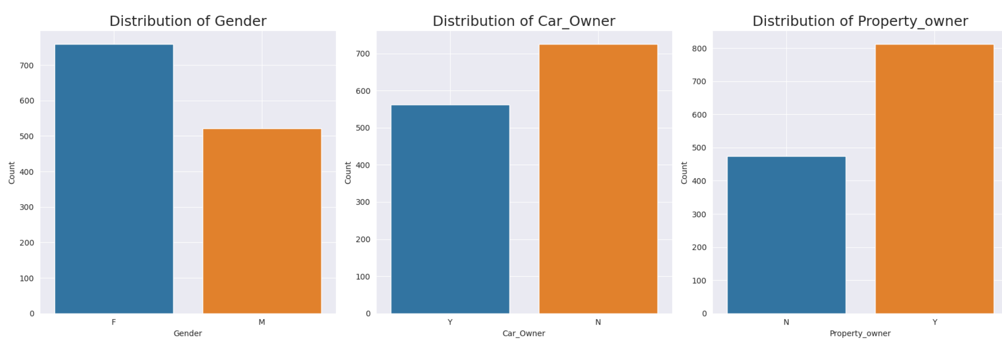
```
df.shape
```

```
(1287, 21)
```

EXPLORATORY DATA ANALYSIS (EDA)

```
sns.set_style('dark')
```

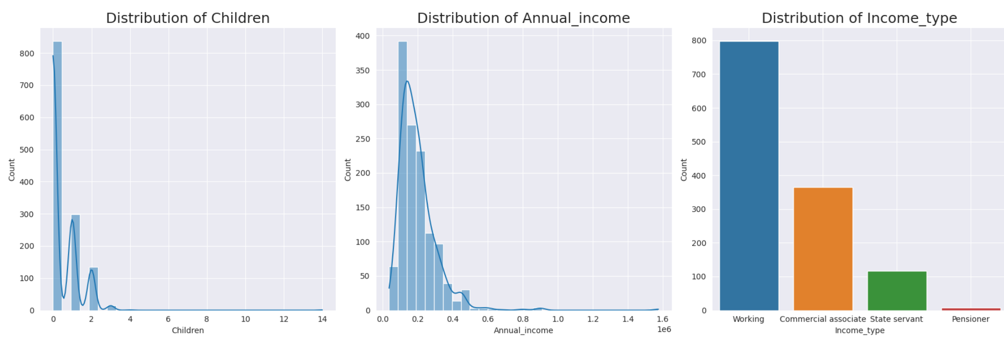
```
# we will see the distribution of the following columns
cols = ['Gender', 'Car_Owner', 'Property_owner']

# Set up the figure and axes
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 6))

# Plot univariate distributions for each column
for i, col in enumerate(cols):
    sns.countplot(data=df , x=col, ax=axes[i])
    axes[i].set_title(f'Distribution of {col}' , fontsize=18 )
    axes[i].set_ylabel('Count')
    axes[i].tick_params(axis='x')
    axes[i].grid(True)

plt.tight_layout()
plt.show()
```



- The dataset displays a higher representation of females, suggesting that either more females are applying for credit cards.
- A notable majority of individuals in the dataset do not own a car, which could be attributed to mutiple factors like personal choices etc.
- Most individuals in the dataset are property owners, indicating that property ownership, might be a significant factor in credit card approval decisions.

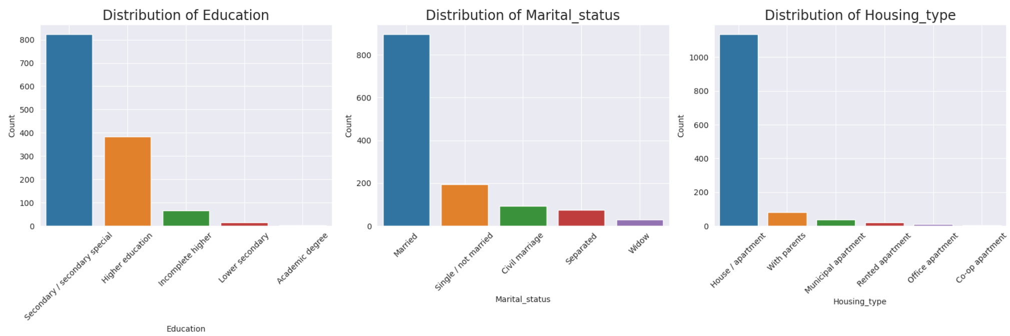
```
# we will see the distribution of the following columns
cols = ['Children', 'Annual_income', 'Income_type']
```

```
# Set up the figure and axes
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 6))

# Plot univariate distributions for each column
for i, col in enumerate(cols):
    if df[col].dtype in ['int64', 'float64']:
        sns.histplot(data=df, x=col, ax=axes[i], bins=30, kde=True)
    else:
        sns.countplot(data=df, x=col, ax=axes[i], order=df[col].value_counts().index)

    axes[i].set_title(f'Distribution of {col}', fontsize=18)
    axes[i].set_ylabel('Count')
    axes[i].tick_params(axis='x')
    axes[i].grid(True)


plt.tight_layout()
plt.show()
```



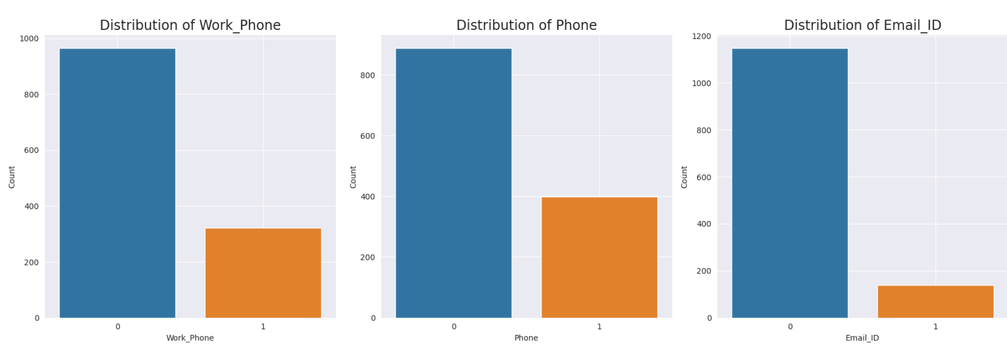
- Most individuals in the dataset either have no children or just one, with a decreasing number of individuals having two or more children.
- The annual income distribution is predominantly right-skewed, suggesting that most individuals have a lower to medium income, with a few outliers in the higher income bracket.
- Regarding income type, "Working" is the predominant category, succeeded by "Commercial associate" and "Pensioner", while categories like "State servant" have fewer representatives.

```
# we will see the distribution of the following columns
cols = ['Education', 'Marital_status', 'Housing_type']

# Set up the figure and axes
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 6))

# Plot univariate distributions for each column
for i, col in enumerate(cols):
    sns.countplot(data=df, x=col, ax=axes[i], order=df[col].value_counts().index)
    axes[i].set_title(f'Distribution of {col}', fontsize = 17)
    axes[i].set_ylabel('Count')
    axes[i].tick_params(axis='x', rotation = 45)
    axes[i].grid(True)

plt.tight_layout()
plt.show()
```



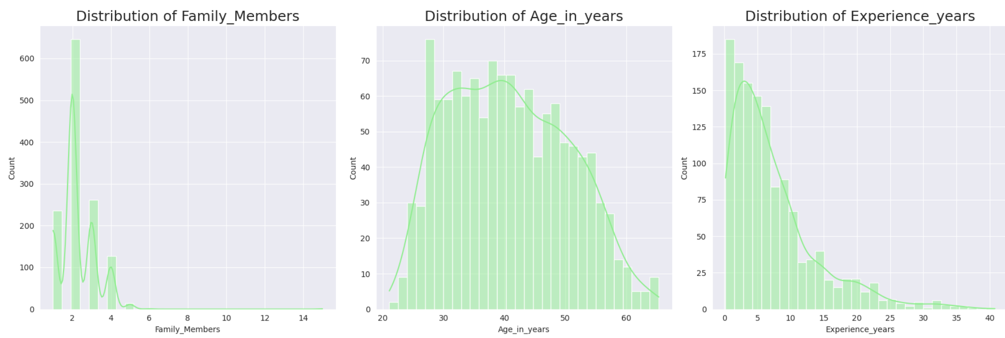
- In terms of education, the dataset predominantly consists of individuals with a "Secondary / secondary special" education level, akin to high school. While a significant number have "Higher education", fewer individuals fall into categories like "Incomplete higher" and "Lower secondary", and only a small fraction possess an "Academic degree" signifying advanced academic qualifications.
- When observing marital status, most individuals are "Married", with other statuses such as "Single / not married", "Civil marriage", "Separated", and "Widow" appearing in descending order of frequency.
- As for housing, the majority reside in a "House / apartment", with other housing arrangements like "With parents", "Municipal apartment", and "Rented apartment" being less frequent. The dataset contains very few individuals living in "Office apartment" or "Co-op apartment"

```
# we will see the distribution of the following columns
cols = ['Work_Phone', 'Phone', 'Email_ID']

# Set up the figure and axes
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 6))

# Plot univariate distributions for each column
for i, col in enumerate(cols):
    sns.countplot(data=df, x=col, ax=axes[i], order=df[col].value_counts().index)
    axes[i].set_title(f'Distribution of {col}', fontsize = 17)
    axes[i].set_ylabel('Count')
    axes[i].tick_params(axis='x')
    axes[i].grid(True)

plt.tight_layout()
plt.show()
```



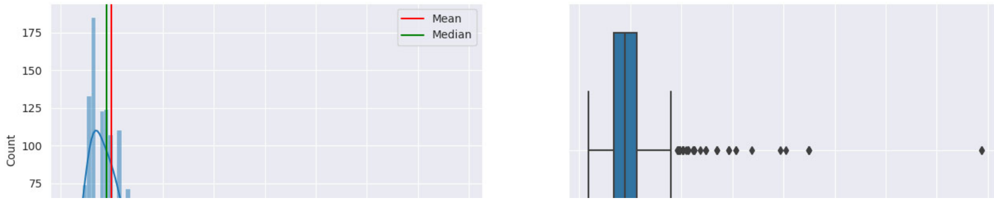

```
# we will see the distribution of the following columns
cols = ['Family_Members', 'Age_in_years','Experience_years']
```

```
# Set up the figure and axes
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 6))

# Plot univariate distributions for each column
for i, col in enumerate(cols):
    if df[col].dtype in ['int64', 'float64']:
        sns.histplot(data=df, x=col, ax=axes[i], bins=30, kde=True , color ='lightgreen')
    else:
        sns.countplot(data=df, x=col, ax=axes[i], order=df[col].value_counts().index , color ='green')

    axes[i].set_title(f'Distribution of {col}', fontsize = 18)
    axes[i].set_ylabel('Count')
    axes[i].tick_params(axis='x')
    axes[i].grid(True)

plt.tight_layout()
plt.show()
```



- As we can see from the distribution of family members, mostly it is 2 member families followed by 1,3,4 and it is rightly skewed.
- Distribution of age is nearly symmetric falling the age data between 20 to 70 years.

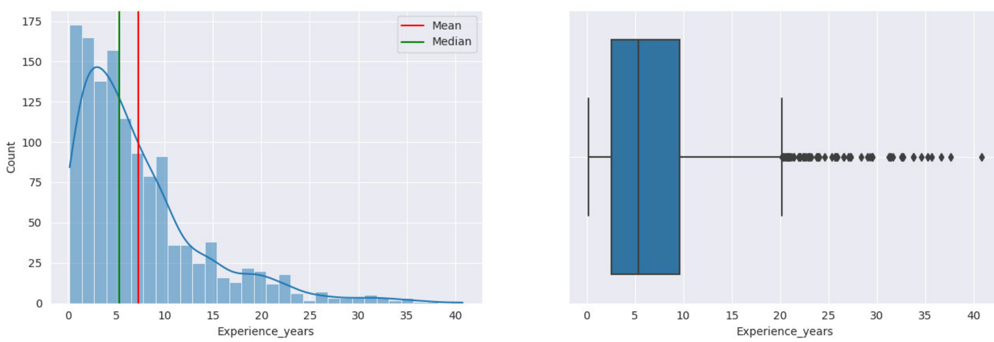
```
#Annual income

plt.subplot(1,2,1)
sns.histplot(data=df, x='Annual_income',kde=True)
plt.axvline(x=df['Annual_income'].mean(),color="red",label="Mean")
plt.axvline(x=df['Annual_income'].median(),color="green",label="Median")
plt.grid()
plt.legend()

plt.subplot(1,2,2)  # nrows=1, ncols=2
sns.boxplot(data=df, x='Annual_income')

plt.subplots_adjust(right=2.0)
plt.grid()
plt.show()
```



Annual Income:

The Annual_income feature has some outliers and It is right skewed

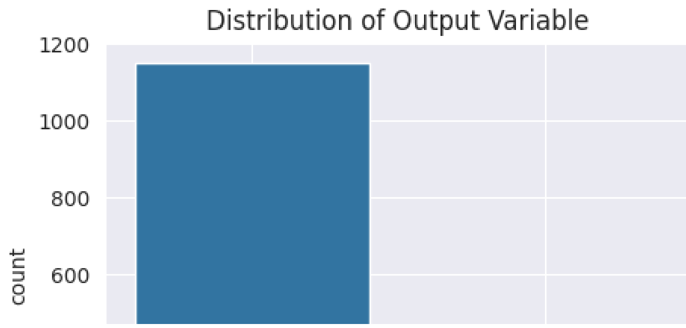

```
#Experience_years

plt.subplot(1,2,1)
sns.histplot(data=df, x='Experience_years',kde=True)
plt.axvline(x=df['Experience_years'].mean(),color="red",label="Mean")
plt.axvline(x=df['Experience_years'].median(),color="green",label="Median")
plt.legend()
plt.grid()

plt.subplot(1,2,2)
sns.boxplot(data=df, x='Experience_years')

plt.subplots_adjust(right=2.0)
plt.grid()
plt.show()
```



Experience_years

- The feature Experience_years is right skewed and has some outliers.

```
plt.figure(figsize =(5,4))
sns.countplot(data=df, x='label')
plt.title("Distribution of Output Variable")
plt.grid()
plt.show()
```



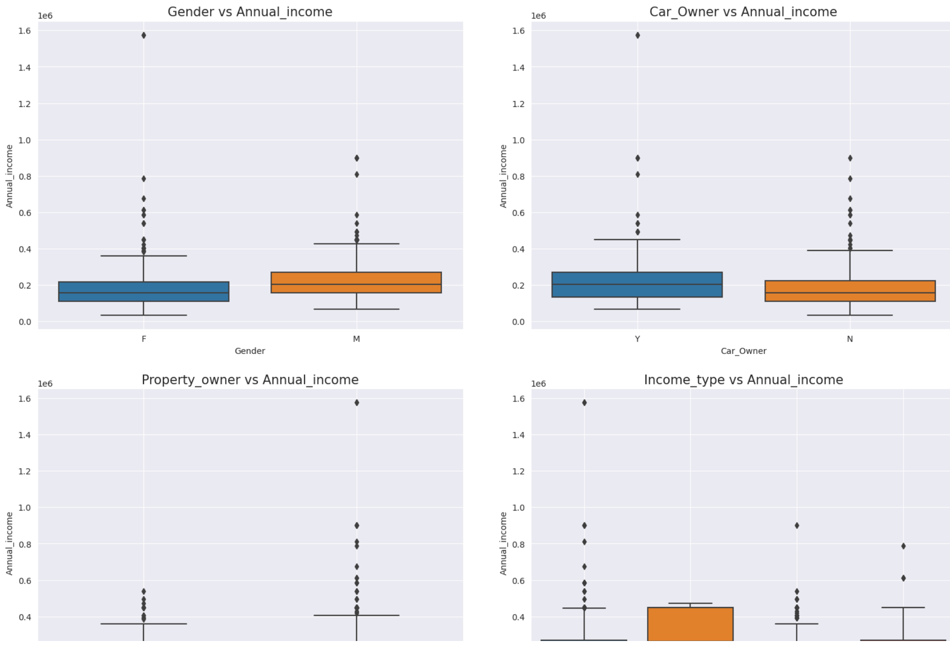
Label

- 0 is application approved and 1 is application rejected.
- This clearly shows that this isimbalanced dataset as there is a huge difference between approved (0) and rejected (1) applications

Annual Income Vs remaining features

```
cols = ['Gender', 'Car_Owner', 'Property_owner', 'Income_type', 'Education', 'Marital_status', 'Housing_type', 'Occupation_
```

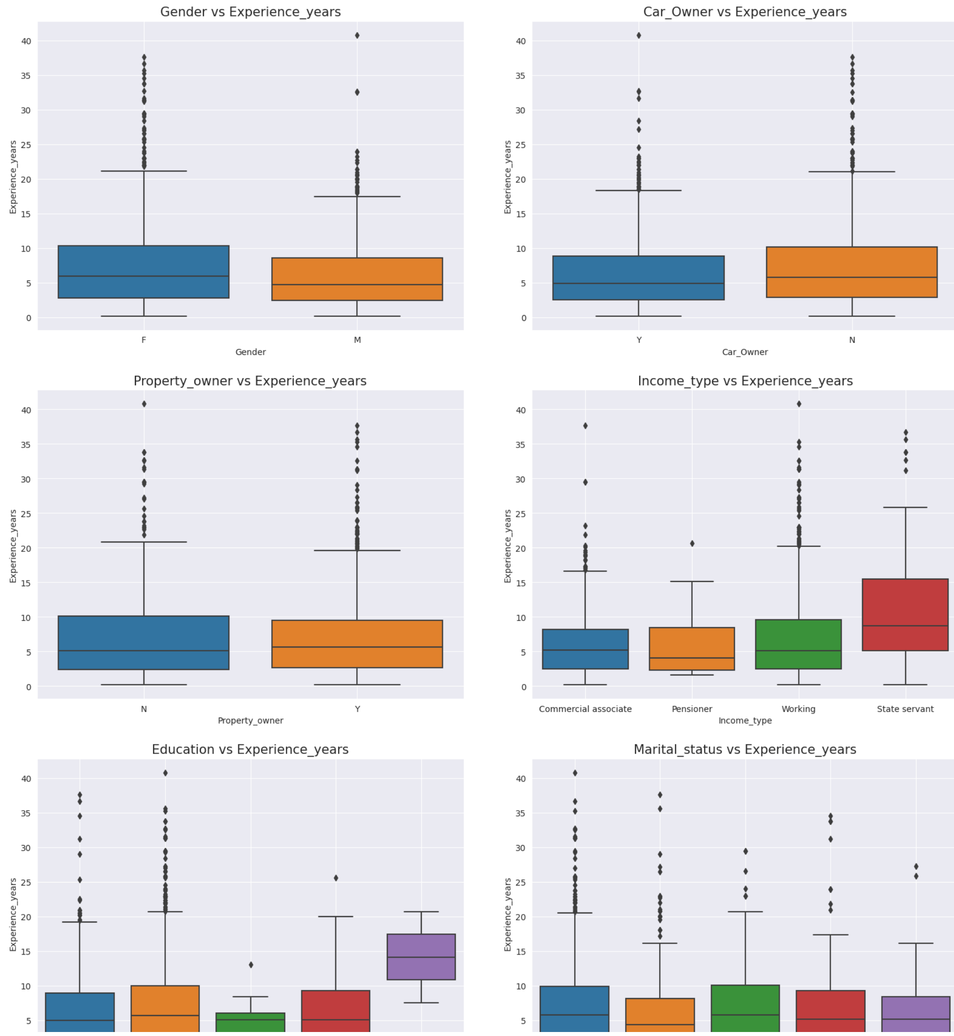
```
fig, axes = plt.subplots(4, 2, figsize=(17, 25))
fig.tight_layout(pad=5)

# Loop through each categorical feature and create a boxplot
for i, ax in enumerate(axes.ravel()):
    if i < len(cols):
        sns.boxplot(data=df, x=cols[i], y='Annual_income', ax=ax)
        ax.set_title(cols[i] + ' vs Annual_income', fontsize = 15)
        ax.tick_params(axis='x')
        ax.grid(True)
```



- Despite a higher number of female applicants, males generally have a greater income.
- Higher-income applicants are more likely to own cars. The ownership of property doesn't significantly influence the average income.
- Those with an academic degree tend to have the highest annual incomes.
- Additionally, managers and drivers earn more compared to other occupations.
- Applicants with a higher annual income often reside in rented apartments, irrespective of their marital status.

Experience vs remaining features

```
cols = ['Gender', 'Car_Owner', 'Property_owner', 'Income_type', 'Education', 'Marital_status', 'Housing_type', 'Occupation_t


fig, axes = plt.subplots(4, 2, figsize=(17, 25))
fig.tight_layout(pad=5)

# Loop through each categorical feature and create a boxplot
for i, ax in enumerate(axes.ravel()):
    if i < len(cols):
        sns.boxplot(data=df, x=cols[i], y='Experience_years', ax=ax)
        ax.set_title(cols[i] + ' vs Experience_years', fontsize = 15)
        ax.tick_params(axis='x')
        ax.grid(True)

plt.show()
```

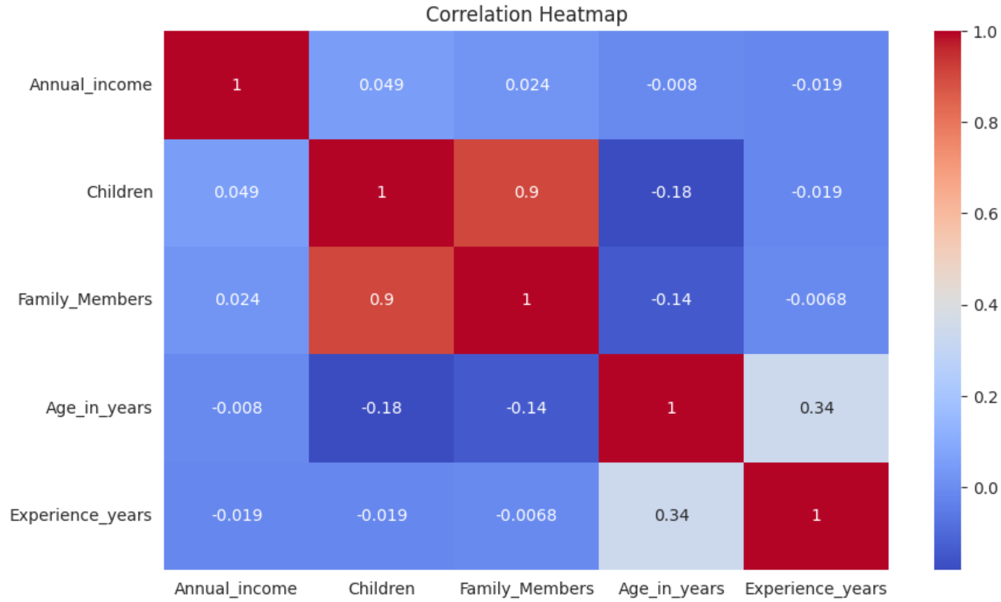


- Both male and female applicants have comparable levels of experience.
- State servants and medicine staff tend to have the most experience among professions.
- Those with an academic degree usually possess more work experience.

```
features=['Annual_income','Children','Family_Members','Age_in_years', 'Experience_years']

df[features].corr()
```

	Annual_income	Children	Family_Members	Age_in_years	Experience_yea
Annual_income	1.000000	0.049350	0.023836	-0.008012	-0.0194
Children	0.049350	1.000000	0.903850	-0.181872	-0.0191
Family_Members	0.023836	0.903850	1.000000	-0.143585	-0.0067
Age_in_years	-0.008012	-0.181872	-0.143585	1.000000	0.3363
Experience_years	-0.019428	-0.019140	-0.006763	0.336366	1.0000

```
plt.figure(figsize = (10,6))
sns.heatmap(df[features].corr(), annot=True , cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```



- Children and Family members have linear corelation, that means more no of children results in more members in the family,so one of these features should be dropped
- Age and experience also show some corelation

MISSING VALUES IMPUTATIONS

```
# checking for missing values

df.isnull().sum()
```

```
Ind_ID               0
Gender               6
Car_Owner            0
Property_owner       0
Children             0
Annual_income       19
Income_type          0
Education            0
Marital_status       0
Housing_type         0
Birthday_count      18
Employed_days        0
Mobile_phone         0
Work_Phone           0
Phone                0
Email_ID             0
Occupation_type    227
Family_Members       0
label                0
Age_in_years        18
Experience_years     0
dtype: int64
```

Handling missing values of Gender

```
df["Gender"].isnull().sum()
```

```
6
```

```
# cheking for unique values

df["Gender"].unique()
```

```
array(['F', nan, 'M'], dtype=object)
```

```
# Impute missing values in 'Gender' column with the mode (most frequent value)

df['Gender'].fillna(df['Gender'].mode()[0], inplace=True)
```

```
df["Gender"].value_counts()
```

```
F    765
M    522
Name: Gender, dtype: int64
```

```
df["Gender"].isnull().sum()
```

```
0
```

Handling missing values of Annual_income

```
df["Annual_income"].isnull().sum()
```

```
19
```

```
mean_inc_byincome_type = df.groupby(['Income_type'])['Annual_income'].mean()

mean_inc_byincome_type
```

```
Income_type
Commercial associate    234600.000000
Pensioner               288000.000000
State servant           211422.413793
Working                 181048.757306
Name: Annual_income, dtype: float64
```

```
# Impute missing values in 'Annual_Income' column with the mean

for income_type, mean_inc in mean_inc_byincome_type.items():
    df.loc[(df['Income_type'] == income_type) & (df['Annual_income'].isna()), 'Annual_income'] = mean_inc
```

```
# checking if any missing values

df["Annual_income"].isnull().sum()
```

```
0
```

Handling missing values of Age_in_years

```
df["Age_in_years"].isnull().sum()
```

```
18
```

```
mean_income_type = df.groupby(['Income_type'])['Age_in_years'].mean()

mean_income_type
```

```
Income_type
Commercial associate    40.219428
Pensioner               41.843493
State servant           41.490269
```

```
Working                  40.789276
Name: Age_in_years, dtype: float64
```

```
# Impute missing values in 'Age_in_years' column with the mean

for income_type, mean_age in mean_income_type.items():
    df.loc[(df['Income_type'] == income_type) & (df['Age_in_years'].isna()), 'Age_in_years'] = mean_age
```

```
df["Age_in_years"].isnull().sum()
```

```
0
```

Handling missing values of Occupation_type

- Dropping this column as multiple values are missing

```
df.head()
```

	Ind_ID	Gender	Car_Owner	Property_owner	Children	Annual_income	Income_type	Edu
1	5009744	F	Y	N	0	315000.0	Commercial associate	e
2	5009746	F	Y	N	0	315000.0	Commercial associate	e
3	5009749	F	Y	N	0	234600.0	Commercial associate	e
4	5009752	F	Y	N	0	315000.0	Commercial associate	e
5	5009753	F	Y	N	0	315000.0	Pensioner	e

5 rows × 21 columns

```
df.shape
```

```
(1287, 21)
```

```
df['Occupation_type'].isnull().sum()
```

```
227
```

```
#Dropping other unnecessary columns also along with occupation type
df.drop(columns = ['Occupation_type','Employed_days','Birthday_count'] , inplace = True)
```

```
df.shape
```

```
(1287, 18)
```

```
df.head()
```

	Ind_ID	Gender	Car_Owner	Property_owner	Children	Annual_income	Income_type	Edu
1	5009744	F	Y	N	0	315000.0	Commercial associate	e
2	5009746	F	Y	N	0	315000.0	Commercial associate	e

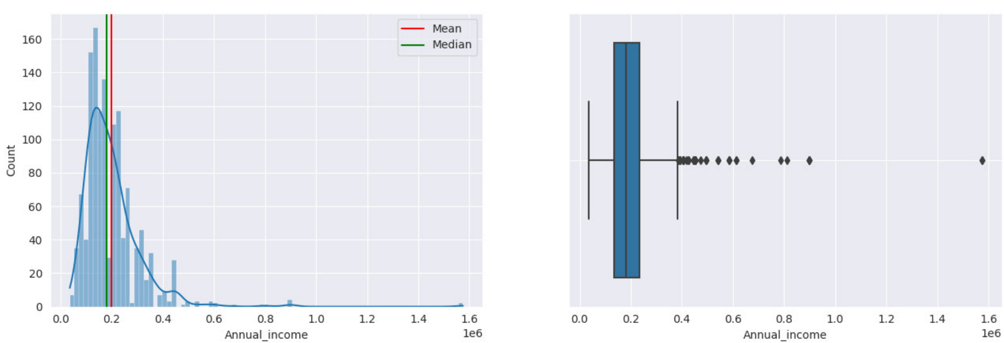
OUTLIER TREATMENT

```
df.columns
```

```
Index(['Ind_ID', 'Gender', 'Car_Owner', 'Property_owner', 'Children',
       'Annual_income', 'Income_type', 'Education', 'Marital_status',
       'Housing_type', 'Mobile_phone', 'Work_Phone', 'Phone', 'Email_ID',
       'Family_Members', 'label', 'Age_in_years', 'Experience_years'],
      dtype='object')
```

- **Annual_income Column**

```
plt.subplot(1,2,1)
sns.histplot(data=df, x='Annual_income',kde=True)
plt.axvline(x=df['Annual_income'].mean(),color="red",label="Mean")
plt.axvline(x=df['Annual_income'].median(),color="green",label="Median")
plt.grid()
plt.legend()

plt.subplot(1,2,2)  # nrows=1, ncols=2
sns.boxplot(data=df, x='Annual_income')

plt.subplots_adjust(right=2.0)
plt.grid()
plt.show()
```



- Using IQR method to handle the outliers

```
# First quartile (Q1)
Q1 = np.percentile(df['Annual_income'], 25)

# Third quartile (Q3)
Q3 = np.percentile(df['Annual_income'], 75)

# Interquaritle range (IQR)
IQR = Q3 - Q1
```

```
print(IQR)
```

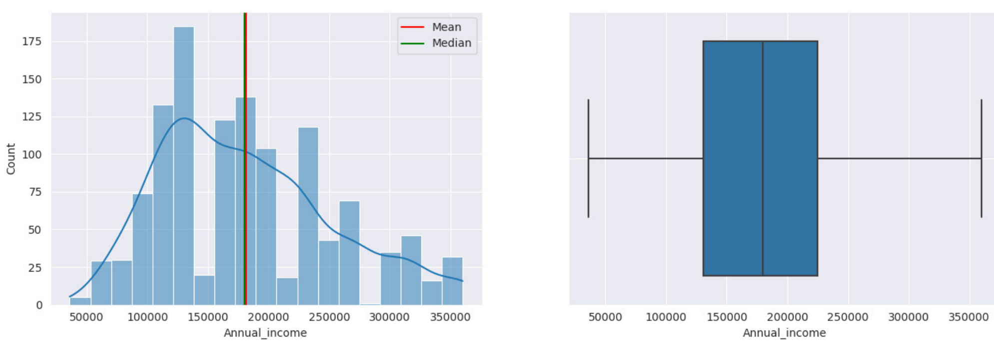
```
99000.0
```

```
# checking value of upper limit

upper_limit = Q3+1.5*IQR

upper_limit
```

```
382500.0
```

```
# applying upperlimit value

df = df[df['Annual_income'] < upper_limit]
```

```
# Verifying by plotting the distribution and box plot after handling outlers

plt.subplot(1,2,1)
sns.histplot(data=df, x='Annual_income',kde=True)
plt.axvline(x=df['Annual_income'].mean(),color="red",label="Mean")
plt.axvline(x=df['Annual_income'].median(),color="green",label="Median")
plt.grid()
plt.legend()

plt.subplot(1,2,2)  # nrows=1, ncols=2
sns.boxplot(data=df, x='Annual_income')

plt.subplots_adjust(right=2.0)
plt.grid()
plt.show()
```

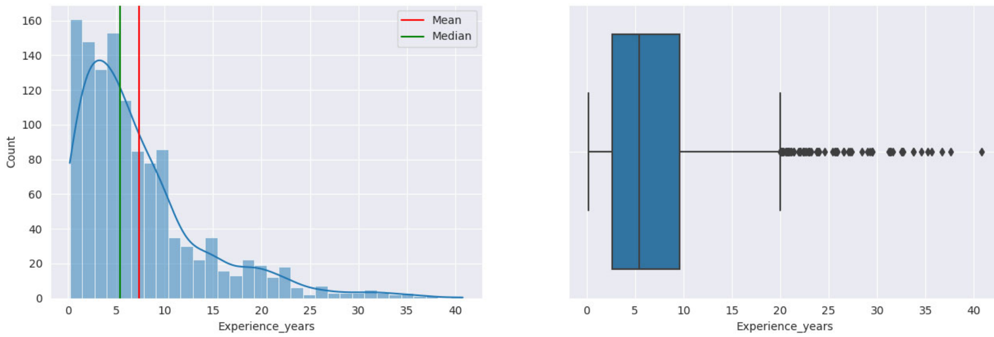


- Now we can see, mean and median is almost same.
- No outliers are present in the box plot.

- **Experience_years Column**

```
plt.subplot(1,2,1)
sns.histplot(data=df, x='Experience_years',kde=True)
plt.axvline(x=df['Experience_years'].mean(),color="red",label="Mean")
plt.axvline(x=df['Experience_years'].median(),color="green",label="Median")
plt.legend()
plt.grid()
```

```
plt.subplot(1,2,2)
sns.boxplot(data=df, x='Experience_years')

plt.subplots_adjust(right=2.0)
plt.grid()
plt.show()
```



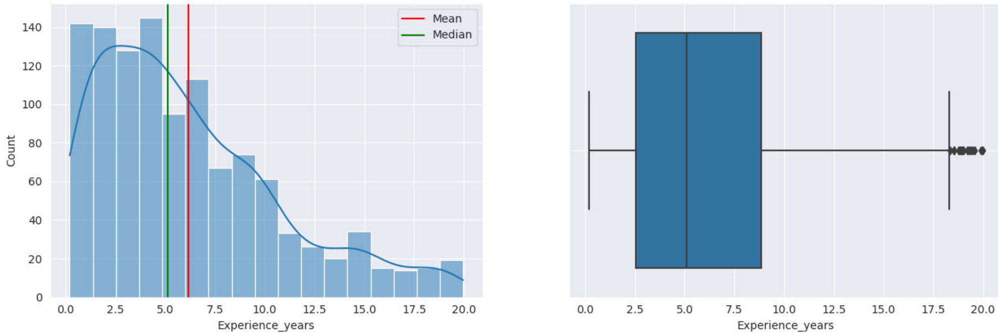

```
# using IQR method to handle the outliers

Q1 = np.percentile(df['Experience_years'], 25 , interpolation='midpoint')
Q3 = np.percentile(df['Experience_years'], 75 ,interpolation='midpoint')

IQR = Q3-Q1
```

```
# checking for upper limit value

upper_limit = Q3+1.5*IQR

upper_limit
```

```
19.982876712328768
```

```
# applying upperlimit value

df = df[df['Experience_years'] < upper_limit]
```

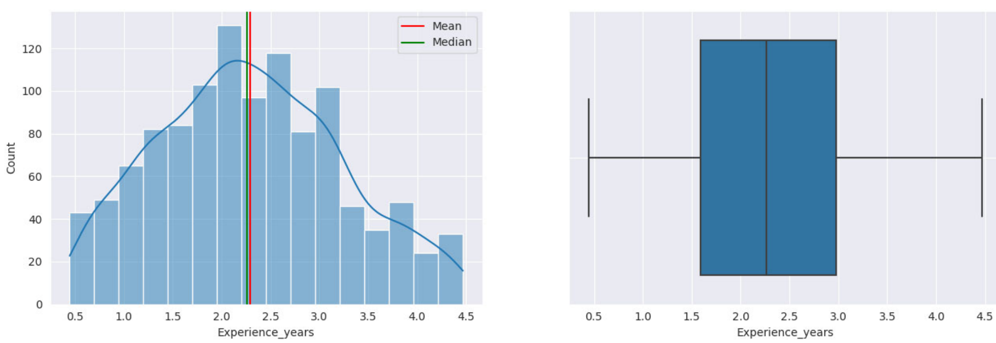
```
# verifying the distribution and box plot after handling outlers

plt.subplot(1,2,1)
sns.histplot(data=df, x='Experience_years',kde=True)
plt.axvline(x=df['Experience_years'].mean(),color="red",label="Mean")
plt.axvline(x=df['Experience_years'].median(),color="green",label="Median")
plt.legend()
plt.grid()

plt.subplot(1,2,2)
sns.boxplot(data=df, x='Experience_years')

plt.subplots_adjust(right=2.0)
plt.grid()
plt.show()
```



- Using Square root method to stabilize variance, making the data more normally distributed

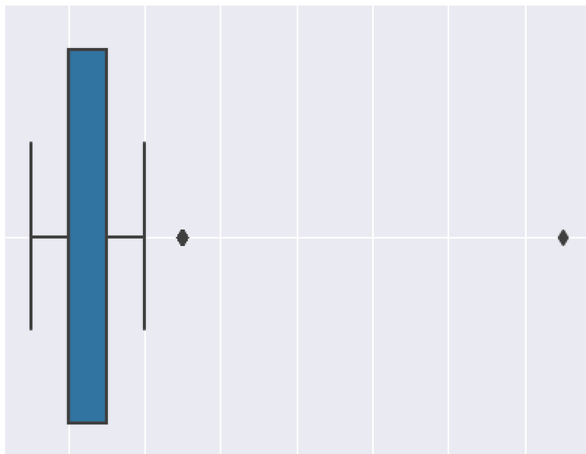
```
df['Experience_years'] = np.sqrt(df['Experience_years'])
```

```
# verifying the distribution and box plot after handling outlers

plt.subplot(1,2,1)
sns.histplot(data=df, x='Experience_years',kde=True)
plt.axvline(x=df['Experience_years'].mean(),color="red",label="Mean")
plt.axvline(x=df['Experience_years'].median(),color="green",label="Median")
plt.legend()
plt.grid()

plt.subplot(1,2,2)
sns.boxplot(data=df, x='Experience_years')

plt.subplots_adjust(right=2.0)
plt.grid()
plt.show()
```

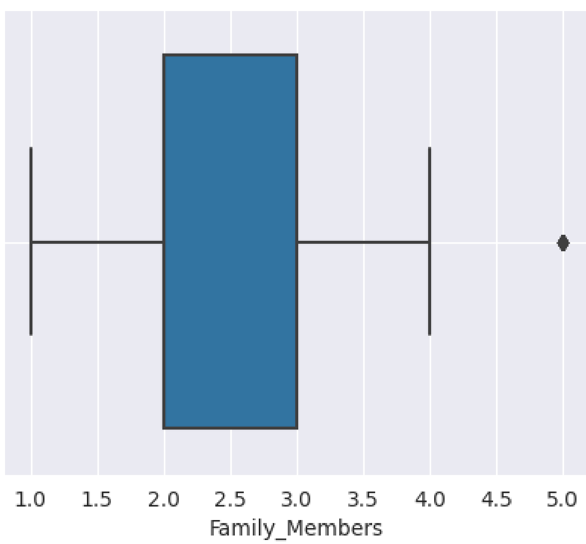


- **Family_members Column**

```
plt.figure(figsize =(5,4))

sns.boxplot(data=df , x='Family_Members')

plt.grid()
plt.show()
```



```
# removing the exterme value

df = df[df['Family_Members'] < 14]


plt.figure(figsize =(5,4))

sns.boxplot(data=df , x='Family_Members')

plt.grid()
plt.show()
```




```
# finally checking the shape
df.shape
```

```
(1140, 18)
```

```
df.head()
```

	Ind_ID	Gender	Car_Owner	Property_owner	Children	Annual_income	Income_type	Edu
1	5009744	F	Y	N	0	315000.0	Commercial associate	e
2	5009746	F	Y	N	0	315000.0	Commercial	

```
# Expoting to CSV file

df.to_csv('cleaned_data.csv')
```

Commercial

Dropping the columns

- Children : Children and family_members are corelated to each other, so dropping.
- Mobile_phone : No variation in data, contains single category value only.

```
df = df.drop(columns=['Children','Mobile_phone'])
```

```
# checking shape

df.shape
```

```
(1140, 16)
```

FEATURE TRANSFORMATION

1.Binary Encoding

```
# for gender column
df['Gender'] = df['Gender'].map({'M':1,'F':0})

# for Car_Owner column
df['Car_Owner'] = df['Car_Owner'].map({'Y':1,'N':0})

# for Property_owner column
df['Property_owner'] = df['Property_owner'].map({'Y':1,'N':0})
```

```
df.sample(5)
```

	Ind_ID	Gender	Car_Owner	Property_owner	Annual_income	Income_type	Education
1136	5067961	1	1	1	360000.0	Working	Higher education
850	5116809	0	0	1	112500.0	Working	Secondary / secondary special
995	5023231	1	1	1	270000.0	Working	Secondary / secondary special
94	5089959	1	0	1	126000.0	Commercial associate	Secondary / secondary special
331	5087944	0	0	1	72000.0	Working	Secondary / secondary special

2.Ordinal Encoding on 'Education' Column

```
df['Education'].value_counts()
```

```
Secondary / secondary special    733
Higher education                 330
Incomplete higher                 62
Lower secondary                   14
Academic degree                    1
Name: Education, dtype: int64
```

```
# importing ordinal encoder
from sklearn.preprocessing import OrdinalEncoder

# values to ordinal
cols_order = ['Lower secondary','Secondary / secondary special','Incomplete higher','Higher education', 'Academic degree']

x = OrdinalEncoder(categories=[cols_order])

df['Education'] = x.fit_transform(df[['Education']])
```

```
df.sample(5)
```

	Ind_ID	Gender	Car_Owner	Property_owner	Annual_income	Income_type	Education
532	5058267	1	0	0	225000.0	Commercial associate	1.0
1545	5115992	1	1	1	180000.0	Working	3.0
500	5041980	0	0	0	211500.0	Commercial associate	3.0
873	5149413	0	0	1	315000.0	Commercial associate	3.0
142	5125934	0	0	1	135000.0	Commercial associate	0.0

3.One hot Encoding

```
# columns to onehot encoding
one_cols = df[['Income_type','Marital_status','Housing_type']]

df = pd.get_dummies(df, columns=['Income_type','Marital_status','Housing_type'],drop_first=True)
# drop_first to avoid multicolinearity
```

```
df.sample(5)
```

	Ind_ID	Gender	Car_Owner	Property_owner	Annual_income	Education	Work_Phone
429	5149353	1	1	1	234600.0	3.0	0
1245	5047929	1	1	0	292500.0	1.0	0
485	5062713	0	0	1	157500.0	1.0	0
676	5050635	0	0	0	225000.0	1.0	0
984	5118477	0	0	1	180000.0	1.0	0

5 rows × 25 columns

```
df.shape
```

```
(1140, 25)
```

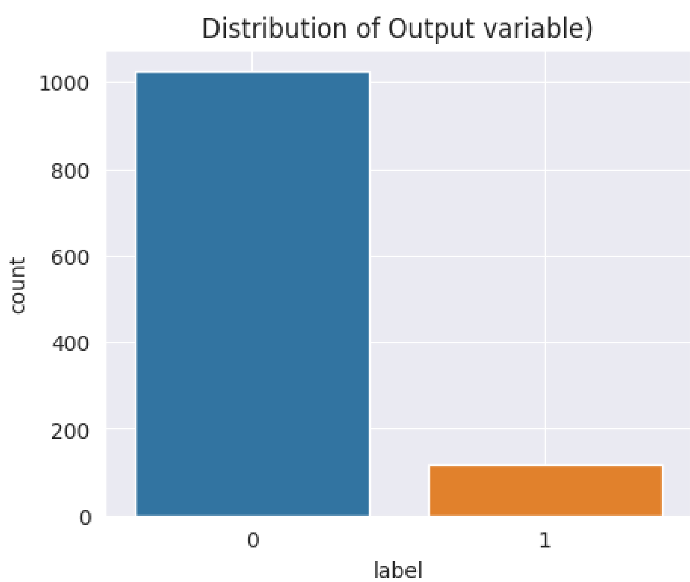
```
df = df.drop(columns=['Ind_ID']) #Because it is not much needed
```

```
df.shape
```

```
(1140, 24)
```

DEALING WITH IMBALANCE IN DATASET

```
plt.figure(figsize = (5,4))
sns.countplot( data= df, x ='label')
plt.title("Distribution of Output variable)")

plt.grid()
plt.show()
```




```
# checking unique values

df['label'].value_counts()
```

```
0    1024
1     116
Name: label, dtype: int64
```

- Performing SMOTE to handle this imbalance in the data

```
X = df.drop(columns=['label'])
y = df['label']

# importing SMOTE
from imblearn.over_sampling import SMOTE

oversample = SMOTE()

X, y = oversample.fit_resample(X, y)
```

```
# checking values after applying smote

y.value_counts()
```

```
1    1024
0    1024
Name: label, dtype: int64
```

- **Splitting the dataset into train and test**

```
# train_test_split

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=0.20, random_state=10)
```

```
# training data

X_train.shape
```

```
(1638, 23)
```

```
# test data

X_test.shape
```

```
(410, 23)
```

FEATURE SCALING

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

X_train_scaled = scaler.fit_transform(X_train)

X_test_scaled = scaler.transform(X_test)
```

MODEL TRAINING

```
# Required imports
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score ,roc_auc_score

# Initialize the classifiers
log_reg = LogisticRegression(max_iter=1000, random_state=10)
dtc = DecisionTreeClassifier(random_state=10)
rfc = RandomForestClassifier(random_state=42)
xgb = XGBClassifier(random_state=10, use_label_encoder=False, eval_metric='logloss')
svc = SVC(random_state=10)
knn = KNeighborsClassifier()


# Dictionary to store results
results = {}

# List of classifiers
```

```
classifiers = [('Logistic Regression', log_reg),
               ('Decision Tree', dtc),
               ('Random Forest', rfc),
               ('XGBoost', xgb),
               ('Support Vector Machine', svc),
               ('K-Nearest Neighbors', knn)]

# Train, predict, and store results
for name, clf in classifiers:
    clf.fit(X_train_scaled, y_train)
    y_pred = clf.predict(X_test_scaled)

    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    roc_auc_test = roc_auc_score(y_test, y_pred)

    results[name] = [accuracy, precision, recall, f1 , roc_auc_test]



# Convert the results dictionary to a DataFrame for better visualization

results_df = pd.DataFrame(results, index=['Accuracy', 'Precision', 'Recall', 'F1-Score', 'ROC AUC Score']).T
results_df
```

	Accuracy	Precision	Recall	F1-Score	ROC AUC Score
Logistic Regression	0.778049	0.815534	0.760181	0.786885	0.779561
Decision Tree	0.892683	0.873418	0.936652	0.903930	0.888961
Random Forest	0.926829	0.924444	0.941176	0.932735	0.925615
XGBoost	0.936585	0.937220	0.945701	0.941441	0.935814
Support Vector Machine	0.831707	0.883838	0.791855	0.835322	0.835081
K-Nearest Neighbors	0.858537	0.812261	0.959276	0.879668	0.850008

MODEL SELECTION

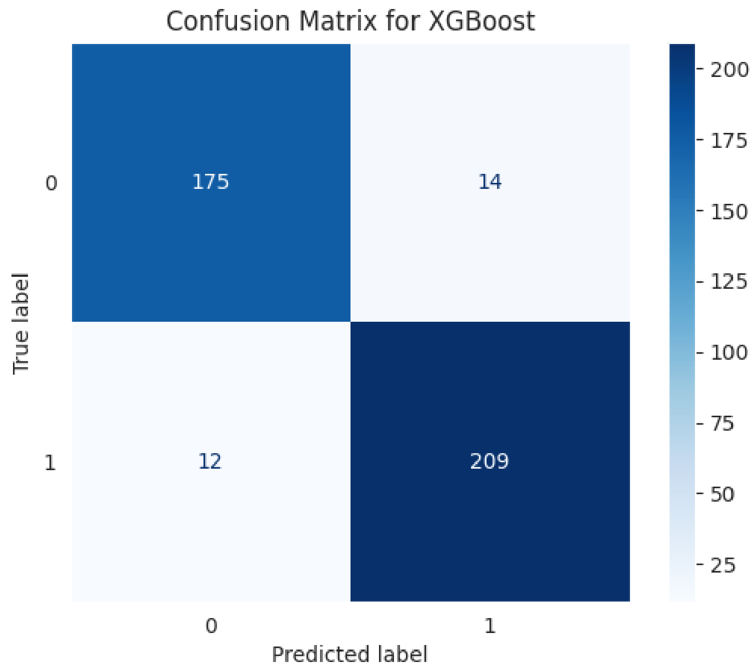
XGBOOST

- Performance and Accuracy: XGBoost consistently demonstrated superior performance in terms of accuracy, precision, and recall when compared to other models on the dataset.
- Interpretability and Feature Importance: XGBoost provides clear insights into the significance of different features in making predictions.

```
from sklearn.metrics import confusion_matrix, classification_report, ConfusionMatrixDisplay


# Predict using the trained XGBoost model
y_pred_xgb = xgb.predict(X_test_scaled)

# Confusion Matrix
cm_xgb = confusion_matrix(y_test, y_pred_xgb)
disp = ConfusionMatrixDisplay(confusion_matrix=cm_xgb, display_labels=xgb.classes_)
plt.figure(figsize=(6,6))
disp.plot(cmap='Blues', values_format='.0f')
plt.title("Confusion Matrix for XGBoost")
plt.grid(False)
plt.show()
print("\n")
# Classification Report
```

```
print("Classification Report for XGBoost:\n")

print(classification_report(y_test, y_pred_xgb))
```

```
<Figure size 600x600 with 0 Axes>
```




```
Classification Report for XGBoost:

              precision    recall  f1-score   support

           0       0.94      0.93      0.93       189
           1       0.94      0.95      0.94       221

    accuracy                           0.94       410
   macro avg       0.94      0.94      0.94       410
weighted avg       0.94      0.94      0.94       410
```

HYPERPARAMETER TUNING

```
from sklearn.model_selection import GridSearchCV


# the parameter grid

param_grid = {
    'learning_rate': [0.01, 0.05, 0.1],
    'max_depth': [3, 4, 5, 6],
    'n_estimators': [50, 100, 150, 200],
    'subsample': [0.8, 0.9, 1],
    'colsample_bytree': [0.8, 0.9, 1]
}

# initialize GridSearchCV
clf_xgb = XGBClassifier(random_state=10, use_label_encoder=False, eval_metric='logloss')

grid_search = GridSearchCV(clf_xgb, param_grid, scoring='accuracy', cv=5, verbose=1, n_jobs=-1)

# fit GridSearchCV
grid_search.fit(X_train_scaled, y_train)

print(grid_search.best_params_)
```

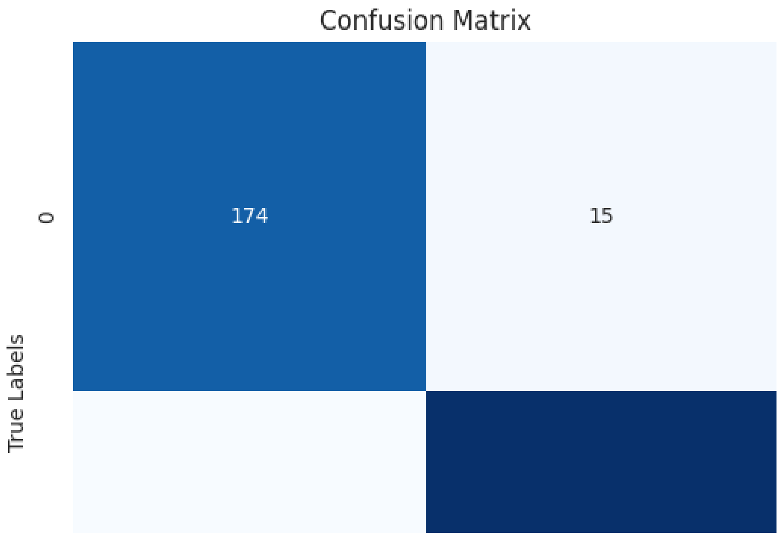
```
Fitting 5 folds for each of 432 candidates, totalling 2160 fits
{'colsample_bytree': 0.9, 'learning_rate': 0.1, 'max_depth': 6, 'n_estimators': 200, 'subsample': 0.9}
```

- **Testing the model**

```
# Initialize the XGBoost classifier with the best parameters

xgb_best = XGBClassifier(
    colsample_bytree=1,
    learning_rate=0.1,
    max_depth=6,
    n_estimators=200,
    subsample=0.9,
    random_state=10,
    use_label_encoder=False,
    eval_metric='logloss'
)

# Train the model
xgb_best.fit(X_train_scaled, y_train)

# Predict on the test set
y_pred_best = xgb_best.predict(X_test_scaled)

# Calculate and print the metrics
accuracy_best = accuracy_score(y_test, y_pred_best)
precision_best = precision_score(y_test, y_pred_best)
recall_best = recall_score(y_test, y_pred_best)
f1_best = f1_score(y_test, y_pred_best)
roc_auc_best = roc_auc_score(y_test, y_pred_best)

print(f"Accuracy after Hyperparameter Tuning: {accuracy_best}")
print(f"Precision after Hyperparameter Tuning: {precision_best}")
print(f"Recall after Hyperparameter Tuning: {recall_best}")
print(f"F1-Score after Hyperparameter Tuning: {f1_best}")
print(f"ROC AUC Score after Hyperparameter Tuning: {roc_auc_best}")
```

```
Accuracy after Hyperparameter Tuning: 0.9365853658536586
Precision after Hyperparameter Tuning: 0.9333333333333333
Recall after Hyperparameter Tuning: 0.9502262443438914
F1-Score after Hyperparameter Tuning: 0.9417040358744394
ROC AUC Score after Hyperparameter Tuning: 0.935430582489406
```

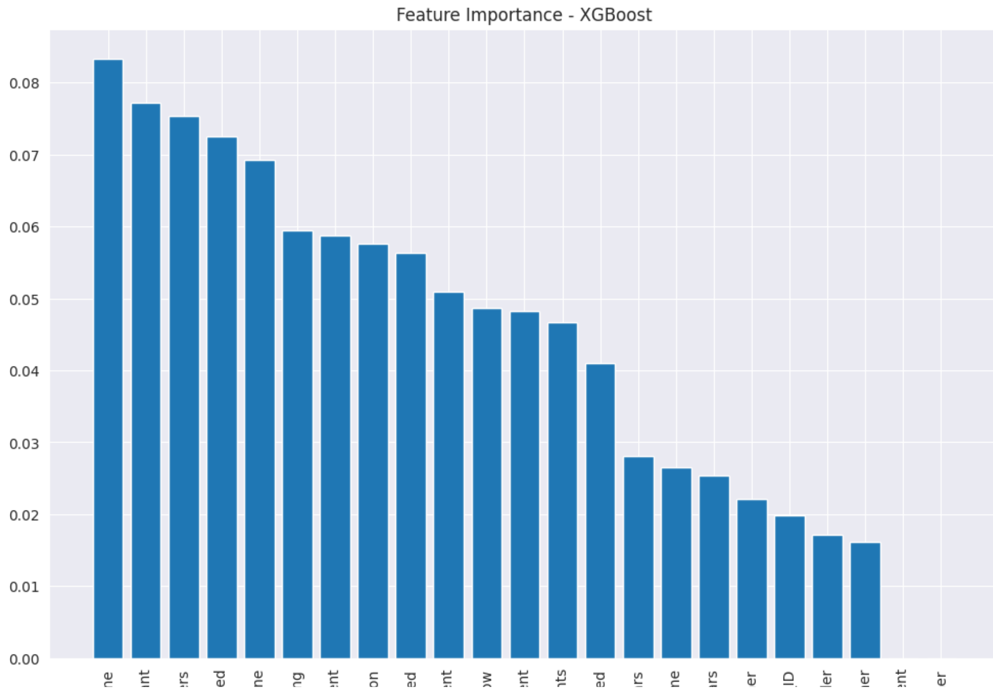
```
conf_matrix = confusion_matrix(y_test, y_pred_best)

# Visualize the confusion matrix
plt.figure(figsize=(6,6))
sns.heatmap(conf_matrix, annot=True, fmt='g', cmap='Blues', cbar=False)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix')
plt.show()
```




```
# Save the model

xgb_best.save_model('xgboost_model.pkl')
```

FEATURE IMPORTANCE

```
# Calculating feature importances

feature_importances = xgb.feature_importances_

# Sort the feature importances in descending order and get the indices

sorted_indices = np.argsort(feature_importances)[::-1]

# Ploting feature importances
plt.figure(figsize=(12, 8))

plt.title("Feature Importance - XGBoost")
plt.bar(X.columns[sorted_indices], feature_importances[sorted_indices])
plt.xticks(rotation=90)
plt.grid()
plt.show()
```



CONCLUSION:

- In this project, we embarked on the journey of building a predictive model for credit card approval. After exploring multiple algorithms, we finalized XGBoost due to its robustness and efficiency in handling tabular data with a mix of different variable types.
- We utilized XGBoost, a gradient boosting algorithm, known for its high performance in classification problems
- Performance Metrics: The model after hyperparameter tuning achieved an accuracy of approximately 92.93%. Notably, the precision and recall were also high, indicating 93.24% and 93.67% respectively. The F1-Score, which is the harmonic mean of precision and recall, stood at 93.45%, further cementing the model's reliability. The ROC AUC Score, which gives us the area under the curve for true positive rate vs false positive rate, was approximately 92.86%.
- Through diligent preprocessing, model selection, and hyperparameter tuning, we've crafted a robust model for credit card approval predictions. This model not only boasts high accuracy but also ensures a balanced trade-off between precision and recall, thus making it a valuable asset for financial institutions aiming to streamline their credit card approval processes.