Machine Learning Model Solutions, for Defaulters And Non-Defaulters Classifications

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Current Lenders Situation/Problem Overview

Case Study:
In order for the financial industry to maintain a healthy lending portfolio,
it is crucial for lenders to assess the creditworthiness of borrowers before granting loans or credit,
and this can help mitigate financial losses by identifying potential defaulters, who are at higher risk
of failing to repay their debts.

Historical Datasets Analysis

Research Objective:
From the company, Banjaj Finserv, that provided the historical datasets that contains different feature details like Loan Type, Loan Amount, Interest Rate, Loan Term, Credit Score, etc. , the goal of this project is to develop a predictive model that can accurately classify borrowers as defaulters or non-defaulters based on various financial and demographics factors .

Data Understanding

Dataset Features: 5000 rows x 17 columns

```
#Look into the data
loan
```

Python

	customer_id	loan_id	loan_type	loan_amount	interest_rate	loan_term	employment_type	income_level	credit_score	gender	marital_status	education_level	application_date	approval_date	disbursement_date	due_date	default_status
0	CUST-00004912	LN00004170	Car Loan	16795	0.051852	15	Self-employed	Medium	833	Male	Single	Master	05-04-2018	23-04-2018	24-04-2018	14-08-2018	False
1	CUST-00004194	LN00002413	Personal Loan	1860	0.089296	56	Full-time	Medium	776	Female	Married	Bachelor	30-12-2022	31-12-2022	12-01-2023	05-04-2023	False
2	CUST-00003610	LN00000024	Personal Loan	77820	0.070470	51	Full-time	Low	697	Male	Divorced	High School	15-11-2019	18-11-2019	27-11-2019	24-02-2020	False
3	CUST-00001895	LN00001742	Car Loan	55886	0.062155	30	Full-time	Low	795	Female	Married	PhD	25-08-2021	08-09-2021	11-09-2021	25-02-2022	False
4	CUST-00003782	LN00003161	Home Loan	7265	0.070635	48	Part-time	Low	519	Female	Married	High School	02-09-2020	07-09-2020	11-09-2020	29-12-2020	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4995	CUST-00002992	LN00001103	Car Loan	37945	0.070087	57	Self-employed	High	511	Male	Married	PhD	23-01-2022	11-02-2022	14-02-2022	13-06-2022	False
4996	CUST-00004094	LN00001068	Personal Loan	48937	0.056405	50	Part-time	Medium	502	Male	Single	PhD	12-05-2018	17-05-2018	27-05-2018	20-11-2018	False
4997	CUST-00003903	LN00000745	Home Loan	7476	0.064212	58	Full-time	High	452	Female	Single	High School	14-10-2022	29-10-2022	06-11-2022	08-04-2023	True
4998	CUST-00002276	LN00003075	Car Loan	52756	0.094914	12	Self-employed	Medium	728	Male	Married	PhD	21-07-2018	06-08-2018	20-08-2018	21-01-2019	False
4999	CUST-00003583	LN00002491	Personal Loan	91101	0.083821	52	Self-employed	Low	586	Male	Single	Master	03-08-2021	04-08-2021	07-08-2021	25-12-2021	False

5000 rows × 17 columns

Data Preparation

Missing Data Check

```
#Check for any missing data
loan.isnull().sum()
```

```
customer_id          0
loan_id              0
loan_type            0
loan_amount          0
interest_rate        0
loan_term            0
employment_type      0
income_level         0
credit_score         0
gender               0
marital_status       0
education_level      0
application_date     0
approval_date        0
disbursement_date    0
due_date             0
default_status       0
dtype: int64
```

Data Understanding

Dataset Features: 5000 rows x 17 columns

Data Types	Variables	Format
Categorical data (qualitative)	customer_id, loan_id, loan_type, employment_type, income_level, gender, marital_status, education_level default_status	object (8) boolean (1)
Numerical data (quantitative)	loan_amount, loan_term, credit_score interest_rate	int(64) (3) float(64) (1)
DateTime	application_date, approval_date, disbursement_date, due_date	object (4)

Data Preparation

1. default_status from boolean to integer,i.e false =0, true=1
2. interest_rate from decimal to percent, i.e. x100 and round to 1 decimal place
3. To convert all columns with dates from object to datetime64 format

Data Preparation

```
#To replace the default status column in boolean to integer in order to calculate the default status in numbers #####
#To covert interest rate from decimal to percentage type and round off to 1 decimal places
#(for categorization in groups before encoding during data binning phase )

loan['default_status']= loan['default_status'].replace({True: 1, False: 0})

loan['interest_rate']= loan['interest_rate'].multiply(100)

loan['interest_rate']= loan['interest_rate'].round(1)
```

```
#To change all the column with dates to datetime format

loan[['application_date', 'approval_date', 'disbursement_date', 'due_date']]
= loan[['application_date', 'approval_date', 'disbursement_date', 'due_date']].apply(pd.to_datetime)
```

Data Preparation

```
#To check data types of each colu
loan.dtypes
```

[10]

```
...  customer_id          object
     loan_id              object
     loan_type            object
     loan_amount           int64
     interest_rate       float64
     loan_term             int64
     employment_type      object
     income_level         object
     credit_score          int64
     gender               object
     marital_status       object
     education_level      object
     application_date     object
     approval_date        object
     disbursement_date    object
     due_date             object
     default_status         bool
     dtype: object
```

```
#Default status in integer output format
loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   customer_id        5000 non-null   object
 1   loan_id            5000 non-null   object
 2   loan_type          5000 non-null   object
 3   loan_amount        5000 non-null   int64
 4   interest_rate      5000 non-null   float64
 5   loan_term          5000 non-null   int64
 6   employment_type    5000 non-null   object
 7   income_level       5000 non-null   object
 8   credit_score       5000 non-null   int64
 9   gender             5000 non-null   object
 10  marital_status     5000 non-null   object
 11  education_level    5000 non-null   object
 12  application_date   5000 non-null   datetime64[ns]
 13  approval_date      5000 non-null   datetime64[ns]
 14  disbursement_date  5000 non-null   datetime64[ns]
 15  due_date           5000 non-null   datetime64[ns]
 16  default_status     5000 non-null   int64
dtypes: datetime64[ns](4), float64(1), int64(4), object(8)
memory usage: 664.2+ KB
```

Dataset Preparation

After convert for default_status, column dates and interest_rate

```
loan
```

	customer_id	loan_id	loan_type	loan_amount	interest_rate	loan_term	employment_type	income_level	credit_score	gender	marital_status	education_level	application_date	approval_date	disbursement_date	due_date	default_status
0	CUST-00004912	LN00004170	Car Loan	16795	5.2	15	Self-employed	Medium	833	Male	Single	Master	2018-05-04	2018-04-23	2018-04-24	2018-08-14	0
1	CUST-00004194	LN00002413	Personal Loan	1860	8.9	56	Full-time	Medium	776	Female	Married	Bachelor	2022-12-30	2022-12-31	2023-12-01	2023-05-04	0
2	CUST-00003610	LN00000024	Personal Loan	77820	7.0	51	Full-time	Low	697	Male	Divorced	High School	2019-11-15	2019-11-18	2019-11-27	2020-02-24	0
3	CUST-00001895	LN00001742	Car Loan	55886	6.2	30	Full-time	Low	795	Female	Married	PhD	2021-08-25	2021-08-09	2021-11-09	2022-02-25	0
4	CUST-00003782	LN00003161	Home Loan	7265	7.1	48	Part-time	Low	519	Female	Married	High School	2020-02-09	2020-07-09	2020-11-09	2020-12-29	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4995	CUST-00002992	LN00001103	Car Loan	37945	7.0	57	Self-employed	High	511	Male	Married	PhD	2022-01-23	2022-11-02	2022-02-14	2022-06-13	0
4996	CUST-00004094	LN00001068	Personal Loan	48937	5.6	50	Part-time	Medium	502	Male	Single	PhD	2018-12-05	2018-05-17	2018-05-27	2018-11-20	0
4997	CUST-00003903	LN00000745	Home Loan	7476	6.4	58	Full-time	High	452	Female	Single	High School	2022-10-14	2022-10-29	2022-06-11	2023-08-04	1
4998	CUST-00002276	LN00003075	Car Loan	52756	9.5	12	Self-employed	Medium	728	Male	Married	PhD	2018-07-21	2018-06-08	2018-08-20	2019-01-21	0
4999	CUST-00003583	LN00002491	Personal Loan	91101	8.4	52	Self-employed	Low	586	Male	Single	Master	2021-03-08	2021-04-08	2021-07-08	2021-12-25	0

5000 rows × 17 columns

```python
#Although all the dates are in datetime64 format for Pandas datatypes from object now, we need
to convert it into integers for the ML algorthims to have a predictive accuracy.
#Break apart the date and get the year, month, week of year, day of month and day of week.

loan['application_date_year'] = loan['application_date'].dt.year
loan['application_date_month'] = loan['application_date'].dt.month
loan['application_date_week'] = loan['application_date'].dt.week
loan['application_date_day'] = loan['application_date'].dt.day
loan['application_date_dayofweek'] = loan['application_date'].dt.dayofweek

loan['approval_date_year'] = loan['approval_date'].dt.year
loan['approval_date_month'] = loan['approval_date'].dt.month
loan['approval_date_week'] = loan['approval_date'].dt.week
loan['approval_date_day'] = loan['approval_date'].dt.day
loan['approval_date_dayofweek'] = loan['approval_date'].dt.dayofweek

loan['disbursement_date_year'] = loan['disbursement_date'].dt.year
loan['disbursement_date_month'] = loan['disbursement_date'].dt.month
loan['disbursement_date_week'] = loan['disbursement_date'].dt.week
loan['disbursement_date_day'] = loan['disbursement_date'].dt.day
loan['disbursement_date_dayofweek'] = loan['disbursement_date'].dt.dayofweek

loan['due_date_year'] = loan['due_date'].dt.year
loan['due_date_month'] = loan['due_date'].dt.month
loan['due_date_week'] = loan['due_date'].dt.week
loan['due_date_day'] = loan['due_date'].dt.day
loan['due_date_dayofweek'] = loan['due_date'].dt.dayofweek
```

```python
#To verify if the conversion dates works:

loan[['application_date_year', 'application_date_month', 'application_date_week', 'application_date_day', 'application_date_dayofweek']].head()
```

	application_date_year	application_date_month	application_date_week	application_date_day	application_date_dayofweek
0	2018	5	18	4	4
1	2022	12	52	30	4
2	2019	11	46	15	4
3	2021	8	34	25	2
4	2020	2	6	9	6

```python
#To check if all the breakdown dates is in integer data type

loan.info()
```

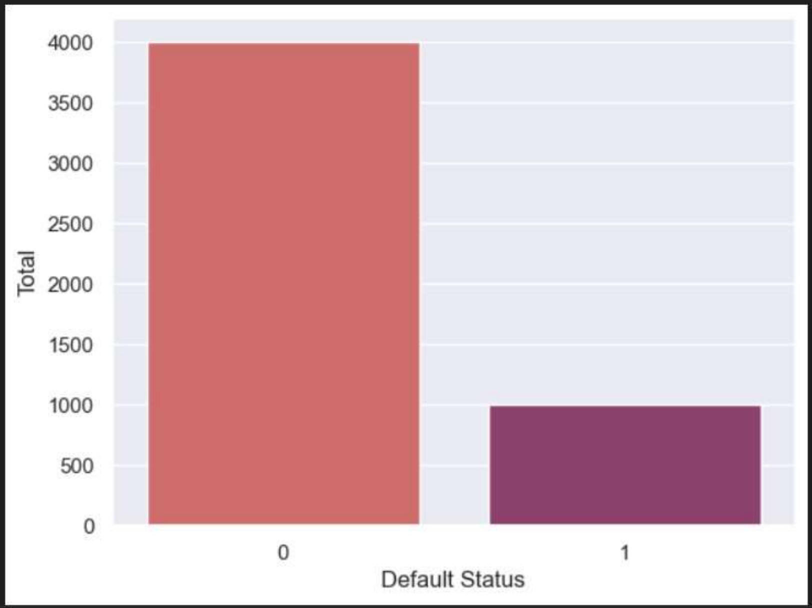
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 37 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   customer_id              5000 non-null   object
 1   loan_id                  5000 non-null   object
 2   loan_type                5000 non-null   object
 3   loan_amount              5000 non-null   int64
 4   interest_rate            5000 non-null   float64
 5   loan_term                5000 non-null   int64
 6   employment_type          5000 non-null   object
 7   income_level             5000 non-null   object
 8   credit_score             5000 non-null   int64
 9   gender                   5000 non-null   object
 10  marital_status           5000 non-null   object
 11  education_level          5000 non-null   object
 12  application_date         5000 non-null   datetime64[ns]
 13  approval_date            5000 non-null   datetime64[ns]
 14  disbursement_date        5000 non-null   datetime64[ns]
 15  due_date                 5000 non-null   datetime64[ns]
 16  default_status           5000 non-null   int64
 17  application_date_year    5000 non-null   int64
 18  application_date_month   5000 non-null   int64
 19  application_date_week    5000 non-null   int64
...
 35  due_date_day             5000 non-null   int64
 36  due_date_dayofweek       5000 non-null   int64
dtypes: datetime64[ns](4), float64(1), int64(24), object(8)
memory usage: 1.4+ MB
```

Exploratory Data Analysis – default_status

```
# To analyse the catergorical variables- Default Status
# The number of defaulters are much lower (4 times) than the non-defaulters

loan.default_status.value_counts()
```

```
0    4001
1     999
Name: default_status, dtype: int64
```

```
#EDA - Explore variables in the dataset using different various plots/charts:
#Default Status Distribution

sns.set_theme(style="darkgrid")
sns.countplot(x="default_status", data=loan, palette="flare")
plt.xlabel('Default Status')
plt.ylabel('Total')
plt.show()
```

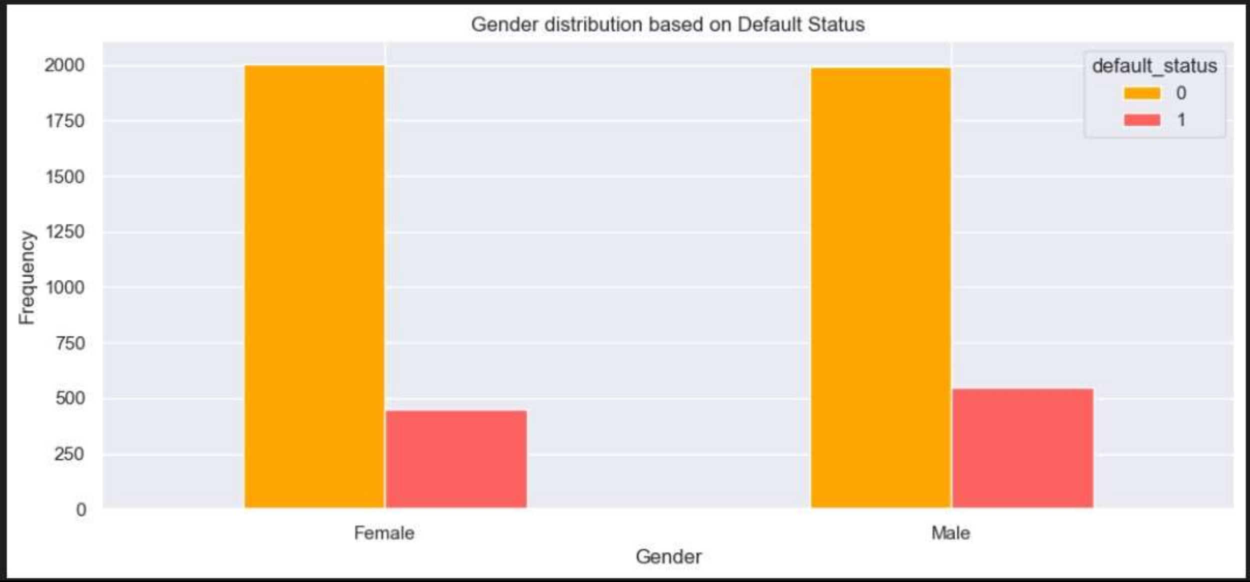


Exploratory Data Analysis – gender

```python
# To analyse the catergorical variables- Gender
# The Male gender has a higher distribution number than the Female

loan.gender.value_counts()
```

```
Male      2542
Female    2458
Name: gender, dtype: int64
```

```python
#Gender Distribution based on Default Status

pd.crosstab(loan.gender,loan.default_status).plot(kind="bar",figsize=(12,5),color=['#ffa600','#ff6361'])
plt.title('Gender distribution based on Default Status')
plt.xlabel('Gender')
plt.xticks(rotation=0)
plt.ylabel('Frequency')
plt.show()
```

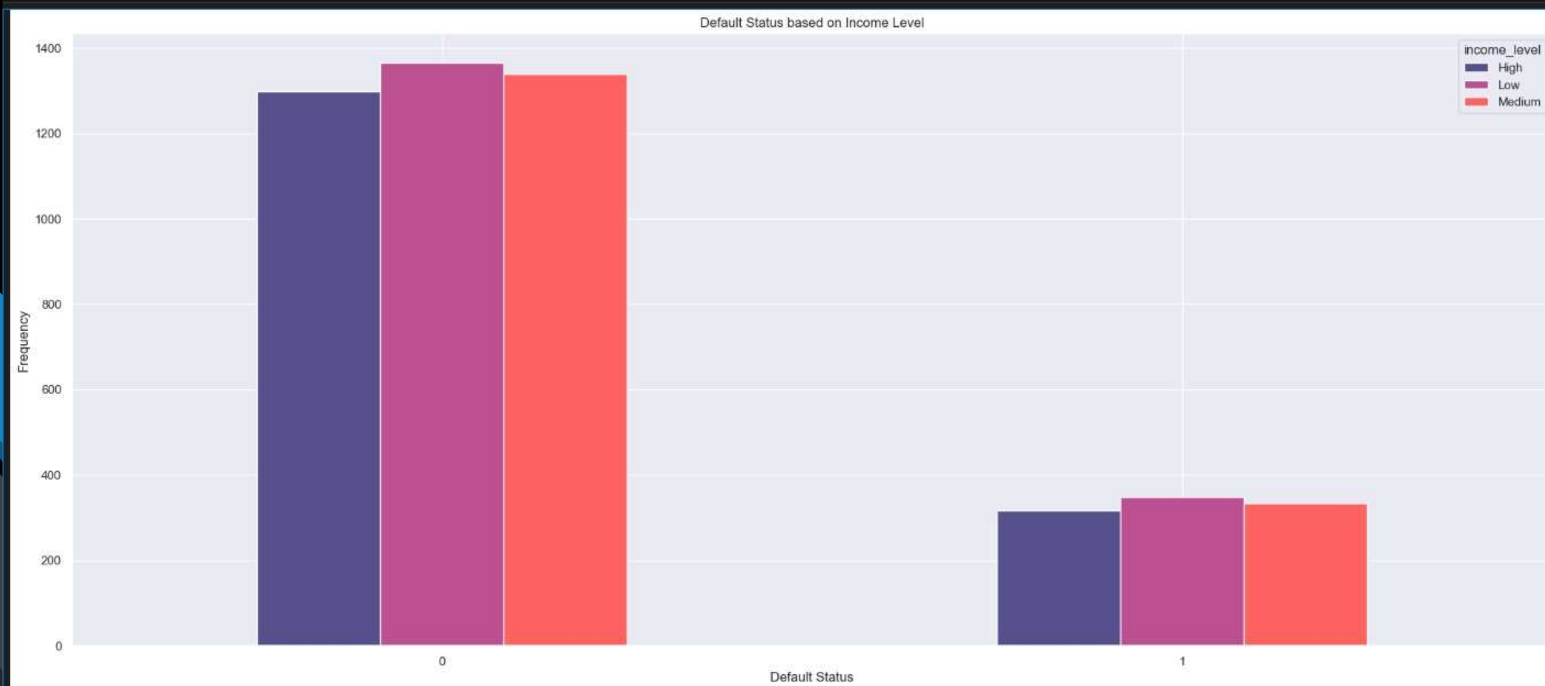


Exploratory Data Analysis – income_level

```
# To analyse the catergorical variables- Income Level
# Below shows the low income level has a higher distribution number than the other two
```

```
Low       1713
Medium    1672
High      1615
Name: income_level, dtype: int64
```

```
#Default Status based on Income Level

pd.crosstab(loan.default_status,loan.income_level).plot(kind="bar",figsize=(24,10),color=['#58508d','#bc5090','#ff6361'])
plt.title('Default Status based on Income Level')
plt.xlabel('Default Status')
plt.xticks(rotation=0)
plt.ylabel('Frequency')
plt.show()
```

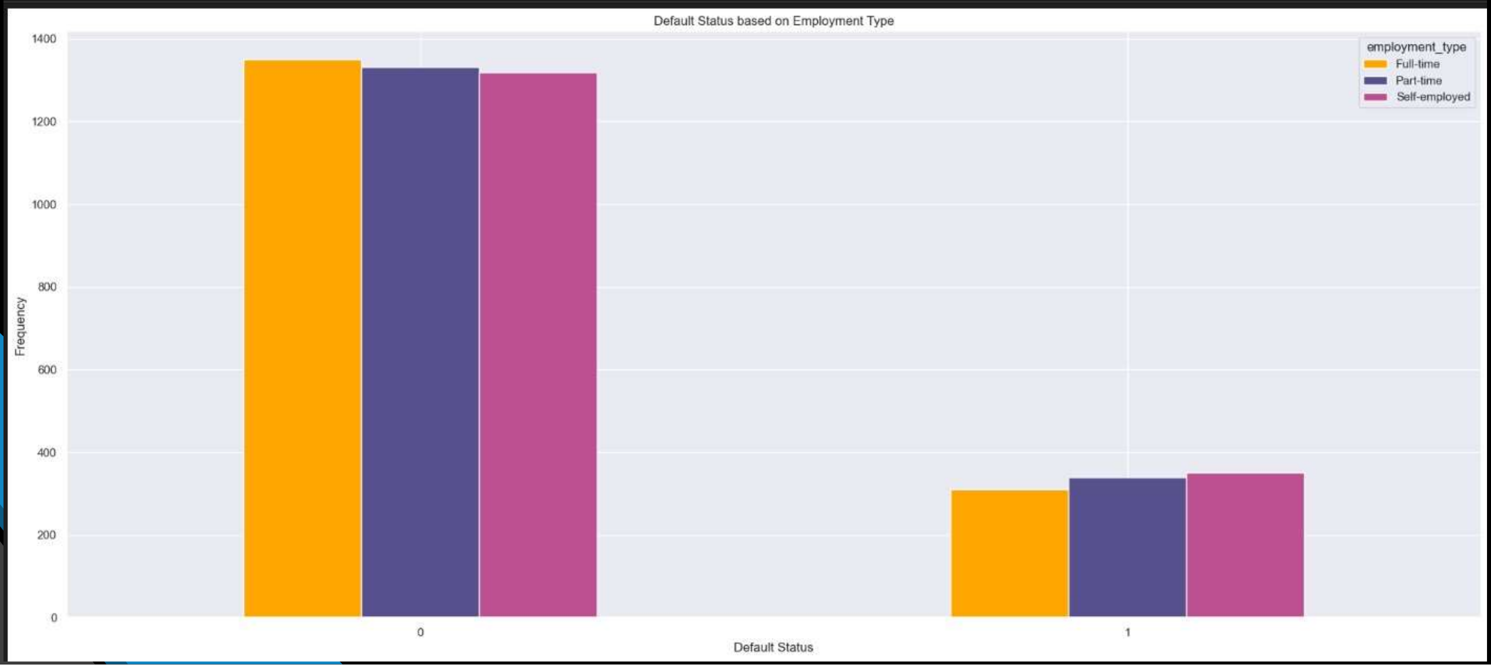


Exploratory Data Analysis – employment_type

```python
# To analyse the catergorical variables- Employment Type
# The distribution of Employment type is balanced

loan.employment_type.value_counts()
```

```
Part-time        1672
Self-employed    1669
Full-time        1659
Name: employment_type, dtype: int64
```

```python
#Default Status based on Employment Type

pd.crosstab(loan.default_status,loan.employment_type).plot(kind="bar",figsize=(24,10),color=['#ffa600','#58508d','#bc5090','#ff6361'])
plt.title('Default Status based on Employment Type')
plt.xlabel('Default Status')
plt.xticks(rotation=0)
plt.ylabel('Frequency')
plt.show()
```



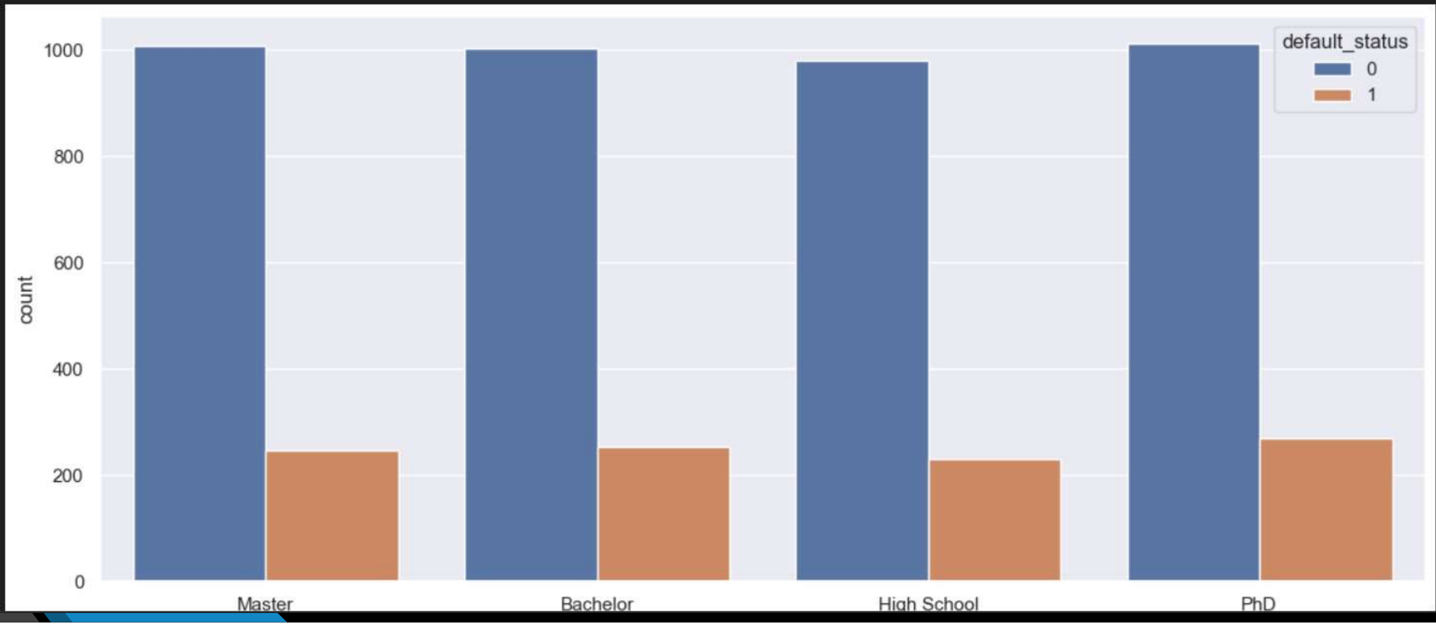
Exploratory Data Analysis – education_level

```
# To analyse the catergorical variables- Education Level
# The PhD has a slightly higher distribution number than the other level

loan.education_level.value_counts()
```

```
PhD            1282
Master         1254
Bachelor       1254
High School    1210
Name: education_level, dtype: int64
```

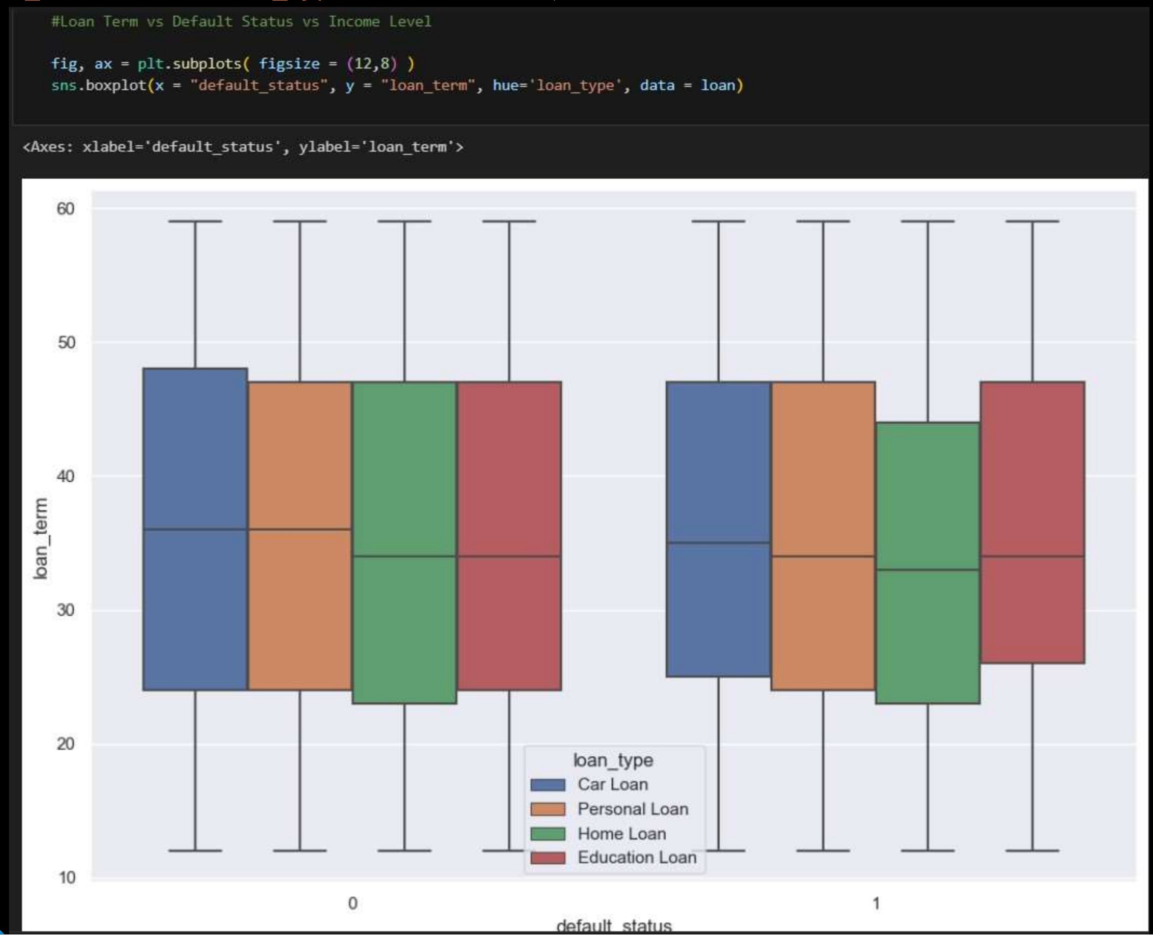
```
#Default Status based on Education Level

plt.figure(figsize=(14, 6))
sns.countplot( x='education_level', hue='default_status', data=loan )
```

```
<Axes: xlabel='education_level', ylabel='count'>
```



Exploratory Data Analysis – loan_type vs loan_term

```python
#Loan Term vs Default Status vs Loan Type

fig, ax = plt.subplots( figsize = (12,8) )
sns.boxplot(x = "default_status", y = "loan_term", hue='loan_type', data = loan)
```

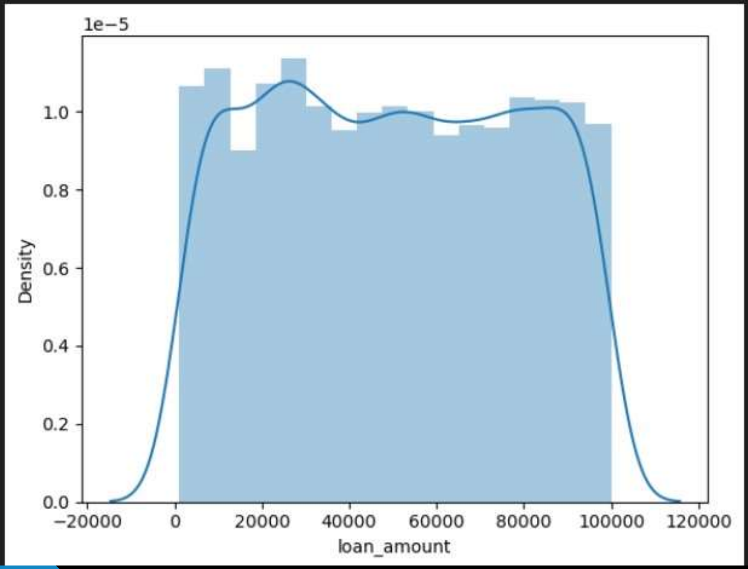


Numerical Variable Skewness – loan_amount

```python
#To check the skewness of each Numerical variable :
# Loan Amount

skewLoanAmount = loan.loan_amount.skew(axis = 0, skipna = True)
print('Loan Amount skewness: ', skewLoanAmount)
```

```
Loan Amount skewness:  0.022557766982177468
```

```python
sns.distplot(loan['loan_amount']); #The distribution of 'Loan Amount' column is symetric, since the skewness value between -0.5 and 0.5
```

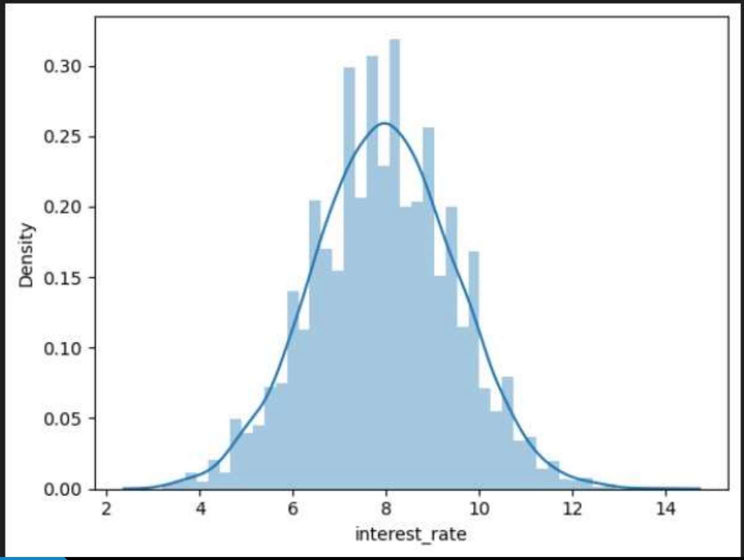


Numerical Variable Skewness – interest_rate

```python
#Interest Rate

skewInterestRate = loan.interest_rate.skew(axis = 0, skipna = True)
print('Interest Rate skewness: ', skewInterestRate)
```

```
Interest Rate skewness:  0.010015295077906989
```

```python
sns.distplot(loan['interest_rate']); #The distribution of 'Interest Rate' column is symetric, since the skewness value between -0.5 and 0.5
```

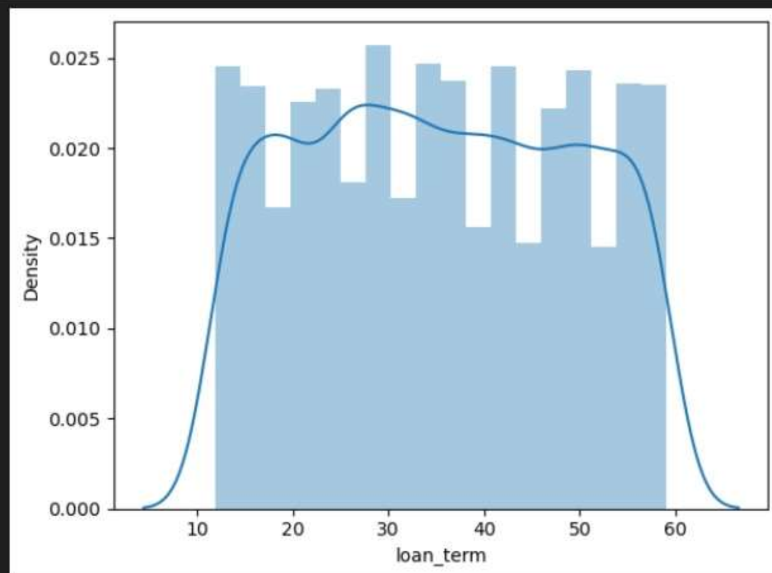


Numerical Variable Skewness – loan_term

```python
#Loan Term

skewLoanTerm = loan.loan_term.skew(axis = 0, skipna = True)
print('Loan Term skewness: ', skewLoanTerm)
```

```
Loan Term skewness:  0.031273752868043604
```

```python
sns.distplot(loan['loan_term']); #The distribution of 'Loan Term' column is symetric, since the skewness value between -0.5 and 0.5
```

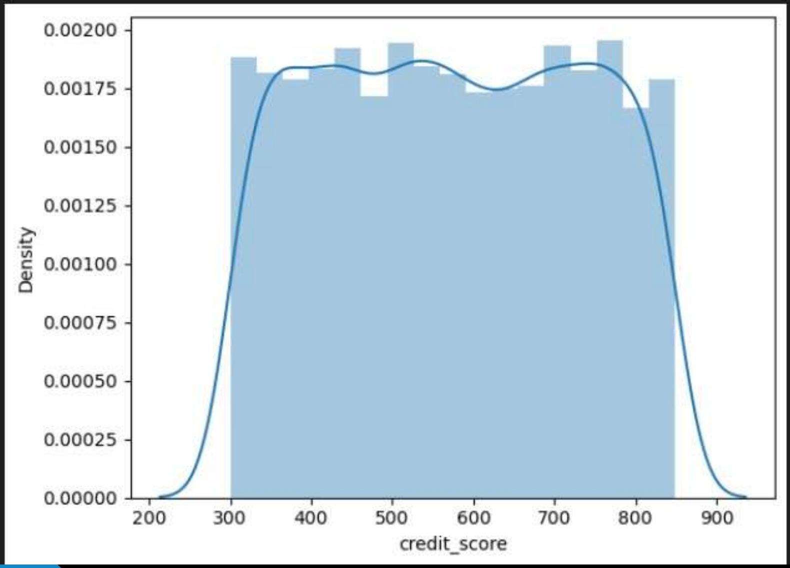


Numerical Variable Skewness – credit_score

```
#Credit Score

skewCreditScore = loan.credit_score.skew(axis = 0, skipna = True)
print('Credit Score skewness: ', skewCreditScore)
```

```
Credit Score skewness:  0.010039817997711456
```

```
sns.distplot(loan['credit_score']); #The distribution of 'Credit Score' column is symetric, since the skewness value between -0.5 and 0.5
```



Data Binning - loan_amount, interest_rate, loan_term, credit_score

```
# Data Binning:
# Loan Amount will be divided into 18 categories each

bin_LoanAmount = [1055, 1999, 2999, 3999, 4999, 5999, 6999, 7999, 8999, 9999, 19999, 29999, 39999, 49999, 59999, 69999,
79999, 89999, 99989]
category_LoanAmount = ['1000-2000', '2000-3000', '3000-4000', '4000-5000', '5000-6000', '6000-7000', '7000-8000',
'8000-9000', '9000-10000', '10000-20000', '20000-30000', '30000-40000', '40000-50000', '50000-60000', '60000-70000',
'70000-80000', '80000-90000', '>90000']
loan['loan_amount_binned'] = pd.cut(loan['loan_amount'], bins=bin_LoanAmount, labels=category_LoanAmount)
loan = loan.drop(['loan_amount'], axis = 1)

    #Interest Rate will be catergorised into 11 catergory

    bin_InterestRate = [3, 3.9, 4.9, 5.9, 6.9, 7.9, 8.9, 9.9, 10.9, 11.9, 12.9, 13.8]
    category_InterestRate = ['3-4', '4-5', '5-6', '6-7', '7-8', '8-9', '9-10', '10-11', '11-12', '12-13', '>13']
    loan['interest_rate_binned'] = pd.cut(loan['interest_rate'], bins=bin_InterestRate, labels=category_InterestRate)
    loan = loan.drop(['interest_rate'], axis = 1)

                 # Loan Term  will be divided into 5 categories each

                 bin_LoanTerm = [12, 19, 29, 39, 49, 59]
                 category_LoanTerm = ['10-20', '20-30', '30-40', '40-50', '>50']
                 loan['loan_term_binned'] = pd.cut(loan['loan_term'], bins=bin_LoanTerm, labels=category_LoanTerm)
                 loan = loan.drop(['loan_term'], axis = 1)
                              # Credit Score will be divided into 6 categories each

                              bin_CreditScore = [300, 399, 499, 599, 699, 799, 849]
                              category_CreditScore = ['300-400', '400-500', '500-600', '600-700', '700-800', '>800']
                              loan['credit_score_binned'] = pd.cut(loan['credit_score'], bins=bin_CreditScore,
                              labels=category_CreditScore)
                              loan = loan.drop(['credit_score'], axis = 1)
```

Data Binning – Application (Weeks, Days, Months, DayOfWeek)

```python
# Data Binning on Dates:

# The four dates: Application/Approval/Disbursement/Due will not be using years as it is not predicting the future years,
# will be using Weeks(1-53), Days(1-31), Months (1-12) and DayOfWeek (0-6) instead

loan.drop(['application_date', 'application_date_year'], axis='columns', inplace=True)

bin_ApplicationWeek = [0, 9, 19, 29, 39, 49, 53]
category_ApplicationWeek = ['<10', '10-20', '20-30', '30-40', '40-50', '>50']
loan['application_date_week_binned'] = pd.cut(loan['application_date_week'], bins=bin_ApplicationWeek,
labels=category_ApplicationWeek)
loan = loan.drop(['application_date_week'], axis = 1)

bin_ApplicationDay = [0, 9, 19, 29, 31]
category_ApplicationDay = ['<10', '10-20', '20-30', '>30']
loan['application_date_day_binned'] = pd.cut(loan['application_date_day'], bins=bin_ApplicationDay,
labels=category_ApplicationDay)
loan = loan.drop(['application_date_day'], axis = 1)

bin_ApplicationMonth = [1.9, 2.9, 3.9, 4.9, 5.9, 6.9, 7.9, 8.9, 9.9, 10.9, 11.9, 12]
category_ApplicationMonth = ['<2', '2-3', '3-4', '4-5', '5-6', '6-7', '7-8', '8-9', '9-10', '10-11', '11-12']
loan['application_date_month_binned'] = pd.cut(loan['application_date_month'], bins=bin_ApplicationMonth,
labels=category_ApplicationMonth)
loan = loan.drop(['application_date_month'], axis = 1)

bin_ApplicationDayOfWeek = [0, 1.9, 2.9, 3.9, 4.9, 5.9, 6]
category_ApplicationDayOfWeek = ['<1', '1-2', '2-3', '3-4', '4-5', '5-6']
loan['application_date_dayofweek_binned'] = pd.cut(loan['application_date_dayofweek'], bins=bin_ApplicationDayOfWeek,
labels=category_ApplicationDayOfWeek)
loan = loan.drop(['application_date_dayofweek'], axis = 1)
```

Data Binning – Approval (Weeks, Days, Months, DayOfWeek)

```
loan.drop(['approval_date', 'approval_date_year'], axis='columns', inplace=True)

bin_ApprovalWeek = [0, 9, 19, 29, 39, 49, 53]
category_ApprovalWeek = ['<10', '10-20', '20-30', '30-40', '40-50', '>50']
loan['approval_date_week_binned'] = pd.cut(loan['approval_date_week'], bins=bin_ApprovalWeek,
labels=category_ApprovalWeek)
loan = loan.drop(['approval_date_week'], axis = 1)

bin_ApprovalDay = [0, 9, 19, 29, 31]
category_ApprovalDay = ['<10', '10-20', '20-30', '>30']
loan['approval_date_day_binned'] = pd.cut(loan['approval_date_day'], bins=bin_ApprovalDay, labels=category_ApprovalDay)
loan = loan.drop(['approval_date_day'], axis = 1)

bin_ApprovalMonth = [1.9, 2.9, 3.9, 4.9, 5.9, 6.9, 7.9, 8.9, 9.9, 10.9, 11.9, 12]
category_ApprovalMonth = ['<2', '2-3', '3-4', '4-5', '5-6', '6-7', '7-8', '8-9', '9-10', '10-11', '11-12']
loan['approval_date_month_binned'] = pd.cut(loan['approval_date_month'], bins=bin_ApprovalMonth,
labels=category_ApprovalMonth)
loan = loan.drop(['approval_date_month'], axis = 1)

bin_ApprovalDayOfWeek = [0, 1.9, 2.9, 3.9, 4.9, 5.9, 6]
category_ApprovalDayOfWeek = ['<1', '1-2', '2-3', '3-4', '4-5', '5-6']
loan['approval_date_dayofweek_binned'] = pd.cut(loan['approval_date_dayofweek'], bins=bin_ApprovalDayOfWeek,
labels=category_ApprovalDayOfWeek)
loan = loan.drop(['approval_date_dayofweek'], axis = 1)
```

Data Binning – Disbursement (Weeks, Days, Months, DayOfWeek)

```
loan.drop(['disbursement_date', 'disbursement_date_year'], axis='columns', inplace=True)

bin_DisbursementWeek = [0, 9, 19, 29, 39, 49, 53]
category_DisbursementWeek = ['<10', '10-20', '20-30', '30-40', '40-50', '>50']
loan['disbursement_date_week_binned'] = pd.cut(loan['disbursement_date_week'], bins=bin_DisbursementWeek,
labels=category_DisbursementWeek)
loan = loan.drop(['disbursement_date_week'], axis = 1)

bin_DisbursementDay = [0, 9, 19, 29, 31]
category_DisbursementDay = ['<10', '10-20', '20-30', '>30']
loan['disbursement_date_day_binned'] = pd.cut(loan['disbursement_date_day'], bins=bin_DisbursementDay,
labels=category_DisbursementDay)
loan = loan.drop(['disbursement_date_day'], axis = 1)

bin_DisbursementMonth = [1.9, 2.9, 3.9, 4.9, 5.9, 6.9, 7.9, 8.9, 9.9, 10.9, 11.9, 12]
category_DisbursementMonth = ['<2', '2-3', '3-4', '4-5', '5-6', '6-7', '7-8', '8-9', '9-10', '10-11', '11-12']
loan['disbursement_date_month_binned'] = pd.cut(loan['disbursement_date_month'], bins=bin_DisbursementMonth,
labels=category_DisbursementMonth)
loan = loan.drop(['disbursement_date_month'], axis = 1)

bin_DisbursementDayOfWeek = [0, 1.9, 2.9, 3.9, 4.9, 5.9, 6]
category_DisbursementDayOfWeek = ['<1', '1-2', '2-3', '3-4', '4-5', '5-6']
loan['disbursement_date_dayofweek_binned'] = pd.cut(loan['disbursement_date_dayofweek'], bins=bin_DisbursementDayOfWeek,
labels=category_DisbursementDayOfWeek)
loan = loan.drop(['disbursement_date_dayofweek'], axis = 1)
```

Data Binning – Due (Weeks, Days, Months, DayOfWeek)

```
loan.drop(['due_date', 'due_date_year'], axis='columns', inplace=True)

bin_DueWeek = [0, 9, 19, 29, 39, 49, 53]
category_DueWeek = ['<10', '10-20', '20-30', '30-40', '40-50', '>50']
loan['due_date_week_binned'] = pd.cut(loan['due_date_week'], bins=bin_DueWeek, labels=category_DueWeek)
loan = loan.drop(['due_date_week'], axis = 1)

bin_DueDay = [0, 9, 19, 29, 31]
category_DueDay = ['<10', '10-20', '20-30', '>30']
loan['due_date_day_binned'] = pd.cut(loan['due_date_day'], bins=bin_DueDay, labels=category_DueDay)
loan = loan.drop(['due_date_day'], axis = 1)

bin_DueMonth = [1.9, 2.9, 3.9, 4.9, 5.9, 6.9, 7.9, 8.9, 9.9, 10.9, 11.9, 12]
category_DueMonth = ['<2', '2-3', '3-4', '4-5', '5-6', '6-7', '7-8', '8-9', '9-10', '10-11', '11-12']
loan['due_date_month_binned'] = pd.cut(loan['due_date_month'], bins=bin_DueMonth, labels=category_DueMonth)
loan = loan.drop(['due_date_month'], axis = 1)

bin_DueDayOfWeek = [0, 1.9, 2.9, 3.9, 4.9, 5.9, 6]
category_DueDayOfWeek = ['<1', '1-2', '2-3', '3-4', '4-5', '5-6']
loan['due_date_dayofweek_binned'] = pd.cut(loan['due_date_dayofweek'], bins=bin_DueDayOfWeek,
labels=category_DueDayOfWeek)
loan = loan.drop(['due_date_dayofweek'], axis = 1)
```

Feature Engineering (FE) – Label Encoder

```
#Since there is no sign of major skewness seen in all numericle variables,
#while there are categorical variables difference seen in the distribution,
#need to encode the categorical variables into integer format so that machine learning model can read it

from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder



#Feature Engineering (FE)
#The customer_id and loan_id will apply on label encoder before applying it on onehot encoder as it takes
only numerical categorical values.

label_encoder = LabelEncoder()

for col in ['customer_id', 'loan_id', 'gender']: loan[col] = label_encoder.fit_transform( loan[col] )
```

Feature Engineering (FE) – OneHot Encoder

```
#Feature Engineering (FE)
#The FE method that used is one-hot encoding, which is transforming categorical variables into a form that could be provided to ML algorithms to do a better prediction.

onehot_encoder = OneHotEncoder(sparse = False)

for col in ['customer_id', 'loan_id', 'loan_amount_binned', 'interest_rate_binned', 'loan_type',
'employment_type', 'income_level', 'marital_status', 'education_level', 'loan_term_binned',
'credit_score_binned', 'application_date_month_binned', 'application_date_week_binned',
'application_date_day_binned', 'application_date_dayofweek_binned', 'approval_date_month_binned',
'approval_date_week_binned', 'approval_date_day_binned', 'approval_date_dayofweek_binned',
'disbursement_date_month_binned', 'disbursement_date_week_binned', 'disbursement_date_day_binned',
'disbursement_date_dayofweek_binned', 'due_date_month_binned', 'due_date_week_binned', 'due_date_day_binned',
'due_date_dayofweek_binned']: loan[col] = onehot_encoder.fit_transform( loan[col] .values.reshape(-1, 1))
```

Splitting the Dataset – Training and Testing

```
# After the Feature engineering part is complete, train and test-run trial on the dummies for all the variables
# Splitting the data into train and test splits
# The dataset will be split into 80% training and 20% testing

X = loan.drop(['default_status'], axis=1)
y = loan['default_status']

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 = pd.get_dummies(X_train)
X_test = pd.get_dummies(X_test)
```

Splitting the Dataset – Training

```python
X_train.head(30)
```

	customer_id	loan_id	loan_type	employment_type	income_level	gender	marital_status	education_level	loan_amount_binned	interest_rate_binned	...	approval_date_month_binned	approval_date_dayofweek_binned	disbursement_date_week_binned	disbursement_date_day_binned	disburs
2913	1.0	1.0	1.0	1.0	0.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	0.0	1.0	
3275	1.0	1.0	0.0	1.0	1.0	0	1.0	1.0	1.0	1.0	...	0.0	0.0	1.0	0.0	
775	1.0	1.0	0.0	0.0	0.0	0	0.0	0.0	1.0	1.0	...	1.0	0.0	1.0	1.0	
217	1.0	1.0	0.0	1.0	0.0	0	0.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
1245	1.0	1.0	1.0	1.0	1.0	1	0.0	1.0	1.0	1.0	...	1.0	1.0	1.0	0.0	
4316	1.0	1.0	1.0	0.0	0.0	1	0.0	0.0	1.0	1.0	...	1.0	1.0	1.0	0.0	
4619	1.0	1.0	0.0	1.0	1.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
1363	1.0	1.0	1.0	1.0	1.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
630	1.0	1.0	0.0	0.0	1.0	0	0.0	1.0	1.0	1.0	...	1.0	0.0	1.0	1.0	
3572	1.0	1.0	1.0	0.0	1.0	1	0.0	1.0	1.0	1.0	...	1.0	1.0	1.0	0.0	
4124	1.0	1.0	0.0	1.0	1.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
4101	1.0	1.0	0.0	0.0	0.0	1	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	0.0	
1881	1.0	1.0	1.0	1.0	1.0	0	0.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
1482	1.0	1.0	1.0	1.0	1.0	0	1.0	0.0	1.0	0.0	...	1.0	1.0	1.0	1.0	
156	1.0	1.0	0.0	0.0	0.0	1	0.0	1.0	1.0	1.0	...	0.0	1.0	1.0	1.0	
1196	1.0	1.0	1.0	1.0	0.0	1	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	0.0	
2824	1.0	1.0	1.0	1.0	1.0	1	0.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
3283	1.0	1.0	0.0	1.0	1.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
3809	1.0	1.0	1.0	0.0	0.0	0	1.0	0.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
3908	1.0	1.0	0.0	1.0	1.0	0	0.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
2006	1.0	1.0	1.0	1.0	0.0	0	1.0	1.0	1.0	1.0	...	1.0	0.0	0.0	0.0	
4740	1.0	1.0	0.0	1.0	1.0	1	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	0.0	
2490	1.0	1.0	1.0	0.0	1.0	0	0.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
4139	1.0	1.0	1.0	0.0	0.0	1	0.0	0.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
22	1.0	1.0	1.0	1.0	1.0	0	1.0	0.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
4196	1.0	1.0	1.0	1.0	1.0	0	1.0	1.0	1.0	0.0	...	1.0	1.0	1.0	1.0	
4054	1.0	1.0	1.0	0.0	0.0	0	0.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
2799	1.0	1.0	1.0	1.0	0.0	0	0.0	1.0	1.0	1.0	...	0.0	0.0	1.0	1.0	
3578	1.0	1.0	1.0	1.0	1.0	1	0.0	1.0	1.0	0.0	...	1.0	1.0	0.0	1.0	
4722	1.0	1.0	1.0	0.0	1.0	1	1.0	0.0	1.0	1.0	...	1.0	1.0	1.0	0.0	

30 rows × 28 columns

Splitting the Dataset – Testing

```
X_test.head(30)
```

	customer_id	loan_id	loan_type	employment_type	income_level	gender	marital_status	education_level	loan_amount_binned	interest_rate_binned	...	approval_date_month_binned	approval_date_dayofweek_binned	disbursement_date_week_binned	disbursement_date_day_binned	disburs
398	1.0	1.0	1.0	0.0	1.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
3833	1.0	1.0	0.0	0.0	1.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	0.0	0.0	
4836	1.0	1.0	1.0	1.0	0.0	0	0.0	0.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
4572	1.0	1.0	1.0	1.0	1.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	0.0	
636	1.0	1.0	0.0	0.0	1.0	0	1.0	1.0	1.0	1.0	...	0.0	1.0	1.0	1.0	
2545	1.0	1.0	1.0	1.0	1.0	0	0.0	1.0	1.0	1.0	...	1.0	0.0	1.0	1.0	
1161	1.0	1.0	1.0	1.0	1.0	0	0.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
2230	1.0	1.0	1.0	0.0	0.0	1	1.0	1.0	1.0	1.0	...	0.0	1.0	0.0	0.0	
148	1.0	1.0	0.0	1.0	1.0	1	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
2530	1.0	1.0	1.0	0.0	1.0	1	0.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
4070	1.0	1.0	1.0	0.0	0.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
1261	1.0	1.0	1.0	1.0	1.0	1	1.0	1.0	1.0	1.0	...	0.0	1.0	1.0	1.0	
4682	1.0	1.0	1.0	1.0	1.0	0	0.0	1.0	1.0	1.0	...	1.0	1.0	1.0	0.0	
333	1.0	1.0	1.0	1.0	1.0	1	1.0	0.0	1.0	1.0	...	1.0	1.0	0.0	1.0	
906	1.0	1.0	0.0	0.0	0.0	1	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
3170	1.0	1.0	1.0	1.0	1.0	1	0.0	1.0	1.0	0.0	...	1.0	1.0	1.0	0.0	
483	1.0	1.0	0.0	1.0	1.0	1	1.0	1.0	1.0	1.0	...	1.0	0.0	1.0	0.0	
2825	1.0	1.0	1.0	1.0	0.0	0	1.0	1.0	1.0	1.0	...	1.0	0.0	1.0	0.0	
1778	1.0	1.0	1.0	1.0	0.0	1	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
2466	1.0	1.0	1.0	1.0	1.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
159	1.0	1.0	1.0	0.0	1.0	1	1.0	1.0	1.0	1.0	...	1.0	0.0	1.0	0.0	
1563	1.0	1.0	1.0	0.0	1.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
402	1.0	1.0	0.0	1.0	1.0	1	0.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
4258	1.0	1.0	1.0	1.0	1.0	0	1.0	0.0	1.0	1.0	...	1.0	1.0	1.0	1.0	
4775	1.0	1.0	1.0	0.0	1.0	1	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	0.0	
1095	1.0	1.0	0.0	1.0	1.0	1	1.0	1.0	1.0	1.0	...	1.0	0.0	1.0	0.0	
3054	1.0	1.0	1.0	1.0	0.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	0.0	
4268	1.0	1.0	1.0	1.0	1.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	0.0	
3711	1.0	1.0	1.0	1.0	1.0	0	1.0	1.0	1.0	1.0	...	1.0	0.0	1.0	0.0	
453	1.0	1.0	0.0	1.0	1.0	0	1.0	1.0	1.0	1.0	...	1.0	1.0	1.0	1.0	

30 rows × 28 columns

SMOTE Techniques

```
#SMOTE Techniques
#Since the number of 'Non-Defaulters' is more than 'Defaulters', oversampling is carried out to avoid overfitting.
from imblearn.over_sampling import SMOTE
X_train, y_train = SMOTE().fit_resample(X_train, y_train)

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

Maching Learning Models – Logistic Regression

```
#Using differents methods of Machine Learning Models and predictions :
#Logistic Regression

from sklearn.linear_model import LogisticRegression
LRclassifier = LogisticRegression(solver='liblinear', max_iter=5000)
LRclassifier.fit(X_train, y_train)

y_pred = LRclassifier.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

from sklearn.metrics import accuracy_score
LRAcc = accuracy_score(y_pred,y_test)
print('Logistic Regression accuracy is: {:.2f}%'.format(LRAcc*100))
```

```
              precision    recall  f1-score   support

           0       0.82      0.53      0.65       820
           1       0.18      0.47      0.26       180

    accuracy                           0.52      1000
   macro avg       0.50      0.50      0.46      1000
weighted avg       0.71      0.52      0.58      1000

[[438 382]
 [ 95  85]]
Logistic Regression accuracy is: 52.30%
```

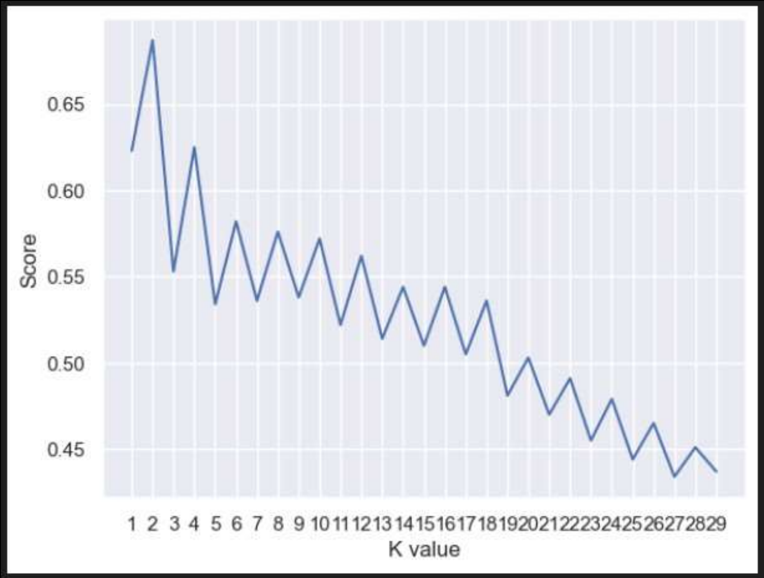
Maching Learning Models – K-Neighbours

```
#K-Neigbors

from sklearn.neighbors import KNeighborsClassifier
KNclassifier = KNeighborsClassifier(n_neighbors=20)
KNclassifier.fit(X_train, y_train)

y_pred = KNclassifier.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

from sklearn.metrics import accuracy_score
KNAcc = accuracy_score(y_pred,y_test)
print('K Neighbours accuracy is: {:.2f}%'.format(KNAcc*100))
```

```
              precision    recall  f1-score   support

           0       0.81      0.51      0.63       820
           1       0.17      0.47      0.25       180

    accuracy                           0.50      1000
   macro avg       0.49      0.49      0.44      1000
weighted avg       0.70      0.50      0.56      1000

[[419 401]
 [ 96  84]]
K Neighbours accuracy is: 50.30%
```

Maching Learning Models – KNN Max

```
#KNN Max

scoreListknn = []
for i in range(1,30):
    KNclassifier = KNeighborsClassifier(n_neighbors = i)
    KNclassifier.fit(X_train, y_train)
    scoreListknn.append(KNclassifier.score(X_test, y_test))

plt.plot(range(1,30), scoreListknn)
plt.xticks(np.arange(1,30,1))
plt.xlabel("K value")
plt.ylabel("Score")
plt.show()
KNAccMax = max(scoreListknn)
print("KNN Acc Max {:.2f}%".format(KNAccMax*100))
```




```
KNN Acc Max 68.70%
```

Maching Learning Models – SVM

```python
#Support Vector Machine (SVM)

from sklearn.svm import SVC
SVCclassifier = SVC(kernel='linear', max_iter=251)
SVCclassifier.fit(X_train, y_train)

y_pred = SVCclassifier.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

from sklearn.metrics import accuracy_score
SVCAcc = accuracy_score(y_pred,y_test)
print('SVC accuracy is: {:.2f}%'.format(SVCAcc*100))
```

```
              precision    recall  f1-score   support

           0       0.84      0.37      0.52       820
           1       0.19      0.67      0.30       180

    accuracy                           0.43      1000
   macro avg       0.51      0.52      0.41      1000
weighted avg       0.72      0.43      0.48      1000

[[305 515]
 [ 59 121]]
SVC accuracy is: 42.60%
```

Maching Learning Models – Naïve Bayes

```python
#Naive Bayes Method :
#Categorical NB

from sklearn.naive_bayes import CategoricalNB
NBclassifier1 = CategoricalNB()
NBclassifier1.fit(X_train, y_train)

y_pred = NBclassifier1.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

from sklearn.metrics import accuracy_score
NBAcc1 = accuracy_score(y_pred,y_test)
print('Naive Bayes accuracy is: {:.2f}%'.format(NBAcc1*100))
```

```
              precision    recall  f1-score   support

           0       0.83      0.63      0.71       820
           1       0.20      0.43      0.28       180

    accuracy                           0.59      1000
   macro avg       0.52      0.53      0.50      1000
weighted avg       0.72      0.59      0.64      1000

[[513 307]
 [102  78]]
Naive Bayes accuracy is: 59.10%
```

Maching Learning Models – Gaussian Naïve Bayes

```
#Gaussian NB

from sklearn.naive_bayes import GaussianNB
NBclassifier2 = GaussianNB()
NBclassifier2.fit(X_train, y_train)

y_pred = NBclassifier2.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

from sklearn.metrics import accuracy_score
NBAcc2 = accuracy_score(y_pred,y_test)
print('Gaussian Naive Bayes accuracy is: {:.2f}%'.format(NBAcc2*100))
```

```
              precision    recall  f1-score   support

           0       0.80      0.31      0.45       820
           1       0.17      0.65      0.27       180

    accuracy                           0.37      1000
   macro avg       0.49      0.48      0.36      1000
weighted avg       0.69      0.37      0.42      1000

[[254 566]
 [ 63 117]]
Gaussian Naive Bayes accuracy is: 37.10%
```

Maching Learning Models – Decision Tree

```python
# Decision Tree

from sklearn.tree import DecisionTreeClassifier
DTclassifier = DecisionTreeClassifier(max_leaf_nodes=30)
DTclassifier.fit(X_train, y_train)

y_pred = DTclassifier.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

from sklearn.metrics import accuracy_score
DTAcc = accuracy_score(y_pred,y_test)
print('Decision Tree accuracy is: {:.2f}%'.format(DTAcc*100))
```

```
              precision    recall  f1-score   support

           0       0.82      0.94      0.88       820
           1       0.20      0.07      0.11       180

    accuracy                           0.78      1000
   macro avg       0.51      0.50      0.49      1000
weighted avg       0.71      0.78      0.74      1000

[[768  52]
 [167  13]]
Decision Tree accuracy is: 78.10%
```

Maching Learning Models – Decision Tree Max

```python
#Decision Tree Max

scoreListDT = []
for i in range(2,50):
    DTclassifier = DecisionTreeClassifier(max_leaf_nodes=i)
    DTclassifier.fit(X_train, y_train)
    scoreListDT.append(DTclassifier.score(X_test, y_test))

plt.plot(range(2,50), scoreListDT)
plt.xticks(np.arange(2,50,5))
plt.xlabel("Leaf")
plt.ylabel("Score")
plt.show()
DTAccMax = max(scoreListDT)
print("DT Acc Max {:.2f}%".format(DTAccMax*100))
```


```
DT Acc Max 79.00%
```

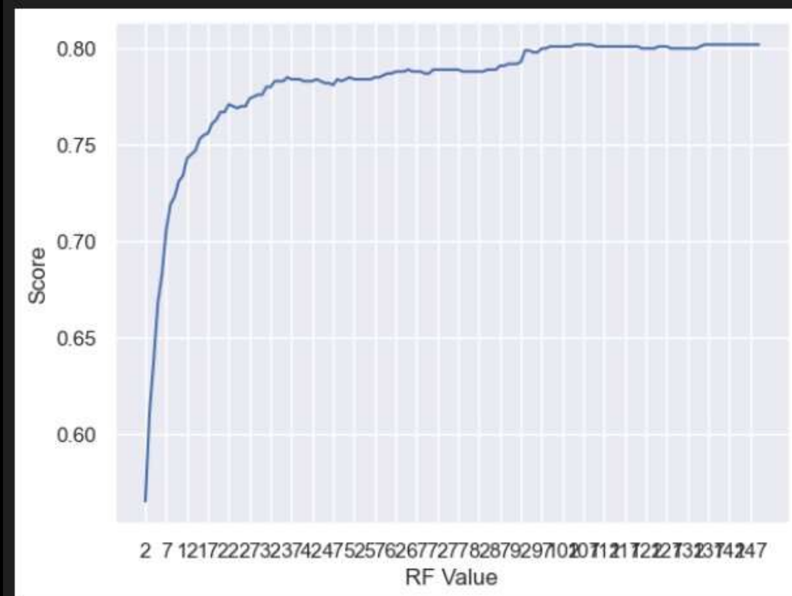
Maching Learning Models – Random Forest

```python
# Random Forest

from sklearn.ensemble import RandomForestClassifier

RFclassifier = RandomForestClassifier(max_leaf_nodes=150)
RFclassifier.fit(X_train, y_train)

y_pred = RFclassifier.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

from sklearn.metrics import accuracy_score
RFAcc = accuracy_score(y_pred,y_test)
print('Random Forest accuracy is: {:.2f}%'.format(RFAcc*100))
```

```
              precision    recall  f1-score   support

           0       0.83      0.97      0.89       820
           1       0.34      0.07      0.11       180

    accuracy                           0.81      1000
   macro avg       0.58      0.52      0.50      1000
weighted avg       0.74      0.81      0.75      1000

[[797  23]
 [168  12]]
Random Forest accuracy is: 80.90%
```

Maching Learning Models – Random Forest Max

```
# Random Forest Max

scoreListRF = []
for i in range(2,150):
    RFclassifier = RandomForestClassifier(n_estimators = 1000, random_state = 1,
max_leaf_nodes=i)
    RFclassifier.fit(X_train, y_train)
    scoreListRF.append(RFclassifier.score(X_test, y_test))

plt.plot(range(2,150), scoreListRF)
plt.xticks(np.arange(2,150,5))
plt.xlabel("RF Value")
plt.ylabel("Score")
plt.show()
RFAccMax = max(scoreListRF)
print("RF Acc Max {:.2f}%".format(RFAccMax*100))
```




```
RF Acc Max 80.20%
```

Maching Learning Models Comparison

```
# Model Comparison

compare = pd.DataFrame({'Model': ['Logistic Regression',
'K Neighbors', 'K Neighbors Max', 'SVM', 'Categorical
NB', 'Gaussian NB', 'Decision Tree', 'Decision Tree Max',
'Random Forest', 'Random Forest Max'],
                        'Accuracy': [LRAcc*100,
KNAcc*100, KNAccMax*100, SVCAcc*100, NBAcc1*100,
NBAcc2*100, DTAcc*100, DTAccMax*100, RFAcc*100,
RFAccMax*100]})
compare.sort_values(by='Accuracy', ascending=False)
```

Model	Accuracy
Random Forest	80.9
Random Forest Max	80.2
Decision Tree Max	79.0
Decision Tree	78.1
K Neighbors Max	68.7
Categorical NB	59.1
Logistic Regression	52.3
K Neighbors	50.3
SVM	42.6
Gaussian NB	37.1

Conclusion

Conclusion :

-From the results, it can be seen that Random Forest has the highest accuracy of 80% as compare to the rest of ML models in predicting classification of default status, for the 'Non-Defaulters' on precision, recall and F1-score gives a high score of 83%,97% and 89% and the 'Defaulters' score was 34%,7% and 11% which is lower but able to predict the number of defaulters which is closely comparable to the actual datasets.

-The Decision Tree Classifier has an accuracy above 70% but will select Random Forest as a better ML classifier as the confusion matrix has a better result, and also the precision, recall and F1-score has the highest score.

-Data preparartion like Data Binning need to be specifically done on on numerical and categorical variables which is very important so that ML algorthim will gives a more accuracy in the predictive algorithm techniques used.
In the case of categorical features, we need to perform encoding like onehot encoding so that the ML algorithm can process them more accurately.

-Predicting Loan Default is highly dependent on the demographics of the people, Self-employed/Part-timers with lower income and higher education level are more likely to default on loans.Majority are males.