In [105…

```
# Import required libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns


from sklearn import metrics


from sklearn import linear_model
from sklearn.metrics import mean_squared_error, r2_score


from sklearn.model_selection import train_test_split
from sklearn import metrics


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

from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

In [106…

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

In [107…

```
# read csv file

df = pd.read_csv("loan.csv")

df.head(10)
```

Out[107]:

	customer_id	loan_id	loan_type	loan_amount	interest_rate	loan_term	employment_type
0	CUST-00004912	LN00004170	Car Loan	16795	0.051852	15	Self-employed
1	CUST-00004194	LN00002413	Personal Loan	1860	0.089296	56	Full-time
2	CUST-00003610	LN00000024	Personal Loan	77820	0.070470	51	Full-time
3	CUST-00001895	LN00001742	Car Loan	55886	0.062155	30	Full-time
4	CUST-00003782	LN00003161	Home Loan	7265	0.070635	48	Part-time
5	CUST-00002287	LN00003606	Car Loan	83386	0.077232	13	Self-employed
6	CUST-00004571	LN00003372	Car Loan	38194	0.070929	26	Part-time
7	CUST-00002572	LN00002092	Car Loan	88498	0.046917	13	Part-time
8	CUST-00001416	LN00001061	Home Loan	45131	0.093456	22	Self-employed
9	CUST-00000009	LN00003352	Education Loan	61263	0.099123	56	Self-employed

Descriptive Analysis

In [108…

```
# show columns in dataframe

df.columns
```

Out[108]:

```
Index(['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'],
      dtype='object')
```

In [109…

```
# dimensions of the dataframe, (rows, columns)

df.shape
```

Out[109]:

```
(5000, 17)
```

In [194…

```
# remove unwanted columns
# needed columns added into new dataframe

drop_col = ['customer_id', 'loan_id', 'application_date', 'approval_date', 'disburs

df1 = df.drop(drop_col, axis = 1)

df1.head()
```

Out[194]:

	loan_type	loan_amount	interest_rate	loan_term	employment_type	income_level	credit_score
0	Car Loan	16795	0.051852	15	Self-employed	Medium	833
1	Personal Loan	1860	0.089296	56	Full-time	Medium	776
2	Personal Loan	77820	0.070470	51	Full-time	Low	697
3	Car Loan	55886	0.062155	30	Full-time	Low	795
4	Home Loan	7265	0.070635	48	Part-time	Low	519

In [195…

```
# show columns in new dataframe

df1.shape
```

Out[195]:

```
(5000, 11)
```

In [196…

```
# dimensions of the new dataframe, (rows, columns)

df1.columns
```

Out[196]:

```
Index(['loan_type', 'loan_amount', 'interest_rate', 'loan_term',
       'employment_type', 'income_level', 'credit_score', 'gender',
       'marital_status', 'education_level', 'default_status'],
      dtype='object')
```

In [197…

```
# information about the categories, rows, missing values and data type

df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   loan_type        5000 non-null   object
 1   loan_amount      5000 non-null   int64
 2   interest_rate    5000 non-null   float64
 3   loan_term        5000 non-null   int64
 4   employment_type  5000 non-null   object
 5   income_level     5000 non-null   object
 6   credit_score     5000 non-null   int64
 7   gender           5000 non-null   object
 8   marital_status   5000 non-null   object
 9   education_level  5000 non-null   object
 10  default_status   5000 non-null   bool
dtypes: bool(1), float64(1), int64(3), object(6)
memory usage: 395.6+ KB
```

In [198…

```
# statistics for numerical columns/variables

df1.describe()
```

Out[198]:

	loan_amount	interest_rate	loan_term	credit_score
count	5000.000000	5000.000000	5000.000000	5000.000000
mean	49929.868000	0.079579	35.263000	573.206000
std	28721.249529	0.015230	13.792501	158.647522
min	1055.000000	0.031685	12.000000	300.000000
25%	24953.500000	0.069240	24.000000	435.000000
50%	49730.000000	0.079533	35.000000	571.000000
75%	75083.500000	0.089984	47.000000	712.000000
max	99989.000000	0.138894	59.000000	849.000000

In [199…

```
# total number of times for each category under the categorical variable

df1['default_status'].value_counts()
```

Out[199]:

```
False    4001
True      999
Name: default_status, dtype: int64
```

In [115…

```
# checking total empty values in each column/variable

df1.isnull().sum()
```

Out[115]:

```
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
default_status     0
dtype: int64
```

In [116…

```
# correlation between numerical variables

df1.corr()
```

Out[116]:

	loan_amount	interest_rate	loan_term	credit_score	default_status
loan_amount	1.000000	-0.017317	0.004763	-0.004780	-0.007309
interest_rate	-0.017317	1.000000	-0.014311	0.016064	0.028963
loan_term	0.004763	-0.014311	1.000000	-0.023735	-0.012358
credit_score	-0.004780	0.016064	-0.023735	1.000000	-0.007346
default_status	-0.007309	0.028963	-0.012358	-0.007346	1.000000

In [117…

```
# Fill any missing values
# Numeric columns: fill with median
df1 = df1.fillna(df.median(numeric_only=True))
```

In [118…

```
# Encode categorical columns
# Identify which columns are categorical (object type)
```

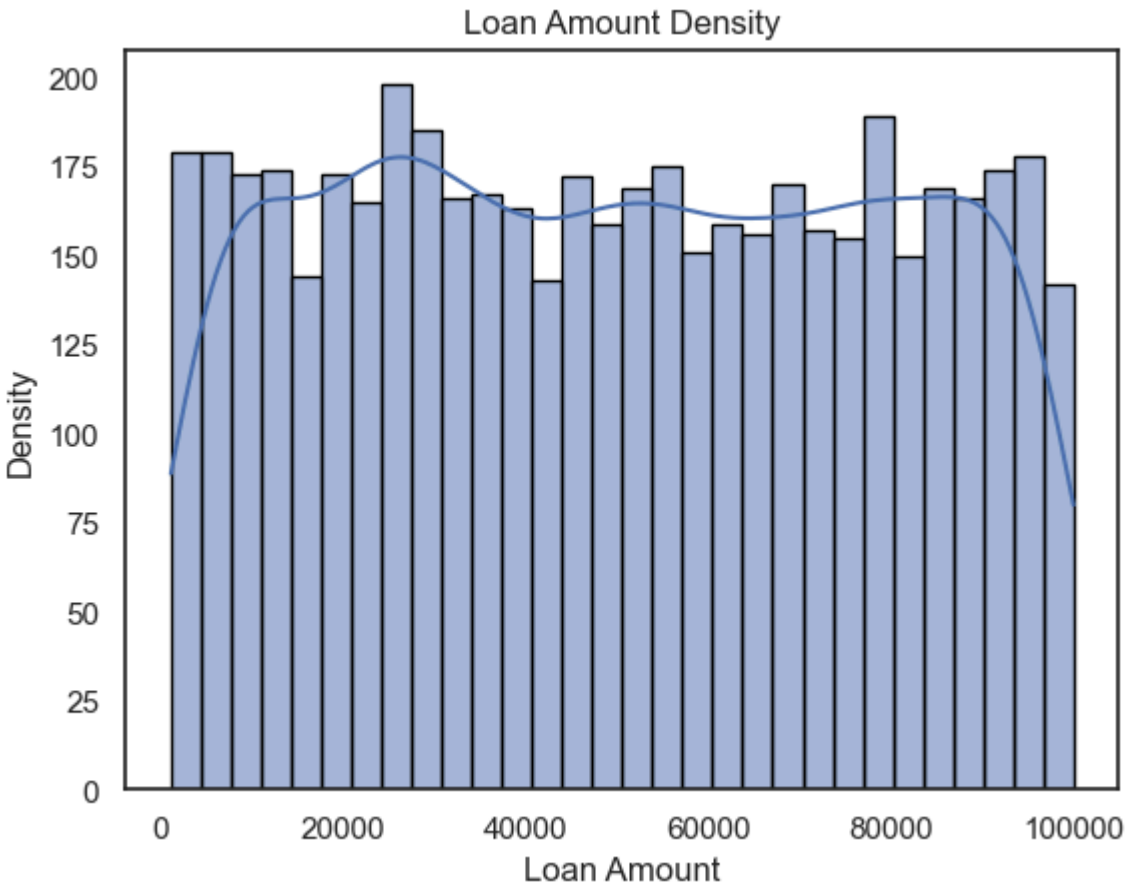
```
categorical_cols = df1.select_dtypes(include=['object']).columns
categorical_cols
```

Out[118]:
```
Index(['loan_type', 'employment_type', 'income_level', 'gender',
       'marital_status', 'education_level'],
      dtype='object')
```

In [119…
```
# Fill categorical columns
categorical_cols = df1.select_dtypes(include=['object']).columns.tolist()
for col in categorical_cols:
    df1[col] = df1[col].fillna(df1[col].mode()[0])
```

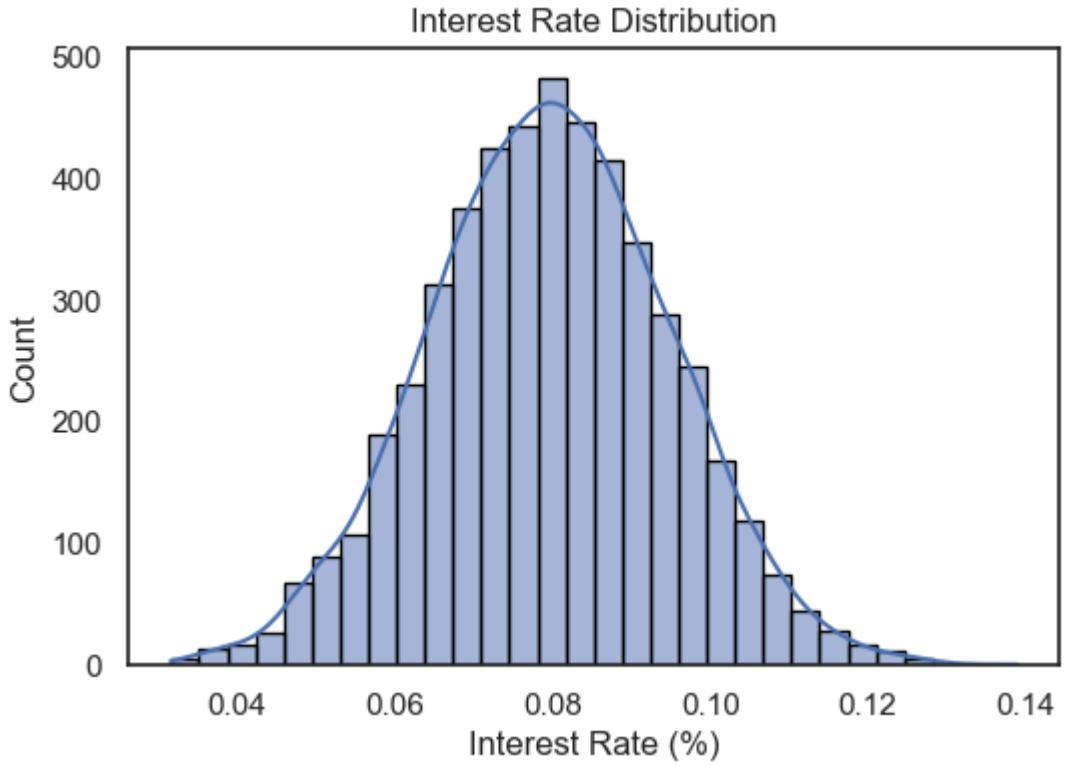
Spread of Data

In [121…
```
# distribution plot for numerical variable
# variable is about symmetric

# sns.set_theme(style="white")
# sns.distplot(df1['loan_amount'])

sns.histplot(df1['loan_amount'], kde=True, bins=30,edgecolor="black")
plt.title('Loan Amount Density')
plt.xlabel('Loan Amount')
plt.ylabel('Density')
plt.show()
```



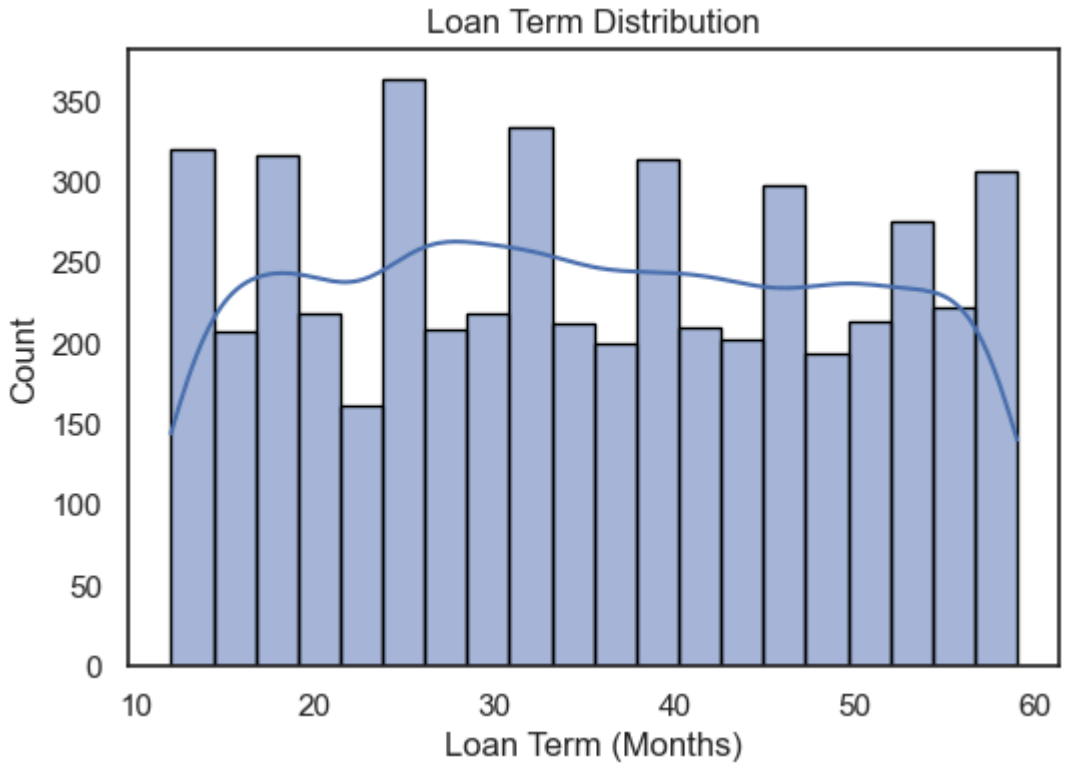
In [122…
```
# distribution plot for numerical variable
# variable is symmetric

# sns.distplot(df1['interest_rate'])

plt.figure(figsize=(6,4))
sns.histplot(df1['interest_rate'], kde=True, bins=30, edgecolor="black")
```

```
plt.title('Interest Rate Distribution')
plt.xlabel('Interest Rate (%)')
plt.ylabel('Count')
plt.show()
```



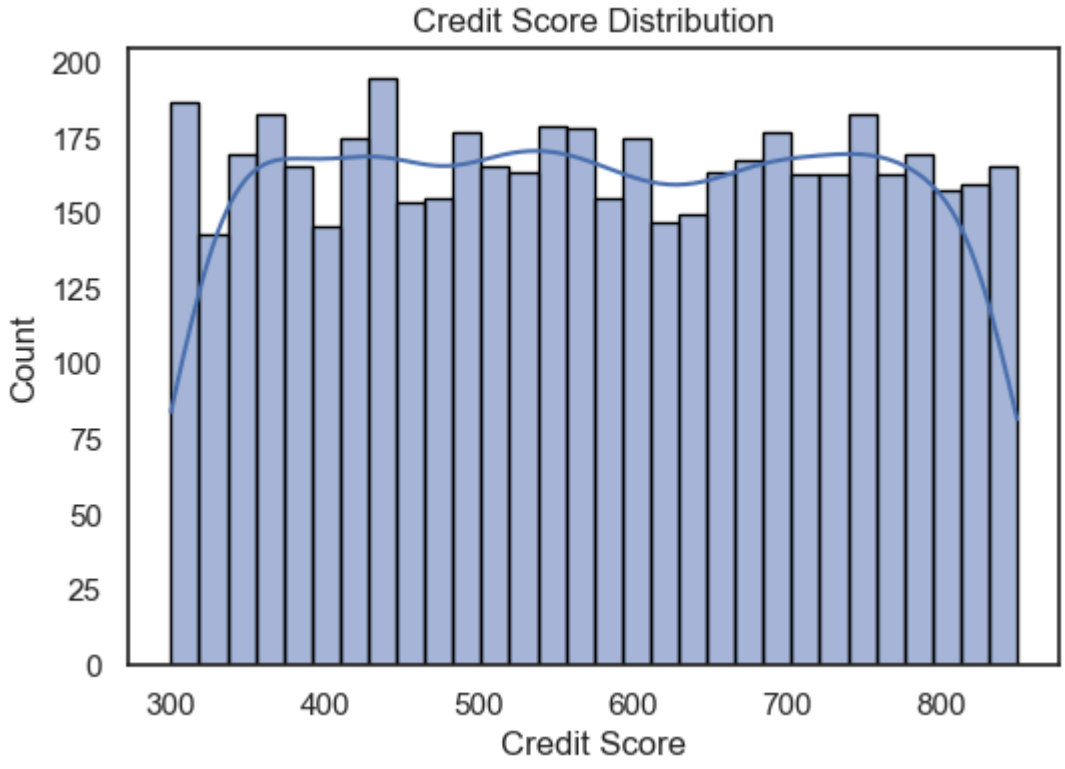
In [123…

```
# distribution plot for numerical variable
# variable is about symmetric

# sns.distplot(df1['loan_term'])

plt.figure(figsize=(6,4))
sns.histplot(df1['loan_term'], kde=True, bins=20, edgecolor="black")
plt.title('Loan Term Distribution')
plt.xlabel('Loan Term (Months)')
plt.ylabel('Count')
plt.show()
```



In [124…

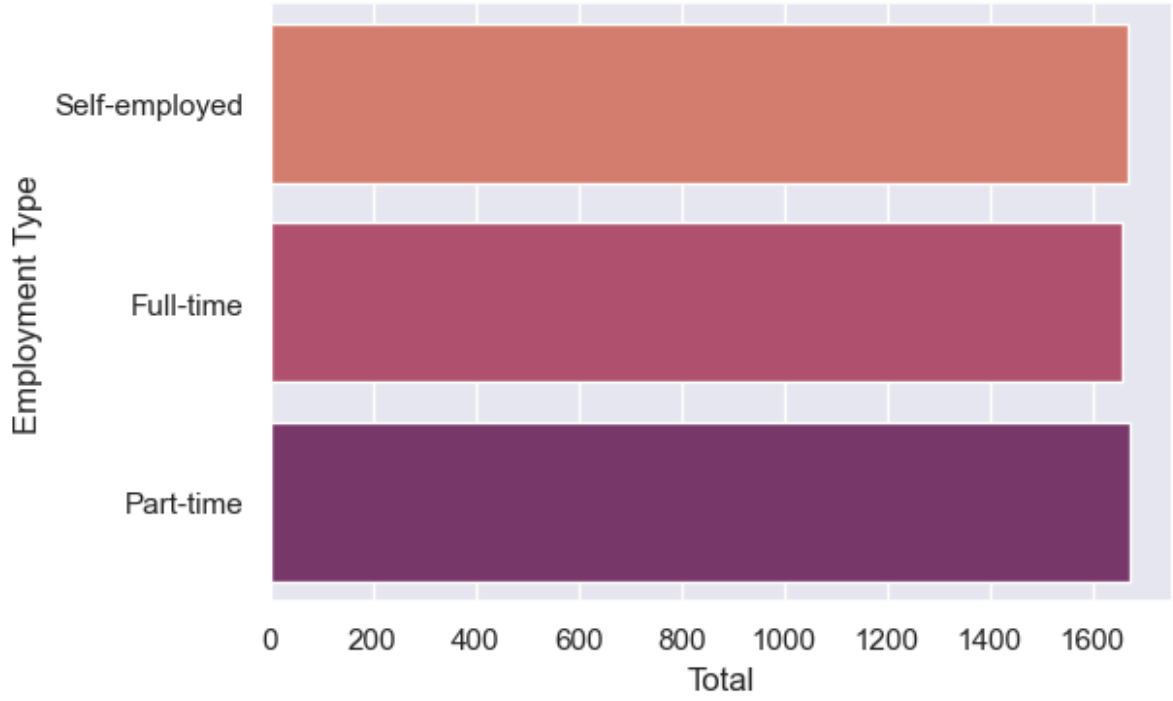
```
# distribution plot for numerical variable
# variable is about symmetric

# sns.distplot(df1['credit_score'])

plt.figure(figsize=(6,4))
sns.histplot(df1['credit_score'], kde=True, bins=30, edgecolor="black")
plt.title('Credit Score Distribution')
plt.xlabel('Credit Score')
plt.ylabel('Count')
plt.show()
```



Exploratory Data Analysis (EDA)

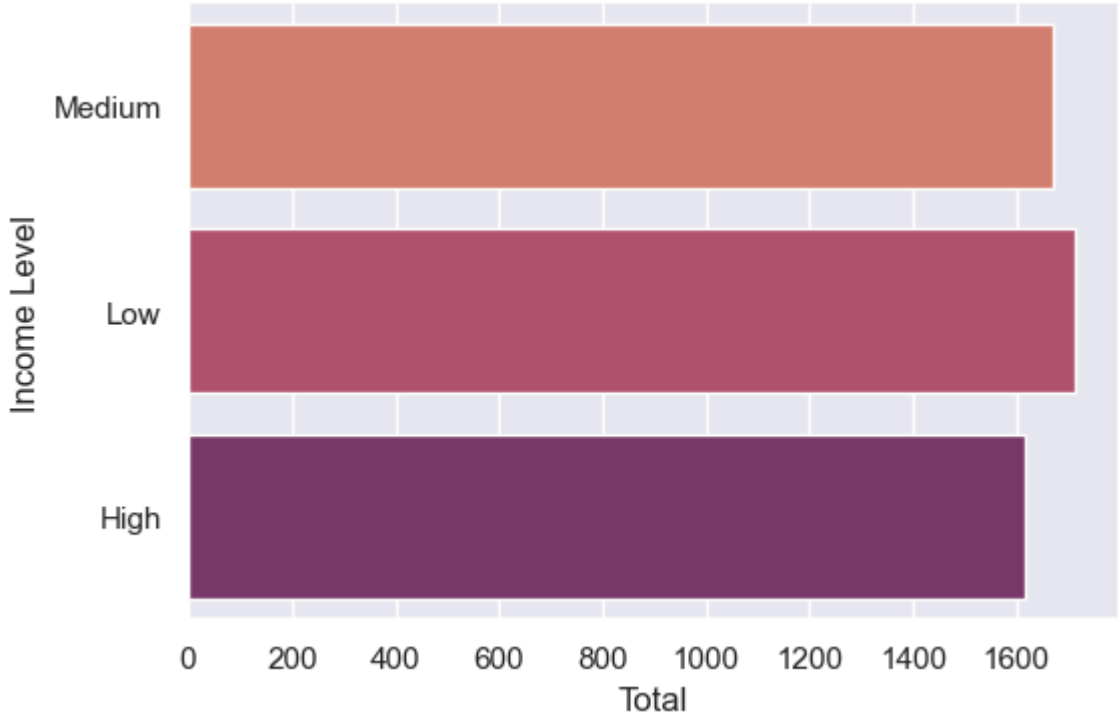
In [125…

```
# bar graph for categories of categorical variable
# shows the total number for each category under the categorical variable

# sns.countplot(x='employment_type', data=df1)
# plt.title('Employment Type Distribution')
# plt.xlabel('Employment Type')
# plt.ylabel('Count')
# plt.show()

plt.figure(figsize=(6,4))
sns.set_theme(style="darkgrid")
sns.countplot(y="employment_type", data=df1, palette="flare")
plt.ylabel('Employment Type')
plt.xlabel('Total')
plt.show()
```



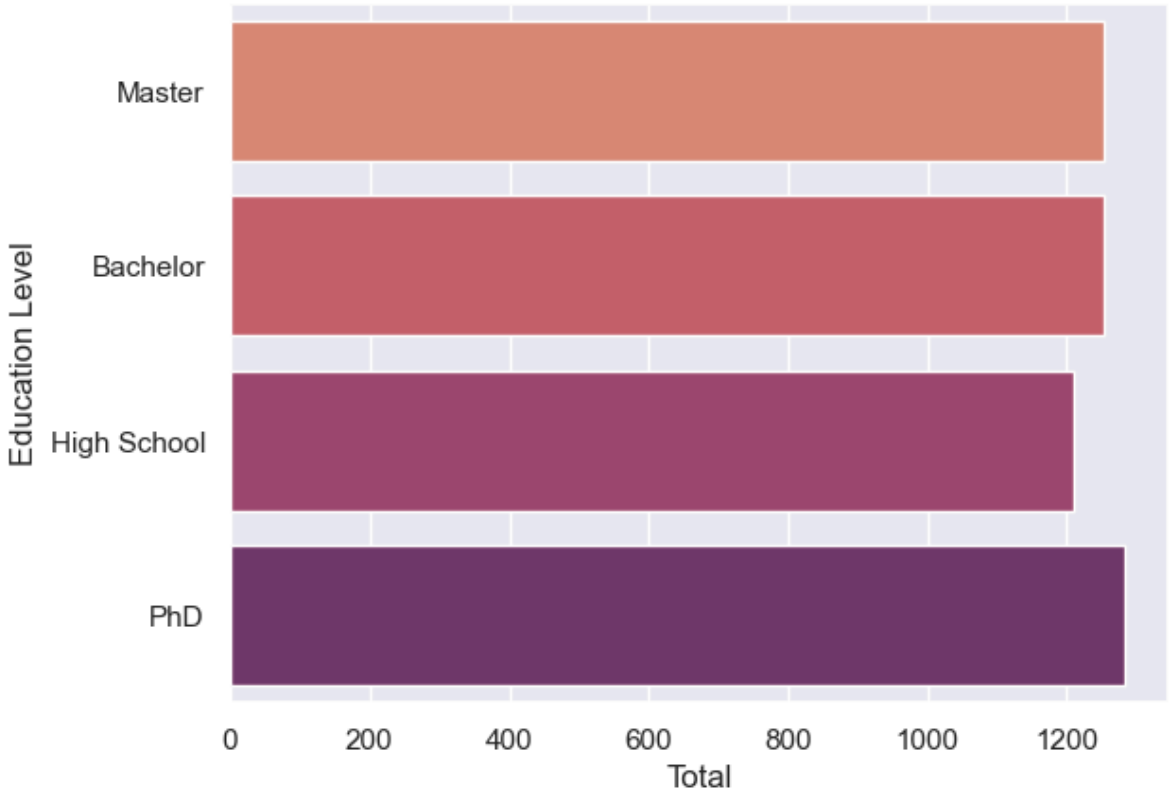
In [126…

```
# bar graph for categories of categorical variable
# shows the total number for each category under the categorical variable

plt.figure(figsize=(6,4))
sns.set_theme(style="darkgrid")
sns.countplot(y="income_level", data=df1, palette="flare")
plt.ylabel('Income Level')
plt.xlabel('Total')
plt.show()
```



In [127…

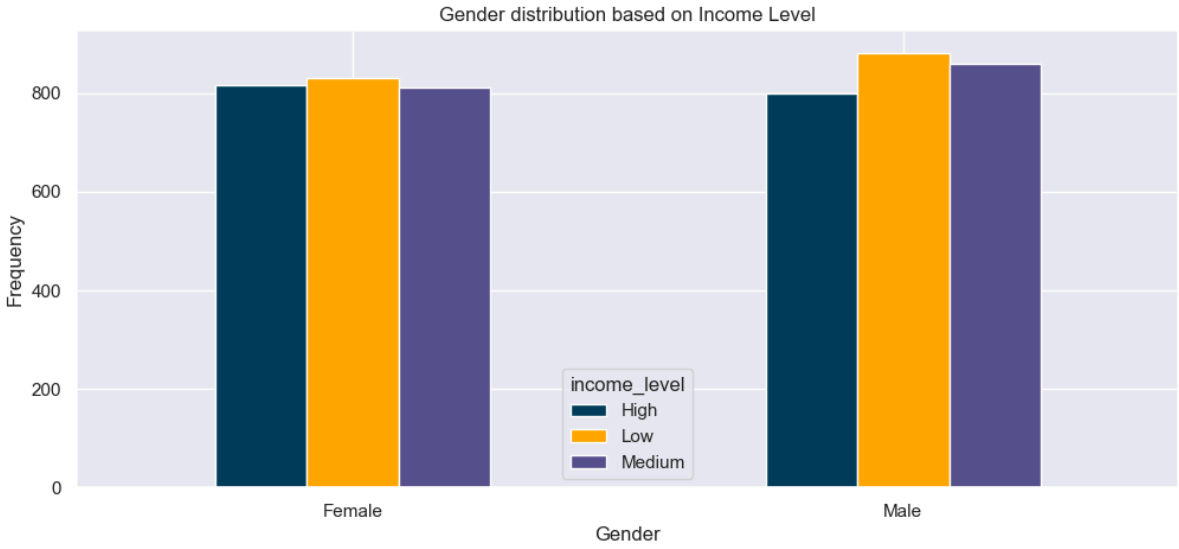
```
# bar graph for categories of categorical variable
# shows the total number for each category under the categorical variable

sns.set_theme(style="darkgrid")
sns.countplot(y="education_level", data=df1, palette="flare")
plt.ylabel('Education Level')
plt.xlabel('Total')
plt.show()
```



In [128…

```
# column graph for gender based on income level

pd.crosstab(df1.gender,df1.income_level).plot(kind="bar",figsize=(12,5),color=['#00
plt.title('Gender distribution based on Income Level')
```

```
plt.xlabel('Gender')
plt.xticks(rotation=0)
plt.ylabel('Frequency')
plt.show()
```

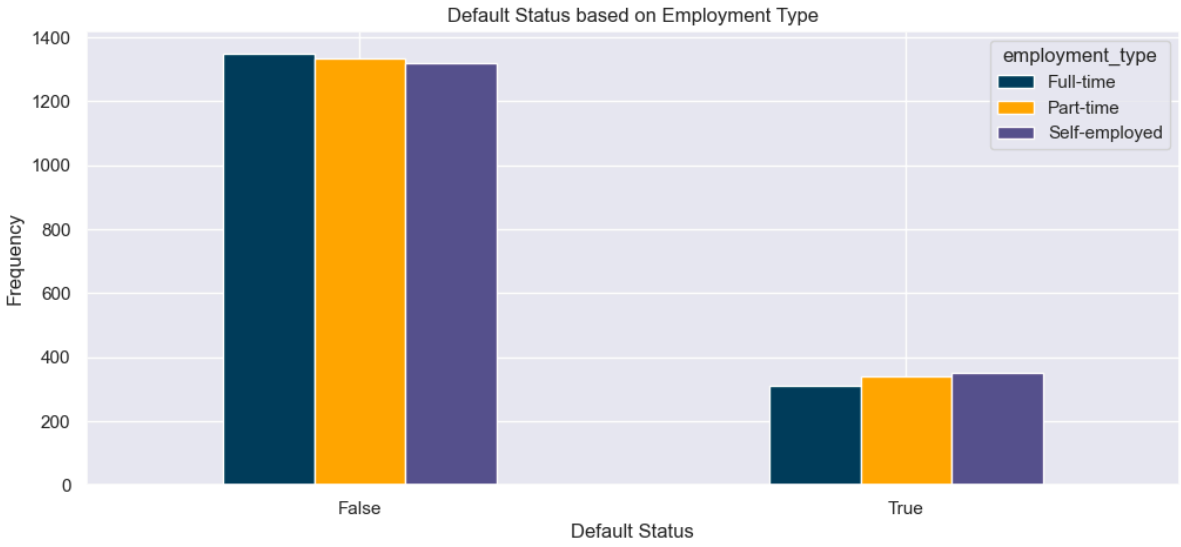


In [129…

```
# column graph for default status(target variable) based on income level

pd.crosstab(df1.default_status,df1.income_level).plot(kind="bar",figsize=(12,5),col
plt.title('Default Status based on Income Level')
plt.xlabel('Default Status')
plt.legend(title= 'income level')
plt.xticks(rotation=0)
plt.ylabel('Frequency')
plt.show()
```

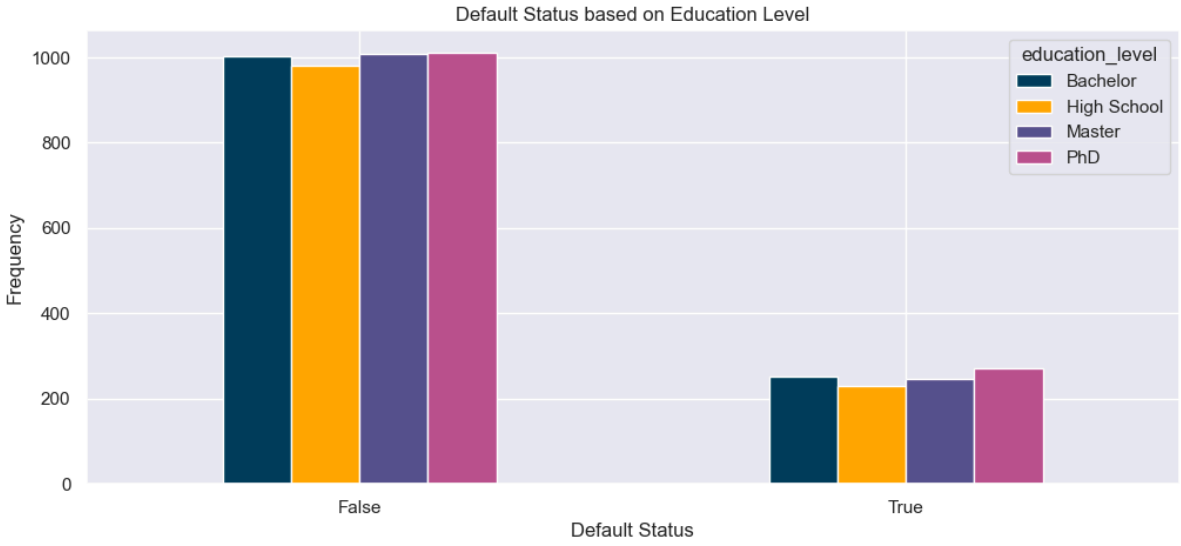
In [130…

```
# column graph for default status based on employment type

pd.crosstab(df1.default_status,df1.employment_type).plot(kind="bar",figsize=(12,5),
plt.title('Default Status based on Employment Type')
plt.xlabel('Default Status')
plt.xticks(rotation=0)
plt.ylabel('Frequency')
plt.show()
```



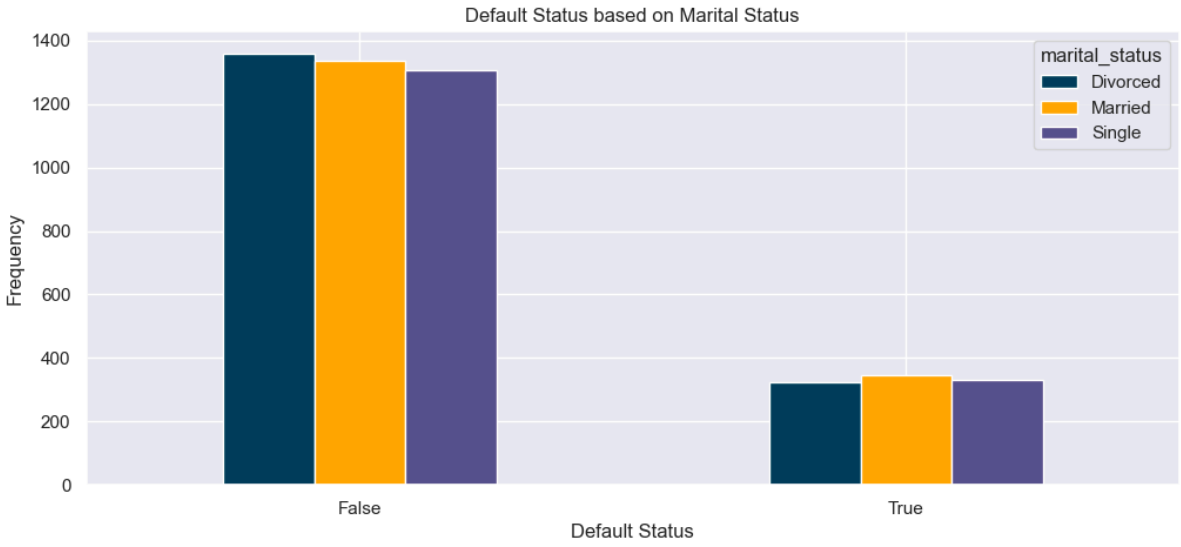
In [131…

```
# column graph for default status based on education type

pd.crosstab(df1.default_status,df1.education_level).plot(kind="bar",figsize=(12,5),
plt.title('Default Status based on Education Level')
plt.xlabel('Default Status')
plt.xticks(rotation=0)
plt.ylabel('Frequency')
plt.show()
```



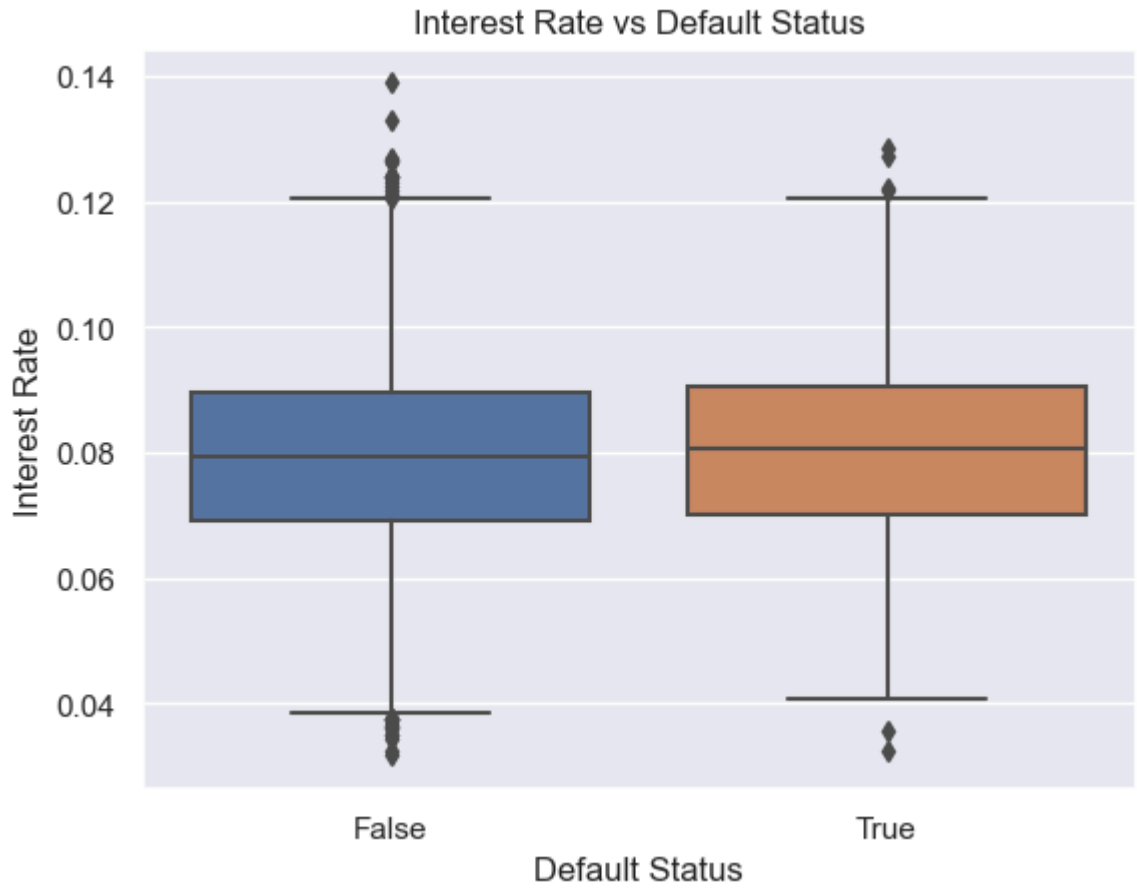
In [132…

```
# column graph for default status based on marital status

pd.crosstab(df1.default_status,df1.marital_status).plot(kind="bar",figsize=(12,5),
plt.title('Default Status based on Marital Status')
plt.xlabel('Default Status')
plt.xticks(rotation=0)
plt.ylabel('Frequency')
plt.show()
```



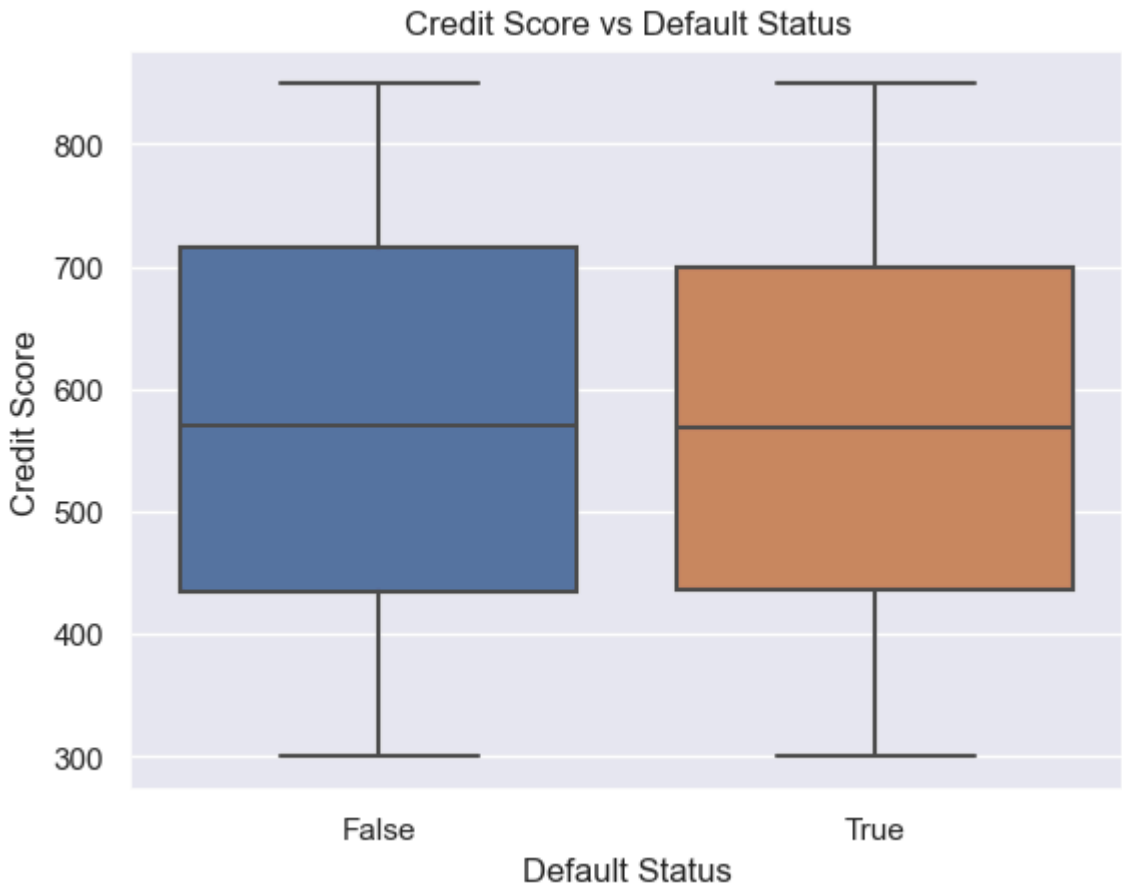
In [133…

```
# boxplot for interest rate vs default status

sns.boxplot(x = 'default_status', y = 'interest_rate', data = df1)
plt.xlabel('Default Status')
plt.ylabel('Interest Rate')
plt.title('Interest Rate vs Default Status')
plt.show()
```



In [134…

```
# boxplot for credit score vs default status

sns.boxplot(x = 'default_status', y = 'credit_score', data = df1)
plt.xlabel('Default Status')
plt.ylabel('Credit Score')
plt.title('Credit Score vs Default Status')
plt.show()
```



Data Preparation

In [135…

```
# view first few rows

df1.head()
```

Out[135]:

	loan_type	loan_amount	interest_rate	loan_term	employment_type	income_level	credit_score
0	Car Loan	16795	0.051852	15	Self-employed	Medium	833
1	Personal Loan	1860	0.089296	56	Full-time	Medium	776
2	Personal Loan	77820	0.070470	51	Full-time	Low	697
3	Car Loan	55886	0.062155	30	Full-time	Low	795
4	Home Loan	7265	0.070635	48	Part-time	Low	519

In [136…

```
# Converting text to integer
# loan_type column:
# Car Loan - 1
# Personal Loan - 2
# Home Loan - 3
# Education Loan - 4

df1['loan_type'] = df1['loan_type'].map({ "Car Loan": 1, "Personal Loan": 2,
                                          "Home Loan": 3, "Education Loan": 4})
```

```
df1.head()
```

Out[136]:

	loan_type	loan_amount	interest_rate	loan_term	employment_type	income_level	credit_score
0	1	16795	0.051852	15	Self-employed	Medium	833
1	2	1860	0.089296	56	Full-time	Medium	776
2	2	77820	0.070470	51	Full-time	Low	697
3	1	55886	0.062155	30	Full-time	Low	795
4	3	7265	0.070635	48	Part-time	Low	519

In [137…

```
# Converting text to integer
# marital_status column:
# Single - 1
# Married - 2
# Divorced - 3

df1['marital_status'] = df1['marital_status'].map({ "Single": 1, "Married": 2, "Div

df1.head()
```

Out[137]:

	loan_type	loan_amount	interest_rate	loan_term	employment_type	income_level	credit_score
0	1	16795	0.051852	15	Self-employed	Medium	833
1	2	1860	0.089296	56	Full-time	Medium	776
2	2	77820	0.070470	51	Full-time	Low	697
3	1	55886	0.062155	30	Full-time	Low	795
4	3	7265	0.070635	48	Part-time	Low	519

In [138…

```
# Converting text to integer
# gender column:
# Male - 1
# Female - 2

df1['gender'] = df1['gender'].map({'Male': 1, 'Female': 2})

df1.head()
```

Out[138]:

	loan_type	loan_amount	interest_rate	loan_term	employment_type	income_level	credit_score
0	1	16795	0.051852	15	Self-employed	Medium	833
1	2	1860	0.089296	56	Full-time	Medium	776
2	2	77820	0.070470	51	Full-time	Low	697
3	1	55886	0.062155	30	Full-time	Low	795
4	3	7265	0.070635	48	Part-time	Low	519

In [139…

```
# Converting text to integer
# education_level column:
```

```
# High School - 1
# Bachelor - 2
# Master - 3
# PhD - 4

df1['education_level'] = df1['education_level'].map({ "PhD": 4, "Master": 3,
                                                      "Bachelor": 2, "High School":

df1.head()
```

Out[139]:

	loan_type	loan_amount	interest_rate	loan_term	employment_type	income_level	credit_score
0	1	16795	0.051852	15	Self-employed	Medium	833
1	2	1860	0.089296	56	Full-time	Medium	776
2	2	77820	0.070470	51	Full-time	Low	697
3	1	55886	0.062155	30	Full-time	Low	795
4	3	7265	0.070635	48	Part-time	Low	519

In [140…

```
# Converting text to integer
# employment_type column:
# Self-employed - 1
# Part-time - 2
# Full-time - 3

df1['employment_type'] = df1['employment_type'].map({ "Full-time": 3, "Part-time":
                                                     "Self-employed": 1})

df1.head()
```

Out[140]:

	loan_type	loan_amount	interest_rate	loan_term	employment_type	income_level	credit_score
0	1	16795	0.051852	15	1	Medium	833
1	2	1860	0.089296	56	3	Medium	776
2	2	77820	0.070470	51	3	Low	697
3	1	55886	0.062155	30	3	Low	795
4	3	7265	0.070635	48	2	Low	519

In [141…

```
# Converting text to integer
# income_level column:
# Low - 1
# Medium - 2
# High - 3

df1["income_level"] = df1["income_level"].map({ "Low": 1, "Medium": 2, "High": 3})

df1.head()
```

Out[141]:

	loan_type	loan_amount	interest_rate	loan_term	employment_type	income_level	credit_score
0	1	16795	0.051852	15	1	2	833
1	2	1860	0.089296	56	3	2	776
2	2	77820	0.070470	51	3	1	697
3	1	55886	0.062155	30	3	1	795
4	3	7265	0.070635	48	2	1	519

In [142…

```
# Converting true/false (boolean) text to integer
# default_status column:
# False - 0
# True - 1

df1["default_status"] = df1["default_status"].astype(int)

df1.head()
```

Out[142]:

	loan_type	loan_amount	interest_rate	loan_term	employment_type	income_level	credit_score
0	1	16795	0.051852	15	1	2	833
1	2	1860	0.089296	56	3	2	776
2	2	77820	0.070470	51	3	1	697
3	1	55886	0.062155	30	3	1	795
4	3	7265	0.070635	48	2	1	519

Modelling

In [145…

```
# separate into train and test fror non-target variables
# and target variables
# 70 % train 30% test

X = df1.drop(["default_status"], axis=1)
y = df1["default_status"]
```

In [146…

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_s
```

In [147…

```
# Scaling:
# All features are on a similar scale and avoid bias.
# Standardizes numeric inputs so no feature dominates just because it has bigger nu

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Logistic Regression

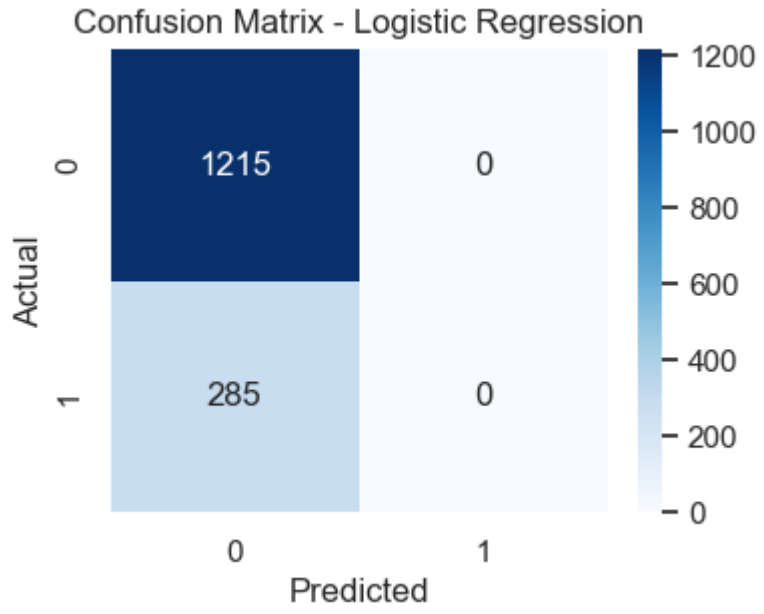
In [148…

```
lr = LogisticRegression()
lr.fit(X_train_scaled, y_train)
y_pred_lr = lr.predict(X_test_scaled)

print("Logistic Regression Results:")
print("Accuracy:", accuracy_score(y_test, y_pred_lr))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_lr))
print("Classification Report:\n", classification_report(y_test, y_pred_lr))
```

```
Logistic Regression Results:
Accuracy: 0.81
Confusion Matrix:
 [[1215    0]
 [ 285    0]]
Classification Report:
              precision    recall  f1-score   support

           0       0.81      1.00      0.90      1215
           1       0.00      0.00      0.00       285

    accuracy                           0.81      1500
   macro avg       0.41      0.50      0.45      1500
weighted avg       0.66      0.81      0.72      1500
```

In [162…

```
#            Predicted
#            | 0 | 1 |
#          -------------
# Actual  0 | TN | FP |
#          -------------
# Actual  1 | FN | TP |

# TN: True Negative
# FP: False Positive
# FN: False Negative
# TP: True Positive

# Actuals are y-test
# Heatmap

# Get confusion matrix
cm_lr = confusion_matrix(y_test, y_pred_lr)

# Plot heatmap
plt.figure(figsize=(4,3))
sns.heatmap(
    cm_lr,
    annot=True,
    fmt="d",
    cmap="Blues"
)
plt.title("Confusion Matrix - Logistic Regression")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [175…

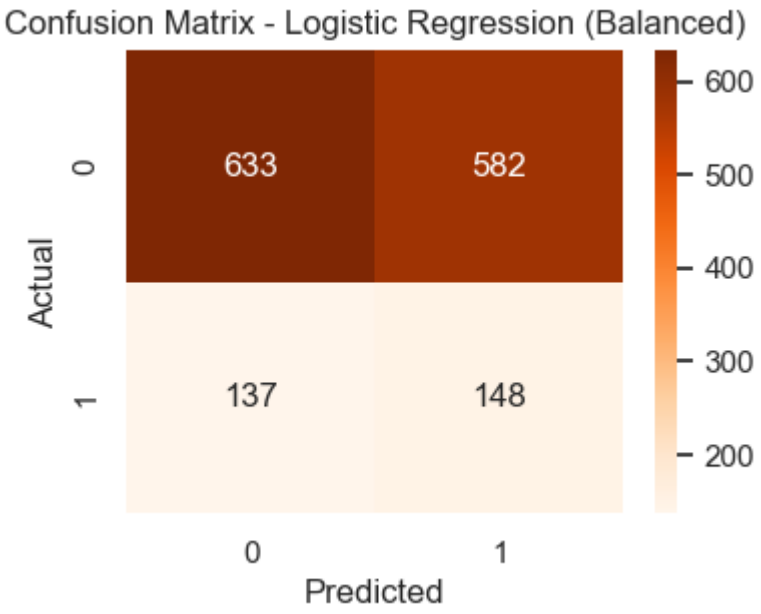
```
# Balanced Logistic Regression
lr_bal = LogisticRegression(
    class_weight="balanced",
    max_iter=1000,      # More iterations for convergence
    random_state=42
)

# Fit the model
lr_bal.fit(X_train_scaled, y_train)

# Predict
y_pred_lr_bal = lr_bal.predict(X_test_scaled)

# Evaluate
print("Logistic Regression (Balanced) Results:")
print("Accuracy:", accuracy_score(y_test, y_pred_lr_bal))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_lr_bal))
print("Classification Report:\n", classification_report(y_test, y_pred_lr_bal))
```

```
Logistic Regression (Balanced) Results:
Accuracy: 0.5206666666666667
Confusion Matrix:
 [[633 582]
 [137 148]]
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.52      0.64      1215
           1       0.20      0.52      0.29       285

    accuracy                           0.52      1500
   macro avg       0.51      0.52      0.46      1500
weighted avg       0.70      0.52      0.57      1500
```

In [189…

```
#            Predicted
#             | 0 | 1 |
#           -------------
# Actual  0 | TN | FP |
#           -------------
# Actual  1 | FN | TP |

# TN: True Negative
```

```
# FP: False Positive
# FN: False Negative
# TP: True Positive

# Actuals are y-test
# Heatmap

cm_lr_bal = confusion_matrix(y_test, y_pred_lr_bal)

plt.figure(figsize=(4,3))
sns.heatmap(cm_lr_bal, annot=True, fmt="d", cmap="Oranges")

plt.title("Confusion Matrix - Logistic Regression (Balanced)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



Decision Tree

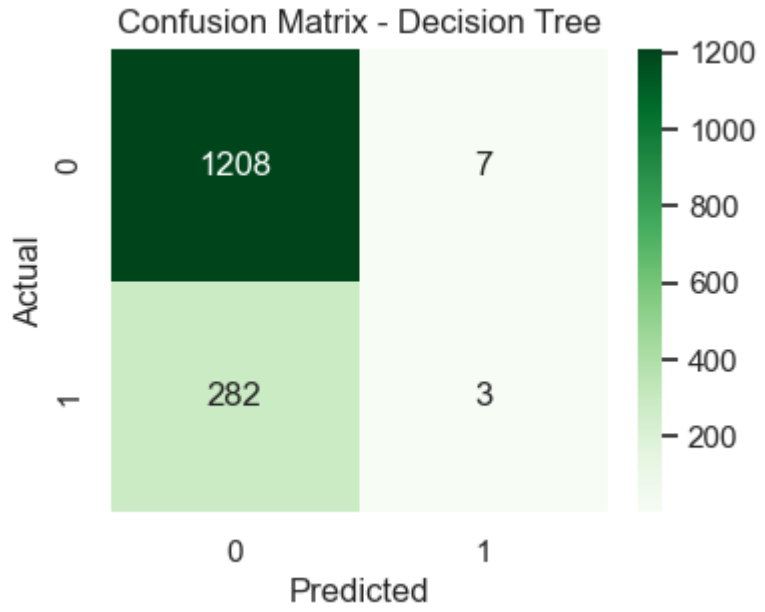
In [159…

```
dt = DecisionTreeClassifier(max_depth=4, random_state=42)
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)

print("Decision Tree Results:")
print("Accuracy:", accuracy_score(y_test, y_pred_dt))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_dt))
print("Classification Report:\n", classification_report(y_test, y_pred_dt))
```

```
Decision Tree Results:
Accuracy: 0.8073333333333333
Confusion Matrix:
 [[1208    7]
 [ 282    3]]
Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.99      0.89      1215
           1       0.30      0.01      0.02       285

    accuracy                           0.81      1500
   macro avg       0.56      0.50      0.46      1500
weighted avg       0.71      0.81      0.73      1500
```

In [190…

```python
#            Predicted
#            | 0 | 1 |
#          -------------
# Actual  0 | TN | FP |
#          -------------
# Actual  1 | FN | TP |

# TN: True Negative
# FP: False Positive
# FN: False Negative
# TP: True Positive

# Actuals are y-test
# Heatmap

# Get confusion matrix
cm_dt = confusion_matrix(y_test, y_pred_dt)

# Plot heatmap
plt.figure(figsize=(4,3))
sns.heatmap(
    cm_dt,
    annot=True,
    fmt="d",
    cmap="Greens"
)
plt.title("Confusion Matrix - Decision Tree")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [172…

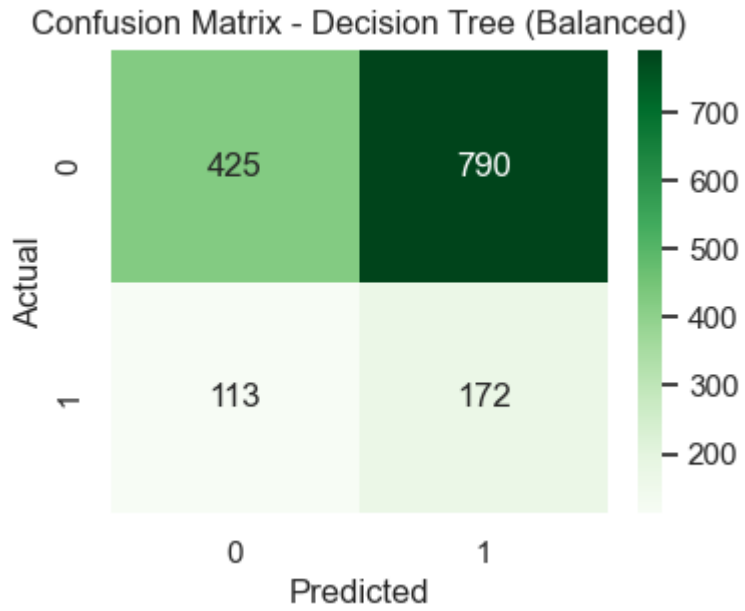
```
dt_bal = DecisionTreeClassifier(max_depth=4, class_weight="balanced", random_state=
dt_bal.fit(X_train, y_train)
y_pred_dt_bal = dt_bal.predict(X_test)

print("Decision Tree (Balanced) Results:")
print("Accuracy:", accuracy_score(y_test, y_pred_dt_bal))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_dt_bal))
print("Classification Report:\n", classification_report(y_test, y_pred_dt_bal))
```

```
Decision Tree (Balanced) Results:
Accuracy: 0.398
Confusion Matrix:
 [[425 790]
 [113 172]]
Classification Report:
              precision    recall  f1-score   support

           0       0.79      0.35      0.48      1215
           1       0.18      0.60      0.28       285

    accuracy                           0.40      1500
   macro avg       0.48      0.48      0.38      1500
weighted avg       0.67      0.40      0.45      1500
```

In [174…

```
#            Predicted
#             | 0 | 1 |
#           -------------
# Actual  0 | TN | FP |
#           -------------
# Actual  1 | FN | TP |

# TN: True Negative
# FP: False Positive
# FN: False Negative
# TP: True Positive

# Actuals are y-test
# Heatmap

# Get confusion matrix
cm_dt_bal = confusion_matrix(y_test, y_pred_dt_bal)
```

```
# Plot heatmap
plt.figure(figsize=(4,3))
sns.heatmap(
    cm_dt_bal,
    annot=True,     # Show counts in the cells
    fmt="d",        # Format numbers as integers
    cmap="Greens"    # Color palette
)

plt.title("Confusion Matrix - Decision Tree (Balanced)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



Support Vector Machine (SVM)

In [168…

```
svm = SVC()
svm.fit(X_train_scaled, y_train)
y_pred_svm = svm.predict(X_test_scaled)

print("SVM Results:")
print("Accuracy:", accuracy_score(y_test, y_pred_svm))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_svm))
print("Classification Report:\n", classification_report(y_test, y_pred_svm))
```

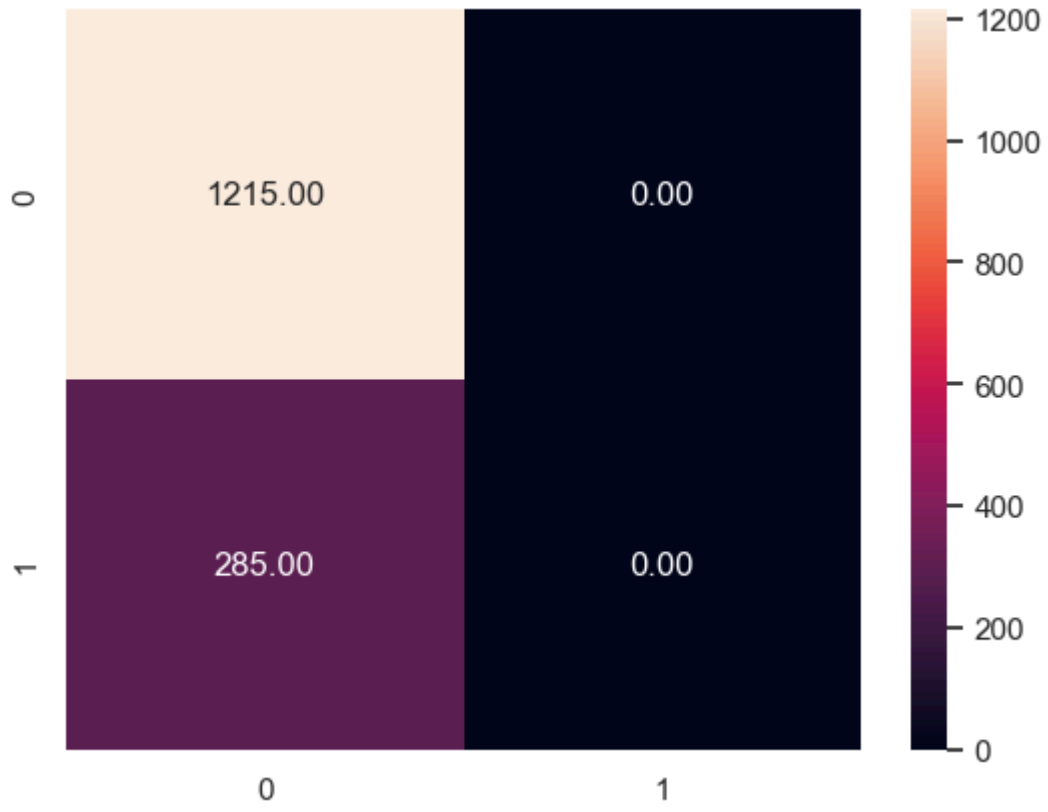
```
SVM Results:
Accuracy: 0.81
Confusion Matrix:
 [[1215    0]
 [ 285    0]]
Classification Report:
              precision    recall  f1-score   support

           0       0.81      1.00      0.90      1215
           1       0.00      0.00      0.00       285

    accuracy                           0.81      1500
   macro avg       0.41      0.50      0.45      1500
weighted avg       0.66      0.81      0.72      1500
```

In [169…

```
#            Predicted
#            | 0 | 1 |
#          -------------
# Actual  0 | TN | FP |
#          -------------
# Actual  1 | FN | TP |

# TN: True Negative
# FP: False Positive
# FN: False Negative
# TP: True Positive

# Actuals are y-test
# Heatmap

sns.heatmap(confusion_matrix(y_test, y_pred_svm), annot = True, fmt = '.2f')
```

Out[169]:

```
<Axes: >
```



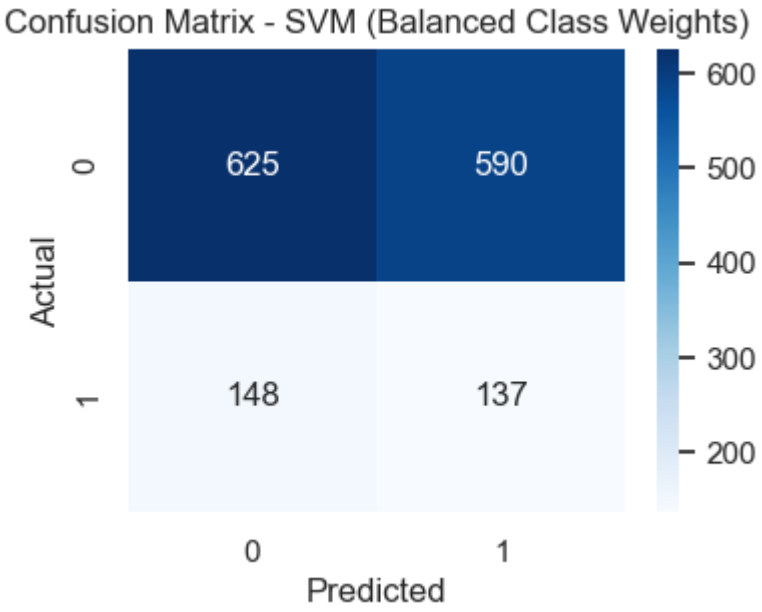
In [170…

```
svm = SVC(class_weight="balanced")
svm.fit(X_train_scaled, y_train)
y_pred_svm_bal = svm.predict(X_test_scaled)

print("SVM Results with Balanced Class Weights:")
print("Accuracy:", accuracy_score(y_test, y_pred_svm_bal))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_svm_bal))
print("Classification Report:\n", classification_report(y_test, y_pred_svm_bal))
```

```
SVM Results with Balanced Class Weights:
Accuracy: 0.508
Confusion Matrix:
 [[625 590]
 [148 137]]
Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.51      0.63      1215
           1       0.19      0.48      0.27       285

    accuracy                           0.51      1500
   macro avg       0.50      0.50      0.45      1500
weighted avg       0.69      0.51      0.56      1500
```

In [171…

```python
#            Predicted
#            | 0 | 1 |
#          -------------
# Actual  0 | TN | FP |
#          -------------
# Actual  1 | FN | TP |

# TN: True Negative
# FP: False Positive
# FN: False Negative
# TP: True Positive

# Actuals are y-test
# Heatmap

# Get confusion matrix
cm_svm_bal = confusion_matrix(y_test, y_pred_svm_bal)

# Plot heatmap
plt.figure(figsize=(4,3))
sns.heatmap(
    cm_svm_bal,
    annot=True,     # Show counts in the cells
    fmt="d",        # Format numbers as integers
    cmap="Blues"    # Color palette
)

plt.title("Confusion Matrix - SVM (Balanced Class Weights)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



Model Comparision

In [165…

```
# Compare accuracies

# accuracy_lr = accuracy_score(y_test, y_pred_lr)
# accuracy_dt = accuracy_score(y_test, y_pred_dt)
# accuracy_svm = accuracy_score(y_test, y_pred_svm)

# print("\nModel Comparison:")
# print(f"Logistic Regression Accuracy: {accuracy_lr:.2f}")
# print(f"Decision Tree Accuracy: {accuracy_dt:.2f}")
# print(f"SVM Accuracy: {accuracy_svm:.2f}")

results = pd.DataFrame({'Model': ['Logistic Regression', 'Decision Tree', 'SVM'],
                        'Accuracy': [accuracy_score(y_test, y_pred_lr),
                                     accuracy_score(y_test, y_pred_dt),
                                     accuracy_score(y_test, y_pred_svm)]})

results['Accuracy'] = (results['Accuracy'] * 100).round(1)

results
```

Out[165]:

	Model	Accuracy
0	Logistic Regression	81.0
1	Decision Tree	80.7
2	SVM	81.0

In [192…

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# Logistic Regression (Unbalanced)

acc_lr = accuracy_score(y_test, y_pred_lr)
prec_lr = precision_score(y_test, y_pred_lr, zero_division=0)
rec_lr = recall_score(y_test, y_pred_lr, zero_division=0)
f1_lr = f1_score(y_test, y_pred_lr, zero_division=0)

# Decision Tree (Unbalanced)
acc_dt = accuracy_score(y_test, y_pred_dt)
```

```
prec_dt = precision_score(y_test, y_pred_dt, zero_division=0)
rec_dt = recall_score(y_test, y_pred_dt, zero_division=0)
f1_dt = f1_score(y_test, y_pred_dt, zero_division=0)

# SVM (Unbalanced)
acc_svm = accuracy_score(y_test, y_pred_svm)
prec_svm = precision_score(y_test, y_pred_svm, zero_division=0)
rec_svm = recall_score(y_test, y_pred_svm, zero_division=0)
f1_svm = f1_score(y_test, y_pred_svm, zero_division=0)

# Logistic Regression (Balanced)
acc_lr_bal = accuracy_score(y_test, y_pred_lr_bal)
prec_lr_bal = precision_score(y_test, y_pred_lr_bal, zero_division=0)
rec_lr_bal = recall_score(y_test, y_pred_lr_bal, zero_division=0)
f1_lr_bal = f1_score(y_test, y_pred_lr_bal, zero_division=0)

# Decision Tree (Balanced)
acc_dt_bal = accuracy_score(y_test, y_pred_dt_bal)
prec_dt_bal = precision_score(y_test, y_pred_dt_bal, zero_division=0)
rec_dt_bal = recall_score(y_test, y_pred_dt_bal, zero_division=0)
f1_dt_bal = f1_score(y_test, y_pred_dt_bal, zero_division=0)

# SVM (Balanced)
acc_svm_bal = accuracy_score(y_test, y_pred_svm_bal)
prec_svm_bal = precision_score(y_test, y_pred_svm_bal, zero_division=0)
rec_svm_bal = recall_score(y_test, y_pred_svm_bal, zero_division=0)
f1_svm_bal = f1_score(y_test, y_pred_svm_bal, zero_division=0)


results_df = pd.DataFrame({
    "Model": [
        "Logistic Regression",
        "Decision Tree",
        "SVM",
        "Logistic Regression (Balanced)",
        "Decision Tree (Balanced)",
        "SVM (Balanced)"
    ],
    "Accuracy (%)": [
        round(acc_lr*100, 1),
        round(acc_dt*100, 1),
        round(acc_svm*100, 1),
        round(acc_lr_bal*100, 1),
        round(acc_dt_bal*100, 1),
        round(acc_svm_bal*100, 1)
    ],
    "Precision": [
        round(prec_lr, 2),
        round(prec_dt, 2),
        round(prec_svm, 2),
        round(prec_lr_bal, 2),
        round(prec_dt_bal, 2),
        round(prec_svm_bal, 2)
    ],
    "Recall": [
        round(rec_lr, 2),
        round(rec_dt, 2),
        round(rec_svm, 2),
        round(rec_lr_bal, 2),
        round(rec_dt_bal, 2),
        round(rec_svm_bal, 2)
    ],
    "F1-score": [
        round(f1_lr, 2),
```

```
        round(f1_dt, 2),
        round(f1_svm, 2),
        round(f1_lr_bal, 2),
        round(f1_dt_bal, 2),
        round(f1_svm_bal, 2)
    ]
})

results_df
```

Out[192]:

	Model	Accuracy (%)	Precision	Recall	F1-score
0	Logistic Regression	81.0	0.00	0.00	0.00
1	Decision Tree	80.7	0.30	0.01	0.02
2	SVM	81.0	0.00	0.00	0.00
3	Logistic Regression (Balanced)	52.1	0.20	0.52	0.29
4	Decision Tree (Balanced)	39.8	0.18	0.60	0.28
5	SVM (Balanced)	50.8	0.19	0.48	0.27

In [ ]: