```
import pandas as pd
```

```
df = pd.read_csv('loan_data_1248_with_missing.csv')
```

```
## Data preprocessing
```

Data preprocessing

```
df.head()
```

	income	loan_amount	term	credit_history	defaulted
0	60940.854754	17402.715471	60	1.0	1
1	49511.242579	6664.626123	36	0.0	0
2	63658.393686	17985.281393	60	0.0	1
3	79414.537415	21001.173770	36	1.0	0
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

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```
df.shape
```

```
(1248, 5)
```

```
df.columns.to_list()
```

```
['income', 'loan_amount', 'term', 'credit_history', 'defaulted']
```

```
df.dtypes
```

	0
income	float64
loan_amount	float64
term	int64
credit_history	float64
defaulted	int64

```
## Converting defaulted to boolean
#df["defaulted"] = df["defaulted"].astype(bool)
```

```
df.dtypes
```

	0
income	float64
loan_amount	float64
term	int64
credit_history	float64
defaulted	int64

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

	0
income	120
loan_amount	122
term	0
credit_history	112
defaulted	0

```
#fulling missing values
```

```
df.fillna({'income':df['income'].median()}, inplace=True)
```

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

	0
income	0
loan_amount	122
term	0
credit_history	112
defaulted	0

```
df.fillna({'loan_amount' : df['loan_amount'].median()}, inplace=True)
```

```
df.fillna({'loan_amount' : df['loan_amount'].median()}, inplace=True)
```

```
df.fillna({'credit_history' : df['credit_history'].mode()[0]}, inplace=True)
```

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

	0
income	0
loan_amount	0
term	0
credit_history	0
defaulted	0

```
df.describe()
```

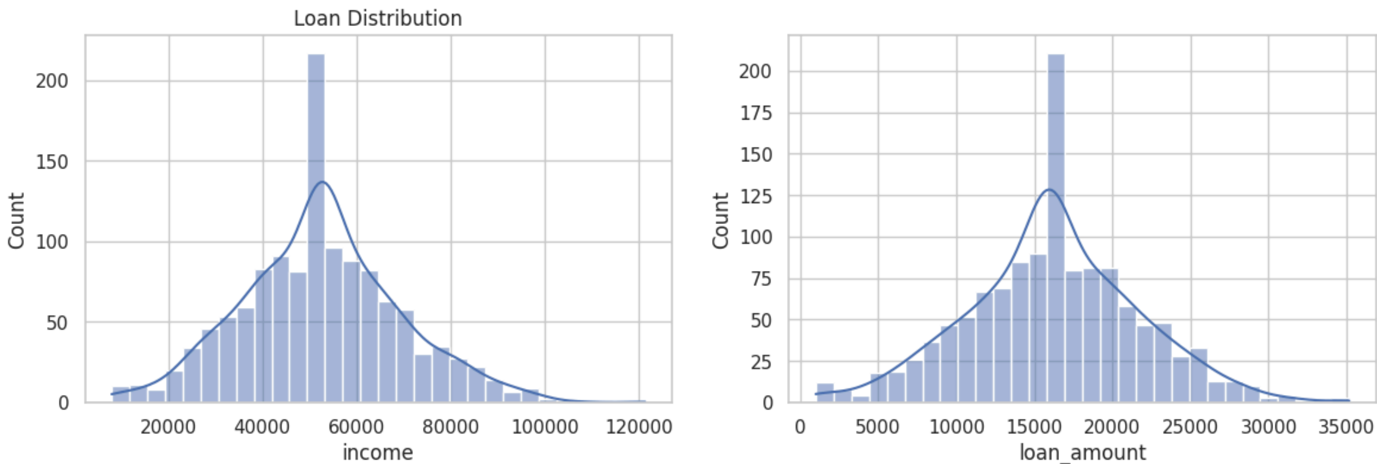
	income	loan_amount	term	credit_history	defaulted
count	1248.000000	1248.000000	1248.000000	1248.000000	1248.000000
mean	52500.945298	16167.787505	48.000000	0.771635	0.414263
std	16967.161028	5541.521139	12.004811	0.419948	0.492792
min	8000.000000	1000.000000	36.000000	0.000000	0.000000
25%	41673.912889	12772.722413	36.000000	1.000000	0.000000
50%	52462.564119	16052.247335	48.000000	1.000000	0.000000
75%	62987.634437	19610.211517	60.000000	1.000000	1.000000

```
## Data Visualizations
```

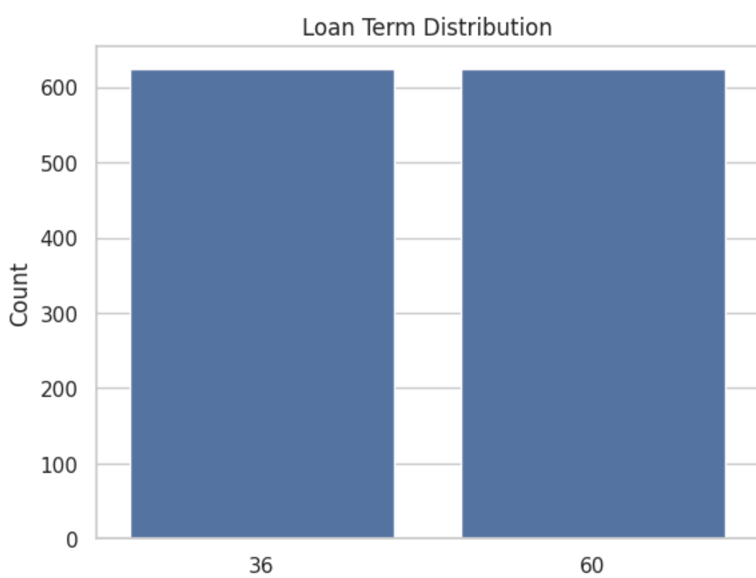
Data Visualizations

```
import matplotlib.pyplot as plt
import seaborn as sns


## Setting seaborn theme
sns.set(style='whitegrid')
fig, axes = plt.subplots(1,2, figsize = (14,4))

sns.histplot(df['income'], kde =True, bins=30, ax=axes[0])
axes[0].set_title("Income Distribution")

sns.histplot(df['loan_amount'], kde =True, bins=30, ax = axes[1])
axes[0].set_title("Loan Distribution")
```

```
Text(0.5, 1.0, 'Loan Distribution')
```

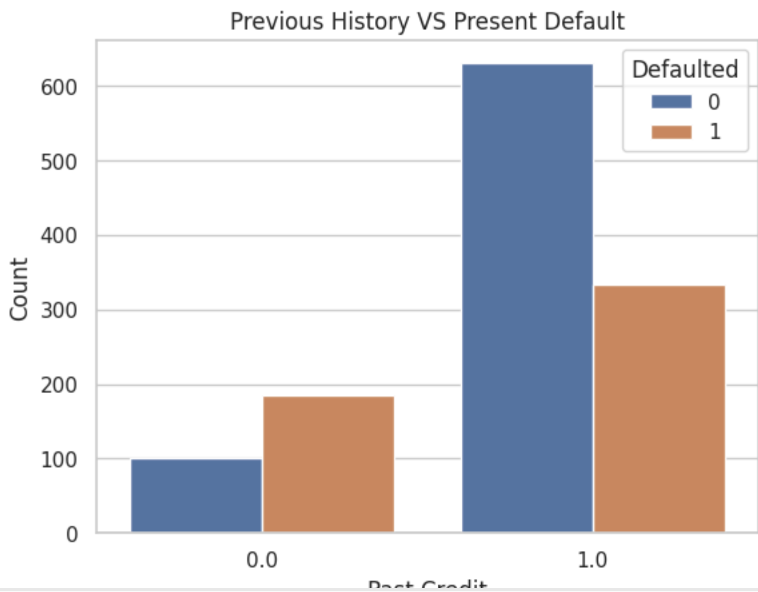



```
## Count of Loan term
sns.countplot(x='term', data=df)
plt.title("Loan Term Distribution")
plt.xlabel("Loan Term in months")
plt.ylabel("Count")
plt.show()
```

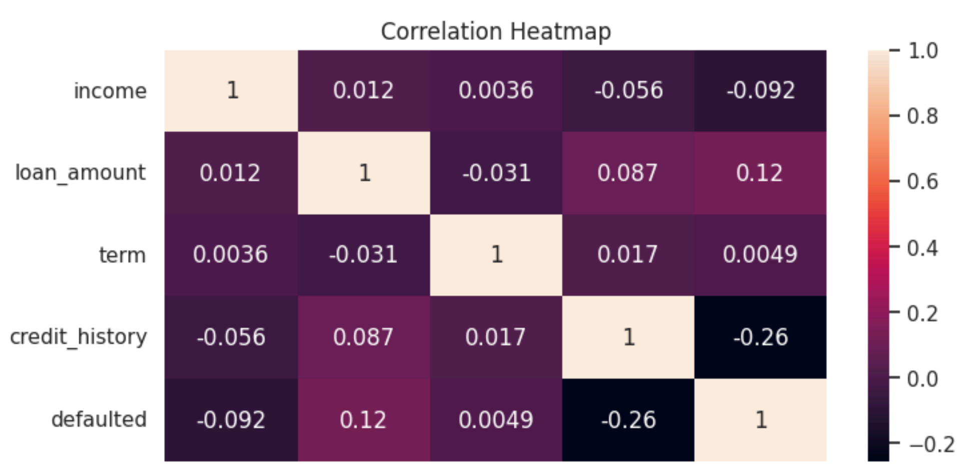


Start coding or generate with AI.

```
## Credit History

sns.countplot(x='credit_history', hue='defaulted', data=df)
plt.title("Previous History VS Present Default")
plt.xlabel("Past Credit")
plt.ylabel("Count")
plt.legend(title='Defaulted')
plt.show()
```




```
## Correlation Heatmap
plt.figure(figsize= (8,4))
sns.heatmap(df.corr(), annot=True)
plt.title ("Correlation Heatmap")
plt.show()
```



Start coding or generate with AI.

Feature Engineering

```
## Converting Catagorical Features
```

```
## Converting "term" 36---->0 and 60---->1
df['term_in_binary'] = df['term'].apply(lambda x: 0 if x == 36 else 1)
```

```
df.head()
```

	income	loan_amount	term	credit_history	defaulted	term_in_binary
0	60940.854754	17402.715471	60	1.0	1	1
1	49511.242579	6664.626123	36	0.0	0	0
2	63658.393686	17985.281393	60	0.0	1	1
3	79414.537415	21001.173770	36	1.0	0	0

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```
## Creating Derived Feature. Converting income & loan_amount to log

import numpy as np
df['income_log'] = np.log1p(df['income'])
df['loan_amount_log'] = np.log1p(df['loan_amount'])
df.head()
```

	income	loan_amount	term	credit_history	defaulted	term_in_binary	income_log	loan_amount_log
0	60940.854754	17402.715471	60	1.0	1	1	11.017675	9.764439
1	49511.242579	6664.626123	36	0.0	0	0	10.809975	8.804719
2	63658.393686	17985.281393	60	0.0	1	1	11.061302	9.797365
3	79414.537415	21001.173770	36	1.0	0	0	11.282449	9.952381

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Feature Selection.

```
Select_features = ['income_log',  'loan_amount_log', 'credit_history']
target = 'defaulted'
```

Model Training

Feature Scaling (StandardScaler from sklearn)

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
features_scaling = ['income_log', 'loan_amount_log']
df[features_scaling] = scaler.fit_transform(df[features_scaling])
df.head()
```

	income	loan_amount	term	credit_history	defaulted	term_in_binary	income_log	loan_amount_log
0	60940.854754	17402.715471	60	1.0	1	1	0.555865	0.335135
1	49511.242579	6664.626123	36	0.0	0	0	0.010029	-1.753786
2	63658.393686	17985.281393	60	0.0	1	1	0.670515	0.406800
3	79414.537415	21001.173770	36	1.0	0	0	1.251689	0.744209

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Double-click (or enter) to edit

Train & Split. 80% training and 20% testing

```
from sklearn.model_selection import train_test_split
X = df[Select_features]
y = df[target]


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Model Pipeline

```
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix


models = {
    'Logistic_Regression': LogisticRegression(),
    'Random_Forest': RandomForestClassifier(),
    'Decision_Tree': DecisionTreeClassifier()
}


for name, model in models.items():
    pipe = Pipeline([
        ('model', model)
    ])
    pipe.fit(X_train, y_train)
    y_pred = pipe.predict(X_test)
    print(f"Model: {name}")
    print(f"Accuracy: {accuracy_score(y_test, y_pred)}")
    print(f"Classification Report:\n{classification_report(y_test, y_pred)}")
```

```
Model: Logistic_Regression
Accuracy: 0.652
Classification Report:
              precision    recall  f1-score   support

           0       0.65      0.86      0.74       143
           1       0.67      0.37      0.48       107

    accuracy                           0.65       250
   macro avg       0.66      0.62      0.61       250
weighted avg       0.66      0.65      0.63       250

Model: Random_Forest
Accuracy: 0.6
Classification Report:
              precision    recall  f1-score   support

           0       0.63      0.72      0.67       143
           1       0.54      0.44      0.48       107

    accuracy                           0.60       250
   macro avg       0.59      0.58      0.58       250
weighted avg       0.59      0.60      0.59       250

Model: Decision_Tree
Accuracy: 0.552
Classification Report:
              precision    recall  f1-score   support

           0       0.60      0.64      0.62       143
           1       0.47      0.43      0.45       107

    accuracy                           0.55       250
   macro avg       0.54      0.54      0.54       250
weighted avg       0.55      0.55      0.55       250
```