In [34]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split
import seaborn as sns
```

In [35]:
```
df = pd.read_csv("data.csv")
df.columns.to_list()
```

Out[35]:
```
['person_age',
 'person_income',
 'person_home_ownership',
 'person_emp_length',
 'loan_intent',
 'loan_grade',
 'loan_amnt',
 'loan_int_rate',
 'loan_status',
 'loan_percent_income',
 'cb_person_default_on_file',
 'cb_person_cred_hist_length']
```

Features

- person_age: Age of the individual applying for the loan.
- person_income: Annual income of the individual.
- person_home_ownership: Type of home ownership of the individual.
- rent: The individual is currently renting a property.
- mortgage: The individual has a mortgage on the property they own.
- own: The individual owns their home outright.
- other: Other categories of home ownership that may be specific to the dataset.
- person_emp_length: Employment length of the individual in years.
- loan_intent: The intent behind the loan application.
- loan_grade: The grade assigned to the loan based on the creditworthiness of the borrower.
  - A: The borrower has a high creditworthiness, indicating low risk.
  - B: The borrower is relatively low-risk, but not as creditworthy as Grade A.
  - C: The borrower's creditworthiness is moderate.
  - D: The borrower is considered to have higher risk compared to previous grades.
  - E: The borrower's creditworthiness is lower, indicating a higher risk.
  - F: The borrower poses a significant credit risk.
  - G: The borrower's creditworthiness is the lowest, signifying the highest risk.
- loan_amnt: The loan amount requested by the individual.
- loan_int_rate: The interest rate associated with the loan.
- loan_status: Loan status, where 0 indicates non-default and 1 indicates default.
  - 0: Non-default - The borrower successfully repaid the loan as agreed, and there was no default.

  - 1: Default - The borrower failed to repay the loan according to the agreed-upon terms and defaulted on the loan.
- loan_percent_income: The percentage of income represented by the loan amount.
- cb_person_default_on_file: Historical default of the individual as per credit bureau records.
  - Y: The individual has a history of defaults on their credit file.
  - N: The individual does not have any history of defaults.
- cb_person_cred_hist_length: The length of credit history for the individual.

Hypothesis

• Given a factors, is it possible to predict if an individual will default on their credit? aka target = loan_status

Extension: what are the features that influence whether someone will default?

In [36]:

```
# Do EDA to understand the data
df.describe()
# have to clean person_age, person_emp_length, loan_pct_income = 0?
```

Out[36]:

	person_age	person_income	person_emp_length	loan_amnt	loan_int
count	32581.000000	3.258100e+04	31686.000000	32581.000000	29465.0C
mean	27.734600	6.607485e+04	4.789686	9589.371106	11.0
std	6.348078	6.198312e+04	4.142630	6322.086646	3.24
min	20.000000	4.000000e+03	0.000000	500.000000	5.42
25%	23.000000	3.850000e+04	2.000000	5000.000000	7.9C
50%	26.000000	5.500000e+04	4.000000	8000.000000	10.99
75%	30.000000	7.920000e+04	7.000000	12200.000000	13.47
max	144.000000	6.000000e+06	123.000000	35000.000000	23.22

Check for null values and duplicates

There are null values - we either handle them by deletion or imputation later. As for duplicated rows they can be removed first.

In [37]:

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

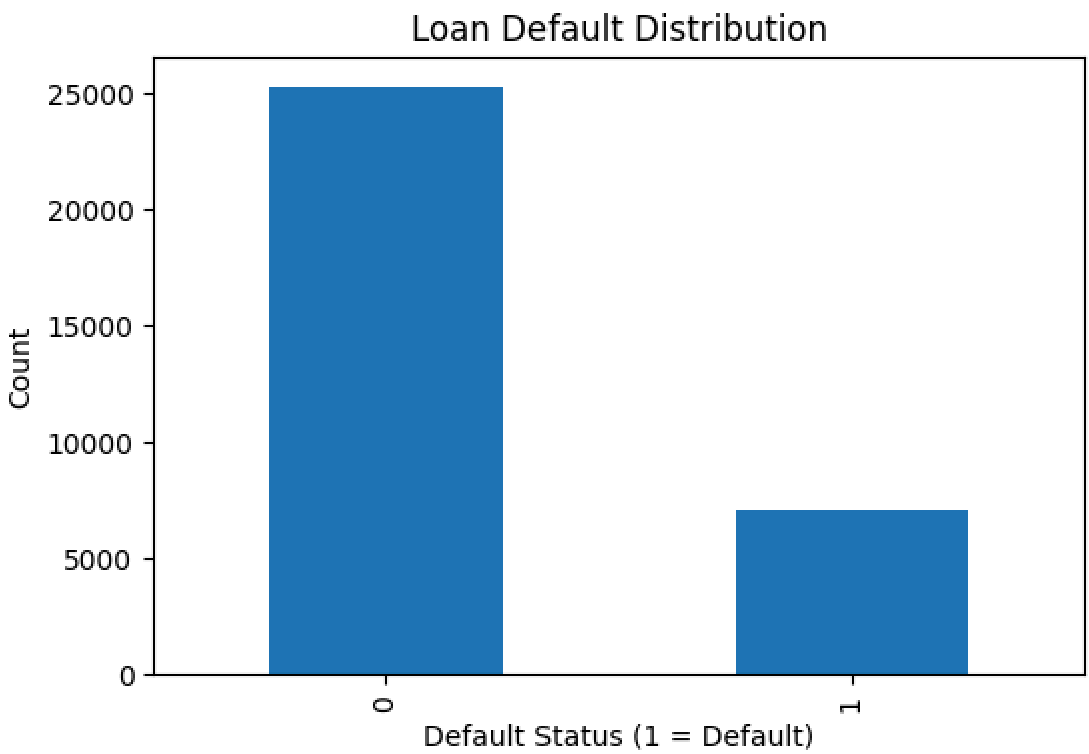
Out[37]:
```
person_age                    0
person_income                 0
person_home_ownership         0
person_emp_length           895
loan_intent                   0
loan_grade                    0
loan_amnt                     0
loan_int_rate              3116
loan_status                   0
loan_percent_income           0
cb_person_default_on_file     0
cb_person_cred_hist_length    0
dtype: int64
```

In [38]:
```
print(df.duplicated().sum())
df = df.drop_duplicates()
```

```
165
```

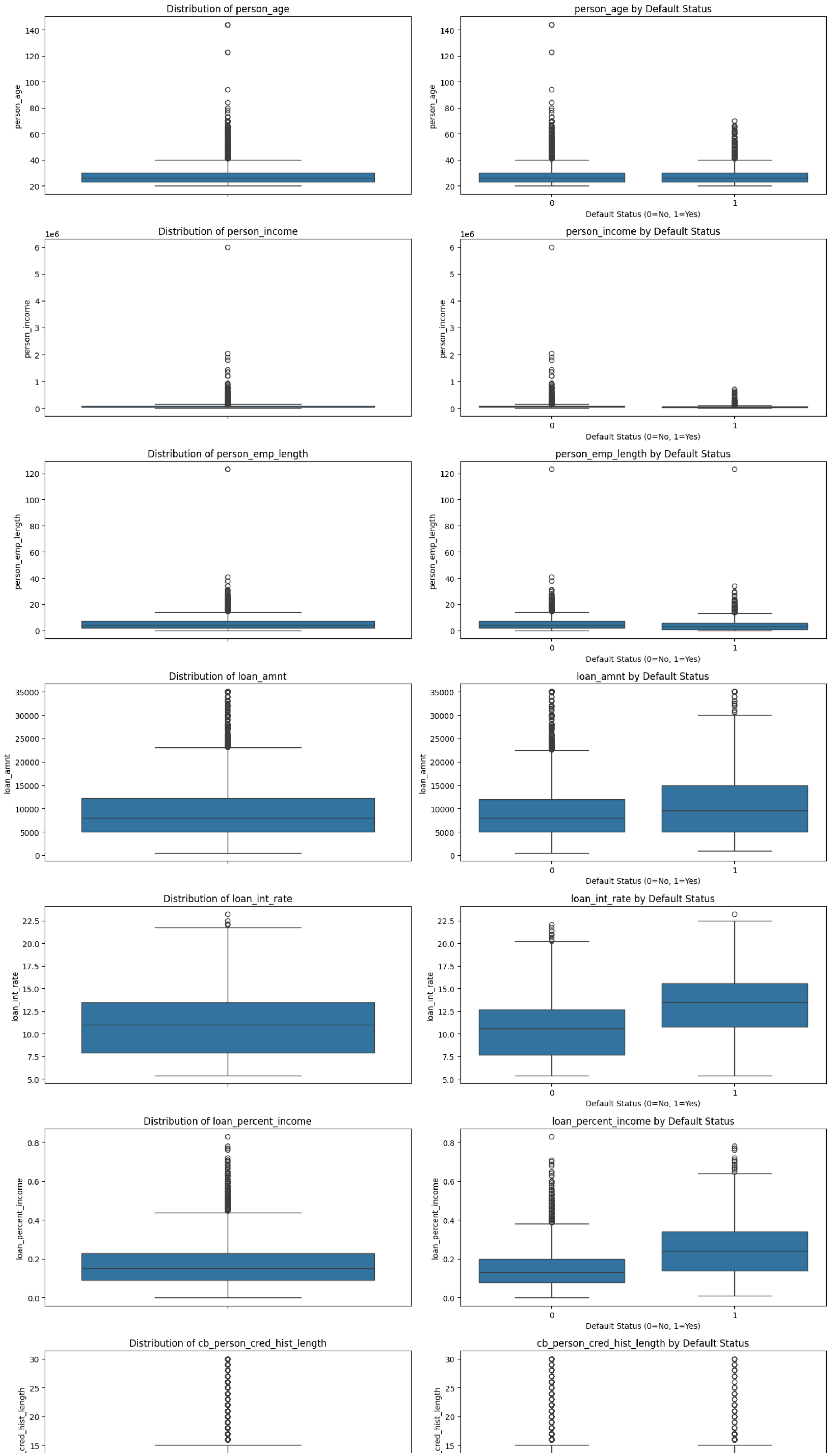
In [39]:
```
print(df["loan_status"].value_counts(normalize=True))
# 21% of the loans are defaulted
plt.figure(figsize=(6, 4))
df["loan_status"].value_counts().plot(kind="bar")
plt.title("Loan Default Distribution")
plt.xlabel("Default Status (1 = Default)")
plt.ylabel("Count")
plt.show()
```

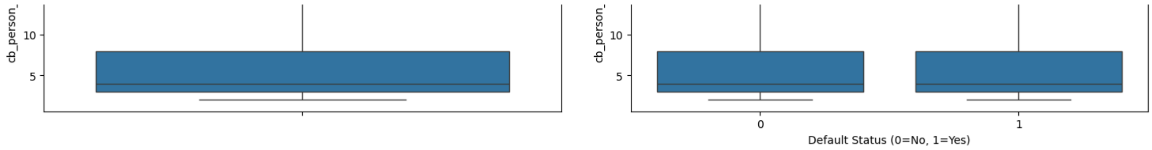
```
loan_status
0    0.781312
1    0.218688
Name: proportion, dtype: float64
```



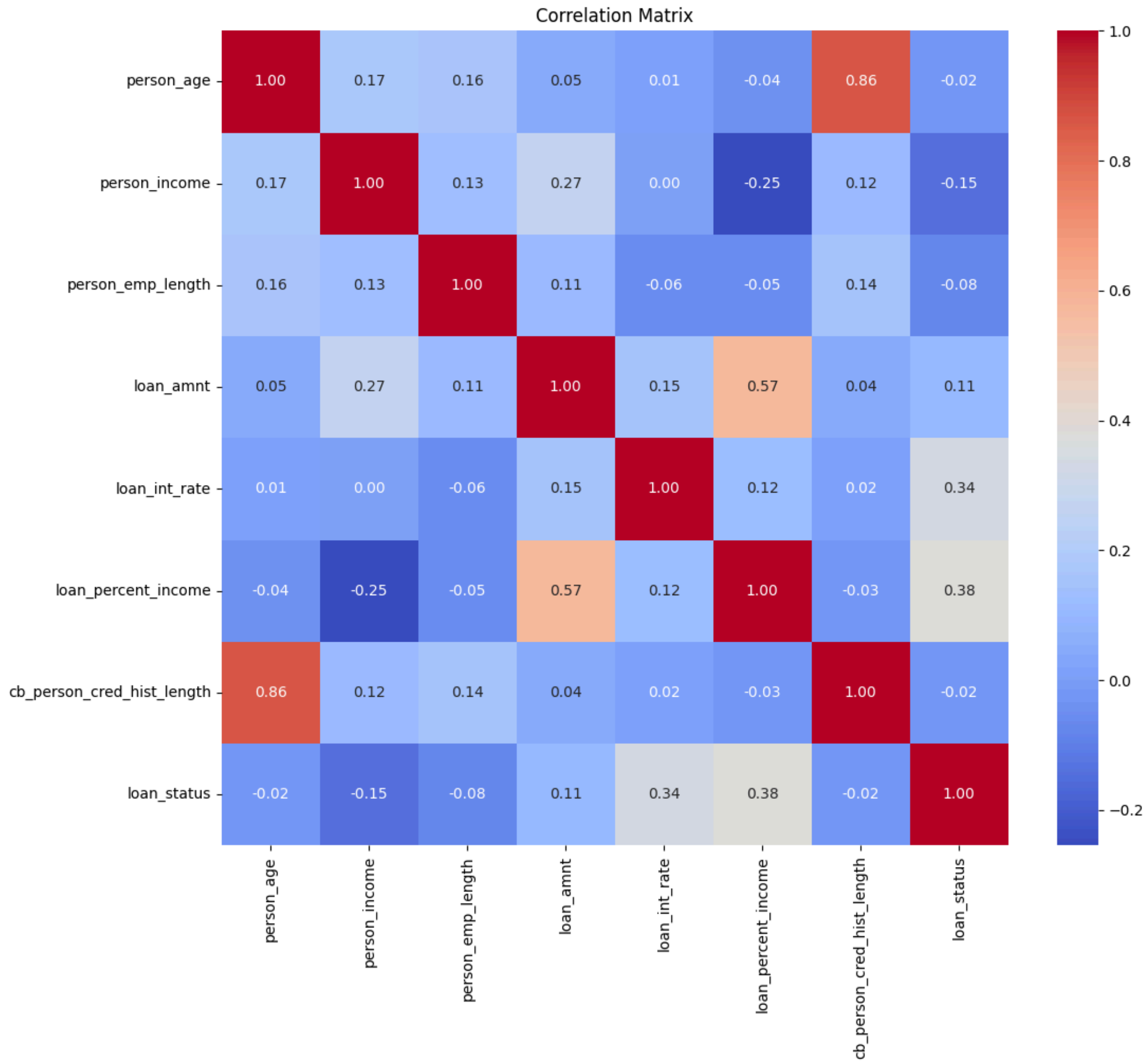
In [40]:
```
"""
'person_age', - Numerical
 'person_income', - Numerical
 'person_home_ownership', - Categorical
```

```
 'person_emp_length',   - Numerical
 'loan_intent', - Categorical
 'loan_grade', - Categorical
 'loan_amnt', - Numerical
 'loan_int_rate', - Numerical
 'loan_status', - Target
 'loan_percent_income',- Numerical
 'cb_person_default_on_file',- Categorical
 'cb_person_cred_hist_length'"- Numerical
"""

# Numerical features
num_features = [
    "person_age",
    "person_income",
    "person_emp_length",
    "loan_amnt",
    "loan_int_rate",
    "loan_percent_income",
    "cb_person_cred_hist_length",
]

fig, axes = plt.subplots(len(num_features), 2, figsize=(15, 4 * len(num_f
for i, feature in enumerate(num_features):
    # Box plot for overall distribution
    sns.boxplot(y=df[feature], ax=axes[i, 0])
    axes[i, 0].set_title(f"Distribution of {feature}")
    axes[i, 0].set_ylabel(feature)

    # Boxplot by target
    sns.boxplot(x="loan_status", y=feature, data=df, ax=axes[i, 1])
    axes[i, 1].set_title(f"{feature} by Default Status")
    axes[i, 1].set_xlabel("Default Status (0=No, 1=Yes)")
    axes[i, 1].set_ylabel(feature)

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


Distribution of person_age
person_age by Default Status
person_age
Default Status (0=No, 1=Yes)
Distribution of person_income
person_income by Default Status
person_income
1e6
Distribution of person_emp_length
person_emp_length by Default Status
person_emp_length
Distribution of loan_amnt
loan_amnt by Default Status
loan_amnt
Distribution of loan_int_rate
loan_int_rate by Default Status
loan_int_rate
Distribution of loan_percent_income
loan_percent_income by Default Status
loan_percent_income
Distribution of cb_person_cred_hist_length
cb_person_cred_hist_length by Default Status
_cred_hist_length



In [41]:
```
plt.figure(figsize=(12, 10))
corr = df[num_features + ["loan_status"]].corr()
sns.heatmap(corr, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Matrix")
plt.show()
```



INSIGHTS: We thought person_age and person_employment_length would've had a higher correlation, since age and credit history length has a very strong correlation. We investigate this below.

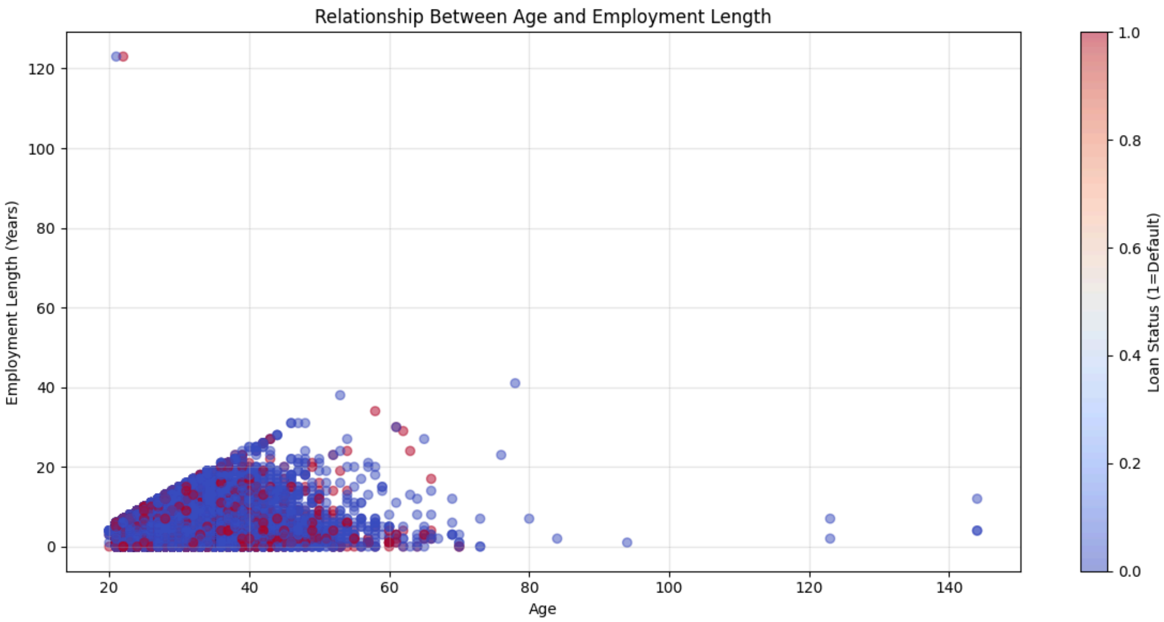
The higher the income, the lower the loan expressed as % of income. The higher the income, the higher the loan amount might be

The higher the loan amount, the higher they were as % of income, i.e. people with lower income take loans that result in higher leverage (to buy big ticket items)

Interest rates show almost no correlation to loan profile which is true in practice since they are driven by mkt forces

Of special interest to us, loan status (last row) has **highest correlation magnitude with loan_perent_income and loan_int_rate and person_income.**

In [42]:
```
# Visualize relationship between age and employment length


# Scatter plot with color by loan status, turned into function since it w
def drawGraph(df):
    plt.figure(figsize=(12, 6))
    scatter = plt.scatter(
        df["person_age"],
        df["person_emp_length"],
        c=df["loan_status"],
        alpha=0.5,
        cmap="coolwarm",
    )

    plt.colorbar(scatter, label="Loan Status (1=Default)")
    plt.xlabel("Age")
    plt.ylabel("Employment Length (Years)")
    plt.title("Relationship Between Age and Employment Length")

    plt.grid(True, alpha=0.3)
    plt.tight_layout()
    plt.show()


drawGraph(df)
```

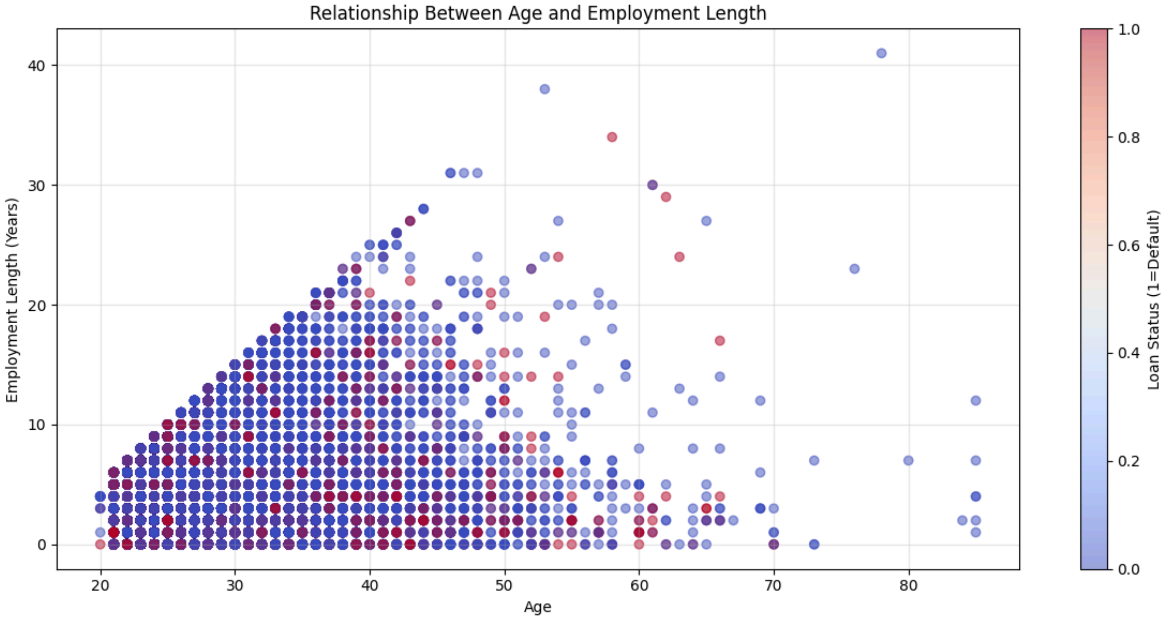


Anomaly Cleaning:

It seemed weird that the correlation between employment length is so weak, so we visualized it. As expected, the correlation is affected by the presence of anomlous data at the top right. Upon closer examination, having an employment length exceeding age is also anomalous, so we removed that as well. This allows our data to fall within a much more reasonable spread.

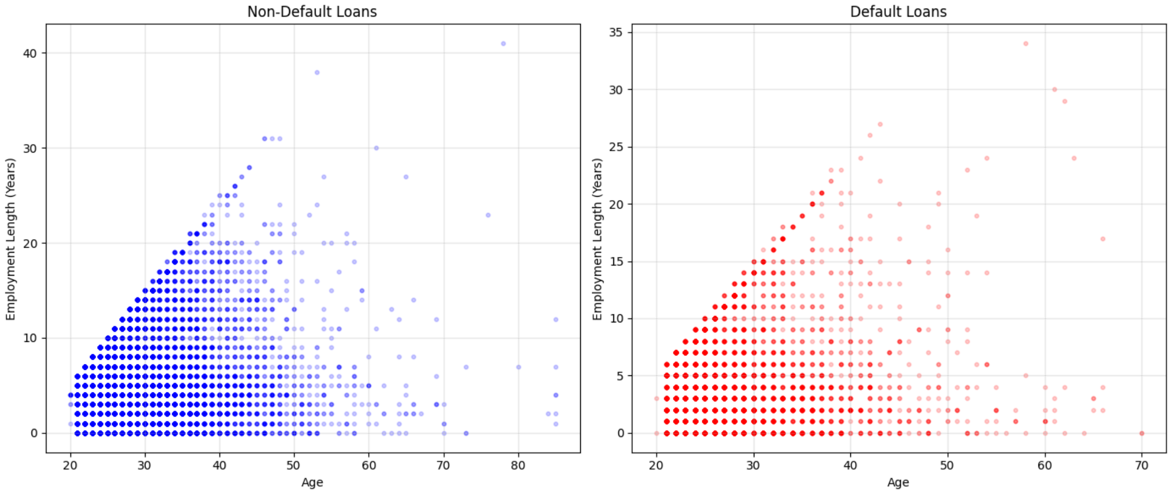
In [43]:
```
# Remove outliers
df["person_emp_length"] = df["person_emp_length"].clip(upper=45)
df["person_age"] = df["person_age"].clip(upper=85)
plt.figure(figsize=(12, 6))

# Remove outliers
df = df[df["person_emp_length"] < df["person_age"]]

drawGraph(df)
```

```
<Figure size 1200x600 with 0 Axes>
```



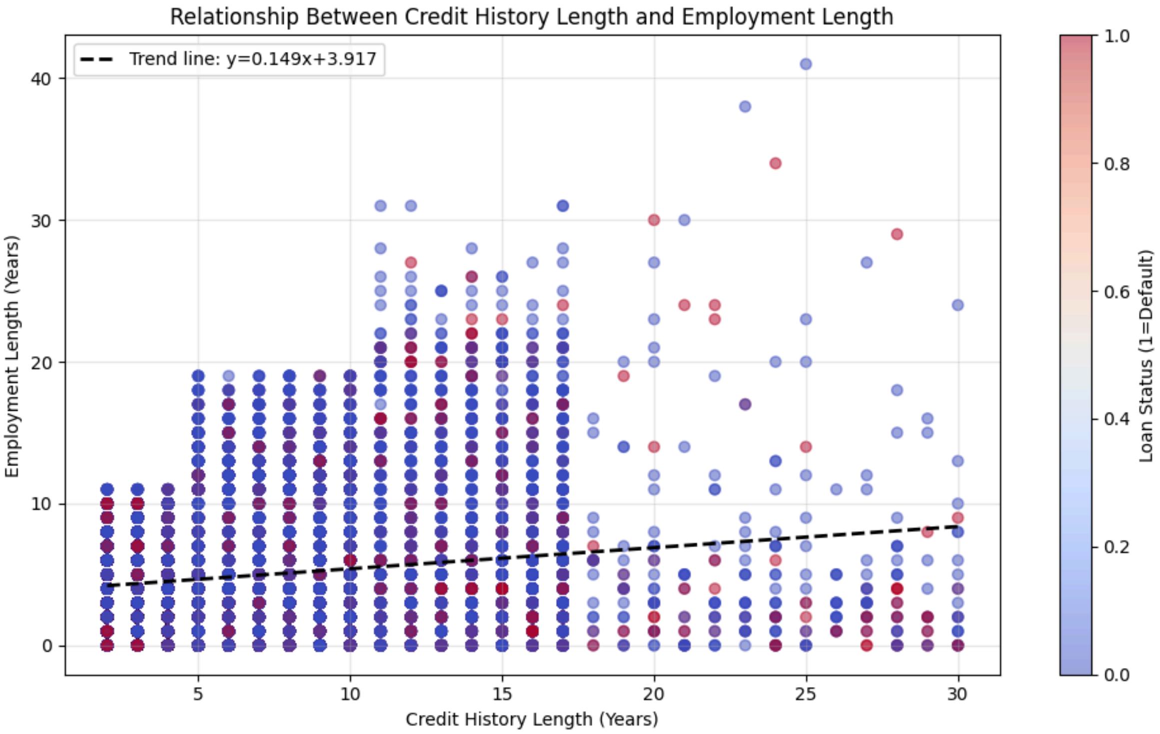
In [44]:
```
# Visualize the distribution of the two features in default VS non-defaul
plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
plt.scatter(
    df[df["loan_status"] == 0]["person_age"],
    df[df["loan_status"] == 0]["person_emp_length"],
    alpha=0.2,
    color="blue",
    s=10,
)
plt.xlabel("Age")
plt.ylabel("Employment Length (Years)")
plt.title("Non-Default Loans")
plt.grid(True, alpha=0.3)

plt.subplot(1, 2, 2)
plt.scatter(
    df[df["loan_status"] == 1]["person_age"],
    df[df["loan_status"] == 1]["person_emp_length"],
    alpha=0.2,
    color="red",
    s=10,
)
plt.xlabel("Age")
plt.ylabel("Employment Length (Years)")
plt.title("Default Loans")
plt.grid(True, alpha=0.3)
```

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



In [45]:

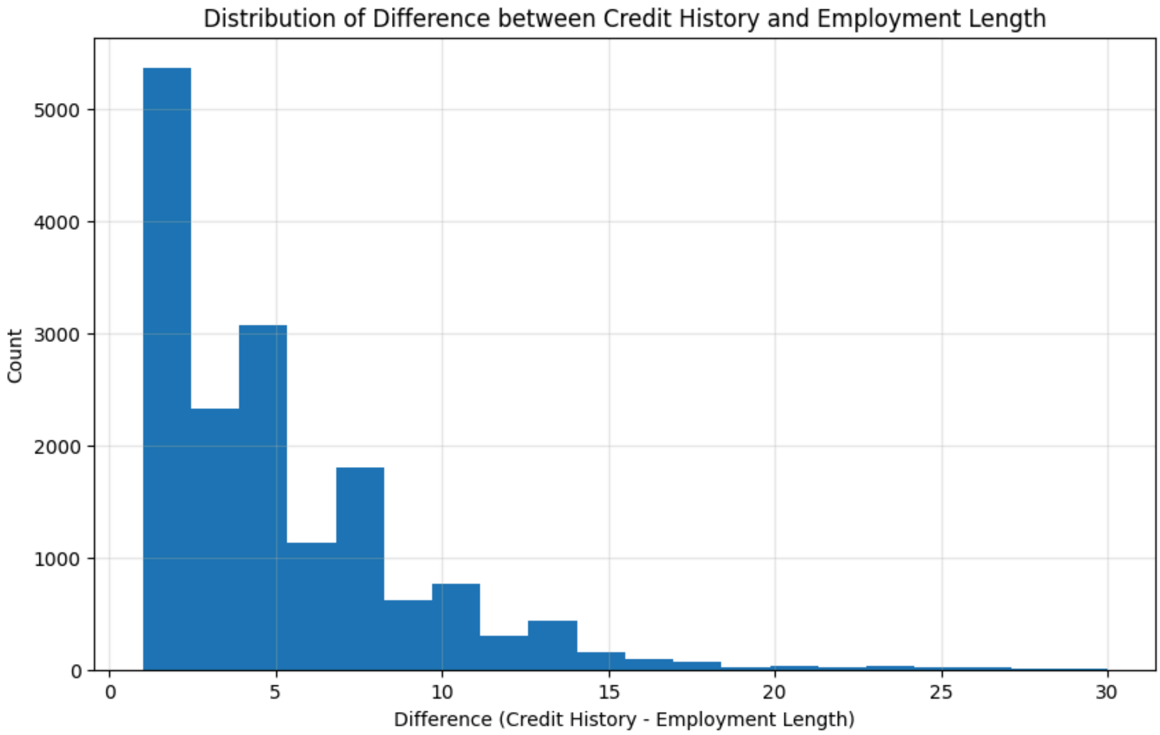
```
# Visualize the relationship between credit history length and employment
plt.figure(figsize=(10, 6))

# Create scatter plot with color by loan status
scatter = plt.scatter(
    df["cb_person_cred_hist_length"],
    df["person_emp_length"],
    c=df["loan_status"],
    alpha=0.5,
    cmap="coolwarm",
)

# Add regression line
z = np.polyfit(df["cb_person_cred_hist_length"], df["person_emp_length"],
p = np.poly1d(z)
plt.plot(
    df["cb_person_cred_hist_length"],
    p(df["cb_person_cred_hist_length"]),
    "k--",
    linewidth=2,
    label=f"Trend line: y={z[0]:.3f}x+{z[1]:.3f}",
)

plt.colorbar(scatter, label="Loan Status (1=Default)")
plt.xlabel("Credit History Length (Years)")
plt.ylabel("Employment Length (Years)")
plt.title("Relationship Between Credit History Length and Employment Leng
plt.legend()
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```



In [46]:

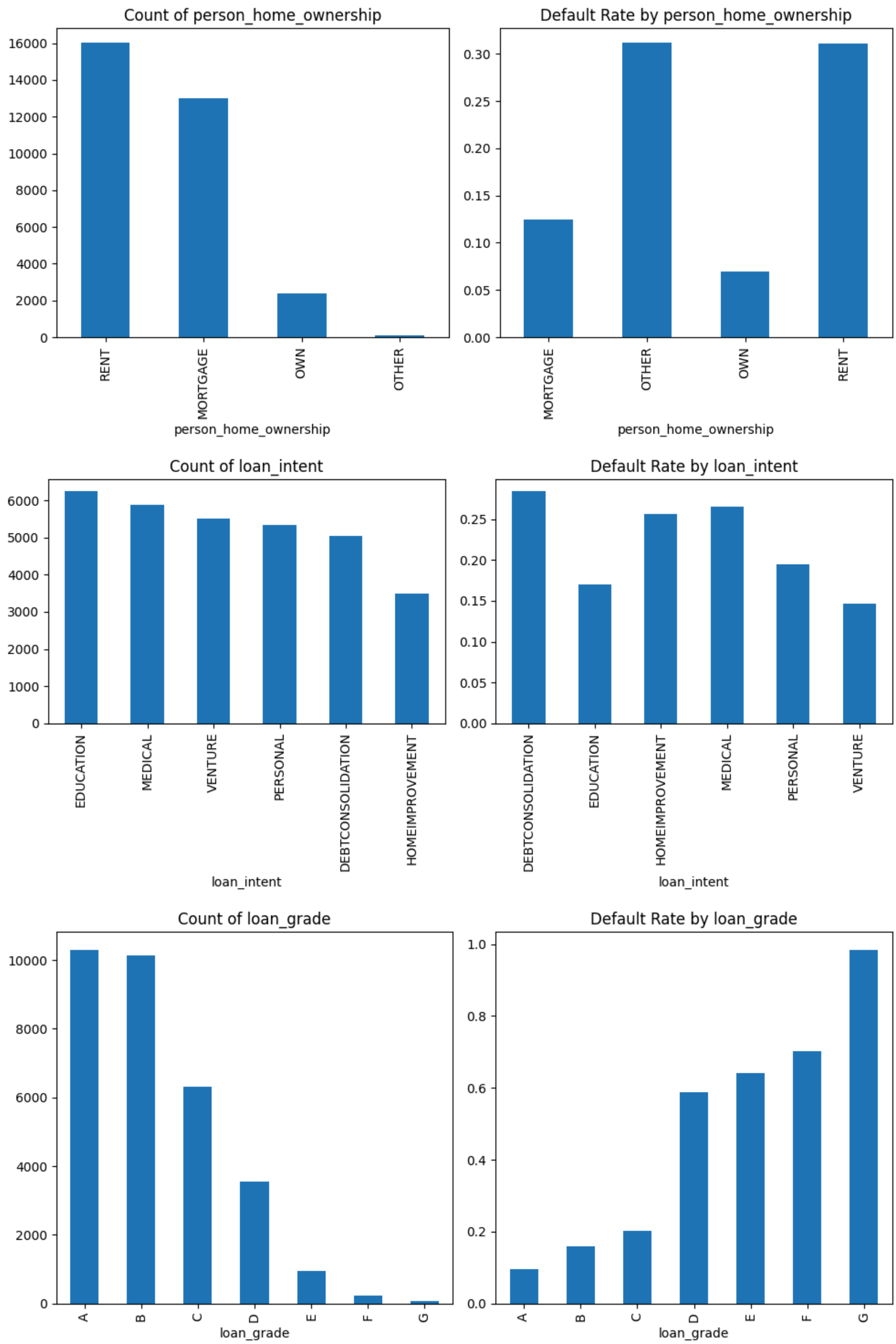
```
credit_longer_than_employment = df[
    df["cb_person_cred_hist_length"] > df["person_emp_length"]
].copy()

percentage = (len(credit_longer_than_employment) / len(df)) * 100

print(
    f"Number of people with credit history longer than employment: {len(c
)

credit_longer_than_employment["history_employment_diff"] = (
    credit_longer_than_employment["cb_person_cred_hist_length"]
    - credit_longer_than_employment["person_emp_length"]
)

plt.figure(figsize=(10, 6))
plt.hist(credit_longer_than_employment["history_employment_diff"], bins=2
plt.title("Distribution of Difference between Credit History and Employme
plt.xlabel("Difference (Credit History - Employment Length)")
plt.ylabel("Count")
plt.grid(True, alpha=0.3)
plt.show()
```

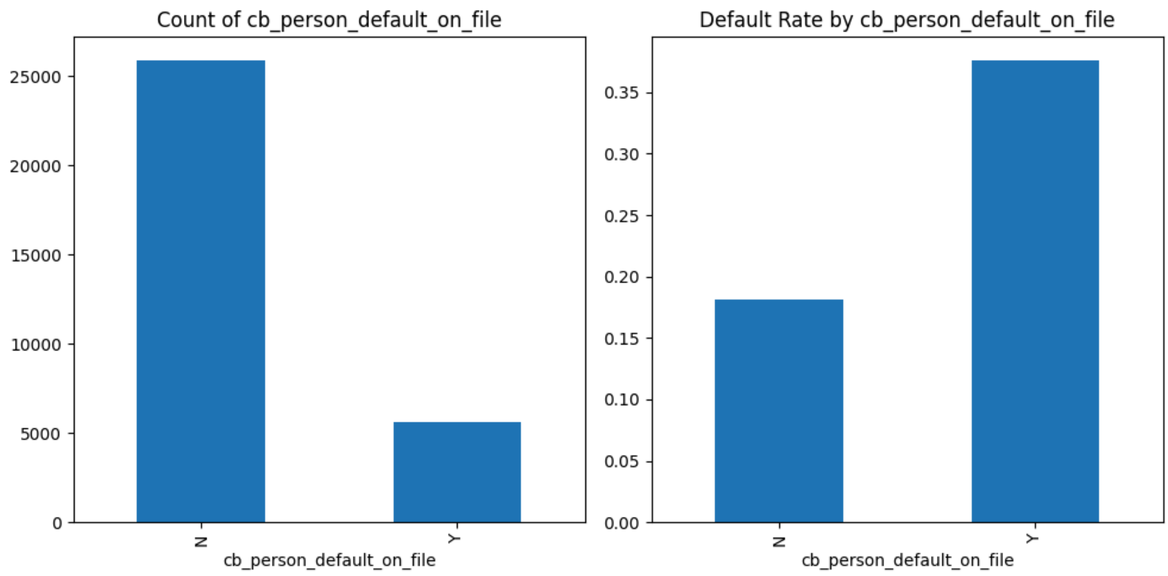
```
Number of people with credit history longer than employment: 16333 (51.81%
of total)
```



As you can see - too much of our data exhibits this peculiar behavior. Either there's some part of how credit history works in the US that we're not understanding, or that this synthetic dataset simply didn't model this relationship enough during generation. Either way, we decided to leave it as is.

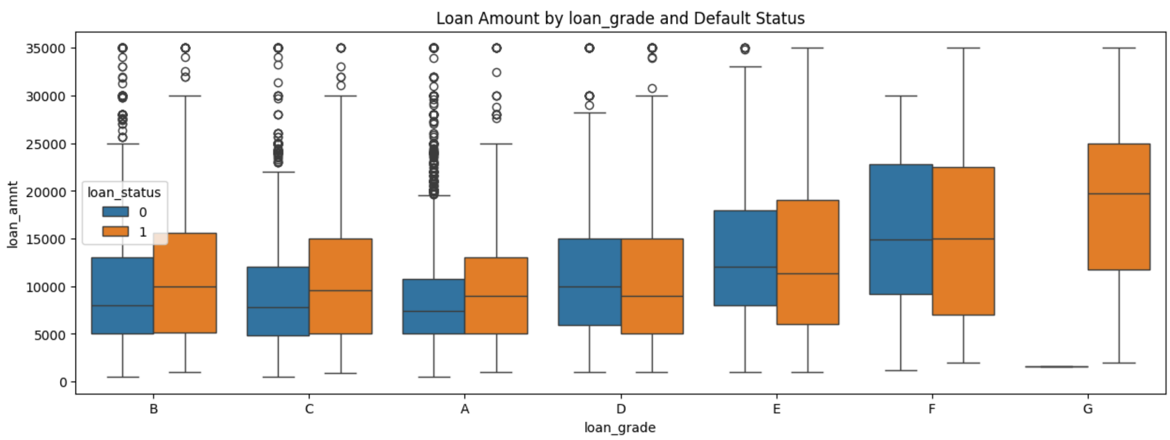
In [47]:
```
# categorical features visualization
cat_features = [
    "person_home_ownership",
    "loan_intent",
    "loan_grade",
    "cb_person_default_on_file",
]

for feature in cat_features:
    plt.figure(figsize=(10, 5))

    # Count by category
    plt.subplot(1, 2, 1)
    df[feature].value_counts().plot(kind="bar")
    plt.title(f"Count of {feature}")

    # Default rate by category
    plt.subplot(1, 2, 2)
    df.groupby(feature)["loan_status"].mean().plot(kind="bar")
    plt.title(f"Default Rate by {feature}")
    plt.tight_layout()
    plt.show()
```

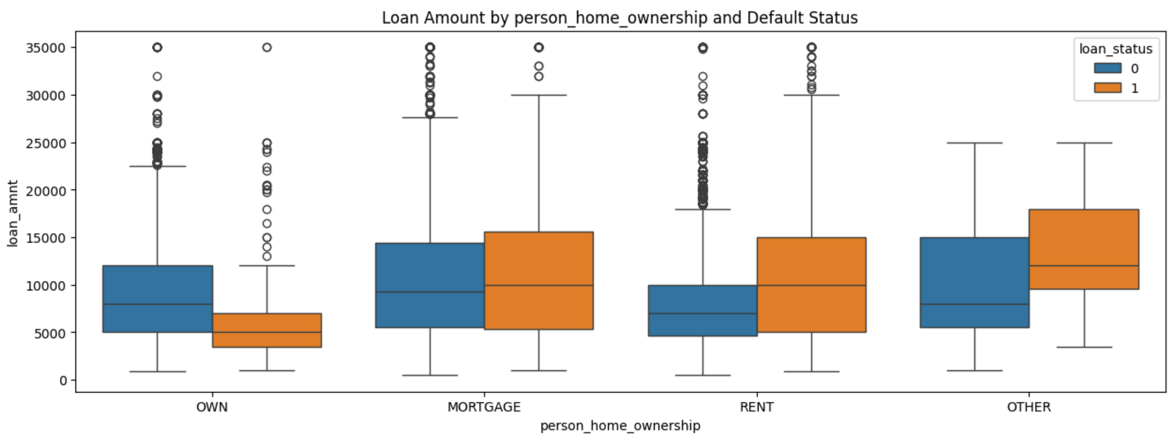

Count of person_home_ownership
16000
14000
12000
10000
8000
6000
4000
2000
0
RENT
MORTGAGE
OWN
OTHER
person_home_ownership
Default Rate by person_home_ownership
0.30
0.25
0.20
0.15
0.10
0.05
0.00
MORTGAGE
OTHER
OWN
RENT
person_home_ownership
Count of loan_intent
6000
5000
4000
3000
2000
1000
0
EDUCATION
MEDICAL
VENTURE
PERSONAL
DEBTCONSOLIDATION
HOMEIMPROVEMENT
loan_intent
Default Rate by loan_intent
0.25
0.20
0.15
0.10
0.05
0.00
DEBTCONSOLIDATION
EDUCATION
HOMEIMPROVEMENT
MEDICAL
PERSONAL
VENTURE
loan_intent
Count of loan_grade
10000
8000
6000
4000
2000
0
A
B
C
D
E
F
G
loan_grade
Default Rate by loan_grade
1.0
0.8
0.6
0.4
0.2
0.0
A
B
C
D
E
F
G
loan_grade



In [48]:

```
# For key categorical variables, analyze numerical features by category
for cat in ["loan_grade", "person_home_ownership"]:
    plt.figure(figsize=(15, 5))
    sns.boxplot(x=cat, y="loan_amnt", hue="loan_status", data=df)
    plt.title(f"Loan Amount by {cat} and Default Status")
    plt.show()
```





Data Preprocessing

Principally, categorical labels need to be encoded into numerical ones.

We also investigate two strategies --> impute missing data VS delete missing data records

One thing that stood out was how home ownership type = OTHER had a high 30% default rate. There are a few strategies:

1. Treat as RENT on the basis that their default rates are almost the same
2. Delete the record entirely
3. Do nothing

In [49]:
```
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split

# https://contrib.scikit-learn.org/category_encoders/
# other encoders we can try:
import category_encoders as ce
```

In [50]:
```
encoder = ce.OneHotEncoder(
    cols=cat_features,
    return_df=True,
    use_cat_names=True,
)

df = encoder.fit_transform(df)
df
```

Out[50]:

	person_age	person_income	person_home_ownership_OWN	person_home_
1	21	9600	1	
2	25	9600	0	
3	23	65500	0	
4	24	54400	0	
5	21	9900	1	
...	...	...	...	
32576	57	53000	0	
32577	54	120000	0	
32578	65	76000	0	
32579	56	150000	0	
32580	66	42000	0	

31527 rows × 27 columns

Approach 1: Data Imputation

Based on checking the null values from above, the data that needs to be imputed are all numerical (person_emp_length and interest_rate).

In [51]:
```
X = df.drop("loan_status", axis=1)
y = df["loan_status"]
```

In [52]:
```
# train test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

In [53]:
```
# Standardize numerical features with StandardScaler
# Scale numerical features
scaler = StandardScaler()
numerical_cols = [
    col
    for col in X_train.columns
    if X_train[col].dtype in ["int64", "float64"]
    and "person_home_ownership_" != col  # these are all categorical
    and "loan_intent_" != col
    and "loan_grade_" != col
    and "cb_person_default_on_file_" != col
]
```

In [54]:
```
# Get the names of columns with missing values
columns_with_nulls = X_train.columns[X_train.isnull().any()].tolist()

# Impute missing values for numerical features
numerical_imputer = SimpleImputer(strategy="mean")

# Create a copy to avoid modifying the original
X_train_imputed = X_train.copy()
X_test_imputed = X_test.copy()


# Impute missing values
X_train_imputed[columns_with_nulls] = numerical_imputer.fit_transform(
    X_train[columns_with_nulls]
)
X_test_imputed[columns_with_nulls] = numerical_imputer.transform(
    X_test[columns_with_nulls]
)


X_train_imputed[numerical_cols] = scaler.fit_transform(X_train_imputed[nu
X_test_imputed[numerical_cols] = scaler.transform(X_test_imputed[numerica

print(f"Training data shape: {X_train_imputed.shape}")
print(f"Testing data shape: {X_test_imputed.shape}")
print(f"Number of features: {X_train_imputed.shape[1]}")
```

```
Training data shape: (25221, 26)
Testing data shape: (6306, 26)
Number of features: 26
```

Approach 2 (Our Actual Approach):

Doing data imputation requires us to split the data first (so that information of the mean doesn't leak across sets).

However, a different approach is to just drop the rows where there are null values present.

To keep things simple, we opted to continue the notebook by using the deletion method over imputation. (We did not use the data imputed above). We thus continue our analysis below using this simplistic method.

Introducing Pycaret

PyCaret is a framework that allows us to test the dataset against different kinds of classifiers out there. It is considered an auto-ML framework in that once we have our dataset prepared properly, it basically does everything else for us.

In [55]:
```
from pycaret.classification import *

model = setup(data=df, target="loan_status")
```

	Description	Value
0	Session id	8770
1	Target	loan_status
2	Target type	Binary
3	Original data shape	(31527, 27)
4	Transformed data shape	(31527, 27)
5	Transformed train set shape	(22068, 27)
6	Transformed test set shape	(9459, 27)
7	Numeric features	26
8	Rows with missing values	9.6%
9	Preprocess	True
10	Imputation type	simple
11	Numeric imputation	mean
12	Categorical imputation	mode
13	Fold Generator	StratifiedKFold
14	Fold Number	10
15	CPU Jobs	-1
16	Use GPU	False
17	Log Experiment	False
18	Experiment Name	clf-default-name
19	USI	e6d6

PyCaret is an AutoML framework that uses a collection of different classifiers to see which performs the best. We use this as a reference for what we should expect to get with our own implementations.

In [56]:
```
best = compare_models()
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	T (
lightgbm	Light Gradient Boosting Machine	0.9371	0.9468	0.7274	0.9750	0.8329	0.7952	0.8083	0
xgboost	Extreme Gradient Boosting	0.9366	0.9489	0.7434	0.9528	0.8348	0.7964	0.8060	0
rf	Random Forest Classifier	0.9346	0.9302	0.7198	0.9696	0.8259	0.7868	0.8002	0
gbc	Gradient Boosting Classifier	0.9280	0.9278	0.7110	0.9415	0.8098	0.7665	0.7782	0
et	Extra Trees Classifier	0.9205	0.9134	0.6861	0.9265	0.7881	0.7405	0.7533	0
dt	Decision Tree Classifier	0.8893	0.8446	0.7660	0.7331	0.7490	0.6780	0.6784	0
ada	Ada Boost Classifier	0.8866	0.8989	0.6447	0.7916	0.7104	0.6408	0.6462	0
lda	Linear Discriminant Analysis	0.8655	0.8689	0.5883	0.7361	0.6537	0.5715	0.5772	0
ridge	Ridge Classifier	0.8610	0.8688	0.5190	0.7614	0.6169	0.5358	0.5506	0
lr	Logistic Regression	0.8537	0.8563	0.4701	0.7611	0.5810	0.4983	0.5197	0
knn	K Neighbors Classifier	0.8317	0.8087	0.4932	0.6442	0.5583	0.4567	0.4631	0
nb	Naive Bayes	0.8157	0.7675	0.3244	0.6480	0.4311	0.3356	0.3648	0
qda	Quadratic Discriminant Analysis	0.7964	0.8644	0.1234	0.6523	0.2072	0.1488	0.2185	0
dummy	Dummy Classifier	0.7841	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	0
svm	SVM - Linear Kernel	0.7557	0.7335	0.2249	0.4004	0.2031	0.1322	0.1645	0

In [57]:
```
evaluate_model(best)
```

```
interactive(children=(ToggleButtons(description='Plot Type:', icons=('',), options=(('Pipeline Plot', 'pipelin…
```

In [58]:
```
from sklearn.decomposition import PCA

scaler = StandardScaler()
```

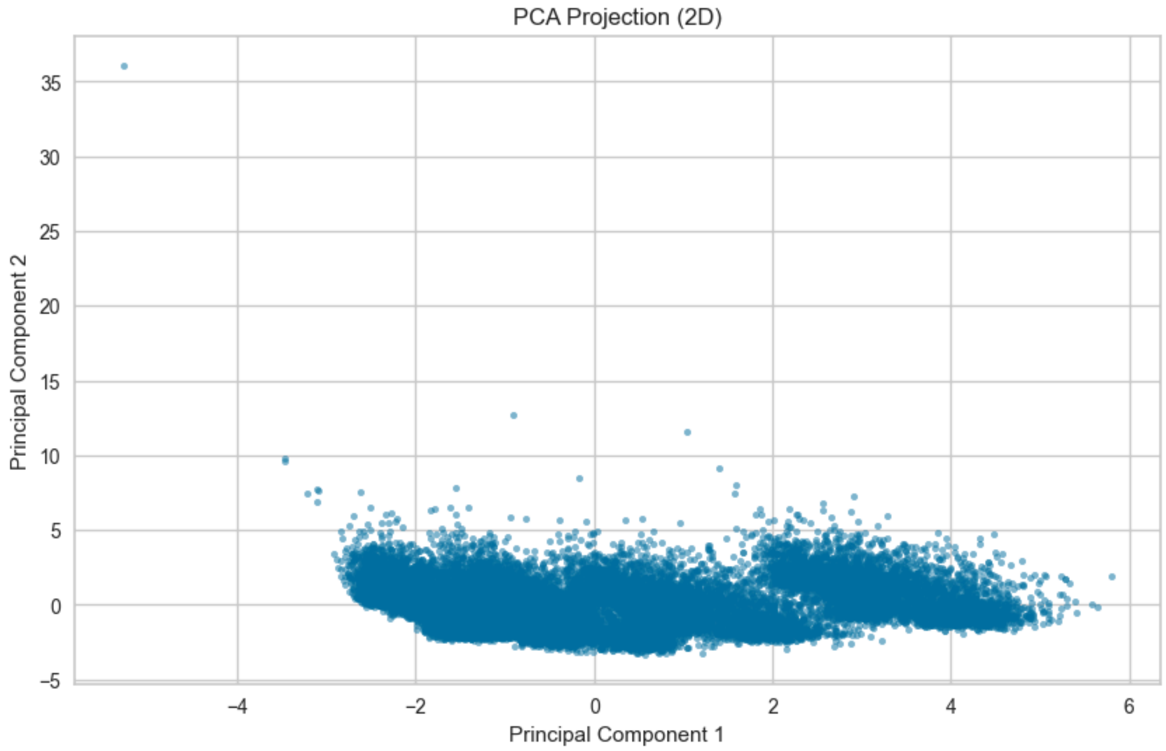
```python
df_clean = df.dropna()
scaled_data = scaler.fit_transform(df_clean)

# Perform PCA
pca = PCA(n_components=2)
principal_components = pca.fit_transform(scaled_data)

# Convert to DataFrame
pca_df = pd.DataFrame(data=principal_components, columns=["PC1", "PC2"])

# Show explained variance
print(pca.explained_variance_ratio_)
```

```
[0.13189015 0.08532481]
```

In [59]:
```python
print(pca_df)
```

```
            PC1       PC2
0     -0.957522 -1.430459
1      1.319681 -0.939564
2      2.541408 -1.666157
3      4.579694 -0.319884
4     -1.133638 -1.694136
...         ...       ...
28494 -0.046952  4.685323
28495 -2.069325  4.001129
28496  0.890104  2.914141
28497 -1.179385  4.666782
28498 -0.598310  2.517073

[28499 rows x 2 columns]
```

In [60]:
```python
plt.figure(figsize=(10, 6))
plt.scatter(pca_df["PC1"], pca_df["PC2"], alpha=0.5, s=10)
plt.title("PCA Projection (2D)")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.grid(True)
plt.show()
```

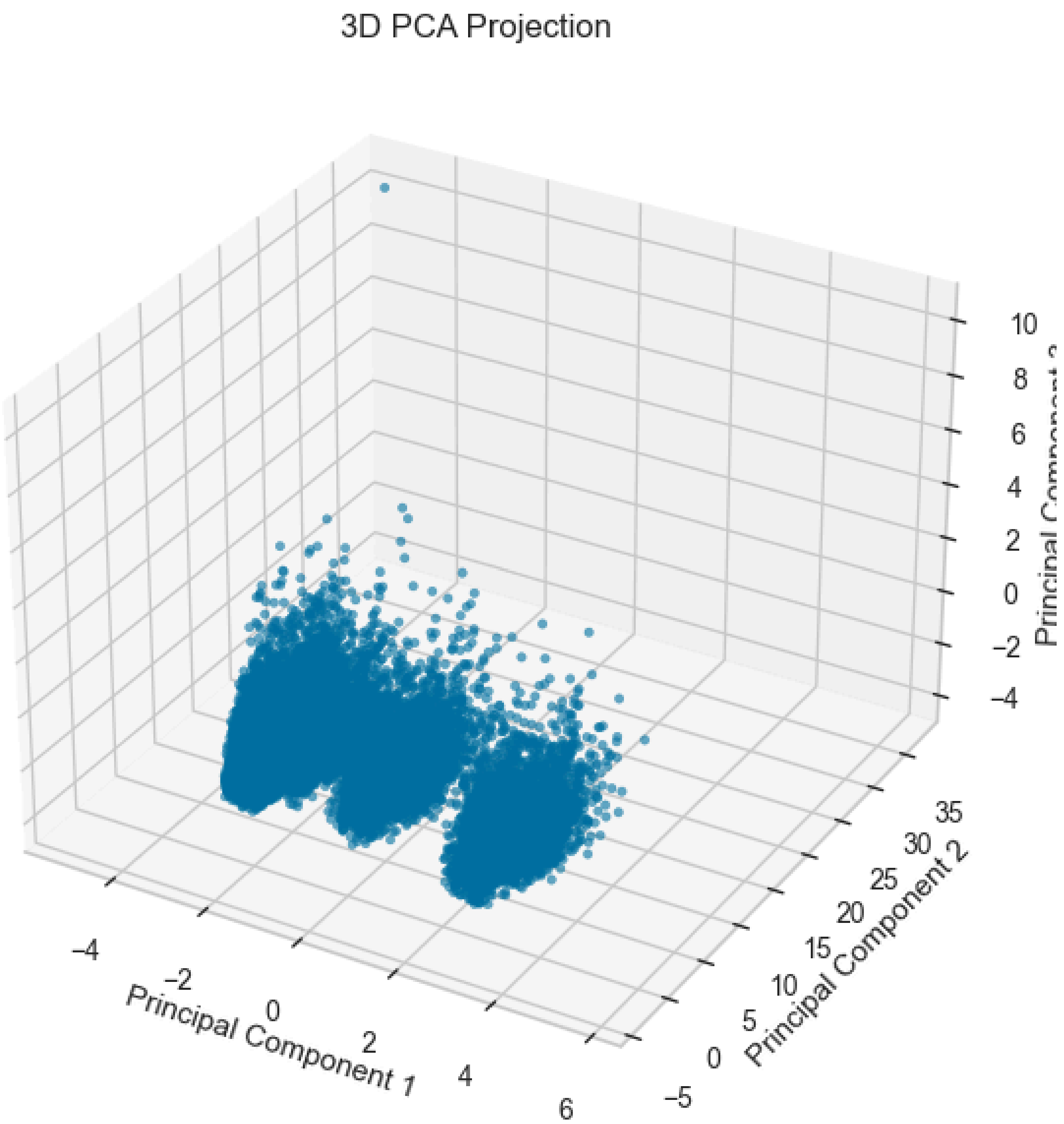


In [61]:
```
df_clean = df.dropna()
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df_clean)

pca = PCA(n_components=3)
principal_components = pca.fit_transform(scaled_data)

pca_df = pd.DataFrame(principal_components, columns=["PC1", "PC2", "PC3"]

# Show explained variance
print(pca.explained_variance_ratio_)
```

```
[0.13188918 0.08530775 0.07152489]
```

Low explained variance for each Principal Components suggests that most of the important variation is spread out across more components (data is likely high-dimensional and complex), meaning we have to keep more features for a good model Also means that linear models will likely struggle

In [62]:
```
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection="3d")

ax.scatter(pca_df["PC1"], pca_df["PC2"], pca_df["PC3"], alpha=0.6, s=10)

ax.set_title("3D PCA Projection")
ax.set_xlabel("Principal Component 1")
ax.set_ylabel("Principal Component 2")
ax.set_zlabel("Principal Component 3")

plt.show()
```



Visually it appears that there are 3 distinct clusters

Since data is highly complex, try Neural Network which can effectively capture non linear relationships

In [63]:
```
import torch
import torch.nn as nn
import torch.optim as optim
```

In [33]:
```
df_cleaned = df.dropna()
X = df_cleaned.drop("loan_status", axis=1).to_numpy(dtype=np.float32)
y = df_cleaned["loan_status"].to_numpy(dtype=np.float32).reshape(-1, 1)

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42
)

# Convert to tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float32)
```

```
y_train_tensor = torch.tensor(y_train, dtype=torch.float32)
X_test_tensor = torch.tensor(X_test, dtype=torch.float32)
y_test_tensor = torch.tensor(y_test, dtype=torch.float32)
```

In [64]:
```
assert not torch.isnan(X_train_tensor).any(), "NaNs in training data"
assert not torch.isnan(y_train_tensor).any(), "NaNs in training labels"
```

Below are our trial and error attempts at modifying the neural network to produce better results. We produce models that demonstrate about 92-93% accuracy on the held out test set.

In [65]:
```
class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.fc1 = nn.Linear(input_size, 32)
        self.relu1 = nn.ReLU()
        self.fc2 = nn.Linear(32, 16)
        self.relu2 = nn.ReLU()
        self.fc3 = nn.Linear(16, 1)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        x = self.relu1(self.fc1(x))
        x = self.relu2(self.fc2(x))
        x = self.sigmoid(self.fc3(x))
        return x


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
epochs = 1000
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

# Evaluation
model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/1000], Loss: 0.7343
Epoch [20/1000], Loss: 0.7040
Epoch [30/1000], Loss: 0.6732
Epoch [40/1000], Loss: 0.6385
Epoch [50/1000], Loss: 0.5990
Epoch [60/1000], Loss: 0.5561
Epoch [70/1000], Loss: 0.5131
Epoch [80/1000], Loss: 0.4739
Epoch [90/1000], Loss: 0.4405
Epoch [100/1000], Loss: 0.4127
Epoch [110/1000], Loss: 0.3897
Epoch [120/1000], Loss: 0.3708
Epoch [130/1000], Loss: 0.3552
Epoch [140/1000], Loss: 0.3423
Epoch [150/1000], Loss: 0.3317
Epoch [160/1000], Loss: 0.3229
Epoch [170/1000], Loss: 0.3156
Epoch [180/1000], Loss: 0.3093
Epoch [190/1000], Loss: 0.3039
Epoch [200/1000], Loss: 0.2989
Epoch [210/1000], Loss: 0.2945
Epoch [220/1000], Loss: 0.2904
Epoch [230/1000], Loss: 0.2867
Epoch [240/1000], Loss: 0.2833
Epoch [250/1000], Loss: 0.2803
Epoch [260/1000], Loss: 0.2775
Epoch [270/1000], Loss: 0.2749
Epoch [280/1000], Loss: 0.2725
Epoch [290/1000], Loss: 0.2702
Epoch [300/1000], Loss: 0.2680
Epoch [310/1000], Loss: 0.2660
Epoch [320/1000], Loss: 0.2639
Epoch [330/1000], Loss: 0.2619
Epoch [340/1000], Loss: 0.2600
Epoch [350/1000], Loss: 0.2582
Epoch [360/1000], Loss: 0.2564
Epoch [370/1000], Loss: 0.2547
Epoch [380/1000], Loss: 0.2531
Epoch [390/1000], Loss: 0.2516
Epoch [400/1000], Loss: 0.2501
Epoch [410/1000], Loss: 0.2486
Epoch [420/1000], Loss: 0.2472
Epoch [430/1000], Loss: 0.2458
Epoch [440/1000], Loss: 0.2445
Epoch [450/1000], Loss: 0.2433
Epoch [460/1000], Loss: 0.2421
Epoch [470/1000], Loss: 0.2410
Epoch [480/1000], Loss: 0.2400
Epoch [490/1000], Loss: 0.2390
Epoch [500/1000], Loss: 0.2381
Epoch [510/1000], Loss: 0.2372
Epoch [520/1000], Loss: 0.2364
Epoch [530/1000], Loss: 0.2356
Epoch [540/1000], Loss: 0.2349
Epoch [550/1000], Loss: 0.2341
Epoch [560/1000], Loss: 0.2334
Epoch [570/1000], Loss: 0.2327
Epoch [580/1000], Loss: 0.2320
Epoch [590/1000], Loss: 0.2313
Epoch [600/1000], Loss: 0.2306
```

```
Epoch [610/1000], Loss: 0.2300
Epoch [620/1000], Loss: 0.2293
Epoch [630/1000], Loss: 0.2287
Epoch [640/1000], Loss: 0.2281
Epoch [650/1000], Loss: 0.2275
Epoch [660/1000], Loss: 0.2269
Epoch [670/1000], Loss: 0.2263
Epoch [680/1000], Loss: 0.2257
Epoch [690/1000], Loss: 0.2251
Epoch [700/1000], Loss: 0.2245
Epoch [710/1000], Loss: 0.2239
Epoch [720/1000], Loss: 0.2233
Epoch [730/1000], Loss: 0.2228
Epoch [740/1000], Loss: 0.2223
Epoch [750/1000], Loss: 0.2218
Epoch [760/1000], Loss: 0.2212
Epoch [770/1000], Loss: 0.2207
Epoch [780/1000], Loss: 0.2202
Epoch [790/1000], Loss: 0.2196
Epoch [800/1000], Loss: 0.2191
Epoch [810/1000], Loss: 0.2186
Epoch [820/1000], Loss: 0.2180
Epoch [830/1000], Loss: 0.2175
Epoch [840/1000], Loss: 0.2170
Epoch [850/1000], Loss: 0.2166
Epoch [860/1000], Loss: 0.2162
Epoch [870/1000], Loss: 0.2157
Epoch [880/1000], Loss: 0.2153
Epoch [890/1000], Loss: 0.2149
Epoch [900/1000], Loss: 0.2145
Epoch [910/1000], Loss: 0.2141
Epoch [920/1000], Loss: 0.2137
Epoch [930/1000], Loss: 0.2133
Epoch [940/1000], Loss: 0.2129
Epoch [950/1000], Loss: 0.2125
Epoch [960/1000], Loss: 0.2121
Epoch [970/1000], Loss: 0.2117
Epoch [980/1000], Loss: 0.2114
Epoch [990/1000], Loss: 0.2110
Epoch [1000/1000], Loss: 0.2107

Train Accuracy: 0.9308

Test Accuracy: 0.9174
```

Large difference between train and test accuracy implies overfitting

Add dropout to reduce overfitting

In [67]:

```python
first_layer_neurons = 128


# Increase the number of neurons in each layer by a factor of 4
class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.fc1 = nn.Linear(input_size, first_layer_neurons)
        self.relu1 = nn.ReLU()
        self.fc2 = nn.Linear(first_layer_neurons, first_layer_neurons //
        self.relu2 = nn.ReLU()
```

```
        self.fc3 = nn.Linear(first_layer_neurons // 2, 1)
        self.sigmoid = nn.Sigmoid()
        self.dropout1 = nn.Dropout(0.3)
        self.dropout2 = nn.Dropout(0.3)

    def forward(self, x):
        x = self.relu1(self.fc1(x))
        x = self.dropout1(x)
        x = self.relu2(self.fc2(x))
        x = self.dropout2(x)
        x = self.sigmoid(self.fc3(x))
        return x


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
epochs = 1000
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/1000], Loss: 0.5418
Epoch [20/1000], Loss: 0.4720
Epoch [30/1000], Loss: 0.4164
Epoch [40/1000], Loss: 0.3817
Epoch [50/1000], Loss: 0.3580
Epoch [60/1000], Loss: 0.3433
Epoch [70/1000], Loss: 0.3306
Epoch [80/1000], Loss: 0.3196
Epoch [90/1000], Loss: 0.3132
Epoch [100/1000], Loss: 0.3054
Epoch [110/1000], Loss: 0.3020
Epoch [120/1000], Loss: 0.2948
Epoch [130/1000], Loss: 0.2926
Epoch [140/1000], Loss: 0.2873
Epoch [150/1000], Loss: 0.2851
Epoch [160/1000], Loss: 0.2810
Epoch [170/1000], Loss: 0.2807
Epoch [180/1000], Loss: 0.2787
Epoch [190/1000], Loss: 0.2717
Epoch [200/1000], Loss: 0.2703
Epoch [210/1000], Loss: 0.2680
Epoch [220/1000], Loss: 0.2659
Epoch [230/1000], Loss: 0.2616
Epoch [240/1000], Loss: 0.2607
Epoch [250/1000], Loss: 0.2596
Epoch [260/1000], Loss: 0.2572
Epoch [270/1000], Loss: 0.2560
Epoch [280/1000], Loss: 0.2547
Epoch [290/1000], Loss: 0.2538
Epoch [300/1000], Loss: 0.2521
Epoch [310/1000], Loss: 0.2489
Epoch [320/1000], Loss: 0.2507
Epoch [330/1000], Loss: 0.2489
Epoch [340/1000], Loss: 0.2460
Epoch [350/1000], Loss: 0.2438
Epoch [360/1000], Loss: 0.2418
Epoch [370/1000], Loss: 0.2435
Epoch [380/1000], Loss: 0.2413
Epoch [390/1000], Loss: 0.2399
Epoch [400/1000], Loss: 0.2393
Epoch [410/1000], Loss: 0.2374
Epoch [420/1000], Loss: 0.2369
Epoch [430/1000], Loss: 0.2357
Epoch [440/1000], Loss: 0.2372
Epoch [450/1000], Loss: 0.2342
Epoch [460/1000], Loss: 0.2324
Epoch [470/1000], Loss: 0.2328
Epoch [480/1000], Loss: 0.2328
Epoch [490/1000], Loss: 0.2305
Epoch [500/1000], Loss: 0.2325
Epoch [510/1000], Loss: 0.2303
Epoch [520/1000], Loss: 0.2267
Epoch [530/1000], Loss: 0.2292
Epoch [540/1000], Loss: 0.2273
Epoch [550/1000], Loss: 0.2261
Epoch [560/1000], Loss: 0.2265
Epoch [570/1000], Loss: 0.2233
Epoch [580/1000], Loss: 0.2256
Epoch [590/1000], Loss: 0.2230
Epoch [600/1000], Loss: 0.2232
```

```
Epoch [610/1000], Loss: 0.2232
Epoch [620/1000], Loss: 0.2234
Epoch [630/1000], Loss: 0.2209
Epoch [640/1000], Loss: 0.2205
Epoch [650/1000], Loss: 0.2225
Epoch [660/1000], Loss: 0.2210
Epoch [670/1000], Loss: 0.2202
Epoch [680/1000], Loss: 0.2200
Epoch [690/1000], Loss: 0.2186
Epoch [700/1000], Loss: 0.2177
Epoch [710/1000], Loss: 0.2177
Epoch [720/1000], Loss: 0.2196
Epoch [730/1000], Loss: 0.2174
Epoch [740/1000], Loss: 0.2167
Epoch [750/1000], Loss: 0.2173
Epoch [760/1000], Loss: 0.2153
Epoch [770/1000], Loss: 0.2161
Epoch [780/1000], Loss: 0.2184
Epoch [790/1000], Loss: 0.2162
Epoch [800/1000], Loss: 0.2150
Epoch [810/1000], Loss: 0.2148
Epoch [820/1000], Loss: 0.2123
Epoch [830/1000], Loss: 0.2133
Epoch [840/1000], Loss: 0.2147
Epoch [850/1000], Loss: 0.2120
Epoch [860/1000], Loss: 0.2119
Epoch [870/1000], Loss: 0.2130
Epoch [880/1000], Loss: 0.2118
Epoch [890/1000], Loss: 0.2114
Epoch [900/1000], Loss: 0.2132
Epoch [910/1000], Loss: 0.2109
Epoch [920/1000], Loss: 0.2131
Epoch [930/1000], Loss: 0.2133
Epoch [940/1000], Loss: 0.2116
Epoch [950/1000], Loss: 0.2113
Epoch [960/1000], Loss: 0.2108
Epoch [970/1000], Loss: 0.2093
Epoch [980/1000], Loss: 0.2081
Epoch [990/1000], Loss: 0.2095
Epoch [1000/1000], Loss: 0.2100

Train Accuracy: 0.9336

Test Accuracy: 0.9261
```

As expected, test accuracy increased

We can try to improve the overall accuracy by adding more layers

Try lesser epochs to reduce overfitting

In [68]:
```python
first_layer_neurons = 1024


# Increase the number of neurons in each layer by a factor of 4
class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.fc1 = nn.Linear(input_size, first_layer_neurons)
```

```
        self.relu1 = nn.ReLU()
        self.fc2 = nn.Linear(first_layer_neurons, first_layer_neurons //
        self.relu2 = nn.ReLU()
        self.fc3 = nn.Linear(first_layer_neurons // 2, first_layer_neuron
        self.relu3 = nn.ReLU()
        self.fc4 = nn.Linear(first_layer_neurons // 4, first_layer_neuron
        self.relu4 = nn.ReLU()
        self.fc5 = nn.Linear(first_layer_neurons // 8, 1)
        self.relu5 = nn.ReLU()
        self.sigmoid = nn.Sigmoid()
        self.dropout1 = nn.Dropout(0.3)
        self.dropout2 = nn.Dropout(0.3)
        self.dropout3 = nn.Dropout(0.3)
        self.dropout4 = nn.Dropout(0.3)
        self.dropout5 = nn.Dropout(0.3)

    def forward(self, x):
        x = self.relu1(self.fc1(x))
        x = self.dropout1(x)
        x = self.relu2(self.fc2(x))
        x = self.dropout2(x)
        x = self.relu3(self.fc3(x))
        x = self.dropout3(x)
        x = self.relu4(self.fc4(x))
        x = self.dropout4(x)
        x = self.fc5(x)
        x = self.sigmoid(x)
        return x


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
epochs = 200
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/200], Loss: 0.4419
Epoch [20/200], Loss: 0.3765
Epoch [30/200], Loss: 0.3497
Epoch [40/200], Loss: 0.3111
Epoch [50/200], Loss: 0.2821
Epoch [60/200], Loss: 0.2672
Epoch [70/200], Loss: 0.2559
Epoch [80/200], Loss: 0.2486
Epoch [90/200], Loss: 0.2402
Epoch [100/200], Loss: 0.2354
Epoch [110/200], Loss: 0.2279
Epoch [120/200], Loss: 0.2242
Epoch [130/200], Loss: 0.2212
Epoch [140/200], Loss: 0.2185
Epoch [150/200], Loss: 0.2163
Epoch [160/200], Loss: 0.2135
Epoch [170/200], Loss: 0.2103
Epoch [180/200], Loss: 0.2071
Epoch [190/200], Loss: 0.2045
Epoch [200/200], Loss: 0.2016

Train Accuracy: 0.9377

Test Accuracy: 0.9261
```

Change from sigmoid to BCEWithLogitsLoss which is more stable by avoiding issues with vanishing gradients

In [69]:
```
first_layer_neurons = 1024


# Increase the number of neurons in each layer by a factor of 4
class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.fc1 = nn.Linear(input_size, first_layer_neurons)
        self.relu1 = nn.ReLU()
        self.fc2 = nn.Linear(first_layer_neurons, first_layer_neurons //
        self.relu2 = nn.ReLU()
        self.fc3 = nn.Linear(first_layer_neurons // 2, first_layer_neuron
        self.relu3 = nn.ReLU()
        self.fc4 = nn.Linear(first_layer_neurons // 4, first_layer_neuron
        self.relu4 = nn.ReLU()
        self.fc5 = nn.Linear(first_layer_neurons // 8, 1)
        self.relu5 = nn.ReLU()
        self.dropout1 = nn.Dropout(0.3)
        self.dropout2 = nn.Dropout(0.3)
        self.dropout3 = nn.Dropout(0.3)
        self.dropout4 = nn.Dropout(0.3)
        self.dropout5 = nn.Dropout(0.3)

    def forward(self, x):
        x = self.relu1(self.fc1(x))
        x = self.dropout1(x)
        x = self.relu2(self.fc2(x))
        x = self.dropout2(x)
        x = self.relu3(self.fc3(x))
        x = self.dropout3(x)
        x = self.relu4(self.fc4(x))
```

```
        x = self.dropout4(x)
        x = self.fc5(x)
        return x


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
epochs = 200
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/200], Loss: 0.4184
Epoch [20/200], Loss: 0.3683
Epoch [30/200], Loss: 0.3243
Epoch [40/200], Loss: 0.2886
Epoch [50/200], Loss: 0.2697
Epoch [60/200], Loss: 0.2587
Epoch [70/200], Loss: 0.2490
Epoch [80/200], Loss: 0.2401
Epoch [90/200], Loss: 0.2343
Epoch [100/200], Loss: 0.2290
Epoch [110/200], Loss: 0.2245
Epoch [120/200], Loss: 0.2199
Epoch [130/200], Loss: 0.2194
Epoch [140/200], Loss: 0.2144
Epoch [150/200], Loss: 0.2093
Epoch [160/200], Loss: 0.2088
Epoch [170/200], Loss: 0.2046
Epoch [180/200], Loss: 0.2043
Epoch [190/200], Loss: 0.2024
Epoch [200/200], Loss: 0.1972

Train Accuracy: 0.9375

Test Accuracy: 0.9219
```

Increase epoch to reduce bias and add weight decay (L2 regularization) to reduce variance/overfitting

In [70]:
```
first_layer_neurons = 1024


# Increase the number of neurons in each layer by a factor of 4
class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.fc1 = nn.Linear(input_size, first_layer_neurons)
        self.relu1 = nn.ReLU()
        self.fc2 = nn.Linear(first_layer_neurons, first_layer_neurons //
        self.relu2 = nn.ReLU()
        self.fc3 = nn.Linear(first_layer_neurons // 2, first_layer_neuron
        self.relu3 = nn.ReLU()
        self.fc4 = nn.Linear(first_layer_neurons // 4, first_layer_neuron
        self.relu4 = nn.ReLU()
        self.fc5 = nn.Linear(first_layer_neurons // 8, 1)
        self.relu5 = nn.ReLU()
        self.dropout1 = nn.Dropout(0.3)
        self.dropout2 = nn.Dropout(0.3)
        self.dropout3 = nn.Dropout(0.3)
        self.dropout4 = nn.Dropout(0.3)
        self.dropout5 = nn.Dropout(0.3)

    def forward(self, x):
        x = self.relu1(self.fc1(x))
        x = self.dropout1(x)
        x = self.relu2(self.fc2(x))
        x = self.dropout2(x)
        x = self.relu3(self.fc3(x))
        x = self.dropout3(x)
        x = self.relu4(self.fc4(x))
        x = self.dropout4(x)
        x = self.fc5(x)
        return x


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
# Add regularization in weight decay
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-5)

# Training loop
epochs = 500
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
```

```
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/500], Loss: 0.4348
Epoch [20/500], Loss: 0.3690
Epoch [30/500], Loss: 0.3272
Epoch [40/500], Loss: 0.2910
Epoch [50/500], Loss: 0.2707
Epoch [60/500], Loss: 0.2592
Epoch [70/500], Loss: 0.2503
Epoch [80/500], Loss: 0.2440
Epoch [90/500], Loss: 0.2366
Epoch [100/500], Loss: 0.2317
Epoch [110/500], Loss: 0.2266
Epoch [120/500], Loss: 0.2222
Epoch [130/500], Loss: 0.2213
Epoch [140/500], Loss: 0.2168
Epoch [150/500], Loss: 0.2131
Epoch [160/500], Loss: 0.2107
Epoch [170/500], Loss: 0.2066
Epoch [180/500], Loss: 0.2060
Epoch [190/500], Loss: 0.2020
Epoch [200/500], Loss: 0.1994
Epoch [210/500], Loss: 0.1970
Epoch [220/500], Loss: 0.1955
Epoch [230/500], Loss: 0.1951
Epoch [240/500], Loss: 0.1949
Epoch [250/500], Loss: 0.1877
Epoch [260/500], Loss: 0.1876
Epoch [270/500], Loss: 0.1858
Epoch [280/500], Loss: 0.1838
Epoch [290/500], Loss: 0.1789
Epoch [300/500], Loss: 0.1768
Epoch [310/500], Loss: 0.1767
Epoch [320/500], Loss: 0.1750
Epoch [330/500], Loss: 0.1735
Epoch [340/500], Loss: 0.1707
Epoch [350/500], Loss: 0.1687
Epoch [360/500], Loss: 0.1667
Epoch [370/500], Loss: 0.1662
Epoch [380/500], Loss: 0.1634
Epoch [390/500], Loss: 0.1601
Epoch [400/500], Loss: 0.1567
Epoch [410/500], Loss: 0.1604
Epoch [420/500], Loss: 0.1530
Epoch [430/500], Loss: 0.1517
Epoch [440/500], Loss: 0.1485
Epoch [450/500], Loss: 0.1456
Epoch [460/500], Loss: 0.1450
Epoch [470/500], Loss: 0.1479
Epoch [480/500], Loss: 0.1414
Epoch [490/500], Loss: 0.1391
Epoch [500/500], Loss: 0.1386

Train Accuracy: 0.9566

Test Accuracy: 0.9186
```

Try increase dropout to prevent overfitting

Increase weight decay by factor of 10 to reduce overfitting and increase dropout to 0.5

In [71]:
```
first_layer_neurons = 1024
dropout_rate = 0.4


class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.fc1 = nn.Linear(input_size, first_layer_neurons)
        self.relu1 = nn.ReLU()
        self.fc2 = nn.Linear(first_layer_neurons, first_layer_neurons //
        self.relu2 = nn.ReLU()
        self.fc3 = nn.Linear(first_layer_neurons // 2, first_layer_neuron
        self.relu3 = nn.ReLU()
        self.fc4 = nn.Linear(first_layer_neurons // 4, first_layer_neuron
        self.relu4 = nn.ReLU()
        self.fc5 = nn.Linear(first_layer_neurons // 8, 1)
        self.relu5 = nn.ReLU()
        self.dropout1 = nn.Dropout(dropout_rate)
        self.dropout2 = nn.Dropout(dropout_rate)
        self.dropout3 = nn.Dropout(dropout_rate)
        self.dropout4 = nn.Dropout(dropout_rate)
        self.dropout5 = nn.Dropout(dropout_rate)

    def forward(self, x):
        x = self.relu1(self.fc1(x))
        x = self.dropout1(x)
        x = self.relu2(self.fc2(x))
        x = self.dropout2(x)
        x = self.relu3(self.fc3(x))
        x = self.dropout3(x)
        x = self.relu4(self.fc4(x))
        x = self.dropout4(x)
        x = self.fc5(x)
        return x


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
# Add regularization in weight decay
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-3)

# Training loop
epochs = 500
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
```

```
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/500], Loss: 0.4170
Epoch [20/500], Loss: 0.3730
Epoch [30/500], Loss: 0.3425
Epoch [40/500], Loss: 0.3022
Epoch [50/500], Loss: 0.2809
Epoch [60/500], Loss: 0.2661
Epoch [70/500], Loss: 0.2596
Epoch [80/500], Loss: 0.2489
Epoch [90/500], Loss: 0.2429
Epoch [100/500], Loss: 0.2363
Epoch [110/500], Loss: 0.2324
Epoch [120/500], Loss: 0.2293
Epoch [130/500], Loss: 0.2278
Epoch [140/500], Loss: 0.2237
Epoch [150/500], Loss: 0.2215
Epoch [160/500], Loss: 0.2198
Epoch [170/500], Loss: 0.2181
Epoch [180/500], Loss: 0.2134
Epoch [190/500], Loss: 0.2169
Epoch [200/500], Loss: 0.2131
Epoch [210/500], Loss: 0.2120
Epoch [220/500], Loss: 0.2105
Epoch [230/500], Loss: 0.2096
Epoch [240/500], Loss: 0.2074
Epoch [250/500], Loss: 0.2055
Epoch [260/500], Loss: 0.2058
Epoch [270/500], Loss: 0.2037
Epoch [280/500], Loss: 0.2052
Epoch [290/500], Loss: 0.2030
Epoch [300/500], Loss: 0.2020
Epoch [310/500], Loss: 0.2007
Epoch [320/500], Loss: 0.2003
Epoch [330/500], Loss: 0.2031
Epoch [340/500], Loss: 0.1994
Epoch [350/500], Loss: 0.1984
Epoch [360/500], Loss: 0.1962
Epoch [370/500], Loss: 0.1949
Epoch [380/500], Loss: 0.1938
Epoch [390/500], Loss: 0.1938
Epoch [400/500], Loss: 0.1926
Epoch [410/500], Loss: 0.1913
Epoch [420/500], Loss: 0.1913
Epoch [430/500], Loss: 0.1923
Epoch [440/500], Loss: 0.1911
Epoch [450/500], Loss: 0.1890
Epoch [460/500], Loss: 0.1882
Epoch [470/500], Loss: 0.1963
Epoch [480/500], Loss: 0.1923
Epoch [490/500], Loss: 0.1878
Epoch [500/500], Loss: 0.1847

Train Accuracy: 0.9395

Test Accuracy: 0.9246
```

Try with lesser neurons

In [72]:
```
first_layer_neurons = 512
dropout_rate = 0.4
```

```
class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.fc1 = nn.Linear(input_size, first_layer_neurons)
        self.relu1 = nn.ReLU()
        self.fc2 = nn.Linear(first_layer_neurons, first_layer_neurons //
        self.relu2 = nn.ReLU()
        self.fc3 = nn.Linear(first_layer_neurons // 2, first_layer_neuron
        self.relu3 = nn.ReLU()
        self.fc4 = nn.Linear(first_layer_neurons // 4, first_layer_neuron
        self.relu4 = nn.ReLU()
        self.fc5 = nn.Linear(first_layer_neurons // 8, 1)
        self.relu5 = nn.ReLU()
        self.dropout1 = nn.Dropout(dropout_rate)
        self.dropout2 = nn.Dropout(dropout_rate)
        self.dropout3 = nn.Dropout(dropout_rate)
        self.dropout4 = nn.Dropout(dropout_rate)
        self.dropout5 = nn.Dropout(dropout_rate)

    def forward(self, x):
        x = self.relu1(self.fc1(x))
        x = self.dropout1(x)
        x = self.relu2(self.fc2(x))
        x = self.dropout2(x)
        x = self.relu3(self.fc3(x))
        x = self.dropout3(x)
        x = self.relu4(self.fc4(x))
        x = self.dropout4(x)
        x = self.fc5(x)
        return x


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
# Add regularization in weight decay
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-3)

# Training loop
epochs = 500
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
```

```
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/500], Loss: 0.5262
Epoch [20/500], Loss: 0.4100
Epoch [30/500], Loss: 0.3815
Epoch [40/500], Loss: 0.3523
Epoch [50/500], Loss: 0.3227
Epoch [60/500], Loss: 0.3045
Epoch [70/500], Loss: 0.2848
Epoch [80/500], Loss: 0.2775
Epoch [90/500], Loss: 0.2700
Epoch [100/500], Loss: 0.2631
Epoch [110/500], Loss: 0.2565
Epoch [120/500], Loss: 0.2525
Epoch [130/500], Loss: 0.2458
Epoch [140/500], Loss: 0.2427
Epoch [150/500], Loss: 0.2393
Epoch [160/500], Loss: 0.2347
Epoch [170/500], Loss: 0.2323
Epoch [180/500], Loss: 0.2308
Epoch [190/500], Loss: 0.2294
Epoch [200/500], Loss: 0.2266
Epoch [210/500], Loss: 0.2249
Epoch [220/500], Loss: 0.2242
Epoch [230/500], Loss: 0.2217
Epoch [240/500], Loss: 0.2196
Epoch [250/500], Loss: 0.2201
Epoch [260/500], Loss: 0.2175
Epoch [270/500], Loss: 0.2138
Epoch [280/500], Loss: 0.2157
Epoch [290/500], Loss: 0.2134
Epoch [300/500], Loss: 0.2145
Epoch [310/500], Loss: 0.2148
Epoch [320/500], Loss: 0.2143
Epoch [330/500], Loss: 0.2109
Epoch [340/500], Loss: 0.2103
Epoch [350/500], Loss: 0.2117
Epoch [360/500], Loss: 0.2079
Epoch [370/500], Loss: 0.2097
Epoch [380/500], Loss: 0.2073
Epoch [390/500], Loss: 0.2081
Epoch [400/500], Loss: 0.2056
Epoch [410/500], Loss: 0.2047
Epoch [420/500], Loss: 0.2043
Epoch [430/500], Loss: 0.2050
Epoch [440/500], Loss: 0.2034
Epoch [450/500], Loss: 0.2029
Epoch [460/500], Loss: 0.2014
Epoch [470/500], Loss: 0.2021
Epoch [480/500], Loss: 0.2030
Epoch [490/500], Loss: 0.2035
Epoch [500/500], Loss: 0.2019

Train Accuracy: 0.9367

Test Accuracy: 0.9261
```

In [73]:

```
first_layer_neurons = 256
dropout_rate = 0.3
```

```
class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.model = nn.Sequential(
            # nn.Linear(, 256),
            # nn.BatchNorm1d(256),
            # nn.ReLU(),
            # nn.Dropout(dropout_rate),
            nn.Linear(input_size, 128),
            nn.BatchNorm1d(128),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(128, 64),
            nn.BatchNorm1d(64),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(64, 32),
            nn.BatchNorm1d(32),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(32, 1),
        )

    def forward(self, x):
        return self.model(x)  # Use if you're sticking with BCELoss


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
# Add regularization in weight decay
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-3)

# Training loop
epochs = 500
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/500], Loss: 0.7350
Epoch [20/500], Loss: 0.6287
Epoch [30/500], Loss: 0.5676
Epoch [40/500], Loss: 0.5266
Epoch [50/500], Loss: 0.4984
Epoch [60/500], Loss: 0.4739
Epoch [70/500], Loss: 0.4519
Epoch [80/500], Loss: 0.4338
Epoch [90/500], Loss: 0.4138
Epoch [100/500], Loss: 0.3993
Epoch [110/500], Loss: 0.3836
Epoch [120/500], Loss: 0.3690
Epoch [130/500], Loss: 0.3554
Epoch [140/500], Loss: 0.3449
Epoch [150/500], Loss: 0.3342
Epoch [160/500], Loss: 0.3255
Epoch [170/500], Loss: 0.3162
Epoch [180/500], Loss: 0.3052
Epoch [190/500], Loss: 0.3022
Epoch [200/500], Loss: 0.2958
Epoch [210/500], Loss: 0.2909
Epoch [220/500], Loss: 0.2866
Epoch [230/500], Loss: 0.2790
Epoch [240/500], Loss: 0.2767
Epoch [250/500], Loss: 0.2702
Epoch [260/500], Loss: 0.2702
Epoch [270/500], Loss: 0.2637
Epoch [280/500], Loss: 0.2627
Epoch [290/500], Loss: 0.2596
Epoch [300/500], Loss: 0.2561
Epoch [310/500], Loss: 0.2528
Epoch [320/500], Loss: 0.2501
Epoch [330/500], Loss: 0.2482
Epoch [340/500], Loss: 0.2460
Epoch [350/500], Loss: 0.2428
Epoch [360/500], Loss: 0.2415
Epoch [370/500], Loss: 0.2397
Epoch [380/500], Loss: 0.2391
Epoch [390/500], Loss: 0.2388
Epoch [400/500], Loss: 0.2340
Epoch [410/500], Loss: 0.2310
Epoch [420/500], Loss: 0.2298
Epoch [430/500], Loss: 0.2269
Epoch [440/500], Loss: 0.2289
Epoch [450/500], Loss: 0.2220
Epoch [460/500], Loss: 0.2220
Epoch [470/500], Loss: 0.2248
Epoch [480/500], Loss: 0.2199
Epoch [490/500], Loss: 0.2212
Epoch [500/500], Loss: 0.2184

Train Accuracy: 0.9302

Test Accuracy: 0.9249
```

In [74]:
```python
first_layer_neurons = 256
dropout_rate = 0.3


class LoanDefaultNN(nn.Module):
```

```python
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.model = nn.Sequential(
            # nn.Linear(, 256),
            # nn.BatchNorm1d(256),
            # nn.ReLU(),
            # nn.Dropout(dropout_rate),
            nn.Linear(input_size, 26),
            nn.BatchNorm1d(26),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(26, 13),
            nn.BatchNorm1d(13),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(13, 6),
            nn.BatchNorm1d(6),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(6, 1),
        )

    def forward(self, x):
        return self.model(x)  # Use if you're sticking with BCELoss


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
# Add regularization in weight decay
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-3)

# Training loop
epochs = 2000
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/2000], Loss: 0.6066
Epoch [20/2000], Loss: 0.5785
Epoch [30/2000], Loss: 0.5595
Epoch [40/2000], Loss: 0.5420
Epoch [50/2000], Loss: 0.5271
Epoch [60/2000], Loss: 0.5143
Epoch [70/2000], Loss: 0.5022
Epoch [80/2000], Loss: 0.4888
Epoch [90/2000], Loss: 0.4791
Epoch [100/2000], Loss: 0.4721
Epoch [110/2000], Loss: 0.4596
Epoch [120/2000], Loss: 0.4519
Epoch [130/2000], Loss: 0.4449
Epoch [140/2000], Loss: 0.4365
Epoch [150/2000], Loss: 0.4313
Epoch [160/2000], Loss: 0.4245
Epoch [170/2000], Loss: 0.4148
Epoch [180/2000], Loss: 0.4115
Epoch [190/2000], Loss: 0.4052
Epoch [200/2000], Loss: 0.3971
Epoch [210/2000], Loss: 0.3942
Epoch [220/2000], Loss: 0.3890
Epoch [230/2000], Loss: 0.3830
Epoch [240/2000], Loss: 0.3777
Epoch [250/2000], Loss: 0.3749
Epoch [260/2000], Loss: 0.3710
Epoch [270/2000], Loss: 0.3664
Epoch [280/2000], Loss: 0.3589
Epoch [290/2000], Loss: 0.3588
Epoch [300/2000], Loss: 0.3546
Epoch [310/2000], Loss: 0.3531
Epoch [320/2000], Loss: 0.3467
Epoch [330/2000], Loss: 0.3447
Epoch [340/2000], Loss: 0.3390
Epoch [350/2000], Loss: 0.3363
Epoch [360/2000], Loss: 0.3331
Epoch [370/2000], Loss: 0.3313
Epoch [380/2000], Loss: 0.3253
Epoch [390/2000], Loss: 0.3212
Epoch [400/2000], Loss: 0.3170
Epoch [410/2000], Loss: 0.3170
Epoch [420/2000], Loss: 0.3140
Epoch [430/2000], Loss: 0.3087
Epoch [440/2000], Loss: 0.3070
Epoch [450/2000], Loss: 0.3033
Epoch [460/2000], Loss: 0.3031
Epoch [470/2000], Loss: 0.2977
Epoch [480/2000], Loss: 0.2962
Epoch [490/2000], Loss: 0.2953
Epoch [500/2000], Loss: 0.2945
Epoch [510/2000], Loss: 0.2891
Epoch [520/2000], Loss: 0.2889
Epoch [530/2000], Loss: 0.2847
Epoch [540/2000], Loss: 0.2837
Epoch [550/2000], Loss: 0.2836
Epoch [560/2000], Loss: 0.2837
Epoch [570/2000], Loss: 0.2789
Epoch [580/2000], Loss: 0.2824
Epoch [590/2000], Loss: 0.2742
Epoch [600/2000], Loss: 0.2769
```

```
Epoch [610/2000], Loss: 0.2801
Epoch [620/2000], Loss: 0.2739
Epoch [630/2000], Loss: 0.2742
Epoch [640/2000], Loss: 0.2753
Epoch [650/2000], Loss: 0.2740
Epoch [660/2000], Loss: 0.2711
Epoch [670/2000], Loss: 0.2715
Epoch [680/2000], Loss: 0.2706
Epoch [690/2000], Loss: 0.2684
Epoch [700/2000], Loss: 0.2689
Epoch [710/2000], Loss: 0.2707
Epoch [720/2000], Loss: 0.2692
Epoch [730/2000], Loss: 0.2686
Epoch [740/2000], Loss: 0.2688
Epoch [750/2000], Loss: 0.2680
Epoch [760/2000], Loss: 0.2686
Epoch [770/2000], Loss: 0.2664
Epoch [780/2000], Loss: 0.2685
Epoch [790/2000], Loss: 0.2644
Epoch [800/2000], Loss: 0.2638
Epoch [810/2000], Loss: 0.2644
Epoch [820/2000], Loss: 0.2625
Epoch [830/2000], Loss: 0.2617
Epoch [840/2000], Loss: 0.2598
Epoch [850/2000], Loss: 0.2593
Epoch [860/2000], Loss: 0.2646
Epoch [870/2000], Loss: 0.2633
Epoch [880/2000], Loss: 0.2581
Epoch [890/2000], Loss: 0.2615
Epoch [900/2000], Loss: 0.2614
Epoch [910/2000], Loss: 0.2601
Epoch [920/2000], Loss: 0.2617
Epoch [930/2000], Loss: 0.2591
Epoch [940/2000], Loss: 0.2594
Epoch [950/2000], Loss: 0.2602
Epoch [960/2000], Loss: 0.2563
Epoch [970/2000], Loss: 0.2599
Epoch [980/2000], Loss: 0.2583
Epoch [990/2000], Loss: 0.2570
Epoch [1000/2000], Loss: 0.2568
Epoch [1010/2000], Loss: 0.2553
Epoch [1020/2000], Loss: 0.2557
Epoch [1030/2000], Loss: 0.2557
Epoch [1040/2000], Loss: 0.2534
Epoch [1050/2000], Loss: 0.2592
Epoch [1060/2000], Loss: 0.2568
Epoch [1070/2000], Loss: 0.2538
Epoch [1080/2000], Loss: 0.2560
Epoch [1090/2000], Loss: 0.2569
Epoch [1100/2000], Loss: 0.2517
Epoch [1110/2000], Loss: 0.2511
Epoch [1120/2000], Loss: 0.2510
Epoch [1130/2000], Loss: 0.2545
Epoch [1140/2000], Loss: 0.2526
Epoch [1150/2000], Loss: 0.2528
Epoch [1160/2000], Loss: 0.2545
Epoch [1170/2000], Loss: 0.2532
Epoch [1180/2000], Loss: 0.2519
Epoch [1190/2000], Loss: 0.2541
Epoch [1200/2000], Loss: 0.2535
```

```
Epoch [1210/2000], Loss: 0.2525
Epoch [1220/2000], Loss: 0.2507
Epoch [1230/2000], Loss: 0.2508
Epoch [1240/2000], Loss: 0.2517
Epoch [1250/2000], Loss: 0.2524
Epoch [1260/2000], Loss: 0.2503
Epoch [1270/2000], Loss: 0.2512
Epoch [1280/2000], Loss: 0.2497
Epoch [1290/2000], Loss: 0.2515
Epoch [1300/2000], Loss: 0.2544
Epoch [1310/2000], Loss: 0.2515
Epoch [1320/2000], Loss: 0.2510
Epoch [1330/2000], Loss: 0.2492
Epoch [1340/2000], Loss: 0.2530
Epoch [1350/2000], Loss: 0.2498
Epoch [1360/2000], Loss: 0.2478
Epoch [1370/2000], Loss: 0.2502
Epoch [1380/2000], Loss: 0.2485
Epoch [1390/2000], Loss: 0.2507
Epoch [1400/2000], Loss: 0.2495
Epoch [1410/2000], Loss: 0.2484
Epoch [1420/2000], Loss: 0.2469
Epoch [1430/2000], Loss: 0.2486
Epoch [1440/2000], Loss: 0.2477
Epoch [1450/2000], Loss: 0.2471
Epoch [1460/2000], Loss: 0.2467
Epoch [1470/2000], Loss: 0.2466
Epoch [1480/2000], Loss: 0.2481
Epoch [1490/2000], Loss: 0.2462
Epoch [1500/2000], Loss: 0.2484
Epoch [1510/2000], Loss: 0.2480
Epoch [1520/2000], Loss: 0.2472
Epoch [1530/2000], Loss: 0.2481
Epoch [1540/2000], Loss: 0.2510
Epoch [1550/2000], Loss: 0.2464
Epoch [1560/2000], Loss: 0.2479
Epoch [1570/2000], Loss: 0.2476
Epoch [1580/2000], Loss: 0.2477
Epoch [1590/2000], Loss: 0.2463
Epoch [1600/2000], Loss: 0.2489
Epoch [1610/2000], Loss: 0.2464
Epoch [1620/2000], Loss: 0.2496
Epoch [1630/2000], Loss: 0.2470
Epoch [1640/2000], Loss: 0.2508
Epoch [1650/2000], Loss: 0.2475
Epoch [1660/2000], Loss: 0.2500
Epoch [1670/2000], Loss: 0.2475
Epoch [1680/2000], Loss: 0.2449
Epoch [1690/2000], Loss: 0.2472
Epoch [1700/2000], Loss: 0.2500
Epoch [1710/2000], Loss: 0.2469
Epoch [1720/2000], Loss: 0.2453
Epoch [1730/2000], Loss: 0.2453
Epoch [1740/2000], Loss: 0.2483
Epoch [1750/2000], Loss: 0.2449
Epoch [1760/2000], Loss: 0.2433
Epoch [1770/2000], Loss: 0.2457
Epoch [1780/2000], Loss: 0.2450
Epoch [1790/2000], Loss: 0.2464
Epoch [1800/2000], Loss: 0.2475
```

```
Epoch [1810/2000], Loss: 0.2477
Epoch [1820/2000], Loss: 0.2430
Epoch [1830/2000], Loss: 0.2461
Epoch [1840/2000], Loss: 0.2471
Epoch [1850/2000], Loss: 0.2469
Epoch [1860/2000], Loss: 0.2453
Epoch [1870/2000], Loss: 0.2468
Epoch [1880/2000], Loss: 0.2471
Epoch [1890/2000], Loss: 0.2454
Epoch [1900/2000], Loss: 0.2481
Epoch [1910/2000], Loss: 0.2457
Epoch [1920/2000], Loss: 0.2441
Epoch [1930/2000], Loss: 0.2474
Epoch [1940/2000], Loss: 0.2460
Epoch [1950/2000], Loss: 0.2472
Epoch [1960/2000], Loss: 0.2467
Epoch [1970/2000], Loss: 0.2444
Epoch [1980/2000], Loss: 0.2407
Epoch [1990/2000], Loss: 0.2449
Epoch [2000/2000], Loss: 0.2450

Train Accuracy: 0.9321

Test Accuracy: 0.9282
```

In [75]:

```
first_layer_neurons = 256
dropout_rate = 0.2


class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.model = nn.Sequential(
            # nn.Linear(, 256),
            # nn.BatchNorm1d(256),
            # nn.ReLU(),
            # nn.Dropout(dropout_rate),
            nn.Linear(input_size, 26),
            nn.BatchNorm1d(26),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(26, 13),
            nn.BatchNorm1d(13),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(13, 6),
            nn.BatchNorm1d(6),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(6, 1),
        )

    def forward(self, x):
        return self.model(x)  # Use if you're sticking with BCELoss


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
# Add regularization in weight decay
```

```
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-3)

# Training loop
epochs = 2000
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/2000], Loss: 0.8835
Epoch [20/2000], Loss: 0.8384
Epoch [30/2000], Loss: 0.8035
Epoch [40/2000], Loss: 0.7787
Epoch [50/2000], Loss: 0.7556
Epoch [60/2000], Loss: 0.7368
Epoch [70/2000], Loss: 0.7202
Epoch [80/2000], Loss: 0.7051
Epoch [90/2000], Loss: 0.6904
Epoch [100/2000], Loss: 0.6752
Epoch [110/2000], Loss: 0.6604
Epoch [120/2000], Loss: 0.6456
Epoch [130/2000], Loss: 0.6327
Epoch [140/2000], Loss: 0.6172
Epoch [150/2000], Loss: 0.6016
Epoch [160/2000], Loss: 0.5894
Epoch [170/2000], Loss: 0.5728
Epoch [180/2000], Loss: 0.5602
Epoch [190/2000], Loss: 0.5470
Epoch [200/2000], Loss: 0.5357
Epoch [210/2000], Loss: 0.5211
Epoch [220/2000], Loss: 0.5110
Epoch [230/2000], Loss: 0.4979
Epoch [240/2000], Loss: 0.4868
Epoch [250/2000], Loss: 0.4750
Epoch [260/2000], Loss: 0.4654
Epoch [270/2000], Loss: 0.4562
Epoch [280/2000], Loss: 0.4488
Epoch [290/2000], Loss: 0.4392
Epoch [300/2000], Loss: 0.4341
Epoch [310/2000], Loss: 0.4229
Epoch [320/2000], Loss: 0.4177
Epoch [330/2000], Loss: 0.4131
Epoch [340/2000], Loss: 0.4042
Epoch [350/2000], Loss: 0.3980
Epoch [360/2000], Loss: 0.3925
Epoch [370/2000], Loss: 0.3891
Epoch [380/2000], Loss: 0.3846
Epoch [390/2000], Loss: 0.3791
Epoch [400/2000], Loss: 0.3743
Epoch [410/2000], Loss: 0.3707
Epoch [420/2000], Loss: 0.3672
Epoch [430/2000], Loss: 0.3636
Epoch [440/2000], Loss: 0.3596
Epoch [450/2000], Loss: 0.3537
Epoch [460/2000], Loss: 0.3507
Epoch [470/2000], Loss: 0.3489
Epoch [480/2000], Loss: 0.3431
Epoch [490/2000], Loss: 0.3389
Epoch [500/2000], Loss: 0.3292
Epoch [510/2000], Loss: 0.3196
Epoch [520/2000], Loss: 0.3169
Epoch [530/2000], Loss: 0.3115
Epoch [540/2000], Loss: 0.3055
Epoch [550/2000], Loss: 0.3063
Epoch [560/2000], Loss: 0.2981
Epoch [570/2000], Loss: 0.2962
Epoch [580/2000], Loss: 0.2933
Epoch [590/2000], Loss: 0.2925
Epoch [600/2000], Loss: 0.2866
```

```
Epoch [610/2000], Loss: 0.2868
Epoch [620/2000], Loss: 0.2816
Epoch [630/2000], Loss: 0.2834
Epoch [640/2000], Loss: 0.2801
Epoch [650/2000], Loss: 0.2777
Epoch [660/2000], Loss: 0.2769
Epoch [670/2000], Loss: 0.2743
Epoch [680/2000], Loss: 0.2728
Epoch [690/2000], Loss: 0.2713
Epoch [700/2000], Loss: 0.2700
Epoch [710/2000], Loss: 0.2720
Epoch [720/2000], Loss: 0.2674
Epoch [730/2000], Loss: 0.2650
Epoch [740/2000], Loss: 0.2643
Epoch [750/2000], Loss: 0.2663
Epoch [760/2000], Loss: 0.2609
Epoch [770/2000], Loss: 0.2613
Epoch [780/2000], Loss: 0.2578
Epoch [790/2000], Loss: 0.2592
Epoch [800/2000], Loss: 0.2561
Epoch [810/2000], Loss: 0.2538
Epoch [820/2000], Loss: 0.2538
Epoch [830/2000], Loss: 0.2543
Epoch [840/2000], Loss: 0.2512
Epoch [850/2000], Loss: 0.2533
Epoch [860/2000], Loss: 0.2503
Epoch [870/2000], Loss: 0.2522
Epoch [880/2000], Loss: 0.2507
Epoch [890/2000], Loss: 0.2480
Epoch [900/2000], Loss: 0.2470
Epoch [910/2000], Loss: 0.2476
Epoch [920/2000], Loss: 0.2466
Epoch [930/2000], Loss: 0.2460
Epoch [940/2000], Loss: 0.2440
Epoch [950/2000], Loss: 0.2453
Epoch [960/2000], Loss: 0.2442
Epoch [970/2000], Loss: 0.2430
Epoch [980/2000], Loss: 0.2434
Epoch [990/2000], Loss: 0.2447
Epoch [1000/2000], Loss: 0.2403
Epoch [1010/2000], Loss: 0.2408
Epoch [1020/2000], Loss: 0.2405
Epoch [1030/2000], Loss: 0.2428
Epoch [1040/2000], Loss: 0.2404
Epoch [1050/2000], Loss: 0.2431
Epoch [1060/2000], Loss: 0.2413
Epoch [1070/2000], Loss: 0.2395
Epoch [1080/2000], Loss: 0.2397
Epoch [1090/2000], Loss: 0.2395
Epoch [1100/2000], Loss: 0.2381
Epoch [1110/2000], Loss: 0.2408
Epoch [1120/2000], Loss: 0.2399
Epoch [1130/2000], Loss: 0.2405
Epoch [1140/2000], Loss: 0.2391
Epoch [1150/2000], Loss: 0.2397
Epoch [1160/2000], Loss: 0.2386
Epoch [1170/2000], Loss: 0.2360
Epoch [1180/2000], Loss: 0.2404
Epoch [1190/2000], Loss: 0.2380
Epoch [1200/2000], Loss: 0.2354
```

```
Epoch [1210/2000], Loss: 0.2361
Epoch [1220/2000], Loss: 0.2389
Epoch [1230/2000], Loss: 0.2356
Epoch [1240/2000], Loss: 0.2361
Epoch [1250/2000], Loss: 0.2357
Epoch [1260/2000], Loss: 0.2359
Epoch [1270/2000], Loss: 0.2338
Epoch [1280/2000], Loss: 0.2401
Epoch [1290/2000], Loss: 0.2326
Epoch [1300/2000], Loss: 0.2369
Epoch [1310/2000], Loss: 0.2323
Epoch [1320/2000], Loss: 0.2345
Epoch [1330/2000], Loss: 0.2324
Epoch [1340/2000], Loss: 0.2346
Epoch [1350/2000], Loss: 0.2336
Epoch [1360/2000], Loss: 0.2354
Epoch [1370/2000], Loss: 0.2350
Epoch [1380/2000], Loss: 0.2329
Epoch [1390/2000], Loss: 0.2335
Epoch [1400/2000], Loss: 0.2332
Epoch [1410/2000], Loss: 0.2346
Epoch [1420/2000], Loss: 0.2352
Epoch [1430/2000], Loss: 0.2367
Epoch [1440/2000], Loss: 0.2342
Epoch [1450/2000], Loss: 0.2352
Epoch [1460/2000], Loss: 0.2329
Epoch [1470/2000], Loss: 0.2340
Epoch [1480/2000], Loss: 0.2323
Epoch [1490/2000], Loss: 0.2314
Epoch [1500/2000], Loss: 0.2334
Epoch [1510/2000], Loss: 0.2325
Epoch [1520/2000], Loss: 0.2303
Epoch [1530/2000], Loss: 0.2321
Epoch [1540/2000], Loss: 0.2331
Epoch [1550/2000], Loss: 0.2317
Epoch [1560/2000], Loss: 0.2336
Epoch [1570/2000], Loss: 0.2331
Epoch [1580/2000], Loss: 0.2328
Epoch [1590/2000], Loss: 0.2300
Epoch [1600/2000], Loss: 0.2327
Epoch [1610/2000], Loss: 0.2345
Epoch [1620/2000], Loss: 0.2314
Epoch [1630/2000], Loss: 0.2377
Epoch [1640/2000], Loss: 0.2335
Epoch [1650/2000], Loss: 0.2318
Epoch [1660/2000], Loss: 0.2312
Epoch [1670/2000], Loss: 0.2327
Epoch [1680/2000], Loss: 0.2292
Epoch [1690/2000], Loss: 0.2320
Epoch [1700/2000], Loss: 0.2323
Epoch [1710/2000], Loss: 0.2330
Epoch [1720/2000], Loss: 0.2314
Epoch [1730/2000], Loss: 0.2326
Epoch [1740/2000], Loss: 0.2327
Epoch [1750/2000], Loss: 0.2291
Epoch [1760/2000], Loss: 0.2317
Epoch [1770/2000], Loss: 0.2303
Epoch [1780/2000], Loss: 0.2344
Epoch [1790/2000], Loss: 0.2325
Epoch [1800/2000], Loss: 0.2292
```

```
Epoch [1810/2000], Loss: 0.2313
Epoch [1820/2000], Loss: 0.2324
Epoch [1830/2000], Loss: 0.2338
Epoch [1840/2000], Loss: 0.2330
Epoch [1850/2000], Loss: 0.2310
Epoch [1860/2000], Loss: 0.2293
Epoch [1870/2000], Loss: 0.2315
Epoch [1880/2000], Loss: 0.2290
Epoch [1890/2000], Loss: 0.2306
Epoch [1900/2000], Loss: 0.2281
Epoch [1910/2000], Loss: 0.2336
Epoch [1920/2000], Loss: 0.2283
Epoch [1930/2000], Loss: 0.2277
Epoch [1940/2000], Loss: 0.2308
Epoch [1950/2000], Loss: 0.2304
Epoch [1960/2000], Loss: 0.2316
Epoch [1970/2000], Loss: 0.2315
Epoch [1980/2000], Loss: 0.2286
Epoch [1990/2000], Loss: 0.2280
Epoch [2000/2000], Loss: 0.2290

Train Accuracy: 0.9339

Test Accuracy: 0.9293
```

In [76]:

```python
first_layer_neurons = 256
dropout_rate = 0.3


class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.model = nn.Sequential(
            # nn.Linear(, 256),
            # nn.BatchNorm1d(256),
            # nn.ReLU(),
            # nn.Dropout(dropout_rate),
            nn.Linear(input_size, 64),
            nn.BatchNorm1d(64),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(64, 32),
            nn.BatchNorm1d(32),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(32, 16),
            nn.BatchNorm1d(16),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(16, 8),
            nn.BatchNorm1d(8),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(8, 4),
            nn.BatchNorm1d(4),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(4, 1),
        )
```

```
    def forward(self, x):
        return self.model(x)  # Use if you're sticking with BCELoss


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
# Add regularization in weight decay
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-3)

# Training loop
epochs = 1000
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/1000], Loss: 0.7695
Epoch [20/1000], Loss: 0.7368
Epoch [30/1000], Loss: 0.7066
Epoch [40/1000], Loss: 0.6839
Epoch [50/1000], Loss: 0.6661
Epoch [60/1000], Loss: 0.6514
Epoch [70/1000], Loss: 0.6359
Epoch [80/1000], Loss: 0.6255
Epoch [90/1000], Loss: 0.6136
Epoch [100/1000], Loss: 0.6021
Epoch [110/1000], Loss: 0.5913
Epoch [120/1000], Loss: 0.5828
Epoch [130/1000], Loss: 0.5743
Epoch [140/1000], Loss: 0.5632
Epoch [150/1000], Loss: 0.5564
Epoch [160/1000], Loss: 0.5501
Epoch [170/1000], Loss: 0.5404
Epoch [180/1000], Loss: 0.5336
Epoch [190/1000], Loss: 0.5251
Epoch [200/1000], Loss: 0.5194
Epoch [210/1000], Loss: 0.5090
Epoch [220/1000], Loss: 0.5043
Epoch [230/1000], Loss: 0.4987
Epoch [240/1000], Loss: 0.4946
Epoch [250/1000], Loss: 0.4875
Epoch [260/1000], Loss: 0.4788
Epoch [270/1000], Loss: 0.4739
Epoch [280/1000], Loss: 0.4675
Epoch [290/1000], Loss: 0.4648
Epoch [300/1000], Loss: 0.4586
Epoch [310/1000], Loss: 0.4542
Epoch [320/1000], Loss: 0.4490
Epoch [330/1000], Loss: 0.4455
Epoch [340/1000], Loss: 0.4386
Epoch [350/1000], Loss: 0.4359
Epoch [360/1000], Loss: 0.4250
Epoch [370/1000], Loss: 0.4233
Epoch [380/1000], Loss: 0.4218
Epoch [390/1000], Loss: 0.4167
Epoch [400/1000], Loss: 0.4085
Epoch [410/1000], Loss: 0.4055
Epoch [420/1000], Loss: 0.4010
Epoch [430/1000], Loss: 0.3994
Epoch [440/1000], Loss: 0.3960
Epoch [450/1000], Loss: 0.3917
Epoch [460/1000], Loss: 0.3884
Epoch [470/1000], Loss: 0.3853
Epoch [480/1000], Loss: 0.3832
Epoch [490/1000], Loss: 0.3775
Epoch [500/1000], Loss: 0.3734
Epoch [510/1000], Loss: 0.3715
Epoch [520/1000], Loss: 0.3670
Epoch [530/1000], Loss: 0.3667
Epoch [540/1000], Loss: 0.3634
Epoch [550/1000], Loss: 0.3619
Epoch [560/1000], Loss: 0.3622
Epoch [570/1000], Loss: 0.3557
Epoch [580/1000], Loss: 0.3568
Epoch [590/1000], Loss: 0.3529
Epoch [600/1000], Loss: 0.3514
```

```
Epoch [610/1000], Loss: 0.3499
Epoch [620/1000], Loss: 0.3413
Epoch [630/1000], Loss: 0.3400
Epoch [640/1000], Loss: 0.3402
Epoch [650/1000], Loss: 0.3413
Epoch [660/1000], Loss: 0.3375
Epoch [670/1000], Loss: 0.3358
Epoch [680/1000], Loss: 0.3334
Epoch [690/1000], Loss: 0.3328
Epoch [700/1000], Loss: 0.3321
Epoch [710/1000], Loss: 0.3275
Epoch [720/1000], Loss: 0.3270
Epoch [730/1000], Loss: 0.3234
Epoch [740/1000], Loss: 0.3209
Epoch [750/1000], Loss: 0.3227
Epoch [760/1000], Loss: 0.3206
Epoch [770/1000], Loss: 0.3223
Epoch [780/1000], Loss: 0.3182
Epoch [790/1000], Loss: 0.3205
Epoch [800/1000], Loss: 0.3181
Epoch [810/1000], Loss: 0.3144
Epoch [820/1000], Loss: 0.3155
Epoch [830/1000], Loss: 0.3147
Epoch [840/1000], Loss: 0.3135
Epoch [850/1000], Loss: 0.3135
Epoch [860/1000], Loss: 0.3114
Epoch [870/1000], Loss: 0.3122
Epoch [880/1000], Loss: 0.3105
Epoch [890/1000], Loss: 0.3122
Epoch [900/1000], Loss: 0.3099
Epoch [910/1000], Loss: 0.3042
Epoch [920/1000], Loss: 0.3082
Epoch [930/1000], Loss: 0.3050
Epoch [940/1000], Loss: 0.3087
Epoch [950/1000], Loss: 0.3027
Epoch [960/1000], Loss: 0.3015
Epoch [970/1000], Loss: 0.3040
Epoch [980/1000], Loss: 0.3027
Epoch [990/1000], Loss: 0.3019
Epoch [1000/1000], Loss: 0.3008

Train Accuracy: 0.9364

Test Accuracy: 0.9302
```

In [77]:

```python
first_layer_neurons = 256
dropout_rate = 0.3


class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(input_size, 52),
            nn.BatchNorm1d(52),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(52, 26),
            nn.BatchNorm1d(26),
            nn.LeakyReLU(0.01),
```

```
            nn.Dropout(dropout_rate),
            nn.Linear(26, 13),
            nn.BatchNorm1d(13),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(13, 6),
            nn.BatchNorm1d(6),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            # nn.Linear(6, 3),
            # nn.BatchNorm1d(3),
            # nn.LeakyReLU(0.01),
            # nn.Dropout(dropout_rate),
            nn.Linear(6, 1),
        )

    def forward(self, x):
        return self.model(x)  # Use if you're sticking with BCELoss


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
# Add regularization in weight decay
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-3)

# Training loop
epochs = 1500
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/1500], Loss: 0.6404
Epoch [20/1500], Loss: 0.6045
Epoch [30/1500], Loss: 0.5781
Epoch [40/1500], Loss: 0.5572
Epoch [50/1500], Loss: 0.5399
Epoch [60/1500], Loss: 0.5214
Epoch [70/1500], Loss: 0.5088
Epoch [80/1500], Loss: 0.4972
Epoch [90/1500], Loss: 0.4843
Epoch [100/1500], Loss: 0.4705
Epoch [110/1500], Loss: 0.4596
Epoch [120/1500], Loss: 0.4509
Epoch [130/1500], Loss: 0.4404
Epoch [140/1500], Loss: 0.4324
Epoch [150/1500], Loss: 0.4260
Epoch [160/1500], Loss: 0.4140
Epoch [170/1500], Loss: 0.4095
Epoch [180/1500], Loss: 0.3994
Epoch [190/1500], Loss: 0.3937
Epoch [200/1500], Loss: 0.3859
Epoch [210/1500], Loss: 0.3788
Epoch [220/1500], Loss: 0.3731
Epoch [230/1500], Loss: 0.3710
Epoch [240/1500], Loss: 0.3601
Epoch [250/1500], Loss: 0.3601
Epoch [260/1500], Loss: 0.3558
Epoch [270/1500], Loss: 0.3479
Epoch [280/1500], Loss: 0.3445
Epoch [290/1500], Loss: 0.3415
Epoch [300/1500], Loss: 0.3382
Epoch [310/1500], Loss: 0.3365
Epoch [320/1500], Loss: 0.3314
Epoch [330/1500], Loss: 0.3281
Epoch [340/1500], Loss: 0.3267
Epoch [350/1500], Loss: 0.3228
Epoch [360/1500], Loss: 0.3193
Epoch [370/1500], Loss: 0.3184
Epoch [380/1500], Loss: 0.3143
Epoch [390/1500], Loss: 0.3112
Epoch [400/1500], Loss: 0.3119
Epoch [410/1500], Loss: 0.3105
Epoch [420/1500], Loss: 0.3060
Epoch [430/1500], Loss: 0.3028
Epoch [440/1500], Loss: 0.3057
Epoch [450/1500], Loss: 0.3024
Epoch [460/1500], Loss: 0.2968
Epoch [470/1500], Loss: 0.2988
Epoch [480/1500], Loss: 0.2947
Epoch [490/1500], Loss: 0.2920
Epoch [500/1500], Loss: 0.2898
Epoch [510/1500], Loss: 0.2884
Epoch [520/1500], Loss: 0.2877
Epoch [530/1500], Loss: 0.2835
Epoch [540/1500], Loss: 0.2836
Epoch [550/1500], Loss: 0.2824
Epoch [560/1500], Loss: 0.2841
Epoch [570/1500], Loss: 0.2812
Epoch [580/1500], Loss: 0.2775
Epoch [590/1500], Loss: 0.2768
Epoch [600/1500], Loss: 0.2789
```

```
Epoch [610/1500], Loss: 0.2782
Epoch [620/1500], Loss: 0.2758
Epoch [630/1500], Loss: 0.2756
Epoch [640/1500], Loss: 0.2759
Epoch [650/1500], Loss: 0.2723
Epoch [660/1500], Loss: 0.2728
Epoch [670/1500], Loss: 0.2718
Epoch [680/1500], Loss: 0.2714
Epoch [690/1500], Loss: 0.2719
Epoch [700/1500], Loss: 0.2691
Epoch [710/1500], Loss: 0.2715
Epoch [720/1500], Loss: 0.2677
Epoch [730/1500], Loss: 0.2705
Epoch [740/1500], Loss: 0.2710
Epoch [750/1500], Loss: 0.2656
Epoch [760/1500], Loss: 0.2696
Epoch [770/1500], Loss: 0.2665
Epoch [780/1500], Loss: 0.2646
Epoch [790/1500], Loss: 0.2648
Epoch [800/1500], Loss: 0.2646
Epoch [810/1500], Loss: 0.2662
Epoch [820/1500], Loss: 0.2646
Epoch [830/1500], Loss: 0.2671
Epoch [840/1500], Loss: 0.2623
Epoch [850/1500], Loss: 0.2639
Epoch [860/1500], Loss: 0.2634
Epoch [870/1500], Loss: 0.2626
Epoch [880/1500], Loss: 0.2630
Epoch [890/1500], Loss: 0.2610
Epoch [900/1500], Loss: 0.2614
Epoch [910/1500], Loss: 0.2646
Epoch [920/1500], Loss: 0.2603
Epoch [930/1500], Loss: 0.2617
Epoch [940/1500], Loss: 0.2599
Epoch [950/1500], Loss: 0.2603
Epoch [960/1500], Loss: 0.2584
Epoch [970/1500], Loss: 0.2584
Epoch [980/1500], Loss: 0.2589
Epoch [990/1500], Loss: 0.2593
Epoch [1000/1500], Loss: 0.2614
Epoch [1010/1500], Loss: 0.2592
Epoch [1020/1500], Loss: 0.2592
Epoch [1030/1500], Loss: 0.2588
Epoch [1040/1500], Loss: 0.2583
Epoch [1050/1500], Loss: 0.2587
Epoch [1060/1500], Loss: 0.2595
Epoch [1070/1500], Loss: 0.2575
Epoch [1080/1500], Loss: 0.2552
Epoch [1090/1500], Loss: 0.2584
Epoch [1100/1500], Loss: 0.2585
Epoch [1110/1500], Loss: 0.2541
Epoch [1120/1500], Loss: 0.2581
Epoch [1130/1500], Loss: 0.2580
Epoch [1140/1500], Loss: 0.2561
Epoch [1150/1500], Loss: 0.2565
Epoch [1160/1500], Loss: 0.2549
Epoch [1170/1500], Loss: 0.2556
Epoch [1180/1500], Loss: 0.2542
Epoch [1190/1500], Loss: 0.2550
Epoch [1200/1500], Loss: 0.2565
```

```
Epoch [1210/1500], Loss: 0.2530
Epoch [1220/1500], Loss: 0.2556
Epoch [1230/1500], Loss: 0.2523
Epoch [1240/1500], Loss: 0.2561
Epoch [1250/1500], Loss: 0.2553
Epoch [1260/1500], Loss: 0.2541
Epoch [1270/1500], Loss: 0.2561
Epoch [1280/1500], Loss: 0.2551
Epoch [1290/1500], Loss: 0.2555
Epoch [1300/1500], Loss: 0.2519
Epoch [1310/1500], Loss: 0.2532
Epoch [1320/1500], Loss: 0.2550
Epoch [1330/1500], Loss: 0.2520
Epoch [1340/1500], Loss: 0.2555
Epoch [1350/1500], Loss: 0.2588
Epoch [1360/1500], Loss: 0.2519
Epoch [1370/1500], Loss: 0.2555
Epoch [1380/1500], Loss: 0.2555
Epoch [1390/1500], Loss: 0.2522
Epoch [1400/1500], Loss: 0.2531
Epoch [1410/1500], Loss: 0.2552
Epoch [1420/1500], Loss: 0.2528
Epoch [1430/1500], Loss: 0.2527
Epoch [1440/1500], Loss: 0.2502
Epoch [1450/1500], Loss: 0.2528
Epoch [1460/1500], Loss: 0.2518
Epoch [1470/1500], Loss: 0.2524
Epoch [1480/1500], Loss: 0.2522
Epoch [1490/1500], Loss: 0.2514
Epoch [1500/1500], Loss: 0.2498

Train Accuracy: 0.9372

Test Accuracy: 0.9319
```

In [78]:

```python
first_layer_neurons = 256
dropout_rate = 0.3


class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(input_size, 52),
            nn.BatchNorm1d(52),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(52, 26),
            nn.BatchNorm1d(26),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(26, 13),
            nn.BatchNorm1d(13),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            # nn.Linear(13, 6),
            # nn.BatchNorm1d(6),
            # nn.LeakyReLU(0.01),
            # nn.Dropout(dropout_rate),
            # nn.Linear(6, 3),
```

```
            # nn.BatchNorm1d(3),
            # nn.LeakyReLU(0.01),
            # nn.Dropout(dropout_rate),
            nn.Linear(13, 1),
        )

    def forward(self, x):
        return self.model(x)  # Use if you're sticking with BCELoss


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
# Add regularization in weight decay
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-3)

# Training loop
epochs = 800
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/800], Loss: 0.6724
Epoch [20/800], Loss: 0.6161
Epoch [30/800], Loss: 0.5721
Epoch [40/800], Loss: 0.5406
Epoch [50/800], Loss: 0.5123
Epoch [60/800], Loss: 0.4936
Epoch [70/800], Loss: 0.4742
Epoch [80/800], Loss: 0.4570
Epoch [90/800], Loss: 0.4417
Epoch [100/800], Loss: 0.4273
Epoch [110/800], Loss: 0.4145
Epoch [120/800], Loss: 0.4034
Epoch [130/800], Loss: 0.3913
Epoch [140/800], Loss: 0.3820
Epoch [150/800], Loss: 0.3718
Epoch [160/800], Loss: 0.3629
Epoch [170/800], Loss: 0.3538
Epoch [180/800], Loss: 0.3467
Epoch [190/800], Loss: 0.3412
Epoch [200/800], Loss: 0.3351
Epoch [210/800], Loss: 0.3274
Epoch [220/800], Loss: 0.3243
Epoch [230/800], Loss: 0.3191
Epoch [240/800], Loss: 0.3157
Epoch [250/800], Loss: 0.3128
Epoch [260/800], Loss: 0.3094
Epoch [270/800], Loss: 0.3032
Epoch [280/800], Loss: 0.3012
Epoch [290/800], Loss: 0.2987
Epoch [300/800], Loss: 0.2958
Epoch [310/800], Loss: 0.2948
Epoch [320/800], Loss: 0.2883
Epoch [330/800], Loss: 0.2848
Epoch [340/800], Loss: 0.2852
Epoch [350/800], Loss: 0.2838
Epoch [360/800], Loss: 0.2791
Epoch [370/800], Loss: 0.2803
Epoch [380/800], Loss: 0.2758
Epoch [390/800], Loss: 0.2737
Epoch [400/800], Loss: 0.2723
Epoch [410/800], Loss: 0.2690
Epoch [420/800], Loss: 0.2696
Epoch [430/800], Loss: 0.2664
Epoch [440/800], Loss: 0.2634
Epoch [450/800], Loss: 0.2624
Epoch [460/800], Loss: 0.2607
Epoch [470/800], Loss: 0.2585
Epoch [480/800], Loss: 0.2579
Epoch [490/800], Loss: 0.2556
Epoch [500/800], Loss: 0.2557
Epoch [510/800], Loss: 0.2533
Epoch [520/800], Loss: 0.2538
Epoch [530/800], Loss: 0.2517
Epoch [540/800], Loss: 0.2455
Epoch [550/800], Loss: 0.2504
Epoch [560/800], Loss: 0.2463
Epoch [570/800], Loss: 0.2450
Epoch [580/800], Loss: 0.2446
Epoch [590/800], Loss: 0.2449
Epoch [600/800], Loss: 0.2446
```

```
Epoch [610/800], Loss: 0.2420
Epoch [620/800], Loss: 0.2403
Epoch [630/800], Loss: 0.2396
Epoch [640/800], Loss: 0.2360
Epoch [650/800], Loss: 0.2401
Epoch [660/800], Loss: 0.2357
Epoch [670/800], Loss: 0.2335
Epoch [680/800], Loss: 0.2345
Epoch [690/800], Loss: 0.2319
Epoch [700/800], Loss: 0.2344
Epoch [710/800], Loss: 0.2311
Epoch [720/800], Loss: 0.2328
Epoch [730/800], Loss: 0.2327
Epoch [740/800], Loss: 0.2320
Epoch [750/800], Loss: 0.2317
Epoch [760/800], Loss: 0.2290
Epoch [770/800], Loss: 0.2306
Epoch [780/800], Loss: 0.2285
Epoch [790/800], Loss: 0.2296
Epoch [800/800], Loss: 0.2272

Train Accuracy: 0.9324

Test Accuracy: 0.9289
```

In [79]:
```
first_layer_neurons = 256
dropout_rate = 0.3


class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(input_size, 104),
            nn.BatchNorm1d(104),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(104, 52),
            nn.BatchNorm1d(52),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(52, 26),
            nn.BatchNorm1d(26),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            # nn.Linear(26, 13),
            # nn.BatchNorm1d(13),
            # nn.LeakyReLU(0.01),
            # nn.Dropout(dropout_rate),
            # nn.Linear(13, 6),
            # nn.BatchNorm1d(6),
            # nn.LeakyReLU(0.01),
            # nn.Dropout(dropout_rate),
            # nn.Linear(6, 3),
            # nn.BatchNorm1d(3),
            # nn.LeakyReLU(0.01),
            # nn.Dropout(dropout_rate),
            nn.Linear(26, 1),
        )
```

```python
    def forward(self, x):
        return self.model(x)  # Use if you're sticking with BCELoss


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
# Add regularization in weight decay
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-3)

# Training loop
epochs = 2000
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/2000], Loss: 0.6166
Epoch [20/2000], Loss: 0.5379
Epoch [30/2000], Loss: 0.4846
Epoch [40/2000], Loss: 0.4485
Epoch [50/2000], Loss: 0.4231
Epoch [60/2000], Loss: 0.3999
Epoch [70/2000], Loss: 0.3807
Epoch [80/2000], Loss: 0.3657
Epoch [90/2000], Loss: 0.3506
Epoch [100/2000], Loss: 0.3408
Epoch [110/2000], Loss: 0.3321
Epoch [120/2000], Loss: 0.3200
Epoch [130/2000], Loss: 0.3133
Epoch [140/2000], Loss: 0.3088
Epoch [150/2000], Loss: 0.3015
Epoch [160/2000], Loss: 0.2961
Epoch [170/2000], Loss: 0.2918
Epoch [180/2000], Loss: 0.2855
Epoch [190/2000], Loss: 0.2821
Epoch [200/2000], Loss: 0.2777
Epoch [210/2000], Loss: 0.2759
Epoch [220/2000], Loss: 0.2753
Epoch [230/2000], Loss: 0.2699
Epoch [240/2000], Loss: 0.2704
Epoch [250/2000], Loss: 0.2634
Epoch [260/2000], Loss: 0.2599
Epoch [270/2000], Loss: 0.2606
Epoch [280/2000], Loss: 0.2561
Epoch [290/2000], Loss: 0.2540
Epoch [300/2000], Loss: 0.2526
Epoch [310/2000], Loss: 0.2513
Epoch [320/2000], Loss: 0.2470
Epoch [330/2000], Loss: 0.2468
Epoch [340/2000], Loss: 0.2462
Epoch [350/2000], Loss: 0.2464
Epoch [360/2000], Loss: 0.2417
Epoch [370/2000], Loss: 0.2419
Epoch [380/2000], Loss: 0.2395
Epoch [390/2000], Loss: 0.2384
Epoch [400/2000], Loss: 0.2376
Epoch [410/2000], Loss: 0.2319
Epoch [420/2000], Loss: 0.2325
Epoch [430/2000], Loss: 0.2319
Epoch [440/2000], Loss: 0.2285
Epoch [450/2000], Loss: 0.2299
Epoch [460/2000], Loss: 0.2251
Epoch [470/2000], Loss: 0.2233
Epoch [480/2000], Loss: 0.2248
Epoch [490/2000], Loss: 0.2226
Epoch [500/2000], Loss: 0.2209
Epoch [510/2000], Loss: 0.2169
Epoch [520/2000], Loss: 0.2207
Epoch [530/2000], Loss: 0.2164
Epoch [540/2000], Loss: 0.2158
Epoch [550/2000], Loss: 0.2153
Epoch [560/2000], Loss: 0.2153
Epoch [570/2000], Loss: 0.2137
Epoch [580/2000], Loss: 0.2144
Epoch [590/2000], Loss: 0.2118
Epoch [600/2000], Loss: 0.2102
```

```
Epoch [610/2000], Loss: 0.2109
Epoch [620/2000], Loss: 0.2070
Epoch [630/2000], Loss: 0.2076
Epoch [640/2000], Loss: 0.2087
Epoch [650/2000], Loss: 0.2078
Epoch [660/2000], Loss: 0.2072
Epoch [670/2000], Loss: 0.2066
Epoch [680/2000], Loss: 0.2064
Epoch [690/2000], Loss: 0.2069
Epoch [700/2000], Loss: 0.2033
Epoch [710/2000], Loss: 0.2025
Epoch [720/2000], Loss: 0.2021
Epoch [730/2000], Loss: 0.2014
Epoch [740/2000], Loss: 0.2037
Epoch [750/2000], Loss: 0.2032
Epoch [760/2000], Loss: 0.2015
Epoch [770/2000], Loss: 0.2027
Epoch [780/2000], Loss: 0.2003
Epoch [790/2000], Loss: 0.2018
Epoch [800/2000], Loss: 0.2025
Epoch [810/2000], Loss: 0.1999
Epoch [820/2000], Loss: 0.2004
Epoch [830/2000], Loss: 0.1988
Epoch [840/2000], Loss: 0.1950
Epoch [850/2000], Loss: 0.1997
Epoch [860/2000], Loss: 0.1977
Epoch [870/2000], Loss: 0.1986
Epoch [880/2000], Loss: 0.1967
Epoch [890/2000], Loss: 0.1976
Epoch [900/2000], Loss: 0.1970
Epoch [910/2000], Loss: 0.1985
Epoch [920/2000], Loss: 0.1967
Epoch [930/2000], Loss: 0.1940
Epoch [940/2000], Loss: 0.1955
Epoch [950/2000], Loss: 0.1945
Epoch [960/2000], Loss: 0.1945
Epoch [970/2000], Loss: 0.1919
Epoch [980/2000], Loss: 0.1946
Epoch [990/2000], Loss: 0.1958
Epoch [1000/2000], Loss: 0.1931
Epoch [1010/2000], Loss: 0.1948
Epoch [1020/2000], Loss: 0.1898
Epoch [1030/2000], Loss: 0.1939
Epoch [1040/2000], Loss: 0.1933
Epoch [1050/2000], Loss: 0.1936
Epoch [1060/2000], Loss: 0.1936
Epoch [1070/2000], Loss: 0.1958
Epoch [1080/2000], Loss: 0.1921
Epoch [1090/2000], Loss: 0.1921
Epoch [1100/2000], Loss: 0.1914
Epoch [1110/2000], Loss: 0.1929
Epoch [1120/2000], Loss: 0.1894
Epoch [1130/2000], Loss: 0.1918
Epoch [1140/2000], Loss: 0.1944
Epoch [1150/2000], Loss: 0.1949
Epoch [1160/2000], Loss: 0.1903
Epoch [1170/2000], Loss: 0.1871
Epoch [1180/2000], Loss: 0.1894
Epoch [1190/2000], Loss: 0.1913
Epoch [1200/2000], Loss: 0.1879
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Epoch [1210/2000], Loss: 0.1910
Epoch [1220/2000], Loss: 0.1909
Epoch [1230/2000], Loss: 0.1863
Epoch [1240/2000], Loss: 0.1900
Epoch [1250/2000], Loss: 0.1867
Epoch [1260/2000], Loss: 0.1863
Epoch [1270/2000], Loss: 0.1874
Epoch [1280/2000], Loss: 0.1896
Epoch [1290/2000], Loss: 0.1882
Epoch [1300/2000], Loss: 0.1883
Epoch [1310/2000], Loss: 0.1881
Epoch [1320/2000], Loss: 0.1878
Epoch [1330/2000], Loss: 0.1869
Epoch [1340/2000], Loss: 0.1879
Epoch [1350/2000], Loss: 0.1863
Epoch [1360/2000], Loss: 0.1874
Epoch [1370/2000], Loss: 0.1902
Epoch [1380/2000], Loss: 0.1873
Epoch [1390/2000], Loss: 0.1842
Epoch [1400/2000], Loss: 0.1865
Epoch [1410/2000], Loss: 0.1850
Epoch [1420/2000], Loss: 0.1858
Epoch [1430/2000], Loss: 0.1863
Epoch [1440/2000], Loss: 0.1842
Epoch [1450/2000], Loss: 0.1860
Epoch [1460/2000], Loss: 0.1852
Epoch [1470/2000], Loss: 0.1856
Epoch [1480/2000], Loss: 0.1845
Epoch [1490/2000], Loss: 0.1878
Epoch [1500/2000], Loss: 0.1888
Epoch [1510/2000], Loss: 0.1853
Epoch [1520/2000], Loss: 0.1844
Epoch [1530/2000], Loss: 0.1844
Epoch [1540/2000], Loss: 0.1863
Epoch [1550/2000], Loss: 0.1855
Epoch [1560/2000], Loss: 0.1833
Epoch [1570/2000], Loss: 0.1865
Epoch [1580/2000], Loss: 0.1846
Epoch [1590/2000], Loss: 0.1841
Epoch [1600/2000], Loss: 0.1866
Epoch [1610/2000], Loss: 0.1848
Epoch [1620/2000], Loss: 0.1841
Epoch [1630/2000], Loss: 0.1853
Epoch [1640/2000], Loss: 0.1871
Epoch [1650/2000], Loss: 0.1831
Epoch [1660/2000], Loss: 0.1863
Epoch [1670/2000], Loss: 0.1857
Epoch [1680/2000], Loss: 0.1857
Epoch [1690/2000], Loss: 0.1832
Epoch [1700/2000], Loss: 0.1830
Epoch [1710/2000], Loss: 0.1819
Epoch [1720/2000], Loss: 0.1822
Epoch [1730/2000], Loss: 0.1800
Epoch [1740/2000], Loss: 0.1827
Epoch [1750/2000], Loss: 0.1862
Epoch [1760/2000], Loss: 0.1848
Epoch [1770/2000], Loss: 0.1829
Epoch [1780/2000], Loss: 0.1844
Epoch [1790/2000], Loss: 0.1853
Epoch [1800/2000], Loss: 0.1830
```

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Epoch [1810/2000], Loss: 0.1830
Epoch [1820/2000], Loss: 0.1822
Epoch [1830/2000], Loss: 0.1815
Epoch [1840/2000], Loss: 0.1831
Epoch [1850/2000], Loss: 0.1841
Epoch [1860/2000], Loss: 0.1840
Epoch [1870/2000], Loss: 0.1824
Epoch [1880/2000], Loss: 0.1842
Epoch [1890/2000], Loss: 0.1811
Epoch [1900/2000], Loss: 0.1825
Epoch [1910/2000], Loss: 0.1801
Epoch [1920/2000], Loss: 0.1844
Epoch [1930/2000], Loss: 0.1824
Epoch [1940/2000], Loss: 0.1811
Epoch [1950/2000], Loss: 0.1852
Epoch [1960/2000], Loss: 0.1807
Epoch [1970/2000], Loss: 0.1807
Epoch [1980/2000], Loss: 0.1813
Epoch [1990/2000], Loss: 0.1827
Epoch [2000/2000], Loss: 0.1835

Train Accuracy: 0.9404

Test Accuracy: 0.9282
```

In [80]:

```python
first_layer_neurons = 256
dropout_rate = 0.3


class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(input_size, 256),
            nn.BatchNorm1d(256),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(256, 64),
            nn.BatchNorm1d(64),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(64, 16),
            nn.BatchNorm1d(16),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            # nn.Linear(26, 13),
            # nn.BatchNorm1d(13),
            # nn.LeakyReLU(0.01),
            # nn.Dropout(dropout_rate),
            # nn.Linear(13, 6),
            # nn.BatchNorm1d(6),
            # nn.LeakyReLU(0.01),
            # nn.Dropout(dropout_rate),
            # nn.Linear(6, 3),
            # nn.BatchNorm1d(3),
            # nn.LeakyReLU(0.01),
            # nn.Dropout(dropout_rate),
            nn.Linear(16, 1),
        )
```

```
    def forward(self, x):
        return self.model(x)  # Use if you're sticking with BCELoss


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
# Add regularization in weight decay
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-3)

# Training loop
epochs = 2000
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/2000], Loss: 0.5050
Epoch [20/2000], Loss: 0.4627
Epoch [30/2000], Loss: 0.4346
Epoch [40/2000], Loss: 0.4147
Epoch [50/2000], Loss: 0.3965
Epoch [60/2000], Loss: 0.3795
Epoch [70/2000], Loss: 0.3667
Epoch [80/2000], Loss: 0.3521
Epoch [90/2000], Loss: 0.3400
Epoch [100/2000], Loss: 0.3303
Epoch [110/2000], Loss: 0.3196
Epoch [120/2000], Loss: 0.3096
Epoch [130/2000], Loss: 0.3046
Epoch [140/2000], Loss: 0.2967
Epoch [150/2000], Loss: 0.2889
Epoch [160/2000], Loss: 0.2854
Epoch [170/2000], Loss: 0.2791
Epoch [180/2000], Loss: 0.2745
Epoch [190/2000], Loss: 0.2719
Epoch [200/2000], Loss: 0.2683
Epoch [210/2000], Loss: 0.2622
Epoch [220/2000], Loss: 0.2584
Epoch [230/2000], Loss: 0.2562
Epoch [240/2000], Loss: 0.2531
Epoch [250/2000], Loss: 0.2485
Epoch [260/2000], Loss: 0.2489
Epoch [270/2000], Loss: 0.2458
Epoch [280/2000], Loss: 0.2436
Epoch [290/2000], Loss: 0.2425
Epoch [300/2000], Loss: 0.2416
Epoch [310/2000], Loss: 0.2355
Epoch [320/2000], Loss: 0.2357
Epoch [330/2000], Loss: 0.2350
Epoch [340/2000], Loss: 0.2312
Epoch [350/2000], Loss: 0.2298
Epoch [360/2000], Loss: 0.2275
Epoch [370/2000], Loss: 0.2275
Epoch [380/2000], Loss: 0.2283
Epoch [390/2000], Loss: 0.2257
Epoch [400/2000], Loss: 0.2211
Epoch [410/2000], Loss: 0.2192
Epoch [420/2000], Loss: 0.2176
Epoch [430/2000], Loss: 0.2188
Epoch [440/2000], Loss: 0.2170
Epoch [450/2000], Loss: 0.2148
Epoch [460/2000], Loss: 0.2129
Epoch [470/2000], Loss: 0.2136
Epoch [480/2000], Loss: 0.2104
Epoch [490/2000], Loss: 0.2099
Epoch [500/2000], Loss: 0.2084
Epoch [510/2000], Loss: 0.2060
Epoch [520/2000], Loss: 0.2080
Epoch [530/2000], Loss: 0.2065
Epoch [540/2000], Loss: 0.2034
Epoch [550/2000], Loss: 0.2020
Epoch [560/2000], Loss: 0.2047
Epoch [570/2000], Loss: 0.1995
Epoch [580/2000], Loss: 0.1971
Epoch [590/2000], Loss: 0.1960
Epoch [600/2000], Loss: 0.1975
```

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Epoch [610/2000], Loss: 0.1955
Epoch [620/2000], Loss: 0.1940
Epoch [630/2000], Loss: 0.1924
Epoch [640/2000], Loss: 0.1942
Epoch [650/2000], Loss: 0.1916
Epoch [660/2000], Loss: 0.1937
Epoch [670/2000], Loss: 0.1926
Epoch [680/2000], Loss: 0.1886
Epoch [690/2000], Loss: 0.1912
Epoch [700/2000], Loss: 0.1878
Epoch [710/2000], Loss: 0.1868
Epoch [720/2000], Loss: 0.1856
Epoch [730/2000], Loss: 0.1881
Epoch [740/2000], Loss: 0.1837
Epoch [750/2000], Loss: 0.1847
Epoch [760/2000], Loss: 0.1845
Epoch [770/2000], Loss: 0.1808
Epoch [780/2000], Loss: 0.1839
Epoch [790/2000], Loss: 0.1833
Epoch [800/2000], Loss: 0.1826
Epoch [810/2000], Loss: 0.1811
Epoch [820/2000], Loss: 0.1816
Epoch [830/2000], Loss: 0.1806
Epoch [840/2000], Loss: 0.1794
Epoch [850/2000], Loss: 0.1768
Epoch [860/2000], Loss: 0.1748
Epoch [870/2000], Loss: 0.1775
Epoch [880/2000], Loss: 0.1754
Epoch [890/2000], Loss: 0.1773
Epoch [900/2000], Loss: 0.1752
Epoch [910/2000], Loss: 0.1766
Epoch [920/2000], Loss: 0.1746
Epoch [930/2000], Loss: 0.1724
Epoch [940/2000], Loss: 0.1751
Epoch [950/2000], Loss: 0.1697
Epoch [960/2000], Loss: 0.1718
Epoch [970/2000], Loss: 0.1693
Epoch [980/2000], Loss: 0.1688
Epoch [990/2000], Loss: 0.1679
Epoch [1000/2000], Loss: 0.1705
Epoch [1010/2000], Loss: 0.1678
Epoch [1020/2000], Loss: 0.1675
Epoch [1030/2000], Loss: 0.1680
Epoch [1040/2000], Loss: 0.1675
Epoch [1050/2000], Loss: 0.1674
Epoch [1060/2000], Loss: 0.1659
Epoch [1070/2000], Loss: 0.1672
Epoch [1080/2000], Loss: 0.1664
Epoch [1090/2000], Loss: 0.1613
Epoch [1100/2000], Loss: 0.1618
Epoch [1110/2000], Loss: 0.1643
Epoch [1120/2000], Loss: 0.1634
Epoch [1130/2000], Loss: 0.1638
Epoch [1140/2000], Loss: 0.1632
Epoch [1150/2000], Loss: 0.1599
Epoch [1160/2000], Loss: 0.1634
Epoch [1170/2000], Loss: 0.1591
Epoch [1180/2000], Loss: 0.1592
Epoch [1190/2000], Loss: 0.1599
Epoch [1200/2000], Loss: 0.1611
```

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Epoch [1210/2000], Loss: 0.1593
Epoch [1220/2000], Loss: 0.1592
Epoch [1230/2000], Loss: 0.1621
Epoch [1240/2000], Loss: 0.1584
Epoch [1250/2000], Loss: 0.1599
Epoch [1260/2000], Loss: 0.1549
Epoch [1270/2000], Loss: 0.1588
Epoch [1280/2000], Loss: 0.1567
Epoch [1290/2000], Loss: 0.1585
Epoch [1300/2000], Loss: 0.1551
Epoch [1310/2000], Loss: 0.1590
Epoch [1320/2000], Loss: 0.1591
Epoch [1330/2000], Loss: 0.1552
Epoch [1340/2000], Loss: 0.1546
Epoch [1350/2000], Loss: 0.1534
Epoch [1360/2000], Loss: 0.1547
Epoch [1370/2000], Loss: 0.1545
Epoch [1380/2000], Loss: 0.1522
Epoch [1390/2000], Loss: 0.1520
Epoch [1400/2000], Loss: 0.1557
Epoch [1410/2000], Loss: 0.1535
Epoch [1420/2000], Loss: 0.1503
Epoch [1430/2000], Loss: 0.1502
Epoch [1440/2000], Loss: 0.1553
Epoch [1450/2000], Loss: 0.1542
Epoch [1460/2000], Loss: 0.1528
Epoch [1470/2000], Loss: 0.1513
Epoch [1480/2000], Loss: 0.1547
Epoch [1490/2000], Loss: 0.1527
Epoch [1500/2000], Loss: 0.1528
Epoch [1510/2000], Loss: 0.1505
Epoch [1520/2000], Loss: 0.1533
Epoch [1530/2000], Loss: 0.1506
Epoch [1540/2000], Loss: 0.1503
Epoch [1550/2000], Loss: 0.1474
Epoch [1560/2000], Loss: 0.1493
Epoch [1570/2000], Loss: 0.1496
Epoch [1580/2000], Loss: 0.1507
Epoch [1590/2000], Loss: 0.1487
Epoch [1600/2000], Loss: 0.1492
Epoch [1610/2000], Loss: 0.1497
Epoch [1620/2000], Loss: 0.1456
Epoch [1630/2000], Loss: 0.1456
Epoch [1640/2000], Loss: 0.1448
Epoch [1650/2000], Loss: 0.1486
Epoch [1660/2000], Loss: 0.1453
Epoch [1670/2000], Loss: 0.1476
Epoch [1680/2000], Loss: 0.1455
Epoch [1690/2000], Loss: 0.1488
Epoch [1700/2000], Loss: 0.1481
Epoch [1710/2000], Loss: 0.1473
Epoch [1720/2000], Loss: 0.1444
Epoch [1730/2000], Loss: 0.1479
Epoch [1740/2000], Loss: 0.1502
Epoch [1750/2000], Loss: 0.1467
Epoch [1760/2000], Loss: 0.1429
Epoch [1770/2000], Loss: 0.1461
Epoch [1780/2000], Loss: 0.1421
Epoch [1790/2000], Loss: 0.1432
Epoch [1800/2000], Loss: 0.1508
```

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Epoch [1810/2000], Loss: 0.1433
Epoch [1820/2000], Loss: 0.1461
Epoch [1830/2000], Loss: 0.1452
Epoch [1840/2000], Loss: 0.1439
Epoch [1850/2000], Loss: 0.1466
Epoch [1860/2000], Loss: 0.1456
Epoch [1870/2000], Loss: 0.1428
Epoch [1880/2000], Loss: 0.1457
Epoch [1890/2000], Loss: 0.1448
Epoch [1900/2000], Loss: 0.1438
Epoch [1910/2000], Loss: 0.1460
Epoch [1920/2000], Loss: 0.1439
Epoch [1930/2000], Loss: 0.1400
Epoch [1940/2000], Loss: 0.1429
Epoch [1950/2000], Loss: 0.1440
Epoch [1960/2000], Loss: 0.1423
Epoch [1970/2000], Loss: 0.1412
Epoch [1980/2000], Loss: 0.1415
Epoch [1990/2000], Loss: 0.1414
Epoch [2000/2000], Loss: 0.1427

Train Accuracy: 0.9559

Test Accuracy: 0.9281
```

In [81]:

```python
dropout_rate = 0.4


class LoanDefaultNN(nn.Module):
    def __init__(self, input_size):
        super(LoanDefaultNN, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(input_size, 104),
            nn.BatchNorm1d(104),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(104, 52),
            nn.BatchNorm1d(52),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            nn.Linear(52, 26),
            nn.BatchNorm1d(26),
            nn.LeakyReLU(0.01),
            nn.Dropout(dropout_rate),
            # nn.Linear(26, 13),
            # nn.BatchNorm1d(13),
            # nn.LeakyReLU(0.01),
            # nn.Dropout(dropout_rate),
            # nn.Linear(13, 6),
            # nn.BatchNorm1d(6),
            # nn.LeakyReLU(0.01),
            # nn.Dropout(dropout_rate),
            # nn.Linear(6, 3),
            # nn.BatchNorm1d(3),
            # nn.LeakyReLU(0.01),
            # nn.Dropout(dropout_rate),
            nn.Linear(26, 1),
        )

    def forward(self, x):
```

```
        return self.model(x)  # Use if you're sticking with BCELoss


# Initialize model, loss, optimizer
model = LoanDefaultNN(X_train.shape[1])
criterion = nn.BCEWithLogitsLoss()
# Add regularization in weight decay
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-3)

# Training loop
epochs = 2000
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(X_train_tensor)
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
with torch.no_grad():
    test_preds = model(X_train_tensor)
    test_predicted_classes = (test_preds > 0.5).float()
    test_accuracy = (test_predicted_classes == y_train_tensor).float().me
    print(f"\nTrain Accuracy: {test_accuracy.item():.4f}")
    preds = model(X_test_tensor)
    predicted_classes = (preds > 0.5).float()
    accuracy = (predicted_classes == y_test_tensor).float().mean()
    print(f"\nTest Accuracy: {accuracy.item():.4f}")
```

```
Epoch [10/2000], Loss: 0.6861
Epoch [20/2000], Loss: 0.6102
Epoch [30/2000], Loss: 0.5577
Epoch [40/2000], Loss: 0.5176
Epoch [50/2000], Loss: 0.4910
Epoch [60/2000], Loss: 0.4661
Epoch [70/2000], Loss: 0.4457
Epoch [80/2000], Loss: 0.4286
Epoch [90/2000], Loss: 0.4122
Epoch [100/2000], Loss: 0.3970
Epoch [110/2000], Loss: 0.3861
Epoch [120/2000], Loss: 0.3719
Epoch [130/2000], Loss: 0.3641
Epoch [140/2000], Loss: 0.3505
Epoch [150/2000], Loss: 0.3449
Epoch [160/2000], Loss: 0.3349
Epoch [170/2000], Loss: 0.3253
Epoch [180/2000], Loss: 0.3196
Epoch [190/2000], Loss: 0.3138
Epoch [200/2000], Loss: 0.3077
Epoch [210/2000], Loss: 0.3032
Epoch [220/2000], Loss: 0.2978
Epoch [230/2000], Loss: 0.2936
Epoch [240/2000], Loss: 0.2913
Epoch [250/2000], Loss: 0.2866
Epoch [260/2000], Loss: 0.2831
Epoch [270/2000], Loss: 0.2821
Epoch [280/2000], Loss: 0.2776
Epoch [290/2000], Loss: 0.2756
Epoch [300/2000], Loss: 0.2716
Epoch [310/2000], Loss: 0.2722
Epoch [320/2000], Loss: 0.2716
Epoch [330/2000], Loss: 0.2636
Epoch [340/2000], Loss: 0.2660
Epoch [350/2000], Loss: 0.2614
Epoch [360/2000], Loss: 0.2594
Epoch [370/2000], Loss: 0.2574
Epoch [380/2000], Loss: 0.2548
Epoch [390/2000], Loss: 0.2525
Epoch [400/2000], Loss: 0.2531
Epoch [410/2000], Loss: 0.2505
Epoch [420/2000], Loss: 0.2468
Epoch [430/2000], Loss: 0.2470
Epoch [440/2000], Loss: 0.2406
Epoch [450/2000], Loss: 0.2417
Epoch [460/2000], Loss: 0.2380
Epoch [470/2000], Loss: 0.2387
Epoch [480/2000], Loss: 0.2389
Epoch [490/2000], Loss: 0.2369
Epoch [500/2000], Loss: 0.2343
Epoch [510/2000], Loss: 0.2289
Epoch [520/2000], Loss: 0.2316
Epoch [530/2000], Loss: 0.2293
Epoch [540/2000], Loss: 0.2295
Epoch [550/2000], Loss: 0.2305
Epoch [560/2000], Loss: 0.2286
Epoch [570/2000], Loss: 0.2286
Epoch [580/2000], Loss: 0.2247
Epoch [590/2000], Loss: 0.2240
Epoch [600/2000], Loss: 0.2257
```

```
Epoch [610/2000], Loss: 0.2259
Epoch [620/2000], Loss: 0.2231
Epoch [630/2000], Loss: 0.2237
Epoch [640/2000], Loss: 0.2217
Epoch [650/2000], Loss: 0.2240
Epoch [660/2000], Loss: 0.2226
Epoch [670/2000], Loss: 0.2199
Epoch [680/2000], Loss: 0.2197
Epoch [690/2000], Loss: 0.2195
Epoch [700/2000], Loss: 0.2189
Epoch [710/2000], Loss: 0.2207
Epoch [720/2000], Loss: 0.2201
Epoch [730/2000], Loss: 0.2196
Epoch [740/2000], Loss: 0.2201
Epoch [750/2000], Loss: 0.2149
Epoch [760/2000], Loss: 0.2158
Epoch [770/2000], Loss: 0.2154
Epoch [780/2000], Loss: 0.2149
Epoch [790/2000], Loss: 0.2135
Epoch [800/2000], Loss: 0.2143
Epoch [810/2000], Loss: 0.2138
Epoch [820/2000], Loss: 0.2173
Epoch [830/2000], Loss: 0.2152
Epoch [840/2000], Loss: 0.2137
Epoch [850/2000], Loss: 0.2126
Epoch [860/2000], Loss: 0.2105
Epoch [870/2000], Loss: 0.2133
Epoch [880/2000], Loss: 0.2094
Epoch [890/2000], Loss: 0.2116
Epoch [900/2000], Loss: 0.2138
Epoch [910/2000], Loss: 0.2115
Epoch [920/2000], Loss: 0.2091
Epoch [930/2000], Loss: 0.2111
Epoch [940/2000], Loss: 0.2107
Epoch [950/2000], Loss: 0.2109
Epoch [960/2000], Loss: 0.2107
Epoch [970/2000], Loss: 0.2086
Epoch [980/2000], Loss: 0.2102
Epoch [990/2000], Loss: 0.2101
Epoch [1000/2000], Loss: 0.2071
Epoch [1010/2000], Loss: 0.2105
Epoch [1020/2000], Loss: 0.2088
Epoch [1030/2000], Loss: 0.2132
Epoch [1040/2000], Loss: 0.2096
Epoch [1050/2000], Loss: 0.2088
Epoch [1060/2000], Loss: 0.2103
Epoch [1070/2000], Loss: 0.2083
Epoch [1080/2000], Loss: 0.2101
Epoch [1090/2000], Loss: 0.2073
Epoch [1100/2000], Loss: 0.2085
Epoch [1110/2000], Loss: 0.2064
Epoch [1120/2000], Loss: 0.2067
Epoch [1130/2000], Loss: 0.2088
Epoch [1140/2000], Loss: 0.2066
Epoch [1150/2000], Loss: 0.2073
Epoch [1160/2000], Loss: 0.2052
Epoch [1170/2000], Loss: 0.2063
Epoch [1180/2000], Loss: 0.2051
Epoch [1190/2000], Loss: 0.2071
Epoch [1200/2000], Loss: 0.2063
```

```
Epoch [1210/2000], Loss: 0.2074
Epoch [1220/2000], Loss: 0.2054
Epoch [1230/2000], Loss: 0.2067
Epoch [1240/2000], Loss: 0.2057
Epoch [1250/2000], Loss: 0.2050
Epoch [1260/2000], Loss: 0.2065
Epoch [1270/2000], Loss: 0.2046
Epoch [1280/2000], Loss: 0.2045
Epoch [1290/2000], Loss: 0.2038
Epoch [1300/2000], Loss: 0.2067
Epoch [1310/2000], Loss: 0.2051
Epoch [1320/2000], Loss: 0.2055
Epoch [1330/2000], Loss: 0.2042
Epoch [1340/2000], Loss: 0.2034
Epoch [1350/2000], Loss: 0.2049
Epoch [1360/2000], Loss: 0.2057
Epoch [1370/2000], Loss: 0.2044
Epoch [1380/2000], Loss: 0.2040
Epoch [1390/2000], Loss: 0.2028
Epoch [1400/2000], Loss: 0.2041
Epoch [1410/2000], Loss: 0.2048
Epoch [1420/2000], Loss: 0.2028
Epoch [1430/2000], Loss: 0.2033
Epoch [1440/2000], Loss: 0.2038
Epoch [1450/2000], Loss: 0.2037
Epoch [1460/2000], Loss: 0.2036
Epoch [1470/2000], Loss: 0.2007
Epoch [1480/2000], Loss: 0.2023
Epoch [1490/2000], Loss: 0.2031
Epoch [1500/2000], Loss: 0.2027
Epoch [1510/2000], Loss: 0.2029
Epoch [1520/2000], Loss: 0.2012
Epoch [1530/2000], Loss: 0.2025
Epoch [1540/2000], Loss: 0.2039
Epoch [1550/2000], Loss: 0.2010
Epoch [1560/2000], Loss: 0.2035
Epoch [1570/2000], Loss: 0.2010
Epoch [1580/2000], Loss: 0.2020
Epoch [1590/2000], Loss: 0.2050
Epoch [1600/2000], Loss: 0.2040
Epoch [1610/2000], Loss: 0.2024
Epoch [1620/2000], Loss: 0.2054
Epoch [1630/2000], Loss: 0.2005
Epoch [1640/2000], Loss: 0.2041
Epoch [1650/2000], Loss: 0.2033
Epoch [1660/2000], Loss: 0.2011
Epoch [1670/2000], Loss: 0.1986
Epoch [1680/2000], Loss: 0.2022
Epoch [1690/2000], Loss: 0.2016
Epoch [1700/2000], Loss: 0.2014
Epoch [1710/2000], Loss: 0.2018
Epoch [1720/2000], Loss: 0.2022
Epoch [1730/2000], Loss: 0.2024
Epoch [1740/2000], Loss: 0.2024
Epoch [1750/2000], Loss: 0.2031
Epoch [1760/2000], Loss: 0.1989
Epoch [1770/2000], Loss: 0.1983
Epoch [1780/2000], Loss: 0.2004
Epoch [1790/2000], Loss: 0.1994
Epoch [1800/2000], Loss: 0.2009
```

```
Epoch [1810/2000], Loss: 0.2024
Epoch [1820/2000], Loss: 0.2020
Epoch [1830/2000], Loss: 0.2008
Epoch [1840/2000], Loss: 0.1977
Epoch [1850/2000], Loss: 0.2001
Epoch [1860/2000], Loss: 0.2011
Epoch [1870/2000], Loss: 0.1998
Epoch [1880/2000], Loss: 0.2053
Epoch [1890/2000], Loss: 0.2009
Epoch [1900/2000], Loss: 0.2022
Epoch [1910/2000], Loss: 0.1985
Epoch [1920/2000], Loss: 0.2019
Epoch [1930/2000], Loss: 0.2001
Epoch [1940/2000], Loss: 0.2008
Epoch [1950/2000], Loss: 0.1982
Epoch [1960/2000], Loss: 0.2012
Epoch [1970/2000], Loss: 0.1999
Epoch [1980/2000], Loss: 0.1993
Epoch [1990/2000], Loss: 0.1994
Epoch [2000/2000], Loss: 0.2001

Train Accuracy: 0.9384

Test Accuracy: 0.9305
```

ML Method 2: Decision Trees:

Decision trees are highly effective for our use case because they offer clear interpretability.

Unlike neural networks, which often operate as "black boxes" with complex internal structures, decision trees provide greater observability and tracaeability.

We tested multiple tree types : single multi-variable trees, random forest, and XGBOOST. and consolidated all their results and code into a single cell below

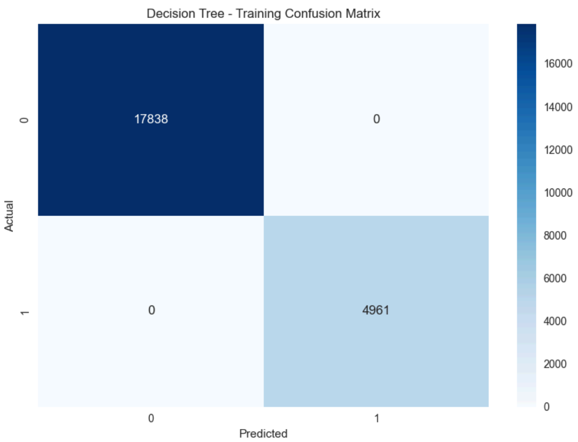
In [82]:
```python
df = df.dropna()
X = df.drop("loan_status", axis=1)
y = df["loan_status"]
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=1015
)
```

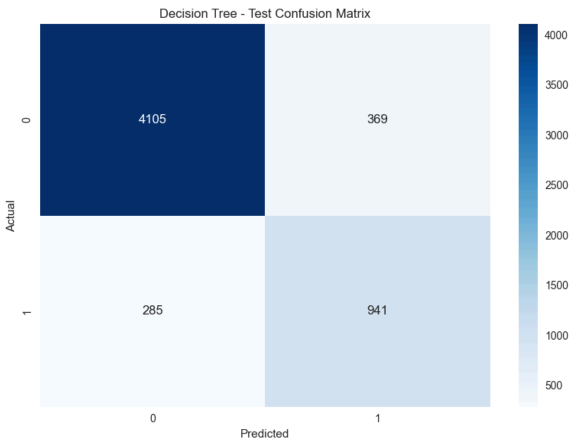
In [83]:
```python
import pandas as pd
import xgboost as xgb
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import (
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    confusion_matrix,
```

```python
    classification_report,
)


# Create a function to train, evaluate and visualize models
def evaluate_model(model, model_name, X_train, X_test, y_train, y_test):
    # Train the model
    model.fit(X_train, y_train)

    # Make predictions on train and test sets
    y_train_pred = model.predict(X_train)
    y_test_pred = model.predict(X_test)

    # Calculate metrics for training data
    train_accuracy = accuracy_score(y_train, y_train_pred)
    train_precision = precision_score(y_train, y_train_pred)
    train_recall = recall_score(y_train, y_train_pred)
    train_f1 = f1_score(y_train, y_train_pred)

    # Calculate metrics for test data
    test_accuracy = accuracy_score(y_test, y_test_pred)
    test_precision = precision_score(y_test, y_test_pred)
    test_recall = recall_score(y_test, y_test_pred)
    test_f1 = f1_score(y_test, y_test_pred)

    # Print results
    print(f"\n--- {model_name} Results ---")
    print(f"Training Metrics:")
    print(f"Accuracy: {train_accuracy:.4f}")
    print(f"Precision: {train_precision:.4f}")
    print(f"Recall: {train_recall:.4f}")
    print(f"F1 Score: {train_f1:.4f}")

    print(f"\nTest Metrics:")
    print(f"Accuracy: {test_accuracy:.4f}")
    print(f"Precision: {test_precision:.4f}")
    print(f"Recall: {test_recall:.4f}")
    print(f"F1 Score: {test_f1:.4f}")

    # Print classification reports
    print(f"\nTraining Classification Report:")
    print(classification_report(y_train, y_train_pred))

    print(f"\nTest Classification Report:")
    print(classification_report(y_test, y_test_pred))

    # Calculate confusion matrices
    train_cm = confusion_matrix(y_train, y_train_pred)
    test_cm = confusion_matrix(y_test, y_test_pred)

    # Print confusion matrices
    print(f"\nTraining Confusion Matrix:")
    print(train_cm)

    print(f"\nTest Confusion Matrix:")
    print(test_cm)

    # Plot confusion matrices
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 6))
```

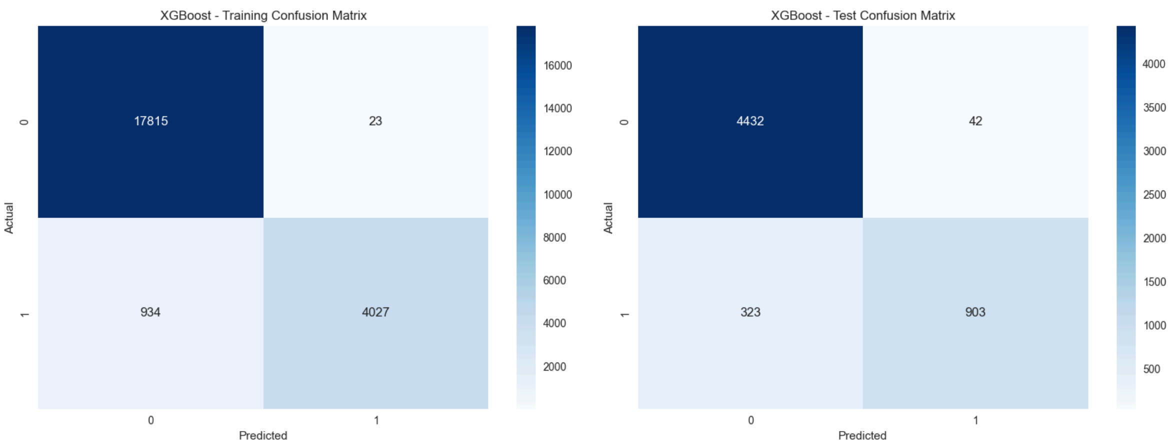
```python
    # Training confusion matrix
    sns.heatmap(
        train_cm,
        annot=True,
        fmt="d",
        cmap="Blues",
        xticklabels=["0", "1"],
        yticklabels=["0", "1"],
        ax=ax1,
    )
    ax1.set_xlabel("Predicted")
    ax1.set_ylabel("Actual")
    ax1.set_title(f"{model_name} - Training Confusion Matrix")

    # Test confusion matrix
    sns.heatmap(
        test_cm,
        annot=True,
        fmt="d",
        cmap="Blues",
        xticklabels=["0", "1"],
        yticklabels=["0", "1"],
        ax=ax2,
    )
    ax2.set_xlabel("Predicted")
    ax2.set_ylabel("Actual")
    ax2.set_title(f"{model_name} - Test Confusion Matrix")

    plt.tight_layout()
    plt.show()


# Initialize the models
decision_tree_model = DecisionTreeClassifier(random_state=1015)
xgboost_model = XGBClassifier(random_state=1015, eval_metric="logloss")
random_forest_model = RandomForestClassifier(random_state=1015)

# Evaluate each model
evaluate_model(decision_tree_model, "Decision Tree", X_train, X_test, y_t
evaluate_model(xgboost_model, "XGBoost", X_train, X_test, y_train, y_test
evaluate_model(random_forest_model, "Random Forest", X_train, X_test, y_t
```

```
--- Decision Tree Results ---
Training Metrics:
Accuracy: 1.0000
Precision: 1.0000
Recall: 1.0000
F1 Score: 1.0000

Test Metrics:
Accuracy: 0.8853
Precision: 0.7183
Recall: 0.7675
F1 Score: 0.7421

Training Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     17838
           1       1.00      1.00      1.00      4961

    accuracy                           1.00     22799
   macro avg       1.00      1.00      1.00     22799
weighted avg       1.00      1.00      1.00     22799


Test Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.92      0.93      4474
           1       0.72      0.77      0.74      1226

    accuracy                           0.89      5700
   macro avg       0.83      0.84      0.83      5700
weighted avg       0.89      0.89      0.89      5700


Training Confusion Matrix:
[[17838     0]
 [    0  4961]]

Test Confusion Matrix:
[[4105  369]
 [ 285  941]]
```

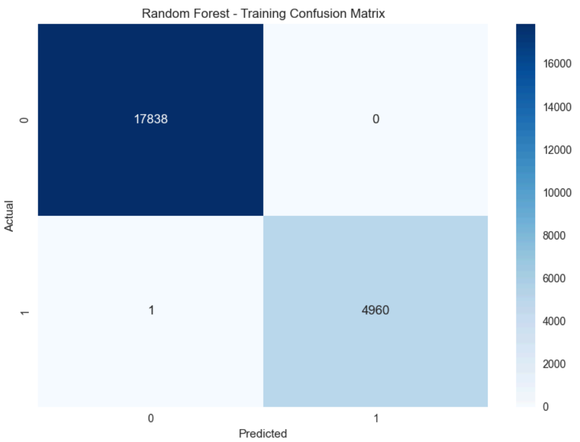


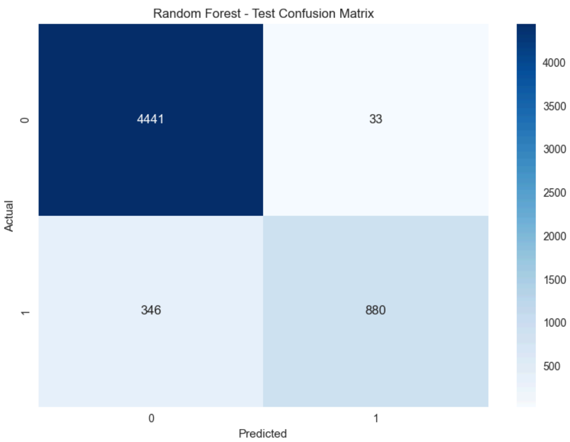


```
--- XGBoost Results ---
Training Metrics:
Accuracy: 0.9580
Precision: 0.9943
Recall: 0.8117
F1 Score: 0.8938

Test Metrics:
Accuracy: 0.9360
Precision: 0.9556
Recall: 0.7365
F1 Score: 0.8319

Training Classification Report:
              precision    recall  f1-score   support

           0       0.95      1.00      0.97     17838
           1       0.99      0.81      0.89      4961

    accuracy                           0.96     22799
   macro avg       0.97      0.91      0.93     22799
weighted avg       0.96      0.96      0.96     22799


Test Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.99      0.96      4474
           1       0.96      0.74      0.83      1226

    accuracy                           0.94      5700
   macro avg       0.94      0.86      0.90      5700
weighted avg       0.94      0.94      0.93      5700


Training Confusion Matrix:
[[17815    23]
 [  934  4027]]

Test Confusion Matrix:
[[4432   42]
 [ 323  903]]
```



```
--- Random Forest Results ---
Training Metrics:
Accuracy: 1.0000
Precision: 1.0000
Recall: 0.9998
F1 Score: 0.9999

Test Metrics:
Accuracy: 0.9335
Precision: 0.9639
Recall: 0.7178
F1 Score: 0.8228

Training Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     17838
           1       1.00      1.00      1.00      4961

    accuracy                           1.00     22799
   macro avg       1.00      1.00      1.00     22799
weighted avg       1.00      1.00      1.00     22799


Test Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.99      0.96      4474
           1       0.96      0.72      0.82      1226

    accuracy                           0.93      5700
   macro avg       0.95      0.86      0.89      5700
weighted avg       0.94      0.93      0.93      5700


Training Confusion Matrix:
[[17838     0]
 [    1  4960]]

Test Confusion Matrix:
[[4441   33]
 [ 346  880]]
```



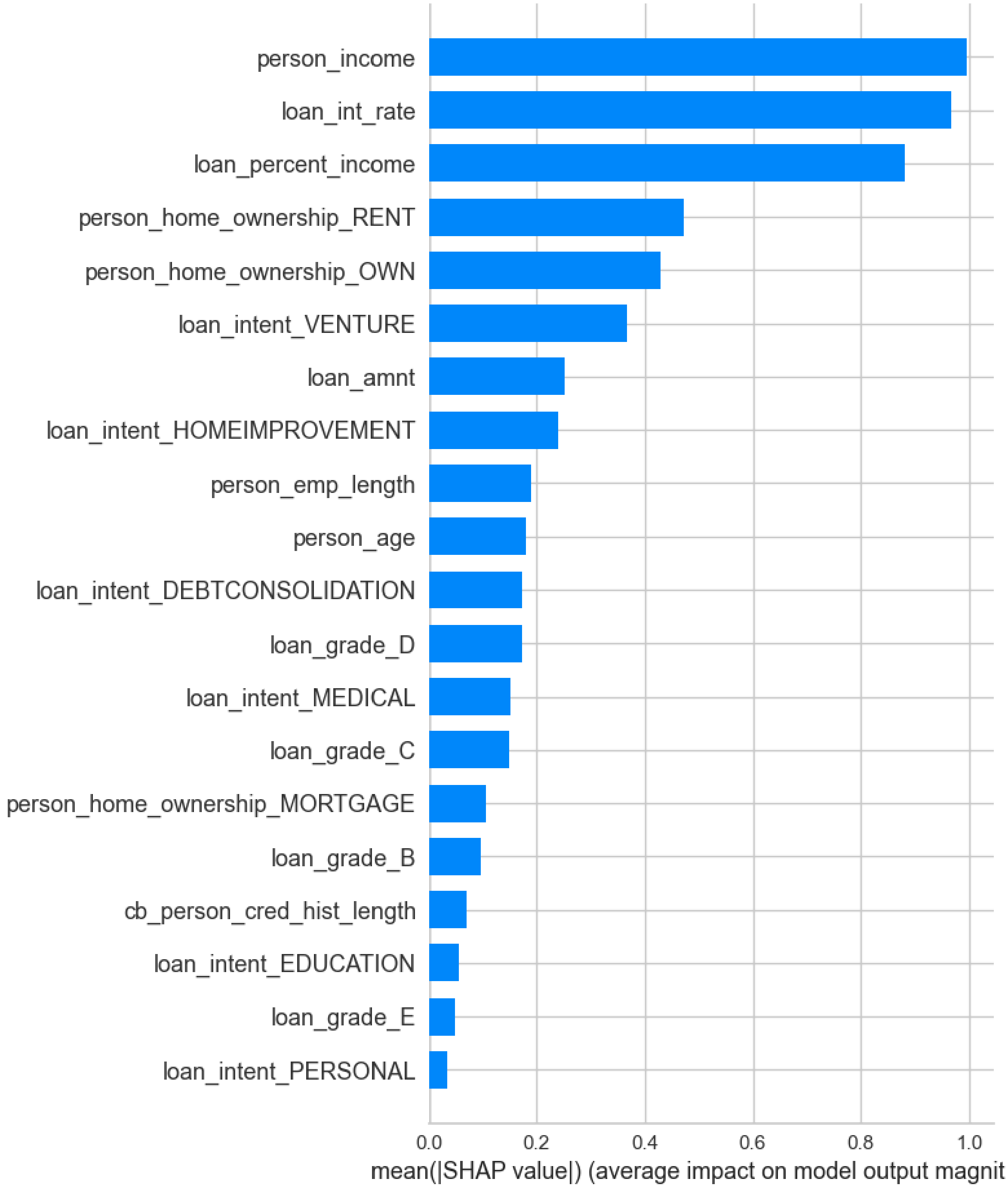


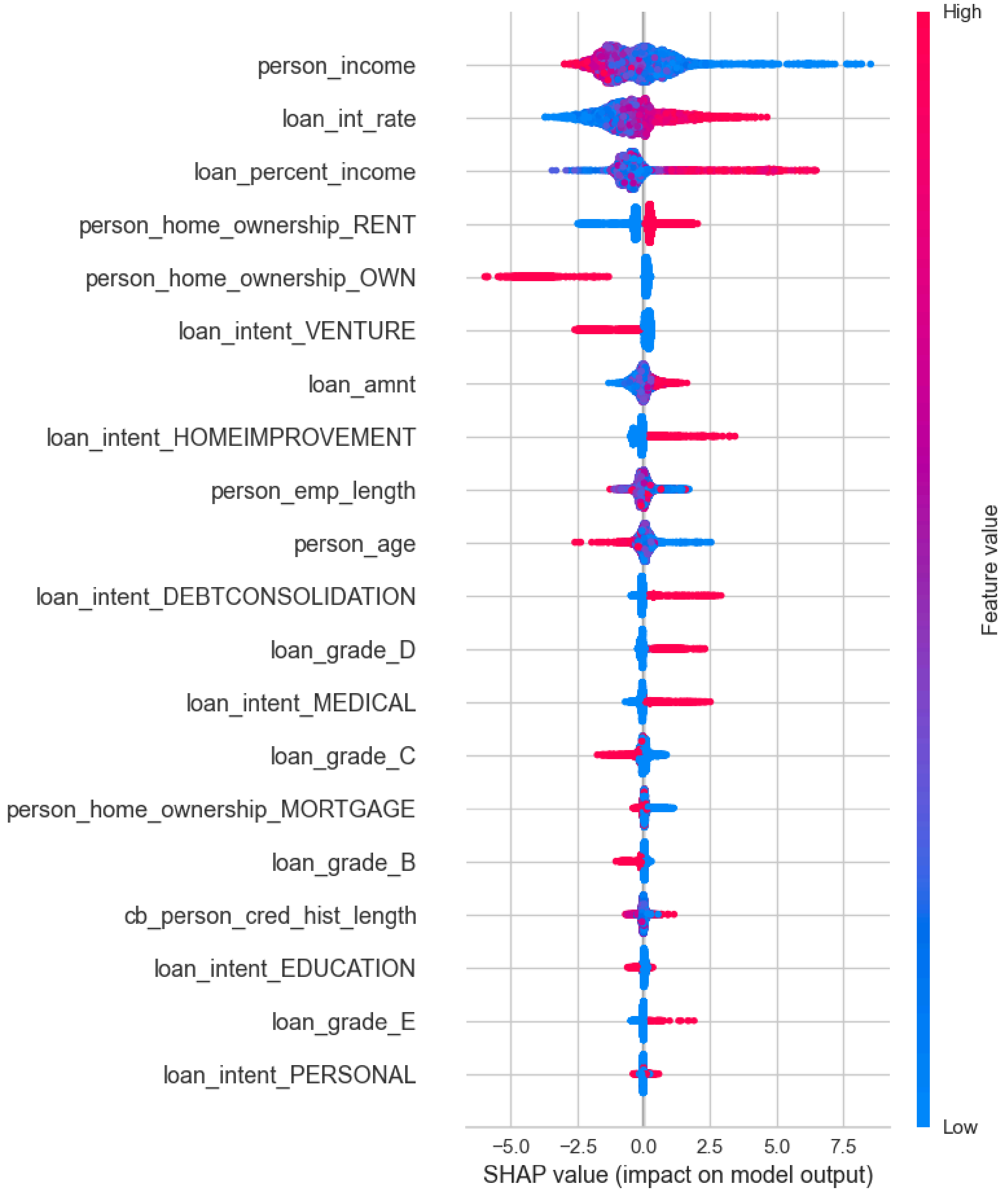
2.3 Applying SHAP to XGBOOST

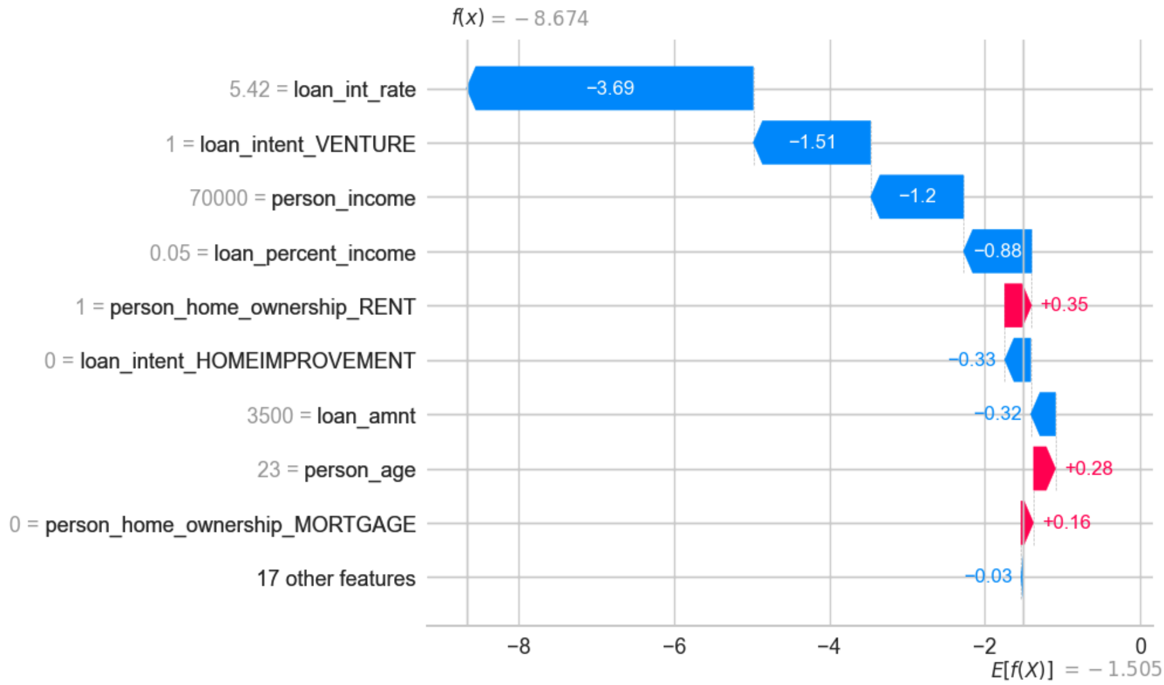
SHAP (SHapley Additive exPlanations) provides a principled way to interpret machine learning models by assigning each feature a contribution value for individual predictions, based on game theory.

- In this code, summary_plot (bar) shows which features have the greatest average impact across all predictions, while the default summary_plot (dot) reveals how feature values (high vs. low) influence predictions.
- The waterfall plot breaks down one prediction, showing how each feature nudges the output up or down from the model's baseline.
- Finally, the scatter plots (dependence plots) highlight how individual feature values affect their SHAP contributions, revealing trends and potential interactions.

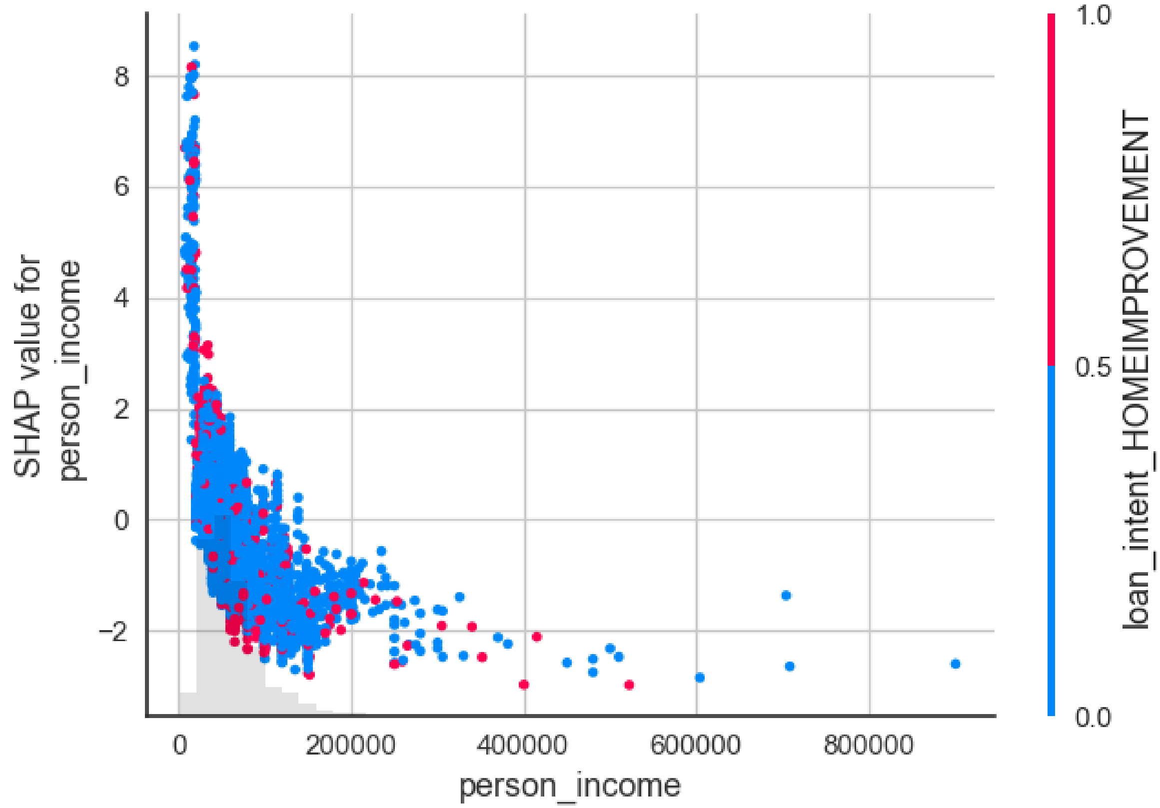
In [84]:
```
import shap

# SHAP Analysis
# Create a SHAP explainer object
explainer = shap.Explainer(xgboost_model)

# Calculate SHAP values
shap_values = explainer(X_test)

# Summary plot of SHAP values
shap.summary_plot(shap_values, X_test, plot_type="bar")
shap.summary_plot(shap_values, X_test)

# SHAP force plot for a specific prediction (e.g., first test instance)
shap.plots.waterfall(shap_values[0])

# SHAP dependence plots for top features
# Get feature names (adjust this if your X_test doesn't have column names
feature_names = (
    X_test.columns
    if hasattr(X_test, "columns")
    else [f"feature_{i}" for i in range(X_test.shape[1])]
)

# Plot dependence plots for top 3 features based on mean absolute SHAP va
top_features_idx = np.argsort(-np.abs(shap_values.values).mean(0))[:3]
for idx in top_features_idx:
    shap.plots.scatter(shap_values[:, idx], color=shap_values)
```


person_income
loan_int_rate
loan_percent_income
person_home_ownership_RENT
person_home_ownership_OWN
loan_intent_VENTURE
loan_amnt
loan_intent_HOMEIMPROVEMENT
person_emp_length
person_age
loan_intent_DEBTCONSOLIDATION
loan_grade_D
loan_intent_MEDICAL
loan_grade_C
person_home_ownership_MORTGAGE
loan_grade_B
cb_person_cred_hist_length
loan_intent_EDUCATION
loan_grade_E
loan_intent_PERSONAL
0.0
0.2
0.4
0.6
0.8
1.0
mean(|SHAP value|) (average impact on model output magnit

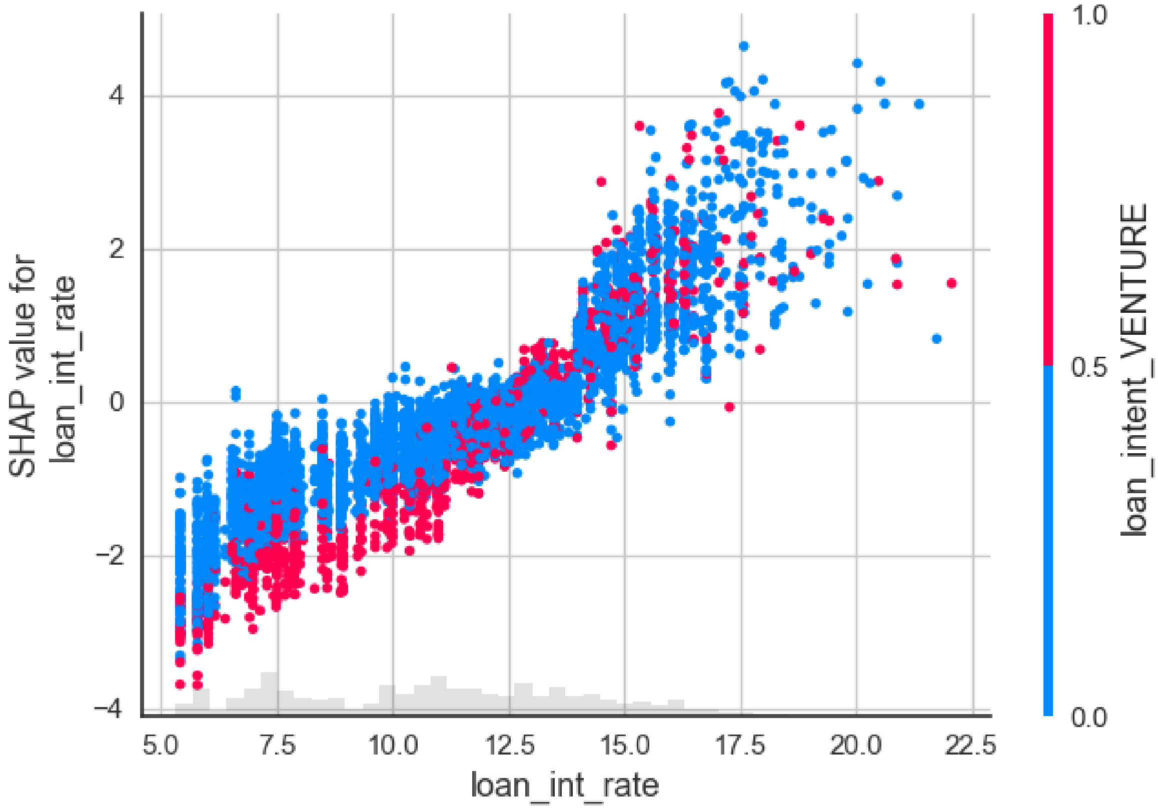

person_income
loan_int_rate
loan_percent_income
person_home_ownership_RENT
person_home_ownership_OWN
loan_intent_VENTURE
loan_amnt
loan_intent_HOMEIMPROVEMENT
person_emp_length
person_age
loan_intent_DEBTCONSOLIDATION
loan_grade_D
loan_intent_MEDICAL
loan_grade_C
person_home_ownership_MORTGAGE
loan_grade_B
cb_person_cred_hist_length
loan_intent_EDUCATION
loan_grade_E
loan_intent_PERSONAL
−5.0 −2.5 0.0 2.5 5.0 7.5
SHAP value (impact on model output)
High
Feature value
Low

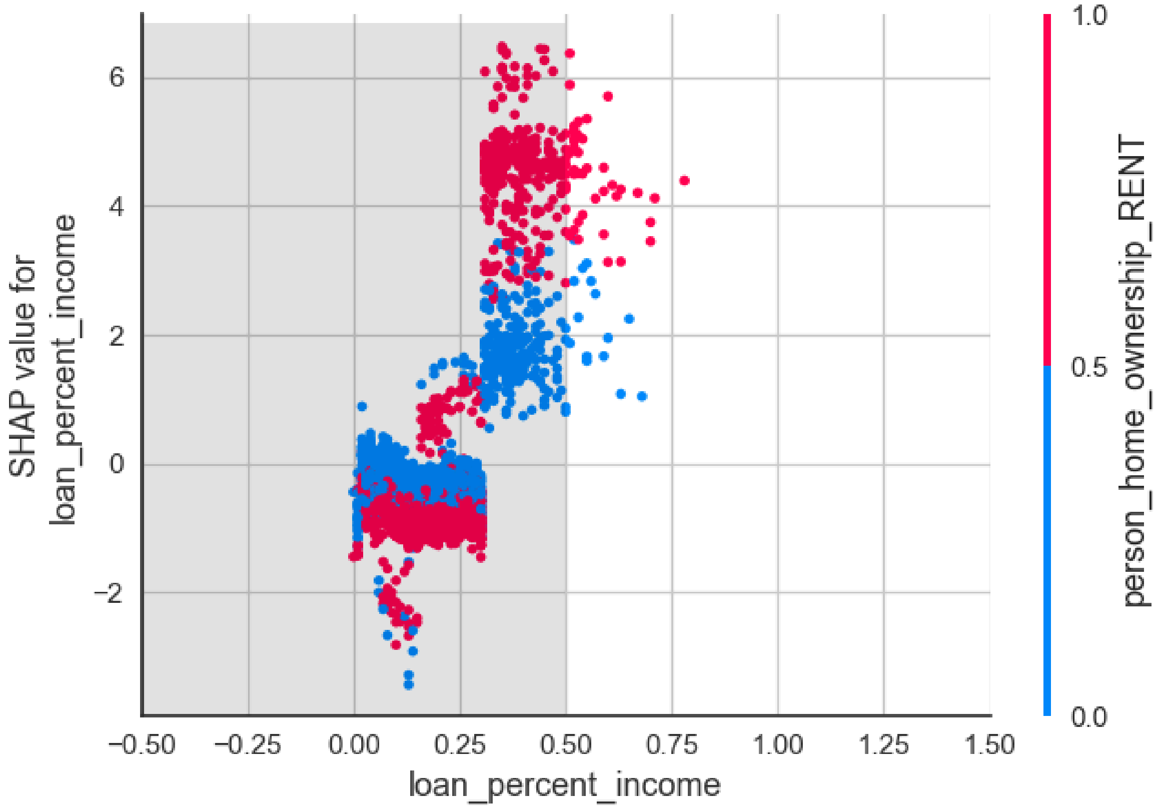


f(x) = −8.674
5.42 = loan_int_rate
1 = loan_intent_VENTURE
70000 = person_income
0.05 = loan_percent_income
1 = person_home_ownership_RENT
0 = loan_intent_HOMEIMPROVEMENT
3500 = loan_amnt
23 = person_age
0 = person_home_ownership_MORTGAGE
17 other features
−3.69
−1.51
−1.2
−0.88
+0.35
−0.33
−0.32
+0.28
+0.16
−0.03
−8
−6
−4
−2
0
E[f(X)] = −1.505



SHAP value for person_income
person_income
loan_intent_HOMEIMPROVEMENT
8
6
4
2
0
−2
0
200000
400000
600000
800000
1.0
0.5
0.0


SHAP value for
loan_int_rate
4
2
0
-2
−4
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5
loan_int_rate
1.0
0.5
0.0
loan_intent_VENTURE


SHAP value for
loan_percent_income
6
4
2
0
−2
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
1.50
loan_percent_income
1.0
0.5
0.0
person_home_ownership_RENT