Loan Paid Back Analysis and Prediction

Team:

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Course: CISB 60 – ML and DL (Fall, 2024)

Dataset Variable Description

- credit_policy: Indicates whether the borrower meets the lending institution's credit underwriting criteria (1 = Yes, 0 = No).
- purpose: The purpose of the loan, represented as categorical values such as "debt_consolidation," "credit_card," etc.
- int_rate: The interest rate on the loan.
- installment: The fixed monthly payment to be made by the borrower.
- log_annual_inc: The natural logarithm of the borrower's self-reported annual income.
- dti: Debt-to-income ratio, calculated as the total monthly debt payments divided by monthly income.
- fico: The borrower's FICO. credit score
- days_with_cr_line: The number of days the borrower has had a credit line.
- revol_bal: The borrower's revolving balance (total balance on credit cards and other revolving credit accounts).
- revol_util: Revolving line utilization rate, the amount of credit the borrower is using relative to their credit limit.
- inq_last_6mths: The number of inquiries by lenders in the borrower's credit report in the last 6 months.
- delinq_2yrs: The number of delinquent credit lines in the borrower's credit history in the past 2 years.
- pub_rec: The number of derogatory public records (e.g., bankruptcies, tax liens).
- not_fully_paid: A binary variable indicating whether the borrower did not fully pay back the loan (1 = loan was not fully paid, 0 = loan was fully paid).

Objective of the project

- This project aims to explore the relationship between the several variables and the loan fully paid back result or status within the customers who meet the credit policy by using the logistic regression. By leveraging a dataset of loan attributes, the project identifies how variations influence the target.

- **Keywords:** Data Cleaning, Logistic Regression, Data Analysis, Machine Learning, Feature Selection, Model Evaluation, confusion, accuracy, precision, recall and TensorBoard

Methodology

1. Explan ML and DL metodology
2. Introduce the topics you used in your project

- Model 1
  - Logistic Regression in machine learning
  - Logistic regression is a simple, efficient, and interpretable supervised standalone machine learning algorithm for binary classification tasks. It predicts probabilities using the sigmoid function and makes class predictions based on a threshold.
- Model 2
  - Logistic Regression in deep learning
  - Logistic regression is not a standalone model in deep learning but is often used as the final layer of a neural network for binary classification tasks.
  - The difference between logistic regression as a machine learning model and its use in deep learning primarily lies in the context and scale of application. While the core mathematical concept of logistic regression remains the same.

Required packages

- Add instructions to install the required packages

In [1]:
```
import numpy as np
import pandas as pd
# Import the visualization libraries
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# Import LogisticRegression model and its functions libraries
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, classification_report, accuracy_
from sklearn.metrics import ConfusionMatrixDisplay

# Ignore warnings in Jupyter
import warnings
warnings.filterwarnings('ignore')
```

Exploratory Data Analysis(EDA)

In [2]:
```python
# Load the data
df= pd.read_csv('loan_data.csv')
df.head()
```

Out[2]:

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.lin
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.95833
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.00000
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.00000
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.95833
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.00000

In [3]:
```python
df.tail()
```

Out[3]:

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.c
9573	0	all_other	0.1461	344.76	12.180755	10.39	672	10474.0
9574	0	all_other	0.1253	257.70	11.141862	0.21	722	4380.0
9575	0	debt_consolidation	0.1071	97.81	10.596635	13.09	687	3450.0
9576	0	home_improvement	0.1600	351.58	10.819778	19.18	692	1800.0
9577	0	debt_consolidation	0.1392	853.43	11.264464	16.28	732	4740.0

In [4]:
```python
# Replace the dot in the column names with an underscore
df.columns = df.columns.str.lower().str.replace('.', '_')

string_columns = list(df.dtypes[df.dtypes == 'object'].index)

for col in string_columns:
    df[col] = df[col].str.lower().str.replace('.', '_')

df.head()
```

Out[4]:

	credit_policy	purpose	int_rate	installment	log_annual_inc	dti	fico	days_with_cr
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.95
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.00
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.00
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.95
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.00

In [5]:
```
df.tail()
```

Out[5]:

	credit_policy	purpose	int_rate	installment	log_annual_inc	dti	fico	days_wi
9573	0	all_other	0.1461	344.76	12.180755	10.39	672	104
9574	0	all_other	0.1253	257.70	11.141862	0.21	722	43
9575	0	debt_consolidation	0.1071	97.81	10.596635	13.09	687	34
9576	0	home_improvement	0.1600	351.58	10.819778	19.18	692	18
9577	0	debt_consolidation	0.1392	853.43	11.264464	16.28	732	47

In [6]:
```
# Display unique values in the 'purpose' column
unique_values = df['purpose'].unique()
print("Unique values in 'purpose':", unique_values)
```

```
Unique values in 'purpose': ['debt_consolidation' 'credit_card' 'all_other'
'home_improvement'
 'small_business' 'major_purchase' 'educational']
```

In [7]:
```
# I deliberately did not encode 'all-other' in order to avoid the problem of pe
df['debt_consolidation'] = np.where(df['purpose']=='debt_consolidation',1,0)
df['credit_card'] = np.where(df['purpose']=='credit_card',1,0)
df['home_improvement'] = np.where(df['purpose']=='home_improvement',1,0)
df['small_business'] = np.where(df['purpose']=='small_business',1,0)
df['major_purchase'] = np.where(df['purpose']=='major_purchase',1,0)
df['educational'] = np.where(df['purpose']=='educational',1,0)
```

In [8]:
```
df
```

Out[8]:

	credit_policy	purpose	int_rate	installment	log_annual_inc	dti	fico	days_
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	
...	...	...	...	...	...	...	...	
9573	0	all_other	0.1461	344.76	12.180755	10.39	672	1
9574	0	all_other	0.1253	257.70	11.141862	0.21	722	
9575	0	debt_consolidation	0.1071	97.81	10.596635	13.09	687	
9576	0	home_improvement	0.1600	351.58	10.819778	19.18	692	
9577	0	debt_consolidation	0.1392	853.43	11.264464	16.28	732	

In [9]:
```
df.shape
```

Out[9]: (9578, 20)

In [10]:
```
# display a concise summary of a DataFrame
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 20 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   credit_policy      9578 non-null   int64  
 1   purpose            9578 non-null   object 
 2   int_rate           9578 non-null   float64
 3   installment        9578 non-null   float64
 4   log_annual_inc     9578 non-null   float64
 5   dti                9578 non-null   float64
 6   fico               9578 non-null   int64  
 7   days_with_cr_line  9578 non-null   float64
 8   revol_bal          9578 non-null   int64  
 9   revol_util         9578 non-null   float64
 10  inq_last_6mths     9578 non-null   int64  
 11  delinq_2yrs        9578 non-null   int64  
 12  pub_rec            9578 non-null   int64  
 13  not_fully_paid     9578 non-null   int64  
 14  debt_consolidation 9578 non-null   int32  
 15  credit_card        9578 non-null   int32  
 16  home_improvement   9578 non-null   int32  
 17  small_business     9578 non-null   int32  
 18  major_purchase     9578 non-null   int32  
 19  educational        9578 non-null   int32  
dtypes: float64(6), int32(6), int64(7), object(1)
memory usage: 1.2+ MB
```

In [11]:
```
# get a summary of statistics for numerical columns in df
df.describe()
```

Out[11]:

	credit_policy	int_rate	installment	log_annual_inc	dti	fico	days_w
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9
mean	0.804970	0.122640	319.089413	10.932117	12.606679	710.846314	4
std	0.396245	0.026847	207.071301	0.614813	6.883970	37.970537	2
min	0.000000	0.060000	15.670000	7.547502	0.000000	612.000000	
25%	1.000000	0.103900	163.770000	10.558414	7.212500	682.000000	2
50%	1.000000	0.122100	268.950000	10.928884	12.665000	707.000000	4
75%	1.000000	0.140700	432.762500	11.291293	17.950000	737.000000	5
max	1.000000	0.216400	940.140000	14.528354	29.960000	827.000000	17

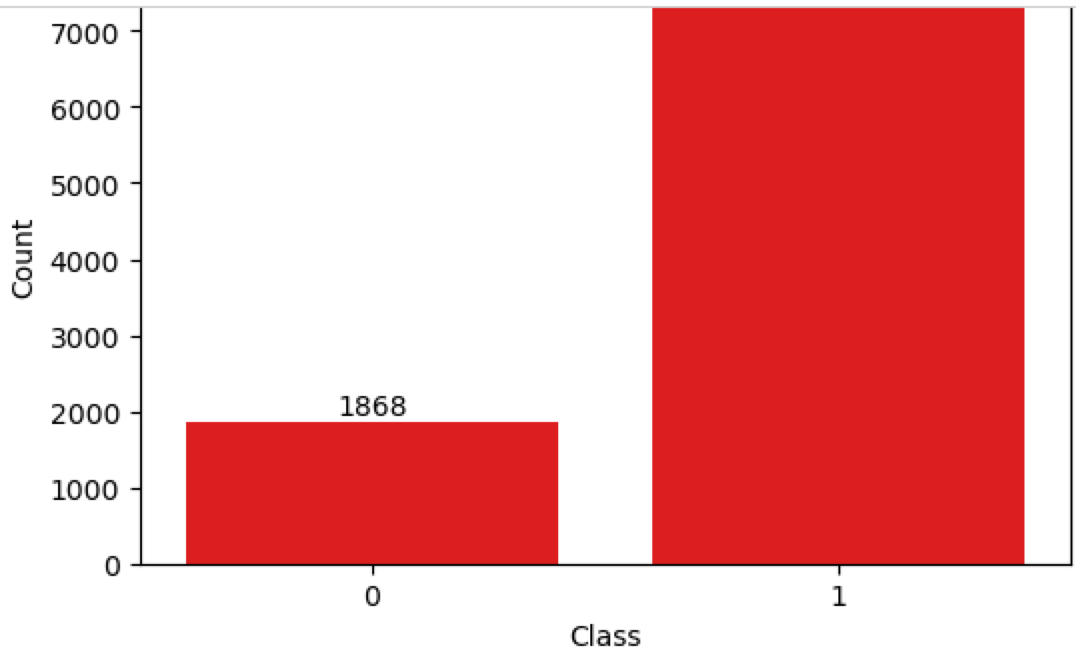
In [12]:
```
# display all columns
df.columns.tolist()
```

Out[12]:
```
['credit_policy',
 'purpose',
 'int_rate',
 'installment',
 'log_annual_inc',
 'dti',
 'fico',
 'days_with_cr_line',
 'revol_bal',
 'revol_util',
 'inq_last_6mths',
 'delinq_2yrs',
 'pub_rec',
 'not_fully_paid',
 'debt_consolidation',
 'credit_card',
 'home_improvement',
 'small_business',
 'major_purchase',
 'educational']
```

In [13]:
```
# check if there is missing data
df.isnull().sum()
```

Out[13]:
```
credit_policy         0
purpose               0
int_rate              0
installment           0
log_annual_inc        0
dti                   0
fico                  0
days_with_cr_line     0
revol_bal             0
revol_util            0
inq_last_6mths        0
delinq_2yrs           0
pub_rec               0
not_fully_paid        0
debt_consolidation    0
credit_card           0
home_improvement      0
small_business        0
major_purchase        0
educational           0
dtype: int64
```

In [14]:
```
# Create a bar plot that shows the total counts per class value of 'credit_pol
plt.figure(figsize=(6,4))
ax = sns.countplot(data=df, x='credit_policy', palette=['red'])
# Add count annotations on top of each bar
for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', fontsize=10, color='black', xytext=(
                textcoords='offset points')
#plt.xticks(rotation=0)

# Add labels and title
plt.title('Count of credit_policy')
plt.xlabel('Class')
plt.ylabel('Count')

# Show the plot
plt.show()
```



In [15]:
```
df.groupby('credit_policy')['not_fully_paid'].mean()
```

Out[15]:
```
credit_policy
0    0.277837
1    0.131518
Name: not_fully_paid, dtype: float64
```

This means:

- For customers who did not meet the credit policy (credit_policy = 0), 28% of loans were not fully paid.
- For customers who met the credit policy (credit_policy = 1), 13% of loans were not fully paid.

In [16]:
```
# Calculate the Percentage of customers who meet or not meet the credit policy
meet = df[df['credit_policy'] == 1]
print(f"Percentage of meeting: {round(100 * len(meet[meet['credit_policy'] == 

not_meet = df[df['credit_policy'] == 0]
print(f"Percentage of not meeting: {round(100 * len(not_meet[not_meet['credit_
```

```
Percentage of meeting: 80.5%
Percentage of not meeting: 19.5%
```

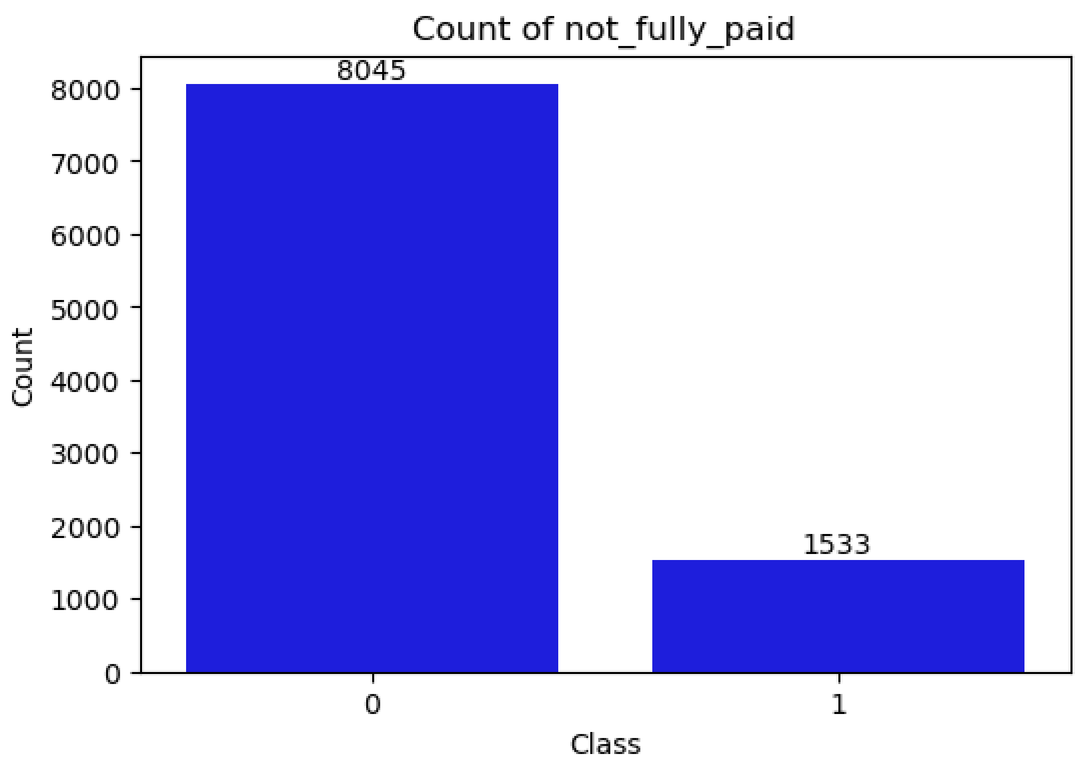
In [17]:
```
df.groupby('purpose')['not_fully_paid'].mean()
```

Out[17]:
```
purpose
all_other             0.166023
credit_card           0.115689
debt_consolidation    0.152388
educational           0.201166
home_improvement      0.170111
major_purchase        0.112128
small_business        0.277868
Name: not_fully_paid, dtype: float64
```

This indicates:

- Loans taken out for small_business have the highest proportion of being not fully paid (27.8%).
- This suggests that loans for small businesses are the riskiest among these purposes.
- Loans taken out for major_purchase and credit_card have the lowest proportion of being not fully paid (11.2%).
- This suggests that loans for major purchases and credit card are relatively safer.

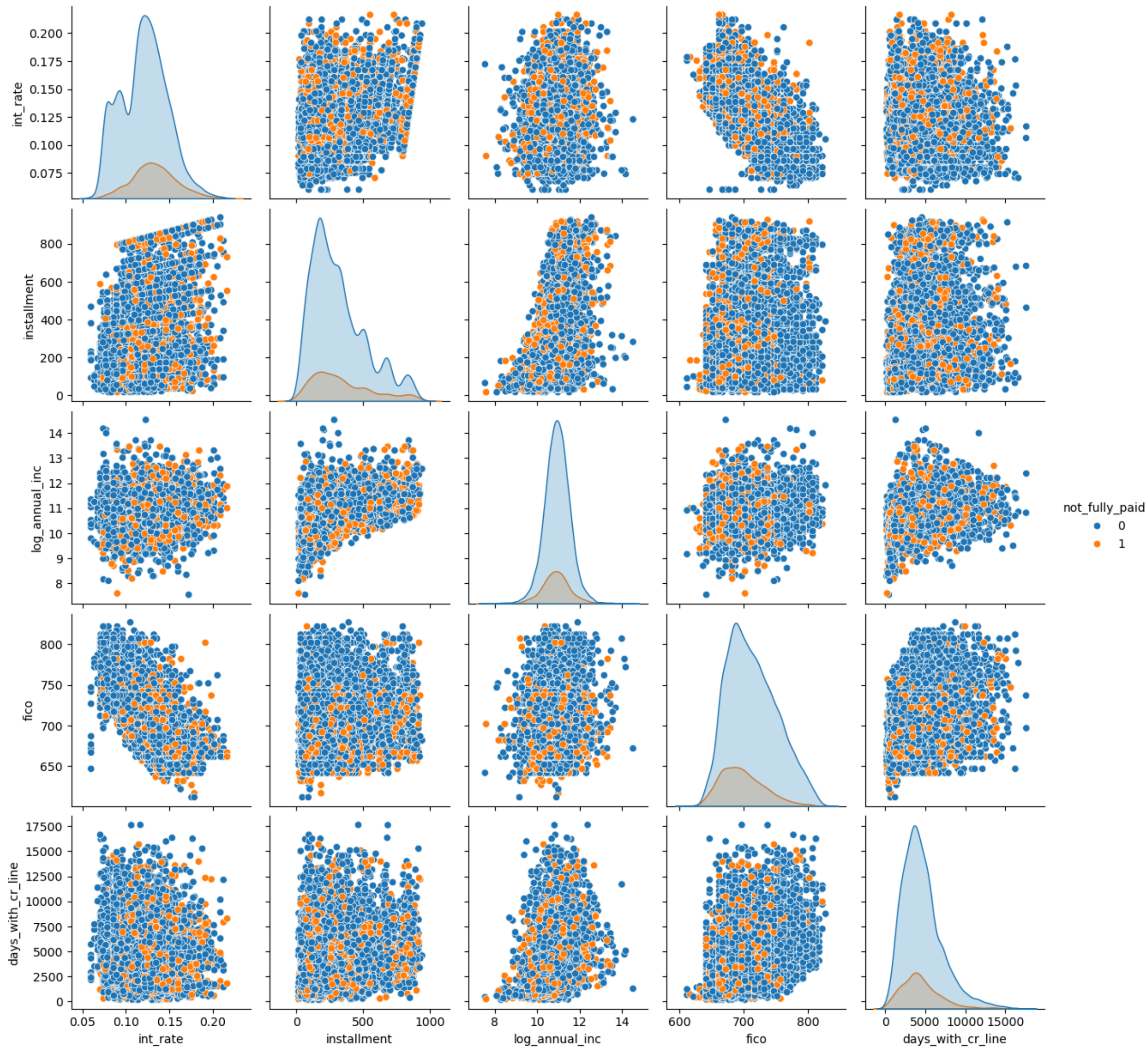
In [18]:
```
# Create a bar plot that shows the total counts per class value of 'not_fully_p
plt.figure(figsize=(6,4))
ax = sns.countplot(data=df, x='not_fully_paid', palette=['blue'])
# Add count annotations on top of each bar
for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', fontsize=10, color='black', xytext=(
                textcoords='offset points')
#plt.xticks(rotation=0)

# Add labels and title
plt.title('Count of not_fully_paid')
plt.xlabel('Class')
plt.ylabel('Count')

# Show the plot
plt.show()
```



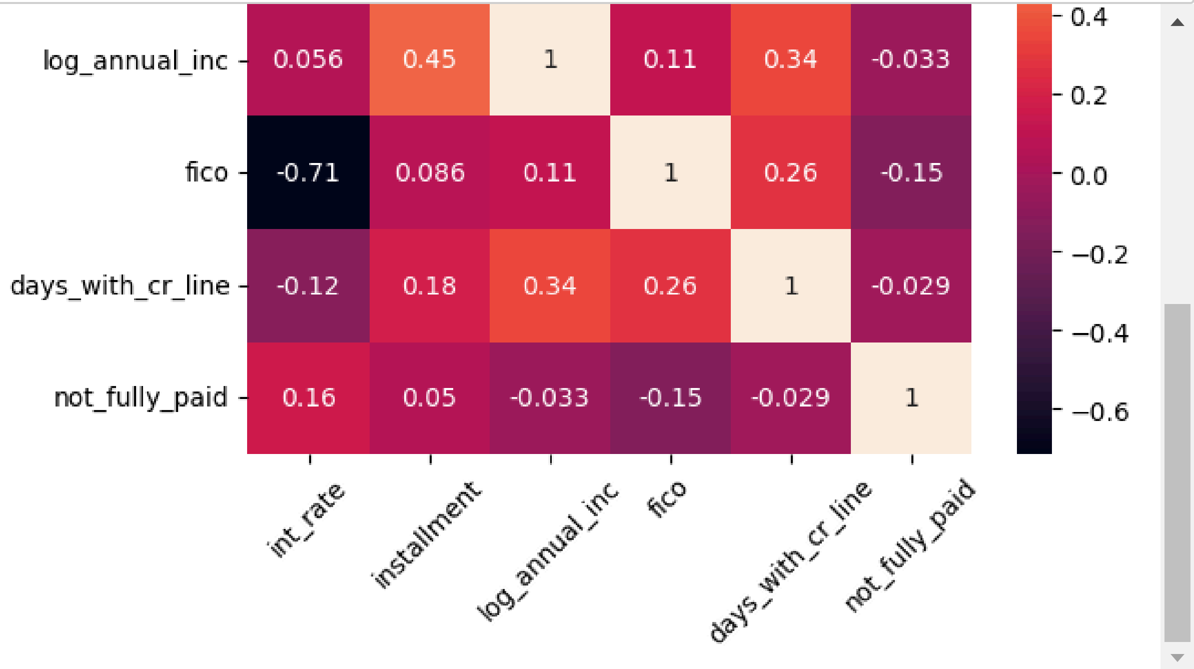
In [19]:
```
# Calculate the Percentage of fully paid or not in 'not_fully_paid' column
paid = df[df['not_fully_paid'] == 0]
print(f"Percentage of fully paid: {round(100 * len(paid[paid['not_fully_paid']]

not_paid = df[df['not_fully_paid'] == 1]
print(f"Percentage of not fully paid: {round(100 * len(not_paid[not_paid['not_
```

```
Percentage of fully paid: 83.99%
Percentage of not fully paid: 16.01%
```

In [20]:
```
# Create a pairplot that displays the relationships between
['int_rate', 'installment', 'log_annual_inc', 'fico', 'days_with_cr_line', 'no

# Select the columns
selected_columns = df[['int_rate', 'installment', 'log_annual_inc', 'fico', 'da
#print(selected_columns)

# Create a pairplot for the selected columns
sns.pairplot(selected_columns, hue='not_fully_paid')
plt.show()
```



In [21]:
```
# Create a heatmap that displays the correlation between these columns
sns.heatmap(selected_columns.corr(), annot=True)
# Rotate x-ticks
plt.xticks(rotation=45)
```



Correlation values range from -1 to 1

- The score of -0.71 reflects a strong negative correlation between interest rates and FICO scores, confirming that borrowers with higher creditworthiness (higher FICO scores) tend to receive significantly lower interest rates. This aligns with common financial practices and offers insights for both lenders and borrowers.

In [22]:
```
# remove rows where 'credit_policy' is equal to 0, we just need to analysis the
# the result more insightful.because those customer who don't meet credit polic
dfn = df[df['credit_policy'] != 0]

# Reset the index (optional, for a cleaner dataset)
dfn.reset_index(drop=True, inplace=True)
dfn
```

Out[22]:

	credit_policy	purpose	int_rate	installment	log_annual_inc	dti	fico	days_wi
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	56
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	27
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	47
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	26
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	40
...	...	...	...	...	...	...	...	
7705	1	home_improvement	0.1189	663.28	11.012050	2.89	742	36
7706	1	small_business	0.1739	716.95	11.034890	13.51	697	43
7707	1	all_other	0.1114	393.65	11.225243	7.82	737	31
7708	1	home_improvement	0.1379	851.89	11.238489	4.45	717	52
7709	1	major_purchase	0.1287	840.83	11.459525	0.13	757	21

7710 rows × 20 columns

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  - The difference between logistic regression as a machine learning model and its use in deep learning primarily lies in the context and scale of application. While the core mathematical concept of logistic regression remains the same.

Machine Learning Section

In [23]:
```
# Select relevant columns
dfn = dfn[['log_annual_inc', 'dti', 'fico', 'days_with_cr_line', 'revol_bal',
           'debt_consolidation', 'credit_card', 'home_improvement',
       'small_business', 'major_purchase', 'educational']]

# Separate the features from the labels into X and y, Define features (X) and t
X = dfn[['log_annual_inc', 'dti', 'fico','days_with_cr_line', 'revol_bal', 're
         'debt_consolidation', 'credit_card', 'home_improvement',
       'small_business', 'major_purchase', 'educational']]  # Predictor
y = dfn['not_fully_paid']            # Target
```

In [24]:
```
# Perform a train test split on the data, with test size of 30% and random_sta
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rando
```

In [26]:
```
# split the training set into training and validation sets
X_train, X_validate, y_train, y_validate = train_test_split(X_train, y_train, 
```

In [27]:
```
# Display the sizes of the datasets
print(f"Number of training samples: {len(X_train)}")
print(f"Number of validation samples: {len(X_validate)}")
print(f"Number of test samples: {len(X_test)}")
```

```
Number of training samples: 4317
Number of validation samples: 1080
Number of test samples: 2313
```

In [28]:
```
# Create and Fit a Logistic Regression model

logistic_model = LogisticRegression()
logistic_model.fit(X_train, y_train)
```

Out[28]:
```
▾ LogisticRegression (https://scikit-learn.org/1.5/modules/generated/sklearn.linear_model.LogisticRe

LogisticRegression()
```

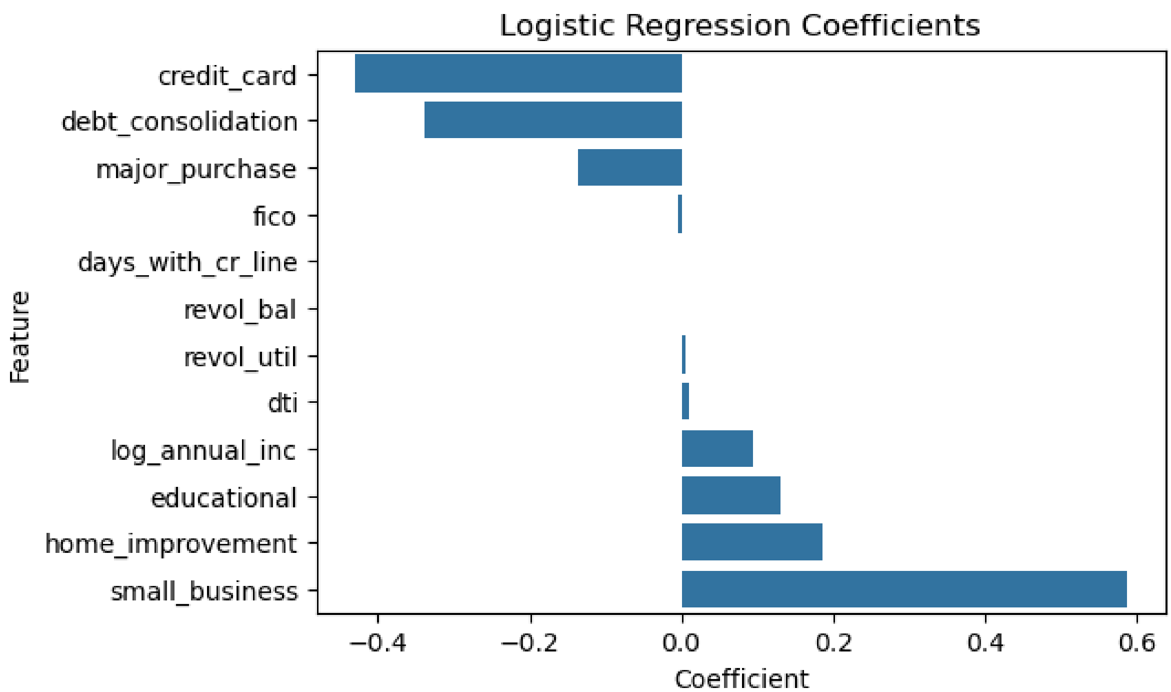
In [29]:
```
# Get The model's coefficients and print the values
logistic_model.coef_
```

Out[29]:
```
array([[ 9.41943743e-02,  1.14902399e-02, -4.48068879e-03,
        -3.02404052e-05, -4.23599008e-07,  6.45088025e-03,
        -3.37612428e-01, -4.30296370e-01,  1.86353963e-01,
         5.87325587e-01, -1.35480849e-01,  1.31283836e-01]])
```

TASK: Create a visualization of the coefficients by using a barplot of their values and sort the plot.

In [30]:
```
# Get the coefficients
coefficients = logistic_model.coef_.flatten()

# Create a DataFrame for the coefficients
coef_dfn = pd.DataFrame({'Feature': X.columns,'Coefficient': coefficients})

# Sort the coefficients by their values
coef_dfn_sorted = coef_dfn.sort_values(by='Coefficient', ascending=True)
```

In [31]:
```
# Create a barplot of the coefficients
plt.figure(figsize=(6, 4))
sns.barplot(x='Coefficient', y='Feature', data=coef_dfn_sorted)
plt.title('Logistic Regression Coefficients')
plt.show()
```



Explanation

Cred Card

- A negative coefficient means that loans taken out for the purpose of credit cards are less likely to result in "not fully paid". Borrowers using loans for credit card purposes are less risky.These loans likely have higher repayment rates compared to other loan purposes.Lenders may view loans for credit card purposes as relatively safer.

Small Business

- A positive coefficient means that loans taken out for small businesses are more likely to result in "not fully paid". Borrowers using loans for small businesses are riskier.These loans likely have higher default rates compared to other purposes. Lenders may charge higher interest rates for small business loans to compensate for the increased risk or impose

Model Performance Evaluation

TASK: Evaluate the model on the remaining 20% of the data, the test set.

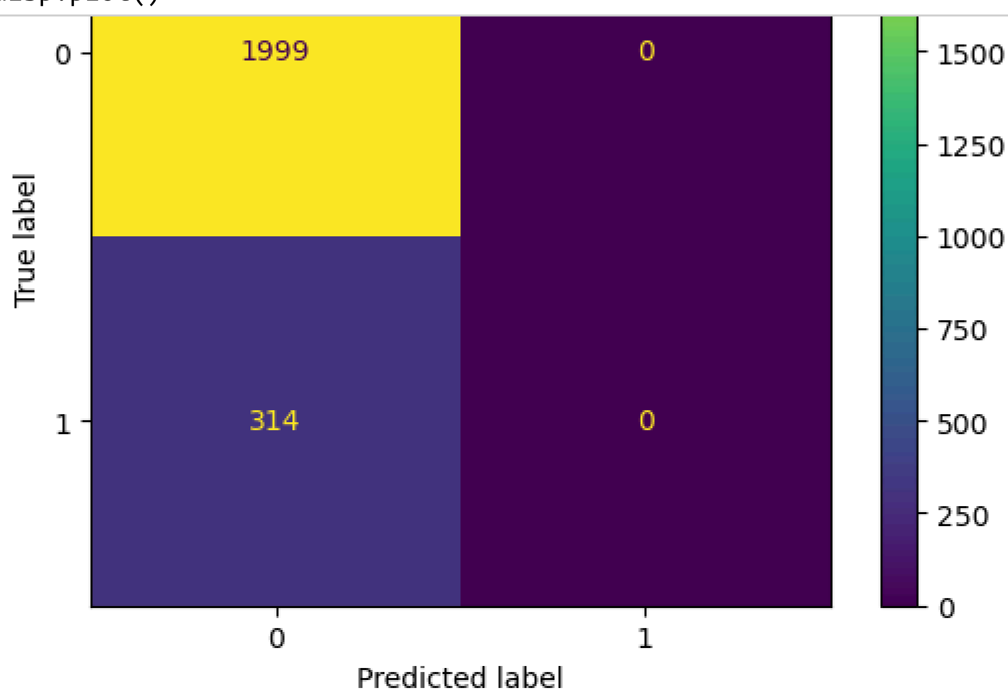
TASK: Create the following evaluations:

- Confusion Matrix Array
- Confusion Matrix Plot
- Classification Report
- Precision-Recall Curve
- ROC Curve

In [32]:
```
# make Predictions and create Confusion Matrix array
y_pred = logistic_model.predict(X_test)
cm = confusion_matrix(y_test, y_pred)

print("Confusion Matrix:\n", cm)
```

```
Confusion Matrix:
 [[1999    0]
 [ 314    0]]
```

In [33]:
```
# Create Confusion Matrix Plot
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=logistic_mod
disp.plot()
```



Structure of the Confusion Matrix

** A confusion matrix for binary classification looks like this:**

- Predicted: 0 / Predicted: 1
- Actual: 0 True Negatives (TN) / False Positives (FP)
- Actual: 1 False Negatives (FN) / True Positives (TP)

  Where:
- True Negatives (TN): 1347 | The model correctly predicted 0 for 1347 samples that are actually 0.
- False Positives (FP): 0 | The model never incorrectly predicted 1 for samples that are actually 0.
- False Negatives (FN): 195 | The model incorrectly predicted 0 for 195 samples that are actually 1.
- True Positives (TP): 0 | The model never correctly predicted 1 for samples that are actually 1.

  ### Key Observations
- - No Positive Predictions:
- The entire second column (Predicted: 1) contains only zeros, meaning the model never predicted the positive class (1) for any sample.
- - High False Negatives:
- There are 195 false negatives, meaning the model misclassified all 1s as 0s.
- - Perfect for Class 0:
- The model performs perfectly on the negative class (0), with all 1347 true negatives and no false positives.

In [34]:
```
# Print  the Classification Report
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.86      1.00      0.93      1999
           1       0.00      0.00      0.00       314

    accuracy                           0.86      2313
   macro avg       0.43      0.50      0.46      2313
weighted avg       0.75      0.86      0.80      2313
```

Precision and Recall:

- Precision for class 1: Undefined (0 means no positive predictions).
- Recall for class 1: 0 means very poor recall.

  ### Conclusion:
- The confusion matrix highlights that the model has significant issues predicting the positive class (1). It may perform well on the negative class (0), but its inability to predict any

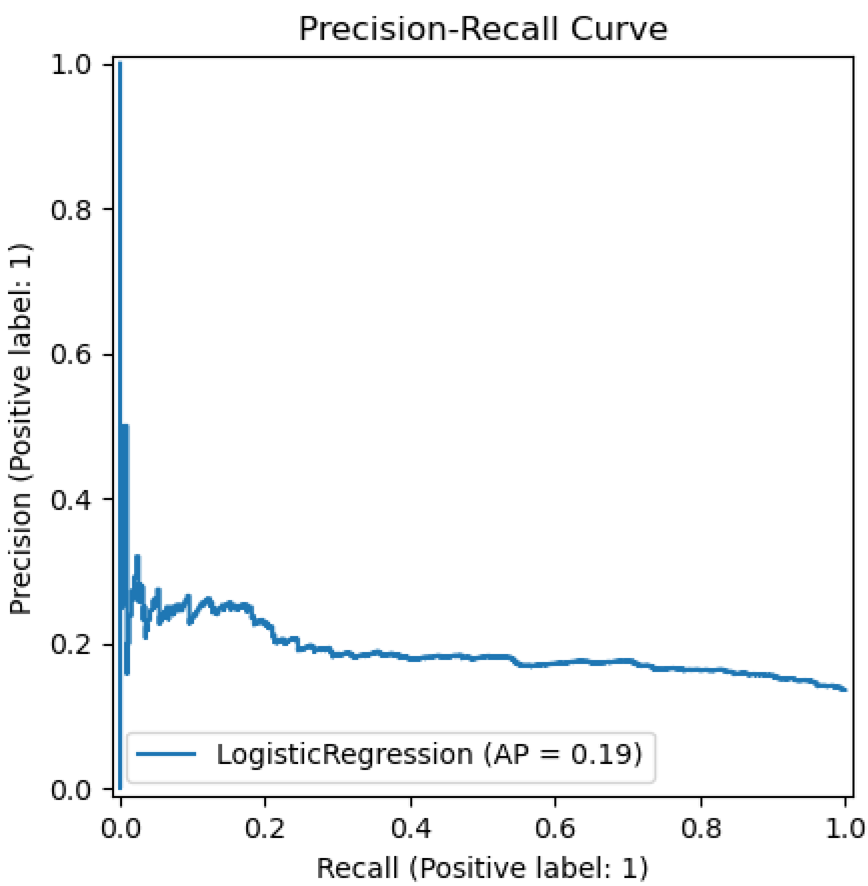
positives suggests problems like class imbalance, poor feature representation, or suboptimal thresholding.

Performance Curves¶

TASK: Create both the Precision Recall Curve and the ROC Curve.

In [35]:
```
# Import required libraries: precision_recall_curve, roc_curve, roc_auc_score
from sklearn.metrics import PrecisionRecallDisplay, RocCurveDisplay
from sklearn.metrics import precision_recall_curve  # For generating precision
from sklearn.metrics import roc_curve, auc  # For generating ROC curve data an
```

In [36]:
```
# Create the precision recall curve
PrecisionRecallDisplay.from_estimator(logistic_model, X_test, y_test)
plt.title('Precision-Recall Curve')
plt.show()
```



Interpretation of the Curve

** Performance Overview:

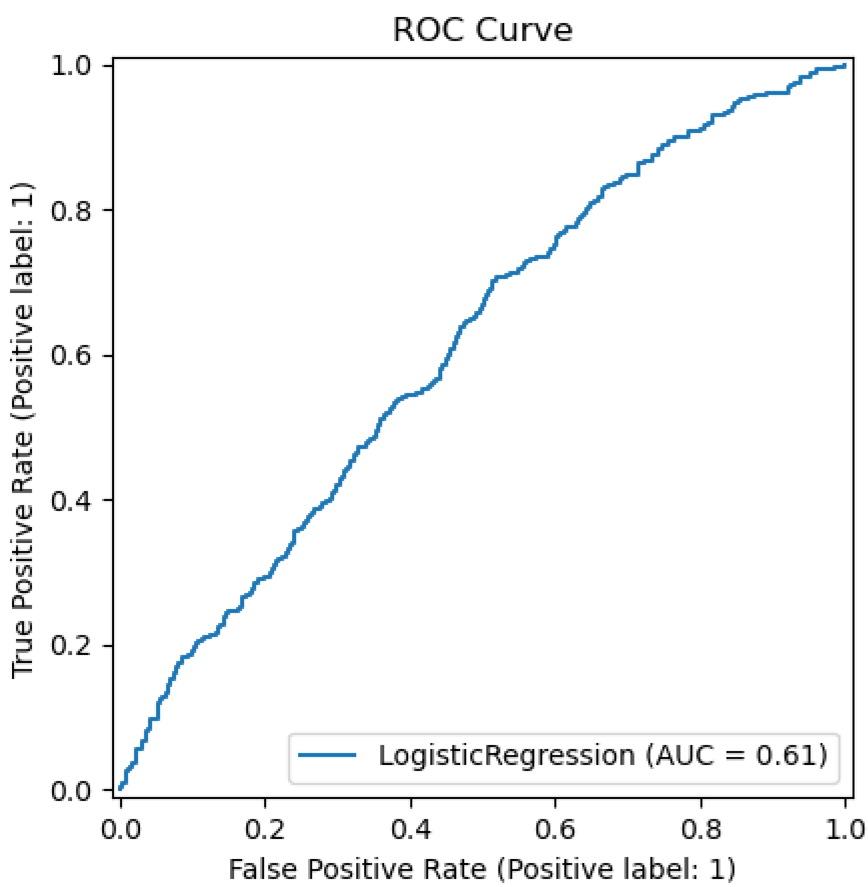
- The curve shows the trade-off between precision and recall for the logistic regression model.
- A good model will have a curve that stays in the upper-right region (high precision and high recall).

- ▪ Low Precision:
- The precision values are quite low, starting below 0.2 and generally staying under this level.
- This suggests a high number of false positives relative to true positives.
- ▪ Decent Recall:
- The recall starts at 1.0 (all samples are classified as positive) and decreases as the threshold increases.
- The model does identify many positive cases (good recall), but the low precision indicates that it does so at the cost of many false positives.
- ▪ Average Precision (AP = 0.16):
- The AP score is the area under the PR curve. It summarizes the model's ability to balance precision and recall across all thresholds.
- An AP of 0.16 is relatively poor, suggesting the model struggles to achieve both high precision and high recall.

Conclusion

- The PR curve indicates that the logistic regression model has poor performance, especially with precision, as reflected by the Average Precision (AP) = 0.16. To improve the model, consider addressing class imbalance, refining features, or trying more advanced methods to better balance precision and recall.

In [37]:
```
# Plot the ROC Curve
RocCurveDisplay.from_estimator(logistic_model, X_test, y_test)
plt.title('ROC Curve')
plt.show()
```



Interpretation of the Curve

** Diagonal Shape:

- The ROC curve is close to the diagonal line (random classifier line), which represents a model with no discriminatory power.
- This indicates that the model is only slightly better than random guessing.

** Area Under the Curve (AUC = 0.56):

- AUC summarizes the model's overall ability to distinguish between positive and negative classes.
- AUC ranges from 0.5 to 1 means a random model with no skill to a perfect model, So, an AUC of 0.56 is just slightly better than random, indicating poor model performance.

Conclusion

- The ROC curve indicates that the logistic regression model performs poorly, with an AUC = 0.56, only slightly better than random guessing. To improve performance, focus on addressing data issues, improving feature quality, and considering alternative algorithms.

Clear any logs from previous runs

In [38]:

```python
import os
import shutil

# shutil module is part of the Python standard library and provides a
# collection of utility functions for working with files and directories.

folder_path = "logs/"

# Check if the folder exists before attempting to delete it
if os.path.exists(folder_path):
    # Remove the folder and its contents recursively
    shutil.rmtree(folder_path)
    print(f"The folder '{folder_path}' has been deleted.")
else:
    print(f"The folder '{folder_path}' does not exist.")
```

```
The folder 'logs/' has been deleted.
```

In [39]:
```
# Delete the ".tensorboard-info" directory

folder_path = "C:/Users/userAdmin/AppData/Local/Temp/.tensorboard-info/"

# Check if the folder exists before attempting to delete it
if os.path.exists(folder_path):
    # Remove the folder and its contents recursively
    shutil.rmtree(folder_path)
    print(f"The folder '{folder_path}' has been deleted.")
else:
    print(f"The folder '{folder_path}' does not exist.")
```

```
The folder 'C:/Users/userAdmin/AppData/Local/Temp/.tensorboard-info/' has bee
n deleted.
```

Deep Learning Section

In [40]:
```
# import the required libraries in Tensorflow/Keras framwork
import os
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
# import TensorBoard
from tensorflow.keras.callbacks import TensorBoard
import datetime
# Load the TensorBoard notebook extension
%load_ext tensorboard
```

In [41]:
```
# print the current tensorflow version
print('Tensorflow version', tf.__version__)
```

```
Tensorflow version 2.18.0
```

In [42]:
```
# Select relevant columns
dfn = dfn[['log_annual_inc', 'dti', 'fico', 'days_with_cr_line', 'revol_bal',
           'debt_consolidation', 'credit_card', 'home_improvement',
       'small_business', 'major_purchase', 'educational']]

# Separate the features from the labels into X and y, Define features (X) and t
X = dfn[['log_annual_inc', 'dti', 'fico','days_with_cr_line', 'revol_bal', 're
         'debt_consolidation', 'credit_card', 'home_improvement',
       'small_business', 'major_purchase', 'educational']]  # Predictor
y = dfn['not_fully_paid']    # target
```

In [43]:
```
# Perform a train test split on the data, with test size of 20% and random_stat
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
```

In [44]:
```
# split the training set into training and validation sets
X_train, X_validate, y_train, y_validate = train_test_split(X_train, y_train, 
```

In [45]:
```
X.shape, y.shape
```

Out[45]:
```
((7710, 12), (7710,))
```

In [46]:
```
X_train.shape, y_train.shape
```

Out[46]:
```
((4934, 12), (4934,))
```

In [47]:
```
X_validate.shape, y_validate.shape
```

Out[47]:
```
((1234, 12), (1234,))
```

In [48]:
```
import tensorflow as tf
import os
import datetime
from tensorflow.keras.callbacks import TensorBoard

# Create a Log Directory for TensorBoard Logs
log_dir = os.path.join("logs", "fit")
```

In [49]:
```
# Define the model with its structure
def create_model():
    return tf.keras.models.Sequential([
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(1, activation='sigmoid')
  ])

model = create_model()

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy

# TensorBoard log directory
log_dir = "logs/fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard_callback = TensorBoard(log_dir=log_dir, histogram_freq=1)

# Train the model with TensorBoard callback
history = model.fit(X_train, y_train, epochs=50, validation_data=(X_test, y_te
```

```
Epoch 1/50
155/155 3s 5ms/step - accuracy: 0.7033 - loss: 365.6676
- val_accuracy: 0.8735 - val_loss: 138.1128
Epoch 2/50
155/155 0s 3ms/step - accuracy: 0.7893 - loss: 185.5717
- val_accuracy: 0.8735 - val_loss: 92.6122
Epoch 3/50
155/155 0s 3ms/step - accuracy: 0.7726 - loss: 174.4221
- val_accuracy: 0.8735 - val_loss: 86.8090
Epoch 4/50
155/155 0s 2ms/step - accuracy: 0.7728 - loss: 98.3676 -
val_accuracy: 0.8735 - val_loss: 54.1657
Epoch 5/50
155/155 0s 2ms/step - accuracy: 0.7883 - loss: 84.5389 -
val_accuracy: 0.8735 - val_loss: 33.9490
Epoch 6/50
155/155 0s 2ms/step - accuracy: 0.7537 - loss: 54.8628 -
val_accuracy: 0.8722 - val_loss: 19.2176
Epoch 7/50
155/155 0s 2ms/step - accuracy: 0.7509 - loss: 39.5126 -
val_accuracy: 0.8722 - val_loss: 18.9728
Epoch 8/50
155/155 0s 2ms/step - accuracy: 0.7790 - loss: 22.1343 -
val_accuracy: 0.8729 - val_loss: 9.1224
Epoch 9/50
155/155 0s 2ms/step - accuracy: 0.7930 - loss: 15.6963 -
val_accuracy: 0.8709 - val_loss: 5.5105
Epoch 10/50
155/155 0s 3ms/step - accuracy: 0.7679 - loss: 7.2419 -
val_accuracy: 0.8690 - val_loss: 3.0086
Epoch 11/50
155/155 0s 2ms/step - accuracy: 0.7927 - loss: 5.6684 -
val_accuracy: 0.7737 - val_loss: 1.5242
Epoch 12/50
155/155 0s 2ms/step - accuracy: 0.7788 - loss: 3.5129 -
val_accuracy: 0.8696 - val_loss: 2.8209
Epoch 13/50
155/155 0s 2ms/step - accuracy: 0.7872 - loss: 3.9943 -
val_accuracy: 0.3424 - val_loss: 5.0885
Epoch 14/50
155/155 0s 3ms/step - accuracy: 0.7420 - loss: 5.0059 -
val_accuracy: 0.8729 - val_loss: 4.4290
Epoch 15/50
155/155 0s 3ms/step - accuracy: 0.7808 - loss: 2.4718 -
val_accuracy: 0.8735 - val_loss: 0.9425
Epoch 16/50
155/155 0s 2ms/step - accuracy: 0.8195 - loss: 1.8240 -
val_accuracy: 0.8658 - val_loss: 0.5304
Epoch 17/50
155/155 0s 2ms/step - accuracy: 0.7943 - loss: 1.4884 -
val_accuracy: 0.8690 - val_loss: 0.5687
Epoch 18/50
155/155 0s 2ms/step - accuracy: 0.7921 - loss: 1.2067 -
val_accuracy: 0.8735 - val_loss: 1.9027
Epoch 19/50
155/155 0s 2ms/step - accuracy: 0.8191 - loss: 1.3798 -
val_accuracy: 0.8709 - val_loss: 0.8806
```

```
Epoch 20/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8025 - loss: 1.1058 - val_accuracy: 0.8735 - val_loss: 1.8214
Epoch 21/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7923 - loss: 1.6063 - val_accuracy: 0.8735 - val_loss: 0.8029
Epoch 22/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8139 - loss: 1.1052 - val_accuracy: 0.8735 - val_loss: 2.1118
Epoch 23/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8049 - loss: 1.2175 - val_accuracy: 0.8690 - val_loss: 0.4507
Epoch 24/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8135 - loss: 1.0628 - val_accuracy: 0.6861 - val_loss: 0.7573
Epoch 25/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8116 - loss: 0.9963 - val_accuracy: 0.8735 - val_loss: 0.5179
Epoch 26/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8341 - loss: 0.8779 - val_accuracy: 0.8735 - val_loss: 0.4532
Epoch 27/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8357 - loss: 0.8078 - val_accuracy: 0.8735 - val_loss: 0.7845
Epoch 28/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8271 - loss: 0.9988 - val_accuracy: 0.8735 - val_loss: 0.5014
Epoch 29/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8261 - loss: 0.9283 - val_accuracy: 0.8729 - val_loss: 0.4514
Epoch 30/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8439 - loss: 0.5665 - val_accuracy: 0.8735 - val_loss: 0.4220
Epoch 31/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8319 - loss: 0.7671 - val_accuracy: 0.8735 - val_loss: 0.5003
Epoch 32/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8404 - loss: 0.6844 - val_accuracy: 0.8560 - val_loss: 0.4426
Epoch 33/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8254 - loss: 0.8072 - val_accuracy: 0.8735 - val_loss: 0.5835
Epoch 34/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8535 - loss: 0.5327 - val_accuracy: 0.8696 - val_loss: 0.3921
Epoch 35/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8432 - loss: 0.6434 - val_accuracy: 0.8735 - val_loss: 0.4853
Epoch 36/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8489 - loss: 0.5458 - val_accuracy: 0.8735 - val_loss: 0.5085
Epoch 37/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8554 - loss: 0.5615 - val_accuracy: 0.8735 - val_loss: 0.5010
Epoch 38/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8608 - loss: 0.5048 - val_accuracy: 0.8735 - val_loss: 0.4054
```

```
Epoch 39/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8541 - loss: 0.4872 -
val_accuracy: 0.8684 - val_loss: 0.4317
Epoch 40/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8583 - loss: 0.5597 -
val_accuracy: 0.8735 - val_loss: 0.4072
Epoch 41/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8485 - loss: 0.4677 -
val_accuracy: 0.8735 - val_loss: 0.3947
Epoch 42/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8642 - loss: 0.4611 -
val_accuracy: 0.8735 - val_loss: 0.4009
Epoch 43/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8645 - loss: 0.4284 -
val_accuracy: 0.8735 - val_loss: 0.4440
Epoch 44/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8607 - loss: 0.4750 -
val_accuracy: 0.8735 - val_loss: 0.3838
Epoch 45/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8676 - loss: 0.4162 -
val_accuracy: 0.8735 - val_loss: 0.3850
Epoch 46/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8595 - loss: 0.4195 -
val_accuracy: 0.8742 - val_loss: 0.3843
Epoch 47/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8713 - loss: 0.3931 -
val_accuracy: 0.8735 - val_loss: 0.3884
Epoch 48/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8663 - loss: 0.4060 -
val_accuracy: 0.8735 - val_loss: 0.3819
Epoch 49/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8626 - loss: 0.4186 -
val_accuracy: 0.8735 - val_loss: 0.3872
Epoch 50/50
155/155 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8673 - loss: 0.4028 -
val_accuracy: 0.8735 - val_loss: 0.3895
```

In [50]:
```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 64)	832
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65

Total params: 2,693 (10.52 KB)

Trainable params: 897 (3.50 KB)

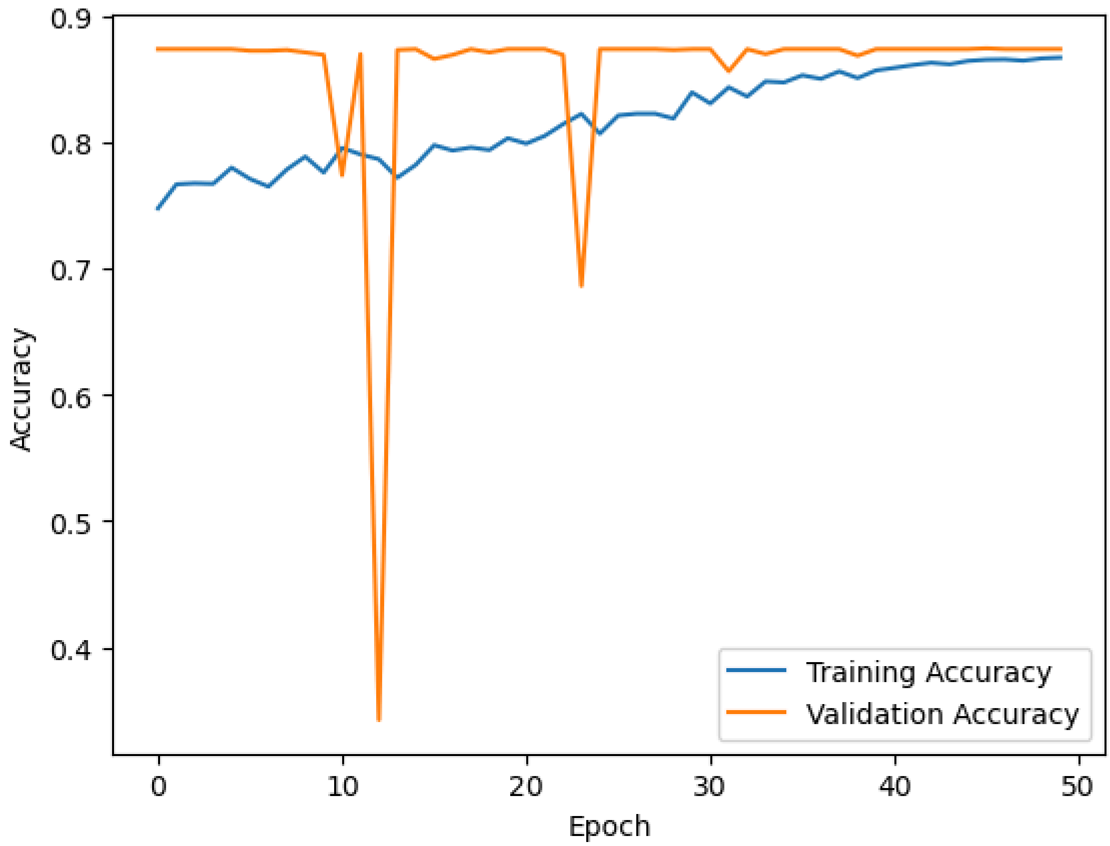
Non-trainable params: 0 (0.00 B)

Optimizer params: 1,796 (7.02 KB)

In [51]:
```
# Evaluate the model on test data
test_loss, test_accuracy = model.evaluate(X_test, y_test)
print("Test Loss:", test_loss)
print("Test Accuracy:", test_accuracy)
```

```
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8632 - loss: 0.4014
Test Loss: 0.3895450532436371
Test Accuracy: 0.8735408782958984
```

In [52]:
```
# Plot the training and validation accuracy
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



Key Observations

** Training Accuracy (Blue Line):

- The training accuracy improves gradually over time, showing a smooth upward trend as the model learns from the training data.
- There is no significant drop or fluctuation, which is expected behavior for a well-behaved training process.

** Validation Accuracy (Orange Line):

- The validation accuracy shows unusual behavior;
- Initially, it is higher than training accuracy (which can happen for a small dataset or certain regularization techniques).
- Around epoch 12, there’s a sharp drop in validation accuracy to a very low value (possibly caused by data issues or instability during training).
- After epoch 23, the validation accuracy recovers and starts aligning with training accuracy, improving consistently and stabilizing near the end.

General Observations About Training and Validation Accuracy

** Consistent Accuracy:

- Towards the end (epochs 30-50), the training and validation accuracies align, indicating that the model is generalizing well to unseen data.

** Overfitting is Not Apparent:

- Validation accuracy does not degrade significantly compared to training accuracy, suggesting no major overfitting.

Conclusion

- The training and validation accuracies eventually stabilize, indicating good generalization.
- The sharp drop in validation accuracy around epoch 15 suggests possible instability or anomalies in training/validation data or learning rate issues.
- With proper adjustments to hyperparameters, validation data handling, and regularization, this instability can be minimized.

In [53]:
```
# Predict probabilities for the test set
y_pred_probs = model.predict(X_test)

# Convert probabilities to binary predictions (0 or 1) using a threshold of 0.!
y_pred = (y_pred_probs > 0.5).astype(int)
```

```
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

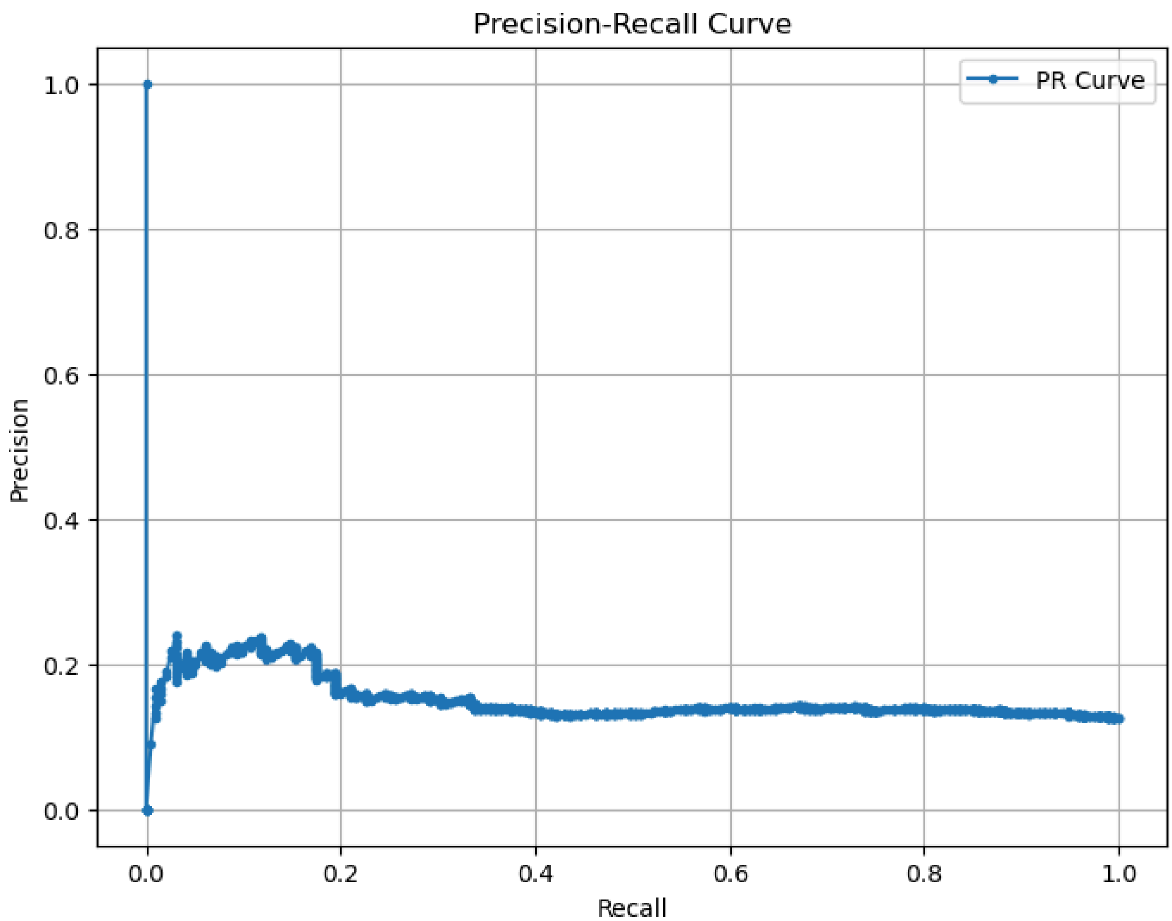
In [54]:
```
# Generate the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Print the confusion matrix
print("Confusion Matrix:")
print(conf_matrix)
```

```
Confusion Matrix:
[[1347    0]
 [ 195    0]]
```

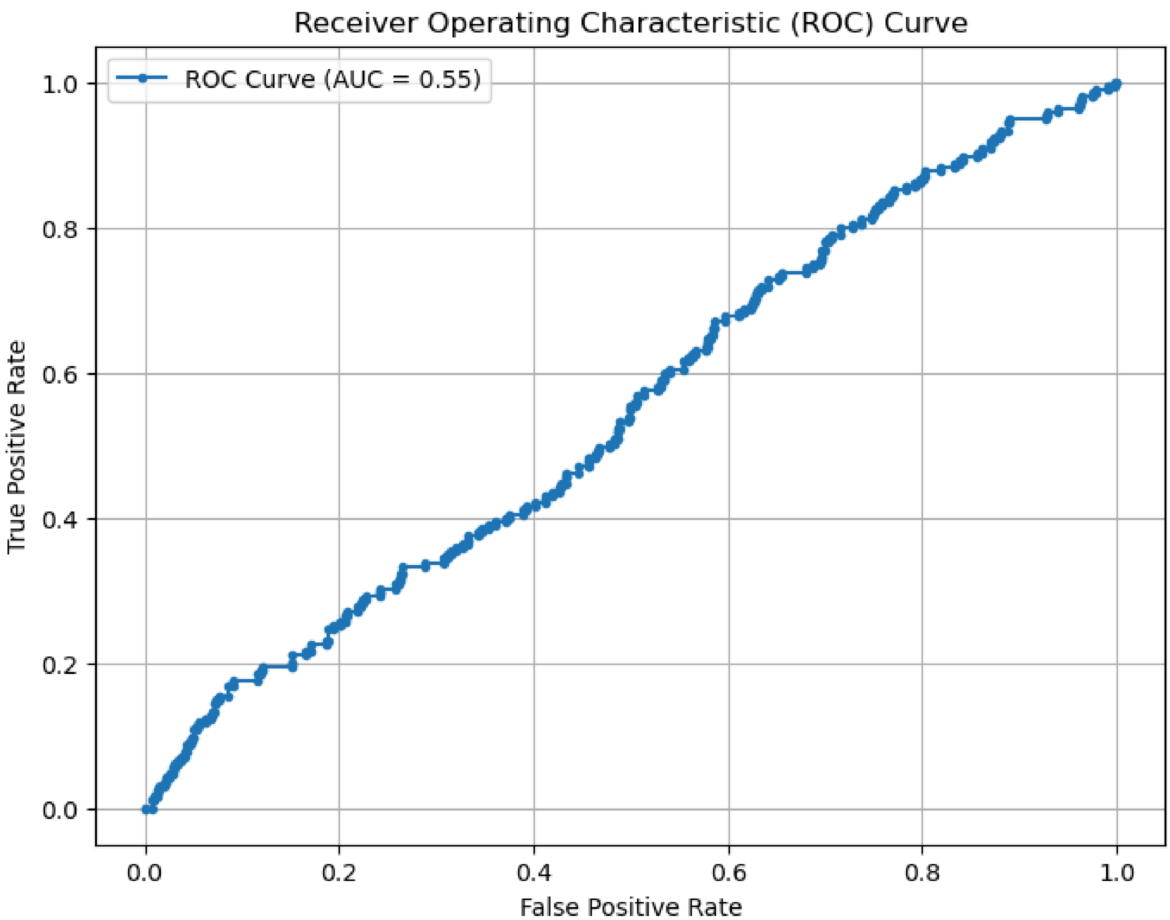
In [55]:
```
# Print the classification report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      1.00      0.93      1347
           1       0.00      0.00      0.00       195

    accuracy                           0.87      1542
   macro avg       0.44      0.50      0.47      1542
weighted avg       0.76      0.87      0.81      1542
```

In [56]:
```
# Calculate precision, recall, and thresholds
precision, recall, thresholds = precision_recall_curve(y_test, y_pred_probs)

# Plot the Precision-Recall Curve
plt.figure(figsize=(8, 6))
plt.plot(recall, precision, marker='.', label='PR Curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend()
plt.grid(True)
plt.show()
```



In [57]:
```
# Calculate False Positive Rate (FPR), True Positive Rate (TPR), and threshol
fpr, tpr, thresholds = roc_curve(y_test, y_pred_probs)

# Calculate AUC
auc = roc_auc_score(y_test, y_pred_probs)

# Plot the ROC Curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, marker='.', label=f'ROC Curve (AUC = {auc:.2f})')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.grid(True)
plt.show()
```



Two Models Comparision

** Now we can find that the classification report, Precision-Recall Curve, and ROC Curve are almost the same between the logistic regression machine learning model and its deep learning implementation, it indicates that the two models are performing very similarly.

Possible Causes

- If the dataset has linearly separable data or the relationships between the features and the target variable are inherently linear, a logistic regression model is sufficient. Adding layers in a deep learning model won't significantly improve performance since the problem doesn't require modeling non-linearities.

- Deep learning models are typically used for complex problems (e.g., image recognition, natural language processing) that require non-linear representations.If the problem is simple and doesn't require complex feature extraction or non-linear decision boundaries, the deep learning model's added complexity is unnecessary and doesn't yield better results.
- Since the deep learning model performs similarly to the logistic regression model, it suggests that the deep learning model Was not overfitting, which could happen when using complex architectures on simple data.

Examples of Situations Where This Occurs

- Structured Data: Logistic regression often performs as well as deep learning models for tabular datasets with simple relationships (e.g., credit scoring, medical diagnosis).
- Linearly Separable Problems: If the classes are well-separated in the feature space by a linear boundary, adding complexity doesn't improve results.
- Small Datasets: With limited data, deep learning models may not have enough information to justify their complexity, leading to similar performance as logistic regression.

Summary and Conclusion

The similar performance between the logistic regression machine learning model and its deep learning counterpart suggests that the problem is simple, linear, or well-suited for logistic regression. In such cases, using logistic regression is often preferable due to its simplicity, interpretability, and lower computational requirements. Deep learning models offer no significant advantage unless the problem involves non-linear or high-dimensional complexities.

In [ ]:
```
# Launch TensorBoard
# Command: tensorboard --logdir=logs/fit
```

In [ ]:
```
# End of Project
```