Data Mining Algorithms for Credit Default Risk

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Authors' Note

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Abstract

The final team project uses different modeling techniques for consumer credit default. The objective was to develop Logistic Regression and Naïve Bayesian Classification models by using different characteristics to predict the likelihood of default on credit payments. The response variable was a binary indicator of default, and 23 explanatory variables were used to build and compare models. After thorough data analysis, both models were implemented and evaluated. The Naïve Bayesian model outperformed the Logistic Regression model by a small margin. This report documents the preliminary data analysis, the model selection, training and results and assesses the strengths and weaknesses of both models when analyzing credit default risk.

Keywords: credit default, logistic regression, Naïve Bayesian Classification analysis, binary classification, predictive modeling

Data Mining Algorithms for Credit Default Risk

Accurately predicting the credit default rate is critical for financial institutions in helping with risk management. As Yeh and Lien (2009) stated, "whether or not the estimated probability of default produced from data mining methods can represent the 'real' probability of default is an important problem" (p. 2473). This research is an analysis of evaluating different data mining algorithms on a dataset of 30,000 credit card clients with 24 features provided by Yeh (2009) via the UCI Machine Learning Repository..

The goal was to analyze the performance of the Logistic Regression versus Naïve Bayesian Classification models in predicting default credit risk.

Our hypothesis was as follows:

- Null Hypothesis (H_0): There is no statistically significant relationship between the predictor variables and the likelihood of default.
- Alternative Hypothesis (H_1): There exists a statistically significant relationship between one or more predictor variables and the likelihood of default.

The data was composed of 30,000 rows and had 1 response variable, default payment (Yes = 1, No = 0), and 23 explanatory variables as shown below:

- LIMIT_BAL: Amount of the given credit (NT dollar): it includes both the individual consumer credit and his/her family (supplementary) credit.
- SEX: Gender (1 = male; 2 = female).
- EDUCATION: Education (1 = graduate school; 2 = university; 3 = high school; 4 = others).

- MARRIAGE: Marital status (1 = married; 2 = single; 3 = others).
- AGE: Age (year).
- PAY_0-PAY_6: History of past payment.
    - The past monthly payment records (from April to September 2005) are as follows:
        - 0 = The Repayment Status in September 2005;
        - 2 = The Repayment Status in August 2005;
        - 6 = The Repayment Status in April 2005.
    - The measurement scale for the repayment status is:
        - -1 = Pay Duly;
        - 1 = Payment Delay for one month;
        - 2 = Payment Delay for two months;
        - 8 = Payment Delay for eight months;
        - 9 = Payment Delay for nine months and above.
- BILL_AMT1-BILL_AMT6: Amount of bill statement (NT dollar).
    - 1 = Amount of Bill Statement in September 2005;
    - 2 = Amount of Bill Statement in August 2005;
    - 6 = Amount of Bill Statement in April 2005.
- PAY_AMT1-PAY_AMT6: Amount of previous payment (NT dollar).
    - 1 = Amount Paid in September 2005;
    - 2 = Amount Paid in August 2005;
    - 6 = Amount Paid in April 2005.

Data Cleaning and Preparation

Several preprocessing steps were applied to the original data. The preprocessing of the data was needed to improve clarity and increase the interpretability of explanatory variables.

The BILL_AMT and PAY_AMT columns were consolidated. The original dataset contained one separate column for each pay and bill amount, starting at the most recent and spanning 6 months of history. To quantify the effect of payment amounts and bill amounts as unitary variables, a weighted average was calculated for each subject, using a linear decay factor (highest weight for most recent).

Segmentation of certain continuous variables into contiguous segments. The effect of certain continuous variables was hard to interpret because of the small size of the granularity. The data was derived and adjusted into four equal-sized bins. This transformation enhanced interpretability and mitigated the influence of outliers. The following variables were consolidated into a reduced number of contiguous blocks:

- AGE;
- LIMIT_BAL;
- WEIGHTED_BILL_AMT;
- WEIGHTED_PAY_AMT;

The boundaries between the blocks were made to match the quartiles for each series. Quartile ranges were determined as follows:

- AGE: Overall Range: 21-79
    - 21–28;
    - 28–34;

  - 34–41;
  - 41–79.

- LIMIT_BAL: Overall Range: 10,000-1,000,000
  - 10,000–50,000;
  - 50,000–140,000;
  - 140,000–240,000;
  - 240,000–1,000,000.
- WEIGHTED_BILL_AMT / PAY_AMT: Overall Range: -29464.95-873217.38
  - -29464.95-4888.90;
  - 1228.08-2488.14;
  - 2488.14-5696.19;
  - 5696.19-805849.48.

Some redundant payment history variables were removed. The PAY_2 - PAY-6 variables were duplicative of PAY_0, since they measured payment delay in months for multiple months in a row. Since there were not many additional insights to be gained from them beyond what is already included in PAY_0, and to avoid cannibalizing coefficient capital from other more meaningful variables, a decision was made to remove them altogether.

Some values in PAY_0 were re-coded. -1 means “paid duly”. The next possible value was 1 which indicates “1 month behind”. To ensure a consistent step size from baseline for interpreting the odds ratio in logistic regression, we re-coded -1 to 0.

To evaluate the effectiveness of the models, we subdivided the data into two parts:

- A training sample containing 70% of samples from the original dataset selected at random;
- A testing sample containing the remaining 30% of the samples.

This division ensured unbiased model evaluation and reduced the risk of overfitting during training.

Exploratory Data Analysis

Descriptive statistics and visualizations were run on the dataset as shown below.

Figure 1 shows the distribution of the SEX variable. It shows an uneven split between 60.4% of females and 39.6% of males.

Figure 1

Sex Distribution

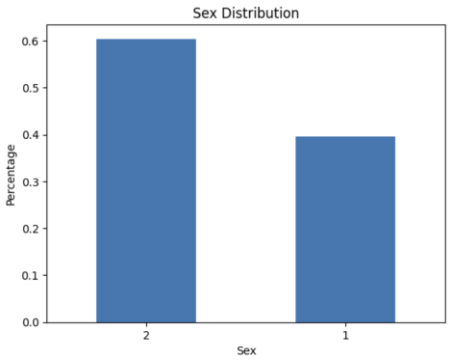


Figure 2 shows the distribution of the AGE variable. It shows a right skewed distribution with the majority of ages between 20-40. Figure 3 shows the distribution plotted as a box plot and the presence of outliers.

Figure 2

Age Histogram

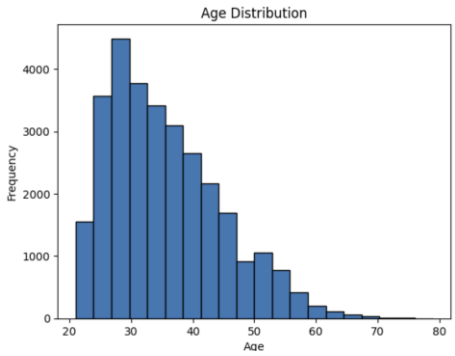


Figure 3

Age Box Plot

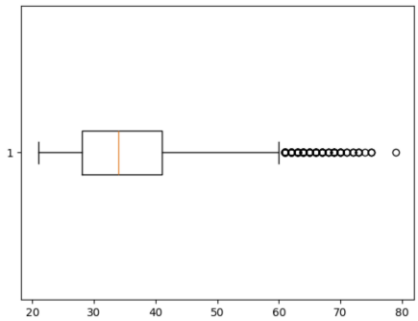


Figure 4 shows the LIMIT_BALANCE distribution. It shows a heavy right skew distribution with a few outliers with a higher limit. Figure 5 shows the distribution and the outliers on a box plot.

Figure 4

Balance Histogram

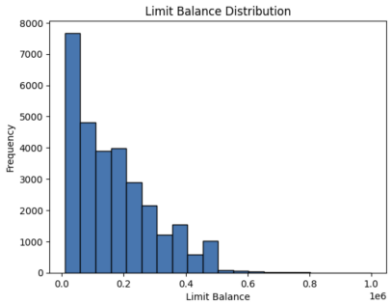


Figure 5

Balance Box Plot

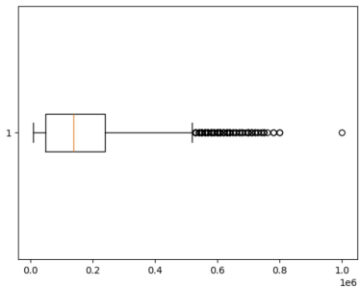
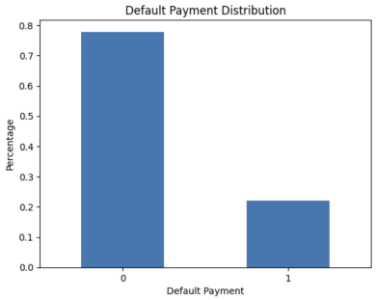


Figure 6 shows the distribution of the DEFAULT variable. It shows 22% had defaulted, and 78% did not default.

Figure 6

Default Distribution

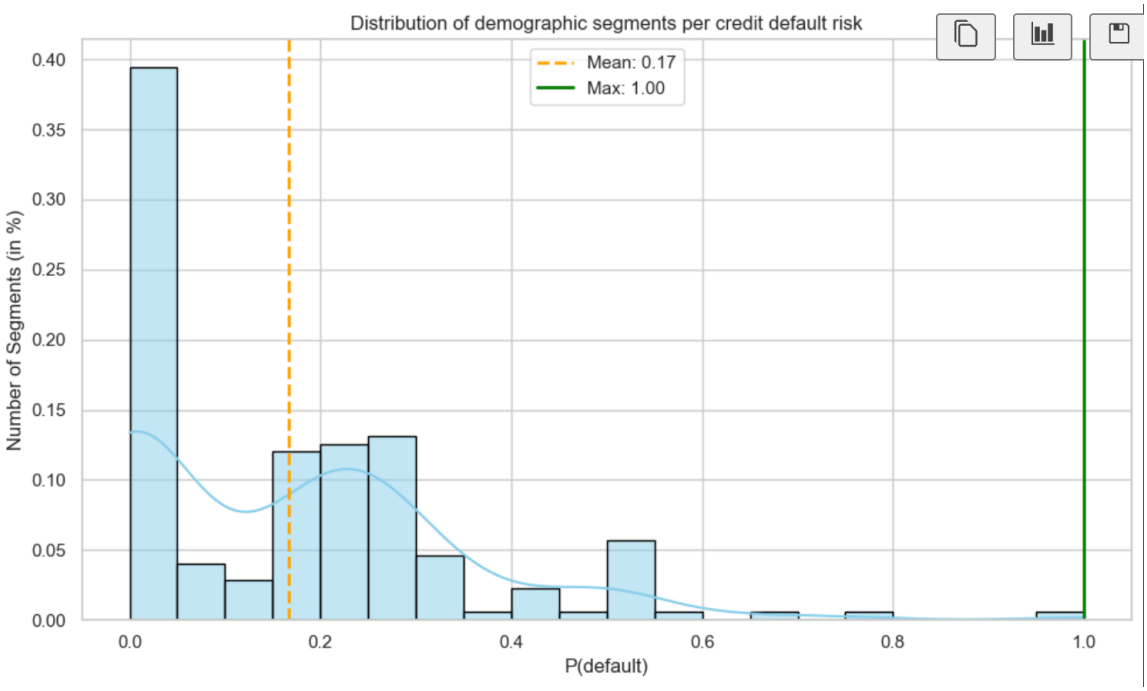


In Figure 7, we subdivided the samples into distinct demographic segments characterized by unique combinations of Sex, Education, Marriage and Age. We then calculated the credit default rate for each segment and plotted the count of segments for each probability on a histogram.

The resulting distribution is skewed to the right with 40% of the segments having near 0 credit default risk and 12% of the segments having average credit default risk. This shows that demographic variables have a meaningful effect on credit default risk, or else we would see a normal distribution centered around the mean.

Figure 7

Distribution by Demographic Segments



Model Selection and Analysis

The two statistical models chosen were Naïve Bayesian Classification and Logistic Regression.

Naïve Bayesian Classifier

A Gaussian Naive Bayes model was trained on a dataset consisting of 30,000 clients, using financial and demographic predictors. The dataset was cleaned and transformed as described in the data cleaning and preparation section. The dataset was split into training and testing sets using a 70:30 ratio, and model performance was evaluated using accuracy and a classification report (Table 1).

- Overall Accuracy: 0.81 (or 81%),
- Classification Report:

Table 1

Naïve Bayes Performance Report

Class	Precision	Recall	F1-score
No Default (0)	0.83	0.95	0.89
Default (1)	0.63	0.32	0.43

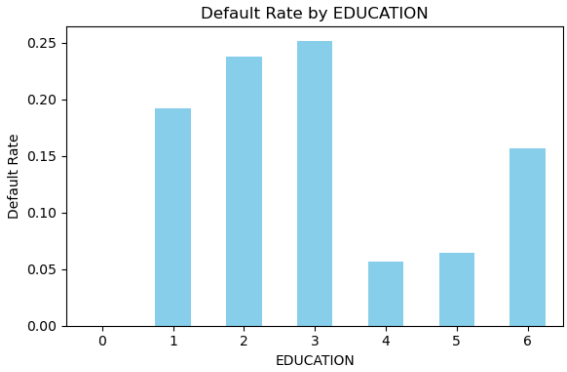
- Accuracy: 81% of the model's predictions were correct.
- Positive Predictive Value (Precision): The probability that a client actually defaulted given that the model predicted a default (precision) is 63%.
- Sensitivity (recall): The percentage of actual defaulters that were correctly identified by the model (true positive rate) is 32%.
- Specificity: The percentage of non-defaulters that were correctly identified by the model (true negative rate) is 95%.

Demographic Model Analysis

The default rate seems to decrease with higher education levels (Figure 8). Clients with only a high school education or lower, showed significantly higher default rates than those with university or graduate degrees. This aligns with the hypothesis that financial literacy and income stability may increase with education.

Figure 8

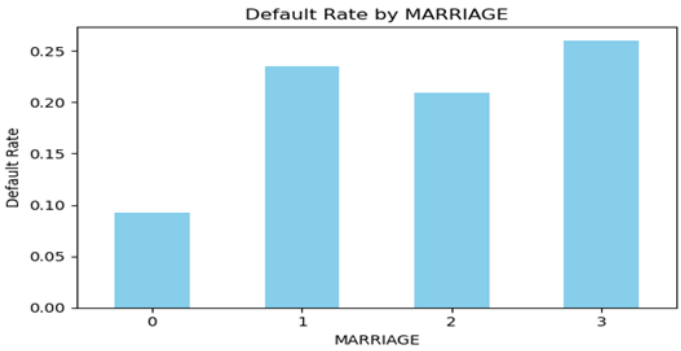
Education Default Rate



Divorced\Widowed clients showed slightly higher default rates than married or single clients (Figure 9). This could reflect different levels of financial responsibility or dual income benefits in married households.

Figure 9

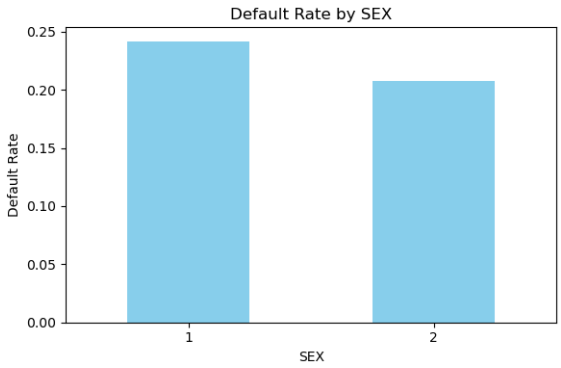
Marriage Default Rate



The difference in default rates between male and female clients looks marginal (Figure 10). However, females had a slightly lower default rate, indicating potential gender-related behavioral or income differences.

Figure 10

Sex Default Rate

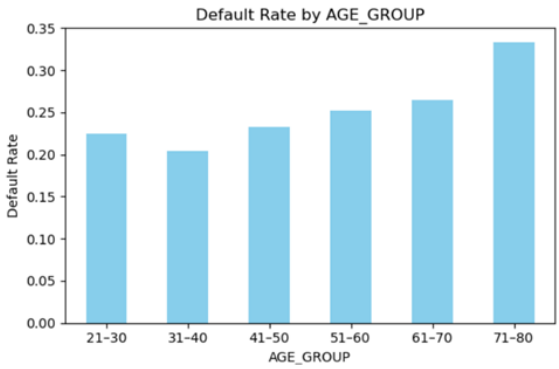


Older adults (71–80) show a surprisingly high default rate (Figure 11), which could be due to fixed income, retirement, or small sample bias. Older adults have a

moderately high default rate, this is consistent with financial maturity increasing with age, as younger clients may be more credit inexperienced. Younger adults (21–30) have a moderate default rate, possibly due to limited credit experience.

Figure 11

Age Default Rate



Logistic Regression

Background

Linear regression models quantify the effects of each explanatory variable (while adjusting for the others) on the response variable, resulting in a prediction equation which looks like:

$$E(Y_i) = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}$$

where:

- x_{ij} is the value of explanatory variable j for subject i ;
- p is the count of explanatory variables.

They assume a normal distribution and constant variance in the response variable at each combination of explanatory variables.

In the case of predicting credit defaults, the response variable is a Bernoulli variable and the standard linear regression model is inadequate because:

- the normality assumption is violated because the distribution is binomial;
- the constant variance assumption is also violated because its variance depends on its mean: $\mu(1-\mu)$;
- the predicted values are not constrained to [0, 1].

In this case we turn to GLMs (Generalized Linear Models), which are a family of models which extend the linear regression dynamics to fit data which badly violates the assumptions of the normal linear model (Agresti & Kateri, 2022).

GLMs are characterized by three components:

- the random component (the response variable);
- the systematic component (the explanatory variable);
- the link function (a transformation function which allows the predicted value to be non-linearly related to the explanatory variables).

For Bernoulli variables such as the credit default variable, we need to model the probability that the outcomes fall in one of two categories: success or failure. This makes this problem a classification problem and one for which the logistic regression model is particularly well suited.

The link function of logistic regression models is called the logit and can be expressed as:

$$\log\left(\frac{\mu_i}{1-\mu_i}\right)$$

Therefore, the full prediction equation is:

$$\log\left(\frac{\mu_i}{1-\mu_i}\right) = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}$$

The results produced by the logistic regression model would need to be converted back to a probability of default π by reversing the effects of the logit function:

$$\pi_i = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip})}}$$

Another way to read the model is to characterize the change in Y based on a one-unit increment of a given explanatory variable, this is done by looking at the individual coefficients themselves: $\beta_1, \ldots, \beta_p$. The coefficients give you the log-odds of changes for each explanatory variable (adjusting for the others). Reversing the transformation gives you the corresponding odds ratio, answering the question "by how much do the odds of default change when that explanatory variable changes?"

$$odds\,ratio_i = e^{\beta_i}$$

Results

Figure 12 Shows the raw results of training the model on the training dataset.

Figure 12

Regression Results

Generalized Linear Model Regression Results

Dep. Variable:	default_status	No. Observations:	21000
Model:	GLM	Df Residuals:	20991
Model Family:	Binomial	Df Model:	8
Link Function:	Logit	Scale:	1.0000
Method:	IRLS	Log-Likelihood:	-9704.7
Date:	Fri, 20 Jun 2025	Deviance:	19409.
Time:	17:00:20	Pearson chi2:	2.48e+04
No. Iterations:	5	Pseudo R-squ. (CS):	0.1242
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-0.0883	0.134	-0.661	0.509	-0.350	0.174
LIMIT_BAL_Q	-0.1406	0.019	-7.402	0.000	-0.178	-0.103
SEX	-0.1528	0.037	-4.160	0.000	-0.225	-0.081
EDUCATION	-0.0860	0.025	-3.461	0.001	-0.135	-0.037
MARRIAGE	-0.1505	0.038	-3.912	0.000	-0.226	-0.075
AGE_Q	0.0432	0.018	2.426	0.015	0.008	0.078
PAY_0	0.8101	0.021	38.912	0.000	0.769	0.851
WEIGHTED_BILL_AMT_Q	-0.0015	0.021	-0.072	0.943	-0.042	0.039
WEIGHTED_PAY_AMT_Q	-0.2511	0.022	-11.209	0.000	-0.295	-0.207

The parameters of the trained model give us the estimated effect for each explanatory variable, along with a set of metrics which indicate the statistical significance of the effect and their confidence levels.

These metrics are:

- the standard error,
- the z-score,
- the p-value,
- the confidence interval.

The standard error measures the sampling distribution's normalized deviation around the true proportion of defaults if H_0 was true and the z-score gives us the number of standard

errors away from where it would be under H_0. The larger the z-score, the less likely it is due to normal sampling variations.

The p-value gives us the probability of arriving at an effect of that magnitude if the true effect was 0 (adjusting for the effects of all the other variables). In this study, we use $\alpha = 0.05$, therefore, all p-values below 0.05 indicate that the effect is statistically significant.

Out of all the explanatory variables, only WEIGHTED_BILL_AMT_Q was not statistically significant (p-value = 0.990).

Among the remaining variables, we observed the following effects, ranked by strength:

- PAY_0 has the strongest effect on credit default likelihood: for each additional month that a client is late, the odds of defaulting increase by 133%.
- PAY_AMT (weighted and split into quartiles) has the second strongest effect. For each increase of one quartile in the adjusted amount paid, the odds of defaulting decrease by 23%. This indicates that people who pay small amounts (like the minimum amount) are more likely to default than people who make bigger payments.
- MARRIAGE has the third strongest effect. The odds of defaulting decrease by 14% when the client is married compared to being single.
- LIMIT_BAL_Q has the fourth strongest effect. For each quartile-over-quartile increase in credit limits, the odds of defaulting decrease by 13%. This indicates that people with small credit limits are more likely to default than people who have higher credit limits.

- SEX has the fifth strongest effect, with the odds of defaulting decreasing by 11% when the client is female.
- EDUCATION has the sixth strongest effect, with odds of default decreasing by 6% with each increment.
- AGE has the weakest effect on credit defaults, with each quartile-over-quartile increment increasing the risk of default by 4%.

Model Validation

Performing credit default classification on the 30% of samples set aside for testing allowed us to assess the performance of the model on previously unseen data. The results were as follows:

- Overall Accuracy: 0.8057 (or 80.57%),
- Additional results are shown in Table 3.

Table 3

Logistic Regression Performance Summary

Class	Precision	Recall	F1-score
No Default (0)	0.82	0.97	0.89
Default (1)	0.70	0.25	0.37

- Accuracy: 80.57% of the model's predictions were correct.
- Positive Predictive Value (Precision): The probability that a client actually defaulted given that the model predicted a default (precision) is 70%.
- Sensitivity (recall): The percentage of actual defaulters that were correctly identified by the model (true positive rate) is 25%.

- Specificity: The percentage of non-defaulters that were correctly identified by the model (true negative rate) is 97%.

Conclusions and Recommendations

In this paper, we demonstrated the extent to which the Naïve Bayesian and the Logistic Regression model could predict credit defaults from an assorted set of predictors. Our analysis shows that there is an association between the explanatory variables and credit default, notably, the Logistic Regression model parameters indicate that the strength of the effects of payment history, payment amount, marriage, credit limit, sex, education and age on credit default are statistically significant, therefore we hereby reject H_0 and accept H_1.

In our study, both models exhibited similar performances, with the Naïve Bayesian model showing a slight advantage. The aggregated model performance measurements are displayed in Table 4.

Table 4

Model Performance Comparison

Class	Precision		Recall		F1-score	
	Bayesian	Logistic	Bayesian	Logistic	Bayesian	Logistic
No Default (0)	0.83	0.82	0.95	0.97	0.89	0.89
Default (1)	0.63	0.70	0.32	0.25	0.43	0.37

- The precision for class 1 (the probability that a person actually defaulted when the model predicted a default) is decent for both models, the Logistic Regression

model slightly outperforms the Naïve Bayesian model meaning that the Naïve Bayesian model would trigger more false positives (wrongly flagging a client as credit default risk).

- The precision for class 0 (the probability that a person did not actually default when the model predicted a non-default) is high for both models, but the Logistic Regression model underperforms the Naïve Bayesian, potentially leading to higher risk (clearing clients when they should be flagged).
- Notably, both models perform poorly at recall for class 1 (percentage of actual defaulters in the test sample correctly identified), indicating that both models underestimate risk. This phenomenon can be explained by the smaller proportion of defaulting samples in the dataset, leading to an imperfect fit for both models. The Naïve Bayesian model did perform significantly better than Logistic Regression (0.32 vs 0.25).

The recommendations based on the findings and model analysis, are the following:

- Model Variations: Explore more advanced model algorithms.
- Enhanced Variables: Adding variables such as income level, employment stability, or length of credit history to improve results.
- Bias Auditing: Assess the model for potential bias across demographic groups (e.g., sex, age, marital status) to ensure fairness and compliance with ethical AI standards since there were more females than males on the dataset.
- Resampling Techniques: Apply oversampling balancing techniques to address the default class imbalance.

Overall, while both models provided similar results for credit risk prediction, continued refinement and ethical evaluation will ensure ethical and responsible analysis in the future.

References

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Yeh, I. (2009). Default of Credit Card Clients [Dataset]. UCI Machine Learning Repository. https://doi.org/10.24432/C55S3H.

Yeh, I.-C., & Lien, C.-H. (2009). The comparisons of data mining techniques for the predictive accuracy of probability of default of credit card clients. *Expert Systems with Applications, 36*(2), 2473–2480. https://doi.org/10.1016/j.eswa.2007.12.020

Appendix

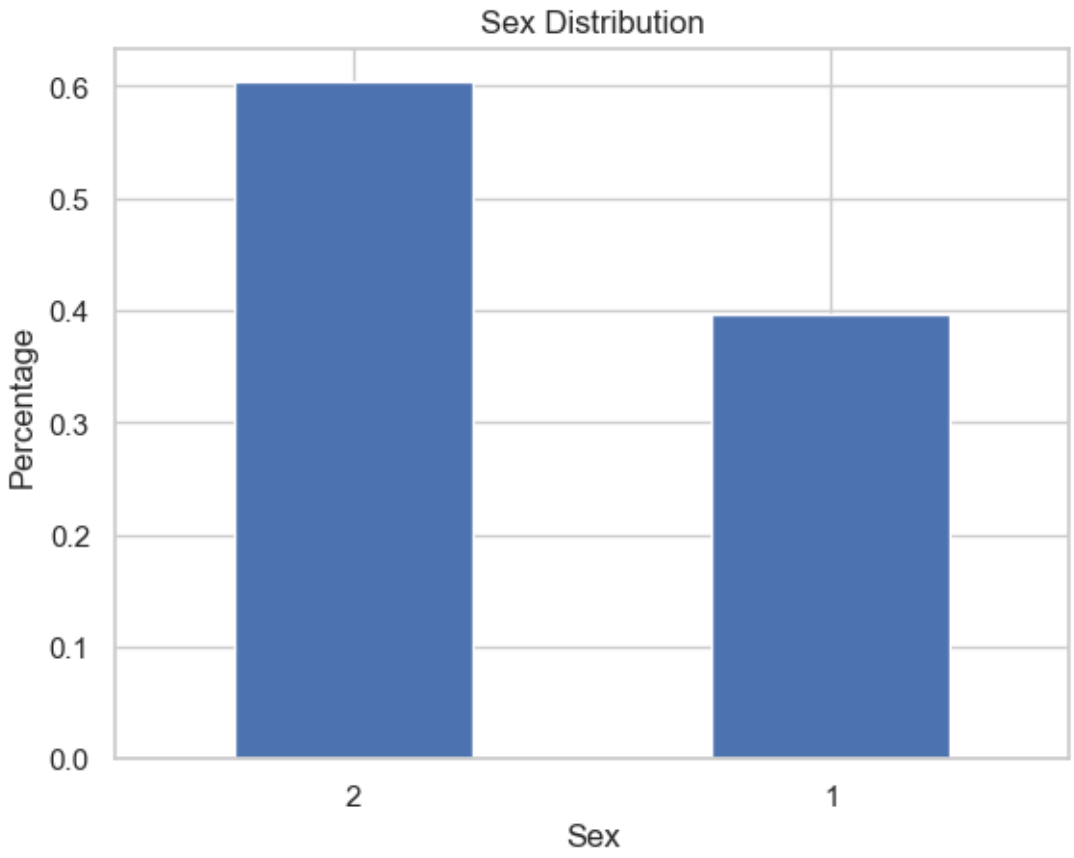
June 23, 2025

[307]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

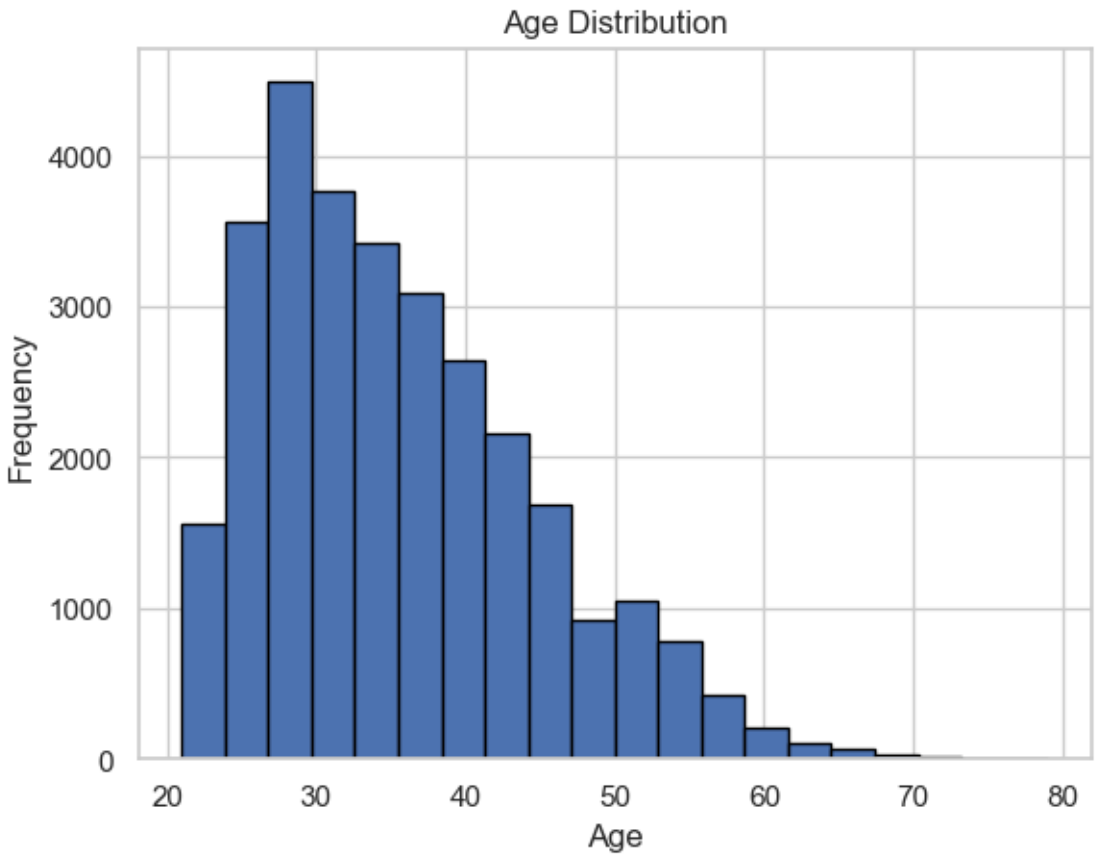
[308]:
```
df = pd.read_csv('Datasets/Credit.csv')
```

[309]:
```
sex = df['SEX']

males = df[sex == 1]
females = df[sex == 2]

proportion_males = len(males) / len(df)
proportion_females = len(females) / len(df)

print("Proportion of males: ", proportion_males)
print("Proportion of females: ", proportion_females)

counted = sex.value_counts(normalize=True)
counted.plot.bar()

plt.title('Sex Distribution')
plt.xlabel('Sex')
plt.ylabel('Percentage')
plt.xticks(rotation=0)
plt.show()
```

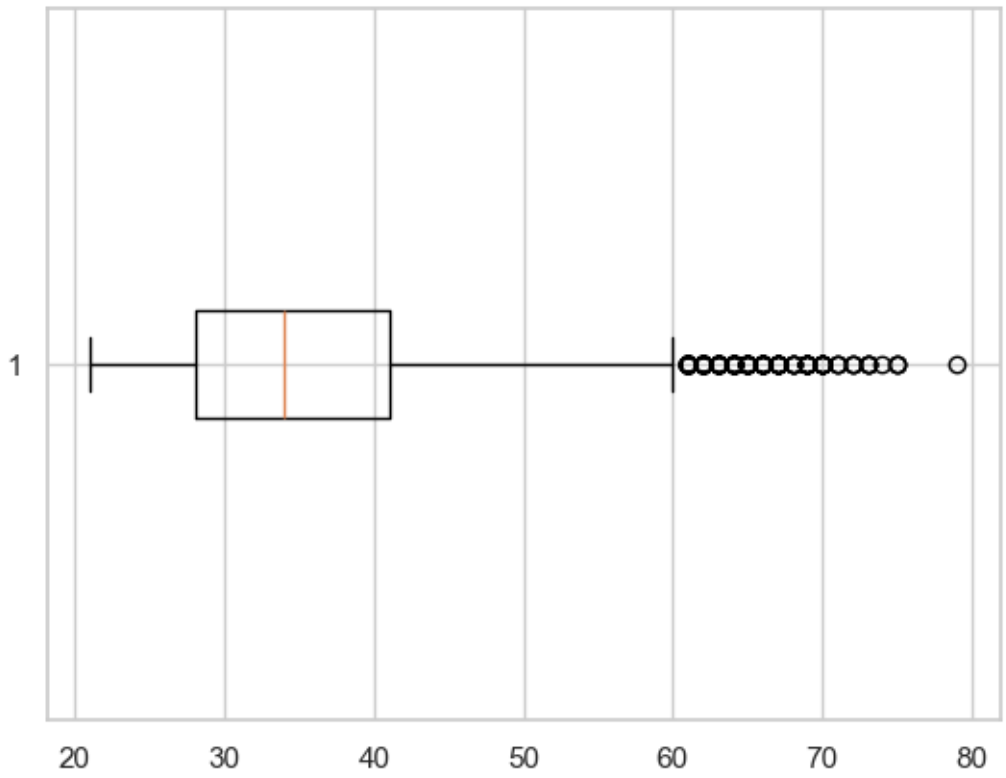
```
Proportion of males:  0.39626666666666666
Proportion of females:  0.6037333333333333
```



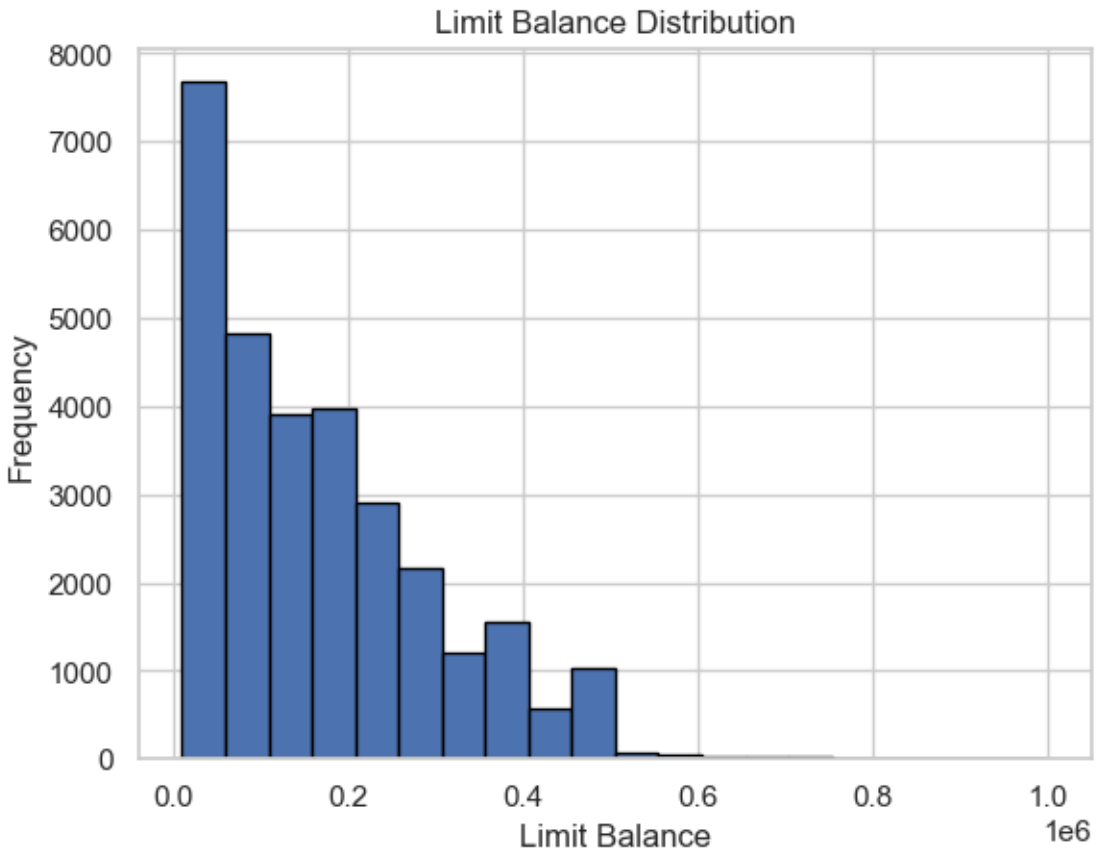
[310]:
```
age = df['AGE']
plt.hist(age, bins=20, edgecolor='black')
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



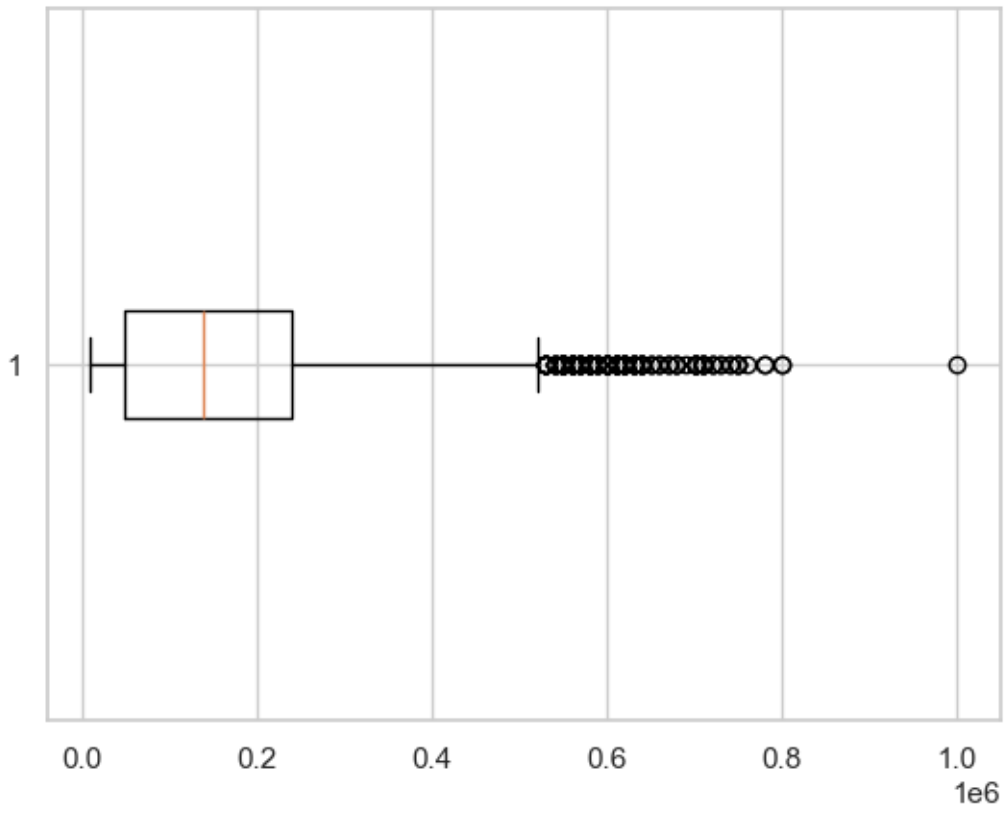
[311]:
```
plt.boxplot(age, vert=False)
plt.show()
```



[312]:
```
limit_balance = df['LIMIT_BAL']
plt.hist(limit_balance, bins=20, edgecolor='black')
plt.title('Limit Balance Distribution')
plt.xlabel('Limit Balance')
plt.ylabel('Frequency')
plt.show()
```



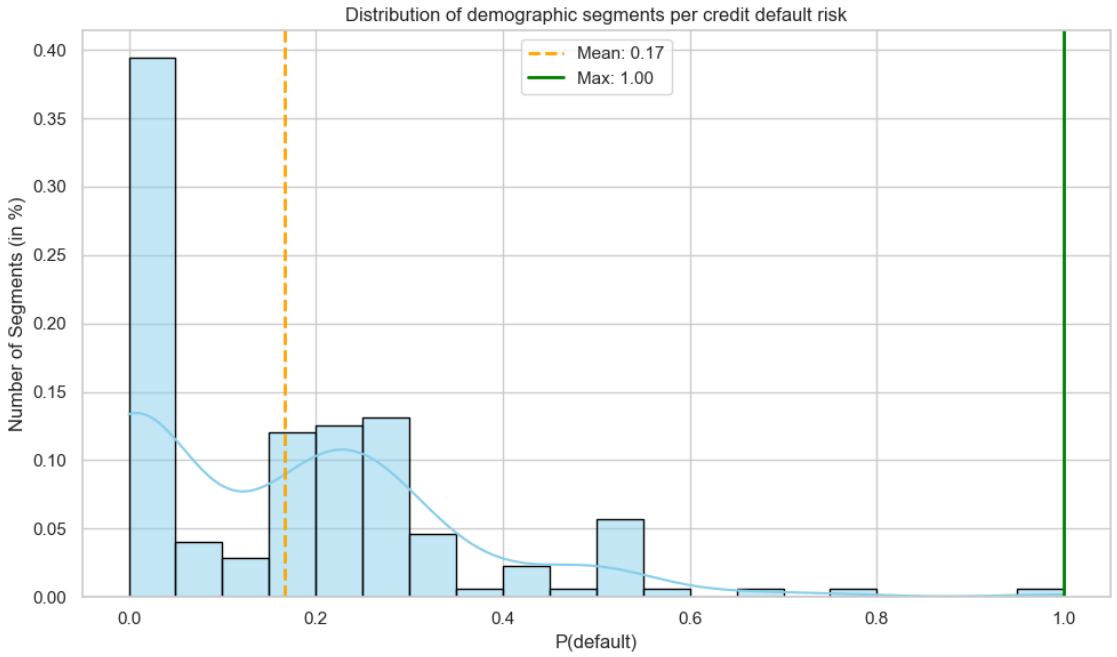
[313]:
```
plt.boxplot(limit_balance, vert=False)
plt.show()
```



[314]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df2 = pd.read_csv('Datasets/Credit.csv')

# Create AGE groups
age_bins = [20, 30, 40, 50, 60, 70, 80]
age_labels = ['20s', '30s', '40s', '50s', '60s', '70s']
df2['AGE_GROUP'] = pd.cut(df2['AGE'], bins=age_bins, labels=age_labels,␣
 ↪right=False)

# Define population segments
segment_columns = ['SEX', 'EDUCATION', 'MARRIAGE', 'AGE_GROUP']
segment_group = df2.groupby(segment_columns)

# Count total and on-time payments per segment
segment_stats = segment_group['default payment next month'].agg(
    total='count',
    default=lambda x: (x == 1).sum()
).reset_index()
```

```
# Calculate Probability
segment_stats['probability'] = segment_stats['default'] / segment_stats['total']

# Plot histogram with KDE
plt.figure(figsize=(10, 6))
sns.histplot(segment_stats['probability'], bins=20, kde=True, color='skyblue',␣
 ↪edgecolor='black', stat='probability')

# Add vertical lines
mean_prob = segment_stats['probability'].mean()
max_prob = segment_stats['probability'].max()

plt.axvline(mean_prob, color='orange', linestyle='--', linewidth=2,␣
 ↪label=f'Mean: {mean_prob:.2f}')
plt.axvline(max_prob, color='green', linestyle='-', linewidth=2, label=f'Max:␣
 ↪{max_prob:.2f}')

# Labels and legend
plt.title("Distribution of demographic segments per credit default risk")
plt.xlabel("P(default)")
plt.ylabel("Number of Segments (in %)")
plt.legend()
plt.tight_layout()
plt.show()
```

```
/var/folders/ck/sr6gtz6n0jx9dmp9nlplxl_w0000gn/T/ipykernel_65554/2844974901.py:1
4: FutureWarning: The default of observed=False is deprecated and will be
changed to True in a future version of pandas. Pass observed=False to retain
current behavior or observed=True to adopt the future default and silence this
warning.
  segment_group = df2.groupby(segment_columns)
```



[315]:
```
df.rename(columns={df.columns[-1]: 'default_status'}, inplace=True)

# Define the columns
bill_columns = ['BILL_AMT1', 'BILL_AMT2', 'BILL_AMT3', 'BILL_AMT4',␣
 ↪'BILL_AMT5', 'BILL_AMT6']
pay_columns = ['PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5',␣
 ↪'PAY_AMT6']

# Method 1: Linear decay weights (most recent gets highest weight)
# Weights: [6, 5, 4, 3, 2, 1] for [AMT1, AMT2, AMT3, AMT4, AMT5, AMT6]
linear_weights = np.array([6, 5, 4, 3, 2, 1])
linear_weights = linear_weights / linear_weights.sum()  # Normalize to sum to 1

print("Linear weights:", linear_weights)

# Calculate weighted averages
df['WEIGHTED_BILL_AMT'] = np.average(df[bill_columns], weights=linear_weights,␣
 ↪axis=1)
df['WEIGHTED_PAY_AMT'] = np.average(df[pay_columns], weights=linear_weights,␣
 ↪axis=1)

def create_numeric_percentile_bins(df, column_name, num_bins=4):
    """
    Create percentile bins with ascending numeric codes (1, 2, 3, 4)
    """
```

```
    # Create percentile bins and assign numeric labels
    binned_column = pd.qcut(df[column_name], q=num_bins, labels=range(1,␣
 ↪num_bins + 1), duplicates='drop')

    # Get the actual bin edges for reference
    _, bin_edges = pd.qcut(df[column_name], q=num_bins, retbins=True,␣
 ↪duplicates='drop')

    return binned_column.astype(int), bin_edges

# Apply numeric percentile binning
variables_to_bin = ['AGE', 'LIMIT_BAL', 'WEIGHTED_BILL_AMT', 'WEIGHTED_PAY_AMT']

print("Creating numeric percentile-based bins (1=lowest quartile, 4=highest␣
 ↪quartile)...")
print("=" * 80)

for var in variables_to_bin:
    # Create numeric bins
    binned_col, edges = create_numeric_percentile_bins(df, var, num_bins=4)

    # Add the binned column to dataframe
    df[f'{var}_Q'] = binned_col

    # Print bin information
    print(f"\n{var}_Q:")
    print(f"  Overall range: {df[var].min():.2f} to {df[var].max():.2f}")
    print(f"  Quartile boundaries and coding:")

    for i in range(len(edges) - 1):
        quartile_num = i + 1
        start_val = edges[i]
        end_val = edges[i + 1]
        count = (df[f'{var}_Q'] == quartile_num).sum()
        percentage = count / len(df) * 100

        print(f"    {quartile_num}: {start_val:8.2f} to {end_val:8.2f} | {count:
 ↪,} obs ({percentage:.1f}%)")

    # Show the numeric distribution
    print(f"  Value counts: {dict(df[f'{var}_Q'].value_counts().sort_index())}")



df.head()
```

```
Linear weights: [0.28571429 0.23809524 0.19047619 0.14285714 0.0952381
```

```
0.04761905]
Creating numeric percentile-based bins (1=lowest quartile, 4=highest
quartile)…
================================================================================

AGE_Q:
  Overall range: 21.00 to 79.00
  Quartile boundaries and coding:
    1:    21.00 to    28.00 | 8,013 obs (26.7%)
    2:    28.00 to    34.00 | 7,683 obs (25.6%)
    3:    34.00 to    41.00 | 6,854 obs (22.8%)
    4:    41.00 to    79.00 | 7,450 obs (24.8%)
  Value counts: {1: np.int64(8013), 2: np.int64(7683), 3: np.int64(6854), 4:
np.int64(7450)}

LIMIT_BAL_Q:
  Overall range: 10000.00 to 1000000.00
  Quartile boundaries and coding:
    1: 10000.00 to 50000.00 | 7,676 obs (25.6%)
    2: 50000.00 to 140000.00 | 7,614 obs (25.4%)
    3: 140000.00 to 240000.00 | 7,643 obs (25.5%)
    4: 240000.00 to 1000000.00 | 7,067 obs (23.6%)
  Value counts: {1: np.int64(7676), 2: np.int64(7614), 3: np.int64(7643), 4:
np.int64(7067)}

WEIGHTED_BILL_AMT_Q:
  Overall range: -29464.95 to 873217.38
  Quartile boundaries and coding:
    1: -29464.95 to  4888.90 | 7,500 obs (25.0%)
    2:  4888.90 to 21980.29 | 7,500 obs (25.0%)
    3: 21980.29 to 60405.44 | 7,500 obs (25.0%)
    4: 60405.44 to 873217.38 | 7,500 obs (25.0%)
  Value counts: {1: np.int64(7500), 2: np.int64(7500), 3: np.int64(7500), 4:
np.int64(7500)}

WEIGHTED_PAY_AMT_Q:
  Overall range: 0.00 to 805849.48
  Quartile boundaries and coding:
    1:     0.00 to  1228.08 | 7,500 obs (25.0%)
    2:  1228.08 to  2488.14 | 7,500 obs (25.0%)
    3:  2488.14 to  5696.19 | 7,500 obs (25.0%)
    4:  5696.19 to 805849.48 | 7,500 obs (25.0%)
  Value counts: {1: np.int64(7500), 2: np.int64(7500), 3: np.int64(7500), 4:
np.int64(7500)}
```

[315]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	\
0	1	20000	2	2	1	24	2	2	-1	-1	

```
1   2     120000    2          2          2   26     -1      2      0      0
2   3      90000    2          2          2   34      0      0      0      0
3   4      50000    2          2          1   37      0      0      0      0
4   5      50000    1          2          1   57     -1      0     -1      0

   …  PAY_AMT4  PAY_AMT5  PAY_AMT6  default_status  WEIGHTED_BILL_AMT  \
0  …         0         0         0               1        1987.809524
1  …      1000         0      2000               1        2639.619048
2  …      1000      1000      5000               0       18487.761905
3  …      1100      1069      1000               0       42508.380952
4  …      9000       689       679               0       16363.571429

   WEIGHTED_PAY_AMT  AGE_Q  LIMIT_BAL_Q  WEIGHTED_BILL_AMT_Q  \
0        164.047619      1            1                    1
1        666.666667      1            2                    1
2       1457.523810      2            2                    2
3       1587.285714      3            1                    3
4      12593.428571      4            1                    2

   WEIGHTED_PAY_AMT_Q
0                   1
1                   1
2                   2
3                   2
4                   4

[5 rows x 31 columns]
```

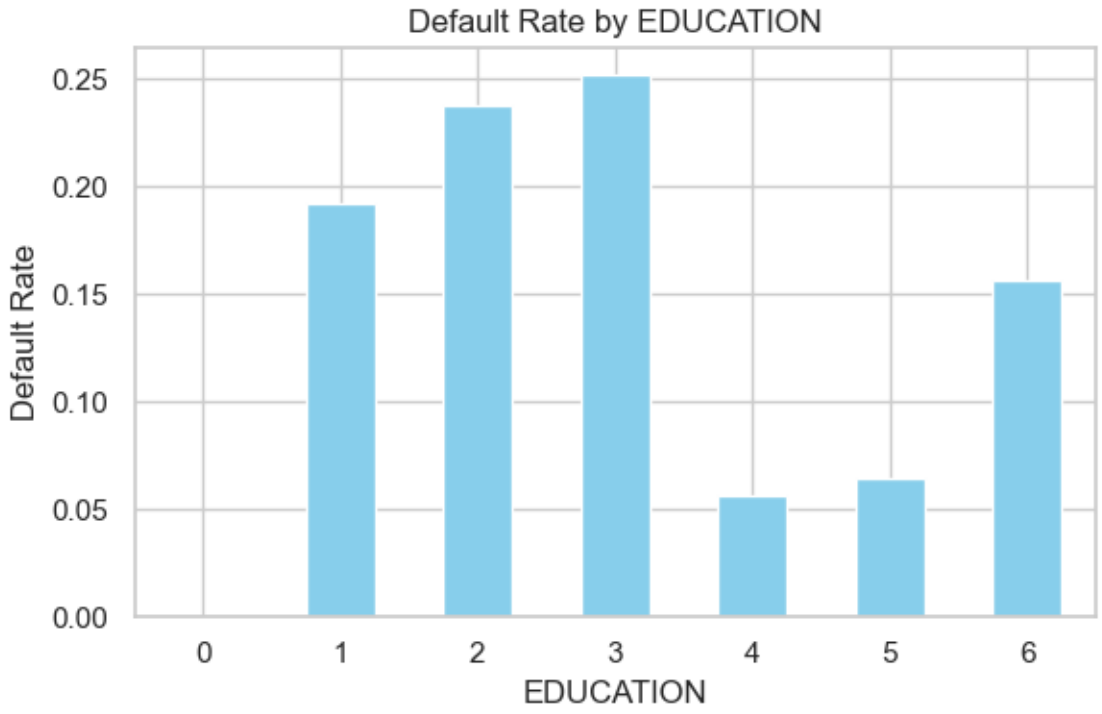
[316]:
```
# replace -1 with 0
df['PAY_0'] = df['PAY_0'].replace(-1, 0)
```

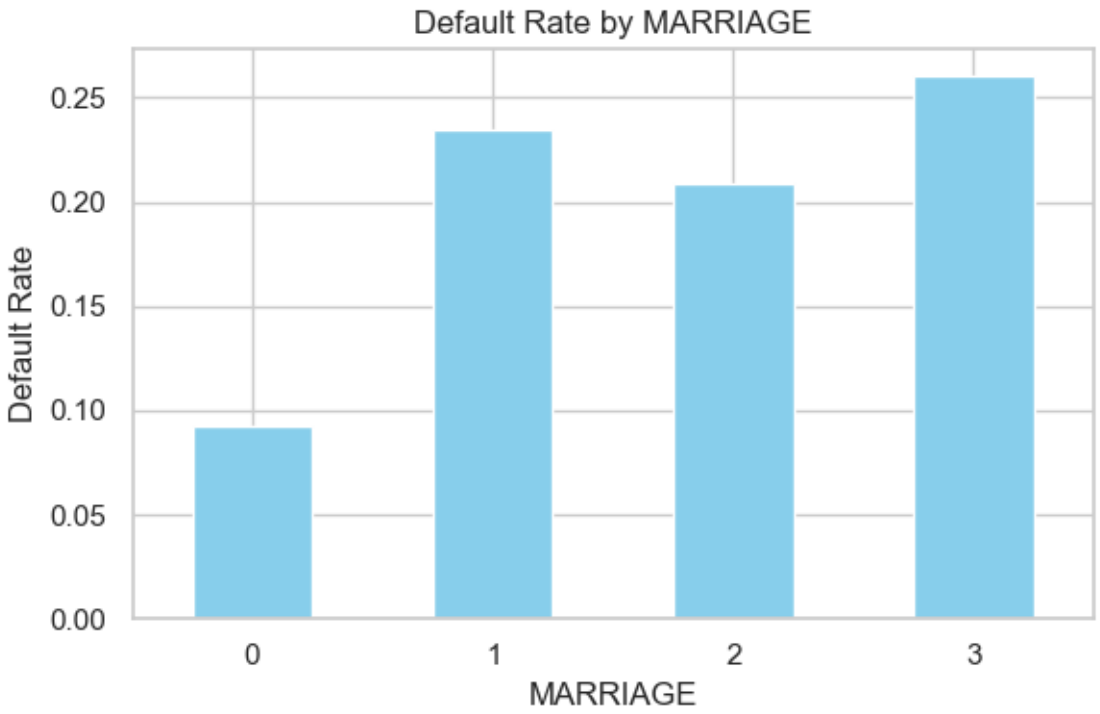
[317]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import classification_report, accuracy_score

# Load the data
df_bayes = pd.read_csv('Datasets/Credit.csv')

# Strip any whitespace from column names
df_bayes.columns = df_bayes.columns.str.strip()

# Rename columns for clarity
df_bayes.columns = ['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE',
                    'PAY_0', 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6',
```

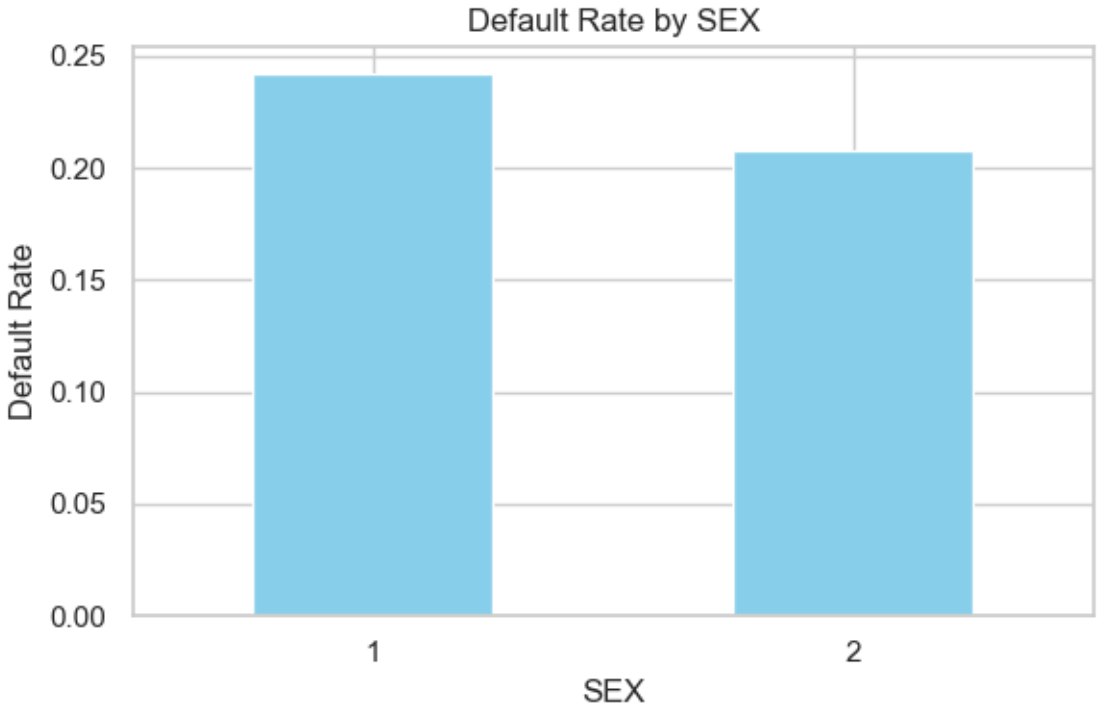
```
            'BILL_AMT1', 'BILL_AMT2', 'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5',␣
 ↪'BILL_AMT6',
            'PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5',␣
 ↪'PAY_AMT6', 'default']

# Clean AGE column and create AGE_GROUP
df_bayes['AGE'] = pd.to_numeric(df_bayes['AGE'], errors='coerce')
df_bayes = df_bayes.dropna(subset=['AGE'])

age_bins = [20, 30, 40, 50, 60, 70, 80]
age_labels = ['21-30', '31-40', '41-50', '51-60', '61-70', '71-80']
df_bayes['AGE_GROUP'] = pd.cut(df_bayes['AGE'], bins=age_bins,␣
 ↪labels=age_labels)

# Generating the Plot default rates
for col in ['EDUCATION', 'MARRIAGE', 'SEX', 'AGE_GROUP']:
    plt.figure(figsize=(6, 4))
    df_bayes.groupby(col)['default'].mean().plot(kind='bar', color='skyblue')
    plt.title(f'Default Rate by {col}')
    plt.ylabel('Default Rate')
    plt.xlabel(col)
    plt.xticks(rotation=0)
    plt.tight_layout()
    plt.show()




# Define feature list
features = ['LIMIT_BAL_Q', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE_Q', 'PAY_0',␣
 ↪'WEIGHTED_BILL_AMT_Q', 'WEIGHTED_PAY_AMT_Q']

# Preparing features and target
X = df[features]
y = df['default_status']


# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=42)

# Training Naive Bayes classifier
model = GaussianNB()
model.fit(X_train, y_train)

# Predict and evaluate
y_pred = model.predict(X_test)
```

```
y_proba = model.predict_proba(X_test)[:, 1]

print("\nAccuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

# Optional: Show sample predictions
sample = pd.DataFrame({
    'Actual': y_test.values[:5],
    'Predicted Probability': y_proba[:5]
})
print("\nSample Predictions:")
print(sample)

#Printing my explanation of the result-set based on the Naive Bayes classifier

print("Accuracy is 0.377888 -- This means 38%  of the customers were correctly␣
 ↪classified - either as likely to default (1) or not (0).")
print()
print("The report breaks down precision, recall, and F1-score for each class")
print()
print("For Class 0 -- No Default")
print("Precision = 0.88: 88% of those predicted as -- No Default were correct")
print("Recall = 0.24: 24% of the actual -- no default customers correctly␣
 ↪predicted.")
print("F1 = 0.37 -- Weak ability to detect actual non-defaulters.")
print()
print("For Class 1 -- Default")
print("Precision = 0.24: 24% of predicted defaulters were actually defaulters")
print("Recall = 0.88: 88% of actual defaulters -- Postive case of how many␣
 ↪prdicted to be defaulted")
print("F1 = 0.38: Weak ability to detect actual defaulter")
print(" Tha model is too conservative - reluctant to label someone as a␣
 ↪defaulter.")
print("For credit risk, recall on Class 1 is critical - you want to catch as␣
 ↪many defaulters as possible!")

print()
print()
print(" --- Sample Predictions ---")
print("Actual: The true class -- 0 = no default, 1 = default")
print("Predicted Probability: Model's confidence that the customer will␣
 ↪default")

print()
```

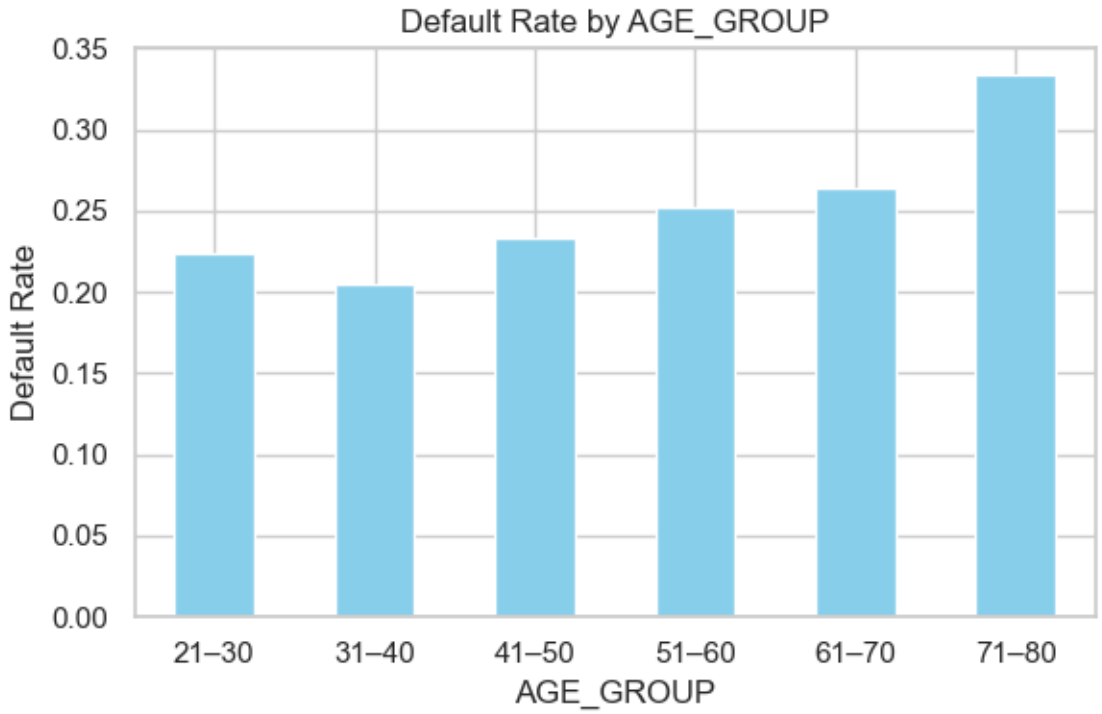
```
print("Row 0: True label is 0 (no default), model predicts 87% chance of␣
 ↪default -  correct and confident.")
print("Row 4: True label is 1 (default), model predicts 87% -  somewhat␣
 ↪confident, borderline.")

print()

print(" --- Recommendations --- ")
print("Improve recall on defaulters: Try different models like (e.g., logistic␣
 ↪regression, random forest), oversampling (SMOTE), or cost-sensitive learning.
 ↪")
print("Threshold tuning: Adjust default classification threshold (not just 0.5)␣
 ↪to balance precision/recall.")
```




Default Rate by MARRIAGE
Default Rate
0.25
0.20
0.15
0.10
0.05
0.00
0
1
2
3
MARRIAGE


Default Rate by SEX
Default Rate
0.25
0.20
0.15
0.10
0.05
0.00
1
2
SEX

```
/var/folders/ck/sr6gtz6n0jx9dmp9nlplxl_w0000gn/T/ipykernel_65554/3526147253.py:3
0: FutureWarning: The default of observed=False is deprecated and will be
changed to True in a future version of pandas. Pass observed=False to retain
current behavior or observed=True to adopt the future default and silence this
warning.
  df_bayes.groupby(col)['default'].mean().plot(kind='bar', color='skyblue')
```




```
Accuracy: 0.8107777777777778

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.95      0.89      7040
           1       0.63      0.32      0.43      1960

    accuracy                           0.81      9000
   macro avg       0.73      0.63      0.66      9000
weighted avg       0.79      0.81      0.79      9000


Sample Predictions:
   Actual  Predicted Probability
0       0               0.276783
```

```
1       0               0.067038
2       0               0.113744
3       0               0.148218
4       1               0.225503
Accuracy is 0.377888 -- This means 38%  of the customers were correctly
classified - either as likely to default (1) or not (0).

The report breaks down precision, recall, and F1-score for each class

For Class 0 -- No Default
Precision = 0.88: 88% of those predicted as -- No Default were correct
Recall = 0.24: 24% of the actual -- no default customers correctly predicted.
F1 = 0.37 -- Weak ability to detect actual non-defaulters.

For Class 1 -- Default
Precision = 0.24: 24% of predicted defaulters were actually defaulters
Recall = 0.88: 88% of actual defaulters -- Postive case of how many prdicted to
be defaulted
F1 = 0.38: Weak ability to detect actual defaulter
 Tha model is too conservative - reluctant to label someone as a defaulter.
For credit risk, recall on Class 1 is critical - you want to catch as many
defaulters as possible!


 --- Sample Predictions ---
Actual: The true class -- 0 = no default, 1 = default
Predicted Probability: Model's confidence that the customer will default

Row 0: True label is 0 (no default), model predicts 87% chance of default -
correct and confident.
Row 4: True label is 1 (default), model predicts 87% -  somewhat confident,
borderline.

 --- Recommendations ---
Improve recall on defaulters: Try different models like (e.g., logistic
regression, random forest), oversampling (SMOTE), or cost-sensitive learning.
Threshold tuning: Adjust default classification threshold (not just 0.5) to
balance precision/recall.
```

[318]:
```python
# train logistic regression model

import statsmodels.formula.api as smf
import statsmodels.api as sm

# separate between train and test

train_df = df.sample(frac=0.7, random_state=42)
```

```
test_df = df.drop(train_df.index)

train_df.shape

model = smf.glm('default_status ~ LIMIT_BAL_Q + SEX + EDUCATION + MARRIAGE +␣
↪AGE_Q + PAY_0 + WEIGHTED_BILL_AMT_Q + WEIGHTED_PAY_AMT_Q', data=train_df,␣
↪family=sm.families.Binomial())

results = model.fit()

results.summary()
```

[318]:

Dep. Variable:	default_status	**No. Observations:**	21000
Model:	GLM	**Df Residuals:**	20991
Model Family:	Binomial	**Df Model:**	8
Link Function:	Logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-9560.6
Date:	Mon, 23 Jun 2025	**Deviance:**	19121.
Time:	01:11:10	**Pearson chi2:**	2.57e+04
No. Iterations:	5	**Pseudo R-squ. (CS):**	0.1311
Covariance Type:	nonrobust		

	coef	std err	z	P> |z|	[0.025	0.975]
Intercept	-0.1974	0.134	-1.474	0.140	-0.460	0.065
LIMIT_BAL_Q	-0.1390	0.019	-7.296	0.000	-0.176	-0.102
SEX	-0.1118	0.037	-3.014	0.003	-0.185	-0.039
EDUCATION	-0.0605	0.025	-2.415	0.016	-0.110	-0.011
MARRIAGE	-0.1505	0.039	-3.890	0.000	-0.226	-0.075
AGE_Q	0.0377	0.018	2.105	0.035	0.003	0.073
PAY_0	0.8464	0.021	39.870	0.000	0.805	0.888
WEIGHTED_BILL_AMT_Q	-0.0003	0.021	-0.013	0.990	-0.041	0.040
WEIGHTED_PAY_AMT_Q	-0.2598	0.022	-11.572	0.000	-0.304	-0.216

[319]:
```
# analyze results

summary_df = pd.concat([results.params, results.pvalues], axis=1, keys=['coef',␣
↪'pvalue'])

# absolute value of the coefficients for sorting
summary_df = summary_df.assign(abs_coef=summary_df['coef'].abs())

# get labels of variables with p > 0.05
removed_labels = summary_df.index[summary_df['pvalue'] > 0.05].tolist()

# keep only variables with p <= 0.05
summary_df = summary_df[summary_df['pvalue'] <= 0.05]
```

```python
# sort by effect size
summary_df = summary_df.sort_values(by='abs_coef', ascending=False)

# rounding
summary_df['pvalue'] = summary_df['pvalue'].map('{:.5f}'.format)

# print labels of variables with p > 0.05
print("p > 0.05: \n\n{}".format(removed_labels))

print("\n---------------------------------\n")

print("Sorted by effect size: \n{}".format(summary_df))
print("\n---------------------------------\n")

# sort by pvalue
summary_df = summary_df.sort_values(by='pvalue', ascending=True)

print("\n---------------------------------\n")

print("Sorted by p-value: \n{}".format(summary_df))
print("\n---------------------------------\n")
```

```
p > 0.05:

['Intercept', 'WEIGHTED_BILL_AMT_Q']

---------------------------------

Sorted by effect size:
                        coef   pvalue  abs_coef
PAY_0                0.846440  0.00000  0.846440
WEIGHTED_PAY_AMT_Q -0.259782  0.00000  0.259782
MARRIAGE           -0.150458  0.00010  0.150458
LIMIT_BAL_Q        -0.138968  0.00000  0.138968
SEX                -0.111832  0.00258  0.111832
EDUCATION          -0.060463  0.01573  0.060463
AGE_Q               0.037691  0.03530  0.037691

---------------------------------


---------------------------------

Sorted by p-value:
                        coef   pvalue  abs_coef
PAY_0                0.846440  0.00000  0.846440
WEIGHTED_PAY_AMT_Q -0.259782  0.00000  0.259782
LIMIT_BAL_Q        -0.138968  0.00000  0.138968
```

```
MARRIAGE           -0.150458  0.00010  0.150458
SEX                -0.111832  0.00258  0.111832
EDUCATION          -0.060463  0.01573  0.060463
AGE_Q               0.037691  0.03530  0.037691

--------------------------------
```

[320]:
```
odds_ratios = pd.Series(
    data=round(np.exp(summary_df['coef']), 2),
    index=summary_df.index,
    name='odds_ratio'
)

print(odds_ratios)
```

```
PAY_0                2.33
WEIGHTED_PAY_AMT_Q   0.77
LIMIT_BAL_Q          0.87
MARRIAGE             0.86
SEX                  0.89
EDUCATION            0.94
AGE_Q                1.04
Name: odds_ratio, dtype: float64
```

[321]:
```
# Make examples

class Person:

    def __init__(self, age, sex, education, marriage, limit_balance,␣
 ↪bill_amount, payment_amount, payment_history):
        self.age = age
        self.sex = sex
        self.education = education
        self.marriage = marriage
        self.limit_balance = limit_balance
        self.bill_amount = bill_amount
        self.payment_amount = payment_amount
        self.payment_history = payment_history

    def calculate_probability(self):
        intercept = results.params['Intercept']
        age_coef = results.params['AGE_Q']
        sex_coef = results.params['SEX']
        education_coef = results.params['EDUCATION']
        marriage_coef = results.params['MARRIAGE']
        limit_balance_coef = results.params['LIMIT_BAL_Q']
        bill_amount_coef = results.params['WEIGHTED_BILL_AMT_Q']
```

```
        payment_amount_coef = results.params['WEIGHTED_PAY_AMT_Q']
        payment_history_coef = results.params['PAY_0']

        probability = 1 / (1 + np.exp(-(intercept + age_coef * self.age +␣
 ↪sex_coef * self.sex + education_coef * self.education + marriage_coef * self.
 ↪marriage + limit_balance_coef * self.limit_balance + bill_amount_coef * self.
 ↪bill_amount + payment_amount_coef * self.payment_amount +␣
 ↪payment_history_coef * self.payment_history)))

        return probability



jake = Person(age=1, sex=1, education=0, marriage=0, limit_balance=1,␣
 ↪bill_amount=2, payment_amount=0, payment_history=0)
print("jake:", round(jake.calculate_probability(), 4))

john = Person(age=1, sex=1, education=4, marriage=3, limit_balance=1,␣
 ↪bill_amount=4, payment_amount=0, payment_history=8)
print("john:", round(john.calculate_probability(), 4))

penelope = Person(age=4, sex=2, education=1, marriage=1, limit_balance=4,␣
 ↪bill_amount=1, payment_amount=3, payment_history=0)
print("penelope:", round(penelope.calculate_probability(), 4))

ricardo = Person(age=1, sex=1, education=1, marriage=0, limit_balance=4,␣
 ↪bill_amount=4, payment_amount=1, payment_history=6)
print("ricardo:", round(ricardo.calculate_probability(), 4))

stella = Person(age=2, sex=2, education=3, marriage=2, limit_balance=1,␣
 ↪bill_amount=1, payment_amount=1, payment_history=0)
print("stella:", round(stella.calculate_probability(), 4))
```

```
jake: 0.3987
john: 0.9966
penelope: 0.1398
ricardo: 0.9807
stella: 0.2267
```

[334]:
```
# calculate metrics

from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score, confusion_matrix, roc_auc_score, roc_curve
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Generate predictions on test set
# Get predicted probabilities
test_probabilities = results.predict(test_df)

# Convert probabilities to binary predictions using 0.5 threshold
test_predictions = (test_probabilities > 0.5).astype(int)

# Get actual values
test_actual = test_df['default_status'].values

print(f"Test set size: {len(test_df)}")
print(f"Number of actual defaults in test set: {sum(test_actual)}")
print(f"Number of predicted defaults: {sum(test_predictions)}")


# Calculate confusion matrix
cm = confusion_matrix(test_actual, test_predictions)
print("Confusion Matrix:")
print(cm)

# Extract components
tn, fp, fn, tp = cm.ravel()
print(f"\nBreakdown:")
print(f"True Negatives (TN): {tn}")
print(f"False Positives (FP): {fp}")
print(f"False Negatives (FN): {fn}")
print(f"True Positives (TP): {tp}")

# Class 1 precision
precision_1 = tp / (tp + fp)


# Class 1 recall
recall_1 = tp / (tp + fn)


# Class 1 f1-score
f1_1 = 2 * (precision_1 * recall_1) / (precision_1 + recall_1)


# Class 0 precision
precision_0 = tn / (tn + fn)


# Class 0 recall
recall_0 = tn / (tn + fp)
```

```
# Class 0 f1-score
f1_0 = 2 * (precision_0 * recall_0) / (precision_0 + recall_0)

# make dataframe


df_metrics = pd.DataFrame({
    'Class 0': [round(precision_0, 2), round(recall_0, 2), round(f1_0, 2)],
    'Class 1': [round(precision_1, 2), round(recall_1, 2), round(f1_1, 2)]
}, index=['Precision', 'Recall', 'F1-Score']).T

print("\nModel Performance Metrics:")

print("\n")

print(df_metrics)



# Calculate all performance metrics
accuracy = accuracy_score(test_actual, test_predictions)
precision = precision_score(test_actual, test_predictions)
sensitivity_recall = recall_score(test_actual, test_predictions)  # Same as␣
 ↪sensitivity
f1 = f1_score(test_actual, test_predictions)

# Calculate specificity manually (no direct sklearn function)
specificity = tn / (tn + fp)

print("\n")

print("=== MODEL PERFORMANCE METRICS ===")
print(f"Accuracy: {accuracy:.4f} ({accuracy*100:.2f}%)")
print(f"Precision: {precision:.4f} ({precision*100:.2f}%)")
print(f"Sensitivity (Recall): {sensitivity_recall:.4f} ({sensitivity_recall*100:
 ↪.2f}%)")
print(f"Specificity: {specificity:.4f} ({specificity*100:.2f}%)")
print(f"F1-Score: {f1:.4f}")

print("\n=== METRIC INTERPRETATIONS ===")
print(f"• Accuracy: {accuracy*100:.1f}% of all predictions were correct")
print(f"• Precision: {precision*100:.1f}% of predicted defaults were actually␣
 ↪defaults")
print(f"• Sensitivity: {sensitivity_recall*100:.1f}% of actual defaults were␣
 ↪correctly identified")
```

```
print(f"• Specificity: {specificity*100:.1f}% of actual non-defaults were␣
  ↪correctly identified")
print(f"• F1-Score: Harmonic mean of precision and recall = {f1:.3f}")
```

```
Test set size: 9000
Number of actual defaults in test set: 2039
Number of predicted defaults: 738
Confusion Matrix:
[[6737  224]
 [1525  514]]

Breakdown:
True Negatives (TN): 6737
False Positives (FP): 224
False Negatives (FN): 1525
True Positives (TP): 514

Model Performance Metrics:


         Precision  Recall  F1-Score
Class 0       0.82    0.97      0.89
Class 1       0.70    0.25      0.37


=== MODEL PERFORMANCE METRICS ===
Accuracy: 0.8057 (80.57%)
Precision: 0.6965 (69.65%)
Sensitivity (Recall): 0.2521 (25.21%)
Specificity: 0.9678 (96.78%)
F1-Score: 0.3702

=== METRIC INTERPRETATIONS ===
• Accuracy: 80.6% of all predictions were correct
• Precision: 69.6% of predicted defaults were actually defaults
• Sensitivity: 25.2% of actual defaults were correctly identified
• Specificity: 96.8% of actual non-defaults were correctly identified
• F1-Score: Harmonic mean of precision and recall = 0.370
```