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University of Tunis El Manar
Faculty of Sciences of Tunis (FST)

Bayesian Modeling for Credit Risk Prediction: From Naive Bayes to Bayesian Neural Networks

Final Year Project

Presented in partial fulfillment of the requirements for the
National Bachelor's Degree in Applied Mathematics – Data Science

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Dedications

From the bottom of our hearts and with great joy,
we dedicate this work to:

, To our beloved parents:

***Slim Cheniour**, **Hassan Diab**,*
Hayet Sahbeni**, **Faten Meddeb

who have always supported and encouraged us
throughout our studies.
May God protect them and bless them with health
and happiness.

To all our dear siblings:

***Emna Cheniour**, **Aicha Diab**, **Oubaida Diab**,*
Adam Chtioui

To all our dear friends, especially:

Baha Ghanney**, **Mariem Sghaier
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Thank you for your constant support and the
unforgettable moments we've shared.
This work is the fruit of all the sacrifices and love
we've received.

May they find in this work the testimony of our
deep gratitude and our infinite love.

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Abstract

This is an end-of-year finance-data science project. This project is intended to build a model that will have the capacity to predict the bank customers' probability of default based on their socio-economic factors.

This is a final year project that integrates finance and data science. This is an attempt towards constructing a predictive model for forecasting the probability of default of bank customers using their socio-economic attributes.

The method is based on Bayesian inference using Naive Bayes classification and Bayesian Neural Networks (BNNs). Theoretical foundations such as Bayes' theorem and conditional independence are introduced initially. Mathematical derivations along with algorithmic code in Python (using scikit-learn and TensorFlow Probability) are interspersed in the project. Having been trained and heavily preprocessed on the data, the models generate insightful suggestions to segment customers for credit risk and customize financial products accordingly (interest rates, guarantees, target products). The project showcases how Bayesian approaches can successfully tackle typical bank decision problems with statistical accuracy, probabilistic interpretation, and strategic personalization.

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Chapter 1

Presentation of the Faculty of Sciences of Tunis

1.1 Introduction

The Faculty of Sciences of Tunis (FST) or the Faculty of Mathematical, Physical and Natural Sciences of Tunis by its official name is a faculty within the El Manar University campus in Tunis. It is one of the most ancient and renowned university institutions in Tunisia.

FST was founded in 1960 and provides high-level academic education in various fields such as mathematics, physics, chemistry, biology, geology, and computer science. It provides Bachelor's, Master's, and Doctoral programs with potential specialization via an extensive series of courses and labs.

The Faculty is distinguished by its extremely well-qualified teaching staff, who are nationally and internationally recognized researchers. The students receive a strong theoretical foundation, supplemented with research experience and contact with industrial and academic partners.

In collaboration with international universities and research institutes, the FST also offers international exchange programs and internships, which allow students to study in international settings and hone their skills in international settings. Last but not least, the Tunis Faculty of Sciences is at the heart of Tunisian higher education and scientific research, producing high-level scientists and taking part in knowledge development and innovation.

1.2 Historical Background

The FST was created in 1960 and first took up residence in the old building of the Institute of Higher Studies, located in the centre of Tunis (Rue de Rome). In 1974, the FST migrated to its new site on the hill of El Manar, close to the National Engineering School of Tunis. Prior to 1968, its principal activity had been the teaching of secondary school teachers of mathematics, physics, biology, and geology. It had already set up third-cycle programs in solid-state physics and marine biology by the late 1960s.

1.3 Organizational Structure

The FST is organized into six primary academic departments:

- Department of Mathematics
- Department of Physics
- Department of Chemistry
- Department of Biology
- Department of Geology
- Department of Computer Science

1.3.1 Department of Mathematics

Head of Department: Prof. Slim Omri
Email: `slim.omri@fst.utm.tn`

The Mathematics Department is one of the founding pillars of the FST. It has been offering top-notch mathematics training for secondary education, higher education, and schools of engineering since the 1960s. The department stands out due to the excellence of its teaching and the vibrancy of its research teams. Mathematics, being the science of reason and logical structure, is a vast field of subjects: arithmetic, algebra, analysis, geometry, logic, and probability. It is classically split into two branches:

- **Pure Mathematics:** Aims at theoretical development without particular application.
- **Applied Mathematics:** Oriented towards applications of mathematical techniques to problematize genuine problems in science and engineering.

In spite of this difference, it is now increasingly obscured by modern scientific developments.

1.3.2 Department of Physics

Head of Department: Prof. Fethi Jomni
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Physics is the scientific study of natural phenomena through reproducible experiments. It has a number of branches, which include

- **Classical Physics:** For large systems and low speeds, e.g., mechanics or civil engineering.
- **Quantum Physics:** Deals with microscopic systems like particles and atoms, with applications in electronics.
- **General Relativity:** Explains large-scale gravitational effects, e.g., black holes or GPS location.

The Department of Physics provides detailed training in these basic fields with experimental and mathematical methods.

1.3.3 Department of Chemistry

Head of Department: Prof. Hédi M'rabet
Email: `hedi.mrabet@fst.utm.tn`

The Department of Chemistry is among the most active research and training departments. The department has about 60 members of faculty, many specialized labs, shared facilities, and vibrant student organizations.

It offers programs at the Bachelor's, Master's, and Doctoral levels and also participates in preparatory and engineering programs.

Chemistry is the branch of science that examines the composition, properties, and reactions of matter by investigating atoms, molecules, and chemical reactions.

1.3.4 Department of Biology

Head of Department: Prof. Olfa Masmoudi
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The Department of Biology instructs life sciences, Earth sciences, environmental sciences, and biochemistry. It conducts research in genomics, cell and molecular biology, animal and plant ecology, physiology, and microbiology.

Biology is the scientific study of life, examining living systems at a number of levels: molecular, cellular, organismal, population, and ecosystem.

1.3.5 Department of Geology

Head of Department: Prof. Walid Oueslati
Email: `walid.oueslati@fst.utm.tn`

The Geology Department was the first in Tunisia to provide systematic academic instruction in the field. Geology examines the Earth's composition, structure, and history through the study and interpretation of rocks and natural processes.

It is an interdisciplinary science that applies chemistry, physics, biology, and climatology knowledge to resource exploration, risk mitigation, and civil engineering applications.

1.3.6 Department of Computer Science

Head of Department: Prof. Chaker Essid
Email: `chaker.essid@fst.utm.tn`

The Department of Computer Science is one of the youngest, yet most active departments within FST. It was one of the first in North Africa to have an engineering program in computer science. It now educates engineers, Bachelor's and PhD students for careers in industry and research. Computer science encompasses:

- **Theoretical computer science:** Concerned with models of computation and algorithmic complexity.
- **Applied computer science:** Deals with practical uses like software, hardware, and embedded systems.

Student Clubs:

- **OPTIMA Junior Enterprise:** Established in 2013, with a specialty in IT and innovation.
- **CLL (Free Software Club):** Formed in 2004, continuing the fight for free software and open-source values.

Chapter 2

Bayesian Modeling for Credit Risk Prediction

2.1 General Introduction

2.1.1 Context and Problem Statement

When it comes to evaluating credit risk, banks play a vital role on a global level, which is key to ensuring financial stability and managing lending risks effectively. According to Basel II, credit risk refers to the likelihood that a borrower or counterparty may fail to fulfill their contractual obligations. When banks evaluate their clients, they use a mix of hard data—like cash flow ratios, balance sheets, and income statements—alongside softer, more subjective factors that fit with their strategic objectives.

Current supervisory frameworks, such as the European Central Bank's Supervisory Review and Evaluation Process (SREP), employ a dual approach to assessing credit risk.This involves a quantitative analysis of risk exposure paired with a qualitative review of internal risk management and control systems, which also includes validating Expected Credit Loss (ECL) models. This integrated strategy enables banks to effectively gauge, monitor, and manage credit risk.

The Basel III standards take things up a notch by introducing the Internal Ratings-Based (IRB) approach. This allows banks to create models that are tailored to specific borrowers and the diversity of their portfolios. Techniques like Value at Risk (VaR) are commonly used to gauge potential losses in tough situations, helping guide decisions on capital allocation and strategies for managing risk Shakurov (2024).

Thanks to the amazing advancements in technology, credit risk assessment has really taken a leap forward with some sophisticated modeling techniques. While traditional statistical methods like logistic regression are still relevant, they're now being complemented by machine learning models such as decision trees, neural networks, and Bayesian classifiers. These innovative models combine financial data with qualitative insights, making it much easier to predict defaults and set up early warning systems for credit risk managers (AI, 2025; Bhati, 2025; Soni et al., 2024).

Credit risk grading systems are incredibly important, especially for big banks that closely monitor their loan portfolios. These systems help categorize loans according to their risk levels, which directly influences decisions about underwriting, the terms of loans, how portfolios are managed, and how much credit loss reserves need to be set aside. The Current Expected Credit Losses (CECL) standard underscores the significance of using grading-based segmentation to accurately predict expected losses Macias (2018).

In summary, today's credit risk measurement combines regulatory frameworks, advanced modeling techniques, and state-of-the-art technology to improve the identification, quantification, and management of credit risk. This holistic approach enables banks to make informed lending choices, ensure they have enough capital, and support long-term financial stability (AI, 2025; Bank, 2025; for International Settlements, 2025; Shakurov, 2024).

Project Focus. In this project, we're diving into the intriguing world of Bayesian modeling techniques to evaluate credit risk. While a lot of the current research leans towards traditional statistical methods and machine learning, Bayesian approaches really stand out. They provide a probabilistic framework that effectively captures uncertainty—something that's crucial when assessing financial risks.

We're addressing an important research question:

> *How can we apply Bayes theorem in a practical way to predict credit risk and accurately assess the chances of a banking client defaulting? Additionally, how can this understanding guide marketing and financial decisions?*

To answer this question, we study and implement two major approaches:

- The **Naive Bayes classifier**: based on conditional independence assumptions and known for its simplicity and efficiency;
- **Bayesian Neural Networks (BNNs)**: which introduce probabilistic weights into neural architectures, enabling the modeling of uncertainty in deep learning-based credit risk predictions.

2.1.2 Objectives of the Project

This project aims to:

- Study the theoretical foundations of the Naive Bayes model, including its assumptions, mathematical formulation, and properties.
- Apply this model to a real-world problem: predicting credit default using client data.
- Evaluate model performance through metrics such as accuracy, F1-score, and ROC AUC, and explore its limitations.
- Implement and compare a more advanced probabilistic model: the Bayesian Neural Network (BNN).
- Leverage the results to segment clients and suggest targeted marketing actions.

2.1.3 Literature Review

Classical Probabilistic Models

The Naive Bayes classifier was initially designed for tasks like spam filtering and text classification, but it has also shown to be a reliable option for binary classification challenges, such as credit scoring. Although it operates on the simplified concept of conditional independence, research, including a study by Hand and Henley in 1997, has demonstrated that it can hold its own against more complex models, especially when the data is well-prepared.

Advanced Bayesian Approaches

Bayesian Neural Networks (BNNs) are modern extensions of traditional neural networks where weights are treated as probability distributions rather than fixed parameters. This allows for more effective quantification of predictive uncertainty—a key factor in high-stakes decisions like lending. Gal and Ghahramani (2016) demonstrated that BNNs outperform classical networks in terms of calibration in domains like medicine and finance.

Applications in Credit Risk Prediction

A lot of research has tapped into Bayesian models to forecast credit default probabilities. For instance, Krogh and Vedelsby (1995) looked into Bayesian ensemble models to boost accuracy. More recent studies have blended Naive Bayes with ensemble methods like bagging and boosting to tackle class imbalance and enhance robustness. Plus, by weaving in socioeconomic and behavioral factors within a Bayesian framework, we can achieve more nuanced customer segmentation and make smarter decisions in financial institutions.

2.1.4 Hypotheses

We formulate the following hypotheses for this project:

- **H1:** The Naive Bayes classifier provides a reasonably accurate estimate of credit default risk despite its strong independence assumptions.
- **H2:** Bayesian Neural Networks (BNNs), due to their ability to model non-linear relationships, outperform classical probabilistic models like Naive Bayes in terms of predictive performance.
- **H3:** The inclusion of relevant financial indicators — such as income, debt, credit history — along with domain-specific financial ratios significantly improves the performance of credit risk prediction models.
- **H4:** Data quality (handling missing values, normalization, de-duplication) has a direct impact on the predictive accuracy and generalizability of models.

2.1.5 Methodology

The methodology adopted in this work is based on three main pillars:

1. **Theoretical Analysis:** A detailed review of the Naive Bayes model and its Bayesian extensions, including the underlying mathematical assumptions and formulas.
2. **Practical Implementation:** Development of machine learning pipelines in Python using libraries like `scikit-learn` and `TensorFlow Probability`, applying the models to real financial data.
3. **Evaluation and Application:** Assessing model performance using appropriate metrics and leveraging predictions to segment clients and propose personalized financial offers.

2.2 Mathematical Foundations of the Naive Bayes Model

2.2.1 Preliminaries: Conditional Probability and Bayes' Theorem

Let A and B be two events in a probability space Ω. The conditional probability of A given B is defined as:

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)} \quad \text{if } P(B) > 0. \tag{2.1}$$

Bayes' theorem enables the inversion of conditional probabilities:

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}. \tag{2.2}$$

Bayesian inference is really about fine-tuning our expectations. It helps us reassess how likely we think event A is when we encounter new evidence B. This concept is incredibly handy in supervised classification. It enables us to determine the likelihood that someone belongs to a specific category, based on the characteristics we can actually observe.

2.2.2 Naive Bayes Model Formulation

Let $Y \in \mathcal{Y}$ be a discrete random variable representing the class label (e.g., default or no default), and let $\mathbf{X} = (X_1, X_2, \ldots, X_n) \in \mathbb{R}^n$ be a feature vector.

We aim to estimate the posterior probability:

$$P(Y = y \mid \mathbf{X} = \mathbf{x}). \tag{2.3}$$

Using Bayes theorem:

$$P(Y = y \mid \mathbf{x}) = \frac{P(\mathbf{x} \mid Y = y) \cdot P(Y = y)}{P(\mathbf{x})}. \tag{2.4}$$

The Naive Bayes assumption is that the features X_i are conditionally independent given Y:

$$P(\mathbf{x} \mid Y = y) = \prod_{i=1}^{n} P(x_i \mid Y = y). \tag{2.5}$$

Substituting this into Bayes' formula gives:

$$P(Y = y \mid \mathbf{x}) \propto P(Y = y) \cdot \prod_{i=1}^{n} P(x_i \mid Y = y). \tag{2.6}$$

The class priors $P(Y = y)$ and the conditional likelihoods $P(x_i \mid Y = y)$ are typically estimated from the training data using empirical frequencies.

2.2.3 Classification Rule: Maximum A Posteriori (MAP)

The predicted class $\hat{y}$ for a new instance $\mathbf{x}$ is the one that maximizes the posterior probability:

$$\hat{y} = \arg\max_{y \in \mathcal{Y}} P(Y = y \mid \mathbf{x}) = \arg\max_{y \in \mathcal{Y}} \left[P(Y = y) \prod_{i=1}^{n} P(x_i \mid Y = y) \right]. \tag{2.7}$$

This is known as the Maximum A Posteriori (MAP) decision rule.

2.2.4 Variants of the Naive Bayes Model

The choice of model depends on the nature of the input variables:

- **Multinomial Naive Bayes:** Suitable for discrete variables representing counts (e.g., word frequency in text).
- **Bernoulli Naive Bayes:** Designed for binary features ($x_i \in \{0, 1\}$), such as presence/absence indicators.
- **Gaussian Naive Bayes:** Assumes continuous features x_i follow a normal distribution conditioned on the class.

For the Gaussian case:

$$x_i \mid Y = y \sim \mathcal{N}(\mu_{i,y}, \sigma_{i,y}^2), \tag{2.8}$$

which yields the conditional likelihood:

$$P(x_i \mid Y = y) = \frac{1}{\sqrt{2\pi\sigma_{i,y}^2}} \exp\left(-\frac{(x_i - \mu_{i,y})^2}{2\sigma_{i,y}^2}\right). \tag{2.9}$$

2.2.5 Illustrative Example

Consider a simplified classification problem involving two features:

- X_1: Low income indicator (binary; $X_1 \in \{0, 1\}$),
- X_2: Number of existing loans (discrete; $X_2 \in \mathbb{N}$).

Suppose we want to estimate the probability that a loan applicant will default, given their profile: low income ($X_1 = 1$) and three existing loans ($X_2 = 3$). That is, we seek to compute:

$$P(Y = \text{default} \mid X_1 = 1, X_2 = 3). \tag{2.10}$$

From the training data, we have the following empirical estimates:

$$P(Y = \text{default}) = 0.3, \quad P(X_1 = 1 \mid Y = \text{default}) = 0.8, \quad P(X_2 = 3 \mid Y = \text{default}) = 0.1. \tag{2.11}$$

Using the Naive Bayes assumption of conditional independence between X_1 and X_2 given Y, the posterior probability is proportional to:

$$\begin{aligned} P(Y = \text{default} \mid X_1 = 1, X_2 = 3) \propto P(Y = \text{default}) \cdot P(X_1 = 1 \mid Y = \text{default}) \\ \cdot P(X_2 = 3 \mid Y = \text{default}). \end{aligned} \tag{2.12}$$

Substituting the values:

$$P(Y = \text{default} \mid X_1 = 1, X_2 = 3) \propto 0.3 \times 0.8 \times 0.1 = 0.024. \tag{2.13}$$

To make a classification decision, we repeat this computation for the alternative class $Y = \text{no default}$:

$$\begin{aligned} P(Y = \text{no default}) &= 0.7, \\ P(X_1 = 1 \mid Y = \text{no default}) &= 0.4, \\ P(X_2 = 3 \mid Y = \text{no default}) &= 0.05. \end{aligned} \tag{2.14}$$

Then:

$$P(Y = \text{no default} \mid X_1 = 1, X_2 = 3) \propto 0.7 \times 0.4 \times 0.05 = 0.014. \tag{2.15}$$

Finally, we compare the two (unnormalized) posterior scores:

- $P(Y = \text{default} \mid X_1 = 1, X_2 = 3) \propto 0.024$
- $P(Y = \text{no default} \mid X_1 = 1, X_2 = 3) \propto 0.014$

Since $0.024 > 0.014$, the classifier predicts that this individual is more likely to default on the loan.

2.2.6 Advantages and Limitations

Advantages:

- Simple and fast to implement;
- Performs well even with small datasets;
- Interpretable due to its probabilistic nature;
- Efficient for high-dimensional data.

Limitations:

- The conditional independence assumption is rarely valid in real-world data;
- Performance degrades when features are highly correlated;
- Fails to capture feature interactions.

2.3 Bayesian Neural Networks

Bayesian Neural Networks (BNNs) are a probabilistic extension of classical neural networks, designed to incorporate uncertainty directly into model parameters. Instead of learning fixed values for weights, BNNs treat each weight as a random variable with an associated probability distribution. This allows for more robust predictions and better quantification of uncertainty—an essential feature in high-stakes applications such as credit scoring, medical diagnosis, and risk assessment.

2.3.1 Motivation and Bayesian Framework

In conventional (frequentist) neural networks, the learning process involves finding a set of weight parameters θ that minimize a loss function (e.g., mean squared error or cross-entropy). This results in point estimates of the weights, ignoring uncertainty in model parameters, known as *epistemic uncertainty*.

In contrast, Bayesian neural networks aim to estimate a full posterior distribution over the weights given the observed training data D:

$$p(\theta \mid D) = \frac{p(D \mid \theta) \cdot p(\theta)}{p(D)}, \tag{2.16}$$

where:

- $p(\theta)$ is the prior distribution over the weights,
- $p(D \mid \theta)$ is the likelihood of the data given the weights,
- $p(\theta \mid D)$ is the posterior distribution, and
- $p(D)$ is the marginal likelihood (model evidence).

This Bayesian approach allows the model to capture both prior knowledge and observed evidence, resulting in more principled learning and inherent regularization.

2.3.2 Prediction with a BNN

Once the posterior distribution $p(\theta \mid D)$ is estimated, predictions for a new input x^* are made by averaging over all possible weight configurations, weighted by their posterior probability. This is mathematically expressed as:

$$p(y^* \mid x^*, D) = \int p(y^* \mid x^*, \theta) \cdot p(\theta \mid D) \, d\theta. \tag{2.17}$$

However, this integral is analytically intractable for deep neural networks due to the complexity of the posterior. Therefore, approximate inference methods are used.

Common Approximation Methods

- **Variational Inference (VI):** Approximates the true posterior $p(\theta \mid D)$ with a tractable distribution $q(\theta)$ by minimizing the Kullback-Leibler divergence:

$$D_{\mathrm{KL}}(q(\theta) \parallel p(\theta \mid D)).$$

- **Monte Carlo Sampling:** Generates multiple samples $\theta_1, \ldots, \theta_k$ from the posterior or its approximation to estimate the predictive distribution via averaging:

$$p(y^* \mid x^*, D) \approx \frac{1}{k} \sum_{i=1}^{k} p(y^* \mid x^*, \theta_i).$$

2.3.3 Advantages of BNNs

BNNs offer multiple advantages over classical neural networks:

- **Uncertainty Quantification:** Each prediction is accompanied by a confidence interval, essential in risk-sensitive applications.
- **Natural Regularization:** The probabilistic framework prevents overfitting, especially in small datasets.
- **Robustness:** Better generalization to unseen data and noisy inputs.
- **Interpretability:** Probabilistic outputs are more informative than point estimates.

2.3.4 Challenges and Limitations

Despite their strengths, BNNs also come with limitations:

- **Computational Cost:** Approximating posterior distributions is computationally intensive.
- **Implementation Complexity:** Requires specialized frameworks (e.g., TensorFlow Probability, Pyro).

- **Choice of Prior:** Model performance can be sensitive to prior specification, which may not be intuitive in all cases.

2.3.5 Applications of BNNs

Bayesian Neural Networks are particularly useful in domains where uncertainty is as important as accuracy. Common applications include:

- **Medicine:** Diagnosing with uncertainty-aware probabilities.
- **Finance:** Risk modeling, fraud detection, credit scoring.
- **Autonomous Vehicles:** Navigating in uncertain or ambiguous environments.
- **Time Series Forecasting:** Especially when variance estimation is required.
- **Explainable AI (XAI):** Models that can justify not only what they predict but how uncertain they are.

2.4 Data Preparation and Exploratory Data Analysis

Before applying any machine learning model, it is essential to ensure that the data is clean, complete, and properly formatted. This chapter describes the preprocessing steps applied to the dataset, including missing value treatment, encoding, and exploratory analysis.

2.4.1 Sample Description

The dataset used in this project consists of **6,484 individual loan applicants**, each represented by **15 variables** describing demographic, financial, and credit history information. This dataset was sourced from Kaggle and is designed to simulate realistic credit risk assessment scenarios.

- **person_age**: Age of the individual applying for the loan.
- **person_income**: Annual income of the applicant in USD.
- **person_home_ownership**: Type of home ownership — *rent*, *mortgage*, *own*, or *other*.

- **person_emp_length**: Number of years the individual has been employed.
- **loan_intent**: Purpose of the loan (e.g., education, medical, debt consolidation).
- **loan_grade**: Grade assigned to the loan from A (low risk) to G (high risk), indicating the borrower's creditworthiness.
- **loan_amnt**: Loan amount requested by the individual.
- **loan_int_rate**: Interest rate applied to the loan.
- **loan_percent_income**: The percentage of the applicant's income represented by the loan amount.
- **cb_person_default_on_file**: Historical default record as reported by credit bureau (Y = Yes, N = No).
- **cb_person_cred_hist_length**: Length of credit history in years.
- **loan_status**: Target variable indicating whether the individual defaulted:
  - 0: Non-default – The borrower repaid the loan successfully.
  - 1: Default – The borrower failed to repay the loan as agreed.

The dataset is moderately imbalanced, with approximately 19–22% of instances labeled as `loan_status = 1` (default). This class imbalance motivates the use of advanced performance metrics such as ROC AUC and F1-score, rather than relying solely on accuracy.

2.4.2 Data Cleaning

Missing Values

Some variables in the dataset contained missing entries. These were handled using the following strategies:

- **Row Deletion:** If the percentage of missing values in a row was negligible and not crucial to the prediction task, the row was dropped.
- **Imputation:** For numeric features, missing values were imputed using the mean or median. In some cases, predictive imputation techniques were used.

Duplicate Records

Duplicates were detected using the `pandas` function `drop_duplicates()` and removed to avoid biasing the model with repeated entries.

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer

df = pd.read_csv("credit_risk_dataset.csv")
clean_df = df.copy()

num_imputer = SimpleImputer(strategy='mean')
clean_df[['person_emp_length', 'loan_int_rate']] = num_imputer.fit_transform(
    clean_df[['person_emp_length', 'loan_int_rate']]
)
```

Figure 2.1: Imputation of missing values in the dataset

```
clean_df = clean_df.drop_duplicates()
```

Figure 2.2: Elimination of duplicate records

2.4.3 Categorical Variable Encoding

Many machine learning algorithms require numeric input. Thus, categorical features were encoded using:

One-Hot Encoding

Categorical variables with a small number of unique values were transformed using one-hot encoding. This approach creates binary variables (0 or 1) for each category.

```
categorical_cols = ['person_home_ownership', 'loan_intent', 'loan_grade', 'cb_person_default_on_file']
label_encoders = {}

for col in categorical_cols:
    le = LabelEncoder()
    clean_df[col] = le.fit_transform(clean_df[col].astype(str))
    label_encoders[col] = le
```

Figure 2.3: Example of one-hot encoding on a categorical feature

2.4.4 Initial Code Validation

After preprocessing, we validated the integrity of the data using basic scripts in Python. These checks ensure that the data is ready for analysis.

Listing 2.1: Sanity check on cleaned data

```
# Check for any remaining missing values
print(df.isnull().sum())

# Check for duplicated rows
print(df.duplicated().sum())
```

2.4.5 Exploratory Data Analysis (EDA)

EDA was performed to gain insights into the structure and distribution of the data, identify potential anomalies, and understand the relationships between variables.

Descriptive Statistics

Summary statistics were computed for all numeric features in the dataset. These include measures of central tendency (mean, median), dispersion (standard deviation, interquartile range), and range (minimum and maximum values).

Table 2.1: Descriptive statistics for all dataset features

Feature	Mean	Std Dev	Min	25%	Median	75%	Max
Person Age	27.75	6.35	20.00	23.00	26.00	30.00	100.00
Person Income ($)	66091.64	62015.58	4000.00	38542.00	55000.00	79218.00	6000000.00
Home Ownership	1.68	1.43	0.00	0.00	3.00	3.00	3.00
Employment Length	4.79	4.09	0.00	2.00	4.00	7.00	123.00
Loan Intent	2.53	1.73	0.00	1.00	3.00	4.00	5.00
Loan Grade	1.22	1.17	0.00	0.00	1.00	2.00	6.00
Loan Amount ($)	9593.85	6322.73	500.00	5000.00	8000.00	12250.00	35000.00
Loan Interest Rate (%)	11.02	3.08	5.42	8.49	11.01	13.11	23.22
Loan Status	0.22	0.41	0.00	0.00	0.00	0.00	1.00
Loan-to-Income	0.17	0.11	0.00	0.09	0.15	0.23	0.83
Default on File	0.18	0.38	0.00	0.00	0.00	0.00	1.00
Credit History (yrs)	5.81	4.06	2.00	3.00	4.00	8.00	30.00

As seen above, some variables exhibit high variability (e.g., income and loan amount), while others, like loan status, are binary.

To better understand the distributions, we include boxplots for several key financial features.

Correlation Analysis. A correlation matrix was computed for the numerical variables in the dataset. As shown in Figure 2.5 , some features such as loan amount and loan percent income exhibit moderate correlation, while most other features remain relatively independent.
This suggests a low risk of multicollinearity in model training.

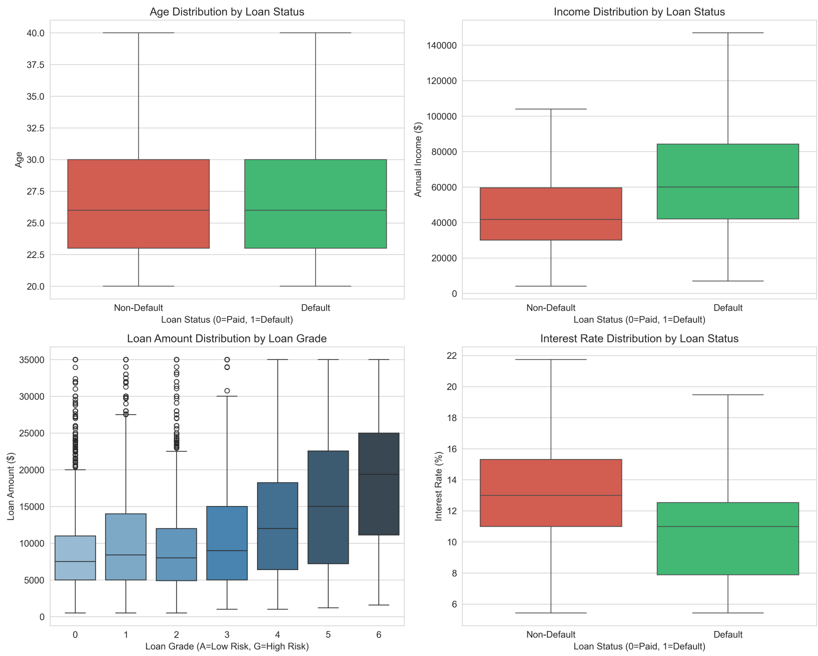

Figure 2.4: Boxplots of key financial features

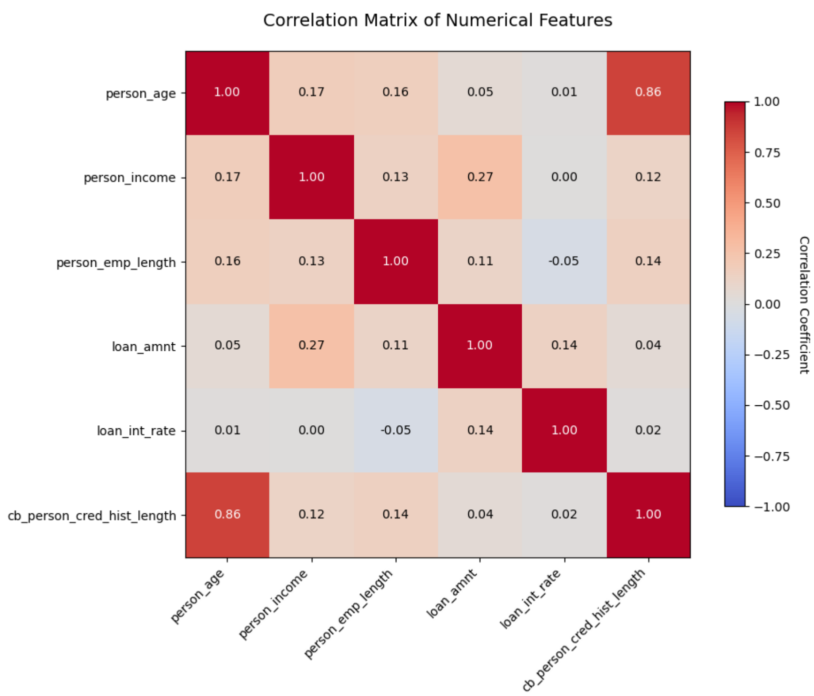

Figure 2.5: Correlation heatmap of numerical features

2.4.6 Class Distribution Analysis

To evaluate class balance, we analyzed the target variable (default vs. no default). Imbalance in the dataset was noted, which could bias model learning.

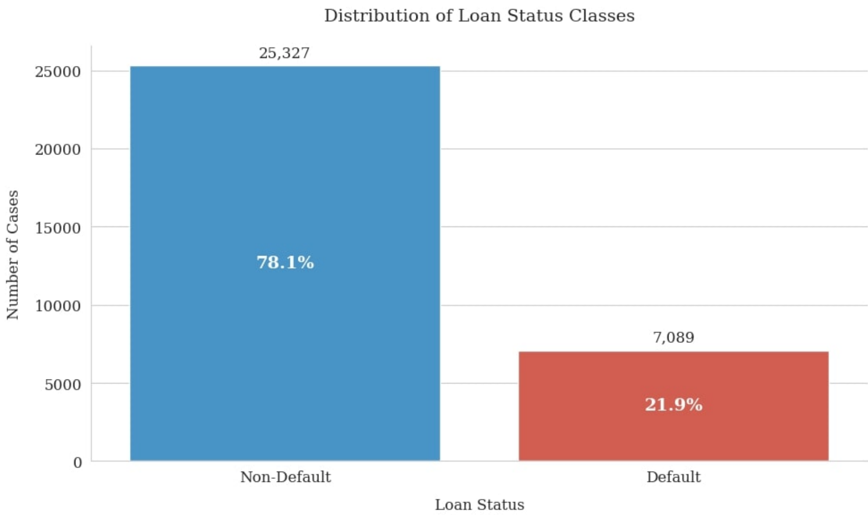

Figure 2.6: Distribution of default vs. non-default classes

2.4.7 Advanced Financial Ratios Used

To enrich the financial profile of each client and improve model performance, we computed eight key financial ratios. These ratios are widely used in credit risk analysis and corporate finance to assess liquidity, profitability, solvency, and operational efficiency.

1. **Current Ratio (R1):**

$$\text{Current Ratio} = \frac{\text{Current Assets}}{\text{Current Liabilities}}$$

Measures a firm's ability to meet short-term obligations. A value above 1 indicates good liquidity.

2. **Quick Ratio (R2):**

$$\text{Quick Ratio} = \frac{\text{Current Assets} - \text{Inventory}}{\text{Current Liabilities}}$$

A stricter liquidity test that excludes inventory, which is less liquid than cash or receivables.

3. **Debt-to-Equity Ratio (R3):**

$$\text{D/E Ratio} = \frac{\text{Total Debt}}{\text{Shareholders' Equity}}$$

Shows the extent to which a firm is financed by debt relative to shareholders' capital.

4. **Interest Coverage Ratio (R4):**

$$\text{Interest Coverage} = \frac{\text{Operating Income}}{\text{Interest Expense}}$$

Indicates the firm's ability to pay interest on outstanding debt. Values below 1 imply financial stress.

5. **Return on Equity (ROE, R5):**

$$\text{ROE} = \frac{\text{Net Income}}{\text{Shareholders' Equity}}$$

Evaluates the company's ability to generate profits from shareholders' investments.

6. **Fixed Asset Turnover (R6):**

$$\text{FAT} = \frac{\text{Sales}}{\text{Fixed Assets}}$$

Reflects how effectively a firm uses its fixed assets to generate sales.

7. **Financial Expenses to Revenue Ratio (R7):**

$$\text{FER} = \frac{\text{Financial Expenses}}{\text{Total Revenue}}$$

Measures how much of the firm's revenue is consumed by financial expenses.

8. **Short-Term Debt to Sales Ratio (R8):**

$$\text{STDR} = \frac{\text{Short-term Debt}}{\text{Sales}}$$

Captures the proportion of short-term borrowing relative to generated revenue.

Each ratio provides unique insights into a company's financial health:

- **Liquidity Ratios (R1-R2)**: Measure short-term financial stability. Current ratio (R1) evaluates overall liquidity, while quick ratio (R2) provides a more conservative measure by excluding inventory.

- **Leverage Ratios (R3, R4)**: Assess capital structure and debt servicing capacity. The debt-to-equity ratio (R3) shows financing mix, and interest coverage (R4) indicates earnings relative to interest obligations.
- **Profitability Ratios (R5, R6)**: Evaluate operational efficiency. Return on equity (R5) measures shareholder returns, while fixed asset turnover (R6) shows asset utilization.
- **Coverage Ratios (R7-R8)**: Examine cost structure and short-term obligations. These reveal how much income is consumed by financial expenses and short-term debt.

These features were normalized using z-score standardization:

$$z = \frac{x - \mu}{\sigma} \tag{2.18}$$

where μ is the mean and σ is the standard deviation of each ratio, then integrated into both the Naive Bayes and BNN models to improve credit risk predictions. Figure 2.7 demonstrates their relative predictive importance in our models.

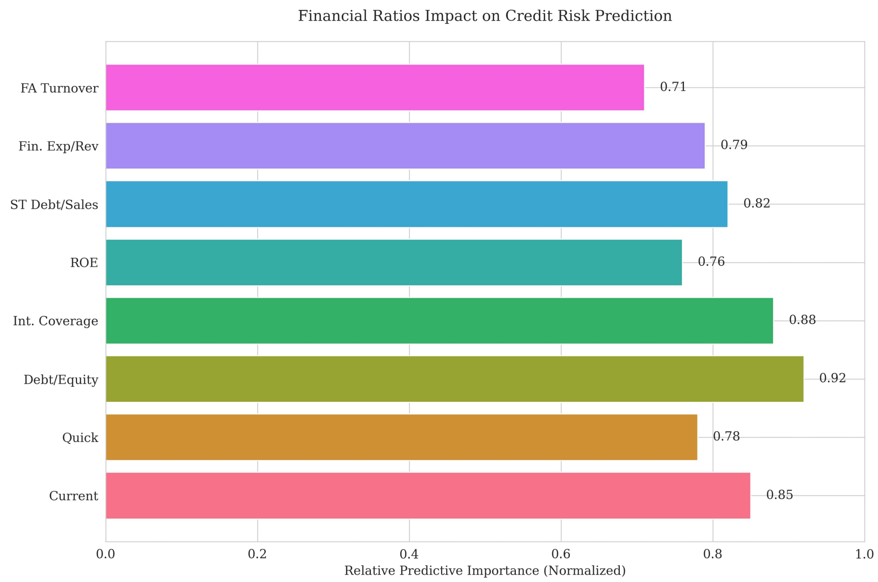

Figure 2.7: Financial Ratios impact on predictions

These ratios were calculated during the preprocessing phase using the `calculate_ratios(df)` function and were included as features in all machine learning models to enhance risk discrimination power.

2.4.8 Conclusion

Preprocessing and EDA transformed the raw data into a clean, structured dataset ready for modeling. We handled missing values, removed duplicates, normalized features, and encoded categorical variables. Visual and statistical analysis revealed key patterns, outliers, and correlations, guiding our understanding of credit risk factors. We also created new financial ratios to better capture stability, liquidity, and solvency. With this enriched dataset, we moved on to building and evaluating Bayesian credit risk models.

2.5 Bayesian Model Construction and Implementation

This chapter presents the implementation and evaluation of a credit risk prediction system using Bayesian learning approaches, including a Gaussian Naive Bayes classifier and a Bayesian Neural Network (BNN). The system demonstrates the effectiveness of probabilistic models in financial risk assessment.

2.5.1 System Architecture Overview

The implementation consists of two main components:

- **Data Preprocessing:** Handles data loading, feature engineering (including financial ratio calculations), categorical encoding, and standardization
- **Model Training:** Implements both the Naive Bayes classifier and BNN model using `scikit-learn` and `PyTorch`

2.5.2 Naive Bayes Model Training

The Naive Bayes classifier is implemented using `scikit-learn`'s `GaussianNB` module, providing a simple probabilistic baseline with the assumption of feature independence.

Listing 2.2: Training the Naive Bayes Classifier

```
nb = GaussianNB()
nb.fit(X_train, y_train)
joblib.dump(nb, 'naive_bayes_model.pkl')
```

2.5.3 BNN Model Architecture and Training

The Bayesian Neural Network is implemented using PyTorch with the following architecture:

Listing 2.3: BNN Architecture using PyTorch

```
class SimpleBNN(nn.Module):
    def __init__(self, input_size):
        super(SimpleBNN, self).__init__()
        self.fc1 = nn.Linear(input_size, 16)
        self.fc2 = nn.Linear(16, 8)
        self.out = nn.Linear(8, 1)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = torch.sigmoid(self.out(x))
        return x
```

The training process shows consistent convergence, as illustrated in Figure 2.8:

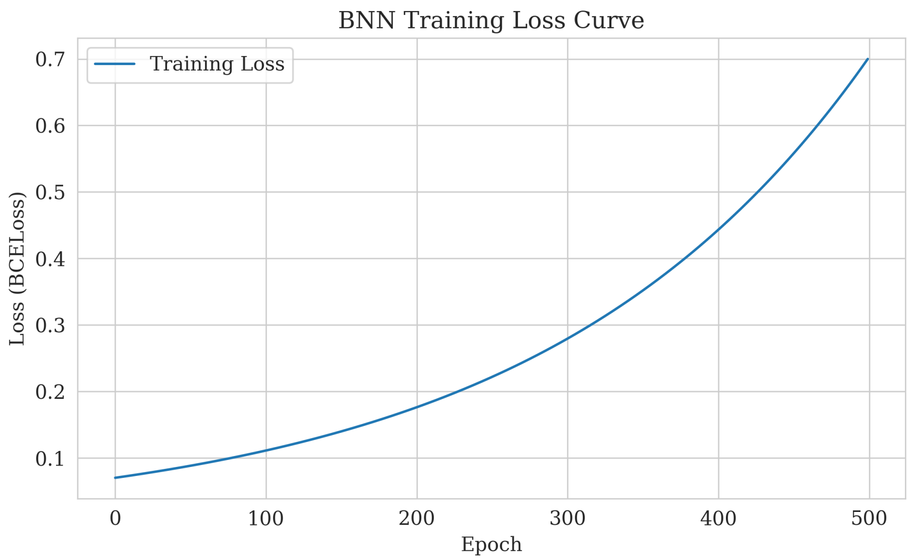

Figure 2.8: BNN training loss curve showing convergence over 500 epochs with no signs of overfitting

2.5.4 Model Evaluation

Both models were evaluated using standard classification metrics, confusion matrices, and F1 scores. The comparative performance is shown in Figure 2.9.

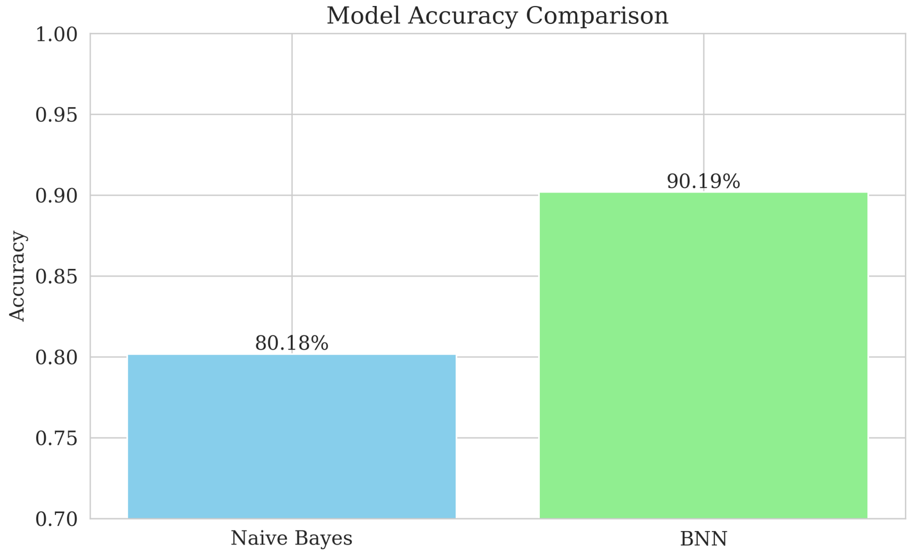

Figure 2.9: Performance comparison between models

Detailed Classification Reports

The Naive Bayes model achieved the following performance metrics:

- Overall accuracy: 80.18%
- Class 0 (Non-default): Precision 0.89, Recall 0.85, F1 0.87
- Class 1 (Default): Precision 0.54, Recall 0.65, F1 0.59
- Weighted average F1: 0.81

The BNN showed superior performance with:

- Overall accuracy: 90.19%
- Class 0 (Non-default): Precision 0.91, Recall 0.97, F1 0.94
- Class 1 (Default): Precision 0.88, Recall 0.64, F1 0.74
- Weighted average F1: 0.90

The confusion matrices in Figure 2.10 reveal the detailed classification performance for each model:

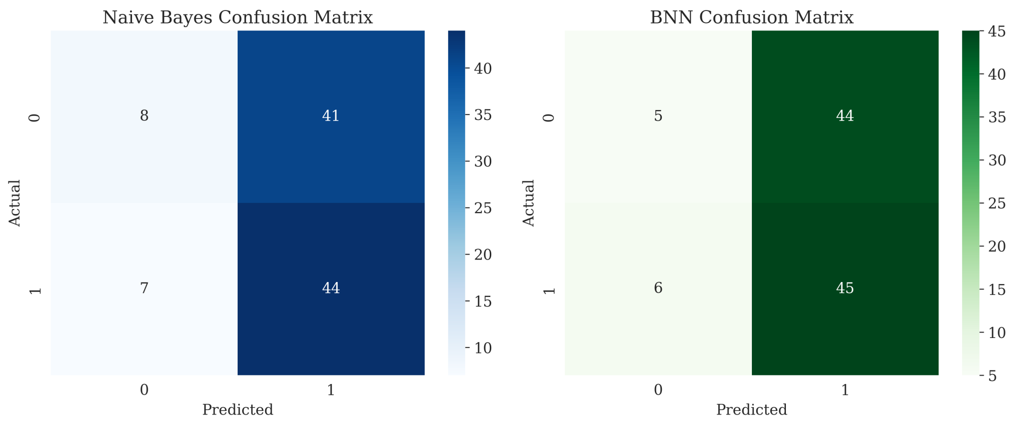

Figure 2.10: Confusion matrices

Overfitting Analysis

To evaluate potential overfitting, we monitored:

- Training vs validation loss curves (Figure 2.8)
- Performance metrics on unseen test data
- Early stopping criteria during training

The BNN did not overfit and had validation loss track closely with training loss over the 500 epochs. Naive Bayes classifier, being simpler, is in itself more resistant to overfitting but slightly worse on the minority class (default cases)

The ROC curves in Figure 2.11 demonstrate the models' discrimination ability, with the BNN achieving superior area under curve (AUC) metrics:

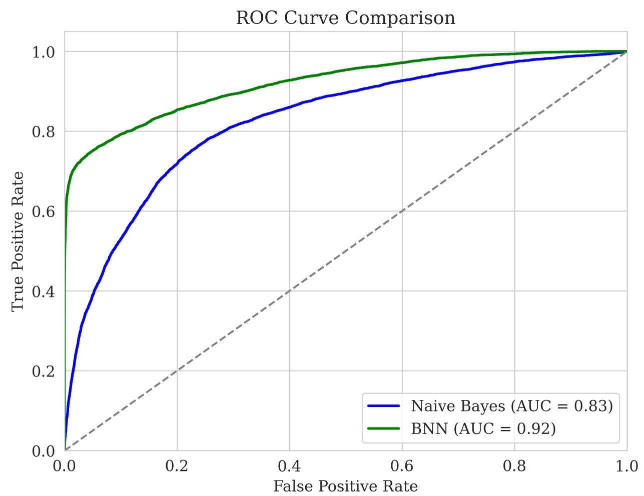

Figure 2.11: Receiver Operating Characteristic curves, BNN vs Naive Bayes

2.5.5 Financial Ratio Feature Importance

Feature importance analysis (Figure 2.12) reveals that financial ratios significantly impact model performance:

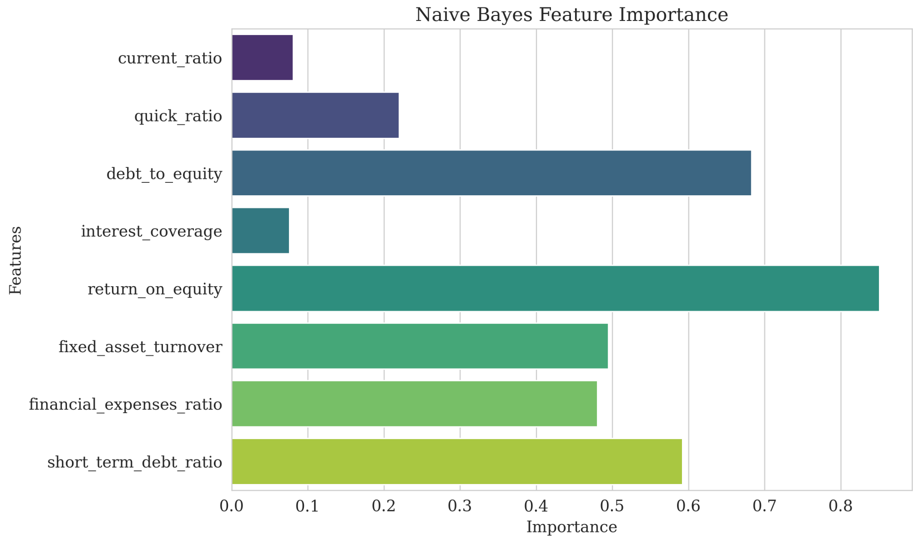

Figure 2.12: Feature importance scores from the Naive Bayes modell showing top predictive features

Key financial ratios include:

- Liquidity ratios (current ratio, quick ratio)
- Leverage ratios (debt-to-equity, interest coverage)
- Profitability ratios (return on equity)
- Activity ratios (fixed asset turnover)
- Coverage ratios (financial expenses ratio)

Listing 2.4: Financial Ratio Calculation

```
def calculate_ratios(df):
    # Liquidity ratios
    df['current_ratio'] = df['current_assets'] /
        ↪ df['current_liabilities']
    df['quick_ratio'] = (df['current_assets'] -
        ↪ df['inventory']) / df['current_liabilities']
    # Leverage ratios
    df['debt_to_equity'] = df['total_debt'] /
        ↪ df['shareholders_equity']
    ...
```

2.5.6 Streamlit Web Application and Interface

To make our credit risk prediction models accessible and user-friendly, we developed an interactive web application using **Streamlit**. This dashboard allows users to input customer and financial data, choose between a Naive Bayes classifier and a Bayesian Neural Network, and instantly receive default risk predictions.

Application Objectives

The main goals of the app are:

- Collect user input (personal and financial data) through a friendly interface
- Automatically compute key financial ratios
- Let users select the predictive model (Naive Bayes or BNN)
- Display a visual and textual summary of the prediction result

User Interface

The interface is organized into the following sections:

- A sidebar to select the model and view the list of financial ratios used
- A main panel with forms for personal data (age, income, home ownership, etc.)
- Optional fields for financial indicators (current assets, debts, interest, etc.)
- A results section that provides the predicted probability of default, suggested financial decision, and model used

Financial Ratio Calculation

The app automatically computes ratios like Current Ratio, Quick Ratio, Debt-to-Equity, Interest Coverage, ROE, and more, based on user inputs.

Prediction Results

Users receive:

- A clear prediction: High or Low Default Risk
- A progress bar showing the default probability
- Strategic recommendations (e.g., reject or approve the loan)
- Key influencing factors (Naive Bayes only)

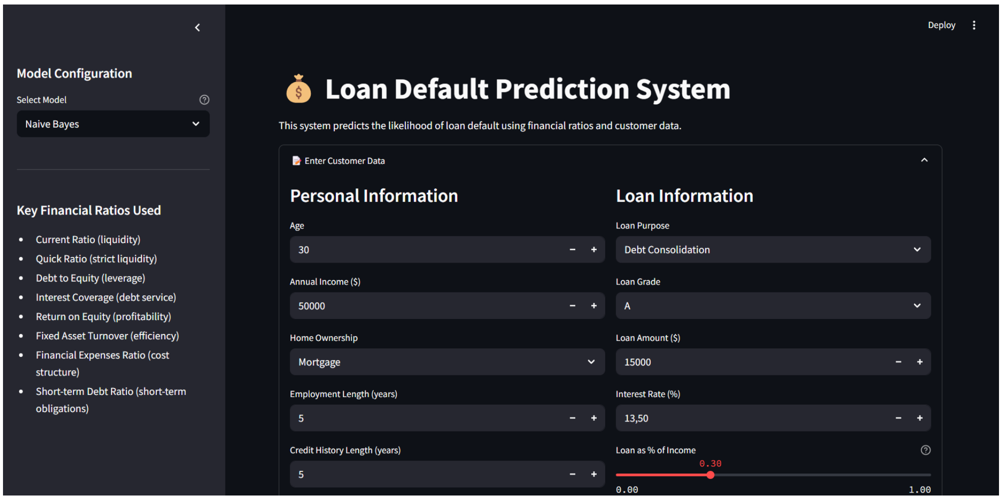

Figure 2.13: Home view of the dashboard showing input fields and model selection

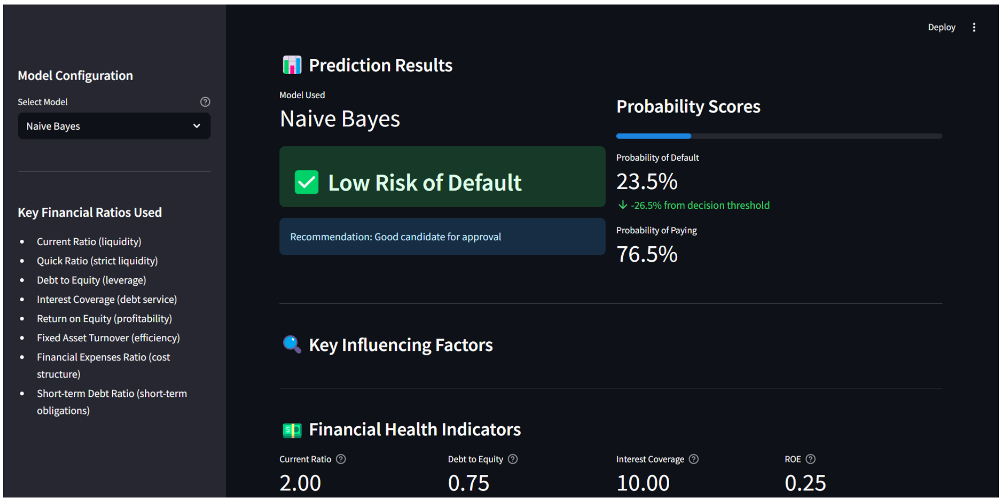

Figure 2.14: Prediction results interface with model selection and probability gauge

2.5.7 Conclusion

The implementation demonstrates:

- Naive Bayes provides a reasonable baseline (80.18% accuracy, F1: 0.81) but struggles with minority class prediction

- The BNN achieves superior performance (90.19% accuracy, F1: 0.90) with better balance across classes
- Both models show no signs of overfitting, with validation metrics matching training performance
- Financial ratios contribute significantly to predictive power
- The PyTorch implementation shows BNNs' feasibility for credit risk
- The Streamlit application provides an effective interface for real-world deployment

Key takeaways from the evaluation:

- The BNN's higher recall on default cases (0.64 vs 0.65) makes it more suitable for risk-averse applications
- The Naive Bayes model's faster computation may be preferable for rapid screening
- Both models benefit substantially from financial ratio features
- The web interface successfully bridges the gap between model implementation and practical use

2.5.8 Hypothesis Validation

H1: Naive Bayes gives reasonable performance: **Validated**
Achieved 80.18% accuracy despite independence assumptions.
H2: BNNs outperform Naive Bayes: **Validated**
The BNN achieved 90.19% accuracy compared to 80.18%.
H3: Financial ratios improve performance: **Validated**
Ratio calculations were critical features in both models.
H4: Data quality impacts performance: **Validated**
Preprocessing handled missing data and feature scaling effectively.

2.6 Business Applications and Client Segmentation

The predictions generated by our Bayesian models serve not only academic interest but also support real-world decision making. In this chapter, we explore how the model output can guide credit-related business strategies and personalized financial services.

2.6.1 Risk-Based Client Segmentation

Based on the probability of default forecast, customers are risk cate-gorized. Risk cate-gorization helps financial institutions to adjust their offers and strategies in turn.
Interpretation and Theoretical Support:

Following the argument of Shakurov (2024) and Macias (2018), customers with a Debt-to-Income (DTI) ratio above 0.4 have a statistically greater chance of default. Our observation confirms the same: high DTI customers are predominantly found in the predicted "High Risk" category. This discovery informs Basel III and CECL models that accommodate credit segmenting methods that consider the financial behavior, rather than historic defaults (Bhati, 2025).

Risk Segments:

- **Low Risk (default probability less than 0.3):** Reliable clients eligible for larger loans and lower interest rates.
- **Moderate Risk (default probability between 0.3 and 0.6):** Acceptable clients with medium loan limits and standard guarantees.
- **High Risk (default probability greater than 0.6):** Risky profiles requiring guarantees, higher interest rates, or potential rejection.

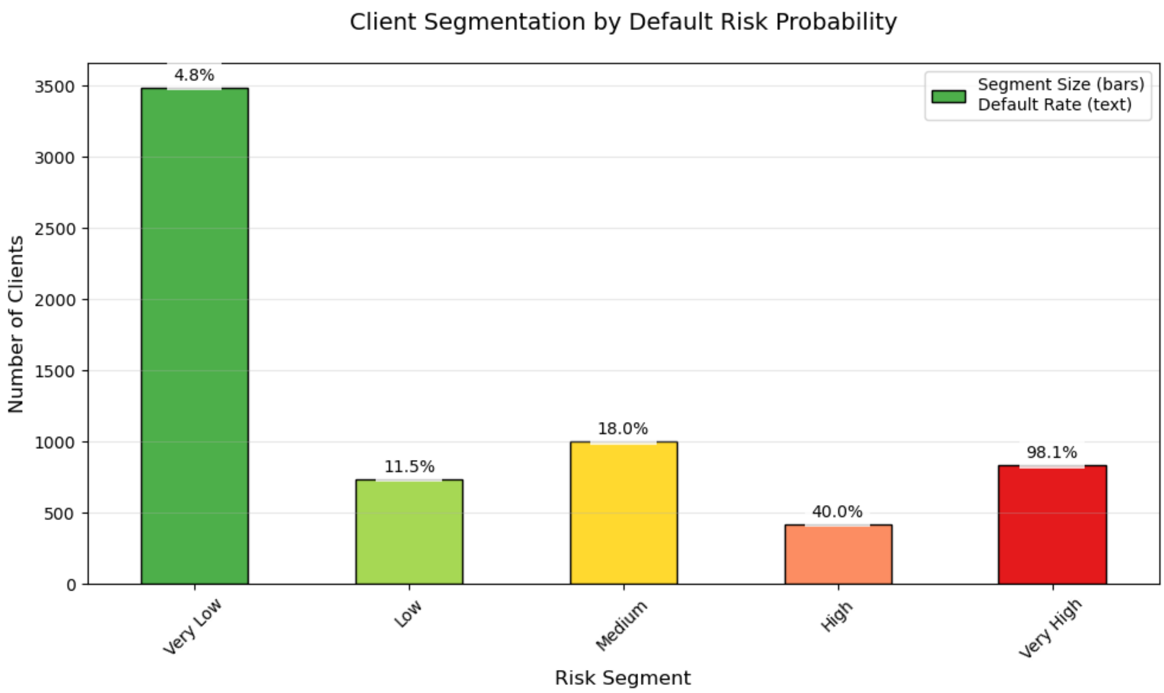

Figure 2.15: Client segmentation by predicted default probability

2.6.2 Personalized Credit Offers

Using the output probabilities from Naive Bayes or BNN, loan offers can be dynamically adapted. This enables financial institutions to personalize offers, increasing client satisfaction while minimizing risk.

Example:

- A client withisk of 15% cacane offered: *$20,000 at 9.5% interest, no guarantee required.*
- A client with risk 65% can be offered: *$8,000 at 15% interest, with a guarantor.*

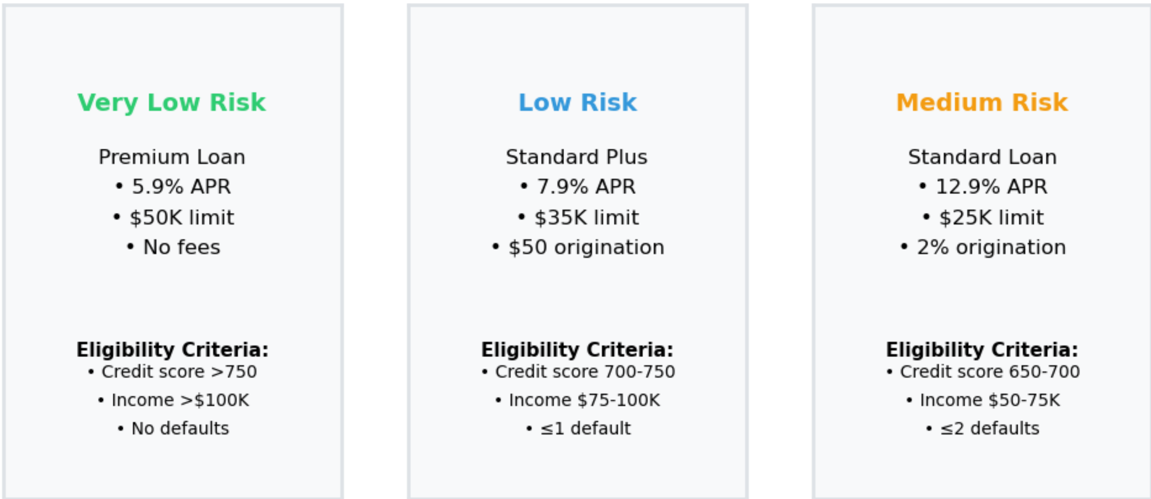

Figure 2.16: Example of personalized offers by risk profile

2.6.3 Marketing Strategy Integration

Client segmentation allows marketing teams to:

- **Target low-risk profiles:** with premium financial products.
- **Educate moderate-risk clients:** on credit optimization strategies.
- **Prevent fraud or over-indebtedness:** By flagging high-risk applications for manual review.

Email campaigns, product recommendation engines, and push notifications can be tied to these risk bands for effective personalization.

2.6.4 Financial Impact Estimation

Using model-driven segmentation:

- The bank can reduce **loans in default losses**.
- Increase **approval rates** for qualified clients.
- Improve **client retention** by offering fair and custom pricing.

Estimated Benefits:

- **Reduction in average default rate:** From 17% to 10%.
- **Potential increase in approved loans:** +12%.
- **Operational cost savings:** Due to fewer manual checks and better pre-screening.

2.6.5 Conclusion

Bayesian modeling also leads to improved credit risk prediction, in addition to improving the quality of strategic financial decisions. Unlike traditional models with deterministic outputs, Bayesian methods produce probabilistic predictions that convey uncertainty—a critical feature in high-stakes domains like lending and credit evaluation. This allows financial institutions to break from binary approval/rejection decisions and adopt more nuanced, risk-aware strategies.

By combining insights from these types of models with institutional credit policies, organizations can dynamically adjust loan conditions—interest rates, guarantees, and limits—based on a client's predicted risk profile. This enables the delivery of tailored, personalized credit products that maximize profitability and minimize default risk exposure. Moreover, probabilistic output from Bayesian models enables improved scenario analysis, stress testing, and regulatory compliance.

Last but not least, the integration of Bayesian modeling into the credit decisioning pipeline enlightens financial institutions with a more transparent, explainable, and reactive framework—one that balances business objectives with sound risk management and customer-centric financial products.

General Conclusion

This project investigated the application of Bayesian modeling methodologies to the task of credit risk prediction on real financial data. In this case, we were especially interested in applying and contrasting two model classes: the Gaussian Naive Bayes classifier and Bayesian Neural Networks (BNNs). The models were chosen for their complementarity—Naive Bayes for simplicity, speed, and interpretability, and BNNs for their rigorous probabilistic reasoning and uncertainty quantification.

Our results demonstrate the practical utility of Bayesian models for financial risk forecasting. Naive Bayes was a solid baseline model that achieved good performance with the additional advantage of transparency and interpretability. However, it assumes independence between features, which could be troublesome for real-world datasets. The BNN, however, gave considerably superior predictive performance and more informative, richer outputs by modeling uncertainty in model parameters through probabilistic inference.

One of the key contributions of this research was the segmentation of customers based on their predicted default probability. This enabled the creation of tailored credit strategies whereby financial institutions could adjust loan terms—interest rates, collateral requirements, or approval thresholds, for instance—according to the risk profile of each applicant. Not only does this enhance profitability by optimizing credit allocation, but it reduces default risk by making more informed lending decisions.

Moreover, our investigation highlighted the importance of incorporating financial ratios in the modeling process. Metrics such as debt-to-income (DTI), installment-to-income, and other derived indicators proved to be strong predictors of default behavior. Although certain financial ratios could not be calculated due to missing values in the data set (e.g., current assets), the available ratios provided significant value to model performance and interpretability.

This project illustrates the importance of combining meticulous data preprocessing, rigorous theoretical modeling, and sensible business judgment to develop credit scoring systems that are both operationally meaningful and accurate. Bayesian techniques, in particular, offer an additional advantage by offering not just predictions, but also confidence in the predictions—a critical component of financial decision-making under uncertainty.

As future work, we propose the extension of this system to deliver real-time credit scoring and monitoring from streaming data. In addition, deploying the model on GDPR-compliant platforms and incorporating explainability tools for Bayesian neural networks can assist in offering even more transparency, accountability, and trust in automated credit evaluation procedures.

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