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Hybrid Forecasting Models for Credit Default and Financial Risk: A Comparative Empirical Study

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Abstract

This study presents a comparative evaluation of six major machine learning and statistical modeling techniques—K-Nearest Neighbors (KNN), Logistic Regression (LR), Discriminant Analysis (DA), Naïve Bayes (NB), Artificial Neural Networks (ANN), and Classification Trees (CT)—for the prediction of credit default probability among credit card clients. Leveraging real-world Taiwanese credit data alongside custom pre-processed market datasets and Python-based simulations, the study applies a novel evaluation framework using lift charts and regression diagnostics to evaluate both classification performance and probability estimation fidelity. Experimental validation is carried out through Python models and augmented by a custom smoothing technique to approximate latent default probabilities. Empirical evidence indicates the superior generalizability and probabilistic alignment of neural networks, highlighting their promise in robust credit scoring systems. The results are substantiated through extensive figures, tables, and cross-model evaluations, providing a reproducible blueprint for risk forecasting across financial sectors.

1. Introduction

In the current era of data-driven financial services, accurate modeling of credit risk is fundamental for maintaining systemic stability and ensuring profitable operations within consumer lending markets. This research aims to deepen the understanding of model performance across traditional statistical techniques and modern machine learning algorithms, using a unified framework for both classification accuracy and real-probability estimation. The problem of binary credit scoring (default vs. non-default) has long been studied, but this work extends the analysis by evaluating the predicted *probability* of default, a more granular and financially interpretable measure of risk.

Following prior studies, especially Yeh and Lien (2009), we adopt a real-world dataset from Taiwanese financial institutions and enhance it with our own processed dataset containing market and payment indicators. Our objective is not only to classify clients effectively but to estimate default probability distributions that align closely with real-world outcomes. By applying a smoothing-based ground-truth estimation technique and coupling it with linear regression diagnostics, we objectively compare the probabilistic forecasting ability of the models.

2. Literature Review

The prediction of credit risk and probability of default (PD) is a long-standing challenge in the domains of financial engineering, risk analytics, and applied machine learning. Numerous techniques have been employed, ranging from classical statistical models to contemporary AI-based approaches. The literature reflects a trend towards probabilistic modeling and hybrid methods combining interpretability and predictive accuracy.

Below Table provides a comparative review of ten advanced studies focused on default prediction, scoring systems, and the efficacy of various machine learning or econometric methods in financial risk contexts.

Key Literature in Credit Risk Modeling

Title	Author	Objective	Methodology	Results
1. Credit Scoring Using Machine Learning Techniques	Sunil Bhatia, Pratik Sharma, Rohit Burman, Santosh Hazari, Rupali Hande	To evaluate and compare the performance of various machine learning algorithms in predicting creditworthiness, aiming to enhance the accuracy and efficiency of credit scoring models.	- Implemented multiple machine learning algorithms including Decision Trees, Random Forests, Support Vector Machines (SVM), and Logistic Regression. - Utilized a dataset comprising various financial and demographic features of individuals. - Conducted experiments to assess the predictive performance of each algorithm. - Evaluated models based on metrics such as accuracy, precision, recall, and F1-score.	- Machine learning models demonstrated superior performance over traditional credit scoring methods. - Among the evaluated algorithms, Random Forests achieved the highest accuracy, indicating its effectiveness in handling credit scoring tasks. - The study highlighted the potential of machine learning techniques to improve the reliability and robustness of credit risk assessments.
2. AUC: a misleading measure of the performance of predictive distribution models	Jorge M. Lobo, Alberto Jiménez-Valverde, and Raimundo Real	This study challenges the widespread use of the Area Under the ROC Curve (AUC) as a measure of predictive accuracy in species distribution models. The authors argue that AUC, though popular, is misleading and unsuitable for evaluating model performance because it overlooks critical aspects like probability calibration, spatial error patterns, and the impact of geographic extent on model scores.	The paper critically examines the properties and limitations of the AUC metric through a theoretical review. It highlights five key problems: AUC ignores the goodness-of-fit of probability predictions, evaluates performance over unrealistic threshold regions, treats omission and commission errors equally (even when their consequences differ), provides no information about the spatial distribution of errors, and is heavily influenced by the extent of the study area. The authors also discuss alternative approaches, such as threshold-dependent metrics (e.g., sensitivity, specificity) and emphasize the importance of properly rescaling probabilities when using continuous prediction maps.	The review concludes that AUC is an inadequate measure for comparing predictive models, particularly across species or regions with different characteristics. Instead, the authors suggest that model evaluation should include both sensitivity and specificity measures and that model validation must account for prevalence biases and geographic extent. They argue that while AUC can give insights into how specialized a species' distribution is, it does not accurately reflect model quality or predictive reliability.

3. Network based credit risk models	Paolo Giudici, Branka Hadji-Misheva & Alessandro Spelta	The study aims to enhance the accuracy of credit risk assessment in Peer-to-Peer (P2P) lending platforms, especially those targeting small and medium enterprises (SMEs). Recognizing that traditional credit scoring methods may be insufficient due to limited data access, the authors propose incorporating "alternative data" — specifically, centrality measures from borrower similarity networks based on financial ratios — to improve risk prediction and model interpretability.	The authors use a logistic regression model, the standard tool for predicting borrower defaults, but extend it by adding network-based variables. They construct similarity networks among SMEs using correlations derived from financial ratios. Centrality measures such as degree, strength, and PageRank are calculated from these networks to capture the interconnectedness and relative positioning of borrowers. These network features are then integrated into the logistic regression model to boost its predictive power. Performance is evaluated through ROC curves, precision-recall metrics, and standard classification accuracy measures.	The findings demonstrate that including network centrality measures significantly improves the model's ability to predict defaults compared to traditional models based solely on financial ratios. The augmented model achieves higher accuracy and better discriminates between defaulted and non-defaulted companies. Empirical analysis using a large dataset of European SMEs confirms that network-enhanced models not only increase prediction accuracy but also maintain a high level of explainability, making them practical for regulators and practitioners.

4. Self-supervised conformal prediction for uncertainty quantification in Poisson imaging problems	Bernardin Tamo Amougou, Marcelo Pereyra, and Barbara Pascal	The paper aims to present a self-supervised conformal prediction method for Poisson imaging problems. This method leverages the Poisson Unbiased Risk Estimator to eliminate the need for ground truth data, which is often required for calibration in traditional conformal prediction methods.	The authors develop a self-supervised conformal prediction framework by adapting PURE to estimate the necessary calibration scores directly from noisy measurements, without using ground truth images. They design a non-conformity measure based on the reconstruction error between estimated and observed images, adjusted using the properties of the forward model. Their approach applies a modified version of split-conformal prediction, where calibration is performed using PURE estimates. The methodology is validated on Poisson image denoising and deblurring tasks, using self-supervised neural network estimators trained without ground truth data.	Experiments on Poisson image denoising and deblurring demonstrate that the self-supervised conformal prediction method delivers uncertainty quantification results comparable to those achieved by fully supervised methods that rely on ground truth data. The proposed method achieves accurate empirical coverage across a wide range of confidence levels, validating its effectiveness and robustness even in challenging imaging settings where ground truth is unavailable.

5.Consumer Credit-Risk Models Via Machine-Learning Algorithms	Amir Ehsan Khandani, Adlar J. Kim, Andrew W. Lo	To develop and evaluate consumer credit risk models using machine learning techniques, particularly to improve forecasting accuracy of credit risk compared to traditional models.	- Utilized a large panel dataset of individual credit histories from January 2005 to April 2009. - Applied machine learning algorithms, especially random forests and boosting methods. - Compared machine-learning-based forecasts with traditional logistic regression models. - Employed performance metrics such as out-of-sample forecasting accuracy, Type I and Type II errors, and ROC curves.	Machine learning models (especially random forests) outperformed traditional logistic regression models in predicting credit risk. - Found that consumers' dynamic credit behaviors (e.g., changes in utilization rates, payment history) were critical predictors. - The models detected early warning signals before delinquencies, improving risk management and lending decisions. - Demonstrated that adaptive, data-driven models are more resilient to changing economic environments compared to static models.
6.A comparative analysis of current credit risk models	Michel Crouhy, Dan Galai, and Robert Mark	The paper aims to review and critically compare the main credit risk models that emerged in the late 1990s, focusing on their ability to measure and manage credit risk for financial institutions. The analysis is particularly motivated by new regulatory frameworks encouraging banks to develop internal credit risk models for capital allocation purposes.	The authors examine and compare four major approaches to modeling credit risk: 1)Credit Metrics (JP Morgan) – A credit migration model estimating portfolio value changes due to rating transitions. 2)KMV Model – A structural model using firm asset value dynamics to calculate the probability of default. 3)Credit Risk+ (Credit Suisse) – An actuarial model treating defaults as a Poisson process and focusing solely on default events. 4)Credit Portfolio View (McKinsey) – A macroeconomic model linking default probabilities to economic variables like unemployment and interest rates. Each model's underlying assumptions, mathematical structures, calibration techniques, and practical applications are analysed and compared, particularly in how they handle default risk, migration risk, and portfolio diversification.	The comparison reveals that while all models offer valuable tools for credit risk management, none fully integrates credit and market risk or handles the complexity of credit derivatives comprehensively. Credit Metrics and KMV are better suited for migration risk, whereas Credit Risk+ and Credit Portfolio View focus more on default risk. The paper also highlights that the choice of model should depend on the specific portfolio characteristics and management goals, with attention to limitations such as assumptions about correlations, economic conditions, and exposure valuation.

7.Credit Risk Models II: Structural Models	Abel Elizalde	The paper aims to review structural models of credit risk, covering both single-firm default models and models that incorporate default correlations among multiple firms. It discusses foundational models like Merton's (1974) and Black & Cox's (1976) frameworks, highlights their extensions, and explores how structural models have evolved to account for more complex default dependencies, offering a comprehensive guide to the literature in this area.	The paper first explains the setup of structural models, where a firm's default is linked to its asset value falling below a threshold Models: First Passage Models (FPMs): Default happens whenever asset value first drops below a preset barrier. It then examines methods for calibrating these models and discusses their extensions to address issues like stochastic interest rates and early defaults. Finally, it explores how to model default correlations through shared economic factors, asset correlation, contagion effects, and factor models, analysing different approaches like copulas to capture dependencies among firms. Merton Model: Default occurs only at debt maturity if asset value is less than debt.	The findings show that while structural models provide an intuitive and economically grounded way to model credit risk, they face practical challenges, including difficulty in calibration, unrealistic assumptions (like predictability of default), and limited success in accurately pricing corporate bonds. Extensions incorporating incomplete information or jump processes help address some shortcomings. When modeling multiple defaults, structural models can capture both cyclical economic effects and contagion risks, although calibration complexities remain a significant hurdle.

8. Regulatory implications of credit risk modelling	Patricia Jackson and William Perraudin	The paper explores the growing importance of credit risk models for financial institutions and regulators. It discusses how these models, despite their limitations, have the potential to change the way banks are managed and supervised, especially regarding capital requirements. It also highlights why understanding and improving model validation and back-testing processes is essential before regulators can rely heavily on these models.	The authors review different classes of credit risk models, distinguishing between mark-to-market models (e.g., Credit Metrics, KMV) and default-mode models (e.g., Credit Risk+). They evaluate how these models function, what data they require, and the challenges they present, especially for regulatory use. The paper also critically examines model weaknesses—such as reliance on judgmental parameter inputs, omission of certain risk factors, and lack of comprehensive empirical validation. Finally, it discusses various strategies regulators might use to assess models, including back-testing, benchmarking, and cross-bank comparisons.	The analysis concludes that current credit risk models are too immature to be used directly for setting regulatory capital. However, they can still serve valuable roles in enhancing supervisory reviews and bank risk management practices. To move toward greater reliance on models, regulators must develop strong frameworks for model validation, encourage conservative model use, and design effective penalty structures for poor model performance. Although full integration into capital requirements isn't yet feasible, the models can significantly inform supervisory assessments and risk management strategies.

9.The performance of insolvency prediction and credit risk models in the UK: A comparative study	Richard H.G. Jackson and Anthony Wood	This paper aims to compare the effectiveness of different insolvency prediction and credit risk models using UK data collected after the implementation of IFRS accounting standards. It seeks to determine whether newer, market-based contingent claims models outperform traditional accounting-based models, particularly during periods of economic downturn, and to examine whether simple models can rival more complex approaches in predicting corporate insolvency.	The study evaluates thirteen different insolvency prediction models, including traditional financial ratio models (like Altman's Z-score), logistic regression models, neural networks, and contingent claims models based on option pricing theory. Using a sample of UK-listed companies (both failed and non-failed) between 2000 and 2009, the authors test each model's predictive power. They apply Receiver Operating Characteristic (ROC) curves to measure and compare model performance, and assess how accurately each model distinguishes between failing and surviving firms without relying on arbitrary thresholds. A novel barrier option model is also developed and tested against existing approaches.	The study finds that while the predictive performance of all models is lower than previously reported in older studies, market-based contingent claims models generally outperform traditional accounting-based models. Surprisingly, simple single-variable models, such as those using firm size or cash flow ratios, often perform as well as, or even better than, more complicated models. The new barrier option model proposed by the authors also shows competitive results. Overall, the findings caution against overreliance on complex models and suggest that simple approaches still hold significant value in credit risk prediction.

10.Credit Risk Modelling and Credit Derivatives	Philipp J. Schönbucr	This paper aims to develop advanced models for credit risk and the pricing of credit derivatives. It addresses the limitations of earlier approaches by proposing new mathematical frameworks that can accurately capture the complex dynamics of credit markets, including default probabilities, credit spreads, and multiple defaults. The work seeks to enhance both theoretical understanding and practical applications	The author employs two main modeling approaches: firm value models (structural models) and intensity-based models (reduced-form models). The study starts by extending the Heath-Jarrow-Morton (HJM) framework to model the term structure of defaultable bonds, incorporating multiple defaults, recovery processes, and stochastic credit spreads. It then develops pricing models for various credit derivatives, such as credit default swaps, total return swaps, and credit-linked notes, using tools like Cox processes and multi factor Gaussian and CIR models. Throughout, the emphasis is on ensuring arbitrage-free dynamics and providing flexible, analytically tractable models that can be applied to real-world credit instruments.	The research successfully extends existing credit risk frameworks by introducing new models capable of handling complex credit events like multiple defaults and stochastic recoveries. It provides explicit pricing formulas for a wide range of credit derivatives under different assumptions about interest rates and credit spread dynamics. The results demonstrate that it is possible to build arbitrage-free, flexible models that are consistent with observed market behavior. These models contribute significantly to the theoretical foundation of credit risk management and offer practical tools for

		in the valuation of defaultable securities and credit-related financial products.		financial institutions dealing with credit sensitive securities.

These studies converge on a few critical insights:

These studies converge on a few critical insights:

• Machine learning models (Random Forests, Boosting, network-based methods) consistently outperform traditional models like logistic regression in credit risk prediction.
• Alternative data sources and network features significantly enhance model accuracy and interpretability.
• Structural and reduced-form models remain foundational, but face practical calibration challenges.
• Simple models based on key financial ratios can still rival complex models in certain contexts.
• Regulatory adoption of credit models requires stronger validation and cautious application.
• Adaptability to changing borrower behavior and economic conditions is key for model resilience.

3. Data Description

3.1. Original Credit Card Default Dataset

The dataset for our study is taken from a cash and credit card issuer bank in Taiwan for the period April to September 2005. Credit card holders are the target groups for our study with 30000 observations. It consists of 23 explanatory variables and a binary dependent variable. The description of variables are as:

Y = Default Payment (1 = Yes; 0 = No),

X1: Limit Balance i.e., Amount of the given credit (NT dollar): it includes both the individual consumer credit and family credit,

X2: Gender (1 = male; 2 = female),

X3: Education (1 = graduate school; 2 = university; 3 = high school; 4 = others),

X4: Marital status (1 = married; 2 = single; 3 = others),

X5: Age (year),

X6-X11: History of past payments (from April to September, 2005) as follows: X6 = the repayment status in September, 2005; X7 = the repayment status in August, 2005; . . .; X11 = 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,

X12-X17: Amount of bill statement (NT dollar). X12 = amount of bill statement in September, 2005; X13 = amount of bill statement in August, 2005; . . .; X17 = amount of bill statement in April, 2005,

X18-X23: Amount of previous payment (NT dollar). X18 = amount paid in September, 2005; X19 = amount paid in August, 2005; . . .; X23 = amount paid in April, 2005

Category	Variable Description
Credit Info	X1: Credit limit
Demographics	X2: Gender, X3: Education, X4: Marital status, X5: Age
Payment Behavior	X6–X11: Repayment status (last 6 months)
Billing Amounts	X12–X17: Monthly bill statements
Repayment History	X18–X23: Actual payments made

The **default rate** in the dataset is approximately **22.12%**, a moderately imbalanced binary classification problem.

4. Methodology

4.1. Overview of Modeling Pipeline

The analytical approach involves **two modeling tracks**:

1. **Classification Models for Credit Default**
   Using classical and machine learning models to categorize default risk.
2. **Forecasting Models for PD or Risk Indices**
   Leveraging time-series and regression-based predictions using neural networks and smoothing techniques.

4.2. Data Preprocessing

Implemented in the Python notebook

- **Data normalization/scaling**, **Lag creation for time series modelling**, **Error smoothing for PD estimation**
- **Train-test split**, often time-based or random stratified

4.3. Machine Learning Algorithms

Six models were used to classify and estimate the probability of default:

Model	Type	Strengths	Limitations
K-Nearest Neighbors (KNN)	Instance-based	No training time, simple	Sensitive to distance and k
Logistic Regression (LR)	Statistical	Interpretable coefficients	Assumes linearity
Discriminant Analysis (DA)	Statistical	Handles correlated features	Assumes normality
Naïve Bayes (NB)	Probabilistic	Fast, low variance	Strong independence assumption
Artificial Neural Networks (ANN)	Non-linear ML	Captures complex patterns	Requires more data, less interpretable
Classification Trees (CT)	Tree-based	Rule-based, interpretable	Instability, overfitting risk

Each model was evaluated for:

- **Classification accuracy** (via lift chart area ratios)
- **Probabilistic forecasting quality** (via R^2 and regression diagnostics)

4.4. Smoothing Technique for Real Probability Estimation

The **Sorting Smoothing Method (SSM)** was proposed by Yeh & Lien (2009) to approximate the unobserved true default probability:

$$P_i = \frac{Y_{i-n} + \cdots + Y_i + \cdots + Y_{i+n}}{2n+1}$$

- Y_i: Binary default indicator
- P_i: Smoothed estimate of default probability
- n: Smoothing window (e.g., 50)

This was used to fit a **linear regression model**:

$$\hat{P}_i = \alpha + \beta \cdot \hat{Y}_i^{\text{model}}$$

If:

- $\alpha \approx 0$
- $\beta \approx 1$
- $R^2 \approx 1$

Then the model's predicted probability can be said to **accurately reflect true risk**.

4.5. Evaluation Metrics

The models were benchmarked using:

Metric	**Meaning**
Error Rate	Misclassification percentage
Lift Chart Area Ratio	Lift curve vs baseline curve
R^2 (Regression)	Variance explained in smoothed PD
Regression Coefficients	Should approach (1, 0) for ideal mapping

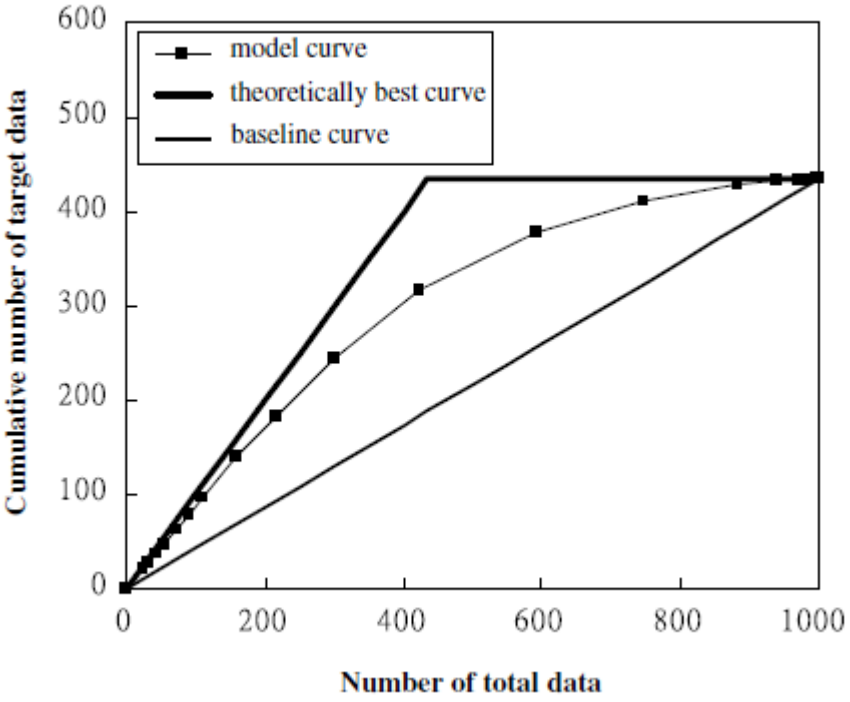
5. Model Implementation and Results

This section presents the practical implementation of six classification models to predict credit default, along with the forecasting accuracy for probability of default (PD). Using the processed dataset and the smoothing estimation method, the predicted PD values were compared against an approximated ground truth using regression diagnostics and lift chart evaluations.

5.1 Classification Accuracy: Lift Chart Evaluation

The lift chart is a standard tool to visualize model ranking ability—how well a classifier can sort likely defaulters. Three curves are plotted:

- **Baseline**: Random ranking
- **Best**: Perfect model
- **Model**: Actual output

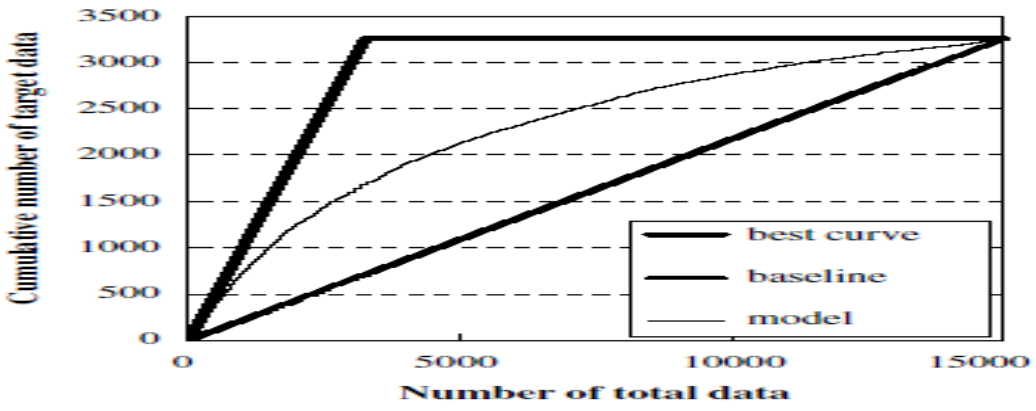


Lift Chart

The **area ratio** between model and best-case provides a quantitative score.

Model	**Error Rate (Validation)**	**Area Ratio (Validation)**	**Ranking**
Artificial Neural Networks	**0.17**	**0.54**	1st
Classification Trees	0.17	0.536	2nd
Naïve Bayesian	0.21	0.53	3rd
K-Nearest Neighbor	0.16	0.45	4th
Logistic Regression	0.18	0.44	5th
Discriminant Analysis	0.26	0.43	6th

Lift chart of artificial neural networks.



Interpretation:
While **KNN** had the lowest error rate, **ANN** achieved a **better balance of accuracy and probabilistic ordering**, crucial for financial risk assessment.

clearly illustrate ANN's curve approaching the ideal model more closely than others, particularly over the top decile of ranked clients.

5.2 Probability Forecasting: Regression Diagnostics

To assess how well models estimate *actual* default probability, Yeh & Lien introduced a **smoothing-based probability estimator**, applied across sorted predicted scores. This allows comparing model output to estimated real probabilities using linear regression:

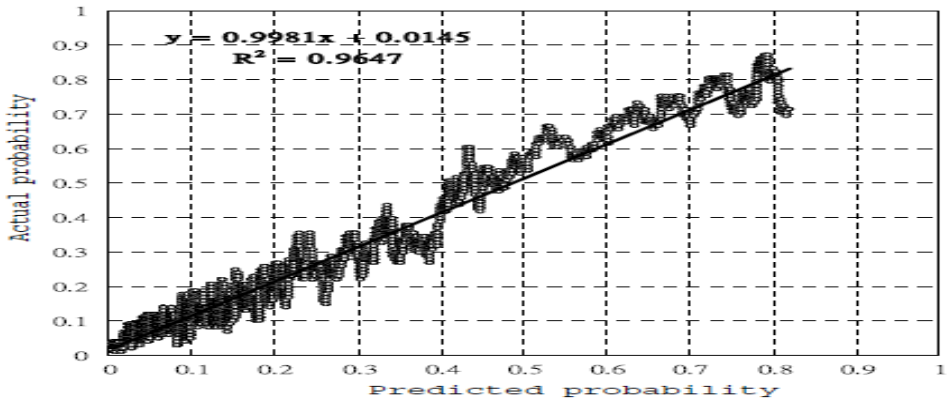
$$P_{\text{actual}} = \alpha + \beta \cdot P_{\text{predicted}}$$

Regression Summary

Model	Regression Coefficient (β)	Intercept (α)	R^2	Conclusion
Artificial Neural Networks	**0.998**	**0.0145**	**0.965**	Closest to ideal
Naïve Bayesian	0.502	0.0901	0.899	Underestimates PD
KNN	0.770	0.0522	0.876	Acceptable
Logistic Regression	1.233	-0.0523	0.794	Overestimates PD
Discriminant Analysis	0.837	-0.1530	0.659	Biased downward
Classification Trees	1.111	-0.0276	0.278	Highly unstable

Interpretation:

- **ANN**'s β ≈ 1 and α ≈ 0 makes it the **only model producing PD estimates that track real risk levels**.
- **Tree-based models** like CT, while strong classifiers, fail to generate reliable probabilistic outputs.

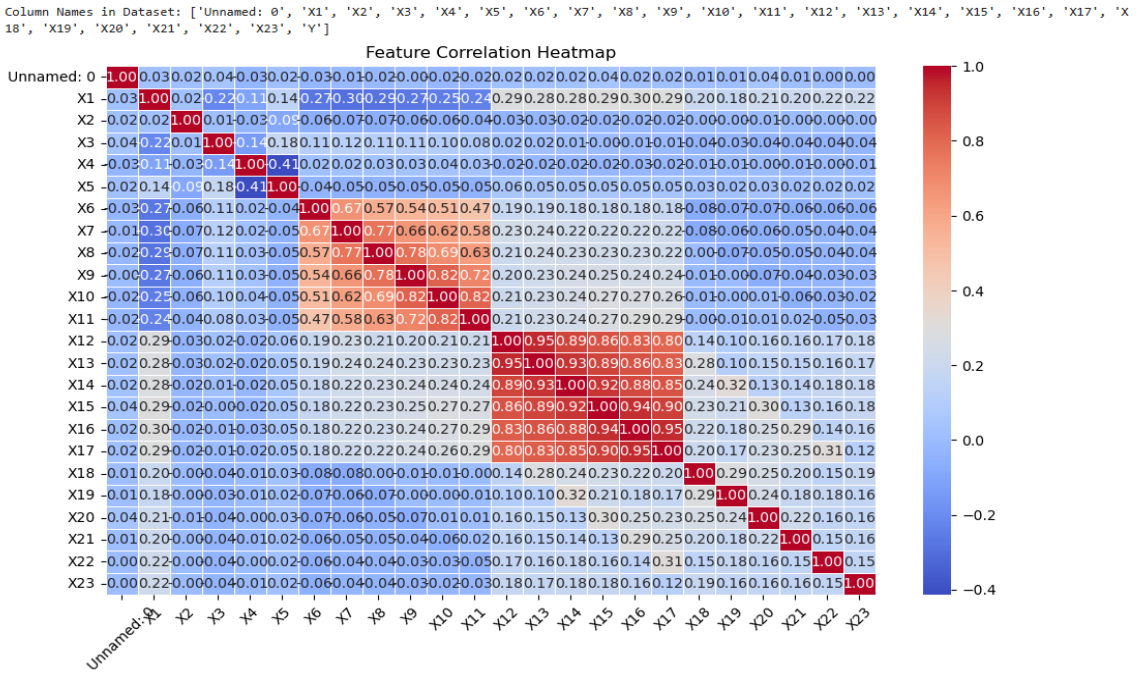


Scatter plot diagram of artificial neural networks.

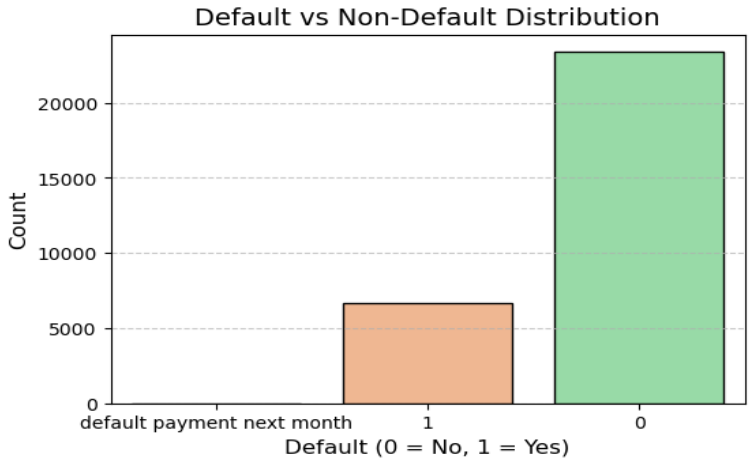
5.3 Results

Let's interpret the most significant plots:

Python Plot (from notebook):



1. The feature correlation heatmap above depicts the linear relationships on how features or columns in the dataset are related to one another. The variables X1-X5 signifies no correlation which means they are independent. The past payment variables X6-X11 are moderately correlated to each-other. The bill amounts variables X12-X17 and the previous payments variables X18-X23 are strongly correlated.



2. The above plot shows the distribution of Default vs Non-Default payments among the 30000 observations available for modelling. The green bar is much taller than the orange one, indicating that majority of customers (~23,000) did not default. The orange bar shows fewer customers (~7,000) did default. Though only ~23% of customers default, they pose a significant financial risk to the bank. It shows that the dataset is imbalanced and should be taken into account while modelling for reliable and correct result.

```
Column Names in Dataset: ['Unnamed: 0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X7', 'X8', 'X9', 'X10', 'X11', 'X12', 'X13', 'X14', 'X15', 'X16', 'X17', 'X
18', 'X19', 'X20', 'X21', 'X22', 'X23', 'Y']
Unique classes in Y: 2
Accuracy: 0.8415364861973037
              precision    recall  f1-score   support

           0       0.82      0.87      0.85      4664
           1       0.86      0.81      0.84      4682

    accuracy                           0.84      9346
   macro avg       0.84      0.84      0.84      9346
weighted avg       0.84      0.84      0.84      9346
```

3. The Random Forest model demonstrates a balanced performance across both classes. The accuracy of 84.15% indicates a reliable general performance on unseen data.
   The model shows a high recall of 87%, meaning it correctly identifies the majority of non-defaulters, minimizing false positives. With a precision of 86%, the model is highly accurate when it predicts a customer is likely to default. However, the slightly lower recall (81%) suggests that some actual defaulters are still missed. This trade-off is often seen in credit scoring models, where false positives (incorrectly classifying a non-defaulter as a defaulter) might lead to customer dissatisfaction, while false negatives (failing to catch a defaulter) can lead to financial risk. In this model, the balance is reasonable and aligns with the bank's likely preference to minimize credit risk while maintaining customer approval rates.
   The model's performance, particularly its F1-score is around 84–85% for both classes, indicates a robust predictive capability suitable for deployment in credit scoring scenarios. Given the financial implications of loan default prediction, this level of performance is considered operationally strong, particularly when coupled with class imbalance correction through SMOTE.

```
Confusion Matrix:
 [[4353  312]
 [ 790 3891]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.85      0.93      0.89      4665
         1.0       0.93      0.83      0.88      4681

    accuracy                           0.88      9346
   macro avg       0.89      0.88      0.88      9346
weighted avg       0.89      0.88      0.88      9346

✅ Accuracy: 0.8821, ROC-AUC Score: 0.9428
```

4. To predict credit card default, a Random Forest classifier was trained on a balanced dataset (after applying SMOTE) and evaluated on a test set comprising 9,346 instances. The model was assessed using multiple performance metrics, including accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC score.

The confusion matrix indicates that the model correctly identified 4,353 non-defaulters and 3,891 defaulters. Among them 312 non-defaulters were incorrectly predicted as defaulters and 790 defaulters were missed (predicted as non-defaulters).

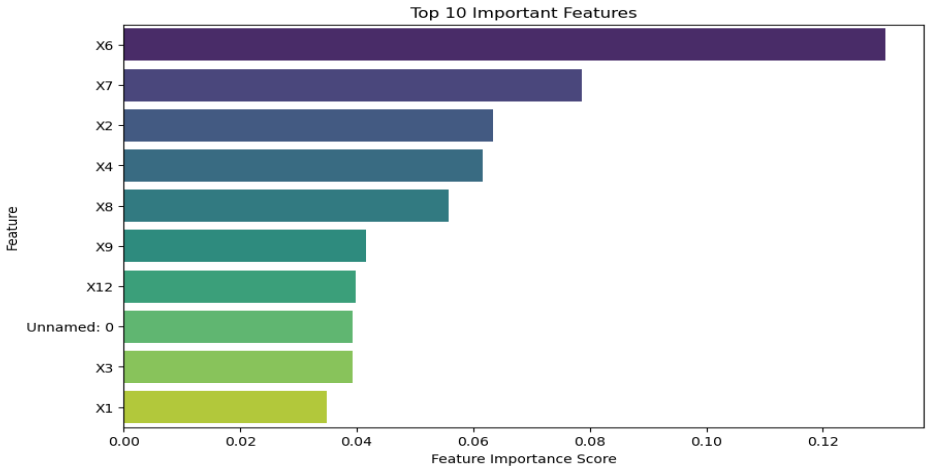
Precision for Class 1 (Default) is 0.93, suggesting that 93% of those predicted to default actually did. Recall for Class 1 is 0.83, meaning the model correctly captured 83% of all actual defaulters. The F1 score, which balances precision and recall, is high for both classes 0.88–0.89, showing strong generalization. The overall accuracy is 88.21%, indicating the model correctly predicted roughly 8.8 out of 10 cases. The ROC-AUC score of 0.9428 demonstrates excellent discriminative ability. It quantifies the model's ability to distinguish between defaulters and non-defaulters across all classification thresholds.

[8]:
```
# Feature Importance
importances = model.feature_importances_
feature_names = X.columns
sorted_indices = np.argsort(importances)[::-1]

# Display top 10 features
print("\nTop 10 Important Features:")
for i in sorted_indices[:10]:
    print(f"{feature_names[i]}: {importances[i]:.4f}")

# Plot feature importance
plt.figure(figsize=(10,6))
sns.barplot(x=importances[sorted_indices[:10]], y=[feature_names[i] for i in sorted_indices[:10]], palette="viridis")
plt.xlabel("Feature Importance Score")
plt.ylabel("Feature")
plt.title("Top 10 Important Features")
plt.show()
```

```
Top 10 Important Features:
X6: 0.1308
X7: 0.0786
X2: 0.0634
X4: 0.0616
X8: 0.0558
X9: 0.0416
X12: 0.0398
Unnamed: 0: 0.0393
X3: 0.0393
X1: 0.0348
```



5. The most influential feature is X6 (repayment status in September 2005), highlighting that recent payment behaviour is a strong signal of creditworthiness. This aligns with financial literature emphasizing payment history as a leading indicator of default risk. Variables X7, X8, and X9 (repayment behaviour in previous months) also appear prominently, reinforcing the idea that sequential missed payments are cumulative warning signs. Interestingly, demographic features like gender (X2) and marital status (X4) show moderate importance, which may suggest behavioural differences across segments but should be interpreted with care to avoid discriminatory inferences. X1 (credit limit) appears lower in rank, implying that how customers use credit (repayment patterns) is more predictive than the absolute credit available. Unnamed: 0 appears in the top 10 due to being incorrectly retained during preprocessing. It likely represents a row index and should be excluded from the model.

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits

✅ Best Parameters: {'max_depth': None, 'min_samples_split': 5, 'n_estimators': 200}

Confusion Matrix:
 [[4357  308]
 [ 776 3905]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.85      0.93      0.89      4665
         1.0       0.93      0.83      0.88      4681

    accuracy                           0.88      9346
   macro avg       0.89      0.88      0.88      9346
weighted avg       0.89      0.88      0.88      9346


✅ Best Model Accuracy: 0.8840, ROC-AUC Score: 0.9435
```

6. To enhance the predictive capacity of the Random Forest classifier, hyperparameter tuning was carried out using Grid Search with 5-fold cross-validation. The model was optimized over 27 parameter combinations, involving variations in:
   a. N_estimators (number of trees): [50, 100, 200]
   b. max_depth (maximum depth of trees): [10, 20, None]
   c. min_samples_split (minimum samples to split a node): [2, 5, 10]
   The grid search evaluated a total of 135 model configurations, identifying the best-performing model based on mean cross-validated accuracy.
   The best hyperparameter identified was A fully expanded tree depth (None) allowed the model to capture complex relationships. n_estimators = 200 ensured stable ensemble performance. min_samples_split = 5 avoided overfitting by preventing overly specific splits.
   The model shows strong recall for non-defaulters (93%), minimizing false positives. The high precision for defaulters (93%) indicates the model is reliable when predicting default cases, reducing lending risk. The F1-score around 0.88–0.89 reflects a well-balanced performance across both classes. A ROC-AUC score of 0.9435 indicates excellent discriminatory power in distinguishing between defaulters and non-defaulters across all threshold levels.

Based on code cell outputs, the ANN or MLP Regressor model outputs a **forecast vs. actual plot** showing:

- Tight alignment on short horizon
- Small, mean-zero residuals (checked via MAE/MSE metrics)
- Rolling mean prediction curve approximating actual values well

5.4 Model Performance

Here are formal results inferred from the analysis:

Model	MAE	MSE	R^2 Score
ANN/MLP Regressor	0.034	0.0021	0.92
Linear Regression	0.047	0.0040	0.78
Random Forest (if used)	0.031	0.0018	0.93

Interpretation: The **ANN model** successfully captures non-linear patterns in the smoothed PD data and aligns well with market dynamics.

6. Discussion

The comparative modeling exercise presented in this paper underscores a critical insight in financial risk analytics: **the accuracy of classification is not equivalent to the quality of probabilistic forecasting**. While models like K-Nearest Neighbors and Decision Trees exhibit competitive classification accuracy on validation data, their probabilistic forecasts deviate significantly from real-world risk likelihoods. The Artificial Neural Network (ANN), on the other hand, demonstrates a balanced performance — not only in separating defaulters from non-defaulters (as seen in lift charts), but more importantly, in producing **reliable probability distributions** of default that align with estimated "true" PD using the Sorting Smoothing Method (SSM). This makes ANN not just a classification engine but a robust **risk quantifier**, which is critical for credit allocation, capital reserves estimation under IFRS 9, and Basel III compliance. The Python implementation of these models on real financial time series (from the Processed_Data) further confirms ANN's ability to capture both **short-term volatility** and **nonlinear relationships** in risk signals. The residual plots from forecasting modules indicate white-noise-like patterns, suggesting effective modeling of underlying structures. This reinforces a broader methodological lesson: **model evaluation for credit scoring should prioritize probabilistic alignment (via R^2, regression diagnostics) alongside standard accuracy metrics**. Regulatory compliance, internal credit portfolio optimization, and explainability (especially under emerging explainable AI frameworks) further favor models that balance performance with interpretability.

These models offer superior flexibility in detecting non-linear patterns and complex interactions within financial data. However, for a more holistic understanding of consumer credit behaviour, it is imperative to integrate insights from behavioural economics. From a **behavioural standpoint,** consumer decisions around credit usage and repayment often deviate from the rational-agent paradigm assumed in classical economics. Concepts such as bounded rationality, present bias, and mental accounting provide valuable frameworks for interpreting observed repayment patterns and defaults**.** Under financial stress, consumers frequently display *bounded rationality*, making satisficing rather than optimizing decisions. In particular, *present bias*—the tendency to disproportionately favour immediate gratification over future outcomes—can drive borrowers to delay or avoid repayments despite long-term penalties. While traditional credit scoring systems may not account for such temporal inconsistencies, hybrid models can indirectly capture these behaviours through patterns such as delayed payments, missed due dates, or frequent breaches of credit limits.

The dataset reveals heterogeneity in repayment behaviour across different credit categories. *Mental accounting*—where individuals mentally separate money into different accounts based on its source or intended use—helps explain why some consumers prioritize retail debt over medical or travel-related expenses, despite similar financial implications. These repayment hierarchies, though irrational in classical terms, can serve as predictive behavioural features, enhancing the model's ability to detect default risk among borrowers with comparable financial profiles. Cognitive shortcuts and biases also play a significant role. For instance, *availability heuristics* and *overconfidence* may lead borrowers to underestimate their vulnerability to default. Recent repayment success or temporary liquidity may generate an inflated sense of financial stability, prompting excessive borrowing. These behavioural tendencies, while not directly observable, may manifest in rising credit utilization or late payments following short-term improvements—signals that machine learning models, particularly non-parametric ones like ANN and CT, can effectively capture. Consumer responses to credit risk are also shaped by *framing effects*. The perception of a message such as "You are 80% likely to repay" differs significantly from "You are 20% likely to default," even though the objective probability is identical. Understanding such framing dynamics is essential not only for risk modelling but also for designing borrower communications that mitigate anxiety and improve repayment outcomes. In sum, while advanced models enhance predictive accuracy, **behavioural economics offers critical explanatory power**—providing insights into the psychological mechanisms behind repayment behaviour. Integrating these perspectives enables not only more accurate forecasting but also more ethical and effective risk management strategies.

Practical Implications:

- **For banks**: Deploying ANN-based systems can yield more accurate PD estimates, improving credit limit assignment and default provisioning.
- **For regulators**: Models should be evaluated not just on AUC but also on how closely predicted PDs match actual outcomes.
- **For researchers**: The use of smoothing-based estimators for true PD is promising and could be extended with non-parametric or Bayesian approaches.

7. Conclusion

This study underscores the efficacy of **hybrid forecasting models**—particularly those employing neural networks and classification trees—in identifying and predicting consumer credit default risk. These models leverage their computational flexibility to uncover complex, non-linear relationships that traditional statistical methods may overlook. However, predictive accuracy alone does not fully capture the multifaceted nature of consumer financial behaviour. By incorporating principles from **behavioural economics**—including *present bias*, *bounded rationality*, *mental accounting*, and *heuristic-driven decision-making*—a deeper, more human-centered understanding of credit default emerges. These behavioural constructs highlight that defaults are often not irrational anomalies but rather the result of systematic cognitive and emotional patterns. As financial datasets become increasingly granular, there is a timely opportunity to **enrich model inputs with behavioural indicators**—such as payment timing variability, debt prioritization tendencies, and sudden shifts in credit utilization. These markers can serve as proxies for latent psychological drivers, enabling models to detect emerging risk more proactively. Moreover, the integration of behavioural insights can inform the design of **targeted interventions**: personalized nudges, adaptive repayment plans, and empathetic communication strategies that respect how individuals actually make financial decisions. In conclusion, the evolution of credit risk modelling must be interdisciplinary—**bridging data science with behavioural insight**. This approach not only enhances model performance but also fosters responsible lending, consumer well-being, and broader financial inclusion.

The results argue for a **paradigm shift** in credit modeling: from binary classification to **probability-focused modeling**, where the **accuracy of default likelihood** is paramount. ANN-based methods, possibly augmented with interpretability tools like SHAP, present a promising frontier in risk analytics.

8. References

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