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Applied
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Capstone Project

Enhanced Loan Default Prediction Using Machine Learning and AI: Integrating Industry Segmentation and Sentiment Analysis

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Abstract

In the current financial landscape, accurate risk assessment methodologies are paramount for banks and lenders to prevent potential losses. This project aims to develop a risk assessment technique to predict loan defaulters by leveraging machine learning and AI. Traditional methods often overlook industry-specific nuances, relying on broad classifications or subjective assessments. This project addresses these limitations by exploring the intricate relationship between employee titles, industry classifications, and default risk. The dataset used is from Lending Club, a US-based peer-to-peer lending company, encompassing details about previous loan applicants and their default status. Key features include loan amount, interest rate, employment length, and annual income, among others. The methodology involves data preprocessing, feature engineering, model selection, and evaluation. Various machine learning algorithms, including decision trees, random forests, extreme gradient boosting, and neural networks, will be employed to segment loan applicants and predict default probability. This project aims to empower financial institutions with robust tools for industry classification and default prediction, fostering more informed decision-making and risk management practices in the lending domain.

Keywords: Risk assessment; Loan default prediction; Industry classification; Machine learning; Sentiment analysis; Financial technology; LendingClub.

1. Introduction

In today's financial scenario, credit risk assessment is crucial for calculating the probability that a borrower may default, aiding in informed decision-making. Numerous studies emphasize the necessity of integrating machine learning and AI into credit risk assessment. This project will contribute to this body of knowledge by incorporating both traditional financial data and industry sentiment analysis to enhance the predictive accuracy of loan defaults, also to understand the relation between default rates and macroeconomic factors. This study will explore the critical role of industry classification in credit risk assessment. Different sectors demonstrate varying levels of risk due to economic cycles, market conditions, and regulatory environments. By monitoring industry sentiment over time, it is possible to identify potential risk factors before they become evident in financial data. For example, a sudden decline in customer sentiment for a specific industry could signal upcoming economic challenges and potentially higher loan defaults.

2. Literature Review

The banking sector is evolving with technological advancements and the integration of data science, transforming the landscape of financial institutions (Maheswari and Narayana, 2020). However, there is a risk of significant capital losses if loans are approved without assessing default risk beforehand (Maheswari and Narayana, 2020). Therefore, accurate predictive systems are crucial for financial institutions

(Maheswari and Narayana, 2020). The uncertainty of a customer making a loan payment in each period can be quantified by the Probability of Default (PD), which indicates the likelihood that a customer will default on a payment within a specified time frame (Singh et al., 2013). Predicting loan defaulters is critical, given the abundance of data banks possess, including customer data and transaction behavior (Maheswari and Narayana, 2020).

Loss-given default (LGD) indicates the severity of loss after a loan default and represents the percentage of the unrecoverable amount (Bessis, 2015; Bandyopadhyay, 2016). Collateral is used by banks to mitigate losses in the event of default. When a debtor defaults, the lender tries to recover the debt by selling the collateral, but the amount recovered is often less than the amount due to recovery expenses (Bessis, 2015).

Machine learning plays a significant role in credit risk assessment:

Pandey et al. (2010) emphasize that predicting loan defaulters is one of the most challenging tasks for banks, but it can significantly reduce losses and improve asset quality. They applied machine learning algorithms such as Logistic Regression, Decision Trees, Support Vector Machines, and Random Forests, finding Support Vector Machines most accurate in predicting loan acceptance (Pandey et al., 2010).

Chang et al. (2016) compared logistic regression, the Cox model, and decision tree models to predict short-term loan defaults. Their decision tree model had 81.9% specificity and 83.3% precision, outperforming other models in short-term default prediction.

Chang et al. (2016) using Lending Club dataset implemented Logistic Regression initially achieved 92.9% test accuracy and 75.8% specificity, which improved to 77.1% after feature selection. Gaussian Naive Bayes outperformed other distributions with 80.4% specificity, though adding census data only marginally improved accuracy. For SVM, the linear kernel provided the best results, and feature expansion along with parameter tuning led to incremental performance gains.

Abid et al. (2018) used logistic regression and discriminant analysis on a Tunisian commercial bank's dataset of 603 loans, which had a 56.55% default rate. Their logistic regression model showed 99.41% sensitivity and 98.47% specificity, outperforming discriminant analysis.

Various studies have used metrics like classification accuracy, sensitivity, specificity, and ROC curves to evaluate prediction models. Lessmann et al. (2015) compared 41 learning algorithms and found that advanced classifiers like random forests outperformed logistic regression. Zhu et al. (2019) achieved high performance with random forests, showing 98% accuracy and 99% sensitivity.

Silva et al. (2020) examined default risk using logistic regression on a Portuguese credit dataset with 3221 individuals and a 10% default rate. Key variables included "Spread," "Term," "Age," "Credit cards," "Salary," and "Tax echelon," achieving a classification accuracy of 89.79%, with 0.94% sensitivity and 99.55% specificity.

Other research, including studies by Xia et al. (2017) and Tian et al. (2020), highlighted the effectiveness of models like XGBoost and gradient-boosting trees. These studies often lacked specificity or AUC data but generally supported the superiority of advanced machine-learning techniques over traditional methods.

Sheikh (2020) argues the importance of predicting loan defaulters in banking systems, highlighting that a bank's profitability heavily relies on loan repayment behavior. Their study using logistic regression suggests that incorporating personal attributes such as age, credit history, and wealth indicators like checking account information improves default prediction accuracy (Sheikh,2020).

Ndayisenga et al. (2021) worked with commercial banks to predict borrower behavior using data from the Bank of Kigali, demonstrating Gradient Boosting as the most effective model for predicting loan default, followed by XGBoosting, with Decision Trees, Random Forest, and Logistic Regression performing less effectively (Ndayisenga et al., 2021).

Orji et al. evaluate the classification accuracy of six computational intelligence methods across diverse datasets, highlighting the importance of selecting methods tailored to specific dataset characteristics (Orji et al., 2022).

Research such as "The sensitivity of the loss given default rate to systematic risk" (Caselli et al., 2008) has highlighted the connection between default rates and macroeconomic factors. Therefore, to develop a more comprehensive set of features, in this paper we will incorporate industry sentiments data, including information over time, to train our models.

3. Data Description

LendingClub, which is a US-based peer-to-peer lending company is among the largest marketplaces for personal loans, business loans, and medical financing globally. (All Lending Club loan data)

When the company receives a loan application, the company has to decide for loan approval based on the applicant’s profile. Two types of risks are associated with the bank’s decision: (Sayah, 2023)

1) If the applicant is likely to repay the loan, then not approving the loan results in a loss of business to the company. (Sayah, 2023)

2) If the applicant is not likely to repay the loan, i.e. he/she is likely to default, then approving the loan may lead to a financial loss for the company. (Sayah, 2023)

The provided dataset includes details about previous loan applicants and their default status. The goal is to detect patterns that suggest the likelihood of default, enabling actions like loan denial, reducing loan amounts, or offering loans to risky applicants at higher interest rates. (Sayah, 2023)

3.1. Dataset/Features Description

Traditional Financial Data (Lending Club from Kaggle): There are 151 features with 2260701 rows. The dataset timeframe ranges from 2007-2018Q4. Some of the important features are FICO score, payment history. We have 113 numeric float columns and 38 categorical columns in the dataset.

Industry Sentiment Analysis: Now, we are creating another dataset where we have utilized pretrained models from Hugging Face, from where we are getting the sentiment score for the industries with the content of review. We will utilize this once we have segmented the customers into their respective sectors to understand the sentiment of the industries over time.

3.2. Methodology

There is a significant reduction in the data since we are considering only the customers who are fully paid and are flagged as default (Charged Off) leading to the data shape of (1345310, 151).

a) Data Cleaning:

Handling the Missing values: The columns with more than 30% missing values are identified and removed. 58 columns with more than 30% missing values are removed making the shape of the data (1345310, 93). The other missing values are imputed by median for numerical columns and mode for categorical columns.

Identifying the Outliers: The columns with outliers are detected and the columns having more than 3% are removed from the dataset. We are utilizing the Z score value to calculate the outliers. Absolute z-scores for the specified column, indicating how many standard deviations away each value is from the mean. A subset of the column containing only the outlier values, where the absolute z-score exceeds the specified threshold is created. The percentage of values in the column that are considered outliers based on the z-score threshold are then calculated. The remaining outliers are not imputed with values. For this financial analysis, we need to consider extreme situations and values in the model building process.

b) Data Transformation: The date columns, which are object data types, are converted into datetime data types. In this dataset, we have the issue date, indicating when the loan was issued, and the last payment date, which are converted to datetime type.

c) Feature Engineering: One of the most crucial roles in this analysis is feature engineering, capturing the nuances of industry-specific data. This may involve extracting relevant information from employee titles, such as job roles, specialized skills and categorizing them into major industries, e.g. Education, Finance, IT, Healthcare, Manufacturing. A key aspect is this segmentation of loan applicants into industry-specific segments. This segmentation allows for building more targeted models that can capture the unique characteristics and risk profiles of different industries.

Assuming job titles such as Software Engineer, IT Specialist, Software Developer, Senior Software Engineer, Systems Analyst, Tech, Project Engineer, IT Manager, Business Analyst etc. to be in the IT sector. Similarly, assuming titles such as Teacher, Professor, Instructor, Principal are from Education, Registered Nurse, Physician, Pharmacist, Nurse Practitioner, Respiratory Therapist, Physician Assistant is from Healthcare, Engineer, Quality control, Mechanical Engineer, Operations Manager, Technician, Operator from Manufacturing and Accountant, Financial advisor, Banker, Personal Banker, Loan Officer, Auditor, Account Manager, Branch Manager from Finance and Banking.

Once we have the sectors, the sentiment score throughout the years 2007 to 2018 is merged to the data. Considering the loan issue date and the last payment date, we will analyze the sentiment scores of customers industries from the year the loan was issued until the year of the final payment. Now considering only these major sectors we are filtering the dataset, with the additional sentiment analysis, the dataset is in the shape (146231, 107)

d) Dimensionality Reduction: For this analysis, irrelevant or redundant columns in the dataset have been removed. Specifically, columns such as id, url, zip_code, title (since it overlaps with the purpose of the loan), and emp_title (since industry segmentation is available) were excluded. Following one-hot encoding, the dataset comprised approximately 158 features. Instead of applying dimensionality reduction techniques, all columns were utilized in the model-building process. Feature selection was conducted using a combination of correlation analysis and recursive feature elimination (RFE). Features with a high correlation to the target variable (loan status) were prioritized, while multicollinearity among features was minimized to enhance model interpretability and performance.

3.3. Exploratory Data Analysis

The target column for this analysis is loan status with values Fully Paid and Charged Off., borrowers labeled as "charged-off" represent defaulters and contribute significantly to the lenders' losses.

There is around 119467 Fully paid customers and 26764 Defaulters. There is a class imbalance in the target variable with 18% of the data being Defaulters, and instead of accuracy, we will evaluate the performance of the model using the F1 score. Evaluating the model using the F1 score is a proven approach, especially when dealing with class

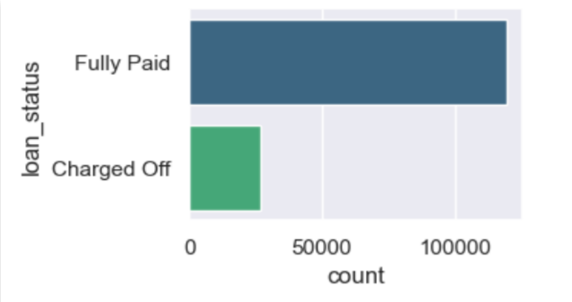

Fig. 1. Denoting an imbalance in the class of target variable.

imbalance. F1 score balances precision and recall, which can be more informative than accuracy in such cases.

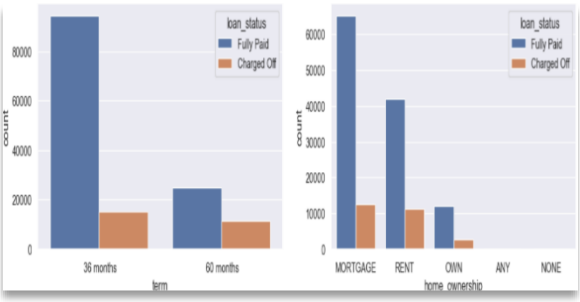

Fig. 2. Term, home ownership status underscores the popularity of fixed-term loans and the prevalence of mortgage holders seeking loan consolidation

In Figures 2 of the analysis, it is evident that most customers opt for a 36-month term for loan repayment. Mortgage is the predominant home ownership status among customers, and most applications have a verification status of verified. The primary purpose for taking loans across all loan statuses is debt consolidation, indicating a common financial goal among applicants. These findings underscore the popularity of fixed-term loans and the prevalence of mortgage holders seeking loan consolidation, with a significant proportion having their verification status confirmed.

We can see that in Fig 3 credit card, debt consolidation, home improvement, house, major purchase, and renewable energy are some of the purposes for loan requests with high loan amounts.

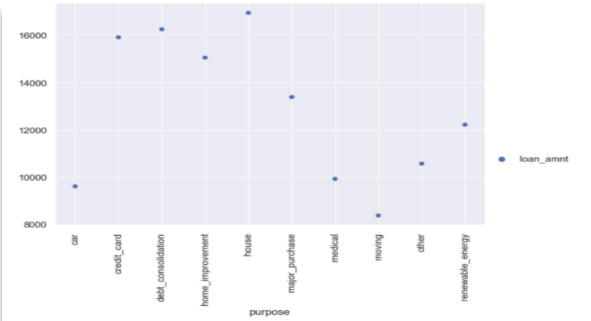

Fig. 3. Purposes for loan requests with high loan amounts.

The plot Fig 4 shows that there is a positive correlation between annual income and loan status. This means that as annual income increases, the likelihood of a loan being fully paid also increases. For example, in the plot, there are very few data points in the bottom left corner (where annual income is low and loan status is "Charged Off"). There are many more data points in the top right corner (where annual income is high and loan status is "Fully Paid").

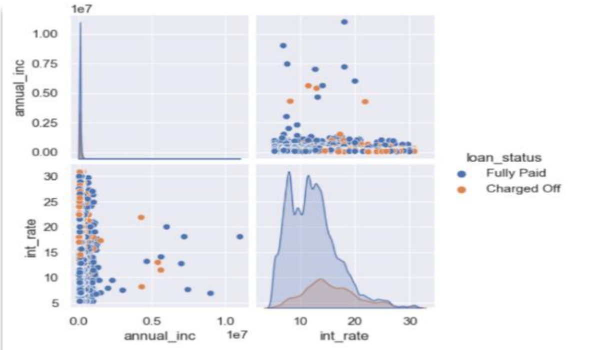

Fig. 4. The plot shows that there is a positive correlation between annual income and loan status.

From the plot Fig 5, we can see that both the class of the target has similar interest rates by grades.

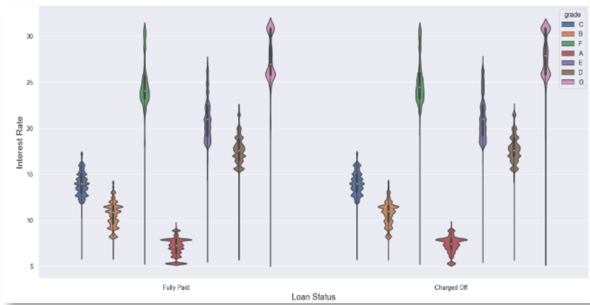

Fig. 5. Loan status classes with distribution of interest rate based on grades.

Employee titles such as Teacher, Nurse, Manager, Accountant, and Engineer are among the most common among loan customers from 2007 to 2018. We can see that Fig 6 most of the employees are in the IT sector with 27% as per our classification, followed by Manufacturing and Healthcare with 20% respectively.

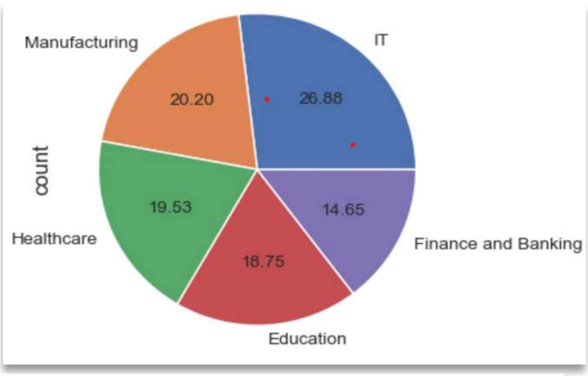

Fig. 6. Industry segmentation based on employee titles.

As we can see in the Fig 7, Healthcare has some of the highest sentiment scores, followed by IT and Finance over the period. All industries experienced a dip in sentiment scores in 2009, indicating a negative sentiment trend, likely due to the global economic crisis affecting all sectors.

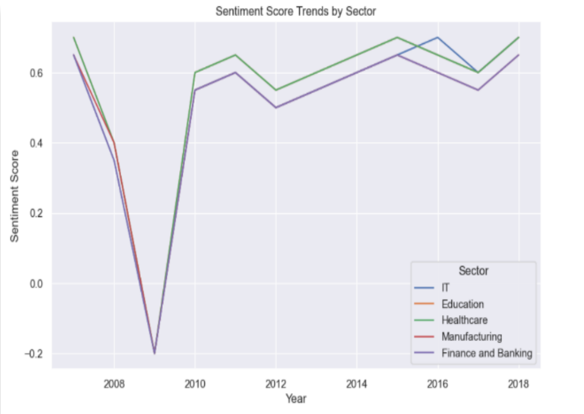

Fig. 7. Sentiment Score Trends over the year for the segmented sectors.

Statistical Test: Performed a chi-square test to find the association between loan status and industry segment. The p-value associated with the chi-square statistic is approximately 1.62. This extremely small p-value suggests strong evidence against the null hypothesis, indicating that there is a significant association between the two categorical variables.

Correlation between the features and target variable: The last fico range high, last payment amount, total received principle, collection recovery fee, recoveries, and interest rate are some of the features positively and negatively highly correlated with the loan status target variable with a maximum 0.68 correlation coefficient.

Features positively correlated with loan status (up to 0.68 correlation coefficient):
Last FICO Range High: This indicates a borrower's creditworthiness. A higher FICO range suggests a better credit history, potentially implying a lower risk of defaulting on the loan. In other words, borrowers with a history of managing credit responsibly are more likely to repay their loans.
Features negatively correlated with loan status (up to -0.5 correlation coefficient):
Collection Recovery Fee: This fee being higher typically means past difficulty repaying loans, as this fee is typically applied when a borrower has missed payments in the past.
Recoveries: A borrower who has defaulted on a loan, the amount recovered is named as recoveries. A high recovery value might indicate past defaults, potentially making it more likely for the borrower to default again.

3.4. Limitations

The project aims to provide actionable insights for lenders, including recommendations for industry-specific risk mitigation strategies and potential enhancements to loan approval processes. Challenges anticipated during implementation include data quality issues, algorithmic complexity, and the interpretation of nuanced industry dynamics.

Temporal changes in economic conditions and lending practices over the dataset's timeframe (2007-2018) introduce variability that static models might struggle to capture. The model's generalization to other types of lending institutions or geographic regions may be limited, as it is trained specifically on Lending Club data.

Segmentation based on industry and job titles assumes homogeneity within each segment, potentially overlooking the diversity of risk profiles within industries. Incorporating industry sentiments into the analysis adds a layer of complexity due to the temporal nature of sentiment dynamics. There are challenges as to understating the sentiments of the industry with respect to the timeframe of the loan, as the sentiment of the industries fluctuates with time. Accurately classifying employee titles and industry sectors poses challenges, as misclassification can lead to errors in segmentation and model performance. The accuracy of the sentiment analysis depends on the quality of the review data and the chosen pre-trained model.

Finally, the extensive dataset and the use of multiple machine learning algorithms require significant computational resources, which may limit feasibility for some institutions. Despite these challenges, the project highlights the potential of machine learning to enhance default prediction accuracy, providing financial institutions with better tools for risk management and decision-making.

4. Prediction Models

The LendingClub dataset was preprocessed to handle missing values, categorical variables, and scaling of numerical features. Missing values were imputed using median values for numerical features and mode for categorical features. Categorical variables were encoded using one-hot encoding. All numerical features were standardized using standard scaler.

Feature selection was performed using a combination of correlation analysis and recursive feature elimination (RFE). Features highly correlated with the target variable (loan status) were prioritized, while multicollinearity among features was minimized to improve model interpretability and performance. As shown in Fig 9 in Appendix.

- >85% correlation removal (remaining 146 variables)
- >60% correlation removal (remaining 115 variables)
- Removing the most important feature (remaining 114 variables)

Several Machine Learning models were considered for predicting loan defaulters:

1) Logistic Regression (LR): A linear model suitable for binary classification problems. Chang et al. (2016)
2) Random Forest (RF): An ensemble learning method based on decision trees, which improves predictive performance by reducing overfitting. Chang et al. (2016)
3) Decision Tree (DT): A simple and interpretable model that splits data based on feature values. Chang et al. (2016)
4) XGBoost (XGB): An optimized gradient boosting algorithm designed to be highly efficient, flexible, and portable. Chang et al. (2016)
5) Gaussian Naive Bayes (GNB): A probabilistic classifier based on applying Bayes' theorem with strong (naive) independence assumptions between features. Chang et al. (2016)
6) Neural Network Chang et al. (2022): After training a three-layer dense Keras sequential model for 100 epochs, we achieved an accuracy from 18 to 80% for different feature sets. The same results were obtained when utilizing the Keras optimizer. This encourages us to further enhance the machine learning models, as their performance surpasses that of the Keras model.

Model Training: The dataset was split into training (80%) and testing (20%) subsets. The models were trained using the training data and evaluated on the test data. Given the class imbalance in the target variable, with only 18% of the data representing Defaulters, we chose to evaluate model performance using the F1 score, ROC-AUC score instead of accuracy. To address the class imbalance, SMOTE (Synthetic Minority Over-sampling Technique) as well was implemented.

5. Experimental Result

Model Evaluation: Model performance was assessed using precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC).
Evaluation Metrics:

• Classification Report: Provides precision, recall, F1-score (weighted average) for each class, overall accuracy, and macro/weighted averages.

• ROC-AUC Score: Reflects how well the model distinguishes between defaulters and non-defaulters (higher is better).

• Confusion Matrix: Shows the number of correct and incorrect predictions for each class.

• Feature Importance: Shows how much each feature influences the model's predictions (available for LR, CART, RF, XGB).

Hyperparameter Tuning: Hyperparameter tuning is performed using grid search and cross-validation to identify the optimal set of hyperparameters for each model. This process will involve iterating over predefined parameter grids and evaluating model performance through k-fold cross-validation.

Model Performance (Comparison between with and without sentiment scores):

The Logistic Regression model demonstrated exceptional performance across both scenarios, with an F1 score of 1 and a near-perfect ROC-AUC value of 0.9990 when industry segmentation and sentiment scores were included. Without these additional features, the model maintained its perfect F1 score and achieved a slightly lower ROC-AUC value of 0.9989, indicating consistent precision and recall.

The Classification Tree model also exhibited high performance in both scenarios. With industry segmentation and sentiment scores, it achieved an F1 score of 0.99 and a ROC-AUC value of 0.9973. Without these features, the F1 score remained at 0.99, and the ROC-AUC value slightly increased to 0.9980, reflecting marginally improved precision and recall.

K-Nearest Neighbors displayed moderate performance, with an F1 score of 0.79 and a ROC-AUC value of 0.8520 when industry segmentation and sentiment scores were considered. Without these features, the F1 score remained the same, but the ROC-AUC value showed no change, indicating that these features did not significantly affect the model's performance.

The Random Forest model consistently delivered high performance regardless of the inclusion of industry segmentation and sentiment scores. With these features, it achieved an F1 score of 0.99 and a ROC-AUC value of 0.9986. Without them, the F1 score was still 0.99, and the ROC-AUC value increased to 0.9991, demonstrating stable and reliable performance.

Extreme Gradient Boosting proved to be the top-performing model overall. With industry segmentation and sentiment scores, it achieved perfect F1 scores and a near-perfect ROC-AUC value of 0.9994. Without these additional features, the F1 score remained perfect, and the ROC-AUC value increased to 0.9996, highlighting its robustness and excellent performance.

Naive Bayes showed high performance as well, with an F1 score of 0.96 and a ROC-AUC value of 0.9875 when industry segmentation and sentiment scores were included. Without these features, the F1 score remained at 0.96, and the ROC-AUC value slightly decreased to 0.9875, indicating consistent precision and recall with a minor variation.

In summary, Logistic Regression, Classification Tree, Random Forest, and Extreme Gradient Boosting models showed high performance in terms of both F1 Score and ROC-AUC values. K-Nearest Neighbors exhibited moderate performance, while Naive Bayes maintained high performance with a slight advantage when using industry segmentation and sentiment scores. Overall, Extreme Gradient Boosting models consistently achieved high precision and recall, demonstrating their robustness and reliability.

Model Performance (Feature set comparison): The Logistic Regression model demonstrated the highest performance with an F1 score of 1 and a ROC-AUC value of 0.9990 when more than 85% multicollinearity was removed. However, its performance declined to an F1 score of 0.93 and a ROC-AUC value of 0.9217 when over 60% multicollinearity was removed, and further to an F1 score of 0.76 and a ROC-AUC value of 0.8031 with the removal of the most important feature. Similarly, the Classification Tree showed high performance initially (F1: 0.99, ROC-AUC: 0.9973) with a gradual decrease (F1: 0.81, ROC-AUC: 0.7818) upon removing the most important feature. K-Nearest Neighbors exhibited moderate performance across the board, starting with an F1 score of 0.79 and a ROC-AUC value of 0.8520, declining further when more features were removed. Random Forest and Extreme Gradient Boosting maintained high performance initially (Random Forest F1: 0.99, ROC-AUC: 0.9986; Extreme Gradient Boosting F1: 1, ROC-AUC: 0.9994), with a slight decline as features were removed. Naive Bayes showed high performance initially (F1: 0.96, ROC-AUC: 0.9875) but also saw a decrease (F1: 0.80, ROC-AUC: 0.7539) when the most important feature was removed.

Feature Importance: Some of the most important features in the three feature sets include:

Collection Recovery Fee: This indicates past difficulty repaying loans and is a strong predictor of future defaults (important in all models). Due to its high importance in feature sets 1,2, it is removed and analyzed without the feature in feature set 3 as shown in Fig 10 in the Appendix.

FICO Range: This indicates a borrower's creditworthiness. In other words, both high and low FICO range borrowers have an impact on predicting the risk of defaulting on the loan.

Sentiment Scores (2013-2018) appear as features in models in the top 15-20 ranges, but their importance is relatively low compared to financial factors.

Model Performance Summary: 60% multicollinearity removal is considered as the optimal feature set. A higher threshold (like 85%) allows more multicollinearity, which means fewer features are removed, potentially leading to a more complex model. Reducing the threshold to 60% ensures a stricter removal of correlated features, thus lowering the model's complexity and improving stability. XGBoost consistently outperformed other models, achieving the highest ROC-AUC score of 0.9300, indicating superior predictive power considering both the techniques and all the feature sets.

Statistical test of Significance: To assess the impact of including industry sentiment scores, we focused on the XGBoost model with Removed > 60% Multicollinearity, which demonstrated the best performance. We ran the XGBoost model 31 times both with and without the industry sentiment scores, calculating the mean ROC-AUC score for each scenario. A t-test was then applied to these mean scores. The resulting p-value was less than 0.05, indicating that the performance difference between the model with industry sentiment scores and the model without is statistically significant.
T-statistic: 58.70688006661183, P-value: 1.589331160385529e-32

6. Conclusion

The results of our analysis demonstrate a significant enhancement in loan default prediction accuracy through the integration of machine learning techniques and industry-specific insights. By leveraging the comprehensive Lending Club dataset, we explored the intricate relationships between borrower attributes, industry classifications, and default risk. Although industry sentiment data emerged as a novel feature, it provided valuable context that traditional financial metrics alone could not capture. However, the overall conclusions indicate that although financial factors outweighed the importance of borrower sentiment, the

Technique	Model Name	Removed > 85% Multicollinearity		Removed > 60% Multicollinearity		Removed most Important Feature		Model Parameters (for the best feature set i.e. (Removed > 60% Multicollinearity))
		F1 Score	ROC-AUC Value	F1 Score	ROC-AUC Value	F1 Score	ROC-AUC Value	
With Industry segmentation and Sentiment scores	Logistic Regression	1	0.9990	0.93	0.9217	0.76	0.8031	Model Params {'C': 100, 'solver': 'lbfgs'}
	Classification Tree	0.99	0.9973	0.93	0.9111	0.81	0.7818	Model Params {'max_depth': 15, 'min_samples_split': 20}
	K-Nearest Neighbors	0.79	0.8520	0.72	0.7668	0.68	0.7243	Model Params {'n_neighbors': 10, 'weights': 'distance'}
	Random Forest	0.99	0.9986	0.94	0.9090	0.82	0.7804	Model Params {'max_features': 'log2', 'n_estimators': 20}
	Extreme Gradient Boosting	1	0.9994	0.94	0.9300	0.83	0.8259	Model Params {'learning_rate': 0.1, 'max_depth': 7, 'n_estimators': 100}
	Naive Bayes	0.96	0.9875	0.90	0.9005	0.80	0.7539	NA
Without Industry segmentation and Sentiment scores	Logistic Regression	1	0.9989	0.93	0.9143	0.75	0.7812	Model Params {'C': 100, 'solver': 'lbfgs'}
	Classification Tree	0.99	0.9980	0.93	0.8965	0.78	0.6895	Model Params{'max_depth': 15, 'min_samples_split': 20}
	K-Nearest Neighbors	0.79	0.8520	0.74	0.7704	0.68	0.7083	Model Params{'n_neighbors': 10, 'weights': 'distance'}
	Random Forest	0.99	0.9991	0.94	0.8996	0.81	0.7514	Model Params {'max_features': 'log2', 'n_estimators': 20}
	Extreme Gradient Boosting	1	0.9996	0.94	0.91827	0.82	0.7891	Model Params {'learning_rate': 0.1, 'max_depth': 7, 'n_estimators': 200}
	Naive Bayes	0.96	0.9875	0.91	0.8842	0.80	0.73911	NA

Table 1: Summary of metrics obtained for test data using the below algorithms to predict default or non-default considering with industry segmentation and without industry segmentation.

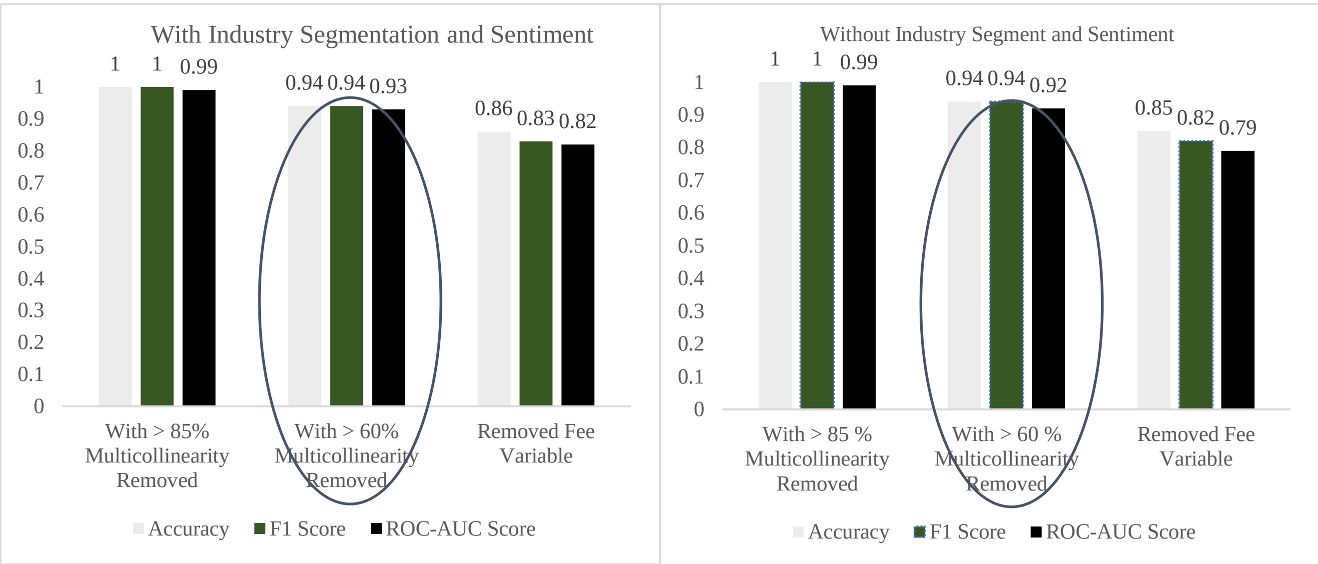

Fig. 8. XGBoost performance comparison between with and without industry segmentation (analyzing Accuracy, F1 Score and ROC-AUC Score)

industry sentiment scores did significantly improve the model's performance.

Among the models tested, XGBoost consistently outperformed others, achieving the highest ROC-AUC score of 0.9300, indicating superior predictive power. While the inclusion of industry sentiment scores did refine the models, the overall performance gains were limited, suggesting that sector-specific dynamics play a secondary role in credit risk assessment. Critical predictors of loan defaults included features such as collection recovery fee, debt settlement flag, interest rate, loan term, and total recorded late fees. These financial indicators were followed by sentiment scores, highlighting their relative importance in predicting loan defaults.

The findings advocate for a multi-faceted approach to credit risk assessment, incorporating both traditional financial indicators and nuanced industry sentiments. This approach empowers financial institutions with more robust tools for risk management, enabling more informed and effective decision-making processes. Despite challenges such as data quality issues and class imbalance, the project underscores the potential of advanced machine learning algorithms to enhance predictive accuracy and provide actionable insights for the lending domain. Future research should focus on real-time sentiment analysis and the integration of broader economic indicators to further refine default prediction models. Future work could also involve further refining the classification to encompass more specific industries, rather than just a broad 5-industry classification. In summary, this project endeavors to empower financial institutions with robust tools for industry classification and default prediction, ultimately fostering more informed decision-making and risk management practices in the lending domain.

7. References

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APPENDIX

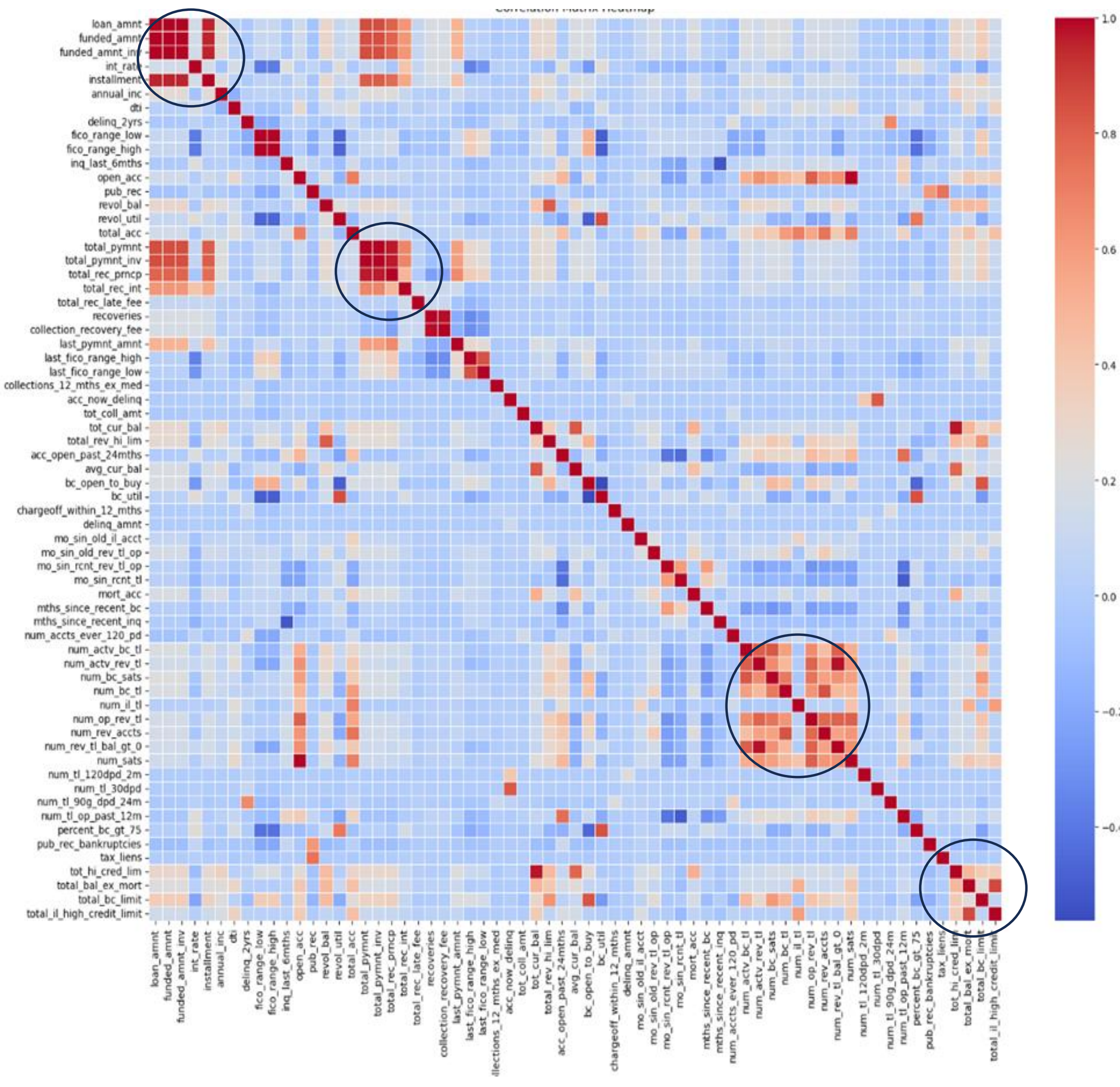
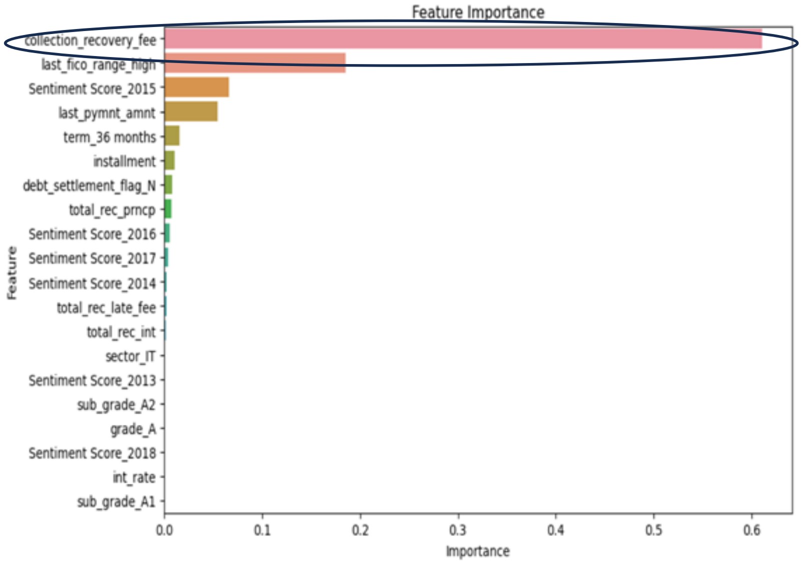
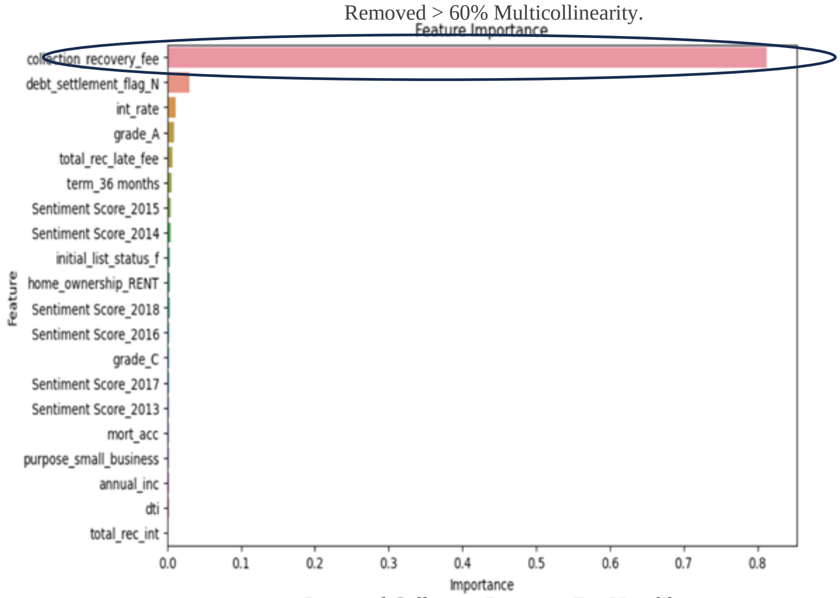


Fig. 9. Pearson Correlation for the variables (highlighting areas of multicollinearity)

Removed > 90% Multicollinearity.



Removed > 60% Multicollinearity.



Removed Collection Recovery Fee Variable

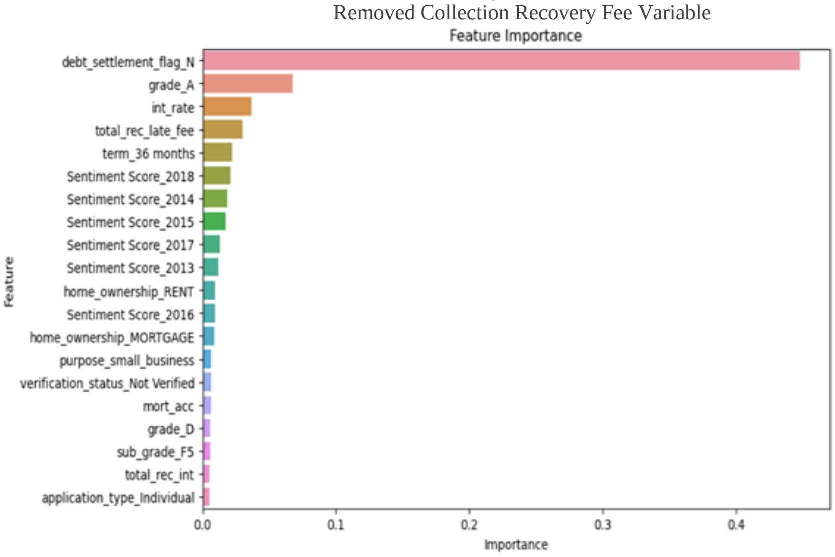


Fig. 10. Feature importance of XGBoost models for the three feature sets (highlighting collection fee variable as the most important feature in the first two feature sets)