Comparative Analysis of FICO Score Bucketing Techniques for Loan Default Prediction

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Abstract

This study investigates the effectiveness of various FICO score bucketing techniques in predicting loan defaults. Four methods are compared: Mean Squared Error (MSE) Minimization, Log-Likelihood Maximization, Bayesian Optimization, and Agglomerative Clustering. Using a dataset of 1000 loan records, these techniques are evaluated based on their precision-recall curves and Receiver Operating Characteristic (ROC) curves. Our findings suggest that Bayesian Optimization outperforms other methods in terms of predictive power, while Log-Likelihood Maximization shows the weakest performance.

1. Introduction

Credit scoring is a crucial element in assessing the risk of loan defaults. The FICO score, a widely used credit score in the United States, plays a pivotal role in this assessment. However, the continuous nature of FICO scores poses practical challenges in assigning them to discrete risk categories. This study explores various bucketing techniques to discretize FICO scores and evaluates their effectiveness in predicting loan defaults.

2. Methodology

2.1 Data Description

The dataset comprises 1000 loan records, each containing information on credit lines, loan amounts, total debt, income, years employed, FICO score, and default status. The FICO scores in our dataset range from 440 to 826.

2.2 Bucketing Techniques

Four bucketing techniques are utilized:

1. **MSE Minimization**: Uses K-means clustering to minimize the within-bucket mean squared error of FICO scores.
2. **Log-Likelihood Maximization**: Optimizes bucket boundaries to maximize the log-likelihood of the observed default rates within each bucket.
3. **Bayesian Optimization**: Applies Bayesian optimization to find the optimal number of buckets that minimizes MSE.
4. **Agglomerative Clustering**: Employs a bottom-up hierarchical clustering approach to group FICO scores.

2.3 Evaluation Metrics

Performance of each bucketing technique is evaluated using:

1. Precision-Recall curves
2. Receiver Operating Characteristic (ROC) curves
3. Area Under the ROC Curve (AUC)

3. Results

3.1 Precision-Recall Curves

The precision-recall curves (Figure 1) show that Bayesian Optimization consistently maintains higher precision across different recall levels compared to other methods. MSE Minimization and Agglomerative Clustering show similar performance, while Log-Likelihood Maximization performs poorly, especially at higher recall levels.

3.2 ROC Curves and AUC Scores

The ROC curves (Figure 2) and their corresponding AUC scores provide further insights:

1. Bayesian Optimization: AUC = 0.51
2. MSE Minimization: AUC = 0.46
3. Agglomerative Clustering: AUC = 0.37
4. Log-Likelihood Maximization: AUC = 0.28

Bayesian Optimization achieves the highest AUC score, indicating superior overall performance in distinguishing between defaulting and non-defaulting loans across various threshold settings.

4. Discussion

The results demonstrate that the choice of bucketing technique significantly impacts the predictive power of FICO scores in loan default prediction.

Bayesian Optimization emerges as the most effective method, consistently outperforming other techniques across both precision-recall and ROC curve analyses. This suggests that optimizing the number of buckets can lead to more informative FICO score categorizations.

MSE Minimization and Agglomerative Clustering show similar performance, indicating that both variance-based and hierarchical approaches to bucketing can yield reasonable results.

Surprisingly, Log-Likelihood Maximization, despite its theoretical grounding in statistical principles, performs poorly in this context. This unexpected result warrants further investigation and may be due to overfitting or the presence of local optima in the optimization process.

5. Limitations and Future Work

Several limitations of this study present opportunities for future research:

1. **Sample Size**: The dataset of 1000 records is relatively small. Future studies should validate these findings on larger, more diverse datasets.
2. **Feature Interaction**: This study focused solely on FICO scores. Investigating the interaction between FICO score buckets and other features could provide more comprehensive insights.
3. **Temporal Aspects**: The current analysis does not account for potential temporal changes in the relationship between FICO scores and default rates. A longitudinal study could address this limitation.
4. **Alternative Techniques**: Exploring other bucketing techniques, such as decision tree-based approaches or quantile-based methods, could yield additional insights.
5. **Calibration Analysis**: Future work should include an analysis of the calibration of probability estimates produced by each bucketing technique.

6. Conclusion

This study provides valuable insights into the effectiveness of various FICO score bucketing techniques for loan default prediction. Bayesian Optimization emerges as the most promising approach, offering superior predictive power compared to traditional methods like MSE Minimization and Agglomerative Clustering.

These findings have significant implications for credit risk assessment in the lending industry. By adopting more effective bucketing techniques, financial institutions can improve their ability to predict loan defaults, potentially leading to better risk management and more informed lending decisions.

Future research should focus on validating these results with larger datasets, exploring feature interactions, and investigating the temporal stability of these bucketing techniques. Such efforts will contribute to the ongoing refinement of credit risk assessment methodologies in the financial sector.

References

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Appendix

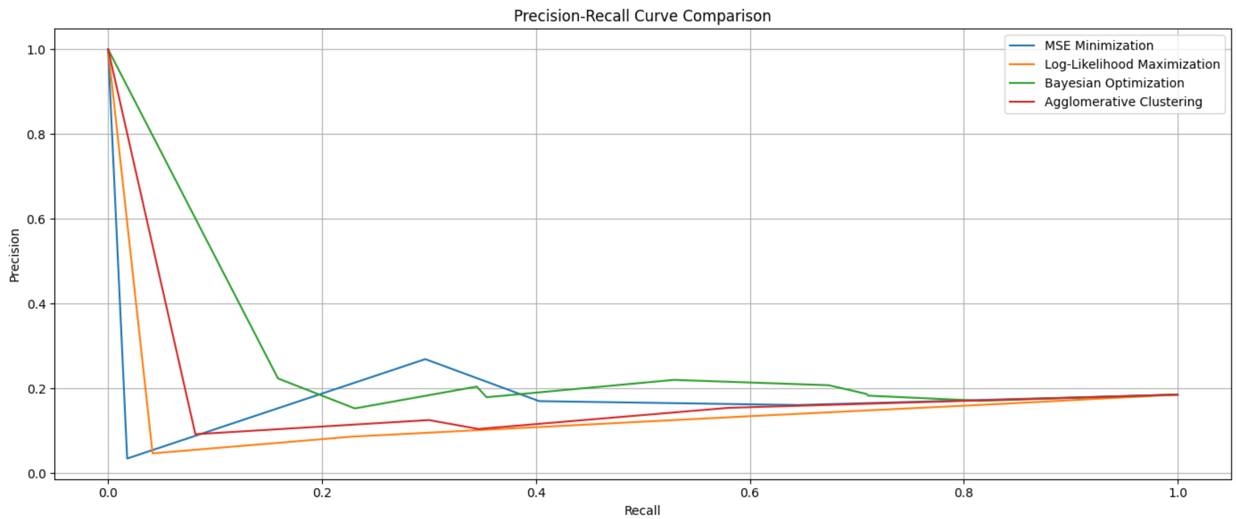

Figure 1: Precision-Recall Curve Comparison

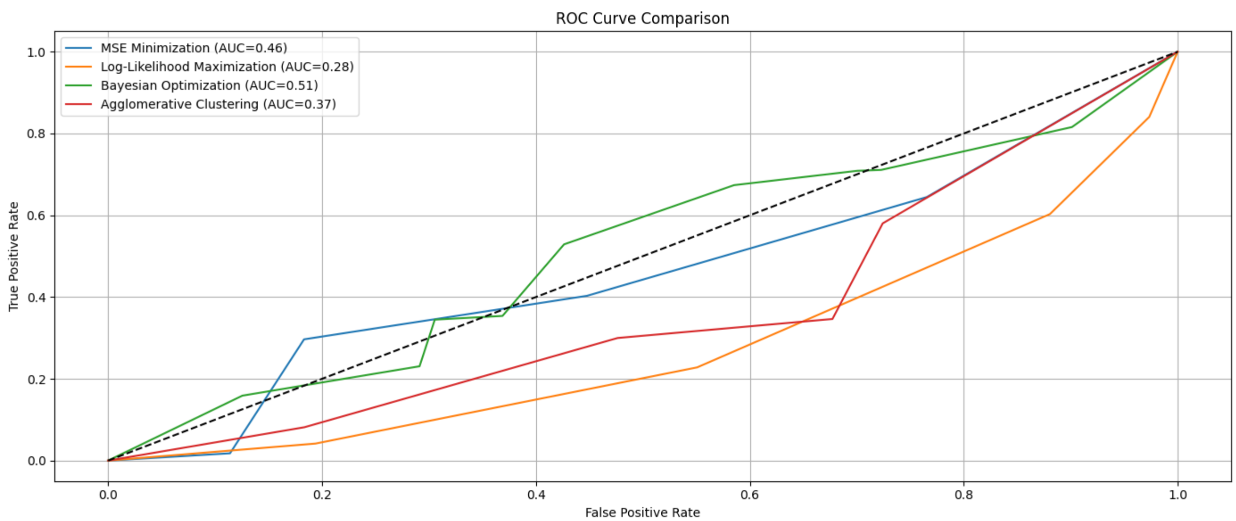

Figure 2: ROC Curve Comparison