Machine Learning System for Credit Risk

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This thesis explores the application and integration of machine learning techniques to assess and manage consumer credit risk, discussing various models and addressing key challenges.

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Outline

Literature Review

- **Context:** Credit risk assessment is central to lending. Regulations (Basel III, IFRS 9) require transparent and quantitative estimation of Expected Loss (EL). [1]
- **Objective:**
  - Build 3 interpretable models: Probability of Default, Loss Given Default, Exposure at Default and a model scorecard
  - Formation of Expected Loss, Return-on-Investment
  - Establish and apply different score-based lending policies.
- **Scope:** Personal loans, historical data from Lending Club

[1] Bank for International Settlements (BIS), "Basel Framework: Credit Risk - Standardised Approach (Chapter CRE 32)." `https://www.bis.org/basel_framework/chapter/CRE/32.htm?inforce=20230101&published=20200327`, 2020. Effective: 2023-01-01, Accessed: 2025-07-12.

Rationale for Topic Selection

- Real-world deployment requires explainability (white-box models $>$ black-box models)
- Academic gap: many studies pursuit high predictive power of PD models rather than a full risk-component. [2]
- Practical value: transparent Expected Loss (supported by Return-on-Invest and Annual. ROI) $\rightarrow$ better loan pricing, approval decisions
- Personal interest: applying machine learning to finance, risk scoring, and modeling human behavior in credit

[2] Lessmann, Stefan, Bart Baesens, Hsin-Vonn Seow, and Lyn C. Thomas. "Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research." *European Journal of Operational Research* 247, no. 1 (2015): 124-136. DOI: `https://doi.org/10.1016/j.ejor.2015.05.030`.

Thesis Methodology

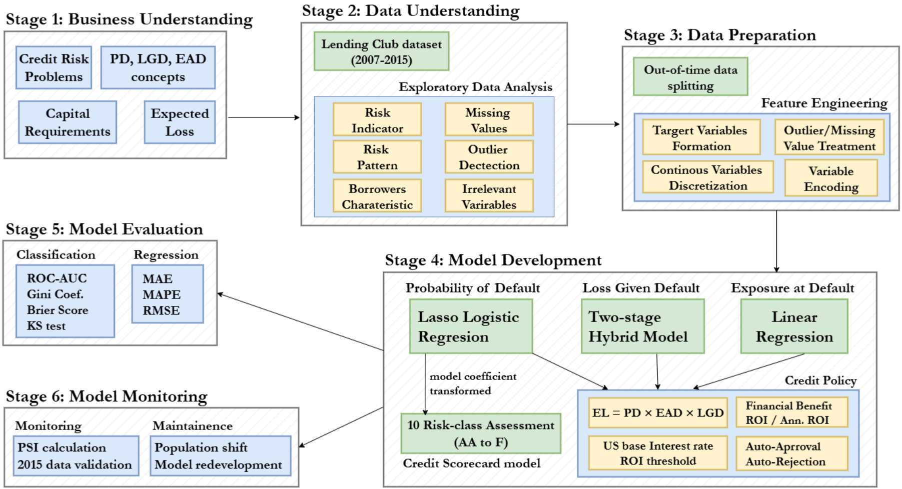

Figure: Overview of the Thesis Methodology

Risk-component and Machine Learning models

Risk Component	Model	Target Variable	Additional Techniques
PD	LASSO LogReg	Default Indicator (binary)	Z-test, Wald Test
LGD	(1) LASSO LogReg (2) OLS Regression	Recovery Indicator (> 0) Recovery Rate (if recovered)	
EAD	OLS Regression	Credit Conversion Factor	Scaled to credit limit (EAD $=$ CCF $\times$ limit)

Table: Model overview by risk component.

Results of PD model

The PD model achieved the following performance metrics on the train and test set:

Metric	Train Value	Test Value
KS	0.268	0.298
AUC	0.684	0.703
Gini	0.367	0.407
Brier	0.101	0.062

Table: PD model performance metrics on training and test sets

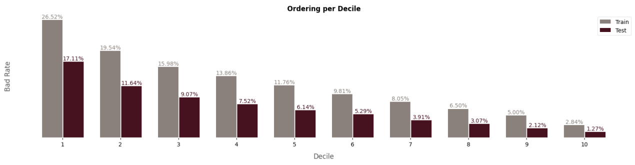

Figure: The decile analysis of PD model indicates a good performance

Results of LGD models

Stage 1:

Threshold	ROC–AUC	Recall_0	Recall_1	Accuracy
0.50 (default)	0.61	48%	67%	54%
0.48 (optimized)	0.61	44%	72%	53%

Table: The performance of Stage 1 model before and after adjust the threshold.

Stage 2:

Model	MAE	MAPE	RMSE
LGD Linear Regression	0.0523	63.2022	0.0825

Table: Stage 2 LGD model performance on the test set

Results of EAD model

The EAD model demonstrates relatively high prediction errors with an MAE of 13.53 percentage points.

Model	**MAE**	**MAPE**	**RMSE**
EAD Linear Regression	0.1353	16.0853	0.1597

Table: EAD model performance on the test set

Scorecard Model formation result

The credit scorecard model is created with 10 risk-class and a score range from 300 to 850 (with and industry-standard like FICO/VantageScore) [3]

Risk Class	Credit Score Range	Risk Level
AA	688–850	Lowest
A	657–687	Very Low
...	...	...
DD	531–554	Very High
F	300–530	Highest

Table: Risk Classifications and Credit Score Ranges

[3] FICO, "Understanding FICO scores." https://www.myfico.com/credit-education-static/doc/education/Understanding_FICO_Scores_5181BK.pdf, 2023. Accessed: July 12, 2025.

Credit Policy

A credit policy is implemented to examine, this includes

- Auto-accept/reject: risk class that will be automatically accepted/rejected
- Expected Loss: derived from the 3 risk-components
- Financial Ratio: ROI which is calculated with U.S. base interest rate (e.g., the interest rate of U.S. Treasury Yield on 10-year-note in 2015)

The implemented credit policy shows influence on the test set, compared to the original one.

Metric	**Previous**	**After**
Default rate (%)	6.71	5.65
Expected loss (%)	6.91	5.77

Table: Business impact of the implemented credit Policy

Credit Policy result

4 other policies are established to show the trade-offs between metrics.

Scenario	Approval Rate	Default Rate	EL (%)	EL ($)	Loan Amount	Avg. ROI
No Policy	94.14%	7.04%	7.22%	$93.16M	$1.29B	3.84%
Current Policy	88.66%	5.64%	5.76%	$70.12M	$1.22B	3.59%
Less Conservative	89.47%	5.61%	5.73%	$70.69M	$1.23B	3.58%
More Conservative	77.98%	4.94%	5.03%	$53.31M	$1.06B	3.50%
Very Conservative	68.26%	4.32%	4.40%	$40.75M	$0.93B	3.38%

Table: Comparison of Credit Policy Scenarios

The more conservative the credit policy is, the more default rate reduction it get, and so forth for other metrics.

Scenario	Δ Default Rate	Δ EL ($)	Δ Loan Amount	Δ Avg. ROI
Current Policy	–1.40%	–$23.03M	–$71.87M	–0.25%
Less Conservative	–1.43%	–$22.47M	–$56.90M	–0.26%
More Conservative	–2.10%	–$39.85M	–$229.72M	–0.34%
Very Conservative	–2.72%	–$52.40M	–$363.90M	–0.46%

Table: Improvements Compared to No Policy

Conclusion

Findings:

- A complete credit risk modeling framework using three interconnected models (PD, EAD, LGD) following the Basel regulatory.
- A conservative credit policy that decreases default rates from 6.71% to 5.65% and expected losses from 6.91% to 5.7%

Strengths:

- Model Architecture: comprehensive framework, industry-standard approach, interpretable design.
- Credit Scorecard: standard score range (FICO), mathematical soundness
- Credit Policy: Risk-based segmentation (AA to F), ROI integration

Limitations:

- Model Performance: satisfactory result although not impressive
- Technical Limitations: linear models reliance, static threshold
- Policy Design: binary decision, no partial approvals

Future Works

More improvements/advance can be considered in the future

- **Advanced modeling techniques:** ensemble methods, deep learning with explainability machine learning concepts.
- **In-depth credit policy:** multi-criteria decision, partial loan amounts for borderline cases
- **Champion-Challenger Framework:** A/B test new models against current ones

Main References

B. for International Settlements (BIS), "Basel framework: Credit risk - standardised approach (chapter cre 32)." https://www.bis.org/basel_framework/chapter/CRE/32.htm?inforce=20230101&published=20200327, 03 2020. Effective: 2023-01-01, Accessed: 2025-07-12.

S. Lessmann, B. Baesens, H.-V. Seow, and L. C. Thomas, "Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research," *European Journal of Operational Research*, vol. 247, no. 1, pp. 124–136, 2015.

FICO, "Understanding fico scores." https://www.myfico.com/credit-education-static/doc/education/Understanding_FICO_Scores_5181BK.pdf, 2023. Accessed: July 12, 2025.

Thank you for your attention!