2025 Illinois Statistics Datathon

Team Conquistadors
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Our goal was to build a **Predictive Framework** for managing **Credit Lines**

Forecasting customer spending for Q4 2025

Segmenting accounts by credit line eligibility & risk

Recommending personalized credit line increases or no change

What we analysed

- Financials
- 8 Structured Tables
- Credit Behaviors
- Fraud metrics
- Account summaries

Preprocessing the Data

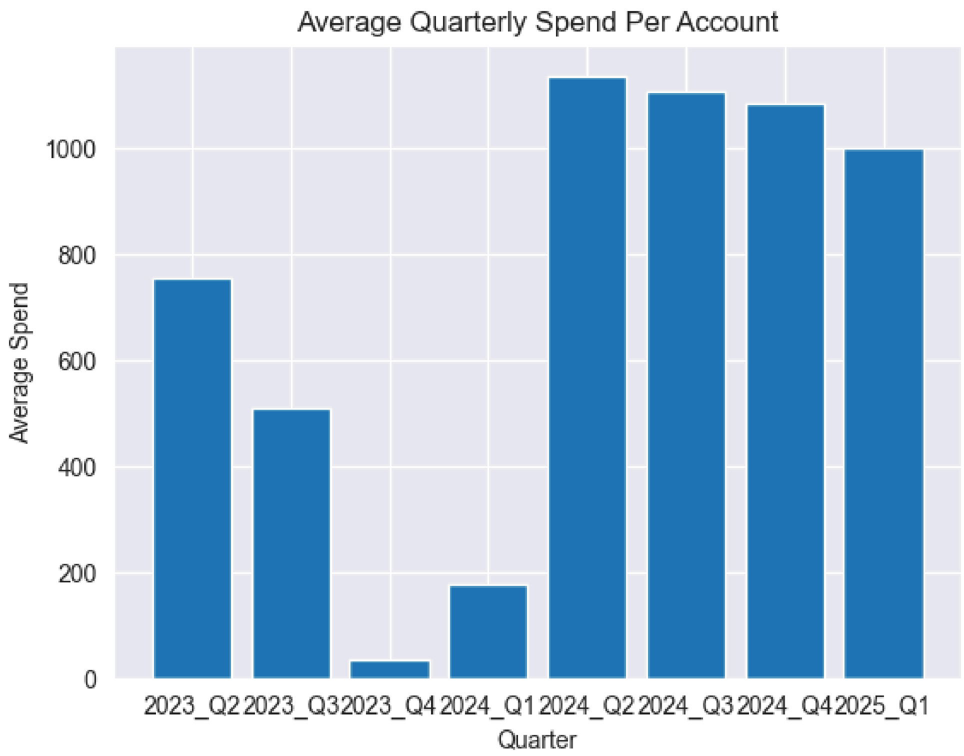
Data Cleaning and Merging

The data consisted of 8 structured tables covering financials, credit behaviour, fraud measures, delinquencies, and account summaries.

- Columns with **>70% missing values** were removed to ensure data quality.
- Tables were combined using primary and foreign keys as stated in the mapping specification.
- Accounts with **null credit line values** were excluded, since they are not eligible for limit adjustments.
- Retained only **active accounts**.

Exploratory Data Analysis

Insights from Historical Data



- Examined average quarterly spending patterns(i.e Q2 2023 to Q1 2025)
- Observed correlation between Confidence Level & Credit Line
- Evaluated customer spending across multiple periods to assess repeat behavior and brand loyalty.

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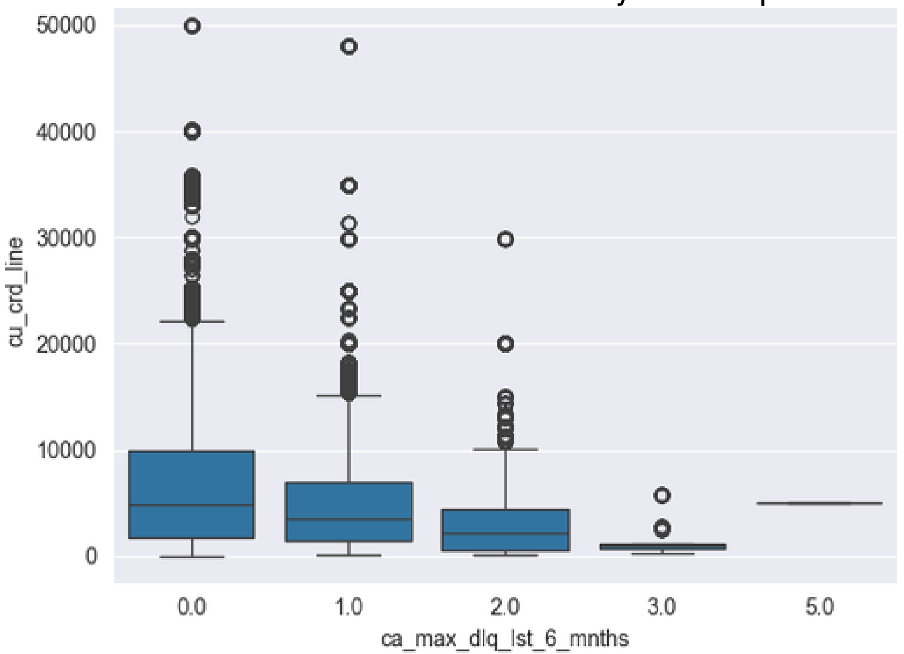
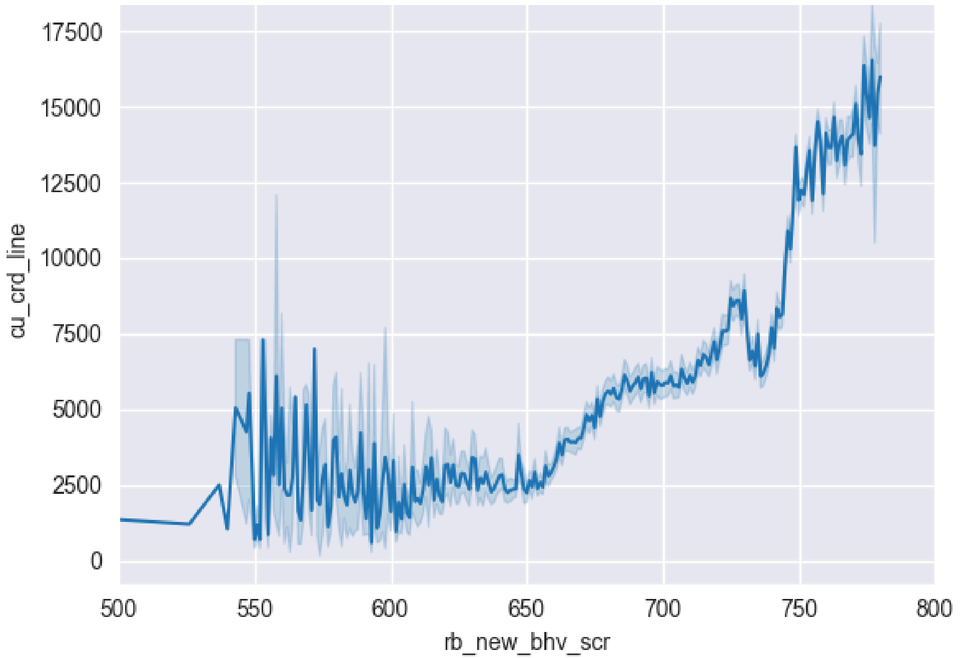
Exploratory Data Analysis

Insights from Historical Data

Credit Line vs Number of Days Delinquent



Credit Line vs Behaviour Score



- Examined correlation between Delinquency, Customer Behaviour Score with Credit Line.
- Observed Negative correlation between Delinquency & Credit Line.
- Observed Positive correlation with Behavioral Score & Credit Line.
- Since there is a visible correlation between these metrics we used them in making predictions for future Q4 credit line adjustments.

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Feature Engineering

Total Accounts

13,841

Engineered features

43

Features Including

Average Quarterly Spend
(from Q2 2023 to Q1 2025)

Average Quarterly Open-to-Buy (OTB)
(from Q3 2024 to Q1 2025)

Total Net Fraud Amount & Excl Flag
If an account is tagged for exclusion from credit limit changes and an account's total fraud amount

Credit Utilization
(balance / credit limit)

Behavioral Scores
(internal and bureau)

Delinquency metrics:
days past due, NSF counts, returned checks

Objective 1: Predict Q4 2025 Customer Spending

Model Used: GradientBoostingRegressor

Input Features (X): **All behavioral, credit, and historical spending features**

Target Variable (y): **avg_spend_2025_Q4 (predicted)**

Training Data Range: Q2 2023 – Q1 2025

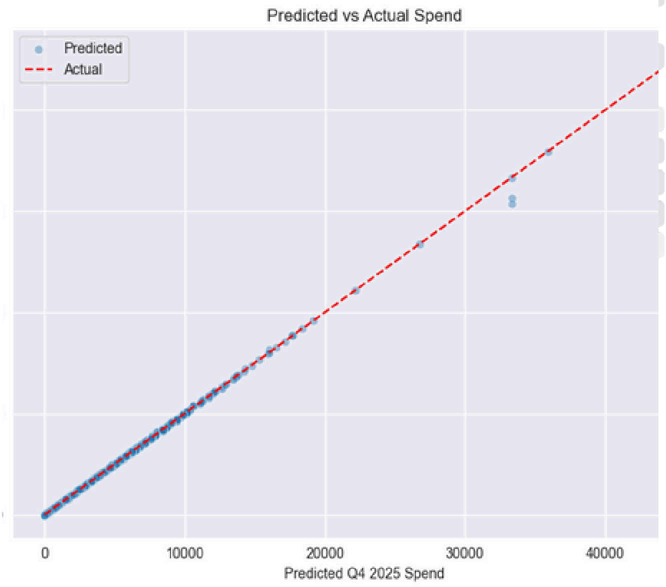
Verification method: Used avg_spend_2024_Q4 as proxy for validation

Model Metrics

RMSE: 64.046

R^2 Score: 0.9985

Result - Predicted vs Actual Q4 2025 Spend



Objective 2: Segment Accounts for Credit Line Eligibility

Step 1: Manual Labeling using Business Logic

1. Eligible – No Risk (Class 0):
• Predicted Q4 spend > $300
• Utilization > 50%
• Bureau Score > 600 and Behavioral Score > 550

2. Eligible – With Risk (Class 1):
• High spenders with good utilization but low credit scores

3. No Increase Required (Class 2):
• Moderate/low spenders or underutilized accounts

4. Non-Performing / High Risk (Class 3): • Fraud > $100 • NSF count > 3
• Days delinquent > 60
• Behavior score < 400
• Returned checks > 3

Step 2: Model Used

- We experimented with multiple models like XGBoost Classifier, RandomForestClassifier is used for the final analysis.
- Due to class imbalance, we implemented SMOTE to address the issue.
- We tested combinations of SMOTE with Random Forest and SMOTE with XGBoost.
- After evaluation, we concluded that SMOTE + XGBoost provided the best performance.

Model Performance

High Accuracy for Majority Classes
6,510 No-Increase accounts correctly predicted
3,894 Eligible-Safe accounts correctly predicted
Only **9** No-Increase accounts wrongly predicted as Eligible-Risk

Rare Class Segmentation Still Effective
70 Eligible-Risk accounts correctly classified
2,788 High-Risk accounts correctly predicted
0 misclassifications of High-Risk customers

Model Performance

Class	Description	Precision	Recall	F-1 Score	Support
0	No Increase Required	0.89	0.87	0.88	1372
1	Eligible – No Risk	0.80	0.82	0.81	824
2	Eligible – With Risk	0.47	0.53	0.50	15
3	Non-Performing / High Risk	1.00	1.00	1.00	558
accuracy				0.88	2769
macro avg		0.79	0.81	0.80	2769
weighted avg		0.88	0.88	0.88	2769

Insights

- Overall Accuracy: 88%
- Excellent at classifying high-risk and low-risk groups eligible for increase
- Slight underperformance in minority class (Class 2) due to class imbalance
- Weighted Average F1 Score: 0.88 confirms general robustness of the model.

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Objective 3 :Recommend Credit Line Adjustments

To recommend **personalized credit line increases**, we built a **regression-based framework** that balances **spending demand, utilization trends, and risk factors.**

Model
RandomForestRegressor

Applied to
Accounts from Segments 1 (without risk) and 2(with risk)

Features
Current credit line, utilization, spending, behavioral scores

Output
Personalized credit line increase per account

High Risk Check
1 in 173 accounts expected to commit fraud
• 3+ NSF incidents • 2+ returned Checks YTD • 45+ Delinquent or max deliquency in 6 months > 30 • Low behavioral or recent risk scores <400

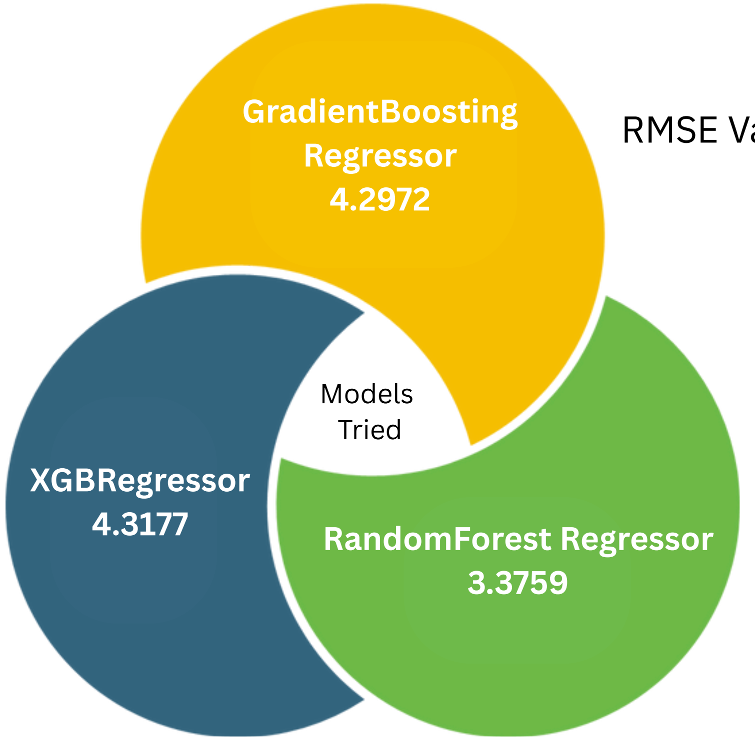
Spending Demand Logic

Spend to Limit Ratio	Credit Line Increase
> 1.2 and utilization > 60%	30%
> 1.0	20%
>0.8	10%
Otherwise	No increase

Step 2:Model Training and Evaluation

Features Used:

- Predicted Q4 spend
- Credit utilization (3M, 6M, current)
- Risk and delinquency signals
- Historical spend and fraud markers
- Available credit and current balance
- Credit line segmentation



RMSE Values of Models

✅ **Final Output**

The best model (RandomForestRegressor)was used to predicted credit line increase amount for all accounts in the eligible segments. The model was off by just **$3.3759** on an average.

This approach allowed us to recommend data-backed, risk-aware credit line increases tailored to each customer's financial profile.

Conclusion

Key Achievements

- Developed a comprehensive predictive framework addressing all three challenge objectives
- Achieved exceptional model performance:
  - Spending Prediction: R^2 of **0.9985** (GBRegressor)
  - Customer Segmentation: **88%** accuracy (XGBClassifier + SMOTE)
  - Credit Line Recommendations: MAE of **$3.38** (RandomForestRegressor)

Business Impact

- Enables data-driven decisions for credit line management
- Identifies high-value customers while mitigating risk exposure
- Provides personalized recommendations balancing growth opportunities with risk management

"Our solution provides Synchrony with a powerful, data-driven framework to optimize credit line decisions, maximize customer value, and minimize financial risk - all built on robust machine learning foundations."