Team 84: Exploring Trends in Consumer Debt in the United States

Mark Yun Kiu Chan
ychan76@gatech.edu

Adam Bishop
abishop41@gatech.edu

Annu Kumari
akumari36@gatech.edu

Megha Gulati
mgulati30@gatech.edu

INTRODUCTION

Consumer debt has shown an increasing and accelerated trend within the United States. It impacts numerous domains within society from the cost and quality of living to that of government policy. An industry that is often overlooked in relation to this subject is that of debt collections. Entities that work within this space often face the challenge of how to appropriately assess the likelihood of debt repayment for a consumer given that consumer's demographic makeup and the broader macroeconomic environment affecting them. Uncovering and implementing these key features which provide strong predictive power can add efficiency within collection efforts by speeding up repayment times, establishing optimal repayment schedules, and reducing the invested costs made by those entities in the purchase of consumer data. An analysis of this kind can provide great insight to financial institutions (banks, credit card companies, loan servicers, etc.), debt collectors, policymakers, and even the consumers themselves [6][14].

Current methodologies in consumer debt research traditionally rely upon statistical models employing either difference-in-differences (DID) [1] or OLS regression techniques [3]. These models are often constructed in such a way that they tend to either address individual factors [13] or macroeconomic factors [4][1], solely. This project aims to significantly enhance this methodology by observing all of these factors together and employing additional analytical techniques ranging from random forest to time series analysis.

Ultimately, the primary objective of this project is to uncover the features that significantly predict the likelihood of a consumer to begin the repaying of a debt within 5 years of that debt being charged-off by an originating creditor, and then to apply those features for prediction to current consumers. Second to this primary objective, we also plan to examine the following: finding the probability of the debt being satisfactorily repaid (paid-in-full or settled-in-full) within 5 years of initial payment, identifying pre and post COVID-19 trends in overall debt repayment, and finding the optimal repayment schedule, monthly, for a given consumer.

PROBLEM DEFINITION

The problem of our primary objective can be formally stated through two questions:

[obj1] "What are the demographic and macroeconomic features that are significant in predicting whether or not a consumer begins repayment of a debt within 5 years of an initial charge-off date?"

[obj2] "Using those identified features, what is the probability that a current consumer, who has yet to begin repayment, but that is still within that timeframe (charge-off dates on or after 4/1/2019), to begin repaying their debt?"

Questions related to our subobjectives can formally be stated as such:

[subobj1] "Given that a consumer has begun repayment within 5 years, what is the probability of that debt being satisfactorily repaid (paid-in-full or settled-in-full) within 5 years of that initial payment?"

[subobj2] "Are there any differences or trends that exist for debts charged-off prior to and post COVID-19?"

LITERATURE SURVEY

We have reviewed several sources of data for our project. Studies by Moroke and Exler and Tertilt [4] explored how economic factors influence household debt, guiding us to consider both individual and macroeconomic variables in our research. Ha and Krishnan's [12] work on credit card debt repayment prediction inspired our use of machine learning techniques for forecasting. Additionally, insights from Bellotti et al.[6] on forecasting loan recovery rates contributed to our approach in predicting debt repayment probabilities.

During the COVID-19 pandemic, research by Kurowski [5] highlighted the impact of the crisis on household debt, while Buckley and Chhugani's [7] analysis emphasized the urgency of understanding rising consumer debt trends. Weinstock's [16] examination of geographic cost-of-living differences further informed our understanding of regional debt variations. By drawing from these studies, we aim to build a robust framework for analyzing consumer debt trends, empowering decision-makers with actionable insights in debt collection strategies.

PROPOSED METHOD

Our approach is novel in that it: 1. blends both individual and macroeconomic factors together, as opposed to those limited approaches previously mentioned; 2. uses modern machine learning techniques, and 3. attempts to explore differing trends in consumer debt prior to and after COVID-19, which is previously unseen [5]. Our dataset is sampled directly from an active entity within the U.S. debt collection industry and is exceptionally comprehensive in terms of consumer demographics and transaction history [11].

We focus on several key success factors. The outline of sequential activities is listed as follows:

A. Acquire data, Data wrangling

Following approval for data usage from our source entity, we will then transfer the bulk of our raw data over a secured link into a local MySQL environment. Additional data pertaining to macroeconomic factors will largely be collected from U.S. Government websites and repositories and added to this same workspace. Altogether, more than five comprehensive data tables will be joined together, cleaned, transformed, and prepared for further analysis [11]. Encompassed within this process, includes handling missing values, dealing with outliers, standardizing formats, and ensuring data consistency.

B. Data Analytics and data processing

Article [6] provides great direction suggesting that rule-based algorithms like random forest have been found to be more predictive than others [12]. We will begin by following suit for our classification models to increase our quality of analysis. The definition of success within our models will vary with the corresponding objective/subobjective under consideration. For [obj1] and [obj2], it will be related to the existence of a payment within the 5-year time period, and for [subobj1], it will relate to the presence of an account's ending status in paid-in-full (PIF) or settled-in-full (SIF). The features of our model will consist of whether an active place of employment or bank account has been found for the debtor, whether a judgment presently exists on the outstanding debt, the judgment amount that was issued, average repayment amounts and frequencies, and other consumer demographics. Additionally, we will integrate macroeconomic data to provide a comprehensive view of the features influencing debt repayment, which is also an unprecedented approach [4][11]. These features include cost of living indices [16], inflation rates, and GDP growth. We may employ other models as we see fit during the study [12]. Overall, this phase will include feature engineering, model exploration and training, and evaluation until satisfactory predictive results of the testing dataset prevail.

1) Classification Models

[obj1] and [subobj1] can be answered with the use of classification models, and [obj2] will be answered via prediction using our top-ranked model created from [obj1]

Target variable for [obj1]: Boolean variable on whether an account receives an initial repayment of a debt within 5 years from an initial chargeoff.

Target variable for [subobj1]: Boolean variable on whether an account is being satisfactorily repaid (paid-in-full or settled-in-full) within 5 years of its initial repayment date.

The set of features, as mentioned in part B, are then used for training these two models. New features are created to capture characteristics that describe consumer behavior, including total payment amount, payment duration, frequency, average payment, and days between key events. Both models are unprecedented due to the rare acquisition of clean and comprehensive corporate datasets which allows us to create precise models. Another innovation at our disposal lies within model development and training. We have used Microsoft Azure's Machine Learning Studio to preprocess the dataset using their notebook feature and pipeline design. This feature has allowed us to conveniently split the datasets into training and testing sets following the 80/20 convention. Following this, we can use Automated ML functionality to run multiple classification models in parallel, ranking the top model with best weighted AUC, and then performing evaluation on the testing dataset automatically. This implementation has made the model training process much more efficient and enabled us to evaluate model performance iteratively. We're able to train more than 50 algorithms in parallel which provides us with a higher chance of getting the best model than traditional techniques.

2) **Time Series Analysis: - [Trends for Debts Charged-off Pre and Post COVID-19]**
Data Segmentation: Split the dataset based on charge-off dates: pre and post March 2020.
Descriptive statistics: Evaluate days between charge-off and judgment dates and between charge-off and initial repayment.
Cost of Living Analysis: Conduct comparative analysis to understand the impact of economic conditions on charge-off rates.

3) **Data Analysis and Modeling: - [Optimal Repayment Amount for Debt Satisfaction within first 5 Years of payment]**
Data Grouping: Group all Paid in Full (PIF) or Settled in Full (SIF) accounts by region, and then calculate the average monthly repayment amount for individuals in each region.
Predictive Modeling: Employ survival analysis models, like Cox proportional Hazard Model to estimate the time until an event of interest (debt repayment) occurs.

C. *Interactive Visualization*

With Tableau as our visualization tool, we have crafted interactive dashboards. Unlike traditional static maps, we have curated an interactive map with charts that highlight varying trends across U.S. states and regions pre and post COVID-19. We also made use of python library **Plotly** to generate plots as part of our time series analysis.

Feature Importance Heat Maps & Filter UI for [obj1] & [subobj1]: We will visualize critical factors influencing their respective probabilities via heatmaps, geomaps, as well as a comprehensive filter board to allow users to interactively check on their specific scenarios.

Regional Analysis for [obj1] & [subobj1]: We will map the average minimum payment within 5 years of charge-off across US regions.

[Subobj2] Analyzing Differences Pre and Post COVID-19: We will visualize key metrics at both the U.S. state and region levels, macroeconomic factors at the U.S. region level, considering both demographic and macroeconomic influences.

Our approach will allow stakeholders, such as debt collectors, financial institutions, and policymakers, to interactively explore and visualize the results.

Experiments/ Evaluation

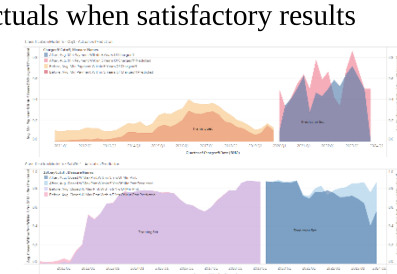
1) Classification Model for [obj1] & [subobj1]

Preprocessing and Feature Engineering
The raw dataset has been prepared using Jupyter notebook and stored in a table format on Azure.

Model Training
With AutoML, we have trained more than 50 models in total. To summarize the model used: ensemble models combine predictions from multiple models with different techniques to leverage their strengths – including Voting Ensembles (hard/soft voting), Stack Ensemble (meta-classifier), Gradient Boosting, Random Forest, Extreme Random Trees (Refer to Appendix 1 for other models and description.) Hyperparameters for each model are automatically adjusted but can be extracted in the final model selected for prediction.

Evaluation (All vizzes in this part can be found here)
Voting Ensemble achieved the best AUC weighted in both models (Obj1: 0.85; Subobj1: 0.99). Refer to Appendix 2 & 3 for top 10 models' results.
Obj1: The model achieved an accuracy of 0.88, indicating that it correctly predicts **[obj1]** for ~88% of the instances in the test set. The ROC and Precision-Recall curves shows the model performs well in discriminating between the two classes. Confusion matrix however shows a high false negative (1131 or ~60%), suggesting the model wrongly predicted that a consumer who began repayment within 5 years would not repay.
Subobj1: The model achieved an accuracy of 0.97, indicating that it is highly successful in predicting **[subobj1]**. ROC and Precision-Recall curves are also very close to the ideal top-left corner.

Prediction [Obj2]:
Our model successfully predicted **[obj1]** (pink) and **[subobj1]** (light blue) with data post 2019 (Viz). Blue area in both diagrams post 2019 only shows partial actuals when satisfactory results have already happened, but yet to have the required 5 years to be definite.



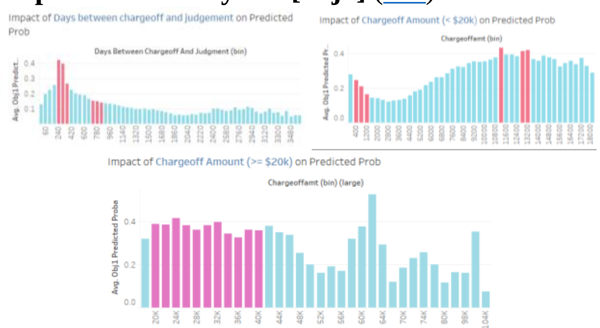
Observations

Feature importance for Obj1 – Top 7

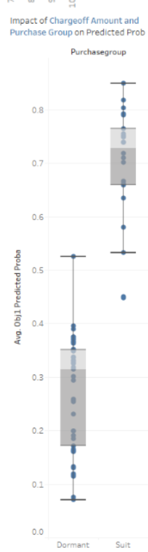
Category	Importance
days_between_chargeoff_and_judgment	0.3152
chargeoffamt	0.2993
purchasegroup	0.2274
chargeoffamt_present	0.2131
agency_ever	0.1933
verification_completed	0.1884
region	0.1724

This suggest that the time between charge-off and judgment, the charge-off amount, and the purchase group are important factors in predicting **[obj1]**.

Top features analysis - [obj1] (Viz)



A clear negative correlation is shown between the number of days between charge-off and judgment and **[obj1]** (top left). This suggests that quicker legal action after charge-off is associated with a higher likelihood of initial payment. Higher charge-off amounts initially decrease **[obj1]** (top right) until $3k. $20k-$40k group (purple) is more stable and higher **[obj1]**. Purchase group is also a key differentiator where Suit is much higher **[obj1]**

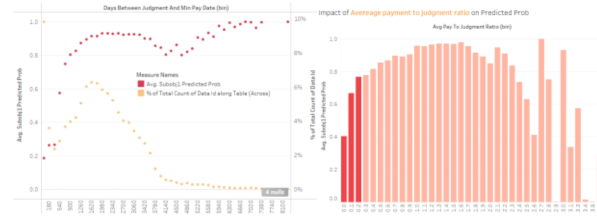


Feature importance for SubObj1 – Top 7

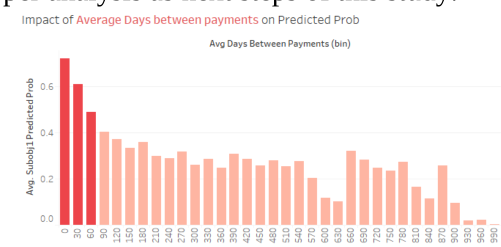
Category	Importance
days_between_judgment_and_min_pay_date	1.8909
avg_pay_to_judgment_ratio	0.9970
days_between_chargeoff_and_min_pay_date	0.7286
avg_days_between_payments	0.5309
avg_monthly_payment(duration>=365days)	0.3950
purchasegroup	0.3027
judgment_active	0.1979

Time between key events (judgment, charge-off, first payment) and the average payment behaviour are important factors in predicting **[subobj1]**.

Top features analysis - [subobj1] (Viz)



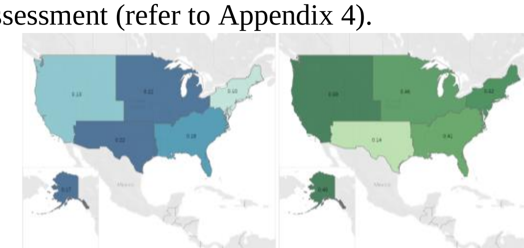
Judgment date and date of first payment ranging 4.4-8.8 years are higher **[subobj1]** (left). Payment to judgment ratios between 1-1.6 are highest **[subobj1]** (likely one-off payments) but 70% consumers lie below 0.3 (right), both warrant a deeper analysis as next steps of this study.



Average Days Between Payments shows the clearest inverse relationship with **[subobj1]**, suggesting more frequent payment (< 60 days) leads to a higher chance of resolving the debt.

Visualization

We have created a first-ever Tableau UI (Viz) that presents the most influential features on **[obj1]** & **[subobj1]**, and have them as filters so that they can be adjusted based on one's specific scenario to obtain an average predicted probability for deep assessment (refer to Appendix 4).



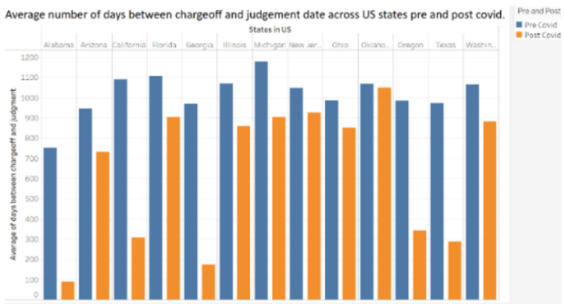
We have also demonstrated the actual and predicted **[obj1]** with side-by-side maps to allow one to do a regional difference comparison (Viz).

[subobj2] Trend analysis across COVID

Upon identifying key features influencing debt repayment behavior, we explored following trends

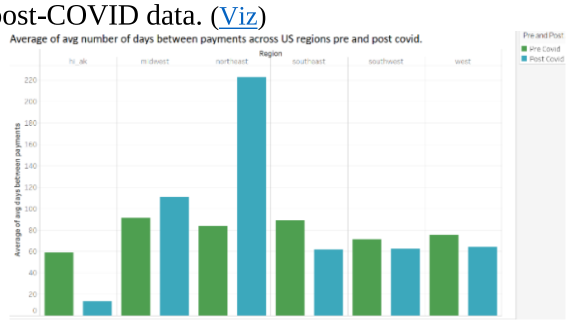
pre and post Covid-19 period:
Bias Note: Given the limited availability of post-COVID data, it’s crucial to acknowledge potential biases inherent in the dataset.

1. **Time Between Charge-Off and Judgment Dates:** Excluded states (Alaska, Hawaii, New York, and Pennsylvania) due to the absence of post-COVID data. (Viz)



There's a notable decrease in the time between charge-off and judgment dates post-COVID
State Variances: While most states show reduced times post-COVID, differences exist. For example, California saw a substantial decrease from 1091.8 days to 307.5 days, whereas Oklahoma's reduction was less significant, from 1068.7 to 1049.9 days.
Regional Diff: Post-COVID, regional variations in debt processing are apparent. States like Washington and Oregon have longer average times between charge-off and judgment compared to states like Texas and Florida.

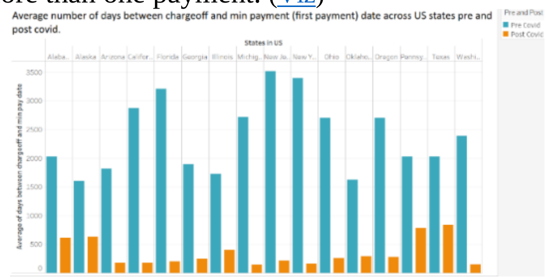
2. **Time Between Charge-Off and first payment dates:** Hawaii excluded due to lack of post-COVID data. (Viz)



Similar to charge-off to judgment dates, there's a noticeable decrease in average time to first payment post-COVID across most states.
State Variation: Some states, like New Jersey and New York, show substantial reductions, dropping from thousands of days pre-COVID to less than 300 days post-COVID. Others, like Alaska and Alabama, also exhibit significant reductions, although with smaller absolute values.

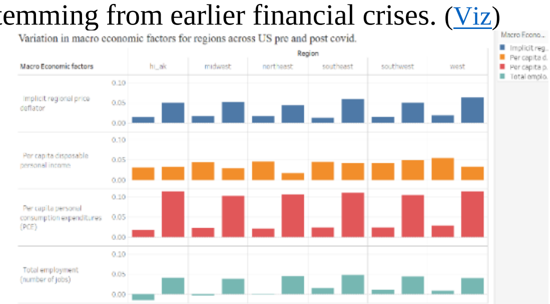
Regional Diff: States like Florida and Michigan display relatively higher reductions, suggesting potentially faster debt repayment or changes in collection practices compared to other regions.

3. **Time between payment dates:** Calculated the average of the average number of days between payment dates across US regions pre and post-COVID, considering only regions with more than one payment. (Viz)



Variation in Payment Frequency Post-COVID: Some regions show an increase (Northeast, Midwest), while others show a decrease (Southeast, Southwest, West) in the average number of days between payments.
Northeast Region: Significant increase post-COVID, indicating a potential slowdown in payment frequency. **Southeast and Southwest Regions**: Decrease post-COVID, suggesting faster payment frequency. **West Region**: Experiences a moderate decrease post-COVID, indicating some improvement in payment frequency.

4. **Macro-Economic factors across US regions:** To ensure a fair comparison, we chose pre-COVID data from 2015 to mitigate biases stemming from earlier financial crises. (Viz)



Implicit Regional Price Deflator: All regions show a notable increase post-COVID, signaling inflationary pressures, with the highest rise observed in the West. This suggests that the purchasing power of consumers has decreased as prices have risen.
Per Capita Disposable Personal Income: Mixed trends post-COVID across regions, indicating varying financial health, with some experiencing increases (e.g., Southeast) and others decreases

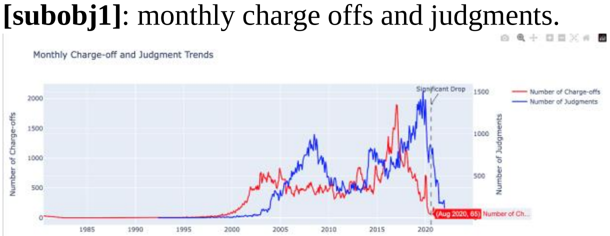
(Northeast, West). The impact of this could be observed in the significant slowdown in payment frequency in Northeast Region post-COVID.

Per Capita Personal Consumption Expenditures: Similar mixed trends post-COVID, with some regions seeing more consumer spending (Southeast) and others decreases (Northeast).

Total Employment (Number of Jobs): General increase post-COVID across all regions, highlighting labor market recovery, with Southeast notably experiencing significant job creation.

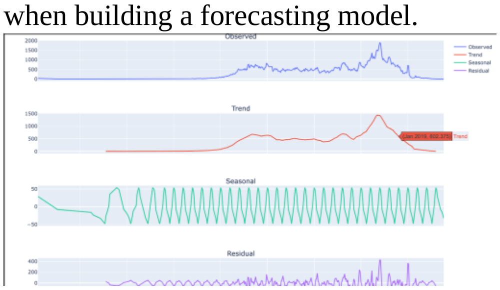
Time Series Analysis: (Observe trends in Pre and post COVID 19) [Python for analysis and matplotlib + plotly for visualization]

[subobj1]: monthly charge offs and judgments.



The plot highlights a significant drop around Aug 2020, which we found similar observations in [17]

II) Seasonal Decomposition: It allows us to account for and explicitly model the components when building a forecasting model.



Observed: The actual data collected over time.

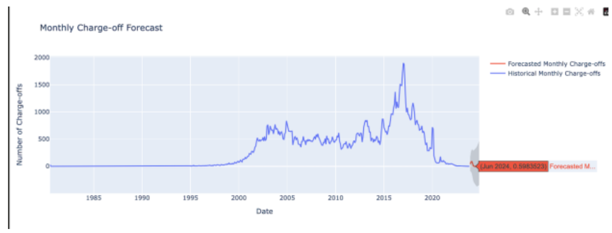
Trend: The long-term progression of the series, showing movements that are not due to seasonality or irregular factors. This is usually smoothed to highlight underlying trends in the data.

Seasonal: The repeating short-term cycle in the series. This captures the regular pattern that occurs at fixed intervals - daily, monthly, or quarterly.

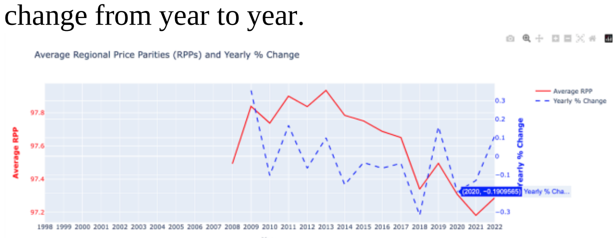
Residual: The remainder of the time series after the trend and seasonal components have been removed. This shows irregular effects that are not attributed to the seasonality or the trend and can sometimes be thought of as "noise."

III) SARIMA - for forecasting future charge-offs. SARIMA is particularly suited for data with trends and seasonal patterns, making it a good fit for this analysis. This step requires identifying the optimal parameters for the SARIMA model. This process involves understanding the order of seasonality (S), autoregression (AR), differencing (I), and moving average (MA) components.

1st Iteration – overfitting (Appendix 5)
2nd Iteration- adjust parameters (after dicky-fuller-test) (Appendix 6)
3rd-Iteration – successful forecast



[subobj2]: **average cost of living (using RPP).** The plot below visualizes the trend of Average Regional Price Parities (RPPs) over time alongside the yearly percentage change, indicating fluctuations in RPP values and their rates of change from year to year.



Structural Break Analysis (Chow Test) – Appx. 7

CONCLUSIONS AND DISCUSSION

Our project arrive at several notable insights. Our models for primary objectives show, as expected, that the sooner an account receives a judgment, the more likely repayment from that given consumer. This tie in with those accounts purchased as Suit, which are designated to be placed out to law firms in shorter timeframes, to receive judgments and promptly be collected on. Surprisingly, accounts with charge-offs between $20k-$40k had a higher success rate, possibly due to this range coinciding with average student loan debt, and federal loans: loans for which one is unable to default on or file bankruptcy, are thus more likely to be repaid.

The AUC of 0.99 for subobjective 1 suggests a potential error or bias within our model, warranting further analysis. Accounts with average payment-to-judgment ratios close to 1 were the highest in being paid off, suggesting that either: 1. creditors are willing to settle for smaller amounts as time goes on, or that 2. the amount of interest that accumulates over time dramatically affects the amount a consumer has to repay incrementally. Concerning subobjective 2, the sudden dropoff in charge-off and acquired judgments was expected due to a potential lag within the court system following COVID-19, The weak correlation between macroeconomic and account-level data was surprising, possibly limited by the lack of data for 2023-2024. Nevertheless, there was some correlation visible when observing southern states, where job growth coincided with reduced average payment days post-COVID, suggesting consumers within these states may have been able to repay their debts following the acquisition of a new job. Overall, we consider this project highly successful, with equal contributions from all team members. We believe our findings pave the way for future analytical exploration in this industry.

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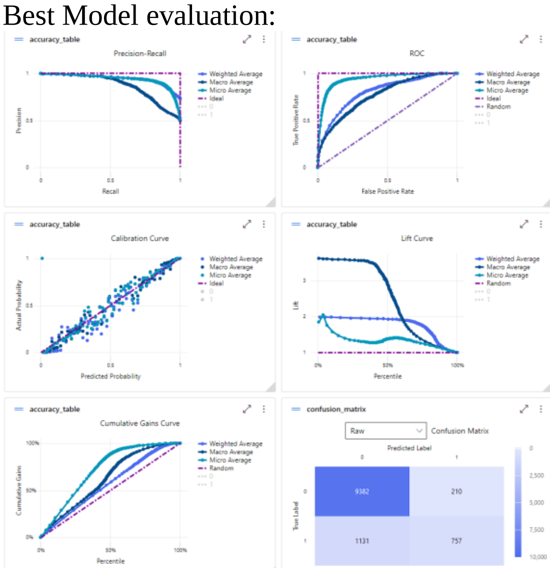
Appendix 1 – other models trained and description

XGBoostClassifier: uses optimized distributed gradient boosting; LightGBM: is also gradient boosting but uses tree-based learning algorithm; Logistic Regression: uses a statistical approach. Scalers and Normalizers are also used to further scale/ standardize/ transform features to fit each model. They include Max Abs Scaler, Standard Scaler Wrapper, and Sparse Normalizer.

Appendix 2 – obj1 Top 10 model results

Algorithm name	AUC weighted ↓
VotingEnsemble	0.84798
StackEnsemble	0.84770
SparseNormalizer, XGBoostClassifier	0.83753
StandardScalerWrapper, XGBoostClassifier	0.83651
StandardScalerWrapper, XGBoostClassifier	0.83640
MaxAbsScaler, XGBoostClassifier	0.83550
SparseNormalizer, XGBoostClassifier	0.83248
MaxAbsScaler, LightGBM	0.83211
SparseNormalizer, XGBoostClassifier	0.83176
StandardScalerWrapper, XGBoostClassifier	0.83108

Best Model evaluation:

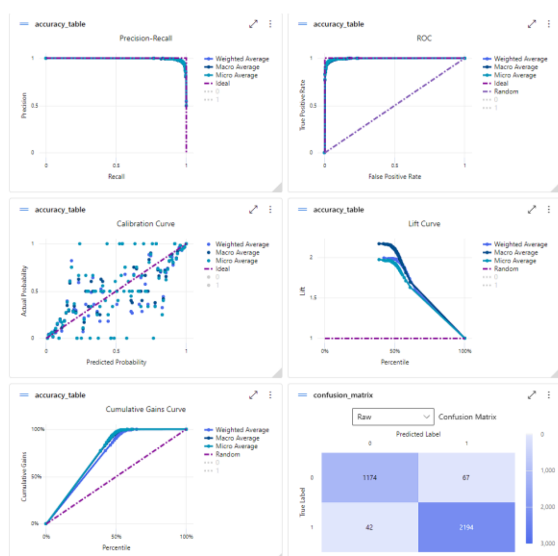


accuracy	AUC_macro	AUC_micro	AUC_weighted	average_precision_sco...	average_precision_sco...	average_precision_sco...	balanced_accuracy	f1_score_macro
0.8831882	0.8479758	0.9400882	0.8479758	0.8042139	0.9374912	0.9083687	0.6895301	0.7317989
f1_score_micro	f1_score_weighted	log_loss	matthews_correlation	norm_macro_recall	precision_score_macro	precision_score_micro	precision_score_weigh...	recall_score_macro
0.8831882	0.8670224	0.3083876	0.5059262	0.3790601	0.8376262	0.8831882	0.8743965	0.6895301

Appendix 3 – subobj1 Top 10 model results

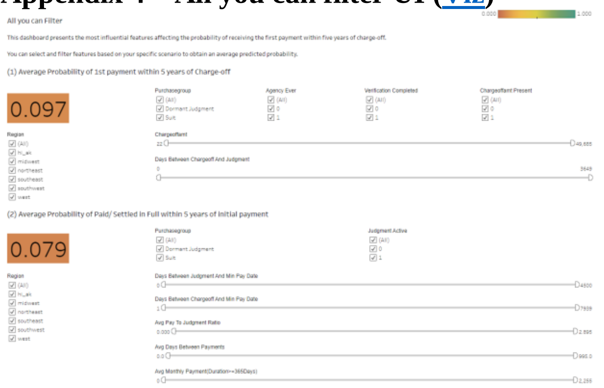
Algorithm name	AUC weighted ↓
VotingEnsemble	0.99523
StackEnsemble	0.99511
MaxAbsScaler, XGBoostClassifier	0.99474
StandardScalerWrapper, XGBoostClassifier	0.99469
StandardScalerWrapper, XGBoostClassifier	0.99463
MaxAbsScaler, LightGBM	0.99459
MaxAbsScaler, LightGBM	0.99447
StandardScalerWrapper, XGBoostClassifier	0.99424
StandardScalerWrapper, XGBoostClassifier	0.99330
MaxAbsScaler, LightGBM	0.99312

Best Model evaluation:

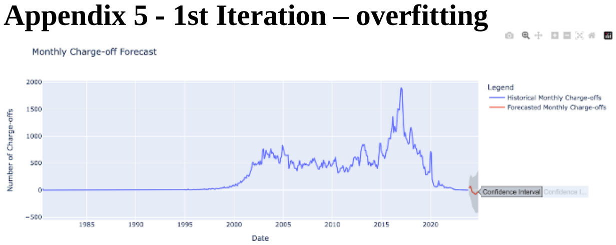


accuracy	AUC_macro	AUC_micro	AUC_weighted	average_precision_sco...	average_precision_sco...	average_precision_sco...	balanced_accuracy	f1_score_macro
0.9686511	0.9952347	0.9954254	0.9952347	0.9945571	0.9955106	0.9953673	0.9636139	0.9656993
f1_score_micro	f1_score_weighted	log_loss	matthews_correlation	norm_macro_recall	precision_score_macro	precision_score_micro	precision_score_weigh...	recall_score_macro
0.9686511	0.9685788	0.08641225	0.9315178	0.9272277	0.9679138	0.9686511	0.9686159	0.9636139

Appendix 4 – All you can filter UI (Viz)



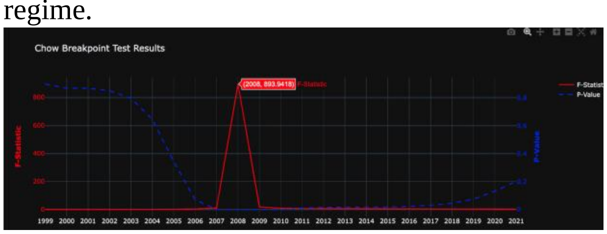
Appendix 5 - 1st Iteration – overfitting



Appendix 6 - 2nd Iteration- adjust parameters (after dicky-fuller-test)

Appendix 7 - Structural Break Analysis (Chow Test)

used to determine if there is a point in time where the statistical properties of a time series change significantly. This is often indicative of a fundamental shift in the data-generating process, such as a change in policy or an economic regime.



Looking at the provided plot, there is a prominent peak in the F-Statistic around the year 2008, suggesting a significant structural break in that year. Given that the corresponding p-value is likely below the common significance threshold (which is typically 0.05 or 5%), we can conclude that there is strong statistical evidence of a structural break in the time series around 2008(The Great Recession).