Transforming Complaints into Strategy: Empowering Business Decisions through Visualization of Financial Complaint Insights

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INTRODUCTION & PROBLEM DEFINITION

Our goal was to transform the way consumer finance complaints from the Consumer Finance Protection Bureau (CFPB) database are visualized, understood, and addressed. Using Tableau, Python, and R, we highlight patterns and trends in customer complaints, predict future complaint trajectories, and offer actionable insights and areas for improvement. We have also added data from the 2020 US Census to make our insight more specific to demographics around the US.

The CFPB's current method of categorizing complaints by product and issue, while useful, lacks depth. It provides insights on complaint volume and category, but it fails to provide a comprehensive analysis of complaint narratives alongside demographic and external event data. Our goal is to provide a more nuanced and insightful analysis of consumer complaints.

LITERATURE SURVEY

Gimpel, Haendler and Heimer mapped zip code data with US demographics to highlight patterns for specific categories of complaints in low-socioeconomic neighborhoods [5,6] and identified patterns in outcomes, but focused on smaller subsets of complaint types. Kesari identified the effect of new legislation on consumer complaints [8], but filtered patterns on only keywords in complaint narratives. These studies are limited to visualizing narrow trends in a filtered dataset.

Incorporating the GIS-based approach used by Sigal Kaplan [10] into our visualization can benefit stakeholders such as the CFPB and financial institutions. Our research approach integrates advanced text analysis [15], predictive analytics, sentiment analysis [9,15], and demographic data integration [14] to enhance the understanding of consumer complaints in financial services. By drawing on techniques from key studies, we aim to uncover demographic patterns, complaint topics, and resolutions, thereby providing a detailed and nuanced view of consumer experiences [16,9].

Starting with text analysis and topic modeling, we build upon the work of Alghamdi et al. [14], focusing on sentiment assessment and growth analysis. Their findings underscore the insights to improve consumer protection. We extend this by incorporating Spark-NLP for efficient text mining, as demonstrated by Kuilboer and Stull [7], and enhancing topic modeling through BERT-based embedding, a method shown by S. Vasudeva Raju and colleagues [13] to improve topic coherence and diversity significantly. We can gain insights on even short text clustering [1, 18] where words are generally expected to only show up once in a sentence or two.

Predictive analytics allows for the proactive identification of emerging trends and sourcing of insights to create timely interventions by financial institutions and regulators, via methods like Holt-Winters and ARIMA [12]. This forward-looking analysis will be informed by current gaps in sentiment analysis within the CFPB's practices. We propose to expand on the work of Medhat et al. [17], on product review analyses by applying Aspect-Based Sentiment Analysis [11] to our dataset. This method, which identifies the main object of a complaint and the associated emotion, will help address specific challenges, such as differentiating degrees of frustration among complainants while attempting to address challenges seen in this approach [3].

Our analysis also incorporated demographic data to explore financial services across diverse groups. Following Taylor et al.'s [15] use of linear regression to link demographic characteristics with service quality, we will delve deeper into how themes from complaints relate to consumer satisfaction, taking into account demographic factors similar to [4].

PROPOSED METHOD

Intuition for our approach: The current state of CFPB's website includes low level state-wide, product-wide, and sub-product-wide visualizations. This data delivery should be improved because of what we see in the results, that complaints are forecasted to increase. The system should become better than the current state of the art in order to proactively reduce the number of registered complaints, rather than just more effectively address complaints after they have been registered.

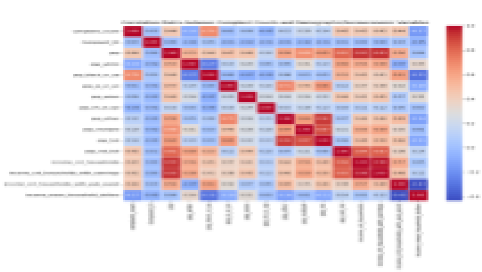
Our approach gives a unique insight into how demographics and socio-economic conditions of different areas affect consumer satisfaction and helps predict their progress in the future, packaged in an interactive visual analytics tool on narratives and complaint data that was not previously available, allowing for policymakers, financial institutions, and other players to generate actionable insights from the complaints data.

The algorithms and user interface will be described in detail in the Experiments section.

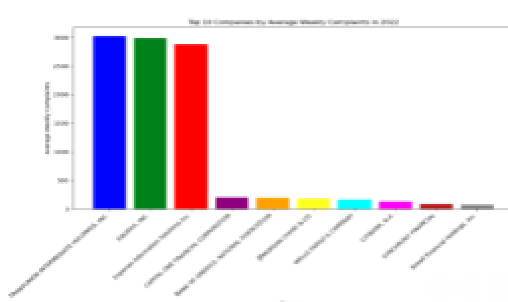
APPROACH & EXPERIMENTS

Data : Complaint data from 1/1/2018 through 12/31/2022 from the CFPB public dataset, (2) 2020 Decennial Census data from the US Census Bureau, and (3) United States Zip Codes.

Exploratory Data Analysis (EDA) : We performed a detailed analysis of complaints, pinpointing zip codes and states with the highest volumes. We analyzed company responses to consumer complaints, categorizing and summarizing the types of responses provided, calculated correlations between complaint counts and various demographic factors (e.g., population demographics and income levels) to identify trends and significant predictors.



Correlation between complaint count and regional census demographic and socioeconomic attributes

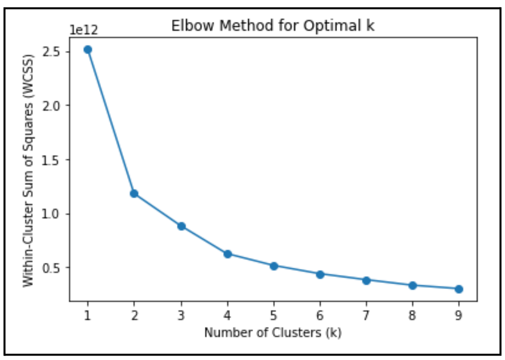


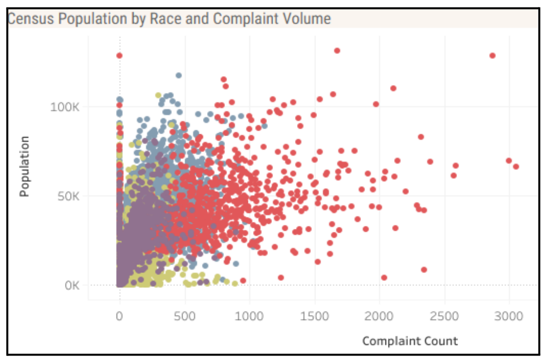
Companies with highest complaint volume

Data Cleaning : The final dataset is CFPB complaint data filtered to include responses from 2018 to 2022 for two reasons: (1) the decennial census data in 2020 is centered in that period, and (2) the CFPB altered how they collected data in both 2017 and 2023. We created geographic layered visualizations based on zip code and found that not all zip codes in the CFPB dataset were correct or complete. We validated against US standards and rolled up to state regional areas for visualization.

Clustering Model: We performed clustering analyses on demographic and complaint attributes by employing KMeans clustering to group zip codes and complaint types. The optimal number of clusters was determined using the elbow method. Similarly, clustering among attributes for race population and complaint volume alongside state and zip codes identified clusters with the highest complaint counts. The elbow method determined k=4 best for clustering.

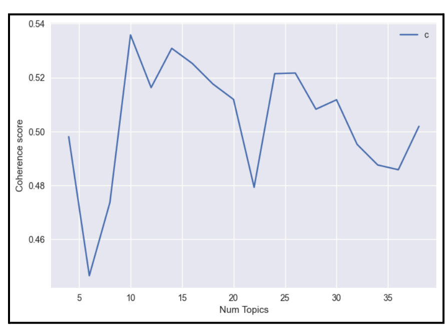
To standardize numerical features and encode categorical features we implemented a preprocessing pipeline, ensuring proper data preparation. Established a clustering pipeline integrating preprocessing steps and KMeans clustering with respective cluster sizes. Upon fitting the pipeline to the merged dataset, assigned cluster labels to each data point and generated cluster summaries by calculating various statistics. Identified the most common product and state within each cluster using the mode() function.





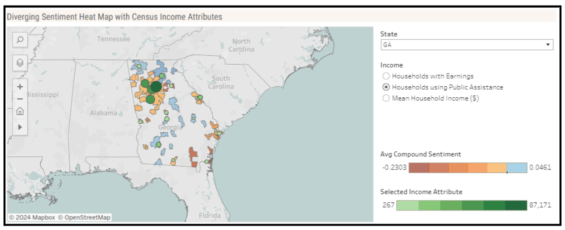
Cluster 0 is urban communities with a high white population, moderate complaint volume whereas and concentration of complaints in CA and in MD zip code 21144. Cluster 1 is suburban areas with higher complaint counts compared to Cluster 0 and a moderate population diversity. Complaint issues predominantly observed in CA. Cluster 2 is rural regions with lower population density and diversity, indicating potentially lower community engagement. Cluster 3 is high-populated urban areas with a significant African American population, concentrated in GA, demonstrating the highest complaint counts among all clusters, notably PA zip code 19050.

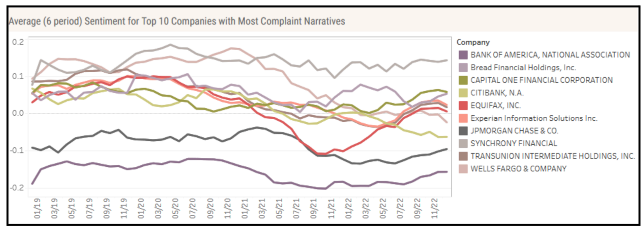
Sentiment Analysis: Modeling topics were done using Latent Dirichlet Allocation (LDA) model. The best model was picked using a coherency score for all models by varying the number of topics. A compound sentiment score computed for each narrative based on the VADER Sentiment analysis. Furthermore, we examined correlations between complaint sentiment scores and demographic and socioeconomic factors.The line chart below provides a visualization of how



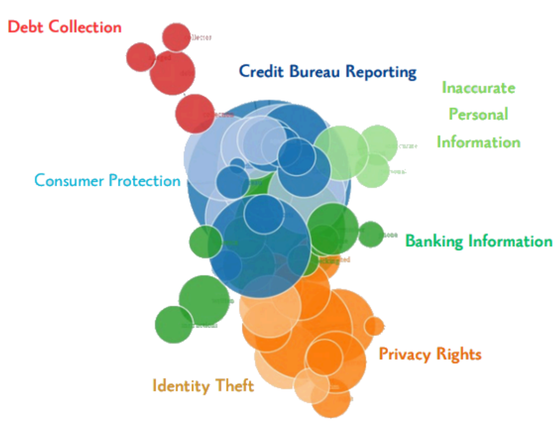
sentiment in the complaints changes over time for the 10 companies that received the greatest number of complaints.

It is notable that a large portion of the complaints with negative sentiments are from areas that received public assistance. This possibly indicates that a disproportionate number of people from lower economic backgrounds are affected by actions of financial companies and credit reporting agencies. Also, analyzing the trends of complaints shows a steep decline in sentiment for Equifax in 2022, as data leaks became public.

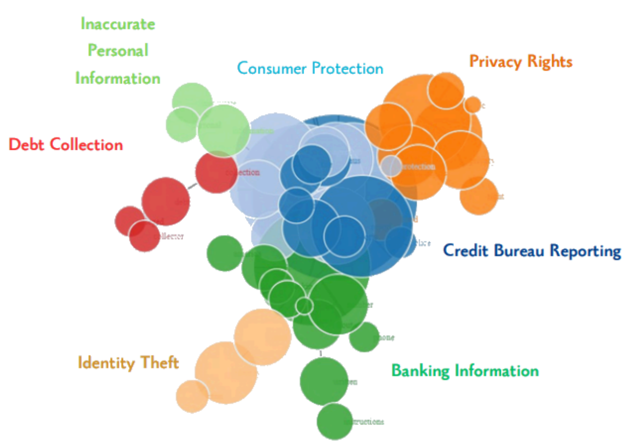




Narrative Structure: For narrative clustering, we have a bigram network graph showing top complaint structures. 20% of complaints were duplicates, unusual for free form text data. We speculate consumers are reporting through financial aid agencies who submit complaints using narrative templates. Running models with narrative duplicates included (DI) represents the real weight of all complaints as entered, and de-duplicated complaints (DD) shows the true free-form sentence structure. Louvain detected 7 communities for both structures: Credit Bureau Reporting, Consumer Protection, Privacy Rights, Identity Theft, Banking Information, Inaccurate Personal Data, and Debt Collection. The most noticeable visual difference between the two is between the Privacy Rights and Identity Theft clusters, heavily connected in the DI run, and separate in the DD run.



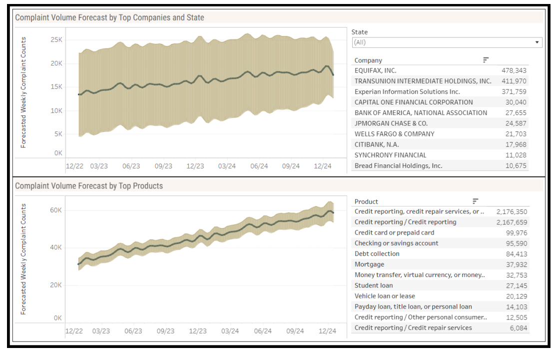
Duplicate Included Sentence Structure



De-Duplicated Sentence Structure

Time Series Forecasting : We experimented with ARIMA, SARIMAX, and Facebook Prophet, achieving best results with Facebook Prophet for time series analysis, which is ideal for handling daily, weekly, and yearly seasonality along with holiday effects making it particularly suited for non-stationary data like consumer complaints. We ran complaint forecasts across the entire dataset by company across all states and across all products.

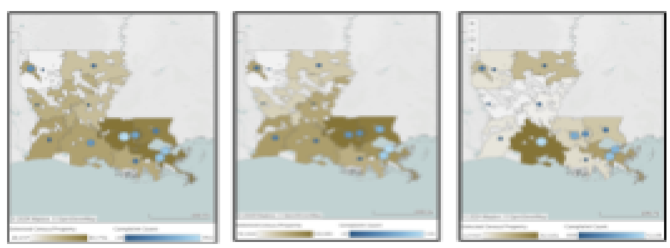
Forecasted trends provided by Facebook Prophet models show a clear upward trajectory. The forecasts show a steady increase in complaints through 2023 and 2024, with regular seasonal fluctuations but no signs of overall decline. From our forecasts by Products, mortgage and debt collection grievances are expected to decline, and student loan complaints will remain below their 2022 peak.



Forecasting Optimization and Evaluation :
Models were tuned adjusting hyper parameters for number and flexibility. Cross validation withheld a prior year of data for 2022 and compared predictions to actual values. Best performing model had the lowest RMSE, MAE and MSE.Furthermore, the Root Mean Squared Error, now at approximately 2155.42, indicates that the forecasted values are, on average, within this deviation from the observed values

The forecast approach yielded key predictions for 2023-2024 including (1) a clear upward trajectory for most categories of complaints, (2) expected highest complaint volume by company (Equifax, Transunion, and Experian), and (3) a list of the classes of complains that will increase the most (credit reporting) and the least (mortgage and debt collection complaints).

Interactive Visualization : We published an interactive dashboard on Tableau Public, named Complainalyzer, with six interactive pages: EDA exploratory graphs for complaint and census data, a heat map layering complaints and census attributes, a bar chart race to see complaint type changes over time, forecasting results by company and product, clustering results with geographic and scatterplot census comparison, and narrative analysis with sentiment comparisons across companies and zip code regions. Data was loaded from summarized EDA and modeling result files and joined in Tableau on matching zip code columns. Varying data file row granularity was addressed using attribute functions in Tableau to properly summarize for each visualization. Each section has interactions with census and complaint data, allowing users to explore all results in a single tool.



Louisiana Heat Map of (1) Mean Household Income with Debt Collection Complaints, (2) Mean Household Income with Mortgage Complaints, and (3) Households with Public Assistance Income with Credit Reporting Complaints

EVALUATION

The primary question to be evaluated for our project is the usability and usefulness of our visualization tool, the Tableau Complainalyzer, and its usefulness for generating actionable insights. This tool would be aimed at CFPB executives, policymakers, and employees of financial institutions (getting their feedback was outside the scope of this project), however per our qualitative analysis of the results it is a success. The tool successfully incorporates all of the methods mentioned above, and provides insights at each step of the process, as described in the prior EXPERIMENTS section.

CONCLUSIONS AND DISCUSSIONS

The motivation for this project was to generate learnings that would help financial institutions better serve their customers, via actionable learnings. As shown in the visualization tool, some of the most important findings are as follows:

- The total number of complaints is expected to increase ~40% in 2023, indicating that financial institutions have work to do to get in front of the problems.
- Credit reporting complaints will both increase the most in 2023, and be the most common class of complaint, as Credit bureaus like Equifax, Transunion, and Experian will receive the lion's share of the complaints.
- Co-occurence of complaints is common due to form complaints covering multiple topics per complaint. It is a possibility that agencies are submitting complaint templates, artificially driving complaint topics into less unique, more overlapping complaints.
- Companies like Bank of America have had consistently negative complaints, while others like Equifax are shown to be able to recover from periods of extra negative complaints, and have the opportunity to tighten the relationship with their customer base.
- Widespread instances of "Incorrect information on your report" across multiple states such as California, New York, and Georgia highlight the growing need for improving credit reporting accuracy.
- The prevalence of debt-related notifications, particularly in densely populated urban areas like zip code 10001 in Manhattan, New York City, highlights the importance of resources for debt management, as do the high level of mortgage-related complaints in urban communities specifically seen in south LA.

We are pleased that our analyses have identified so many learnings, and we encourage the reader to dig into our visualization tool to find more him/herself.

BUILDING ON OUR WORK

Going forward, we believe there is more work to be done connecting the complaints to data tables outlining economic data, looking at what context surrounds complaint spikes such as interest rate changes or data leaks. We would use our LDA in conjunction with our sentence structure to find the best number of clusters between the two analysis methods. We would also have liked to explore more time series combinations to determine which shows the highest certainty for predicting future complaints, for example, complaint volume by product has much smaller confidence intervals than complaints by top company and state, but is it the very best combination? Applying variable selection may be the best way to determine which attribute of the complaint best predicts the complaints.

ACTIVITIES

All team members have contributed a similar amount of effort to the project to date.

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