FeedViz: Visualizing Automated Insights from Customer Feedback through NLP Techniques

Maham Mukaram
University of Toronto
Toronto, Canada
maham.mukaram@mail.utoronto.ca

ABSTRACT
This research introduces FeedViz, a groundbreaking system designed to automate the analysis and visualization of customer feedback using advanced Natural Language Processing (NLP) techniques. FeedViz employs a systematic four-step methodology that begins with Semantic Chunking, utilizing SpaCy for precise sentence segmentation, followed by Sentiment Analysis using the specialized Twitter-roBERTa-base model. The third step involves Topic Modelling with CorEx, a flexible algorithm adept at handling short texts and multi-domain reviews, enabling the identification of key themes and topics across different sentiments. The final component of FeedViz is an Interactive Visualization dashboard built with Dash and Plotly. This user-friendly interface allows stakeholders to explore sentiment-specific treemaps, sentiment distribution bar graphs, and yearly progression histograms, facilitating a comprehensive understanding of customer sentiment and preferences. FeedViz not only streamlines the process of extracting actionable insights from customer reviews but also enhances the overall accuracy and efficiency of customer feedback analysis. By empowering businesses with valuable insights, FeedViz aims to drive improvements in product quality, customer satisfaction, and overall business performance.

Author Keywords
Visualization; Semantic Chunking; Sentiment Analysis; Topic Modelling; Customer Feedback.

INTRODUCTION
In the era of digital transformation, businesses are inundated with vast volumes of customer feedback across various platforms. Understanding this feedback is paramount for driving improvements in product quality, enhancing customer satisfaction, and ultimately, boosting business performance. Traditional methods of analyzing customer feedback often involve manual processing, which is time-consuming, subjective, and prone to errors. With the advent of advanced Natural Language Processing (NLP) techniques, there has been a paradigm shift towards automating the analysis of customer feedback, offering businesses the opportunity to extract actionable insights more efficiently and accurately.

This research paper introduces FeedViz, an innovative system meticulously designed to automate the analysis and visualization of customer feedback. FeedViz leverages cutting-edge NLP techniques to transform the way businesses interpret customer sentiments and preferences. The system employs a systematic four-step methodology, starting with Semantic Chunking using SpaCy for precise sentence segmentation, followed by Sentiment Analysis utilizing the specialized Twitter-roBERTa-base model. The third step involves Topic Modelling with CorEx, a flexible algorithm adept at handling short texts and multi-domain reviews. Finally, FeedViz offers an Interactive Visualization dashboard built with Dash and Plotly, empowering stakeholders to explore sentiment-specific treemaps, sentiment distribution bar graphs, and yearly progression histograms.

By streamlining the process of extracting actionable insights from customers feedback, FeedViz aims to revolutionize the way businesses harness the power of customer feedback. This research paper provides an in-depth exploration of the methodologies and technologies underpinning FeedViz, demonstrating its efficacy through a comprehensive analysis of Amazon product reviews for the Amazon Fire Tablet.

The contributions of this paper include:

1. Introducing a three step NLP based approach to extract sentiment-based themes from reviews with minimal human input.
2. Presenting an interactive visualization dashboard for extracting actionable insights from customer feedback.

RELATED WORKS
This section should discuss the prior studies in the following four categories:

Semantic chunking: This involves identifying and grouping words or phrases that convey coherent meaning within a sentence or larger text. Previous studies have explored various methods for semantic chunking, ranging from rule-based approaches [1], to machine learning-based techniques [2]. Techniques using natural language processing tools like SpaCy [4] and NLTK [3] have been employed to segment text into coherent and meaningful chunks. The Langchain Character Text Splitter [5] works by recursively dividing the text at specific characters. It is especially useful for generic text and leads to a much more concise density of cluster lengths.

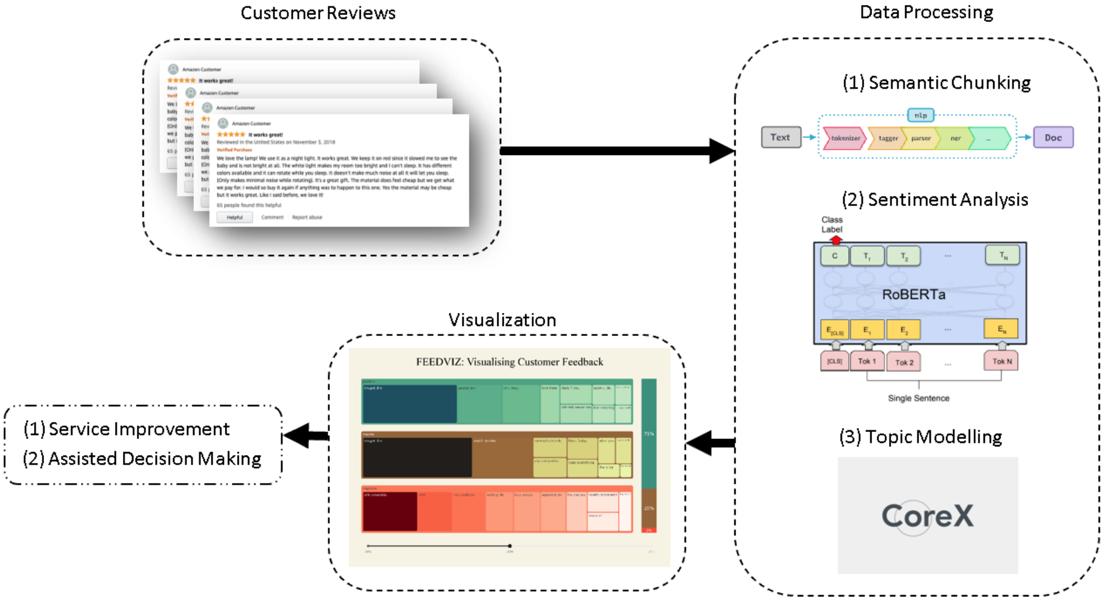

Figure 1. FeedViz approach pipeline consisting of three steps within data processing to extract sentiment-based key themes from customer reviews. These are then visualized in FeedViz dashboard to extract actionable insights.

The SpaCy library has been used in this research to gain complete and coherent semantic review chunks.

Sentiment analysis: This has been a widely researched area, especially in the context of analyzing feedback data. Libraries such as TextBlob [6] and Vader [7] are good launching points when it comes to sentiment classification. Flair [8] comprises popular and state-of-the-art word embeddings and is popular in sentiment prediction. Zero-shot classification models have also risen in popularity due to their high accuracy in sentiment prediction. The Twitter-roBERTa-base model [9] used in this research has been specifically fine-tuned for sentiment analysis, leveraging the unique characteristics of tweet data to enhance accuracy.

Topic modelling: This method has been extensively used to identify and extract thematic information from text. Methods such as Latent Dirichlet Allocation (LDA) [10] and CorEx [11] have been employed to uncover latent topics and themes within large sets of reviews (Brown et al., 2017). While LDA relies on a probabilistic generative model, CorEx offers a more flexible approach, capable of handling short texts and multi-domain reviews without making strong assumptions about the underlying data generating process.

Visualization of Feedback Data: Visualization plays a pivotal role in presenting feedback data in an understandable and actionable manner. OpinionSeer [12] and Oelke et al. (2009) [13] both introduce innovative ways to visualize customer feedback. Li et al. (2022) [14] inspired the treemap design in FeedViz. While the paper's approach offers valuable insights, it is domain-specific and may not be well-suited for analyzing customer feedback across multiple products on platforms like e-commerce websites, as it requires extensive human input for each domain-specific model.

APPROACH

FeedViz employs a systematic pipeline consisting of four main steps: Semantic Chunking, Sentiment Analysis, Topic Modelling, and Visual Design. Each step is meticulously designed to address specific challenges in processing and interpreting feedback data, ultimately culminating in an interactive visualization dashboard that facilitates intuitive exploration and understanding of customer sentiment and preferences.

Semantic Chunking

The primary objective of this phase is to segment reviews into coherent and complete semantic chunks, thereby facilitating focused analysis and interpretation of the customer feedback. The SpaCy library uses a dependency parser for accurate and context-aware sentence segmentation. This approach ensures that the syntactic and semantic integrity of the original text is preserved, allowing for a more precise analysis of individual opinions and sentiments within the reviews.

Following segmentation, sentences are transformed into numerical vectors using SpaCy's embeddings. This transformation captures the nuanced semantic relationships between words and phrases. Cosine similarity is then used for grouping adjacent sentences with high semantic similarity. By setting a cosine similarity threshold of 0.6, a balance is struck between granularity and coherence, ensuring that the resulting chunks are neither too fragmented nor overly broad. Additionally, length filtering is applied to further refine the chunks, maintaining consistency in chunk size and enhancing the interpretability of the subsequent analysis. This comprehensive approach to semantic chunking ensures that the segmented chunks are coherent and representative, laying a solid foundation for the subsequent steps of sentiment analysis and topic modeling.

Sentiment Analysis

The objective of this phase is to categorize semantic chunks into distinct sentiments. The Twitter-roBERTa-base model is meticulously selected for this task. This choice is predicated on the model's proven efficacy in handling informal and opinionated text, which closely mirrors the nature of customer reviews. Furthermore, the model's fine-tuning on tweet data equips it with the capability to discern and capture the subtle nuances of sentiment prevalent in customer feedback, thereby augmenting the accuracy and reliability of sentiment labeling.

By systematically assigning sentiments—be it Positive, Neutral, or Negative—to the semantic chunks, the analytical framework gains structural clarity. Doing topic modelling separately for reviews in each sentiment ensures a more accurate extraction of key themes. Therefore it is necessary to divide the reviews based on the sentiment they reflect before moving on to theme extraction.

Topic Modelling

The principal objective of this phase in the project is to extract and categorize key themes from sentiment-labeled semantic chunks, thereby revealing common subjects that are frequently discussed within the reviews.

In the pursuit of this objective, the selection of CorEx as the preferred model over LDA is underpinned by CorEx's intrinsic capability to identify "maximally informative" topics without imposing rigid or restrictive assumptions. This inherent flexibility of CorEx proves to be particularly advantageous when analyzing short and diverse reviews. Unlike predefined topic structures that might fail to capture the nuanced complexity and variability inherent in customer feedback, CorEx adapts dynamically to the inherent intricacies of the data, ensuring a more accurate and insightful topic extraction process.

Furthermore, the determination of the optimal number of topics is guided by the method of observing the Total Correlation (TC) distribution within CorEx. This approach to topic selection is instrumental in ensuring that the number of topics encapsulates the most significant and distinct themes resonating within the reviews. This precision in topic selection enhances the relevance and interpretability of the extracted topics. CorEx's capability to map semantic chunks to multiple topics through a one-to-many mapping approach proves invaluable. For example, a review chunk such as, ‘The product was great quality and was inexpensive’, should ideally fall under both the ‘Quality’ and ‘Price’ themes, which is a requirement met by CorEx.

The major theme is then extracted from the keywords and phrases associated in each topic, based on occurrence using the bag of words approach. Each sentiment therefore has corresponding clusters of reviews semantically chunked having common major themes.

Visualization

The ultimate objective of this phase in the project is to visually represent the sentiment distribution and extracted themes in an interactive and intuitive manner. The project leverages the combined capabilities of Dash and Plotly to develop a dynamic and user-friendly visualization platform. Dash's proficiency in creating interactive web applications seamlessly integrates with Plotly's versatile visualization options, enabling the design and implementation of visually captivating and informative displays that cater to a wide range of user needs and preferences.

In terms of design elements, the utilization of treemaps serves as a cornerstone for providing a hierarchical visualization of sentiments and themes. This structured representation facilitates a layered exploration of review insights, aiding in the identification of sentiment-specific themes. Additionally, the incorporation of a bar graph offers a succinct overview of sentiment distribution across reviews. This graphical summary serves as a quick reference point for understanding the overall sentiment trends. The integration of a year slider further enriches the visual experience by enabling users to filter reviews based on the year of receipt. This feature fosters temporal analysis, facilitating performance tracking over time.

Interactive pop-up windows complement the visualization platform by offering users a detailed view of reviews corresponding to selected themes and sentiments. This feature not only enhances user engagement but also facilitates deeper exploration of specific topics or issues, fostering a more comprehensive understanding of customer feedback. Lastly, the inclusion of yearly progression histograms below the review lists serves to visualize the temporal evolution of each theme. These histograms highlight evolving trends and patterns over time, providing businesses with the visual temporal context required to track performance, measure the impact of interventions, and proactively identify emerging issues or opportunities. Collectively, these visualization elements contribute to creating an interactive and intuitive platform that empowers businesses to derive actionable insights from customer feedback, driving continuous improvement and enhancing customer satisfaction.

USE CASES

In Figure 1, we employ FeedViz to analyze and visualize Amazon product reviews for the Amazon Fire Tablet spanning the years 2015, 2016, and 2017. The primary objective is to demonstrate how interactive visualization tools integrated within FeedViz can facilitate comprehensive analysis, enabling users to derive actionable insights from customer feedback. The dataset utilized in this study comprises of reviews for the Amazon Fire Tablet, sourced from a public Kaggle dataset. To achieve the visualization objectives, the study leverages a suite of visualization tools integrated within FeedViz .

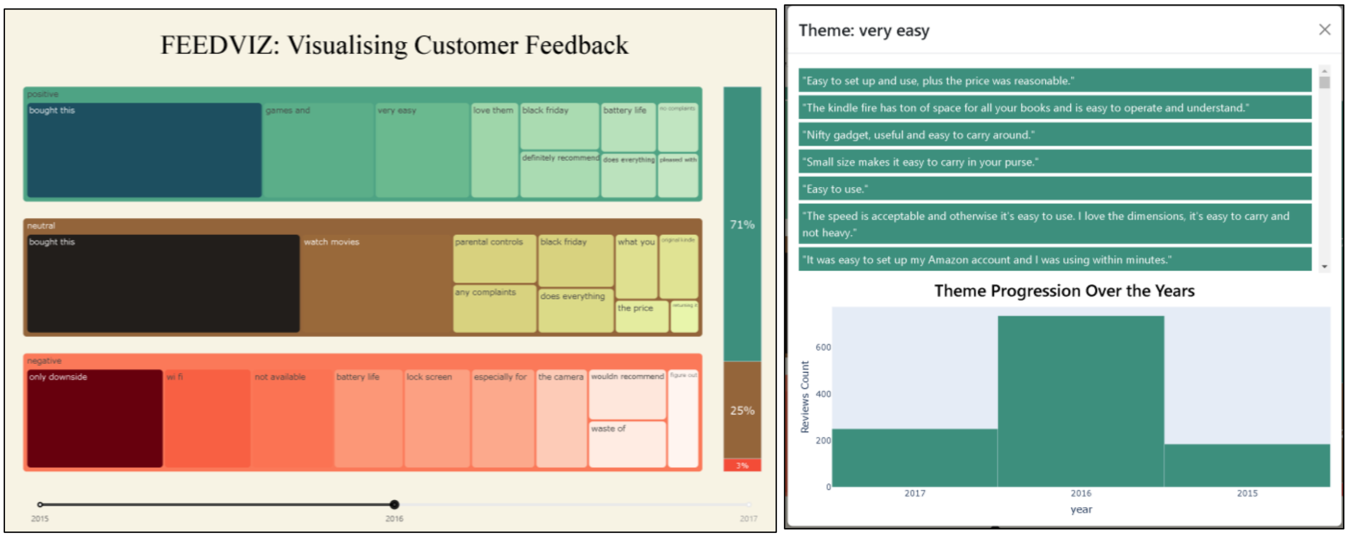

Figure 2. FeedViz layout for reviews pertaining to Amazon Fire Tablet. (Left) The main FeedViz dashboard consisting of sentiment based Treemaps with Major themes extracted from the reviews as elements of the treemaps. The Bar graph indicates a percentage breakdown of the number of reviews in each corresponding Sentiment label. The Slider provides filtering option with respect to the year the review was received. (Right) The pop-up window that opens upon clicking the 'very easy' theme of the positive sentiment treemap (as reflected by the colours used in the pop-up window). This window consists of a list of reviews specific to the selected theme within the selected sentiment treemap. Below is a histogram that provides a yearly analysis of the theme.

In Figure 1(left), we see this data mapped onto the main FeedViz dashboard. The year slider enables users to visualize changes in sentiment distribution across the selected years, 2015, 2016, and 2017. Concurrently, the bar graph provides a graphical summary of sentiment distribution, facilitating the identification of fluctuations in sentiment levels over time. Treemaps serve as a pivotal tool for hierarchical visualization of sentiments and themes. Through the treemaps, users can track the prevalence and importance of major themes associated with each sentiment across the years. Users can track which yearly promotions or campaigns worked well or which didn't based on the change in major themes within the sentiments over time. They can also discern which themes had the most impact within a sentiment based on the area they cover. The sentiments behind product updates can also be tracked well. This comprehensive approach ensures a nuanced understanding of the review landscape, fostering informed decision-making beyond just the overall sentiment.

Furthermore, the interactive nature of treemaps allows users to click on individual themes to within a sentiment and gain further knowledge on them through a pop-up window [Fig. 1(right)]. Users can delve deeper into the specific reasons underlying the emergence of particular themes within the respective sentiments. The interactive pop-up windows display a detailed list of reviews corresponding to selected themes and sentiments, enabling users to discern context and specific reasons for the emergence of themes. This feature also allows users to pinpoint sub-themes or specific aspects discussed within broader themes, offering a deeper understanding of customer feedback. The reviews list also further enhances the reliability of insights by enabling users to verify the correctness and accuracy of the visualizations through cross-referencing with the actual data. By examining the reviews listed in the pop-up windows, users can distinguish between valid and useful reviews, ensuring that the analysis is grounded in genuine and relevant customer feedback. Additionally, the yearly progression histograms visualize the temporal evolution of each theme, highlighting evolving trends and patterns over time. Through analysis of these progressions, users can predict which measures or interventions may have influenced the theme's progression and customer sentiment effectively.

LIMITATIONS AND FUTURE WORK

Despite the remarkable advancements in Natural Language Processing (NLP) techniques, understanding the intricacies and nuances of human language continues to pose significant challenges. Ambiguity, sarcasm, and context-dependent meanings inherent in human communication can complicate the accuracy and reliability of sentiment analysis and theme extraction algorithms. These complexities can potentially lead to misinterpretations of customer feedback, thereby impacting the precision of insights derived from such analyses. Another limitation of the current system lies in its limited filtering options and scalability. While the system offers comprehensive visualization tools and features for analyzing and interpreting customer feedback, it may lack robust filtering mechanisms to handle large datasets efficiently. As businesses continue to grow and generate vast volumes of customer feedback data, the need for scalable and efficient filtering options becomes paramount to ensure timely and accurate analysis. Furthermore, the current system does not support real-time updates, which can be a significant constraint for businesses operating in dynamic and rapidly evolving markets. In today's fast-paced business environment, timely insights derived from customer feedback are crucial for making informed decisions and implementing timely interventions. The lack of real-time updates in the system can potentially hinder businesses from responding promptly to emerging trends, issues, or opportunities identified through customer feedback analysis.

As we look towards future work, addressing these limitations will be pivotal in enhancing the robustness, scalability, and real-time capabilities of the system. Future iterations of the system could focus on refining sentiment analysis and theme extraction algorithms to better handle linguistic nuances and complexities, thereby improving the accuracy and reliability of insights derived from customer feedback. Additionally, investing in the development of scalable filtering options and incorporating real-time update capabilities will be essential to meet the evolving needs of businesses and ensure timely and actionable insights from customer feedback analysis.

CONCLUSION

FeedViz emerges as an innovative solution in the realm of customer feedback analysis, bridging the gap between raw data and actionable insights through its systematic four-step methodology. By automating the process of extracting, categorizing, and visualizing customer feedback, FeedViz not only enhances the efficiency and accuracy of feedback analysis but also empowers businesses with valuable insights to drive continuous improvement. Despite the existing limitations related to linguistic nuances, scalability, and real-time updates, the potential of FeedViz in revolutionizing customer feedback analysis is undeniable. As businesses continue to evolve in the digital age, the need for advanced tools like FeedViz will only intensify, underscoring the significance of this research in shaping the future of customer-centric decision-making and business intelligence.

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