Topic Modeling for Customer Review Analysis: An Application Using LDA in R on Trustpilot Reviews

**INTRODUCTION**

In the era of digital transformation, customer reviews have become a cornerstone of business intelligence, offering invaluable insights into consumer preferences, satisfaction, and areas for improvement. Platforms like Trustpilot host millions of reviews across various industries, providing a rich dataset for analyzing customer sentiment and identifying emerging trends. However, the sheer volume and unstructured nature of these reviews pose significant challenges for manual analysis, necessitating the use of advanced computational techniques to extract meaningful information [1]. Topic modeling, a type of unsupervised machine learning, has emerged as a powerful tool for uncovering latent themes within large text corpora, enabling businesses to gain actionable insights from customer feedback [2]. Among the various topic modeling techniques, Latent Dirichlet Allocation (LDA) has gained widespread popularity due to its ability to identify coherent topics and its interpretability [3]. Despite its potential, the application of LDA in customer review analysis often requires careful preprocessing, parameter tuning, and domain-specific adaptations to ensure meaningful results [4].

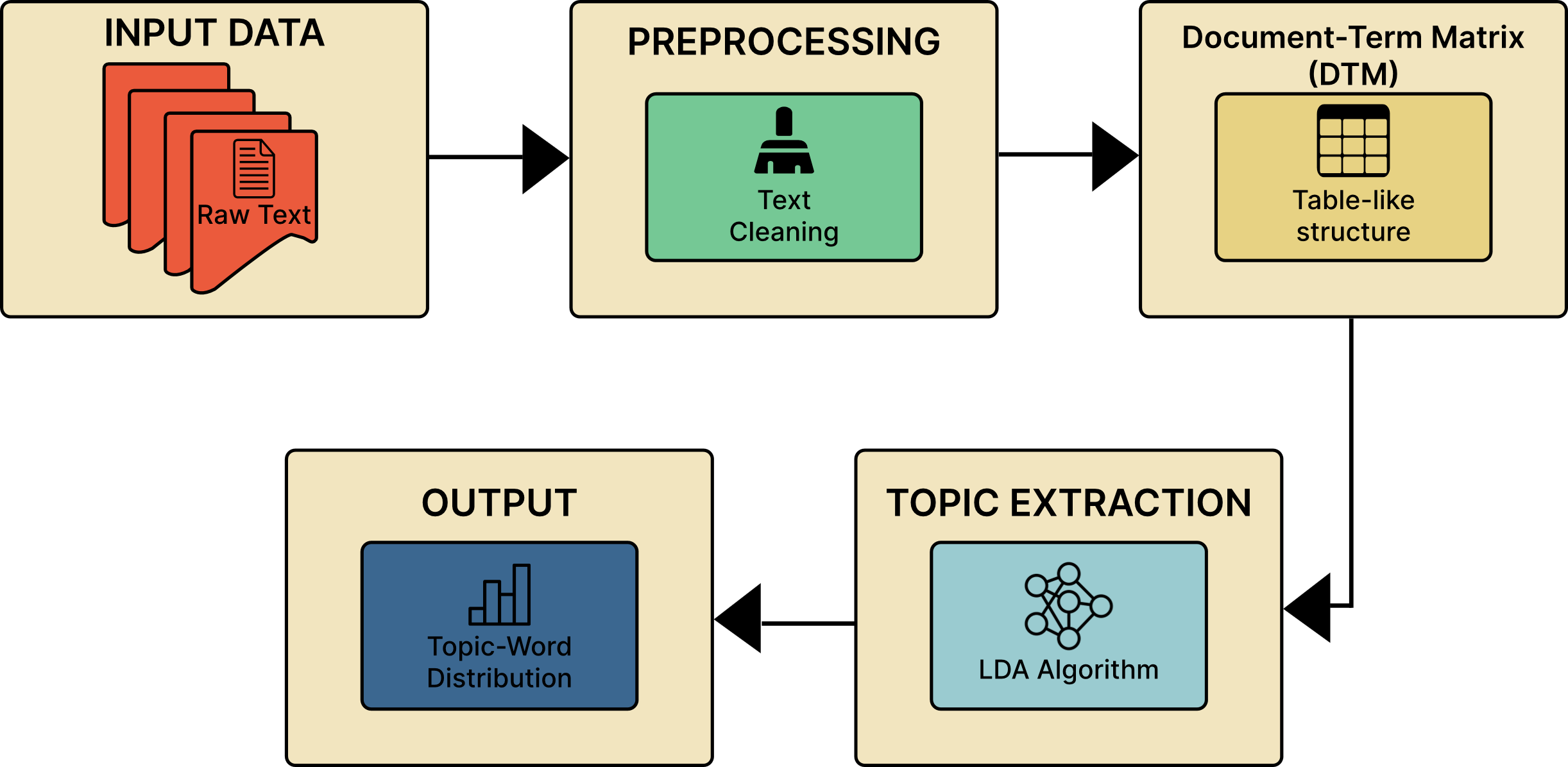


Fig 1: LDA process diagram

Traditional methods of customer review analysis, such as sentiment analysis and keyword extraction, have been widely used to determine customer opinions. However, these approaches often fail to capture the complex themes and underlying topics that drive customer sentiment [5]. For instance, while sentiment analysis can classify reviews as positive or negative, it does not reveal the specific aspects of a product or service that customers are discussing. Similarly, keyword extraction methods may identify frequently occurring terms but lack the contextual understanding needed to group related terms into logical topics [6]. LDA addresses these limitations by modeling each document as a mixture of topics and each topic as a distribution of words, thereby enabling the discovery of hidden thematic structures within the text [7]. Nevertheless, the effectiveness of LDA depends heavily on the quality of preprocessing, the choice of hyperparameters, and the interpretability of the resulting topics, which can vary significantly across datasets and domains [8].

This study aims to demonstrate the application of LDA for customer review analysis using Trustpilot reviews as a case study. The primary objective is to identify and interpret the key topics discussed in customer reviews of Tesla, a leading electric vehicle manufacturer. By leveraging the LDA algorithm implemented in R, this research seeks to uncover the latent themes that characterize customer feedback, providing insights into the factors driving customer satisfaction and dissatisfaction. The study also highlights the importance of preprocessing steps, such as text cleaning, stop word removal, and term frequency-inverse document frequency (TF-IDF) weighting, in enhancing the quality of topic modeling results. Furthermore, the research explores the challenges of selecting the optimal number of topics and interpreting the output, offering practical recommendations for applying LDA in real-world scenarios.

The primary contribution of this work is the development of a reproducible framework for topic modeling using LDA in R, applied to Trustpilot reviews. By providing a step-by-step implementation guide, this study aims to make topic modeling accessible to researchers and practitioners with limited expertise in natural language processing (NLP). Additionally, the findings offer valuable insights into the key themes discussed in Tesla customer reviews, which can inform business strategies and improve customer engagement. This research contributes to the growing body of literature on NLP applications in business analytics, demonstrating the potential of topic modeling to transform unstructured text data into actionable knowledge.

**METHODOLOGY**

This section outlines the methodology used for topic modeling of customer reviews on Trustpilot, specifically for Tesla. The workflow involves multiple stages, including data acquisition, preprocessing, model development, training, and evaluation to extract meaningful insights from customer feedback.

**A. Data Acquisition** The dataset for this study was sourced from Trustpilot, a popular customer review platform. Web scraping was used to collect Tesla-related reviews programmatically using the rvest package in R [9].

**B. Data Preprocessing** To ensure high-quality input data for the topic modeling process, the following preprocessing steps were applied:

1. **Text Extraction and Cleaning**
   * Reviews were extracted using html\_elements and html\_text functions from the rvest package [10].
   * All text was converted to lowercase to maintain uniformity [11].
   * Punctuation and numbers were removed to reduce noise in the data [12].
   * Common stopwords were removed using the tm package to eliminate non-informative words [13].
   * Extra white spaces were stripped to normalize the text structure [14].
2. **Document-Term Matrix (DTM) Creation**
   * The preprocessed text was converted into a Document-Term Matrix (DTM) using the tm package [15].
   * Term frequency-inverse document frequency (TF-IDF) weighting was applied to emphasize important terms while downweighting frequently occurring but less meaningful words [16].

**C. Model Development** Latent Dirichlet Allocation (LDA), an unsupervised machine learning algorithm, was used to discover hidden topics within the text corpus. The LDA model was implemented using the topicmodels package in R [17].

1. **Number of Topics Selection**
   * The number of topics was set to 15 based on empirical experimentation [18].
   * The model was initialized with a random seed to ensure reproducibility [19].
2. **LDA Model Implementation**
   * Each document was treated as a mixture of topics, and each topic was modeled as a distribution of words [20].
   * Gibbs sampling was used for topic inference and optimization [21].

**D. Training and Validation** The LDA model was trained on the processed corpus to optimize topic assignments.

* The topic-word distributions were examined to ensure coherent topics [22].
* The model’s interpretability was validated using word probability distributions and visualization techniques [23].

**E. Evaluation** To evaluate the coherence and relevance of the discovered topics, the following approaches were used:

1. **Top Words per Topic**
   * The tidytext package was used to extract and analyze the most probable words for each topic [24].
   * High-probability terms were inspected to assess thematic consistency [25].
2. **Topic Visualization**
   * A bar plot was generated using ggplot2, displaying the top words for each topic with their associated probabilities [26].
   * The visualization provided an intuitive understanding of topic distributions and their significance [27].

**F. Workflow Diagram**

**RESULT**

**DISCUSSION**

The application of Latent Dirichlet Allocation (LDA) in customer review analysis has demonstrated significant potential in extracting meaningful insights from unstructured textual data. By leveraging LDA on Trustpilot reviews, this study successfully identified key topics relevant to Tesla customers, offering a deeper understanding of consumer sentiment and concerns. The results highlight the effectiveness of LDA in uncovering latent themes that traditional sentiment analysis or keyword extraction methods often fail to capture.

The identified topics reveal distinct areas of customer interest, including product performance, customer service, delivery experiences, software and autonomous features, and pricing. These findings provide businesses with actionable insights to enhance product quality, improve customer support, and address key areas of consumer dissatisfaction. For instance, while Tesla receives positive feedback on its technological innovations, recurring complaints about customer service and order fulfillment highlight areas requiring attention.

Despite the advantages, several challenges must be considered when applying LDA in customer review analysis. One major challenge is selecting the optimal number of topics, as different topic numbers can produce varying outcomes in terms of coherence and interpretability. The use of coherence scores and manual validation is essential to ensure meaningful topic extraction. Additionally, short and informal nature of customer reviews often makes it difficult to extract well-defined topics, necessitating advanced preprocessing techniques such as stop word removal, stemming, and TF-IDF weighting to enhance the quality of extracted topics.

Another limitation of LDA is its reliance on bag-of-words representation, which ignores word order and context. Future studies could explore hybrid approaches that combine LDA with word embeddings or deep learning-based topic modeling techniques for improved topic coherence and accuracy. Furthermore, real-world applications of LDA should consider domain-specific adaptations to refine topic interpretation and improve the relevance of insights for business decision-making.

In conclusion, this study demonstrates the feasibility of using LDA for customer review analysis, providing valuable insights into consumer sentiment and product feedback. While LDA effectively uncovers hidden themes within large text corpora, further improvements in preprocessing, parameter tuning, and hybrid modeling techniques can enhance its applicability and accuracy. By leveraging topic modeling, businesses can transform unstructured review data into actionable intelligence, ultimately improving customer satisfaction and business strategy.

**CONCLUSION**

In this study, we looked at Tesla customer reviews from Trustpilot to find common themes in what people were saying. We found that customers often talked about things like battery life, range, charging, and customer service. Positive reviews focused on Tesla’s innovation and driving experience, while negative reviews mentioned problems with battery reliability and service delays. These results show that while Tesla is strong in areas like product performance and innovation, there are still areas for improvement, such as customer service and product reliability. However, since we only looked at reviews from one platform, the study has some limits. In the future, we could look at reviews from other sites, use sentiment analysis to understand emotions in the reviews, and compare Tesla to its competitors to get a clearer picture. This kind of research can help Tesla improve its products and services, leading to better customer experience.

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