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ON

PRUS: Product Recommender System Based on User Specifications and Customer Reviews

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This is to certify that this Term Paper titled "PRUS: Product Recommender System Based on User Specification and Customer Reviews" is the study conducted by **ORUGANTI MONIK PAPARAO (Y22CS139) , PENDYALA SKANDA BHAGAVAN (Y22CS145), TULAM SAI SUDHEER (Y22CS184)** submitted in partial fulfillment of the requirements to CS 363- Term Paper during the Academic Year 2024-2025.

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ABSTRACT

The growing popularity of online shopping has led to a continuous influx of product reviews, which play a crucial role in shaping consumer purchasing decisions. Many research studies have focused on ranking products using these reviews. However, most methodologies tend to overlook the impact of negative sentiments when evaluating products based on customer preferences. This research aims to address this gap by incorporating both positive and negative polarity in product ranking.

To achieve this, the proposed method first breaks down reviews into individual sentences, allowing for a more granular analysis of sentiment at the phrase level. By extracting key elements from these reviews, the approach effectively determines the polarity of different product features. The next step involves linking these polarities to sentence-level attributes within the review. To ensure that product rankings align with user preferences, relative importance is assigned to each polarity based on specific needs.

The effectiveness of this approach has been tested using the Amazon review dataset, where experimental evaluations were conducted using rank score (RS) and normalized discounted cumulative gain (nDCG) score. Results demonstrate that the proposed ranking system, PRUS, enables users to customize their recommended product lists by prioritizing either positive or negative aspects based on their preferences.

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LIST OF ABBREVIATIONS

PRUS	-	Product Recommender System Based on User Specification
AAS	-	Average Aspect Score
RS	-	Rank Score
QAM	-	Query Aspect Modeling
NLP	-	Natural Language Processing
SVM	-	Super Vector Machine
GP	-	Genetic Programming
NLTK	-	Natural Language Toolkit
DCG	-	Discounted Cumulative Gain
nDCG	-	Normalized Discounted Cumulative Gain
IDCG	-	Ideal Discounted Cumulative Gain

1. INTRODUCTION

1.1 Background

The rapid expansion of the e-commerce industry has significantly transformed the way people shop. With the increasing convenience of online platforms, consumers are shifting from traditional in-store purchases to digital shopping experiences. The ability to browse a wide range of products, compare prices, read detailed descriptions, and access customer reviews from the comfort of their homes has made online shopping the preferred choice for many. The dominance of online sales has created an environment where customer feedback plays a crucial role in shaping purchasing decisions.

One of the key outcomes of the e-commerce boom is the proliferation of customer reviews on various platforms. Consumers frequently share their experiences by posting feedback on e-commerce websites (e.g., Amazon, eBay, Flipkart), social media platforms, and specialized review websites. These reviews typically highlight both the positive and negative aspects of products, offering valuable insights to potential buyers. For instance, a review of a smartphone might praise its battery life and camera quality but criticize its screen resolution. Similarly, a review of a vacuum cleaner might highlight its suction power as a positive but point out issues with its noise level or durability. These detailed reviews help potential buyers make informed purchasing decisions by offering real-world insights that go beyond product descriptions and marketing claims.

Fig-1.1.1

Customer reviews not only benefit potential buyers but also offer valuable data for companies. Businesses use this feedback to identify product strengths and weaknesses, improve existing products or develop new ones based on customer preferences, and enhance customer service by addressing common complaints or issues.

While customer reviews provide valuable insights, the sheer volume of online reviews makes it difficult to extract meaningful information efficiently. As e-commerce platforms grow, the number of reviews for popular products can reach into the thousands, making manual analysis impractical.

1.2 Problem Statement

While customer reviews provide valuable insights, they often contain mixed sentiments about different product features, which most existing product ranking methods fail to capture. These methods typically focus on the overall sentiment of reviews rather than evaluating individual aspects. For example, a review might praise a smartphone’s camera and battery life but criticize its screen resolution. Despite the negative feedback on a specific feature, the review may still be classified as positive overall, which can mislead potential buyers.

Many current ranking models overlook feature-specific sentiments, relying heavily on general polarity. This makes it difficult for users to identify products that align with their specific preferences. For instance, a phone with an excellent camera but poor battery life might be ranked higher due to its overall positive sentiment, even though a buyer prioritizing battery performance would find it unsuitable.

Furthermore, reviews often contain contradictory opinions, such as praising a product's build quality but criticizing its customer service. By only considering the overall sentiment, such contrasting feedback is flattened into a single polarity, making the review less informative.

To address this, aspect-based sentiment analysis (ABSA) offers a more precise approach by identifying and extracting sentiments related to specific product features. This allows for more detailed and transparent product evaluations, helping buyers filter products based on the aspects that matter most to them. By integrating ABSA, e-commerce platforms can offer more accurate and personalized product recommendations, enhancing the shopping experience.

1.3 Objectives

The primary objectives of this research are:

- **Development of the PRUS framework**: Propose a Product Recommendation based on

User Specification (PRUS) framework to generate a customized product list by considering user-specified features and preferences. This framework aims to offer more tailored recommendations by addressing individual needs rather than relying on generalized rankings.

- **Multi-polarity sentiment extraction**: Implement a technique to identify and separate positive and negative sentiments within a single review, ensuring that conflicting opinions are not flattened into a single polarity. This allows the system to capture diverse opinions accurately.
- **Weighted sentiment scoring**: Introduce a technique to assign weights to both positive and negative sentiments of product features. This enables the ranking system to prioritize products based on the user's specific preferences, such as giving more importance to certain features (e.g., battery life) over others.
- **User-defined prioritization**: Allow users to define the importance of different product aspects when generating recommendations. This ensures the final ranked list reflects the user's unique needs and preferences, making the recommendations more relevant and valuable.
- **Customized product ranking**: Implement a dynamic ranking mechanism that reorders products based on the weighted sentiment scores of their aspects. This ensures that products with stronger performance in the features valued by the user are ranked higher.
- **Experimental validation**: Perform extensive evaluations using the Amazon review dataset to validate the effectiveness and accuracy of the PRUS framework. Use performance metrics such as rank score (RS) and normalized discounted cumulative gain (nDCG) to measure the precision and reliability of the system.
- **Improved decision-making**: Enhance the decision-making process for both consumers and businesses by providing more accurate, aspect-based product insights. This will help buyers make better-informed decisions and allow companies to identify product strengths and areas for improvement.
- **Scalability and adaptability**: Ensure that the PRUS framework is scalable and adaptable to different product categories and review datasets. This will make the system applicable to a wide range of e-commerce platforms.

1.4 Limitations of Existing Systems

Despite the availability of various product ranking systems, several limitations persist in existing approaches:

- **Focus on overall sentiment**: Most existing methods primarily consider the overall sentiment of reviews, overlooking the detailed opinions on individual product features. By only capturing the general polarity of a review, these systems fail to account for feature-specific strengths and weaknesses. This can lead to inaccurate and generalized recommendations, preventing users from identifying products that align with their specific needs.
- **Lack of user-specific customization**: Many systems do not allow users to specify the importance of particular features when generating product recommendations. As a result, all product aspects are treated with equal significance, regardless of the user's priorities. For instance, a customer looking for a laptop with long battery life may receive recommendations that prioritize display quality or performance, which may not match their needs. The absence of user-driven customization reduces the relevance and effectiveness of the recommendations.
- **Inefficient sentiment extraction**: Existing models often struggle to accurately extract and link sentiments to specific product aspects. Sentiments expressed in reviews can be ambiguous or multi-faceted, making it challenging to associate the correct polarity with the appropriate feature. For example, a review mentioning, "*The phone's display is stunning, but the battery drains quickly*" contains contrasting sentiments about different aspects. However, many ranking systems fail to distinguish between them, resulting in less precise and unreliable recommendations.
- **Limited consideration of negative polarity**: Most product ranking systems prioritize positive sentiment while neglecting the significance of negative opinions. This creates a bias toward favourable reviews, leading to misleading recommendations. Negative feedback often highlights critical product flaws, such as poor durability or customer service issues, which are valuable for potential buyers. By underweighting or ignoring negative polarity, existing systems provide incomplete and overly optimistic product evaluations, making it harder for users to make informed decisions.
- **Inability to handle mixed or conflicting sentiments**: Many reviews contain conflicting opinions about different product features, but existing methods often fail to distinguish between them.

- This simplified interpretation reduces the accuracy of the recommendations, as the nuanced user experience is lost.
- **Failure to capture context-specific sentiments**: Sentiment analysis models often

miss contextual nuances, such as sarcasm, irony, or subtle expressions of dissatisfaction. For instance, the sentence "*The product works... when it feels like it*" expresses negative sentiment with sarcasm, but many models misinterpret it as neutral or positive. This leads to inaccurate sentiment classification.

- **Limited adaptability across product categories**: Many existing systems are designed for specific product types, making them less adaptable to other categories. A ranking model tailored for electronics may not effectively capture the features and sentiments relevant to clothing or home appliances, limiting its applicability across diverse e-commerce platforms.
- **Static product ranking models**: Most systems generate static product rankings that do not dynamically update based on evolving user preferences or review trends. As customer opinions and product performance shift over time, static models become outdated, providing irrelevant or obsolete recommendations.
- **Lack of multi-polarity analysis**: Existing models often fail to perform multi-polarity sentiment analysis, where both positive and negative opinions within a single review are evaluated independently. For example, if a review praises a product's design but criticizes its functionality, both polarities should be considered separately. However, many systems merge conflicting sentiments, reducing the granularity and accuracy of the analysis.
- **Insufficient consideration of review credibility**: Current systems do not adequately account for fake or biased reviews, which can distort product rankings. Spam reviews or paid promotions often create misleading sentiments, making the recommendations unreliable.
- **Ineffective performance evaluation metrics**: Many existing models rely on basic evaluation metrics, which do not fully capture the effectiveness and accuracy of the ranking system. As a result, the performance of the models in real-world scenarios may not be properly measured, leading to suboptimal recommendations.
- **Reduced user satisfaction**: The inability to personalize rankings based on user preferences, coupled with the incomplete sentiment analysis, often results in irrelevant product recommendations. This reduces user trust in the system and diminishes the overall shopping experience.

2. LITERATURE REVIEW

2.1. Opinion-based entity ranking

Model Proposed by Kavita Ganesan and Cheng Xiang Zhai et. al.

The paper focuses on developing an opinion-based entity ranking system that ranks products, businesses, and people based on user preferences and existing opinions about those entities. With the rise of Web 2.0 technologies, there has been an exponential growth in the availability of user-generated reviews and opinions. These opinions are valuable for making various decisions, such as purchasing products, booking hotels, or selecting services. However, the challenge lies in efficiently processing and leveraging the large volume of reviews to offer meaningful recommendations. The authors propose a system that directly ranks entities by how well the aggregated opinions about them match the user's preferences. Instead of merely summarizing opinions, the approach prioritizes entities based on how closely they satisfy the specified preferences, which offers more direct and effective support for decision-making tasks.

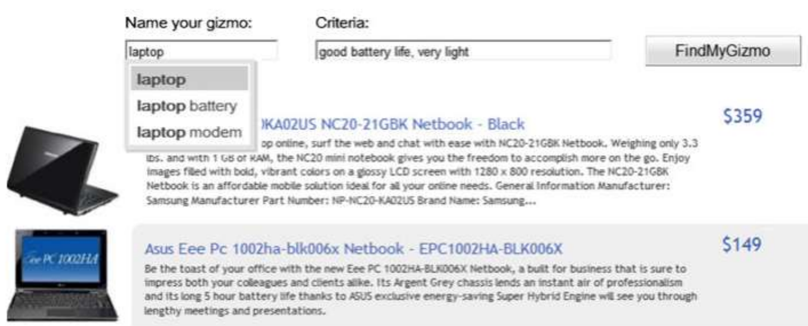

Fig. 2.1.1

The paper presents a series of innovative retrieval models designed to enhance the ranking mechanism for opinionated content, particularly in the context of online reviews. Traditionally, retrieving relevant reviews involves matching user queries with individual review documents. However, this approach often fails to capture the full spectrum of opinions related to a product or service. Instead, the paper proposes a more holistic approach by treating all reviews related to a specific entity—such as a hotel or car—as a single "opinion document." This aggregation allows for a more comprehensive representation of user feedback on the entity, facilitating a more accurate ranking of the entities based on how well the aggregated content aligns with the user's specific query preferences. By considering the entirety of reviews for each entity, the system can better reflect the overall sentiment and common themes found across different user opinions, rather than focusing solely on individual, potentially isolated reviews.

To implement this ranking mechanism, the authors combine traditional retrieval models, such as BM25, with two novel techniques: query aspect modeling (QAM) and opinion expansion. BM25, a standard in information retrieval, is effective at ranking documents based on keyword matches and term frequency. However, in the context of opinionated content, such as user reviews, this model might miss more nuanced aspects of user preferences. The QAM technique addresses this issue by breaking down user queries into different aspects—such as price, location, comfort, or service quality. By identifying these aspects, the system is able to better match user queries with relevant opinionated content that addresses specific facets of a product or service. This segmentation improves the matching process by ensuring that the system aligns more accurately with the user's intent, rather than providing generic results based solely on keywords.

In addition to query aspect modeling, the paper introduces opinion expansion, a technique that enhances the user's original query with related terms. The goal of opinion expansion is to broaden the scope of the query to capture a wider range of relevant opinions that may use different phrasing or terminology. For example, if a user queries for "comfortable hotel rooms," the opinion expansion mechanism might automatically expand the query to include terms like "spacious," "well-furnished," or "relaxing," which could be used in reviews that express similar sentiments but do not use the exact words from the original query. This broader search increases the chances of retrieving relevant reviews that might otherwise be overlooked due to vocabulary differences. Together, QAM and opinion expansion ensure that the ranking system is more robust and can capture a wider range of relevant content.

Through extensive experiments on datasets of hotel and car reviews, the authors demonstrate the effectiveness of these enhancements. Their results show that both query aspect modeling and opinion expansion significantly improve the ranking accuracy compared to standard retrieval models. The system's ability to aggregate reviews into opinion documents and refine queries based on aspects and expanded terms makes the process of finding relevant opinions more efficient for users. Instead of manually sifting through large numbers of individual reviews, users can quickly access a concise, preference-based ranking list that aligns closely with their specific needs and interests. This not only streamlines the decision-making process but also enhances the user experience by providing tailored, high-quality recommendations. The improvements in ranking accuracy and relevance highlighted in the experiments underscore the potential of these techniques to revolutionize the way users interact with and derive insights from online reviews.

2.2. Aspect-based opinion ranking framework forproduct reviews using a Spearman's rank correlation coefficient method:

Model Proposed by A. Kumar and S. Abirami et. al.

Opinion mining, also known as sentiment analysis, is a field of natural language processing (NLP) that focuses on identifying and interpreting people's opinions, emotions, and sentiments expressed in textual data. It is widely used to analyse structured, semi-structured, and unstructured content from various social media platforms, e-commerce websites, and review forums. Sentiment analysis is typically performed at multiple levels:

- **Document level:** Determines the overall sentiment of an entire document (e.g., whether a review is positive, negative, or neutral).
- **Sentence level:** Identifies the sentiment of individual sentences.
- **Word level:** Examines the sentiment conveyed by specific words or phrases.
- **Aspect level:** Focuses on specific attributes or features of an entity mentioned in the text, providing more granular insights into customer preferences.

In aspect-level sentiment analysis, the system goes beyond general sentiment classification by detecting people's likes and dislikes associated with particular product features. For instance, in a smartphone review, it can identify whether the battery life is praised but the camera quality is criticized. This makes aspect-level sentiment analysis particularly valuable for product ranking and recommendation systems, as it captures feature-specific opinions rather than an overall sentiment.

The paper introduces a new framework for ranking products based on aspect-level sentiment analysis. The process involves five key steps:

1. **Aspect Identification**:
    - The system first identifies the aspects of products by extracting relevant keywords and phrases from customer reviews.
    - For example, in laptop reviews, aspects could include battery life, display, performance, and price.
    - This step ensures that the analysis captures specific product features rather

than just general sentiment.

2. **Aspect and Opinion Word Visualization**:
    - The framework uses the Harel–Koren fast multiscale layout to visualize the aspects and their associated opinion words.
    - This layout is a graph-drawing algorithm that effectively displays large-scale network data with improved readability.
    - In this case, it creates a network visualization showing the relationship between aspects and their related opinion words (e.g., "battery life" linked to "long-lasting" or "poor").
    - This visual representation helps identify positive and negative clusters of opinions associated with each aspect.
3. **Network Construction and Modelling**:
    - The system constructs a network model where products, aspects, and opinion words are interconnected.
    - The Spearman's rank correlation coefficient is applied to measure the correlation between the polarity of opinion words and product rankings.
    - Products are ranked based on the positive and negative sentiment scores derived from the reviews.
    - The Spearman's coefficient helps in determining how closely the product ranks align with the polarity scores.
    - For example, if two products have similar positive and negative scores, they will have a high correlation, indicating they are ranked similarly.
4. **Aspect-Based Sentiment Classification:**
    - The framework uses supervised learning methods to classify the sentiment polarity of each aspect.
    - Three machine learning algorithms are applied:
        - Naïve Bayes (NB): A probabilistic classifier that uses Bayes' theorem to determine the likelihood of a sentiment being positive, negative, or neutral.
        - Maximum Entropy (ME): A model that estimates the probability distribution that best represents the data, considering all constraints. It is effective in handling imbalanced datasets.
        - Support Vector Machine (SVM): A popular machine learning algorithm that classifies data by creating a hyperplane that separates

positive and negative sentiment categories.

- These classifier are train on labelled data to detect and classify sentiments.

2.3. Opinion-Based Entity Ranking using learning to rank

S. Bashir, W. Afzal, and A. R. Baig et. al.

The paper addresses the Opinion-Based Entity Ranking (OpER) task, which aims to rank entities based on how well the opinions about them match with user queries. With the growth of social media and e-commerce, online opinions have become a key source of information for users making purchasing or decision-making choices. However, the vast quantity of reviews makes it difficult for individuals to manually read and evaluate them. OpER offers a solution by directly ranking entities according to how closely their opinions align with user preferences. This eliminates the need for users to sift through numerous reviews, providing a more efficient and targeted recommendation process.

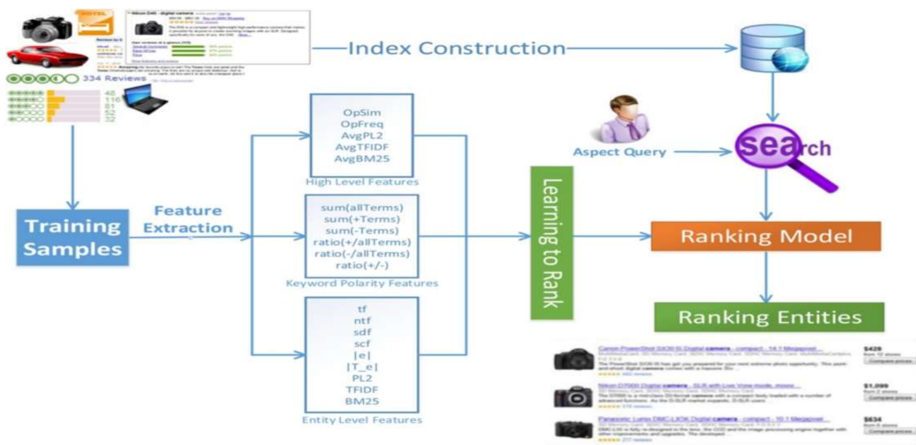

Fig. 2.3.1

The authors introduce an extensive list of ranking features designed to capture the relevance of query keywords with individual opinions of the entities. Unlike previous approaches, which treated all opinions of an entity as a single text field, the proposed method considers the subjectivity and relevance of individual opinions to the query. This ensures that entities with positive judgments and strong relevance to the query keywords are ranked higher than those with poor relevance or negative sentiments. To further improve the effectiveness of the OpER system, the authors employ genetic programming (GP) and a learning-to-rank approach. By combining multiple ranking features, the model enhances the accuracy of the entity ranking process.

The framework is evaluated on two datasets, and the results indicate that the proposed OpER model is significantly more effective than standard retrieval models. The use of genetic programming allows the system to automatically identify and combine the most relevant ranking features, leading to better performance and more accurate recommendations. The study highlights the potential of OpER in helping users quickly find the most relevant entities without the need to read through large volumes of opinions.

2.4. A Two-Fold Rule-Based Model for Aspect Extraction

Model Proposed by T. A. Rana and Y.-N. Cheah et. al.

The paper focuses on opinion target extraction or aspect extraction, a key subtask in aspect-based sentiment analysis (ABSA). This task involves identifying the specific targets of user opinions or sentiments from online reviews, such as product features or attributes. Over recent years, syntactic pattern-based approaches have shown promising results in aspect extraction by leveraging dependency parsers to establish syntactic relations based on grammatical rules and language constraints. However, these approaches have significant limitations. Since users often express opinions informally without adhering to grammatical conventions, syntactic-based models become vulnerable to inaccuracies. Additionally, review platforms do not enforce grammatical correctness, making it harder for these methods to consistently extract aspects accurately.

To overcome these limitations, the authors propose a Two-Fold Rules-Based Model (TF-RBM) that uses sequential patterns mined from customer reviews to extract aspects. The framework consists of two phases:

1. **Domain-Independent Aspect Extraction**: The first phase extracts aspects associated with general opinion words (domain-independent), which are commonly used across multiple domains.
2. **Domain-Dependent Aspect Extraction**: The second phase focuses on aspects linked to domain-specific opinion words, capturing more specialized and context-specific features.

   To further enhance accuracy, the authors apply frequency- and similarity-based approaches. These methods improve the precision and recall of aspect extraction by identifying recurring and semantically similar terms in reviews. Through experimental evaluation, the proposed TF-RBM model demonstrates better performance compared to state-of-the-art models, achieving higher accuracy and consistency in aspect extraction tasks. The results highlight the model's effectiveness in identifying product features from unstructured customer reviews, making it highly valuable for opinion mining and product ranking systems.

2.5. Aspect Term Extraction (ATE) and Opinion Target Extraction (OTE) Model Proposed by C. Wu, F. Wu, S. Wu, Z. Yuan, and Y. Huang

1. Introduction to ATE and OTE:

In the field of fine-grained sentiment analysis, Aspect Term Extraction (ATE) and Opinion Target Extraction (OTE) play a crucial role in identifying and analyzing specific components of opinions. ATE focuses on extracting the particular features or attributes of an entity being discussed. For example, in a product review, the sentence *"The battery life is impressive"* contains the aspect term "battery life", as it highlights the specific feature being evaluated. By identifying these aspects, businesses can understand which features customers find satisfactory or problematic, allowing them to make targeted improvements. On the other hand, Opinion Target Extraction (OTE) identifies the targets of opinions, which are the objects or entities receiving the sentiment. For instance, in the sentence *"The camera is fantastic"*, the term "camera" is the opinion target, as it is the object being praised. OTE is essential for linking opinions to their corresponding targets, enabling more precise sentiment classification. Without OTE, it would be difficult to determine whether a sentiment refers to the entire product or a specific component, leading to inaccurate or vague insights.

Both ATE and OTE are essential for fine-grained sentiment analysis because they allow businesses and organizations to gain a detailed understanding of customer feedback. Rather than simply identifying whether a review is positive or negative, these methods break down the text to reveal which features are driving satisfaction or dissatisfaction. This granularity is especially valuable in industries such as e-commerce, hospitality, and technology, where customer feedback often mentions multiple aspects of a product or service.

By applying ATE and OTE, companies can enhance their customer experience strategies, prioritize improvements on specific product features, and develop more accurate recommendation systems. For example, an e-commerce platform could use ATE and OTE to analyze product reviews and recommend items based on the specific aspects that users frequently praise. Similarly, a hotel chain could identify recurring complaints about "room cleanliness" or "customer service" and take targeted action to address them.

In summary, Aspect Term Extraction and Opinion Target Extraction are vital components of fine-grained sentiment analysis. They provide detailed, actionable insights by identifying the specific aspects and targets of opinions, enabling businesses to make informed decisions, improve services, and enhance overall customer satisfaction.

2. Existing Approaches:

Rule-based Methods:

- Use linguistic rules to extract patterns.
- Are usually unsupervised but cannot utilize high-level semantic features.

Supervised Learning Methods:

- Require a large amount of labeled data.
- Outperform rule-based methods but are expensive and time-consuming due to the need for manual annotation.

3. Proposed Hybrid Method:

- Combines Rules with Machine Learning:
- Uses linguistic rules at the chunk level to extract nominal phrase chunks as candidate aspects and opinion targets.
- Applies domain correlation filtering to remove irrelevant candidates.
- Uses the filtered candidates as pseudo-labeled data to train a deep Gated Recurrent Unit (GRU) network.
- GRU Network:
  - A deep learning model suitable for handling sequential data.
  - Learns contextual information from the pseudo-labeled samples.

4. Key Steps in the Hybrid Approach:

- Chunk-level Extraction: Linguistic rules identify nominal phrases (e.g., noun phrases) as candidate opinion targets/aspects.
- Domain Correlation Filtering: Removes irrelevant or contextually weak candidates.
- GRU Network Training: The filtered candidates are used as pseudo-labeled data to train the GRU model, enhancing its ability to extract ATE and OTE.

5. Experimental Validation:

Benchmark Datasets: The method is tested on standard datasets for fine-grained sentiment analysis.

Effectiveness: The hybrid approach achieves high accuracy and effectiveness with minimal manual annotation, making it efficient and practical.

Fig. 2.5.1

2.6. Extracting prominent review aspects from customer feedback

Model Proposed by Z. Luo, S. Huang, F. F. Xu, B. Y. Lin

Many existing systems for analyzing and summarizing customer reviews about products or services typically rely on a set of predefined, prominent review aspects. These aspects are usually determined manually, often through the analysis of a small set of example reviews or through expert knowledge. However, this conventional approach is highly labor-intensive, requiring substantial time and resources to identify key features for each product category. Furthermore, as the number of product types increases, particularly in large-scale platforms such as Amazon, Taobao, or Yelp, the task becomes increasingly difficult. New products are constantly introduced, and customer feedback on these products must be analyzed continuously. This makes the manual identification of review aspects not only costly but also unsustainable in the long run, especially for large-scale, cross-domain services where there are thousands of products and thousands of new reviews being generated every day.

In the face of these challenges, the existing methods fail to scale effectively to large datasets. Platforms like Amazon.com and Taobao.com, with their constantly growing and diverse inventories, require systems that can automatically identify the most relevant aspects of customer reviews without manual intervention. Traditional methods that rely on predefined categories or manual tagging are simply too slow and inefficient to process the massive volume of reviews generated across various product types. Moreover, the traditional approaches often lack the flexibility needed to adapt to the constantly changing landscape of products and services. This has created a significant need for more automated, scalable solutions capable of addressing these challenges.

To address these issues, we propose a novel framework called ExtRA (Extracting Review Aspects). ExtRA is designed to automatically identify the most prominent aspects or features of a given product type from large sets of textual customer reviews. Unlike conventional methods, ExtRA operates without supervision, meaning that it does not require predefined labels or manual input. Instead, the framework automatically extracts the most relevant aspect terms or phrases directly from the review data. These aspects are selected such that they are semantically distinct and do not overlap, ensuring that the extracted terms reflect truly unique features or concerns expressed by the customers. This unsupervised approach significantly reduces the cost and effort involved in extracting review aspects and makes the process scalable for use across different domains and product types.

One of the key innovations of ExtRA is its ability to automatically identify the K most prominent aspect terms or phrases for a product category. This selection process is performed without any semantic overlap, meaning that the terms identified are not redundant but represent distinct facets of customer feedback. This makes the framework highly efficient at capturing the full range of customer concerns and preferences. Whether it's the quality of the product, its durability, its price, or other features, ExtRA is capable of capturing all relevant aspects that customers tend to focus on. This capability allows businesses to gain deeper insights into the specific strengths and weaknesses of their products based on customer feedback, helping them make informed decisions about improvements, marketing strategies, and customer engagement.

Extensive experiments have been conducted to evaluate the effectiveness of ExtRA, and the results show that it outperforms existing methods in terms of accuracy and efficiency. The framework has been tested on a diverse dataset containing reviews from multiple product categories, and it has consistently shown superior performance when compared to previous aspect extraction techniques. This is particularly notable in the context of cross-domain analysis, where ExtRA was able to handle a wide range of products with varying characteristics and customer expectations. By using a range of evaluation metrics, it was demonstrated that ExtRA not only identifies the most relevant aspects but does so in a way that reflects the underlying sentiments and opinions expressed by customers. The framework has proven to be highly versatile, adaptable, and scalable, making it a powerful tool for large platforms with diverse product catalogs.

The implications of ExtRA's performance are significant for businesses operating in the online retail and service sectors. By automatically extracting the key aspects from customer reviews, businesses can quickly identify trends and customer pain points across different product types. This, in turn, can guide product development, marketing strategies, and customer service initiatives. For example, if customers repeatedly mention concerns about the durability of a product, the company can prioritize improvements in that area. Additionally, customer sentiment analysis can be enhanced by focusing on the most relevant aspects, providing businesses with a more nuanced understanding of customer preferences and satisfaction. This not only saves time but also ensures that businesses are responsive to their customers' needs.

In conclusion, ExtRA represents a significant advancement in the field of customer review analysis. Its ability to extract the most relevant and distinct aspects from customer reviews, without requiring manual input or supervision, makes it a highly scalable and efficient tool for businesses operating in large, dynamic environments. The framework's success in diverse product domains demonstrates its adaptability and potential for wide application, particularly in platforms with rapidly evolving product catalogs. By reducing the need for manual intervention, ExtRA helps businesses automate the process of understanding customer feedback, ultimately leading to better products, improved customer satisfaction, and more effective marketing and service strategies.

2.7. Association rule mining using fuzzy logic and whale optimization Model Proposed by S. Sharmila and S. Vijayarani

Association rule mining (ARM) is a widely recognized and essential data mining technique, commonly used for uncovering patterns or relationships within large transactional datasets. The primary goal of ARM is to discover frequent item sets—sets of items that appear together frequently in transactions—and generate meaningful association rules based on these item sets. These association rules are pivotal in various domains, such as retail, healthcare, and market basket analysis, where businesses use them to derive actionable insights like cross-selling opportunities or customer purchasing patterns. In the process of association rule mining, two critical steps are involved: frequent item recognition and association rule generation. Both these steps rely on measures such as minimum support and confidence to ensure that the discovered patterns and rules are statistically significant and useful.

To generate these association rules, ARM typically involves multiple iterations of the dataset to identify frequent item sets that meet the predefined support threshold. The rules themselves are then formed by evaluating the strength of relationships between different item sets based on their co-occurrence. However, as datasets grow in size and complexity, the computational cost associated with identifying frequent item sets and generating association rules becomes prohibitively high. Specifically, the number of database scans required increases significantly as the size of the dataset expands. This challenge is further compounded by the fact that not all transactions and items in the dataset contribute equally to the discovery of meaningful patterns. Thus, the need for techniques that reduce the dataset's dimensionality and computational complexity becomes increasingly important.

To address these issues, the first step in the proposed research focuses on dimensionality reduction techniques to significantly reduce the size of the dataset. This step is crucial because it helps in eliminating irrelevant items and transactions that do not contribute meaningfully to the mining process, thus improving the overall efficiency of the algorithm. The dimensionality reduction technique implemented in this research utilizes two primary methods: low variance and hash table techniques. Low variance methods focus on identifying features or items with low variance that are less likely to influence the association rules, allowing for their removal from the dataset. Meanwhile, the hash table method helps in mapping items and transactions in a more compact manner, further reducing the computational burden. By applying these techniques, the algorithm effectively narrows down the data to include only the most significant transactions and items, ensuring that subsequent analysis is focused on the most relevant parts of the dataset.

A key challenge that arises in dimensionality reduction is dealing with datasets that have a high number of dimensions or features, particularly when the number of items in the transactional database exceeds what the algorithm can efficiently handle. This issue becomes even more pronounced when dealing with large-scale, high-dimensional datasets where irrelevant or less significant items are abundant. The proposed algorithm tackles this challenge by systematically reducing both the dimensionality of the items and the transactions in the dataset, removing unnecessary or less relevant data from the analysis. The algorithm is designed to retain only those items and transactions that are likely to contribute to the discovery of frequent item sets, thereby reducing the size of the dataset while maintaining the integrity of the analysis. In the proposed method, the dimensionality reduction process is evaluated and compared against other techniques, such as extended frequent pattern (EFP) and intersection set theory, as well as dimensionality reduction using frequency count. These comparisons focus on various performance metrics, including item reduction, transaction reduction, execution time, and memory usage, all of which are critical factors in assessing the efficiency of the algorithm.

In the second step of the proposed research, a fuzzy logic-based approach is integrated with a whale optimization algorithm for frequent item set identification and association rule generation. Fuzzy logic is particularly useful in this context because it allows for the representation of uncertain or imprecise relationships between items, which is often the case in real-world transactional data. This addition makes the algorithm more flexible and capable of handling fuzzy, ambiguous relationships that might otherwise be overlooked using traditional crisp-set methods. Whale optimization is then used to further enhance the process of frequent item identification and rule generation by optimizing the search for relevant item sets and improving the overall quality of the generated rules. Whale optimization is inspired by the social behavior of humpback whales and is known for its strong performance in solving optimization problems. By combining fuzzy logic with whale optimization, the proposed algorithm is able to efficiently identify significant item sets and generate highly accurate association rules, even in complex and noisy datasets.

The performance of the proposed algorithm is rigorously evaluated and compared with several well-established optimization techniques, such as particle swarm optimization (PSO), genetic algorithms (GA), and fuzzy frequent item set-Miner (FFIM). These comparisons focus on several key performance metrics, including the number of frequent items identified, the number of association rules generated, execution time, and memory requirements. Experimental results from these evaluations show that the proposed algorithm outperforms the competing methods in all aspects. Specifically, the algorithm identifies a higher number of frequent item sets, generates more accurate association rules, and does so in a significantly shorter amount of time while consuming less memory. This demonstrates the effectiveness of the proposed fuzzy and whale optimization-based approach, especially in the context of large-scale datasets where computational efficiency and scalability are of paramount importance.

In conclusion, the proposed algorithm represents a significant advancement in the field of association rule mining. By incorporating dimensionality reduction techniques and leveraging fuzzy logic and whale optimization for efficient frequent item set identification and association rule generation, the algorithm is able to handle large, high-dimensional datasets effectively. The results of extensive experiments highlight the algorithm's superior performance in terms of both accuracy and efficiency, making it a promising tool for real-world applications that require the analysis of complex transactional data. With its ability to reduce dimensionality, improve computational efficiency, and generate high-quality association rules, the proposed approach has the potential to revolutionize how businesses and researchers analyze transactional datasets, leading to more actionable insights and better decision-making.

2.8. Opinion fraud detection in online reviews by network effects

Model Proposed by L. Akoglu

User-generated online reviews have become an essential component of the decision-making process for consumers when evaluating products, services, and establishments like hotels or restaurants. Positive reviews can significantly boost a product's reputation and sales, while negative reviews can cause harm to a business's credibility. However, the authenticity of online reviews is often compromised by opinion spammers—individuals or automated bots who create fraudulent reviews to either artificially inflate the reputation of a product or service or damage the reputation of a competitor. These fraudulent reviews distort the perceived quality of products, leading to a misleading representation of their true value. To counteract the impact of these fraudulent activities, it is crucial to develop reliable methods for identifying and filtering out fake reviews. In this regard, we propose a fast and effective framework, FRAUDEAGLE, designed to spot fraudsters and fake reviews in online review datasets.

The main advantage of FRAUDEAGLE lies in its innovative approach to detecting fraudulent reviews. Unlike most existing methods that rely solely on analyzing review text or user behavior patterns, FRAUDEAGLE leverages the network effect among reviewers and products. This network effect can reveal the underlying connections between users and products, allowing the framework to identify suspicious patterns that may not be evident when only considering individual reviews or users in isolation. For example, a fraudulent reviewer may repeatedly post fake reviews for a specific product or may be linked to other suspicious users or products, forming a pattern that can be detected using network-based methods. By focusing on these connections, FRAUDEAGLE is able to uncover fraudulent activity that traditional text analysis or behavior-based methods might miss.

The framework is structured in two complementary steps. The first step involves scoring users and reviews for fraud detection. Here, FRAUDEAGLE assigns a fraud score to both the users posting the reviews and the reviews themselves, based on the identified patterns in the network of interactions. This allows the system to detect both fake reviews and users who engage in fraudulent activities. The second step focuses on grouping—this is the process of clustering suspicious reviews and reviewers together for visualization and sense making. By grouping potentially fraudulent reviews and users, the framework allows analysts to easily spot clusters of suspicious activity, providing valuable insights into patterns of fraudulent behavior. This approach not only enhances the detection process but also aids in understanding the context and scale of the fraudulent activities.

One of the standout features of FRAUDEAGLE is that it operates in an unsupervised fashion, meaning it does not require any labeled data to train the model. This is particularly advantageous because acquiring labeled data for fraud detection is both labor-intensive and expensive. Most existing fraud detection systems rely on manually labeled examples of fraudulent and genuine reviews, which can be time-consuming and may not scale well. In contrast, FRAUDEAGLE requires no prior knowledge about which reviews or users are fraudulent, making it highly adaptable to different datasets and easily deployable across various platforms. Furthermore, FRAUDEAGLE can incorporate side information if available, such as the reputation or activity level of users, which can help improve the accuracy of fraud detection without requiring a complete labeled dataset.

Another significant benefit of FRAUDEAGLE is its scalability. The framework is designed to handle large datasets efficiently, with its runtime growing linearly with the size of the network. This makes it suitable for large-scale applications, such as analyzing reviews on major online platforms where the volume of reviews can reach millions. As the amount of data continues to increase, the ability to scale becomes crucial, and FRAUDEAGLE's linear time complexity ensures that it remains efficient even as the dataset grows. This scalability also means that the framework can be applied to real-time data, allowing businesses and platforms to detect and respond to fraudulent activities as they occur.

To validate the effectiveness of FRAUDEAGLE, we conducted experiments on both synthetic and real datasets, including a large-scale online app review database. The results demonstrated that FRAUDEAGLE was able to successfully identify fraud-bots—automated systems designed to post fake reviews—in a real-world scenario. By analyzing the network of interactions among users and products, FRAUDEAGLE was able to uncover suspicious patterns that were indicative of fraudulent activities. These findings highlight the robustness and real-world applicability of the framework in detecting fraud on large platforms where traditional fraud detection methods might struggle due to the sheer volume of data.

In conclusion, FRAUDEAGLE represents a significant advancement in the field of fraud detection for online reviews. Its innovative use of network-based methods, unsupervised operation, and scalability makes it an ideal solution for tackling the growing problem of fraudulent reviews in large datasets. By focusing on the relationships between users and products, FRAUDEAGLE is able to uncover hidden patterns of fraudulent activity that other methods may overlook. Its ability to operate without labeled data and scale efficiently with increasing dataset size further enhances its practicality for deployment on large-scale review platforms. As online reviews continue to play an integral role in consumer decision-making, frameworks like FRAUDEAGLE are essential for maintaining the integrity and trustworthiness of these review systems.

3. METHODOLOGIES USED

3.1 Architecture

The PRUS framework (Product Recommendation based on User Specification) is an advanced system designed to deliver personalized product recommendations by leveraging aspect-level sentiment analysis. Unlike traditional product ranking methods that rely on overall review polarity, PRUS focuses on individual product features, ensuring that the recommendations align with user-specified preferences. The framework consists of several key stages, each contributing to the accurate extraction, evaluation, and ranking of products based on their aspect-level sentiments.

The process begins with the data retrieval phase, where the system collects customer reviews from a review dataset. These reviews form the input data for the recommendation system. Instead of analyzing the reviews as a whole, PRUS breaks them down into individual sentences, allowing the system to conduct granular sentiment analysis. This segmentation is crucial because customer reviews often contain mixed opinions. For instance, a single review may praise a smartphone's camera but criticize its battery life. By analyzing sentences individually, the framework ensures that both positive and negative sentiments associated with different features are captured separately, preventing misleading overall sentiment interpretations.

In the feature extraction phase, each sentence is processed to identify specific product features and the corresponding sentiment polarity (positive, negative, or neutral). To enhance the accuracy and relevance of the recommendations, the framework employs information gain (IG) as an evaluation method. Information gain, based on entropy calculation, measures how much predictive value a particular feature contributes to the overall classification. Features with higher information gain are deemed more informative and influential, increasing their importance in the ranking process. For example, in a laptop review, features such as battery performance or processing speed may carry more weight if they are frequently mentioned and have a significant impact on the overall user experience. This weighted evaluation ensures that the most relevant and influential product features are prioritized.

Once the features and their associated sentiments are extracted, the system appends the sentiment polarity to the respective feature. The next step is to match these extracted features with the user-specified preferences. This enables the system to prioritize products that align with the user's desired attributes.

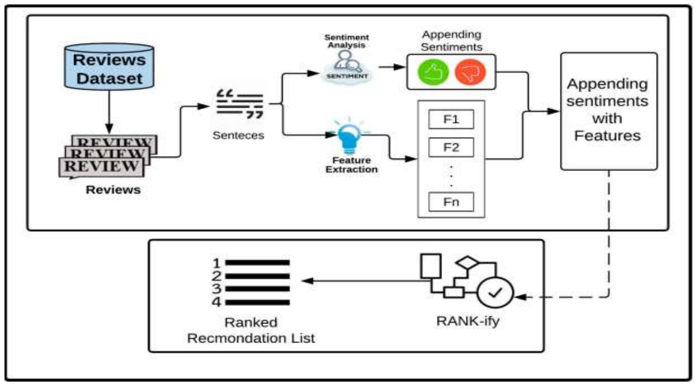

Fig. 3.1.1

The ranking phase is executed using the **RANK-ify algorithm**, which plays a crucial role in assigning weights based on sentiment polarity. The algorithm increases the weight of features with positive sentiments, making them more influential in the final ranking. Conversely, features with negative sentiments are assigned lower weights, decreasing their influence. This weighted sentiment scoring ensures that products with more favourable feedback on the desired features appear higher in the recommendation list. By considering both positive and negative sentiments, the system offers a balanced and realistic evaluation of products, preventing bias towards only positive opinions.

Finally, the ranked recommendation list presents the products along with their features and corresponding sentiment scores, weighted according to the user's preferences. This output provides a personalized, sentiment-driven ranking, making it easier for users to identify products that best match their specific needs. For example, a user seeking a smart phone with a good camera and long battery life would receive a list where products excelling in these areas are ranked higher, regardless of their overall review sentiment.

The PRUS framework offers several key advantages:

- **Granular sentiment analysis:** By breaking reviews into sentences, it captures feature-specific opinions instead of general sentiments.
- **Enhanced precision with information gain:** The use of information gain ensures that the most relevant and informative features carry greater influence.
- **Personalized recommendations:** The framework prioritizes products based on user-defined preferences, ensuring tailored recommendations.
- **Balanced sentiment weighting:** By applying the **RANK-ify algorithm**, the system balances positive and negative sentiments, offering fair and accurate product rankings.

3.2 Datasets Used

The dataset used in this study consists of 413,840 reviews, primarily collected through a data crawler from Amazon, specifically focusing on mobile phone reviews from various brands and companies. The dataset contains three key attributes:

- **Product title**: The name of the mobile phone being reviewed.
- **Brand**: The company that manufactures the mobile phone.
- **Review text**: The actual customer feedback or opinion.

3.2.1 Data Preprocessing

To ensure the quality and consistency of the data, a thorough preprocessing phase was conducted. During this step:

- Reviews with missing product titles or brand names were removed, as they were considered incomplete and irrelevant.
- Reviews containing fewer than five words were also eliminated, as they were unlikely to offer any meaningful feature or sentiment information.
- The remaining review text underwent cleaning and normalization processes to reduce noise and enhance the quality of the data. This included:
  - Removing stop words and punctuation to eliminate irrelevant terms.
  - Converting integers into words for consistency.
  - Stemming and lemmatizing using the WordNet Lemmatizer, which reduced words to their base or root form. This helped minimize word variations and standardize different writing styles, making the feature extraction process more effective.

	A	B	C
1	Product Title	Brand	Review Text
2	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	I feel so LUCKY to have found this used (phone to us & not used hard at all), phone on line from someone who
3	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	nice phone, nice up grade from my pantach revue. Very clean set up and easy set up. never had an android p
4	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	Very pleased
5	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	It works good but it goes slow sometimes but its a very good phone I love it
6	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	Great phone to replace my lost phone. The only thing is the volume up button does not work, but I can still go in
7	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	I already had a phone with problems... I know it stated it was used, but dang, it did not state that it did not charg
8	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	The charging port was loose. I got that soldered in. Then needed a new battery as well. $100 later (not includin
9	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	Phone looks good but wouldn't stay charged, had to buy new battery. Still couldn't stay charged long so I trash
10	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	I originally was using the Samsung S2 Galaxy for Sprint and wanted to return back to the Samsung EPIC 4G for
11	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	It's battery life is great. It's very responsive to touch. The only issue is that sometimes the screen goes black an
12	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	My fiance had this phone previously, but caused many problems. So, of course, we decided to browse amazo
13	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	This is a great product it came after two days of ordering it. There was only one little blemish on the side,but wh
14	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	These guys are the best! I had a little situation with my item but they quickly fixed the issue. I was pleased and w
15	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	I'm really disappointed about my phone and service. The phone went out on me over a week ago. Instead of ha
16	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	Ordered this phone as a replacement for the same model until my contract expires and I can get a new one. Se
17	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	Had this phone before and loved it but was not working so I got this phone. One thing is the SD card slot does n
18	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	I was able to get the phone I previously owned...with a keyboard and touch screen. It's the best phone and I lov
19	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	I brought this phone as a replacement for my daughter, who is very hard on cell phones. I must say it was a grea
20	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	I love the phone. It does everything I need and works great. I purchased four of these phones through a seller t
21	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	unfortunately Sprint could not activate the phone due to the blocking issue with the phone, the matter was har
22	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	The battery was old & had been over used because it barely holds a charge. Otherwise, no issues with the pho
23	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	pros-beautiful screen,capable of running chrome,take good pictures,the keyboard is comfy,fits in my pocket
24	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	I purchased this phone in December as a christmas present to my son. I called sprint to activate the phone onl
25	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	Phone good just a little slow phone old but it's a great phone temporary right now. thank you for the great deal
26	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	Phone's speaker little low. Overall very happy with the phone. I would purchase another cell phone from Chub
27	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	the phone was great and in good condition. My Daughter is so happy the be a andriod user now !!!!!!!!!!!!!!!!!!!!
28	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	the reasons for the 3 star rating was it was in my opinion better than my iphone 4s but it tends to randomly cras
29	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	Phone works great. No problems at all
30	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	was not in good condition but does work good
31	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	Just... not good. The phone has great screen resolution, storage is low, you need an SD card to do anything.
32	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	as described, fast ship!
33	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	Perfect in every way.
34	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	One of the phones have a bad charger port. I want to send it back
35	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	Just got this phone and it is a great phone. It's easy to use.
36	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	The phone was great but it had gotten old so it was time for a replacement.it was great while it lasted.
37	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	This phone came in great condition! Great price and it brings back great memories of owning this phone!
38	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D700	Samsung	Met all of my expectations. I can't complain at all. Great price!
39	"Nokia Asha 302 Unlocked GSM Phone with 3.2MP Cam	Nokia	Phone is working on, I was planning to use it for whatsapp anyway. The oh problem, I can't change the idiom
40	"Nokia Asha 302 Unlocked GSM Phone with 3.2MP Cam	Nokia	excellent product in perfect condition
41	"Nokia Asha 302 Unlocked GSM Phone with 3.2MP Cam	Nokia	excellent
42	"Nokia Asha 302 Unlocked GSM Phone with 3.2MP Cam	Nokia	excelente
43	"Nokia Asha 302 Unlocked GSM Phone with 3.2MP Cam	Nokia	excelente
44	"Nokia Asha 302 Unlocked GSM Phone with 3.2MP Cam	Nokia	I like these phone I bought it for my mom and she loves it
45	"Nokia Asha 302 Unlocked GSM Phone with 3.2MP Cam	Nokia	It came with arabian keyboard :(
46	"Nokia Asha 302 Unlocked GSM Phone with 3.2MP Cam	Nokia	I love the phone, but one problem and one problem only............once the mic goes that's it. No more mic. But it
47	"Nokia Asha 302 Unlocked GSM Phone with 3.2MP Cam	Nokia	I love it!

Table No. 3.2.1

3.2.2 Refined Dataset

After the preprocessing phase, the dataset was refined and reduced to 316,811 reviews, which were used for the experimental evaluation of the proposed PRUS framework. The cleaning process ensured that the dataset contained high-quality, meaningful reviews by eliminating incomplete, short, or irrelevant entries. The reduced dataset offers a substantial and diverse sample for analysis, making the evaluation process more reliable and robust.

The cleaned dataset covers 371 different mobile phone brands, representing a broad spectrum of manufacturers. This diversity allows the framework to be tested across a variety of products, ensuring that the evaluation is not limited to a few popular brands. The inclusion of both major and lesser-known brands adds depth to the dataset, making the analysis more comprehensive.

Upon further examination, it was found that approximately 40% of the reviews were related to just three major brands: Samsung, BLU, and Apple. This indicates the dominance and popularity of these brands in the dataset. Their higher review volume reflects their market influence and customer base, making them significant players in the analysis. The concentration of reviews around these three brands also suggests that they attract more customer attention and engagement, possibly due to their widespread availability, brand reputation, and extensive marketing efforts.

The dataset spans reviews for approximately 4,300 different mobile phone models, showcasing a large and varied product sample. This diversity ensures that the PRUS framework is tested on a wide range of products with different specifications, performance levels, and customer experiences. Analyzing such a large number of models helps the system generalize better, making it applicable to a variety of products and not just a limited subset.

The analysis further revealed that the top ten most reviewed products in the dataset received between 800 and 1000 reviews each, indicating their popularity and high customer engagement. The large volume of reviews for these products highlights their frequent customer feedback, making them ideal candidates for detailed sentiment analysis. The presence of multiple reviews allows the PRUS framework to accurately identify trends, patterns, and recurring sentiments associated with these products. The higher review count also makes the sentiment analysis more reliable, as a larger sample size reduces the impact.

4. PROPOSED MODEL

The PRUS framework (Product Recommendation based on User Specification) follows a systematic process to extract aspect-level sentiments and generate a ranked product recommendation list.

- **Sentence Segmentation**

The process begins by breaking the review into individual sentences. This step is performed using the Python Natural Language Toolkit (NLTK) library, which enables efficient sentence tokenization. The purpose of this segmentation is to analyze each sentence independently, as reviews often contain mixed sentiments about different product features. By splitting the review into sentences, the system can separately evaluate each feature's sentiment, rather than relying on the overall review polarity.

- **Sentiment Analysis and Feature Extraction**

In the second phase, sentiment analysis and feature extraction are applied to the segmented sentences. This is implemented using the Python TextBlob library, which performs polarity classification by categorizing each sentence as positive, negative, or neutral. Simultaneously, TextBlob extracts the features mentioned in each sentence. For example:

  - In the sentence, *"The phone has an excellent camera but poor battery life"*, the features "camera" and "battery life" are extracted.
  - The sentiment polarity is positive for the camera and negative for the battery life.
    - This process is applied to all the product reviews in the dataset. Each sentence is analyzed to extract both the features and their associated sentiments, which are appended together.
  - Labelling Features with Sentiment
    - Once the features and their sentiments are extracted, they are labelled accordingly:
  - If a sentence expresses positive sentiment, the associated features are marked as positively reviewed.
  - If a sentence has negative sentiment, its features are labelled as negatively reviewed.
  - Sentences classified as neutral result in the features being labelled as neutrally reviewed.
    - This labelling enables the system to quantify the sentiment distribution for each product feature, providing a detailed sentiment breakdown.

- Sentiment Scoring
  - The system then calculates sentiment scores by counting the number of times each feature is labelled as positive, negative, or neutral across all reviews for a specific product.
- The total positive, negative, and neutral counts for each feature are aggregated.
- The sentiment score for a feature is computed using the following formula:
  - *Score = (Positive count−Negative count) / Total Count*
- This formula ensures that features with more positive occurrences receive higher scores, while those with frequent negative mentions receive lower scores.
- The neutral mentions balance the score by preventing extreme polarity shifts.
  - For instance, if the feature "camera" appears 100 times in the reviews, with 60 positive mentions, 30 negative mentions, and 10 neutral mentions, the score would be:

    Score = (60-30) / 100 = 0.3
  - This indicates a moderately positive sentiment for the camera.

- **Ranking with RANK-ify Algorithm**
  - Finally, the system applies the RANK-ify algorithm to generate the ranked product recommendation list. The algorithm uses the calculated sentiment scores to rank the products:
  - Products with higher positive sentiment scores for the user-specified features are ranked higher.
  - Products with more negative mentions or lower sentiment scores are ranked lower.
  - The RANK-ify algorithm ensures that the recommendations reflect both user preferences and sentiment-based feature evaluations, providing a personalized and accurate ranking.
  - Key Benefits of the PRUS Process
  - Granular Sentiment Analysis: By analyzing sentence-level sentiments, the system captures aspect-specific opinions, preventing misleading overall polarity judgments.
  - Comprehensive Feature Scoring: The system quantifies the positivity and negativity of each feature, making the ranking more accurate and meaningful.
  - Balanced Recommendations: By considering both positive and negative sentiments, the framework provides realistic and reliable product recommendations.
  - Efficient Ranking: The use of RANK-ify ensures that the final ranked list

prioritizes products with strong positive sentiments for the features specified by the user.

4.1 Rank – ify Algorithm

The RANK-ify algorithm is a core component of the PRUS framework, designed to rank products based on feature scores in accordance with user-specified preferences. Its goal is to generate a personalized, relevance-based product list by prioritizing products that exhibit strong positive sentiment for the features the user specifies in their query. The algorithm considers both positive and negative occurrences of the features, ensuring a balanced and realistic ranking.

4.1.1. Input Parameters and Initialization

The RANK-ify algorithm takes three input parameters:

- **k**: Represents the maximum number of products to be returned in descending order of relevance, i.e., from the most relevant to the least relevant according to the user's query.
- **Lp**: Refers to the set of all products in the dataset that have been reviewed. This set contains the features associated with each product along with the positive and negative occurrence counts of these features.
- **Q:** Represents the list of features extracted from the user's query, specifying the aspects that the user prioritizes in the product search.

4.1.2. Iterative Feature Matching

The algorithm iterates over:

- Every feature of each product (Line 4) and
- Each feature in the user query (Line 5).

For each product, the algorithm checks if the user-specified feature exists in the list of features associated with the product (Line 6). If the queried feature is present, the algorithm proceeds to calculate the Feature Score (FeaSco) for that feature using Equation 1 (Line 7):

$$FeaSco(f)=(w1*c(f+)-w2*c(f-)) / (c(f+)+c(f-))$$

Where:

- c(f+) → The **count of positive occurrences** of the feature fff.
- c(f−) → The **count of negative occurrences** of the feature.
- w1 → The **weight assigned to positive occurrences**.
- w2→ The **weight assigned to negative occurrences**.
- **Condition Sum of w1 and w2 should equals to One Always!!!**

4.1.3. Weighted Sentiment Scoring

The weight attributes w1 and w2 control the impact of positive and negative occurrences on the final ranking. Since users may value positive and negative opinions differently, these weights allow the system to adjust the influence of each sentiment.

- For example, if the user is more concerned with positive feedback, w1 will be larger than w2.
- Conversely, if the user gives more importance to negative feedback, w2 will be larger.
- To maintain balance and prevent one sentiment from dominating the ranking excessively, the algorithm enforces the condition:

$$w1+w2=1$$

This ensures that the influence of both sentiment polarities is normalized.

4.1.4. Rank-Score Calculation

Once the FeaSco is calculated for each user-specified feature in every product, the algorithm sums these feature scores to compute the overall Rank-Score of the product (Line 10). This Rank-Score represents the combined sentiment impact of all features in relation to the user’s query.

- Products with higher Rank-Scores exhibit stronger positive alignment with the user’s preferences.
- Products with more negative sentiment or fewer matching features receive lower scores.

Sorting and Final Recommendation

After calculating the Rank-Score for all products, the algorithm sorts the products in descending order (Line 12), prioritizing those with higher Rank-Scores.

- The top-k products from the sorted list are returned to the user (Line 13), providing a personalized and ranked recommendation list that closely matches their preferences.

Example Execution

For example, if a user queries for a smartphone with good battery life and camera, the algorithm:

- Iterates through all products and checks if they contain these features.
- Calculates the FeaSco for both battery life and camera by considering the positive and negative occurrences.

- Combines the FeaSco values into an overall Rank-Score for each product.
- Sorts the products based on their Rank-Score and presents the top-k ranked products to the user.

Algorithm 1 RANK-Ify Algorithm

k =Number of Products in Dataset
L_p =List of Products in Dataset
Q =Features in User Query
for $p \in L_p$ **do**
  for $U_f \in Q$ **do**
    if $U_f \in p$ **then**
      $FS(U_f) = FeaSco(U_f)$
    end if
  end for
  $RS(p) = \sum_{U_f \in Q} FS(U_f)$
end for
Sort L_p w.r.t. RS
Return top-k from L_p

Fig. 4.1.4.1

4.2. Key Benefits of the RANK-ify Algorithm

- **Granular Sentiment Evaluation:** By considering both positive and negative occurrences, the algorithm offers a balanced ranking.
- **Weighted Scoring:** The weight parameters allow the system to customize the impact of positive and negative feedback, aligning with user priorities.
- **Efficient and Scalable:** The algorithm efficiently processes large datasets by iterating over relevant features only, making it suitable for scalable e-commerce platforms.
- **Personalized Recommendations:** By prioritizing products based on user-specified features, the algorithm generates accurate and personalized recommendations, enhancing the user experience.

  Overall, the **RANK-ify algorithm** is a robust and efficient method for ranking products based on aspect-level sentiment analysis. Its ability to consider both positive and negative occurrences, apply weight-based scoring, and provide personalized recommendations makes it highly effective for e-commerce product ranking systems.

5. DISCUSSIONS ON THE PROPOSED OUTPUT

5.1 Experiments and Results

The experimental evaluation of the PRUS framework demonstrates its effectiveness in generating personalized product recommendations by ranking products based on aspect-level sentiment analysis. The evaluation was conducted using a preprocessed Amazon dataset containing mobile phone reviews from various brands. The system was tested by extracting features from a user query and generating a ranked recommendation list based on the Discounted Cumulative Gain (DCG) measure. The results highlight the accuracy and reliability of the PRUS framework in providing feature-specific recommendations, overcoming the limitations of overall review-based scoring.

Sentiment-Driven Feature Scoring

In the proposed approach, TextBlob was used to perform sentiment analysis, assigning individual sentiment scores to the features of each product. These scores were normalized on a scale of 1 to 10 to ensure consistent evaluation across all products. The framework calculates the Average Aspect Score (AAS) for each product usingthebelow equation:

$$AAS(p, Q) = 1/Count(\sum_{i=1}^{count} S(i))$$

Here, for a product p, all the features relevant to the user query (Q) are considered. Their sentiment scores are averaged, providing a composite score that reflects the product's overall feature relevance. This ensures that products are ranked based on the sentiment scores of the features that matter most to the user, rather than relying on an overall rating.

For example, in a review stating:

"The screen quality is good, but the battery life is poor,"

The **screen quality** receives a **sentiment score of 8.65**, while the **battery life is assigned score of 3.7**, indicating positive and negative sentiments for different features. Traditional systems would assign a single overall rating, which could be misleading, while PRUS assigns individual scores to each feature, offering more precise and granular sentiment analysis.

DCG and nDCG-Based Ranking

Once the AAS values are calculated for all products, the DCG score is computed using the below Equation:

$$DCG_p = AAS_1(p, Q) + \sum_{a=1}^{p} \frac{AAS_a(p, Q)}{log_2 a}$$

The DCG score quantifies how effectively a product matches the user-specified features and their associated sentiment scores. To ensure a fair and unbiased ranking, the system calculates the Ideal DCG (IDCG) using the below Equation:

$$IDCG_p = \sum_{i=1}^{p} \frac{AAS_i}{log_2(i+1)}$$

The IDCG represents the optimal ranking scenario, where the most relevant products receive the highest scores. Finally, nDCG is calculated using the below Equation:

$$nDCG_P = \frac{DCG_P}{IDCP_P}$$

The nDCG value ensures that the ranking is normalized, making it more consistent and reliable across different product lists.

Demonstration of the Output

To demonstrate the effectiveness of PRUS, the authors conducted an example evaluation using a user query that requested a mobile phone with a good camera and high screen resolution. The system successfully displayed the top 10 ranked products based on:

- Rank Score (RS): Calculated using the RANK-ify algorithm.
- nDCG values: Derived using Equation 5.

  The results showed that the highest-ranked products were those that received strong positive sentiment scores for both camera quality and screen resolution. While several products shared the same Rank Score (0.9), the nDCG values varied, allowing the system to further differentiate the products based on their overall sentiment relevance.
- The products with higher nDCG scores appeared at the top of the recommendation list, as they exhibited stronger positive feedback for the features specified by the user.
- The products with lower nDCG scores were ranked lower, reflecting their weaker alignment with the user's query.
- This two-layer ranking system ensures that the most relevant products are placed higher, even when multiple products have the same Rank Score.

Key Advantages of the PRUS Output

The experimental results demonstrate several key benefits of the PRUS framework:

- Feature-Specific Ranking: Unlike traditional models that rely on overall ratings, PRUS assigns individual sentiment scores to product features, ensuring more accurate and personalized recommendations.
- Granular Sentiment Analysis: The system successfully captures both positive and negative opinions about different product features, preventing misleading overall ratings.
- DCG-Based Normalization: The use of nDCG values ensures that products are ranked fairly and consistently, even when their Rank Scores are identical.
- Improved Decision-Making: The feature-based scoring allows users to make better-informed decisions by clearly identifying products that excel in the specific features they care about.
- Efficient Query-Based Personalization: PRUS effectively tailors the recommendations to user preferences, offering a highly customized product ranking.

Discussion on Practical Implications

The PRUS framework offers a significant improvement over traditional product ranking methods, especially for e-commerce platforms. The ability to prioritize features based on user-specified preferences ensures that the recommendations are:

- Highly relevant and tailored to individual needs.
- Accurate, as the system captures fine-grained feature sentiments rather than relying on general product ratings.
- Efficient, by applying DCG and nDCG scoring, making the ranking fair and consistent across products.

For example, a customer searching for a laptop with long battery life and lightweight design would benefit from PRUS, as it ranks products based on aspect-specific sentiment scores rather than general ratings.

Overall, the experimental output of the PRUS framework demonstrates its effectiveness, reliability, and practicality in delivering accurate, feature-specific, and personalized product recommendations.

5.2 Performance Analysis of the PRUS Method

The **PRUS framework** was subjected to a series of experiments to evaluate its performance and effectiveness in generating ranked product recommendations based on user-specified features. The experiments were conducted by varying the weights w1w1w1 and w2w2w2, which control the influence of positive and negative occurrences of product features, respectively. The key objective was to observe the impact of these weight variations on the Rank Score (RS) and Normalized Discounted Cumulative Gain (nDCG), which are used as evaluation metrics.

5.2.1. Experiment Setup and Weight Variations

In the experiments, the **weights were alternated** in such a way that their **sum equals 1**, i.e.,w1+w2=1

The weights were varied over a range of **0.1 to 0.9**, creating different **combinations of positive and negative influence** on the final product ranking. The **product list (P1 to P10)** represents the **top-ranked products** based on the **RS and nDCG scores** corresponding to the different weight combinations. The **results of these experiments** are summarized in the below Table**.**

Product		**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**
Rank		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
PW=0.9 NW=0.1	Rank Score	2.7	2.7	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8
	nDCG Score	0.94	2.06	2.81	3.59	4.06	4.44	4.94	4.94	5.81	6.67
PW=0.8 NW=0.2	Rank Score	2.24	2.24	1.61	1.61	1.61	1.61	1.61	1.61	1.61	1.61
	nDCG Score	1.00	2.06	2.92	3.65	4.15	4.55	4.90	5.37	5.91	6.36
PW=0.7 NW=0.7	Rank Score	2.1	2.1	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
	nDCG Score	1.00	2.06	3.06	3.59	3.77	4.57	4.85	5.27	5.50	6.44
PW=0.6 NW=0.4	Rank Score	1.8	1.8	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2
	nDCG Score	0.94	2.06	2.79	3.60	4.02	4.44	4.58	5.15	5.97	6.72
PW=0.5 NW=0.5	Rank Score	1.5	1.5	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	nDCG Score	0.94	2.06	3.07	3.39	4.02	4.57	4.84	5.47	5.70	6.03
PW=0.4 NW=0.6	Rank Score	1.2	1.2	1	1	1	0.85	0.84	0.82	0.80	0.80
	nDCG Score	1	2.06	2.73	3.29	3.47	4.57	5.41	6.13	7.36	8.07
PW=0.3 NW=0.7	Rank Score	1	1	1	0.9	0.9	0.71	0.7	0.7	0.68	0.65
	nDCG Score	0.488	1.04	1.97	4.05	5.40	4.62	2.23	2.65	14.9	15.8
PW=0.2 NW=0.8	Rank Score	1	1	1	0.8	0.8	0.6	0.6	0.6	0.57	0.52
	nDCG Score	0.48	1.00	2.09	1.42	1.99	6.67	8.35	6.00	14.7	17.2
PW=0.1 NW=0.9	Rank Score	1	1	0.9	0.9	0.63	0.5	0.42	0.360	0.36	0.52
	nDCG Score	1.89	2.65	1.93	3.60	3.97	5.64	13.2	8.01	9.13	17.2

Table No. 5.2.1.1

5.2.2. Impact of Positive and Negative Weights on nDCG

The nDCG scores represent the relevance of the ranked products based on the user-specified features and their associated sentiments. The experimental results reveal the following trends:

- When the positive weight (w1) ranges between 0.9 and 0.5, there is no significant change in the overall nDCG scores. This indicates that as long as positive sentiments dominate, the relevance of the product ranking remains consistent.

- However, as soon as the negative weight (w2) increases beyond 0.5, there is a sudden increase in the nDCG scores. This happens because products with more negative mentions gain higher weight, making them more prominent in the ranking.
- This outcome demonstrates that nDCG scores increase when negative feedback is given more importance, reflecting a shift in product relevance towards products with more critical sentiments.

5.2.3. Impact on Rank Score (RS)

The **Rank Score (RS)**, calculated using the **RANK-ify algorithm**, represents the overall product ranking based on both positive and negative occurrences of the features. The experimental results show the following trend:

- When the positive weight (w1) is high (greater than 0.5), products with more positive feature sentiments receive higher Rank Scores.
- As the negative weight (w2) crosses 0.5, the RS begins to decline. This is because the increased influence of negative feedback causes products with more negative mentions to be ranked higher, lowering the RS for products with predominantly positive reviews.
- This behaviour aligns with the FeaSco formula (Equation 1), which defines the Feature Score as:

$$FeaSco(f)=(w1*c(f+)-w2*c(f-)) / (c(f+)+c(f-))$$

Where:

- w1 → The positive weight.
- w2 → The negative weight.
- c(f+) → The count of positive occurrences.
- c(f−) → The count of negative occurrences.
- Increasing w2 reduces the overall FeaSco value, leading to lower Rank Scores for products with more positive mentions.

5.2.4. Influence of Weight Variation on the Product List

The product list (P1 to P10) varies significantly as the positive and negative weights are adjusted.

- With higher positive weights, the products with strong positive sentiment for the user-specified features dominate the top ranks.
- As the negative weight increases, the list becomes populated with products that have more negative mentions for the specified features, reflecting the increased influence of negative sentiment.

- This highlights the flexibility of the PRUS framework, allowing users to adjust the ranking by controlling the impact of positive and negative occurrences.

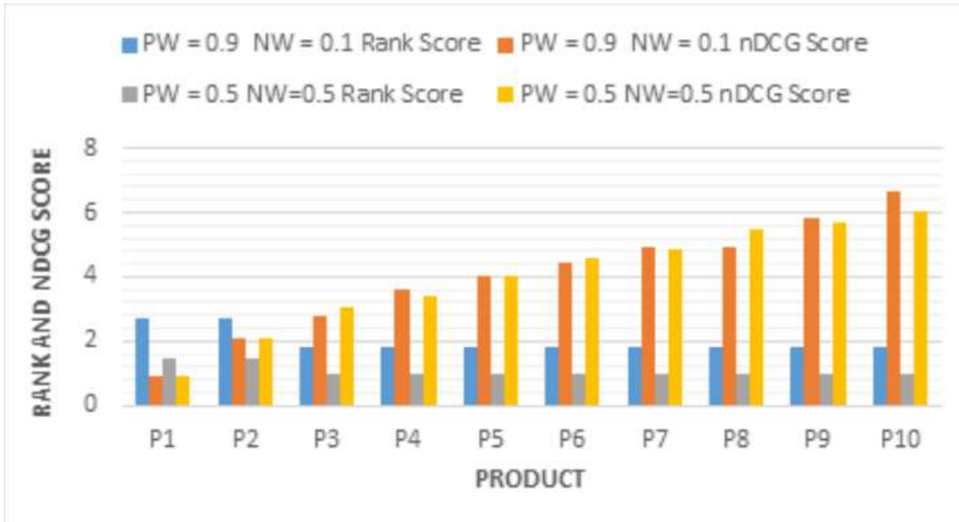

Fig. 5.2.4.1

5.2.5. Key Observations from the Performance Analysis

The experiments reveal several key insights into the performance of the PRUS framework that was discussed in the paper:

- No Major Change in nDCG with Higher Positive Weight: When the positive weight ranges between 0.9 and 0.5, there is no substantial change in the nDCG scores. This suggests that as long as positive sentiment dominates, the overall relevance of the recommendations remains stable.
- nDCG Increases with Higher Negative Weight: As the negative weight increases beyond 0.5, nDCG scores rise sharply. This is because the system prioritizes products with more negative feedback, making critical reviews more prominent in the ranking.
- Rank Scores Decrease with Increasing Negative Weight: When negative sentiment gains more influence (w2 > 0.5), the Rank Scores decline. This occurs because negative features are weighted more heavily, reducing the overall RS of products with predominantly positive reviews.
- User-Controlled Sentiment Influence: The PRUS framework provides users with the ability to control the degree of positive and negative influence on the final product list. This makes the system highly flexible and customizable, catering to individual preferences.

6. CONCLUSION AND FUTURE WORK

6.1. Conclusion

In this study, a Product Recommendation based on User Specification (PRUS) framework was proposed to generate a personalized, ranked list of products by analyzing customer reviews. Unlike existing methods, the PRUS approach incorporates both positive and negative sentiments of individual product features, enabling more accurate and personalized recommendations. While traditional ranking models often prioritize products based on overall sentiment, PRUS addresses the granularity issue by performing aspect-level sentiment analysis, ensuring that feature-specific opinions influence the ranking process.

The PRUS framework operates in three phases:

1. **Feature and Sentiment Extraction**: The system extracts features and their associated sentiments from individual sentences of customer reviews, capturing both positive and negative opinions at the sentence level.
2. **Feature-Sentiment Association**: The extracted features are appended with their respective sentiment polarities, allowing the system to quantify the positive and negative occurrences of each feature.
3. **Ranking Phase**: The user-specified features are extracted from the query, and the products are ranked using the RANK-ify algorithm based on their Rank Scores (RS). The RS considers both positive and negative weights, providing a balanced and realistic ranking.

   The PRUS framework offers flexibility by allowing users to adjust the weight parameters associated with positive and negative sentiments. This gives users the ability to customize the ranking based on their individual preferences. Through extensive experiments, the PRUS framework demonstrated its effectiveness and accuracy in generating personalized recommendations, showing that:

- Increasing the negative weight results in a higher nDCG score, as products with more negative mentions become more prominent in the ranking.
- Increasing the positive weight causes the Rank Score to increase, prioritizing products with more positive sentiment.

  The experimental results validated the reliability and accuracy of the PRUS framework, making it a robust solution for e-commerce platforms and other review-based product ranking systems.

6.2. Future Work

While the PRUS framework has demonstrated promising results, several avenues for future research remain open. These directions aim to enhance the framework's flexibility, scalability, and applicability in real-world scenarios:

1. **Multilingual Product Review Datasets**:
    - The current PRUS framework is applied to English-language reviews only. A natural extension of this work would be to implement multilingual support.
    - This would enable the framework to process reviews in multiple languages, making it applicable to global e-commerce platforms.
    - Future work could incorporate language translation models or multilingual sentiment analysis techniques to extract feature-level sentiments across diverse languages.
2. **User-Controlled Polarity Customization**:
    - The PRUS framework currently allows users to adjust the weight parameters associated with positive and negative sentiments, offering some flexibility in ranking.
    - Future enhancements could provide more advanced customization options, allowing users to:
        - Specify individual sentiment thresholds for specific features.
        - Define custom polarity preferences, such as favoring features with balanced sentiments or discounting neutral feedback.
    - This would result in more dynamic and user-centric recommendations.
3. **Incorporating Contextual and Temporal Factors**:
    - Future research could enhance the PRUS framework by incorporating contextual information such as time-sensitive reviews or trending sentiments.
    - This would allow the system to prioritize recent reviews or consider seasonal trends when ranking products, making the recommendations more relevant and timely.
4. **Real-Time Product Recommendation System**:
    - To make the PRUS framework more practical for real-world applications, future work could focus on real-time product ranking.
    - This would enable the system to dynamically rank products as new reviews are added, ensuring that the recommendations remain current and accurate.

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