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ANALYZING CONSUMER PREFERENCE DYNAMICS IN AMAZON REVIEW DATA USING DOUBLE PROPAGATION-BASED SENTIMENT ANALYSIS

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ABSTRACT

This research proposes an innovative approach to extracting consumer preferences using Sentiment Analysis, addressing the limitations of traditional methods like Conjoint Analysis. Consumer preferences, influenced by factors such as product quality, experience, and emotions, are crucial for shaping marketing strategies and product development. While Conjoint Analysis faces issues like small sample sizes and high costs, Sentiment Analysis, particularly Aspect-Level Sentiment Analysis (ABSA), provides a more detailed and dynamic method by analyzing sentiments toward specific product attributes. Leveraging big data from e-commerce reviews, this technique offers real-time insights, is cost-effective, and does not require predefined sentiment dictionaries. The study utilizes the Double Propagation (DP) technique, which enhances sentiment accuracy through bidirectional analysis. This approach offers a more efficient, automated, and adaptive solution for understanding consumer preferences. The evaluation, conducted on Amazon Review Data, confirms the moderate effectiveness of DP in aspect extraction, with room for enhancement in dependency rules and aspect identification algorithms. The results of experiment also highlight the variability in DP's aspect-level accuracy, with consistently strong results for Price and Performance, but challenges in Port, Design, and Storage.

Keywords: *Consumer preference, Conjoint analysis, Sentiment analysis, Aspect, Opinion word*

1. INTRODUCTION

Consumer preference is the tendency of individuals to choose a product, service, or brand based on their needs, desires, and experiences [1]. This preference reflects what consumers consider important or satisfying in a product [2]. In the context of marketing and product development, understanding consumer preferences is a crucial step to creating effective business strategies, improving product quality, and gaining a competitive edge in the market [3].

Consumer preferences are typically influenced by various factors that shape their choices and opinions about products. One key factor is the product itself, where aspects such as quality, price, design, durability, or additional features play a significant role. For instance, a consumer might favor a smartphone with a "high-resolution camera" because it aligns with their needs and expectations. Another crucial factor is user experience, as positive or negative interactions with a product can strongly affect preferences. Reviews like "fast service" or "slow delivery" highlight how experiences impact consumer satisfaction. Psychological and emotional factors also contribute significantly, with elements like brand loyalty, trust in a product's reputation, and positive associations driving preferences. Furthermore, social context, including the opinions of friends, family, or online communities, often influences how consumers evaluate and choose products [4]. For example, reviews on platforms like Amazon can shape perceptions by providing insights from other users. On such platforms, consumer preferences are often expressed through textual reviews, which are rich in information. These reviews not only convey sentiment, whether positive or negative, but also reveal specific details about

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what consumers like or dislike, offering valuable insights into their preferences [5].

For companies, understanding consumer preferences offers several strategic benefits that can enhance their competitiveness in the market. One of the key advantages lies in product development, as insights into what consumers like or dislike enable companies to improve product quality and align it with customer expectations. Additionally, analyzing consumer preferences helps in market segmentation by allowing companies to identify specific market segments [6] based on unique needs and characteristics, making it easier to tailor products or services for targeted audiences. Moreover, consumer preferences provide a solid foundation for designing more relevant and engaging marketing strategies, ensuring that promotional messages resonate with the intended audience. Lastly, leveraging data from consumer reviews supports data-driven decision-making, enabling companies to make more accurate and informed choices to meet market demands effectively [7]. These benefits highlight the importance of understanding consumer preferences as a critical factor for business success.

A common technique used to extract consumer preferences is known as **Conjoint Analysis**. In marketing research and consumer preference analysis, Conjoint Analysis is frequently employed to measure how consumers evaluate the importance of various attributes or aspects of a product [8]. This technique is widely used in marketing research to understand how consumers make decisions based on a combination of product attributes or features. Conjoint Analysis helps identify which product attributes are most important to consumers and how these attributes influence their preferences. Surveys are the primary approach for collecting the data required for Conjoint Analysis [9].

Conjoint Analysis works by asking respondents to evaluate different combinations of product attributes, allowing researchers to quantitatively understand consumer preferences for each attribute [10]. For example, in selecting a smartphone, the attributes being evaluated might include "price," "camera quality," "battery life," and "storage capacity." By using Conjoint Analysis, researchers can determine which attributes have the greatest influence on consumers' purchasing decisions [11].

Although widely used, Conjoint Analysis has several fundamental limitations that reduce its effectiveness, particularly in today's era of big data [2]. One major limitation is the small sample size, as this method typically relies on surveys conducted with a limited number of respondents. This can result in findings that fail to represent the broader consumer preferences, especially in highly diverse markets such as e-commerce [12]. Additionally, the process of designing surveys, collecting data, and performing the analysis is time-consuming and costly, making it less practical for frequent use. Another drawback lies in its reliance on consumer awareness; Conjoint Analysis only captures preferences for attributes explicitly identified in the survey, potentially overlooking important aspects that consumers may value but are not consciously aware of. Respondent bias is another concern, as survey answers can be influenced by perceptions or social pressures, leading to results that do not always reflect genuine preferences. Finally, the method's lack of dynamism poses a challenge in rapidly changing markets [13]. Consumer preferences can shift quickly, but the nature of Conjoint Analysis makes it difficult to conduct repeated surveys in the short term, rendering it less responsive to these changes.

To address the limitations of survey-based Conjoint Analysis, this study proposes an alternative approach that is more effective and efficient, namely consumer preference extraction using Sentiment Analysis techniques. Sentiment Analysis is a branch of Natural Language Processing (NLP) that aims to identify, extract, and analyze opinions, emotions, or attitudes in text. Sentiment Analysis is used to determine whether the sentiment in a text is positive, negative, or neutral, as well as to measure the intensity of the emotions or sentiment contained within [14]. Sentiment Analysis has become a highly beneficial technique, especially in e-commerce ecosystems such as Amazon, Shopee, or Tokopedia. This is supported by the large volume of consumer review data generated every day. Each transaction and consumer interaction leaves a trace in the form of opinions, product reviews, or ratings, which are rich in information about their experiences and preferences. E-commerce platforms like Amazon have millions of active users who leave reviews on various products every day. This data includes: 1) Textual opinions containing descriptions of consumer experiences, both positive and negative, 2) Numerical ratings: Scores given to indicate satisfaction levels, 3) Tags or metadata: Indicators such as date, location, or product category [15]. For example, popular product categories like electronics, clothing, or household items can accumulate thousands of reviews in a short period. This makes e-commerce review data a valuable but challenging resource to analyze manually [16].

The advantages of sentiment analysis based on review data include cost and time efficiency, as this approach does not require survey design processes, questionnaire distribution, or manual data collection. Consumer review data is already available in real-time and can be easily accessed. This significantly reduces the time and costs compared to traditional surveys [17]. Additionally, the analysis results have a broader representation opportunity, as consumer review data includes millions of opinions from diverse consumer backgrounds, providing a more representative picture of market preferences. Most importantly, the analysis can be conducted dynamically and continuously in real-time, adapting to changes in trends or market behavior. This is crucial in the digital age, where consumer needs and expectations can change rapidly [18].

There are two types of approaches in Sentiment Analysis: 1) Document-level sentiment analysis and 2) Aspect-level sentiment analysis. Document-level sentiment analysis focuses on assessing the overall sentiment of a document or review. In this approach, sentiment is calculated globally, classifying the text as positive, negative, or neutral [19]. This technique is well-suited for reviews or short texts that discuss a single topic or object, as it provides a quick overview of the user's feelings toward the product or service. However, this approach is less effective in capturing deeper sentiments towards specific elements within the text. On the other hand, Aspect-Level Sentiment Analysis (ABSA) offers a more detailed analysis by identifying and evaluating sentiment toward specific aspects or features of the object discussed in the text. For example, in product reviews, ABSA allows us to determine whether consumers like the camera quality, battery life, or product design separately [20]. This makes ABSA particularly useful for longer reviews or those covering multiple aspects, such as product reviews on e-commerce platforms. Although ABSA is more complex and requires more advanced processing techniques, such as aspect extraction or machine learning models, this approach provides deeper and more precise insights into understanding user preferences and experiences. This study proposes consumer preference extraction based on Double Propagation (DP) technique from Bing Liu [21]. The ABSA technique based on DP from Bing Liu is a rule-based method that does not require training data, making it highly advantageous in processing.

One of the main advantages of the Double Propagation technique is its ability to operate without relying on existing sentiment dictionaries. By leveraging patterns that emerge from the data, this technique can learn to identify aspects and associated sentiments without depending on external sources, which are often limited or incomplete. Because this technique takes into account the reciprocal relationship between aspects and sentiment, the accuracy of sentiment extraction and classification is improved. Bidirectional propagation helps capture deeper relationships between aspects and feelings, which are not always easy to understand by simply looking at the text unilaterally.

Based on the description above, the novelty of this research lies in the following aspects: 1) Utilization of Big Data: Unlike traditional techniques based on manual surveys with Conjoint Analysis, this approach leverages large-scale review data. 2) Automation of Preference Extraction: By utilizing methods such as Double Propagation, preference analysis is carried out automatically and systematically. 3) Real-Time Insights: This approach enables dynamic and adaptive analysis in response to changes in consumer behavior. 4) Focus on Aspect-Level Analysis: This technique not only analyzes overall preferences but also explores preferences at a more detailed aspect level, providing deeper insights.

2. METHODS

The entire process of extracting consumer preferences is explained in Figure 1. This study utilizes the Amazon Review dataset to extract aspect-opinion word pairs using the Double Propagation (DP) technique. Double Propagation, introduced by Bing Liu, is a rule-based approach that leverages linguistic patterns and syntactic relations to identify both aspects and opinion words without requiring labeled training data. Amazon Review Data is a collection of customer reviews and ratings provided by users after purchasing and using products sold on the Amazon platform. This dataset is a rich source of consumer feedback, offering valuable insights into customer preferences, product performance, and overall satisfaction. Reviews include various details such as review text, star ratings (usually ranging from 1 to 5), review metadata like the review date, the number of helpful votes received, and anonymized information about the reviewers. Some reviews also include multimedia attachments, such as photos or videos, which strengthen the feedback provided.

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Amazon Review Data is widely used in research and business applications, such as sentiment analysis to understand customer emotions and satisfaction, the development of recommendation systems to suggest products based on user preferences, and market research to identify trends, gaps in product offerings, or to evaluate competitors. Additionally, this dataset is utilized for product quality monitoring, where recurring complaints or negative reviews help businesses address product defects or improve services. In the fields of artificial intelligence and machine learning, Amazon Review Data is often employed to train models for tasks such as text classification, language modeling, and consumer behavior analysis. This dataset is publicly available for non-commercial research purposes, such as through the Amazon Customer Review Dataset provided by Amazon Web Services (AWS), which offers structured review data across various product categories.

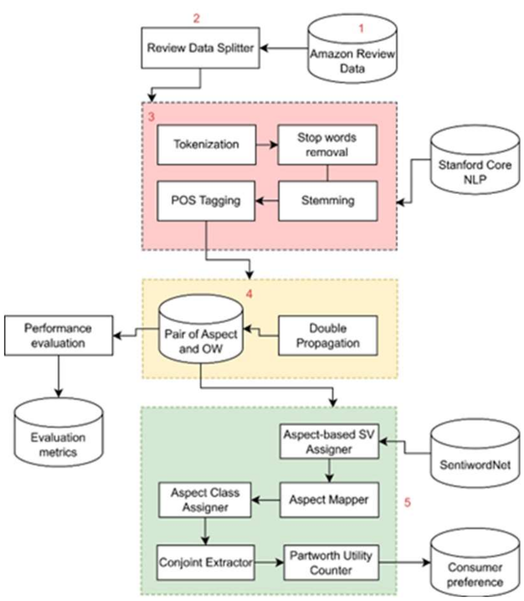

Figure 1: Proposed method

In the next step we employ Stanford CoreNLP to perform text preprocessing step. Stanford CoreNLP is a powerful and widely-used natural language processing (NLP) toolkit developed by Stanford University. It provides a comprehensive set of tools for analyzing and processing text in multiple languages. CoreNLP performs various linguistic tasks, such as tokenization, part-of-speech (POS) tagging, lemmatization, named entity recognition (NER), dependency parsing, sentiment analysis, and coreference resolution. Designed as a pipeline-based system, it allows users to chain multiple annotations for seamless text processing. With support for both command-line use and integration with programming languages like Java, Python, and others, Stanford CoreNLP is a versatile tool for researchers, developers, and data scientists working on NLP projects.

Text preprocessing using Stanford CoreNLP involves several essential stages to prepare raw text for analysis. The process begins with tokenization, where the text is divided into smaller units called tokens, such as words, numbers, or punctuation marks. This step transforms unstructured text into a structured format, making it easier to process. After tokenization, stopword removal is performed to eliminate common words like "is," "the," and "and" that do not carry significant meaning in the context of the analysis, reducing noise in the data. Following this, stemming is applied to reduce words to their root or base form, often by removing suffixes. For example, words like "running," "runs," and "ran" are reduced to "run," ensuring consistency across similar terms. Finally, part-of-speech (POS) tagging is conducted, where each token is assigned a grammatical category, such as noun, verb, or adjective, to understand its role in the sentence. The POS tagging step is important for the implementation of Dooble Propagation (DP) in the next step

We utilize Double Propagation (DP) to extract pairs of aspect and opinion words. DP is a well-established technique in sentiment analysis and opinion mining, designed to extract and interpret sentiment from textual data, particularly in scenarios involving multiple entities and their associated aspects. The method operates through a two-phase process: first, identifying the sentiment of entities and their corresponding features, and second, propagating this sentiment throughout the text based on linguistic relationships. Initially, sentiment is assigned to entities (e.g., products or services) and their aspects (e.g., product quality or battery life) by analyzing the contextual information. Once this initial sentiment assignment is complete, it is further propagated across the text through the relationships between entities and their aspects. For instance, if a product is evaluated positively, its related aspects, such as "battery life," will also inherit that positive sentiment, and conversely, negative discussions about aspects will influence the sentiment of the entity. This approach significantly enhances the accuracy and contextual relevance of sentiment analysis by accounting for the interactions between entities and their attributes. DP is particularly effective in addressing complex sentiment expressions, such as those found in product reviews, where multiple opinions regarding various features are often expressed within a single sentence. This enables a more comprehensive understanding of consumer preferences and refines sentiment classification. In our implementation, we apply eight DP rules using the Stanford CoreNLP toolkit. As an example, here we outline the first rule of DP in formula (1) where the output is t=T.

$$0 \rightarrow 0 - DEP \rightarrow T \; s.t \; 0 \in \{0\},\; 0 - Dep \in \{MR\}, POS(T) \in \{NN\} \quad (1)$$

After extracting the pairs of aspect and opinion words, we assign a sentiment value to the opinion word using SentiWordNet. SentiWordNet is a specialized lexical resource created to support sentiment analysis and opinion mining. It builds on WordNet—a lexical database that organizes English words into synonym sets, or synsets, based on their meanings—but differs by assigning sentiment scores to each synset. These scores help determine the sentiment orientation of a word in a specific context. Each synset is annotated with three numerical scores representing positivity, negativity, and neutrality (or objectivity), which range from 0 to 1 and always add up to 1. This approach allows words with multiple meanings, such as "cold," which can refer to temperature or emotions, to have distinct sentiment scores for each interpretation. Since we do not address word ambiguity in this implementation, we select the first sense of the word from SentiwordNet's synset.

Adopting conjoint analysis formula, for posA and negA, which represent the positive and negative sentiment scores of an aspect, respectively, psA and nsA refer to the total positive and negative sentiment scores for aspect A across the entire document. If m denotes the total number of documents, psA_ji and nsA_ji can be computed using equations (1) and (2). Additionally, sC represents the conjoint score, β_j denotes the partworth utility of aspect A_j, n is the total number of successfully extracted aspects, and μ is the linear coefficient. The value of β_j is then determined using equation (3).

$$psA_{ji} = \sum_{i=1}^{m} posA_{ji} \quad (2)$$

$$nsA_{ji} = \sum_{i=1}^{m} negA_{ji} \quad (3)$$

$$sC = \left(\sum_{j=1}^{m} \beta_j * A_j\right) + \mu \quad (4)$$

3. RESULTS AND DISCUSSION

To evaluate the performance of Double Propagation in extracting aspects, precision, recall, F-measure, and accuracy are utilized as key metrics. Precision measures the proportion of correctly extracted aspects relative to the total aspects identified by DP, reflecting its ability to minimize false positives and extract only relevant terms. Recall, on the other hand, assesses how well DP captures all relevant aspects in the dataset, with lower values indicating that some important aspects are missed. The F-measure, which harmonizes precision and recall, provides a balanced evaluation of the model's performance, particularly when there is a trade-off between these two metrics. Accuracy offers an overall measure of correctness by considering both correctly extracted aspects and correctly ignored non-aspects. In this experiment, the results suggest that DP demonstrates moderate to strong performance across these metrics, but variations between precision, recall, and F-measure highlight areas for improvement. Enhancing dependency rules or refining aspect identification algorithms could further boost both precision and recall, ultimately improving the overall reliability of DP for aspect extraction.

The evaluation of DP for aspect extraction is conducted using the Amazon Review Data as the dataset. This dataset is well-suited for the experiment, as it contains a large volume of customer reviews rich in opinions and aspect-related terms, making it an ideal resource for analyzing sentiment and extracting key aspects. The diversity of product categories and the variety of linguistic expressions in the reviews present a realistic challenge for DP, testing its ability to identify relevant aspects across different contexts.

For the experiment, we utilize subsets of the Amazon Review Data, specifically focusing on categories such as Baby Products, Automotive, Electronics, and the Kindle Store. These categories provide diverse contexts and varying levels of complexity in language use, allowing for a comprehensive evaluation of Dependency Parsing (DP) in aspect extraction. Each category presents unique challenges; for instance, reviews in Baby Products often focus on safety and usability, while Automotive reviews emphasize performance and durability. Similarly, Electronics reviews commonly highlight technical specifications and features,

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whereas Kindle Store reviews may include more abstract opinions about digital content.

The sentiment analysis experiment demonstrates a moderate performance level based on the given evaluation metrics. The result is presented in Fig. 2. Precision values range from 0.482 to 0.578, indicating that the model performs relatively well in predicting positive cases, though some false positives remain. Recall scores, ranging from 0.502 to 0.573, show the model's ability to identify true positives consistently, but there is still room for improvement in capturing more relevant cases. The F-measure, balancing precision and recall, varies between 0.492 and 0.575, reflecting an overall stable yet moderate performance. The accuracy, ranging from 0.788 to 0.842, highlights the model’s strong ability to predict correctly across all instances, demonstrating reliability in a broader sense. Despite these promising results, further optimization in data preprocessing, model parameters, or algorithm selection could enhance the precision and recall, ultimately improving the overall performance of the sentiment analysis system.

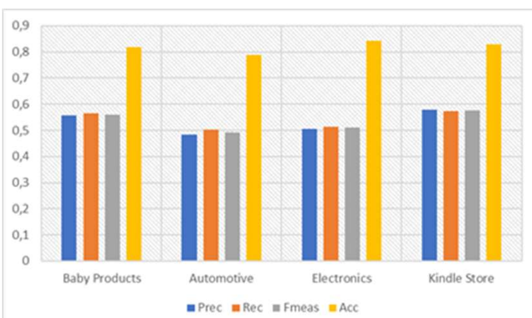

Figure. 2 Result of experiment in document level ground truth using Amazon Review Data.

We also calculate accuracy for aspect level ground truth using several datasets grabbed from Amazon platform. The category of the grabbed datasets is Computers, namely: Asus E410, Acer Aspire 3 and Lenovo Ideapad 3i. For the ground truth, we manually annotated 4 aspect namely Storage, Price, Design, Port and Perform. The result of accuracy for aspect level ground truth is presented in Fig. 3. In aspect-level sentiment analysis, accuracy is calculated by comparing the model's predictions for specific aspects of a product or service with the labeled ground truth data. Ground truth consists of annotated data that specifies the correct aspect-sentiment pairs, such as identifying "battery life" as an aspect and tagging its sentiment as positive, negative, or neutral. To compute accuracy, the model's predictions are evaluated based on their alignment with these labels. For instance, if the model predicts "battery life: positive" and this matches the ground truth, it is considered correct. Challenges in this computation include handling synonyms (e.g., "shipping speed" vs. "delivery time") and nuanced sentiments where polarities may be difficult to classify. Measuring accuracy at the aspect level helps assess how well the model captures consumer preferences and opinions, which is critical for evaluating the effectiveness of a sentiment analysis framework, such as one based on the Double Propagation technique. High accuracy reflects a model’s ability to identify and analyze consumer preferences with precision, providing valuable insights into the aspects that influence customer satisfaction.

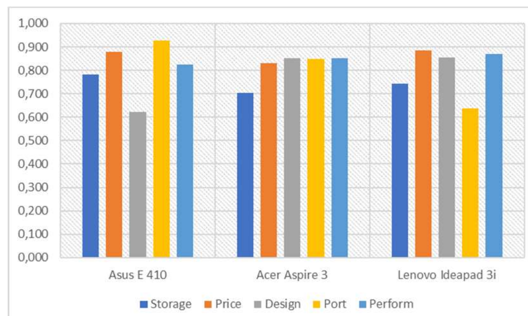

Figure 3: The accuracy of DP in the aspect level ground truth

The results of the experiment using Double Propagation for aspect-level ground truth analysis reveal distinct patterns in accuracy across different product aspects for the three laptop models. The Asus E410 demonstrates excellent accuracy in identifying aspects related to Port (0.927) and Price (0.880), but it struggles with Design (0.623), indicating potential challenges in detecting sentiment for this feature. On the other hand, the Acer Aspire 3 achieves balanced accuracy across all aspects, with strong performance in Design (0.851), Port (0.850), and Performance (0.852). However, it shows slightly lower accuracy in recognizing Storage (0.704). For the Lenovo Ideapad 3i, the model performs exceptionally well in aspects like Price (0.885), Design (0.853), and Performance (0.868), but it faces challenges in analyzing Port (0.637). Overall, while the model demonstrates consistent strength in Price and Performance detection across all products, there is noticeable variability in handling Port, Design, and Storage, suggesting areas for further improvement in the algorithm's aspect recognition capability.

4. CONCLUSION

In conclusion, understanding consumer preferences is essential for effective product development, marketing, and business strategies to maintain a competitive advantage. These preferences are shaped by factors such as product quality, user experience, psychological influences, and social context. While Conjoint Analysis is a widely used method for extracting consumer preferences, it has drawbacks, including small sample sizes and dependency on survey data. In contrast, sentiment analysis of consumer reviews is more efficient and offers more accurate, real-time insights. By employing the Double Propagation (DP) technique for preference extraction, this process can be automated and conducted continuously, enabling companies to swiftly adapt to shifting consumer demands. Additionally, aspect-level sentiment analysis provides detailed insights into specific product features, allowing businesses to make more informed, data-driven decisions. The evaluation, conducted on Amazon Review Data, confirms the moderate effectiveness of DP in aspect extraction, with room for enhancement in dependency rules and aspect identification algorithms. The results of experiment also highlight the variability in DP's aspect-level accuracy, with consistently strong results for Price and Performance, but challenges in Port, Design, and Storage.

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