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SENTIMENT-BASED RECOMMENDATION FOR ONLINE SHOPPING

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ABSTRACT

In E-commerce, a widely used strategy to improve the customer shopping experience and address information overload is the implementation of recommendation systems. Many E-commerce platforms have their proprietary recommendation algorithms, with content-based filtering being a commonly employed approach. This algorithm provides non-personalized suggestions to users based on the similarity of content. The shopping experience involves the decision-making process, with a significant focus on information search. In online shopping, customers heavily rely on information search to gain in-depth insights into products, as physical interaction is not possible. Customer reviews play a crucial role in this information search, offering shoppers the opportunity to learn from the experiences of previous customers. Despite the importance of customer reviews, existing recommendation solutions often overlook this aspect in their product recommendations. To address this gap, sentiment analysis, a natural language processing task frequently used in reviews, is employed to classify, and quantify text based on its polarity. This research introduces a recommendation pipeline that combines content-based filtering, utilizing cosine similarity calculations, and sentiment analysis, utilizing a pre-trained RoBERTa language model. The focus is on quantifying customer reviews from an E-commerce platform in Malaysia. The goal of this research is to develop an embedded system that recommends products to users based not only on their similarity but also on high ratings from various E-commerce sites.

Keywords: *Sentiment Analysis, Content-Based Recommendation, Sentiment-Based Ranking, Product Review Analysis*

1. INTRODUCTION

The evolution of commerce has undergone a remarkable transformation, sculpting a landscape characterized by heightened accessibility and seamless communication between vendors and consumers. This metamorphosis revolves around the concept of electronic commerce or e-commerce, wherein business operations harness the power of the internet and information technology. The expeditious growth of e-commerce is propelled by influential factors like mobile technology and internet connectivity, ushering in an era where transactions effortlessly transcend geographical boundaries [1].

The recent global pandemic, COVID-19, has acted as a catalyst, expediting this trend. It has compelled individuals and businesses to embrace online platforms, driven by the constraints posed by physical limitations. Moreover, e-commerce offers a dynamic platform for small and medium-sized enterprises to expand their market reach by establishing a digital footprint.

Nonetheless, despite its advantages, various challenges emerge from online shopping, notably, information overload. This occurs when a consumer has access to an abundance of readily available information so it will be difficult for them to make an informed decision. Furthermore, online shopping is deemed to be time-consuming. Research done by [2] held a survey and discovered that 43% of the customers spent more than 7 hours a day and 26% of the customers spent 4-6 hours a day scrolling through e-commerce websites regardless of whether they ended up purchasing the item or not. 65% of them also stated to open e-commerce websites more than 10 times a day. Decision-

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making is a big part of the process undergone by consumers before purchasing a product. An activity that needs to be highlighted is the information search process, which is commonly the most time-consuming part of online shopping, having to collect information about the product. [3] argued that online shopping takes more time and effort even compared to visiting physical shops due to this stage of decision-making having to constantly search for new information and ensure the choices they have made.

Enhanced by empirical evidence, customer reviews emerge as a pivotal determinant influencing purchasing decisions. As substantiated by [4], the mere inclusion of an item's ratings on a page yields a remarkable surge in sales, witnessing a notable increase of 12.97%. Moreover, the significance of written reviews should not be underestimated, as they play a crucial role in instilling confidence in potential buyers. This is underscored by the acknowledgement from [5] that consumers heavily rely on the experiences of others when making purchasing decisions, with a particular emphasis on negative encounters to mitigate potential risks.

Numerous strategies have been devised to enhance the customer decision-making process. Among these, recommendation systems are frequently employed to address challenges associated with information overload, utilizing sophisticated algorithms to forecast user preferences [6]. Many e-commerce platforms boast proprietary, in-house algorithms capable of delivering personalized suggestions to users. Nevertheless, these solutions often overlook inputs from alternative e-commerce sources, and textual reviews are not given due consideration. Additionally, a multitude of endeavors have been undertaken to facilitate cross-website product comparisons, manifesting in the development of price comparison systems.

While there has been a lack of automated solutions considering the diverse range of consumer purchase experiences, their influence on consumer decisions cannot be understated. Innovative technologies, particularly Artificial Intelligence (AI) and Natural Language Processing (NLP), hold the potential to alleviate information overload. NLP, a subset of AI, can recommend listings by analyzing textual data, including product descriptions and feedback. This enables content-based filtering and sentiment analysis, streamlining the decision-making process.

Despite the touted benefits of e-commerce, such as timesaving, research suggests that online shopping can be time-consuming, with users spending significant hours browsing. Decision-making in online shopping, particularly information search, is highlighted as a major time-consuming activity. Reviews play a crucial role in purchasing decisions, with positive ratings and detailed feedback boosting confidence, although an overabundance of positive reviews can raise suspicion due to potential manipulation. Online shopping is argued to require more time and effort than physical stores due to the constant need for information search and decision-making. Various solutions have been proposed, including personalized recommendations and price comparison systems, but there's a lack of automated solutions considering other consumers' experiences, which significantly influence purchasing decisions.

In this investigation, a sophisticated recommendation system has been designed to suggest consumer products. The system relies on a dual approach, leveraging content similarity and sentiment analysis of written reviews to pinpoint the most highly rated listings. By incorporating sentiment analysis, the algorithm not only considers the inherent characteristics of the products (content similarity) but also factors in the sentiments expressed in user reviews. As the user's presently viewed listing serves as the input, the algorithm adeptly identifies and recommends analogous products by scrutinizing the listing's title and description. This method ensures a nuanced and comprehensive recommendation process, enhancing the overall user experience.

2. LITERATURE REVIEW

Prioritizing recommendations in e-commerce, [7] underscored various elements within a Content-based Recommender Information Filtering architecture. The aim was to streamline the necessary processes inherent in content-based filtering. When delving into the analysis of unstructured data, a precise pre-processing method becomes imperative to transform it into structured data for subsequent processing, specifically for feature extraction. Multiple techniques are available for feature extraction, encompassing concepts, keywords, and n-grams.

In recommender systems, personalized recommendations have become the standard. However, there is a notable exception in the e-commerce domain, where non-personalized recommendations are predominantly employed, particularly on an e-commerce homepage where standardization is key, leading to identical outcomes for all users. The exploration of non-personalized recommendation implementations in recommender systems is thoroughly examined in the study conducted by [8]. This study emphasizes two widely used algorithms in this context: the aggregated opinion approach and the basic association recommender.

A separate investigation by [9] aimed to deliver both personalized (UBCF) and non-personalized (IBCF) recommendations for top N movies. The non-personalized recommendations leveraged the k-fold algorithm, wherein users were randomly assigned to different groups. Subsequently, a weighted sum was calculated to generate recommendations, with ratings serving as weights following similarity computations between the input and target movies.

Concerning sentiment analysis, Lexicon-based sentiment analysis stands out as a widely embraced methodology. It involves gauging the sentiment of a text or document by ascribing sentiment scores to individual words and subsequently amalgamating them. In this context, [10] devised a human sentiment analysis model capable of conducting sentiment analysis across diverse domains, eliminating the necessity for specific domain expertise. The model operates on a dictionary-based lexicon approach, leveraging the SentiWordNet tool. This tool encompasses an extensive vocabulary list, attributing sentiment scores to each word, such as "excellent: +3". Following the assignment of scores to each word within the text, the overarching polarity score of the lexicon is derived by summing the scores of all words present in the document.

A study conducted by [11] delved into an analysis of various pre-trained transformer models. Among the transformer pre-trained models scrutinized were ULMFiTm Transformer, GPT-2, BiGRU, BERT, Transformer-XL, and XLNet. The evaluation focused on BERT and BiGRU, the two most recent models, utilizing IMDb movie review datasets to gauge their performance. In the pursuit of determining dataset polarity, the researchers recognized XLNet as an outperformer compared to other models. However, it was noted that XLNet demands substantial computational complexity, necessitating robust hardware for optimal performance. Despite this, the examination of the two models revealed that BERT exhibited superior accuracy, registering an impressive 0.904, as opposed to BiGRU, which achieved an accuracy of 0.7206.

BERT has emerged as a prevalent choice for NLP tasks, particularly in the realm of opinion mining, owing to its remarkable accuracy in sentiment classification. This study, inspired by [12], delves into the application of BERT for sentiment analysis. The model underwent fine-tuning using an unlabeled dataset sourced from Indonesian Mobile Applications, acquired through web scraping from the Google Play website. Two BERT models were employed in this study namely, the multilingual BERT-Base and IndoBERT Base models.

In a study conducted by [13], a mobile application was developed to conduct real-time sentiment analysis on product reviews. Specifically designed for e-commerce platforms, the researchers utilized datasets extracted from Amazon reviews. Employing SVM techniques, the system efficiently classified reviews into positive and negative categories, leveraging one of the simplest algorithms known for its high accuracy. The interface visually represented the distribution of positive and negative reviews in a clear listing. Notably, this system did not incorporate the consideration of neutral reviews. The model demonstrated a commendable 93.54% F1 score, indicating a high level of accuracy in its predictions. This research holds relevance to our project, as it shares a similar objective of implementing real-time analysis on product reviews sourced directly from e-commerce platforms. It serves as a valuable reference, guiding our approach while acknowledging that our system will diverge in its functionality. Unlike the mentioned study, our intended system aims to provide recommendations or rankings based on the polarity of the reviews, adding a unique dimension to the analytical process.

In a study conducted by [14], a comprehensive framework was developed for food recommendation based on sentiment analysis. This sophisticated framework encompasses the classification of both food and sentiments. Each food item is categorized into one of four distinct courses, allowing for a nuanced analysis. Subsequently, the system identifies the most favourably reviewed food items based on the sentiments expressed in the reviews. To gauge sentiments, the reviews are evaluated using an AFINN scoring system, which spans from -5 to 5. The research explored various classification models, including Support Vector Machines (SVM), Random Forest, Logistic Regression, and AdaBoost. Notably, SVM demonstrated superior performance in sentiment classification, achieving an impressive 98.9% validation accuracy. In addition to the advanced classification models, the Bag of Words technique was employed for feature extraction. This technique contributed to the model's ability to distil essential information from the reviews. The outcome of this process was a top-n list of recommended foods for each category. It's noteworthy that the model primarily relied on the Bag of Words technique for feature extraction, resulting in a recommendation system that, while effective, is non-personalized. Future enhancements could explore incorporating more personalized features to tailor recommendations to individual preferences.

3. SYSTEM OVERVIEW

The system incorporates an embedded framework designed with the specific aim of suggesting users superiorly reviewed products, tailored to their selected preferences.

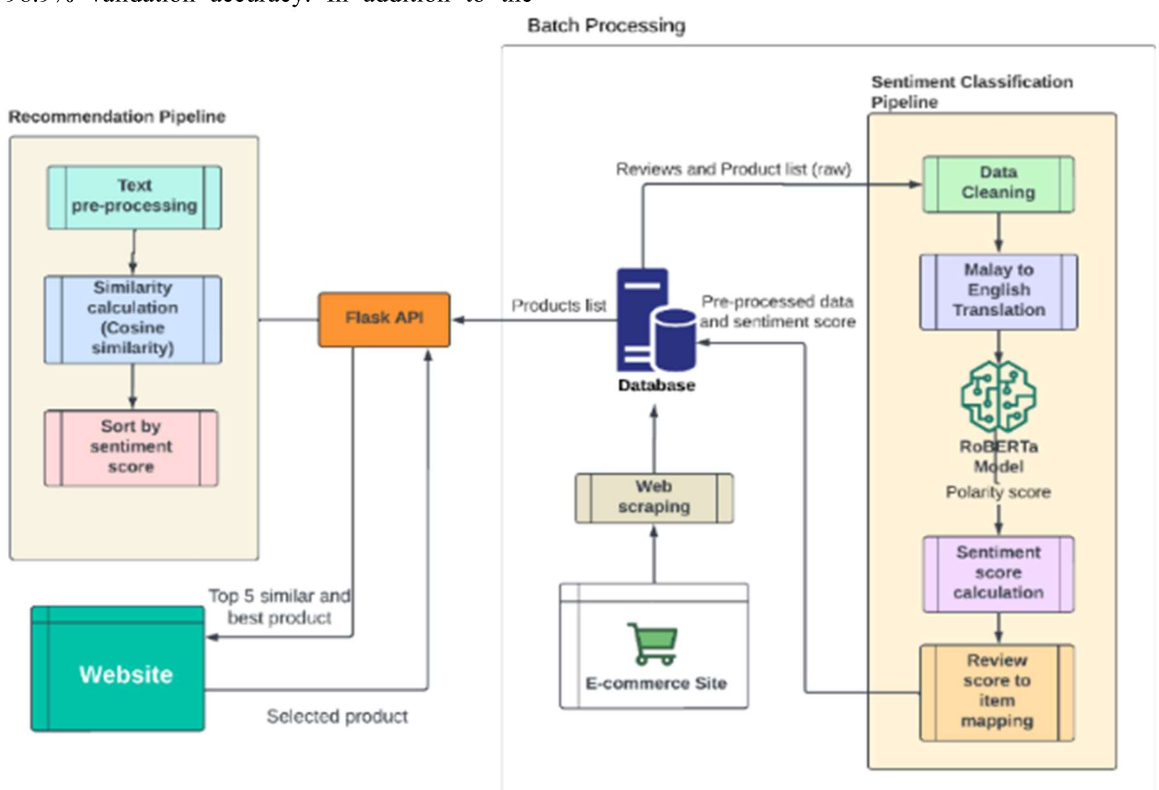

Figure 1: Proposed System Design

Fig. 1 elegantly illustrates the essential components and data flow intricacies within the system. Prominent elements include the sentiment classification pipeline, recommendation pipeline (API), database, web scraping algorithm, and website. The data flow commences at the E-commerce site, where information is meticulously gathered through

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web scraping and then meticulously stored in the database.

The raw data undergoes a meticulous transformation via the sentiment classification pipeline, involving text pre-processing, sentiment classification, sophisticated scoring using a RoBERTa-based model, and subsequent score aggregation. Reviews are systematically processed in batches before seamlessly reintegrating into the database. This meticulously curated database serves as a cornerstone for the recommendation process, orchestrated by the Flask API housing the recommendation pipeline.

Initiating the recommendation process is a user's input of a specific product, setting in motion a series of intricate algorithms. The refined outcomes of this process are thoughtfully relayed back to the system's website, culminating in a seamlessly integrated and enriched user experience.

4. METHODOLOGY

4.1 Initial Research

The requirement validation process was meticulously executed through the administration of a survey using Google Forms, engaging actively with a cohort of 36 respondents. The survey itself was thoughtfully organized into three distinct sections, each strategically crafted to elicit comprehensive insights.

In the initial segment, participants graciously shared their demographic details, thereby enriching our understanding of their diverse backgrounds. Shifting our focus to the subsequent section, we delved into the expansive realm of online shopping, aiming to grasp participants' overarching perceptions and experiences within this digital landscape. The concluding section, a meticulous exploration of consumer behaviour and attitudes regarding customer reviews, played an indispensable role in affirming the development and pertinence of the proposed system. The survey, comprising 21 meticulously formulated questions, was designed to meticulously unravel the tapestry of participants' perspectives and opinions.

4.2 Data Collection

The data is meticulously gathered from an eCommerce platform in Malaysia, specifically focusing on the men's bag category. This comprehensive collection encompasses both product details and customer reviews. The resultant dataset is thoughtfully organized into two distinct categories: one housing product-related information and the other dedicated to customer reviews. The collected dataset is as follows:

Product Dataset
- Product name
- Product rating
- Number of ratings
- Number of products sold
- Shop name
- Product URL
- Product description
- Product price
- Product Image URL

Review Dataset
- Review time
- Product variant
- Review content

The information was systematically gathered in a series of five batches, with each batch comprising approximately 60 rows of products and 7300 rows of reviews.

4.3 Data Pre-processing

In the process of sentiment scoring and classification, a pre-trained model was employed, and a set of minor pre-processing steps were applied primarily to standardize the scraped data.

4.3.1 Data Cleaning

Refining data through the meticulous identification and correction of noise, inconsistencies, and inaccuracies. This comprehensive process encompasses the removal of duplicates, handling missing values, standardization, and other refinements to ensure data integrity and reliability.

4.3.2 Text Translation

Harnessing the power of translation APIs to seamlessly convert textual data from a designated language into another specified language.

4.3.3 Data Transformation

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The transformation process involves alterations in units or data types within designated columns.

4.3.4 Data Integration

Creating a harmonious synthesis of information gathered from various origins, amalgamating diverse data sources to form a cohesive whole.

4.4 Text Encoding and Sentiment Scoring

This section involves the text encoding process to transform texts into a format that is suitable to be processed by the model and the sentiment classification task using a pre-trained transformers model retrieved from HuggingFace.

In this section, we delve into the intricacies of the text encoding process, a crucial step in transforming textual data into a format conducive to model processing. Our approach involves leveraging a pre-trained transformers model sourced from HuggingFace.

The linchpin of our methodology is the Multilingual XLM-roBERTa-base model, an exemplary pre-trained model fine-tuned on a vast corpus of approximately 198 million tweets. This fine-tuning process, orchestrated by [15], specifically tailors the model for sentiment analysis across multiple languages. It is noteworthy that this adept model extends its support to languages such as English and Mandarin, rendering the need for a Malay to Mandarin translation superfluous.

The key instrument in this encoding endeavour is the AutoTokenizer, a dynamic component drawn from the pre-trained model. This tokenizer plays a pivotal role in encoding the textual data, paving the way for subsequent processing by the model. Following the encoding process, the model seamlessly generates sentiment scores, providing valuable insights into the sentiment of the text under scrutiny. The results of the analysis in a dictionary form are as follows:

{negative: "negative probability score",

positive: "positive probability score",

neutral: "neutral probability score"}

The sentiments in the reviews are categorized based on their highest probability scores, creating a refined classification. The sentiment distribution is shown in Fig. 2 along with the sentiment word clouds as shown in Fig. 3, 4, & 5.

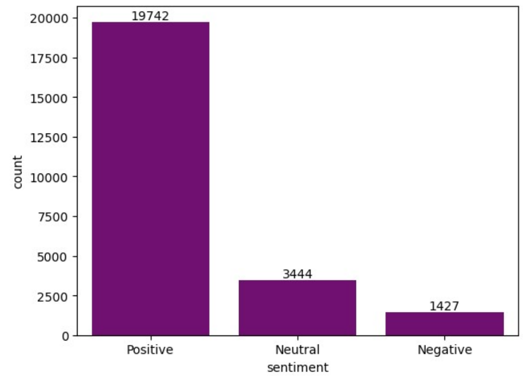

Figure 2: Polarity Distribution of Product Reviews

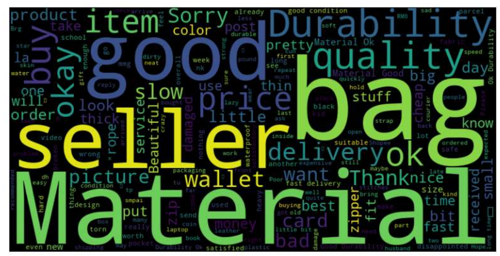

Figure 3: Word Cloud of Negative Category Reviews

Figure 4: Word Cloud of Positive Category Reviews

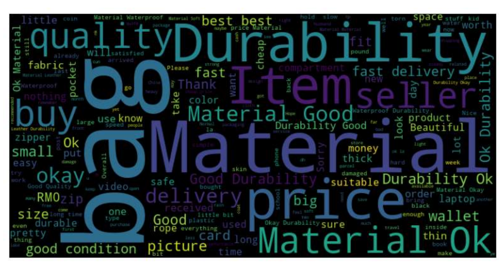

Figure 5: Word Cloud of Neutral Category Reviews

4.5 Score Accumulation and Mapping

Following the retrieval of sentiment distribution scores, these scores undergo consolidation into a singular metric. Positive reviews contribute a score of 2 points, negative reviews incur a score of -2 points, and neutral reviews are assigned 1 point. Subsequently, the

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cumulative sum of these values is computed. The equations are as follows:

$$2\,pos + 1\,neu - 2\,neg$$

A new column was formed to contain the accumulated value of the sentiment scoring. The final shape of the review dataset in a dictionary form is as follows:

{review_id: “review unique id”,

item_id: “id of product review are associated with”,

review_date: ”date where review was made”,

variant: “variant of product review refers to”,

review_content: ”review written content”,

polarity_score: ”score generated from model”,

review_sentiment: “sentiment classification of review”,

accu_polarity_score: ”aggregation of polarity score”}

After the scores had been accumulated, based on the ‘item_id’, the reviews were grouped and ‘accu_polarity_score’ values were aggregated where the average score was taken to be mapped to each product in the product dataset. The final shape of the review dataset in a dictionary form is as follows:

{

item_id: "product unique id",

item_name: "product title",

item_rating: "overall ratings of product",

rating_num: "number of product ratings",

item_sold: "number of product sold",

shop_name: "name of shop that sells the product",

item_url: "URL of Shopee page",

item_description: "product description",

item_price: "product price",

accu_score: "aggregated polarity score from reviews dataset",

item_image: "image URL of item"

}

4.6 Content-based Recommendation

In this section, we delve into the methodology of content-based recommendation, aiming to unearth similarities among products by analyzing both product titles and descriptions. By leveraging the intrinsic content of these elements, we seek to enhance the precision of our recommendation system, providing users with more relevant and personalized suggestions.

4.6.1 Text Cleaning

The procedure involves eliminating punctuation and special characters, as well as standardizing the text.

4.6.2 Text Encoding

The texts transformed into formats conducive to processing as a TF-IDF Matrix.

Cosine Similarity: A prevalent method for computing similarities between vectors, specifically the values within the generated TF-IDF Matrix, is employed as the common similarity calculation measure. The formula for Cosine Similarity calculation is in equation (1).

$$\frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \qquad (1)$$

The outcome is expressed as a numerical value ranging from 0 to 1, where proximity to 1 signifies a higher degree of similarity, whereas proximity to 0 indicates greater dissimilarity.

4.6.3 Similarity and Sentiment Ranking

The generated results consist of the top N most similar items, meticulously re-sorted according to their accumulated polarity scores, creating a refined and aesthetically pleasing presentation of the findings.

5. IMPLEMENTATION

5.1 Sentiment Analysis Pipeline

Following the retrieval of the data, an intricately designed sentiment analysis pipeline was established. This pipeline incorporated a systematic approach, conducting processing and scraping in well-organized batches to mitigate

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the potential for errors during the intricate processing stages.

Upon the successful retrieval of data, organized into a comprehensive CSV file through a series of meticulous batches, a thorough exploration ensued. This exploratory phase encompassed essential tasks, such as identifying any instances of missing or duplicate data, ascertaining the dimensions of the dataset by meticulously counting rows and columns, and employing suitable functions to discern the data types across all columns.

After completing the initial checks, we proceeded with essential pre-processing steps. In addition to fundamental tasks like eliminating duplicates, addressing missing values, and transforming data types, we meticulously pre-processed the textual content within the reviews. This involved tasks such as removing symbols and characters, as well as rectifying irregular spacing. These actions were executed using regular expression (regex) functions to ensure the refinement of the text data.

After completing the cleaning phase, we utilized the Google Translate API to seamlessly translate all Malay reviews into English. Notably, some nuances, like abbreviations and informal language such as slang, posed challenges for the API, necessitating manual translation by our developers for these specific terms.

It's important to highlight that we opted against introducing an additional translation layer, even though the text retained Chinese characters. This decision was informed by the fact that our sentiment scoring and classification model underwent specialized training in various languages, encompassing Mandarin and English. This proficiency empowered the pre-trained model to adeptly navigate and interpret the intricacies of these language blends.

Upon generating sentiment scores, a novel metric emerged through the application of the formula. This metric signifies the cumulative sentiment scoring. Subsequently, the mean of this metric, organized by item ID, was correlated with their corresponding products, introducing a fresh attribute into the product dataset. This attribute assumes significance as a pivotal determinant within the recommendation pipeline, enriching the decision-making process.

At last, the various batches of review and product datasets were meticulously consolidated into distinct JSON-type files, ready for seamless importation into the database.

5.2 Recommendation Pipeline

The recommendation pipeline seamlessly became part of the API, enhancing user experience by calculating similarity from input data. Just as a meticulous pre-processing stage precedes sentiment analysis, the text underwent refinement. Employing regular expressions, special characters and punctuation gracefully vanished. An assortment of punctuation marks, meticulously curated from the string library, found their place in a dedicated list. Through the artistry of regex once more, this list orchestrated the removal of punctuation from the text. A finishing touch of elegance ensued as alphabet case standardization gracefully transformed all text into lowercase.

Following the initial encoding step, the text transformed TF-IDF matrices through the utilization of the TfidfVectorizer function. This facilitated the creation of a comprehensive similarity matrix, housing correlation values between the TF-IDF matrices. The subsequent arrangement of this matrix in a descending order allowed for the extraction of the top N products manifesting the highest similarities. Given that the sorting of similarity matrices was conducted by the product index, each matrix found its correlation with the corresponding items. Consequently, when a specific product was designated as the input, the system seamlessly referenced the associated similarity matrix to derive the top 10 products exhibiting the greatest resemblance.

Further refinement ensued, with the selection process homing in on the top sentiment scores of these 10 products. Ultimately, 5 items were cherry-picked based on their superior sentiment rankings, culminating in a more streamlined and refined output.

5.3 Database Development

After generating the JSON file, it was imported into MySQL. SQL queries were then utilized to adjust the data types accordingly. The

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database was seamlessly connected to the backend API through the flask_mysqldb library.

5.4 Web Development

The web development of this project involves the development of the backend and front end. The backend was developed using the Python Flask framework where it could run locally in port 5000. The flask API consisted of three routes: /main, /input, and /result. /main takes all products from the database and returns them to the front end as options for the users. /input retrieves the user's selection and processes them through the recommendation pipeline. /result retrieves results calculated by the recommendation pipeline or /input route and returns them in JSON format to the front end.

HTML. CSS and JavaScript were otherwise used to develop the website's front end using the ReactJS framework to ease the development of repetitive containers using the component concept in ReactJS. The React App was run in port 3000. The React App however needs to communicate to the backend API running on port 5000 where it has to be defined in the package.json file by adding the following line:

"proxy": "http://localhost:5000",

Two pages were made for the website such as inputPage.js and resultPage.js as shown in Fig. 6, 7, 8 & 9. Where inputPage consisted of all available products in the database for users to select. Users then be directed to resultPage where the recommendation results are shown to the user.

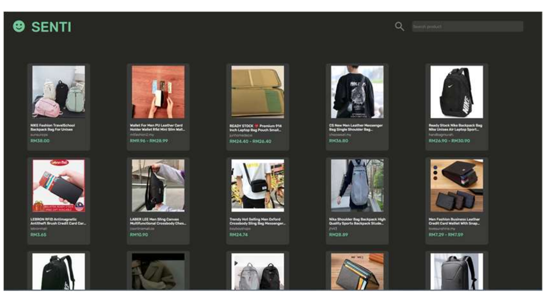

Figure 6: Site Main Page (1)

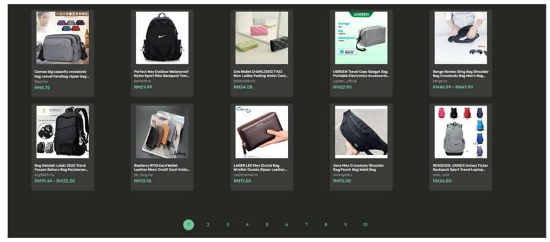

Figure 7: Site Main Page (2)

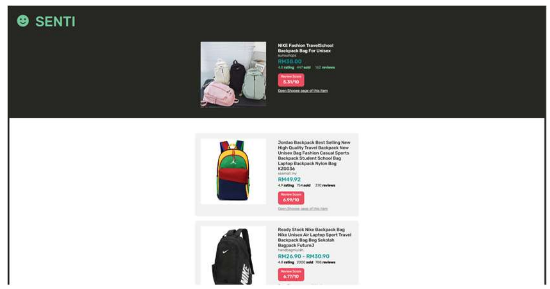

Figure 8: Site Result Page (1)

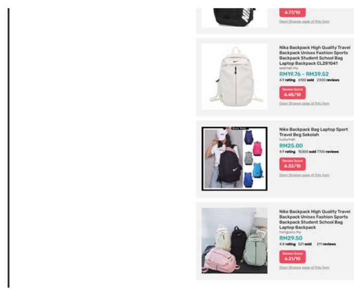

Figure 9: Site Result Page (2)

The validation process for the system comprised two main testing approaches: unit testing and user acceptance testing. Unit testing, conducted by the developer, involved assessing each functionality to ensure proper operation. The results showed successful interactions and all components working as expected, with no encountered bugs. For user acceptance testing, students from different academic backgrounds were chosen to evaluate the system. They conducted a thorough assessment of functionalities, identified potential bugs, measured system speed, and rated the user interface and overall experience. Overall, the participants were satisfied with the system's functionality, reported no bugs, and found the system's performance speed satisfactory.

Participants found the interface navigable and user-friendly, giving positive feedback on its design. However, two participants suggested improving the user experience by adding clickable containers alongside product titles for easier selection. Additionally, one participant suggested incorporating initial page instructions for better user orientation, particularly for users with an engineering background. Despite these suggestions, the system was considered satisfactory and successful by the users. They recognized the relevance and usefulness of the system's recommendations in addressing issues. Participants expressed a desire for additional features to provide more comprehensive analyses and product review details. In conclusion, user acceptance testing validated the system's functionality, user interface, and relevance, setting a positive path for further improvements based on valuable user feedback.

Two common techniques such as content-based filtering and collaborative filtering, are typically used in recommendation systems. However, implementing collaborative filtering faces challenges due to limited publicly available user behavior data. To address this, a simplified approach employing item-based collaborative filtering, like content-based filtering, will be utilized.

This system aims to complement existing e-commerce platforms rather than replace them, thus focusing on integrating seamlessly into users' browsing experiences. To achieve this, the solution will be implemented as a Chrome extension, automatically extracting data from visited pages to provide recommendations without requiring manual input from users. This integration not only enhances user-friendliness but also streamlines the recommendation process by eliminating the need to navigate to a separate platform.

6. CONCLUSION AND FUTURE ENHANCEMENT

This endeavor confronts the growing hurdles presented by the swift growth of the e-commerce sector. Chief among these challenges are the overwhelming amount of information and the time constraints faced by users. To address these issues, a recommendation system has been implemented. Nevertheless, there remains a significant gap in understanding the significant impact of written reviews on the effectiveness of these recommendations and their subsequent influence on consumer purchasing choices. To bridge this crucial gap, an innovative system has been devised. This system places its emphasis on delivering real-time recommendations, employing a groundbreaking methodology that incorporates the comprehensive sentiment score extracted from product listings. This refined approach seeks to elevate the user experience and streamline the decision-making journey for consumers navigating the ever-evolving realm of e-commerce.

Through a thorough exploration of relevant literature and existing systems, this project aims to explore novel pathways to enrich the shopping experience by integrating recommendation systems and sentiment analysis. The implementation phase of this endeavor focuses on designing the system architecture, formulating the project plan, executing the implementation, and validating the effectiveness of the system. The author has carefully crafted a system architecture, outlining the vital components necessary for achieving the system's objectives. Following the implementation of the code, a comprehensive project plan is crafted to meticulously document the various iterations of the system and orchestrate a systematic launch. This plan includes a blueprint for evaluating the system's performance. Subsequently, after the development of the system's code, a rigorous testing and evaluation phase is initiated, involving three participants in the process.

In the face of time limitations, the project encountered difficulties in broadening its range of features, especially when it came to conducting in-depth review analyses. The challenge primarily stemmed from a lack of readily available data regarding product specifics and reviews. This scarcity of accessible information led to a constrained selection of labeled datasets, which in turn impeded the crucial process of refining the model through fine-tuning. Without a sufficient pool of labeled data, it became challenging to thoroughly assess the effectiveness of the model.

Despite these obstacles, it's important to highlight that overcoming this limitation remains a possibility for future improvements. There is potential for addressing this issue through further exploration and enhancements in the project. This could involve delving deeper into the available data sources, developing strategies to collect more labeled datasets, or employing alternative methodologies to improve the model's performance and effectiveness in analyzing reviews and product details.

Prospective improvements to the system should prioritize the enhancement of the user interface, aiming for a more polished and intuitive design. Clearer descriptions should be incorporated to elevate user-friendliness, as recommended by one of the participants. Furthermore, introducing a comprehensive dashboard for in-depth analysis of product reviews will contribute advanced features to the system. This dashboard is envisioned to empower users with deeper insights into sentiment analysis results and product feedback.

To further elevate the system's performance and reliability, it is imperative to integrate a meticulous data labelling process. This involves methodically assigning sentiment labels to the data, a pivotal step that will undoubtedly contribute to the refinement of a more resilient and precise sentiment analysis model. Additionally, incorporating a user-centric feature to evaluate the system's performance would be a commendable enhancement. This user feedback mechanism catalyzes the perpetual refinement of recommendation algorithms, ensuring their alignment with the ever-evolving preferences and requirements of users.

Furthermore, for heightened user convenience, consider adapting the deployment method to create a sophisticated Chrome extension. This strategic modification not only streamlines user access but also seamlessly integrates the recommendation system into the user's browsing experience on e-commerce sites. By doing so, the overall shopping experience is elevated, and the system's accessibility is substantially increased. This innovative approach not only fosters a more user-friendly environment but also positions the system as a cutting-edge solution in the realm of personalized recommendations.

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