Aspect-Based Summarization for Product Reviews

INFO 5731

Computational Methods for Information Systems -Section 021

Jagadeesh Rao Daggu
University of North Texas

Akshitha Voruganti
University of North Texas

Kurra Nagasowmika
University of North Texas

Ramabhadra Raju Namburi
University of North Texas

Bobba Sandeep
University of North Texas

May 6, 2024

1 Introduction

The emerging digital era prompted a hyper-expansion of e-commerce and online platforms and thus an inconceivable surge of user-generated content, and product reviews. Consumer reviews are precious for shoppers who are provided with a quick peek into the product to support their buy/drop decision. Meanwhile, such a significant number of reviews renders them impractical to look through for users to draw the picture or generate insights. The problem domain fits into the broader theme of NLP and information retrieval – a prospered field in which technology is developed to process and condense massive flows of text data in an unstructured form, treating them into a more accessible shape. Research Problem In this domain, the research problem addressed by this work is the requirement for an efficient methodology for aspect- based summarization of product reviews. Existing summarization methods are unable to accurately represent reviewer opinions and emotions regarding different aspects or features of a product. As a result, users are compelled to literally read huge quantities of reviews to acquire necessary information about the most important aspects of the product for the decision-making process. Furthermore, this problem is exacerbated by the fact that products are different, and that the importance of aspects differs for different users.

This project bridges the research gap by creating an ABS system that automatically identifies and summarizes the opinions or sentiments in product reviews, considering the aspects of the product they discuss. The system then generates a short, well-structured summary of a product based on some chosen product aspect. This way, users can grasp the good and bad sides of the product from different perspectives and quickly decide about the product when buying hence more informed purchases. Moreover, it will be of great significance to independent entrepreneurs/investors that want to analyze the customer reviews fast and ensure that they meet the customers' satisfaction or even compare them to the competitors.

The implications of this study are critical and extend beyond the scope of this case and the application of e-commerce. Despite the availability of review summaries, it is still time-consuming for consumers to search through many reviews and see what each one said about the few product traits or aspects that they care about. As one might anticipate, consumers pay close attention not just to the general feelings voiced in reviews, yet also to how reviewers speak about and rate specific key elements or elements of the product. The present research addresses both by proposing a high-performance aspect-based summarization system of product reviews that uses ensemble methods and LLMs.

The proposed system will be evaluated thoroughly through automatic and manual assessments to ensure the effectiveness of the system in producing precise and informative aspect- focused summaries. Some of the terms in this study are aspect-based summarization, which involves the creation of short summaries focusing on a product's feature or aspect, as contained in the reviews. The contributing factors or variables comprise of how to determine the relevant aspects, employ sentiment analysis approaches to measure opinions and sentiments of the aspect, and create effective summarization algorithms crafted for the aspect-based nature

1.1 Need for Aspect-based summarization models

Failure to solve this research problem can negatively affect both consumers and manufacturers. For consumers, the lack of a reliable aspect-based summarization mechanism results in their inability to navigate the sea of re- views, consequently forcing them to make poorer choices or miss out on a great opportunity. For manufacturers, the current approach to aspect-based summarization represents a lost opportunity to use customer feedback to improve products. Finally, this research enables aspect-based summarization tools to be developed at a later time with powerful APIs that allow users to make informed decisions and manufacturers to refine products.

1.2 Objectives

The primary problem that this study seeks to resolve is the following question: What is the most effective way to create an aspect-based summarization system that can automatically detect and summarize the opinions and sentiments expressed in a product review while remaining focused on the relevant aspects or features of the product? The following objectives need to be achieved in order to find a solution to this issue: develop aspect identification, sentiment analysis, and summarize tools and integrate them into a complete aspect-based summarization system that in a focused and general manner may constitute summaries for the user's individual requirements.

1.3 Contributions

The contributions of this work are at threefold: first the development of novel techniques to aspect identification and sentiment analysis in the context of product reviews; second, the integration of these techniques with state-of-the-art summarization algorithms, specifically designed for aspect-based summarization; and third, from a theoretical perspective, an advancement of our understanding of the relationship between aspect identification, sentiment analysis and summarization that sets the stage for future work in this area. From a practical perspective, the aspect-based summarization system implemented in this investigation possesses the potential to change the ways that users access and consume data on product reviews. As a result, technology will enhance the way users access and use data on product reviews.

2 Literature review

The research area of aspect-based summarization has its roots in the fields of natural language processing (NLP) and information retrieval, with contributions from various disciplines such as computer science, linguistics, and machine learning.

Aspect-based summarization gained prominence in the late 2000s and early 2010s, primarily driven by the increasing volume of user-generated content, such as product reviews, on e-commerce platforms and social media. Researchers recognized the need to develop techniques that could automatically extract and summarize the opinions and sentiments expressed towards specific aspects or features of products and services.

One of the earliest and seminal works in this area is the paper (Ku, Liang, & Chen, 2006) . This paper introduced the concept of aspect-based sentiment analysis and summarization, where they proposed a method to extract aspects from product reviews and generate aspect-specific summaries. They employed a rule-based approach and exploited linguistic patterns to identify product aspects and associated sentiments.

Another influential work that marked the beginning of this field is the paper Popescu and Etzioni (2005). This paper proposed a method for extracting aspects and associated opinion expressions from product reviews using a combination of supervised learning and heuristic techniques. They introduced the concept of aspect-based opinion mining, which paved the way for further research in aspect-based summarization.

These early works laid the foundation for subsequent research in aspect-based summarization by introducing the key concepts, methodologies, and challenges involved in the task. Researchers built upon these ideas and proposed more advanced techniques, such as using machine learning algorithms, neural networks, and language models, to improve the performance of aspect extraction, sentiment analysis, and summarization components.

In the field of aspect-based summarization, there are several known and accepted concepts, as well as areas that remain unexplored or subject to debate. One widely accepted notion is the importance of accurately identifying and extracting relevant aspects or features from text data, such as product reviews. This aspect extraction step is crucial for generating meaningful and focused summaries.

A paper by Hai et al. (2011) proposes a method for aspect extraction using Conditional Random Fields (CRFs) and extraction patterns. The authors demonstrate the effectiveness of their approach in identifying aspect-opinion pairs from reviews, which is a key step in aspect-based summarization.

However, there is an ongoing debate surrounding the most appropriate techniques for aspect extraction. While some researchers favor rule-based or pattern-based approaches, others argue for the superiority of machine learning methods, such as deep learning models like BERT (Bidirectional Encoder Representations from Transformers).

In this context, the paper Lau et al. (2022) explores the use of BERT for aspect-based sentiment analysis. The authors find that fine-tuning BERT on a large, diverse dataset can lead to improved performance in aspect extraction and sentiment analysis across multiple domains.

Another area of active research is the development of effective summarization algorithms tailored for aspect-based summarization. Traditional extractive and abstractive summarization techniques may not be optimal for this task, as they often fail to capture the nuanced opinions and sentiments expressed towards specific aspects.

The paper Masruri, Maliki, and Hadi (2022) proposes a novel approach that combines aspect extraction, sentiment analysis, and a graph-based summarization algorithm. Their method aims to generate informative summaries that accurately reflect the opinions and sentiments expressed towards different aspects of a product. Furthermore, researchers have explored the potential of leveraging large language models (LLMs) for aspect-based summarization.

The paper Zhang et al. (2023) investigates the use of LLMs like GPT-3 for this task. The authors propose a prompting strategy that effectively incorporates aspect information into the summarization process, leading to improved aspect-focused summaries. While progress has been made in aspect-based summarization, there remain challenges and controversies. One area of debate is the trade-off between the complexity of models and their performance. While sophisticated deep learning models and LLMs show promising results, they often require significant computational resources and may not be feasible for all applications.

Another challenge lies in the evaluation of aspect-based summaries. While automatic evaluation metrics like ROUGE (Recall-Oriented Understudy for Gisting Evaluation) are widely used, they may not fully capture the nuances of aspect-focused summaries. There is a need for more comprehensive evaluation frameworks that consider both content quality and aspect coverage.

In terms of promising research directions, the integration of knowledge graphs or ontologies into aspect-based summarization systems could be a fruitful avenue. By leveraging structured knowledge about product domains and aspects, these systems could generate more informative and context-aware summaries.

Additionally, the development of personalized aspect-based summarization systems, which adapt summaries based on individual user preferences or requirements, represents an exciting area for future research.

The paper Wan (2018) proposes a novel unsupervised approach for text summarization using reinforcement learning. The methodology involves a hierarchical reinforced sequence operation model that learns to extract and compress salient content from the input text. The model is trained end-to-end using reinforcement learning, without requiring labeled data or hand-crafted rules. The authors demonstrate the effectiveness of their approach on various summarization tasks, including aspect-based summarization of product reviews.

The paper Jiang, Sui, Lan, and Ye (2019) introduces a hierarchical deep multi-task learning framework for aspect-based sentiment analysis. The proposed methodology jointly learns aspect extraction, sentiment classification, and aspect-sentiment association tasks in a unified model. The authors leverage a hierarchical attention mechanism to capture the interdependence's between these tasks, leading to improved performance on aspect-based sentiment analysis and, consequently, aspect-based summarization.

Cao et al. (2021) proposes a multi-task semi-supervised approach for abstractive text summarization, called Summarised. The methodology involves pre-training a transformer-based model on a large corpus of unlabeled data using self-supervised objectives, such as masked language modeling and document reconstruction. The pre-trained model is then fine-tuned on a smaller labeled dataset for the summarization task. The authors demonstrate the effectiveness of their approach on various summarization tasks, including aspect-based summarization of product reviews.

Tian et al. (2021) addresses the task of multimodal aspect-based summarization, where the input includes both text reviews and associated product images. The proposed methodology involves a multimodal transformer model that learns to attend to both textual and visual information relevant to different aspects. The model is trained using a multi-task learning approach, combining aspect extraction, sentiment analysis, and summarization objectives. The authors demonstrate the effectiveness of their approach in generating aspect-focused summaries that leverage both textual and visual information.

In terms of how I would like this topic to be taught, I would appreciate a comprehensive and practical approach that combines theoretical concepts with hands-on exercises and real-world examples. The course should begin with an introduction to the fundamentals of natural language processing, text summarization, and aspect-based sentiment analysis. It should then delve into the specific techniques and methodologies used in aspect-based summarization, such as aspect extraction, sentiment analysis, and summarization algorithms. Practical sessions should be included, where students can implement and experiment with different models and techniques using popular libraries and frameworks. Case studies and industry examples should be presented to illustrate the real-world applications and challenges of aspect-based summarization. Additionally, the course should cover evaluation metrics, dataset creation, and deployment considerations for aspect-based summarization systems.

3 Methodology

The following steps can be summarized in the general methodological approach of this aspect-based summarization project: unsupervised natural language processing approach for named entity recognition to identify features, retrieval-augmented generation approach to extract related texts using the identified features, and manual curation. The work is to be done in three parts: Aspect extraction, retrieval of reviews by aspects and then summarization of the retrieved reviews.

The study's dependent variables are named entity, entity frequency, relevant reviews, summary quality, retrieval effectiveness, and reranking improvement. Named entities are the entity frequencies of the potential product aspects or features extracted from the review text using NER models, and their count of occurrences in the dataset is termed as its frequency. Relevant reviews are the subset of reviews which are deemed relevant for their context to analyze these, the retrieval process must generate the appropriate subset. Summary quality is a metric that depends on aspects like clarity, accuracy, and coverage obtained from an evaluation of the generated summaries. Retrieval effectiveness may be measured on metrics such as precision, recall, and F1-score depending on the ability to retrieve the relevant reviews for each aspect. Lastly, the ranking improvement in the reranking step will be seen by comparing relevance rankings before and after.

In this study, the data collection will be the integrity of web scraping on Amazon reviews using Python packages such as BeautifulSoup and Selenium. In the beginning, a dataset of around 1,000 reviews will be collected in the software product or any other domain of in-

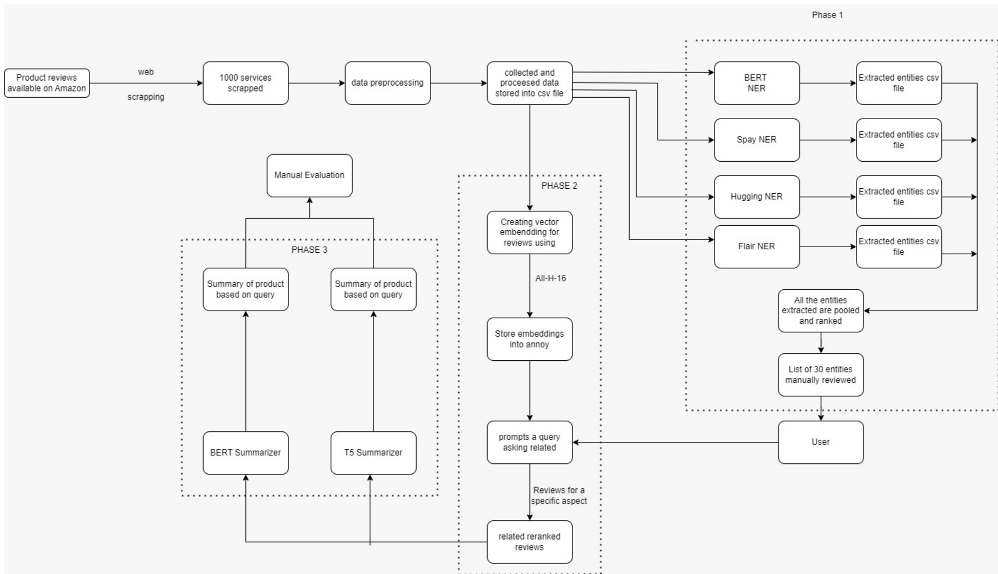


Figure 1: Product Review Analysis and Summarization Pipeline

terest. The developed script will run automatically, browse the Amazon product pages and do the following: extract the review text, organize it in a favorable way, such as a CSV file or database. This also guarantees that I conform to the ethical data collection standards, comply with my target's websites and does not have an undue negative impact on the goal servers. Finally, measures will be put in place for existing and potential difficulty including dynamic page rendering and IP blocking or rate-limiting constraints.

3.1 Detailed Plan

Subsequent to collecting data, we split the project into three stages; Specifically, we use unsupervised Named Entity Recognition models as follows BERT- NER , Flair NER, Hugging Face Trans- formers NER , spaCy NER to extract possibly useful aspects or entities from large volumes of text reviews. To guarantee the precise and competent entity extraction, we preprocess the review text through the essential cleaning and normalization steps. They include removing HTML tags, special characters, URLs, and punctuation, expanding the contractions, and tackling the misspellings. Then, once the named entities are extracted, they are aggregated, and their frequency count is computed to determine the prominent features. Next, after manual review and based on domain knowledge, the will select and formalize the 30 most important and relevant entities of software products, which will make up a complete ontology of software products. The second phase of our project will use the Retrieval Augmented Generation approach to find reviews on each considered soft-ware product's aspects from the first phase. We will embed individual reviews from the dataset considering a pre-trained language model. vote, we were planning to use the jina-embeddings-v2-base-en model. Even though the OpenAI Embeddings model could provide better-reasoned results, we selected the jina-embeddings model as an open-source solution.

Next, after manual review and based on domain knowledge, the 30 most important and relevant entities of software products will be selected and formalized, which will make up a complete ontology of software products. The second phase of our project will use the Retrieval Augmented Generation approach to find reviews on each considered software product's aspects from the first phase. We will embed individual reviews from the dataset considering a pre-trained language model. We were planning to use the jina-embeddings-v2-base-en model. Even though the OpenAI Embeddings model could provide better-reasoned results, we selected the Jina-embeddings model as an open-source solution.

But after spending a lot of time and going through documents a few errors remained unsolved. So, we used the all-MiniLM-L6-v2 to create vector embeddings. The case is the same with the FAISS vector database. Initially we planned to use FAISS to store vec- tor embeddings. But, all the materials avail- able had their implementation with embeddings created using GPT APIs. Since we used all-MiniLM-L6-v2 to create vector embeddings, we opted for another database from the langchain library named ANNOY. Finally to summarize the reviews based on the required aspect the BERT API and the t5-small model which belongs to the T5 (Text-to-Text Transfer Transformer) family of models developed by Google is used. The summaries generated by the T5 transformer were not clear and did not cover the retrieved reviews. As a solution we planned to use BERT (Bidirectional Encoder Representations from Transformers) which gave better results. In the next paragraph we discuss the reason for the usage of the above mentioned tools and their specifications.

BERT-NER – Google's BERT model fine-tuned for NER . BERT, or Bidirectional Encoder Representations from Transform- ers, is useful for any NER task where capturing context is essential. However, using a generic BERT-based NER model may not be optimal if specific goals must be achieved. That is why the creation of BERT-NER, a model fine-tuned for named entity recognition, allows obtaining better results. Pre-training on a large corpus of text allows BERT to apply well to various NER tasks and in any specific domain.

There are several strong and easy-to-use NER models that can be fast integrated into the project. Flair NER models are powerful NER: models Hugging Face Transformers NER – Hugging Face library gathers a wide range of pre-trained transformer models including several fine-tuned NER models. They can be easily loaded with a few lines of code. spaCy NER – spaCy is an efficient Python NLP library, and it also comes with pre-trained NER embeddings in multiple languages. While not as strong as transformer-based embeddings, it can be a good lightweight and speed option.

Since the previous NERs employed were transformer-based, we used this to determine the performance of the non-transformer-based NERs compared to transformer-based NERs. Afterward, we filtered the extracted features based on their occurrence count and manually selected 30 features from the filtered features. In the subsequent task, the entire dataset was given vector embedding, which would later be used to compute cosine similarity to fetch related reviews. To execute the task, we utilized the all-MiniLM-L6-v2 embedding model, which is under the MiniLM family. MiniLM has been developed to better balance the trade-off between efficiency, throughput, and encapsulation necessary for resource-constrained circumstances as a smaller and quicker variant of the BERT model.

The stored vector embeddings generated are put into the ANNOY vector database ANNOY (Approximate Nearest Neighbors Oh Yeah) is a C++ library with Python bindings for maintain the effective search of approximate nearest neighbors in high dimensional areas. It is used for activities such as nearest or most similar search and retrieval of nearest neighbors. ANNOY uses tree structure-building technique which can quickly focus on some of the near neighbors without the need to check all the pupils. After related reviews are recovered, they are reranked with RandomForestRegressor: RandomForestRegressor was used in this case for reranking due to its ensemble learning method, which could combine many decisions tree regressors to increase predictive accuracy and reduce overfitting. Due to a reranking task, this method is even more useful if the function does not have a linear shape or depends on many variables, whereas RandomForestRegressor can handle non-linear features. In addition, when working with messy information, RandomForestRegressor is not sensitive to noise or outliers. Furthermore, the ability to gauge the relevance of features provided by RandomForestRegressor helps to reveal mediating variables without which the task will not be solved. T5 was built for a variety of natural language processing functions, such as text generation, translation, summative evaluation, and inquiry response. Repeatedly, BERT is a robust option when it comes to the use of a pre-trained model for summary generation for many reasons. First, BERT is a bidirectional model, and this means it understands context from both sides of text, and thus summaries generated are coherent and contextually accurate. Second, BERT could be fine-tuned under the summarization task, ensuring the BART model is adapted into the task and to certain nuances, and in the process, one could outperform. Third, BERT is pre-trained massively on a large corpus, capturing general representation of language and nuances, and this boosts generated summaries' quality. Fourth, representations are given at the level of tokens, and this ensures the summaries are detailed and granular. Finally, BERT is highly used and supported in the NLP community, and thus, it can offer the best possible results due to multiple resources available, including

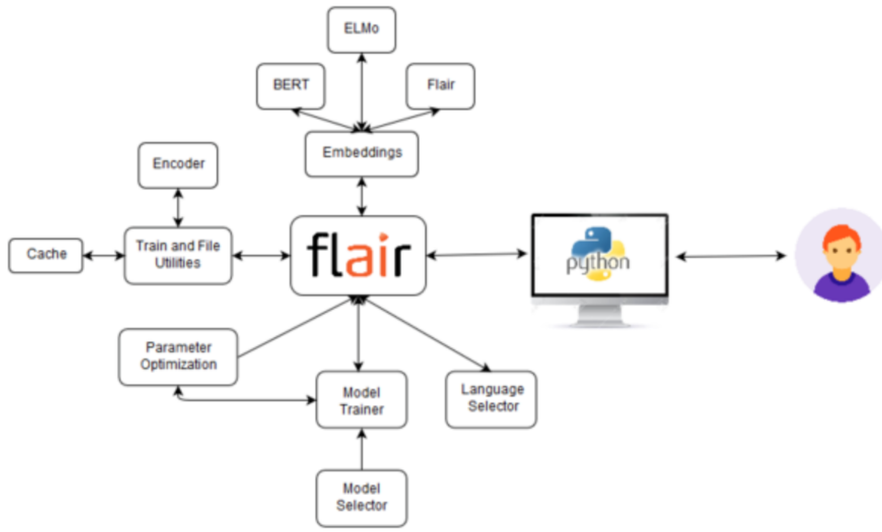


Figure 2: Flair NLP Library Architecture

pre-trained models making it a great choice for summarization tasks.

4 Data analysis and results

We can analyze the developed model on the final outcome. Summarization Component Analysis: After the reviews are retrieved based on the prompt, they are fed to Bidirectional Encoder Representations from Transformers. The final yet crucial step of the project is to analyze or evaluate the summaries generated by the model. After going through some projects we concluded to manually evaluate the generated summaries on 3 criteria.

1. Clarity: The ease with which the summary can be understood.
2. Coverage: The extent to which the summary captures the key information from the retrieved reviews.
3. Accuracy: the correctness of the information presented in the summary compared to the retrieved reviews.

These are general variables drawn for our understanding. But, it is necessary to arrive at a numerical value to rate the efficiency of the model. So, we try to formulate these 3 criteria to give a number ranging between 1-10. To do this we use a weighted sum approach where we assign weights to each criterion based on their importance. The formulated weights are $Weight_{clarity}$, $Weight_{coverage}$, $Weight_{accuracy}$. The formula will be

$$Overall_Score = Weight_{clarity} * ClarityScore + Weight_{coverage} * CoverageScore + Weight_{accuracy} * Accuracyscore$$

where, the Clarityscore, Coveragescore, Accuracyscore are the scores given to each review based on manual analysis ranging from 1 to 10 where 1 is lowest, 10 is highest; while the values of weights $Weight_{clarity}$, $Weight_{coverage}$, $Weight_{accuracy}$ sum up to 1; and on inserting all the necessary values into the equation, the value of $Overall/-Score$ ranges from 1 to 10; 1 being the worst and 10 being the best possible score. The value of the weights $Weight_{clarity}$, $Weight_{coverage}$, $Weight_{accuracy}$ are assigned to be 1/3 assuming that all the criteria are equally important. The final formula used to evaluate the model is:

$$Overall_Score = (1/3) * (ClarityScore + CoverageScore + Accuracyscore)$$

In the course of this project a total of 34 aspects or features were identified. Using all these features a query was run to extract related reviews. Then on feeding these reviews to t5 and BERT summarizes we get the aspect based summaries for product reviews. These reviews are rated on the scale of 1-10 as specified earlier and using the above mentioned formula we calculated the overall_score for summaries of each aspect.

Following are a few samples of output produced by the designed model at each stage:

1. Query: resolution
   - Related Reviews: ["My ONLY issues are: 1) the screen/video resolution won't increase to a higher resolution then 1024 x 60", 'The screen is very large and crystal clear with amazing colors and resolution.', 'Bigger HD, better graphics card, and a bid HD.', 'they improved nothing else such as Resolution, appearance, cooling system, graphics card, etc.', "Quality Display I love HP,, it's the only computer/printer we will buy."]
   - Summary:The screen is very large and crystal clear with amazing colors and resolution. Small screen somewhat limiting but great for travel. The screen is framed by half- to a full-inch margin that is obviously unnecessary, reduces the screen size and increases
   - Clarity: 8, Coverage: 8,Accuracy: 9, Overall score: 8.3
2. Query: worth
   - Related Reviews: ['A little pricey but it is well, well worth it.', 'Completely worth every single penny dime and nickel.', 'With all the goodies inside this machine, it is a value.', 'Worth the investment and truly a fine piece of equipment.', 'All for such a great price.']
   - Summary:A little pricey but it is well, well worth it. Completely

	Clariy	Coverage	Accuracy	Overall Score
Total	177	210	184	187.6
Average	5.53	6.56	5.75	5.58

Figure 3: Total Scores and Average Scores for each criteria of the model

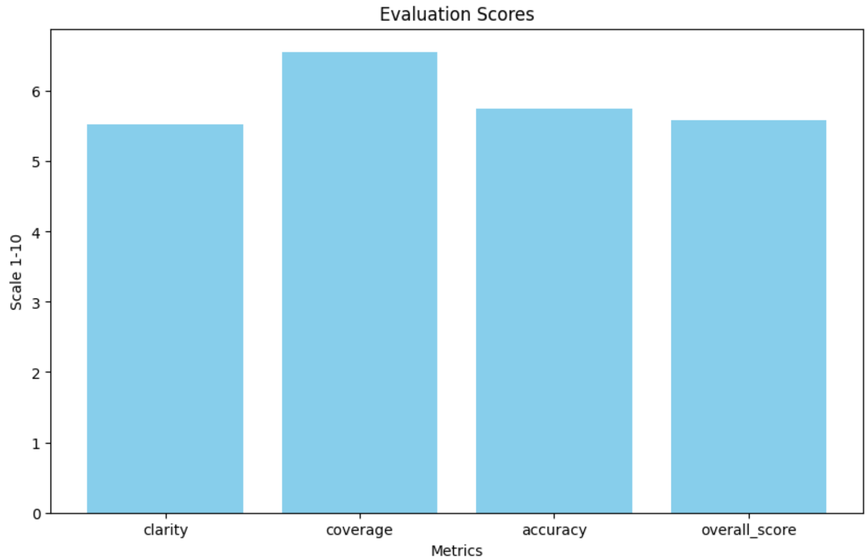
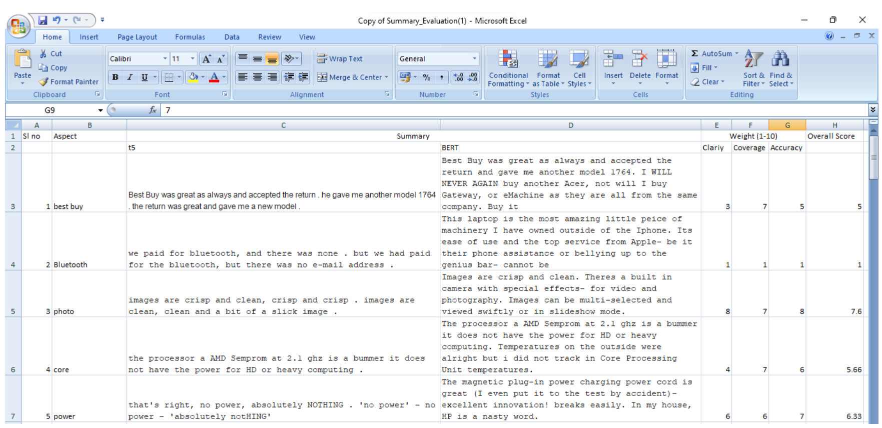


Figure 4: Evaluated metrics



Sl no	Aspect	Summary		Weight (1-10)			Overall Score
		t5	BERT	Clariy	Coverage	Accuracy	
1	best buy	Best Buy was great as always and accepted the return . he gave me another model 1764 . the return was great and gave me a new model .	Best Buy was great as always and accepted the return and gave me another model 1764. I WILL NEVER AGAIN buy another Acer, not will I buy Gateway, or eMachine as they are all from the same company. Buy it	3	7	5	5
2	Bluetooth	we paid for bluetooth, and there was none . but we had paid for the bluetooth, but there was no e-mail address .	This laptop is the most amazing little peice of machinery I have owned outside of the Iphone. Its ease of use and the top service from Apple- be it their phone assistance or bellying up to the genius bar- cannot be	1	1	1	1
3	photo	images are crisp and clean, crisp and crisp . images are clean, clean and a bit of a slick image .	Images are crisp and clean. Theres a built in camera with special effects- for video and photography. Images can be multi-selected and viewed swiftly or in slideshow mode.	8	7	8	7.6
4	core	the processor a AMD Semprom at 2.1 ghz is a bummer it does not have the power for HD or heavy computing .	The processor a AMD Semprom at 2.1 ghz is a bummer it does not have the power for HD or heavy computing. Temperatures on the outside were alright but i did not track in Core Processing Unit temperatures.	4	7	6	5.66
5	power	that's right, no power, absolutely NOTHING . 'no power' - no power - 'absolutely notHING'	The magnetic plug-in power charging power cord is great (I even put it to the test by accident)- excellent innovation! breaks easily. In my house, HP is a nasty word.	6	6	7	6.33

Figure 5: An image of how the summaries are evaluated

worth every single penny dime and nickel. High price tag, however. Overall though, for the money spent it's a great deal.

- Clarity: 9, Coverage: 8,Accuracy: 9, Overall Score: 8.6

3. Query: fingerprint

   - Related Reviews: ["If you don't like fingerprints, this might not be the laptop for you.", 'Really like the textured surface which shows no fingerprints.', 'The only thing that I have, is the key broad is a little dark to see the letters, would help if it was a little lighter then it is.', 'Once open, the leading edge is razor sharp.', 'In the shop, these MacBooks are encased in a soft rubber enclosure - so you will never know about the razor edge until you buy it, get it home, break the seal and use it (very clever con).']
   - Summary:If you don't like fingerprints, this might not be the laptop for you. Once open, the leading edge is razor sharp. Images are crisp and clean. Still trying to learn how to use it.
   - Clarity: 2, Coverage: 4,Accuracy: 1, Overall Score: 3.3

5 Conclusion

To conclude, in this project we have designed an aspect-based summarization model for product reviews. The designed model is evaluated manually on a formula considering 3 criteria: clarity, coverage, and accuracy. After evaluation the model stands to be good at covering all the related reviews retrieved in the final summary with a score of 6.56. While performance is less than coverage; at 5.53 and 5.75 respectively, the model can be given 5.58 out of 10. On the one hand, with a relatively small margin for performance, we can get much more information about the main features of identification, retrieve related reviews, and summarize. There have been multiple advances in the research direction of aspect-based summarization over the last years due to the show progress in the field of natural language processing and authors demonstrate the potential of large language models. However, there is much more room to reach their true potential, primarily through accuracy and coherence of the generated summaries, but also through more efficient and less wasteful retrieval. Personally, I am looking forward to the application of this development in such interesting and practical domains as e-commerce market and analytical systems and product review analysis.

In the future, more sophisticated aspect extraction methods could be explored, multimodal data could be incorporated into the summarization process, and personalized summaries specific to each user's preferences could be generated.

6 Individual Contributions

- Jagadeesh Rao Daggu: Contributed to the Introduction and Literature Review sections of the project and identified and extracted one Named Entity Recognition (NER) for feature extraction. Additionally, contributed to creating a PowerPoint presentation for the project.

- Akshitha Voruganti: Participated in data collection and preprocessing. Identified and extracted 2 Named Entity Recognition's (NERs) for feature extraction. Additionally, contributed to writing the report, including reviewing relevant research papers.

- Kurra Nagasowmika: Identified and extracted a single Named Entity Recognition (NER) for feature extraction, and involved in reranking features and concentrated on the second phase, specifically working on query-based related review retrieval. Additionally, contributed to summarizing the retrieved reviews using two models and participated in preparing the PowerPoint presentation.

- Ramabhadra Raju Namburi: Concentrated on the second phase, specifically working on query-based related review retrieval. Participated in summarizing the retrieved reviews using two models, as well as in the manual evaluation of the models and analysis of the results. Also contributed to writing the report.

- Bobba Sandeep: Engaged in conducting a literature review and identifying relevant research papers. Contributed to writing the report, specifically the methodology and conclusion sections, in addition to participating in drawing conclusions from the research findings.

References

Cao, S., Wang, X., Lyu, Y., Wang, Y., Chen, L., & Zheng, X. (2021). Summrewriter: A multi-task semi-supervised approach for abstractive text summarization. In *Proceedings of the 2021 conference on empirical methods in natural language processing* (pp. 9723–9734).

Hai, Z., Kurupati, G., Gong, J., Zhu, S. K., Joshi, S., Chen, J. L., ... Moustafa, M. (2011). Identifying sources of opinions with conditional random fields and extraction patterns. In *Proc. of hlt* (pp. 1886–1892).

Jiang, B., Sui, Z., Lan, M., & Ye, Q. (2019). Aspect-based sentiment analysis with hierarchical deep multi-task learning. In *Proceedings of the 2019 conference on empirical methods in natural language processing and the 9th international joint conference on natural language processing (emnlp-ijcnlp)* (pp. 5469–5477).

Ku, L.-W., Liang, Y.-T., & Chen, H.-H. (2006). Summarizing product reviews using aspect extraction. In *Lncs (lnai)* (Vol. 4093, pp. 46–55). Springer.

Lau, R., Chan, A. R. K., Liu, H. Y., Shi, C., Li, J., Liu, H., ... others (2022). Aspect-based sentiment analysis with bert: An investigation across domains. *arXiv preprint arXiv:2205.09969*.

Masruri, H., Maliki, B., & Hadi, S. (2022). Aspect-based summarization of product reviews. *Journal of Information Systems Engineering and Business Intelligence*, *8*(1), 19–28.

Popescu, A.-M., & Etzioni, O. (2005). Aspect and entity extraction for opinion mining. In *Lnai* (Vol. 3741, pp. 1–12).

Tian, L., Sun, X., Wang, J., Yan, S., Xie, X., Zhou, Z., ... Li, W. (2021). Aspect-aware multimodal summarization for product reviews. In *Proceedings of the 59th annual meeting of the association for computational linguistics and the 11th international joint conference on natural language processing (volume 1: Long papers)* (pp. 7369–7384).

Wan, X. (2018). A hierarchical reinforced sequence operation method for unsupervised text summarization. In *Proceedings of the 56th annual meeting of the association for computational linguistics (volume 2: Short papers)* (pp. 596–602).

Zhang, W., Wang, X., Wang, X., Chen, Z., Zhang, S., Feng, S., ... Huang, X. (2023). Aspect-based summarization with large language models. *arXiv preprint arXiv:2303.12046*.