IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

SUMMARIZATION OF TEXT USING SEQUENCE-TO-SEQUENCE MODEL WITH ABSTRACTIVE TECHNIQUES.

[1]Midhunadharshini G, [2]Dr.E.Uma

[1]Pg Student, [2]Associate professor

[1]Department Of Information Technology,

[1]College Of Engineering Guindy, Chennai, India

Abstract: E-commerce platforms facilitate customers in posting reviews for a wide range of products. Typically, a single product can accumulate numerous lengthy and repetitive reviews, making it challenging for customers to gather relevant information for informed decision-making. Therefore, the application of automatic review summarization holds immense potential in assisting customers by delivering concise and genuine summaries of online reviews on E-commerce websites. In this study, we propose a Fine-Tuning Pre-Trained Model, which produces more precise summaries closely resembling those generated by humans. Additionally, our system evaluates the overall sentiment of the generated summaries, enabling customers to quickly grasp the underlying tone of the text. For sentiment analysis, a supervised learning model using the Naive Bayes classifier has been trained on social media sentiment analysis data, achieving an accuracy exceeding 98%. The abstractive summarization model adopts a Sequence-to-Sequence approach with an attention mechanism, resulting in reasonably good review summaries.

***Index Terms* -Fine-Tuning Pre-Trained Model, abstractive summarization,seq2seq model, sentiment prediction.**

I. Introduction

In the era of the Internet, information is abundantly available. News and events from any corner of the world can travel across the globe in an instant, ensuring easy access to information is no longer a concern. According to statistics from Google Search Engine, approximately one billion articles, posts, or pieces of information are published each day for a single focused keyword. However, for consumers, the vast amount of web-based information can be overwhelming unless it is transformed in a way that facilitates comprehensive understanding. To provide users with the right amount of information they require, it is essential to condense the content into precise and accurate points. By offering the essence of extensive content, the burden of processing unnecessary information is reduced for consumers[5], while providers can efficiently deliver meaningful data. This is where summaries play a crucial role, representing a significant amount of information in a concise form. Summaries have proven to be beneficial across numerous platforms. Creating a summary manually would require users to revisit the entire content, negating the purpose of summaries themselves. Fine-tuning a pre-training model is common in natural language processing (NLP) tasks, such as Amazon review summarization. It involves taking a pre-trained language model. The process of fine-tuning begins with a large-scale pre-training phase, where the language model is trained on a massive corpus of text from the internet. This initial pre-training enables the model to learn general language patterns, grammar, and a broad understanding of various topics. However, it lacks task-specific knowledge and requires further adaptation for specific applications. For Amazon review summarization, the fine-tuning process involves training the pre-trained model on a dataset containing pairs of Amazon reviews and their corresponding summaries. The model learns to predict the summary given the review text during this fine-tuning phase. The dataset is usually prepared by collecting a large number of reviews from Amazon's product listings and generating or extracting summaries for each review. During fine-tuning, the model's weights are updated using gradient-based optimization techniques, such as stochastic gradient descent or Adam optimization. The objective is to minimize the difference between the predicted summary and the actual summary provided in the training data. The model learns to capture important information, sentiment, and key aspects of the reviews, enabling it to generate concise and informative summaries. Fine-tuning typically involves multiple iterations, where the model is trained on the dataset in batches. After each iteration, the performance of the model is evaluated on a separate validation dataset to monitor its progress and make any necessary adjustments. Once the fine-tuning process is complete, the model can be used for summarizing Amazon reviews. Given a review text as input, the fine-tuned model generates a summary that captures the essence of the review, providing users with a condensed version of the information. It's important to note that the success of fine-tuning depends on the quality and representativeness of the training data, as well as the architecture and initial pre-training of the language model. Fine-tuning is a powerful technique that leverages pre-trained models to adapt to specific tasks, saving time and resources compared to training from scratch. This is where automatic summary generators[2] come into play. These generators provide summaries based on the input text provided to the system. The applications of automatic summary generators are diverse, ranging from education, content creation, e-commerce, and marketing. As long as vast amounts of information need to be processed in daily life, automatic summarizers will continue to be relevant.

II. LITERATURE REVIEW

Chetana Badgujar et al[1] proposed that haveGraph-based methods can represent the relationships between sentences or concepts in a document. This can help capture the contextual dependencies and coherence necessary for generating meaningful summaries. Moye Chen et al [2]proposed that multi-view models can generate summaries that convey essential information and reflect the sentiment or opinion expressed in the original text. This can be valuable in scenarios where the sentiment or attitude of the source document is of particular interest. Peal, M et al[3] proposed that reading through numerous consumer reviews can be time-consuming. Summaries enable users to quickly understand the overall sentiment, key features, or common issues mentioned in the reviews without having to go through each review individually.H. Nainwal et al [4]have proposed that by summarizing customer reviews, businesses can aggregate and analyze feedback more efficiently. This allows them to gain valuable insights into customer preferences, satisfaction levels, and areas where improvements are needed.N. Aishwarya et al [5]proposed that review platforms often have an overwhelming number of reviews, making it challenging for users to process all the information. Summarization and prioritization techniques can alleviate information overload by highlighting the most important and credible reviews.S. Choi et al[6] proposed that the paper contributes to the existing literature on online review by offering empirical evidence and insights. It adds to the academic knowledge base in the field of decision support systems and provides a foundation for future research on the topic.J.Shah et al[7] have proposed that the paper focuses on abstractive text summarization, which aims to generate concise and coherent summaries that capture the key information and meaning of the original reviews. This approach can provide more human-like and informative summaries compared to extractive summarizations.A. K. Mohammad Masum et al[8]proposed that the paper utilizes sequence-to-sequence RNN models for text summarization. These models have shown promising results in various natural language processing tasks, including text summarization. The use of RNNs allows for capturing sequential dependencies and generating contextually rich summaries.N. Yadav et al[9] proposed have The paper also incorporates sentiment analysis, which aims to determine the sentiment or opinion expressed in the reviews. By combining summarization with sentiment analysis, the study provides a comprehensive analysis of online reviews, enabling a better understanding of the sentiment associated with the summarized information. Y. Bai et al [10]proposed the paper utilizing a pre-trained model, indicating the use of transfer learning or pre-training techniques in the research. Pre-trained models can capture general knowledge and language understanding from large-scale data, leading to improved performance and efficiency in specific tasks.

III. PROBLEM STATEMENT

The increasing volume of customer reviews on e-commerce platforms, such as Amazon, poses a challenge for users to efficiently extract meaningful information about products. Manually reading through numerous reviews is time-consuming and impractical. Therefore, the need arises for an automated system that can summarize Amazon reviews effectively, providing concise and informative summaries of customer opinions. The problem at hand is to develop a robust and accurate review summarization system specifically tailored for Amazon product reviews. This system should be able to process a large corpus of reviews, capture the key aspects and sentiments expressed by customers, and generate concise summaries that accurately reflect the overall sentiment and important features of the product. Furthermore, it should address challenges like handling noisy and biased reviews, dealing with varying review lengths, and ensuring the summaries are coherent and representative of the original reviews. The ultimate goal is to provide users with a valuable tool that enables them to quickly grasp the collective sentiment and key insights from Amazon reviews, empowering them to make informed purchasing decisions without the need to extensively analyze a large number of reviews manually.

IV. RESEARCH METHODOLOGY

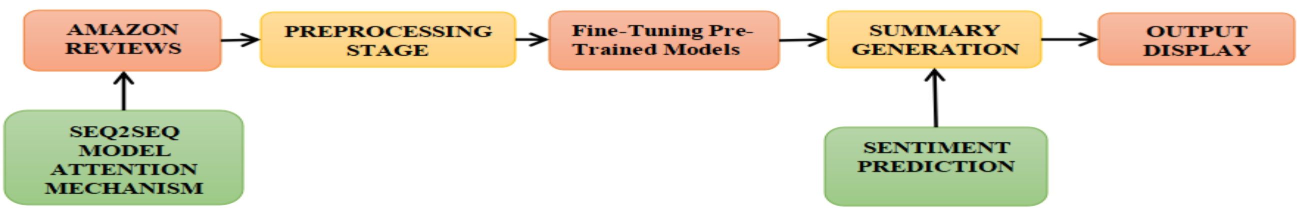

Fig.1System architecture

3.1 Training the model

The system utilizes two machine learning models. The first model is responsible for generating summaries of reviews, while the second model is utilized to determine the sentiment expressed in the reviews. To train the summary generation model, a dataset comprising approximately 700,000 Amazon product reviews and their corresponding summaries is employed. This dataset is fed into a Seq2Seq model [12]equipped with an attention mechanism, consisting of an encoder, a decoder, an attention layer and Fine-Tuning Pre-Trained Model. The model is trained on this dataset to generate a summary for each review. Subsequently, the performance of the trained model is evaluated using a separate testing dataset comprised of reviews. Once the model's performance is verified, it is saved for future use in summarizing desired reviews. For sentiment analysis,[24] a Naive Bayes model is trained using a Twitter sentiment analysis dataset, which contains tweets along with their associated sentiment labels. The purpose of this model is to accurately determine the sentiment expressed in a given sentence. The model is trained on the Twitter dataset to learn the patterns and characteristics indicative of sentiment. To evaluate its accuracy, the model is tested with sample sentences. This assessment helps gauge the model's ability to correctly identify the sentiment in different contexts.

3.2 Input data

In an information system, raw data is provided as input, which undergoes processing to generate the desired output. To generate a review summary for a specific product, the end user enters the product's name through an auto-complete drop-down menu. The system maps the product name to its corresponding product ID and forwards it to the next module.

Algorithm for inputting the product name

Input: Product name
Output: Product ID
1. Begin
2. Receive the product name from the drop-down list.
3. If the user selected "x", then
4. Retrieve the corresponding product ID from the database.
5. Send the product ID to the back-end server
9. End

3.2 Data collection

The collected Amazon reviews regarding the chosen product are gathered and forwarded to the subsequent stage known as the preprocessing stage.

Algorithm for Data Collection

Input: The product ID
Output: Reviews corresponding to the product ID
1. For each row in the data frame (df), do the following:
2. If the product ID in the selected row is the same as the specified product ID (PID), then
3. Append the row to the result.
4. End.

3.3 Data preprocessing

The purpose of preprocessing is to transform the collected data into a more manageable format, enabling the improved performance of the machine learning algorithms. This phase encompasses various tasks such as tokenization, elimination of stop words, lemmatization, POS tagging, and abbreviation resolution. These steps collectively cleanse the data and convert it into an integer sequence, which the model can comprehend more effectively.

Algorithm for preprocessing

Input: User review data
Output: Preprocessed review data
1. Tokenize the words in the data.
2. Remove the stop words from the input data.
3. Resolve abbreviations in the data.
4. Perform lemmatization on the data.

3.4 Fine-Tuning Pre-Trained Model

Pre-trained language models, such as GPT, have shown great potential in various natural language processing tasks. Future work can involve fine-tuning these models specifically for Amazon review analysis. Fine-tuning allows the model to adapt to the specific characteristics and language patterns found in Amazon reviews, leading to improved performance.

Algorithm for Fine-Tuning Pre-Trained Model

1. Load a pre-trained language model, such as aGPT.
2. Prepare a dataset with paired input and target summary examples.
3. Replace or add additional layers to the pre-trained model to create an encoder-decoder architecture suitable for summarization.
4. Freeze the weights of the pre-trained encoder layers to retain their learned representations.
5. Initialize the decoder layers with random weights or pre-trained weights specifically for summarization.
6. Define the loss function for the summarization task, such as cross-entropy loss or sequence-to-sequence loss.
7. Split the dataset into training and validation sets.
8. Iterate over the training set in batches such as a Forward pass
9. Evaluate the model's performance on the validation set periodically to monitor progress.
10. Repeat steps 8 and 9 until convergence or a desired number of epochs is reached.
11. Optionally, evaluate the fine-tuned model on a separate test set for final performance assessment.

3.5 Summary Generation and Sentiment Prediction

The preprocessed data is inputted into the trained seq2seq model to generate a summary. This summary is then passed on to the web application. The generated summary is abstractive, creating novel phrases and sentences that capture the essential information from the source text. The most pertinent summaries are chosen to be transmitted to the web application. Additionally, the preprocessed data is forwarded to the sentiment analysis model. The model calculates the percentage of positive and negative sentiment obtained from all the preprocessed reviews, which is then generated and sent to the web application.

Algorithm for Fine-Tuning Pre-Trained Model

For each row in the data frame (df), do the following:
1. Invoke the trained Naive Bayes model on the review in row i.
2. If the predicted sentiment is positive, then
3. Increment the count of positive sentiments (sent-pos) by 1.
4. Otherwise,
5. Increment the count of negative sentiments (sent-neg) by 1.
6. End.

3.6 Output Display

The web application receives the generated summary and sentiment, which are then presented to the user using a sweet alert. This alert includes the product's name, image, price, summary, rating, and sentiment for the selected item.

V. RESULTS AND DISCUSSION

The web application of the system features an auto-complete drop-down list that allows users to enter the product name. When the submit button is pressed, the selected product's ID is transmitted to the back end of the application. The back end then retrieves and preprocesses the reviews associated with the product. Subsequently, the preprocessed reviews are passed to the trained Naive Bayes model to determine the sentiment of each review. The percentage of positive and negative reviews is calculated. Additionally, the reviews are fed into a trained deep-learning model to generate summaries. The resulting summaries, along with the sentiment percentage and the average rating, are returned to the front end for user viewing. The back-end application's response, consisting of summaries, sentiment percentages, and average ratings, is presented to the user via a sweet alert box. This alert box showcases the product name, image, and price, with the summaries displayed as a bulleted list. Thumbs-up and thumbs-down images indicate the percentage of positive and negative reviews respectively. The filled stars at the bottom represent the average rating on a scale of 5, and the background color reflects the product rating range.

4.1 Training of Test Data

Training results on the test data are represented for the different machine learning algorithms

ML algorithm	Accuracy	Precision	Recall	F1-score
Linear SVM	0.86	0.86	0.86	0.86
Multinomial NB	0.85	0.87	0.82	0.84
LSTM network	0.90	0.92	0.87	0.90
Fine-Tuning Pre-Trained Model	0.98	0.94	0.92	0.92

Table.2 Training of test data

As shown in Table 2, we get the highest accuracy with the Fine-Tuning Pre-Trained Model. The other performance metrics, such as F1-score, are also higher with the Fine-Tuning Pre-Trained Model compared with the other algorithms. Therefore, we consider this algorithm as the most suitable for the sentiment analysis on Amazon reviews and used it to classify the reviews of the evaluation datasets.

VI. CONCLUSION

An abstractive summarization method has been employed to develop a user review consolidation[4] system, aimed at condensing lengthy product reviews found on e-commerce websites. This system not only provides concise summaries but also incorporates additional features such as overall rating and sentiment analysis. The system utilizes a dataset consisting of Amazon reviews from e-commerce platforms to generate summaries. Moreover, it determines the general sentiment expressed by customers for each product and calculates the average rating based on the available reviews. For sentiment analysis, a supervised learning model using the Naive Bayes classifier has been trained on social media sentiment analysis data, achieving an accuracy exceeding 98%. The abstractive summarization model adopts a Sequence-to-Sequence approach with an attention mechanism, resulting in reasonably good review summaries.

VII. FUTURE SCOPE

Multi-modal summarization With the increasing availability of multimedia content, such as images and videos, incorporating multi-modal summarization techniques can provide a more comprehensive and informative summary. This could involve analyzing both the textual content of reviews and the associated visual or auditory information, allowing for a richer understanding of customer feedback. Developing real-time and dynamic review summarization systems would enable businesses to monitor and respond to customer feedback in near real time. Such systems could automatically update summaries as new reviews are posted, allowing for timely insights and quicker responses to customer concerns.

REFERENCES

[1] Chetana Badgujar, Vimla Jethani and Tushar Ghorpade "Abstractive Summarization using Graph-Based Methods" Proceedings of the 2nd International Conference on Inventive Communication and Computational Technologies (ICICCT 2018), IEEE 2018

[2] Moye Chen, Lei Li, Wei Liu "A Multi-View Abstractive Summarization Model Jointly Considering Semantics and Sentiment", Proceedings of CCIS2018Peal,

[3] M., Hossain, M.S. & Chen, J. Summarizing consumer reviews. J Intell Inf Syst 59, 193–212 (2022).

[4] H.Nainwal, A. Garg, A. Chakraborty, and D. Bathla, "Text Summarization of Amazon Customer Reviews using NLP," 2023 10th International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 2023, pp. 43-47.

[5] P.Aishwarya, B. L. S and K. N, "Summarization and Prioritization of Amazon Reviews based on multi-level credibility attributes," 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), Bangalore, India, 2021, pp. 5-9, doi: 10.1109/RTEICT52294.2021.9573744.

[6] H.S. Choi and S. Leon, "An empirical investigation of online review helpfulness: A big data perspective", Decision Support Systems, vol. 139, Dec. 2020.

[7] H.Shah, M. Sagathiya, K. Redij and V. Hole, "Natural Language Processing based Abstractive Text Summarization of Reviews", Proc. of the 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Jul. 2020.

[8] A.K. Mohammad Masum, S. Abujar, M. A. Islam Talukder, A. K. M.S. Azad Rabby and S. A. Hossain, "Abstractive method of text summarization with sequence-to-sequence RNNs", Proc. of the 2019 10th International Conference on Computing Communication and Networking Technologies (ICCCNT), Jul. 2019.

[9] N.Yadav, R. Kumar, B. Gour and A. U. Khan, "Extraction-Based Text Summarization and Sentiment Analysis of Online Reviews Using Hybrid Classification Method", Proc. of the 2019 Sixteenth International Conference on Wireless and Optical Communication Networks (WOCN), Dec. 2019.

[10]Y.Bai, Y. Li and L. Wang, "A Joint Summarization and Pre-Trained Model for Review-Based Recommendation", Information, vol. 12, no. 6, May 2021.

[11]M. Siering, J. Muntermann and B. Rajagopalan, "Explaining and predicting online review helpfulness: The role of content and reviewer-related signals", Decision Support Systems, vol. 108, pp. 1-12, 2018.

[12]A. Y. Chua and S. Banerjee, "Understanding review helpfulness as a function of reviewer reputation review rating and review depth", Journal of the Association for Information Science and Technology, vol. 66, no. 2, pp. 354-362, 2015.

[13]M. Abulaish, M. N. Do_ja and T. Ahmad, "Feature and opinion mining for customer review summarization", International Conference on Pattern Recognition and Machine Intelligence, pp. 219-224, 2009.

[14]Z. Singla, S. Randhawa and S. Jain, "Statistical and sentiment analysis of consumer product reviews", 8th International Conference on Computing Communication and Networking Technologies (ICCCNT), pp. 1-6, 2017.

[15]A. Jeyapriya and C. K. Selvi, "Extracting aspects and mining opinions in product reviews using supervised learning algorithm", 2nd International Conference on Electronics and Communication Systems (ICECS), pp. 548-552, 2015.

[16]Q. Ye, Z. Zhang and R. Law, "Sentiment classification of online reviews to travel destinations by supervised machine learning approaches", Expert systems with applications, vol. 36, no. 3, pp. 6527-6535, 2009.

[17]A. Tripathy, A. Agrawal and S. K. Rath, "Classification of sentiment reviews using n-gram machine learning approach", Expert Systems with Applications, no. 57, pp. 117-126, 2016.

[18]P. Kalaivani and K. L. Shunmuganathan, "Sentiment classification of movie reviews by supervised machine learning approaches", Indian Journal of Computer Science and Engineering, vol. 4, no. 4, pp. 285-292, 2013.

[19]M. Taboada, J. Brooke, M. Tofiloski, K. Voll and M. Stede, "Lexicon-based methods for sentiment analysis", Computational linguistics, vol. 37, no. 2, pp. 267-307, 2011.

[20]Z. Hailong, G. Wenyan and J. Bom, "Machine learning and lexicon-based methods for sentiment classification: A survey", 11th Web Information System and Application Conference, pp. 262-265, 2014.

[21]L. Zhang, R. Ghosh, M. Dekhil, M. Hsu and B. Liu, "Combining lexicon-based and learning-based methods for Twitter sentiment analysis", HP Laboratories Technical Report HPL-20ll, no. 89, 2011.

[22]L. Augustyniak, T. Kajdanowicz, P. Szymanski, W. Tuliglowicz, P. Kazienko, R. Alhajj, et al., "Simpler is better? Lexicon-based ensemble sentiment classification beats supervised methods", IEEE/ ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), pp. 924-929, 2014.

[23]C. S. Yang and H. P. Shih, "A Rule-Based Approach For Effective Sentiment Analysis", InPACIS., pp. 181, 2012.

[24]R. Piryani, V. Gupta, V. K. Singh and U. Ghose, "A linguistic rule-based approach for aspect-level sentiment analysis of movie reviews" in Advances in Computer and Computational Sciences, Singapore: Springer, pp. 201-209, 2017.

[25]S. Poria, E. Cambria and A. Gelbukh, "Aspect extraction for opinion mining with a deep convolutional neural network", Knowledge-Based Systems, vol. 108, pp. 42-49, 2016.

[26]J. Wang, L. C. Yu, K. R. Lai and X. Zhang, "Dimensional sentiment analysis using a regional CNN - LSTM model", Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, vol. 2, pp. 225-230, 2016.

[27]Y. Ma, H. Peng, T. Khan, E. Cambria and A. Hussain, "Sentic LSTM: a hybrid network for targeted aspect-based sentiment analysis", Cognitive Computation, vol. 10, no. 4, pp. 639-650, 2018.

[28]G. Rao, W. Huang, Z. Feng and Q. Cong, "LSTM with sentence representations for document-level sentiment classification", Neurocomputing, no. 308, pp. 49-57, 2018.