



Brevity AI using NLP and Emotion Polarity Detection

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Abstract : The capacity to effectively extract important information is essential in the fast-paced world of today. This demand is met by Brevity AI, a state-of-the-art natural language processing (NLP) model that summarizes long texts while maintaining their essential content. This study explores how to improve Brevity AI so that it can identify the polarity of emotions.

The resulting summary can transmit both factual information and the emotional tone of the original text by assessing the mood represented in it. This capability is especially helpful in domains where knowing the underlying emotion can yield insightful information, such as content analysis, market research, and customer service.

The methodology used to incorporate emotion polarity detection into Brevity AI is described in the study. This involves applying pre-trained sentiment analysis models and refining techniques to ensure both the accuracy and relevance of the summaries that are generated, maintaining their precision and practical applicability. Brevity AI is a more flexible and educational tool for text summarizing as a consequence of experimental results demonstrating the effectiveness of the improved model which captures both factual content and emotional nuances.

IndexTerms - Brevity AI, NLP, Emotion Polarity Detection, Text Summarization, Sentiment Analysis, Pre-trained models.

I. INTRODUCTION

The ability to effectively analyze and understand large amounts of information is becoming increasingly important in today's rapidly evolving digital world. Recent advancements in artificial intelligence, particularly in natural language processing (NLP), have enabled machines to interpret and process human language. One of the most promising applications of NLP is summaries recovered from text, which involves shortening lengthy documents into smaller, more manageable information while preserving the key aspects. However, traditional text summarization methods, despite their effectiveness in highlighting essential facts, often overlook the emotional nuances that significantly affect human understanding. Emotions play a major role in how we perceive and interpret information. By careful understanding the emotional tone of the original text, a generated summary can convey both factual details and the emotional context of the source material.

II. MOTIVATION

2.1 Text and Textual communication

Even while texting is quite convenient, there are some disadvantages. On the one hand, it has many advantages, such as instantaneous connection, accessibility from anywhere at any time, and the capacity to express oneself more thoughtfully and thoughtfully than in real-time talks. For example, without feeling compelled to reply right away, one can take your time to formulate a thoughtful answer to a challenging issue or to voice a nuanced opinion. However, misconceptions may result from text communication's absence of nonverbal clues. For instance, sarcasm in writing can be mistaken for sincere criticism. Furthermore, since nonverbal clues like tone of voice and facial expressions are important for establishing rapport, focusing only on text can impede the growth of deeper emotional relationships.

2.2 The Role of Emotions in Textual Communication

Human communication relies heavily on emotions, which affect how we perceive, understand, and react to information. In addition to processing the text's factual information, we also take in the emotional messages conveyed through language, tone, and context as we read or listen to it. These emotional cues have the power to profoundly affect how we comprehend and retain the information. A news report about a natural disaster, for instance, might provide accurate details about the incident, including the location, level of harm, and number of fatalities. However, the article's emotional tone—which is conveyed through word choice and emotive language—can have a big impact on how we view the incident. While a news story that highlights the victims' pain and loss may arouse sympathy and sadness, one that highlights their resiliency and efforts to rehabilitate may arouse feelings of hope and optimism.

Effective communication and information processing depend on an understanding of the emotional undertones in language. Incorporating emotion polarity recognition into text summary allows us to produce summaries that give readers a more thorough and interesting experience by capturing the emotional tone of the original text in addition to factual information.

III. ADVANTAGES

Enhanced service: This tone detection so that agents can communicate better according to the mood of the customer, resulting in higher satisfaction levels.

Time Efficiency: Summarizers summarize long documents into short ones, enabling readers to understand the key points in a few minutes. It is quite helpful for information-heavy industries such as research, legal, or news.

Improved Comprehension: Summarizers, more so the extractive or abstractive techniques, bring forth key points. This lessens the mental effort by the reader.

Content Filtering: Summarizers are focused on the main ideas to filter out noise. Thus, all relevant information is easier to find, which improves the accuracy of information retrieval.

Scalability: NLP-based summarization can automatically process high volumes of text. This becomes useful for organizations operating large databases, be it customer reviews, support tickets, or academic papers.

Sentiment Analysis: It involves the extraction of tone, be it positive, neutral, or negative, showing public sentiments from social media, reviews, or feedback that will lead to direct decisions in marketing, customer care, or product development.

Content Moderation: Tone detection can flag potentially harmful or inappropriate content, making it an invaluable tool for online platforms in maintaining safety and constructiveness.

IV. LITERATURE ANALYSIS

4.1 Survey

The literature survey for the paper "Brevity AI using NLP and Emotion Polarity Detection" is as follows

Restricted Boltzmann Machine: A Restricted Boltzmann Machine is a neural network that is mainly used for the purposes of dimensionality reduction, feature learning, and summarization. The architecture of a Restricted Boltzmann Machine will contain two layers: one visible layer (input) and one hidden layer; there are no intra-layer connections. RBMs learn a probability distribution over its input data. First, the RBM models the relationship between the sentences and the important features that help in selecting the most relevant sentences to form a summary. The RBM embeds the sentences into a latent space and spots a pattern characterizing the textual content. While they are not as widely used in modern summarization tasks, whose state-of-the-art approaches include more recent methods using RNNs or transformers, RBMs have provided the basis for early unsupervised learning approaches to extractive summarization.

Variational Auto-Encoder: VAE, as the name says, is a generative model with an encoder-decoder architecture. It finds wide applications in image generation, anomaly detection, and text summarization. In the VAE, the encoder compresses the input data onto a latent space, while the goal of the decoder is to reconstruct the data from this latent representation. What separates VAEs from standard autoencoders is that they can sample new data points; they are not limited in reconstructing the input only. In text summarization, VAEs are usually used to perform meaningful, concise abstraction by encoding long documents into compact, continuous representations and then decoding such representations into short summaries. The generative nature of VAEs is most suitable for abstractive summarization, whereby the system generates new sentences rather than selecting existing ones. Essentially, VAEs have become a powerful tool for new age NLP tasks with the capability of capturing and generating coherent text representations.

Recurrent Neural Network: A Recurrent Neural Network (RNN) is a type of neural network tailored for handling sequential data, maintaining a hidden state that retains information from prior time steps. In text summarization, RNNs are particularly effective, as they process text in sequence, making them ideal for capturing sentence context and flow within a document. Variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs) are especially valuable in avoiding the vanishing gradient issue, enabling them to manage longer sequences effectively. SummaRuNNer is a popular RNN-based model that uses GRUs to rank and extract sentences for summarization. By processing each sentence in context, RNNs can decide which sentences contribute most to the overall meaning of the document. RNNs have been foundational in extractive summarization but have largely been replaced by more advanced models like transformers for modern text generation tasks due to their limitations in handling very long sequences.

Extractive summarization: This model creates summary by choosing sentences obtained from the original text. Popularly known and used, this approach identifies significant sections of a document by considering factors like frequency, relevance, and sentence importance. Algorithms like TextRank and LexRank model sentences as nodes within a graph, ranking them based on sentence similarity to determine their importance.

Machine learning models which are based on Support Vector Machines (SVMs) and decision trees are also used to classify and rank sentences based on features like sentence position, length, and content. Extractive summarization excels in preserving the original wording and structure of the document, making it a reliable approach for producing summaries that are factual and accurate. However, it lacks flexibility in rephrasing content, often leading to less coherent summaries compared to abstractive methods. Extractive techniques are ideal for tasks where precision and factual consistency are more critical than fluency, such as legal document summarization.

Abstractive summarization: Abstractive summarization generates summaries by rephrasing and creating new sentences rather than selecting from the original text. This method requires a deep understanding of the content and structure of the input text, often achieved through sequence-to-sequence models. Models like Pointer-Generator networks help balance extractive and abstractive capabilities by copying words from the input while also generating new words. Transformer-based models have significantly advanced abstractive summarization, enabling systems to generate more fluent, human-like summaries. BERT excels in understanding the context of sentences, while Pegasus is designed specifically for abstractive tasks by generating masked-out sentences in the training data. These models allow for a greater degree of abstraction, producing summaries that capture the core meaning while avoiding redundancy. However, abstractive summarization is more complex and computationally intensive compared to extractive methods, requiring sophisticated models to ensure coherence and accuracy.

Hybrid Approaches: Hybrid approaches to text summarization merges the best of both worlds i.e extractive and abstractive methods. In the hybrid, key sentences or phrases are selected using extractive techniques that are then rephrased or summarized by an abstractive model for better readability and coherence. In this way, it ensures that key information is preserved while allowing a smoother flow of the summary. Hybrid models seem particularly powerful in cases when the summary generated by the extractive method sounds repetitive or incoherent, and an abstractive model alone may omit some important details. For example, a model can utilize extractive algorithms, such as TextRank to choose the most important sentences and further use the rephrasing sequence-to-sequence model. In the real world, most applications use a hybrid approach, since most need to find a trade-off between the factual precision of extractive summarization and the fluency of abstractive summarization.

Transformer-based architecture: A Transformer-based architecture has become the backbone of many state-of-the-art models in NLP, including BART, BERT, and GPT. Transformers use self-attention mechanisms to capture relationships between words in a text, regardless of their distance from each other. Importantly, this enables the parallel processing of input sequences, and in recurrent models, input is processed sequentially. Finally, in BART's architecture, there is a Bidirectional Encoder, which processes an entire input context at once, joined with a token-by-token autoregressive decoder. This mixture lets BART excel both at understanding and generation tasks. The transformer architecture have made it the de facto model for a vast amount of Natural Language Processing applications, from machine translation and text summarization to question answering and dialogue generation. Its ability to handle long-range dependencies in text and its flexibility in various noising and generation tasks have made it a powerful tool in modern NLP.

Noising Techniques: Noising techniques are essential components of BART's denoising autoencoder framework. These techniques involve deliberately corrupting the input text and training the model to reconstruct the original, clean text. The common noising techniques include text infilling, where spans of text are replaced with mask tokens; sentence shuffling, where the order of sentences in a document is randomly altered; token deletion, where random tokens are removed from the text; and document rotation, where the beginning of a document is shifted to another position. These methods force the model to learn how to recover coherent text from disrupted input, making it robust in various natural language tasks. By applying noising techniques during pre-training, BART and similar models develop a deep understanding of language structure, enabling them to perform well in tasks such as summarization and translation by accurately predicting missing or corrupted information.

BART (Denoising Autoencoder Approach): BART is a powerful model in deep learning that uses a denoising autoencoder approach for NLP and summarization tasks. In this approach, the input text is noised by random processes such as sentence shuffling and token deletion along with text infilling, while the model is trained to reconstruct the original input text. BART consists of a bidirectional encoder that processes corrupted input text and an autoregressive decoder that generates reconstructed or summarized output. Particular tasks which require text generation and summarization this model has been effective and has provided state-of-the-art results on summarization benchmarks such as CNN/DailyMail and XSum datasets. The key advantage of BART is flexibility, with various types of noising functions: it allows a model to learn from corrupted input and handle a wide range of NLP tasks, like text summarization, translation, and question answering. Its ability to handle both extractive and abstractive elements makes BART versatile in summarization.

4.2 Understandings from the literature survey

Table 1 Shows the key understandings from the survey carried out

Authors	Title of the Paper	Methods	Contribution
Divakar Yadav, Jalpa Desai, Arun Kumar Yadav	Automatic Text Summarization Methods: A Comprehensive Review	- Extractive - Abstractive - Hybrid methods	- Review various summarization techniques. Examine datasets and evaluation methods.

Huyen Nguyen, Haihua Chen, Lavanya Pobbathi, Junhua Ding	A Comparative Study of Quality Evaluation Methods for Text Summarization	- ROUGE, BLEU - BERTScore, SummaC - LLM-based evaluation	- Compare evaluation metrics - Explore new LLM-based evaluation approaches
Akinul Islam Jony, Anika Tahsin Rithin, Siam Ibne Edrish,	A Comparative Study and Analysis of Text Summarization Methods	- Extractive - Abstractive - Hybrid models	- Compare extractive and abstractive summarization - Explore effectiveness for various content types
Shivangiraj Singh, Anmol Sawhney, Aayush Singh, Deepa Krishnan	Extractive Text Summarization Techniques of News Articles	-Web extraction techniques - Extractive summarization - Evaluation with ROUGE	- Analyze extractive methods for news articles - Explore efficient techniques for summarizing news content
Mrs.Kajal Jewani, Ojas Damankar, Nitesh Janyani, Disha Mhatre, Sahil Gangwani	A Brief Study on for Approaches Extractive Summarization	-TF-IDF, clustering, neural networks, fuzzy logic, graph-based summarization	- Explore various extractive summarization methods - Evaluate strengths and weaknesses of each technique
Asha Rani Mishra, V.K Panchal, Pawan Kumar	Extractive Text Summarization - An Effective Approach to Extract Information from Text	- Topic modeling (LDA) - TextRank (graph-based) -Cosine similarity measures.	- Investigate extractive summarization methods - Analyze machine learning and NLP methods
Devika M D, Sunitha C, Amal Ganesha	Sentiment Analysis: A Comparative Study on Different Approaches	- Machine learning (SVM, Naive Bayes, MaxEnt, K-NN) - Lexicon-based, rule-based approaches	- Compare analysis methods - Test how these approaches handle different datasets
Walaa Medhat ,Ahmed Hassanb,Hoda Korashy	Sentiment Analysis Algorithms and Applications: A Survey	- Aspect-, sentence-, and document-level analysis - Lexicon-based, SVM, Naive Bayes, MaxEnt approaches	- Provide a comprehensive review of sentiment analysis methods - Explore applications in business, politics, and finance
Kian Long Tan, Chin Poo Lee, Kian MingLim	A Survey of Sentiment Analysis: Approaches, Datasets, and Future Research	- Deep learning (LSTMs, ensemble techniques) - Traditional methods (SVM, Naive Bayes) - Embedding-based feature extraction(Word2Vec, GloVe)	- Review current sentiment analysis approaches - Explore challenges with feature extraction and classification
Mike Lewis, Yinhan Liu, Naman Goyal, et al	BART: Denoising Sequence-to-Sequence Pre-training for NLP	- Denoising autoencoder -Transformer-based, bidirectional encoder, autoregressive decoder	- Introduce BART model - Enhance effectiveness in tasks involving text creation, translation, and understanding.

V. CONCLUSION

In conclusion, this project titled "Brevity AI using NLP and Emotional Polarity Detection" aims to provide a comprehensive evaluation of Brevity AI, powered by TextBlob, demonstrates significant potential to transform fields such as content analysis, market research, and customer service by incorporating tone into traditional text summarization.

TextBlob, with its robust ability to process text sentiment and polarity, enables Brevity AI to go beyond mere factual summarization. It not only condenses long texts into concise summaries but also captures the underlying emotional tones, delivering a more insightful analysis. This fusion of factual summarization and sentiment analysis ensures that the system can recognize both the key information and the emotional context, which is invaluable for industries.

Brevity AI can identify positive, negative, or neutral emotions in the text, refining the summarization process to include emotional nuances. This dual capability makes it a powerful tool in areas where understanding customer feedback, market trends, or public opinion requires sensitivity to emotional context as well as factual data. In the future the research should aim at enhancing

TextBlob's sentiment analysis accuracy and expanding Brevity AI's application to different industries. Improvements in emotion-aware summarization will help industries gain deeper insights, enabling more effective strategies.

REFERENCES

- [1] D. Yadav, J. Desai, and A. K. Yadav, "Automatic Text Summarization Methods: A Comprehensive Review," arXiv (Cornell University), Jan.2022, doi: 10.48550/arxiv.2204.01849.
- [2] H. Nguyen, H. Chen, L. Pobbathi, and J. Ding, "A comparative study of quality evaluation methods for text summarization," arXiv (Cornell University), Jun. 2024, doi: 10.48550/arxiv.2407.00747.
- [3] N. Munot and S. S. Govilkar, "Comparative study of text summarization methods," International Journal of Computer Applications, vol. 102, no.12, pp. 33–37, Sep. 2014, doi: 10.5120/17870-8810.
- [4] S. Singh, A. Singh, S. Majumder, A. Sawhney, D. Krishnan, and S.Deshmukh, "Extractive Text Summarization Techniques of news Articles: Issues, challenges and Approaches," 2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN), Mar. 2019, doi: 10.1109/vitecon.2019.8899706.
- [5] K. Jewani, O. Damankar, N. Janyani, D. Mhatre and S. Gangwani,"A Brief Study on Approaches for Extractive Summarization," 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), Coimbatore, India, 2021, pp. 601-608, doi:10.1109/ICAIS50930.2021.9396031.
- [6] Mishra, Asha ,Panchal, V.K , Kumar, Pawan. (2019). Extractive Text Summarization - An effective approach to extract information from Text. 252-255. 10.1109/IC3I46837.2019.9055636
- [7] Devika M D, Sunitha C, Amal Ganesha, "Sentiment Analysis:A Comparative Study on Different Approaches", Fourth International Conference on Recent Trends in Computer Science and Engineering(Peer-review under responsibility of the Organizing Committee of ICRTCSE(2016), doi: 10.1016/j.procs.2016.05.124
- [8] W. Medhat, A. Hassan, and H. Korashy, "Sentiment Analysis Algorithms and Applications: A survey," Ain Shams Engineering Journal, vol. 5, no.4, pp. 1093–1113, May 2014, doi: 10.1016/j.asej.2014.04.011.
- [9] K. L. Tan, C. P. Lee, and K. M. Lim, "A survey of sentiment analysis: Approaches, datasets, and future research," Applied Sciences, vol. 13,no. 7, p. 4550, Apr. 2023, doi: 10.3390/app13074550.
- [10] D. Suleiman and A. Awajan, "Deep learning based abstractive text summarization: approaches, datasets, evaluation measures, and challenges,"Mathematical Problems in Engineering, vol. 2020, pp. 1–29, Aug. 2020, doi: 10.1155/2020/9365340.
- [11] S. Thange, J. Dange, V. Karjule, and J. Sase, "A survey on text summarization Techniques," International Journal of Scientific and Research Publications, vol. 13, no 11, pp.528,535,Nov.2023,doi:10.29322/ijsrp.13.11.2023.p14355.
- [12] M. Lewis et al., "BART: Denoising Sequence-to-Sequence Pre-trainingfor natural language generation, Translation, and Comprehension," arXiv(Cornell University), Jan. 2019, doi: 10.48550/arxiv.1910.13461
- [13] Vishwa Patel, Nasseh Tabrizi, "An Automatic Text Summarization: A Systematic Review", doi: 10.13053/CyS-26-3-4347
- [14] Awasthi, Ishitva Gupta, Kuntal Bhogal, Prabjot Anand, Sahejpreet Soni, Piyush. (2021). Natural Language Processing (NLP) based Text Summarization - A Survey. 1310-1317. 10.1109/ICICT50816.2021.9358703.
- [15] Snehal Shah, Akshata Bhat, Sumitra Singh, Arya Chavan, and Aryan Singh, "Sentiment Analysis", International Journal of Progressive Research in Engineering Management and Science, doi:https://doi.org/10.58257/IJPREMS33384
- [16] R. Sharma, S. Chaudhary, and S. Tyagi, "TEXT SUMMARIZER USING NLP NATURAL LANGUAGE PROCESSING,"International Research Journal of Modernization in Engineering Technology and Science, vol. 05–05, no. 04, Apr.2023,[Online].Available:https://www.irjmets.com/uploadedfiles/paper/issue_4_april_2023/37776/final/fin_irjmets168322272_2.pdf.
- [17] Manik Bhandari, Pranav Gour, Atabak Ashfaq, Pengfei Liu, Graham Neubig, "Re-evaluating Evaluation in Text Summarization"DOI:doi.org/10.48550/arXiv.2010.07100
- [18] Jonathan Pilault, Raymond Li, Sandeep Subramanian, Christopher Pal,"On Extractive and Abstractive Neural Document Summarization with Transformer Language Models",DOI:doi.org/10.18653/v1/2020.emnlpmain.748
- [19] Chhinder Kaur, Anand Sharma, "Social Issues Sentiment Analysis using Python", 2020 5th International Conference on Computing, Communication and Security (ICCCS), DOI:10.1109/icccs49678.2020.9277251
- [20] "Proceedings of the 5th Clinical Natural Language Processing Workshop -ACLAnthology." https://aclanthology.org/2023.clinicalnlp-1.