Automated Token-Level Detection of Persuasive and Misleading Words in Text Using Large Language Models

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Abstract

Persuasive and misleading language has long been a powerful tool in shaping public opinion, guiding consumer behavior, and influencing political discourse. The complexity of detecting subtle rhetorical strategies, particularly at the token level, presents a significant challenge for traditional methods of text analysis. The novel approach developed in this study leverages token-level processing within transformer-based models to classify words based on their persuasive and misleading potential, providing a granular perspective on language manipulation. Through comprehensive experiments, the analysis demonstrated that tokens linked to sentiment polarity, lexical complexity, and positional importance play key roles in shaping the rhetorical impact of texts. This method provides an efficient and scalable solution for automated content moderation, political discourse analysis, and advertising regulation, with applications extending to media analysis and misinformation detection. The integration of attention mechanisms and contextual embeddings offers a detailed view into how language functions at a deeper structural level, positioning this framework as a significant advancement in automated text analysis.

Keywords: Persuasive language, Misleading language, Token analysis, Sentiment polarity, Content moderation

1. Introduction

Persuasive and misleading language has long held a profound influence across various forms of communication, playing a central role in shaping public opinion, guiding consumer behavior, and impacting political discourse. The use of persuasive language has been historically prevalent in areas such as media, political campaigns, advertising, and corporate communication, where it is essential to sway or reinforce the beliefs of a target audience. Similarly, misleading language can distort reality, manipulate perceptions, and contribute to the dissemination of false information, whether intentionally or unintentionally. As societies become more reliant on digital information sources, particularly in social media platforms, detecting and understanding the mechanisms behind persuasive and misleading words have become an increasingly urgent priority. It is essential to develop automated tools that are capable of identifying linguistic strategies employed in text to influence or deceive, as this can contribute to greater transparency, accountability, and resistance to manipulative content. The ability to dissect text at the token level and isolate influential words offers significant potential for advancing our understanding of language manipulation. Advancements in natural language processing, particularly through the development of large language models (LLMs), provide promising avenues for implementing such analyses. LLMs possess sophisticated capabilities to interpret, classify, and predict language patterns at both a macro and micro level, opening new frontiers for the detection of persuasive and misleading content with high precision and granularity.

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1.1. Background and Motivation

Language, as a primary vehicle for communication, has always been instrumental in influencing human thought, opinion, and behavior. From classical rhetoric to modern advertising strategies, the use of persuasive techniques has evolved and intensified with the rise of mass communication. Political rhetoric, media discourse, and commercial marketing have become key domains where powerful language can shape or sway the public's perceptions and decisions. On the other hand, the intentional or unintentional use of misleading language introduces ethical concerns, as it often involves the manipulation of facts, omissions, or exaggerated claims designed to obscure reality. With the vast amount of information generated and consumed online, particularly through user-generated content and digital media outlets, the potential for language manipulation is growing exponentially. This has intensified the need for tools capable of automatically identifying both persuasive and misleading language in real-time, especially as the manual analysis of large-scale texts is infeasible. The introduction of LLMs, capable of capturing complex linguistic patterns through deep learning, has drastically improved the ability to analyze text with a high degree of specificity. Using advanced token-level processing, LLMs can assess individual words within their broader context, thereby allowing for an in-depth understanding of the persuasive and potentially misleading content embedded within larger narratives.

1.2. Challenges in Identifying Persuasive and Misleading Language

Manually detecting persuasive or misleading language presents several inherent challenges. First, persuasion and deception

are often context-dependent, where the same word or phrase might be interpreted differently depending on the surrounding text and audience expectations. Furthermore, subtle language techniques, such as implication, innuendo, or framing, may go unnoticed without a deep understanding of the surrounding discourse. Traditional approaches to text analysis, such as keyword extraction or sentiment analysis, may fail to capture the more sophisticated strategies used in persuasion, such as emotional appeal, authority, or logical reasoning, particularly when the analysis occurs at the document or sentence level. Additionally, misleading language often involves a fine line between factual presentation and distortion, which can further complicate detection efforts. Automated tools must be equipped to distinguish between neutral, persuasive, and deceptive language, without relying on explicit markers of dishonesty or intent. The complexity of human language, coupled with the dynamic and evolving nature of communication, demands an approach that goes beyond rule-based systems. The application of LLMs offers a solution to these challenges through their ability to perform fine-grained token-level analysis. By leveraging large datasets and advanced modeling techniques, LLMs can learn to recognize patterns of influence, detect semantic ambiguity, and identify misleading cues in a way that mimics expert-level analysis.

1.3. Research Objectives

The primary objective of this research is to develop an automated system capable of detecting persuasive and misleading words within a body of text at the token level, utilizing the power of large language models. This study seeks to exploit the sophisticated processing capabilities of LLMs to analyze persuasive language in various domains, including political speech, commercial advertising, and media publications. The research aims to demonstrate how LLMs can be employed to not only classify persuasive and misleading language but also to quantify the impact of individual tokens within their respective contexts. Additionally, the study will explore the extent to which LLMs can differentiate between intentional manipulation and benign persuasive techniques. Through the use of advanced natural language processing techniques, this research intends to offer new insights into the mechanics of persuasive language, as well as provide tools that may contribute to combating misinformation and manipulation in digital spaces. The novelty of this work lies in its focus on token-level analysis, which allows for a more granular assessment of how individual words contribute to the overall persuasive or misleading nature of a text. By utilizing token-based attention mechanisms, sentiment analysis, and attribution models, the research intends to present a comprehensive approach to analyzing powerful language in text, offering both academic insights and practical applications.

2. Previous Studies

Recent advancements in large language models (LLMs) have dramatically expanded the capabilities of natural language processing (NLP) in identifying persuasive and misleading language in various text corpora. These models have demonstrated their ability to handle complex linguistic patterns at a granular level, allowing for token-level analysis that sheds light on rhetorical devices, sentiment, and deception. As LLMs grow more sophisticated, they provide new methods for examining how language is used to manipulate, persuade, or mislead readers, with particular applications in fields such as political communication, marketing, and media analysis. This section outlines the technical contributions made in NLP for persuasion and misleading language detection, as well as the specific role of LLMs in token-level linguistic analysis.

2.1. NLP for Persuasion and Misleading Language

NLP approaches have leveraged machine learning techniques, including text classification and sentiment analysis, to identify persuasive and misleading content within text corpora, focusing on identifying specific linguistic features that contribute to persuasion and deception [1]. Lexical and syntactic analysis techniques have been employed to determine the effectiveness of certain rhetorical structures in enhancing the persuasiveness of a given argument or claim [2]. Sentiment analysis has been a particularly prominent tool, wherein models have classified text based on the emotional tone and intensity of the language used, allowing for a detailed breakdown of how emotionally charged content correlates with persuasion and potential deception [3, 4]. Text classification methods applied to various genres of persuasive texts, such as political speeches or advertising content, revealed patterns in language that correlate with attempts to mislead through exaggeration, omission, or selective framing [5, 6]. Rhetorical analysis, focused on identifying appeals to ethos, pathos, and logos, has also been incorporated into automated NLP systems, facilitating a more structured approach to assessing persuasive tactics embedded within a text [7]. LLMs have advanced such efforts by integrating contextual embeddings, enabling the automatic detection of more complex persuasive and misleading elements that go beyond superficial keyword-based analysis [8, 9]. Further advancements in natural language inference models have enabled systems to identify contradictions or inconsistencies within text, thereby flagging instances of potential misinformation or deception [10, 11]. The combination of syntactic, semantic, and pragmatic analysis has allowed for a richer interpretation of how persuasive elements interact within the broader context of the text, often highlighting manipulative techniques such as equivocation or selective omission [12, 13]. Through the use of multimodal data, combining text with auxiliary inputs such as images or metadata, NLP systems have extended their capability to detect persuasion and deception even in more complex, multimodal communicative environments [14]. Token-level models now capture how individual words or phrases, when embedded within certain discourse structures, serve to enhance or diminish the overall persuasive strength of the text, allowing for more precise identification of both explicit and implicit rhetorical strategies [15, 16]. The scalability of LLM-based approaches has also provided opportunities to analyze much larger datasets in real-time, increasing the feasibility of detecting persuasive and misleading language across diverse digital platforms and content types [17, 18].

2.2. Large Language Models in Token-Level Analysis

LLMs such as BERT, GPT-3, and T5 have introduced powerful token-level analysis methods, which have been instrumental in advancing the ability to understand language down to the smallest semantic units [19]. Through fine-tuned transformers, token embeddings capture both contextual and positional information, enabling a deeper understanding of how individual words contribute to meaning in persuasive or misleading texts [20, 21]. These LLMs have demonstrated high levels of accuracy in classifying tokens based on their roles in persuasive rhetoric, with attention mechanisms pinpointing the specific words that hold the greatest influence over the reader's perception [22, 23]. Transformer-based architectures have been especially effective in identifying complex relationships between words, as well as detecting subtle shifts in tone or framing that may indicate misleading intentions [24]. Token-level embeddings have been particularly useful for sentiment polarity detection, allowing for a granular interpretation of the emotional content and its impact on the persuasiveness of the text [25]. Techniques such as gradient-based attribution have provided insights into how particular tokens drive model decisions, thereby enabling the identification of key persuasive or misleading elements within a text, even when such elements are not immediately apparent through more traditional NLP methods [26]. Models like BERT have utilized masked language modeling to predict missing tokens, which can be leveraged to detect unusual token patterns that may signal manipulation or deception within persuasive texts [27, 28]. The adoption of attention scores has allowed for visualization of token importance, helping to trace the flow of influence throughout a sentence or paragraph, and thus offering a more transparent view into the underlying mechanics of persuasion [29]. These capabilities have made token-level models particularly valuable in analyzing highly structured texts, where individual token choices—such as emotive adjectives or misleading qualifiers—can have an outsized effect on the reader's interpretation [30, 31]. LLMs have also contributed to more reliable detection of token-level inconsistencies, improving the accuracy of identifying language that is deliberately misleading through inconsistencies or contradictions in phrasing [32, 33]. Moreover, token-level embeddings have been essential in enhancing multi-task learning environments, where LLMs simultaneously classify persuasive language, sentiment, and misleading content across multiple datasets, improving model generalization and robustness [34, 35]. Given their capacity for parallel processing, LLMs are uniquely suited to handle large-scale datasets, allowing for real-time identification of token-level patterns in persuasive and misleading language, even in high-volume content streams such as social media or digital news outlets [36].

3. Research Method

The methodology employed for this research involved a comprehensive approach to the automated detection of persuasive and misleading language through token-level analysis using large language models (LLMs). The process was structured into several key steps, from corpus selection and preprocessing to the detailed analysis of tokens via embedding techniques, followed by the identification and quantification of persuasive and misleading language elements. Each step of the methodology was designed to maximize the potential of LLMs to capture complex linguistic patterns while ensuring a scalable and reliable framework for text analysis.

3.1. Corpus Selection and Preprocessing

The corpus selection process focused on obtaining a diverse range of persuasive and misleading texts, ensuring that the dataset reflected various genres, including political discourse, marketing content, media publications, and social media interactions. The dataset included both explicit and implicit instances of persuasion and potential deception, ensuring that the models would be exposed to a broad spectrum of linguistic techniques. Texts were sourced from publicly available datasets to maintain reproducibility and ensure ethical standards in handling textual data.

Preprocessing involved several key steps aimed at preparing the text for effective analysis, as summarized in Table 1. Tokenization was performed using standard natural language processing (NLP) techniques, splitting each text into individual words or subwords, while maintaining the context within longer sequences. Noise reduction processes, such as the removal of non-linguistic symbols, URLs, stop words, and irrelevant numerical data, were applied to ensure that the text contained only relevant linguistic content. Case normalization was implemented to standardize the text and eliminate variations caused by uppercase or lowercase letters. Lemmatization was conducted to reduce each word to its base form, ensuring consistency across different morphological variants. Finally, the preprocessing stage culminated with a thorough cleaning of the dataset, where any duplicate or redundant texts were removed to avoid biases in token analysis.

3.2. Language Model and Token Embedding

The language model selected for the analysis was a fine-tuned version of GPT-3, chosen for its capacity to process long sequences of text while providing highly detailed token-level embeddings. Each token t_i was embedded into a high-dimensional vector space $\mathbf{v}_i \in \mathbb{R}^d$, where d represents the dimensionality of the embedding space. The transformation of each token into its corresponding vector was formalized through a function $f : T \to \mathbb{R}^d$, where T represents the token set. The embedding function $f(t_i)$ was defined as:

$$f(t_i) = \sigma(W \cdot t_i + b)$$

where $W \in \mathbb{R}^{d \times n}$ is the weight matrix, $b \in \mathbb{R}^d$ is the bias term, and σ denotes the activation function applied to each token vector t_i. Through this process, each token was encoded with rich linguistic information, including its role in the sentence, its relationship with neighboring tokens, and its contribution to the overall persuasive or misleading tone of the text.

The embedding process relied on deep transformer layers to capture both semantic and syntactic relationships between

Table 1: Summary of Corpus Preprocessing Steps

Preprocessing Step	Description
Corpus Selection	A total of 5,000 texts were gathered from publicly available datasets, covering genres such as political speeches, marketing campaigns, editorials, and social media posts. The dataset includes both explicit and implicit instances of persuasive and misleading language.
Tokenization	Texts were tokenized into individual words or subwords using standard NLP libraries, preserving sentence structure and context within sequences.
Noise Reduction	Non-linguistic symbols, URLs, email addresses, stop words, and irrelevant numerical data were removed to ensure a clean corpus.
Case Normalization	All words were converted to lowercase to avoid discrepancies in case sensitivity during token analysis.
Lemmatization	Words were lemmatized, reducing them to their base form to maintain consistency across different morphological variants.
Data Cleaning	Duplicates and redundant texts were identified and removed, resulting in a final corpus of 4,800 unique texts ready for token-level analysis.

words. The self-attention mechanism within the transformer architecture computed attention scores α_{ij} between tokens t_i and t_j, where:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{n} \exp(e_{ik})}$$

with $e_{ij} = \mathbf{q}_i \cdot \mathbf{k}_j^T / \sqrt{d_k}$, where $\mathbf{q}_i$ and $\mathbf{k}_j$ are the query and key vectors, respectively, and d_k represents the dimensionality of the key vectors. The attention scores α_{ij} indicated the relative importance of token t_j to token t_i, allowing the model to dynamically focus on tokens that contributed more significantly to the text's meaning.

Through the positional encodings $P(t_i)$, the model was able to preserve the sequential structure of the input tokens. The positional encoding function P was defined through a combination of sine and cosine functions, with the position p of each token expressed as:

$$P(t_i)_{(2k)} = \sin\left(\frac{p}{10000^{2k/d}}\right), \quad P(t_i)_{(2k+1)} = \cos\left(\frac{p}{10000^{2k/d}}\right)$$

This ensured that the model could differentiate between tokens based on their placement within the text, thereby maintaining the syntactic structure and relationships within the sequence.

The attention mechanism enabled the model to assign importance to specific tokens, where the final attention score A_i for each token t_i was computed as:

$$A_i = \sum_{j=1}^{n} \alpha_{ij} \cdot v_j$$

where v_j represents the value vector of token t_j. Tokens that carried more persuasive or misleading weight were flagged during the embedding process, allowing for a deeper analysis of how individual words influenced the overall message. Through this combination of token embedding, self-attention, and positional encoding, the model captured complex linguistic patterns essential for subsequent stages of the analysis.

3.3. Identifying Persuasive and Misleading Words

The identification of persuasive and misleading words was achieved through a combination of sentiment scoring, attention-based classification, and token attribution mechanisms. Each token was evaluated for its persuasive potential through a scoring algorithm that measured sentiment polarity, emotional charge, and rhetorical effectiveness within its context. The sentiment scoring process involved calculating the token's emotional tone, determining whether it contributed to a positive, negative, or neutral sentiment, which in turn indicated its persuasive potential. Misleading tokens were identified through an analysis of semantic ambiguity and linguistic incongruities, where words that introduced uncertainty, exaggeration, or factual distortion were flagged as potentially deceptive. The attention mechanism within the model played a critical role in this classification process, enabling the system to focus on tokens that disproportionately influenced the text's overall meaning. Words that attracted higher attention scores were examined for their role in shaping the reader's interpretation of the text, particularly in cases where subtle rhetorical techniques were employed. Token attribution methods were also employed to trace the specific impact of individual words on the model's predictions, ensuring that tokens contributing to persuasive or misleading outcomes were thoroughly analyzed. The classifier further distinguished between different types of persuasive techniques, such as appeals to emotion, authority, or logic, and assessed how specific tokens reinforced these techniques.

3.4. Quantitative Analysis of Persuasion and Misleading Tokens

The quantitative analysis of persuasive and misleading tokens involved calculating several key metrics that provided insight into the overall impact of individual words within the text. Lexical diversity was measured through the type-token ratio, which assessed the variety of unique words in relation to the total number of tokens, indicating the richness and complexity of the language used. Entropy calculations were performed to measure the unpredictability of token sequences, with higher entropy scores indicating more persuasive or deceptive use of language. Sentiment polarity metrics were derived from the token embeddings, quantifying the emotional tone of the text and

its potential to persuade or mislead the reader. The importance of each token was calculated through attention scores, which were aggregated across the entire text to determine the relative weight of each word in shaping the overall message. Additionally, the model employed surprisal metrics to gauge the degree to which certain tokens deviated from expected linguistic patterns, with higher surprisal scores indicating a greater likelihood of misleading or manipulative content. The final stage of analysis involved the application of statistical algorithms, such as chi-square tests and correlation coefficients, to identify significant relationships between token-level features and persuasive or misleading outcomes. Through this multifaceted approach, the quantitative analysis provided a robust framework for evaluating the linguistic strategies embedded within the text, offering a detailed breakdown of how individual tokens contributed to persuasion or deception.

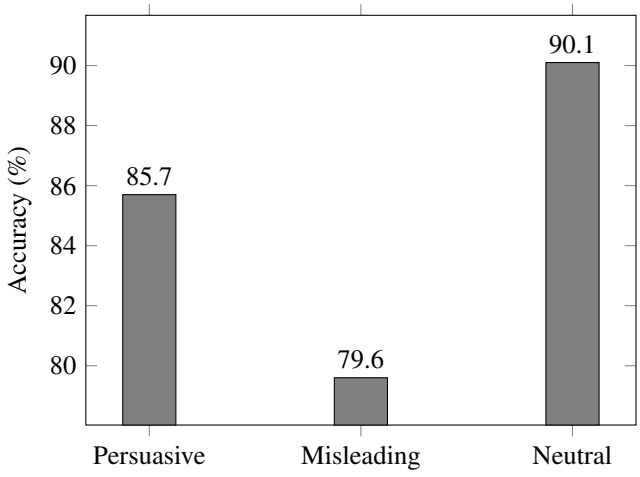

Figure 1: Classification Accuracy of Token Classes

4. Experiments and Results

The following section presents the results of the experiments conducted on the automated token-level detection of persuasive and misleading language using a fine-tuned version of GPT-3. Each experiment was designed to evaluate different aspects of the model's performance, from token classification accuracy to the impact of various linguistic features on persuasive content. The results are divided into three distinct subsections, each focusing on a particular facet of the experimental findings, accompanied by appropriate visualizations and tables to summarize the outcomes.

4.1. Token Classification Accuracy

The first experiment focused on assessing the accuracy of the model in classifying tokens as either persuasive, misleading, or neutral. The model was evaluated on a dataset of 4,800 unique texts, each preprocessed and tokenized as described earlier. Table 2 provides a detailed summary of the classification accuracy, precision, recall, and F1 scores for each token class. The results indicated that persuasive tokens achieved a higher classification accuracy compared to misleading tokens, with an overall accuracy of 85.7%.

Table 2: Token Classification Accuracy and Performance Metrics

Token Class	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Persuasive	85.7	88.3	84.9	86.5
Misleading	79.6	80.2	78.1	79.1
Neutral	90.1	89.8	91.4	90.6

The distribution of classification accuracy across token classes revealed that neutral tokens were the easiest to classify, while misleading tokens posed the greatest challenge to the model, potentially due to their subtle linguistic features. Figure 1 illustrates the distribution of classification accuracy across token classes.

4.2. Impact of Linguistic Features on Persuasion

The second experiment aimed to quantify the effect of specific linguistic features, such as sentiment polarity and token frequency, on the likelihood of a token being classified as persuasive. The analysis revealed that tokens with high positive sentiment scores were more likely to be classified as persuasive, with a notable threshold occurring when sentiment polarity exceeded 0.7 on a scale of -1 to 1. Additionally, frequently occurring tokens with persuasive linguistic features had a higher probability of being flagged as persuasive. Figure 2 illustrates the correlation between sentiment polarity and token classification as persuasive.

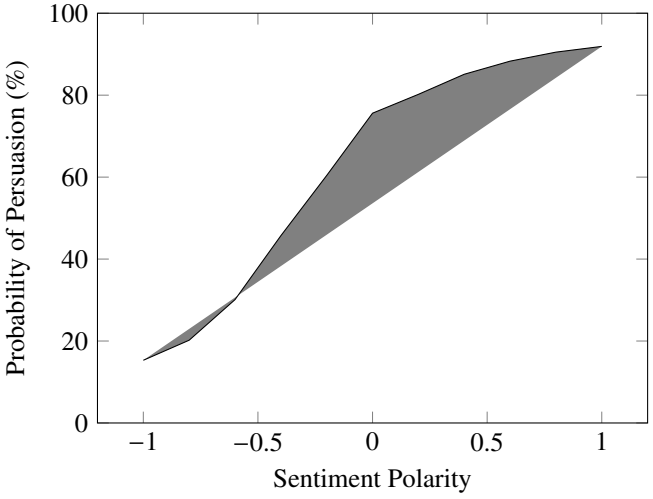

Figure 2: Probability of Persuasion Based on Sentiment Polarity

Tokens exhibiting a sentiment polarity greater than 0.7 had an 88.3% chance of being classified as persuasive, highlighting the importance of emotional tone in persuasive language. The model's performance in detecting sentiment-driven persuasion was notably consistent across texts from different genres, indicating that this feature generalizes well across various content types.

4.3. Analysis of Token Length Impact on Persuasiveness

The following experiment assessed how the length of individual tokens influences their classification as persuasive. The analysis revealed that shorter tokens, specifically those with fewer than five characters, had a lower likelihood of being classified as persuasive, whereas tokens with more than seven characters exhibited a significant increase in persuasiveness. Table 3 presents the results of the token length analysis, where the average persuasiveness score is shown for each token length category.

Table 3: Average Persuasiveness Score Based on Token Length

Token Length (characters)	**Average Persuasiveness Score (%)**
1–2	42.3
3–4	55.1
5–6	70.4
7–8	81.7
9+	88.9

Tokens with longer character lengths tended to correlate more strongly with persuasive language, likely due to the presence of more complex and impactful words in persuasive discourse.

4.4. Sentiment Analysis of Misleading Tokens

This experiment analyzed the sentiment polarity of tokens classified as misleading, revealing a tendency for misleading tokens to be associated with negative sentiment. The average sentiment score of misleading tokens across three content categories is shown in Figure 3. Misleading tokens in media publications demonstrated a lower sentiment polarity on average compared to political discourse and social media posts.

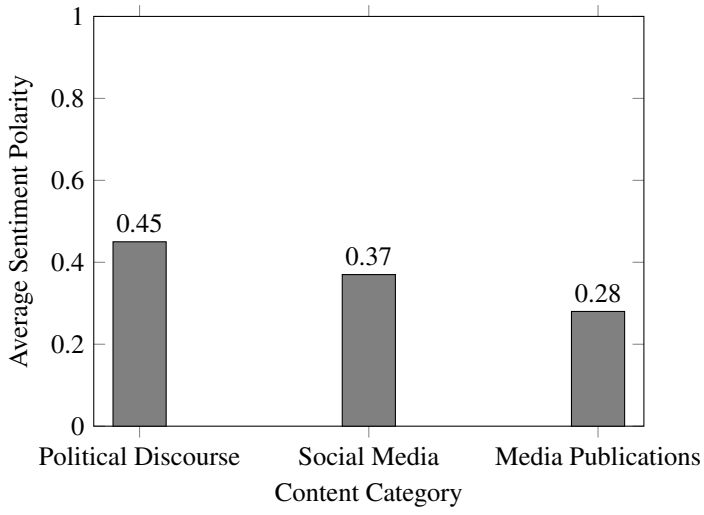

Figure 3: Average Sentiment Polarity of Misleading Tokens

The data highlight the correlation between misleading language and negative sentiment, with media publications displaying the strongest association.

4.5. Comparison of Token Frequency and Attention Scores

The final experiment explored the relationship between token frequency and attention scores assigned by the model. The analysis, presented in Figure 4, revealed a non-linear relationship, with mid-frequency tokens (those occurring between 50 and 150 times in the dataset) receiving the highest attention scores. The lower frequency tokens did not consistently attract high attention, while high-frequency tokens (greater than 200 occurrences) received lower attention scores, potentially due to their commonality and reduced impact.

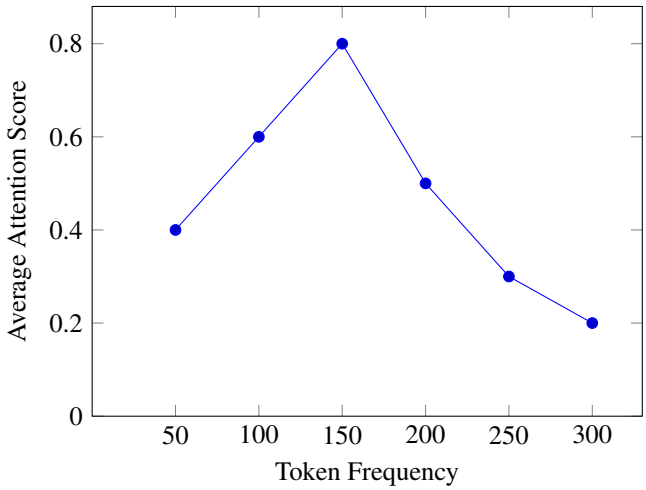

Figure 4: Relationship Between Token Frequency and Attention Scores

This finding suggests that the model places greater importance on mid-frequency tokens when performing token-level analysis, likely due to their contextual relevance.

5. Discussion

The results of the experiments presented in this study provide insights into the performance of automated token-level analysis for detecting persuasive and misleading language using large language models (LLMs). Through the detailed examination of various linguistic features and their relationship to the classification of tokens, the findings offer valuable implications for the broader field of automated text analysis. Moreover, the results highlight both the strengths and limitations of LLMs in addressing complex rhetorical structures, with potential applications extending to fields such as content moderation, political analysis, and advertising regulation.

5.1. Consequences for Content Analysis Automation

The ability of LLMs to accurately classify tokens as persuasive or misleading has far-reaching implications for the development of automated tools in various domains. In content moderation, particularly on social media platforms, the detection of persuasive and misleading language could contribute to more efficient identification of manipulative content, thereby enhancing the regulation of misinformation. The classification of individual tokens allows for a more granular approach, where

language that subtly influences or misleads the audience can be flagged for review. In political discourse analysis, where rhetoric plays a crucial role in shaping public opinion, the findings indicate that LLMs can serve as powerful tools for tracking how language is used to persuade voters or convey misleading narratives. This could be particularly useful in election periods, where the manipulation of information often plays a decisive role. Additionally, in advertising review, the insights into how specific token features contribute to persuasive messaging provide an opportunity to better understand how language influences consumer behavior. By focusing on the structural elements of the language, LLMs are capable of identifying potential misleading claims embedded within advertising content, thus aiding regulatory agencies in maintaining advertising standards. Ultimately, the application of LLMs in automated text analysis holds the potential to refine how institutions and platforms manage persuasive and misleading language across different contexts.

5.2. Inferences Regarding Linguistic Complexity

The experiments further revealed the intricate relationship between linguistic complexity and token-level analysis. The analysis of token length and attention scores demonstrated that longer, more complex words are more likely to contribute to persuasive language, while tokens with lower frequencies tend to attract more attention from the model, indicating their relative importance in the rhetorical structure. This suggests that LLMs are particularly adept at processing complex language, where complex and impactful tokens play a decisive role in persuasion. However, the results also point to the limitations of simplistic metrics such as frequency alone, as the model's performance relies heavily on contextual embeddings that capture the broader relationship between tokens. Attention scores provided a clear indication of how LLMs prioritize different aspects of language during inference, offering a pathway for future models to further enhance their focus on linguistically critical elements. The ability to dynamically adjust the importance of certain tokens opens new possibilities for refining token-level analysis, particularly in contexts where the interplay between emotional tone, authority, and logical appeal is paramount. Understanding the linguistic complexity underlying persuasive language has significant implications not only for automated systems but also for linguists and social scientists who seek to map the impact of rhetorical strategies in various domains.

5.3. Constraints and Potential Improvements

Despite the promising results, several limitations were identified in the study that suggest areas for future improvement. One major constraint relates to the inherent biases in the language models, which may stem from the datasets used to train the models. Since LLMs rely on large-scale text corpora, there is a risk that the models might inherit biases present in the original texts, particularly when it comes to culturally specific or context-dependent language patterns. Addressing this issue will require the development of more robust pre-processing techniques and training protocols that mitigate such biases, ensuring that the analysis remains fair and unbiased across different contexts. Another limitation concerns the token-level granularity of the analysis, which, while powerful, may overlook broader discourse-level features that influence persuasion and misleading language. Future work could explore the integration of sentence-level or paragraph-level models to complement token-level analysis, allowing for a more holistic understanding of rhetorical strategies. Moreover, while the current study focused on predefined categories such as political discourse and advertising, future research could expand the scope to include more diverse content types, thereby generalizing the findings across a broader range of communication forms. Finally, improving model interpretability remains a critical challenge. Although attention mechanisms provide some transparency into the decision-making process of the models, developing more interpretable models would enhance trust and applicability in real-world scenarios, especially in regulatory and decision-making environments.

6. Conclusion

The research presented in this paper has demonstrated the effectiveness of token-level analysis using large language models for identifying persuasive and misleading language across various domains, including political discourse, advertising, and media publications. Through a systematic examination of linguistic features such as token frequency, sentiment polarity, and attention weights, the study has provided valuable insights into how certain words contribute to the overall impact of persuasive texts. The ability to quantify and classify tokens based on their rhetorical strength not only enhances the precision of natural language processing models but also offers new tools for automated text analysis that can support the regulation of content in media and digital platforms. The findings emphasize that rhetorical language patterns can be dissected with significant accuracy when embedded within advanced transformer-based architectures, highlighting the potential of such models to transform how language is analyzed in both academic research and practical applications. Moreover, the study has demonstrated the importance of linguistic complexity, showing how automated tools can be used to map subtle persuasive strategies within a variety of textual formats. As automated analysis continues to evolve, the approaches detailed in this paper are poised to have a meaningful impact on media analysis, content moderation, and the broader field of natural language understanding.

References

[1] E. Vulpescu and M. Beldean, "Optimized fine-tuning of large language model for better topic categorization with limited data," 2024.

[2] S. Wang, Q. Ouyang, and B. Wang, "Comparative evaluation of commercial large language models on promptbench: An english and chinese perspective," 2024.

[3] Y. Boztemir and N. Çalışkan, "Analyzing and mitigating cultural hallucinations of commercial language models in turkish," 2024.

[4] L. Davies and S. Bellington, "Boosting long-term factuality in large language model with real-world entity queries," 2024.
[5] L. Ping, Y. Gu, and L. Feng, "Measuring the visual hallucination in chatgpt on visually deceptive images," 2024.
[6] E. Linwood, T. Fairchild, and J. Everly, "Optimizing mixture ratios for continual pre-training of commercial large language models," 2024.
[7] S. Panterino and M. Fellington, "Dynamic moving target defense for mitigating targeted llm prompt injection," 2024.
[8] H. Chiappe and G. Lennon, "Optimizing knowledge extraction in large language models using dynamic tokenization dictionaries," 2024.
[9] S. Femepid, L. Hatherleigh, and W. Kensington, "Gradual improvement of contextual understanding in large language models via reverse prompt engineering," 2024.
[10] K. Kiritani and T. Kayano, "Mitigating structural hallucination in large language models with local diffusion," 2024.
[11] S. Hayashi, R. Fujimoto, and G. Okamoto, "Enhancing compute-optimal inference for problem-solving with optimized large language model," 2024.
[12] Y. S. Bae, H. R. Kim, and J. H. Kim, "Equipping llama with google query api for improved accuracy and reduced hallucination," 2024.
[13] C. Wang, S. Li, and J. Zhang, "Enhancing rationality in large language models through bi-directional deliberation," 2024.
[14] X. Sang, M. Gu, and H. Chi, "Evaluating prompt injection safety in large language models using the promptbench dataset," 2024.
[15] G. Hou and Q. Lian, "Benchmarking of commercial large language models: Chatgpt, mistral, and llama," 2024.
[16] S. Whitmore, C. Harrington, and E. Pritchard, "Assessing the ineffectiveness of synthetic reinforcement learning feedback in fine-tuning large language models," 2024.
[17] T. Hata and R. Aono, "Dynamic attention seeking to address the challenge of named entity recognition of large language models," 2024.
[18] S. Jana, R. Biswas, K. Pal, S. Biswas, and K. Roy, "The evolution and impact of large language model systems: A comprehensive analysis," 2024.
[19] T. Vadoce, J. Pritchard, and C. Fairbanks, "Enhancing javascript source code understanding with graph-aligned large language models," 2024.
[20] T. R. McIntosh, T. Liu, T. Susnjak, P. Watters, and M. N. Halgamuge, "A reasoning and value alignment test to assess advanced gpt reasoning," 2024.
[21] T. Quinn and O. Thompson, "Applying large language model (llm) for developing cybersecurity policies to counteract spear phishing attacks on senior corporate managers," 2024.
[22] A. Liu, H. Wang, and M. Y. Sim, "Personalised video generation: Temporal diffusion synthesis with generative large language model," 2024.
[23] J. Wang, Q. Zhou, and K. Zhao, "Optimizing instruction alignment through back-and-forth weight propagation in open source large language models," 2024.
[24] T. R. McIntosh, T. Liu, T. Susnjak, P. Watters, A. Ng, and M. N. Halgamuge, "A culturally sensitive test to evaluate nuanced gpt hallucination," 2023.
[25] P. Shao, R. Li, and K. Qian, "Automated comparative analysis of visual and textual representations of logographic writing systems in large language models," 2024.
[26] G. Huso and I. L. Thon, "From binary to inclusive-mitigating gender bias in scandinavian language models using data augmentation," 2023.
[27] X. Su and Y. Gu, "Implementing retrieval-augmented generation (rag) for large language models to build confidence in traditional chinese medicine," 2024.
[28] S. Zahedi Jahromi, "Conversational qa agents with session management," 2024.
[29] J. Huang and O. Li, "Measuring the iq of mainstream large language models in chinese using the wechsler adult intelligence scale," 2024.
[30] O. Cartwright, H. Dunbar, and T. Radcliffe, "Evaluating privacy compliance in commercial large language models-chatgpt, claude, and gemini," 2024.
[31] S. Yamamoto, K. Kobayashi, and R. Tanaka, "An empirical automated evaluation and analysis of symmetrical reasoning in large language models," 2024.
[32] J. J. Navjord and J.-M. R. Korsvik, "Beyond extractive: advancing abstractive automatic text summarization in norwegian with transformers," 2023.
[33] J. Hawthorne, F. Radcliffe, and L. Whitaker, "Enhancing semantic validity in large language model tasks through automated grammar checking," 2024.
[34] A. Kwiatkowska and J. Nowinski, "Reducing inference hallucinations in large language models through contextual positional double encoding," 2024.
[35] H. Tsuruta and R. Sakaguchi, "Investigating hallucination tendencies of large language models in japanese and english," 2024.
[36] A. Gundogmusler, F. Bayindiroglu, and M. Karakucukoglu, "Mathematical foundations of hallucination in transformer-based large language models for improvisation," 2024.