INVESTIGATING YOUTH OPINIONS ON SUSTAINABLE FASHION ON SOCIAL MEDIA: GOING BEYOND SENTIMENT

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00 ABSTRACT

In the dynamic fashion industry, it's crucial to tap into the younger generation's nuanced perspectives. Traditional sentiment analysis falls short, merely scratching the surface of complex opinions on sustainability and policy in fashion. To deepen our understanding, we trained and compared various sentiment analysis models, ultimately leveraging Large Language Models (LLMs) for their superior performance. The LLM-based approach offered a more nuanced and detailed analysis of youth opinions on pivotal fashion issues, markedly enhancing the accuracy and depth of our insights. This advanced method underscores the potential of LLMs to revolutionize sentiment analysis, providing richer, more actionable intelligence for industry stakeholders.

01 RESEARCH QUESTIONS

- How do various sentiment analysis models, especially LLMs, differ in capturing and interpreting young people's views on fashion sustainability and policy?
- What methods can improve sentiment analysis models, especially LLMs, for more accurate analysis of youth opinions on sustainable and ethical fashion?

02 SUSTAINABLE FASHION

Eco-friendly and less waste: It emphasizes reducing waste and utilizing eco-conscious practices throughout the production process.
Ethical making of clothes: Ensuring fair labor practices and humane working conditions are foundational to its ethos.
Chooses better materials: Opting for sustainable, non-toxic materials is crucial to minimize environmental impact.
Long-lasting wear: The movement encourages the creation of durable garments that resist the fast fashion cycle.
Thoughtful buying: It promotes mindful purchasing decisions, encouraging consumers to buy less and choose well.
Good for the environment and people: Ultimately, sustainable fashion aims to benefit the planet and its inhabitants, fostering a healthier relationship between consumers and their clothing.

03 OUR DATASET

The dataset captures discussions from over 175 undergraduates in a social media group on sustainable fashion, highlighting their responses to government intervention topics. Spanning two years, it reflects active student engagement and insights into their perspectives on sustainability and policy.

04 CONSUMER ATTITUDES

Pro-Intervention: Regulations are crucial for enforcing environmental standards and ethical practices in the fashion industry.
Anti-Intervention: Government oversight may hinder innovation and burden small businesses, suggesting market-driven solutions and consumer awareness are preferable for promoting sustainability.

05 SENTIMENT ANALYSIS [VADER]

Lexicon-Based: VADER utilizes a specially curated lexicon of words and phrases associated with sentiment, each scored for its positive or negative valence.

Rule-Based: It incorporates a set of grammatical and syntactical rules to interpret intensity, conjunctions, punctuation, and capitalization, enhancing the accuracy of sentiment assessment.

Sentiment Quantification: VADER analyzes texts to quantify their emotional content, categorizing and scoring them as positive, negative, or neutral, thus offering a nuanced understanding of sentiment in language.

Context Awareness: VADER is designed to understand context and sentiment nuances, adjusting valence scores based on modifiers and contextual clues, which helps in accurately reflecting the sentiment expressed in text.

06 SENTIMENT ANALYSIS [LLM]

Input Processing:
- The LLM receives a text input, such as a sentence or a paragraph.
- The text is tokenized, meaning it is broken down into smaller pieces like words or subwords that the model can understand.

Model Understanding:
- The tokenized input is fed into the LLM.
- The LLM processes the input through its multiple layers, each layer transforming the representation of the text, adding more context and understanding.

Contextualization:
- As the input passes through the layers, the model leverages its pre-trained knowledge to understand the context.
- The LLM identifies key sentiment-indicating words and phrases, considering their context within the sentence or paragraph.

Sentiment Prediction:
- The model applies its trained understanding to evaluate the sentiment of the text.
- It assesses whether the overall sentiment is positive, negative, or neutral based on the aggregate understanding from all layers.

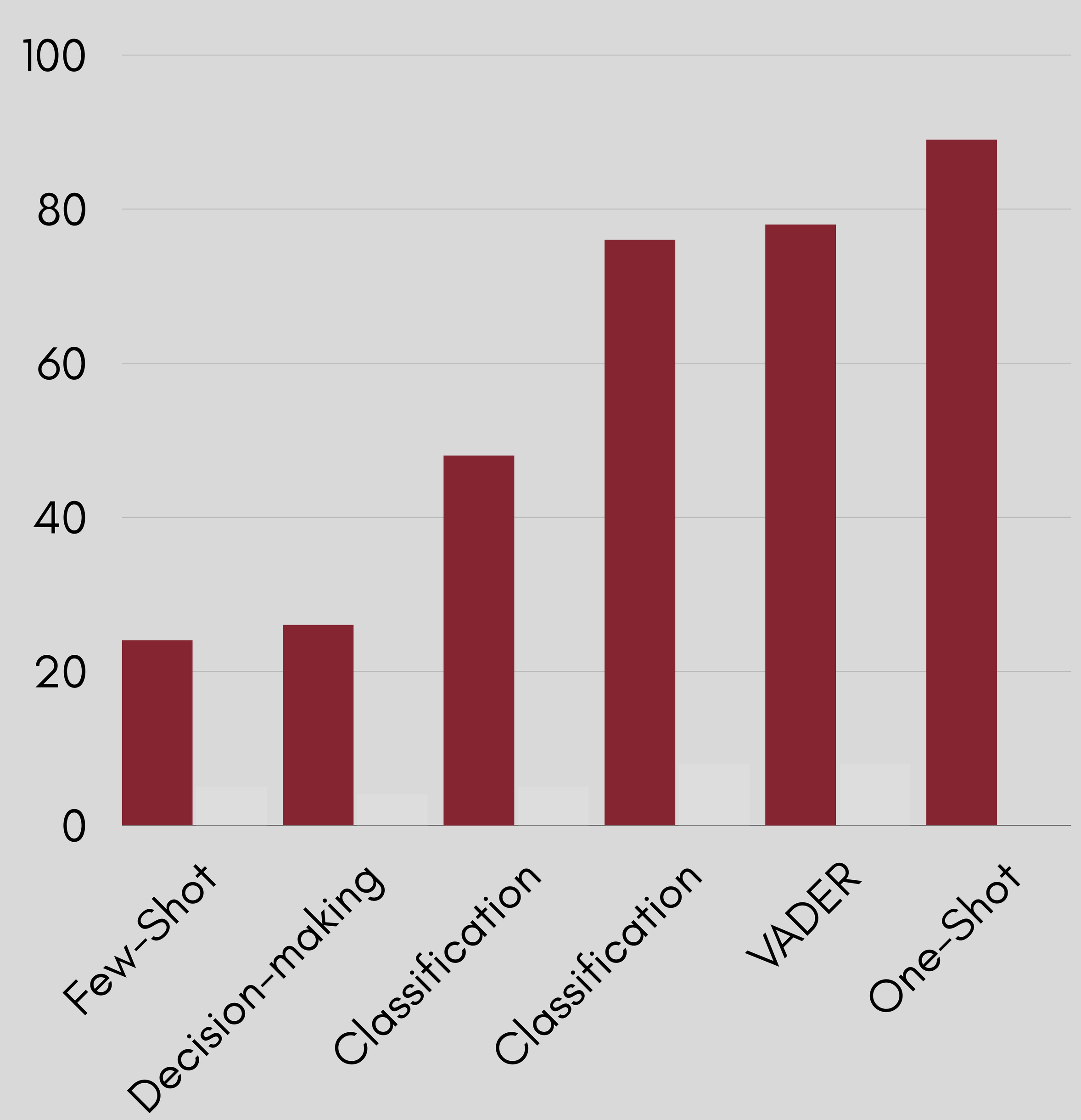
Output Generation:
- The LLM generates an output that categorizes the sentiment of the input text.
- The output can be a direct sentiment label (e.g., positive, negative, neutral) or a more nuanced sentiment score.
- Post-Processing (if applicable): Any post-processing steps are applied, such as adjusting the sentiment score based on specific criteria or calibrating the output for a particular application.

07 SENTIMENT ANALYSIS [LLM]

Prompting in sentiment analysis involves guiding large language models (LLMs) with specific questions or statements to analyze text for emotional content. This approach enables LLMs to focus on sentiment aspects, yielding targeted and nuanced interpretations of emotions in text.

- **Classification Prompting (2)**
- **Decision-making Prompt (1)**
- **One-Shot Prompt (1)**
- **Few-Shot Prompt (1)**

08 PERFORMANCE



09 CONCLUSION

- Classic Sentiment Analysis can deliver satisfactory performance, as demonstrated by our example with an accuracy of 76%.
- However, when using large language models, the Prompting Technique employed is critical to the model's performance. Different prompting techniques resulted in a significant variation in accuracy, ranging from 24% to 90%.
- The best results were achieved using the One-Shot Prompting Method.
- Overall, if one is not competent in prompting techniques, it is advisable to perform classic sentiment analysis rather than using LLM.