Commander-GPT: Fully Unleashing the Sarcasm Detection Capability of Multi-Modal Large Language Models

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Abstract

Sarcasm detection, as a crucial research direction in the field of Natural Language Processing (NLP), has attracted widespread attention. Traditional sarcasm detection tasks have typically focused on single-modal approaches (e.g., text), but due to the implicit and subtle nature of sarcasm, such methods often fail to yield satisfactory results. In recent years, researchers have shifted the focus of sarcasm detection to multi-modal approaches. However, effectively leveraging multi-modal information to accurately identify sarcastic content remains a challenge that warrants further exploration. Leveraging the powerful integrated processing capabilities of Multi-Modal Large Language Models (MLLMs) for various information sources, we propose an innovative multi-modal Commander-GPT framework. Inspired by military strategy, we first decompose the sarcasm detection task into six distinct sub-tasks. A central commander (decision-maker) then assigns the best-suited large language model to address each specific sub-task. Ultimately, the detection results from each model are aggregated to identify sarcasm. We conducted extensive experiments on MMSD and MMSD 2.0, utilizing four multi-modal large language models and six prompting strategies. Our experiments demonstrate that our approach achieves state-of-the-art performance, with a 19.3% improvement in F1 score, without necessitating fine-tuning or ground-truth rationales.

1 Introduction

In recent years, the rapid development of Large Language Models (LLMs) has led more and more scholars to use them for sarcasm detection. With massive amounts of training data and trillion-level parameters, LLMs have excelled in various general tasks. A typical example is ChatGPT, which, since its release, has demonstrated astonishing human-like intelligence. This presents both a huge challenge and an opportunity for industries, academia, and daily life. However, sarcasm detection remains a very tricky problem, primarily because sarcastic language requires consideration of more information (such as context, scenario, cultural background, body language, and facial expressions). Yet, the information we can input into LLMs is often incomplete or fragmented. Therefore, the single-modality detection approach typically performs unsatisfactorily in sarcasm recognition tasks.

It is precisely because of these limitations that the development of multimodal sarcasm detection has emerged. Multimodal sarcasm detection can comprehensively analyze and understand sarcasm through multiple types of information, such as text, audio, video, and images. It can capture more subtle facial expression changes, thereby improving the accuracy of sarcasm detection. As shown in Figure 1, LLMs cannot accurately and effectively recognize word information from a single modality (image or text). For example, the sentence "the PA welcome center is hopping today" is a neutral

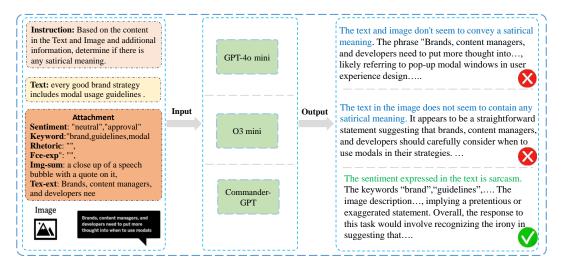


Figure 1: The model's judgment results for sarcasm recognition in unimodal (image or text) and multimodal (image and text) scenarios.

statement about facts with no emotional connotation, so the final result would be "non-sarcastic," which would be the same if evaluated with an image. However, when a multimodal large language model (MLLM) simultaneously considers both text and image content, it makes the correct judgment: "From the image, the parking lot of the Pennsylvania Welcome Center is almost empty, which contrasts sharply with the statement 'the PA welcome center is hopping today,' suggesting it is very busy. This exaggerated description does not match the reality, making it ironic. Therefore, the sentence is sarcastic."

In recent years, numerous studies have proposed various methods for multimodal detection. For instance, Li et al. (2024b) employed cross-modal affective inconsistency detection mechanisms, contextual scene inconsistency detection mechanisms, and cross-modal segment attention mechanisms. These mechanisms enable the generation of richer and more nuanced feature representations, thereby capturing the essence of sarcasm more effectively. Similarly, Aggarwal et al. (2024) introduced an innovative multimodal sarcasm detection framework capable of processing input triples. Two components of the triples include the textual input provided in the dataset and its associated image. Additionally, the study incorporated a supplementary modality—descriptive image captions. Yue et al. (2023) proposed a novel model named KnowleNet, which leverages the ConceptNet knowledge base to introduce prior knowledge and assess text-image relevance through sample-level and word-level cross-modal semantic similarity detection. Wang et al. (2024a) conducted a systematic study of the role of visual large language models in zero-shot multimodal sarcasm detection tasks and proposed a multi-perspective agent framework, S3 Agent, to enhance performance in zero-shot multimodal sarcasm detection.

While current multimodal sarcasm detection methods indeed improve the accuracy of sarcasm recognition, they also suffer from a critical limitation: most existing approaches fine-tune a specific model or framework tailored to a particular task. Undoubtedly, the adage "Three heads are better than one" applies here. Even a state-of-the-art model like ChatGPT-4 may underperform compared to a smaller, fine-tuned, or carefully designed model in specific downstream tasks. Inspired by this observation and adhering to the principle of "maximizing individual potential and resource utilization," we propose "Commander-GPT." In this framework, a highly intelligent large language model (e.g., GPT-4) serves as the commander. Based on our research, we identified that certain elements, such as image content (scene descriptions, facial expressions, textual content in images) and textual content (sentiment, keywords, rhetorical devices), play a decisive role in sarcasm detection. Drawing on these insights, we conducted a comprehensive evaluation and selected six different models, each excelling in a specific skill, to act as generals. These include:

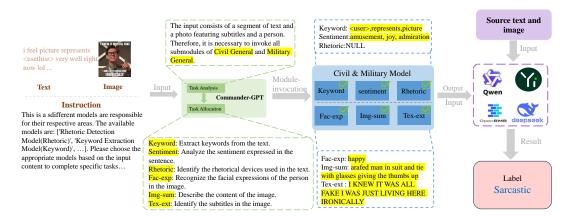


Figure 2: Commander-GPT: Description and Example. The "Commander" analyzes the input text and images, selects the most appropriate "C&W" for task processing, and then integrates the outputs from each module. Finally, it forms a complete reasoning chain for sarcasm detection.

Generals (Image): BLIP (image captioning) Li et al. (2022), vit-face-expression¹, and OCR-2.0 (text extraction) Wei et al. (2024).

Generals (Text): GPT-40 (rhetorical device recognition)², MiniLM-L6-v2 (keyword extraction)³, and roberta-base-go_emotions (sentiment analysis)⁴.

Initially, the commander determines the appropriate "general(s)" based on the input content (text and image) to perform specific, singular tasks. In this process, the generals do not provide any conclusions regarding sarcasm; instead, they focus on completing individual components of the sarcasm detection task within their areas of expertise. Finally, the commander collects and aggregates all results to form a new data file. The process is illustrated in detail in Figure 2.

Our proposed Commander-GPT has achieved state-of-the-art (SOTA) results, outperforming almost all previous methods on the MMSD and MMSD 2.0 datasets. On the MMSD dataset, Commander-GPT achieved f1 and accuracy scores of 72.5% and 74.5%, respectively, demonstrating significant improvements compared to the current state-of-the-art methods. On the MMSD 2.0 dataset, Commander-GPT achieved f1 and accuracy scores of 83.2% and 83.8%, respectively, also achieving remarkable accuracy improvements. Our contributions are as follows:

- We propose a novel multimodal reasoning framework, Commander-GPT, which efficiently
 integrates language and visual information to perform logical reasoning and task decomposition
- We leverage the advanced cognitive abilities of Commander-GPT, enabling it to act as multiple "experts" to handle the complex requirements of different sub-tasks, thereby significantly enhancing reasoning performance.
- We validate the effectiveness of Commander-GPT on two challenging benchmark datasets, MMSD and MMSD 2.0, where it significantly outperforms existing methods, demonstrating its immense potential in multimodal tasks.

2 Related Work

2.1 Multimodal Large Language Models

In recent years, multimodal large language models (MLLMs) have demonstrated strong multimodal perception and reasoning capabilities by integrating various types of information, including text,

 $^{^{}m 1}$ https://huggingface.co/motheecreator/vit-Facial-Expression-Recognition

²https://openai.com/index/hello-gpt-4o/

³https://huggingface.co/valurank/MiniLM-L6-Keyword-Extraction

⁴https://huggingface.co/SamLowe/roberta-base-go_emotions

images, video, and audio. For instance, Wang et al. (2024c) proposed the LongLLaVA model through a hybrid architecture design, which significantly improved the ability of MLLMs to process large amounts of images. Ye et al. (2024) introduced the mPLUG-Owl2 model, which enhances MLLMs' performance through a modality collaboration mechanism. Jiao et al. (2024) explored MLLMs' understanding of detection information and found that fine-tuning methods can effectively enhance the model's comprehension of such information. Jiang et al. (2024) proposed the E5-V framework, applying MLLMs to generate universal multimodal embeddings. Yang et al. (2024) developed the EmoLLM model for multimodal emotion understanding. Jin et al. (2024) created the MM-Soc benchmark to evaluate the understanding capabilities of MLLMs on social media platforms. Li et al. (2024a) introduced the SEED-Bench benchmark to assess the hierarchical capabilities of MLLMs.

2.2 Single-model sarcasm detection

In the early stages, sarcasm detection tasks primarily focused on unimodal data (e.g., text), where scholars proposed various methods and models to improve the accuracy of sarcasm text recognition. In recent years, researchers have introduced numerous approaches in the field of unimodal sarcasm detection, ranging from traditional feature engineering to deep learning models, leveraging various datasets and techniques to enhance detection accuracy. For instance, Kumar et al. (2020) extracted key features using traditional feature engineering methods to boost model performance. Addressing the issue of noisy labels in datasets associated with traditional methods, Misra & Arora (2019) introduced new datasets, including sarcastic and genuine news headlines, and proposed a hybrid neural network architecture with an attention mechanism. Additionally, deep learning methods have gradually become the mainstream approach. Zhang et al. (2016) compared the effectiveness of traditional handcrafted features with automatically extracted features using deep learning, demonstrating that neural network features achieve higher accuracy in sarcasm detection. Notably, user behavior and background knowledge have also been incorporated into sarcasm detection models. For example, Rajadesingan et al. (2015) were the first to adopt a behavior modeling approach, utilizing behavioral features from users' historical tweets to capture tendencies toward sarcastic expression. Li et al. (2021) employed the pre-trained COMET model to generate commonsense knowledge and enhanced model performance through a knowledge-text integration module. Furthermore, Joshi et al. (2015) focused on capturing both explicit and implicit inconsistency features. Compared to these approaches, our research leans towards multimodality, as single-text modalities often fail to comprehensively capture the complexity of sarcastic sentiments. Our approach integrates multimodal information, such as images and text, to more accurately interpret the implicit meanings behind sarcastic expressions.

2.3 Multimodal Sarcasm Detection

However, sarcasm, as a complex linguistic phenomenon, remains a challenging task for detection. To address this challenge, researchers have started exploring the application of MLLMs to multimodal sarcasm detection tasks. For example, Tang et al. (2024) proposed a multimodal sarcasm detection method based on generative MLLMs, which improves the model's understanding of sarcastic expressions by utilizing instruction templates and demonstration retrieval modules. Wang et al. (2024a) introduced the S^3 Agent framework, which employs a visual large language model and triple-perspective analysis. Wang et al. (2024b) developed the RCLMuFN model, which enhances the model's generalization ability through relational context learning and multi-path fusion networks. These studies demonstrate the great potential of MLLMs in multimodal sarcasm detection, offering new perspectives and methods for research in this field. This paper aims to address the current limitations of MLLMs in sarcasm detection by introducing the Commander-GPT framework to enhance the robustness and accuracy of MLLMs in sarcasm detection tasks, further advancing research in this area.

3 Methods

To enhance the ability of MLLMs to understand multimodal sarcastic content, we propose a novel framework, Commander-GPT, designed to unlock multimodal agent functionality for more effective sarcasm detection. This framework achieves its goal through three key core steps: role-playing, task assignment, and result integration. During this process, the framework conducts an in-depth analysis of the sarcasm task and selects the most suitable sub-models for specific tasks, thereby extracting

critical clues for solving the problem. As these clues accumulate and improve, they ultimately form a complete reasoning chain, leading to the efficient recognition of sarcastic content.

In our study, the first step involves selecting a multimodal large language model (MLLM) with basic text and image recognition capabilities, such as GPT-40, to serve as the "commander" within the Commander-GPT framework. It is noteworthy that the chosen MLLM does not require specific fine-tuning or complex prompt designs, as its primary task is not to directly perform sarcasm detection, but rather to handle the most fundamental "surface tasks," such as preliminary text and image recognition. Specifically, the model's functions include, but are not limited to, basic structural analysis of the input, sentiment detection, and initial recognition of visual elements. To verify the effectiveness of our approach, we used simple and straightforward expressions when constructing prompts, such as: "Based on the input text and image, select the most appropriate sub-model and provide a rationale." This design enables the "commander" to quickly comprehend its task and make reasonable selections. While more complex prompt strategies can be employed to enhance performance, the simple approach has already yielded ideal results at this initial stage. We will now elaborate on how the Commander-GPT framework selects sub-models:

- 1. Role Assignment. Within the Commander-GPT framework, the MLLM is assigned the role of the "commander." We instruct the MLLM to view itself as the leader of a sarcasm detection task, overseeing three "civil officials" (C) skilled in text processing, and three "military officers" (W) specialized in image content processing (hereafter referred to collectively as "C&W"). For example, the prompt may state: "You are the 'commander' of a sarcasm detection task, and your mission is to select the most appropriate 'C&W' based on the input multimodal content." This setup clearly defines the MLLM's role as the commander, enabling it to efficiently manage multimodal inputs.
- **2. Introduction of "C&W".** Each "C&W" excels in specific task domains. In the framework design, we clearly communicate the capabilities of these sub-models to the "commander" to ensure precise decision-making. For example:
 - Keyword: Extract keywords from the text.
 - Sentiment: Analyze the sentiment expressed in the sentence.
 - Rhetoric: Identify the rhetorical devices used in the text.
 - Fac-exp: Recognize the facial expressions of individuals in the image.
 - Img-sum: Describe the content of the image.
 - Tex-ext: Identify the subtitles in the image.

Based on these specializations, the "commander" can select the appropriate "C&W" for processing the input content. For instance, if the input contains both text and an image with subtitles, the commander would select the "civil official" skilled in subtitle recognition for processing.

- **3. Task Allocation.** Upon receiving a multimodal input, the commander performs an initial analysis of the text and image, identifying key elements in the image (such as facial expressions and descriptions of the image content), and selects the appropriate "C&W" for processing based on this information. For example, when the text input contains complex rhetorical devices, the commander will call upon the "civil official" specializing in rhetoric analysis; if the image content requires interpretation, the commander will select a "military officer" for analysis. Each sub-model, upon receiving the commander's command, performs its task independently and in an orderly manner, ensuring efficient and accurate information processing.
- **4. Result Integration.** The commander consolidates the clues (i.e., results) provided by each "C&W" into a complete chain of evidence, which is then used by the MLLM to perform sarcasm detection.

The proposed Commander-GPT framework effectively addresses the potential "hallucination" issue in MLLMs when processing multimodal information, i.e., when the model may overlook important information (such as neglecting the image modality) under multimodal inputs. Moreover, the framework helps prevent content loss or misunderstanding that may occur due to the complexity of the input, especially when both text and image are presented together, as some MLLMs may fail to properly integrate these two types of information. Furthermore, our framework enhances the accuracy and efficiency of sarcasm detection. First, the "C&W" sub-models have a distinct advantage over general multimodal large language models in their ability to process text and image data with greater

Table 1: Introduction to the MMSD Dataset and MMSD 2.0 Dataset

Dataset	Train	Validation	Test	Sarcastic	Non-sarcastic	Source
MMSD	19816	2410	2409	10560	14075	Twitter
MMSD 2.0	19816	2410	2409	11651	12980	Twitter

precision. Second, the Commander-GPT framework does not require additional training, significantly saving computational resources, time, and training costs, making this method more practical for real-world applications.

4 Experiments

In this section, we tested our proposed method on two multimodal datasets (MMSDCai et al. (2019) and MMSD 2.0Qin et al. (2023)). The experimental results demonstrate that our method outperforms existing baselines, further validating the effectiveness of our approach.

4.1 Datasets

MMSD: The MMSD dataset is a multimodal sarcasm detection dataset that combines textual and visual information. It consists of tweets paired with images, where each tweet is annotated with a sarcasm label. The textual content of the dataset may contain sarcastic statements, while the accompanying images provide additional contextual information, aiding the model in better understanding the meaning of sarcasm.

MMSD 2.0: The MMSD 2.0 dataset is an upgraded version of the MMSD dataset, specifically designed for multimodal sarcasm detection tasks. Compared to the original MMSD dataset, MMSD 2.0 offers improvements in both the diversity of image data and the quality of the text-image pairings. A detailed description of the dataset is provided in Table 1.

4.2 Experimental settings

In this study, we employed GPT-4 as the "commander" and selected a series of lightweight models as part of the "C&V" strategy (for detailed descriptions of each sub-model, please refer to the Introduction section). To evaluate the performance of different methods, we used several metrics, including F1-score, accuracy (Acc.), precision (P), and recall (R). Among these, F1-score was chosen as the primary performance evaluation criterion because it balances precision and recall, making it especially suitable for imbalanced class problems. It provides a comprehensive assessment of a model's accuracy and completeness. Currently, most relevant literature also uses F1-score as the core metric for model evaluation.

In this experiment, we selected five representative prompting strategies as baseline references, which include: Plan-and-Solve Wang et al. (2023), Zero-shot CoT Kojima et al. (2022), Generated Knowledge Prompting Liu et al. (2021), Automatic Prompt Engineer Zhou et al. (2022), and the Agent Wang et al. (2024a). Additionally, the final complete prompts generated by the Commander-GPT framework were evaluated by four multimodal large language models (MLLMs): Yi-VL(6B) Young et al. (2024), DeepSeek-VL-Chat(7B) Lu et al. (2024), Qwen-VL-Chat(9B) Bai et al. (2023), and MiniCPM-V-2(2.8B) Hu et al. (2024). Through testing on these different models, we comprehensively assessed the performance of the proposed strategy.

4.3 Main results

Based on the experimental results in Table 2, we can draw the following conclusions:

1.Our method demonstrates exceptional performance in sarcasm detection. The method proposed in this study performs excellently on two sarcasm datasets and four multimodal large language models (MLLMs). The F1 scores of all multimodal large language models exceed 55.0%, with some models achieving scores above 72.5%. Compared to existing methods, the improvement is nearly 20%. This

Table 2: Main Experimental Results. We reported the F1, accuracy (acc.), precision (pre.), and recall (rec.) scores. The bolded numbers indicate the best performance achieved by the method for the current model and metric. Additionally, we calculated the increase in the F1 score.

Model	Paramters	Open	Method	MMSD				MMSD 2.0			
Model	raranners		Method	fl.	acc.	pre.	rec.	fl.	acc.	pre.	rec.
	6B	Yes	Zero-shot CoT	45.8	59.2	51.4	41.4	6.1	16.2	6.0	6.3
Yi-VL			Automatic Prompt Enginner	49.4	53.3	45.0	54.7	4.3	14.2	4.2	4.5
			Plan-and-Solve	51.3	62.6	56.2	47.2	4.4	9.2	4.0	4.8
			Generated Knowledge Prompting	52.7	55.7	47.5	59.2	4.3	11.2	4.0	4.6
			S ³ Agent	52.3	41.4	39.6	77.0	31.7	54.3	44.4	24.6
			Ours	59.1 (6.8 ↑)	70.8	71.2	50.5	55.3(23.6↑)	67.9	69.0	46.1
			Zero-shot CoT	54.4	65.3	60.1	49.8	48.8	62.8	59.8	41.3
	7B	Yes	Automatic Prompt Enginner	55.1	68.0	66.4	47.6	46.6	62.3	59.7	38.2
Daniel VI Chat			Plan-and-Solve	54.9	61.9	54.3	55.5	48.3	63.0	60.5	40.2
DeepSeek-VL-Chat			Generated Knowledge Prompting	55.6	56.8	48.7	65.0	27.5	58.1	53.8	18.5
			S ³ Agent	59.7	45.3	43.1	59.7	52.0	64.9	63.3	44.1
			Ours	61.1 (1.4 ↑)	69.4	64.9	57.7	60.5 (8.5↑)	46.7	44.4	94.7
	9B	Yes	Zero-shot CoT	66.4	66.0	56.5	80.7	33.6	40.0	32.0	35.3
			Automatic Prompt Enginner	64.5	60.5	51.6	86.0	33.3	40.4	32.1	34.5
Owen-VL-Chat			Plan-and-Solve	59.4	64.8	57.2	61.8	34.8	38.7	32.1	38.0
Qwen-vL-Chat			Generated Knowledge Prompting	50.9	67.1	64.7	40.9	28.0	38.9	38.4	37.6
			S ³ Agent	68.1	67.5	57.6	83.3	58.6	63.3	57.0	60.4
			Ours	69.3(1.2↑)	68.2	58.0	86.2	68.9 (10.3↑)	67.7	58.8	83.2
	2.8B	Yes	Zero-shot CoT	61.4	68.1	62.1	60.7	33.0	51.6	40.9	27.7
MiniCPM-V-2			Automatic Prompt Enginner	63.2	69.2	63.1	63.4	31.2	48.0	36.2	27.4
			Plan-and-Solve	60.9	66.0	58.5	63.5	37.7	46.8	38.0	37.4
			Generated Knowledge Prompting	63.2	67.5	59.9	66.8	47.5	47.3	41.6	55.3
			S ³ Agent	60.8	66.6	59.6	62.0	49.2	62.9	60.0	41.8
			Ours	72.5 (9.3↑)	74.5	65.9	80.8	72.0 (22.8↑)	73.9	66.8	78.1

result robustly confirms the effectiveness and strong generalization ability of our method in sarcasm detection tasks.

- **2.Complex Chain-of-Thought (COT) prompts have limited effectiveness in sarcasm detection.** Sarcasm, as a complex linguistic phenomenon, still poses challenges for multimodal large language models, even when using sophisticated COT prompts. This indicates that simple and precise prompts may be more effective in assisting sarcasm detection than complex reasoning processes. Therefore, providing more direct and concise auxiliary information to multimodal large language models could be a more feasible strategy to enhance detection performance.
- **3.The relationship between model parameters and performance is not linear.** The experimental results show that despite QWen-VL-Chat having the largest number of parameters, its F1 score is still lower than that of MiniCPM-V-2, which has 2.8B parameters. This phenomenon may be due to differences in the task preferences of different models, suggesting that performance improvements are not solely dependent on an increase in the number of parameters.

4.4 Case Study

Table 3 presents examples of sarcasm detection predictions across multiple LLM-based methods. We analyze key error patterns in model performance below.

- (1) Contextual misunderstanding. Models like Zero-shot COT struggled with sarcasm tied to implicit contextual cues. In Example 2 ("the pa welcome center is hopping today"), the term "hopping" sarcastically contrasts the likely quiet reality of a welcome center, but Zero-shot COT misclassified it as non-sarcastic. Similarly, Example 6 ("a bit of a # mantub revival") relies on niche cultural references, which AutoPE failed to interpret, leading to incorrect predictions.
- (2) Literal interpretation. Models often prioritized surface-level semantics over implied tones. For instance, Example 5 ("do you suffer from this related problem?:)"), where the emoji and phrasing mock faux concern, was misclassified by Plan-and-Solve as non-sarcastic. Conversely, Example 9 ("protein pizza coming soon!") uses hyperbolic language to mock food trends, yet Golden labeled it non-sarcastic, reflecting over-reliance on literal keyword associations.
- (3) Bias toward hashtag patterns. Models like GenKPrompt exhibited bias toward hashtags as sarcasm markers. Example 1 ("# nihilistmemes") was correctly classified by Golden but mislabeled by S² Agent due to overemphasis on the hashtag. Conversely, Example 8 ("# womensmarch") combines serious activism with sarcastic phrasing ("welcome to your first day"), causing Ours to misinterpret it as non-sarcastic, likely due to conflating topic-specific hashtags with earnest intent.

Table 3: Typical examples for case study.

Example	Text	Image	Golden	Zero-shot COT	AutoPE	Plan-and-Solve
1	happy new year , everyone! xoxo # year2016 # partyhard # nihilistmemes		Sarcastic	•		•
2	the pa welcome center is hopping today .	MIRO	Sarcastic	×	×	•
3	because every mildly successful cgi film needs an animated spinoff .	Choose R	Sarcastic	Ø	•	•
4	dad 's handy work . can 't tell at all .	MYLEVEL OF	Sarcastic	•		×
5	do you suffer from this related problem ? :)	SARGASM MODELLY THE PROFESSION 1994T CROSS FTM CROSS CRISCT	Sarcastic	•	•	
6	meanwhile, back in the # cbb house, there 's been a bit of a # mantub revival	4	Non-sarcastic			×
7	borry baudini 1014 selerized by dana skeller		Non-sarcastic	•	5	5
/	harry houdini 1914 . colorized by dana r keller .		Non-sarcastic	J	u	۵
8	we will not go away . welcome to your first day . # womensmarch		Non-sarcastic	×	×	
9	best news of 2017 - protein pizza coming soon!		Non-sarcastic	×	×	
10 Example	everyone please take a moment and give thanks for Text	Image	Non-sarcastic Golden	* GenKPrompt	S ³ Agent	Ours
1	happy new year , everyone! xoxo # year2016 # partyhard # nihilistmemes		Sarcastic	•	☑	•
2						
	the pa welcome center is hopping today .	MIRU OA / CROODS	Sarcastic	Ø	×	•
3	the pa welcome center is hopping today . because every mildly successful cgi film needs an animated spinoff .	MIRU DE PLANTE DE LA COMPANION	Sarcastic Sarcastic	2	×	2
3		WINDS CARRES				
	because every mildly successful cgi film needs an animated spinoff.	MT LEVEL OF SARCASM.	Sarcastic	•	Ø	•
4	because every mildly successful cgi film needs an animated spinoff . dad 's handy work . can 't tell at all .	SARCASM SARCASM	Sarcastic Sarcastic	5	⊠ ×	2
4 5	because every mildly successful cgi film needs an animated spinoff . dad 's handy work . can 't tell at all . do you suffer from this related problem ? :)	MI GREEN SARCELS ME TO THE SAR	Sarcastic Sarcastic	2	×	2
4 5	because every mildly successful cgi film needs an animated spinoff . dad 's handy work . can 't tell at all . do you suffer from this related problem ? :)	Miles of Market SARCASM	Sarcastic Sarcastic	2	×	2
4 5 6	because every mildly successful cgi film needs an animated spinoff . dad 's handy work . can 't tell at all . do you suffer from this related problem ? :) meanwhile , back in the # cbb house , there 's been a bit of a # mantub revival	SARCAS III	Sarcastic Sarcastic Sarcastic Non-sarcastic	2 2 2	×	2 2 2
4 5 6	because every mildly successful cgi film needs an animated spinoff. dad 's handy work . can 't tell at all . do you suffer from this related problem ? :) meanwhile , back in the # cbb house , there 's been a bit of a # mantub revival harry houdini 1914 . colorized by dana r keller .	MIGRI WILLIAM TO THE SARGEST OF THE	Sarcastic Sarcastic Non-sarcastic		×	2 2 2 2
4 5 6	because every mildly successful cgi film needs an animated spinoff. dad 's handy work . can 't tell at all . do you suffer from this related problem ? :) meanwhile , back in the # cbb house , there 's been a bit of a # mantub revival harry houdini 1914 . colorized by dana r keller .	SARCASM SARCASM SARCASM	Sarcastic Sarcastic Non-sarcastic		×	2 2 2 2

This analysis highlights the need for LLMs to better disentangle contextual subtleties, mitigate literal bias, and reduce overfitting to surface-level markers like hashtags in sarcasm detection tasks.

5 Quantitative Analysis

In this section, we provide a detailed description of Commander-GPT to better understand its working mechanism.

Figure 3 presents a statistical analysis of the number of calls to each "C&W" model. It can be observed that the models Keyword, Sentiment, and Img-sum are the most frequently invoked, with 2,409 calls each. This indicates that these three models are utilized in every instance of clue information extraction. This is because each text inevitably requires keyword extraction and sentiment analysis, while every image must first undergo a preliminary summarization of its content. On the other hand, the TEx-ext model has the fewest calls, primarily because a significant portion of images do not contain subtitles. Following this, the fac-exp model is invoked less frequently, with nearly half of the images in the dataset featuring facial expressions. This observation underscores the critical significance of facial expressions for sarcasm detection. We conducted ablation experiments using

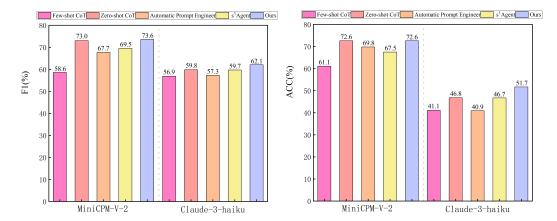


Figure 3: The F1 and ACC scores of MiniCPM-V-2 and Claude-3 on SemEval 2018 Task 3 were statistically evaluated.

two MLLMs: MiniCPM-V-2 and DeepSeek-VL-Chat. Table 3 illustrates the data, showing that the model's performance consistently declines, to varying degrees, when any module is removed. To verify the effectiveness of each module, we tested the models by sequentially removing individual modules. On the MMSD 2.0 and MMSD datasets, we found that removing the Rhetoric module resulted in the most significant decline in F1 score, with an average decrease of 11.1%. This may be attributed to the critical role of rhetoric in sarcasm detection, as sarcasm is often conveyed through rhetorical devices such as exaggeration and irony. Additionally, removing the Tex-ext module led to an approximate 10% drop in the average F1 score. This can be explained by the inability of MLLMs to process subtitle information in images effectively, resulting in the omission of crucial textual information. The Tex-ext module compensates for this limitation by enabling MLLMs to extract subtitle content from images. Furthermore, we observed that the removal of the Sentiment module caused the smallest average F1 score decrease, at 1.1%. This minimal impact may be due to the fact that sarcasm often conveys emotions opposite to the apparent sentiment, making simple sentiment analysis somewhat useful but not highly effective.

In summary, the results of the ablation experiments demonstrate that all modules play a significant role in multimodal sarcasm detection, with the Rhetoric module contributing most prominently to performance improvement. The Tex-ext module effectively addresses the challenge of processing subtitle information in images, while the Sentiment module has relatively limited impact. These findings further validate the rationality and necessity of the module design, providing strong support for optimizing multimodal sarcasm detection systems.

To validate the generalization ability of our method, we conducted sarcasm detection tests using a unimodal (pure text) approach. Specifically, we tested various methods on the SemEval 2018 Task 3 dataset Van Hee et al. (2018). We removed the image-related modules, such as Fac-exp, Img-sum, and Tex-ext, while retaining the modules responsible for text processing. Additionally, we selected a

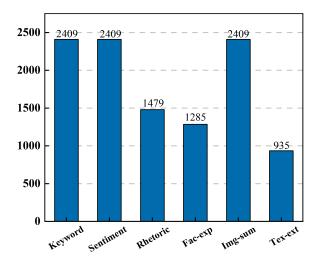


Figure 4: The statistics for the number of calls to "C&W" on the MMSD 2.0 dataset are presented. Note that the number of calls to the Rhetoric module in MMSD (1461 calls) differs from that in MMSD 2.0, while the other modules remain consistent. This discrepancy may be attributed to the modifications made in MMSD 2.0, which involved removing spurious cues and re-annotating unreasonable samples, thereby resulting in changes in the Rhetoric module.

Table 4: The performance of different MLLMs was analyzed after removing a specific "C&W," where "w/o XXX" indicates the absence of the "XXX" module.

MMSD 2.0											
N	DeepSeek-VL-Chat										
	f1.	acc.	pre.	rec.		f1.	acc.	pre.	rec.		
w/o Rhetoric	67.9	72.3	67.7	68.0	w/o Rhetoric	60.0	42.5	42.3	92.2		
w/o Keyword	72.1	73.6	66.1	79.3	w/o Keyword	59.4	43.1	42.9	96.7		
w/o Sentiment	71.2	71.6	63.1	81.8	w/o Sentiment	59.0	42.9	42.7	95.4		
w/o Img-sum	71.9	73.3	65.7	79.4	w/o Img-sum	59.5	43.0	42.9	97.1		
w/o Tex-ext	67.9	62.2	53.5	92.8	w/o Tex-ext	60.2	43.1	43.1	99.9		
w/o Fce-exp	71.5	72.4	64.4	80.2	w/o Fce-exp	59.7	43.2	43.0	97.8		
Ours	72.0	73.9	66.8	78.1	Ours	60.5	46.7	44.4	94.7		
	MMSD										
N	1iniCPN	M-V-2			DeepSeek-VL-Chat						
		f1.	acc.	pre.	rec.						
w/o Rhetoric	66.0	72.4	67.8	64.2	w/o Rhetoric	27.9	63.9	84.0	16.7		
w/o Keyword	72.4	73.9	64.8	82.0	w/o Keyword	56.9	70.9	74.3	46.1		
w/o Sentiment	71.3	72.2	62.7	82.8	w/o Sentiment	60.2	71.9	73.6	50.9		
w/o Img-sum	71.4	73.1	64.2	80.4	w/o Img-sum	43.8	67.3	77.5	30.5		
w/o Tex-ext	69.4	71.5	62.9	77.3	w/o Tex-ext	28.8	63.4	76.4	17.7		
w/o Fac-exp	71.2	72.2	62.7	82.3	w/o Fce-exp	41.7	66.8	77.9	28.5		
Ours	72.5	74.5	65.9	80.8	Ours	61.1	69.4	64.9	57.7		

multimodal large language model, MiniCPM-V-2, and a pure text large language model, Claude-3⁵, for the tests. We reported the F1 and ACC scores, as shown in Figure 3. As can be seen, even with only three submodules retained, our method outperformed many prompt-based strategies and achieved state-of-the-art performance. The average F1 score of our method increased by 5.1%, and the average ACC improved by 6.4%. This demonstrates that even in the absence of multimodal information (such as images), our method still outperforms existing approaches, further confirming the strong generalization ability of our method.

⁵https://claude.ai/

6 Conclusion

In this paper, we propose a novel framework for sarcasm detection, named Commander-GPT. The framework operates by assigning specific subproblems to the most specialized modules to achieve optimal performance, with a central command module consolidating all the clues to ultimately form a complete solution. Our framework achieves the state-of-the-art performance on the same dataset, demonstrating its effectiveness. We also conduct extensive experiments to validate the efficacy, robustness, and generalization capabilities of our approach. We hope that this research can provide valuable insights for future studies on sarcasm detection and contribute to the advancement of sentiment analysis.

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