Towards Explainable Harmful Meme Detection through Multimodal Debate between Large Language Models

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ABSTRACT

The age of social media is flooded with Internet memes, necessitating a clear grasp and effective identification of harmful ones. This task presents a significant challenge due to the implicit meaning embedded in memes, which is not explicitly conveyed through the surface text and image. However, existing harmful meme detection methods do not present readable explanations that unveil such implicit meaning to support their detection decisions. In this paper, we propose an explainable approach to detect harmful memes, achieved through reasoning over conflicting rationales from both harmless and harmful positions. Specifically, inspired by the powerful capacity of Large Language Models (LLMs) on text generation and reasoning, we first elicit multimodal debate between LLMs to generate the explanations derived from the contradictory arguments. Then we propose to fine-tune a small language model as the debate judge for harmfulness inference, to facilitate multimodal fusion between the harmfulness rationales and the intrinsic multimodal information within memes. In this way, our model is empowered to perform dialectical reasoning over intricate and implicit harm-indicative patterns, utilizing multimodal explanations originating from both harmless and harmful arguments. Extensive experiments on three public meme datasets demonstrate that our harmful meme detection approach achieves much better performance than state-of-the-art methods and exhibits a superior capacity for explaining the meme harmfulness of the model predictions.

CCS CONCEPTS

• **Computing methodologies → Natural language processing**.

KEYWORDS

harmful meme detection, explainability, multimodal debate, LLMs

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1 INTRODUCTION

The increasing prevalence of social media has led to the emergence of a novel multimodal entity: *meme*. A meme consists of a picture combined or embedded with a concise textual component. Due to their ease of dissemination, memes have the capability to rapidly proliferate across various online media platforms. While memes are often humorously perceived, they become a potential source of harm when the amalgamation of the image and text is strategically employed in the context of political and socio-cultural divisions.

Harmful memes[1] are generally defined as "multimodal units consisting of an image and accompanying text that has the potential to cause harm to an individual, an organization, a community, or the whole society" [52]. For instance, during the COVID-19 pandemic, a widely circulated meme shown in Figure 1 was produced by anti-vaccination groups via spoofing the image of Bill Gates. The widespread circulation of such multimodal scaremongering content[2] about COVID-19 vaccines inflicted significant damage on both Bill Gates' personal reputation and the efforts to establish strong immune defenses [30, 31]. Therefore, it becomes imperative to develop automatic approaches for harmful meme detection to effectively unveil the dark side of memes on the Web. This task, as suggested in [44], extends beyond mere analysis of meme images and texts in isolation. It demands a comprehensive examination, aiming not only to decipher their intrinsic semantics but also to provide the explainability of prediction results from the detection models.

Previous studies [21, 44] straightforwardly utilized pre-trained vision-language models [27, 38] to classify harmful meme by training additional task-specific classification layers. Pramanick et al. [45] proposed a multimodal framework to achieve state-of-the-art performance on harmful meme detection by modeling the deep multimodal interactions from the global and local perspectives. More recently, Cao et al. [5] proposed a prompt-based method with

[1] **Disclaimer:** This paper contains content that may be disturbing to some readers.
[2] https://www.bbc.com/news/55101238

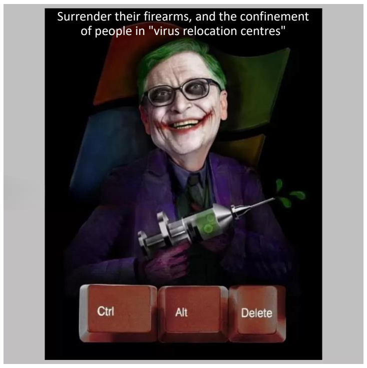

Surrender their firearms, and the confinement of people in "virus relocation centres"
Ctrl
Alt
Delete

Figure 1: Example of trending memes on social media. Meme text: *Surrender their firearms, and the confinement of people in "virus relocation centres".*

the meme text and image caption as the prompt for masked language modeling [10, 37] to predict whether the meme is harmful. A follow-up study [4] tailored additional hand-crafted questions as the prompt of frozen pre-trained vision-language models, to further improve image captioning for better meme classification performance. However, these approaches for harmful meme detection only capture superficial harmfulness patterns for classification in a black-box manner [14], which often overlooks or oversimplifies the supportive basis to explain the final harmfulness prediction.

Generally, understanding and analyzing memes poses a significant challenge due to their implicit meaning that is not explicitly conveyed through the surface text and image. Providing explanations for why a particular meme is deemed harmful, is crucial to the content moderation process on social media, as both moderators and users may want to comprehend the harmful content behind a flagged meme [20, 28]. Nevertheless, a comprehensive explanation requires a deep understanding of commonsense and cultural context. For example, to explain the harmfulness of the meme in Figure 1, a human checker needs the socio-cultural knowledge that the character with a vaccine gun represents Bill Gates from Microsoft, who is often the target of anti-vaccination campaigners' memes due to his promotion of vaccine development; and also should know that the "Ctrl Alt Delete" key combination makes reference to the mandatory reboot function in Microsoft Windows, satirizing vaccine injection when combating the virus. In contrast, conventional detection models lack such natural sentences with multimodal reasoning chains, hindering their ability to provide informative explanations for harmfulness predictions.

We contend that the challenge lies in delivering clear and accurate explanations that consistently assist in deciphering the concealed semantics within the multimodal nature of memes. In this paper, we consider the following key principles in the design of our approach: 1) To capture implicit meanings of memes, we elicit and harness the rich prior knowledge embedded in Large Language Models (LLMs) [3, 6, 55]; 2) As the knowledge elicited directly from LLMs may exhibit variation and bias, we resort to a core element of human problem-solving, *i.e.*, debate, to stimulate dialectical thinking [2] among LLMs, thereby facilitating complex reasoning for enhancing the accuracy and explainability of harmful meme detection; 3) The semantic interaction between the meme and the harmfulness rationales extracted from the LLM debate could serve to augment multimodal feature representation, thereby fostering a deeper contextual understanding of the model in the context of harmfulness inference. To all these ends, we propose an **Explain**able approach for **H**armful **M**eme detection, ExplainHM, by leveraging the powerful text generation capacity of LLMs via Chain-of-Thought (CoT) prompting [23, 61]. Specifically, we inspire LLMs for divergent thinking by conducting a multimodal debate between two LLM debaters, to generate the rationales derived from harmless and harmful perspectives. Based on the generated harmfulness rationales, we fine-tune a small language model as the debate judge for harmfulness prediction, to align the multimodal features between the meme and the harmfulness rationales. In this manner, our model can effectively focus on contrasting and implicit signals that indicate harmfulness in the debated arguments, while avoiding excessive attention to trivial samples that lack inherent controversy. Our contributions are summarized as follows in three folds:

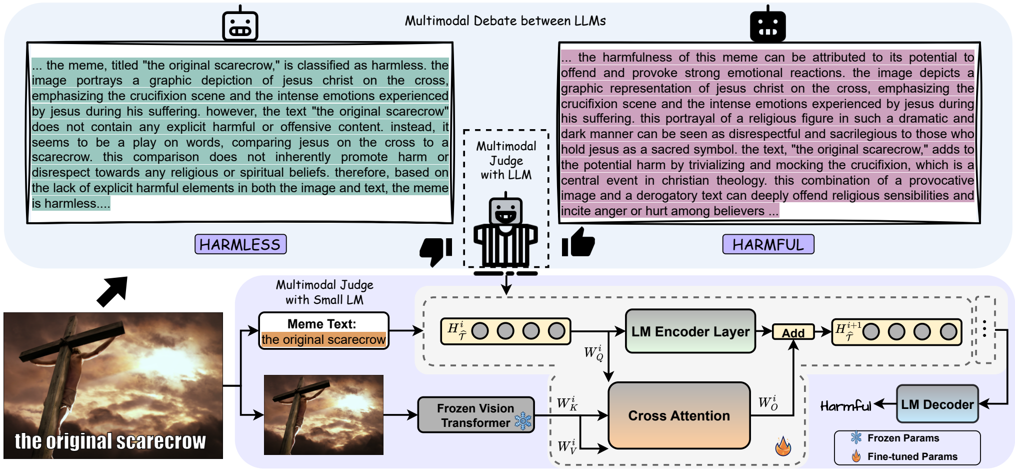
- To our best knowledge, we are the first to study harmful meme detection from a fresh perspective on harmfulness explainability in natural texts, by harnessing advanced LLMs.[3]
- We propose an explainable approach to conduct a multimodal debate between LLMs on memes for explanation generation from harmless and harmful arguments, which facilitates harmfulness inference with multimodal fusion.
- Extensive experiments conducted on three meme datasets confirm that our universal framework could yield superior performance than previous state-of-the-art baselines for harmful meme detection, and provide informative explanations for better dialectical thinking on meme harmfulness.

2 RELATED WORK

Harmful Meme Detection. Harmful meme detection is a rapidly growing area in the research community, driven by the recent availability of large meme benchmarks [19, 44, 53]. The Hateful Memes Challenge organized by Facebook [21] further encouraged researchers to develop solutions for detecting harmful memes in hate speech [9]. More recently, Pramanick et al. [44] formally defined the harmful meme concept and demonstrated its dependence on contextual factors. The complex nature of memes, which often rely on multiple modalities, makes them challenging to yield good performance only using unimodal detection methods like BERT [10] or Faster R-CNN [13, 49]. Therefore, recent studies attempted to apply multimodal approaches on the harmful meme detection task.

Previous studies have employed classical two-stream models that integrate text and vision features, which are learned from text and image encoders, typically using attention-based mechanisms and multimodal fusion techniques for classifying harmful memes [19, 21, 53]. Another branch was to fine-tune pre-trained multimodal models specifically for the task [15, 34, 40, 58]. Recent efforts have also sought to explore the use of data augmentation techniques [66, 68], ensemble methods [50, 58, 69] and harmful target disentanglement [25]. Lately, Pramanick et al. [45] proposed a multimodal framework by using global and local perspectives to detect harmful memes, which achieves state-of-the-art performances. The follow-up prompt-based approaches [5, 17] attempted to concatenate the meme text and extracted image captions and

[3] Our code is available at https://github.com/HKBUNLP/ExplainHM-WWW2024.



... the meme, titled "the original scarecrow," is classified as harmless. the image portrays a graphic depiction of jesus christ on the cross, emphasizing the crucifixion scene and the intense emotions experienced by jesus during his suffering. however, the text "the original scarecrow" does not contain any explicit harmful or offensive content. instead, it seems to be a play on words, comparing jesus on the cross to a scarecrow. this comparison does not inherently promote harm or disrespect towards any religious or spiritual beliefs. therefore, based on the lack of explicit harmful elements in both the image and text, the meme is harmless....

... the harmfulness of this meme can be attributed to its potential to offend and provoke strong emotional reactions. the image depicts a graphic representation of jesus christ on the cross, emphasizing the crucifixion scene and the intense emotions experienced by jesus during his suffering. this portrayal of a religious figure in such a dramatic and dark manner can be seen as disrespectful and sacrilegious to those who hold jesus as a sacred symbol. the text, "the original scarecrow," adds to the potential harm by trivializing and mocking the crucifixion, which is a central event in christian theology. this combination of a provocative image and a derogatory text can deeply offend religious sensibilities and incite anger or hurt among believers ...

Figure 2: The overall pipeline of our method. We first conduct the multimodal debate between LLMs, to generate the conflicting rationales from the harmless (green) and harmful (lilac) positions. Then the generated rationales are used to train a small task-specific LM judge with multimodal inputs of memes.

fine-tune masked language models [37] for harmful meme detection. A more recent study [4] further improved the image captions with pre-trained vision-language models. However, existing solutions only focused on performing harmful meme classification with limited explanations for its prediction [14]. In this paper, we delve into the explainability of harmful meme detection, aiming to convey the accuracy of predictive models using natural language and assisting users in gaining a better understanding.

Large Language Models. LLMs have demonstrated remarkable capabilities in complex reasoning [3, 6, 47, 55], such as generating intermediate inference procedures with CoT prompting before the final output [23, 41, 61, 63]. Advanced sampling strategies have been explored to improve CoT by generating diverse reasoning paths, *e.g.*, Self-Consistency [60], Auto-CoT [63], Complexity-based Consistency [12], Multi-Chain Reasoning [62], and Progressive-Hint Prompting [65]. More recently, some vision LLMs [8, 35, 67] have emerged, showing excellent generalization performance in multimodal tasks. Specifically, LLaVA [35] projects the output of a visual encoder as input to LLaMA [56] and trains both the alignment network and the LLM on synthetic data. Unfortunately, the large size of LLMs restricts their deployment on detecting harmful memes with different modalities, regardless of how they are enhanced with strategic text prompting [64]. In this work, we conduct a multimodal debate between LLMs by using the potential labels as prompting arguments, which further advocates an explainable paradigm to fine-tune smaller language models (LMs) for boosting harmful meme detection.

3 OUR APPROACH

3.1 Problem Statement

We define a harmful meme detection dataset as a set of memes, where each meme $M = \{\mathcal{I}, \mathcal{T}\}$ is a tuple representing an image $\mathcal{I}$ that is associated with a text sequence $\mathcal{T}$. Following previous work [3, 5, 36], to better transfer and utilize the knowledge learned in pre-trained LMs, this task is formulated as a *natural language generation* problem, where our model takes the meme text $\mathcal{T}$ and the meme image $\mathcal{I}$ as input and generates a textual output of the label $y \in \{\texttt{harmful}, \texttt{harmless}\}$ to clearly express whether the meme is harmful or not.

Our core idea is to facilitate reasoning in the model for harmful meme detection with conflicting rationales and dialectical thinking [2], which involves arguments holding different points of view about a subject and strives to arrive at a higher level of resolution, by leveraging LLMs to elicit textual rationales from harmless and harmful perspectives as additional knowledge of the model. The LLM rationale corresponding to the harmfulness prediction of our model could be naturally output as the explanatory basis of the model's decision.

The overview of our framework is shown in Figure 2. It consists of the Multimodal Debate module between LLMs (§3.2), the Multimodal Judge module with LLM (§3.3), and the Multimodal Judge module with Small LM (§3.4).

3.2 Multimodal Debate between LLMs

With the aid of LLMs, it becomes plausible to generate natural language rationales that delve into the implicit meaning of memes, facilitating the determination of whether they have harmful implications and serving as a basis to evaluate their harmfulness. However, it is very likely that the rationales generated directly from LLMs can be biased by preconceptions, potentially leading to wrong labels and hampering detection performance [18, 29]. Taking the harmful meme in Figure 2 as an example, directly prompted with "Is this meme harmless or harmful?", the LLM tends to perceive it as harmless with the rationale that it is a playful comparison between the surface image of Jesus and scarecrows while ignoring the depth of its relevant cultural and religious background. In this paper, we resort to a fundamental characteristic of human problem-solving, *i.e.*, debate, to encourage divergent thinking for harmful meme detection. Fostering the model to explore different viewpoints and reasoning pathways, we design a method to inspire a multimodal debate about the memes between LLMs, in which two agents express their own arguments in the state of "tit for tat" from harmless and harmful perspectives. And then, based on such a bipartisan type of thought chains, a judge agent will be able to infer meme harmfulness by indicating which rationale is more reasonable. In this section, we focus on the prompting method for debate generation.

Given a meme sample $M = \{\mathcal{I}, \mathcal{T}\}$, we curate a prompt template p^* that consists of the meme text $\mathcal{T}$ and the potential harmfulness label $* \in \{hl, hf\}$[4] that denotes "harmless" or "harmful" as observed attributes to prompt the vision LLMs, *i.e.*, LLaVA [35]. Each debater will generate a rationale r^*, which elicits the reasoning knowledge about how to infer a given harmfulness label $*$ based on the interplay of the meme text $\mathcal{T}$ and the meme image $\mathcal{I}$.

Specifically, we design the prompt template p^* as follows:

"*Given the meme, with the Text: [$\mathcal{T}$] embedded in the Image, please provide a streamlined explanation associated with the text and the image by using the contextual background commonsense knowledge, to explicitly explain how the harmfulness of the meme is reasoned as [$*$].*".

Based on the template, each LLaVA debater employs a variant of texts, *i.e.*, either p^{hl} or p^{hf}, as the prompt to generate a corresponding rationale r^{hl} or r^{hf}, derived from the harmless and harmful positions, respectively. As we provide the potential harmfulness label as part of the attributes in each specific prompt, the rich contextual background knowledge could be activated to generate a rationale for supporting the argument that intends to promote the potential harmfulness label separately in each debate. In this way, the contextual nuances of memes that contribute to the respective candidate harmfulness categories could be better presented and contrasted, so that the true harmfulness will be revealed and reasoned by the rest of the model from dialectical views.

3.3 Multimodal Judge with LLM

Inspired by the CoT prompting [61], we exploit the competing arguments from the multimodal debate to provide dialectical reasoning chains for an LLM judge with emergent abilities, enabling it to decide whether memes are harmful or not. Thus, we feed the conflicting rationales as reasoning steps into the LLM judge for inferring the predicted harmfulness label.

While the judge can be implemented using any LLM with comparable or even stronger capabilities than the debaters, we opt to employ the same LLM for the judge to ensure that no additional variates, such as different kinds of inductive biases, are introduced. Specifically, we cast the rationales r^{hl} and r^{hf} into a conflicting thought chain using the CoT prompting method [61, 63], acting as the textual prompt of the LLM judge:

"*Given the meme, with the Text: [$\mathcal{T}$] embedded in the Image, and the following two meme rationales: (1) Harmless: [r^{hl}]; (2) Harmful: [r^{hf}], is this meme harmless or harmful?* "

Following the input prompt, the LLM judge infers the harmfulness label, which actually provides its *preference* over the two labels indicating which corresponding explanation from the debate is more reasonable than the other one. This could be either taken as the final output alone, or used as an extra reference for a more accurate prediction model described in the subsequent section.

3.4 Multimodal Judge with Small LM

Although the LLM judge is enhanced by the multifaceted information provided from the multimodal debate, its inference still could be unreliable due to the inherent limitations of LLMs [1, 16]. On the other hand, it is impractical to fine-tune the LLM judge for this task due to the huge amount of model parameters. For a more reliable judgment, we propose to fine-tune a smaller LM judge that classifies memes as harmful or harmless, by leveraging the rationales derived from the contradictory harmfulness arguments as prior knowledge. This design strives to facilitate multimodal interactions, allowing the rationales from the LLM debaters to effectively synergize with the intrinsic multimodal information present in memes.

For a meme sample $M = \{\mathcal{I}, \mathcal{T}\}$, we first concatenate the meme text $\mathcal{T}$ and the harmfulness rationales as the input text of our Small LM judge. Similar to the fixed input order of rationales in the LLM judge, we initialize the input text $\widehat{\mathcal{T}}$ of the Small LM judge as:

$$\widehat{\mathcal{T}} = [\mathcal{T}, r^{hl}, r^{hf}], \tag{1}$$

where $[\cdot, \cdot, \cdot]$ denotes the concatenation operation.

Alternatively, we can refer to the harmfulness inference result given by the LLM judge when fine-tuning the Small LM judge. In this setting, we place the one rationale that the LLM judge deems more reasonable in front of the other one. Specifically, we prepare the input text $\widehat{\mathcal{T}}$ as:

$$\widehat{\mathcal{T}} = [\mathcal{T}, r^{(1)}, r^{(2)}], \tag{2}$$

where $(1) \succ (2)$, denoting that the LLM judge prefers $r^{(1)}$ to $r^{(2)}$, and $(1), (2) \in \{hl, hf\}$. Compared to a fixed sequence of rationales in Equation 1, adjusting the rationale order based on the prior from the LLM judge aims to implicitly leverage LLM knowledge and insights. This adjustment helps the Small LM judge prioritize challenging training examples that were misjudged by the LLM judge, while avoiding excessive attention to trivial examples that have already been correctly detected by the LLM judge. By standing upon the shoulders of giants, we hypothesize that the model can better refine its understanding of the memes while learning to rectify the misperception of the LLM judge with the training data.

Then we encode the input text $\widehat{\mathcal{T}}$ and the meme image $\mathcal{I}$ to obtain their embedding vectors as follows:

$$H^0_{\widehat{\mathcal{T}}} = \mathrm{TE}(\widehat{\mathcal{T}}),\ H_{\mathcal{I}} = \mathrm{VE}(\mathcal{I}), \tag{3}$$

where $\mathrm{TE}(\cdot)$ denotes the text embedding layer of the LM Encoder. And $H^0_{\widehat{\mathcal{T}}} \in \mathbb{R}^{m \times d}$ is the token embeddings output by the embedding layer of Transformer encoder [57], where m is the text length of $\widehat{\mathcal{T}}$ and d is the size of the hidden states. Benefiting from the Relative Position Encoding of LMs [48], the judgment by LLM could be injected into the Small LM judge based on the relative position information of the input sequence. $\mathrm{VE}(\cdot)$ is the Vision Extractor based on a pre-trained vision Transformer [46] with frozen parameters. It is used to fetch the patch-level features of the image with n patches, which are projected into the visual representations $H_{\mathcal{I}} \in \mathbb{R}^{n \times d}$.

To support semantic alignment between the meme sample and the harmfulness rationales for better cross-modal context understanding, we exploit a cross-attention mechanism to attend the visual representations to the textual ones, for Multimodal Fusion

[4] Here the potential harmfulness labels are just used to formalize two opposite standpoints to argue regardless of what the ground-truth label is.

of the textual and visual information in our Small LM judge:

$$H^i_{\mathcal{I}} = \text{softmax}\left(\frac{Q_{\widehat{\mathcal{T}}} K^{\top}_{\mathcal{I}}}{\sqrt{d_k}}\right) V_{\mathcal{I}}, \tag{4}$$

where the query, key and value are defined as $\{Q_{\widehat{\mathcal{T}}}, K_{\mathcal{I}}, V_{\mathcal{I}}\} = \{H^i_{\widehat{\mathcal{T}}} W^i_Q, H_{\mathcal{I}} W^i_K, H_{\mathcal{I}} W^i_V\}$, $\{W^i_Q, W^i_K, W^i_V\} \in \mathbb{R}^{d \times d_k}$ are trainable weights, $H^i_{\widehat{\mathcal{T}}}$ is the input hidden states of the i-th LM Encoder layer and $H^i_{\mathcal{I}}$ is the attended visual features. Then we can fuse $H^i_{\mathcal{I}}$ with $H^i_{\widehat{\mathcal{T}}}$ to attain the interplay representations for a meme:

$$H^{i+1}_{\widehat{\mathcal{T}}} = \text{LME}^i\left(H^i_{\widehat{\mathcal{T}}}\right) + H^i_{\mathcal{I}} W^i_O, \tag{5}$$

where $\text{LME}^i(\cdot)$ is the i-th layer of the LM Encoder, W^i_O denotes the linear projection, and $0 \le i \le L-1$ given the total L layers in the LM Encoder. We denote $\widehat{H} = H^L_{\widehat{\mathcal{T}}}$ as the final interplay representations.

Model Training. We feed the interplay representations $\widehat{H} \in \mathbb{R}^{m \times d}$ into the LM Decoder, implemented as a Transformer-based decoder, to generate the predicted label. With the generative objective [48] adapted to pre-trained LMs, the Small LM judge could leverage prior reasoning knowledge absorbed in the pre-training stage to better deduce harmfulness prediction. Specifically, our Small LM judge denoted as $f(\mathcal{I}, \widehat{\mathcal{T}})$ is trained by minimizing the loss:

$$\mathcal{L} = \text{CE}\left(f(\mathcal{I}, \widehat{\mathcal{T}}), y\right), \tag{6}$$

where $\text{CE}(\cdot)$ denotes the cross-entropy loss [54] between the generated label token and the ground-truth harmfulness label y.

When the LLM judge is not considered, the relative positions between the harmfulness rationales are invariant. Thus, the order information might not affect the model's learning much. When integrated with the LLM judge, our model can be aware of the variation of relative positions between the harmfulness rationales given the prior preference of the LLM judge, which would encourage the model to learn by contrasting with the ground-truth labels. To this end, we utilize the T5 encoder-decoder architecture [7, 48] with Relative Position Encoding to initialize our model. In this manner, during the task-specific fine-tuning process, our Small LM judge is able to attend over the implicit harm-indicative patterns in the rationales that were incorrectly inferred by the LLM judge, thus improving the overall detection performance. Meanwhile, the rationale indicated by the final prediction could serve as a supportive basis to explain the decision in natural language.

4 EXPERIMENTS

4.1 Experimental Setup

Datasets. We use three publicly available meme datasets for evaluation: (1) Harm-C [44], (2) Harm-P [45], and (3) FHM [21]. Harm-C and Harm-P consist of memes related to COVID-19 and US politics, respectively. FHM was released by Facebook as part of a challenge to crowd-source multimodal harmful meme detection in hate speech solutions. Different from FHM that each meme was labeled as *harmful* or *harmless*, Harm-C and Harm-P were originally labeled with three classes: *very harmful*, *partially harmful*, and *harmless*. For a fair comparison, we merge the *very harmful* and *partially harmful* memes into the *harmful* class, following the setting of recent work [4, 5, 45].

Table 1: Harmful meme detection results on three datasets. The accuracy and macro-averaged F1 score (%) are reported as the metrics. The best and second test results are in bold and underlined, respectively.

Dataset	Harm-C		Harm-P		FHM	
Model	Acc.	Mac-F_1	Acc.	Mac-F_1	Acc.	Mac-F_1
Text BERT [10]	70.17	66.25	80.12	78.35	57.12	41.52
Image-Region [13]	68.74	62.97	73.14	72.77	52.34	34.19
Late Fusion [44]	73.24	70.25	78.26	78.50	59.14	44.81
MMBT [19]	73.48	67.12	82.54	80.23	65.06	61.93
VisualBERT [27]	81.36	80.13	86.80	86.07	61.48	47.26
ViLBERT [38]	78.70	78.09	87.25	86.03	64.70	55.78
MOMENTA [45]	83.82	82.80	89.84	88.26	61.34	57.45
MaskPrompt [5]	84.47	81.51	88.17	87.09	72.98	65.24
Pro-Cap [4]	85.01	83.17	89.32	87.91	74.95	71.68
ExplainHM	**87.00**	**86.41**	**90.73**	**90.72**	**75.60**	**75.39**

Baselines. We compare our model with several state-of-the-art (SoTA) harmful meme detection systems: 1) **Text BERT** [10]; 2) **Image-Region**[13, 49]; 3) **Late Fusion** [44]; 4) **MMBT** [19]; 5) **VisualBERT** [27, 33]; 6) **ViLBERT** [38]; 7) **MOMENTA** [45]; 8) **MaskPrompt** [5]; 9) **Pro-Cap** [4]. We use the accuracy and macro-averaged F1 score as the evaluation metrics.

4.2 Harmful Meme Detection Performance

Table 1 demonstrates the performance of our proposed method ExplainHM versus all the compared harmful meme detection methods on the Harm-C, Harm-P and FHM datasets. It is observed that 1) The performance of the baselines in the first group is significantly lower, primarily because they only utilize unimodal features such as either text or image. On the other hand, the remaining baselines effectively leverage the multimodal features extracted from both text and image parts of memes. 2) The multimodal models in the second group outperform the unimodal ones. The early-fusion models with multimodal pre-training (*i.e.*, VisualBERT and ViLBERT) outperform the simple fusion with unimodal pre-training (*i.e.*, Late Fusion and MMBT) on Harm-C and Harm-P datasets, while MOMENTA performs relatively better in the second group by considering global and local information of memes, especially on the Harm-P dataset. 3) However, as the images in FHM datasets are more informative and high-quality, MaskPrompt outperforms MOMENTA by incorporating additional extracted entities and demographic information of the image into the masked language models, besides just captioning the image into the prompt. Based on MaskPrompt, Pro-Cap further improves image captioning with pre-trained vision-language models [26], which leads to the best performance among all the baselines.

Under the full setting (*i.e.*, with the integration of the LLM judge and Small LM judge), our ExplainHM improves over the best baselines by 3.24%, 2.46%, and 3.71% in terms of Macro-F1 score on Harm-C, Harm-P, and FHM datasets, respectively. We observe that 1) The improvements observed on the Harm-P dataset are relatively subdued compared to the advancements made on the other

Table 2: Ablation studies by removing components from our proposed framework.

Dataset	Harm-C		Harm-P		FHM	
Model	Acc.	Mac-F_1	Acc.	Mac-F_1	Acc.	Mac-F_1
ExplainHM	87.00	86.41	90.73	90.72	75.60	75.39
w/o MD	83.33	81.44	88.17	88.17	73.60	73.41
w/o LLMJ	85.59	84.80	88.44	88.43	71.40	70.94
w/o SLMJ	58.19	56.17	56.11	52.59	57.00	56.61
w/o HlD	82.20	81.76	89.06	89.05	70.60	69.55
w/o HfD	85.31	84.78	88.75	88.74	72.60	72.26
w/o MF	83.90	83.30	88.44	88.43	72.80	72.20
w/o UR	85.59	84.80	89.38	89.37	73.40	73.24

Table 3: Ablation studies by adding paradigms on LLMs.

Dataset	Harm-C		Harm-P		FHM	
Model	Acc.	Mac-F_1	Acc.	Mac-F_1	Acc.	Mac-F_1
LLaVA	50.28	49.70	49.84	34.86	51.20	46.51
w/ MD_CoT	58.19	56.17	56.11	52.59	57.00	56.61
w/ ExplainHM	87.00	86.41	90.73	90.72	75.60	75.39
ChatGPT	70.06	64.05	59.87	58.02	56.20	55.50
w/ MD_CoT	68.08	65.82	62.07	61.69	62.00	61.62
w/ ExplainHM	86.16	85.22	90.00	89.98	76.60	76.39

two datasets. Moreover, there are minimal discrepancies in the performance of all the baselines on the Harm-P dataset. This can be attributed to the scale of the Harm-P dataset, which not only has the smallest volume of data but also exclusively comprises politics-related harmful memes. 2) A similar phenomenon is evident in the Harm-C and FHM datasets, where ExplainHM demonstrates greater performance improvements as the scale and the difficulty of the dataset increase. ExplainHM showcases consistent and adaptable performance across all benchmark datasets for harmful meme detection, thanks to its astute discernment of harmful memes. The key differentiator lies in the fact that while all the baselines solely focus on recognition, our model is equipped with rationales from multimodal debate, which empowers our model to unveil harmful content by leveraging seemingly unrelated textual and visual elements within memes.

4.3 Ablative Studies

We perform ablative studies on several variants of ExplainHM: 1) *w/o Multimodal Debate (MD)*: Simply fine-tune the Smaller LM judge with the multimodal fusion of the meme text and the meme image without the stage of multimodal debate between LLMs; 2) *w/o LLM Judge (LLMJ)*: Simply concatenate the harmfulness rationales into the input text in a fixed order as Equation 1 without pre-ranked by the LLM judge; 3) *w/o Small LM Judge (SLMJ)*: Simply use the output of the LLM judge as the final prediction, as depicted in §3.3; 4) *w/o Harmless Debater (HlD)*: Only concatenate the rationale from the harmful argument together with the meme text as the input text of the Small LM judge; 5) *w/o Harmful Debater (HfD)*: Only concatenate the rationale from the harmless argument together with the meme text as the input text of the Small LM judge; 6) *w/o Multimodal Fusion (MF)*: Instead of the fusion mechanism on the multimodal features in our Small LM judge, we only append the linguistic features from image captioning together with the input text during encoding; 7) *w/o Unpreferred Rationale (UR)*: Only concatenate the rationale preferred by the LLM judge and the meme text as the input text of the Small LM judge.

As demonstrated in Table 2, the ablative models suffer different degrees of performance degradation, indicating the effectiveness of our proposed components for harmful meme detection by multimodal debate between LLMs and multimodal fusion with small LM. Specifically, the performance of ExplainHM largely decreases in the '*w/o MD*' setting due to the lack of multimodal rationales generated from LLMs about the seemingly uncorrelated modalities in memes. The '*w/o LLMJ*' setting also achieves worse performance than ExplainHM, suggesting that the prior preference of the LLM judge on the rationales from different positions plays an important role and provides positive guidance in identifying the harm-indicative elements in memes. For '*w/o SLMJ*', the decrease is significant, underscoring the importance of the Small LM judge fine-tuned specifically for this task. ExplainHM makes improvements over '*w/o HlD*' and '*w/o HfD*', which implies the promoting role of our multimodal debate mechanism that incorporates rationales from the harmless and harmful arguments into the language model. Moreover, the '*w/o HlD*' setting leads to a larger performance drop than '*w/o HfD*', because the amount of the harmless meme samples in the training data is more than that of the harmful ones. Compared with ExplainHM, the performance of '*w/o MF*' also significantly decreases, highlighting the importance of the cross-attention fusion mechanism to mitigate the possible misalignments, like the information loss about the meme images in the rationales. In the '*w/o UR*' setting, we further remove the rationale not preferred by the LLM judge in the input text of the Small LM judge, which also results in performance degradation. This reaffirms the usefulness of the conflicting rationales appended in the input text that make our model hardly compromised when there could be discrepancies between the LLM judge and the ground truth.

To enhance the robustness of the detection performance evaluation, we further conduct the ablative studies by adding the paradigms on LLMs to draw more insightful comparisons among variants of LLMs, as shown in Table 3. LLaVA and ChatGPT are selected as the representative LLMs from the vision and language perspectives. We devise three variants of paradigms based on LLMs for the harmful meme detection task: 1) *LLaVa/ChatGPT*: Directly prompt a representative LLM, to infer harmfulness for harmful meme detection; 2) *w/ MD_CoT*: The LLM judge with Multimodel Debate CoT reasoning but without the presence of Small LM judge, the similar setting to '*w/o SLMJ*' in Table 2; 3) *w/ ExplainHM*: Our proposed paradigm ExplainHM under full setting based on the integration of the LLM judge and Small LM judge, where LLMs are LLaVA or ChatGPT.

We have the following observations: 1) The direct deployment of both LLaVA and ChatGPT struggles since the models are not specifically designed for this task, highlighting the necessity of our Multimodal Debate mechanism to alleviate the issues of directly promoting LLMs for harmfulness prediction. 2) The '*w/ MD_CoT*' prompting strategy could effectively enhance the detection performance of LLMs, especially LLaVA, which suggests that the conflicting rationale generation from the Multimodal Debate stage is a reasonable way to optimize the reasoning chains for LLMs applied to the harmful meme detection task. 3) Besides using the

Table 4: Automatic GPT-4 evaluation of the explanation quality on harmful memes in FHM dataset.

Explanations	LLaVA	ChatGPT	Human
Informativeness	4.07	4.94	2.27
Readability	4.71	4.98	2.36
Soundness	4.25	4.87	2.99
Conciseness	3.93	3.19	4.07
Persuasiveness	4.03	4.82	2.64

Table 5: Human evaluation of the explanation quality on harmful memes in FHM dataset.

Explanations	LLaVA	ChatGPT	Human
Informativeness	4.05	4.01	2.64
Readability	3.99	3.95	3.96
Soundness	3.81	3.97	2.94
Conciseness	3.25	3.12	4.30
Persuasiveness	3.75	3.76	2.78

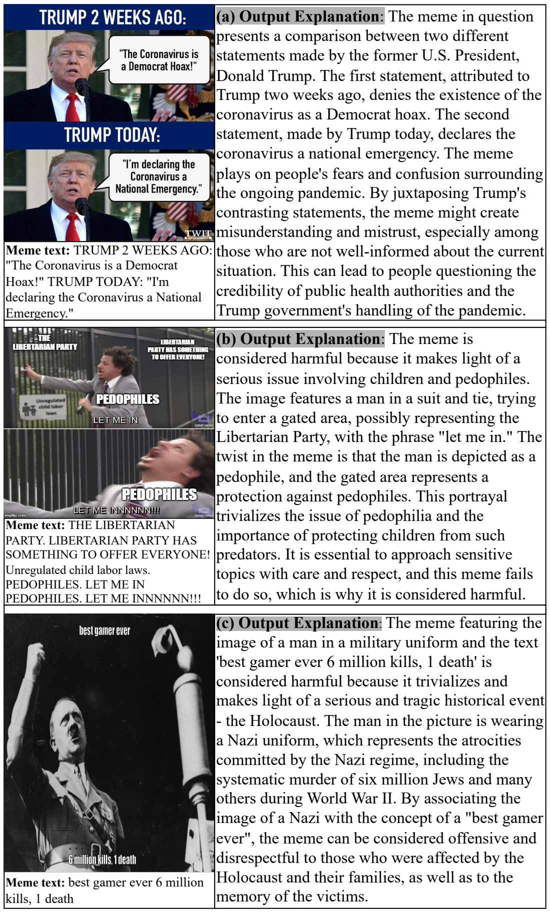
'*w/ MD_CoT*' prompting strategy in the LLM judge, our proposed paradigm '*w/ ExplainHM*' further improves the model's performance by focusing on the fine-tuning of the Small LM judge to avoid impractical fine-tuning of the LLM judge while considering the prior preference given by the LLM judge. Furthermore, the '*w/ ExplainHM*' setting achieves excellent performance based on both LLaVA and ChatGPT, which demonstrates that the choice of LLMs is orthogonal to our proposed paradigm that can be easily augmented with existing LLMs without any other change.

4.4 Evaluation of Explainability

Automatic Evaluation. Generally, there is no gold explanation about memes for the harmful meme detection task due to the diverse forms of textual expression. Devising reliable metrics without reference is not a straightforward task and can also be problematic. Furthermore, different types of text necessitate the evaluation of distinct aspects, such as informativeness, fluency, soundness, etc. [11, 39], which makes it hard to design metrics for each type of text and dimension separately. Nowadays, GPT-4 [42] has revolutionized the field of LLMs with a more powerful expressive capacity. In this subsection, we present a new automatic evaluation using GPT-4 in a reference-free mode, to evaluate the text quality of the explanations generated by our approach from LLaVA and ChatGPT.

We randomly selected 3,000 harmful samples from the FHM dataset. For a more comprehensive comparison, we further provide GPT-4 with human-written explanations in hate speech by drawing the practice of previous literature [14] for the sampled memes. Specifically, GPT-4 is prompted to score the explanations w.r.t. each meme according to the following criteria: 1) *Informativeness*: the explanation provides new information, such as explaining the background and additional context; 2) *Readability*: the explanation follows proper grammar and structural rules; 3) *Soundness*: the explanation seems valid and logical; 4) *Conciseness*: the explanation contains less redundant information; 5) *Persuasiveness*: the explanation seems convincing. For each criterion, a 5-point Likert scale was employed, where 1 meant the poorest quality and 5 the best.

Table 4 demonstrates the averaged scores of the explanation evaluation by GPT-4 on the three sources (*i.e.*, LLaVA, ChatGPT, and Human) regarding the five criteria. We could observe that: 1) Compared with LLaVA and ChatGPT, the explanations written by human beings [14] are generally scored the highest in Conciseness but the lowest in the other aspects, because the mean explanation length is 13.62 which is shorter than that of LLaVA (125.37) and ChatGPT (180.82). 2) Interestingly, although GPT-4 is more powerful than LLaVA and ChatGPT, it tends to give higher scores to ChatGPT overall than LLaVA. We speculate the reason for such a bias is that both GPT-4 and ChatGPT are developed as successors of the LLM InstructGPT [43], so that the generated explanation by ChatGPT is more to the taste of GPT-4. 3) The performance of LLaVA evaluated by GPT-4 achieves an excellent balance between Conciseness and Persuasiveness, which implies that the LLaVA-generated explanations could succinctly impress GPT-4.


TRUMP 2 WEEKS AGO:
"The Coronavirus is a Democrat Hoax!"
TRUMP TODAY:
"I'm declaring the Coronavirus a National Emergency."
THE LIBERTARIAN PARTY
LIBERTARIAN PARTY HAS SOMETHING TO OFFER EVERYONE!
Unregulated child labor laws
PEDOPHILES
LET ME IN
PEDOPHILES
LET ME INNNNNN!!!
best gamer ever
6 million kills, 1 death

Meme text: TRUMP 2 WEEKS AGO: "The Coronavirus is a Democrat Hoax!" TRUMP TODAY: "I'm declaring the Coronavirus a National Emergency."

(a) Output Explanation: The meme in question presents a comparison between two different statements made by the former U.S. President, Donald Trump. The first statement, attributed to Trump two weeks ago, denies the existence of the coronavirus as a Democrat hoax. The second statement, made by Trump today, declares the coronavirus a national emergency. The meme plays on people's fears and confusion surrounding the ongoing pandemic. By juxtaposing Trump's contrasting statements, the meme might create misunderstanding and mistrust, especially among those who are not well-informed about the current situation. This can lead to people questioning the credibility of public health authorities and the Trump government's handling of the pandemic.

Meme text: THE LIBERTARIAN PARTY. LIBERTARIAN PARTY HAS SOMETHING TO OFFER EVERYONE! Unregulated child labor laws. PEDOPHILES. LET ME IN PEDOPHILES. LET ME INNNNNN!!!

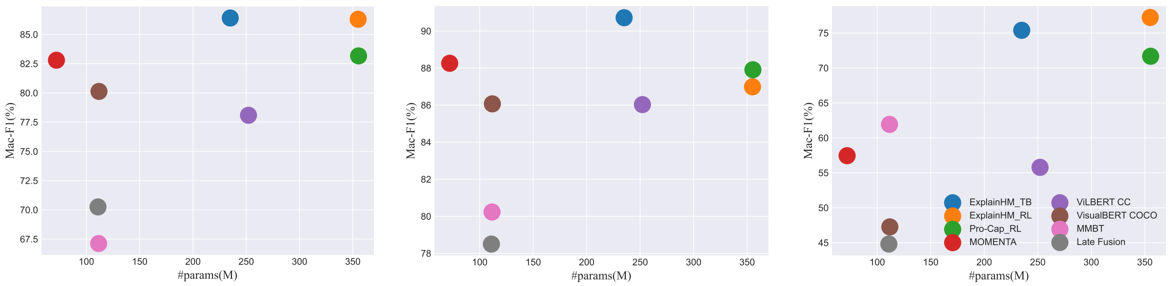
(b) Output Explanation: The meme is considered harmful because it makes light of a serious issue involving children and pedophiles. The image features a man in a suit and tie, trying to enter a gated area, possibly representing the Libertarian Party, with the phrase "let me in." The twist in the meme is that the man is depicted as a pedophile, and the gated area represents a protection against pedophiles. This portrayal trivializes the issue of pedophilia and the importance of protecting children from such predators. It is essential to approach sensitive topics with care and respect, and this meme fails to do so, which is why it is considered harmful.

Meme text: best gamer ever 6 million kills, 1 death

(c) Output Explanation: The meme featuring the image of a man in a military uniform and the text 'best gamer ever 6 million kills, 1 death' is considered harmful because it trivializes and makes light of a serious and tragic historical event - the Holocaust. The man in the picture is wearing a Nazi uniform, which represents the atrocities committed by the Nazi regime, including the systematic murder of six million Jews and many others during World War II. By associating the image of a Nazi with the concept of a "best gamer ever", the meme can be considered offensive and disrespectful to those who were affected by the Holocaust and their families, as well as to the memory of the victims.

Figure 3: Examples of correctly predicted harmful memes in (a) Harm-C, (b) Harm-P, and (c) FHM datasets.

Human Evaluation. Considering that automatic evaluation cannot realistically measure the quality of the chosen explanations generated by the multimodal debate between LLMs, we further conduct the human subjects study to evaluate the overall quality of explainability. 50 harmful samples are randomly selected from the FHM test set and 10 professional linguistic annotators are asked to evaluate the explanations of our model from LLaVA [35] and ChatGPT [43], further with those written by Human [14]. The metrics of human evaluation are the same as the automatic evaluation.



(a) Harm-C (b) Harm-P (c) FHM

Figure 4: The performance of our ExplainHM and other multimodal baselines with respect to the parameter size.

The scores of human evaluation are shown in Table 5. Note that the intra-class agreement score is 0.625. The average Spearman's correlation coefficient between any two annotators is 0.682. We can observe that: 1) The readability scores of all sources are high, which is because LLMs can generate fluent sentences as human beings towards the harmful meme explanation with commonsense knowledge. Compared with the automatic GPT-4 evaluation, the readability score of human-written explanations largely improved in human evaluation. 2) Except for the readability scores, the scores of human-written explanations in the other four metrics are similar in both human evaluation and automatic GPT-4 evaluation. 3) It is worth noting that although the explanations generated by our framework from the multimodal debate on ChatGPT received relatively lower scores in the human evaluation compared to those under automatic GPT-4 evaluation, it still, along with LLaVA, both achieved an overall superior performance to the human-written explanations from previous work [14], which do not explicitly explain the complex and integrated semantic information present in the memes. 4) According to the feedback of the evaluators, LLaVA can efficiently generate more concise explanations with correct key contents than ChatGPT which tends to generate lengthy and inclusive sentences. Overall, although there is still room for developing a more comprehensive metric for evaluating harmfulness explanations, the results reveal that it is feasible and reasonable for us to devise such a universal framework for harmful meme detection and explanation, by leveraging the impressive abilities of text generation in LLMs.

4.5 Case Study

One key advantage of our model is that the rationales generated in the multimodal debate between LLMs could serve as the output explanations for predicted results. For the correctly predicted harmful meme test samples, the output explanation refers to the rationale from the harmful argument, to understand the model predictions more transparently and intuitively, as exemplified in Figure 3.

From the explanations in natural text, we observe that 1) the multimodal information related to the meme text and image could be well understood with commonsense knowledge. For example, in Figure 3(a), the character in the image is recognized as "the former U.S. President", which could be linked to the "TRUMP" in the text; in Figure 3(b), the recognized "gated area" in the image could be recognized as protection against "PEDOPHILES" to satire "THE LIBERTARIAN PARTY" in the text; and in terms of Figure 3(c), the man in the image could be associated with "the Nazi regime" related to "gamer" in the text. 2) Furthermore, the interplay of multimodal information could be cognized with advanced reasoning. Benefitting from the rich multimodal understanding of the memes, the "comparison between two different statements" in Figure 3(a) can be reasoned to cause harmful consequences like "misunderstanding and mistrust"; the juxtaposition of a political party with the harmful topics "involving children and pedophiles" could be reasoned as trivializing such a serious issue in Figure 3(b); and the meme in Figure 3(c) shows disrespects to "those who were affected by the Holocaust and their families". In this way, the rich but implicit correlations between the meme text and image could be explained in readable snippets, which are also potentially valuable for aiding human checkers to verify the model predictions.

4.6 Impact of Model Size and Backbones

We provide a comparison of performance with regard to the number of trainable parameters for ExplainHM and the other multimodal baselines in Figure 4. We can observe that our model (ExplainHM_TB) has already achieved outstanding performance on the three benchmarks with T5_{Base} as the Small LM judge, which has a smaller size than the SoTA baseline Pro-Cap_RL based on $\text{RoBERTa}_{\text{Large}}$. We revise our Small LM judge with the backbone of Pro-Cap_RL to build the ExplainHM_RL model. We observed that ExplainHM_RL still outperforms all the baselines on Harm-C and FHM datasets by a large margin, yet is competitive on Harm-P due to the smaller data scale.

5 CONCLUSION AND FUTURE WORK

We proposed an explainable approach for harmful meme detection. We first conducted a multimodal debate between LLMs about the meme to generate contradictory rationales from harmless and harmful arguments. Then utilizing these rationales, we designed a tunable language model as the judge to infer meme harmfulness. Our proposed framework is evaluated on three meme benchmarks, demonstrating its effectiveness in both detection and explainability. Moving forward, we plan to further enhance the automatic evaluation of the explanation quality as part of our future work.

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A BASELINES

We compare our model with several state-of-the-art harmful meme detection systems: 1) **Text BERT**: BERT [10] is utilized as the unomodal text-only model; 2) **Image-Region**: a unimodal visual-only model that processes meme images using Faster R-CNN [49] with ResNet-152 [13] to feed into a classification layer; 3) **Late Fusion**: a multimodal model uses the average prediction scores of BERT and ResNet-152 for harmful meme detection [44]; 4) **MMBT**: a multimodal Bi-Transformer [19] that captures the intra-modal and inter-modal dynamics of the two modalities; 5) **VisualBERT**: Visual BERT [27] pre-trained on the COCO dataset [33]; 6) **ViLBERT**: Vision and Language BERT [38] trained on an intermediate multimodal objective [51] for task-agnostic joint representations of image and text; 7) **MOMENTA**: a multimodal harmful meme detection system [45] that takes the global and local information in two modalities of memes into account; 8) **MaskPrompt**: a prompt learning approach [5] that concatenates the meme text and the image caption as the prompt for masked language modeling [37]; 9) **Pro-Cap**: a caption-enhanced version [4] of MaskPrompt, by leveraging pre-trained vision-language models with probing queries, to improve the image caption in the text prompt.

B IMPLEMENTATION DETAILS

B.1 Prompting LLaVA for Multimodal Debate and Judge

As depicted in §3.2 and §3.3, we utilize the vision LLM, *i.e.*, LLaVA [35], specifically the "llava-13b-v1-1" version[5] as the implementation of the debaters and the judge. The detailed prompting design is exemplified in §**??**. To ensure our results are reproducible, we set the temperature as 0 and the maximum length as 256 without any sampling mechanism.

B.2 Prompting ChatGPT Debaters for Multimodal Debate

We have introduced the prompting design for LLaVA to conduct the multimodal debate. Here we would introduce how to prompt ChatGPT [43], a widely used LLM developed by OpenAI, specifically utilizing the "gpt-3.5-turbo" version, as another variant of our approach in the ablative studies. To prompt ChatGPT for the multimodal debate, we need to convert the meme's image into an acceptable textual input for ChatGPT. We first in-paint the memes by combining MMOCR [24] with SAM [22] to extract the text and pure image in memes. Then for a fair comparison with LLaVA, we apply LLaVA to generate textual descriptions about the dominant objects or events in the memes' image. To make our results reproducible, we set the temperature as 0 and the maximum length as 256 in ChatGPT.

For the system prompt to ChatGPT Debaters, we design the message as follows:

[5] https://huggingface.co/liuhaotian/LLaVA-13b-delta-v1-1

"*You have been specially designed to perform abductive reasoning for the harmful meme detection task. Your primary function is that, according to a harmfulness label about an image with a text embedded, please provide a streamlined rationale, without explicitly indicating the label, for how it is reasoned as the given harmfulness label. The image and the textual content in the meme are often uncorrelated, but its overall semantic information is presented holistically. Thus it is important to note that you are prohibited from relying on your own imagination, as your goal is to provide the most accurate and reliable rationale possible so that people can infer the harmfulness according to your reasoning about the background context and relationship between the given text and image caption.*".

Moreover, to prompt ChatGPT to generate reasonable rationales with the triplet $\{*, \tilde{\mathcal{I}}, \mathcal{T}\}$ as observed attributes, where $\tilde{\mathcal{I}}$ is the image caption, we design the template p^* for the user prompt as:

"*Given a Text: [$\mathcal{T}$], which is embedded in an Image: [$\tilde{\mathcal{I}}$]; and a harmfulness label [$*$], please give me a streamlined explanation associated with the meme, without explicitly indicating the label, to explain how the harmfulness of the meme is reasoned as [$*$].*".

B.3 Prompting ChatGPT to Judge Multimodal Debate

For prompting a ChatGPT Judge, we design the system prompt as follows:

"*Suppose you are a harmful meme detector. There will be two debaters involved in a meme explanation competition for harmful meme detection. As there must be a winner and a loser in a debate, your job is to determine whether a meme is harmful or harmless by evaluating their stated explanations on different positions (harmful or harmless). The image and the text may not be harmful when considered in isolation, but are harmful when taken as a whole and vice versa. Thus it is important to note that you are prohibited from relying on your own imagination and being affected by exaggerated or misinterpreted explanations, as your goal is to provide the most accurate and reliable judgment possible.*".

Moreover, to prompt ChatGPT to make a judgment with the tuple $\{\tilde{\mathcal{I}}, \mathcal{T}\}$ as observed attributes, where $\tilde{\mathcal{I}}$ is the image caption, we design the user prompt as:

"*Given a Text: [$\mathcal{T}$], which is embedded in an Image: [$\tilde{\mathcal{I}}$]; with the following two rationales: (1) Harmless: [r^{hl}]; (2) Harmful: [r^{hf}], is this meme harmless or harmful?*".

For the input order of the harmless and harmful rationales, we found there is not much difference between the judgment results for the input of the different order into the LLM judge using ChatGPT or LLaVA.

B.4 Implementation of Small LMs

Our ExplainHM model utilizes the T5 encoder-decoder architecture [7, 48] as its foundational framework, specifically utilizing the "flan-t5-base" version. For the extraction of image features, following previous work [45], we adopted the state-of-the-art vision Transformer known as CLIP-ViT-B/32 [46], and this module remains static throughout the training process. To effectively integrate the multimodal information, we incorporated a simple one-head cross-attention mechanism in each layer of the T5 encoder. The maximum length of textual input is set as 512. During the fusion process, the text features are utilized as the query, while the image features act as the key and value. It is noteworthy that these fusion modules were initialized randomly. The dimension d of the hidden states is set as 768, and d_k is set as 384. For the training phase, we provide a comprehensive list of the hyper-parameters in Table 6. Drawing the practice of previous work [4, 5, 28] on FHM data, we augmented the input text with image entities and demographic information for better multimodal fusion. Results are averaged over ten random runs. All experiments were conducted on a single V100 32GiB GPU.

Table 6: Hyper-parameters.

Hyper-Parameter	Harm-C	Harm-P	FHM
epoch	20	20	20
batch size	32	32	32
Learning Rate	5e-5	5e-4	1e-4
Warmup Step	0.1	0.1	0.1
Warmup Strategy	Linear	Linear	Linear
Image Size	224	224	224

B.5 Prompting GPT-4 for Automatic Evaluation of Explainability

Different from the LLM judge for the detection purpose, as we need to evaluate the quality of the explanations generated from different LLMs like LLaVA and ChatGPT, to avoid the automatic evaluator showing a preference to the side with the same LLM [59], currently the more powerful LLM than LLaVA and ChatGPT, *i.e.*, GPT-4, is the best choice to conduct the explanation evaluation. During the period of this work, the GPT-4 API could be utilized in the language-only modality, similar to ChatGPT, so we extracted the text caption of the meme image by LLaVA as the meme caption to describe the image in the user prompt. For the system prompt to the GPT-4 model, we design the message as follows:

"*Suppose you have been specially designed to perform an explanation evaluation for the harmful meme detection task, you are required to score the provided explanations given the meme text and image. The image and the textual content in the meme are often uncorrelated, but its overall semantic information is presented holistically. Thus it is important to note that you are prohibited from relying on your own imagination, as your goal is to provide the most accurate and reliable score possible.*".

Moreover, to prompt GPT-4 for the automatic explanation evaluation in each criterion, we designed the template for the user prompt as:

"*Given a Text: [**Meme_text**], which is embedded in an Image: [**Meme_caption**], with a harmfulness label 'harmful', please assign the three explanations respectively with three corresponding score values in Integer, on a rating scale from 1 (worst) to 5 (best) with respect to the [**Criterion**]: 1) [**Explanation_chatgpt**]; 2) [**Explanation_llava**]; 3) [**Explanation_human**].*".

C AUTOMATIC EVALUATION OF EXPLAINABILITY ON HARM-C/P DATA

We further provide the results of automatic GPT-4 evaluation on Harm-C and Harm-P data, as shown in Table 7. Note that as there

Table 7: Automatic GPT-4 evaluation of the explanation quality on Harm-C/P test sets, where the explanations are generated by LLaVA and ChatGPT.

Data	Harm-C		Harm-P	
Explanations	LLaVA	ChatGPT	LLaVA	ChatGPT
Informativeness	3.70	4.64	3.97	4.74
Readability	4.29	4.96	4.56	4.99
Soundness	3.71	4.83	3.92	4.83
Conciseness	3.70	3.38	3.91	3.23
Persuasiveness	3.63	4.71	3.83	4.69

are no existing human-written explanations for the Harm-C and Harm-P data, we only evaluate the text quality of the explanations generated by our model variants from LLaVA and ChatGPT. Although Hee et al. [14] has presented human-written explanations, it is labor-intensive and limited that only focuses on the FHM dataset and explains why the meme is harmful or not but without the reasoning thought chains for how the two multimodalities of memes interact with each other to derive the harmfulness. Moreover, the explanations automatically generated from LLMs could provide new benchmarks for future studies about explainable harmful meme detection and automatic evaluation of the explanation quality.

D HELPFULNESS OF CONFLICTING RATIONALES ON HUMAN SUBJECTS

We have evaluated the detection performance and the text quality of the output explanations, respectively, in the main paper. We further design a human subject study to evaluate the helpfulness of the conflicting rationales for human beings to make correct harmfulness predictions. Specifically, we first randomly selected 100 samples (50 harmful samples and 50 harmless samples) from Harm-C, Harm-P and FHM datasets. Then ten English-speaking evaluators are asked to test on the selected samples. Their average detection performance was 58.50% accuracy. Afterward, we provide the same samples with conflicting rationales from both harmless and harmful arguments for each sample. The average detection performance of the evaluators improved to 77.52% accuracy. The study shows that, by considering both the positive and negative aspects of harmfulness, the conflicting rationales can provide human users or checkers with dialectical thinking that allows them to better decode the underlying meaning of memes and mitigate the harmful information. We further provide more case studies and error analysis in the longer version of this paper[6].

E LIMITATIONS AND FUTURE WORK

There are multiple ways to further improve this work: 1) Overall, the explainability of this work focuses on that the model’s decision is explainable with the rationales. However, there might be a deeper level of explainability of the model that is not touched on in this paper, which is to explain how a neural model works internally. We would further improve our research to facilitate the interpretability of the model architecture. 2) We heuristically designed the prompt of LLMs for the multimodal debate in only one turn. But in some error examples, the generated text may miss the details of the meme like the race. We would further update our prompt for the design of multi-turn debates with LLMs, to activate the commonsense reasoning knowledge related to vulnerable targets in harmful content, improve the visual feature extraction for exploring better multimodal reasoning thoughts, and avoid several common deficiencies of existing language models including hallucination and limited generalization as much as possible. 3) Despite this work utilizing GPT-4 for the automatic evaluation of explanation quality, the evaluation results still have minor gaps with the human subject study, like GPT-4 tends to judge the explanations from ChatGPT with higher scores than those from other sources or models. Moreover, if GPT-4 is incorporated into the multimodal debate stage, we need to seek more powerful language models to evaluate the explanations generated by GPT-4. Thus more accurate automatic evaluation of the explanation quality is needed, meanwhile, more comprehensive human subject studies could be conducted on a larger crowd of evaluators in an organized manner. 4) Generally, the distribution drift in datasets over time is a potential limitation for almost all data-driven tasks [32], especially for the memes on the Web. However, one of the contributions of this work is proposing a novel paradigm to leverage commonsense reasoning knowledge in LLMs for the harmful meme detection task. The proposed framework is general enough, which should still work with newly released stronger LLMs or new meme data appearing on the Web. For example, in the future, we could publish a plug-and-play interface to incorporate a broader range of LLMs into our framework for the multimodal debate stage, even the GPT-4V[7] if there is sufficient financial support for some users.

F ETHICS AND BROADER IMPACT

The purpose of this work is to prevent the spread of harmful meme information and to ensure that people are not subjected to prejudice or racial and gender discrimination. Nevertheless, we are aware of the potential for malicious users to reverse-engineer and create memes that go undetected or misunderstood by ExplainHM-trained AI systems. This is strongly discouraged and condemned. Intervention with human moderation would be required in order to ensure that this does not occur. Research indicates that evaluating harmful or hateful content can have negative effects. To protect our human evaluators, we establish three guidelines: 1) ensuring their acknowledgment of viewing potentially harmful content, 2) limiting weekly evaluations and encouraging a lighter daily workload, and 3) advising them to stop if they feel overwhelmed. Finally, we regularly check in with evaluators to ensure their well-being. Another consideration is the usage of Facebook’s meme dataset; users will have to agree with Facebook’s usage agreement to gain access to the memes. The usage of Facebook’s memes in this study is in accordance with its usage agreement. All the datasets only include memes and do not contain any user information.

[6] https://arxiv.org/pdf/2401.13298.pdf

[7] https://openai.com/research/gpt-4v-system-card