



## I know what you MEME! Understanding and Detecting Harmful Memes with Multimodal Large Language Models

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Presented by







Background

**Motivation** 

Method

Experiment

Conclusion

## What is a Meme?

A meme is a viral social media format that combines images and text

to convey ideas, humor, or culture.





## **The Dark Side of Memes - Harmful Meme**



**Motivation** 

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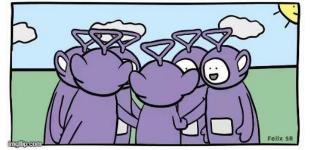


#### Malicious Users

ers



ANDEMIC





**Social Platform** 





**Online Users** 



**Challenges in Harmful Meme Detection** 

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### Multimodal semantic fusion

The interplay between text and images in memes can convey both subtle and overt harmful content.

### Meme composition

The arrangement of visual elements influences perception, potentially masking harmful intent.

### Meme propaganda techniques

The use of strategic rhetorical and psychological tactics can influence opinions or behaviors, potentially obscuring harmful content.



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## Challenge 1 - Multimodal semantic fusion

### > Dataset

HatReD<sup>[5]</sup>, contains human semantic annotations of harmful memes.

### Measurement

#### **Evaluation: BERTScore**

- $R_{\text{BERT}} = \frac{1}{|x|} \sum_{x_i \in x} \max_{\hat{x}_j \in \hat{x}} x_i^\top \hat{x}_j$  $P_{\text{BERT}} = \frac{1}{|\hat{x}|} \sum_{\hat{x}_j \in \hat{x}} \max_{x_i \in x} x_i^\top \hat{x}_j$  $F_{\text{BERT}} = 2 \cdot \frac{P_{\text{BERT}} \cdot R_{\text{BERT}}}{P_{\text{BERT}} + R_{\text{BERT}}}$
- x human interpretation of the meme  $\hat{x}$  - model's interpretation of the meme  $x_i, \hat{x_j}$  - Token embeddings from BERT  $x_i^{T} \hat{x_j}$  - similarity between token embeddings

[5] M. S. Hee, W.-H. Chong, and R. K.-W. Lee, "Decoding the underlying meaning of multimodal hateful memes," in Proceedings of the ThirtySecond International Joint Conference on Artificial Intelligence, 2023, pp. 5995–6003.



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## Challenge 1 - Multimodal semantic fusion

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Model	BERTScore					
	$P_{\mathbf{BERT}}$	$R_{\text{BERT}}$	$F_{\mathbf{BERT}}$			
VisualBERT	0.5	0.45	0.47			
VL-T5	0.47	0.41	0.45			
LLaVA	0.77	0.80	0.79			
GPT-4	0.84	0.83	0.83			

Remark 1 - The challenge of multimodal semantic fusion for traditional models, and the ability of MLLM in meme understanding

- *x* human interpretation of the meme
- $\widehat{x}$  model's interpretation of the meme
- $x_i$ ,  $\hat{x_j}$  Token embeddings from BERT
- $x_i^{\mathsf{T}} \widehat{x_j}$  similarity between token embeddings

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From the perspective of visual arts, meme composition is the arrangement of visual elements

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- > Number of Panels
- > Type of the Images
- > Scale
- > Movement



### > Number of Panels



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Single

When you find out your normal daily lifestyle is called "quarantine"



Stitching



### > Type of the Images

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Photo

James Woods @ @RealJames... 13 Aug ~ This is our last stand, folks. And here's your last defender. If they take him down, America is gone forever. Vote for @realDonaldTrump like your life depends on it.



Screenshot



'It's irresponsible and it's dangerous': Experts rip Trump's idea of injecting disinfectant to treat COVID-19

### Illustration



Scale

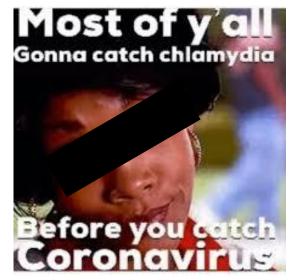
Background

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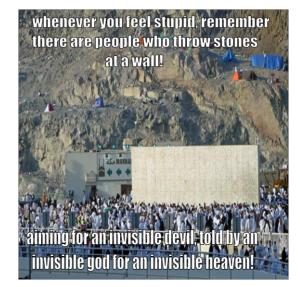
Conclusion



**Close up** 



**Medium Shot** 



Long Shot



### > Movement

Background

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Physical





**Emotional** 

Casual



	Category	Subcategory Proportion		True Positive Rate (TPR)				
Background	Cutegory	Subcutegory	of Meme		LLaVa	GPT-4	Avg.	
	N	Single	67%	67.03%	18.18%	61.54%	52.35%	
Motivation	Number of Panels	Stitching	33%	42.42%	16.48%	33.3%	35.18%	
		Illustration	17%	71.43%	14.29%	66.67%	57.15%	
Method	Type of the Images	Photo	50%	63.04%	17.39%	58.7%	51.09%	
		Screenshot	33%	73.91%	17.39%	65.22%	54.35%	
		Close-up shot	20%	75%	42.86%	85.71%	68.75%	
Experiment	Scale	Medium shot	76%	63.64%	12.99%	59.74%	50%	
		Long shot	4%	80%	0%	0%	40%	
Conclusion		Physical movement	56%	61.36%	18.18%	63.64%	52.27%	
Conclusion	Movement	Emotional movement	39%	67.74%	16.13%	61.29%	52.42%	
		Causal movement	5%	75%	0%	25%	37.5%	



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		Long shot	4%	80%	0%	0%	40%	
Conclusion		Physical movement	56%	61.36%	18.18%	63.64%	52.27%	
	Movement	Emotional movement	39%	67.74%	16.13%	61.29%	52.42%	
		Causal movement	5%	75%	0%	25%	37.5%	

Remark 2 - Meme composition challenges harmful meme detection particularly with stitched images, which complicate understanding visually.



## Challenge 3 - Propaganda Techniques

The use of strategic rhetorical and psychological tactics can influence opinions or behaviors, potentially obscuring harmful content.

#### Background

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#### Conclusion

#### - Name calling or labeling

- Appeal to fear/ prejudices
- Whataboutism
- Misrepresentation of someone's position
- Flag-waving
- Causal oversimplification
- Black-and-white fallacy or dictatorship
- Reductio ad hitlerum
- Smears
- Loaded language
- Doubt

- Exaggeration/ Minimisation
- Slogans
- Appeal to authority
- Thought-terminating cliche
- Repetition
- Obfuscation, Intentional vagueness, Confusion
- Presenting irrelevant data
- Bandwagon
- Glittering generalities
- Appeal to strong emotions
- Transfer

[6] D. Dimitrov, B. Ali, S. Shaar, F. Alam, F. Silvestri, H. Firooz, P. Nakov, G. Da San Martino et al., "Detecting propaganda techniques in memes," in ACL-IJCNLP 2021-59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, Proceedings of the Conference. Association for Computational Linguistics (ACL), 2021, pp. 6603–6617.



## Challenge 3 - Propaganda Techniques

#### > Appeal to strong emotions:

Uses emotionally charged imagery to evoke fear/anger, linking modern Democrats with extreme historical groups

#### Background

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#### > Name-calling:

Labels Democrats as "extremists" or "racists" to provoke negative associations

#### > Smears:

Damages the reputation of Democrats by associating them with negative stereotypes

#### > Transfer:

Associates negative qualities of historical groups with modern Democrats





## **Challenge 3 - Propaganda Techniques**

Background
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Motivation

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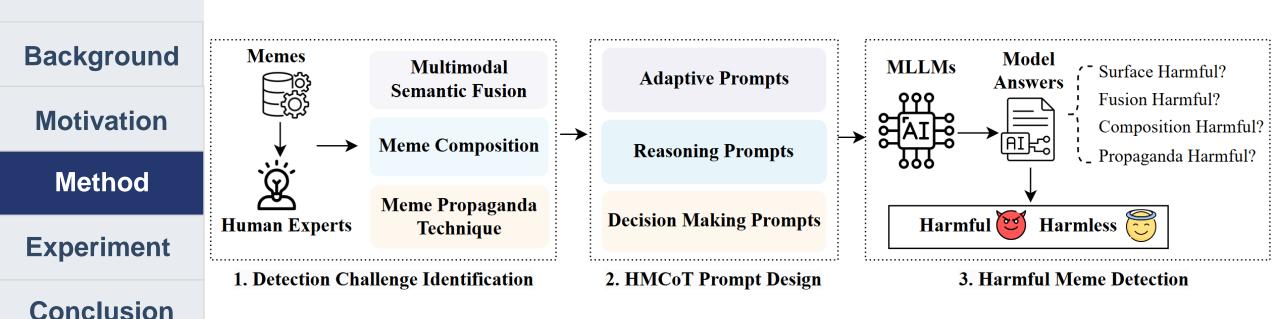
Conclusion

Catetory	Proportion	<b>True Positive Rate (TPR)</b>					
currenty	of Meme	ExplainHM	LLaVa	GPT-4	Avg.		
w/o propaganda techniques	57.3%	75%	17.31%	60%	50.77%		
w/ propaganda techniques	42.7%	53.85%	15%	48.08%	38.98%		

Remark 3 - Meme propaganda technique poses challenges for detecting harmful content, as it makes the expression more subtle and less detectable.



### **Overview of HMGuard**



Conclusion



#### Background

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## **Overview of HMCoT**

Adaption: This is a meme, using text and images for humor or satire, shaped by cultural and contexts. You are a content moderation specialist. Your task is to pinpoint any instances of hate speech, explicit violence, discrimination, or any other type of content that may be considered harmful.

Q1: What are the words and images contained in the meme, and do the semantics of the text and image directly convey harmful content?

**Q2:** What are the explicit or implicit relationships between text and image, and does the relationship between the text and the image potentially reveal harmful content?

Q3a: Is the meme a stitching image?

#### Yes ↓

**Q3b:** Consider the relationship of images, and understand whether the stitching images are trying to express explicit or implicit harmful content.

Q4: Are the following propaganda techniques used to explicitly or implicitly express harmful content?

Q5: Does the meme intend to have any targeted derogatory, humiliating, insulting, satirical, or disparaging meaning?

**Final Decision:** Combining the analysis from the previous questions, please make the final decision on whether this meme is harmful or harmless. You need to make sure that your answers are consistent with the questions above.

#### **Adaptive Prompt**

#### **Reasoning Prompt**

**Decision Making Prompt** 





### Dataset

Dataset	# Memes	# Harmful	# Harmless
HarMeme	289	110	179
FHM	711	422	289
Total	1000	532	468

### Baselines

(1) MOMENTA [24]: Multimodal harmful meme detection system, released the Harmeme dataset.

(2) HateDetectron [48]: Wining the Meta's Hateful Meme Challenge with FHM dataset.

(3) MR.HARM [14]: LLM-based harmful meme detection system.

(4) ExplainHM [29]: Uses LLMs' argumentative abilities for diverse explanations, achieving state-of-the-art detection.

(5) GPT-4 [16]: Advanced MLLM with strong reasoning capabilities.

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### Compare to baselines

Background	Detector	Detector FHM				HarMeme			
Daonground		Accuracy	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score
Motivation	MOMENTA	0.61	0.66	0.51	0.57	0.77	0.69	0.45	0.55
	HateDetectron	0.69	$\overline{0.54}$	0.73	0.58	0.8	0.77	0.62	0.68
	MR.HARM	$\overline{0.58}$	0.34	$\overline{0.65}$	0.45	0.8	$\overline{0.56}$	0.82	0.66
Method	ExplainHM	0.48	0.35	0.55	0.48	0.73	0.25	0.62	0.71
	GPT-4	0.61	0.55	0.64	0.6	0.74	0.72	0.5	0.69
Experiment	HMGUARD	0.86	0.88	0.83	0.85	0.92	0.83	0.98	0.91
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Note: Underline represents the best results in baselines; Bolding represents the best results among all approaches.

Conclusion



B

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### Effectiveness of addressing the challenges

	Category of H	Category of Harmful Meme		
	Number of Panels	Single	97.44%	30.41%
ackground	Inumber of Fahers	Stitching images	96.88%	54.46%
		Illustration	99.99%	28.56%
lotivation	Type of the Images	Photo	97.44%	34.40%
		Screenshot	95%	21.09%
Method		Close-up shot	99.99%	14.28%
	Scale	Medium shot	96.92%	33.28%
xperiment		Long shot	99.99%	19.99%
		Physical movement	94.59%	30.95%
onclusion	Movement	Emotional movement	99.99%	32.25%
		Causal movement	99.99%	24.99%
	w/o propagar	w/o propaganda techniques		
		w/ propaganda techniques		



## **Detecting "in-the-wild" Harmful Memes**

Detector	Accuracy	Percision	Recall	F1-score
HateDetectron MR.HARM	0.7 0.73	0.53 0.57	0.52 0.52	0.51 0.5
HMGUARD	0.88	0.83	0.89	0.86





### Conclusion

### Contributions

Background

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- New understanding of harmful memes from novel perspectives
- New framework for harmful meme detection.
- Extensive evaluation of HMGUARD.

### Future Work

- Multilingual harmful meme detection
- Promising approaches such as RAG and AI Agent





# Thanks for your attention! Q&A

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Presented by





### Example

