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## Introduction:

#### • Internet memes

- typically, an **image** and a **short piece of overlaid text**
- popular medium of expression
- empowerment through associated virality
- o funny

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## • Internet memes

- typically, an image and a short piece of overlaid text
- $\circ$  popular medium of expression
- empowerment through associated virality
- o funny
- Challenging for analysis
  - multimodality
  - **context**-dependency
  - morphed image
  - noisy/manipulated text

<sup>1</sup>The Hateful Memes Challenge, Kiela et al., NeurIPS'20

<sup>2</sup>Multimodal meme dataset for identifying offensive content, Suryawanshi et al., , LREC-TRAC '20

## Introduction:

- Internet memes can be harmful and even weaponized
  - hateful memes<sup>1</sup>
  - $\circ$  offensive memes<sup>2</sup>
- Harm is a more general concept than hate and offense

## **Our Contributions:**

 We extend our recently released dataset HarMeme<sup>1</sup>, which covered COVID-19, with a new topic US Politics and thus ending up with two datasets: Harm-C and Harm-P

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- We benchmark the two datasets against several state-of-the-art unimodal and multimodal models, and we discuss the limitations of these models.
- We propose MOMENTA, a novel multimodal framework that systematically analyzes the local and the global perspective of the input meme and relates it to the background context.

<sup>1</sup>Detecting Harmful Memes and Their Targets, Pramanick et al., ACL'21

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- We propose MOMENTA, a novel multimodal framework that systematically analyzes the local and the global perspective of the input meme and relates it to the background context.
- We perform extensive experiments on both datasets, and we show that MOMENTA outperforms the baselines.

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## **Data Collection & Annotation:**

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- Removal of duplicates
- Annotation guidelines
- Annotation process
  - Dry run  $\rightarrow$
  - Final annotation  $\rightarrow$
  - Consolidation  $\rightarrow$

pybossa	Community	Projects	Create	About
MEME a	nnotat	tion p	oroje	ct: Contribute
6				Harmful Intensity



O Not harmful Target of harmful content

○ Targeting an individual

○ Somewhat harmful

○ Targeting an organization

○ Targeting a community

O Harmful to the society, or the general public

**Guidelines** 

**Reject Cartoon** 

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#### **Dataset Summary:**

Datasat	Split	#N.f.		Harmfulness		#Mamor	Target					
Dataset	Spiit	#Ivientes	Very Harmful	Partially Harmful	Harmless	#Memes	Individual	Organization	Community	Society		
	Train	3,013	182	882	1,949	1,064	493	66	279	226		
Harm C	Validation	177	10	51	116	61	29	3	16	13		
Harm-C	Test	354	21	103	230	124	59	7	32	26		
	Total	3,544	213	1,036	2,295	1,249	582	75	t Community Soc 279 16 32 327 111 2 12 125	265		
	Train	3,020	216	1,270	1,534	1,451	797	470	111	73		
Horm D	Validation	177	17	69	91	85	70	12	2	1		
папп-г	Test	355	25	148	182	170	96	54	12	8		
	Total	3,552	258	1487	1,807	1,706	963	536	t Community 5 279 16 32 327 111 2 12 125	82		

Statistics about the Harm-P and Harm-C datasets. Very harmful and partially harmful memes are annotated with one of the following four targets: *individual, organization, community,* or society.

### **Lexical Summary:**

Detect		Harmfulness	2	Target						
Dataset	Very harmful	Partially harmful	Harmless	Individual	Organization	Community	Society			
Harm-C	mask (0.0512)	trump (0.0642)	you (0.0264)	trump (0.0541)	deadline (0.0709)	china (0.0665)	mask (0.0441)			
	trump (0.0404)	president (0.0273)	home (0.0263	president (0.0263)	associated (0.0709)	chinese (0.0417)	vaccine (0.0430)			
	wear (0.0385)	obama (0.0262)	corona (0.0251)	donald (0.0231)	extra (0.0645)	virus (0.0361)	alcohol (0.0309)			
	thinks (0.0308	donald (0.0241)	work (0.0222)	obama (0.0217)	ensure (0.0645)	wuhan (0.0359)	temperatures (0.0309)			
	killed (0.0269)	virus (0.0213)	day (0.0188)	covid (0.0203)	qanon (0.0600)	cases (0.0319)	killed (0.0271)			
Harm-P	photoshopped (0.0589)	democratic (0.0164)	party (0.02514)	biden (0.0331)	libertarian (0.0358)	liberals (0.0328)	crime (0.0201)			
	married (0.0343)	obama (0.0158)	debate (0.0151)	joe (0.0323)	republican (0.0319)	radical (0.0325)	rights (0.0195)			
	joe (0.0309)	libertarian (0.0156)	president (0.0139)	obama (0.0316)	democratic (0.0293)	islam (0.0323)	gun (0.0181)			
	trump (0.0249)	republican (0.0140)	democratic (0.0111)	trump (0.0286)	green (0.0146)	black (0.0237)	taxes (0.0138)			
	nazis (0.0241)	vote (0.0096)	green (0.0086)	putin (0.0080)	government (0.0097)	mexicans (0.0168)	law (0.0135)			

Top-5 most frequent words per (class/dataset). The tf-idf score per word is given within parenthesis.

## **Baselines:**

- Unimodal Models
  - Text Only
    - BERT
  - Image Only
    - VGG19
    - DenseNet-161
    - ResNet-152
    - ResNeXt-101

## **Baselines:**

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- VGG19
- DenseNet-161
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- Multimodal Models (Image + Text)
  - Unimodal Pre-training (Text)
    - Late Fusion (Avg.)
    - Concat BERT
    - MMBT
  - Multimodal Pre-training
    - VILBERT CC
    - VisualBERT COCO

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Access our dataset and implementation using this QR Code



## **MOMENTA:**



• We encode each image-text pair using CLIP<sup>1</sup>, a pre-trained visual-linguistic model.

<sup>1</sup>Learning Transferable Visual Models From Natural Language Supervision, Radford et al., ICML '21

## **MOMENTA:**



 In addition, we include meme object proposals (faces and foreground objects) and web attributes/entities.

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- Intra-modality attention object proposals + CLIP image features and web attributes/entities + CLIP text features

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• We encode each image-text pair using CLIP<sup>1</sup>, a pre-trained visual-linguistic model.

- In addition, we include meme object proposals (faces and foreground objects) and web attributes/entities.
- Intra-modality attention object proposals + CLIP image features and web attributes/entities + CLIP text features
- Cross-modality attention fusion (CMAF) with two major parts: modality attention generation and weighted feature concatenation

<sup>1</sup>Learning Transferable Visual Models From Natural Language Supervision, Radford et al., ICML '21

#### **Evaluation:**

 In terms of accuracy, we observe that MOMENTA achieves sizable improvements for the 2-class and 3-class tasks over the best multimodal models on both Harm-C and Harm-P datasets.

			Harmf	ul Meme De	tection o	on Harm	n-C	Harmful Meme Detection on Harm-P					
Modality	Model	2-Cla	ass Class	sification	3-Cla	ass Class	sification	2-Cl	ass Clas	sification	3-Cla	ass Class	sification
1943		Acc ↑	$F1\uparrow$	$\mathbf{MMAE}\downarrow$	Acc ↑	<b>F1</b> ↑	<b>MMAE</b> ↓	Acc ↑	<b>F1</b> ↑	$\mathbf{MMAE}\downarrow$	Acc ↑	<b>F1</b> ↑	$\mathbf{MMAE}\downarrow$
	Human <sup>†</sup>	90.68	83.55	0.1723	86.10	65.10	0.4857	94.40	88.47	0.1028	92.12	70.35	0.6274
	Majority	64.76	39.30	0.5000	64.76	26.20	1.0000	51.27	33.39	0.5000	51.27	22.59	1.0000
Text (T) Only	TextBERT	70.17	66.25	0.2911	68.93	48.72	0.5591	80.12	78.35	0.1660	74.55	54.08	0.7742
	VGG19	68.12	61.86	0.3190	66.24	41.76	0.6487	70.65	70.46	0.1887	73.65	51.89	0.8466
Trans (T) Only	DenseNet-161	68.42	62.54	0.3125	65.21	42.15	0.6326	74.05	73.68	0.1845	71.80	50.98	0.8388
Image (I) Only	ResNet-152	68.74	62.97	0.3114	65.29	43.02	0.6264	73.14	72.77	0.1800	71.02	50.64	0.8900
	ResNeXt-101	69.79	63.68	0.3029	66.55	43.68	0.6499	73.91	73.57	0.1812	71.84	51.45	0.8422
T I T (Unimodal	Late Fusion	73.24	70.25	0.2927	66.67	45.06	0.6077	78.26	78.50	0.1674	76.20	55.84	0.7245
1 + 1 (Unimodal	Concat BERT	71.82	71.82	0.3156	65.54	43.37	0.5976	77.25	76.38	0.1743	76.04	55.95	0.7450
Pre-training)	MMBT	73.48	67.12	0.3258	68.08	50.88	0.6474	82.54	80.23	0.1413	78.14	58.03	0.7008
I + T (Multimodal	ViLBERT CC	78.53	78.06	0.1881	75.71	48.82	0.5329	87.25	86.03	0.1276	84.66	64.70	0.6982
Pre-training)	V-BERT COCO	81.36	80.13	0.1857	74.01	53.85	0.5303	86.80	86.07	0.1318	84.02	63.68	0.7020
	CLIP	74.23	73.85	0.2955	67.04	44.25	0.6228	80.55	80.25	0.1659	77.00	56.85	0.7852
Deserved Content	CLIP + Proposals	77.65	76.90	0.2142	70.52	45.60	0.5955	84.16	83.80	0.1556	81.06	60.65	0.7122
Proposed System	CLIP + Attributes	78.10	77.64	0.2010	71.05	45.55	0.5887	84.02	83.85	0.1508	80.75	60.23	0.7058
and variants	MOMENTA w/o CMAF	80.75	80.17	0.1896	74.85	51.25	0.5360	86.20	85.55	0.1355	83.85	63.02	0.6990
	MOMENTA	83.82	82.80	0.1743	77.10	54.74	0.5132	89.84	88.26	0.1314	87.14	66.66	0.6805
Δ <sub>MOMENTE</sub>	-best_model	2.46	2.67	0.0114	1.39	0.89	0.0171	2.59	2.23	0.0038	2.48	1.96	0.0177

#### **Evaluation:**

- In terms of accuracy, we observe that MOMENTA achieves sizable improvements for the 2-class and 3-class tasks over the best multimodal models on both Harm-C and Harm-P datasets.
- The corresponding Macro-F1 scores also improve by a similar margin.

			Harmf	ul Meme De	tection o	n Harm	I-C		Harmful Meme Detection on Harm-P					
Modality	Model	2-Cla	ass Class	sification	3-Cla	ass Class	sification	2-Cla	ass Clas	sification	3-Cla	ass Class	sification	
1.222		Acc ↑	$F1\uparrow$	<b>MMAE</b> ↓	Acc ↑	<b>F1</b> ↑	<b>MMAE</b> ↓	Acc ↑	<b>F1</b> ↑	$\mathbf{MMAE}\downarrow$	Acc ↑	<b>F1</b> ↑	$\mathbf{MMAE}\downarrow$	
	Human <sup>†</sup>	90.68	83.55	0.1723	86.10	65.10	0.4857	94.40	88.47	0.1028	92.12	70.35	0.6274	
	Majority	64.76	39.30	0.5000	64.76	26.20	1.0000	51.27	33.39	0.5000	51.27	22.59	1.0000	
Text (T) Only	TextBERT	70.17	66.25	0.2911	68.93	48.72	0.5591	80.12	78.35	0.1660	74.55	54.08	0.7742	
	VGG19	68.12	61.86	0.3190	66.24	41.76	0.6487	70.65	70.46	0.1887	73.65	51.89	0.8466	
	DenseNet-161	68.42	62.54	0.3125	65.21	42.15	0.6326	74.05	73.68	0.1845	71.80	50.98	0.8388	
Image (I) Only	ResNet-152	68.74	62.97	0.3114	65.29	43.02	0.6264	73.14	72.77	0.1800	71.02	50.64	0.8900	
	ResNeXt-101	69.79	63.68	0.3029	66.55	43.68	0.6499	73.91	73.57	0.1812	71.84	51.45	0.8422	
T I T (Unimodal	Late Fusion	73.24	70.25	0.2927	66.67	45.06	0.6077	78.26	78.50	0.1674	76.20	55.84	0.7245	
1 + 1 (Unimodal Dra training)	Concat BERT	71.82	71.82	0.3156	65.54	43.37	0.5976	77.25	76.38	0.1743	76.04	55.95	0.7450	
Pre-training)	MMBT	73.48	67.12	0.3258	68.08	50.88	0.6474	82.54	80.23	0.1413	78.14	58.03	0.7008	
I + T (Multimodal	ViLBERT CC	78.53	78.06	0.1881	75.71	48.82	0.5329	87.25	86.03	0.1276	84.66	64.70	0.6982	
Pre-training)	V-BERT COCO	81.36	80.13	0.1857	74.01	53.85	0.5303	86.80	86.07	0.1318	84.02	63.68	0.7020	
	CLIP	74.23	73.85	0.2955	67.04	44.25	0.6228	80.55	80.25	0.1659	77.00	56.85	0.7852	
Duana and Sustan	CLIP + Proposals	77.65	76.90	0.2142	70.52	45.60	0.5955	84.16	83.80	0.1556	81.06	60.65	0.7122	
Proposed System	CLIP + Attributes	78.10	77.64	0.2010	71.05	45.55	0.5887	84.02	83.85	0.1508	80.75	60.23	0.7058	
and variants	MOMENTA w/o CMAF	80.75	80.17	0.1896	74.85	51.25	0.5360	86.20	85.55	0.1355	83.85	63.02	0.6990	
	MOMENTA	83.82	82.80	0.1743	77.10	54.74	0.5132	89.84	88.26	0.1314	87.14	66.66	0.6805	
Δ <sub>momenta</sub>	-best_model	2.46	2.67	0.0114	1.39	0.89	0.0171	2.59	2.23	0.0038	2.48	1.96	0.0177	

Performance of MOMENTA for harmful meme detection (2-class, 3-class) on both Harm-C and Harm-P datasets.

#### **Evaluation:**

• Similar trend is observed for target identification

Modelity	Madal	Tar	get on H	larm-C	Target on Harm-P			
wodanty	Widdel	Acc ↑	<b>F1</b> ↑	$\mathbf{MMAE}\downarrow$	Acc ↑	<b>F1</b> ↑	<b>MMAE</b> ↓	
	Human <sup>†</sup>	87.55	82.01	0.3647	90.58	72.68	0.6324	
	Majority	46.60	15.89	1.5000	56.47	18.05	1.5000	
Text (T) only	TextBERT	69.35	55.60	0.8988	72.54	60.36	0.8895	
	VGG19	63.48	53.60	1.0549	68.24	55.24	1.0225	
Image (I) only	DenseNet-161	64.52	53.51	1.0065	69.40	57.95	0.9540	
mage (1) only	ResNet-152	65.75	53.78	1.0459	68.75	57.00	0.9667	
	ResNeXt-101	65.82	53.95	0.9277	1.0003 $09.40$ $57.93$ $0.9540$ $1.0459$ $68.75$ $57.00$ $0.9667$ $0.9277$ $70.22$ $59.67$ $0.9245$ $0.6318$ $73.25$ $64.28$ $0.8541$ $0.8879$ $72.46$ $60.87$ $0.8655$ $0.6318$ $74.65$ $65.12$ $0.8441$			
L . T (Unimodal	Late Fusion	72.58	58.43	0.6318	73.25	64.28	0.8541	
I + I (Unimodal Protroining)	Concat BERT	67.74	49.77	0.8879	72.46	60.87	0.8655	
Fleuranning)	MMBT	72.58	58.35	0.6318	74.65	65.12	0.8441	
I + T (Multimodal	ViLBERT CC	72.58	57.17	0.8035	77.25	67.39	0.8410	
Pretraining)	V-BERT COCO	75.81	65.77	0.5036	77.28	66.90	0.8536	
	CLIP	72.47	62.14	0.6312	72.40	65.66	0.8557	
Dropood System	CLIP + Proposals	74.85	64.38	0.5746	75.85	66.13	0.8482	
Proposed System	CLIP + Attributes	74.56	61.38	0.6015	76.20	66.34	0.8491	
and variants	MOMENTA w/o CMAF	76.16	64.80	0.5422	77.54	67.25	0.8430	
	MOMENTA	77.95	69.65	0.4225	78.54	68.83	0.8295	
$\Delta_{\text{moment}}$	$A-best_model$	2.14	3.88	0.0811	1.26	1.44	0.0115	

Performance of MOMENTA for target identification of harmful memes on both Harm-C and Harm-P datasets.

#### **Evaluation:**

- Similar trend is observed for target identification
- MOMENTA outperforms the best models by 2.14 points absolute in terms of accuracy and by 3.88 points in terms of F1 score on Harm-C, and by 1.26 points of accuracy and 1.44 points of F1 on Harm-P

Madality	Madal	Tar	get on H	larm-C	Target on Harm-P			
wooanty	Widdei	Acc ↑	$F1\uparrow$	<b>MMAE</b> ↓	Acc ↑	<b>F1</b> ↑	<b>MMAE</b> ↓	
	Human <sup>†</sup>	87.55	82.01	0.3647	90.58	72.68	0.6324	
	Majority	46.60	15.89	1.5000	56.47	18.05	1.5000	
Text (T) only	TextBERT	69.35	55.60	0.8988	72.54	60.36	0.8895	
	VGG19	63.48	53.60	1.0549	68.24	55.24	1.0225	
Imaga (I) only	DenseNet-161	64.52	53.51	1.0065	69.40	57.95	0.9540	
image (1) only	ResNet-152	65.75	53.78	1.0459	68.75	57.00	0.9667	
	ResNeXt-101	65.82	53.95	0.9277	70.22	arget on Harm-PF1 $\uparrow$ MMAE $\downarrow$ 72.680.632418.051.500060.360.889555.241.022557.950.954057.000.966759.670.924564.280.854160.870.865565.120.844166.900.853665.660.855766.130.848266.340.849167.250.843068.830.82951.440.0115		
L . T (Unimedal	Late Fusion	72.58	58.43	0.6318	73.25	64.28	0.8541	
I + I (Unimodal	Concat BERT	67.74	49.77	0.8879	72.46	60.87	0.8655	
Pretraining)	MMBT	72.58	58.35	0.6318	74.65	65.12	0.8441	
I + T (Multimodal	ViLBERT CC	72.58	57.17	0.8035	77.25	67.39	0.8410	
Pretraining)	V-BERT COCO	75.81	65.77	0.5036	77.28	66.90	0.8536	
	CLIP	72.47	62.14	0.6312	72.40	65.66	0.8557	
Dropood System	CLIP + Proposals	74.85	64.38	0.5746	75.85	66.13	0.8482	
Proposed System	CLIP + Attributes	74.56	61.38	0.6015	76.20	66.34	0.8491	
and variants	MOMENTA w/o CMAF	76.16	64.80	0.5422	77.54	67.25	0.8430	
	MOMENTA	77.95	69.65	0.4225	78.54	68.83	0.8295	
$\Delta_{\text{moment}}$	$A-best_model$	2.14	3.88	0.0811	1.26	1.44	0.0115	

Performance of MOMENTA for target identification of harmful memes on both Harm-C and Harm-P datasets.

#### **Transferability:**

		l i	Harm-C			Harm-P	)	Combined			
		<b>H-2</b> †	<b>H-3</b> ‡	Tar*	<b>H-2</b> †	<b>H-3</b> ‡	Tar*	<b>H-2</b> †	<b>H-3</b> ‡	Tar*	
	ViLBERT	78.06	48.82	57.17	74.20	51.39	54.10	74.85	44.15	46.52	
Harm-C	<b>V-BERT</b>	80.13	53.85	68.77	74.56	52.87	53.46	75.04	45.20	47.66	
	MOMENTA	82.80	54.74	69.65	80.25	61.87	58.39	81.66	49.83	50.12	
	ViLBERT	71.28	42.57	48.20	86.03	64.70	67.39	75.88	44.18	45.82	
Harm-P	V-BERT	72.58	45.10	54.07	86.07	63.68	66.90	76.20	45.69	47.38	
	MOMENTA	76.30	50.46	58.33	88.26	66.66	68.83	80.75	49.70	50.28	
	ViLBERT	73.48	43.11	51.45	76.92	56.50	60.20	79.20	53.65	58.12	
Combined	<b>V-BERT</b>	74.88	46.28	60.82	76.85	56.07	58.22	80.45	53.98	58.76	
	MOMENTA	79.50	51.07	62.56	81.09	62.85	61.87	85.20	58.44	61.20	

 When training and testing on the same dataset, all models yield high F1 scores.

Transferability of the two best-performing baselines and MOMENTA on Harm-C, on Harm-P, and on the combination.

The models are trained on the dataset in the row and tested on the one in the column. All scores are Macro F1.

#### **Transferability:**

		(	Harm-C	;		Harm-P		Combined			
		<b>H-2</b> †	<b>H-3</b> ‡	Tar*	<b>H-2</b> †	<b>H-3</b> ‡	Tar*	<b>H-2</b> †	<b>H-3</b> ‡	Tar*	
	ViLBERT	78.06	48.82	57.17	74.20	51.39	54.10	74.85	44.15	46.52	
Harm-C	<b>V-BERT</b>	80.13	53.85	68.77	74.56	52.87	53.46	75.04	45.20	47.66	
	MOMENTA	82.80	54.74	69.65	80.25	61.87	58.39	81.66	49.83	50.12	
	ViLBERT	71.28	42.57	48.20	86.03	64.70	67.39	75.88	44.18	45.82	
Harm-P	V-BERT	72.58	45.10	54.07	86.07	63.68	66.90	76.20	45.69	47.38	
	MOMENTA	76.30	50.46	58.33	88.26	66.66	68.83	80.75	49.70	50.28	
	ViLBERT	73.48	43.11	51.45	76.92	56.50	60.20	79.20	53.65	58.12	
Combined	<b>V-BERT</b>	74.88	46.28	60.82	76.85	56.07	58.22	80.45	53.98	58.76	
	MOMENTA	79.50	51.07	62.56	81.09	62.85	61.87	85.20	58.44	61.20	

- When training and testing on the same dataset, all models yield high F1 scores.
  - However, MOMENTA shows
    much better transferability
    capabilities. When trained on
    one dataset and tested on a
    different one, MOMENTA yields
    much better results both for
    harmful detection and for target
    identification.

Transferability of the two best-performing baselines and MOMENTA on Harm-C, on Harm-P, and on the combination.

The models are trained on the dataset in the row and tested on the one in the column. All scores are Macro F1.

## Analysis:





(a) LIME image - MOMENTA.

(b) LIME image - ViLBERT





• The fine-grained face detection and the robust CLIP encoder help MOMENTA to better identify subtle harmful elements in the image.

Example of explanation by LIME on both modalities for MOMENTA and ViLBERT.

(c) LIME text - MOMENTA.

## **Conclusion:**

- We introduced two large-scale datasets, **Harm-C** and **Harm-P**, for detecting harmful memes and their targets.
- We benchmarked Harm-C and Harm-P against state-of-the-art unimodal and multimodal models.
- We proposed **MOMENTA**, a novel multimodal deep neural network that systematically analyzes the local and the global perspective of the input meme.
- Extensive experiments showed the efficacy of MOMENTA, which outperforms various state-of-the-art baselines for both tasks.
- We demonstrated model transferability and interpretability.
- In future work, we plan to extend the datasets with more domains and languages.

# Thank You!