Towards a Multi-agent Sytem for Online Hate Speech Detection

Objectives

- Detect hate speech in online social platforms from multimodal posts
- Propose a multi-agent system to moderate hateful content online

Introduction

To tackle hate speech online, a system should:

- have intelligent agents for each modality working together and
- ultimately recommend a human user what actions to take in the real world





Approach

Proposed an end-to-end pipeline for hate speech detection using adaptive fusion methods:

- Auto-Fusion: Train an autoencoder model to capture intermodal dynamics by maximizing correlation between multimodal inputs.
- GAN-Fusion: Train adversarial networks to align cross-modal embeddings.

Given a social media post with text, and visual input (p_t, p_v) , we first obtain their respective latent feature vectors z_t, z_v . Next, we obtain z_{fuse} using a fusion mechanism. Finally, we use z_{fuse} to **classify** the post as hateful or not.

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Important Result

• Introducing input from multiple modalities enhances the • Cross-modal adversarial alignment (GAN-fusion) best m

Results

Model	Classes	Input modes	Fusion type	P	R	F
BiL	binary	text	none	70.08	63.31	66.52
TKM	binary	image+text+caption	Concat	_	_	70.1
SCM	binary	image+text+caption	Concat	_	_	70.2
FCM	binary	image+text+caption	Concat	_	_	70.4
BiL	multi	text	none	45.18	33.4	38.41
BiL	multi	text+caption	none	45.38	33.67	38.67
VBiL	multi	image+text+caption	Concat	55.27	35.54	43.04
VBiL	multi	image+text+caption	Auto-Fusion	59.65	43.87	50.56
VBiL	multi	image+text+caption	GAN-Fusion	61.33	51.34	55.89

Table: Precision (P), Recall (R), F1-score (F) for multimodal hate speech detection on MMHS150K [1].

Model	Input modes	Fusion type	Р	\mathbf{R}	\mathbf{F}	A
E1	audio	none	57.3	57.3	57.3	56.6
E2	text	none	71.4	63.2	67.1	64.9
BiL1	text	none	53.2	40.6	43.4	43.6
BiL2	audio+text	Concat	66.1	65.0	65.5	64.2
E3	audio+text	Concat	72.9	71.5	72.2	70.1
MDRE	audio+text	Concat	-	-	-	71.8
MHA-2	audio+text	Concat	-	-	-	76.5
M1	audio+text	Auto-Fusion	75.3	77.4	76.3	77.8
M2	audio+text	GAN-Fusion	77.3	79.1	78.2	79.2

Model	Input modes	Fusion type	Ρ	\mathbf{R}	\mathbf{F}	Α
E1	audio	none	57.3	57.3	57.3	56.6
E2	text	none	71.4	63.2	67.1	64.9
BiL1	text	none	53.2	40.6	43.4	43.6
BiL2	audio+text	Concat	66.1	65.0	65.5	64.2
E3	audio+text	Concat	72.9	71.5	72.2	70.1
MDRE	audio+text	Concat	-	_	-	71.8
MHA-2	audio+text	Concat	-	_	-	76.5
M1	audio+text	Auto-Fusion	75.3	77.4	76.3	77.8
M2	audio+text	GAN-Fusion	77.3	79.1	78.2	79.2

Table: Precision (P), Recall (R), F1-score (F), and Accuracy (A) for emotion recognition on the IEMOCAP dataset. The results confirm general value of the multimodal architecture.

e efficacy of hate speech detection.
nodels context in a multi-modal sample.



Loss Functions

• Auto-Fusion: The MSE loss is given by: $J_{tr} = || \; \boldsymbol{\hat{z}_m^k} - \boldsymbol{z_m^k} \; ||^2$ (1)• **GAN-Fusion:** Overall adversarial loss: $J_{adv} = J_{adv}^t + J_{adv}^v$ where,

 $\min_{G} \max_{D} J^{i}_{adv}(D,G) = \mathbb{E}_{x \sim p_{\boldsymbol{z}_{\boldsymbol{j}}}(x)}[\log D(x)] \quad (2)$ $+ \mathbb{E}_{\boldsymbol{z} \sim p_{z_i}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]$ where $i \neq j \forall i, j \in \{t, v\}$.

Conclusion & Future Work

• We sketch a solution to the problem of hate speech detection through a multi-agent system. • We demonstrate the effectiveness of adaptive fusion techniques for coordinating text processing and image processing.

• The proposed system can be used by a human user to moderate content online.

• It aligns with previous work [2] which proposes intelligent recommendation systems as social good for the management of social networks.

• We plan to embed external knowledge base to enhance context capturing ability of the system.

References

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