



西安交通大学
XI'AN JIAOTONG UNIVERSITY



国防科技大学
NATIONAL UNIVERSITY
OF DEFENSE TECHNOLOGY



FNDPro: Evaluating the Importance of Propagations during Fake News Spread

Herun Wan¹ & Ningnan Wang¹ & Xiang Zhao²
& Rui Li¹ & Hui Yang³ & Minnan Luo¹✉

Xi'an Jiaotong University¹, National University of Defense Technology²,
The 30th Research Institute of China Electronics Technology Group Corporation³

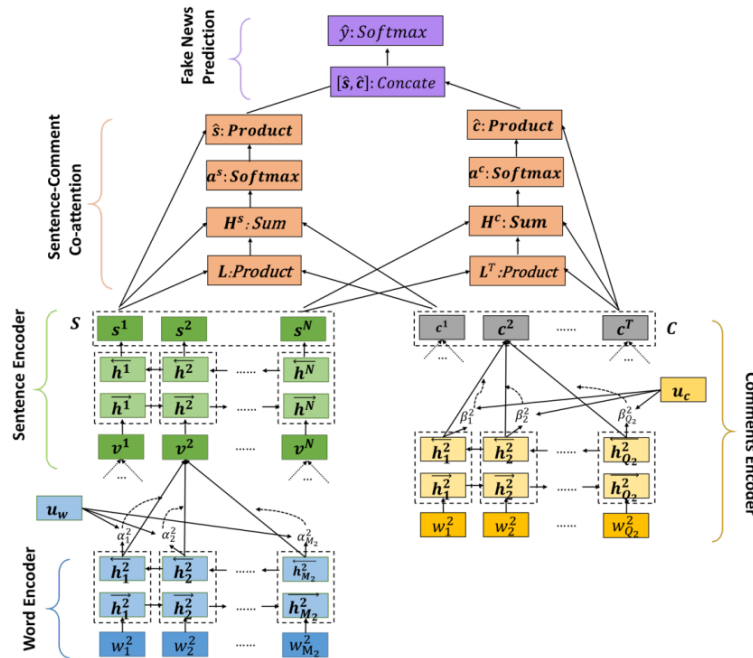
Background

- The rise of social media has led to an unprecedented spread of misinformation and disinformation.
- Fake news can disrupt social order and has harmful societal effects.

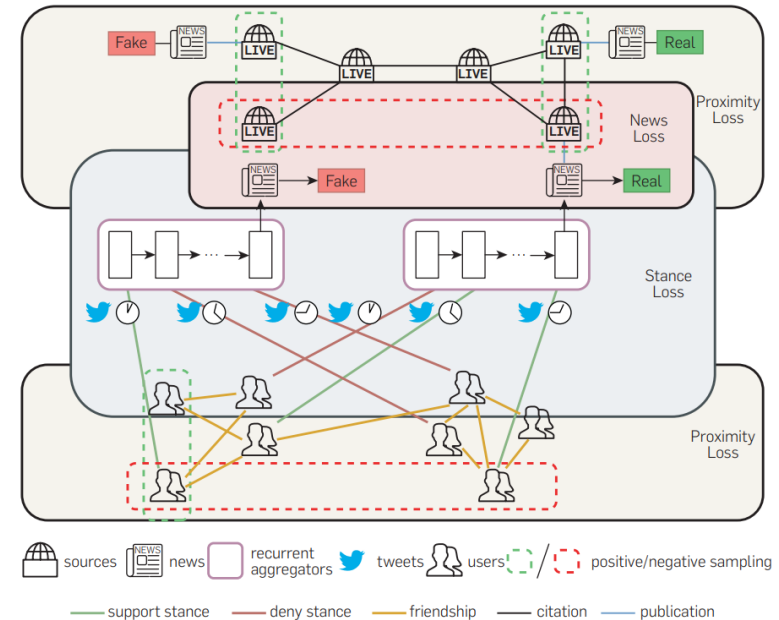


Previous Works

- The majority of the existing approaches are text-based and graph-based.



Text-based model, cite from DEFEND[1]



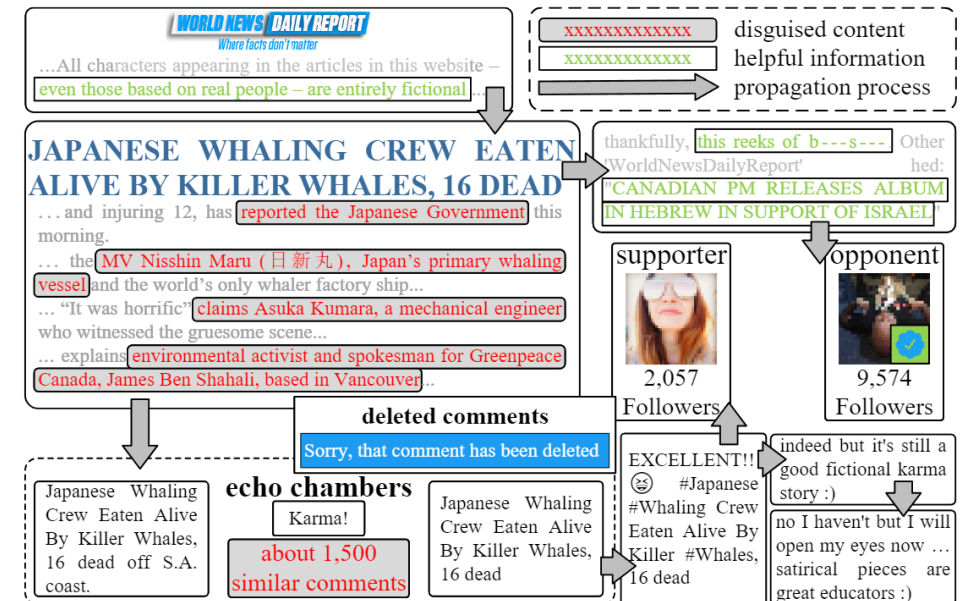
Graph-based model, cite from FANG[2]

[1] Shu, Kai, et al. "defend: Explainable fake news detection." SIGKDD. 2019.

[2] Nguyen, Van-Hoang, et al. "Fang: Leveraging social context for fake news detection using graph representation." CIKM. 2020.

Challenges

- Disguised fake news content makes it hard for content-based models to identify fake news.
- Echo chambers created by repeated fake news and manipulation of comments can confuse traditional graph-based models.

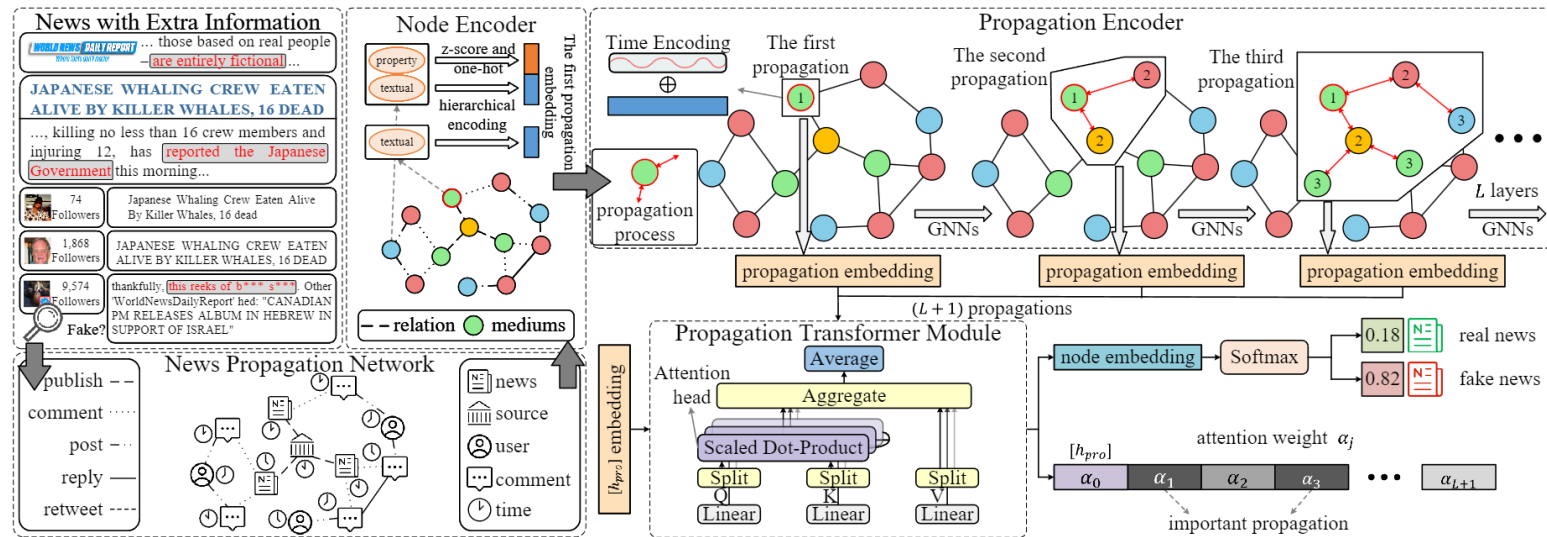


A model that can *dynamically evaluate the contribution of each propagation* and identify critical ones during the news spread.

Our Approach

- Overview
 - FNDPro models the news propagation process as a heterogeneous dynamic graph.
 - It treats news as the first propagation and ℓ -hop neighbors as the $(\ell+1)$ -th propagation.

Our Approach

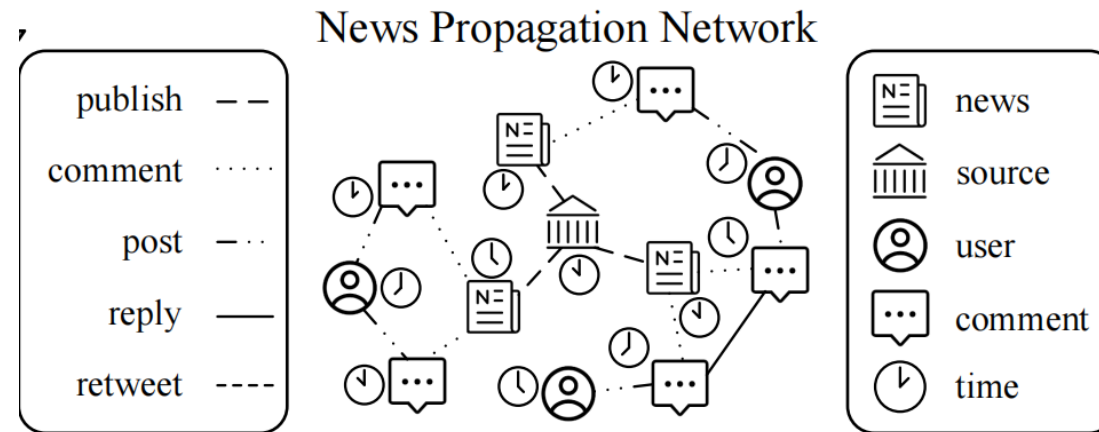


- **Multi-modality encoder:** Encodes each media.
- **Propagation encoder:** Encodes each propagation.
- **Propagation transformer module:** Interacts with propagation embeddings to obtain the importance score of each propagation.

Technical Approach

- Graph Construction

- News, sources, users, comments, and different edges among the media form the heterogeneous dynamic graph.



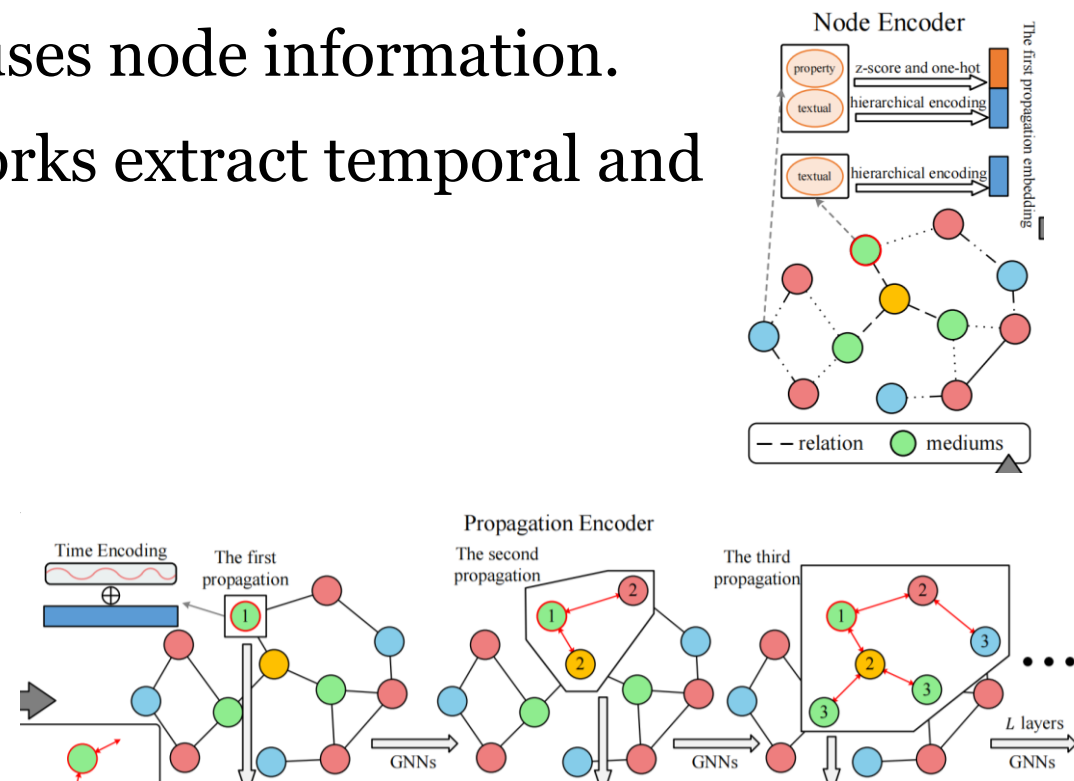
Technical Approach

- Propagation Embedding
 - Multi-modality encoder extracts and fuses node information.
 - Time encoding and graph neural networks extract temporal and spatial information.

$$r_v = \bar{r}_v + \text{mean}_{(u,v) \in \mathcal{E}} (\text{enc}_{\psi(u,v)}(\mathcal{T}(u) - \mathcal{T}(v)))$$

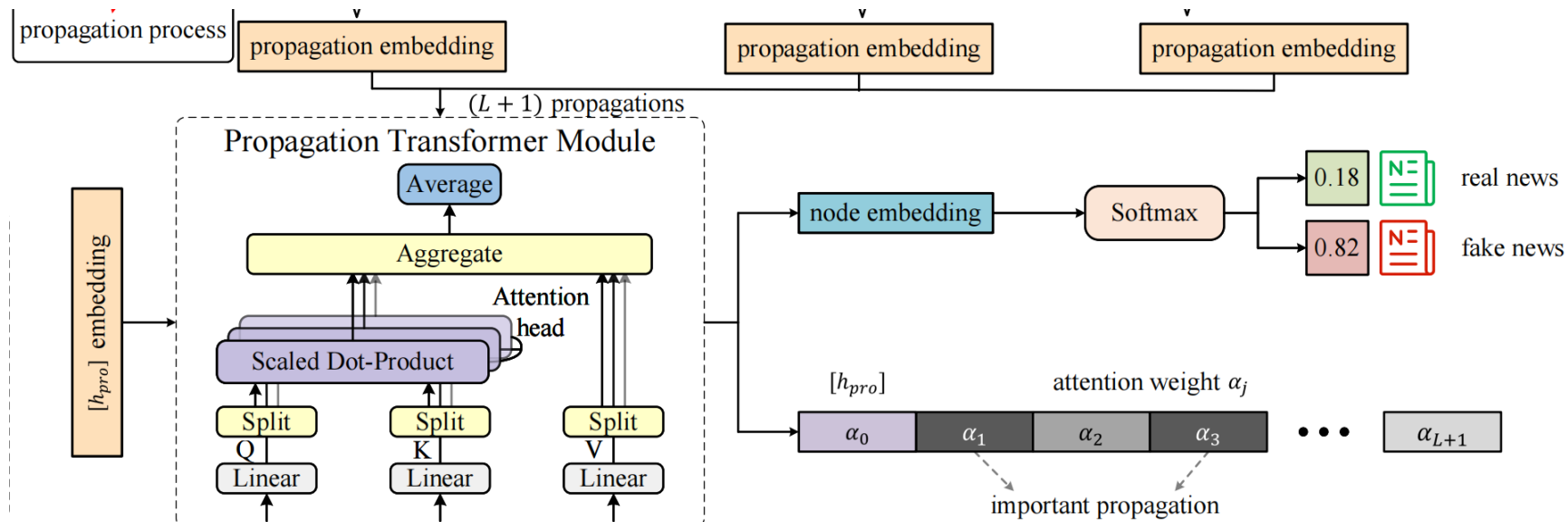
$$h_{\mathcal{N}_{\mathcal{R}}(u)}^{(\ell)} = \text{Prop}(\{h_v^{(\ell-1)} : v \in \mathcal{N}_{\mathcal{R}}(u)\}, \mathcal{R} \in \mathcal{R}^e,$$

$$h_u^\ell = \text{Aggr}(\{h_{\mathcal{N}_{\mathcal{R}}(u)}^\ell : \mathcal{R} \in \mathcal{R}^e\}, h_u^{(\ell-1)}).$$



Technical Approach

- Propagation Transformer Module
 - Dynamically evaluates the contribution of different propagations.
 - Attention weights indicate the importance of each propagation.



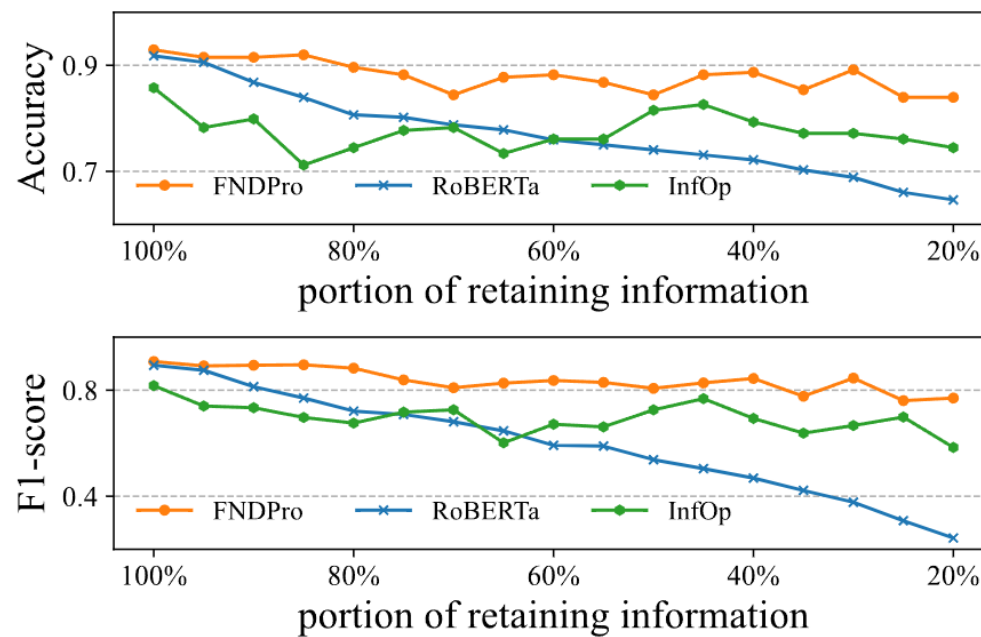
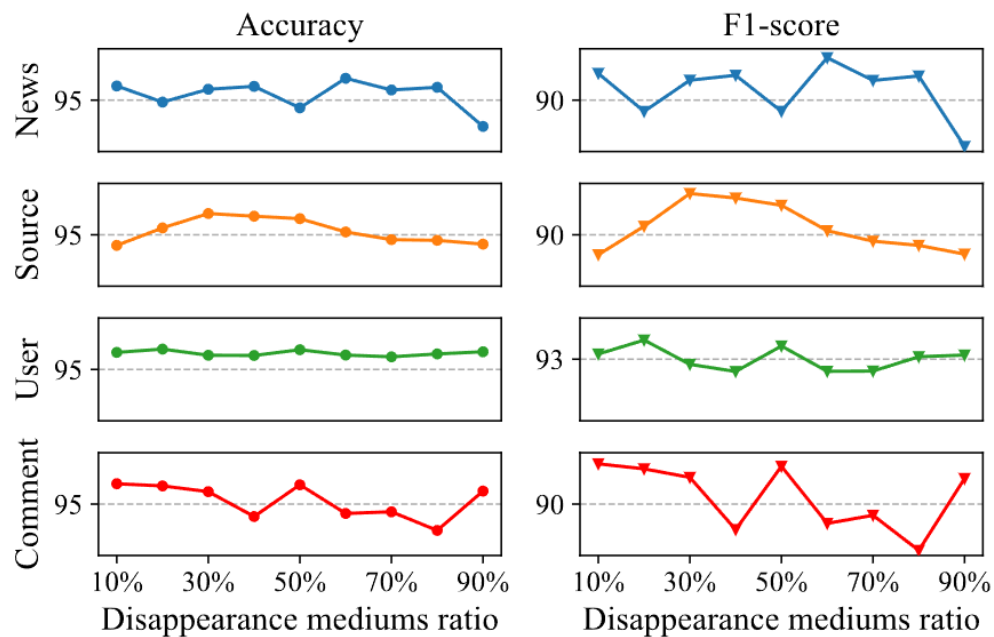
Main Results

Type	Models	Merged		Politifact		Gossipcop	
		Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score
Content-based	DEFEND [30]	84.1 (± 4.1)*	67.8 (± 6.9)*	84.4 (± 1.0)*	78.5 (± 2.5)*	87.4 (± 2.8)*	73.0 (± 6.5)*
	RoBERTa [49]	85.5 (± 0.2)*	67.6 (± 1.1)*	88.8 (± 0.3)*	86.4 (± 0.3)*	86.3 (± 0.3)*	69.7 (± 1.0)*
	UPF [†] [34]	94.4 (± 0.2)*	86.0 (± 0.4)*	86.8 (± 0.6)*	84.4 (± 0.7)*	95.2 (± 0.0)*	88.0 (± 0.1)*
	NEP [29]	81.8 (± 0.1)*	58.8 (± 1.5)*	87.5 (± 0.4)*	84.0 (± 0.5)*	82.1 (± 0.1)*	59.9 (± 1.4)*
	CMTR [9]	91.8 (± 0.7)*	82.1 (± 3.0)*	83.4 (± 1.9)*	77.3 (± 3.3)*	93.3 (± 0.6)*	86.2 (± 0.5)*
	FInERFACT [†] [14]	95.5 (± 0.1)*	91.6 (± 0.2)*	86.2 (± 0.1)*	88.1 (± 0.2)*	95.9 (± 0.1)*	93.1 (± 0.2)*
Graph-based	HPN [†] [32]	87.3 (± 0.2)*	82.4 (± 0.3)*	78.1 (± 0.7)*	81.2 (± 0.6)*	87.1 (± 0.1)*	81.4 (± 0.2)*
	Bi-GCN [1]	90.4 (± 0.5)*	90.0 (± 0.7)*	77.1 (± 1.4)*	74.7 (± 2.2)*	90.8 (± 0.3)*	90.4 (± 0.3)*
	FANG [25]	81.3 (± 0.2)*	53.7 (± 1.5)*	80.3 (± 1.5)*	75.4 (± 3.1)*	82.7 (± 0.1)*	51.2 (± 1.2)*
	UPFN [†] [5]	93.6 (± 1.0)*	93.7 (± 0.8)*	89.5 (± 2.1)*	87.2 (± 2.6)*	95.8 (± 0.8)*	95.8 (± 0.8)*
	CROSS-D [†] [35]	89.8 (± 0.3)*	86.1 (± 0.4)*	88.3 (± 0.9)*	87.8 (± 0.9)*	90.3 (± 0.3)*	87.1 (± 0.5)*
	INFOp [22]	95.8 (± 0.1)*	91.5 (± 0.2)*	85.8 (± 1.3)*	81.7 (± 1.6)*	96.1 (± 0.1)*	92.2 (± 0.1)*
	GET [41]	91.3 (± 0.4)*	81.5 (± 1.7)*	88.5 (± 0.2)*	83.8 (± 0.7)*	91.1 (± 1.4)*	82.9 (± 0.5)*
	FNDPro	97.0 (± 0.2)	93.9 (± 0.3)	92.9 (± 0.5)	90.8 (± 0.6)	97.4 (± 0.1)	94.7 (± 0.2)

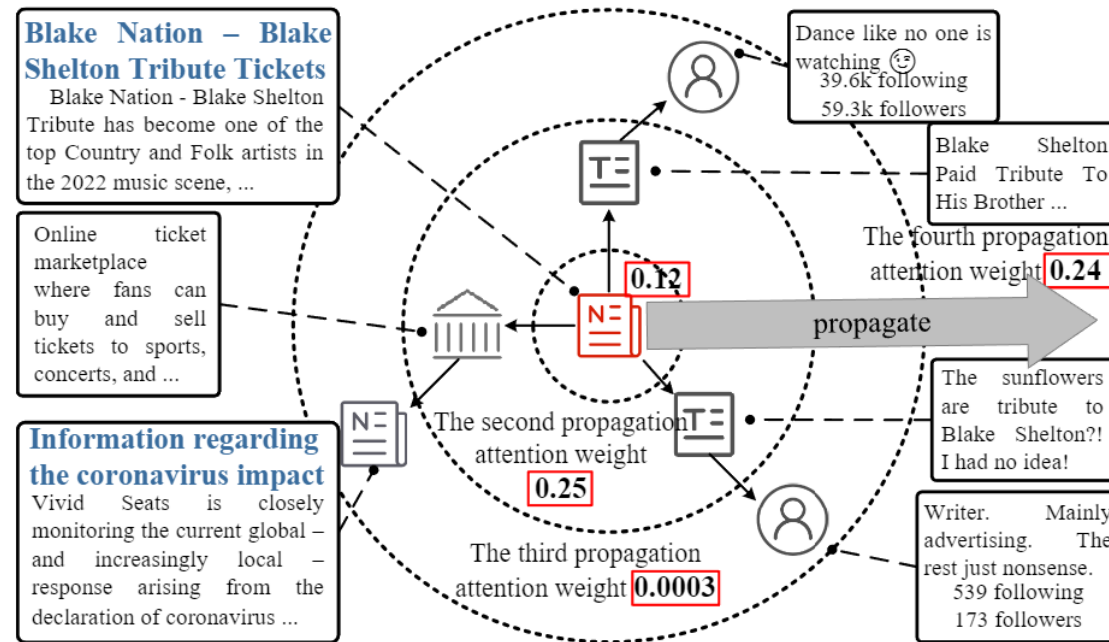
Ablation Study

Module	Accuracy	Difference	F1-score	Difference
First	84.9 (± 0.3)*	-12.1	64.9 (± 1.3)*	-29.0
Last	96.2 (± 0.5)**	-0.9	92.3 (± 0.7)**	-1.6
Mean	85.7 (± 1.0)*	-11.3	76.0 (± 1.2)*	-17.9
Max	95.9 (± 0.4)*	-1.1	91.8 (± 0.7)*	-2.1
MLP	96.0 (± 0.6)**	-1.0	92.0 (± 1.1)**	-1.9
GRU	94.3 (± 0.9)*	-2.7	89.2 (± 1.4)*	-4.7
FNDP_{RO}	97.0 (± 0.2)	0	93.9 (± 0.3)	0

Analysis



Case Study



Conclusion

- FNDPro dynamically evaluates the importance of propagations during fake news spread.
- It effectively addresses challenges posed by disguised content and echo chambers.
- Thank the conference organizers, collaborators, and funding agencies.

Q&A

- Contact Details

Herun Wan: wanherun@stu.xjtu.edu.cn

- GitHub Repository



<https://github.com/whr000001/FNDPro>