HG-SL: Jointly Learning of Global and Local User Spreading Behavior for Fake News Early Detection

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Introduction

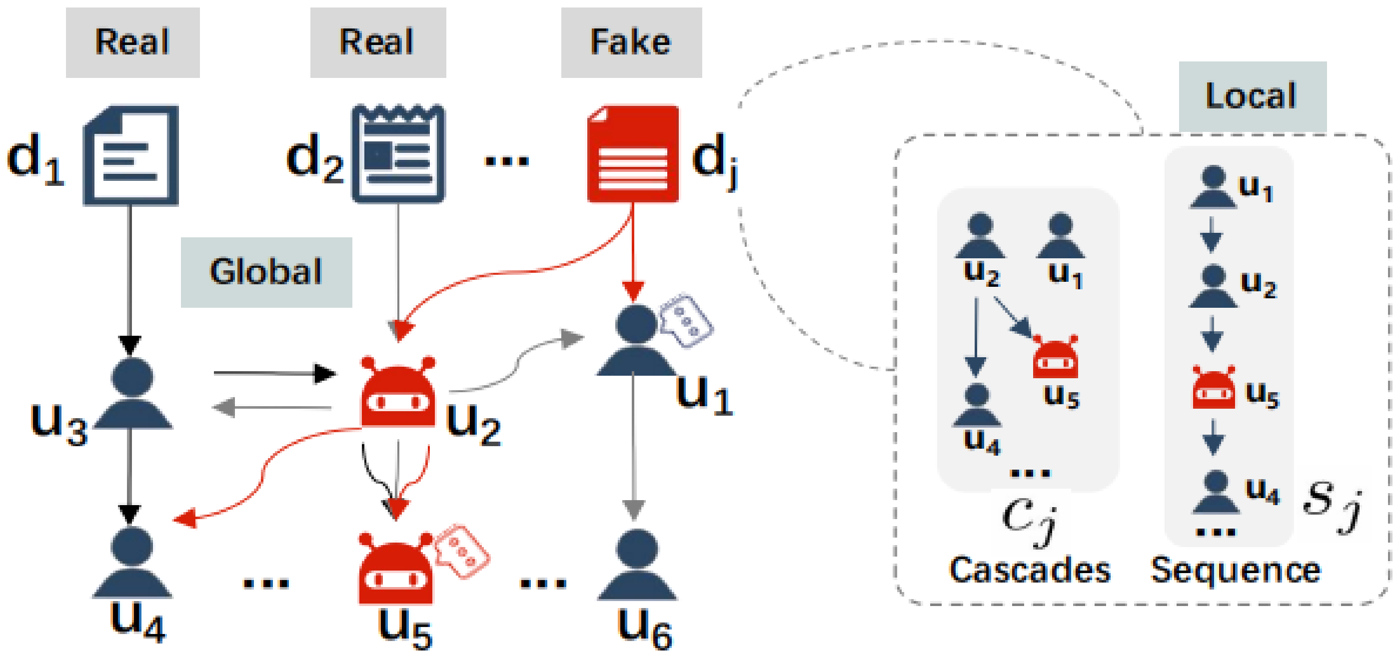
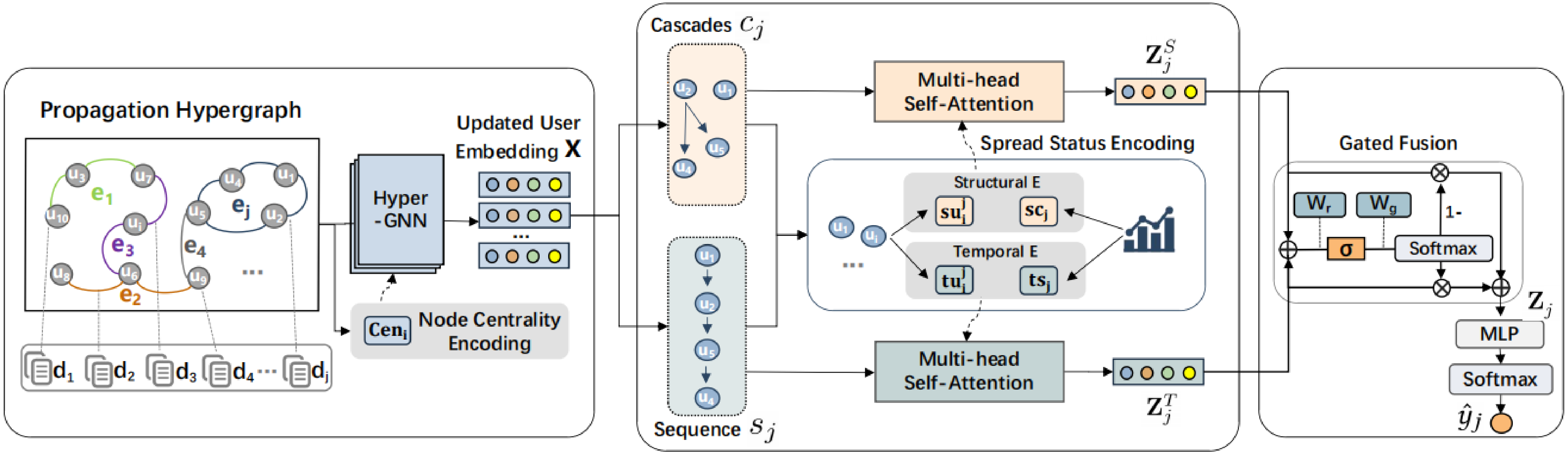


Figure 1: Illustration of global and local user spreading behavior, fake objects and abnormal users are highlighted in red. The abnormal user u_2 tricks a normal user u_4 to spread the fake news d_j, and u_5 cooperates with u_2 to make fake comments, further causing confusion.

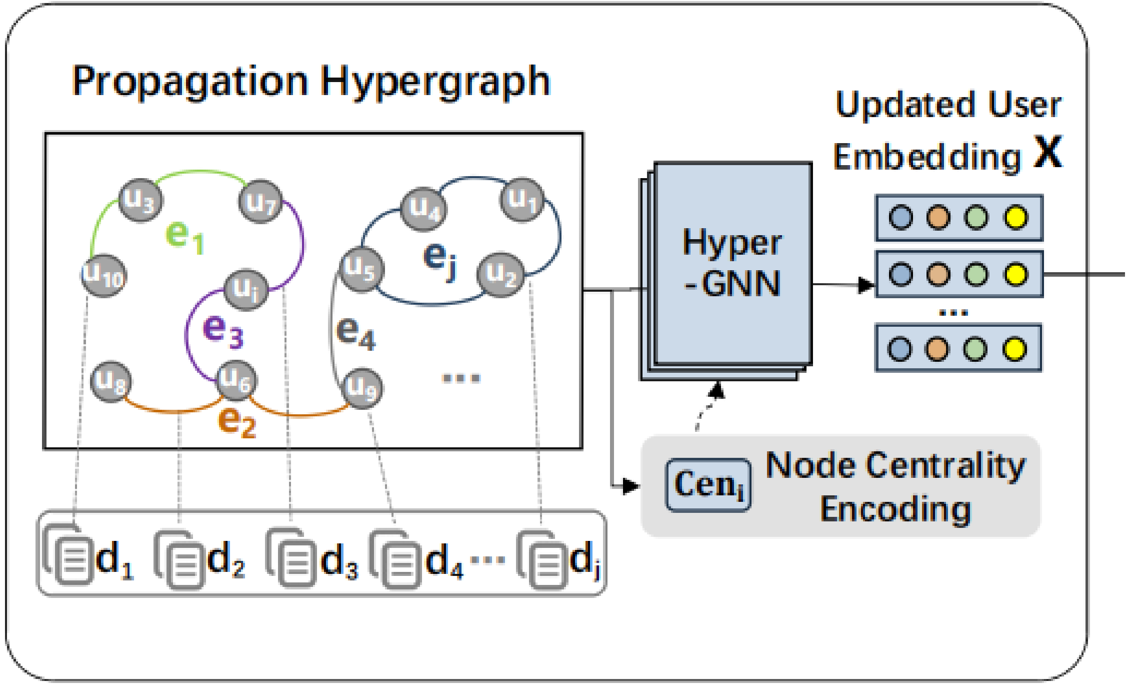
Method



(a) Hypergraph-based Global Interaction Learning (HG) (b) Self-attention-based Local Context Learning (SL) (c) Fusion & Detection

Figure 2: An overview of the architecture of HG-SL which consists of three major components: (1) Global interaction learning module uses hypergraph neural networks and node centrality encoding to learn the global relations of users, (2) local structural and temporal features are learned in local context learning module through multi-head self-attention mechanism and spread status encoding, and (3) in fusion & detection module, news propagation representations from structural and temporal aspects are merged for detection through gated fusion mechanism.

Method



(a) Hypergraph-based Global Interaction Learning (HG)

$$D = \{d_1, d_2, ..., d_m\}$$

$$U = \{u_1, u_2, ..., u_n\}$$

$$G = (U, E)$$

Activity degree

$$Act_i = |\mathcal{E}_i|$$

$$Cen_i$$

$$x_i^0 = x_i^{ini} + Cen_i$$

Hypergraph Neural Network

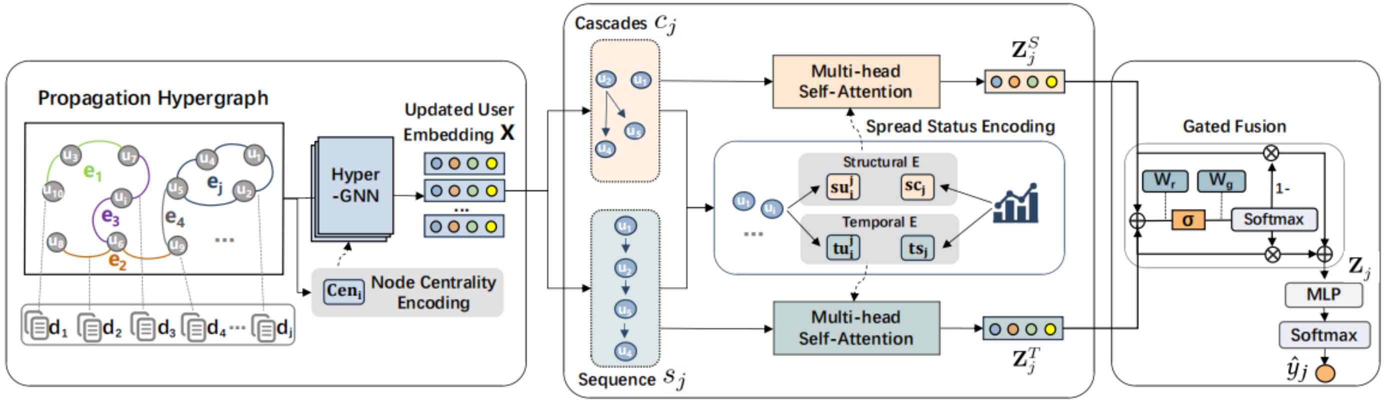
Nodes-to-edge Aggregation.

$$\mathbf{a}_j^l = \sigma\left(\sum_{u_i \in e_j} \frac{1}{|e_j|} \mathbf{W}_1 \mathbf{x}_i^{l-1}\right) \quad (1)$$

Edges-to-node Aggregation.

$$\mathbf{x}_i^l = \sigma\left(\sum_{e_j \in \mathcal{E}_i} \frac{1}{|\mathcal{E}_i|} \mathbf{W}_2 \mathbf{a}_j^l\right) \quad (2)$$

Method



(a) Hypergraph-based Global Interaction Learning (HG) (b) Self-attention-based Local Context Learning (SL) (c) Fusion & Detection

$$D \text{ as } C = \{c_1, c_2, \ldots, c_m\} \text{ and } S = \{s_1, s_2, \ldots, s_m\}$$

$$c_j = \{c_{j,1}, c_{j,2}, \ldots, c_{j,k}\}$$

$$c_{j,p} = \left\{(u_i, L_i^{j,p}, I_i^{j,p}) | u_i \in U\right\}$$

$$s_j = \left\{(u_i, t_i^j) | u_i \in U\right\}$$

Local Temporal Learning

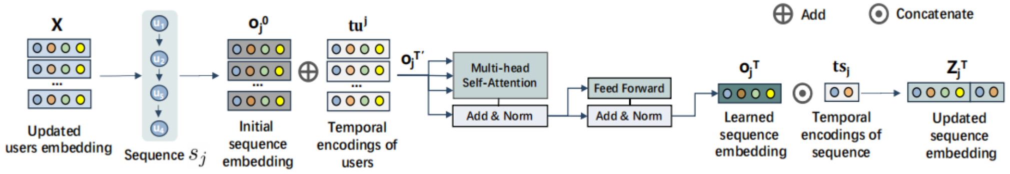


Figure 3: Temporal learning process of multi-head self-attention module. User-level temporal encodings are introduced before learning, while encodings of sequence level are supplemented after self-attention learning.

$$\mathbf{o}_j^{T'} = [(\mathbf{x}_i + tu_{i,1}^j + tu_{i,2}^j) | u_i \in s_j].$$

$$\mathrm{Att}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \mathrm{softmax}\left(\frac{\mathbf{QK}''}{\sqrt{d^d/H}}\right)\mathbf{V} \quad (3)$$

$$\mathbf{h}_{q,j}^T = \mathrm{Att}\left(\mathbf{o}_j^{T'}\mathbf{W}_q^{QT}, \mathbf{o}_j^{T'}\mathbf{W}_q^{KT}, \mathbf{o}_j^{T'}\mathbf{W}_q^{VT}\right)$$

$$\mathbf{h}_j^T = [\mathbf{h}_{1,j}^T; \mathbf{h}_{2,j}^T; \ldots; \mathbf{h}_{H,j}^T]\,\mathbf{W}_O^T \quad (4)$$

$$\mathbf{o}_j^T = \mathrm{MEAN}(\mathbf{W}_{A_2}\sigma\left(\mathbf{W}_{A_1}(\mathbf{h}_j^T)'' + \mathbf{b}_1\right) + \mathbf{b}_2) \quad (5)$$

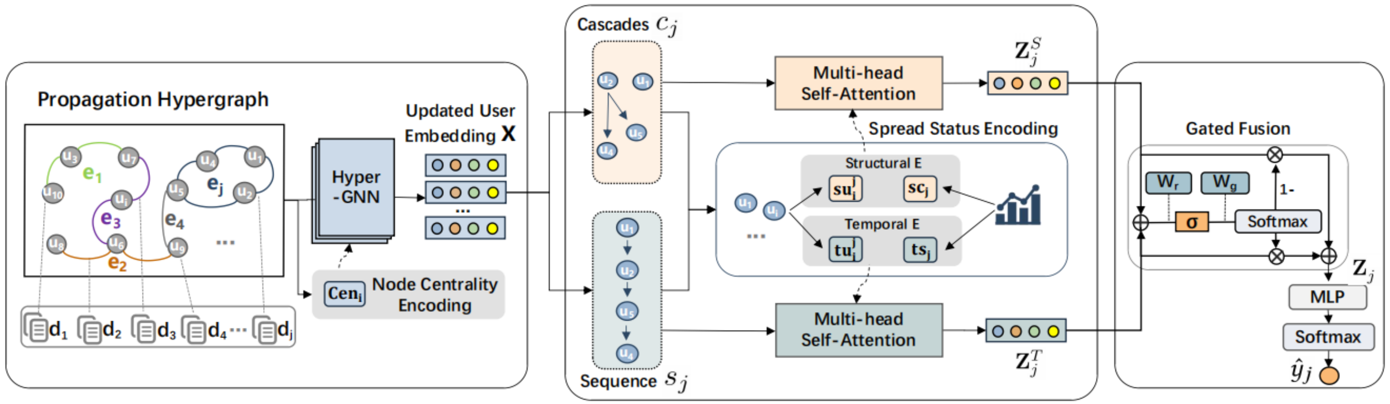
$$\mathbf{Z}_j^T = [\mathbf{o}_j^T, ts_j]$$

Method

Local Structural Learning

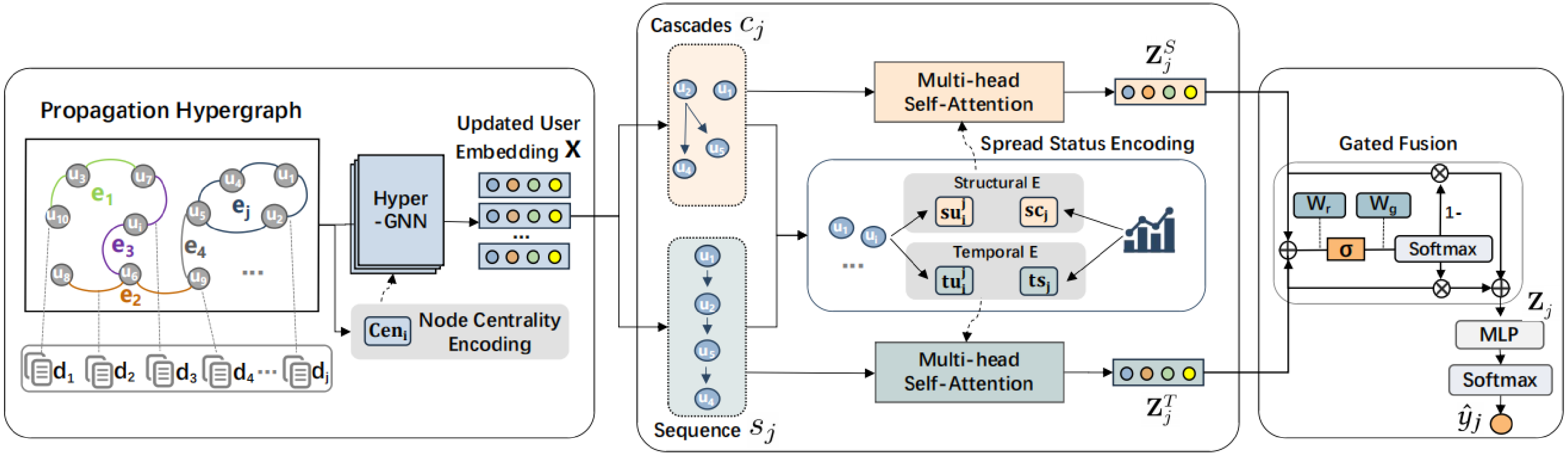
$$\mathbf{o}_j^{S'} = [(\mathbf{x}_i + su_{i,1}^{j,p} + su_{i,2}^{j,p}) | u_i \in c_{j,p}]$$

$$\mathbf{Z}_j^S = [\mathbf{o}_j^S, \mathbf{sc}_j]$$



(a) **H**ypergraph-based **G**lobal Interaction Learning **(HG)** (b) **S**elf-attention-based **L**ocal Context Learning **(SL)** (c) Fusion & Detection

Method



(a) Hypergraph-based Global Interaction Learning (HG) (b) Self-attention-based Local Context Learning (SL) (c) Fusion & Detection

Fusion & Detection

$$\mathbf{Z}_j = g\mathbf{Z}_j^S + (1-g)\mathbf{Z}_j^T$$

$$g = \frac{\exp(\mathbf{W}_g\sigma(\mathbf{W}_r\mathbf{Z}_j^S))}{\exp(\mathbf{W}_g\sigma(\mathbf{W}_r\mathbf{Z}_j^T))+\exp(\mathbf{W}_g\sigma(\mathbf{W}_r\mathbf{Z}_j^S))} \quad (6)$$

$$\hat{y}_j = \mathrm{softmax}(\mathbf{W}_p\mathbf{Z}_j + \mathbf{b}_p) \quad (7)$$

$$\mathcal{J}(\theta) = -\frac{1}{m}\left(\sum_{j=1}^{m} y_j \log(\hat{y}_j) + (1-y_j)\log(1-\hat{y}_j)\right) \quad (8)$$

Experiments

Datasets	PolitiFact	GossipCop
# Fake news	157	2,732
# Real news	157	2,732
# Users	28,049	65,064
# Spreads	36,481	291,043
Avg. # Participants / News	116	53
Max # Participants / News	759	195
Min # Participants / News	1	1

Table 1: Statistics of datasets used in our experiments

Experiments

Method	Considerations						Politifact				Gossipcop			
	Text	Temp.	Stru.	User	Local	Global	Acc.	Prec.	Rec.	F1	Acc.	Prec.	Rec.	F1
GRU	✓	✓			✓		62.73	63.82	61.30	60.98	78.92	82.33	78.57	80.36
PPC		✓		✓	✓		64.21	64.56	61.07	62.82	90.38	90.33	91.10	90.71
CSI	✓	✓		✓	✓	✓	75.33	83.36	74.20	75.82	78.20	82.34	78.32	80.89
BiGCN			✓	✓	✓		78.83	80.39	76.26	78.71	89.02	92.79	84.81	88.97
GCNFN	✓		✓	✓	✓		82.35	86.85	76.80	82.24	95.61	94.40	97.02	95.59
GLAN	✓		✓	✓	✓	✓	82.34	84.68	<u>83.59</u>	84.13	95.52	94.63	93.29	93.96
UPFD	✓		✓	✓	✓	✓	<u>84.31</u>	<u>87.14</u>	81.03	<u>84.25</u>	<u>97.09</u>	<u>96.91</u>	<u>97.31</u>	<u>97.07</u>
HPFN	✓	✓	✓		✓		75.63	71.46	85.40	77.80	86.39	85.66	87.41	86.53
Ours		✓	✓		✓	✓	**90.05**	**92.30**	**88.61**	**89.93**	**98.04**	**98.40**	**97.68**	**98.01**

Table 2: Performance comparison of our proposed HG-SL with baselines (%).

Experiments

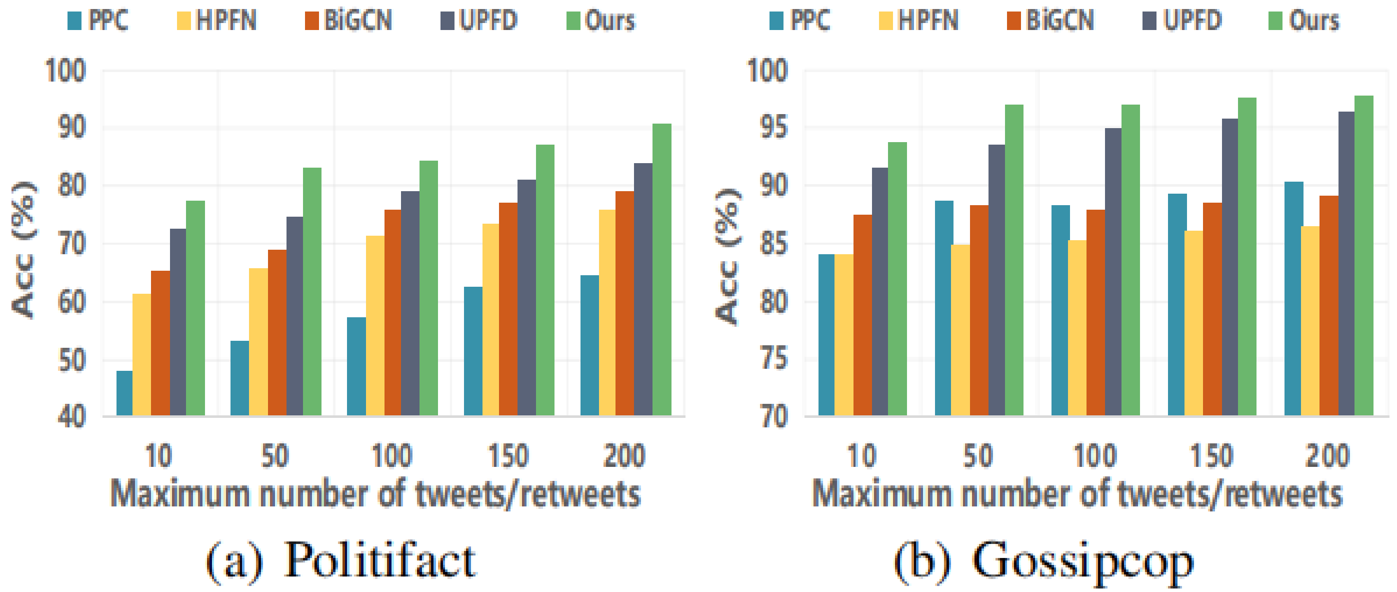
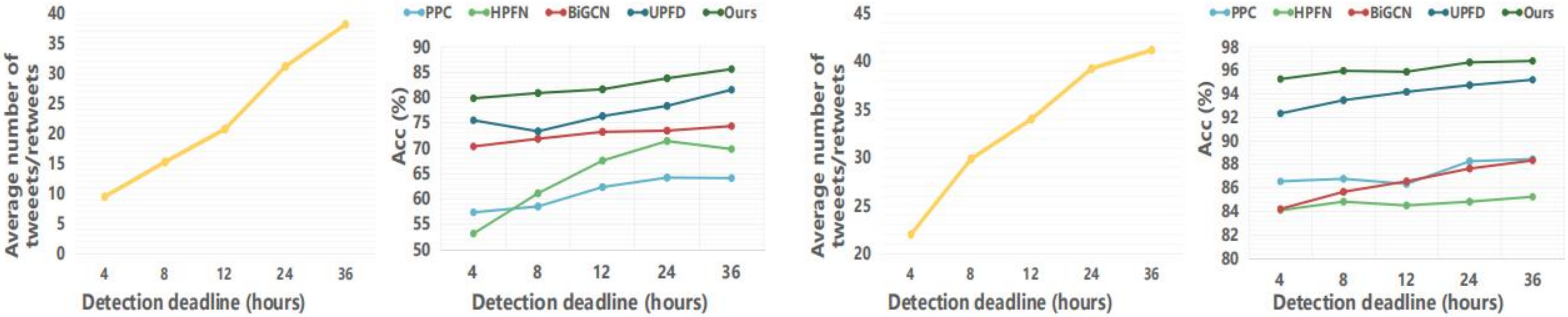


Figure 4: Performance comparison under different maximum engagements (tweets/retweets).

Experiments



(a) Politifact: engagement trends (b) Politifact: detection Acc. (c) Gossipcop:engagement trends (d) Gossipcop: detection Acc.

Figure 5: Performance comparison with different detection deadlines

Experiments

Encodings		Politifact							Gossipcop						
		Fake			Real			P-value	Fake			Real			P-value
		Min	Max	Avg	Min	Max	Avg		Min	Max	Avg	Min	Max	Avg	
Stru.	**SC_1**	1	282	79.4	1	450	62.7	**0.05**	1	173	26.1	1	187	60.6	**0.0**
	SC_2	0	1	0.17	0	1	0.19	**0.30**	0	1	0.15	0	1	0.04	**8e-198**
Temp.	**TS_1**	0	3517.6	262.5	0	4143.5	1495.1	**3.9e-21**	0	3692.6	322.3	0	3555.3	62.7	**1.5e-72**
	TS_2	0	1195.1	32.5	0	3355.4	490.2	**4.1e-12**	0	3692.5	137.9	0	3239.6	21.9	**2.9e-34**

Table 3: Analysis of statistical spread status features. (p-value less than 0.05 is significant)

Experiments

Method	Politifact		Gossipcop	
	Acc.	F1	Acc.	F1
- HG	78.73	78.07	96.00	95.97
- SL	85.52	85.43	97.69	97.67
- Structural SL	88.23	88.11	97.80	97.78
- Temporal SL	85.97	85.91	97.83	97.80
- Node centrality E	89.59	89.55	97.72	97.70
- Structural E	88.68	88.65	97.88	97.86
- Temporal E	87.97	87.84	97.85	97.83
- Gated fusion	89.59	89.46	97.97	97.58
HG-SL	**90.05**	**89.93**	**98.04**	**98.01**

Table 4: Ablation study (%).

Thanks