Understanding Political Polarization via Jointly Modeling Users, Connections and Multimodal Contents on Heterogeneous Graphs

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Introduction

- A 2016 Pew Research study [1] found that of all U.S. adults, 67% use social media platforms with 44% using the platforms to discover news
- Social media is found to shape political discourse in the U.S. and the whole world [2]
- The extent to which the opinions on an issue are opposed is termed "political polarization" [3]. The formation of such political polarization is not necessarily a serious problem, but the concern is that the opinions may become increasingly polarized when they are shared, viewed and discussed in a homogeneous community [2]
- Therefore, understanding political polarization on social platforms is important
- We introduce an efficient framework based on bipartite heterogeneous graph neural networks (GNN) to learn user embeddings **without requiring political ideology labels**. The learned embeddings are then used to detect the political ideology of social media users and understand online political polarization

Method and Material

Datasets: We employ two large-scale Twitter datasets that record online discussions on economy (inflation) and public health (COVID-19 vaccination) to demonstrate the effectiveness of our framework. The total size of these two datasets is **significantly larger** than most public datasets for ideology detection.

Table 1: Statistics of the *inflation* and *vaccine* datasets.

Dataset	# unique users	# unique tweets	# tweets
inflation	8,824	22,661	42,297
vaccine	2,214	10,998	20,331

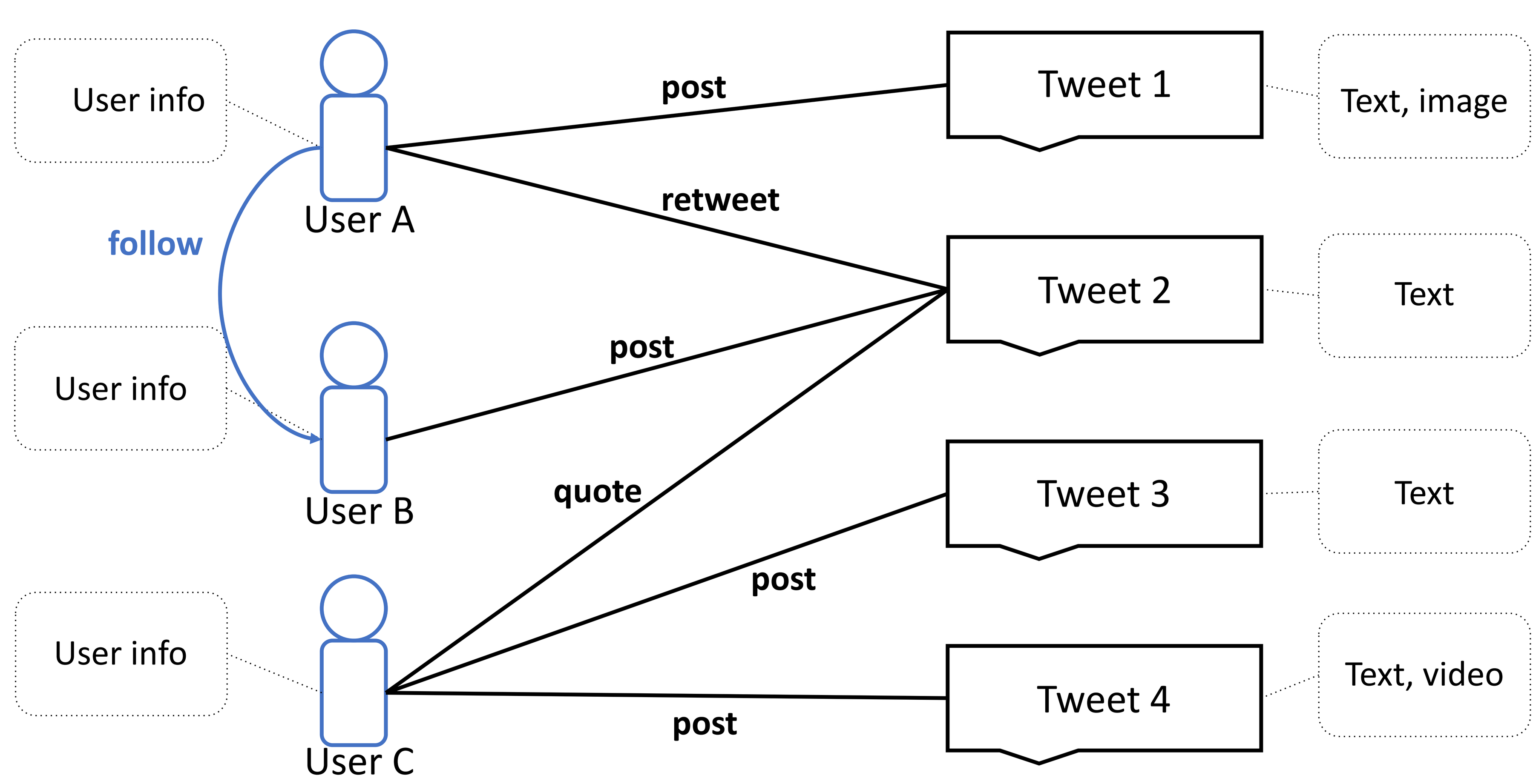

Figure 1: An example of different node types and relation types on Twitter.

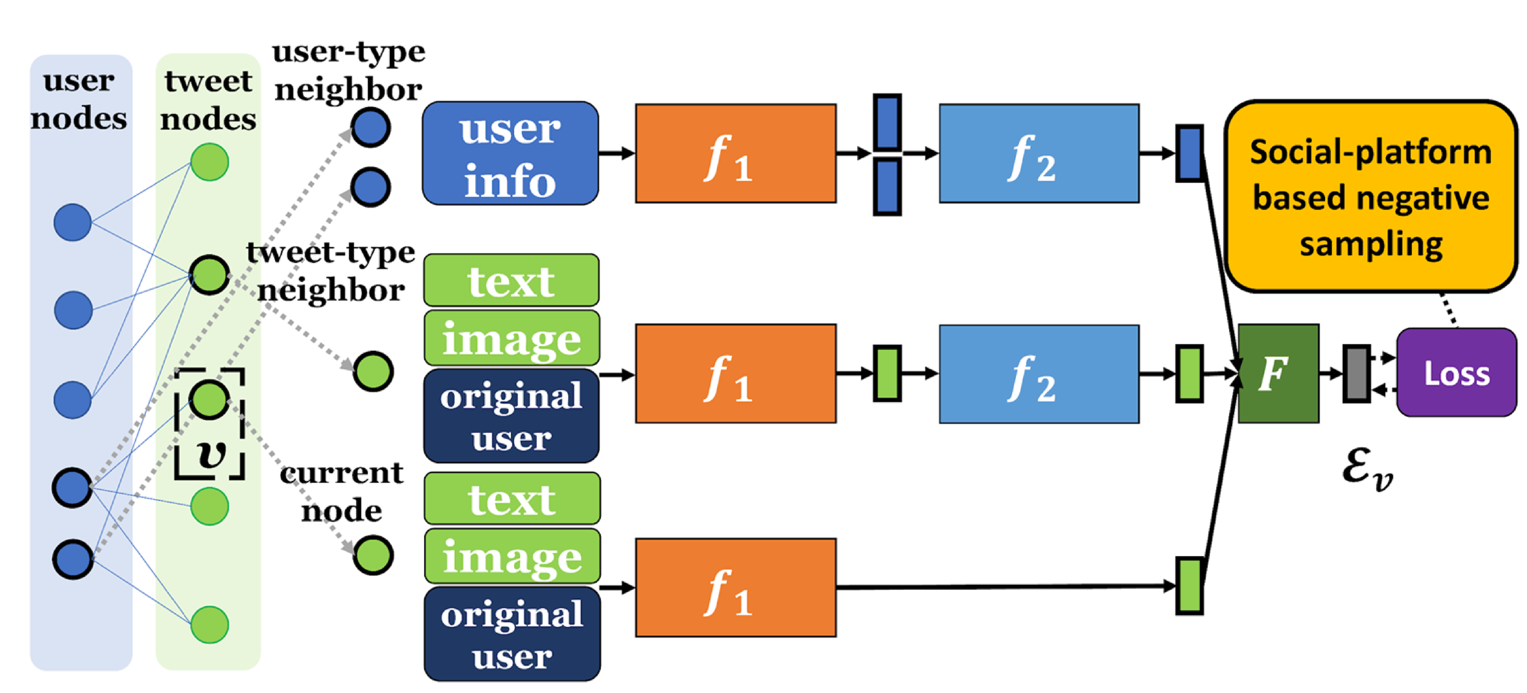

Figure 2: The diagram of our framework.

Results

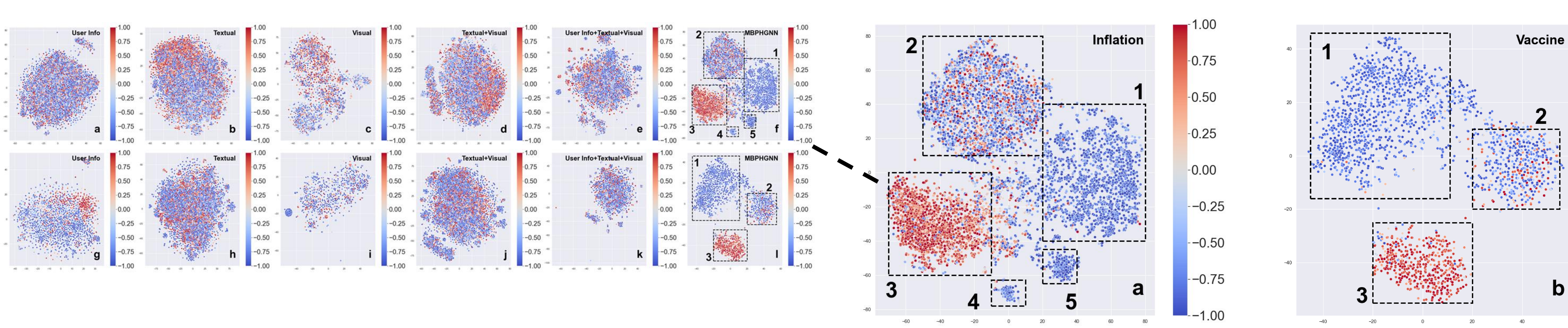

Figure 3: t-SNE visualization.

Table 2: Results using the logistic regression model (The best results are highlighted in bold).

Dataset	**Representation**	Accuracy	Precision	Recall	F1	AUROC
Inflation	User Info	0.65 +/- 0.01	0.38 +/- 0.08	0.03 +/- 0.01	0.06 +/- 0.01	0.50 +/- 0.00
	Textual	0.71 +/- 0.01	0.61 +/- 0.03	**0.68 +/- 0.03**	0.64 +/- 0.02	0.70 +/- 0.01
	Visual	0.55 +/- 0.09	0.44 +/- 0.06	0.33 +/- 0.41	0.24 +/- 0.21	0.51 +/- 0.00
	Textual + Visual	0.70 +/- 0.01	0.60 +/- 0.03	0.68 +/- 0.04	0.64 +/- 0.02	0.70 +/- 0.01
	User Info + Textual + Visual	0.64 +/- 0.02	0.53 +/- 0.03	0.60 +/- 0.03	0.56 +/- 0.02	0.63 +/- 0.02
	Late fusion	0.66 +/- 0.04	0.60 +/- 0.07	0.51 +/- 0.19	0.52 +/- 0.08	0.63 +/- 0.04
	GCN (Kipf and Welling 2016)	0.72 +/- 0.02	0.71 +/- 0.03	0.32 +/- 0.02	0.44 +/- 0.02	0.62 +/- 0.01
	GAT (Veličković et al. 2018)	0.74 +/- 0.02	0.70 +/- 0.03	0.45 +/- 0.02	0.55 +/- 0.02	0.67 +/- 0.01
	MBPHGNN	**0.83 +/- 0.01**	**0.84 +/- 0.02**	0.64 +/- 0.02	**0.73 +/- 0.02**	**0.79 +/- 0.01**
Vaccine	User Info	0.84 +/- 0.02	0.78 +/- 0.05	0.58 +/- 0.04	0.67 +/- 0.04	0.76 +/- 0.02
	Textual	0.78 +/- 0.03	0.74 +/- 0.07	0.28 +/- 0.07	0.40 +/- 0.07	0.62 +/- 0.03
	Visual	0.73 +/- 0.03	0.35 +/- 0.45	0.01 +/- 0.01	0.02 +/- 0.02	0.50 +/- 0.01
	Textual + Visual	0.78 +/- 0.02	0.76 +/- 0.10	0.28 +/- 0.05	0.40 +/- 0.05	0.62 +/- 0.02
	User Info + Textual + Visual	0.82 +/- 0.04	0.66 +/- 0.09	0.66 +/- 0.05	0.66 +/- 0.07	0.77 +/- 0.04
	Late fusion	0.77 +/- 0.03	0.87 +/- 0.20	0.30 +/- 0.16	0.39 +/- 0.10	0.63 +/- 0.05
	GCN (Kipf and Welling 2016)	0.72 +/- 0.02	0.39 +/- 0.39	0.02 +/- 0.02	0.03 +/- 0.03	0.50 +/- 0.01
	GAT (Veličković et al. 2018)	0.72 +/- 0.02	0.23 +/- 0.20	0.01 +/- 0.01	0.03 +/- 0.02	0.50 +/- 0.01
	MBPHGNN	**0.92 +/- 0.02**	**0.91 +/- 0.05**	**0.80 +/- 0.05**	**0.85 +/- 0.05**	**0.88 +/- 0.03**

Figure 4: User descriptions and the multimodal post contents related to the users of the *Left*, *Middle*, and *Right* clusters of the *inflation* dataset.

References

[1] Gottfried, J.; and Shearer, E. 2016. News use across social media platforms 2016.
[2] Conover, M. D.; Ratkiewicz, J.; Francisco, M.; Gonçalves, B.; Menczer, F.; and Flammini, A. 2011. Political polarization on twitter. In Fifth international AAAI conference on weblogs and social media.
[3] DiMaggio, P.; Evans, J.; and Bryson, B. 1996. Have American's social attitudes become more polarized? American journal of Sociology 102(3): 690–755.