Meta-Path-based Fake News Detection Leveraging Multi-level Social Context Information

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Outline

Introduction

Fake News Detection

- Wide dissemination of fake news has become a major social problem in the world.
- The most recent and infamous distribution of fake news was in 2020 US presidential election fraud and COVID-19 rumors.
- Both industry and government are making efforts to prevent the spread of fake news.
- Fake news verification still relies on human experts and their manual efforts in analyzing the news contents with additional evidence.
- Therefore, there should be an automatic and efficient way to identify the veracity of the news.

Introduction

Typical way to detect fake news

- Applying NLP techniques on the news content.
- Even people struggle in identifying the news authenticity by the news content alone, these NLP solutions are ineffective.
    - Thus, more information is required to improve fake news detection.

Introduction

More information

- First important information is users in social media.
  - Even though regular users use social media as a communication tool, some users, known as instigators, intentionally spread fake news.
  - Instigators usually have a highly partisan-biased personal description and a lot of followers and followings, which is significantly different from the profiles of regular users.

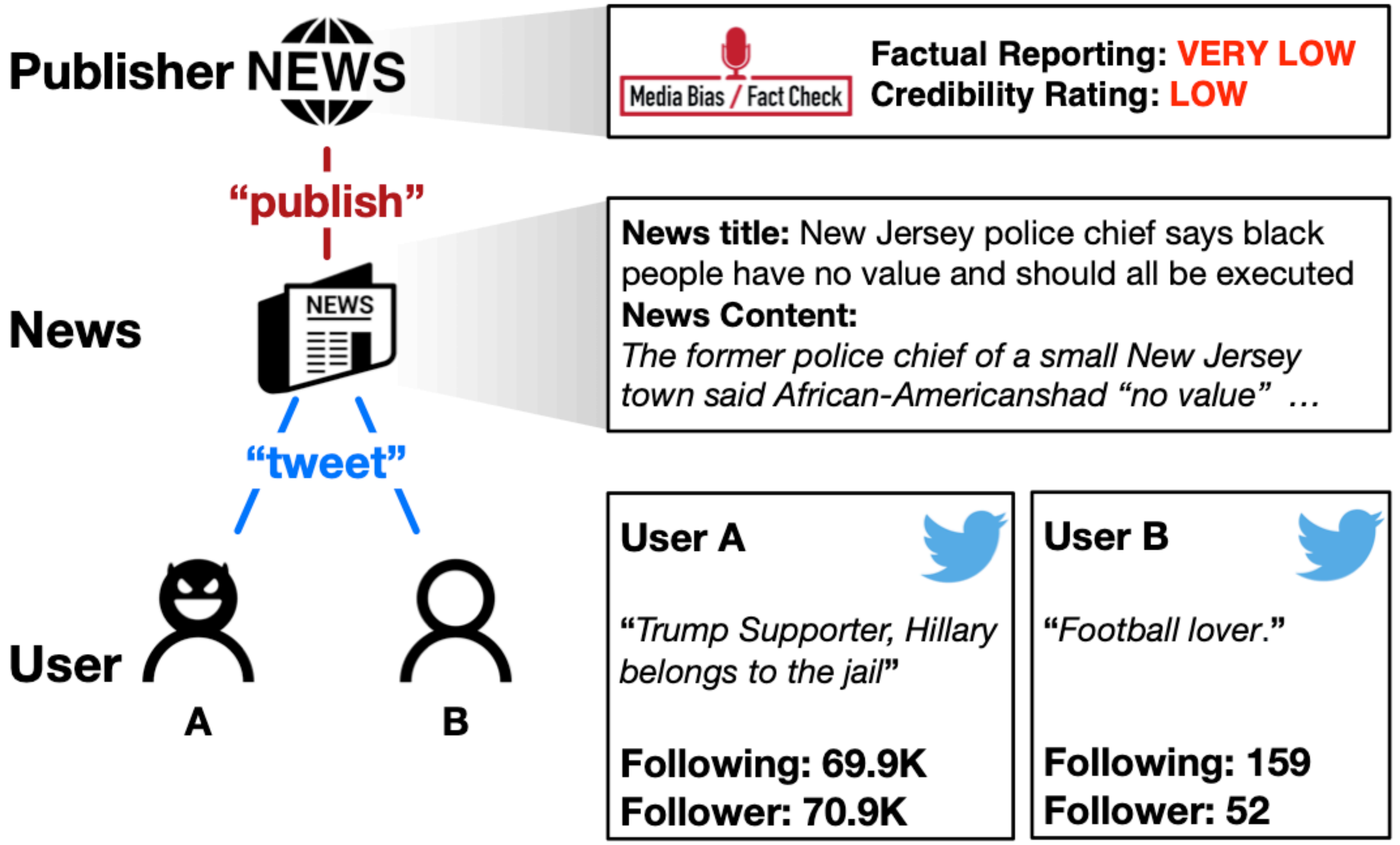


Figure 1: Example of fake news distribution and dissemination. Publishers publish the news, and users tweet the news. Some publishers are regarded as low credibility sources according to the famous fact-checking website, MBFC. User A is an example of an instigator in Twitter, and User B is an example of a regular user.

Introduction

Multi-level social context information

- Analyzing the users engaged in the news can provide additional evidence for identifying news authenticity.
- Publisher information can also play an important role because certain partisan-biased publishers are more likely to publish fake news.
- Information on users and publishers can be viewed as multi-level social context information.
    - Also provide additional clues for fake news detection.

Introduction
Temporal information

- Temporal information of user engagement (temporal information for short) is another instrumental information in fake news detection.
- Fake and real news show different propagation properties in social media.
    - Fake news is periodically mentioned by people and usually lasts longer.
    - Real news receives attention only at the beginning of the news publication.
- In this context, the temporal information should be included in the news representation along with multi-level social context information.

Introduction

Three chronic difficulties

- Due to the heterogeneity of multi-level social context information.
  - It's hard to use this information without loss.
- Temporal information is hard to be used along with multi-level social context.
  - Graph is a typical way to present social context and its connectivity to the news.
  - Graph itself has complications in presenting temporal information.

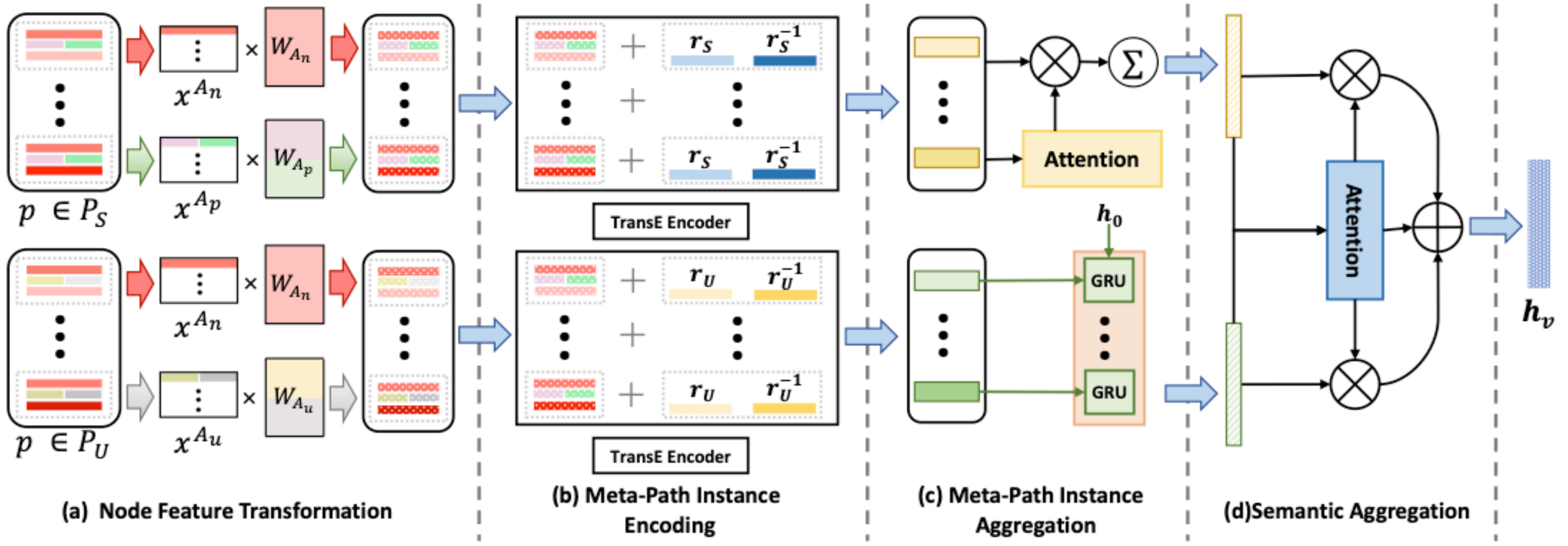
Introduction

Three chronic difficulties.

- Learn news representation end-to-end.
  - Multi-level social context and temporal information are two different kinds of information.
    - Increases the difficulty of adopting end-to-end learning while utilizing both information.
  - To promise a high-performing fake news detection, it's necessary to adopt end-to-end learning.
    - Enable to eliminate the effect from the sub-tasks and optimize the training parameters with a single news detection objective.

Introduction

Hetero-SCAN



- Proposed a novel fake news detection framework, Hetero-SCAN.
- To preserve multi-level social context information, use the Meta-Path.
- Meta-Path is a composite relation connecting two node types.
  - Aiming to capture the semantics in the heterogeneous graph.
- Define two Meta-Paths containing different aspects of news (users and publishers) to extract multi-level social context information without information loss.
- Meta-Path instance encoding and aggregation methods are proposed to capture the temporal information of user engagement and learn the news representation end-to-end.

Introduction

Contributions

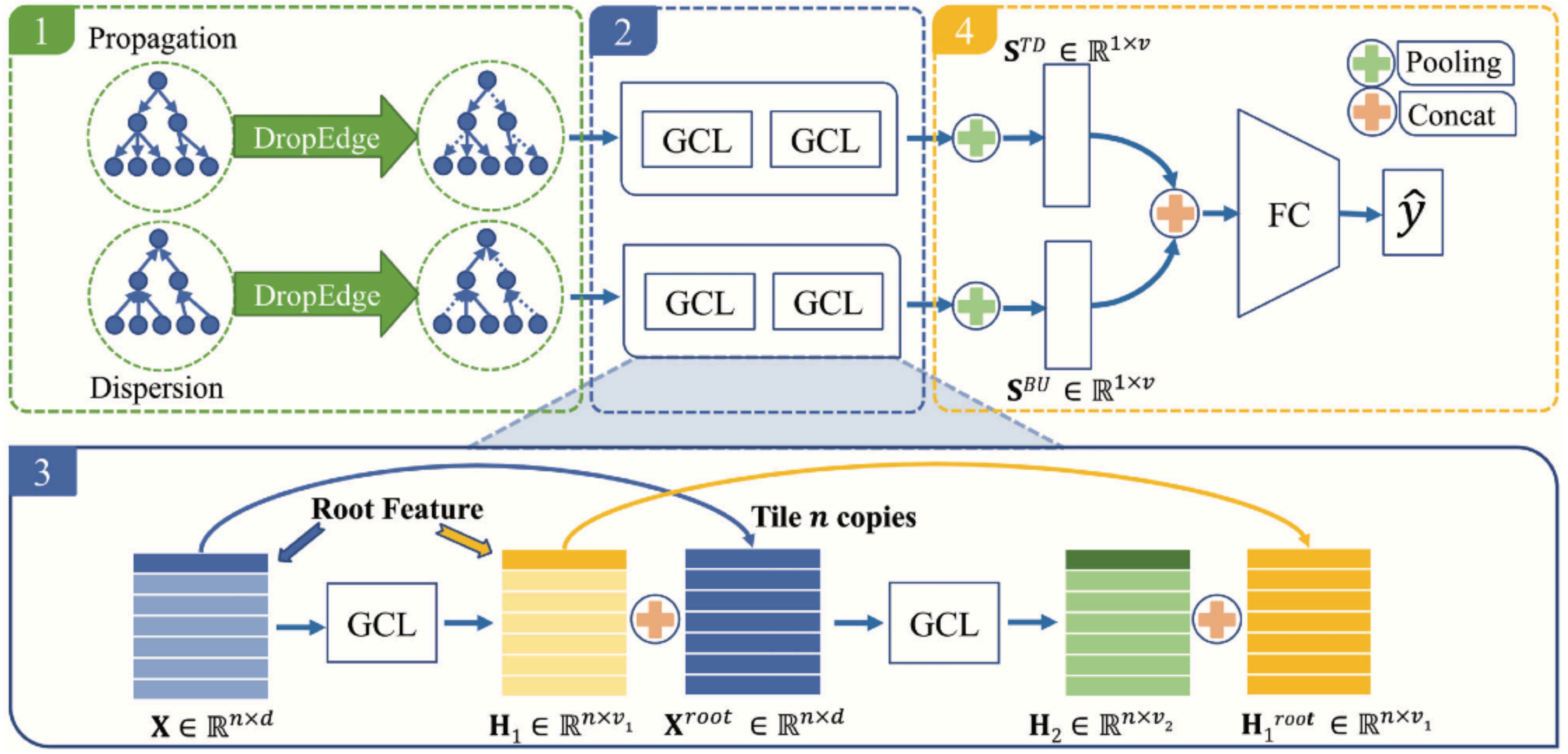
- Pose three chronic difficulties in social context aware fake news detection and address them by proposing a novel fake news detection framework, Hetero-SCAN.
- Conduct diverse experiments on the two real-world fake news datasets, covering the broad definition of fake news.
    - Demonstrate that Hetero-SCAN shows better performance than existing solutions.
- Provide new insights into the difference in the behavior of engaged users between intentional and unintentional fake news.

Related Works
Fake News Detection

- Can be categorized into two types:
  - Content-based
    - Use headline or body text to detect news authenticity.
    - Utilizes linguistic features such as stylometry, psycholinguistic properties, and rhetorical relation.
    - Combination of visual and linguistic features to verify the news authenticity.
  - Graph-based

Related Works

Graph-based approaches



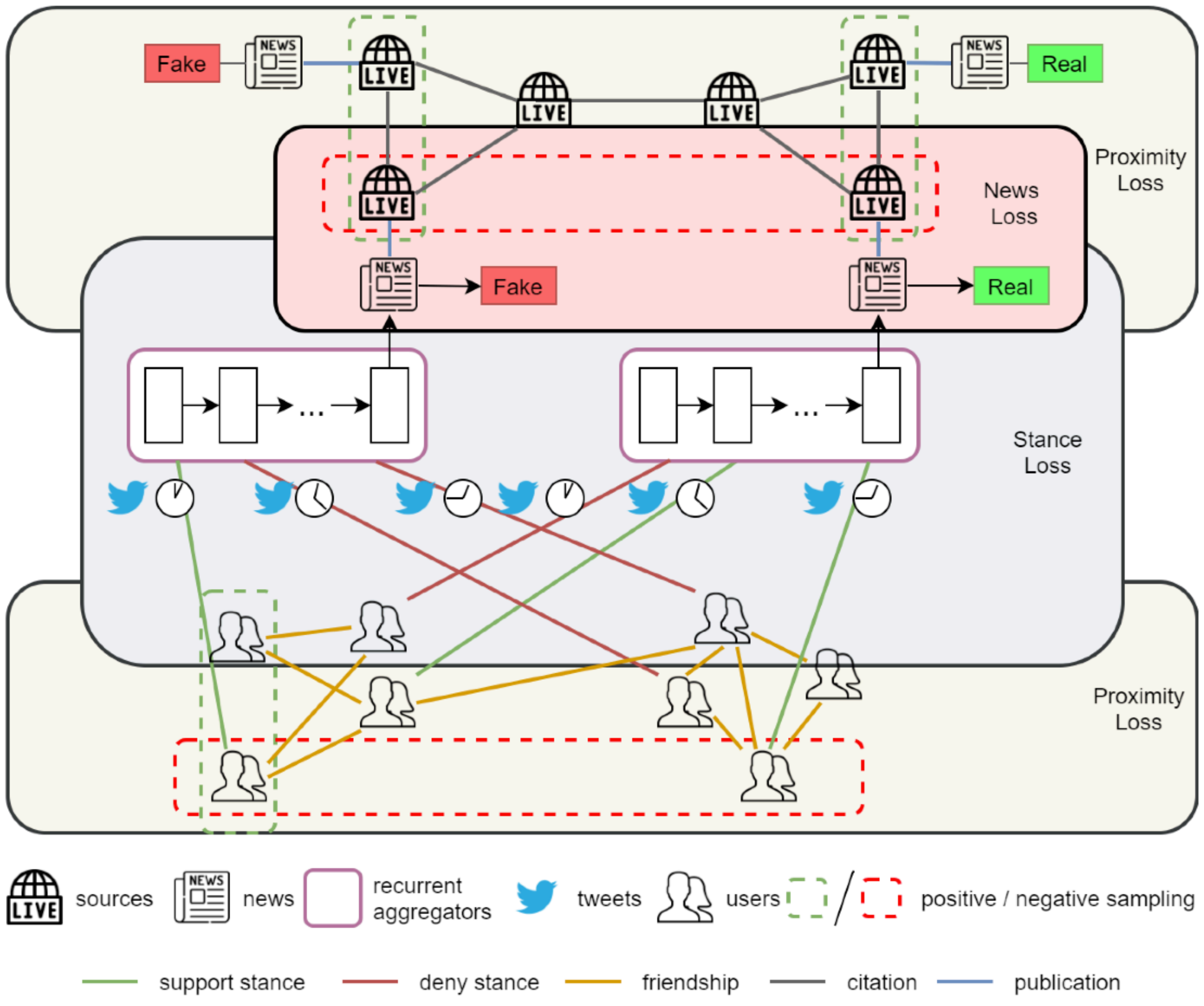
Bi-GCN

- Also knows as the social context aware approach.
  - Add auxiliary information of the user or publisher to model the news.
- CSI (CIKM'17) aims to capture the information of user and their temporal engagements.
  - Doesn't consider publishers, and the connection between users and news was also ignored.
- Bi-GCN (AAAI'20) and SAFER (arXiv'20) use GCN to obtain the news representation with user information.
  - Suffer from a severe information loss since they present news and user information in a homogeneous graph.

Related Works

Graph-based approaches.

- FANG (CIKM'20) is proposed to preserve information by dividing the fake news detection task into several sub-tasks.
  - E.g. text encoding & stance detection.
  - Dividing into sub-tasks cause the error propagation problem.

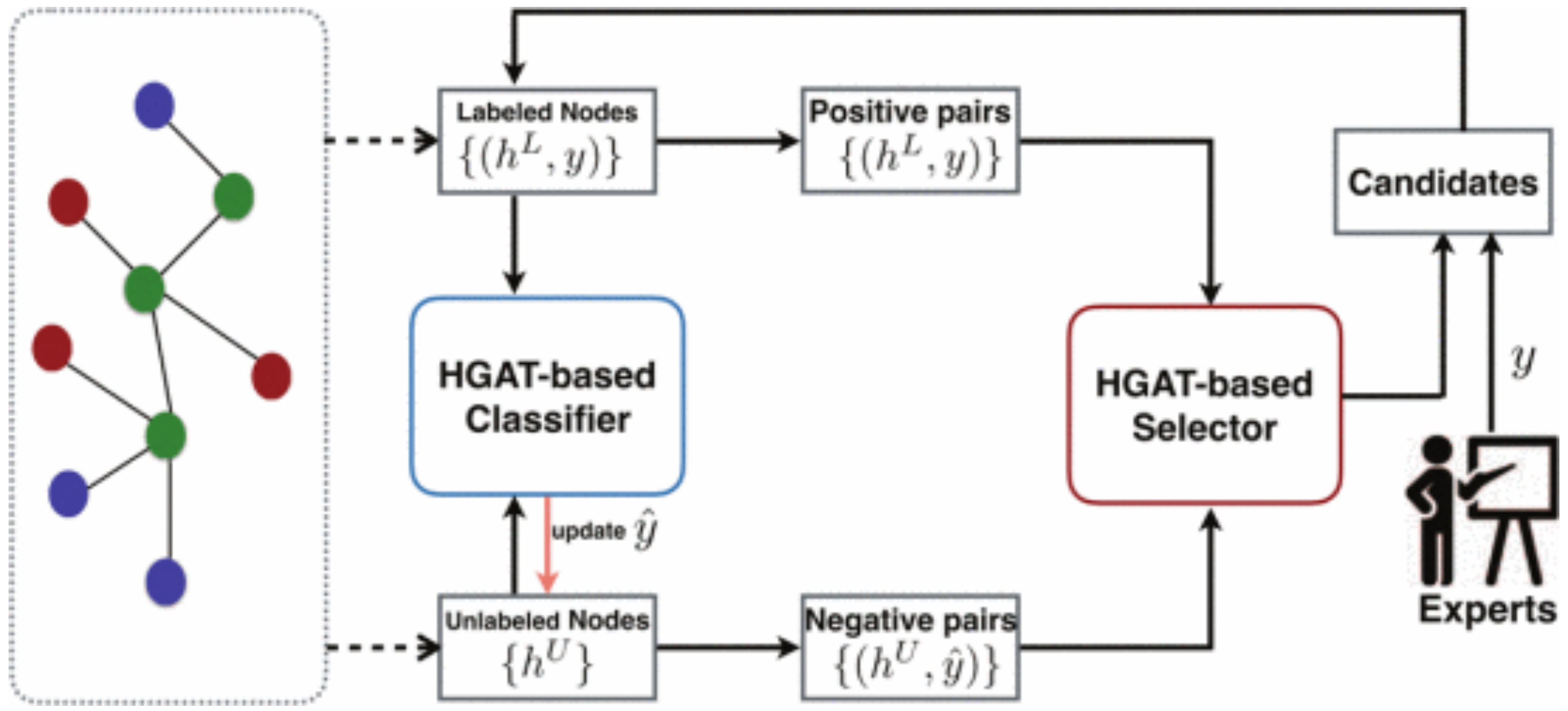


FANG

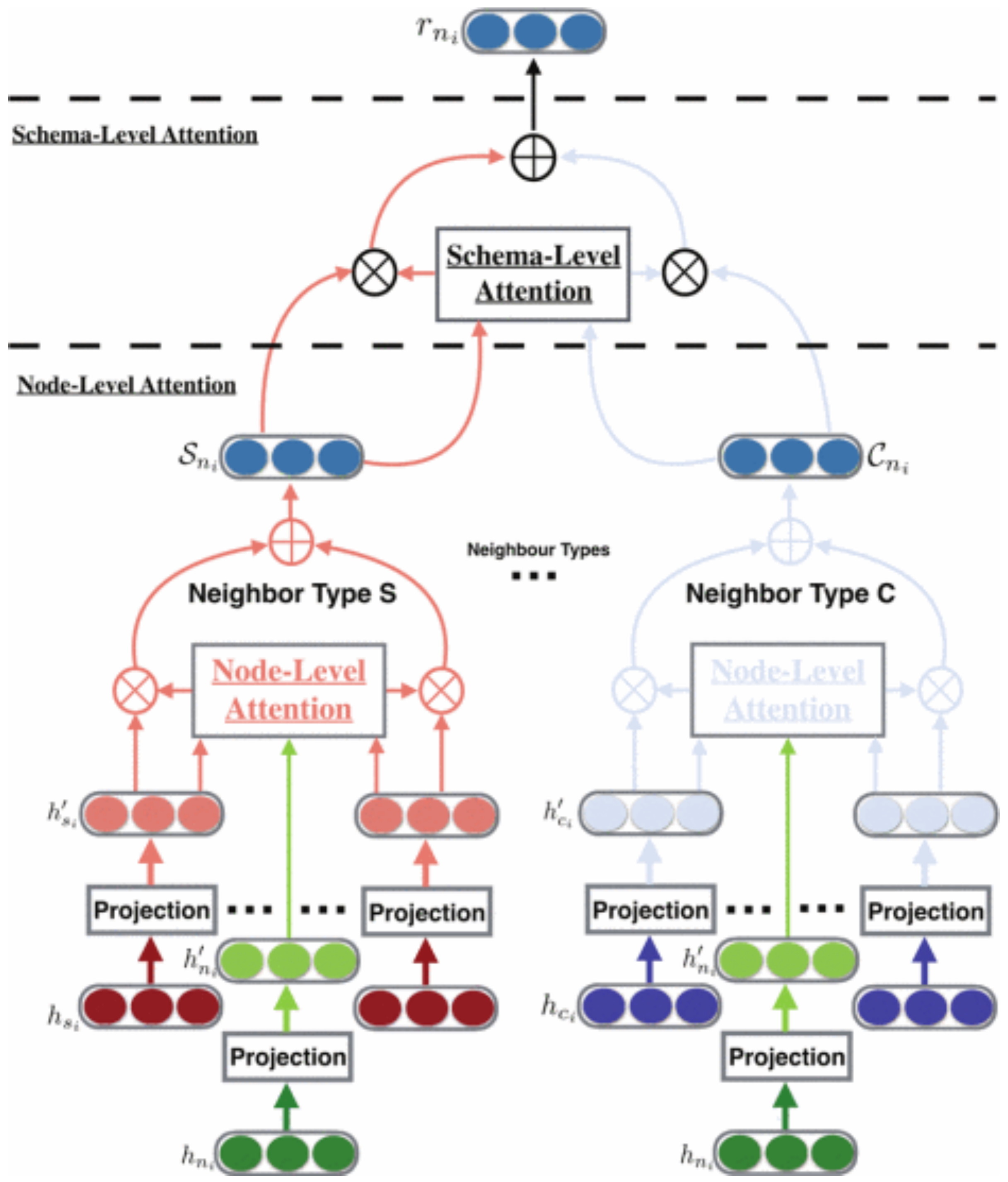
Related Works

Graph-based approaches..

- AA-HGNN (ICDM'20) use adversarial active learning and extends GAT into the heterogeneous graph to learn the news representation with limited training data.
  - Not considered information of users and their temporal information.



Overall framework



Hierarchical Graph Attention Neural Network (HGAT)

Related Works

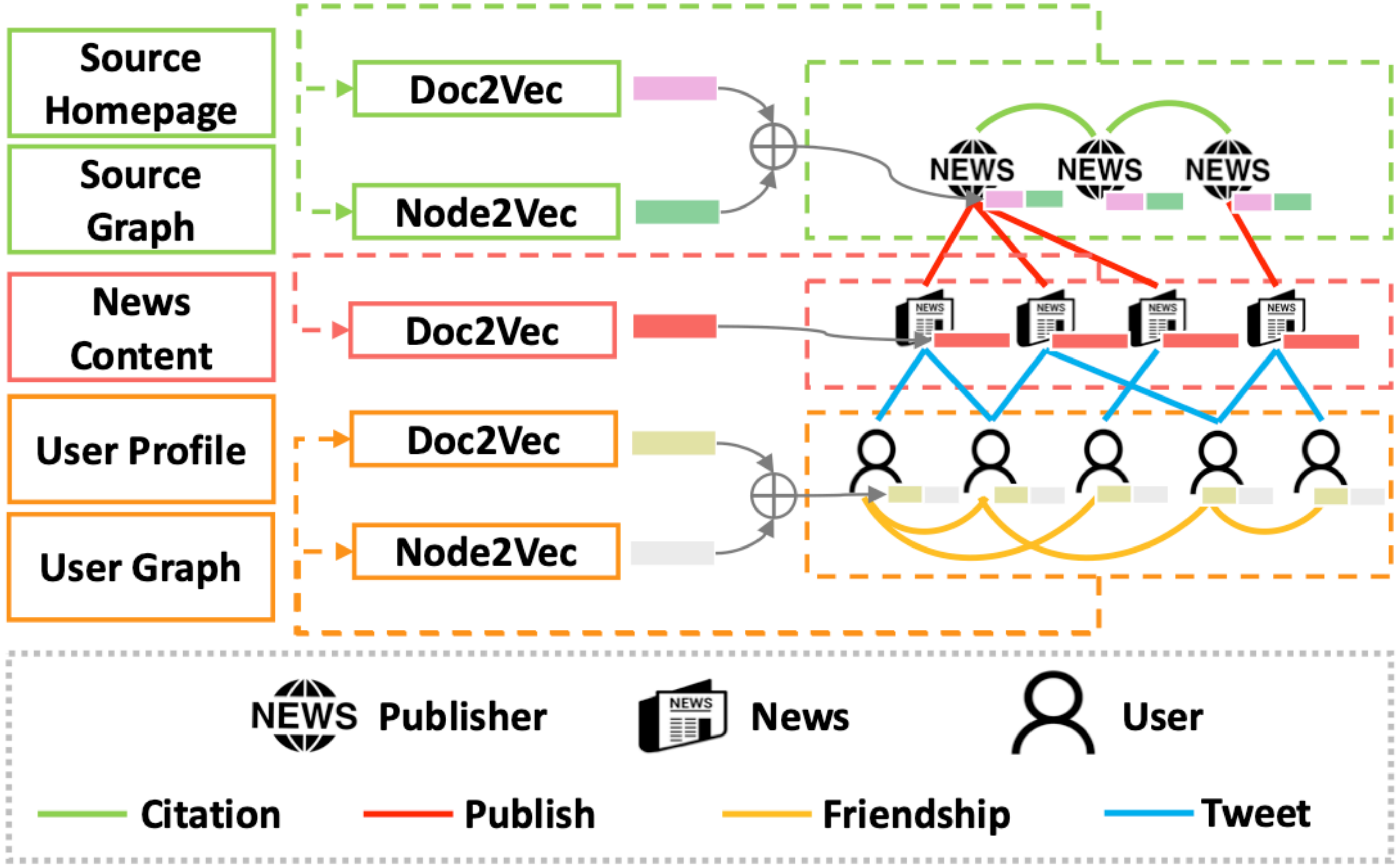
Graph-based approaches...

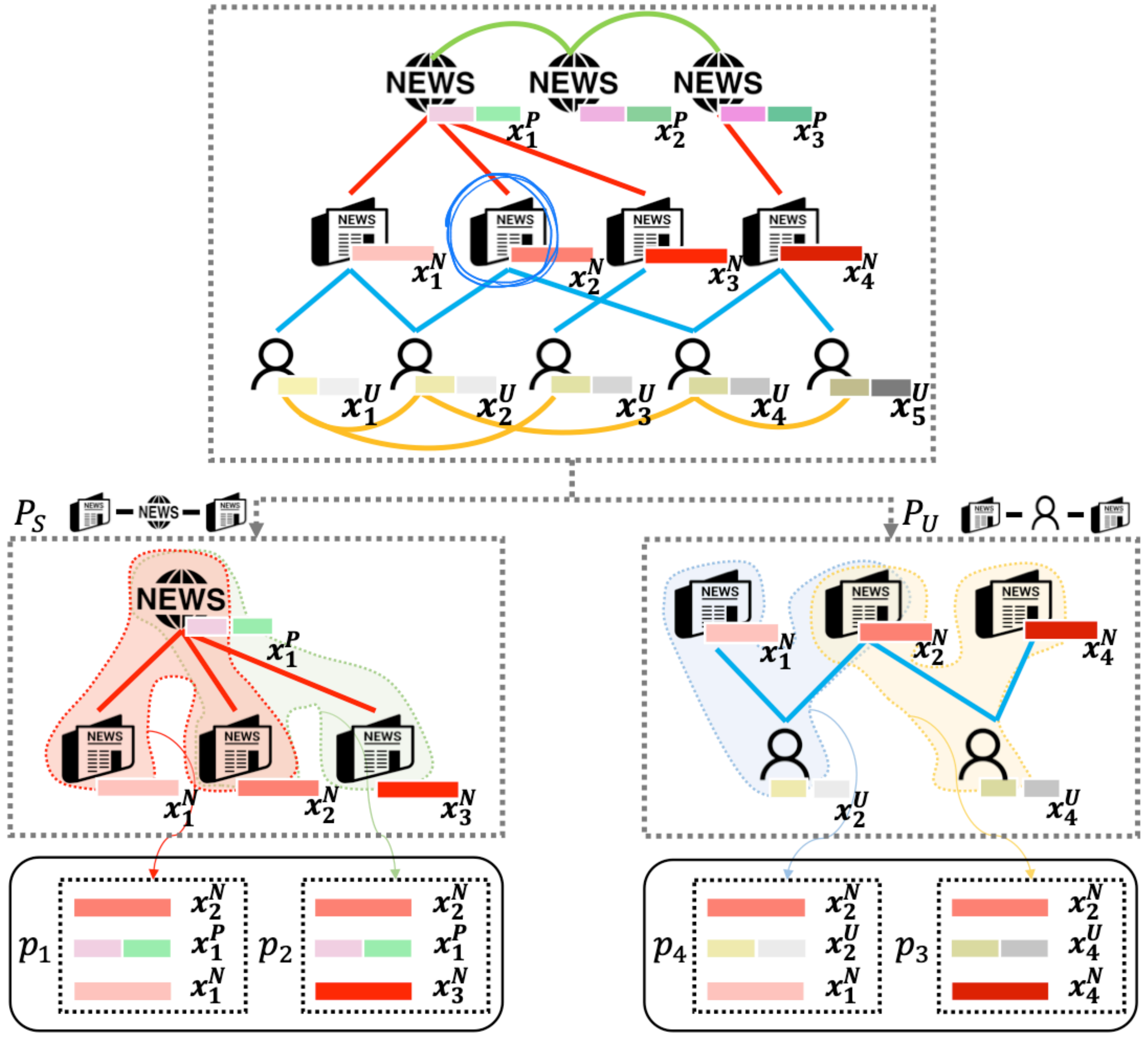
Table 1: Comparison of *Hetero-SCAN* with exiting graph-based fake news detection methods.

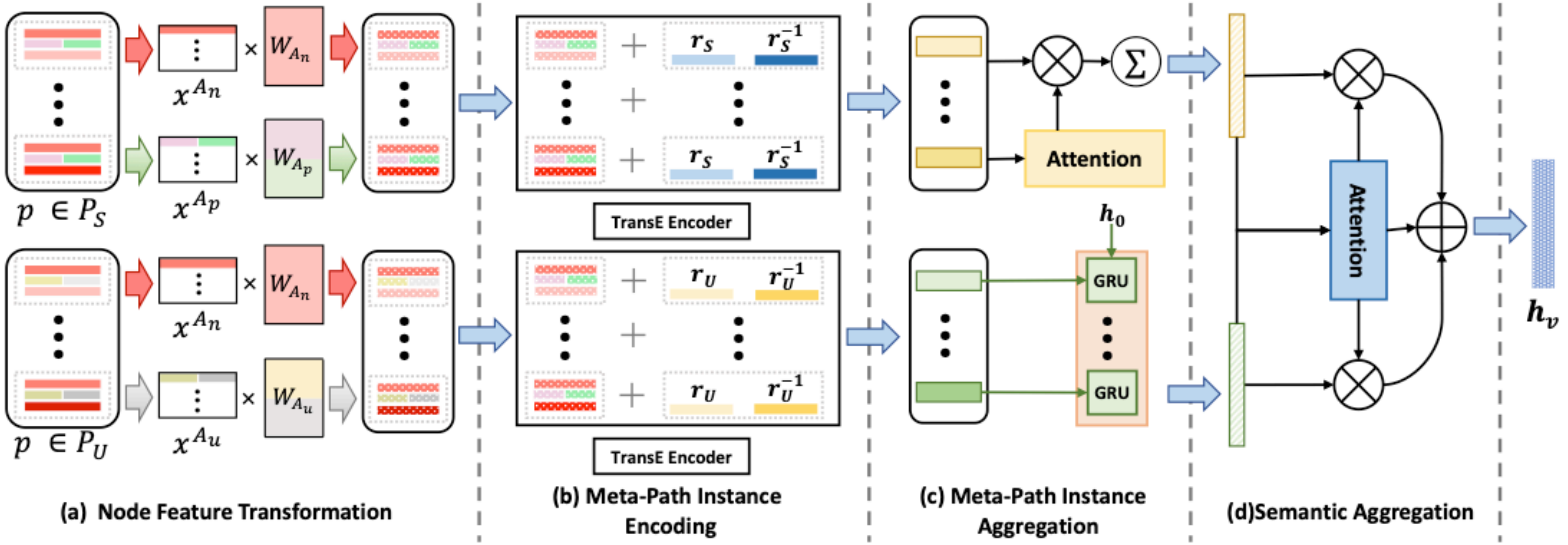
	Multi-level Social Context	Information Preserving	Temporal Information	End-to -end
CSI [39] CIKM'17	✗	✓	✓	✓
SAFER [13] arXiv'20	✗	✗	✗	✓
FANG [32] CIKM'20	✓	✓	✓	✗
AA-HGNN [37] ICDM'20	✗	✓	✗	✓
Hetero-SCAN	✓	✓	✓	✓

Methodology

Hetero-SCAN



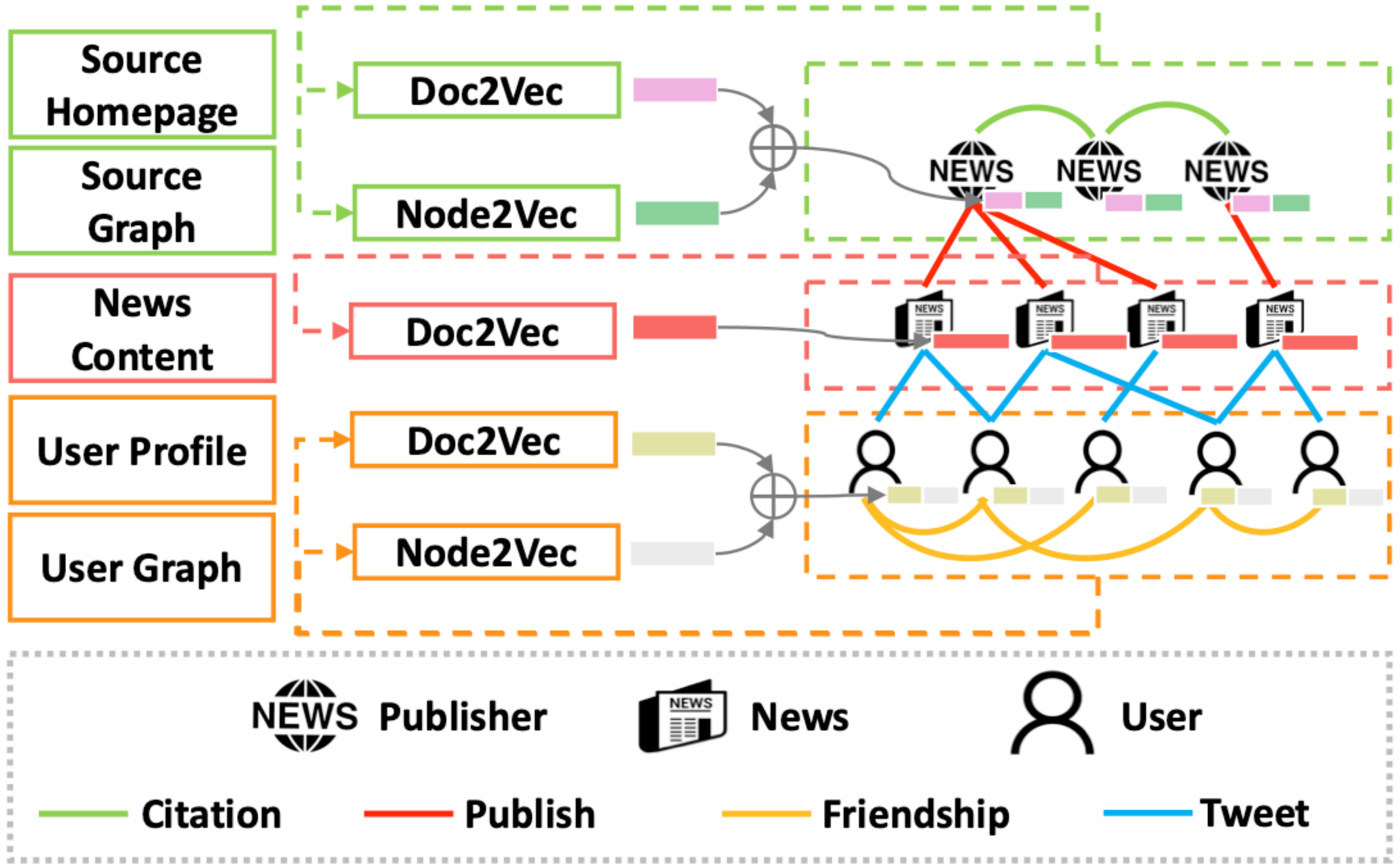




Methodology

Graph Construction & Feature Engineering

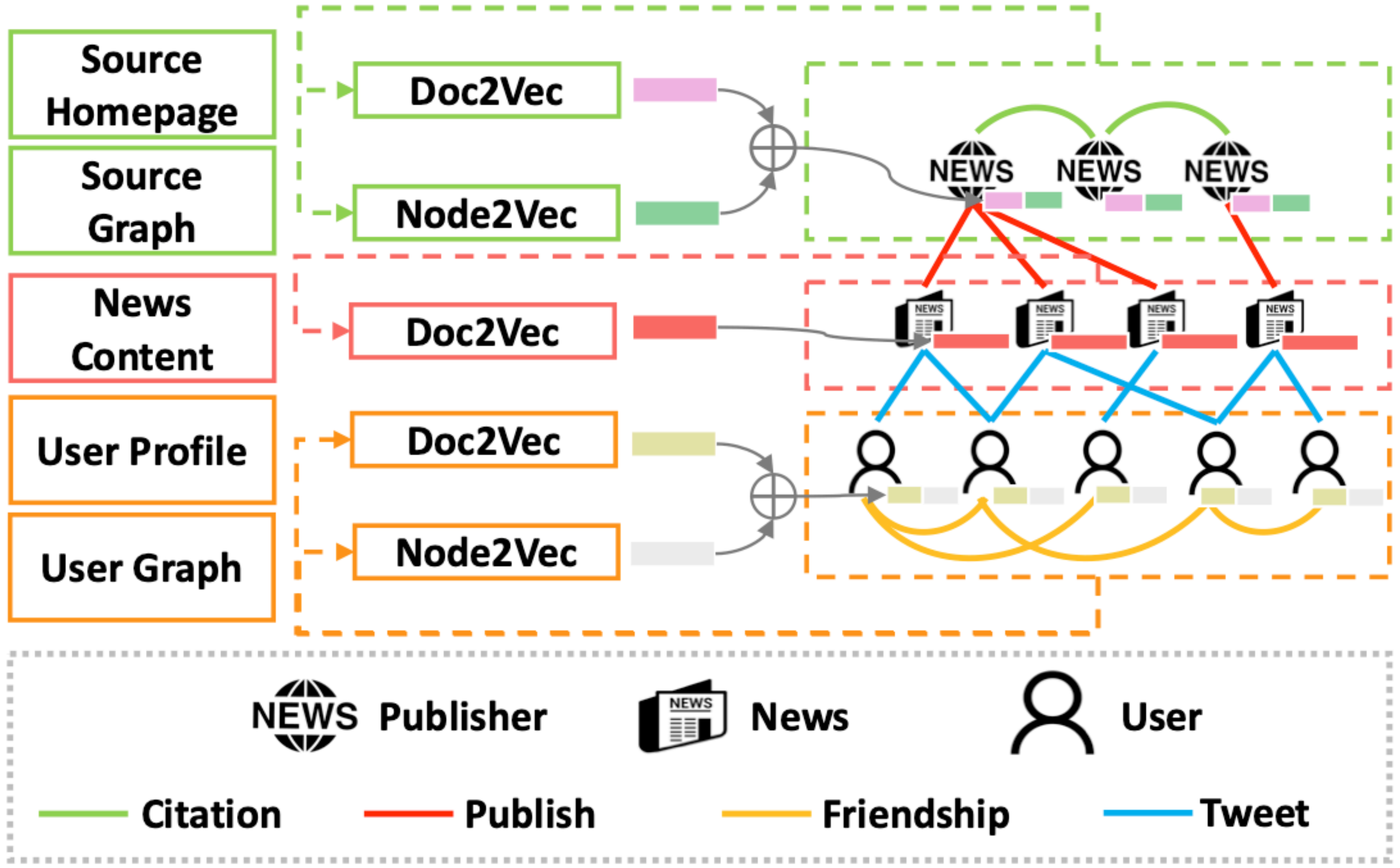
- To integrate multi-level social context information, build a heterogenous graph of news.
- Consist of 3 types of nodes & 4 types of edges.
  - Publisher, news, and users.
  - Citation, publication, tweet, and following.
- Heterogenous graph of news is noted as $\mathcal{G}(\mathcal{V}, \mathcal{E})$.
- The set of 3 types are symbolized as $\mathcal{A} = \{A_p, A_n, A_u\}$



Methodology

Graph Construction & Feature Engineering

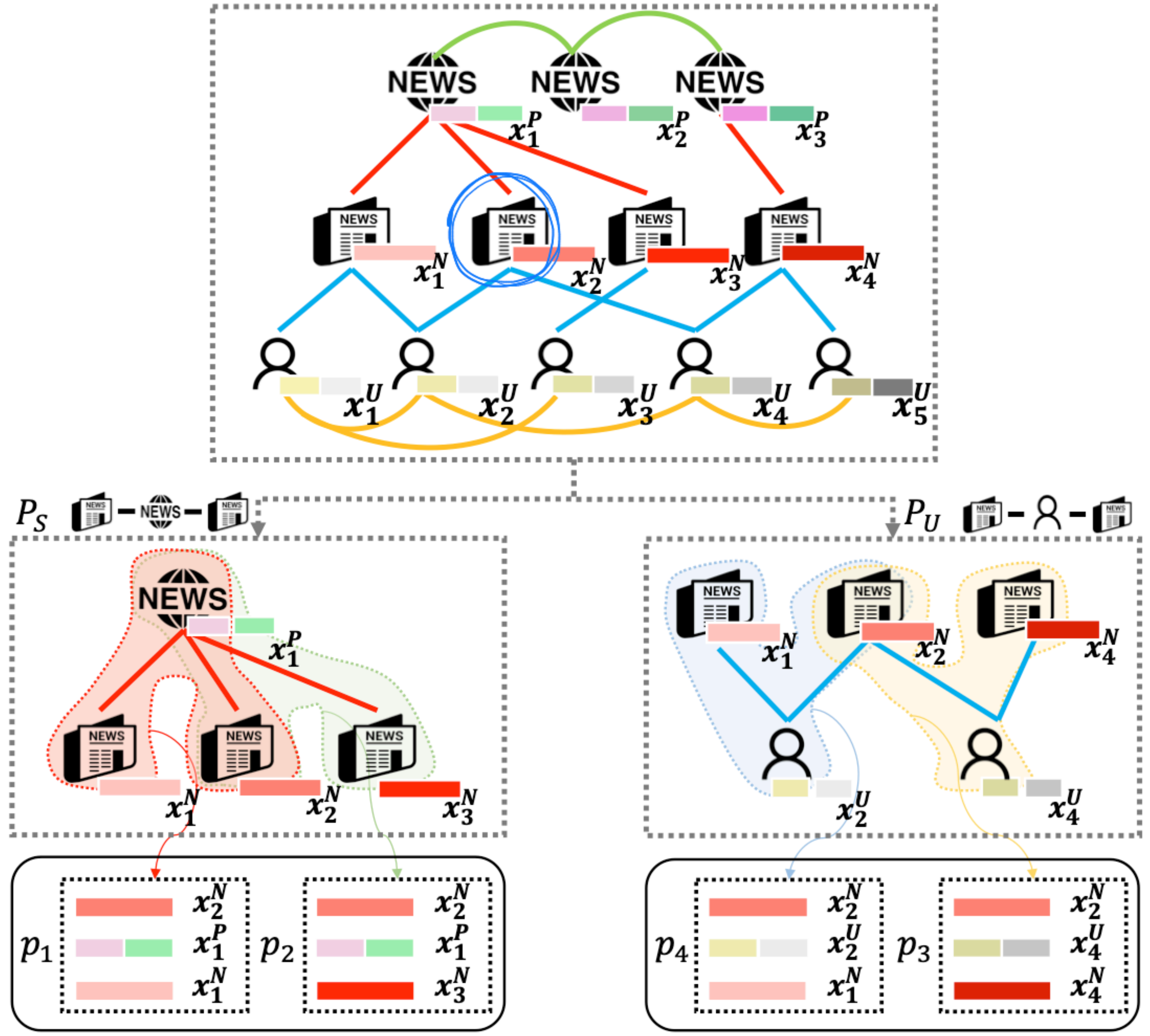
- Before utilizing this heterogenous graph, it's necessary to construct initial node features for 3 types of nodes in the graph.
- News nodes: Doc2Vec is applied to the news article.
- User and publisher nodes: Concatenating the 2 vector.
  - Doc2Vec is applied to leverage user profile and publisher about-us page content.
  - Apply Node2Vec to capture user connections and citations among publishers as features.



Methodology

Meta-Path Instance Extraction

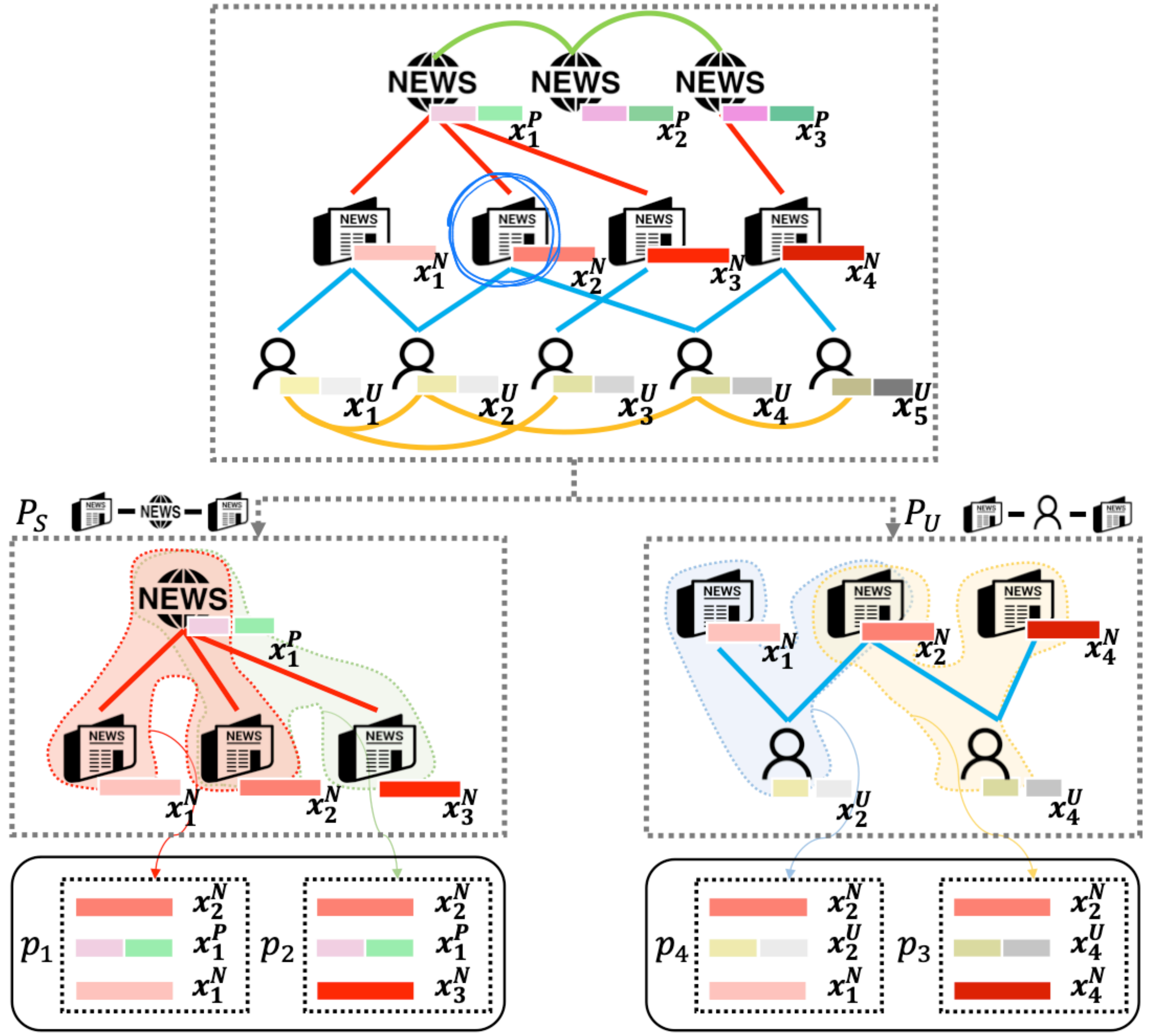
- Then need to learn representation containing multi-level social context and temporal information.
- To avoid information loss, use concept, Meta-Path.
- Meta-Path can be used to extract meaningful social context with respect to publishers and users.
- Define 2 Meta-Paths that reflect the method used for actual news verification.



Methodology

Meta-Path Instance Extraction

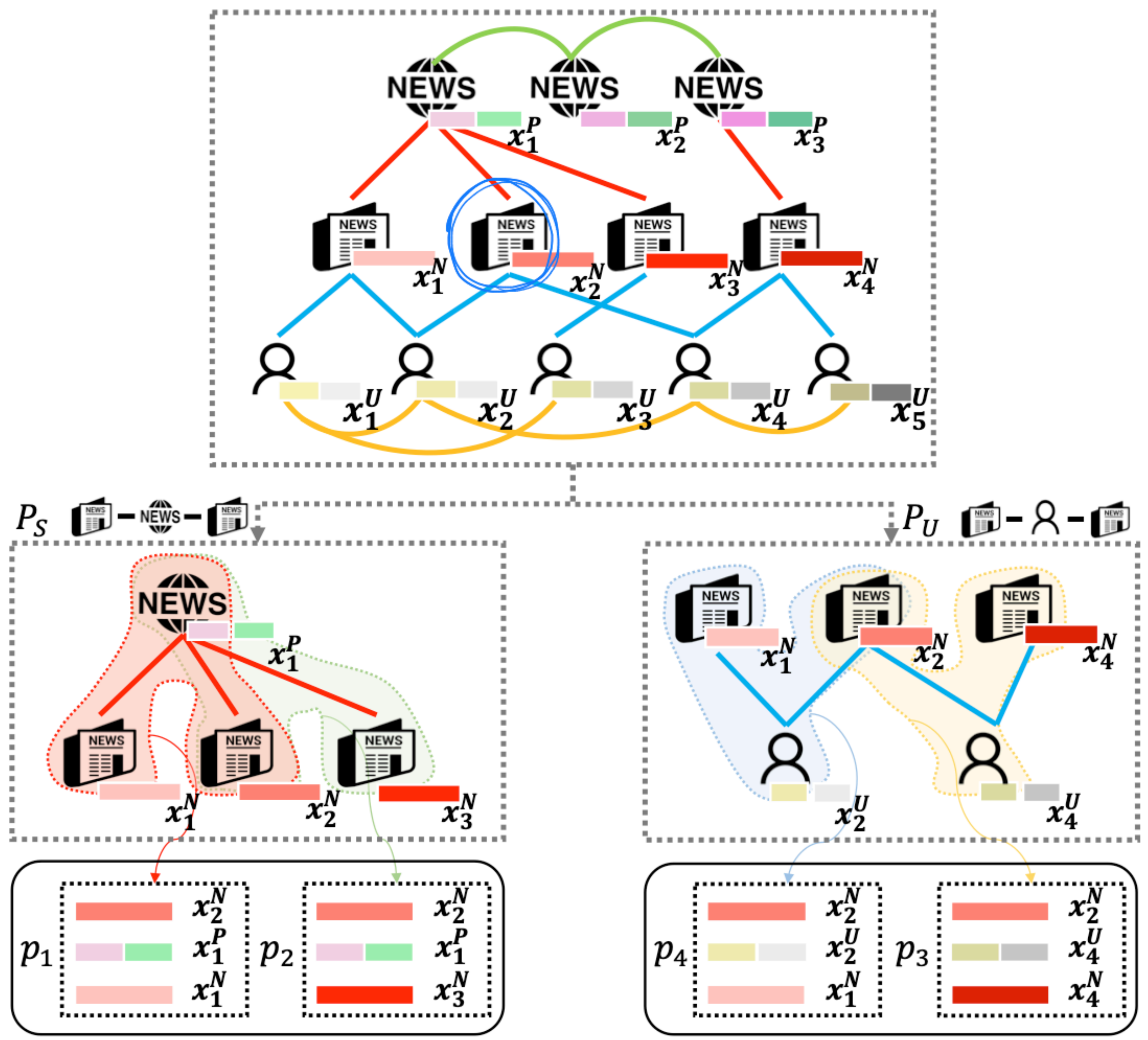
- When people verify the news authenticity, they need to cross-check both publisher and the news published by this publisher.
- The same as for users, news tweet by the users, needs to be reviewed.
- From these intuitions, a set of Meta-Path that find useful is defined as below:
    - $\mathscr{P} \in \{\mathscr{P}_U, \mathscr{P}_S\}$
    - $\mathscr{P}_U$: News→User→News, $\mathscr{P}_S$: News→Publisher→News



Methodology

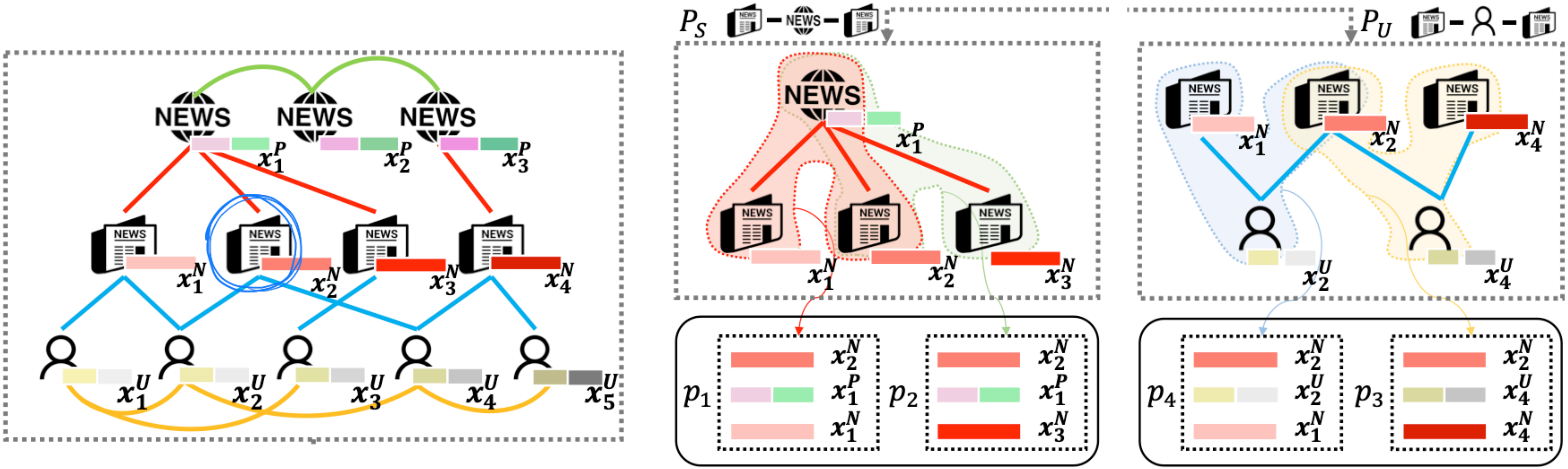
Meta-Path Instance Extraction

- After defining a set of Meta-Path, extract Meta-Path instances p following each Meta-Path.
- To efficiently extract instances, first divide the whole graph into 2 sub-graphs, which only contain the nodes types specified in the Meta-Path.
- Then, in each sub-graph, instances following each Meta-Path are extracted.
- The corresponding collection of features are fed into Hetero-SCAN to get the final representation of the target news node.



Methodology

For instance to extract news node x_2^N

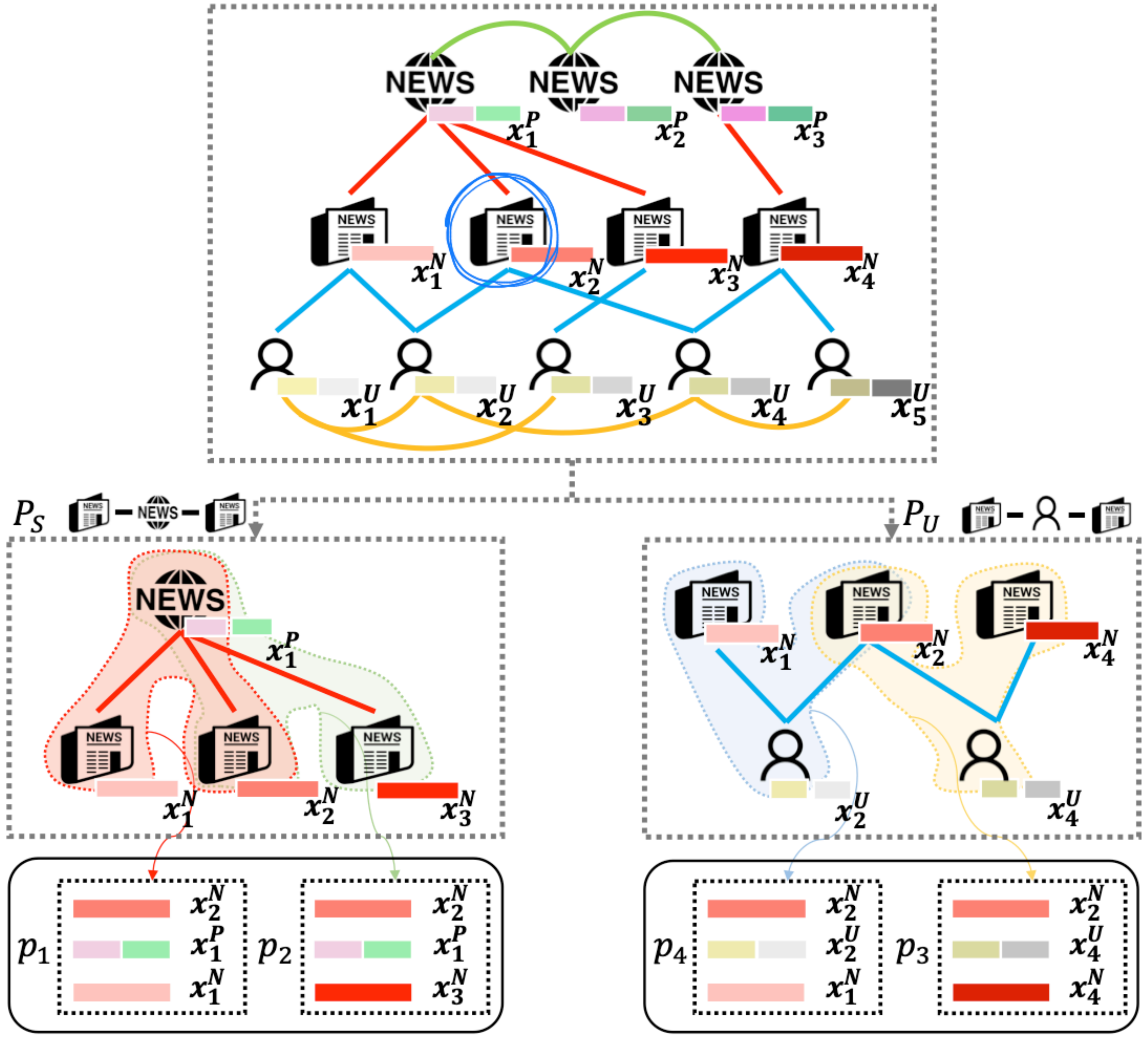


- In this case, $\mathbf{P}_S = \{p1,p2\}$ and $\mathbf{P}_U = \{p3,p4\}$ are set of Meta-Path instances of x_2^N.

Methodology

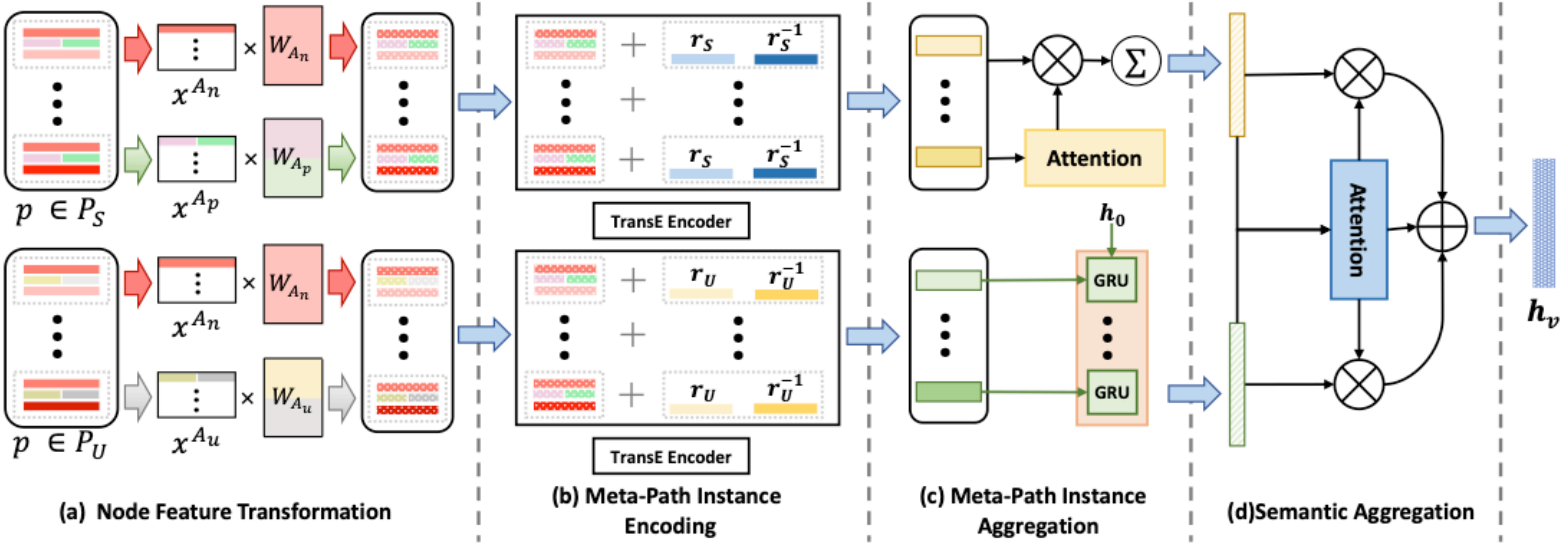
Meta-Path Instance Extraction

- Usually a large number of users engaged per news in real world.
- Extract instances from graph with random sampling.
- At last, in order to capture the temporal information, the model should be aware of the chronological information of instances.
    - Thus $\mathscr{P}_U$ are sorted chronologically before being fed into the proposed model.



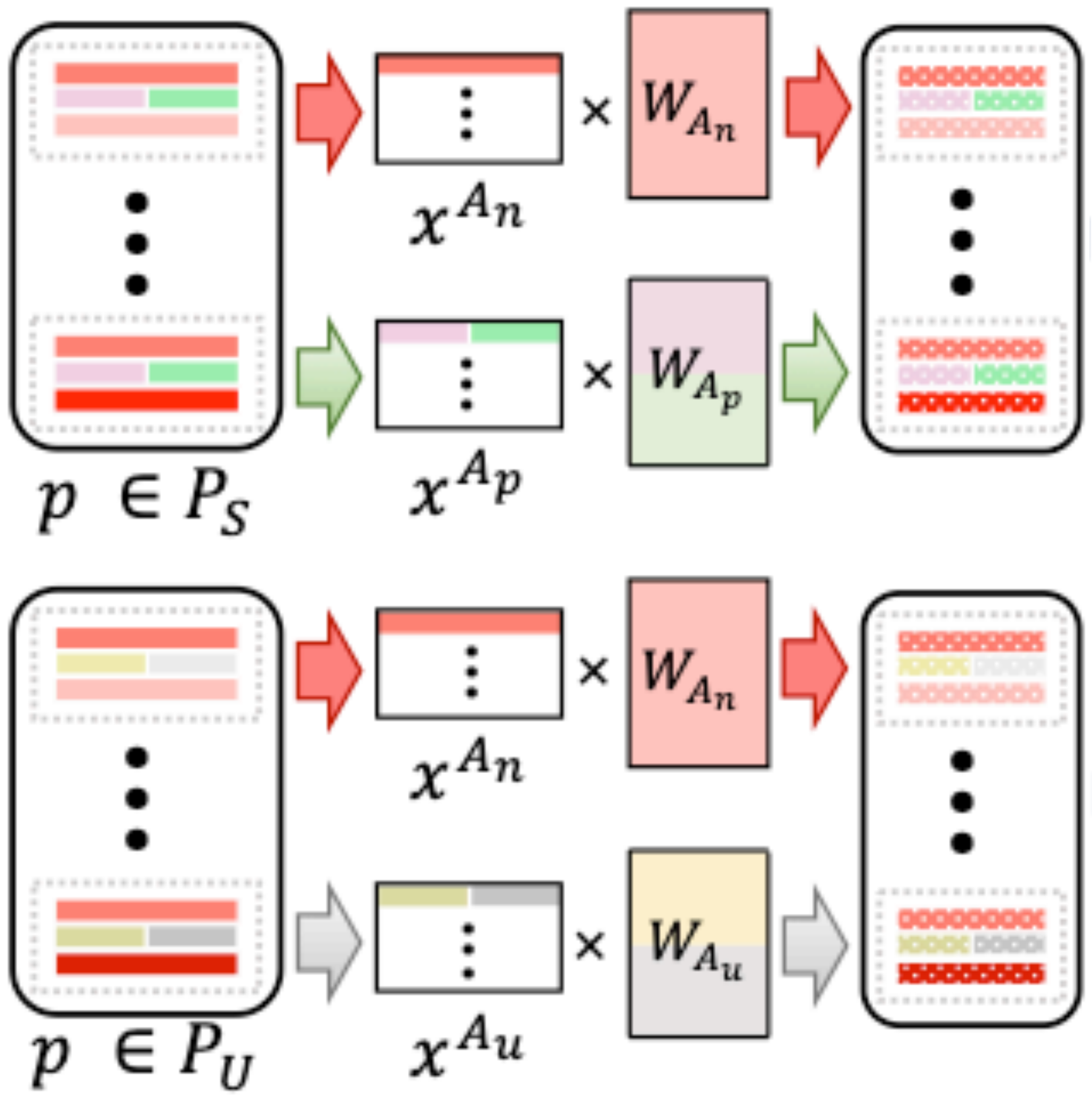
Methodology

Model architecture



Methodology

Node feature transformation



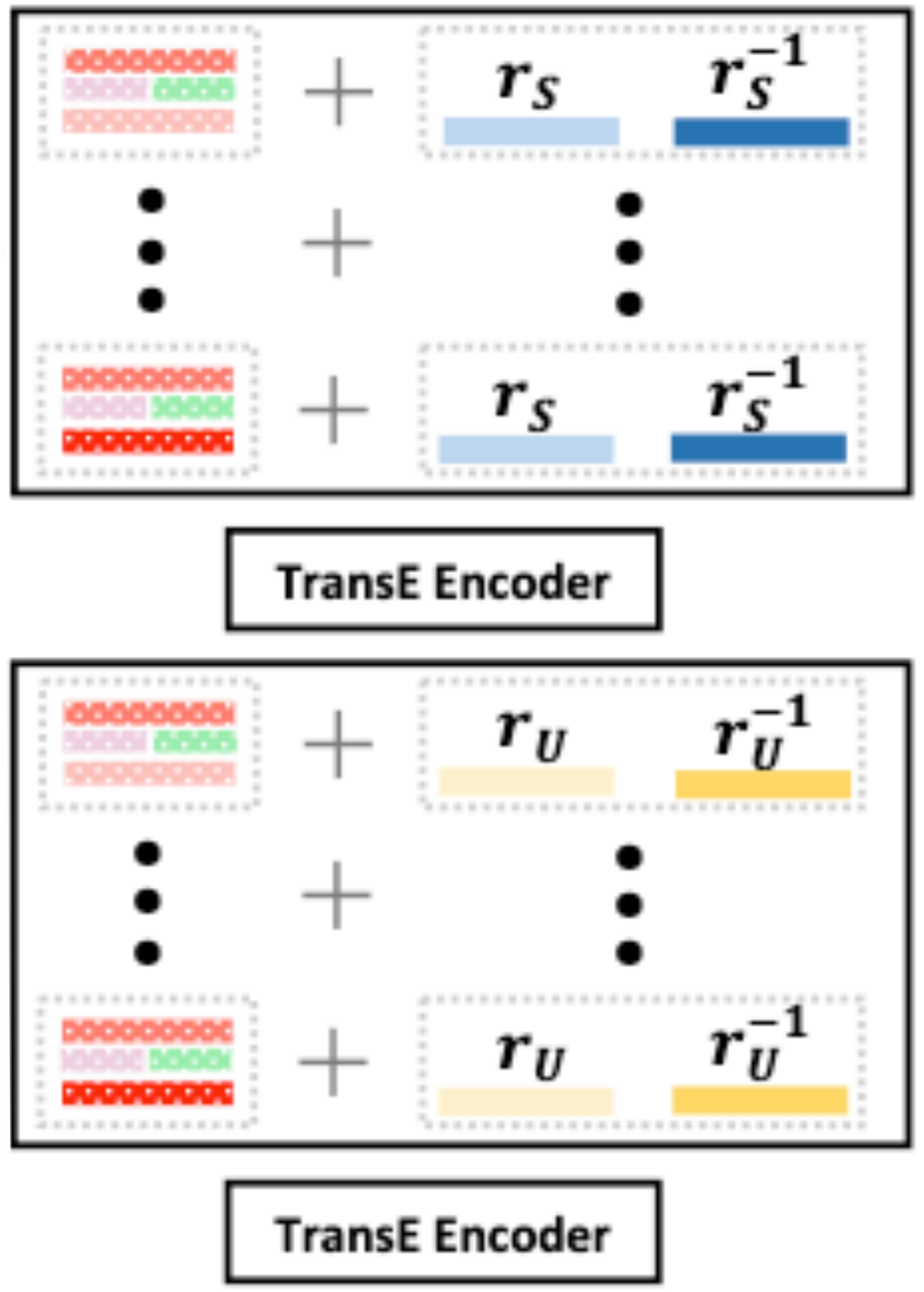
(a) Node Feature Transformation

- Initial node features have different dimensions.
- Apply the type-specific linear transform on the features of each type of node.
- The transformed feature for a node v of type A:
  - $\mathbf{h}_v^A = \mathbf{W}_A \cdot \mathbf{x}_v^A$
  - $\mathbf{x}_v \in \mathbb{R}^{d_A}$: initial feature of node v
  - $\mathbf{W}_A \in \mathbb{R}^{d' \times d_A}$: learnable type-specific weight matrix for node type A

Methodology

Meta-Path Instance Encoding

- Then need to efficiently summarize the instances for remaining aggregation steps.
- Capturing temporal information and learning the representation end-to-end.



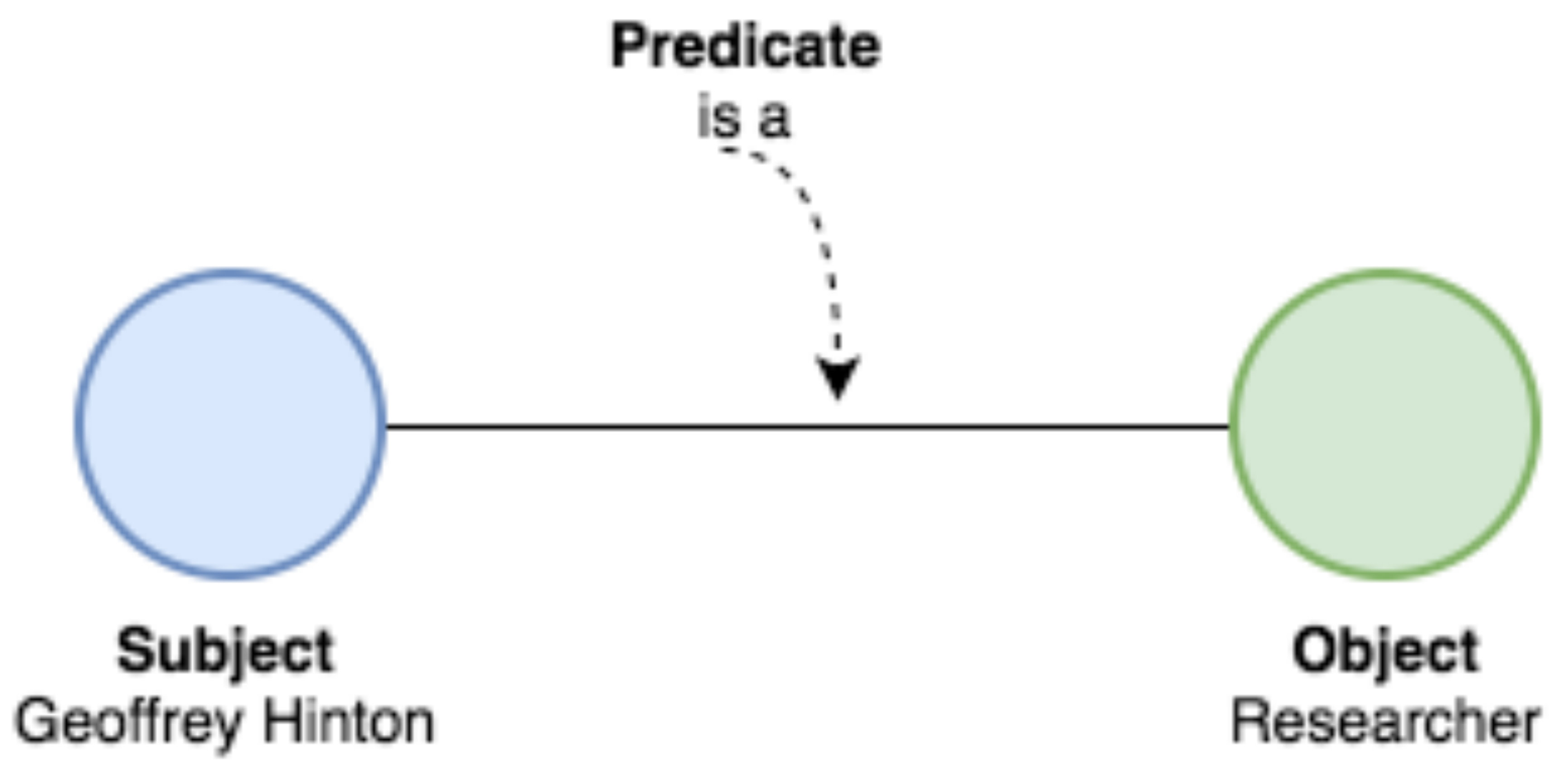
(b) Meta-Path Instance Encoding

- Adopted the method that shows excellent performance in knowledge graph triple embedding.
- The structural similarity between knowledge graph triples and Meta-Paths.

Methodology

Meta-Path Instance Encoding

- Knowledge graph triple: $\mathbf{e}_s \xrightarrow{\mathbf{e}_p} \mathbf{e}_o$ (subject, predicate, and object)
- Meta-Path: $\mathbf{h}_u \xrightarrow{r} \mathbf{h}_w \xrightarrow{r^{-1}} \mathbf{h}_v$
    - $v, u \in A_n, w \in \{A_p, A_u\}$
    - r, r^{-1}: relation between u, w and w, v
    - $\mathbf{h}$: transformed embedding



Knowledge Graph

Meta-Path

Methodology

Meta-Path Instance Encoding

- Several research on knowledge graph domain tackle the triple embedding problem.
- Use TransE as main encoding method for proposed model.
- In knowledge graph, there are usually explicit features for predicated (e_p).
- But in this case, there's no explicit features for relations (r), so use learnable embedding vector to present relations.
- For instance, if define r as the embedding of Publisher→News, the inverse relationship, News→Publisher is $r^{-1} = -r$.
- Encoding function f_{enc} is defined as: $\mathbf{h}_p = f_{enc}(p) = f_{enc}(\mathbf{h}_u, r, \mathbf{h}_w, r^{-1})$

Methodology

Meta-Path Instance Encoding

- Existing knowledge graph triple embedding methods designed for 2 nodes and the relation between them.
- In Meta-Path, have 3 nodes and 2 relations in a Meta-Path instance.
- Deal with this by slightly tuning the formulation to fulfill needs.
- $\mathbf{e}_s \xrightarrow{\mathbf{e}_p} \mathbf{e}_o$
- $\mathbf{h}_u \xrightarrow{r} \mathbf{h}_w \xrightarrow{r^{-1}} \mathbf{h}_v$

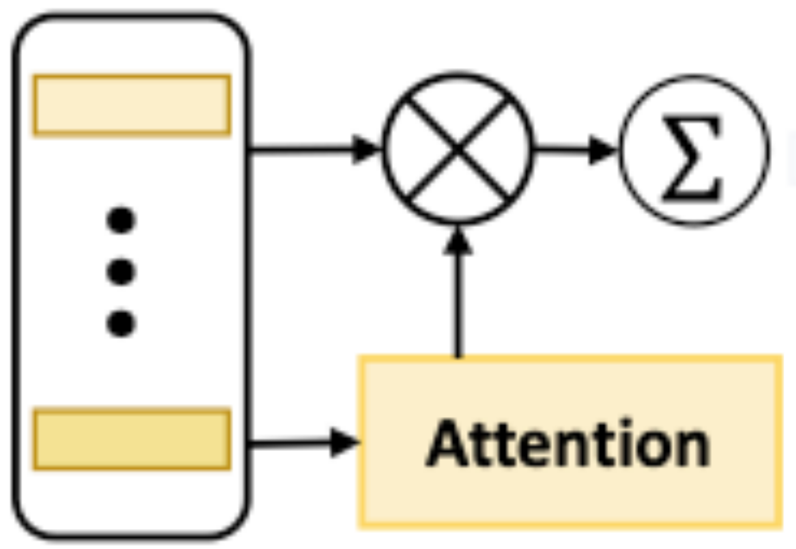
Table 2: Formulation of Encoding Method.

Method	Original	In Our Paper
TransE	$\mathbf{e}_s + \mathbf{e}_p$	$MEAN[(\mathbf{h}_u + r + r^{-1}), (\mathbf{h}_w + r^{-1})]$
ConvE	$[\mathbf{e}_s \parallel \mathbf{e}_p] * \mathbf{W}$	$[\tilde{\mathbf{h}}_u \parallel \tilde{r} \parallel \tilde{\mathbf{h}}_w \parallel \tilde{r}^{-1}] * \mathbf{W}$
RotatE	$\mathbf{e}_s \odot \mathbf{e}_p$	$MEAN[(\mathbf{h}_u \odot r \odot r^{-1}), (\mathbf{h}_w \odot r^{-1})]$

Methodology

Meta-Path Instance Aggregation

- Encoded vectors from 2 different Meta-Paths are aggregated by using different methods.
- $\mathscr{P}_S$: News→Publisher→News
- Not all news will contain valuable information for detection.
- Thus, the model should "focus" on some of the news published by this publisher and include this information in the aggregated representation.

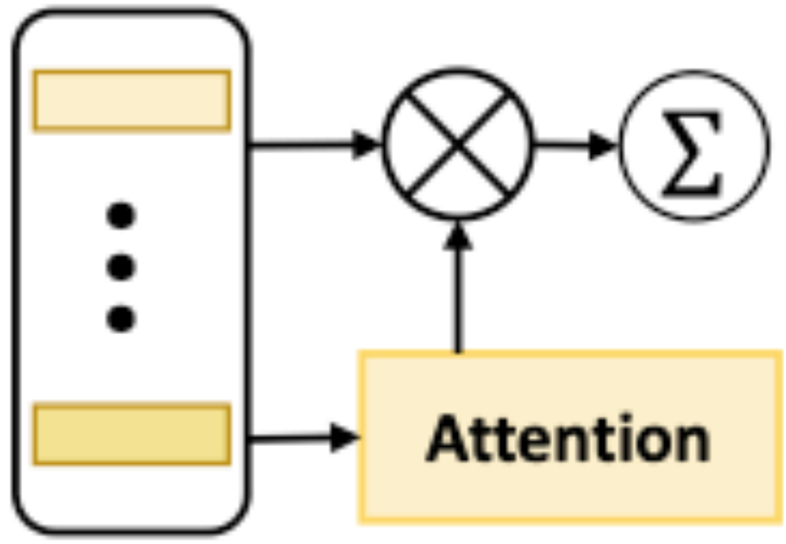


(c) Meta-Path Instance Aggregation

Methodology

Meta-Path Instance Aggregation

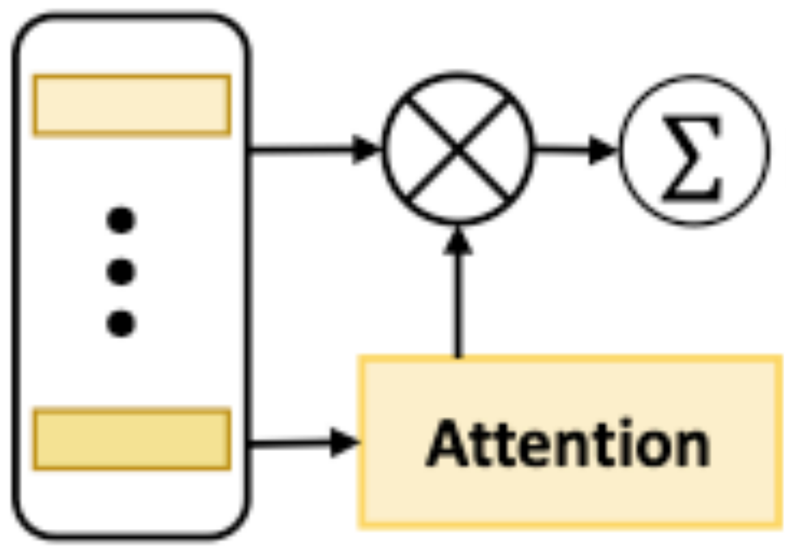
- For each Meta-Path instance $p \in \mathbf{P}_S$:
- $e_p = LeakyReLU(\mathbf{a}^T \cdot \mathbf{h}_p)$
- $\alpha_p = \text{softmax}(e_p) = \dfrac{\exp(e_p)}{\sum_{p' \in \mathrm{P}_S} \exp(e_{p'})}$
- e_p: attention value, $\mathbf{a} \in \mathbb{R}^{2d'}$: attention vector
- a_p: It's normalized by a softmax function over all instances of the target node.



(c) Meta-Path Instance Aggregation

Methodology
Meta-Path Instance Aggregation

- To alleviate the effect of the high variance of the data in a heterogeneous graph.
- Adopt multi-head attention mechanism.
- K independent attention mechanisms execute the transformation, and their features are concatenated after they pass the activation function.
- $$\mathbf{h}_v^{\mathscr{P}_S} = \|_{k=1}^{K} \sigma\Big(\sum_{p \in \mathrm{P}_S} [\alpha_p]_k \cdot \mathbf{h}_p \Big)$$



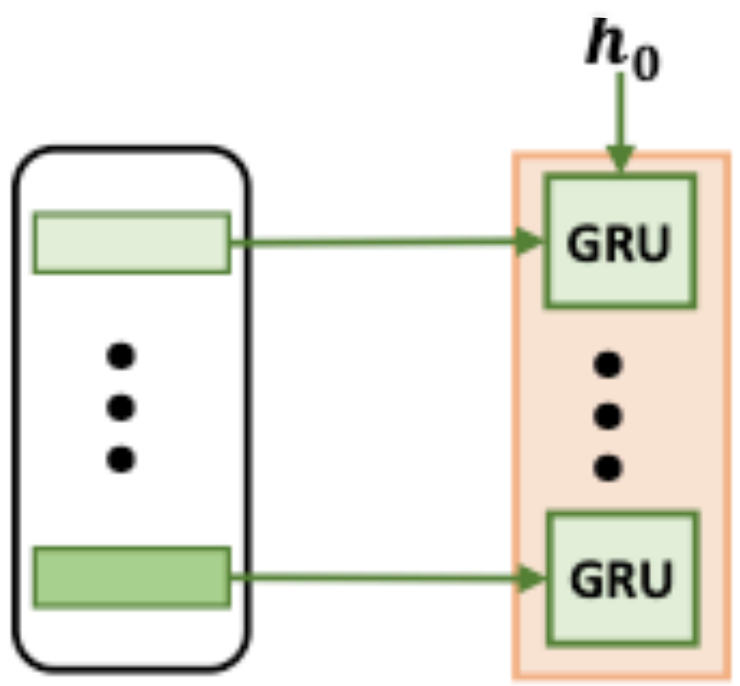
(c) Meta-Path Instance Aggregation

- $[\alpha_p]_k$: normalized attention value of Meta-Path instance p of target node v at k-th attention head.

Methodology

Meta-Path Instance Aggregation

- To capture the temporal information, aggregate $\mathscr{P}_U$ through RNN.
- Since instances are already encoded in previous step, so directly feed them into the RNN.
- There are usually a large # of users engaged per news, so choose GRU as RNN unit to avoid the vanishing or exploding gradients problem.
- $\mathbf{h}_v^{\mathscr{P}_U} = \mathbf{GRU}(\mathbf{h}_{p_1}, \mathbf{h}_{p_2}, \ldots, \mathbf{h}_{p_n}), p_i \in \mathbf{P}_\mathrm{U}$

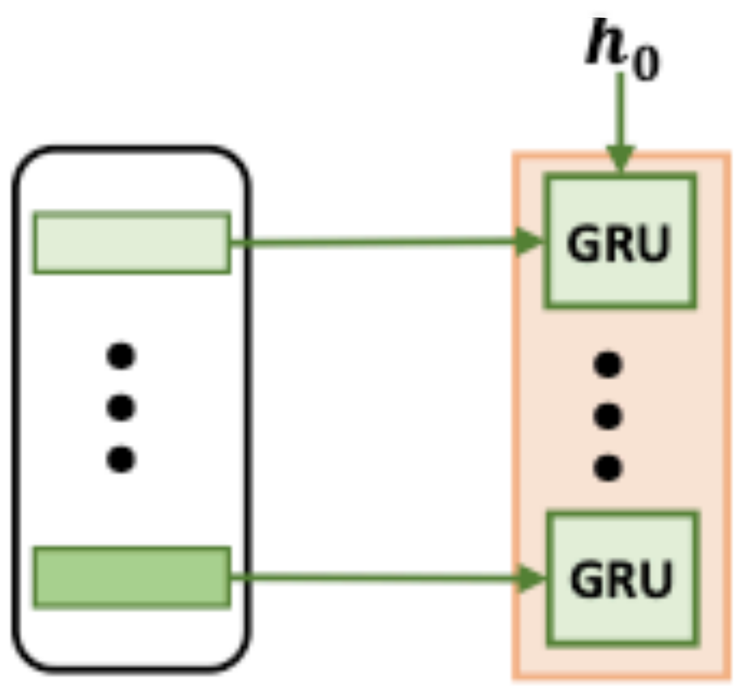


(c) Meta-Path Instance Aggregation

Methodology

Meta-Path Instance Aggregation

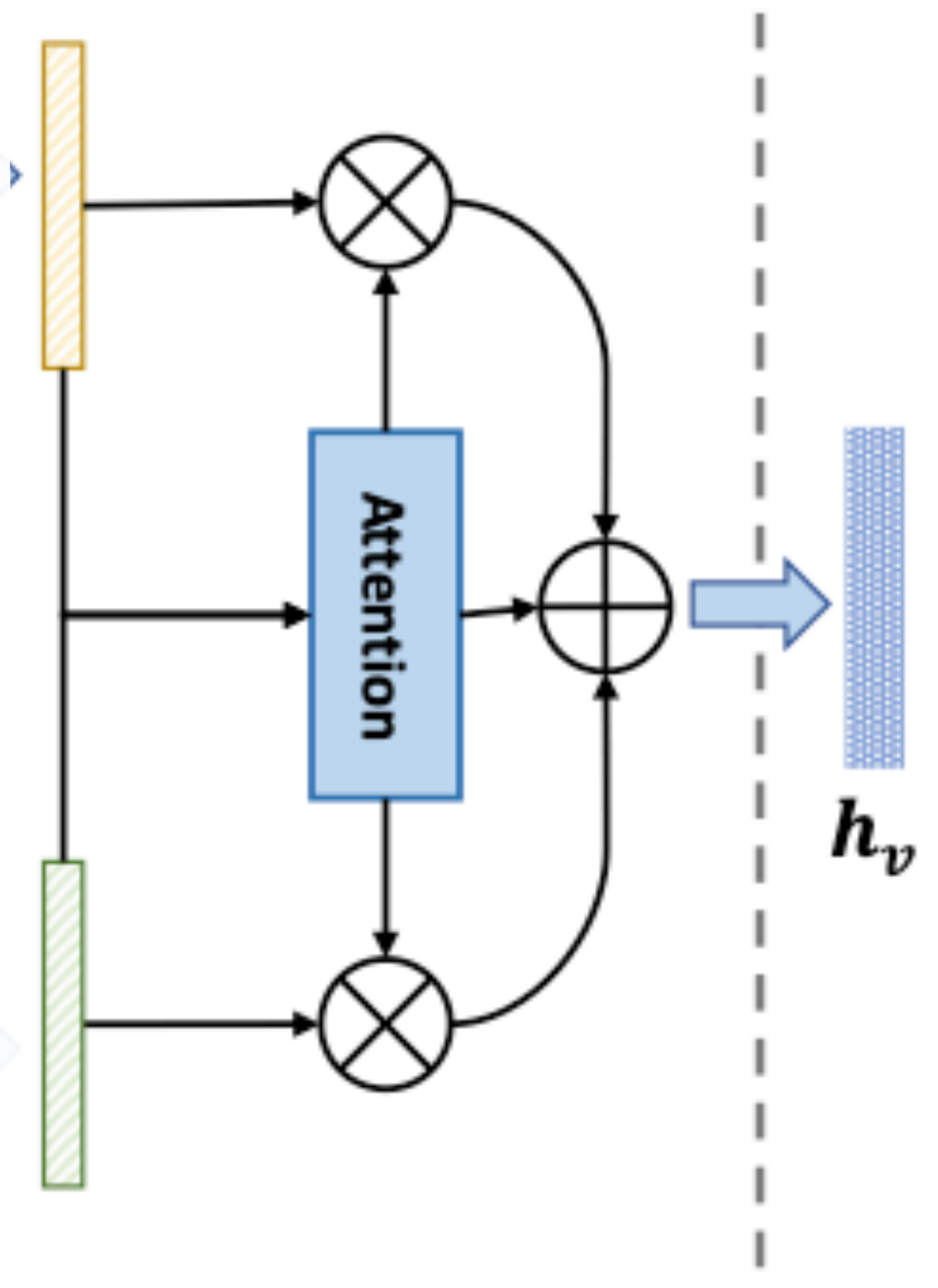
- The last hidden state of the GRU.
  - Used for downstream task as it's the high-level representation.
  - Summarizes the temporal information of the user engagement.



(c) Meta-Path Instance Aggregation

Methodology
Semantic Aggregation

- The final news representation is produced by fusing $\mathbf{h}_v^{\mathscr{P}_S}, \mathbf{h}_v^{\mathscr{P}_U}$.
- Enable us to learn the news representation end-to-end.
- Model should be able to weigh the importance of the two aspects with different news.
- To this end, adopt another attention mechanism.
- Before applying the attention mechanism, non-linear transformations are applied to summarize.



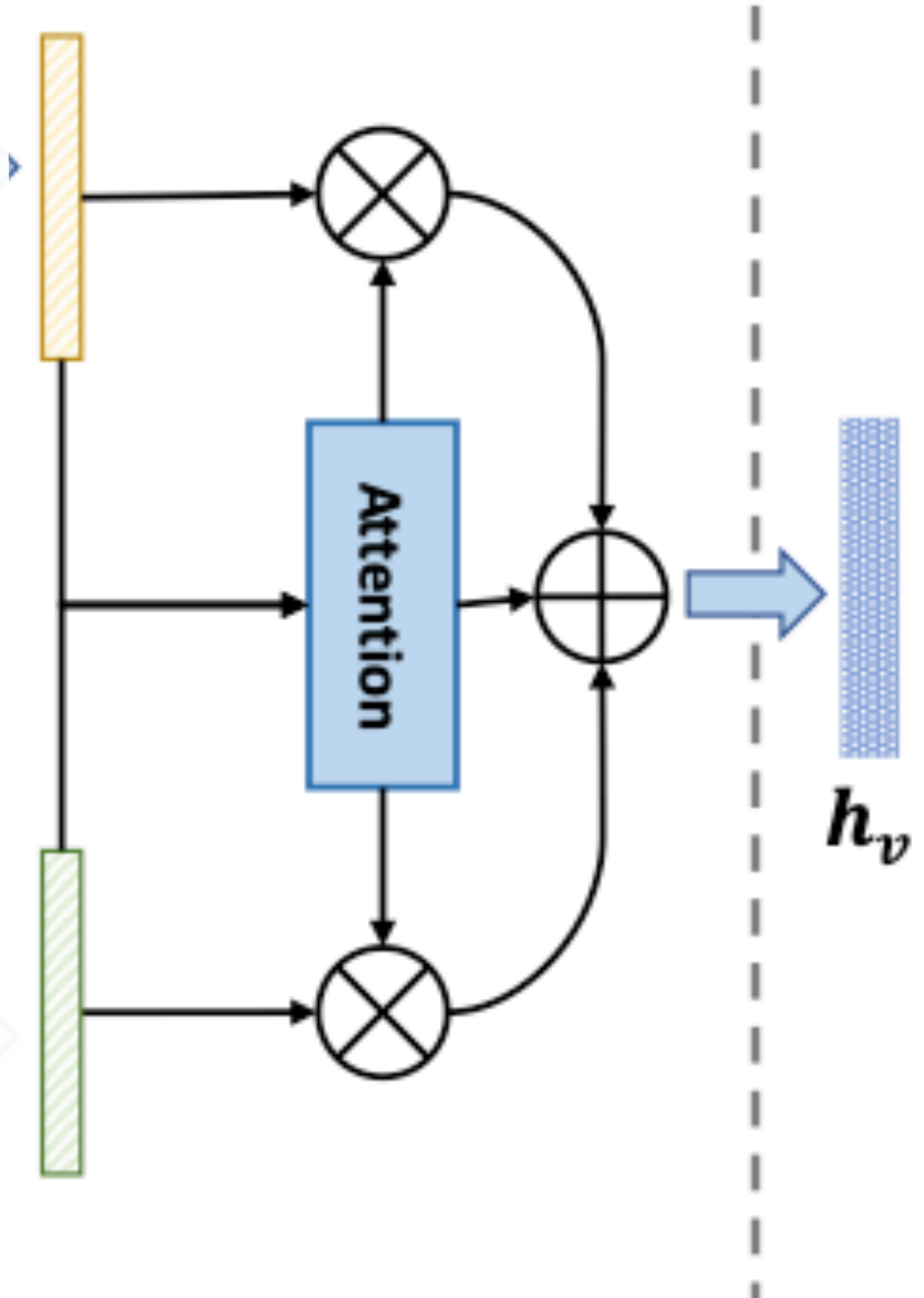
(d)Semantic Aggregation

Methodology

Semantic Aggregation

- $s_P = \frac{1}{|\mathscr{V}|} \sum_{v \in \mathscr{V}} \tanh(\mathbf{M}_A \cdot \mathbf{h}_v^P + \mathbf{b}_A)$
- $e_P = \tanh(q^T \cdot s_P)$
- $\beta_P = \frac{\exp(e_P)}{\sum_{P' \in \mathscr{P}} \exp(e_{P'})}$
- $\mathbf{h}_v = \sum_{P \in \mathscr{P}} \beta_p \cdot \mathbf{h}_v^P$

- $\mathbf{M}_A \in \mathbb{R}^{d_m \times d'}$, $\mathbf{b} \in \mathbb{R}^{d_m}$: learnable weight matrix and bias vector.
- $\mathscr{V}$: set of news nodes.
- $q \in \mathbb{R}^{d_m}$: attention vector
- β_P: normalized importance of Meta-Path P.
- $\mathbf{h}_v$: final news representation.



(d)Semantic Aggregation

Methodology

Training

- Final representation of the target news vector is passed to the classification layer to get the classification result.
- During training,
  - predictions and labels are used to calculate the loss
  - update the learnable parameters of the model by using back propagation algorithm
- The loss function used in Hetero-SCAN is cross-entropy loss
- $\mathscr{L} = -\sum y \log \mathbf{P}_{fake} + (1 - y) \log \mathbf{P}_{real}$

Experiments

Dataset and Settings

	FANG	HealthStory
# Users	52,357	63,723 (sampled)
# News	1,054	1,638
# of Users per News	71.9	227.26
# Fake News	448	460
# Real News	606	1,178
# Publishers	442	31

- Conducted our experiments with two real-world datasets: FANG & FakeHealth
- FANG are obtained from two well-known fact-checking websites: Snopes and PolitiFact.
- FakeHealth is another publicly available benchmark dataset, mainly focused on the healthcare domain.
- In each dataset, used 70% of news articles as our training set, and the remaining 30% of news articles are further divided into equal sizes of validation and test set.
  - 70% : 15% : 15%

Experiments

Dataset analysis

- Disinformation v.s. Misinformation
- Disinformation behaves significantly differently from real information.
- But misinformation behaves in a similar manner to real news.

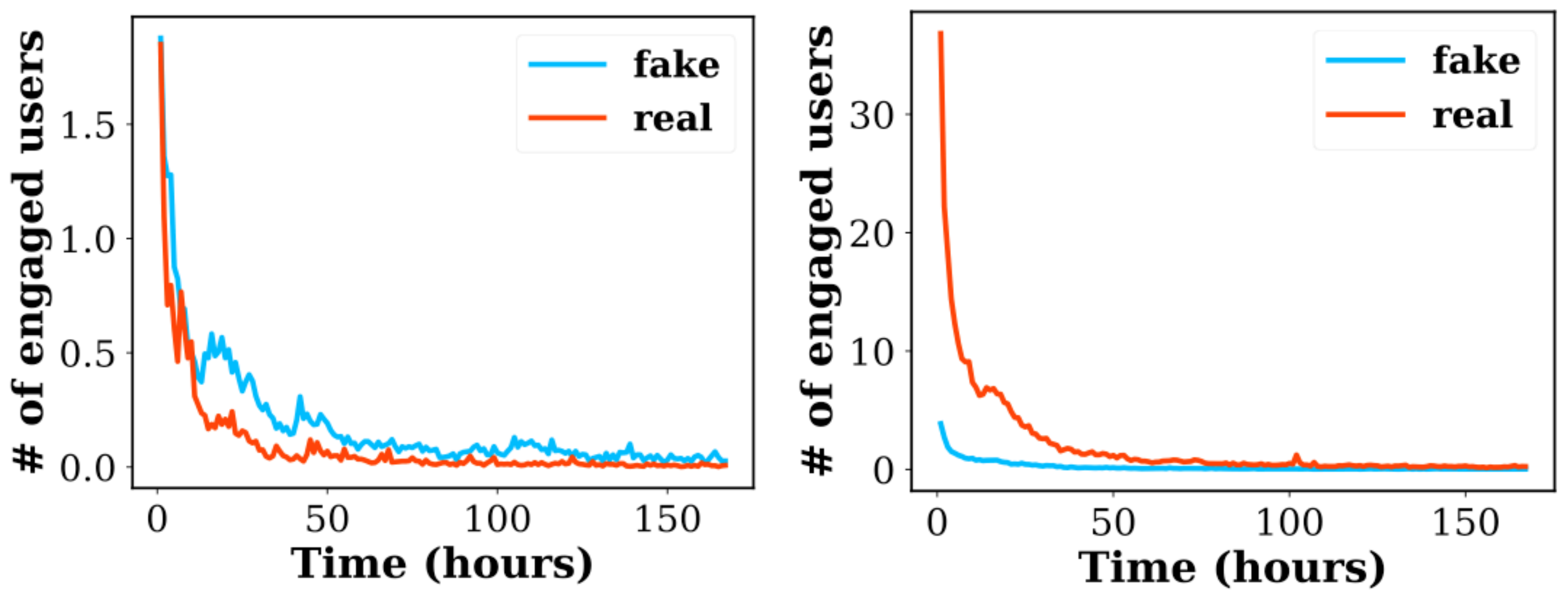


Figure 5: Comparison of temporal behaviours on two datasets. Both figures show the # of engagements (tweets) per news vs. time (hours) for FANG (left) and HealthStory (right).

Experiments

Ablation study

- RNN-based approach performs better than the other one in FANG.
- But for the HealthStory dataset, the performance is better when the attention is applied.

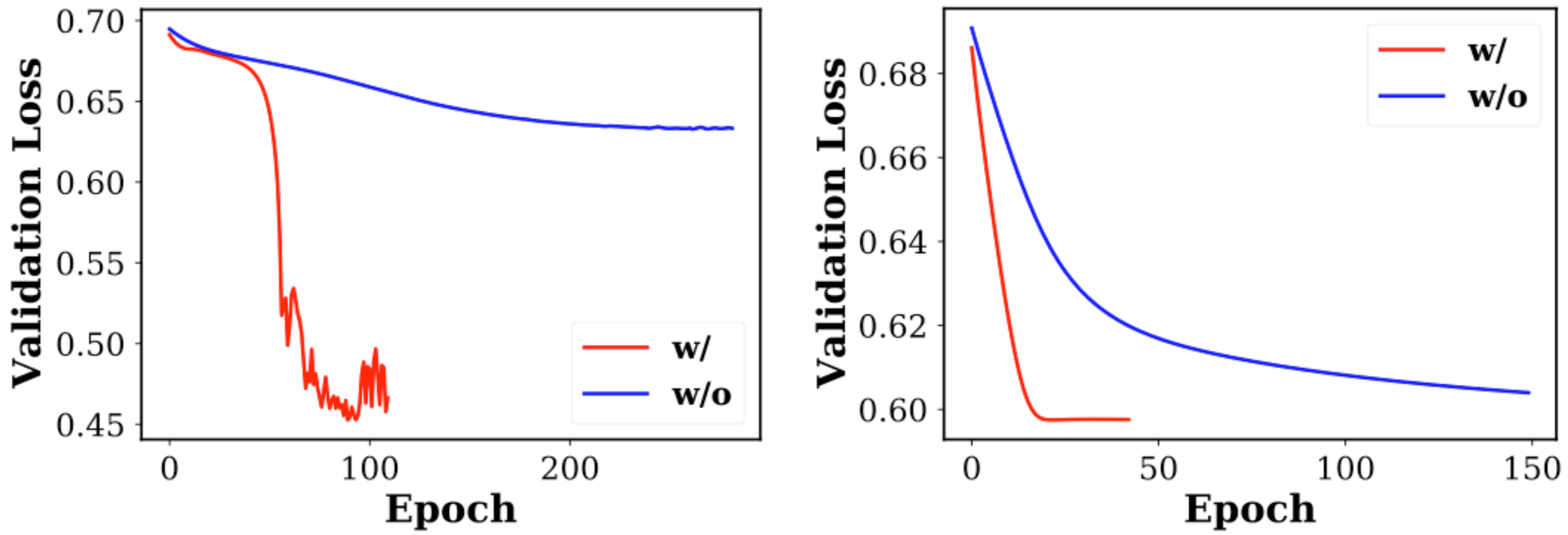
Table 5: Performance of the *Hetero-SCAN* with and withou temporal information.

Dataset	*Hetero-SCAN*	F1	Accuracy	AUC
FANG	*w/ temporal*	**0.831**	**0.831**	**0.900**
	w/o temporal	0.759	0.760	0.823
HealthStory	*w/ temporal*	0.526	0.520	0.513
	w/o temporal	**0.614**	**0.595**	**0.636**

Experiments

Ablation study

- In FANG, the validation loss of Hetero-SCAN with RNN converges much faster than the one with attention mechanism.
- The convergence speed of the 2 approaches is similar in the HealthStory dataset.



(a) FANG (b) HealthStory

Figure 6: Validation loss during training. (Red line indicates the validation loss of *Hetero-SCAN* with temporal information, blue line indicates the validation loss of *Hetero-SCAN* without temporal information.)

Experiments
Baselines

- Text-based Methods: TF-IDF+SVM, LIWC+SVM, Doc2Vec+SVM
- Graph-based Methods:
    - SAFER: uses GCN and pre-trained RoBERTa model to embed news nodes in the heterogeneous graph.
    - CSI: aims to model the response, text, and user engagement of the news.
    - FANG: divides the detection task into several sub-tasks, such as textual encoding and stance detection.
    - AA-HGNN: uses active learning to tackle the limited training data problem and extends GAT to learn the news representation in the graph.

Experiments
Baselines

- GNN baselines:
  - GCN
  - GAT: attention mechanism to replace the statically normalized convolution operation in GCN.
  - GraphSAGE: inductive framework that learns a node representation by sampling its neighbors and aggregating features of sampled nodes.
  - R-GCN: GCN framework for modeling relational data. Edges can represent different relations.
  - HAN: an extension of GAT on the heterogeneous graph. Meta-Path extraction strategy and attention mechanism are adopted to learn the representation of a node.

Experiments
Result

- Hetero-SCAN outperforms existing text-based or graph-based fake news detection methods.
- CSI and SAFER didn't use multi-level social context, and they also incurred some information loss as they ignored the node and relation types.
- AA-HGNN, including SAFER, miss temporal information in the news representation.
- AA-HGNN also didn't use users as social context.

Table 6: Comparison with other methods. The AUC score of the CSI is from FANG, the F1 score and AUC score are not reported in this paper.

Category	Method	F1	Accuracy	AUC
Text-based	TF.IDF + SVM	0.746	0.750	0.735
	LIWC + SVM	0.512	0.550	0.511
	Doc2Vec + SVM	0.561	0.560	0.554
Graph-based	CSI	-	-	0.741
	SAFER	0.678	0.680	0.669
	FANG	0.676	0.687	0.750
	AA-HGNN	0.726	0.662	0.654
GNN-baselines	GCN	0.645	0.650	0.633
	GAT	0.642	0.650	0.630
	GraphSAGE	0.779	0.780	0.773
	R-GCN	0.765	0.770	0.753
	HAN	0.662	0.660	0.658
	Hetero-SCAN	**0.831**	**0.831**	**0.900**

Experiments

Result

- For GNN baselines, the methods made for homogeneous graphs (GCN, GAT and GraphSAGE).
  - Didn't give ideal results since node types and relations are ignored in these cases.
- R-GCN & HAN, designed for heterogeneous graph, also has no significant improvement.
- Implies that Hetero-SCAN is better than a simple application of these graph embedding methods on the heterogenous graph of news.

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	Hetero-SCAN	**0.831**	**0.831**	**0.900**

Experiments

Result

- The fail of GNN baselines target on the heterogeneous graph.
  - Can attribute to the missing temporal information of user engagement.

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Experiments

Limited training data

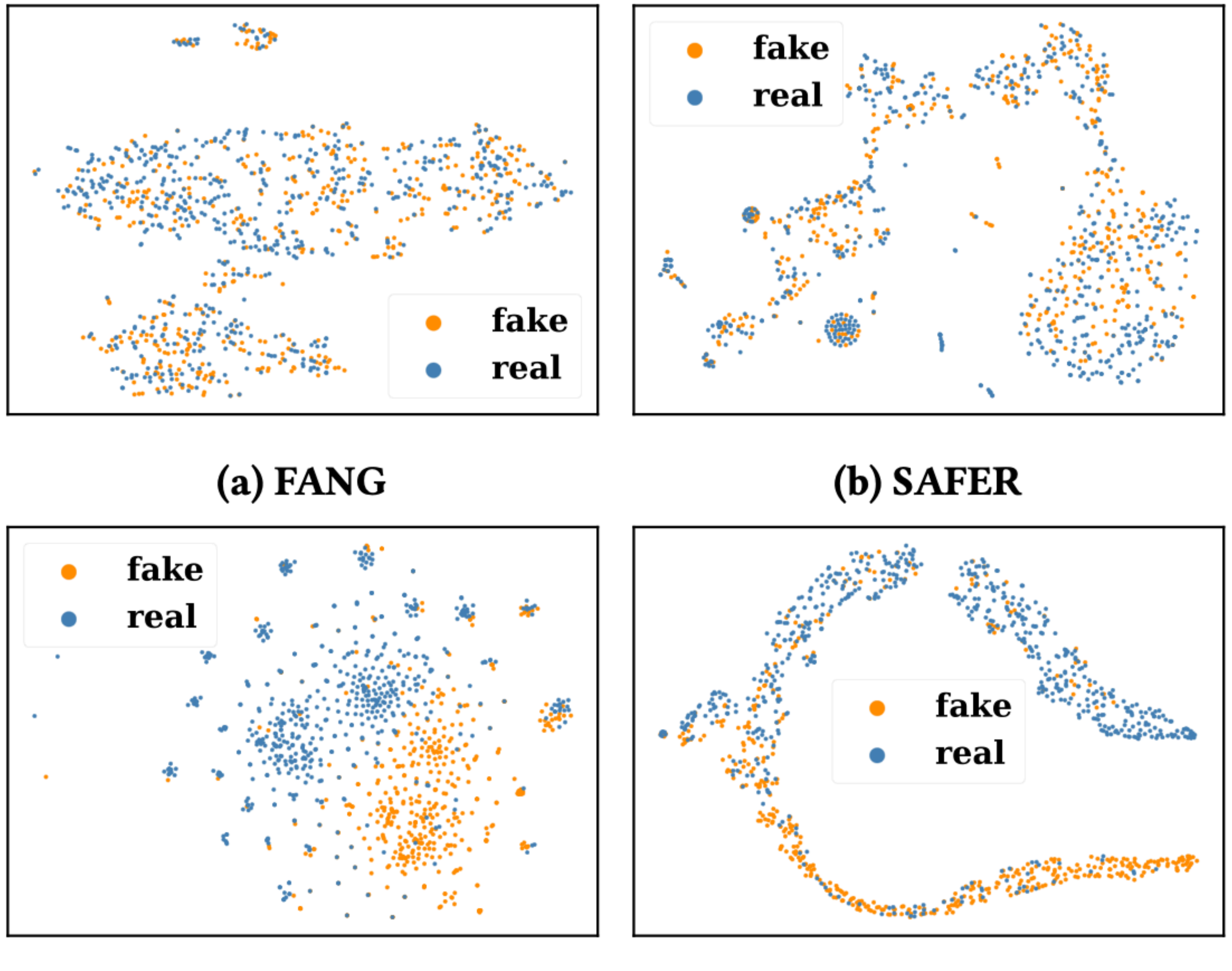
- The AUC score of Hetero-SCAN achieves over 0.8 with only 30% of training data even outperforms the rest of the methods with 90% of the training data.
- AA-HGNN is designed to overcome the scarcity of training data issues.
  - But Hetero-SCAN is still better than AA-HGNN even when the size of training data is small.

Table 7: Comparison of AUC score against other fake news detection methods by varying the size of the training data.

	10%	**30%**	**50%**	**70%**	**90%**
CSI	0.636	0.671	0.670	0.689	0.691
SAFER	0.546	0.689	0.666	0.692	0.669
FANG	0.669	0.704	0.717	0.723	0.752
AA-HGNN	0.573	0.598	0.656	0.657	0.642
Hetero-SCAN$_{w/o\ time}$	0.594	0.707	0.776	0.749	0.751
Hetero-SCAN$_{w/\ time}$	**0.764**	**0.835**	**0.878**	**0.889**	**0.900**

Experiments
Visualization

- Apply t-SNE on FANG, SAFER, Hetero-SCAN.
- Representations of Hetero-SCAN are clustered tighter than the other methods.
    - Implying a significant improvement over existing methods.



(c) *Hetero-SCAN* (w/o temporal information) (d) *Hetero-SCAN* (w/ temporal information)

Figure 7: t-SNE visualization of news representations.

Conclusions and Future Work

- Pose three difficulties in social context aware fake news detection and address them by proposing a novel fake news detection framework Hetero-SCAN.
- Proposed model overcomes the shortcomings of the previous graph-based approaches and exhibits SOTA performance.
- Provide insight about misinformation and disinformation by clarifying their different propagation properties.
- Finding relevant tweets for particular news is left as future work.

Comments

of Hetero-SCAN

- Effective combine social context information & temporal information.
- Text-only method.
  - Consider user quote-tweet.
- Meta-Path extraction concept.