FANG: Leveraging Social Context for Fake News Detection Using Graph Representation

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Outline

Introduction

Related Work

Methodology

Experiments

Discussion

Conclusion

Comments

Introduction

Fake News Detection

- During critical events such as a political election or a pandemic outbreak, disinformation with malicious intent, commonly known as “fake news”.
- As part of the fight against COVID-19, the WHO also addressed the *infodemic* caused by fatal disinformation related to infections and cures.
- Many sites and social media have devoted efforts to identify disinformation.
    - Facebook encourages users to report non-credible posts and employs professional fact-checkers to expose questionable news.
    - Manual fact-checking is also used by fact-checking websites such as Snopes, FactCheck, PolitiFact and Full Fact.

Introduction
Recent work

- In order to scale with the increasing amount of information, automated news verification systems consider external knowledge databases as evidence.
- Evidence-based approaches achieve high accuracy and offer potential explainability, but they also take considerable human effort.
- Some recent work observed distinctive engagement patterns when social users face versus factual news.

Column 2 shows the time since publication
Columns 4–7 show the distribution of stances (S: Support, D: Deny, C: Comment, and R: Report)

Introduction

Engagement of social media users with respect to fake and real news articles

News title (Label)	Time	# Posts	S	D	C	R	Noticeable responses
Virginia Republican Wants Schools To Check Children's Genitals Before Using Bathroom **(Fake)**	3h	38	0.00	0.03	0.19	0.78	"DISGUSED SO TRASNPHOBIC", "FOR GODS SAKE GET REAL GOP", "You cant make this up folks"
	3h - 6h	21	0.00	0.10	0.10	0.80	"Ok This cant be real", "WTF IS THIS BS", "Rediculous RT"
	6h+	31	0.00	0.10	0.14	0.76	"Cant make this shit up", "how is this real", "small government", "GOP Cray Cray Occupy Democrats"
1,100,000 people have been killed by guns in the U.S.A. since John Lennon was shot and killed on December 8, 1980 **(Real)**	3h	9	0.56	0.00	0.00	0.44	"#StopGunViolence", "guns r the problem"
	3h+	36	0.50	0.00	0.11	0.39	"Some 1.15 million people have been killed by firearms in the United States since Lennon was gunned down", "#StopGunViolence"

- The fake news had many engagements shortly after its publication.
- These are mainly verbatim re-circulations with negative sentiment of the original post explained by the typically appalling content of fake news.
- After that short time window, see denial posts questioning the validity of the news, and the stance distribution stabilizes afterwards with virtually no support.

Column 2 shows the time since publication
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Introduction

Engagement of social media users with respect to fake and real news articles

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- The real news invokes moderate engagement, mainly comprised of supportive posts with neutral sentiment that stabilize quickly.

- Such temporal shifts in user perception serve as important signals for distinguishing fake from real news.

Introduction
Pervious work

- Previous work proposed partial representations of social context with news, sources and users as major entities, and stances, friendship, and publication as major interactions.

- However, they didn't put much emphasis on the quality of representation, modeling of entities and their interactions, and minimally supervised settings at all.

Introduction

Pervious work

- Naturally, the social context of news dissemination can be represented as a heterogeneous network where nodes and edges represent the social entities and the interactions between them, respectively.

- Network representations have several advantages over some existing Euclidean-based methods in terms of structural modeling capability for several phenomena such as echo chambers of users or polarized networks of news media.

Introduction

Graphical models

- Graphical models allow entities to exchange information via

    (i) Homogeneous edges (user-user relationships, source-source citations)

    (ii) Heterogeneous edges (user-news stance expression, source-news publication)

    (iii) High-order proximity (between users who consistently support or deny certain sources)

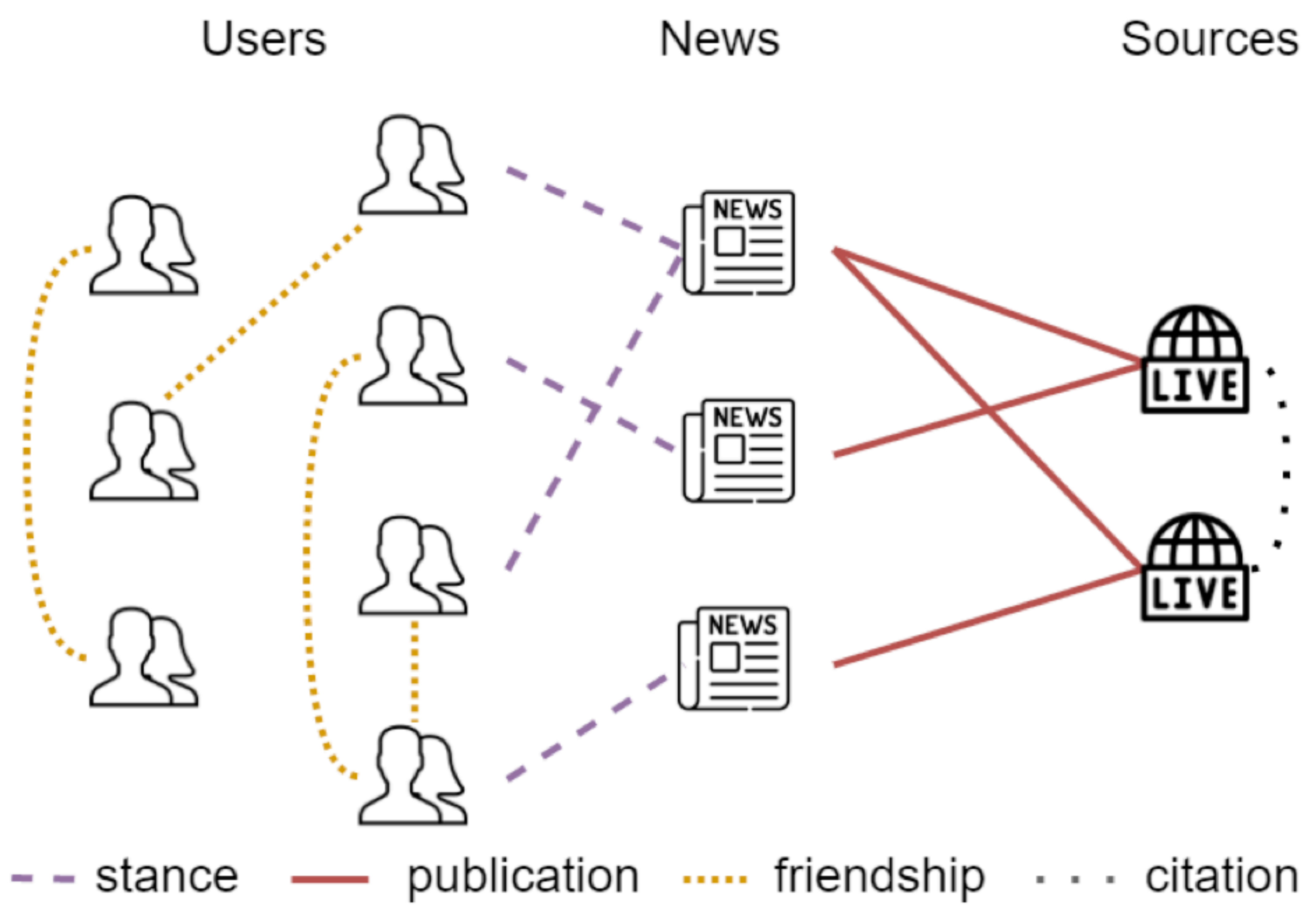


Figure 1: Graph representation of social context.

Introduction

Graphical models

- This allows the representation of heterogeneous entities to be dependent, leveraging not only fake news detection but also related social analysis tasks such as malicious user detection and source factuality prediction.
- FANG focuses on improving contextual fake news detection by enhancing representations of social entities.

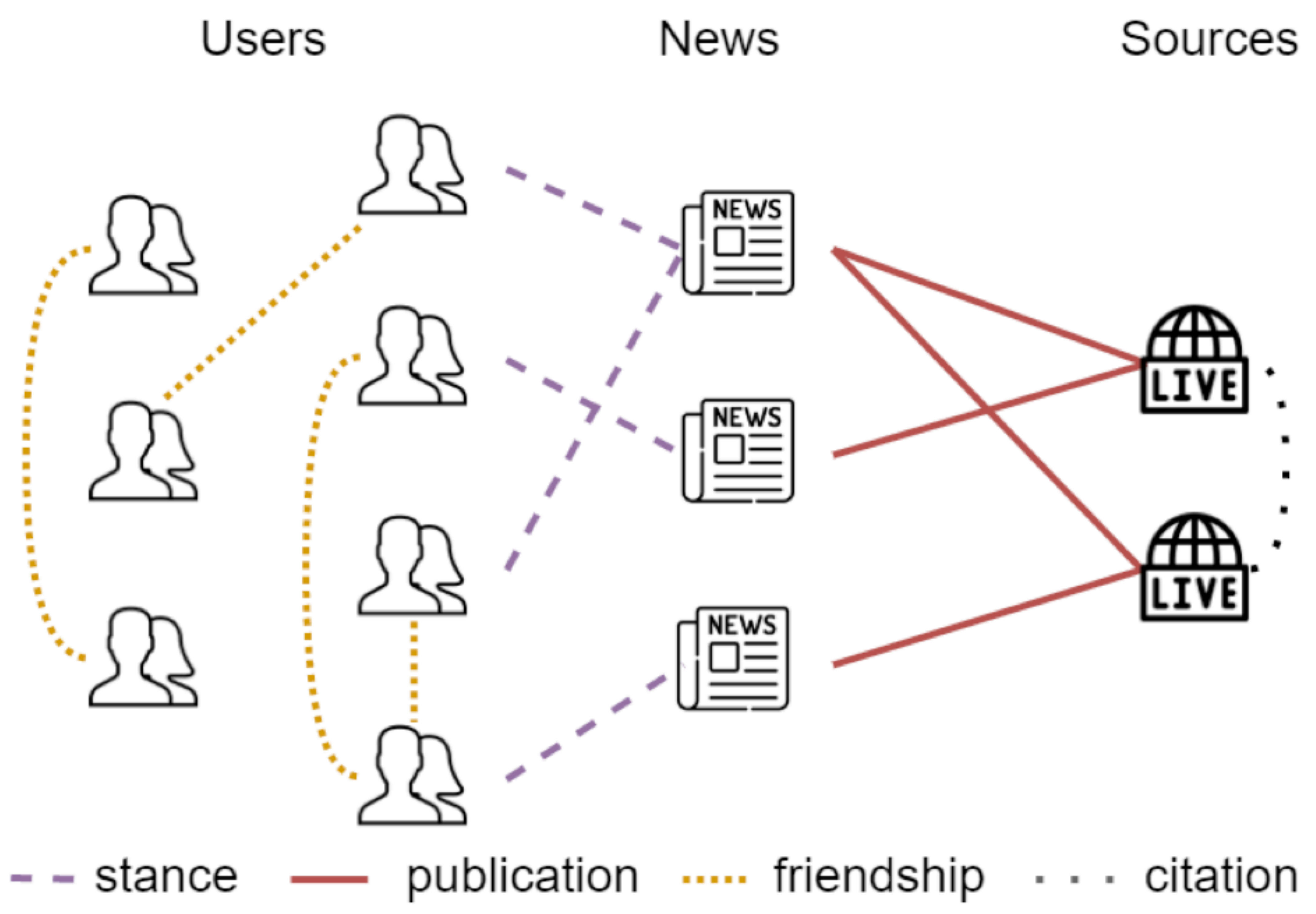


Figure 1: Graph representation of social context.

Introduction

Contributions

- Novel graph representation that models all major social actors and their interactions.
- Factual News Graph (FANG), an inductive graph learning framework
  - Capture the social structure and engagement patterns to improve representation quality
  - Robust given limited training labels
  - Generalizable to related credibility assessment tasks (i.e., predicting the factuality of a news medium)

Related Work

Comparison between representation learning frameworks

Approach	Social Entities & Interactions	Temporal	Graphical	Deep	Inductive	Representative
Feature engineering [6, 26, 32, 44]	1, 2				✓	
Popat [33]	2, 3, 6	✓				
CSI [35]	1, 2, 4, 5	✓		✓	✓	
TriFN [39]	1, 2, 3, 4, 5, 6		✓			✓
MVDAM [21]	2, 3, 6, 7		✓	✓		
Monti [29]	1, 2, 4, 5	✓	✓			
GLAN [45]	1, 2, 5		✓	✓		
FANG (Our proposed approach)	1, 2, 3, 4, 5, 6, 7	✓	✓	✓	✓	✓

Comparison between representation learning frameworks for social entities (1. users, 2. news, 3. sources) and interactions (4. user-user friendship, 5. user–news engagement, 6. source–news publication, 7. source–source citation) on whether they consider engagement time, graph modeling of social context, deep learning, inductiveness, and representation learning.

Methodology

Definition

- $A = \{a_1, a_2, \cdots\}$: list of questionable **news articles**
- $S = \{s_1, s_2, \cdots\}$: list of **news sources**
- $U = \{u_1, u_2, \cdots\}$: list of **social users**
- $E = \{e_1, e_2, \cdots\}$: list of **interactions**
    - $e = \{v_1, v_2, t, x_e\}$
    - $v_1, v_2 \in A \cap S \cap U$: entities
    - t: timestamp
    - x_e: interaction type label

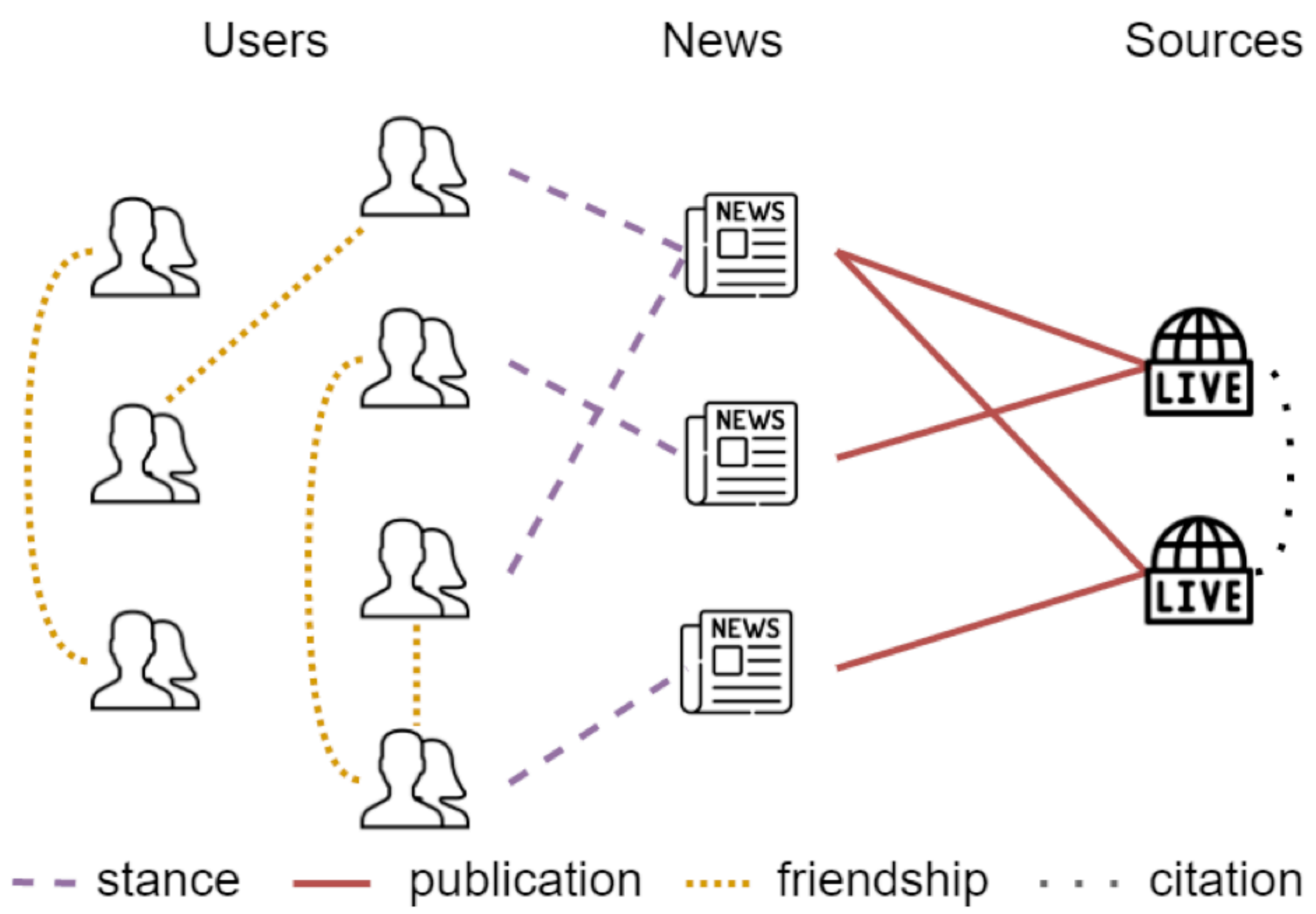


Figure 1: Graph representation of social context.

Methodology
Definition

	User (U)	News (A)	Source (S)
User (U)	Friendship	Stance	
News (A)	Stance		Publication
Source (S)		Publication	Citation

Social Interactions

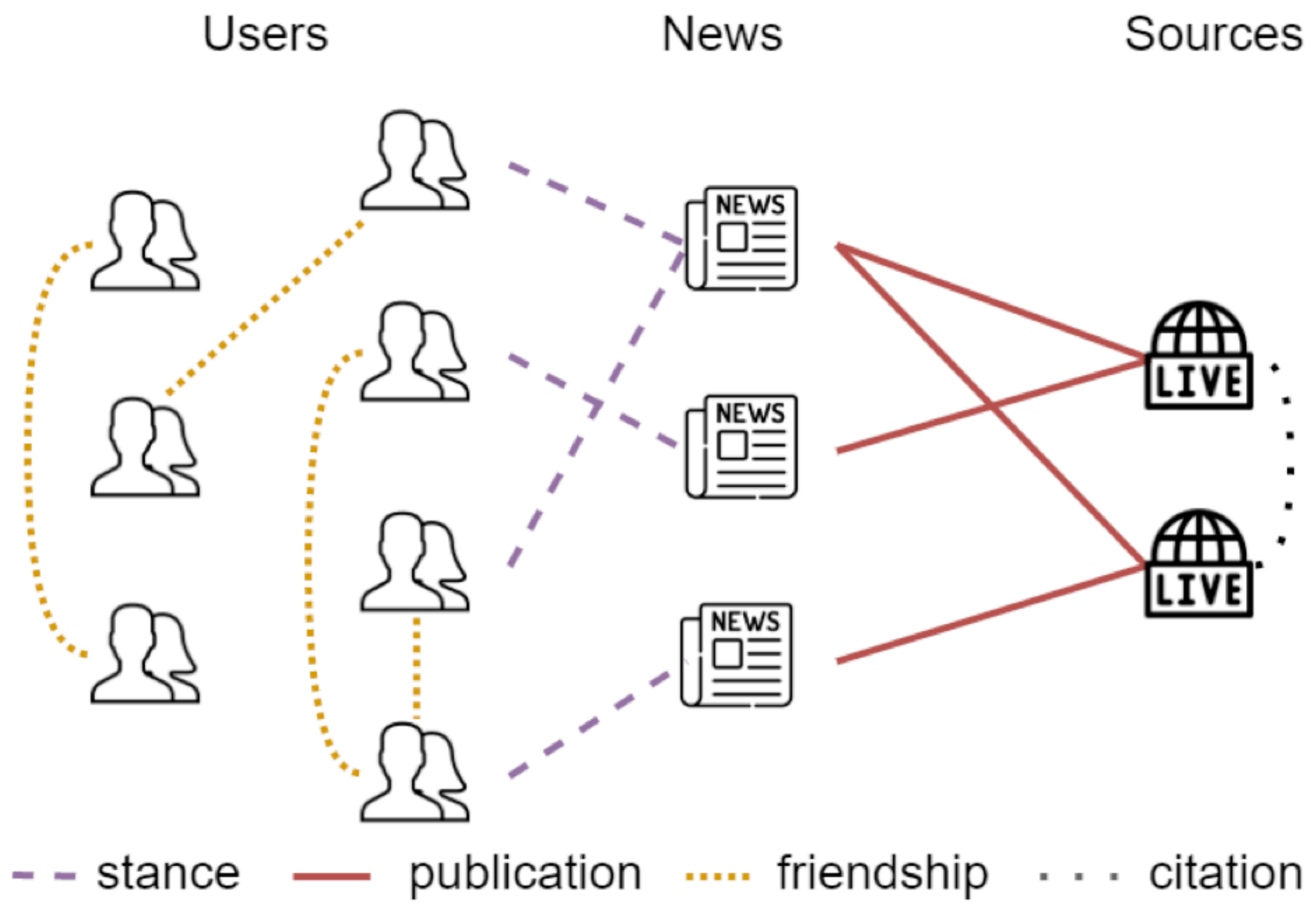


Figure 1: Graph representation of social context.

Methodology
Definition

- *Context-based fake news detection*: Given a social context $G = (A, S, U, E)$, context-based fake news detection is defined as the binary classification task to predict whether a news article $a \in A$ is fake or real.
- $F_C(a) = \begin{cases} 0 & \text{if } a \text{ is a fake article} \\ 1 & \text{otherwise} \end{cases}$

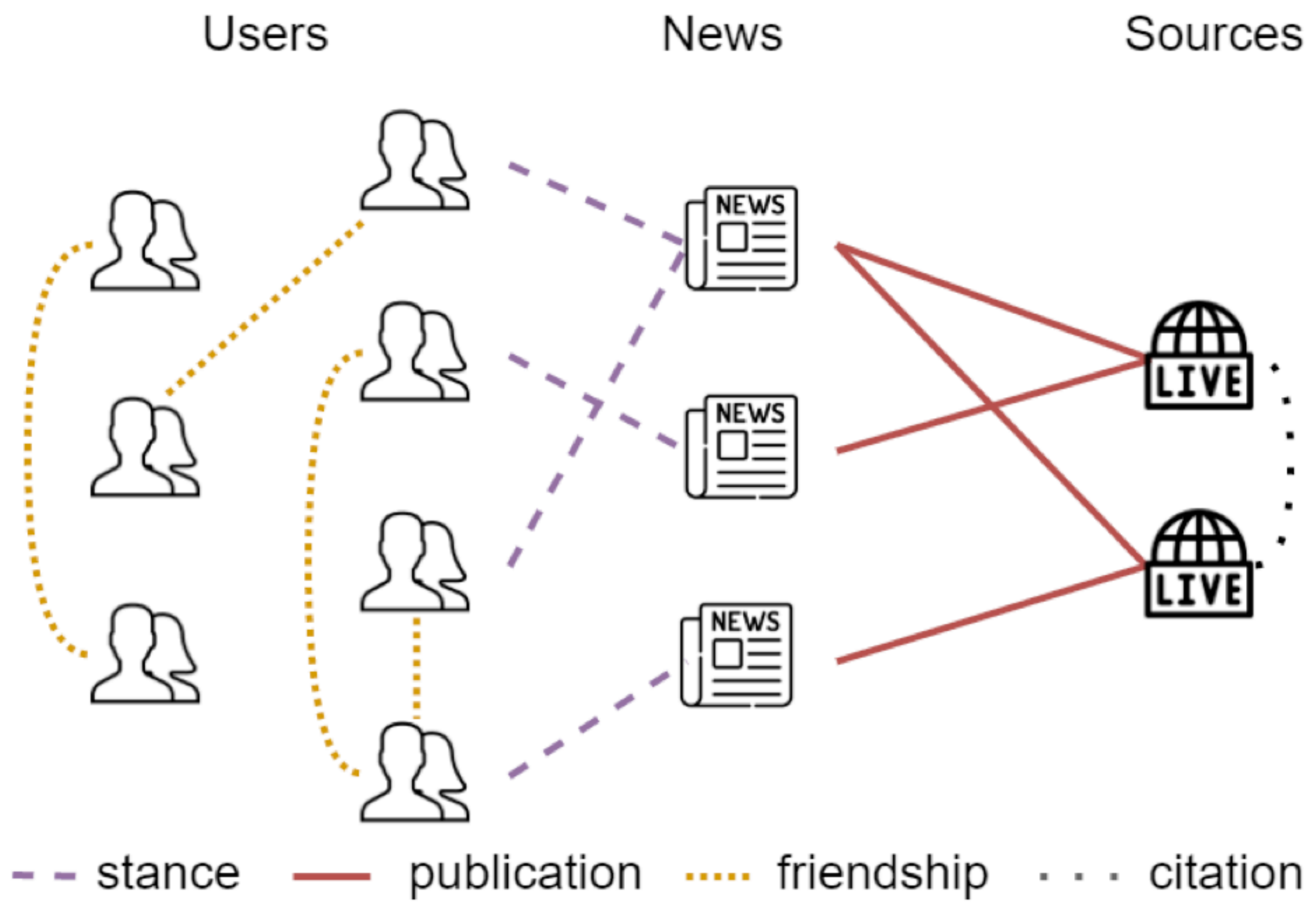
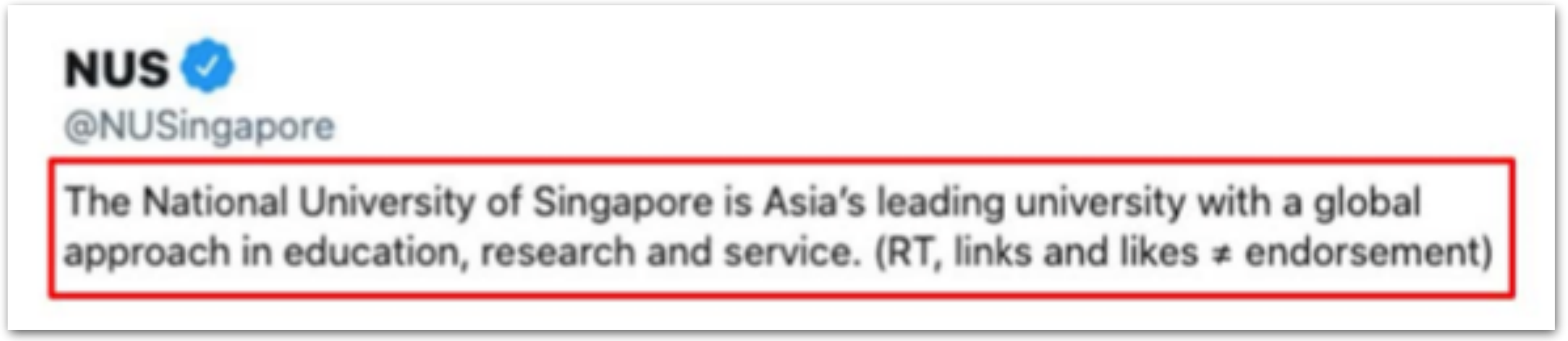


Figure 1: Graph representation of social context.

Methodology

Graph Construction from Social Context - Users

- Feature
  - TF-IDF vector + weight word-embedding
  - From user's twitter descriptions
- Relations
  - Friendship



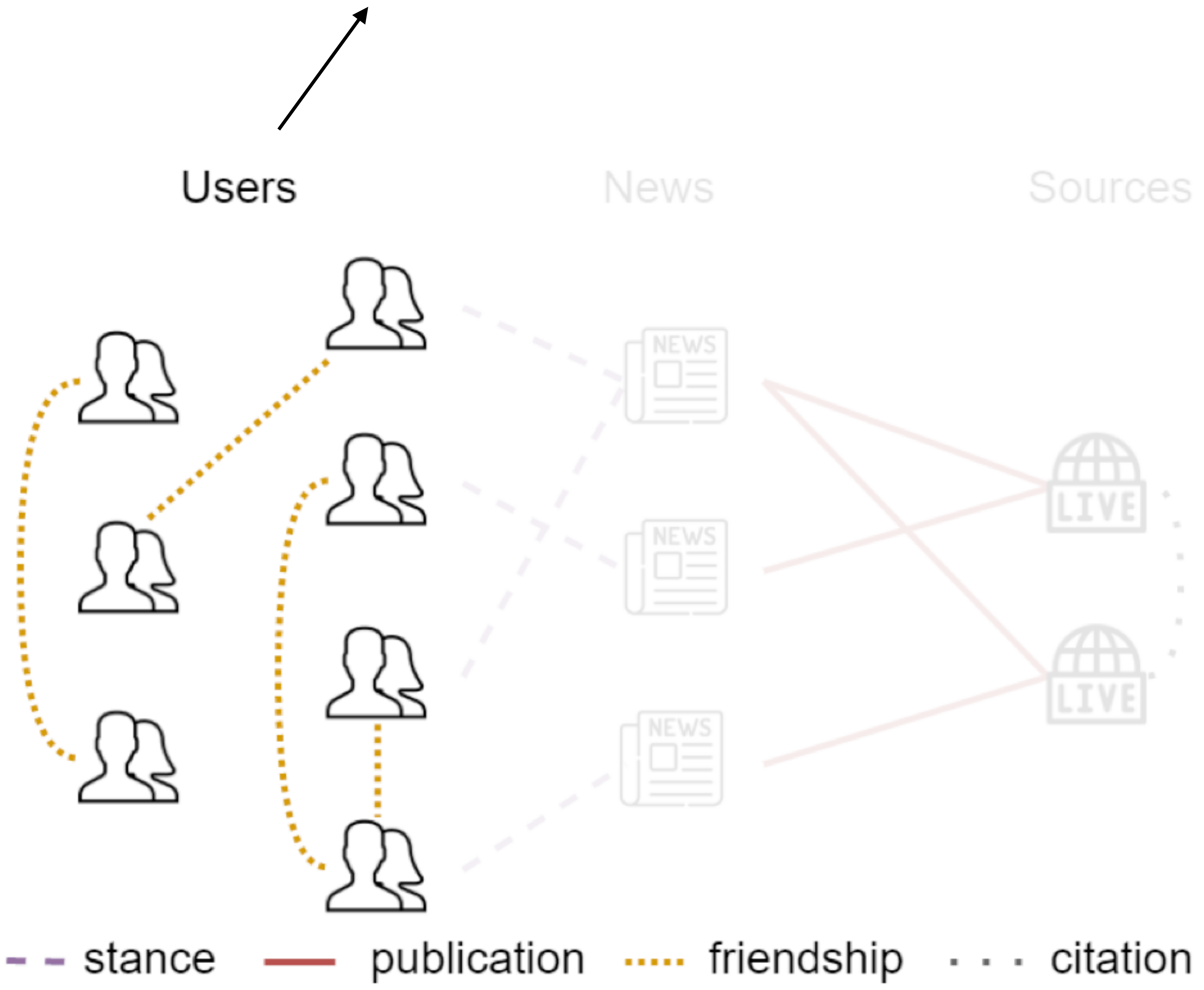


Figure 1: Graph representation of social context.

Methodology
Graph Construction from Social Context - Sources

- Feature
  - TF-IDF vector + weight word-embedding
  - From homepage and about us content
- Relations
  - Citations

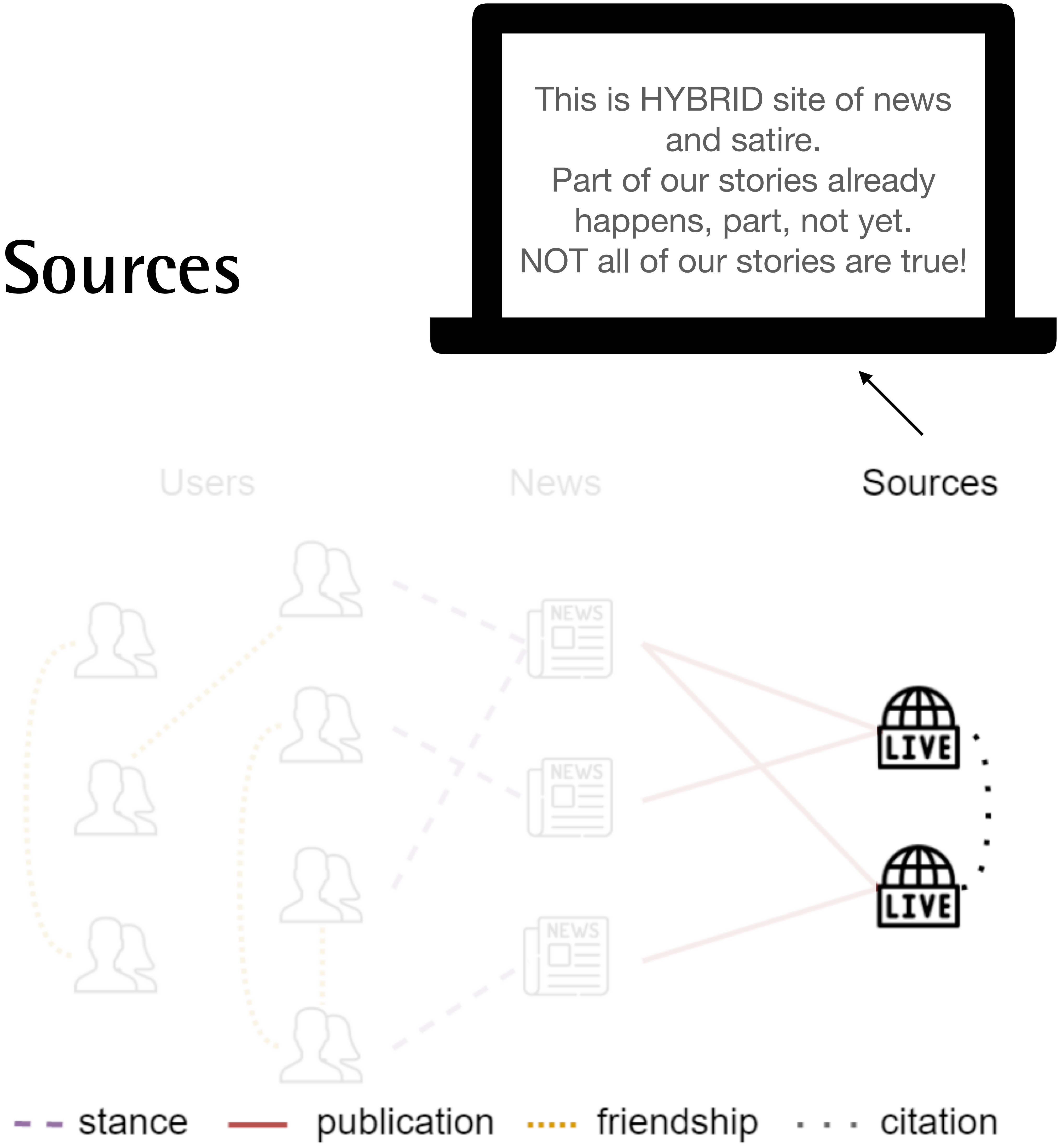


Figure 1: Graph representation of social context.

Methodology

Graph Construction from Social Context - News

- Feature
  - TF-IDF vector + weight word-embedding
  - From news content
- Relations
  - Source-news publication
  - User-news stance: neutral support, negative support, deny, report

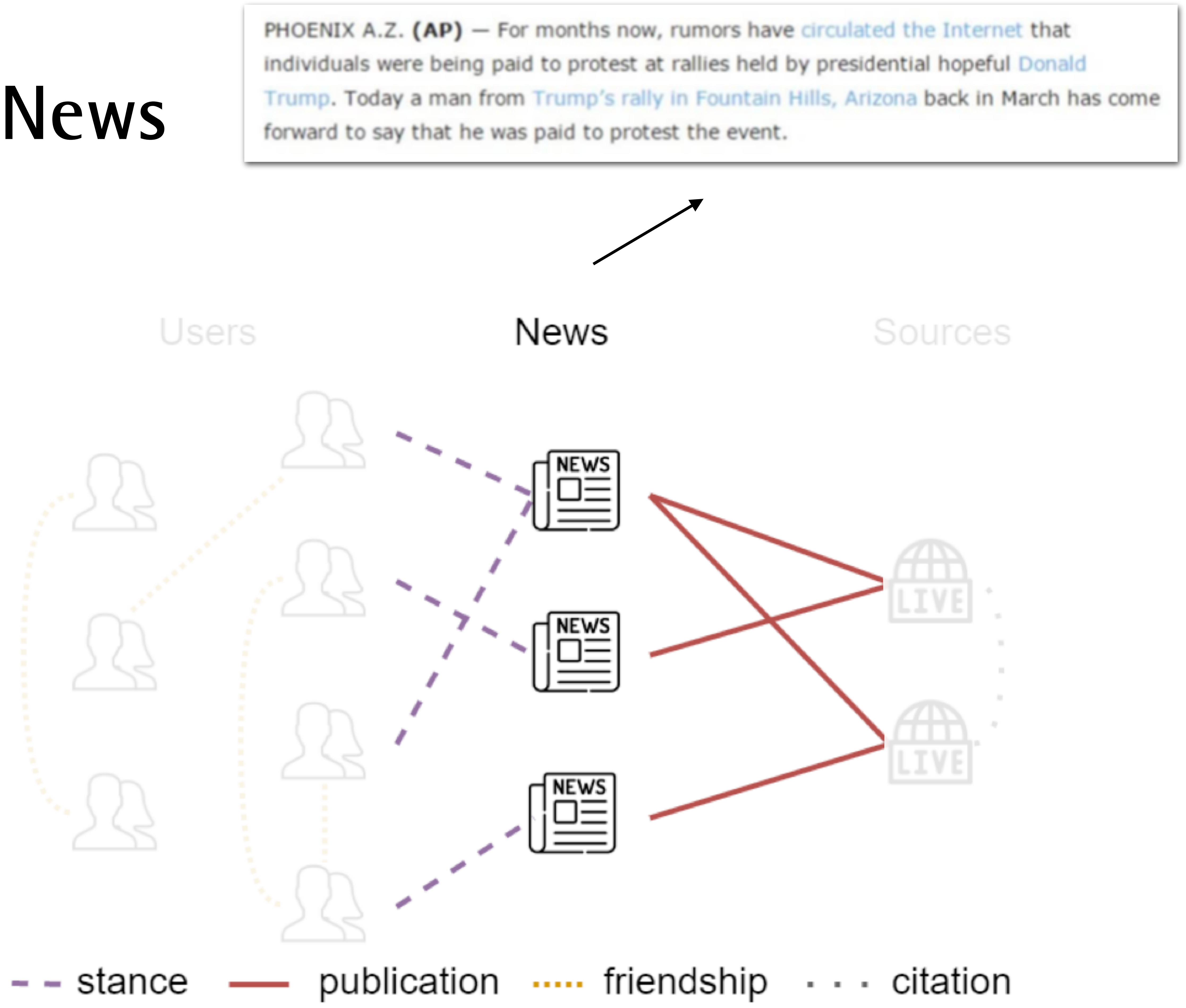


Figure 1: Graph representation of social context.

Methodology

Graph Construction from Social Context - Stance Detection

- Use user reply with respect to the title of a questionable news article.
- Classify a post as verbatim reporting of the news article if it match the title after clean process.
- Remaining post train a stance detector to classify the remaining post → support, deny
- In order to further classify support posts into neutral and with negative sentiment, we fine-tuned a similar architecture on the Yelp Review Polarity dataset to obtain a sentiment classifier.

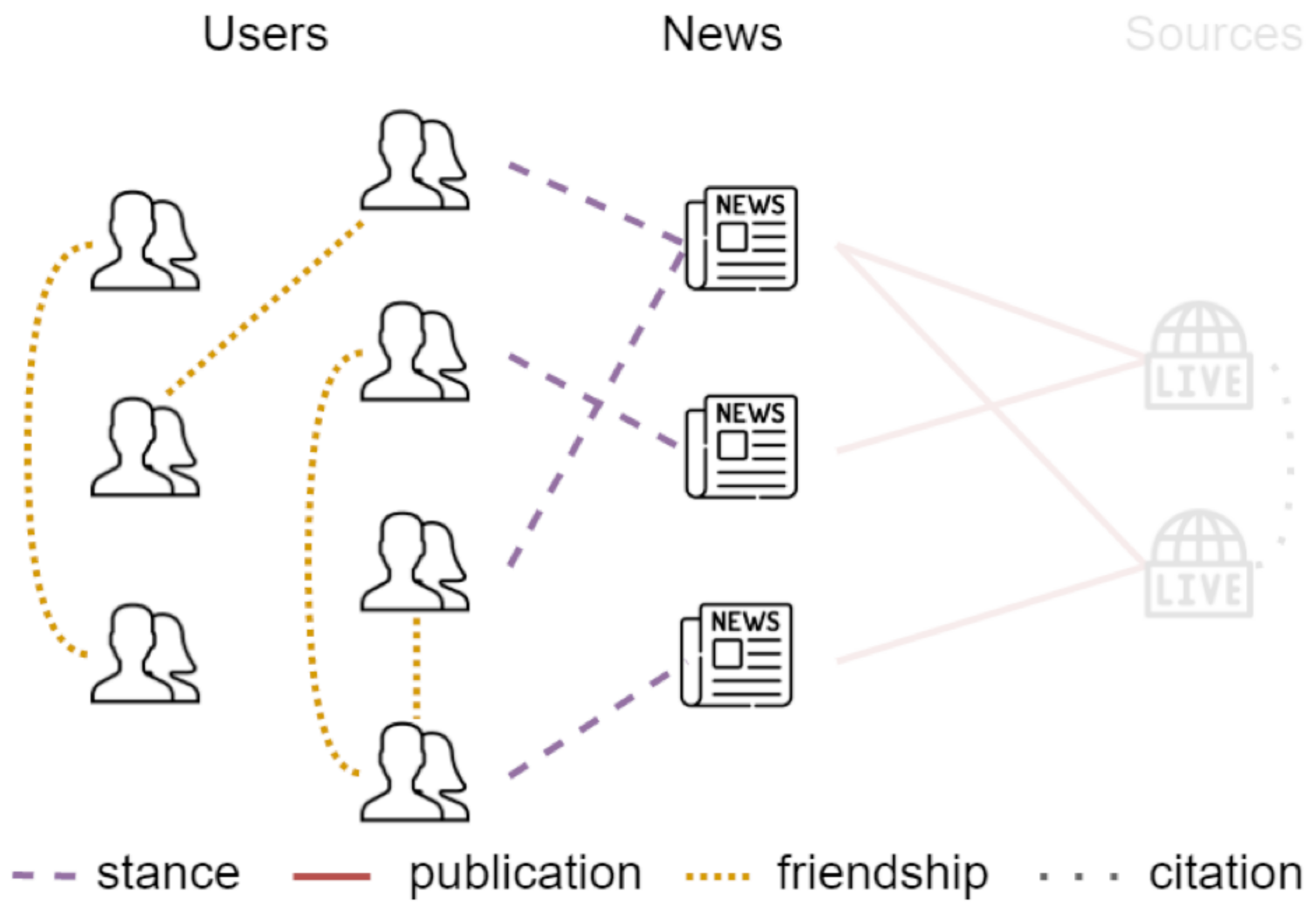
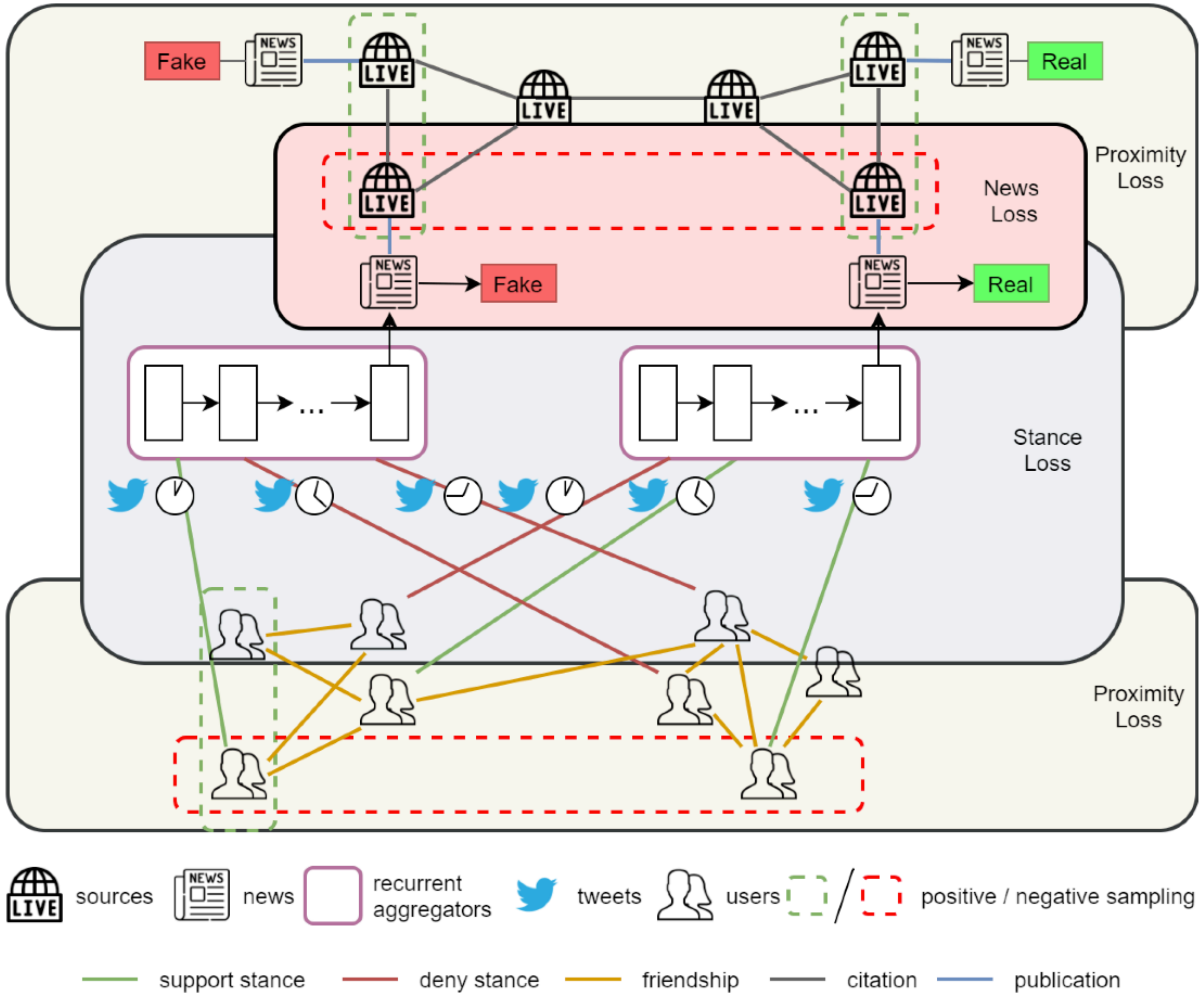


Figure 1: Graph representation of social context.

Methodology

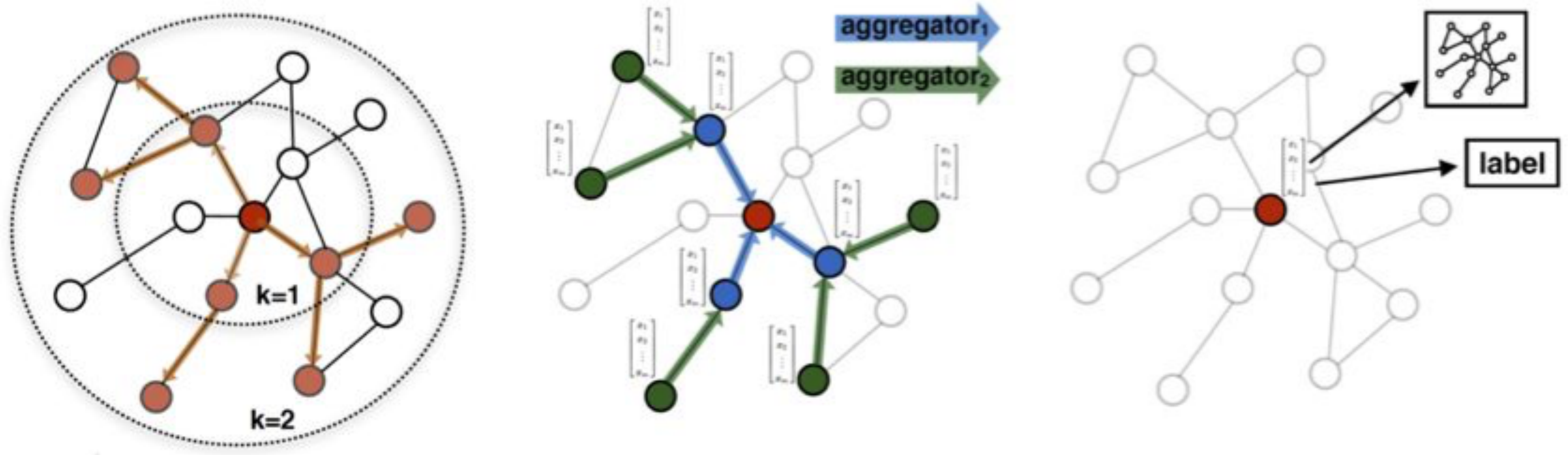
Factual News Graph (FANG) Framework

- While optimizing for the fake news detection objective, FANG also learns generalizable representations for the social entities.
- This is achieved by optimizing three concurrent losses:
  - Unsupervised Proximity Loss
  - Self-supervised Stance Loss
  - Supervised Fake News Detection Loss



Methodology

FANG - Representation Learning



GraphSage

- Like Deep Walk and node2vec compute a node embedding by sampling its neighborhood, and then optimizing for the proximity loss similarly to word2vec.
  - Now the neighborhood is defined by the graph structure.
  - Recently, GraphSage was proposed to overcome this limitation by allowing auxiliary node features to be used jointly with proximity sampling as part of the representation learning.

Methodology

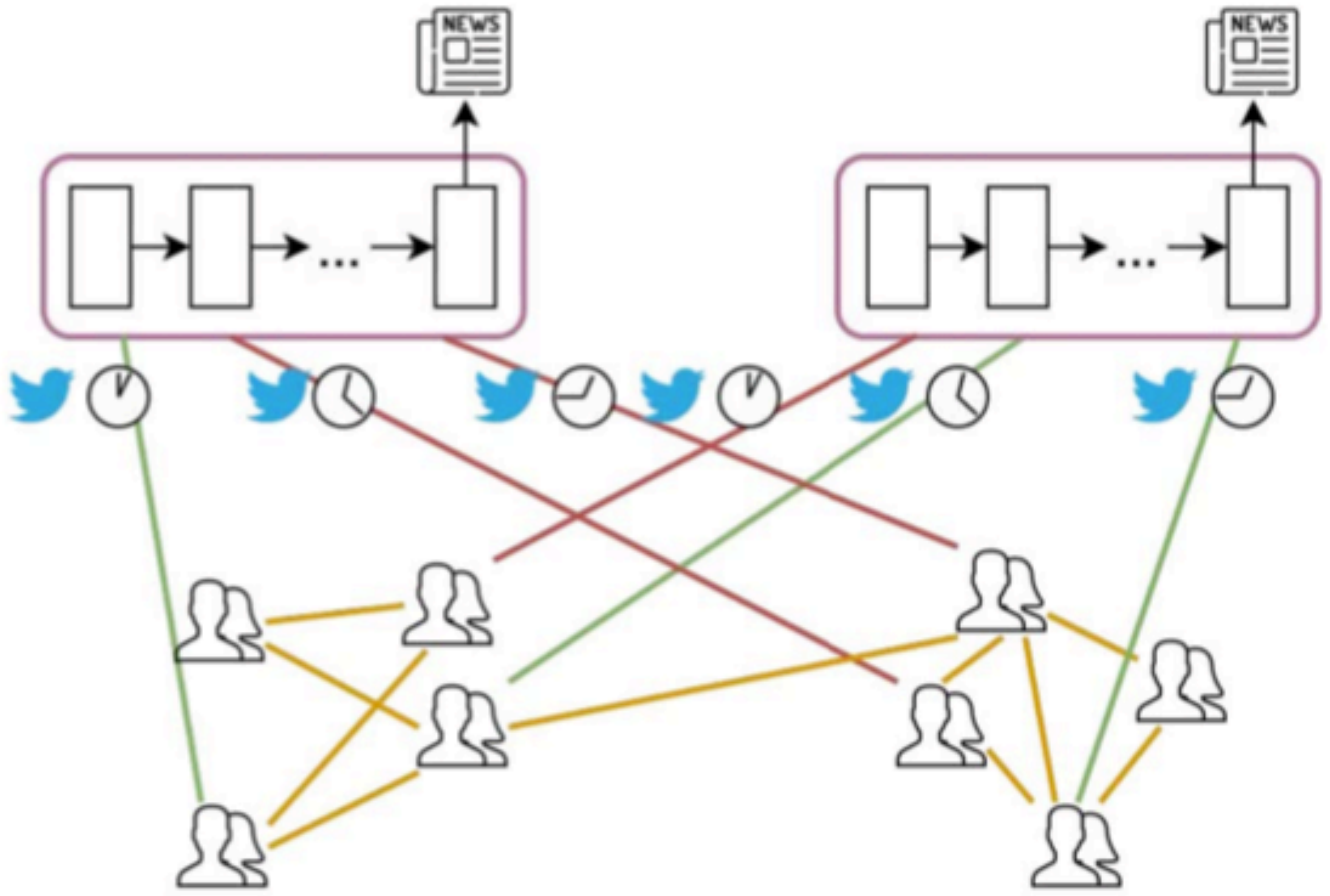
FANG - Representation Learning

- Let $GraphSage(\cdot)$ be GraphSage's node encoding function
    - Now obtain the structural representation z_u for any user u and source node r as $z_r = GraphSage(r)$
    - For news node, further enrich their structural representation with user engagement temporal representation with user engagement temporality.
    - This can be formulated as learning an aggregation function $F(a, U)$ to get a temporal representation v_a^{temp} that captures a's engagement pattern.
    - Combine the temporal and the structural representations of a news a into a single representation: $z_a = v_a^{temp} + GraphSage(a)$

Methodology

Temporal Engagement Aggregator

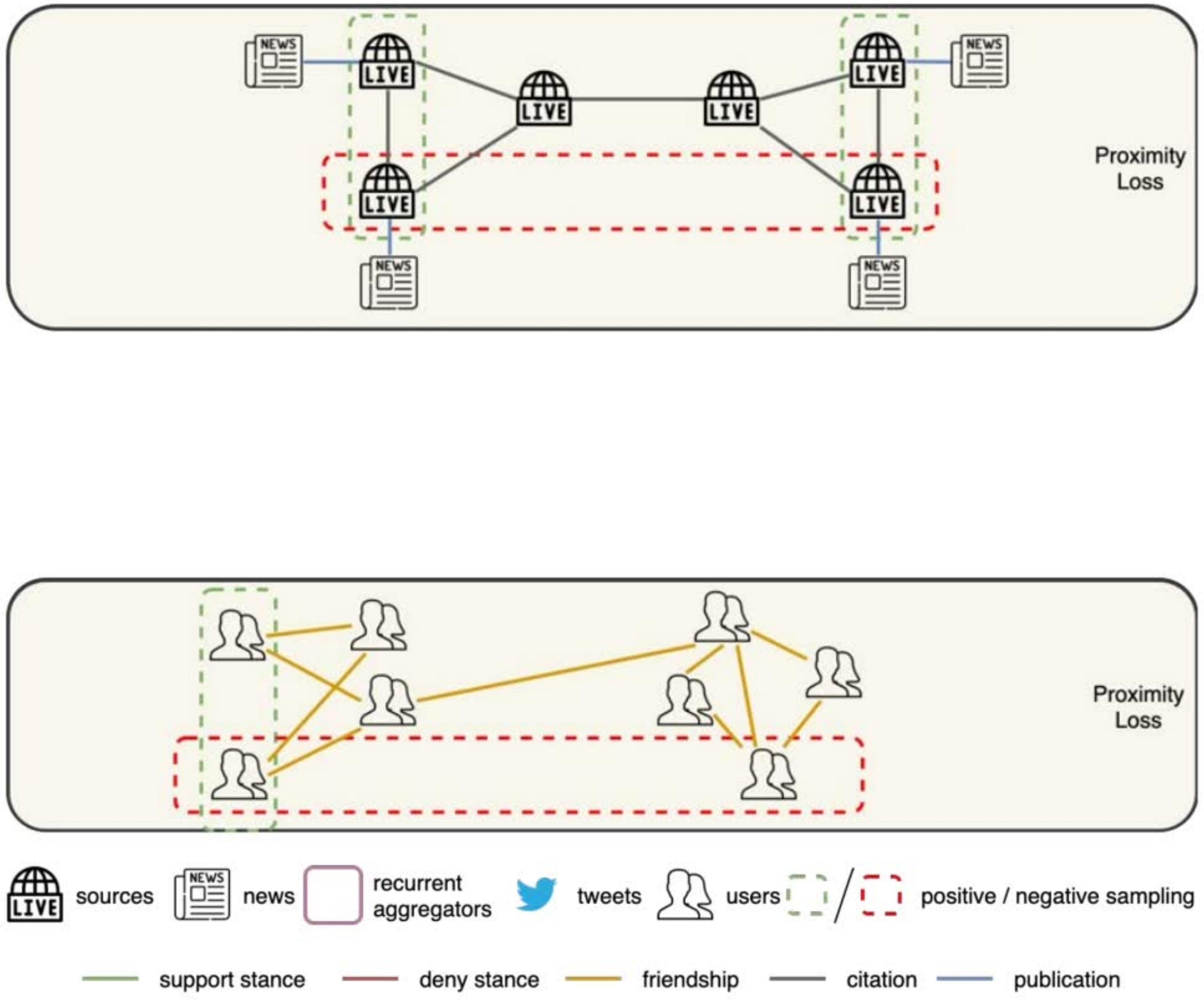
- Use Bi-LSTM as aggregator model, with user representation, timestamp, engagement stance as inputs
- On the top of Bi-LSTM, further incorporate an attention mechanism to better encode long series of engagements.
- Attention is not only expect to improve the model quality but also its explainability.



Methodology

FANG - Unsupervised Proximity Loss

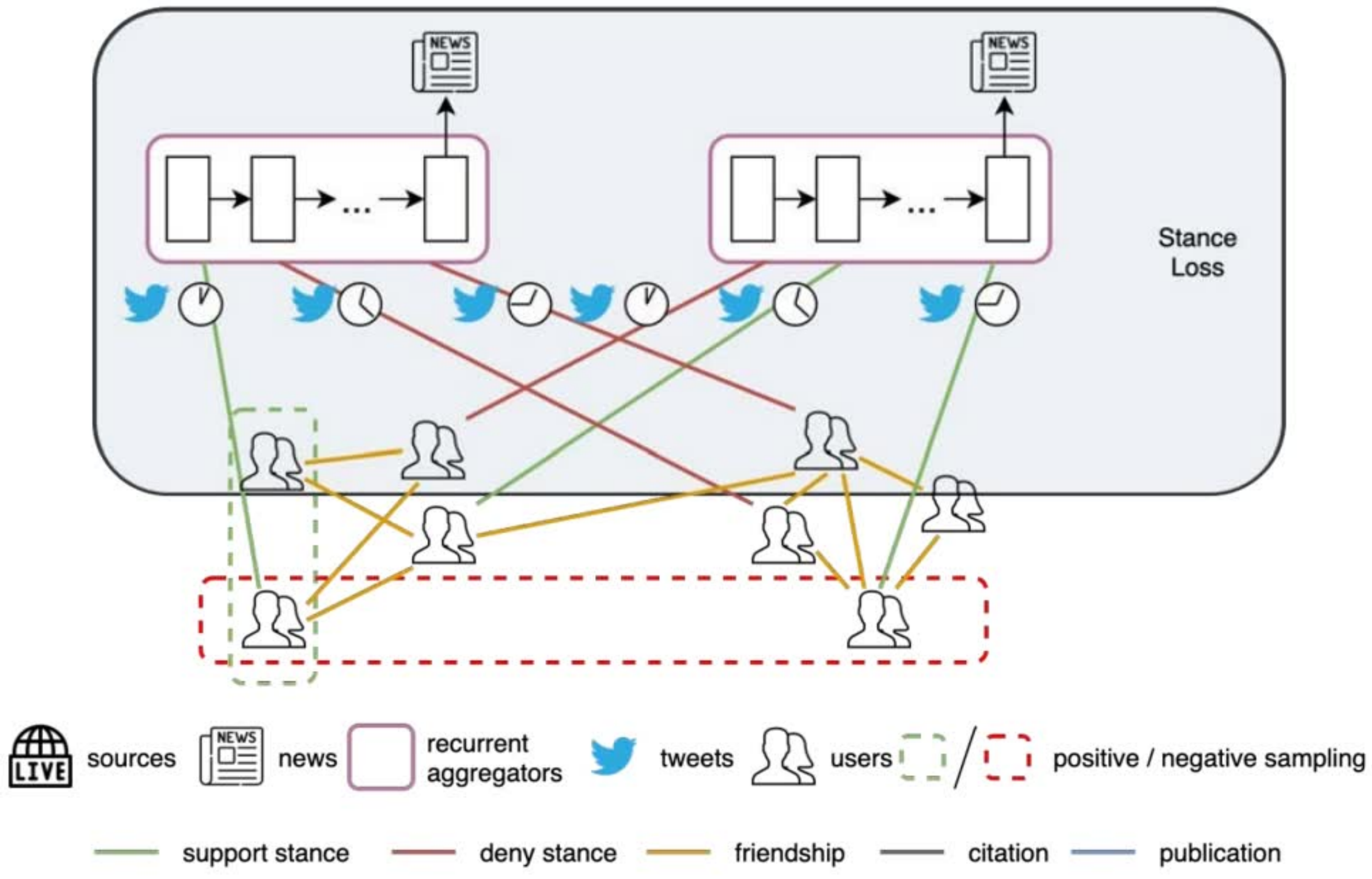
- Derive the Proximity Loss from the hypothesis that closely connected social entities often behave similarly.
  - motivated by the echo chamber phenomenon
- Within each sub-graph G' (news source & users), loss function:
- $$\mathscr{L}_{\text{prox}} = -\sum_{u \in G'} \boxed{\sum_{r_p \in P_r} \log\left(\sigma\left(z_r^\top z_{r_p}\right)\right)} + \boxed{Q \cdot \sum_{r_n \in N_r} \log\left(\sigma\left(-z_r^\top z_{r_n}\right)\right)}$$
  - Minimizing the distances between neighboring (positive) nodes
  - Maximizing the distances between remote (negative) nodes



Methodology

FANG - Self-supervised Stance Loss

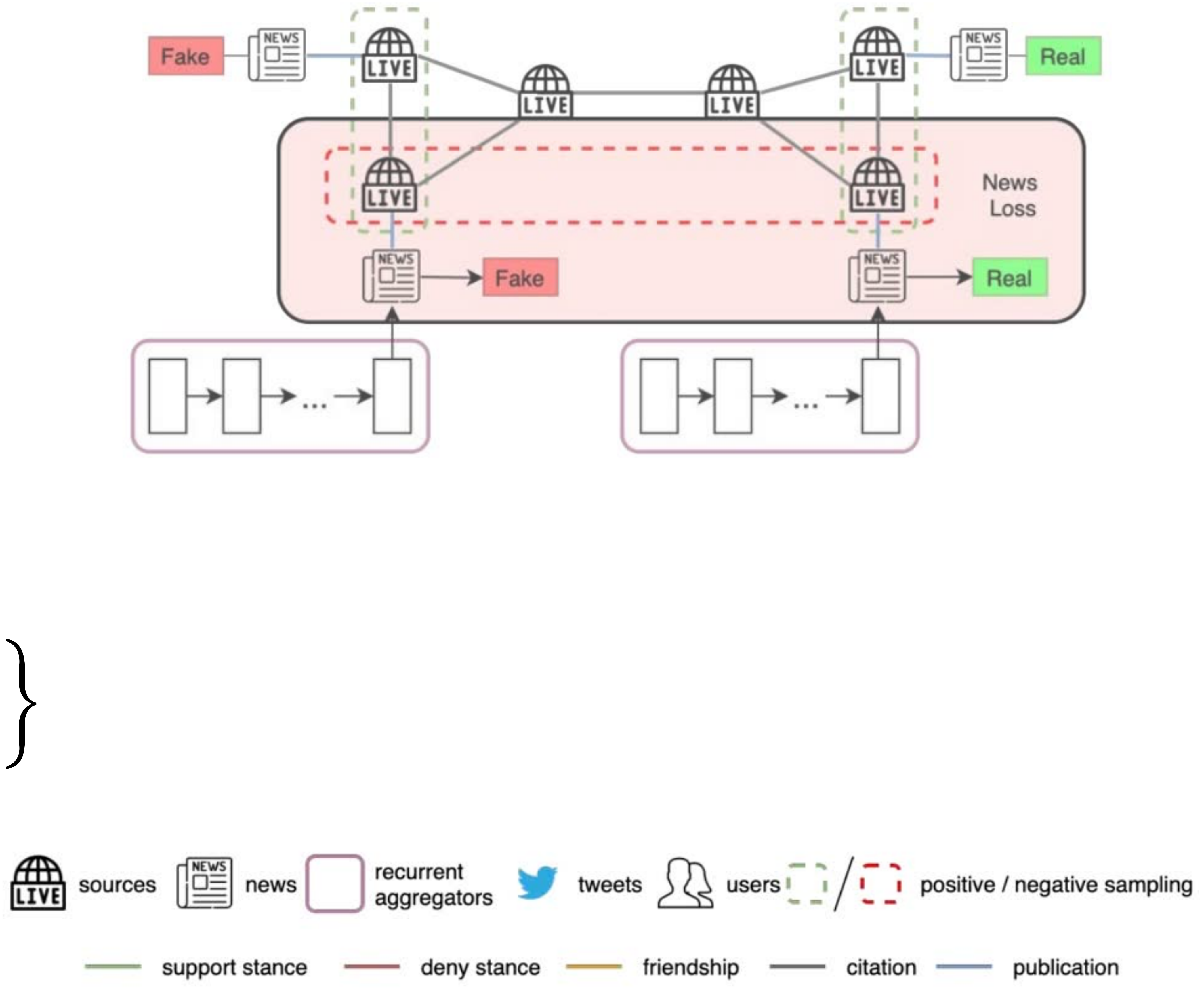
- Common stance → close representation
- Projection function from representation space to stance space c
  - User projection function: $\alpha_c(u) = \mathrm{A}_c z_u$
  - News article projection function: $\beta_c(a) = \mathrm{B}_c z_a$
- Stance loss function:
- $$\mathcal{L}_{\text{stance}} = -\sum_{u,a,c} y_{u,a,c} \log(f(u,a,c))$$
- Stance detector: $f(u,a,c) = softmax(\alpha_c(u)^\top \beta_c(a))$



Methodology

FANG - Supervised Fake News Loss

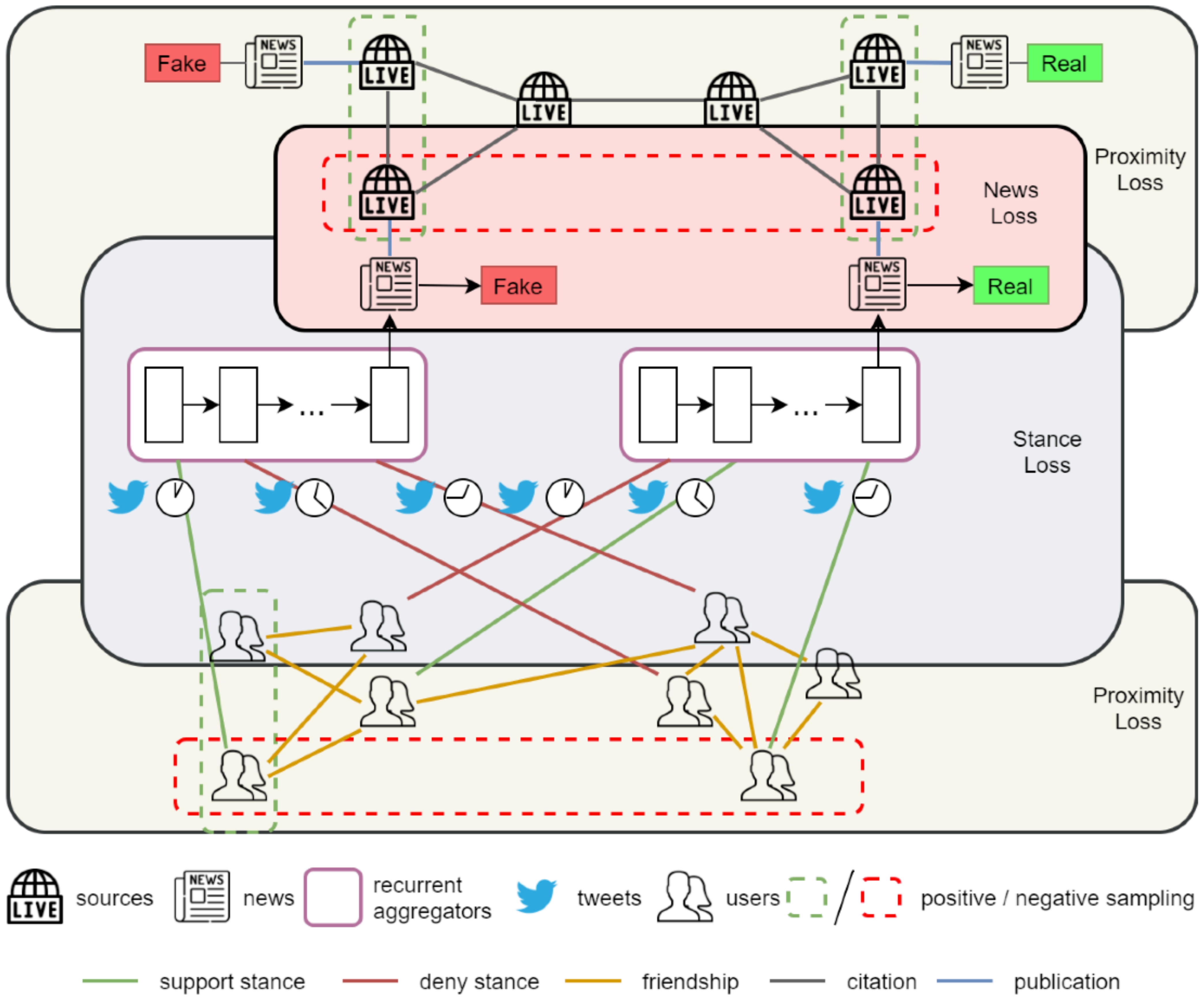
- Combine the representation of an article and its source: $v_a = (z_a, z_s)$
- Passed through a fully connected layer: $o_a = \mathrm{W}v_a + b$
- Cross-entropy loss:
  - $\mathscr{L}_{\text{news}} = \frac{1}{T}\sum_a \left\{ y_a \cdot \log\left(\sigma\left(o_a\right)\right) + \left(1 - y_a\right) \cdot \log\left(1 - \sigma\left(o_a\right)\right) \right\}$



Methodology

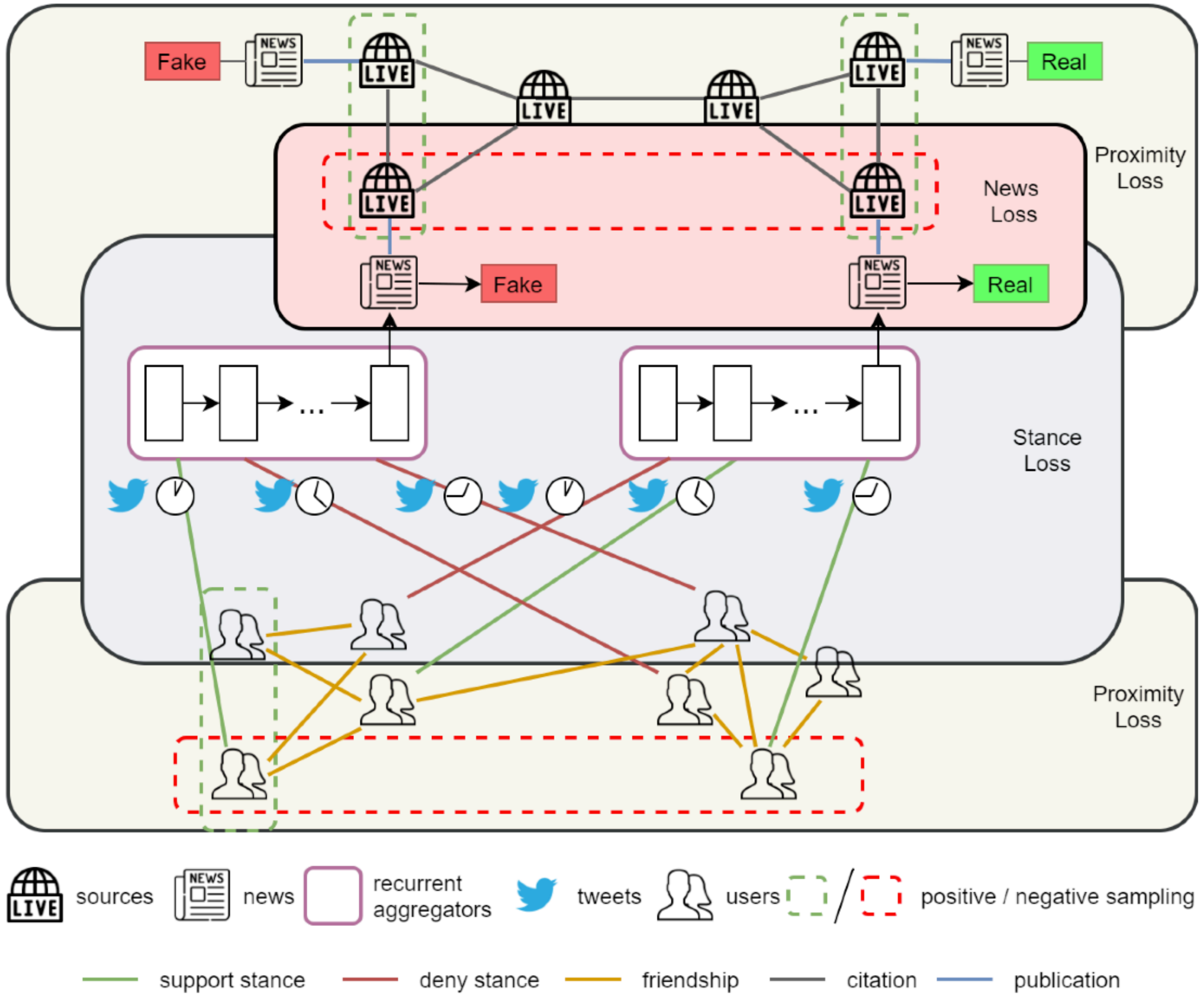
FANG: Total loss function

- This is achieved by optimizing three concurrent losses:
  - Unsupervised Proximity Loss
  - Self-supervised Stance Loss
  - Supervised Fake News Detection Loss
- Define the total loss by linearly combining these three component losses:
- $\mathscr{L}_{\text{total}} = \mathscr{L}_{\text{prox}} + \mathscr{L}_{\text{stance}} + \mathscr{L}_{\text{news}}$



Methodology

FANG: Total loss function



Algorithm 1: FANG Learning Algorithm

Input : The social context graph $G = (A, S, U, E)$
The news labels Y_A, and the stance labels $Y_{U,A,C}$
Output: FANG-optimized parameters θ
Initialize θ;
while *θ has not converged* **do**
  for *each news batch $A_i \subset A$* **do**
    for *each news $a \in A_i$* **do**
      $U_a \leftarrow$ users who have engaged with a;
      $z_a \leftarrow$ Equation (2);
      $z_s \leftarrow GraphSage(s)$;
      for *each user $u \in U_a$* **do**
        $z_u \leftarrow GraphSage(u)$;
        $\mathcal{L}'_{stance} \leftarrow$ Equation (4);
      end
    end
    $\mathcal{L}'_{news} \leftarrow$ Equation (5);
  end
  for *each news–source or user sub-graph G'* **do**
    for *each entity $r \in G'$* **do**
      $P_r \leftarrow$ positive samples of r in G';
      $N_r \leftarrow$ negative samples of r in G';
      $\mathcal{L}'_{prox.} \leftarrow$ Equation (3);
    end
  end
  $\mathcal{L}_{total} \leftarrow \mathrm{SUM}(\mathcal{L}'_{stance}, \mathcal{L}'_{news}, \mathcal{L}'_{prox.})$;
  $\theta \leftarrow$ Backpropagate$(\mathcal{L}_{total})$;
end
return θ

Experiments
Dataset

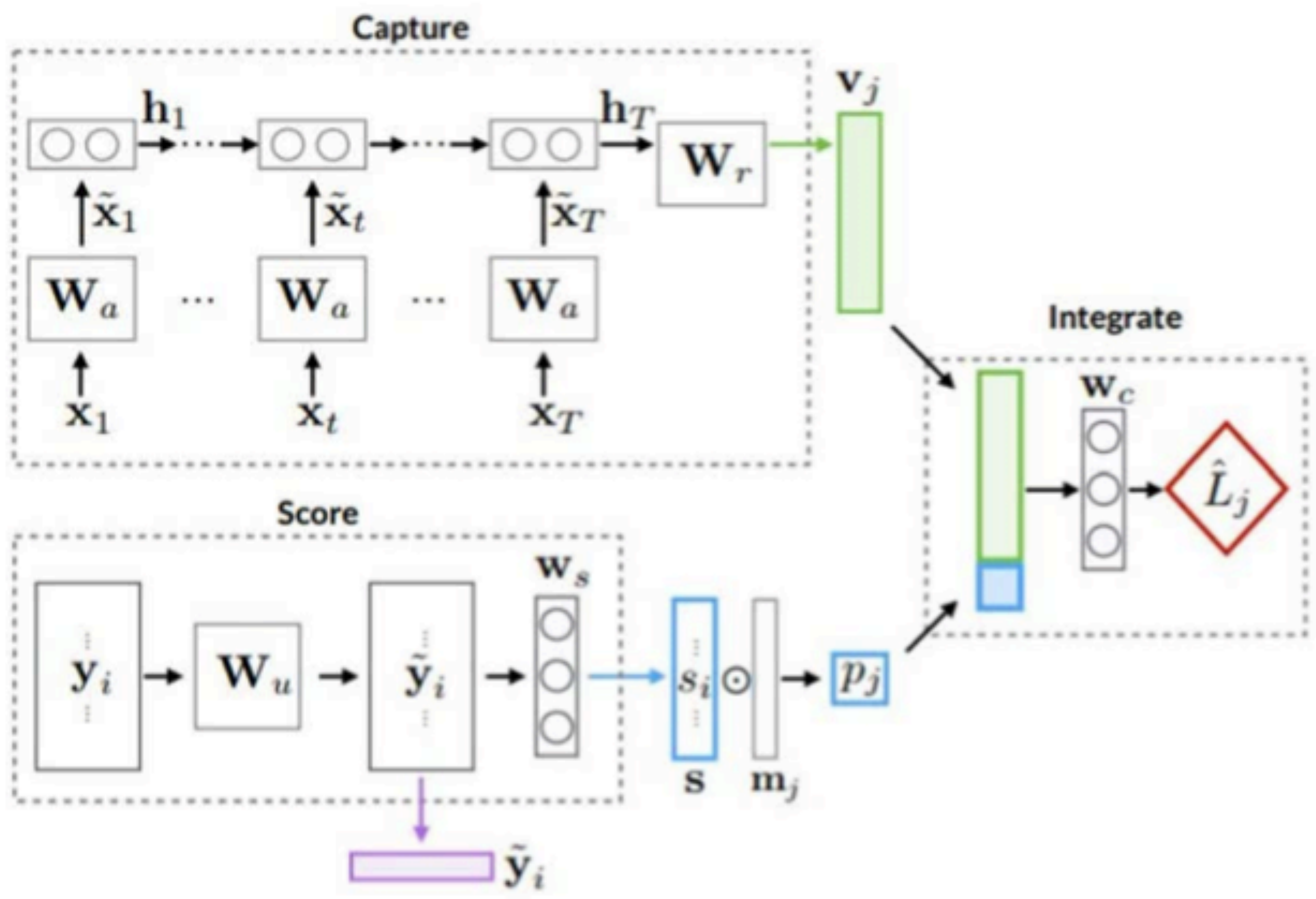
Fake	448	Publications / source	2.38	Cites / source	8.38
Real	606	Engagements / news	71.9	Friends / user	58.25
Sources	442	Neu. support / news	19.07	Deny / news	5.27
Users	54461	Neg. support / news	10.83	Report / news	36.73

- Twitter dataset
- For each article, collected its source, a list of engaged users, and their tweets if they were not already available in the previous dataset.
    - Also includes Twitter profile description and the list of Twitter profiles each user follows.
- Further crawled additional data about media sources, including the content of their *Homepage* and their *About us* page, together with their frequently cited sources on their *Homepage*.
- Label obtained from Snopes and Politifact

Experiments

Baselines

- **SVM** (content-only)
- **CSI** (Euclidean contextual)
  - Aggregate social engagements using LSTM
  - Models social context as a Euclidean object, not graph
- **GCN** (graph learning)
- **FANG** (proposed method)
- To verify the importance of modeling temporality by experimenting on two variants of CSI and FANG
  - CSI(-t), FANG(-t) without time in the engagement e's representation x_e



CSI (Ruchansky et al., 2017)

Experiments

Performance Comparison

Model	Contextual	Temporal	Graphical	AUC
Feature SVM				0.5525
CSI(-t) (without $time(e)$)	✓			0.6678
CSI	✓	✓		0.6911
GCN	✓		✓	0.7064
FANG(-t) (without $time(e)$)	✓		✓	0.7179
FANG	✓	✓	✓	**0.7518**

- Improvement from context modeling: 0.1153 for CSI(-t), 0.199 for FANG
- This demonstrates that considering social context is helpful for fake news detection.

Experiments

Performance Comparison

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FANG(-t) (without $time(e)$)	✓		✓	0.7179
FANG	✓	✓	✓	**0.7518**

- Improvement from temporality: 0.0233 for CSI, 0.0339 for FANG
- These results demonstrate the importance of modeling the temporality of news spreading.

Experiments

Performance Comparison

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FANG(-t) (without $time(e)$)	✓		✓	0.7179
FANG	✓	✓	✓	**0.7518**

- Improvement from multi-relational graph: 0.0386 for GCN, 0.0501 for FANG(-t)
- This demonstrates the effectiveness of our social graph representation.

Discussion
Research Questions

- Aim to answer the following research questions (RQ) to better understand FANG's performance under different scenarios:
  - **RQ1:** Does FANG work well with limited training data?
  - **RQ2:** Does FANG differentiate between fake and real news based on their contrastive engagement temporality?
  - **RQ3:** How effective is FANG's representation learning?

Discussion

Research Questions

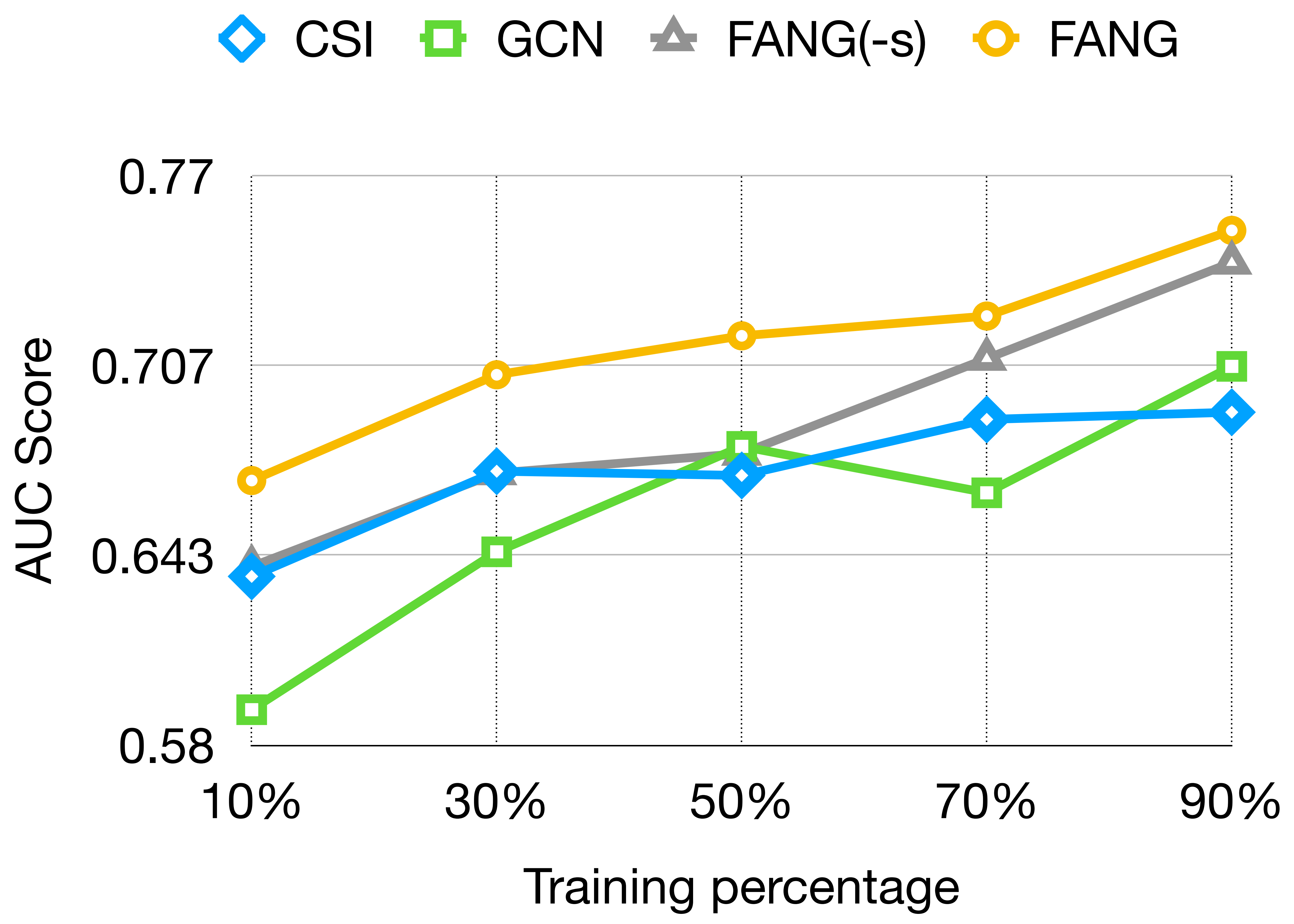
- Aim to answer the following research questions (RQ) to better understand FANG's performance under different scenarios:
  - **RQ1:** Does FANG work well with limited training data?
  - **RQ2:** Does FANG differentiate between fake and real news based on their contrastive engagement temporality?
  - **RQ3:** How effective is FANG's representation learning?

Discussion

RQ1: Limited Training Data

- Conducted the experiments using different sizes of the training dataset.
- Observe that consistent improvements over the baselines under both limited and sufficient data conditions.

Systems	AUC score at different training percentages				
	10%	30%	50%	70%	90%
CSI	0.6363	0.6714	0.6700	0.6887	0.6911
GCN	0.5918	0.6445	0.6797	0.6642	0.7064
FANG(-*s*) (without stance loss)	0.6396	0.6708	0.6773	0.7090	0.7411
FANG	**0.6683**	**0.7036**	**0.7166**	**0.7232**	**0.7518**



Discussion

RQ1: Limited Training Data

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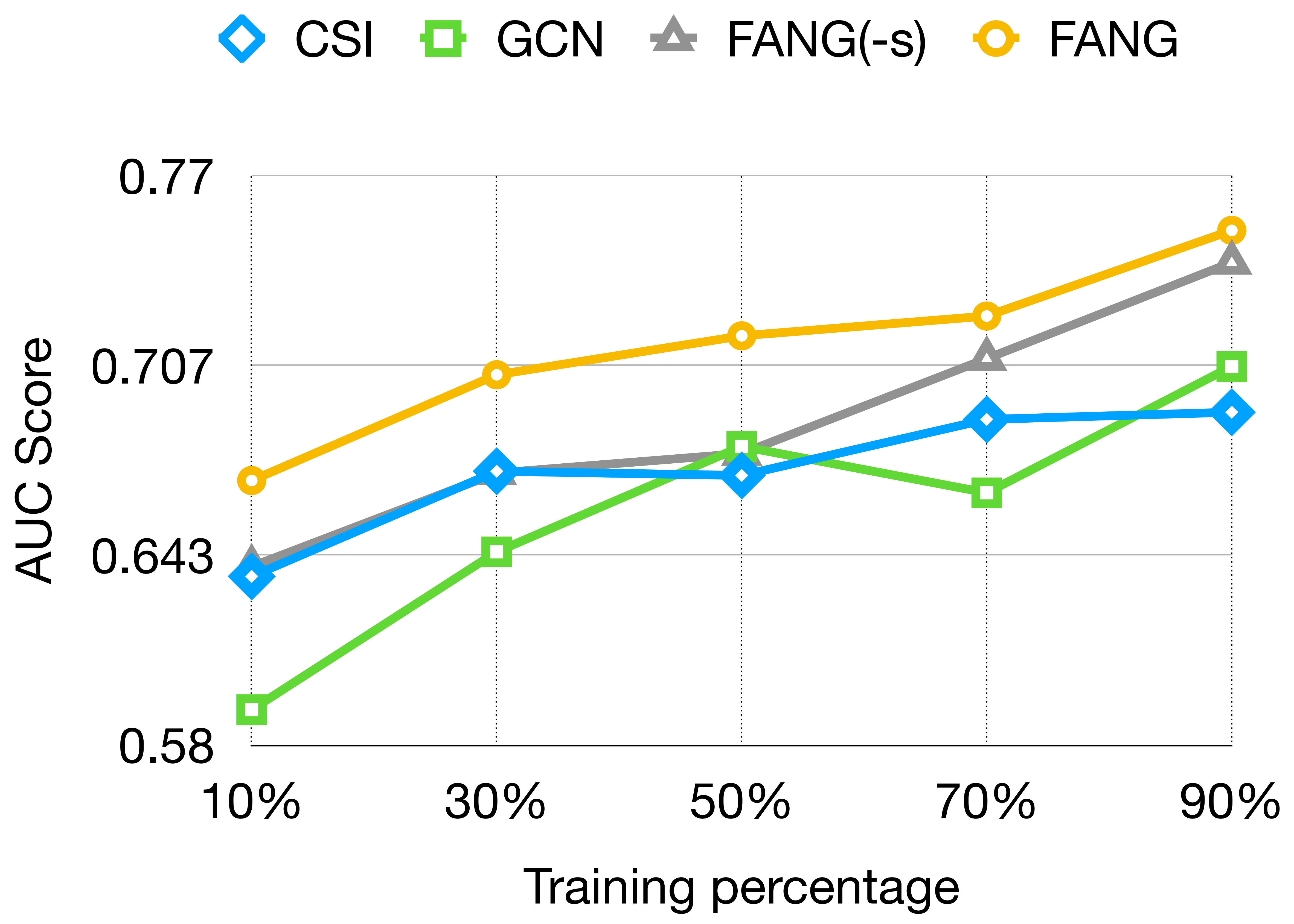
- CSI's AUC drops by 7.93%
- GCN's AUC drops by 16.22%
- FANG's AUC drops by 11.11%
- The experimental results emphasize our model's effectiveness even at low training data availability compared to the ablated version, GNN and Euclidean.



Discussion

RQ1: Limited Training Data

- FANG(-s): removed the stance loss, highlights the importance of this self-supervised objective.
- Relative underperforming margin of FANG(-s) compared to FANG:
  - At least: 1.42% at 90%
  - At most: 6.39% at 30%

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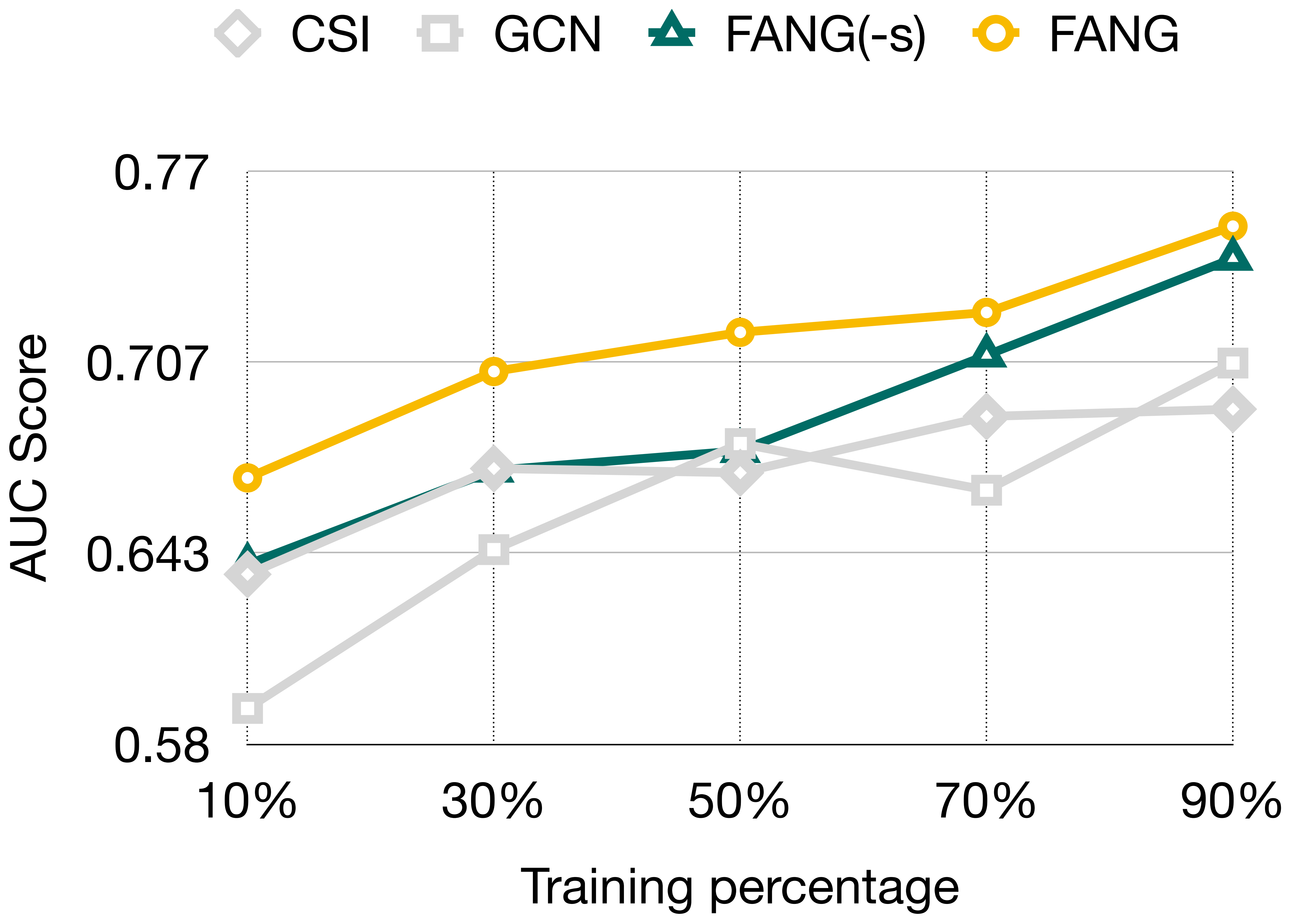
FANG(-*s*) (without stance loss)	0.6396	0.6708	0.6773	0.7090	0.7411
FANG	**0.6683**	**0.7036**	**0.7166**	**0.7232**	**0.7518**



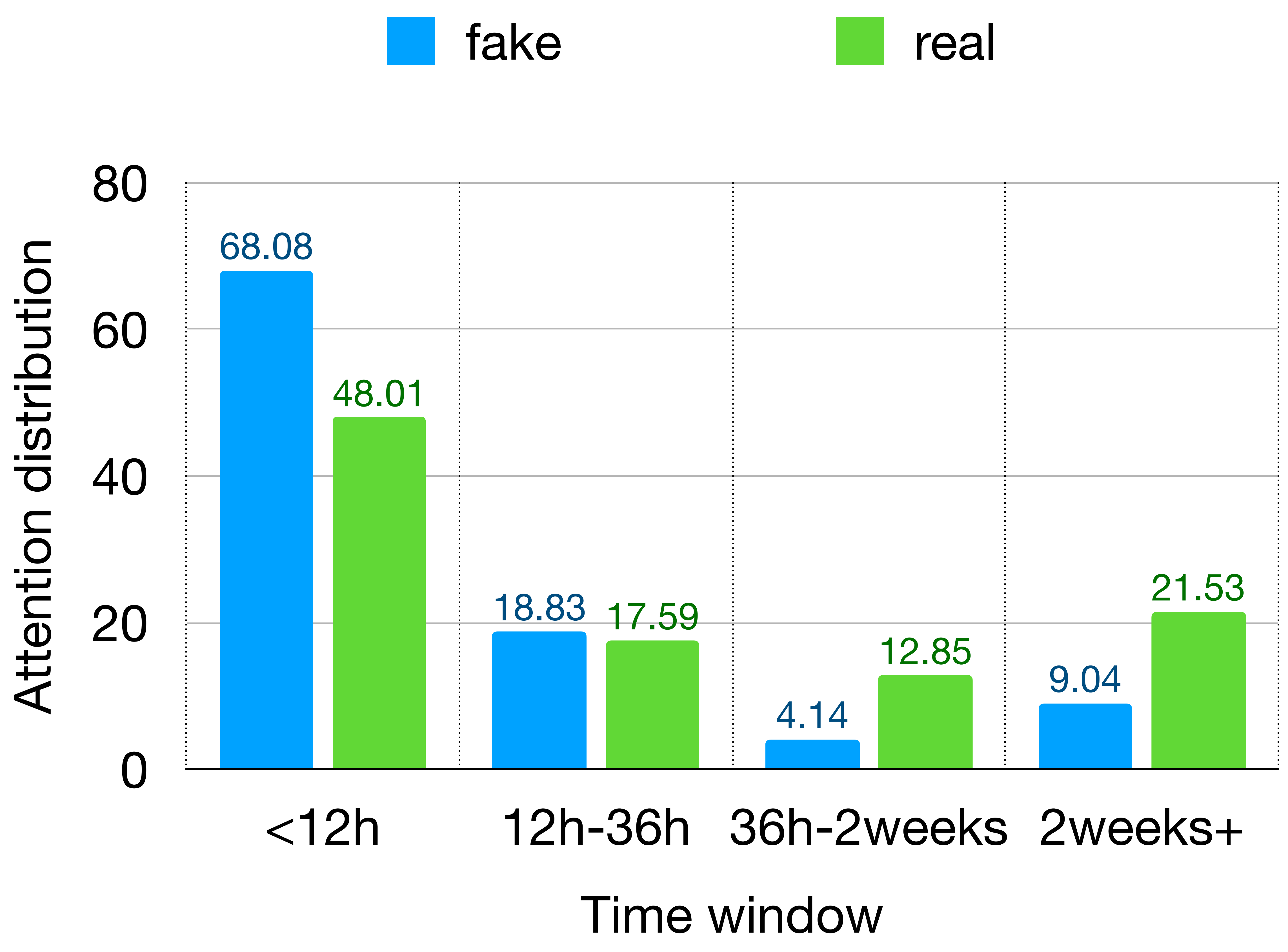
Discussion
Research Questions

- Aim to answer the following research questions (RQ) to better understand FANG's performance under different scenarios:
  - **RQ1:** Does FANG work well with limited training data?
  - **RQ2:** Does FANG differentiate between fake and real news based on their contrastive engagement temporality?
  - **RQ3:** How effective is FANG's representation learning?

Discussion

RQ2: Engagement Temporality Study

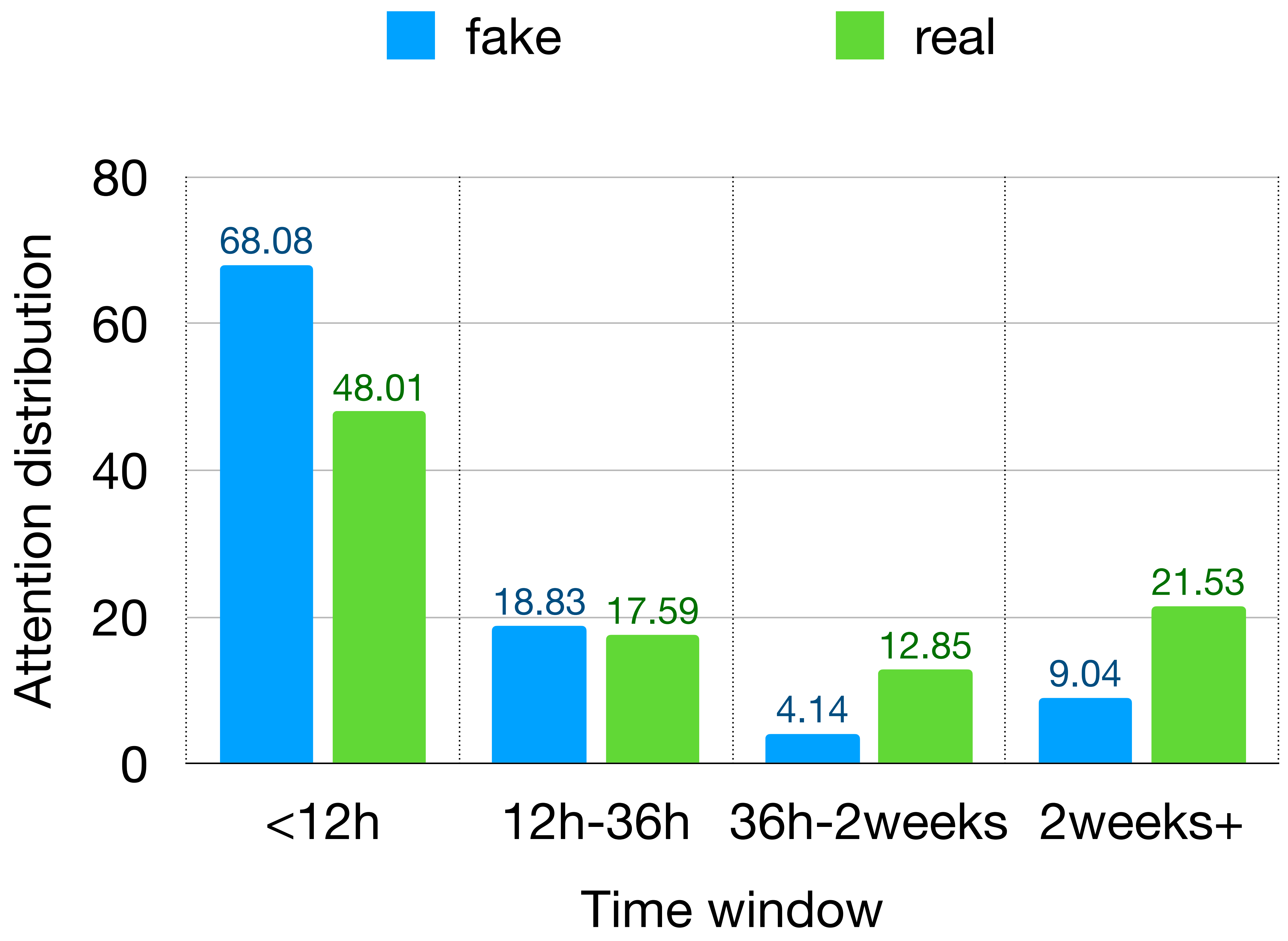
- Examined FANG's attention mechanism.
- Accumulated the attention weights produced by FANG within each time window.



Discussion

RQ2: Engagement Temporality Study

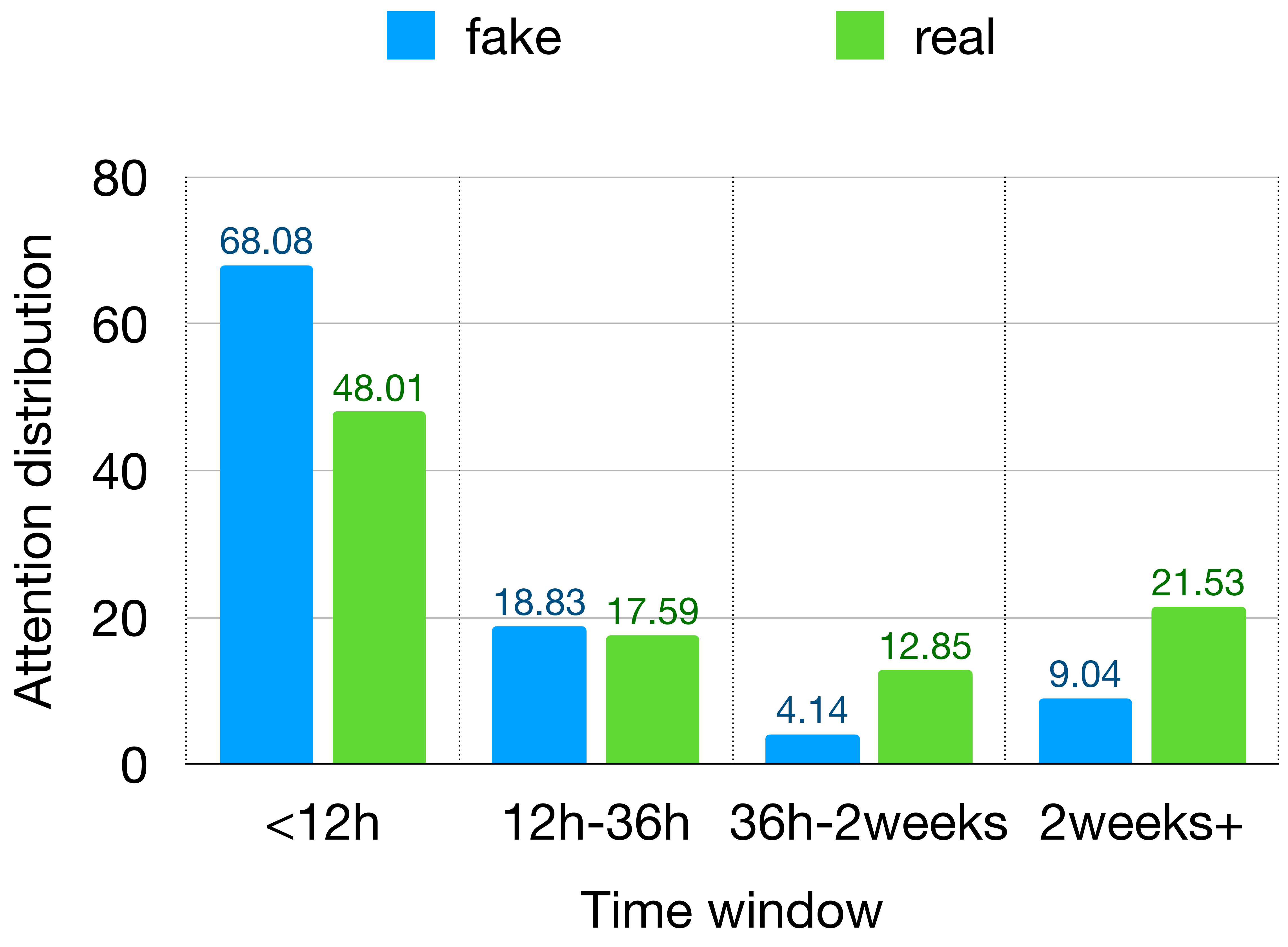
- Fake news
  - 68.08% attention on first 12h
  - Decrease to 18.83% for next 24h
  - Not much attention after first 36h
- Real News
  - 48.01% attention on first 12h
  - Decrease to 17.59% for next 24h
  - Moderate attention after first 36h



Discussion

RQ2: Engagement Temporality Study

- Fake news
  - Generates the most engagements within a short period of time after its publication.
  - It's reasonable that the model places much emphasis on these crucial engagements.
- Real News
  - Attracts fewer engagements, but it is circulated for a longer period of time.
  - Explain FANG's persistent attention even after two weeks after publication.



Discussion
Research Questions

- Aim to answer the following research questions (RQ) to better understand FANG's performance under different scenarios:
  - **RQ1:** Does FANG work well with limited training data?
  - **RQ2:** Does FANG differentiate between fake and real news based on their contrastive engagement temporality?
  - **RQ3:** How effective is FANG's representation learning?

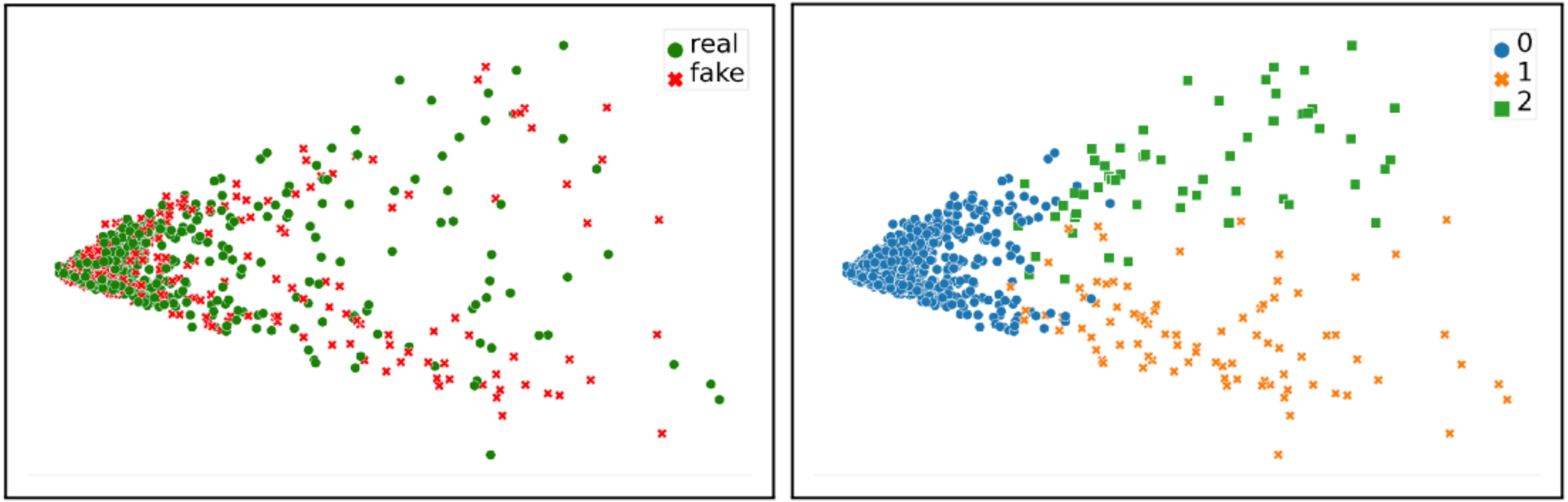
Discussion

RQ3: Representation Learning - Intrinsic Evaluation

- Verify how generalizable the minimally supervised news representations are for the fake news detection task.
- First optimize both GCN and FANG on 30% of the training data to obtain news representations.
- Then cluster these representations using an unsupervised clustering algorithm OPTICS, measure the homogeneity score - the extent to which clusters contain a single class.
- The higher the homogeneity score, the more likely the news articles of the same factuality label are to be close to each other, which yields the higher quality representation.

Discussion

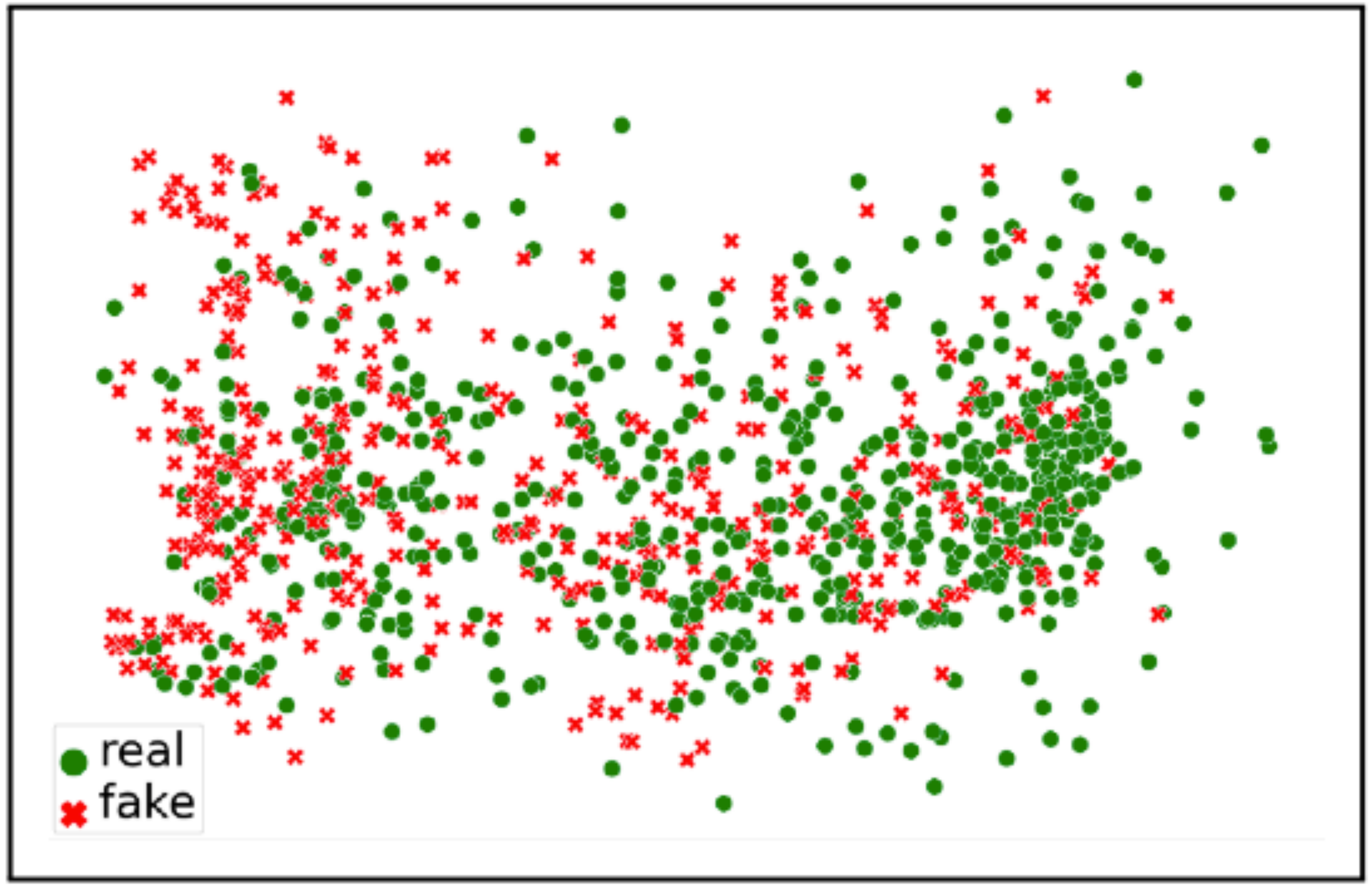
RQ3: Representation Learning - Intrinsic Evaluation

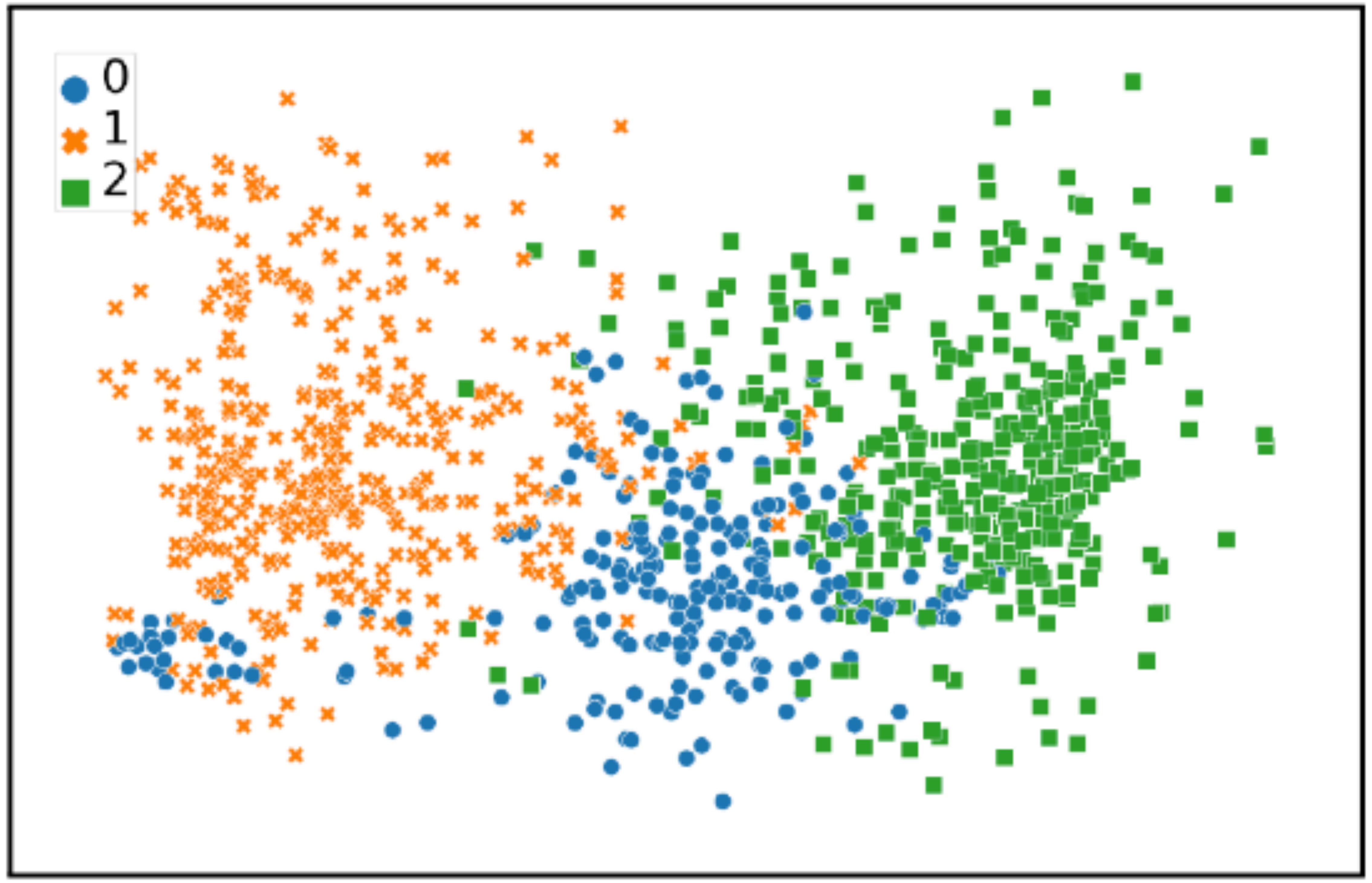


2D PCA plot of GCN's representation, Homogeneity score: 0.0006 (no correlation exists)

Discussion

RQ3: Representation Learning - Intrinsic Evaluation



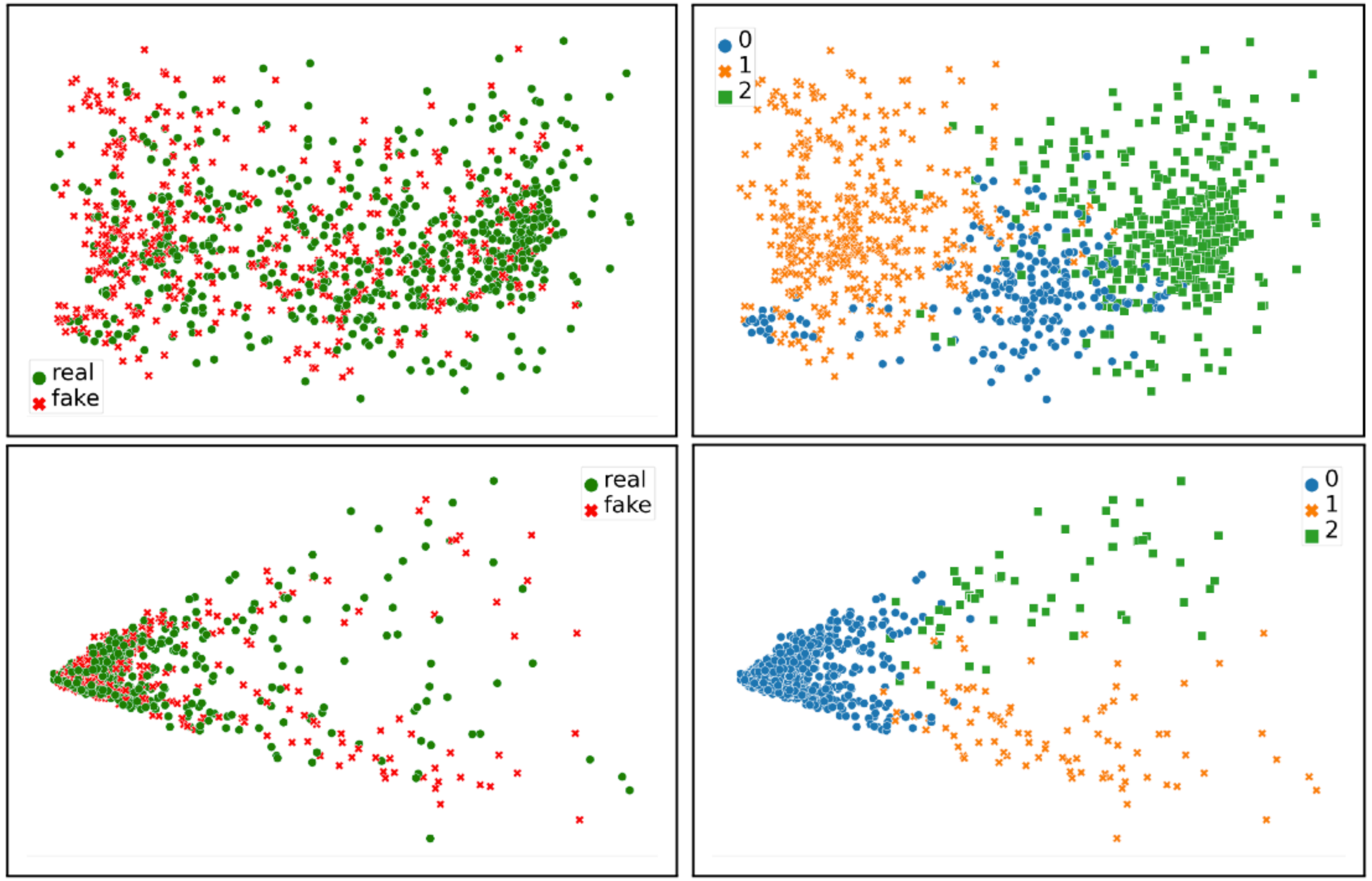


2D PCA plot of FANG's representation, Homogeneity score: 0.051 (correlation exists)

Discussion

RQ3: Representation Learning – Intrinsic Evaluation

- Homogeneity score
  - FANG (Top): 0.051
  - GCN (Bottom): 0.0006
- Demonstrates FANG's strong representation closeness within both the fake and the real news groups.
- Indicating that FANG yields improved representation learning over another fully supervised graph neural framework.



2D PCA plot of FANG's representation (Top), GCN's representation (Bottom)

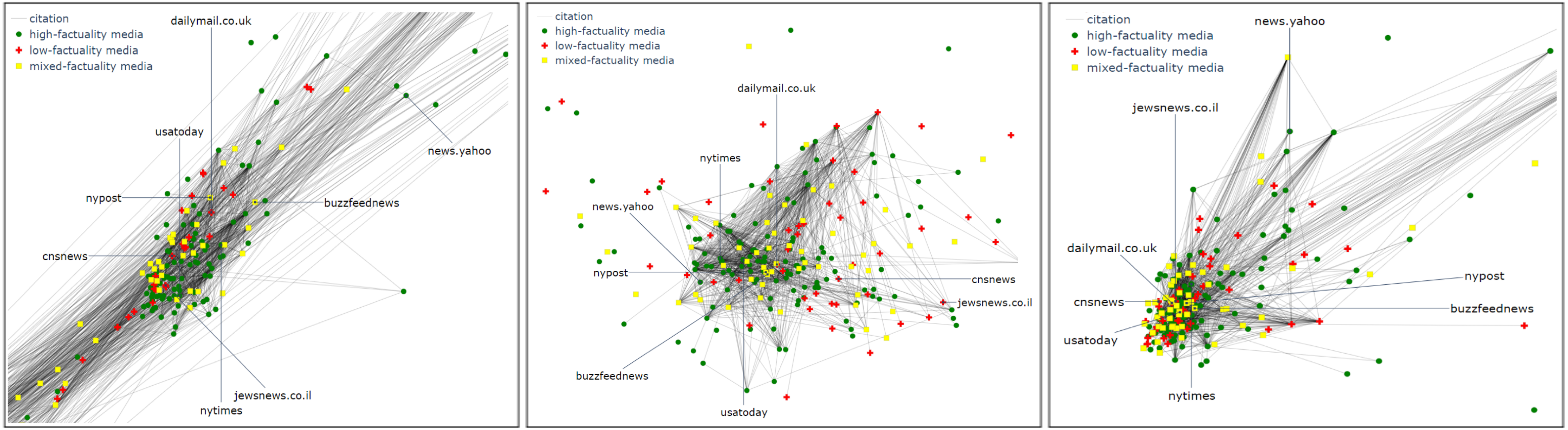
Discussion

RQ3: Representation Learning - Extrinsic Evaluation

- Verify how generalizable the supervised source representations are for a new task: source factuality prediction.
- Dataset: 129 sources of high factuality & 103 sources of low factuality annotated using mediabiasfactcheck.com and politifact.com
- SVM binary classification with textual and FANG's contextual representation as input
- 0.2207 absolute F1 improvement (0.5842 → 0.8049) compared with textual feature baseline

Discussion

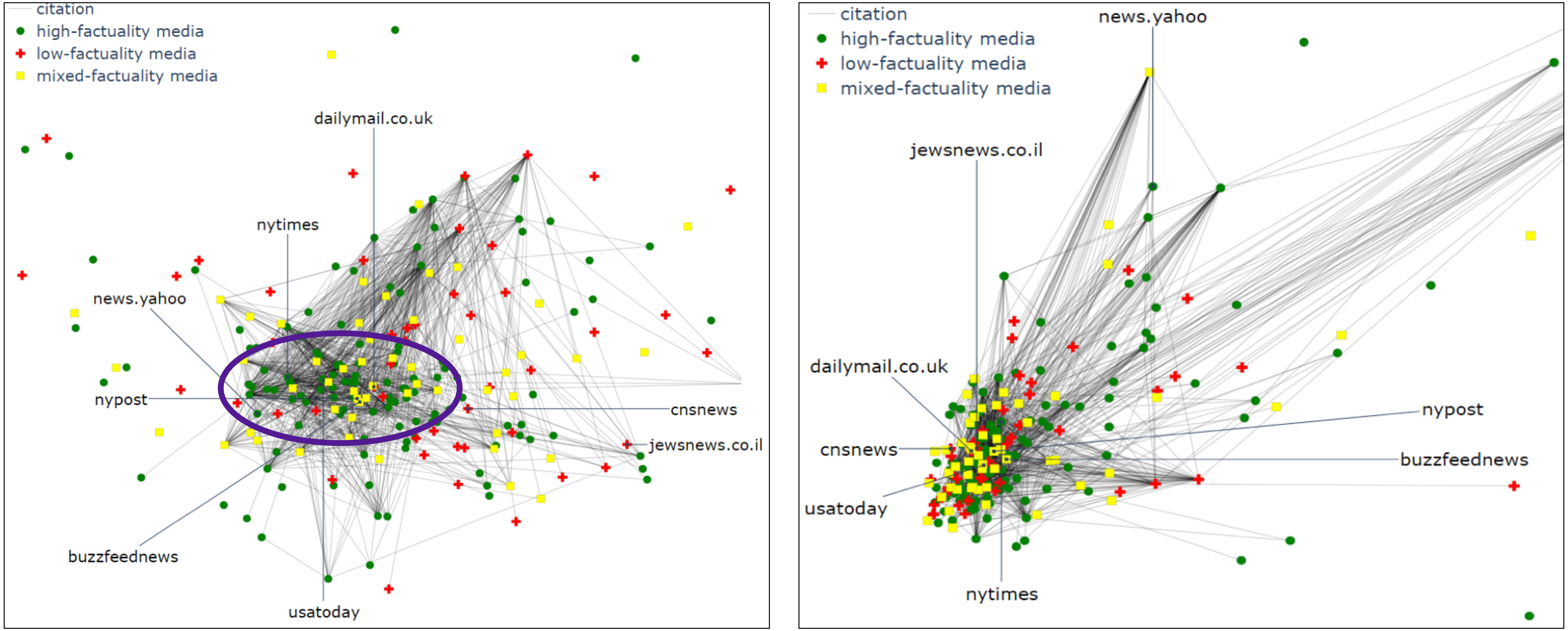
RQ3: Representation Learning – Extrinsic Evaluation



Plots for source representations using textual features (left), GCN (middle), and FANG (right) with factuality labels

Discussion

RQ3: Representation Learning - Extrinsic Evaluation

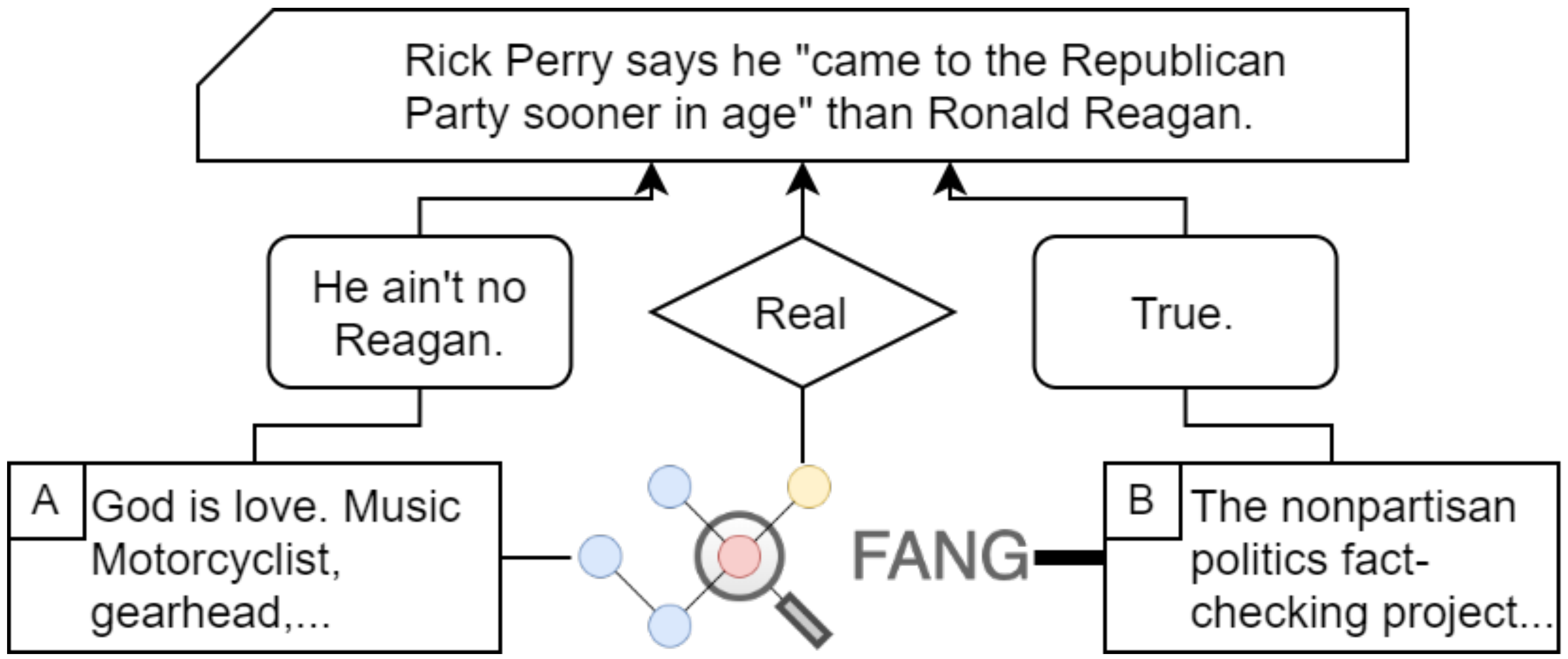


Better representation of media sources from FANG (left) than from GCN (right)

Discussion

Microscopic Analysis

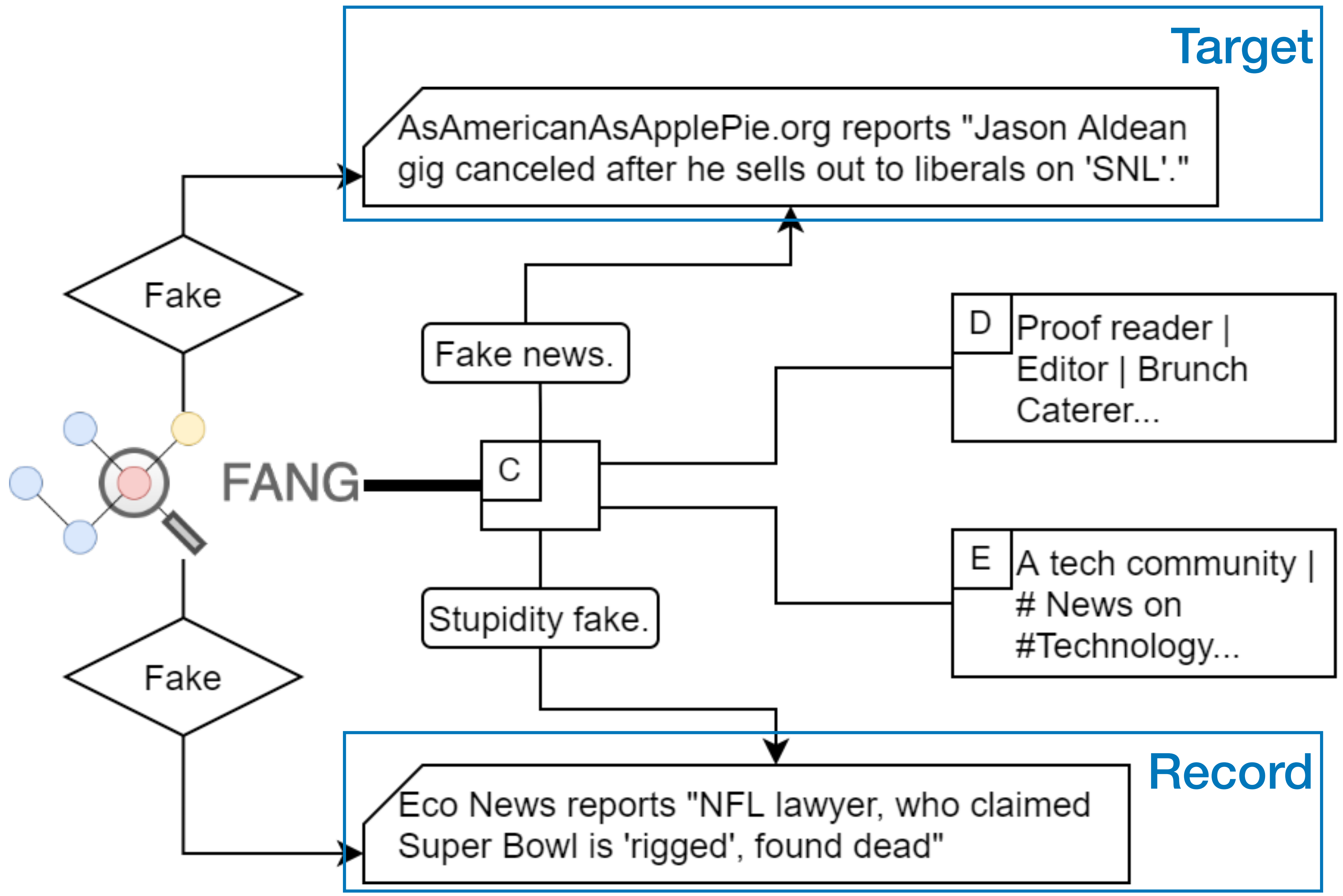
- FANG pays most of its attention to a tweet by user B.
- This can be explained by B's Twitter profile description of a fact-checking organization, which indicates high reliability.
- In contrast, a denying tweet from user A is not paid so much attention, due to the insignificant description of its author's profile.



Discussion

Microscopic Analysis

- FANG pays most attention to a tweet by user C.
- Although this profile does not provide any description, it has a record of correctly denying the fake news about the dead NFL lawyer.
- Furthermore, the profiles that follow Twitter user C, namely user D and user E, have credible descriptions of a proof reader and of a tech community, respectively.
- This explains why our model bases its prediction of the news being fake thanks to the reliable denial, which is again the correct label.



Conclusion

- Presented the advantage of graphical representation of social context in fake news detection
- Proposed FANG that enhances representation quality by capturing the rich social interactions between users, articles and media.
- Demonstrate the benefits of stance detection & proximity modeling objective
- Experiments show the efficiency of FANG with limited training data and its capability distinctive temporal pattern with a highly explainable attention mechanism.

Comments
of Factual News Graph (FANG)

- Fully use the social network features (profile, website descriptions, reply stance…)
    - Not all dataset can handle
- Effective on temporal engagements with attention mechanism
    - Need temporal data or user need retweet or reply with opinion
- Can training on limited data
- Not easily can defend from forge description from account
- Evaluation metric only AUC-ROC