DynGraph-GAT: Adaptive Edge Construction for Content-Based Few-Shot Fake News Detection

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Outline

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- Related Work
- Background (Few-Shot Learning / GNN)
- Methodology
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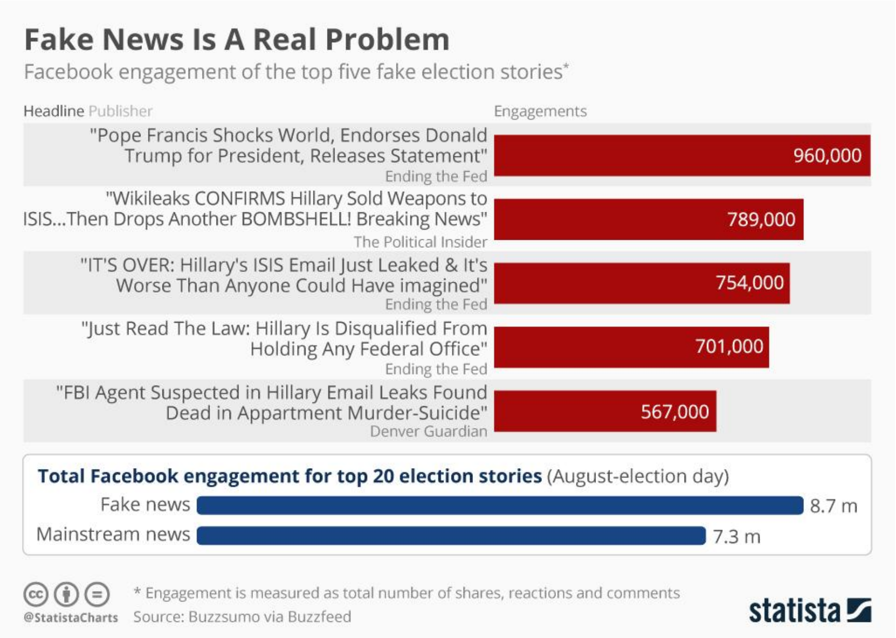
Introduction - Fake News

- Fake news has become a major threat to public trust and social stability, especially on social media platforms.

- According to Vosoughi et al. (Science, 2018), **false news spreads much faster and further than true news.**



Vosoughi S, Roy D, Aral S. The spread of true and false news online. Science. 2018;359(6380):1146–1151. doi: 10.1126/science.aap9559.

Challenges - Few-Shot Fake News Detection

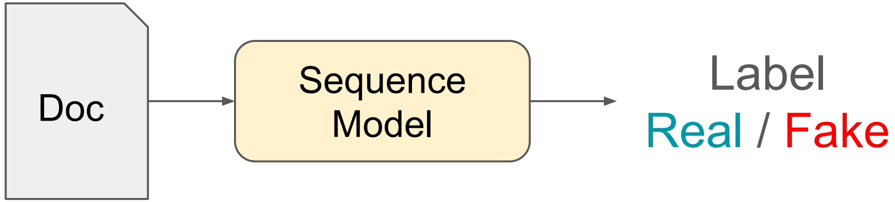
- **Limited Labeled Data:**
  Real-world fake news detection often faces a few-shot scenario, with very few labeled examples available for new or emerging topics.

- **No Propagation or User Data:**
  Many existing methods rely on user interactions or propagation structures, which are often unavailable due to privacy concerns or platform restrictions.

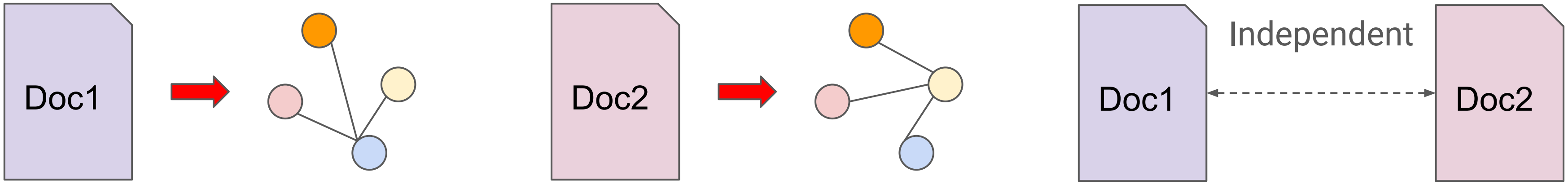
- **Semantic Relationship Modeling:**
  Capturing subtle and meaningful semantic relationships between news articles using only content features is difficult, especially in sparse data settings.

Related Work - Content-based Fake News Detection

1. Traditional MLP/Sequence Model: BERT, RoBERTa, RNN
    - - Focus on surface-level linguistic features
    - Process documents independently



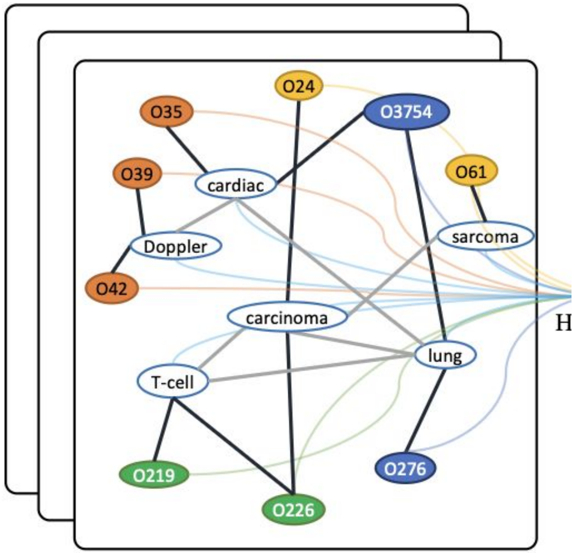
2. Content Graph: Text-GCN, BERTGCN
    - Document-word or sentence-level graphs
    - Static structures, miss inter-document relationships



Related Work - Graph Methods & Few-Shot Learning

- **Graph Neural Networks:**
  - Propagation-based: User-news interaction graphs
    - Task: Node classification on social networks
    - Effective but require social data (privacy issues)
  - Content-based: Document-word homogeneous graphs
    - Task: Graph classification for entire documents
    - Miss direct news-to-news semantic relationships

- **Few-Shot Learning in Fake News**
  - Challenge: Emerging topics with scarce labeled data
  - Most methods require large annotated datasets



Word Document Graph

Yao et al., "Graph Convolutional Networks for Text Classification", AAAI 2019

Background - Few-Shot Learning

- **Definition:**
  - Few-shot learning is a machine learning framework in which an AI model learns to make accurate predictions by training on a very small number of labeled examples.
- **Key Terminology:**
  - N-way-K-shot: Classification with N classes, K examples per class
  - In our task: 2-way (real/fake news) with K=3-16 labeled samples per class
- **Key Challenges:**
  - Traditional deep learning requires large labeled datasets
  - Model overfitting when training data is scarce

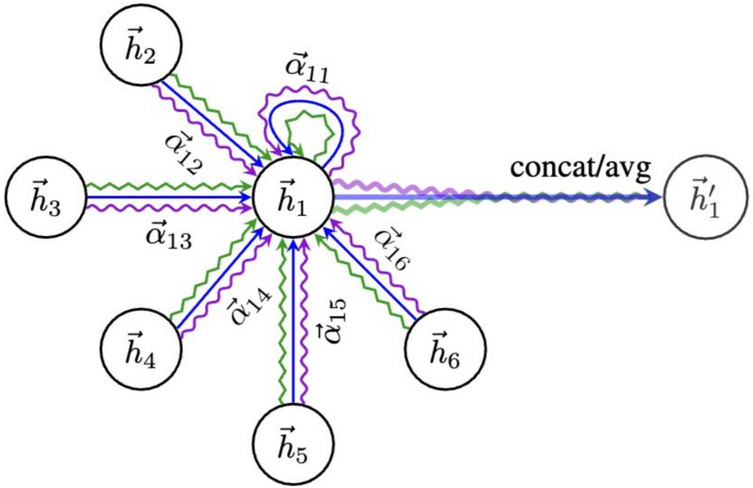
Background - Graph Neural Network(GNN)

Graph Neural Networks (GNNs) are a class of deep learning models designed to operate on graph-structured data, where information is represented as nodes connected by edges.

Message Passing

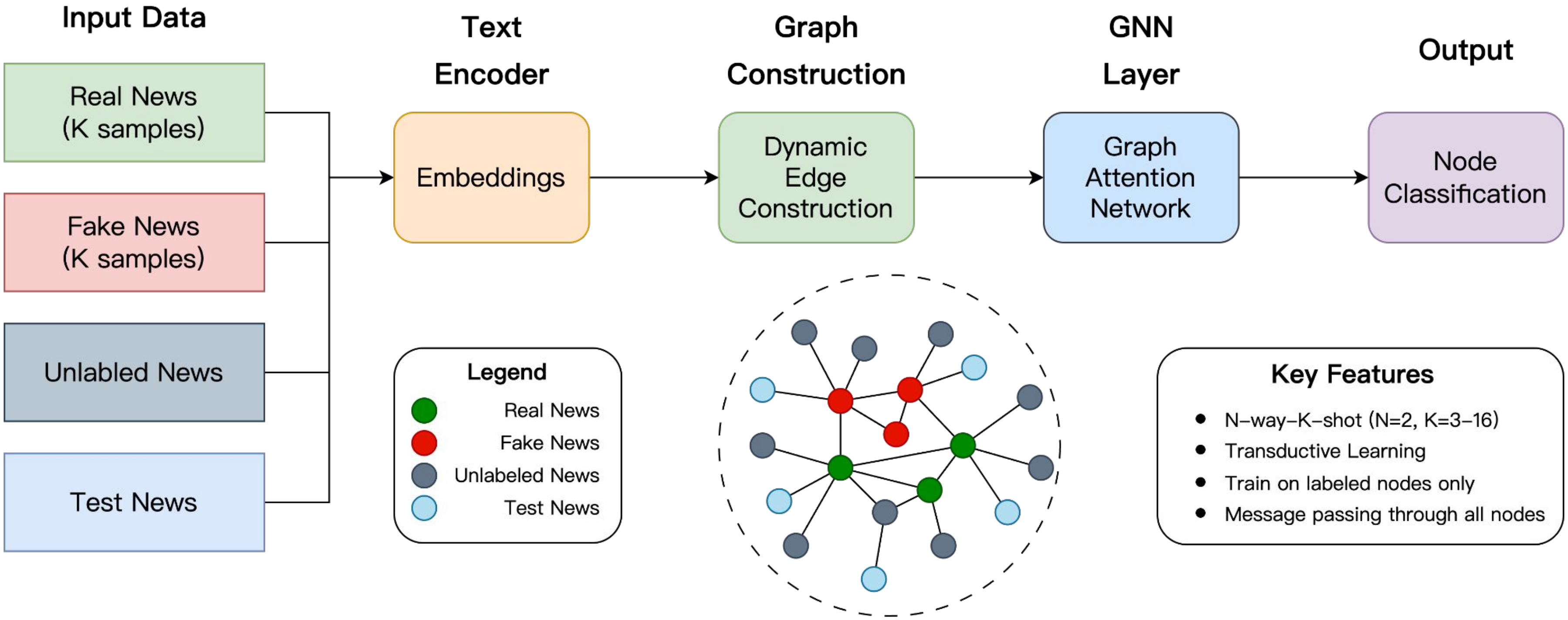
GNNs iteratively update each node's representation by aggregating information from its neighbors, enabling the model to capture both local and global graph structure.

$$\mathbf{h}_v^{(l+1)} = \mathrm{AGGREGATE}\left(\left\{\mathbf{h}_u^{(l)} : u \in \mathcal{N}(v)\right\}\right)$$

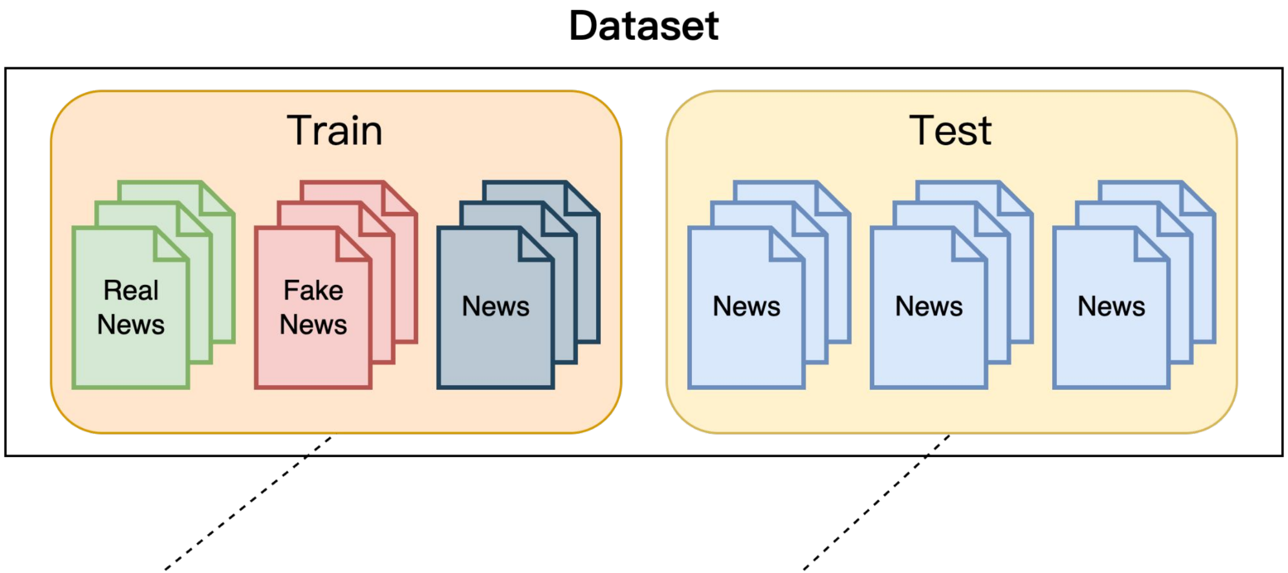


Veličković et al., "Graph Attention Networks," ICLR 2018, arXiv:1710.10903

Methodology - Architecture



Methodology - Input Data

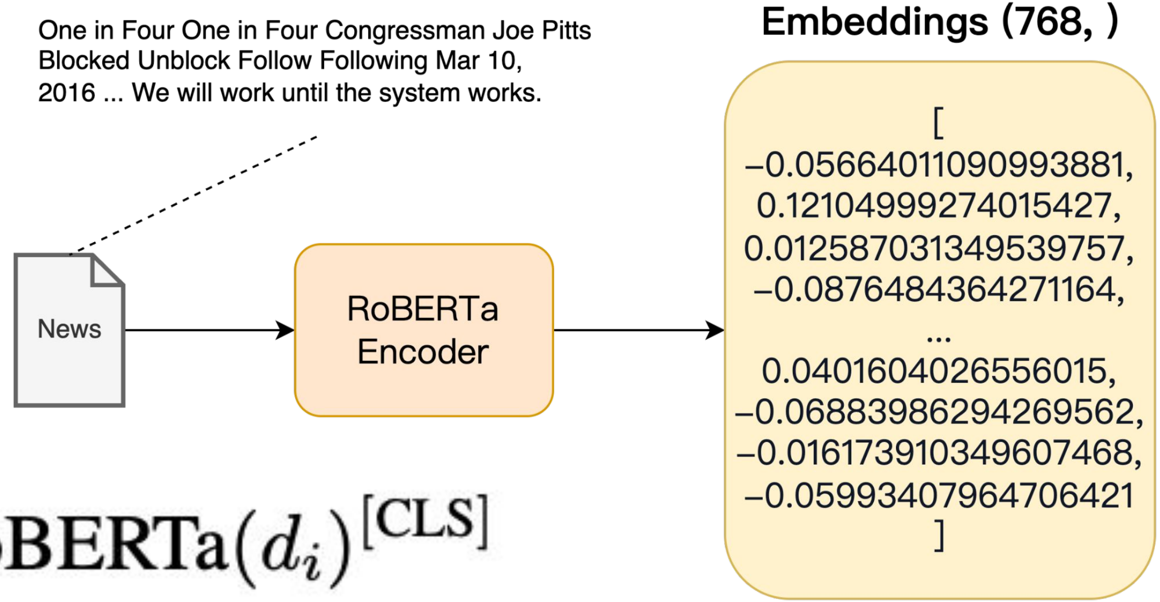


- k real news (with label)
- k fake news (with label)
- rest news without label

test news to be predicted

Methodology - Text Encoder

Each news is encoded as a node in our graphs using RoBERTa Embeddings



$$x_i = \mathrm{RoBERTa}(d_i)^{[\mathrm{CLS}]}$$

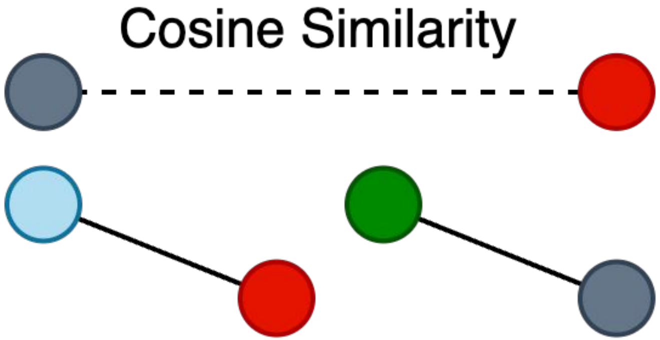
Methodology - Graph (Edge) Construction

Calculates global similarity statistics across document embeddings

- Sets a threshold based on the mean and standard deviation of similarities
- Creates edges between documents with similarity exceeding this threshold

$$\tau = \mu + \alpha\sigma$$

μ is the mean similarity
σ is the standard deviation
α default set to 0.5



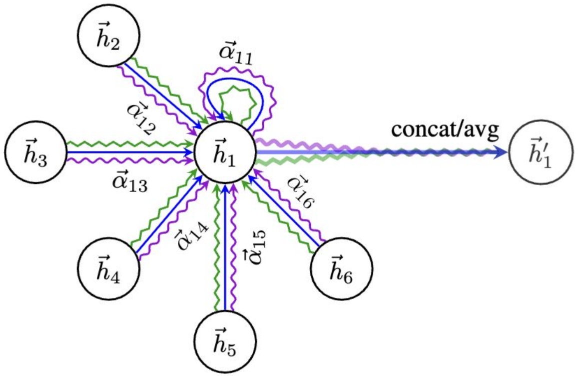
Methodology - GNN Layer

Graph Attention Network (GAT) as GNN layer:

- Computes dynamic attention coefficients (αij) unlike traditional GCNs
- Selectively aggregates information from semantically relevant neighbors
- Focuses on discriminative relationships crucial for few-shot learning
- Adapts to varying importance of news document connections

$$\alpha_{ij} = \frac{\exp(\mathrm{LeakyReLU}(\mathbf{a}^T[\mathbf{W}\mathbf{h}_i \| \mathbf{W}\mathbf{h}_j]))}{\sum_{k \in \mathcal{N}_i} \exp(\mathrm{LeakyReLU}(\mathbf{a}^T[\mathbf{W}\mathbf{h}_i \| \mathbf{W}\mathbf{h}_k]))} \quad (3)$$

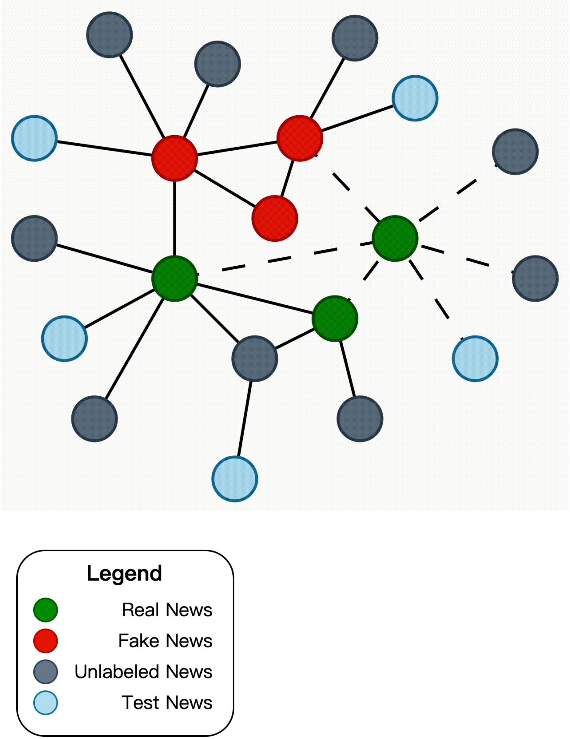
$$\mathbf{h}_i^{(l+1)} = \sigma\left(\sum_{j \in \mathcal{N}_i} \alpha_{ij} \mathbf{W}\mathbf{h}_j^{(l)}\right) \quad (4)$$



Methodology - Transductive Learning

- **Key Principle:**
  - All nodes (labeled + unlabeled + test) participate in message passing
  - Only labeled nodes contribute to loss calculation
  - Unlabeled data assists in representation learning

- **Few-Shot Learning Advantage:**
  - Leverages graph structure with limited labeled data
  - Improves generalization through neighborhood information
  - Privacy-preserving (no user interaction required)



Methodology - Loss & Output

- Cross-Entropy Loss (Labeled Nodes Only)

$$\mathcal{L} = -\frac{1}{|V_L|} \sum_{i \in V_L} y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)$$

V_L = set of labeled nodes
y_i = ground truth label (0: real, 1: fake)
$\hat{y}_i$ = predicted probability

- Output:
  - Binary Classification: Real(0) vs Fake(1)
  - Node-level predictions on test set
  - F1-Score evaluation metric

Experiments - Dataset from FakeNewsNet (Benchmark)

Dataset	Split	Real	Fake	Total
PolitiFact	Train	246	135	381
	Test	73	29	102
GossipCop	Train	7955	2033	9988
	Test	2169	503	2672

Key Features:

- **Professional verification:** Labels verified by fact-checkers
- **Content-only:** We use only news text (no social context)
- **Benchmark standard:** Widely used in fake news research

[Shu et al., ASONAM 2018]

Experiments - Train Labeled / Train Unlabeled / Test Set

N-way-K-shot Learning:

N: 2 (real / fake), K: 3 ~ 16 (K samples per class)

Baseline Models

Category	Methods	Description
Traditional	MLP, LSTM	Using RoBERTa embeddings
Language Models	BERT, RoBERTa	Fine-tuned for classification
Graph Methods	GAT (KNN-5)	Fixed K-nearest neighbor
Our Method	GAT (DTH)	Dynamic threshold construction

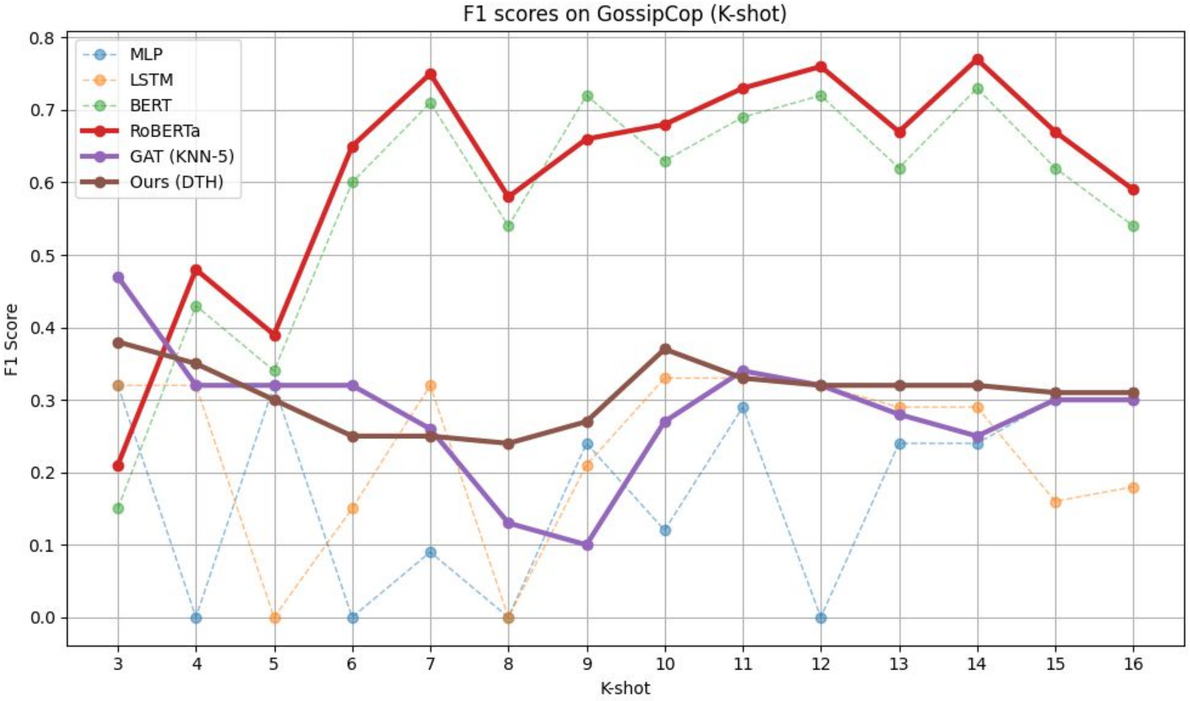
Results - GossipCop

Challenging dataset:
All methods show lower performance compared to PolitiFact

Stable performance:
Our GAT (DTH) maintains consistent 0.30-0.38 F1 across K values

Domain-specific challenges:
Entertainment news more difficult to distinguish

Baseline comparison:
Competitive with traditional methods in few-shot scenarios



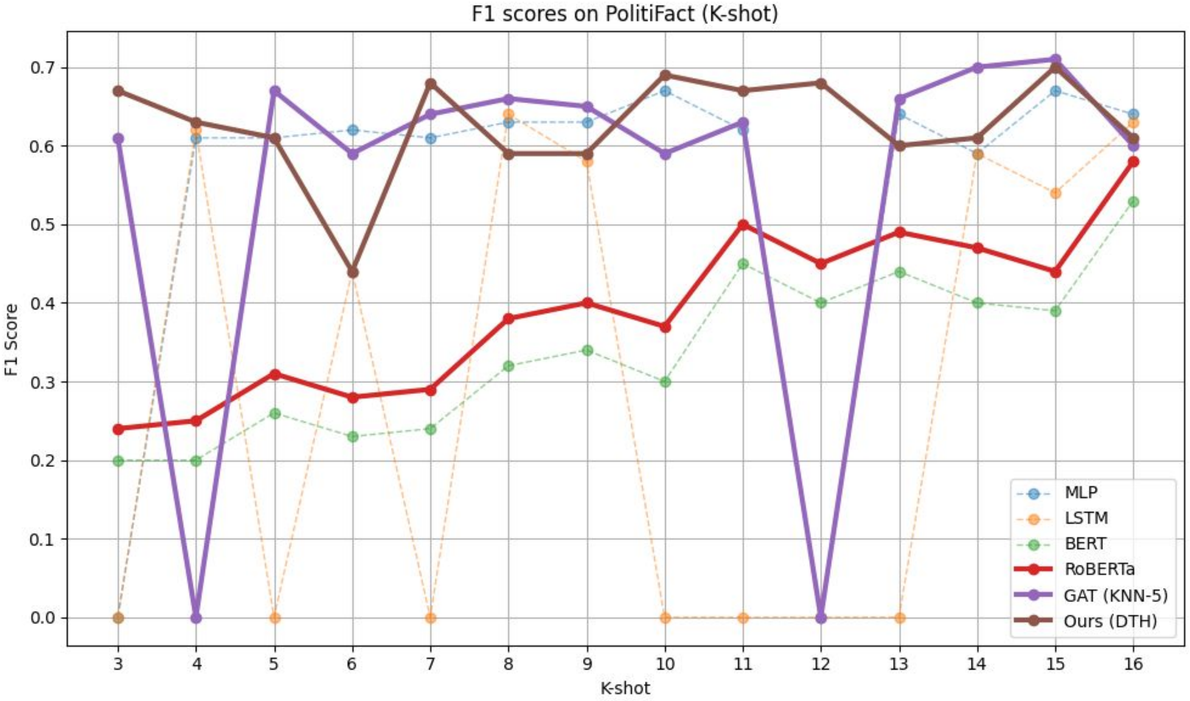
Results - PolitiFact

Few-shot performance:
0.67 F1 with only 3-shot learning

Significant improvement:
Outperforms BERT (0.20) and RoBERTa (0.24) by >3x

Consistent across K values:
Stable performance from 3-shot to 16-shot

Dynamic threshold advantage:
GAT (DTH) consistently better than GAT (KNN-5)



Conclusion

- **Key Contributions**
  - First pure content-based news-to-news graph neural network for few-shot fake news node classification
  - Dynamic threshold edge construction outperforms fixed KNN approaches by 4.1% F1-score
  - Achieves 0.67 F1-score with just 3 samples per class on PolitiFact, significantly outperforming BERT (0.20) and RoBERTa (0.24)

- **Key Insights**
  - Semantic relationships between news content provide reliable authenticity signals
  - Dynamic graph sparsification improves information flow in sparse data environments
  - Transductive learning effectively leverages unlabeled data to improve feature representation

Future Work

- **Technical Enhancement:**
  - **LLM-Enhanced Edge Construction:**
    Utilize large language models to generate richer semantic relationships beyond embedding similarity

- **Broader Application:**
  - **Cross-Domain Evaluation:**
    Test on multilingual datasets and across different domains (e.g., political to health misinformation)
  - **Multimodal Integration:**
    Extend framework to incorporate image and video content

Thanks