GemGNN: Generative Multi-view Interaction Graph Neural Networks for Few-shot Fake News Detection

生成式多視角互動圖神經網路之少樣本假新聞偵測

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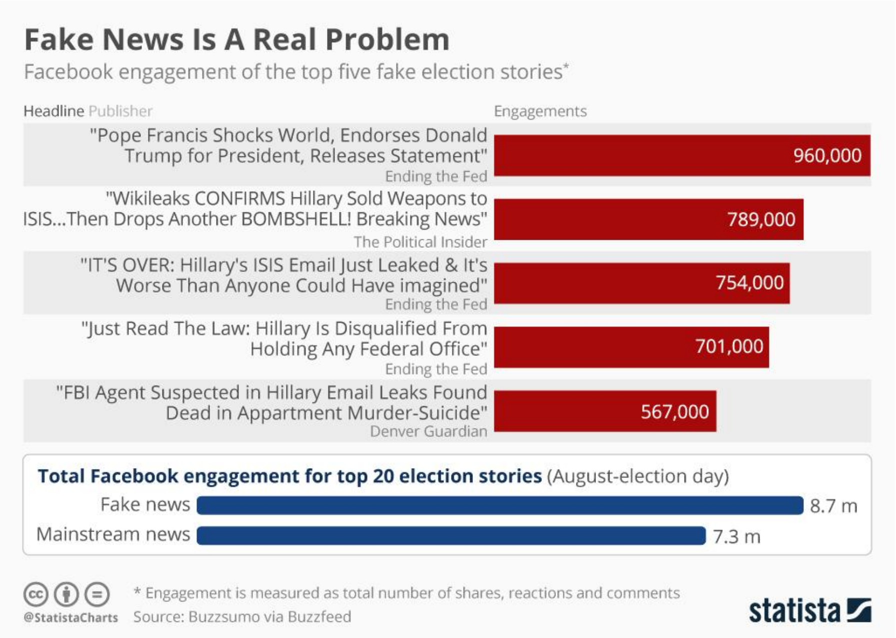
Outline

- Introduction & Challenges
- Related Work
- Background (Few-Shot Learning / GNN)
- Our Approach vs. Existing Methods
- Methodology
- Experiments
- Results
- Ablation Study
- Conclusion

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.

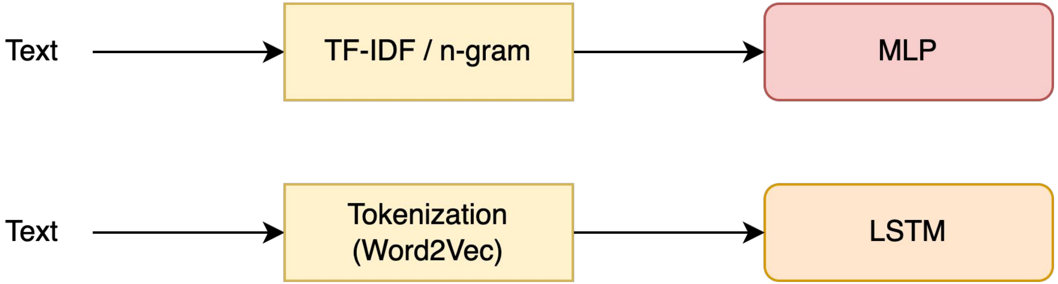
- **No Propagation or User Data:**
  Many existing methods rely on user interactions or propagation structures, which are often unavailable due to privacy concerns or platform restrictions.

- **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 - Traditional Model (MLP/LSTM)

- **MLP:**
  Early Feature Engineering Approaches - TF-IDF/n-gram + MLP

- **LSTM & RNN:**
  Sequential Modeling Advantages - Captures long-term dependencies in text

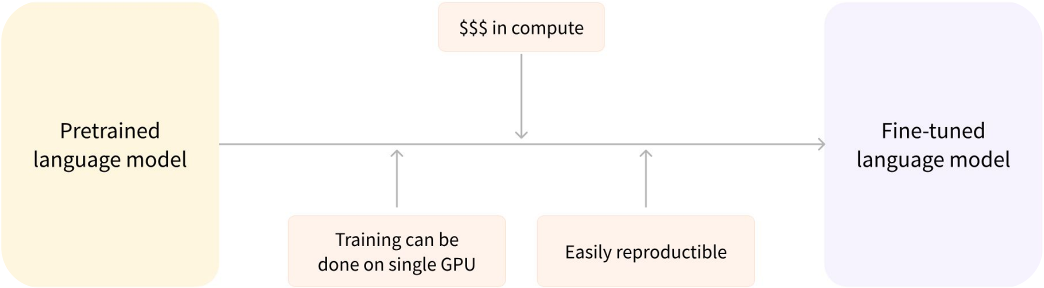


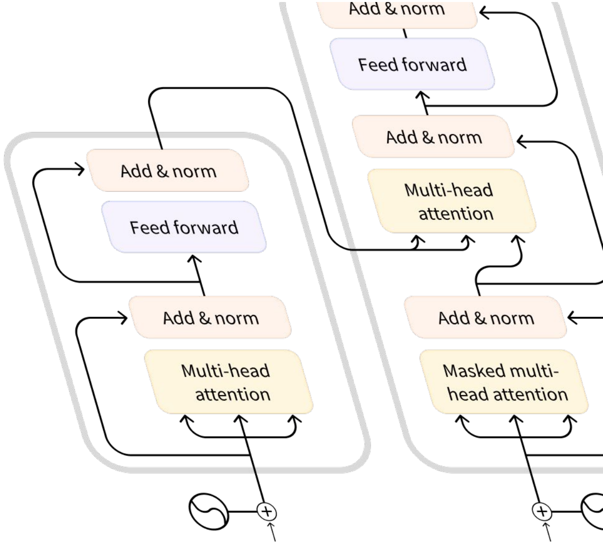
Social Media Fake News Detection Using Machine Learning Models and Feature Extraction Techniques
Enhanced Fake News Detection with Bi-LSTM Networks and TF-IDF

Related Work - Language Model

BERT & Transformer Architecture(Encoder)

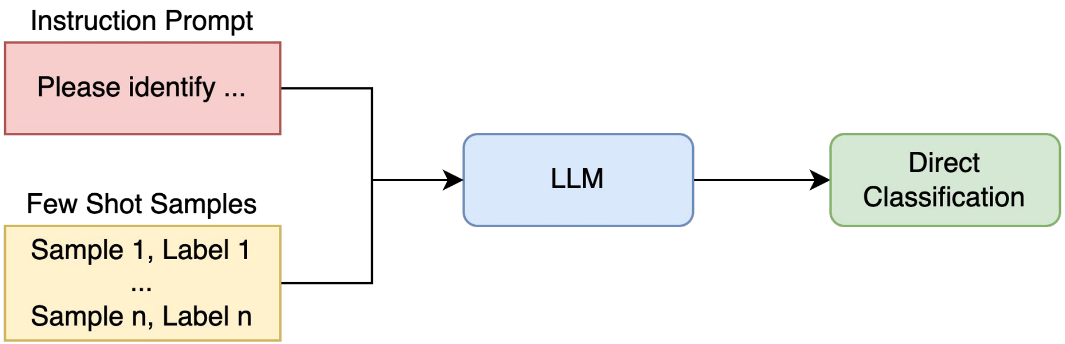
- **Bidirectional Context Understanding:**
  - Masked Language Model (MLM) pre-training
  - Natural Language Understanding(NLU)
- **Fine-tuning Paradigm:**
  - Task-specific adaptation with minimal architecture changes





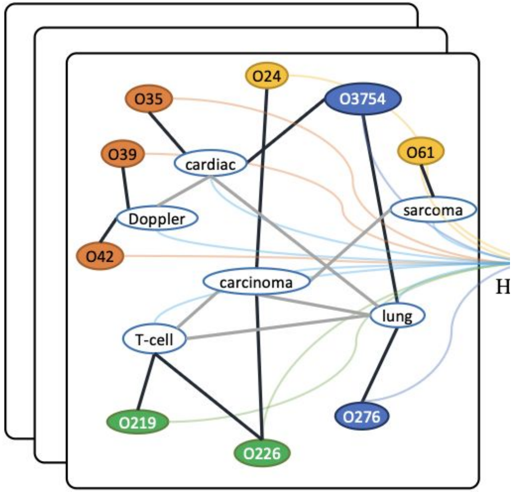
Related Work - Large Language Model

- **Zero-shot Learning Capabilities:**
  - Leverages pre-trained knowledge for novel tasks
  - Direct application to fake news detection without fine-tuning
- **In-context Learning (Few-shot Demonstrations):**
  - Learn from K=1-5 examples within context window
  - Rapid adaptation to new domains and topics



Related Work - Document-level Graph Classification

- **Heterogeneous Graph Design:**
  - Documents and vocabulary words as different node types
  - Global co-occurrence patterns across entire corpus
- **Graph Classification Task:**
  - Each document corresponds to one graph structure
  - Classify entire document graph as real/fake
- **Key Limitations:**
  - Large Data Requirements - Poor few-shot performance
  - Missing Document Relationships - Focus on word-level connections

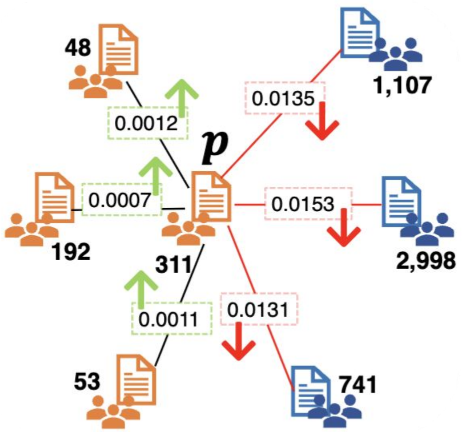


Word Document Graph

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

Related Work - Node Classification w/ User Propagation

- **Propagation-based Modeling:**
    - Message Passing Mechanism
    - Temporal Dynamics
- **Semi-supervised Node Classification Task:**
    - User-news interaction graph
    - Node Features: User profiles + News content embeddings
- **Key Limitations:**
    - Privacy Concerns - Requires user interaction data, raising privacy issues
    - Data Availability - Difficulty obtaining social media platform data
    - Cold Start Problem - Emerging topics lack sufficient propagation data



Wu et al., "DECOR: Degree-Corrected Social Graph Refinement for Fake News Detection", KDD 2023

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

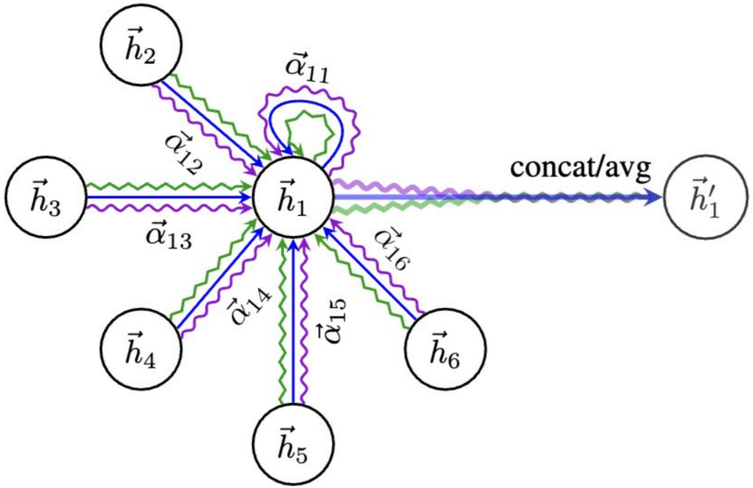
Background - Graph Neural Network(GNN)

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.

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

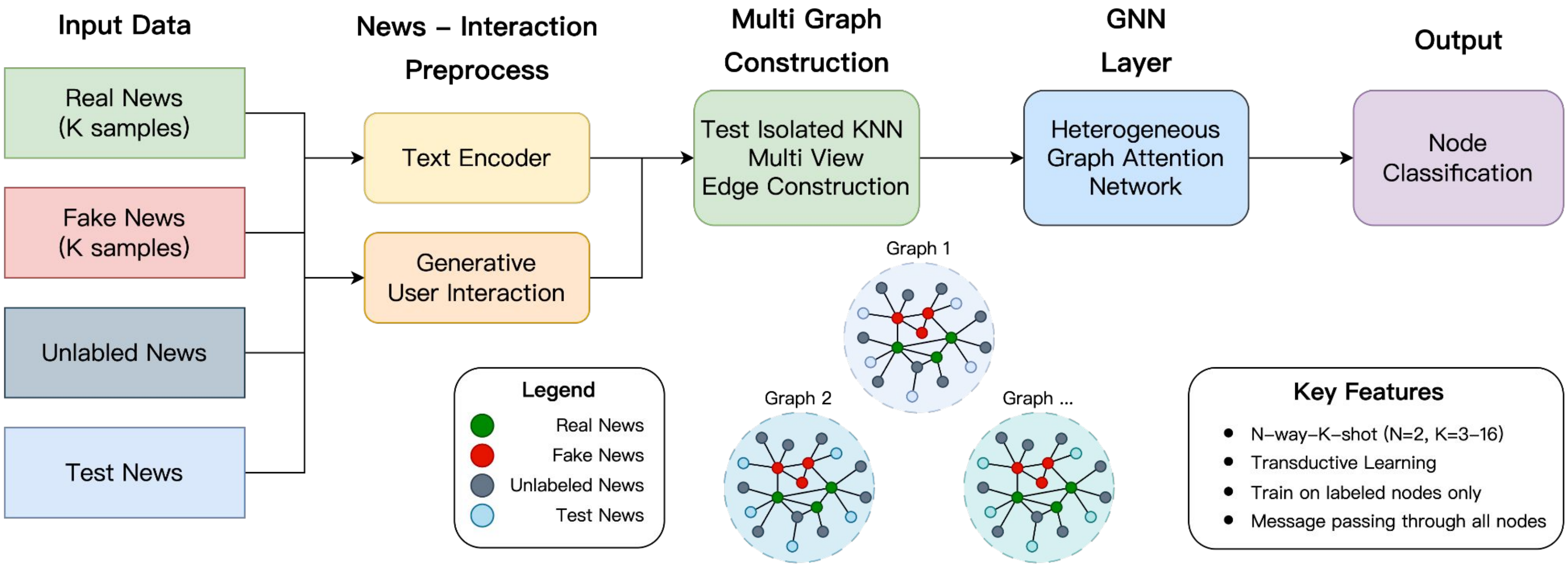


Veličković et al., "Graph Attention Networks," ICLR 2018, arXiv:1710.10903

Our Approach vs. Existing Methods

Method	**Core Mechanism**	**Data Requirements**	**Limitation**
Languge Model	Fine-tuning pre-trained encoders	Large labeled datasets	High annotation cost for task-specific data
LLM	Zero-shot & in-context learning via prompts	None for zero-shot Few examples for in-context	Limited control over reasoning; potential hallucinations
Document-Level Graph Classificaiton	Text-GCN, BERT-GCN: document-word heterogeneous graphs	Large corpora with word co-occurrences	Static co-occurrence; misses direct document–document semantics
User-Propagation Node Classification	user–news interaction graphs	Social interaction logs	Privacy issues; data availability; cold start on new topics
Ours (GemGNN)	**Generative Interaction from pure news content**	**News Content only**	**Relies on quality of embedding similarity**

Methodology - Architecture

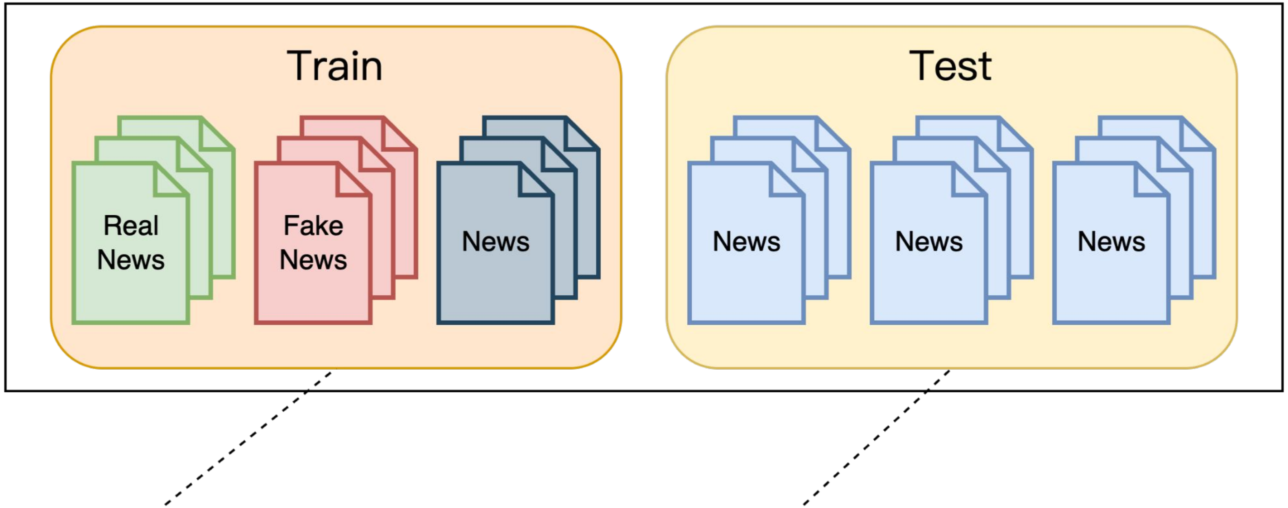


Key Features

- N–way–K–shot (N=2, K=3–16)
- Transductive Learning
- Train on labeled nodes only
- Message passing through all nodes

Methodology - Input Data

Dataset

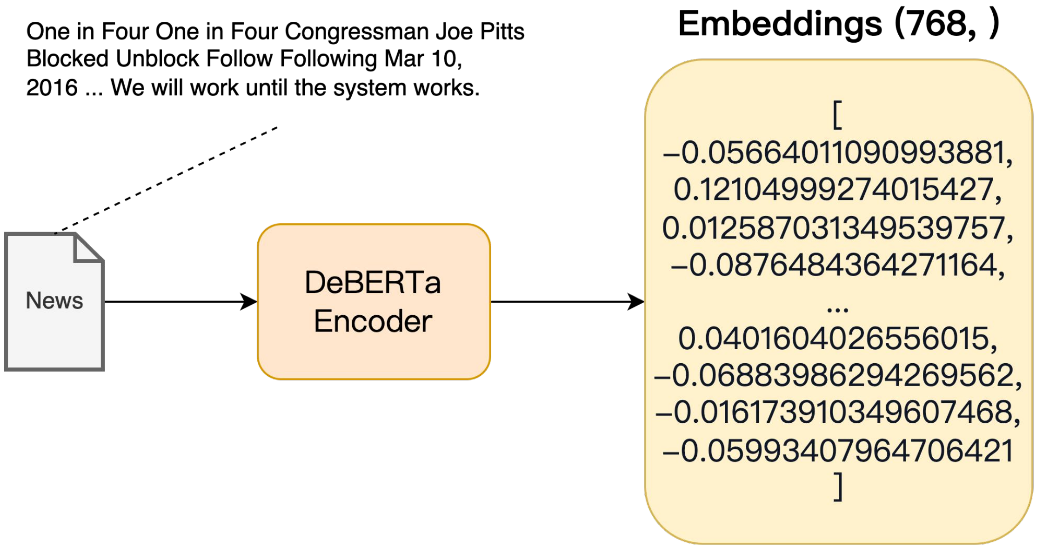


- k real news (with label)
- k fake news (with label)
- rest news without label

test news to be predicted

Methodology - Text Encoder

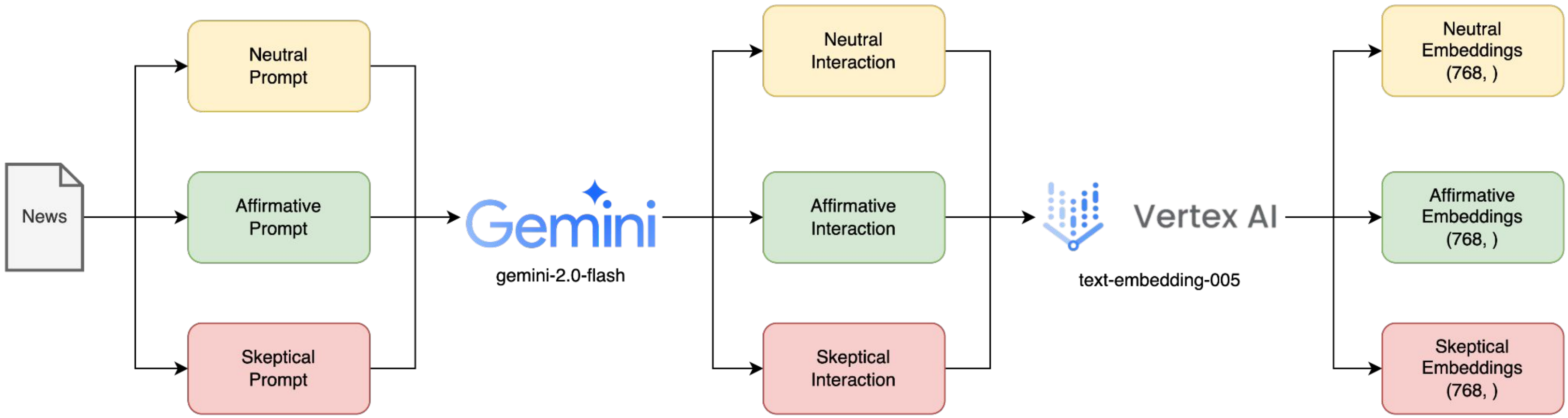
Each news is encoded as a node in our graphs using DeBERTa Embeddings



Methodology - User Interaction

Neutral Prompt

Please act as a reader who is confused about this news
Please act as a reader who wants to know more details about this news
Please act as a reader who has a neutral attitude toward this news
Please act as a curious reader and ask questions about this news



Affirmative Prompt

Please act as a reader who actively participates in the discussion and shares personal opinions
Please act as a reader who agrees with this news
Please act as a reader who wants to share this news with friends
Please act as a reader who feels excited about the content of this news

Skeptical Prompt

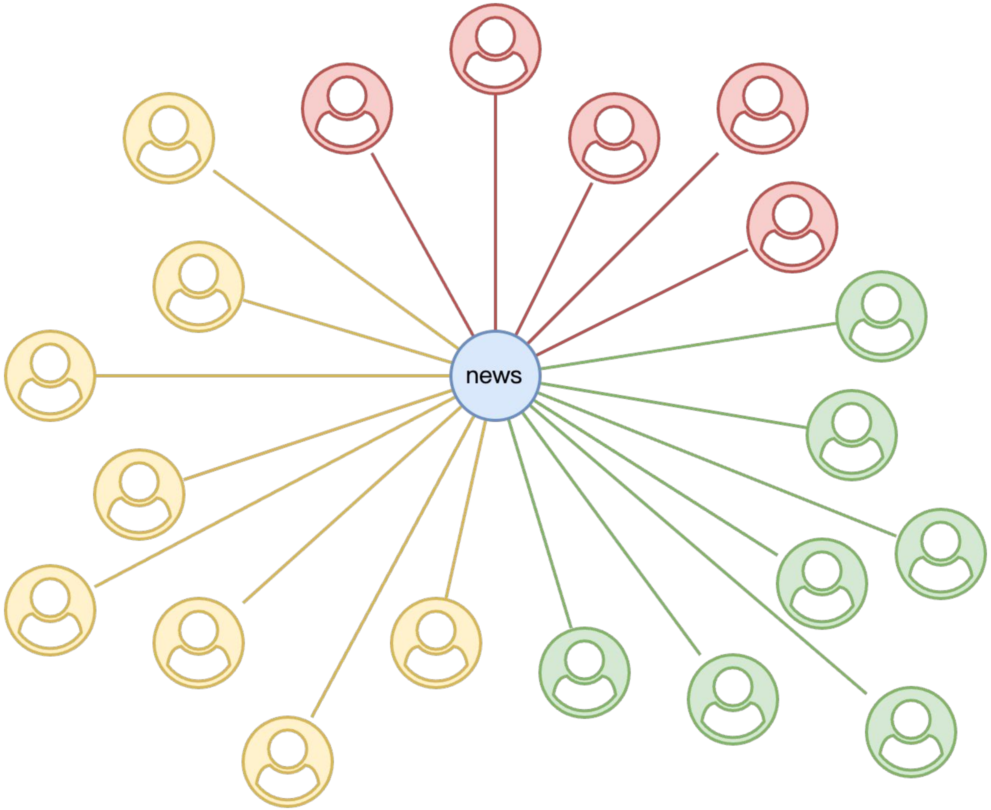
Please act as a reader who questions the authenticity of the news and provides evidence
Please act as a reader who raises doubts about this news
Please act as a reader who questions the source or credibility of this news
Please act as a reader who requests clarification or more information about this news

Methodology - News Interaction Node

Each news has 20 interactions with different tones:

- Neutral * 8
- Affirmative * 7
- Skeptical * 5

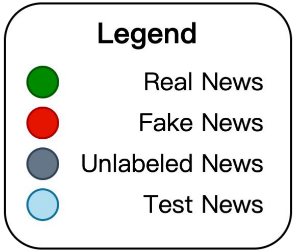
tone is encoded as attribute when creating the edge

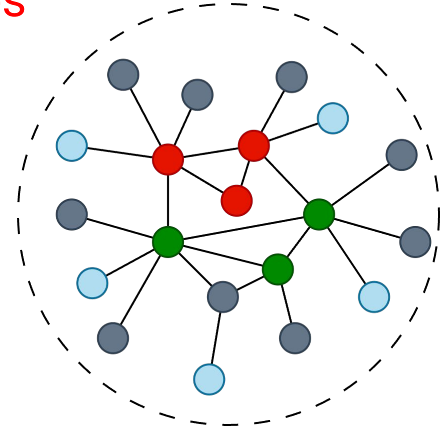


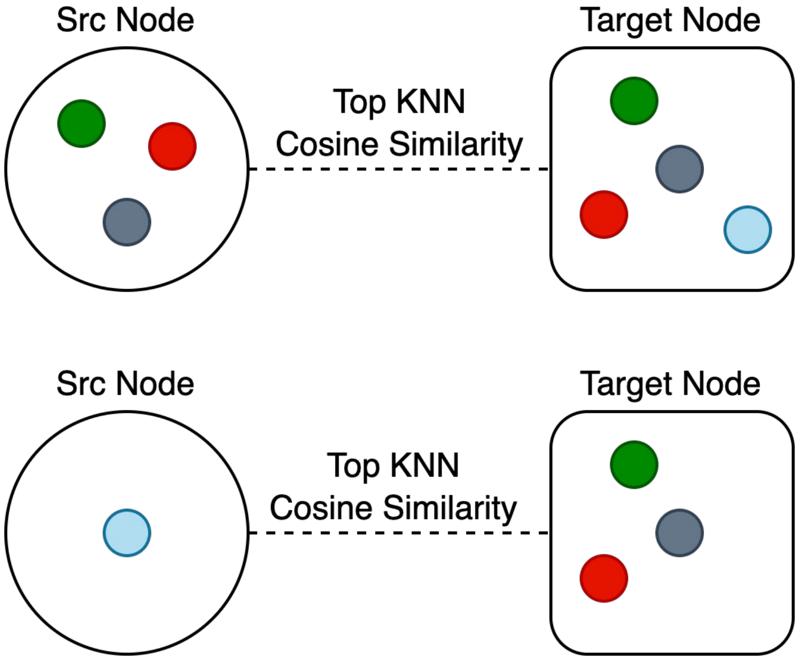
Methodology - Edge Construction (Test Isolated KNN)

- For Real/Fake/Unlabeled Nodes: Select top k nearest nodes for each src nodes.

- We disable test nodes connect to other test nodes





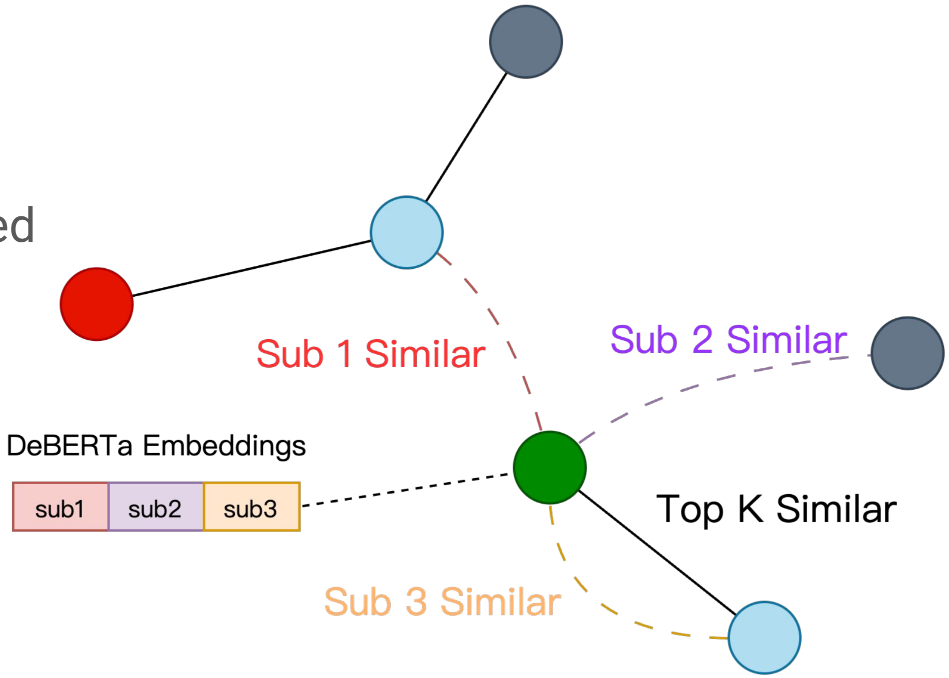


Methodology - Edge Construction (Multi-View)

We divide embeddings into 3 subsets

Enable each node redo the test isolated KNN strategy

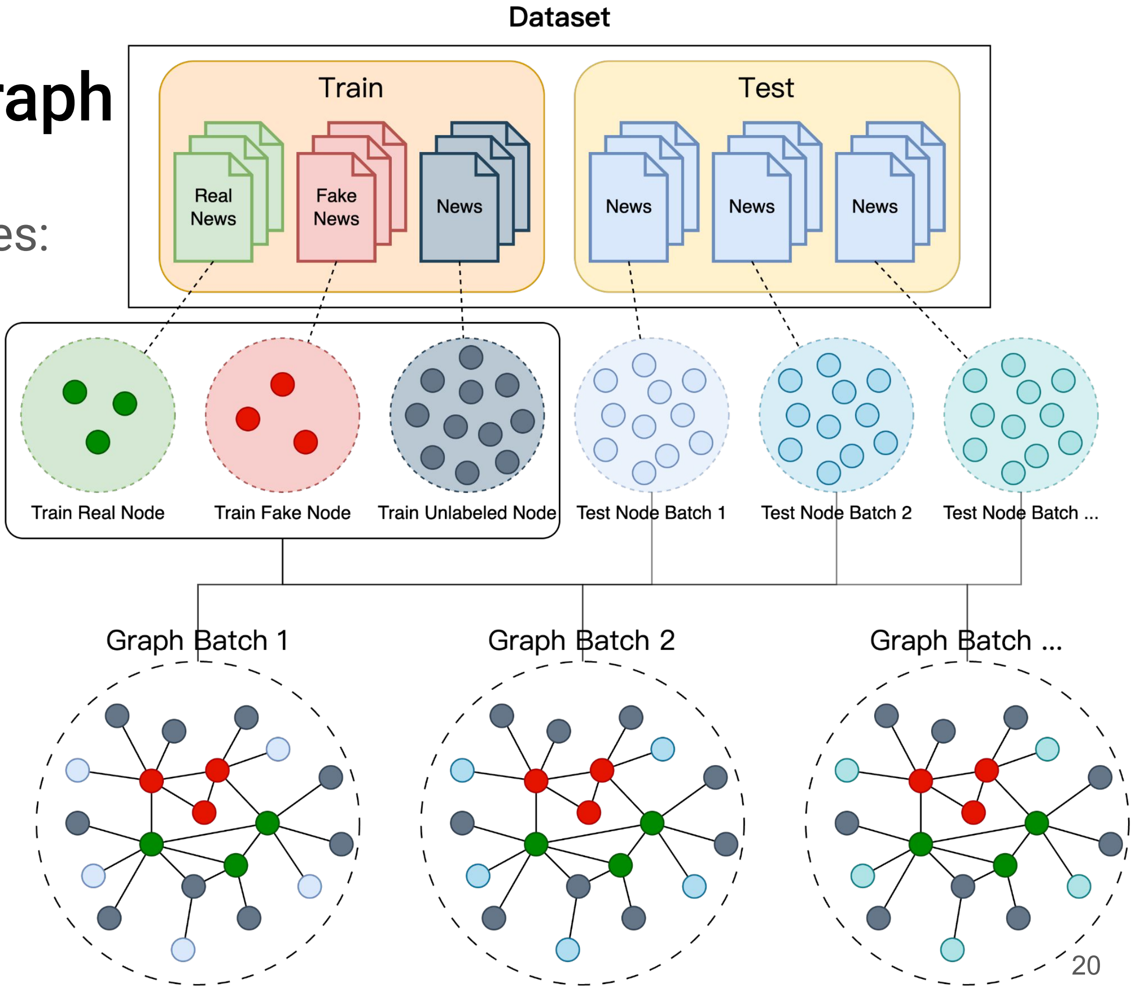
MultiView gives more information on different point of view

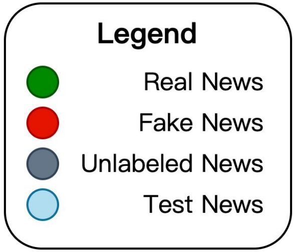


Methodology - Multi-Graph

For each graph, there exists nodes:

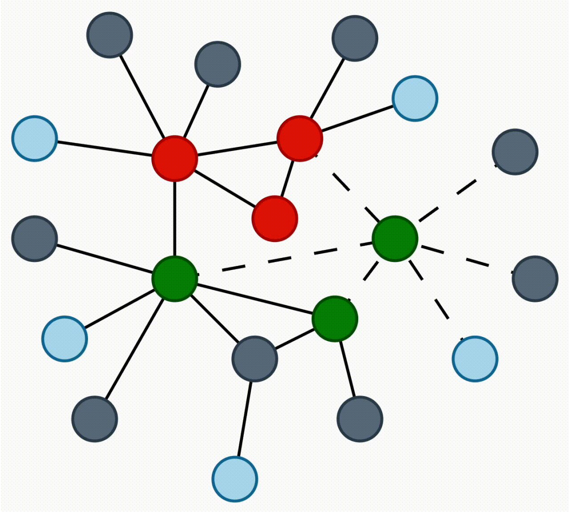
- K real/fake
- 2*k*M(5) train unlabeled
- B(50) test nodes





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

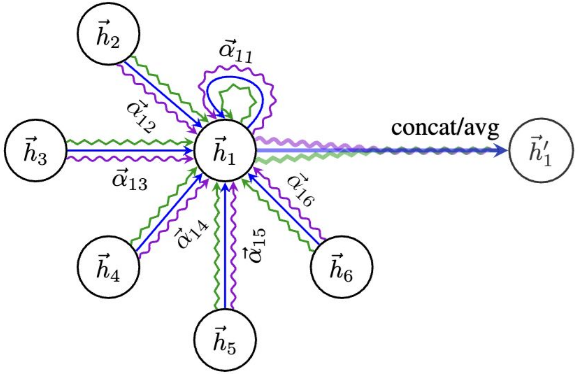
Methodology - GNN Layer (HAN / GAT)

We use Heterogenous Graph Attention Network for our base model

- 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 - GNN Layer (HAN)

We use Heterogenous Graph Attention Network for our base model

- Supports multiple node and edge types (news, interaction, topic, etc.)
- Type-specific attention: learns importance of each neighbor type
- Hierarchical aggregation: meta-path or edge-type level fusion
- Captures complex semantic relations among news, entities, and topics

Key Equations:

- Node-level attention (per type):

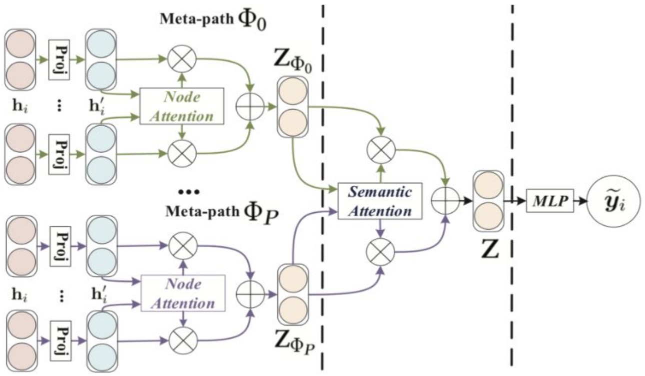
$$\alpha_{ij}^{(t)} = \frac{\exp(\mathrm{LeakyReLU}(\mathbf{a}^{(t)T}[\mathbf{W}^{(t)}\mathbf{h}_i \| \mathbf{W}^{(t)}\mathbf{h}_j]))}{\sum_{k\in\mathcal{N}_i^{(t)}} \exp(\mathrm{LeakyReLU}(\mathbf{a}^{(t)T}[\mathbf{W}^{(t)}\mathbf{h}_i \| \mathbf{W}^{(t)}\mathbf{h}_k]))}$$

- Semantic-level attention (meta-path/edge-type):

$$\beta_t = \frac{\exp(\mathbf{q}^T \cdot \tanh(\mathbf{W}_s\mathbf{h}_i^{(t)} + \mathbf{b}_s))}{\sum_{t'} \exp(\mathbf{q}^T \cdot \tanh(\mathbf{W}_s\mathbf{h}_i^{(t')} + \mathbf{b}_s))}$$

- Final node representation:

$$\mathbf{h}_i = \sum_t \beta_t \mathbf{h}_i^{(t)}$$



(a) Node-Level Attention (b) Semantic-Level Attention (c) Prediction

Methodology - Loss & Output

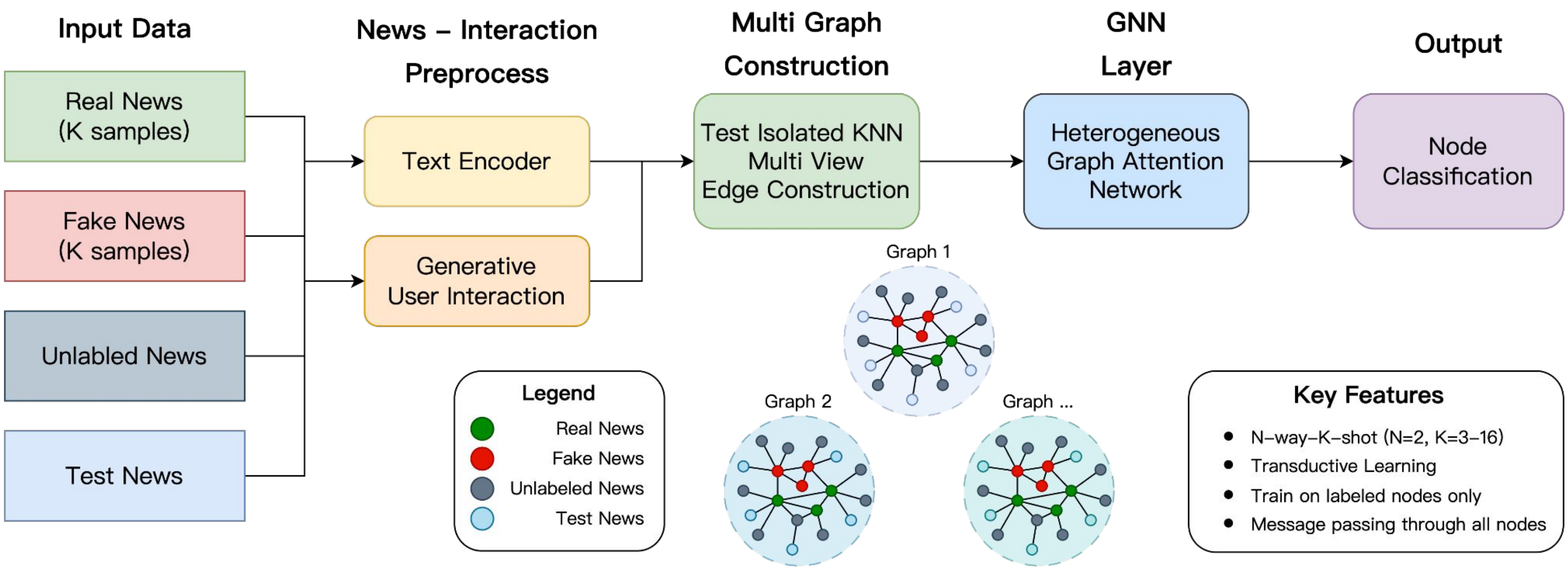
- Cross-Entropy Loss (Labeled Nodes Only)

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

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

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

Methodology - Architecture



Experiments - Dataset from FakeNewsNet (Benchmark)

Dataset	Split	Real	Fake	Total
PolitiFact (4:1)	Train	246	135	381
	Test	73	29	102
GossipCop (8:2)	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

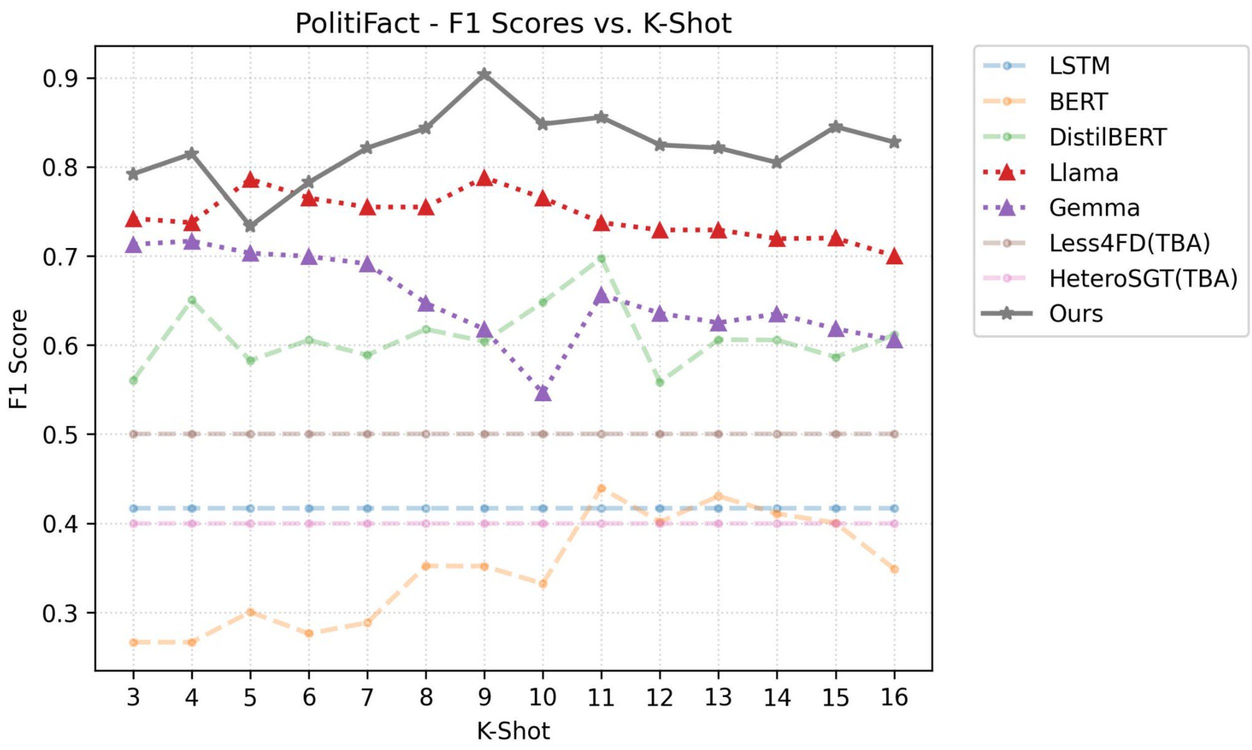
N-way-K-shot Learning:

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

Category	**Methods**	**Description**
Traditional	MLP, LSTM	Using RoBERTa embeddings
Language Models	BERT, RoBERTa	Fine-tuned for classification
LLM	Llama, Gemma	In-Context Learning
Graph Methods	Less4FD, HeteroSGT	TBA
Our Method	GenAI + Test-Isolated KNN + Multi-View + Multi-Graph	Utilize LLM to enrich the content-based graph construction

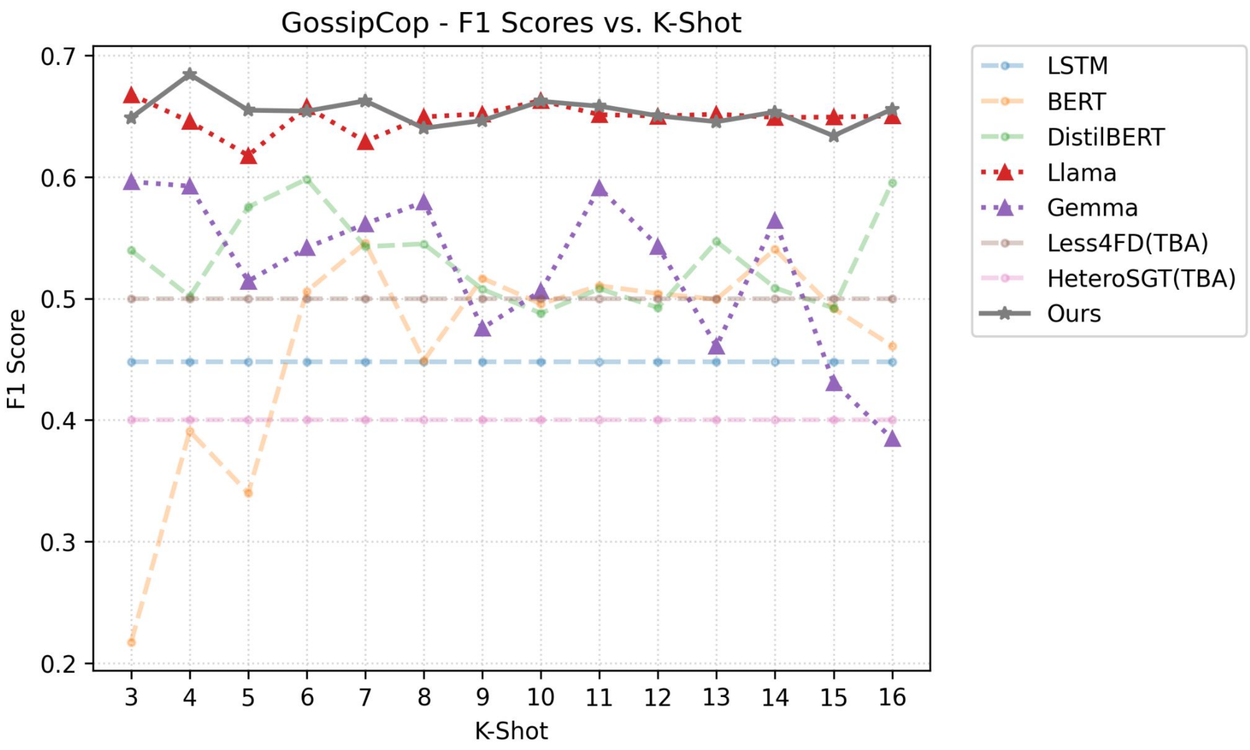
Results - PolitiFact

澄清一下，our performance最終是平均落在0.81



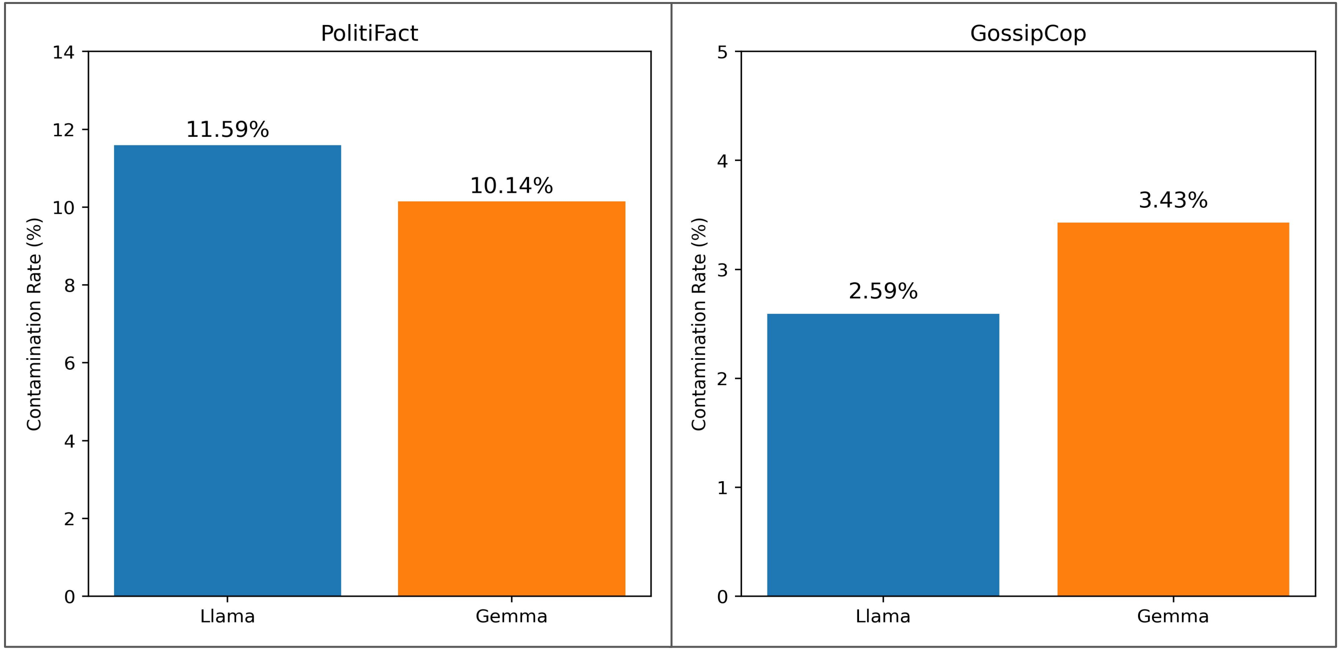
Results - GossipCop

澄清一下，our performance最終是平均落在0.61



Results on LLM

LLM may have seen the dataset



Ablation Study

Our work introduces 5 key components:

- Generative User Propagation
- Test Isolated KNN
- Ensure Test-Train Neighborhood
- Multi-View
- Multi-Graph

Ablation Study - PolitiFact / 8-shot

Table 1: Component analysis on the PolitiFact dataset with an 8-shot setting. We start with a base model and add key components to show their contribution to the final F1-Score.

Model Configuration	**Macro F1-Score**
Single Components:	
(A) Test Isolated KNN only	0.8146
(B) Multi-view only	0.8212
(C) Multi-graph only	0.8012
Component Combinations:	
(A) + (B)	0.8212
(A) + (C)	0.8111
(B) + (C)	0.8012
(A) + (B) + (C) Full Model	**0.8212**

Ablation Study - GossipCop / 8-shot

Table 2: Component analysis on the GossipCop dataset with an 8-shot setting. We start with a base model and add key components to show their contribution to the final F1-Score.

Model Configuration	Macro F1-Score
Single Components:	
(A) Test Isolated KNN only	0.5815
(B) Multi-view only	0.5857
(C) Multi-graph only	0.5815
Component Combinations:	
(A) + (B)	0.5854
(A) + (C)	0.5823
(B) + (C)	0.5820
(A) + (B) + (C) Full Model	**0.5800**

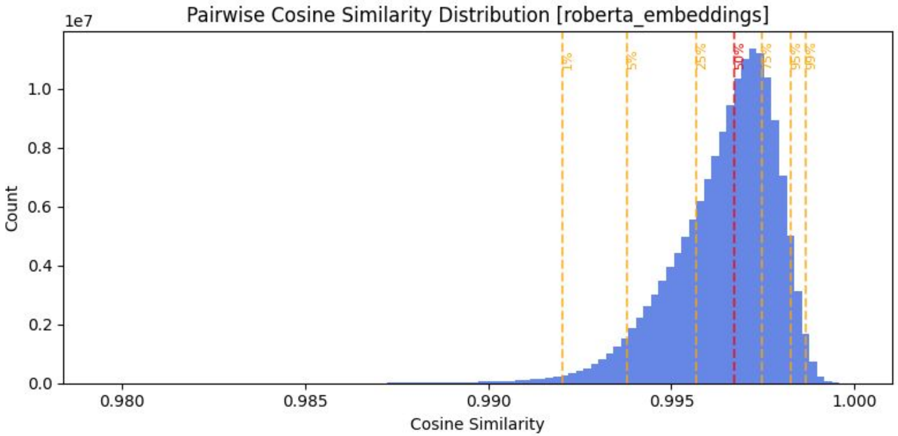
Conclusion

- **Key Contributions**
  - Introduced a **generative graph enrichment** method using an LLM (Gemini) to synthesize user interactions, overcoming the data dependency of traditional propagation-based models.
  - Developed a **Test-Isolated KNN** edge construction strategy that enforces a stricter, more realistic evaluation by preventing information leakage among test nodes.

- **Key Insights**
  - Transductive learning effectively leverages unlabeled data to improve feature representation
  - **Multi-View provides a holistic understanding of similarity,** forcing the model to learn from diverse semantic perspectives within the news content.
  - **Multi-Graph training acts as graph-level data augmentation,** exposing the model to varied structural contexts to learn more robust and generalizable features.

Future Work

With



Thanks

Feedback

- 用 column 來呈現各model有什麼feature
- Problem Statement, Notation
- 研究問題(Problem Statement)
- Few-Shot Learning 當 background
- Introduction: component 解決哪些challenge (contribution)
- Why related work can’t do well on few-shot learning
- Our Approach (Unsupervised or Supervised)
- why DeBERTa not RoBERTa
- Dataset 重組
- Page 16, 17: why tones? why interaction(motivation)?
- Page 18: why test-isolated KNN

Feedback

- Why not single-graph (Motivation)
- more GNN related work
- Highlight Loss
- Page 30, how contamination
- Ablation Study (Homogenous GenAI)
- HyperParameters
- Base GNN

Feedback

Problem Statement