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Graph Neural Networks for Fake News Detection

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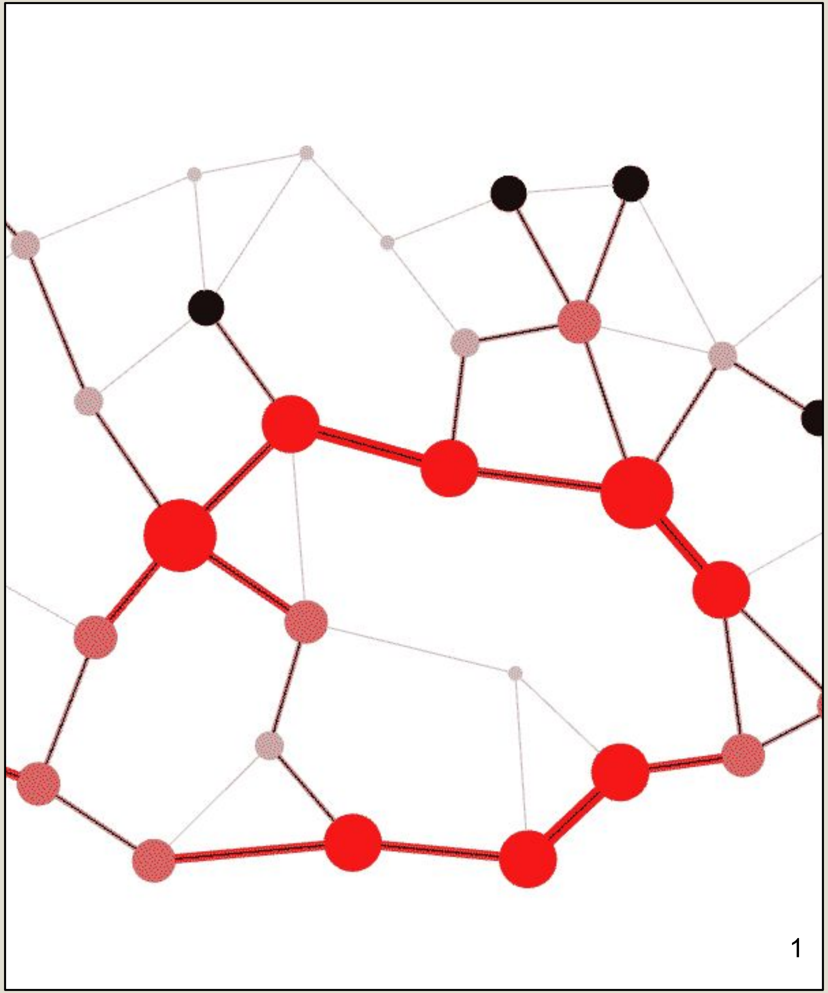

Figure 1. Graph Neural Network [1]

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Graph Neural Networks

- Encode nodes/edges in a multi-dimensional space (similar to encoding tokens in sentences for language models)
- Feed the encoding of nodes in a neural network for multiple usages
  - Node prediction
  - Graph prediction
  - Edge prediction
  - etc.

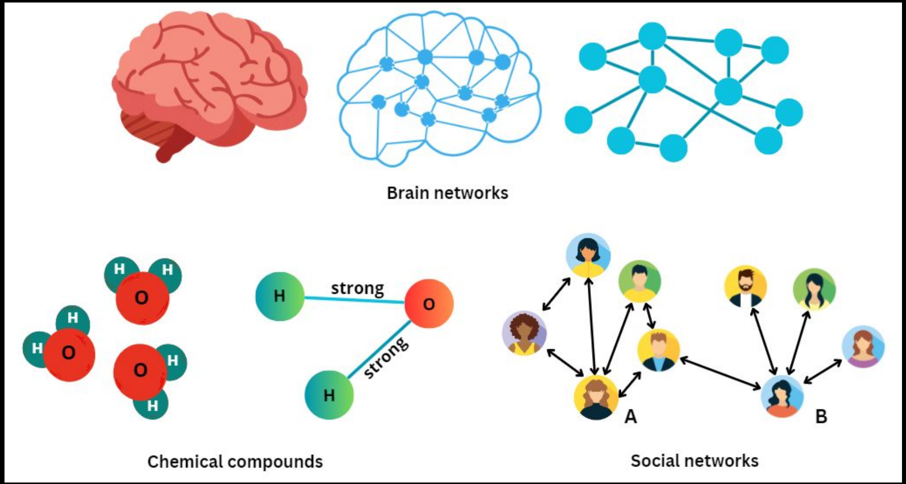

Figure 2. Examples of Graph Neural Network uses and applications [2]

Fake News

- Fabricated information, mimics news media content
- Intended to mislead audiences, influence public opinion, generate revenue or cause confusion
- Forms
    - Entirely false stories
    - Misleading headlines/partial truths
    - Satire/parody out of context

Figure 3. Donald Trump [3]

LIAR Dataset

- 12 800 human-labeled short statements
- Labeled as:
  - 0 (pants-fire)
  - 1 (false)
  - 2 (barely-true)
  - 3 (half-true)
  - 4 (mostly-true)
  - 5 (true)
- Features
  - Statement
  - Speaker's name
  - Job-title
  - Political party affiliation
  - State
  - Historical credibility record
  - Context of statement

Statement: *"The last quarter, it was just announced, our gross domestic product was below zero. Who ever heard of this? Its never below zero."*
Speaker: Donald Trump
Context: presidential announcement speech
Label: Pants on Fire
Justification: According to Bureau of Economic Analysis and National Bureau of Economic Research, the growth in the gross domestic product has been below zero 42 times over 68 years. Thats a lot more than "never." We rate his claim Pants on Fire!

Statement: *"Newly Elected Republican Senators Sign Pledge to Eliminate Food Stamp Program in 2015."*
Speaker: Facebook posts
Context: social media posting
Label: Pants on Fire
Justification: More than 115,000 social media users passed along a story headlined, "Newly Elected Republican Senators Sign Pledge to Eliminate Food Stamp Program in 2015." But they failed to do due diligence and were snookered, since the story came from a publication that bills itself (quietly) as a "satirical, parody website." We rate the claim Pants on Fire.

Figure 4. Example data from the LIAR Dataset [4]

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Graph Attention Networks (GAT)

- Dynamic neighbor weighting
    - Through attention mechanism
- Computed independently for each node and its immediate neighbors
- Learnable aggregation

- Used in previous classification of fake news data
- Adaptively focus on most relevant neighbors based on node features and edge characteristics

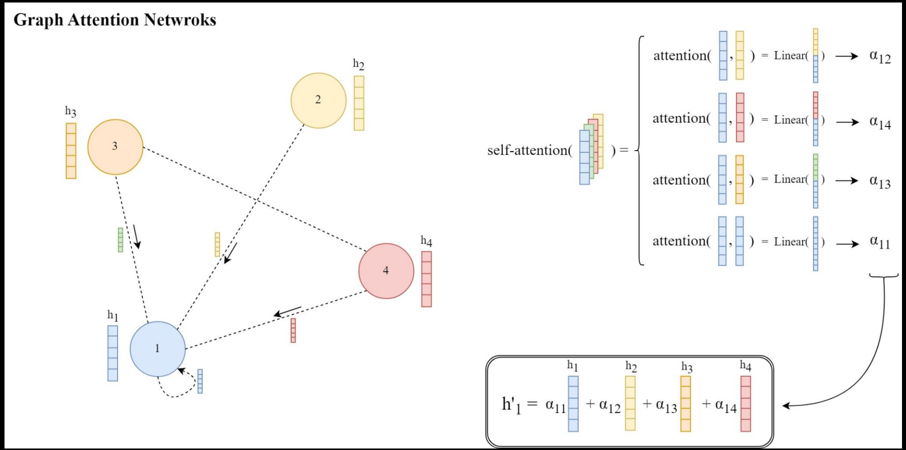

Figure 5. Graph Attention Network in action [5]

DHGAT

- Decision-based Heterogeneous GAT
- Processes heterogeneous graphs
  - Can handle multiple node and edge types
- Decision based relation selection
  - Dynamically decides which types of edges are more relevant for message passing
- Incorporates attention mechanism
- Gumbel-Softmax for discrete selection of edge types
- Achieved SOTA on LIAR Dataset [6]

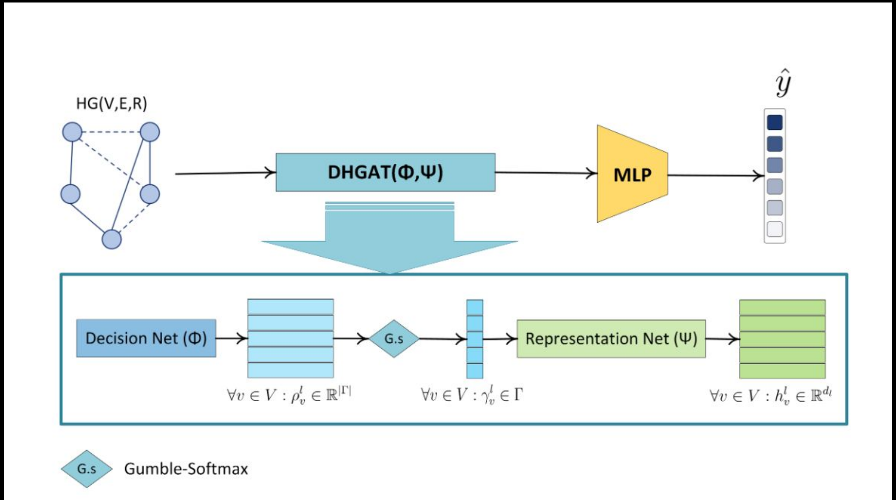

Figure 6. DHGAT Architecture [6]

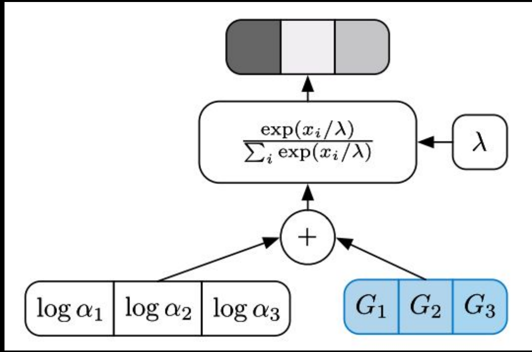

Figure 7. Gumbel-Softmax Equation [7]

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Our Model

- Inspired on DHGAT Model (adaptive process of feature information, learnable importance)
- Two graphs side by side
    - Content Graph (semantic link)
    - Social graph (user relational links)
- Content GATConv Stack and
- Social GATConv Stack
- Dual-channel attention module
- Feature concatenation
- MLP with residuals, then classification of output

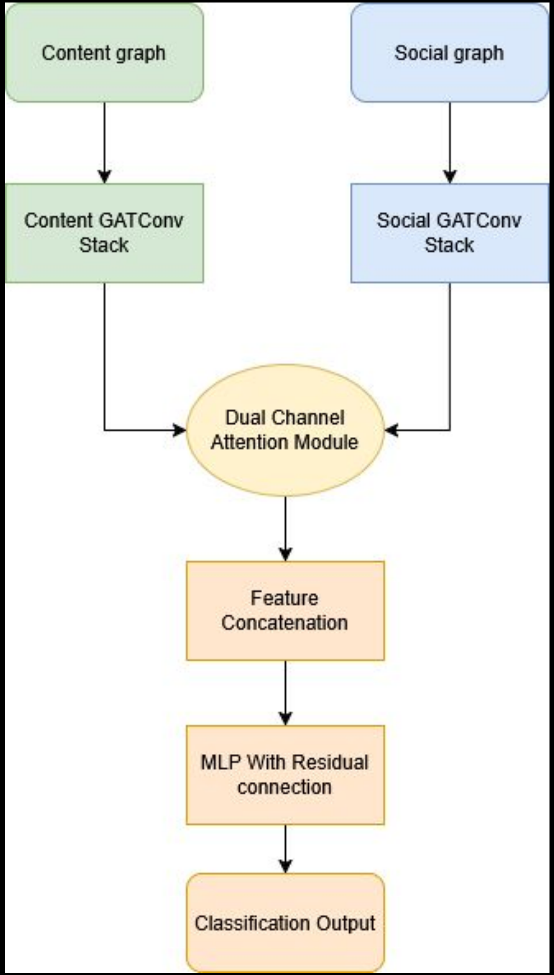


Figure 8. Model Architecture

Classification on LIAR dataset

Testing on 3 models

- Graph Convolution Network (GCN)
- Graph Attention Network (GAT)
- Our implementation inspired by DHGAT

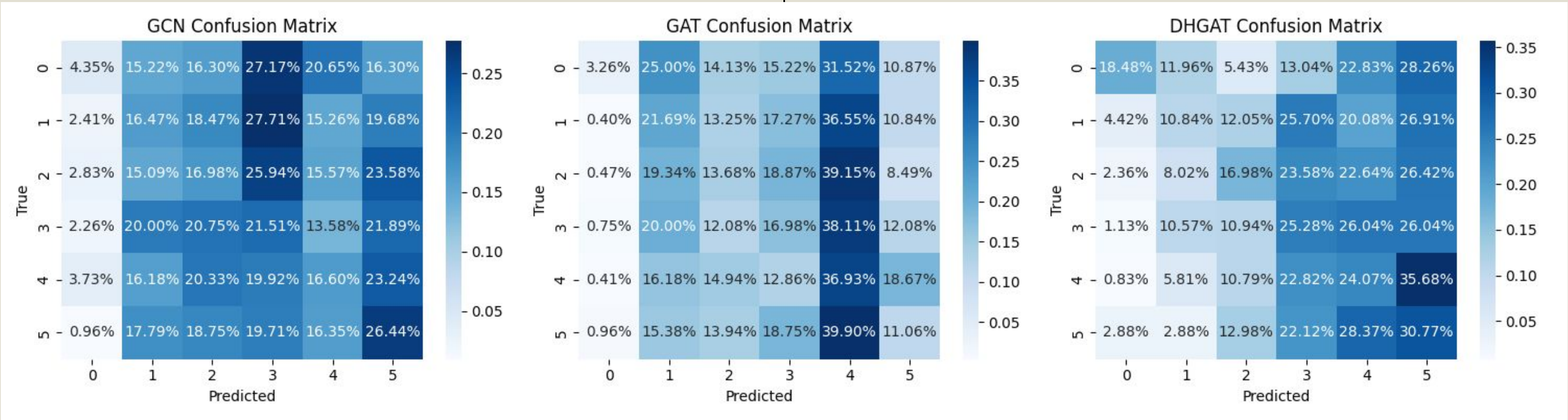
Parameters

- Adam optimizer
- Patience of 20 epochs for early stopping
- Weight decay = 5×10^-4
- Attention heads = 1 (same as paper)

```
class Config:
    # General training parameters
    seed = 42
    batch_size = 64
    learning_rate = 0.001
    weight_decay = 0.0005
    early_stopping_patience = 20

    # Model specific parameters
    class GCN:
        input_dim = 310  # 300 (content) + 10 (social)
        hidden_dim = 128
        output_dim = 6
        num_layers = 3
        dropout = 0.3
        num_epochs = 200

    class GAT:
        input_dim = 310
        hidden_dim = 256
        output_dim = 6
        num_layers = 4
        dropout = 0.3
        num_heads = 3
        num_epochs = 200

    class DHGAT:
        content_dim = 300
        social_dim = 10
        hidden_dim = 256  # Base hidden dimension
        output_dim = 6
        num_layers = 3
        dropout = 0.3
        attention_dropout = 0.2
        num_heads = 3
        num_epochs = 20  # Increased epochs for better convergence
```

Figure 9. Model parameters

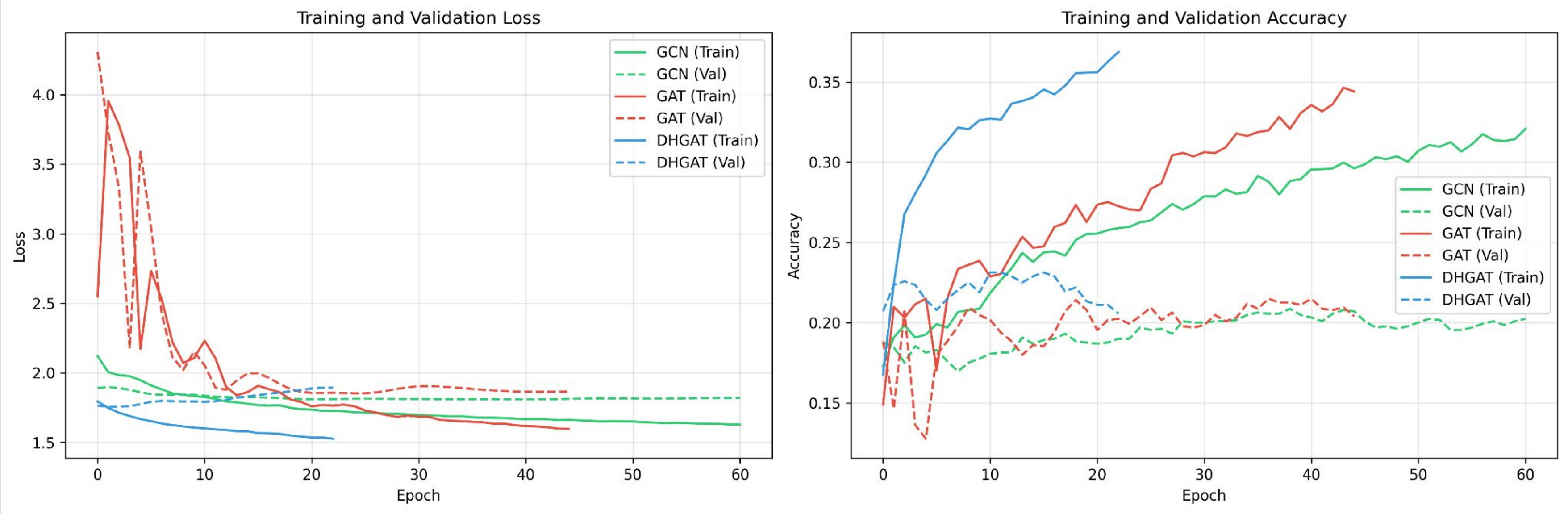
Results 1: Confusion matrix



DHGAT offers a more diagonal confusion matrix than other 2 models

GAT seems to favor classifying nodes as label 4 (mostly-true)

Results 2: Training curves

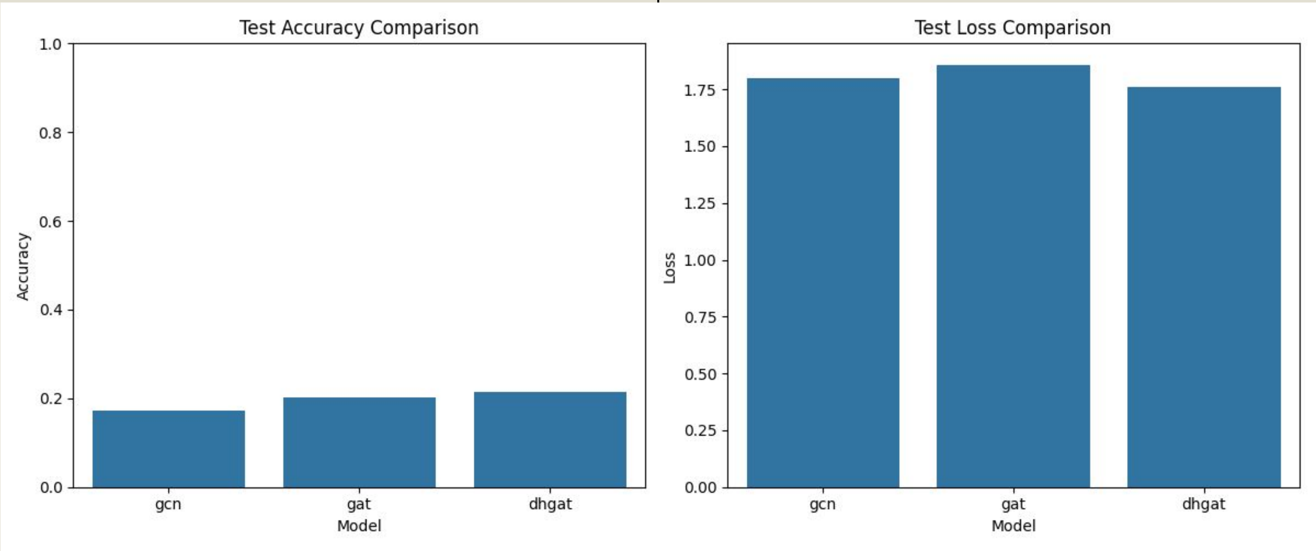


DHGAT gets lower loss quicker than other 2 models

DHGAT's accuracy on training reached above 35% with time (on 6 class classification), But validation accuracy seems to stagnate quick

- **Difficult to prevent overfitting on graph data**

Results 3: Model comparison



DHGAT gets a slightly higher test accuracy than other two models

- **Not as high as paper accuracy (~43%)**

DHGAT gets lower test loss than other 2 models

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Strengths

- Dual-channel modeling captures content and social signals separately.
- Dynamic attention adapts to the most informative modality.
- Simpler and more interpretable than full heterogeneous graphs.
- Strong theoretical foundations based on recent GNN research.

Weaknesses

- Only modest accuracy gains over GCN/GAT baselines.
- Social features too simple or noisy.
- LIAR dataset is small, sparse, and noisy.
- Simple k-NN graph may not capture true social relations.

Lessons Learned

- Graph construction and feature engineering are crucial.
- Model complexity must match data richness.
- Architectural innovations need careful empirical validation.

Future Work

- Use richer datasets (e.g., Twitter, Weibo).
- Model temporal evolution of misinformation.
- Extend to full heterogeneous graphs with multiple node/edge types.

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Conclusion

- Graph Neural Networks (GNNs) can effectively capture fake news patterns.
- Combining content features and social context improves detection.
- Dual-channel attention offers a flexible and interpretable modeling approach.
- Modest performance gains highlight the importance of rich relational data.

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[4] https://aclanthology.org/P17-2067.pdf

[5] https://arxiv.org/pdf/1710.10903

[6] https://arxiv.org/pdf/2501.03290

[7] https://sassafras13.github.io/GumbelSoftmax/