2-R: Graph-Based Prediction for TruthfulQA

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Introduction

- **Motivation**
  - LLMs, including GPT-4, perform poorly on True/False QA tasks such as TruthfulQA, achieving ~60% accuracy.
    - Main reason is hallucination and lack of factual grounding.
    - We aim to improve truthfulness prediction by modeling questions and answers as a graphs.
- **Approach**
  - Reformulate truth prediction as a link prediction task, where each model predicts correctness from Q-A connectivity.
  - Apply two graph-based models
    - Apply encoded nodes by Sentence-BERT to R-GCN, RAT

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Dataset

- **TruthfulQA Benchmark → Graph Dataset**
  - TruthfulQA Benchmark is designed to evaluate whether language models produce factually accurate answers.
    - 817 multiple-choice questions across 38 categories
  - **Transformation into a graph structure**
    - Nodes: Sentence is a node, labeled as question, answer.
    - Features: Each node is represented by embedding from SentenceTransformer's all-MiniLM-L6-v2
    - Edges: Indicate factual validity: 1.0 (true), 0.0 (false)
    - example :
      (node) Q : What U.S. state produces the most peaches?,
      (edge) correctness : 0
      (node) A : California produces the most peaches in the U.S.,

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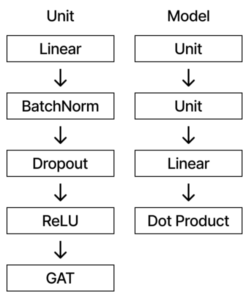
GAT Model Structure

- **GAT Model**
  - A 2-layer Graph Attention Network that learns to reason over sentence-level relationships
    - **Input:** SBERT embeddings (per node)
    - **Architecture**: Two GAT Layers + Feedforward block + node projection
  - Graph variants: unidirectional / bidirectional
    - Unidirectional: Q→A
    - Bidirectional : Q↔A



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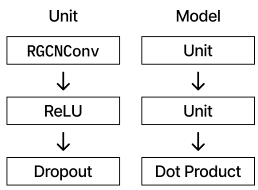
R-GCN Model Structure

- **R-GCN Model**
  - 2-layer R-GCN for binary link prediction
    - **Input:** SBERT embeddings (per node)
    - **Architecture**: Two RGCN Units + node projection
- Graph Construction
  - Each QA pair forms two directed edges
    Q → A (relation_id = 0), A → Q (relation_id = 1)
  - Both directions share the same correctness label



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Baseline Model Explanation

- **Simple-MLP Model**
  - Baseline model that ignores graph structure
    - **Input:** Concatenated SBERT embeddings of a question and answer
    - **Architecture:** Simple 2-layer MLP
- **GPT-4o**
  - OpenAI's GPT-4o via API.
    - **Prompt format:** Is the answer "{answer}" to the question "{question}" true? Answer in yes or no.
    - **Parsing:** The first "yes"/"no" in the output is mapped to 1 or 0
- **Training**
  - All models are trained with a 70:15:15 inductive split and use early stopping based on validation accuracy.

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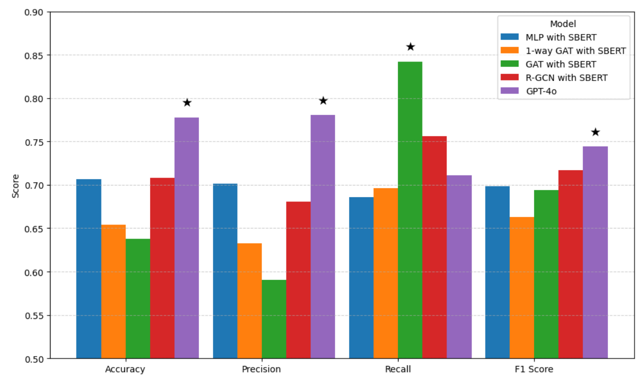
Accuracy, Precision, Recall, F1: Model Comparison



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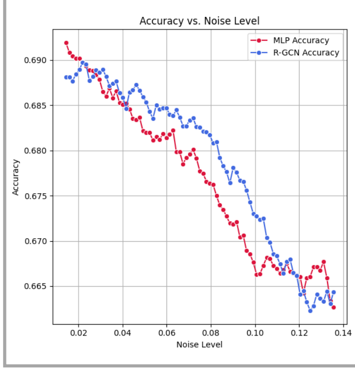
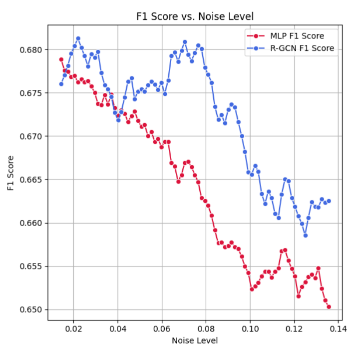
Robustness to Label Noise





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Conclusion

- **Conclusion**
  - Performance Comparison
    - GPT-4o achieves high overall scores, likely due to large-scale pretraining, but shows lower recall than graph-based models.
    - Bidirectional GAT achieves the best recall, suggesting that structured attention links helps capture truth-indicative signals.
  - Robustness to Label Noise
    - R-GCN outperforms MLP, demonstrating greater robustness to supervision noise.
    - Graph structure facilitates generalization, especially under imperfect annotations.

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