

GraphChain: Large Language Models for Large-scale Graph Analysis via Tool Chaining

Chunyu Wei¹, Wenji Hu¹, Xingjia Hao², Xin Wang¹, Yifan Yang³,

Yueguo Chen¹, Yang Tian², Yunhai Wang^{1*}

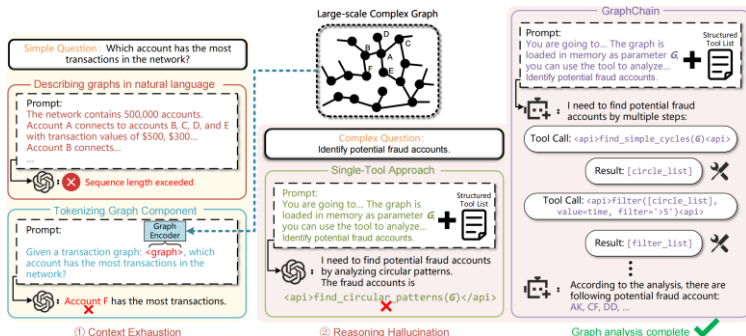
¹Renmin University of China, China ²Guangxi University, China ³Beijing Jiaotong University, China

39th Conference on Neural Information Processing Systems (NeurIPS 2025)

Outline

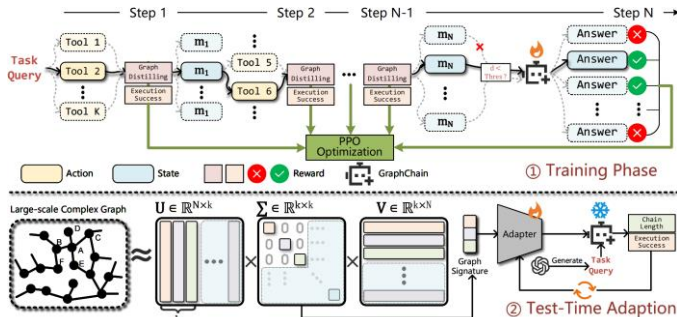
- 1 Motivation and Challenges
- 2 GraphChain Overview
- 3 Key Methods
- 4 Experimental Results
- 5 Conclusion and Contributions

Motivation and Challenges



- Graphs ubiquitous: Social networks, finance, molecules (e.g., fraud detection on 200k+ nodes)
- LLMs struggle: Context Exhaustion (graphs exceed windows) and Reasoning Hallucination (single tools fail complex tasks)
- Prior work limitations: Text-based (NLGraph) limited by size; Tool-based (GraphForge) lacks adaptive chaining
- Inspiration: Mimic human exploration – broad to focused

GraphChain Overview



Framework: LLMs chain specialized tools (NetworkX-based) for dynamic graph analysis

MDP Modeling: States (query + memory), Actions (tool selection), Rewards (success + distillation)

Innovations:

Progressive Graph Distillation: RL to reduce complexity while keeping relevance

Structure-aware Test-Time Adaption: Adapt to topologies via SVD fingerprint and lightweight adapter

Key Methods

- Distillation: Quantify GDL (volume) and Relevance; Reward for reduction + gain; PPO optimization
- Adaptation: Graph fingerprint zG from Laplacian SVD; Adapter generates prompt for frozen LLM
- Self-supervised: Minimize chain length + KL on auxiliary queries
- Benefits: Scales to large graphs, no retraining

$$R_t = \begin{cases} w_1 \cdot \hat{r}_t^{\text{Succ}} + w_2 \cdot \hat{r}_t^{\Delta\text{GDL}} + w_3 \cdot \hat{r}_t^{\Delta\text{Rel}} & \text{if } t < N \\ w_{\text{solve}} \cdot \text{EvaluateTaskSuccess}(\mathcal{Q}, s_{N+1}) & \text{if } t = N \end{cases}$$

$$L_{\text{STTA}}(\psi) = \mathbb{E}_{\mathcal{Q}_{\text{aux}}, i, \tau_i \sim \pi_{\psi}(\cdot | s; G_{\text{test}})} \left[w_L N_{\tau_i} + w_{KL} \sum_{t=0}^{N_{\tau_i}-1} D_{KL}(\pi_{\psi}(\cdot | s_t; G_{\text{test}}) || \pi_{\text{orig}}(\cdot | s_t)) \right]$$

Experimental Results

- Datasets: 5 domains (Cora, Facebook, QM9, etc.) – Table 1 stats
- GraphChain: 84.7% avg. accuracy (+20.7% over GraphForge at 70.2%)
- Baselines: Text (GPT-4o: 59.4%); Tools (GraphForge: 70.2%)
- Scalability: Consistent on 200k nodes; Ablations confirm distillation/STTA value

Text-Instruction Methods							
Model	Parameters	Financial Network	Chemical Molecule	Social Network	Citation Graph	Traffic Network	Average
Claude-3-Sonnet	-	21.7 \pm 1.8	47.0 \pm 2.2	21.5 \pm 3.2	17.7 \pm 2.1	16.8 \pm 2.0	24.9 \pm 2.3
GPT-3.5-turbo	~175B	36.6 \pm 2.1	23.0 \pm 3.7	18.2 \pm 3.6	12.2 \pm 0.8	19.4 \pm 1.9	21.9 \pm 2.4
Claude-3-Haiku	~20B	12.2 \pm 3.0	52.9 \pm 3.2	50.3 \pm 3.4	19.8 \pm 2.0	13.9 \pm 2.4	29.8 \pm 2.8
Claude-3-Opus	~137B	23.6 \pm 2.1	42.4 \pm 1.4	51.9 \pm 1.3	36.7 \pm 3.1	43.4 \pm 3.3	39.6 \pm 2.2
GraphWiz	13B	41.1 \pm 3.9	52.4 \pm 2.6	61.5 \pm 3.5	68.0 \pm 2.1	38.4 \pm 1.9	52.3 \pm 2.9
NLGraph	~100B	52.1 \pm 3.4	58.4 \pm 2.5	65.2 \pm 2.3	59.4 \pm 0.5	39.8 \pm 1.8	55.0 \pm 2.1
GPT-4o	~200B	57.5 \pm 1.9	62.7 \pm 3.6	65.2 \pm 3.9	71.5 \pm 3.4	43.4 \pm 1.6	59.4 \pm 2.6
Claude-4-Sonnet	-	58.2 \pm 2.1	62.9 \pm 1.7	61.7 \pm 4.3	77.5 \pm 1.4	32.8 \pm 1.9	58.6 \pm 2.3
GPT-4.1	-	52.2 \pm 1.5	63.4 \pm 2.6	67.4 \pm 2.3	70.0 \pm 1.9	55.5 \pm 3.1	61.7 \pm 2.2
Gemini-2.5-Flash	-	25.1 \pm 1.3	67.3 \pm 1.6	28.1 \pm 2.1	24.1 \pm 1.8	24.9 \pm 1.8	33.9 \pm 1.7
Tool-Instruction Methods							
Graph-ToolFormer	8B	47.5 \pm 1.9	68.1 \pm 4.8	74.7 \pm 4.2	61.4 \pm 3.4	65.8 \pm 4.5	62.4 \pm 3.5
GraphForge	8B	63.5 \pm 3.5	<u>70.9 \pm 5.4</u>	<u>80.4 \pm 4.2</u>	63.4 \pm 4.4	<u>73.5 \pm 3.1</u>	<u>70.2 \pm 3.8</u>
ToolGen	8B	75.8 \pm 1.1	57.9 \pm 2.9	79.4 \pm 2.3	61.2 \pm 1.3	62.7 \pm 1.5	67.4 \pm 1.8
GraphChain	7B	81.5 \pm 2.2	81.1 \pm 0.7	89.6 \pm 2.0	83.6 \pm 2.6	84.1 \pm 0.3	84.7 \pm 1.8
Relative improvement (%)	-	+7.5%	+14.4%	+11.4%	+7.9%	+14.4%	+20.7%

Conclusion and Contributions

- GraphChain enables scalable LLM graph analysis via chaining
- Contributions: RL distillation, topology adaptation, +20.7% SOTA, open-source code
- Future: More tools, online adaptation