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LLM4DyG: Can Large Language Models Solve Spatial-Temporal Problems on Dynamic Graphs

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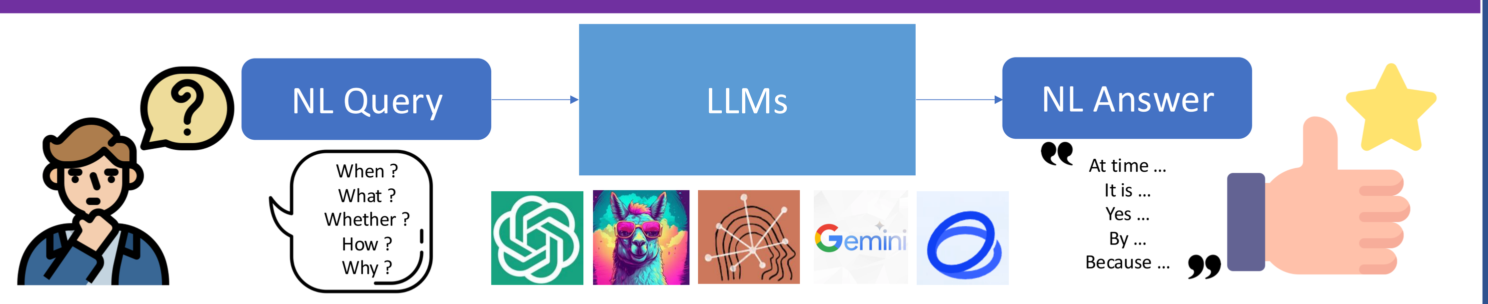
1 Background & Motivation

① In the era of LLMs, we handle data with natural language (NL)

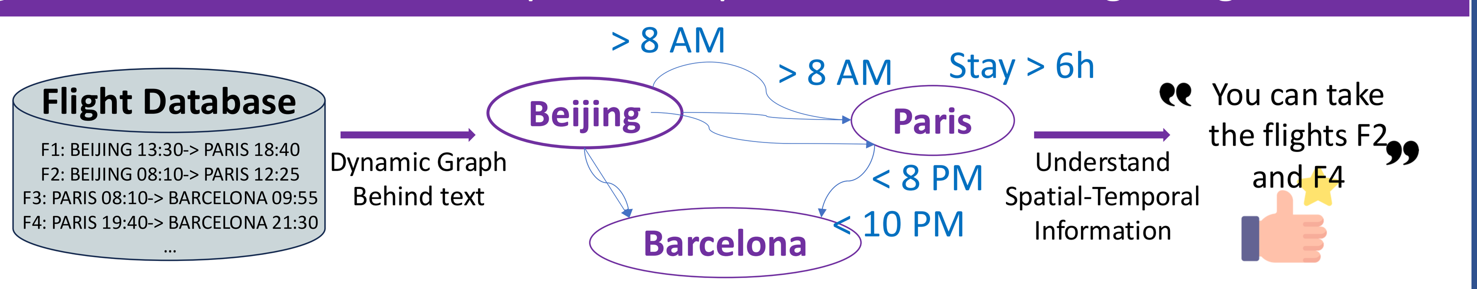


② NL Queries Can Include Implicit Dynamic Graphs (Spatio-Temporal Relations)

For example, ...

I'd like to fly from Beijing to Barcelona, with a departure time no earlier than 8:00 AM and an arrival time no later than 10:00 PM. Additionally, I'd like to have a half-day layover in Paris during the daytime to visit friends. Could you please suggest suitable flights?

③ LLMs have to understand spatial-temporal information to give right answers

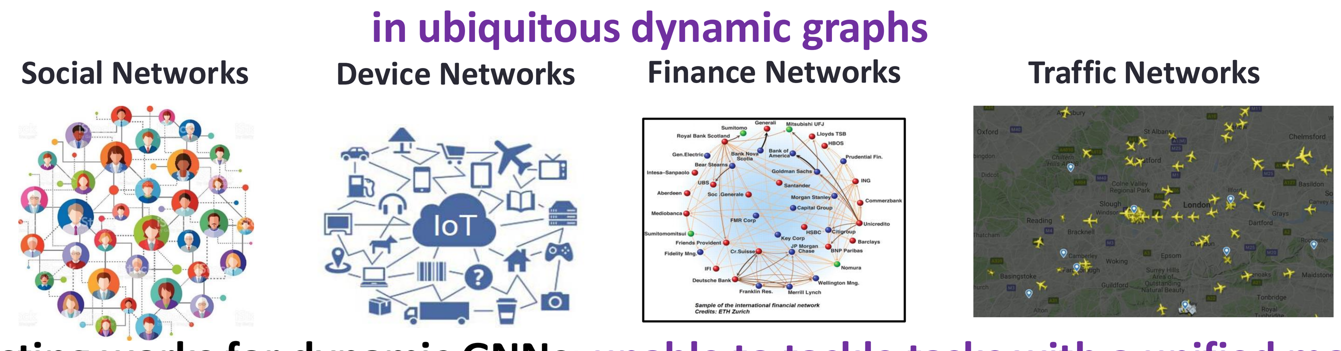


④ **But, can LLMs understand the spatial-temporal information on dynamic graphs in natural language?**

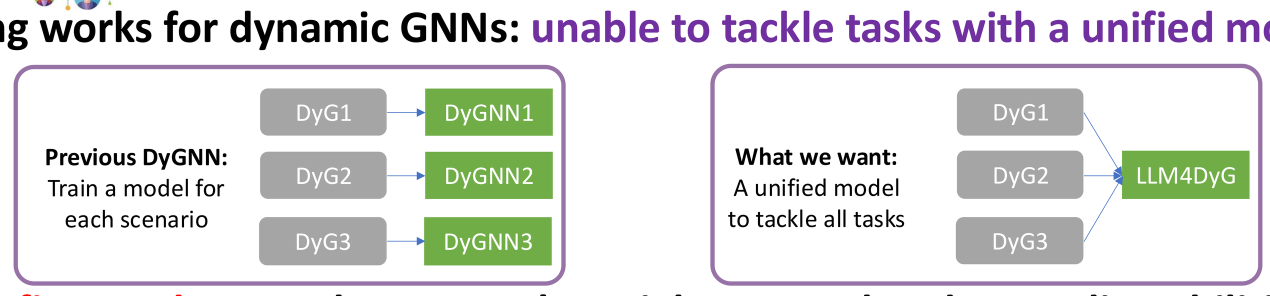
Remained Unexplored !

2 Problem & Challenge

① **Existing works of LLMs for static graphs: ignore the rich temporal information in ubiquitous dynamic graphs**



② **Existing works for dynamic GNNs: unable to tackle tasks with a unified model**



③ **The first study to evaluate LLMs' spatial-temporal understanding abilities on dynamic graphs**

④ **However, we face several challenges**

- How to assess **temporal and structural information** separately and simultaneously ?
- How to investigate the **complex and mixed interactions** of spatial and temporal dimensions?
- How to design **prompts** to consider spatial-temporal information in natural language?

⑤ **Our main contribution**

- We propose LLM4DyG: **nine** specially designed tasks for LLMs with **controllable environments and data generation**.
- We **analyze the impacts of various factors:** including different data generators, data statistics, prompting techniques, and LLMs on the model performance.
- We propose **Disentangled Spatial-Temporal Thoughts (DST2)** prompt method for to enhance LLMs' spatial-temporal understanding abilities.

5 Contact Information

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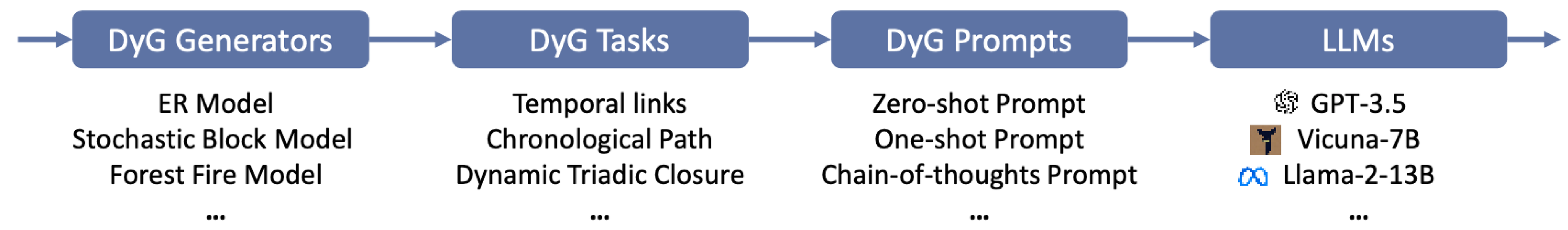
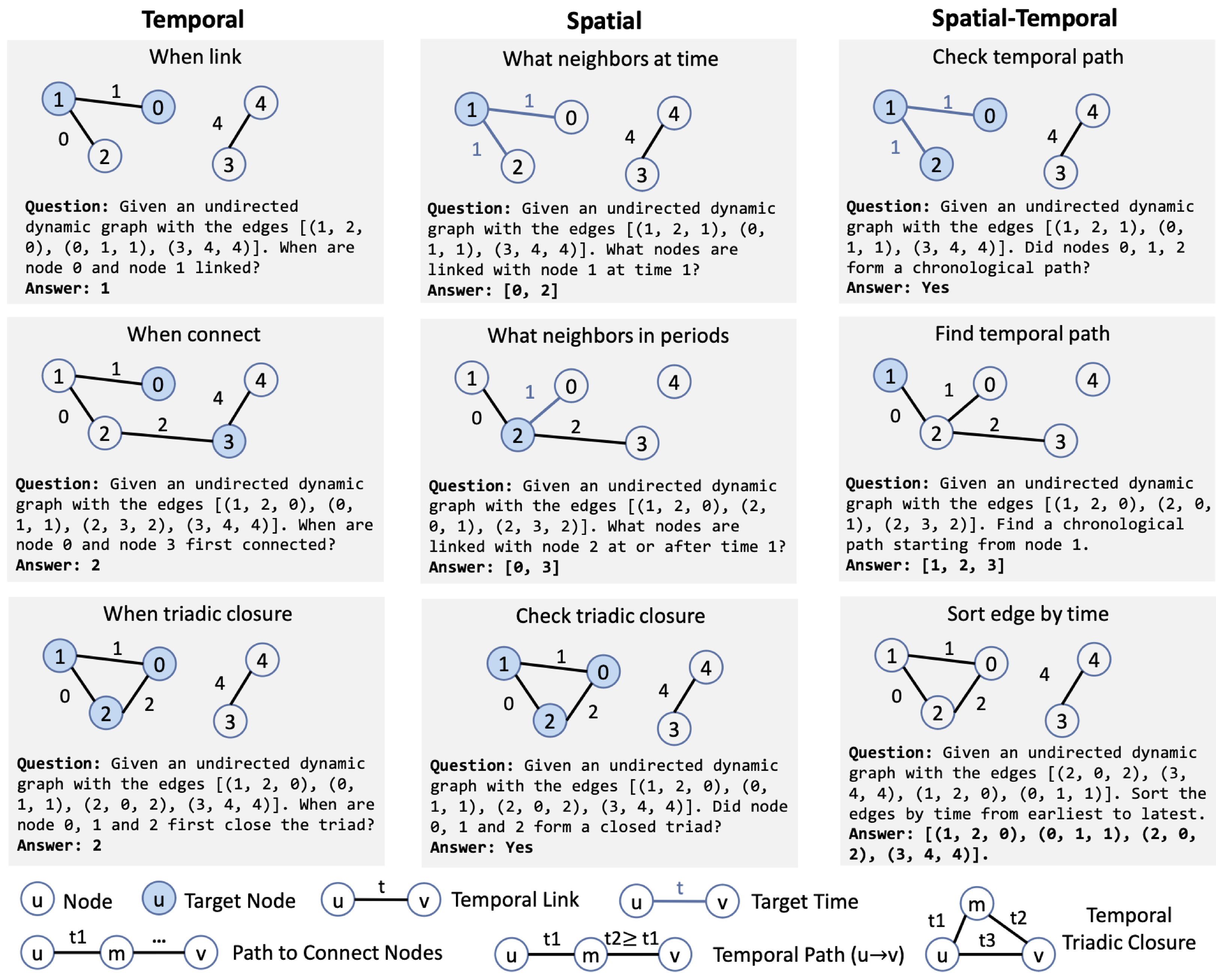
Code (Easy to Use!): https://github.com/wondergo2017/LLM4DyG

3 Framework: LLM4DyG

① **LLM4DyG Benchmark & Pipeline with controlled environments and data**



② **Designed Tasks: *When*, *What*, *Whether* spatial-temporal patterns take place**



③ **Disentangled Spatial-Temporal Thoughts (DST2)**

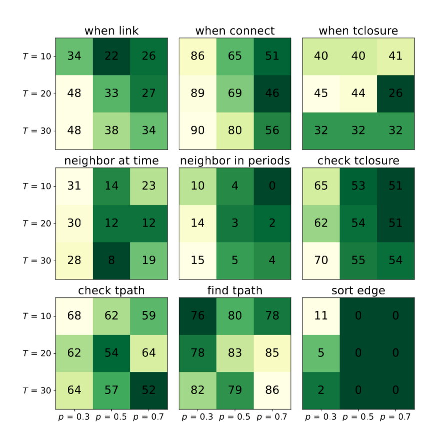
Task	Temporal			Spatial		Spatial-Temporal			
Prompting methods	when link	when connect	when tclosure	neighbor at time	neighbor in periods	check tclosure	check tpath	find tpath	sort edge
one-shot prompt	33.7±2.1	77.0±2.9	73.0±1.6	34.0±1.4	15.7±4.2	66.7±4.5	**63.7**±2.6	78.3±6.0	29.3±4.0
v1: Think (about) nodes and then time	40.0±1.6	77.0±4.1	**74.0**±1.4	34.0±0.8	15.0±4.2	**69.3**±1.7	61.0±3.3	**79.0**±7.5	30.0±3.6
v2: Think (about) time and then nodes	37.3±2.6	76.7±3.4	73.3±0.5	31.7±1.9	15.7±3.4	67.0±2.9	61.3±1.9	**79.0**±7.5	**30.7**±3.9
v3: Pick nodes and then time	59.3±2.1	**77.0**±2.4	68.0±0.8	35.0±2.9	**16.7**±4.7	65.0±3.7	62.3±2.9	78.0±5.4	30.0±2.9
v4: Pick time and then nodes	**76.7**±1.7	76.3±3.9	68.7±0.9	**35.7**±2.5	15.3±3.3	65.3±2.9	63.3±2.6	78.3±5.8	29.3±2.9

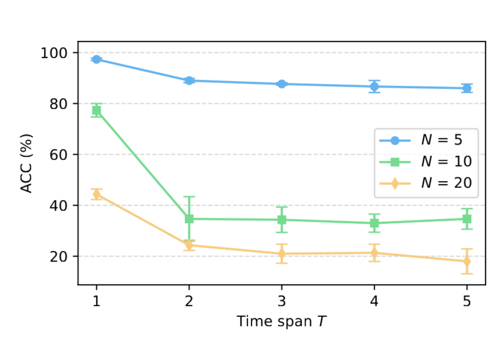
4 Results and Analyses

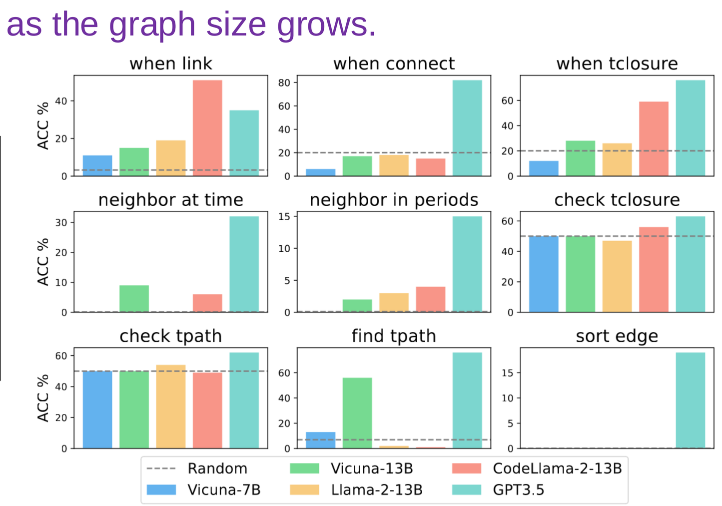
Task		Temporal			Spatial		Spatial-Temporal			
Data	model	when link	when connect	when tclosure	neighbor at time	neighbor in periods	check tclosure	check tpath	find tpath	sort edge
N = 5	GPT-3.5	68.0±2.8	97.7±0.9	52.7±2.4	86.0±2.2	42.3±1.7	69.0±2.2	58.7±2.1	79.0±4.1	78.0±1.4
	Random	3.2	20.0	20.0	3.2	3.2	50.0	50.0	9.3	13.1
	Δ	+64.8	+77.7	+32.7	+82.8	+39.1	+19.0	+8.7	+69.7	+64.9
N = 10	GPT-3.5	33.7±2.1	77.0±2.9	73.0±1.6	34.0±1.4	15.7±4.2	66.7±4.5	63.7±2.6	78.3±6.0	29.3±4.0
	Random	3.2	20.0	20.0	0.1	0.1	50.0	50.0	6.7	0.0
	Δ	+30.4	+57.0	+53.0	+33.9	+15.6	+16.7	+13.7	+71.6	+29.3
N = 20	GPT-3.5	40.3±1.7	17.7±4.2	63.3±0.9	17.7±1.7	2.0±0.8	64.3±7.3	57.0±2.2	85.0±0.8	0.0±0.0
	Random	3.2	20.0	20.0	0.0	0.0	50.0	50.0	7.3	0.0
	Δ	+37.1	-2.3	+43.3	+17.7	+2.0	+14.3	+7.0	+77.7	0.0
Avg.	GPT-3.5	47.3±1.2	64.1±0.3	63.0±1.0	45.9±3.1	20.0±0.8	66.7±2.9	59.8±0.8	80.8±0.3	35.8±2.0
	Random	3.2	20.0	20.0	1.1	1.1	50.0	50.0	7.8	4.4
	Δ	+44.1	+44.1	+43.0	+44.8	+18.9	+16.7	+9.8	+73.0	+31.4

Obs.1. LLMs show preliminary spatial-temporal abilities

Obs.2. Tasks have increasing difficulties for LLMs as the graph size grows.







Obs.3. The difficulties are not sensitive to the time span but sensitive to the graph density

Obs. 4. Temporal information adds additional difficulties compared to static graphs.

Obs. 6. Training on codes usually helps

Generation Model	ER Model	SB Model	FF Model
zero-shot	2.3±0.5	7.7±1.7	5.3±2.5
one-shot	**33.7**±2.1	**46.0**±2.9	**48.0**±7.1
zero-shot COT	1.0±0.8	5.7±3.1	2.0±1.6
one-shot COT	10.3±0.5	15.3±0.9	13.0±2.9

Task	Temporal			Spatial		Spatial-Temporal			
Prompt Method	when link	when connect	when tclosure	neighbor at time	neighbor in periods	check tclosure	check tpath	find tpath	sort edge
zero-shot	2.3±0.5	73.3±2.1	68.0±0.8	**36.0**±4.3	4.3±2.1	**70.7**±1.7	**66.0**±5.4	56.3±9.0	33.7±7.4
one-shot	**33.7**±2.1	**77.0**±2.9	73.0±1.6	34.0±1.4	**15.7**±4.2	66.7±4.5	63.7±2.6	78.3±6.0	29.3±4.0
zero-shot COT	1.0±0.8	58.3±1.2	70.0±1.6	32.0±0.8	4.3±2.6	55.0±1.4	62.3±2.9	58.0±9.1	**44.7**±0.5
one-shot COT	10.3±0.5	76.0±2.4	**80.0**±1.6	27.7±1.9	13.0±3.6	57.7±2.1	57.7±3.4	**81.3**±2.6	24.7±2.4

Obs. 5. General prompting techniques do not consistently help