

# LLMs Can Simulate Standardized Patients via Agent Coevolution

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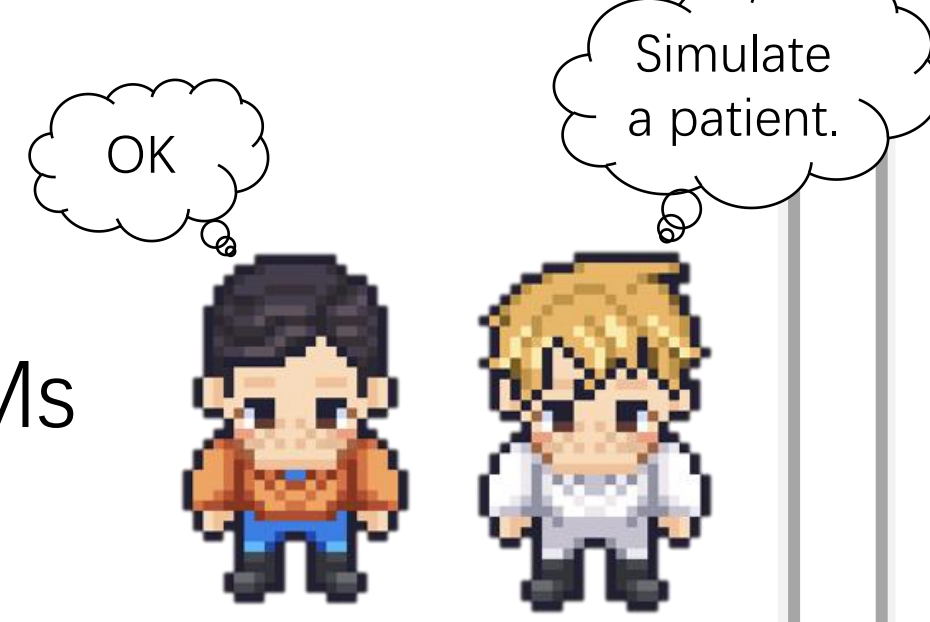
## Introduction

SPs simulate real patients for education propose.

- They are used to enhance doctor's **clinical skills**.
- SPs incur significant **operational costs**.
- Negative impact on individuals.
- Requirements and data are hard to follow by LLMs

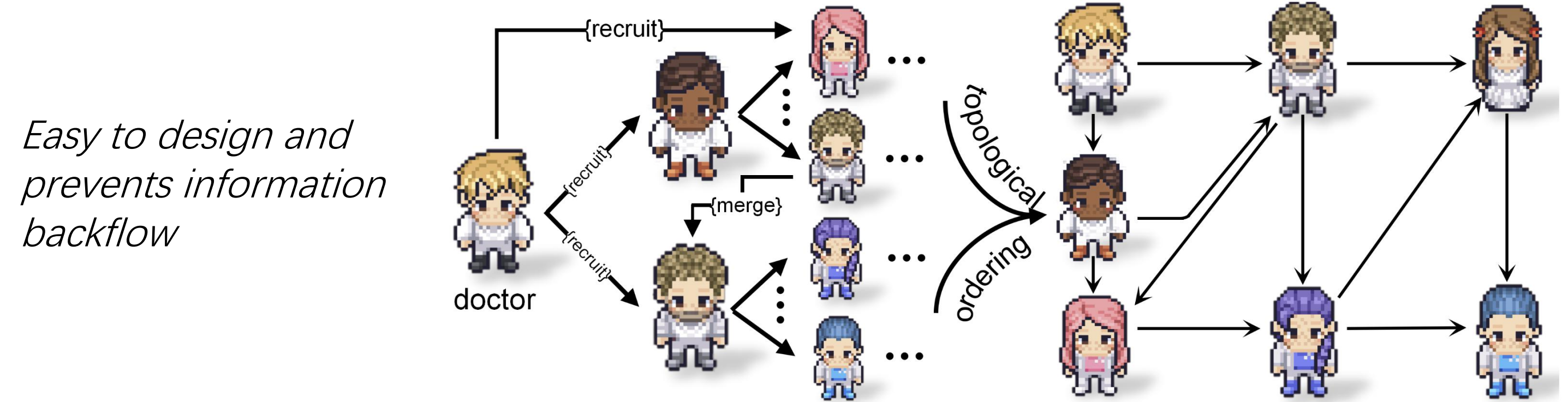
Previous solutions:

- Establish knowledge graphs. (No expression improvement)
- Elicit principles from human feedback. (Costly)



## Method

We mirror the diagnostic process into a series of phases. Then we assign an **agent pair** in the diagnosis process containing a **patient agent** with various profiles and RAG, **doctor agents** that can make dynamic recruitment.



Attention Library (Patient side):

- If validated, the relevant information will be stored in the library in an organized quadruple of:

<questions, records, answers, attention requirements>.

- Use as few shots for answer generation.

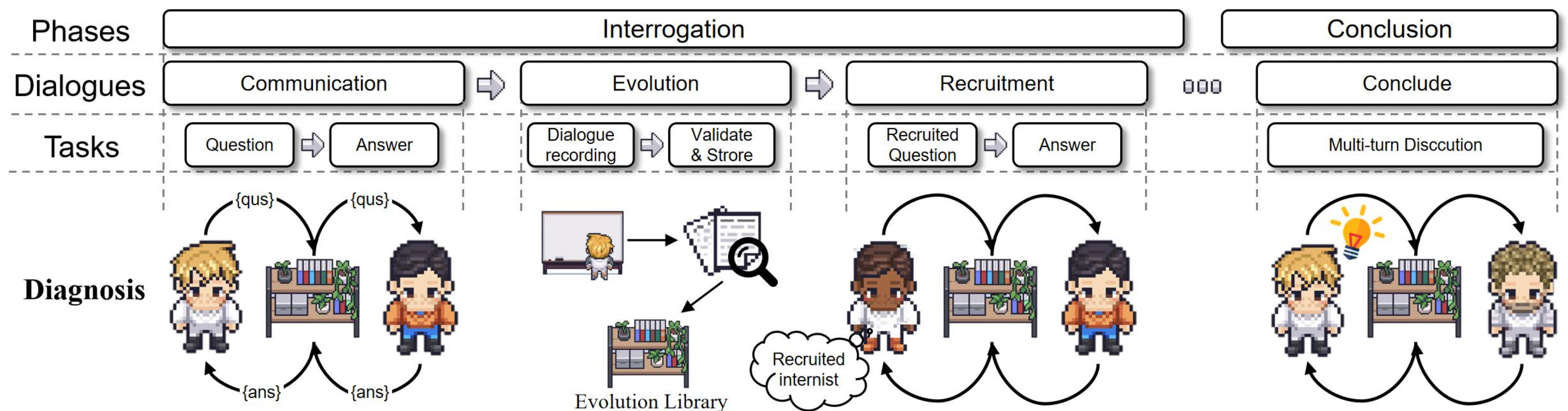
$$r_a, d = \mathbb{k}(\text{sim}(q, \mathcal{L})) \quad (\mathcal{P} \mid r_a, d) \rightarrow SP,$$

Trajectories Library (Doctor side):

- We validate and store high-quality dialogues series as a prediction-trajectories.

$$t_i = \{(q_{j-1}, a_{j-1}, q_j, a_j) \mid q \in \mathcal{Q}, a \in \mathcal{A}\}$$

By effectively using these libraries, we successfully standardized agents in our framework.



## Result

### Overall Analysis

Overall performance of simulated SP methods

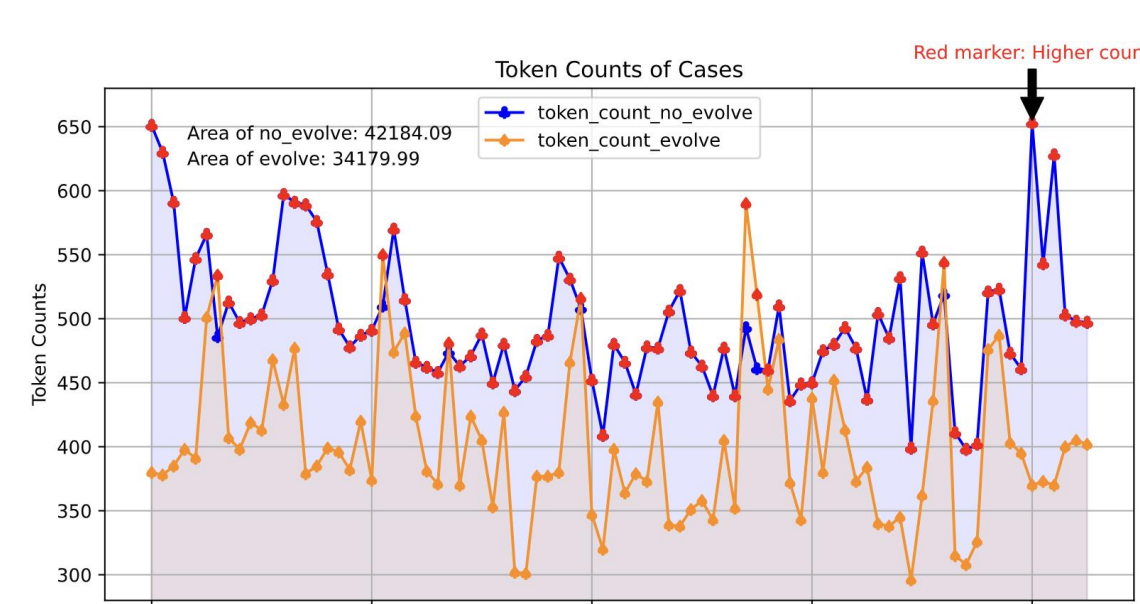
Method	Paradigm	Relevance	Faithfulness	Robustness	Ability
CoT		0.7157 <sup>†</sup>	0.5571 <sup>†</sup>	0.6714 <sup>†</sup>	0.6481 <sup>†</sup>
CoT-SC (3)		0.7337 <sup>†</sup>	0.6123 <sup>†</sup>	0.7002 <sup>†</sup>	0.6821 <sup>†</sup>
ToT		0.7469 <sup>†</sup>	0.7143 <sup>†</sup>	0.7714 <sup>†</sup>	0.7442 <sup>†</sup>
Self-Align		0.7205 <sup>†</sup>	0.7273 <sup>†</sup>	0.8148 <sup>†</sup>	0.7542 <sup>†</sup>
Few-shot (2)		0.7252 <sup>†</sup>	0.7419 <sup>†</sup>	0.8207 <sup>†</sup>	0.7626 <sup>†</sup>
Online Library		0.6903	0.7372 <sup>†</sup>	0.7624 <sup>†</sup>	0.7300 <sup>†</sup>
EvoPatient		<b>0.7589</b>	<b>0.8786</b>	<b>0.9412</b>	<b>0.8597</b>

State-of-the-art performance

Good reliability on various question

### Computational Analysis

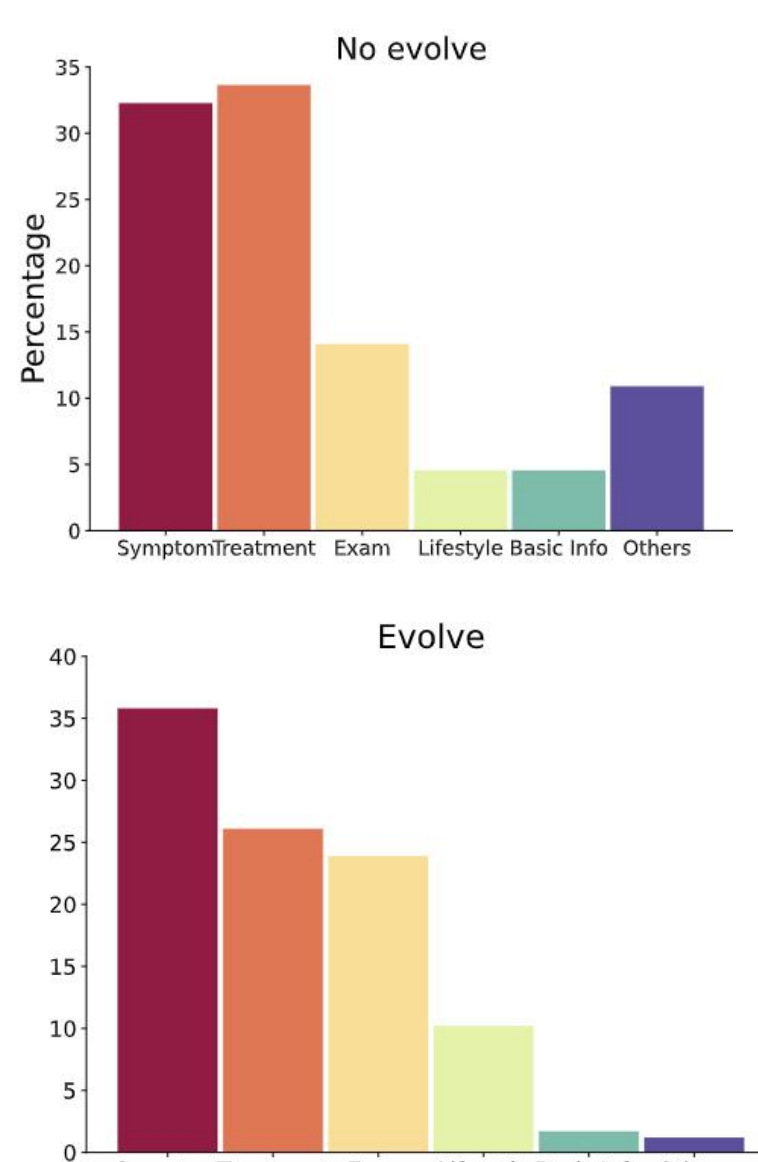
Method	Duration (s)	#Tokens	#Words
CoT	04.7500	0782.0571	45.7429
CoT-SC (3)	12.5559	5837.0286	49.8667
ToT	21.7040	2679.3428	38.9143
Self-Align	09.5146	1307.9435	51.0636
Few-shot (2)	<b>04.7182</b>	0959.4355	35.6334
(50) cases	06.7808	0445.3482	36.5571
EvoPatient	06.6922	<b>0401.5882</b>	<b>32.2432</b>
Δ compared to CoT	<b>↑01.9422</b>	<b>↓0380.4689</b>	<b>↓13.4997</b>



Good balance on computational complexity

### Doctor Incremental Study

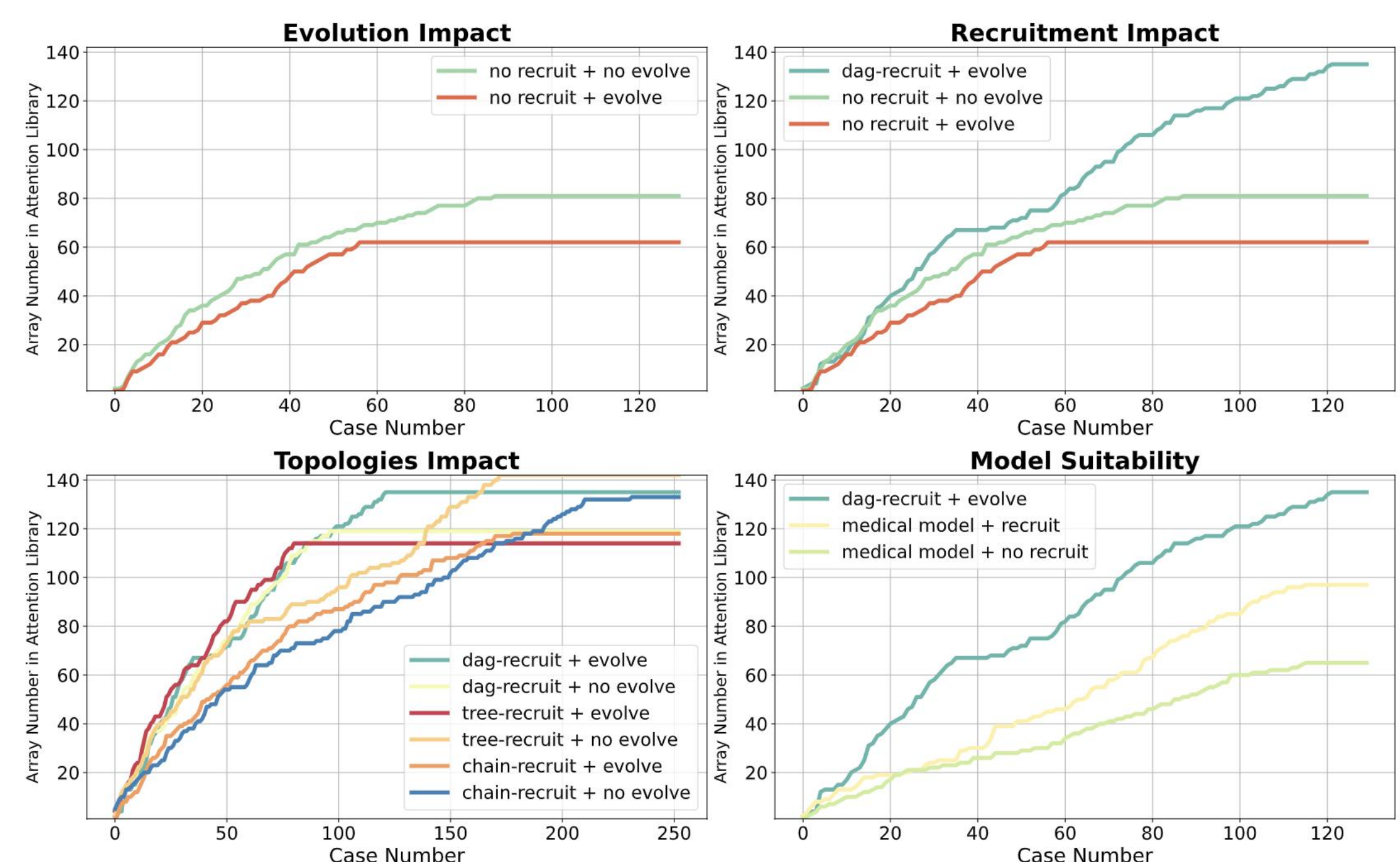
Method	Specificity	Targetedness	Professionalism	Quality
Doctor Agent	0.4713	0.2414	0.4904	0.4010
+ evolve	0.4725	0.2500	0.5650	0.4292
+ pool	0.5825	0.3200	0.5800	0.4942
+ profile	0.4148	0.3215	0.4952	0.4105
+ evolve + pool	0.4659	0.2079	0.7384	0.4707
+ evolve + profile	0.4884	0.3092	0.7023	0.5000
+ pool + profile	0.5925	0.3100	0.6450	0.5158
+ all component	<b>0.6275</b>	0.3100	<b>0.7625</b>	<b>0.5667</b>
Δ compared to Vanilla	<b>+0.1562</b>	<b>+0.0686</b>	<b>+0.2721</b>	<b>+0.1657</b>
Medical model doctor	0.5076	<b>0.4512</b>	0.6524	0.5371



Our doctor agent successfully forster patient agent into a SP agent

### Discovering Visual Relations

Accumulation rate in the Attention Library



Recruitment improves questions diversity

DAG is a efficient recruitment topology

Method	Relevance	Faithfulness	Robustness	Ability
Doctor agent	0.7297	0.8000	0.8533	0.7943
+ dag-recruit	0.7455	0.8233	0.8733	0.8140
\ designed recruit	-	-	-	-
\ memory control	-	-	-	-
+ evolve	0.7311	0.8402	0.9100	0.8271
+ chain-recruit + evolve	0.7405	0.8424	0.8929	0.8253
+ tree-recruit + evolve	0.7488	0.8545	0.9101	0.8378
+ dag-recruit + evolve	<b>0.7573</b>	<b>0.8767</b>	<b>0.9333</b>	<b>0.8558</b>
Δ compared to Vanilla	<b>+0.0276</b>	<b>+0.0767</b>	<b>+0.0800</b>	<b>+0.0615</b>

Every components contributes positively

Recruitment in DAG topology boost the evolution process.

Contact us!



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Try our demo!

<http://192.168.43.6:7513/>



睿医实验室



<https://github.com/ZJUMAI>