

# Advancing Spatial Reasoning in Large Language Models: An In-Depth Evaluation and Enhancement Using the StepGame Benchmark

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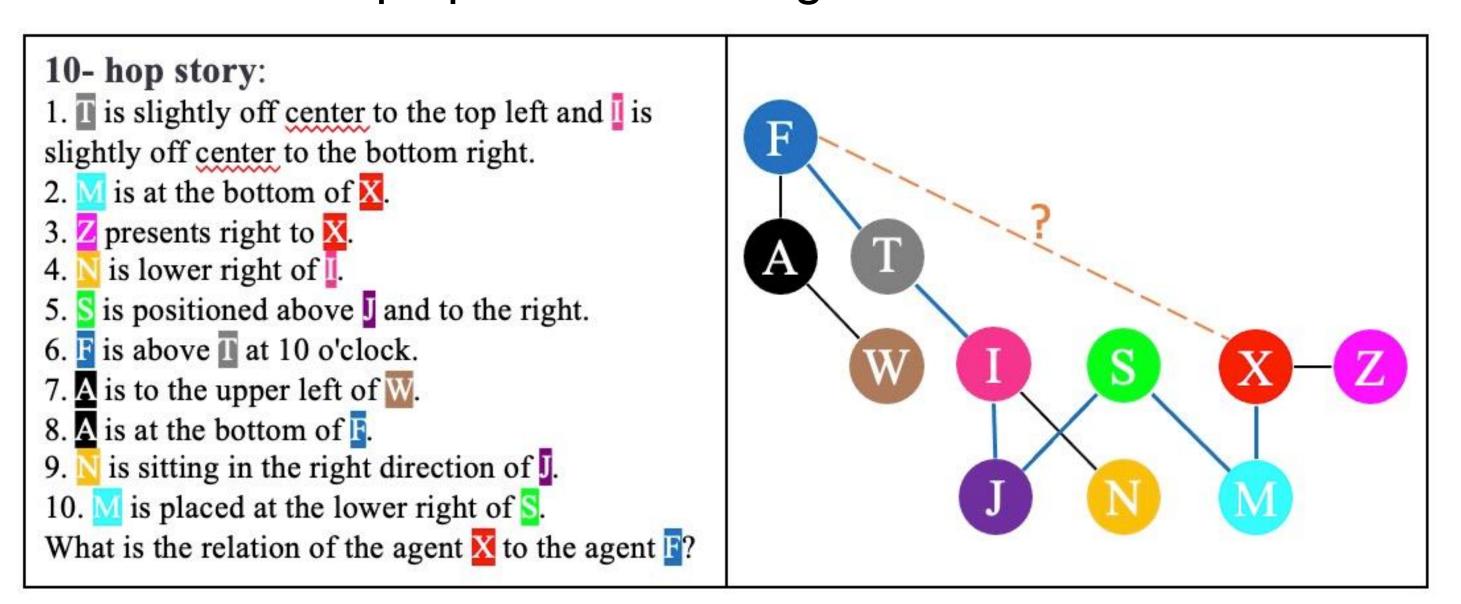
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#### Introduction

Al has made remarkable progress across various domains, with large language models (LLMs) like ChatGPT gaining substantial attention for their human-like text-generation capabilities. However, spatial reasoning remains a significant challenge, with ChatGPT's performance on spatial benchmarks like StepGame being unsatisfactory. Our analysis of GPT's spatial reasoning on a rectified StepGame benchmark identifies its proficiency in mapping text to spatial relations, yet it struggles with complex reasoning. We provide a flawless solution to the benchmark by combining template-to-relation mapping with logic-based reasoning. To address the limitations of GPT models in spatial reasoning, we deploy Chain-of-Thought (CoT) and Tree-of-Thoughts (ToT) prompting strategies, offering insights into GPT's "cognitive process", and achieving notable improvements in accuracy.

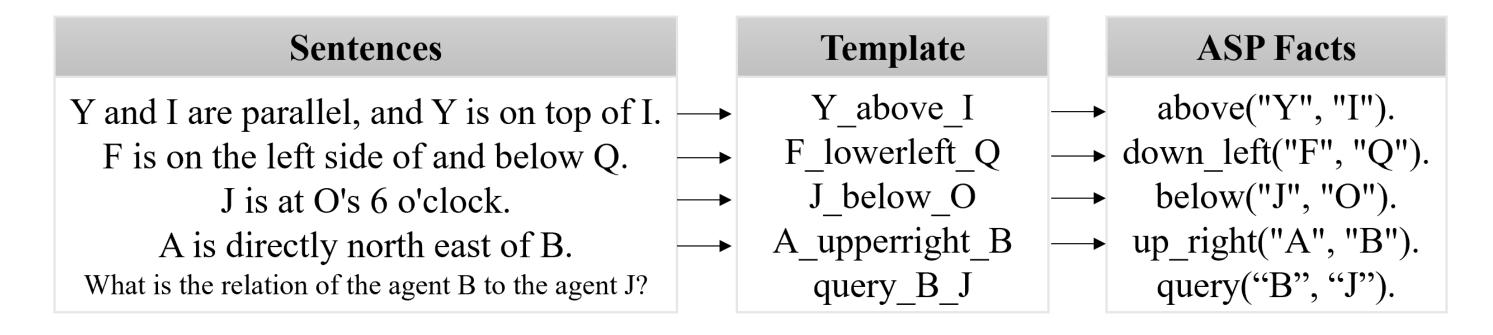
### The StepGame Benchmark

Task: multi-hop spatial reasoning in texts

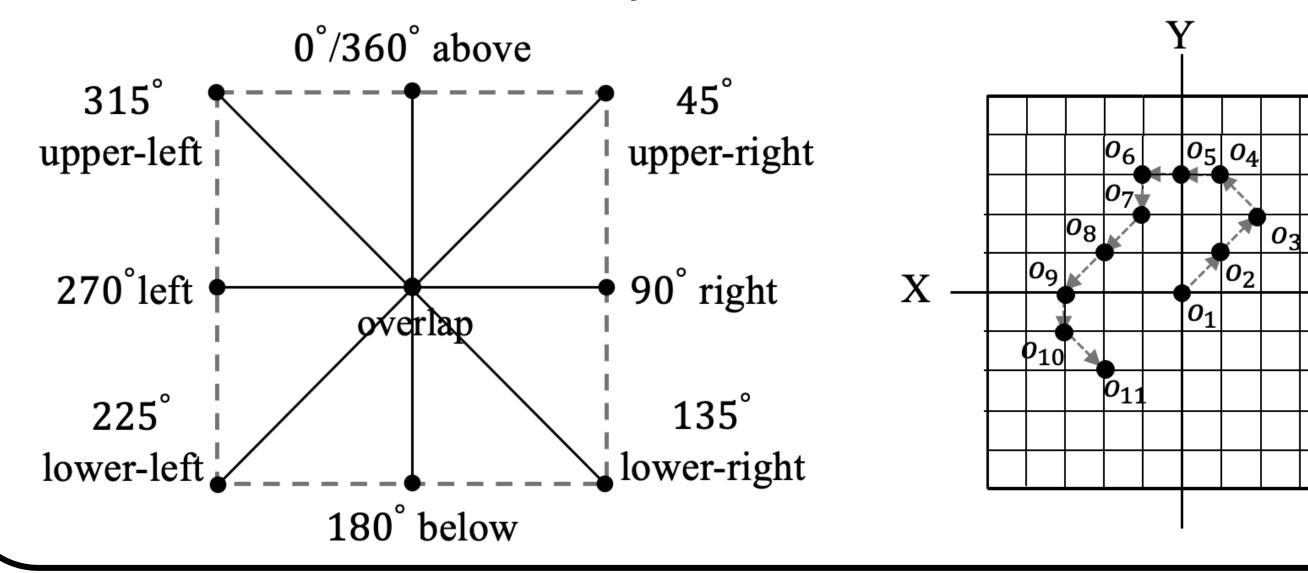


### Solution to StepGame

Sentence-to-Relation Mapping + ASP Reasoner

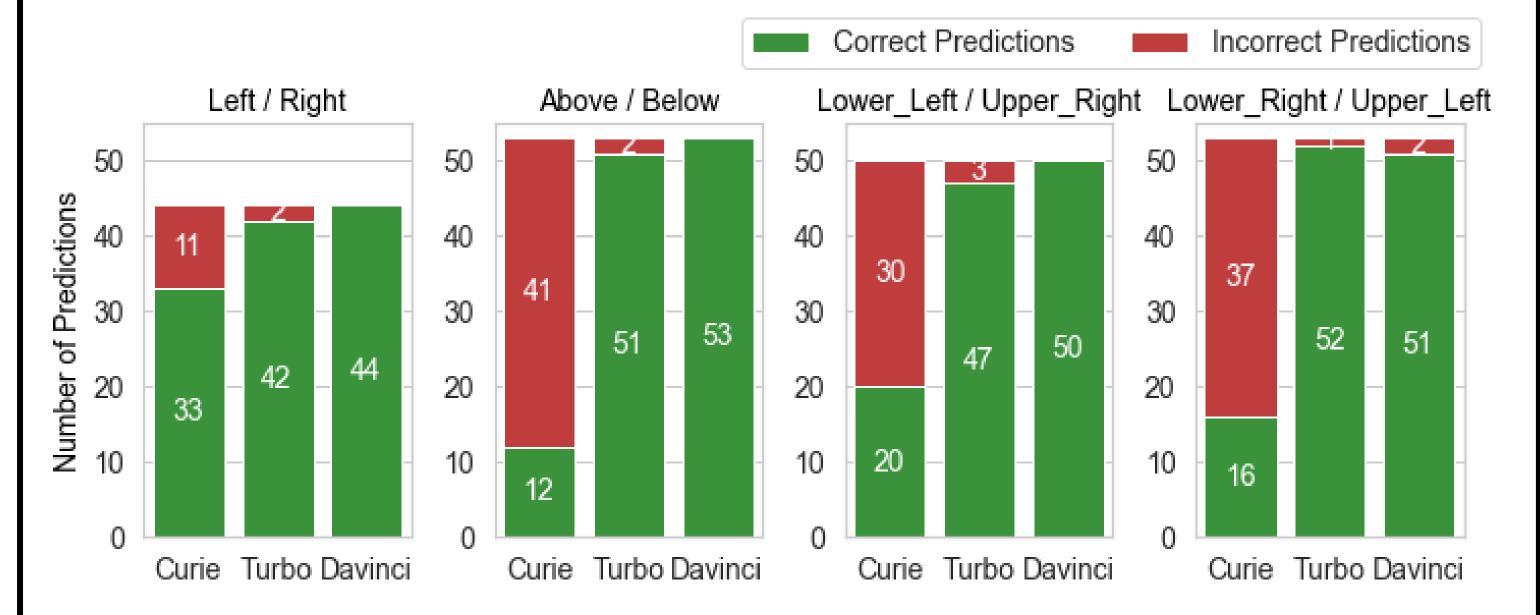


The ASP module calculates the location of  $o_i$  to  $o_i$  by adding the offsets  $v(o_i, o_i)$ .



## LLM + ASP

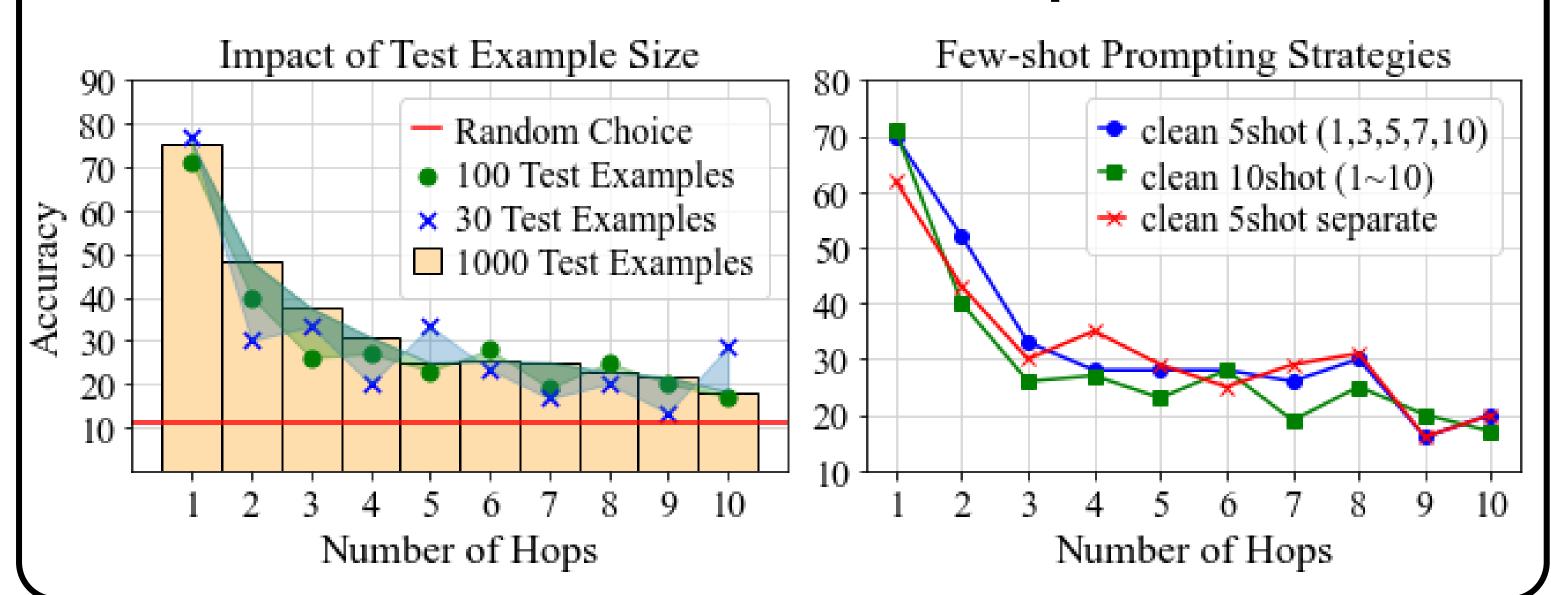
The relation extraction performance of GPT models.



### Results of LLMs for relation extraction + ASP Reasoner

	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
Map+ASP	100	100	100	100	100	100	100	100	100	100
Curie+ASP	46	43	42	59	67	67	57	56	58	61
Davinci+ASP	100	100	99	100	100	99	100	100	100	100
SOTA	92.6	89.9	89.1	93.8	92.9	91.6	91.2	90.4	89.0	88.3

# **Evaluation of GPT-3.5 Turbo on StepGame**



### Methods

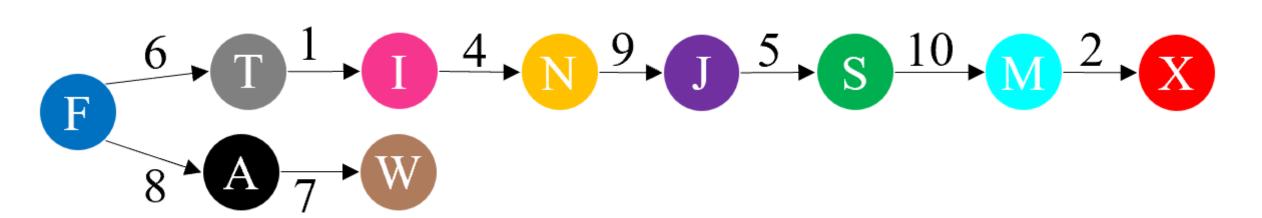
Our CoT approach decomposes each step of thought  $c_i$ to incorporate a coherent and detailed reasoning process.

At reasoning step i,  $c_i = [c_i^{link}, c_i^{map}, c_i^{calcu}]$ 

• $c_i^{link}$ : guide LLMs to examine all relations in story (R = $[r^1, ..., r^j, ..., r^k]$ ) and select candidate  $r^j$  for each i

• $c_i^{map}$ : map  $r^j$  to simple relation description  $o_i$  is to the v of  $o_{i+1}$ 

• $c_i^{calcu}$ : calculate the coordinate of  $o_{i+1}$  with  $r^j$ ,  $o_{i+1} = o_i + c_i^{calcu}$  $v(r^j) = (x_{o_i}, y_{o_i}) + (x_v, y_v) = (x_{o_{i+1}}, y_{o_{i+1}})$ 



Our ToT approach is designed to enhance the chain building process, allowing LLMs to consider different pathways.

Require: LLM, input x

- $1: S_0 \leftarrow Init(x)$
- $2: i \leftarrow 1$
- 3: while no  $s_f \in S_{i-1}$  has arrived at  $o_t$  do
- 4:  $S'_i \leftarrow \{s \cdot c | c \in G(s, j) \land ChainExtn(c) \land s \in S_{i-1}\}$
- 5: if  $S'_i = \emptyset$  then return failure
- 6:  $S_i \leftarrow select(b, \{\langle s, y \rangle | s \in S_i' \land y = \sum_{i=1}^n \sigma(V(s))\})$
- 7: i = i + 1
- 8: end while
- **9:** return  $Link(s_f)$

### Results - Accuracy

		k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
	base	62	43	30	35	29	25	29	31	16	20
Turbo	CoT	/	34	40	36	28	28	26	31	25	24
	ToT	/	/	35	35	25	45	15	40	40	35
	base	77	42	21	26	25	30	23	23	22	22
Davinci	CoT	/	48	53	46	46	48	40	45	41	32
	ToT	/	/	65	50	45	60	50	50	55	50
	base	100	70	55	45	40	25	40	35	35	25
GPT-4	CoT	/	80	75	95	85	85	90	80	60	65
	ToT	/	/	85	85	90	90	85	90	100	95