

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

Fangjun Li<sup>1</sup>, David C. Hogg<sup>1</sup>, Anthony G. Cohn<sup>1,2</sup>

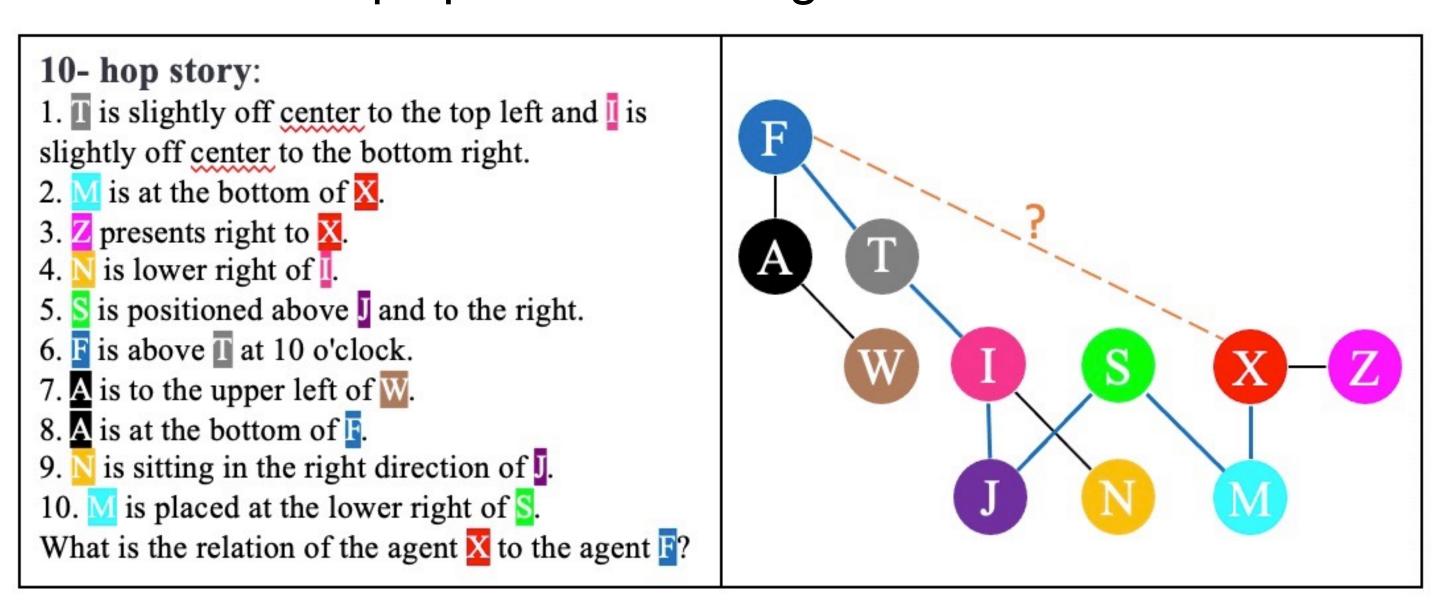
<sup>1</sup>University of Leeds, UK <sup>2</sup>Alan Turing Institute, UK

#### Introduction

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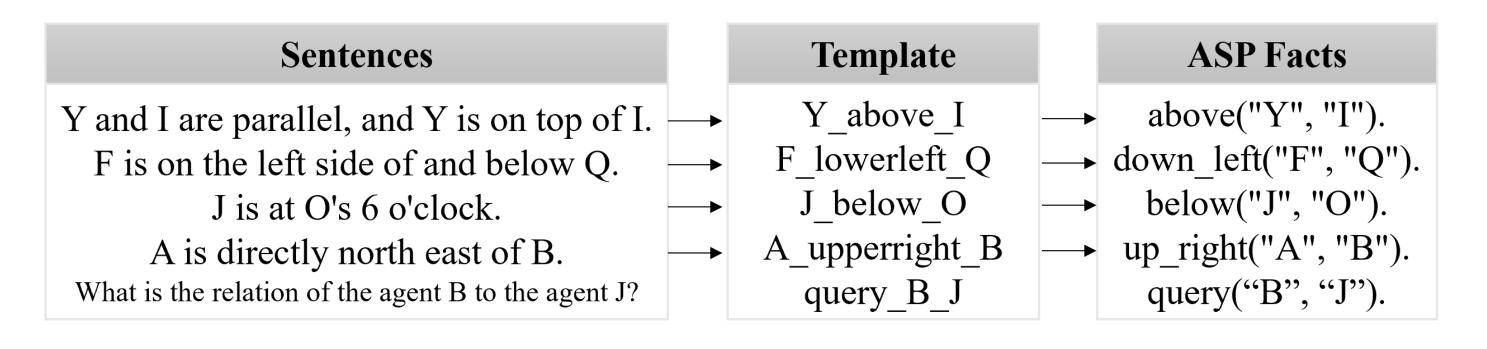
## The StepGame Benchmark

Task: multi-hop spatial reasoning in texts

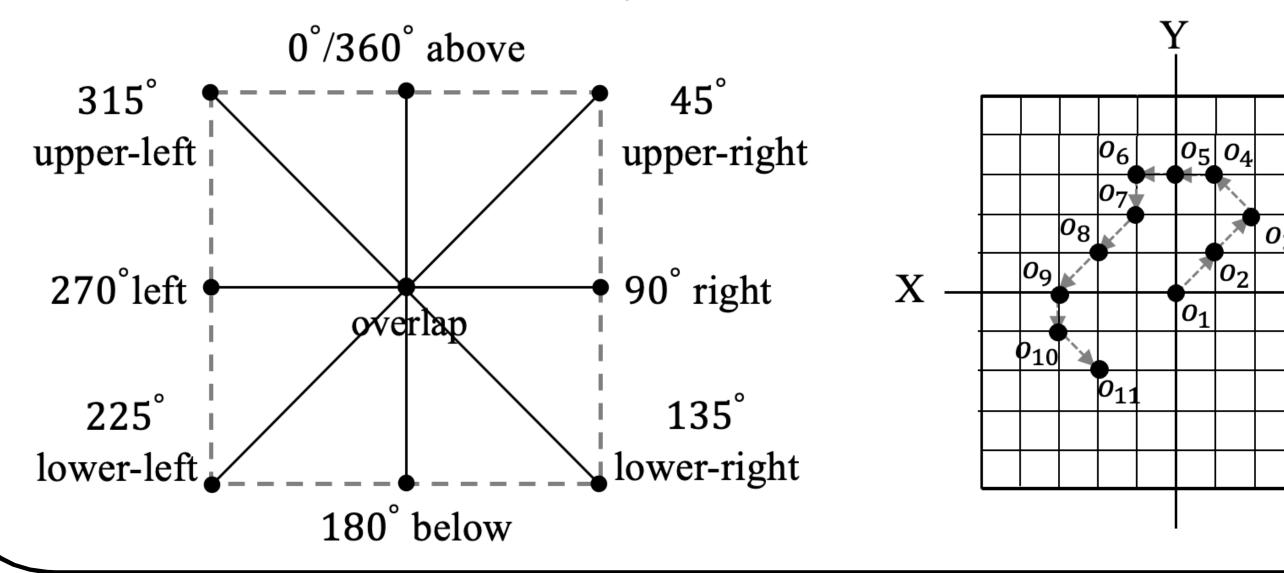


## Solution to StepGame

Sentence-to-Relation Mapping + ASP Reasoner

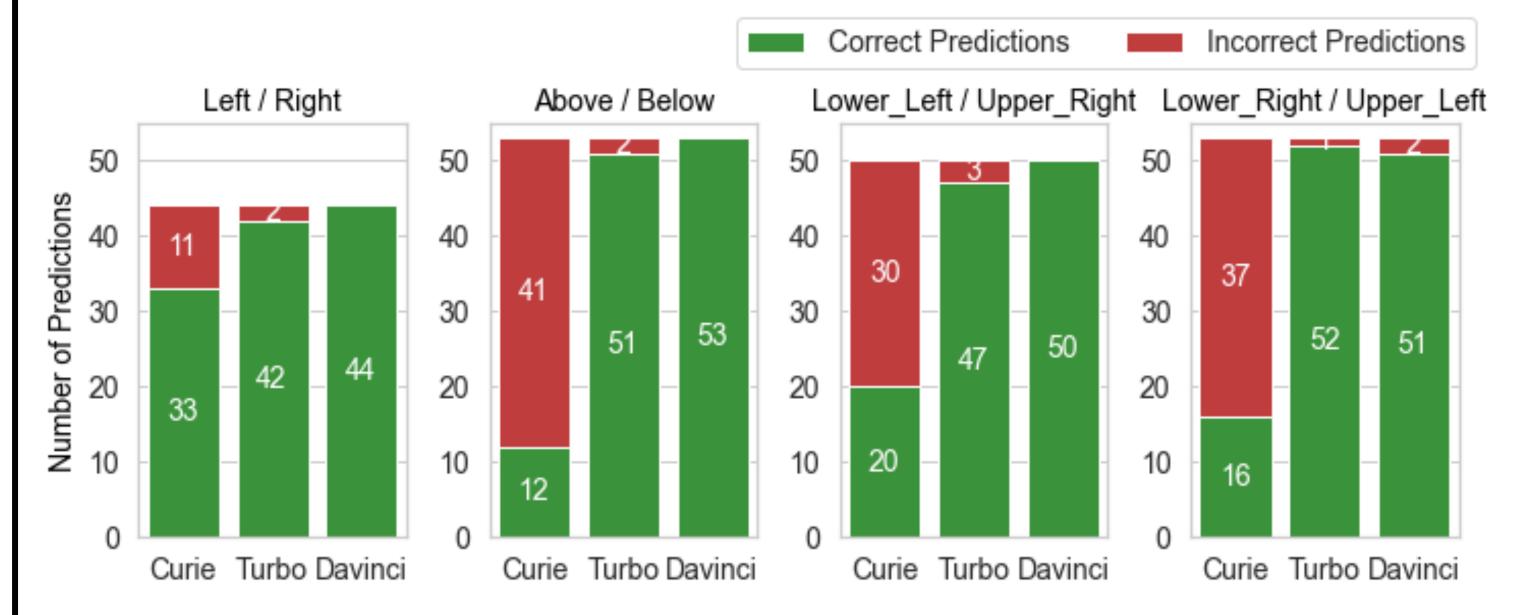


The ASP module calculates the location of  $o_i$  to  $o_j$  by adding the offsets  $v(o_i, o_j)$ .



## LLM + ASP

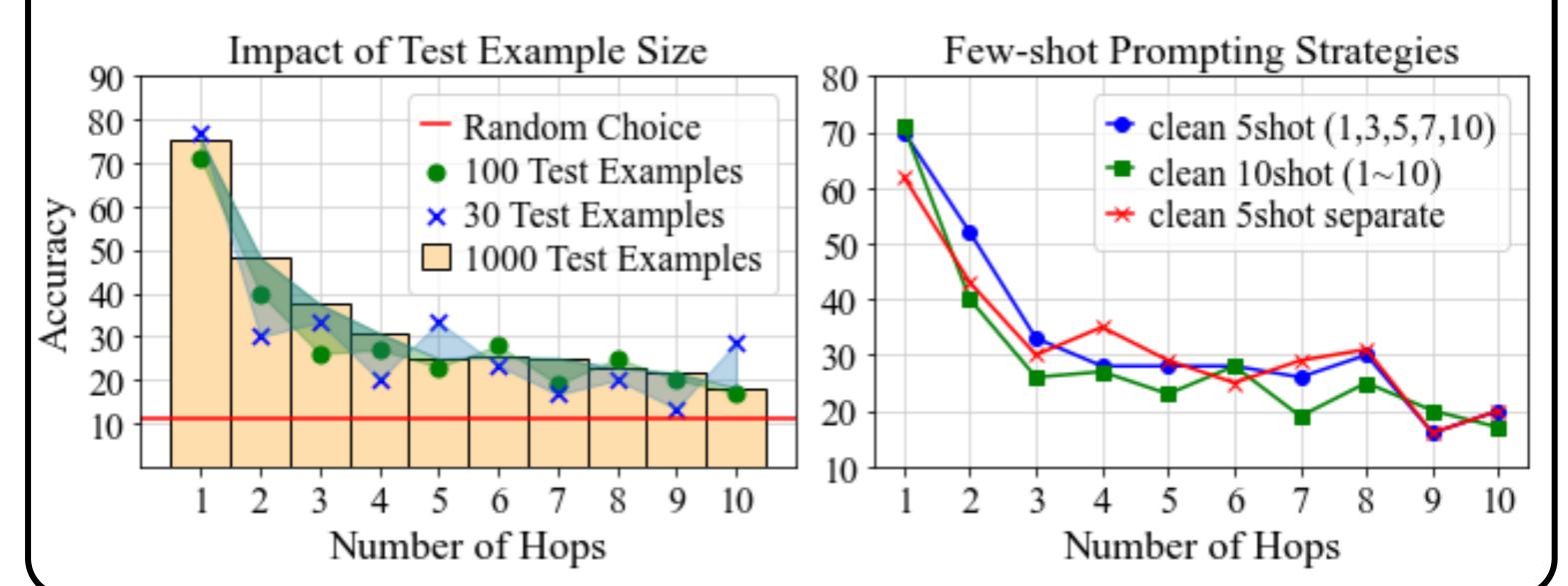
The relation extraction performance of GPT models.



#### 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

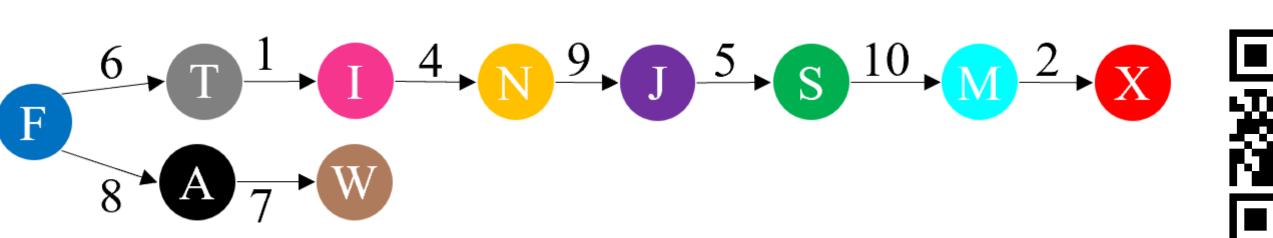
Our CoT approach decomposes each step of thought  $c_i$  to incorporate a coherent and detailed reasoning process.

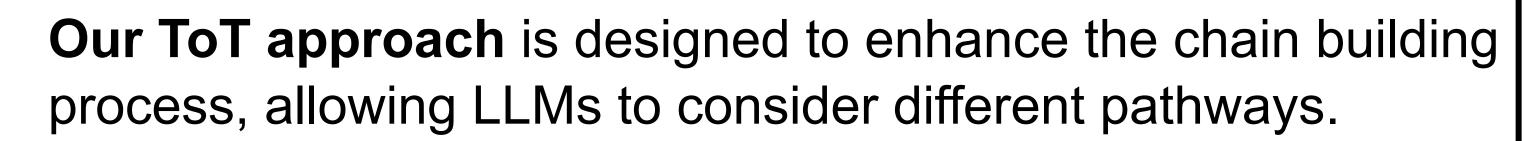
At reasoning step i,  $c_i = [c_i^{link}, c_i^{map}, c_i^{calcu}]$ 

• $c_i^{link}$ : 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  $r^j$ ,  $o_{i+1} = o_i + v(r^j) = (x_{o_i}, y_{o_i}) + (x_v, y_v) = (x_{o_{i+1}}, y_{o_{i+1}})$ 





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
	CoT	/	34	40	36	28	28	26	31	25	24
Turbo	ToT	/	/	35	35	25	45	15	40	40	35
	base	77	42	21	26	25	30	23	23	22	22
	CoT	/	48	53	46	46	48	40	45	41	32
Davinci	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
GPT-4	ToT	/	/	85	85	90	90	85	90	100	95

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



Link X and F

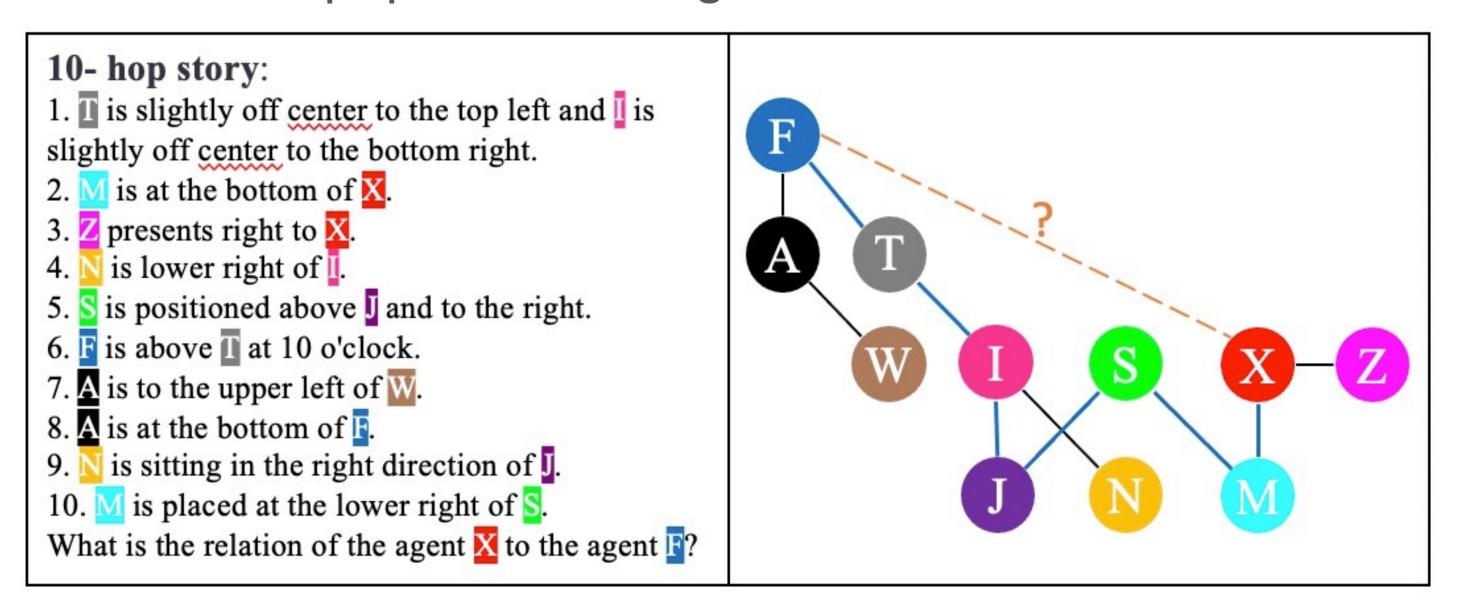
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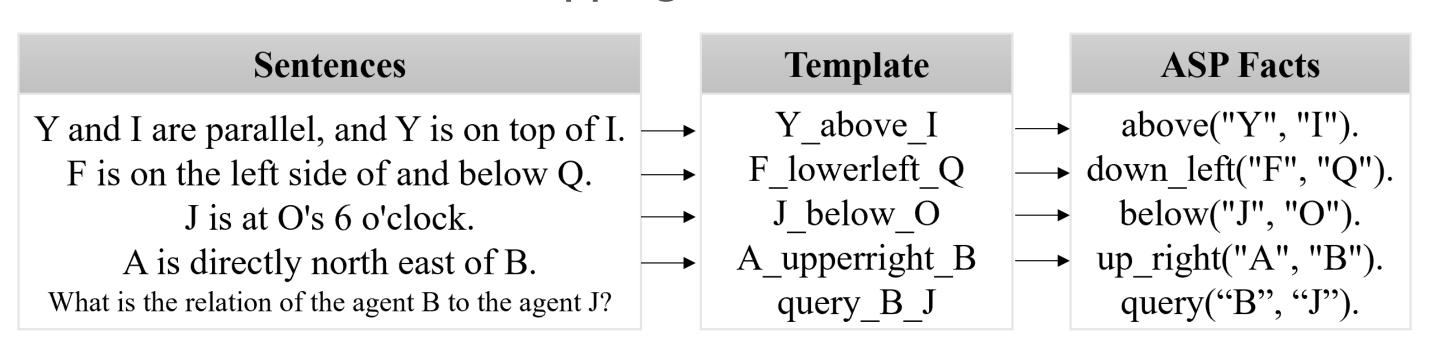
### The StepGame Benchmark

Task: multi-hop spatial reasoning in texts

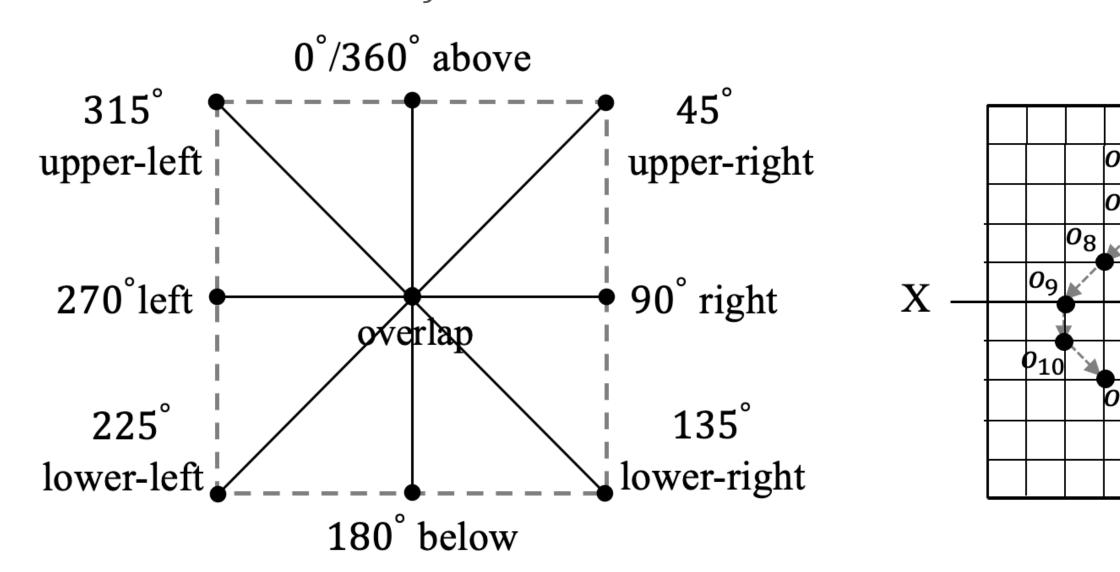


## Solution to StepGame

Sentence-to-Relation Mapping + ASP Reasoner

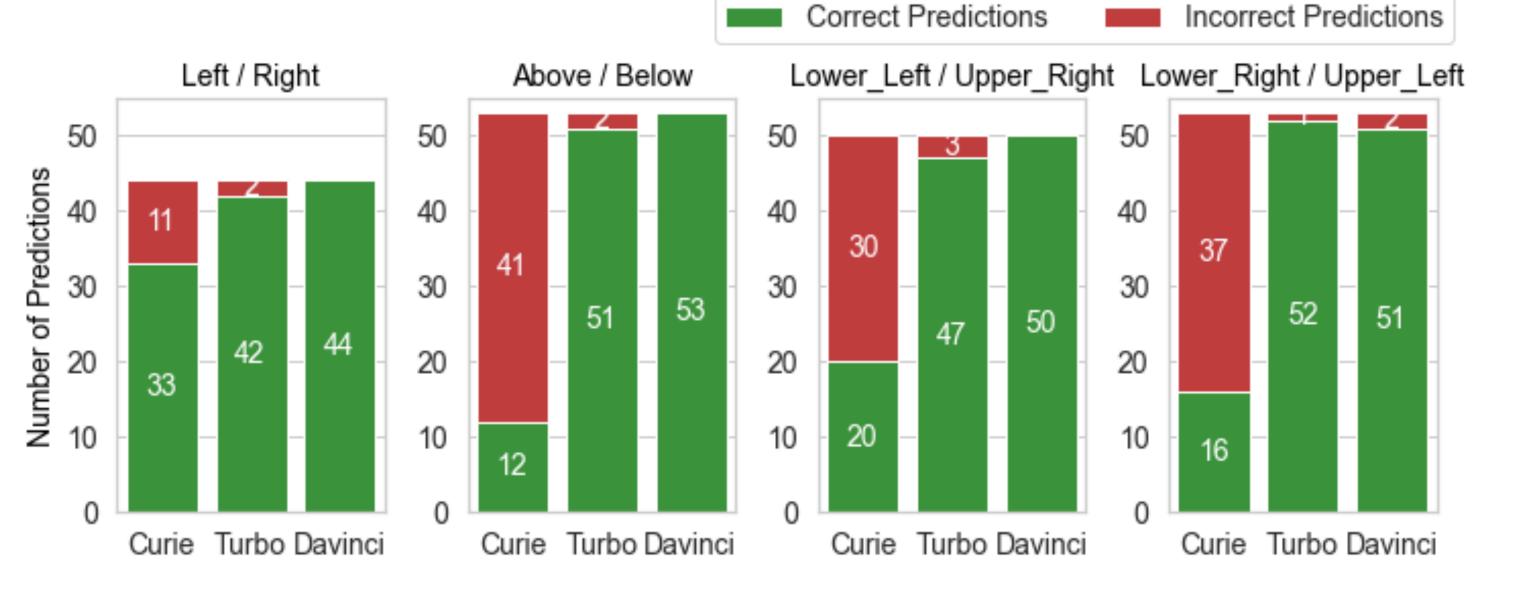


The ASP module calculates the location of  $o_i$  to  $o_j$  by adding the offsets  $v(o_i, o_i)$ .



#### LLM + ASP

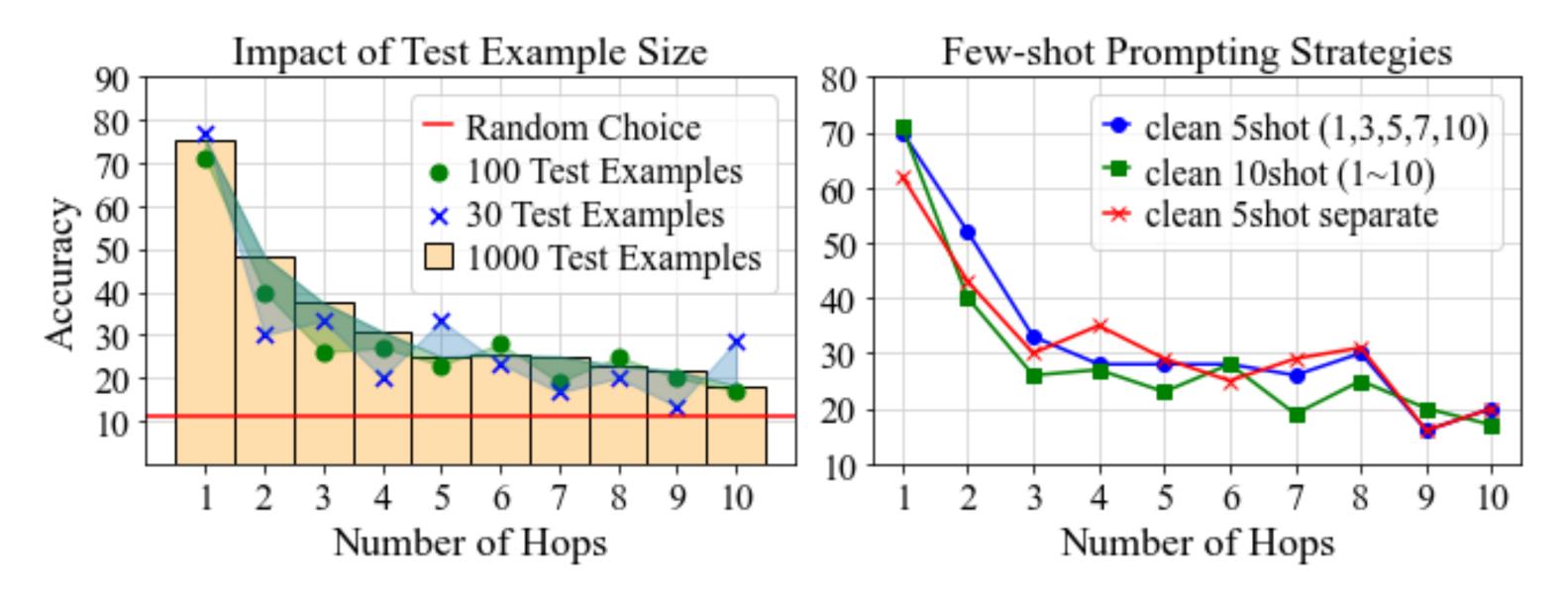
The relation extraction performance of GPT models.



Accuracy results of LLMs for relation extraction + ASP Reasoner

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100	100	100	100	100	100	100	100	100	100
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100	100	99	100	100	99	100	100	100	100
92.6	89.9	89.1	93.8	92.9	91.6	91.2	90.4	89.0	88.3
	100 46 100	100       100         46       43         100       100	100       100       100         46       43       42         100       100       99	100       100       100       100         46       43       42       59         100       100       99       100	100       100       100       100       100         46       43       42       59       67         100       100       99       100       100	100       100       100       100       100       100         46       43       42       59       67       67         100       100       99       100       100       99	100       100       100       100       100       100       100       100         46       43       42       59       67       67       57         100       100       99       100       100       99       100	100       100       100       100       100       100       100       100       100         46       43       42       59       67       67       57       56         100       100       99       100       100       99       100       100	46   43   42   59   67   67   57   56   58

### **Evaluation of GPT Models on Rectified 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;

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

## Require: LLM, input x

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#### Results

Accuracy comparison of GPT models

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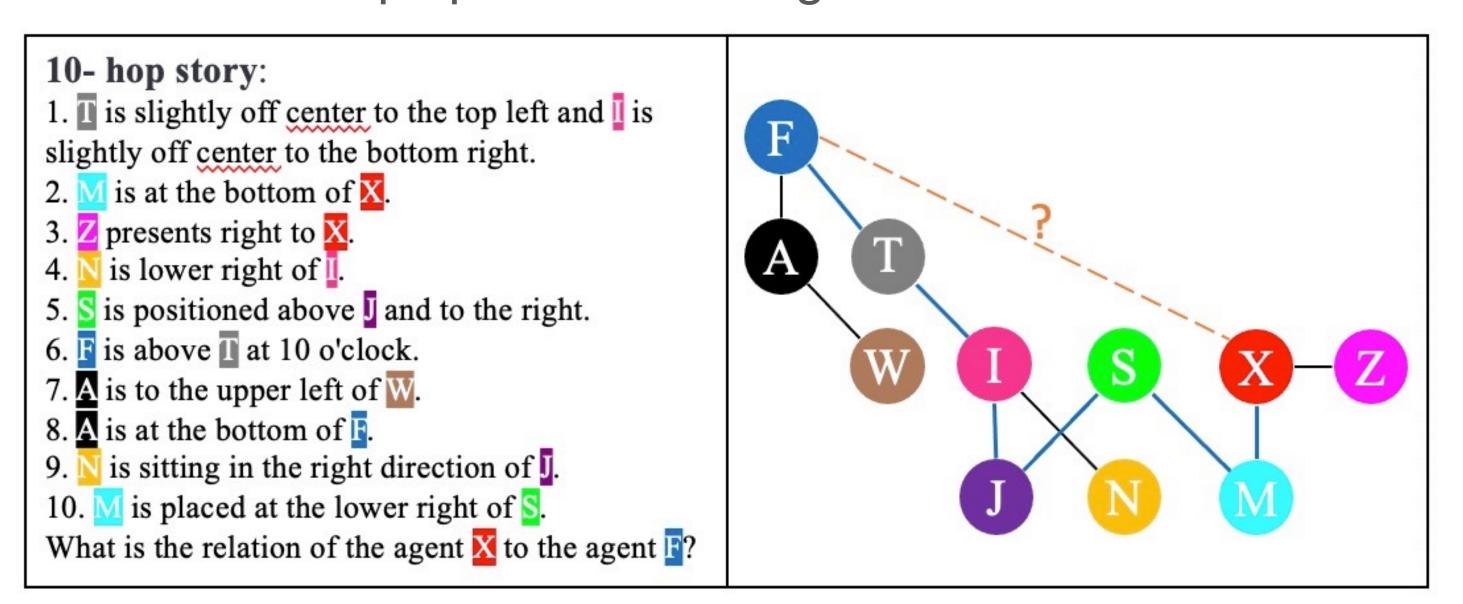
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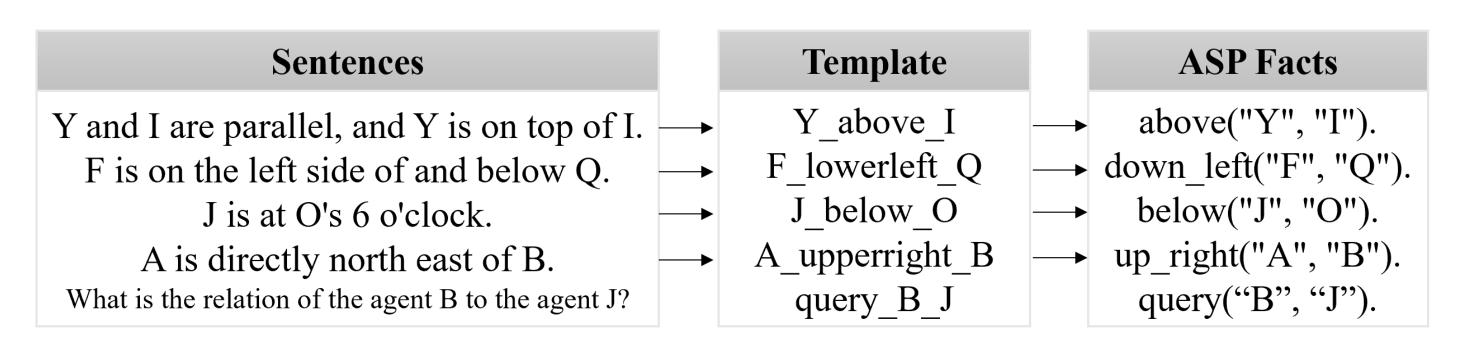
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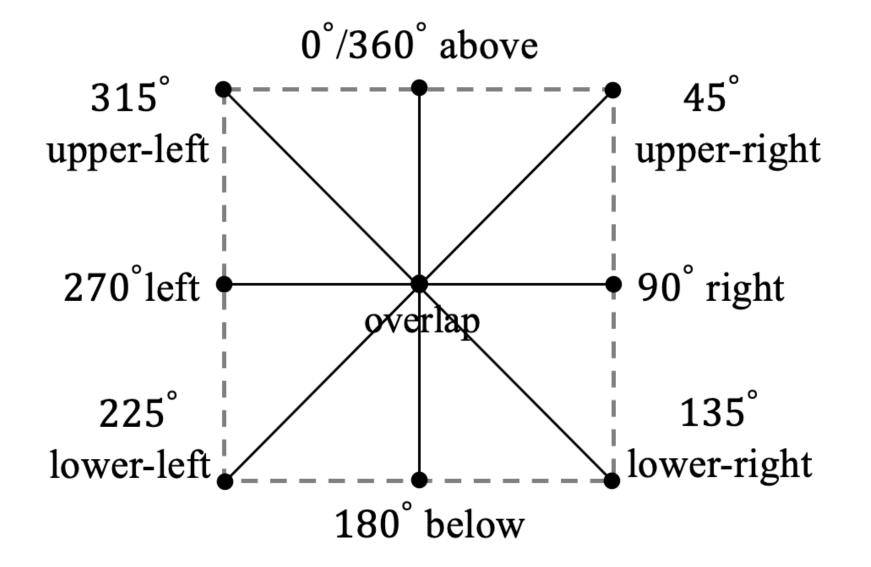


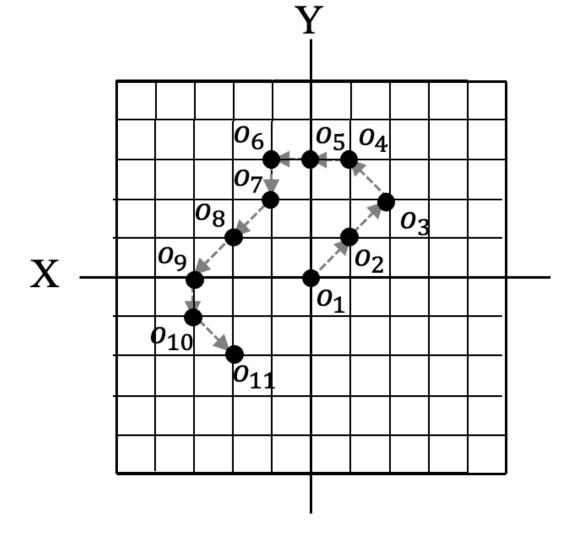
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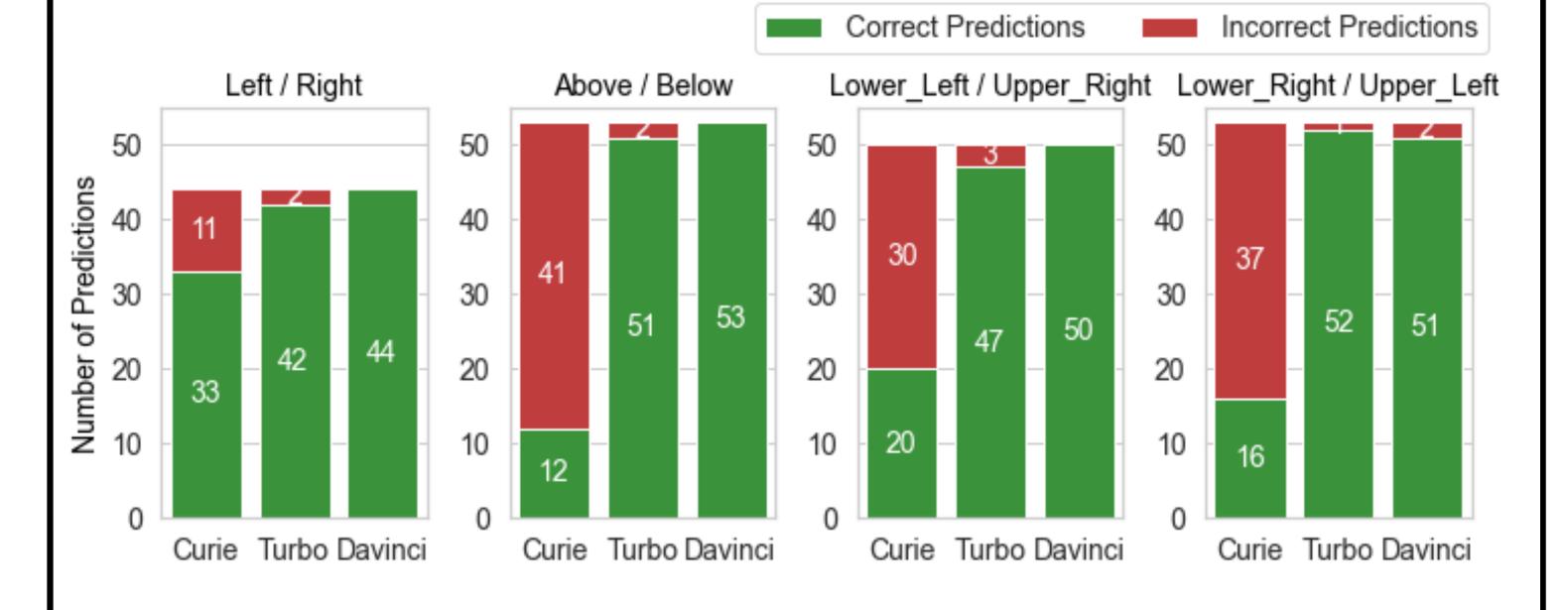
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#### LLM + ASP

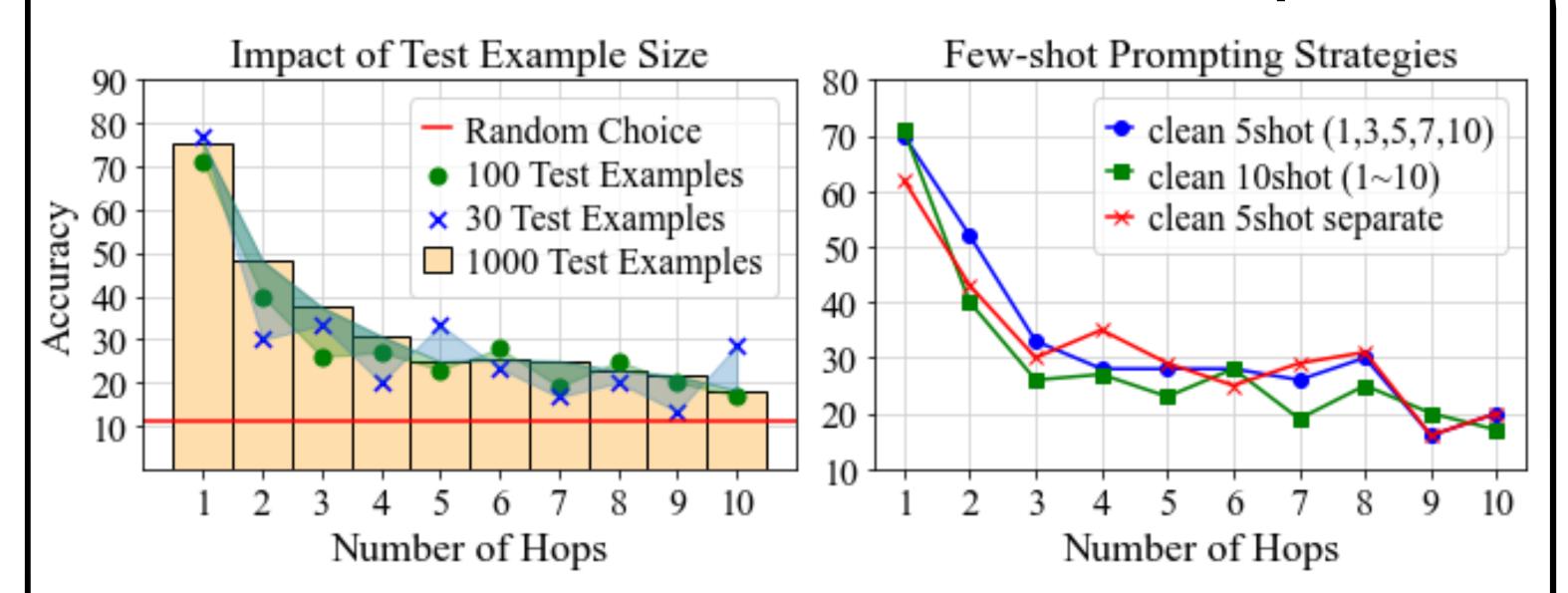
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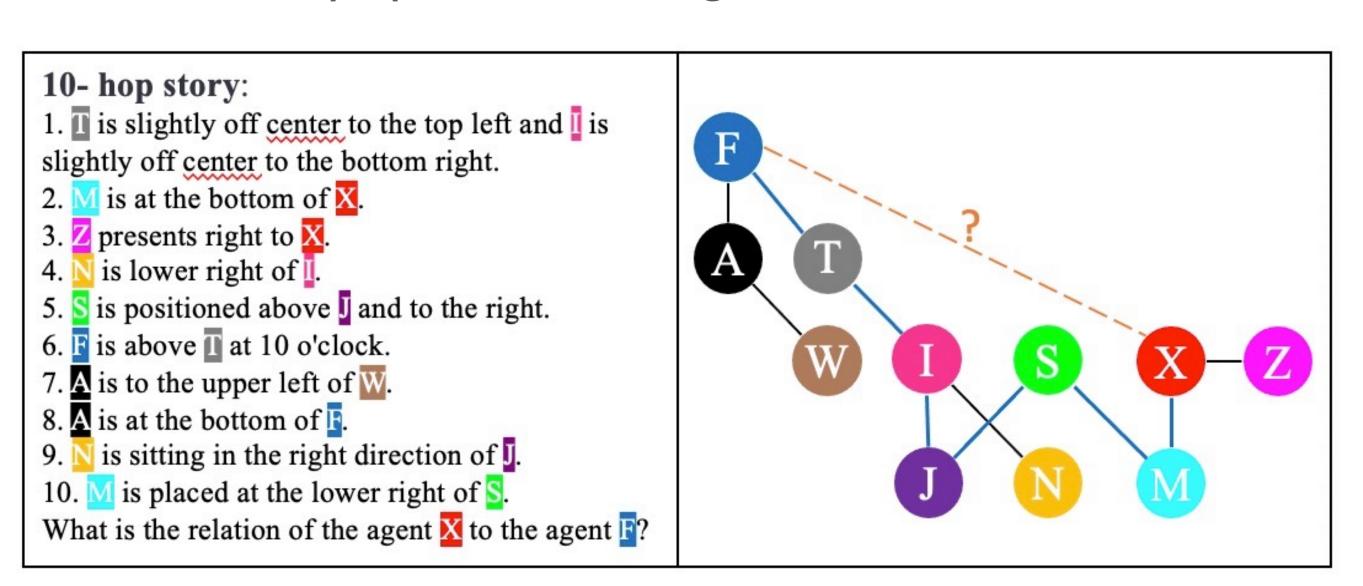
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#### Introduction

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## The StepGame Benchmark

Task: multi-hop spatial reasoning in texts



## **Template Errors in StepGame**

Mapping	Original Incorrect Statement
	AA and BB are parallel, and AA on the right of BB.
DD wight AA	AA and BB are parallel, and AA is to the right of BB.
BB_right_AA	AA and BB are horizontal and AA is to the right of BB
	AA and BB are both there with the object AA is to the right of object BB.
	AA is placed at the bottom of BB.
BB_below_AA	AA is at the bottom of BB and is on the same vertical plane.
	AA presents below BB.
AA_lowerleft_BB	BB is there and AA is at the 10 position of a clock face.
AA_lowellelt_bb	BB is positioned below AA and to the left
DD uppomisht AA	Object A is above object BB and to the right of it, too.
BB_upperright_AA	AA is diagonally to the upper right of BB.
AA_lowerright_BB	AA is to the right and above BB at an angle of about 45 degrees.
DD ummorloft A A	BB is to the right and above AA at an angle of about 45 degrees.
BB_upperleft_AA	BB is diagonally left and above BB.

 k=1
 k=2
 k=3
 k=4
 k=5
 k=6
 k=7
 k=8
 k=9
 k=10

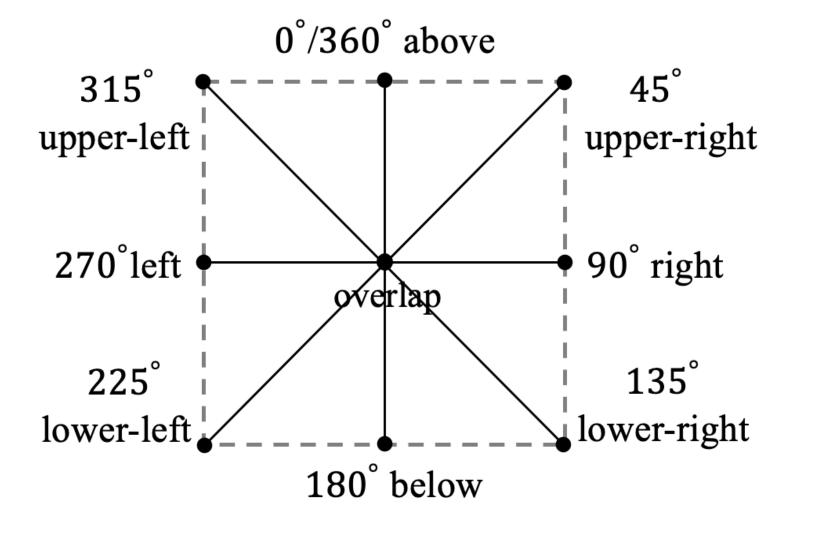
 Clean
 7.64
 15.03
 20.87
 26.39
 32.54
 37.66
 41.71
 47.20
 51.50
 **54.29** 

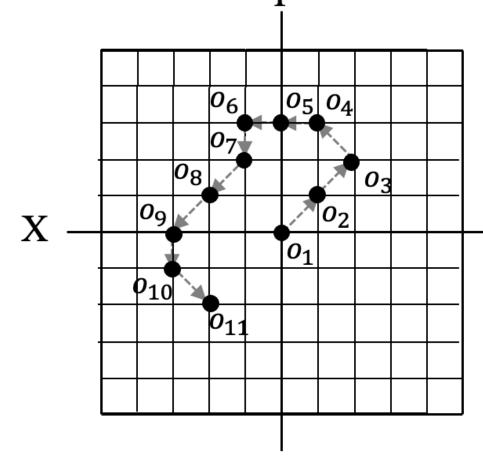
 Noise
 20.43
 30.19
 34.59
 48.18
 57.13
 61.14
 63.60
 69.45
 72.84
 **74.21**

#### Solution to StepGame

Sentence-to-Relation Mapping + ASP Reasoner

Sentences		Template		ASP Facts
Y and I are parallel, and Y is on top of I.	<b></b>	Y_above_I	-	above("Y", "I").
F is on the left side of and below Q.	<b></b>	F_lowerleft_Q		down_left("F", "Q").
J is at O's 6 o'clock.		J_below_O		below("J", "O").
A is directly north east of B.		A_upperright_B		up_right("A", "B").
What is the relation of the agent B to the agent J?		query_B_J		query("B", "J").



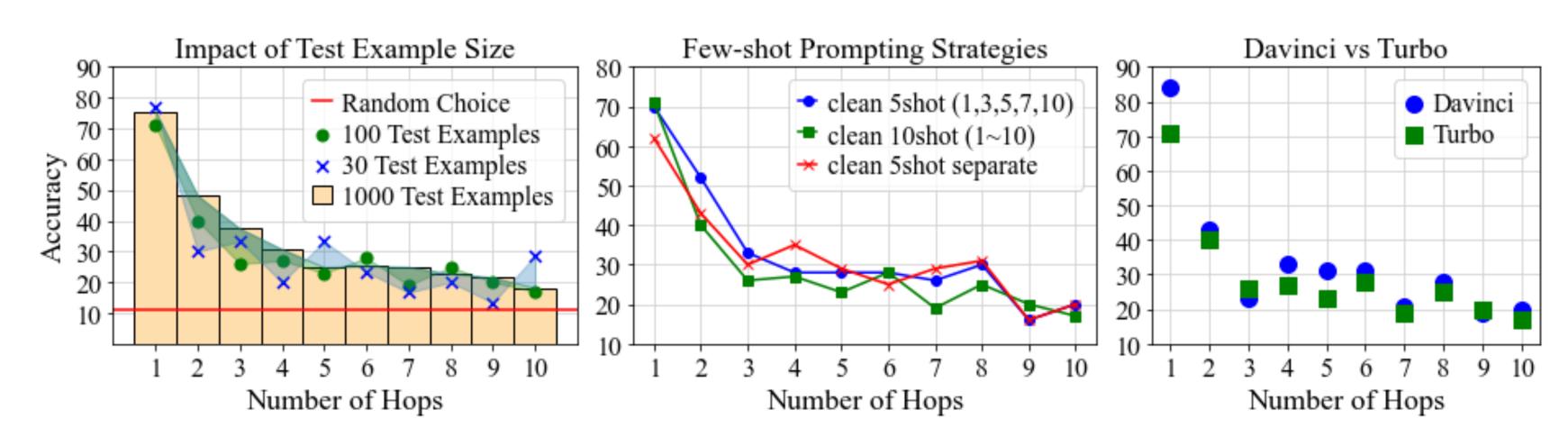


#### LLM + ASP

LLM for relation extraction + ASP Reasoner

	left/	above	lower_left/	lower_right/
	right	/below	upper_right	upper_left
total	44	53	50	53
text-curie-001	11	41	30	37
text-davinci-003	0	0	0	2
gpt-3.5-turbo	2	2	3	1

## **Evaluation of GPT Models on Revised StepGame**



#### Methods

Given a story about spatial relations Reasoning: among objects, answer the relation Suppose F is at (0,0). Link X and F using the between two queried objects. Possible relations in the story. relations are: overlap, above, below, **Start from F.** According to 6. F is above T at 10 o'clock. So T is to the lower-right of F. T= F+ left, right, upper-left, upper-right, loweroffset(lower-right) = (0,0)+(1,-1)=(1,-1). left, and lower-right. If a sentence in the |0|story is describing clock-wise Then search for T. According to 1. T is slightly off center to the top left and I is slightly off center to information, then 12 denotes above, 1 and 2 denote upper-right, 3 denotes the bottom right. So I is to the lower-right of T. I= T+ offset(lower-right) = (1,-1)+(1,-1)=(2,-2). right, 4 and 5 denote lower-right, 6 Then search for I. According to 4. N is lower right denotes below, 7 and 8 denote lowerleft, 9 denote left, 10 and 11 denote of I. So N is to the lower-right of I. N= I+ upper-left. If the sentence is describing offset(lower-right) = (2,-2)+(1,-1)=(3,-3). cardinal directions, then north denotes Then search for N. According to 9. N is sitting in above, east denotes right, south the right direction of J. So J is to the left of N. J= N+ offset(left) = (3,-3)+(-1,0)=(2,-3). denotes below, and west denotes left. In all the spatial relations, assume that Then search for J. According to 5. S is positioned all agents occupy a position on a grid above J and to the right. So S is to the upper-right point of equally spaced points in the of J. S = J + offset(upper-right) = (2,-3)+(1,1)=vertical and horizontal directions and (3,-2).that agents occupy the nearest grid Then search for S. According to 10. M is placed point consistent with the spatial relation. at the lower right of S. So M is to the lower-right of The offsets of 9 spacial relations: S. M = S + offset(lower-right) = (3,-2)+(1,-1)=(4,-3). offset(overlap) = (0,0); offset(top) = Then search for M. According to 2. M is at the (0,1); offset(down) = (0,-1); offset(left) = bottom of X. So X is above M. X= M+ (-1,0); offset(right) = (1,0); offset(above) = (4,-3)+(0,1)=(4,-2). Come to X, offset(top\_left) = (-1,1); offset(top\_right) = (1,1); offset(down\_left) = (-1,1); ended. F(0,0), X(4,-2), so X is to the lower-right of Answer: lower-right offset(down right) = (1,1)

### Algorithm 1: Our ToT Approach

#### Require: LLM, input x

- 1:  $S_0 \leftarrow Init(x)$
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- 3: while no  $s_f \in S_{i-1}$  has arrived at  $o_t$  do
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#### Results

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	ToT_CoT	/	/	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_CoT	/	/	85	85	90	90	85	90	100	95