

TIST Paper Summary

Reasoning Abilities of Large Language Models: In-Depth Analysis on the Abstraction and Reasoning Corpus

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Introduction

"Can LLMs think?"

LLMs had shown strong ability on various tasks



Prior researches are lacking in 2 points

- 1) How LLMs' reasoning process differs from humans
- 2) How to measure LLMs' reasoning ability quantitatively



Contribution

- 1) Bring perspective of human thinking :
Language of Thought Hypothesis (LoTH)
- 2) Abstraction and Reasoning Corpus (ARC) as benchmark

Preliminaries

What is Language of Thought Hypothesis(LoTH)?



Jerry A. Fodor
(April 22, 1935 – November 29, 2017)

LoTH is ...

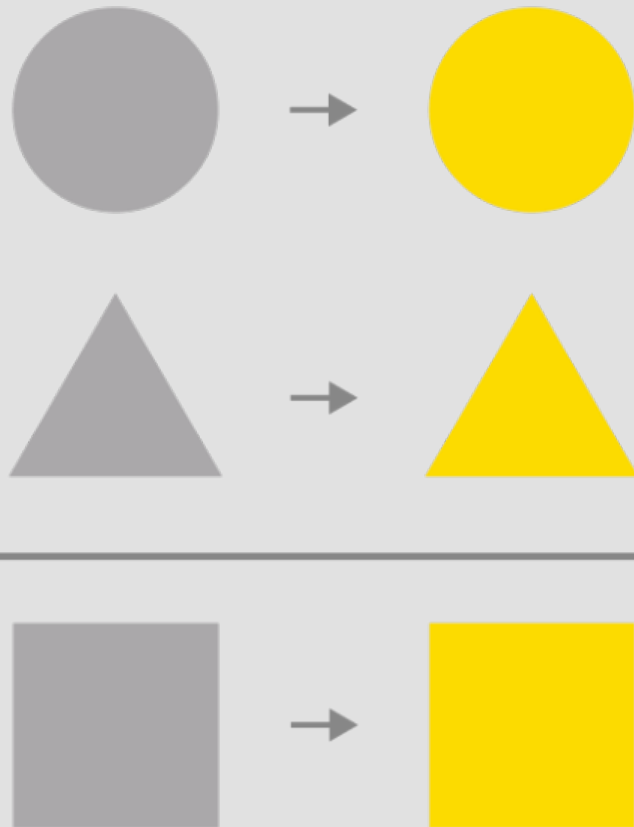
- One hypothesis for a human thinking process
- Proposes that thinking occurs in a mental language
- LoTH argues that mental language have 3 Properties

Preliminaries

3 Properties of Human Thought

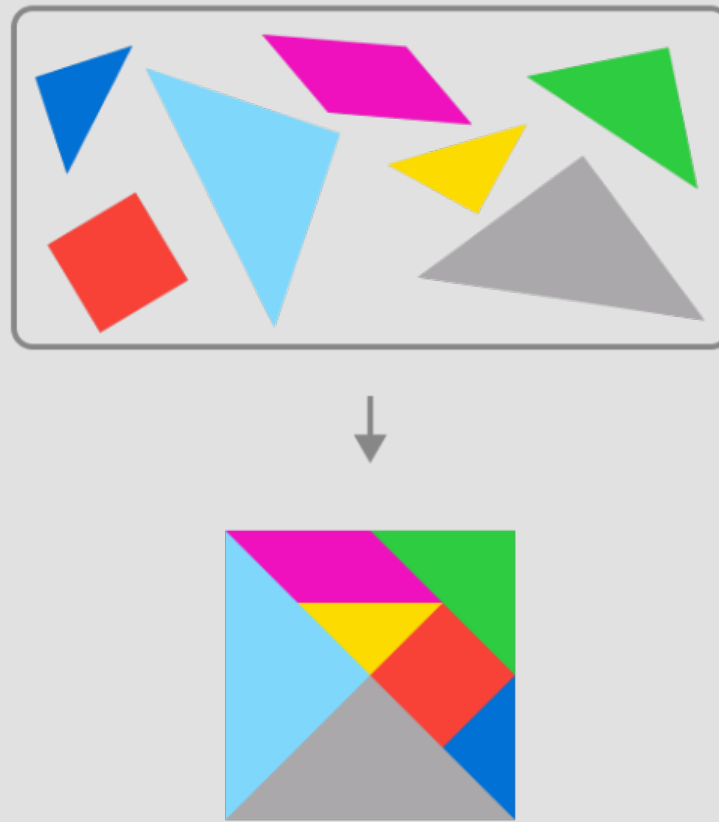
Logical Coherence

Find the *common rule*



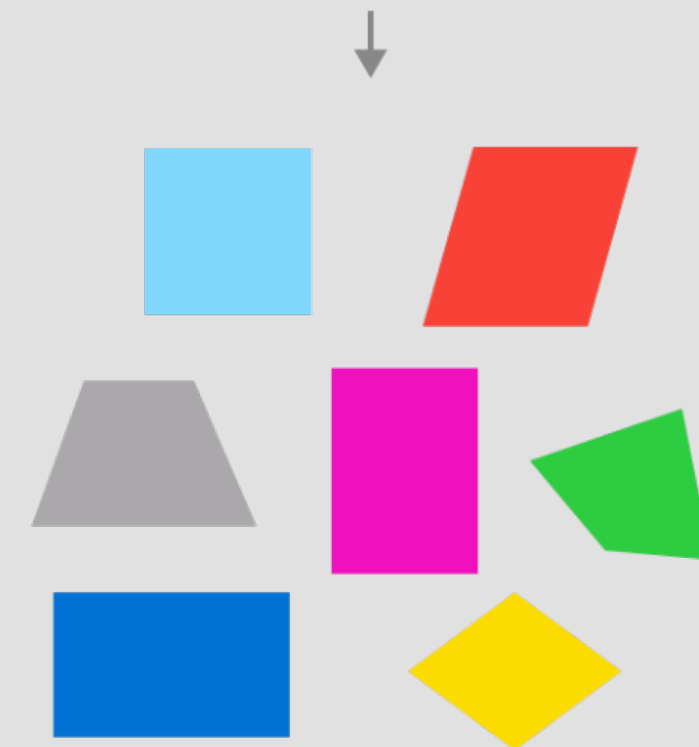
Compositionality

Make a *square*



Productivity

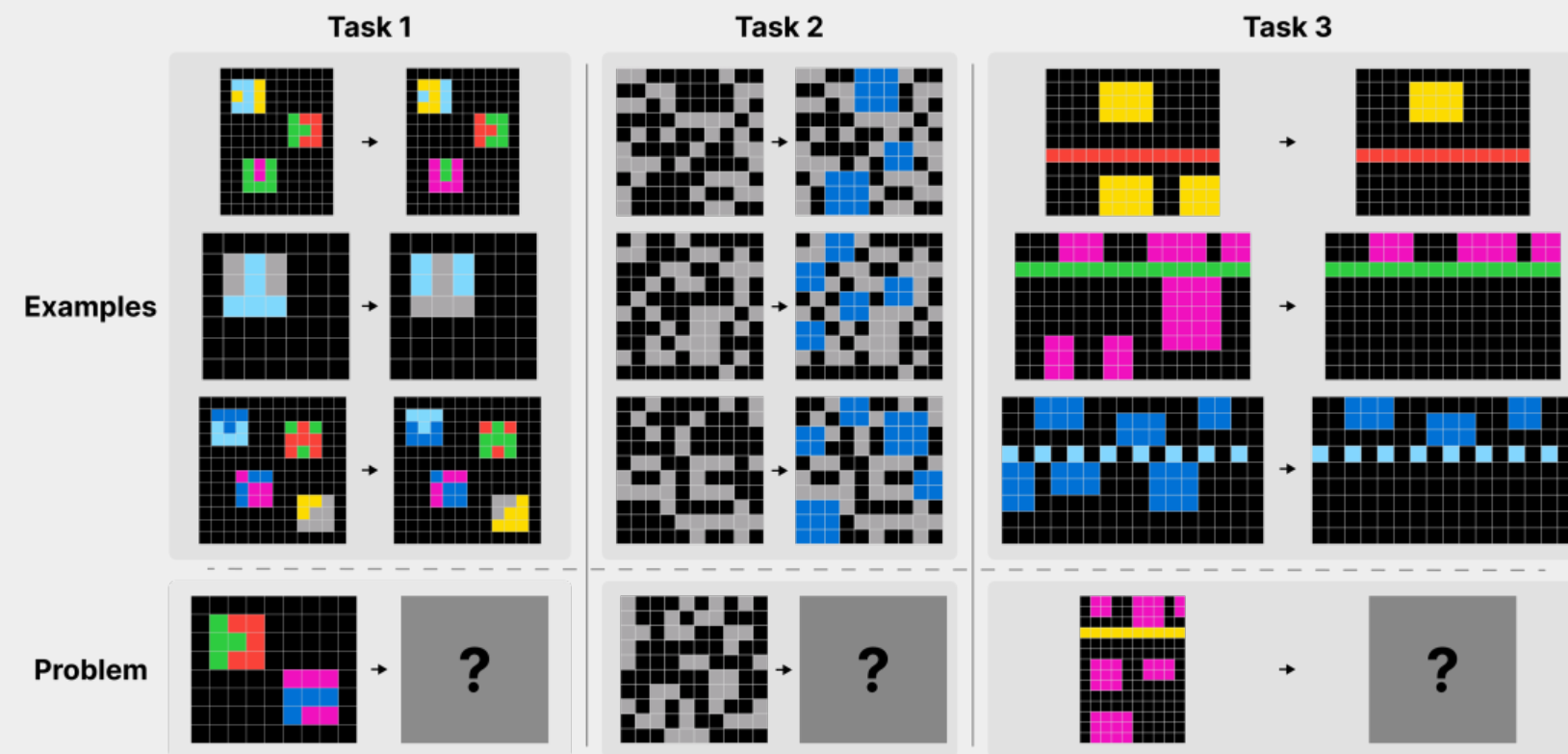
Make objects with *four edges and four vertices*



3 properties of human thinking

Preliminaries

What is Abstraction and Reasoning Corpus(ARC)?



Example of ARC tasks

ARC Description

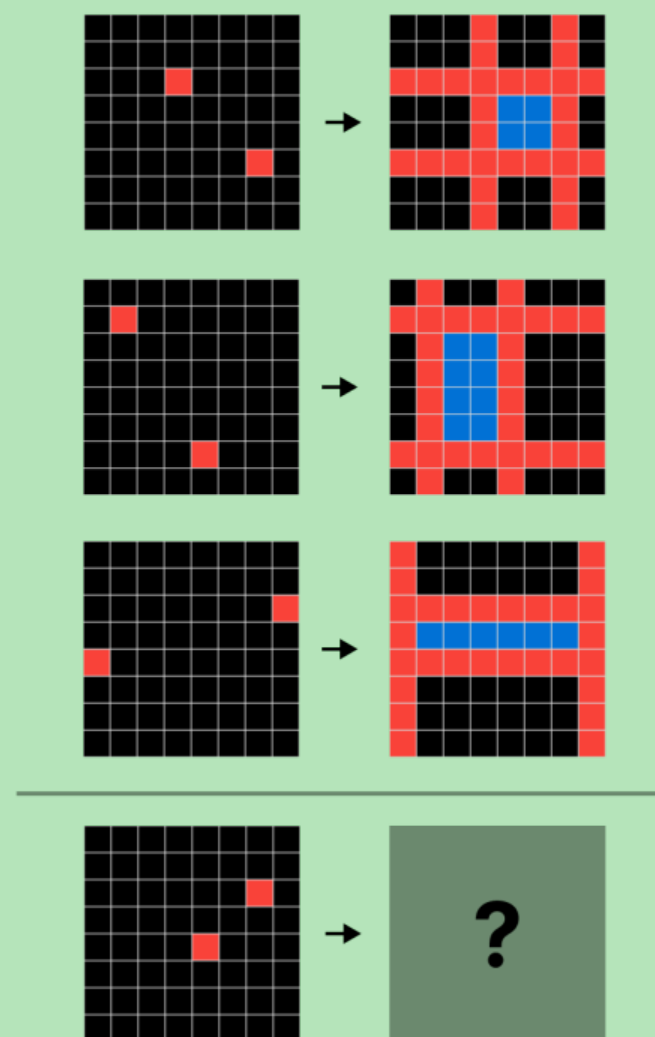
- 1) Consists of 2-5 example pairs and a problem input grid
- 2) Goal is to infer rules from given example pairs and apply them to the problem input grid
- 3) Input and output grid size can vary from a minimum of 1X1 to a maximum of 30X30, with each grid having up to 10 different colors

Experiments

Whole View of All 3 Experiments

3.1 Logical Coherence

Find the *common rule*

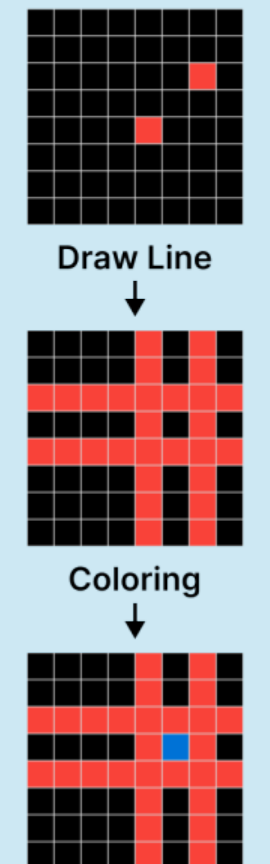


The diagram shows three rows of input grids on the left, each with a few red squares. Arrows point to three corresponding output grids on the right. Each output grid is a 5x5 grid with a complex pattern of red and blue squares. The first two rows show a similar pattern, while the third row shows a different pattern. A horizontal line separates the three rows. Below the line, a fourth row shows an input grid with a few red squares and an arrow pointing to a grey square with a question mark.

3.2 Compositionality

Make a *correct output grid*

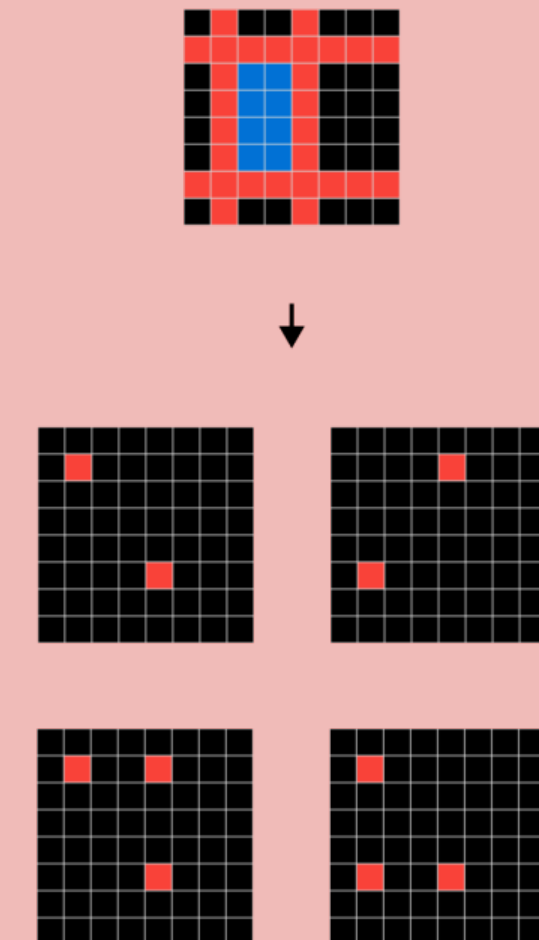
Move	Flip
Fill	Rotate
Draw Line	Coloring



The diagram shows a sequence of operations. It starts with a 5x5 grid with a few red squares. An arrow labeled "Draw Line" points to a grid where a red cross has been drawn. Another arrow labeled "Coloring" points to a grid where the cross is filled with red and a blue square is added in the center.

3.3 Productivity

Make *possible inputs* corresponding to a target output



The diagram shows a target output grid at the top, which is a 5x5 grid with a complex pattern of red and blue squares. An arrow points down to four smaller 5x5 grids arranged in a 2x2 grid. Each of these four grids has a different pattern of red squares, representing possible inputs that could result in the target output.

Overview of 3 experiments

(https://github.com/GIST-DSLab/ARC_Prompt)

Experiments - Logical Coherence

Method

Sample Task

If the input grids are:

```
[[0, 3, 0, 0, 0, 0],
 [0, 3, 0, 2, 0, 0],
 [0, 0, 0, 2, 0, 0],
 [0, 8, 0, 0, 2, 2],
 [0, 0, 0, 0, 2, 2],
 [6, 6, 6, 0, 0, 0]]
```

then the correct output grids are:

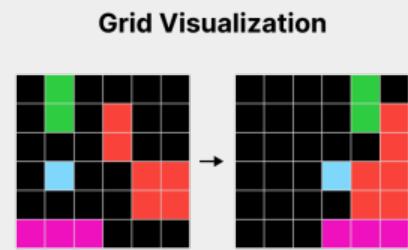
```
[[0, 0, 0, 0, 3, 0],
 [0, 0, 0, 0, 3, 2],
 [0, 0, 0, 0, 0, 2],
 [0, 0, 0, 8, 2, 2],
 [0, 0, 0, 0, 2, 2],
 [0, 0, 0, 6, 6, 6]]
```

{additional examples}

To solve this task, follow the sub-tasks below.

1. Identify objects in the input grid.
2. Try to move each object to the right.
3. Stop when objects touch the right corner or other objects.

Following these steps will lead to the output grid.



Decomposing

If the input grids are:

```
[[0, 0, 0, 0, 0, 0],
 [0, 0, 3, 0, 0, 0],
 [0, 3, 0, 3, 0, 0],
 [0, 0, 3, 0, 3, 0],
 [0, 0, 0, 3, 0, 0],
 [0, 0, 0, 0, 0, 0]]
```

then the correct output grids are:

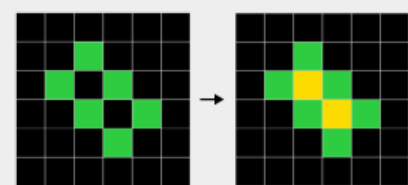
```
[[0, 0, 0, 0, 0, 0],
 [0, 0, 3, 0, 0, 0],
 [0, 3, 4, 3, 0, 0],
 [0, 0, 3, 4, 3, 0],
 [0, 0, 0, 3, 0, 0],
 [0, 0, 0, 0, 0, 0]]
```

{additional examples}

To solve this task, decompose the task into sub-tasks like below.

1. Identify the places surrounded by "3"s in the input grid.
2. Fill in the places you found with "4".

Following these steps will lead to the output grid.



Target Task

If the input grids are:

```
[[0, 0, 0, 0, 0, 0, 0],
 [0, 5, 8, 5, 0, 0, 0],
 [0, 5, 8, 5, 0, 0, 0],
 [0, 8, 8, 8, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0]]
```

then the correct output grids are:

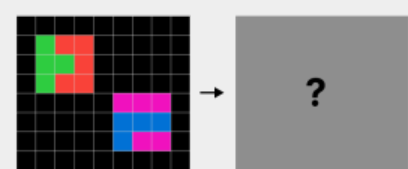
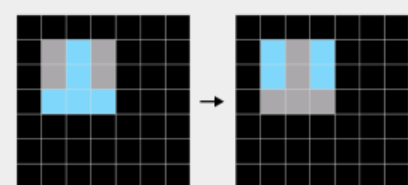
```
[[0, 0, 0, 0, 0, 0, 0],
 [0, 8, 5, 8, 0, 0, 0],
 [0, 8, 5, 8, 0, 0, 0],
 [0, 5, 5, 5, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0]]
```

{additional examples}

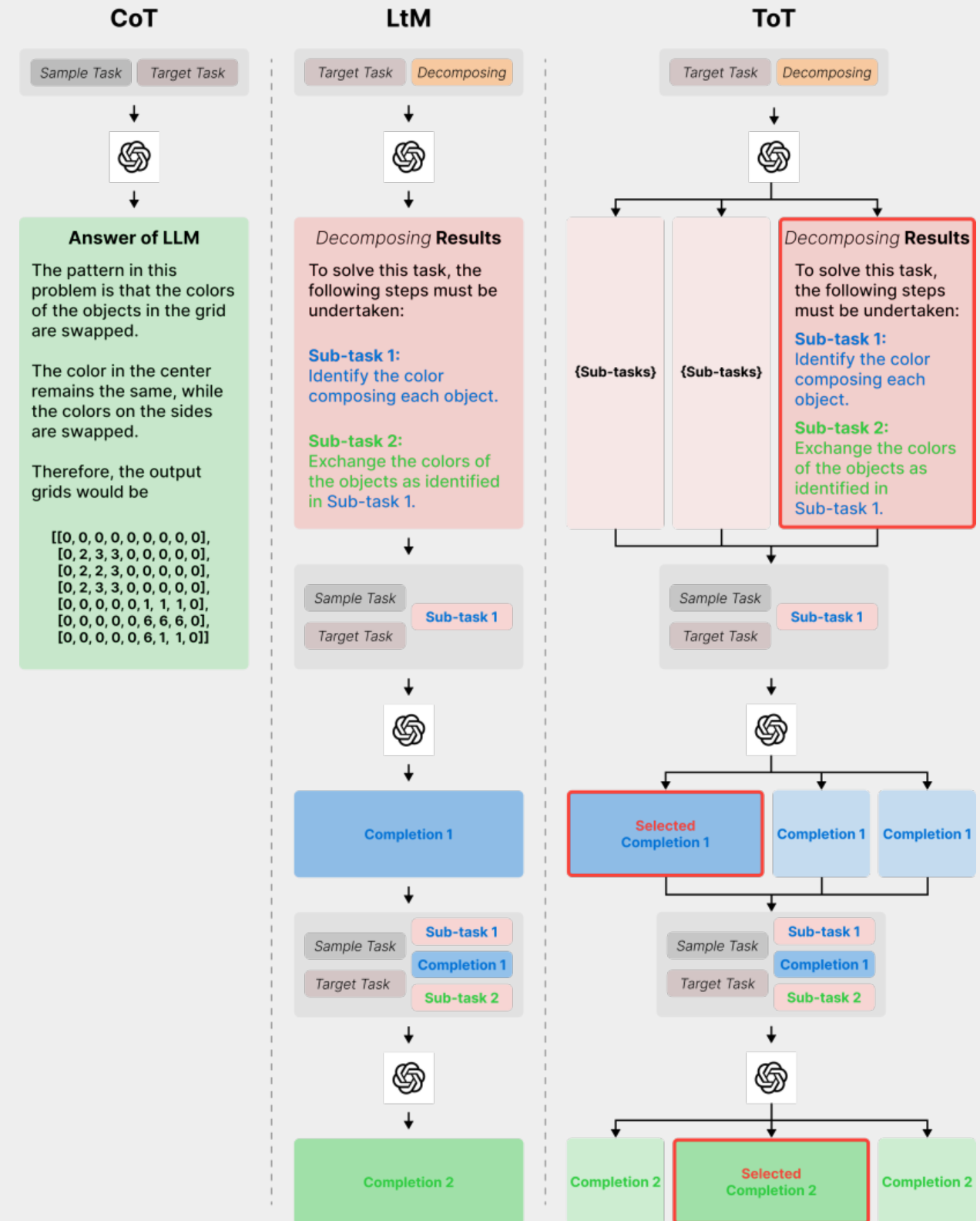
If the input grid are:

```
[[0, 0, 0, 0, 0, 0, 0, 0],
 [0, 3, 2, 2, 0, 0, 0, 0],
 [0, 3, 3, 2, 0, 0, 0, 0],
 [0, 3, 2, 2, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 6, 6, 6],
 [0, 0, 0, 0, 0, 1, 1, 1],
 [0, 0, 0, 0, 0, 1, 6, 6]]
```

What is the correct output grid?



3 types of prompts



Experiment architecture

Experiments - Logical Coherence

Results

Average accuracy

Iteration	CoT	LtM	ToT
1	11% (3%)	6% (4%)	7% (3%)
2	10% (2%)	7% (4%)	5% (1%)
3	10% (5%)	6% (3%)	7% (2%)
4	10% (4%)	4% (2%)	7% (4%)
5	12% (6%)	5% (2%)	6% (2%)
Average	10.6% (4.0%)	5.6% (3.0%)	6.4% (2.4%)

Averaged performance of each prompting technique

- 1) 100 tasks, 5 iterations
- 2) CoT showed higher accuracy, compared to LtM and ToT

Experiments - Logical Coherence

Results

Difference between solved and unsolved tasks

	Entry	Easy	Medium	Hard
Tasks	2	20	46	14
Trials	10	100	230	70
CoT	100.00%	30.00%	0.00%	0.00%
LtM	20.00%	19.00%	0.00%	2.85%
ToT	50.00%	22.00%	0.00%	0.00%
Average	56.67%	23.67%	0.00%	0.95%

Analyzing LLMs' reasoning capabilities by task difficulty,
following ARC-GAME categorization
(<https://github.com/volotat/ARC-Game>)

1) The perceived difficulty levels for different problems showed similar tendencies between LLM and human.

2) Difficult problems shared two commonalities:

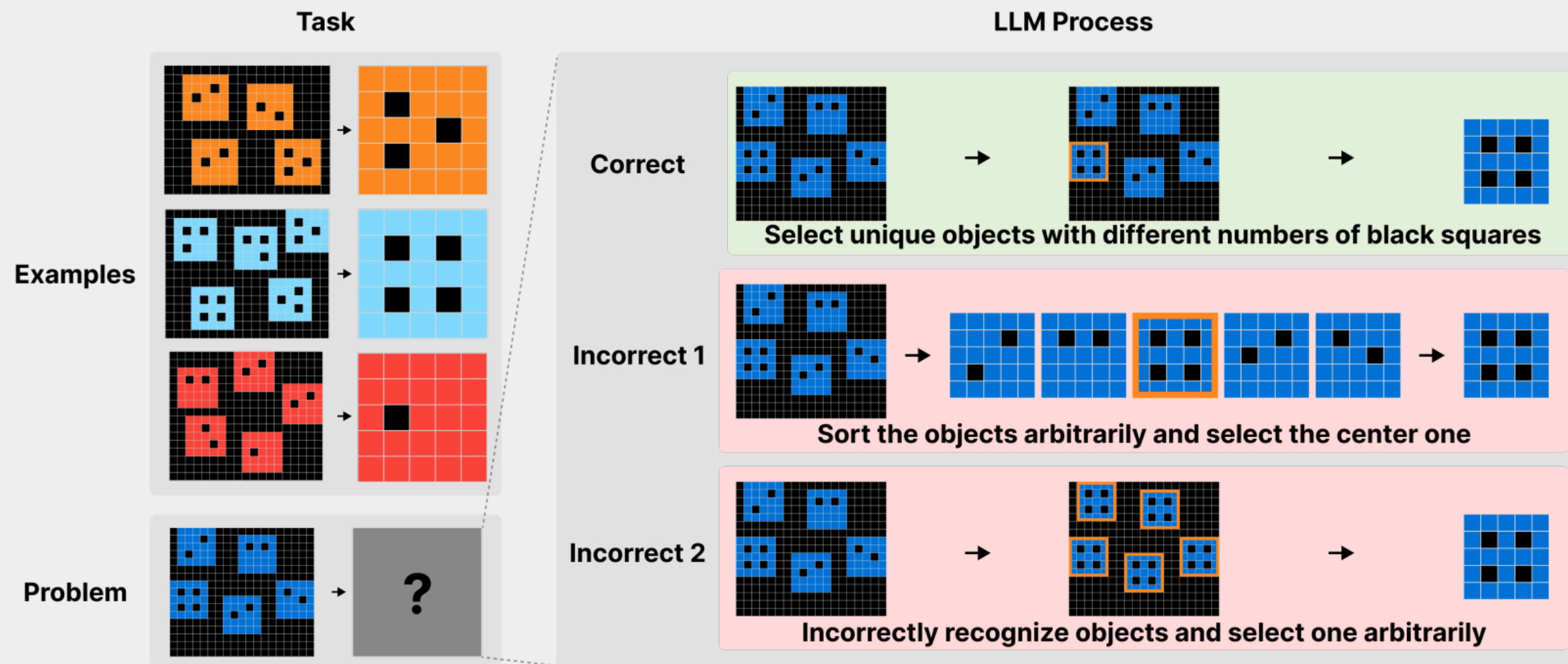
(1) Long inference process

(2) The need to consider multiple problems concurrently

Experiments - Logical Coherence

Results

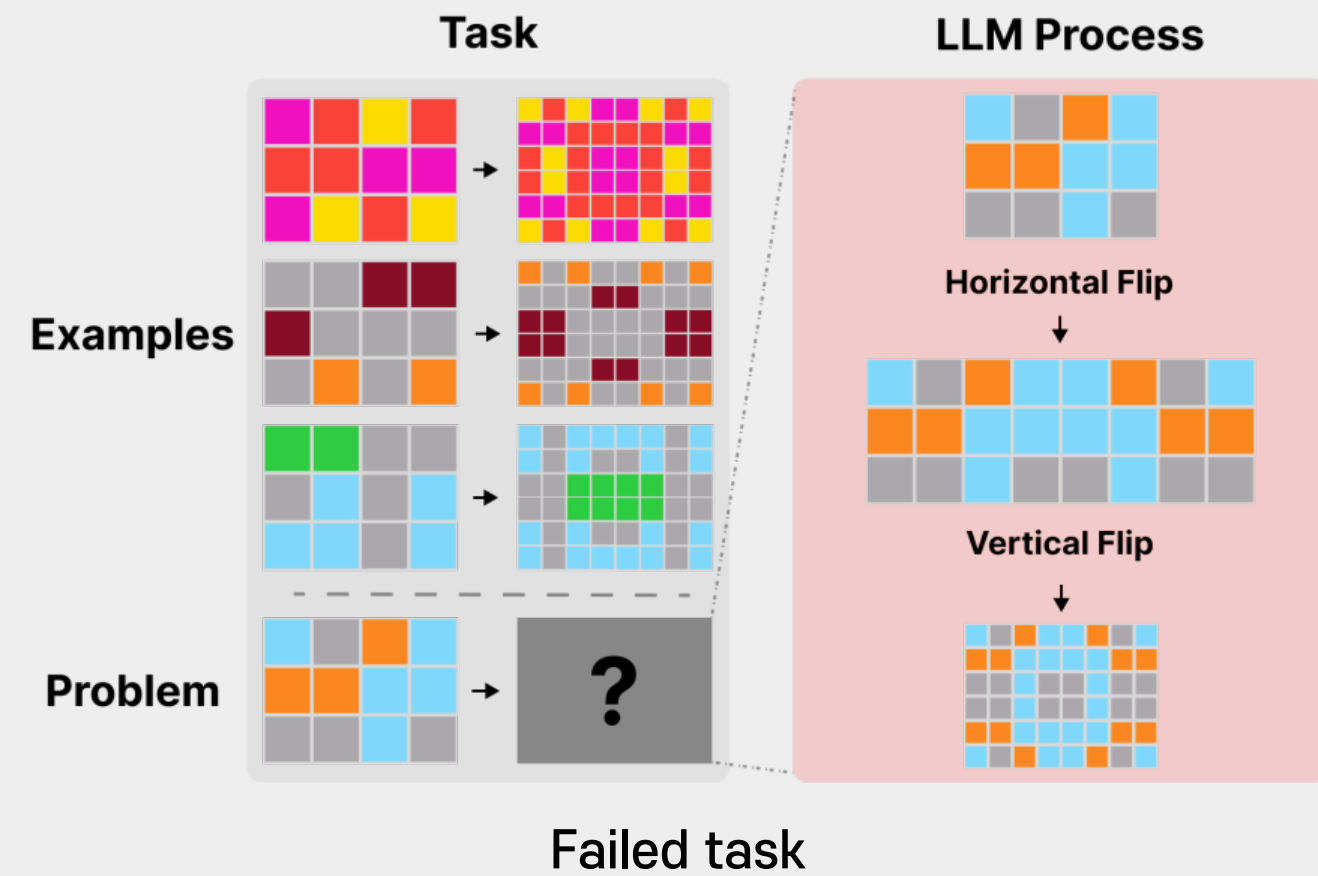
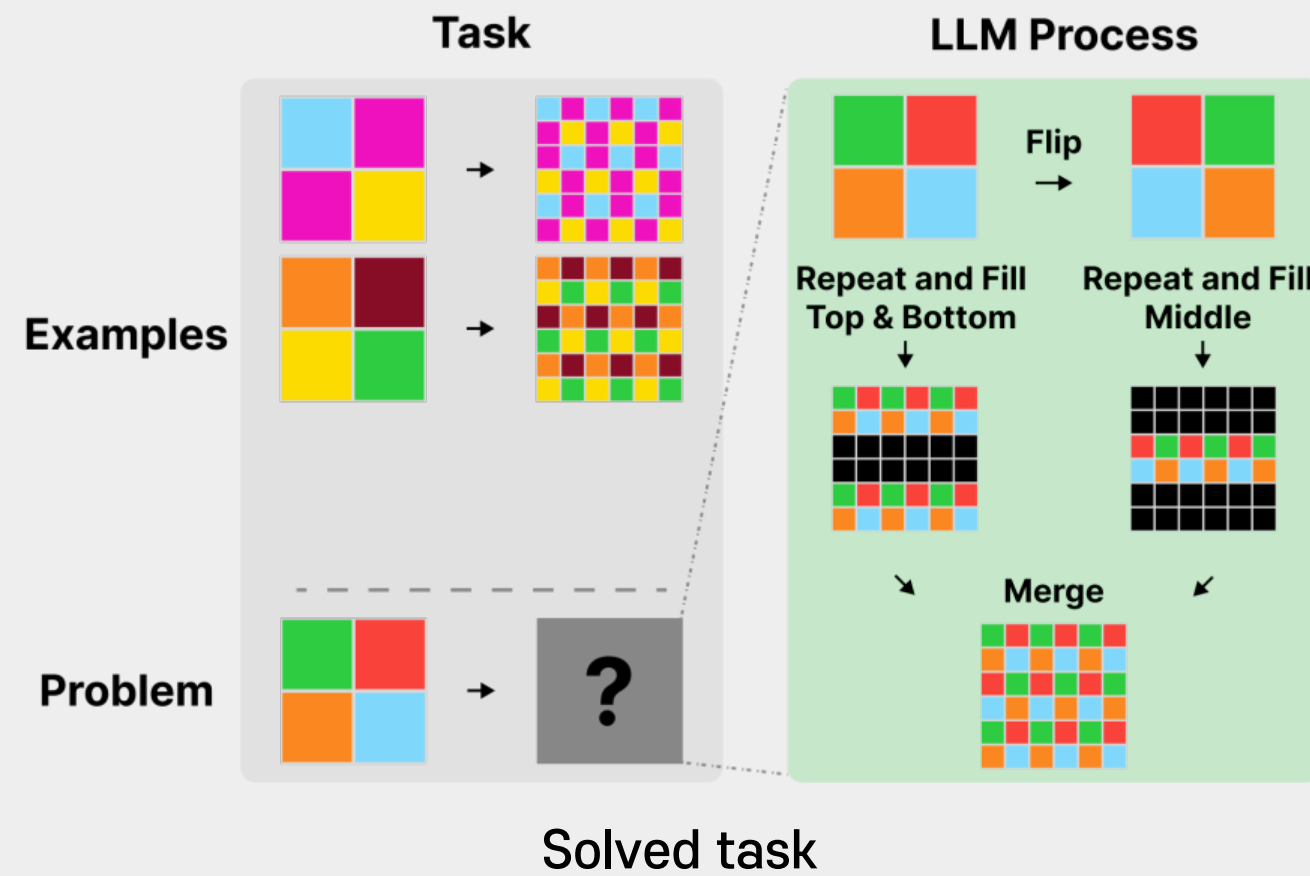
Incorrect reasoning processes



Experiments - Logical Coherence

Results

Inconsistent task solving



Experiments - Logical Coherence

Conclusion

Summary

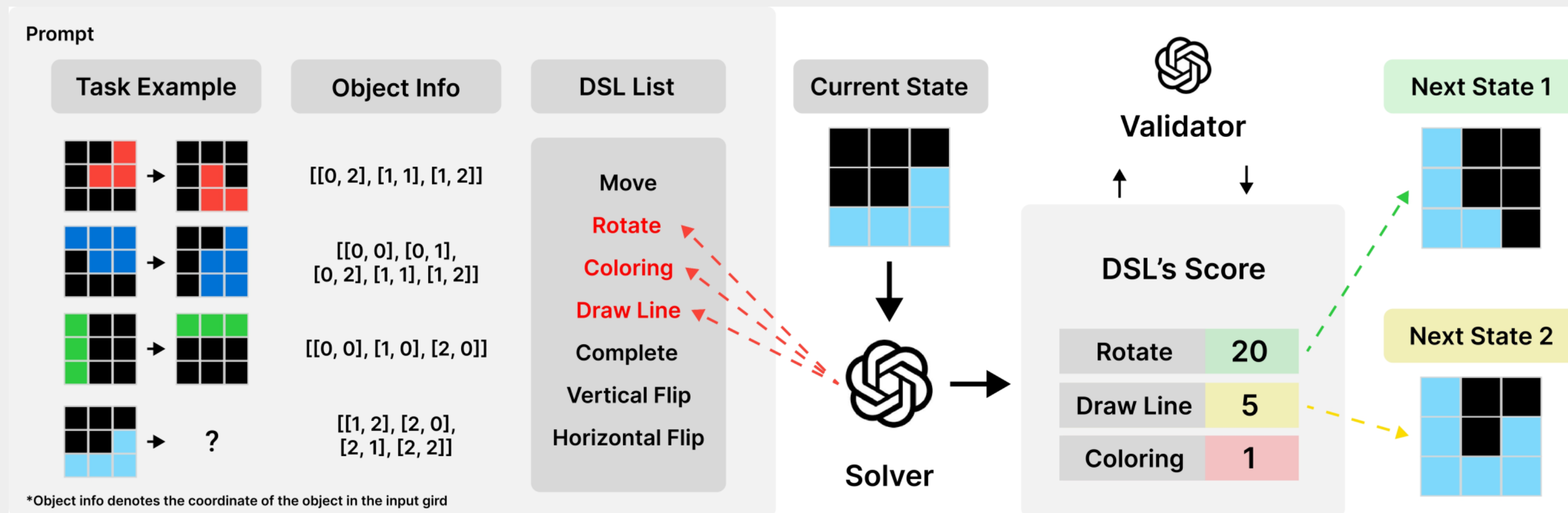
- 1) Showed an accuracy range from 4% to 12%
- 2) Variability in the reasoning performance depending on the prompting approach employed
- 3) LLMs displayed a rudimentary level of logical ability on simpler tasks, a deeper qualitative examination exposed underlying inconsistencies

Further Researches

- 1) This study focused on assessing logical capabilities only through varying prompting techniques
- 2) Alternative strategies such as domain-specific model fine-tuning or exploring diverse LLM architectures might yield different insights into their logical abilities and coherence

Experiments - Compositionality

Method

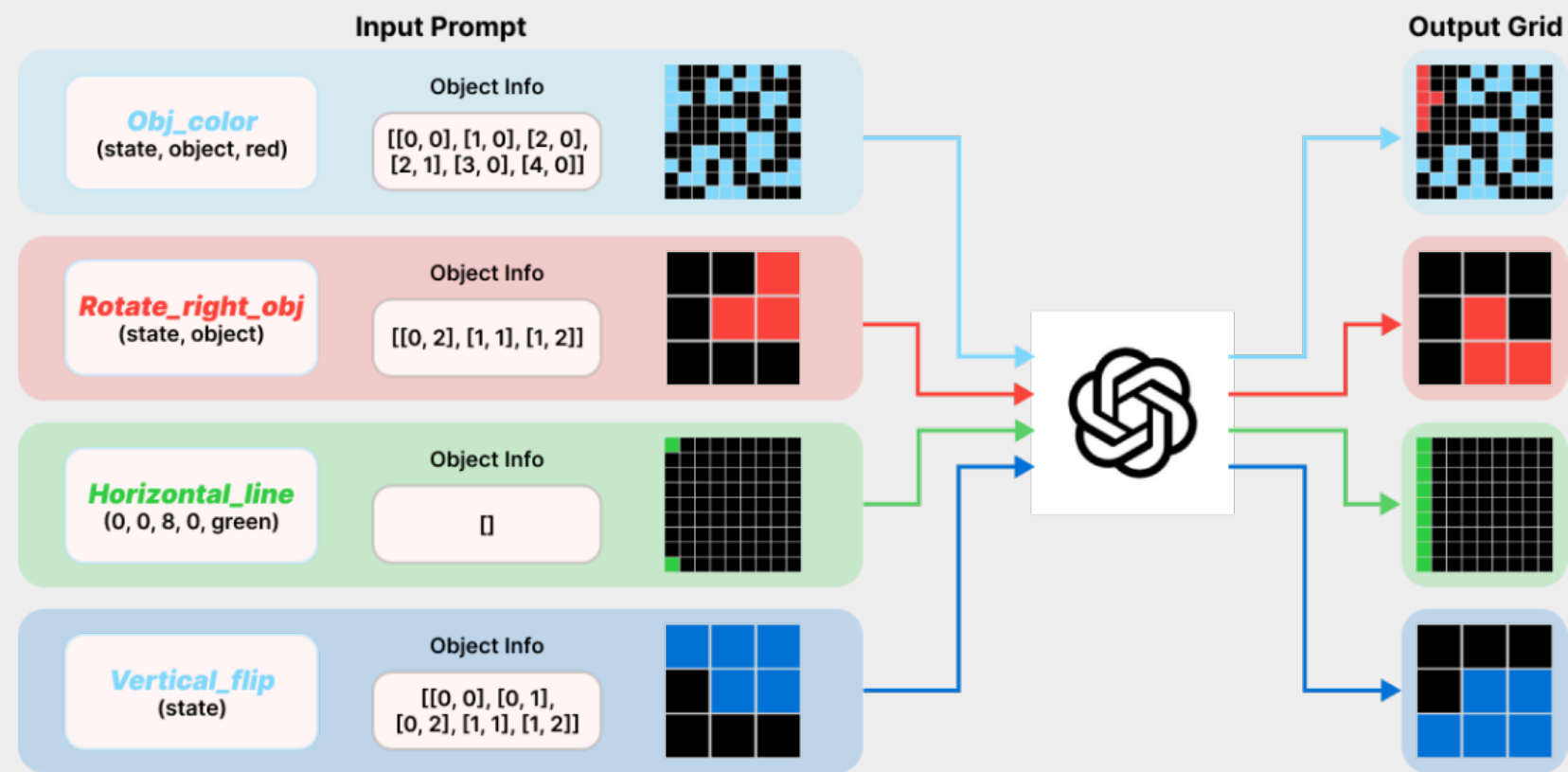


An example of the single step in an experimental process

Experiments - Compositionality

Result

Lack of compositionality



Examples of answers LLM made

1) Solved none out of 99 tasks

2) LLM Understand image and functions properly, however, LLM showed lack of compositional ability

Experiments - Compositionality

Additional Analysis

1) Solved 2 out of 260 tasks

2) LLM called function "complete" for 119 out of 260 tasks

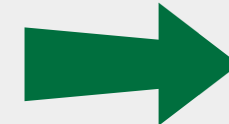
Average step about first calling "complete" : 5.773

The number of continual calling "complete" : 50

The number of non continual calling "complete" : 69

Average frequency of calling complete on non continual calling "complete" : 2.304

3) LLM showed preference on specific functions such as "object coloring" and "complete"



1) Lack of planning ability : LLM has difficulty on recognizing steps to solve specific task

2) Functions should be assessed whether it is fair or not, and need to add more complicated functions

Experiments - Compositionality

Conclusion

Summary

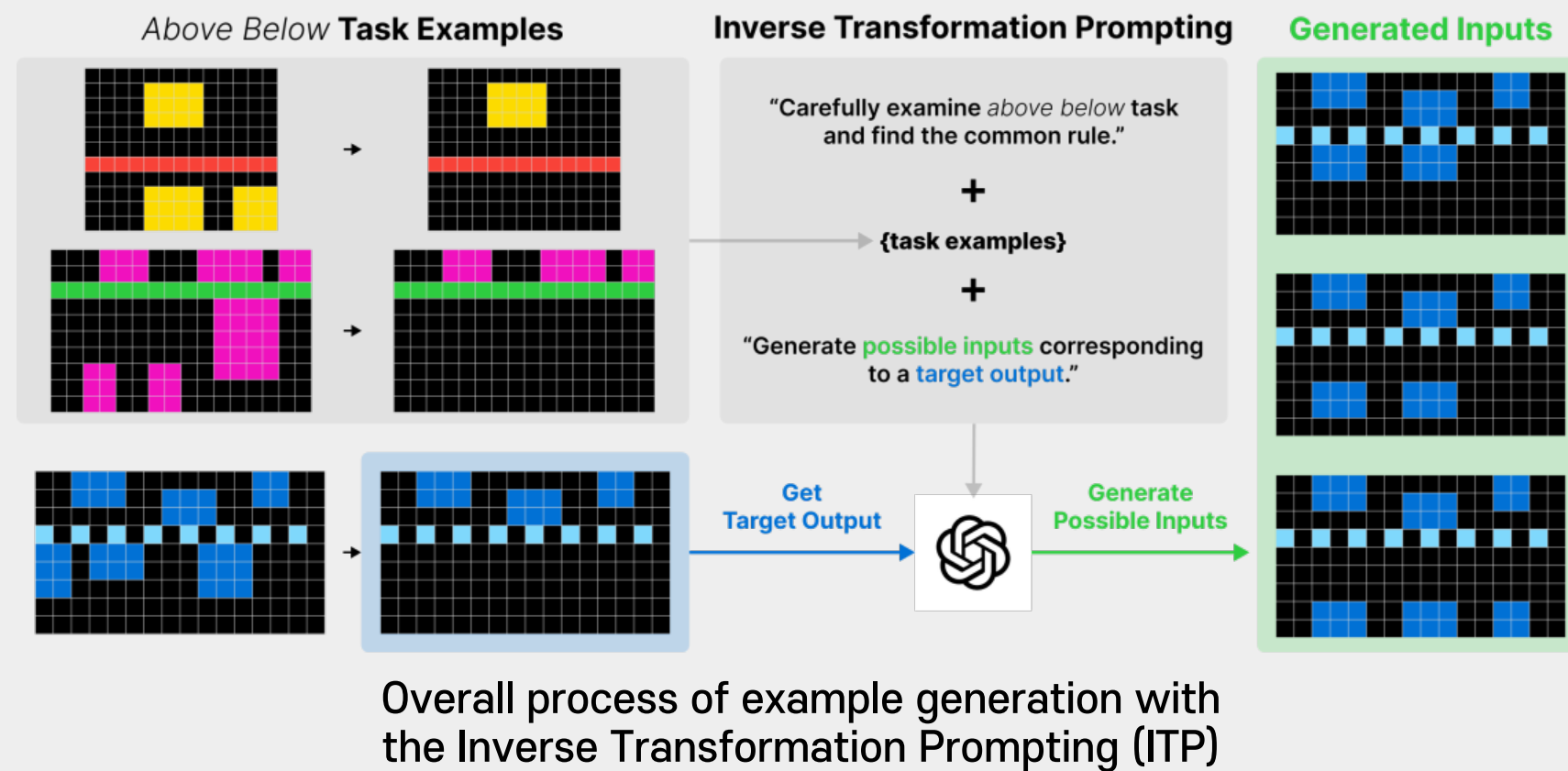
- 1) LLM contains an ability to understand inputs including functions and grids
- 2) The ability to analyze the combination of steps to decompose the task into smaller sub-tasks and achieve the desired result is weak

Further Researches

- 1) Should leverage of LLMs' planning ability by improving prompting techniques or fine-tuning the model
- 2) Further research on designing functions which can solve more general tasks should be conducted

Experiments - Productivity

Method



Details of experiment

- 1) Developed abstract rules based on the category of ConceptARC, which organizes a subset of ARC tasks into 16 distinct categories according to human classification criteria
- 2) Used Inverse Transformation Prompting (ITP) for for augmentation
 - (1) Data-efficient than the method of generating both input and output
 - (2) Increasing likelihood of generating valid responses

Experiments - Productivity

Result

Validity of augmentation

Category	Generated Examples	Valid Examples	Validity
Above Below	158	34	21.52%
Center	236	35	14.83%
Clean Up	183	83	45.36%
Complete Shape	147	37	25.17%
Copy	153	4	2.61%
Count	202	29	14.36%
Extend To Boundary	167	8	4.79%
Extract Objects	176	21	11.93%
Filled Not Filled	203	29	14.29%
Horizontal Vertical	114	7	6.14%
Inside Outside	191	24	12.57%
Move To Boundary	165	12	7.27%
Order	162	26	16.05%
Same Different	246	76	30.89%
Top Bottom 2D	255	59	23.14%
Top Bottom 3D	215	25	11.63%
Total	2,913	509	17.12%

Ratio of valid examples

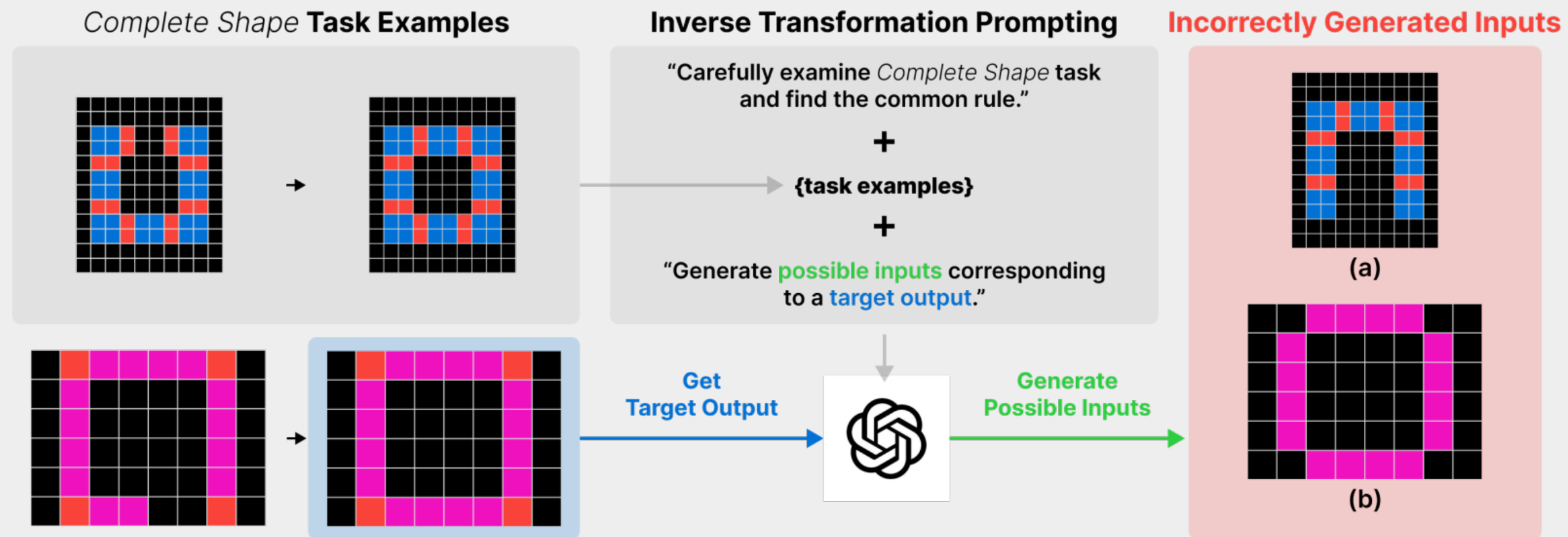
1) LLM has strong power on creating different image outputs

2) However, valid outputs which fit into the rule of given ARC task remained about 17%, which shows LLMs' limitation on productivity

Experiments - Productivity

Result

Weak step-wise productivity



Two examples of the wrong generations for the task of completing the square shape

Experiments - Productivity

Conclusion

Summary

- 1) Showed strong ability on creating images
- 2) However, rule-based production seems to be weak point, since LLM fails to produce valid data given abstract rules
- 3) These results indicate that the process by which LLMs generate outputs is closer to mimicking human-generated results and achieving human-level generation abilities for LLMs is challenging

Further Researches

- 1) The current experiment has limitation on determining whether the generated tasks were created following a human-like generation process or if they simply appear valid
- 2) Need to analyze whether the process of incorrect generation resembles that of humans or not

Conclusion

To sum up...

- 1) We used ARC as benchmark testing LLMs' reasoning ability in three different components: Logical coherence, Compositionality, Productivity.
- 2) Although LLM showed high ability on simple logical inference and production, it seems to mimic the answer of humans' instead of reason by itself.
- 3) Finally, we explored meaningful research directions for LLM to acquire inference capabilities from the LoTH perspective, as well as alternative approaches beyond ARC.