

# Abstract Reasoning via Logic-guided Generation

Sihyun Yu<sup>1</sup>, Sangwoo Mo<sup>1</sup>, Sungsoo Ahn<sup>2</sup>, Jinwoo Shin<sup>1</sup>

<sup>1</sup>Korea Advanced Institute of Science and Technology (KAIST), <sup>2</sup>Mohamed bin Zayed University of Artificial Intelligence (MBZUAI)

## TL;DR: We propose a generative framework in abstract reasoning with a propositional logical prior.

### Summary

Generative DNN framework for abstract reasoning via propositional logic

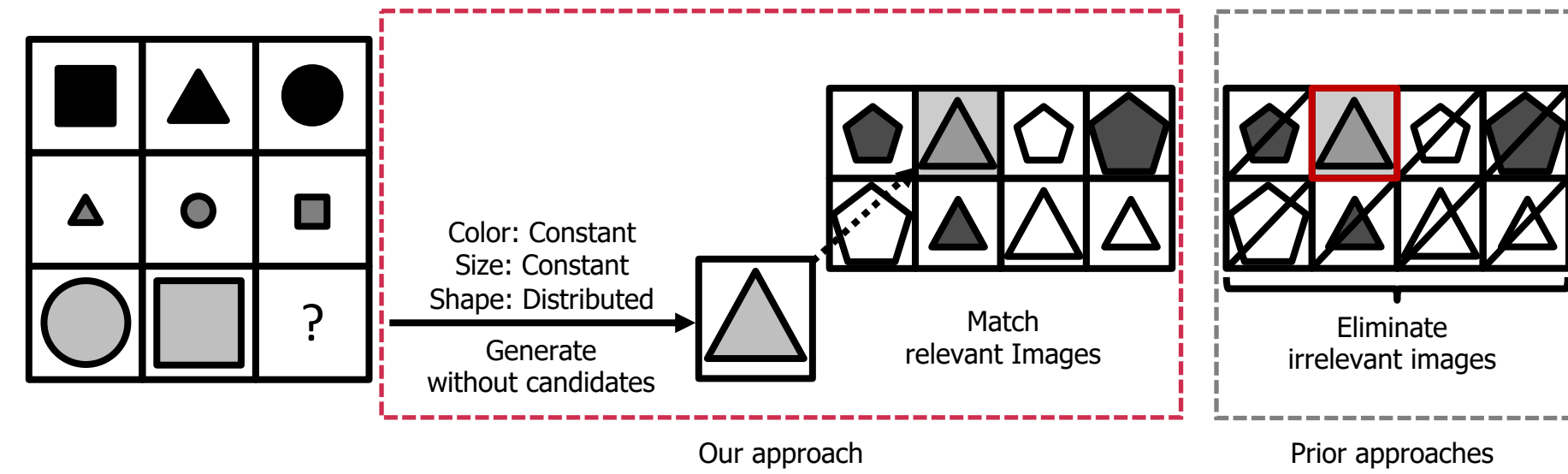


Fig 1. Two strategies to solve an abstract reasoning problem

**Goal:** we use deep neural networks to solve **abstract reasoning problem**, i.e., inferring common patterns from observations and find the answer.

**Contribution:** we propose **logic-guided generation (LoGe)**, a generative framework that employs propositional logical prior.

- We show how abstract reasoning problems can be reduced to the combinatorial **optimization problem in propositional logic**.
- Empirically, our algorithm achieves **improved performance** both quantitatively and qualitatively in RAVEN benchmark.

### Abstract Reasoning as Propositional Logic

Our main idea

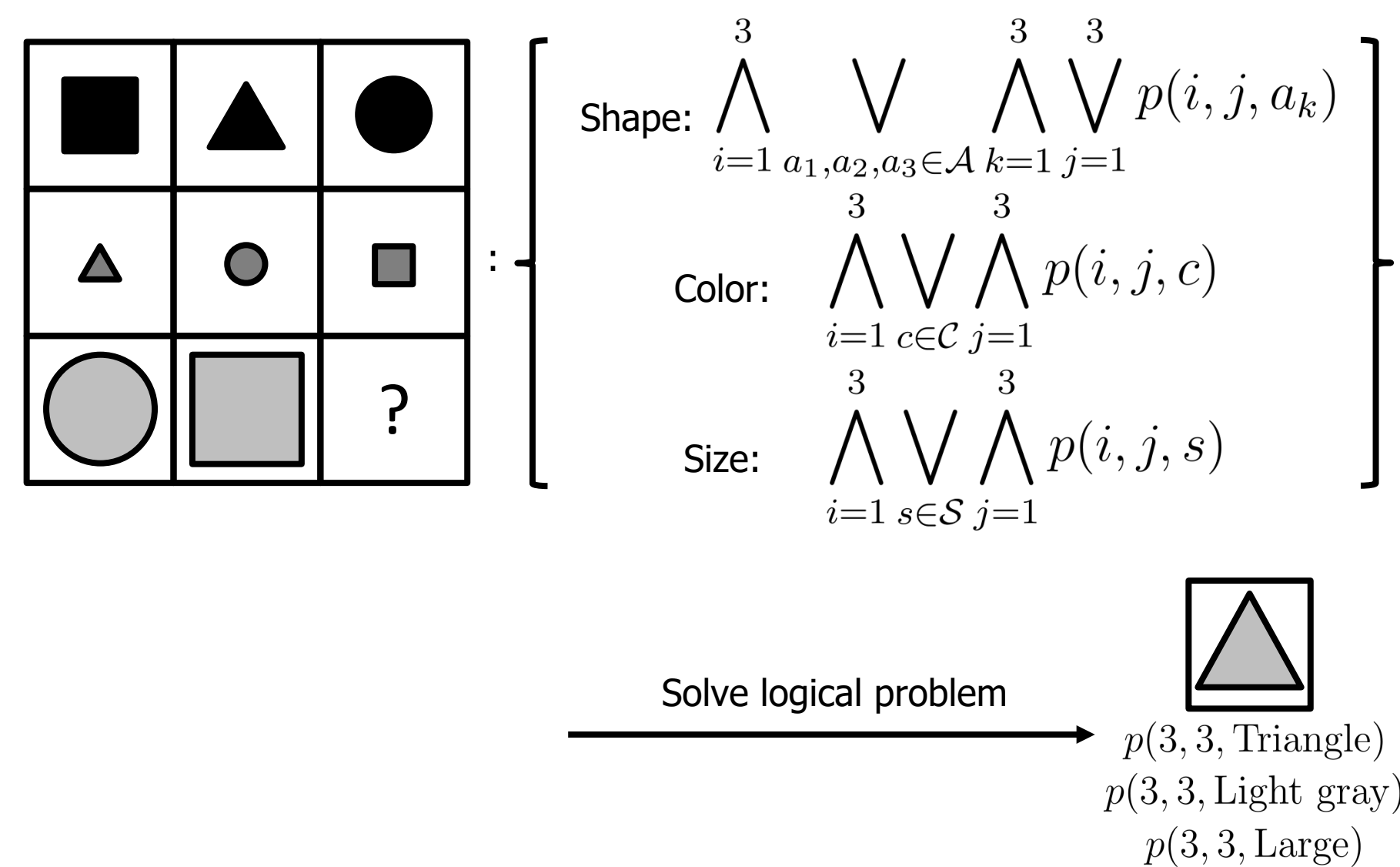


Fig 2. Illustration of reduction of the abstract reasoning problem into the propositional logic.

- Common patterns in the problem can be represented as a **propositional logical formula** with appropriate propositional variables.
- Inferring missing element of the problem is reduced into **MAXSAT problem**, a combinatorial optimization in propositional logic.

### Logic-guided Generation

Our main contribution

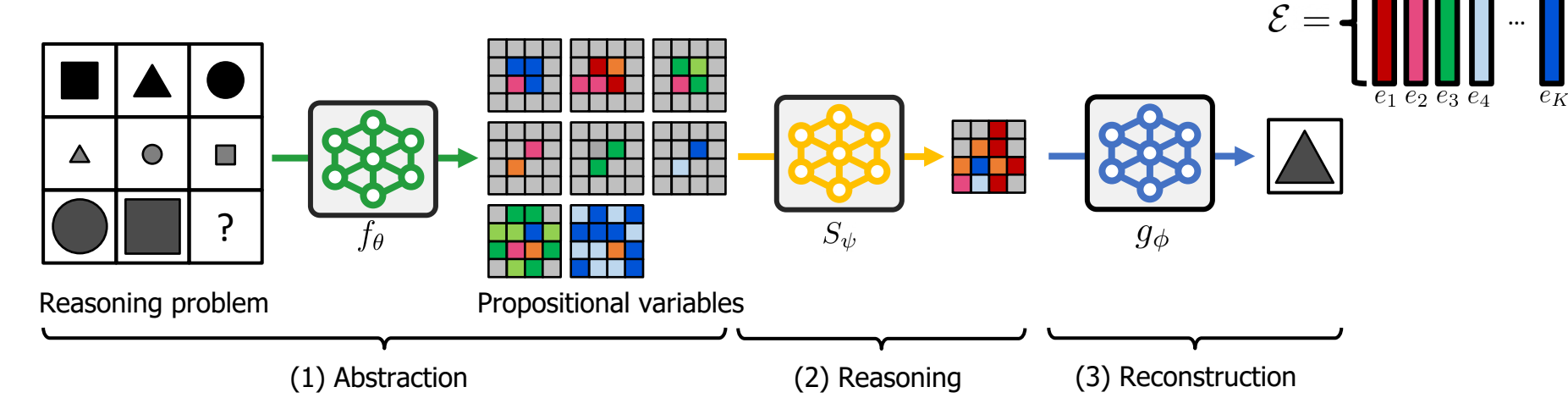


Fig 3. Overall illustration of our LoGe framework

- With this knowledge, we propose a **three-step generative framework**: abstraction, reasoning, and reconstruction.
- As only images are provided **without exact propositional variables**, LoGe utilizes discrete embeddings from images as those variables.

### Abstraction

Discrete embeddings based on vector quantization

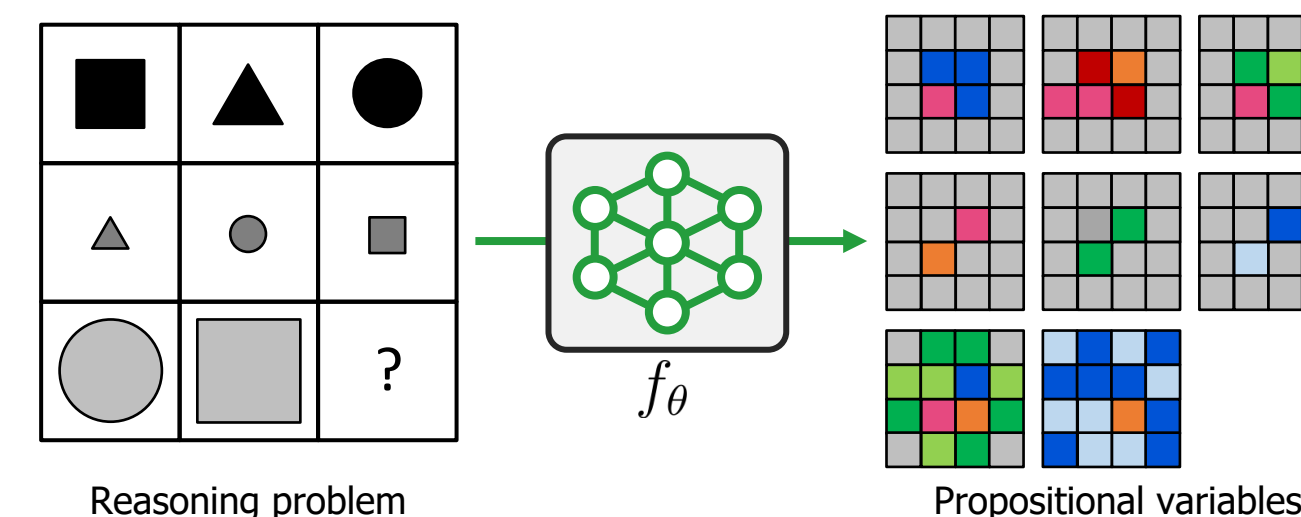


Fig 4. Illustration of the abstraction step in our framework

- Our encoder employs **vector quantization** [Van Den Oord et al., 2017] to have discrete embedding from images.
- We treat **indices of quantized vectors** as propositional variables.

### Reasoning

Prediction of discrete embeddings based on differentiable MAXSAT solver

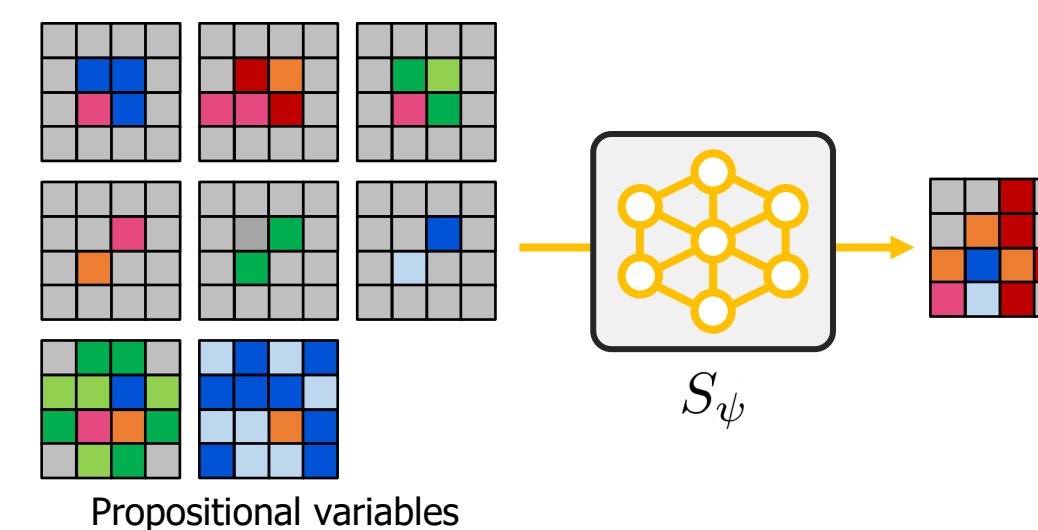


Fig 5. Illustration of the reasoning step in our framework

- LoGe predicts propositional variables of the answer by employing **SATnet layer**, a differentiable MAXSAT problem solver layer [Wang et al., 2019].
- Propositional logical formulas of common patterns are learned as SATNet layer weights from data.

### Reconstruction

Answer generation based on the predicted embeddings

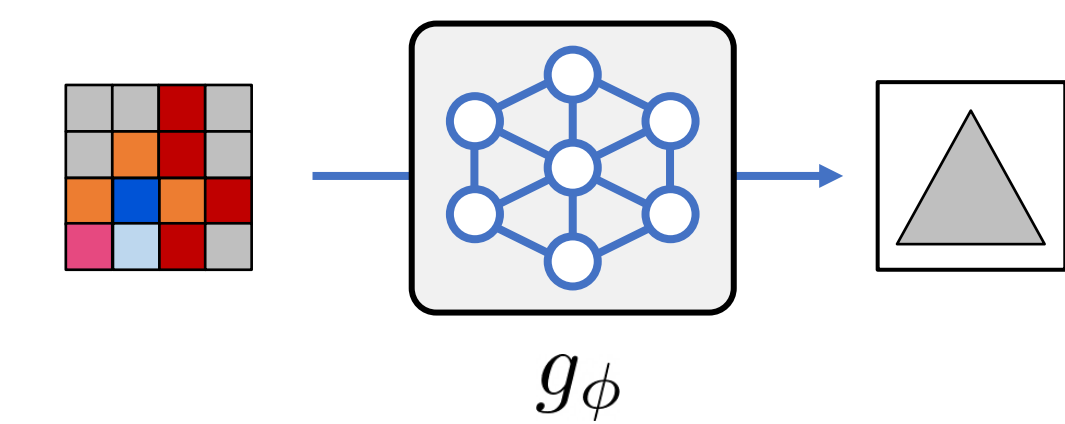


Fig 6. Illustration of the reconstruction step in our framework

- With predicted variables and the decoder network, LoGe **generates the answer image**.

### Experiments

Results from RAVEN [Zhang et al., 2019] benchmark

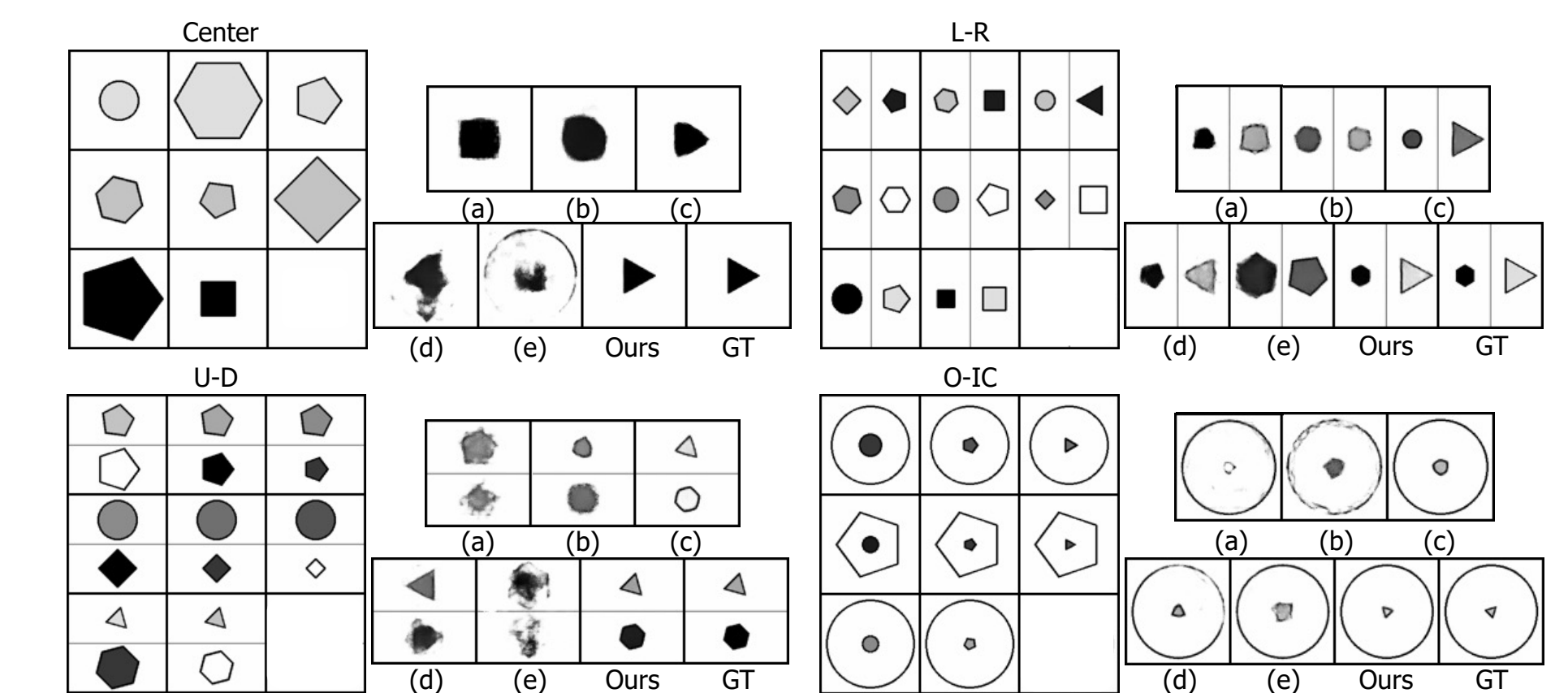


Fig 6. Qualitative results of various configurations in RAVEN benchmark

Method	Center	U-D	L-R	O-IC
LSTM (Zhang et al., 2019a)	12.3	10.3	12.7	12.9
WReN (Santoro et al., 2018)	23.3	15.2	16.5	16.8
LEN (Zheng et al., 2019)	42.5	28.1	27.6	32.9
CoPINet (Zhang et al., 2019b)	50.4	40.8	40.0	42.7
SRAN (Hu et al., 2021)	53.4	43.1	41.4	44.0
<b>LoGe (Ours)</b>	<b>87.5</b>	<b>64.0</b>	<b>51.7</b>	<b>48.5</b>

Fig 7. Quantitative results of the discriminative task in RAVEN benchmark

- We consider **RAVEN benchmark** to validate the effectiveness.
- Qualitatively, LoGe **strongly outperforms other black-box DNN generative methods** without propositional logical prior on the framework.
- LoGe also shows **improved results in a discriminative task**, compared with other prior approaches on discriminative abstract reasoning.