One Demo Is All It Takes: Planning Domain Derivation with LLMs from A Single Demonstration

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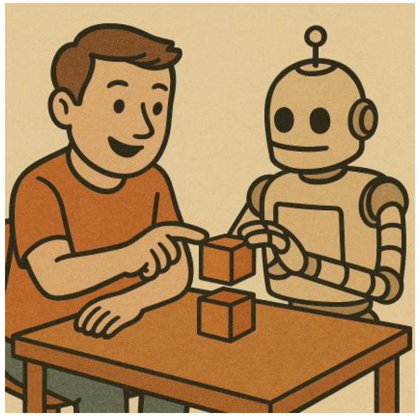
Background

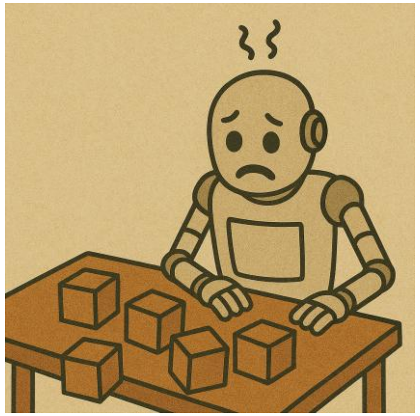
How Human Learn

1. Learn from easy cases to solve harder ones
2. Transfer knowledge across different skills and combine
3. Use logical and symbolic reasoning instead of memorizing object details

How Robot Learn

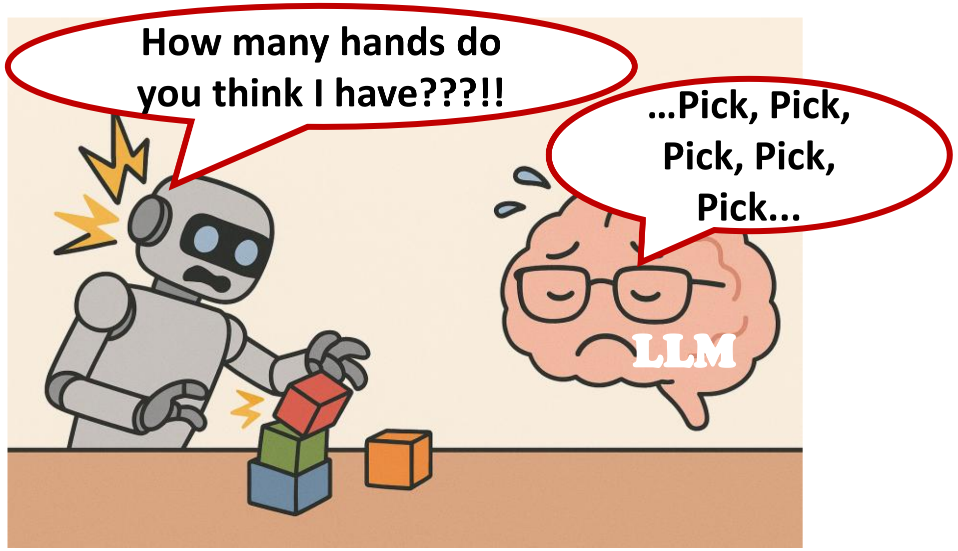
1. Learns by imitation rather than reasoning
2. Struggles to generalize beyond training data
3. Lacks abstraction, remembers raw inputs not Logical structure





Related work

Pre-trained foundation models



Advantages:

- Generalization Across Tasks.
- Semantic understanding.
- Reduced manual engineering.

Disadvantages:

- Lack of robustness.
- Struggles with long-horizon reasoning.
- Limited understanding of physical interactions.

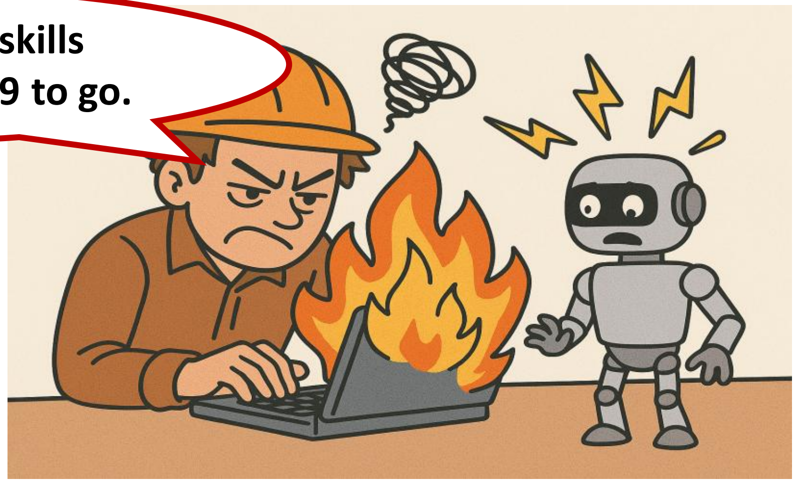
Traditional Task and Motion Planning (TAMP)

Advantages:

- Guarantee robust plan.
- High performance in long-horizontal planning.
- Strict adherence to physical and logical constraints:

Disadvantages:

- Requires task-specific planning domains.
- High engineering effort.
- Challenges in logic–continuous space integration



Related work & Contribution

Prior Work

Predicates

- Partially or completely predefined logical abstractions (predicates) [1-9]
- Detailed natural language description of the planning domain [10]

Actions

- Assume motion planning skills available beforehand [2, 3, 5,6, 7, 8,10]
- Require training data for the motion planning policy[1,9]

PDDLLM Contribution

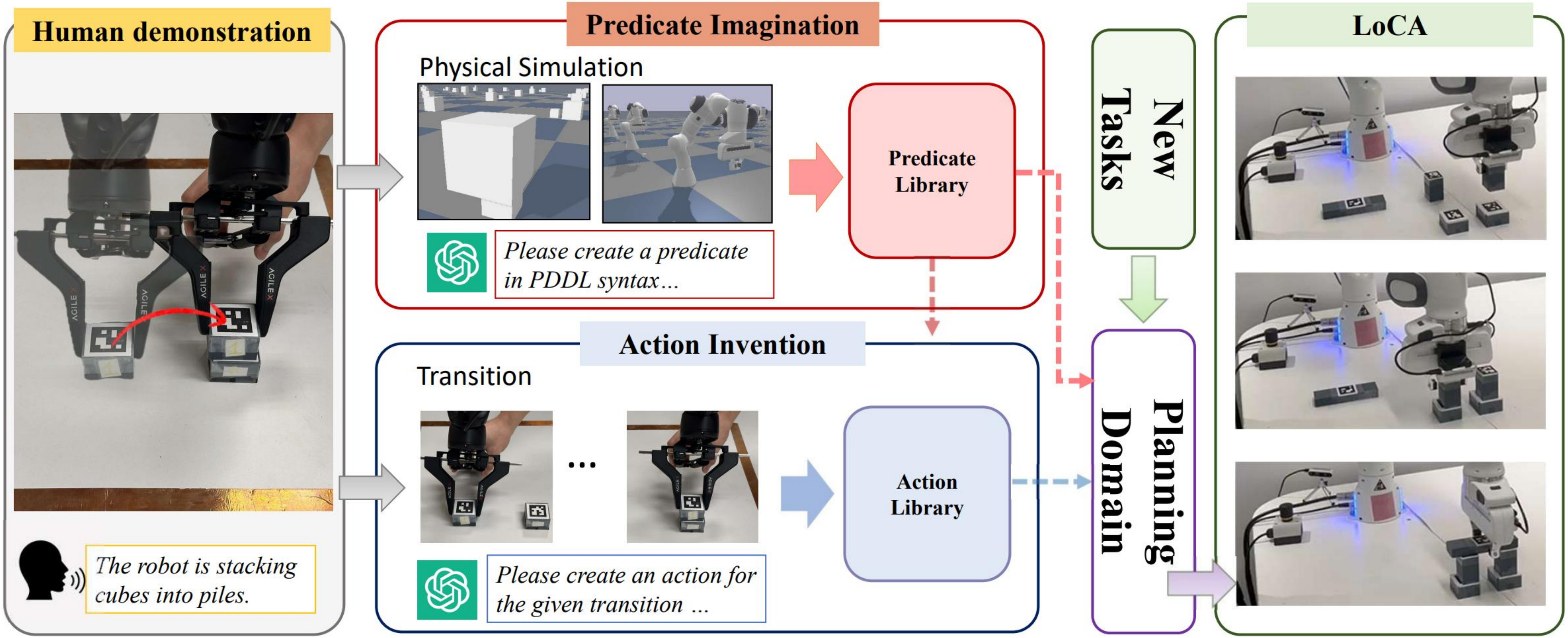
Predicates

- Generate human-readable predicates entirely from scratch.
- Only short phrase of task description is required.

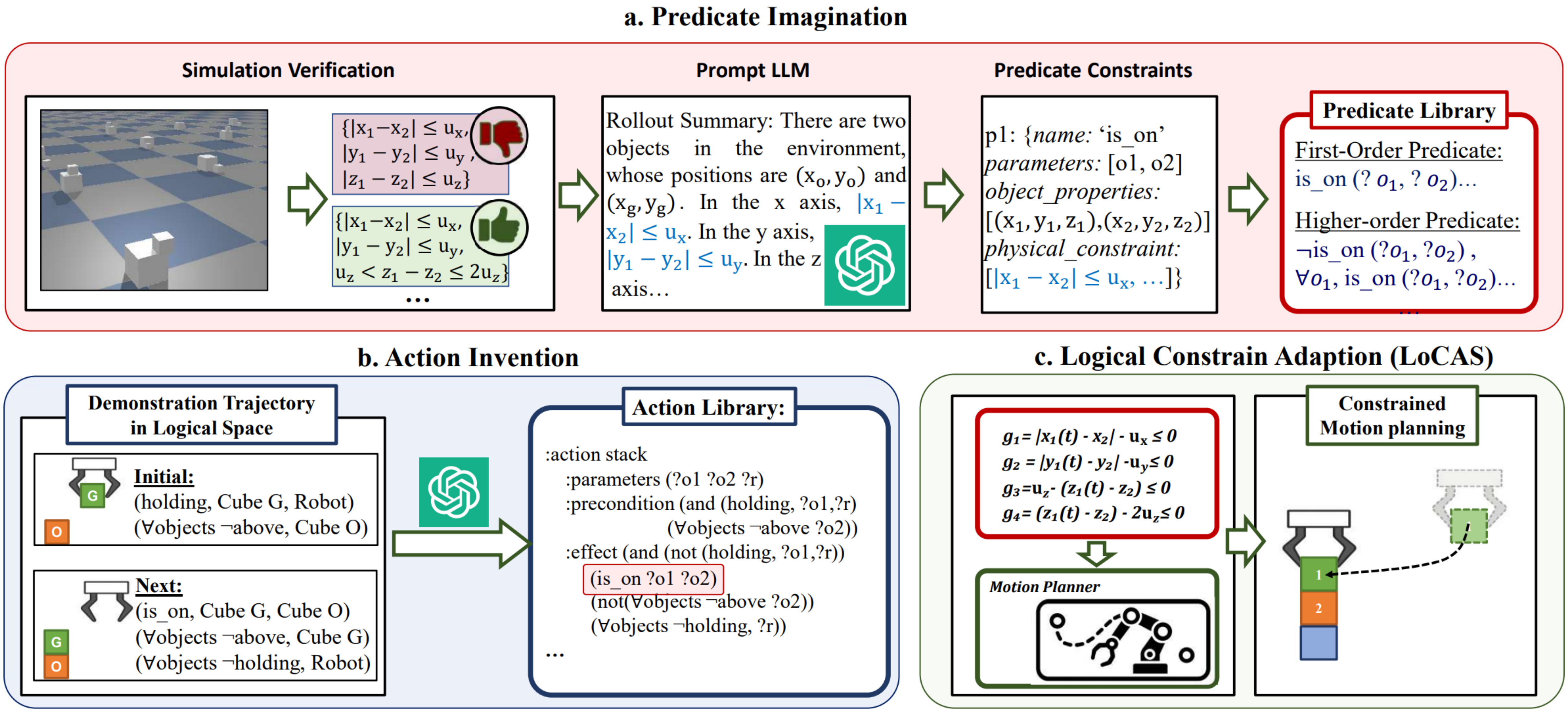
Actions

- Automatically generate logical actions.
- Automatically generate corresponding motion planning skills without training.

Method Overview



Method Details



Result

- Superior Planning Performance Against Baselines
- Robustness in Difficult Tasks
- Generalization across Diverse Tasks

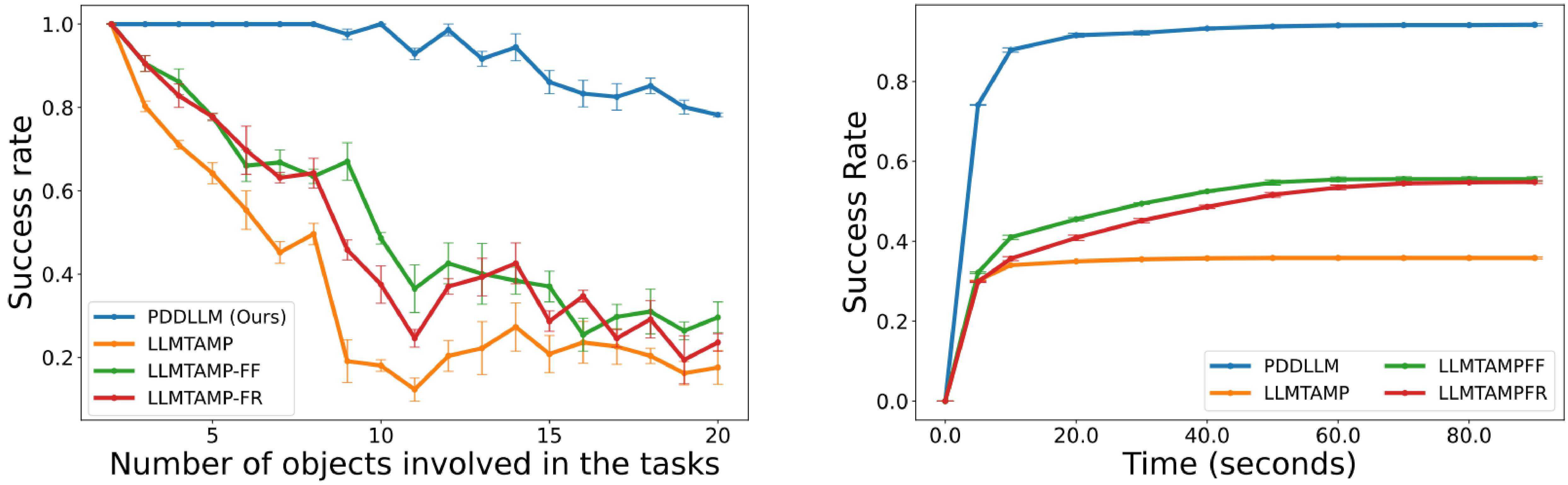
Table 1. Planning success rate (%) across tasks for all methods (time limit = 50 s).

Method	**Expert**	**LLMTAMP**	**LLMTAMP-FF**	**LLMTAMP-FR**	**RuleAsMem**	**PDDLLM**
Stack	98.5 ± 0.8	41.7 ± 4.3	70.8 ± 1.4	64.2 ± 3.1	85.5 ± 2.9	$\mathbf{97.5 \pm 1.6}$
Unstack	100 ± 0.0	89.4 ± 1.5	94.6 ± 0.9	92.1 ± 2.3	88.4 ± 1.2	$\mathbf{97.7 \pm 0.7}$
Color Classification	100 ± 0.0	18.1 ± 1.5	36.4 ± 1.1	49.0 ± 3.0	88.7 ± 2.3	$\mathbf{100 \pm 0.0}$
Alignment	100 ± 0.0	31.1 ± 3.1	52.0 ± 2.7	40.0 ± 2.4	96.0 ± 0.8	$\mathbf{100 \pm 0.0}$
Parts Assembly	98.9 ± 0.6	33.3 ± 1.5	53.9 ± 1.1	41.3 ± 1.2	95.0 ± 0.6	$\mathbf{100 \pm 0.0}$
Rearrange	73.3 ± 0.6	5.6 ± 1.0	17.4 ± 1.1	11.8 ± 1.8	1.1 ± 0.6	$\mathbf{64.3 \pm 0.7}$
Burger Cooking	100 ± 0.0	27.8 ± 2.8	50.0 ± 4.8	48.6 ± 6.9	27.8 ± 2.8	$\mathbf{91.7 \pm 4.8}$
Bridge Building	100 ± 0.0	43.3 ± 3.3	53.3 ± 3.8	51.7 ± 2.5	20.0 ± 0.0	$\mathbf{87.2 \pm 4.3}$
Tower of Hanoi	100 ± 0.0	14.3 ± 0.0	14.3 ± 0.0	14.3 ± 0.0	14.3 ± 0.0	$\mathbf{100 \pm 0.0}$
Overall	95.7 ± 0.1	35.7 ± 0.5	52.5 ± 0.4	48.6 ± 0.8	69.9 ± 0.7	$\mathbf{93.3 \pm 0.7}$

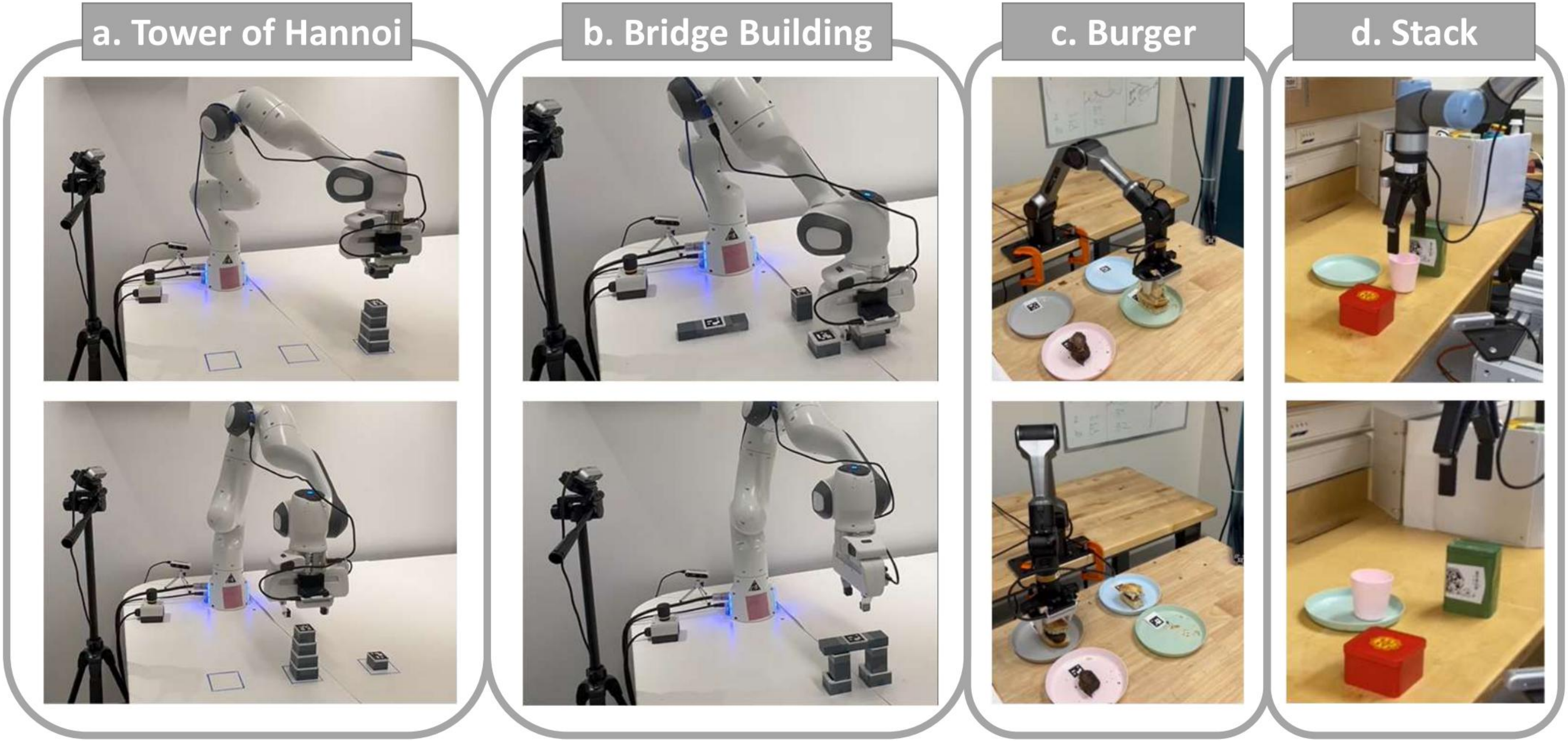
Result

- Robustness against task complexity
- Superior Time Efficiency

Figure 3. (left) Planning success rate trend across increasing object counts. (right) Overall planning success rate under varying time limits.



Real-Robot Deployment



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