

# A Survey of Robotic Language Grounding: Tradeoffs between Symbols and Embeddings

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# Robotic Language Grounding

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1. What grounding representation to use?
2. How to ground natural language to the grounding representation of choice?

# Robotic Language Grounding



# Grounding Language to Symbols



## Symbols

- Discrete
- More Structure; More bias
- Unambiguous
- Verifiable
- Interpretable

# Grounding Language to Embeddings



## Symbols

- Discrete
- More Structure; More bias
- Unambiguous
- Verifiable
- Interpretable

## High-dimensional Embeddings

- Continuous
- Less structure; More variance
- Adaptive

# Grounding Language to Logic





# Grounding Language to Logic



## Pros

- Unambiguous semantics
- Verifiable
- Interpretable
- Reduce search space

# Grounding Language to Logic



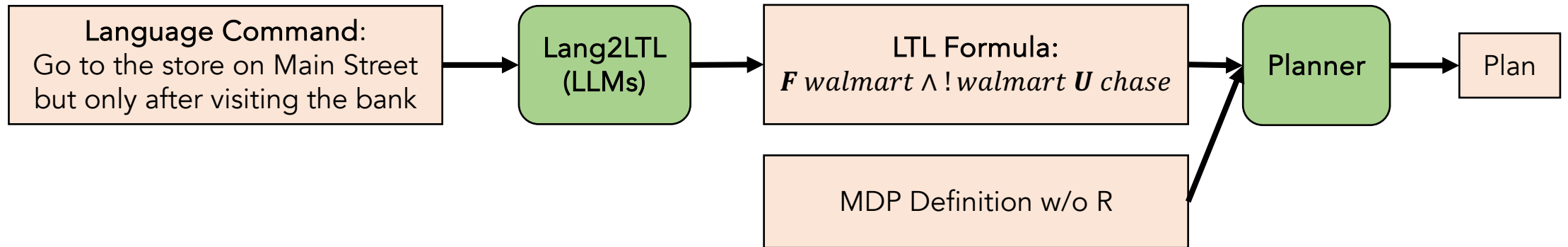
## Pros

- Unambiguous semantics
- Verifiable
- Interpretable
- Reduce search space

## Cons

- Require manually defined structures
- Difficult to represent low-level control

# Grounding Language to Logic: Lang2LTL



## Lang2LTL

- Natural language navigation command
- Modular system produces a grounded linear temporal logic (LTL) formula
- Given MDP definition
- Planner outputs a trajectory

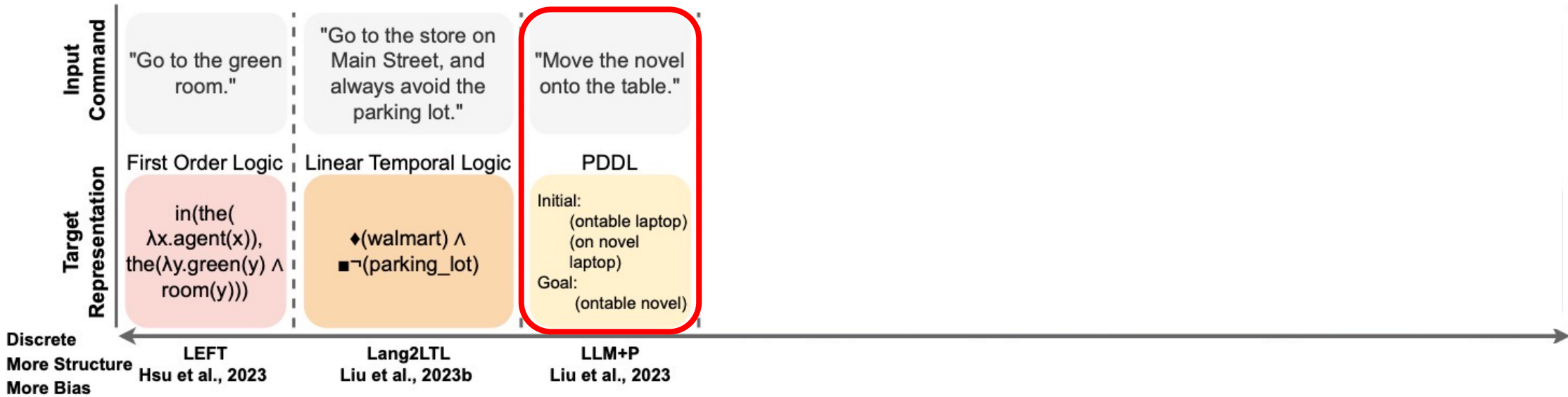
# Grounding Language to Logic



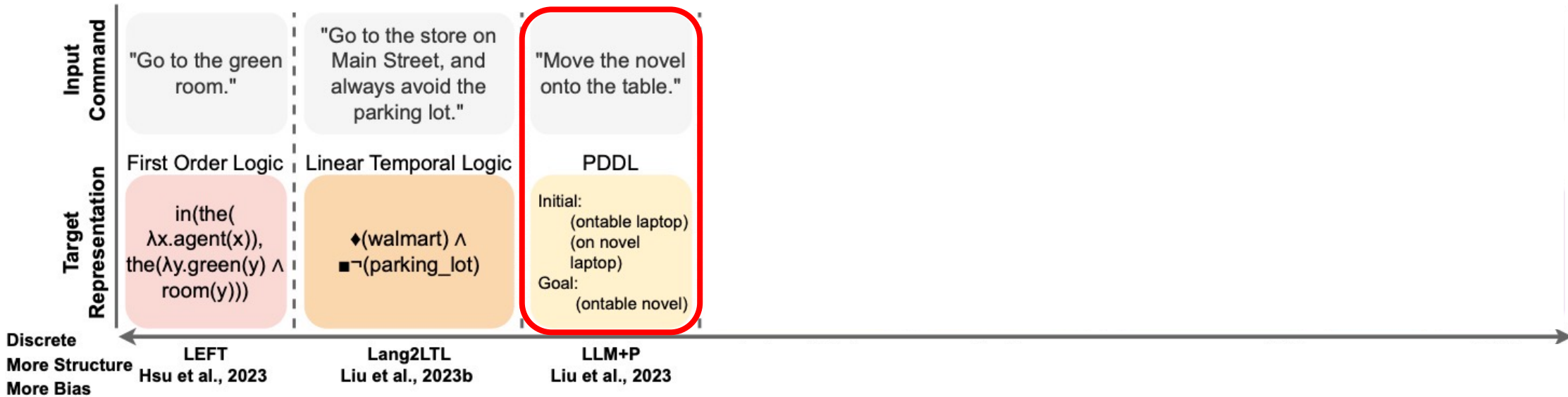
## More Papers

- Lang2LTL-2: Grounding Spatiotemporal Navigation Commands Using Large Language and Vision-Language Models [Liu et al. 2024]
- AutoTAMP: Autoregressive Task and Motion Planning with LLMs as Translators and Checkers [Chen et al. 2024]
- NL2TL: Transforming Natural Languages to Temporal Logics using Large Language Models [Chen et al. 2023]
- NL2LTL: a Python Package for Converting Natural Language (NL) Instructions to Linear Temporal Logic (LTL) Formulas [Fuggitti and Chakraborti 2023]

# Grounding Language to PDDL



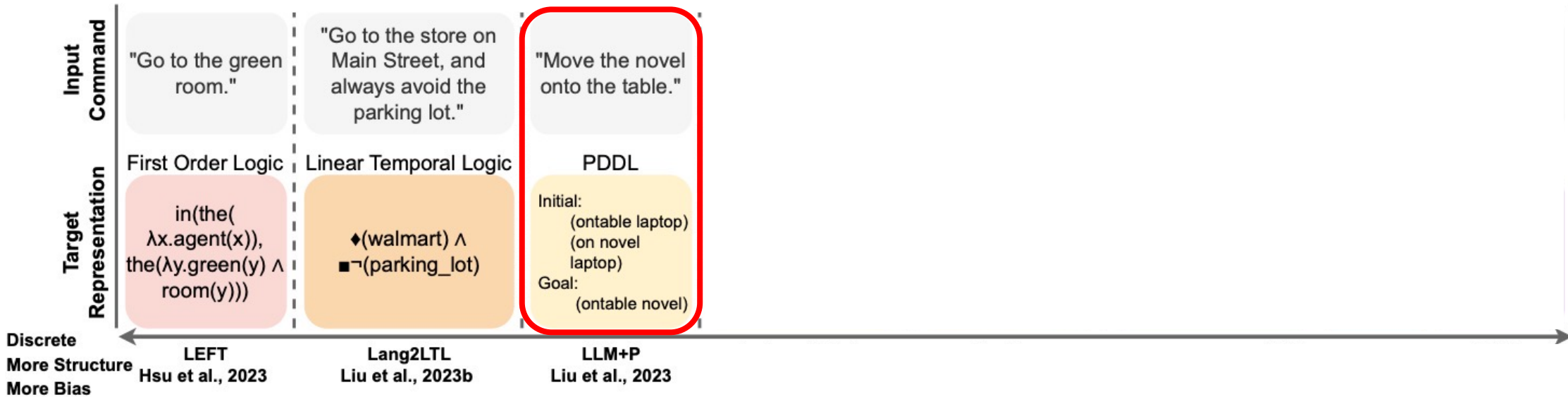
# Grounding Language to PDDL



## Pros

- Sound
- Complete
- (Often) Optimal

# Grounding Language to PDDL



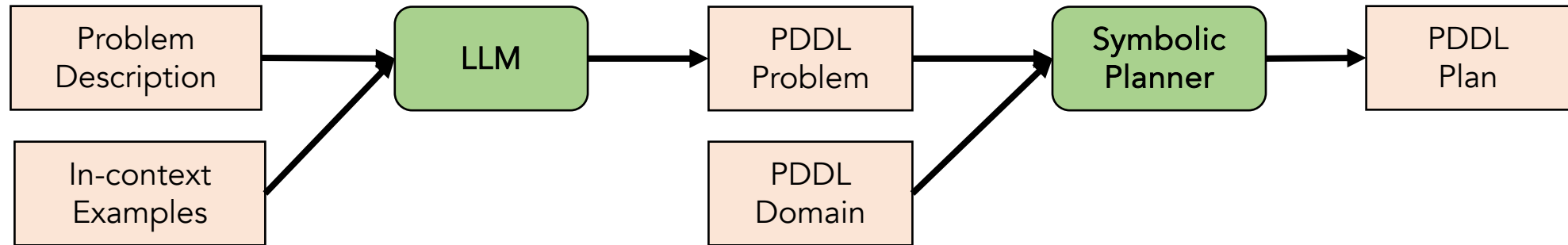
## Pros

- Sound
- Complete
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## Cons

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# Grounding Language to PDDL: LLM+P

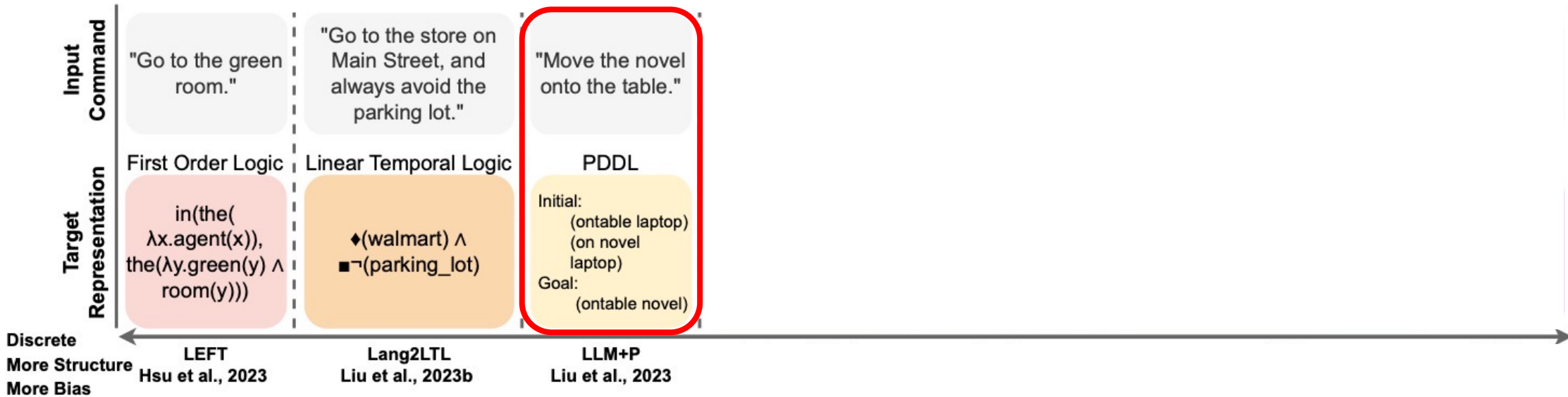


## LLM+P

- Natural language description of a planning problem
- LLM translates it to PDDL problem
- Given a PDDL domain description, i.e., action preconditions and effects
- Symbolic planner solves PDDL



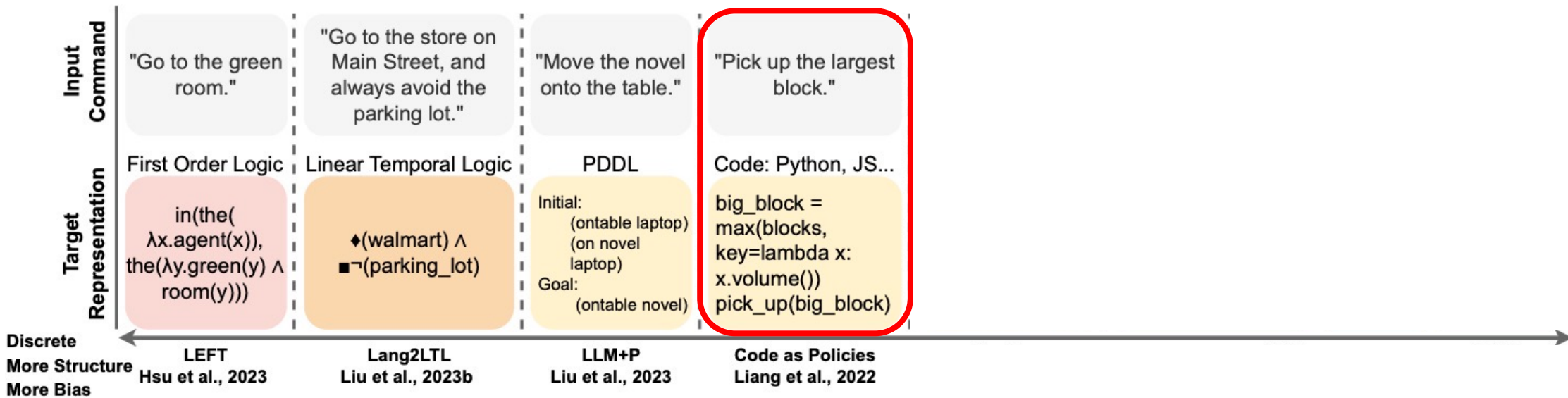
# Grounding Language to PDDL



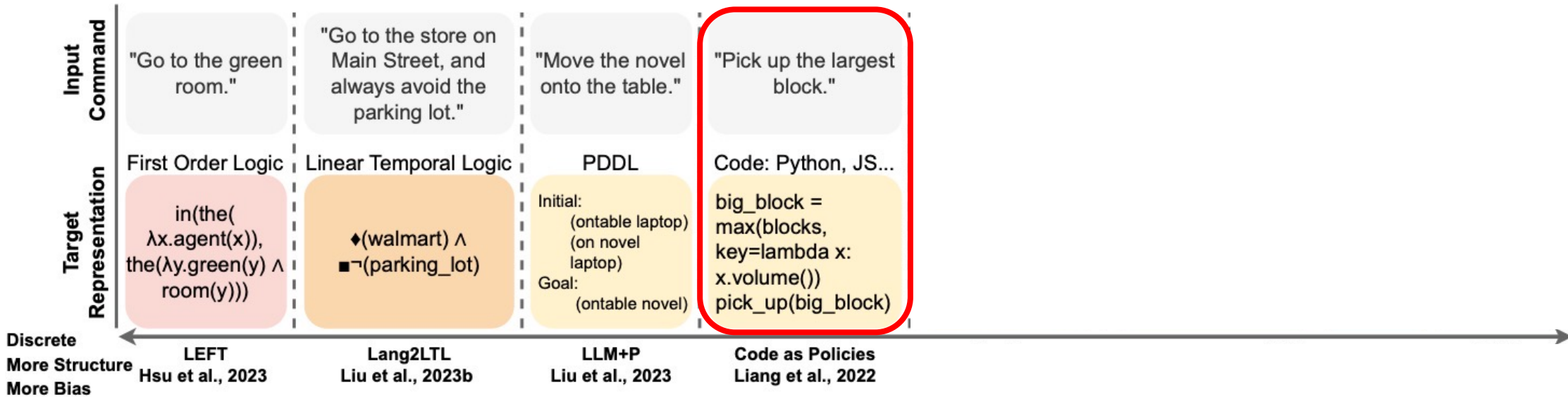
## More Papers

- Translating Natural Language to Planning Goals with Large-Language Models [Xie et al. 2023]
- Structured, Flexible, and Robust: Benchmarking and Improving Large Language Models Towards More Human-like Behavior in Out-of-distribution Reasoning Tasks [Collins et al. 23]
- Leveraging Pre-trained Large Language Models to Construct and Utilize World Models for Model-based Task Planning [Guan et al. 2023]
- PlanBench: An Extensible Benchmark for Evaluating Large Language Models on Planning and Reasoning about Change [Valmeekam et al. 2023]
- On the Planning Abilities of Large Language Models : A Critical Investigation [Valmeekam et al. 2023]

# Grounding Language to Code



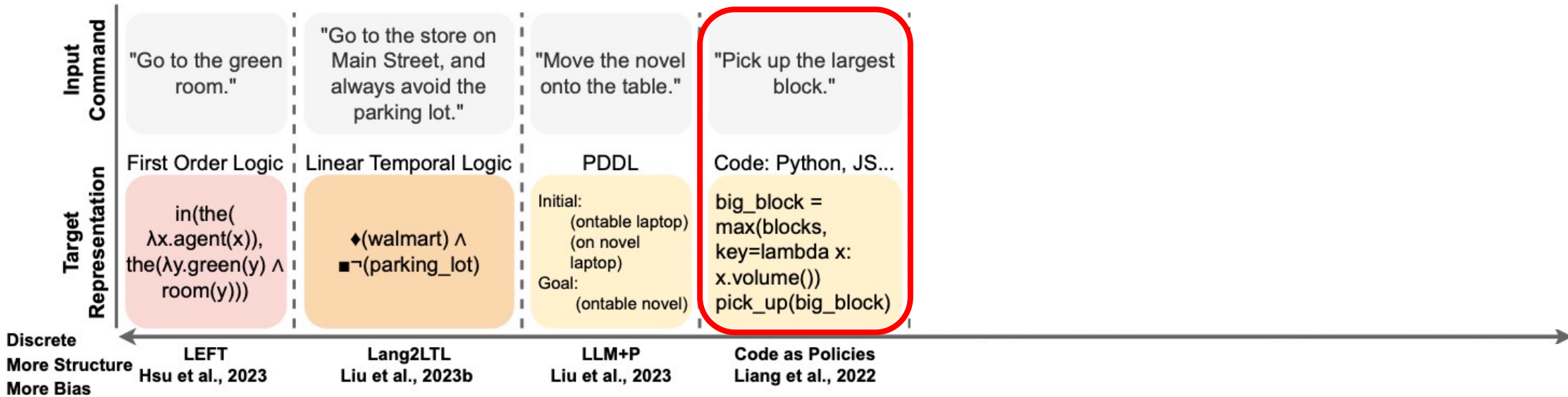
# Grounding Language to Code



## Pros

- Flexible
- High-level plan and low-level control

# Grounding Language to Code



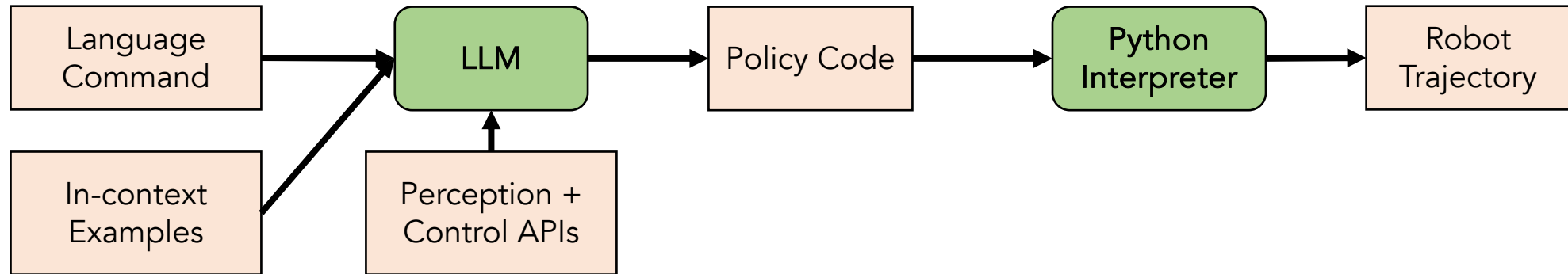
## Pros

- Flexible
- High-level plan and low-level control

## Cons

- Require predefined perception and control models in specific domains

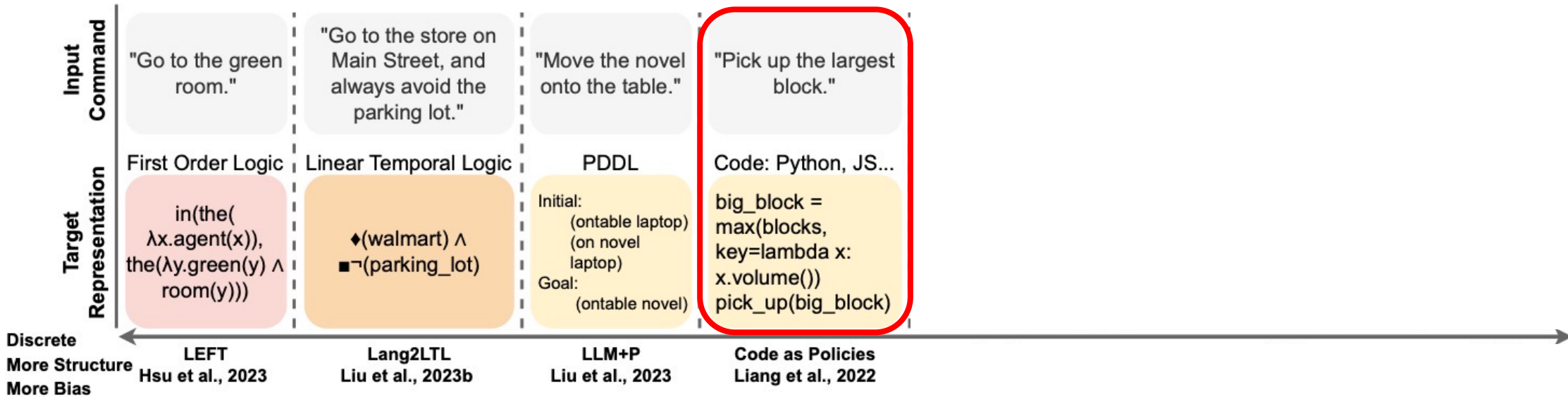
# Grounding Language to Code: Code as Policies



## Code as Policies

- Natural language command
- Given predefined perception and control models
- Code-writing LLM outputs executable code

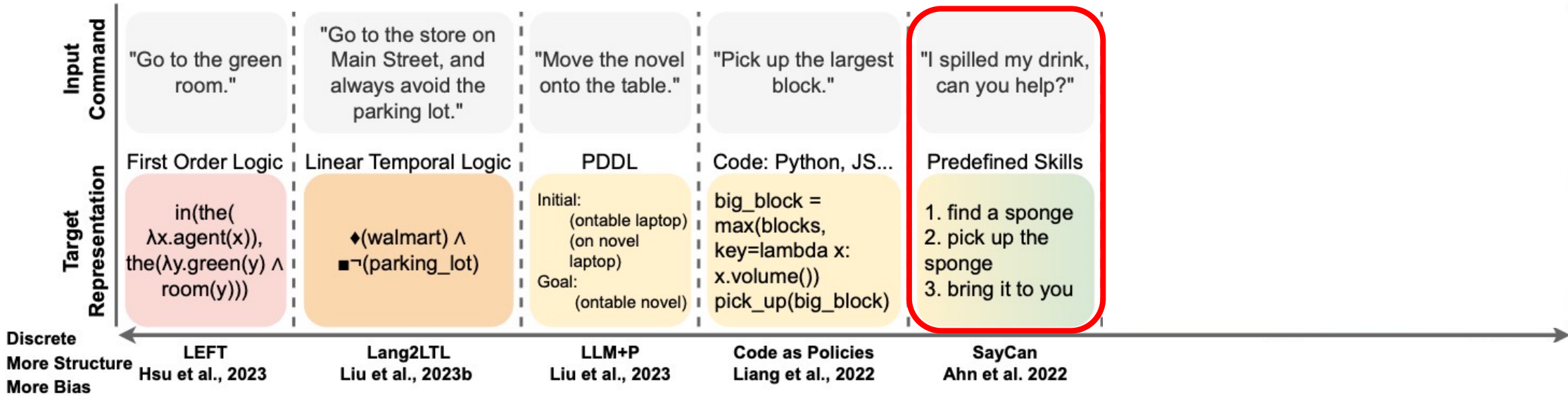
# Grounding Language to Code



## More Papers

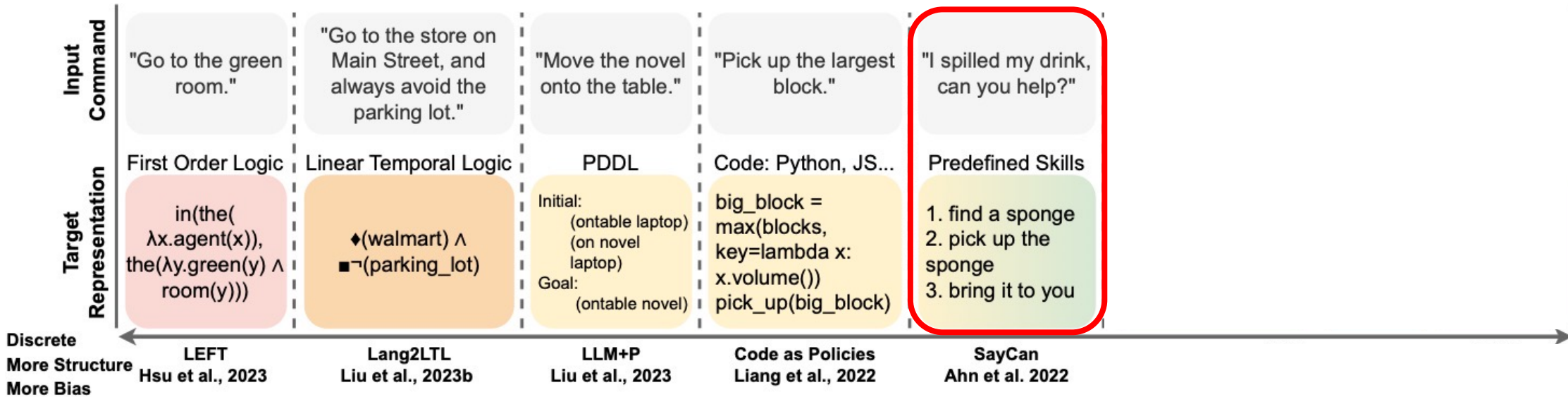
- Embodied AI with Two Arms: Zero-shot Learning, Safety and Modularity [Varley et al. 2024]
- ProgPrompt: Generating Situated Robot Task Plans using Large Language Models [Singh et al. 2023]
- Socratic Models: Composing Zero-Shot Multimodal Reasoning with Language [Zeng et al. 2023]
- ITP: Interactive Task Planning with Language Models [Li et al. 2023]
- Voyager: An Open-ended Embodied Agent with Large Language Models [Wang et al. 2023]

# Grounding Language to Predefined Skills





# Grounding Language to Predefined Skills

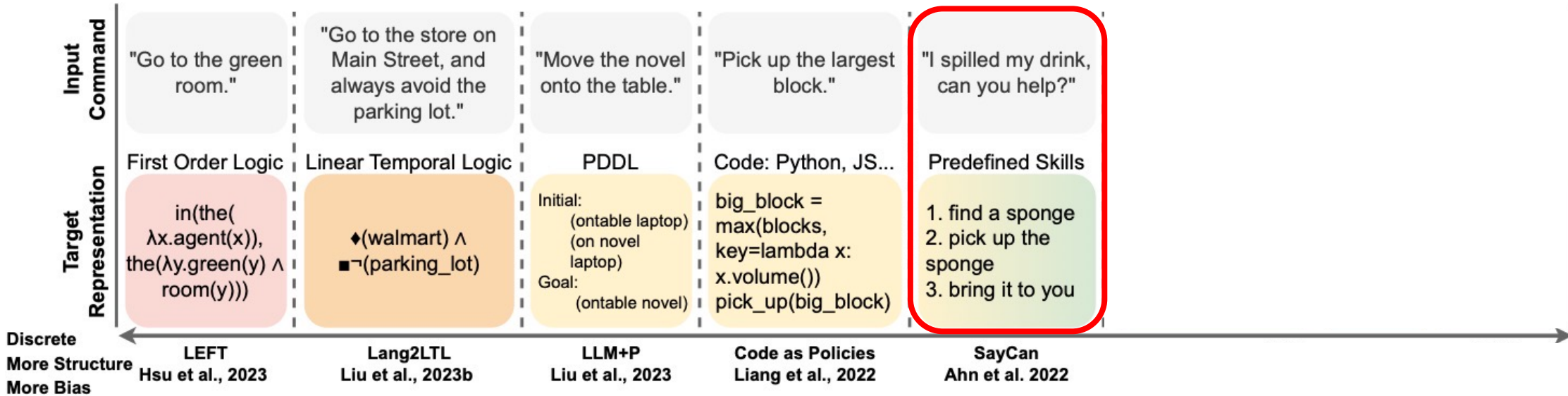


## Pros

- Adaptive



# Grounding Language to Predefined Skills



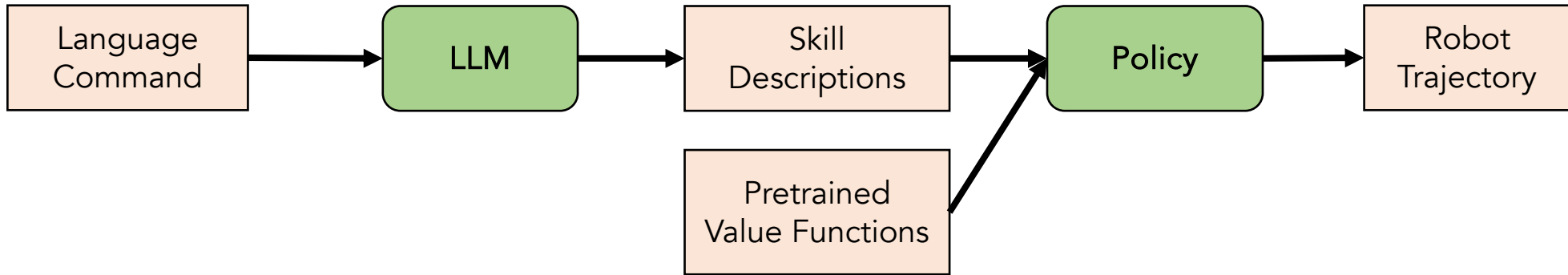
## Pros

- Adaptive

## Cons

- Require predefined skills
- Possibly incorrect plans

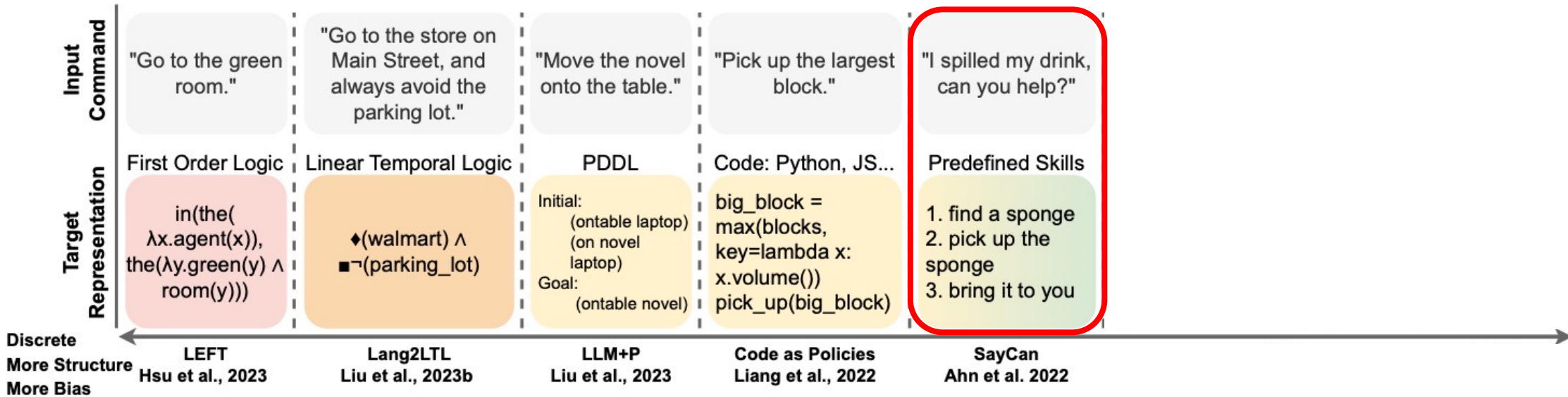
# Grounding Language to Predefined Skills: SayCan



## SayCan

- Natural language command
- LLM proposes candidate skills every step
- Pretrained value functions to rank available skills
- Language-conditioned policies execute the top skill

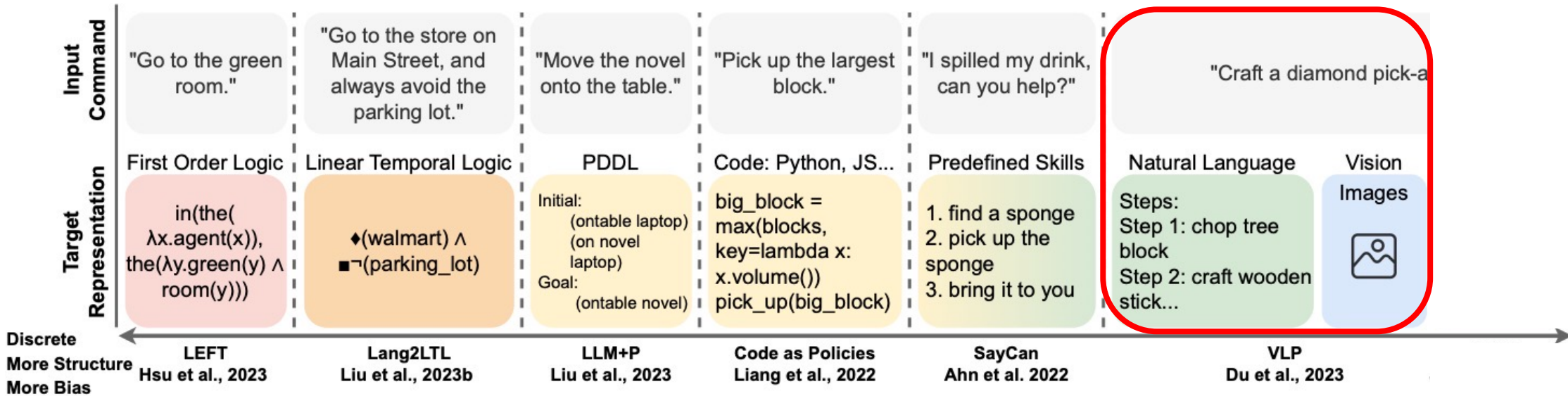
# Grounding Language to Predefined Skills



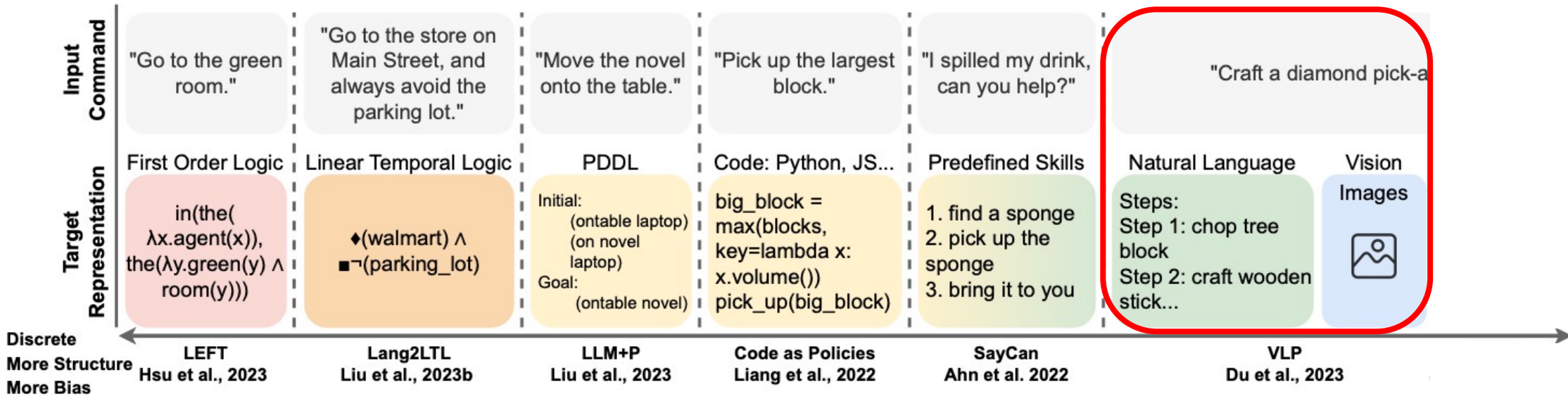
## More Papers

- CAPE: Planning with Large Language Models via Corrective Re-prompting [Raman et al. 2024]
- Inner Monologue: Embodied Reasoning through Planning with Language Models [Huang et al. 2022]
- Language Models as Zero-shot Planners: Extracting Actionable Knowledge for Embodied Agent [Huang et al. 2022]

# Grounding Language to Subgoals



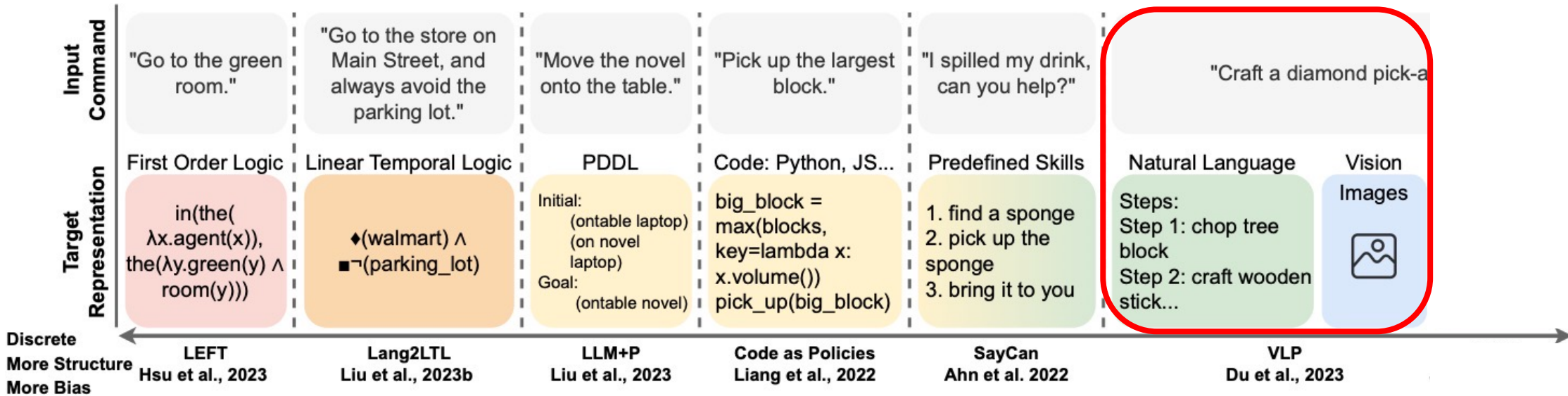
# Grounding Language to Subgoals



## Pros

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# Grounding Language to Subgoals



## Pros

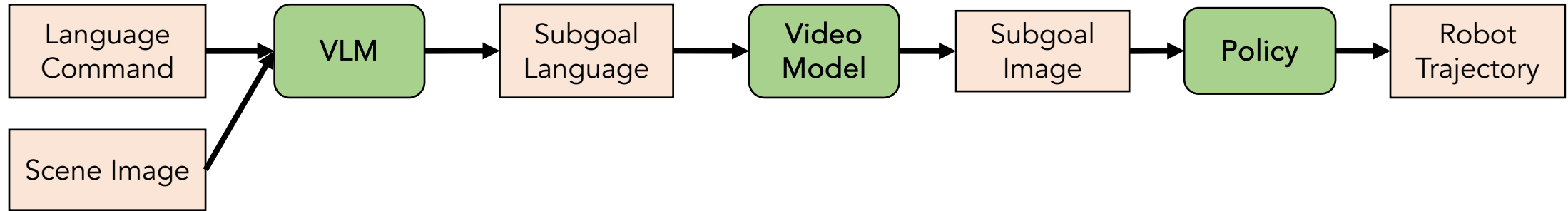
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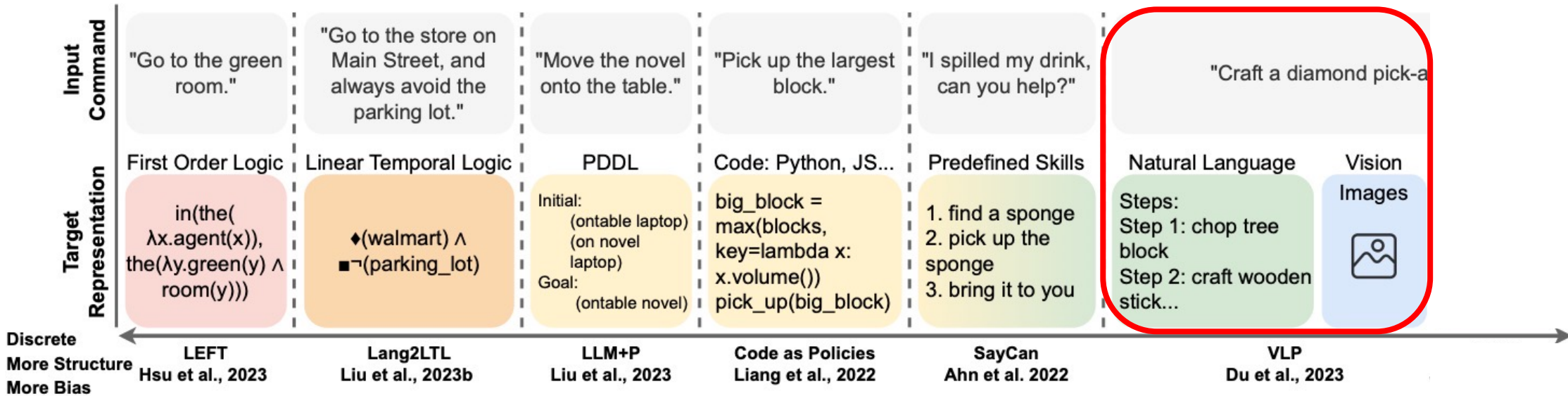
# Grounding Language to Subgoals: VLP



## Video Language Planning (VLP)

- Tree search
- VLM proposes language subgoals
- Video model conditioned on text generates image subgoals
- Policy conditioned on image executes the plan

# Grounding Language to Subgoals

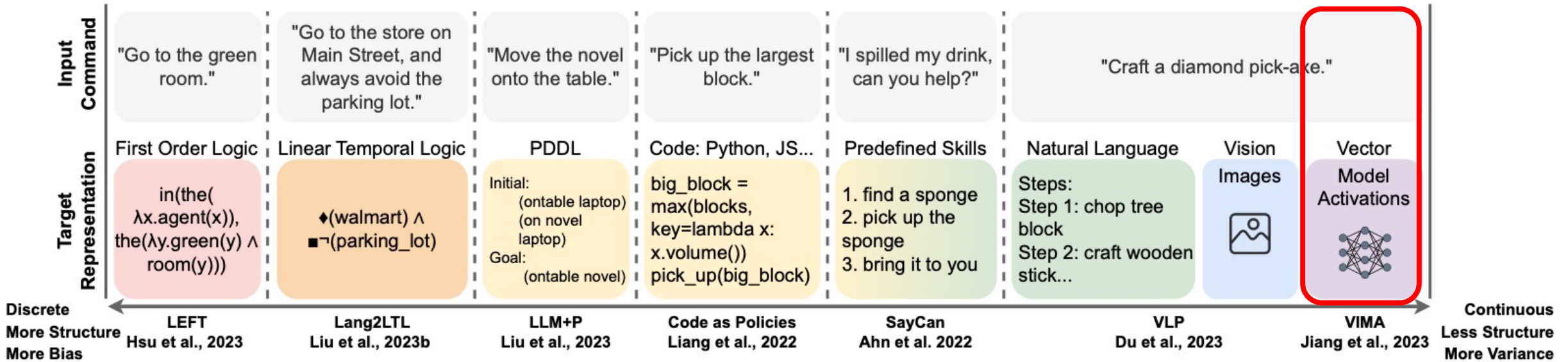


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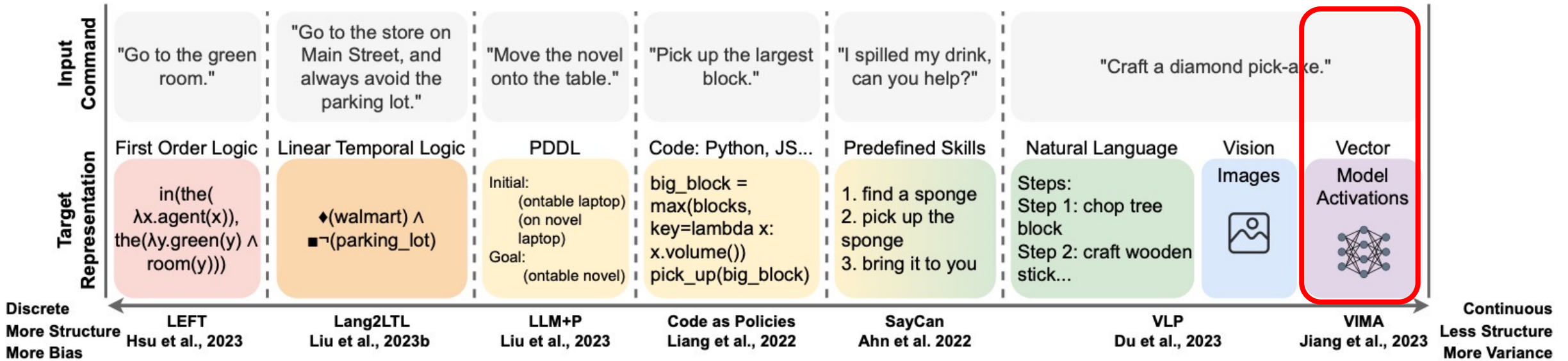
- Zero-Shot Robotic Manipulation with Pretrained Image-Editing Diffusion Models [Black et al. 2023]
- UniSim: A Neural Closed-Loop Sensor Simulator [Yang et al. 2023]
- GAIA-1: A Generative World Model for Autonomous Driving [Hu et al. 2023]



# Grounding Language to Embeddings



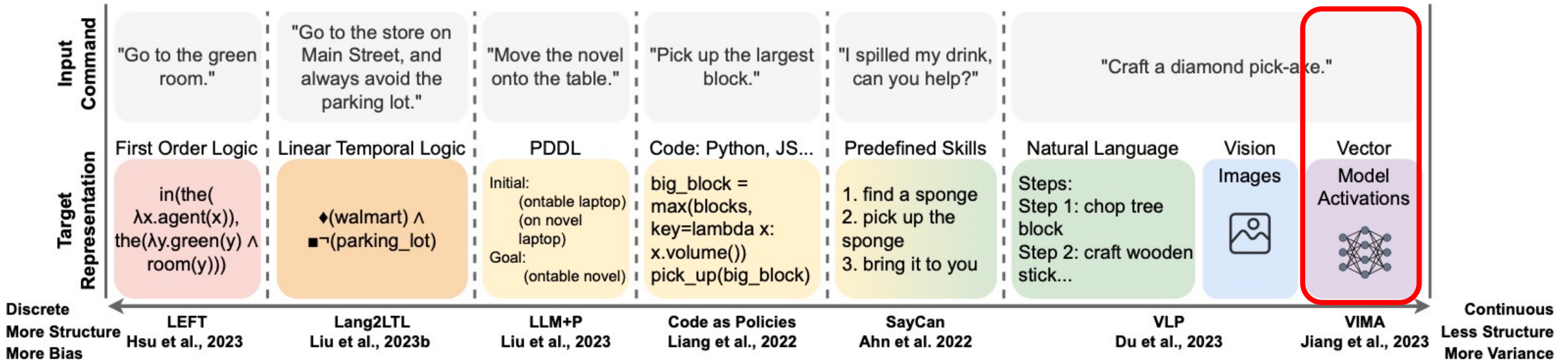
# Grounding Language to Embeddings



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# Grounding Language to Embeddings



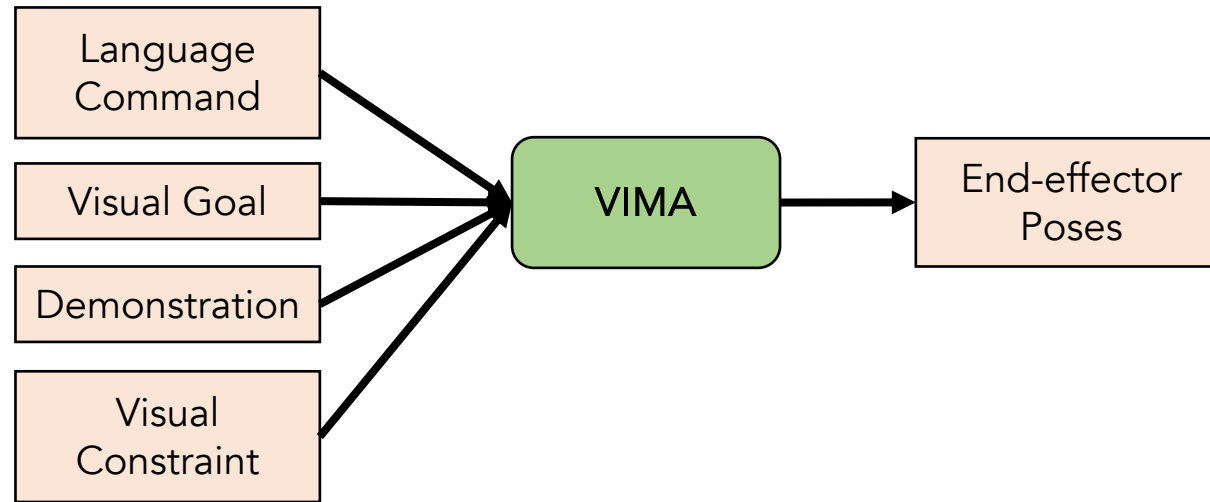
## Pros

- Adaptive

## Cons

- Large training set and compute
- Possibly incorrect actions

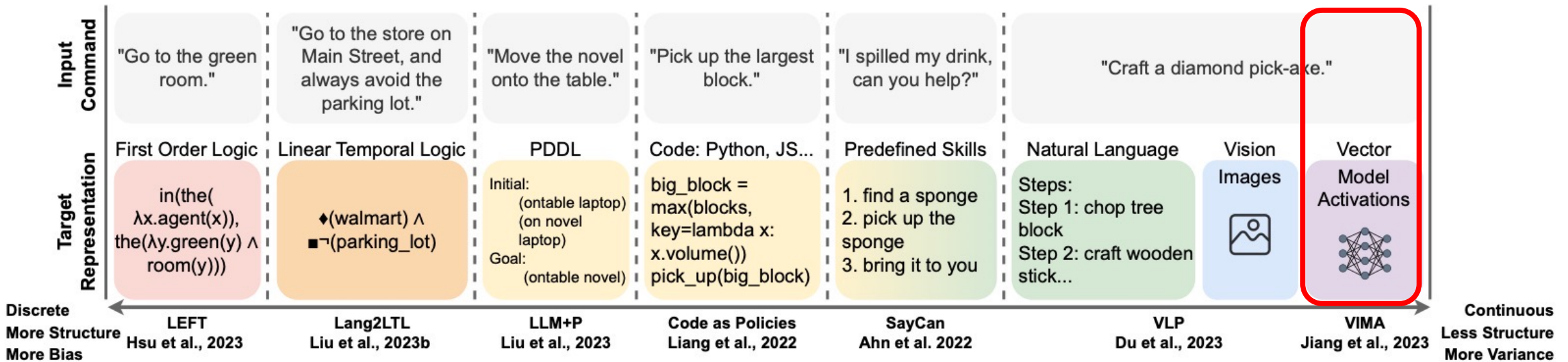
# Grounding Language to Embeddings: VIMA



## VIMA

- Tokenize multimodal input
- Transformer architecture
- Output end-effector poses

# Grounding Language to Embeddings

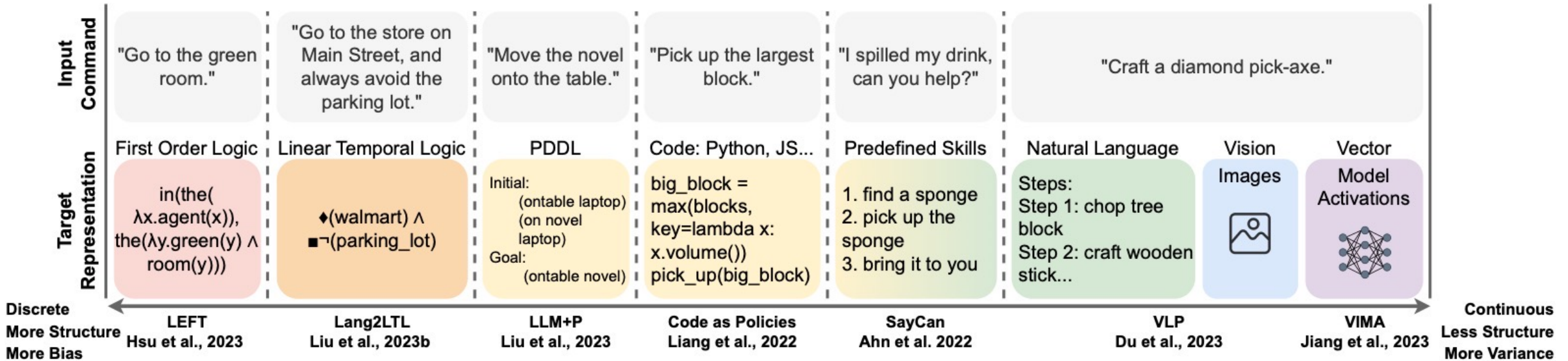


## More Papers

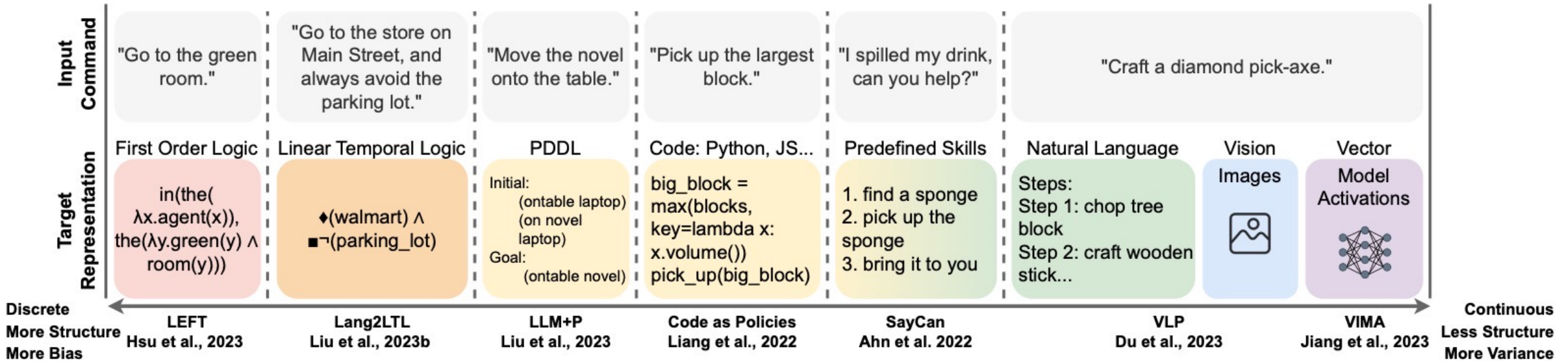
- Octo: An Open-Source Generalist Robot Policy [Octo Model Team 2024]
- Open X-Embodiment: Robotic Learning Datasets and RT-X Models [Open X-Embodiment Collaboration 2024]
- RT-2: Vision-Language-Action Models Transfer Web Knowledge to Robotic Control [Brohan et al. 2023]
- RT-1: Robotics Transformer for Real-World Control at Scale [Brohan et al. 2023]
- PaLM-E: an Embodied Multimodal Language Model [Driess et al. 2023]
- Vision-Language Foundation Models as Effective Robot Imitators [Li et al. 2023]
- GATO: A Generalist Agent [Reed et al. 2022]
- Perceiver-Actor: A Multi-Task Transformer for Robotic Manipulation [Shridhar et al. 2022]
- Video PreTraining (VPT): Learning to Act by Watching Unlabeled Online Videos [Baker et al. 2022]



# Language Grounding for Robots



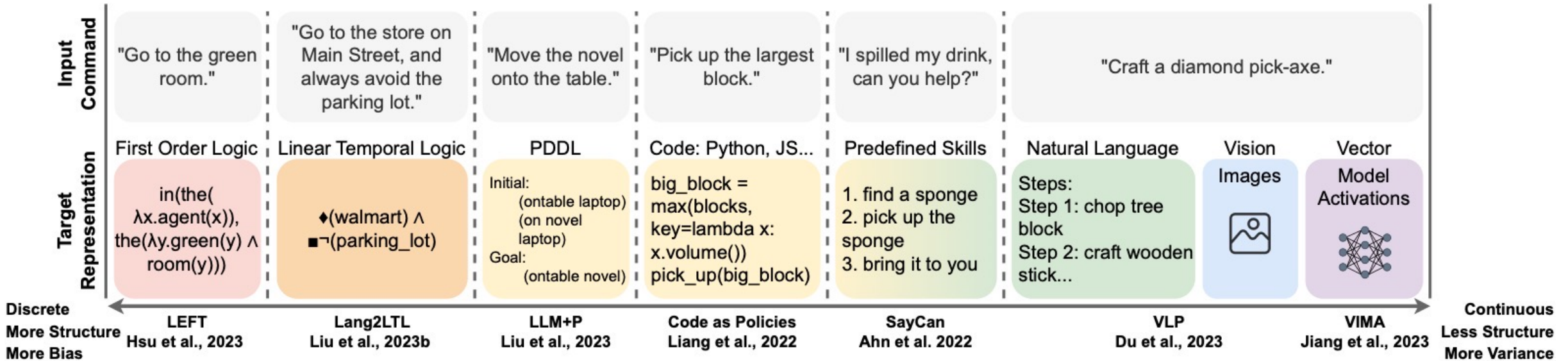
# Language Grounding for Robots



## Discrete Symbols

- Logic
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- Code
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## High-dimensional Embeddings

- Language and image subgoals
- Neural embeddings



# Open Problems and Future Directions

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  - POMDP and PDDL planners
  - Deep learning models with generalizable representations
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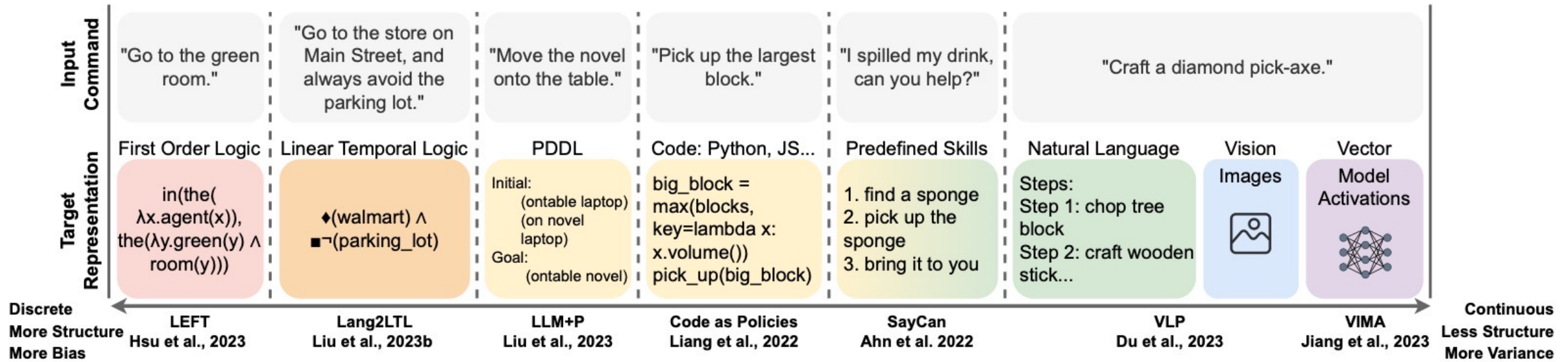
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- **Verification and Safety**
  - Formal methods

# Conclusion



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Poster Location:  
E15

<https://arxiv.org/abs/2405.13245>