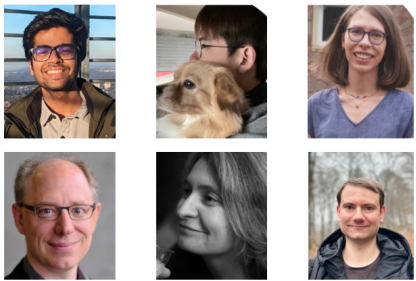
On the Ability of Transformers to Verify Plans

Yash Sarrof[†,1], Yupei Du[*,1], Katharina Stein[*,1],
Alexander Koller[1], Sylvie Thiébaux[2,3], Michael Hahn[1]

[1]Saarland University [2]Australian National University [3]University of Toulouse / LAAS-CNRS

[†]Led Theory [*]Led Experiments



Prior Work: Inconsistent Transformer Success

- Transformer-based LLMs have had mixed results in planning tasks.[1,2]
- They can perform well in distribution, but on longer plans or OOD, their performance drops.
- Why does this happen?
- We take *first steps* towards *understanding* this.

Domain	In-Distrib.		Long	
	valid. rate	*exec. rate*	*valid. rate*	*exec. rate*
BLOCKS	98.5%	98.5%	13.5%	23.5%
LOGISTICS	**100%**	**100%**	14.0%	20.5%
BARMAN	**100%**	**100%**	25.0%	43.5%
CHILDSNACK	**100%**	**100%**	66.0%	67.0%
DEPOTS	98.5%	98.5%	31.0%	37.0%
DRIVERLOG	**100%**	**100%**	31.0%	50.7%
GRIPPERS	99.0%	99.0%	50.5%	76.0%
SATELLITE	99.0%	99.2%	51.5%	53.0%

Domain	Unseen	
	valid. rate	*exec. rate*
HANOI	**0%**	35%
STORAGE	**0%**	**1%**

Domain	Obfuscated	
	valid. rate	*exec. rate*
BLOCKS	**0%**	**0%**
LOGISTICS	**0%**	**0%**

Table 1: Performance of the fine-tuned LLM across various test sets with no additional strategies applied. Although the LLM performs well on in-distribution, it struggles to generalize to OOD cases.

Table from Fritzsche et al.[2]

[1] Huang et al. "Chasing Progress, Not Perfection: Revisiting Strategies for End-to-End LLM Plan Generation." ICAPS, 2025.

[2] Fritzsche et al. "Symmetry-Aware Transformer Training for Automated Planning." ICAPS, 2026.

Some Preliminaries

Planning Domain

A domain $\mathcal{D} = \langle \mathcal{P}, \mathcal{A} \rangle$ consists of predicates and action schemas that act as templates.

- $\mathcal{P}$: templates for propositions that define the state of the world.
- $\mathcal{A}$: templates for actions (each has preconditions and effects) that change the state.

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Planning Instance

A planning instance instantiates a domain with concrete objects, an initial state, and a goal state.

$$\Pi = \langle \mathcal{D}, \mathcal{O}, I, G \rangle$$

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Plan & Validity

A plan is a sequence of actions $\pi = [a_1, \ldots, a_n]$.
It is valid if every action is applicable and starting from the initial state, our final state is the goal.

Example of a Domain

Colors Domain

Predicates:

$\mathcal{P} = \{\text{bag}(b),\ \text{color}(c),\ \text{hasColor}(b, c)\}$

Action $\text{add}(c, b)$
Pre: $\{\text{bag}(b),\ \text{color}(c)\}$
Eff: $\{\text{hasColor}(b, c)\}$

Action $\text{remove}(c, b)$
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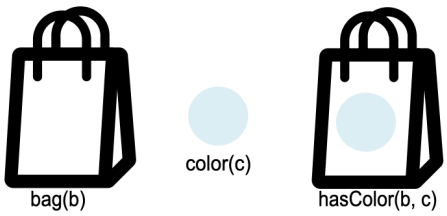

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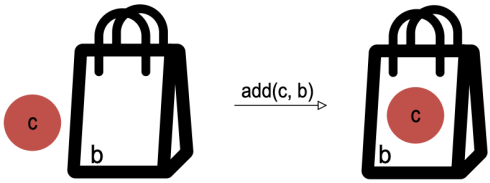

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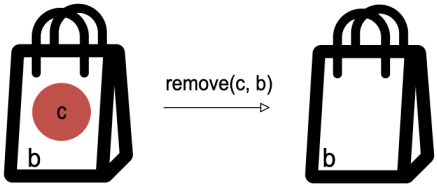

Example of an Instance

Objects = {O4, O7, O11, O13}

Initial = {bag(O4), bag(O13), color(O7), color(O11)}

Goal = {hasColor(O4, O7), hasColor(O4, O11)}

Example of a Valid Plan

Generalization: Longer Plans & More Objects

Train on small examples $\Longrightarrow$ verify harder examples

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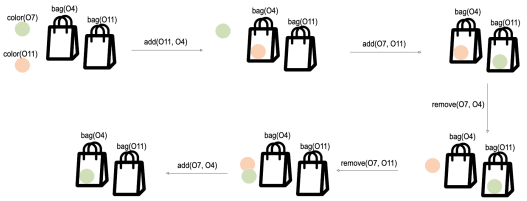
Fixed Universe

- (I, G) change, O is fixed.



Generalization: Longer Plans & More Objects

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Fixed Universe

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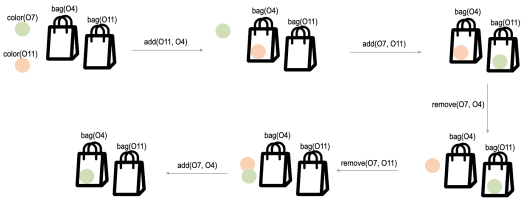
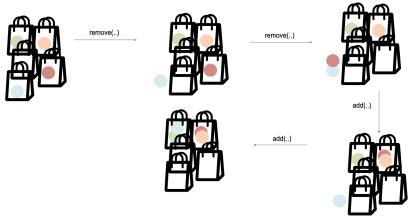
Variable Universe

- (I, G, O) can change.





A framework for length generalization

C-RASP[1]

Symbolic Programming language.

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ICLR 2025

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Boolean-Valued Operations	
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Boolean	$P(i) := \neg P_1(i)$ $P(i) := P_1(i) \wedge P_2(i)$
Positional	$P(i) := \phi(i) \text{ for } \phi \in \Phi$
Constant	$P(i) := \top$
Comparison	$P(i) := C_1(i) \leq C_2(i)$

Count-Valued Operations	
Counting	$C(i) := \#\left[j \leq i, \psi(i,j)\right] \; P(j)$ for $\psi \in \Psi \cup \{\top\}$
Conditional	$C(i) := P(i) \; ? \; C_1(i) : C_2(i)$
Add/Subtract	$C(i) := C_1(i) \pm C_2(i)$
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Guarantee [2]

Transformers are predicted to length generalize on tasks for which a **C-RASP** program exists.

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Introducing **C*-RASP**: Framework for length and symbolic generalization

Problem

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- **C*-RASP** program exists $\rightarrow$ Transformers generalize to longer lengths + bigger vocabulary.

Main Results about Planning Classes

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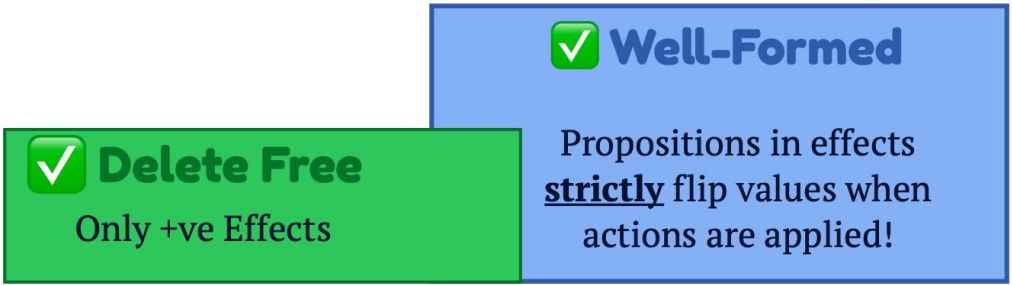

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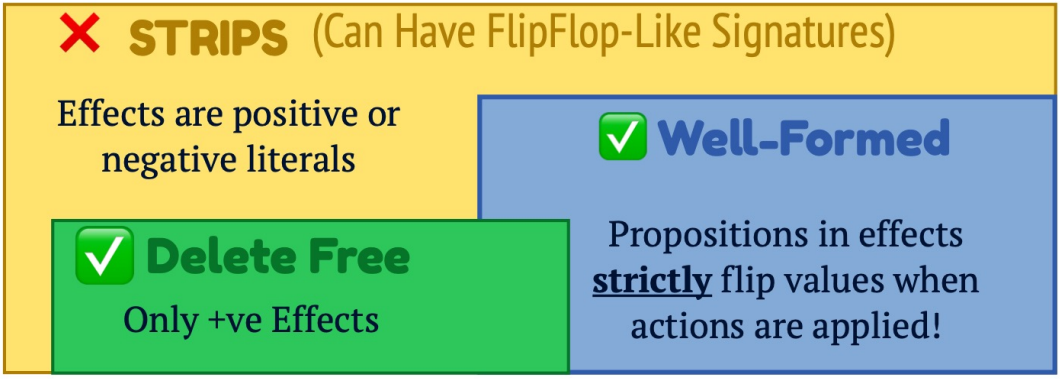

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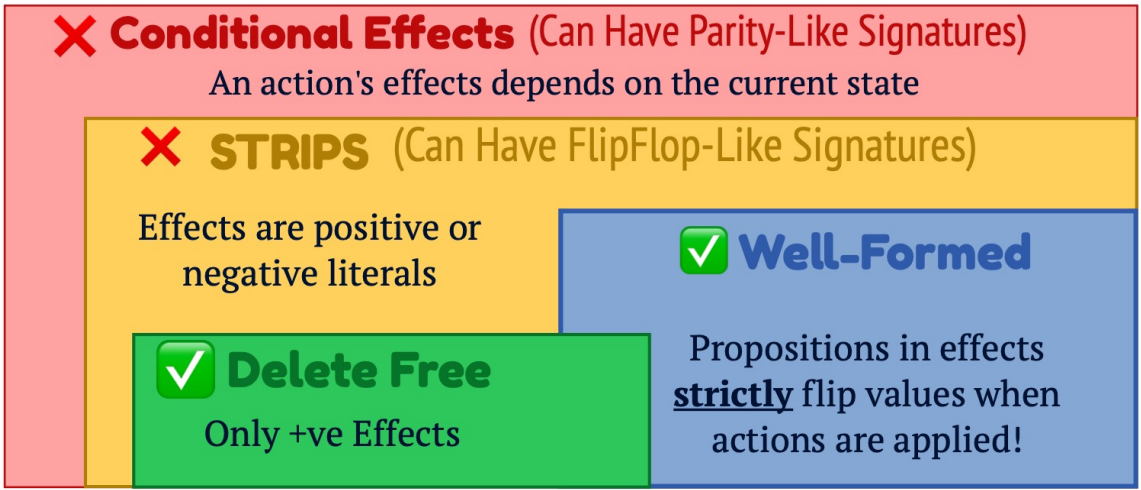
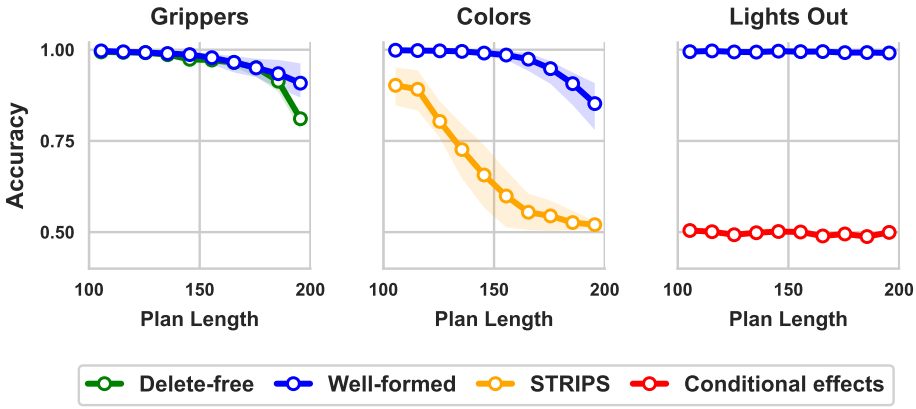


Minimal pair of experiments validate our theory!



Limitations & Takeaways

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Takeways

- **C*-RASP** can be used to understand generalization in planning.
  - longer plans
  - more objects
- The formulation of the planning problem can enable/inhibit transformer generalization.