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LTL2Action: Generalizing LTL Instructions for Multi-Task RL

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SCHWARTZ REISMAN INSTITUTE FOR TECHNOLOGY AND SOCIETY

CIFAR

Motivation

How can humans specify high-level objectives to an RL agent?

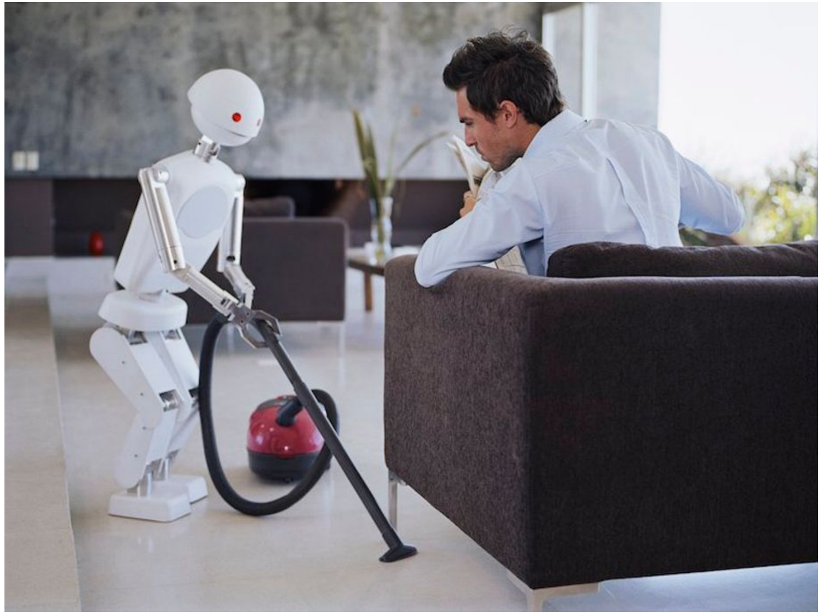

Photo: Javier Pierin (Getty Images)

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via Reward Function?

Infeasible for humans to program for every possible task.

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via Natural Language?

Unclear what reward to optimize.

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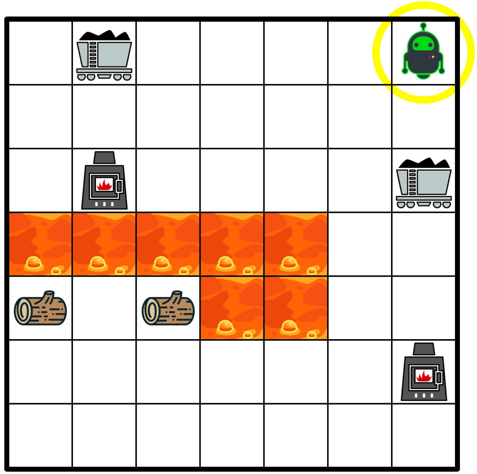

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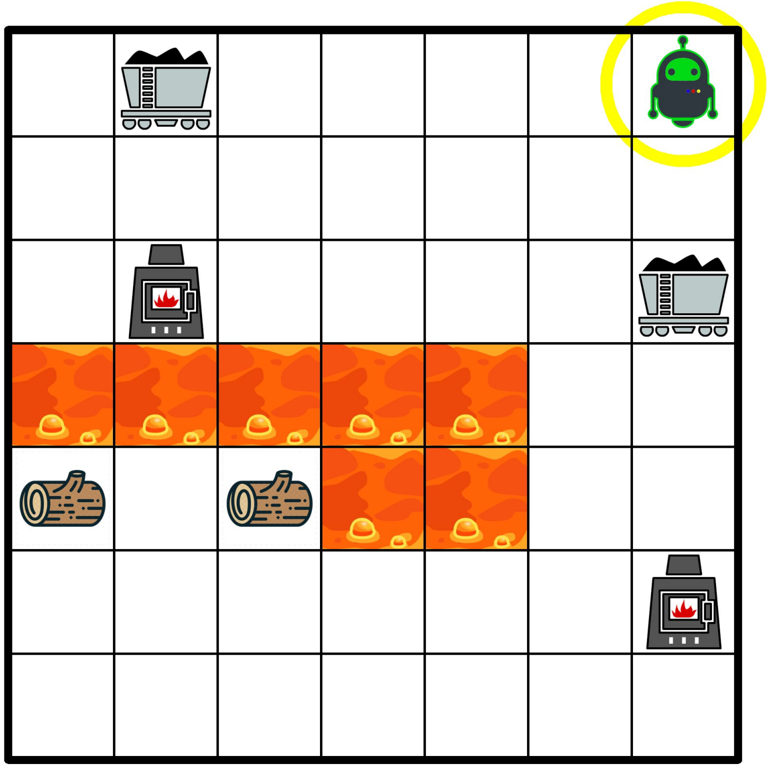
  - **Zero-shot generalization** to unseen and larger instructions

What tasks can be expressed in LTL?



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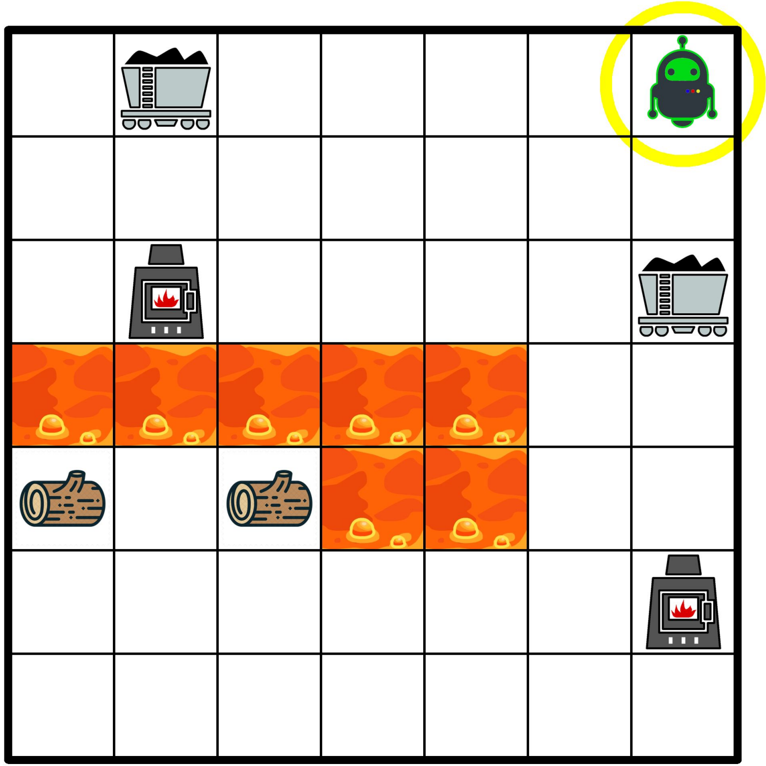

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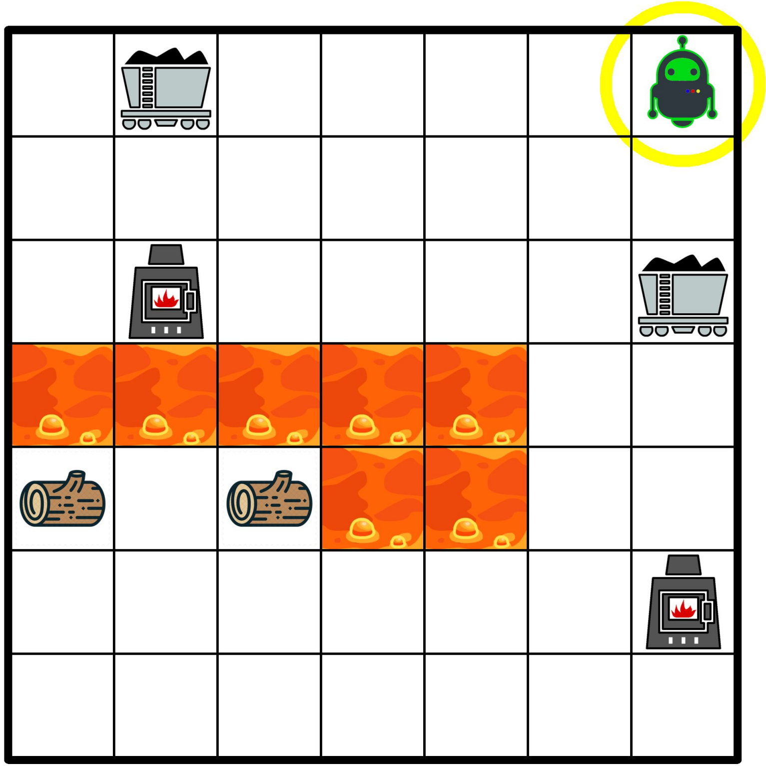

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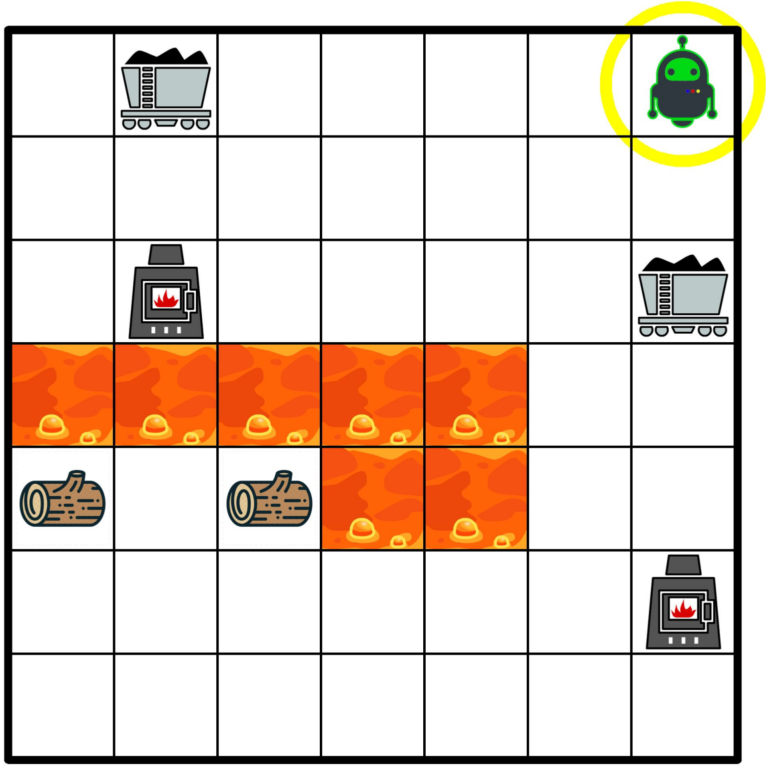

Assume agent can detect primitive high-level events:

- `pickup_coal`
- `pickup_wood`
- `use_furnace`
- `on_lava`

Tasks in LTL

Task Type	LTL Formula	English
Single Goal	`eventually pickup_coal`	“Get coal”
Ordered Goals	`eventually (pickup_coal and (eventually use_furnace))`	“Get coal, then use the furnace”
Unordered Goals	`(eventually pickup_coal) and (eventually pickup_wood)`	“Get coal and get wood, in any order”
Disjunctive Goals	`(eventually pickup_coal) or (eventually pickup_wood)`	“Get coal or get wood”
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LTL Instruction → Reward

$$R = \begin{cases} 1 & \text{if instruction is } \textbf{satisfied} \\ -1 & \text{if instruction is } \textbf{falsified} \\ 0 & \text{otherwise} \end{cases}$$

Task Decomposition

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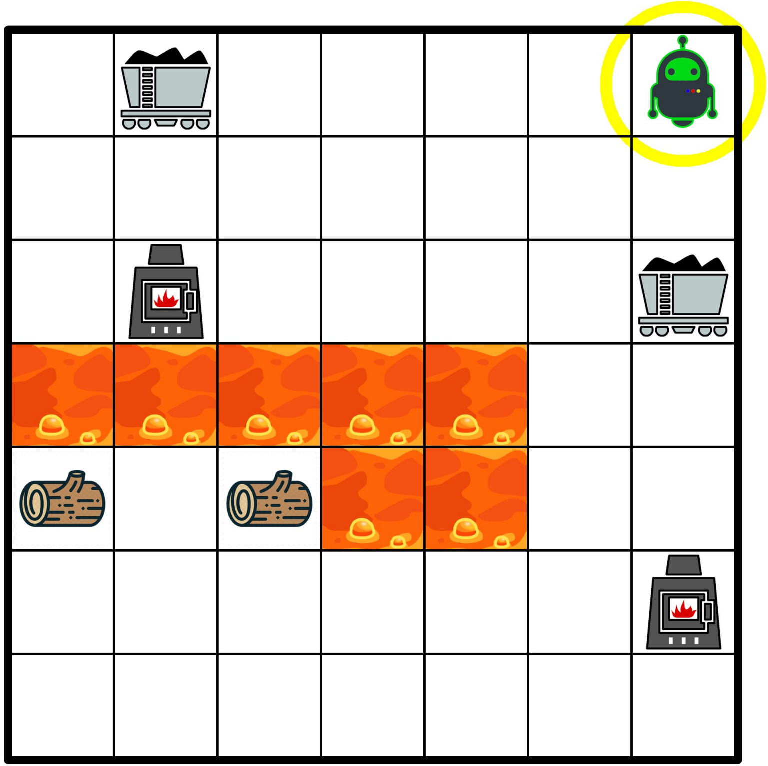
LTL Progression *[Bacchus & Kabanza, 2000]*

- Formally defined for all LTL formulas
- **Simplify instructions** once parts of the task are solved

LTL Progression — Example



“Get coal or wood, then use the furnace.”

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eventually ((pickup_coal or pickup wood)
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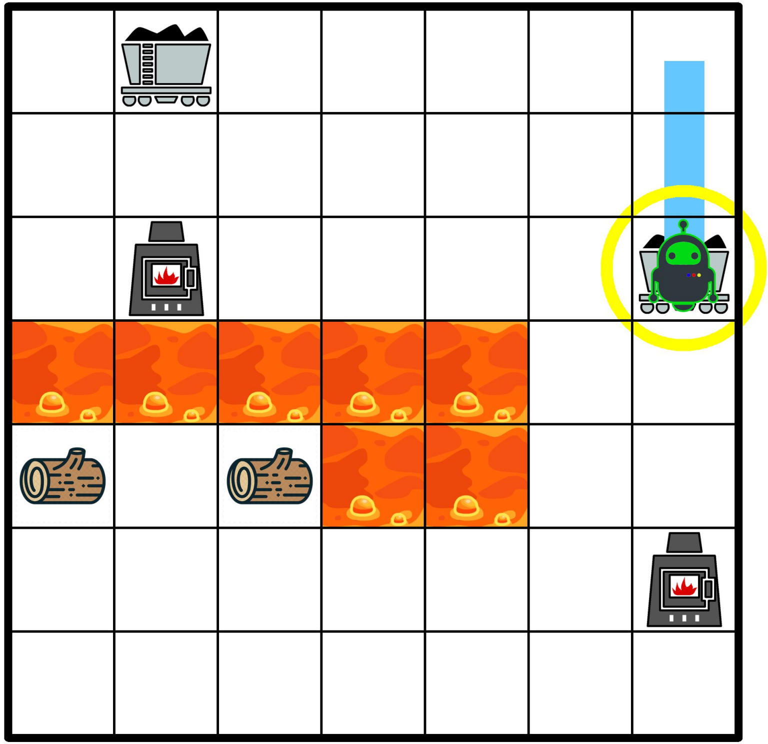

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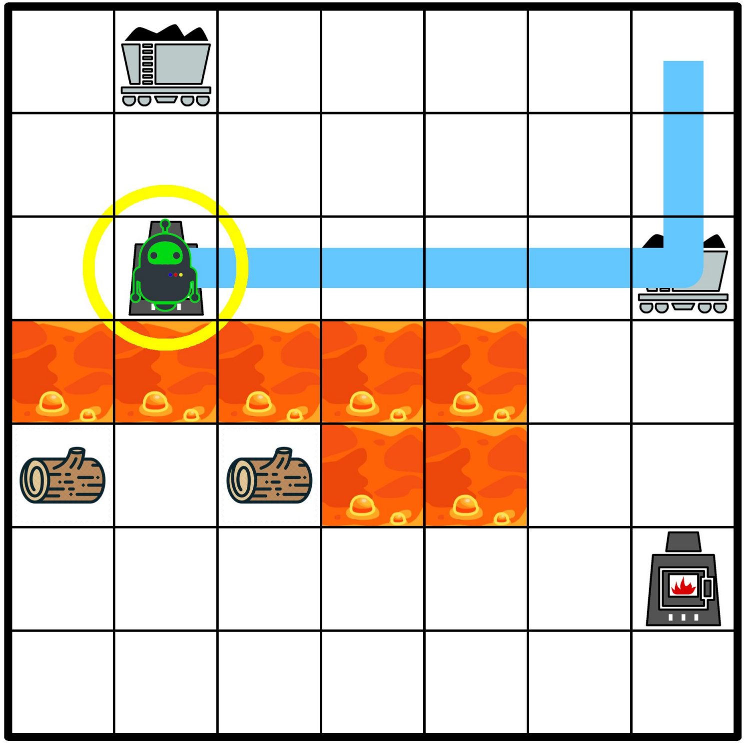

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"Use the furnace."

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eventually use_furnace
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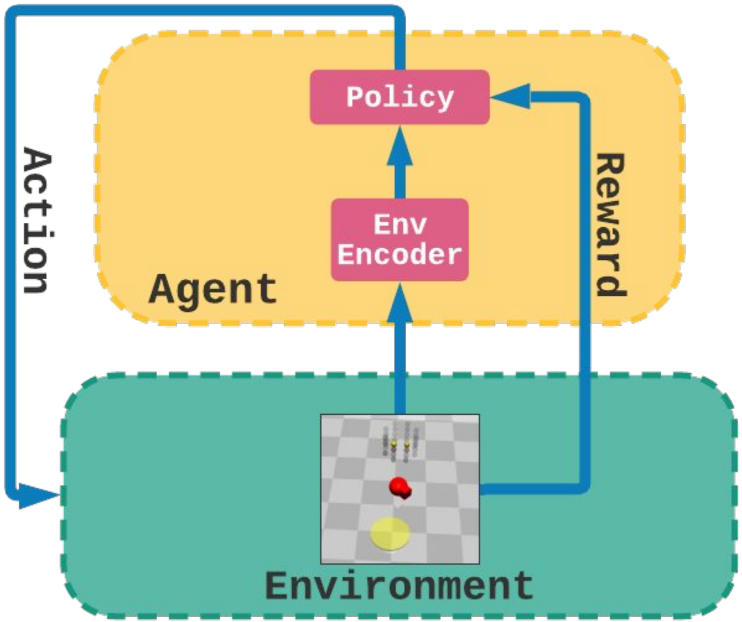
Complete

```
True
```

Our Approach



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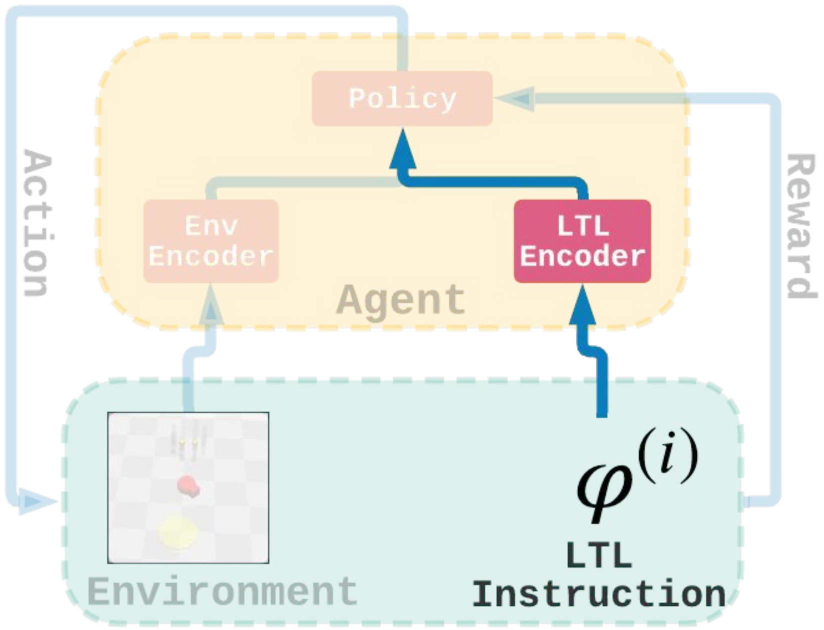

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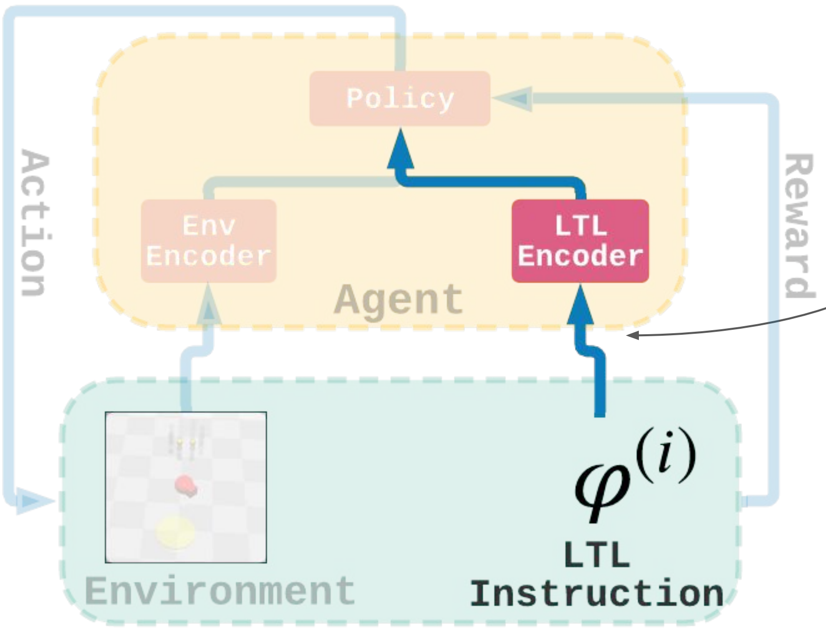
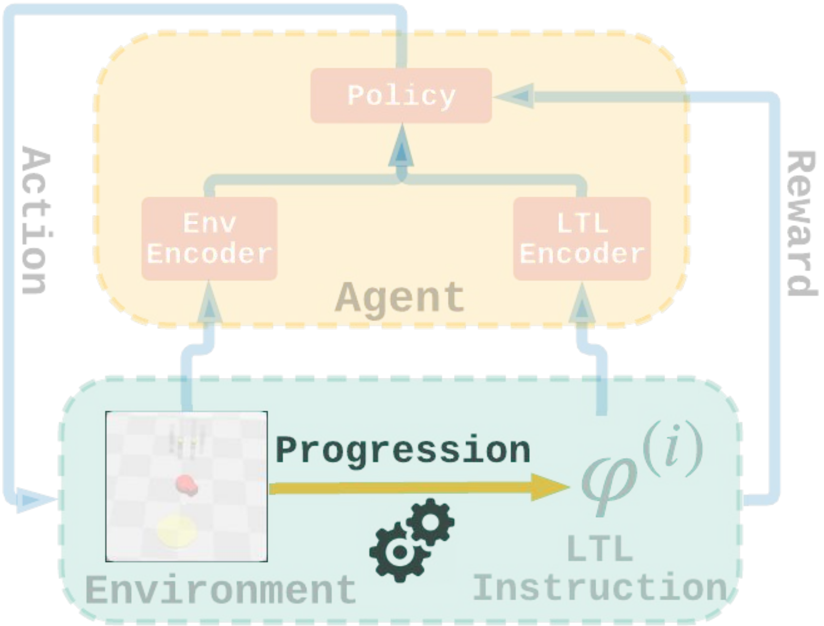


Can encode any LTL
instruction!

Our Approach



Theorems

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- ✓ Retains optimal convergence guarantees

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- ✓ Markov assumptions hold

Results

Avoidance Tasks

(> 970 million possible tasks)

$$
\begin{aligned}
\mathrm{formula} &:= \mathrm{sequence} \wedge \mathrm{formula} \mid \mathrm{sequence} \\
\mathrm{sequence} &:= \neg\mathsf{prop}(\mathsf{prop} \wedge \mathrm{sequence}) \mid \neg\mathsf{prop}\,\mathsf{prop}
\end{aligned}
$$

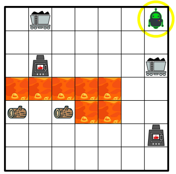
Partially-Ordered Tasks

(> 10^{39} possible tasks)

$$
\begin{aligned}
\mathrm{formula} &:= \mathrm{sequence} \wedge \mathrm{formula} \mid \mathrm{sequence} \\
\mathrm{sequence} &:= \Diamond(\mathrm{term} \wedge \mathrm{sequence}) \mid \Diamond\mathrm{term} \\
\mathrm{term} &:= \mathsf{prop} \mid \mathsf{prop} \vee \mathsf{prop}
\end{aligned}
$$

Results

Gridworld (Discrete)



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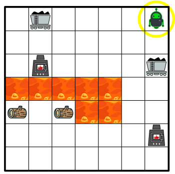
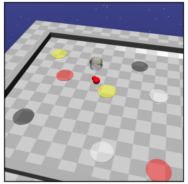


MuJoCo (Continuous)



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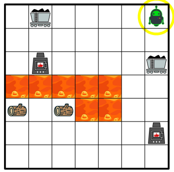
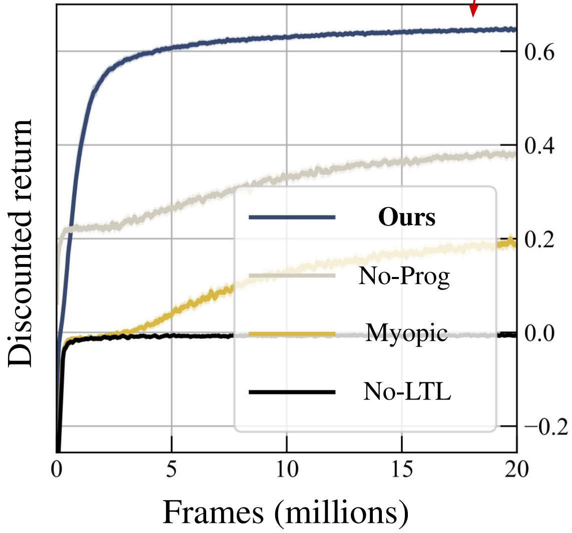
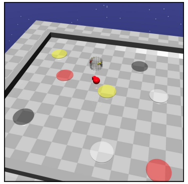
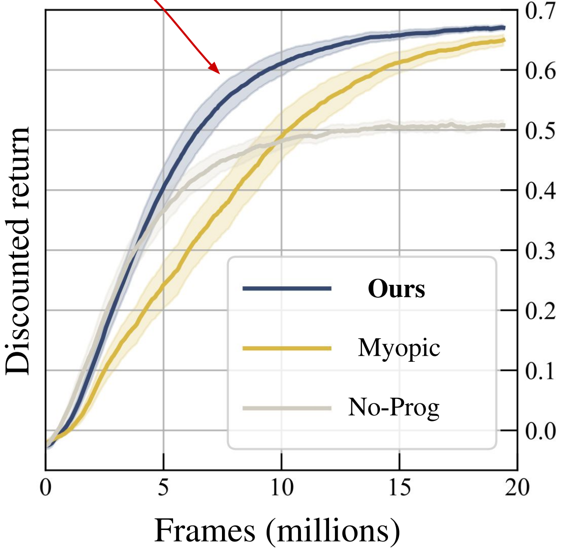




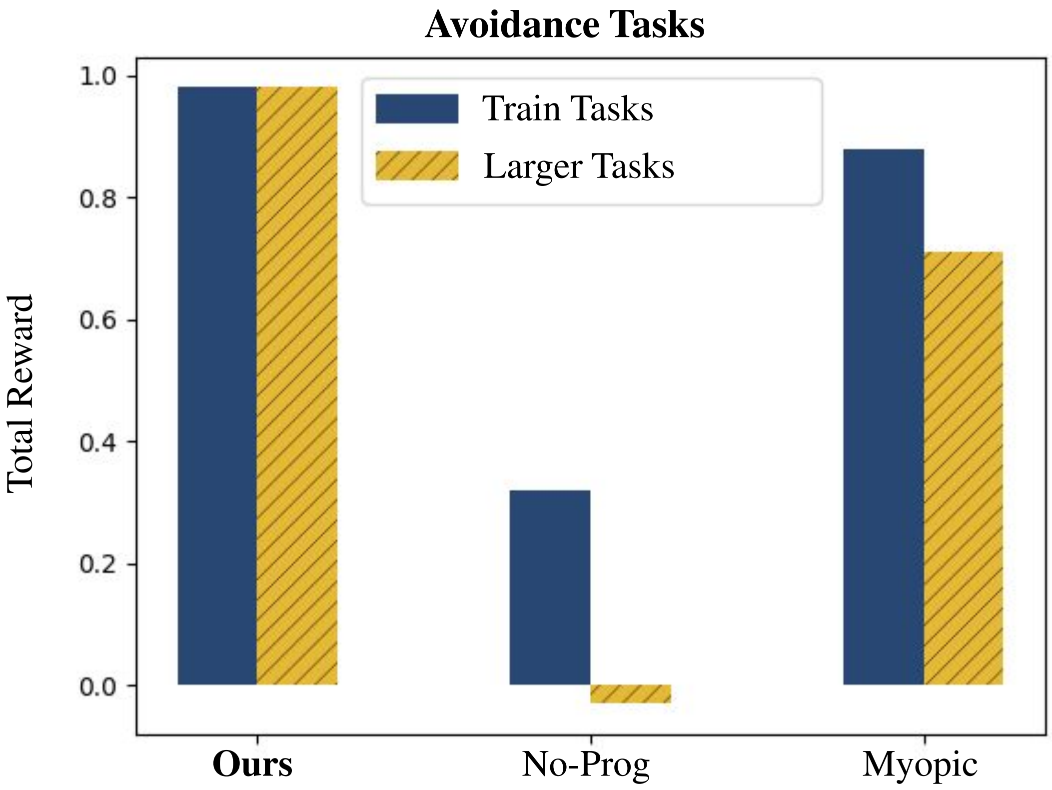
Ours

MuJoCo (Continuous)





Zero-Shot Generalization



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Come to our poster!

Code is available at:

https://github.com/LTL2Action/LTL2Action