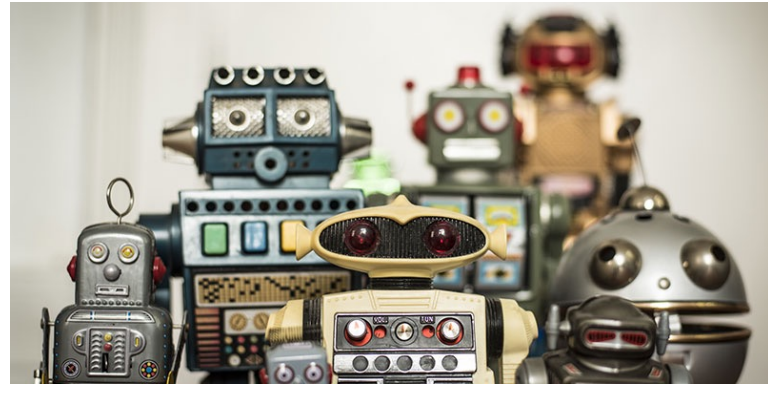


## Research Question

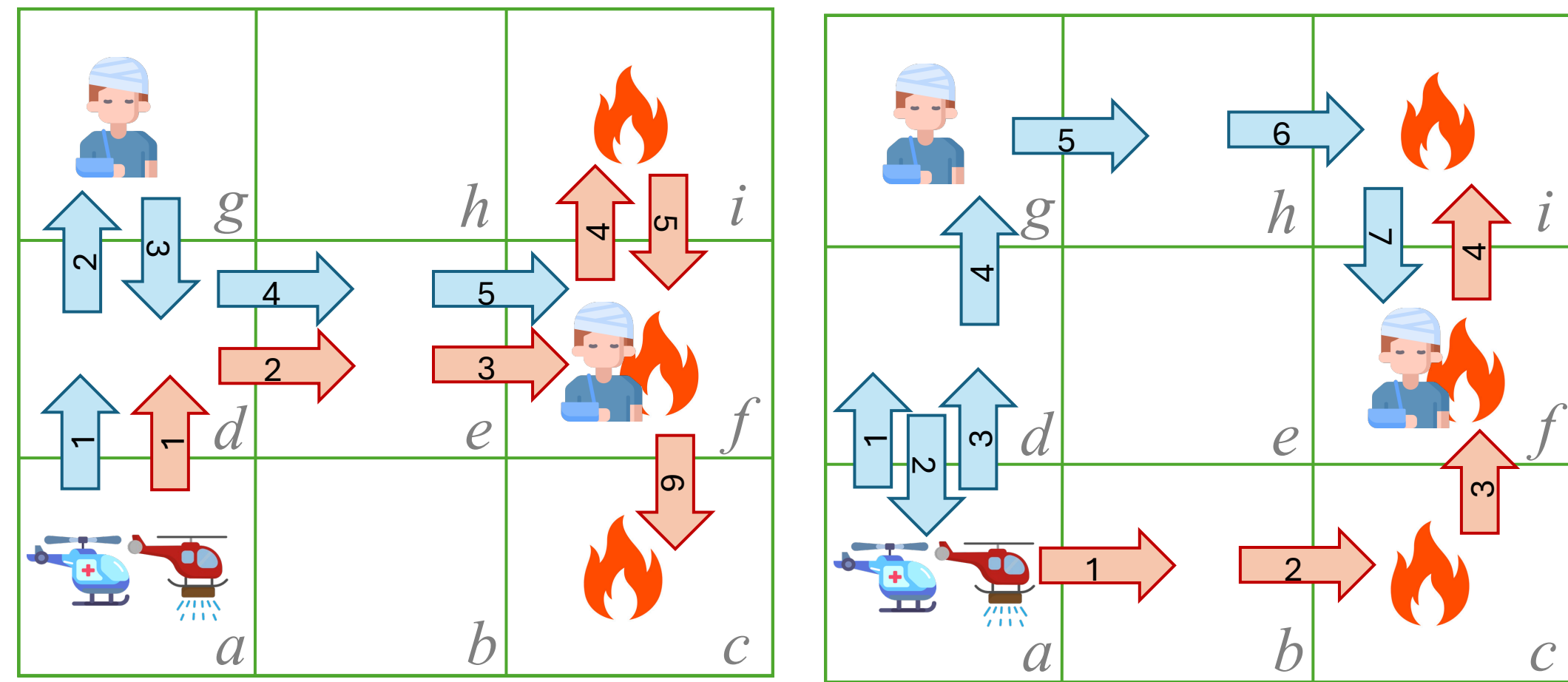


Multi-Objective

Multi-Agent

How to Shape  
Optimal **Reward Functions**?

## Motivating Example



## Real-World Applications



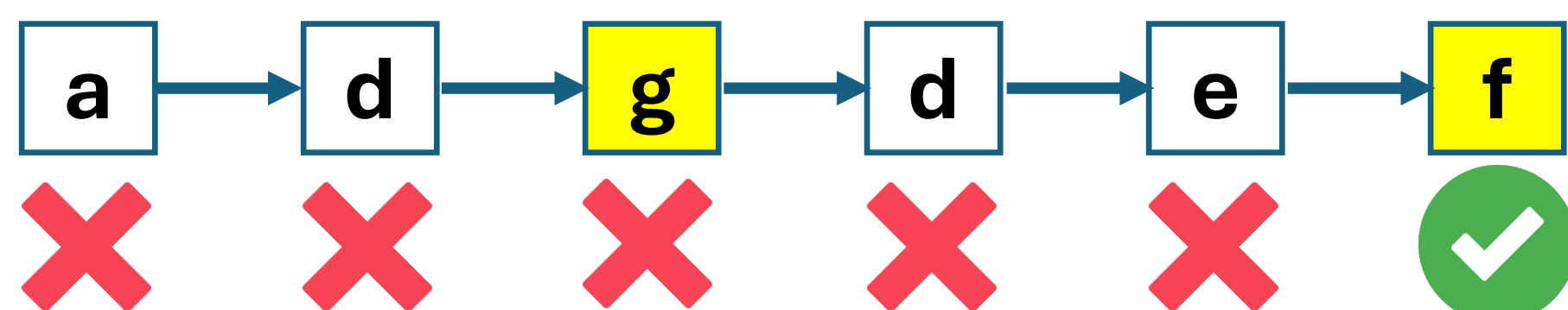
swarm drones

large-language  
models

energy management  
system

## Linear Temporal Logic (LTL)

- LTL formalizes evolving, **multi-objective** tasks
- $(\diamond g \wedge \diamond f)$  means eventually reaches both zones to save victims (i.e., goal of )



- LTL can encode objectives in **single-agent** setting by recording each episode as a trace and checking it against some logical formula.
- For **multi-agent** settings, relations among traces are captured through **hyperproperties**.

# HypRL: Reinforcement Learning of Control Policies for Hyperproperties

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## What are Hyperproperties?

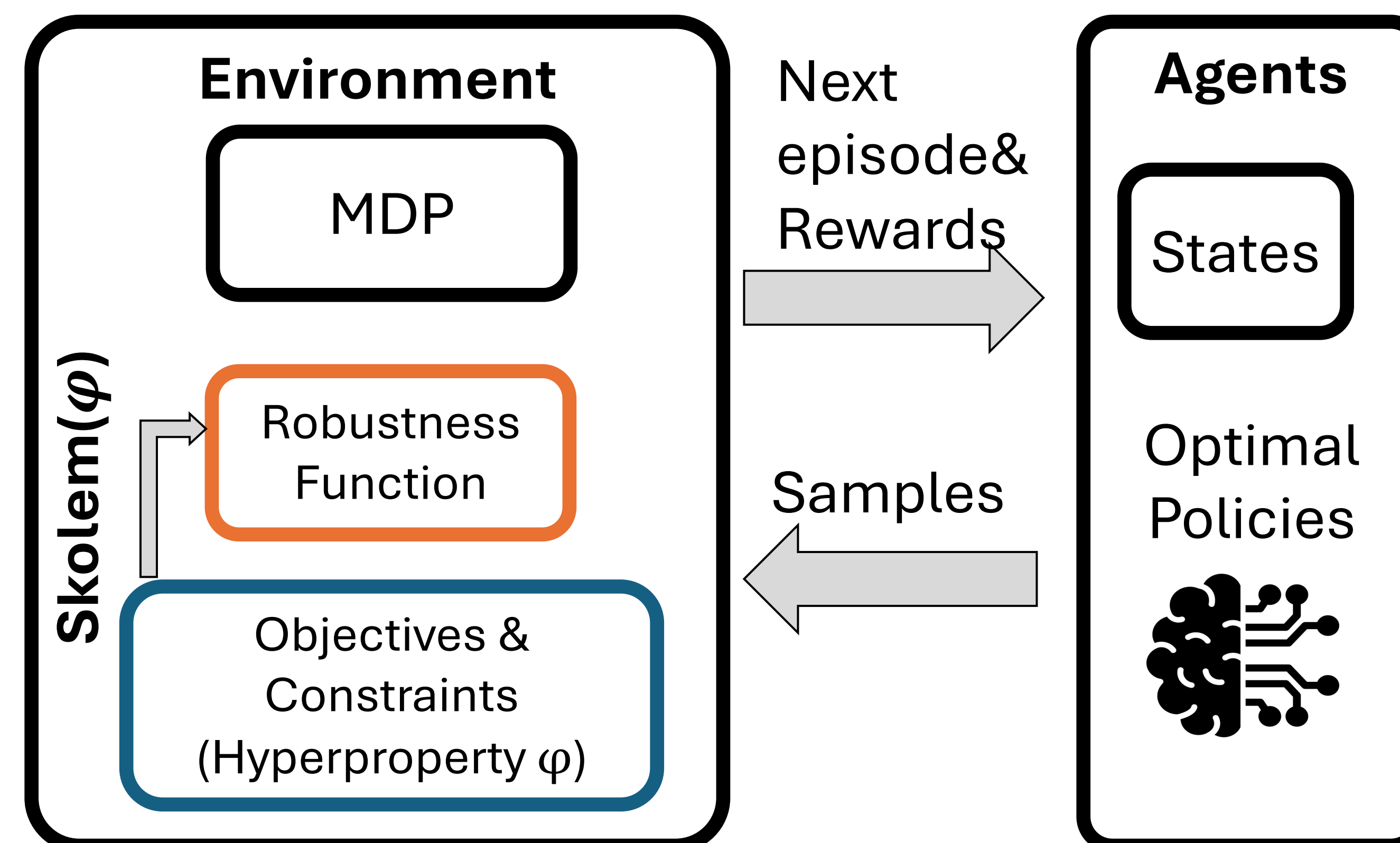
- Hyperproperties characterize requirements over sets of execution traces, allowing the specification of behaviors that involve multiple agents.
- A **HyperLTL** formula that captures all objectives and constraints of the example:

$$\varphi_{\text{rescue}} = \forall \tau_1. \exists \tau_2. (\psi_{\text{dist}} \wedge \psi_{\text{fire}} \wedge \psi_{\text{save}})$$

## Challenges

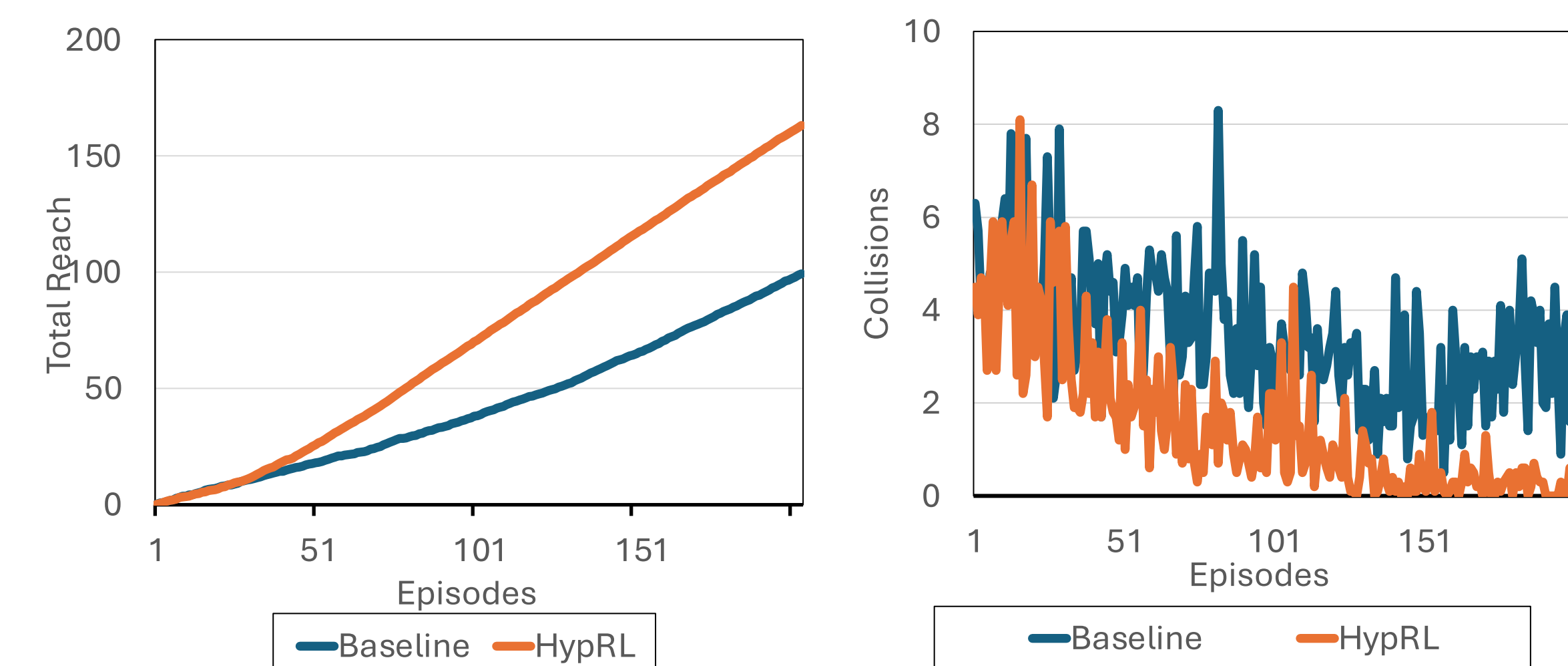
- The **quantifier alternations** introduce interaction or dependencies between multiple traces.
- We use **Skolemization** technique:  
 $\text{Skolem}(\varphi_{\text{rescue}}) = \exists f_2(\tau_1). \forall \tau_1$
- We define **robustness functions** that assigns a robustness value to a trace for a formula, serving as quantifiable rewards in RL.

## HypRL

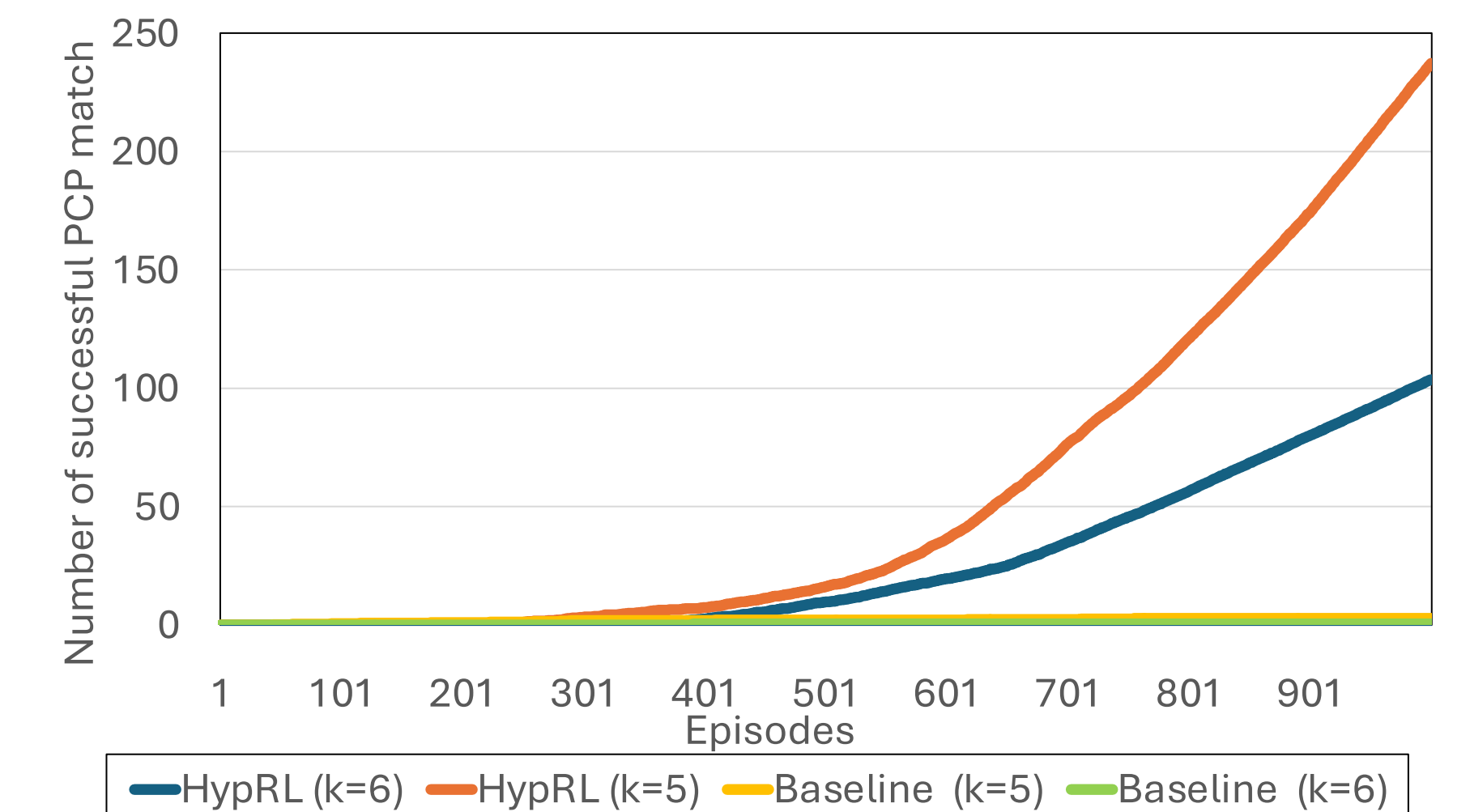


## How efficient is HypRL?

### Safe RL



### Post Correspondence Problem



### Deep Sea Treasures

Method	$\xi$	Measurements		Method	$\xi$	Measurements	
		$\sum \text{reward}$	$\sum \text{reward} / \beta$			$\sum \text{reward}$	$\sum \text{reward} / \beta$
PPO	500	8.89	0.35	DQN	500	1.39	0.05
PPO + HypRL	500	21.80	0.87	DQN + HypRL	500	4.12	0.16
PPO	1000	8.19	0.352	DQN	1000	0.69	0.02
PPO + HypRL	1000	18.16	0.72	DQN + HypRL	1000	4.43	0.17

## Take Aways!

- Hyperproperties capture objectives and constraints for multi-agent RL.
- HypRL turns any HyperLTL spec into a reward function, by Skolemizing formulas with quantifier alternations.
- HypRL outperforms baseline reward functions, used in traditional RL frameworks.