

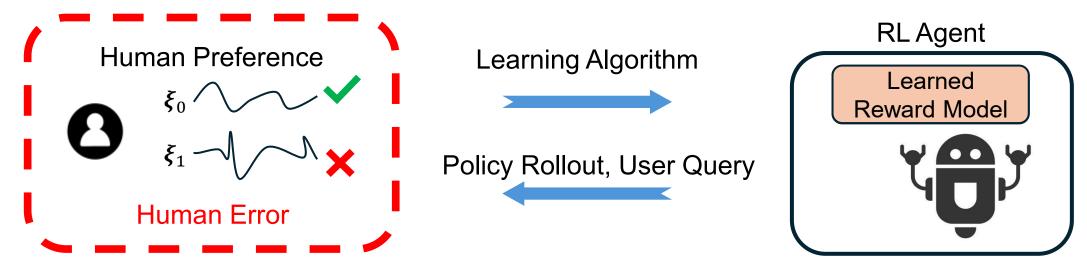
Robust Reward Alignment via Hypothesis Space Batch Cutting

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Motivation: Preference-Based RL Suffers from Erroneous Feedback



B-Pref Benchmark: Up to 20% downgrade with 10% error rate¹

Recent effort: Filtering False Feedback



Prior Knowledge Computation Overhead

Target:

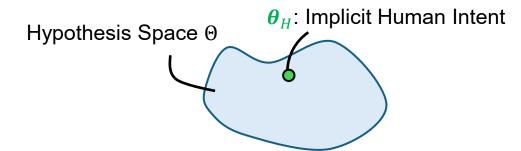
- 1. Certifiable human data efficiency
- 2. Provable robustness

Without explicitly identifying the error.

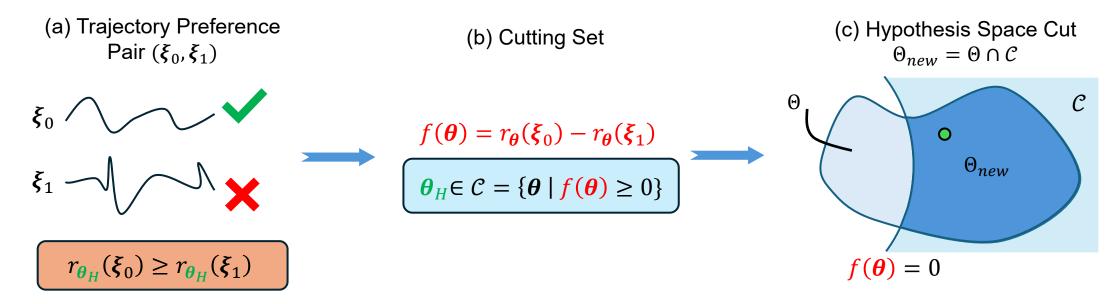
1: Lee, Kimin, et al. "B-pref: Benchmarking preference-based reinforcement learning." arXiv preprint arXiv:2111.03026 (2021).

Preferences as Hypothesis Space Cuts

Hypothesis Space: The space of reward function (parameters), containing implicit human intent.



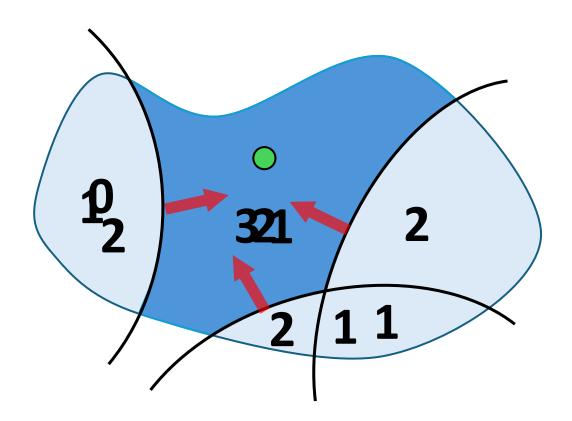
Searching for θ_H : Use preferences to induce cuts and remove the hypothesis space inconsistent with preference!



Batched Cutting as Voting

Use a batch of preference to vote, update the hypothesis space base on vote function:

$$V(\boldsymbol{\theta}) = \#$$
 of satisfied cuts for given $\boldsymbol{\theta}$



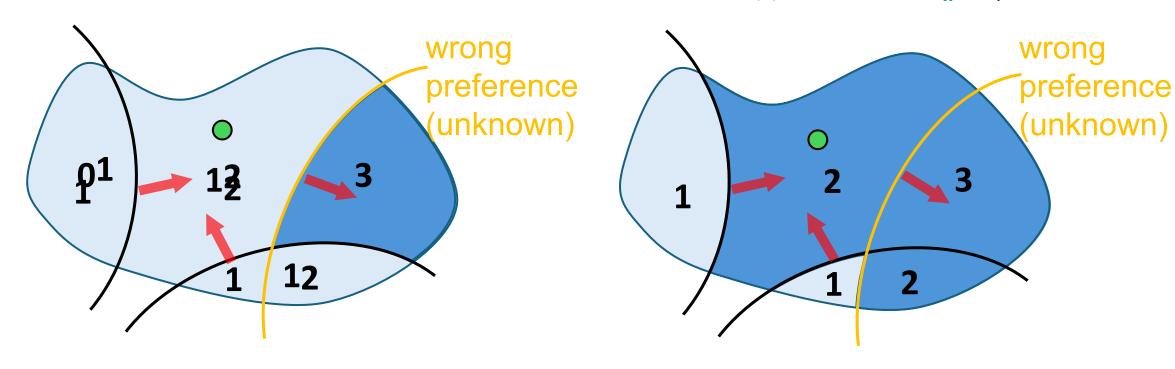
Update the hypothesis space using threshold $V(\theta) \geq 3!$

Key Idea: Batched Cutting with Conservativeness

Use Lower threshold to perform conservative update:

Threshold $V(\theta) \geq 3$: Cut out θ_H

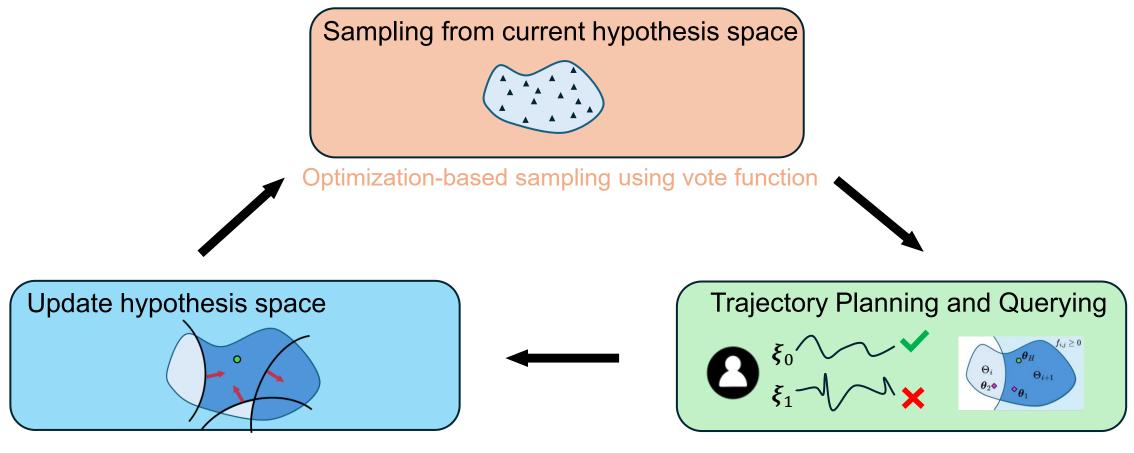
Threshold $V(\theta) \geq 2$: Preserve θ_H in update



With batch size N: $V(\theta) \ge (1 - \gamma)N$, conservativeness $0 < \gamma < 1$

Provably Robustness, Error Agnostic!

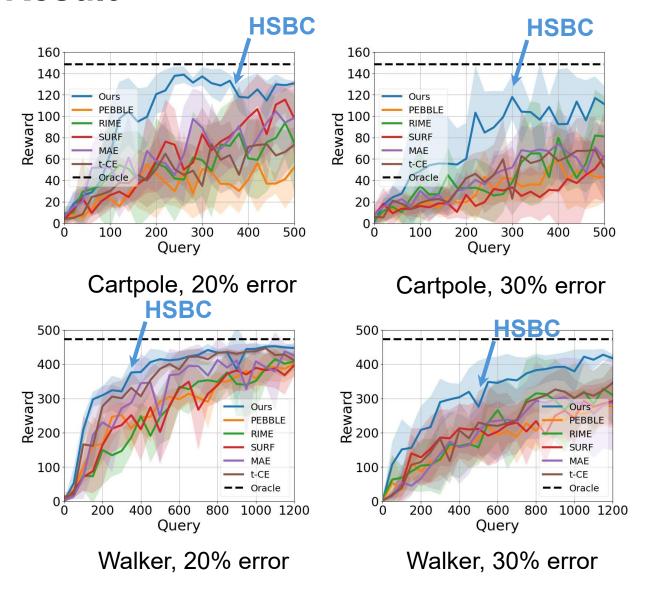
Hypothesis Space Batch Cutting (HSBC) Overview

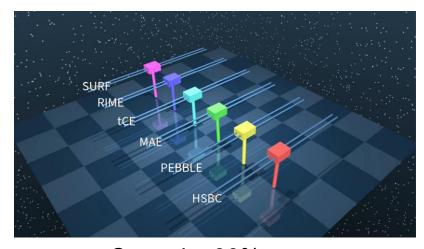


Batched Cutting with Conservativeness

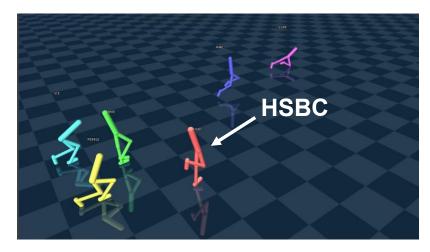
Disagreement-based Querying

Result





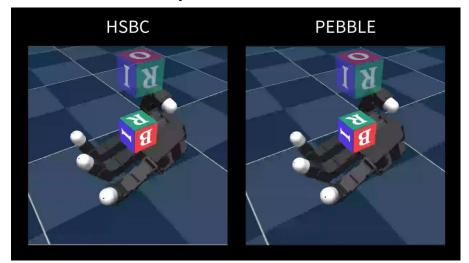
Cartpole, 30% error



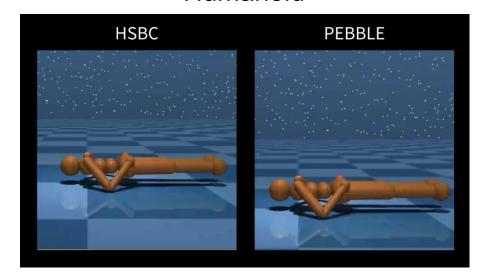
Walker, 30% error

Result

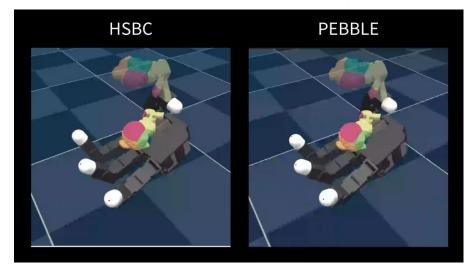
Manipulation: Cube



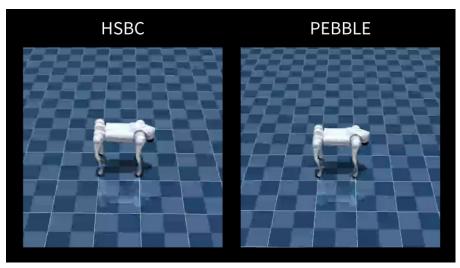
Humanoid



Manipulation: Bunny



Go2



Thanks for Listening!

Project Page

