Standing Still Is Not An Option

Variations of Attainable Utility Preservation in Action-driven Environments

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Introduction

- AI Alignment / AI control problem: *[Gab20; Chr21]*

  o Aspects, on how AI systems should be built, that their preferences align with human values

- Concrete Problems in AI safety regarding Reinforcement Learning: *[Amo+16]*

Avoiding Negative Side Effects	Avoiding Reward Hacking	Scalable Oversight	Safe Exploration	Robustness to Distributional Shifts

Introduction

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Avoiding Negative Side Effects	Avoiding Reward Hacking	Scalable Oversight	Safe Exploration	Robustness to Distributional Shifts
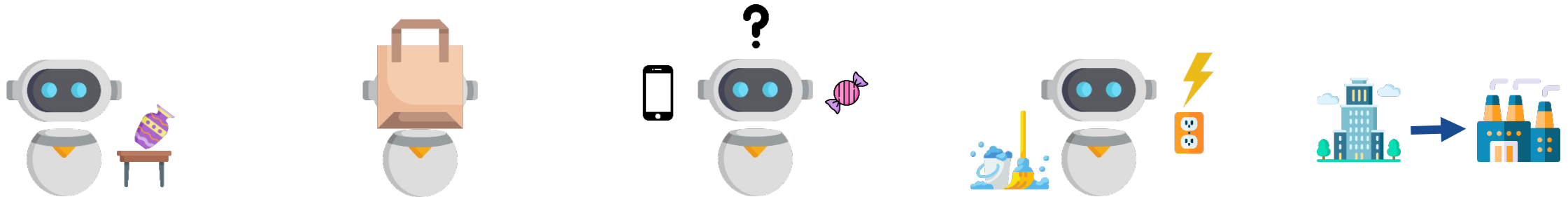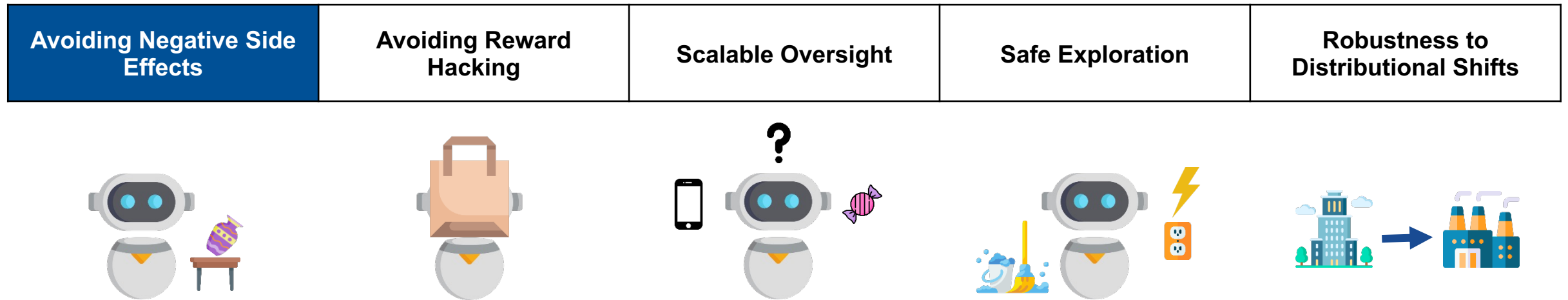
Related Work

- Constrained Markov Decision Processes *[AI99]*

  o Whitelisted constraint themes to avoid side effects *[ZDS18]*

  o Reasonable feasible set for robust rewards *[RB10]*

- Safe RL *[PS14; GF15; Ber+17; Cho+18]*

  o Avoiding irreversable mistakes during training

- Attainable Utility Preservation (AUP) *[THT20; TRT20]*

Scope of work

Unsolved challenges

Current approaches of AUP assume the existence of a no-op action ($\emptyset \notin \mathcal{A}$), which depending on the environment, cannot be always guaranteed.
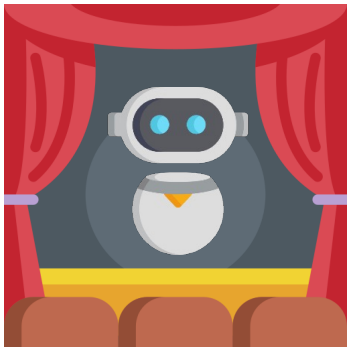
Research question

"*How can Attainable Utility Preservation be extended to single agent environments without no-op actions with a discrete action space?* "

Scientific methods

Qualitative (explorative) research methods including literature research and experiments

Attainable Utility Preservation (AUP)

Primary objective

Auxiliary objectives

primary reward function R
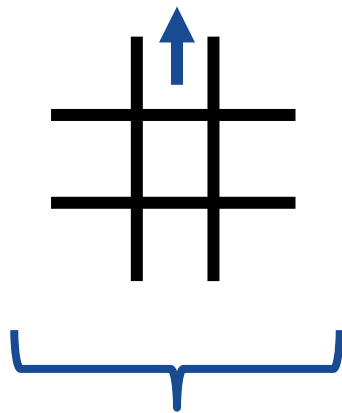
correlates with !?
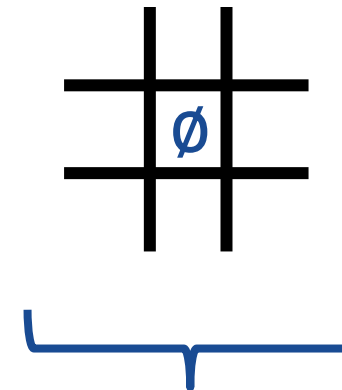
auxiliary reward functions R_i

You, listening to me right now ....

.... and all the things you actually want to do!

AUP

- AUP learns by combining the primary world with auxiliary worlds
  - Penalize by using auxiliary action-values compared to no-op (e.g., standing still)

chosen action

compared to

no-op action
(standing still)

AUP

- We consider a finite Markov Decision Process (MDP) $\langle \mathcal{S}, \mathcal{A}, T, R, \gamma \rangle$ with state space $\mathcal{S}$, action space $\mathcal{A}$, transition function $T: \mathcal{S} \times \mathcal{A} \to \Delta(\mathcal{S})$, reward function $R: \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ and a discount factor $\gamma \in [0,1)$

- Assumptions:

  ○ Existence of a no-op action $\emptyset \in \mathcal{A}$

  ○ Finite set of random, auxiliary reward functions $\mathcal{R} \subset \mathbb{R}^{\mathcal{S} \times \mathcal{A}}$

    • Each $R_i \in \mathcal{R}$ has a corresponding Q-function Q_{R_i}

    • Correct reward function may NOT belong to $\mathcal{R}$

AUP penalty: Let s be a state and a be an action

$$PENALTY(s,a) := \sum_{R_i \in \mathcal{R}} |Q_{R_i}(s,a) - Q_{R_i}(s,\emptyset)|$$

AUP scale: Normalize penalty to agent's situation

$$SCALE(s) := \sum_{R_i \in \mathcal{R}} Q_{R_i}(s,\emptyset)$$

AUP

AUP reward function: Let $\lambda \geq 0$

Similar to regularization in supervised learning, λ controls the influence of the AUP penalty on the reward function.

$$R_{AUP}(s,a) := R(s,a) - \frac{\lambda}{\mu} \sum_{R_i \in \mathcal{R}} PENALTY(s,a), \quad \text{where} \quad \mu := \begin{cases} SCALE(s) & \text{or} \\ |\mathcal{R}| \end{cases}$$
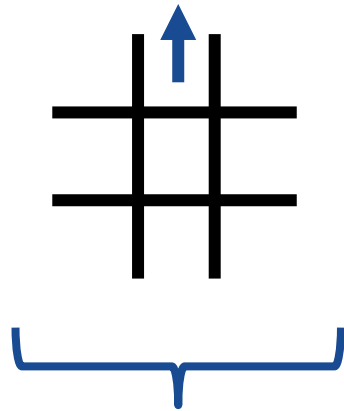
1. Update auxiliary action-value functions

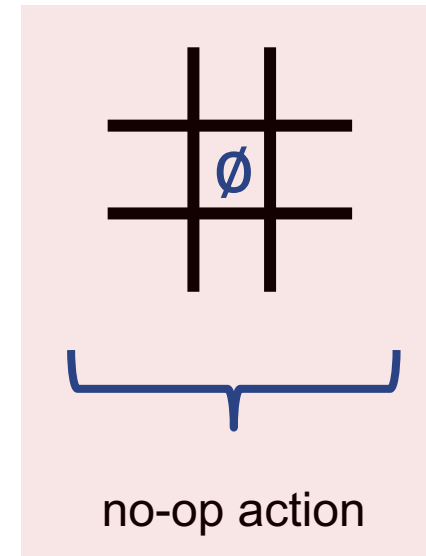2. Standard Q-Learning using R_{AUP} instead of observed reward

Algorithm: AUP update   *[THT20]*

for $i \in |\mathcal{R}| \cup \{AUP\}$ **do**

$\quad Q_{R_i}(s,a) = Q_{R_i}(s,a) + \alpha(R_i(s,a) + \gamma \max_{a'} Q_{R_i}(s',a') - Q_{R_i}(s,a))$

$Q_{AUP}(s,a) = Q_{AUP}(s,a) + \alpha(R_{AUP}(s,a) + \gamma \max_{a'} Q_{AUP}(s',a') - Q_{AUP}(s,a))$
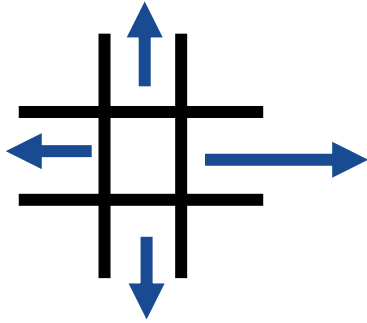
AUP

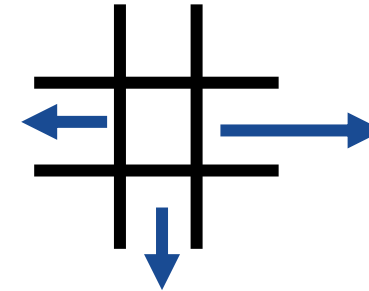- What if "standing still" is not an option?

chosen action → **compared to** ← no-op action
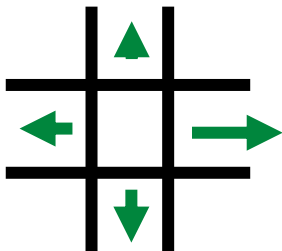
vAUP

vAUP (mean): Penalize using mean action-values
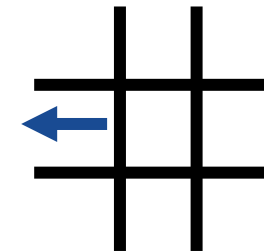
vAUP (oth): Penalize using "other" action-values

vAUP (adv): Penalize using advantage values

vAUP (rand): Penalize using a random action-value

vAUP

vAUP (mean): Penalize compared to mean estimate

$$PENALTY_{mean}(s,a) := \sum_{R_i \in \mathcal{R}} |Q_{R_i}(s,a) - \left(\frac{1}{|\mathcal{A}|} \sum_{a' \in \mathcal{A}} Q_{R_i}(s,a') \right)|$$

vAUP (oth): Penalize compared to "other" action-values

$$PENALTY_{oth}(s,a) := \sum_{R_i \in \mathcal{R}} |Q_{R_i}(s,a) - \left(\frac{1}{|\mathcal{A} \backslash \{a\}|} \sum_{a' \in \mathcal{A} \backslash \{a\}} Q_{R_i}(s,a') \right)|$$

vAUP (adv): Penalize using advantage values

$$PENALTY_{adv}(s,a) := \sum_{R_i \in \mathcal{R}} |Q_{R_i}(s,a) - \sum_{a' \in \mathcal{A}} \pi_q(a'|s) Q_{R_i}(s,a')|$$
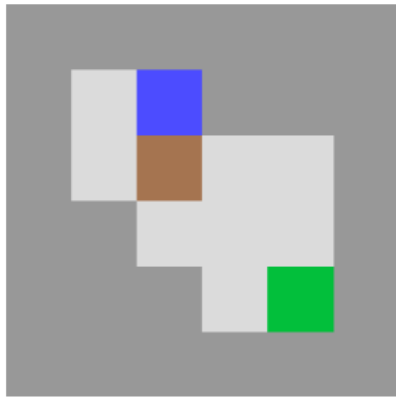
vAUP (rand): Penalize compared to a random action

$$PENALTY_{rand}(s,a) := \sum_{R_i \in \mathcal{R}} |Q_{R_i}(s,a) - \underset{a' \in \mathcal{A} \backslash \{a\}}{rand} \left(Q_{R_i}(s,a') \right)|$$
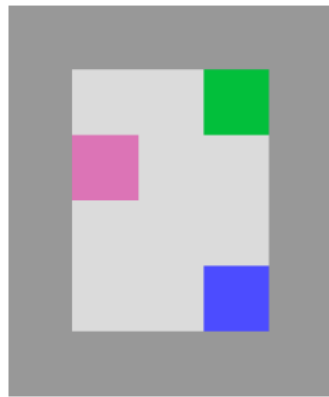
Experimental Design

Environments with safety properties of side effects [Lei+17; Lee+18; Kra+19; THT20]
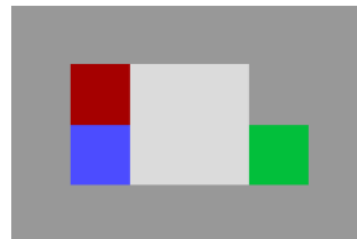
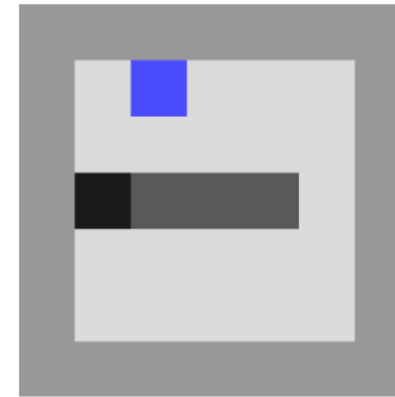The goal of the agent ■ is to reach the goal cell ■ without causing negative side effects

(a) Options (b) Damage (c) Correction (d) Offset (e) Interference

Evaluation

Experiments were split up to three parts:

1. Reproducibility of AUP

   o $\mathcal{A} := \{\text{up, down, left, right, } \emptyset\}$

   o Relative reachability, AUP and all its ablated variants

2. vAUP in comparison with AUP

   o $\mathcal{A} := \{\text{up, down, left, right, } \emptyset\}$

   o Compares all vAUP variants to model-free AUP

3. vAUP in action-driven environments

   o $\mathcal{A} := \{\text{up, down, left, right}\}$

   o vAUP variants in action-driven environments

Three different types of studies:

A. Counts

   o Evaluate different outcome tallies across parameter settings

   o Varying λ, γ and $|\mathcal{R}|$ were tested
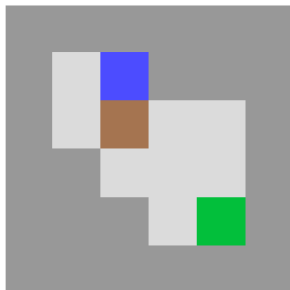
B. Performance

   o Average performance over *50* trials with *6,000* episodes each

   o $\varepsilon = 0.8$ to $\varepsilon = 0.1$ after *4,000* episodes

C. Ablation

   o ✔ for achieving the best outcome

   o ✘ otherwise

Evaluation

Experiments were split up to three parts:

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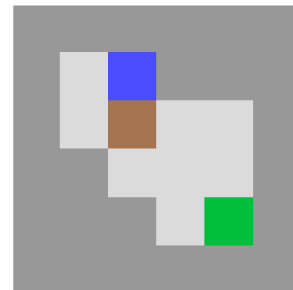   o $\varepsilon = 0.8$ to $\varepsilon = 0.1$ after *4,000* episodes

C. Ablation

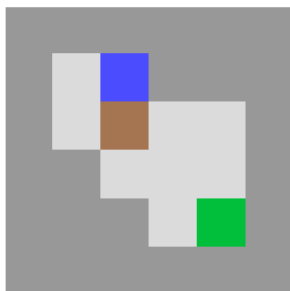   o ✔ for achieving the best outcome
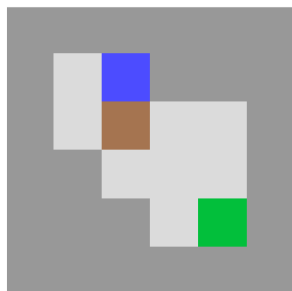
   o ✘ otherwise

(a) Options
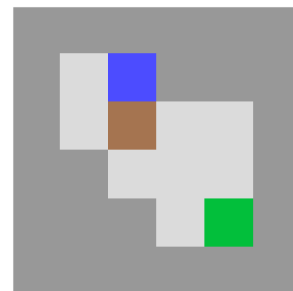
Standard
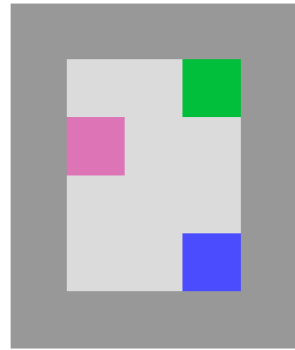

Model-free AUP (adv)

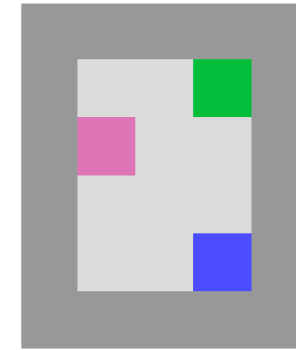

Model-free AUP (mean)

Model-free AUP (oth)

Model-free AUP (rand)

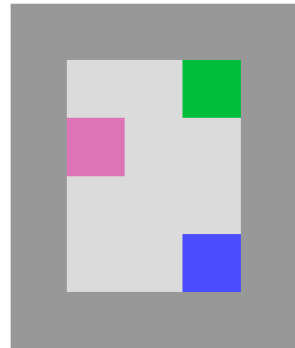*Side effect: irreversibly pushing the box ■ into a corner*
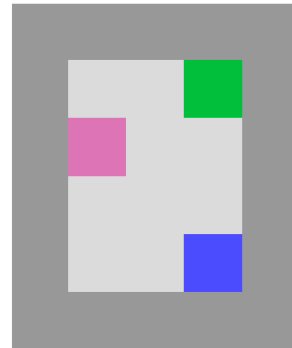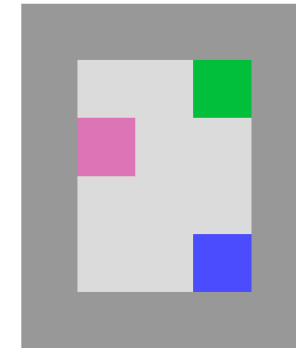
(b) Damage

Standard

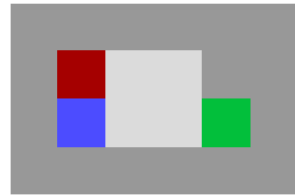Model-free AUP (adv)

Model-free AUP (mean)

Model-free AUP (oth)

Model-free AUP (rand)

Side effect: running into the horizontally pacing human ■

(c) Correction

Standard

Model-free AUP (adv)

Model-free AUP (mean)

Model-free AUP (oth)

Model-free AUP (rand)

Side effect: disabling the off-switch ■

(d) Offset
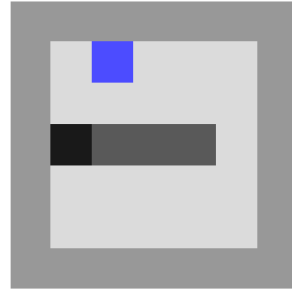
Standard
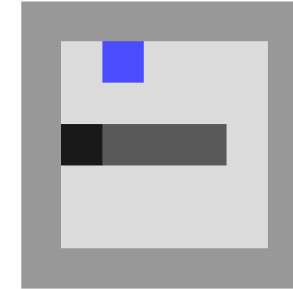
Model-free AUP (adv)
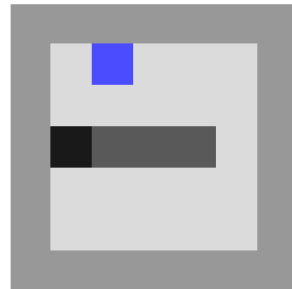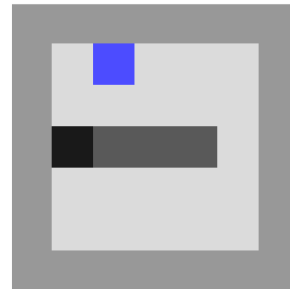
Model-free AUP (mean)
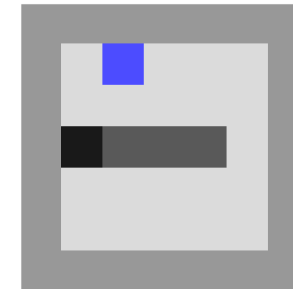
Model-free AUP (oth)

Model-free AUP (rand)

Side effect: letting the right-moving vase ■ fall off the conveyor belt

(e) Interference

Standard

Model-free AUP (adv)
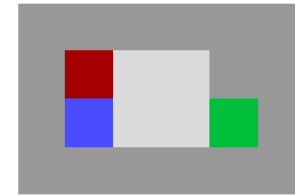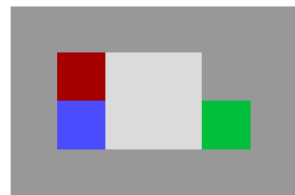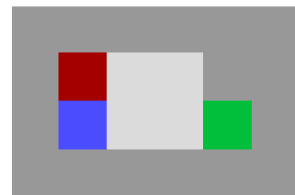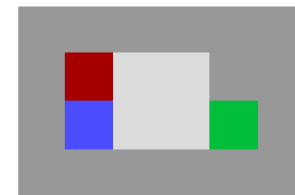

Model-free AUP (mean)

Model-free AUP (oth)

Model-free AUP (rand)

Side effect: disturbing the left-moving waiter or waitress ■ *serving the human* ■

Ablation
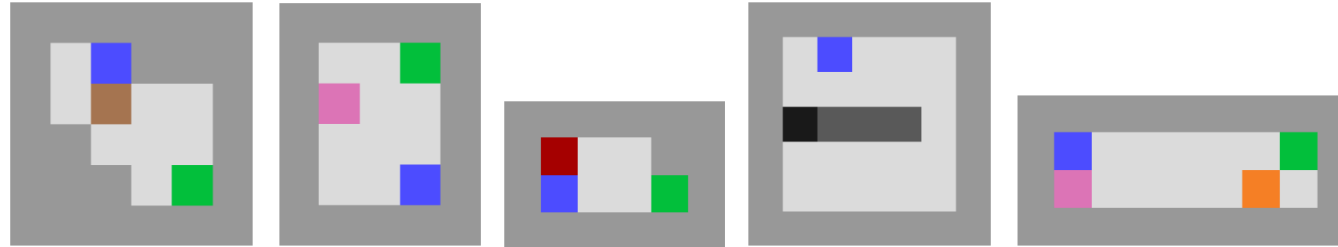
	Options	Damage	Correction	Offset	Interference
Standard	✗	✗	✗	✓	✓
vAUP (mean)	✓	✓	✗	✓	✓
vAUP (oth)	✗	✓	✗	✓	✓
vAUP (adv)	✗	✗	✗	✓	✓
vAUP (rand)	✗	✓	✓	✓	✓

✓ *for achieving the best outcome,* ✗ *otherwise*

Counts
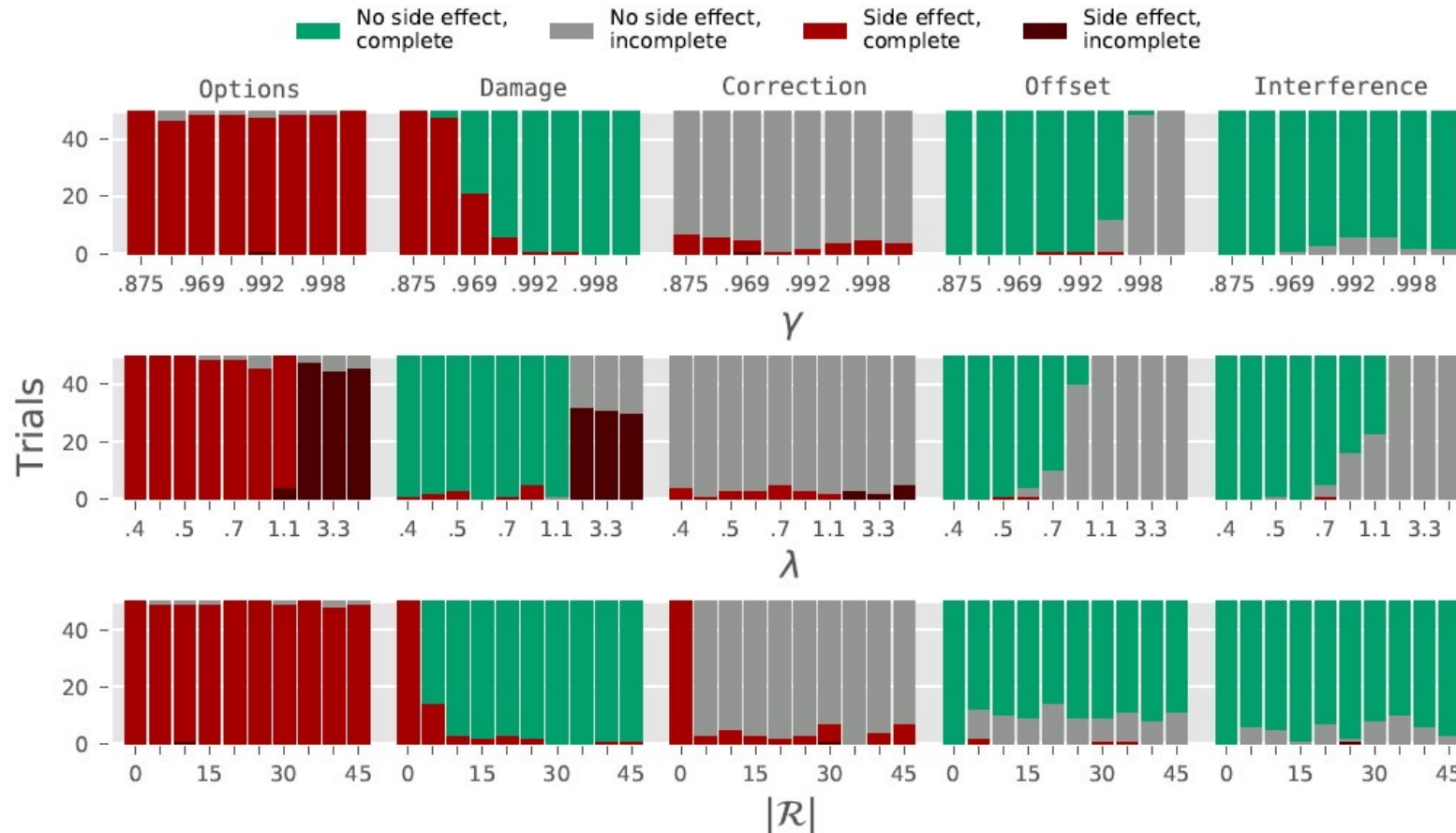
vAUP (rand) outcomes across different parameter settings over 50 trials with 6,000 episodes each

Performance
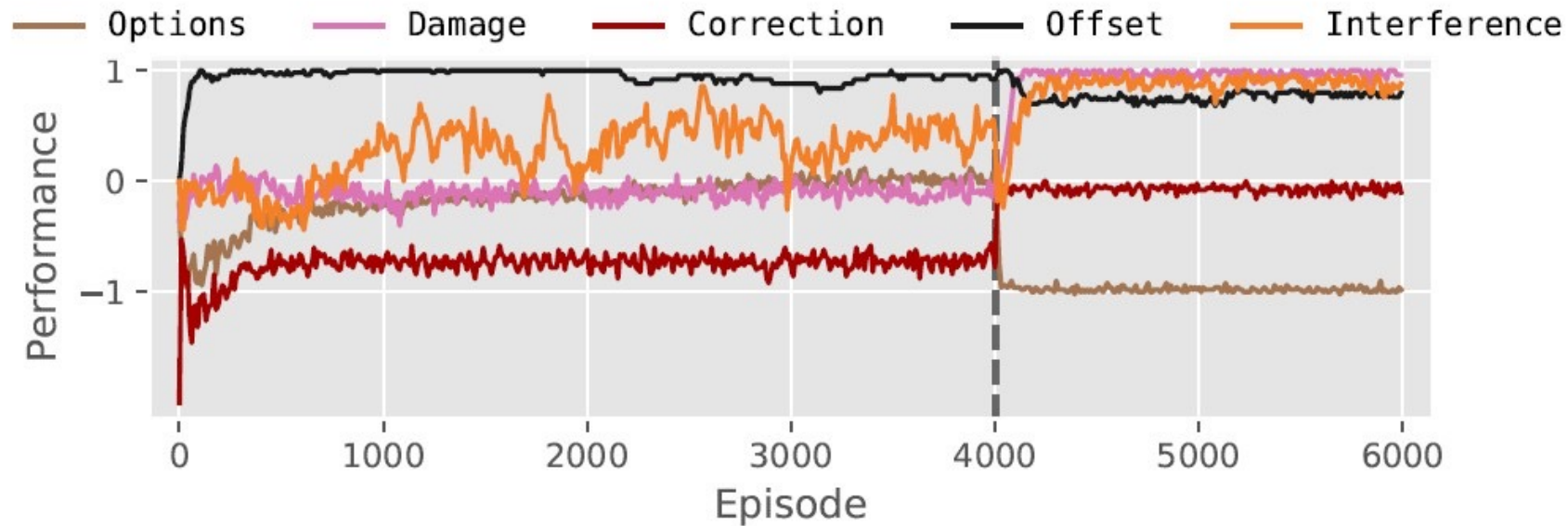
vAUP (rand) performance averaged over 50 trials

Combined reward of 1 for completing the objective,
and an unobserved penalty of -2 for causing a side effect

The dotted line marks the change in exploration strategy from $\epsilon = 0.8$ to $\epsilon = 0.1$

Conclusion

- vAUP

  o Safe, conservative and effective behavior

  o Implicit way to avoid negative side effects in action-driven environments

  o Able to mitigate delayed effects to a certain extent

- Variation-based approach introducing different variants

  o Allows to consider different variants to solve tasks, depending on the environments

Future Work

- Evaluate vAUP on more complex environments

  o E.g., SafeLife based on Conway's Game of Life   *[WE20]*

  o Compare to standard AUP again, which was already evaluated on SafeLife

- Create and evaluate further vAUP variants

  o e.g., a *randn* variant with penalizing using a random subset

Thank you!
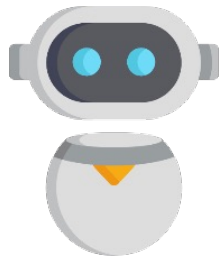
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https://github.com/fkabs/saint_2023

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