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Standing Still Is Not An Option

Variations of Attainable Utility Preservation in Action-driven Environments

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Introduction

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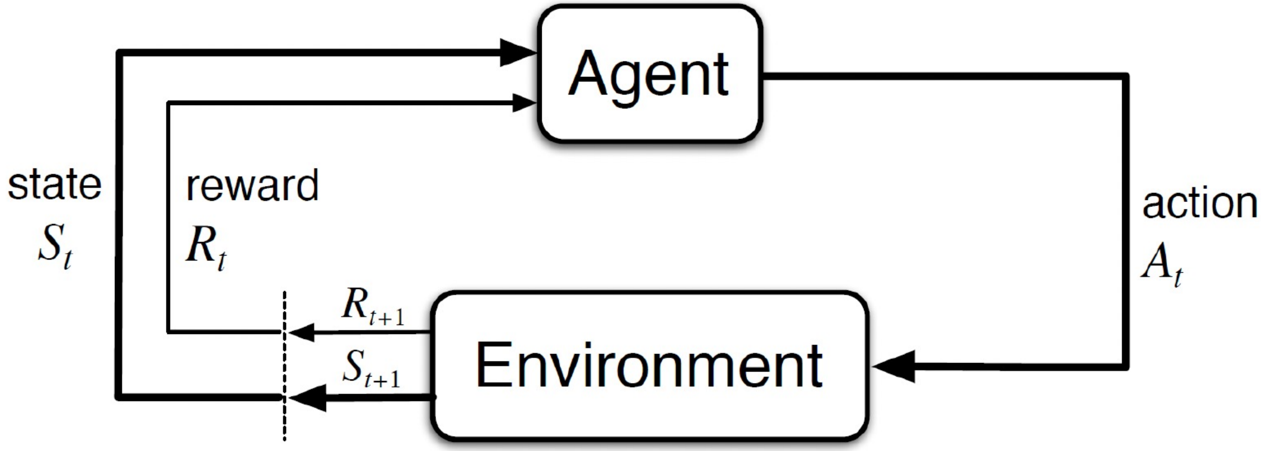
- Unlike (un)supervised learning, Reinforcement Learning does not focus on data itself
  - *Agent* and *Environment* stand in a cyclic relationship with each other
  - *Agent* observes states and rewards from the *Environment* and takes actions



Agent-environment interaction in Reinforcement Learning *[SB18]*

Introduction

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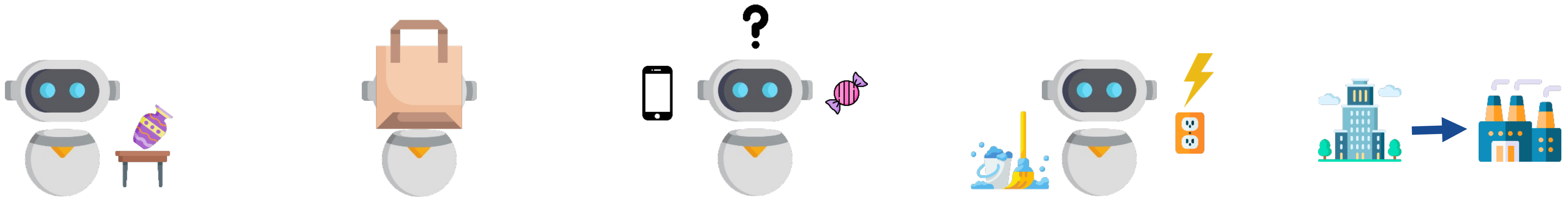
- AI Alignment / AI control problem: *[Gab20; Chr21]*
  - Aspects, on how AI systems should be built, that their preferences align with human values

- 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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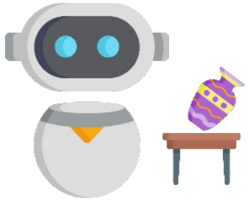
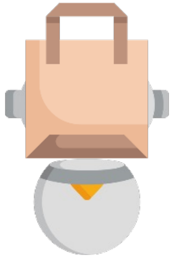
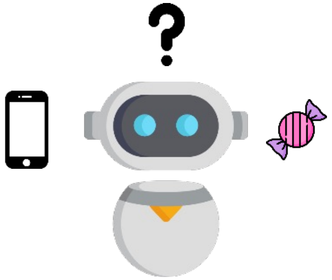
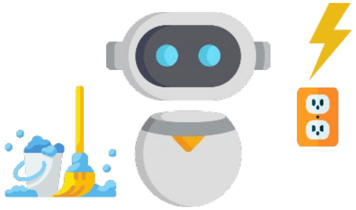
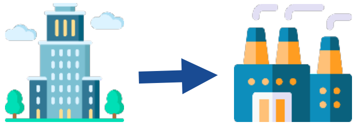

Related Work

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- Constrained Markov Decision Processes *[AI99]*
    - Whitelisted constraint themes to avoid side effects *[ZDS18]*
    - Reasonable feasible set for robust rewards *[RB10]*
- Safe RL *[PS14; GF15; Ber+17; Cho+18]*
    - Avoiding irreversable mistakes during training
- Attainable Utility Preservation (AUP) *[THT20; TRT20]*

Scope of work

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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)

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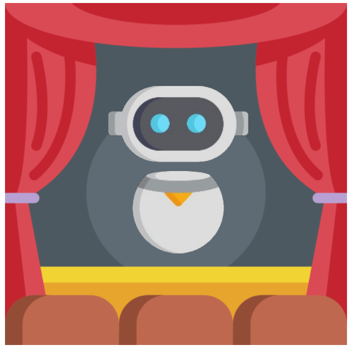
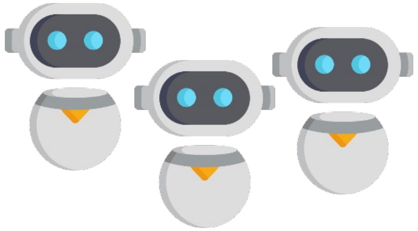
Primary objective





You, listening to me right now ....

primary reward function R

correlates with !?

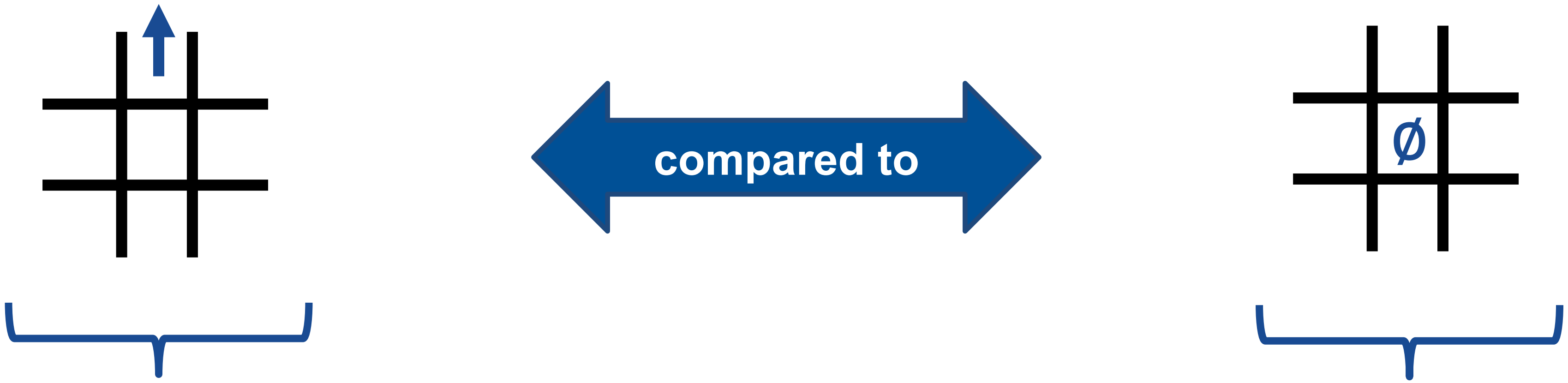
auxiliary reward functions R_i

Auxiliary objectives

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

AUP

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



chosen action

no-op action
(e.g., standing still)

AUP

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- 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 $T: \mathcal{S} \times \mathcal{A} \rightarrow \Delta(\mathcal{S})$, reward function $R: \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ 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

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

AUP scale: Normalize penalty to agent's situation

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

AUP

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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.

$$R_{AUP}(s,a) \coloneqq R(s,a) - \frac{\lambda}{\mu} \sum_{R_i \in \mathcal{R}} PENALTY(s,a), \quad \text{where} \quad \mu \coloneqq \begin{cases} SCALE(s) & \text{or} \\ |\mathcal{R}| \end{cases}$$

1. Update auxiliary action-value functions
2. Standard Q-Learning using R_{AUP} instead of observed reward

Algorithm: AUP update *[THT20]*

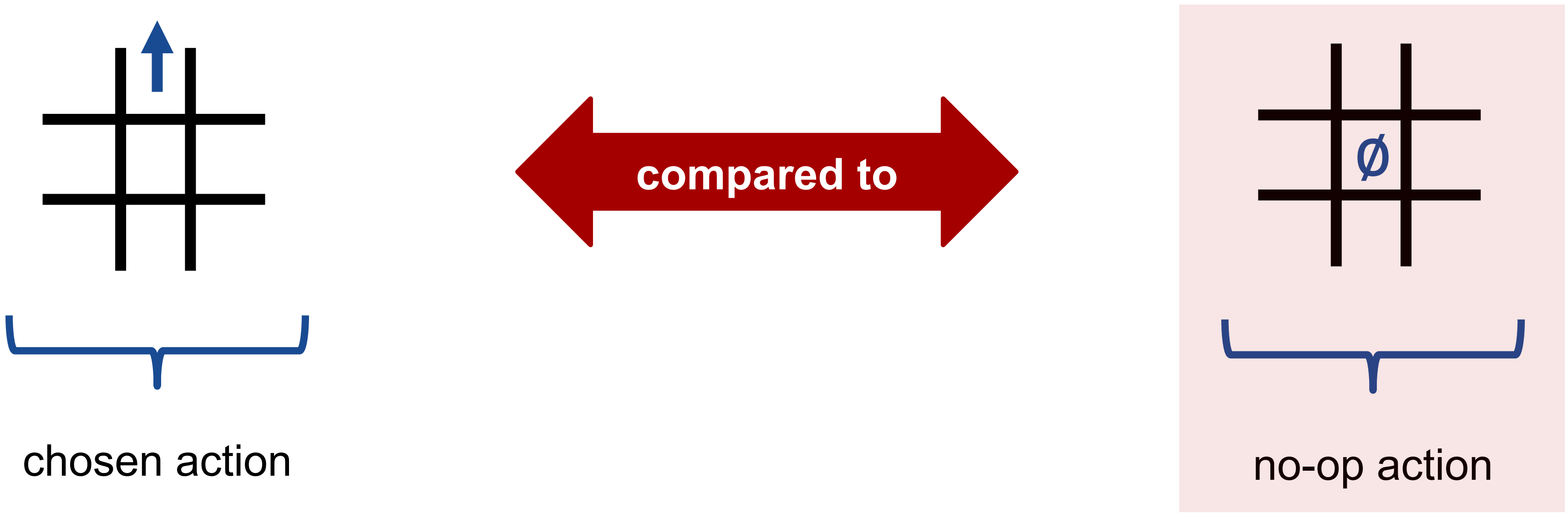
for $i \in |\mathcal{R}| \cup$ *{AUP}* **do**

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

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

AUP

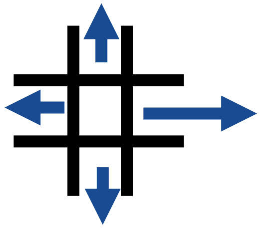
- What if ”standing still” is not an option?



vAUP

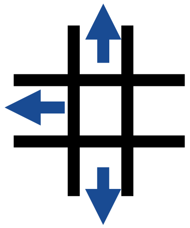
vAUP (mean): Penalize compared to mean estimate

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



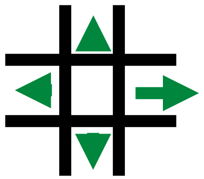
vAUP (oth): Penalize compared to “other” action-values

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



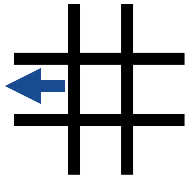
vAUP (adv): Penalize using advantage values

$$PENALTY_{adv}(s,a) \coloneqq \sum_{R_i \in \mathcal{R}} \left| Q_{R_i}(s,a) - \sum_{a' \in \mathcal{A}} \pi_q(a'|s) Q_{R_i}(s,a') \right|$$



vAUP (rand): Penalize compared to a random action

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



Experimental Design

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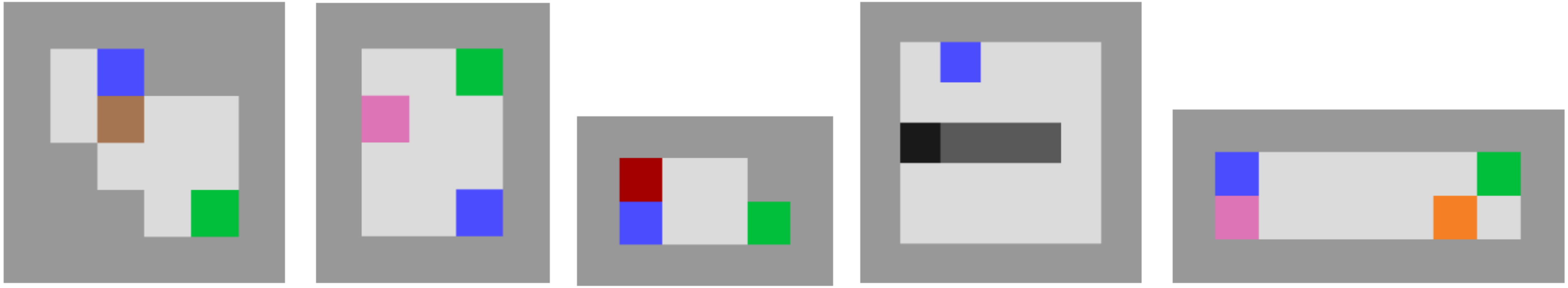
Environments with safety properties of side effects *[Lei+17; Lee+18; Kra+19; THT20]*

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

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Experiments were split up to three parts:

1. Reproducibility of AUP
   - $\mathcal{A} \coloneqq \{\text{up}, \text{down}, \text{left}, \text{right}, \emptyset\}$
   - Relative reachability, AUP and all its ablated variants
2. vAUP in comparison with AUP
   - $\mathcal{A} \coloneqq \{\text{up}, \text{down}, \text{left}, \text{right}, \emptyset\}$
   - Compares all vAUP variants to model-free AUP
3. vAUP in action-driven environments
   - $\mathcal{A} \coloneqq \{\text{up}, \text{down}, \text{left}, \text{right}\}$
   - vAUP variants in action-driven environments

Three different types of studies:

A. `Counts`
   - Evaluate different outcome tallies across parameter settings
   - Varying λ, γ and $|\mathcal{R}|$ were tested

B. `Performance`
   - Average performance over *50* trials with *6,000* episodes each
   - $\varepsilon = 0.8$ to $\varepsilon = 0.1$ after *4,000* episodes

C. `Ablation`
   - ✓ for achieving the best outcome
   - ✗ otherwise

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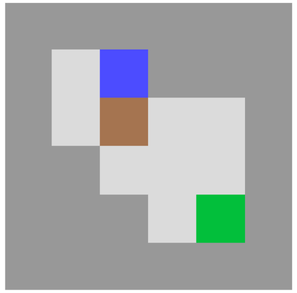
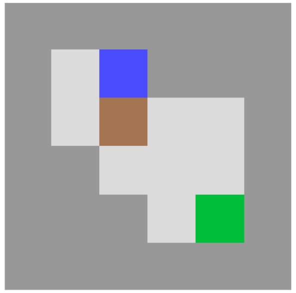
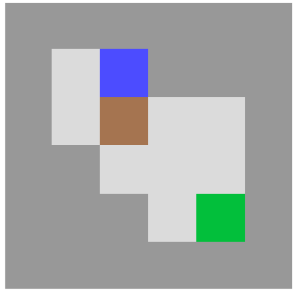
(a) Options



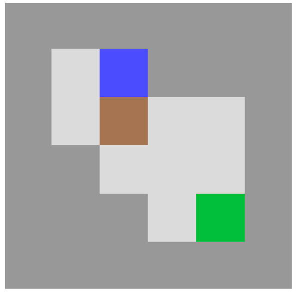
Standard



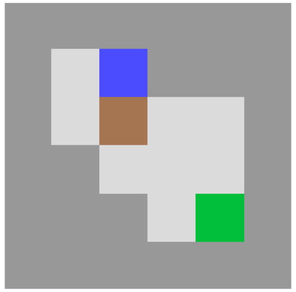
Model-free AUP (adv)



Model-free AUP (mean)



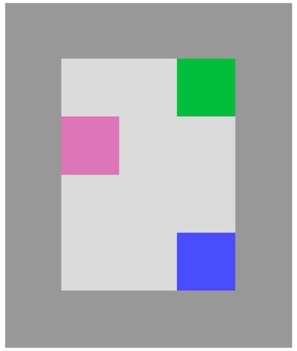
Model-free AUP (oth)



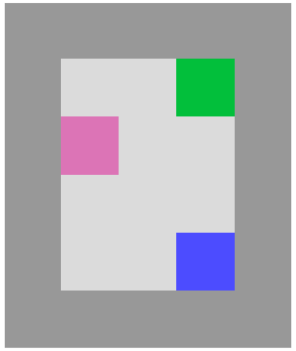
Model-free AUP (rand)

Side effect: irreversibly pushing the box ■ into a corner

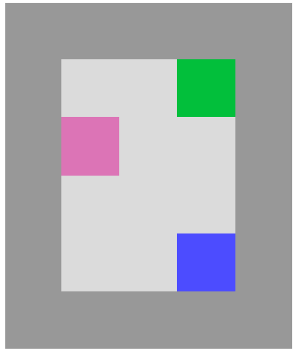
(b) Damage



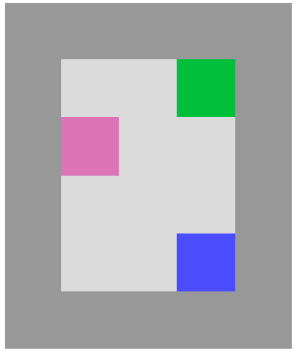
Standard



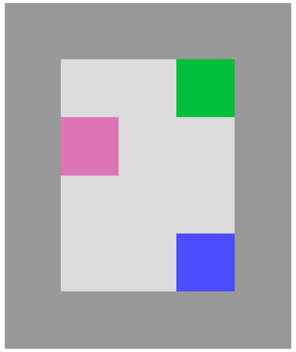
Model-free AUP (adv)



Model-free AUP (mean)



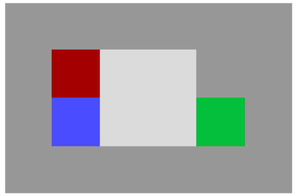
Model-free AUP (oth)



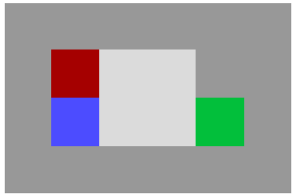
Model-free AUP (rand)

Side effect: running into the horizontally pacing human

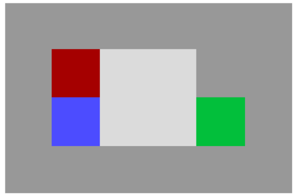
(c) Correction



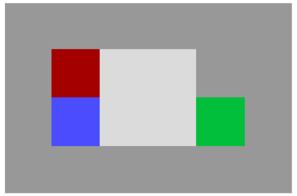
Standard



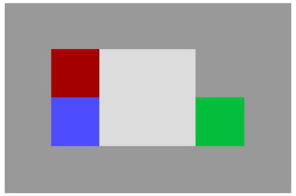
Model-free AUP (adv)



Model-free AUP (mean)



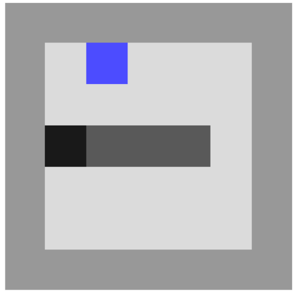
Model-free AUP (oth)



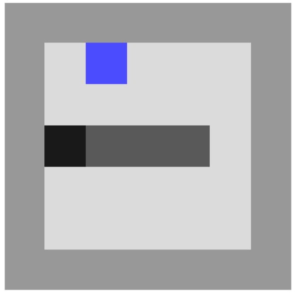
Model-free AUP (rand)

Side effect: disabling the off-switch

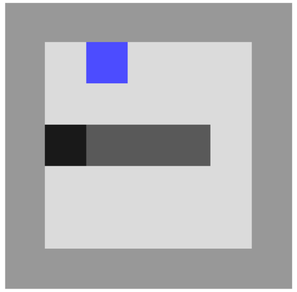
(d) Offset



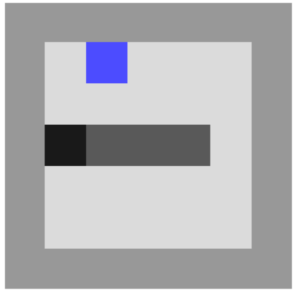
Standard



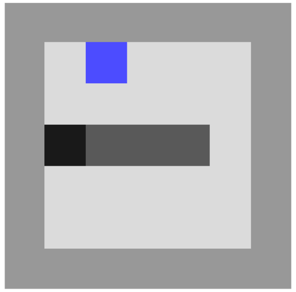
Model-free AUP (adv)



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)

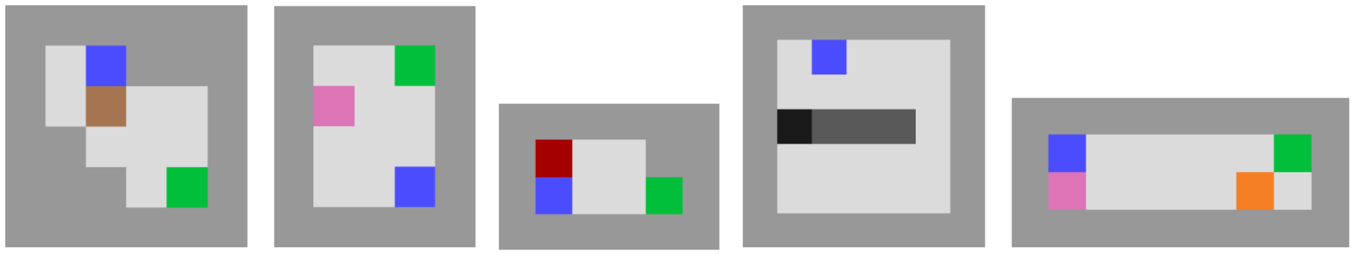
Model-free AUP (mean)

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

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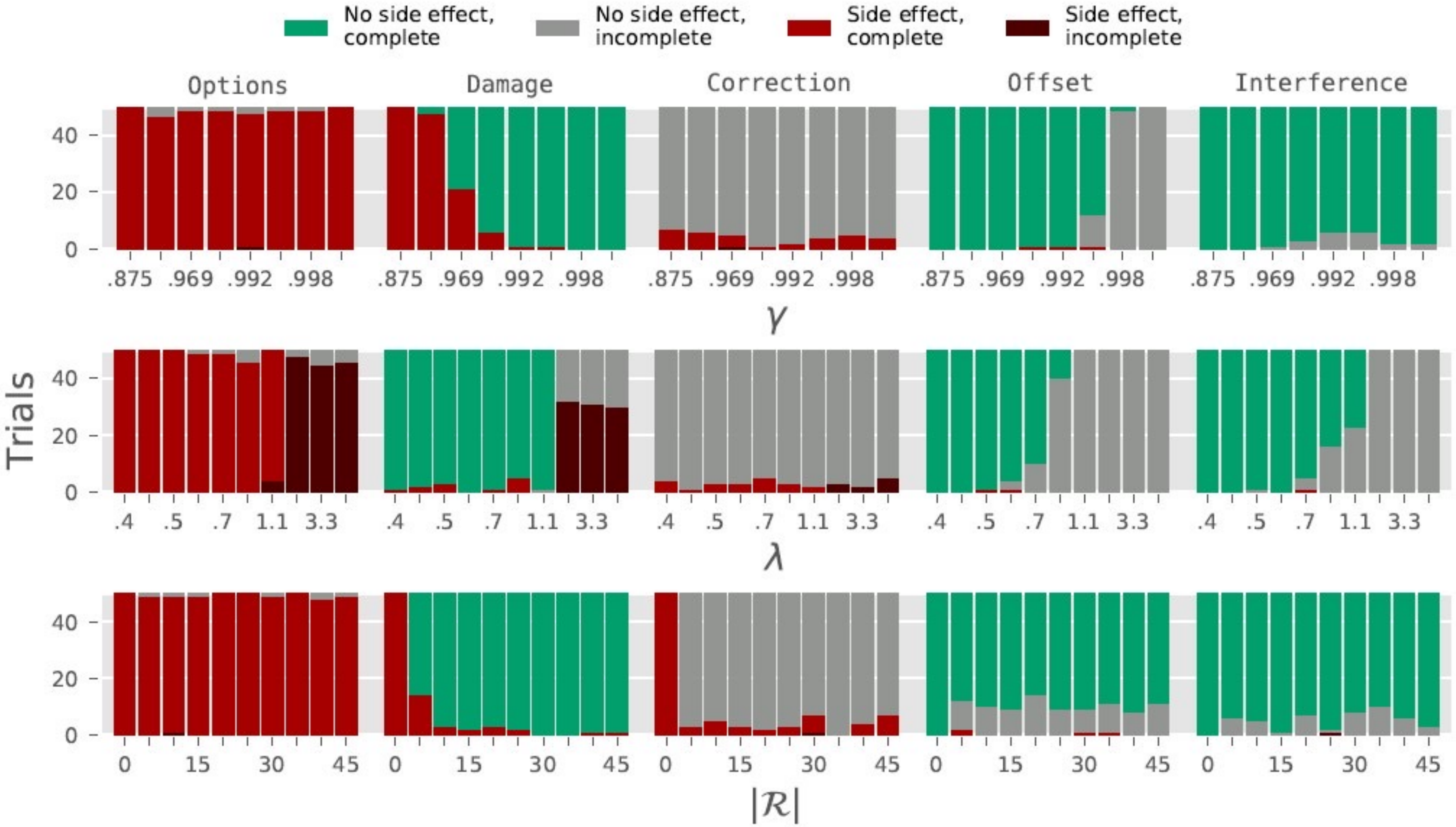

vAUP (rand) outcomes across different parameter settings over 50 trials with 6,000 episodes each

Performance

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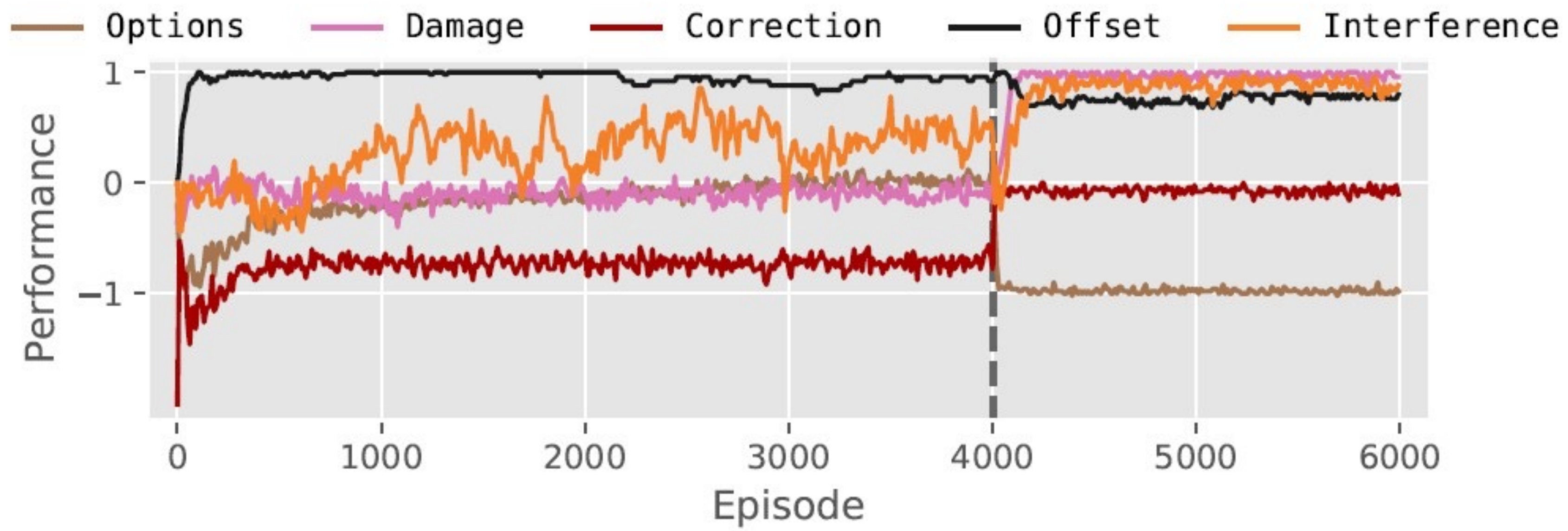

vAUP (rand) performance averaged over 50 trials

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

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- vAUP
  - Safe, conservative and effective behavior
  - Implicit way to avoid negative side effects in action-driven environments
  - Able to mitigate delayed effects to a certain extent

- Variation-based approach introducing different variants
  - Allows to consider different variants to solve tasks, depending on the environments

Future Work

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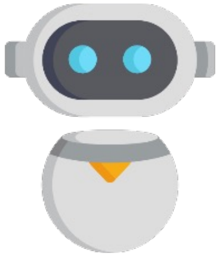
- Evaluate vAUP on more complex environments
  - E.g., SafeLife based on Conway's Game of Life [WE20]
  - Compare to standard AUP again, which was already evaluated on SafeLife

- Create and evaluate further vAUP variants
  - e.g., a *randn* variant with penalizing using a random subset

Thank you!



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https://github.com/fkabs/ytic_2023

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