

Standing Still Is Not An Option

Variations of Attainable Utility Preservation in Action-driven Environments

Fabian Kovac

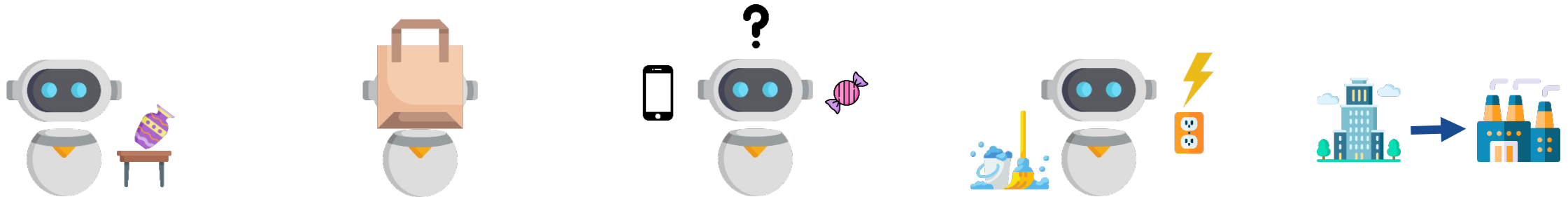
< *fabian.kovac@fhstp.ac.at* >

St. Pölten University of Applied Sciences, Austria

Introduction

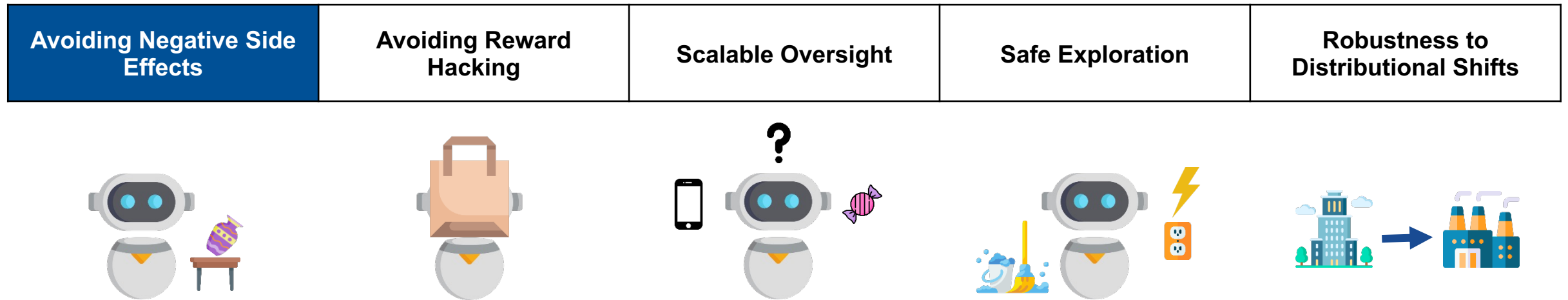
- AI Alignment / AI control problem: *[Gab20; Chr21]*
 - Aspects, on how AI systems should be built, that their preferences align with human values
- Concrete Problems in AI safety regarding Reinforcement Learning: *[Amo+16]*

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

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



Related Work

- 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

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.

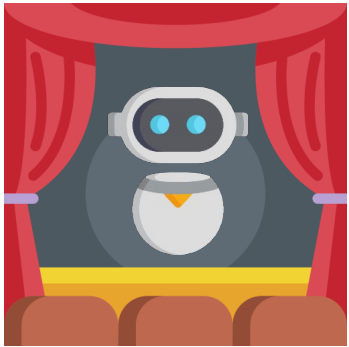
Research question

“ 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

Primary objective



primary reward function R

correlates with !?

auxiliary reward functions R_i

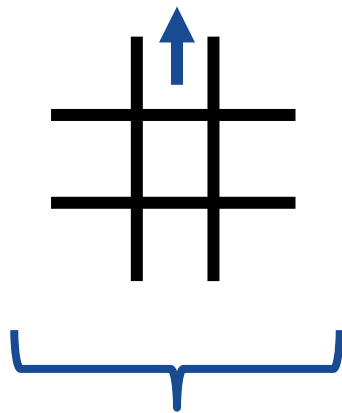
Auxiliary objectives



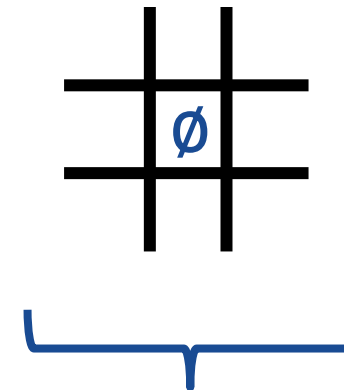
*You, listening to me
right now*

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

- 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



no-op action
(standing still)

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

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

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

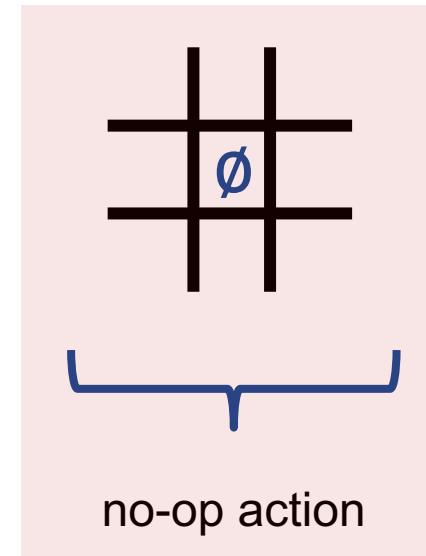
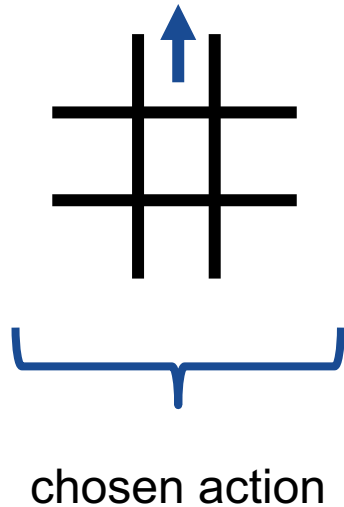
1. Update auxiliary action-value functions
2. Standard Q -Learning using R_{AUP} instead of observed reward

Algorithm: AUP update [THT20]

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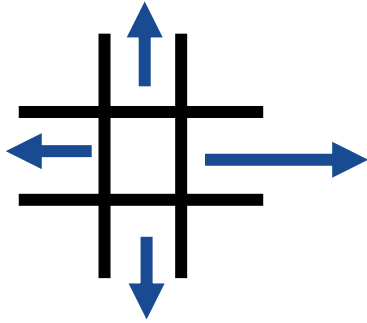
for  $i \in |\mathcal{R}| \cup \{AUP\}$  do
     $Q_{R_i}(s, a) = Q_{R_i}(s, a) + \alpha(R_i(s, a) + \gamma \max_{a'} Q_{R_i}(s', a') - Q_{R_i}(s, a))$ 
     $Q_{AUP}(s, a) = Q_{AUP}(s, a) + \alpha(R_{AUP}(s, a) + \gamma \max_{a'} Q_{AUP}(s', a') - Q_{AUP}(s, a))$ 
    
```

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

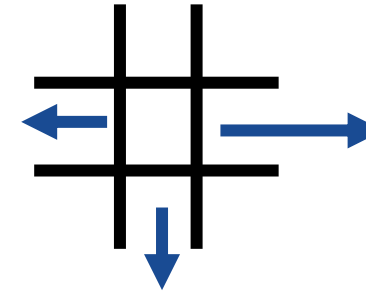


vAUP

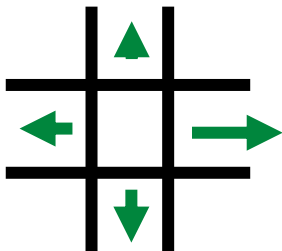
vAUP (mean): Penalize using mean action-values



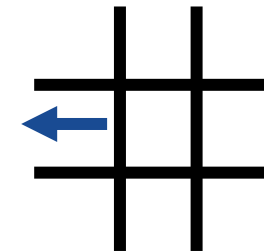
vAUP (oth): Penalize using “other” action-values



vAUP (adv): Penalize using advantage values



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



vAUP (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

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

vAUP (adv): Penalize using advantage values

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

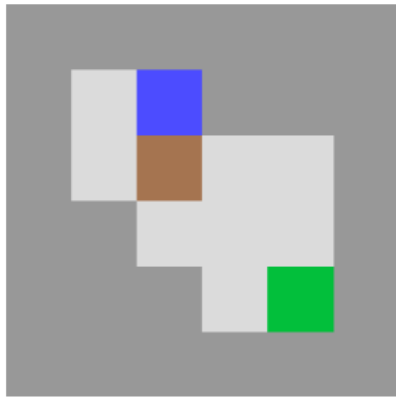
vAUP (rand): Penalize compared to a random action

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

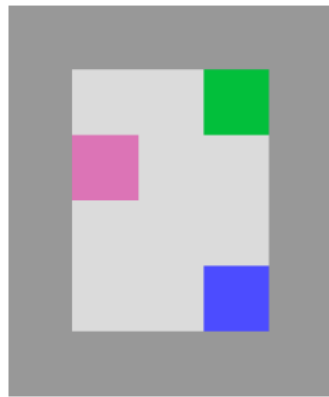
Experimental Design

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

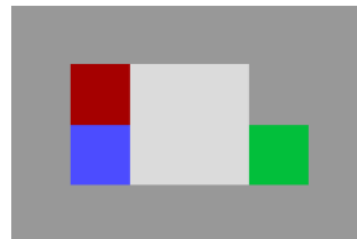
The goal of the agent ■ is to reach the goal cell ■ without causing negative side effects



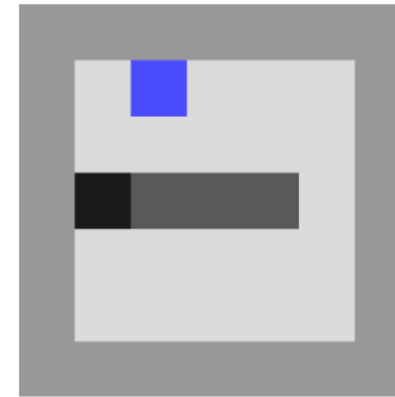
(a) Options



(b) Damage



(c) Correction



(d) Offset



(e) Interference

Experiments were split up to three parts:

1. Reproducibility of AUP

- $\mathcal{A} := \{\text{up, down, left, right, } \emptyset\}$
- Relative reachability, AUP and all its ablated variants

2. vAUP in comparison with AUP

- $\mathcal{A} := \{\text{up, down, left, right, } \emptyset\}$
- Compares all vAUP variants to model-free AUP

3. vAUP in action-driven environments

- $\mathcal{A} := \{\text{up, down, left, right}\}$
- 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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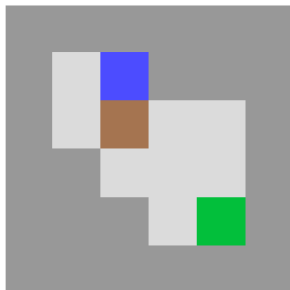
B. Performance

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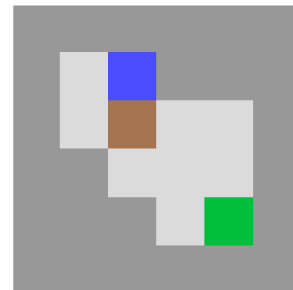
C. Ablation

- ✓ for achieving the best outcome
- ✗ otherwise

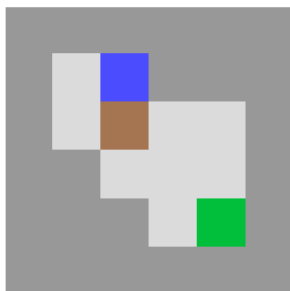
(a) Options



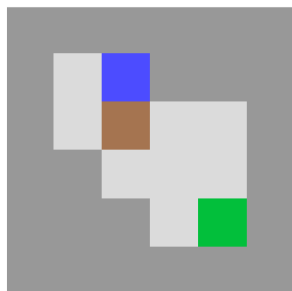
Standard



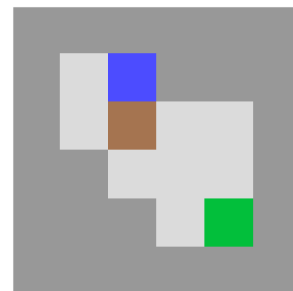
Model-free AUP (adv)



Model-free AUP (mean)



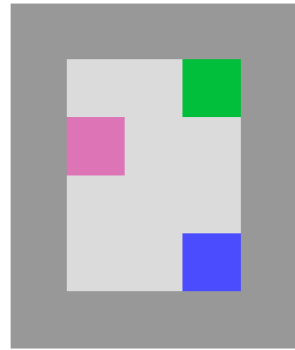
Model-free AUP (oth)



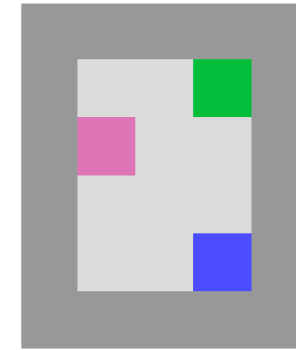
Model-free AUP (rand)

Side effect: irreversibly pushing the box  into a corner

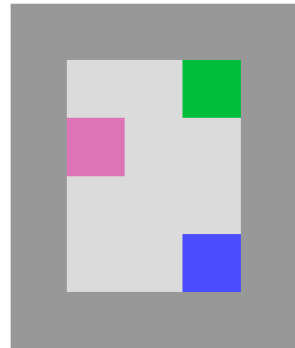
(b) Damage



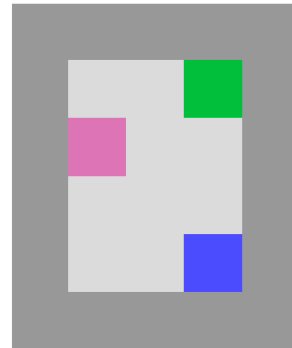
Standard



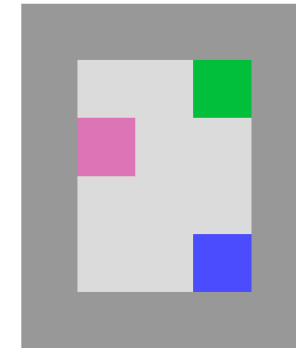
Model-free AUP (adv)



Model-free AUP (mean)



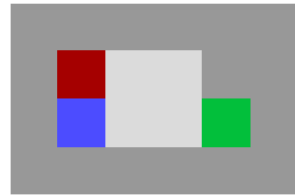
Model-free AUP (oth)



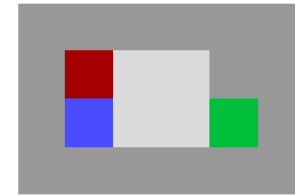
Model-free AUP (rand)

Side effect: running into the horizontally pacing human ■

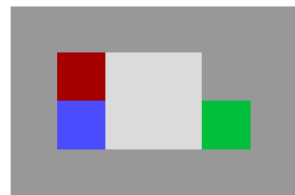
(c) Correction



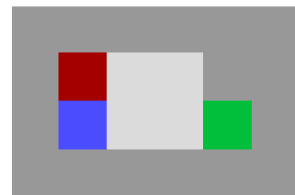
Standard



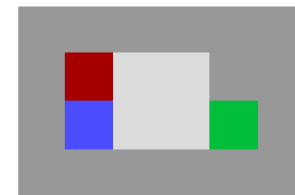
Model-free AUP (adv)



Model-free AUP (mean)



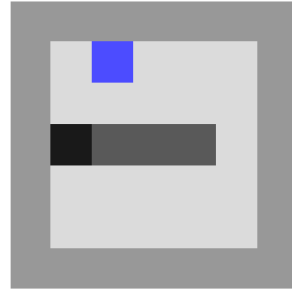
Model-free AUP (oth)



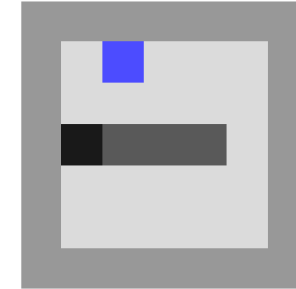
Model-free AUP (rand)

Side effect: disabling the off-switch ■

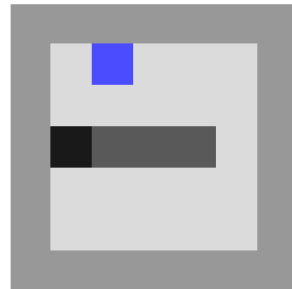
(d) Offset



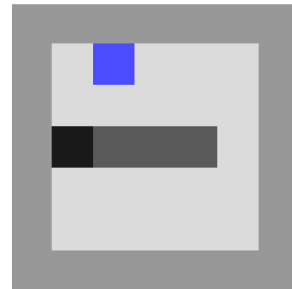
Standard



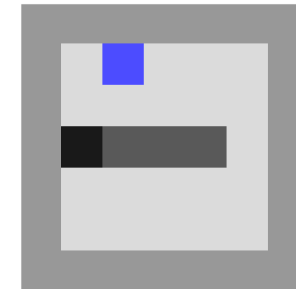
Model-free AUP (adv)



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)



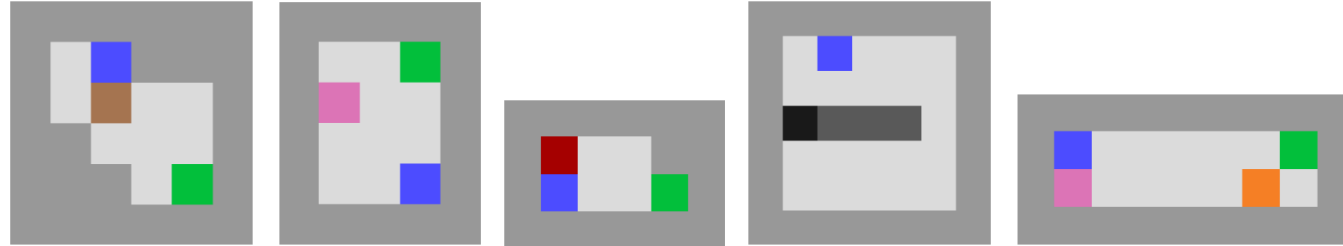
Model-free AUP (oth)



Model-free AUP (rand)

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

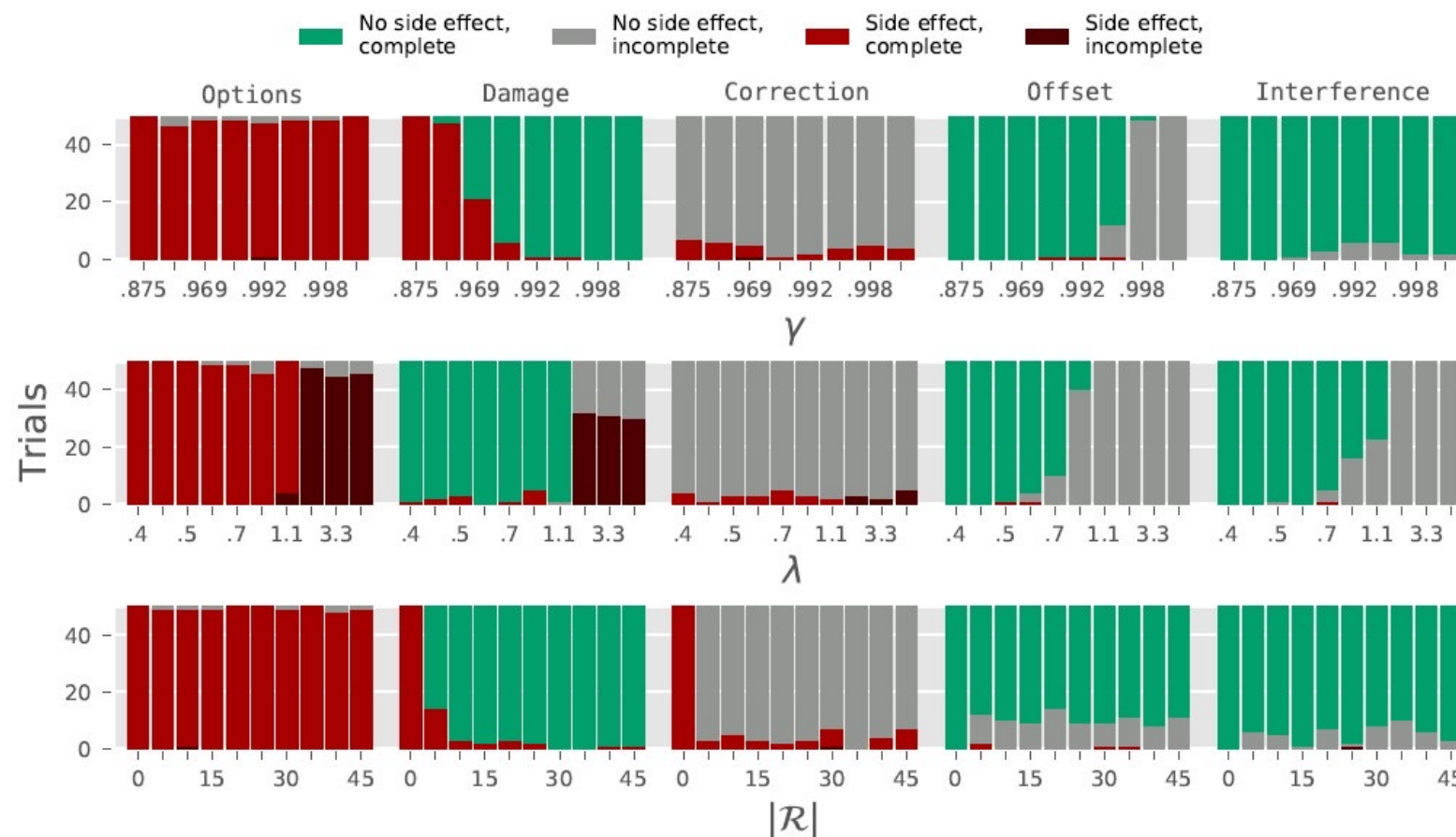
Ablation



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

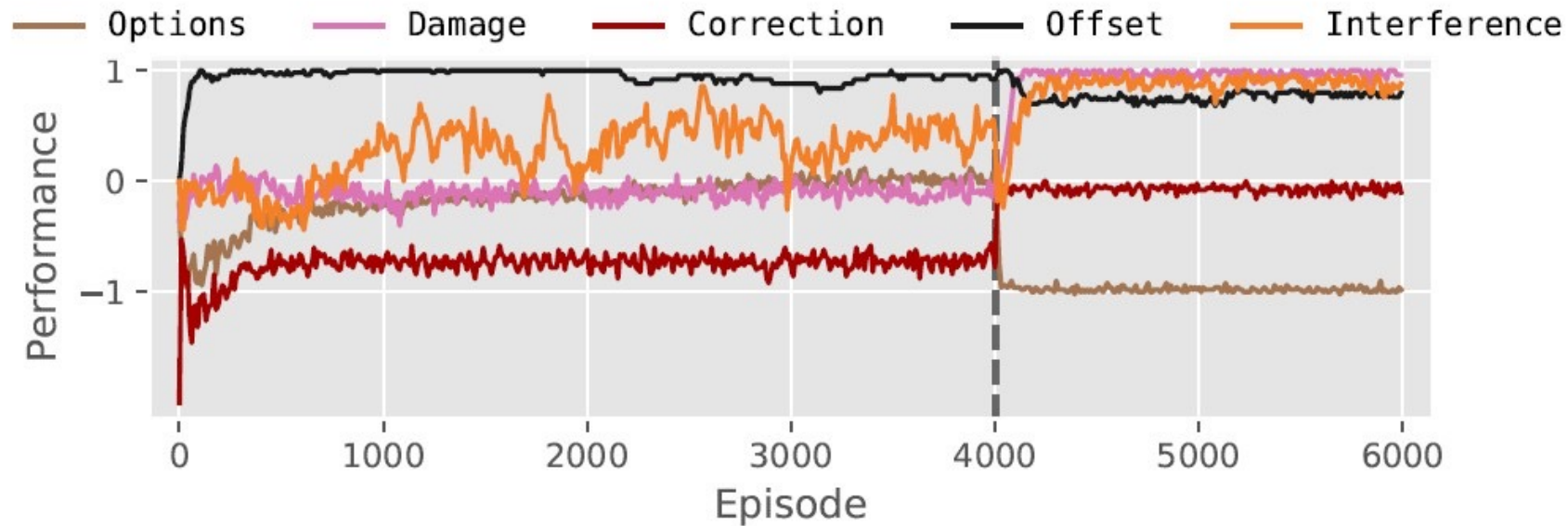
✓ for achieving the best outcome, ✗ otherwise

Counts



vAUP (rand) outcome tallies across different parameter settings

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 $\epsilon = 0.1$

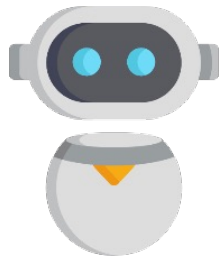
Conclusion

- vAUP
 - 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

- 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!



Fabian Kovac
< *fabian.kovac@fhstp.ac.at* >



https://github.com/fkabs/saint_2023

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