

# Standing Still Is Not An Option

## Variations of Attainable Utility Preservation in Action-driven Environments

Fabian Kovac

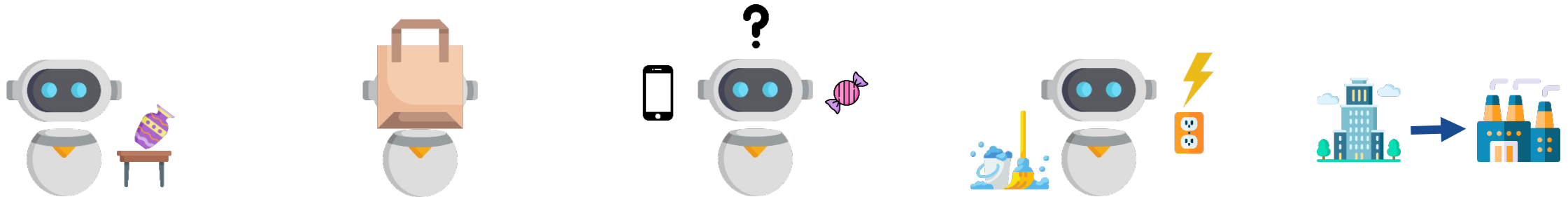
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# Introduction

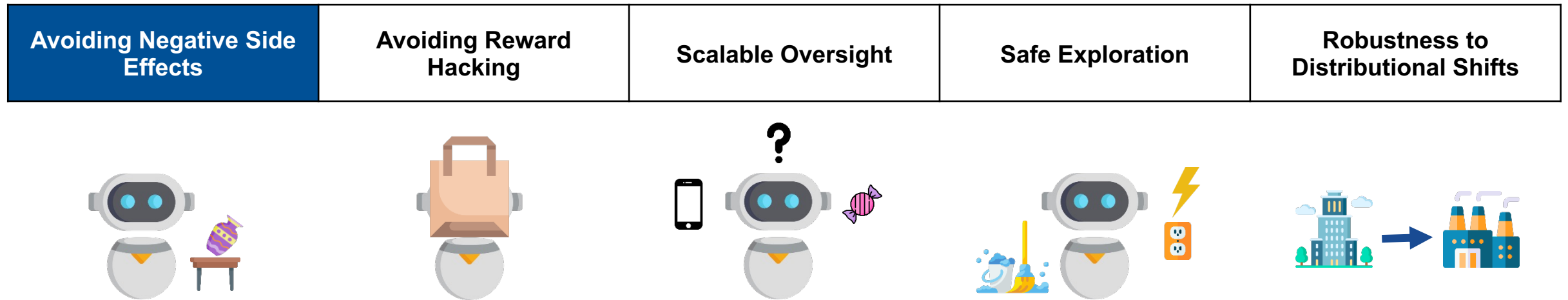
- AI Alignment / AI control problem: *[Gab20; Chr21]*
  - Aspects, on how AI systems should be built, that their preferences align with human values
- Concrete Problems in AI safety regarding Reinforcement Learning: *[Amo+16]*

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

- 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]*



# 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.

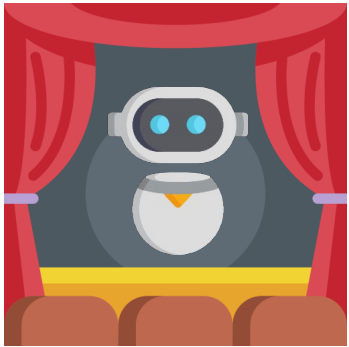
## Research question

*“ 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  $R_i$

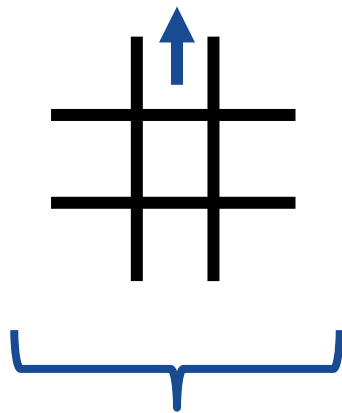
## Auxiliary objectives



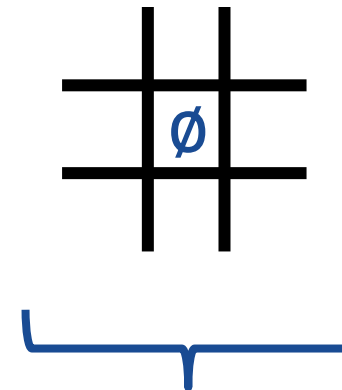
*You, listening to me  
right now ....*

*.... 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,  $\lambda$  controls the influence of the AUP penalty on the reward function.

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

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

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### Algorithm: AUP update [THT20]

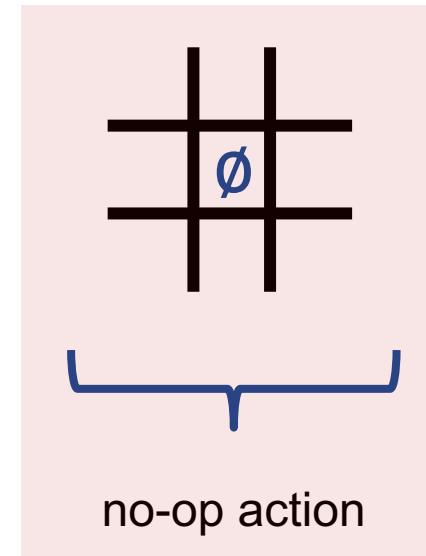
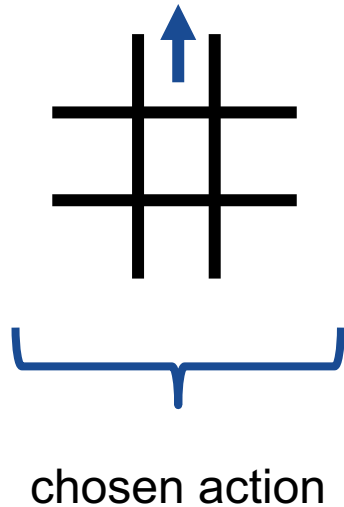
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for  $i \in |\mathcal{R}| \cup \{AUP\}$  do
     $Q_{R_i}(s, a) = Q_{R_i}(s, a) + \alpha(R_i(s, a) + \gamma \max_{a'} Q_{R_i}(s', a') - Q_{R_i}(s, a))$ 
     $Q_{AUP}(s, a) = Q_{AUP}(s, a) + \alpha(R_{AUP}(s, a) + \gamma \max_{a'} Q_{AUP}(s', a') -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

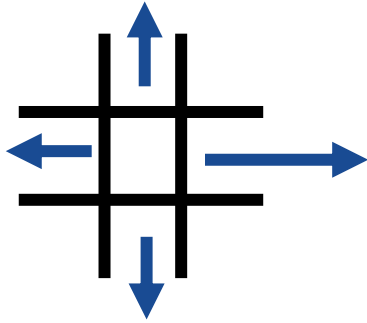
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- What if "standing still" is not an option?

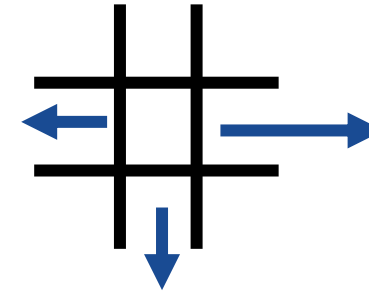


# vAUP

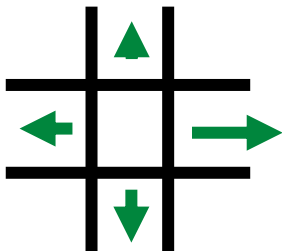
**vAUP (mean):** Penalize using mean action-values



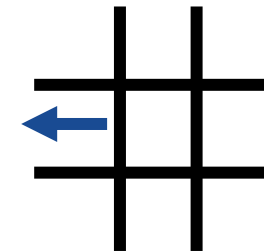
**vAUP (oth):** Penalize using “other” action-values



**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

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

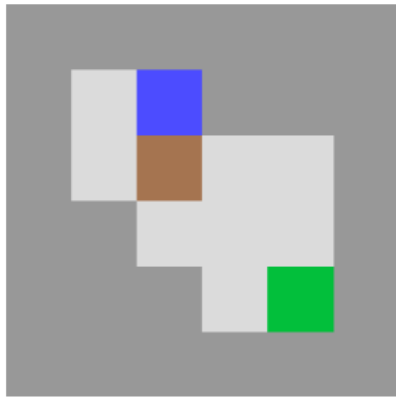
**vAUP (rand):** Penalize compared to a random action

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

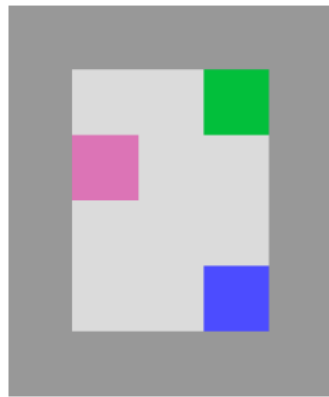
# Experimental Design

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

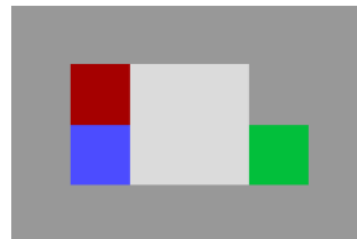
The goal of the agent ■ is to reach the goal cell ■ without causing negative side effects



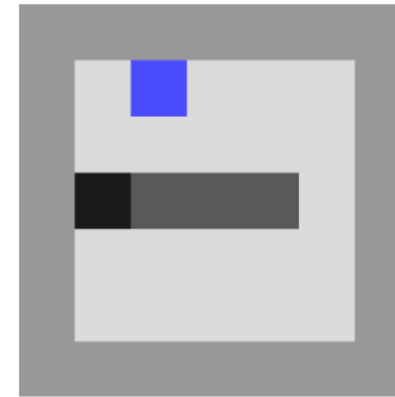
(a) Options



(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  $\lambda, \gamma$  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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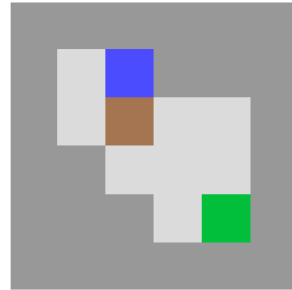
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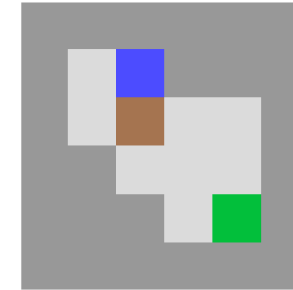
### C. Ablation

- ✓ for achieving the best outcome
- ✗ otherwise

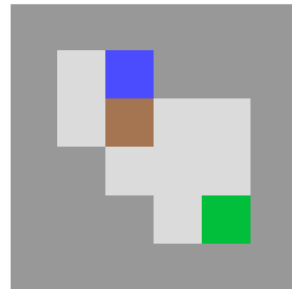
# (a) Options



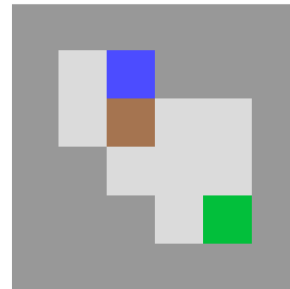
Standard



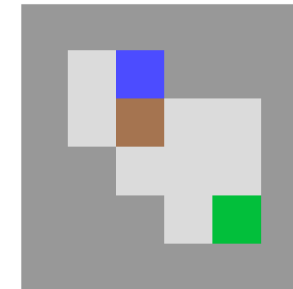
Model-free AUP (adv)



Model-free AUP (mean)



Model-free AUP (oth)

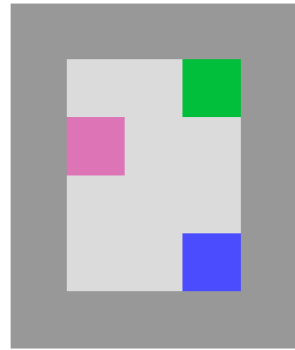


Model-free AUP (rand)

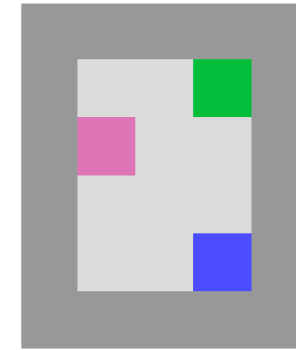
*Side effect: irreversibly pushing the box ■ into a corner*



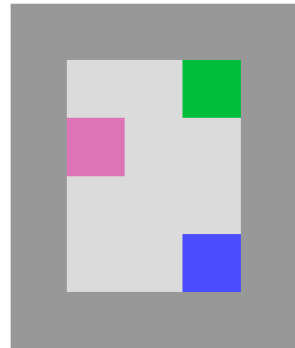
# (b) Damage



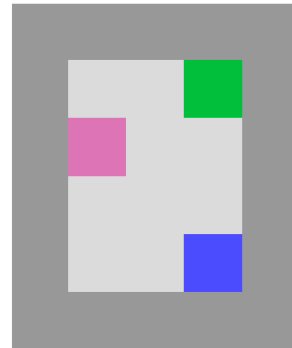
Standard



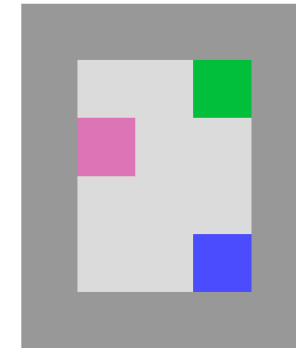
Model-free AUP (adv)



Model-free AUP (mean)



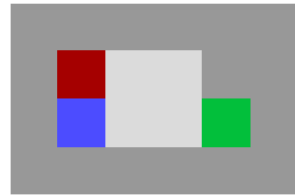
Model-free AUP (oth)



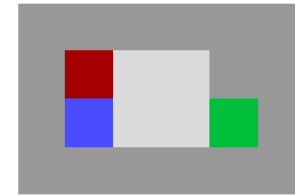
Model-free AUP (rand)

*Side effect: running into the horizontally pacing human* ■

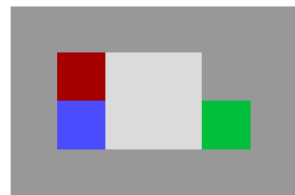
# (c) Correction



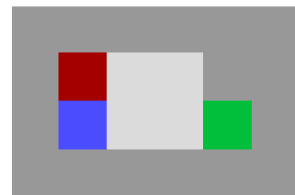
Standard



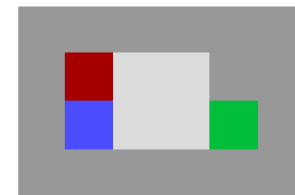
Model-free AUP (adv)



Model-free AUP (mean)



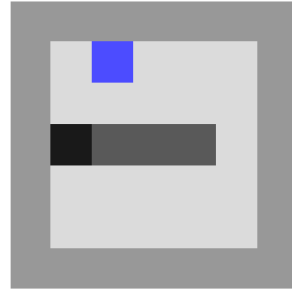
Model-free AUP (oth)



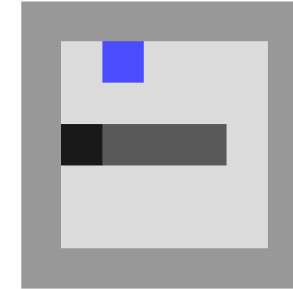
Model-free AUP (rand)

*Side effect: disabling the off-switch* ■

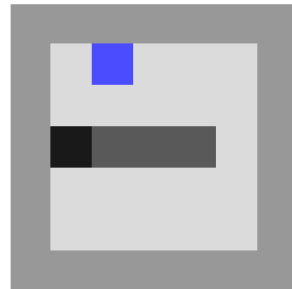
# (d) Offset



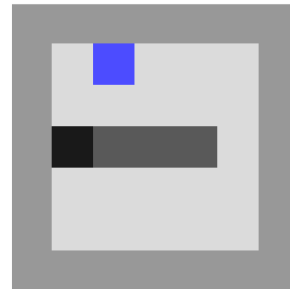
Standard



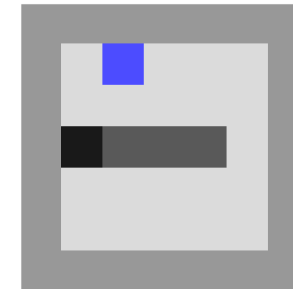
Model-free AUP (adv)



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)



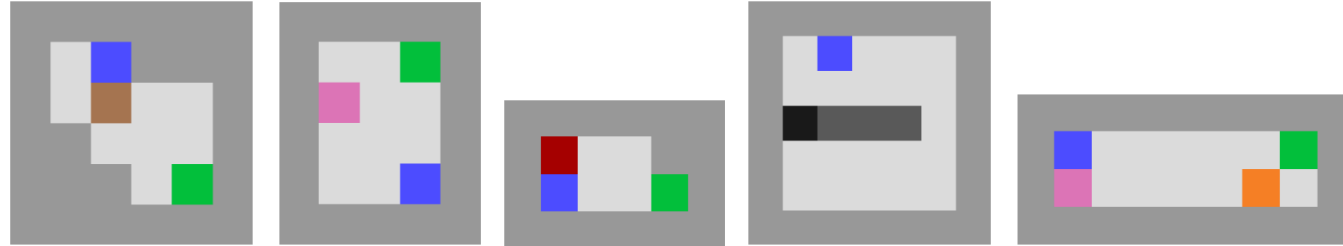
Model-free AUP (oth)



Model-free AUP (rand)

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

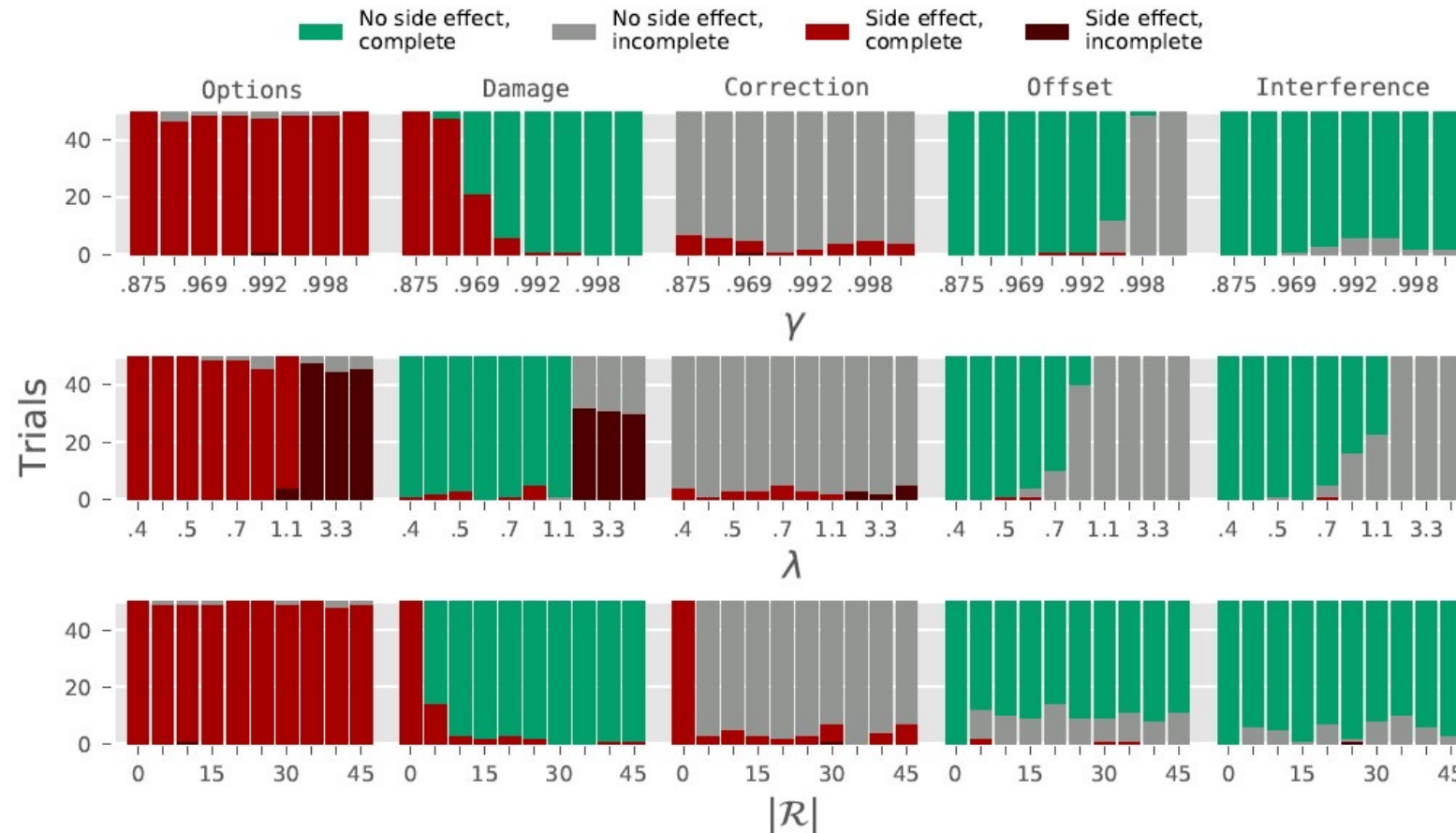
# Ablation



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

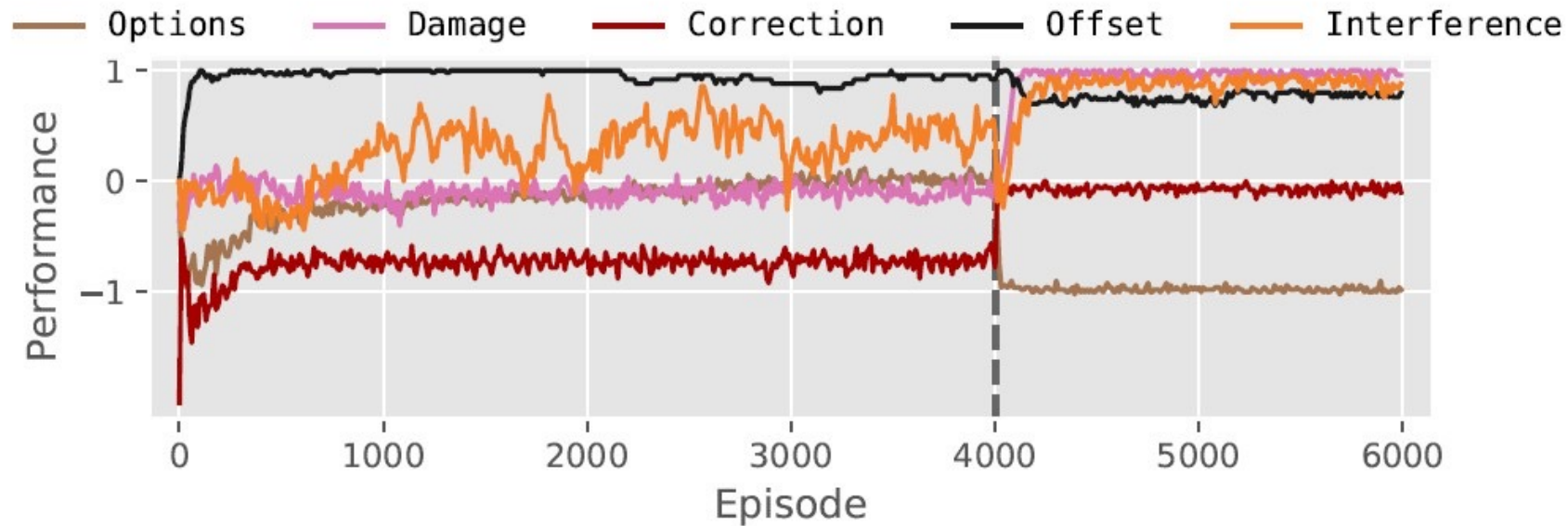
✓ for achieving the best outcome, ✗ otherwise

# 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

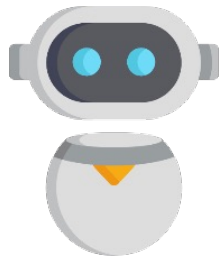
- vAUP
  - Safe, conservative and effective behavior
  - Implicit way to avoid negative side effects in action-driven environments
  - Able to mitigate delayed effects to a certain extent
- Variation-based approach introducing different variants
  - Allows to consider different variants to solve tasks, 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!



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*<https://github.com/fkabs/attainable-utility-preservation>*

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