ST. PÖLTEN UNIVERSITY
OF APPLIED SCIENCES

research

Standing Still Is Not An Option

Variations of Attainable Utility Preservation in Action-driven Environments

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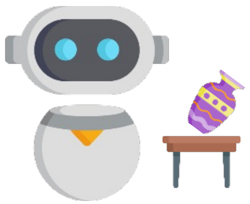
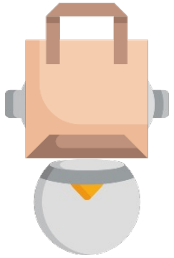
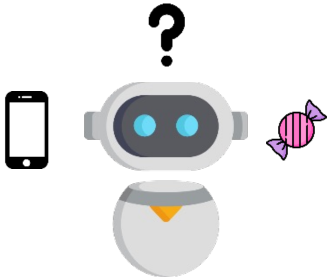
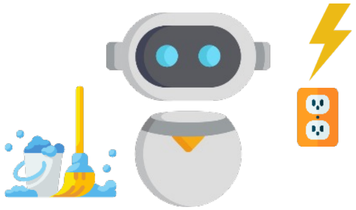
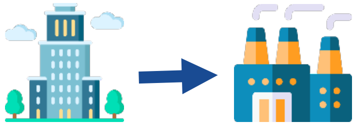
Introduction

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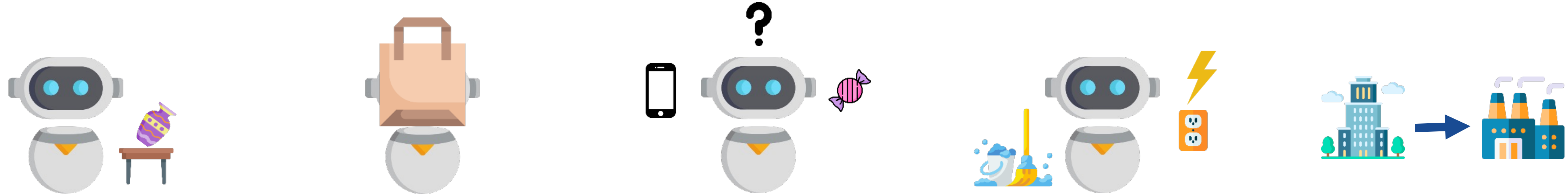

Related Work

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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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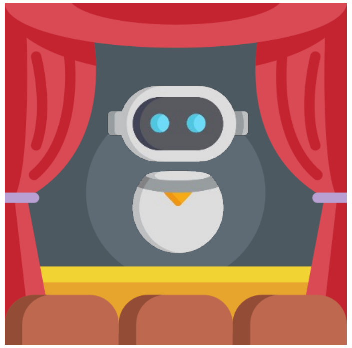
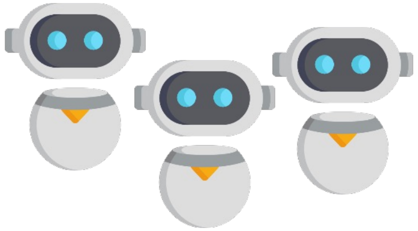
Primary objective





You, listening to me right now ....

primary reward function R

correlates with !?

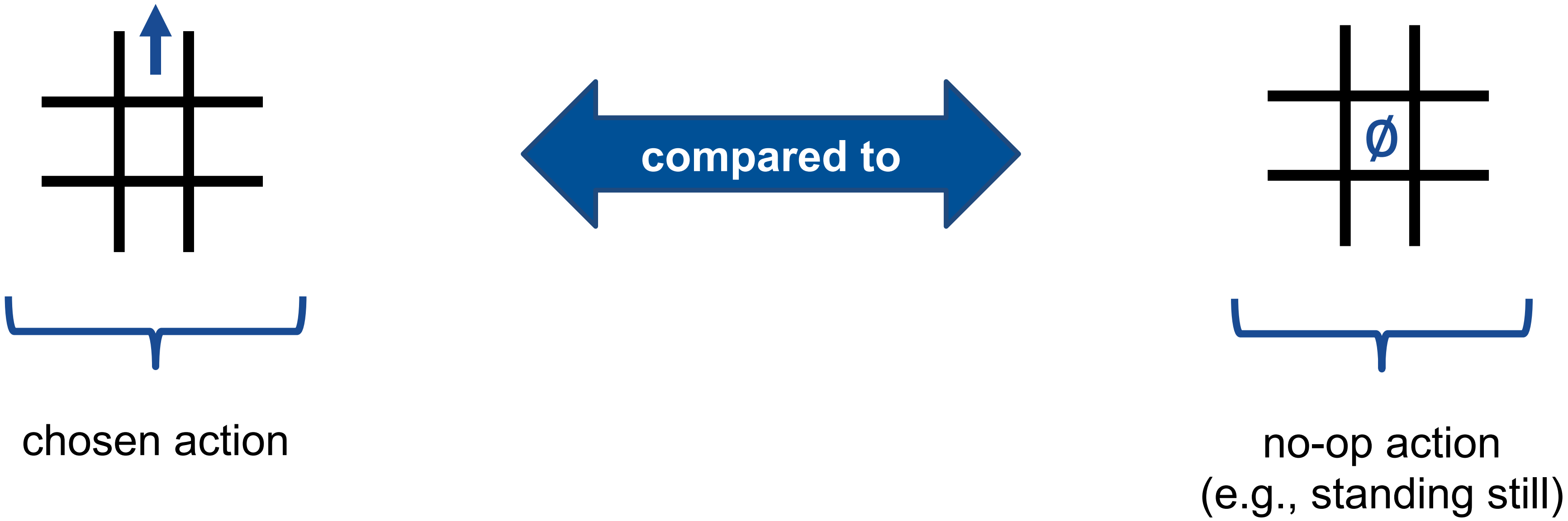
auxiliary reward functions R_i

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



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**

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

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

AUP

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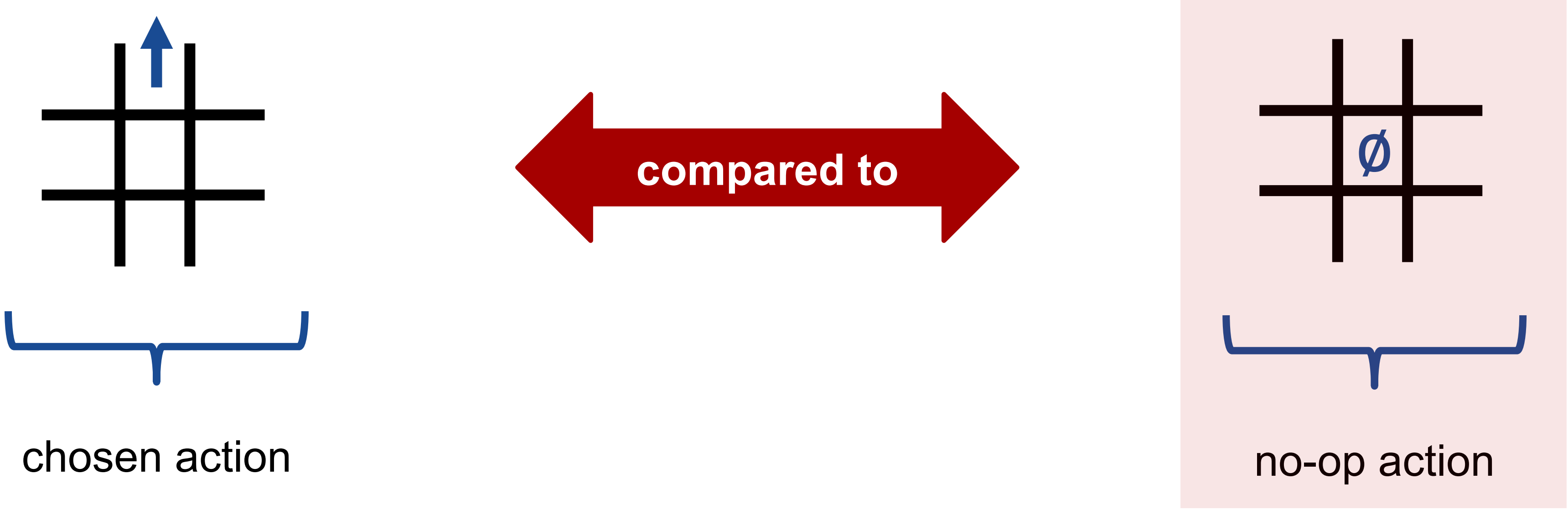
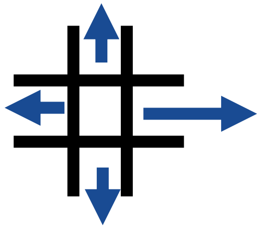
- What if ”standing still” is not an option?



vAUP

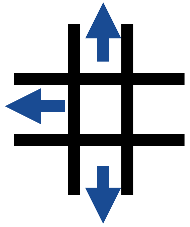
vAUP (mean): Penalize compared to mean estimate

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



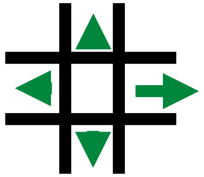
vAUP (oth): Penalize compared to “other” action-values

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



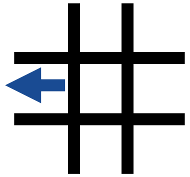
vAUP (adv): Penalize using advantage values

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



vAUP (rand): Penalize compared to a random action

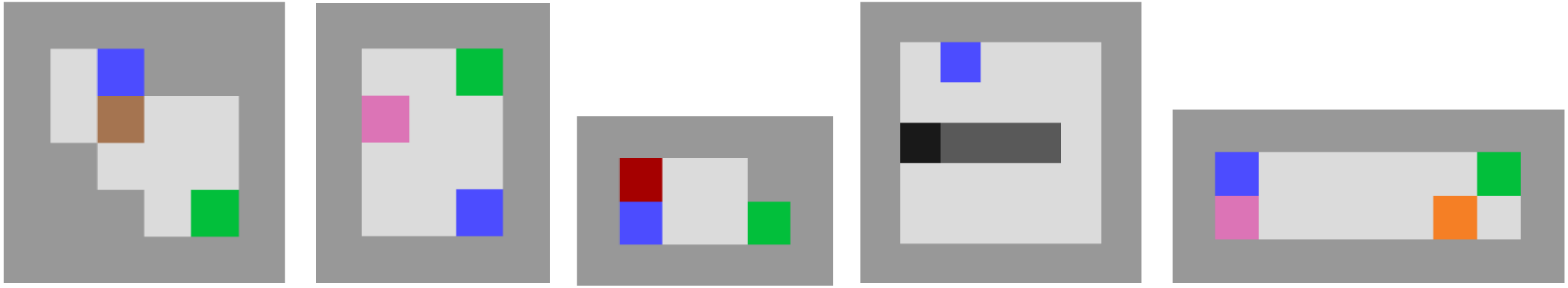
$$PENALTY_{rand}(s,a) \coloneqq \sum_{R_i \in \mathcal{R}} \left| Q_{R_i}(s,a) - \underset{a' \in \mathcal{A} \setminus \{a\}}{rand} \left(Q_{R_i}(s,a') \right) \right|$$



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

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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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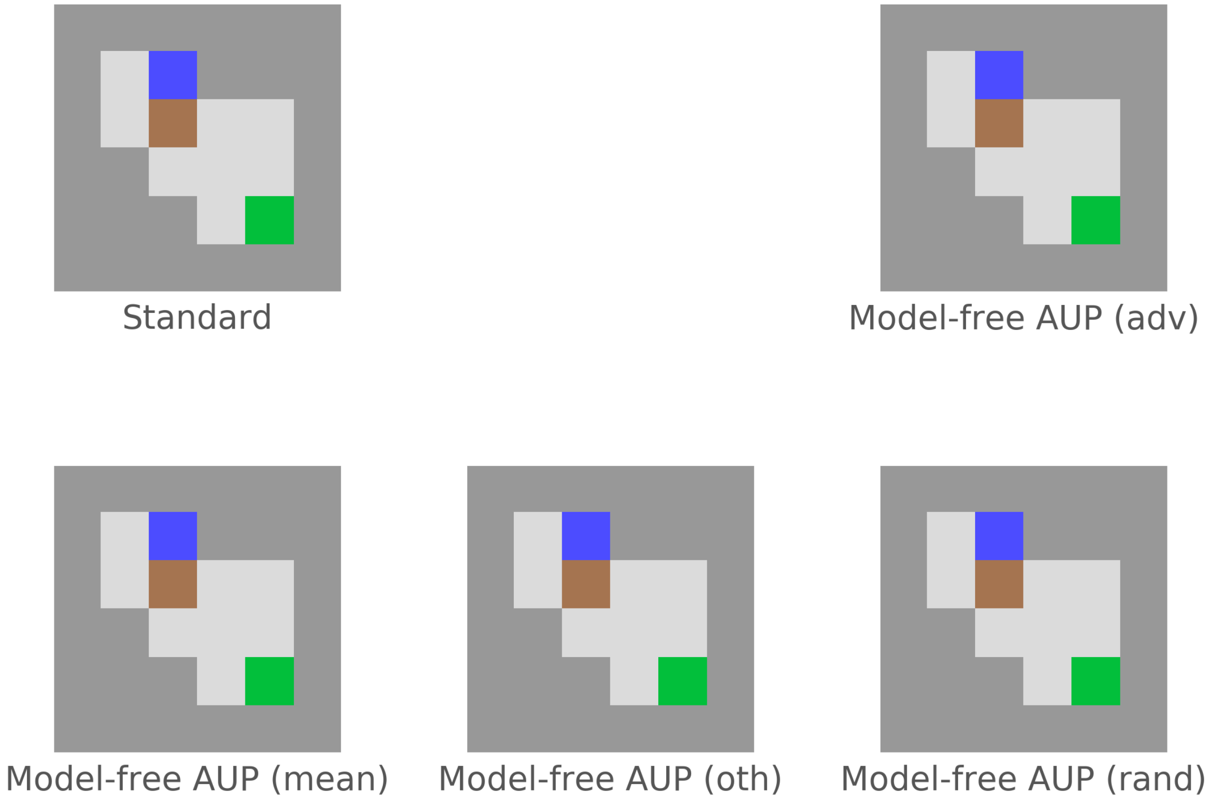
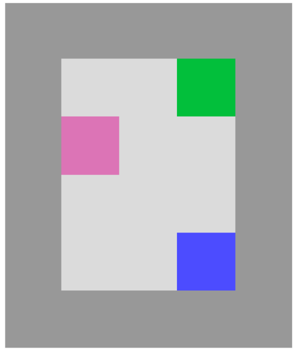
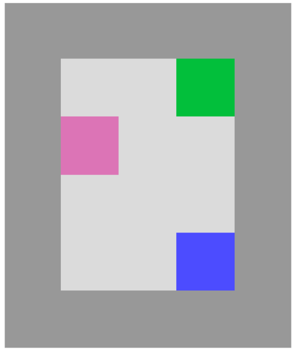
(a) Options

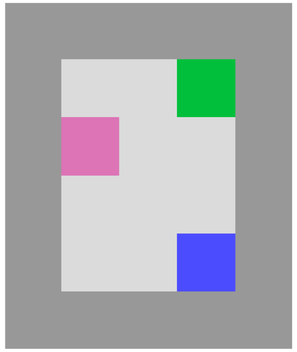


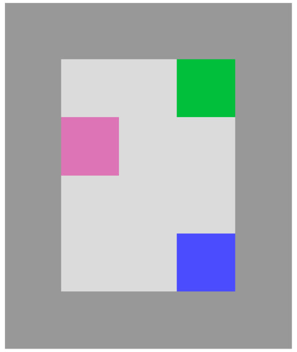
Side effect: irreversibly pushing the box into a corner

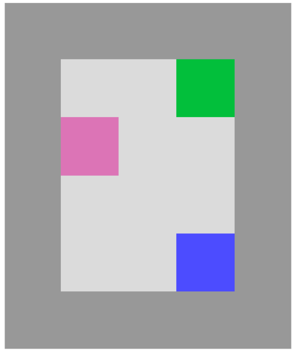
(b) Damage


Standard


Model-free AUP (adv)

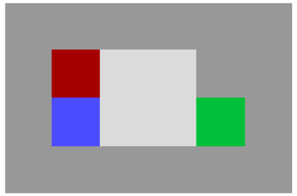

Model-free AUP (mean)


Model-free AUP (oth)

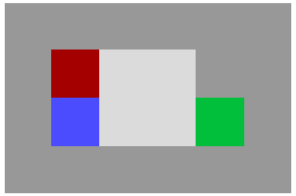

Model-free AUP (rand)

Side effect: running into the horizontally pacing human

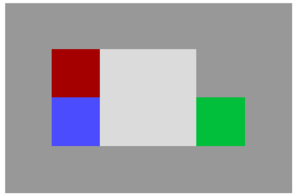
(c) Correction



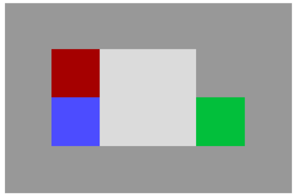
Standard



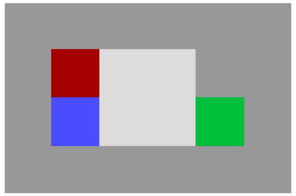
Model-free AUP (adv)



Model-free AUP (mean)



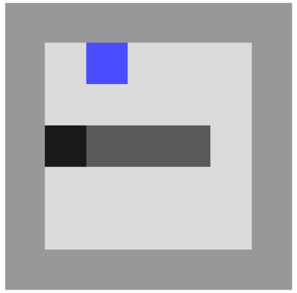
Model-free AUP (oth)



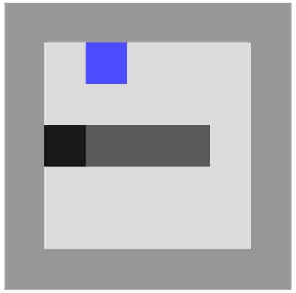
Model-free AUP (rand)

Side effect: disabling the off-switch ■

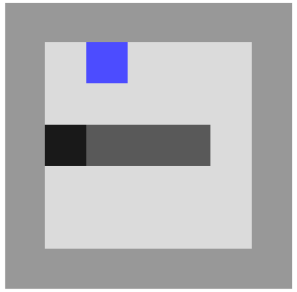
(d) Offset



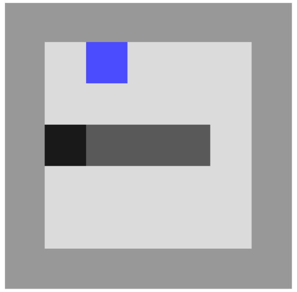
Standard



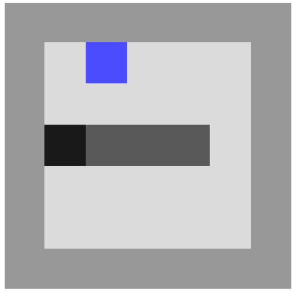
Model-free AUP (adv)



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

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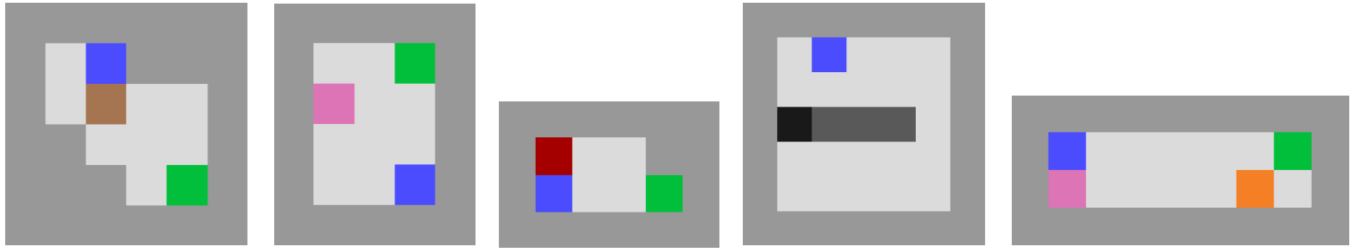
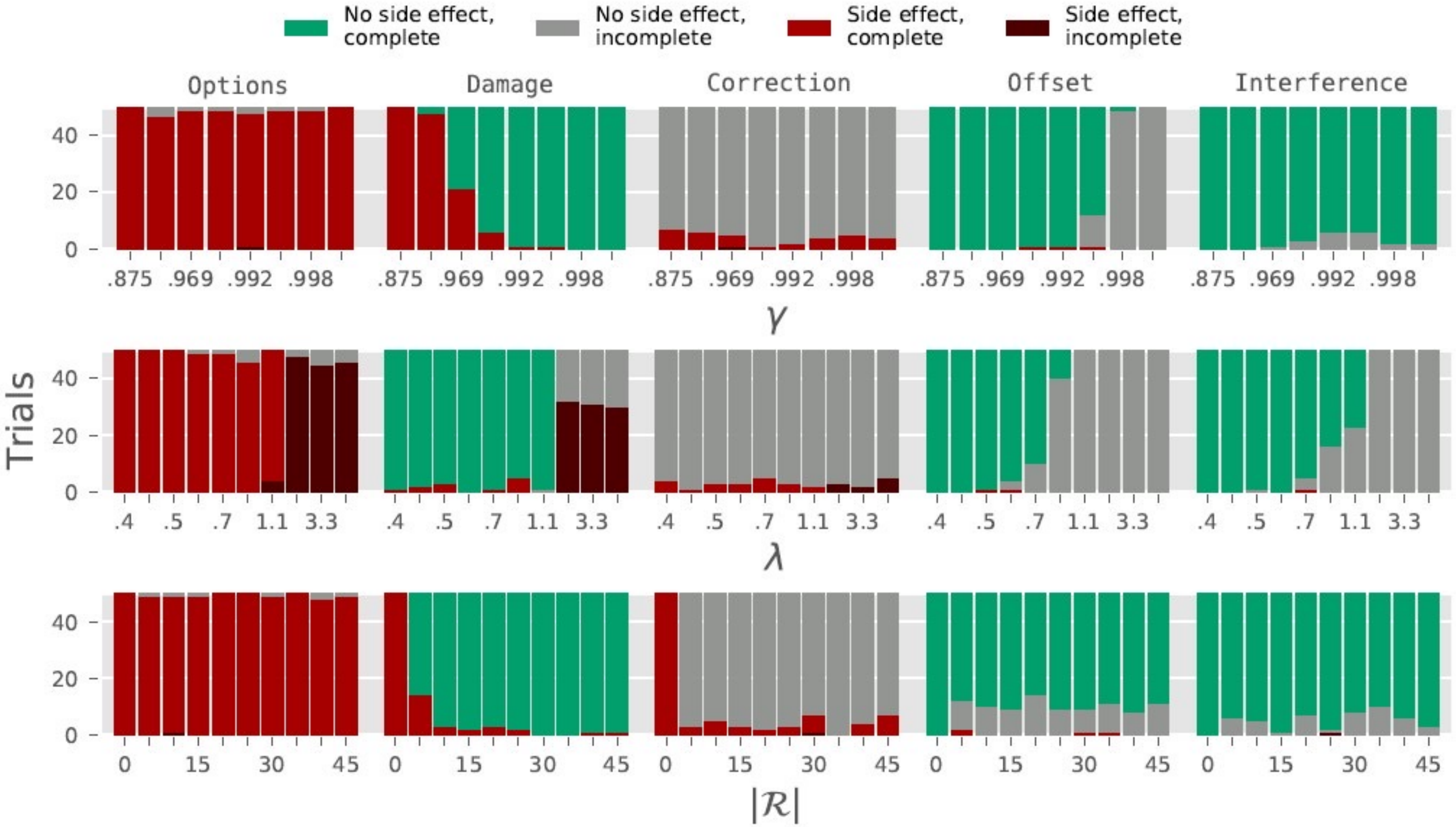


	Options	Damage	Correction	Offset	Interference
Standard	✗	✗	✗	✓	✓
vAUP (mean)	✓	✓	✗	✓	✓
vAUP (oth)	✗	✓	✗	✓	✓
vAUP (adv)	✗	✗	✗	✓	✓
vAUP (rand)	✗	✓	✓	✓	✓

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

Counts



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

Performance

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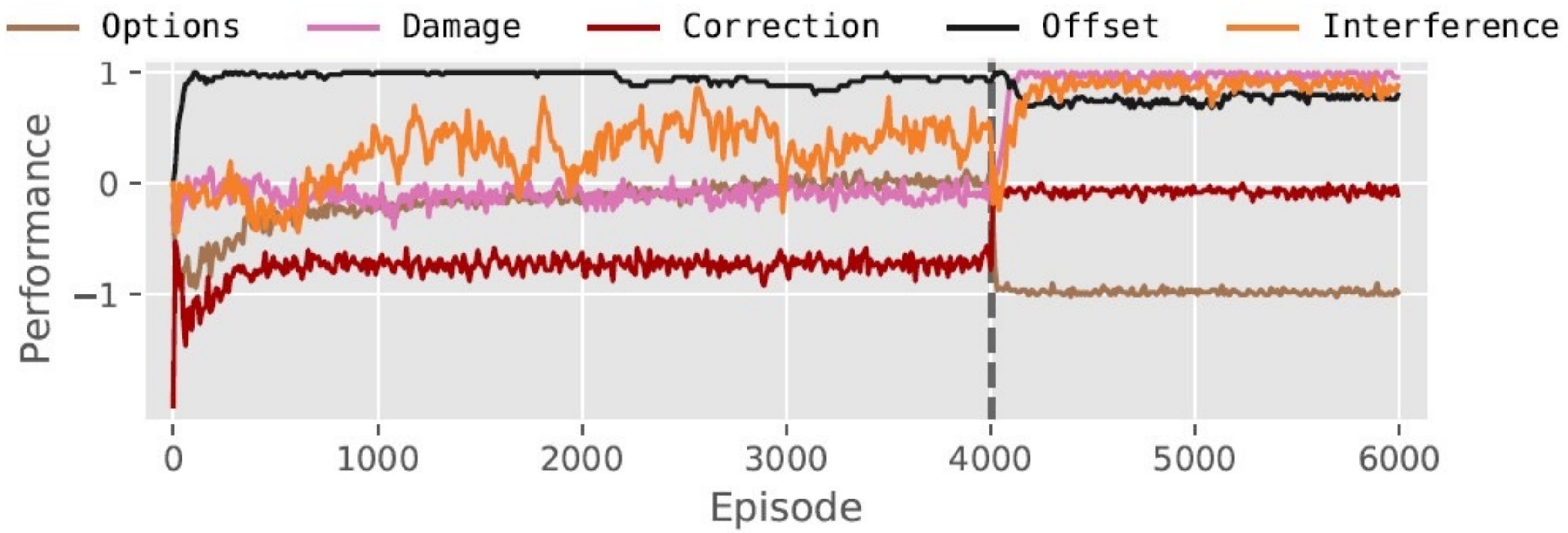

vAUP (rand) performance averaged over 50 trials

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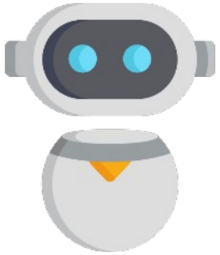
- Evaluate vAUP on more complex environments
    - E.g., SafeLife based on Conway's Game of Life *[WE20]*
    - Compare to standard AUP again, which was already evaluated on SafeLife

- 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/saint_2023

References

I. Gabriel, “Artificial Intelligence, Values, and Alignment,” *Minds & Machines*, vol. 30, no. 3, pp. 411–437, Sep. 2020, doi: 10.1007/s11023-020-09539-2.

B. Christian, *The alignment problem: machine learning and human values*. 2021.

D. Amodei, C. Olah, J. Steinhardt, P. Christiano, J. Schulman, and D. Mané, “Concrete Problems in AI Safety,” *arXiv:1606.06565 [cs]*, Jul. 2016, Accessed: Dec. 10, 2021. [Online]. Available: http://arxiv.org/abs/1606.06565

E. Altman, *Constrained Markov decision processes*. Boca Raton ; London: Chapman & Hall/CRC, 1999.

S. Zhang, E. H. Durfee, and S. Singh, “Minimax-Regret Querying on Side Effects for Safe Optimality in Factored Markov Decision Processes,” pp. 4867–4873, 2018.

K. Regan and C. Boutilier, “Robust policy computation in reward-uncertain MDPs using nondominated policies,” in *Proceedings of the twenty-fourth AAAI conference on artificial intelligence, AAAI 2010*, Georgia, USA, Jul. 2010. [Online]. Available: http://www.aaai.org/ocs/index.php/AAAI/AAAI10/paper/view/1610

A. M. Turner, N. Ratzlaff, and P. Tadepalli, “Avoiding Side Effects in Complex Environments,” in *Advances in Neural Information Processing Systems*, virtual, Dec. 2020, vol. 33, pp. 21406–21415. Accessed: Oct. 27, 2021. [Online]. Available: https://proceedings.neurips.cc/paper/2020/hash/f50a6c02a3fc5a3a5d4d9391f05f3efc-Abstract.html

A. M. Turner, D. Hadfield-Menell, and P. Tadepalli, “Conservative Agency via Attainable Utility Preservation,” in *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, New York, NY, USA, Feb. 2020, pp. 385–391. doi: 10.1145/3375627.3375851.

J. Leike *et al.*, “AI Safety Gridworlds.” arXiv, Nov. 28, 2017. doi: 10.48550/arXiv.1711.09883.

References

C. L. Wainwright and P. Eckersley, “SafeLife 1.0: Exploring side effects in complex environments,” in *Proceedings of the workshop on artificial intelligence safety, co-located with 34th AAAI conference on artificial intelligence*, New York City, NY, USA, Feb. 2020, vol. 2560, pp. 117–127. [Online]. Available: http://ceur-ws.org/Vol-2560/paper46.pdf

V. Krakovna, L. Orseau, M. Martic, and S. Legg, “Penalizing Side Effects using Stepwise Relative Reachability,” in *Proceedings of the Workshop on Artificial Intelligence Safety 2019*, Macao, China, Aug. 2019, vol. 2419. Accessed: Dec. 10, 2021. [Online]. Available: http://ceur-ws.org/Vol-2419/#paper1

G. Leech, K. Kubicki, J. Cooper, and T. McGrath, “Preventing Side-effects in Gridworlds,” AI Safety Camp, Gran Canaria, Apr. 22, 2018. [Online]. Available: https://www.gleech.org/grids

M. Pecka and T. Svoboda, “Safe Exploration Techniques for Reinforcement Learning – An Overview,” in *Modelling and Simulation for Autonomous Systems*, Cham, May 2014, vol. 8906, pp. 357–375. doi: 10.1007/978-3-319-13823-7_31.

J. García and F. Fernández, “A comprehensive survey on safe reinforcement learning,” *J. Mach. Learn. Res.*, vol. 16, no. 1, pp. 1437–1480, Jan. 2015.

F. Berkenkamp, M. Turchetta, A. Schoellig, and A. Krause, “Safe model-based reinforcement learning with stability guarantees,” in *Advances in neural information processing systems*, 2017, vol. 30. [Online]. Available: https://proceedings.neurips.cc/paper/2017/file/766ebcd59621e305170616ba3d3dac32-Paper.pdf

Y. Chow, O. Nachum, E. Duenez-Guzman, and M. Ghavamzadeh, “A Lyapunov-based Approach to Safe Reinforcement Learning,” in *Advances in Neural Information Processing Systems*, 2018, vol. 31. Accessed: Aug. 21, 2022. [Online]. Available: https://proceedings.neurips.cc/paper/2018/hash/4fe5149039b52765bde64beb9f674940-Abstract.html