Human in the Loop, Safe Reinforcement Learning for Continuous Control

DDP Final Review

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2. Literature Survey
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Introduction

We aim to develop a framework to ensure safety during both the training and deployment phases of an RL by using human input.

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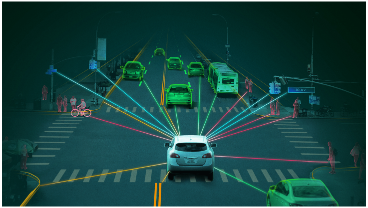
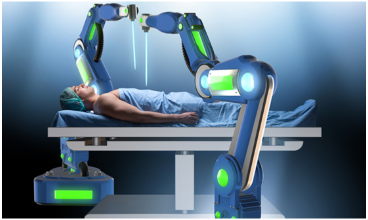
Motivation:

- Safety Critical Tasks: Autonomous Driving, Healthcare Robotics etc
- As humans entrust autonomous agents with increasingly complex tasks, their involvement in the learning process becomes crucial.





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Literature Survey

We performed a comprehensive literature review from two directions and a taxonomy was developed:

- Safe Reinforcement Learning [1, 2, 3, 4]
- Human in the Loop RL [5, 6, 7, 8]

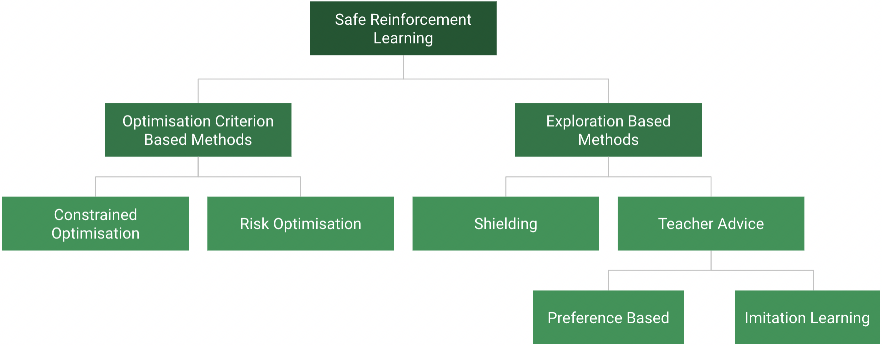

Figure: Safe RL Taxonomy

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- Consider a Markov Decision Process $(\mathcal{S}, \mathcal{A}, f, \mathcal{R}, \gamma)$ with a State Space S, Action Space A, Transition Function f s.t $s' = f(s, a)$, Reward Structure R and discounting factor γ
- The objective is to learn a policy $\pi : \mathcal{S} \to \mathcal{A}$ which maximises the expected cumulative reward while ensuring safety in both training and deployment i.e $\forall s \in \mathcal{X}_s, f(s, \pi(s)) \in \mathcal{X}_s$

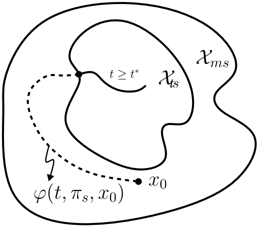

Figure: Depiction of Safe Sets

Notation	Meaning
$\mathcal{X}_{ts}$	Truly Safe State Space
$\mathcal{X}_{ms}$	Marginally Safe State Space
$\mathcal{X}_s$	Safe State Space $\mathcal{X}_{ts}$
CSP or π_s	Conservative Safe Policy

Figure: Notations

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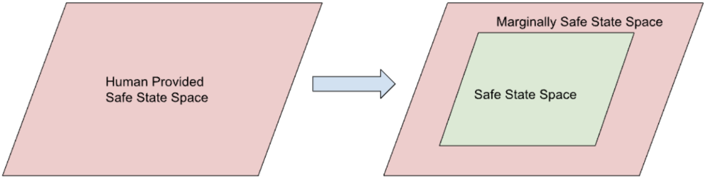
Algorithm

Pseudo Code

- Initialise Policy and Critic Parameters (θ and ϕ) of the DDPG Model
- Repeat
  - If $s \in S_{safe}$, $a = \pi_\theta(s)$
  - Elif $s \in S_{marginally\ safe}$, $a = argmax_{a' \in A_{safe}(s)} Q_\phi(s, a')$
  - The Replay Buffer is populated with the tuples (s, a, s', r)
  - $\nabla_\phi L(\phi) = \nabla_\phi \frac{1}{|B|} \sum \left(r + \gamma Q_{\phi_{targ}}(s', \mu_{\theta_{targ}}(s')) - Q_\phi(s, a)\right)^2$
  - $\nabla_\theta L(\theta) = \nabla_\theta \frac{1}{|B|} \sum_{s \in B}(Q_\phi(s, \mu_\theta(s)) + (a - \mu_\theta(s))^2)$
  - The weights are updated using the gradients as defined above
- Until Convergence



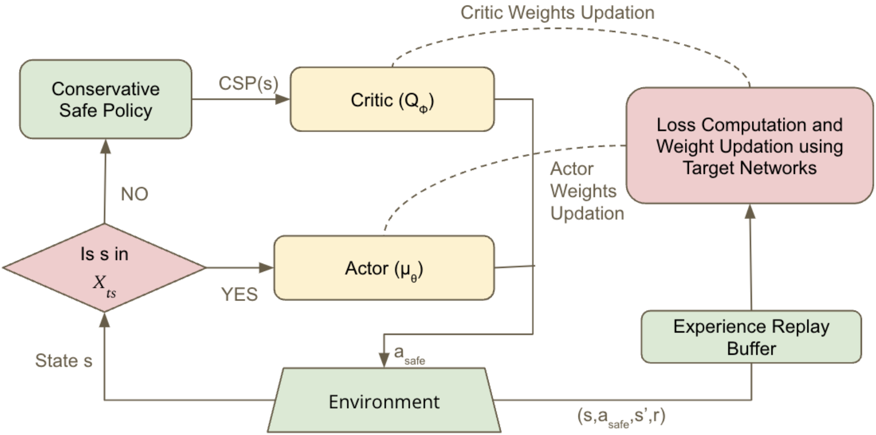


Figure: Model Pipeline

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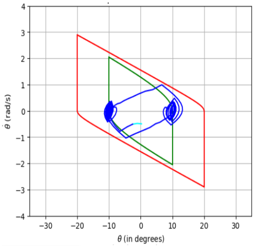
Simulation Experiments and Results



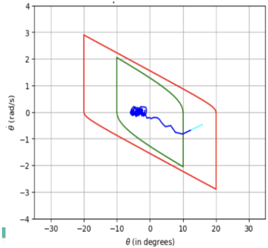


Figure: Trajectories of Episodes during Training and Testing

- During training, we see that the trajectory often enters the marginally safe region and is immediately pushed back into the safe region using the human provided conservative actions
- During testing, we see that the trained agent learns to stay inside the safe region

Some Training Curves - Safety Gymnasium Environment

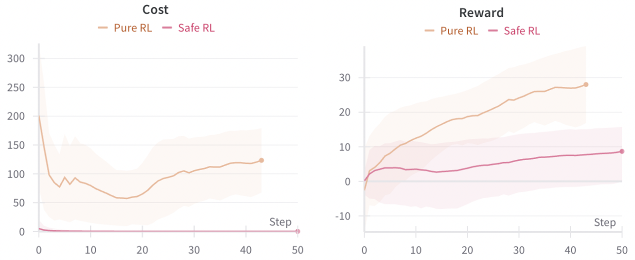


Figure: Metrics for Implementations with and without safety layer

Algorithm	Reward	Cost
Pure RL	47.6	203
Pure RL (Modified Reward)	2.85	0
Pure CSP	4.70	0
Safe RL	22.10	0

Table: Reward and Cost during Evaluation/Deployment

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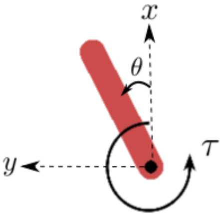
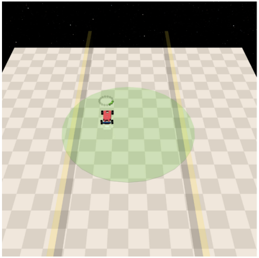
Conclusion

- A comprehensive literature survey was performed and a taxonomy was developed.
- A modified version of the Deep Deterministic Policy Gradient algorithm was implemented with a safety layer for continuous control.
- The algorithm was tested in the inverted pendulum environment and the safety-gymnasium environment which is a benchmark library for safe RL
- **Won 3rd Place for the Best Poster Award** with during the WSAI Annual Research Showcase 2024.





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What Next?

- We are aiming to submit our work to the International Conference on Control, Automation, Robotics and Vision (ICARCV 2024) which has a deadline of June 30, 2024.
- There are multiple directions this work can be continued in by the future students
  - The provided CSP can be formulated as a distribution and probabilistic guarantees of safety can be established.
  - The work presently assumes that CSP and SSS are readily provided by the human. Model dynamics perhaps can be used to automate this to some extent.
  - Experiments can be performed on Real Life Mobile Robots

Thank you!
Questions?

J. Garcıa and F. Fernández, "A comprehensive survey on safe reinforcement learning," *Journal of Machine Learning Research*, vol. 16, no. 1, pp. 1437–1480, 2015.

L. Brunke, M. Greeff, A. W. Hall, Z. Yuan, S. Zhou, J. Panerati, and A. P. Schoellig, "Safe learning in robotics: From learning-based control to safe reinforcement learning," *Annual Review of Control, Robotics, and Autonomous Systems*, vol. 5, pp. 411–444, 2022.

J. Achiam, D. Held, A. Tamar, and P. Abbeel, "Constrained policy optimization," in *International conference on machine learning*, pp. 22–31, PMLR, 2017.

G. Dalal, K. Dvijotham, M. Vecerik, T. Hester, C. Paduraru, and Y. Tassa, "Safe exploration in continuous action spaces," *arXiv preprint arXiv:1801.08757*, 2018.

P. F. Christiano, J. Leike, T. Brown, M. Martic, S. Legg, and D. Amodei, "Deep reinforcement learning from human preferences," *Advances in neural information processing systems*, vol. 30, 2017.

W. Saunders, G. Sastry, A. Stuhlmueller, and O. Evans, "Trial without error: Towards safe reinforcement learning via human intervention," *arXiv preprint arXiv:1707.05173*, 2017.

C. Frye and I. Feige, "Parenting: Safe reinforcement learning from human input," *arXiv preprint arXiv:1902.06766*, 2019.

H. Hoang, T. Mai, and P. Varakantham, "Imitate the good and avoid the bad: An incremental approach to safe reinforcement learning," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 38, pp. 12439–12447, 2024.