Evidence-Driven Learning for Interpretability

Minwoo Lee & Giang Dao May 5, 2022

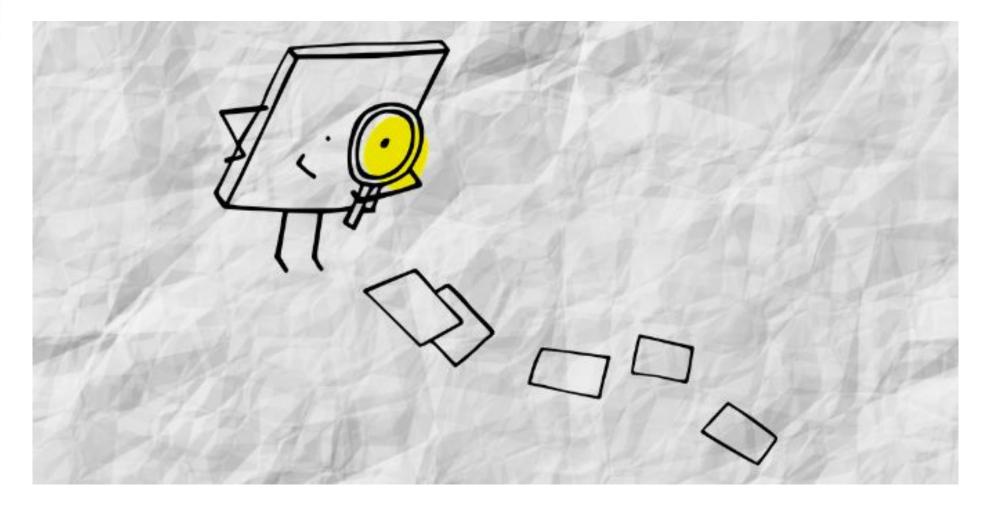








Evidence-Driven Learning

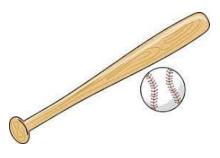




Evidence-Driven Learning







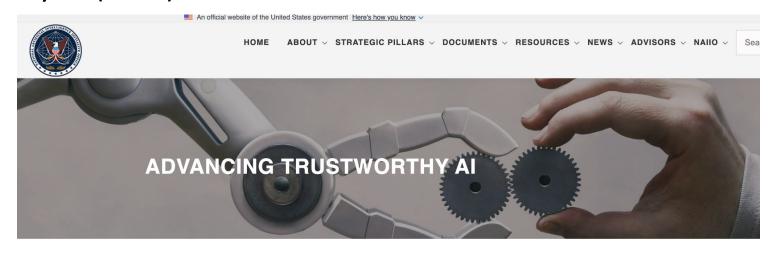






Why Interpretability or Explainability?

Towards trustworthy AI (Kush)



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ADVANCING TRUSTWORTHY AI

To be trustworthy, AI technologies must appropriately reflect characteristics such as accuracy, explainability and interpretability, privacy, reliability, robustness, safety, and security or resilience to attacks – and ensure that bias is mitigated. Factors such as fairness and transparency should be considered, particularly during deployment or use. In addition, the broader impacts of AI on society must be considered, such as implications for the workforce. Developing and using AI in ways that are ethical, reduce bias, promote fairness, and protect privacy is essential for fostering a positive effect on society consistent with core U.S. values.

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Contents [hide]

Advancing Trustworthy Al

Advancing Trustworthy Al

Research and Development for Trustworthy Al

Metrics, Assessment Tools, and Technical Standards for Al

Prights,

Use of Al in the Private Sector

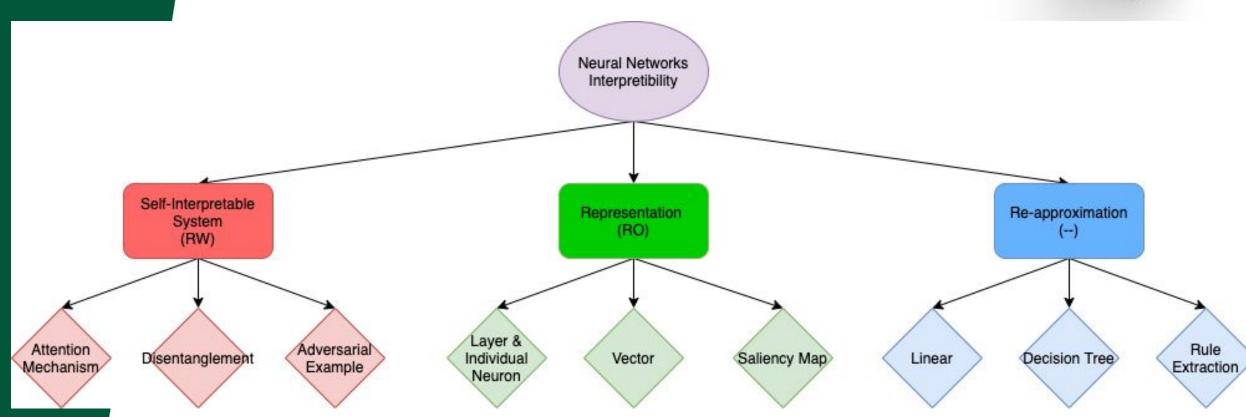
Use of Al by the Federal Government

Engaging stakeholders, experts, and the public



Opening the Black Box

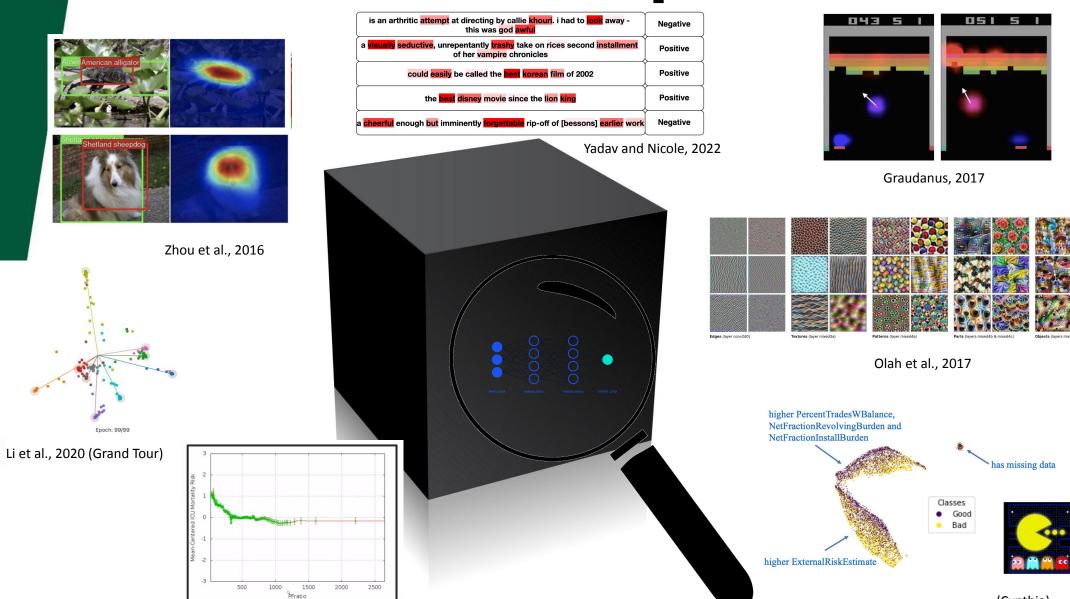






What Do We Need for Interpretation?

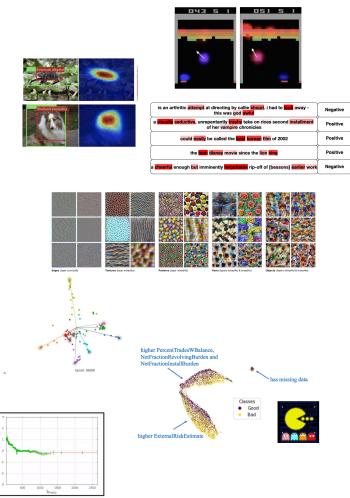
(Rich)



(Cynthia)



Sources of Interpretation

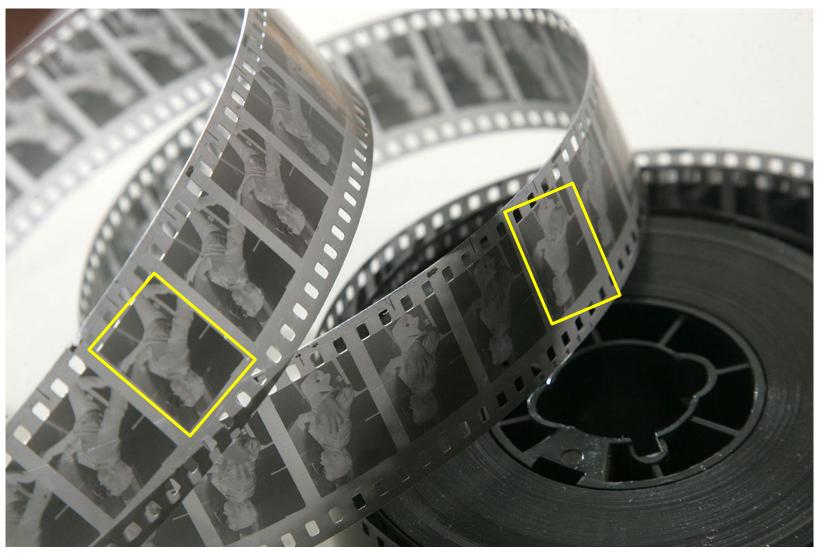








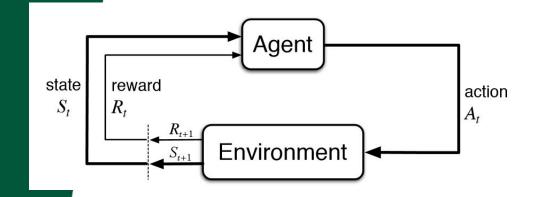
Sources of Interpretation => Evidence

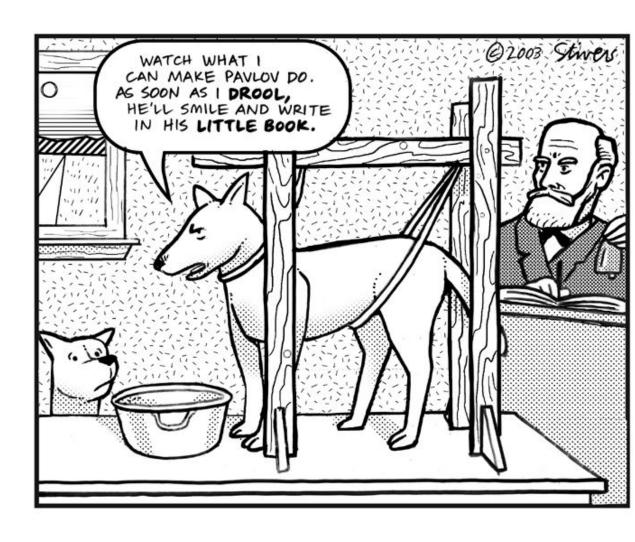


https://en.wikipedia.org/wiki/35_mm_movie_film#/media/File:35mm_movie_negative.jpg



Reinforcement Learning





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RL Applications

Reinforcement Learning in Healthcare: A Survey

Chao Yu, Jiming Liu, Fellow, IEEE, and Shamim Nemati

Abstract—As a subfield of machine learning, reinforcement learning (RL) aims at empowering one's capabilities in behavioural decision making by using interaction experience with the world and an evaluative feedback. Unlike traditional supervised learning methods that usually rely on one-shot, exhaustive and supervised reward signals, RL tackles with sequential decision making problems with sampled, evaluative

feedback and the new state from the environment. The goal of the agent is to learn an optimal policy (i.e., a mapping from the states to the actions) that maximizes the accumulated reward it receives over time. Therefore, agents in RL do

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Article Open Access Published: 16 February 2022

Magnetic control of tokamak plasmas through deep reinforcement learning

Jonas Degrave, Federico Felici ⊠, ... Martin Riedmiller + Show authors

Nature 602, 414-419 (2022) | Cite this article

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Spotify Reinforcement Learning Recommendation System

Posted on December 14, 2019





HARVARD

School of Engineering and Applied Sciences

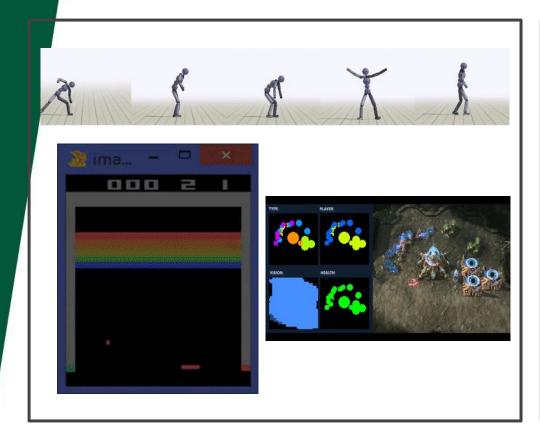


Team members: Feng Qian, Sophie Zhao, Yizhou Wang





RL Challenges





RL in simulations RL in the real world



RL Challenges

RL Challenges



Robustness/ Scalability

Focuses on being able to learn

Alignment



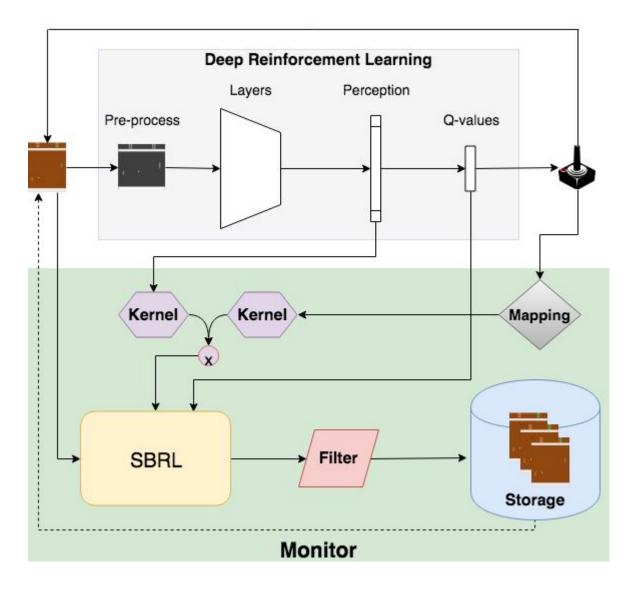
Focuses on learning as intended

Let us collect "Evidence"





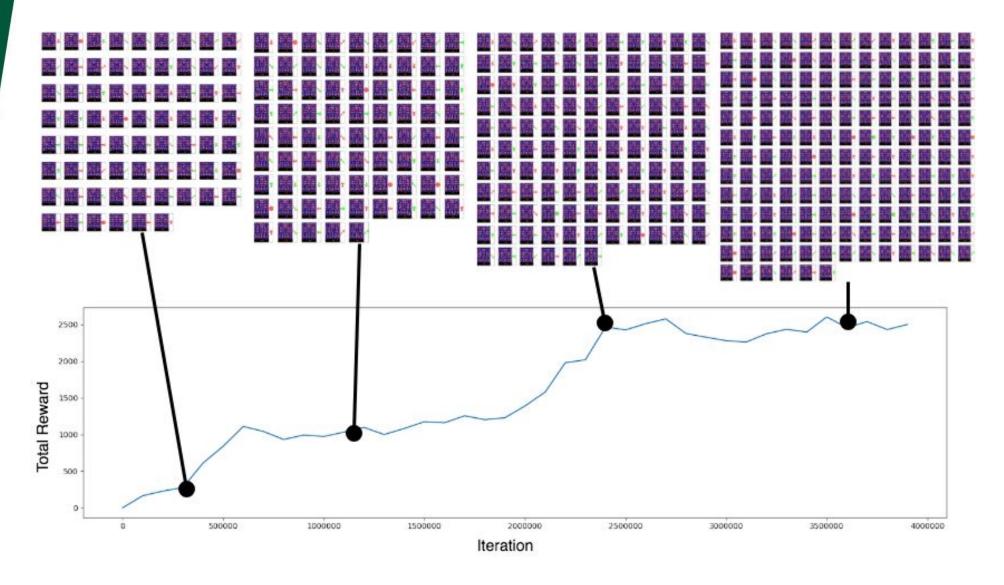
DRL-Monitor



Dao and Lee (2018). Deep Reinforcement Learning Monitor for Snapshot Recording.



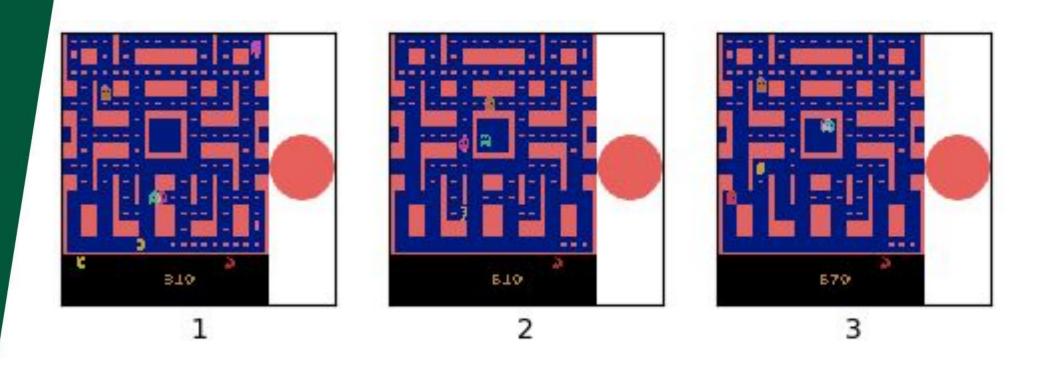
DRL-Monitor



Maze - 20 - 12 26.76±1.13 19.86±1.41

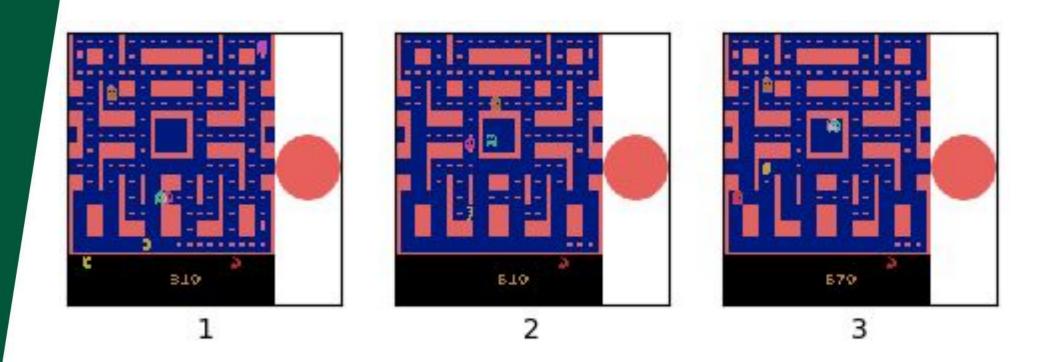


Ms PacMan (after 300K iterations)





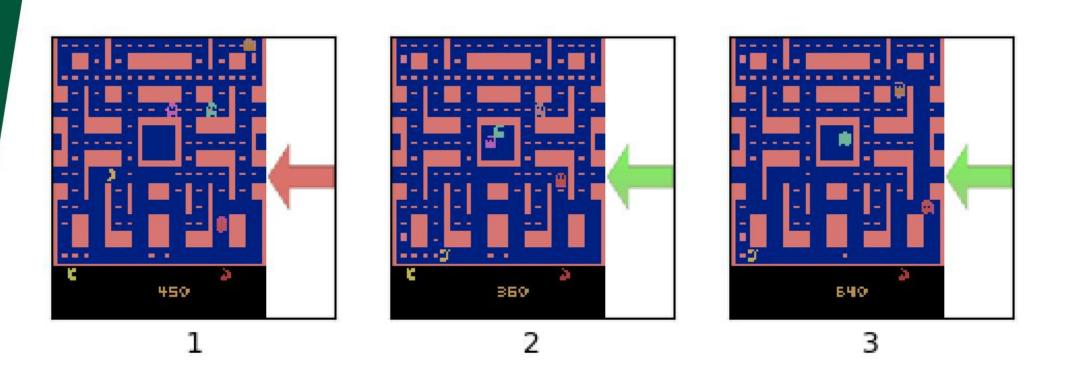
Ms PacMan (after 300K iterations)



No action (not moving) does not help!

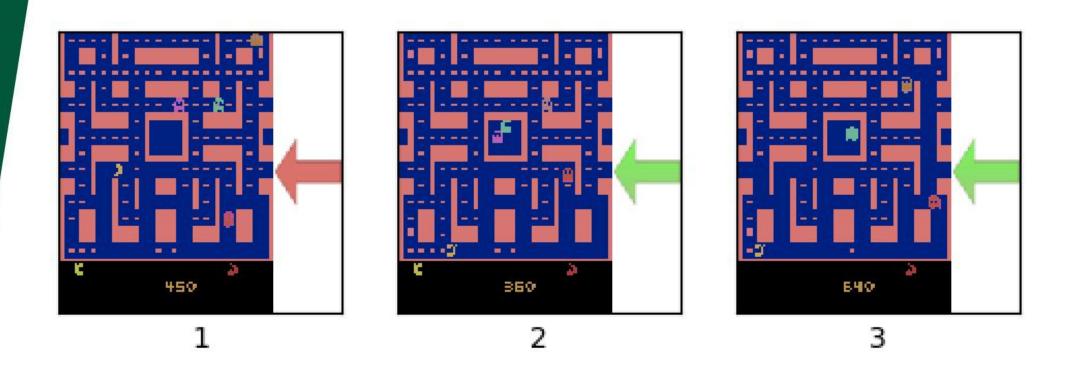


Ms PacMan (after 1.2M iterations)





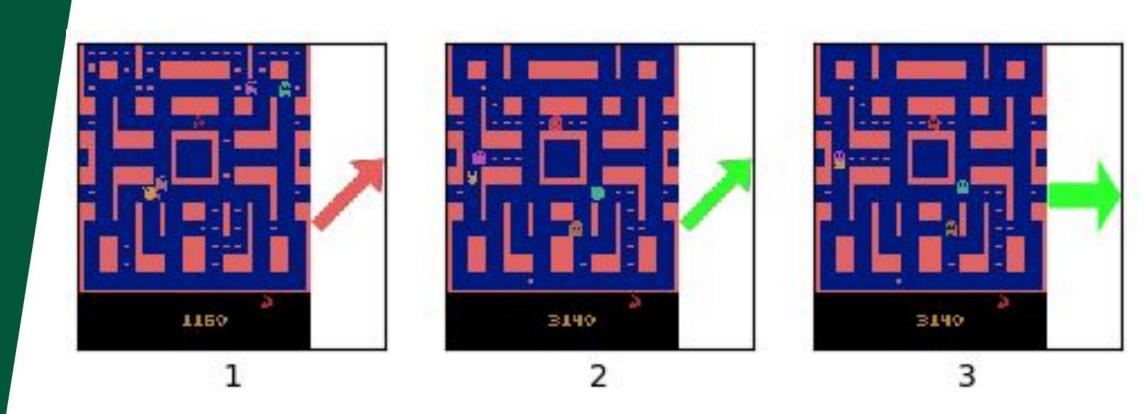
Ms PacMan (after 1.2M iterations)



Craving for food. Heading towards the food is good, and moving away from it is bad.

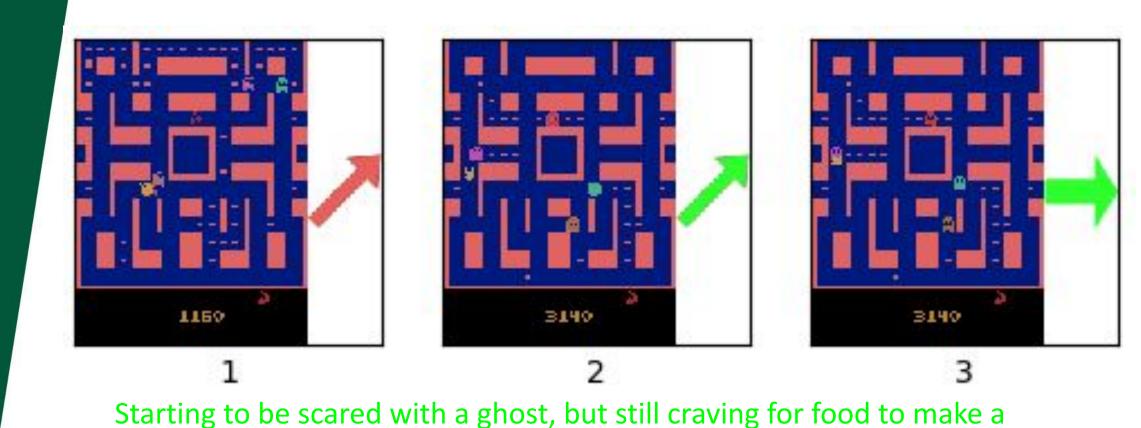


Ms PacMan (after 2.4M iterations)





Ms PacMan (after 2.4M iterations)



Dao and Lee (2018). Deep Reinforcement Learning Monitor for Snapshot Recording.

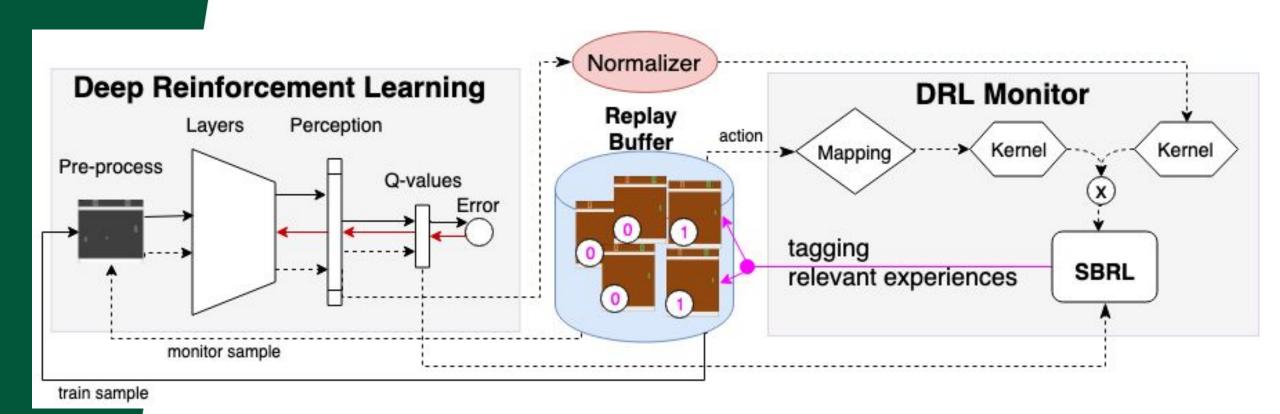
wrong decision.

Overcoming Interpretability-Performance Tradeoff



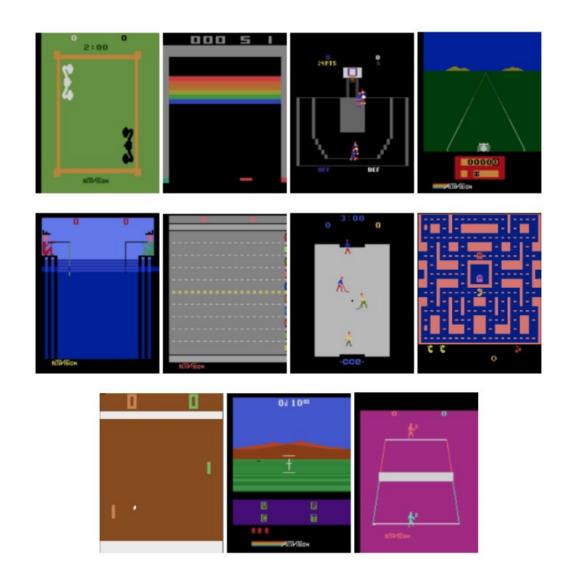


Relevance Experience Replay



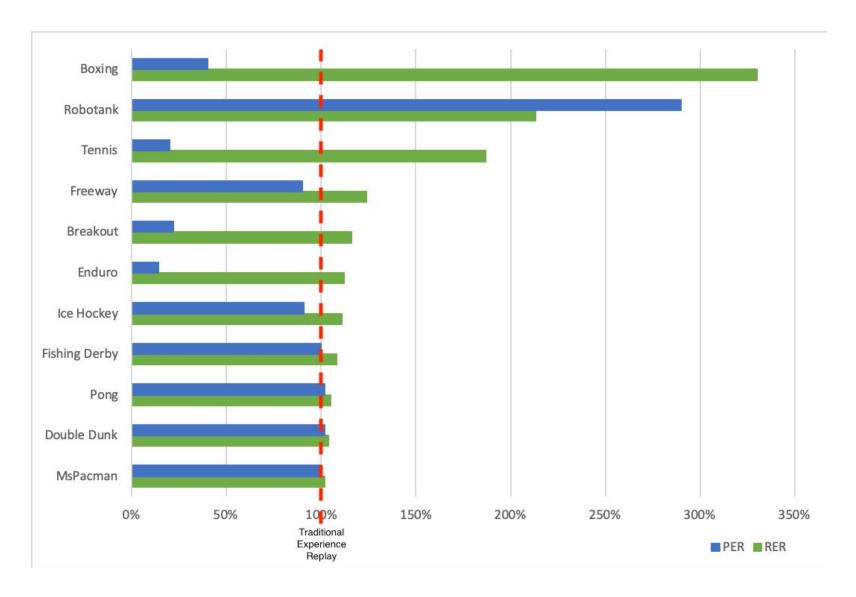


Atari Games





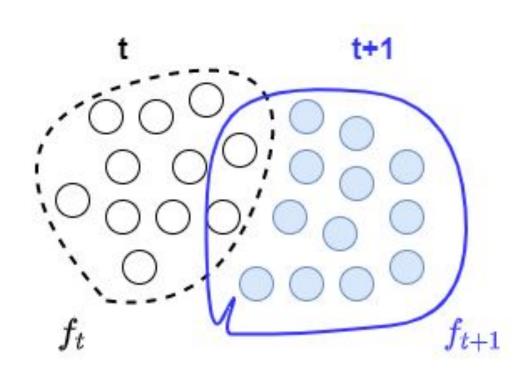
Atari Games



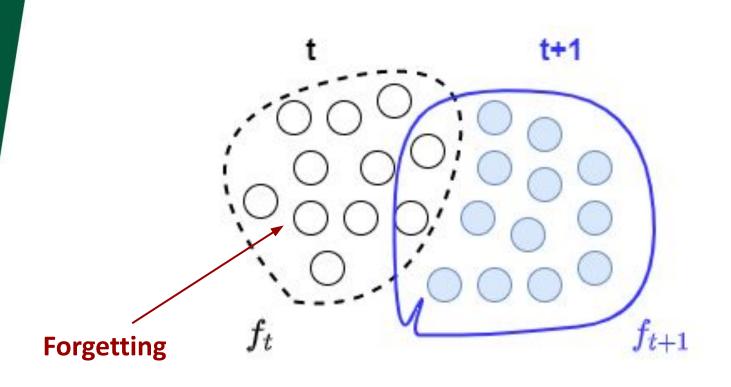
Continual / Lifelong Learning



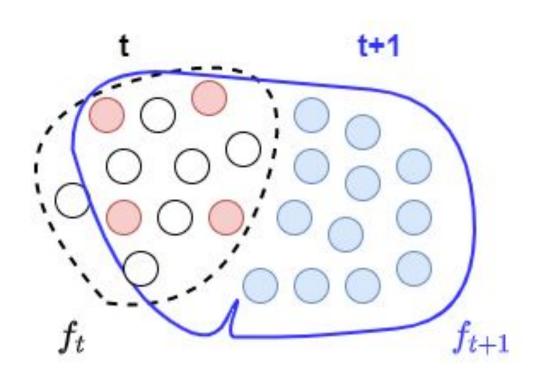




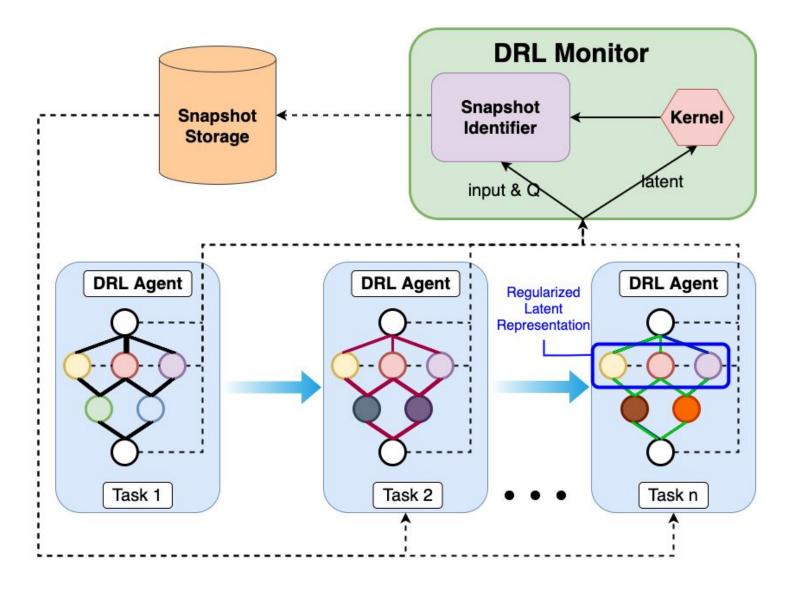




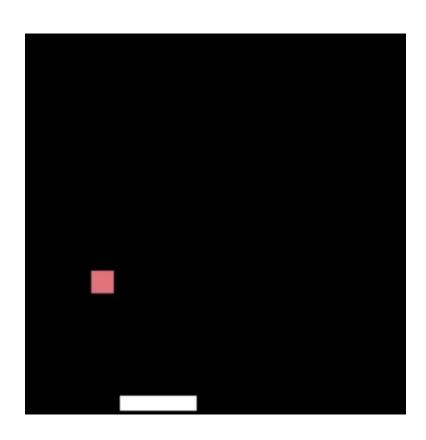


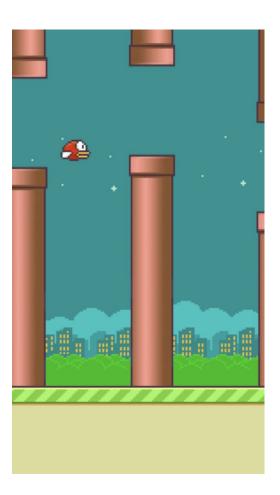




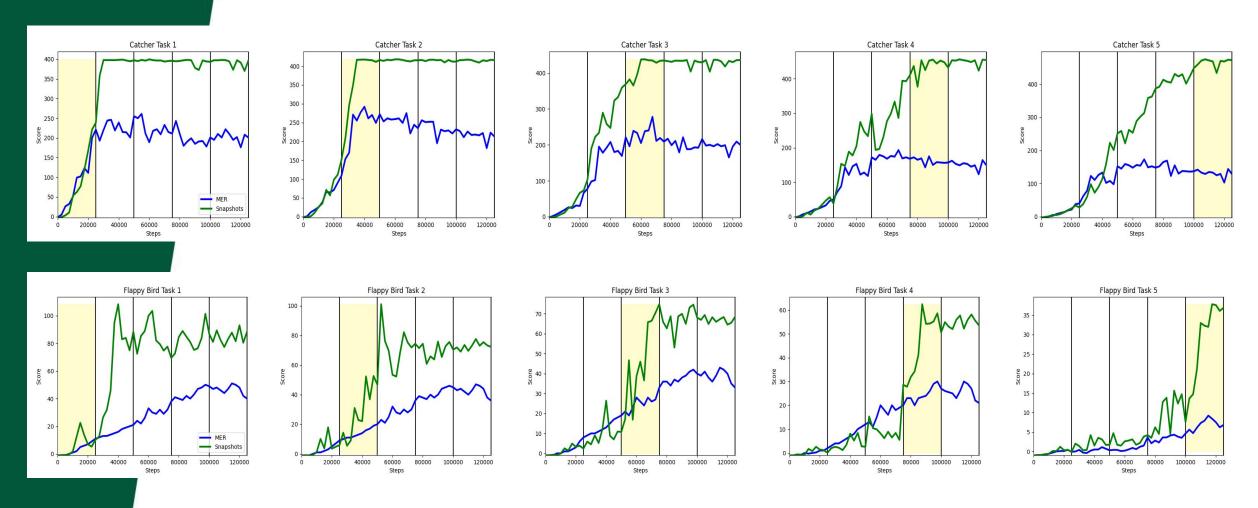




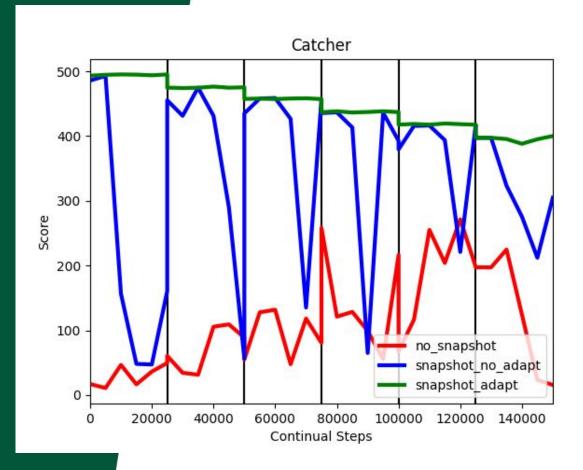


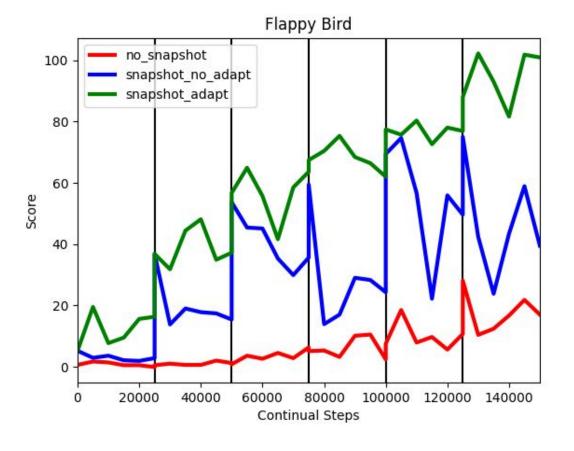




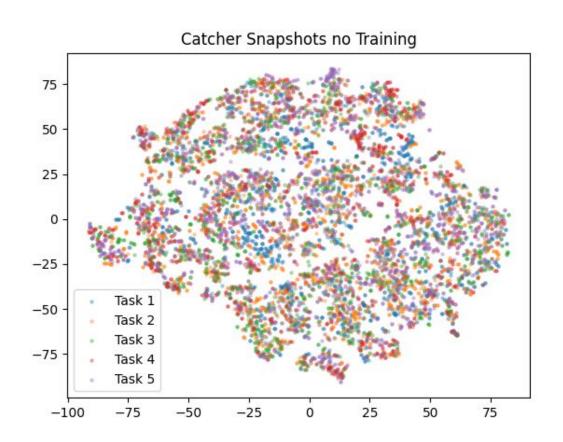


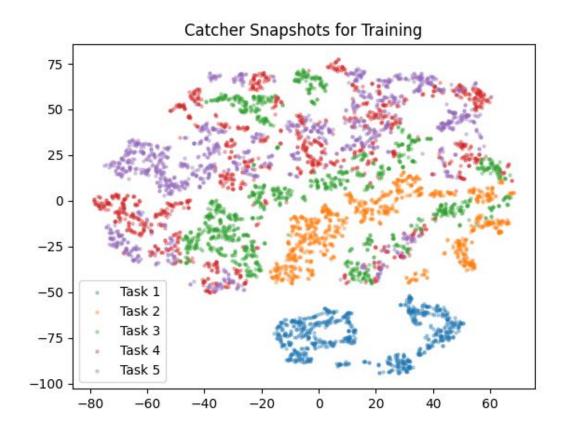














Closing...

- Evidence-Driven Reinforcement Learning
- Interpretation of Evidence
- Use of Evidence for Efficient Learning
- Evidence for Continual Learning
 - Mitigate forgetting problem
- Can be combined with existing methods
- Can collect evidence in all training stages of DRL

Are the most representative samples are evident?

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Closing...

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Further exploration:

- Evidence-driven communication with Human
- Kernel tricks for stronger evidence selection
- Non-Bayesian Approximation
- Sparse Evidence / Local Evidence



Giang Dao PhD student



Benjamin Poole PhD student



@ SHAIR Lab



CHARLOTTE