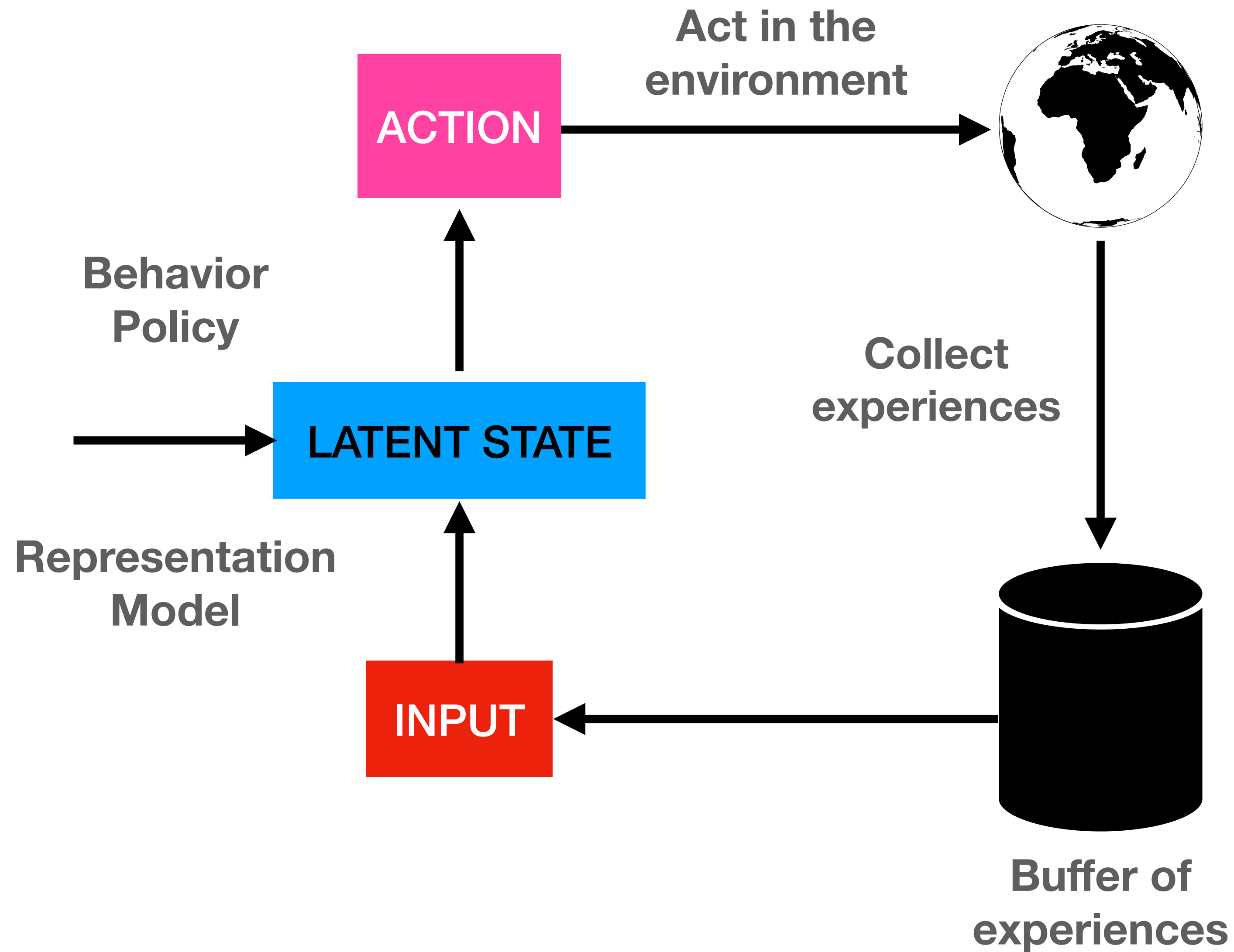


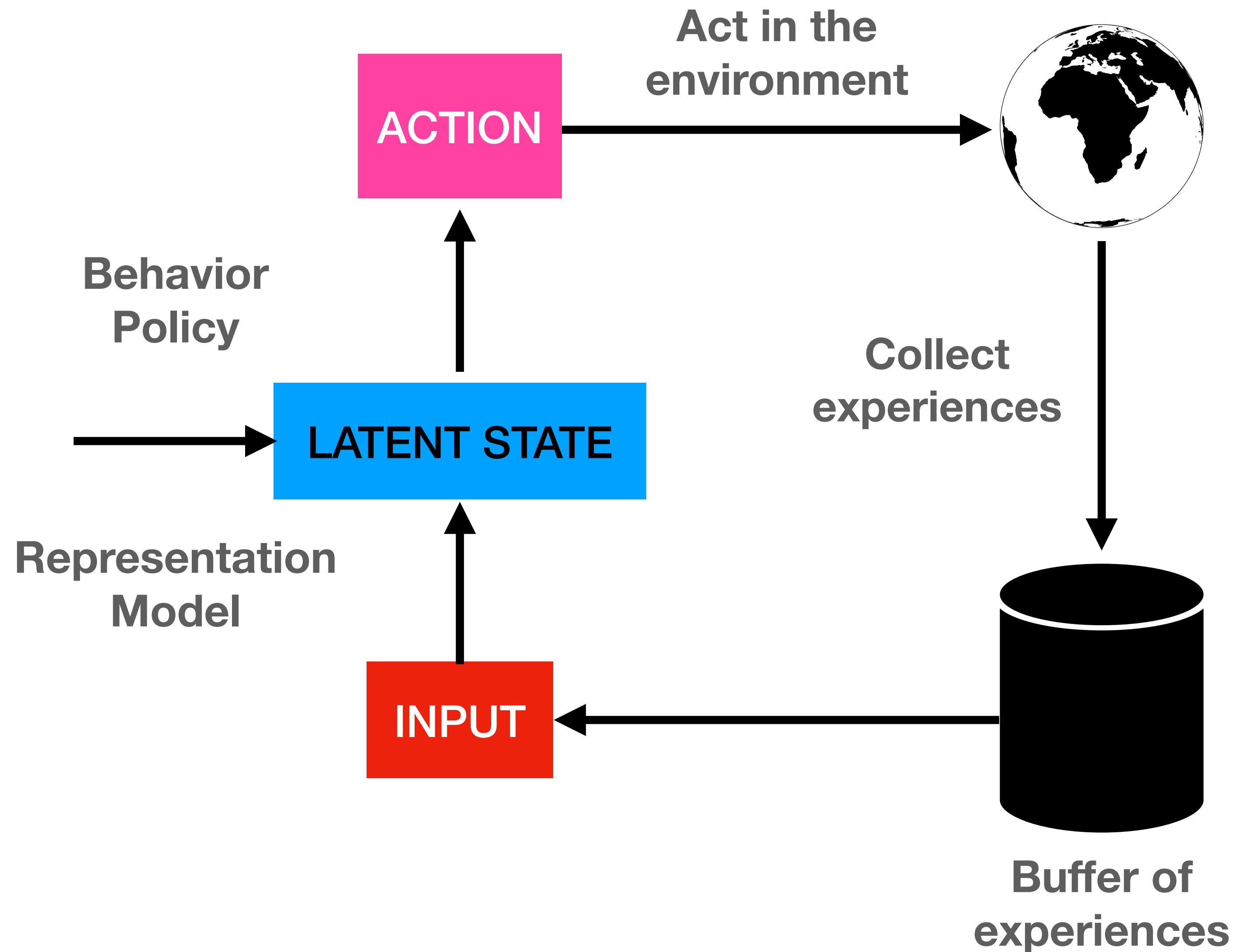
Retrieval Augmented RL: Amortized Inference over Entire Dataset (ICML'22)

Abram L. Friesen*, Andrea Banino*, Theophane Weber*, Nan Rosemary Ke*, Adria Puigdomenech Badia,
Arthur Guez, Mehdi Mirza, Peter C. Humphreys, Ksenia Konyushkova, Laurent Sifre, Michal Valko,
Simon Osindero, Timothy Lillicrap, Nicolas Heess, Charles Blundell

Perception-Action Loop



Perception-Action Loop

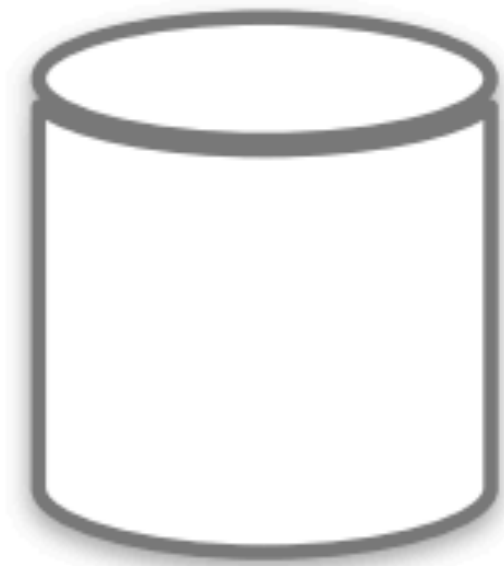


Two Limitations

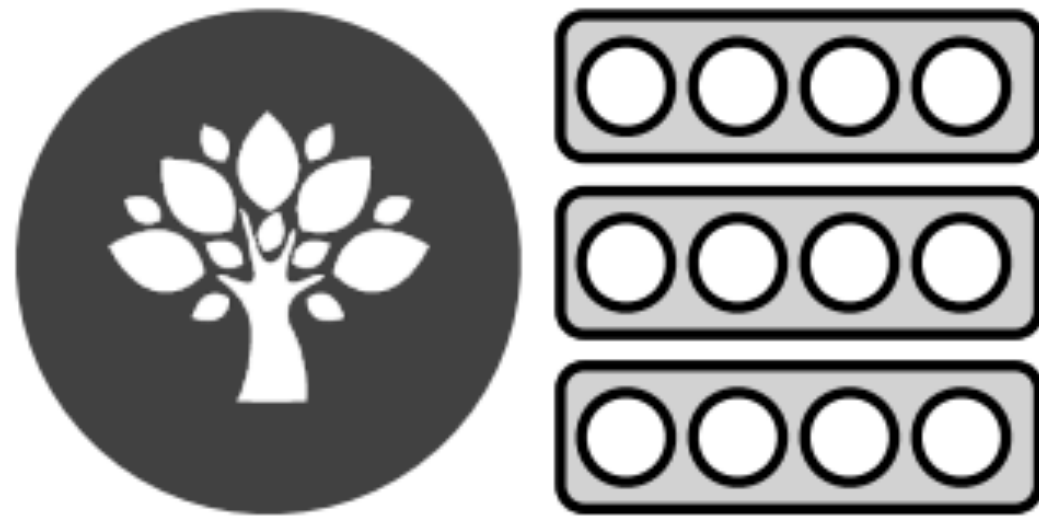
Agent's past experiences no longer play a direct role in the agent's behavior.

Not exploit specific guidance that a handful of past experiences may provide

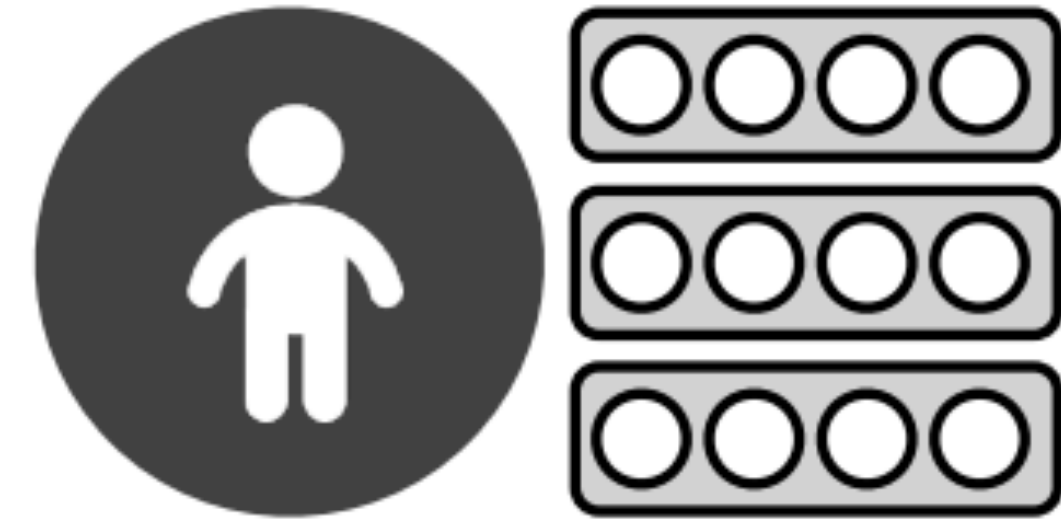
Transfer of Knowledge Across Tasks



Data



Representation Model



Behavior Policy

Higher



Lower

Flexibility

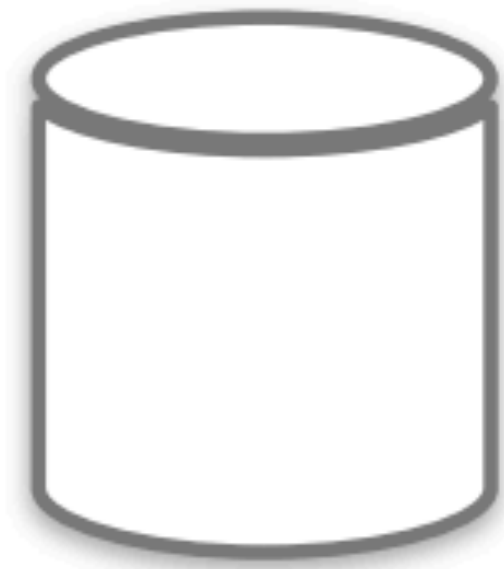
Lower



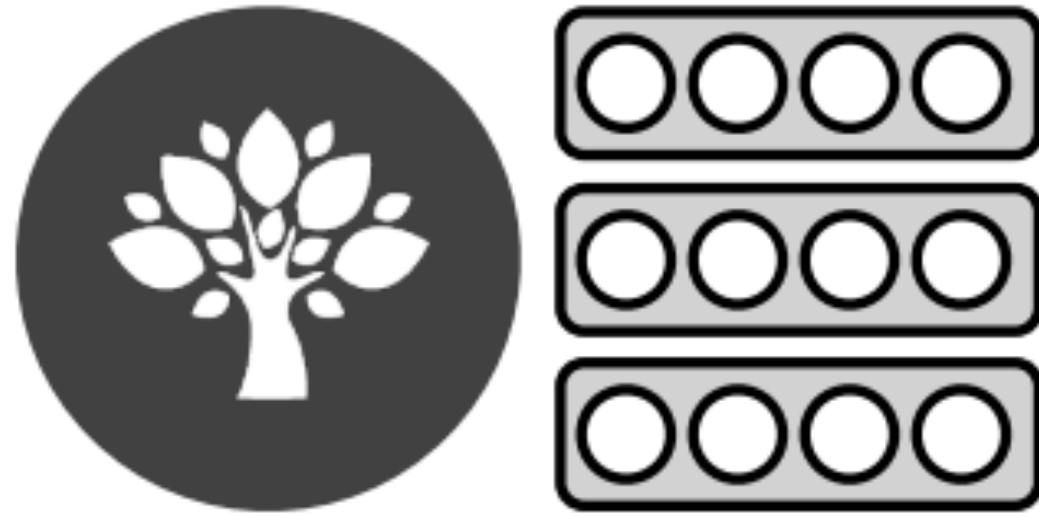
Higher

Efficiency of use

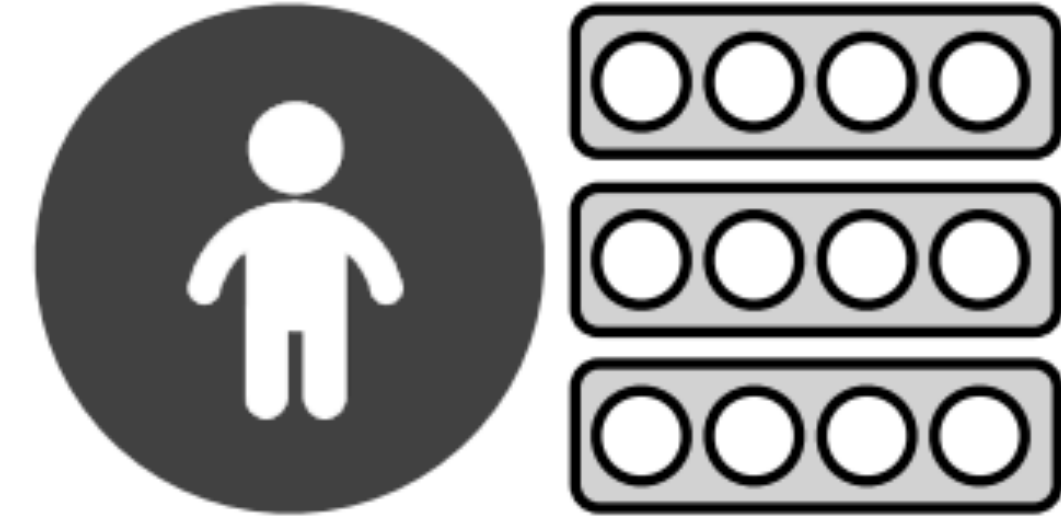
Transfer of Knowledge Across Tasks



Data



Representation Model



Behavior Policy

Higher



Lower

Flexibility

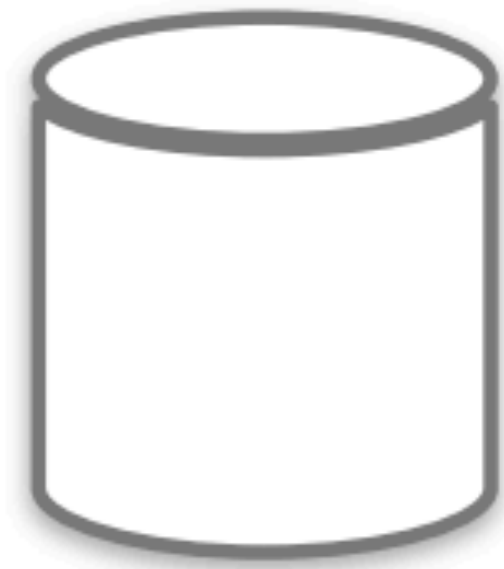
Lower



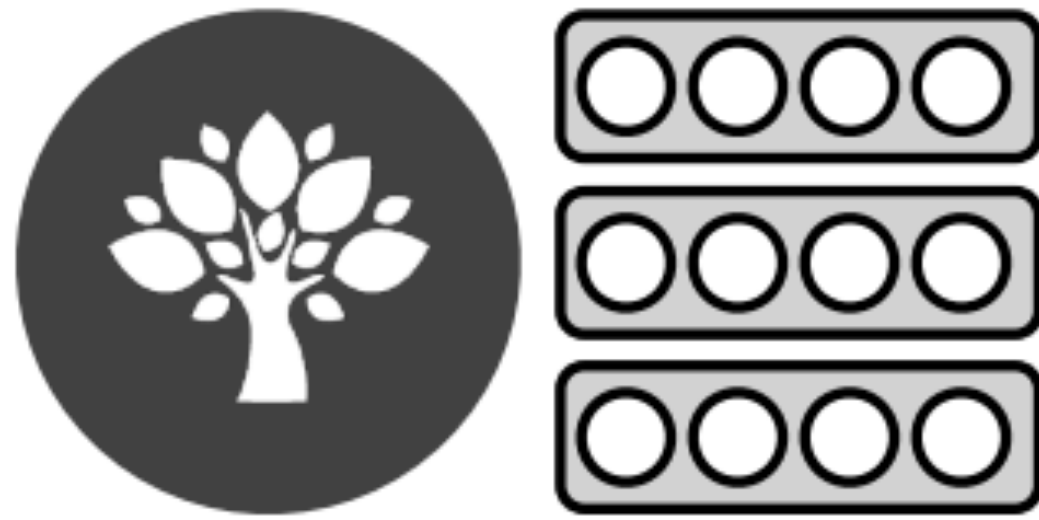
Higher

Efficiency of use

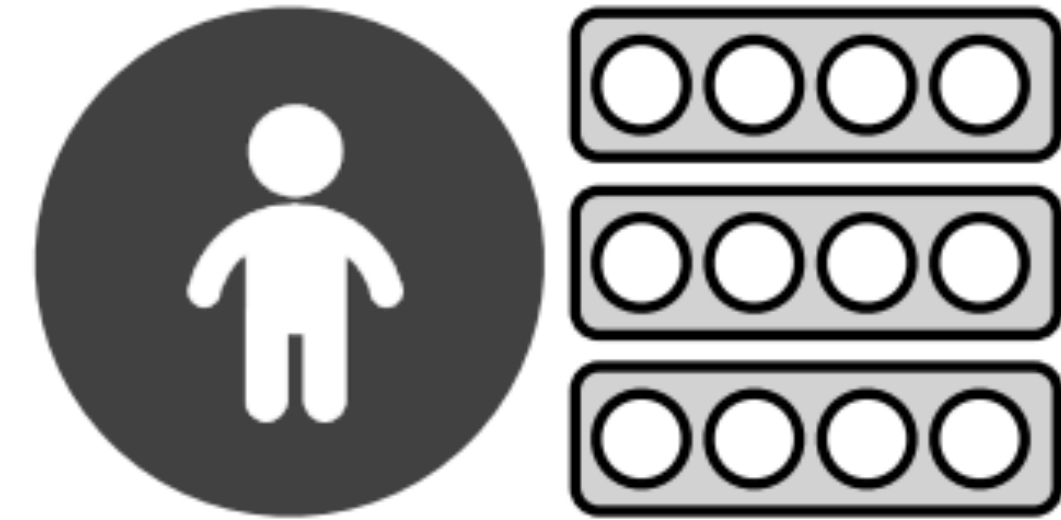
Transfer of Knowledge Across Tasks



Data



Representation Model



Behavior Policy

Higher



Lower

Flexibility

Lower



Higher

Efficiency of use

Different Sources of Data for Training RL Algorithms

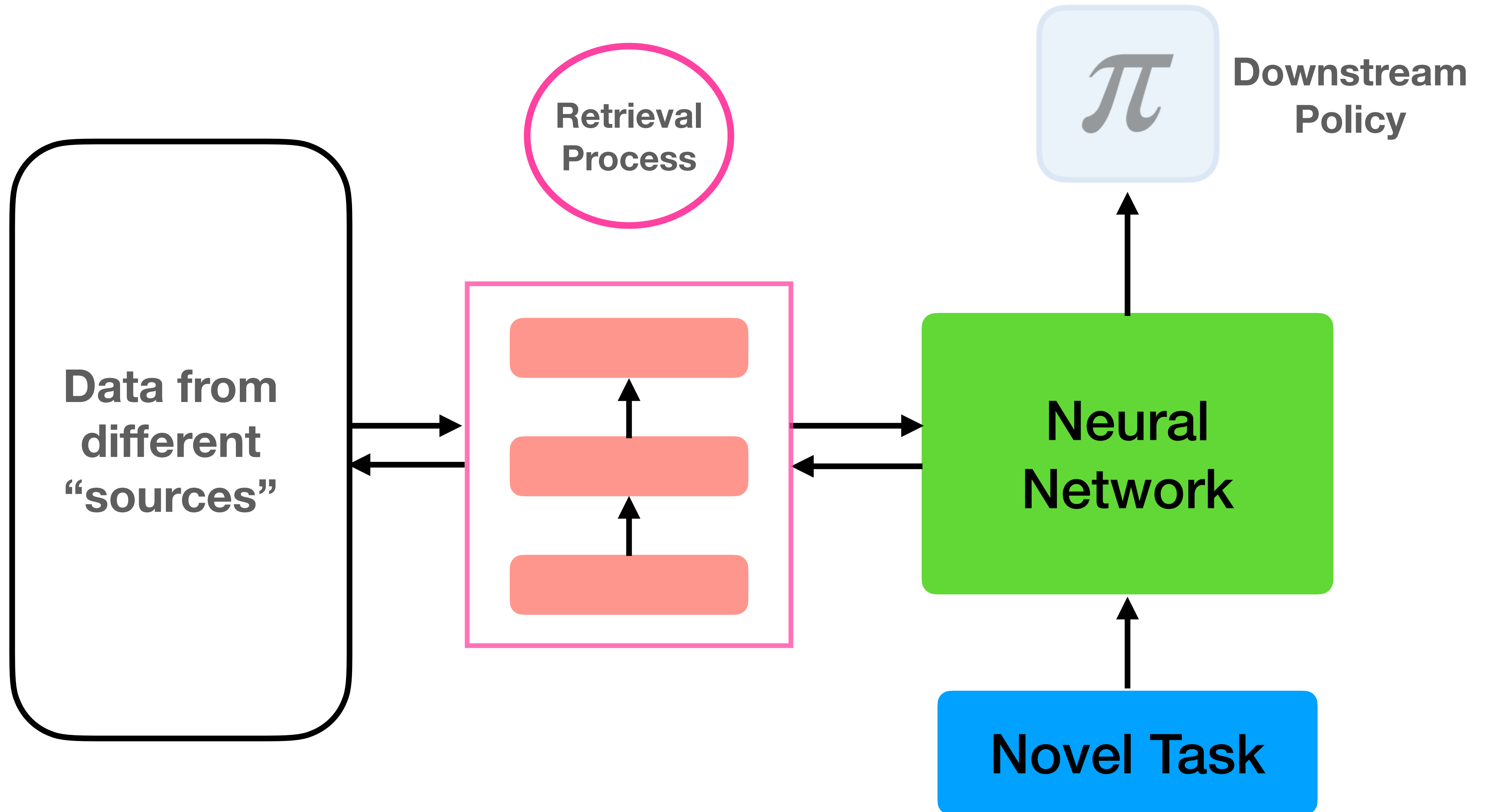
We want to create new RL algorithms that:

1. Harness data from a ***variety of sources***:

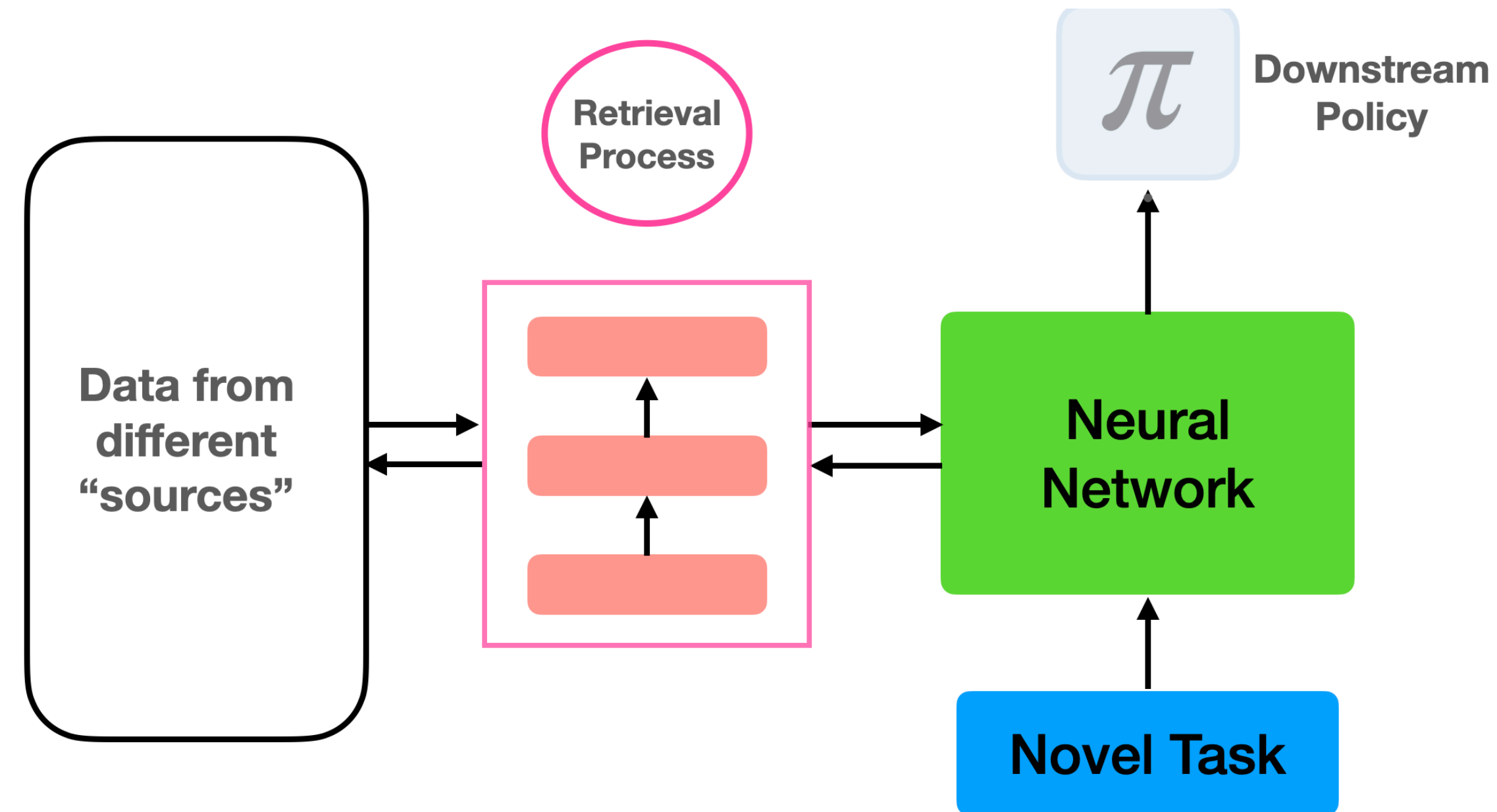
- Past experiences of the agent,
- Past experiences of the other agents.
- Even imagined rollouts.

2. ***Predict & plan*** with a jumpy models that ***stitches together information*** across all of these experience types.

Retrieval Augmented Reinforcement Learning (RARL)



Retrieval Augmented Reinforcement Learning (RARL)



- Learned function encodes the data in the replay dataset.
- Retrieval process queries for data relevant to the agent in its current context.
- Agent process uses the retrieved information to shape the value function.
- At test time, agent can "generalize" to novel behaviors.

Retrieval Process and Agent Process

Dataset of experiences (\mathcal{B})

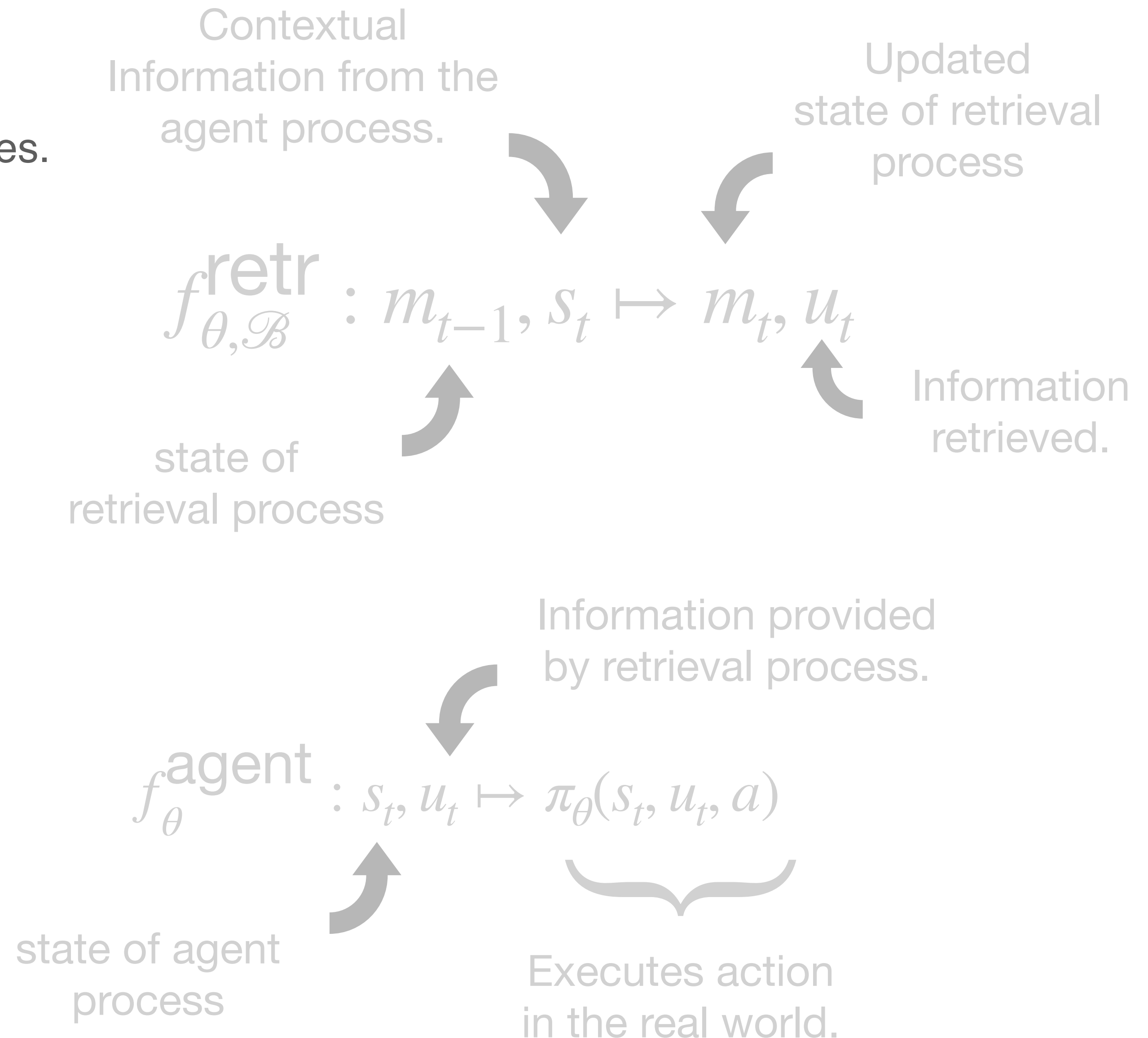
- Contains raw data in the form of trajectories.

Retrieval Process

- Parameterized as a neural network.
- Retrieves information from dataset.

Agent Process

- Parameterized as a neural network.



Retrieval Process and Agent Process

Dataset of experiences (\mathcal{B})

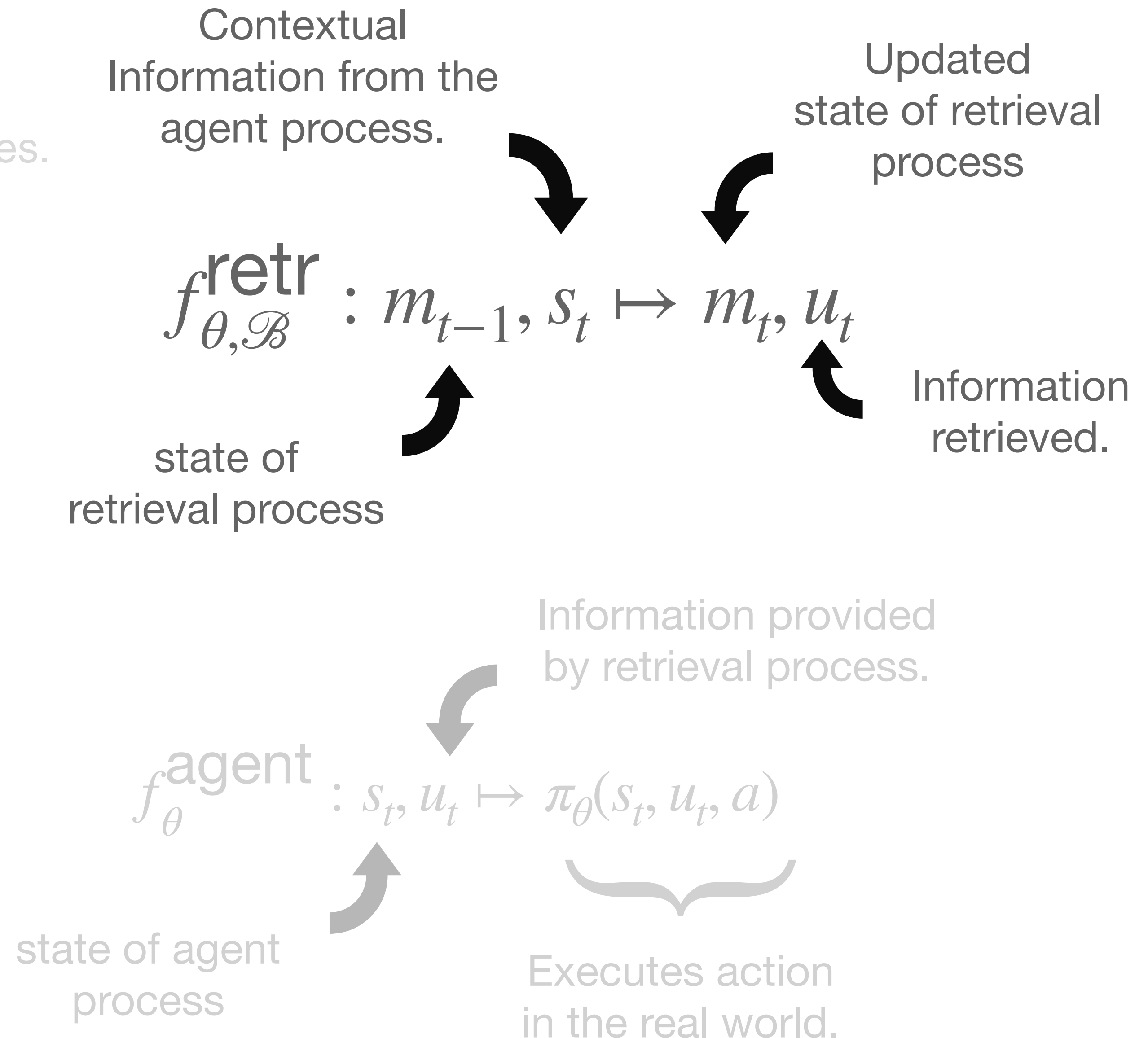
- Contains raw data in the form of trajectories.

Retrieval Process

- Parameterized as a neural network.
- Retrieves information from dataset.

Agent Process

- Parameterized as a neural network.



Retrieval Process and Agent Process

Dataset of experiences (\mathcal{B})

- Contains raw data in the form of trajectories.

Retrieval Process

- Parameterized as a neural network.
- Retrieves information from dataset.

Contextual
Information from the
agent process.

Updated
state of retrieval
process

$$f_{\theta, \mathcal{B}}^{\text{retr}} : m_{t-1}, s_t \mapsto m_t, u_t$$

state of
retrieval process

Information
retrieved.

Agent Process

- Parameterized as a neural network.

Information provided
by retrieval process.

$$f_{\theta}^{\text{agent}} : s_t, u_t \mapsto \pi_{\theta}(s_t, u_t, a)$$

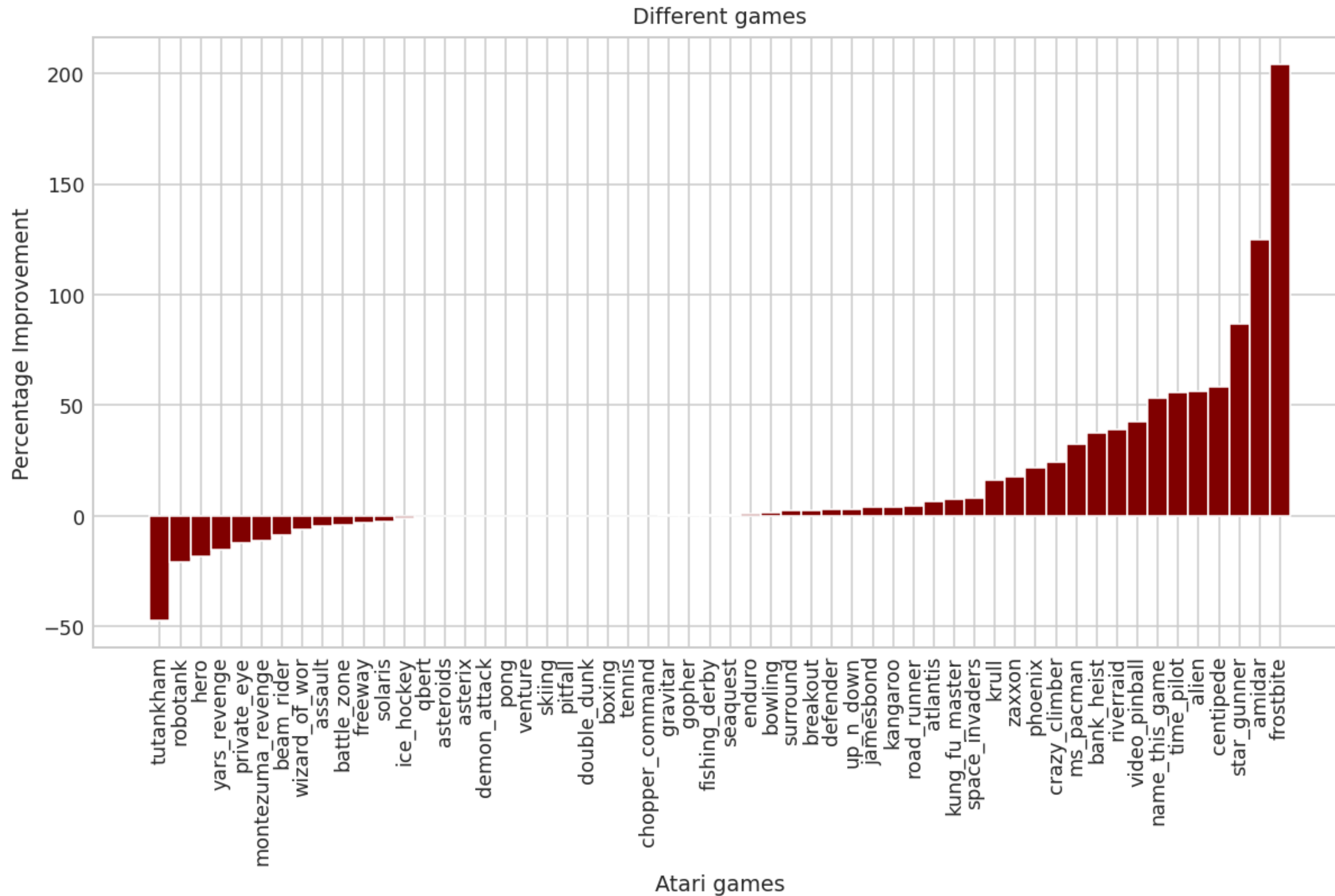
state of agent
process

Executes action
in the real world.

Experiments


- Past experiences in the dataset [off policy RL/on-policy RL]
- (Multi-task) Data from other policies [offline RL]
- Online RL but access to (offline) dataset
- Test time generalization to new “dataset”

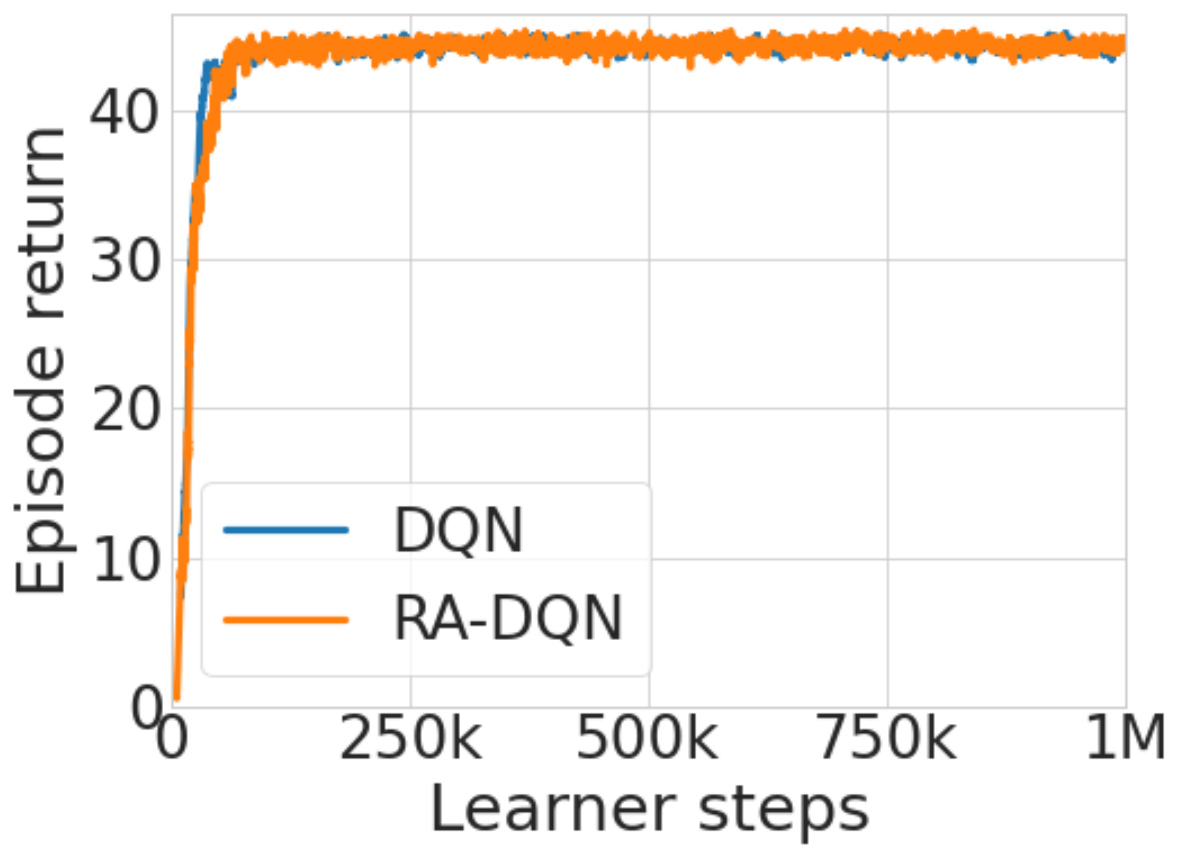
Atari Single Task: Retrieval Augmented Reinforcement Learning



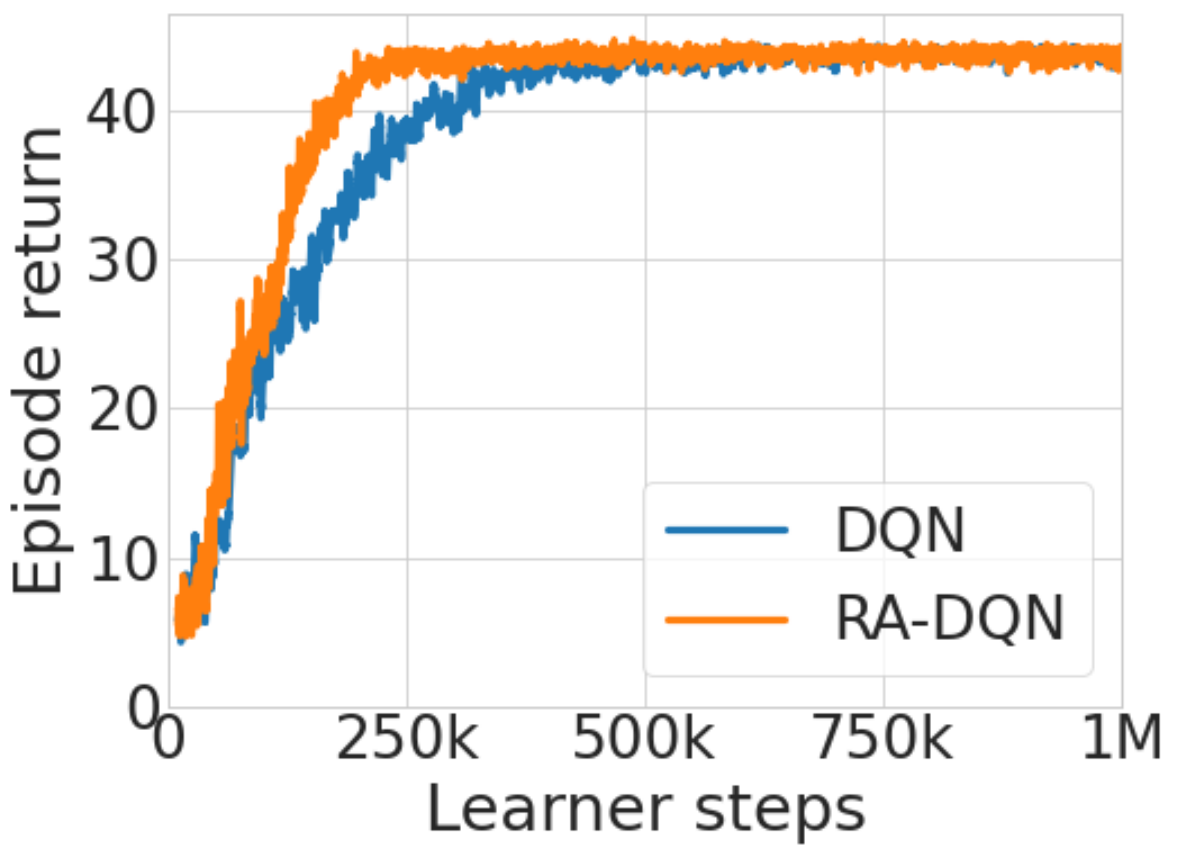
Atari: Relative percentage improvement in mean human normalized score of RA-R2D2 vs vanilla R2D2.

Multi-tasking Offline RL: Retrieval Augmented Reinforcement Learning

Increasing number of tasks (10, 20 and 30 tasks) 

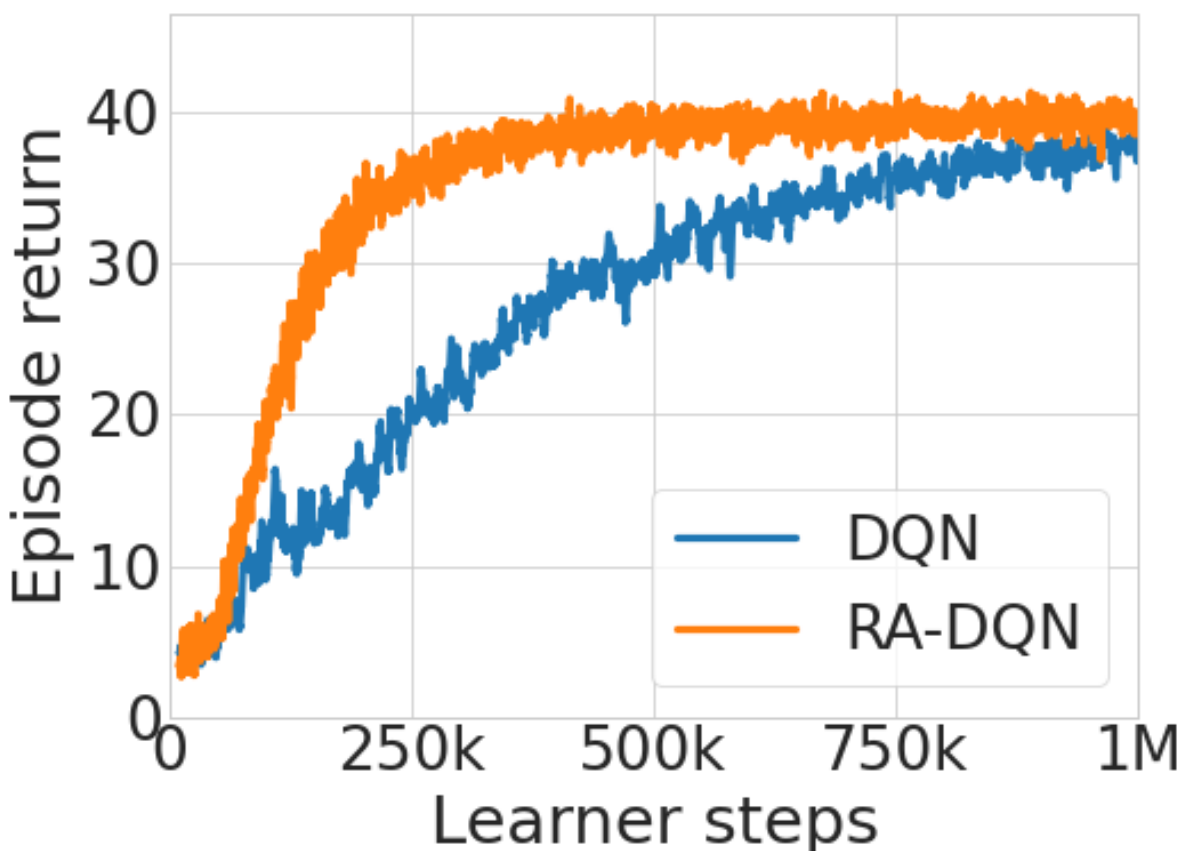


10 training tasks

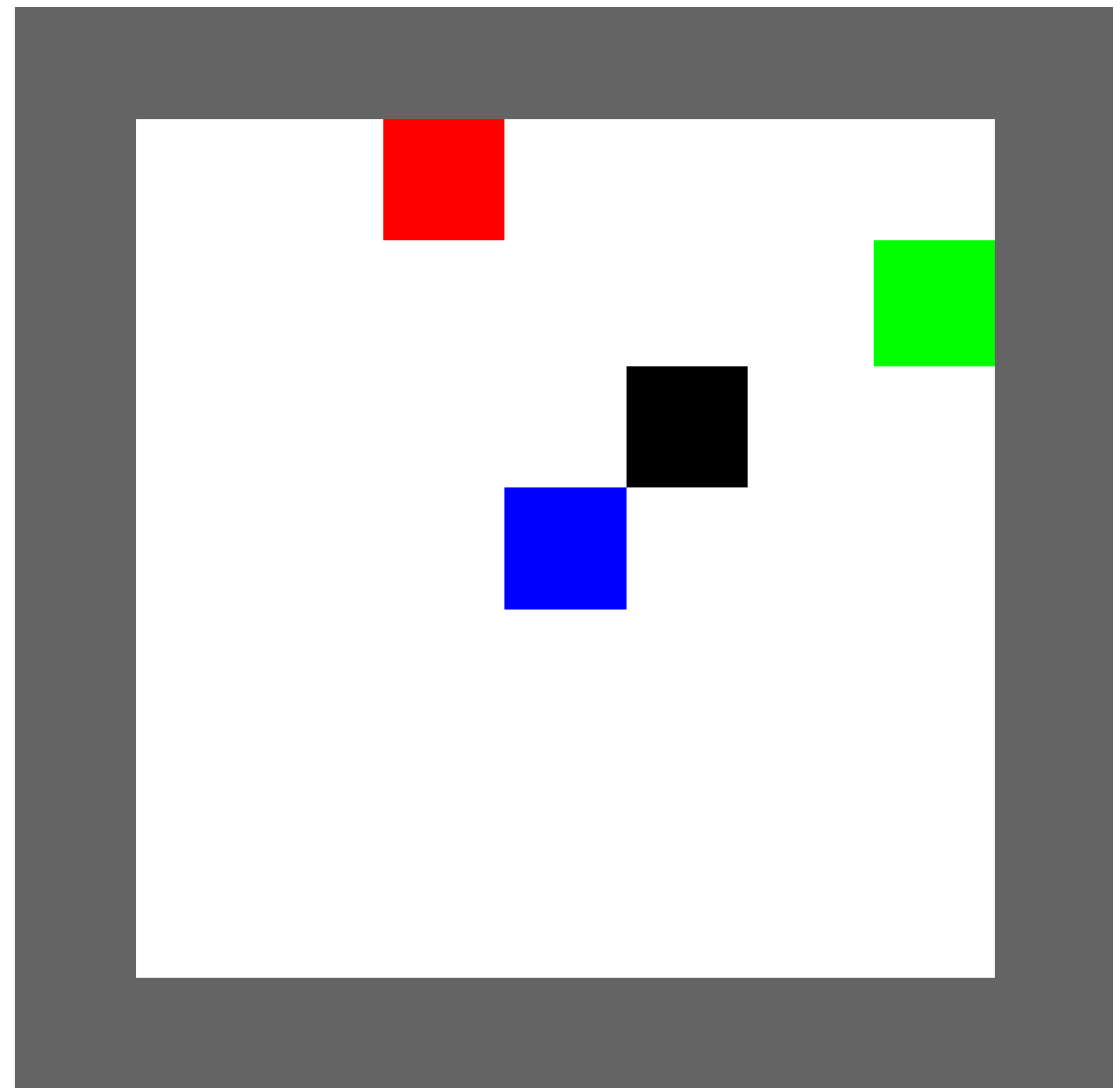


20 training tasks

DQN (blue)
RA-DQN (Proposed, Orange)



30 training tasks



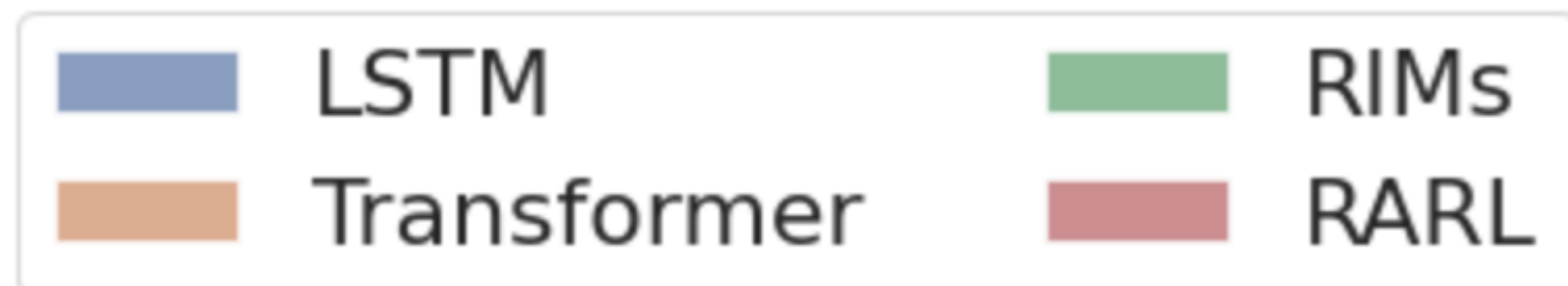
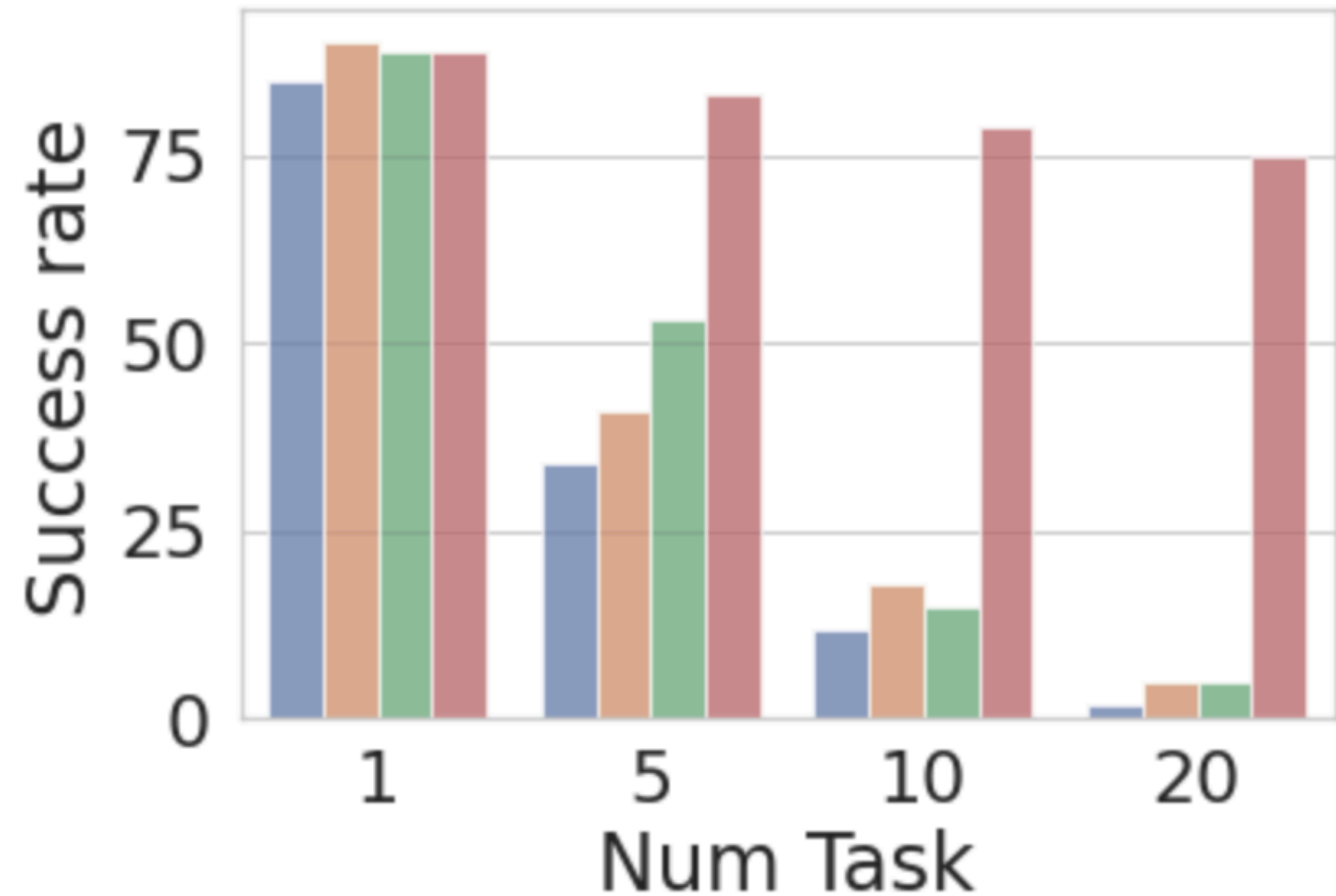
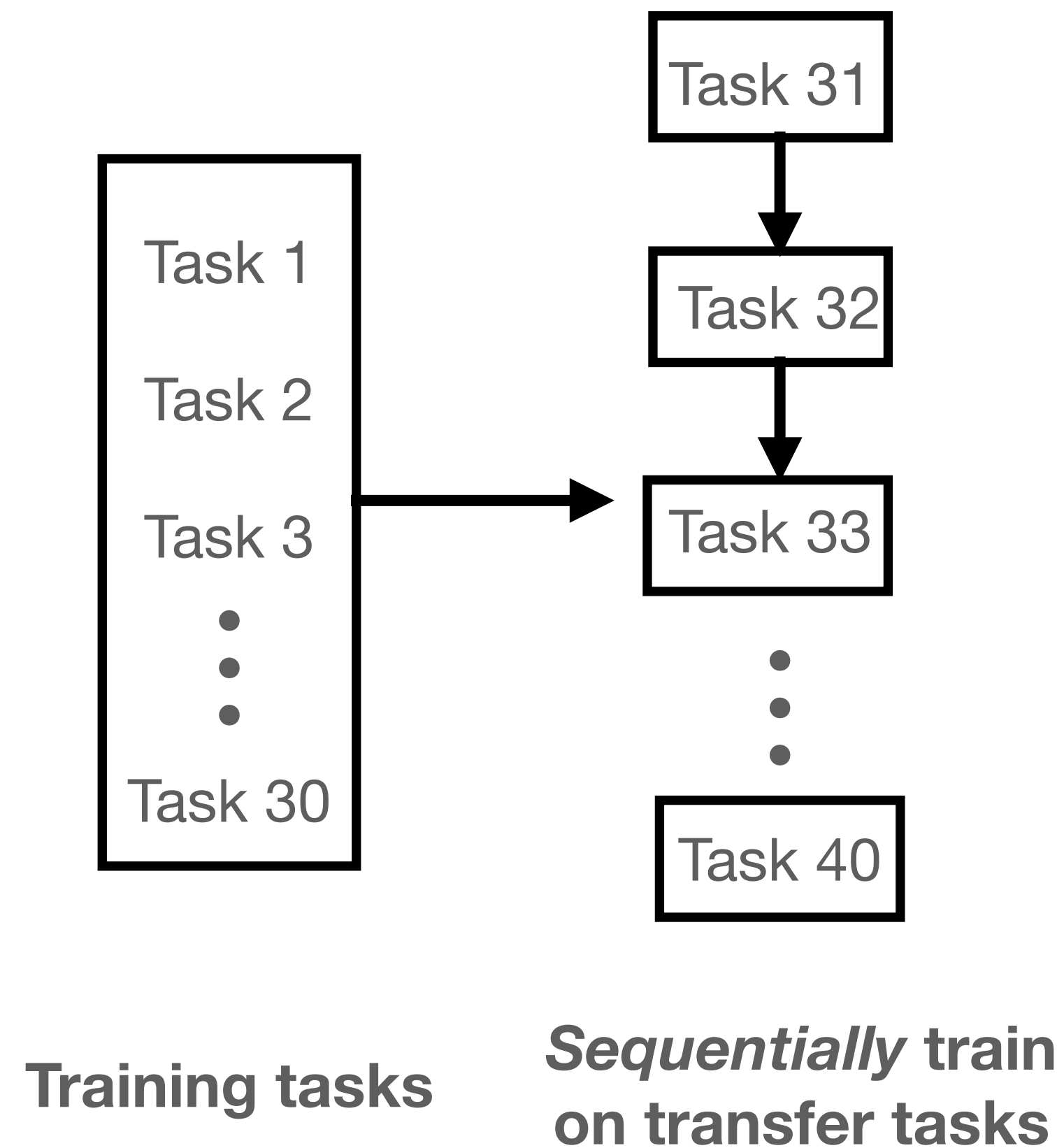
GridRoboman Env:

Task: On the board there are three colored objects and the robot is represented by a black block. The robot can move itself and move the objects.

On increasing number of tasks, the retrieval-augmented agent learns much more effectively than the baseline DQN agent.

Continual Learning Results: Instruction Following

First training on training tasks, and then *sequential* “adaptation” on transfer tasks.



Takeaway Lesson

