Offline Meta Reinforcement Learning

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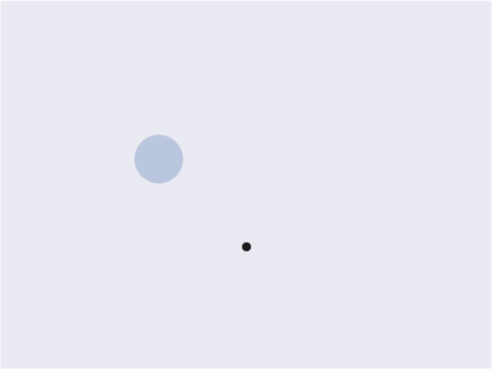
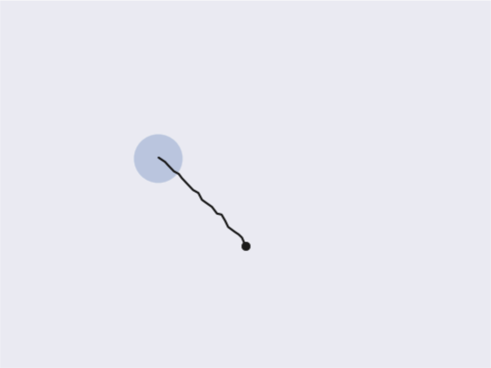
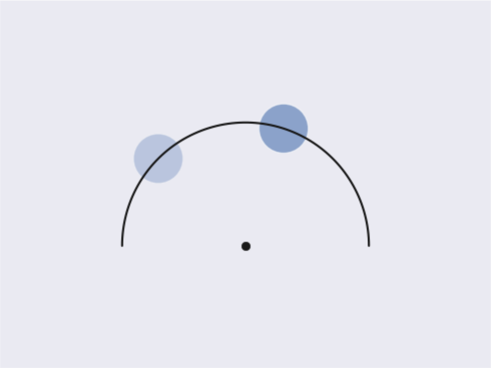
Joint work with Prof. Aviv Tamar



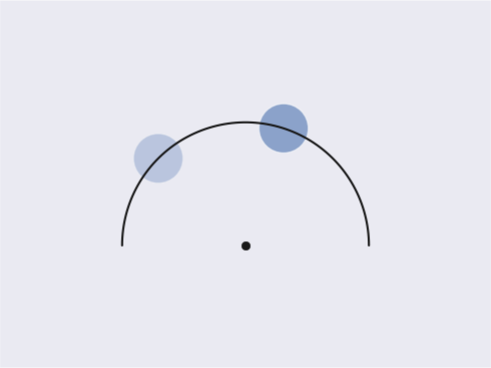
How to reach the goal?



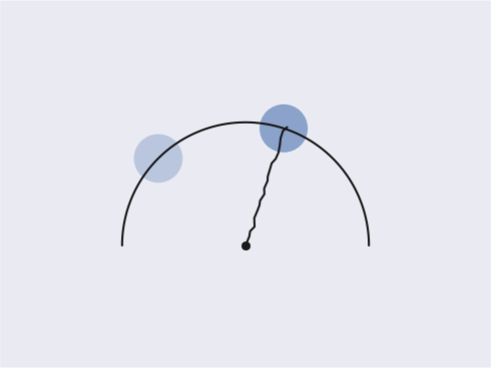
What if goal location is unknown, but we have **data** from agents trained to reach **different goals, all lie on a semi-circle**?



1. Sample possible goal



1. Sample possible goal
2. Pretend goal is correct and plan



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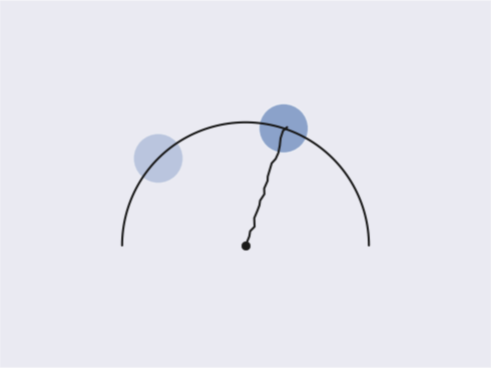
2. Pretend goal is correct and plan
3. Execute, observe evidence and update possible goals

Thompson Sampling



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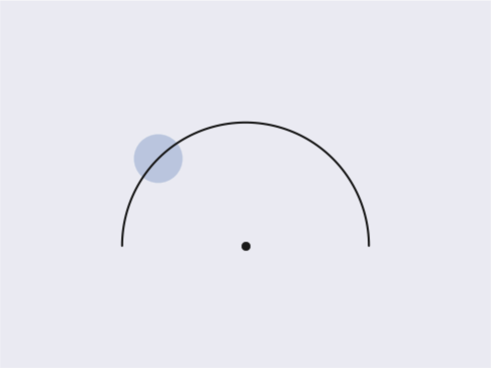
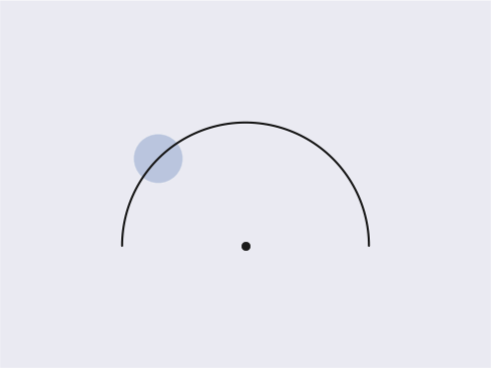


Is that the optimal thing to do?



Is that the optimal thing to do? No!

1. Search optimally across semi-circle

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2. Go to found goal

Bayes-optimal exploration

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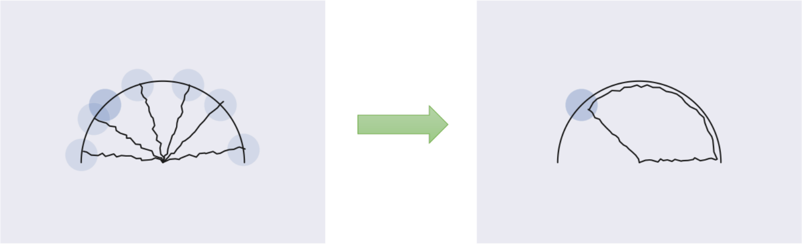
Can we use collected data to learn Bayes-optimal behavior?



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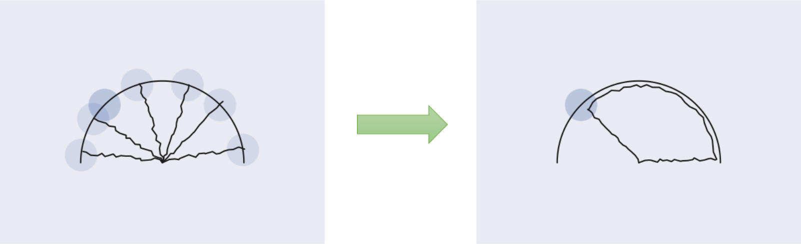

Suppose we can.. Why is it important?

Exploration generally requires **online** data collection.

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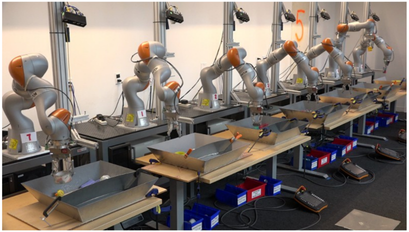
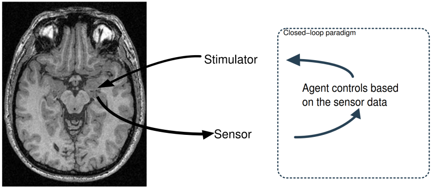
Data collection can be expensive/unsafe: Robotics, Healthcare, AD, ...





Levine et. al. (2020). Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems.

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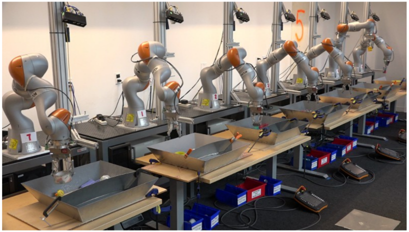
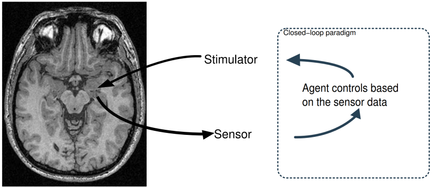




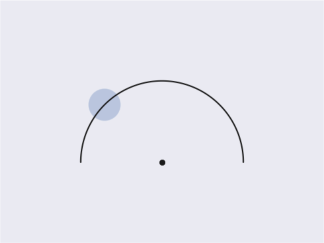
Learn to explore from **offline** data

Levine et. al. (2020). Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems.

Reinforcement Learning (RL)

- Markov Decision Process (MDP) $\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{P})$.

$\mathcal{S}$ – state space
$\mathcal{A}$ – action space
$\mathcal{R}$ – reward function
$\mathcal{P}$ – transition function



- **Goal:** Find *policy* π that maximizes

$$\mathbb{E}\left[\sum_{t=0}^{H} \mathcal{R}(s_t, a_t)\right] .$$

- There exists an optimal policy π^* which is Markov, i.e., $\pi^* : \mathcal{S} \to \mathcal{A}$.

Exploration in RL

How to discover high reward strategies?

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No prior information

- UCRL
- E^3
- R-max
- Exploration bonuses
- Count-based
- ...

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Efficiently search state space

Regret bounds, PAC bounds, ...

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Prior over MDPs

- Bayesian RL

Optimal exploration

Bayesian RL (BRL)

- Prior distribution over MDP parameters, $p(\mathcal{R}, \mathcal{P})$.
- **Goal:** Find *policy* π that maximizes

$$\mathbb{E}_{\mathcal{R},\mathcal{P}\sim p(\cdot,\cdot)}\left[\sum_{t=0}^{H}\mathcal{R}(s_t, a_t)\right] .$$

- In general, the optimal policy is **history-dependent**.
- Optimally balance exploration-exploitation: *An optimal agent takes actions that reduce its uncertainty, only if such leads to higher rewards.*

BRL as Partially-Observed MDP

- $\mathcal{R}, \mathcal{P}$ are unobserved variables.
- Collect samples:

$$h_{:t} = (s_0, a_0, r_1, s_1, \ldots, r_t, s_t) \ .$$

- Maintain *belief*:

$$b_{t+1}(\mathcal{R}, \mathcal{P}) = P(\mathcal{R}, \mathcal{P} | h_{:t+1}) \propto P(s_{t+1}, r_{t+1} | h_{:t}, \mathcal{R}, \mathcal{P}) b_t(\mathcal{R}, \mathcal{P}),$$
$$b_0(\mathcal{R}, \mathcal{P}) = p(\mathcal{R}, \mathcal{P}) \ .$$

- **Bayes-optimal policy** is of the form $\pi^*(s, b)$.

Bayes-Adaptive MDP (BAMDP)

- Hyper-state space:

$$\mathcal{S}^+ = \mathcal{S} \times \mathcal{B}$$

- Transition function:

$$\mathcal{P}^+(s^+_{t+1} | s^+_t, a_t) = \underbrace{\mathbb{E}_{b_t}\left[\mathcal{P}(s_{t+1} | s_t, a_t)\right]}_{\text{state transition}} \underbrace{\delta(b_{t+1} = P(\mathcal{R}, \mathcal{P} | h_{:t+1}))}_{\text{belief update}}$$

- Reward function:

$$\mathcal{R}^+(s^+_t, a_t) = \mathbb{E}_{b_t}\left[\mathcal{R}(s_t, a_t)\right]$$

- **Maximizing the BRL objective amounts to solving the BAMDP!**

Duff (2002). Optimal Learning: Computational Procedures for Bayes-Adaptive Markov Decision Processes.

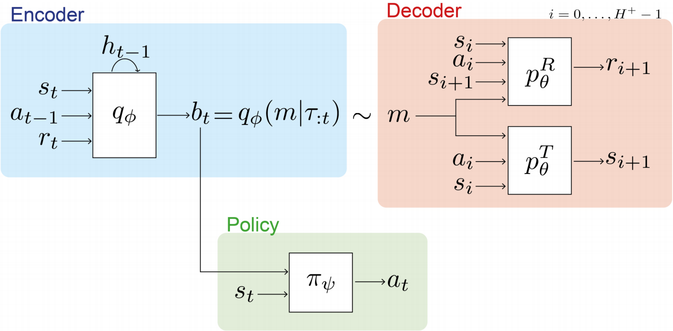
© Shimon Whiteson, NeurIPS 2019 Deep Reinforcement Learning Workshop.

- Intractable posterior update
- Intractable planning in belief space

Variational Bayes-Adaptive Deep RL (VariBAD)

Approximate using Meta-RL and Variational Inference.

- Train variational autoencoder to approximate belief.
- Train on-policy RL agent, conditioned on belief.



Zintgraf et. al. (2020). VariBAD: A Very Good Method for Bayes-Adaptive Deep RL via Meta-Learning. ICLR.

Meta-RL

- Given access to train tasks $\mathcal{M}_1, \dots, \mathcal{M}_N \sim p(\mathcal{M}) = p(\mathcal{R}, \mathcal{P})$.
- Describe MDP $\mathcal{M}_i$ with learned latent variable m_i:

$$\mathcal{P}_i(s_{t+1}|s_t, a_t) \approx \mathcal{P}(s_{t+1}|s_t, a_t, m_i)$$
$$\mathcal{R}_i(s_t, a_t) \approx \mathcal{R}(s_t, a_t|m_i)$$

- Infer m_i by interaction with $\mathcal{M}_i$:

$$p(m_i|\tau^i_{:t}) = \mathbb{P}(m_i|s^i_0, a^i_0, r^i_1, s^i_1, \dots, r^i_t, s^i_t) \ .$$

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Variational Inference

Model trajectories using variational autoencoder.

- Generative model:

$$P(\tau_{:H}^{s,r}|a_{:H-1}) = \int p_\theta(m) p_\theta(\tau_{:H}^{s,r}|m, a_{:H-1}) dm$$

- Approximate posterior:

$$q_\phi(m|\tau_{:t}) = \mathcal{N}(\mu(\tau_{:t}), \Sigma(\tau_{:t}))$$

- Variational lower bound (ELBO):

$$\begin{aligned} \log P(\tau_{:H}^{s,r}|a_{:H-1}) &\geq \mathbb{E}_{q_\phi(m|\tau_{:t})}\left[\log p_\theta(\tau_{:H}^{s,r}|m, a_{:H-1})\right] - D_{KL}(q_\phi(m|\tau_{:t})||p_\theta(m)) \\ &\equiv ELBO_t \end{aligned}$$

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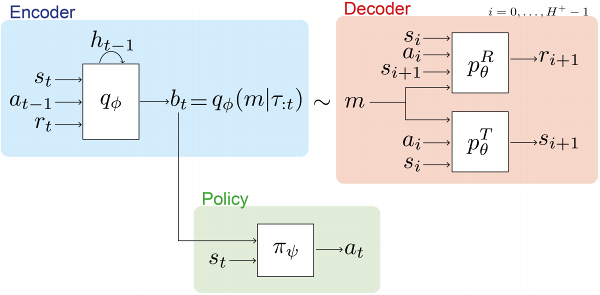
Training Procedure



1. For $i = 1, \dots, N$:
   Collect trajectories from $\mathcal{M}_i$
2. Optimize $\mathcal{L}_{\text{RL}} + \lambda \mathcal{L}_{\text{VAE}}$

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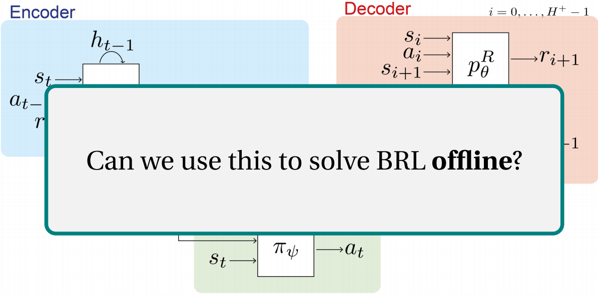

Can we use this to solve BRL **offline**?

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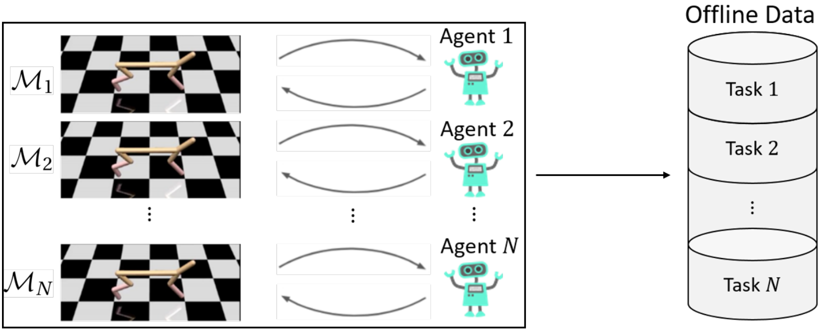
Offline Setting

In this work, offline data is **entire** training histories of RL agents.



State Relabelling

- Train VAE using trajectories in data.

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- Relabel states:
  1. Run encoder on every partial trajectory $\tau_{:t}$. Obtain $b_t \approx (\mu_t, \Sigma_t)$.
  2. Replace each s_t in data with $s_t^+ = (s_t, \mu_t, \Sigma_t)$.

Off-policy VariBAD

Can't use on-policy RL in offline setting! For off-policy, need tuples (s, a, r, s')

Ideal

$$r \sim \mathcal{R}^+ = \mathbb{E}_b \mathcal{R}$$
$$s' \sim \mathcal{P}^+ = \mathbb{E}_b \mathcal{P}$$

Reality

$$\begin{matrix} r \sim \mathcal{R}_\mathcal{M} \\ s' \sim \mathcal{P}_\mathcal{M} \end{matrix}, \mathcal{M} \sim p(\mathcal{M})$$

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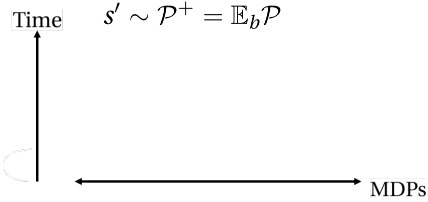

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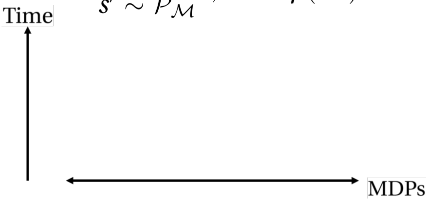

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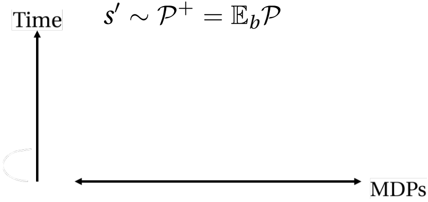

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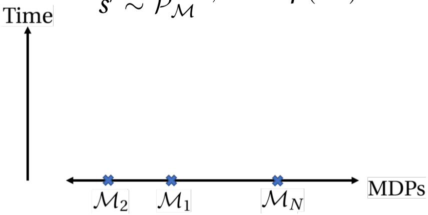

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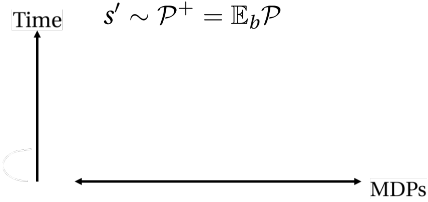

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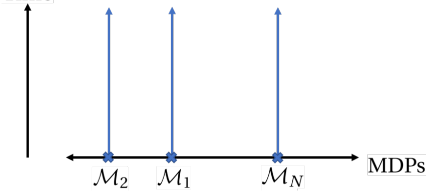

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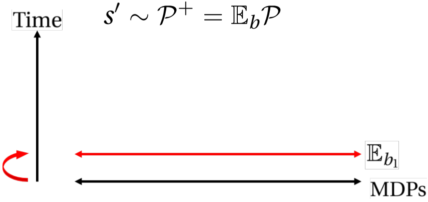

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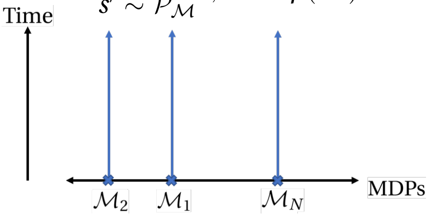

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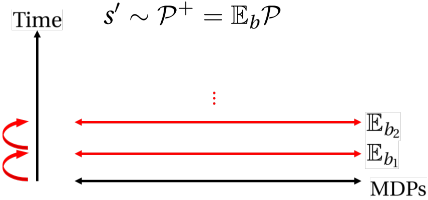

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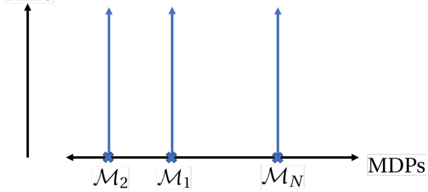

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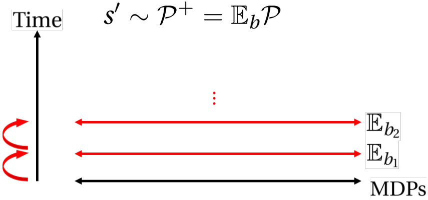

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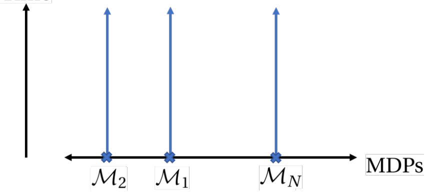
$$r \sim \mathcal{R}_{\mathcal{M}}, \quad s' \sim \mathcal{P}_{\mathcal{M}}, \quad \mathcal{M} \sim p(\mathcal{M})$$



Equivalent!

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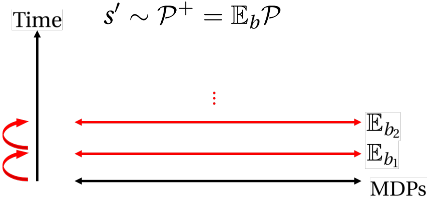

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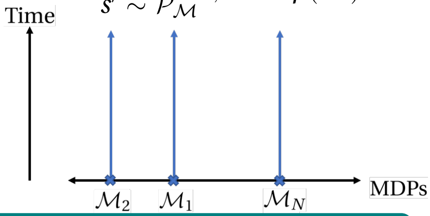

Proposition

Sample $\mathcal{R}, \mathcal{P} \sim p(\mathcal{R}, \mathcal{P})$. Collect trajectory according to $a_t \sim \pi(\cdot|h_{:t})$, $s_{t+1} \sim \mathcal{P}(\cdot|s_t, a_t)$ and $r_{t+1} \sim \mathcal{R}(\cdot|s_t, a_t)$. Then,

$$\mathbb{P}(s_{t+1}|s_0, a_0, r_1, \ldots, s_t, a_t) = \mathbb{E}_{\mathcal{R},\mathcal{P}\sim b_t} \mathcal{P}(s_{t+1}|s_t, a_t),$$
$$\mathbb{P}(r_{t+1}|s_0, a_0, r_1, \ldots, s_t, a_t) = \mathbb{E}_{\mathcal{R},\mathcal{P}\sim b_t} \mathcal{R}(r_{t+1}|s_t, a_t).$$

Off-policy VariBAD

Conclusion

Any off-policy RL algorithm can be used on the hyper-state tuples in our data.

Off-policy VariBAD

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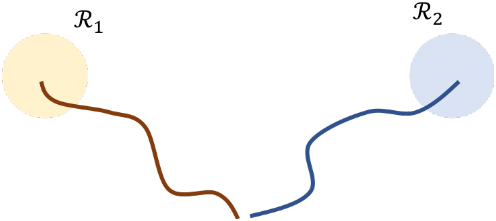
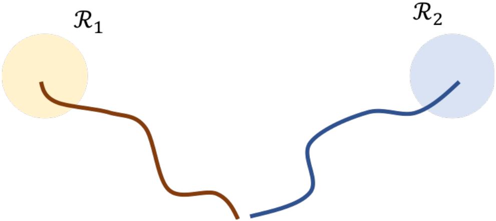
Is that it?

The MDP Ambiguity Problem



Two different MDPs or a single MDP with rewards at both circles?

The MDP Ambiguity Problem



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Unique problem to the offline Meta-RL setting!

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During the VAE training

Reward Relabelling

- **Problem:** For each MDP, different part of state space is visited.

Reward Relabelling

- **Problem:** For each MDP, different part of state space is visited.
- Make state distribution uniform across MDPs:

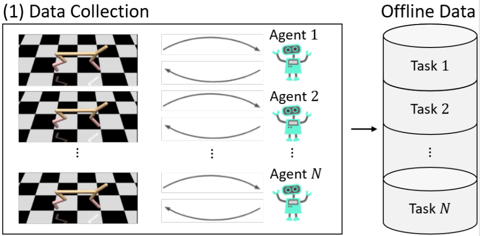
  1. Let $\tau^i = \left(s_0^i, a_0^i, r_1^i, s_1^i, \ldots, r_H^i, s_H^i\right)$ from $\mathcal{M}_i$.
  2. Sample randomly $i' \neq i$. Relabel rewards:

$$\hat{\tau}^i = \left(s_0^i, a_0^i, \hat{r}_1^i, s_1^i, \ldots, \hat{r}_H^i, s_H^i\right)$$

where $\hat{r}_{t+1}^i = \mathcal{R}_{i'}(s_t^i, a_t^i)$

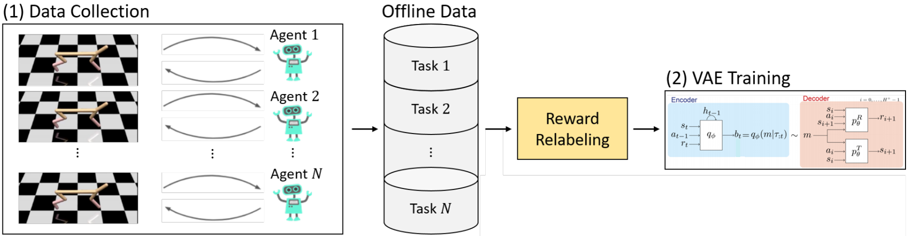
- Requires access to $\mathcal{R}_i$ for each $\mathcal{M}_i$.

Our Method

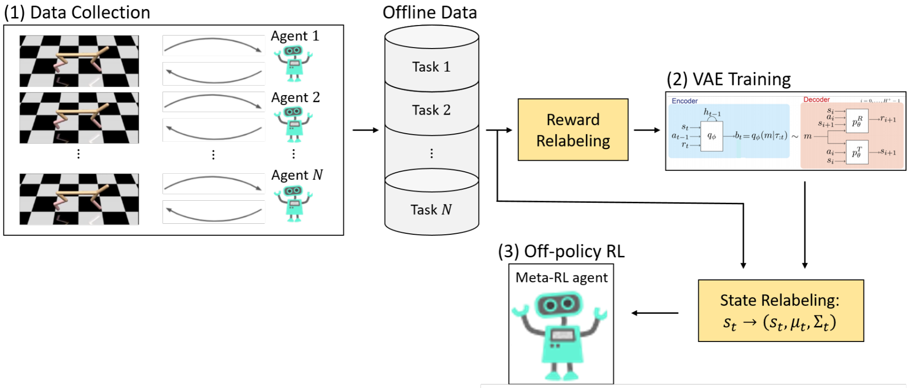


(1) Data Collection
Agent 1
Agent 2
Agent N
Offline Data
Task 1
Task 2
Task N

Our Method

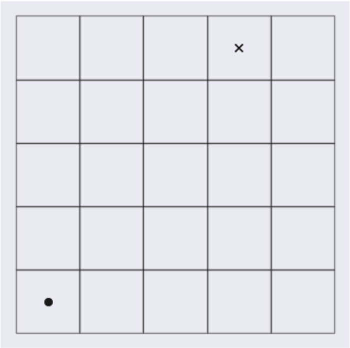

(1) Data Collection
Agent 1
Agent 2
Agent N
Offline Data
Task 1
Task 2
Task N
Reward Relabeling
(2) VAE Training
Encoder
Decoder

Our Method

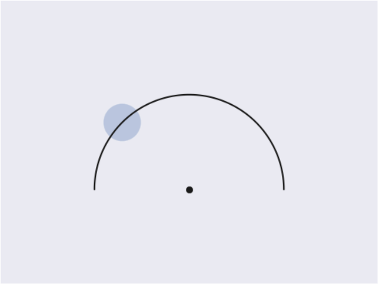

(1) Data Collection
Agent 1
Agent 2
Agent N
Offline Data
Task 1
Task 2
Task N
Reward Relabeling
(2) VAE Training
Encoder
Decoder
(3) Off-policy RL
Meta-RL agent
State Relabeling:
$s_t \rightarrow (s_t, \mu_t, \Sigma_t)$

Illustrative Domains

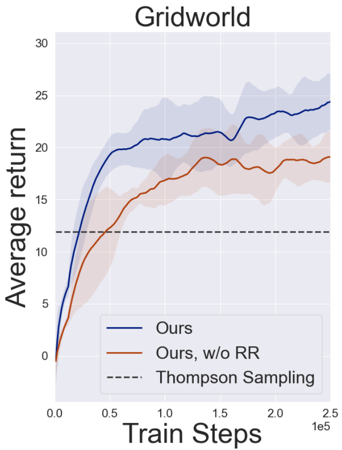
Gridworld

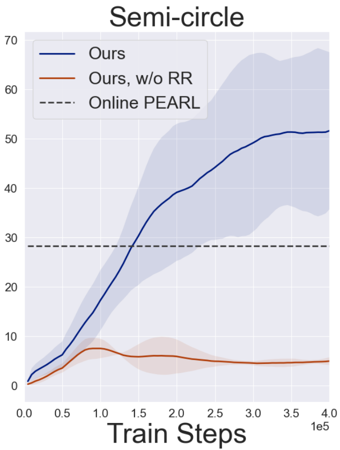


Semi-circle



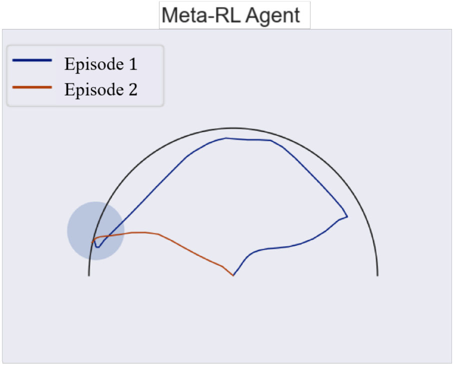
Illustrative Domains - Performance





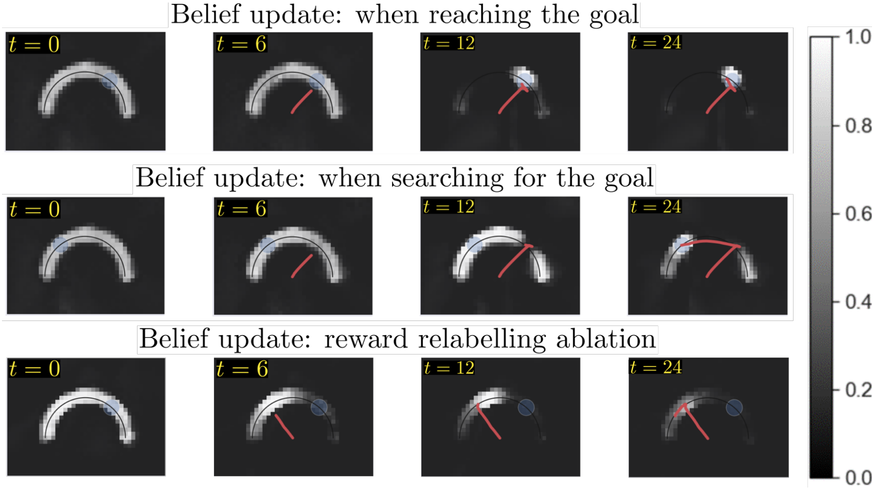
Semi-circle

Offline Data
Agent 1
Agent 2
Agent 3
Agent 4



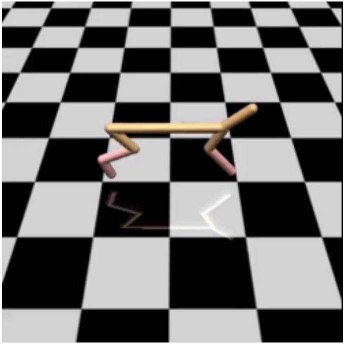
Meta-RL Agent
Episode 1
Episode 2

Semi-circle - Belief Visualization

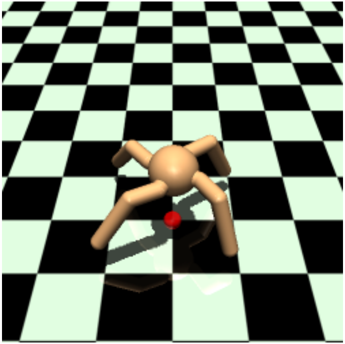


MuJoCo Domains

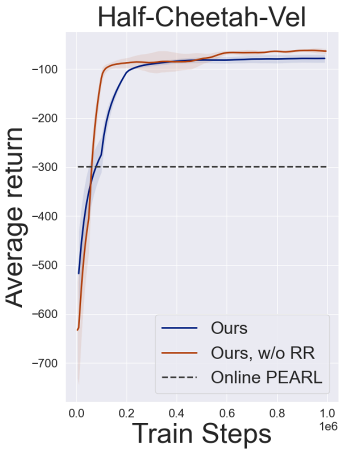
Half-Cheetah-Vel

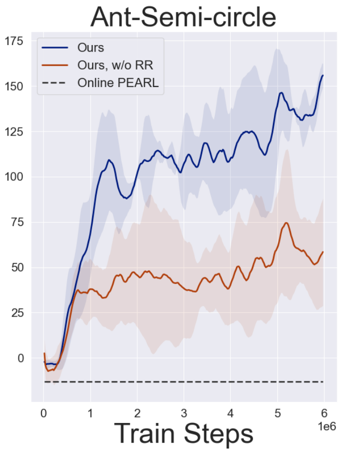


Ant-Semi-circle



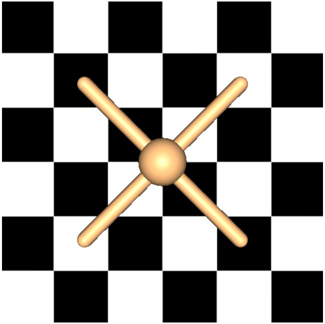
MuJoCo Domains - Performance



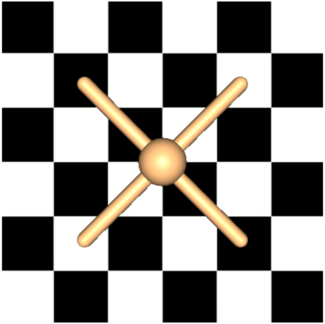


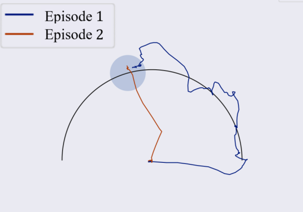
Ant-Semi-circle

Episode 1

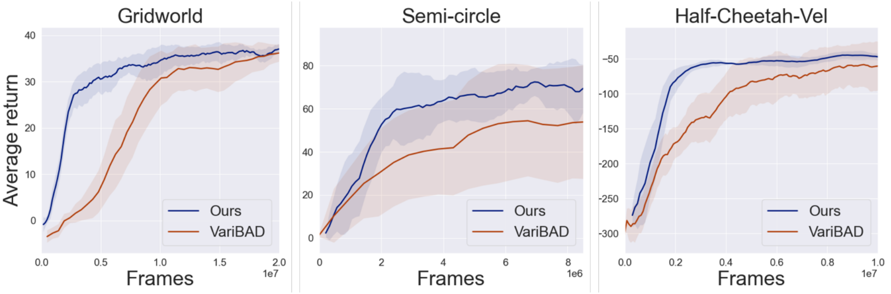


Episode 2



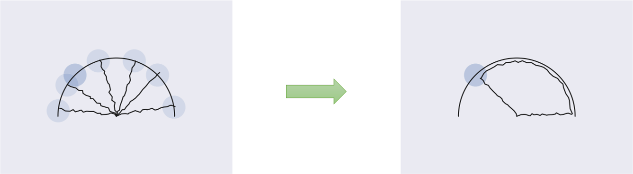


Online Setting Performance



Summary

- Formalized offline Meta-RL as BRL.



- Demonstrated learning an approximately Bayes-optimal policy.
- Sample efficient off-policy RL optimization.