人工智能实践
Artificial Intelligence Practice

DCS3015 Autumn 2022

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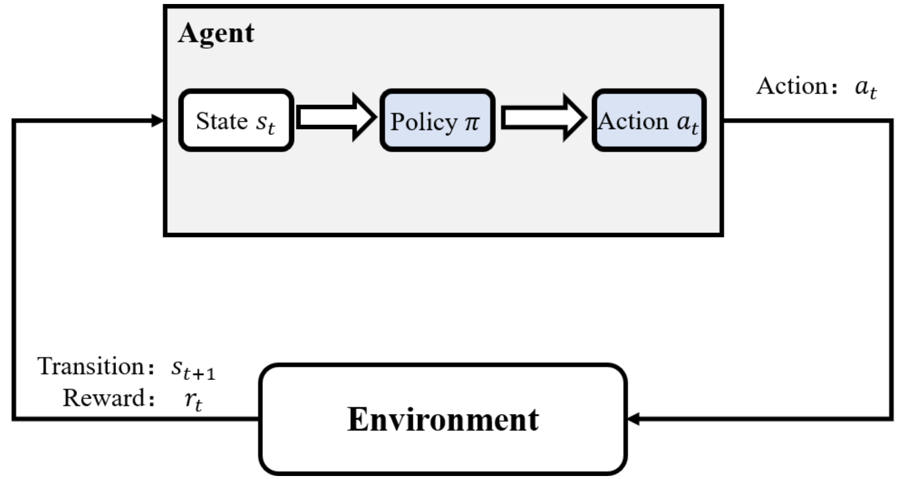
Lecture 8： Model-based RL

15th December 2022

Quick Recap

- States $S \in \mathbb{R}^s$
- Actions $A \in \mathbb{R}^a$
- Reward Function $R: S \times A \rightarrow \mathbb{R}$
- Transition Function $T: S \times A \rightarrow S$
- Discounted Factor $\gamma \in (0,1)$
- Policy $\pi: S \rightarrow A$



$$\max_{\pi} \sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)$$

Subject to $a_t = \pi(s_t)$, $s_{t+1} = T(s_t, a_t)$

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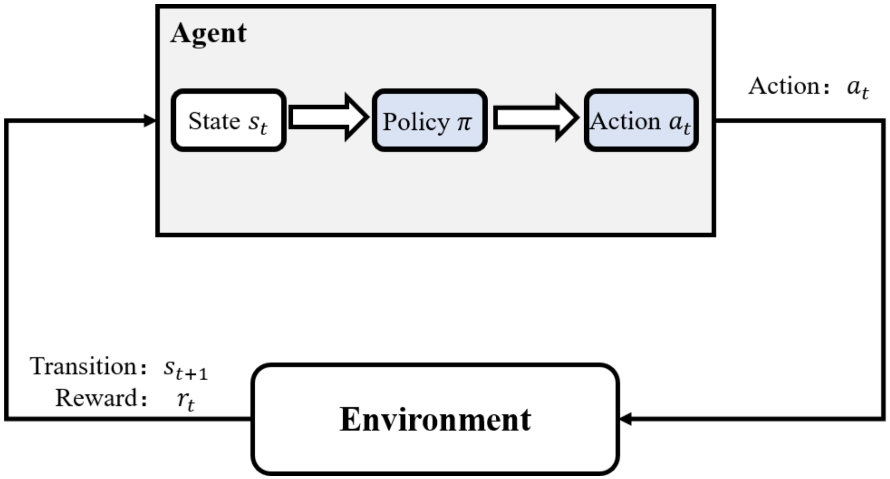

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Model-free RL vs. Model-based RL

Collect data

$$\mathcal{D} = \{s_t, a_t, r_{t+1}, s_{t+1}\}_{t=0}^{T}$$

Model-free: learn policy directly from data

$$\mathcal{D} \rightarrow \pi$$

e.g. Q-learning, policy gradient

Model-based: learn model, then use it to learn or improve a policy

$$\mathcal{D} \rightarrow f \rightarrow \pi$$

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Why Model-based ?

	Model-free	Model-based
Asymptotic Performance	+	- / +
Computation	+	-
Sample Efficiency	-	+
Exploration	-	+

Model-free RL vs. Model-based RL

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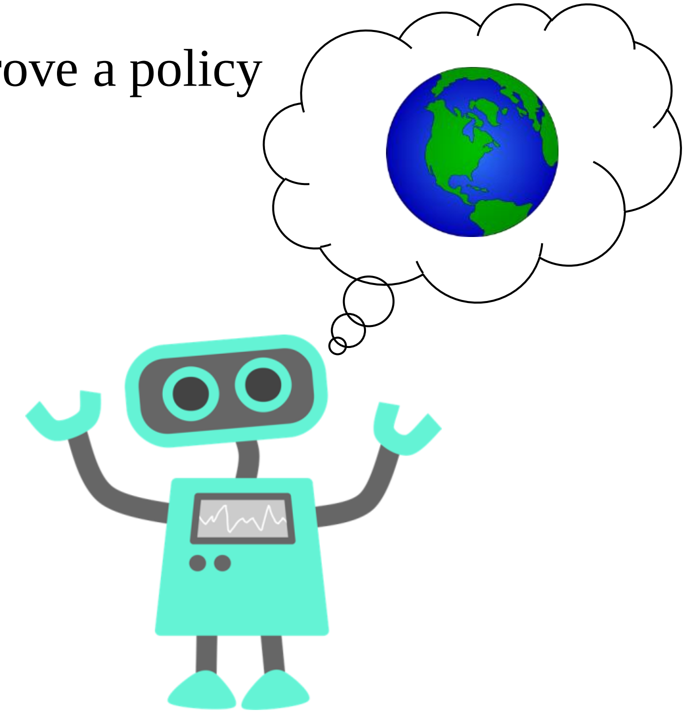

□ What is a Model ?

What is a Model ?

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$$\mathcal{D} \to f \to \pi$$

☐ What is a Model ?

Definition: a model is a representation that **explicitly** encodes knowledge about the structure of the environment and task. state_next, reward, terminate, infos = env.step(action)

A transition/dynamics model: $s_{t+1} = f_s(s_t, a_t)$

A rewards model: $r_{t+1} = f_r(s_t, a_t)$

A inverse transition/dynamics model: $a_t = f_s^{-1}(s_t, s_{t+1})$

What is a Model ?

Collect data

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Typically what is meant by the model in model-based RL

A inverse transition/dynamics model: $a_t = f_s^{-1}(s_t, s_{t+1})$

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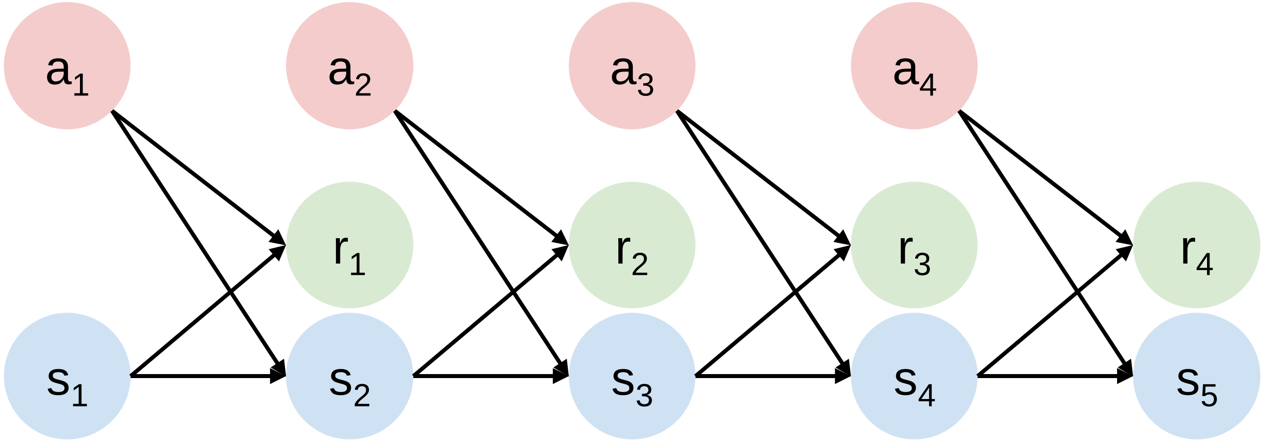
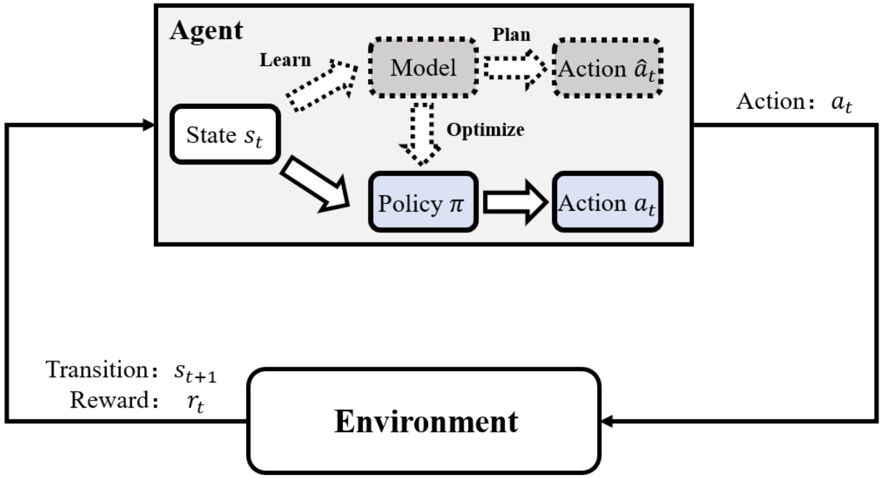


Model-based RL

Model-based RL Process:



Run base policy $\pi_0(a_t|s_t)$ to collect data $\mathcal{D} = \{(s_t, a_t, s_{t+1})_i\}$

For _ do

Learn transition/dynamics model $f(s, a)$

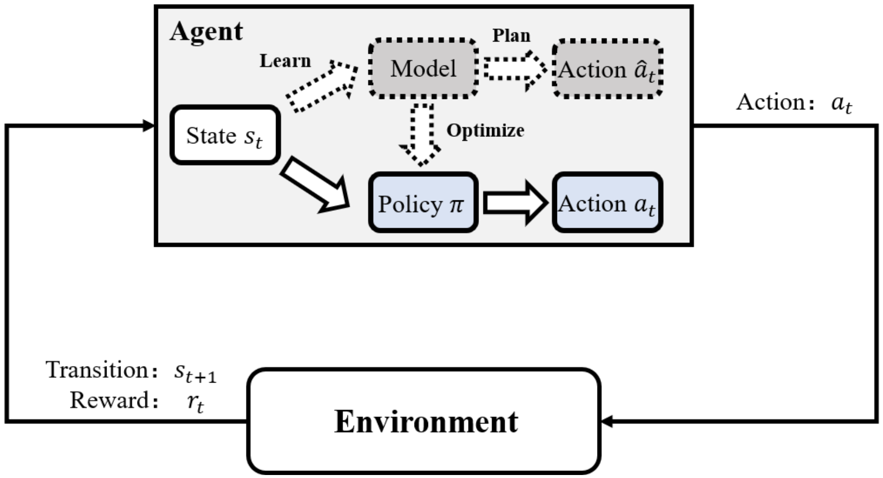
Use model $f(s, a)$ to assist agent to update policy $\pi(a_t|s_t)$

Execute $\pi(a_t|s_t)$ and add the resulting data $\{(s_t, a_t, s_{t+1})_j\}$ to $\mathcal{D}$

End For

Model-based RL

Model-based RL Process:



Run base policy $\pi_0(a_t|s_t)$ to collect data $\mathcal{D} = \{(s_t, a_t, s_{t+1})_i\}$

For _ do

Learn transition/dynamics model $f(s, a)$ **Model Building**

Use model $f(s, a)$ to assist agent to update policy $\pi(a_t|s_t)$ **Model Utilizing**

Execute $\pi(a_t|s_t)$ and add the resulting data $\{(s_t, a_t, s_{t+1})_j\}$ to $\mathcal{D}$

End For

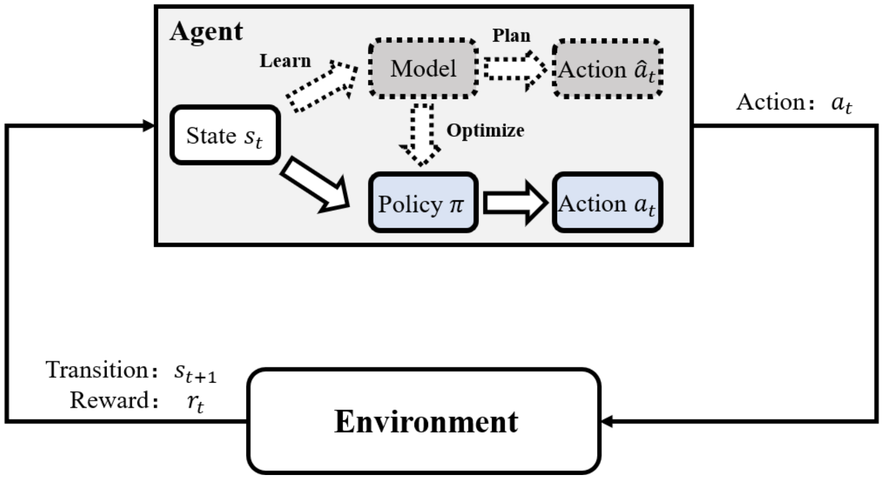
Model-based RL

◻ Model Building

Collect data $\mathcal{D} = \{(s_t, a_t, s_{t+1})_i\}$

$\Downarrow$

Deterministic Model or **Probabilistic Model**



Model-based RL

Model Building

Collect data $\mathcal{D} = \{(s_t, a_t, s_{t+1})_i\}$

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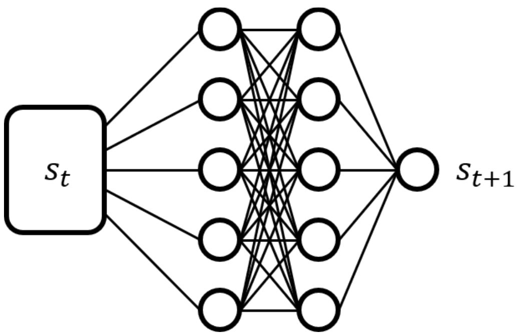
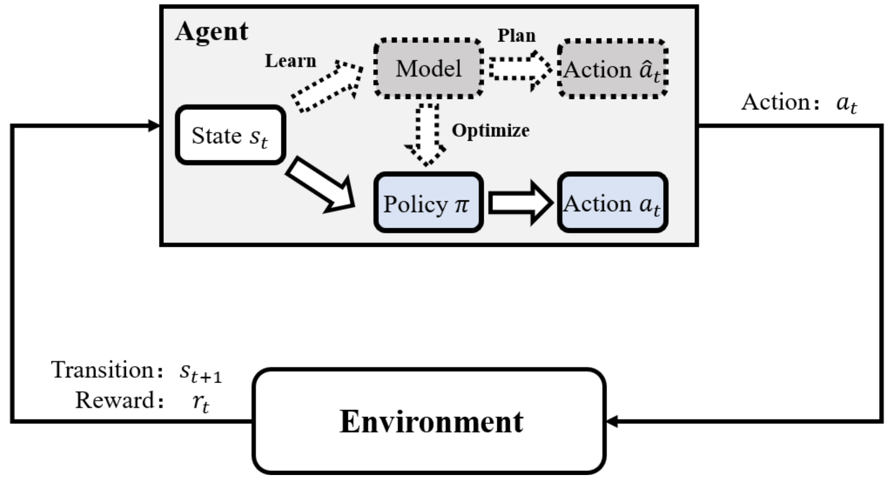


$$\hat{s}_{t+1} \sim f(s_t, a_t)$$

Incremental Predict:

$$\hat{s}_{t+1} \sim s_t + f(s_t, a_t)$$



Learn transition model $f(s, a)$ to minimize **Mean Squared Error (MSE):**

$$\mathcal{L}_{MSE} = \mathbb{E}_{(s_t, a_t, s_{t+1}) \sim \mathcal{D}} \left[f\left(s_t, a_t\right) - s_{t+1} \right]^2 .$$

Model-based RL

Model Building

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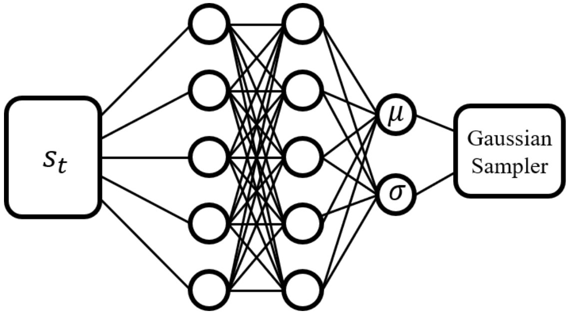
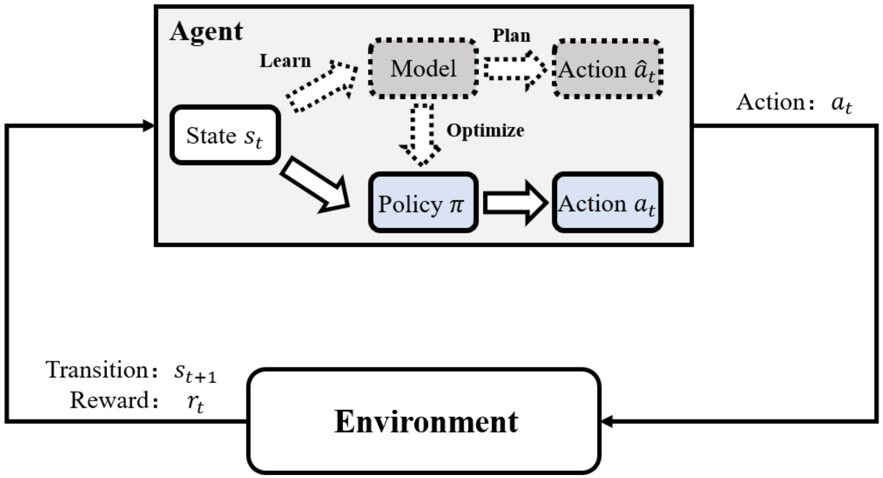


$$\hat{s}_{t+1} \sim \mathcal{N}\left(\mu(s_t, a_t), \sigma(s_t, a_t)\right)$$

Learn transition model $f(s, a)$ to optimize **Negative Log Likelihood (NLL)**

$$\mathcal{L}_{NLL} = \mathbb{E}_{(s_t, a_t, s_{t+1}) \sim \mathcal{D}} \left(\frac{\left[\mu(s_t, a_t) - s_{t+1}\right]^2}{\sigma(s_t, a_t)} + \log \sigma(s_t, a_t) \right)$$



Model-based RL

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Collect data $\mathcal{D} = \{(s_t, a_t, s_{t+1})_i\}$

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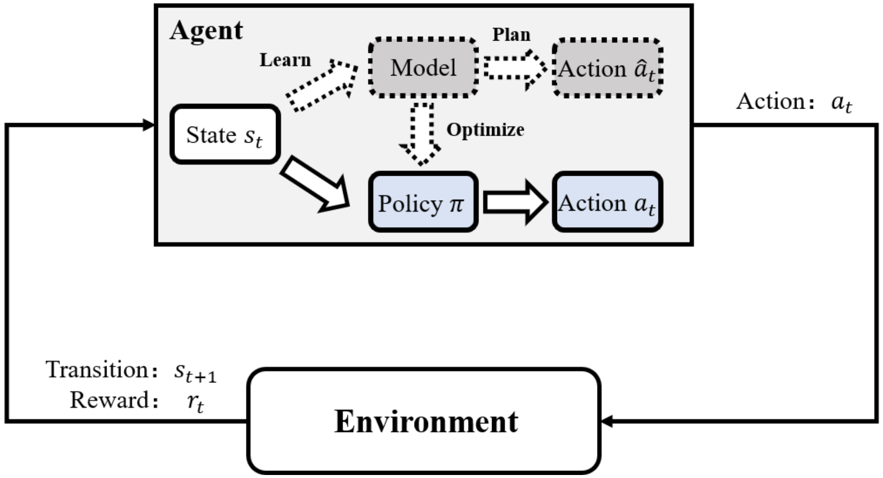
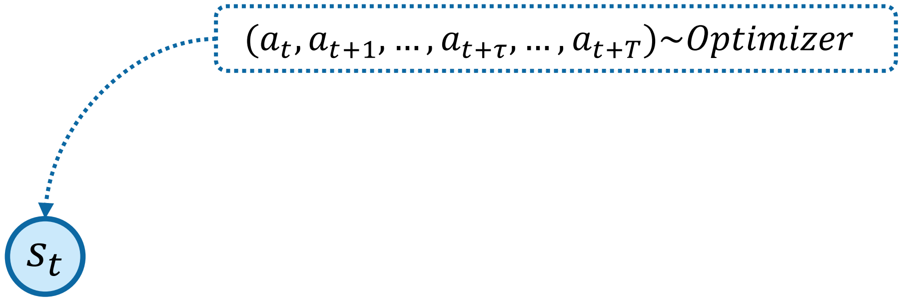
$$\sum_i \|f(s_t, a_t) - s_{t+1}\|^2$$



Decision-Time Method (Plan):

Model Predictive Control (MPC) without Policy Function π



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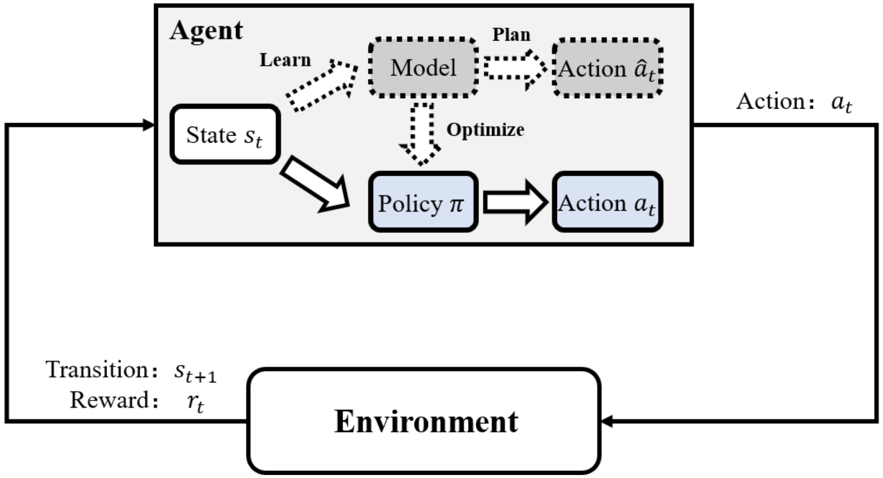

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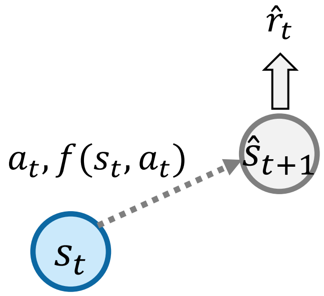

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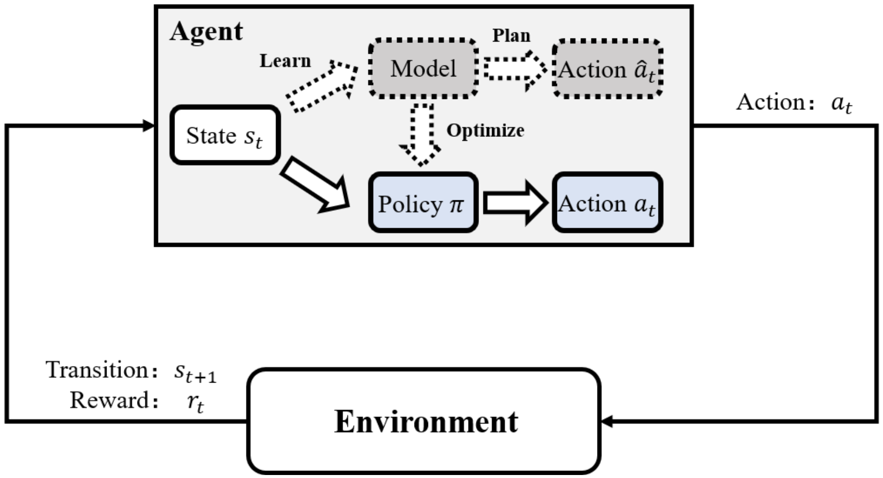

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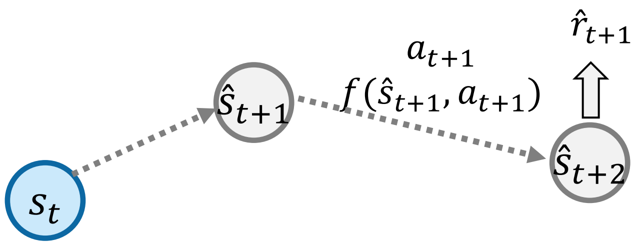

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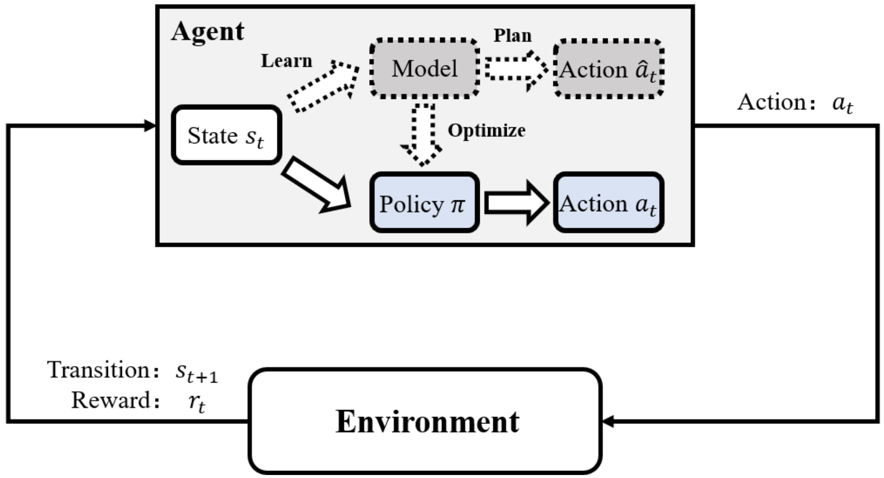

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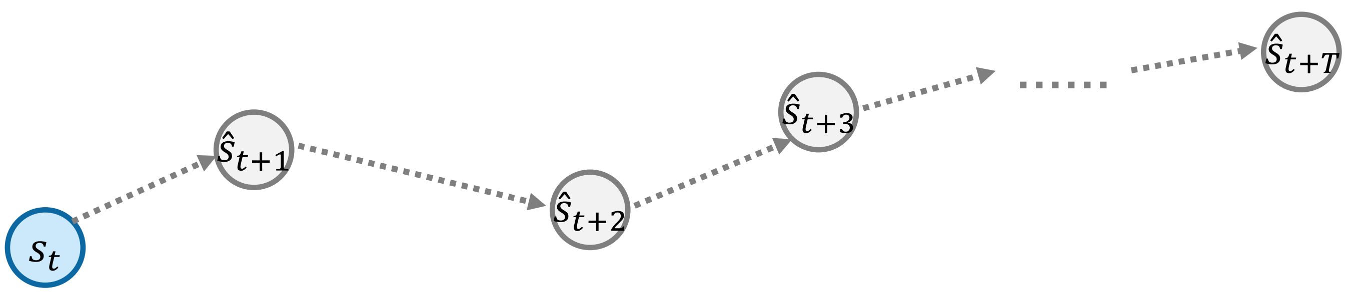

$$\Longrightarrow \sum_{\tau=t}^{t+T-1} \hat{r}(s_\tau, a_\tau)$$

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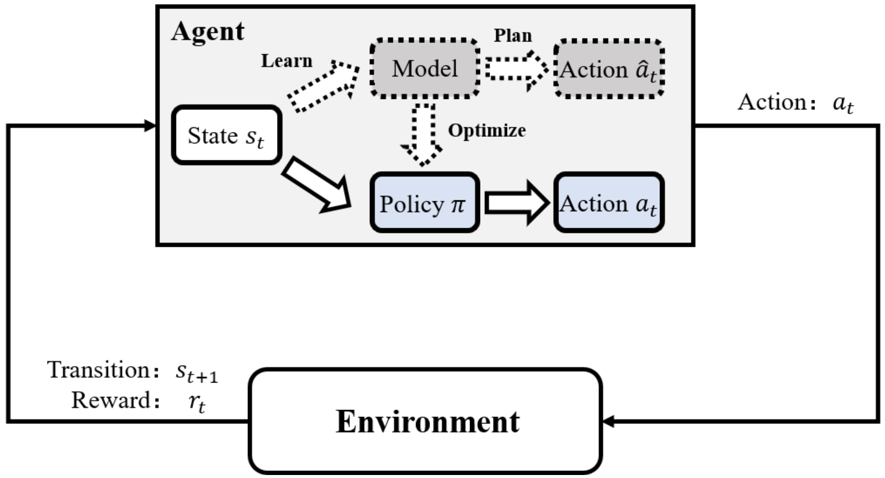

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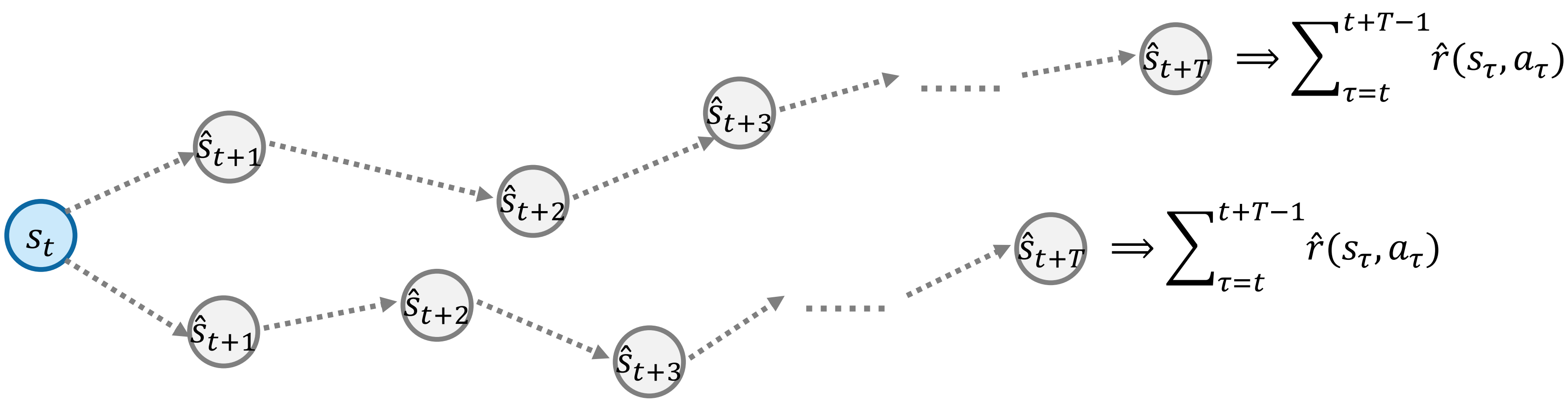

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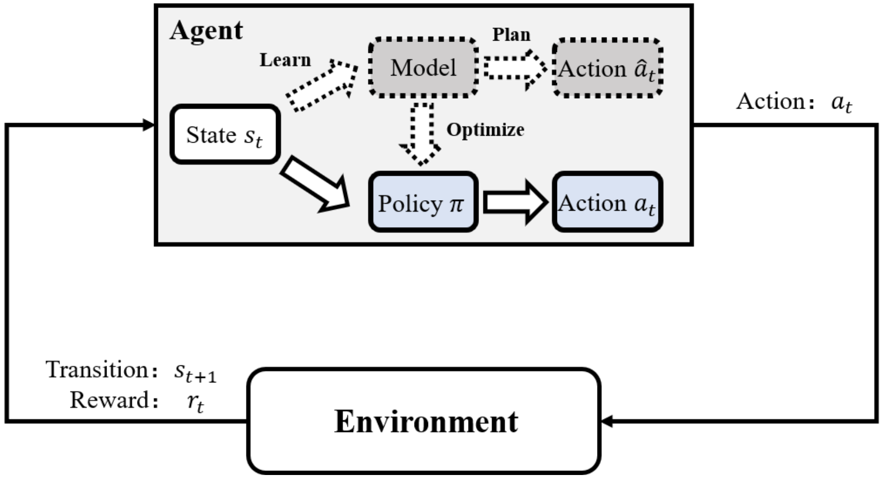

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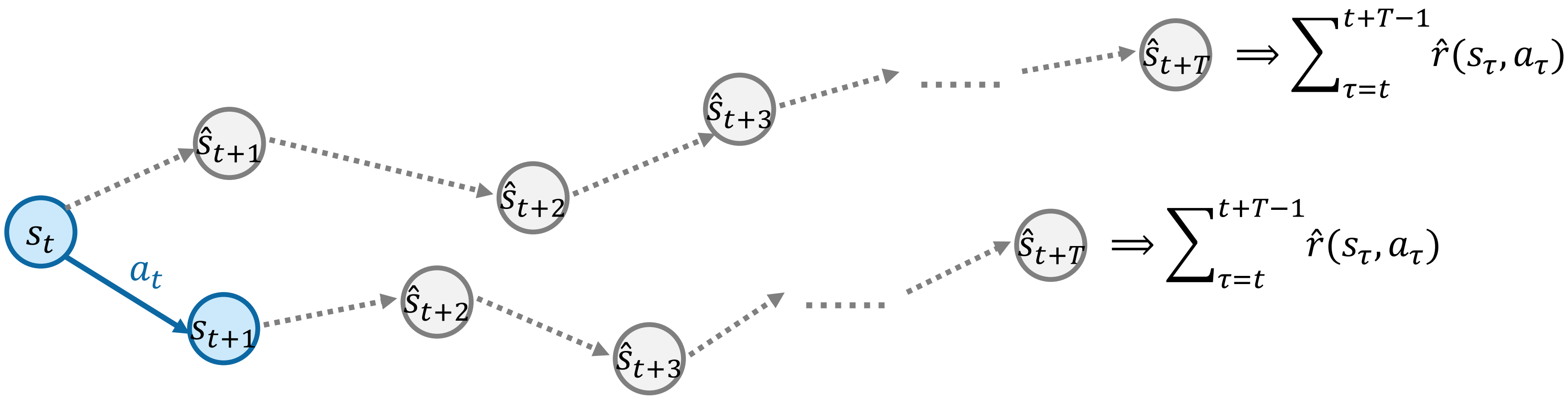

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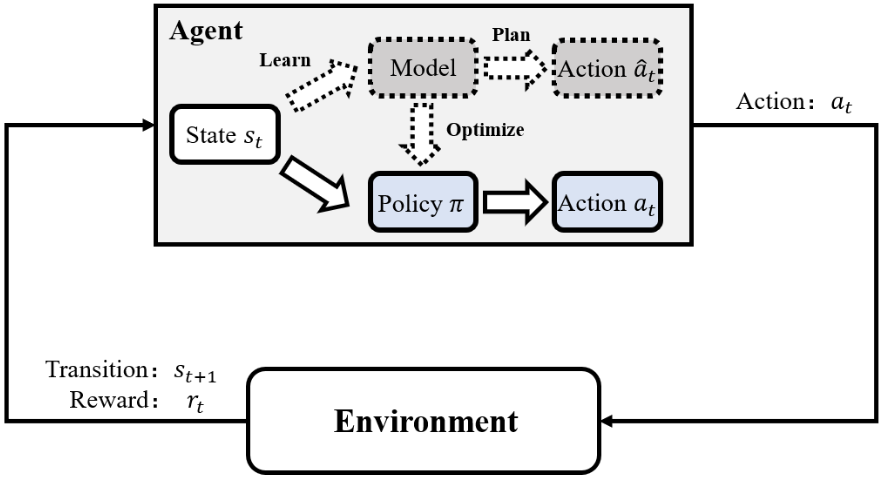

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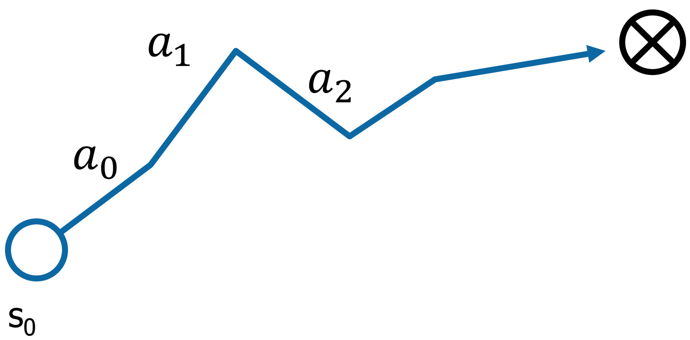

Trajectory Optimization with Action Sequence:

$$s_t \rightarrow a_t \rightarrow s_{t+1} \rightarrow a_{t+1} \rightarrow \cdots$$

$$J(a_0, \ldots, a_H) = \sum_{t=0}^{H} \gamma^t r_t$$

Model-based RL

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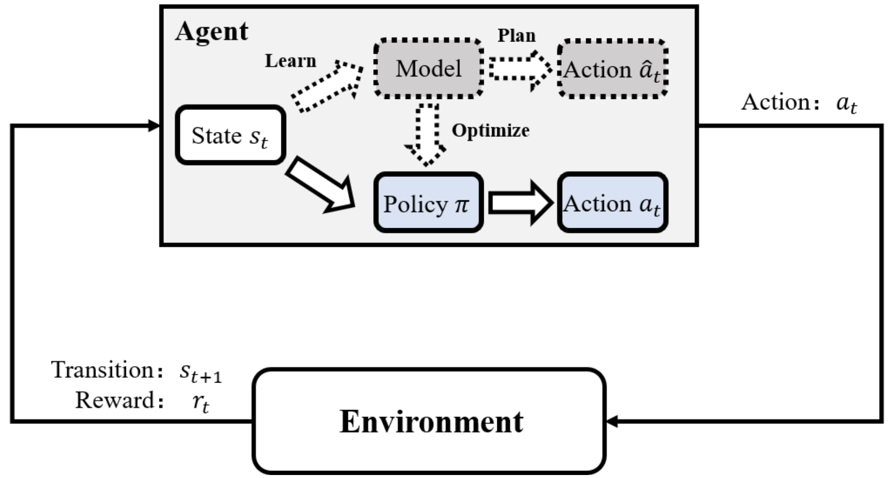
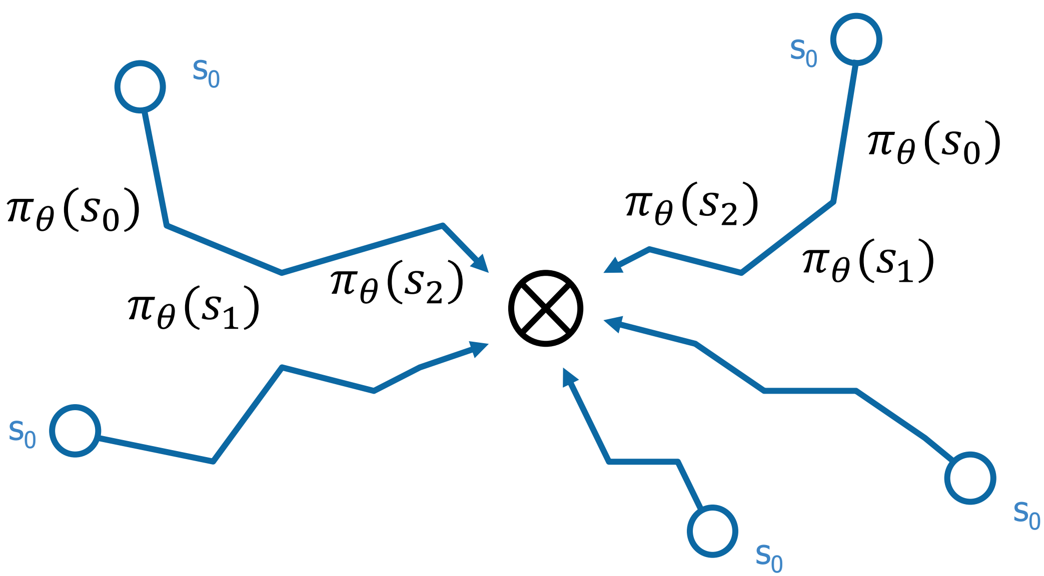
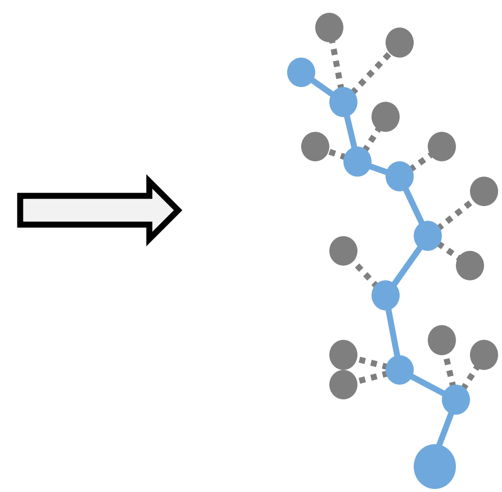


Background Method (Optimize):



Mix real and model-generated experience and apply additional policy updates.



Model-based RL

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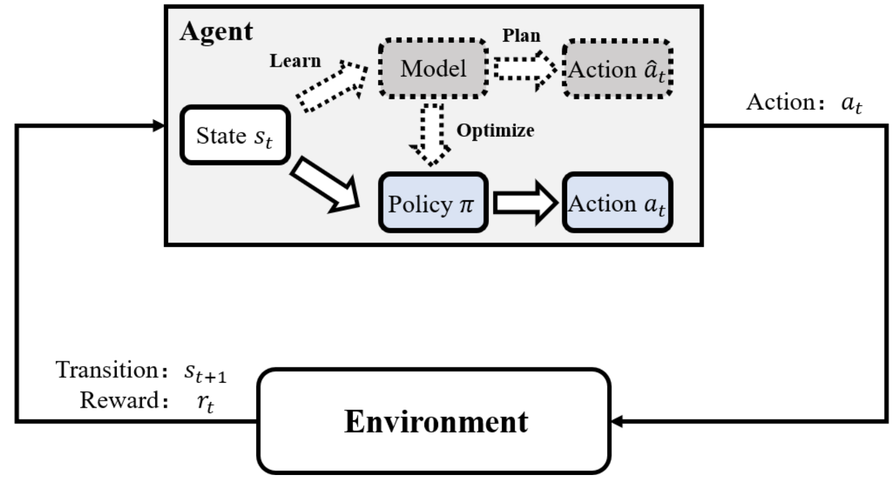

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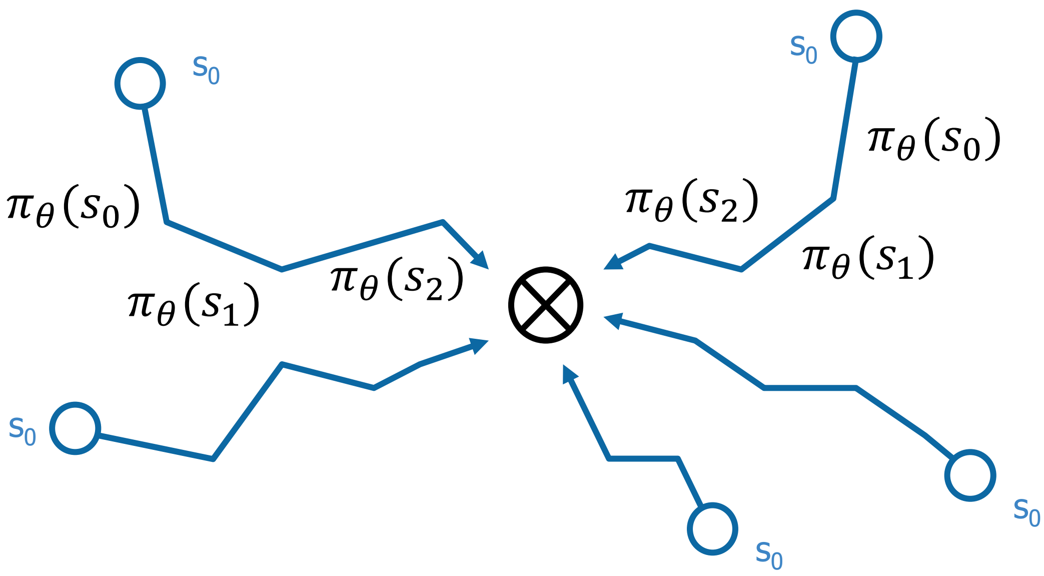


Policy Optimization with parameter θ :

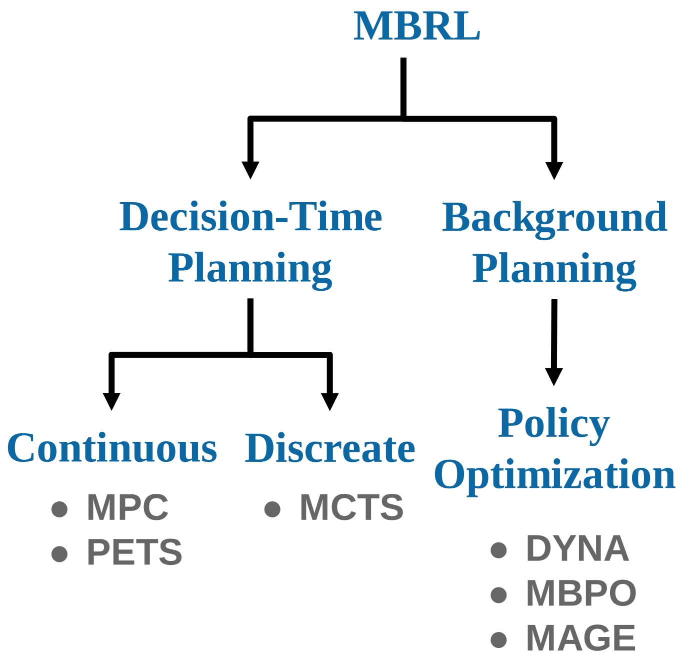
$$s_t \rightarrow \pi_\theta(s_t) \rightarrow s_{t+1} \rightarrow \pi_\theta(s_{t+1}) \rightarrow \cdots$$

$$J(\theta) = \mathbb{E}_{s_0}\left[\sum_{t=0}^{H} \gamma^t r_t\right], \quad a_t = \pi_\theta(s_t)$$

Model-based RL

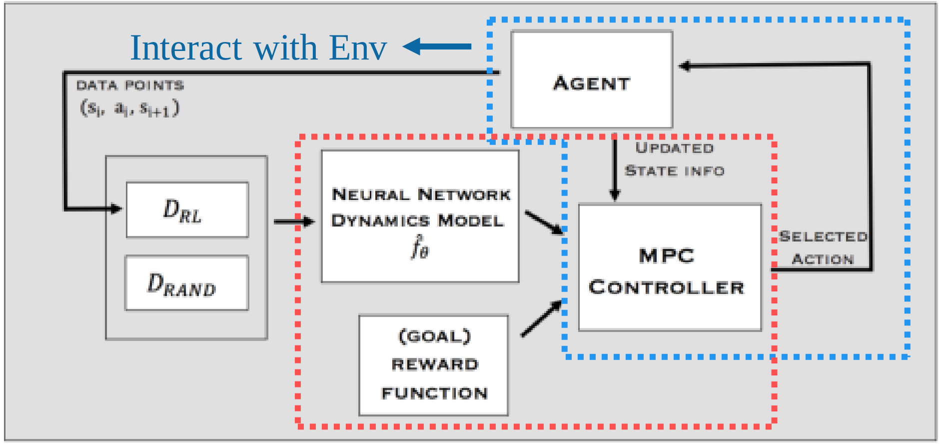
Background vs. Decision-Time

	Background	Decision-Time
Act without Learning	-	+
Unfamiliar situations	-	+
Computation	+	-
Predictability Coherence	+	-
Discrete and Continuous	+	-



MPC with Neural Network Model

- $\mathcal{D}_{RL} = \{(s_t, a_t, s_{t+1})_i\}$ to train neural network dynamic model.
- $\mathcal{D}_{RAND} = \{(a_1, a_2, \dots, a_T)\}$ to store the sampled actions sequence.
- (Goal) Reward Function



1. Planning based on Model
2. Agent action selection

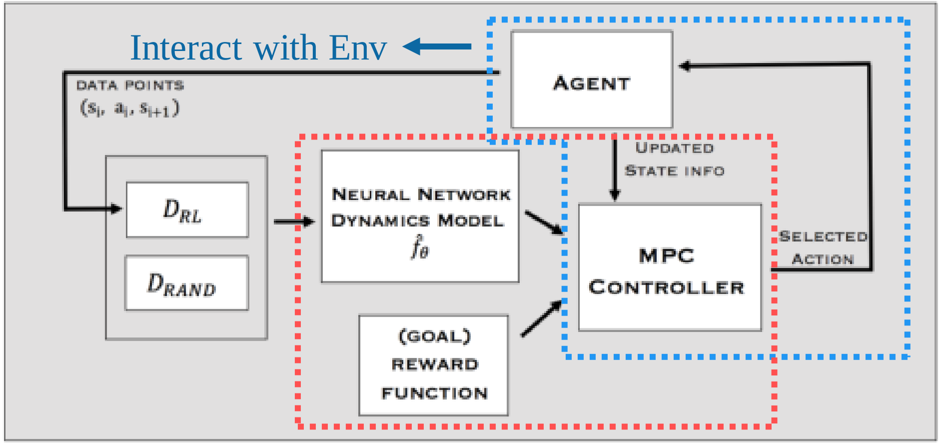
Nagabandi, Anusha, et al. "Neural network dynamics for model-based deep reinforcement learning with model-free fine-tuning.", ICRA. 2018.

Decision-Time

MPC with Neural Network Model

Algorithm 1 Model-based Reinforcement Learning

gather dataset $\mathcal{D}_{\text{RAND}}$ of random trajectories
initialize empty dataset $\mathcal{D}_{\text{RL}}$, and randomly initialize $\hat{f}_\theta$
for iter=1 **to** max_iter **do**
  train $\hat{f}_\theta(\mathbf{s}, \mathbf{a})$ by performing gradient descent on Eqn. 2, using $\mathcal{D}_{\text{RAND}}$ and $\mathcal{D}_{\text{RL}}$
  for $t = 1$ **to** T **do**
    get agent's current state $\mathbf{s}_t$
    use $\hat{f}_\theta$ to estimate optimal action sequence $\mathbf{A}_t^{(H)}$ (Eqn. 4)
    execute first action $\mathbf{a}_t$ from selected action sequence $\mathbf{A}_t^{(H)}$
    add $(\mathbf{s}_t, \mathbf{a}_t)$ to $\mathcal{D}_{\text{RL}}$
  end for
end for



1. Planning based on Model
2. Agent action selection

$$\hat{\mathbf{s}}_{t+1} = \mathbf{s}_t + \hat{f}_\theta(\mathbf{s}_t, \mathbf{a}_t)$$

$$\mathcal{E}(\theta) = \frac{1}{|\mathcal{D}|} \sum_{(\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{t+1}) \in \mathcal{D}} \frac{1}{2} \|(\mathbf{s}_{t+1} - \mathbf{s}_t) - \hat{f}_\theta(\mathbf{s}_t, \mathbf{a}_t)\|^2 \quad (1)$$

$$\mathbf{A}_t^{(H)} = \arg\max_{\mathbf{A}_t^{(H)}} \sum_{t'=t}^{t+H-1} r(\hat{\mathbf{s}}_{t'}, \mathbf{a}_{t'}) \quad :$$
$$\hat{\mathbf{s}}_t = \mathbf{s}_t, \hat{\mathbf{s}}_{t'+1} = \hat{\mathbf{s}}_{t'} + \hat{f}_\theta(\hat{\mathbf{s}}_{t'}, \mathbf{a}_{t'}). \qquad (3)$$

Random Shooting (RS):

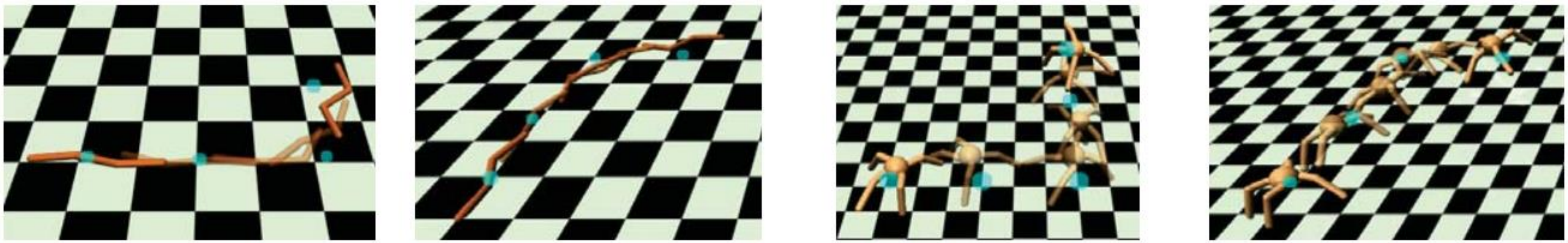
For $t = 1$ to T do:

$$random\ (a_t) \in A \ \rightarrow \mathcal{D}_{RAND}$$

Nagabandi, Anusha, et al. "Neural network dynamics for model-based deep reinforcement learning with model-free fine-tuning.", ICRA. 2018.

Decision-Time

MPC with Neural Network Model



(a) Swimmer left turn (b) Swimmer right turn (c) Ant left turn (d) Ant right turn

(a) Swimmer (b) Cheetah (c) Ant (d) Hopper

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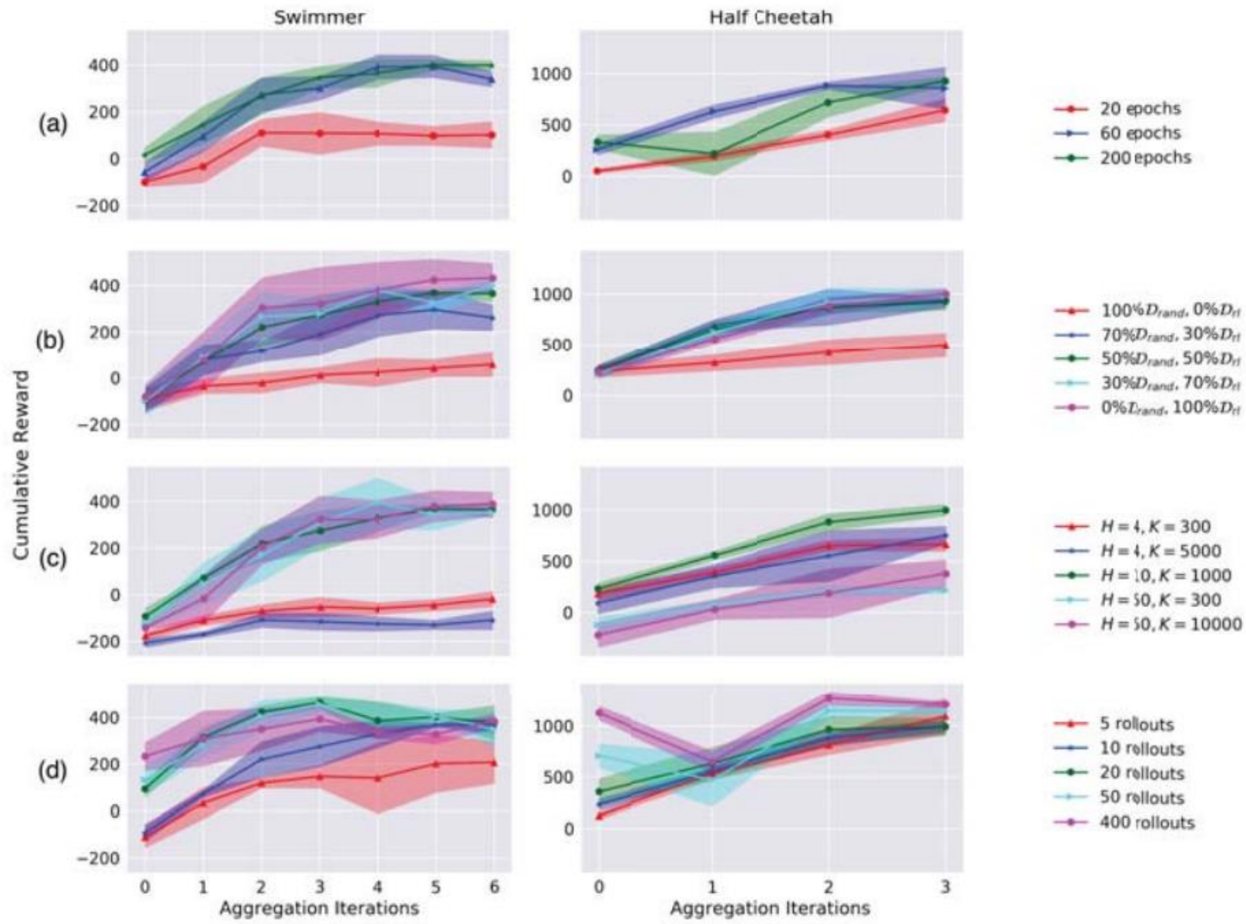
Decision-Time

MPC with Neural Network Model



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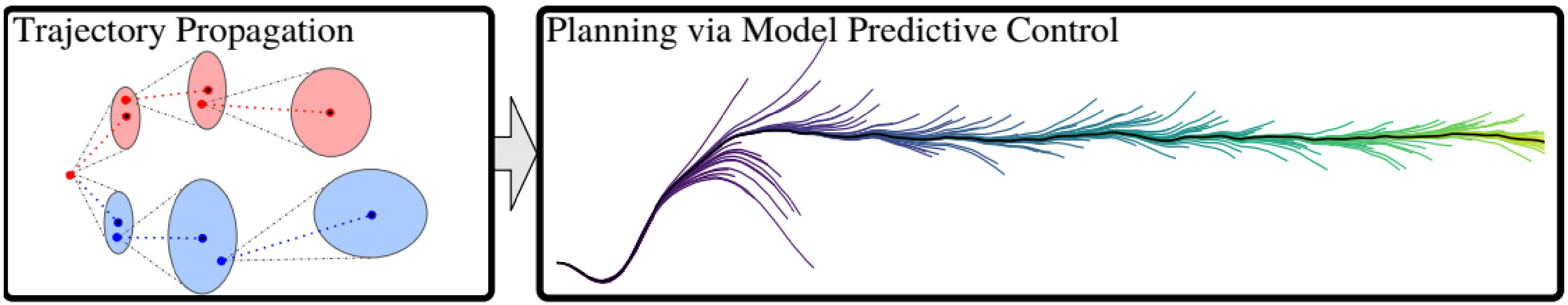
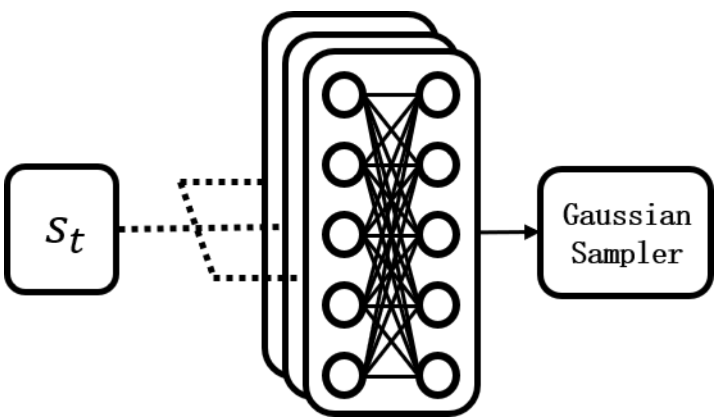
Decision-Time

Probabilistic Ensemble with Trajectory Sampling (PETS)



- Probabilistic Model Networks to capture **aleatoric uncertainty**.
- Model Ensembles to capture **epistemic uncertainty**.



Model Ensemble Output:

$$\hat{s}_{t+1} = random\left(f_1(s_t, a_t), f_2(s_t, a_t), \ldots, f_M(s_t, a_t)\right)$$

$$\hat{s}_{t+1} = \frac{1}{M}\sum_{j=1}^{M} f_j(s_t, a_t).$$

Chua, Kurtland, et al. "Deep reinforcement learning in a handful of trials using probabilistic dynamics models." , NIPS, 2018.

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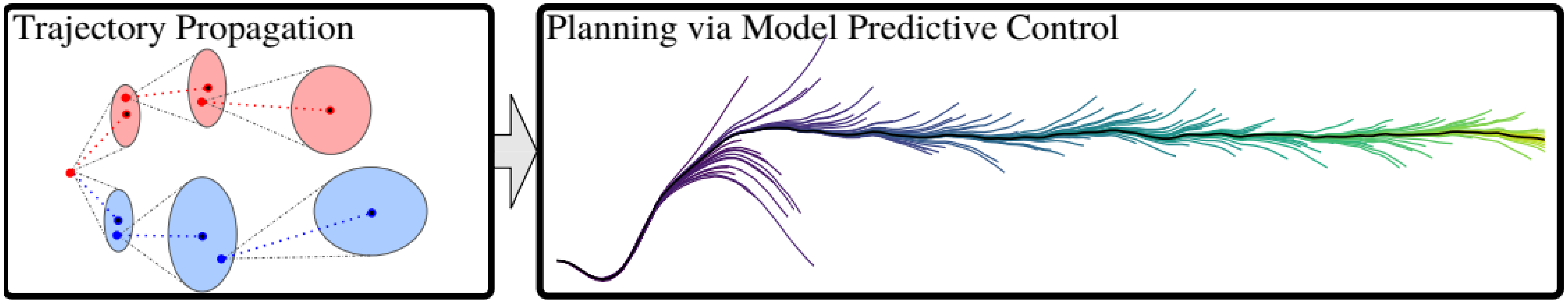
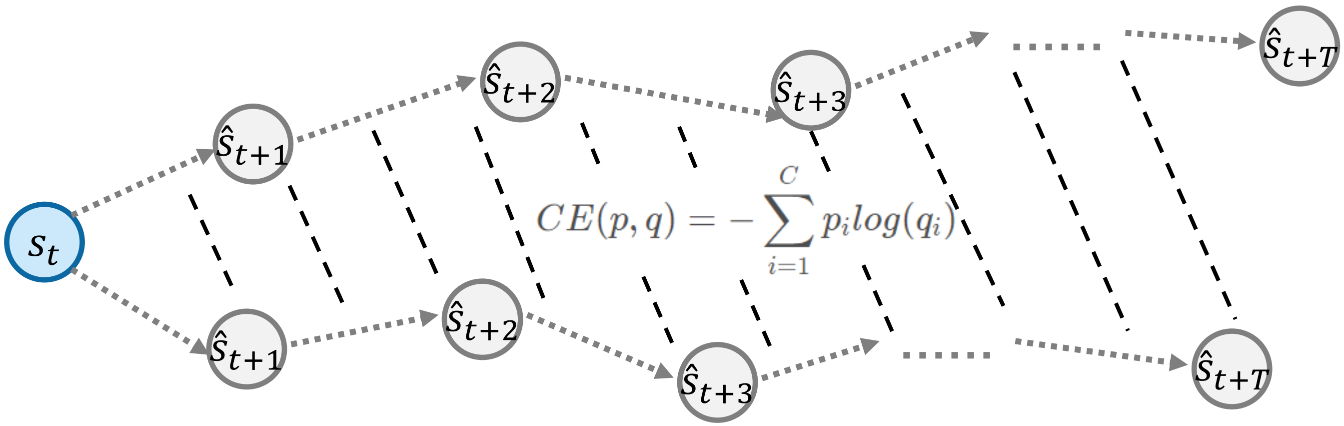


Cross Entropy Method (CEM) instead of Random Shooting (RS)



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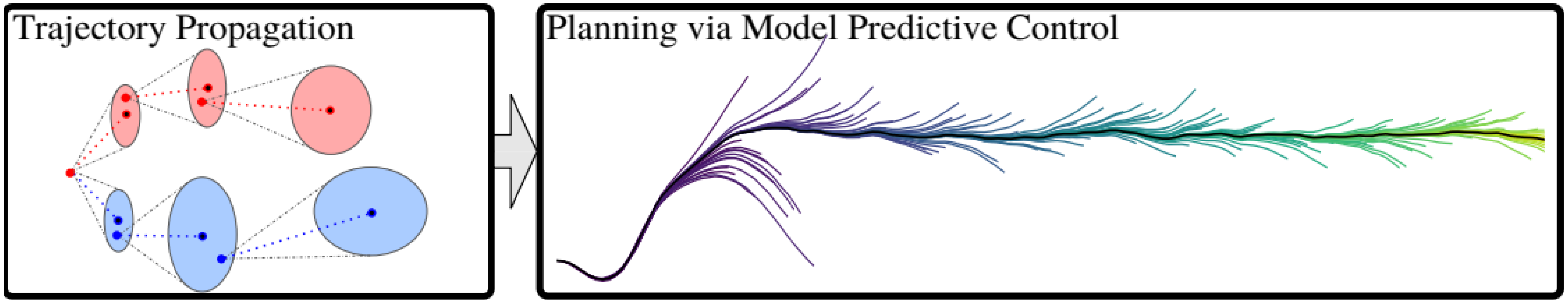

Algorithm 1 Our model-based MPC algorithm '*PETS*':

Initialize data $\mathbb{D}$ with a random controller for one trial.
for Trial $k = 1$ to K **do**
  Train a *PE* dynamics model $\widetilde{f}$ given $\mathbb{D}$.
  for Time $t = 0$ to TaskHorizon **do**
    for Actions sampled $\boldsymbol{a}_{t:t+T} \sim \text{CEM}(\cdot)$, 1 to NSamples **do**
      Propagate state particles $\boldsymbol{s}_\tau^p$ using *TS* and $\widetilde{f}|\{\mathbb{D}, \boldsymbol{a}_{t:t+T}\}$.
      Evaluate actions as $\sum_{\tau=t}^{t+T} \frac{1}{P} \sum_{p=1}^{P} r(\boldsymbol{s}_\tau^p, \boldsymbol{a}_\tau)$
      Update CEM$(\cdot)$ distribution.
    Execute first action $\boldsymbol{a}_t^*$ (only) from optimal actions $\boldsymbol{a}_{t:t+T}^*$.
    Record outcome: $\mathbb{D} \leftarrow \mathbb{D} \cup \{\boldsymbol{s}_t, \boldsymbol{a}_t^*, \boldsymbol{s}_{t+1}\}$.

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Decision-Time

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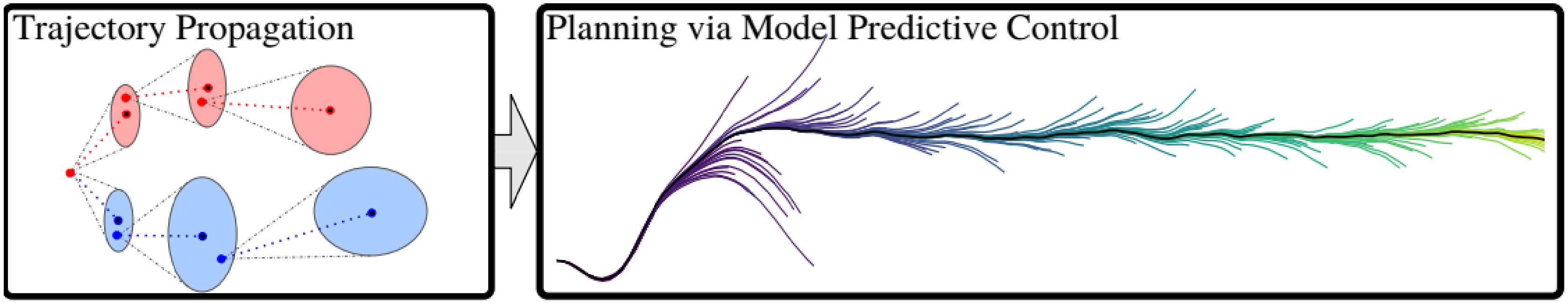
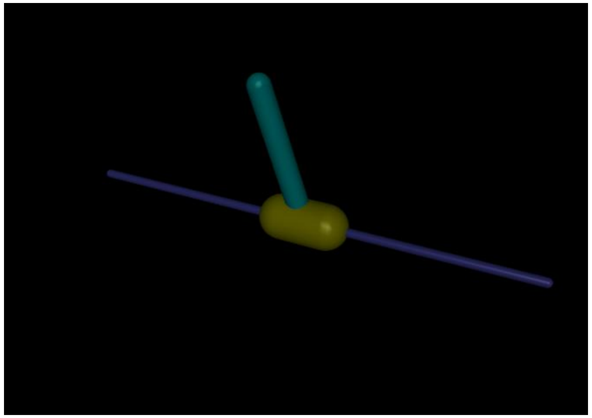
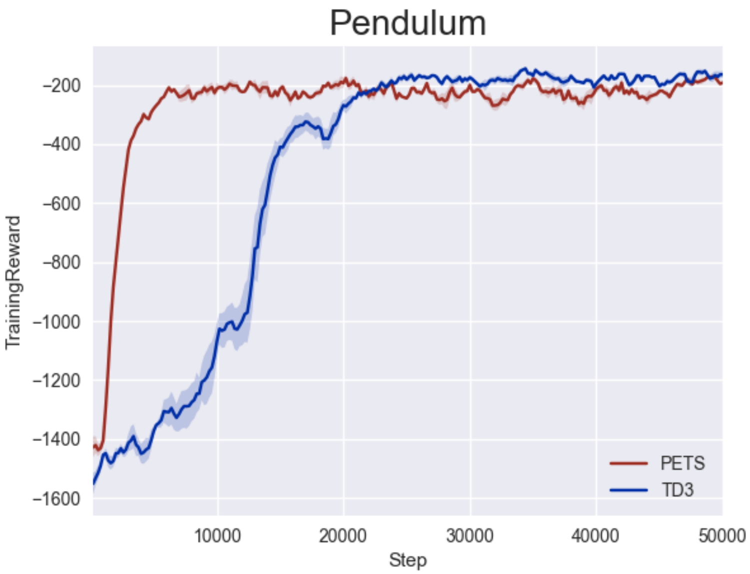


Experiments



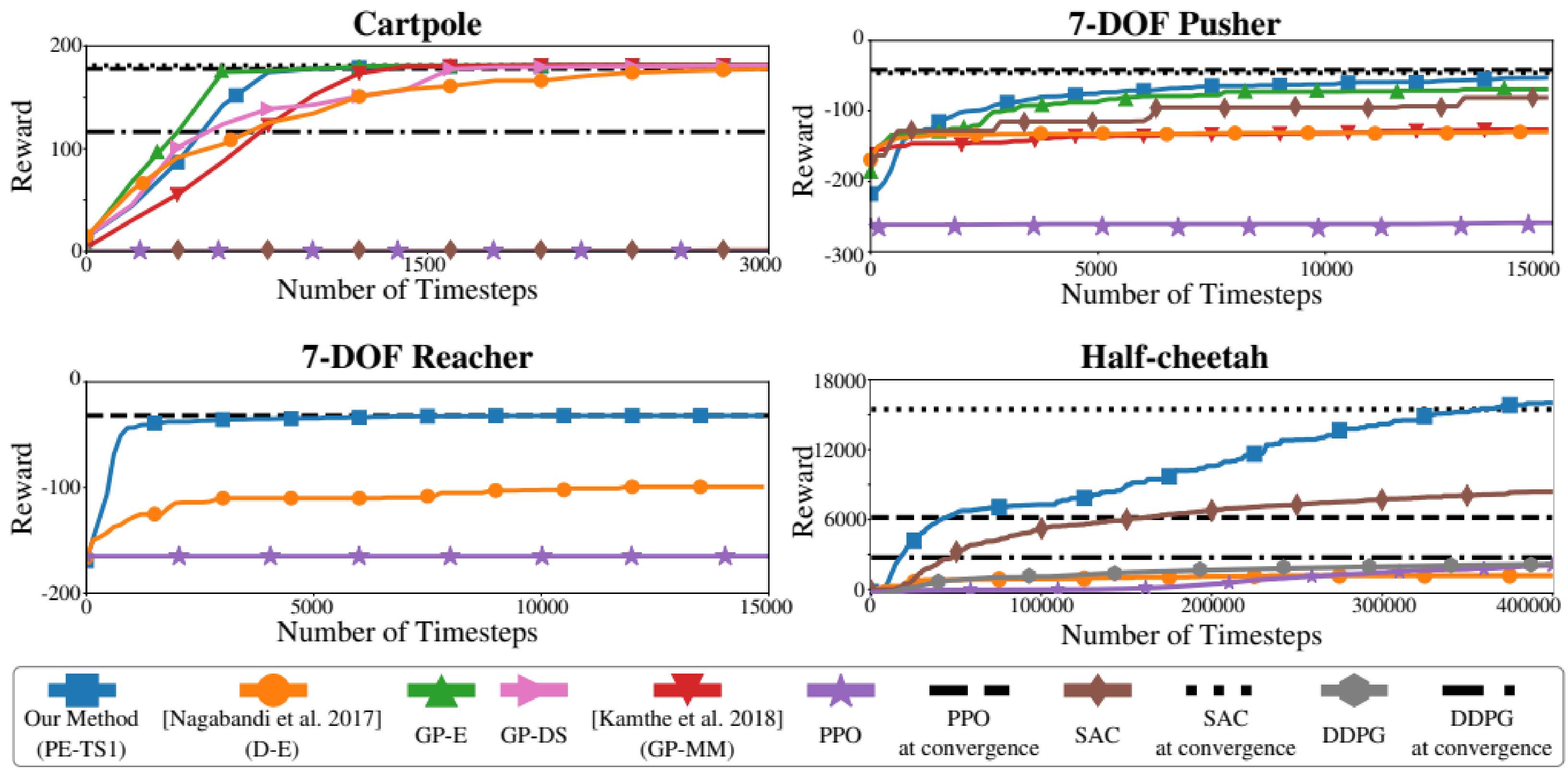


https://github.com/ShAw7ock/PETS-MuJoCo

Decision-Time

Probabilistic Ensemble with Trajectory Sampling (PETS)

Experiments



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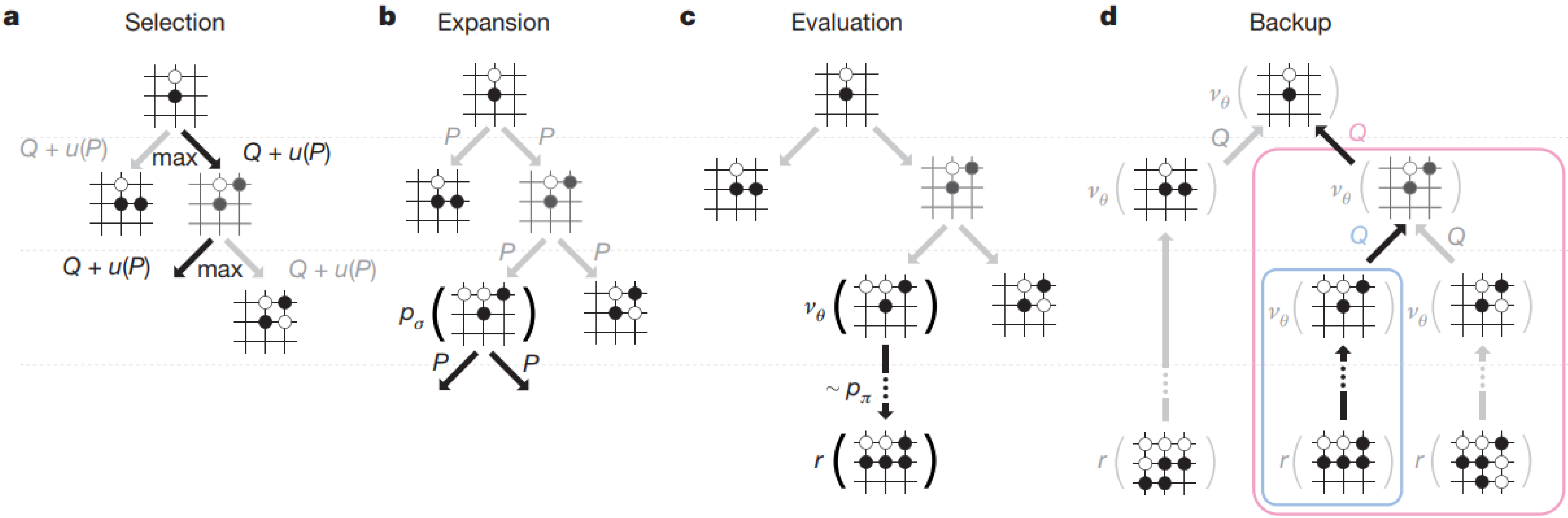
Decision-Time

MuZero: Mastering Atari, Go and Chess

Monte-Carlo Tree Search (MCTS) with Dynamics Model



Schrittwieser, Julian, et al. "Mastering atari, go, chess and shogi by planning with a learned model." Nature. 2020.

Decision-Time

MuZero: Mastering Atari, Go and Chess

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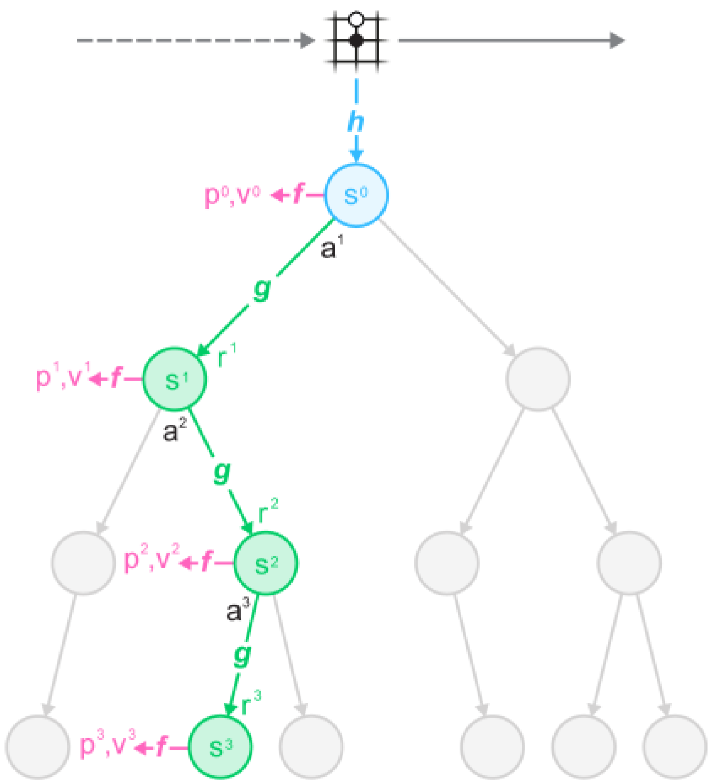

- Representation Function: $s^0 = h_\theta(o_1, \ldots, o_n)$ to encode past observations.
- Dynamic Function: $r^k, s^k = g_\theta(s^{k-1}, a^k)$
- Prediction Function: $\boldsymbol{p}^k, v^k = f_\theta(s^k)$

MCTS Backup:

$$Q_{k+1}(s,a) = \frac{Q_k(s,a)\cdot N_k(s,a) + R}{N_k(s,a)+1}$$

$$N_{k+1}(s,a) = N_k(s,a) + 1$$

Schrittwieser, Julian, et al. "Mastering atari, go, chess and shogi by planning with a learned model." Nature. 2020.

MuZero: Mastering Atari, Go and Chess

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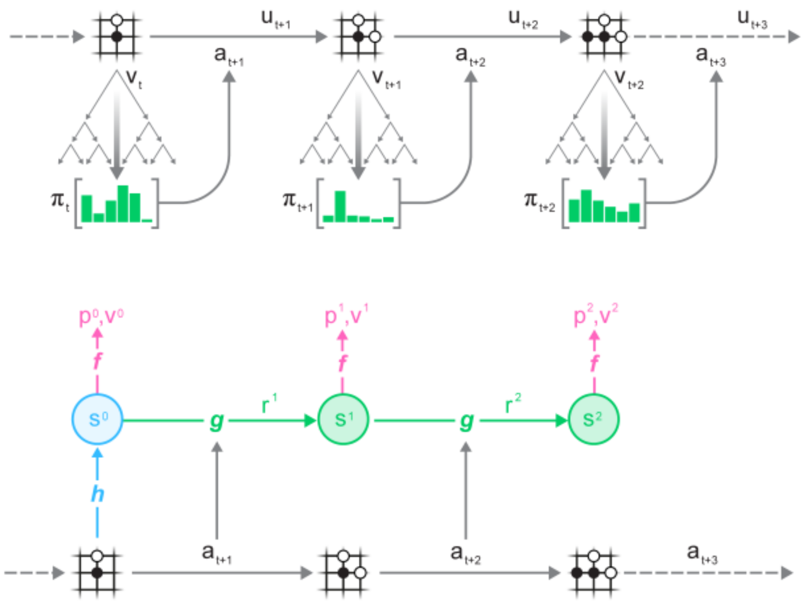

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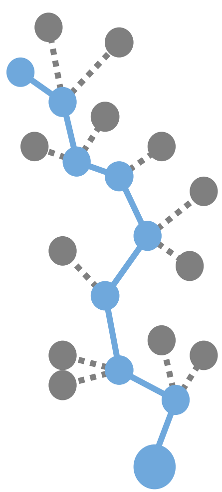
Background

Dyna-Q

- **Mix real and model-generated experiences and apply for additional policy updates.**



Tabular Dyna-Q

Initialize $Q(s,a)$ and $Model(s,a)$ for all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$
Loop forever:
(a) $S \leftarrow$ current (nonterminal) state
(b) $A \leftarrow \varepsilon$-greedy(S,Q)
(c) Take action A; observe resultant reward, R, and state, S'
(d) $Q(S,A) \leftarrow Q(S,A) + \alpha\big[R + \gamma \max_a Q(S',a) - Q(S,A)\big]$
(e) $Model(S,A) \leftarrow R, S'$ (assuming deterministic environment)
(f) Loop repeat n times:
$S \leftarrow$ random previously observed state
$A \leftarrow$ random action previously taken in S
$R, S' \leftarrow Model(S,A)$
$Q(S,A) \leftarrow Q(S,A) + \alpha\big[R + \gamma \max_a Q(S',a) - Q(S,A)\big]$

Update Q values with real transitions

Update Q values with model transitions

Sutton, Richard S. "Dyna, an integrated architecture for learning, planning, and reacting." ACM Sigart Bulletin, 1991.

Background

Model-Based Policy Optimization (MBPO)

- **Dyna-Q updates the policy with both real and model-generated transitions.**
- **How to guarantee the policy improvement if we only use the model-generated transitions ?**

Definition: Errors in the model can be exploited during policy optimization, resulting in large discrepancies between the predicted returns of the policy under the model and under the true dynamics.

$$\eta[\pi] \geq \hat{\eta}[\pi] - C.$$

$\eta[\pi]$: the returns of the policy in true MDP; $\hat{\eta}[\pi]$: the returns under learned model.

Janner, Michael, et al. "When to trust your model: Model-based policy optimization." NIPS, 2019.

Background

Model-Based Policy Optimization (MBPO)

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Definition: Errors in the model can be exploited during policy optimization, resulting in large discrepancies between the predicted returns of the policy under the model and under the true dynamics.

$$\eta[\pi] \geq \hat{\eta}[\pi] - C.$$

The gap between true and model returns can be expressed in:

- **Generalization Error**: $\epsilon_m = \mathbb{E}_{s,a\sim D_{env}}[D_{TV}(p(s'|s,a)||p_\theta(s'|s,a))]$

- **Policy Distribution**: $\epsilon_\pi = D_{TV}(\pi_D\ (s)||\pi(s))$

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Model-Based Policy Optimization (MBPO)

- Dyna-Q updates the policy with both real and model-generated transitions.
- How to guarantee the policy improvement if we only use the model-generated transitions ?

The gap between:

$$\begin{aligned}
|\eta_1 - \eta_2| &= |\sum_{s,a}(p_1(s,a) - p_2(s,a))r(s,a)| \\
&= |\sum_{s,a}(\sum_t \gamma^t p_1^t(s,a) - p_2^t(s,a))r(s,a)| \\
&= |\sum_t \sum_{s,a} \gamma^t (p_1^t(s,a) - p_2^t(s,a))r(s,a)| \\
&\leq \sum_t \sum_{s,a} \gamma^t |p_1^t(s,a) - p_2^t(s,a)| r(s,a) \\
&\leq r_{\max} \sum_t \sum_{s,a} \gamma^t |p_1^t(s,a) - p_2^t(s,a)|
\end{aligned}$$

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Background

Model-Based Policy Optimization (MBPO)

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- How to guarantee the policy improvement if we only use the model-generated transitions ?

The gap between:

$$|\eta_1 - \eta_2| \leq r_{\max} \sum_t \sum_{s,a} \gamma^t |p_1^t(s,a) - p_2^t(s,a)|$$

Lemma:

Lemma B.1 (TVD of Joint Distributions). *Suppose we have two distributions $p_1(x,y) = p_1(x)p_1(y|x)$ and $p_2(x,y) = p_2(x)p_2(y|x)$. We can bound the total variation distance of the joint as:*

$$D_{TV}(p_1(x,y)||p_2(x,y)) \leq D_{TV}(p_1(x)||p_2(x)) + E_{x\sim p_1}[D_{TV}(p_1(y|x)||p_2(y|x))]$$

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Background

Model-Based Policy Optimization (MBPO)

- Dyna-Q updates the policy with both real and model-generated transitions.
- How to guarantee the policy improvement if we only use the model-generated transitions ?

The gap between:

$$|\eta_1 - \eta_2| \leq r_{\max} \sum_t \sum_{s,a} \gamma^t |p_1^t(s,a) - p_2^t(s,a)|$$

$$\epsilon_m = \max_t E_{s\sim\pi_{D,t}} \left[D_{TV} \left(p(s', r|s,a) \| p_\theta (s', r|s,a) \right) \right]$$

Lemma:

$$\max_s D_{TV}(\pi \| \pi_D) \leq \epsilon_\pi$$

Lemma B.2 (Markov chain TVD bound, time-varying). *Suppose the expected KL-divergence between two transition distributions is bounded as* $\max_t E_{s\sim p_1^t(s)} D_{KL}(p_1(s'|s) \| p_2(s'|s)) \leq \delta$, *and the initial state distributions are the same –* $p_1^{t=0}(s) = p_2^{t=0}(s)$. *Then the distance in the state marginal is bounded as:*

$$D_{TV}(p_1^t(s) \| p_2^t(s)) \leq t\delta$$

$$\delta = \epsilon_m + \epsilon_\pi$$

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Background

Model-Based Policy Optimization (MBPO)

- Dyna-Q updates the policy with both real and model-generated transitions.
- How to guarantee the policy improvement if we only use the model-generated transitions ?

The gap between:

$$
\begin{aligned}
|\eta_1 - \eta_2| &\le r_{\max} \sum_t \sum_{s,a} \gamma^t |p_1^t(s,a) - p_2^t(s,a)| \\
&\le 2r_{\max} \sum_t \gamma^t t(\epsilon_m + \epsilon_\pi) + \epsilon_\pi \\
&\le 2r_{\max}\left(\frac{\gamma(\epsilon_\pi + \epsilon_m)}{(1-\gamma)^2} + \frac{\epsilon_\pi}{1-\gamma}\right)
\end{aligned}
$$

$$D_{TV}(p_1^t(s)||p_2^t(s)) \le t(\epsilon_m + \epsilon_\pi)$$

$$D_{TV}(\pi_1(a|s)||\pi_2(a|s)) \le \epsilon_\pi$$

The returns and model returns of the policy are bounded as:

$$\eta[\pi] \ge \hat{\eta}[\pi] - \underbrace{\left[\frac{2\gamma r_{\max}(\epsilon_m + 2\epsilon_\pi)}{(1-\gamma)^2} + \frac{4r_{\max}\epsilon_\pi}{(1-\gamma)}\right]}_{C(\epsilon_m,\epsilon_\pi)}$$

Janner, Michael, et al. "When to trust your model: Model-based policy optimization." NIPS, 2019.

Model-Based Policy Optimization (MBPO)

- **Dyna-Q updates the policy with both real and model-generated transitions.**
- **How to guarantee the policy improvement if we only use the model-generated transitions ?**
- **H-steps Q-target objective:**

Model-based Critic Loss Function:

$$Loss_{critic} = \frac{1}{2}\left(y - Q(s_t, a_t)\right)^2$$

Dyna-Q one-step Q-target:

$$y = \hat{r}(s_t, a_t) + \gamma Q(\hat{s}_{t+1}, \hat{a}_{t+1})$$

Multi-steps Q-target:

$$y = \sum_{k=t}^{H-1} \gamma^{k-t} \hat{r}_k + \gamma^H Q(\hat{s}_H, \hat{a}_H)$$

Janner, Michael, et al. "When to trust your model: Model-based policy optimization." NIPS, 2019.

Background

Model-Based Policy Optimization (MBPO)

- **Dyna-Q updates the policy with both real and model-generated transitions.**
- **How to guarantee the policy improvement if we only use the model-generated transitions ?**
- **H-steps Q-target objective**
- **MBPO Algorithm:**

Algorithm 2 Model-Based Policy Optimization with Deep Reinforcement Learning

Initialize policy π_ϕ, predictive model p_θ, environment dataset $\mathcal{D}_{\text{env}}$, model dataset $\mathcal{D}_{\text{model}}$
for N epochs **do**
  Train model p_θ on $\mathcal{D}_{\text{env}}$ via maximum likelihood
  for E steps **do**
    Take action in environment according to π_ϕ; add to $\mathcal{D}_{\text{env}}$
    for M model rollouts **do**
      Sample s_t uniformly from $\mathcal{D}_{\text{env}}$
      Perform k-step model rollout starting from s_t using policy π_ϕ; add to $\mathcal{D}_{\text{model}}$
    for G gradient updates **do**
      Update policy parameters on model data: $\phi \leftarrow \phi - \lambda_\pi \hat{\nabla}_\phi J_\pi(\phi, \mathcal{D}_{\text{model}})$

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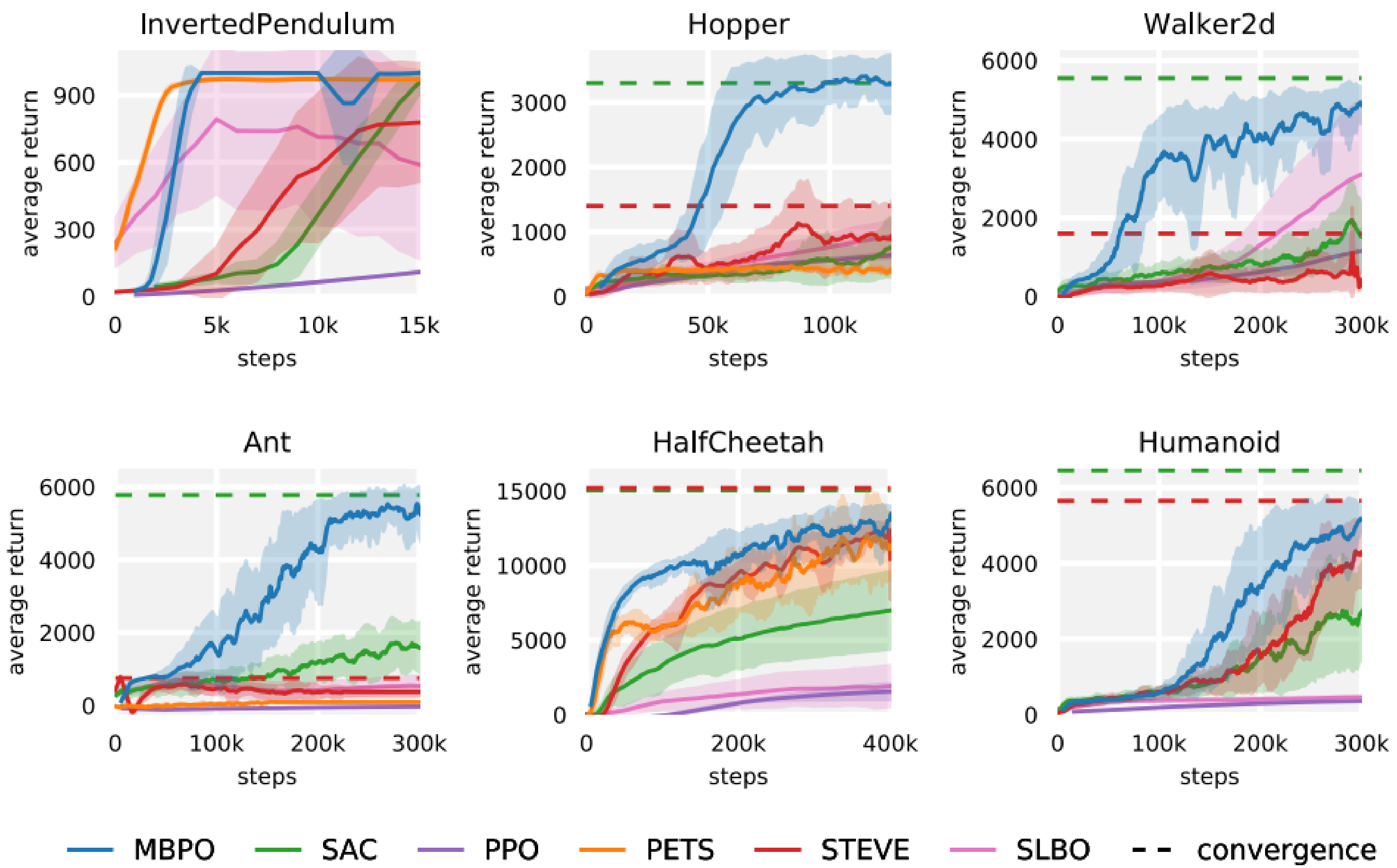
Background

Model-Based Policy Optimization (MBPO)

Experiments



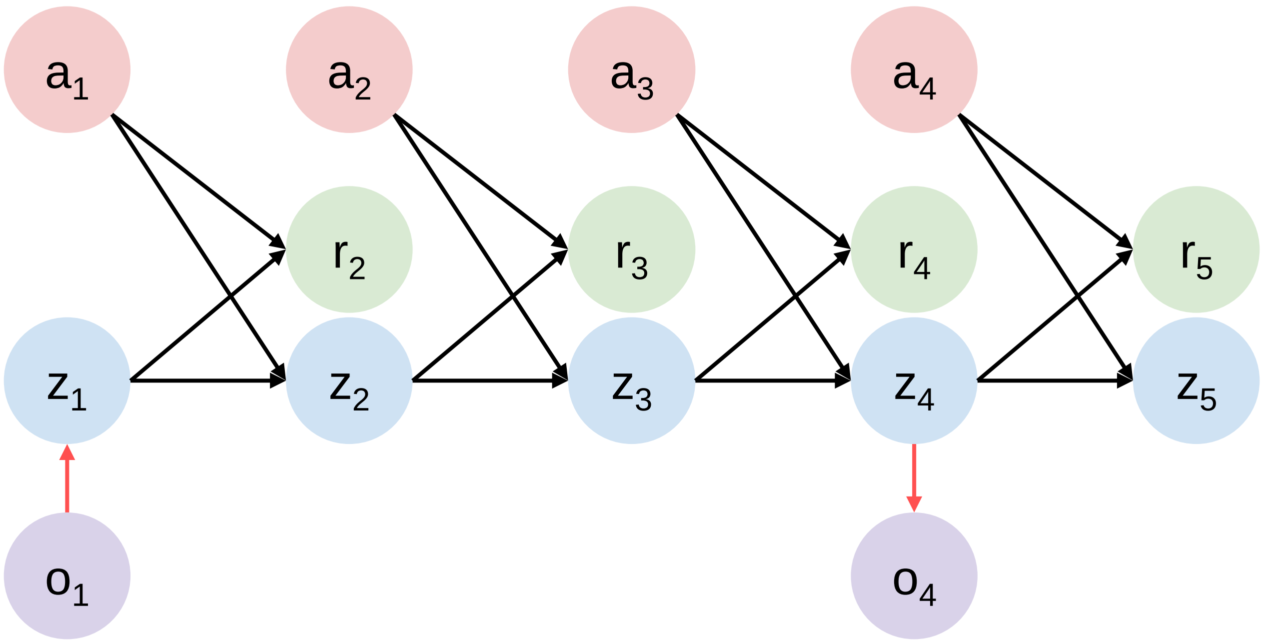
Janner, Michael, et al. "When to trust your model: Model-based policy optimization." NIPS, 2019.

Model-based RL with Images

Dreamer: Latent Imagination

- Latent state-transition models

Reconstruct high-level observation to low-level **latent state**



Hafner, Danijar, et al. "Dream to control: Learning behaviors by latent imagination." arXiv preprint arXiv:1912.01603 (2019).

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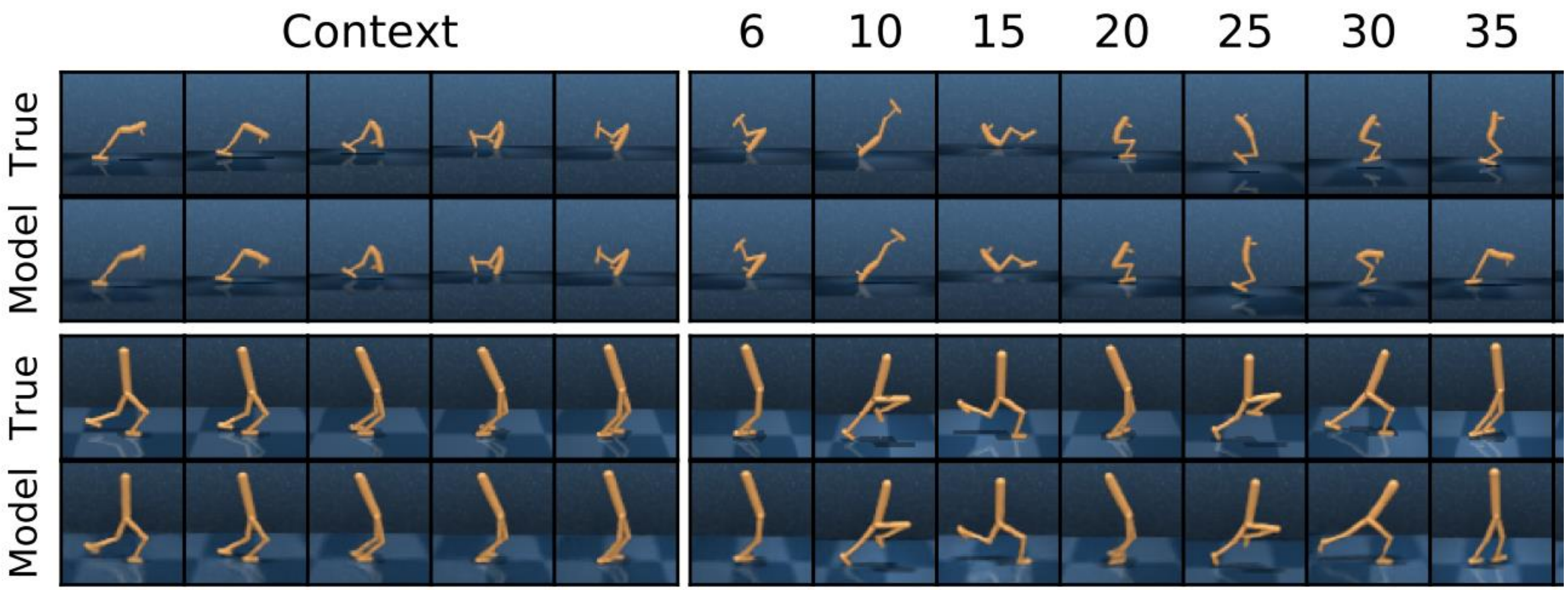
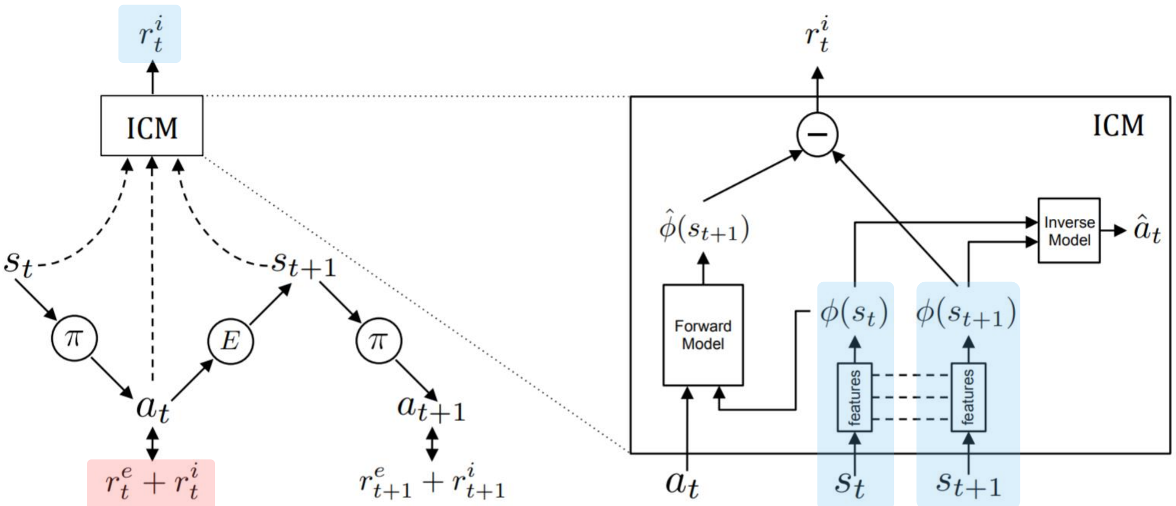


Hafner, Danijar, et al. "Dream to control: Learning behaviors by latent imagination." arXiv preprint arXiv:1912.01603 (2019).

Inverse Model

Intrinsic Curiosity Module (ICM)

- Besides extrinsic reward, agent set **intrinsic reward** to express its familiarity with the true environment. (Curiosity Driven)
- Model Prediction: $f(s_t, a_t) \rightarrow s_{t+1}$
- Intrinsic Reward: $r_t^{in} \sim \| f(s_t, a_t) - s_{t+1} \|_2^2$



- **Forward Dynamics Model:**

  $f_{\psi F}(\phi(s_t), a_t) \rightarrow \hat{\phi}(s_{t+1})$

- **Inverse Model:**

  $g_{\psi I}(\phi(s_t), \phi(s_{t+1})) \rightarrow \hat{a}_t.$

- **Intrinsic Reward:**

  $r_t^i = \left\| \hat{\phi}(s_{t+1}) - \phi(s_{t+1}) \right\|_2^2$

Pathak, Deepak, et al. "Curiosity-driven exploration by self-supervised prediction." International conference on machine learning. ICML, 2017.

Deep Reinforcement Learning

谢 谢！

中山大学计算机学院