On the Design of Variational RL Algorithms

Joseph Marino[1], Alexandre Piché[2], Yisong Yue[1]
[1]*California Institute of Technology,* [2]*Mila, Université de Montréal*

Contributions:

- Discuss variational EM framework containing several recent algorithms.
- Propose iterative amortized inference for soft actor-critic (SAC).

variational RL

Set-Up

Markov Decision Process

state	$\mathbf{s}_t \in \mathcal{S}$	dynamics	$p_{\text{env}}(\mathbf{s}_{t+1}\|\mathbf{s}_t, \mathbf{a}_t)$
action	$\mathbf{a}_t \in \mathcal{A}$	agent	$p_\theta(\mathbf{a}_t\|\mathbf{s}_t)$
reward	$r_t = r(\mathbf{s}_t, \mathbf{a}_t)$	return	$\mathcal{R}(\tau) = \sum_t \gamma^t r_t$
trajectory	$\tau = (\mathbf{s}_1, \mathbf{a}_1, \dots)$		

trajectory dist. $p(\tau) = \rho(\mathbf{s}_1) \prod_{t=1}^{T} p_{\text{env}}(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t) p_\theta(\mathbf{a}_t|\mathbf{s}_t)$

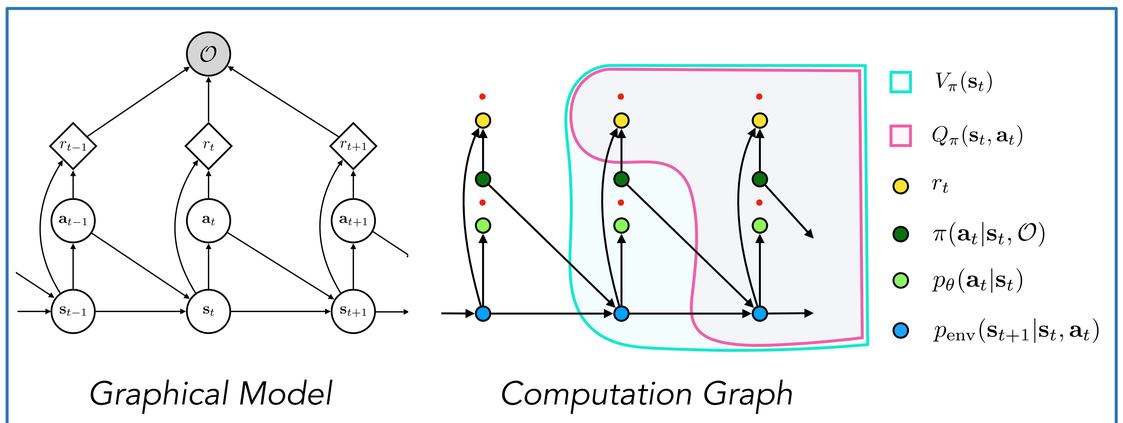
Variational RL

optimality $p(\mathcal{O} = 1|\tau) \propto \exp\big(\mathcal{R}(\tau)/\alpha\big)$

approx. posterior $\pi(\tau|\mathcal{O}) = \rho(\mathbf{s}_1) \prod_{t=1}^{T} p_{\text{env}}(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t) \pi(\mathbf{a}_t|\mathbf{s}_t, \mathcal{O})$

variational lower bound $\mathcal{J}(\pi, \theta) = \mathbb{E}_{\substack{\mathbf{s}_t, r_t \sim p_{\text{env}} \\ \mathbf{a}_t \sim \pi}} \left[\sum_{t=1}^{T} r_t - \alpha \log \frac{\pi(\mathbf{a}_t|\mathbf{s}_t, \mathcal{O})}{p_\theta(\mathbf{a}_t|\mathbf{s}_t)} \right]$

optimal policy (Boltzmann), *non-parametric* $\pi^{\mathcal{B}}(\mathbf{a}_t|\mathbf{s}_t, \mathcal{O}) = \frac{p_\theta(\mathbf{a}_t|\mathbf{s}_t) \exp(Q_\pi(\mathbf{s}_t, \mathbf{a}_t)/\alpha)}{\int p_\theta(\mathbf{a}_t|\mathbf{s}_t) \exp(Q_\pi(\mathbf{s}_t, \mathbf{a}_t)/\alpha) d\mathbf{a}_t}$



Graphical Model *Computation Graph*

Variational EM for RL

E-Step: infer/approximate the posterior, $\pi(\tau|\mathcal{O})$

- *non-parametric:* estimate $\pi^{\mathcal{B}}(\tau|\mathcal{O})$
- *parametric:* maximize $\mathcal{J}$ w.r.t. $\pi(\tau|\mathcal{O})$

M-Step: learn the the prior, $p(\tau)$, by maximizing $\mathcal{J}$ w.r.t. θ

				Approximate Posterior: Parametric	Approximate Posterior: Non-Parametric
Prior	Uniform	**Conditional Likelihood**	Model-Free	*SAC* [Haarnoja et al., 2018], [Schulman et al., 2017]	*SQL* [Haarnoja et al., 2017]
			Model-Based	–	*SMCP* [Piché et al., 2017]
	Learned		Model-Free	*MPO* [Abdolmaleki et al., 2018a], [Galashov et al., 2019], [Tirumala et al., 2019]	*MPO* [Abdolmaleki et al., 2018a], *RERPI* [Abdolmaleki et al., 2018b], *V-MPO* [Song et al., 2019], *Distral* [Teh et al., 2017]
			Model-Based	–	–

3 Main Design Choices

- Prior (Uniform / Learned)
- Approximate Posterior (Parametric / Non-Parametric)
- Conditional Likelihood Estimate (Model-Free / Model-Based)

SAC + iterative inference

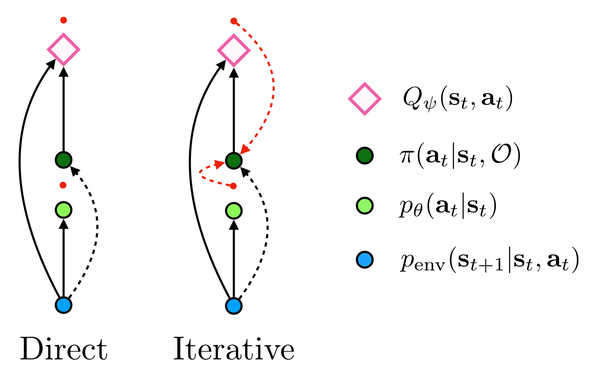
Soft actor-critic (SAC) [Haarnoja et al., 2018] is a state-of-the-art off-policy deep RL algorithm. We replace the ***direct*** amortized inference procedure in SAC with an ***iterative*** amortized inference procedure [Marino et al., 2018].

Parametric Policy:

$$\mathbf{u}_t \sim \mathcal{N}(\mathbf{u}_t; \boldsymbol{\mu}_\mathbf{u}, \text{diag}(\boldsymbol{\sigma}_\mathbf{u}^2))$$
$$\mathbf{a}_t = \tanh(\mathbf{u}_t)$$

Direct Amortization (SAC):

$$\boldsymbol{\mu}_\mathbf{u} = f_{\phi,\boldsymbol{\mu}}(\mathbf{s}_t)$$
$$\boldsymbol{\sigma}_\mathbf{u} = f_{\phi,\boldsymbol{\sigma}}(\mathbf{s}_t)$$



Iterative Amortization (with gated update):

$$\boldsymbol{\mu}_\mathbf{u} \leftarrow \boldsymbol{\omega}_{\phi,\boldsymbol{\mu}} \odot \boldsymbol{\mu}_\mathbf{u} + (1 - \boldsymbol{\omega}_{\phi,\boldsymbol{\mu}}) \odot f_{\phi,\boldsymbol{\mu}}(\mathbf{s}_t, \nabla_{\boldsymbol{\mu}_\mathbf{u}} \tilde{\mathcal{J}})$$

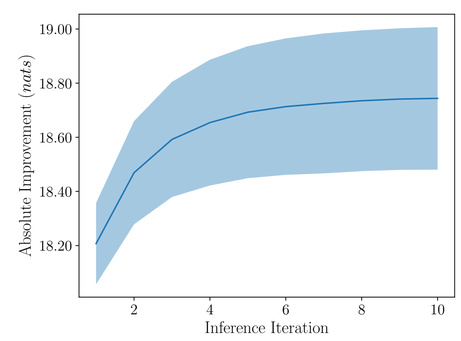
$$\boldsymbol{\sigma}_\mathbf{u} \leftarrow \boldsymbol{\omega}_{\phi,\boldsymbol{\sigma}} \odot \boldsymbol{\sigma}_\mathbf{u} + (1 - \boldsymbol{\omega}_{\phi,\boldsymbol{\sigma}}) \odot f_{\phi,\boldsymbol{\sigma}}(\mathbf{s}_t, \nabla_{\boldsymbol{\sigma}_\mathbf{u}} \tilde{\mathcal{J}})$$

results

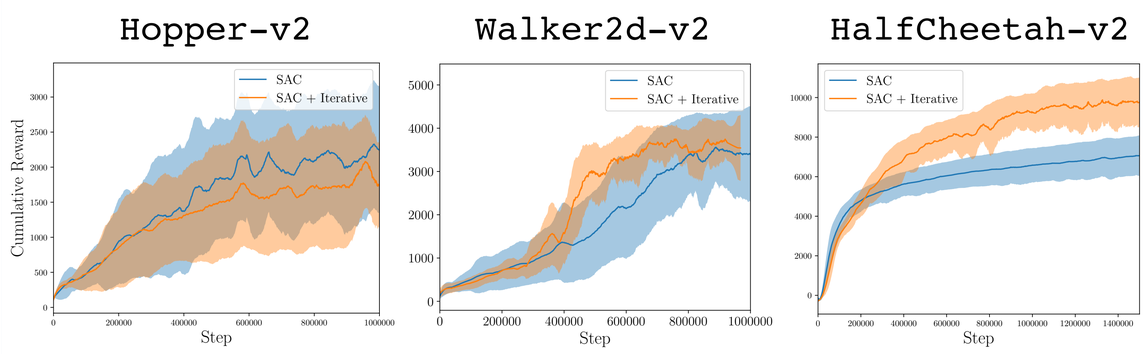
Inference Improvement

→ *with 10 inference iterations / step*

- performance increases across iterations
- diminishing improvement at each iteration



Performance Comparison on Continuous Control Tasks



discussion

Limitations

- iterative inference models require more computation per step
- smaller iterative inference models can result in *worse* performance than direct inference models

Benefits

- potentially more flexible inference (policy estimation) procedure
- can be readily combined with other conditional likelihood (action-value) estimators, such as learned models

Variational EM provides a common framework for many recent algorithms.

Variational EM also provides clear directions for improving current methods: more expressive priors, approximate posteriors, and conditional likelihoods, as well as better inference and learning procedures.

Iterative amortized inference can result in performance improvements over direct amortized methods employed in current parametric (policy-based) algorithms.