Deep Reinforcement Learning and Control

Sim2Real

Katerina Fragkiadaki
The requirement of large number of samples for RL, only possible in simulation, renders RL a model-based framework, we can’t really rely (solely) on interaction in the real world (as of today)

• In the real world, we usually finetune model and policies learnt in simulation
Physics Simulators

Mujoko, bullet, gazebo, etc.
Pros of Simulation

- We can afford many more samples!
- Safety
- Avoids wear and tear of the robot
- Good at rigid multibody dynamics
Cons of Simulation

- **Under-modeling**: many physical events are not modeled.

- **Wrong parameters**. Even if our physical equations were correct, we would need to estimate the right parameters, e.g., inertia, frictions (system identification).

- Systematic discrepancy w.r.t. the real world regarding:
  - observations
  - dynamics

As a result, policies that learnt in simulation do not transfer to the real world.

- Hard to simulate deformable objects (finite element methods are very computational intensive)
What has shown to work

- Domain randomization (dynamics, images)
  - With enough variability in the simulator, the real world may appear to the model as just another variation”
- Learning not from pixels but rather from label maps-> semantic maps between simulation and real world are closer than textures
- Learning higher level policies, not low-level controllers, as the low level dynamics are very different between Sim and REAL
Domain randomization for detecting and grasping objects

Tobin et al., 2017
arXiv:1703.06907
Let’s try a more fine grained task

Cuboid Pose Estimation
Data generation
Data generation
Regressing to vertices
Data generation

Data - Contrast and Brightness
Surprising Result
Baxter’s camera
Car detection

VKITTI

domain rand

data generation

Training Deep Networks with Synthetic Data: Bridging the Reality Gap by Domain Randomization, NVIDIA
Dynamics randomization
EPOpt: Learning Robust Neural Network Policies Using Model Ensembles

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Ideas:

- Consider a \textit{distribution over simulation models} instead of a single one for learning policies robust to modeling errors that work well under many ``worlds''. Hard model mining

- Progressively \textit{bring the simulation model distribution} closer to the real world.
Learn a policy that performs best in expectation over MDPs in the source domain distribution:

$$\mathbb{E}_{p \sim \mathcal{P}} \left[ \mathbb{E}_\pi \left[ \sum_{t=0}^{T-1} \gamma^t r_t(s_t, a_t) \mid p \right] \right]$$

$p$: simulator parameters
Policy Search under model distribution

Learn a policy that performs best in expectation over MDPs in the source domain distribution:

$$\mathbb{E}_{p \sim \mathcal{P}} \left[ \mathbb{E}_{\mathcal{F}} \left[ \sum_{t=0}^{T-1} \gamma^t r_t(s_t, a_t) \bigg| p \right] \right]$$

$p$: simulator parameters

Hard world model mining

Learn a policy that performs best in expectation over the worst \( \epsilon \)-percentile of MDPs in the source domain distribution

$$\max_{\theta, y} \int_{\mathcal{F}(\theta)} \eta_{\mathcal{M}}(\theta, p) \mathcal{P}(p) dp \quad s.t. \quad \mathbb{P}(\eta_{\mathcal{M}}(\theta, P) \leq y) = \epsilon$$
Algorithm 1: EPQopt-$\epsilon$ for Robust Policy Search

1. **Input:** $\psi, \theta_0, \text{niter}, N, \epsilon$
2. **for** iteration $i = 0, 1, 2, \ldots \text{niter}$ **do**
3. 3. **for** $k = 1, 2, \ldots N$ **do**
4. 4. sample model parameters $p_k \sim P_\psi$
5. 5. sample a trajectory $\tau_k = \{s_t, a_t, r_t, s_{t+1}\}_{t=0}^{T-1}$ from $M(p_k)$ using policy $\pi(\theta_i)$
6. **end**
7. compute $Q_\epsilon = \epsilon$ percentile of $\{R(\tau_k)\}_{k=1}^N$
8. select sub-set $T = \{\tau_k : R(\tau_k) \leq Q_\epsilon\}$
9. Update policy: $\theta_{i+1} = \text{BatchPolOpt}(\theta_i, T)$
10. **end**
Hard model mining results

Hard world mining results in policies with high reward over wider range of parameters
Adapting the source domain distribution

Sample a set of simulation parameters from a sampling distribution $S$. Posterior of parameters $p_i$:

$$
P(p_i | \tau_k) \propto \prod_t P(S_{t+1} = s_{t+1}^{(k)} | s_t^{(k)}, a_t^{(k)}, p_i) \times \frac{P_P(p_i)}{P_S(p_i)}$$

Fit a Gaussian model over simulator parameters based on posterior weights of the samples.

Fit of simulation parameter samples: how probable is an observed target state-action trajectory, the more probable the more we prefer such simulation model.
Source Distribution Adaptation
Performance on hopper policies trained on Gaussian distribution of mean mass 6 and standard deviation 1.5 trained on single source domains.
Idea: the driving policy is not directly exposed to raw perceptual input or low-level vehicle dynamics.
Main idea

**pixels to steering wheel** learning is not SIM2REAL transferable

- textures/car dynamics mismatch

**label maps to waypoint** learning is SIM2REAL transferable

- label maps are similar between SIM and REAL and a low-level controller will take the car from waypoint to waypoint
Figure 4: Quantitative evaluation of goal-directed navigation in simulation. We report the success rate over 25 navigation trials in four town-weather combinations. The models have been trained in Town 1 and Weather 1. The evaluated models are: \textit{img2ctrl} – predicting low-level control from color images; \textit{img2wp} – predicting waypoints from color images; \textit{seg2ctrl} – predicting low-level control from the segmentation produced by the perception module; \textit{ours} – predicting waypoints from the segmentation produced by the perception module. Suffix \textit{‘+’} denotes models trained with data augmentation, and \textit{‘+dr’} denotes the model trained with domain randomization.
Deep Reinforcement Learning and Control

Maximum Entropy Reinforcement Learning

CMU 10703

Katerina Fragkiadaki

Parts of slides borrowed from Russ Salakhutdinov, Rich Sutton, David Silver
RL objective

\[ \pi^* = \arg \max_{\pi} \mathbb{E}_\pi \left[ \sum_t R(s_t, a_t) \right] \]
MaxEntRL objective

Promoting stochastic policies

\[ \pi^* = \arg \max_{\pi} \mathbb{E}_{\pi} \left[ \sum_{t=1}^{T} R(s_t, a_t) + \alpha H(\pi( \cdot | s_t)) \right] \]

Why?

- Better exploration
- Learning alternative ways of accomplishing the task
- Better generalization, e.g., in the presence of obstacles a stochastic policy may still succeed.
Policies that generate similar rewards, should be equally probable.

We do not want to commit to one policy over the other.

Why?

- Better exploration
- Learning alternative ways of accomplishing the task
- Better generalization, e.g., in the presence of obstacles a stochastic policy may still succeed.
Algorithm S3  Asynchronous advantage actor-critic - pseudocode for each actor-learner thread.

// Assume global shared parameter vectors $\theta$ and $\theta_v$ and global shared counter $T = 0$
// Assume thread-specific parameter vectors $\theta'$ and $\theta'_v$
Initialize thread step counter $t \leftarrow 1$

repeat
  Reset gradients: $d\theta \leftarrow 0$ and $d\theta_v \leftarrow 0$.
  Synchronize thread-specific parameters $\theta' = \theta$ and $\theta'_v = \theta_v$
  $t_{\text{start}} = t$
  Get state $s_t$
  repeat
    Perform $a_t$ according to policy $\pi(a_t \mid s; \theta')$
    Receive reward $r_t$ and new state $s_t | 1$
    $t \leftarrow t + 1$
    $T' \leftarrow T + 1$
  until terminal $s_t$ or $t - t_{\text{start}} = t_{\text{max}}$

$R = \begin{cases} 
0 & \text{for terminal } s_t \\
V(s_t, \theta'_v) & \text{for non-terminal } s_t
\end{cases}$
// Bootstrap from last state

for $i \in \{t - 1, \ldots, t_{\text{start}}\}$ do
  $R \leftarrow r_i + \gamma R$
  Accumulate gradients wrt $\theta'$: $d\theta \leftarrow d\theta + \nabla_{\theta'} \log \pi(a_i \mid s; \theta')(R - V(s_i; \theta'_v) + \beta \nabla_{\theta'} H(\pi(s_i; \theta')))$
  Accumulate gradients wrt $\theta'_v$: $d\theta_v \leftarrow d\theta_v + \partial (R - V(s_i; \theta'_v)) \partial \theta'_v$
end for

Perform asynchronous update of $\theta$ using $d\theta$ and of $\theta_v$ using $d\theta_v$.

until $T > T_{\text{max}}$

"We also found that adding the entropy of the policy $\pi$ to the objective function improved exploration by discouraging premature convergence to suboptimal deterministic policies. This technique was originally proposed by (Williams & Peng, 1991)"
Algorithm S3: Asynchronous advantage actor-critic - pseudocode for each actor-learner thread.

// Assume global shared parameter vectors $\theta$ and $\theta_v$ and global shared counter $T = 0$
// Assume thread-specific parameter vectors $\theta'$ and $\theta'_v$
Initialize thread step counter $t \leftarrow 1$

repeat
  Reset gradients: $d\theta \leftarrow 0$ and $d\theta_v \leftarrow 0$.
  Synchronize thread-specific parameters $\theta' = \theta$ and $\theta'_v = \theta_v$
  $t_{start} = t$
  Get state $s_t$
  repeat
    Perform $a_t$ according to policy $\pi(a_t | s_t; \theta')$
    Receive reward $r_t$ and new state $s_{t+1}$
    $t \leftarrow t + 1$
    $T \leftarrow T + 1$
  until terminal $s_t$ or $t - t_{start} = t_{max}$

$R = \begin{cases} 
0 & \text{for terminal } s_t \\
V(s_t, \theta'_v) & \text{for non-terminal } s_t \end{cases}$ // Bootstrap from last state

for $i \in \{t - 1, \ldots, t_{start}\}$ do
  $R \leftarrow r_i + \gamma R$
  Accumulate gradients wrt $\theta'$: $d\theta \leftarrow d\theta + \nabla_{\theta} \log \pi(a_i | s_i; \theta') \left( R - V(s_i; \theta'_v) + \beta \nabla_{\theta} H(\pi(s_i; \theta')) \right)$
  Accumulate gradients wrt $\theta'_v$: $d\theta_v \leftarrow d\theta_v + \partial (R - V(s_i; \theta'_v))$ / $\partial \theta'_v$
end for

Perform asynchronous update of $\theta$ using $d\theta$ and of $\theta_v$ using $d\theta_v$.

until $T > T_{max}$

This is just a regularization: such gradient just maximizes entropy of the current time step, not of future timesteps.
MaxEntRL objective

Promoting stochastic policies

\[ \pi^* = \arg \max_{\pi} \mathbb{E}_\pi \left[ \sum_{t=1}^{T} R(s_t, a_t) + \alpha H(\pi(\cdot | s_t)) \right] \]

How can we maximize such an objective?
\[ q_\pi(s, a) = r(s, a) + \gamma \sum_{s' \in S} T(s' | s, a) \sum_{a' \in A} \pi(a' | s') q_\pi(s', a') \]
Back-up Diagrams for MaxEnt Objective

\[ \pi^* = \arg \max_{\pi} \mathbb{E}_\pi \left[ \sum_{t=1}^{T} R(s_t, a_t) + \alpha H(\pi(\cdot | s_t)) \right] \]

\[ H(\pi(\cdot | s')) = -\mathbb{E}_a \log \pi(a' | s') \]
Back-up Diagrams for MaxEnt Objective

\[
\pi^* = \arg \max_{\pi} \mathbb{E}_\pi \left[ \sum_{t=1}^{T} R(s_t, a_t) + \alpha H(\pi(\cdot | s_t)) \right]
\]

\[
q_\pi(s, a) \leftarrow s, a
\]

\[
q_\pi(s', a') \leftarrow a'
\]

\[
-q_\pi(s', a') = r(s, a) + \gamma \sum_{s' \in \mathcal{S}} T(s' | s, a) \sum_{a' \in \mathcal{A}} \pi(a' | s') \left( q_\pi(s', a') - \log(\pi(a' | s')) \right)
\]
(Soft) policy evaluation

**Soft Bellman backup equation:**

\[ q_\pi(s, a) = r(s, a) + \gamma \sum_{s'} T(s' | s, a') \sum_{a'} \pi(a' | s') \left( q_\pi(s', a') - \log(\pi(a' | s')) \right) \]

**Bellman backup equation:**

\[ q_\pi(s, a) = r(s, a) + \gamma \sum_{s' \in S} T(s' | s, a) \sum_{a' \in A} \pi(a' | s') q_\pi(s', a') \]

**Soft Bellman backup update operator-unknown dynamics:**

\[ Q(s_t, a_t) \leftarrow r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1}, a_{t+1}} \left[ Q(s_{t+1}, a_{t+1}) - \log \pi(a_{t+1} | s_{t+1}) \right] \]

**Bellman backup update operator-unknown dynamics:**

\[ Q(s_t, a_t) \leftarrow r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1}, a_{t+1}} Q(s_{t+1}, a_{t+1}) \]
Soft Bellman backup update operator is a contraction

\[ Q(s_t, a_t) \leftarrow r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1},a_{t+1}} \left[ Q(s_{t+1}, a_{t+1}) - \log \pi(a_{t+1} | s_{t+1}) \right] \]

\[ Q(s_t, a_t) \leftarrow r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1} \sim \rho, a_{t+1} \sim \pi} Q(s_{t+1}, a_{t+1}) + \gamma \mathbb{E}_{s_{t+1} \sim \rho} \mathbb{E}_{a_{t+1} \sim \pi} [ -\log \pi(a_{t+1} | s_{t+1}) ] \]

\[ \leftarrow r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1} \sim \rho, a_{t+1} \sim \pi} Q(s_{t+1}, a_{t+1}) + \gamma \mathbb{E}_{s_{t+1} \sim \rho} H(\pi( \cdot | s_{t+1})) \]

Rewrite the reward as:

\[ r_{soft}(s_t, a_t) = r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1} \sim \rho} H(\pi( \cdot | s_{t+1})) \]

Then we get the old Bellman operator, which we know is a contraction
Soft Bellman backup update operator

\[ Q(s_t, a_t) \leftarrow r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1}, a_{t+1}} [Q(s_{t+1}, a_{t+1})] - \log \pi(a_{t+1} \mid s_{t+1}) \]

\[ Q(s_t, a_t) \leftarrow r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1} \sim \rho} [\mathbb{E}_{a_{t+1} \sim \pi} [Q(s_{t+1}, a_{t+1})] - \log \pi(a_{t+1} \mid s_{t+1})] \]

\[ \leftarrow r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1} \sim \rho, a_{t+1} \sim \pi} Q(s_{t+1}, a_{t+1}) + \gamma \mathbb{E}_{s_{t+1} \sim \rho} \mathbb{E}_{a_{t+1} \sim \pi} [-\log \pi(a_{t+1} \mid s_{t+1})] \]

\[ \leftarrow r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1} \sim \rho, a_{t+1} \sim \pi} Q(s_{t+1}, a_{t+1}) + \gamma \mathbb{E}_{s_{t+1} \sim \rho} H(\pi( \cdot \mid s_{t+1})) \]

We know that:

\[ Q(s_t, a_t) \leftarrow r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1} \sim \rho} [V(s_{t+1})] \]

Which means that:

\[ V(s_t) = \mathbb{E}_{\pi_t} [Q(s_t, a_t) - \log \pi(a_t \mid s_t)] \]
Soft Policy Iteration

Soft policy iteration iterates between two steps:

1. **Soft policy evaluation**: Fix policy, apply Bellman backup operator till convergence

   \[ q_\pi(s, a) = r(s, a) + \mathbb{E}_{s', a'} \left( q_\pi(s', a') - \log(\pi(a' \mid s')) \right) \]

   This converges to \( q_\pi \)

2. **Soft policy improvement**: Update the policy:

   \[
   \pi' = \arg \min_{\pi_k \in \Pi} D_{KL} \left( \pi_k(\cdot \mid s_t) \mid \frac{\exp(Q_\pi(s_t, \cdot))}{Z_\pi(s_t)} \right)
   \]
SoftMax

\[ S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}} \]

Logits Scores:
- 2.0 → \( y \)
- 1.0 → \( y \)
- 0.1 → \( y \)

Probabilities:
- \( p = 0.7 \)
- \( p = 0.2 \)
- \( p = 0.1 \)
Soft Policy Iteration

Soft policy iteration iterates between two steps:

1. **Soft policy evaluation**: Fix policy, apply Bellman backup operator till convergence

\[
q_\pi(s, a) = r(s, a) + \mathbb{E}_{s', a'} \left( q_\pi(s', a') - \log(\pi(a' | s')) \right)
\]

This converges to \( q_\pi \)

2. **Soft policy improvement**: Update the policy:

\[
\pi' = \arg \min_{\pi_k \in \Pi} D_{KL} \left( \pi_k(\cdot | s_t) \parallel \frac{\exp(Q_\pi(s_t, \cdot))}{Z_\pi(s_t)} \right)
\]

Leads to a sequence of policies with monotonically increasing soft q values

This so far concerns tabular methods. Next we will use function approximations for policy and action values
Use function approximations for policy, state and action value functions

\[ V_\psi(s_t) \quad Q_\theta(s_t) \quad \pi_\phi(a_t \mid s_t) \]

1. Learning the state value function:

\[
J_V(\psi) = \mathbb{E}_{s_t \sim D} \left[ \frac{1}{2} \left( V_\psi(s_t) - \mathbb{E}_{a_t \sim \pi_\phi} [Q_\theta(s_t, a_t) - \log \pi_\phi(a_t \mid s_t)] \right)^2 \right]
\]

\[
\hat{V}_\psi J_V(\psi) = \nabla_\psi V_\psi(s_t) (V_\psi(s_t) - Q_\theta(s_t, a_t) + \log \pi_\phi(a_t \mid s_t))
\]
Soft Policy Iteration - Approximation

Use function approximations for policy, state and action value functions

\[ V_\psi(s_t) \quad Q_\theta(s_t) \quad \pi_\phi(a_t \mid s_t) \]

2. Learning the state-action value function:

\[
J_Q(\theta) = \mathbb{E}_{(s_t, a_t) \sim D} \left[ \frac{1}{2} \left( Q_\theta(s_t, a_t) - \hat{Q}(s_t, a_t) \right)^2 \right]
\]

\[ \hat{Q}(s_t, a_t) = r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1} \sim p} \left[ V_\psi(s_{t+1}) \right] \]

\[ \hat{\nabla}_\theta J_Q(\theta) = \nabla_\theta Q_\theta(a_t, s_t) \left( Q_\theta(s_t, a_t) - r(s_t, a_t) - \gamma V_\psi(s_{t+1}) \right) \]
Soft Policy Iteration - Approximation

Use function approximations for policy, state and action value functions

\[ V_\psi(s_t) \quad Q_\theta(s_t, a_t) \quad \pi_\phi(a_t | s_t) \]

3. Learning the policy:

\[
J_\pi(\phi) = \mathbb{E}_{s_t \sim D} \left[ D_{KL} \left( \pi_\phi(\cdot | s_t) \left\| \frac{\exp(Q_\theta(s_t, \cdot))}{Z_\theta(s_t)} \right. \right) \right]
\]

\[
\nabla_\phi J_\pi(\phi) = \nabla_\phi \mathbb{E}_{s_t \in D} \mathbb{E}_{a_t \sim \pi_\phi(a | s_t)} \log \frac{\pi_\phi(a_t | s_t)}{\exp(Q_\theta(s_t, a_t))}
\]

\[ Z_\theta(s_t) = \int \exp(Q_\theta(s_t, a_t))da_t \]

The variable w.r.t. which we take gradient parametrizes the distribution inside the distribution.
Use function approximations for policy, state and action value functions:

\[ V_\psi(s_t), \quad Q_\theta(s_t), \quad \pi_\phi(a_t | s_t) \]

3. Learning the policy:

\[
\nabla_\phi J_\pi(\phi) = \nabla_\phi \mathbb{E}_{s_t \in D} \mathbb{E}_{a_t \sim \pi_\phi(a|s_t)} \log \frac{\pi_\phi(a_t | s_t)}{\exp(Q_\theta(s_t, a_t))}
\]

Reparametrization trick. The policy becomes a deterministic function of Gaussian random variables (fixed Gaussian distribution):

\[
a_t = f_\phi(s_t, \epsilon) = \mu_\phi(s_t) + \epsilon \Sigma_\phi(s_t), \quad \epsilon \sim \mathcal{N}(0, I)
\]

\[
\nabla_\phi J_\pi(\phi) = \nabla_\phi \mathbb{E}_{s_t \in D, \epsilon \sim \mathcal{N}(0, I)} \log \frac{\pi_\phi(a_t | s_t)}{\exp(Q_\theta(s_t, a_t))}
\]
Algorithm 1 Soft Actor-Critic

Initialize parameter vectors $\psi$, $\bar{\psi}$, $\theta$, $\phi$.

for each iteration do
  for each environment step do
    $a_t \sim \pi_\phi(a_t | s_t)$
    $s_{t+1} \sim p(s_{t+1} | s_t, a_t)$
    $\mathcal{D} \leftarrow \mathcal{D} \cup \{(s_t, a_t, r(s_t, a_t), s_{t+1})\}$
  end for
  for each gradient step do
    $\psi \leftarrow \psi - \lambda_V \hat{\nabla}_\psi J_V(\psi)$
    $\theta_i \leftarrow \theta_i - \lambda_Q \hat{\nabla}_{\theta_i} J_Q(\theta_i)$ for $i \in \{1, 2\}$
    $\phi \leftarrow \phi - \lambda_\pi \hat{\nabla}_\phi J_\pi(\phi)$
    $\bar{\psi} \leftarrow \tau \psi + (1 - \tau)\bar{\psi}$
  end for
end for
Imagine we want to satisfy two objectives at the same time, e.g., pick an object up while avoiding an obstacle. We would learn a policy to maximize the addition of the corresponding reward functions:

$$r_C(s, a) = \frac{1}{|C|} \sum_{i \in C} r_i(s, a)$$

MaxEnt policies permit to obtain the resulting policy’s optimal Q by simply adding the constituent Qs:

$$Q_C^*(s, a) \approx Q_\Sigma(s, a) = \frac{1}{|C|} \sum_{i \in C} Q_i^*(s, a)$$

We can theoretically bound the suboptimality of the resulting policy w.r.t. the policy trained under the addition of rewards. We cannot do this for deterministic policies.
Fig. 2. Two independent policies are trained to push the cylinder to the orange line and blue line, respectively. The colored circles show samples of the final location of the cylinder for the respective policies. When the policies are combined, the resulting policy learns to push the cylinder to the lower intersection of the lines (green circle indicates final location). No additional samples from the environment are used to train the combined policy. The combined policy learns to satisfy both original goals, rather than simply averaging the final cylinder location.
Composable Deep Reinforcement Learning for Robotic Manipulation

Tuomas Haarnoja, Vitchyr Pong, Aurick Zhou, Murtaza Dalal, Pieter Abbeel, and Sergey Levine

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https://youtu.be/wdexoLS2cWU