Robot Learning

Deep RL Tutorial

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November 7, 2022

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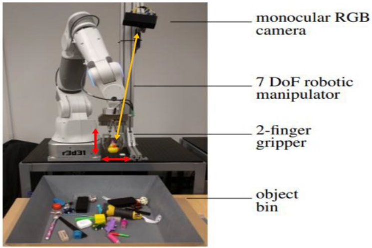
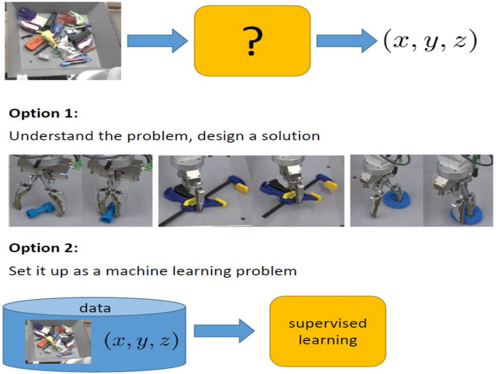
- Some material from Levine DeepRL Course

Outline





- There are many situations where traditional models are challenged - Large state spaces - Non-linear dynamics - Discontinuous contacts

What Problem is DeepRL Solving?

No feature engineering!

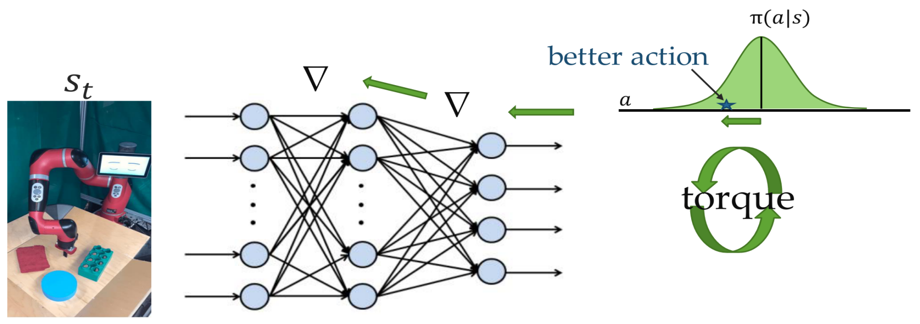


Figure: Deep Learning and Reinforcement Learning

- The perception and planning problem in a more general way.

What Problem is DeepRL Solving?

Sensor Motor Loop

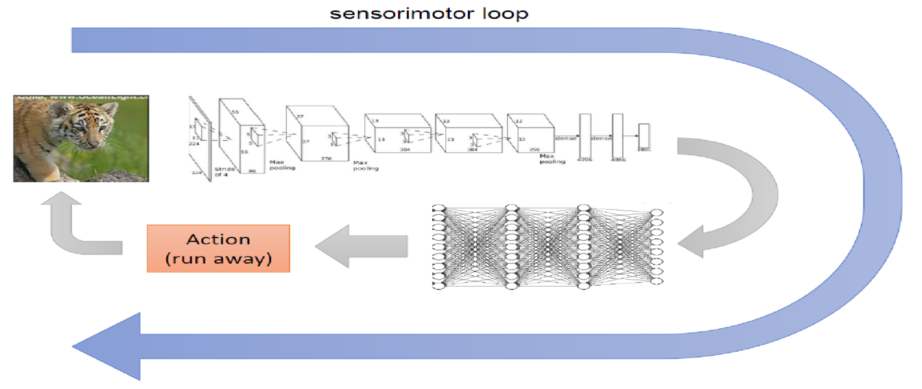


Figure: Sensory motor loop

- RL agents collect their own data to solve a task
  - No need for expert data

Supervised learning

- given $\mathcal{D} = \{x_i, y_i\}$
  - learn to predict y_i given x_i, $y \leftarrow f(x)$
- Assumptions in supervised learning
  - Data is Independant and Identically Distributed (IID)
    - This is rarely the case in the real world
  - True optimal action y is known
- Example:
  - $L(\theta) = ||f(x|\theta) - y||^2$

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Reinforcement Learning

- Previous outputs influence future inputs
  - Data is not IID
- Optimal action y is known
  - Instead we have a scalar reward function
- **reward** function
  - $r \leftarrow R(s, a)$
  - **weighted regression**
- Example:
  - $L(\theta) = ||f(s|\theta) - a||^2 R(s, a)$

What is Reinforcement Learning

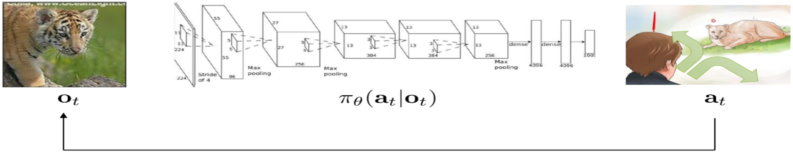
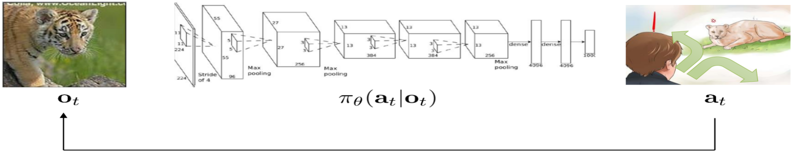


Figure: First terms

- a_t - Action
- $\mathbf{a}_t$ - Continuous action
- $\mathbf{s}_t$ - State
- $\mathbf{o}_t$ - Observation

What is Reinforcement Learning



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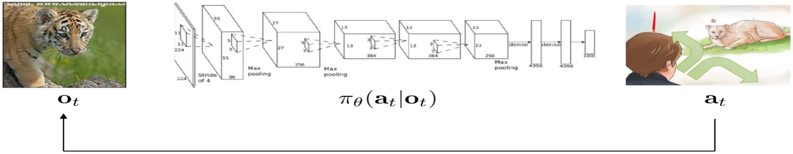
- $\pi(\mathbf{a}_t|\mathbf{s}_t, \theta)$ fully observed policy

What is Reinforcement Learning



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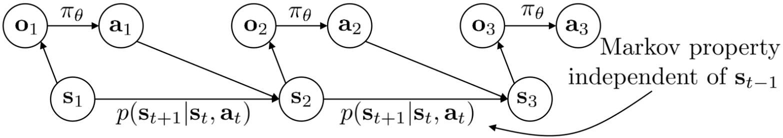


Figure: Markov property

Reinforcement Learning Objective

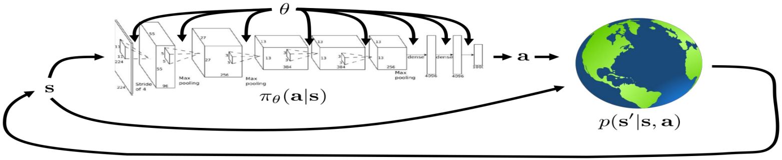


Figure: Reinforcement Learning Environment

Reinforcement Learning Objective

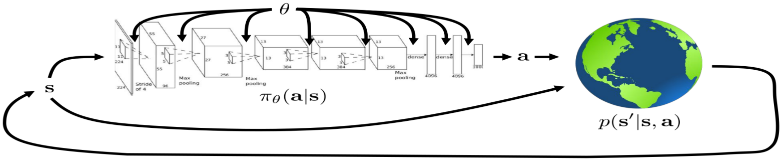
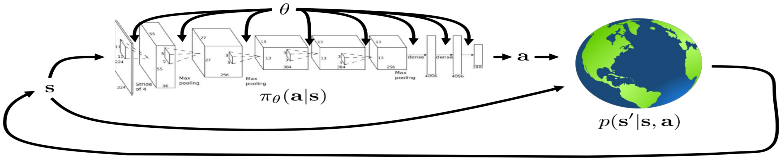


Figure: Reinforcement Learning Environment

- Distribution over trajectories $p(\tau|\theta)$ using chain rule of probability

$$\underbrace{p(\mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T, \mathbf{a}_T|\theta)}_{p(\tau|\theta)} = \underbrace{p(\mathbf{s}_1)}_{\text{unknown}} \prod_{t=1}^{T} \pi(\mathbf{a}_t|\mathbf{s}_t, \theta) \underbrace{p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)}_{\text{unknown}} \tag{1}$$

Reinforcement Learning Objective



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- RL objective is over this distribution

$$\arg\max_{\theta^*} \mathbb{E}_{\tau \sim p(\tau|\theta)} \left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t) \right] \tag{2}$$

Basic Reinforcement Learning Loop: (1) Collect Data

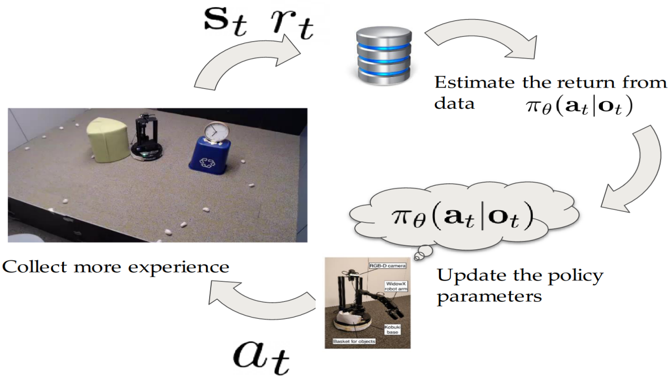


Figure: Sensory motor loop

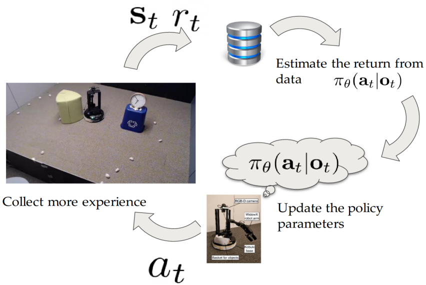
Basic Reinforcement Learning Loop: (1) Collect Data

Collect Data

```
import gym
env = gym.make("LunarLander-v2") ## Create an instance of the control environm
observation, info = env.reset(seed=42, return_info=True) ## Reset the environm
buff = [] ## Array to store experience
for _ in range(1000):
   env.render()  ## Render the environment if desired
   action = policy(observation)  # User-defined policy function
   next_observation, reward, done, info = env.step(action) ## Take a step in t
   buff.append([observation, action, reward, next_observation])
   observation = next_observation
   if done:
      observation, info = env.reset(return_info=True) ## Reset if the robot ha

env.close()
```

Basic Reinforcement Learning Loop: (2) Estimate Return/Score



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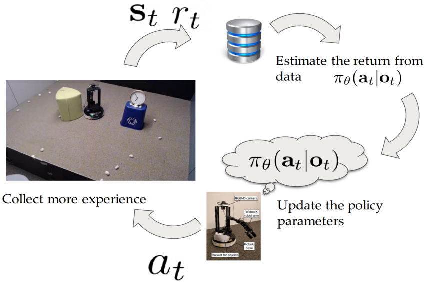

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Estimate the return for θ

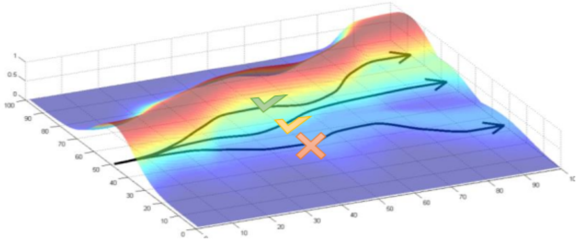
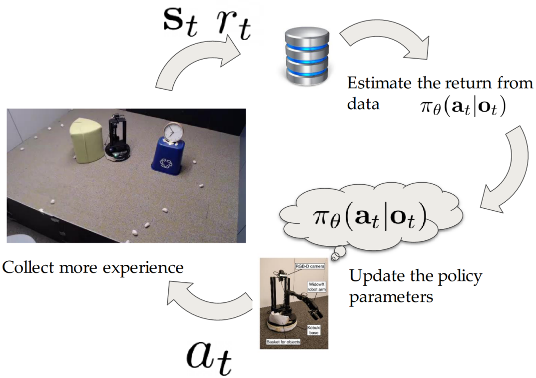


Figure: Policy Gradient

$$J(\theta) = \mathbb{E}_{\tau \sim p(\tau|\theta)} \left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t) \right] \tag{3}$$

Basic Reinforcement Learning Loop: (3) Update The Policy



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Update the policy

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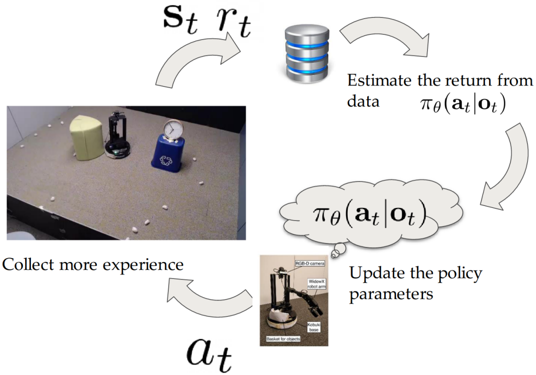

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Update the policy

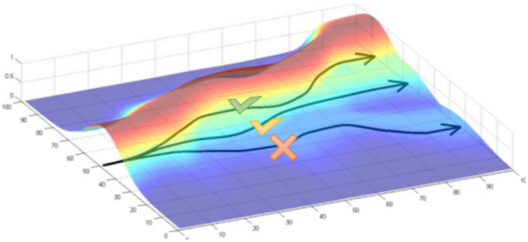

Figure: Policy Gradient

- $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$
- α is the learning rate

You need to train a model

- Model-Based Reinforcement Learning (MBRL)
- Why learn a model?
  - For most problems the dynamics are unknown
  - If we have $\mathbf{s}_{t+1} = f(\mathbf{s}_t, \mathbf{a}_t)$ we can plan (see last week)
- Then all we need to do is learn $\mathbf{s}_{t+1} = f(\mathbf{s}_t, \mathbf{a}_t)$, that should be *easy*.

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- MBRL
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Basic MBRL

1. Collect experience $< \mathbf{s}_{t+1}, \mathbf{s}_t, \mathbf{a}_t > \in \mathcal{D}_{\text{train}}$ from the environment with $\pi_0(\mathbf{a}_t|\mathbf{s}_t)$
2. Train θ to minimize $\sum_i ||f(\mathbf{s}_t, \mathbf{a}_t, \theta) - \mathbf{s}_{t+1}||$
3. Use $f(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t, \theta)$ to plan high reward trajectories

(Wang *et al.*, 2018)

Model-Based Reinforcement Learning

How Well Does Basic MBRL work

- Not that well, why?

How Well Does Basic MBRL work

- Not that well, why?

Basic MBRL

1: Collect experience $< \mathbf{s}_{t+1}, \mathbf{s}_t, \mathbf{a}_t > \in \mathcal{D}_{\text{train}}$ from the environment with $\pi_{\text{rand}}(\mathbf{a}_t|\mathbf{s}_t)$
2: Train θ to minimize $\sum_i ||f(\mathbf{s}_t, \mathbf{a}_t, \theta) - \mathbf{s}_{t+1}||$
3: Use $f(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t, \theta)$ to plan high value trajectories

- Goal: Move higher
- But: $\pi_{\text{rand}}(\mathbf{a}_t|\mathbf{s}_t) \neq \pi(\mathbf{a}_t|\mathbf{s}_t, \theta)$

- Problem grows with model complexity

How to train a forward model

- How to reduce $\pi_{\text{rand}}(\mathbf{a}_t|\mathbf{s}_t) \neq \pi(\mathbf{a}_t|\mathbf{s}_t, \theta)$
- Ideas?

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OnPolicy MBRL

1: Collect experience $< \mathbf{s}_{t+1}, \mathbf{s}_t, \mathbf{a}_t > \in \mathcal{D}_{\text{train}}$ from the environment with $\pi_{\text{rand}}(\mathbf{a}_t|\mathbf{s}_t)$
2: **while** true **do**
3: Train θ to minimize $\sum_i ||f(\mathbf{s}_t, \mathbf{a}_t, \theta) - \mathbf{s}_{t+1}||$
4: Use $f(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t, \theta)$ to plan high value trajectories
5: Collect experience $< \mathbf{s}_{t+1}, \mathbf{s}_t, \mathbf{a}_t > \in \mathcal{D}_{\text{train}}$from the environment with $f(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t, \theta)$
6: **end while**

How to train a forward model

- How to reduce $\pi_{\text{rand}}(\mathbf{a}_t|\mathbf{s}_t) \neq \pi(\mathbf{a}_t|\mathbf{s}_t, \theta)$
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while true **do**
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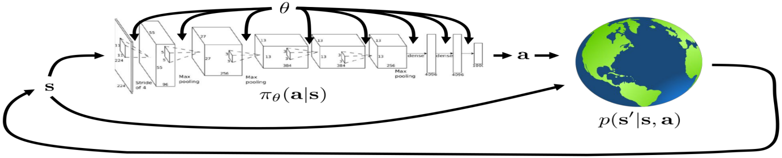
end while

- What is wrong with this algorithm?
    - Hint: What objective is it optimizing?

(Deisenroth and Rasmussen, 2011; Chua *et al.*, 2018; Hafner *et al.*, 2019)



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- RL objective is over this distribution

$$\arg\max_{\theta^*} \mathbb{E}_{\tau\sim p(\tau|\theta)} \left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t)\right] \tag{5}$$

- **MBRL is not optimizing for this objective.** (Joseph *et al.*, 2013; Farahmand *et al.*, 2017; Janner *et al.*, 2019; Grimm *et al.*, 2020; Lambert *et al.*, 2020; Nikishin *et al.*, 2022)

The Policy Gradient

$$\theta^* = \arg\max_{\theta} \underbrace{\mathbb{E}_{\tau \sim p(\tau|\theta)} \left[\sum_{t} r(\mathbf{s}_t, \mathbf{a}_t) \right]}_{J(\theta)} \quad (6)$$

- How can we use this?

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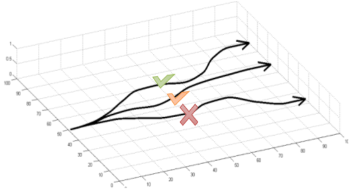

Figure: Simple policy Gradient

- How can we use this?
- Approximate with samples from the environment

$$J(\theta) = \mathbb{E}_{\tau \sim p(\tau|\theta)} \left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t) \right] \approx \frac{1}{N} \sum_n^N \sum_t^T r(\mathbf{s}_{n,t}, \mathbf{a}_{n,t}) \quad (7)$$

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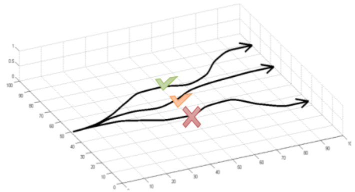

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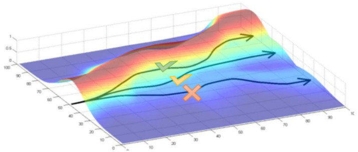
- **Unbiased** estimate of the expected value
- Simple to perform direct gradient ascent

Examples: Reinforce (Williams, 1992; Sutton *et al.*, 2000)

Basic Reinforcement Learning Loop: Update Policy

Reducing Variance: Baselines

- $\nabla_\theta J(\theta) = \frac{1}{N}\sum_{i=1}^{N} \nabla \log p(\tau) r(\tau)$
- Average reward
    - $b_t = \frac{1}{N}\sum_{i=1}^{N} r(\tau)$
    - Reweight trajectories by their average performance



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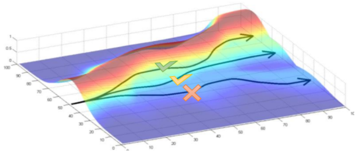

Figure: Policy Gradient

- Will this change the optimal policy?
- $\mathbb{E}[\nabla_\theta \log p(\tau|\theta) b] = \int p(\tau) \nabla_\theta \log p(\tau|\theta) b d\tau$
  - Use identity
- $\int \nabla_\theta p(\tau|\theta) b d\tau = b \nabla_\theta \int p(\tau|\theta) d\tau = b \nabla_\theta 1 = 0$
  - Same optimal policy

Load your robot model

- Create a simulated environment for the control loop
  - Or a real environment
- Create a reward function
  - Easy in simulation, often difficult in the real world

OpenAiGym API

```
env = gym.make(env_id)
env = gym.wrappers.RecordEpisodeStatistics(env)
```

DeepRL and Robotics

OpenAIGym Wrappers for Preprocesing

```
## Deep Networks like outputs in [-1,1]
env = gym.wrappers.ClipAction(env)
## Deep Networks like inputs in [-1,1]
env = gym.wrappers.NormalizeObservation(env)
env = gym.wrappers.TransformObservation(env, lambda obs: np.clip(obs, -10, 10)
## DeepRL likes rewards [-1,1]
env = gym.wrappers.NormalizeReward(env, gamma=gamma)
env = gym.wrappers.TransformReward(env, lambda reward: np.clip(reward, -10, 1
```

- This way learning rates, etc have meaning

Many RL libraries to use

- Stable Baselines: Good place to start
- cleanrl: simple implimentations of RL algorithms
- rlkit: Designed for robotics applications
- tf_agents: Based on deepmind applications
- Many others..

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- Learn how to use RL first with simple examples
  - See my class
- Then upgrade to code for real experiments.

DeepRL Tutorial

- cleanrl:
- Setup code here.
  - https://github.com/milarobotlearningcourse/cleanrl/blob/master/roble_install.md

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- Fix code in ppo_continuous_action.py
  - https://github.com/milarobotlearningcourse/cleanrl/blob/master/cleanrl/ppo_continuous_a
  - look for “TODO ##”
  - Ask questions!

Scratch

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