Robot Learning

Deep Reinforcement Learning: Tutorial

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Outline

Why Robot Learning With DeepRL?

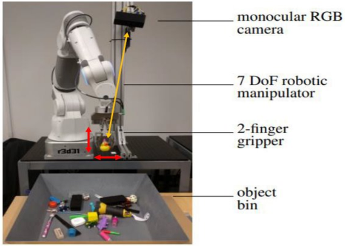
Supervised Learning vs Reinforcement Learning

Model-Based Reinforcement Learning

Model-Free Reinforcement Learning

Creating an RL Environment for a Robot

Why Robot Learning With DeepRL?

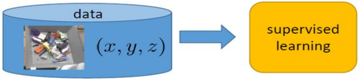


Option 1:

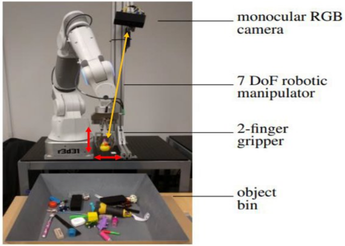
Understand the problem, design a solution

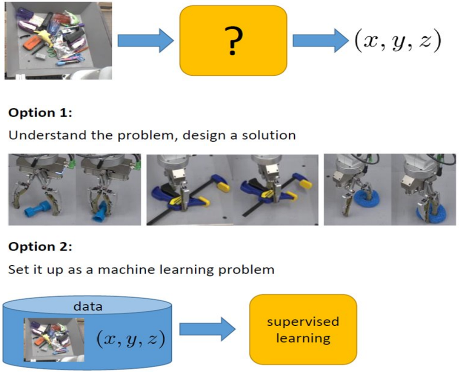
Option 2:

Set it up as a machine learning problem



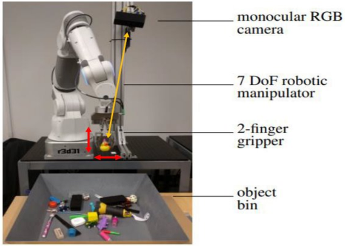
Why Robot Learning With DeepRL?





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

Why Robot Learning With DeepRL?



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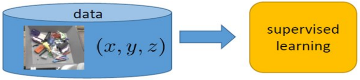

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What Problem is DeepRL Solving?

No feature engineering!

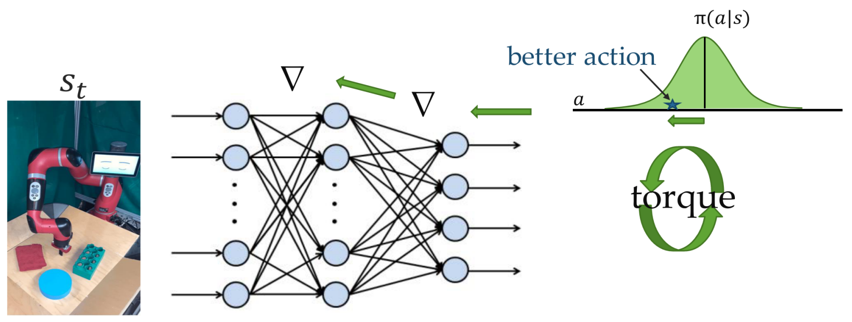

Figure: Deep Learning and Reinforcement Learning

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

What Problem is DeepRL Solving?

Sensor Motor Loop

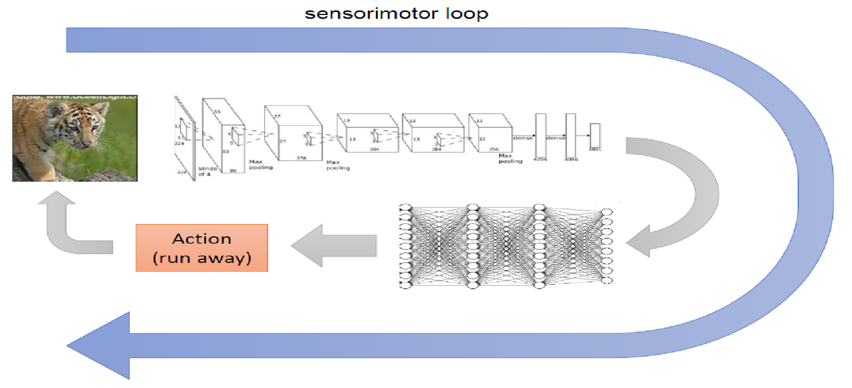

Figure: Sensory motor loop

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

Supervised Learning vs Reinforcement Learning

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 Independent 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

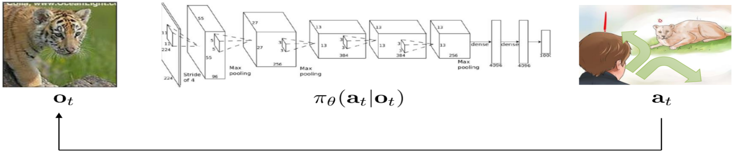
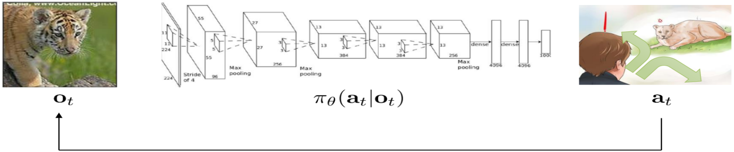


Figure: First terms

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

What is Reinforcement Learning



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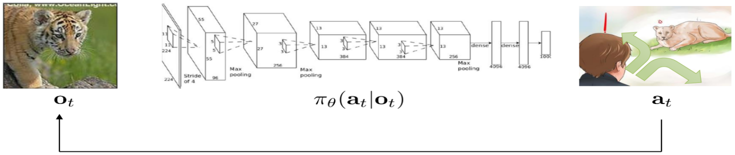
- $\pi(\mathbf{a}_t|\mathbf{s}_t, \theta)$ fully observed policy

What is Reinforcement Learning



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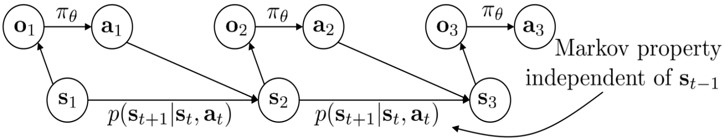

Figure: Markov property

Reinforcement Learning Optimization

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

- Finite horizon case

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

- Infinite horizon case

Reinforcement Learning Optimization

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- Infinite horizon case

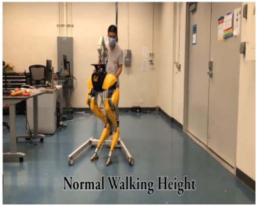
- Reinforcement Learning uses Expectations

Figure: Discontinuous Rewards

- $r(s, a)$ - **not smooth**
- $\pi(a = fall|s, \theta)$
- $\mathbb{E}_{\pi(\cdot|s,\theta)}[r(s, a)]$ - smooth wrt θ

Deep Reinforcement Learning Success Stories

Image courtesy: The Guardian



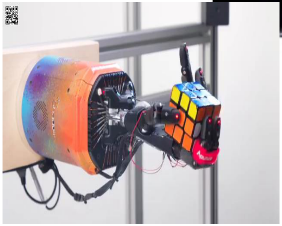


Figure: Success Stories
(Silver *et al.*, 2016; OpenAI *et al.*, 2019; Berner *et al.*, 2019; Li *et al.*, 2021)

Reinforcement Learning Objective

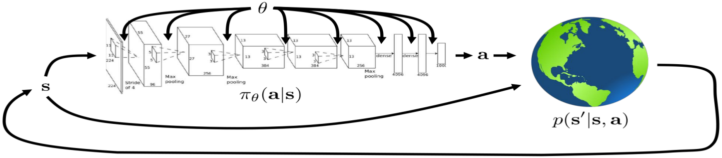


Figure: Reinforcement Learning Environment

Reinforcement Learning Objective

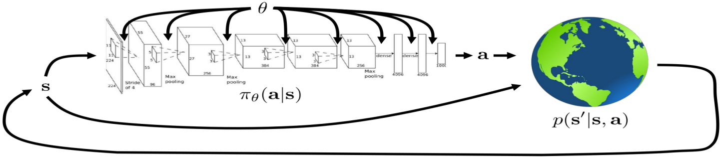


Figure: Reinforcement Learning Environment

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

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

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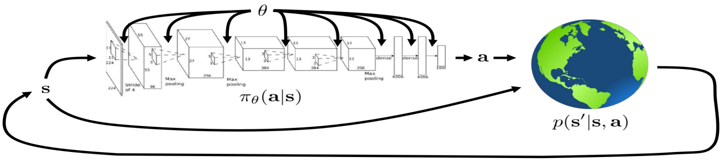

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- RL objective is over this distribution

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

Basic Reinforcement Learning Loop: (1) Collect Data

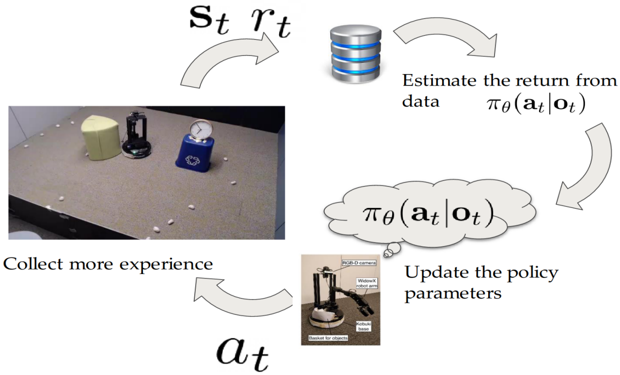


Figure: Sensory motor loop

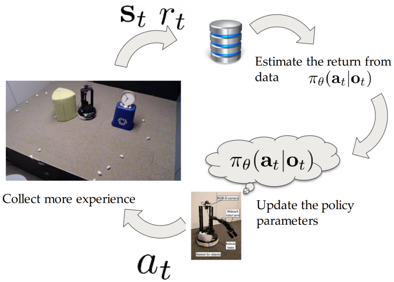
Basic Reinforcement Learning Loop: (1) Collect Data

Collect Data

```
import gym
env = gym.make("LunarLander-v2") ## Create an instance of the control envi
observation, info = env.reset(seed=42, return_info=True) ## Reset the envi
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 i
    buff.append([observation, action, reward, next_observation])
    observation = next_observation
    if done:
        observation, info = env.reset(return_info=True) ## Reset if the robot

env.close()
```

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



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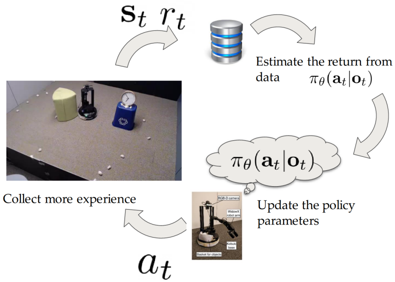

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Estimate the return for θ

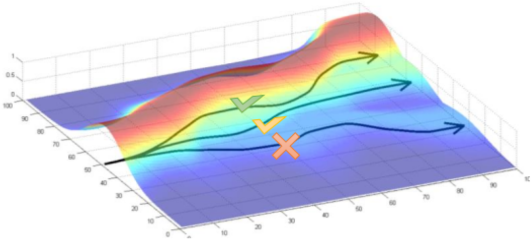


Figure: Policy Gradient

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

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

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

Estimate Return

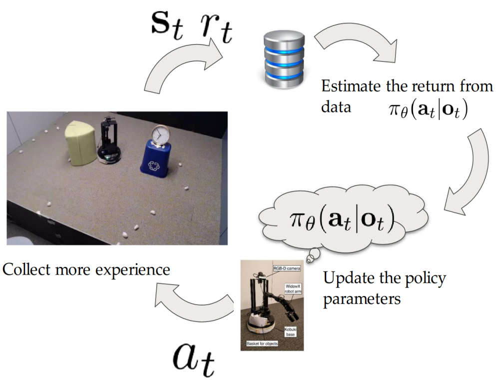
```
# create list at each index (t') is gamma^(t') * r_{t'}
discounted_rewards = discounts * rewards

# scalar: sum_{t'=0}^T gamma^(t') * r_{t'}
sum_of_discounted_rew = sum(discounted_rewards)

# list where each entry t contains the same thing
# it contains sum_{t'=0}^T gamma^t' r_{t'}
discounted_returns = np.ones_like(rewards) * sum_of_discounted_rew

# For each (s_t, a_t), discounted sum of rewards over trajectory
# Aka: value of (s_t, a_t) = sum_{t'=0}^T gamma^t' r_{t'}
q_values = np.concat([self._discounted_return(r) for r in rews_list])
```

Basic Reinforcement Learning Loop: (3) Update The Policy



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Update the policy

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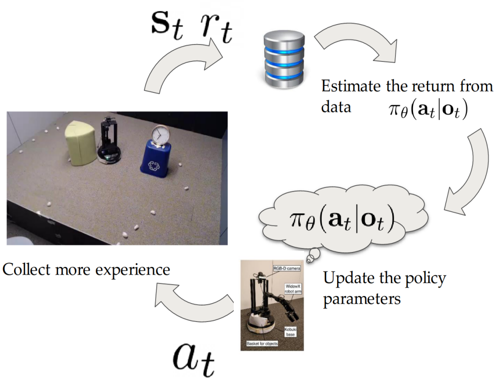

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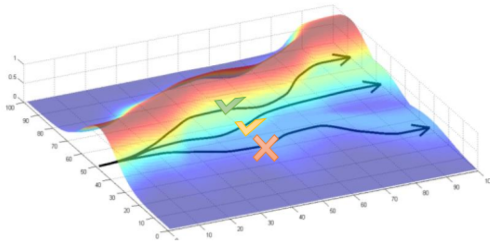

Figure: Policy Gradient

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

Model-Based Reinforcement Learning

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

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Start by training a model.

Must 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
- 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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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)

How Well Does Basic MBRL Work?

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- 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

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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**

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

How to train a forward model

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

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

Model-Free Reinforcement Learning

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

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- RL objective is over this distribution

$$\arg\max_{\theta^*} \mathbb{E}_{\tau \sim p(\tau|\theta)} \left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t) \right] \tag{6}$$

- **MBRL is not optimizing for the RL 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

$$\theta^* = \arg\max_\theta \underbrace{\mathbb{E}_{\tau \sim p(\tau|\theta)} \left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t) \right]}_{J(\theta)} \tag{7}$$

- How can we use this?

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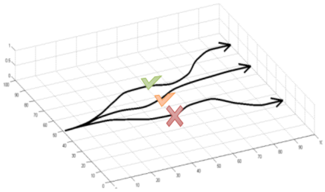

Figure: Simple policy Gradient

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

$$J(\theta) = \mathbb{E}_{\tau \sim p(\tau|\theta)} \left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t) \right] \approx \frac{1}{N} \sum_n^N \sum_t^T r(\mathbf{s}_{n,t}, \mathbf{a}_{n,t}) \tag{8}$$

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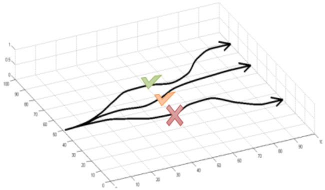

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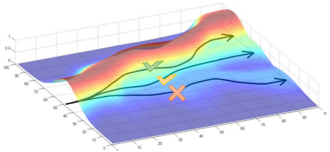
- **Unbiased** estimate of the expected value
- Simple to perform direct gradient ascent

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

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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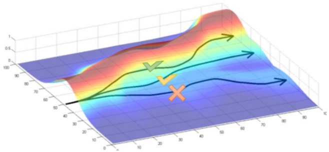

Figure: Policy Gradient

- 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

Basic Reinforcement Learning Loop: Update Policy

Update Policy

```
def update(self, observations, acs_na, adv_n=None, acs_labels_na=None, qval
    observations = ptu.from_numpy(observations)
    actions = ptu.from_numpy(acs_na)
    adv_n = ptu.from_numpy(adv_n)
    action_distribution = self.policy(observations)
    loss = - action_distribution.log_prob(actions) * adv_n
    loss = loss.mean()
    self.optimizer.zero_grad()
    loss.backward()
    self.optimizer.step()
```

Creating an RL Environment for a Robot

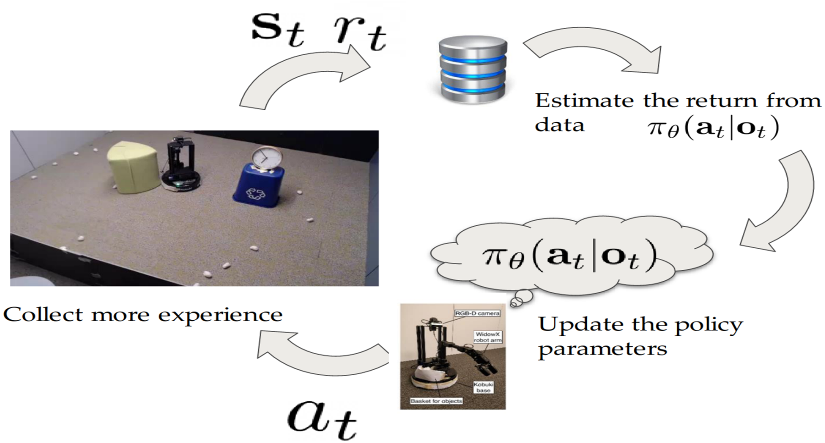

Figure: Robot: sensory motor loop

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 Preprocessing

```
## 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,
## DeepRL likes rewards [-1,1]
env = gym.wrappers.NormalizeReward(env, gamma=gamma)
env = gym.wrappers.TransformReward(env, lambda reward: np.clip(reward, -10,
```

- This way, learning rates, etc, have meaning

Deep Reinforcement Learning Algorithms

- Model-Based Reinforcement Learning
- Stochastic Policy Gradients
- Reinforce, NPO, TRPO, PPO, Actor-Critic
- Q-Learning
- Approximate Dynamic Programming
- Important to consider the Deep Network ingredient.

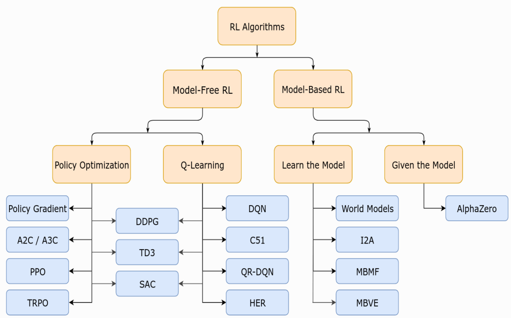

Figure: RL algorithm taxonomy (spi, 2020)

Many RL libraries to use

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

Many RL libraries to use

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

Example: Distributed PPO

- Learning to navigate obstacles from vision
- Works across morphologies
- Used distributed computation to speed up training speed
- Not the best motion...
- Heess *et al.* (2017)

Figure: Emergent Behaviours

parkor

Q-learning (off-policy)

- Estimate the action valued function
  - $Q^{\pi}(\mathbf{s}_t, \mathbf{a}_t) = \mathbb{E}_{p_\theta}\left[\sum_{t'=t}^{T} r(\mathbf{s}_{t+1}, \mathbf{a}_{t+1}) \mid \mathbf{s}_t, \mathbf{a}_t\right]$
- Reward for taking action $\mathbf{a}_t$ in state $\mathbf{s}_t$ and then following policy $Q^{\pi}(\mathbf{s}_t, \mathbf{a}_t)$
- Recursive definition, use dynamic programming
  - $\mathcal{L} = \mathbb{E}_{(s,a,s')\sim p_{\text{data}}} \| Q_\phi(\mathbf{s}_t, \mathbf{a}_t) - (r(\mathbf{s}_t, \mathbf{a}_t) + \gamma \max_{a'} Q_\phi(s', a') \|^2$
- How to use
  - Act using $\mathbf{a}_t^* \leftarrow \arg\max_{\mathbf{a}_t} Q(\mathbf{s}_t, \mathbf{a}_t, \phi)$
- Stability issues training Q functions
- Policy changes rapidly, Q values unbounded

Example: DQN (Atari)

- Playing Atari with deep reinforcement learning, Mnih *et al.* (2015)
- Q-learning with convolutional neural networks
- Epsilon greedy exploration
- Target Networks

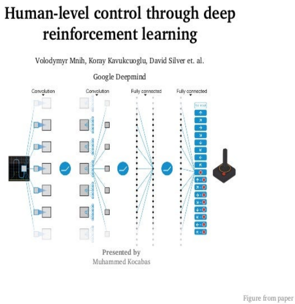

Figure: DQN on Atari

Breakout

Many RL Algorithms

- Different trade-offs
  - Sample efficiency
  - Ease of coding and stability
- Different environment assumptions
  - Episodic vs infinite horizon
  - Continuous/Discrete
  - Deterministic vs Stochastic
- Different types of MDPs
  - Real-world constraints
- When to use which one?

Often Not about Sample Efficiency

- Often about stability
- Will the algorithm converge with enough data?
- What does it converge to?

Often Not about Sample Efficiency

- Often about stability
- Will the algorithm converge with enough data?
- What does it converge to?
- Supervised learning doesn't have these concerns
  - Can always use gradient descent
- Reinforcement learning: often not gradient descent
  - Q-learning: fixed point iteration
  - Model-based RL: model is not optimized for expected reward
  - Policy gradient: is gradient descent, but also often the least efficient

What are we even doing..?

- Value function fitting
  - At best, minimizes error of fit ("Bellman error")
    - Not the same as expected reward
  - At worst, doesn't optimize anything
    - Many popular deep RL value fitting algorithms are not guaranteed to converge to anything in the nonlinear or non-tabular case
- Model-based RL
  - Model minimizes error of fit
    - This does converge
  - No guarantee that better model = better policy
- Policy gradient
  - The only method actually performs gradient descent (ascent) on the true objective

So-called Assumptions

- Common assumption #1: full observability
  - Often assumed when training the value function
  - Or can be compensated with LSTM
- Common assumption #2: episodic learning
  - Often assumed by pure policy gradient methods
  - Assumed by some model-based RL methods
- Common assumption #3: continuity or smoothness
  - Assumed by some continuous value function learning methods
  - Often assumed by some model-based RL methods

DeepRL Tutorial

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

- cleanrl:
- Setup code here.
  - https://github.com/milarobotlearningcourse/cleanrl/blob/master/roble_install.md
- Fix code in ppo_continuous_action.py
  - https://github.com/milarobotlearningcourse/cleanrl/blob/master/cleanrl/ppo_continuous_
  - look for "TODO ##"
  - Ask questions!

Scratch

Scratch

- Possibly some material from Sergey Levine's deepRL course

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