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Reinforcement Learning

Lecture 11 - Recent advances and remaining challenges

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Repetition

- **The return:** $G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots$
- **State-value function:** $v_\pi(s) = \mathbb{E}_\pi[G_t \mid S_t = s]$
- **Action-value function:** $q_\pi(s) = \mathbb{E}_\pi[G_t \mid S_t = s, A_t = a]$
- **Policy:** rules for how the agent should act in different states: $a \sim \pi(a \mid s)$

- One approach to RL is to find an estimate Q of the optimal q-function. Then use the policy $\pi(s) = \arg\max_a Q(s, a)$
- During training, however, we need exploration (e.g., ε-greedy, UCB)
- **Tabular:** if both $\mathcal{S}$ and $\mathcal{A}$ are finite we can represent $Q(s, a)$ as a table with one element for each s/a-pair
- **Monte Carlo:** let $Q(S, A)$ be the average G we have seen from S, A
- **SARSA:** (on-policy, bootstrapping)

$$Q(S, A) \leftarrow Q(S, A) + \alpha(R + \gamma Q(S', A') - Q(S, A))$$

- **Q-learning:** (off-policy, bootstrapping)

$$Q(S, A) \leftarrow Q(S, A) + \alpha(R + \gamma \max_a Q(S', a) - Q(S, A))$$

- If the state space is very large (or even continuous) it is not suitable to represent $Q(s, a)$ with a table:
  - The table will be too big (or even infinitely big)
  - No generalization: only s/a-pairs seen will be updated
- **Idea:** represent q with function approximation:

$$\hat{q}(s, a, \boldsymbol{w}) \approx q(s, a)$$

- **Stochastic (semi)-gradient:** the target U_t is some approximation of $q(s, a)$,

$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t + \alpha[U_t - \hat{q}(S_t, A_t, \boldsymbol{w}_t)]\nabla\hat{q}(S_t, A_t, \boldsymbol{w}_t)$$

- **Monte Carlo:** use $U_t = G_t$ computed from experience.
- **SARSA:** use $U_t = R_{t+1} + \gamma\hat{q}(S_{t+1}, A_{t+1}, \boldsymbol{w}_t)$ from experience and bootstrapping

- Define a feature vector $\boldsymbol{x}(s, a)$ and use

$$\hat{q}(s, a, \boldsymbol{w}) = \boldsymbol{w}^\top \boldsymbol{x}(s, a)$$

- **Gradient:** $\nabla \hat{q}(s, a, \boldsymbol{w}) = \boldsymbol{x}(s, a)$
- Existing results show that gradient methods based on SARSA converge
- Can often encode prior knowledge into features
- To get good results in complex environments, we need a good choice of features

Convergence of prediction algorithms

Are there convergence guarantees?

On-policy methods

Method	Tabular	Linear	Nonlinear
MC	Yes	Yes	Yes
TD	Yes	Yes	No
Gradient-TD	Yes	Yes	Yes

Off-policy methods

Method	Tabular	Linear	Nonlinear
MC	Yes	Yes	Yes
TD	Yes	No	No
Gradient-TD	Yes	Yes	Yes

Convergence of control

Method	Tabular	Linear	Nonlinear
MC	Yes	(Yes)	No
SARSA	Yes	(Yes)	No
Q-learning	Yes	No	No
Gradient Q-learning	Yes	Yes	No

Policy gradient: REINFORCE converges to a local minimum even for nonlinear.

Some actor-critic algorithms have similar convergence properties.

The deadly triad

- Function approximation
- Bootstrapping
- Off-policy learning

When we combine these three concepts, we risk instability and divergence!

See textbook Chapter 11.3 for more discussion.

Do we need all of them?

- Function approximation needed for more complex environments
- We have seen that bootstrapping helps a lot for reducing variance
- Off-policy can help with sample efficiency (reuse old data)

Nonlinear: In the book they talk about function approximation in general. When we consider nonlinear cases (e.g. deep RL), the situation is even worse.

Deep Learning

- The goal is to find a function that maps inputs $\boldsymbol{x}$ to output y
- Using parametrized functions and find estimate $\widehat{\boldsymbol{\theta}}$,

$$\hat{y} = g(\boldsymbol{x}; \boldsymbol{\theta})$$

- **Linear regression:** use

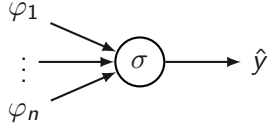
$$g(\boldsymbol{x}; \boldsymbol{\theta}) = \boldsymbol{\varphi}(\boldsymbol{x})^\top \boldsymbol{\theta}$$

  - $\boldsymbol{\varphi}(\boldsymbol{x})$ should contain features that can describe the function we try to estimate
  - Analytical solutions, and a lot of theory
- **Nonlinear regression:** when $g(\boldsymbol{x}; \boldsymbol{\theta})$ depends on $\boldsymbol{\theta}$ in a nonlinear way
  - No analytical solution in general
  - Common to use the idea of stochastic gradient descent

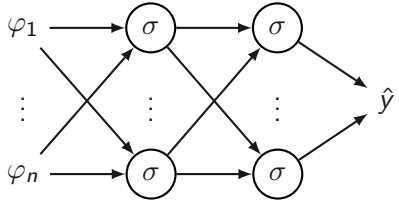
We can generalize linear regression by adding a nonlinear transformation:

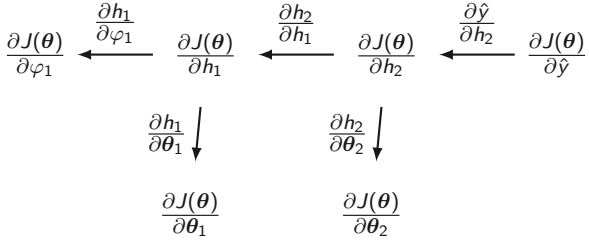
$$\hat{y} = \sigma(\boldsymbol{\varphi}(\boldsymbol{x})^\top \boldsymbol{\theta}),$$

where $\sigma(\cdot)$ is often called an *activation function*.



Can combine several of these and make the network deeper





- Assume we want to estimate a function $g(\boldsymbol{x}; \boldsymbol{\theta})$ using a deep neural network
- Choose a **loss function**, e.g., $J(\boldsymbol{\theta}) = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$
- Try to find

$$\widehat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} J(\boldsymbol{\theta})$$

- Can use the chain rule to compute gradient via **backpropagation**

- Sample gradient of expected loss $\bar{J}(\boldsymbol{\theta}) = \mathbb{E}[J(\boldsymbol{\theta})]$

$$\frac{\partial J(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \sim \mathbb{E}\left[\frac{\partial J(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right] = \frac{\partial \bar{J}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}$$

- Adjust $\boldsymbol{\theta}$ down the sampled gradient

$$\Delta\theta \propto \frac{\partial \bar{J}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}$$

Deep Reinforcement Learning

Deep learning + reinforcement learning

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- Deep learning is a general-purpose framework for representation learning:
  - Given an **objective**
  - Learn **representation** that is required to achieve objective
  - Directly from **raw inputs**
  - Using minimal domain knowledge
- Reinforcement learning defines the objective

- Approximate the model, policy, and/or value functions using deep neural networks
- Several papers using neural networks in RL during the 1980s
- TD-Gammon (1992) used a multi-layered neural network for function approximation to play backgammon
- Really took of around 2013 with DQN playing Atari games and AlphaGO beating professional Go players (2015)

Why deep?

- **Universal function approximation theorem:** any continuous function $f(x)$ can be approximated by a neural network with arbitrary precision
- But might need to be large (many neurons and/or deep)

Drawbacks:

- Many parameters, so we often need much more training
- Nonlinear, so we lose many previous convergence guarantees.
- Introduce several new hyperparameters that are hard to tune

Value-based deep RL

Q-learning

- Try to learn $q_\pi(s, a) = \mathbb{E}_\pi[G_t \mid S_t = s, A_t = a]$
- Optimal Q-values should obey Bellman equation

$$q^*(s, a) = \mathbb{E}_{s'}[G_t + \gamma \max_{a'} q^*(s', a') \mid s, a]$$

- Treat expression in expectation as target
- Minimize MSE loss by stochastic gradient descent
- **Converges** to q^* for tabular approaches
- **Diverges** when using neural networks due to
  - Correlations between samples
  - non-stationary targets

Deep Q-networks (DQN): experience replay

- Over time, the agent collects samples $(s_t, a_t, r_{t+1}, s_{t+1})$
- Sample experiences from that collection and apply stochastic gradient descent

$\rightarrow$ Random sampling removes correlations

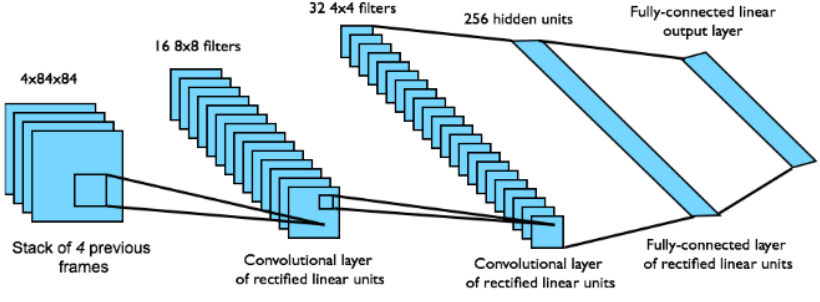
- To deal with non-stationarity, fix target parameters $\boldsymbol{\theta}$ when computing the loss

Human-level control through deep reinforcement learning[1]

- DQN created widespread interest when it learned to play various Atari games at the level of human experts
- It learned $Q(a, s)$ directly from pixels
- Input state s is stack of raw pixels from last four frames
- Output is $Q(s, a)$ for 18 joystick/button positions
- Reward is change in score for that step

[1] Volodymyr Mnih et al., "Human-level control through deep reinforcement learning," Nature, 2015.

DQN in Atari games



Improvements over the last years

- **Double DQN:** use two identical neural network models
  - One is used to actually compute the Q-value, the other to select the next action
  - removes upward bias
- **Prioritized replay:** weight experience according to surprise
  - Sample experiences more often that had a huge learning impact
- **Dueling network:** split Q-network into $V(s, \boldsymbol{v})$ and $A(s, a, \boldsymbol{\theta})$
  - $V(s, \boldsymbol{v})$: value function
  - $A(s, a, \boldsymbol{\theta})$: advantage function
- If we combine all of them, can get three times higher mean Atari score than DQN

Policy-based deep RL

- Represent policy by a deep network with parameters ϕ

$$a = \pi(a \mid s, \phi)$$

- Define objective function as total discounted reward

$$J(\phi) = \mathbb{E}[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \ldots \mid \pi(a \mid s, \phi)]$$

- Optimize objective function end-to-end by stochastic gradient descent

- Gradient of a stochastic policy $\pi(a \mid s, \phi)$:

$$\frac{\partial J(\phi)}{\partial \phi} = \mathbb{E}\left[\frac{\partial \log \pi(a \mid s, \phi)}{\partial \phi} Q^{\pi}(s, a)\right]$$

- **Actor-critic:** estimate value function $Q(s, a, \theta) \approx Q^{\pi}(s, a)$
- Update policy parameters ϕ by stochastic gradient ascent

Asynchronous advantage actor-critic (A3C)[2]

- Estimate state-value function

$$V(s, \boldsymbol{v}) \approx \mathbb{E}[R_{t+1} + \gamma R_{t+2} + \ldots \mid s]$$

- Q-value estimated by an n-step sample

$$Q_t = R_{t+1} + \gamma R_{t+2} + \ldots + \gamma^{n-1} R_{t+n} + \gamma^n V(s_{t+n}, \boldsymbol{v})$$

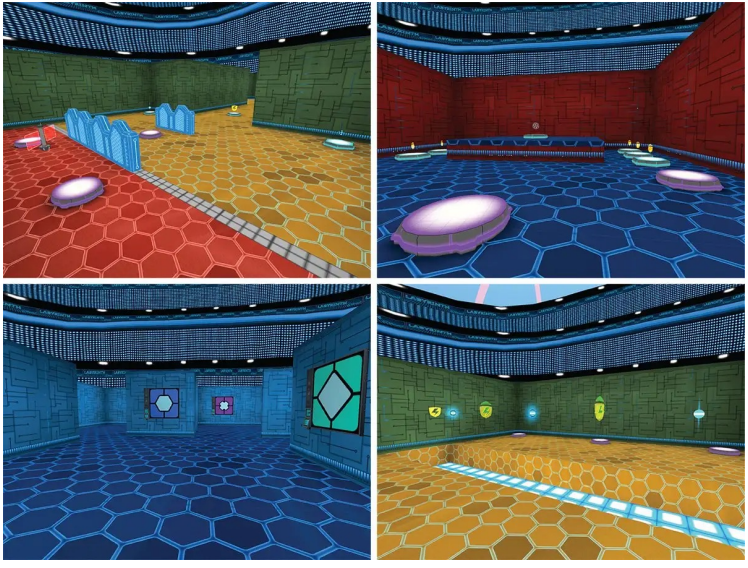
- Actor is updated toward target

$$\frac{\partial J(\phi)}{\partial \phi} = \frac{\partial \log \pi(a_t \mid s_t \phi)}{\partial \phi}(q_t - V(s_t, \phi))$$

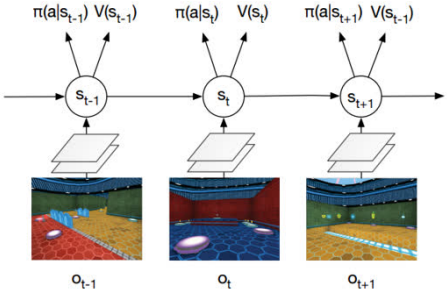
- Critic is updated to minimize MSE w.r.t target

[2]Volodymyr Mnih et al., "Asynchronous methods for deep reinforcement learning," International Conference on Machine Learning, 2016

A3C in Labyrinth



A3C in Labyrinth



- Observations o_t are raw pixels from current frame
- State s_t is a recurrent neural network
- Outputs both $V(s)$ and softmax over actions $\pi(a \mid s)$
- Task is to collect apples and escape
- Demo: https://youtu.be/nMR5mjCFZCw

Model-based deep RL

Model-based vs model-free RL

- In model-based RL we aim at creating a model of the environment and plan based on that model
- Pros:
  - Tends to have higher sample efficiency than model-free RL
  - Transferable to other tasks (more on that later today)
  - Model uncertainty can help to judge how confident we should be in our decision-making
- Cons:
  - Vapnik's principle: "When solving a problem of interest, do not solve a more general problem as an intermediate step"
  - Two sources of errors (model and policy)
  - Computationally more demanding
- Some of the most effective recent approaches combine both

- Usually, we try to learn a model $s_{t+1} = f(s_t, a_t)$
- For Δt small, changes become small and $s_{t+1} = s_t$ may be a good approximation
- Instead: learn $\hat{f}(s_t, a_t, \psi)$ such that $\hat{s}_{t+1} = s_t + \hat{f}(s_t, a_t, \psi)$
- Train dynamics model using stochastic gradient descent on the MSE

- Goal: find action sequence $A_t^H = (a_t, \ldots, a_{t+H})$ such that

$$A_t^H = \arg\max_{A_t^H} \sum_{t'=t}^{t+H} R(\hat{s}_{t'}, a_{t'}) \text{ s.t. } \hat{s}_t = s_t, \hat{s}_{t'+1} = \hat{s}_{t'} + \hat{f}(\hat{s}_{t'}, a_{t'}, \psi)$$

- Exact computation often infeasible but can get approximate solution
- Model predictive control: execute first action in A_t^H, then solve optimization problem again

Hybrid model-based model-free approach[3]

- Model-based approaches often more sample efficient but final performance can be worse than model-free approaches

$\rightarrow$ Initialize model-free learner with model-based learner

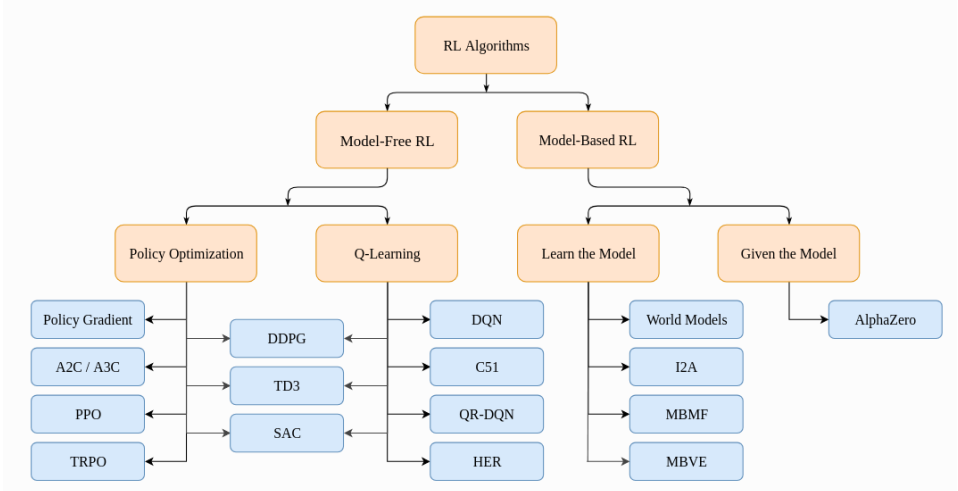
- Demo: https://sites.google.com/view/mbmf

[3] Anusha Nagabandi, Gregory Kahn, Ronald S. Fearing, and Sergey Levine, "Neural network dynamics for model-based deep reinforcement learning with model-free fine tuning," IEEE International Conference on Robotics and Automation, 2018.

Summary of deep RL

Deep reinforcement learning methods

- Last 8-9 years: many new ideas for making deep RL more stable and efficient
- However, still no clear "winner"
- Taxonomy from OpenAI Spinning Up:



A non-exhaustive, but useful taxonomy of algorithms in modern RL. Citations below.

Open challenges and new directions

Open challenges and new directions

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- Deep reinforcement learning (DRL) has seen tremendous successes and breakthroughs in recent years
- However, there are still many open problems
  - DRL often only works for specific tasks (e.g., playing Go)

  $\rightarrow$ Multi-task learning, transfer learning
  - Sample efficiency is a big problem, especially for learning on real systems

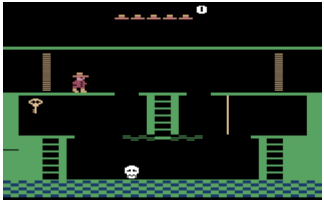
  $\rightarrow$ Meta-learning
  - DRL agents have no deeper understanding of themselves and the world around them

  $\rightarrow$ Causal reinforcement learning

Multi-task and transfer learning

- RL agents have mastered games like Go or StarCraft
- Usually, only able to play one particular game
- Humans can generalize and transfer knowledge about gaming in general obtained from learning, e.g., Go, to other games
- Can we also achieve this for RL?

Recap: Montezuma's revenge



- Why is this game more difficult for DRL agents than for humans?
- We can transfer knowledge from other games, real world experiences
- We know that keys can be used to open doors
- We know that we can use ladders to climb up and down
- We may not know exactly what the skull does but we can guess that it is probably better not to touch it

What can learning agents use to achieve the same?

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- Q-function: which actions and states are good
- Policy: which actions are useful
- Models (in case we use them): what are underlying physical laws
- Features/hidden states: provide us with good representation

Terminology

- **Transfer learning:** using experience from one task or one set of tasks for faster learning and better performance on a new task (task is an MDP)
- **Shot:** how often do we "give it a shot" in the new target domain
- **Forward transfer:** train on one task, transfer to a new task
- **Multi-task transfer:** train on many tasks, transfer to a new task

Forward transfer – overview

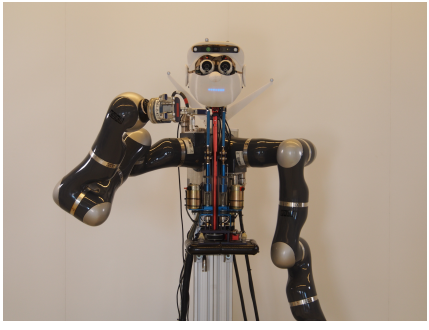
- Why is this challenging?
  - **Domain shift:** What works well in the source domain might not work in the target domain
  - **Different MDPs:** for instance, some actions might only be available in the source domain
- Approaches:
  - We can just train on one task and then hope for the best on the other task
  - We can increase robustness by manipulating the source domain
  - Include some randomness in the environment we use for training
  - Artificially make the source environment more challenging

Forward transfer – example

- In robotics, training on real hardware is time consuming and can damage the hardware

$\rightarrow$ Train agents in simulation and then directly evaluate on hardware

- **But:** simulation and real world are not the same
- Include noise in simulation environment to make it more challenging
- Example: learn resource-aware control policy for robot Apollo

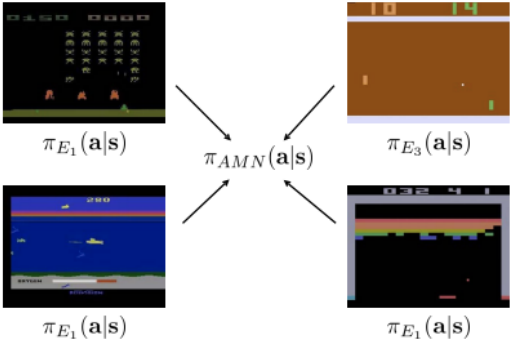


Forward transfer – example

Videos available at
https://sites.google.com/view/learn-event-triggered-control, taken from: Niklas Funk, Dominik Baumann, Vincent Berenz, and Sebastian Trimpe, "Learning event-triggered control from data through joint optimization," IFAC Journal of Systems and Control, 2021.

- We often use model-based reinforcement learning in this setting
- Try to build a model from experience in one set of tasks and adapt the model to the new task
- What is challenging about this?
  - **Gradient interference:** improving in one domain might decrease performance in other domain
  - **Winner-take-all problem:** if we start to be good in one task algorithm might prioritize that one at expense of others
- Approaches:
  - **Distillation:** combine multiple policies into one
  - **Contextual policies:** policies that are told what to do
  - **Modular neural networks** for different tasks

Multi-task transfer – distillation[4]

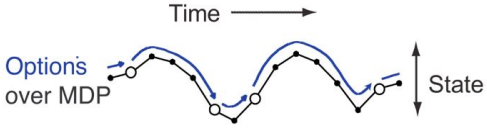


- **Ensemble models:** learn models for different tasks and average their predictions
- **Distillation:** train on the outputs of the ensemble's predictions
- Agent achieved expert-level performance in many Atari games simultaneously

[4] Emilio Parisotto, Jimmy Ba, and Ruslan Salakhutdinov, "Actor-mimic deep multitask and transfer reinforcement learning," arXiv, 2015.

Multi-task transfer – contextual policies

- Recap: contextual bandits from the last lecture
- Bandits whose reward probability depends on a context variable
- Similarly, introduce context for MDP
- Policy $\pi(a \mid s)$ becomes $\pi(a \mid s, c)$ with context parameter c
- Contexts can then represent different tasks

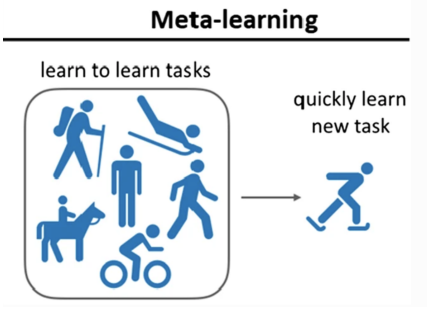


- Learning at different time scales, example: options framework:
  - At each time step, a policy over options determines in which option we are (e.g., which task)
  - For every option, we have an intra-option policy that decides on the action given the current state
  - Can efficiently combine discrete variables (different tasks/contexts) and continuous variables (actions)
- Early reference: Doina Precup, "Temporal abstraction in reinforcement learning," University of Massachusetts Amherst, 2000.

- Assume the dynamics $p(s_{t+1} \mid s_t, a_t)$ are the same in source and target domain but reward function is different
- Examples:
  - Autonomous car learns to drive in one city and then needs to drive in a new one
  - Robot learned various recipes and now needs to cook a new one
- What should we transfer?
  - **Model:** should be independent of reward, so simple to transfer
  - **Value function:** depends on dynamics and reward, so less straightforward
  - **Policy:** possible with contextual policies but otherwise tricky, policy contains *least* dynamics information

Meta learning

Core idea

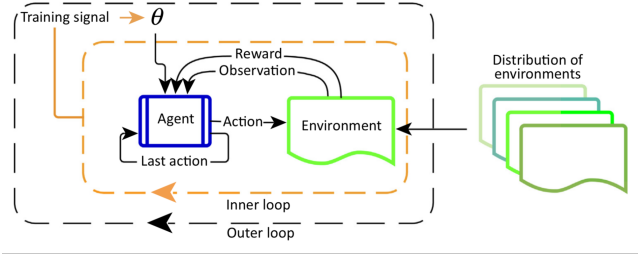


- Learning how to learn

→ End up with an RL agent that can learn more efficiently (fewer samples)

  - Smarter and more efficient exploration
  - Avoid actions we already learned are useless

Meta reinforcement learning problem setting



- Problem setting in regular RL: learn policy for a task $\pi^* = \arg\max_\pi \mathbb{E}_\pi[G_t]$
- Problem setting in meta RL: learn adaptation rule $\pi^* = \arg\max_\pi \sum_{i=1}^{n} \mathbb{E}_{\pi_i}[G_t]$ where i represents the MDP of task i
- Training and testing tasks are different, but from the same family of problems
- For instance, mazes with different layouts, running at different speeds, ...

How and what can we meta learn?

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- Key components:
  - **Model with memory:** e.g., recurrent neural network
  - **Meta learning algorithm:** how to update the weights, often ordinary gradient descent updates
  - **A proper distributions of MDPs** to learn from
- What can we meta learn?
  - Hyperparameters (e.g., the discount factor)
  - The loss function
  - The exploration strategy

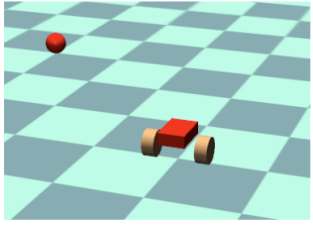
Meta-learning the exploration strategy[5]

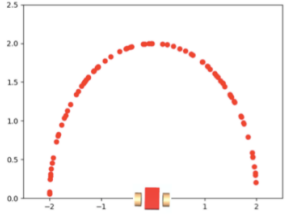
- Trading off exploration and exploitation in RL is difficult (see last lecture)
- Learn structured action noise from prior experience
- Policy $\pi(a \mid s, z_i)$, where $z_i \sim \mathcal{N}(\mu_i, \sigma_i)$

$\rightarrow$ Noise makes sure we explore new actions but we choose its distribution based on the current MDP

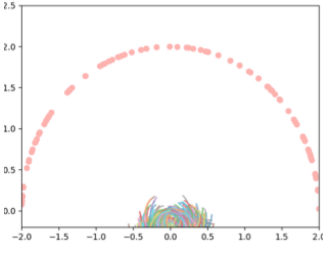
$\rightarrow$ How much should we explore in which task?

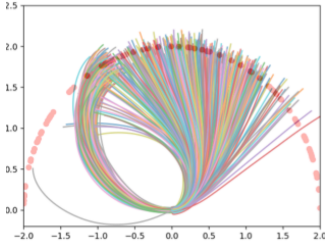
[5] Abhishek Gupta, Russell Mendonca, YuXuan Liu, Pieter Abbeel, and Sergey Levine, "Meta-reinforcement learning of structured exploration strategies," Advances in Neural Information Processing Systems, 2018





- Wheeled robot should learn to reach different goal states
- Comparison: random exploration vs structured action noise





Causal reinforcement learning

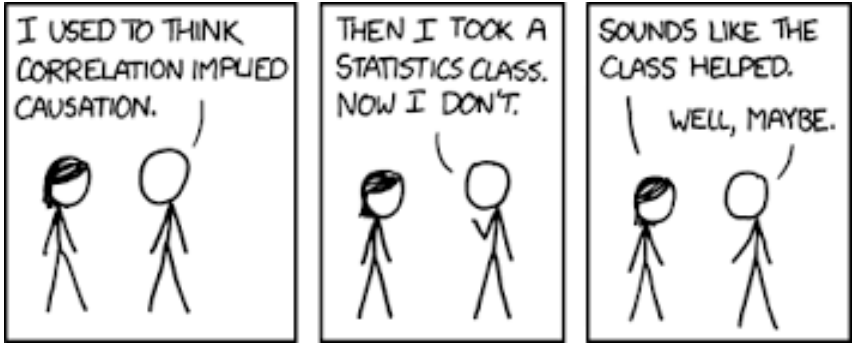
- From general statistics: correlation is not causation[6]
- However, if we had a causal model of the world, it would allow us to ask counterfactual questions and use them to reason about future actions
- What would have happened if I had chosen a certain action?

[6] John Aldrich, "Correlations genuine and spurious in Pearson and Yule," Statistical Science, 1995.

Story of King Midas

- King Midas was offered one free wish by the God Dionysos
- He chose that everything he touches would turn to gold
- That way he turned his whole family into gold
- In the end he died of starvation

$\rightarrow$ If we don't understand the consequences of our actions, we may maximize a short-term reward but deteriorate the long-term reward



- Causality in machine learning has been investigated for some time by a small community but is now gaining more and more interest
- Generally a hard problem, especially in MDPs
- Recently some research on causal reinforcement learning started
- Next slides: six tasks of causal reinforcement learning

Six tasks of causal reinforcement learning – Part I

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1. Generalized policy learning (combining online and offline learning)
   - Generally, for causal inference, we want to perform interventions
   - Often, cannot learn fully online (ethical constraints, expensive)

   $\rightarrow$ Try to get causal knowledge from offline data and leverage for necessary online learning
2. When and where to intervene? (Refine policy space)
   - When do we need interventions, when are there unintended side effects?
   - What should we change?

   $\rightarrow$ More informed and efficient exploration
3. Counterfactual decision-making (changing optimization function based on intentionality, free will, and autonomy)
   - Typically, agents act in a reflexive way without considering the causes for behaving in a particular way

   $\rightarrow$ Make agents aware of their intent through counterfactual reasoning

Example for bad policy learning

- Simple boat racing game: come out first and collect items on the way
- Agent found a sweet spot with many items that respawn
- Gets stuck there and never finishes the race

→ Not aware of its intent, no counterfactual reasoning

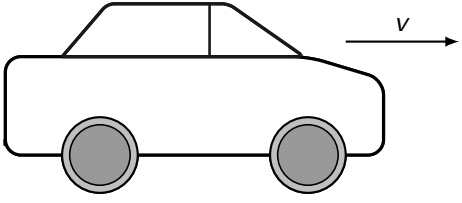
5. Generalizability & robustness of causal claims
   - Knowledge acquired is usually tied to specific environment

   $\rightarrow$ Allow agents to extrapolate
6. Learning causal model by combining observations and experiments
   - Construct fixed causal model from background data, offline information, etc.
   - Systematically combine observations and interventions to construct equivalence class of causal models

   $\rightarrow$ Increase efficiency
7. Causal imitation learning
   - Imitation learning often easier than pure RL
   - If learner and demonstrator have different causal models can have disastrous side effects

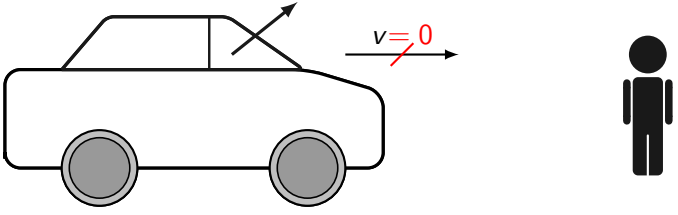
   $\rightarrow$ Understand conditions under which imitation learning is a good idea

A learning agent learns how to drive via imitation learning[7]



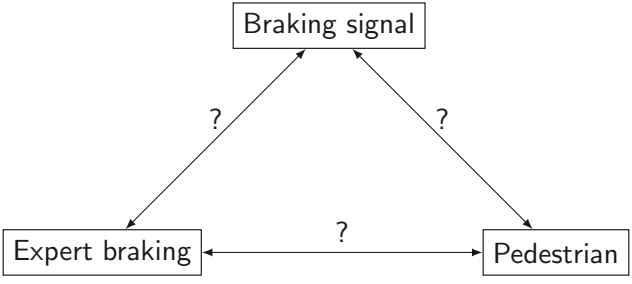
[7] Example from: Pim de Haan, and Dinesh Jayaraman, and Sergey Levine, "Causal confusion in imitation learning," Advances in Neural Information Processing Systems, 2019.

A learning agent learns how to drive via imitation learning[8]



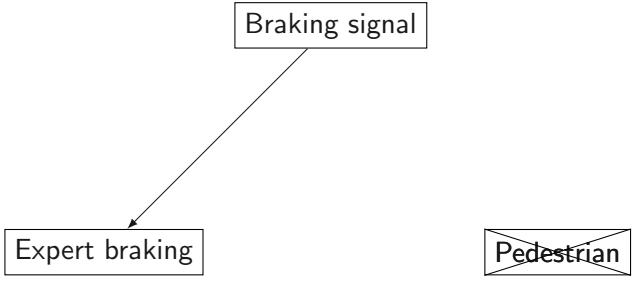
[8]Example from: Pim de Haan, and Dinesh Jayaraman, and Sergey Levine, "Causal confusion in imitation learning," Advances in Neural Information Processing Systems, 2019.

A learning agent learns how to drive via imitation learning[9]



[9]Example from: Pim de Haan, and Dinesh Jayaraman, and Sergey Levine, "Causal confusion in imitation learning," Advances in Neural Information Processing Systems, 2019.

A learning agent learns how to drive via imitation learning[10]



[10]Example from: Pim de Haan, and Dinesh Jayaraman, and Sergey Levine, "Causal confusion in imitation learning," Advances in Neural Information Processing Systems, 2019.

In summary

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- Deep RL has made amazing advancements during the last decade.
- But environments in literature are often "The hardest problem in the set of all simple problems"
- Algorithms are still not as stable and reliable as in supervised learning
- A lot of tricks for improving performance, still not completely clear which tricks are most important

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