Brain Inspired Artificial Intelligence 1: Introduction to Reinforcement Learning

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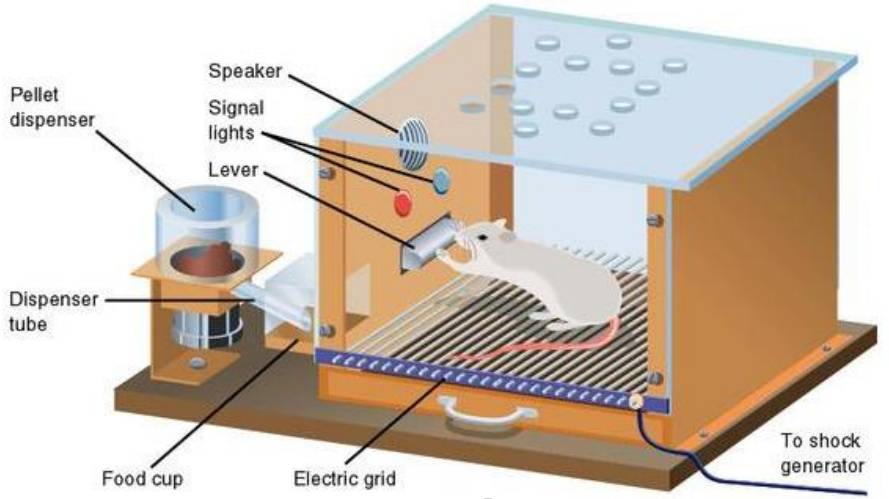
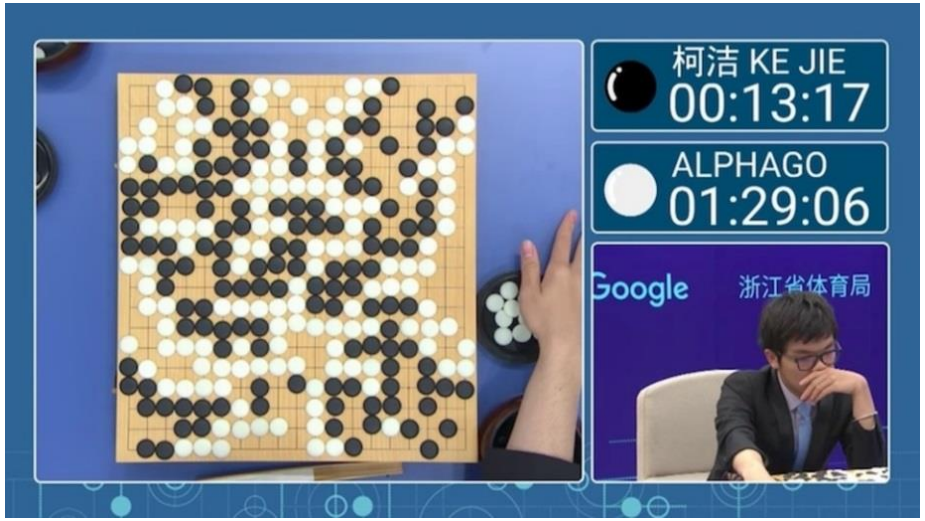
What is Reinforcement Learning (RL)?

- RL is a computational framework to find an optimal policy (controller) by trial and error
- Inspired from psychology
  - Thorndike's law of effect
  - Skinner's principle of reinforcement
- The most famous application is AlphaGo that has defeated top Go masters from across the world
- Learn behaviors from rewards designed by each trainer



[Simply Psychology]



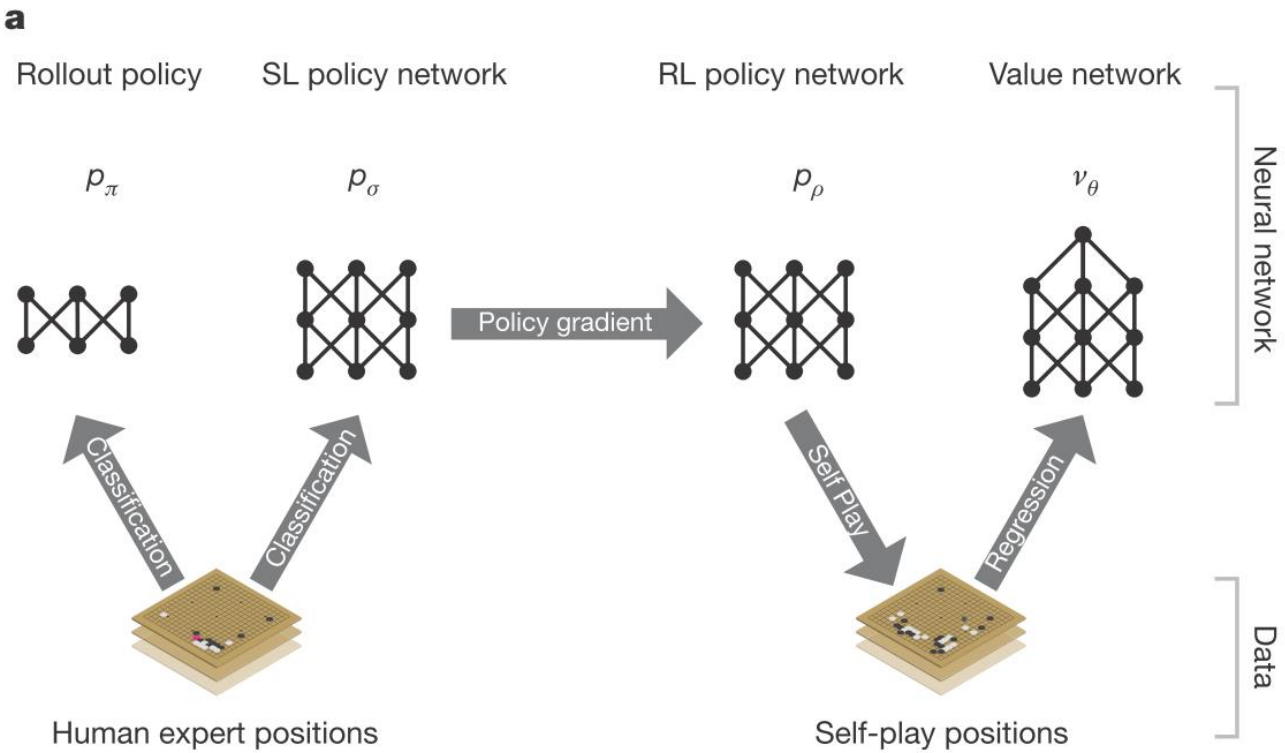
[gizmodo.jp]

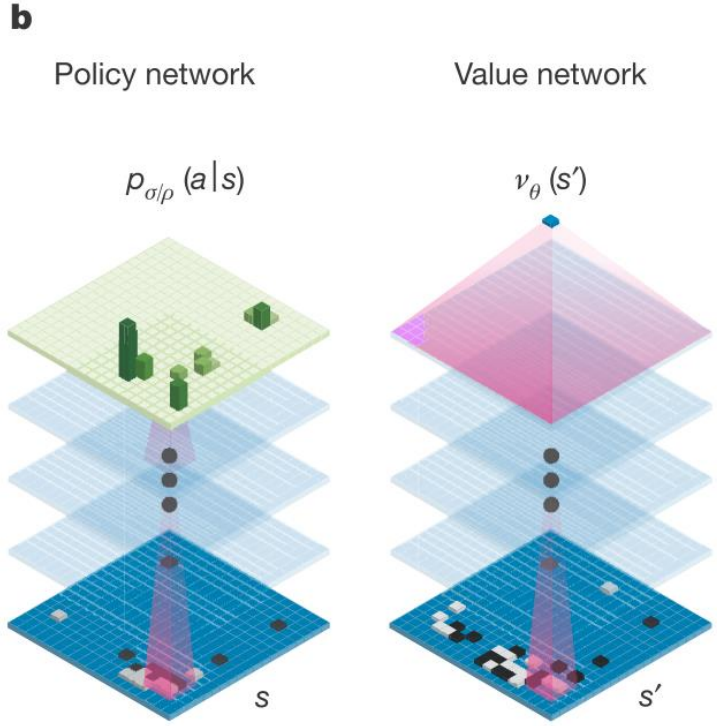
AlphaGo (Go)

- Combination of
  - imitation learning
  - policy gradient reinforcement learning
  - value based learning

Go ratings

Rank	Name	♂♀	Flag	Elo
1	Ke Jie	♂		3615
2	Google AlphaGo			3585
3	Park Jungwhan	♂		3569
4	Iyama Yuta	♂		3532
5	Lee Sedol	♂		3519

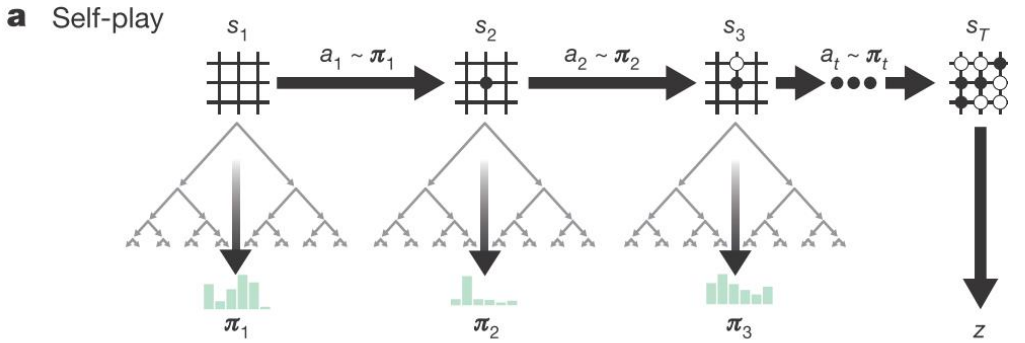


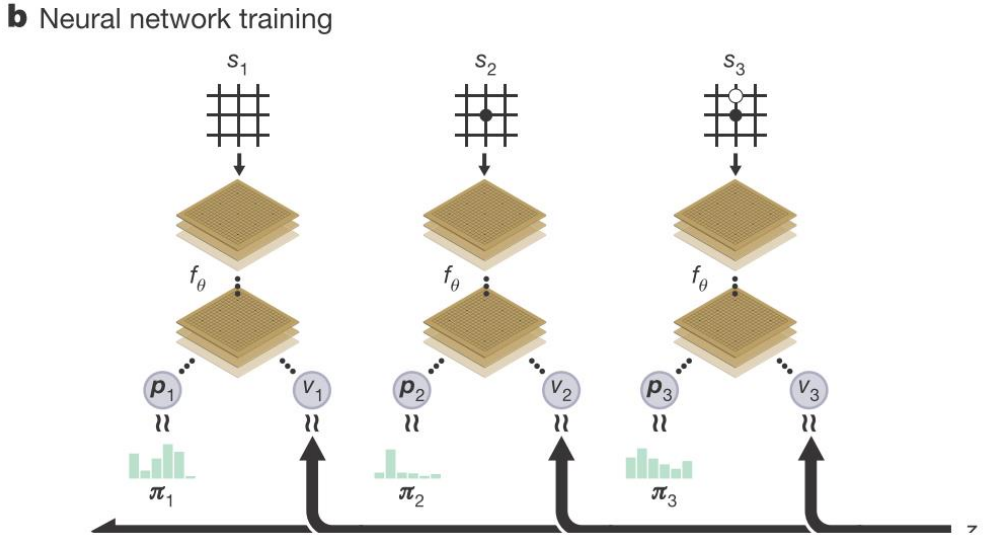


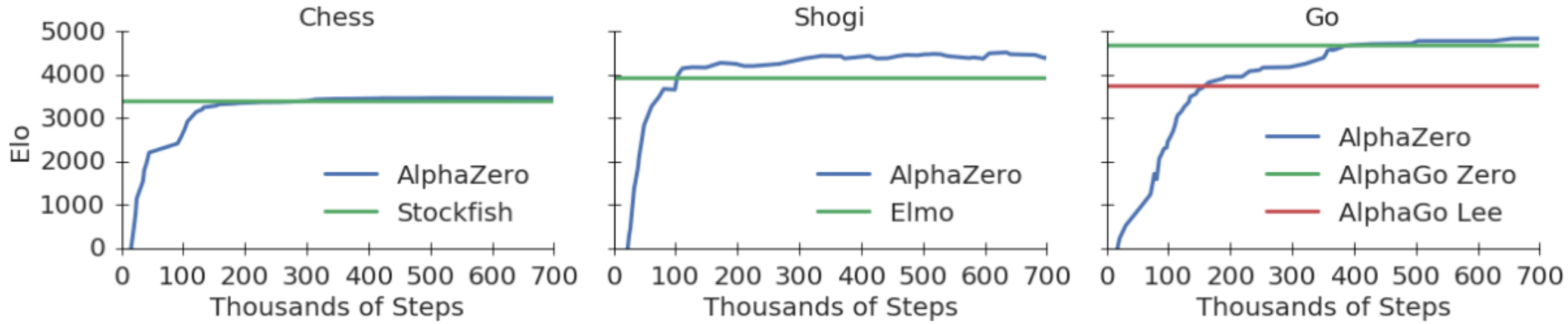
[Silver et al., 2016]

Extension of AlphaGo

- AlphaGo Zero
  [Silver et al., 2017a]
  - self-play, without human play data
  - integrate policy and value network
- Alpha Zero [Silver et al., 2017b]
  - chess, shogi, and go

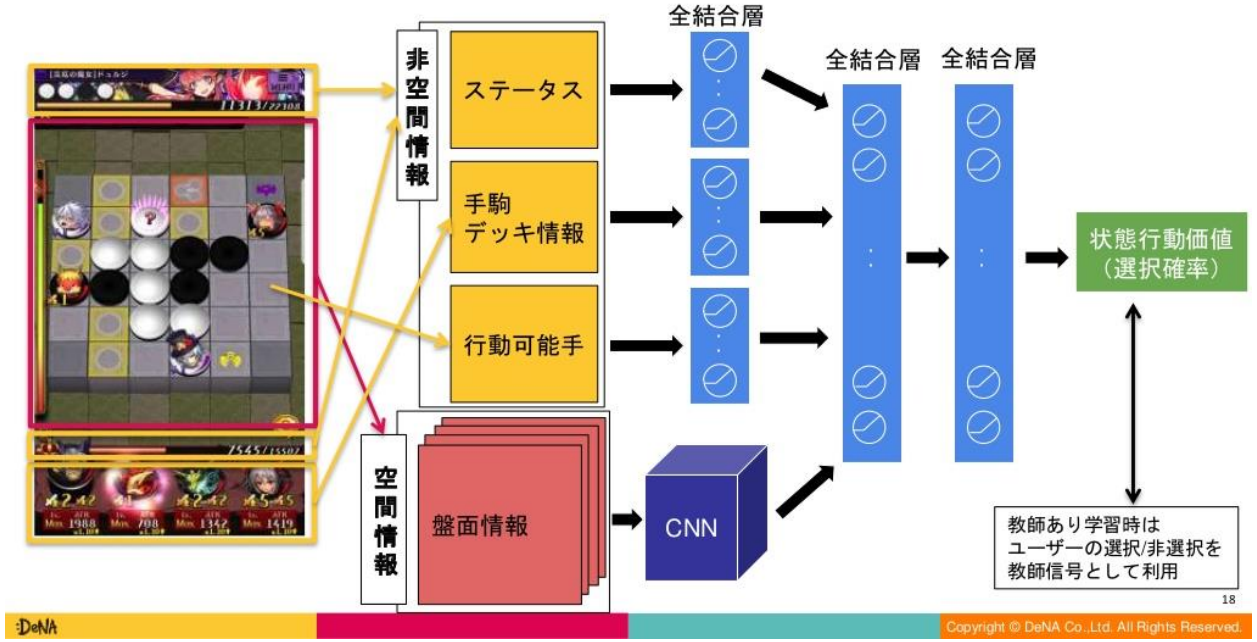


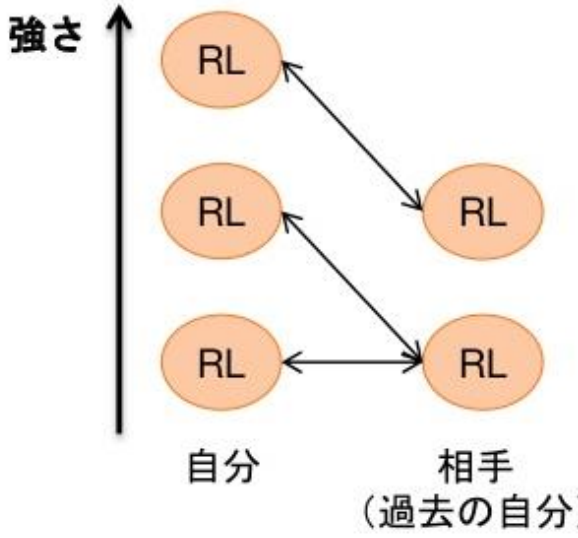




Playing a video game

- RL is applied to a Othello-like game (逆転オセロニア)
- Supervised learning
  - NN architecture is similar to that of DQN
  - use top players data
- Reinforcement learning
  - self-play





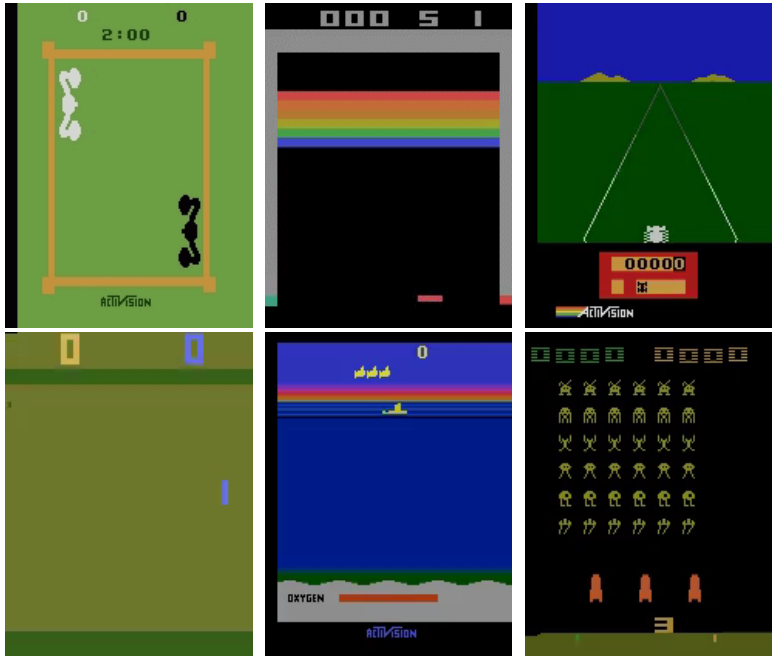
https://youtu.be/p-iCmOo3gUo

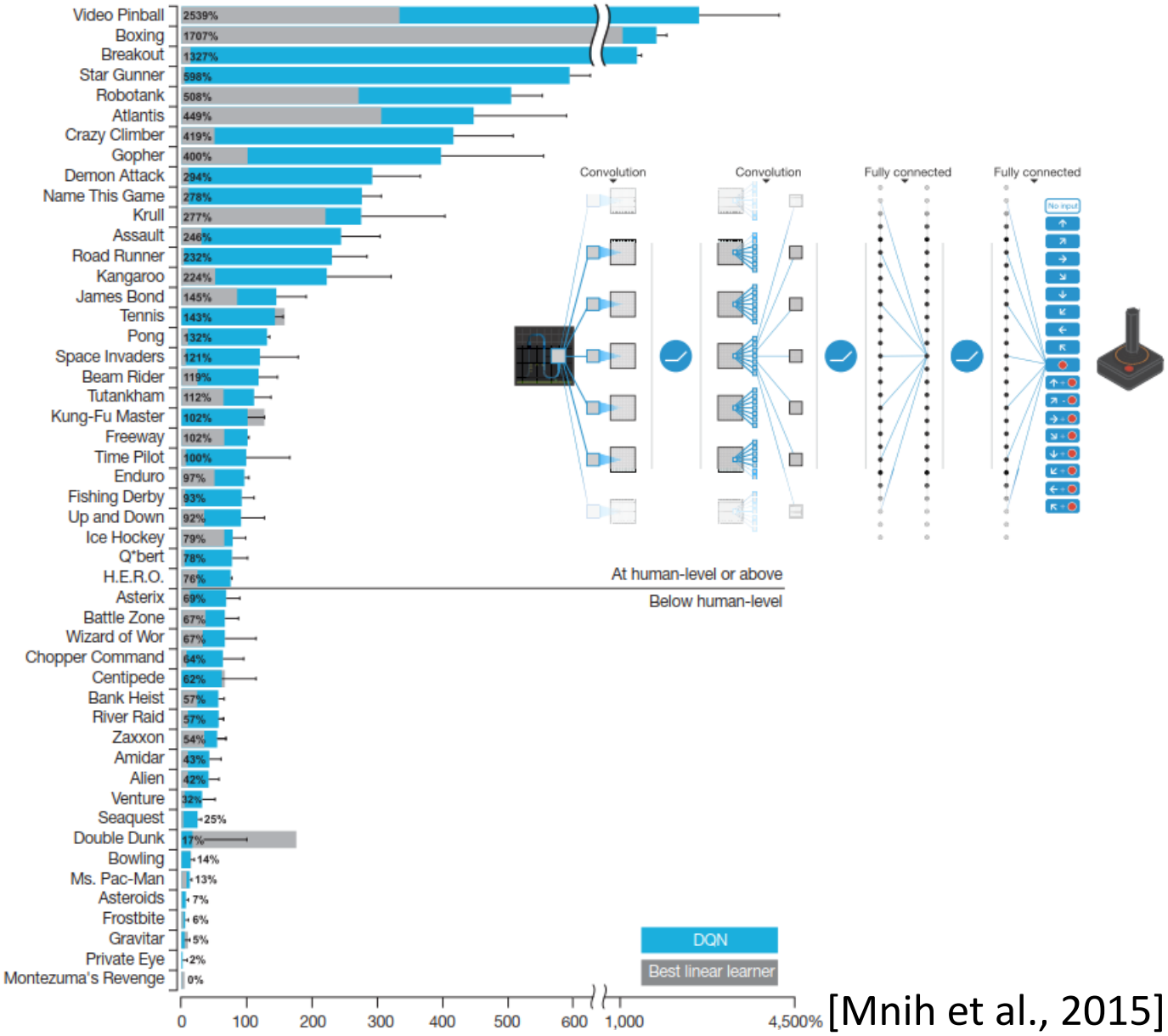
https://fullswing.dena.com/othellonia-ai/

https://www.slideshare.net/juneokumura/ss-82644332

Deep Q Net (Play Video Games)

- Rules of the game are unknowr
- Integrate RL with deep learning
- Learn directly from a sequence of game screens





[Mnih et al., 2015]

Helicopter Control

- Leverage expert demonstrations to efficiently learn good controllers for tasks being demonstrated by an expert

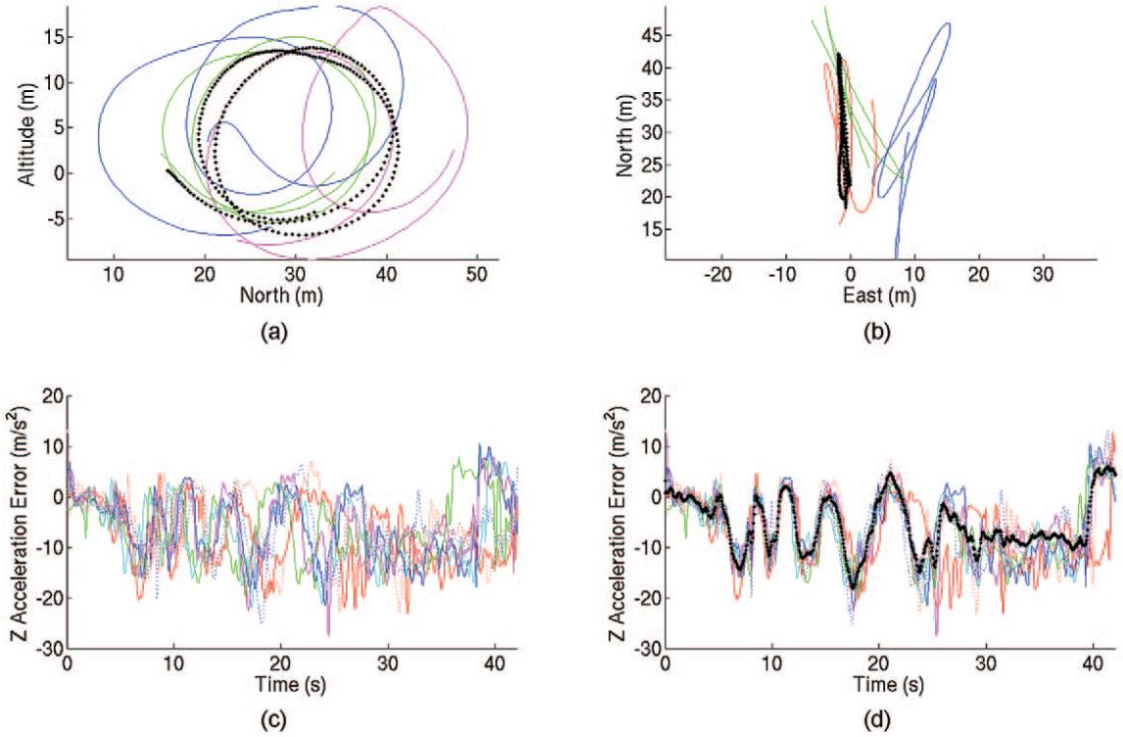
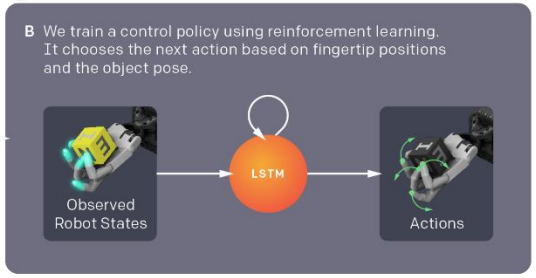


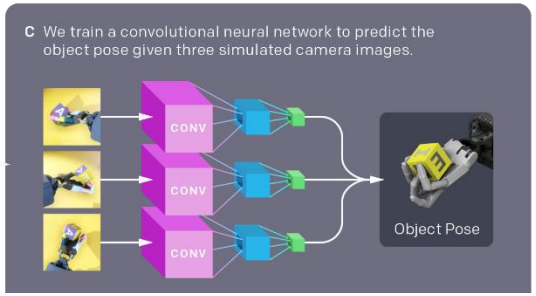
Fig. 6. Colored lines: demonstrations. Black dotted line: trajectory inferred by our algorithm. (See the text for details.)

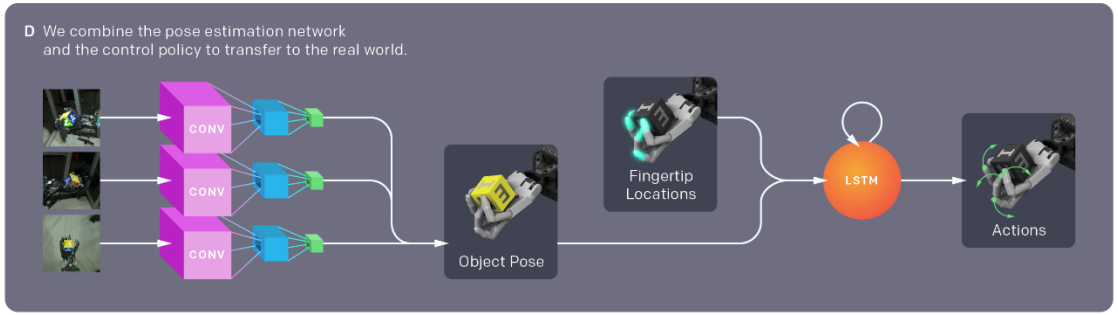
[Abbeel et al., 2010]

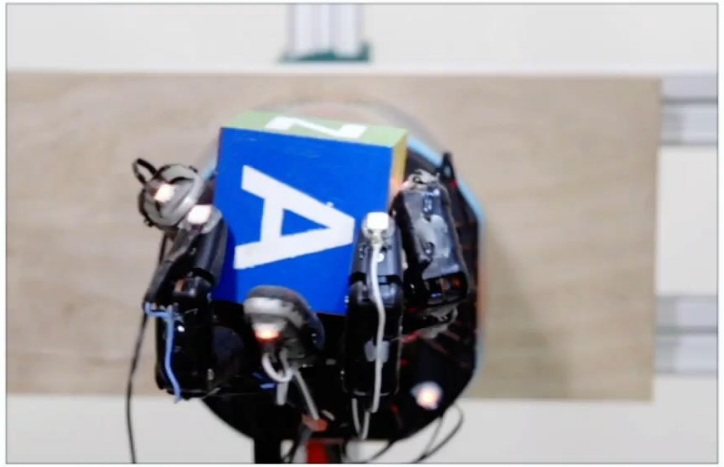
In-hand manipulation

[Andrychowicz et al., 2018]

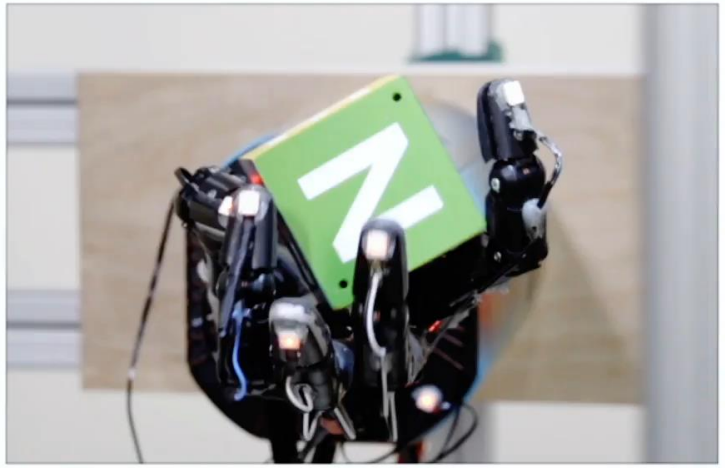




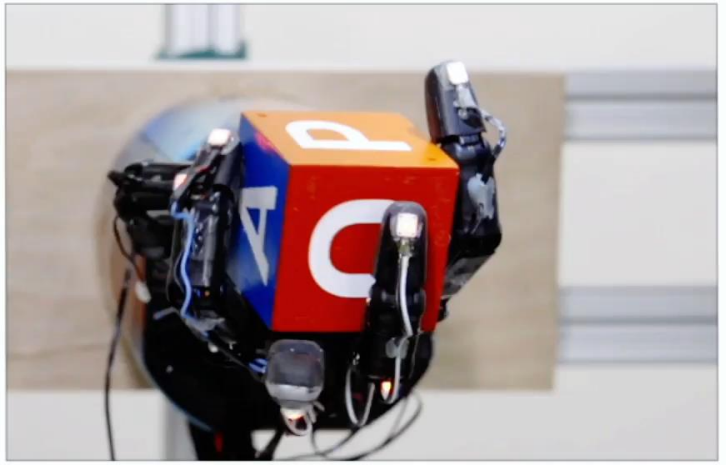




FINGER PIVOTING

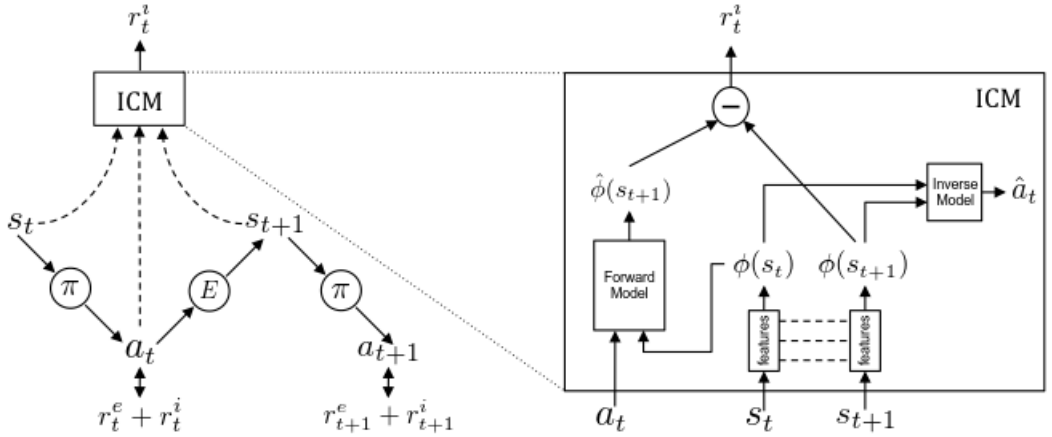


SLIDING



FINGER GAITING

Curiosity-Driven Reinforcement Learning



Curiosity Driven Exploration by Self-Supervised Prediction

ICML 2017

Deepak Pathak, Pulkit Agrawal, Alexei Efros, Trevor Darrell
UC Berkeley

Level Ids	Level-1	Level-2				Level-3			
Accuracy Iterations	Scratch 1.5M	Run as is 0	Fine-tuned 1.5M	Scratch 1.5M	Scratch 3.5M	Run as is 0	Fine-tuned 1.5M	Scratch 1.5M	Scratch 5.0M
Mean $\pm$ stderr	711 ± 59.3	31.9 ± 4.2	466 ± 37.9	399.7 ± 22.5	455.5 ± 33.4	319.3 ± 9.7	97.5 ± 17.4	11.8 ± 3.3	42.2 ± 6.4
% distance $>$ 200	50.0 ± 0.0	0	64.2 ± 5.6	88.2 ± 3.3	69.6 ± 5.7	50.0 ± 0.0	1.5 ± 1.4	0	0
% distance $>$ 400	35.0 ± 4.1	0	63.6 ± 6.6	33.2 ± 7.1	51.9 ± 5.7	8.4 ± 2.8	0	0	0
% distance $>$ 600	35.8 ± 4.5	0	42.6 ± 6.1	14.9 ± 4.4	28.1 ± 5.4	0	0	0	0

[Pathak et al., 2017]

Tax Collections Optimizers

- Optimally managing the tax collection processes at financial institutions
- Use actually in New York State Department of Taxation and Finance

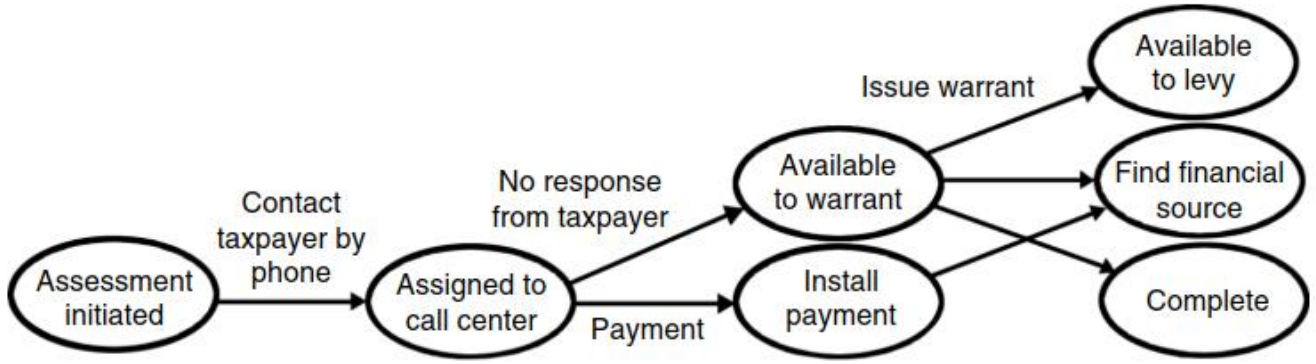
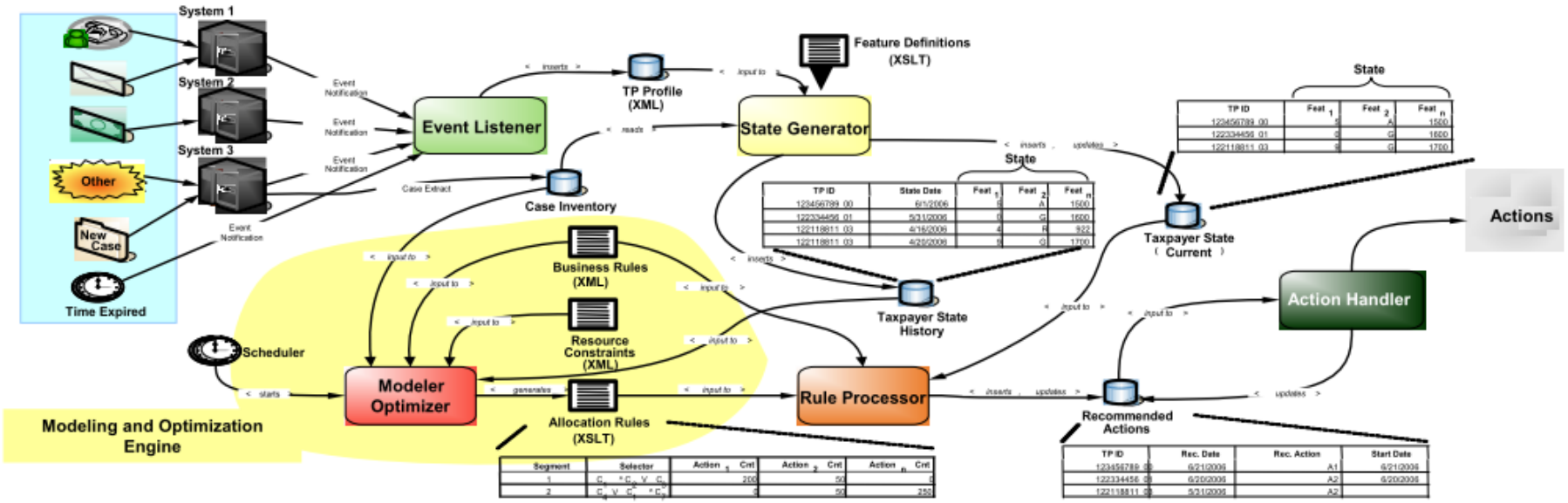


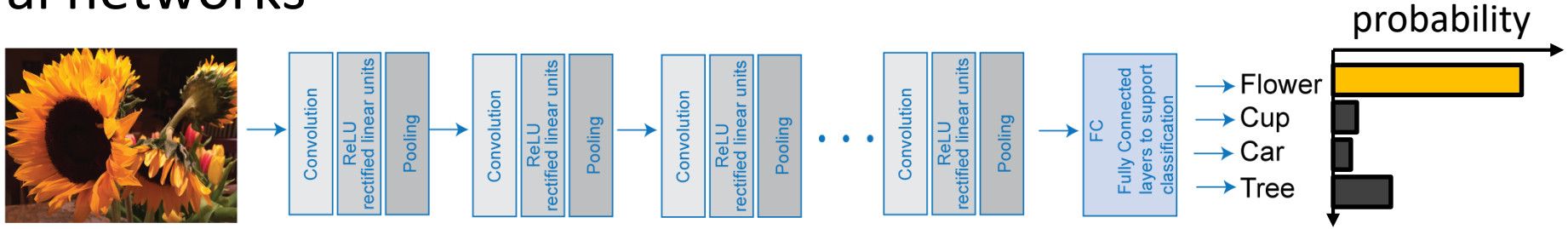
Figure 1: The graphic illustrates an MDP formulation of the collections process.



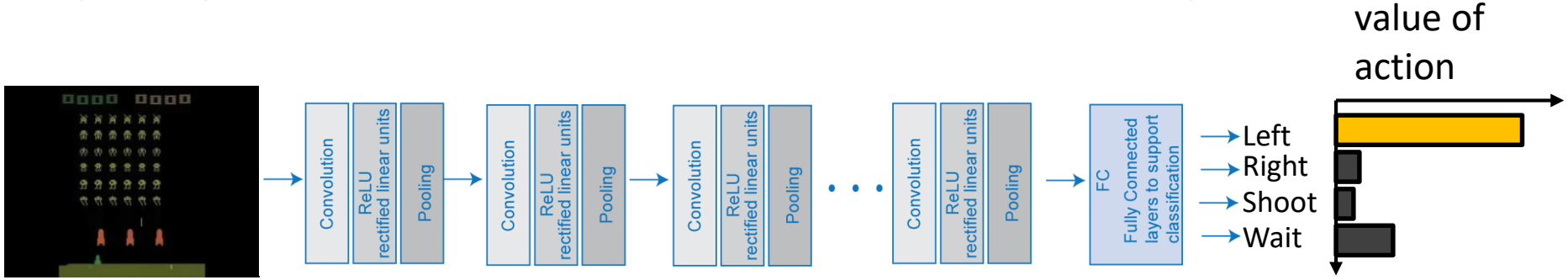
[Abe et al., 2010; Miller et al., 2012]

Difference between Deep Learning and (Deep) Reinforcement Learning

- Deep Learning for Classification
  Take input data and predict a category for that data by using multilayer neural networks



- Deep Reinforcement Learning
  Find a policy that maximizes the sum of rewards by trial and error

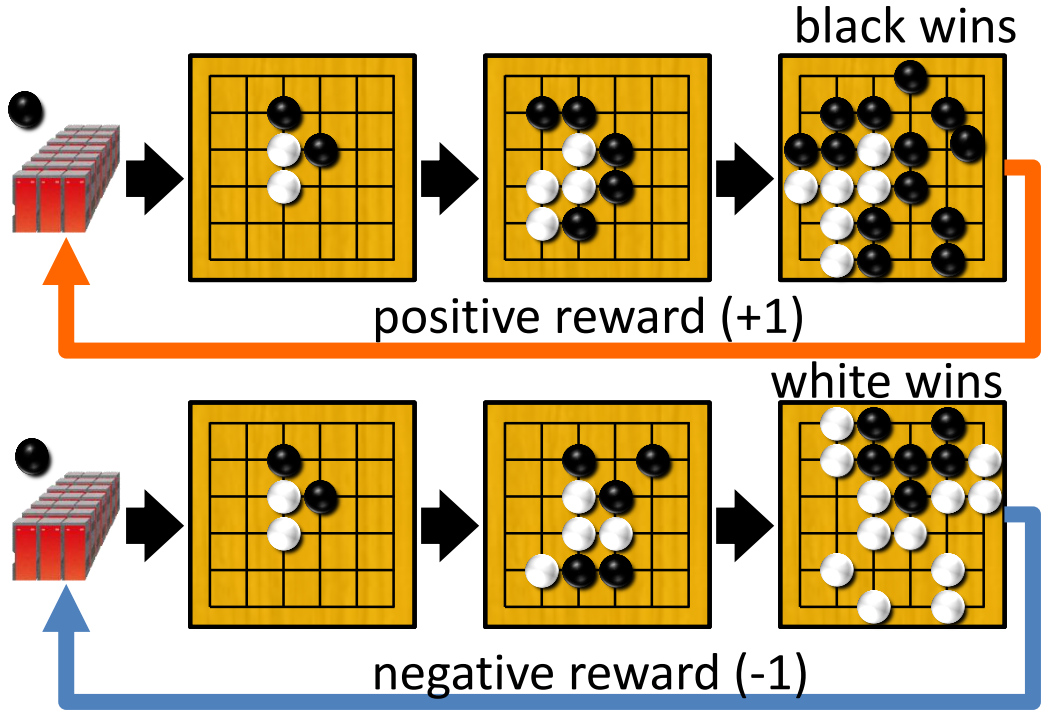


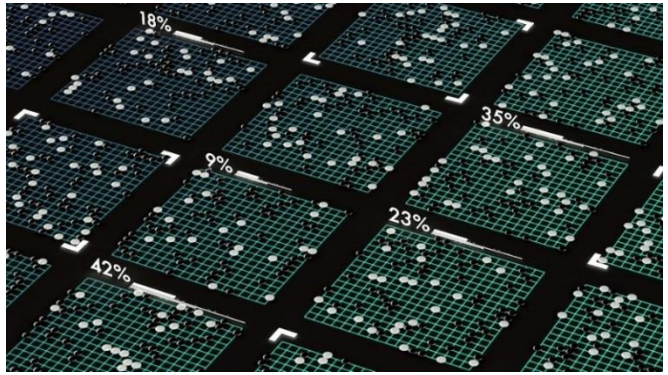
What is Reward?

- In the case of Go
  - positive reward for winning
  - negative reward for losing
  - zero otherwise

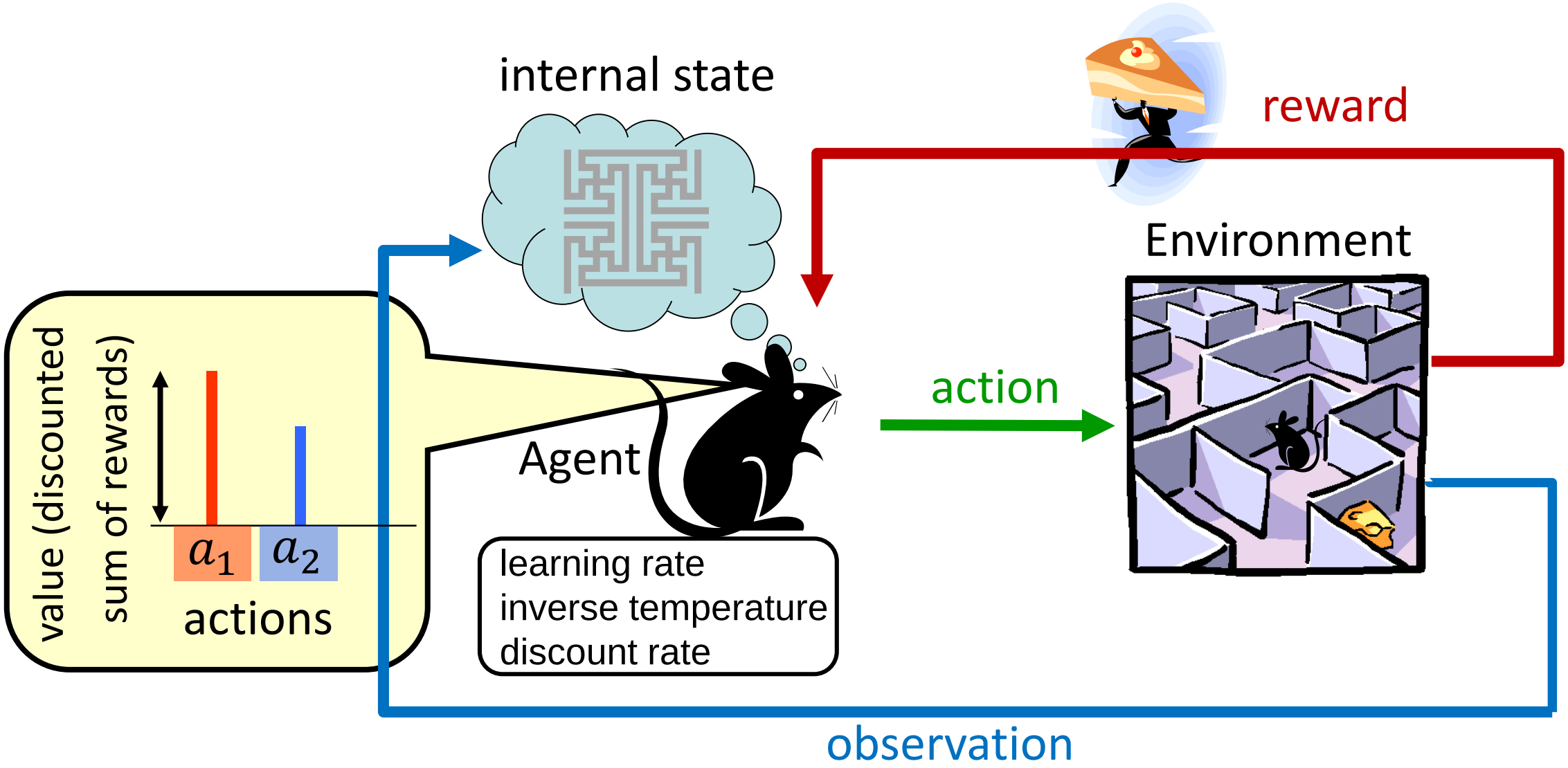
  ➡ very sparse reward
- AlphaGo Zero, which does not use a record of a game of go, needs **4.9 million** games of self-play

  ⬇
- Deep RL is applicable when we can collect samples by using multiple simulators



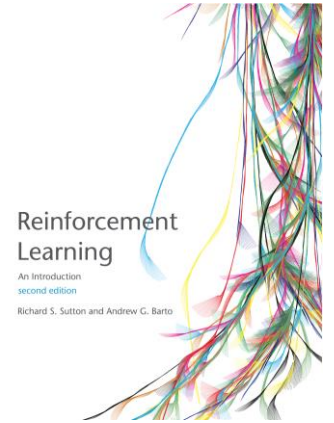


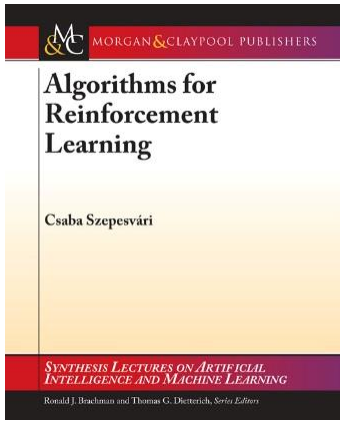
Interaction between Agent and Environment



Textbooks

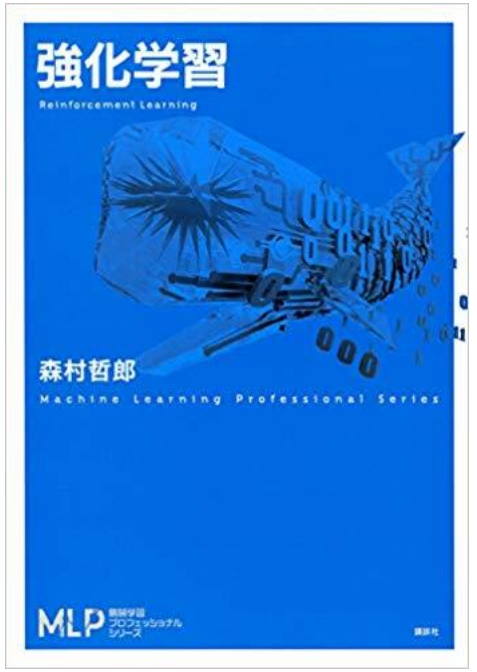
- Sutton, R.S. and Barto, A.G. Reinforcement learning: An introduction. MIT Press
  - First edition (1998), Japanese translation (2000), and Second edition (2018).
  - Must-read for researchers
- Szepesvári, C. (2010). Algorithms for reinforcement learning. Morgan & Claypool.
  - Japanese translation (2017)
  - More compact than Sutton and Barto (1998)





Textbooks

- 牧野貴樹、澁谷長史(編) (2016)
  これからの強化学習. 森北出版
  - Overview of modern reinforcement learning such as policy search methods, deep RL, and inverse RL
- 森村哲郎 (2019). 機械学習
  プロフェッショナルシリーズ 強化学習
  - Theoretical introduction to reinforcement learning with discrete states and actions



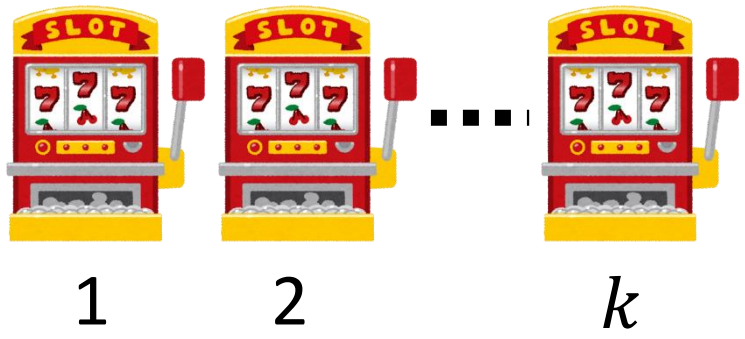
Textbooks

- 久保隆宏 (2019)
  Pythonで学ぶ強化学習 [改訂第2版]
  入門から実践まで . 講談社
  - For practitioners (samples codes)
  - Including inverse reinforcement learning
- 片平 健太郎 (2018).行動データの計算論モデリング: 強化学習モデルを例としてオーム社
  - Computational modeling of behavioral data based on reinforcement learning

Reinforcement Learning for Bandit Problems

Multi-Armed Bandit Problem

- There exist k gambling machines
- Each machine $a \in [1, k]$ has a different unknown probability distribution $p(r \mid a)$ for rewards
  - Action: select a gambling machine
- The goal is to maximize rewards obtained by successively playing gamble machines (the 'arms' of the bandits)



Example: Web Site Optimization

- Former President Obama raised $60 million dollar for the United States presidential election of 2008
- His team experimented with 2 pairs of the sign up form
  - 4 button variations
  - 6 media variations
- They tested 4x6=24 forms

https://www.mailmunch.co/blog/ab-testing-got-obama-60-million/

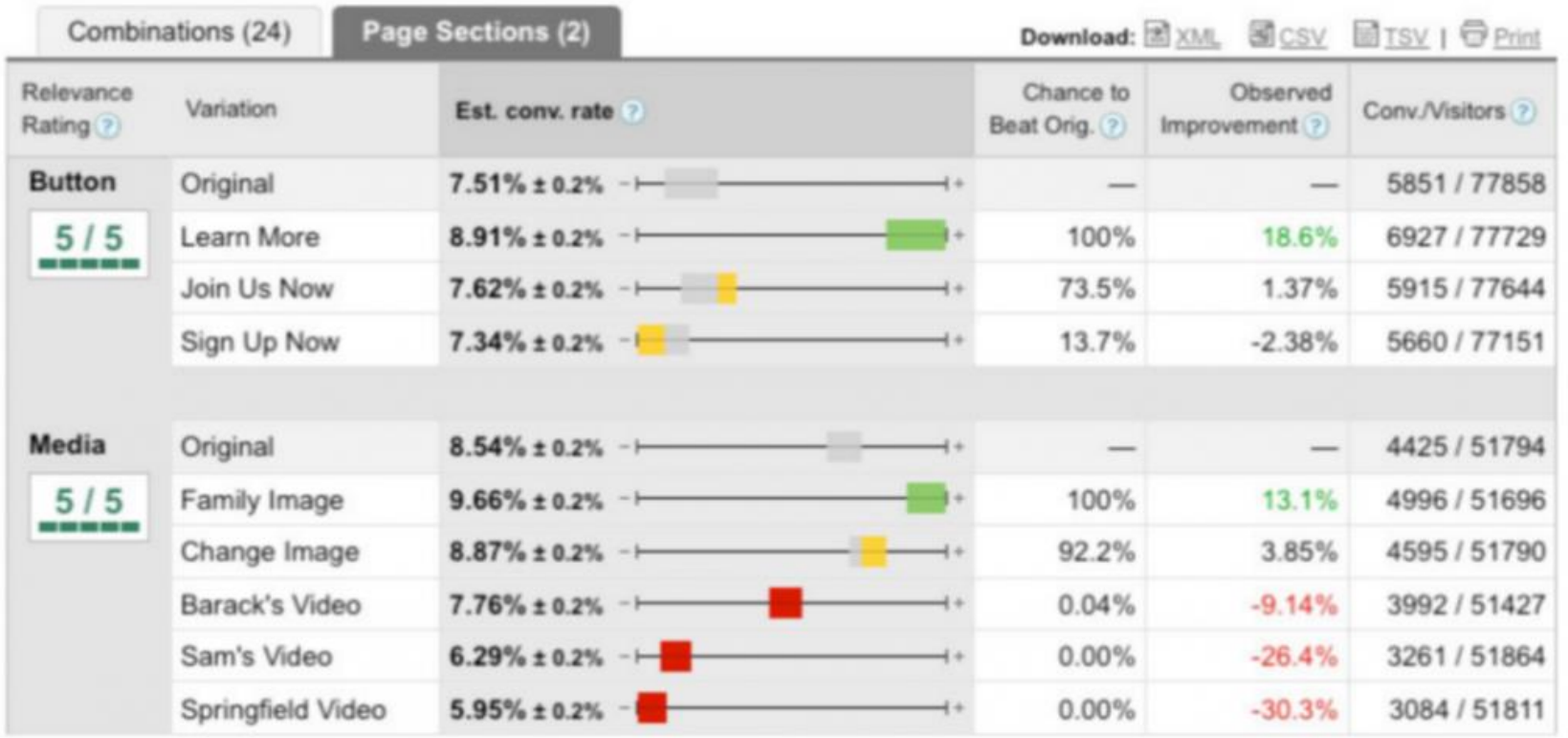
Example: Web site optimization

- 4 button varia
- 6 media varia

https://www.mailmunch.co/blog/ab-testing-got-obama-60-million/

Example: Web site optimization

- The winning variation had a sign-up rate of 11.6% as compared to the original page which had 8.26%
- This test is a special case of bandit problems



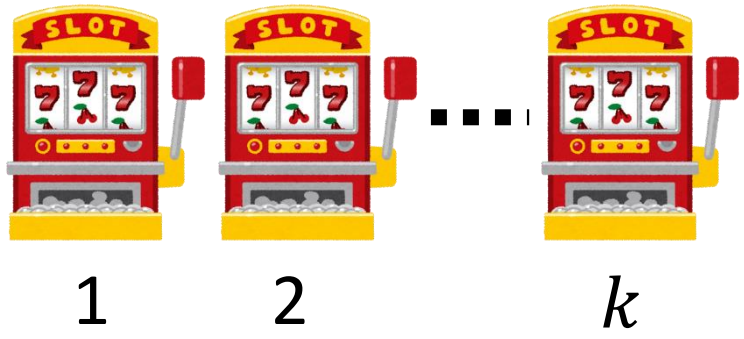
Combinations (24) | Page Sections (2) | Download: XML CSV TSV | Print

Relevance Rating	Variation	Est. conv. rate	Chance to Beat Orig.	Observed Improvement	Conv./Visitors
Button	Original	7.51% ± 0.2%	—	—	5851 / 77858
5 / 5	Learn More	8.91% ± 0.2%	100%	18.6%	6927 / 77729
	Join Us Now	7.62% ± 0.2%	73.5%	1.37%	5915 / 77644
	Sign Up Now	7.34% ± 0.2%	13.7%	-2.38%	5660 / 77151
Media	Original	8.54% ± 0.2%	—	—	4425 / 51794
5 / 5	Family Image	9.66% ± 0.2%	100%	13.1%	4996 / 51696
	Change Image	8.87% ± 0.2%	92.2%	3.85%	4595 / 51790
	Barack's Video	7.76% ± 0.2%	0.04%	-9.14%	3992 / 51427
	Sam's Video	6.29% ± 0.2%	0.00%	-26.4%	3261 / 51864
	Springfield Video	5.95% ± 0.2%	0.00%	-30.3%	3084 / 51811

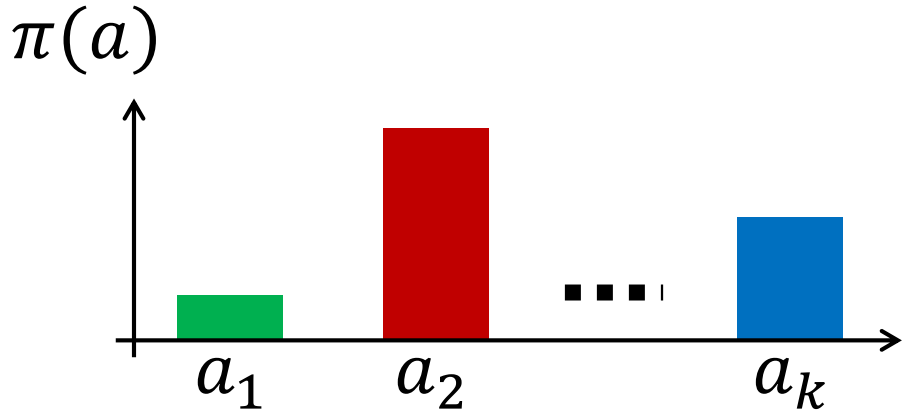
https://www.mailmunch.co/blog/ab-testing-got-obama-60-million/

Components: Action and Policy

- Action
  - Choosing one gambling machine in the bandit problems
    ➡ Discrete action
  - If there exist k machines, it is convenient to define a set of actions by $\mathcal{A} = \{1,2,\dots,k\}$
  - We usually assume discrete actions for simplicity



- Policy (learned by the agent)
  - $\pi(a)$: probability to select an action a
  - $\pi(a) \geq 0, \forall a \in \mathcal{A}$
  - $\sum_{a \in \mathcal{A}} \pi(a) = 1$ ➡ $k-1$ free parameters

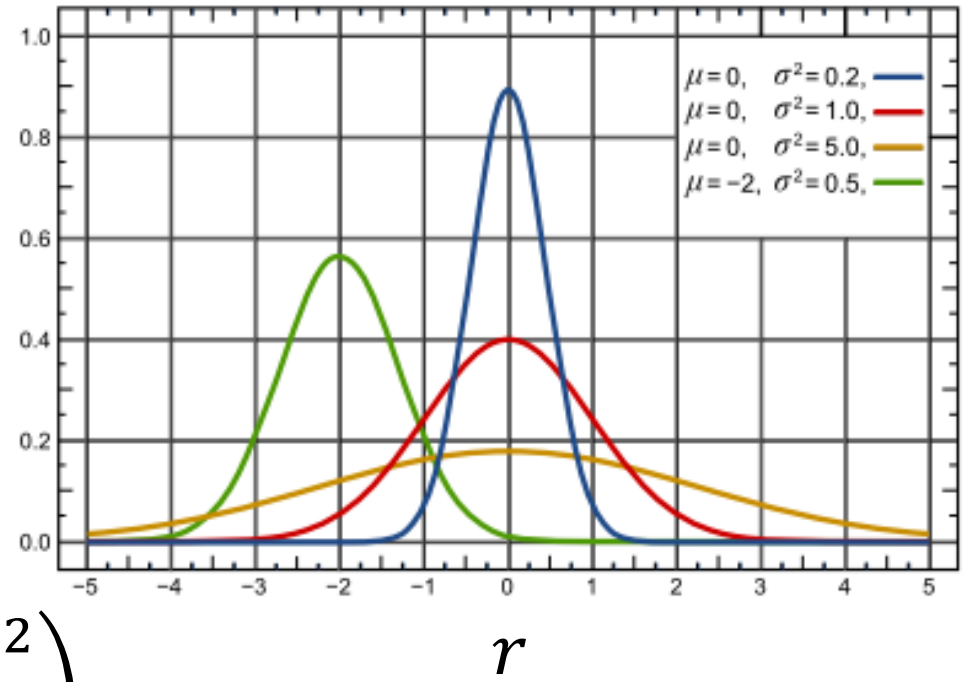


Components: Reward

- Reward (usually unknown to a learning agent)
  - When the agent executes an action A_t at time t, it receives a scalar feedback called reward

$$R_t \sim p(r \mid A_t)$$

  - For example, $p(r \mid a)$ is modeled by a Gaussian distribution with mean $\mu(a)$ and standard deviation $\sigma(a)$



$$p(r \mid a) = \frac{1}{\sqrt{2\pi}\sigma(a)} \exp\left(-\frac{\left(r-\mu(a)\right)^2}{2\sigma(a)^2}\right)$$

Goal of the Learning Agent

- Find a policy π that maximizes the expected reward

$$J(\pi) \triangleq \mathbb{E}_{\pi}[R] = \int rp(r \mid \pi)\mathrm{d}r$$

- $p(r \mid \pi)$ is a probability density function

$$p(r \mid \pi) \triangleq \sum_{a} p(r \mid a)\pi(a)$$

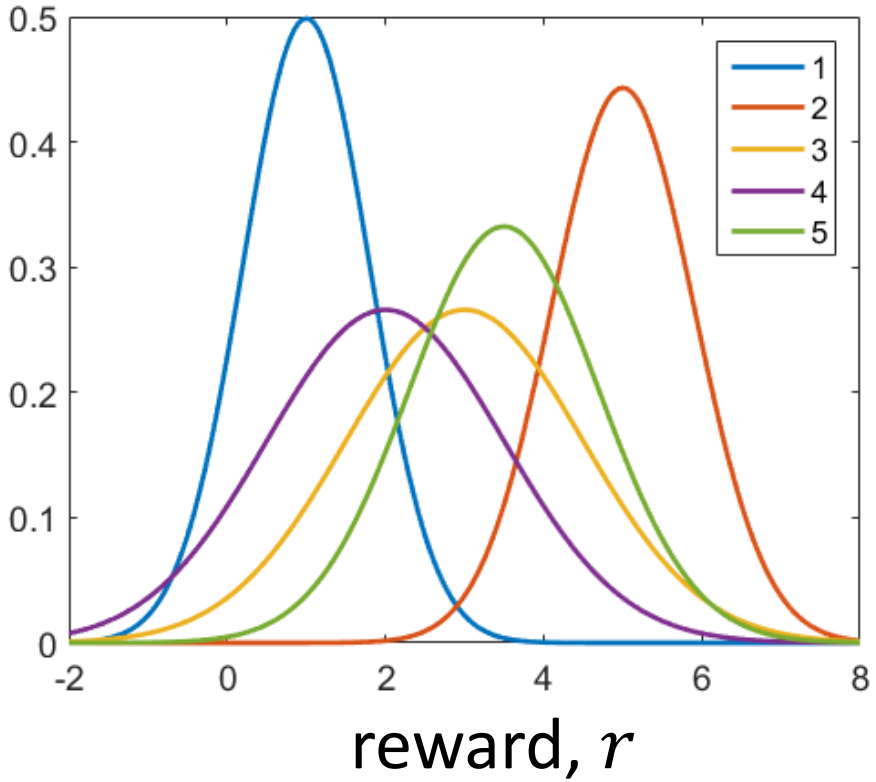
- To simplify notations, we often write the objective function in this lecture

$$J(\pi) = \sum_{r,a} rp(r \mid a)\pi(a)$$

Example

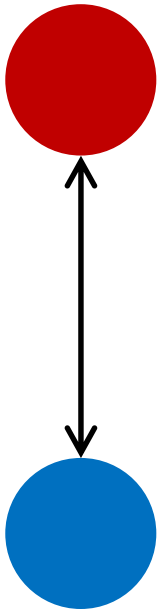
- The rewards of the machine are determined by a Gaussian distribution
  where
    mean
    [1, 5, 3, 2, 3.5]
    standard deviation
    [0.8, 0.9, 1.5, 1.5, 1.2]

$p(r \mid a)$



- The optimal action is to select the machine "2" because it has the highest mean value
- A learning agent does not know these distributions

Two RL Approaches



Value-based approach

- Compute expected rewards for every action
- Select an action according to the expected rewards

Policy-based approach

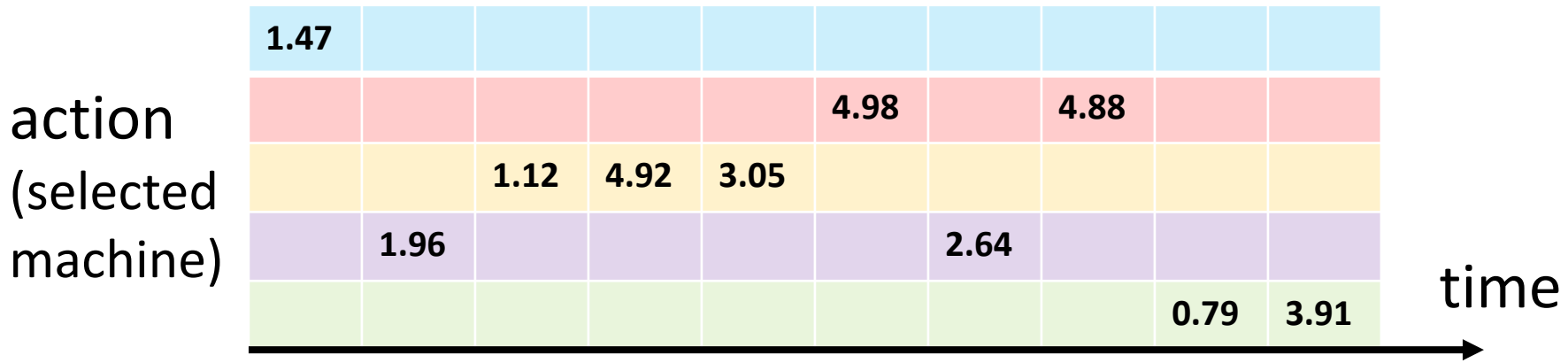
- Compute a gradient of an expected reward under a parametric stochastic policy
- Update a policy by a stochastic gradient ascent

Value-based Approach

- We want to know the expected values of actions

$$q_*(a) \triangleq \mathbb{E}_\pi[R_t \mid A_t = a] = \int rp(r \mid a)\,\mathrm{d}r$$

  - Can't compute it because $p(r \mid a)$ is unknown
- In order to estimate $q_*(a)$, we need to gather samples by playing
- Suppose that an agent gets the following sequence of rewards based on $\pi(a) = 1/5$ for all a



Value-based Approach

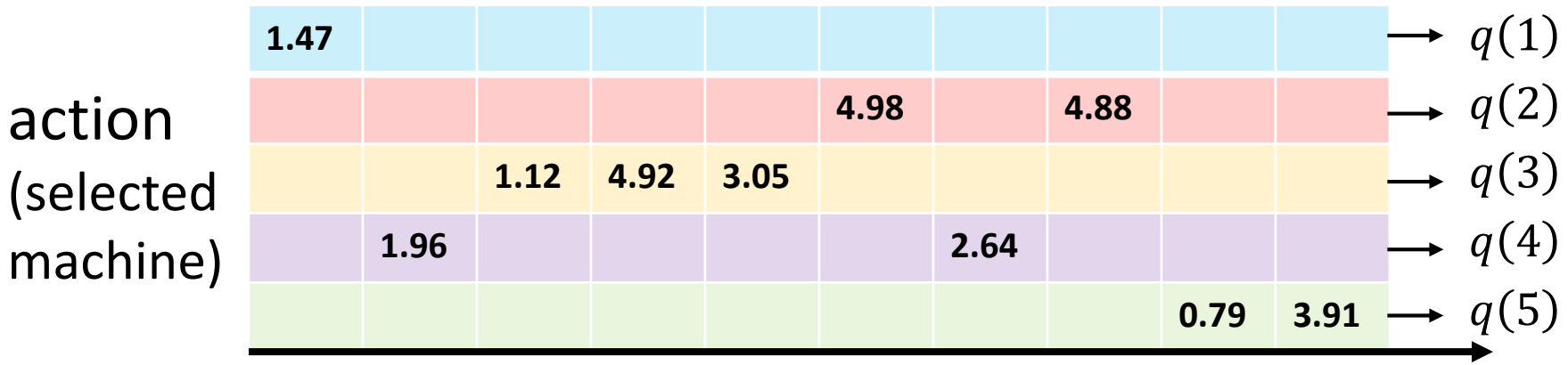
- Estimate by averaging the rewards actually received:

$$Q_t(a) = \frac{\text{sum of rewards when } a \text{ taken prior to } t}{\text{number of times } a \text{ taken prior to } t}$$

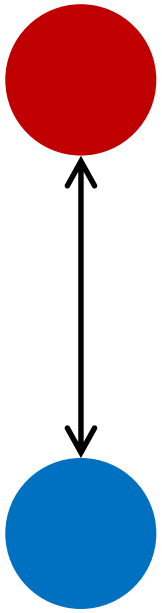
where $Q_t(a)$ is an array estimate of $q(a)$ at time t

- Example

$$Q_5(3) = \frac{1.12 + 4.92 + 3.05}{3} = 3.03$$



Action Selection Strategies during Learning

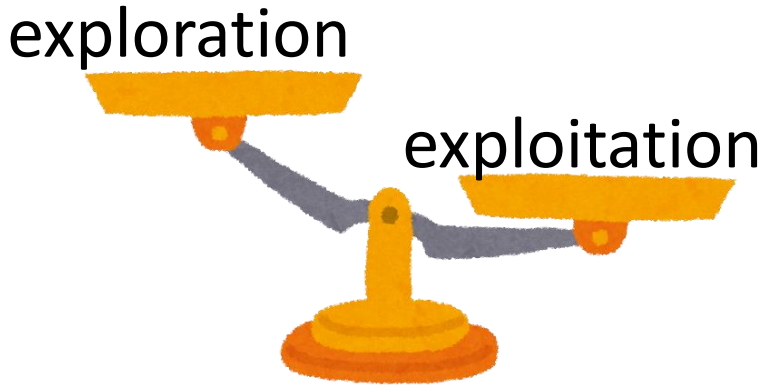


Exploitation

- Use known information to act
- E.g., go to the best restaurant I know

Exploration

- Find more information about machines
- E.g., try a new restaurant



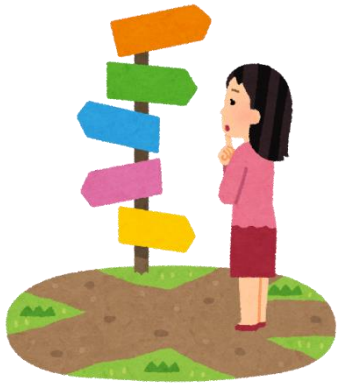
- An RL agent faces the exploration-exploitation dilemma at every time step

Greedy Policy

- If Q_t is sufficiently accurate, it is enough to select an action greedily
  - always choose the action with current best expected reward

$$A_t = \underset{a}{\operatorname{argmax}}\, Q_t(a)$$

- However, a learning agent does not have a correct Q at the beginning of learning
- So, the agent should gather information by trial and error to estimate Q efficiently
- How should the agent select actions during learning?

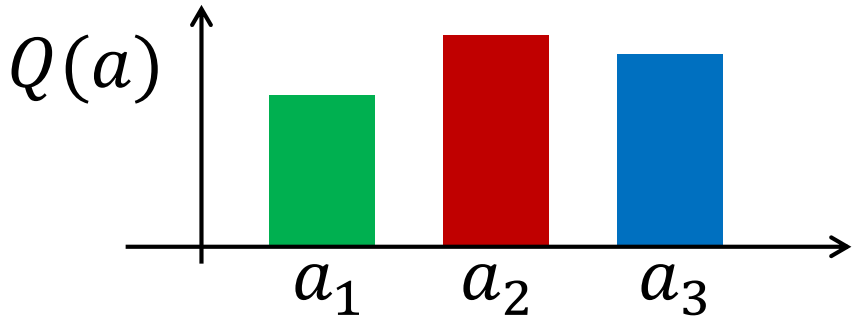


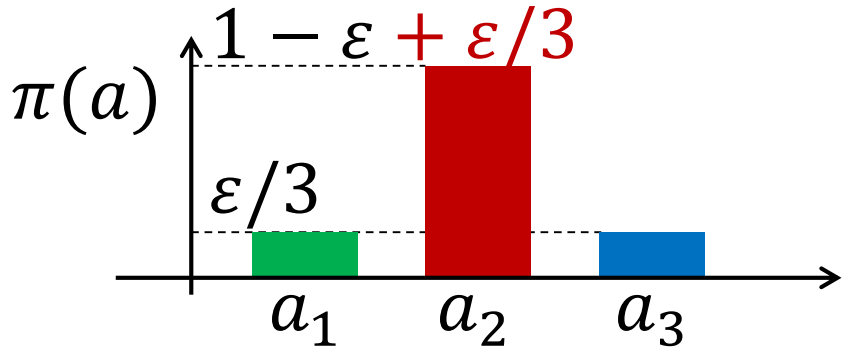
ε-greedy Policy

- Choose the action with current best expected reward with probability $1 - \varepsilon$
- Choose another action randomly with probability ε/k

$$\pi(a) = \begin{cases} \varepsilon/k + 1 - \varepsilon & \text{if } a = \underset{a'}{\operatorname{argmax}}\, Q(a') \\ \varepsilon/k & \text{otherwise} \end{cases}$$

- Exploration insensitive to relative performance levels





$\varepsilon = 1$ —time→ $\varepsilon = 0$

(exploration) (exploitation)

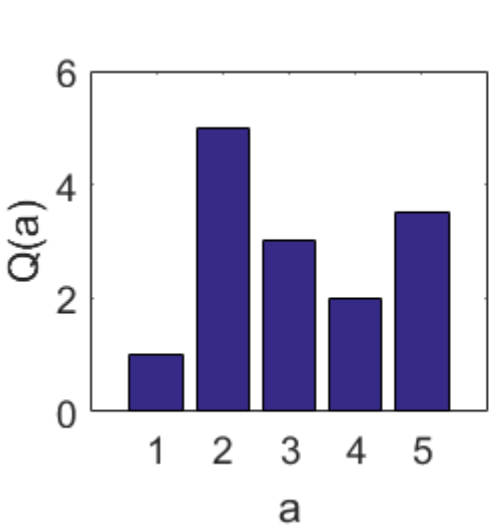
Boltzmann Distribution

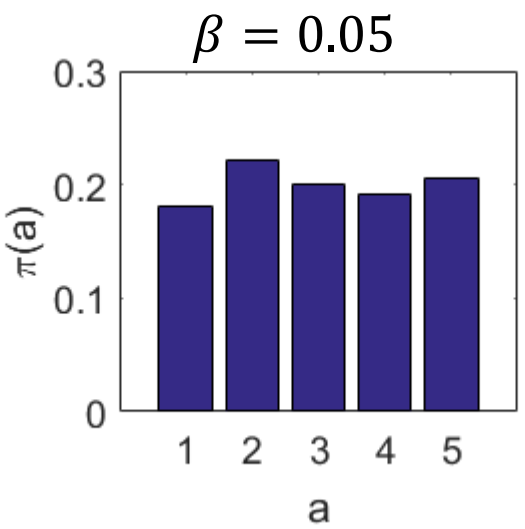
- The policy is calculated from the value

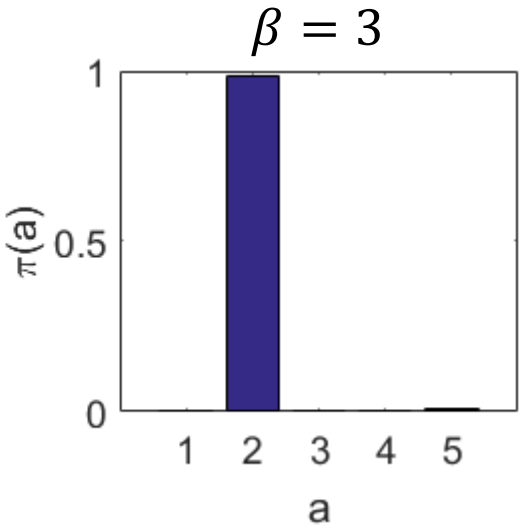
$$\pi(a) = \frac{\exp\big(\beta Q(a)\big)}{\sum_{a' \in \mathcal{A}} \exp\big(\beta Q(a')\big)}$$

where β is an inverse temperature

  - $\beta = 0$: pure exploration (random policy)
  - $\beta \to \infty$: pure exploitation (greedy policy)





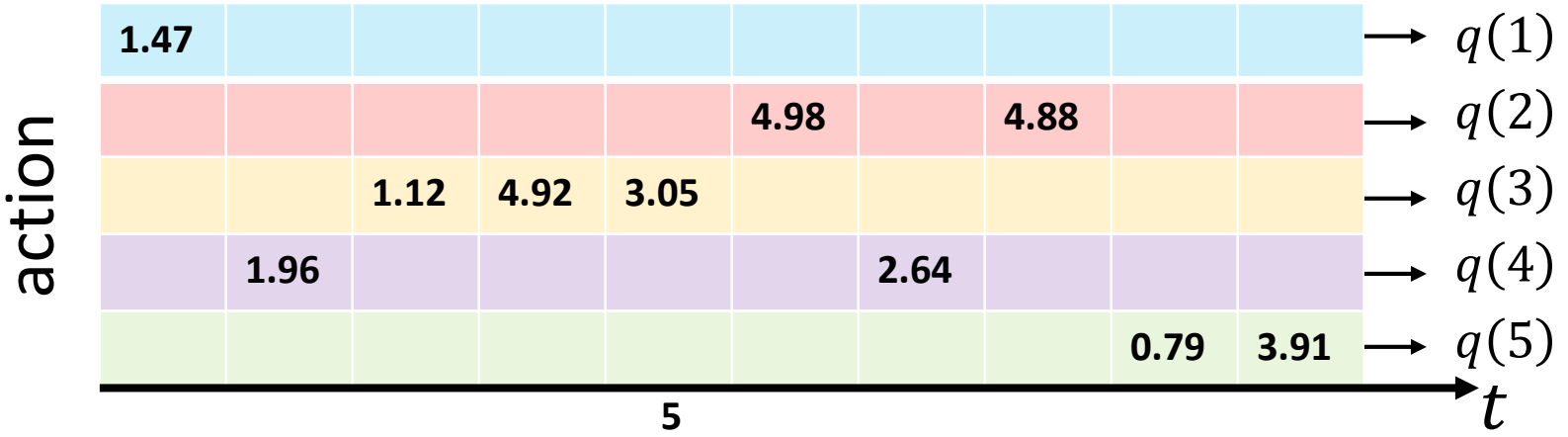


$\beta = 0$ —time→ $\beta = \infty$

(exploration) (exploitation)

Estimation of Q

- Let $R^n(a)$ and $Q^n(a)$ denote the reward received after the n-th selection of a and the estimate of its action value after it has been selected $n-1$ times



  - $R^1(3) = 1.12, R^2(3) = 4.92, R^3(3) = 3.05$
  - $Q^1(3) \triangleq R^1(3) = 1.12$
  - $Q^2(3) = \big(R^1(3) + R^2(3)\big)/2 = 3.02$
  - $Q^3(3) = \big(R^1(3) + R^2(3) + R^3(3)\big)/3 = 3.03$

Incremental Estimation of Q

- It is easy to devise incremental update rule to compute Q

- $$Q^{n+1}(a) = \frac{1}{n}\sum_{i=1}^{n} R^i(a) = \frac{1}{n}\left(R^n(a) + \sum_{i=1}^{n-1} R^i(a)\right)$$
$$= \frac{1}{n}\left(R^n(a) + (n-1)\frac{1}{n-1}\sum_{i=1}^{n-1} R^i(a)\right)$$
$$= \frac{1}{n}(R^n(a) + (n-1)Q^n(a))$$
$$= Q^n(a) + \frac{1}{n}[R^n(a) - Q^n(a)]$$

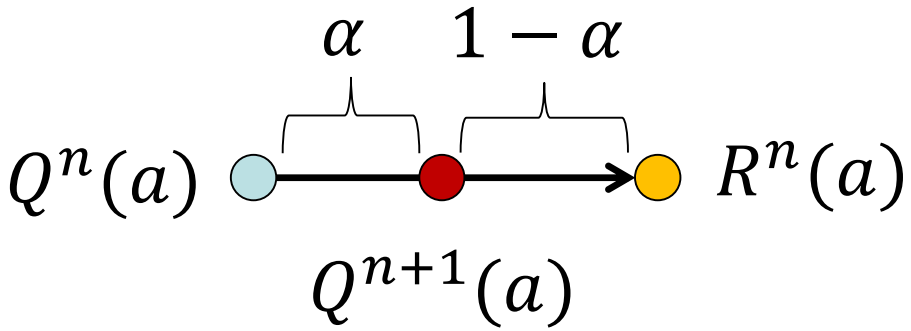
Interpretation of the Update Rule

- $$Q^{n+1}(a) = Q^n(a) + \frac{1}{n}[R^n(a) - Q^n(a)]$$

  new estimate target old estimate

- $\delta \triangleq R^n(a) - Q^n(a)$ represents the error for the old estimate
- $\alpha \triangleq 1/n$ is a learning rate
- Online update rule for estimating rewards

$$Q^{n+1}(a) = (1-\alpha)Q^n(a) + \alpha R^n(a)$$



A Simple Bandit Algorithm

Initialize, for $a = 1$ to k:

$Q(a) \leftarrow 0$

$N(a) \leftarrow 0$

Loop forever:

$$A \leftarrow \begin{cases} \arg\max_a Q(a) & \text{with probability } 1-\varepsilon \quad \text{(breaking ties randomly)} \\ \text{a random action} & \text{with probability } \varepsilon \end{cases}$$

$R \leftarrow \text{bandit}(A)$

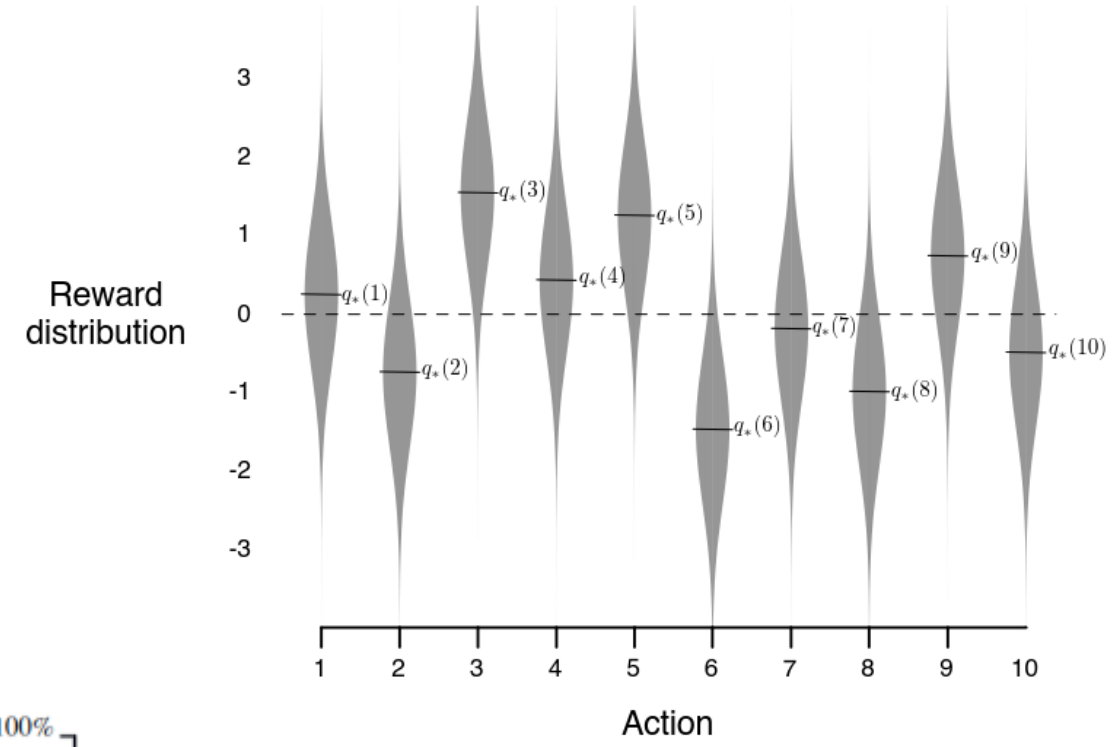
$N(A) \leftarrow N(A) + 1$

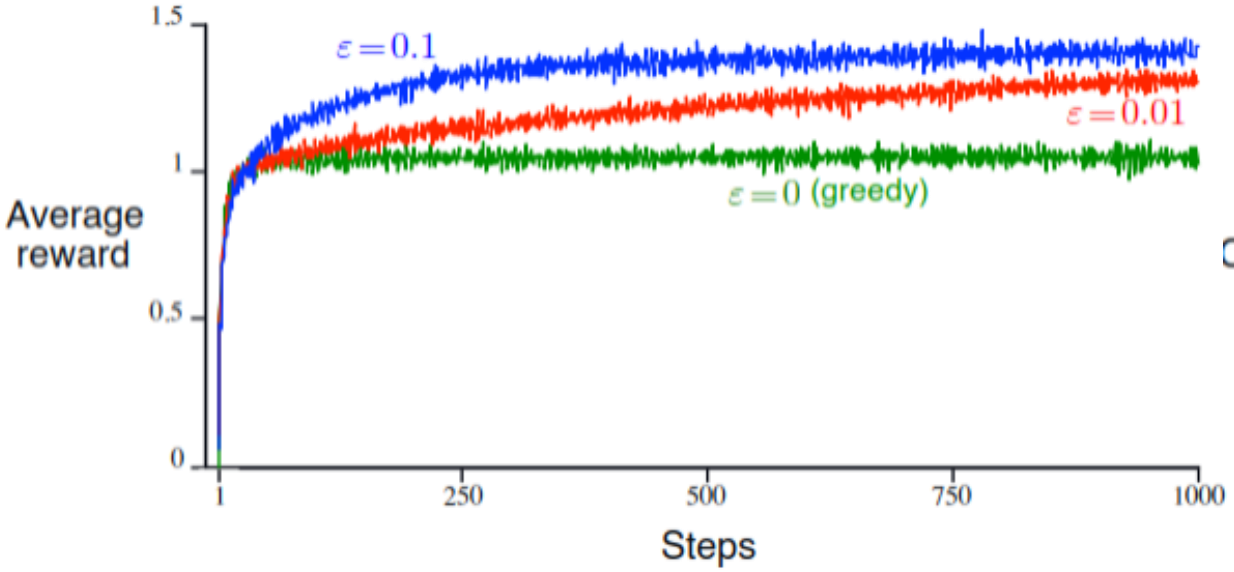
$$Q(A) \leftarrow Q(A) + \frac{1}{N(A)}[R - Q(A)]$$

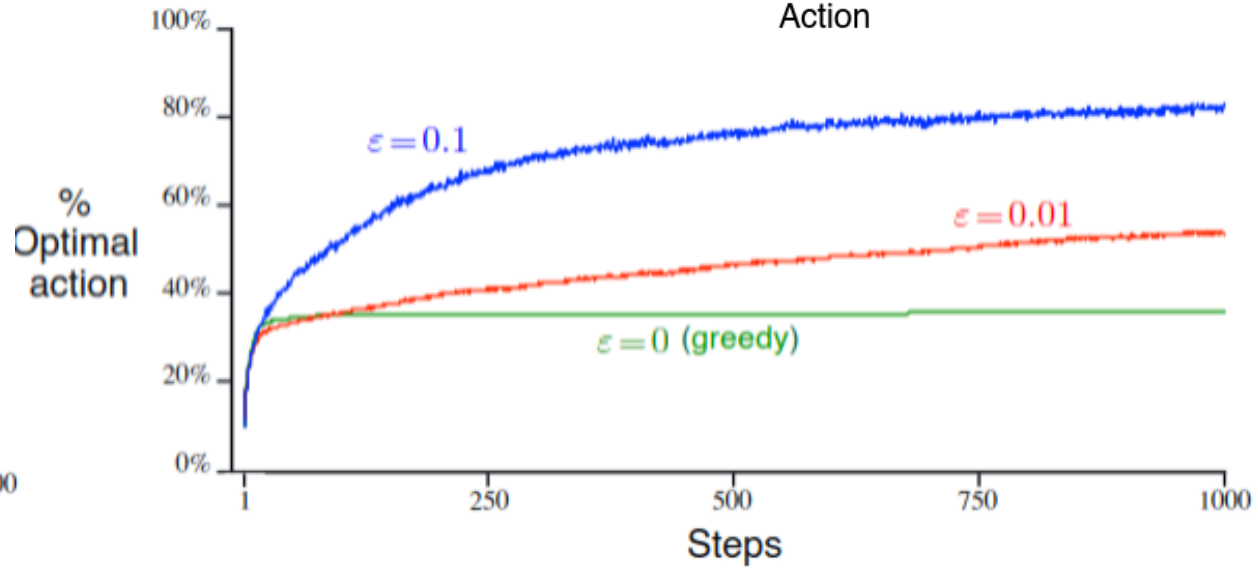
[Sutton and Barto, 2018]

Example: 10-armed Bandit

- Average performance of ε-greedy action-value method







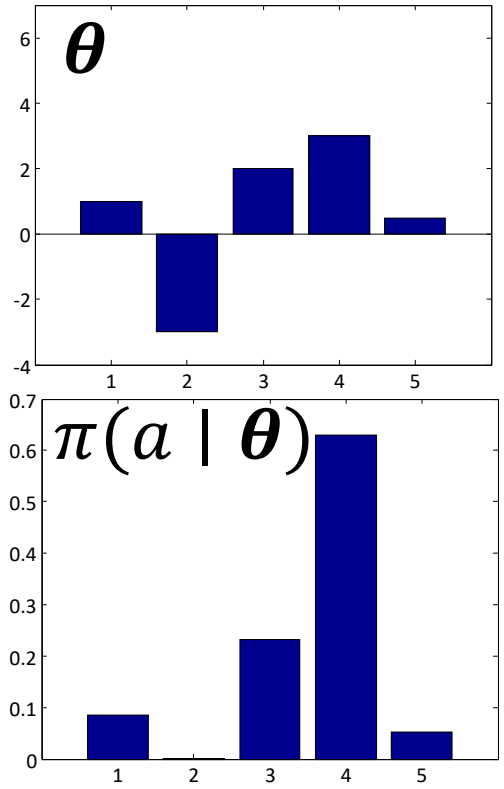
[Sutton and Barto, 2018]

Policy-based Approach

- So far, we explicitly estimate action values from experiences, and they are used to derive a policy
- Next, we consider how to learn the policy directly from experiences
- One way is to parameterize the policy by the Boltzmann distribution
- The Boltzmann policy is given by

$$\pi(a_i \mid \boldsymbol{\theta}) = \frac{\exp(\theta_i)}{\sum_{j=1}^{k} \exp(\theta_j)}$$

where $\boldsymbol{\theta} = [\theta_1, \theta_2, \ldots, \theta_k]^\top$



Policy-based Approach

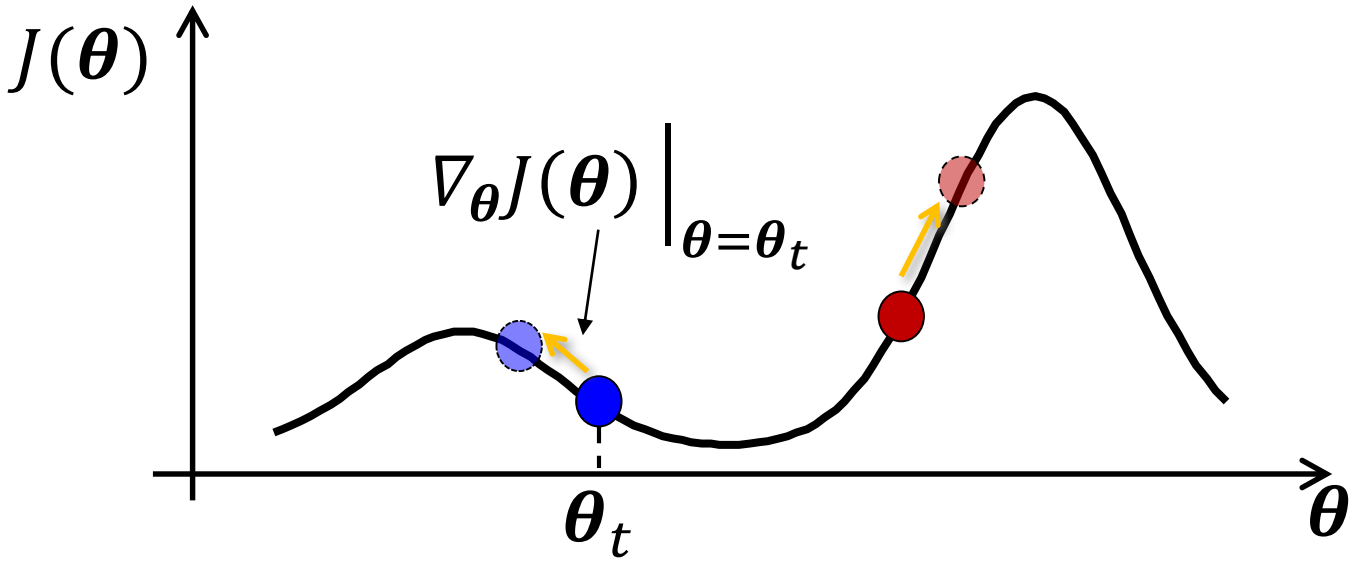
- The expected reward is

$$J(\boldsymbol{\theta}) = \mathbb{E}_{\pi}[R] = \sum_{r,a} rp(r \mid a)\pi(a \mid \boldsymbol{\theta})$$

- The goal is to find $\boldsymbol{\theta}$ that maximizes $J(\boldsymbol{\theta})$
- Use a gradient ascent method to maximize $J(\boldsymbol{\theta})$ with respect to $\boldsymbol{\theta}$

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta})$$

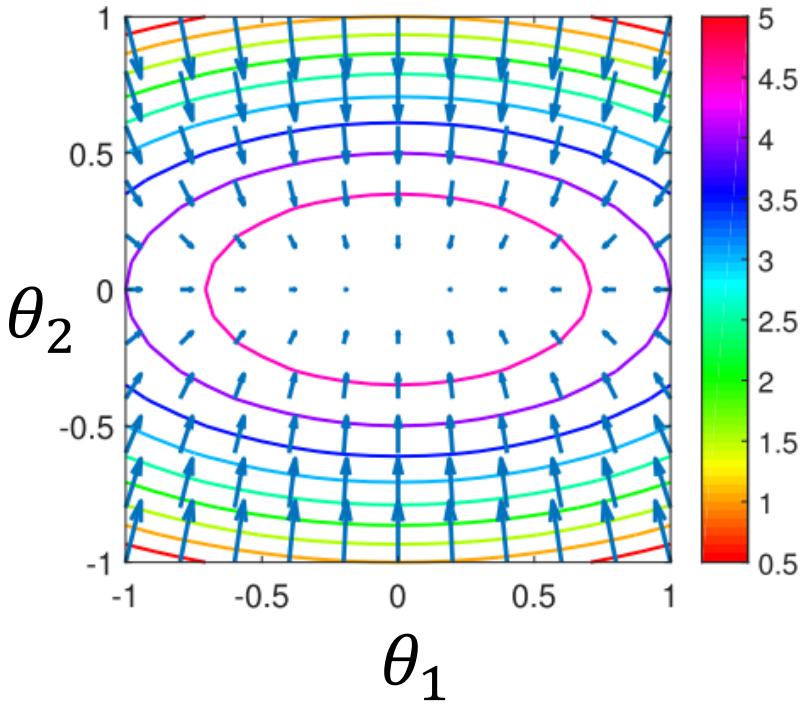
where α is a positive step-size parameter



Gradient of a Function

- $\boldsymbol{\theta} = [\theta_1, \theta_2, \ldots, \theta_k]^\top$: k-dimensional vector
- $J(\boldsymbol{\theta})$: $\mathbb{R}^k \rightarrow \mathbb{R}$: differentiable scalar function
- $\nabla_{\boldsymbol{\theta}} J$: $\mathbb{R}^k \rightarrow \mathbb{R}^k$: its gradient

$$\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) = \nabla_{\boldsymbol{\theta}} J(\theta_1, \ldots, \theta_k) = \begin{bmatrix} \partial J / \partial \theta_1 \\ \vdots \\ \partial J / \partial \theta_k \end{bmatrix} = \frac{\partial J}{\partial \boldsymbol{\theta}}$$



$$J(\boldsymbol{\theta}) = -\theta_1^2 - 4\theta_2^2 + 5$$

$$\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) = \begin{bmatrix} -2\theta_1 \\ -8\theta_2 \end{bmatrix}$$

Gradient Ascent

- Find a local optimal solution

Initialize

$n \leftarrow 0$

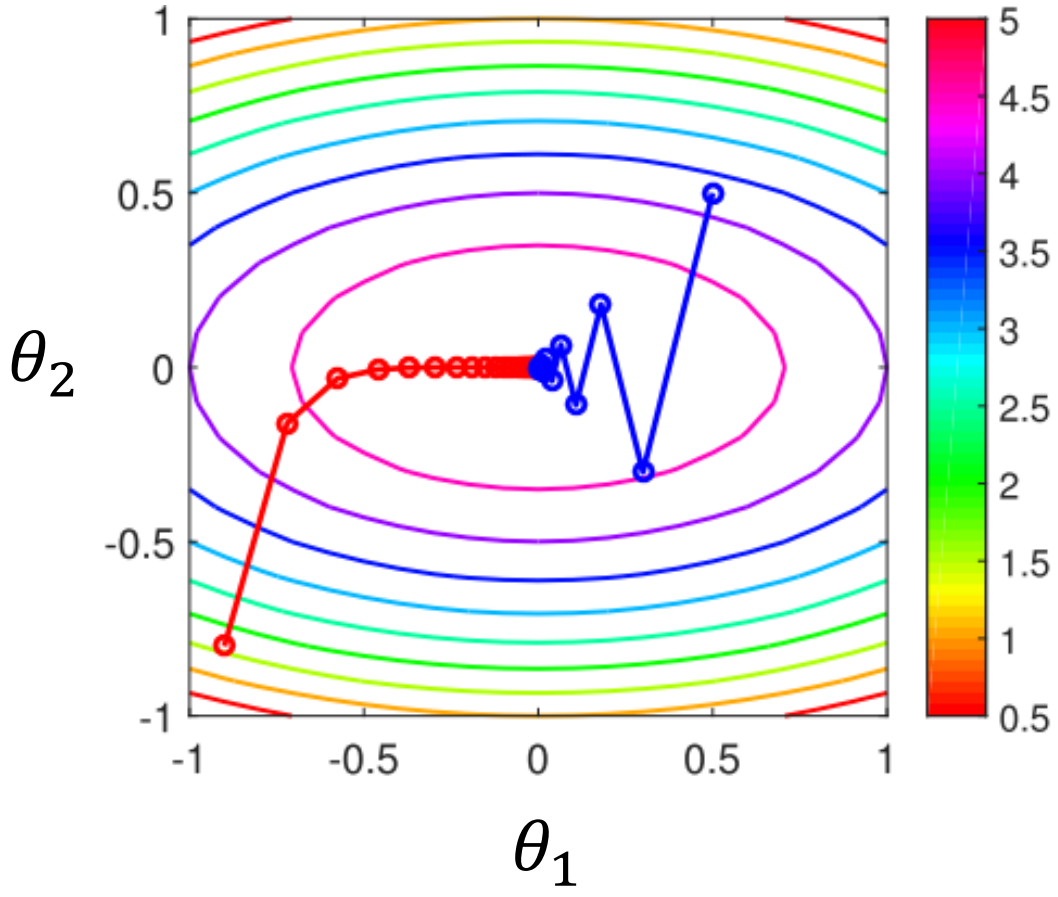
Repeat:

$n \leftarrow n + 1$

$\boldsymbol{\theta}^n \leftarrow \boldsymbol{\theta}^{n-1} + \alpha \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta})$

until stopping_criterion($\boldsymbol{\theta}^n, \boldsymbol{\theta}^{n-1}, \epsilon$)

return $\boldsymbol{\theta}^n$



Calculate $\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta})$

- $$\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) = \frac{\partial}{\partial \boldsymbol{\theta}} \left[\sum_{r,a} r p(r \mid a) \pi(a \mid \boldsymbol{\theta}) \right]$$

$$= \sum_{r,a} r p(r \mid a) \frac{\partial \pi(a \mid \boldsymbol{\theta})}{\partial \boldsymbol{\theta}}$$

$$= \sum_{r,a} r p(r \mid a) \pi(a \mid \boldsymbol{\theta}) \frac{\partial \ln \pi(a \mid \boldsymbol{\theta})}{\partial \boldsymbol{\theta}}$$

$$= \mathbb{E}_{\pi} \left[R \frac{\partial \ln \pi(a \mid \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right]$$

  - $\ln x$ is the natural logarithm of x

Calculate $\partial \ln \pi(a \mid \theta)/\partial \theta$ (1/2)

- $\pi(a_i \mid \boldsymbol{\theta}) = \dfrac{\exp(\theta_i)}{\sum_{j=0}^{k-1} \exp(\theta_j)}$
- $$\frac{\partial \pi(a_i \mid \boldsymbol{\theta})}{\partial \theta_i} = \frac{\exp(\theta_i) \sum_{j=0}^{k-1} \exp(\theta_j) - (\exp(\theta_i))^2}{\left(\sum_{j=0}^{k-1} \exp(\theta_j)\right)^2}$$
$$= \frac{\exp(\theta_i)}{\sum_{j=0}^{k-1} \exp(\theta_j)} - \left(\frac{\exp(\theta_i)}{\sum_{j=0}^{k-1} \exp(\theta_j)}\right)^2 = \pi(a_i \mid \boldsymbol{\theta})\big(1 - \pi(a_i \mid \boldsymbol{\theta})\big)$$
- $$\frac{\partial \ln \pi(a_i \mid \boldsymbol{\theta})}{\partial \theta_i} = \frac{1}{\pi(a_i \mid \boldsymbol{\theta})} \frac{\partial \pi(a_i \mid \boldsymbol{\theta})}{\partial \theta_i} = 1 - \pi(a_i \mid \boldsymbol{\theta})$$

Calculate $\partial \ln \pi(a \mid \theta)/\partial \theta$ (2/2)

- $\dfrac{\partial \pi(a_i \mid \boldsymbol{\theta})}{\partial \theta_j} = -\dfrac{\exp(\theta_i)\exp(\theta_j)}{\left(\sum_{j=0}^{k-1}\exp(\theta_j)\right)^2} = -\pi(a_i \mid \boldsymbol{\theta})\pi(a_j \mid \boldsymbol{\theta})$
- $\dfrac{\partial \ln \pi(a_i \mid \boldsymbol{\theta})}{\partial \theta_j} = \dfrac{1}{\pi(a_i \mid \boldsymbol{\theta})}\dfrac{\partial \pi(a_i \mid \boldsymbol{\theta})}{\partial \theta_j} = -\pi(a_j \mid \boldsymbol{\theta})$

Implementation

- Compute the gradient from experiences

$$\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) = \mathbb{E}_{\pi}[R \nabla_{\boldsymbol{\theta}} \ln \pi(a \mid \boldsymbol{\theta})]$$

- Use the stochastic gradient method
  1. Sample action: $A \sim \pi(a \mid \boldsymbol{\theta})$
  2. Receive the reward R from the environment: $R \sim p(r \mid A)$
  3. Update θ by the stochastic gradient ascent

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha R \frac{\partial \ln \pi(A \mid \boldsymbol{\theta})}{\partial \boldsymbol{\theta}}$$

Variance Reduction

- Although we can estimate policy gradient, it has a large variance in general
- We can further reduce the variance by subtracting a baseline

$$\mathbb{E}_\pi\left[(R-b)\frac{\partial \ln \pi(A \mid \boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right]$$

$$= \mathbb{E}_\pi\left[R\frac{\partial \ln \pi(A \mid \boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right] + b\underbrace{\mathbb{E}_\pi\left[\frac{\partial \ln \pi(A \mid \boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right]}_{=0}$$

Proof Sketch

- We want to prove $\mathbb{E}_\pi \left[\frac{\partial \ln \pi(A \mid \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right] = \mathbf{0}$
- $$\mathbb{E}_\pi \left[\frac{\partial \ln \pi(A \mid \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right] = \sum_{r,a} p(r \mid a)\, \pi(a \mid \boldsymbol{\theta}) \frac{\partial \ln \pi(a \mid \boldsymbol{\theta})}{\partial \boldsymbol{\theta}}$$
$$= \sum_{r,a} p(r \mid a) \frac{\partial \pi(a \mid \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = \frac{\partial}{\partial \boldsymbol{\theta}} \left[\sum_{r,a} p(r \mid a) \pi(a \mid \boldsymbol{\theta}) \right]$$
$$= \frac{\partial}{\partial \boldsymbol{\theta}} [1] = \mathbf{0}$$
- This fact suggests that the policy gradient remains unchanged even though we subtract a baseline constant

Summary

- Introduction to reinforcement learning
- Bandit problem
  - Action, Reward, Value
- Value-based approach: Estimate the value function and derive the policy from the estimated value function
  Indirect approach
- Policy-based approach: Estimate the gradient of the objective function with respect to the policy parameters and update the parameters
  Direct approach

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