Course Content

Part I. Learning in Bandits

- Multi-armed bandits
- Linear bandits
- Contextual bandits
- Adversarial multi-armed bandits
- Adversarial linear bandits

Part II. Basics of MDPs

- Bellman (optimality) equations
- Value iteration
- Policy iteration

Part III. Learning in MDPs

- Approximate value iteration and variants
  - Least-square value iteration
  - Q-Learning
  - DQN
- Policy evaluation
  - Temporal difference
  - Monte Carlo
- Approximate policy iteration and variants
  - Least-square policy iteration
  - (Natural) policy gradient and actor-critic
  - REINFORCE, A2C, PPO
  - DDPG, SAC

Part IV. Offline RL

Student Project Presentation

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Part IV. Offline RL

Student Project Presentation

Bandits

Chen-Yu Wei

Contextual Bandits and Non-Contextual Bandits

Context

Contextual Bandit

a_1 ?

$\boldsymbol{a_2}$ $\mathbf{0.5}$

a_3 ?

Policy: $\pi(a|\text{context})$

Non-Contextual Bandit

a_1 ?

$\boldsymbol{a_2}$ $\mathbf{0.5}$

a_3 ?

Policy: $\pi(a)$

Multi-Armed Bandits

Multi-Armed Bandits

A slot machine

One-armed bandit

A row of slot machines

Multi-armed bandit

Multi-Armed Bandits

Given: arm set $\mathcal{A} = \{1, \dots, A\}$

For time $t = 1, 2, \dots, T$:

Learner chooses an arm $a_t \in \mathcal{A}$

Learner observes $r_t = R(a_t) + w_t$

Arm = Action

Assumption: $R(a)$ is the (hidden) ground-truth reward function

w_t is a zero-mean noise

Goal: maximize the total reward $\sum_{t=1}^{T} R(a_t)$ (or $\sum_{t=1}^{T} r_t$)

How to Evaluate an Algorithm's Performance?

- "My algorithm obtains $0.3T$ total reward within T rounds"
  – Is my algorithm good or bad?

$\Rightarrow \max_a R(a) - \frac{1}{T}\sum_{t=1}^{T} R(a_t) \leq \frac{1}{\sqrt{T}}$

- Benchmarking the problem

$\leq \sqrt{T}$

$$\text{Regret} := \underbrace{\max_{\pi} \sum_{t=1}^{T} R(\pi)}_{\text{The total reward of the best policy}} - \sum_{t=1}^{T} R(a_t) \quad = \max_a T R(a) - \sum_{t=1}^{T} R(a_t)$$

In MAB

- "My algorithm ensures $\text{Regret} \leq 5T^{\frac{3}{4}}$ "
- $\text{Regret} = o(T) \Rightarrow$ the algorithm is as good as the optimal policy asymptotically

Multi-Armed Bandits

- Key challenge: Exploration
- The other three challenges we will discuss for RL
  - Generalization (there is no input in MAB)
  - Temporal credit assignments (there is no delayed feedback)
  - Distribution mismatch (there is no pre-collected data)

- We will discuss about two categories of exploration strategies
  - Based on mean estimation
  - Based on mean and uncertainty estimation

Multi-Armed Bandits

Based on mean estimation

The Exploration and Exploitation Trade-off in MAB

- To perform as well as the best policy (i.e., best arm) asymptotically, the learner has to pull the best arm most of the time

  ⇒ need to **exploit**

- To identify the best arm, the learner has to try every arm sufficiently many times

  ⇒ need to **explore**

A Simple Strategy: Explore-then-Exploit

Explore-then-exploit (Parameter: T_0)

In the first T_0 rounds, sample each arm T_0/A times. **(Explore)**

Compute the **empirical mean** $\hat{R}(a)$ for each arm a

In the remaining $T - T_0$ rounds, draw $\hat{a} = \mathrm{argmax}_a \hat{R}(a)$ **(Exploit)**

What is the *right* amount of exploration (T_0)?

Another Simple Strategy: ϵ-Greedy

Mixing exploration and exploitation in time

ϵ-Greedy (Parameter: ϵ)

In the first A rounds, draw each arm once.

In the remaining rounds $t > A$,

Take action

$$a_t = \begin{cases} \text{uniform}(\mathcal{A}) & \text{with prob. } \epsilon \quad \textbf{(Explore)} \\ \text{argmax}_a \hat{R}_t(a) & \text{with prob. } 1-\epsilon \quad \textbf{(Exploit)} \end{cases}$$

where $\hat{R}_t(a) = \frac{\sum_{s=1}^{t-1} \mathbb{I}\{a_s=a\}\, r_s}{\sum_{s=1}^{t-1} \mathbb{I}\{a_s=a\}}$ is the empirical mean of arm a using samples up to time $t-1$.

Comparison

- ϵ-Greedy is more **robust to non-stationarity** than Explore-then-Exploit
- ϵ-Greedy has a better performance in the early phase of the learning process

Quantifying the Estimation Error

In the exploration phase, we obtain $N = T_0/A$ i.i.d. samples of each arm.

Key Question:

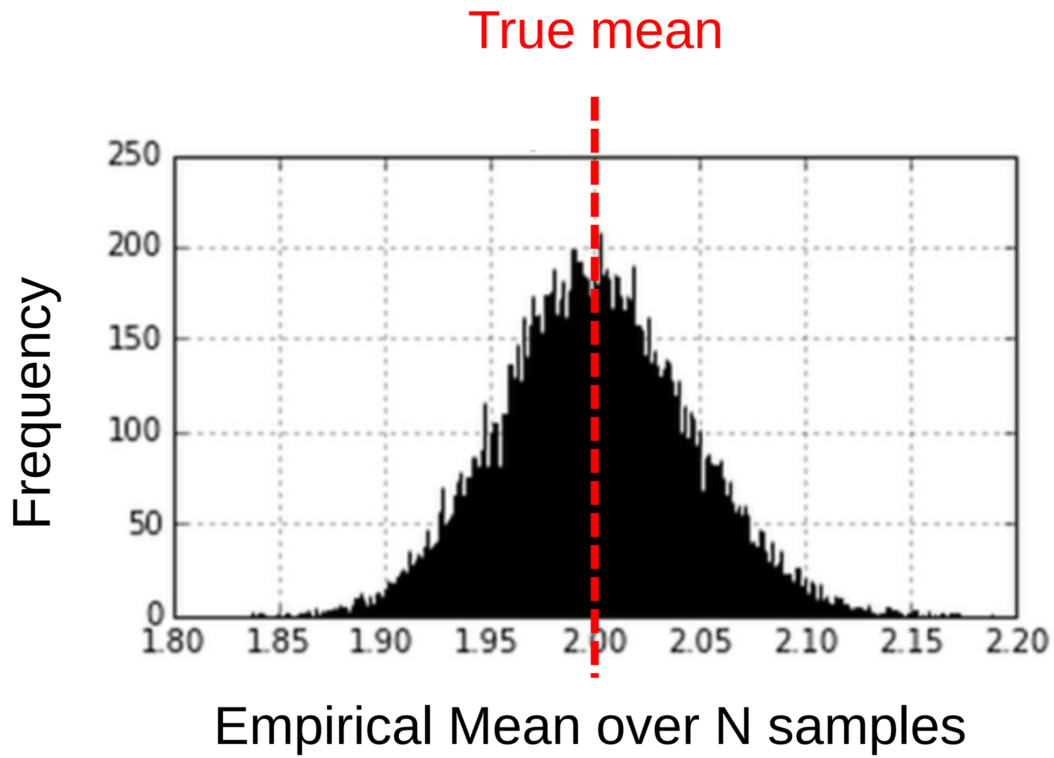
$$\left| \hat{R}(a) - R(a) \right| \leq ?\ f(N)$$

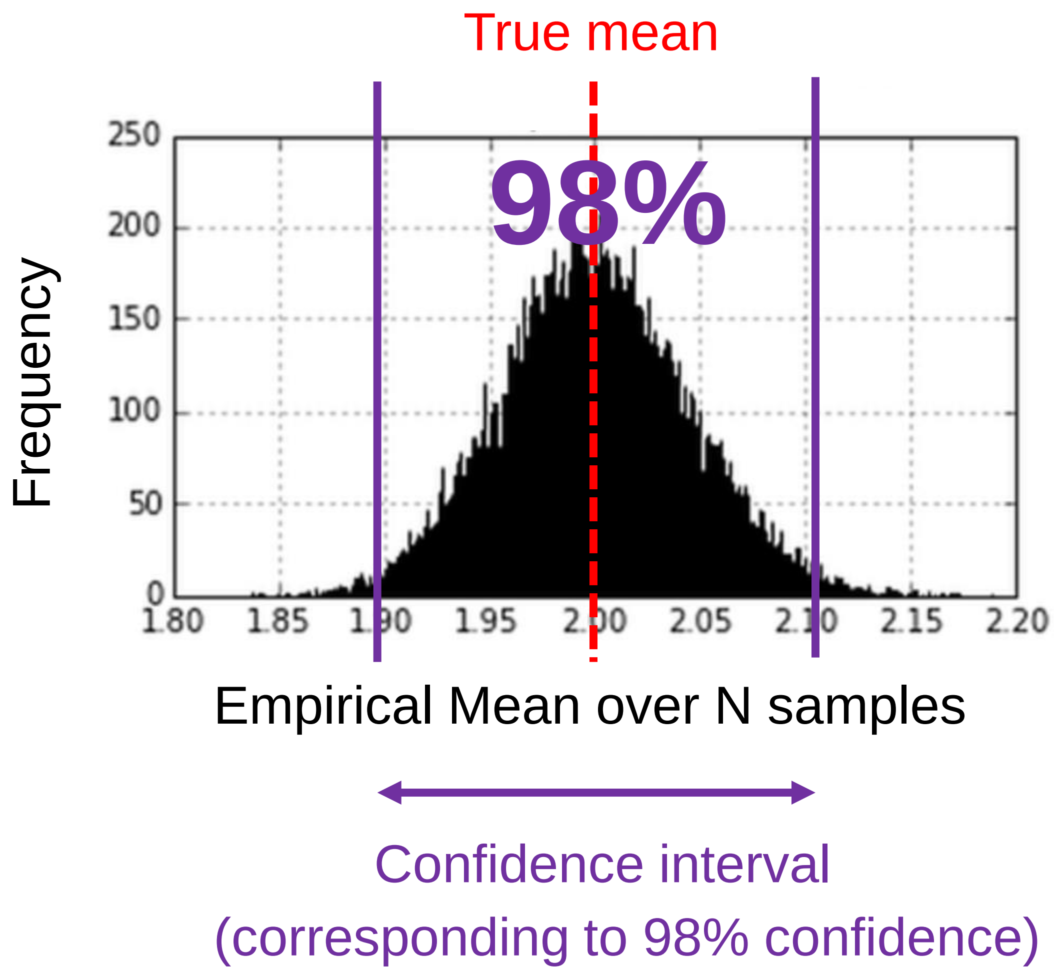
some decreasing function of N

Empirical mean
of N i.i.d. samples

True mean

Quantifying the Estimation Error





Quantifying the Estimation Error

In the exploration phase, we obtain $N = T_0/A$ i.i.d. samples of each arm.

Key Question:

$$\left|\hat{R}(a) - R(a)\right| \leq ?\ f(N)$$

some decreasing function of N

Empirical mean
of N i.i.d. samples

True mean

Quantifying the Estimation Error

In the exploration phase, we obtain $N = T_0/A$ i.i.d. samples of each arm.

Key Question:

0.02

With probability at least $1-\delta$, $= 0.98$

$$\left|\hat{R}(a) - R(a)\right| \leq ?\ f(N,\delta)$$

Empirical mean of N i.i.d. samples

True mean

some decreasing function of N

Quantifying the Error: Concentration Inequality

Theorem. Hoeffding's Inequality

Let $X_1, \dots, X_N$ be independent σ**-sub-Gaussian** random variables.

Then with probability at least $1 - \delta$,

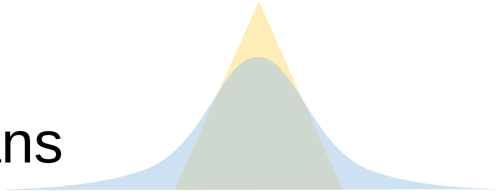
$$\left| \frac{1}{N} \sum_{i=1}^{N} X_i - \frac{1}{N} \sum_{i=1}^{N} \mathbb{E}[X_i] \right| \leq \sigma \sqrt{\frac{2 \log(2/\delta)}{N}} \quad .$$

A random variable is called σ-sub-Gaussian if $\mathbb{E}\left[e^{\lambda(X - \mathbb{E}[X])}\right] \leq e^{\lambda^2 \sigma^2 / 2} \quad \forall \lambda \in \mathbb{R}$.

Fact 1. $\mathcal{N}(\mu, \sigma^2)$ is σ-sub-Gaussian.

Fact 2. A random variable $\in [a, b]$ is $(b - a)$-sub-Gaussian.

Intuition: tail probability $\Pr\{|X - \mathbb{E}[X]| \geq z\}$ bounded by that of Gaussians



Quantifying the Estimation Error

With probability at least $1-\delta$, $\left|\hat{R}(a) - R(a)\right| = O\left(\sqrt{\frac{\log(1/\delta)}{N}}\right)$

Omit constants

With high probability, $\left|\hat{R}(a) - R(a)\right| = \tilde{O}\left(\sqrt{\frac{1}{N}}\right)$

$\left|\hat{R}(a) - R(a)\right| \lesssim \sqrt{\frac{1}{N}}$

Omit constants and $\log(1/\delta)$ factors

Explore-then-Exploit Regret Bound Analysis

In the first T_0 rounds, sample each arm T_0/A times.

Compute the **empirical mean** $\hat{R}(a)$ for each arm a

In the remaining $T - T_0$ rounds, draw $\hat{a} = \mathrm{argmax}_a \hat{R}(a)$

$a^* = \mathrm{argmax}_a R(a)$ (true best arm)

After the exploration phase, we have $\boxed{|\hat{R}(a) - R(a)| \lesssim \sqrt{\frac{1}{N}} = \sqrt{\frac{A}{T_0}}}$

In the exploitation phase,

At any time $t \in$ exploitation phase, $R(a^*) - R(\hat{a})$

$$= \underbrace{\hat{R}(a^*) - \hat{R}(\hat{a})}_{\leq 0} + \underbrace{[R(a^*) - \hat{R}(a^*)]}_{\lesssim \sqrt{\frac{A}{T_0}}} + \underbrace{(\hat{R}(\hat{a}) - R(\hat{a}))}_{\sqrt{\frac{A}{T_0}}}$$

$$\text{Regret} \lesssim \text{cost of exploration} + \sum_{t \in \text{second phase}} (R(a^*) - R(\hat{a})) \lesssim T_0 + (T - T_0) \cdot 2\sqrt{\frac{A}{T_0}}$$

Regret Bound of Explore-then-Exploit and ϵ-Greedy

Theorem. Regret Bound of Explore-then-Exploit

Suppose that $R(a) \in [0,1]$ and w_t is 1-sub-Gaussian.

Then Explore-then-Exploit ensures with high probability,

$$\text{Regret} \lesssim T_0 + T\sqrt{\frac{A}{T_0}} \approx A^{1/3}T^{2/3} \text{ (choosing } T_0 = A^{1/3}T^{2/3}\text{)}$$

Theorem. Regret Bound of ϵ-Greedy (Your Exercise)

Suppose that $R(a) \in [0,1]$ and w_t is 1-sub-Gaussian.

Then ϵ-Greedy ensures with high probability,

$$\text{Regret} \lesssim \epsilon T + \sqrt{\frac{AT}{\epsilon}} \approx A^{1/3}T^{2/3} \text{ (choosing } \epsilon = \left(\frac{A}{T}\right)^{1/3}\text{)}$$

Can We Do Better?

In explore-then-exploit and ϵ-greedy, the probability to choose arms do not depend on the estimated mean (except for the empirically best arm).

… Maybe, the probability of choosing arms can be adaptive to the estimated mean?

Solution: Refine the amount of exploration for each arm **based on the current mean estimation**.

(Has to do this carefully to avoid **under-exploration**)

Refined Exploration

Boltzmann Exploration (Parameter: λ)

In each round, sample a_t according to

$$\pi_t(a) \propto \exp\left(\lambda \hat{R}_t(a)\right)$$

where $\hat{R}_t(a)$ is the empirical mean of arm a using samples up to time $t-1$.

Inverse Gap Weighting (Parameter: λ)

γ_t is a normalization factor that makes $\sum_a \pi_t(a) = 1$

$$\pi_t(a) = \frac{1}{\gamma_t - \lambda \hat{R}_t(a)} = \frac{1}{\gamma_t' + \lambda \mathrm{Gap}_t(a)}$$

where $\mathrm{Gap}_t(a) = \max_b \hat{R}_t(b) - \hat{R}_t(a)$

Refined Exploration

Variant of Inverse Gap Weighting Easier for Implementation (Parameter: λ)

$$\pi_t(a) = \begin{cases} \dfrac{1}{A + \lambda \mathrm{Gap}_t(a)} & \text{if } a \neq \operatorname{argmax} \hat{R}_t(a) \\ 1 - \displaystyle\sum_{a' \neq a} \pi_t(a') & \text{if } a = \operatorname{argmax} \hat{R}_t(a) \end{cases}$$

where $\mathrm{Gap}_t(a) = \max_b \hat{R}_t(b) - \hat{R}_t(a)$

Refined Exploration

- Boltzmann Exploration
  - A quite commonly used exploration strategy (like ϵ-greedy)
  - For fixed parameter $\lambda \geq 2\log t$, there is always a problem instance making BE suffer $\Theta(T)$ regret
  - There is no known regret bound for it yet (?)

Cesa-Bianchi, Gentile, Lugosi, Neu. Boltzmann Exploration Done Right, 2017.
Bian and Jun. Maillard Sampling: Boltzmann Exploration Done Optimally. 2021.

- Inverse Gap Weighting
  - Less known
  - We can show a near-optimal regret bound $\sqrt{AT}$ for it, improving the $A^{1/3}T^{2/3}$ by ϵ-greedy

Foster and Rakhlin. Beyond UCB: Optimal and Efficient Contextual Bandits with Regression Oracles. 2020.

Guarantee of Inverse Gap Weighting

Inverse Gap Weighting ensures with high probability,

$$\text{Regret} \lesssim \frac{A}{\lambda} + \lambda \log T \quad \approx \sqrt{AT \log T} \text{ (choosing } \lambda = \sqrt{\frac{T}{A \log T}}\text{)}$$

D. Foster and A. Rakhlin. Beyond UCB: Optimal and Efficient Contextual Bandits with Regression Oracles. 2020.

See supplementary materials for a formal proof.

Summary: MAB Based on Mean Estimation

For $t = 1, 2, \dots, T$,

Design a distribution $\pi_t(\cdot)$ based on the current mean estimation $\hat{R}_t(\cdot)$

EG	$\pi_t(a) = (1-\epsilon)\mathbb{I}\{a = \operatorname{argmax} \hat{R}_t(\cdot)\} + \frac{\epsilon}{A}$	$A^{1/3}T^{2/3}$
BE	$\pi_t(a) \propto \exp\left(\lambda \hat{R}_t(a)\right)$	XXX
IGW	$\pi_t(a) = \frac{1}{\gamma_t - \lambda \hat{R}_t(a)}$	$\sqrt{AT \log T}$

Sample an arm $a_t \sim \pi_t$ and receive the corresponding reward r_t.

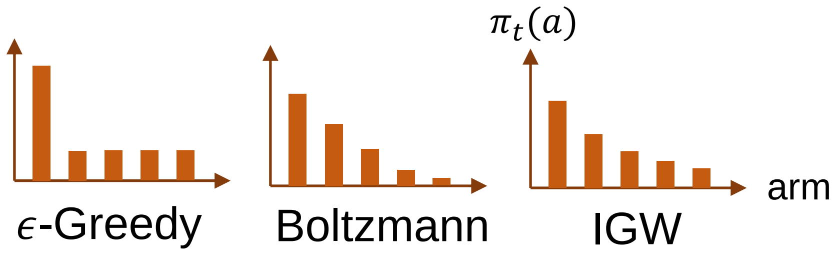
Refine the mean estimation $\hat{R}_{t+1}(\cdot)$ with the new sample (a_t, r_t).

Summary: MAB Based on Mean Estimation

(a_t, r_t)

Mean Estimation $\xrightarrow{\hat{R}_t(\cdot)}$ **Decision Rule** $\xrightarrow{\pi_t(\cdot)}$ Pick action $a_t \sim \pi_t$
Receive r_t

$$\hat{R}_t(a) = \frac{\sum_{s=1}^{t-1} \mathbb{I}\{a_s = a\}\, r_s}{\sum_{s=1}^{t-1} \mathbb{I}\{a_s = a\}}$$



$$\pi_t(a) = (1-\epsilon)\mathbb{I}\{a = \text{argmax}\, \hat{R}_t(\cdot)\} + \frac{\epsilon}{A}$$

$$\pi_t(a) \propto \exp\big(\lambda \hat{R}_t(a)\big)$$

$$\pi_t(a) = \frac{1}{\gamma_t - \lambda \hat{R}_t(a)}$$

Summary: MAB Based on Mean Estimation

- All 3 methods are based on the same **mean estimation**
- The key difference is in the **decision rule**, i.e., the mapping from estimated means $\hat{R}_t$ to a distribution π_t.
  - The shape of the mapping makes differences
- There is a scalar hyperparameter that allows for a tradeoff between exploration and exploitation (ϵ in EG, λ in BE or IGW)

Some Experiments

$T = 10000$ rounds

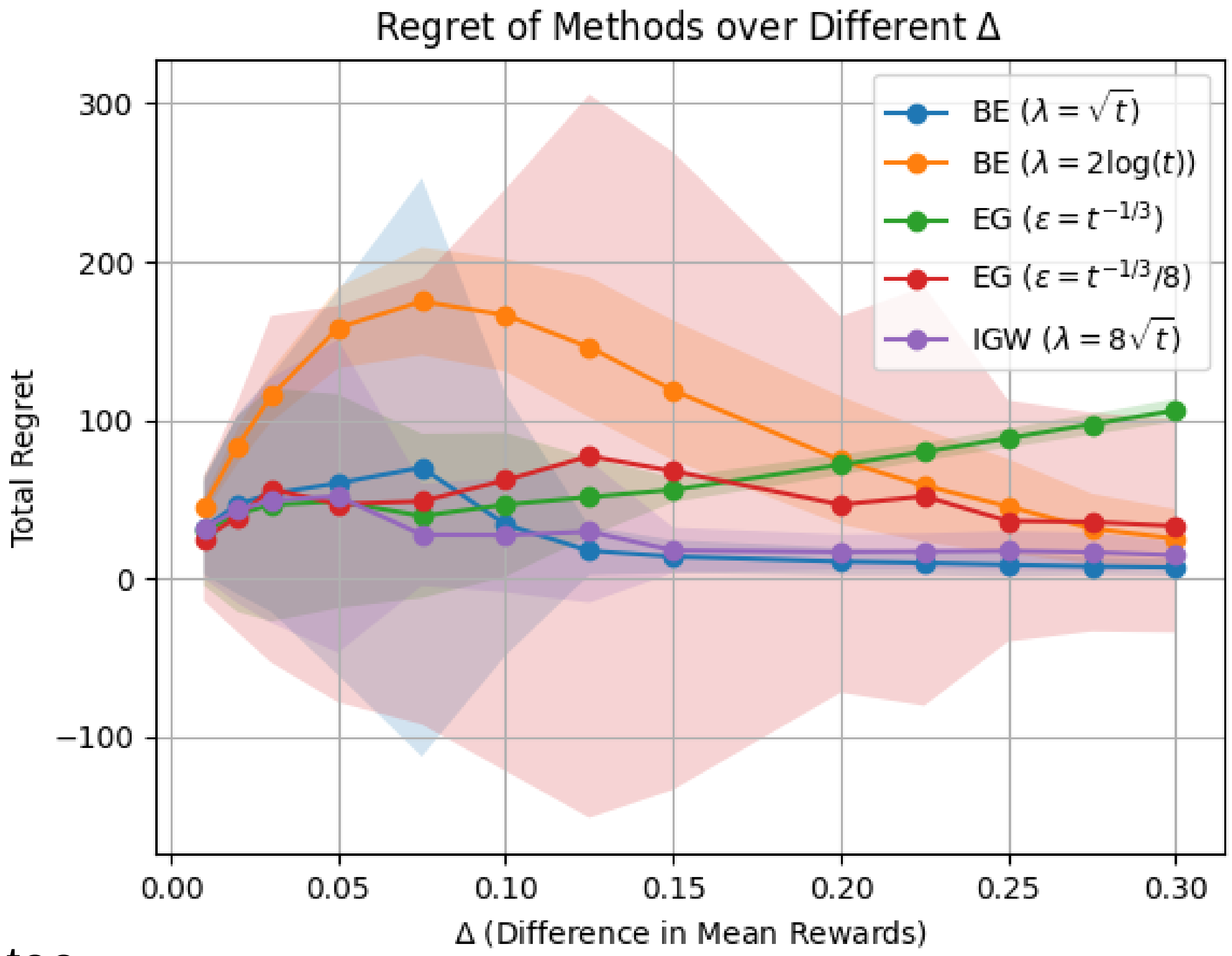
$A = 2$ arms

Reward mean $R = [0.5, 0.5 - \Delta]$

Bernoulli distribution

Time-dependent parameters

30 random seeds



Observations:

- Bound from theory could be loose
  -- theory captures **worst-case** guarantee
- Most algorithms seem to have its worst regret at some intermediate Δ value
  -- will be studied in Homework 1

Contextual Bandits

Based on reward function estimation

Multi-Armed Bandits vs. Contextual Bandits

Multi-Armed Bandit

4.2

?

?

all-user recommendation

Context

Contextual Bandit

4.2

?

?

personalized recommendation

e.g. the user's history, location, social network activity, …

Contextual Bandits Generalizes MAB and SL

Multi-Armed Bandit → 4.2, ?, ?

No input, bandit feedback

- Generalization
- **Exploration**
- Credit assignment

Input → **Supervised Learning** → 4.2, 5.0, 3.1

Takes input, full-information feedback

- **Generalization**
- Exploration
- Credit assignment

Input → **Contextual Bandit** → 4.2, ?, ?

Takes input, bandit feedback

- **Generalization**
- **Exploration**
- Credit assignment

Contextual Bandits

For time $t = 1, 2, \ldots, T$:

Environment generates a context $x_t \in \mathcal{X}$

Learner chooses an action $a_t \in \mathcal{A}$

Learner observes $r_t = R(x_t, a_t) + w_t$

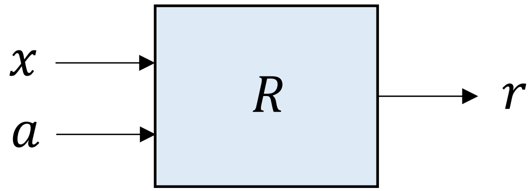
Discussion

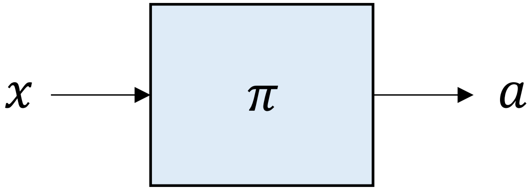
- Contextual bandits is a minimal simultaneous generalization of supervised learning (SL) and multi-armed bandits (MAB)
- We learned a lot about SL in machine learning courses
- We just learned some simple MAB algorithms
  - 3 strategies based on mean estimation

- **Question:** Can you design a contextual bandits algorithm based on the techniques you know for SL and MAB?

Two ways to leverage SL techniques in CB

x: context, a: action, r: reward





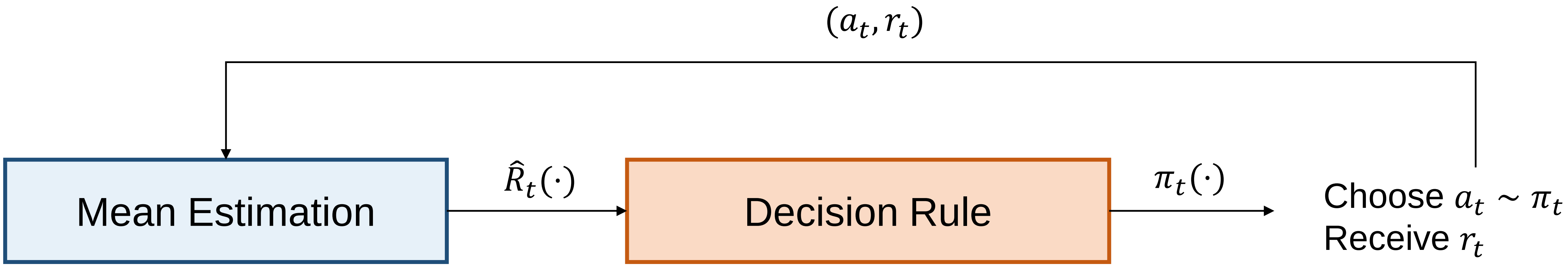
Learn a mapping from
(context, action) to reward

Learn a mapping from
context to action (or action distribution)

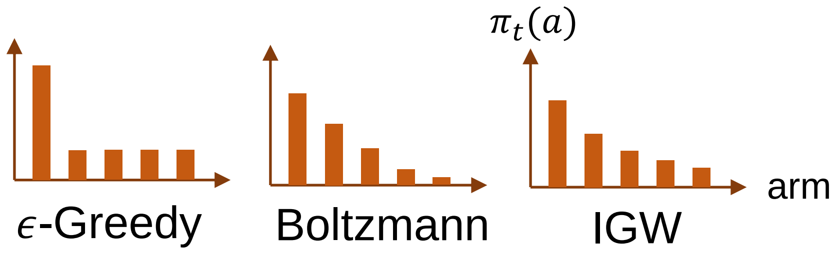
CB with **regression oracle**
Value-based approach
(discussed next)

CB with **classification oracle**
Policy-based approach
(slightly later in the course)

Recall: MAB Based on Mean Estimation



$$\hat{R}_t(a) = \frac{\sum_{s=1}^{t-1} \mathbb{I}\{a_s = a\}\, r_s}{\sum_{s=1}^{t-1} \mathbb{I}\{a_s = a\}}$$

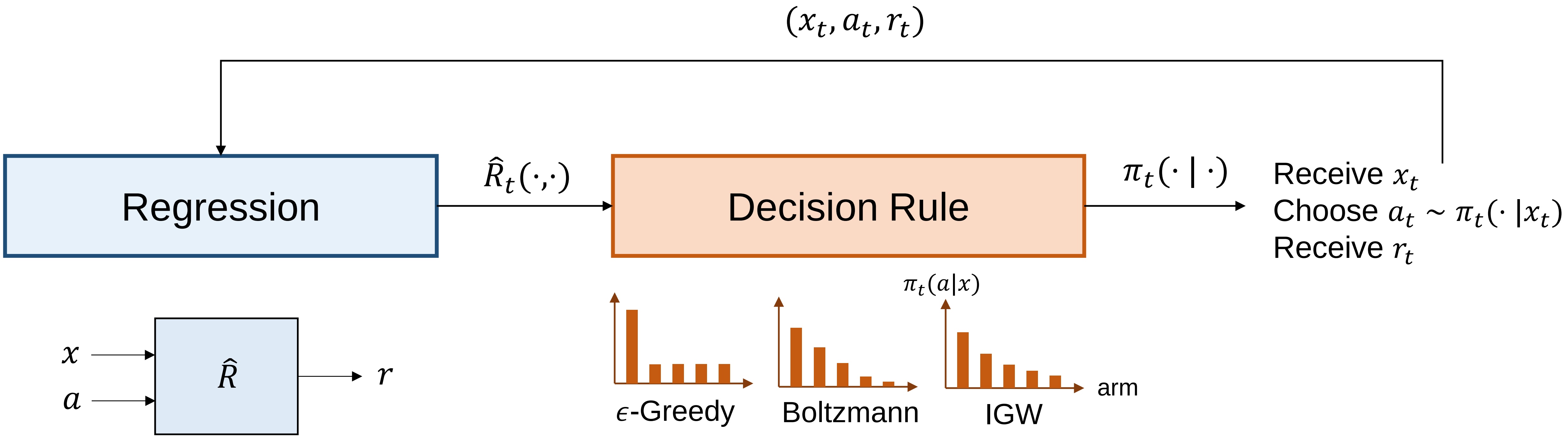


$$\pi_t(a) = (1-\epsilon)\mathbb{I}\{a = \operatorname{argmax} \hat{R}_t(\cdot)\} + \frac{\epsilon}{A}$$

$$\pi_t(a) \propto \exp\left(\lambda \hat{R}_t(a)\right)$$

$$\pi_t(a) = \frac{1}{\gamma_t - \lambda \hat{R}_t(a)}$$

CB Based on Reward Function Estimation (Regression)



Train a $\hat{R}$ such that $r_i \approx \hat{R}(x_i, a_i)$

$$\pi_t(a|x) = (1-\epsilon)\mathbb{I}\{a = \operatorname{argmax} \hat{R}_t(x,\cdot)\} + \frac{\epsilon}{A}$$

$$\pi_t(a|x) \propto \exp\left(\lambda \hat{R}_t(x,a)\right)$$

$$\pi_t(a|x) = \frac{1}{\gamma_t - \lambda \hat{R}_t(x,a)}$$

CB Based on Reward Function Estimation

Instantiate a regression procedure $\hat{R}_1$

For $t = 1, 2, \dots, T$,

Receive context x_t

Design a distribution $\pi_t(\cdot|x_t)$ based on the estimated reward $\hat{R}_t(x_t,\cdot)$

EG $\quad \pi_t(a|x_t) = (1-\epsilon)\mathbb{I}\{a = \operatorname{argmax} \hat{R}_t(x_t,\cdot)\} + \frac{\epsilon}{A}$

BE $\quad \pi_t(a|x_t) \propto \exp\left(\lambda \hat{R}_t(x_t, a)\right)$

IGW $\quad \pi_t(a|x_t) = \frac{1}{\gamma_t - \lambda \hat{R}_t(x_t, a)}$

Sample an action $a_t \sim \pi_t(\cdot\,|x_t)$ and receive the corresponding reward r_t.

Refine the reward estimator $\hat{R}_{t+1}(\cdot,\cdot)$ with the new sample (x_t, a_t, r_t).

Regret in Contextual Bandits

For time $t = 1, 2, \dots, T$:

Environment generates a context $x_t \in \mathcal{X}$

Learner chooses an action $a_t \in \mathcal{A}$

Learner observes $r_t = R(x_t, a_t) + w_t$

$$\text{Regret} = \sum_{t=1}^{T} R(x_t, \pi^\star(x_t)) - \sum_{t=1}^{T} R(x_t, a_t)$$

$$= \sum_{t=1}^{T} \max_{a \in \mathcal{A}} R(x_t, a) - \sum_{t=1}^{T} R(x_t, a_t)$$

Benchmark policy: $\pi^\star(x) = \operatorname{argmax}_{a \in \mathcal{A}} R(x, a)$

Regret in Contextual Bandits

Regret Bound of ϵ-Greedy

ϵ-Greedy ensures

$$\text{Regret} \lesssim \epsilon T + \sqrt{\frac{AT \cdot \text{Err}}{\epsilon}}$$

Regression error

$$\text{Err} = \sum_{t=1}^{T} \left(\hat{R}_t(x_t, a_t) - R(x_t, a_t)\right)^2$$

Regret Bound of Inverse Gap Weighting

IGW ensures

$$\text{Regret} \lesssim \frac{AT}{\lambda} + \lambda \cdot \text{Err}$$

Will be proven in HW1

Summary

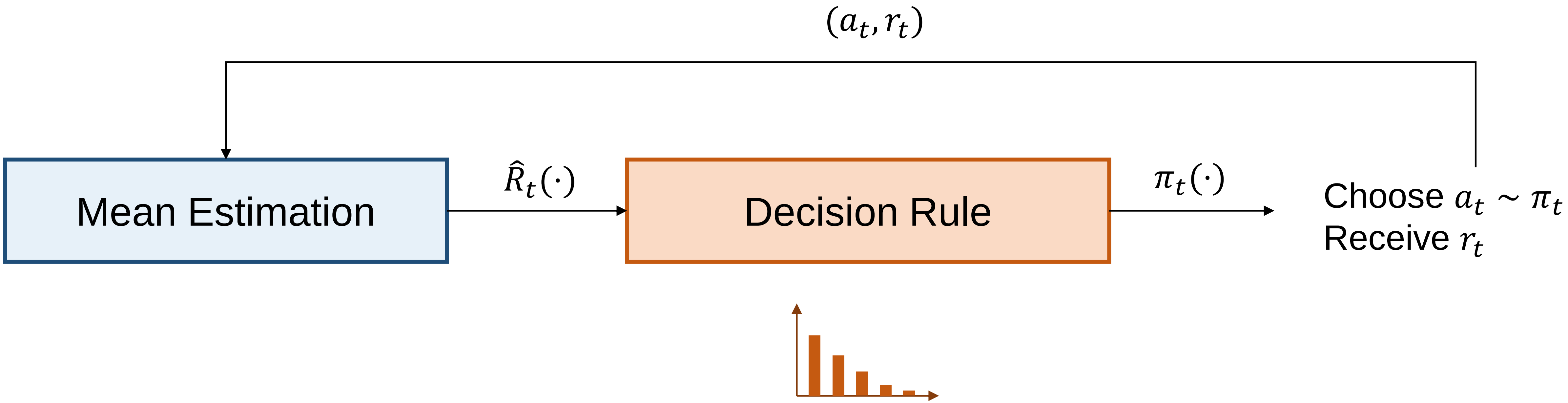
- Contextual bandits (CB) simultaneously generalizes supervised learning (SL) and multi-armed bandits (MAB). It captures the challenges of **generalization** and **exploration** in online RL.

- Any MAB algorithm based on “**mean estimation**” can be lifted as a CB algorithm with “**reward function estimation**” by leveraging a regression oracle.
  - This is a general framework of value-based CB algorithm

Multi-Armed Bandits

Based on mean and uncertainty estimation

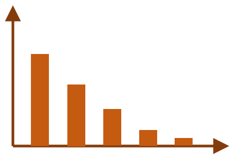
Recall: MAB Based on Mean Estimation



MAB Based on Mean and Uncertainty Estimation

(a_t, r_t)

Mean & Uncertainty Estimation $\xrightarrow{\hat{R}_t(\cdot),\, U_t(\cdot)}$ Decision Rule $\xrightarrow{\pi_t(\cdot)}$ Choose $a_t \sim \pi_t$ Receive r_t



$U_t(a)$: measures the uncertainty of $\hat{R}_t(a)$

$$\left|\hat{R}_t(a) - R(a)\right| \leq \sqrt{\frac{2\log(2/\delta)}{N_t(a)}} \triangleq U_t(a)$$

This inequality is used in the **math analysis** of ϵ-Greedy and IGW, but not in their **algorithm**.

Useful Idea: “Optimism in the Face of Uncertainty”

In words:

Act according to the **best plausible world**.

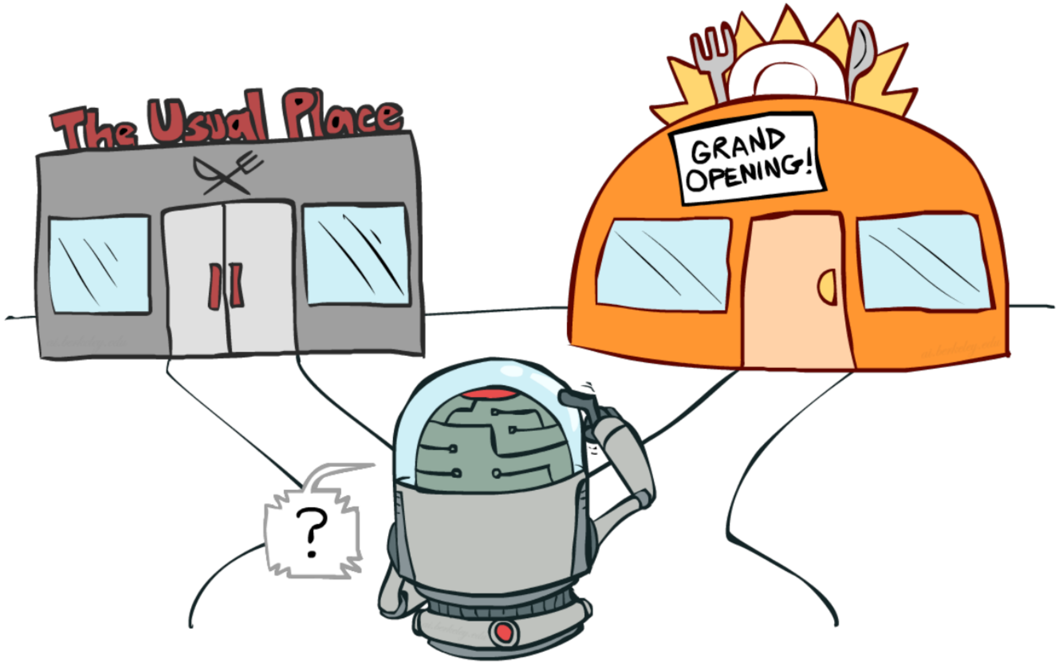


Image source: UC Berkeley CS188

Another Idea: “Optimism in the Face of Uncertainty”

In words:

Act according to the **best plausible world**.

At time t, suppose that arm a has been drawn for $N_t(a)$ times, with empirical mean $\hat{R}_t(a)$.

What can we say about the true mean $R(a)$?

$$\left| R(a) - \hat{R}_t(a) \right| \leq \sqrt{\frac{2\log(2/\delta)}{N_t(a)}} \quad \text{w.p.} \geq 1 - \delta$$

What’s the most optimistic mean estimation for arm a?

$$\hat{R}_t(a) + \sqrt{\frac{2\log(2/\delta)}{N_t(a)}}$$

Upper Confidence Bound (UCB)

UCB (Parameter: δ)

In the first A rounds, draw each arm once.

For the remaining rounds: in round t, draw

$$a_t = \mathrm{argmax}_a \ \ \hat{R}_t(a) + \sqrt{\frac{2\log(2/\delta)}{N_t(a)}}$$

where $\hat{R}_t(a)$ is the empirical mean of arm a using samples up to time $t-1$.

$N_t(a)$ is the number of samples of arm a up to time $t-1$.

P Auer, N Cesa-Bianchi, P Fischer. **Finite-time analysis of the multiarmed bandit problem**, 2002.

Regret Bound of UCB

Theorem. Regret Bound of UCB

UCB ensures with high probability,

$$\text{Regret} \lesssim \sqrt{AT} \quad .$$

UCB Regret Bound Analysis

Visualizing UCB

True mean: [0.2, 0.4, 0.6, 0.7]

Bandits

Summary for value-based approaches

Summary: Exploration

$\hat{R}_t(a)$: mean estimation for arm a at time t

$N_t(a)$: number of samples for arm a at time t

Explore-then-Exploit

$$a_t = \begin{cases} \text{uniform}(\mathcal{A}) & t \le T_0 \\ \text{argmax}_a \hat{R}_{T_0}(a) & t > T_0 \end{cases}$$

ϵ-Greedy

$$a_t = \begin{cases} \text{uniform}(\mathcal{A}) & \text{with prob. } \epsilon \\ \text{argmax}_a \hat{R}_t(a) & \text{with prob. } 1-\epsilon \end{cases}$$

Boltzmann Exploration

$$p_t(a) \propto \exp\big(\lambda_t \hat{R}_t(a)\big)$$

Inverse Gap Weighting

$$p_t(a) = \frac{1}{\gamma_t - \lambda_t \hat{R}_t(a)}$$

UCB

$$a_t = \text{argmax}_a \ \hat{R}_t(a) + \sqrt{\frac{2\log(2/\delta)}{N_t(a)}}$$

Summary: Exploration

	Regret Bound	Approach
Explore-then-Exploit ϵ-Greedy Boltzmann Exploration Inverse Gap Weighting	$A^{1/3}\,T^{2/3}$ $A^{1/3}\,T^{2/3}$ X $\sqrt{AT}$	Mean estimation + decision rule
Upper Confidence Bound Thompson Sampling Arm Elimination	$\sqrt{AT}$	Mean and uncertain estimation + decision rule