

Reinforcement Learning

Some Insights from the Bandit Literature

Emilie Kaufmann



M2 MVA, 2023/2024

RL : Taking a step back

RL \leftrightarrow Learn a good policy in an unknown Markov Decision Process

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Good policy : according to some notion of **value**

$$V^{\pi}(s) = \mathbb{E}^{\pi} \left[\sum_{t=1}^{\infty} \gamma^{t-1} r_t \middle| s_1 = s \right]$$

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or

$$V^{\pi}(s) = \mathbb{E}^{\pi} \left[\sum_{t=1}^H r_t \middle| s_1 = s \right]$$

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Learn : with what constraints ?

- ▶ learn a good policy using few interactions
- ▶ learn a good policy while maximizing rewards

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$$V^{\pi}(s) = \mathbb{E}^{\pi} \left[\sum_{t=1}^H r_t \middle| s_1 = s \right]$$

Learn : with what constraints ?

- ▶ learn a good policy using few interactions (*sample complexity*)
- ▶ learn a good policy while maximizing rewards (*regret*)

Both notions have been mathematically formalized in the (*theoretical*) RL literature, and mostly studied for tabular MDPs

Outline of the last two sessions

- ▶ In-depth study of the simplest MDP : the multi-armed bandit
 - ➔ Stochastic bandit algorithms (and their theoretical guarantees)
 - ➔ Towards a more realistic model : contextual bandits
 - ➔ Regret or Sample complexity ?
- ▶ Bandit tools for reinforcement learning (*next week*)
 - ➔ (Bandit-based) exploration in RL
 - ➔ (Bandit-based) Monte-Carlo Tree Search
 - ➔ AlphaZero

Reinforcement Learning

Lecture 7 : Multi-armed bandits

Emilie Kaufmann

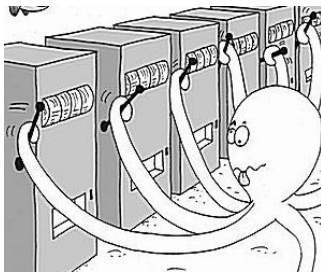


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Stochastic bandit : a simple MDP

A stochastic multi-armed bandit model is an MDP with a single state s_0

- ▶ unknown reward distribution $\nu_{s_0, a}$ with mean $r(s_0, a)$
- ▶ transition $p(s_0 | s_0, a) = 1$
- ▶ the agent repeatedly chooses between the same set of actions



an agent facing arms in a Multi-Armed Bandit

Typical applications

Clinical trials

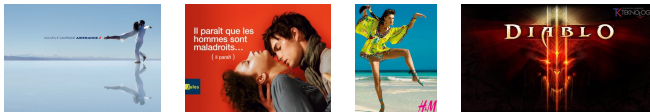
- ▶ K treatments for a given symptom (with unknown effect)



- ▶ What treatment should be allocated to the next patient based on responses observed on previous patients ?

Online advertisement

- ▶ K adds that can be displayed



- ▶ Which add should be displayed for a user, based on the previous clicks of previous (similar) users ?

The Multi-Armed Bandit Setup

K arms $\leftrightarrow K$ rewards streams $(X_{a,t})_{t \in \mathbb{N}}$



At round t , an agent :

- ▶ chooses an arm A_t
- ▶ receives a reward $R_t = X_{A_t,t}$

Sequential sampling strategy (**bandit algorithm**) :

$$A_{t+1} = F_t(A_1, R_1, \dots, A_t, R_t).$$

Goal (for now !) : Maximize $\sum_{t=1}^T R_t$.

The Stochastic Multi-Armed Bandit Setup

K arms $\leftrightarrow K$ probability distributions : ν_a has mean μ_a



ν_1



ν_2



ν_3



ν_4



ν_5

At round t , an agent :

- ▶ chooses an arm A_t
- ▶ receives a reward $R_t = X_{A_t,t} \sim \nu_{A_t}$

Sequential sampling strategy (**bandit algorithm**) :

$$A_{t+1} = F_t(A_1, R_1, \dots, A_t, R_t).$$

Goal (for now !) : Maximize $\mathbb{E} \left[\sum_{t=1}^T R_t \right]$

→ a particular reinforcement learning problem

Clinical trials

Historical motivation [Thompson, 1933]



$\mathcal{B}(\mu_1)$



$\mathcal{B}(\mu_2)$



$\mathcal{B}(\mu_3)$



$\mathcal{B}(\mu_4)$



$\mathcal{B}(\mu_5)$

For the t -th patient in a clinical study,

- ▶ chooses a **treatment** A_t
- ▶ observes a **response** $R_t \in \{0, 1\} : \mathbb{P}(R_t = 1 | A_t = a) = \mu_a$

Goal : maximize the expected number of patients healed

Online content optimization

Modern motivation (\$\$) [Li et al., 2010]
(recommender systems, online advertisement)



ν_1



ν_2



ν_3



ν_4



ν_5

For the t -th visitor of a website,

- ▶ recommend a **movie** A_t
- ▶ observe a **rating** $R_t \sim \nu_{A_t}$ (e.g. $R_t \in \{1, \dots, 5\}$)

Goal : maximize the sum of ratings

Regret decomposition

$N_a(t)$: number of selections of arm a in the first t rounds

$\Delta_a := \mu_\star - \mu_a$: sub-optimality gap of arm a

Regret decomposition

$$\mathcal{R}_\nu(\mathcal{A}, T) = \sum_{a=1}^K \Delta_a \mathbb{E}[N_a(T)].$$

Proof.



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Regret decomposition

$$\mathcal{R}_\nu(\mathcal{A}, T) = \sum_{a=1}^K \Delta_a \mathbb{E}[N_a(T)].$$

A strategy with small regret should :

- ▶ select not too often arms for which $\Delta_a > 0$
- ▶ ... which requires to try all arms to estimate the values of the Δ_a 's

⇒ Exploration / Exploitation trade-off

The greedy strategy

Select each arm once, then **exploit** the current knowledge :

$$A_{t+1} = \operatorname{argmax}_{a \in [K]} \hat{\mu}_a(t)$$

where

- ▶ $N_a(t) = \sum_{s=1}^t \mathbb{1}(A_s = a)$ is the number of selections of arm a
- ▶ $\hat{\mu}_a(t) = \frac{1}{N_a(t)} \sum_{s=1}^t X_s \mathbb{1}(A_s = a)$ is the **empirical mean** of the rewards collected from arm a

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The greedy strategy can fail ! $\nu_1 = \mathcal{B}(\mu_1), \nu_2 = \mathcal{B}(\mu_2), \mu_1 > \mu_2$

$$\mathbb{E}[N_2(T)] \geq (1 - \mu_1)\mu_2 \times (T - 1)$$

→ **Exploitation** is not enough, we need to **add some exploration**

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Explore-Then-Commit

Given $m \in \{1, \dots, T/K\}$,

- ▶ draw each arm m times
- ▶ compute the empirical best arm $\hat{a} = \operatorname{argmax}_a \hat{\mu}_a(Km)$
- ▶ keep playing this arm until round T

$$A_{t+1} = \hat{a} \text{ for } t \geq Km$$

⇒ EXPLORATION followed by EXPLOITATION

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Analysis for two arms. $\mu_1 > \mu_2$, $\Delta := \mu_1 - \mu_2$.

$$\begin{aligned}\mathcal{R}_\nu(\text{ETC}, T) &= \Delta \mathbb{E}[N_2(T)] \\ &= \Delta \mathbb{E}[m + (T - 2m)\mathbb{1}(\hat{a} = 2)] \\ &\leq \Delta m + (\Delta T) \times \mathbb{P}(\hat{\mu}_{2,m} \geq \hat{\mu}_{1,m})\end{aligned}$$

$\hat{\mu}_{a,m}$: empirical mean of the first m observations from arm a

Explore-Then-Commit

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$\hat{\mu}_{a,m}$: empirical mean of the first m observations from arm a

→ requires a concentration inequality

A Concentration Inequality

Sub-Gaussian random variables : $Z - \mu$ is σ^2 -subGaussian if

$$\mathbb{E}[Z] = \mu \quad \text{and} \quad \mathbb{E} \left[e^{\lambda(Z-\mu)} \right] \leq e^{\frac{\lambda^2 \sigma^2}{2}}. \quad (1)$$

Hoeffding inequality

Z_i i.i.d. satisfying (1). For all $s \geq 1$

$$\mathbb{P} \left(\frac{Z_1 + \dots + Z_s}{s} \geq \mu + x \right) \leq e^{-\frac{sx^2}{2\sigma^2}}$$

- ▶ ν_a bounded in $[a, b]$: $(b - a)^2/4$ sub-Gaussian (Hoeffding's lemma)
- ▶ $\nu_a = \mathcal{N}(\mu_a, \sigma^2)$: σ^2 sub-Gaussian

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Analysis for two arms. $\mu_1 > \mu_2$, $\Delta := \mu_1 - \mu_2$.

Assumption : ν_1, ν_2 are bounded in $[0, 1]$.

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→ Hoeffding's inequality

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Analysis for two arms. $\mu_1 > \mu_2$, $\Delta := \mu_1 - \mu_2$.

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For $m = \frac{2}{\Delta^2} \log \left(\frac{T\Delta^2}{2} \right)$,

$$\mathcal{R}_\nu(\text{ETC}, T) \leq \frac{2}{\Delta} \left[\log \left(\frac{T\Delta^2}{2} \right) + 1 \right].$$

Explore-Then-Commit

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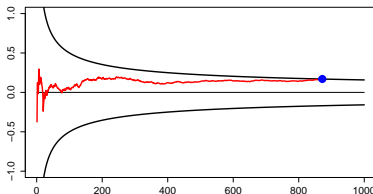
- + logarithmic regret !
- requires the knowledge of T and Δ

Sequential Explore-Then-Commit

- explore uniformly until a **random time** of the form

$$\tau = \inf \left\{ t \in \mathbb{N} : |\hat{\mu}_1(t) - \hat{\mu}_2(t)| > \sqrt{\frac{c \log(T/t)}{t}} \right\}$$

- $\hat{a}_\tau = \operatorname{argmax}_a \hat{\mu}_a(\tau)$ and $(A_{t+1} = \hat{a}_\tau)$ for $t \in \{\tau + 1, \dots, T\}$



- [Garivier et al., 2016] for two Gaussian arms, for $c = 8$, same regret as ETC, without the knowledge of Δ
... but larger regret as that of the best **fully sequential** strategy

Another possible fix : ϵ -greedy

The ϵ -greedy rule [Sutton and Barto, 1998] is a simple randomized way to alternate exploration and exploitation.

ϵ -greedy strategy

At round t ,

- ▶ with probability ϵ

$$A_t \sim \mathcal{U}(\{1, \dots, K\})$$

- ▶ with probability $1 - \epsilon$

$$A_t = \operatorname{argmax}_{a=1, \dots, K} \hat{\mu}_a(t).$$

→ Linear regret : $\mathcal{R}_\nu(\epsilon\text{-greedy}, T) \geq \epsilon \frac{K-1}{K} \Delta_{\min} T.$

$$\Delta_{\min} = \min_{a: \mu_a < \mu_*} \Delta_a$$

Another possible fix : ϵ -greedy

ϵ_t -greedy strategy

At round t ,

- ▶ with probability $\epsilon_t := \min\left(1, \frac{K}{d^2 t}\right)$

$$A_t \sim \mathcal{U}(\{1, \dots, K\})$$

- ▶ with probability $1 - \epsilon_t$

$$A_t = \operatorname{argmax}_{a=1, \dots, K} \hat{\mu}_a(t-1).$$

Theorem [Auer et al., 2002]

If $0 < d \leq \Delta_{\min}$, $\mathcal{R}_\nu(\epsilon_t\text{-greedy}, T) = O\left(\frac{K \log(T)}{d^2}\right)$.

→ requires the knowledge of a lower bound on Δ_{\min}

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The optimism principle

Step 1 : construct a set of statistically plausible models

- For each arm a , build a confidence interval on the mean μ_a :

$$\mathcal{I}_a(t) = [\text{LCB}_a(t), \text{UCB}_a(t)]$$

LCB = Lower Confidence Bound

UCB = Upper Confidence Bound

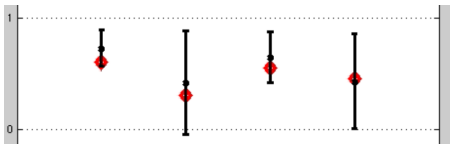


FIGURE – Confidence intervals on the means after t rounds

The optimism principle

Step 2 : act as if the best possible model were the true model
(*optimism in face of uncertainty*)

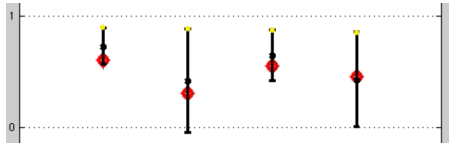


FIGURE – Confidence intervals on the means after t rounds

► That is, select

$$A_{t+1} = \operatorname{argmax}_{a=1,\dots,K} \text{UCB}_a(t).$$

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How to build confidence intervals ?

We need $\text{UCB}_a(t)$ such that

$$\mathbb{P}(\mu_a \leq \text{UCB}_a(t)) \gtrsim 1 - t^{-1}.$$

→ tool : concentration inequalities

Example : rewards are σ^2 sub-Gaussian

Reminder : Hoeffding inequality

Z_i i.i.d. with mean μ s.t. $\mathbb{E}[e^{\lambda(Z_1 - \mu)}] \leq e^{\frac{\lambda^2 \sigma^2}{2}}$. For all $s \geq 1$

$$\mathbb{P}\left(\frac{Z_1 + \dots + Z_s}{s} < \mu - x\right) \leq e^{-\frac{sx^2}{2\sigma^2}}$$

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Z_i i.i.d. with mean μ s.t. $\mathbb{E}[e^{\lambda(Z_i - \mu)}] \leq e^{\frac{\lambda^2 \sigma^2}{2}}$. For all $s \geq 1$

$$\mathbb{P}\left(\frac{Z_1 + \dots + Z_s}{s} < \mu - x\right) \leq e^{-\frac{sx^2}{2\sigma^2}}$$

 Cannot be used directly in a bandit model as the number of observations from each arm is random !

How to build confidence intervals ?

- ▶ $N_a(t) = \sum_{s=1}^t \mathbb{1}_{(A_s=a)}$ number of selections of a after t rounds
- ▶ $\hat{\mu}_{a,s} = \frac{1}{s} \sum_{k=1}^s Y_{a,k}$ average of the first s observations from arm a
- ▶ $\hat{\mu}_a(t) = \hat{\mu}_{a,N_a(t)}$ empirical estimate of μ_a after t rounds

Hoeffding inequality + union bound

$$\mathbb{P} \left(\mu_a \leq \hat{\mu}_a(t) + \sqrt{\frac{6\sigma^2 \log(t)}{N_a(t)}} \right) \geq 1 - \frac{1}{t^2}$$

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$$\mathbb{P} \left(\mu_a \leq \hat{\mu}_a(t) + \sqrt{\frac{6\sigma^2 \log(t)}{N_a(t)}} \right) \geq 1 - \frac{1}{t^2}$$

Proof.

$$\begin{aligned} \mathbb{P} \left(\mu_a > \hat{\mu}_a(t) + \sqrt{\frac{6\sigma^2 \log(t)}{N_a(t)}} \right) &\leq \mathbb{P} \left(\exists s \leq t : \mu_a > \hat{\mu}_{a,s} + \sqrt{\frac{6\sigma^2 \log(t)}{s}} \right) \\ &\leq \sum_{s=1}^t \mathbb{P} \left(\hat{\mu}_{a,s} < \mu_a - \sqrt{\frac{6\sigma^2 \log(t)}{s}} \right) \leq \sum_{s=1}^t \frac{1}{t^3} = \frac{1}{t^2}. \end{aligned}$$

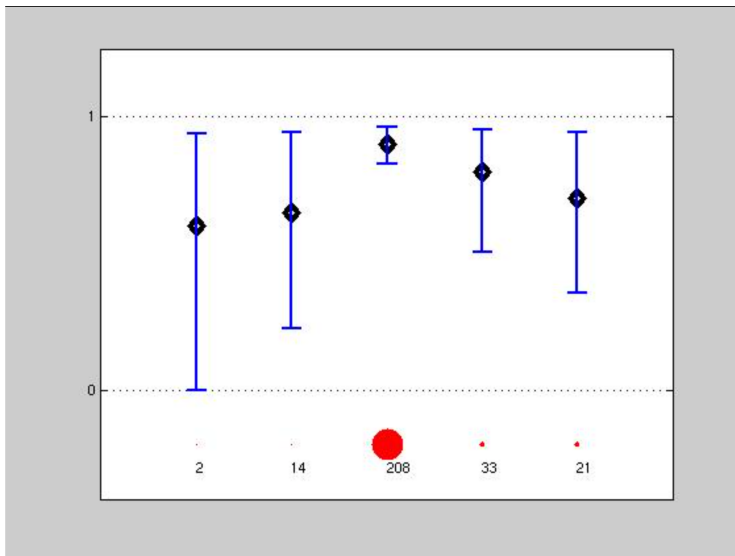
A first UCB algorithm

UCB(α) selects $A_{t+1} = \operatorname{argmax}_a \text{UCB}_a(t)$ where

$$\text{UCB}_a(t) = \underbrace{\hat{\mu}_a(t)}_{\text{exploitation term}} + \underbrace{\sqrt{\frac{\alpha \log(t)}{N_a(t)}}}_{\text{exploration bonus}}.$$

- ▶ this form of UCB was first proposed for Gaussian rewards [Katehakis and Robbins, 1995]
- ▶ popularized by [Auer et al., 2002] for bounded rewards : UCB1, for $\alpha = 2$
- ▶ the analysis of UCB(α) was further refined to hold for $\alpha > 1/2$ in that case [Bubeck, 2010, Cappé et al., 2013]

A UCB algorithm in action



A regret bound for UCB(α)

Theorem

For σ^2 -subGaussian rewards, the UCB algorithm with parameter $\alpha = 6\sigma^2$ satisfies, for any sub-optimal arm a ,

$$\mathbb{E}_{\mu}[N_a(T)] \leq \frac{24\sigma^2}{\Delta_a^2} \log(T) + 1 + \frac{\pi^2}{3}$$

where $\Delta_a = \mu_{\star} - \mu_a$.

Consequence :

$$\mathcal{R}_{\nu}(\text{UCB}(6\sigma^2), T) \leq \left(\sum_{a: \mu_a < \mu_{\star}} \frac{24\sigma^2}{\Delta_a^2} \right) \log(T) + \left(1 + \frac{\pi^2}{3} \right) \sum_{a=1}^K \Delta_a$$

Proof (1/2)

For each arm $i \in \{1, a\}$, define the two ends of the confidence interval :

$$\text{UCB}_i(t) = \hat{\mu}_i(t) + \sqrt{\frac{6\sigma^2 \log(t)}{N_i(t)}}$$

$$\text{LCB}_i(t) = \hat{\mu}_i(t) - \sqrt{\frac{6\sigma^2 \log(t)}{N_i(t)}}$$

and the *good event*

$$\mathcal{E}_t = (\mu_1 < \text{UCB}_1(t)) \cap (\mu_a > \text{LCB}_a(t))$$

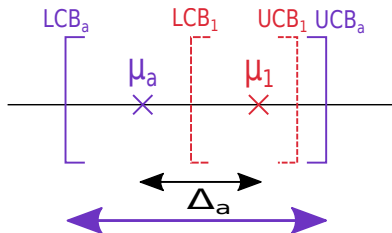
► **Step 1** : Hoeffding inequality + union bound :

$$\mathbb{P}(\mathcal{E}_t^c) \leq \mathbb{P}\left(\mu_1 > \hat{\mu}_1(t) + \sqrt{\frac{6\sigma^2 \log(t)}{N_1(t)}}\right) + \mathbb{P}\left(\mu_a < \hat{\mu}_a(t) - \sqrt{\frac{6\sigma^2 \log(t)}{N_a(t)}}\right) \leq \frac{2}{t^2}$$

Proof (2/2)

- **Step 2** : What happens on the good event ?

$$(A_{t+1} = a) \cap (\mu_1 < \text{UCB}_1(t)) \cap (\mu_a > \text{LCB}_a(t))$$

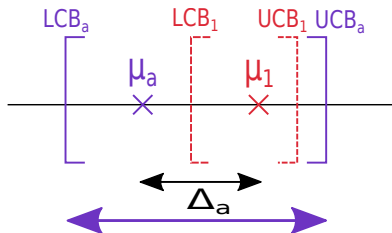


$$\Rightarrow N_a(t) \leq \frac{24\sigma^2 \log(t)}{\Delta_a^2}$$

Proof (2/2)

- **Step 2** : What happens on the good event ?

$$(A_{t+1} = a) \cap (\mu_1 < \text{UCB}_1(t)) \cap (\mu_a > \text{LCB}_a(t))$$



$$\Rightarrow N_a(t) \leq \frac{24\sigma^2 \log(t)}{\Delta_a^2}$$

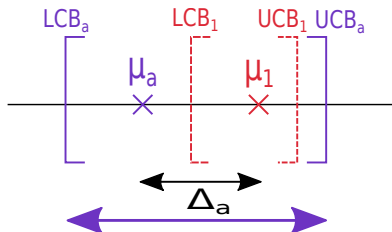
- **Step 3** : Putting everything together

$$\begin{aligned} \mathbb{E}[N_a(T)] &\leq 1 + \sum_{t=K}^{T-1} \mathbb{P}(\mathcal{E}_t^c) + \sum_{t=K}^{T-1} \mathbb{P}(A_{t+1} = a, \mathcal{E}_t) \\ &\leq 1 + \frac{\pi^2}{3} + \sum_{t=K}^{T-1} \mathbb{P}\left(A_{t+1} = a, N_a(t) \leq \frac{24\sigma^2 \log(T)}{\Delta_a^2}\right) \end{aligned}$$

Proof (2/2)

- **Step 2** : What happens on the good event ?

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A worse-case regret bound

Corollary

$$\mathcal{R}_\nu(\text{UCB}(6\sigma^2), T) \leq 10\sqrt{KT \log(T)} + \left(1 + \frac{\pi^2}{3}\right) \left(\sum_{a=1}^K \Delta_a\right)$$

Proof. For any algorithm satisfying $\mathbb{E}[N_a(T)] \leq C \frac{\log(T)}{\Delta_a} + D$ for all sub-optimal arm a , for any $\Delta > 0$,

$$\begin{aligned} \mathcal{R}_\nu(T) &= \sum_{a: \Delta_a \leq \Delta} \Delta_a \mathbb{E}[N_a(T)] + \sum_{a: \Delta_a \geq \Delta} \Delta_a \mathbb{E}[N_a(T)] \\ &\leq \Delta T + \sum_{a: \Delta_a \geq \Delta} \left(C \frac{\log(T)}{\Delta_a} + D \Delta_a \right) \\ &\leq \Delta T + \frac{CK \log(T)}{\Delta} + D \left(\sum_{a=1}^K \Delta_a \right) \\ &= 2\sqrt{CKT \log(T)} + D \left(\sum_{a=1}^K \Delta_a \right) \text{ for } \Delta = \sqrt{\frac{CK \log(T)}{T}} \end{aligned}$$

Best known problem-dependent bound

Context : σ^2 sub-Gaussian rewards

$$\text{UCB}_a(t) = \hat{\mu}_a(t) + \sqrt{\frac{2\sigma^2(\log(t) + c \log \log(t))}{N_a(t)}}$$

($c = 0$ corresponds to $\text{UCB}(\alpha)$ with $\alpha = 2\sigma^2$)

Theorem [Cappé et al.'13]

For $c \geq 3$, the UCB algorithm associated to the above index satisfy

$$\mathbb{E}[N_a(T)] \leq \frac{2\sigma^2}{\Delta_a^2} \log(T) + C_\mu \sqrt{\log(T)}.$$

Summary

For $\text{UCB}(\alpha)$ applied to σ^2 -subGaussian reward, setting $\alpha = 2\sigma^2$ yields

- ▶ a **problem-dependent** regret bound of

$$\left(\sum_{a=1}^K \frac{2\sigma^2}{\Delta_a} \right) \log(T) + o(\log(T))$$

- ▶ a **worse-case** regret of order

$$O\left(\sqrt{KT \log(T)}\right)$$

- ➡ how good are these regret rates?

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A worse-case lower bound

Theorem [Cesa-Bianchi and Lugosi, 2006]

Fix $T \in \mathbb{N}$. For every bandit algorithm \mathcal{A} , there exists a stochastic bandit model ν with rewards supported in $[0, 1]$ such that

$$\mathcal{R}_\nu(\mathcal{A}, T) \geq \frac{1}{20} \sqrt{KT}$$

► worse-case model :

$$\begin{cases} \nu_a &= \mathcal{B}(1/2) \text{ for all } a \neq i \\ \nu_i &= \mathcal{B}(1/2 + \Delta) \end{cases}$$

with $\Delta \simeq \sqrt{K/T}$.

Remark. UCB achieves $\mathcal{O}(\sqrt{KT \log(T)})$ (near-optimal)

There exists worse-case optimal algorithms, e.g., MOSS or Tsallis-Inf
[Audibert and Bubeck, 2010, Zimmert and Seldin, 2021]

The Lai and Robbins lower bound

Context : a **parametric bandit model** where each arm is parameterized by its mean $\nu = (\nu_{\mu_1}, \dots, \nu_{\mu_K})$, $\mu_a \in \mathcal{I}$.

$$\nu \leftrightarrow \mu = (\mu_1, \dots, \mu_K)$$

Key tool : **Kullback-Leibler divergence.**

Kullback-Leibler divergence

$$\text{kl}(\mu, \mu') := \text{KL}(\nu_\mu, \nu_{\mu'}) = \mathbb{E}_{X \sim \nu_\mu} \left[\log \frac{d\nu_\mu}{d\nu_{\mu'}}(X) \right]$$

Theorem

For *uniformly good* algorithm,

$$\mu_a < \mu_\star \Rightarrow \liminf_{T \rightarrow \infty} \frac{\mathbb{E}_\mu[N_a(T)]}{\log T} \geq \frac{1}{\text{kl}(\mu_a, \mu_\star)}$$

[Lai and Robbins, 1985]

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Kullback-Leibler divergence

$$\text{kl}(\mu, \mu') := \frac{(\mu - \mu')^2}{2\sigma^2} \quad (\text{Gaussian bandits})$$

Theorem

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[Lai and Robbins, 1985]

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Key tool : **Kullback-Leibler divergence.**

Kullback-Leibler divergence

$$\text{kl}(\mu, \mu') := \mu \log \left(\frac{\mu}{\mu'} \right) + (1 - \mu) \log \left(\frac{1 - \mu}{1 - \mu'} \right) \quad (\text{Bernoulli bandits})$$

Theorem

For *uniformly good* algorithm,

$$\mu_a < \mu_\star \Rightarrow \liminf_{T \rightarrow \infty} \frac{\mathbb{E}_\mu[N_a(T)]}{\log T} \geq \frac{1}{\text{kl}(\mu_a, \mu_\star)}$$

[Lai and Robbins, 1985]

UCB compared to the lower bound

Gaussian distributions with variance σ^2

► **Lower bound** : $\mathbb{E}[N_a(T)] \gtrsim \frac{2\sigma^2}{(\mu_* - \mu_a)^2} \log(T)$

► **Upper bound** : for UCB(α) with $\alpha = 2\sigma^2$

$$\mathbb{E}[N_a(T)] \lesssim \frac{2\sigma^2}{(\mu_* - \mu_a)^2} \log(T)$$

→ UCB is asymptotically optimal for Gaussian rewards !

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→ UCB is asymptotically optimal for Gaussian rewards !

Bernoulli distributions (bounded, $\sigma^2 = 1/4$)

- ▶ **Lower bound** : $\mathbb{E}[N_a(T)] \gtrsim \frac{1}{\text{kl}(\mu_a, \mu_\star)} \log(T)$
- ▶ **Upper bound** : for UCB(α) with $\alpha = 1/2$

$$\mathbb{E}[N_a(T)] \lesssim \frac{1}{2(\mu_\star - \mu_a)^2} \log(T)$$

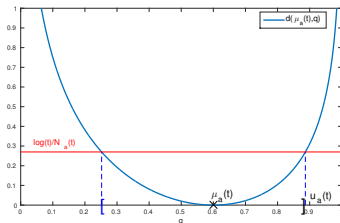
Pinsker's inequality : $\text{kl}(\mu_a, \mu_\star) > 2(\mu_\star - \mu_a)^2$

→ UCB is *not* asymptotically optimal for Bernoulli rewards...

The kl-UCB algorithm

Exploits the KL-divergence in the lower bound !

$$\text{UCB}_a(t) = \max \left\{ q \in [0, 1] : \text{kl}(\hat{\mu}_a(t), q) \leq \frac{\log(t)}{N_a(t)} \right\}.$$



A tighter concentration inequality [Garivier and Cappé, 2011]

For rewards in a one-dimensional exponential family ^a,

$$\mathbb{P}(\text{UCB}_a(t) > \mu_a) \gtrsim 1 - \frac{1}{t \log(t)}.$$

a. e.g., Bernoulli, Gaussian with known variances, Poisson, Exponential

An asymptotically optimal algorithm

kl-UCB selects $A_{t+1} = \operatorname{argmax}_a \text{UCB}_a(t)$ with

$$\text{UCB}_a(t) = \max \left\{ q \in [0, 1] : \text{kl}(\hat{\mu}_a(t), q) \leq \frac{\log(t) + c \log \log(t)}{N_a(t)} \right\}.$$

Theorem [Cappé et al., 2013]

If $c \geq 3$, for every arm such that $\mu_a < \mu_\star$,

$$\mathbb{E}_\mu[N_a(T)] \leq \frac{1}{\text{kl}(\mu_a, \mu_\star)} \log(T) + C_\mu \sqrt{\log(T)}.$$

- **asymptotically optimal** for Bernoulli rewards (and one-dimensional exponential families) :

$$\mathcal{R}_\mu(\text{kl-UCB}, T) \simeq \left(\sum_{a: \mu_a < \mu_\star} \frac{\Delta_a}{\text{kl}(\mu_a, \mu_\star)} \right) \log(T).$$

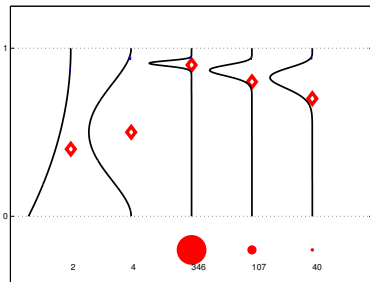
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A Bayesian algorithm

$\pi_a(0)$: prior distribution on μ_a

$\pi_a(t) = \mathcal{L}(\mu_a | Y_{a,1}, \dots, Y_{a,N_a(t)})$: posterior distribution on μ_a



Two equivalent interpretations :

- ▶ [Thompson, 1933] : “randomize the arms according to their posterior probability being optimal”
- ▶ modern view : “draw a possible bandit model from the posterior distribution and act optimally in this sampled model”

Thompson Sampling

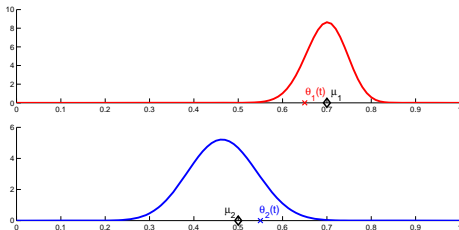
Input : a prior distribution $\pi(0)$

$$\begin{cases} \forall a \in \{1..K\}, \theta_a(t) \sim \pi_a(t) \\ A_{t+1} = \operatorname{argmax}_{a=1..K} \theta_a(t). \end{cases}$$

Thompson Sampling for Bernoulli distributions

$$\nu_a = \mathcal{B}(\mu_a)$$

- ▶ $\pi_a(0) = \mathcal{U}([0, 1])$
- ▶ $\pi_a(t) = \text{Beta}(S_a(t) + 1; N_a(t) - S_a(t) + 1)$



Thompson Sampling

Input : a prior distribution $\pi(0)$

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- ▶ $\pi_a(t) = \text{Beta}(S_a(t) + 1; N_a(t) - S_a(t) + 1)$

Thompson Sampling for Gaussian distributions

$$\nu_a = \mathcal{N}(\mu_a, \sigma^2)$$

- ▶ $\pi_a(0) \propto 1$
- ▶ $\pi_a(t) = \mathcal{N}(\hat{\mu}_a(t); \frac{\sigma^2}{N_a(t)})$

Regret bounds

Upper bound on sub-optimal selections

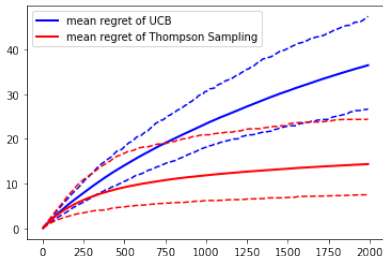
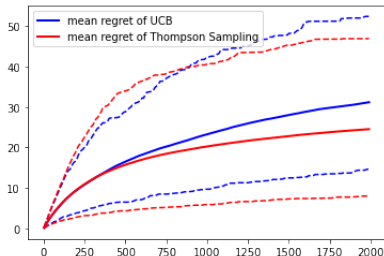
$$\forall a \neq a_*, \quad \mathbb{E}_\mu[N_a(T)] \leq \frac{\log(T)}{\text{kl}(\mu_a, \mu_*)} + o_\mu(\log(T)).$$

where $\text{kl}(\mu_a, \mu_*)$ is the KL divergence between ν_a and ν_{a_*}

- ▶ proved for **Bernoulli bandits**, with a **uniform prior**
[Kaufmann et al., 2012, Agrawal and Goyal, 2013a]
- ▶ for **1-dimensional exponential families**, with a **conjugate prior**
[Agrawal and Goyal, 2017, Korda et al., 2013]
- Thompson Sampling is **asymptotically optimal** in these cases
- ▶ beyond 1-parameter models, the prior has to be well chosen...
[Honda and Takemura, 2014]

Practical performance

Regret curves for UCB ($\alpha = 1/2$) and Thompson Sampling on two Bernoulli bandit problems, averaged over 500 runs.



Who is who? Try it out!

$$\mu_A = [0.45 \ 0.5 \ 0.6]$$

$$\mu_B = [0.1 \ 0.05 \ 0.02 \ 0.01]$$

Summary so far

Several important ideas to tackle the **exploration/exploitation challenge** in a simple multi-armed bandit model with independent arms :

- ▶ Explore then Commit
- ▶ ε -greedy
- ▶ Optimistic algorithms : **Upper Confidence Bounds strategies**
- ▶ Randomized (Bayesian) exploration : **Thompson Sampling**

Can these ideas be extended to more **structured** models that are better suited for applications ?

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Motivation



Which movie should Netflix recommend to a particular user, given the ratings provided by previous users ?

- to make good recommendation, we should **take into account the characteristics of the movies / users**

Arm in $\{1, 2, \dots, K\} \leftrightarrow$ Context vector in some space \mathcal{X}

A **contextual bandit model** incorporates two components :

- ▶ a sequential interaction protocol :
pick an arm, receive a reward
- ▶ a **regression model** for the dependency between context and reward

Generic Contextual Bandit Model

In each round t , the agent

- ▶ is given a set of *arms* $\mathcal{X}_t \subseteq \mathcal{X}$ (can be different in each round)
- ▶ selects an *arm* $x_t \in \mathcal{X}_t$
- ▶ receives a reward

$$r_t = f_*(x_t) + \varepsilon_t$$

where

- $f_* : \mathcal{X} \rightarrow \mathbb{R}$ is an unknown regression function
- ε_t is a centered noise, independent from previous data

Example

- user t : descriptor $c_t \in \mathbb{R}^p$
- item a : descriptor $x_a \in \mathbb{R}^{p'}$
- build a user-item feature vector for $(t, a) : x_{t,a} \in \mathbb{R}^d$

$$\mathcal{X}_t = \{x_{t,a}, a \in \mathcal{K}_t\}$$

Contextual linear bandits

In each round t , the agent

- ▶ receives a (finite) set of arms $\mathcal{X}_t \subseteq \mathbb{R}^d$
- ▶ chooses an arm $x_t \in \mathcal{X}_t$
- ▶ gets a reward $r_t = \theta_\star^\top x_t + \varepsilon_t$

where

- $\theta_\star \in \mathbb{R}^d$ is an unknown regression vector
- ε_t is a centered noise, independent from past data

Assumption : σ^2 - sub-Gaussian noise

$$\forall \lambda \in \mathbb{R}, \mathbb{E} [e^{\lambda X}] \leq e^{\frac{\lambda^2 \sigma^2}{2}}$$

e.g., Gaussian noise, bounded noise.

Contextual linear bandits

In each round t , the agent

- ▶ receives a (finite) set of arms $\mathcal{X}_t \subseteq \mathbb{R}^d$
- ▶ chooses an arm $x_t \in \mathcal{X}_t$
- ▶ gets a reward $r_t = \theta_\star^\top x_t + \varepsilon_t$

where

- $\theta_\star \in \mathbb{R}^d$ is an unknown regression vector
- ε_t is a centered noise, independent from past data

(Pseudo)-regret for contextual bandit

maximizing expected total reward \leftrightarrow minimizing the expectation of

$$R_T(\mathcal{A}) = \sum_{t=1}^T \left(\max_{x \in \mathcal{X}_t} \theta_\star^\top x - \theta_\star^\top x_t \right)$$

→ in each round, comparison to a possibly different optimal action !

Tools

Algorithms will rely on estimates / confidence regions / posterior distributions for $\theta_\star \in \mathbb{R}^d$.

- ▶ design matrix (with regularization parameter $\lambda > 0$)

$$B_t^\lambda = \lambda I_d + \sum_{s=1}^t x_s x_s^\top$$

- ▶ regularized least-square estimate

$$\hat{\theta}_t^\lambda = (B_t^\lambda)^{-1} \left(\sum_{s=1}^t r_s x_s \right)$$

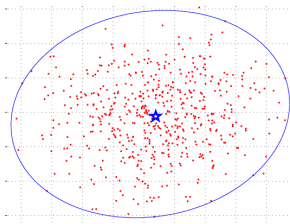
- ▶ estimate of the expected reward of an arm $x \in \mathbb{R}^d$: $x^\top \hat{\theta}_t^\lambda$
- ➔ sufficient for ε -greedy or ETC, but not for smarter algorithms...

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How to build (tight) confidence interval on the mean rewards ?

Idea : rely on a **confidence ellipsoid** around $\hat{\theta}_t^\lambda$



$$\theta_\star \in \left\{ \theta \in \mathbb{R}^d : \|\theta - \hat{\theta}_t^\lambda\|_A \leq \beta_t \right\}$$

Why ? For all invertible matrix positive semi-definite matrix A ,

$$\forall x \in \mathbb{R}^d, \quad \left| x^\top \theta_\star - x^\top \hat{\theta}_t^\lambda \right| \leq \|x\|_{A^{-1}} \left\| \theta_\star - \hat{\theta}_t^\lambda \right\|_A$$

$$\|x\|_A = \sqrt{x^\top A x}$$

How to build (tight) confidence interval on the mean rewards ?

Wanted : $\theta_\star \in \left\{ \theta \in \mathbb{R}^d : \|\theta - \hat{\theta}_t^\lambda\|_A \leq \beta_t \right\}$

Example of threshold [Abbasi-Yadkori et al., 2011]

Assuming that the noise ε_t is σ^2 -sub-Gaussian, and that for all t and $x \in \mathcal{X}_t$, $\|x\| \leq L$, we have

$$\mathbb{P} \left(\exists t \in \mathbb{N}^* : \|\theta_\star - \hat{\theta}_t^\lambda\|_{B_t^\lambda} > \beta(t, \delta) \right) \leq \delta$$

with $\beta(t, \delta) = \sigma \sqrt{2 \log(1/\delta) + d \log(1 + t \frac{L}{d\lambda})} + \sqrt{\lambda} \|\theta_\star\|$.

→ Letting

$$C_t(\delta) = \left\{ \theta \in \mathbb{R}^d : \|\theta - \hat{\theta}_t^\lambda\|_{B_t^\lambda} \leq \beta(t, \delta) \right\},$$

one has $\mathbb{P}(\forall t \in \mathbb{N}, \theta_\star \in C_t(\delta)) \geq 1 - \delta$.

A Lin-UCB algorithm

Consequence :

$$\mathbb{P}\left(\forall t \in \mathbb{N}^*, \forall x \in \mathcal{X}_{t+1}, \underbrace{x^\top \theta_\star}_{\text{unknown mean of arm } x} \leq \underbrace{x^\top \hat{\theta}_t^\lambda + \|x\|_{(B_t^\lambda)^{-1}} \beta(t, \delta)}_{\text{Upper Confidence Bound}}\right) \geq 1 - \delta.$$

One can assign to each arm $x \in \mathcal{X}_{t+1}$

$$\text{UCB}_x(t) = \underbrace{x^\top \hat{\theta}_t^\lambda}_{\text{empirical mean (exploitation term)}} + \underbrace{\|x\|_{(B_t^\lambda)^{-1}} \beta(t, \delta)}_{\text{exploration bonus}}$$

Lin-UCB

In each round $t + 1$, the algorithm selects

$$x_{t+1} = \operatorname{argmax}_{x \in \mathcal{X}_{t+1}} \left[x^\top \hat{\theta}_t^\lambda + \|x\|_{(B_t^\lambda)^{-1}} \beta(t, \delta) \right]$$

(many algorithms of this style, with different choices of $\beta(t, \delta)$)

Theoretical guarantees

We want to bound the **pseudo-regret**

$$R_T(\text{Lin-UCB}) = \sum_{t=1}^T \left(\max_{x \in \mathcal{X}_t} \theta_\star^\top x - \theta_\star^\top x_t \right)$$

or its expectation, the **regret** $\mathcal{R}_T(\text{Lin-UCB}) = \mathbb{E}[R_T(\text{Lin-UCB})]$.

Lemma

One can prove that, with probability larger than $1 - \delta$,

$$\forall T \in \mathbb{N}^*, R_T(\text{Lin-UCB}) \leq C\beta(T, \delta) \sqrt{dT \log(T)}$$

- ▶ with the choice of $\beta(t, \delta)$ presented before, with high probability

$$R_T(\text{Lin-UCB}) = \mathcal{O}(d\sqrt{T} \log(T) + \sqrt{dT \log(T) \log(1/\delta)})$$

- ▶ choosing $\delta = 1/T$, $\mathcal{R}_T(\text{Lin-UCB}) = \mathcal{O}(d\sqrt{T} \log(T))$

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A Bayesian view on Linear Regression

Bayesian model :

- ▶ likelihood : $r_t = \theta_\star^\top x_t + \varepsilon_t$
- ▶ prior : $\theta_\star \sim \mathcal{N}(0, \kappa^2 \mathbf{I}_d)$

Assuming further that the noise is Gaussian : $\varepsilon_t \sim \mathcal{N}(0, \sigma^2)$, the **posterior distribution** of θ_\star has a closed form :

$$\theta_\star | x_1, r_1, \dots, x_t, r_t \sim \mathcal{N}(\hat{\theta}_t^\lambda, \sigma^2 (B_t^\lambda)^{-1})$$

with

- $B_t^\lambda = \lambda \mathbf{I}_d + \sum_{s=1}^t x_s x_s^\top$
- $\hat{\theta}_t^\lambda = (B_t^\lambda)^{-1} (\sum_{s=1}^t r_s x_s)$ is the regularized least square estimate with a regularization parameter $\lambda = \frac{\sigma^2}{\kappa^2}$.

Thompson Sampling for Linear Bandits

Recall the Thompson Sampling principle :

“draw a possible model from the posterior distribution and act optimally in this sampled model”

Thompson Sampling in linear bandits

In each round $t + 1$,

$$\begin{aligned}\tilde{\theta}_t &\sim \mathcal{N}\left(\hat{\theta}_t^\lambda, \sigma^2 (B_t^\lambda)^{-1}\right) \\ x_{t+1} &= \operatorname{argmax}_{x \in \mathcal{X}_{t+1}} x^\top \tilde{\theta}_t\end{aligned}$$

Numerical complexity : one need to draw a sample from a multivariate Gaussian distribution, e.g.

$$\tilde{\theta}_t = \hat{\theta}_t^\lambda + \sigma (B_t^\lambda)^{-1/2} X$$

where X is a vector with d independent $\mathcal{N}(0, 1)$ entries.

Theoretical guarantees

[Agrawal and Goyal, 2013b] analyze a *variant* of Thompson Sampling using some “posterior inflation” :

$$\begin{aligned}\tilde{\theta}_t &\sim \mathcal{N}\left(\hat{\theta}_t^1, \nu^2 (B_t^1)^{-1}\right) \\ x_{t+1} &= \operatorname{argmax}_{x \in \mathcal{X}_{t+1}} x^\top \tilde{\theta}_t\end{aligned}$$

where $\nu = \sigma \sqrt{9d \ln(T/\delta)}$.

Theorem

If the noise is σ^2 -sub-Gaussian, the above algorithm satisfies

$$\mathbb{P}\left(R_T(\text{TS}) = \mathcal{O}\left(d^{3/2} \sqrt{T} \left[\ln(T) + \sqrt{\ln(T) \ln(1/\delta)}\right]\right)\right) \geq 1 - \delta.$$

- ▶ slightly worse than Lin-UCB... in theory
- ▶ do we need the posterior inflation?

Beyond linear bandits

Depending on the application, other parameteric models may be better suited than the simple linear model, for example the **logistic model**.

$$\begin{aligned}\mathbb{P}(r_t = 1|x_t) &= \frac{1}{1 + e^{-\theta_{\star}^{\top} x_t}} \\ \mathbb{P}(r_t = 0|x_t) &= \frac{e^{-\theta_{\star}^{\top} x_t}}{1 + e^{-\theta_{\star}^{\top} x_t}}\end{aligned}$$

e.g., clic / no-clic on an add depending on a user/add feature $x_t \in \mathbb{R}^d$

- ▶ [Filippi et al., 2010] : first UCB style algorithm for Generalized Linear Bandit models
- ▶ Thompson Sampling for logistic bandits [Dumitrescu et al., 2018]
- ▶ going further : UCB/TS for neural bandits !

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 - A simple UCB algorithm
 - Towards optimal algorithms
- 3 Randomized Exploration : Thompson Sampling
- 4 Contextual Bandits
 - Lin-UCB
 - Linear Thompson Sampling
- 5 Bandits beyond Regret

Bandits without rewards ?



$\mathcal{B}(\mu_1)$

$\mathcal{B}(\mu_2)$

$\mathcal{B}(\mu_3)$

$\mathcal{B}(\mu_4)$

$\mathcal{B}(\mu_5)$

For the t -th patient in a clinical study,

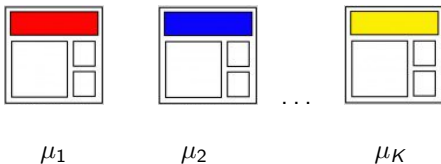
- ▶ chooses a treatment A_t
- ▶ observes a response $X_t \in \{0, 1\} : \mathbb{P}(X_t = 1) = \mu_{A_t}$

Maximize rewards \leftrightarrow cure as many patients as possible

Alternative goal : identify as quickly as possible the best treatment
(without trying to cure patients during the study)

Bandits without rewards ?

Probability that some version of a website generates a conversion :



Best version : $a_* = \operatorname{argmax}_{a=1,\dots,K} \mu_a$

Sequential protocol : for the t -th visitor :

- ▶ display version A_t
- ▶ observe conversion indicator $X_t \sim \mathcal{B}(\mu_{A_t})$.

Maximize rewards \leftrightarrow maximize the number of conversions

Alternative goal : identify the best version

(without trying to maximize conversions during the test)

A Pure Exploration Problem

Goal : identify an arm with mean close to μ_* as quickly and accurately as possible \simeq identify

$$a_* = \operatorname{argmax}_{a=1,\dots,K} \mu_a.$$

Algorithm : made of three components :

- sampling rule : A_t (arm to explore)
- recommendation rule : B_t (current guess for the best arm)
- stopping rule τ (when do we stop exploring?)

Probability of error

The probability of error after T rounds is

$$p_\nu(T) = \mathbb{P}_\nu(B_T \neq a_*).$$

A Pure Exploration Problem

Goal : identify an arm with mean close to μ_\star as quickly and accurately as possible \simeq identify

$$a_\star = \operatorname{argmax}_{a=1,\dots,K} \mu_a.$$

Algorithm : made of three components :

- sampling rule : A_t (arm to explore)
- recommendation rule : B_t (current guess for the best arm)
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Simple regret [Bubeck et al., 2011]

The simple regret after n rounds is

$$r_\nu(n) = \mu_\star - \mu_{B_n}.$$

A Pure Exploration Problem

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Simple regret [Bubeck et al., 2011]

The simple regret after n rounds is

$$r_\nu(n) = \mu_* - \mu_{B_n}.$$

$$\Delta_{\min} p_\nu(T) \leq \mathbb{E}_\nu[r_\nu(T)] \leq \Delta_{\max} p_\nu(T)$$

Several objectives

Algorithm : made of three components :

- **sampling rule** : A_t (arm to explore)
- **recommendation rule** : B_t (current guess for the best arm)
- **stopping rule** τ (when do we stop exploring?)

► **Objectives studied in the literature :**

Fixed-budget setting <u>input</u> : budget T	Fixed-confidence setting <u>input</u> : risk parameter δ (tolerance parameter ϵ)
$\tau = T$ minimize $\mathbb{P}(B_T \neq a_*)$ or $\mathbb{E}[r_T(\nu)]$	minimize $\mathbb{E}[\tau]$ $\mathbb{P}(B_\tau \neq a_*) \leq \delta$ or $\mathbb{P}(r_\nu(\tau) > \epsilon) \leq \delta$
[Bubeck et al., 2011] [Audibert et al., 2010]	[Even-Dar et al., 2006]

Can we use UCB ?

Context : bounded rewards (ν_a supported in $[0, 1]$)

We know good algorithms to maximize rewards, for example $\text{UCB}(\alpha)$

$$A_{t+1} = \operatorname{argmax}_{a=1,\dots,K} \hat{\mu}_a(t) + \sqrt{\frac{\alpha \ln(t)}{N_a(t)}}$$

- How good is it for best arm identification ?

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- How good is it for best arm identification ?

Possible recommendation rules :

Empirical Best Arm (EBA)	$B_t = \operatorname{argmax}_a \hat{\mu}_a(t)$
Most Played Arm (MPA)	$B_t = \operatorname{argmax}_a N_a(t)$
Empirical Distribution of Plays (EDP)	$B_t \sim p_t$, where $p_t = \left(\frac{N_1(t)}{t}, \dots, \frac{N_K(t)}{t} \right)$

[Bubeck et al., 2011]

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[Bubeck et al., 2011]

Can we use UCB ?

► UCB + Empirical Distribution of Plays

$$\begin{aligned}\mathbb{E}[r_\nu(T)] &= \mathbb{E}[\mu_\star - \mu_{B_T}] = \mathbb{E}\left[\sum_{b=1}^K (\mu_\star - \mu_b) \mathbb{1}_{(B_T=b)}\right] \\&= \mathbb{E}\left[\sum_{b=1}^K (\mu_\star - \mu_b) \mathbb{P}(B_T = b | \mathcal{F}_T)\right] \\&= \mathbb{E}\left[\sum_{b=1}^K (\mu_\star - \mu_b) \frac{N_b(T)}{T}\right] \\&= \frac{1}{T} \sum_{b=1}^K (\mu_\star - \mu_b) \mathbb{E}[N_b(T)] \\&= \frac{\mathcal{R}_\nu(T)}{T}.\end{aligned}$$

→ a conversion from cumulative regret to simple regret !

Can we use UCB ?

► UCB + Empirical Distribution of Plays

$$\mathbb{E} [r_{\nu} (\text{UCB}(\alpha), T)] \leq \frac{\mathcal{R}_{\nu}(\text{UCB}(\alpha), T)}{T} \leq \frac{C(\nu) \ln(T)}{T}$$

Can we use UCB ?

► UCB + Empirical Distribution of Plays

$$\mathbb{E} [r_{\nu} (\text{UCB}(\alpha), T)] \leq \frac{\mathcal{R}_{\nu}(\text{UCB}(\alpha), T)}{T} \leq C \sqrt{\frac{K \ln(T)}{T}}$$

Can we use UCB ?

► UCB + Empirical Distribution of Plays

$$\mathbb{E}[r_\nu(\text{UCB}(\alpha), T)] \leq \frac{\mathcal{R}_\nu(\text{UCB}(\alpha), T)}{T} \leq C \sqrt{\frac{K \ln(T)}{T}}$$

► vs. Uniform Sampling

The simple regret or the uniform strategy **decays exponentially** :

$$\mathbb{E}_\nu[r_\nu(\text{Unif}, T)] \leq (K-1)\Delta_{\max} \exp\left(-\frac{1}{2} \frac{T}{K} \Delta_{\min}^2\right)$$

→ UCB does not provably outperform uniform sampling...

Fixed Budget : Sequential Halving

Input : total number of plays T

Idea : split the budget in $\log_2(K)$ phases of equal length, eliminate the worst half of the remaining arms after each phase.

Initialisation : $S_0 = \{1, \dots, K\}$;

For $r = 0$ **to** $\lceil \ln_2(K) \rceil - 1$, **do**

sample each arm $a \in S_r$ $t_r = \left\lfloor \frac{T}{|S_r| \lceil \log_2(K) \rceil} \right\rfloor$ times ;

let $\hat{\mu}_a^r$ be the empirical mean of arm a ;

let S_{r+1} be the set of $\lceil |S_r|/2 \rceil$ arms with largest $\hat{\mu}_a^r$

Output : B_T the unique arm in $S_{\lceil \log_2(K) \rceil}$

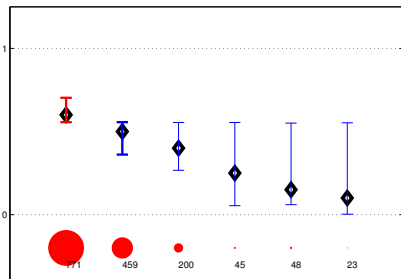
Theorem [Karnin et al., 2013]

Letting $H_2(\nu) = \max_{a \neq a_*} a \Delta_{[a]}^{-2}$, for any bounded bandit instance,

$$\mathbb{P}_\nu(B_T \neq a_*) \leq 3 \log_2(K) \exp\left(-\frac{T}{8 \log_2(K) H_2(\nu)}\right).$$

Fixed Confidence : LUCB

$$\mathcal{I}_a(t) = [\text{LCB}_a(t), \text{UCB}_a(t)].$$



► At round t , draw

$$B_t = \operatorname{argmax}_b \hat{\mu}_b(t)$$

$$C_t = \operatorname{argmax}_{c \neq B_t} \text{UCB}_c(t)$$

► Stop at round t if

$$\text{LCB}_{B_t}(t) > \text{UCB}_{C_t}(t) - \epsilon$$

Theorem [Kalyanakrishnan et al., 2012]

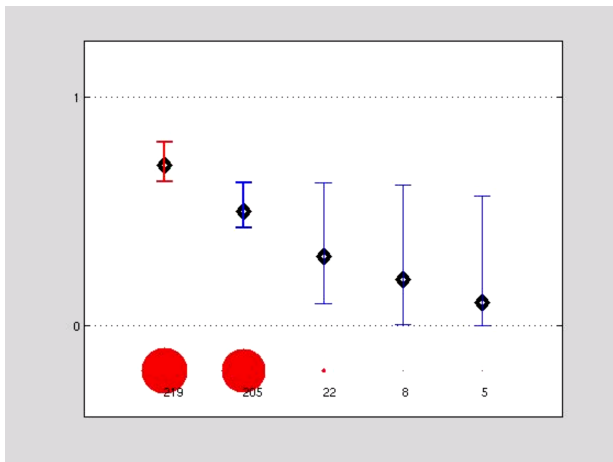
For well-chosen confidence intervals, $\mathbb{P}_\nu(\mu_{B_\tau} > \mu_\star - \epsilon) \geq 1 - \delta$ and

$$\mathbb{E}[\tau_\delta] = O\left(\left[\frac{1}{\Delta_2^2 \vee \epsilon^2} + \sum_{a=2}^K \frac{1}{\Delta_a^2 \vee \epsilon^2}\right] \ln\left(\frac{1}{\delta}\right)\right)$$

(kl)-LUCB in action

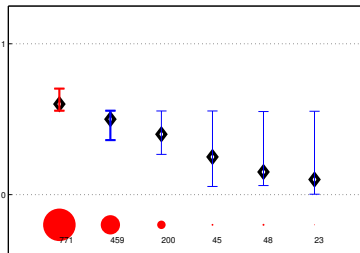
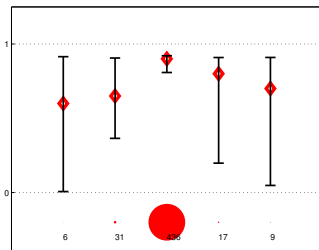
$$\text{UCB}_a(t) = \max \{q \in [0, 1] : N_a(t) \text{kl}(\hat{\mu}_a(t), q) \leq \log(Ct^2/\delta)\}$$

$$\text{LCB}_a(t) = \min \{q \in [0, 1] : N_a(t) \text{kl}(\hat{\mu}_a(t), q) \leq \log(Ct^2/\delta)\}$$



A comparison with UCB

Regret minimizing algorithms and Best Arm Identification algorithms behave quite differently



Number of selections and confidence intervals for KL-UCB (left) and KL-LUCB (right)

Conclusion

In bandits, ε -greedy can be replaced by smarter algorithms

- ▶ both for learning while maximizing rewards *(regret)*
- ▶ and for fast identification of the best action *(sample complexity)*

Two important tools :

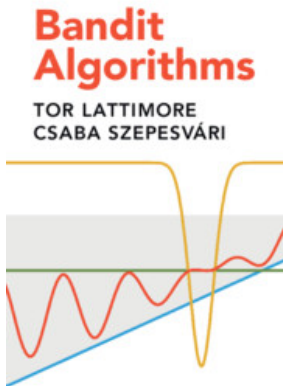
- ▶ confidence intervals
- ▶ posterior distributions

to better take into account the uncertainty and perform more efficient (“directed”) exploration.

Those tools can also be used in contextual bandit models.

How about general [Markov Decision Processes](#) ?

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by [Lattimore and Szepesvari, 2019]



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