Bandit Problems
Part I - Stochastic Bandits (2/2)

RLSS, Lille, July 2019

Outline of the RLSS Bandit Class

PART I: Solving the stochastic MAB

PART II: Structured Bandits

PART III: Bandit for Optimization

RECAPS

The Stochastic Multi-Armed Bandit Stetup

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: Maximize $\mathbb{E}\left[\sum_{t=1}^{T} R_t\right]$

Regret of a bandit algorithm

Bandit instance: $\nu = (\nu_1, \nu_2, \ldots, \nu_K)$, mean of arm a: $\mu_a = \mathbb{E}_{X\sim\nu_a}[X]$.

$$\mu_\star = \max_{a\in\{1,\dots,K\}} \mu_a \qquad a_\star = \underset{a\in\{1,\dots,K\}}{\mathrm{argmax}}\ \mu_a.$$

Maximizing rewards $\leftrightarrow$ selecting $a_\star$ as much as possible
$\leftrightarrow$ minimizing the regret [Robbins, 52]

$$\mathcal{R}_\nu(\mathcal{A}, T) := \underbrace{T\mu_\star}_{\substack{\text{sum of rewards of}\\ \text{an oracle strategy}\\ \text{always selecting } a_\star}} - \underbrace{\mathbb{E}\left[\sum_{t=1}^{T} R_t\right]}_{\substack{\text{sum of rewards of}\\ \text{the strategy} \mathcal{A}}}$$

What regret rate can we achieve?

- $\mathcal{R}_\nu(\mathcal{A}, T) = C_\nu \log(T)$ problem-dependent regret
- $\mathcal{R}_\nu(\mathcal{A}, T) = C\sqrt{KT}$ problem-independent (worse-case) regret

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Maximizing rewards $\leftrightarrow$ selecting $a_\star$ as much as possible
$\leftrightarrow$ minimizing the regret [Robbins, 52]

$$\mathcal{R}_\nu(\mathcal{A}, T) := \sum_{a=1}^{K} \underbrace{(\mu_\star - \mu_a)}_{\substack{\Delta_a\text{:sub-optimality} \\ \text{gap of arm } a}} \times \underbrace{\mathbb{E}_\nu[N_a(T)]}_{\substack{\text{expected number of} \\ \text{selections of arm } a}}$$

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Performance lower bounds

- Problem-dependent for simple parametric model
(Bernoulli, Gaussian with known variance, Exponential,Poisson...)

Theorem [Lai and Robbins, 1985]

For uniformly efficient algorithms, in a regime of large values of T,

$$\mathcal{R}_\nu(\mathcal{A}, T) \gtrsim \left(\sum_{a:\mu_a<\mu_\star} \frac{\Delta_a}{\mathrm{kl}(\mu_a, \mu_\star)} \right) \ln(T).$$

- Problem independent (worse-case)

Theorem [Cesa-Bianchi and Lugosi, 06][Bubeck and Cesa-Bianchi, 12]

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

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

Two naive strategies

- **Idea 1 :** Uniform Exploration

Draw each arm T/K times

- **Idea 2 :** Follow The Leader (FTL)

$$A_{t+1} = \underset{a\in\{1,\dots,K\}}{\text{argmax}} \ \hat{\mu}_a(t)$$

where $\hat{\mu}_a(t)$ is an estimate of the unknown mean μ_a.

→ Linear regret!

(Sequential) Explore-Then-Commit

For 2 (Gaussian) arms:

- explore uniformly until the random time

$$\tau = \inf\left\{ t \in \mathbb{N} : |\hat{\mu}_1(t) - \hat{\mu}_2(t)| > \sqrt{\frac{8\sigma^2 \ln(T/t)}{t}} \right\}$$

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

Logarithmic regret!

$$\mathcal{R}_\nu(\texttt{S-ETC}, T) \leq \frac{4\sigma^2}{\Delta} \ln\left(T\Delta^2\right) + C\sqrt{\ln(T)}.$$

→ this approach can be generalized to more than 2 arms, but cannot be asymptotically optimal (= match Lai and Robbins lower bound)

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

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

$$\mathrm{LCB} = \text{Lower Confidence Bound}$$
$$\mathrm{UCB} = \text{Upper Confidence Bound}$$

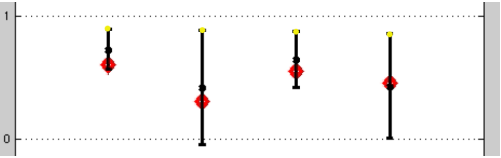


Figure: Confidence intervals on the means after t rounds

- "act as if the the best possible model were the true model"

$$A_{t+1} = \underset{a=1,\dots,K}{\mathrm{argmax}}\ \mathrm{UCB}_a(t).$$

Several UCB algorithm

- UCB for σ^2-sub Gaussian rewards

$$A_{t+1} = \underset{a=1,\dots,K}{\operatorname{argmax}} \ \hat{\mu}_a(t) + \sqrt{\frac{2\sigma^2 \ln t}{N_a(t)}}$$

→ asymptotically optimal for Gaussian distributions, can be used for bounded distribution (with $\sigma^2 = 1/4$).

→ $O(\sqrt{KT\ln(T)})$ worse-case regret

Several UCB algorithms

- kl-UCB with divergence $\mathrm{kl}(x, y)$

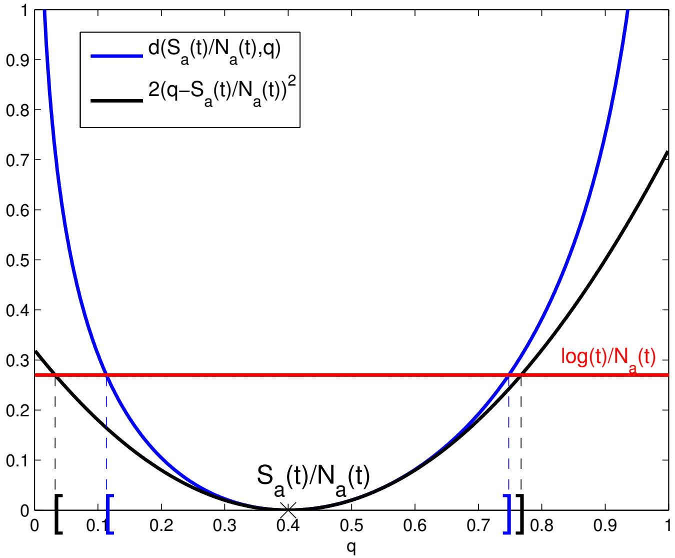
$$A_{t+1} = \underset{a=1,\dots,K}{\mathrm{argmax}} \ \max\left\{q : \mathrm{kl}\left(\hat{\mu}_a(t), q\right) \leq \frac{\ln(t)}{N_a(t)}\right\}$$

➜ asymptotically optimal for Bernoulli distribution and can be used for bounded distributions with

$$\mathrm{kl}_{\mathrm{Ber}}(x, y) = x \ln(x/y) + (1-x)\ln((1-x)/(1-y)).$$

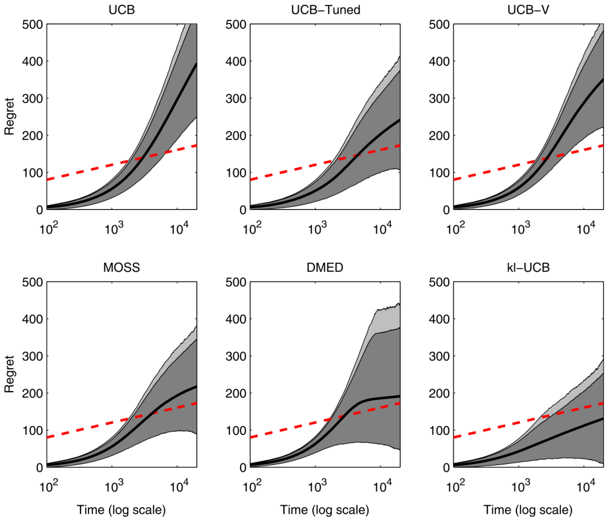
➜ $O(\sqrt{KT\ln(T)})$ worse-case regret

Comparison of the confidence intervals



UCB versus kl-UCB

$$\boldsymbol{\mu} = [0.1\ 0.05\ 0.05\ 0.05\ 0.02\ 0.02\ 0.02\ 0.01\ 0.01\ 0.01]$$



(Credit: Cappé et al.)

A Bayesian Look at the Multi-Armed Bandit Model

Historical perspective

1952 Robbins, formulation of the MAB problem

1985 Lai and Robbins: lower bound, first asymptotically optimal algorithm

1987 Lai, asymptotic regret of kl-UCB

1995 Agrawal, UCB algorithms

1995 Katehakis and Robbins, a UCB algorithm for Gaussian bandits

2002 Auer et al: UCB1 with finite-time regret bound

2009 UCB-V, MOSS...

2011,13 Cappé et al: finite-time regret bound for kl-UCB

Historical perspective

1933 Thompson: a Bayesian mechanism for clinical trials

1952 Robbins, formulation of the MAB problem

1956 Bradt et al, Bellman: optimal solution of a Bayesian MAB problem

1979 Gittins: first Bayesian index policy

1985 Lai and Robbins: lower bound, first asymptocally optimal algorithm

1985 Berry and Fristedt: Bandit Problems, a survey on the Bayesian MAB

1987 Lai, asymptotic regret of kl-UCB + study of its Bayesian regret

1995 Agrawal, UCB algorithms

1995 Katehakis and Robbins, a UCB algorithm for Gaussian bandits

2002 Auer et al: UCB1 with finite-time regret bound

2009 UCB-V, MOSS...

2010 Thompson Sampling is re-discovered

2011,13 Cappé et al: finite-time regret bound for kl-UCB

2012,13 Thompson Sampling is asymptotically optimal

Frequentist versus Bayesian bandit

$\nu_{\boldsymbol{\mu}} = (\nu^{\mu_1}, \dots, \nu^{\mu_K}) \in (\mathcal{P})^K$.

- Two probabilistic models

Frequentist model	**Bayesian model**
$\mu_1, \dots, \mu_K$ unknown parameters	$\mu_1, \dots, \mu_K$ drawn from a prior distribution : $\mu_a \sim \pi_a$
arm a: $(Y_{a,s})_s \overset{\text{i.i.d.}}{\sim} \nu^{\mu_a}$	arm a: $(Y_{a,s})_s \vert \boldsymbol{\mu} \overset{\text{i.i.d.}}{\sim} \nu^{\mu_a}$

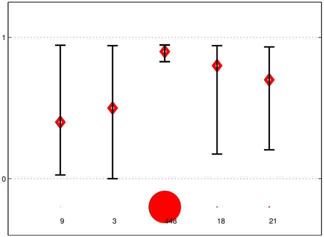
- The regret can be computed in each case

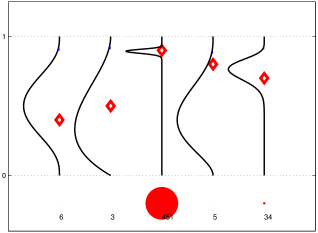
Frequentist regret (regret)	Bayesian regret (Bayes risk)
$\mathcal{R}_{\boldsymbol{\mu}}(\mathcal{A}, T) = \mathbb{E}_{\boldsymbol{\mu}}\left[\sum_{t=1}^{T} (\mu_\star - \mu_{A_t})\right]$	$\mathrm{R}^{\pi}(\mathcal{A}, T) = \mathbb{E}_{\boldsymbol{\mu}\sim\pi}\left[\sum_{t=1}^{T} (\mu_\star - \mu_{A_t})\right] = \int \mathcal{R}_{\boldsymbol{\mu}}(\mathcal{A}, T) d\pi(\boldsymbol{\mu})$

Frequentist and Bayesian algorithms

- Two types of tools to build bandit algorithms:

Frequentist tools	Bayesian tools
MLE estimators of the means Confidence Intervals	Posterior distributions $\pi_a^t = \mathcal{L}(\mu_a \| Y_{a,1}, \dots, Y_{a,N_a(t)})$





Example: Bernoulli bandits

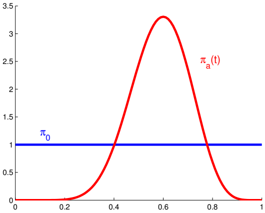
Bernoulli bandit model $\boldsymbol{\mu} = (\mu_1, \dots, \mu_K)$

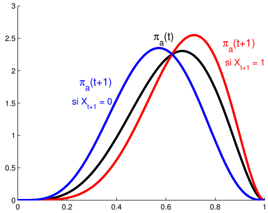
- **Bayesian view**: $\mu_1, \dots, \mu_K$ are random variables

  prior distribution : $\mu_a \sim \mathcal{U}([0,1])$

→ posterior distribution:

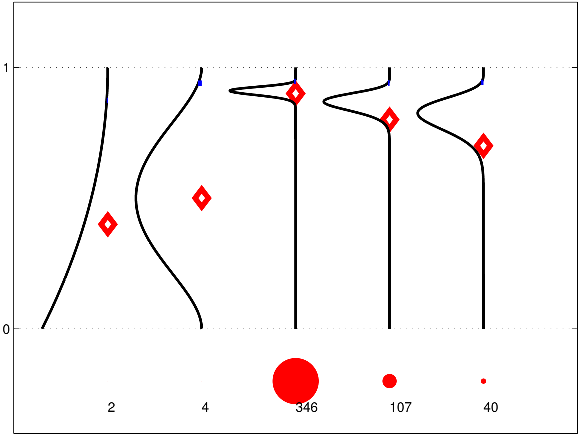
$$\begin{aligned}\pi_a(t) &= \mathcal{L}(\mu_a | R_1, \dots, R_t) \\ &= \mathrm{Beta}\Big(\underbrace{S_a(t)}_{\#ones} + 1, \underbrace{N_a(t) - S_a(t)}_{\#zeros} + 1\Big)\end{aligned}$$





$S_a(t) = \sum_{s=1}^{t} R_s \mathbb{1}_{(A_s = a)}$ sum of the rewards from arm a

A Bayesian bandit algorithm exploits the posterior distributions of the means to decide which arm to select.



Bayesian Bandits

Insights from the Optimal Solution

Bayes-UCB

Thompson Sampling

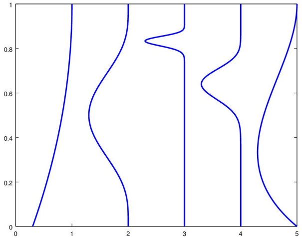
Some insights from the Bayesian solution

Bandit model $(\mathcal{B}(\mu_1), \ldots, \mathcal{B}(\mu_K))$

$$\pi_a^t = \mathrm{Beta}\Big(\underbrace{S_a(t)}_{\#ones}+1, \underbrace{N_a(t) - S_a(t)}_{\#zeros}+1\Big)$$

The posterior distribution is fully summarized by a matrix containing the number of ones and zeros observed for each arm.

$$\Pi^t = \begin{pmatrix} 0 & 2 \\ 3 & 3 \\ 13 & 4 \\ 5 & 2 \\ 1 & 3 \end{pmatrix}$$



"State" Π^t that evolves.

A first Markov Decision Process

After each arm selection A_t, we receive a reward R_t such that

$$\mathbb{P}\left(R_t = 1 | \Pi^{t-1} = \Pi, A_t = a\right) = \underbrace{\frac{\Pi^t(a,1)+1}{\Pi^t(a,1)+\Pi^t(a,2)+2}}_{\text{mean of } \pi_a(t-1)}$$

and the posterior gets updated:

$$\begin{aligned} \Pi^t(A_t,1) &= \Pi^{t-1}(A_t,1) + R_t \\ \Pi^t(A_t,2) &= \Pi^{t-1}(A_t,2) + (1-R_t) \end{aligned}$$

Example of transition:

$$\begin{pmatrix} 1 & 2 \\ 5 & 1 \\ 0 & 2 \end{pmatrix} \xrightarrow{A_t=2} \begin{pmatrix} 1 & 2 \\ 6 & 1 \\ 0 & 2 \end{pmatrix} \textit{ if } R_t = 1$$

$\rightarrow$ Markov Decision Process with state Π^t

A first Markov Decision Process

After each arm selection A_t, we receive a reward R_t such that

$$\mathbb{P}\left(R_t = 1 | \Pi^{t-1} = \Pi, A_t = a\right) = \underbrace{\frac{\Pi^t(a,1)+1}{\Pi^t(a,1)+\Pi^t(a,2)+2}}_{\text{mean of } \pi_a(t-1)}$$

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Example of transition:

$$\begin{pmatrix} 1 & 2 \\ \color{red}{5} & \color{red}{1} \\ 0 & 2 \end{pmatrix} \xrightarrow{\color{red}{A_t=2}} \begin{pmatrix} 1 & 2 \\ \color{red}{5} & \color{red}{2} \\ 0 & 2 \end{pmatrix} \textit{ if } R_t = 0$$

$\rightarrow$ Markov Decision Process with state Π^t

An exact solution

Solving the Bayesian bandit $\leftrightarrow$ maximizing rewards in some Markov Decision Process (modern perspective)

There exists an exact solution to

- The finite-horizon MAB:

$$\underset{(A_t)}{\text{argmax}} \ \mathbb{E}_{\mu\sim\pi}\left[\sum_{t=1}^{T} R_t\right]$$

- The discounted MAB:

$$\underset{(A_t)}{\text{argmax}} \ \mathbb{E}_{\mu\sim\pi}\left[\sum_{t=1}^{\infty} \gamma^{t-1} R_t\right]$$

[Berry and Fristedt, *Bandit Problems*, 1985]

Optimal solution: solution to dynamic programming equations.

Problem: The state space is very large

$\rightsquigarrow$ often intractable

Gittins indices

[Gittins 79]: the solution of the discounted MAB

$$\underset{(A_t)}{\text{argmax}} \ \mathbb{E}_{\boldsymbol{\mu}\sim\pi}\left[\sum_{t=1}^{\infty}\gamma^{t-1}R_t\right]$$

is an **index policy**:

$$A_{t+1} = \underset{a=1\dots K}{\text{argmax}} \ G_\gamma(\pi_a(t)).$$

- **The Gittins indices**:

$$G_\gamma(p) = \inf\{\lambda \in \mathbb{R} : V_\gamma^*(p,\lambda) = 0\},$$

with

$$V_\gamma^*(p,\lambda) = \sup_{\substack{\text{stopping} \\ \text{times } \tau>0}} \ \mathbb{E}_{\substack{Y_t \overset{\text{i.i.d}}{\sim} \mathcal{B}(\mu) \\ \mu\sim p}}\left[\sum_{t=1}^{\tau}\gamma^{t-1}(Y_t-\lambda)\right].$$

"price worth paying for committing to arm $\mu \sim p$
when rewards are discounted by α"

Gittins indices for Finite Horizon?

The solution of the finite horizon MAB

$$\underset{(A_t)}{\text{argmax}} \ \mathbb{E}_{\boldsymbol{\mu}\sim\pi}\left[\sum_{t=1}^{T} R_t\right]$$

is NOT an index policy. [Berry and Fristedt 85]

- **Finite-Horizon Gittins indices**:
  depend on the remaining time to play r

$$G(p, r) = \inf\{\lambda \in \mathbb{R} : V_r^*(p, \lambda) = 0\},$$

with

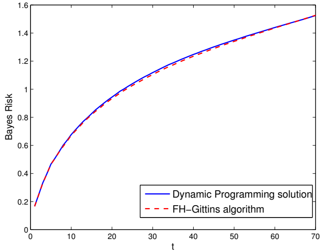
$$V_r^*(p, \lambda) = \sup_{\substack{\text{stopping times} \\ 0<\tau\leq r}} \mathbb{E}_{\substack{Y_t \overset{\text{i.i.d}}{\sim} \mathcal{B}(\mu) \\ \mu\sim p}}\left[\sum_{t=1}^{\tau}(Y_t - \lambda)\right].$$

"price worth paying for playing arm $\mu \sim p$ for at most r rounds"

FH Gittins algorithm:

$$A_{t+1} = \underset{a=1\ldots K}{\text{argmax}} \; G(\pi_a(t-1), T-t)$$

does NOT coincide with the Bayesian optimal solution but is conjectured to be a good approximation!



- good performance in terms of frequentist regret as well
- ... with logarithmic regret [Lattimore, 2016]

Approximating the FH-Gittins indices

- [Burnetas and Katehakis, 03]: when n is large,

$$G(\pi_a(t-1), n) \simeq \max\left\{q : N_a(t) \times \mathrm{kl}\left(\hat{\mu}_a(t), q\right) \leq \ln\left(\frac{n}{N_a(t)}\right)\right\}$$

- [Lai, 87]: the index policy associated to

$$I_a(t) = \max\left\{q : N_a(t) \times \mathrm{kl}\left(\hat{\mu}_a(t), q\right) \leq \ln\left(\frac{T}{N_a(t)}\right)\right\}$$

is a good approximation of the Bayesian solution for large T.

➜ looks like the kl-UCB index, with a different exploration rate...

Bayesian Bandits

Insights from the Optimal Solution

Bayes-UCB

Thompson Sampling

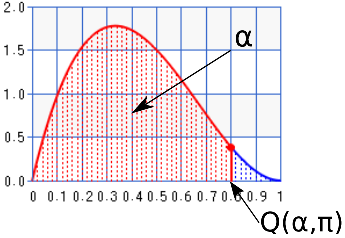
The Bayes-UCB algorithm

- $\Pi_0 = (\pi_1(0), \ldots, \pi_K(0))$ be a prior distribution over $(\mu_1, ..., \mu_K)$
- $\Pi_t = (\pi_1(t), \ldots, \pi_K(t))$ be the posterior distribution over the means $(\mu_1, ..., \mu_K)$ after t observations

The **Bayes-UCB algorithm** chooses at time t

$$A_{t+1} = \underset{a=1,\ldots,K}{\operatorname{argmax}} \ Q\left(1 - \frac{1}{t(\ln t)^c}, \pi_a(t)\right)$$

where $Q(\alpha, \pi)$ is the quantile of order α of the distribution π.



The Bayes-UCB algorithm

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Bernoulli reward with uniform prior:

- $\pi_a(0) \overset{i.i.d}{\sim} \mathcal{U}([0,1]) = \text{Beta}(1,1)$
- $\pi_a(t) = \text{Beta}(S_a(t) + 1, N_a(t) - S_a(t) + 1)$

The Bayes-UCB algorithm

- $\Pi_0 = (\pi_1(0), \dots, \pi_K(0))$ be a prior distribution over $(\mu_1, ..., \mu_K)$
- $\Pi_t = (\pi_1(t), \dots, \pi_K(t))$ be the posterior distribution over the means $(\mu_1, ..., \mu_K)$ after t observations

The **Bayes-UCB algorithm** chooses at time t

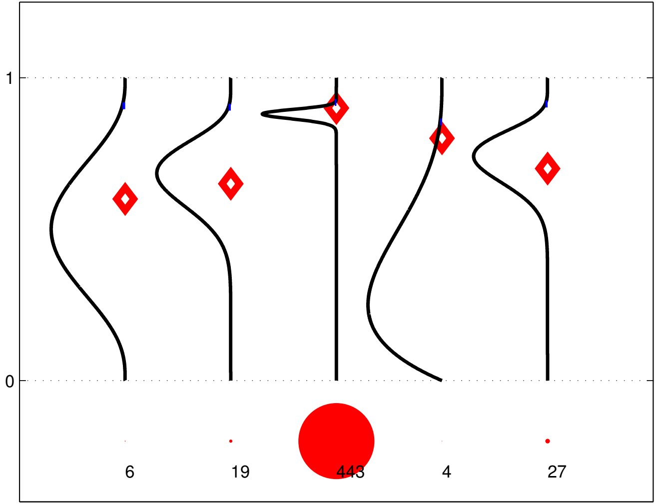
$$A_{t+1} = \underset{a=1,...,K}{\operatorname{argmax}} \ Q\left(1 - \frac{1}{t(\ln t)^c}, \pi_a(t)\right)$$

where $Q(\alpha, \pi)$ is the quantile of order α of the distribution π.

Gaussian rewards with Gaussian prior:

- $\pi_a(0) \overset{i.i.d}{\sim} \mathcal{N}(0, \kappa^2)$
- $\pi_a(t) = \mathcal{N}\left(\frac{S_a(t)}{N_a(t)+\sigma^2/\kappa^2}, \frac{\sigma^2}{N_a(t)+\sigma^2/\kappa^2}\right)$

Bayes UCB in action



- **Bayes-UCB is asymptotically optimal for Bernoulli rewards**

Theorem [K.,Cappé,Garivier 2012]

Let $\epsilon > 0$. The Bayes-UCB algorithm using a uniform prior over the arms and parameter $c \geq 5$ satisfies

$$\mathbb{E}_{\boldsymbol{\mu}}[N_a(T)] \leq \frac{1+\epsilon}{\mathrm{kl}(\mu_a, \mu_\star)} \ln(T) + o_{\epsilon,c}(\ln(T)).$$

Links with kl-UCB

Lemma [K. et al., 12]

The index $q_a(t)$ used by Bayes-UCB satisfies

$$\tilde{u}_a(t) \leq q_a(t) \leq u_a(t)$$

where

$$\begin{aligned} u_a(t) &= \max\left\{q : \mathrm{kl}\left(\frac{S_a(t)}{N_a(t)}, q\right) \leq \frac{\ln(t) + c\ln(\ln(t))}{N_a(t)}\right\} \\ \tilde{u}_a(t) &= \max\left\{q : \mathrm{kl}\left(\frac{S_a(t)}{N_a(t)+1}, q\right) \leq \frac{\ln\left(\frac{t}{N_a(t)+2}\right) + c\ln(\ln(t))}{(N_a(t)+1)}\right\} \end{aligned}$$

Proof: rely on the Beta-Binomial trick :

$$F_{\mathrm{Beta}(a,b)}(x) = 1 - F_{\mathrm{Bin}(a+b-a,x)}(a-1)$$

[Agrawal and Goyal, 12]

Beyond Bernoulli bandits

- For one-dimensional exponential families , Bayes-UCB rewrites

$$A_{t+1} = \underset{a}{\text{argmax}}\ Q\left(1 - \frac{1}{t(\ln t)^c}, \pi_{a,N_a(t),\hat{\mu}_a(t)}\right)$$

Extra assumption: there exists μ^-, μ^+ such that for all a, $\mu_a \in [\mu^-, \mu^+]$

Theorem [K. 17]

Let $\overline{\mu}_a(t) = (\hat{\mu}_a(t) \vee \mu^-) \wedge \mu^+$. The index policy

$$A_{t+1} = \underset{a}{\text{argmax}}\ Q\left(1 - \frac{1}{t(\ln t)^c}, \pi_{a,N_a(t),\overline{\mu}_a(t)}\right)$$

with parameter $c \geq 7$ is such that, for all $\epsilon > 0$,

$$\mathbb{E}_{\mu}[N_a(T)] \leq \frac{1+\epsilon}{\mathrm{kl}(\mu_a, \mu_\star)} \ln(T) + O_\epsilon(\sqrt{\ln(T)}).$$

An interesting by-product

- Tools from the analysis of Bayes-UCB can be used to analyze two variants of kl-UCB

kl-UCB-H$^+$

$$u_a^{H,+}(t) = \max\left\{q : N_a(t) \times \mathrm{kl}\left(\hat{\mu}_a(t), q\right) \leq \ln\left(\frac{T \ln^c T}{N_a(t)}\right)\right\}$$

kl-UCB$^+$

$$u_a^{+}(t) = \max\left\{q : N_a(t) \times \mathrm{kl}\left(\hat{\mu}_a(t), q\right) \leq \ln\left(\frac{t \ln^c t}{N_a(t)}\right)\right\}$$

The index policy associated to $u_a^{H,+}(t)$ and $u_a^{+}(t)$ satisfy, for all $\epsilon > 0$,

$$\mathbb{E}_\mu[N_a(T)] \leq \frac{1+\epsilon}{\mathrm{kl}(\mu_a, \mu_\star)} \ln(T) + O_\epsilon(\sqrt{\ln(T)}).$$

Bayesian Bandits

Insights from the Optimal Solution

Bayes-UCB

Thompson Sampling

Historical perspective

1933 Thompson: in the context of clinical trial, the allocation of a treatment should be some increasing function of its posterior probability to be optimal

2010 Thompson Sampling rediscovered under different names

Bayesian Learning Automaton [Granmo, 2010]

Randomized probability matching [Scott, 2010]

2011 An empirical evaluation of Thompson Sampling: an efficient algorithm, beyond simple bandit models

[Li and Chapelle, 2011]

2012 First (logarithmic) regret bound for Thompson Sampling

[Agrawal and Goyal, 2012]

2012 Thompson Sampling is asymptotically optimal for Bernoulli bandits

[K., Korda and Munos, 2012][Agrawal and Goyal, 2013]

2013- Many successful uses of Thompson Sampling beyond Bernoulli bandits (contextual bandits, reinforcement learning)

Thompson Sampling

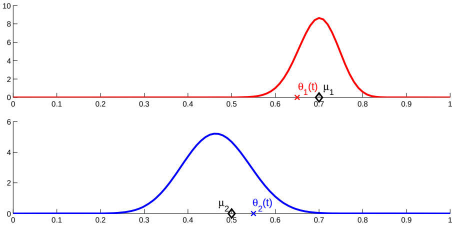
Two equivalent interpretations:

- "select an arm at random according to its probability of being the best"
- "draw a possible bandit model from the posterior distribution and act optimally in this sampled model"

$\neq$ optimistic

Thompson Sampling: a randomized Bayesian algorithm

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



Thompson Sampling is asymptotically optimal

Problem-dependent regret

$$\forall \epsilon > 0, \quad \mathbb{E}_{\boldsymbol{\mu}}[N_a(T)] \leq (1+\epsilon)\frac{1}{\mathrm{kl}(\mu_a, \mu_\star)} \ln(T) + o_{\mu,\epsilon}(\ln(T)).$$

This results holds:

- for Bernoulli bandits, with a uniform prior [K. Korda, Munos 12][Agrawal and Goyal 13]
- for Gaussian bandits, with Gaussian prior[Agrawal and Goyal 17]
- for exponential family bandits, with Jeffrey's prior [Korda et al. 13]

Problem-independent regret [Agrawal and Goyal 13]

For Bernoulli and Gaussian bandits, Thompson Sampling satisfies

$$\mathcal{R}_{\boldsymbol{\mu}}(\mathtt{TS}, T) = O\left(\sqrt{KT\ln(T)}\right).$$

- Thompson Sampling is also asymptotically optimal for Gaussian with unknown mean and variance [Honda and Takemura, 14]

Understanding Thompson Sampling

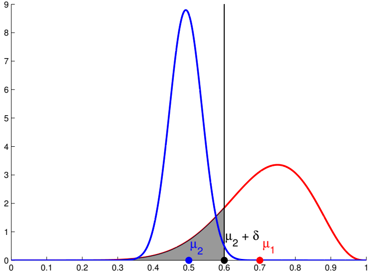
- a key ingredient in the analysis of [K. Korda and Munos 12]

Proposition

There exists constants $b = b(\mu) \in (0,1)$ and $C_b < \infty$ such that

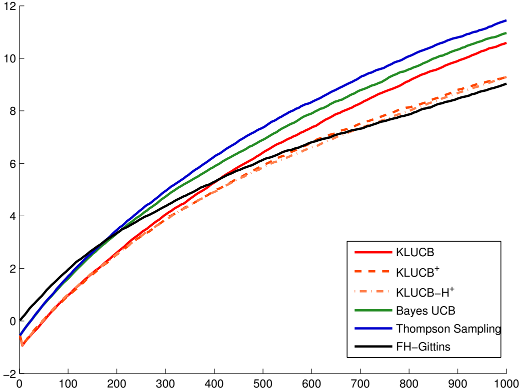
$$\sum_{t=1}^{\infty} \mathbb{P}\left(N_1(t) \leq t^b\right) \leq C_b.$$

$$\left\{N_1(t) \leq t^b\right\} = \{\text{there exists a time range of length at least } t^{1-b} - 1 \text{ with no draw of arm 1 }\}$$



Bayesian versus Frequentist algorithms

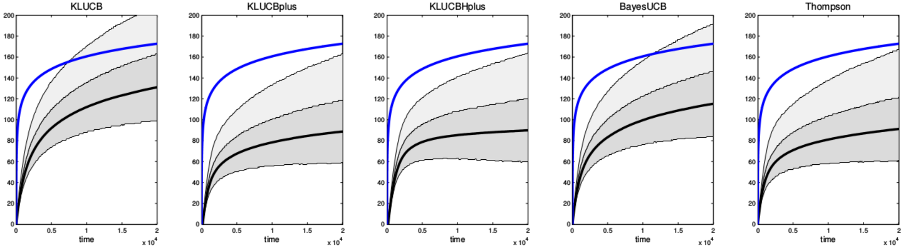
- Short horizon, $T = 1000$ (average over $N = 10000$ runs)



$$\mu_1 = 0.2, \mu_2 = 0.25$$

Bayesian versus Frequentist algorithms

- Long horizon, $T = 20000$ (average over $N = 50000$ runs)



10 arms bandit problem

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

OTHER RANDOMIZED ALGORITHMS

Limitation of existing approaches

Two families of asymptotically optimal algorithms

- Confidence bound algorithms
- Thompson Sampling

- Provably optimal finite-time regret under the assumption that the rewards distribution belong to some class $\mathcal{D}$
- A *different algorithm for each* $\mathcal{D}$: TS or kl-UCB for Bernoulli, Poisson, for Exponential, etc.

Can we build a universal algorithm that would be asymptotically optimal over different classes $\mathcal{D}$?

A Puzzling strategy

Best Empirical Sub-sampling Average

"Sub-sampling for multi-armed bandits",
Baransi, Maillard, Mannor *ECML*, 2014.

BESA

- Competitive regret against state-of-the-art for various $\mathcal{D}$.
- Same algorithm for all $\mathcal{D}$.
- Not relying on upper confidence bounds, not Bayesian...
- ...and extremely simple to implement.

→ How? Optimality? For which distributions ?

Going back to "Follow the leader"

FTL

1. Play each arm once.
2. At time t, define $\tilde{\mu}_a(t) = \hat{\mu}(R^a_{1:N_a(t)})$ for all $a \in \mathcal{A}$.
   - $\hat{\mu}(\mathcal{X})$: empirical average of population $\mathcal{X}$.
   - $R^a_{1:N_a(t)} = \{R_s : A_s = a, s \leq t\}$
3. Choose (break ties in favor of the smallest $N_a(t)$)

$$A_{t+1} = \underset{a' \in \{a,b\}}{\text{argmax}}\, \tilde{\mu}_{a'}(t)\,.$$

Properties

- Generally bad: linear regret.
- A variant (ϵ-greedy) performs ok if well-tuned [Auer et al, 2002].

Follow the FAIR leader (aka BESA)

Idea: Compare two arms based on "equal opportunity" i.e. same number of observations.

BESA at time t for two arms a, b:

1. Sample two sets of indices $\mathcal{I}_a(t) \sim \mathtt{Wr}(N_a(t); N_b(t))$ and $\mathcal{I}_b(t) \sim \mathtt{Wr}(N_b(t); N_a(t))$.
   - $\mathtt{Wr}(n, N)$: sample n points from $\{1, \dots, N\}$ without replacement (return all the set if $n \geq N$).
2. Define $\tilde{\mu}_a(t) = \hat{\mu}(R^a_{1:N_a(t)}(\mathcal{I}_a(t)))$ and $\tilde{\mu}_b(t) = \hat{\mu}(R^b_{1:N_{t,b}}(\mathcal{I}_b(t)))$.
3. Choose (break ties in favor of the smallest $N_{a'}(t)$)

$$A_{t+1} = \underset{a' \in \{a,b\}}{\operatorname{argmax}} \, \tilde{\mu}_{a'}(t) \, .$$

- more than two arms? tournament.

Example

- $\mathcal{X} = (x_1, \dots, x_N)$,a finite population of N real points.

x_1	x_2	x_3	x_4	x_5	$\dots$	x_{N-2}	x_{N-1}	x_N

- Sub-sample of size $n \leq N$ from $\mathcal{X}$: $X_1, \dots, X_n$ picked uniformly randomly without replacement from $\mathcal{X}$.

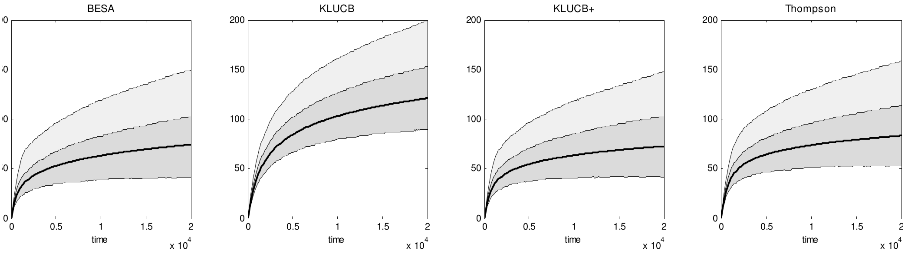
x_1	X_{n-1}	X_1	x_4	X_2	$\dots$	x_{N-2}	X_n	x_N

- Example: $N_a(t) = 3$ and $N_b(t) = 10$:
  $\mathcal{I}_a(t) = \{1, 2, 3\}$,
  $|\mathcal{I}_b(t)| = 3$, sampled without replacement from $\{1, \dots, 10\}$.

Good practical performance ($T = 20,000$, $N = 50,000$)

- 10 **Bernoulli**$(0.1, 3\{0.05\}, 3\{0.02\}, 3\{0.01\})$

	BESA	kl-UCB	kl-UCB+	TS	Others
Regret	**74.4**	121.2	**72.8**	83.4	100-400
Beat BESA	-	1.6%	35.4%	3.1%	
Run Rime	13.9X	2.8X	3.1X	X	



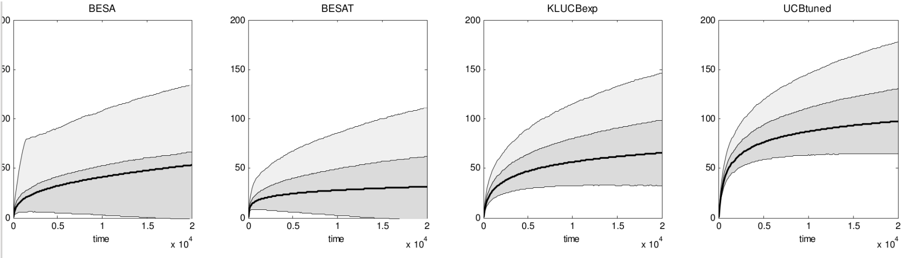
Others: UCB, Moss, UCB-Tunes, DMED, UCB-V.

(Credit: Akram Baransi)

Good practical performance ($T = 20,000$, $N = 50,000$)

- **Exponential**$(\frac{1}{5}, \frac{1}{4}, \frac{1}{3}, \frac{1}{2}, 1)$

	BESA	KL-UCB-exp	UCB-tuned	FTL 10	Others
Regret	**53.3**	65.7	97.6	306.5	60-110,120+
Beat BESA	-	5.7%	4.3%	-	
Run Rime	6X	2.8X	X	-	



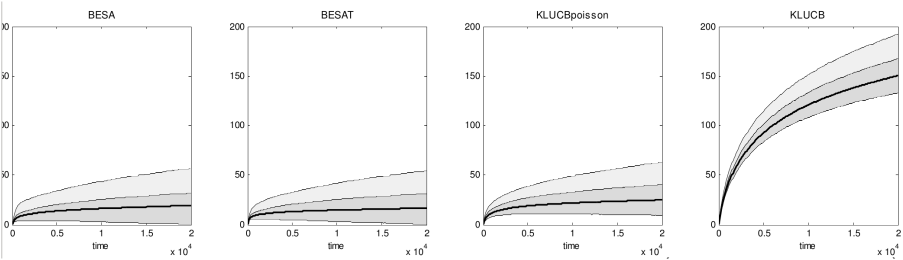
Others: UCB, Moss, kl-UCB,UCB-V.

(Credit: Akram Baransi)

Good practical performance ($T = 20,000$, $N = 50,000$)

- **Poisson**$(\{\frac{1}{2} + \frac{i}{3}\}_{i=1,\dots,6})$

	BESA	KL-UCB-Poisson	kl-UCB	FTL 10
Regret	**19.4**	25.1	150.6	144.6
Beat BESA	-	4.1%	0.7%	-
Run Rime	3.5X	1.2X	X	-



(Credit: Akram Baransi)

Regret bound (slightly simplified statement)

With two arms $\{\star, a\}$, define

$$\alpha(M,n) = \mathbb{E}_{Z^\star \sim \nu_{\star,n}}\left[\left(\mathbb{P}_{Z\sim\nu_{a,n}}(Z > Z^\star) + \frac{1}{2}\mathbb{P}_{Z\sim\nu_{a,n}}(Z = Z^\star)\right)^M\right].$$

Theorem [Baransi et al. 14]

If $\exists \alpha \in (0,1), c > 0$ such that $\alpha(M,1) \leq c\alpha^M$, then

$$\mathcal{R}_\nu(\texttt{BESA}, T) \leq \frac{11\ln(T)}{\mu_\star - \mu_a} + C_\nu + O(1).$$

Example

- Bernoulli $\mu_a, \mu_\star$: $\alpha(M,1) = O\left(\left(\frac{\mu_a \vee (1-\mu_a)}{2}\right)^M\right)$

Future work: understand when BESA fails, and whether it can be asymptotically optimal in some cases...

Adversarial bandits

Another class of (randomized) bandit algorithms that do not exploit any assumption on $\mathcal{D}$ is that of adversarial bandit algorithms.

[Auer, Cesa-Bianchi, Freund, Shapire,
The non-stochastic multi-armed bandit, 2002]

Can we achieve $O(\sqrt{KT})$ regret with respect to the best static action if the rewards are arbitrarily generated?

Some answers in the next classes and practical sessions!

Summary

Take-home messages

Now you are aware of:

- several methods for facing an exploration/exploitation dilemma
- notably two powerful classes of methods
  - optimistic "UCB" algorithms
  - Bayesian approaches, mostly Thompson Sampling

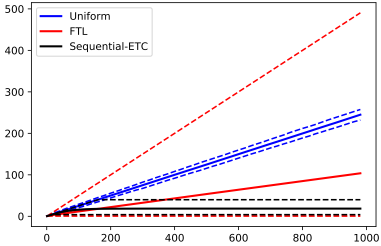
And you are therefore ready to apply them for solving more complex (structured) bandit problems and for Reinforcement Learning!

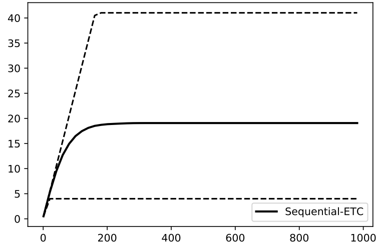
You also saw a bunch of important tools:

- performance lower bounds, guiding the design of algorithms
- Kullback-Leibler divergence to measure deviations
- self-normalized concentration inequalities
- Bayesian tools

First practical session

Objective: run UCB, kl-UCB, Thompson Sampling and some tweaks of those algorithms, and see what performs best (on simulated data).





- visualize expected regret *averaged over multiple runs* / distribution of the regret

Files: link on my webpage

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to be completed!