Instance-Wise Minimax-Optimal Algorithms for Logistic Bandits

Marc Abeille[1], Louis Faury[1,2], Clément Calauzènes[1]

[1]Criteo AI Lab, [2]LTCI Télécom Paris

Motivation

Toward non-linear reward model

- Parametric bandit results mostly concern the linear setting,
- non-linearity often arises in real-world application,
- impact of non-linearity on the exploration-exploitation tradeoff is poorly understood.

The logistic bandit setting

- Non-linear reward signal,
- compact and minimal setting,
- widely used for practical applications.

We characterize the impact of non-linearity for Logistic Bandit:

⇝ first problem-dependent lower-bound,

⇝ minimax-optimal algorithm.

The Logistic Bandit problem

The reward model

- $\mathcal{X} \subset \mathbb{R}^d$ is the arm set,
- $r(x) \in \{0,1\}$ is the reward associated with arm $x \in \mathcal{X}$,
- $\theta_\star \in \mathbb{R}^d$ *unknown* parameter.

[Binary reward]
$r(x) \sim \texttt{Bernoulli}\left(\mu(x^\mathsf{T}\theta_\star)\right)$

[Non-linear link function]
$\mu(z) = \left(1+\exp(-z)\right)^{-1}$

The learning problem

At each step $t \leq T$:

- choose a arm $x_t \in \mathcal{X}$,
- receive $r(x_t)$,

Objective: minimize Regret

$$R_{\theta_\star}(T) = \sum_{t=1}^{T}\left[\max_{x\in\mathcal{X}} \mu(x^\mathsf{T}\theta_\star) - \mu(x_t^\mathsf{T}\theta_\star)\right] .$$

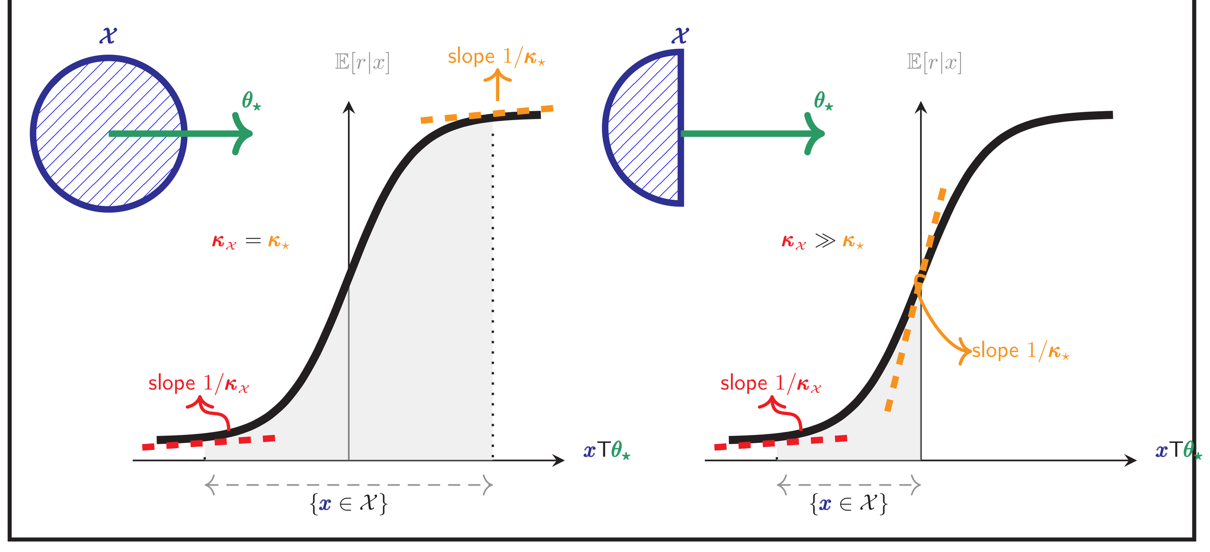
Quantifying non-linearity

We consider two important *problem-dependent* constants:

$$\kappa_\star := 1/\dot{\mu}(\max_{x\in\mathcal{X}} x^\mathsf{T}\theta_\star)$$

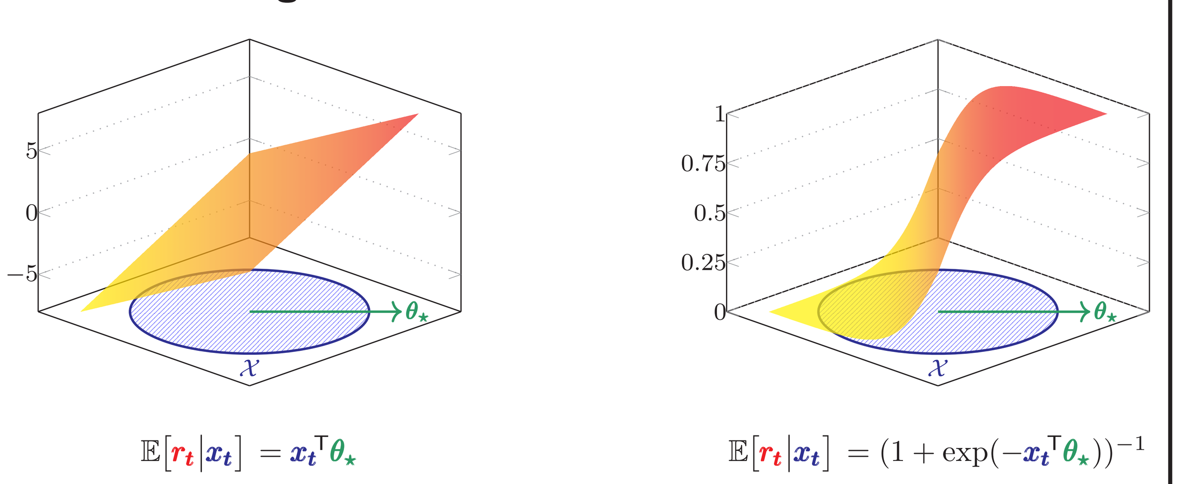
$$\kappa_\mathcal{X} := 1/\min_{x\in\mathcal{X}} \dot{\mu}(x^\mathsf{T}\theta_\star)$$

- $\kappa_\star$: "distance to linearity" around the optimal action,
- $\kappa_\mathcal{X}$: worst-case "distance to linearity" over the decision set.



Non-linearity: blessing or curse ?

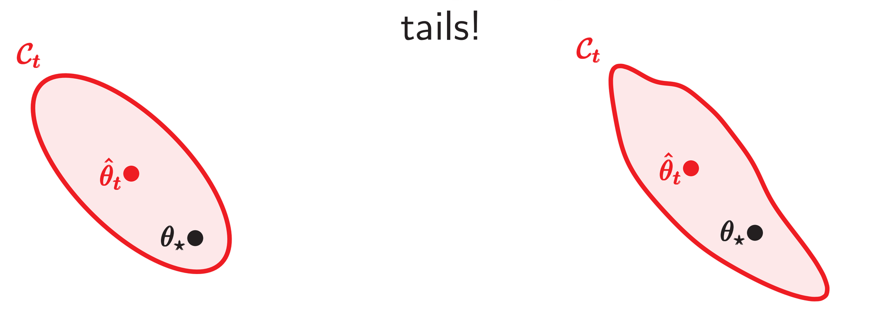
From LB to LogB



Impact on the learning

Different richness of information associated with sampling an arm:

LB same everywhere, **LogB** high in the center, low in the tails!



✓ Despite non-linearity → available conf. set. $\mathcal{C}_t$ for **LogB**,
[Faury et al, Improved Optimistic Algorithms for Logistic Bandits, ICML'20]

✗ Some regions are *harder* to learn that other → the conf. set. $\mathcal{C}_t$ is *not* an ellipsoid!

Impact on the predicted performance

✓ **LogB** deviation in parameters → little to no deviation in performance *in the tails*

$$\|\theta - \theta_\star\| = \delta \quad\Rightarrow\quad \mu(x^\mathsf{T}\theta) \approx \mu(x^\mathsf{T}\theta_\star).$$

Open question: does *easy* prediction cancel out *hard* learning?

Related Work and Contributions

Related work

[Filippi et al., NIPS'10] $R_{\theta_\star}(T) \lesssim \kappa_\mathcal{X} d\sqrt{T}$

[Faury et al., ICML'20] $R_{\theta_\star}(T) \lesssim d\sqrt{T} + \kappa_\mathcal{X}$

[Dong et al., COLT'19] In the worst case, $R_{\theta_\star}(T)$ must increase with $\kappa_\mathcal{X}$

Contributions

Theorem 1. (Regret Upper Bound) The regret of **OFU-Log** satisfies with high-probability:

$$R_{\theta_\star}(T) \lesssim d\sqrt{\frac{T}{\kappa_\star}} + (\kappa_\mathcal{X}).$$

Illustration: if $\mathcal{X} = \{\|x\| \leq 1\}$ then $\kappa_\star = \kappa_\mathcal{X} \approx \exp(\|\theta_\star\|)$:

$$R_{\theta_\star}(T) \lesssim d\sqrt{T/\kappa_\mathcal{X}} ,$$
$$\lesssim d\exp(-\|\theta_\star\|/2)\sqrt{T}$$

⇝ the more non-linear the model, the smaller the regret!
⇝ exponential improvement over existing bounds.

Theorem 2. (Local Lower Bound) Let $\mathcal{X} = \mathcal{S}_d(0,1)$, for any $\theta_\star$ and T large enough, it exists $\epsilon > 0$ such that:

$$\min_{\pi}\max_{\|\theta-\theta_\star\|\leq\epsilon} \mathbb{E}\left[R_\theta^\pi(T)\right] = \Omega\left(d\sqrt{\frac{T}{\kappa_\star}}\right).$$

where ϵ is small enough that $\forall\theta \in \{\|\theta-\theta_\star\| \leq \epsilon\}$ we have $\kappa_\star(\theta) = \Theta(\kappa_\star)$.

⇝ the upper-bound is *optimal* for large T.
⇝ the lower-bound holds for all instances $\theta_\star$.

Ideas Behind the Lower Bound

Objective and approach

- We shoot for a *problem-dependent* lower-bound,
- usual approaches consider worst-case over *all possible instances*,
- inspired by *[Simchowitz et al., ICML'20]* → *local* lower-bound,
- worst-case over nearby alternatives around a given *problem instance*.

High-level idea

- We consider a given instance parametrized by $\theta_\star$,
- let π denote a policy that outputs a sequence of arms, and $R_{\theta_\star}^\pi(T)$ the induced expected regret.

Small regret ↔ low exploration

$$R_{\theta_\star}^\pi(T) \propto 1/\kappa_\star \sum_{t=1}^{T}\|x_t - x_\star(\theta_\star)\|^2, \quad x_\star(\theta_\star) = \arg\max_{x\in\mathcal{X}}\mu(x^\mathsf{T}\theta_\star)$$

- $R_{\theta_\star}^\pi(T)$ small ↔ $x_t \simeq x_\star(\theta_\star)$,
- directions orthogonal to $x_\star(\theta_\star)$ are poorly explored!
- *Larger* $\kappa_\star$ → *smaller* impact when deviating from $x_\star(\theta_\star)$!

Low exploration ↔ large set of plausible alternative

- We quantify the *similarity* between instances θ, $\theta_\star$ under policy π by the *discrepancy*

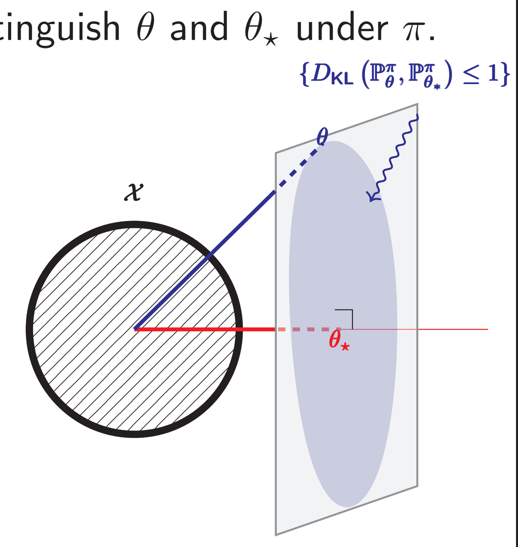
$$D_{\mathrm{KL}}\left(\mathbb{P}_\theta^\pi, \mathbb{P}_{\theta_\star}^\pi\right)$$

large $D_{\mathrm{KL}}\left(\mathbb{P}_\theta^\pi, \mathbb{P}_{\theta_\star}^\pi\right)$ → *easy* to distinguish θ and $\theta_\star$ under π,
small $D_{\mathrm{KL}}\left(\mathbb{P}_\theta^\pi, \mathbb{P}_{\theta_\star}^\pi\right)$ → *hard* to distinguish θ and $\theta_\star$ under π.

$$D_{\mathrm{KL}}\left(\mathbb{P}_\theta^\pi, \mathbb{P}_{\theta_\star}^\pi\right) \propto \sqrt{\frac{T}{\kappa_\star}}\|\theta - \theta_\star\|^2$$

- *large* $\kappa_\star$ degrades the richness of acquired information,

→ $D_{\mathrm{KL}}\left(\mathbb{P}_\theta^\pi, \mathbb{P}_{\theta_\star}^\pi\right)$ decreases with $\kappa_\star$.



Tension and trade-off

- Policy π cannot perform well on two *distinct* instances,
- but may not yield *similar* information.

Trade-off

- Let π perform well for $\theta_\star$,
- consider an alternative instance θ such that $\|\theta-\theta_\star\|^2 \approx \sqrt{\frac{\kappa_\star}{T}}$,
- the regret of π for the instance θ must be large:

$$R_\theta^\pi(T) \approx 1/\kappa_\star\sum_{t=1}^{T}\|x_t - x_\star(\theta)\|^2 \approx 1/\kappa_\star\sum_{t=1}^{T}\|x_\star(\theta_\star) - x_\star(\theta)\|^2$$
$$\approx T\|\theta_\star - \theta\|^2/\kappa_\star \approx \sqrt{T/\kappa_\star}.$$

Ideas Behind the Upper Bound

Permanent and transitory regimes

Regret decomposition

$$R_{\theta_\star}(T) = \underbrace{R^{\text{perm}}(T)}_{\tilde{\mathcal{O}}(\sqrt{T})} + \underbrace{R^{\text{trans}}(T)}_{\tilde{\mathcal{O}}(1)}$$

Permanent regime: intuition

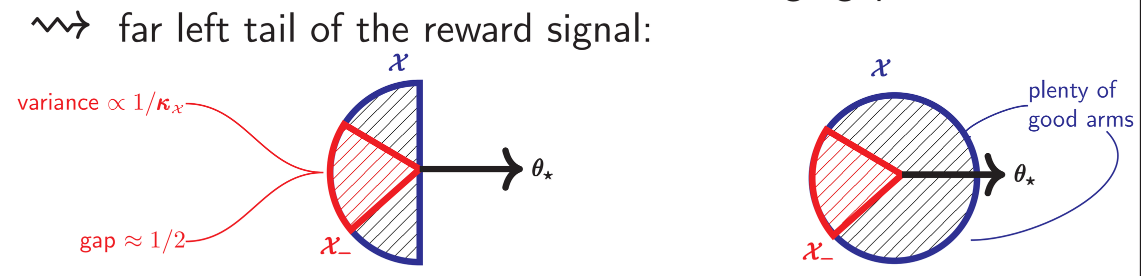
- Sublinear regret ⇒ play mostly around the best arm $x_\star$.
  ⇝ Almost a linear bandit with slope $1/\kappa_\star$.
- A finer analysis is coherent with this conceptual argument:

$$R^{\text{perm}}(T) \leq d\sqrt{\sum_{t=1}^{T}\dot{\mu}(x_t^\mathsf{T}\theta_\star)} \approx d\sqrt{T/\kappa_\star} .$$

- Formal proof: thanks to self-concordance property.

Transitory regime and detrimental arms

- *Detrimental arm* $\mathcal{X}_-$: low-information and large gap:
  ⇝ far left tail of the reward signal:



- Transitory regime: how long before discarding detrimental arms:

$$R^{\text{trans}}{}_{\theta_\star}(T) \leq \min\left(\kappa_\mathcal{X}, \sum_{t=1}^{T}\mathbb{1}(x_t \in \mathcal{X}_-)\right) .$$

- Fast if the proportion of detrimental arms is small:

Proposition 1. (Transitory regret) With h.p :

$$R^{\text{trans}}(T) \lesssim_T d^2 + dK \qquad \text{if } |\mathcal{X}_-| \leq K ,$$
$$R^{\text{trans}}(T) \lesssim_T d^3 \qquad \text{if } \mathcal{X} = \mathcal{B}_d(0,1) .$$

⇝ independent of $\kappa_\mathcal{X}$ for reasonable configurations!

Algorithm and experiments

for $t = \{0, \ldots, T\}$ **do**
  (*Learning*) Solve $\hat\theta_t = \arg\min_\theta \mathcal{L}_t(\theta)$.
  (*Planning*) Solve $(x_t, \theta_t) \in \arg\max_{\mathcal{X},\mathcal{C}_t(\delta)} \mu\left(x^\mathsf{T}\theta\right)$.
  Play x_t and observe reward r_{t+1}.
end for

where $\mathcal{L}_t(\theta)$ and $\mathcal{C}_t(\delta)$ are the log-likelihood function and confidence set associated with the learning problem.

Parameter-based optimism

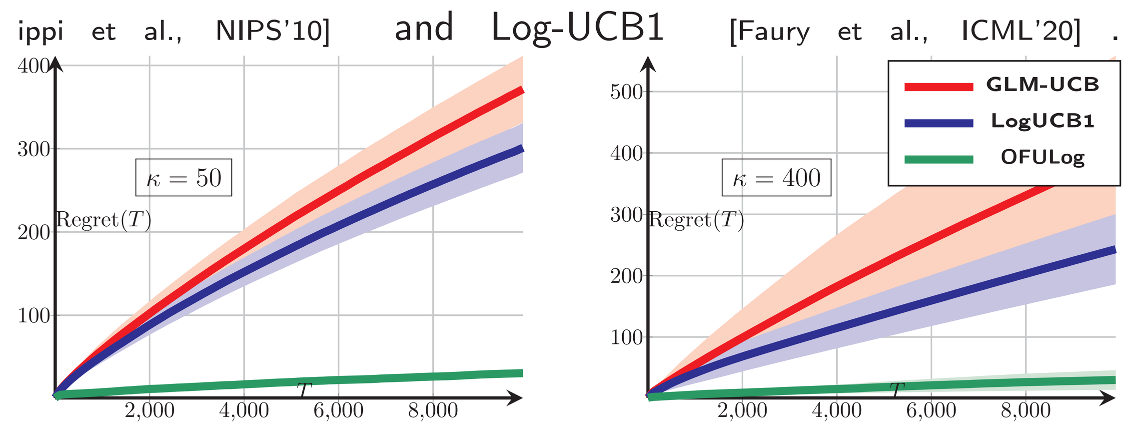
- Enforce optimism through parameter-search (OFUL-like), and not bonus-based approach.
- This yields an *adaptive* algorithm: no tuning needed to adapt to the structure of the decision set.

Tractable algorithm

- We also introduce a *convex relaxation* of the confidence set $\mathcal{C}_t(\delta)$ of [Faury et al., ICML'20] .
- No non-convex optimization routine ($\neq$ previous work).

Practical improvements

- Toy experiment: dramatic improvement over GLM-UCB [Filippi et al., NIPS'10] and Log-UCB1 [Faury et al., ICML'20] .



Conclusion

- Our conclusion contrasts with previous work:

Logistic Bandit: non-linearity makes the problem **easier**!

- Regret-upper bound with exponential improvement.
- First problem-dependent lower-bound for Logistic Bandit.
- Fully tractable, adaptive algorithm thanks to convex relaxation.

References

S. Filippi, O. Cappé, A. Garivier and C. Szepesvári. Parametric Bandits: The Generalized Linear Case. *Proceedings of NIPS*, 2010.

F. Bach. Self-concordant analysis for logistic regression. *Electronic Journal of Statistics*, 2010.

S. Dong, T. Ma and B. Van Roy. On the Performance of Thompson Sampling on Logistic Bandits. *Proceedings of COLT*, 2019.

L. Faury, M. Abeille, C. Calauzène and O. Fercoq. Improved Optimistic Algorithms for Logistic Bandits. *Proceedings of ICML*, 2020.

M. Simchovitz and D. Foster. Naive Exploration is Optimal for Online LQR. *Proceedings of ICML*, 2020.