

# Thompson Sampling for Bandit Convex Optimisation

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COLT 2025

- **Goal:** Understand how **Thompson Sampling (TS)** behaves in **bandit convex optimization (BCO)**.
- **Positive:**
  - $\text{BReg}_n(\text{TS}) = \tilde{O}(\sqrt{n})$  in  $1$ -D convex bandits.
  - $\text{BReg}_n(\text{TS}) = \tilde{O}(d^{2.5}\sqrt{n})$  for  $d$ -D *monotone convex ridge* losses.
- **Negative:**
  - TS can suffer  $\Omega(\exp(d))$  regret for general  $d$ -D convex losses.
  - Classical info-ratio tricks  $\Rightarrow$  no better than  $\tilde{O}(d^{1.5}\sqrt{n})$  for general adversarial BCO, through duality.

# Problem Setup

- Convex action set  $\mathcal{K} \subset \mathbb{R}^d$ .
- $\mathcal{F}$  be a set of convex functions from  $\mathcal{K}$  to  $[0, 1]$ .
- $\xi$  is a known prior on  $\mathcal{F}$ .

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- **Bayesian Regret**

$$\text{BReg}_n(\mathcal{A}, \xi) = \mathbb{E} \left[ \sup_{x \in \mathcal{K}} \sum_{t=1}^n (f(X_t) - f(x)) \right],$$

where  $f \sim \xi$ .

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# Thompson Sampling for BCO

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**Algorithm 1** Thompson Sampling

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- 1: Prior  $\xi$  over convex losses.
  - 2: **for**  $t = 1, \dots, n$  **do**
  - 3:     Sample  $f_t \sim \mathbb{P}(f = \cdot | X_1, Y_1, \dots, X_{t-1}, Y_{t-1})$
  - 4:     Play  $x_t \in \arg \min_{x \in \mathcal{K}} f_t(x)$  and observe  $Y_t$
  - 5: **end for**
- 

- Our analysis studies how

$$\text{BReg}^{\text{TS}}(\mathcal{F}) = \sup_{\xi \in \mathcal{P}(\mathcal{F})} \text{BReg}_n(\text{TS}, \xi),$$

behaves for various natural classes of convex functions  $\mathcal{F}$ .



# Upper bounds - main results

- Positive results for two sets of functions  $f : \mathcal{K} \rightarrow [0, 1]$ :

$\mathcal{F}_{\text{bl}}$  :  $\mathcal{K} \subset \mathbb{R}$  and  $f$  is a 1-Lip and bounded convex function,

$\mathcal{F}_{\text{blrm}}$  :  $\mathcal{K} \subset \mathbb{R}^d$  and  $f(x) = \ell(\langle x, \theta \rangle)$  for some  $\theta \in \mathbb{R}^d$  and a convex 1-Lip bounded *monotone*  $\ell : \mathbb{R} \rightarrow \mathbb{R}$ .

## Upper bounds – 1-D convex functions

TS achieves

$$\text{BReg}^{\text{TS}}(\mathcal{F}_{\text{bl}}) = \tilde{O}(\sqrt{n}),$$

And

$$\text{BReg}^{\text{TS}}(\mathcal{F}_{\text{blrm}}) = \tilde{O}(d^{2.5}\sqrt{n}).$$

## (Generalized) **Information Ratio (IR)**

- Let  $x_g = \operatorname{argmin}_{x \in \mathcal{K}} g(x)$ .
- Let  $(X, f)$  have law  $\pi \otimes \xi$ , and  $\bar{f} = \mathbb{E}[f]$ .
- Define

$$\Delta(\pi, \xi) = \mathbb{E}[\bar{f}(X) - f_\star] \quad \text{and} \quad \mathcal{I}(\pi, \xi) = \mathbb{E}[(f(X) - \bar{f}(X))^2].$$

### Generalized IR

Define generalized information ratio associated with TS as

$$\operatorname{IR}(\mathcal{F}) = \left\{ (\alpha, \beta) \in \mathbb{R}_+^2 : \Delta(\pi_{\text{TS}}, \xi) \leq \alpha + \sqrt{\beta \mathcal{I}(\pi_{\text{TS}}, \xi)}, \forall \xi \right\}.$$

- $(0, \beta) \in \operatorname{IR}(\mathcal{F}) \Rightarrow \Delta(\pi_{\text{TS}}, \xi)^2 / \mathcal{I}(\pi_{\text{TS}}, \xi) \leq \beta$ .

# Upper bounds – regret & IR

## Proposition 1 – regret bound through IR

Suppose that  $\mathcal{F} \in \{\mathcal{F}_{\text{bl}}, \mathcal{F}_{\text{blrm}}\}$  and  $(\alpha, \beta) \in \text{IR}(\mathcal{F})$ . Then, the regret of TS is at most

$$\text{BReg}_n(\text{TS}, \xi) \leq n\alpha + O\left(\sqrt{\beta n d \log(n \text{diam}(\mathcal{K}))}\right).$$

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It remains to bound the IR of TS.

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## Proposition 2 – TS-IR Decomposition

If  $\exists k, m \in \mathbb{N}$  such that for all  $\bar{f} \in \text{conv}(\mathcal{F})$  there is  $\mathcal{F} = \cup_{i=1}^m \mathcal{F}_i$  for which

$$\sup_{f \in \mathcal{F}_i} (\bar{f}(x_f) - f(x_f)) \leq \alpha + \sqrt{\underbrace{\beta \inf_{f_1, \dots, f_k \in \mathcal{F}_i} \sum_{j \neq l \in [k]} (f_j(x_{f_l}) - \bar{f}(x_{f_l}))^2}_{\text{DIS}(\mathcal{F}_i, k)}},$$

for all  $i$ , then  $(\alpha, k(k-1)m\beta) \in \text{IR}(\mathcal{F})$ .

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worst case average regret within  $\mathcal{F}_i$

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TS minimum inf. gain (discrepancy)

for all  $i$ , then  $(\alpha, k(k-1)m\beta) \in \text{IR}(\mathcal{F})$ .

# Upper bounds – IR bound in 1-D

## Theorem 3 – IR bound for 1-D

Suppose that  $d = 1$  and  $\alpha \in (0, 1)$ . Then  $(\alpha, 10^4 \lceil \log(1/\alpha) \rceil) \in \text{IR}(\mathcal{F}_{\text{bl}})$ .

### Proof sketch:

- Use the decomposition lemma  $\Rightarrow$  partition based on  $x_f$  and  $f(x_f)$ .
- Analyze functions with similar gaps (average regret) in  $\mathcal{F}_i$ :

Similar gaps:  $\bar{f}(x_f) - f(x_f) \in [\epsilon, 2\epsilon]$ ,

$\bar{f}$  monotone:  $x_{\bar{f}} \leq x_f \Rightarrow \bar{f}$  (begin 1-D is crucial here).

- Prove that  $\text{DIS}(\mathcal{F}_i, k) \geq c^2 \epsilon_i^2$

$$\inf_{f_1, \dots, f_k \in \mathcal{F}_i} \sum_{j \neq l \in [k]} (f_j(x_{f_l}) - \bar{f}(x_{f_l}))^2 \geq c^2 \epsilon_i^2.$$



# Upper bounds – IR bound in 1-D

**Proof sketch:**(proof by contradiction)

- Fix  $k = 4$ ,  $c \approx 1/16$ , suppose that

$$\inf_{f_1, f_2, f_3, f_4 \in \mathcal{F}_i} \sum_{j \neq l \in [4]} (f_j(x_{f_l}) - \bar{f}(x_{f_l}))^2 \leq c^2 \epsilon_i^2$$
$$\Rightarrow \forall f_1, f_2, f_3, f_4 \in \mathcal{F}_i, \quad f_j(x_{f_l}) - \bar{f}(x_{f_l}) \leq c \epsilon_i.$$

- WLOG, suppose that  $x_{\bar{f}}, x_1 \leq x_2 \leq x_3 \leq x_4$

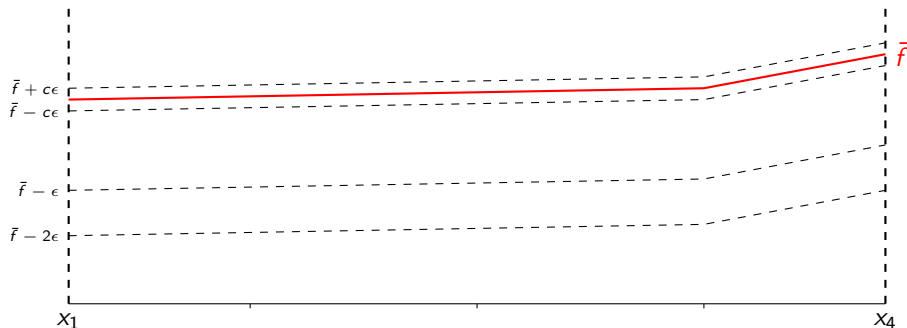
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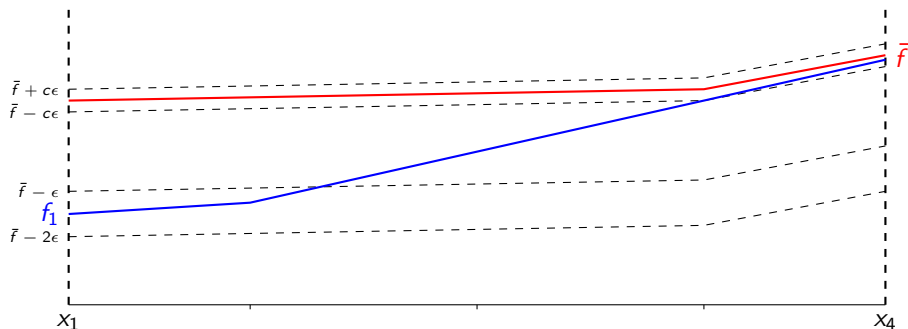
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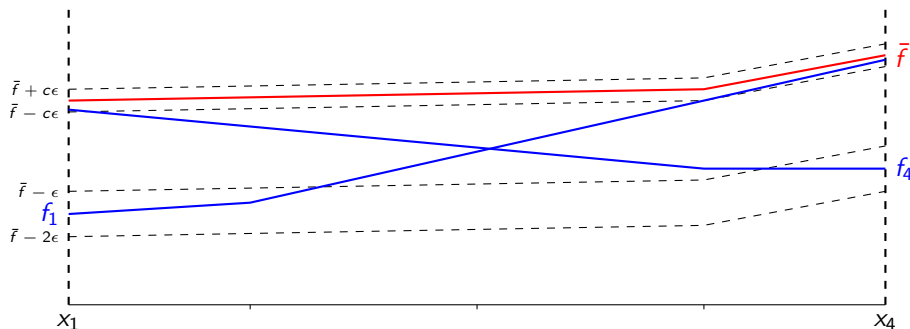
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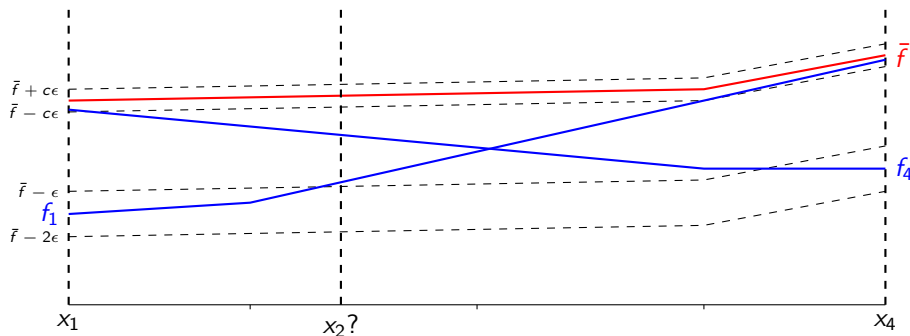
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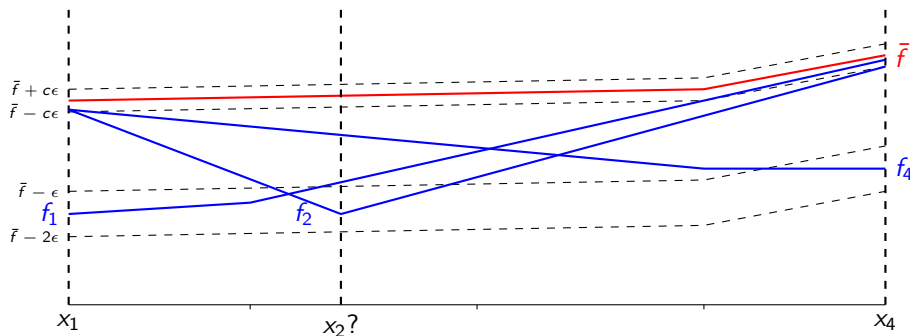
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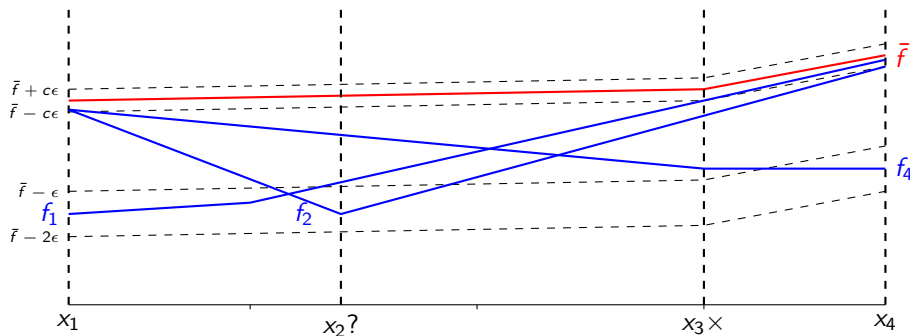
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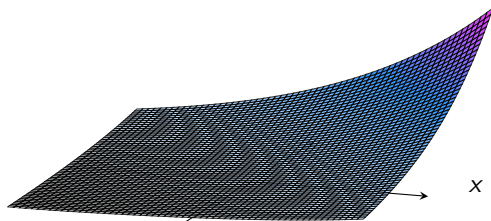


# Upper bounds – IR bound in d-D

## Theorem 7 – IR bound in d-D

$(\alpha, \beta \lceil \log(1/\alpha) \rceil) \in \text{IR}(\mathcal{F}_{\text{blrm}})$  whenever  $\alpha \in (0, 1)$  and

$$\text{BReg}^{\text{TS}}(\mathcal{F}_{\text{blrm}}) = \tilde{O}(d^{2.5} \sqrt{n}).$$



$f(x, y) = e^{x+y}$  — a convex ridge function with  $\theta = (1, 1)$  and  $\ell(t) = e^t$ .



# Lower bounds – main results

The following lower bounds share the same construction.

## Lower Bound 4

When  $\mathcal{K} = \mathbb{B}_1 \subset \mathbb{R}^d$ , there exists a prior  $\xi$  on  $\mathcal{F}_{\text{bl}}$  such that

$$\text{BReg}_n(\text{TS}) \geq \frac{1}{2} \min\left\{n, \frac{1}{4} e^{\Omega(d/32)}\right\}.$$

## Lower Bound 2

Suppose that  $\mathcal{K} = \mathbb{B}_1 \subset \mathbb{R}^d$  and  $d > 256$ . Then there exists a prior  $\xi$  on  $\mathcal{F}_{\text{bl}}$  such that

$$\Delta(\pi, \xi) \geq 2^{-19} \frac{d}{\log(d)} \sqrt{\mathcal{I}(\pi, \xi)},$$

for all policies  $\pi$  on  $K$ .

## Lower bounds – construction

- $f(x) = \epsilon + \frac{1}{2} \|x\|^2$ , a simple bowl shape function in  $\mathbb{B}_1$ ,
- $f_\theta$  which is the largest convex function  $g$  that is smaller than  $f$ , and  $g(\theta) = 0$ .
- $\xi$  is the *uniform* prior over  $f_\theta$ . ( $\theta \sim \text{unif}(\mathbb{S}_1)$ )
- TS lower bound:
  - ① The “perimeter” of these valleys gets smaller exponentially with  $d$ .
  - ② TS only plays on the surface where the minimizers are.
  - ③ TS will suffer  $O(\exp(d))$  regret.
- IR lower bound:
  - ① Both  $\delta$  and  $\mathcal{I}$  of a point  $x \in \mathbb{B}_1$  are a function of its radius  $r$ .
  - ② Optimize for  $r$ .

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