CS 747, Autumn 2022: Lecture 2

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Indian Institute of Technology Bombay

Autumn 2022

Multi-armed Bandits

1. Evaluating algorithms: Regret
2. Achieving sub-linear regret
3. A lower bound on regret

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Visualising Performance

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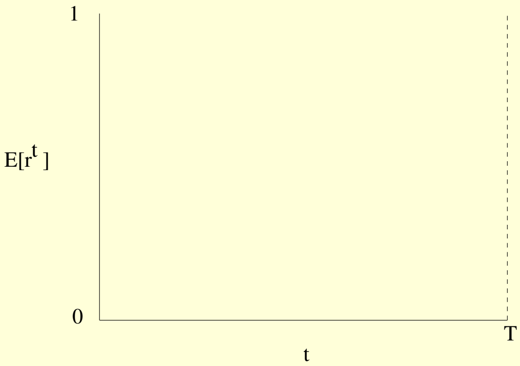

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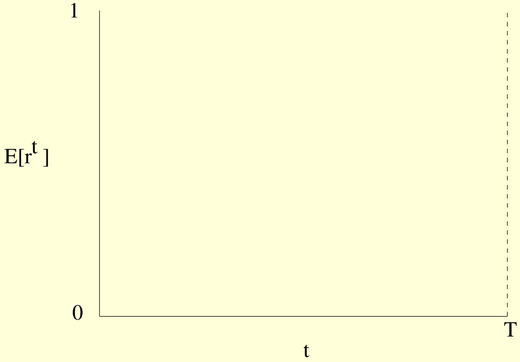

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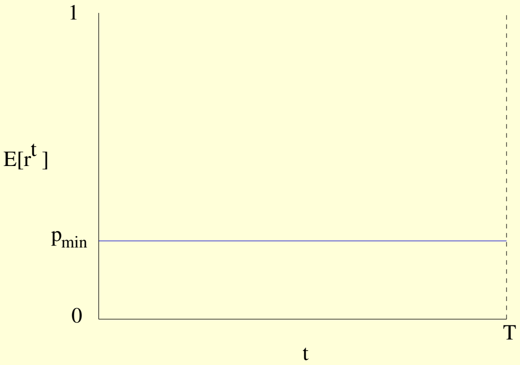

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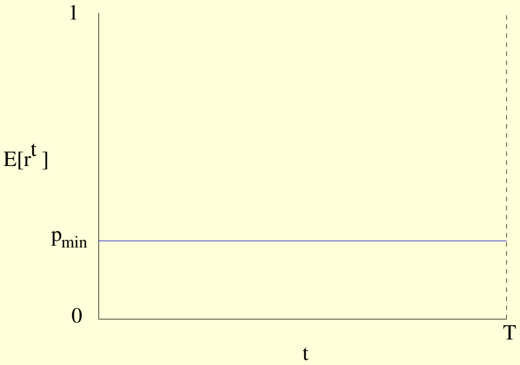

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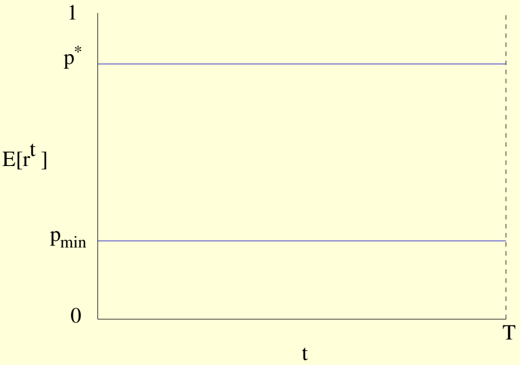

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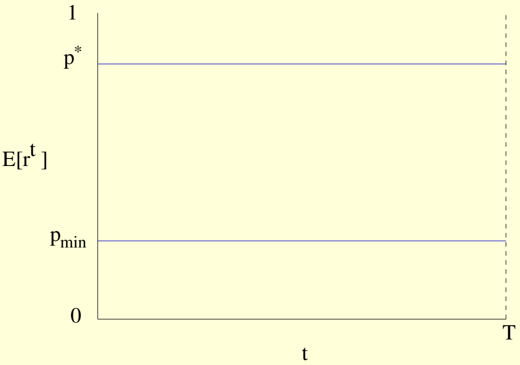

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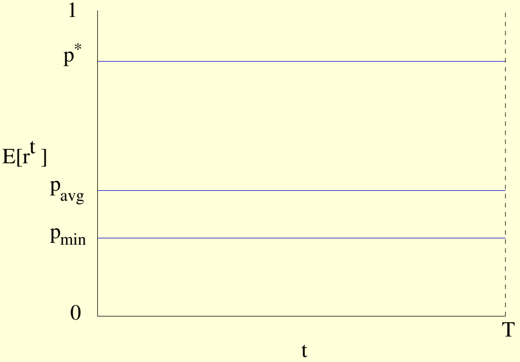

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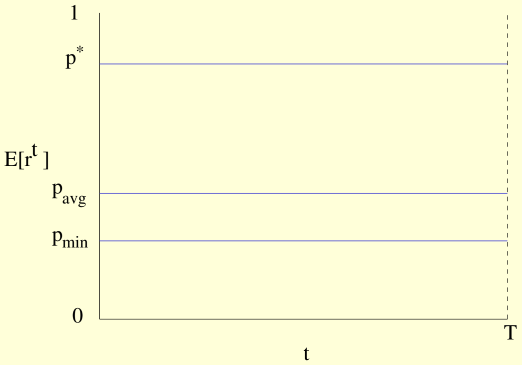

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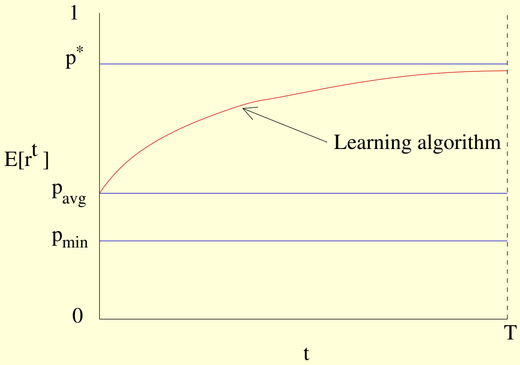

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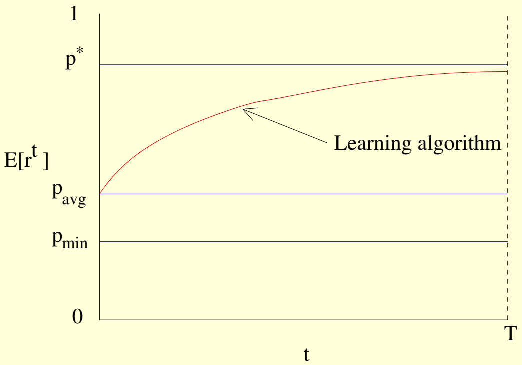

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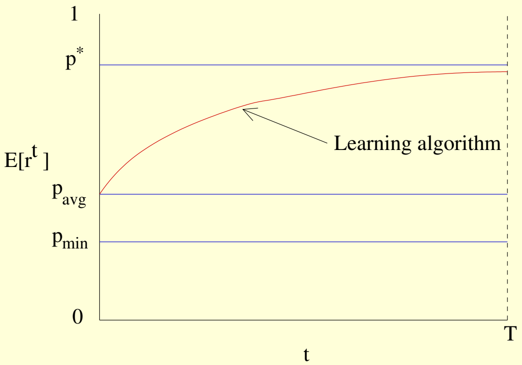

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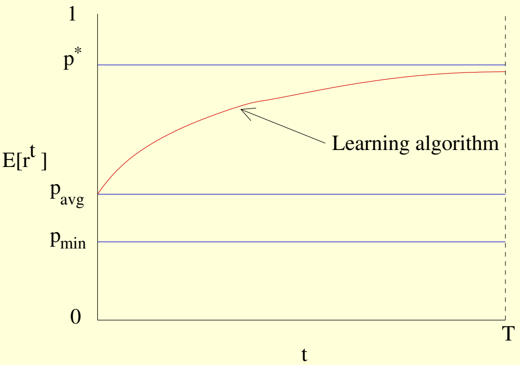

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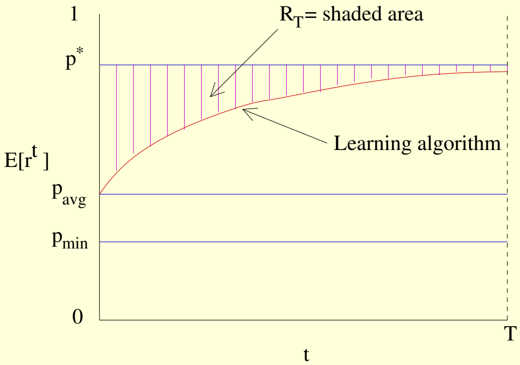

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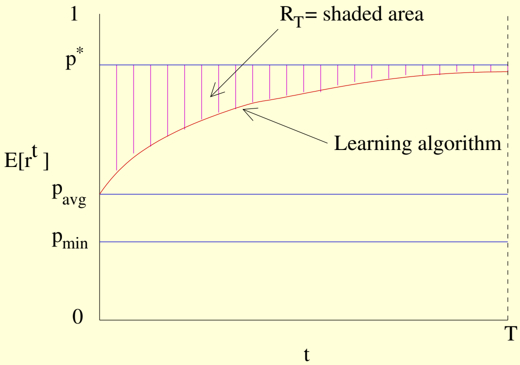

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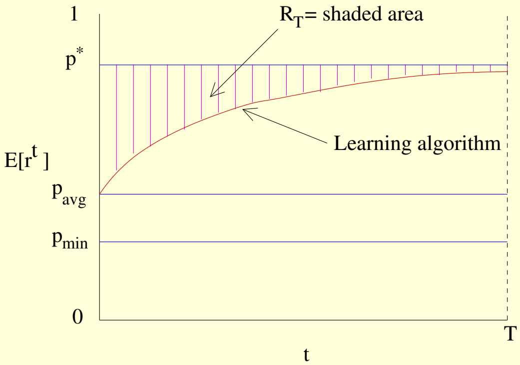

- We would like R_T to be small, in fact for $\lim_{T\to\infty} \frac{R_T}{T} = 0$. Does this happen for ϵG1, ϵG2, ϵG3?

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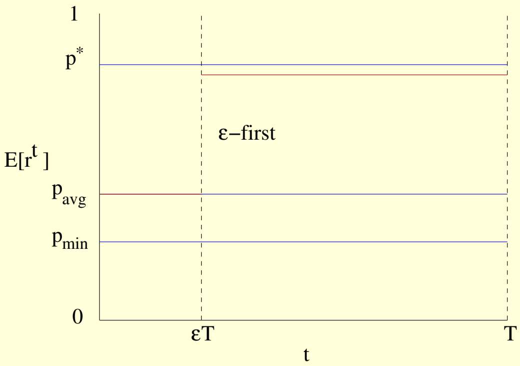

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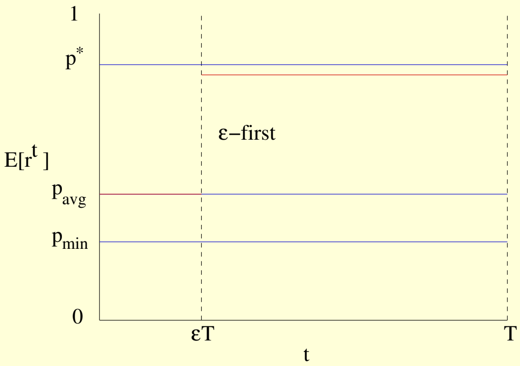

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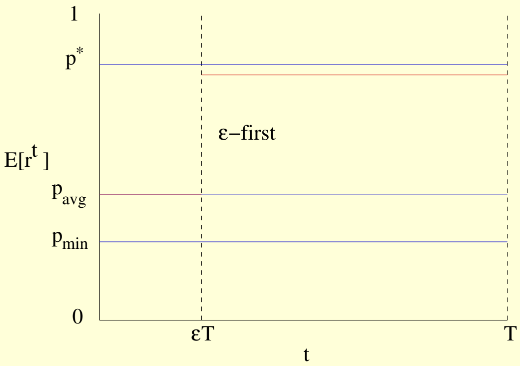

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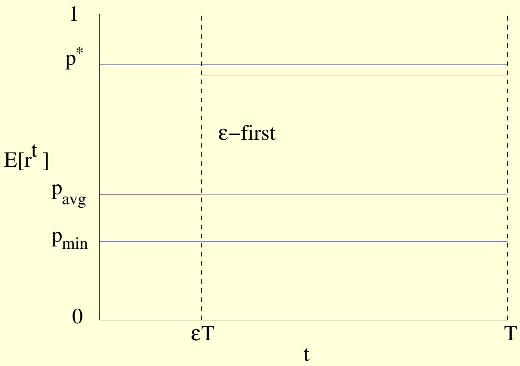

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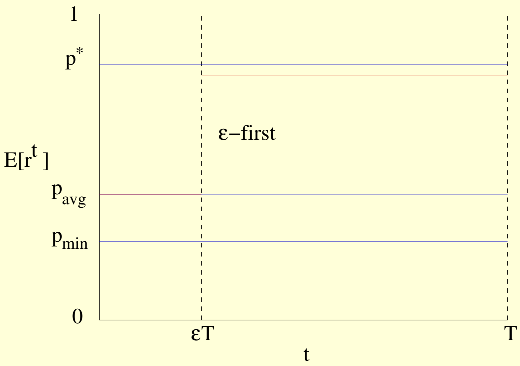

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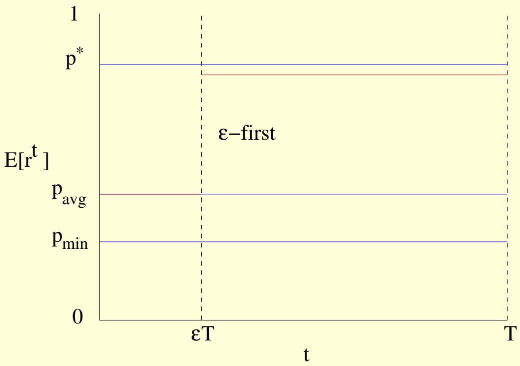

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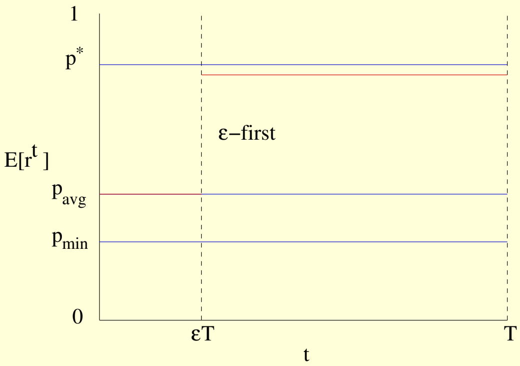

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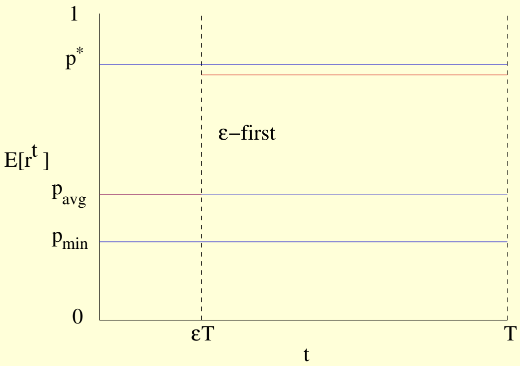

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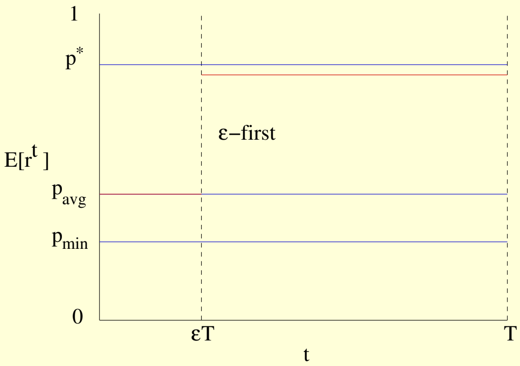

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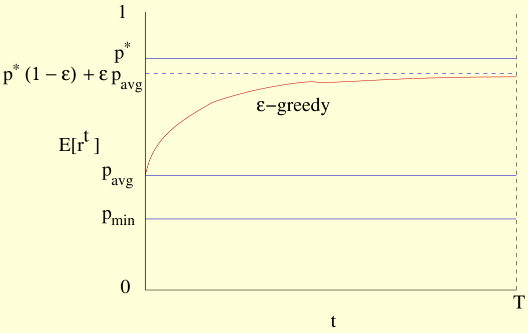

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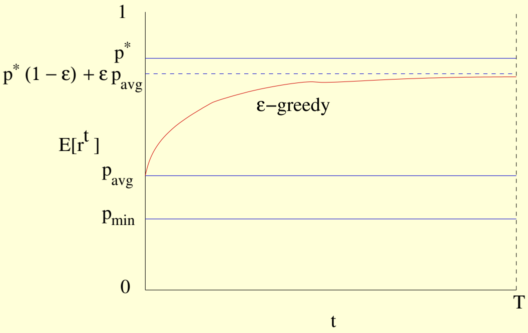

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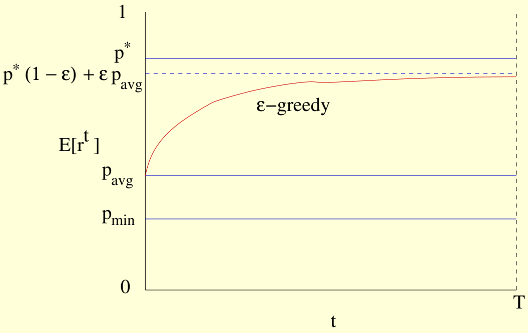

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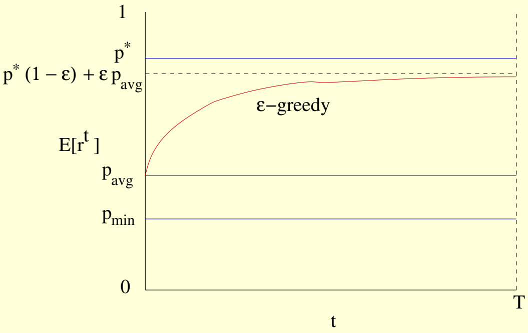

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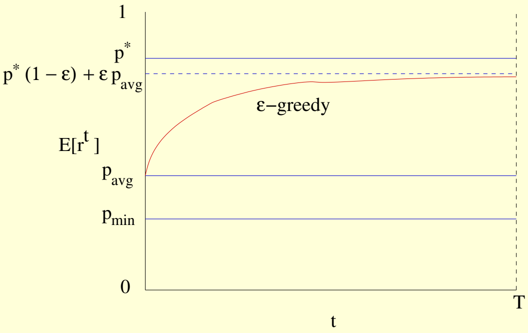

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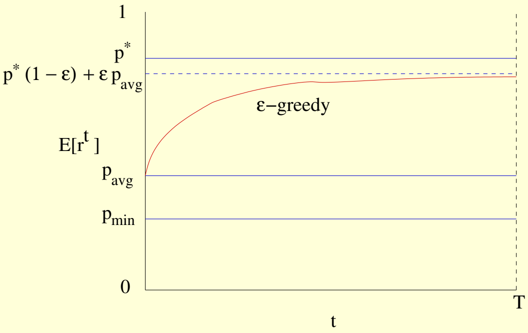

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- On the contrary, suppose we pull some arm a only a finite U times.
- We cannot be 100% sure based on the pulls of a that it is non-optimal.
- Even an optimal arm a will have the lowest possible empirical mean (0) with positive probability $(1 - p^\star)^U$.
- Pulling only arms other than a will give linear regret if no other optimal arms.

How to achieve Sub-linear Regret?

C2. **Greed in the Limit**. Let *exploit*(T) denote the number of pulls that are greedy w.r.t. the empirical mean up to horizon T. For sub-linear regret, we need

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In short: "GLIE" $\iff$ sub-linear regret.

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GLIE-ifying ϵ-Greedy Strategies

- ϵ_T-first with $\epsilon_T = \frac{1}{\sqrt{T}}$.
  Explore for $\epsilon_T \cdot T = \sqrt{T}$ pulls. Thereafter exploit.

  C1 satisfied since each arm gets at least $\Theta(\frac{1}{n}\sqrt{T})$ pulls with high probability.
  C2 satisfied since $\mathbb{E}[exploit(T)] \geq T - \sqrt{T}$.

- ϵ_t-greedy with $\epsilon_t = \frac{1}{t+1}$.
  On the t-th step, explore w.p. ϵ_t, exploit w.p. $1 - \epsilon_t$.

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  What happened when we took $\epsilon_t = \epsilon$? What will happen by taking $\epsilon_t = \frac{1}{(t+1)^2}$?

Multi-armed Bandits

1. Evaluating algorithms: Regret
2. Achieving sub-linear regret
3. A lower bound on regret

A Lower Bound on Regret

- What is the least regret possible?

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A Lower Bound on Regret

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- We desire “low” regret on all instances. What is the best we can do?

A Lower Bound on Regret

Paraphrasing Lai and Robbins (1985; see Theorem 2).

Let L be an algorithm such that for every bandit instance $I \in \bar{\mathcal{I}}$ and for every $\alpha > 0$, as $T \to \infty$:

$$R_T(L, I) = o(T^\alpha).$$

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$$R_T(L, I) = o(T^{\alpha}).$$

Then, for every bandit instance $I \in \bar{\mathcal{I}}$, as $T \to \infty$:

$$\frac{R_T(L, I)}{\ln(T)} \geq \sum_{a: p_a(I) \neq p^\star(I)} \frac{p^\star(I) - p_a(I)}{KL(p_a(I), p^\star(I))},$$

where for $x, y \in [0, 1)$, $KL(x, y) \stackrel{\text{def}}{=} x \ln \frac{x}{y} + (1 - x) \ln \frac{1-x}{1-y}$.

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Next class: Optimal algorithms!