

# **Bounded regret in stochastic multi-armed bandits**

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Bounded regret in stochastic bandits,  
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<https://blogs.princeton.edu/imabandit/>



**Unknown parameters:**  $\nu_1, \dots, \nu_K$  (subgaussian) probability distributions

**Notation:**  $\mu_i = \mathbb{E}_{X \sim \nu_i} X$ ,  $\mu^* = \max_{i \in [K]} \mu_i$ ,  $\Delta_i = \mu^* - \mu_i$

**Game:** For  $t = 1, \dots, n$ , select  $I_t \in \{1, \dots, K\}$  and receive  $Y_t \sim \nu_{I_t}$ .

**Performance measure:**  $R_n = n\mu^* - \mathbb{E} \sum_{t=1}^n Y_t$

**Theorem (Auer, Cesa-Bianchi and Fischer 2002)**

$$R_n(\text{UCB}) \leq c \sum_{i: \Delta_i > 0} \frac{\log n}{\Delta_i}$$

**Theorem (Lai and Robbins 1985)**

Consider a strategy such that if the distributions are Gaussian with variance 1 then  $R_n = o(n^a)$   
 $\forall a > 0$

Then for any Gaussian distributions with variance 1 one has

$$\liminf_{n \rightarrow +\infty} \frac{R_n}{\log n} \geq c \sum_{i: \Delta_i > 0} \frac{1}{\Delta_i}$$

