

Optimization in the Face of Uncertainty.

Pull arm i T_i times we know $|\hat{\theta}_i - \theta_i| \leq c\sqrt{\frac{1}{T_i}}$

Upper confidence Bound Algorithm (UCB) (2002)

Input: n arms, confidence δ

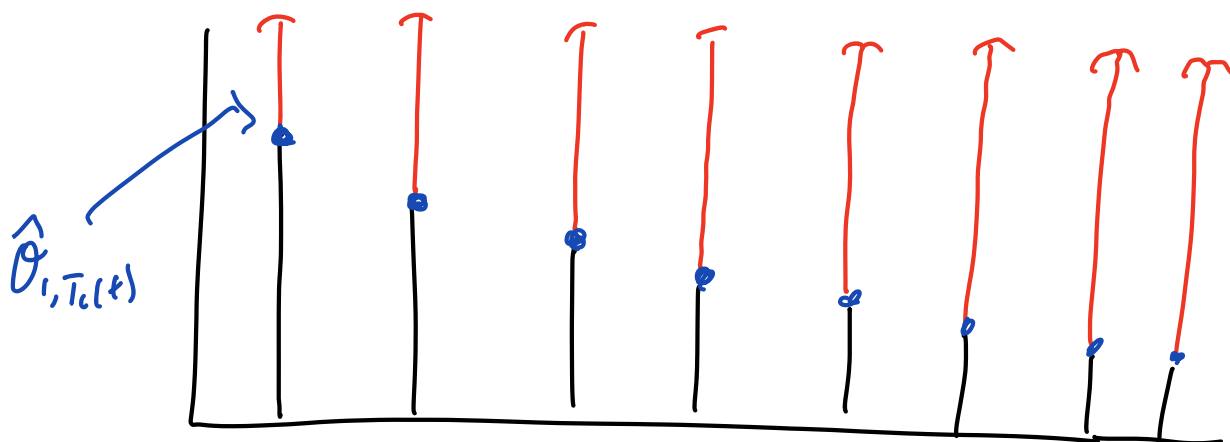
Initialize: Pull every arm once

Let $T_i(t)$ denote # times arm i has been pulled up to time t ,

and let $\hat{\theta}_{i, T_i(t)}$ denote empirical mean

Pull arm $I_t = \operatorname{argmax}_{i \in [n]} \hat{\theta}_{i, T_i(t)} + \sqrt{\frac{2 \log(4n T_i(t)^2 / \delta)}{T_i(t)}}$

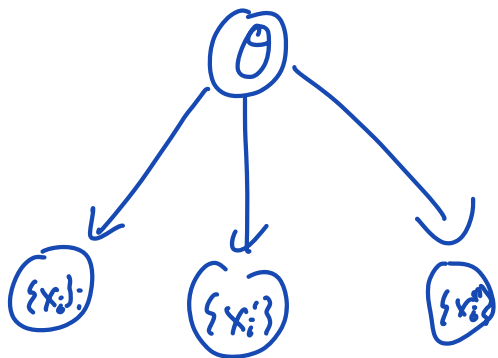
Claim W.p. $\geq 1 - \delta$ $\theta_i \leq \hat{\theta}_{i, T_i(t)} + \sqrt{\frac{2 \log(4n T_i(t)^2 / \delta)}{T_i(t)}} \quad \forall t, i$



Frequentist Statistics

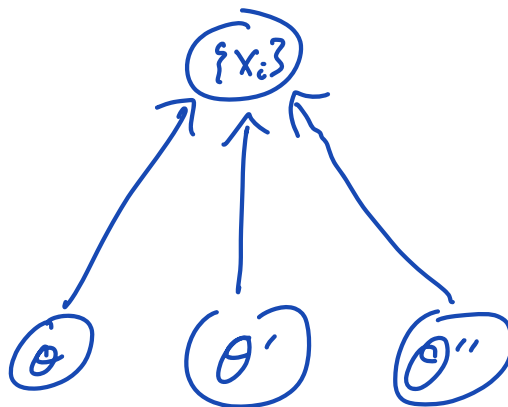
Exists a true parameter θ that is fixed and unknown.

Observe $X_i \stackrel{iid}{\sim} \mathcal{N}(\theta, 1)$



Bayesian Stats

Observe $\{X_i\}$ and it is fixed.



Bayesian Statistics

Before seeing any data you have prior "beliefs" about what values θ could take. Prior dist. P_0

Ex. $\theta \sim \mathcal{N}(0, \sigma^2)$

When I observe $X_i \sim f_\theta(\cdot)$

Ex. $X_i | \theta \sim \mathcal{N}(\theta, \sigma^2)$

Given prior distribution P_0 and $\{X_i\}_{i=1}^n \stackrel{iid}{\sim} f_\theta(\cdot)$

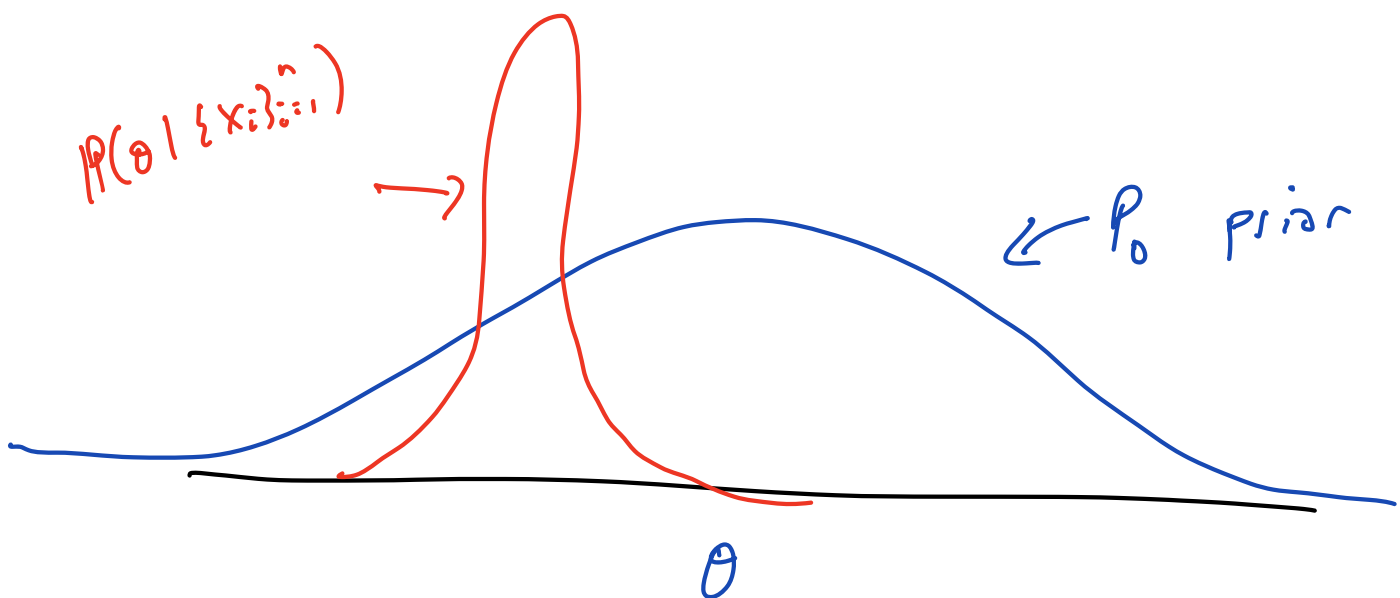
Bayes Rule: For any events A, B $P(B|A) = \frac{P(A, B)}{P(A)}$

$$P(A, B) = P(B|A)P(A)$$

Posterior distribution $P(\theta | X_1, \dots, X_n) = \frac{P(\theta, \{X_i\}_{i=1}^n)}{P(\{X_i\}_{i=1}^n)}$

$$= \frac{P(\{X_i\}_{i=1}^n | \theta) P(\theta)}{P(\{X_i\}_{i=1}^n)}$$

$$= \frac{\prod_{i=1}^n f_{\theta}(X_i) P_0(\theta)}{P(\{X_i\}_{i=1}^n)}$$



$$\theta \sim P_0$$

$$X_i \sim f_\theta \quad i=1, \dots, n$$

Thompson Sampling (1930)

$\theta \in \mathbb{R}^n$, n arms

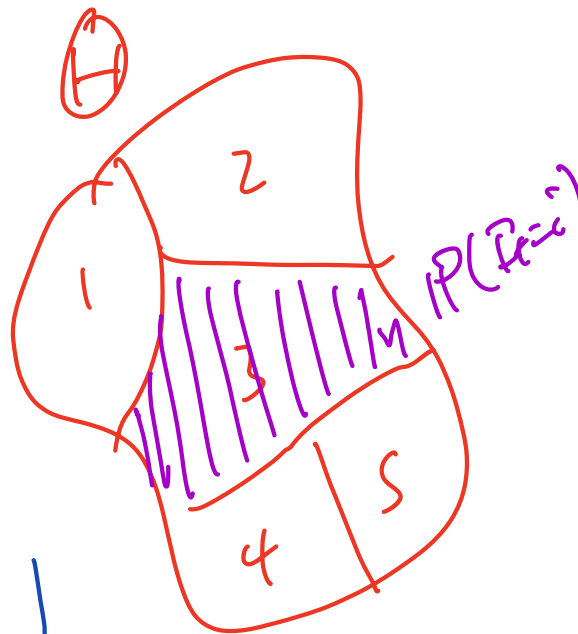
Initialize: $\theta \sim P_0$

for $t=1, 2, \dots$

$$P_{t,i} = \mathbb{P}(i = \arg \max_j \theta_j \mid \{X_{i,T_s(t)}\}_{s=1}^t)$$

$$\left(\sum_{i=1}^n P_{t,i} = 1 \right)$$

$$I_t \sim P_{t,i}$$



$$\mathbb{P}(i = \arg \max_j \theta_j \mid \{X_{i,T_s(t)}\}_{s=1}^t)$$

$$= \int_{\theta} \mathbb{1}\{\theta_i \geq \max_{j \neq i} \theta_j\} P(\theta \mid \{X_{i,T_s(t)}\}_{s=1}^t) d\theta \Rightarrow$$

for $t = 1, 2, \dots$

$$\theta_t \sim P(\theta | \{X_{i,t}(\theta)\}_{i,t})$$

$$\text{Play } I_t = \arg \max_i \theta_{t,i}$$

$$P(I_t = i | \{X_{i,t}\}) = \int_{\theta} P(I_t = i, \theta | \{X_{i,t}\}) d\theta$$

$$= \int_{\theta} \mathbb{1}\{I_t = i\} P(\theta | \{X_{i,t}\}) d\theta$$

Frequentist regret: Think of TS as an algorithm

where the choice of prior P_0 ,
likelihood function f_θ are design choices.

There exists a fixed θ^* and regret

$$\text{is } \sum_{i \neq 1}^n \frac{|\theta_i^* - \theta_i| E[T_i]}{\Delta_i} \lesssim \min \left\{ \sqrt{nT}, \sum_{i \neq 1} \Delta_i^{-1} \log(T) \right\}$$

Bayesian regret: Assume "true" $\theta^* \sim P_0$.

And $f_\theta(x)$ is the "true" likelihood of observing $x \in \mathcal{R}$ given fixed θ . Then regret

is

$$\mathbb{E}_{\theta^* \sim P_0} \left[\sum_{\substack{i: \theta_i^* < \theta_j^* \\ \text{if } \theta_j^* > \theta_i^*}} (\max_{i'} \theta_{i'}^* - \theta_i^*) \mathbb{E}[T_i] \right].$$

$$\leq \sqrt{nT \cdot \underbrace{H(P_0)}_{\uparrow}}$$

entropy of the prior
distribution assigning each
arm to be the best arm.