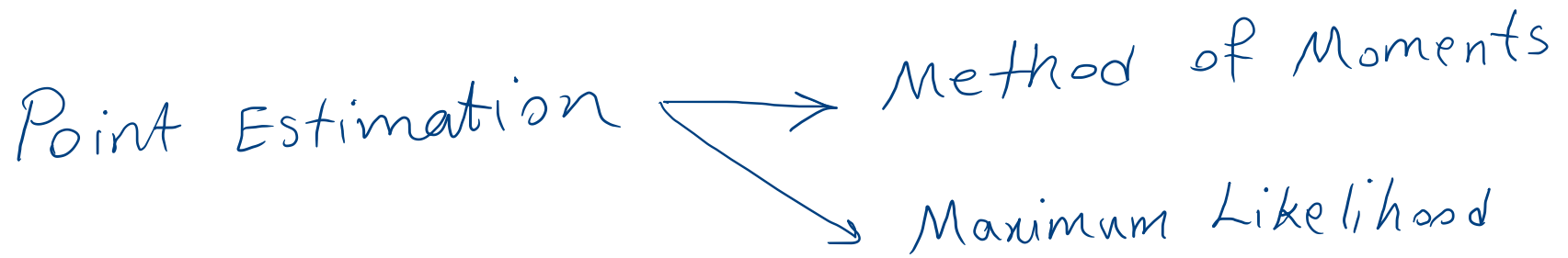


Parameter Estimation



Bayesian

$$x \sim f_x(x; \theta)$$

$$x \sim f_x(x|\theta)$$

$$\theta \sim f(\theta) \longrightarrow \text{prior} \quad \text{احتمال پیشین}$$

$$D = \{x_1, \dots, x_n\}$$


$$f(\theta) \xrightarrow{D} f(\theta|D) \quad \text{posterior} \quad \text{احتمال پسین}$$

Bayesian Estimation

$$\vec{X} = D = \{x_1, x_2, \dots, x_n\} \quad \text{i.i.d.}$$

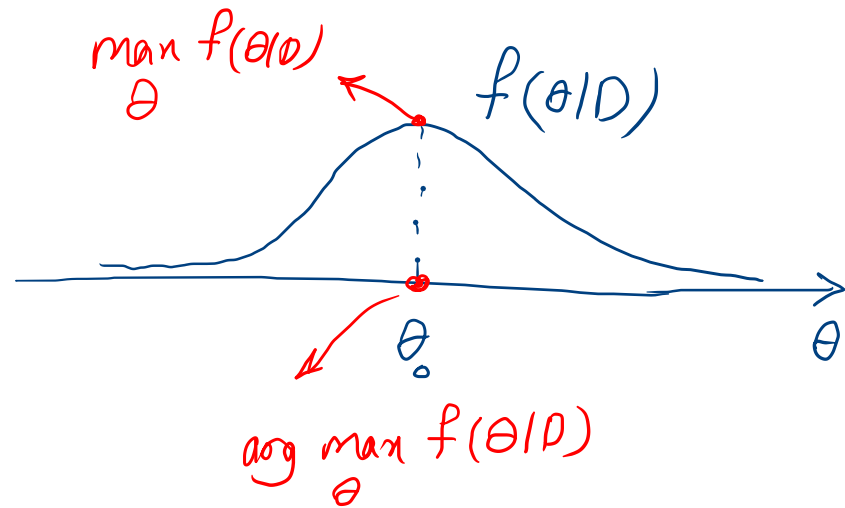
$$f(\theta) \longrightarrow f(\theta|D)$$

$$\underline{f(\theta|D)} = \frac{f(D|\theta) f(\theta)}{f(D)} = \frac{1}{c} f(D|\theta) f(\theta)$$

$$= \frac{1}{c} f(x_1, \dots, x_n | \theta) f(\theta) = \frac{1}{c} \prod_{i=1}^n f(x_i | \theta) f(\theta)$$


conjugate prior | اگر توزیع پست و پیشین از یک جنس باشند، آن گاه $f(\theta)$ میشود

$$\theta \rightarrow f(\theta|D)$$



$$\hat{\theta}_{MAP} = \arg \max_{\theta} f(\theta|D)$$

$$\hat{\theta}_{MAP} = \arg \max_{\theta} \log f(\theta|D)$$

$$P_X(x|\theta) = \theta^x (1-\theta)^{1-x} \quad x \in \{0,1\}$$

$$0 \leq \theta \leq 1$$

1. Jw

$$\theta \sim \text{Beta}(\theta|\alpha, \beta) = \underbrace{c' \theta^{\alpha-1} (1-\theta)^{\beta-1}}_{f(\theta)}$$

$$D = \{x_1, \dots, x_n\}$$

✓ $f(\theta|D) = ?$

$$f(\theta|D) = \frac{1}{c} f(\theta) \prod_{i=1}^n f(x_i|\theta) = \frac{1}{c} c' \theta^{\alpha-1} (1-\theta)^{\beta-1} \prod_{i=1}^n \theta^{x_i} (1-\theta)^{1-x_i}$$

$$= c'' \theta^{\alpha-1} (1-\theta)^{\beta-1} \theta^{\sum_{i=1}^n x_i} (1-\theta)^{n - \sum_{i=1}^n x_i}$$

$$= c'' \theta^{\underbrace{\alpha + \sum_{i=1}^n x_i}_{\alpha'}} (1-\theta)^{\underbrace{\beta + n - \sum_{i=1}^n x_i}_{\beta'}} = \text{Beta}(\theta|\alpha', \beta')$$

$$f_x(x|\lambda) = e^{-\lambda} \frac{\lambda^x}{x!}$$

2.2.1

$$\lambda \sim \text{Gamma}(\lambda|\alpha, \beta) = \underbrace{c' \lambda^{\alpha-1} e^{-\beta\lambda}}_{f(\lambda)}$$

$$f(\lambda|D) = ?$$

$$f(\lambda|D) = \frac{1}{C} f(\lambda) \prod_{i=1}^n f(x_i|\lambda) = \frac{1}{C} c' \lambda^{\alpha-1} e^{-\beta\lambda} \prod_{i=1}^n e^{-\lambda} \frac{\lambda^{x_i}}{x_i!}$$

$$= \underbrace{c''}_{C''} \lambda^{\alpha + \sum_{i=1}^n x_i - 1} e^{-(\beta+n)\lambda} = \text{Gamma}(\lambda|\underbrace{\alpha + \sum_{i=1}^n x_i}_{\alpha'}, \underbrace{\beta+n}_{\beta'})$$

$$\hat{\lambda}_{\text{MAP}} = ? \Rightarrow \hat{\lambda}_{\text{MAP}} = \arg \max_{\lambda} f(\lambda|D)$$

$$\text{Gamma}(\lambda|\alpha, \beta) \longrightarrow \text{mode} = \frac{\alpha-1}{\beta}$$

$$\hat{\lambda}_{\text{MAP}} = \frac{\alpha + \sum_{i=1}^n x_i - 1}{\beta + n}$$

$$\hat{\lambda}_{\text{MAP}} \xrightarrow{n \rightarrow \infty} \hat{\lambda}_{\text{ML}}$$

$$\lim_{n \rightarrow \infty} \hat{\lambda}_{\text{MAP}} = \lim_{n \rightarrow \infty} \frac{\sum_{i=1}^n x_i}{n}$$

$\hat{\lambda}_{\text{ML}}$

$$\hat{\theta}_{\text{MAP}} = \arg \max_{\theta} f(\theta|D) = \arg \max_{\theta} \frac{1}{c} f(\theta) \prod_{i=1}^n f(x_i|\theta)$$

$$= \arg \max_{\theta} \left(\underbrace{\log \frac{1}{c}} + \underbrace{\log f(\theta)}_{\text{prior}} + \sum_{i=1}^n \log f(x_i|\theta) \right)$$

$$\stackrel{n \rightarrow \infty}{=} \arg \max_{\theta} \sum_{i=1}^n \log f(x_i|\theta) = \hat{\theta}_{\text{ML}}$$

$$D = \{x_1, \dots, x_n\}$$

3. J. W.

$$x_i \sim \mathcal{N}(\mu, 1) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x_i - \mu)^2}$$

$$f(\mu) = \frac{\mu}{\sigma^2} \exp\left(-\frac{\mu^2}{2\sigma^2}\right) \quad \mu > 0$$

$$\hat{\mu}_{\text{MAP}} = ? \rightarrow \hat{\mu}_{\text{MAP}} = \arg \max_{\mu} \log f(\mu|D)$$

$$f(\mu|D) = \frac{1}{c} f(\mu) \prod_{i=1}^n f(x_i|\mu) = \frac{1}{c} \frac{\mu}{\sigma^2} \exp\left(-\frac{\mu^2}{2\sigma^2}\right) \prod_{i=1}^n \exp\left(-\frac{1}{2}(x_i - \mu)^2\right)$$

$$\mathcal{L}(\mu) = \log f(\mu|D) = \log \frac{1}{c} + \log \mu - \log \sigma^2 - \frac{\mu^2}{2\sigma^2} + \sum_{i=1}^n -\frac{1}{2}(x_i - \mu)^2$$

$$\frac{d\mathcal{L}}{d\mu} = 0 \Rightarrow \frac{1}{\mu} - \frac{\mu}{\sigma^2} + \sum_{i=1}^n (x_i - \mu) = 0$$

$$\frac{1}{\mu} - \frac{\mu}{\sigma^2} + \underbrace{\sum_{i=1}^n x_i}_Z - n\mu = 0 \Rightarrow -\underbrace{\left(\frac{1}{\sigma^2} + n\right)}_R \mu^2 + Z\mu + 1 = 0$$

$$\Rightarrow R\mu^2 - Z\mu - 1 = 0 \Rightarrow \hat{\mu}_{\text{MAP}} = \frac{Z}{2R} \left(1 + \sqrt{1 + \frac{4R}{Z^2}}\right)$$

MAP: Maximum a posteriori