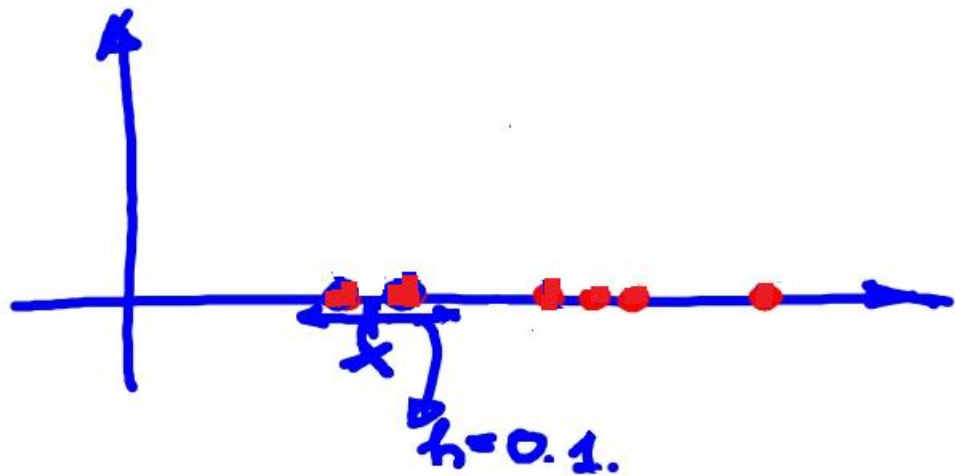
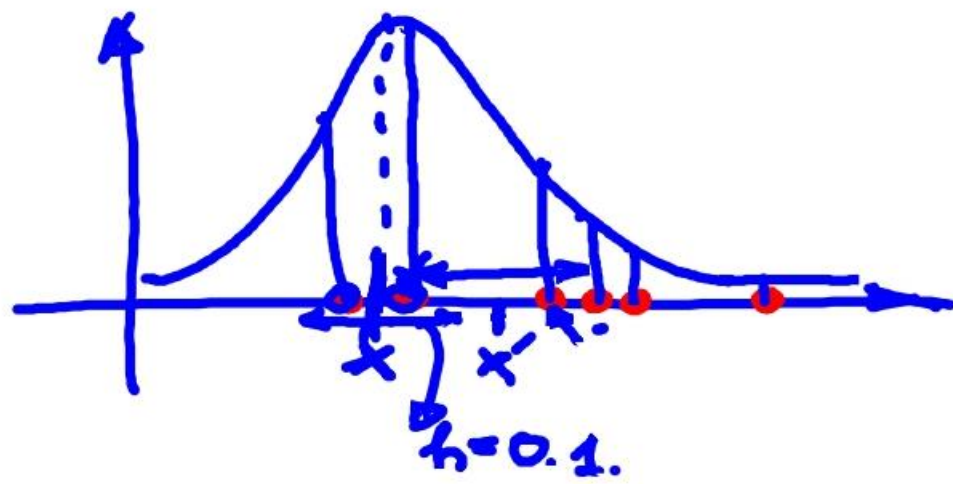
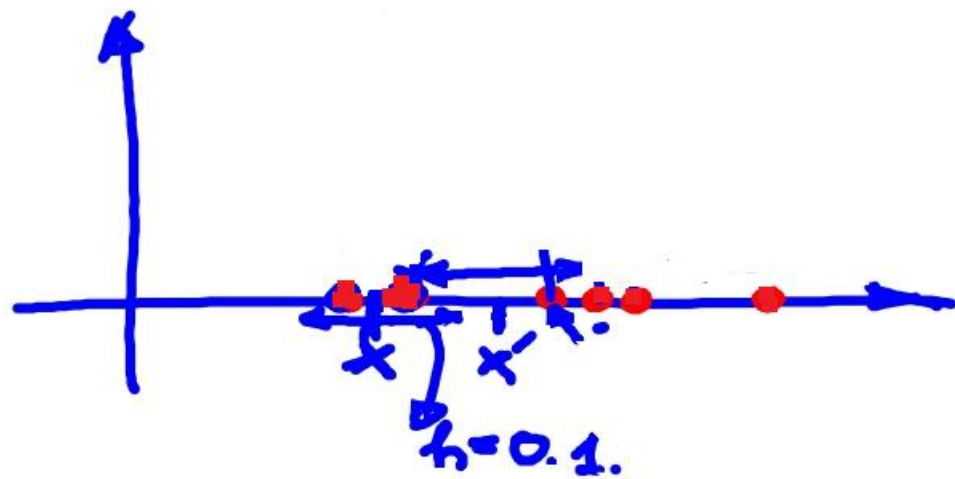


Parzen windows



$$\hat{p}(x) = \frac{2}{6 \cdot 0.1} = \frac{20}{6} = 3.33$$



Maximum likelihood example 2.

$$f(x) = \frac{1}{(2\pi)^{1/2} \sigma} \cdot \exp\left[-\frac{(x-\theta)^2}{2\sigma^2}\right].$$

$$x_1, x_2, \dots, x_N$$

Log likelihood:

$$\mathcal{L} = \ln \left[\prod_{i=1}^N \left[\frac{1}{(2\pi)^{1/2} \sigma} \exp\left[-\frac{(x_i - \theta)^2}{2\sigma^2}\right] \right] \right]$$

$$= -N \ln[(2\pi)^{1/2} \sigma] - \sum_{i=1}^N \frac{(x_i - \theta)^2}{2\sigma^2} = C - N \ln \sigma - \sum_{i=1}^N \frac{(x_i - \theta)^2}{2\sigma^2}$$

$$\frac{\partial \pi}{\partial \sigma} = 0 \Rightarrow -\frac{N}{\sigma} + \sum_{i=1}^N \frac{(x_i - \theta)^2}{\sigma^3} = 0 \Rightarrow$$

$$\hat{\sigma}^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \theta)^2$$

$$\frac{\partial^2 \pi}{\partial \sigma^2} = +\frac{N}{\sigma^2} - 3 \left[\frac{\sum_{i=1}^N (x_i - \theta)^2}{\sigma^4} \right]$$

$$= +\frac{N}{\sigma^2} \left[1 - 3 \frac{\hat{\sigma}^2}{\sigma^2} \right] = -\frac{2N}{\sigma^2} < 0$$

Maximum likelihood, example 3.

Gamma distribution.

$$p(x|a, b) = \frac{x^{a-1}}{\Gamma(a)b^a} \exp\left[-\frac{x}{b}\right].$$

$$\Gamma(z) = \int_0^{\infty} e^{-t} t^{z-1} dt$$

$$x_1, x_2, \dots, x_N$$

Likelihood:

$$\prod_{i=1}^N \frac{x_i^{a-1}}{\Gamma(a) b^a} \exp\left(-\frac{x_i}{b}\right)$$

$$\ln(cd) = \ln c + \ln d.$$
$$\ln(c^d) = d \ln c.$$

Log likelihood:

$$\mathcal{L} = (a-1) \sum_i \ln x_i - N \ln \Gamma(a)$$
$$- Na \ln b - \frac{1}{b} \sum_i x_i$$

$$\frac{\partial \mathcal{L}}{\partial b} = 0 \Rightarrow -\frac{Na}{b} + \frac{1}{b^2} \sum_i x_i = 0$$

$$\Rightarrow \alpha = \frac{\sum_i x_i}{Nb} \Rightarrow b = \frac{\sum x_i}{\alpha}$$

$$\mathcal{L} = N(a-1) \overline{\ln x} - N \ln \Gamma(a) - aN - aN \ln \bar{x} + aN \ln a$$

$$\boxed{\frac{\partial \mathcal{L}}{\partial a} = 0} \Rightarrow \text{find } a.$$

for example: $X = \{1, 2, 3, 4, 5, 6, 7, 8\}$

$$\bar{x} = 4.5$$

$$a \approx 3$$

$$\overline{\ln x} = 1.3256.$$

$$b \approx 1.5.$$

MAP example.

→ Gaussian.

$$p(\theta|X) = p(X|\theta) p(\theta) / p(X)$$

↙ Likelihood.

$$\begin{aligned} p(X|\theta) p(\theta) &= \frac{1}{(2\pi)^{\frac{N+1}{2}} \sigma_n^N \sigma_0} \exp\left[-\sum_{i=1}^N \frac{(x_i - \theta)^2}{2\sigma_n^2}\right] \exp\left[-\frac{(\theta - \theta_0)^2}{2\sigma_0^2}\right] \\ &= \frac{1}{(2\pi)^{\frac{N+1}{2}} \sigma_n^N \sigma_0} \exp\left[-\underbrace{\sum_{i=1}^N \frac{(x_i - \theta)^2}{2\sigma_n^2} - \frac{(\theta - \theta_0)^2}{2\sigma_0^2}}_A\right] \end{aligned}$$

$$A = \frac{-\theta^2 + 2\theta\theta_0 - \theta_0^2}{2\sigma_0^2} - \sum_i \frac{x_i^2 - 2\theta x_i + \theta^2}{2\sigma_n^2}$$

$$= \frac{-\theta^2 \sigma_n^2 + 2\theta\theta_0 \sigma_n^2 - \theta_0^2 \sigma_n^2 - \sum_i [x_i^2 \sigma_0^2 - 2\theta x_i \sigma_0^2 + \theta^2 \sigma_0^2]}{2\sigma_0^2 \sigma_n^2}$$

Numerator of A:

$$-\theta^2 (\sigma_n^2 + N\sigma_0^2) + 2\theta (\theta_0 \sigma_n^2 + \sigma_0^2 \sum_i x_i) + C_0$$

$$A = \frac{-\theta^2 + \frac{2\theta(\theta_0^2 \sigma_n^2 + \sigma_0^2 \sum_i x_i)}{\sigma_n^2 + N\sigma_0^2} + C}{\frac{2\sigma_n^2 \sigma_0^2}{\sigma_n^2 + N\sigma_0^2}}$$

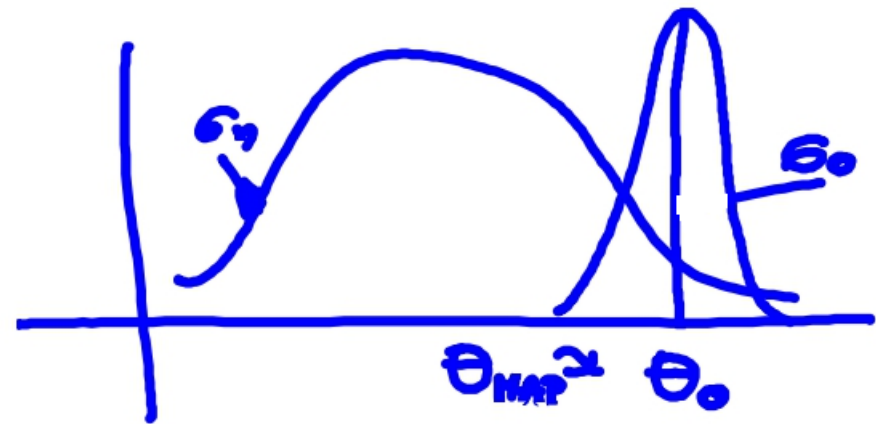
$$-\frac{(\theta - K)^2}{2\Delta^2}$$

Completing the square.

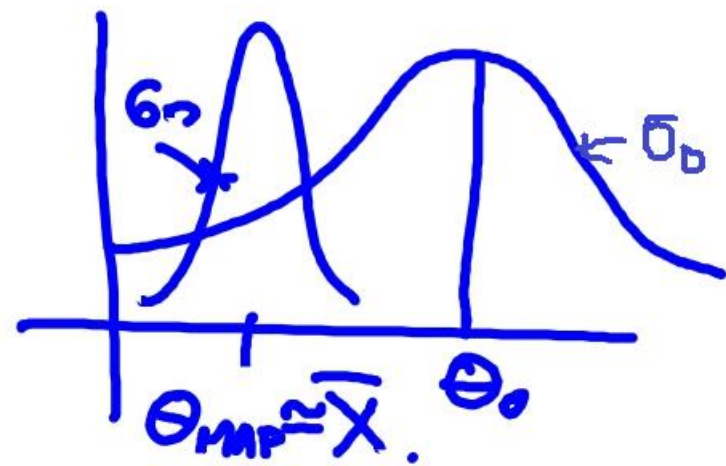
$$\frac{dA}{d\theta} = 0 \quad \Rightarrow \quad -2\theta + \frac{2(\theta_0^2 \sigma_n^2 + \sigma_0^2 \sum_i x_i)}{\sigma_n^2 + N\sigma_0^2} = 0$$

$$\Theta_{\text{MAP}} = \frac{N\sigma_0^2 \bar{X} + \sigma_n^2 \theta_0}{N\sigma_0^2 + \sigma_n^2}$$

$$N \rightarrow \infty \Rightarrow \Theta_{\text{MAP}} \rightarrow \frac{N\sigma_0^2 \bar{X}}{N\sigma_0^2} = \bar{X}$$



$$N = 0 \Rightarrow \Theta_{\text{MAP}} = \frac{\sigma_n^2 \theta_0}{\sigma_n^2} = \theta_0$$



$$\sigma_n \gg \sigma_0 \Rightarrow \Theta_{\text{MAP}} \approx \theta_0$$

$$\sigma_n \ll \sigma_0 \Rightarrow \Theta_{\text{MAP}} \approx \bar{X}$$

Full Bayesian inference:

I add and subtract $\frac{[\theta_0 \sigma_n^2 + \sigma_0^2 \sum_i x_i]^2}{(\sigma_n^2 + N\sigma_0^2)^2}$

to the numerator of A
in order to complete the square.

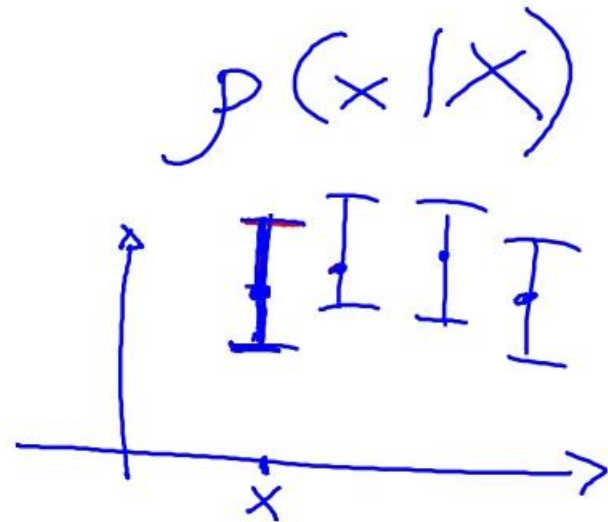
$$A \sim \frac{-\left(\theta - \frac{\theta_0 \sigma_n^2 + \sigma_0^2 \sum_i x_i}{\sigma_n^2 + N\sigma_0^2}\right)^2 + C}{\frac{2 \sigma_n^2 \sigma_0^2}{\sigma_n^2 + N\sigma_0^2}} \Rightarrow \text{Variance mean.}$$

Estimate of θ :

$$\theta_N = \frac{N\sigma_0^2 \bar{x} + \sigma_n^2 \theta_0}{N\sigma_0^2 + \sigma_n^2} \rightarrow \text{Identical to MAP.}$$

uncertainty
variance

$$\sigma_N^2 = \left[\frac{\sigma_n^2 \sigma_0^2}{\sigma_n^2 + N\sigma_0^2} \right].$$



$$p(x|X) = \int p(x|\theta) p(\theta|X) d\theta$$

$$= \int e^{-\frac{(x-\theta)^2}{2\sigma_n^2}} e^{-\frac{(\theta-\theta_N)^2}{2\sigma_N^2}} d\theta$$