

$$x = (x_1, x_2, \dots, x_N)$$

$$P(x) = P(x_1, x_2, \dots, x_N)$$

$$= q(x_1) q(x_2) \dots q(x_N)$$

$$= \prod_{i=1}^N q(x_i)$$

$$\log P(x) = \sum_{i=1}^N \log q(x_i)$$

ML estimate:

$$x_1, \dots, x_N$$

$$ML \text{ estimate of } \mu, \sigma \Rightarrow P(x) = \prod_{i=1}^N \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}}$$

Take log, take  $\frac{d}{dx} = 0$

$$\mu_{ML} = \frac{1}{N} \sum_{i=1}^N x_i$$

$$q(x) \equiv \text{gaussian}(\mu, \sigma), \quad q_2(x) \equiv \text{unf}(a, b)$$

$$u(a|b, b) \Rightarrow P(x) = \prod_{i=1}^N \begin{cases} \frac{1}{b-a}, & \text{if } a \leq x \leq b \\ 0 & \text{otherwise} \end{cases}$$

$$a \leq \min(x_i) \\ b > \max(x_i)$$

Example 1: exponential distribution

$$P_A(x) = \begin{cases} \lambda e^{-\lambda x}, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

$$\log \text{likelihood } L_A(x) = \sum_i \log P_A(x_i)$$

differentiating

Statistics is a function of the sample

$$T(x) = T(x_1, \dots, x_N)$$

for some distributions, computing a few statistics is sufficient for MLE estimate.

→ Ex. of sufficient statistics:

\* sample mean and variance for gaussian distribution.

\* sample mean for exponential distribution.

\* max and min for uniform distribution.

Non-parametric density fun?

if there is  $N$  points.

each kernel area =  $\frac{1}{N}$

~~kernel~~ kernel.

$$P_X(x) = \frac{1}{N} \sum_{i=1}^N K(x - x_i)$$

$$K(x) \geq 0, \quad \forall x$$

$$\int_{-\infty}^{\infty} K(x) dx = 1$$

Assume gaussian kernel:

$$K(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}$$

→ select  $\sigma$  based on a rule of thumb that takes into account the given data.

→ MLE for parametric distribution.

→ Bayesian est.

Take into account a prior belief over parameters

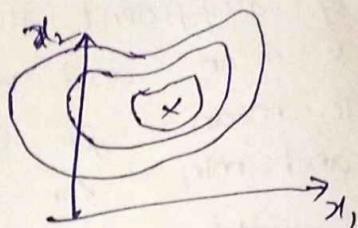
Assume: prior belief  $P_0(\theta)$  instead of marginally  $\int P_0(\theta) d\theta$

$$\text{maximize } \frac{\int P_0(\theta) L_0(x) d\theta}{\int P_0(\theta) L_0(x) d\theta}$$

Multivariate distribution:

$$P(x_1, x_2) \geq 0$$

$$\iint P(x_1, x_2) dx_1 dx_2 = 1$$



$$P(x_2) = \int_{-\infty}^{\infty} P(x_1, x_2) dx_1$$

Marginal:  $P(x_2) = \int_{-\infty}^{\infty} P(x_1, x_2) dx_1$

conditional:  $P(x_2 | x_1 = a) = \frac{P(x_1 = a, x_2)}{P(x_1 = a)}$

Type and coding of variables can be different:

→ Integers can be used to code:

∞ - Nominal / categorical (species, postal codes)

- Ordinal

- True numerical,