Robotics

Estimation and Learning with Dan Lee

Week 1. Gaussian Model Learning

1.2.2 Maximum Likelihood Estimate



Objective

Estimate the mean and the variance given observed data

Likelihood:

$$p(\lbrace x_i \rbrace | \mu, \sigma)$$

Observed data Unknown parameters

Objective

$$\hat{\mu}, \hat{\sigma} = \arg \max_{\mu, \sigma} p(\{x_i\} | \mu, \sigma)$$

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Assuming independence of observations,

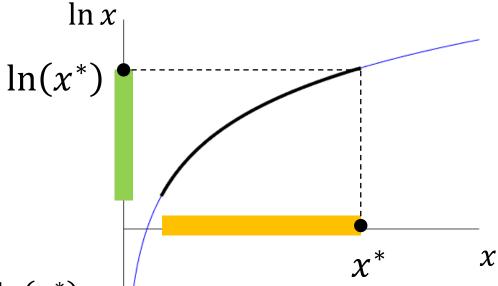
$$p(\lbrace x_i \rbrace | \mu, \sigma) = \prod_{i=1}^{N} p(x_i | \mu, \sigma)$$

$$\hat{\mu}, \hat{\sigma} = \arg\max_{\mu, \sigma} \prod_{i=1}^{N} p(x_i | \mu, \sigma)$$

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(1) Take the log!

$$\hat{\mu}, \hat{\sigma} = \arg \max_{\mu, \sigma} \prod_{i=1}^{N} p(x_i | \mu, \sigma)$$



NOTE 1:

$$x \le x^* \leftrightarrow \ln(x) \le \ln(x^*)$$

$$\hat{\mu}, \hat{\sigma} = \arg \max_{\mu, \sigma} \prod_{i=1}^{N} p(x_i | \mu, \sigma)$$

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$$\arg \max_{\mu,\sigma} \prod_{i=1}^{N} p(x_i|\mu,\sigma) = \arg \max_{\mu,\sigma} \ln \left\{ \prod_{i=1}^{N} p(x_i|\mu,\sigma) \right\}$$

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$$= \arg \max_{\mu,\sigma} \sum_{i=1}^{N} \ln p(x_i|\mu,\sigma)$$

NOTE 2:

$$\log(x_1 \times x_2 \times \dots \times x_k) = \log(x_1) + \log(x_2) + \dots + \log(x_k)$$

$$\hat{\mu}, \hat{\sigma} = \arg\max_{\mu, \sigma} \sum_{i=1}^{N} \ln \frac{p(x_i | \mu, \sigma)}{\sqrt{2\pi\sigma}} \exp\left\{-\frac{(x_i - \mu)^2}{2\sigma^2}\right\}$$
(2) Gaussian!

$$\hat{\mu}, \hat{\sigma} = \arg \max_{\mu, \sigma} \sum_{i=1}^{N} \frac{\ln p(x_i | \mu, \sigma)}{\sqrt{2\pi} \sigma} \exp \left\{ -\frac{(x_i - \mu)^2}{2\sigma^2} \right\}$$

$$= \left\{ -\frac{(x_i - \mu)^2}{2\sigma^2} - \ln \sigma - \ln \sqrt{2\pi} \right\}$$

$$\hat{\mu}, \hat{\sigma} = \arg\max_{\mu, \sigma} \sum_{i=1}^{N} \left\{ -\frac{(x_i - \mu)^2}{2\sigma^2} - \ln \sigma \right\}$$



$$\hat{\mu}, \hat{\sigma} = \arg\min_{\mu, \sigma} \sum_{i=1}^{N} \left\{ \frac{(x_i - \mu)^2}{2\sigma^2} + \ln \sigma \right\}$$

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At optimum,

$$\frac{\partial J}{\partial \mu} = 0 \longrightarrow \hat{\mu}$$

$$\frac{\partial J(\hat{\mu}, \sigma)}{\partial \sigma} = 0 \to \hat{\sigma}$$

• The MLE Solution:

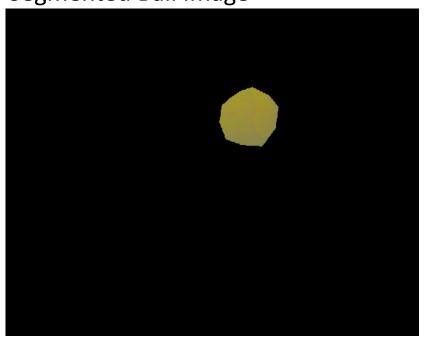
$$\widehat{\mu} = \frac{1}{N} \sum_{i=1}^{N} x_i$$

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

MLE Estimate: Example

Ball color distribution

Segmented Ball Image



$$\hat{\mu} = \frac{1}{N} \sum_{i=1}^{N} x_i$$

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

$$\mu = 52.3$$

$$\sigma = 1.5$$
Hue