

## Lecture Outline

### Reading: Chapter 1

- Gaussian Distribution
- Estimation of Distributional Parameters from Data
- Curve Fitting Reviewed

## 1.2 Probability Theory

### 1.2.4 Gaussian Distribution

The *Gaussian* or *normal* distribution is defined as

$$\begin{aligned} p(x) &\equiv \mathcal{N}(x|\mu, \sigma^2) \\ &= \frac{1}{(2\pi\sigma^2)^{1/2}} \exp\left\{-\frac{1}{2\sigma^2}(x - \mu)^2\right\} \end{aligned} \quad (1)$$

where the two parameters are mean  $\mu$  and variance  $\sigma^2$ . Figure 1 shows the Gaussian pdf.

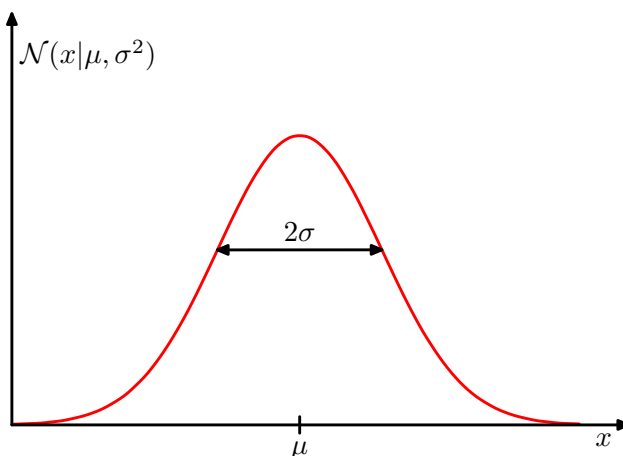


Figure 1: (Figure 1-13)

We have the following:

- The *precision* is  $\beta = 1/\sigma^2$
- The *mode* is the maximum of the distribution. For a Gaussian distribution the mode coincides with the mean.
- The *first moment* or *mean* is calculated as

$$\mathbb{E}[x] = \int_{-\infty}^{\infty} p(x)x dx = \int_{-\infty}^{\infty} \mathcal{N}(x|\mu, \sigma^2)x dx = \mu \quad (2)$$

- The *second moment* is calculated as

$$\mathbb{E}[x^2] = \int_{-\infty}^{\infty} p(x)x^2 dx = \int_{-\infty}^{\infty} \mathcal{N}(x|\mu, \sigma^2)x^2 dx = \mu^2 + \sigma^2 \quad (3)$$

- The *variance* is calculated as

$$\text{var}[x] = \sigma^2 = \mathbb{E}[x^2] - \mathbb{E}[x]^2. \quad (4)$$

For a normally-distributed  $x$ , the probability of  $x$  falling within one standard deviation of the mean is given by

$$p(x \in (\mu - \sigma, \mu + \sigma)) = \int_{\mu - \sigma}^{\mu + \sigma} \mathcal{N}(x|\mu, \sigma^2) dx = 0.682 \quad (5)$$

The  $D$ -dimensional, Gaussian random vector  $\mathbf{x}$  is given by

$$\mathcal{N}(x|\boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{D/2} |\boldsymbol{\Sigma}|^{1/2}} \exp \left\{ -\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right\} \quad (6)$$

where  $\boldsymbol{\mu}$  is the  $D$ -dimensional mean vector,  $\boldsymbol{\Sigma}$  is the  $D \times D$  covariance matrix,

$$\boldsymbol{\Sigma} = \mathbb{E}[\mathbf{x}\mathbf{x}^T] - \mathbb{E}[\mathbf{x}]\mathbb{E}[\mathbf{x}^T] \quad (7)$$

and  $|\boldsymbol{\Sigma}|$  is the matrix determinant of  $\boldsymbol{\Sigma}$ .

## Estimation of Distributional Parameters from Data

In this course, we will often want to statistically model data using a distribution and will need to estimate the distribution's parameters. Suppose that we have a data set of scalar observations

$$\mathbf{x} = (x_1, \dots, x_N)^T \quad (8)$$

drawn independently from a Gaussian distribution,  $\mathcal{N}(x|\mu, \sigma^2)$ , i.e. independent and identically distributed (i.i.d.). Because our data is i.i.d., the likelihood of the data set given model parameters  $\mu, \sigma^2$  is the product of the likelihoods of each data point

$$p(\mathbf{x}|\mu, \sigma^2) = \prod_{n=1}^N \mathcal{N}(x_n|\mu, \sigma^2) \quad (9)$$

as shown in Fig. 2.

One method for determining the distribution parameters from data is to maximize the likelihood function or equivalently, maximize the log-likelihood (for better numerical precision)

$$\ln p(\mathbf{x}|\mu, \sigma^2) = \sum_{n=1}^N \ln \mathcal{N}(x_n|\mu, \sigma^2) \quad (10)$$

Maximizing the likelihood leads to the following solutions for Gaussian data:

$$\mu_{\text{ML}} = \frac{1}{N} \sum_{n=1}^N x_n \quad (11)$$

and

$$\sigma_{\text{ML}}^2 = \frac{1}{N} \sum_{n=1}^N (x_n - \mu_{\text{ML}})^2 \quad (12)$$

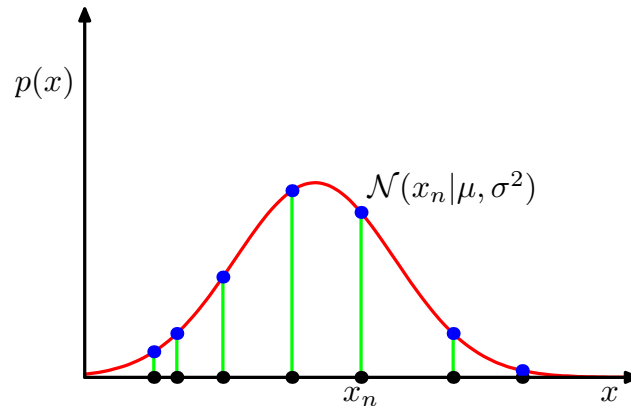


Figure 2: (Figure 1-14—see caption in text!)

which are the sample mean and sample variance respectively. The ML approach on average yields the correct mean

$$\mathbb{E}[\mu_{\text{ML}}] = \mu \quad (13)$$

but underestimates the variance

$$\mathbb{E}[\sigma_{\text{ML}}^2] = \left(\frac{N-1}{N}\right)\sigma^2. \quad (14)$$

However, as the number of data points increases the bias decreases. This effect is shown below

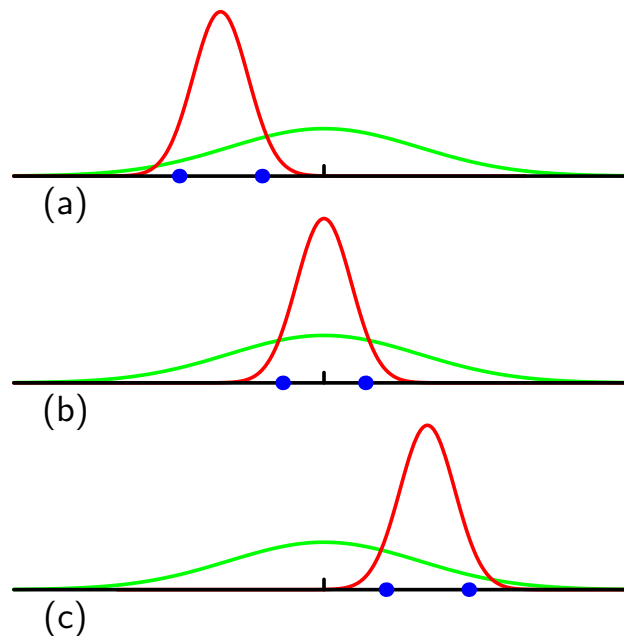


Figure 3: (Figure 1-15)

Note: Some pdfs, such as a Gaussian Mixture Model (GMM), do not have closed-form ML solutions for distribution parameters. In these cases, we turn to iterative approaches to estimate parameters.