L02: The Expectation Operator and Gaussians

* **Def** Expectation Operator

$$E\{x\} = \int_{-\infty}^{+\infty} x\, p(x)\, dx = \mu_x \quad \text{(Weighted average)}$$

- Note: $p(x)$ is a pdf not probability (class conv.)

* Properties of $E\{\}$ — Linear operator

$$E\{A\} = A$$

$$E\{Ax\} = A\, E\{x\}$$

$$E\{A+x\} = A + E\{x\}$$

$$E\{x+y\} = E\{x\} + E\{y\}$$

Proof: $E\{x+y\} = \iint (x+y)\, p(x,y)\, dx\, dy =$

$$= \iint x\, p(x,y)\, dx\, dy + \iint y\, p(x,y)\, dx\, dy =$$

$$= \int x \underbrace{\int p(x,y)\, dy}\, dx + \int y \int p(x,y)\, dx\, dy =$$

marginalization or total probability (see L01.5 on Canvas)

$$= \int x\, p(x)\, dx + \int y\, p(y)\, dy$$

- Anti - properties

$$E\{x \cdot y\} \neq E\{x\} E\{y\} \quad \text{(in general)}$$

If x, y uncorrelated $(\sigma_{xy}^2 = 0) \Rightarrow E\{xy\} = E\{x\}E\{y\}$

If x, y independent $\xRightarrow{} x, y$ uncorrelated

- Expectation of a multidimensional r.v.

$$E\left\{\begin{bmatrix} x \\ y \end{bmatrix}\right\} = \begin{bmatrix} E\{x\} \\ E\{y\} \end{bmatrix}$$

- Conditional expectation $\quad E\{x \mid y\} \triangleq \int_{-\infty}^{\infty} x \, p(x \mid y) \, dx$

Covariance   Scalar form

(Cross covariance)

$$\sigma_{xy}^2 = \operatorname{cov}(x, y) = E\{(x - E\{x\})(y - E\{y\})\}$$

$$\sigma_{xx}^2 = \operatorname{cov}(x, x) = E\{(x - E\{x\})^2\}$$

(Autocovariance or variance)

$$= E\{x^2\} - E\{x\}^2 = \operatorname{var}(x)$$

Exercise: Show this

Property: $\sigma_{xx}^2 \geq 0$

Covariance. Vectorial form

(crosscovariance)

$$\Sigma_{xy} = cov(x,y) = E\{(x-E\{x\})(y-E\{y\})^T\}$$

$$\Sigma_x = cov(x,x) = cov(x) = E\{(x-E\{x\})(x-E\{x\})^T\}$$

Ex: expand Σ_{xy}

$$E\{\, xy^T + x\cdot(-E\{y\})^T - E\{x\}y^T + E\{x\}E\{y\}^T \,\} =$$

$$= E\{xy^T\} - E\{x\,E\{y\}^T\} - E\{E\{x\}y^T\} + E\{E\{x\}E\{y\}^T\} =$$

$$= E\{xy^T\} - E\{x\}E\{y\}^T - \cancel{E\{x\}E\{y\}^T} + \cancel{E\{x\}E\{y\}^T}$$

*Note: $\Sigma_{xy} = 0 \iff E\{xy^T\} = E\{x\}E\{y\}^T$

Uncorrelated

Exer: expand Σ_x

Col 1: Σ_x is symetric: $\Sigma_x = \Sigma_x^T$ (not Σ_{xy}!)

$$\Sigma_x \underset{\mu_x=0}{=} E\{x\cdot x^T\} = E\left\{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}\begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix}\right\} = E\left\{\begin{bmatrix} x_1x_1 & \overset{x_2x_1 \in \mathbb{R}}{\overset{\shortparallel}{x_1x_2}} & \\ x_2x_1 & x_2x_2 & \\ x_3x_1 & x_3x_2 & x_3x_3 \end{bmatrix}\right\}$$

Col 2: Σ_x is Positive Semi definite (psd)

$$v^T \cdot \Sigma_x \cdot v \geq 0 \quad , \quad \forall v$$

proof: $v^T E\{(x-\mu)(x-\mu)^T\} v =$

$$= E\{\underbrace{v^T(x-\mu)}_{u \in \mathbb{R}}(x-\mu)^T v\} = E\{u^2\} \geq 0$$

Sample mean and sample covariance.

$x_i \sim p(x)$ iid (independent and identically distributed)

Sample mean: $\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i$

Sample covariance $\bar{\Sigma}_x = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})(x_i - \bar{x})^T$

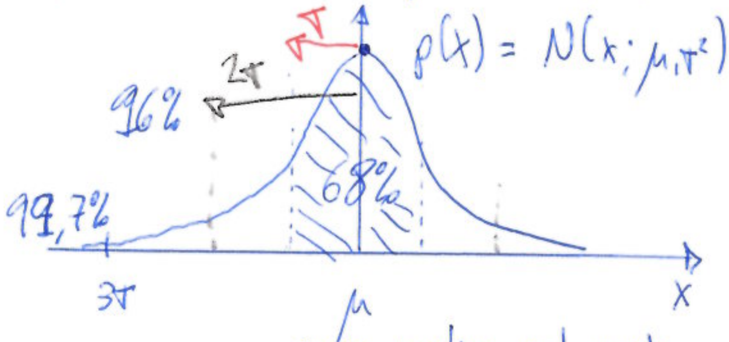
Gaussian distribution (univariate)

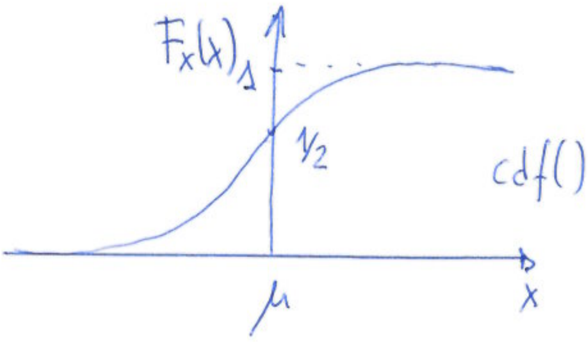
$$p(x) = \underbrace{\frac{1}{\sqrt{2\pi\sigma^2}}}_{\text{normalization factor}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} = N(x; \mu, \sigma^2)$$

normalization factor $\Rightarrow \int N(x; \mu, \sigma^2) dx = 1$

* Probability density function (pdf) — Cumulative distribution f

$p(x) = \mathcal{N}(x; \mu, \sigma^2)$





mean, median and mode.

$$\mu = E\{x\} = \int_{-\infty}^{\infty} x\, p(x)\, dx$$

$$\sigma^2 = \mathrm{cov}(x) = E\{(x-\mu)^2\}$$

All required parameters to describe a Gaussian.

$x \sim \mathcal{N}(\mu, \sigma^2)$ draw a sample. Most functions for $\mu = 0$, $\sigma = 1$

* Multivariate Gaussian.

$$p(x) = \frac{1}{(2\pi)^{k/2} |\Sigma_x|^{1/2}} e^{-\frac{1}{2}(x-\mu)^T \Sigma_x^{-1} (x-\mu)} = \mathcal{N}(x; \mu, \Sigma_x)$$

<u>Ex:</u> Intuition on a 2D Gaussian.

$$\Sigma_x = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

positive correlation.

$$\Sigma_x = \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix}$$

negative correlation.

* Covariance Projection

r.v $x \sim N(\mu_x, \Sigma_x)$, r.v $y = f(x)$

+ Affine transformation f: $y = Ax + b$

· $\mu_y = E\{y\} = E\{Ax+b\} = A\,E\{x\} + b = A\mu_x + b$

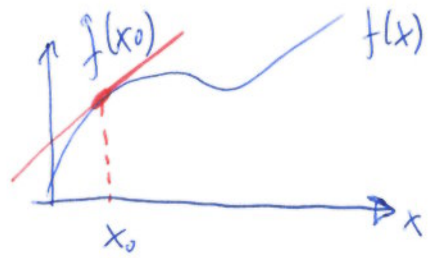
$$\Sigma_y = E\{(y-\mu_y)(y-\mu_y)^T\} = \qquad (AB)^T = B^T A^T$$

$$= E\{(Ax + \cancel{b} - A\mu_x - \cancel{b})(Ax + \cancel{b} - A\mu_x - \cancel{b})^T\} =$$

$$= E\{A\underbrace{(x-\mu_x)(x-\mu_x)^T}_{\Sigma_x}A^T\} = A \cdot \Sigma_x A^T$$

* Non-linear covariance projection

$$y = f(x)$$



- 1D

$$y = f(x_0) + \underbrace{\left.\frac{df(x)}{dx}\right|_{x_0}}(x-x_0) + O\left((x-x_0)^2\right)$$

computed analytically or numerically.

Taylor expansion

- N-Dimentions

$$y = f(x_0) + \underbrace{\sum_{i=1}^{d} \frac{\partial f(x)}{\partial x^i}\Big|_{x_0}} \cdot (x^i - x_0^i) + O(\|x - x_0\|^2) =$$

Jacobian: $\left[\frac{\partial f}{\partial x^1}, \frac{\partial f}{\partial x^2}, \dots, \frac{\partial f}{\partial x^d}\right] = J$

$$= f(x_0) + J \cdot (x - x_0) + O(\|x - x_0\|^2) \simeq$$

$$\simeq f(x_0) + Jx - Jx_0 = \underbrace{J}_{A} \cdot x + \underbrace{f(x_0) - J \cdot x_0}_{b}$$

$$\Rightarrow y \sim N(f(\mu_x), A \Sigma_x A^T)$$

Linearization is not exempt of problems

Error assumed $O(\Delta x^2)$

Uncented transformation allevates this (L07)