# CS-E4895 Gaussian Processes Lecture 0: Example

A.N. Onymous

Aalto University

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# Agenda for today

Motivation for Gaussian processes

2 Course content, format, and evaluation

Warm up for Gaussian processes: Review of the multivariate Gaussian distribution

First assignment

• **Definition** A random vector  $\mathbf{x} = [x_1, x_2, \cdots, x_D]^T$  is said to have the multivariate Gaussian distribution if all linear combinations of  $\mathbf{x}$  are Gaussian distributed:

$$y = a^{T}x = a_{1}x_{1} + a_{2}x_{2} + \dots + a_{D}x_{D} \sim \mathcal{N}(m, v)$$
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for all  $oldsymbol{a} \in \mathbb{R}^D$ , where  $oldsymbol{a} 
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$$(|,) = (2\pi)^{-\frac{D}{2}} ||^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(-)^{T-1}(-)\right] \in \mathbb{R}_{\geq 0}$$
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- ullet  $(\Sigma)_{ij}$  is the covariance between the i'th and j'th elements  $x_i$  and  $x_j$  of  $oldsymbol{x}$

# Interpretation of the covariance matrix - 2D examples

The diagonal of the covariance controls the scaling/marginal variances

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Questions:

- If  $\Sigma$  is diagonal, then  $x_1$  and  $x_2$  are uncorrelated? True or false?
- If  $\Sigma$  is diagonal, then  $x_1$  and  $x_2$  are independent? True or false?
- What is the volume (integral) of density?
- Which of the four densities has the highest peak and why?

More slides..

# The end of todays lecture

- Next thursday 14th, 10pm
  - We will introduce Gaussian processes more formally
  - Read Chapter 1 & 2 of the Gaussian process book gaussianprocess.org/gpml

- Time to work: first assignment
  - Released today, deadline jan 20th, 12:00 (midday)
  - Reviews the basics of Bayesian inference and Gaussians
  - Must be handed in through MyCourses
  - Q&A sessions on 20th and 22th (grants extra point for being present!)