Lecture 3: Gaussian Processes

Jens Kober

Knowledge-Based Control Systems (SC42050)

Cognitive Robotics

3mE, Delft University of Technology, The Netherlands

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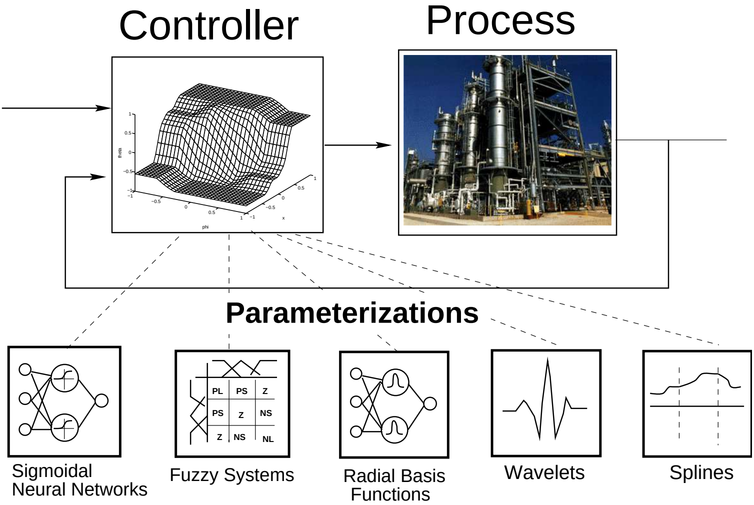
Outline

1. Properties
2. Gaussian distributions
3. Inference
4. A different representation
5. Gaussian processes
6. Kernels
7. Applications

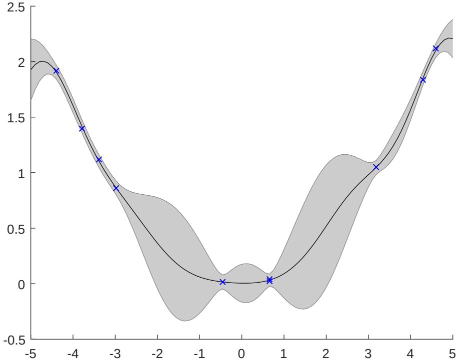
Lecture based on lectures by David MacKay and Oliver Stegle & Karsten Borgwardt

Function Approximators



Properties of Gaussian Processes

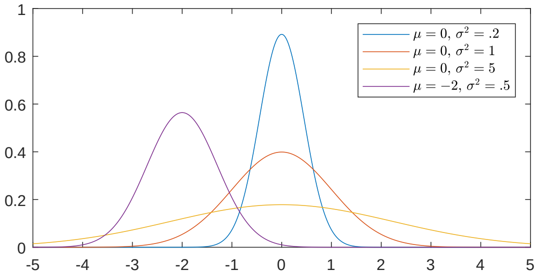
- nonlinear regression
- accurate and flexible
- predictions with error bars
- non-parametric



1D Gaussian Distribution

- Normal distribution
- Probability density function:

$$\mathcal{N}(y|\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\frac{(y-\mu)^2}{\sigma^2}}$$

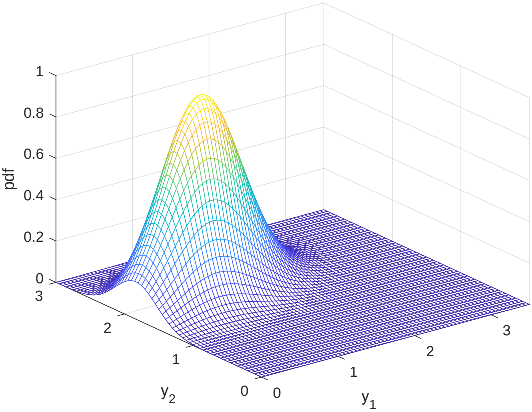


nD Gaussian Distribution

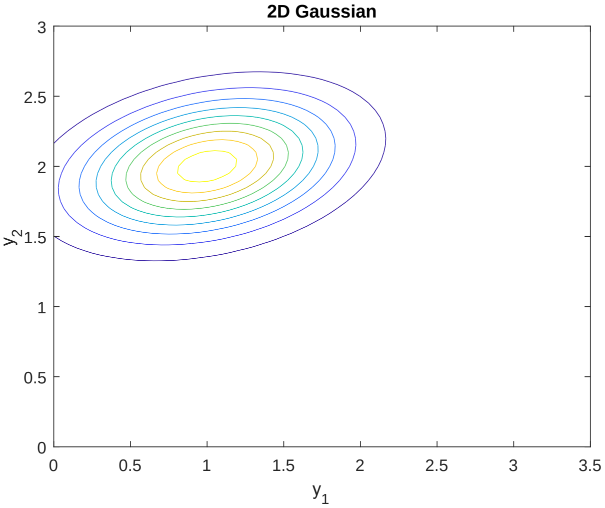
- Probability density function:

$$\mathcal{N}(\boldsymbol{y}|\boldsymbol{\mu}, \boldsymbol{K}) = \frac{1}{\sqrt{\det(2\pi\boldsymbol{K})}} e^{-\frac{1}{2}(\boldsymbol{y}-\boldsymbol{\mu})^\top \boldsymbol{K}^{-1}(\boldsymbol{y}-\boldsymbol{\mu})}$$

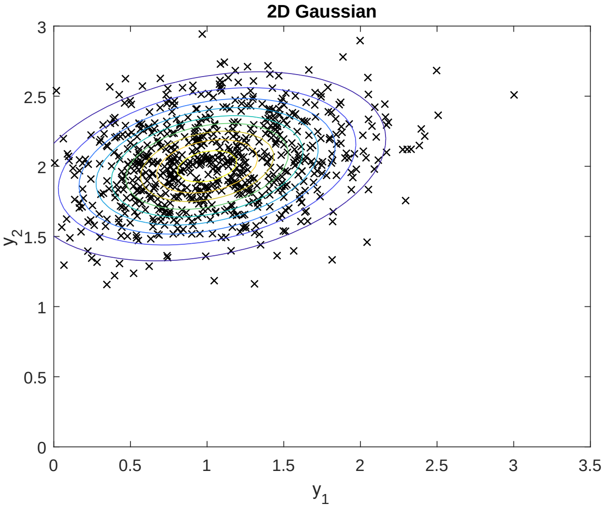
- $\boldsymbol{K}$ is the covariance matrix (or kernel matrix)



2D Gaussian Distribution: Contour

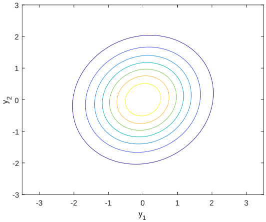


2D Gaussian Distribution: Contour & Samples

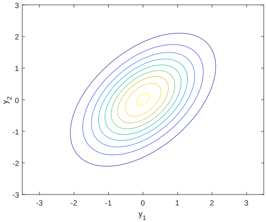


2D Gaussian Distribution: Covariance Matrices

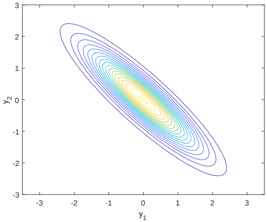
$\boldsymbol{K}$ is positive-semidefinite and symmetric



$$\boldsymbol{K} = \begin{bmatrix} 1 & .1 \\ .1 & 1 \end{bmatrix}$$

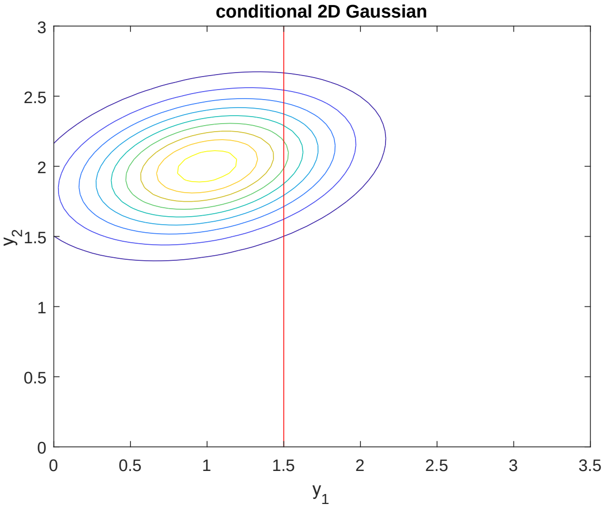


$$\boldsymbol{K} = \begin{bmatrix} 1 & .5 \\ .5 & 1 \end{bmatrix}$$

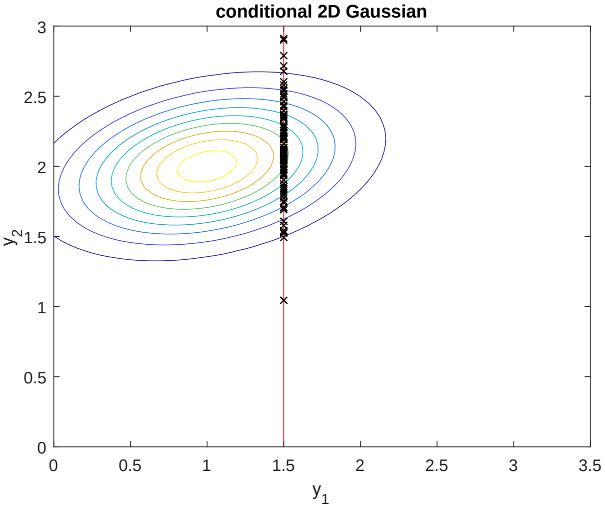


$$\boldsymbol{K} = \begin{bmatrix} 1 & -.9 \\ -.9 & 1 \end{bmatrix}$$

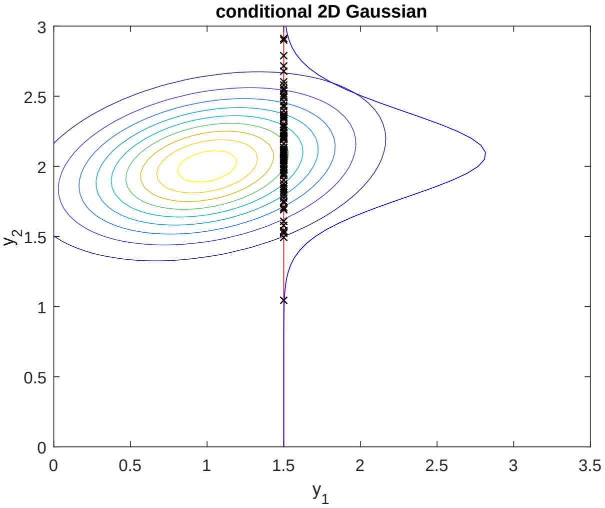
Inference



Inference



Inference



Inference

- Joint probability $p(\boldsymbol{y}_1, \boldsymbol{y}_2 | \boldsymbol{\mu}, \boldsymbol{K}) = \mathcal{N}([\boldsymbol{y}_1, \boldsymbol{y}_2] | \boldsymbol{\mu}, \boldsymbol{K})$

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- Conditional probability $\boldsymbol{y}_1 = \boldsymbol{a}$

$$p(\boldsymbol{y}_2 | \boldsymbol{y}_1, \boldsymbol{\mu}, \boldsymbol{K}) = \frac{p(\boldsymbol{y}_1, \boldsymbol{y}_2 | \boldsymbol{\mu}, \boldsymbol{K})}{p(\boldsymbol{y}_1 | \boldsymbol{\mu}, \boldsymbol{K})} = \mathcal{N}(\boldsymbol{y}_2 | \bar{\boldsymbol{\mu}}, \bar{\boldsymbol{K}})$$

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- Partitioning:

$$\boldsymbol{y} = \begin{bmatrix} \boldsymbol{y}_1 \\ \boldsymbol{y}_2 \end{bmatrix} \qquad \boldsymbol{\mu} = \begin{bmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \end{bmatrix} \qquad \boldsymbol{K} = \begin{bmatrix} \boldsymbol{K}_{11} & \boldsymbol{K}_{12} \\ \boldsymbol{K}_{21} & \boldsymbol{K}_{22} \end{bmatrix}$$

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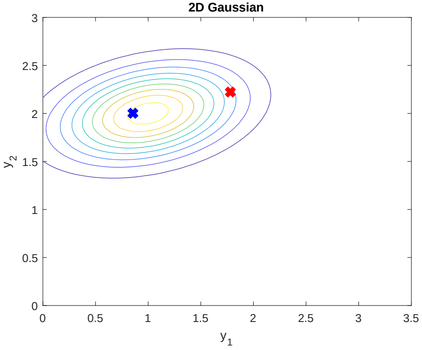
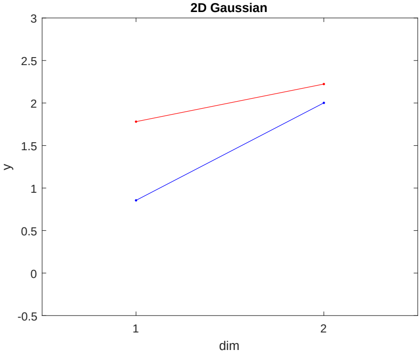
- New mean and covariance

$$\bar{\boldsymbol{\mu}} = \boldsymbol{\mu}_2 + \boldsymbol{K}_{21} \boldsymbol{K}_{11}^{-1} (\boldsymbol{a} - \boldsymbol{\mu}_1) \qquad \bar{\boldsymbol{K}} = \boldsymbol{K}_{22} - \boldsymbol{K}_{21} \boldsymbol{K}_{11}^{-1} \boldsymbol{K}_{12}$$

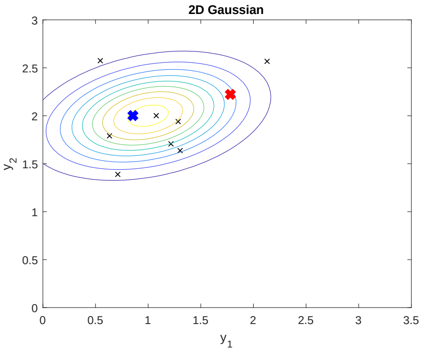
A Different Representation

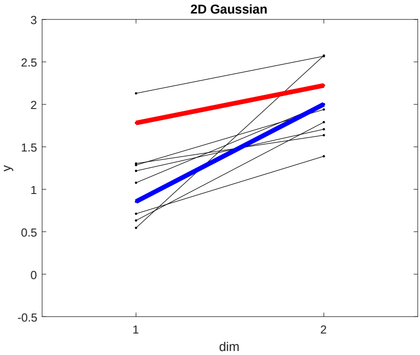




$y = \begin{bmatrix} 0.86 & 2.00 \end{bmatrix}$ $y = \begin{bmatrix} 1.78 & 2.22 \end{bmatrix}$

A Different Representation





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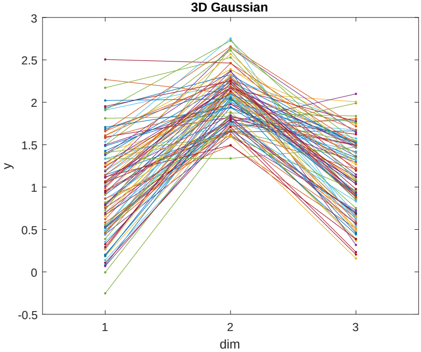
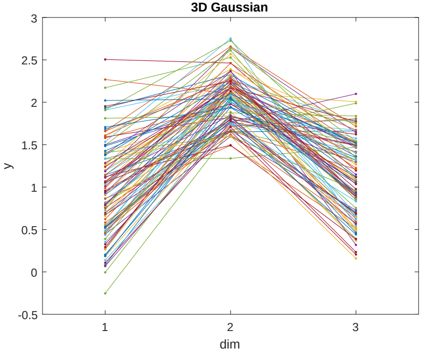
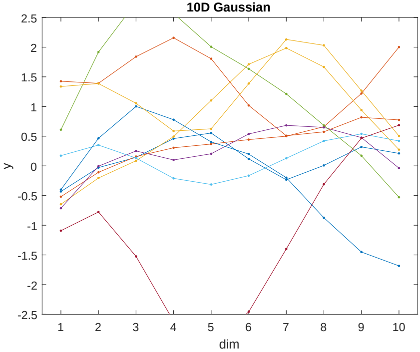
Higher-Dimensional Gaussians

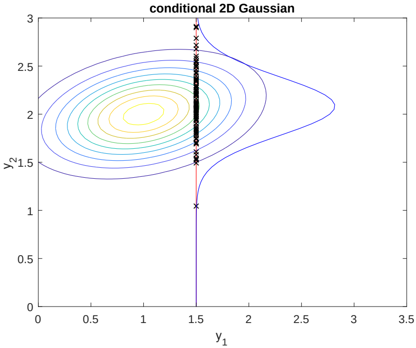


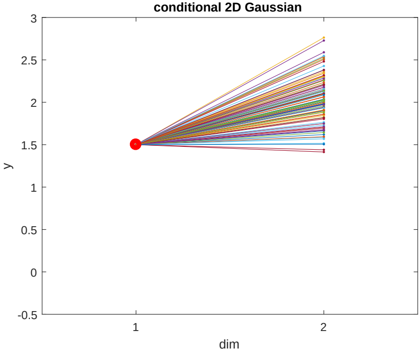
Higher-Dimensional Gaussians



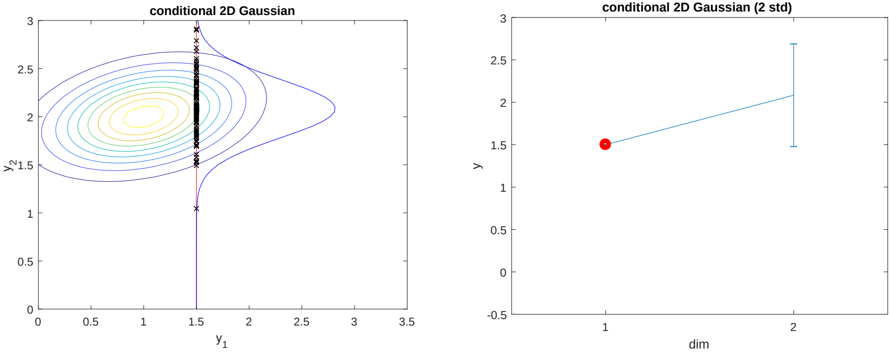


2D Conditional

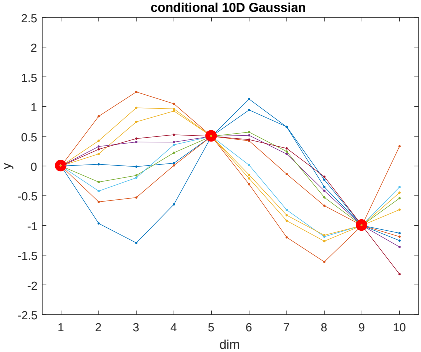


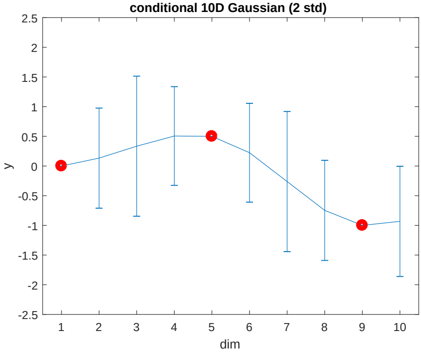


2D Conditional



10D Conditional





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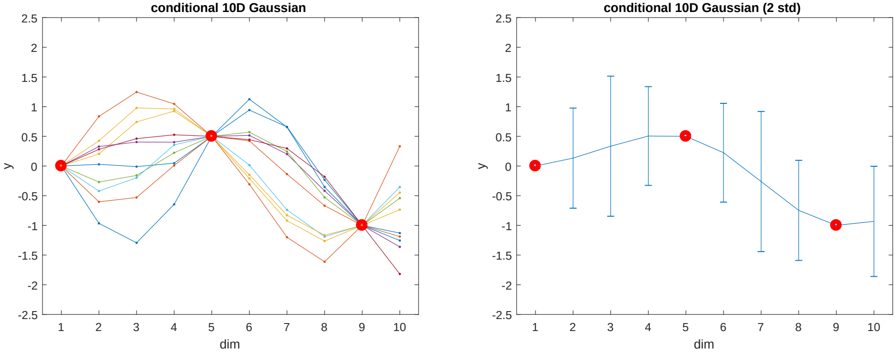
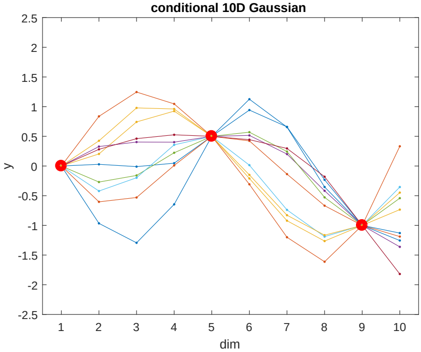
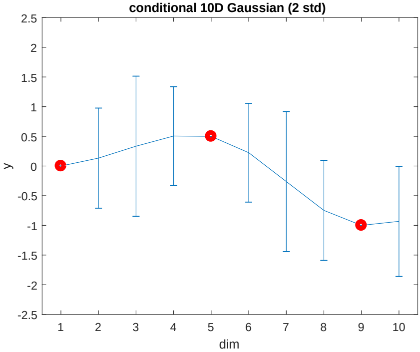


- Looks like nonlinear regression!

10D Conditional





- Looks like nonlinear regression!
- Where did $\boldsymbol{K}$ come from?

10D Conditional: $\boldsymbol{K}$

$$
\boldsymbol{K} = \begin{bmatrix}
1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 & 0.00 & 0.00 & 0.00 \\
0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 & 0.00 & 0.00 \\
0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 & 0.00 \\
0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 \\
0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 \\
0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 \\
0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 \\
0.00 & 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 \\
0.00 & 0.00 & 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 \\
0.00 & 0.00 & 0.00 & 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00
\end{bmatrix}
$$

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$$\boldsymbol{K} = \begin{bmatrix} 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 & 0.00 & 0.00 & 0.00 \\ 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 & 0.00 & 0.00 \\ 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 & 0.00 \\ 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 \\ 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 \\ 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 \\ 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 \\ 0.00 & 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 \\ 0.00 & 0.00 & 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 \\ 0.00 & 0.00 & 0.00 & 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 \end{bmatrix}$$

- Diagonal structure

10D Conditional: $\boldsymbol{K}$

$$\boldsymbol{K} = \begin{bmatrix} 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 & 0.00 & 0.00 & 0.00 \\ 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 & 0.00 & 0.00 \\ 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 & 0.00 \\ 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 \\ 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 \\ 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 \\ 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 \\ 0.00 & 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 \\ 0.00 & 0.00 & 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 \\ 0.00 & 0.00 & 0.00 & 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 \end{bmatrix}$$

- Diagonal structure
- Generated by a covariance function (kernel function)

$$\boldsymbol{K}_{i,j} = k(x_i, x_j; \boldsymbol{\theta}_K)$$

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$$\boldsymbol{K} = \begin{bmatrix} 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 & 0.00 & 0.00 & 0.00 \\ 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 & 0.00 & 0.00 \\ 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 & 0.00 \\ 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 & 0.01 \\ 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 & 0.04 \\ 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 & 0.14 \\ 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 & 0.32 \\ 0.00 & 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 & 0.61 \\ 0.00 & 0.00 & 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 & 0.88 \\ 0.00 & 0.00 & 0.00 & 0.01 & 0.04 & 0.14 & 0.32 & 0.61 & 0.88 & 1.00 \end{bmatrix}$$

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- Here:

$$k_{\mathrm{SE}}(x_i, x_j; \sigma_f, l) = \sigma_f^2 e^{-\frac{1}{2l^2}(x_i - x_j)^2}$$

squared exponential kernel (hyperparameters: l horizontal lengthscale, σ_f vertical lengthscale)

Definition

Gaussian Process

A Gaussian process is a collection of random variables with the property that the joint distribution of any finite subset is a Gaussian.

Function Space View

- Kernel function and hyperparameters = prior belief on function properties (smoothness, lenghtscales, etc.)

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- Prior on function values $\boldsymbol{f} = (f_1, \ldots, f_N)$

$$p(\boldsymbol{f}|\boldsymbol{X}, \boldsymbol{\theta}_K) = \mathcal{N}\left(\boldsymbol{f}|\mathbf{0}, \boldsymbol{K}_{\boldsymbol{X},\boldsymbol{X}}(\boldsymbol{\theta}_K)\right)$$

Noise-free Observations

- Noise-free training data $\mathcal{D} = \{\boldsymbol{x}_n, f_n\}_{n=1}^{N}$

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$$p([\boldsymbol{f}, \boldsymbol{f}^*] | \boldsymbol{X}, \boldsymbol{X}^*, \boldsymbol{\theta}_K) = \mathcal{N}\left([\boldsymbol{f}, \boldsymbol{f}^*] \middle| \mathbf{0}, \begin{bmatrix} \boldsymbol{K}_{\boldsymbol{X},\boldsymbol{X}} & \boldsymbol{K}_{\boldsymbol{X},\boldsymbol{X}^*} \\ \boldsymbol{K}_{\boldsymbol{X}^*,\boldsymbol{X}} & \boldsymbol{K}_{\boldsymbol{X}^*,\boldsymbol{X}^*} \end{bmatrix}\right)$$

(dependence of $\boldsymbol{K}$ on $\boldsymbol{\theta}_K$ dropped for brevity)

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  (dependence of $\boldsymbol{K}$ on $\boldsymbol{\theta}_K$ dropped for brevity)
- Real data is rarely noise-free

Inference

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$$p([\boldsymbol{f}, \boldsymbol{f}^*] | \boldsymbol{X}, \boldsymbol{X}^*, \boldsymbol{y}, \boldsymbol{\theta}_K, \sigma^2) \propto \overbrace{\mathcal{N}\left([\boldsymbol{f}, \boldsymbol{f}^*] \middle| \mathbf{0}, \begin{bmatrix} \boldsymbol{K}_{\boldsymbol{X},\boldsymbol{X}} & \boldsymbol{K}_{\boldsymbol{X},\boldsymbol{X}^*} \\ \boldsymbol{K}_{\boldsymbol{X}^*,\boldsymbol{X}} & \boldsymbol{K}_{\boldsymbol{X}^*,\boldsymbol{X}^*} \end{bmatrix}\right)}^{\text{Prior}} \times \underbrace{\prod_{n=1}^{N} \mathcal{N}\left(y_n | f_n, \sigma^2\right)}_{\text{Likelihood}}$$

Inference

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- Integrating out $\boldsymbol{f}$ yields

$$p([\boldsymbol{y}, \boldsymbol{f}^*] | \boldsymbol{X}, \boldsymbol{X}^*, \boldsymbol{y}, \boldsymbol{\theta}_K, \sigma^2) \propto \mathcal{N}\left([\boldsymbol{y}, \boldsymbol{f}^*] \middle| \boldsymbol{0}, \begin{bmatrix} \boldsymbol{K}_{\boldsymbol{X},\boldsymbol{X}} + \sigma^2 \boldsymbol{I} & \boldsymbol{K}_{\boldsymbol{X},\boldsymbol{X}^*} \\ \boldsymbol{K}_{\boldsymbol{X}^*,\boldsymbol{X}} & \boldsymbol{K}_{\boldsymbol{X}^*,\boldsymbol{X}^*} \end{bmatrix}\right)$$

Predictions

- Turn into conditional distribution

Predictions

- Turn into conditional distribution
- Joint distribution

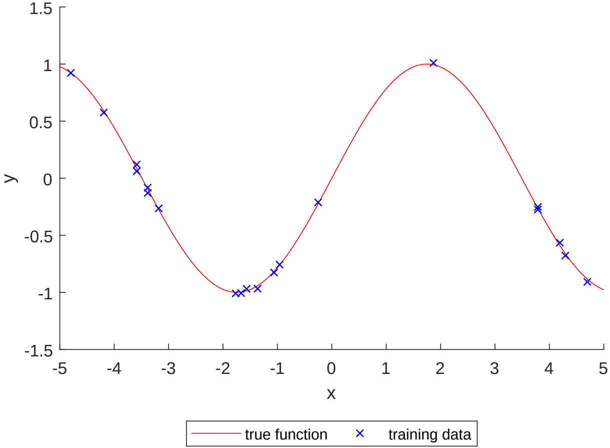
$$p([\boldsymbol{y}, \boldsymbol{f}^*] | \boldsymbol{X}, \boldsymbol{X}^*, \boldsymbol{y}, \boldsymbol{\theta}_K, \sigma^2) \propto \mathcal{N}\left([\boldsymbol{y}, \boldsymbol{f}^*] \middle| \boldsymbol{0}, \begin{bmatrix} \boldsymbol{K}_{\boldsymbol{X},\boldsymbol{X}} + \sigma^2 \boldsymbol{I} & \boldsymbol{K}_{\boldsymbol{X},\boldsymbol{X}^*} \\ \boldsymbol{K}_{\boldsymbol{X}^*,\boldsymbol{X}} & \boldsymbol{K}_{\boldsymbol{X}^*,\boldsymbol{X}^*} \end{bmatrix}\right)$$

- Gaussian predictive distribution for $\boldsymbol{f}^*$
  $p(\boldsymbol{f}^* | \boldsymbol{X}, \boldsymbol{X}^*, \boldsymbol{y}, \boldsymbol{\theta}_K, \sigma^2) = \mathcal{N}(\boldsymbol{f}^* | \boldsymbol{\mu}^*, \boldsymbol{\Sigma}^*)$ with

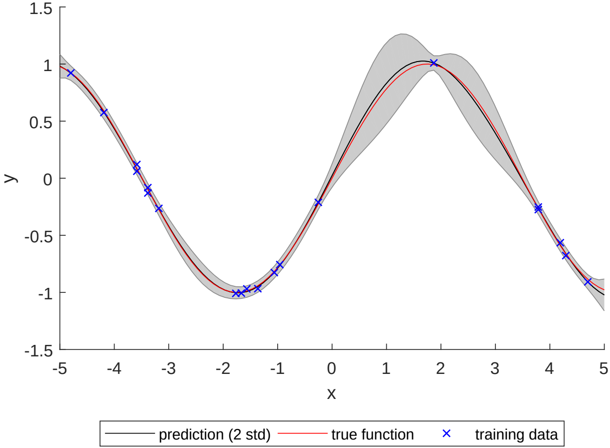
$$\boldsymbol{\mu}^* = \boldsymbol{K}_{\boldsymbol{X}^*,\boldsymbol{X}} \left(\boldsymbol{K}_{\boldsymbol{X},\boldsymbol{X}} + \sigma^2 \boldsymbol{I}\right)^{-1} \boldsymbol{y}$$
$$\boldsymbol{\Sigma}^* = \boldsymbol{K}_{\boldsymbol{X}^*,\boldsymbol{X}^*} + \sigma^2 \boldsymbol{I} - \boldsymbol{K}_{\boldsymbol{X}^*,\boldsymbol{X}} \left(\boldsymbol{K}_{\boldsymbol{X},\boldsymbol{X}} + \sigma^2 \boldsymbol{I}\right)^{-1} \boldsymbol{K}_{\boldsymbol{X},\boldsymbol{X}^*}$$

- Matrix inverse (training) is expensive

Example

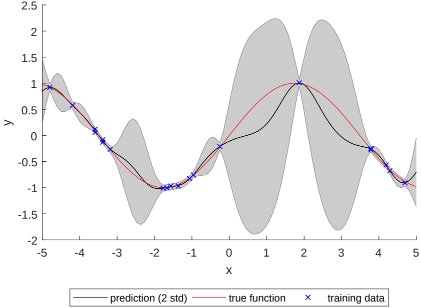


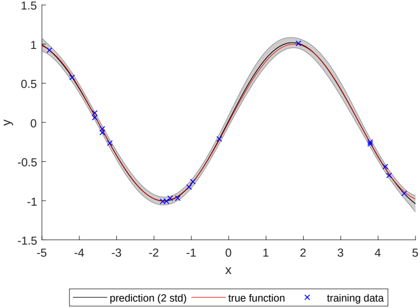
Example


1.5
1
0.5
0
-0.5
-1
-1.5
y
-5
-4
-3
-2
-1
0
1
2
3
4
5
x
prediction (2 std)
true function
training data

Kernel Parameters

horizontal lengthscale (too narrow, too wide)





$\rightarrow$ optimize kernel parameters as part of training

Kernels

- Squared exponential

$$k_{\text{SE}}(x_i, x_j) = \sigma_f^2 \exp\left(-\frac{1}{2}\sum_{d=1}^{D}(x_{d,i} - x_{d,j})^2\, l_d^{-2}\right)$$

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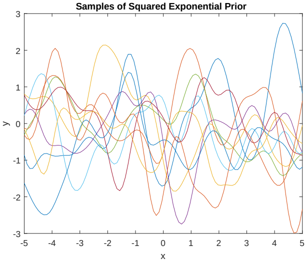
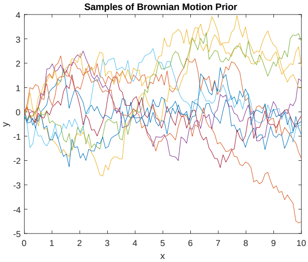
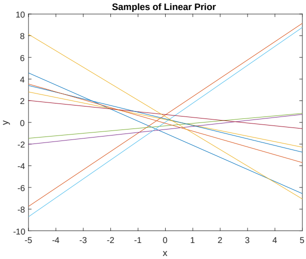
- Many more
(need to correspond to an inner product $k(x_i, x_j) = \boldsymbol{\phi}(x_i)^{\mathsf{T}}\boldsymbol{\phi}(x_j)$)

Examples of priors







Constructing Kernels

- Sum

$$k_{\text{sum}}(x_i, x_j) = k_1(x_i, x_j) + k_2(x_i, x_j)$$

addition of independent processes

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  product of independent processes

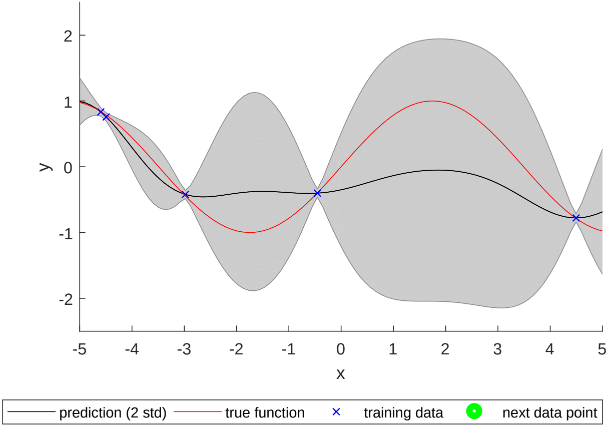
- Convolution

$$k_{\text{conv}}(x_i, x_j) = \int h(x_i, z_i)k(z_i, z_j)h(x_j, z_j)\, dz_i\, dz_j$$

  blurring with kernel h

Active Learning

select next training point (here the one with highest uncertainty)



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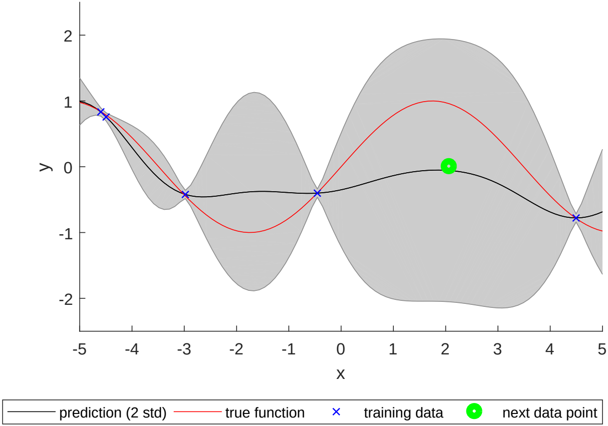

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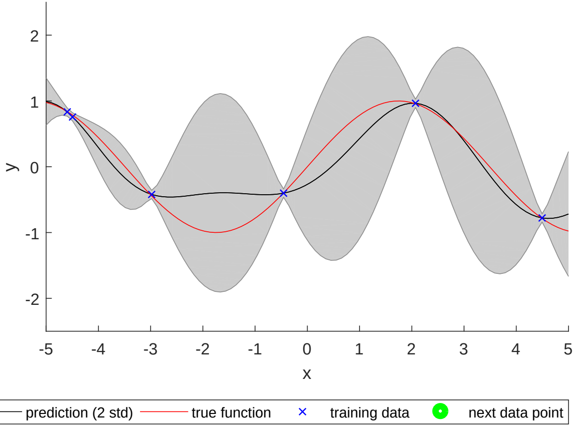

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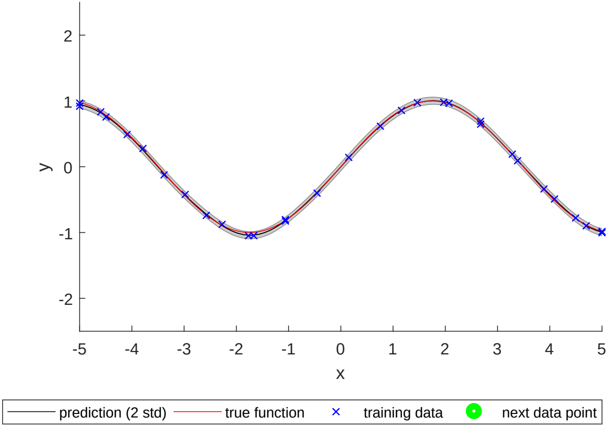
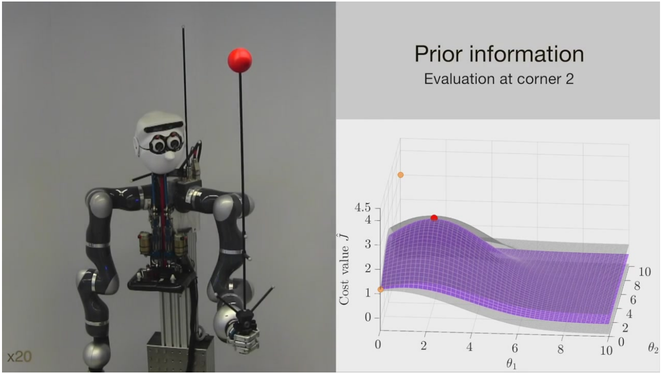


Bayesian Optimization[1]



https://youtu.be/d0ux-bXFCU4

[1] A. Marco, P. Hennig, J. Bohg, S. Schaal, and S. Trimpe (May 2016). "Automatic LQR Tuning Based on Gaussian Process Global Optimization". In: *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*

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  - model with infinite number of parameters

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  - Radial basis functions
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  - Linear (ridge) regression
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- Problems
  - Ill-conditioned
  - N^3 complexity is bad news for $N > 1000 \rightarrow$ approximate/sparse methods