



## Bayesian Optimization

Julien Bect, Emmanuel Vazquez

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# Bayesian Optimization

— Engineering design under uncertainty using  
expensive-to-evaluate numerical models —

Julien Bect and Emmanuel Vazquez

Laboratoire des signaux et systèmes, Gif-sur-Yvette, France

CEA-EDF-INRIA Numerical Analysis Summer School  
Université Pierre et Marie Curie (Paris VI)  
Paris, 2017, July 3–7

## Lecture 1 : From meta-models to UQ

- 1.1 Introduction
- 1.2 Black-box modeling
- 1.3 Bayesian approach
- 1.4 Posterior distribution of a quantity of interest
- 1.5 Complements on Gaussian processes

## Lecture 2 : Bayesian optimization (BO)

- 2.1. Decision-theoretic framework
- 2.2. From Bayes-optimal to myopic strategies
- 2.3. Design under uncertainty

## References

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# Lecture 1 : From meta-models to UQ

## 1.1 Introduction

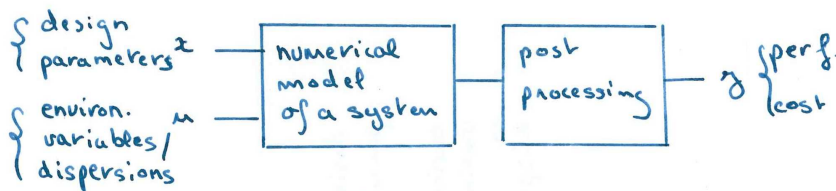
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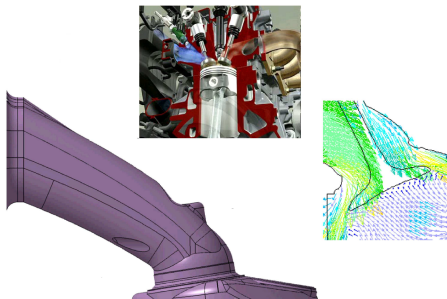
# Computer-simulation based design



- ▶ The numerical model might be time- or resource-consuming
- ▶ Design parameters might be subject to dispersions
- ▶ The system might operate under unknown conditions

# Computer-simulation based design – Example

- ▶ Computer simulations to design a product or a process, in particular
  - ▶ to find the best feasible values for **design parameters** (optimization problem)
  - ▶ to minimize the probability of failure of a product
- ▶ To comply with European emissions standards, the design parameters of combustion engines have to be carefully optimized
- ▶ The shape of intake ports controls airflow characteristics, which have direct impact on
  - ▶ the performances of the engine
  - ▶ emissions of  $\text{NO}_x$  and CO
- ▶  $f : \mathbb{X} \subset \mathbb{R}^d \rightarrow \mathbb{R}$  performance as a function of design parameters ( $d = 20 \sim 100$ )
- ▶ Computing  $f(x)$  **takes 5 ~ 20 hours**
- ▶ Objective: estimate  $x^* = \operatorname{argmax}_x f(x)$



Simulation of an intake port (Navier-Stokes equ.)  
(courtesy of Renault)

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1.2 Black-box modeling

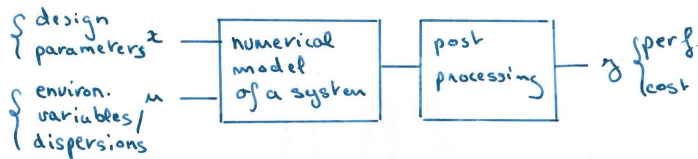
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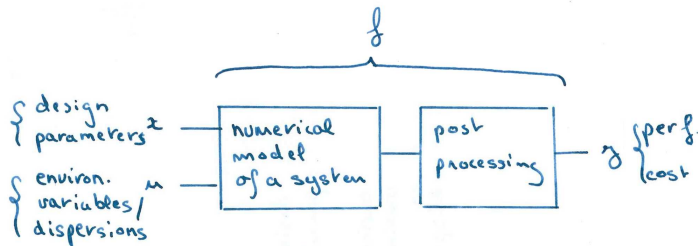
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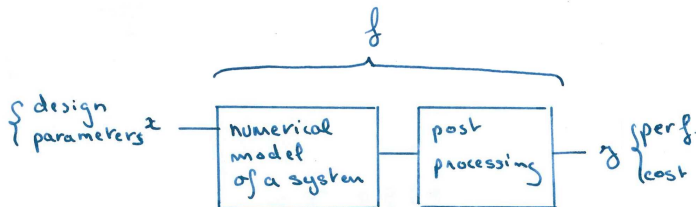
# Black-box modeling



# Black-box modeling



# Black-box modeling



For simplification  $\rightarrow$  drop  $u$

# Black-box modeling

- ▶ Let  $f : \mathbb{X} \rightarrow \mathbb{R}$  be a real function defined on  $\mathbb{X} \subseteq \mathbb{R}^d$ , where
  - ▶  $\mathbb{X}$  is the input/parameter domain of the computer simulation under study, or the **factor** (from Latin, “which acts”) space
  - ▶  $f$  is a **performance** or **cost** function (a function of the outputs of the computer simulation)

# Black-box modeling

- ▶ Let  $x_1, \dots, x_n \in \mathbb{X}$  be  $n$  simulations points
- ▶ Denote by

$$z_1 = f(x_1), \dots, z_n = f(x_n)$$

the corresp. simulation results (observations/evaluations of  $f$ )

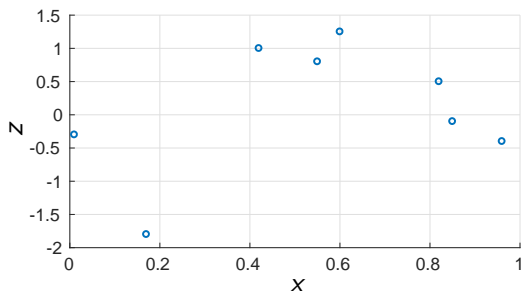
- ▶ Our objective: use the data  $\mathcal{D}_n = (x_i, z_i)_{i=1\dots n}$  to **infer properties** about  $f$
- ▶ Example: given a new  $x \in \mathbb{R}^d$ , predict the value  $f(x)$

# Black-box modeling

- ▶  $f$  is a black-box, only known through evaluation results: query an evaluation at  $x$ , observe the result
  - ▶ Predict the value of  $f$  at a given  $x$ ?
- the problem is that of constructing an **approximation** / an **estimator**  $\hat{f}_n$  of  $f$  from  $\mathcal{D}_n$
- ▶ Such a  $\hat{f}_n$  also called a **model** or a **meta-model** (because the numerical simulator is a model itself) of  $f$

# A simple curve fitting problem

- ▶ Suppose that we are given a data set of  $n$  simulation results, i.e., evaluations results of an unknown function  $f : [0, 1] \rightarrow \mathbb{R}$ , at points  $x_1, \dots, x_n$ .
- ▶ A data set of size  $n = 8$ :



## A simple curve fitting problem

- ▶ Any approximation procedure of  $f$  consists in building a function  $\hat{f}_n = h(\cdot; \theta)$  where  $\theta \in \mathbb{R}^l$  is a vector of parameters, to be estimated from  $\mathcal{D}_n$  and available prior information
- ▶ Fundamental example: **linear model**

$$\hat{f}_n(x) = h(x, \theta) = \sum_{i=1}^l \theta_i r_i(x)$$

where functions  $r_i : \mathbb{X} \rightarrow \mathbb{R}$  are called regressors (e.g.,  $r_1(x) = 1, r_2(x) = x, r_3(x) = x^2 \dots \rightarrow$  polynomial model)

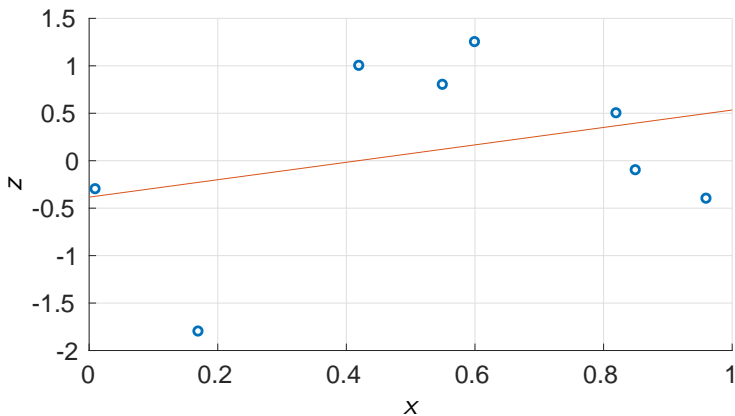
- ▶ Most classical method to obtain a good value of  $b$ :  
**least squares**  $\rightarrow$  minimize the sum of squared errors

$$J(\theta) = \sum_{i=1}^n \left( z_i - \hat{f}_n(x_i) \right)^2 = \sum_{i=1}^n \left( z_i - h(x_i; \theta) \right)^2$$



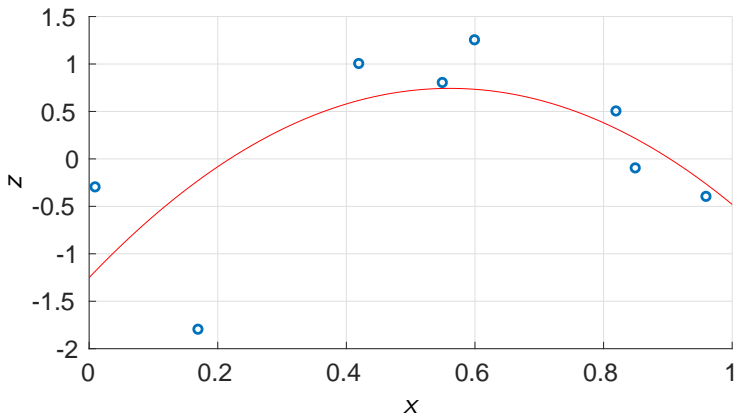
# A simple curve fitting problem

## ► Linear fit



# A simple curve fitting problem

## ► Quadratic fit



# A simple curve fitting problem

- ▶ Poor fit!
- ▶ Why? Model capacity is weak
- ▶ Now, as an example, consider the model

$$\hat{f}_n(x) = \theta^t r(x)$$

with

$$r(x) = (1 \cos(2\pi x) \sin(2\pi x) \dots \cos(2m\pi x) \sin(2m\pi x))^t \in \mathbb{R}^{2m+1}$$

(a truncated Fourier series)

- ▶ The increase in the number of parameters yields an **ill-defined** problem ( $l \gg n$ )

## A simple curve fitting problem

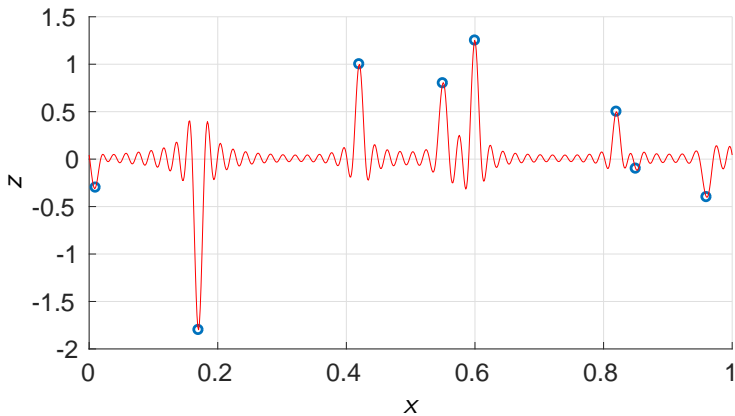
- ▶ When the problem becomes ill-defined (as capacity increases), a classical solution for finding a good value of  $b$  is to minimize the sum of an approximation error and a **regularization** term:

$$J(\theta) = \sum_{i=1}^n (z_i - \theta^t r(x_i))^2 + C \|\theta\|_2^2, \quad C > 0$$

- ▶  $\|\theta\|_2^2$  penalizes vectors  $\theta$  with large elements
- ▶  $C$  strikes a balance between regularization and data fidelity
- ▶ This approach is known as **Tikhonov regularization** (Tikhonov & Arsenin, 1977) → at the basis of numerous approximation methods (ridge regression, splines, RBF, SVM. . . )

## A simple curve fitting problem

- ▶  $n = 8, m = 50, l = 101, C = 10^{-8}$



# A simple curve fitting problem

- ▶ The regularization principle alone is not enough to obtain a good approximation
- ▶ As modeling capacity increases, **overfitting** may arise

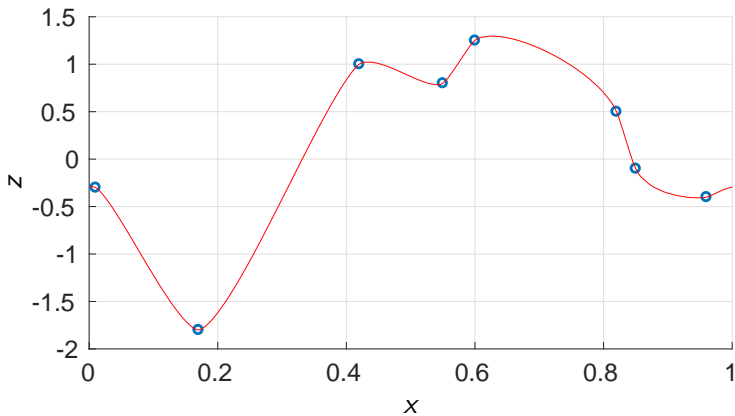
# A simple curve fitting problem

- ▶ To avoid overfitting, we should try a regularization that penalizes high frequencies more
- ▶ For instance, take

$$\|\theta\| = \theta_1^2 + \sum_{k=1}^m \frac{\theta_{2k}^2 + \theta_{2k+1}^2}{(1 + (2k\pi)^\alpha)^2}$$

## A simple curve fitting problem

- $n = 8, m = 50, l = 101, C = 10^{-8}, \alpha = 1.3$





## A simple curve fitting problem

- ▶ From this example, we can see that the construction of a regularization scheme should result from a procedure that takes into account the data (using cross-validation, for instance) an/or prior knowledge (high frequencies  $\ll$  low frequencies, for instance)

# Black-box modeling

- ▶ A large number of methods are available in the literature: polynomial regression, splines, NN, RBF...
- ▶ All methods are based on mixing prior information and regularization principles
- ▶ Instances of “regularization” in regression:
  - ▶ t-tests, F-tests, ANOVA, AIC (Akaike info criterion)... in linear regression
  - ▶ Early stopping in NN
  - ▶ Regularized reproducing-kernel regression
    - ▶ 1960 : splines, (Schoenberg 1964, Duchon 1976–1979)
    - ▶ 1970 : ridge regression (Hoerl, Kennard)
    - ▶ 1980 : RBF, (Micchelli 1986, Powel 1987)
    - ▶ 1995 : SVM, (Vapnik 1995)
    - ▶ 1997 : SVR, (Smola 1997) & semi-param SVR (Smola 1999)

# Black-box modeling

- ▶ How to choose a regularization scheme?
- ▶ The **Bayesian setting** is a principled approach that makes it possible to construct regularized regressions

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**1.3 Bayesian approach**

1.4 Posterior distribution of a quantity of interest

1.5 Complements on Gaussian processes

# Why a Bayesian approach?

- ▶ Objective: infer properties about  $f : \mathbb{X} \rightarrow \mathbb{R}$  through pointwise evaluations
- ▶ Why a Bayesian approach?
  - ▶ a principled approach to choose a regularization scheme according to prior information
  - ▶ through probability calculus and/or Monte Carlo simulations, the user can infer properties about the unknown function
  - ▶ for instance: given prior knowledge and  $\mathcal{D}_n$ , what is the probability that the global maximum of  $f$  is greater than a given threshold  $u \in \mathbb{R}$ ?
- ▶ **Main idea:** use a **statistical model of the observations**, together with a **probability model for the parameter** of the statistical model

# Some reminders about probabilities

- ▶ Recall that a **random variable** is a function that maps a sample space  $\Omega$  to an outcome space  $E$  (e.g.  $E = \mathbb{R}$ ), and that assigns probabilities (weights) to possible outcomes

## Def.

Formally, let  $(\Omega, \mathcal{A}, P)$  be a probability space, and  $(E, \mathcal{E})$  be a measurable outcome space

→ a random variable  $X$  is a measurable function  $(\Omega, \mathcal{A}, P) \rightarrow (E, \mathcal{E})$

- ▶  $X$  is used to assign probabilities to events: for instance

$$P(X \in [0, 1]) = P^X([0, 1]) = 1/2$$

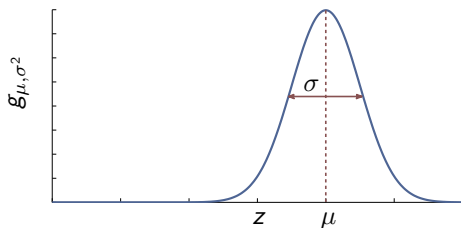
- ▶ Case of a random variable with a density

$$P(X \in [a, b]) = P^X([a, b]) = \int_a^b p^X(x) dx$$

# Gaussian random variables

- ▶ A real-valued random variable  $Z$  is said to be **Gaussian**  $\mathcal{N}(\mu, \sigma^2)$ , if it has the continuous **probability density function**

$$g_{\mu, \sigma^2}(z) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2} \frac{(z - \mu)^2}{\sigma^2}\right)$$



# Gaussian random variables

- ▶ The **mean** of  $Z$  (also called **expectation** or first-order moment) is

$$E(Z) = \int_{\mathbb{R}} z g_{\mu, \sigma^2}(z) dz = \mu$$

and its **second-order** moment is defined as

$$E(Z^2) = \int_{\mathbb{R}} z^2 g_{\mu, \sigma^2}(z) dz = \sigma^2 + \mu^2$$

- ▶ The **variance** of  $Z$  is defined as

$$\text{var}(Z) = E[(Z - E(Z))^2] = E[Z^2] - E[Z]^2 = \sigma^2$$

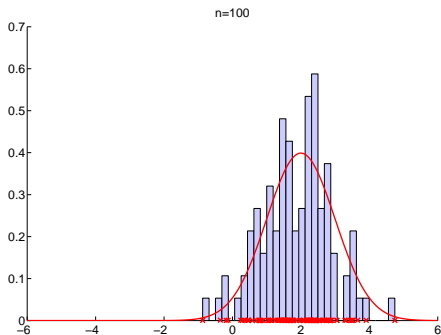


# Gaussian random variables

- ▶ A Gaussian variable  $Z$  can be used as a **stochastic model** of some uncertain real-valued quantity
- ▶ In other words,  $Z$  can be thought as a **prior about some uncertain quantity** of interest

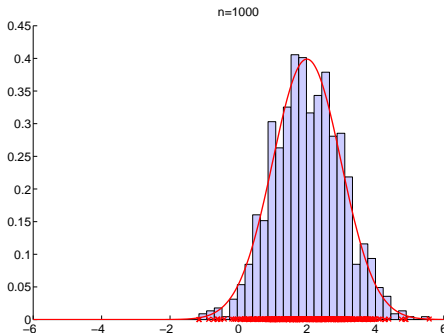
# Gaussian random variables

- Using a random generator, it is possible to “generate” sample values  $z_1, z_2, \dots$  of our model  $Z \rightarrow$  possible values for our **uncertain quantity of interest**



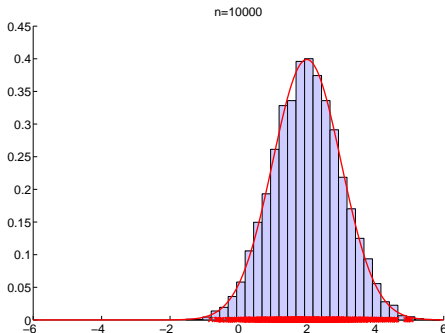
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# Gaussian random variables

- Using a random generator, it is possible to “generate” sample values  $z_1, z_2, \dots$  of our model  $Z \rightarrow$  possible values for our **uncertain quantity of interest**



(as  $n \rightarrow \infty$ , the empirical distribution of the realizations tends to the normal distribution)

# Bayesian model

Formally, recall that a **statistical model** is a triplet  $\mathcal{M} = (\mathcal{Z}, \mathcal{F}, \mathcal{P})$

- ▶  $\mathcal{Z} \rightarrow$  observation space (typically,  $\mathcal{Z} = \mathbb{R}^n$ )
- ▶  $\mathcal{F} \rightarrow \sigma$ -algebra on  $\mathcal{Z}$
- ▶  $\mathcal{P} \rightarrow$  parametric family  $\{P_\theta; \theta \in \Theta\}$  of probability distributions on  $(\mathcal{Z}, \mathcal{F})$

Def.

A **Bayesian model** is defined by the specification of

- ▶ a **parametric statistical model**  $\mathcal{M}$  (model of the observations)
- ▶ a **prior probability distribution**  $\Pi$  on  $(\Theta, \Xi) \rightarrow$  probability model that describes uncertainty about  $\theta$  before an observation is made

# Example

- ▶ Suppose we repeat measurements of a quantity of interest:  
 $z_1, z_2, \dots \in \mathbb{R}$

- ▶ **Model of observations:**  $Z_i \stackrel{iid}{\sim} \mathcal{N}(\theta_1, \theta_2)$ ,  $i = 1, \dots, n$

- ▶ The statistical model can formally be written as the triplet

$$\mathcal{M} = \left( \mathbb{R}^n, \mathcal{B}(\mathbb{R}^n), \{ \mathcal{N}(\theta_1, \theta_2)^{\otimes n} \}_{\theta_1, \theta_2} \right)$$

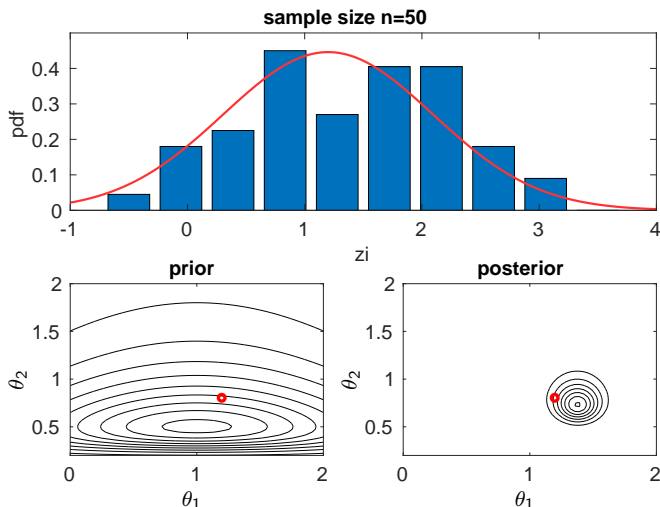
- ▶ Moreover, if we assume a **prior distribution** about  $\theta_1$  and  $\theta_2$   
(e.g.  $\theta_1 \sim \mathcal{N}(1, 1)$ ,  $\theta_2 \sim \mathcal{IG}(3, 2)$ ), we obtain a

**Bayesian model**

- ▶ From this Bayesian model (model of observations + prior), we can compute the **posterior distribution** of  $(\theta_1, \theta_2)$  given  $Z_1, \dots, Z_n$  (will be explained later)

# Example

$$n = 50, \theta_1 = 1.2, \theta_2 = 0.8$$



# Simple curve fitting problem from a Bayesian approach

- Recall our simple curve fitting model

$$\hat{f}_n(x) = \theta^t r(x)$$

with

$$r(x) = (1 \cos(2\pi x) \sin(2\pi x) \dots \cos(2m\pi x) \sin(2m\pi x))^t \in \mathbb{R}^{2m+1}$$

- Bayesian model?



- Assume the following statistical model for the observations:

$$\begin{cases} Z_i = \xi(x_i) + \varepsilon_i, & i = 1, \dots, n \\ \xi(x) = \theta^t r(x), & x \in \mathbb{X} \\ \varepsilon_i \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_\varepsilon^2) \end{cases}$$

or equivalently,

$$Z_i \stackrel{iid}{\sim} \mathcal{N}(\theta^t r(x_i), \sigma_\varepsilon^2), \quad i = 1, \dots, n$$

- Moreover, choose a prior distribution for  $\theta$ :

$$\theta_j \stackrel{\text{indep}}{\sim} \mathcal{N}(0, \sigma_{\theta_j}^2), \quad j = 1, \dots, 2m + 1$$

- The rvs  $Z_i$  constitute a Bayesian model of the observations
- $\xi$  is a random function / random process  $\rightarrow$  prior about  $f$

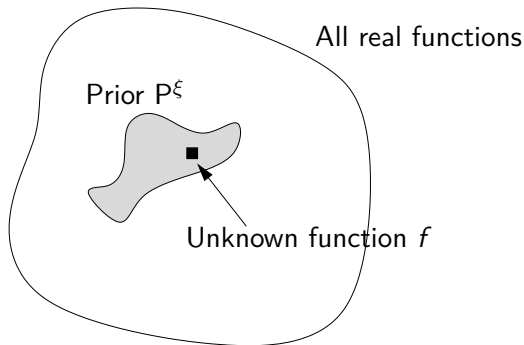
# Random process

Def.

A **random process**  $\xi : (\Omega, \mathbb{X}) \rightarrow \mathbb{R}$  is a collection of random variables  $\xi(\cdot, x) : \Omega \rightarrow \mathbb{R}$  indexed by  $x \in \mathbb{X}$

- ▶ Random processes can be viewed as a generalization of random vectors
- ▶ For a fixed  $\omega \in \Omega$ , the function  $\xi(\omega, \cdot) : \mathbb{X} \rightarrow \mathbb{R}$  is called a **sample path**

- ▶ In our Bayesian setting, we can say that
  - ▶ we use a random process  $\xi$  as a **stochastic model** of the **unknown** function  $f$
  - ▶  $f$  is viewed as as **sample paths** of  $\xi$
  - ▶  $\xi$  represents **our knowledge about  $f$**  before any evaluation has been made
  - ▶ the distribution  $\Pi = P^\xi$  is a **prior** about  $f$

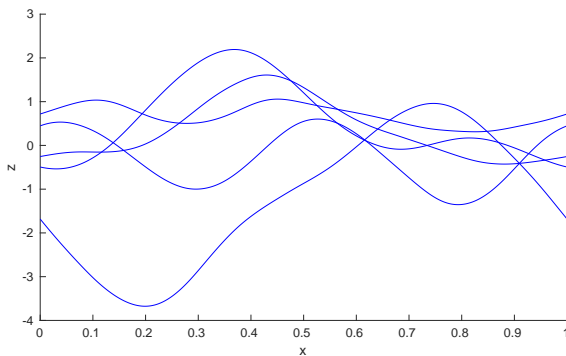


- ▶ Here,  $\xi(\omega, \cdot) = \theta(\omega)^{\text{t}} r(\cdot)$
- ▶ Fixing  $\omega$  (a sample path) amounts to “choosing” a value for the random vector  $\theta$

- Example of sample paths with

$$\begin{cases} \theta_1 \sim \mathcal{N}(0, 1) \\ \theta_{2k}, \theta_{2k+1} \stackrel{\text{indep}}{\sim} \mathcal{N}\left(0, \frac{1}{1+(\omega_0 k)^\alpha}\right), \quad k = 1, \dots, m \end{cases}$$

with  $\omega_0 = \frac{2\pi}{10}$ ,  $\alpha = 4$







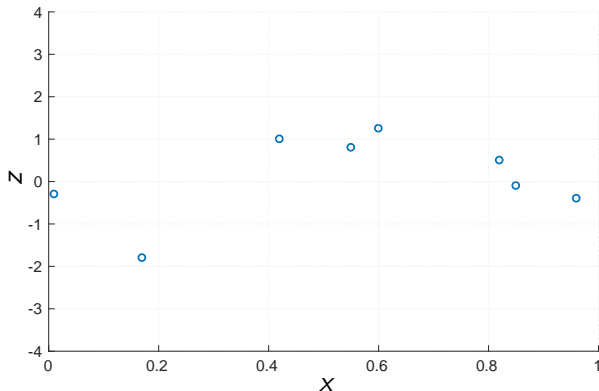
# Bayesian approach

- ▶ The **choice of a prior** in a Bayesian approach reflects the **user's knowledge about uncertain parameters**
- ▶ In the case of function approximation  $\rightarrow$  **regularity** of the function



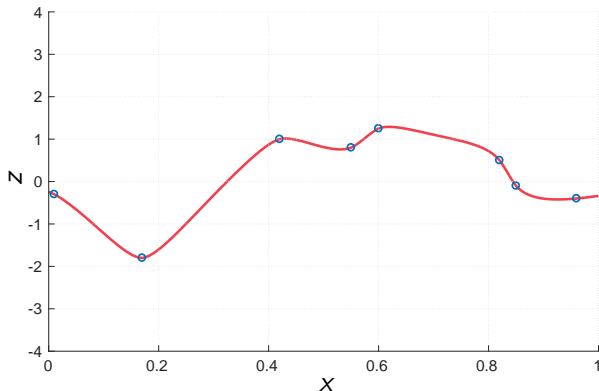
# Bayesian approach

- ▶ Where shall we go now?
- ▶ Objective: compute posterior distributions from data



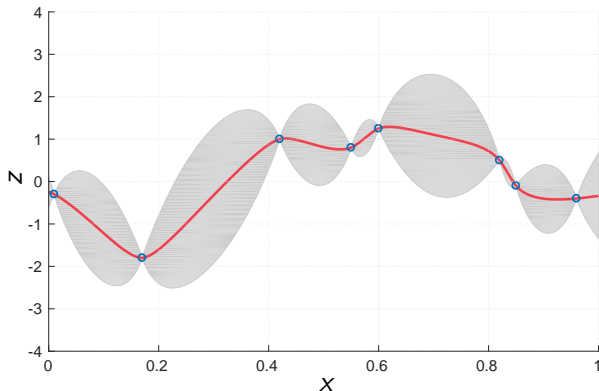
# Bayesian approach

- ▶ Where shall we go now?
- ▶ Objective: compute posterior distributions from data



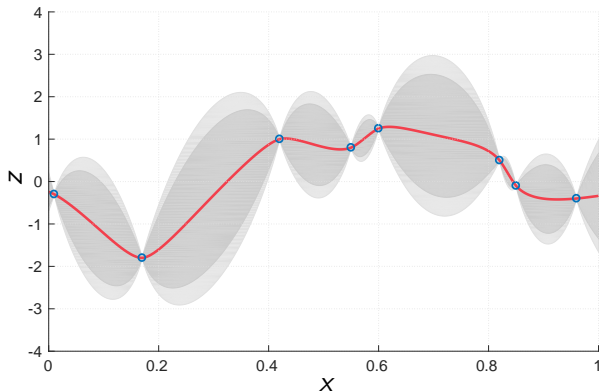
# Bayesian approach

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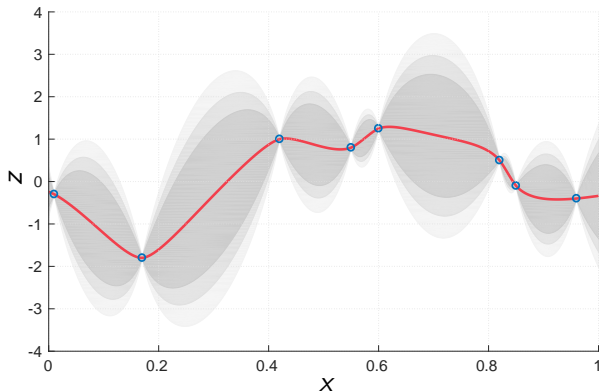
# Bayesian approach

- ▶ Where shall we go now?
- ▶ Objective: compute posterior distributions from data



# Bayesian approach

- ▶ Where shall we go now?
- ▶ Objective: compute posterior distributions from data



# A “simplification” of the Bayesian model for the simple curve fitting problem

- ▶  $\xi = \theta^t r$  (our prior about  $f$ ) is a Gaussian process
- ▶ Why?

# Gaussian random vectors

## Def.

A real-valued random vector  $Z = (Z_1, \dots, Z_d) \in \mathbb{R}^d$  is said to be **Gaussian** iff any linear combination of its components  $\sum_{i=1}^d a_i Z_i$ , with  $a_1, \dots, a_d \in \mathbb{R}$ , is a Gaussian variable

- ▶ A Gaussian random vector  $Z$  is characterized by its **mean** vector,  $\mu = (E[Z_1], \dots, E[Z_d]) \in \mathbb{R}^d$ , and the **covariance** of the pairs of components  $(Z_i, Z_j)$ ,  $i, j \in \{1, \dots, d\}$ ,  
 $\text{cov}(Z_i, Z_j) = E[(Z_i - E(Z_i))(Z_j - E(Z_j))]$
- ▶ If  $Z \in \mathbb{R}^d$  is a Gaussian vector with mean  $\mu \in \mathbb{R}^d$  and covariance matrix  $\Sigma \in \mathbb{R}^{d \times d}$ , we shall write  **$Z \sim \mathcal{N}(\mu, \Sigma)$**

- ▶ Exercise: Let  $Z \sim \mathcal{N}(\mu, \Sigma)$ . Determine  $E\left(\sum_{i=1}^d a_i Z_i\right)$  and  $\text{var}\left(\sum_{i=1}^d a_i Z_i\right)$

- ▶ The correlation coefficient of two components  $Z_i$  and  $Z_j$  of  $Z$  is defined by

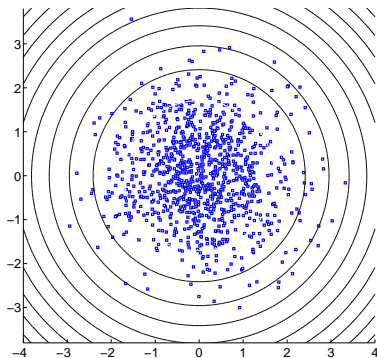
$$\rho(Z_i, Z_j) = \frac{\text{cov}(Z_i, Z_j)}{\sqrt{\text{var}(Z_i)\text{var}(Z_j)}} \in [-1, 1],$$

→ measures the similarity between  $Z_i$  and  $Z_j$

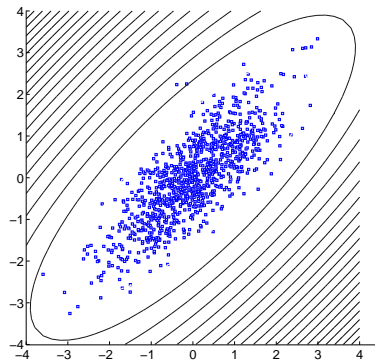


# Gaussian random vectors: correlation

$$\rho = 0$$



$$\rho = 0.8$$



# Gaussian random processes

- ▶ Recall that a random process is a set  $\xi = \{\xi(x), x \in \mathbb{X}\}$  of random variables indexed by the elements of  $\mathbb{X}$
- ▶ Gaussian random process
  - generalization of a Gaussian random vector

Def.

$\xi$  is a **Gaussian random process** iff,  $\forall n \in \mathbb{N}$ ,  $\forall x_1, \dots, x_n \in \mathbb{X}$ , and  $\forall a_1, \dots, a_n \in \mathbb{R}$ , the real-valued random variable

$$\sum_{i=1}^n a_i \xi(x_i)$$

is Gaussian

# Application

► If

$$\begin{cases} \xi(x) = \theta^t r(x), & x \in \mathbb{X} \\ \theta_j \stackrel{\text{indep}}{\sim} \mathcal{N}(0, \sigma_{\theta_j}^2), & j = 1, \dots, 2m+1 \end{cases}$$

then,  $\forall x_1, \dots, x_n \in \mathbb{X}$ , and  $\forall a_1, \dots, a_n \in \mathbb{R}$ ,

$$\begin{aligned} \sum_{i=1}^n a_i \xi(x_i) &= \sum_i a_i \left( \sum_j \theta_j r_j(x_i) \right) \\ &= \sum_j \left( \sum_i a_i r_j(x_i) \right) \theta_j \sim \mathcal{N} \left( 0, \sum_j \left( \sum_i a_i r_j(x_i) \right)^2 \sigma_{\theta_j}^2 \right) \end{aligned}$$

► Thus,  $\xi = \theta^t r$  is a Gaussian process

# Gaussian random processes

- ▶ A Gaussian process is **characterized** by
  - ▶ its **mean function**

$$m : x \in \mathbb{X} \mapsto \mathbb{E}[\xi(x)]$$

- ▶ and its **covariance function**

$$k : (x, y) \in \mathbb{X}^2 \mapsto \text{cov}(\xi(x), \xi(y))$$

- ▶ Notation:  $\xi \sim \mathcal{GP}(m, k)$

► Exercise: determine  $E\left(\sum_{i=1}^d a_i \xi(x_i)\right)$  and  $\text{var}\left(\sum_{i=1}^d a_i \xi(x_i)\right)$

► What is the distribution of  $\sum a_i \xi(x_i)$ ?

→ The distribution of a linear combination of a Gaussian process  $\mathcal{GP}(m, k)$  can be simply obtained as a function of  $m$  and  $k$

# Application

► If

$$\begin{cases} \xi(x) = \theta^{\text{t}} r(x), & x \in \mathbb{X} \\ \theta_j \stackrel{\text{indep}}{\sim} \mathcal{N}(0, \sigma_{\theta_j}^2), & j = 1, \dots, 2m+1 \end{cases}$$

then,

$$\xi \sim \mathcal{GP}(0, k)$$

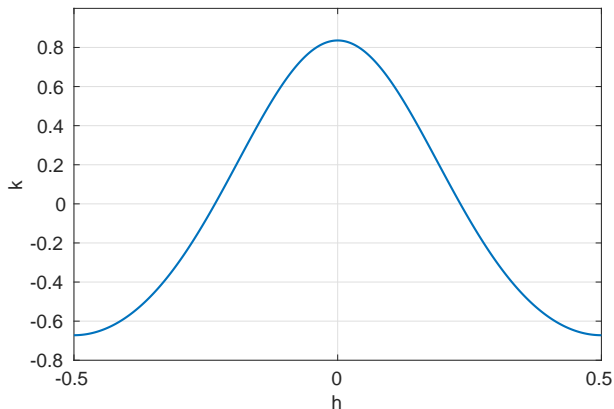
with

$$k : (x, y) \mapsto \sum_j \sigma_{\theta_j}^2 r_j(x) r_j(y)$$

- Covariance function corresponding to

$$\begin{cases} \theta_1 \sim \mathcal{N}(0, 1) \\ \theta_{2k}, \theta_{2k+1} \stackrel{\text{indep}}{\sim} \mathcal{N}\left(0, \frac{1}{1+(\omega_0 k)^\alpha}\right), \quad k = 1, \dots, m \end{cases}$$

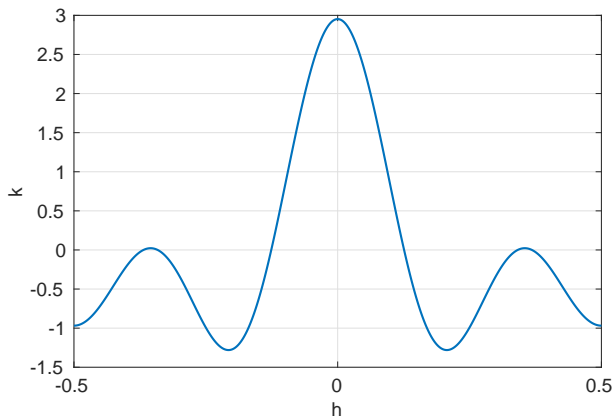
with  $\omega_0 = \frac{2\pi}{10}$ ,  $\alpha = 4$



- Covariance function corresponding to

$$\begin{cases} \theta_1 \sim \mathcal{N}(0, 1) \\ \theta_{2k}, \theta_{2k+1} \stackrel{\text{indep}}{\sim} \mathcal{N}\left(0, \frac{1}{1+(\omega_0 k)^\alpha}\right), \quad k = 1, \dots, m \end{cases}$$

with  $\omega_0 = \frac{2\pi}{50}$ ,  $\alpha = 4$





# The covariance of a Gaussian random process

- ▶ Main properties: a covariance function  $k$  is
  - ▶ **symmetric**:  $\forall x, y \in \mathbb{X}, k(x, y) = k(y, x)$
  - ▶ **positive**:

$$\forall n \in \mathbb{N}, \forall x_1, \dots, x_n \in \mathbb{X}, \forall a_1, \dots, a_n \in \mathbb{R}, \sum_{i,j=1}^n a_i k(x_i, x_j) a_j \geq 0$$

- ▶ In the following, we shall assume that the covariance of  $\xi \sim \mathcal{GP}(m, k)$  is **invariant under translations**, or **stationary**:

$$k(x + h, y + h) = k(x, y), \quad \forall x, y, h \in \mathbb{X}$$

- ▶ When  $k$  is stationary, there exists a **stationary covariance**  $k_{\text{sta}} : \mathbb{R}^d \rightarrow \mathbb{R}$  such that

$$\text{cov}(\xi(x), \xi(y)) = k(x, y) = k_{\text{sta}}(x - y)$$

# Stationary covariances

- ▶ When  $k$  is stationary, the variance

$$\text{var}(\xi(x)) = \text{cov}(\xi(x), \xi(x)) = k(0)$$

does not depend on  $x$

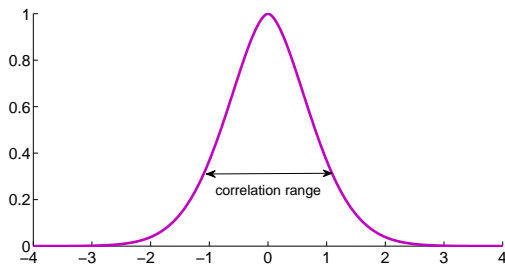
- ▶ The covariance function can be written as

$$k(x - y) = \sigma^2 \rho(x - y),$$

with  $\sigma^2 = \text{var}(\xi(x))$ , and where  $\rho$  is the **correlation function** of  $\xi$ .

# Stationary covariances

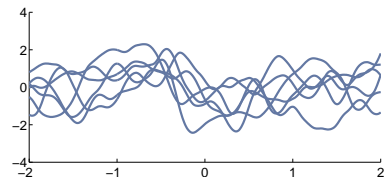
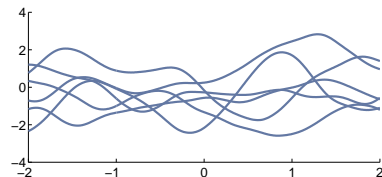
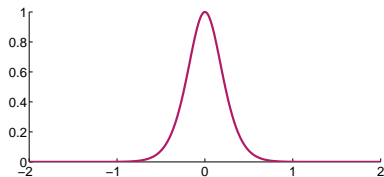
- ▶ The graph of the correlation function is a symmetric “bell curve” shape



- ▶ We have, by C-S,

# Gaussian process simulation

- ▶ Using a random generator, it is possible to “generate” sample paths  $f_1, f_2, \dots$  of a Gaussian process  $\xi$



# Gaussian process simulation

How to simulate sample paths of a zero-mean Gaussian random process?

- ▶ Choose a set of points  $x_1, \dots, x_n \in \mathbb{X}$
- ▶ Denote by  $K$  the  $n \times n$  covariance matrix of the random vector  $\underline{\xi} = (\xi(x_1), \dots, \xi(x_n))^t$  (NB:  $\underline{\xi} \sim \mathcal{N}(0, K)$ )
- ▶ Consider the Cholesky factorization of  $K$

$$K = CC^t,$$

with  $C$  a lower triangular matrix (such a factorization exists since  $K$  is a sdp matrix)

- ▶ Let  $\varepsilon = (\varepsilon_1, \dots, \varepsilon_n)^t$  a Gaussian vector with  $\varepsilon_i \stackrel{\text{i.i.d}}{\sim} \mathcal{N}(0, 1)$
- ▶ Then  $C\varepsilon \sim \mathcal{N}(0, K)$

# “Simplification” of the Bayesian model for the simple curve fitting problem

- Instead of choosing the model

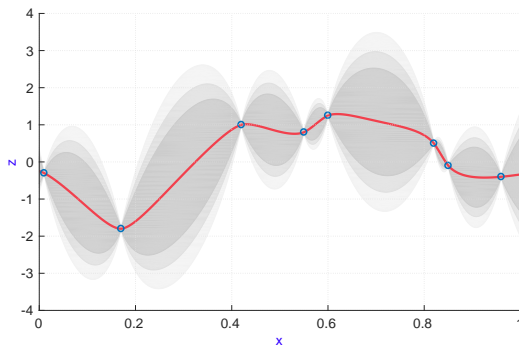
$$\begin{cases} \xi(x) = \theta^{\text{t}} r(x), & x \in \mathbb{X} \\ \theta_j \stackrel{\text{indep}}{\sim} \mathcal{N}(0, \sigma_{\theta_j}^2), & j = 1, \dots, 2m+1 \end{cases}$$

simply choose a covariance function  $k$  and assume  
 $\xi \sim \mathcal{GP}(0, k)$

- More details about how to choose  $k$  will be given below

# Posterior

- How to compute a posterior distribution, given the Gaussian-process prior  $\xi$  and data?





# Conditional distributions

- ▶ Let  $X$  be a random variable modeling an unknown quantity of interest
- ▶ Assume we observe a random variable  $T$ , or a random vector  $T = (T_1, \dots, T_n)$
- ▶ Provided that  $T$  and  $X$  are **not independent**,  $T$  contains **information about  $X$**
- ▶ Aim: define a **notion of distribution of  $X$  “knowing”  $T$**

# Conditional probabilities

Recall the following

Def.

Let  $(\Omega, \mathcal{A}, P)$  be a probability space. Given two events  $A, B \in \mathcal{A}$  such that  $P(B) \neq 0$ , define the **probability of  $A$  given  $B$**  (or conditional on  $B$ ) by

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)}$$

# The notion of conditional density

Def.

Assume that the pair  $(X, T) \in \mathbb{R}^2$  has a density  $p^{(X, T)}$ .

Define the **conditional density** of  $X$  given the event  $T = t$  by

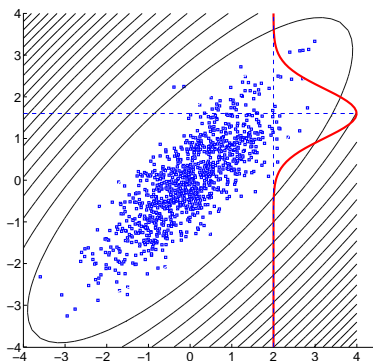
$$p^{X|T}(x | t) = \begin{cases} \frac{p^{(X, T)}(x, t)}{p^T(t)} = \frac{p^{(X, T)}(x, t)}{\int p^{X, T}(x, t) dx} & \text{if } p^T(t) > 0 \\ \text{arbitrary density} & \text{if } p^T(t) = 0. \end{cases}$$

# Application

- ▶ Given a Gaussian random vector  $Z = (Z_1, Z_2) \sim \mathcal{N}(0, \Sigma)$ , what is the distribution of  $Z_2$  “knowing”  $Z_1$ ?
- ▶ Define

$$p^{Z_2|Z_1}(z_2|z_1) = \frac{p^{(Z_2, Z_1)}(z_2, z_1)}{p^{Z_1}(z_1)} = \frac{\sigma_1}{(2\pi)^{1/2}(\det \Sigma)^{1/2}} \exp(-1/2(z^t \Sigma^{-1} z - z_1^2/\sigma_1^2))$$

→ Gaussian distribution!



- ▶ The random variable denoted by  $Z_2 | Z_1$  with density  $p^{Z_2|Z_1}(\cdot | Z_1)$  represents the **residual uncertainty** about  $Z_2$  when  $Z_1$  has been observed
- ▶ High correlation → small residual uncertainty

# Conditional mean/expectation

- A fundamental notion: conditional expectation

Def.

Assume that the pair  $(X, T)$  has a density  $p^{(X, T)}$ . Define the **conditional mean of  $X$  given  $T = t$**  as

$$E(X \mid T = t) \triangleq \int_{\mathbb{R}} x p^{X|T}(x|t) dx = h(t)$$

Def.

The random variable  $E(X \mid T) = h(T)$  is called the **conditional expectation of  $X$  given  $T$**

# Conditional expectation

- ▶ Why conditional expectation is an fundamental notion?
- ▶ We have the following

## Theorem

*Under the previous assumptions, the solution of the problem*

$$\hat{X} = \operatorname{argmin}_Y E[(X - Y)^2]$$

*where the **minimum is taken over all functions of  $T$**  is given by*

$$\hat{X} = E(X \mid T)$$

- ▶ In other words,  $E(X \mid T)$  is the **best approximation** (in the sense of the quadratic mean) **of  $X$  by a function of  $T$**

# Important properties of conditional expectation

- (1)  $E(X \mid T)$  is a random variable depending on  $T \rightarrow$  there exists a function  $h$  such that  $E(X \mid T) = h(T)$
- (2) The operator  $\pi_H : X \mapsto E(X \mid T)$  is a (linear) operator of **orthogonal projection** onto the space of all functions of  $T$  (for the inner product  $X, Y \mapsto (X, Y) = E(XY)$ )
- (3) Let  $X, Y, T \in L^2$ . Then
  - i)  $\forall \alpha \in \mathbb{R}, E(\alpha X + Y \mid T) = \alpha E(X \mid T) + E(Y \mid T)$  a.s.
  - ii)  **$E(E[X \mid T]) = E(X)$**
  - iii) If  $X \perp\!\!\!\perp T$ ,  $E(X \mid T) = E(X)$

# Conditional expectation: Gaussian random variables

- ▶ Recall that the space of second-order random variables  $L^2(\Omega, \mathcal{A}, P)$  endowed with the inner product  $X, Y \mapsto (X, Y) = E(XY)$  is a Hilbert space
- ▶ Gaussian linear space

Def.

A **linear subspace**  $G$  of  $L^2(\Omega, \mathcal{A}, P)$  is **Gaussian** iff  $\forall X_1, \dots, X_n \in G$  and  $\forall a_1, \dots, a_n \in \mathbb{R}$  the random variable  $\sum_i a_i X_i$  is Gaussian

- ▶ In what follows, assume that  $G$  is **centered**, i.e., each element in  $G$  is a zero-mean random variable



## Theorem (Projection theorem in centered Gaussian spaces)

Let  $G$  be a centered Gaussian space. Let  $X, T_1, \dots, T_n \in G$ . Then  $E(X \mid T_1, \dots, T_n)$  is the orthogonal projection (in  $L^2$ ) of  $X$  on  $\mathcal{T} = \text{span}\{T_1, \dots, T_n\}$ .

**proof** Let  $\hat{X} \in G$  be the orthogonal projection of  $X$  on  $\mathcal{T}$ .

- ▶ we have  $X = \hat{X} + \varepsilon$  where  $\varepsilon \in G$  is orthogonal to  $\mathcal{T}$ .

In  $G$ , orthogonality  $\Leftrightarrow$  independence. Thus,  $\varepsilon \perp T_i, i = 1, \dots, n$ .

- ▶ Then,

$$\begin{aligned} E(X \mid T_1, \dots, T_n) &= E(\hat{X} \mid T_1, \dots, T_n) + E(\varepsilon \mid T_1, \dots, T_n) \\ &= \hat{X} + E(\varepsilon) = \hat{X} \end{aligned}$$

The result follows.



## ■ Application

Let  $Z = (Z_1, Z_2)$  be a zero-mean Gaussian random vector, with covariance matrix

$$\begin{pmatrix} \sigma_1^2 & \sigma_{1,2} \\ \sigma_{2,1} & \sigma_2^2 \end{pmatrix}$$

Then  $E(Z_1 \mid Z_2)$  is the orthogonal projection of  $Z_1$  onto  $Z_2$ . Thus

$$E(Z_1 \mid Z_2) = \lambda Z_2$$

with

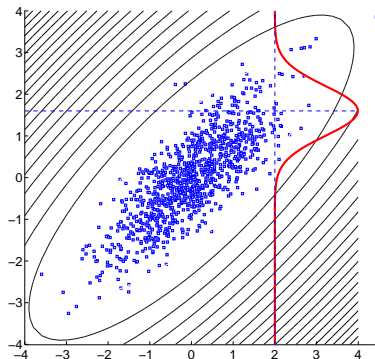
$$(Z_1 - \lambda Z_2, Z_2) = (Z_1, Z_2) - \lambda(Z_2, Z_2) = 0.$$

Hence,

$$\lambda = \frac{\sigma_{1,2}}{\sigma_2^2}$$

# Application

- ▶ Let  $Z = (Z_1, Z_2) \sim \mathcal{N}(0, \Sigma)$  as above  $\rightarrow$  recall that the cond. distrib. of  $Z_2$  given  $Z_1$  is a Gaussian distribution
- ▶ Hence  $Z_2 | Z_1 \sim \mathcal{N}(\mu(Z_1), \sigma(Z_1)^2) \rightarrow \mu ? \sigma ?$



- ▶  $\mu = E(Z_2 | Z_1) = \lambda Z_1$  with  $\lambda = \frac{\sigma_{1,2}}{\sigma_1^2}$
- ▶ Using the property of the orthogonal projection:

$$\begin{aligned}\sigma^2 &= E((Z_2 - E(Z_2 | Z_1))^2 | Z_1) \\ &\stackrel{\perp}{=} E((Z_2 - E(Z_2 | Z_1))^2) \\ &= E((Z_2 - \lambda Z_1)^2) \\ &\stackrel{\perp}{=} E((Z_2 - \lambda Z_1)Z_2) \\ &= \sigma_2^2 - \lambda \sigma_{1,2}\end{aligned}$$

## Generalization

Exercise: Let  $(Z_0, Z_1, \dots, Z_n)$  be a centered Gaussian vector.  
Determine  $E(Z_0 \mid Z_1, \dots, Z_n)$ .

# Application: computation of the posterior distrib. of a GP

- ▶ Let  $\xi \sim \mathcal{GP}(0, k)$
- ▶ Assume we observe  $\xi$  at  $x_1, \dots, x_n \in \mathbb{X}$
- ▶ Given  $x_0 \in \mathbb{X}$ , what is the conditional distrib.—or the posterior distrib. in our Bayesian framework—of

$$\xi(x_0) \mid \xi(x_1), \dots, \xi(x_n) ?$$

- ▶ More generally, what is the **posterior distribution** of the random process

$$\xi(\cdot) \mid \xi(x_1), \dots, \xi(x_n) ?$$

# Computation of the posterior distribution of a GP

## Prop.

Let  $\xi \sim \mathcal{GP}(0, k)$ . The random process  $\xi$  conditioned on  $F_n = \{\xi(x_1), \dots, \xi(x_n)\}$ , denoted by  $\xi \mid F_n$ , is a **Gaussian process** with

- mean  $\hat{\xi}_n : x \mapsto \mathbb{E}(\xi(x) \mid \xi(x_1), \dots, \xi(x_n))$
- covariance  $k_n : x, y \mapsto \mathbb{E}((\xi(x) - \hat{\xi}_n(x))(\xi(y) - \hat{\xi}_n(y)))$

# Computation of the posterior distrib. of a GP

- ▶ By property of the conditional expectation in Gaussian spaces, for all  $x \in \mathbb{X}$ ,  $\hat{\xi}_n(x)$  is a linear combination of  $\xi(x_1), \dots, \xi(x_n)$ :

$$\hat{\xi}_n(x) := \sum_{i=1}^n \lambda_i(x) \xi(x_i)$$

- ▶ Moreover, the posterior mean  $\hat{\xi}_n(x)$  is the orthogonal projection of  $\xi(x)$  onto  $\text{span}\{\xi(x_i), i = 1, \dots, n\}$ , such that
  - ▶  $\hat{\xi}_n(x) = \operatorname{argmin}_Y E[(\xi(x) - Y)^2] \rightarrow$  the variance of the prediction error is minimum
  - ▶  $E(\hat{\xi}_n(x)) = E[E(\xi(x) | F_n)] = E(\xi(x)) = 0 \rightarrow$  unbiased estimation
- ▶  $\hat{\xi}_n(x)$  is the best linear predictor (BLP) of  $\xi(x)$  from  $\xi(x_1), \dots, \xi(x_n)$ , also called the kriging predictor of  $\xi(x)$

# Computation of the posterior distrib. of a GP

- ▶ The posterior covariance, also called **kriging covariance**, is given by

$$\begin{aligned} k_n(x, y) &:= \text{cov}(\xi(x) - \hat{\xi}_n(x), \xi(y) - \hat{\xi}_n(y)) \\ &= k(x - y) - \sum_i \lambda_i(x) k(y - x_i). \end{aligned}$$

- ▶  $k_n$  is the covariance function of the **error of prediction**
- ▶ The posterior variance of  $\xi$ , also called the **kriging variance**, is defined as

$$\sigma_n^2(x) = \text{var}(\xi(x) - \hat{\xi}_n(x)) = k_n(x, x)$$

- ▶  $\sigma_n^2(x)$  is the variance of the **error of prediction**



# Kriging equations

- ▶ How to compute the weights  $\lambda_i(x)$  of the posterior mean/kriging predictor?
- ▶ Weights  $\lambda_i(x)$  are solutions of a **system of linear equations**

$$K\lambda(x) = k(x)$$

with

- $\lambda(x) = (\lambda_1(x), \dots, \lambda_n(x))^t$
- $K$ :  $n \times n$  covariance matrix of the observation vector
- $k(x)$ :  $n \times 1$  vector with entries  $k(x_i, x)$

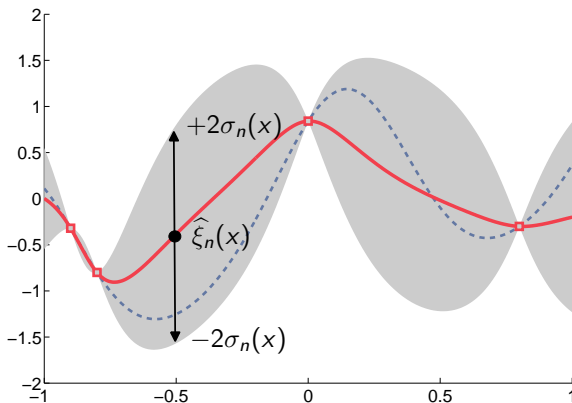
# Kriging equations

**proof**



# Posterior distrib. of a GP

- For all  $x \in \mathbb{X}$ , the random variable  $\xi(x) \mid F_n$  with distrib.  $\mathcal{N}(\hat{\xi}_n(x), \sigma_n^2(x))$  represents the **residual uncertainty** about  $\xi(x)$  when  $\xi(x_1), \dots, \xi(x_n)$  are observed



# Software for kriging/GP regression

## ► R packages

- **BACCO** Bayesian analysis of computer code software
- **fanovaGraph** Building Kriging Models from FANOVA Graphs
- **DiceKriging** **DiceOptim** **GPareto** Dice and ReDice packages
- **MuFiCokriging** Multi-Fidelity Cokriging models
- **RobustInv** Robust inversion based on GP (like KrigInv)
- **tgp** Treed Gaussian processes
- ...

# Software for kriging/GP regression

## ► Matlab/GNU Octave

- **DACE** DACE, a matlab kriging toolbox.
- **FERUM** Finite Element Reliability using Matlab
- **GPML** Gaussian Processes for Machine Learning
- **GPStuff** GP Models for Bayesian analysis
- **scalaGAUSS** Kriging toolbox with a focus on large datasets
- **Matlab Stat & ML toolbox** GP regression from Mathworks
- **STK** Small (Matlab/GNU Octave) Toolbox for Kriging
- **SUMO** **ooDACE** Surrogate Modeling Lab
- **UQLab** Uncertainty quantification framework in Matlab

## ► Python

- **scikit-learn** Machine learning in Python
- **OpenTURNS** Open source lib for UQ
- **Spearmint** Bayesian optimization
- **GPy** Gaussian processes framework in Python

## Generalization: prediction from noisy observations

- ▶ Let  $\xi \sim \text{GP}(0, k)$
- ▶ For  $i = 1, \dots, n$ , we observe  $Z_i = \xi(x_i) + \varepsilon_i$  at points  $x_i$ , where the random variables  $\varepsilon_i$  model an observation noise:
  - ▶  $\varepsilon_i \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma^2)$
  - ▶ independent from  $\xi$
- ▶ As above, the posterior mean  $\hat{\xi}_n(x)$  of  $\xi(x)$  is obtained as the orthogonal projection of  $\xi(x)$  on the linear subspace  $\text{span}\{Z_i, i = 1, \dots, n\}$ :

$$\hat{\xi}_n(x) = \sum_{i=1}^n \lambda_i(x) Z_i$$

with  $\lambda_i(x)$  such that

$$\forall i, \quad \xi(x) - \hat{\xi}_n(x) \perp Z_i$$

# Generalization: prediction from noisy observations

- Thus,  $\forall i$

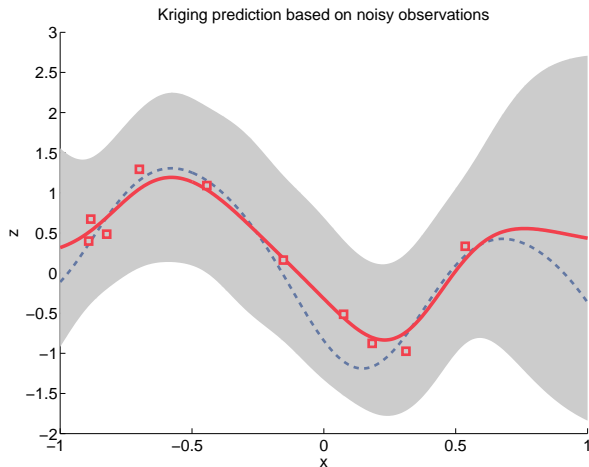
$$\mathbb{E}[(\xi(x) - \hat{\xi}_n(x))Z_i]$$

$$= \mathbb{E}[\xi(x)(\xi(x_i) + \varepsilon_i)] - \sum_{j=1}^n \lambda_j(x) \mathbb{E}[(\xi(x_j) + \varepsilon_j)(\xi(x_i) + \varepsilon_i)]$$

$$= k(x, x_i) - \sum_{j=1}^n \lambda_j(x) (k(x_j, x_i) + \sigma^2 \delta_{i,j})$$

- Under matrix form (exercise):

# Generalization: prediction from noisy observations





# Generalization: prediction from noisy observations

We should use an **approximation instead of an interpolation** in three cases:

- i) The **observations are noisy** (obviously): the computer code is stochastic (for instance, Monte Carlo is used) and running the code twice does not produce the same output
- ii) The **output of the computer code is very irregular**  $\rightarrow$  a smooth approximation is preferred
- iii) The **covariance matrix is ill-conditioned**  $\rightarrow$  adding a small observation noise will regularize the solution of the linear system (why?)

## Lecture 1 : From meta-models to UQ

1.1 Introduction

1.2 Black-box modeling

1.3 Bayesian approach

**1.4 Posterior distribution of a quantity of interest**

1.5 Complements on Gaussian processes

# Posterior of a quantity of interest

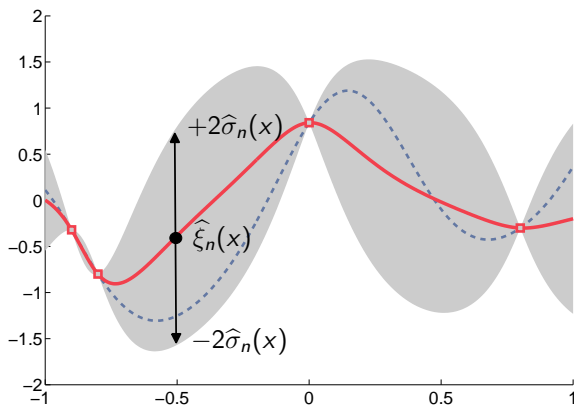
- ▶ Using the posterior distribution of  $\xi$ , we can address questions like
  - ▶ What are plausible values for  $\xi(x)$  at a given  $x$ ? (obviously)
  - ▶ What are plausible values for  $\int g(\xi(x)) d\mu(x)$  for given  $g$  and  $\mu$ ?
  - ▶ What are plausible values for the minimum  $M = \min_x \xi(x)$ ?
  - ▶ Where is the minimizer  $x^* = \operatorname{argmin}_x \xi(x)$ ?
  - ▶ What is the probability that  $\xi(x)$  exceeds a given threshold?
  - ▶ ...

## Example of a quantity of interest: the improvement

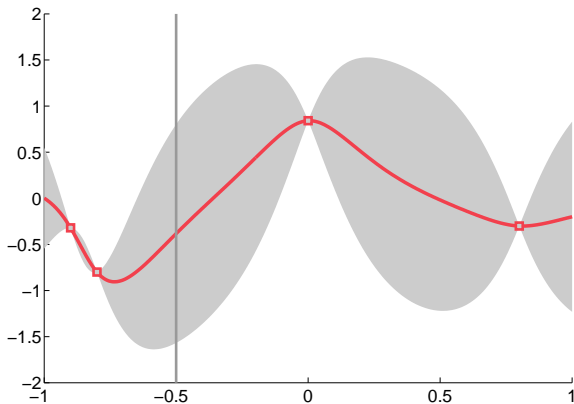
- ▶ Suppose that our objective is to **minimize** an unknown function  $f : \mathbb{X} \rightarrow \mathbb{R}$
- ▶ In our Bayesian approach, we choose a GP prior  $\xi$  for  $f$  (in other words,  $\xi$  is a model of  $f$ )
- ▶ Objective: construct a sequence  $(X_1, X_2, \dots) \in \mathbb{X}$  that converges to  $X^* = \operatorname{argmin}_x \xi(x)$
- ▶ Given  $X_1, \dots, X_{n+1}$ , how to define and choose a “good” point  $X_{n+1}$  in our setting?
- ▶ Let  $m_n = \min_{1 \leq i \leq n} \xi(X_i)$
- ▶ A “good” point  $x \in \mathbb{X}$  is such that  $m_n - \xi(x)$  is large
- ▶ Define the excursion of  $\xi$  at  $x$  below  $m_n$ , a.k.a **the improvement**:

$$I_n = \begin{cases} 0 & \text{if } \xi(x) > m_n \\ m_n - \xi(x) & \text{if } \xi(x) \leq m_n \end{cases}$$

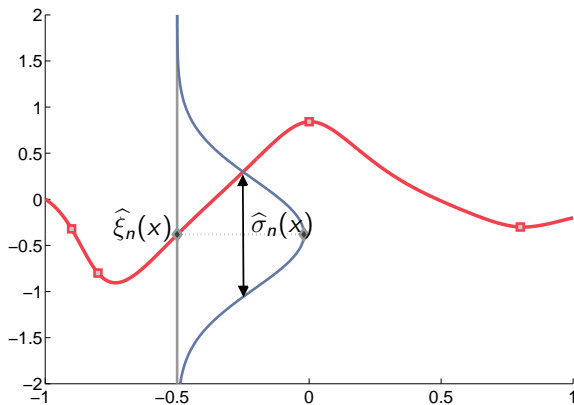
## Example of a quantity of interest: the improvement



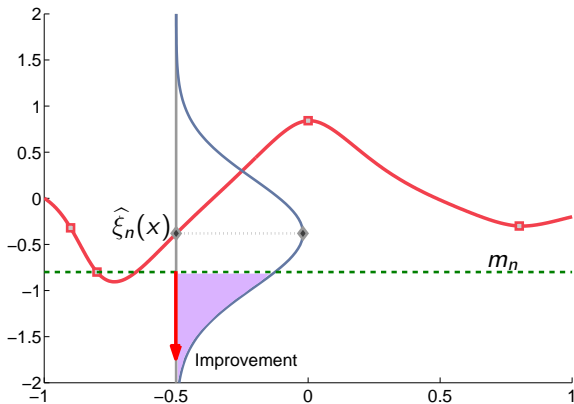
## Example of a quantity of interest: the improvement



## Example of a quantity of interest: the improvement



## Example of a quantity of interest: the improvement





## Example of a quantity of interest: the improvement

- ▶ Regions with high values of the **posterior mean** of  $I_n$  are promising search regions for the minimum of  $\xi$
- ▶ The posterior mean of  $I_n$  may be written as

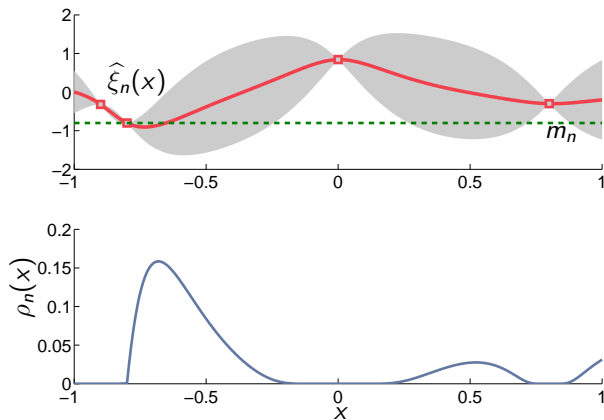
$$\begin{aligned}\rho_n(x) &= E(I_n \mid \xi(X_1), \dots, \xi(X_n)) \\ &= \int_{z=-\inf}^{m_n} (m_n - z) p^{\xi(x) \mid \xi(X_1), \dots, \xi(X_n)}(z) \, dz \\ &= \gamma(m_n - \hat{\xi}_n(x), \sigma_n^2(x))\end{aligned}$$

with

$$\gamma(z, s) = \begin{cases} \sqrt{s} \Phi' \left( \frac{z}{\sqrt{s}} \right) + z \Phi \left( \frac{z}{\sqrt{s}} \right) & \text{if } s > 0, \\ \max(z, 0) & \text{if } s = 0. \end{cases}$$

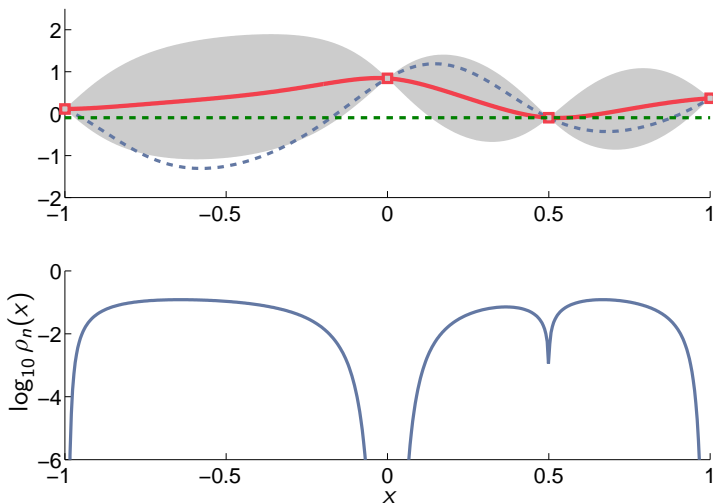
- ▶  $\rho_n$  is called the **expected improvement** [Mockus 78, Schonlau et al. 96, Jones et al. 98]

## Example of a quantity of interest: the improvement



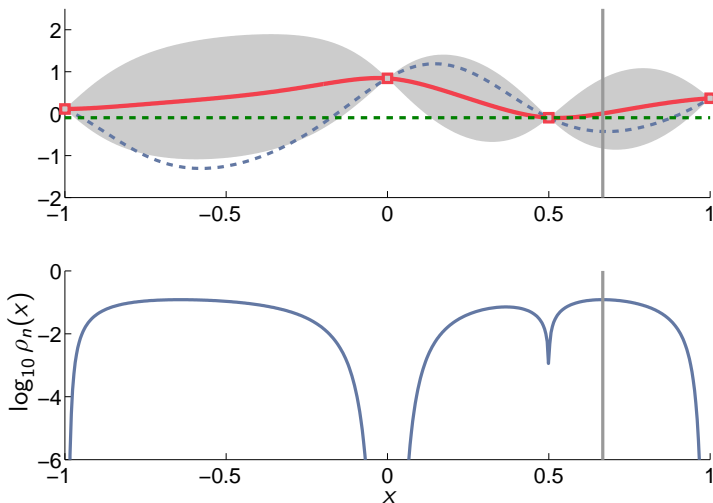
# Insertion into an optimization algorithm

- The EI algorithm:  $X_{n+1} = \arg\max_x \rho_n(x)$



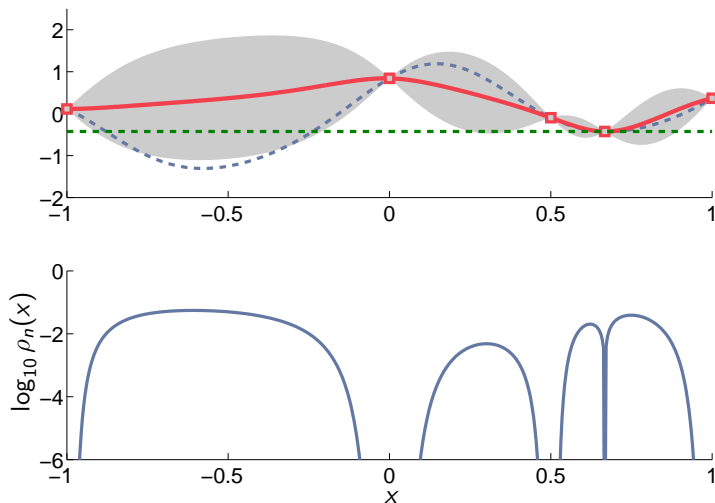
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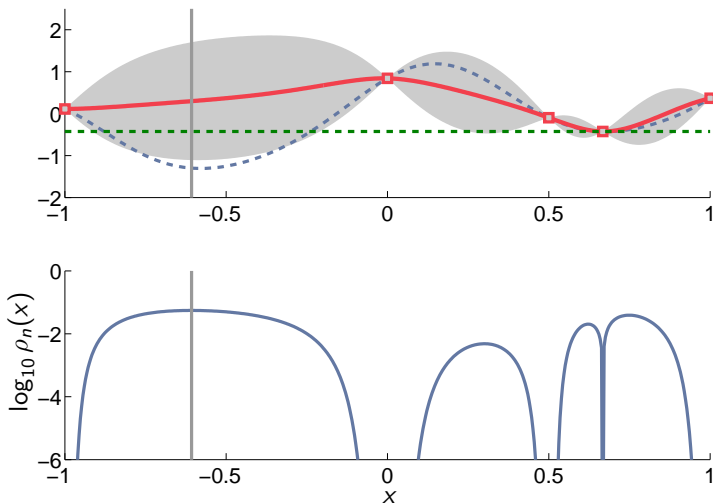
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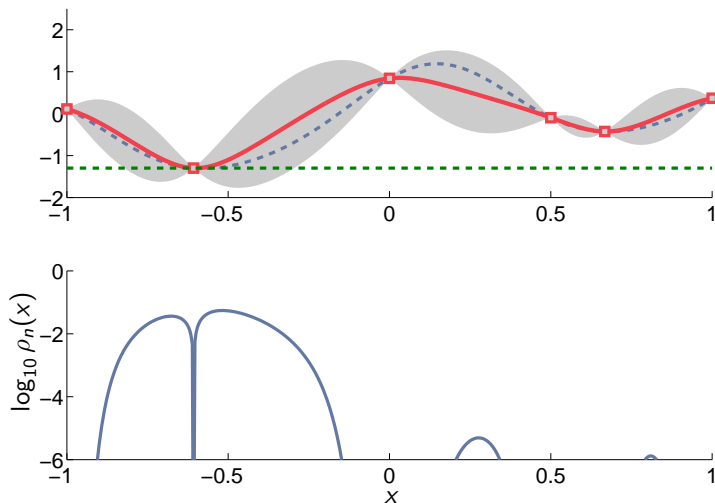
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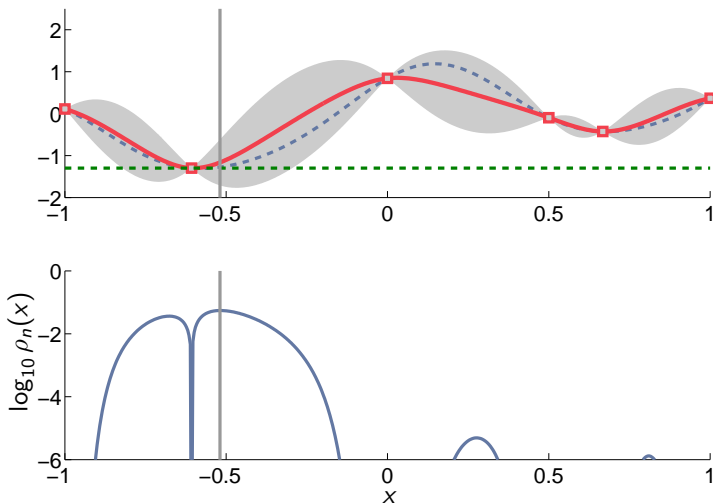
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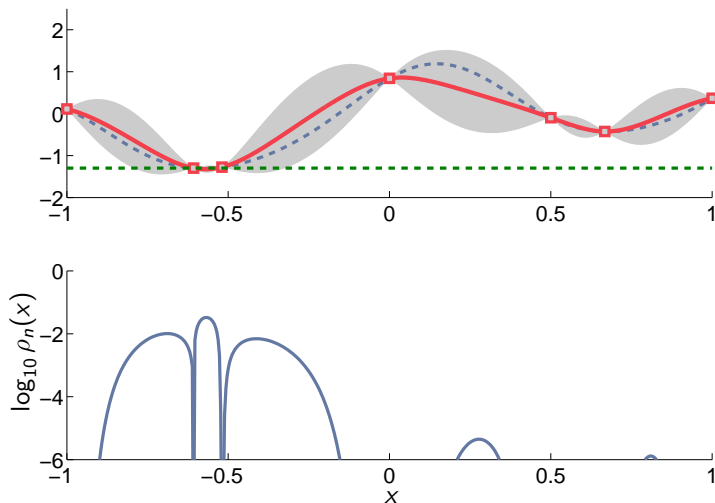
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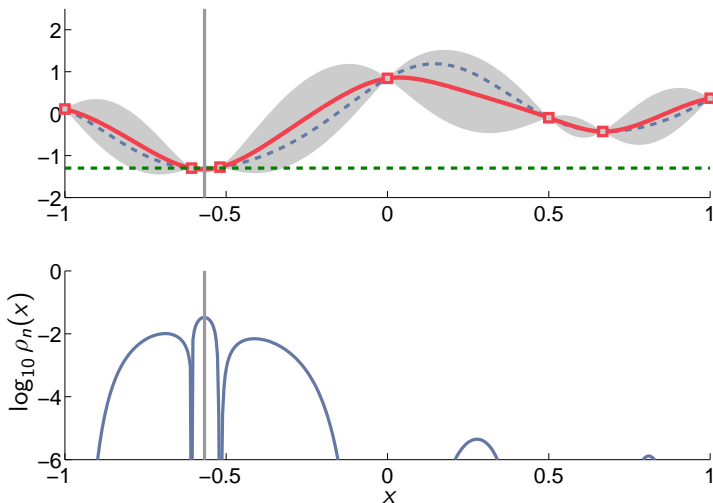
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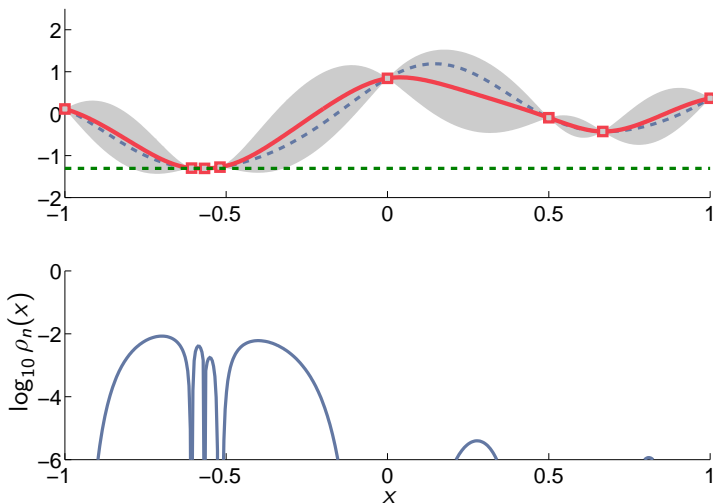
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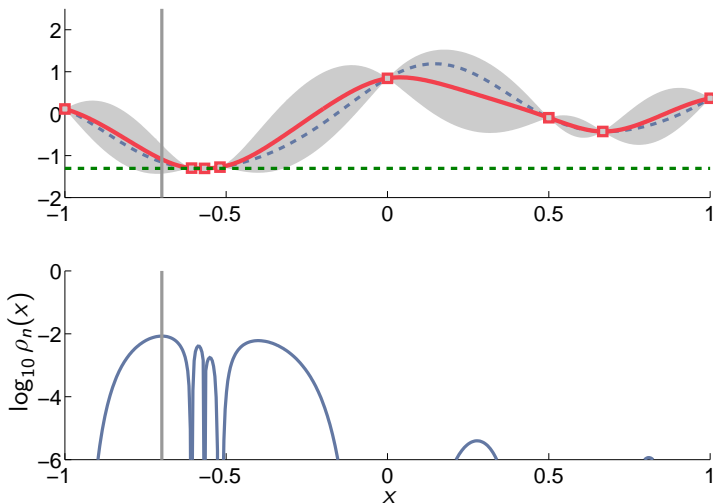
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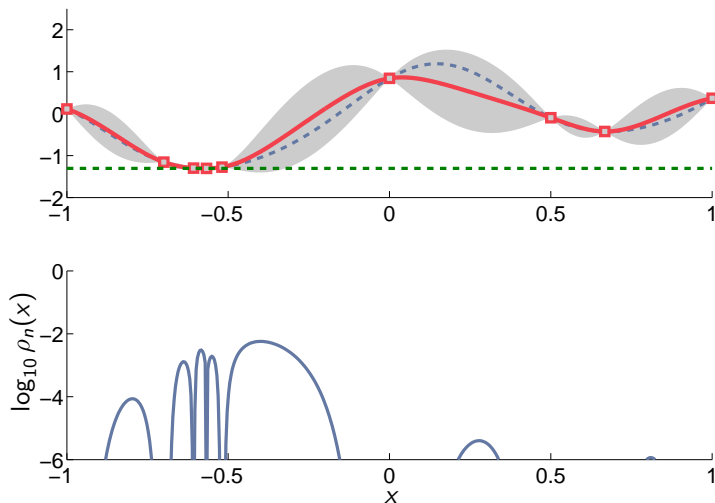
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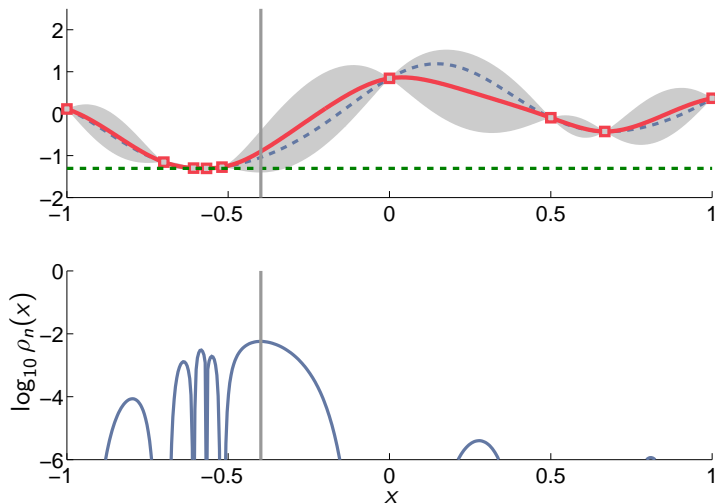
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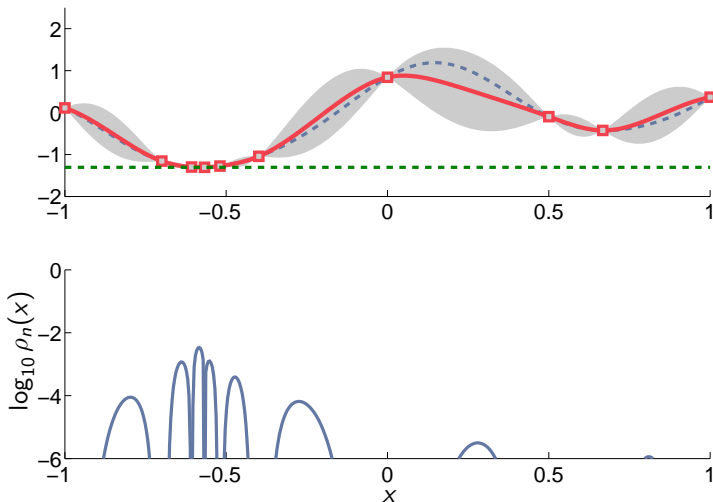
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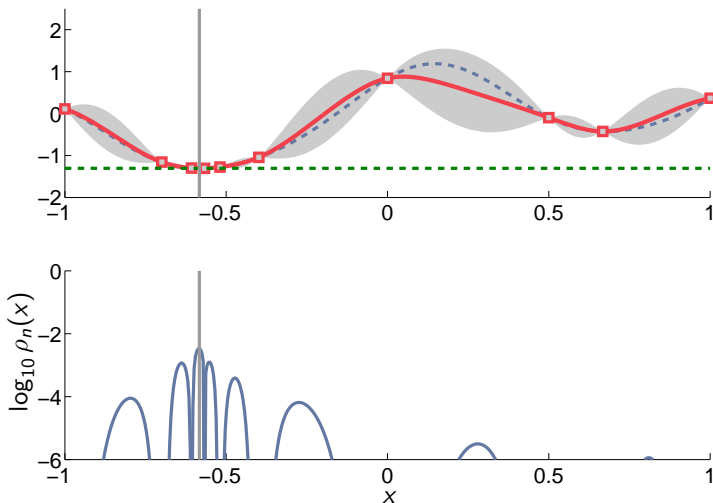
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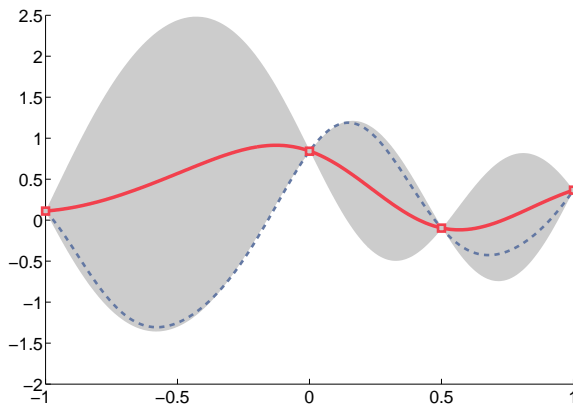
## Example of quantity of interest: the minimizer

- ▶ Assume an unknown function  $f : \mathbb{X} \rightarrow \mathbb{R}$  and suppose we are interested in seeking its **minimizer**:

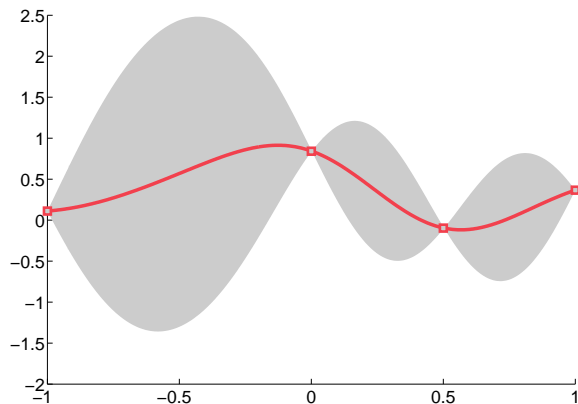
$$x^* = \operatorname{argmin}_x f(x)$$

- ▶ Choose a GP prior  $\xi$  for  $f$ . Given observations  $\xi(x_1), \dots, \xi(x_n)$ , what is the posterior distrib. of  $X^* = \operatorname{argmin}_x \xi(x)$ ?
- ▶ Unlike  $I_n$  above, the distrib. of  $X^*$  does not possess a closed-form expression  $\rightarrow$  resort to an **empirical estimation using conditional sample paths**

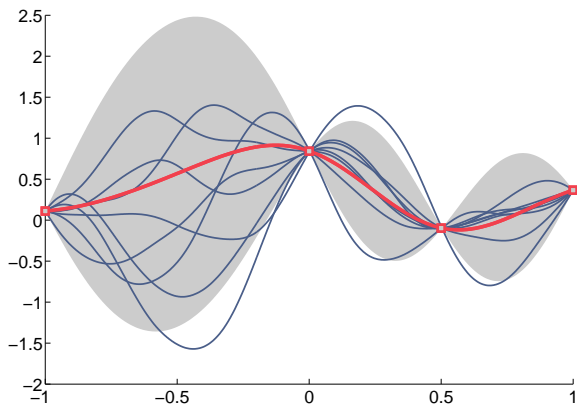
# Empirical posterior density of the minimizer



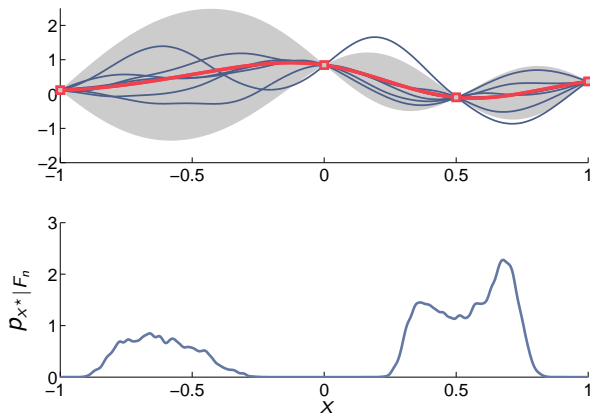
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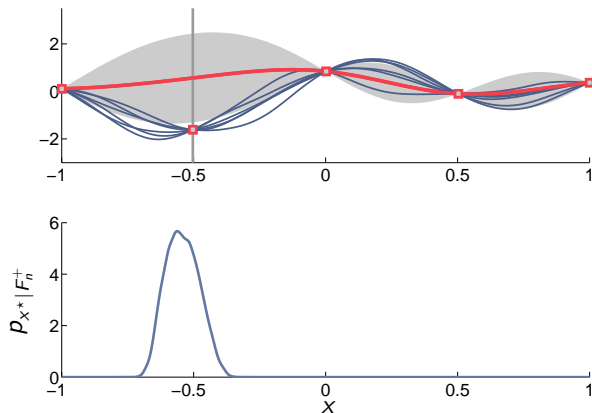
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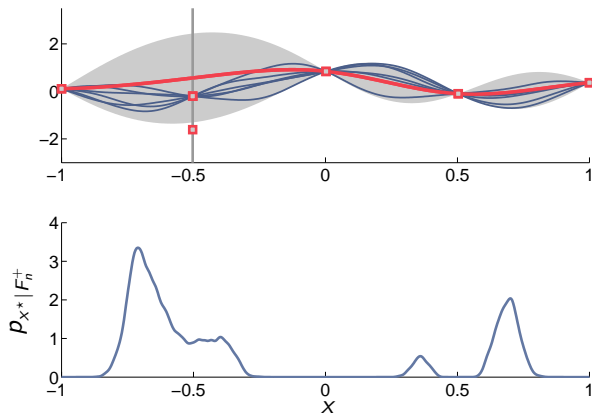
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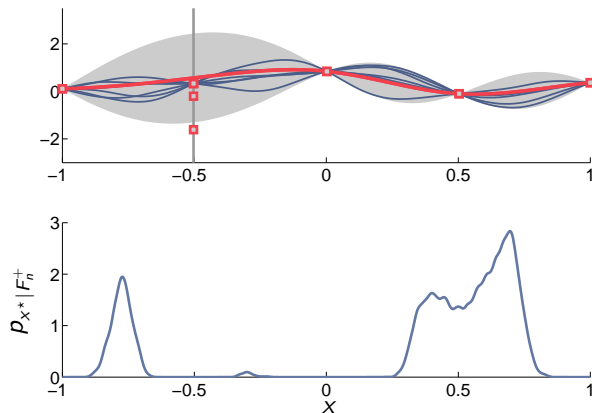
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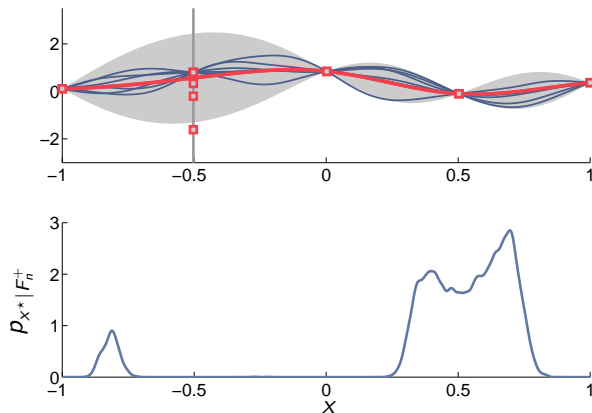


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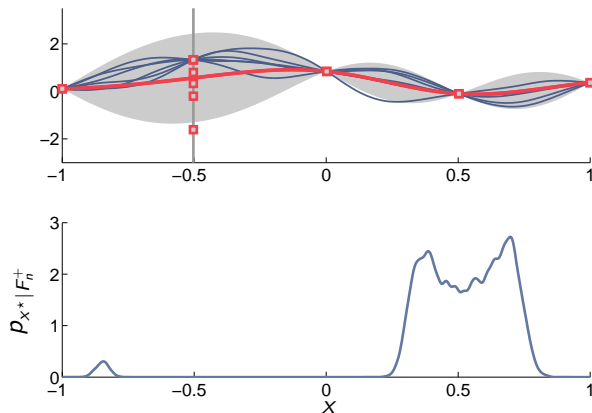




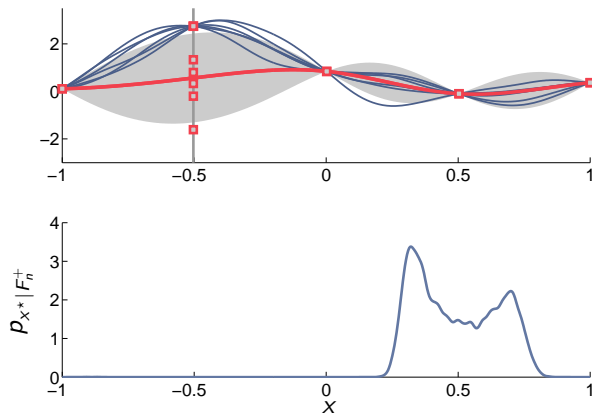
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## Lecture 1 : From meta-models to UQ

1.1 Introduction

1.2 Black-box modeling

1.3 Bayesian approach

1.4 Posterior distribution of a quantity of interest

1.5 Complements on Gaussian processes

# Choosing a centered Gaussian random process

How to choose the covariance function of a GP  $\xi \sim \mathcal{N}(0, k)$ ?

# Regularity properties of a random process

Def.

Given  $x_0 \in \mathbb{R}^d$ , a random process  $\xi$  is said to be **continuous in mean-square** at  $x_0$  iff

$$\lim_{x \rightarrow x_0} E[(\xi(x) - \xi(x_0))^2] = 0$$

Prop.

*Let  $\xi$  be a second-order random process with continuous mean function and stationary covariance function  $k$ .  $\xi$  is continuous in mean-square iff  $k$  is continuous at zero.*

# Regularity properties of a random process

Def.

For  $x, h \in \mathbb{R}^d$ , define the random variable

$$\xi_h(x) = \frac{\xi(x_0 + h) - \xi(x_0)}{\|h\|}$$

$\xi$  is **mean-square differentiable** at  $x_0$  iff there exists a random vector  $\nabla \xi(x_0)$  such that

$$\lim_{h \rightarrow 0} \mathbb{E} \left[ (\xi_h(x_0) - (\nabla \xi(x_0), h))^2 \right] = 0$$

Prop.

*Let  $\xi$  be a second-order random process with differentiable mean function and stationary covariance function  $k$ .  $\xi$  is differentiable in mean-square iff  $k$  is two-time differentiable at zero.*

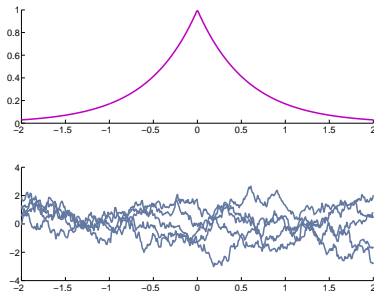
# Regularity properties of a random process

- Differentiability of the covariance function **at the origin**  $\rightarrow$  **mean-square differentiability** of  $\xi$

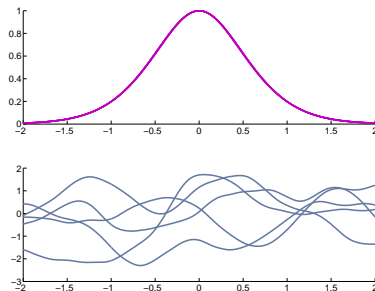


# Influence of the regularity

mean-square continuity



three-time mean-square  
differentiability



## Choice of a covariance

- ▶ A Gaussian process prior carries a high amount of information about  $f$ 
  - it is often difficult to elicit such a prior before any evaluation is made
- ▶ Covariance function of  $\xi$  is usually assumed to belong to some **parametric class of positive definite functions**
- ▶ Parameter values assumed to be unknown
- ▶ Two approaches:
  1. The parameters can be estimated from the evaluation results by **maximum likelihood**, and then used as if they were known (plug-in approach)
  2. We can assume a prior distrib. for the parameters of the covariance and use a **fully Bayesian approach**

# Choice of a parametrized covariance function: the Matérn covariance

- ▶ The **Matérn covariance** function is a conventional covariance function in the literature of computer experiments  
→ offers the possibility to adjust the regularity of  $\xi$  with a single parameter
- ▶ The Matérn function:

$$\kappa_\nu(h) = \frac{1}{2^{\nu-1}\Gamma(\nu)} \left(2\nu^{1/2}h\right)^\nu \mathcal{K}_\nu\left(2\nu^{1/2}h\right), \quad h \in \mathbb{R} \quad (1)$$

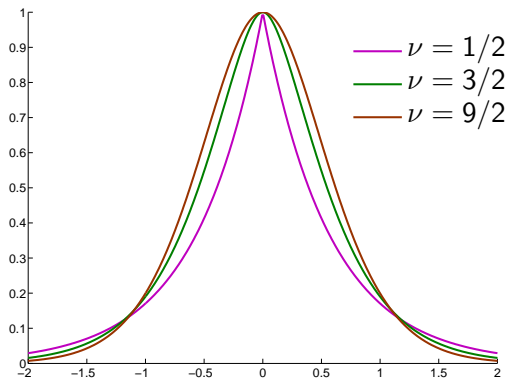
with

- $\Gamma$  the Gamma function
  - $\mathcal{K}_\nu$  the modified Bessel function of the second kind
- ▶ To model a real-valued function defined over  $\mathbb{X} \subset \mathbb{R}$ , we use the Matérn covariance:

$$k_\theta(h) = \sigma^2 \kappa_\nu(|h|/\rho), \quad h \in \mathbb{R} \quad (2)$$

# Choice of a parametrized covariance function: the Matérn covariance

Matérn covariance in one dimension  $\sigma^2 = 1$ ,  $\rho = 0.8$



$\xi$  is  $p$ -time mean-square differentiable iff  $\nu > p$

# Choice of a parametrized covariance function: the Matérn covariance

- ▶ To model a function  $f$  defined over  $\mathbb{X} \subset \mathbb{R}^d$ , with  $d > 1$ , we use the anisotropic form of the Matérn covariance:

$$k_{\theta}(x, y) = \sigma^2 \kappa_{\nu} \left( \sqrt{\sum_{i=1}^d \frac{(x[i] - y[i])^2}{\rho_i^2}} \right), \quad x, y \in \mathbb{R}^d \quad (3)$$

where  $x[i], y[i]$  denote the  $i^{\text{th}}$  coordinate of  $x$  and  $y$ , and the positive scalars  $\rho_i$  represent scale parameters

- ▶ Since  $\sigma^2 > 0, \nu > 0, \rho_i > 0, i = 1, \dots, d$ , in practice, we consider the vector of parameters

$$\theta = \{\log \sigma^2, \log \nu, -\log \rho_1, \dots, -\log \rho_d\} \in \mathbb{R}^{d+2}$$

→ makes parameter estimation easier

# Parameter estimation by maximum likelihood

- ▶ Assume  $\xi$  is a zero-mean Gaussian process
- ▶ The log-likelihood of the data  $\underline{\xi}_n = (\xi(x_1), \dots, \xi(x_n))^t$  can be written as

$$\ell(\underline{\xi}_n; \theta) = -\frac{n}{2} \log(2\pi) - \frac{1}{2} \log \det K(\theta) - \frac{1}{2} \underline{\xi}_n^t K(\theta)^{-1} \underline{\xi}_n, \quad (4)$$

where  $K(\theta)$  is the covariance matrix of  $\underline{\xi}_n$ , which depends on the parameter vector  $\theta$

- ▶ The log-likelihood can be maximized using a gradient-based search method

# Prediction of a Gaussian process with unknown mean function

- ▶ In the domain of computer experiments, the mean of a Gaussian process is generally written as a linear parametric function

$$m(\cdot) = \beta^t \varphi(\cdot), \quad (5)$$

with

- $\beta$  a vector of unknown parameters
  - $\varphi = (\varphi_1, \dots, \varphi_l)^t$  an  $l$ -dimensional vector of functions (in practice, polynomials)
- ▶ Simplest case: the mean function is an unknown constant  $m$ , in which case  $\beta = m$  and  $\varphi : x \in \mathbb{X} \mapsto 1$

## Prediction of a Gaussian process with unknown mean function

- ▶ Define the linear space of functions

$$\mathcal{P} = \left\{ x \mapsto \sum_{i=1}^l \beta_i \varphi_i(x); \beta_i \in \mathbb{R} \right\},$$

- ▶ Define  $\Lambda$  the linear space of finite-support measures on  $\mathbb{X}$ , i.e.

$$\lambda \in \Lambda \implies \lambda = \sum_{i=1}^n \lambda_i \delta_{x_i} \text{ for some } n \in \mathbb{N}$$

- ▶ For  $f : \mathbb{X} \rightarrow \mathbb{R}$ , and  $\lambda = \sum_{i=1}^n \lambda_i \delta_{x_i} \in \Lambda$ ,

$$\langle \lambda, f \rangle = \int_{\mathbb{X}} f \, d\lambda = \sum_{i=1}^n \lambda_i f(x_i)$$

- ▶ Define the linear subspace  $\Lambda_{\mathcal{P}^\perp} \subset \Lambda$  of finite-support measures vanishing on  $\mathcal{P}$ , i.e.

$$\lambda \in \Lambda_{\mathcal{P}^\perp} \implies \langle \lambda, f \rangle = \int_{\mathbb{X}} f \, d\lambda = \sum_{i=1}^n \lambda_i f(x_i) = 0, \quad \forall f \in \mathcal{P}$$



## Prediction of a Gaussian process with unknown mean function

- ▶ Let  $\xi$  be a Gaussian random process with an unknown mean in  $\mathcal{P}$ , and a covariance function  $k$
- ▶ For  $x \in \mathbb{X}$ , the (intrinsic) kriging predictor  $\hat{\xi}_n(x)$  of  $\xi(x)$  from  $\xi(x_1), \dots, \xi(x_n)$  is the linear projection

$$\hat{\xi}_n(x) = \sum_i \lambda_i(x) \xi(x_i)$$

of  $\xi(x)$  onto  $\text{span}\{\xi(x_i), i = 1, \dots, n\}$  such that the variance of the error  $\xi(x) - \hat{\xi}_n(x)$  is minimized, under the constraint

$$\delta_x - \sum \lambda_i(x) \delta_{x_i} \in \Lambda_{\mathcal{P}^\perp}$$

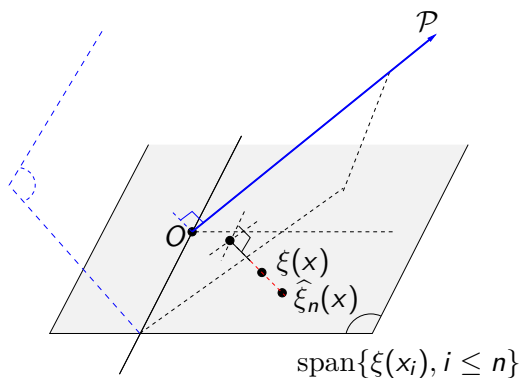
i.e.,

$$\langle \delta_x - \sum \lambda_i(x) \delta_{x_i}, \varphi_j \rangle = \varphi_j(x) - \sum \lambda_i(x) \varphi_j(x_i) = 0, \quad j = 1, \dots, l$$

- ▶ The requirement  $\delta_x - \sum \lambda_i(x) \delta_{x_i} \in \Lambda_{\mathcal{P}^\perp}$  makes the kriging predictor **unbiased, even if the mean of  $\xi$  is unknown**

# Prediction of a Gaussian process with unknown mean function

$\hat{\xi}_n(x)$  is the linear projection of  $\xi(x)$  onto  $\text{span}\{\xi(x_1), \dots, \xi(x_n)\}$  orthogonally to  $\mathcal{P}$



# Prediction of a Gaussian process with unknown mean function

- ▶ The weights  $\lambda_i(x; x_n)$  are again solutions of a **system of linear equations**, which can be written under a matrix form as

$$\begin{pmatrix} K & \underline{\varphi}^t \\ \underline{\varphi} & 0 \end{pmatrix} \begin{pmatrix} \lambda(x) \\ \mu(x) \end{pmatrix} = \begin{pmatrix} k(x) \\ \varphi(x) \end{pmatrix}, \quad (6)$$

with

- $\underline{\varphi}$  an  $l \times n$  matrix with entries  $\varphi_i(x_j)$ ,  $i = 1, \dots, l$ ,  $j = 1, \dots, n$
- $\mu$  a vector of Lagrange coefficients
- $K$ ,  $\lambda(x)$ ,  $k(x)$  as above

## Prediction of a Gaussian process with unknown mean function

- ▶ When the mean is unknown, the **kriging covariance function** (the covariance of the error of prediction) is given by

$$\begin{aligned} k_n(x, y) &:= \text{cov} \left( \xi(x) - \hat{\xi}_n(x), \xi(y) - \hat{\xi}_n(y) \right) \\ &= k(x - y) - \lambda(x)^{\text{t}} k(y) - \mu(x)^{\text{t}} \varphi(y). \end{aligned}$$

### Prop.

Let  $k$  be a covariance function and assume  $m \in \mathcal{P}$ .

$$\text{If } \begin{cases} \xi \mid m \sim \mathcal{GP}(m, k) \\ m : x \mapsto \beta^{\text{t}} \varphi(x), \beta \sim \text{U}(\mathbb{R}^l) \end{cases} \quad \text{then } \xi \mid F_n \sim \mathcal{GP}(\hat{\xi}_n(\cdot), k_n(\cdot, \cdot))$$

with  $\text{U}(\mathbb{R}^l)$  the (improper) uniform distribution over  $\mathbb{R}^l$

→ justifies the use of kriging in a **Bayesian framework** provided that the covariance function of  $\xi$  is known

# Parameter estimation with unknown mean function

- ▶ Objective: estimate the covariance parameters of a Gaussian process with unknown mean
- ▶ **Restricted Maximum Likelihood (REML)** approach  $\rightarrow$  maximize the **likelihood of the increments** (or generalized increments) of the data
- ▶ Let  $\xi$  be a Gaussian process with an **unknown mean** function in  $\mathcal{P}$  and  $\underline{\xi}_n$  the random vector of observations at points  $x_i$ ,  $i = 1, \dots, n$
- ▶ Let  $\underline{\varphi} = (\varphi_i(x_j))_{i,j=1}^{l,n}$  be the  $l \times n$  matrix of basis functions of  $\mathcal{P}$  evaluated on  $\{x_1, \dots, x_n\}$ .

## Parameter estimation with unknown mean function

- ▶ Since the dimension of  $\mathcal{P}$  is  $l$ , the dimension of the space of the measures with support  $\{x_1, \dots, x_n\}$  that cancel out the functions of  $\mathcal{P}$  is  $n - l$ .
- ▶ Assume an  $n \times (n - l)$  matrix  $W$  with rank  $n - l$  has been found, such that

$$\underline{\varphi} W = 0.$$

(The columns of  $W$  are in the kernel of  $\underline{\varphi}$ .)

- ▶ Then  $Z = W^T \underline{\xi}_n$  is a Gaussian random vector taking its values in  $\mathbb{R}^{n-l}$ , with **zero mean** and covariance matrix

$$W^T K(\theta) W$$

where  $K(\theta)$  is the covariance matrix of  $\underline{\xi}_n$  with entries  $k_\theta(x_i - x_j)$

- ▶ The random vector  $Z$  is a **contrast vector**
- ▶ The log-likelihood of the contrasts is given by

$$L(z \mid \theta) = -\frac{n-l}{2} \log 2\pi - \frac{1}{2} \log \det(W^t K(\theta) W) - \frac{1}{2} z^t (W^t K(\theta) W)^{-1} z.$$

- ▶ Various methods may be employed to compute the matrix  $W$
- ▶ We favor the QR decomposition of  $\underline{\varphi}^T$

$$\underline{\varphi}^T = (Q_1 \mid Q_2) \begin{pmatrix} R \\ 0 \end{pmatrix},$$

where  $(Q_1 \mid Q_2)$  is an  $n \times n$  orthogonal matrix and  $R$  is a  $l \times l$  upper triangular matrix

- ▶ It is trivial to check that the columns of  $Q_2$  form a basis of the kernel of  $\underline{\varphi}$
- ▶ So we may chose  $W = Q_2$
- ▶ Note that  $W^T W = I_{n-l}$ .



# Books

- ▶ **M. Stein**, Interpolation of Spatial Data: Some Theory for kriging, Springer, 1999
- ▶ **T. Santner, B. Williams and W. Notz**, The Design and Analysis of Computer Experiments, Springer, 2003
- ▶ **C. Rasmussen and C. Williams**, Gaussian processes for Machine Learning, MIT Press, 2006
- ▶ **A. Forrester, A. Sóbester and A. Keane**, Engineering design via surrogate modelling: a practical guide, John Wiley & Sons, 2008

## Lecture 1 : From meta-models to UQ

- 1.1 Introduction
- 1.2 Black-box modeling
- 1.3 Bayesian approach
- 1.4 Posterior distribution of a quantity of interest
- 1.5 Complements on Gaussian processes

## Lecture 2 : Bayesian optimization (BO)

- 2.1. Decision-theoretic framework
- 2.2. From Bayes-optimal to myopic strategies
- 2.3. Design under uncertainty

## References

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  - ▶ optimization using tools from Bayesian UQ

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  - ▶ optimization using tools from Bayesian UQ
  - ▶ started with **Harold Kushner**'s paper: *A New Method of Locating the Maximum Point of an Arbitrary Multipeak Curve in the Presence of Noise*, J. Basic Engineering, 1964.



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- ▶ a slightly more restrictive definition
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# What is Bayesian optimization ?

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  - ▶ sequential Bayesian decision theory applied to optimization
  - ▶ started with the work of **Jonas Mockus** and **Antanas Žilinskas** in the 70's, e.g., *On a Bayes method for seeking an extremum*, *Avtomatika i Vychislitel'naya Teknika*, 1972 (in Russian)



# What is Bayesian optimization ?

- ▶ a slightly more restrictive definition
  - ▶ sequential Bayesian decision theory applied to optimization
  - ▶ started with the work of Jonas Mockus and Antanas Žilinskas in the 70's, e.g., *On a Bayes method for seeking an extremum*, *Avtomatika i Vychislitel'naya Teknika*, 1972 (in Russian)



- ▶ In this lecture we adopt this second (more constructive !) definition

## Lecture 2 : Bayesian optimization (BO)

2.1. Decision-theoretic framework

2.2. From Bayes-optimal to myopic strategies

2.3. Design under uncertainty



# Decision-theoretic framework

## Decision-theoretic framework

- ▶ Bayesian decision theory (BDT) in a nutshell
  - ▶ a mathematical framework for **decisions under uncertainty**
  - ▶ uncertainty is captured by **probability distributions**
  - ▶ the “Bayesian agent” aims at **minimizing the expected loss**



# Decision-theoretic framework (cont'd)

- ▶ How does this relate to optimization ?

## Decision-theoretic framework (cont'd)

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- ▶ The **agent** is the **optimization algorithm** (or you, if you will)

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### Ingredients of a BDT problem

- ▶ a set of all possible “states of nature”
- ▶ a prior distribution over the states of nature
- ▶ a description of the decisions we have to make
- ▶ and the corresponding “transitions”
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- ▶ Short answer
  - ▶ Everything that “nature” knows but you don't

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- ▶ More practically: depends on the type of problem
  1. the **content of the black box** (expensive numerical model)
  2. for stochastic simulators: **future responses** of the simulator
  3. design under uncertainty: the value of **environmental variables**
  4. ...



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  3. design under uncertainty: the value of environmental variables
  4. ...

## Notation

$$\Omega = \{\text{all possible states } \omega \text{ of nature}\}$$

# States of nature: example

- ▶ Consider the following setting
  - ▶ a **deterministic** numerical model
  - ▶ input space  $\mathbb{X} \subset \mathbb{R}^d$ , output space  $\mathbb{R}^p$
  - ▶ **no environmental** variables in the problem
- ▶ States of nature for this setting
  - ▶  $\Omega = \{f : \mathbb{X} \rightarrow \mathbb{R}^p \mid f \text{ such that } \dots\}$

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- ▶ States of nature for this setting
  - ▶  $\Omega = \{f : \mathbb{X} \rightarrow \mathbb{R}^p \mid f \text{ such that } \dots\}$
  - ▶ e.g.,  $d = 1$ ,  $p = 1$ ,  $\mathbb{X} = [0; 1]$  and  $\Omega = C(\mathbb{X}; \mathbb{R})$
- ▶ Until further notice, we will use this simple (but important) setting to illustrate the basics of Bayesian optimization

# Uncertainty quantification (reminder from Lecture #1)

- ▶ The true state of nature  $\omega^* \in \Omega$  is **unknown**
- ▶ Example (cont'd)
  - ▶ a function  $f^* \in \Omega = C(\mathbb{X}; \mathbb{R})$  is inside the black box ( $\omega^* \equiv f^*$ )
  - ▶ we don't “know”  $f^*(x)$  until we run the code with input  $x$

# Uncertainty quantification (reminder from Lecture #1)

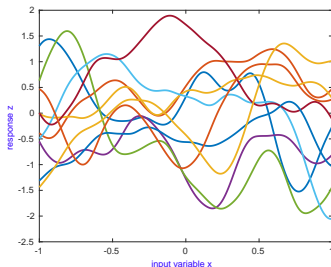
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- ▶ Bayesian approach to UQ
  - ▶ our knowledge of  $\omega^*$  is encoded by a **probability distribution** on the set  $\Omega$  of all possible  $\omega$ 's
  - ▶ technically: proba on  $(\Omega, \mathcal{F})$  for some  $\sigma$ -algebra  $\mathcal{F} \dots$

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- ▶ Sequence of decisions  $\Rightarrow$  **sequence of distributions**  $P_0, P_1, \dots$ 
  - ▶  $P_n$  corresponds to the agent's beliefs after the  $n^{\text{th}}$  decision
  - ▶ A **prior distribution**  $P_0$  needs to be specified

# Uncertainty quantification: example

- ▶ Example (cont'd): if  $f$  is known to look more or less like this:

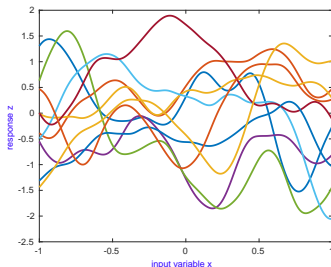


then we can take  $P_0 = \mathcal{GP}(m, k)$

with  $m \sim \mathcal{U}(\mathbb{R})$  and  $k$  a (stationary) Matérn covariance

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- ▶ Gaussian process priors are commonly used because
  - ▶ they are **computationally convenient**
  - ▶ while allowing a certain **modeling flexibility**



# Uncertainty quantification: consequences

- ▶ For clarity, consider again the case of a **deterministic model**:
  - ▶ an **unknown function**  $f \in \Omega$  is in the black box

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    - ▶ compute the **probability** of any (measurable) statement about  $f$
    - ▶ compute the **expectation** of any (measurable) function of  $f$
- i.e., the unknown  $f$  can be **treated as random**

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- i.e., the unknown  $f$  can be treated as random

## Convenient notation

$\xi$  = random function that represents the unknown  $f$

- ▶ we will write, e.g.,  $E_n(\xi(x))$  instead of  $\int_{\Omega} f(x) P_n(df)$  ☺

## Decision-theoretic framework (cont'd)

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- ▶ The agent is the optimization algorithm (or you, if you will)

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# Decisions

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- ▶ Intermediate decisions (simple setting)
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  - ▶ getting the corresponding output (deterministic or random)
- ▶ Intermediate decisions (various extensions)
  - ▶ parallel computing: **batches** of input values
  - ▶ multi-fidelity: choosing the right **fidelity level**
  - ▶ variable run-time: choosing when to **stop a computation**
  - ▶ ...



# Decisions: stopping decision

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  - ▶ **stopping decision**
  - ▶ final decision
- ▶ Stopping decision (standard setting)
  - ▶ a **budget of evaluations**, or computation time, is given
  - ▶ the stopping decision is trivial in this case

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- ▶ Stopping decision (standard setting)
  - ▶ a budget of evaluations, or computation time, is given
  - ▶ the stopping decision is trivial in this case
- ▶ Digression: taking the cost of observations into account?
  - ▶ *in principle*, BO can deal with the stopping decision too
  - ▶ in practice, difficult to translate into a loss (see later)
  - ▶ some “BO papers” propose heuristic stopping rule

# Decisions: final decision

- ▶ Several types of decisions in an optimization procedure:
  - ▶ intermediate decisions
  - ▶ stopping decision
  - ▶ **final decision**
- ▶ Final decision (ex: single-objective minimization pb.)
  - ▶ an **estimate of the minimizer**  $x^* = \operatorname{argmin}_{x \in \mathbb{X}} f(x)$
  - ▶ and/or an **estimate of the minimum**  $M^* = \min_{x \in \mathbb{X}} f(x)$

with  $\mathbb{X}$  a “known” input space

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- ▶ Other settings

- ▶ **multi-objective**: Pareto set / Pareto front (see later),
- ▶ **inequality constraints** (see later), equality constraints (harder !)
- ▶ quasi-optimal region (sublevel set)...

# Decisions: standard setting and notations

- ▶ From now on we focus on the “standard” setting
  - ▶ intermediate decisions  $\equiv$  evaluations (known comput. cost)
  - ▶ stopping: a budget of  $N$  evaluations is given

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## Notations

$X_n(\omega)$  = the  $n^{\text{th}}$  evaluation point

$D_{N+1}(\omega)$  = the “final decision” (estimate of the QoI)

$\underline{D}(\omega) = (X_1(\omega), \dots, X_N(\omega), D_{N+1}(\omega))$

# Transitions: conditioning probability measures

- ▶ Recall that
  - ▶ the agent's knowledge at time  $n$  is described by  $P_n$
  - ▶ the  $(n + 1)^{\text{th}}$  decision induces a transition  $P_n \rightarrow P_{n+1}$





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- ▶ We cannot use information that is not yet available
  - ▶  $X_n(\omega)$  depends on  $\omega$  **through  $F_{n-1}$  only**
  - ▶  $D_{N+1}(\omega)$  depends on  $\omega$  **through  $F_N$  only**
  - ▶  $\underline{D}$  is a decision **strategy** (sequence of **decision rules**)

# Transitions: examples

- ▶ Example (cont'd)
  - ▶ single-output, deterministic code
  - ▶  $I_n = (X_n, \xi(X_n))$  and  $F_n = (X_1, \xi(X_1), \dots, X_n, \xi(X_n))$
  - ▶  $\xi(X_i) = f^*(X_i)$  is the true, scalar, value of the model at  $X_i$

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- ▶ Many other (interesting) settings are possible !
  - ▶ **stochastic simulators**
    - ▶ the output is a random draw  $Z_n \sim$  some distrib.  $\mathbf{P}^{Z_n|X_n}$
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  - ▶ variable run-times, “simulation failures”...

## Decision-theoretic framework (cont'd)

- ▶ How does this relate to optimization ?
- ▶ The agent is the optimization algorithm (or you, if you will)

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# Loss function

- To guide the decisions of the Bayesian agent, we need to specify a **loss function**  $L$

## Notation

$$L : \Omega \times \mathbb{D} \rightarrow \mathbb{R}$$

$$(\omega, \underline{d}) \mapsto L(\omega, \underline{d})$$

where  $\mathbb{D}$  is the set of all possible sequences of decisions

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- The **Bayes-optimal strategy** is, by definition:

$$\begin{aligned} \underline{D} &= \operatorname{argmin} E_0(L(\underline{D})) \\ &= \operatorname{argmin} \int_{\Omega} L(\omega, \underline{D}(\omega)) P_0(d\omega) \end{aligned}$$

where  $\underline{D}$  ranges over all strategies

# Loss function: example

- ▶ Example (cont'd)
  - ▶ Assume that we want to find the minimizer of  $f$ 
    - ▶  $\underline{d} = (x_1, \dots, x_n, \hat{x})$
    - ▶ with  $\hat{x}$  our estimate of  $\operatorname{argmin} f$

# Loss function: example

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- ▶ with  $\hat{x}$  our estimate of  $\operatorname{argmin} f$

- ▶ A standard loss function for this situation is the **linear loss**:

$$L(f, \underline{d}) = L(f, \hat{x}) = f(\hat{x}) - \min f$$

(a.k.a. **opportunity cost**, a.k.a. **instantaneous regret**)

# Loss function: example

## ► Example (cont'd)

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(a.k.a. opportunity cost, a.k.a. instantaneous regret)

## ► Remarks

- $L$  coincides with the  $L^1$  loss of the estimator  $f(\widehat{x})$

$$f(\widehat{x}) \geq \min f \quad \Rightarrow \quad L(f, \widehat{x}) = |f(\widehat{x}) - \min f|$$

- $L$  is a **terminal loss** (does not depend on  $X_1, \xi(X_1), \dots$ )

## Decision-theoretic framework (cont'd)

- ▶ How does this relate to optimization ?
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- ▶ Our BDT framework is complete, let's use it ☺

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## Lecture 2 : Bayesian optimization (BO)

2.1. Decision-theoretic framework

2.2. From Bayes-optimal to myopic strategies

2.3. Design under uncertainty

# Problem statement

- ▶ Assume a standard BO setting
  - ▶ fixed budget  $N$ , terminal cost only
    - ▶  $L(\omega, \underline{d}) = L(\omega, d_{N+1})$
  - ▶ intermediate decisions  $\equiv$  evaluations
    - ▶ one at a time, possibly noisy (stochastic simulator)
    - ▶  $F_n = (X_1, Z_1, \dots, X_n, Z_n)$

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    - ▶ one at a time, possibly noisy (stochastic simulator)
    - ▶  $F_n = (X_1, Z_1, \dots, X_n, Z_n)$
- ▶ Recall the **Bayes-optimal strategy** (algorithm):

$$\begin{aligned}\underline{D}^{\text{Bayes}} &= \operatorname{argmin}_{\underline{D}} E_0(L(D_{N+1})) \\ &= \operatorname{argmin}_{\underline{D}} \int_{\Omega} L(\omega, D_{N+1}(\omega)) P_0(d\omega)\end{aligned}$$

where  $\underline{D}$  ranges over all strategies  $\underline{D} = (X_1, \dots, X_N, D_{N+1})$

# Problem statement

What does this  $\underline{D}^{\text{Bayes}}$  look like ?

Can we actually **build an optimal Bayesian algorithm** ?

# Problem statement (more precisely)

- ▶ Recall that
  - ▶  $X_{n+1}(\omega)$  must depend on  $\omega$  through  $F_n$  only
  - ▶  $D_{N+1}(\omega)$  must depend on  $\omega$  through  $F_N$  only

# Problem statement (more precisely)

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## Notations

$$X_{n+1} = \varphi_n(X_1, Z_1, \dots, X_n, Z_n) = \varphi_n(F_n)$$

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- ▶ Goal: find the functions  $\varphi_0, \dots, \varphi_N$

## Lecture 2 : Bayesian optimization (BO)

### 2.2. From Bayes-optimal to myopic strategies

The optimal terminal decision

Optimal choice of the last evaluation

Bayes-optimal versus “practical Bayes” optimization

Sampling criteria for multi-objective and/or constrained optimization



# Optimal terminal decision

## Notation

$E_n = E(\cdot \mid F_n)$  = conditional expectation with respect to  $F_n$   
= expectation with respect to the probability  $P_n$

# Optimal terminal decision

## Notation

$E_n = E(\cdot \mid F_n)$  = conditional expectation with respect to  $F_n$   
= expectation with respect to the probability  $P_n$

- ▶ Consider any incomplete strategy  $X_1, \dots, X_N$
- ▶ Claim: the **optimal terminal decision** is

$$D_{N+1} = \varphi_N^{\text{Bayes}}(X_1, Z_1, \dots, X_N, Z_N) = \text{argmin}_d E_N(L(d))$$

where  $d$  runs over all possible values for the terminal decision

## Optimal terminal decision: proof

- ▶ Take **any strategy**  $\underline{D} = (X_1, \dots, X_N, D_{N+1})$
- ▶ Consider the **modified strategy**  $\underline{D}' = (X_1, \dots, X_N, D'_{N+1})$   
where  $D'_{N+1} = \varphi_N^{\text{Bayes}}(X_1, Z_1, \dots, X_N, Z_N)$

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- ▶ Then, by definition of  $\varphi_N^{\text{Bayes}}$ ,

$$\begin{aligned} E_N(L(D_{N+1})) &= E_N(L(d))|_{d=D_{N+1}} \\ &\geq \min_d E_N(L(d)) = E_N(L(D'_{N+1})) \end{aligned}$$

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- ▶ and thus

$$\begin{aligned} E_0(L(D_{N+1})) &= E_0(E_N(L(D_{N+1}))) \\ &\geq E_0(E_N(L(D'_{N+1}))) = E_0(L(D'_{N+1})) \quad \blacksquare \end{aligned}$$

## Vocabulary: posterior (Bayes) risk at time $N$

- ▶ Define the **posterior risk** at time  $N$  for the decision  $d$ :

$$R_N(d) = E_N(L(d))$$

(“risk” is a synonym for “expected loss”)

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(“risk” is a synonym for “expected loss”)

- ▶ Define the **posterior Bayes risk** at time  $N$ :

$$R_N^{\text{Bayes}} = \min_d R_N(d)$$

- ▶ Remember: the min attained for  $d = \varphi_N^{\text{Bayes}}(F_N)$

## Example (cont'd): linear loss

- ▶ Recall the setting
  - ▶ goal: minimize  $f$
  - ▶  $d_{N+1} = \hat{x}$  is an estimate of  $X^*(f) = \operatorname{argmin} f$
  - ▶  $L(f, \hat{x}) = f(\hat{x}) - \min f$



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- ▶ Compute the **posterior risk** at time  $N$  for a given  $\hat{x} \in \mathbb{X}$ :

$$\begin{aligned} R_N(\hat{x}) &= \mathbb{E}_N (L(\xi, \hat{x})) = \mathbb{E}_N (\xi(\hat{x}) - \min \xi) \\ &= \hat{\xi}_N(\hat{x}) - \mathbb{E}_N (\min \xi) \end{aligned}$$

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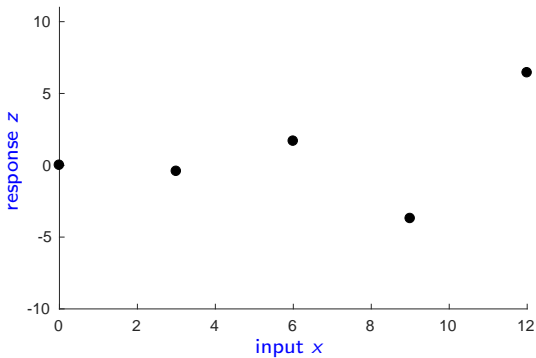
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- ▶ Thus the optimal terminal decision is

$$D_{N+1}^{\text{Bayes}} = \hat{X}^{\text{Bayes}} = \operatorname{argmin}_{x \in \mathbb{X}} \hat{\xi}_N(x)$$

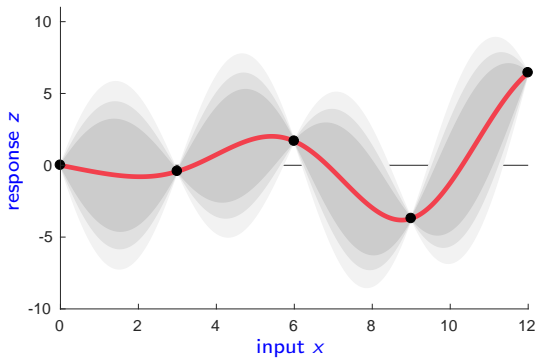
## Example (cont'd): linear loss

Assume that  $n = N = 5$  (a small budget indeed).



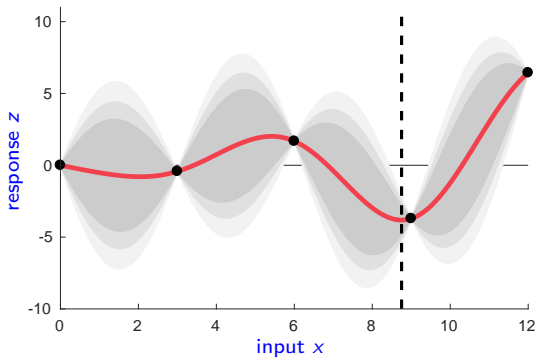
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- ▶ To summarize, we have for this example

$$\hat{X}^{\text{Bayes}} = \operatorname{argmin} \hat{\xi}_N$$

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- ▶ Remark: in general,  $\hat{X}^{\text{Bayes}} \notin \{X_1, \dots, X_N\}$ 
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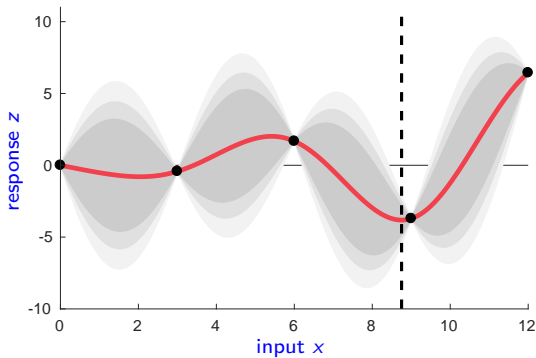
- ▶ Remark: in general,  $\hat{X}^{\text{Bayes}} \notin \{X_1, \dots, X_N\}$ 
  - ▶ the value of the function at  $\hat{X}^{\text{Bayes}}$  is not known
- ▶ Variant: restrict the terminal decision to  $\{X_1, \dots, X_N\}$

$$\hat{X}^{\text{Bayes},1} = \operatorname{argmin}_{x \in \{X_1, \dots, X_N\}} \xi(x)$$

$$R_N^{\text{Bayes},1} = \min_{i \leq N} \xi(X_i) - E_N(\min \xi)$$

## Example (cont'd): linear loss

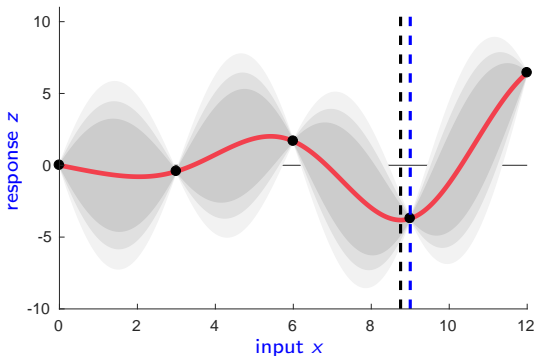
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Remark: the two estimates are equal when  $\hat{\xi}$  does not “overshoot”  
(e.g., for a Brownian motion prior)

## Lecture 2 : Bayesian optimization (BO)

### 2.2. From Bayes-optimal to myopic strategies

The optimal terminal decision

Optimal choice of the last evaluation

Bayes-optimal versus “practical Bayes” optimization

Sampling criteria for multi-objective and/or constrained optimization

## Finding $X_N^{\text{Bayes}}$ (last evaluation point)

- ▶ Let us focus now on the **last evaluation point**
  - ▶ recall that  $\underline{D} = (X_1, \dots, X_{N-1}, \mathbf{X}_N, D_{N+1})$

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### Notation

$E_{n,x}(Y)$  will mean: “compute  $E_n(Y)$ , assuming that  $X_{n+1} = x$ ”

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- ▶ For example, if  $Y = g(X_1, Z_1, \dots, X_n, Z_n, X_{n+1}, Z_{n+1})$ ,

$$E_{n,x}(Y) = E_n(g(X_1, Z_1, \dots, X_n, Z_n, x, Z_x))$$

where  $Z_x$  denotes the result of a new evaluation at  $x$

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- ▶ The corresponding **posterior risk at time  $N - 1$**  is

$$R_{N-1}(x_N) = \mathbb{E}_{N-1, x_N} \left( L(D_{N+1}^{\text{Bayes}}) \right) = \mathbb{E}_{N-1, x_N} \left( R_N^{\text{Bayes}} \right)$$

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- ▶ Remark:  $R_{N-1}$  is used as a “**sampling criterion**”  
(a.k.a. “infill criterion”, a.k.a. “merit function”...)

## Finding $X_N^{\text{Bayes}}$ : proof

- ▶ For **any strategy**  $\underline{D} = (X_1, \dots, X_{N-1}, \mathbf{X}_N, D_{N+1})$ ,

$$\begin{aligned} E_{N-1}(L(D_{N+1})) &= E_{N-1}(R_N(F_N, D_{N+1})) \\ &\geq E_{N-1}(R_N^{\text{Bayes}}(F_N)) = R_{N-1}(F_{N-1}, X_{N-1}) \end{aligned}$$

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- ▶ Thus  $E_0(L(D_{N+1})) \geq E_0(L(D'_{N+1}))$  ■

## Finding $X_N^{\text{Bayes}}$ : example (cont'd)

- Recall our **linear loss** example

$$\hat{X}^{\text{Bayes}} = \operatorname{argmin} \hat{\xi}_N$$

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- Compute the **posterior risk** at time  $N - 1$

$$\begin{aligned} R_{N-1}(F_{N-1}, x_N) &= E_{N-1, x_N} \left( R_N^{\text{Bayes}}(F_N) \right) \\ &= E_{N-1, x_N} \left( \min \hat{\xi}_N \right) - E_{N-1}(\min \xi) \end{aligned}$$

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- The **optimal decision** at time  $N - 1$  is

$$X_N = \operatorname{argmin}_{x_N} E_{N-1, x_N} \left( \min \hat{\xi}_N \right)$$

(first appears (in english) in Mockus, Tiesis & Žilinskas, 1978)



## Finding $X_N^{\text{Bayes}}$ : example (cont'd)

- Equivalently,

$$X_N = \operatorname{argmax}_{x_N} \underbrace{\min \hat{\xi}_{N-1} - E_{N-1, x_N} \left( \min \hat{\xi}_N \right)}_{\rho_{N-1}^{\text{KG}}(x_N) \geq 0}$$

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- Nowadays called the **Knowledge Gradient (KG)** criterion  
(Frazier, Powell & co-authors, 2008, 2009, 2011)

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  - ▶ applicable to “noisy” observations as well
  - ▶ a.k.a. simulation-based optimization

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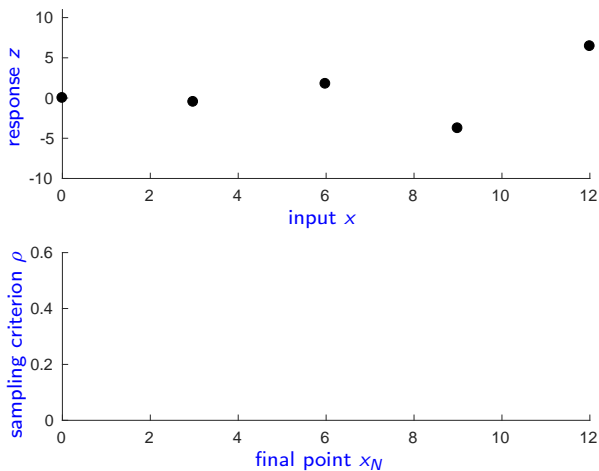
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  - ▶ applicable to “noisy” observations as well
    - ▶ a.k.a. simulation-based optimization
  - ▶ even with a GP prior,  $\rho^{\text{KG}}$  is **not exactly computable** in general
    - ▶ idea: approx. max over a finite grid (more about that later)

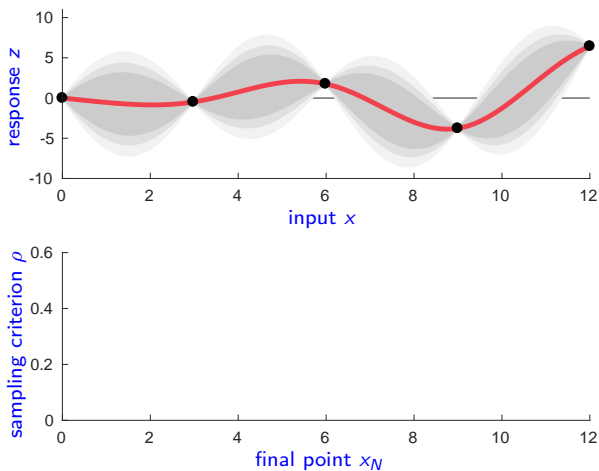
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Same example as before,  $n = 5$ , but assume now that  $N = 6$ .



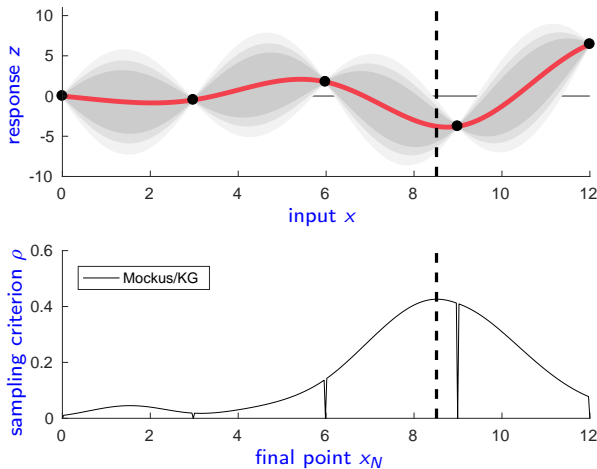
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## Finding $X_N^{\text{Bayes}}$ : example (cont'd)

Same example as before,  $n = 5$ , but assume now that  $N = 6$ .



Warning:  $X_N \neq \arg\max \hat{\xi}_{N-1}$  (uncertainty is taken into account)

## Finding $X_N^{\text{Bayes}}$ : example, variant (cont'd)

- Recall the following variant

$$\hat{X}^{\text{Bayes},1} = \operatorname{argmin}_{x \in \{X_1, \dots, X_N\}} \xi(x)$$

$$R_N^{\text{Bayes},1} = \min_{i \leq N} \xi(X_i) - E_N(\min \xi)$$



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- Set  $M_n = \min_{i \leq n} \xi(X_i)$ . The optimal decision at time  $N - 1$  is

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- This is the **Expected Improvement (EI)** criterion  
(Mockus et al 1978; Jones, Schonlau & Welch, 1998)

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- Recall the following variant

$$\hat{X}^{\text{Bayes},1} = \operatorname{argmin}_{x \in \{X_1, \dots, X_N\}} \xi(x)$$

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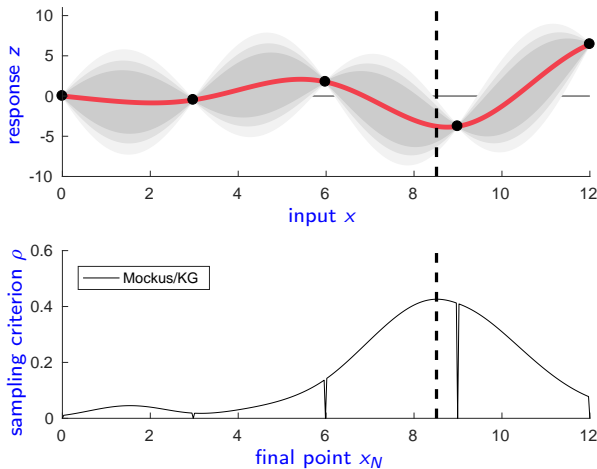
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- This is the Expected Improvement (EI) criterion  
(Mockus et al 1978; Jones, Schonlau & Welch, 1998)
- **Computable analytically** for GP priors  $\Rightarrow$  most commonly used  
(for *deterministic* numerical models)

## Finding $X_N^{\text{Bayes}}$ : example (cont'd)

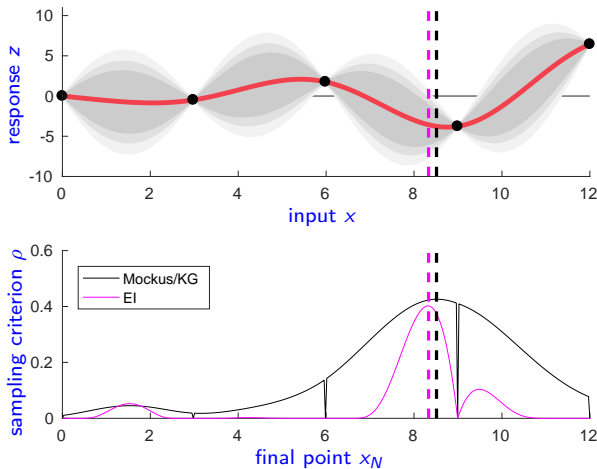
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# The Bayes-optimal strategy

- Recall the optimal terminal decision rule

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# The Bayes-optimal strategy

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$$R_N^{\text{Bayes}}(F_N) = \min_d E_N(L(d))$$

- Recall the **optimal rule for the last evaluation**

$$\varphi_{N-1}^{\text{Bayes}}(F_{N-1}) = \operatorname{argmin}_{x_N} E_{N-1, x_N} \left( R_N^{\text{Bayes}}(F_N) \right)$$

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# The Bayes-optimal strategy

- ▶ The entire **Bayes-optimal strategy** can be written similarly:  $\forall n$ ,

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- ▶ This is called backward induction (or dynamic programming)
- ▶ So what ? Can we use this ?

# The Bayes-optimal strategy

- More explicitly, the optimal decision for the first evaluation is

$$X_1 = \operatorname{argmin}_{x_1} E_{0,x_1} \left( \min_{x_2} E_{1,x_2} \left( \dots \right. \right. \\ \left. \left. \min_{x_N} E_{N-1,x_N} \left( \min_d E_N (L(d)) \right) \right) \right)$$

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- ▶ **Very difficult to use in practice** beyond  $N = 1$  or  $2$ 
  - ▶ each “min” is an optim. problem that needs to be solved...
  - ▶ each “ $E_{n,x}$ ” is an integral that needs to be computed...
  - ▶ none of them are tractable, even for the nicest (GP) priors ☹

# Practical Bayesian optimization: myopic strategies

- ▶ Practical BO algorithms use, in general, **myopic strategies**
  - ▶ a.k.a. one-step look-ahead strategies
  - ▶ principle: **make each decision as if it were the last one**
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## Generic myopic BO algorithm

- ▶ For  $n$  from 0 to  $N - 1$ 
  - ▶ Compute  $X_{n+1} = \operatorname{argmin}_x E_{n, x_{n+1}}(\bar{L}_{n+1})$
  - ▶ Make an evaluation at  $X_{n+1}$
- ▶ Output  $D_{N+1} = \operatorname{argmin} E_N(L(d))$

# Practical Bayesian optimization: hyper-parameters

- ▶ GP models have **hyper-parameters**  $\theta$  (variance, range, etc.)
  - ▶ **fully Bayes** approach (see Benassi 2013, chap. III, and refs)
    1. set up prior distributions on the hyper-parameters
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## Generic myopic BO algorithm with hyper-parameter estimation

- ▶ Init: (space-filling) DoE of size  $n_0$  (rule of thumb:  $n_0 = 10 d$ )
- ▶ For  $n$  from  $n_0$  to  $N - 1$ 
  - ▶ once in a while, Estimate hyper-parameters (plug-in/fully Bayes)
  - ▶ Compute  $X_{n+1} = \operatorname{argmin}_x E_{n, x_{n+1}}(\bar{L}_{n+1})$
  - ▶ Make an evaluation at  $X_{n+1}$
- ▶ Output  $D_{N+1} = \operatorname{argmin} E_N(L(d))$

# Practical Bayesian optimization: EGO

## STK demo

... single-objective box-constrained optimization  
with the EI criterion and a plug-in approach  
(a.k.a. the “EGO” algorithm) ...

# Practical Bayesian optimization: optimization

- ▶ Each iteration involves an **auxiliary optimization problem**

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- ▶ Bayesian optimization  $\Rightarrow$  run-time **overhead**
  - ▶ depends on the model, sampling criterion, optimizer, etc.
  - ▶ BO is appropriate for **expensive-to-evaluate** numerical models



## Lecture 2 : Bayesian optimization (BO)

### 2.2. From Bayes-optimal to myopic strategies

The optimal terminal decision

Optimal choice of the last evaluation

Bayes-optimal versus “practical Bayes” optimization

Sampling criteria for multi-objective and/or constrained optimization

# Multi-objective problems

- ▶ **Several objective functions** to be minimized:  $f = (f_1, \dots, f_p)$ 
  - ▶  $f_j : \mathbb{X} \rightarrow \mathbb{R}, 1 \leq j \leq p$

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## Pareto domination relation

$$z \prec z' \quad \text{if (def)} \quad \begin{cases} z_j \leq z'_j & \text{for all } j \leq p, \\ z_j < z'_j & \text{for at least one } j \leq p. \end{cases}$$

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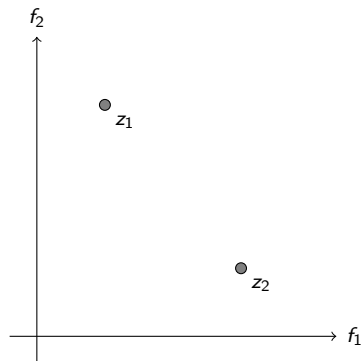
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  - ▶ and/or the **Pareto front**  $\{z \in \mathbb{R}^p : \exists x \in \mathbb{P}, z = f(x)\}$   
(a.k.a. Pareto frontier, Pareto boundary...)

# Multi-objective problems

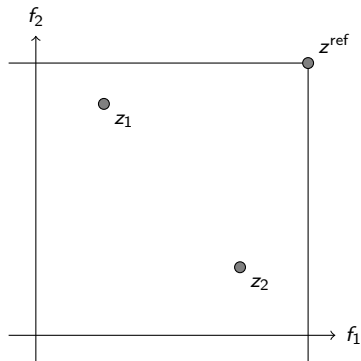
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Noiseless evaluations

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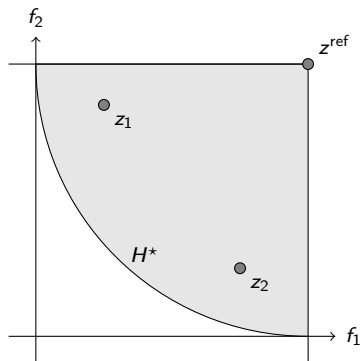


Noiseless evaluations

$$\mathbb{B} = \prod_{j=1}^p ]-\infty; z_j^{\text{ref}}]: \text{ bounding box}$$

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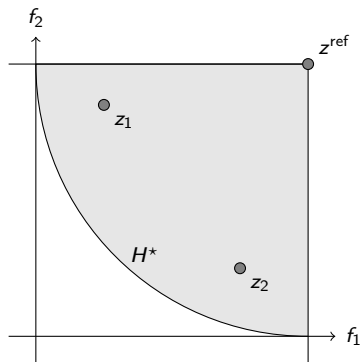
True **dominated region**:

$$H^*(f) = \{z \in \mathbb{B}, \exists x \in \mathbb{X}, f(x) \preceq z\}$$



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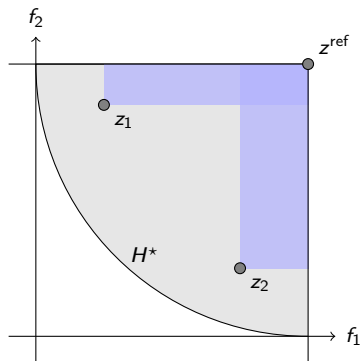
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Loss function:

$$L(f, \hat{H}) = |H^*(f) \Delta \hat{H}|$$

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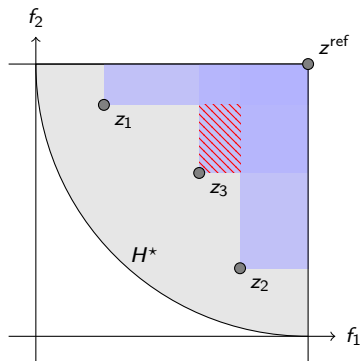
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$$\rho_n^{\text{EHVI}}(x_{n+1}) = \mathbb{E}_{n, x_{n+1}} (|H_{n+1} \setminus H_n|)$$

# Multi-objective problems

- ▶ Implementation

- ▶ Exactly computable for independent GP priors,  $2 \leq p \lesssim 5$
- ▶ **Implemented** in STK (Matlab/Octave), GPareto (R). . .
- ▶ Dependent priors, larger  $p$ : Monte Carlo approx.

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## STK demo

... bi-objective optimization with the EHVI criterion ...

*code by Etienne Leloup, Guillaume Maistre-Bazin, Luca Pouget  
CentraleSupélec final year project for CEA DIF*

# Inequality-constrained problems

- ▶ **Single-objective, inequality-constrained** problem:
  - ▶  $f = (f_o, f_{c,1}, \dots, f_{c,q})$ , with
  - ▶  $f_o : \mathbb{X} \rightarrow \mathbb{R}$ , to be minimized,
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- ▶ Consider the following **loss function**

$$L(f, \hat{x}) = \begin{cases} f_o(\hat{x}) - f_o^* & \text{if } f_c(\hat{x}) \leq 0, \\ +\infty & \text{otherwise.} \end{cases}$$

where  $f_o^* = \min_{x: f_c(x) \leq 0} f_o(x)$



# Inequality-constrained problems

► Assuming

- noiseless evaluations,
- independent priors on objective and constraint functions,
- $\exists i \leq n, \xi_c(X_i) = f_c(X_i) \leq 0$ ,

the following myopic criterion follows (Schonlau et al, 1998)

$$\rho_n^{\text{EIC}}(x_{n+1}) = \rho_{\text{O},n}^{\text{EI}}(x_{n+1}) \cdot \underbrace{\prod_{j=1}^q P_n(\xi_{c,j}(x_{n+1}) \leq 0)}_{\text{Proba of Feasibility (PF)}}.$$

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# Et maintenant une page de pub !

- ▶ BMOO algorithm (Feliot et al 2017)
  - ▶ Unified EI/EHVI/EIC criterion
    - ▶ well-defined even when no feasible point is known
  - ▶ Efficient SMC technique for criterion optimization
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## Announcement

Paul Feliot's PhD defense will take place

on **Wednesday, July 12, 2017**, 2 PM,

at CentraleSupélec (Gif). Venez nombreux !

# Miscellaneous references for further reading

- ▶ **Information-based** BO: a different approach
  - ▶ Risk = **entropy** of the minimizer
  - ▶ See Villemonteix et al (2009), Hennig & Schueller (2012), Hernandez-Lobáto and co-authors (2014, 2015...)

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- ▶ Noisy evaluations / stochastic simulators
  - ▶ will be discussed in the next part 😊

## Lecture 2 : Bayesian optimization (BO)

2.1. Decision-theoretic framework

2.2. From Bayes-optimal to myopic strategies

2.3. Design under uncertainty

## Lecture 2 : Bayesian optimization (BO)

### 2.3. Design under uncertainty

Overview of possible approaches

Optimization of a mean response

RBDO (and other formulations)

# Design under uncertainty

- ▶ Standard **design optimization** problem:
  - ▶ Minimize one **objective** (“cost”) **function**  $f_o(x)$
  - ▶ or several objective functions  $f_{o,1}(x), \dots, f_{o,p}(x)$
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## “Design under uncertainty” framework

- ▶ objective functions:  $f_{o,j}(x, u), 1 \leq j \leq p$
- ▶ constraint functions:  $f_{c,j}(x, u), 1 \leq j \leq q$
- ▶ where  $u$  denotes **factors that the designer cannot control**

## (a few words on the) Worst-case approach

- ▶ Principle of the **worst-case** (minimax) approach
  - ▶ Define an **uncertainty set**  $\mathbb{U}$
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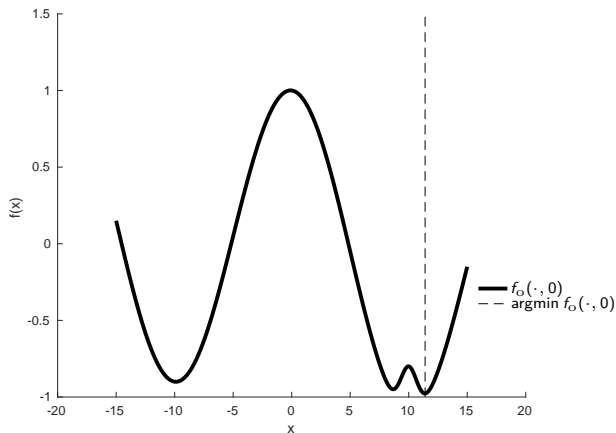
- ▶ If the problem has constraints, they become:

$$\forall j \leq q, \forall u \in \mathbb{U}, f_{c,j}(x, u) \leq 0$$



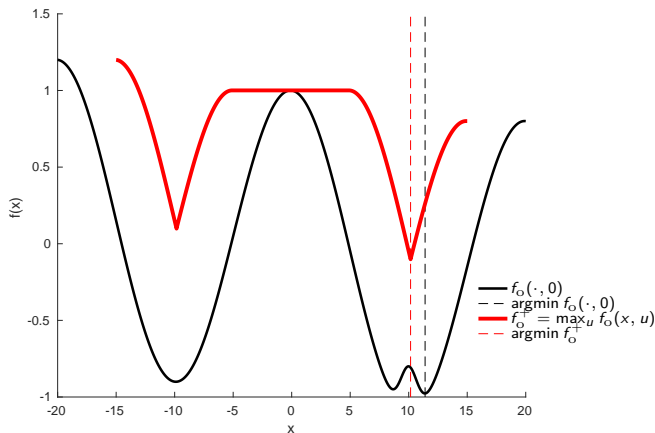
## Example 1: Illustration of the worst-case approach

Example:  $f_o(x, u) = \tilde{f}(x + u)$ , with  $u \in \mathbb{U} = [-\delta; \delta]$ ,  $\delta = 5$



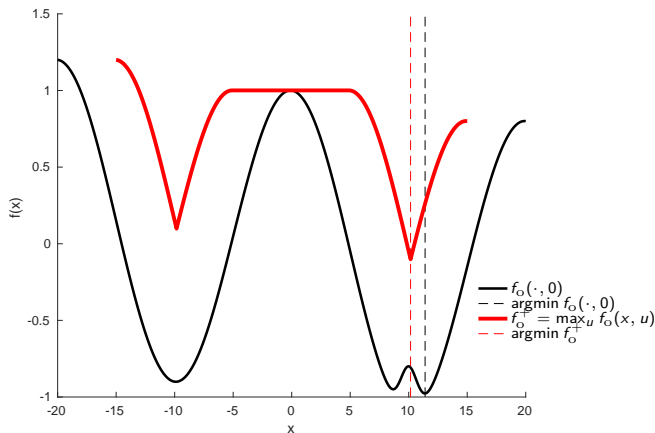
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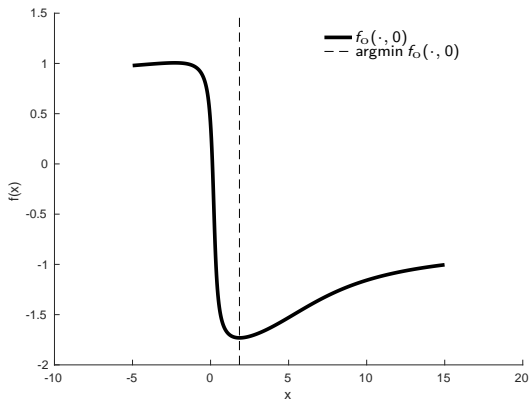
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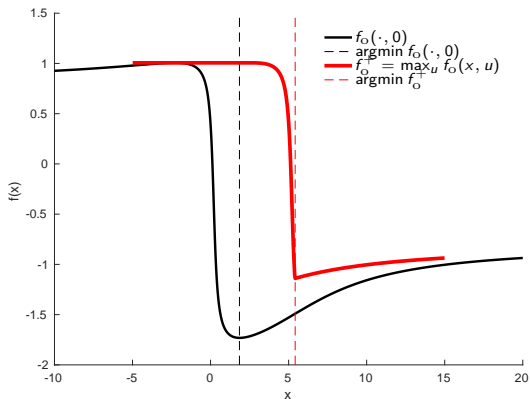
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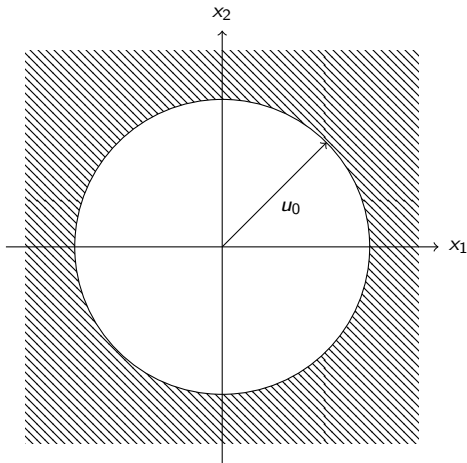
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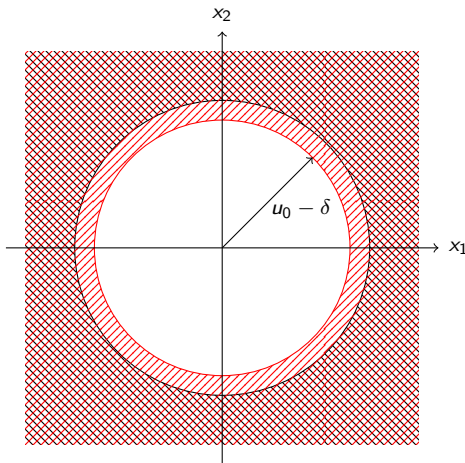
## Another example: worst-case approach for a constraint

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## Another example: worst-case approach for a constraint

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## (a few more words on the) Worst-case approach

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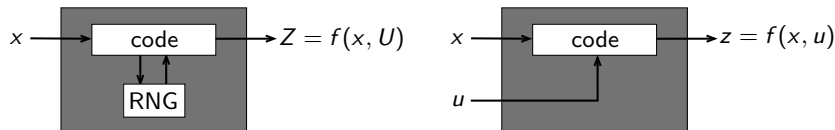
- ▶ In this lecture, we will focus on the probabilistic approach
- ▶ See Marzat, Walter & Piet-Lahanier (2013, 2016) for a “BO treatment” of the worst-case approach (using relaxation)
- ▶ An issue of terminology: in the math literature,
  - ▶ “robust optimization” refers mainly to the worst-case setting (see Ben Tal et al (2009), Bertsimas et al (2011) and refs)
  - ▶ the probabilistic approach is called stochastic programming
- ▶ while engineers use the word “robust” for both ☺

# The probabilistic approach

- ▶ From now, we focus on the **probabilistic approach**
  - ▶  $u$  is considered as **random**  $\rightarrow U \sim P^U$
  - ▶ can be a random vector ( $\in \mathbb{R}^m$ ), or a more complicated object

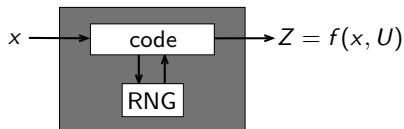
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- ▶ Numerical models: two important settings
  - ▶ stochastic simulators
  - ▶ environmental variables



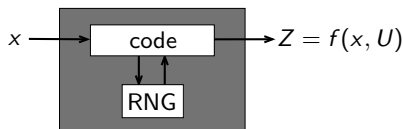
where  $f = (f_{o,1}, \dots, f_{o,p}, f_{c,1}, \dots, f_{c,q})$

# The “stochastic simulator” setting



- ▶ Features of the black box
  - ▶  $U$  is **not directly accessible**
  - ▶ only  **$x$  can be chosen** by the algorithm;  $Z = f(x, U)$  is observed
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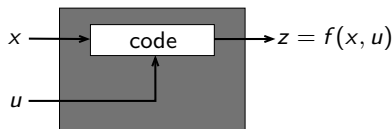
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- ▶ “State of nature” (the things that we don’t know)
  - ▶ the family  $(P_x^Z)$  of conditional distributions
  - ▶ the RV  $U_1, U_2 \dots$  that will be generated when running the computer model with inputs  $x_1, x_2 \dots$
  - ▶ the RV  $U_{\text{real}}$  that defines the  $f(x, U_{\text{real}})$  ultimately realized



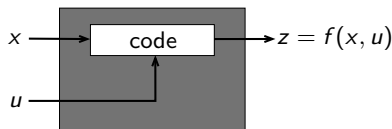
# The “environmental variables” setting



- ▶ Features of the black box
  - ▶ the simulator remains deterministic
  - ▶  $P^U$  is specified separately, usually explicitly
  - ▶ the algorithm can choose  $(x, u)$  pairs to be evaluated
- ▶ “State of nature” (the things that we don’t know)
  - ▶ the **deterministic function**  $f : (x, u) \mapsto f(x, u)$
  - ▶ the RV  $U_{\text{real}}$  that defines the  $f(x, U_{\text{real}})$  ultimately realized



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- ▶ The two settings can be mixed 😊

# Problem formulations

- ▶ Various “robust” formulations can be considered for the design problem, depending mainly on
  - ▶ the number of objective functions,
  - ▶ the presence of (expensive-to-evaluate) constraints,
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  - ▶ the number of objective functions,
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  - ▶ and, of course, how we want to deal with  $U_{\text{real}}$ .
- ▶ In the following, we focus on
  - ▶ **single objective** problems
  - ▶ in the “**environmental variables**” setting
- ▶ and discuss two important cases:
  - ▶ optimization of the **averaged objective** function
  - ▶ **reliability-based design optimization** (RBDO), a.k.a. “chance constrained” optimization, and other formulations

## Lecture 2 : Bayesian optimization (BO)

### 2.3. Design under uncertainty

Overview of possible approaches

Optimization of a mean response

RBDO (and other formulations)

# Optimization of a mean response

- ▶ Assume

- ▶ **single objective**  $f = f_o$ , expensive to evaluate
- ▶ **no** (expensive-to-evaluate) **constraints**
- ▶ remark: cheap constraints allowed in the definition of  $\mathbb{X} \subset \mathbb{R}^d$
- ▶ **“environmental variables”** setting

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  - ▶ no (expensive-to-evaluate) constraints
  - ▶ remark: cheap constraints allowed in the definition of  $\mathbb{X} \subset \mathbb{R}^d$
  - ▶ “environmental variables” setting
- ▶ Consider once again the  $L^1$  loss function

$$\begin{aligned} L((f, u_{\text{real}}), \hat{x}) &= \left| f(\hat{x}, u_{\text{real}}) - \min_x f(x, u_{\text{real}}) \right| \\ &= f(\hat{x}, u_{\text{real}}) - \min_x f(x, u_{\text{real}}) \end{aligned}$$

# Optimization of a mean response

- Compute the **posterior risk** at time  $N$  for an estimate  $\hat{x} \in \mathbb{X}$

$$E_N(L((\xi, U_{\text{real}}), \hat{x})) = E_N(\xi(\hat{x}, U_{\text{real}})) - E_N(\min \xi(\cdot, U_{\text{real}}))$$

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- Same  $L^1$  risk (ignoring last term) as if we were dealing with the

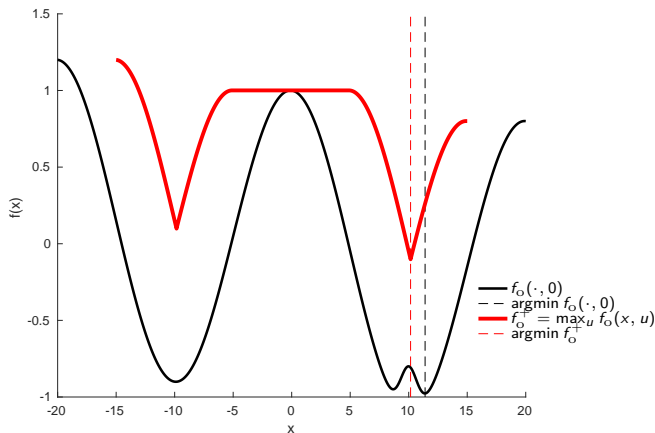
Equivalent “deterministic” problem

$$\min_x \bar{f}(x), \quad \text{with } \bar{f}(x) = \int f(x, u) P^U(du)$$

(Remark: this formulation occurs very naturally in a BO framework 😊)

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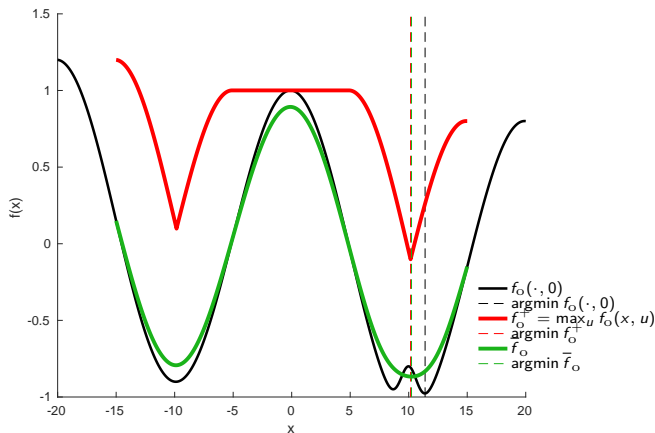
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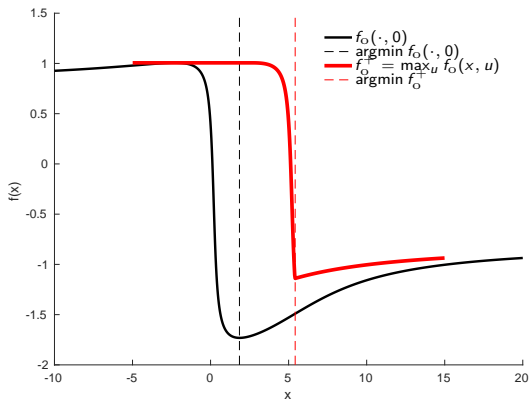
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$\bar{f}_o = E(f_o(\cdot, U))$ , with  $U \sim \mathcal{N}(0, s^2)$ , s.t.  $P(|U| \leq \delta) = 99.9\%$

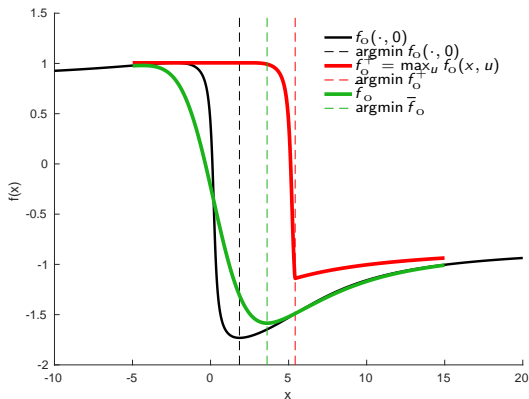
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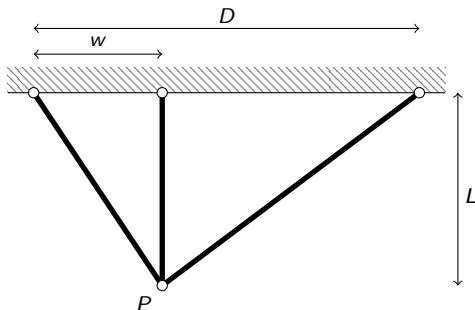
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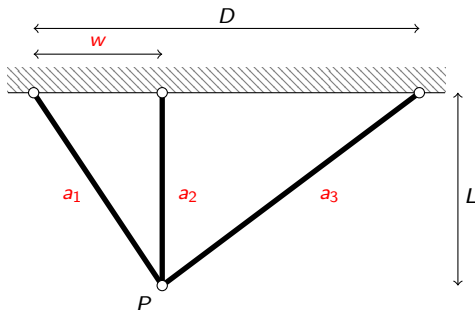


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### Example 3: Three-bar truss (Koski, 1985; Das, 1997)

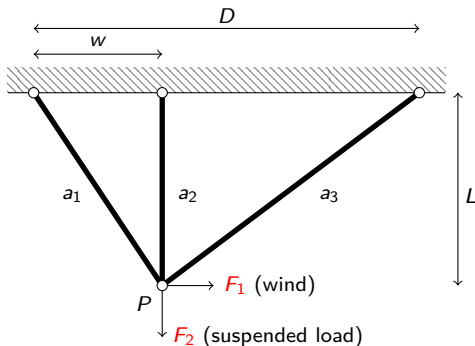


### Example 3: Three-bar truss (Koski, 1985; Das, 1997)



- Design variables:  $x = (a_1, a_2, a_3, w)$ 
  - $a_j$ : cross-section of bar  $j$

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- ▶ Environmental variables:  $U = (F_1, F_2)$



## Example 3: Three-bar truss (Koski, 1985; Das, 1997)

- ▶ Our (supposedly expensive) numerical model computes
  - ▶ the displacement  $y = (y_1, y_2)$  of point  $P$ ,
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  - ▶ under the constraints:  $x_{\min} \leq x \leq x_{\max}$ ,  $V \leq V_{\max}$
- ▶ Remark about constraints
  - ▶ The constraint  $V \leq V_{\max}$  is **cheap to evaluate**

$$V = a_1 \sqrt{L^2 + w^2} + a_2 L + a_3 \sqrt{L^2 + (D - w)^2}$$

- ▶ Additional constraints:  $|\sigma_j| \leq \sigma_{\max}$  can be checked a posteriori

# Breaking the “double loop”

- ▶ Natural “double loop” approach
  - ▶ outer loop: ordinary optimization algorithm applied to  $\bar{f}$
  - ▶ inner loop: integration (MC, quadrature. . . ) to compute  $\bar{f}$

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  - ▶ inner loop: integration (MC, quadrature...) to compute  $\bar{f}$
- ▶ Drawback: typically require large number of evaluations
- ▶ Bayesian optimization **breaks the double loop** 😊
  - ▶ Construct a Bayesian model for  $f$ , not  $\bar{f}$
  - ▶ Remark: can be achieved using other surrogate-model based approaches (see Janusevskis & LeRiche, 2013, and refs therein)

# Prior model

- ▶ There are **two functions of interest** in this setting
  - ▶ the one that can be observed, i.e.,  $f : (x, u) \mapsto f(x, u)$ ,
  - ▶ and the one that want to optimize:  $\bar{f} = \int f(\cdot, u) P^U(du)$
- ▶  $\bar{f}$  is a function of  $f$ 
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Gaussian process priors are, again, very convenient

If  $\underbrace{\xi \sim \mathcal{GP}(m, k)}_{\text{defined on } \mathbb{X} \times \mathbb{U}}$ , then  $\underbrace{\bar{\xi} \sim \mathcal{GP}(m_{\bar{\xi}}, k_{\bar{\xi}})}_{\text{defined on } \mathbb{X}}$ ,

with

$$m_{\bar{\xi}}(x) = \int m(x, u) P^U(du)$$
$$k_{\bar{\xi}}(x, y) = \iint k((x, u), (y, v)) P^U(du) P^U(dv)$$



## Proof

- ▶  $\bar{\xi}$  is Gaussian by linearity of the integral
- ▶ Computation of the mean function: exchange  $\int$  and  $E$

$$\begin{aligned} m_{\bar{\xi}}(x) &= E\left(\bar{\xi}(x)\right) = E\left(\int \xi(x, u) P^U(du)\right) \\ &= \int m(x, u) P^U(du) \end{aligned}$$

- ▶ Computation of the covariance function: idem with bilinearity

$$\begin{aligned} k_{\bar{\xi}}(x, y) &= \text{cov}\left(\bar{\xi}(x), \bar{\xi}(y)\right) \\ &= \text{cov}\left(\int \xi(x, u) P^U(du), \int \xi(y, v) P^U(dv)\right) \\ &= \iint k((x, u), (y, v)) P^U(du) P^U(dv) \quad \blacksquare \end{aligned}$$

## Prior model (cont'd)

- ▶ Actually, we can say much better:

### Jointly Gaussian processes

If  $\xi \sim \mathcal{GP}(m, k)$ , then  $\xi$  and  $\bar{\xi}$  are jointly Gaussian, and

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- ▶ Remark:  $m_{\bar{\xi}}$ ,  $k_{\bar{\xi}}$  and  $k_{\xi, \bar{\xi}}$  can be **computed exactly**
  - ▶ if  $P^U$  is **discrete** ( $P^U = \sum_{j=1}^{n_U} w_j \delta_{u_j}$ )
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  - ▶ see Girard (2004) for exact formulas & approximations

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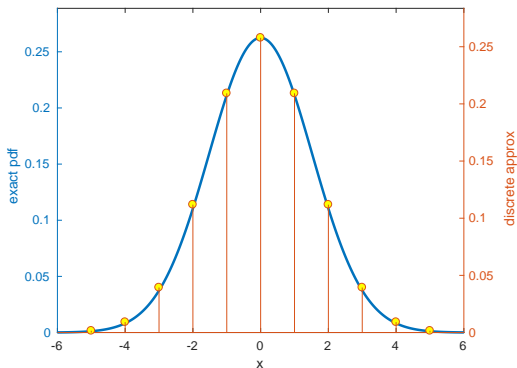
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  - ▶ see Girard (2004) for exact formulas & approximations
- ▶ Important **special case**:  $\xi(x, u) = \tilde{\xi}(x + u)$ 
  - ▶ If  $\xi$  is a GP iff  $\tilde{\xi}$  is a GP
  - ▶  $m_{\xi}(x, u) = m_{\tilde{\xi}}(x + u)$  and  $k_{\xi}((x, u), (u, v)) = k_{\tilde{\xi}}(x + u, y + v)$

## Examples 1 and 2: discretization of $P^U$

- ▶ In the two examples,  $Prob^U = \mathcal{N}(0, s^2)$ , with  $s = 1.52$ 
  - ▶  $P(|U| \leq 5) \approx 99.9\%$

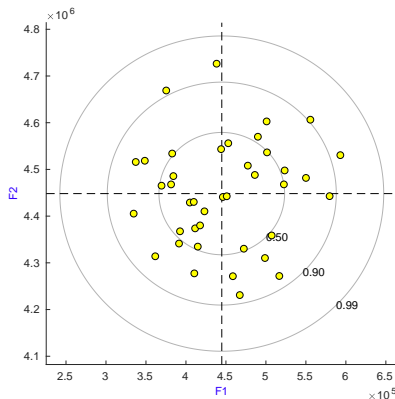
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  - ▶  $P(|U| \leq 5) \approx 99.9\%$
- ▶ We choose to use a **regular discretization with  $n_U = 11$  points**
  - ▶ points regularly spaced on  $[-5; 5]$
  - ▶ weights computed using the normal cdf (using mid-points)



### Example 3: discretization of $P^U$

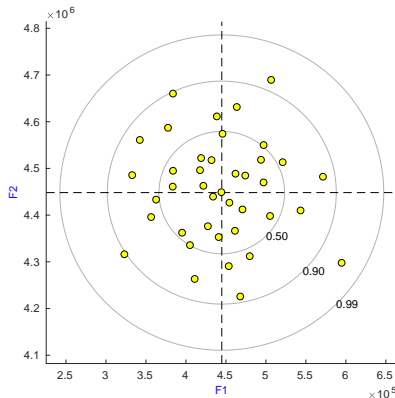
► Here,  $U = \begin{pmatrix} F_1 \\ F_2 \end{pmatrix}$  and  $P^U = \mathcal{N} \left( \begin{pmatrix} \mu_{F_1} \\ \mu_{F_2} \end{pmatrix}, \begin{pmatrix} \sigma_{F_1}^2 & 0 \\ 0 & \sigma_{F_2}^2 \end{pmatrix} \right)$



Monte Carlo sample of size  $n_U = 50$

### Example 3: discretization of $P^U$

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Quasi Monte Carlo (QMC) sample of size  $n_U = 50$



## Sampling strategy: what ?

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  - ▶ numerical model  $f : (x, u) \mapsto f(x, u)$ , defined on  $\mathbb{X} \times \mathbb{U}$
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- ▶ Important special case
  - ▶  $f(x, u) = \tilde{f}(x + u)$
  - ▶ in this case, we must simply select a point  $X_{n+1} \in \mathbb{X}$
- ▶ In the following slides we assume the general case  
(adaptation to the special case poses no difficulty)

# Sampling strategy: how ?

- ▶ How do we build a sampling strategy for this problem ?
  - ▶ in this lecture, we will **apply the standard BO machinery**
    - ▶  $L^1$  loss  $\rightarrow$  risk  $\rightarrow$  “EI like” myopic strategy

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  - ▶ other strategies are proposed in the literature
    - ▶ Williams et al 2000; Janusevkis et Le Riche 2013
    - ▶ Entropy-based methods could be used as well (Villemonais et al 2009, Hennig & Schueller 2012...)

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  - ▶ other strategies are proposed in the literature
    - ▶ Williams et al 2000; Janusevskis et Le Riche 2013
    - ▶ Entropy-based methods could be used as well (Villemonteix et al 2009, Hennig & Schueller 2012...)
- ▶ Assume now the  $L^1$  loss
- ▶ Recall the **posterior risk** at time  $N$  for an estimate  $\hat{x} \in \mathbb{X}$ :

$$E_N(L((\xi, U_{\text{real}}), \hat{x})) = E_N(\bar{\xi}(\hat{x})) - E_N(\min_{\mathbb{X}} \xi(\cdot, U_{\text{real}}))$$

## Sampling strategy: one step look-ahead

- ▶ Let  $\bar{L}_n$  denote the **expected loss** that we would get **if we stopped at time  $n$** :

$$\begin{aligned}\bar{L}_n &= \min_{\mathbb{X}} E_n \left( \bar{\xi}(x) \right) - E_n \left( \min_{\mathbb{X}} \xi(\cdot, U_{\text{real}}) \right) \\ &= \min_{\mathbb{X}} m_{\bar{\xi}, n} - E_n \left( \min_{\mathbb{X}} \xi(\cdot, U_{\text{real}}) \right)\end{aligned}$$

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- ▶ The **one-step look-ahead** (myopic) strategy is

$$(X_{n+1}, U_{n+1}) = \operatorname{argmin}_{x_{n+1}, u_{n+1}} E_{n, (x_{n+1}, u_{n+1})} \left( \bar{L}_{n+1} \right)$$



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- Equivalently,

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- Formally, looks like the KG criterion of Frazier & co, but...

# Sampling strategy: one step look-ahead

- Comparison with KG as presented in the literature

|      | evaluations                        | optimization     |
|------|------------------------------------|------------------|
| KG   | $\xi(x) + \mathcal{N}\text{noise}$ | $\min \xi$       |
| here | $\xi(x, u)$                        | $\min \bar{\xi}$ |

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  1. the function to be optimized is **not observable directly**,
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- There is no real difference mathematically: in both cases
  1. the function to be optimized is not observable directly,
  2. the evaluation results and the function to be optimized are jointly Gaussian.
- Good news: we can then derive an implementable **Approximate KG** criterion as in Scott et al (2011)

# Approximate KG criterion (AKG)

- ▶ Let  $\mathbb{X}_n^{\text{ref}} \subset \mathbb{X}$  denote some finite “reference set”
- ▶ Let  $\tilde{x}_{n+1} = (x_{n+1}, u_{n+1})$ . The **AKG criterion** is:

$$\rho_n^{\text{AKG}}(\tilde{x}_{n+1}) = \min m_{\bar{\xi}, n} - E_{n, \tilde{x}_{n+1}} \left( \min m_{\bar{\xi}, n+1} \right) \geq 0$$

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- ▶ Initially proposed by Scott et al (2011)
  - ▶ under the name KGCP (“KG for continuous parameters”)
  - ▶ with  $\mathbb{X}_n^{\text{ref}} = \{X_1, \dots, X_n\}$
- ▶ Implementation ?
  - ▶ It is **exactly computable** (but not easy to compute...)
  - ▶ Available in STK (Matlab/Octave), DiceOptim (R)...

# Optimization of a mean response: demos

## STK demo

... One dimensional illustration: examples 1 and 2 ...

## STK demo

... Minimization of the mean displacement  
in the 3-bar truss example ...

## (a few words about) The case of stochastic simulators

- ▶ Good news
  - ▶ the **same sampling criteria can be used** in both cases (environmental variables / stochastic simulators)...
  - ▶ ...provided that the observations and the objective function are **jointly Gaussian**.

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- ▶ **Review/benchmark** of existing criteria: Picheny et al (2013)
  - ▶ AKG emerges has one of the most efficient criteria
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  - ▶ Huang et al (2006)'s “augmented EI” also performs well
  - ▶ (Entropy-based criteria not benchmarked)
- ▶ What about simulators with truly **non-Gaussian output** ?
  - ▶ “batch trick” (CLT)
  - ▶ see also Browne et al (2016)...

## Lecture 2 : Bayesian optimization (BO)

### 2.3. Design under uncertainty

Overview of possible approaches

Optimization of a mean response

RBDO (and other formulations)

# Reliability-based (design) optimization (RBO, RBDO)

- ▶ Assume

- ▶ a **single objective**  $f = f_o$ , often cheap to evaluate
- ▶ one or several **expensive-to-evaluate constraints**  $f_{c,1}, \dots, f_{c,q}$
- ▶ “**environmental variables**” setting



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- ▶ “environmental variables” setting

- ▶ The so-called RB(D)O formulation reads:

## Reliability-based (a.k.a. chance-constrained) optimization

Minimize

$$\overline{f_o}(x), \quad \text{where } f_o(x) = E_U(f_o(x, U))$$

under the constraints:  $x \in \mathbb{X}$  and

$$\forall j \leq q, \quad P_U(f_{c,j}(x, U) > 0) \leq p_j^{\text{tol}}$$

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  - ▶ outer loop: ordinary optimization algorithm with constraints
  - ▶ inner loop: reliability analysis method to compute the constraints

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- ▶ Again, algorithms with a “double loop” structure can be used
  - ▶ outer loop: ordinary optimization algorithm with constraints
  - ▶ inner loop: reliability analysis method to compute the constraints
- ▶ Again, surrogate-based methods should be able to “break the double loop” by building a model on  $\mathbb{X} \times \mathbb{U}$

# Why RBDO is harder than mean-response optimization

- ▶ because the thresholds  $p_j^{\text{tol}}$  are usually small
  - ▶ MC-type approx.  $P^U \approx \frac{1}{m} \sum_j \delta_{u_j}$  becomes very expensive or infeasible
  - ▶ Dedicated techniques (e.g., FORM/SORM, IS, subset simulation) needed for an efficient evaluation of the constraints

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  - ▶ Dedicated techniques (e.g., FORM/SORM, IS, subset simulation) needed for an efficient evaluation of the constraints
- ▶ BO: the distribution of  $P_U(\xi_{c,j}(x, U) > 0)$  is intractable
  - ▶ **Posterior mean/variance** can be written as integrals (see, e.g., Villemonteix 2008 chap III), but...
  - ▶ ...the posterior distribution is **not Gaussian** even if  $\xi_c$  is !
  - ▶ Very difficult to derive Bayesian **sampling criteria** that can be implemented efficiently...

# Bayesian RBDO algorithms ?

- ▶ A few GP-based algorithms have been proposed, notably:
  - ▶ Bichon et al (2009): **EGO+EGRA** algorithm
  - ▶ Dubourg and co-authors (2011a, 2011b): **RBDO-N2LA**



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- ▶ Complex, “weakly Bayesian” algorithms... e.g., RBDO-N2LA:

**Algorithm 2** Adaptive surrogate-based nested RBDO strategy

```

1:  $\theta^{(0)}, \theta^L, \theta^U, j := 0$ 
2: for  $i = 1$  to  $n$  do
3:    $q_0^i := \min_{\theta^L \leq \theta \leq \theta^U} F_{\theta}^{-1}(x_i, \theta)$ 
4:    $q_0^i := \max_{\theta^L \leq \theta \leq \theta^U} F_{\theta}^{-1}(x_i, \theta)$ 
5: end for
6:  $w := 1 + 1/q_0^i$ 
7:  $k := \Phi^{-1}(97.5\%)$ ,  $\epsilon_g := 10^{-1}$ 
8: Refine := true, Optimize := true
9: while Refine and Optimize do
10:   while Refine do
11:      $\tilde{G} := \text{RefineKrigingModel}(w, k, \epsilon_g) \rightarrow \text{Use Algorithm 1}$ 
12:   end while
13:    $\tilde{F}^1 := \{x : \mu_{\tilde{G}}(x) \leq 0\}$ 
14:    $\tilde{\beta}^{(1)}, \nabla_{\theta} \tilde{\beta}^{(1)} := \text{ReliabilityAnalysis}(\tilde{F}^1, \theta^{(1)})$ 
15:    $\epsilon^{(1)} := \epsilon(\theta^{(1)}, \nabla_{\theta} \epsilon^{(1)}, \nabla_{\theta} \epsilon^{(1)} := \nabla_{\theta} \epsilon(\theta^{(1)})$ 
16:    $f^{(1)} := f(\theta^{(1)}, \nabla_{\theta} f^{(1)} := \nabla_{\theta} f(\theta^{(1)})$ 
17:    $d^{(1)} := \text{SolveQuasiSQP}(\epsilon^{(1)}, f^{(1)}, \tilde{\beta}^{(1)}, \nabla_{\theta} \epsilon^{(1)}, \nabla_{\theta} f^{(1)}, \nabla_{\theta} \tilde{\beta}^{(1)})$ 
18:    $s^{(1)} := \text{GoldsteinArmijoStepSizeRule}(\epsilon, f, \tilde{\beta}, d^{(1)})$ 
19:    $\theta^{(j+1)} := \theta^{(j)} + s^{(j)} d^{(j)}$ 
20:   for  $i = -1, 0, +1$  do
21:      $\tilde{F}^i := \{x : \mu_{\tilde{G}}(x) + ik\sigma_{\tilde{G}}(x) \leq 0\}$ 
22:      $\tilde{\beta}^i := \text{ReliabilityAnalysis}(\tilde{F}^i, \theta^{(j+1)})$ 
23:   end for
24:   Refine := max  $(\tilde{\beta}^{+1} - \tilde{\beta}^0, \tilde{\beta}^0 - \tilde{\beta}^{-1}) > \epsilon_g$ 
25:   Optimize :=  $\max(|\theta^{(j+1)} - \theta^{(j)}| > \epsilon_0 \text{ or } |\epsilon^{(j+1)} - \epsilon^{(j)}| > \epsilon_e$ 
           or  $\exists i \mid f_i > 0 \text{ or } \tilde{\beta}^i < \beta_0$ 
26: end while
    
```

**Algorithm 1** Population-based adaptive refinement strategy

```

1:  $\mathcal{X} = \emptyset, \mathcal{Y} = \emptyset$ 
2:  $w := x \rightarrow w(x)$ 
3:  $k := \Phi^{-1}(97.5\%)$ ,  $\epsilon_g := 10^{-1}$ 
4: Refine := true
5:  $\mathcal{P}(x \in \mathcal{M}) := x \rightarrow 1$ 
6: while Refine do
7:    $\mathcal{P} := \text{MCMCAlgorithm}(\mathcal{Y})$ 
8:    $\mathcal{X}_{\text{new}} := \text{KMmeansAlgorithm}(\mathcal{P}, K)$ 
9:    $\mathcal{Y}_{\text{new}} := \mathcal{Y}(\mathcal{X}_{\text{new}})$ 
10:   $\mathcal{X} := \{\mathcal{X}, \mathcal{X}_{\text{new}}\}$ ,  $\mathcal{Y} := \{\mathcal{Y}, \mathcal{Y}_{\text{new}}\}$ 
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12:   $\mathcal{P}(x \in \mathcal{M}) := x \rightarrow \Phi\left(\frac{k\sigma_{\tilde{G}}(x) - \mu_{\tilde{G}}(x)}{\sigma_{\tilde{G}}(x)}\right) - \Phi\left(\frac{-k\sigma_{\tilde{G}}(x) - \mu_{\tilde{G}}(x)}{\sigma_{\tilde{G}}(x)}\right)$ 
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- ▶ RBDO-N2LA is available in FERUM (Bourrinet et al, 2009)

# RBDO and other formulations: alternative approach

- ▶ A general alternative approach in two steps
  1. Explore the design space **efficiently** using **multi-objective** BO,
  2. Evaluate probabilities of failure, quantiles, etc. **a posteriori** for non-dominated (and possibly other) solutions,

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  - ▶ becomes:  $\min_x f_{c,j}(x, u_0)$  u.c.  $f_{c,j}(x, u_0) \leq 0$
- ▶ In step 2. no new evaluations need to be carried out
  - ▶ the posterior distribution of  $\xi$  is used to **assess uncertainties**

# RBDO and other formulations: alternative approach

## STK demo

... Robust design through multi-objective optimization ...

## Lecture 1 : From meta-models to UQ

- 1.1 Introduction
- 1.2 Black-box modeling
- 1.3 Bayesian approach
- 1.4 Posterior distribution of a quantity of interest
- 1.5 Complements on Gaussian processes

## Lecture 2 : Bayesian optimization (BO)

- 2.1. Decision-theoretic framework
- 2.2. From Bayes-optimal to myopic strategies
- 2.3. Design under uncertainty

## References



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