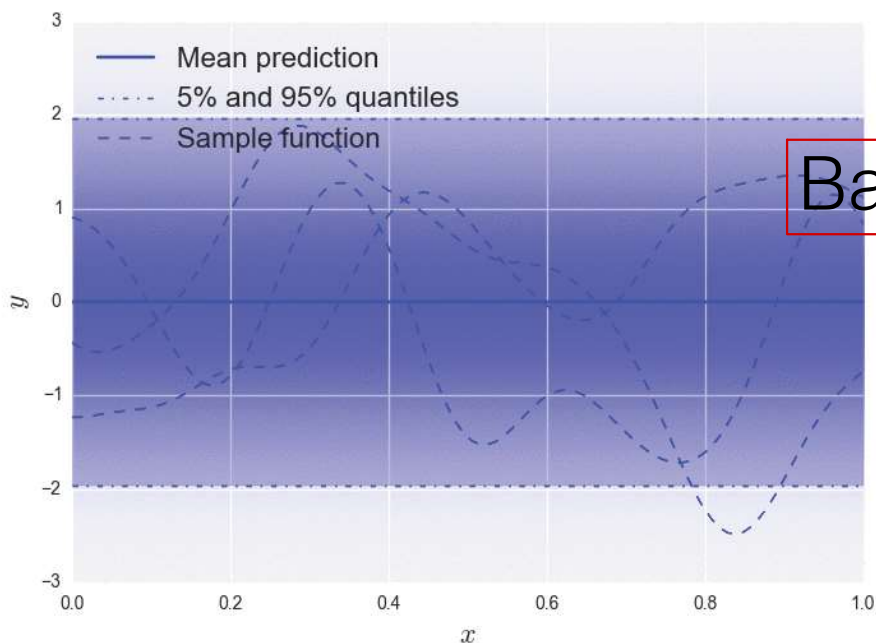


Lecture 22: Gaussian process regression

Professor Ilias Bilonis

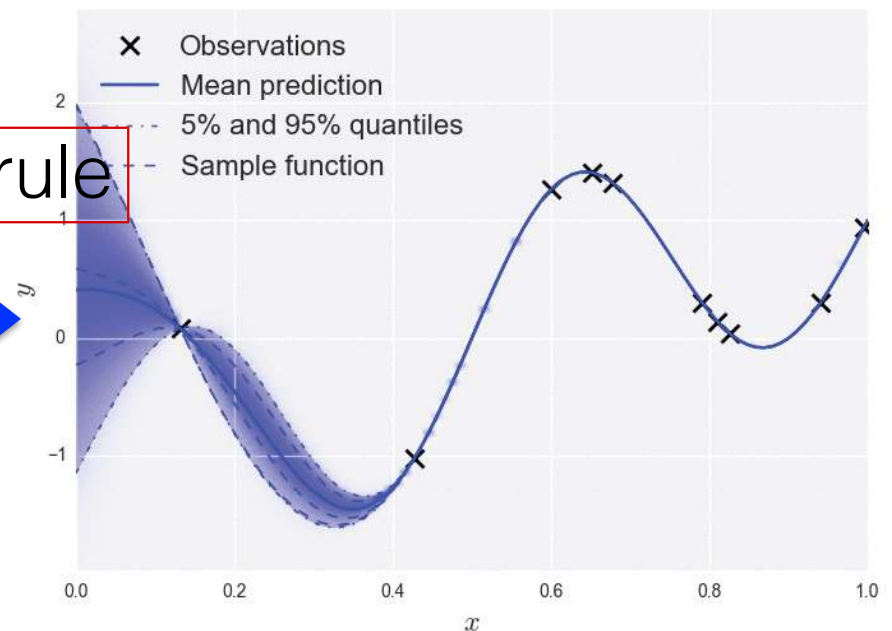
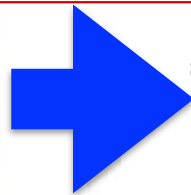
Gaussian process regression without measurement noise

How does Gaussian process regression work?



Prior GP

Bayes' rule



Posterior GP

The joint probability density of observations

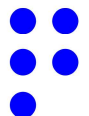
$$\mathbf{x}_{1:n} = (x_1, \dots, x_n) ; f_{1:n} = (f(x_1), \dots, f(x_n))$$

$$f(\cdot) \sim GP(m(\cdot), c(\cdot, \cdot))$$

\Downarrow
 \checkmark

joint observations
conditioned on the inputs

$$p(f_{1:n} | \mathbf{x}_{1:n}) = \mathcal{N} \left(f_{1:n} \mid \begin{matrix} m_{1:n} \\ \parallel \\ \begin{pmatrix} m(x_1) \\ \vdots \\ m(x_n) \end{pmatrix} \end{matrix}, \begin{matrix} C_n \\ \parallel \\ (c(x_i, x_j))_{i,j=1}^n \end{matrix} \right)$$



The joint probability density over observations and test points

Observed: $x_{1:n} = (x_1, \dots, x_n)$; $f_{1:n} = (f(x_1), \dots, f(x_n))$

$$f(\cdot) \sim GP(\mu(\cdot), c(\cdot, \cdot))$$

Test inputs: $x_{1:n^*}^* = (x_1^*, \dots, x_{n^*}^*)$

$$f_{1:n^*}^* = (f(x_1^*), \dots, f(x_{n^*}^*))$$

joint of observed & test function values conditioned on all inputs

$$p(\underbrace{f_{1:n}}_{\text{observed function values}}, \underbrace{f_{1:n^*}^*}_{\text{test function values}} | x_{1:n}, x_{1:n^*}^*) = N\left(\begin{pmatrix} f_{1:n} \\ f_{1:n^*}^* \end{pmatrix} \middle| \begin{pmatrix} \mu_{1:n} \\ \mu_{1:n^*}^* \end{pmatrix}, \begin{pmatrix} C_n & B \\ B^T & C_{n^*} \end{pmatrix}\right)$$

$\begin{pmatrix} \mu_{1:n} \\ \mu_{1:n^*}^* \end{pmatrix} \parallel \begin{pmatrix} \mu(x_1^*) \\ \vdots \\ \mu(x_{n^*}^*) \end{pmatrix}$

$\begin{pmatrix} C_n & B \\ B^T & C_{n^*} \end{pmatrix}$

$B = (c(x_i, x_j^*))_{i=1, j=1}^{n, n^*}$ (cross-covariance size $n \times n^*$)

$C_n = (c(x_i, x_j))_{i,j=1}^n$ (observed)

$C_{n^*} = (c(x_i^*, x_j^*))_{i,j=1}^{n^*}$ (test)

Conditioning on observations

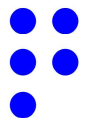
$$p(f_{1:n}, f_{1:n}^* | x_{1:n}, x_{1:n}^*) = N\left(\begin{pmatrix} f_{1:n} \\ f_{1:n}^* \end{pmatrix} \middle| \begin{pmatrix} \mu_{1:n} \\ \mu_{1:n}^* \end{pmatrix}, \begin{pmatrix} C_n & B \\ B^T & C_{n^*} \end{pmatrix}\right)$$

\Downarrow completing the square

$$p(f_{1:n}^* | x_{1:n}, f_{1:n}, x_{1:n}^*) = N\left(f_{1:n}^* \middle| \mu_{1:n}^*, C_{n^*}^*\right)$$

$$\mu_{1:n}^* = \mu_{1:n}^* - B^T C_n^{-1} (f_{1:n} - \mu_{1:n})$$

$$C_{n^*}^* = C_{n^*} - \underbrace{B^T C_n^{-1} B}_{\text{correction terms}}$$



The posterior Gaussian process

summarizes our state of knowledge after the observations are made

$$P(f_{1:n}^* | X_{1:n}, f_{1:n}, X_{1:n}^*) = \mathcal{N}(f_{1:n}^* | \mu_{1:n}^*, C_{1:n}^*)$$

test inputs are arbitrary

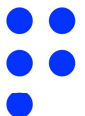
posterior
Gaussian
Process

$$f(\cdot) | X_{1:n}, f_{1:n} \sim \mathcal{GP}(\underbrace{\mu_n^*(\cdot)}_{\text{posterior mean function}}, \underbrace{C_n^*(\cdot, \cdot)}_{\text{posterior covariance function}})$$

$$\mu_n^*(x) = \mu(x) - \underbrace{c(x, X_{1:n})}_{\substack{\text{cross covariance} \\ 1 \times n}} C_n^{-1} (f_{1:n} - \mu_{1:n})$$

$$\left(\underbrace{c(x, x_1)}_{\text{"}}, \dots, c(x, x_n) \right)$$

$$C_n^*(x, x') = c(x, x') - c(x, X_{1:n}) C_n^{-1} \begin{pmatrix} c(X_{1:n}, x') \\ c(x_1, x') \\ \vdots \\ c(x_n, x') \end{pmatrix} \quad n \times 1$$



The point predictive distribution

$$f(\cdot) \mid X_{1:n}, f_{1:n} \sim GP(\mu_n^*(\cdot), C_n^*(\cdot, \cdot))$$

\Downarrow

single test point
↓

$$p(f(x) \mid X_{1:n}, f_{1:n}) = N\left(f(x) \mid \mu_n^*(x), \underline{\underline{\sigma_n^{*2}(x)}}\right)$$

posterior covariance
function

$$\sigma_n^{*2}(x) = C_n^*(x, x).$$

\Downarrow credible interval $\sim 95\%$

$$\star f(x) \in [\mu_n^*(x) - 2\sigma_n^*(x), \mu_n^*(x) + 2\sigma_n^*(x)]$$

Example

