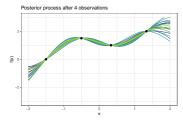
# **Introduction to Machine Learning**

# Gaussian Processes Mean functions for GPs

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#### Learning goals

 Trends can be modeled via specification of the mean function

• It is common but by no means necessary to consider GPs with a zero-mean function

$$m(\mathbf{x}) \equiv 0$$

• Note that this is not necessarily a drastic limitation, since the mean of the posterior process is not confined to be zero

 $\boldsymbol{f}_*|\boldsymbol{\mathsf{X}}_*,\boldsymbol{\mathsf{X}},\boldsymbol{f}\sim\mathcal{N}(\boldsymbol{\mathsf{K}}_*^{\mathsf{T}}\boldsymbol{\mathsf{K}}^{-1}\boldsymbol{f},\boldsymbol{\mathsf{K}}_{**}-\boldsymbol{\mathsf{K}}_*^{\mathsf{T}}\boldsymbol{\mathsf{K}}^{-1}\boldsymbol{\mathsf{K}}_*).$ 

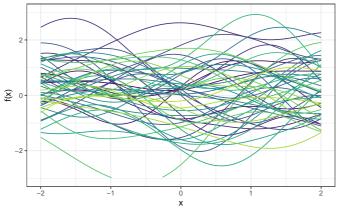
- Yet there are several reasons why one might wish to explicitly model a mean function, including interpretability, convenience of expressing prior informations, ...
- When assuming a non-zero mean GP prior  $\mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$  with mean  $m(\mathbf{x})$ , the predictive mean becomes

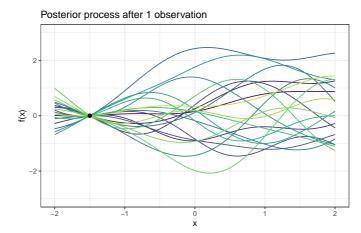
$$m(\mathbf{X}_*) + \mathbf{K}_* \mathbf{K}_y^{-1} (\mathbf{y} - m(\mathbf{X}))$$

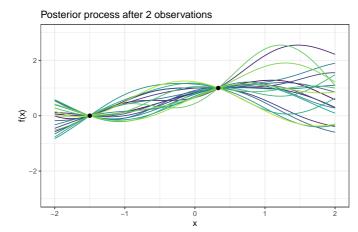
while the predictive variance remains unchanged.

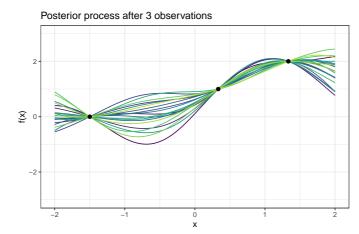
• Gaussian processes with non-zero mean Gaussian process priors are also called Gaussian processes with trend.

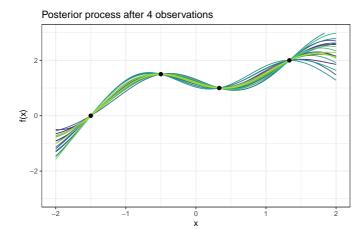
Functions drawn from a Gaussian process prior











- In practice it can often be difficult to specify a fixed mean function
- In many cases it may be more convenient to specify a few fixed basis functions, whose coefficients, β, are to be inferred from the data
- Consider

 $g(\mathbf{x}) = b(\mathbf{x})^{\top} \boldsymbol{\beta} + f(\mathbf{x}), \text{ where } f(\mathbf{x}) \sim \mathcal{GP}\left(0, k(\mathbf{x}, \tilde{\mathbf{x}})\right)$ 

- This formulation expresses that the data is close to a global linear model with the residuals being modelled by a GP.
- For the estimation of  $g(\mathbf{x})$  please refer to Rasmussen, Gaussian Processes for Machine Learning, 2006

