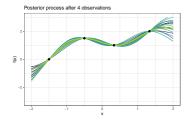
# **Introduction to Machine Learning**

# Gaussian Processes Mean functions for GPs





#### 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

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

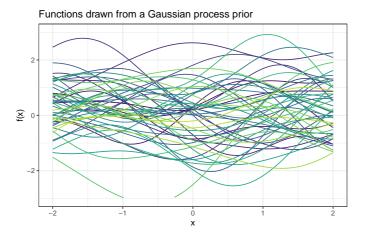
- Yet there are several reasons why one might wish to explicitly model a mean function, including interpretability, convenience of expressing prior informations, ...
- When assuming a non-zero mean GP prior  $\mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$  with mean  $m(\mathbf{x})$ , the predictive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

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

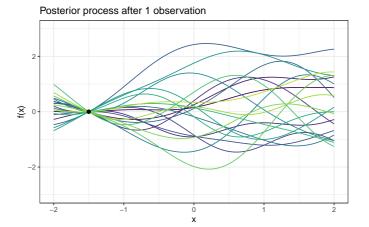
while the predictive variance remains unchanged.



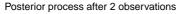
 Gaussian processes with non-zero mean Gaussian process priors are also called Gaussian processes with trend.

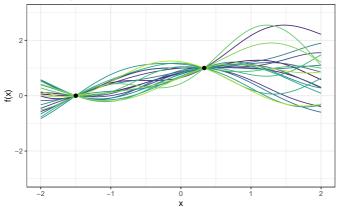








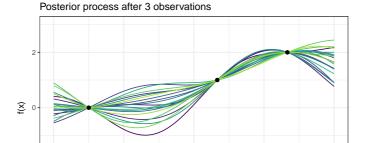




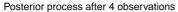


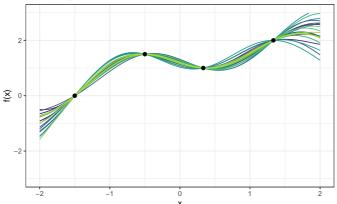
-1

-2-











- 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,  $\beta$ , 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

