Appendix - GPR

A Gaussian process is defined as a collection of random variables that have a joint Gaussian distribution f(x). Using Bayesian inference, we assume that the *prior* distribution can be described by a zero-mean Gaussian process with covariance function k(x, x):

$$\begin{bmatrix} f(\boldsymbol{x}_1) \\ \vdots \\ f(\boldsymbol{x}_n) \end{bmatrix} \sim \mathcal{N} \left(\boldsymbol{0}, \begin{bmatrix} k(\boldsymbol{x}_1, \boldsymbol{x}_1) & \cdots & k(\boldsymbol{x}_1, \boldsymbol{x}_n) \\ \vdots & \ddots & \vdots \\ k(\boldsymbol{x}_n, \boldsymbol{x}_1) & \cdots & k(\boldsymbol{x}_n, \boldsymbol{x}_n) \end{bmatrix} \right)$$

We then use data to train our model, in order to find the *posterior* distribution. In the training process, the functions that pass through the data points are given a higher likelihood and thus have a greater impact on the posterior distribution. Denoting the covariance matrix as K(X, X) and letting f_* describe the function values at the data points, we get a joint distribution of measured values f and predicted values f_* :

$$\begin{bmatrix} \boldsymbol{f} \\ \boldsymbol{f}_* \end{bmatrix} \sim \mathcal{N} \left(\boldsymbol{0}, \begin{bmatrix} K(X,X) & K(X,X_*) \\ K(X_*,X) & K(X_*,X_*) \end{bmatrix} \right)$$

The conditional distribution for the posterior function f_* can then be described as

$$f_*|X, f, X_* \sim \mathcal{N}(\overline{f_*}, \operatorname{cov}(f_*)),$$

where

$$\overline{f_*} = \mathbb{E}[f_*|X, f, X_*] = K(X_*, X)[K(X, X)]^{-1}f$$
$$\operatorname{cov}(f_*) = K(X_*, X_*) - K(X_*, X)[K(X, X)]^{-1}K(X, X_*).$$

The function that we are looking for is $\overline{f_*}$, whereas $cov(f_*)$ helps describe the uncertainty of the predictions. By choosing an apt covariance function for the prior distribution, it is simply a matter of training the model to find the hyperparameters that describe the covariance function of the posterior distribution. Then the mean function can be calculated.