Rainfall Runoff Modelling Using Gaussian Processes

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1. Objective

Runoff predictions with least effort and minimal data requirement.

Input Data:

Timeseries of

- ullet Rainfall $I_t = \left(I_t^1, I_t^2, \dots, I_t^r\right)$ and
- Runoff $Q_t = (Q_t^1, Q_t^2, \dots, Q_t^s)$ where $t \in \{1, 2, \dots, T\}$.

With $x_t := (I_t, Q_t)$ we denote all measurements at timestep t. Assume there is an unknown function

$$f(x_t, x_{t-1}, \dots, x_{t-k}) = Q_{t+1}^* + \epsilon,$$

which predicts future runoff Q_{t+1}^* , but is disturbed by noise ϵ .

Goal:

Find a function \hat{f} which approximates f as good as possible.

3. Covariance Function

- Wide variety of covariance functions
- Incorporate a priori decisions

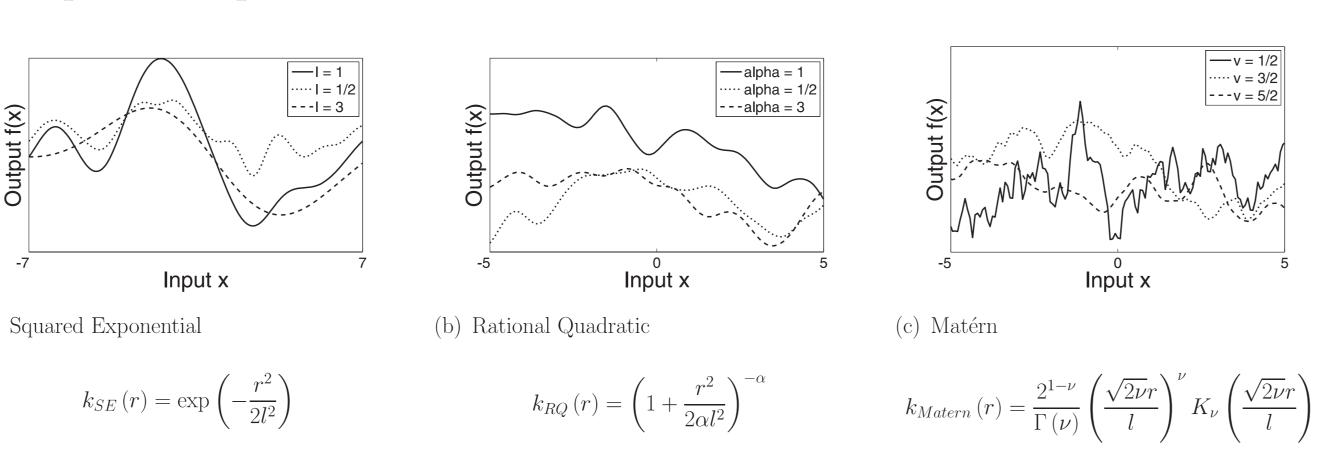
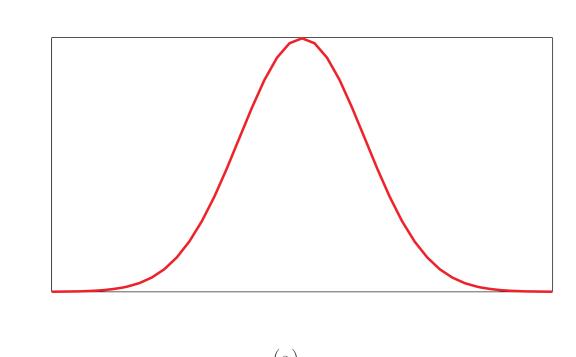


Figure 3: Random functions drawn from Gaussian Processes with different covariance functions and different parameters

2. Gaussian Processes

Think of a multivariate normal distribution with infinite many variables and you get a gaussian process.

Properties:



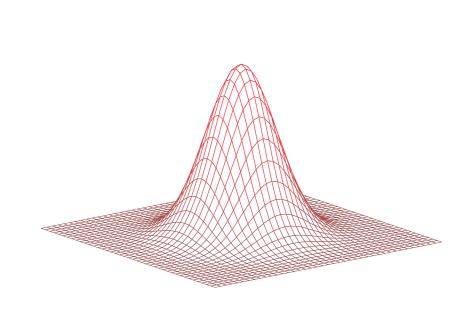


Figure 1: (a) Univariate normal distribution (b) Bivariate normal distribution

- Fully described by **mean function** m(x) and **covariance function** k(x)
- Marginalization property:

$$p(x,y) \sim \mathcal{N}\left(\begin{bmatrix} a \\ b \end{bmatrix}, \begin{bmatrix} A & B \\ B^T & C \end{bmatrix}\right) \Rightarrow p(x) \sim \mathcal{N}\left(a, A\right)$$

• Conditional property:

$$p\left(x,y\right) \sim \mathcal{N}\left(\left[\begin{matrix} a \\ b \end{matrix}\right], \left[\begin{matrix} A & B \\ B^T & C \end{matrix}\right]\right) \Rightarrow p\left(x|y\right) \sim \mathcal{N}\left(a + BC^{-1}\left(y - b\right), A - BC^{-1}B^T\right)$$

This gives information about x, if y is known.

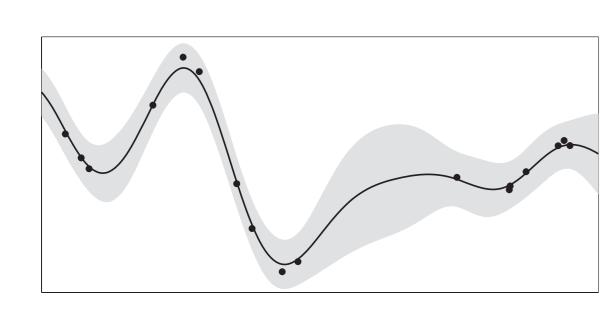


Figure 2: Gaussian Process Regression Example - The shaded region represents the pointwise mean plus and minus two times the standard deviation.

4. How to find a good covariance function?

• Measure of 'goodness': Log Validation Density Loss $\mathcal{L}(\theta)$

$$\mathcal{L}(\theta) = \sum_{i=1}^{n} \log(y_i | X, y_{-i}, \theta) = -\sum_{i=1}^{n} \frac{1}{2} \log \sigma_i^2 - \frac{(y_i - \mu_i)^2}{2\sigma_i^2} - \frac{1}{2} \log 2\pi$$

over Leave - One - Out Crossvalidation (LOO-CV) and parameters θ

- Time Efficient Calculation is possible
- Maximize $\mathcal{L}(\theta)$ over θ via standard optimization method (e.g. Gradient Descent)
- Parameters are interpretable

5. Automatic relevance determination (ARD)

- For each input variable x_i introduce scaling parameter l_i
- Optimize l_i in respect to $\mathcal{L}(\theta)$
- A small value of l_i means that variable x_i has no influence and can be eliminated
- Parameters can easily used to get a sensitivity analysis

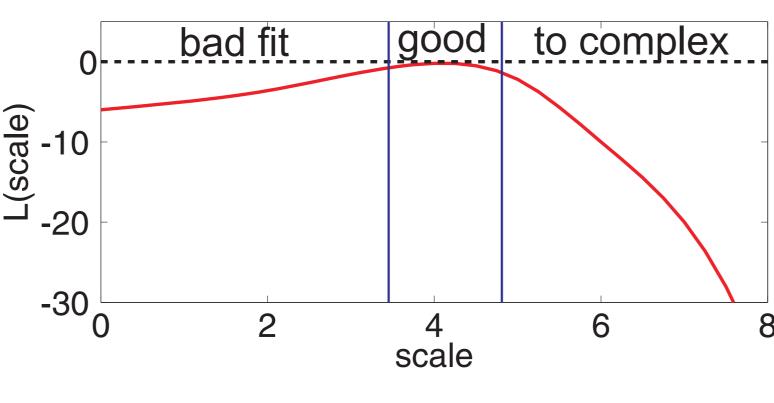
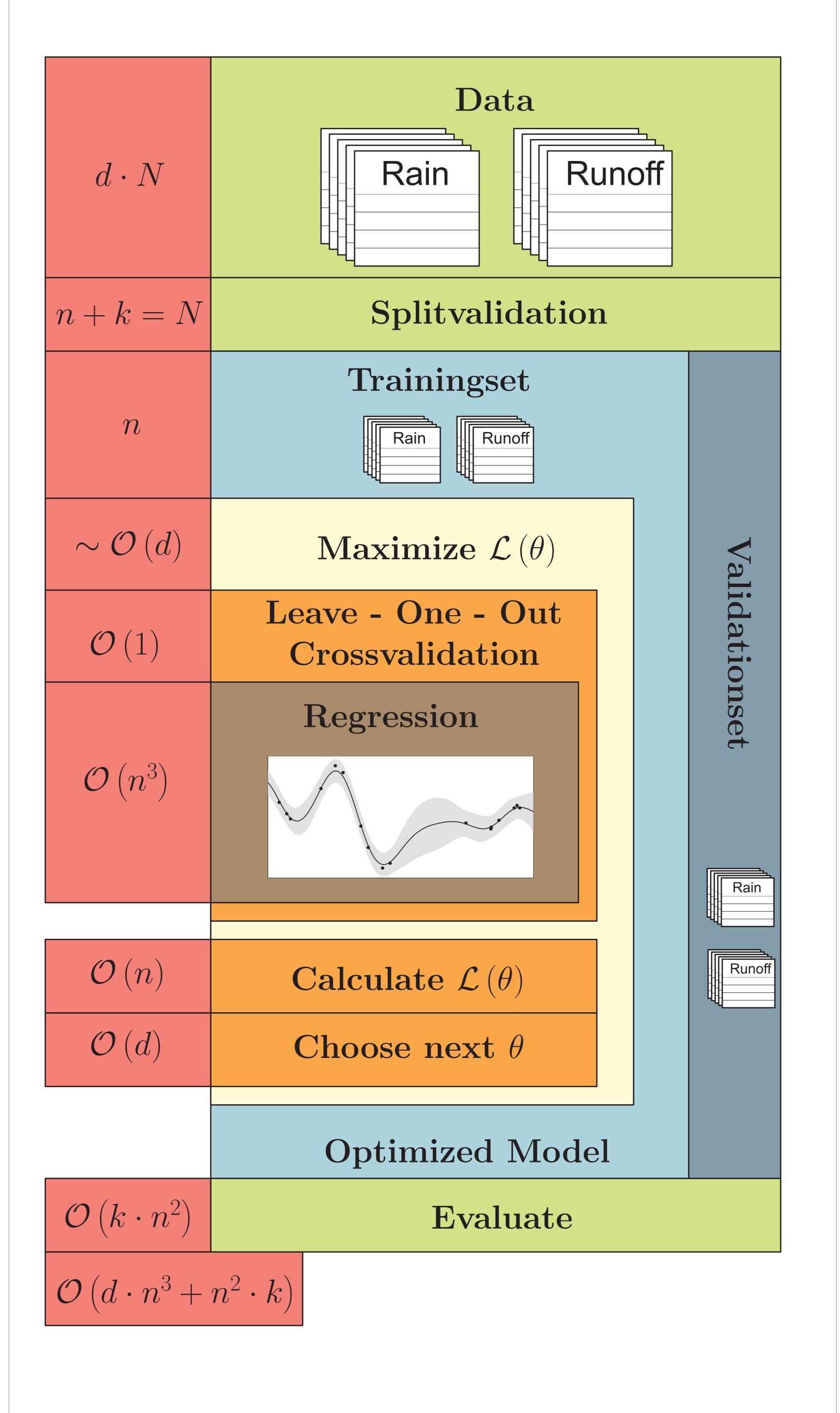


Figure 4: Model complexity and probability in comparison: Small values for l_i produce simple models, which can show bad fitting properties. On the other side, models with high length scales are more complex and tend to overfit the data.

6. Procedure



7. Results Catchment Area - Ouse River Forecast Horizon: 24h Forecast Horizon: 6h Nash Sutcliffe: 0.990.88 Other Catchment Areas This method was tested in other meso scale catchment areas in south eastern germany with a forecast horizon of 24h. It shows good results in all but one Forecast Horizon: 24h Catchment Area - Roda Catchment Area - Wipper Catchment Area - Gera Nash Sutcliffe: $e_2:0.95$ $e_2: 0.54$