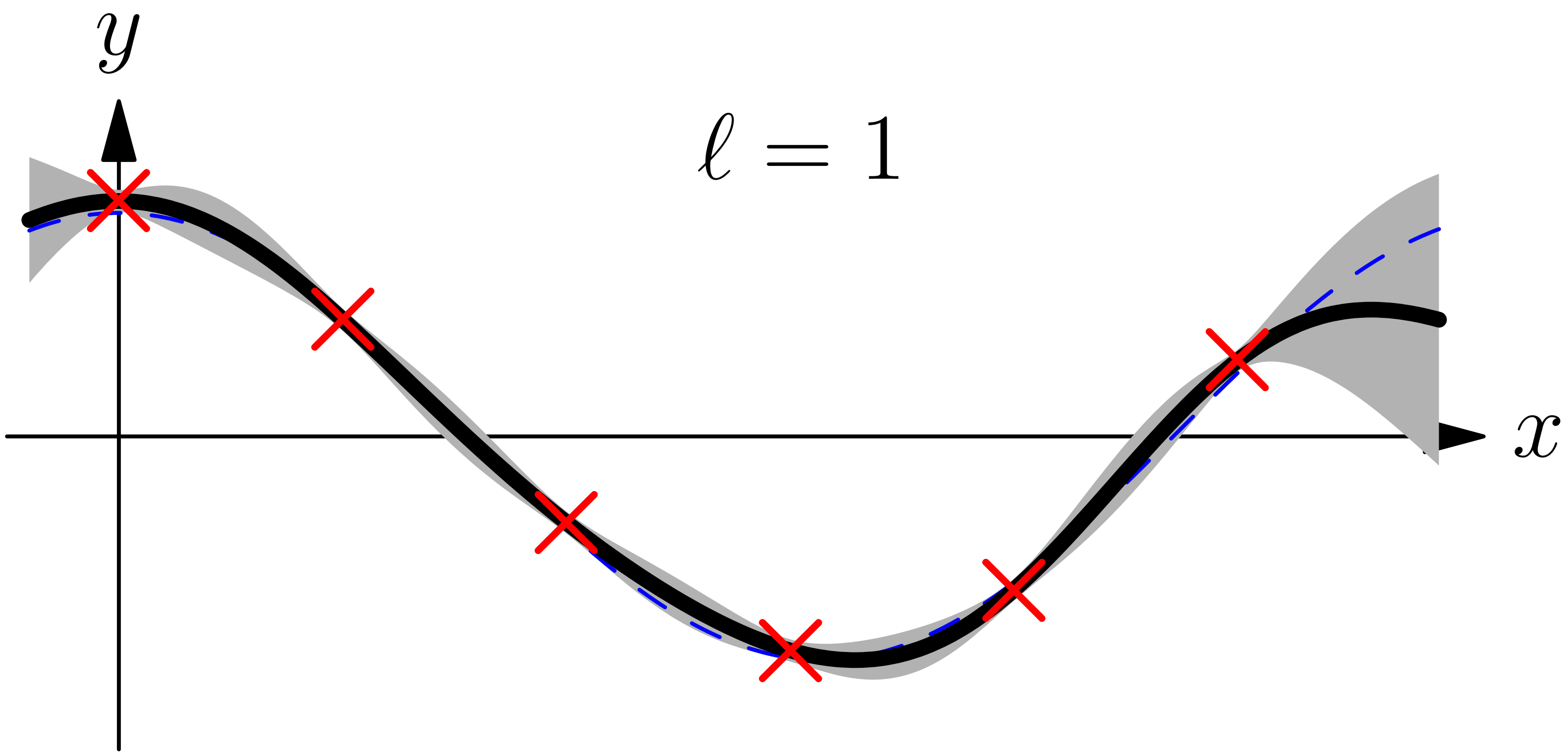
Advanced Machine Learning

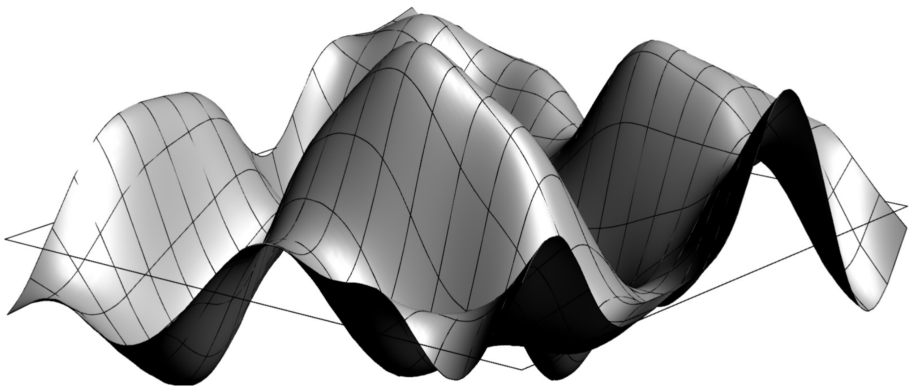
Gaussian Processes



Gaussian Processes, regression

Outline

1. **Introduction**
2. Gaussian Processes
3. Bayesian Inference
4. Hyper-parameters



Gaussian Proccesses

- Gaussian processes (GPs) are a mathematically defined ensemble of functions
- They can be combined with Bayesian inference to give one of the most powerful regression techniques
- Although Bayesian they can be used in a black-box fashion due to the ubiquity of the prior
- Mathematically they are a bit complicated
- In practice they aren't that difficult to use

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Regression

- In regression we try to fit a multi-dimensional function to our data
- (You can use Gaussian Processes for classification, e.g. by inferring the probabilities of being in a class, but we ignore this as regression is where GP excel)
- In regression we have some p dimensional feature vectors $\boldsymbol{x}_i$ and some target $y_i \in \mathbb{R}$
- Our task is to fit a function through all the data points

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Priors on Functions

- We can think of a solution as a function $f(\boldsymbol{x})$
- We can put a prior probability distribution, $p(f)$, on a function, f, that prefers smooth functions
- We can then compute a posterior probability distribution on functions given the data, $p(f|\mathcal{D})$
- As a likelihood, $p(y_i|f(\boldsymbol{x}_i))$, we use the probability of observing y_i given the true function value is $f(\boldsymbol{x}_i)$
- In general, this would be next to impossible to compute

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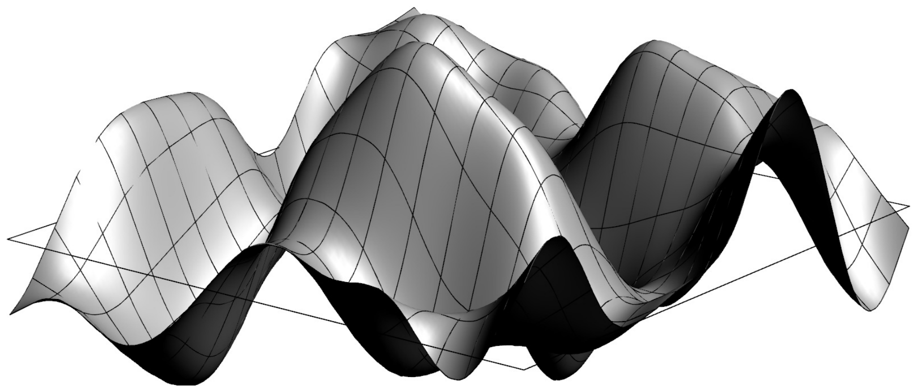

Gaussian Processes

- Gaussian Processes are probability distributions over functions
- (Functions can be viewed as vectors in an infinite dimensional vector space)
- In the Gaussian Process, $\mathcal{GP}(m,k)$, the probability of a function, f, is proportional

$$p(f|m,k) \propto \mathrm{e}^{-\frac{1}{2}\int (f(\boldsymbol{x}) - m(\boldsymbol{x}))k^{-1}(\boldsymbol{x},\boldsymbol{y})(f(\boldsymbol{y}) - m(\boldsymbol{y}))\mathrm{d}\boldsymbol{x}\mathrm{d}\boldsymbol{y}}$$

- The function $m(\boldsymbol{x})$ is the mean $\mathbb{E}[f(\boldsymbol{x})]$ (usually taken to be zero in most inference problems)

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Meaning of GP

- To understand GP's we can discretise space, $\boldsymbol{x}$, into a lattice of points $\{\boldsymbol{x}_i\}$

- Then (assuming $m(\boldsymbol{x}) = 0$)

$$p(f|m,k) \propto \prod_i \mathrm{e}^{-\frac{f_i^2 k^{-1}(\boldsymbol{x}_i,\boldsymbol{x}_i)}{2} + f_i \sum_j k^{-1}(\boldsymbol{x}_i,\boldsymbol{x}_j) f_j}$$

  where $f_i = f(\boldsymbol{x}_i)$

- We see that the value of the function at each point is normally distributed with a mean that depends on functions at neighbouring points

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Covariance function

- $k(\boldsymbol{x}, \boldsymbol{y})$ is a covariance function

$$\mathbb{E}\Big[\big(f(\boldsymbol{x}) - m(\boldsymbol{x})\big)\big(f(\boldsymbol{y}) - m(\boldsymbol{y})\big)\Big] = k(\boldsymbol{x}, \boldsymbol{y})$$

- This is sometimes know as a **kernel**—it must be positive semi-definite

- It is a free "parameter" that the user gets to choose (although we can learn its parameters too)

- If $k(\boldsymbol{x}, \boldsymbol{y})$ is a function of $\boldsymbol{x} - \boldsymbol{y}$ it is **"stationary"**

- If $k(\boldsymbol{x}, \boldsymbol{y})$ is a function of $\|\boldsymbol{x} - \boldsymbol{y}\|$ it is also **"isometric"**

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Popular Choices of GP Kernel Function

- Constant: $k_{\mathrm{C}}(\boldsymbol{x},\boldsymbol{y}) = C$
- Gaussian noise: $k_{\mathrm{GN}}(\boldsymbol{x},\boldsymbol{y}) = \sigma^2 \delta_{\boldsymbol{x},\boldsymbol{y}}$
- Squared exponential: $k_{\mathrm{SE}}(\boldsymbol{x},\boldsymbol{y}) = \exp\left(-\frac{\|\boldsymbol{x}-\boldsymbol{y}\|^2}{2\ell^2}\right)$
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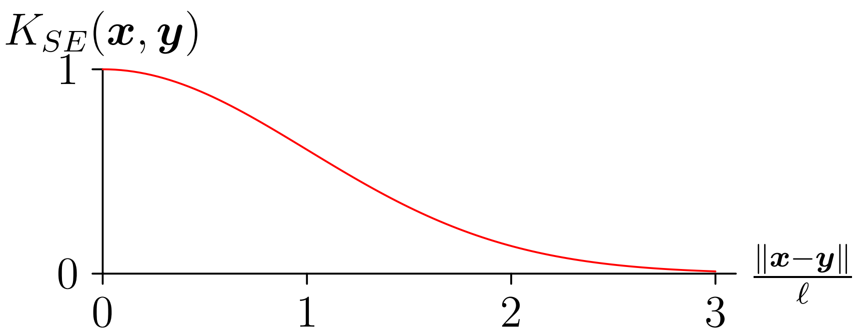

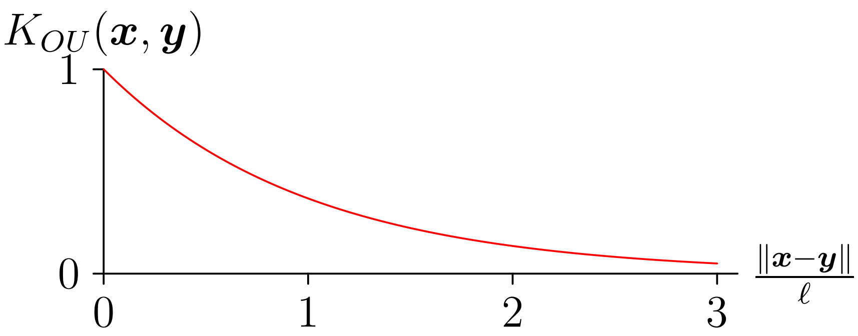

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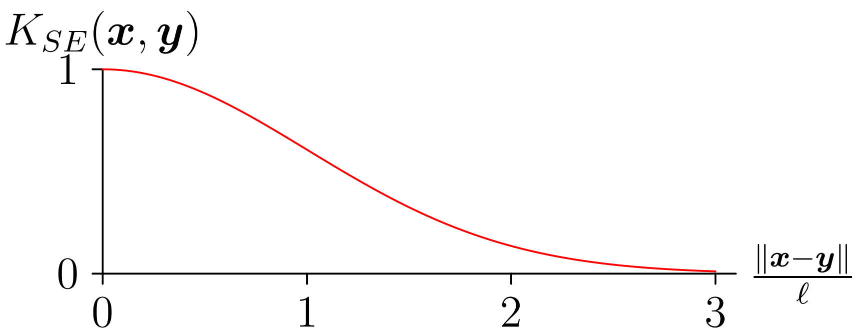

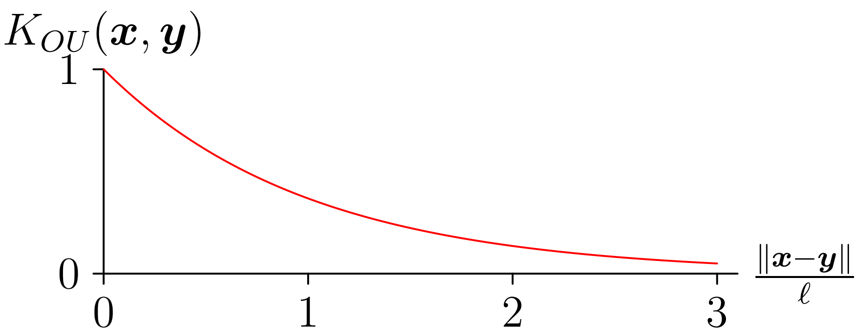

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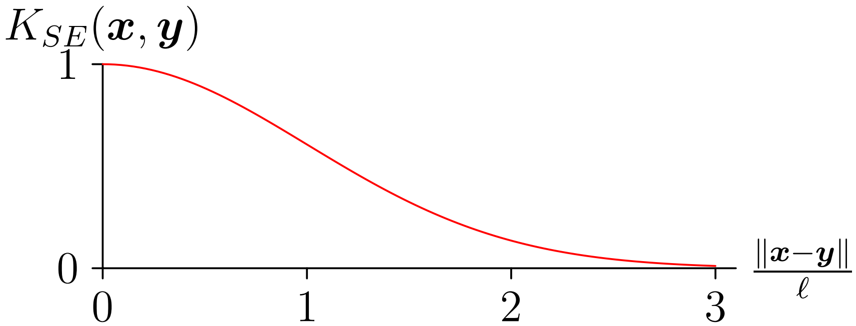

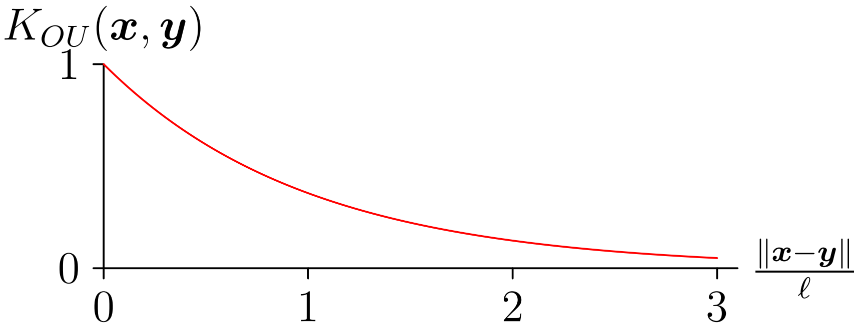

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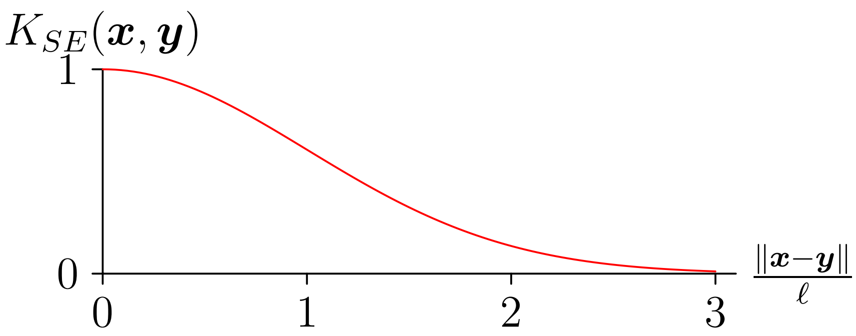
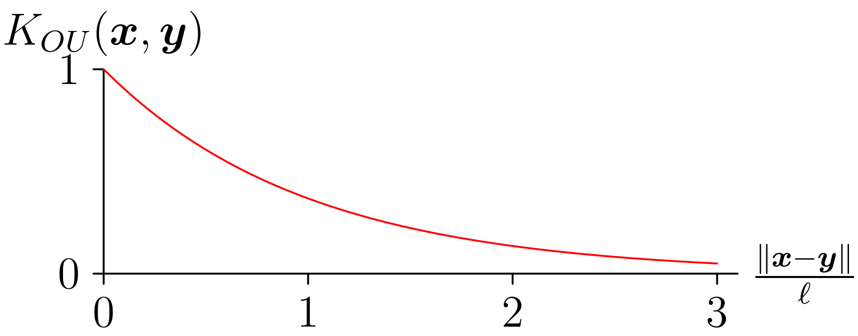
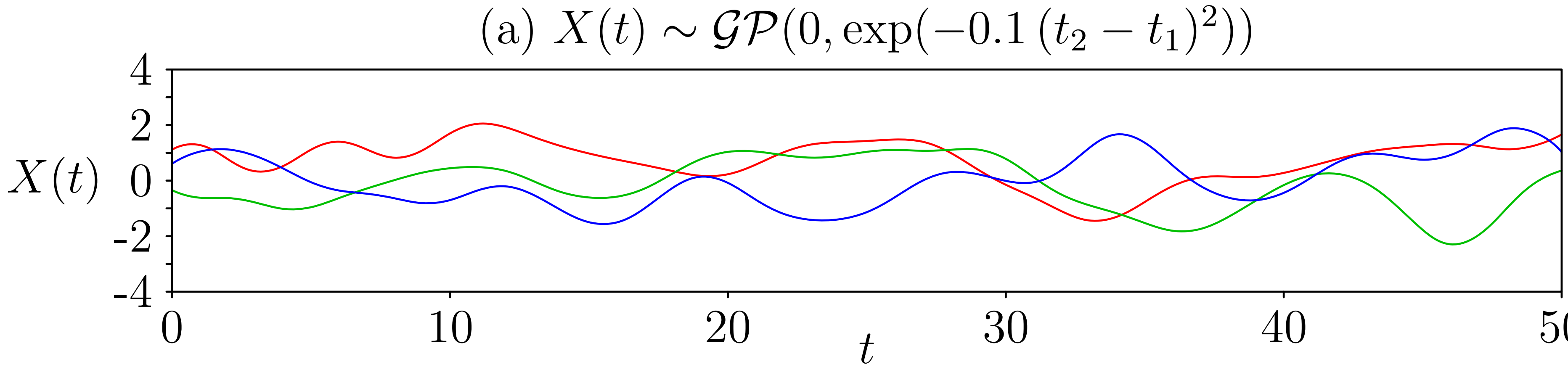




Gaussian Process Worlds



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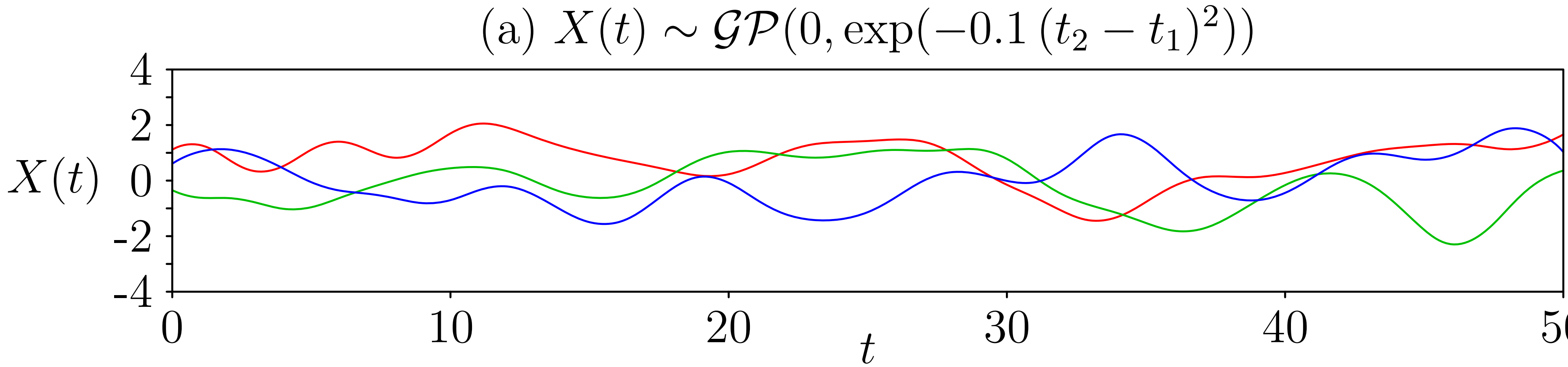
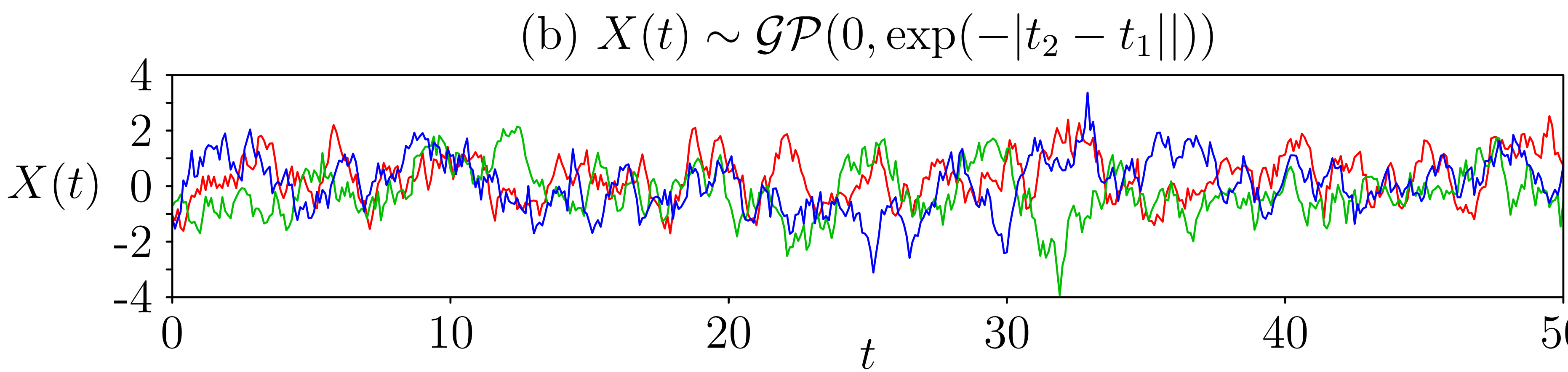
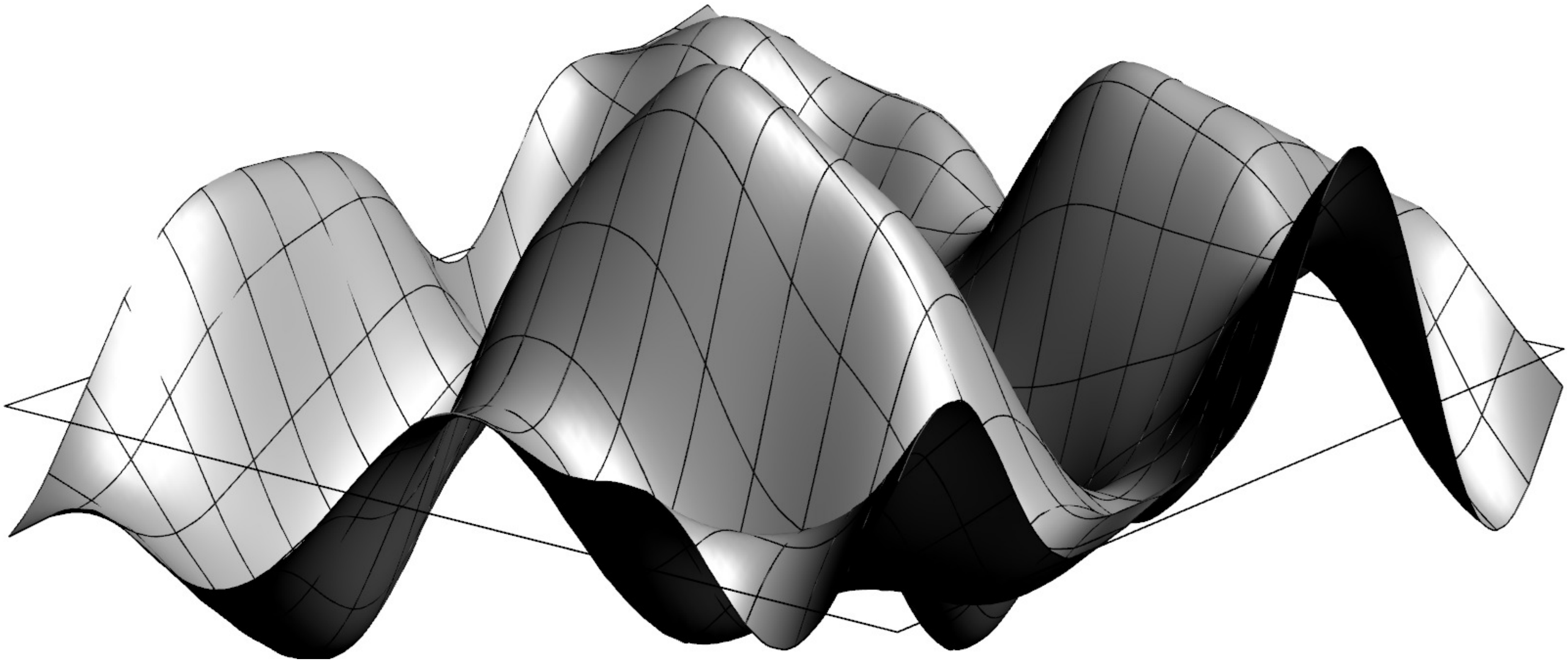




2-D Gaussian Processes



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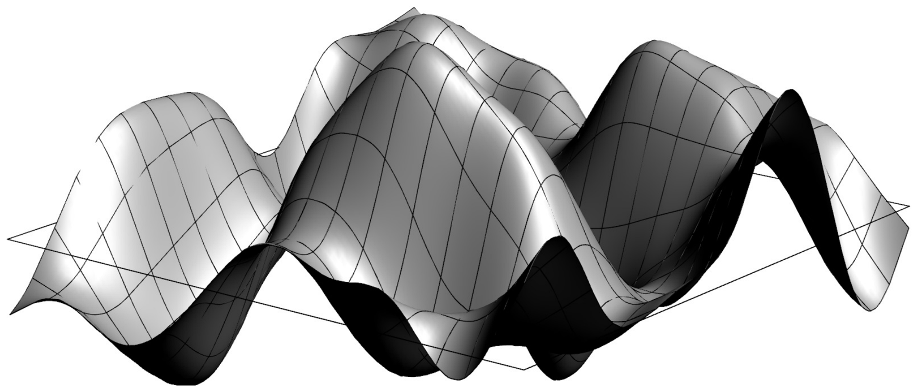

Observed Gaussian Processes

- Given some data points $\mathcal{D} = \big((\boldsymbol{x}_i, y_i)\big| i = 1, \ldots, m\big)$ the likelihood (assuming Gaussian error are independence of the data point) is given by

$$p(\mathcal{D}|f) = \prod_{i=1}^{m} \mathcal{N}\left(y_i \middle| f(\boldsymbol{x}_i), \sigma^2\right)$$

- Using a Gausssian Process prior we can compute a posterior using Bayes's rule

- The posterior is a Gaussian Process with a shifted mean and variance depending on the data-points

- This direct Bayesian derivation gives the answer involving the inverse matrix of the correlation function, $k^{-1}(\boldsymbol{x}, \boldsymbol{y})$

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Alternative Derivation

- Denoting the target values as a vector $\boldsymbol{y}$ with elements y_i
- Denoting the matrices of covariances between data points as $\mathbf{K}$ with elements $k(\boldsymbol{x}_i, \boldsymbol{x}_j)$
- Denoting the covariance between the data points and a particular position, $\boldsymbol{x}_*$ as $\boldsymbol{k}_*$ with elements $k(\boldsymbol{x}_i, \boldsymbol{x}_*)$
- Denoting the variance a point $\boldsymbol{x}_*$ as $k_* = k(\boldsymbol{x}_*, \boldsymbol{x}_*)$
- Then the distribution of function values at points at $\boldsymbol{x}_i$ and $\boldsymbol{x}_*$ is

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Alternative Derivation

- Denoting the target values as a vector $\boldsymbol{y}$ with elements y_i
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Conditional Probability

- To compute the posterior $p(f_*|\boldsymbol{y})$ we use

$$p(f_*|\boldsymbol{y}) = \frac{p(f_*, \boldsymbol{y})}{p(\boldsymbol{y})}$$

- where $p(\boldsymbol{y}) = \int p(f_*, \boldsymbol{y}) \mathrm{d} f_*$

- Because all integrals are Gaussian we can compute the integral to obtain

$$p(f_*|\boldsymbol{y}) = \mathcal{N}\left(f_* \middle| \boldsymbol{k}_*^{\mathsf{T}} (\mathbf{K} + \sigma^2 \mathbf{I})^{-1} \boldsymbol{y}, k - \boldsymbol{k}_*^{\mathsf{T}} (\mathbf{K} + \sigma^2 \mathbf{I})^{-1} \boldsymbol{k}_* \right)$$

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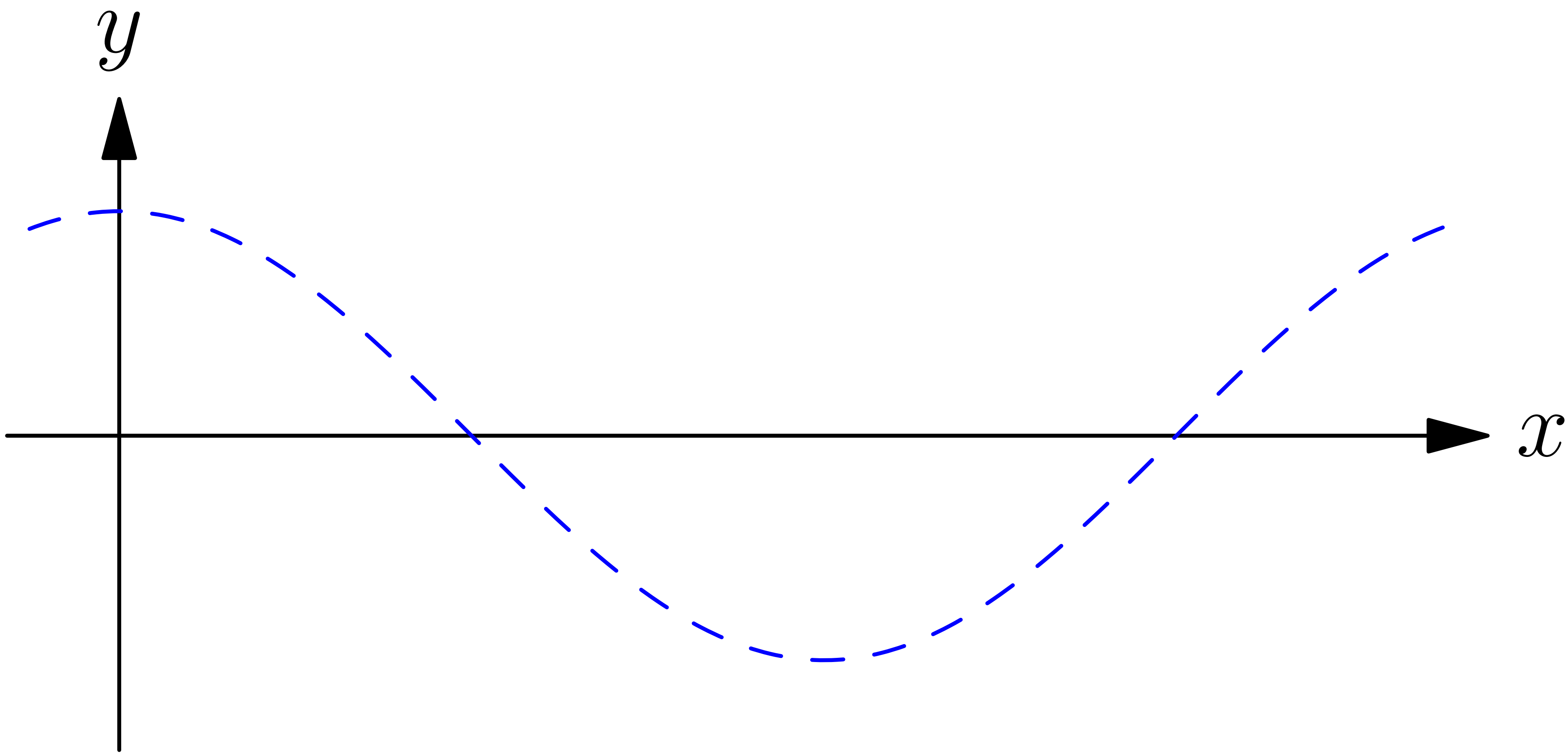
$$K(x,x') = \exp(-(x - x')^2/(2\ell^2))$$



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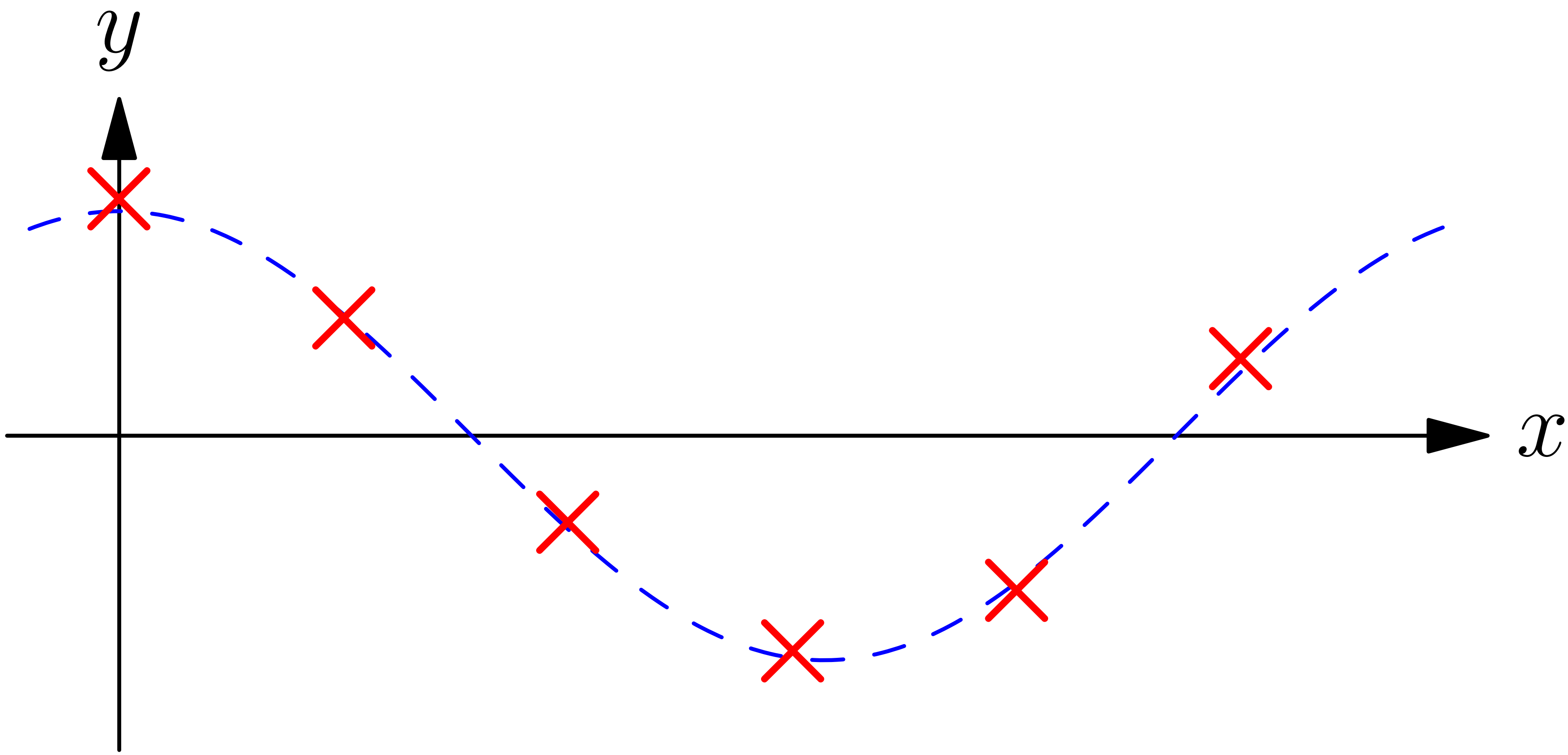

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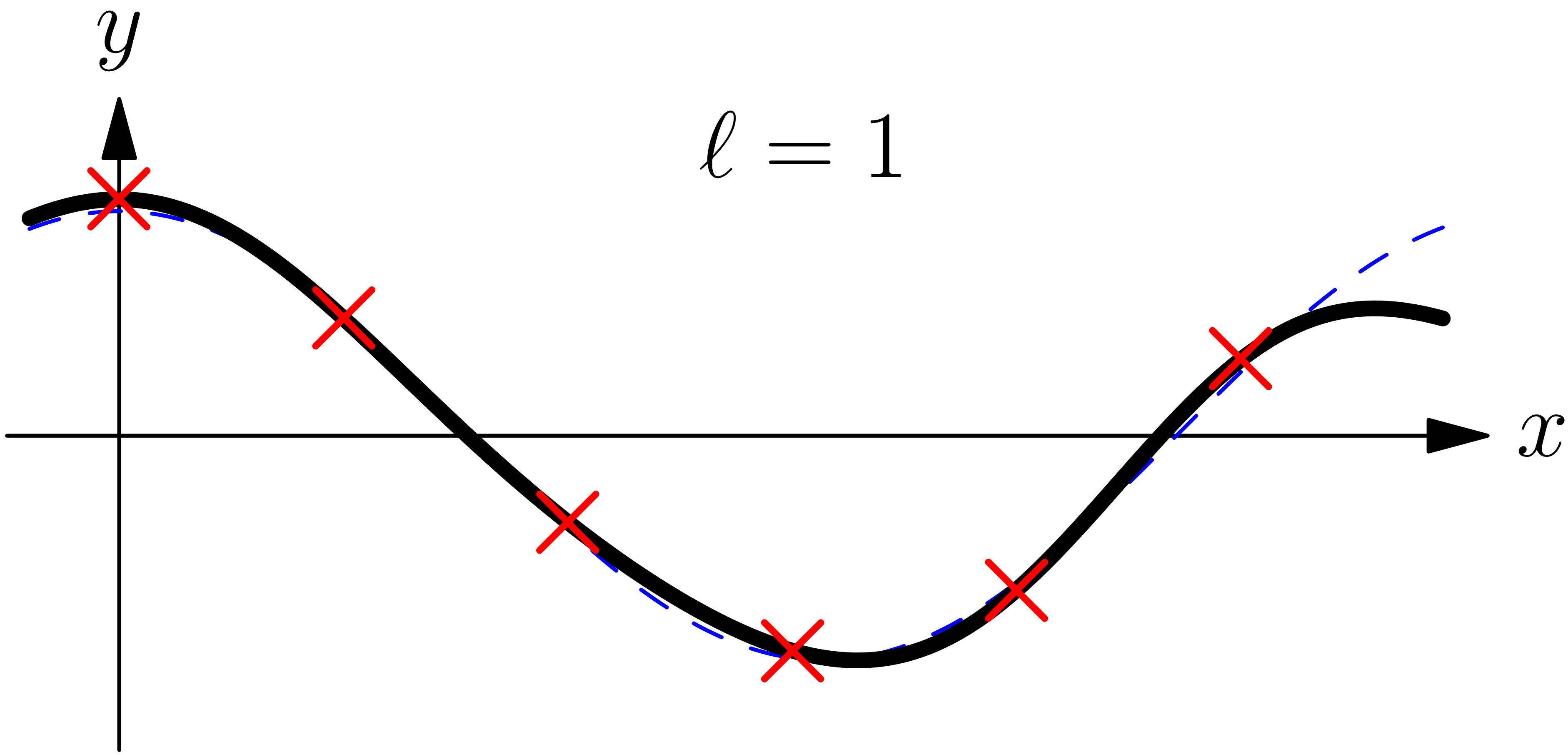

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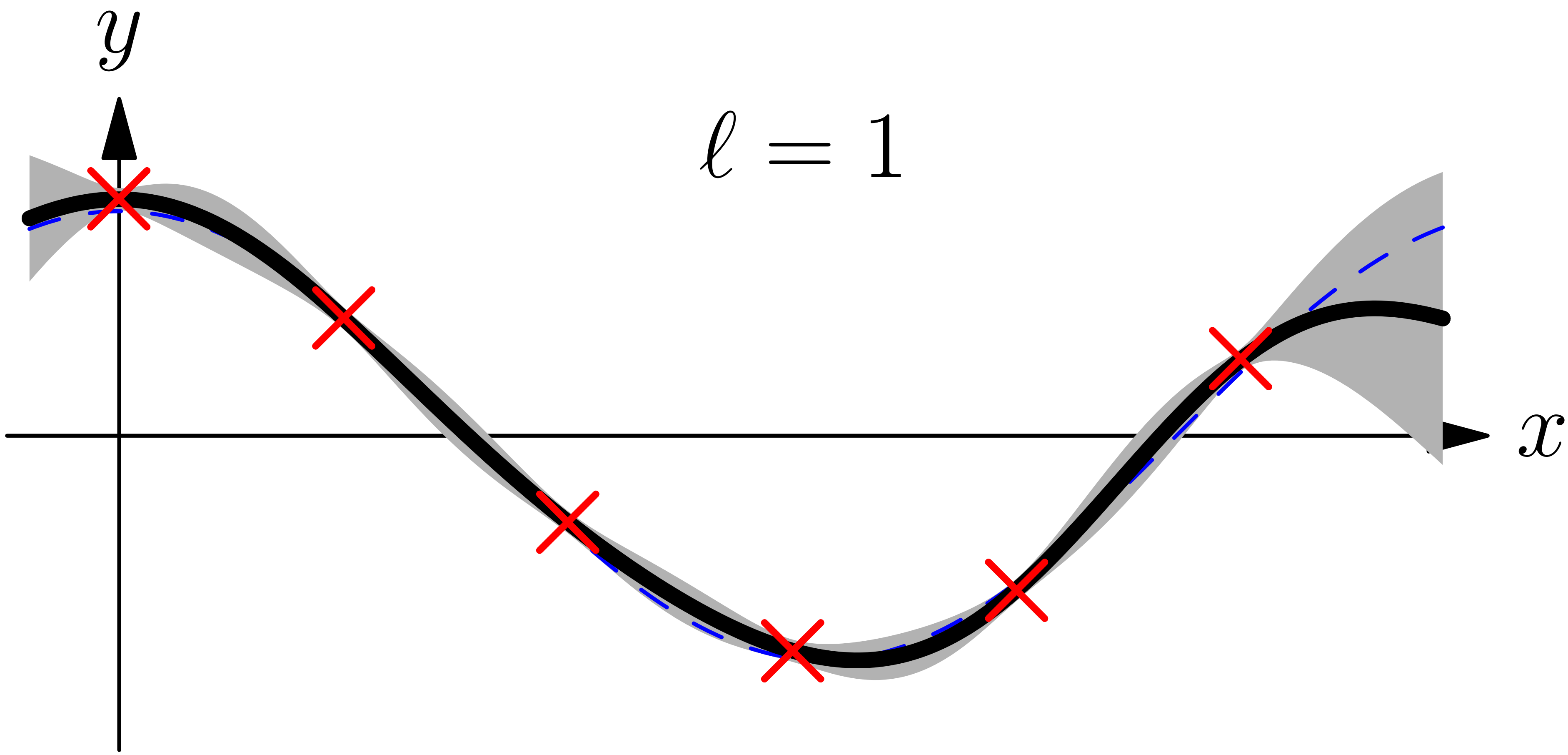

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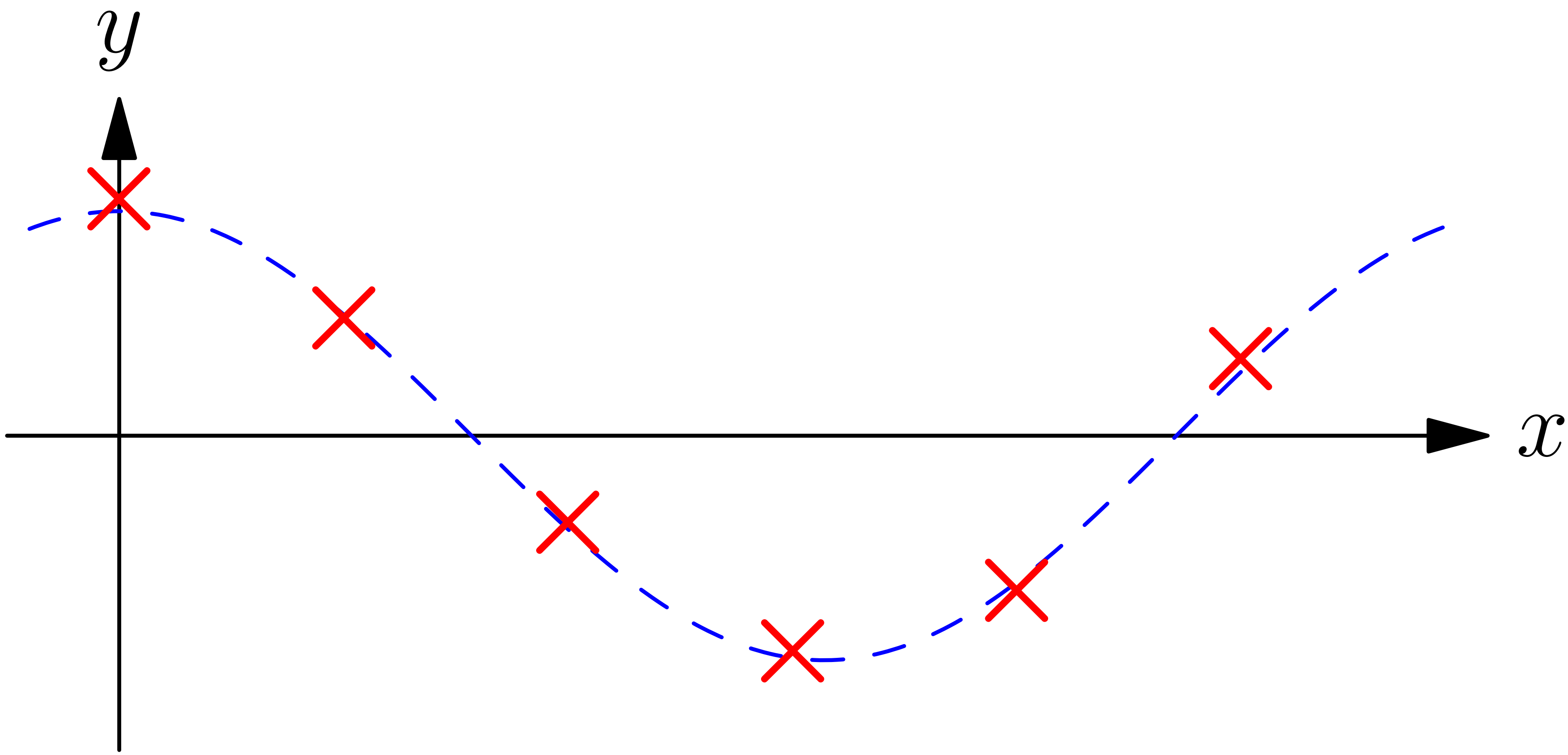

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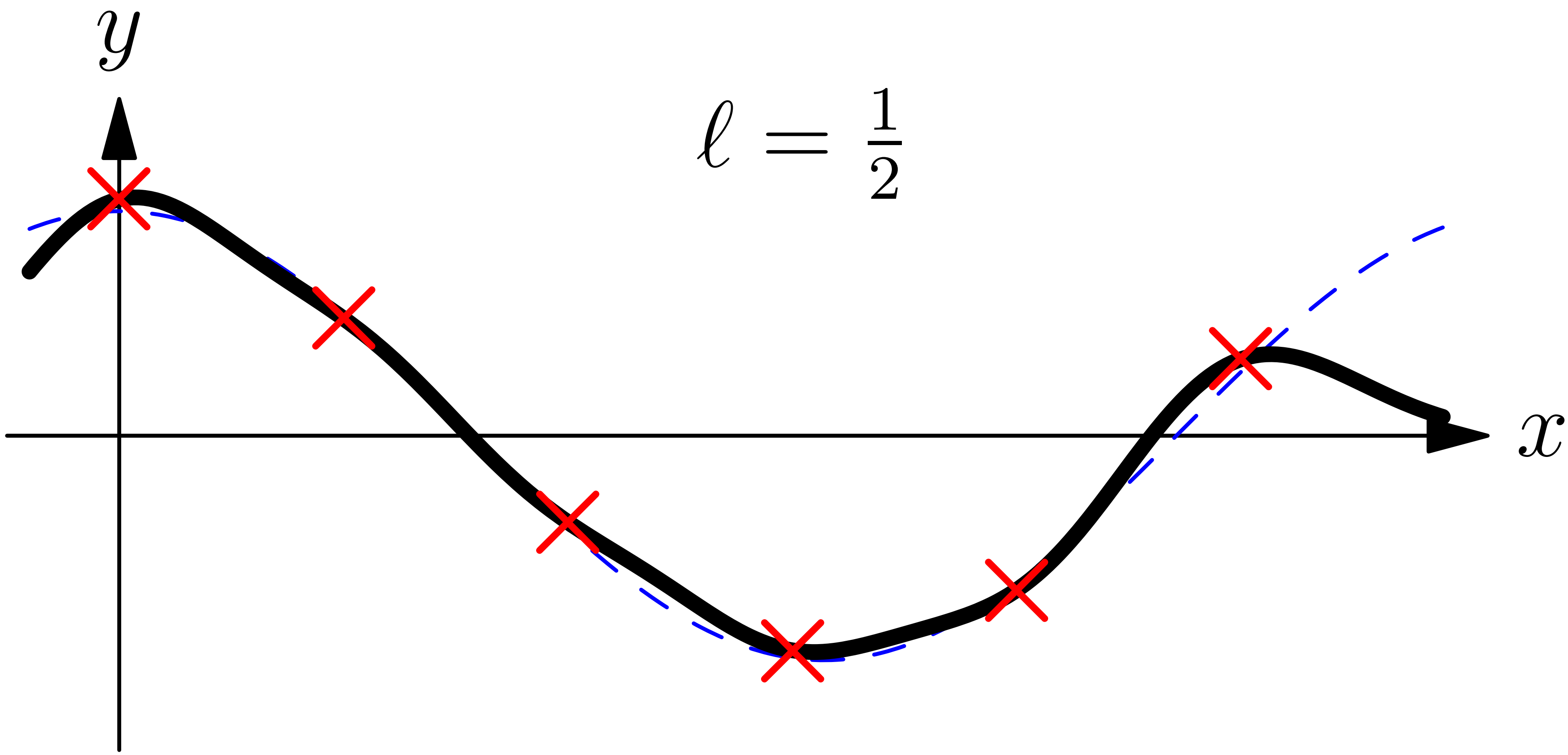

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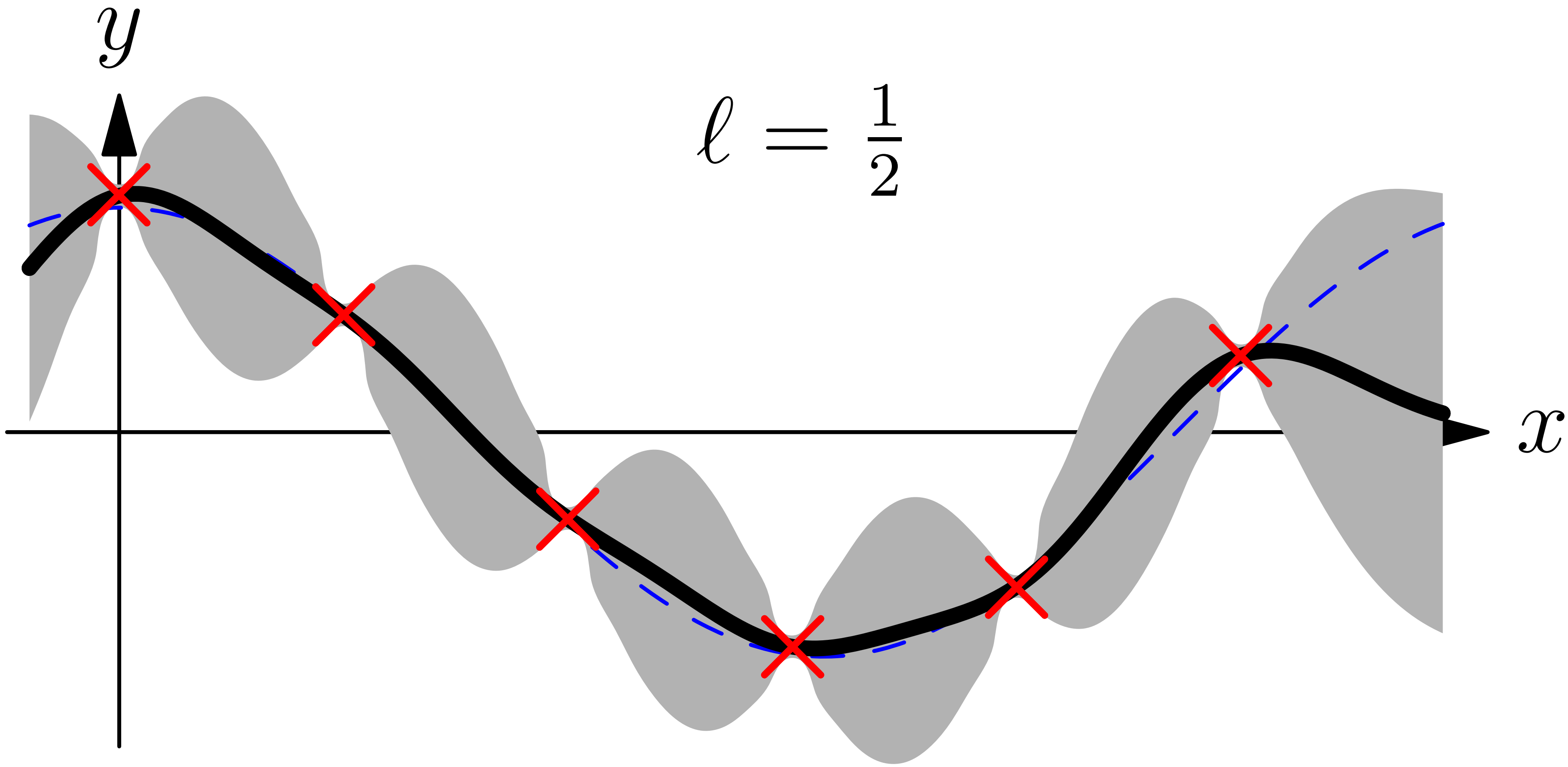

Multi-dimensional Regression

- I've shown a 1-D regression example because it is easy to visualise
- This might be used with a time series
- The much more typical situation in machine learning is for x to have many features so we are doing multi-dimensional regression
- Gaussian process inference were first used in spatial problems where it was known as **krigging**
- It was re-invented by the machine learning community who call it Gaussian Processes (GP)

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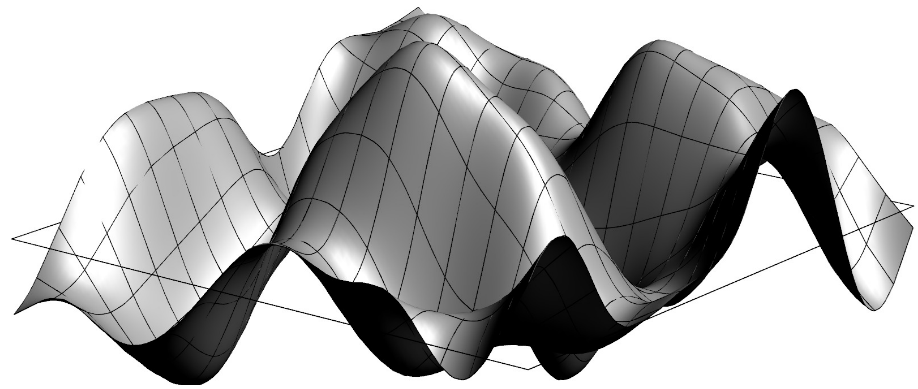
Outline

1. Introduction
2. Gaussian Processes
3. Bayesian Inference
4. **Hyper-parameters**



Choosing the Correct Covariance Function

- Choosing the correct covariance function is critical
- Most covariance functions include a continuous **hyper-parameter** (e.g. the correlation length ℓ) that we have to choose correctly
- This is typical of many Bayesian problems were we have some set of hyper-parameters, ϕ, describing the model
- These are different to the normal parameters we learn (e.g. weights $\boldsymbol{w}$ or in GP the functions $f(\boldsymbol{x})$)
- In Bayesian inference we learn the posterior for these normal parameters

$$p(f|\mathcal{D},\boldsymbol{\phi}) = \frac{p(\mathcal{D}|f,\boldsymbol{\phi})p(f|\boldsymbol{\phi})}{p(\mathcal{D}|\boldsymbol{\phi})}$$

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Evidence Framework

- The normalisation factor, $p(\mathcal{D}|\phi)$ is known as the **marginal likelihood** or **evidence**

$$p(\mathcal{D}|\phi) = \int p(\mathcal{D}|f,\phi)\, p(f|\phi)\, \mathrm{d}f$$

- We can perform a Bayesian calculation at a second level by putting a prior on ϕ

$$p(\phi|\mathcal{D}) = \frac{p(\mathcal{D}|\phi)\, p(\phi)}{p(\mathcal{D})}$$

- From this we can now marginalise out the hyper-parameters

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- The integral

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  usually can't be computed analytically and we have to use Monte Carlo methods (see later lecture)

- An alternative is to use the most likely hyper-parameter

- We can find this by using gradient search of $p(\mathcal{D}|\boldsymbol{\phi})$

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Evidence for GP

- For GP the (log)-evidence can be computed in closed form

$$\log(p(\mathcal{D}|\boldsymbol{\phi})) = -\frac{1}{2}\boldsymbol{y}^{\mathsf{T}}(\mathbf{K}+\sigma^2\mathbf{I})\boldsymbol{y} - \frac{1}{2}\log\bigl(|\mathbf{K}+\sigma^2\mathbf{I}|\bigr) - \frac{m}{2}\log(2\pi)$$

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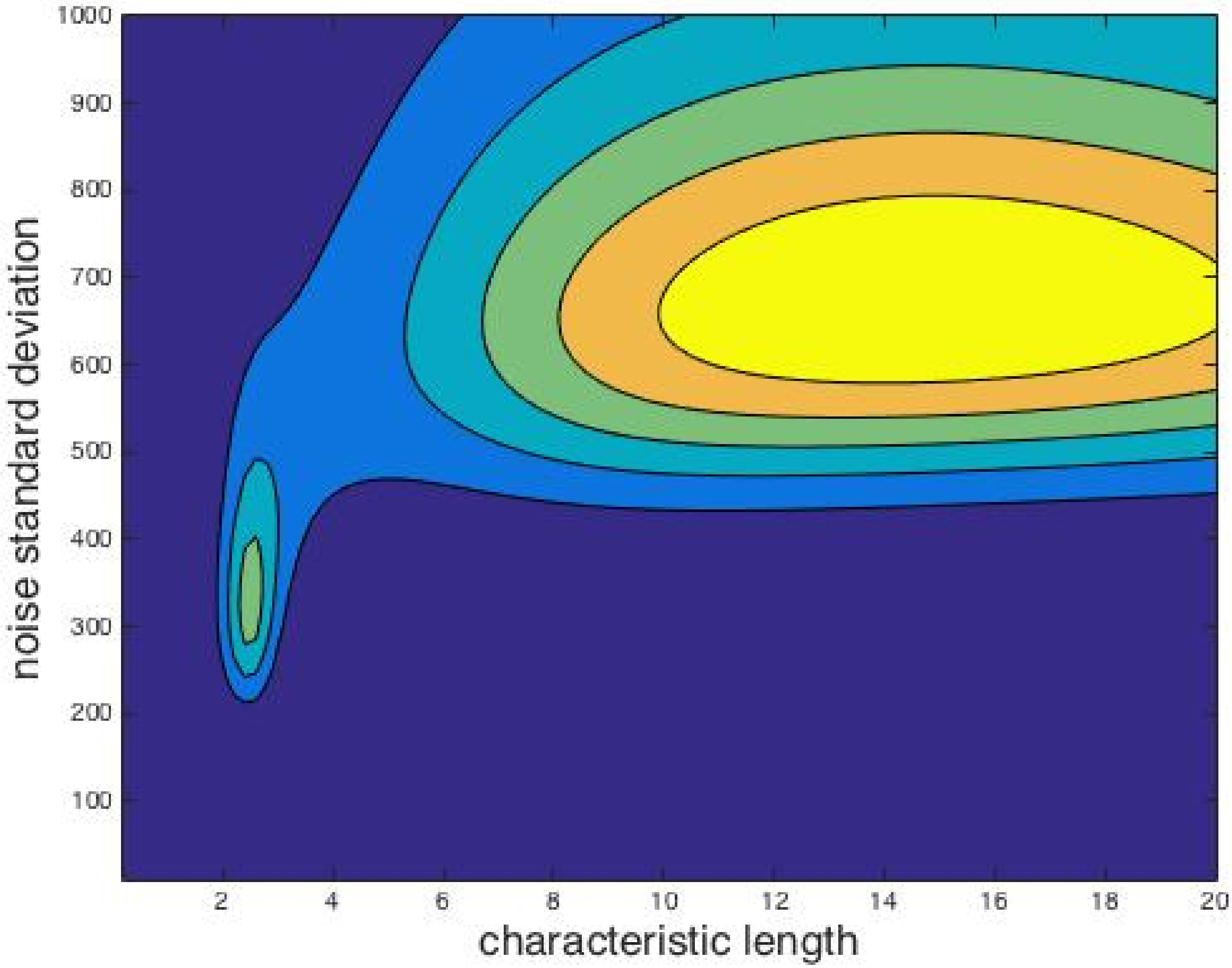
- Could overfit!

Example (slightly pathological)



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