

# Comparing Correlation Functions and Exploring Efficiency and Identifiability Issues for the Gaussian Process

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## Abstract

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# 1 Introduction

## 2 Defining the Gaussian Process

### 2.1 Weight-space view [11]

#### 2.1.1 Standard linear model

The standard linear model summarises that we have some data-generating function  $f(\cdot)$  that linearly combines training data  $X$  and parameters of some model  $W$  to produce an output  $y$ :

$$\begin{aligned} y &= f(X) + \epsilon \\ f(X) &= X^T W \end{aligned} \tag{1}$$

We add a noise term  $\epsilon$  because  $y$  is rarely a perfect observation of  $f(X)$  (e.g. measurement error). The standard linear model assumes that  $\epsilon$  is drawn from a Gaussian distribution  $\epsilon \sim N(0, \sigma_n^2 I)$ . We add a covariance matrix  $I$  to describe how the noise for one observation is related to the noise of another observation.

We can combine our expressions and assumptions for  $f(X)$  and  $\epsilon$  to produce a conditional distribution. Effectively a distribution of errors, this is the distribution from which  $y$  is drawn from after knowing perfectly  $X$  and  $W$ :

$$p(y|X, W) = \mathcal{N}(y|X^T W, \sigma_n^2 I)$$

#### 2.1.2 Determining weights

Our first task is to find  $\hat{W}$  as we typically do not know these in advance. Frequentist approaches focus on arriving at a single estimate of  $W$  ( $\hat{W}$ ) via "maximum likelihood estimation" (MLE).  $p(y|X, W)$  is at its highest density around the expected value  $y|X^T W$  so we can use optimisation methods to find the  $\hat{W}$  at the maximum of  $p(y|X, W)$ . Because we assume  $E[p(y|X, W)] = 0$ , the values of  $W$  at the maximum of  $p(y|X, W)$  are also the values of  $W$  that pushes the squared error  $\|y - X^T W\|^2$  closest to zero. We can communicate uncertainty surrounding  $\hat{W}$  by computing "standard errors", or the ratio between the variance of our errors and the variance of  $X$ . A high variance in errors shows that  $\hat{W}$  is, but a broader range of  $X$  makes it easier to estimate  $W$ .

Instead of producing point estimates for  $\hat{W}$  and uncertainty, Bayesian statistics treats  $W$  as a random variable and specifies an expected value and a variance. Placing  $W$  in a probabilistic framework allows us to propagate uncertainty throughout the model and to encode beliefs (e.g. from domain experts) about the weights before observing the data.

We start with a "prior" distribution of  $W$ , which the Bayesian linear model assumes:

$$p(W) \sim N(0, \Sigma_p) \tag{2}$$

Then, we observe the data and update our beliefs about the weights using Bayes' theorem to produce a "posterior" distribution  $p(W|X, y)$ .

$$p(W|X, y) = \frac{p(y|X, W)p(W)}{p(y|X)}$$

$p(y|X, W)$  is the density of the residuals after applying  $p(W)$  to  $X, W$  under our assumed noise model  $\epsilon$ , and  $p(y|X)$  is the marginal likelihood - how likely the data is given the model.

**2.1.2.1 Deriving our posterior** To understand the relationship between  $p(W|X, y)$  and  $W$ , we can ignore terms that do not vary with  $W$  (e.g. our marginal likelihood) by absorbing them into the proportionality constant:

$$p(W|X, y) \propto p(y|X, W)p(W) \tag{3}$$

TODO fix We can get a probability density function (PDF) for our error distribution by representing  $Y|X^T W$  in squared error form and substituting it into the Gaussian PDF:

$$p(y|X, W) = \exp\left(-\frac{1}{2\sigma_n^2}\|y - X^T W\|^2\right) \tag{4}$$

Reframing  $p(W)$  as a PDF:

$$p(W) = \frac{1}{[\sqrt{\sigma_p}] \sqrt{2\pi}} \exp\left(-\frac{1}{2} \frac{([W] - [0])}{[\Sigma_p]}\right)$$

The first term can be absorbed into the proportionality constant. Rewriting the second term as a negative exponential:

$$p(W) \propto \exp\left(-\frac{1}{2} W^T \Sigma_p^{-1} W\right) \tag{5}$$

Putting both expressions for 4 and 5 into 3:

$$p(W|X, y) \propto \exp\left(-\frac{1}{2\sigma_n^2}\|y - X^T W\|^2\right) \exp\left(-\frac{1}{2} W^T \Sigma_p^{-1} W\right)$$

Expanding  $\|y - X^T W\|^2$  to  $y^T y - 2y^T X W + W^T X^T X W$ :

$$p(W|X, y) \propto \exp\left(-\frac{1}{2\sigma_n^2}(y^T y - 2y^T X W + W^T X^T X W)\right) \exp\left(-\frac{1}{2}W^T \Sigma_p^{-1} W\right)$$

Putting both exponentials together by adding their powers:

$$p(W|X, y) \propto \exp\left(\frac{1}{\sigma_n^2}(y^T y - 2y^T X W + W^T X^T X W) + \left(-\frac{1}{2}W^T \Sigma_p^{-1} W\right)\right)$$

Rearranging the inside term to be a quadratic, linear and constant term in  $W$ :

$$p(W|X, y) \propto \exp\left(\frac{1}{2}W^T \left(\frac{1}{\sigma_n^2}X^T X + \Sigma_p^{-1}\right) W - \left(\frac{1}{\sigma_n^2}y^T X\right) W + \frac{1}{2}y^T y\right)$$

We can ignore the constant final term. Introducing these terms to simplify this result:

$$\begin{aligned} A &= \Sigma_p^{-1} + \frac{1}{\sigma_n^2}X^T X \\ b &= \frac{1}{\sigma_n^2}y^T X \\ p(W|X, y) &\propto \exp\left(-\frac{1}{2}W^T A W + b^T W\right) \end{aligned} \tag{6}$$

**2.1.2.2 Deriving the properties of the posterior by completing the square** Now we have a simplified form of the posterior's PDF, we need to get it into a Gaussian form to recover the properties of the posterior distribution.

Bringing all terms inside the exponential to a single term:

$$-\frac{1}{2}W^T A W + b^T W = \frac{1}{2}(-W^T A W + 2b^T W)$$

Completing the square on our new inner term  $W^T A W - 2b^T W$

$$W^T A W - 2b^T W = (W - A^{-1}b)^T A (W - A^{-1}b) - b^T A^{-1}b \quad p(W|X, y) \propto \exp\left(-\frac{1}{2}((W - A^{-1}b)^T A (W - A^{-1}b) - b^T A^{-1}b)\right) \tag{7}$$

Looking at the Gaussian PDF:

$$N(W|\mu, \Sigma) = \frac{1}{\sqrt{(2\pi)^d |\Sigma|}} \exp\left(-\frac{1}{2}(W - \mu)^T \Sigma^{-1} (W - \mu)\right) \tag{8}$$

Our expression lines up with the Gaussian PDF's "kernel" term  $\exp(-\frac{1}{2}(W - \mu)^T \Sigma^{-1} (W - \mu))$ , where  $\mu = A^{-1}b$  and  $\Sigma = A^{-1}$  ( $\Sigma^{-1} = A$ ). Therefore, 7 can be represented as a Gaussian distribution:

$$p(W|X, y) \sim N(A^{-1}b, A^{-1}) \tag{9}$$

Inside our definition of  $A$  at ??, we are missing an expression for  $\Sigma_p$ . Assuming independence of noise under the linear model, our weight variance  $\Sigma_p$  under the Bayesian linear model is "isotropic", meaning it is the same in all directions.

$$\Sigma_p = \tau^2 I$$

Because we assume independence,  $I$  is an "identity matrix where each diagonal element is 1 and all off-diagonal elements are 0.  $\tau^2$  is a scalar variance term, chosen as a prior.

Substituting the isotropic prior  $\Sigma_p$  into  $A$ :

$$A = \Sigma_p^{-1} + \frac{1}{\sigma_n^2}X^T X = [\tau^2 I]^{-1} + \frac{1}{\sigma_n^2}X^T X = \frac{1}{\tau^2}I + \frac{1}{\sigma_n^2}X^T X$$

Simplifying:

$$A = \frac{1}{\sigma_n^2} \left( X^T X + \frac{\sigma_n^2}{\tau^2} I \right) \tag{10}$$

**2.1.2.3 Gaussian posteriors and ridge regression** So far we have worked exclusively within the Bayesian paradigm, but we can draw some value of  $W$  from our posterior distribution to relate it to a frequentist framework. For Gaussian posteriors, our expected value of  $W A^{-1}b$  is also its mode. This is called the maximum a posteriori (MAP) estimate of  $W$ , and is due to symmetries in linear model and posterior and is not the case in general. Our MAP estimate does not matter within the Bayesian framework but is equivalent to our frequentist  $\hat{W}$ .

Substituting our full expressions for  $A$  10 and  $b$  6 into our MAP estimation:

$$W_{\text{MAP}} = A^{-1}b = \left[ \frac{1}{\sigma_n^2} (X^T X + \frac{\sigma_n^2}{\tau^2} I) \right]^{-1} \cdot \left[ \frac{1}{\sigma_n^2} y^T X \right]$$

Inverting LHS term of  $A$ :

$$A^{-1} = \frac{\sigma_n^2}{X^T X + \frac{\sigma_n^2}{\tau^2} I} = \sigma_n^2 \left( X^T X + \frac{\sigma_n^2}{\tau^2} I \right)^{-1}$$

Substituting this back into  $W_{\text{MAP}}$  cancels out the  $\sigma_n^2$  term in  $A$  with the  $\frac{1}{\sigma_n^2}$  term in  $B$ :

$$W_{\text{MAP}} = \sigma_n^2 \left( X^T X + \frac{\sigma_n^2}{\tau^2} I \right)^{-1} \cdot \frac{1}{\sigma_n^2} y^T X = \left( X^T X + \frac{\sigma_n^2}{\tau^2} I \right)^{-1} \cdot y^T X$$

This is equivalent to the solution to ridge regression, where  $\lambda = \frac{\sigma_n^2}{\tau^2}$ .

$$W_{\text{ridge}} = (X^T X + \lambda I)^{-1} X^T y$$

Ridge regression introduces some bias to lower the variance in a frequentist linear model by shrinking weights, where the  $\lambda$  term controls the amount of shrinkage applied to the weights. This is traditionally useful where variance is particularly high (e.g. multicollinearity) and can be reduced at the cost of little bias.

Our MAP estimation in Bayesian linear regression with isotropic priors is equivalent to ridge regression, where the amount of bias we introduce depends on our confidence in our priors. The more we trust our prior, the higher our  $\lambda$  and the more we shrink our weights towards zero. A lower  $\tau$  means we are more confident in  $p(W)$  and have better priors, whereas a higher  $\sigma_n$  means lower confidence in  $p(y|X, W)$  and worse weights that should be shrunk closer to zero.

### 2.1.3 Predictive distribution

**2.1.3.1 Deriving the predictive distribution** Our second task is to make predictions  $y_*$  using new input data  $X_*$  and our previously learned weights  $W$ . Frequentist methods simply multiply  $\hat{W}$  by  $X_*$ , but this does not propagate uncertainty in  $W$ . In this Bayesian framework, we form a "predictive distribution" which we sample from to get our noise-free function evaluations  $f(X_*)$  (denoted  $f_*$ ) and add  $\epsilon$  to get our noisy predictions  $y_*$ .

$$p(f_*|X_*, X, y) = \int p(f_*|X_*, W) \cdot p(W|X, y) dW$$

$p(f_*|X_*, W)$  is what we think the function looks like after producing a prediction using  $X_*$  and perfect knowledge of  $W$ .  $p(W|X, y)$  is our familiar 9 posterior distribution of weights.  $p(f_*|X_*, W) \cdot p(W|X, y)$  is the joint distribution of our predictions and our posterior weights, which gets us the conditional distribution  $p(f_*, W|X_*, X, y)$  by definition of conditional probability. Because  $p(f_*, W|X_*, X, y)$  relies on our perfect knowledge of  $W$ , which we lack, we integrate over all possible  $W$  to get the final predictive distribution  $p(f_*|X_*, X, y)$

$p(f_*|X_*, W)$  is our error distribution, which we assume to be distributed normally and independently with our  $I$  identity matrix:

$$p(f_*|X_*, W) = \mathcal{N}(f_*|W^T X_*, \sigma_n^2 I)$$

Substituting into 8 and absorbing the LHS term into the proportionality constant:

$$p(f_*|X_*, w) \propto \exp \left( -\frac{1}{2} \frac{1}{\sigma_n^2} (f_* - W^T X_*)^2 \right)$$

Multiplying  $P(f_*|X_*, W)$  and  $p(W|X, y)$  to get our conditional  $p(f_*, W|X_*, X, y)$ , and add the exponents:

$$p(f_*, W|X_*, X, y) \propto \exp \left( \frac{1}{2} (-W^T A W + 2b^T W) + \left( -\frac{1}{2} \frac{1}{\sigma_n^2} (f_* - W^T X_*)^2 \right) \right)$$

Combining the terms inside the exponent:

$$p(f_*, W|X_*, X, y) \propto \exp \left( -\frac{1}{2} \left( W^T A W - 2b^T W + \frac{1}{\sigma_n^2} (f_* - W^T X_*)^2 \right) \right)$$

Expanding the squared term:

$$p(f_*, W|X_*, X, y) \propto \exp \left( -\frac{1}{2} \left( W^T A W - 2b^T W + \frac{1}{\sigma_n^2} (f_*^2 - 2f_* W^T X_* + W^T X_* X_*^T X_*) \right) \right)$$

Similar to our posterior, we can rearrange this to be a quadratic, linear and constant term in  $W$ :

$$p(f_*, W|X_*, X, y) \propto \exp \left( -\frac{1}{2} \left( W^T \left( A + \frac{1}{\sigma_n^2} X_* X_*^T \right) W - 2 \left( b + \frac{1}{\sigma_n^2} f_* X_* \right)^T W + \frac{1}{\sigma_n^2} f_*^2 \right) \right) \quad (11)$$

We can define new terms  $A_*$  and  $b_*$  to simplify this expression:

$$A_* = A + \frac{1}{\sigma_n^2} X_* X_*^T$$

$$b_* = b + \frac{1}{\sigma_n^2} f_* X_*$$

Substituting into 11:

$$p(f_*, W | X_*, X, y) \propto \exp \left( -\frac{1}{2} \left( W^T A_* W - 2b_*^T W + \frac{1}{\sigma_n^2} f_*^2 \right) \right)$$

Integrating out  $W$  to get our predictive distribution:

$$p(f_* | X_*, X, y) = \int p(f_*, W | X_*, X, y) dW \propto \int \exp \left( -\frac{1}{2} \left( W^T A_* W - 2b_*^T W + \frac{1}{\sigma_n^2} f_*^2 \right) \right) dW \quad (12)$$

Factoring out  $\frac{1}{\sigma_n^2} f_*^2$  as it does not depend on  $W$  (since  $\int \exp(X) dX = \exp(X)$ ):

$$= \exp \left( -\frac{1}{2} \frac{1}{\sigma_n^2} f_*^2 \right) \times \int \exp \left( -\frac{1}{2} (W^T A_* W - 2b_*^T W) \right) dW$$

Evaluating the RHS multivariate Gaussian integral:

$$\int \exp \left( -\frac{1}{2} (W^T A_* W - 2b_*^T W) \right) dW = \frac{(2\pi)^{D/2}}{\sqrt{|A_*|}} \exp \left( \frac{1}{2} b_*^T A_*^{-1} b_* \right)$$

Substituting back into 12:

$$p(f_* | X_*, X, y) \propto \exp \left( -\frac{1}{2} \frac{1}{\sigma_n^2} f_*^2 \right) + \frac{(2\pi)^{D/2}}{\sqrt{|A_*|}} \cdot \exp \left( \frac{1}{2} b_*^T A_*^{-1} b_* \right)$$

Now that no part of our expression is dependent on  $W$ , we need an expression for everything that depends on  $f_*$ .

Absorbing the second term (since it does not depend on  $f_*$ ) into the proportionality constant, and combining the remaining exponential terms by adding their powers:

$$p(f_* | X_*, X, y) \propto \exp \left( -\frac{1}{2} \frac{1}{\sigma_n^2} f_*^2 + \frac{1}{2} b_*^T A_*^{-1} b_* \right)$$

Similar to deriving properties from our posterior, we can rearrange this expression and complete the square to derive the properties of our predictive distribution:

$$p(f_* | X_*, W) \sim N(X_*^T A^{-1} b, X_*^T A^{-1} X_*) \quad (13)$$

The variance is quadratic in  $X_*$  with  $A^{-1}$ , showing that predictive uncertainties grow with size of  $X_*$ .

#### 2.1.4 Projections of inputs into feature space

One problem with this model is that it assumes a linear relationship between  $X$  and  $y$ . We can project our inputs into a higher dimensional feature space and apply a linear model in this space to express non-linear relationships between  $X$  and  $y$ .

Defining  $\phi(X)$  as a function that maps a  $D$ -dimensional input vector  $X$  into an  $N$  dimensional feature space, our standard linear model becomes:

$$f(X) = \phi(X)^T W$$

For example, a scalar  $x$  could be projected into the space of powers of  $x$ :  $\phi(x) = [1, x, x^2, \dots, x^d]^T$  for a polynomial basis expansion of degree  $d$  to represent a  $d$ -power relationship between  $x$  and  $y$ . Substituting  $\phi(X)$  for  $X$  in 13:

$$p(f_* | X_*, X, y) = N(\phi(X_*)^T A_\phi^{-1} b_\phi, \phi(X_*)^T A_\phi^{-1} \phi(X_*)) \quad (14)$$

Where  $A_\phi$  and  $b_\phi$  are now:

$$A_\phi = \Sigma_p^{-1} + \frac{1}{\sigma_n^2} \phi(X)^T \phi(X) b_\phi = \frac{1}{\sigma_n^2} \phi(X)^T y$$



### 2.1.5 Computational issues

**2.1.5.1 Avoiding inversion of  $A_\phi$**  14 requires inverting the  $N \times N$  matrix  $A_\phi$ , where  $N$  is dimension of feature space, to get the expected value and variance.

Typically, matrices are inverted using Gaussian elimination. We need to perform a "forward" pass which requires  $N$  pivots on every row and column,  $N$  eliminations per pivot, and up to  $2N$  columns to update, resulting in an  $O(N^3)$  time complexity. Then, we need to perform a backwards pass in the opposite direction which is another  $O(N^3)$  operation. Finally, we need to multiply the inverse by the RHS vector  $b_\phi$ , which is an  $O(N^2)$  operation but appears trivial next to these two cubic steps.

We can mitigate this for a particular class of high-dimensional  $N > n$  problems by restating the predictive distribution in terms of the number of training data points  $n$  which would require inverting an  $n \times n$  matrix instead. For polynomial basis expansions,  $N$  is degree  $D$  multiplied by number of features, so  $N$  can be very large or even infinite (e.g. SE).

Substituting  $b_\phi$  into our predictive distribution mean:

$$\mathbb{E}_{p(f_*|X_*, X, y)}[f_*] = \phi(X_*)^T \cdot A_\phi^{-1} \cdot \left[ \frac{1}{\sigma_n^2} \phi(X)^T y \right]$$

Rearranging to isolate  $A_\phi^{-1} \phi(X)$

$$= \frac{1}{\sigma_n^2} \left[ A_\phi^{-1} \phi(X) \right]^T y$$

We can use the Sherman-Morrison-Woodbury identity (SMW) to get an expression for  $A_\phi^{-1}$  directly, where  $K = \phi(X)^T \Sigma_p \phi(X)$ , since TODO rank

$$A_\phi^{-1} = \Sigma_p - \Sigma_p \phi(X) (K + \sigma_n^2 I)^{-1} \phi(X)^T \Sigma_p$$

For the mean, we can use the SMW identity again to get an expression for  $A_\phi^{-1} \phi(X)$

$$A_\phi^{-1} \phi(X) = \sigma_n^2 \Sigma_p \phi(X) (K + \sigma_n^2 I)^{-1} \quad (15)$$

Substitute in 15 into our 14:

$$\mathbb{E}_{p(f_*|X_*, X, y)}[f_*] = \phi(X_*)^T \frac{1}{\sigma_n^2} \left[ \sigma_n^2 \Sigma_p \phi(X) (K + \sigma_n^2 I)^{-1} \right]^T y$$

$\frac{1}{\sigma_n^2}$  and  $\sigma_n^2$  cancel out, leaving us with this final expression for the mean:

$$\mathbb{E}_{p(f_*|X_*, X, y)}[f_*] = \phi(X_*)^T \cdot \Sigma_p \phi(X) (K + \sigma_n^2 I)^{-1} y \quad (16)$$

For the variance, we cannot use the Sherman-Morrison identity to arrive at an expression for  $A_\phi^{-1} \phi(X_*)$  because  $\phi(X_*)$  is an arbitrary  $N$ -vector, not one of the columns of  $\phi(X)$ . Instead, we use the  $A_\phi^{-1}$  expression we derived earlier to get an expression for  $A_\phi^{-1} \phi(X_*)$ :

$$A_\phi^{-1} \phi(X_*) = \Sigma_p \cdot \phi(X_*) - \Sigma_p \phi(X) (K + \sigma_n^2 I)^{-1} \phi(X)^T \Sigma_p \cdot \phi(X_*)$$

Substituting this into 14:

$$\text{Var}_{p(f_*|X_*, X, y)}[f_*] = \phi(X_*)^T \Sigma_p \phi(X_*) - \phi(X_*)^T \Sigma_p \phi(X) (K + \sigma_n^2 I)^{-1} \phi(X)^T \Sigma_p \phi(X_*) \quad (17)$$

With our alternative mean 16 and variance 17, we can form an alternative expression for our predictive distribution:

$$p(f_*|X_*, X, y) = \mathcal{N} \left( \begin{aligned} &\phi(X_*)^T \Sigma_p \phi(X) (K + \sigma_n^2 I)^{-1} y, \\ &\phi(X_*)^T \Sigma_p \phi(X_*) - \phi(X_*)^T \Sigma_p \phi(X) (K + \sigma_n^2 I)^{-1} \phi(X)^T \Sigma_p \phi(X_*) \end{aligned} \right) \quad (18)$$

With this alternative formulation, we need to invert the  $n \times n$  matrix  $K + \sigma_n^2 I$  only. Geometrically,  $n$  datapoints can span at most  $n$  dimensions in the feature space - if  $N > n$ , the data forms a subspace of the feature space.

**2.1.5.2 Kernels and the kernel trick** In 18,  $\phi(\cdot)$  is always an inner product of a positive definite correlation matrix  $\Sigma_p$ , but with different arrangements of  $\phi(X)$  and  $\phi(X_*)$ . We can define  $k(X, X') = \phi(X)^T \Sigma_p \phi(X')$  as a covariance function or kernel, where  $X$  and  $X'$  are either  $X$  or  $X_*$ . For example, in 18 the definition of  $K = \phi(X)^T \Sigma_p \phi(X)$  becomes  $K = k(X, X)$ .

Introducing  $\psi(X)$  to better represent  $k(X, X')$  as an inner product:

$$\begin{aligned} \psi(X) &= \phi(X) \Sigma_p^{1/2} \\ k(X, X') &= \psi(X)^T \psi(X') \end{aligned}$$

These inner product representations require us to compute  $\phi(X)$  and  $\phi(X')$  in the feature space. A higher-dimensional feature space requires more compute to evaluate  $\phi(X)$  and more memory to store  $\phi(X)$  and  $\phi(X')$ .

Instead, the representer theorem guarantees that we can find an equivelant kernel that does not require us to explicitly compute  $\phi(X)$  or  $\phi(X')$  in the feature space. With this "kernel trick" we avoid the associated memory and computational costs of explicitly computing  $\phi(X)$  and  $\phi(X')$ . Since computing the kernel directly is more convenient than the feature vectors themselves, these kernels become the object of primary interest.

For example, if we had some polynomial transformation  $\phi(X) = [1, x^1, \dots, x^D]^T$  and  $\Sigma_p$  as an identity matrix, we could define  $k(X, X')$  as inner products:

$$\psi(X) = [1, x^1, \dots, x^D]^T k(X, X') = \psi(X)^T \psi(X')$$

This approach requires arranging  $\phi$  and  $\phi(X')$  into a  $D$  sized vector, then taking the dot product. This is trivial for small  $D$ , but as  $D$  becomes infinite (e.g. RBF kernel), arranging a  $D$  sized vector requires too much memory and the dot product becomes computationally expensive.

Instead, we can define  $k(X, X')$  as an equivelant function of  $X$  and  $X'$  directly:

$$k(X, X') = (1 + X \cdot X')^D$$

This is the polynomial kernel, which is equivalent to our original polynomial basis expansion  $\phi(X)$  without explicitly computing  $\phi(X)$ .

## 2.2 Function-space view [11]

### 2.2.1 Gaussian processes (GP)

**2.2.1.1 Bayesian linear model** We can define our Bayesian linear model of a real process  $f(X)$  entirely in terms of mean function  $m(X)$  and covariance function  $k(X, X')$ :

$$\begin{aligned} m(X) &= \phi(X)^T \mathbb{E}[W] = \phi(X)^T [0] = 0 \\ k(X, X') &= \phi(X)^T \mathbb{E}[WW^T] \phi(X') = \phi(X)^T \Sigma_P \phi(X') \end{aligned} \quad (19)$$

Our covariance function here is in inner product form. The kernel trick here uses the squared exponential (SE) covariance function, also known as the radial basis function (RBF) or Gaussian kernel:

$$k(f(X), f(X')) = \exp \left( -\frac{1}{2} \frac{|X - X'|^2}{l^2} \right)$$

It can be shown that SE corresponds to a Bayesian linear regression model with infinite basis functions.

**2.2.1.2 Function evaluations to a random function** We can choose a subset  $X_{*1}$  from our test data  $X_*$  and apply it to our model get some function evaluations  $f(X_{*1})$ .  $f(X_{*1})$  can be described as a multivariate Gaussian distribution, e.g. in the Bayesian linear model  $f(X_{*1}) \sim N(0, k(X_{*1}, X_{*1}))$ . Each output  $f(X_{\theta*1})$  in our  $f(X_{*1})$  vector is a random variable with mean 0 and covariance with each other  $K_{\theta\theta'} = k(X_{\theta*}, X_{\theta'*})$ . There exists some random function  $g(X_{*1})$  for our subsets such that  $f(X_{*1}) = g(X_{*1})$ . We only know the value of  $g(X_{*1})$  at the points  $X_{*1}$ , so  $g(X_{*1}) = X_{*1} : f(X_{*1})$ . Because  $g(X)$  entirely consists of random points, we can think of  $g(X_{*1})$  as a random function and our distribution  $f(X)$  can be seen as a distribution of these random  $g(X)$  functions. We can recover our individual  $g(X_{*1})$  thanks to consistency - if we marginalised out our subset from the entire distribution  $f(X_*)$ , we would recover the subset distribution  $N(0, K_*(X_{*1}, X_{*1}))$  that describes our random function  $g(X_{*1})$ .

**2.2.1.3 Definition of a GP** A GP is a collection of random variables, any finite number of which have a joint Gaussian distribution. Ultimately, GPs describe a distribution of random functions where each drawn function is a  $g(X)$  sample from the GP.

$$\begin{aligned} f(X) &\sim \mathcal{GP}(m(X), k(X, X')), \\ m(X) &= \mathbb{E}[f(X)], \\ k(X, X') &= \text{Cov}(f(X), f(X')) = \mathbb{E}[(f(X) - m(X))(f(X') - m(X'))] \end{aligned}$$

**2.2.1.4 Consistency requirement** This definition implies a consistency requirement - any group of functions drawn from our GP can be described by the same distribution as our GP. For example, if our GP implies that  $(f(X_1), f(X_2)) \sim \mathcal{N}(\mu, \Sigma)$ , then  $(f(X_1) \sim \mathcal{N}(\mu_1, \Sigma) \text{ and } f(X_2) \sim \mathcal{N}(\mu_2, \Sigma))$  where  $\mu_\theta = m(X_\theta)$  and  $\Sigma_{\theta\theta} = k(X_\theta, X_\theta)$ . This requirement is also called the marginalisation property, because to get the smaller distribution of  $f(X_1)$  we marginalise out the larger distribution of  $f(X_1), f(X_2)$  by integrating the larger distribution wrt  $f(X_2)$ . Consistency is automatically gained if our covariance function specifies entries in a covariance matrix.

## 2.2.2 Predictive distributions with noise-free observations

**2.2.2.1 Prior distribution over functions**  $f(X)$  and  $f(X_*)$  are jointly distributed according to the prior:

$$\begin{pmatrix} f(X) \\ f(X_*) \end{pmatrix} \sim N \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} K(X, X) & K(X, X_*) \\ K(X_*, X) & K(X_*, X_*) \end{pmatrix} \right) \quad (20)$$

**2.2.2.2 Posterior distribution of functions** To get the posterior distribution of functions given the training data and our prior, we can condition the joint prior distribution on the training data. Intuitively, this is like generating random functions  $g(X)$  and rejecting those that do not pass through the training data. Probabilistically, we condition our joint Gaussian prior distribution on the observations  $p(f(X_*)|X_*, X, f(X))$ .

Substituting  $p(W)$  and our conditioning  $X$  into the Gaussian multivariate conditioning identity:

$$\begin{aligned} p(f(X_*)|X_*, X, f(X)) \sim N( \\ [0] + [K(X_*, X)][K(X, X)]^{-1}([f(X)] - [0]), \\ [K(X_*, X_*)] - [K(X_*, X)][K(X, X)]^{-1}[K(X, X_*)] \\ ) \end{aligned}$$

Although we condition on  $X_*$ ,  $X$ , and  $f(X)$ , we only substitute  $f(X)$  because  $X_*$  and  $X$  are known constants, but  $f(X)$  is random because it is a sample from the prior. We also swap  $f(X_*)$  and  $f(X)$  in our prior to match the conditioning identity, such that our input vector into the conditioning identity is  $(f(X_*), f(X))^T$ .

Simplifying the last term in the mean:

$$\begin{aligned} p(f(X_*)|X_*, X, f(X)) \sim N( \\ K(X, X_*)K(X, X)^{-1}f(X), \\ K(X_*, X_*) - K(X_*, X)K(X, X)^{-1}K(X, X_*) \\ ) \end{aligned} \quad (21)$$

## 2.2.3 Predictive distributions with noisy observations

**2.2.3.1 Noisy observations prior** It is typical to not have the noise-free function evaluations  $f(X)$  as our training data, but instead our noisy observations  $y$ . We can simply add  $\epsilon$ :

$$\text{Cov}(y_p, y_q) = K(X_p, X_q) + \sigma_n^2 \delta_{pq}$$

$\delta_{pq}$  represents our independence condition in 1D. This is the Kronecker delta, which returns 1 if indices  $(p, q)$  are equal and 0 otherwise.  $\sigma_n^2$  is the noise variance, which is a constant for all observations.

In matrix form:

$$\text{Cov}(Y) = k(X, X) + \sigma_n^2 I$$

This gives us this prior:

$$\begin{pmatrix} Y \\ f(X_*) \end{pmatrix} \sim N \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} K(X, X) + \sigma_n^2 I & K(X, X_*) \\ K(X_*, X) & K(X_*, X_*) \end{pmatrix} \right)$$

**2.2.3.2 Noisy observations posterior** As before, we can form a predictive distribution using the Gaussian multivariate conditioning identity:

$$\begin{aligned} p(f(X_*)|X_*, X, Y) \sim N( \\ K(X_*, X)[K(X, X) + \sigma_n^2 I]^{-1}Y, \\ K(X_*, X_*) - K(X_*, X)[K(X, X) + \sigma_n^2 I]^{-1}K(X, X_*) \\ ) \end{aligned}$$

Substituting  $k(X, X') = \phi(X)^T \Sigma_p \phi(X')$  into here gives us the exact same result as 18.

Our variance is independent of the targets  $y$  and only depends on our inputs  $X$  and  $X_*$ . Our variance is two terms: our prior covariance  $K(X_*, X_*)$ , a term representing the information the observations give us about the function. As before, we can compute the predictive distribution of  $y_*$  by adding the noise term  $\sigma_n^2 I$  to the variance.

## 2.2.4 Marginal likelihood

Even though we are working within the Bayesian paradigm, certain practical subroutines e.g. kernel hyperparameter optimisation algorithms need a likelihood to maximise. The marginal likelihood  $p(Y|X)$  is a measure of how well our GP fits the data:

$$p(Y|X) = \int p(Y|f, X) p(f|X) df \quad (22)$$

$p(f|X)$  is our familiar prior distribution over weights  $\sim N(0, K)$  which we use here to represent the complexity of  $f$ .  $p(y|f, X)$  is the likelihood of our observations given  $p(y|f, X) \sim N(f, \sigma_n^2 I)$ , and represents how well  $f$  maps  $X$  to  $y$ .

Our weight's mean will always be the same under our prior, but our  $K(X, X')$  tells us how "wiggly" our function is. The closer our  $p(f|X)$  distribution is to the true complexity of the function, the higher our marginal likelihood. For example, for SE if our data is close together, then  $|X - X'|$  becomes small and our covariance  $k(X, X')$  on our function distribution prior is large. Therefore, we get a high variety of functions and a higher probability of sampling a more complex function.

We can express  $p(Y|X)$  as a Gaussian integral over the joint distribution of  $f$  and  $Y$  ( $p(Y, f|X)$ ), and marginalise out  $f$  to get this PDF:

$$\log p(Y|X) = -\frac{1}{2}Y^T(K(X, X) + \sigma_n^2 I)^{-1}Y - \frac{1}{2}\log|K + \sigma_n^2 I| - \frac{n}{2}\log(2\pi) \quad (23)$$

Alternatively, from 1 we know that  $y$  is Gaussian. Since both  $y$  and  $f$  are Gaussian, we can simply add their means and variances:

$$p(Y|X) = N(0, K + \sigma_n^2 I)$$

We can plug these mean and variances into the Gaussian PDF 8 to get 23. Assembling the likelihood is necessary for training to select hyperparameters, but the  $K(X, X) + \sigma_n^2 I$  inversion costs  $O(n^3)$  to compute.

## 2.2.5 Algorithm for predictive distribution

1. Take in inputs  $X$ , outputs  $y$ , covariance function  $k$ , noise level  $\sigma_n^2$ , and test input  $X_*$
2.  $L = \text{cholesky}(K(X, X) + \sigma_n^2 I)$ 
  - Invert our  $[K(X, X) + \sigma_n^2 I]$  matrix needed for mean and variance using Cholesky decomposition
3.  $\alpha = L^T \backslash (L \backslash y)$ 
  - Prepare the mean of our predictive distribution in linear combination form by computing the  $\alpha$  vector
4.  $\mu = K(X_*, X)^T \cdot \alpha$ 
  - Compute the mean
5.  $v = L \backslash K(X_*, X)^T$ 
  - Prepare to compute variance by computing  $v$ , the form in which  $L$  is used in the variance
6.  $\text{var} = K(X_*, X_*) - v^T v$ 
  - Compute the variance
7.  $\log p(Y|X) = -\frac{1}{2}y^T \cdot \alpha - \frac{1}{2}\log|K(X, X) + \sigma_n^2 I| - \frac{n}{2}\log(2\pi)$ 
  - Compute the log marginal likelihood
8. Return the mean  $\mu$ , variance  $\text{var}$ , and log marginal likelihood

### 2.2.5.1 TODO Cholesky decomposition

## 3 Exploring Covariance Functions

### 3.1 Characteristics of covariance functions [11]

#### 3.1.1 Covariance matrices

The inner product representations of the covariance for our Bayesian model in function-space 19, weight-space 18, and covariance matrices in general can be represented as a Gram matrices. Given a vector of input points  $X_i | i = 1, \dots, n$  and a covariance function  $k$ , a Gram matrix  $K$  is the  $n \times n$  matrix whose  $(i, j)$ -th entry is  $k(x_i, x_j)$ . This requires any proposed covariance matrix to exhibit the properties of a Gram matrix, namely symmetry and positive semidefiniteness:

$$\begin{aligned} K_{ij} &= K_{ji} \\ X^T K X &\geq 0 \end{aligned}$$

Symmetry is inherent from the inner product property since inner products are symmetric, i.e.  $X_i^T X_j = X_j^T X_i$ , and imposes  $\text{cov}(X_i, X_j) = \text{cov}(X_j, X_i)$ .  $K$  satisfies positive semidefiniteness if, for any vector  $V$  of inputs,  $V^T K V \geq 0$  since:

$$V^T K V = (KV)^T (KV) = \|KV\|^2 \geq 0$$

This means that the covariance matrix must not produce negative variances for any linear combination of inputs.

#### 3.1.2 Eigenvalue and eigenfunctions of covariance matrices

**3.1.2.1 Integral operators** If we wanted to multiply a vector  $\Phi$  by a matrix  $K(X, X')$ , we would use the following matrix-vector multiplication to produce a discrete vector  $[K\phi]$ :

$$[K\phi]_i = \sum_{j=1}^n K_{ij} \Phi_j$$

If we wanted to multiply a function  $\phi(x)$  by our matrix  $K(X, X')$ , we could use an "integral operator"  $K$  to produce a new continuous function  $[K\phi](x')$ :

$$[K\phi](x') = \int K(x, x') \phi(x) dx$$

This specific usage of  $K(X, X')$  is where covariance matrices are known as kernels, but the terms "kernel" and "covariance matrix" are used interchangeably outside of this context. For example, using the linear kernel  $K(x, x') = x \cdot x'$ , a function  $\phi(x) = x^2$ , and the limits of our domain  $a = 0$  and  $b = 1$ :

$$[K\phi](x') = \int x \cdot x' x^2 dx = x' \int_0^1 x^3 dx = x' \left[ \frac{x^4}{4} \right]_0^1 = x' \cdot \frac{1}{4}$$

$[K\phi](x')$  becomes  $x'$  scaled by the RHS integral - the first term depends on our choice of kernel, and the size of the scale depends on  $\phi(x)$  and  $a, b$ .

We can refer to some vector  $\Phi$  as the eigenvector and  $\lambda$  as the eigenvalue of  $K$  if it obeys this equation:

$$[K\Phi] = \lambda \Phi$$

Since our integral operator  $K$  is like an infinite-dimensional matrix whose entries are  $k(x, x')$ , we can refer to a function  $\phi(x)$  as the eigenfunction and  $\lambda$  as the eigenvalue of our integral operator  $K$  if:

$$\int K(x, x') \phi(x) d\mu(x) = \lambda \phi(x')$$

where  $\mu$  is some measure over the domain of  $x$  upon which the integration will occur thus defining the limits of integration  $a, b$ .

**3.1.2.2 Mercer's theorem** If our kernel satisfies the conditions of a Gram matrix (i.e. symmetry and positive semidefiniteness) and our measure  $\mu$  is any compact subset  $C \subset \mathbb{R}^n$  (e.g. the probability space  $[0, 1]$ ), then it conforms to Mercer's theorem. Mercer's theorem states that these eigenvalues  $[\lambda_i]_{i=1}^\infty$  are non-negative and decay to zero, and our kernel itself can be decomposed into a sum of eigenfunctions  $\phi_i$  and eigenvalues  $\lambda_i$ :

$$K(X, X') = \sum_{i=1}^{\infty} \lambda_i \phi_i(X) \phi_i(X') \quad (24)$$

A kernel with infinite rank, or a covariance function that has infinite basis functions (e.g. SE), is called a nondegenerate kernel, else it is degenerate. For example, our  $N$ -dimensional linear kernel  $K(X, X') = X \cdot X'$  results in a degenerate kernel with at most  $N$  non-zero eigenvalues.

### 3.1.3 Varying the length scale

Our covariance functions has some hyperparameters, e.g. the full form of SE in one dimension contains some free parameters  $\sigma_f^2$ ,  $\sigma_n^2$ , and  $l$ :

$$k_y(x, x') = \sigma_f^2 \exp\left(-\frac{1}{2} \frac{|x - x'|^2}{l^2}\right) + \sigma_n^2 \delta_{x, x'}$$

Note that our covariance function is for  $k_y$  as it is for the noisy targets  $y$ , not the function  $f$ .  $\sigma_f^2$  is the signal variance, which controls the overall scale of the function.  $\sigma_n^2$  is the noise variance, which controls the amount of noise in the observations.  $\delta_{X, X'}$  is the Kronecker delta which represents our independence of noise assumption.

$l$  is a "length scale" hyperparameter that controls how sensitive our functions are - if we specify a lower  $l$ , we can "artificially" get a high  $k(X, X')$ . One way to determine  $l$  is by the expected number of "upcrossings" that our kernel is expected to make for a given level  $u$ . A function performs an upcrossing for  $u$  when  $u = f(x)$  and  $dy/dx > 0$ . For example, with  $u = 2$  and  $y = x^2$ , there exists one upcrossing at  $(2, \sqrt{2})$  where  $dy/dx = 4$ , and a downcrossing at  $(2, -\sqrt{2})$  where  $dy/dx = -4$ . For our zero-mean Gaussian processes, the expected number of upcrossings of our (stationary) kernel for a level  $0 < u < 1$  is:

$$\mathbb{E}[N_u] = \frac{1}{2\pi} \sqrt{\frac{-k''(0)}{k(0)}} \exp\left(-\frac{u^2}{2k(0)}\right)$$

We can empirically count the number of upcrossings between 0 and 1  $\hat{N}_u$  and set this equal to the expected number of upcrossings to get a value for  $l$ :

$$\frac{1}{2\pi} \sqrt{\frac{-k''(0)}{k(0)}} \exp\left(-\frac{u^2}{2k(0)}\right) = \hat{N}_u \quad (25)$$

A large amount of upcrossings implies our data-generating function wiggles rapidly, so our  $l$  becomes smaller to produce a covariance function that in turn produces more flexible functions.

### 3.1.4 Mean square continuity and differentiability

To understand how smooth the functions drawn from a Gaussian process are, we need to understand how differentiable and continuous they are. A more differentiable function implies that the function contains higher order polynomials which makes it smoother, and a continuous function avoids any reductions in smoothness produced by discontinuities.

Because the functions drawn from the Gaussian distribution are random functions between datapoints, there are infinitely many possible functions and determining if they are all continuous or differentiable is impossible. TODO

**3.1.4.1 Continuity** Let  $x$  be an infinite-length vector of inputs  $x_1, x_2, \dots$  whose values linearly approach some stable fixed point  $x_*$  as the sequence progresses. Formally:

$$\lim_{k \rightarrow \infty} |x_k - x_*| = 0$$

A regular function  $f$  is continuous at  $x_*$  if three conditions are met.  $x_*$  must exist in the domain of  $f$ , e.g.  $f(X) = 1/x$  is not continuous at  $f(0)$  because 0 is not in the domain of  $f$ . There must be a single limit the function approaches.

$$f(X) = \begin{cases} 0 & \text{if } X < 0 \\ 1 & \text{if } X > 0 \\ 2 & \text{if } X = 0 \end{cases}$$

In this example, at  $f(0)$   $x$  is not continuous at  $x = 0$  since  $f$  approaches both 0 and 1. This single limit needs to be the same as the function evaluation at the limit. If we removed the 0 if  $X < 0$  case to produce a single limit, it would still not be continuous at  $x = 0$  since the limit would be 1 but  $f(0) = 2$ . Formally summarising these three ideas:

$$\lim_{x \rightarrow x_*} |f(x) - f(x_*)| = 0$$

A Gaussian process  $f$  is MS continuous at  $x_*$  if the expected function evaluations  $E[f(x)]$  quadratically approach  $f(x_*)$  as  $x \rightarrow x_*$ . Formally:

$$\lim_{x \rightarrow x_*} \mathbb{E}[(f(x) - f(x_*))^2] = 0$$

Thanks to the quadratic term, we can expand our error term directly into kernel terms. The covariance function  $k$  is defined as the expected value of the product of two function evaluations:

$$\begin{aligned} \mathbb{E}[(f(x) - f(x_*))^2] &= \mathbb{E}[f(x)^2] + \mathbb{E}[f(x_*)^2] - 2\mathbb{E}[f(x)f(x_*)] \\ &= k(x, x) + k(x_*, x_*) - 2k(x, x_*) \end{aligned}$$

Using this expansion in our definition of MS continuity:

$$\lim_{x \rightarrow x_*} |k(x, x) - 2k(x, x_*) + k(x_*, x_*)| = 0 \quad (26)$$

Because  $x_*$  is given,  $k(x_*, x_*)$  is a constant. This limit requires that both  $k(x, x)$  and  $k(x, x_*) \rightarrow k(x_*, x_*)$  as  $x \rightarrow x_*$ , which is the very definition of continuity of  $k$  at  $x_*$  - they guarantee that  $x_*$  is in the domain of  $k$ , that it has a single limit, and this limit of  $k(x, x_*)$  is  $k(x_*, x_*)$  as  $x \rightarrow x_*$ . Therefore, a Gaussian process is MS continuous at  $x_*$  if and only if the covariance function  $k$  is continuous at  $x_*$ .

**3.1.4.2 Differentiability**  $f$  is MS differentiable at  $x_*$  in the  $i$ th direction of our input vector  $X$  if:

$$\lim_{h \rightarrow 0} \mathbb{E} \left[ \left| \frac{f(x_* + he_i) - f(x_*)}{h} - \frac{\partial f}{\partial x_{*i}}(x_*) \right| \right]^2 = 0$$

$e_i = (0_0, \dots, 0_{i-1}, 1_i, 0_{i+1}, \dots, 0_n)$  is a unit vector that constrains the change in  $x$  to only the  $i$ th dimension. We assume  $m(x_*) = 0$  for simplicity, but a non-zero mean does not change the structure of this proof and leads to the same result.

Expanding and creating simplifying  $A$  and  $B$  terms to represent the limit and the proposed derivative respectively:

$$\begin{aligned} \lim_{h \rightarrow 0} \mathbb{E} [(A_h - B)^2] &= \mathbb{E}[A_h^2] + \mathbb{E}[B^2] - 2\mathbb{E}[A_h B] = 0 \\ A_h &= \frac{f(x_* + he_i) - f(x_*)}{h} \\ B &= \frac{\partial f}{\partial x_{*i}}(x_*) \end{aligned}$$

Similar to MS continuity, we expand  $A_h^2$  into kernel terms:

$$\mathbb{E}[A_h^2] = \frac{1}{h^2} (k(x_* + he_i, x_* + he_i) + k(x_*, x_*) - 2k(x_* + he_i, x_*)) \quad (27)$$

$k(x_*, x_*)$  is a constant, but the other terms vary with  $h$ . We can use a second-order Taylor series to approximate these terms if  $k$  is twice continuously differentiable at  $x_*$ . Starting with the univariate  $k(x_* + he_i, x_*)$ :

$$\begin{aligned} k(x_* + he_i, x_*) &= \\ &k(x_*, x_*) \\ &+ h[\partial_{u_i} k](x_*, x_*) \\ &+ \frac{h^2}{2} [\partial_{u_i u_i}^2 k](x_*, x_*) \\ &+ O(h^3) \end{aligned}$$

$u_i$  and  $v_i$  denote the first  $x_* + he_i$  and second  $x_*$  arguments respectively in the  $i$ th direction. TODO explain  $O$  and why it's in terms of  $h^3$  Then, the multivariate  $k(x_* + he_i, x_* + he_i)$ :

$$\begin{aligned} k(x_* + he_i, x_* + he_i) &= \\ &k(x_*, x_*) \\ &+ h[\partial_{u_i} k + \partial_{v_i} k](x_*, x_*) \\ &+ \frac{h^2}{2} [\partial_{u_i u_i}^2 k + \partial_{u_i v_i}^2 k + \partial_{v_i v_i}^2 k](x_*, x_*) \\ &+ O(h^3) \end{aligned}$$

Substituting these approximations into 27:

$$\begin{aligned} \mathbb{E}[A_h^2] &= \frac{1}{h^2} \\ &k(x_*, x_*) + k(x_*, x_*) - 2k(x_*, x_*) \\ &+ h[\partial_{u_i} k + \partial_{v_i} k](x_*, x_*) - 2h[\partial_{u_i} k](x_*, x_*) \\ &+ \frac{h^2}{2} [\partial_{u_i u_i}^2 k + \partial_{u_i v_i}^2 k + \partial_{v_i v_i}^2 k](x_*, x_*) - 2\frac{h^2}{2} [\partial_{u_i u_i}^2 k](x_*, x_*) \\ &+ O(h^3) \end{aligned}$$

The constant  $k(x_*, x_*)$  terms cancel and the  $O(h^3)$  remainders combine but remain the same order.

We can combine the linear partial derivatives to form a single function  $[\partial_{u_i} k + \partial_{v_i} k - 2\partial_{v_i} k]$ . Thanks to the symmetry of the covariance matrix inherited from the Gram matrix,  $k(u, v) = k(v, u)$  and  $\partial_{u_i} k = \partial_{v_i} k$  and substituting in either into our linear term cancels it completely.

Similarly, we can combine the quadratic derivatives:

$$E[A^2] = \frac{1}{h^2} \frac{h^2}{2} [\partial_{u_i u_i}^2 k + \partial_{u_i v_i}^2 k + \partial_{v_i v_i}^2 k](x_*, x_*) - h^2 [\partial_{u_i v_i}^2 k](x_*, x_*)$$

Cancelling  $\frac{1}{h^2}$  and  $\frac{h^2}{2}$  and simplifying:

$$\begin{aligned} &= [\partial_{u_i v_i}^2 k + \partial_{u_i u_i}^2 k + \partial_{v_i v_i}^2 k - \partial_{u_i v_i}^2 k](x_*, x_*) \\ &= [\partial_{u_i u_i}^2 k + \partial_{u_i v_i}^2 k - \partial_{v_i v_i}^2 k](x_*, x_*) \end{aligned}$$

Similarly to the linear terms, using the symmetry of  $k$  to cancel  $\partial_{u_i u_i}^2$  and  $\partial_{v_i v_i}^2$  yields the final expression for  $\mathbb{E}[A_h^2]$ :

$$\mathbb{E}[A_h^2] = \partial_{u_i v_i}^2 k(x_*, x_*) + O(h^3) \quad (28)$$

Because  $B$  is Gaussian, its square is simply its variance:

$$\begin{aligned} \mathbb{E}[B^2] &= \text{Var} \left( \frac{\partial f}{\partial x_{*i}}(x_*) \right) \\ &= \text{Cov} \left( \frac{\partial f}{\partial x_{*i}}(x_*), \frac{\partial f}{\partial x_{*i}}(x_*) \right) \end{aligned}$$

We can substitute our regular limit definition of differentiability outside of MS space, with different small increments  $h$  and  $h'$ :

$$= \text{Cov} \left( \frac{f(x_* + h e_i) - f(x_*)}{h}, \frac{f(x_* + h' e_i) - f(x_*)}{h'} \right)$$

The  $h$  and  $h'$  denominators merely scale the covariance, so we can take them out of the covariance expression:

$$= \frac{1}{hh'} \text{Cov}(f(x_* + h e_i) - f(x_*), f(x_* + h' e_i) - f(x_*))$$

Using additivity TODO explain:

$$\mathbb{E}[B^2] = \frac{1}{hh'} (k(x_* + h e_i, x_* + h' e_i) - k(x_*, x_* + h' e_i) - k(x_* + h e_i, x_*) + k(x_*, x_*))$$

We already have  $k(x_* + h e_i, x_*)$  from ?? directly, and  $k(x_*, x_* + h' e_i)$  by symmetry and substituting  $h'$  for  $h$ . Our multivariate Taylor series  $k(x_* + h e_i, x_* + h' e_i)$  looks similar to ??:

$$\begin{aligned} k(x_* + h e_i, x_* + h' e_i) &= \\ & k(x_*, x_*) \\ & + h[\delta_{u_i} k](x_*, x_*) + h'[\delta_{v_i} k](x_*, x_*) \\ & + \frac{h^2}{2} [\text{partial}_{u_i u_i}^2 k](x_*, x_*) \\ & + hh' [\partial_{u_i v_i}^2 k](x_*, x_*) \\ & + \frac{h'^2}{2} [\partial_{v_i v_i}^2 k](x_*, x_*) \\ & + O(\|(h, h')\|^3) \end{aligned}$$

Substituting these results into  $\mathbb{E}[B^2]$ :

$$\begin{aligned} \mathbb{E}[B^2] &= \frac{1}{hh'} \\ & k(x_*, x_*) \\ & + k(x_*, x_*) + k(x_*, x_*) - k(x_*, x_*) \\ & + h[\delta_{u_i} k](x_*, x_*) - h[\delta_{u_i} k](x_*, x_*) \\ & + h'[\delta_{v_i} k](x_*, x_*) - h'[\delta_{v_i} k](x_*, x_*) \\ & + \frac{h^2}{2} [\partial_{u_i u_i}^2 k](x_*, x_*) - \frac{h^2}{2} [\partial_{u_i u_i}^2 k](x_*, x_*) \\ & + hh' [\partial_{u_i v_i}^2 k](x_*, x_*) \\ & + \frac{h'^2}{2} [\partial_{v_i v_i}^2 k](x_*, x_*) - \frac{h'^2}{2} [\partial_{v_i v_i}^2 k](x_*, x_*) \\ & + O(h^3) + O(h'^3) + O(\|(h, h')\|^3) \end{aligned}$$

All constant, linear  $h$  and  $h'$ , and  $h^2$  and  $h'^2$  terms cancel, leaving the mixed term and the remainders.  $\frac{1}{hh'}$  cancel and the remainders can be combined since TODO:

$$\mathbb{E}[B^2] = \partial_{u_i v_i}^2 k(x_*, x_*) + O(h^2) \quad (29)$$



For  $\mathbb{E}[A_h B]$ , assuming zero-mean:

$$\mathbb{E}[A_h B] = \text{Cov} \left( \frac{f(x_* + h e_i) - f(x_*)}{h}, \frac{\partial f}{\partial x_{*i}}(x_*) \right)$$

Similarly to  $B$ , we can remove the scaling factor  $\frac{1}{h}$ :

$$= \frac{1}{h} \text{Cov} \left( f(x_* + h e_i) - f(x_*), \frac{\partial f}{\partial x_{*i}}(x_*) \right)$$

By linearity of covariance TODO elaborate:

$$= \frac{1}{h} \left[ \text{Cov}(f(x_* + h e_i), \frac{\partial f}{\partial x_{*i}}(x_*)) - \text{Cov}(f(x_*), \frac{\partial f}{\partial x_{*i}}(x_*)) \right]$$

A fundamental identities for Gaussian fields TODO elaborate is:

$$\text{Cov}(f(u), \delta_{u_i} f(v)) = \delta_{u_i} k(u, v)$$

Applying it to both terms:

$$\begin{aligned} \text{Cov}(f(x_* + h e_i), \frac{\partial f}{\partial x_{*i}}(x_*)) &= \delta_{u_i} k(x_* + h e_i, x_*) \\ \text{Cov}(f(x_*), \frac{\partial f}{\partial x_{*i}}(x_*)) &= \delta_{v_i} k(x_*, x_*) \end{aligned}$$

Taylor expanding our first term:

$$\begin{aligned} \delta_{u_i} k(x_* + h e_i, x_*) &= \\ &\delta_{u_i} k(x_*, x_*) \\ &+ h \delta_{u_i v_i}^2 k(x_*, x_*) \\ &+ \frac{h^2}{2} \delta_{u_i u_i u_i}^3 k(x_*, x_*) \\ &+ O(h^3) \end{aligned}$$

We can take advantage of symmetry of  $k$  to cancel out the constant term using the second term in  $\mathbb{E}[A_h B]$  - when  $u = v$ ,  $\delta_{v_i} k(x_*, x_*) = \delta_{u_i} k(x_*, x_*)$ . Substituting this into  $\mathbb{E}[A_h B]$ :

$$\begin{aligned} \mathbb{E}[A_h B] &= \frac{1}{h} \\ &h \delta_{u_i v_i}^2 k(x_*, x_*) + \frac{h^2}{2} \delta_{u_i u_i v_i}^3 k(x_*, x_*) \\ &+ O(h^3) \end{aligned}$$

Dividing by  $h$  reduces the order of the remainder. Simplifying for a final expression:

$$\mathbb{E}[A_h B] = \delta_{u_i v_i}^2 k(x_*, x_*) + \frac{h}{2} \delta_{u_i u_i v_i}^3 k(x_*, x_*) + O(h^2) \quad (30)$$

Substituting 28, 29, and 30 into our original limit definition of MS differentiability:

$$\lim_{h \rightarrow 0} \delta_{u_i v_i}^2 k(x_*, x_*) + O(h^3) + \delta_{u_i v_i}^2 k(x_*, x_*) + O(h^2) - 2 \left( \delta_{u_i v_i}^2 k(x_*, x_*) + \frac{h}{2} \delta_{u_i u_i v_i}^3 k(x_*, x_*) + O(h^2) \right) = 0$$

Redefining  $A = \delta_{u_i v_i}^2 k(x_*, x_*)$  and  $B = \frac{h}{2} \delta_{u_i u_i v_i}^3 k(x_*, x_*)$  for brevity:

$$\lim_{h \rightarrow 0} A + O(h^3) + A + O(h^2) - 2(A + \frac{h}{2} B + O(h^2)) = 0$$

Expanding the last term:

$$\lim_{h \rightarrow 0} A + O(h^3) + A + O(h^2) - 2A - hB - 2O(h^2) = 0$$

All  $A$  terms cancel. Combining and reducing the remainders to the lowest order:

$$\lim_{h \rightarrow 0} hB + O(h) = 0$$

We can absorb  $hB$  into  $O(h)$  since it is a linear term in  $h$ :

$$\lim_{h \rightarrow 0} O(h) = 0 \quad (31)$$

$O(h)$  approaches 0 as  $h \rightarrow 0$ , so our limit definition of MS differentiability is met using a second-order Taylor expansion. We can extend this to any  $k$ -th derivative in MS space by using a  $2k$ -th order Taylor expansion of the covariance functions, which requires the covariance function to be  $2k$ -times continuously differentiable at  $x_*$ .

## 3.2 Stationary covariance functions [11]

### 3.2.1 Stationarity and isotropicism

A stationary covariance function  $k(X - X')$  is some function of  $X - X'$ , and is invariant to the exact locations of  $X$  and  $X'$ . An isotropic covariance function  $k(|X - X'|)$  is a function of  $|X - X'|$ , and is invariant to the direction of  $X - X'$ . For example, SE [eq:se] is both stationary and isotropic because it is a function of  $|X - X'|$ .

### 3.2.2 Spectral density

Bochner's theorem states that the covariance function of a stationary process can be represented as the Fourier transform of some positive finite measure  $\mu$  [5]:

$$k(x, x') = \int_{-\infty}^{\infty} e^{2\pi i \omega(x-x')} d\mu(\omega)$$

The Fourier transform decomposes our covariance function into a sum of sines and cosines that represents the frequencies that make it up, written in a compact form as a complex exponential:

$$e^{-2\pi i \omega(x-x')} = \cos(2\pi \omega(x-x')) - i \sin(2\pi \omega(x-x'))$$

By applying this representation to the covariance function, we get its "spectral density"  $S(\omega)$ :

$$S(\omega) = \int_{-\infty}^{\infty} k(x, x') e^{2\pi i \omega(x-x')} d(x-x')$$

$S(\omega)$  is a complex number representing how much total variance is allocated per unit of frequency around our given frequency  $\omega$ .

The Weiner-Khinchin theorem governs the inversion of the Fourier transform to recover the original covariance function - it states that our covariance function and its spectral density are Fourier duals of each other:

$$k(x, x') = \int_{-\infty}^{\infty} S(\omega) e^{-2\pi i \omega(x-x')} d\omega$$

**3.2.2.1 Smoothness** To remain integratable, our spectral density needs to approach 0 as  $\omega \rightarrow \infty$ . The faster it approaches 0, the less power it contains at high frequencies, and the smoother our resultant GP will be. Ritter et. al. [12] formalised this by taking moments of the spectral density and connecting them to the MS differentiability of our resultant GP. The  $2m$ -th  $\omega$ -th moment of the spectral density is:

$$\int_{-\infty}^{\infty} |\omega|^{2m} S(\omega) d\omega$$

If this  $2m$  moment exists and is finite, our covariance function is  $2m$  differentiable thus our GP is  $m$ -times MS differentiable.

### 3.2.3 GPs from stationary covariance functions in MS space

Putting the stationary kernel  $k(x, x') = k(x - x')$  into 26:

$$\lim_{x \rightarrow x_*} |k(x - x) - 2k(x - x_*) + k(x_* - x_*)| = 0$$

Simplifying the terms inside the kernels and combining like terms:

$$\lim_{x \rightarrow x_*} 2|k(0) - k(x - x_*)| = 0$$

2 is a constant factor and can be ignored. Because  $|k(0) - k(x - x_*)|$  is invariant to direction, we can swap them to align with the definition of continuity at 0:

$$\lim_{x \rightarrow x_*} |k(x_* - x) - k(0)| = 0$$

Thus, a stationary covariance function is MS continuous at  $x_*$  if and only if it is continuous at  $x_* = 0$ . Similarly, it can be shown that stationary covariance functions are MS differentiable at  $x_*$  if and only if they are MS differentiable at  $x_* = 0$ .

## 3.3 Stationary covariance functions [11]

### 3.3.1 Squared exponential (SE)

Here is the already introduced SE:

$$k(X, X_*) = \exp\left(-\frac{|X - X'|^2}{2l^2}\right)$$

This covariance function is infinitely differentiable at  $x - x' = 0$  thanks to the squared difference between  $X$  and  $X'$  in the exponent, so a GP using SE is infinitely mean-squared differentiable which produces extremely smooth functions, which is often not useful for approximating real-world function. The three major attempts to generalise the SE to vary the level of smoothness are the rational quadratic,  $\gamma$ -exponential, and Matern classes of covariance functions.

**3.3.1.1 From feature space to SE** We can derive this form by expanding  $X$  into our feature space  $\phi$  defined by Gaussian-shaped basis functions centred densely in  $X$ . Defining this basis function:

$$\phi_c(x) = \exp\left(-\frac{|x - c|^2}{2l^2}\right)$$

$c$  the centre of our basis functions. With our familiar isotropic Gaussian prior on the weights  $W \sim \mathcal{N}(0, \sigma_p^2 I)$ , we get our familiar covariance function in weight-space:

$$k(x, x') = \sigma_p^2 \sum_{c=1}^N \phi_c(x) \phi_c(x')$$

$N$  represents the number of these basis functions. If  $N = \infty$  with centres everywhere between some interval  $c_{min}$  and  $c_{max}$ , we can simply integrate over the interval:

$$\lim_{N \rightarrow \infty} \sigma_p^2 \sum_{c=1}^N \phi_c(x) \phi_c(x') = \sigma_p^2 \int_{c_{min}}^{c_{max}} \phi_c(x) \phi_c(x') dc$$

Plugging in our basis function:

$$k(x, x') = \sigma_p^2 \int_{c_{min}}^{c_{max}} \exp\left(-\frac{|x - c|^2}{2l^2}\right) \exp\left(-\frac{|x' - c|^2}{2l^2}\right) dc$$

Combining the exponentials:

$$= \sigma_p^2 \int_{c_{min}}^{c_{max}} \exp\left(-\frac{|x - c|^2 + |x' - c|^2}{2l^2}\right) dc$$

Expanding the squared terms, rearranging the fraction and simplifying:

$$= \sigma_p^2 \int_{c_{min}}^{c_{max}} \exp\left(-\frac{1}{l^2} \left[ c^2 - c(x + x') + \frac{x^2 + x'^2}{2} \right]\right) dc$$

We can complete the square on the  $c$  terms to get a product of two exponentials:

$$= \sigma_p^2 \int_{c_{min}}^{c_{max}} \exp\left(-\frac{1}{l^2} \left[ \left(c - \frac{x + x'}{2}\right)^2 - \frac{(x + x')^2}{4} \right]\right) dc$$

Our second term in the exponential does not vary with  $c$  and can be safely factored out of the integral:

$$= \sigma_p^2 \exp\left(\frac{(x + x')^2}{4l^2}\right) \int_{c_{min}}^{c_{max}} \exp\left(-\frac{1}{l^2} \left(c - \frac{x + x'}{2}\right)^2\right) dc$$

If we let our  $c_{min}$  and  $c_{max}$  approach infinity, we can use the standard Gaussian integral:

$$\int_{-\infty}^{\infty} \exp\left(-\frac{1}{l^2} \left(c - \frac{x + x'}{2}\right)^2\right) dc = l\sqrt{\pi}$$

Substituting this in:

$$k(x, x') = \sigma_p^2 l \sqrt{\pi} \exp\left(-\frac{(x - x')^2}{4l^2}\right)$$

We can absorb the  $l\sqrt{\pi}$  into the  $\sigma_p^2$  term to produce our familiar SE with a  $\sqrt{2}$  longer length scale:

$$k(x, x') = \sigma_p^2 \exp\left(-\frac{(x - x')^2}{2(\sqrt{2}l)^2}\right)$$

**3.3.1.2 Length scale** We can observe the role  $l$  plays in SE by finding the value for  $l$  analytically and rearranging it for  $\hat{N}_u$  to see its effect on smoothness.

Using 25:

$$l = \frac{1}{2\pi\hat{N}_u} \exp\left(-\frac{u^2}{2\sigma^2}\right)$$


Setting  $u = 0$  makes our term inside the exponential equal to zero:

$$l = \frac{1}{2\pi\hat{N}_u}$$

Rearranging for  $\hat{N}_u$ :

$$\hat{N}_u = \frac{1}{2\pi l}$$

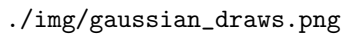
Here,  $l$  behaves as a length scale - a larger  $l$  reduces the number of upcrossings, stretching out the features over longer distances and producing smoother sample paths.



`./img/gaussian_variances.png`

Figure 1: Plot of a Gaussian process using SE applied to a toy dataset. The toy dataset ( $n = 15$ ) is a data-generating function in blue with some Gaussian noise applied to produce the datapoints in black. The black line represents the expected function from the Gaussian process. The green line represents the 90% confidence interval around the predictive distribution without the  $\sigma_n^2$  term, representing the uncertainty surrounding predictions of the noise-free mean function  $f(X)$ . The red line represents the 90% confidence interval with  $\sigma_n^2$ , representing the uncertainty surrounding predictions of the noisy observations  $y$ .

TODO explain



`./img/gaussian_draws.png`

Figure 2: Plots of functions from a Gaussian process using SE applied to the same toy dataset. The blue line and black datapoints and lines are as before, but the green lines here are a sample of functions drawn from the Gaussian process.

TODO explain

### 3.3.2 Rational quadratic (RQ)

RQ controls smoothness by using a mixture of different length scales to capture multiple trends in the data with different frequencies.

$$k(X, X') = \left(1 + \frac{|X - X'|^2}{2\alpha l^2}\right)^{-\alpha}$$

We can derive this form by creating an infinite sum of different instances of SE with a vector of different length-scales  $l$  and some weights  $w_i$  attached to each instance:

$$k(X, X') = \sum_{i=1}^{\infty} w_i \exp\left(-\frac{|X - X'|^2}{2l_i^2}\right)$$

This is a valid covariance function long as the sum remains less than  $\infty$  to maintain PSD. We can turn this into a continuous representation if our  $l$  is very dense, where  $p(l)$  is the PDF for  $l$ :

$$k(X, X') = \int_0^{\infty} p(l) \exp\left(-\frac{|X - X'|^2}{2l^2}\right) dl$$

Defining  $\tau = l^{-2}$ ,  $l = \tau^{-1/2}$ . Putting this into SE:

$$k_{SE}(X, X') = \exp\left(-\frac{|X - X'|^2}{2[\tau^{-1}]}\right) = \exp\left(-\frac{1}{2}\tau|X - X'|^2\right)$$

Before putting this back into the above integral which is in terms of  $l$ , we need to account for the change of variables from  $l$  to  $\tau$ . The Jacobian factor of this transformation is:

$$|\partial_{\tau} l| = \frac{1}{2}\tau^{-3/2}d\tau$$

Defining the transformation  $l(x) = \frac{1}{\sqrt{x}}$ , putting these into the integral changes the PDF from  $p(l)$  to  $p(l(\tau))|\partial_{\tau} l|$ :

$$k(X, X') = \int_0^{\infty} p(l(\tau)) \frac{1}{2}\tau^{-3/2} \exp\left(-\frac{1}{2}\tau|X - X'|^2\right) d\tau$$

We need an expression for the PDF  $p(\tau)$  that integrates to 1 and is PSD. A common choice is the Gamma distribution with shape  $\alpha$  and scale  $\beta$  parameters:  $\tau \sim \Gamma(\alpha, \frac{\beta}{\alpha})$

$$p(\tau) \propto \tau^{\alpha-1} \exp\left(-\frac{\alpha}{\beta}\tau\right)$$

Putting this into the integral:

$$k(X, X') \propto \int_0^{\infty} \left[\tau^{\alpha-1} \exp\left(-\frac{\alpha}{\beta}\tau\right)\right] \frac{1}{2}\tau^{-3/2} \exp\left(-\frac{1}{2}\tau|X - X'|^2\right) d\tau$$

$\frac{1}{2}\tau^{-3/2}$  from  $dl$  and the new  $\tau^{\alpha-1}$  combine, and the new exponential joins the existing one:

$$k(X, X') \propto \int_0^{\infty} \frac{1}{2}\tau^{\alpha-\frac{5}{2}} \exp\left[-\tau\left(-\frac{\alpha}{\beta} + \frac{|X - X'|^2}{2}\right)\right] d\tau$$

We can use the Gamma integral here, but need some rearranging. Absorbing  $\frac{1}{2}$  into the proportionality, setting  $a = \alpha - \frac{3}{2}$  and factoring  $\tau$  out of the exponent for  $c = \frac{\alpha}{\beta}\tau + \frac{|X - X'|^2}{2}$ :

$$k(X, X') \propto \int_0^{\infty} \tau^{a-1} \exp(-\tau c) d\tau$$

Applying the Gamma integral and absorbing  $\Gamma(a)$  into proportionality:

$$k(X, X') \propto c^{-a} \Gamma(a) \propto \left[\frac{\alpha}{\beta} + \frac{|X - X'|^2}{2}\right]^{-([\alpha - \frac{3}{2}])}$$

Now we need to decide on the parameter values of our Gamma distribution. Since the Gamma distribution strictly takes in one Typically,  $\beta = l^{-2}$  such that  $\beta^{-1} = l^2$  and  $\frac{\alpha}{\beta} = a \cdot \beta^{-1} = \alpha l^2$ . Substituting:


$$k(X, X') = \left(\alpha l^2 + \frac{|X - X'|^2}{2}\right)^{-\alpha - \frac{3}{2}}$$

Factoring out  $\alpha l^2$  and absorbing it into the proportionality constant to get our final form:

$$k(X, X') = \left(1 + \frac{|X - X'|^2}{2\alpha l^2}\right)^{-\alpha - \frac{3}{2}}$$

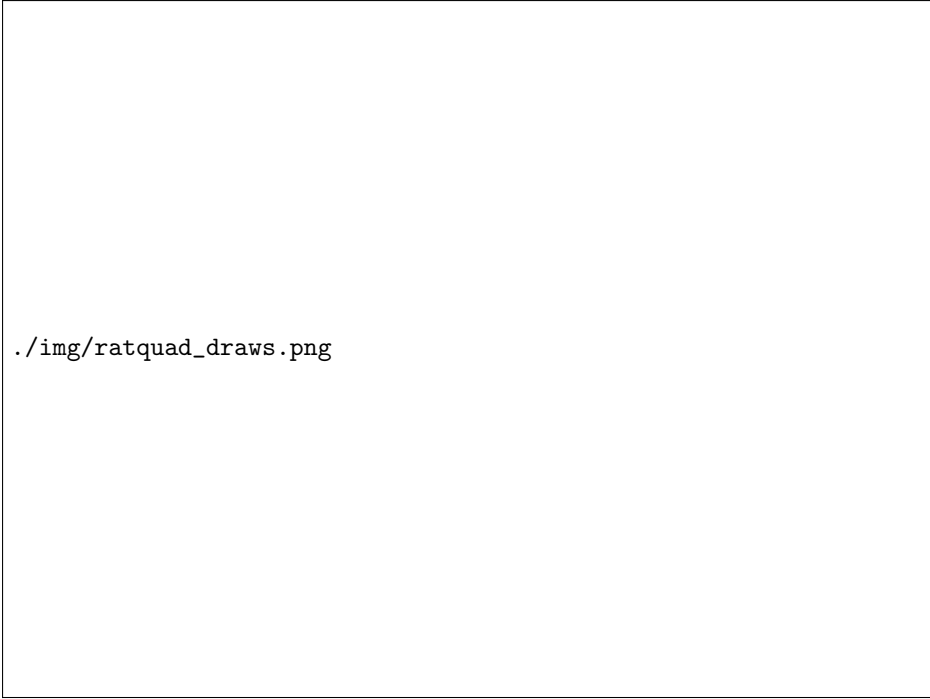
This derivation starts from the discrete length scale  $l$  for illustrative purposes, so includes  $\frac{3}{2}$  to account for the change from length scale to  $\tau$ . In practice, derivations start from  $\tau$  so never have to change units and never include the  $\frac{3}{2}$  term in the exponent.

RQ is infinitely MS differentiable, so produces infinitely smooth functions no matter what the shape parameter of our distribution of length scales  $\alpha$  is. As  $\alpha \rightarrow \infty$ , this distribution becomes sharply peaked at the single analytically chosen length scale  $l$  and RQ becomes SE. However, as  $\alpha \rightarrow 1$ , we get a wider spread of length scales so our functions capture trends at different frequencies.



`./img/ratquad_variances.png`

Figure 3: Plot of a Gaussian process using rational quadratic applied to the toy dataset. For this dataset, the R package GauPro [3] has obtained  $\alpha = 100$  via MLE which produces a kernel close to SE, reflecting the lack of trends in this dataset.



./img/ratquad\_draws.png


Figure 4: Plots of functions from a Gaussian process using rational quadratic applied to the same toy dataset.

### 3.3.3 $\gamma$ -exponential and exponential

SE and RQ have no parameter controlling or reducing its MS differentiability and its smoothness, rendering it a poor approximation of the less smooth functions we often encounter in the real world. We can introduce a differentiability parameter  $\gamma$  to control how differentiable the covariance function is:

$$k(X, X') = \exp\left(-\frac{|X - X'|^\gamma}{l^\gamma}\right)$$

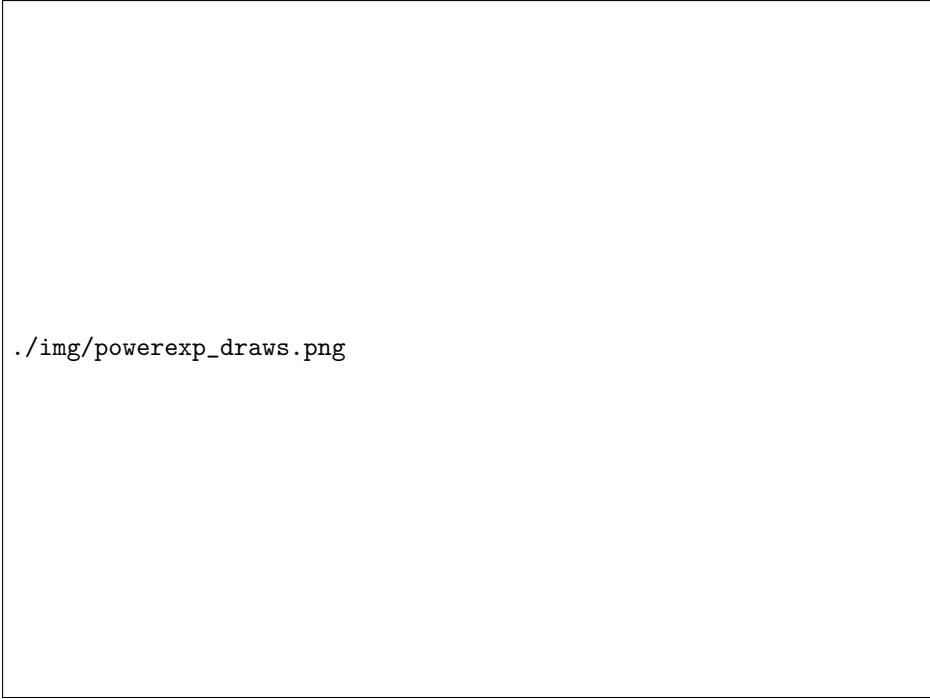
where  $0 < \gamma \leq 2$  controls the smoothness of the covariance function.



./img/powerexp\_variances.png

Figure 5: Plot of a Gaussian process using  $\gamma$ -exponential applied to the toy dataset. For this dataset, the R package GauPro [3] has used  $\gamma = 1.688043$  obtained via MLE.

There are no green lines here because TODO.  $\gamma$ -exponential produces much rougher functions than SE, so its expected function has a lot more wiggle and conforms to the datapoints much closer than SE. In this case, our data-generating function is smooth so SE is closer to the data-generating function than  $\gamma$ -exponential, but real world data-generating functions are often much rougher and would benefit from a kernel flexible enough to pass through the datapoints.




`./img/powerexp_draws.png`

Figure 6: Plots of functions from a Gaussian process using  $\gamma$ -exponential applied to the same toy dataset. These sample function draws are much rougher than SE.

$\gamma = 2$  produces SE for maximal smoothness, while  $\gamma = 1$  produces the exponential covariance function:

$$k(X, X') = \exp\left(-\frac{|X - X'|}{l}\right)$$

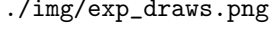
Here, and for all other values of  $\gamma$  other than 2, the covariance function is continuous but not differentiable at all at  $|x - x'| = 0$ , which coincides with the undifferentiable turning point of the modulus function at  $x - x' = 0$ , and produces the roughest functions of all covariance functions we consider.



`./img/exp_variances.png`

Figure 7: Plot of a Gaussian process using exponential applied to the toy dataset. TODO explain





./img/exp\_draws.png

Figure 8: Plots of functions from a Gaussian process using exponential applied to the same toy dataset. These sample function draws are much rougher than SE and  $\gamma$ -exponential.

### 3.3.4 Matern-class

The  $\gamma$ -exponential generalisation is not useful due to its brittleness - it can only produce two covariance functions representing the extremes of the smoothness-roughness scale. The Matern class of covariance functions addresses this by introducing a parameter  $\nu > 0$  that controls the smoothness of the function. The Matern class is defined as:

$$k(X, X') = \frac{2^{1-\nu}}{\Gamma(\nu)} \left( \frac{\sqrt{2\nu}|X - X'|}{l} \right)^\nu K_\nu \left( \frac{\sqrt{2\nu}|X - X'|}{l} \right)$$

$l$  is our familiar length scale hyperparameter. TODO Bessel function  $K_\nu$ , background needed. Therefore, a Gaussian process using a Matern class kernel is  $k$ -times MS differentiable if and only if  $\nu > k$ .

Using half-integers, i.e.  $\nu = p + 1/2$  where  $p$  is a non-negative integer, the covariance function becomes a product of a polynomial and an exponential:

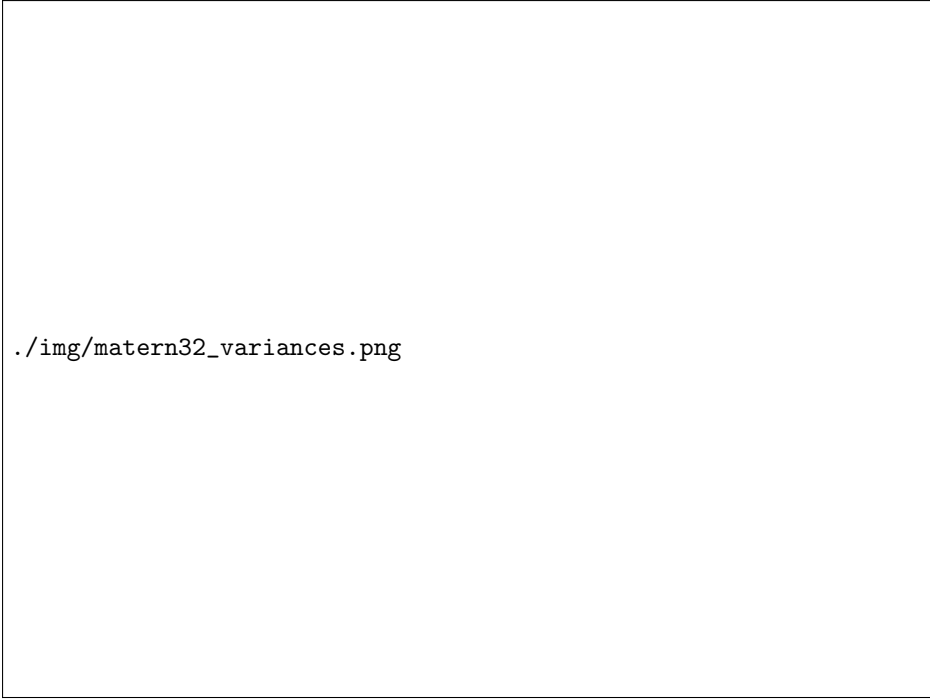
$$k_{\nu=p+1/2}(X, X') = \exp \left( -\frac{\sqrt{2\nu}|X - X'|}{l} \right) \frac{\Gamma(p+1)}{\Gamma(2p+1)} \sum_{i=0}^p \frac{(p+i)!}{i!(p-i)!} \left( \frac{\sqrt{8\nu r}}{l} \right)^{p-i}$$

$\nu = 1/2$  is equivalent to the exponential covariance function. As  $\nu \rightarrow \infty$ , the Matern covariance function approaches the SE covariance function. Practically,  $\nu \geq 7/2$  produces functions that are as smooth as SE, leaving us with two cases of interest:  $\nu = 3/2$  and  $\nu = 5/2$ .

**3.3.4.1 Matern 3/2**  $\nu = 3/2$  produces the following covariance function:

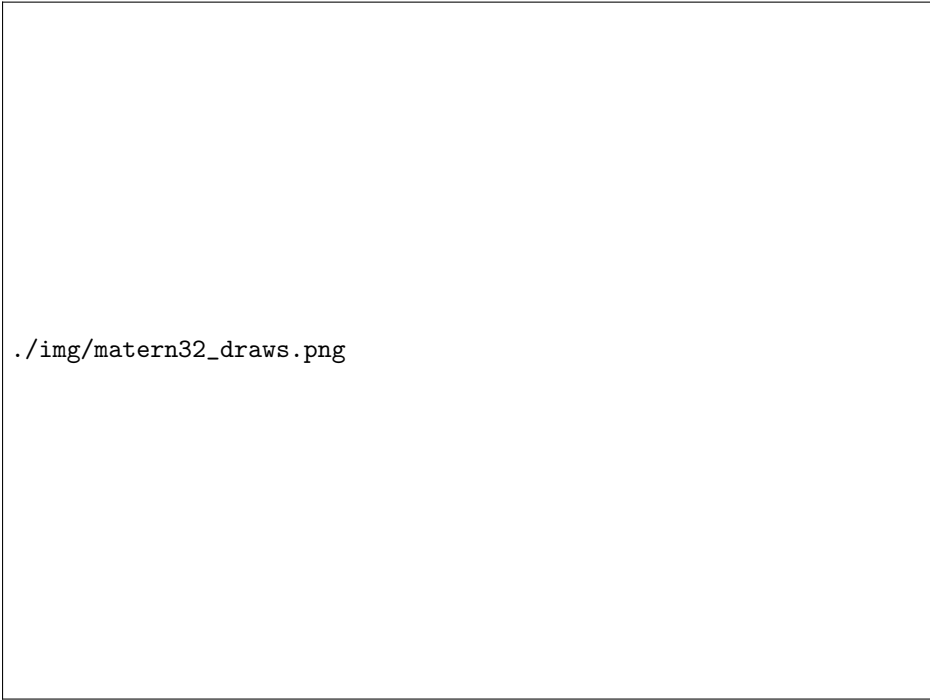
$$k_{3/2}(X, X') = \left( 1 + \frac{\sqrt{3}|X - X'|}{l} \right) \exp \left( -\frac{\sqrt{3}|X - X'|}{l} \right)$$

$3/2$  is one-time MS differentiable, leading to much rougher functions than SE.



`./img/matern32_variances.png`

Figure 9: Plot of a Gaussian process using Matern 3/2 applied to the toy dataset. TODO explain




`./img/matern32_draws.png`

Figure 10: Plots of functions from a Gaussian process using Matern 3/2 applied to the same toy dataset. TODO explain

**3.3.4.2 Matern 5/2**  $\nu = 5/2$  produces the following covariance function:

$$k_{5/2}(X, X') = \left(1 + \frac{\sqrt{5}|X - X'|}{l} + \frac{5|X - X'|^2}{3l^2}\right) \exp\left(-\frac{\sqrt{5}|X - X'|}{l}\right)$$

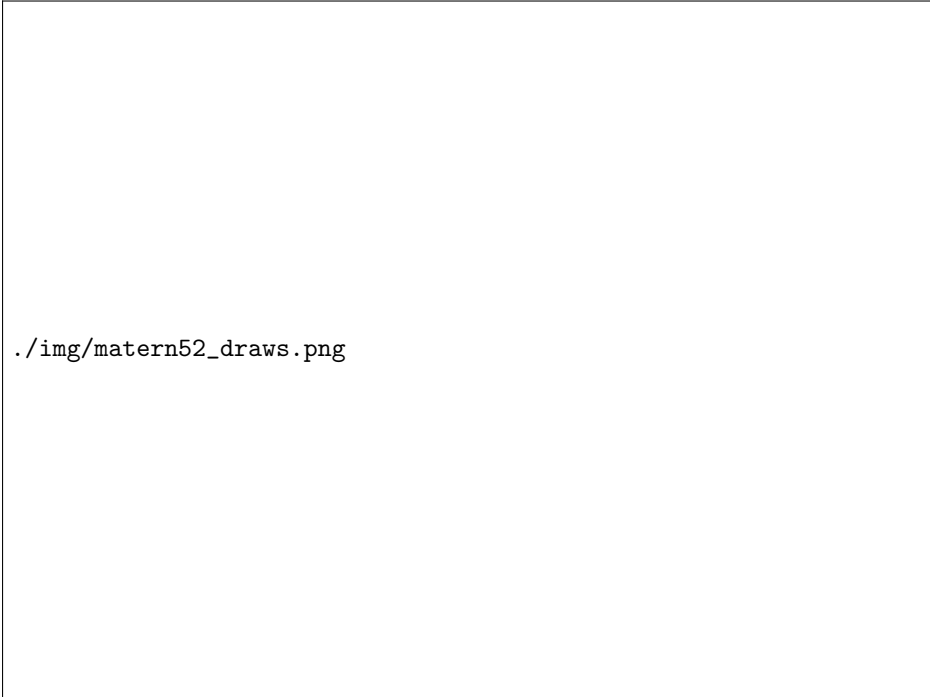
5/2 is twice MS differentiable, producing functions that are slightly smoother than 3/2.



`./img/matern52_variances.png`

Figure 11: Plot of a Gaussian process using Matern  $5/2$  applied to the toy dataset.

The expected function deviates very slightly from datapoints compared to  $3/2$ , but the big difference compared to  $3/2$  is in the variances.  $5/2$  has narrower variances than  $3/2$ , producing smoother functions and functions that are closer to the expected function. SE is still better in this instance because it is the most smooth and our data-generating function is unusually smooth. However,  $5/2$  is generally the most popular covariance function because it achieves this parsimonious balance between smoothness, to still reach some reasonable approximation of the data-generating function, and flexibility, to still pass through the datapoints.



`./img/matern52_draws.png`

Figure 12: Plots of functions from a Gaussian process using Matern  $5/2$  applied to the same toy dataset.

These sample function draws conform more to the expected function than  $3/2$  due to the narrower variances, but are still much rougher than SE and approach the data-points.

## 4 Computational Issues

Inverting the  $[K(X, X) + \sigma_n^2 I]$  matrix in our predictive distribution scales poorly with the number of training data points  $n$ , as inverting the  $n \times n$  matrix  $X$  that represents our training data is  $O(n^3)$ . There exist significantly more powerful approximations of this inversion for "celerite" kernels. Strategies for any covariance function fall into two categories: those that produce a single approximation for the entire dataset, or those that produce several approximations that are "experts" in a particular region of the dataset and combine these local approximations to form a global approximation.

TODO why i didnt investigate local approximations

### 4.1 Sparse kernels [10]

A sparse kernel is a particularly designed kernel that imposes  $k(X, X') = 0$  if  $|X - X'|$  is larger than some threshold  $d$  to create a sparse covariance matrix. This reduces the number of calculations that need to be performed and computational complexity to  $O(an^3)$ , where  $a$  is the proportion of non-zero entries remaining, but the kernel needs to be carefully designed to work with zeroes and ensure all entries are PSD. TODO sparse RBF

### 4.2 Eigenfunction and eigenvalue approximation of covariance matrices [11]

TODO why not sparse kernels?

Mercer's representation of the kernel 24 provides a way of approximating any arbitrary covariance matrix. Instead of summing all the eigenfunctions from 1 to  $\infty$ , we can approximate our kernel to any degree of accuracy  $M < N$  by restricting our sum to the largest  $M$  eigenvalues:

$$K(X, X') \approx \sum_{i=1}^M \lambda_i \phi_i(X) \phi_i(X') \quad (32)$$

and invert this smaller matrix at a lower computational cost  $O(M^3)$ . However, obtaining the eigenfunctions and eigenvalues of an  $N$ -size covariance matrix is  $O(N^3)$  for a total cost of  $O(N^3) + O(M^3)$ . We can reduce the cost of obtaining these eigenfunctions and eigenvalues by solving our eigenproblem on a smaller random sample of  $X$ . These approximations, and subsequent approximations, come with irreducible error which could create a kernel that no longer satisfies the Gram matrix constraint of positive semidefiniteness, violating Mercer's theorem and making them invalid covariance matrices.

Instead of our integral weighing our kernel and eigenfunction with the measure  $\mu$  as before, they become weighed in terms of the PDF of the training data  $p(x)$ :

$$\lambda_i \phi_i(x') = \int K(x, x') p(x) \phi_i(x) dx$$

We can approximate this continuous representation and make it discrete by representing our selected samples as a vector  $X_l$  of size  $l$ :

$$\lambda_i \phi_i(X') \approx \frac{1}{l} \sum_{j=1}^l K(x_j, X') \phi_i(x_j)$$

Defining a vector  $\Phi_i$  of all eigenfunction evaluations  $\phi_i(x_j)$  on the  $X_l$  sample:

$$\lambda_i \phi_i(X') \frac{1}{l} K(X_j, X') \Phi_i$$

Multiplying both sides by  $l$ :

$$n \lambda_i \phi_i(X') = K(X_j, X') \Phi_i$$

Setting  $\lambda_i^{mat} = l \lambda_i$ :

$$K(X_l, X') \phi_i(X') = \lambda_i^{mat} \Phi_i$$

This arrangement requires our covariance matrix to be evaluated with some  $X'$ . Without creating another sample or defeating the point of this approximation by using the whole of  $X$ , the only candidate for  $X'$  is the  $X_l$  sample. Setting  $X' = X_l$ , our  $\phi_i(X')$  becomes the definition of  $\Phi_i$ :

$$K(X_l, X_l) \Phi_i = \lambda_i^{mat} \Phi_i$$

Here,  $\Phi_i$  also plays the role of the eigenvector  $U_i$  of  $K(X_l, X_l)$ , and  $\lambda_i^{mat}$  plays the eigenvalue of  $K(X_l, X_l)$ .

Although we introduced  $\lambda_i^{mat} = l \lambda_i$ ,  $\lambda_i^{mat}$  are the eigenvalues of the eigenproblem produced by sampling, whereas  $\lambda_i$  are the eigenvalues from the original eigenproblem. Thus, it acts as an approximation:

$$\lim_{l \rightarrow \infty} \lambda_i = \frac{1}{l} \lambda_i^{mat}$$

#### 4.2.1 Approximating $\Phi_i$ and $U_i$ with Nystrom

Solving this eigenproblem is  $O(l^3)$  - an improvement on the  $O(n^3)$  cost of solving the previous eigenproblem, and the resulting  $O(l^3) + O(M^3)$  could be lower than the naive  $O(n^3)$  inversion cost (if we use sufficiently low degrees of accuracy  $l$  and  $M$ ). We can improve this further by approximating  $\Phi_i$ .

$\Phi_i$  and  $U_i$  are not exactly equivalent thanks to differing normalisations.  $\Phi_i$ 's normalisation comes from the original Monte Carlo approximation:  $\frac{1}{l} \sum_{j=1}^l K(x_j, X') \phi_i(x_j) \approx 1$ , thus the sum and our  $\|\Phi_i\|_2^2 \approx l$  and  $\|\Phi_i\| \approx \sqrt{l}$ .  $U_i$ 's normalisation comes from solving the eigenproblem, which returns  $\|U_i\|_2^2 = 1$  and  $\|U_i\| = 1$ . We can convert between the two by scaling  $\Phi_i$  by  $\sqrt{l}$  to produce  $U_i$ .

The Nyström method [1] extends this approximation from the sample points  $X_l$  to the full set of points  $X$ :

$$\phi_i(X) \approx \frac{1}{\sqrt{l}} \sqrt{n} K(X_l, X) \Phi_i$$

This approximation further reduces the cost of solving the eigenproblem and inverting the low-rank matrix to  $O(l^2 n) + O(M^3)$ .

#### 4.3 Subset-of-data (SoD) [10]

Matrix approximations like the Nystrom approximation can produce kernels that violate PSD due to the irreducible error involved. Instead of producing a low-rank approximation of the covariance matrix from a full GP, we could guarantee PSD by applying the GP to a subset  $M$  of  $X$  to reduce the cost of inversion to  $O(m^3)$ , where  $m$  is the number of training points in  $M$ . A theoretical graphon analysis showed that choosing  $M$  randomly gives an accuracy of  $O(\log^{-1/4} m)$  for the predictive mean and variance, which produces more accurate predictions with faster runtimes than sparse approximations as  $n$  increases. [6] Subset-of-data also requires no analytic assumptions about the covariance functions.

We can reduce  $m$  needed to achieve the same level of accuracy with a "greedy" approach by determining the gain in likelihood from including each data point  $x_i$  in  $X$ , adding the maximum gain in likelihood point to  $M$  and repeating until the size of  $M$  reaches  $m$ . However, computational savings from reducing  $m$  are smaller than the cost of searching  $X$  for these centroids  $O(n^2 m)$ . Instead, we can use a "matching pursuit" approach - maintain a cache of the already precomputed kernel values, and use these to compute the gain in likelihood for each point in  $X$  in  $O(nm^2)$  time. [9]

#### 4.4 Sparse approximations [10]

SoD throws away all data not in the selected subset of real training data  $m$ , losing information and reducing accuracy. Sparse approximation approaches are more accurate than SoD whilst achieving the same computational cost  $O(nm^2 + m^3)$ , by using potentially imaginary inducing points  $X_m$  that best approximate the full covariance matrix  $K(X, X)$ .

Joining a new prior on  $f(X_m)$  to our previous prior on  $f(X)$  20 gives us a new joint prior:

$$(f(X)f(X_m)) \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} K(X, X) & K(X, X_m) \\ K(X_m, X) & K(X_m, X_m) \end{pmatrix}\right)$$

Similarly to 21, we can use the Gaussian conditioning identity to condition this joint prior on our inducing points  $f(X_m)$  and obtain a posterior distribution over  $f(X)$ :

$$\begin{aligned} p(f(X)|X, X_m, f(X_m)) &\sim \mathcal{N}(\frac{K(X, X_m)K(X_m, X_m)^{-1}f(X_m)}{K(X, X) - K(X, X_m)K(X_m, X_m)^{-1}K(X_m, X)}) \end{aligned} \quad (33)$$

Marginalise out  $f(X_m)$ :

$$p(f(X)) = \int p(f(X)|f(X_m))p(f(X_m))df(X_m)$$

Without any approximations, it can be shown [10] that this integral recovers our full priors on  $f(X)$  ??:

$$p(f(X)) = \mathcal{N}(0, K(X, X))$$

We can also assemble our predictive distribution by forming a new joint prior and a posterior with the testing data  $X_*$  by substituting  $X$  for  $X_*$ :

$$p(f(X_*)|X_*, X, f(X_m)) \sim \mathcal{N}(K(X_*, X_m)K(X_m, X_m)^{-1}f(X_m), K(X_*, X_*) - K(X_*, X_m)K(X_m, X_m)^{-1}K(X_m, X_*))$$

As with training data, marginalising out  $X_m$  yields our original full prior on the training data  $f(X_*) \sim \mathcal{N}(0, K(X_*, X_*))$ .

We have introduced a new first step into the assembly of the predictive distribution that reduces the cost of prediction from  $O(n^3)$  to  $O(mn^2 + m^3)$ , but the cost of assembling the marginal likelihood remains  $O(n^3)$  in training. Approximations aimed at reducing the complexity of computing our marginal likelihoods are divided into two categories: prior approximations which change  $p(f(X)|f(X_m))$ , and posterior approximations which change  $p(f(X), f(X_m)|y)$ .

#### 4.4.1 Prior approximations

**4.4.1.1 Subset-of-Regression (SoR) [8]** SoR sets the variance of 33 to zero:

$$p_{\text{SoR}}(f(X_*)|f(X_m)) \sim \mathcal{N}(K(X_*, X_m)K(X_m, X_m)^{-1}f(X_m), 0)$$

Producing a marginal prior:

$$p_{\text{SoR}}(f(X_*)) = \int p_{\text{SoR}}(f(X_*)|f(X_m))p(f(X_m))df(X_m)$$

Evaluating this integral and representing the result as a Gaussian distribution:

$$p_{\text{SoR}}(f(X_*)) = \mathcal{N}(0, K(X_*, X_m)K(X_m, X_m)^{-1}K(X_m, X_*))$$

Inverting the  $m$ -rank  $K(X_m, X_m)^{-1}$  costs  $O(m^3)$ , and multiplying it by the  $n$ -rank  $K(X_*, X_m)$  and  $K(X_m, X_*)$  costs  $O(n^2m)$ , sped up using SMW 15 to yield  $O(nm^2)$ , for a predictive distribution complexity of  $O(nm^2 + m^3)$ . The resulting likelihood:

$$\begin{aligned} p_{\text{SoR}}(Y) = & -\frac{1}{2} \log(2\pi\sigma_n^2) \\ & -\frac{1}{2\sigma_n^2} Y^T Y \\ & +\frac{1}{2\sigma_n^4} Y^T K(X, X_m) A^{-1} K(X_m, X) Y \\ & -\frac{1}{2} \log |A| \\ & +\frac{1}{2} \log |K(X_m, X_m)| \end{aligned}$$

The only inversion here is the rank- $m$   $A = K(X_m, X_m) + \sigma_n^{-2}K(X_m, X)K(X, X_m)$  matrix, which costs  $O(m^3)$ . This achieves the same computational cost as the Nystrom approximation but does so in a probabilistic framework that guarantees PSD. However, setting our prior's variance to zero produces a predictive distribution that severely underestimates uncertainty, producing GPs that are too confident far from  $X_m$ .

**4.4.1.2 Fully independent training conditional (FITC) [13]** FITC assumes that the new data  $f(X_*)$  is independent given the inducing points  $f(X_m)$ . Formally:

$$p(f(X_*)|f(X_m)) = \prod_{i=1}^n p(f(x_{i*})|f(X_m))$$

TODO more motivation on prior yields. Our new prior distribution is:

$$p_{\text{FITC}}(f(X_*)|f(X_m)) = \mathcal{N}(f(X_*)|K(x_i, X_m)K(X_m, X_m)^{-1}f(X_m), \text{diag}[V_{nn}])$$

$V_{nn} = K(X_*, X_*) - K(X_*, X_m)K(X_m, X_m)^{-1}K(X_m, X_*)$ . Our new predictive distribution becomes:

$$\begin{aligned} p_{\text{FITC}}(f(X_*)) \sim \mathcal{N}( \\ k(X_*, X_m)\lambda^{-1}K(X_m, X_m)f(X_m), \\ K(X_*, X_*) - K(X_*, X_m)K(X_m, X_m)^{-1}K(X_m, X_*) + K(X_*, X_m)\lambda^{-1}K(X_m, X_*) \\ ) \end{aligned}$$

$$\lambda = K(X_m, X_m) + K(X_m, X_*)\text{diag}[V_{nn}]^{-1}K(X_*, X_m).$$

There are three matrices being assembled here: the at-most rank  $n$   $\text{diag}[V]$ , the rank- $m$   $\lambda$  and the final predictive variance of rank  $m$ .  $V$  is similar to SoR and costs  $O(mn^2)$ , whilst getting its diagonal costs  $O(nm)$ , and assembling  $\lambda$  and the predictive variance is also  $O(nm^2)$ . We need to invert  $\lambda$ ,  $K(X_m, X_m)$  and  $\text{diag}[V_{nn}]$  - the first two are rank  $M$ , and inverting a diagonal only costs  $O(n)$ . These operations reduce to an overall inference complexity of  $O(nm^2 + m^3)$ , and the resulting likelihood:

$$\begin{aligned} p_{\text{FITC}}(Y) = & -\frac{n}{2} \log(2\pi) \\ & -\frac{1}{2} \log |\lambda + \sigma_n^2 I_n| \\ & -\frac{1}{2} \log |K(X_m, X_m) + K(X_m, X)[\lambda + \sigma_n^2 I_n]^{-1}K(X, X_m)| \\ & +\frac{1}{2} \log |K(X_m, X_m)| \\ & -\frac{1}{2} y^T [\lambda + \sigma_n^2 I_n]^{-1} y \\ & +\frac{1}{2} y^T [\lambda + \sigma_n^2 I_n]^{-1} K(X, X_m) [K(X_m, X_m) + K(X_m, X)[\lambda + \sigma_n^2 I_n]^{-1}K(X_m, X)[\lambda + \sigma_n^2 I_n]^{-1} y \end{aligned}$$

requires an  $O(m^3)$  inversion of  $K(X_m, X_m) + K(X_m, X)[\lambda + \sigma_n^2 I_n]^{-1}K(X_m, X)$  and an  $O(nm^2)$  inversion of  $\lambda + \sigma_n^2 I_n$ , for an overall training complexity of  $O(nm^2 + m^3)$ .

FITC requires the same training and inference complexity as SoR but achieves a more accurate approximation for variance. Additionally, Bauer et. al. [2] found that the diagonal correlation  $\text{diag}[V_{nn}]$  represents the posterior variances of  $f(X_*)$  given  $f(X_m)$  enables predictive variances to grow in regions far from inducing points, capturing a form of heteroskedasticity. However, Titsias found that approximate priors produce marginal likelihoods that are far from the marginal likelihood produced by the full prior, which degrades the accuracy of GPs trained using this goal. [14]

#### 4.4.2 TODO Posterior approximations

**4.4.2.1 Variational free energy (VFE) [14]** Titsias introduced a variational distribution to approximate the noisy posterior: [14]

$$q(f(X), f(X_m)|y) = p(f(X)|f(X_m)) \cdot q(f(X_m)|y)$$

The Kullback-Leibler (KL) divergence measures how different two probability distributions are. The KL divergence between the true posterior  $p(f(X), f(X_m)|y)$  and our variational distribution  $q(f(X), f(X_m)|y)$  is:

$$D_{KL}(q(f(X), f(X_m)|y)||p(f(X), f(X_m)|y)) = \int q(f(X), f(X_m)|y) \log \frac{q(f(X), f(X_m)|y)}{p(f(X), f(X_m)|y)} df(X) df(X_m)$$

We need this expression in terms of  $\log p(y)$  to form an approximation for the likelihood. We can introduce this term into  $D_{KL}$  by Bayes' theorem:

$$D_{KL}(q(\cdot)||p(\cdot)) = \int q(f(X), f(X_m)|y) \log \frac{q(f(X), f(X_m)|y)}{p(y, f(X), f(X_m)|y)/p(y)} df(X) df(X_m)$$

Simplifying:

$$D_{KL}(q(\cdot)||p(\cdot)) = \int q(f(X), f(X_m)|y) \log \frac{q(f(X), f(X_m)|y)p(y)}{p(y, f(X), f(X_m)|y)} df(X) df(X_m)$$

Splitting the log term:

$$D_{KL}(q(\cdot)||p(\cdot)) = \int q(f(X), f(X_m)|y) \log \frac{q(f(X), f(X_m)|y)}{p(y, f(X), f(X_m)|y)} df(X) df(X_m) + \int q(f(X), f(X_m)|y) \log p(y) df(X) df(X_m)$$

$\log p(y)$  is a constant with respect to  $f(X)$  and  $f(X_m)$  and  $\int q(f(X), f(X_m)|y) df(X) df(X_m) = 1$ , so our second integral is just  $\log p(y)$ . Thus:

$$D_{KL}(q(\cdot)||p(\cdot)) = \int q(f(X), f(X_m)|y) \log \frac{q(f(X), f(X_m)|y)}{p(y, f(X), f(X_m)|y)} df(X) df(X_m) + \log p(y)$$

Rewriting to isolate  $\log p(y)$ :

$$\log p(y) = \int q(f(X), f(X_m)|y) \log \frac{p(y, f(X), f(X_m))}{q(f(X), f(X_m)|y)} df(X) df(X_m) + D_{KL}(q(\cdot)||p(\cdot)) \quad (34)$$

Our first term  $F = \int q(f(X), f(X_m)|y) \log \frac{p(y, f(X), f(X_m))}{q(f(X), f(X_m)|y)} df(X) df(X_m)$  is called the Evidence Lower Bound (ELBO), or the VFE term. Since  $D_{KL}(q(\cdot)||p(\cdot)) \geq 0$ ,  $\log p(y) \geq F$ , and we can maximise  $F$  to approximate the marginal likelihood  $p(y)$ . Maximising  $F$  using the model hyperparameters directly improves the model, and maximising it using the parameters of the variational distribution makes it a better approximation which improves the hyperparameter tuning methods.

For inference, this approximation produces the variational predictive distribution:

$$q(f(X_*)) = \mathcal{N}\left(\begin{aligned} &K(X_*, X_m)K(X_m, X_m)^{-1}\mu, \\ &K(X_*, X_*) - K(X_*, X_m)K(X_m, X_m)^{-1}\Sigma K(X_m, X_m)^{-1}K(X_m, X_*) \end{aligned}\right)$$

$\mu$  and  $\Sigma$  are the mean and covariance of the optimal  $q(f(X_m)|y)$  variational distribution. This requires  $O(nm^2 + m^3)$

time to compute, and the resulting likelihood after computing the Gaussian integrals in 34 is:

$$\begin{aligned}
p_{\text{VFE}}(Y) = & -\frac{1}{2} \log(2\pi\sigma_n^2) \\
& -\frac{1}{2\sigma_n^2} Y^T Y \\
& +\frac{1}{2\sigma_n^4} Y^T K(X, X_m) [K(X_m, X_m) + \sigma_n^{-2} K(X_m, X) K(X, X_m)]^{-1} K(X_m, X) Y \\
& -\frac{1}{2} \log |K(X_m, X_m) + \sigma_n^{-2} K(X_m, X) K(X, X_m)| \\
& +\frac{1}{2} \log |K(X_m, X_m)| \\
& -\frac{1}{2\sigma_n^2} \text{tr} [K(X, X) - K(X_n, X_m) K(X_m, X_m)^{-1} K(X_m, X)]
\end{aligned}$$

The trace term  $\text{tr}[\cdot]$  represents the residual variance the variational distribution has left unexplained. The terms in the likelihood that dominate computational complexity are the  $y^T K(X, X_m) [K(X_m, X_m) + \sigma_n^{-2} K(X_m, X) K(X, X_m)]^{-1} K(X_m, X) y$  and the  $K(X_m, X_m) + \sigma_n^{-2} K(X_m, X) K(X, X_m)$  inversions, which cost  $O(nm^2)$  and  $O(m^3)$  respectively, for an overall training complexity of  $O(nm^2 + m^3)$ . VFE achieves a more accurate approximation of the marginal likelihood than FITC with no additional computational cost incurred.

**4.4.2.1.1 Deriving FITC through the VFE framework [fitc-vfe-unifier]** Bui et. al. found that applying expectation propagation, or minimising the "inclusive" KL where  $p$  and  $q$  are swapped:  $D_{KL}(p(\cdot)||q(\cdot))$  recovers the FITC prior exactly:

$$\begin{aligned}
q(f) = & N( \\
& 0, \\
& K(X, X_m) K(X_m, X_m)^{-1} K(X_m, X) + \text{diag}[V_{nn}] \\
& )
\end{aligned}$$

They defined the power expectation propagation (PEP) objective:

$$\log q_{\text{PEP}}(y) = \log q(y) - \frac{1-\alpha}{2\alpha} \text{tr} \left[ \log(I_n + \frac{\alpha}{\sigma_n^2} V_{nn}) \right]$$

$q(y)$  represents our FITC prior and the trace term represents  $VFE$ . When  $\alpha = 1$ , the trace term vanishes and we recover FITC exactly. As  $\alpha \rightarrow 0$ , the expansion of the  $\frac{1-\alpha}{\alpha} \log(I + \alpha A) \rightarrow \text{tr}[A]$  and we recover VFE in its collapsed form. [fitc-vfe-unifier] TODO improve explanation

#### 4.4.2.2 Stochastic variational GP (SVGP) [7]

#### 4.4.3 TODO Selecting inducing points

#### 4.5 TODO Approximations for Celerite kernels [4]



## 5 TODO Applying a Gaussian Process to Astrostatistics

### 5.1 Introduction

#### 5.1.1 Astrological background [galxy-spectra-101]

#### 5.1.2 Using GP [galaxy-gp-noise]

### 5.2 Methodology

#### 5.2.1 Computational speed

#### 5.2.2 Accuracy

### 5.3 Results

### 5.4 Discussion

### 5.5 Conclusion

## 6 Conclusion

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