MULTI-FREQUENCY SCALE GAUSSIAN REGRESSION FOR NOISY TIME-SERIES DATA

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Abstract: Regression using Gaussian process models is applied to time-series data analysis. To extract from the data separate components with different frequency scales, the Gaussian regression methodology is extended through the use of multiple Gaussian process models. Fast and memory-efficient methods, as required by Gaussian regression to cater for large time-series data sets, are discussed. These methods are based on the generalised Schur algorithm and a procedure to determine the Schur decomposition of matrices, the key step to realising them, is presented. In addition, a procedure to appropriately initialise the Gaussian process model training is presented. The utility of the procedures is illustrated by application of a multiple Gaussian process model to extract separate components with different frequency scales from a 5000-point time-series data set with gaps. Copyright © 2006 USTRATH

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1. INTRODUCTION

Following the early work by MacKay (1998) and Williams (1999), there has been increasing interest in the application of Gaussian process prior models to data analysis (Gibbs and MacKay, 2000; Yoshioka, and Ishii, 2001), including data filtering and fitting, statistical modelling and system identification. Gaussian regression based on models with two stochastic processes is discussed in Leithead et al (2005b). During training of the prior model the two Gaussian processes are conditioned on data subject to the condition that they remain independent. Separate components in the data with different characteristics or, more precisely, their description by probability distributions can then be extracted.

In this paper, the application of Gaussian regression to time-series data analysis is considered. A brief overview of Gaussian regression is given in Section 2. The methodology based on Gaussian process models with two stochastic processes is extended in Section 3 to models with M stochastic processes. When applied to time-series data, separate components with different frequency scales can then be extracted. However, for a data set of size N, many matrix manipulations requiring \(O(N^3)\) operations and \(O(N^2)\) memory-storage, such as matrix inversion and log-determinant, are necessary during training and prediction. Since the matrices, encountered in the application of Gaussian regression to the analysis of large time-series data sets, are Toeplitz-like, fast and memory-efficient methods for matrix manipulation are possible. Methods based on the Schur algorithm rather than the Modified Levinson-Durbin’s algorithm (Zhang and Leithead, 2004), are more general and so are preferred; for example, when analysing time-series data with gaps. Fast and memory-efficient methods based on the Schur algorithm, with the focus on the key step of determining the Schur decomposition, are discussed in Section 4. A procedure to determine the Schur decomposition is proposed. In addition, training of the Gaussian process prior models is non-convex.
Hence, it may be inefficient and can converge on an incorrect model. A procedure to ensure appropriate initialisation, when applying Gaussian regression to time-series data, is presented in Section 5. Finally, the utility of the above procedures is illustrated in Section 6 by application of a multiple Gaussian process model to extract independent components from a time-series data set with gaps.

2. GAUSSIAN PROCESS PRIOR MODELS

A brief explanation of the standard Gaussian regression methodology and its application to data analysis is reviewed in this section. Consider a smooth scalar function \( f(.) \) dependent on the explanatory variable, \( z \in D \subseteq \mathbb{R}^P \). Suppose \( N \) measurements, \( \{(x_i, y_i)\}_{i=1}^N \), of the value of the function with additive Gaussian white measurement noise, i.e. \( y_i = f(x_i) + n_i \), are available and denote them by \( M \). It is of interest here to use this data to learn the function \( f(.) \) or, more precisely, to determine a probabilistic description of \( f(z) \) on the domain, \( D \), containing the data. Note that this is a regression formulation and it is assumed the input \( z \) is noise free. The probabilistic description of the function, \( f(.) \), adopted is the stochastic process, \( f_n \), with the prior covariance function \( \text{E}[f_n] \), as \( z \) varies, interpreted to be a fit to \( f(.) \). By necessity, to define the stochastic process, \( f_n \), the probability distributions of \( f_n \) for every choice of value of \( z \in D \) are required together with the joint probability distributions of \( f_n \) for every choice of finite sample, \( \{x_i, \ldots, x_k\} \), from \( D \), for all \( k > 1 \). Given the joint probability distribution for \( f_n \), \( i = 1, \ldots, N \), and the joint probability distribution for \( n_i \), \( i = 1, \ldots, N \), the joint probability distribution for \( y_i \), \( i = 1, \ldots, N \), is readily obtained since the measurement noise, \( n_i \), and the \( f(z_i) \) (and so the \( f_n \)) are statistically independent. \( M \) is a single event belonging to the joint probability distribution for \( y_i \), \( i = 1, \ldots, N \).

In the Bayesian probability context, the prior belief is placed directly on the probability distributions describing \( f_n \) which are then conditioned on the information, \( M \), to determine the posterior probability distributions. In particular, in the Gaussian process prior model, it is assumed that the prior probability distributions for the \( f_n \) are all Gaussian with zero mean (in the absence of any evidence the value of \( f(z) \) is as likely to be positive as negative). Only a definition of the covariance function \( C(z, z_j) = \text{E}[f(z), f_j] \), for all \( z \) and \( z_j \), is required to complete the statistical description. The resulting posterior probability distributions are also Gaussian. This model is used to carry out inference as follows.

Clearly, by Bayes’ rule, \( p(f_n|M) = \frac{p(M|f_n)p(f_n)}{p(M)} \) where \( p(M) \) acts as a normalising constant. Hence, with the Gaussian prior assumption,

\[
p(f_n|M) \propto \exp \left[ -\frac{1}{2} \left[ f_n - \text{Y}^T \Lambda f_n \right] \right] \]  

where \( Y = [y_1, \ldots, y_N]^T \), \( \Lambda_{11} \) is \( E[f_n, f_n] \), the \( i \)-th element of the covariance matrix \( \Lambda_{22} = E[y_i, y_j] \) and the \( i \)-th element of vector \( \Lambda_{21} \) is \( E[y_i, f_n] \). Both \( \Lambda_{11} \) and \( \Lambda_{22} \) depend on \( z \). Applying the partitioned matrix inversion lemma, it follows that

\[
p(f_n | M) \propto \exp \left[ -\frac{1}{2} \left[ (f_n - \hat{f}_n) \Gamma^{-1} (f_n - \hat{f}_n) \right] \right] \]  

with \( \hat{f}_n = \Lambda_{12} \Lambda_{22}^{-1} Y \), \( \Lambda_2 = \Lambda_{11} - \Lambda_{12} \Lambda_{22}^{-1} \Lambda_{21} \).

Therefore, the prediction from this model is that the most likely value of \( f(z) \) is the mean, \( \hat{f}_n \), with variance \( \Lambda_2 \). Note that \( \hat{f}_n \) is simply a \( z \)-dependent weighted linear combination of the measured data points, \( Y \), using weights \( \Lambda_{12} \Lambda_{22}^{-1} \). The measurement noise, \( n_i \), is statistically independent of \( f(z) \), \( i = 1, \ldots, N \), and has covariance matrix \( B \). Hence the covariances for the measurements, \( y_i \), are simply

\[
E[y_i, f_n] = E[f_n, f_n] + B \ ; E[y_i, y_j] = E[f_n, f_n] = E[f_n, f_n] = 0
\]  

The prior covariance function is generally dependent on a few hyperparameters, \( \theta \). To obtain a model given the data, \( M \), the hyperparameters are adapted to maximise the likelihood, \( p(M|\theta) \), or equivalently to minimise the negative log likelihood, \( L(\theta) \),

\[
L(\theta) = -\frac{1}{2} \log |C(\theta)| + \frac{1}{2} Y^T C(\theta)^{-1} Y
\]  

where \( C(\theta) = \Lambda_{22} \), the covariance of the measurements.

When, as here, the data set is a time series, the explanatory variable is simply time, i.e. \( z = t \). A common choice of the covariance function for time series analysis is \( a \exp[-\frac{1}{2}d(t_i - t_j)^2] \), where the hyperparameter, \( a \), is related to the length-scale of the data and the hyperparameter, \( \sigma^2 \), to the amplitude of the data such that \( a = E[f_n, f_n] \). Assuming the measurement noise is white, its covariance function is \( n \delta_{ij} \), where \( n \) is the noise variance such that \( n = E[n_i, n_j] \). It follows that the covariance function for the measured data and so the \( ij \)-th element of \( C(\theta) \) is

\[
a \exp[-\frac{1}{2}d(t_i - t_j)^2] + b \delta_{ij}
\]  

where \( n = ab \). The hyperparameters for the prior model (2) are \( \theta = (a, d, b) \).

3. MODELS WITH MULTIPLE GAUSSIAN PROCESSES

The procedure outlined in Section 2 is very effective when used to identify a single function. However, suppose that the measurements are the sum of the values of \( M \) functions, each with different characteristics; that is, the measured values are \( y_i = f_1(z_i) + \ldots + f_M(z_i) + n_i \). The case with \( M=2 \) is discussed in detail in (Leithead et al 2005b). A possible probabilistic description of \( h(z) = f_1(z) + \ldots + f_M(z) \) is by means of the sum of \( M \) independent Gaussian processes, \( f_1, \ldots, f_M \). Let the covariance functions for these independent
Gaussian processes be \( C_i(z_1, z_2), \ldots, C_{1_0}(z_1, z_2) \), respectively, then \( h = f_1 + \ldots + f_{1_0} \), is itself a Gaussian process with covariance function \( C_h = C_{i_1} + \ldots + C_{1_0} \).

With \( F_{1_2} = [f_{1_2}, \ldots, f_{1_{2_2}}]^T \), the \( ij \)-th element of \( A_{1_2} \) is \( A_{1_2}^{ij} \). The prior joint probability distribution for \( F_{1_2}, \ldots, F_{1_{2_2}} \) and \( Y \) is Gaussian with mean zero and covariance matrix

\[
\Lambda = \text{E}[[F_{1_2} \ldots F_{1_{2_2}}] Y]^T] = \begin{bmatrix} \Lambda_{1_2} & \cdots & \Lambda_{1_{2_2}} \\ \vdots & \ddots & \vdots \\ \Lambda_{1_{2_2}} & \cdots & \Lambda_{1_{2_2} F_{1_{2_2}}} \end{bmatrix} \Lambda_{1_{2_2}}^{-1} \begin{bmatrix} F_{1_2}^-T \\ \vdots \\ F_{1_{2_2}}^-T \end{bmatrix}
\]

where \( Q = \mathbf{B} + \Lambda_{1_2} F_{1_{2_2}} + \ldots + \Lambda_{1_{2_2}} F_{1_{2_2}} \) and \( \mathbf{B} \) is the noise covariance matrix. Applying the partitioned matrix lemma, the posterior joint probability distribution for \( F_{1_2}, \ldots, F_{1_{2_2}} \) conditioned on the data, \( Y \) remains Gaussian with mean, \( \bar{M} \), and covariance matrix, \( \bar{A} \), where

\[
\bar{M} = [\Lambda_{1_2} F_{1_{2_2}} \ldots \Lambda_{1_{2_2}} F_{1_{2_2}}]^{T} Q^{-1} Y
\]

\[
\bar{A} = \text{diag} \left( \Lambda_{1_2} F_{1_{2_2}} \ldots \Lambda_{1_{2_2}} F_{1_{2_2}} \right) - \left( \Lambda_{1_2} F_{1_{2_2}} \ldots \Lambda_{1_{2_2}} F_{1_{2_2}} \right) Q^{-1} \left( \Lambda_{1_2} F_{1_{2_2}} \ldots \Lambda_{1_{2_2}} F_{1_{2_2}} \right)
\]

The mean and covariance matrix for \( H = F_{1_2} + \ldots + F_{1_{2_2}} \) are, respectively, \( \bar{A}_{1_{2_2}} Q^{-1} Y \) and \( \bar{A}_{1_{2_2}}^{-1} \Lambda_{1_{2_2}} Q^{-1} \Lambda_{1_{2_2}}^{-1} \), where \( \bar{A}_{1_{2_2}} = \Lambda_{1_{2_2}} F_{1_{2_2}} + \ldots + \Lambda_{1_{2_2}} F_{1_{2_2}} \).

However, the requirement here is to determine the posterior probability distribution for \( F_{1_2}, \ldots, F_{1_{2_2}} \), conditioned on the data, subject to the condition that they remain independent. It is met (Leithed et al 2005b) through a transformation of the \( F_{1_2}, \ldots, F_{1_{2_2}} \) such that the mean and covariance of the posterior joint probability distribution become, respectively,

\[
\begin{bmatrix} \Lambda_{1_2} Q^{-1} Y \\ \mathbf{B} Q_{1_2}^{-1} \Lambda_{1_2} Q_{1_2}^{-1} Y \\ \vdots \\ \mathbf{B} Q_{1_{2_2}}^{-1} \Lambda_{1_{2_2}} Q_{1_{2_2}}^{-1} Y \\ \mathbf{B} Q_{1_{2_2}}^{-1} \Lambda_{1_{2_2}} Q_{1_{2_2}}^{-1} Y \end{bmatrix} \text{ and } \begin{bmatrix} \Lambda_{1_2} Q_{1_2}^{-1} \mathbf{B} \\ \mathbf{B} Q_{1_2}^{-1} \Lambda_{1_2} Q_{1_2}^{-1} \mathbf{B} \\ \vdots \\ \mathbf{B} Q_{1_{2_2}}^{-1} \Lambda_{1_{2_2}} Q_{1_{2_2}}^{-1} \mathbf{B} \end{bmatrix}
\]

where \( \Lambda_{1_2} = \Lambda_{1_2} F_{1_{2_2}} + \ldots + \Lambda_{1_{2_2}} F_{1_{2_2}} \) and \( Q_{1_2} = \Lambda_{1_2} + \mathbf{B} \).

(Not, the likelihood of the data remains unaffected by the transformation).

When applied to time-series data, these multiple Gaussian process models enable separate components with different frequency scales to be extracted.

### 4. GENERALISED SCHUR ALGORITHM

For time-series data with a constant sampling interval, as here, the covariance matrix, \( C(\theta) \), is Toeplitz (or, when there are gaps in the data, block-Toeplitz), and has low displacement rank. Applying the generalised Schur algorithm (Kailath and Sayed, 1999), many manipulations of these low displacement rank matrices require only \( O(N^2) \) operations, rather than \( O(N^3) \). These fast memory-efficient methods then enable the use of Gaussian regression with large time-series data.

Consider a positive-definite matrix, \( R \in \mathbb{R}^{N \times N} \). The triangular decomposition is denoted by

\[
R = \mathbf{LDL}^T
\]

where \( D = \text{diag}\{d_0, d_1, \ldots, d_{N-1}\} \) is a diagonal matrix. The lower triangular matrix \( L \) is normalised so that the elements on its main diagonal are the \( \{d_i\} \). This LDL-decomposition can be obtained through the Schur reduction algorithm.

The Schur algorithm applies to strongly regular Hermitian Toeplitz-like matrices, \( R \), satisfying

\[
\Delta R = R - FRF^* \cong GJG^* , \quad J = J^* , J^2 = I \tag{3}
\]

for some full rank generator matrix \( G \), and lower triangular matrix, \( F \), for which the diagonal elements, \( \{f_i\} \), satisfy

\[
1 - f_i f_j^* \neq 0 \quad \text{for all } i, j \tag{4}
\]

The signature matrix, \( J \), is defined to be \( J \)-unitary, \( J = (I_q \otimes -I_p) \), i.e. \( p = q \). \( F \) is the strictly lower-triangular shift matrix, \( F = (Z_{N_q} \otimes Z_{N_q} \otimes Z_{N_q} \otimes \ldots) \), depending on the number of inner Toeplitz-blocks inside \( R \). Matrix \( Z_N \) is defined here to be a square lower-triangular shift matrix with zeros on the first subdiagonal and zeros elsewhere (i.e. a lower-triangular Jordan block with eigenvalue equal to zero). The generator matrix, \( G \), can be obtained by the following procedure.

**Procedure I:**

1) \( \text{Let } R \in \mathbb{R}^{N \times N} \) be a symmetrical and Hermitian matrix, with low displacement rank, \( K < N \), such that the reduced-row echelon form (RREF) is

\[
\Delta R = \begin{bmatrix} \mathbf{A} & \mathbf{B}^* \\ \mathbf{B} & 0 \end{bmatrix} \begin{bmatrix} \mathbf{A} & 0 \\ 0 & \mathbf{A} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{A} & \mathbf{B}^* \\ \mathbf{B} & 0 \end{bmatrix}
\]

where \( \mathbf{B}^* = \begin{bmatrix} \mathbf{A} & \mathbf{B}^* \end{bmatrix} \) and \( \mathbf{A} \in \mathbb{R}^{K \times 2K+2} \) is symmetric. Any symmetric Hermitian block-Toeplitz matrix can be transformed into a matrix with the above RREF by permuting its rows and columns. Let \( \Gamma E = ED \) be the eigen-value decomposition of

\[
\Gamma = \begin{bmatrix} A & I \\ B^* B - AA & 0 \end{bmatrix}
\]

(5)
where $D$ is diagonal. The non-zero eigen-values of $\Delta R$ are real and positive and identical to the eigen-values of $\Gamma$. In addition, the eigen-vectors of $\Delta R$ are real and equal to the columns of $BX + [I \ 0]^T Y$ where $[X^T \ Y^T]^T = E \in \mathbb{R}^{K \times K}$.

2) The values of some of the eigen-values of $G$ can be very similar. For numerical reasons, the computed eigen-values can then include complex conjugate pairs, i.e. $\Delta R$ is not diagonal. However, since all the eigen-values are not distinct, the columns of $\Psi$ are not automatically orthonormal as required. To enforce orthonormality the columns of $\Psi$ are rescaled such that, with the diagonal elements of $\Delta$ is the $i$-th column of $\Psi$. To obtain orthonormality the columns are then rescaled such that, $\forall k$,

$$\Psi_k \rightarrow \Psi_k / \sqrt{\sum_{i} \Psi_i^T \Psi_k}$$

4) With $\Psi \in \mathbb{R}^{N \times K}$, obtained as above, $\Delta R \equiv \Psi D \Psi^T$. $D$ has a decomposition

$$D \rightarrow \text{real}(D)$$

$$E \rightarrow \text{real}(E) + \text{imag}(E)$$

3) Each column of $BX + [I \ 0]^T Y = \Psi \in \mathbb{R}^{N \times K}$ is an eigen-vector of $\Delta R$ with eigen-value unchanged; that is, the diagonal elements of $\Delta$. However, since the imaginary parts of the eigen-vectors can be large. For doing so, when Gaussian regression is applied to time-series data, is presented.

For time-series data, suppose the mean of the data is zero. (if not it can always be made so). The initial values of the hyper-parameters $\theta = (a, d, b)$ for the covariance function (2) are determined by the following procedure. The discussion is illustrated using the power spectral density in Fig.1.

Procedure 2:

1) Provided the time series data is of sufficient length, its variance is roughly equal to $a + n$, since the amplitude hyper-parameter $a = E[f_y, f_y] = Y^T Y/N$ and the noise hyper-parameter $n = E[n, n]$. Let $V_y$ and $V_n$, respectively, be the variances of the measured data and the measurement noise. It follows that

$$v = V_y / V_n \approx n / (a + n) = b / (1 + b)$$

2) The value for $V_y$ is easily estimated. Since different values of the hyperparameters, especially the length-scale hyperparameter, correspond to models with different length-scales, the value for $V_n$ depends on the choice of time-series components that is interpreted to be noise. For example, the spectral density in Fig 1 clearly indicates that the corresponding time series data consists of several components with different length-scales. Only the long length-scale component with frequency less than $\chi_1$ might be of interest when all components with higher frequency are interpreted as noise. In this case, $V_n$ would be estimated as the cumulative sum of the spectrum between $\chi_1$ and $\chi_2$, the Nyquist rate. Hence, $a^*$ and $b^*$, initial value for $a$ and $b$, are obtained from

$$a^* = (1 - v) V_y \quad \text{and} \quad b^* = v / (1 - v) \quad : \quad v = V_y / V_n$$
3) Let \( C(\theta) = aP(d,b) \) in (1). The negative log-likelihood function becomes
\[
L(\theta) = -\frac{1}{2} \log a + \frac{1}{2} \log |P(d,b)| + \frac{1}{2} \log \left| \mathbf{Y} \mathbf{P}(d,b)^{-1} \mathbf{Y} \right|
\]
The length-scale hyperparameter, \( a \), can be explicitly eliminated from \( L(\theta) \) by substituting the minimising value of \( a \) as a function of \( d \) and \( b \). The log likelihood function is thus reformulated to be dependent on only two hyper-parameters, \( d \) and \( b \), instead of three, viz.,
\[
\tilde{L}(d,b) = \log |P(d,b)| + N \log \left( \mathbf{Y} \mathbf{P}(d,b)^{-1} \mathbf{Y} \right)
\]
(6)

The initial value, \( d^* \), for the length-scale hyperparameter, \( d \), is obtained by solving the nonlinear equation
\[
a^* = \mathbf{Y} \mathbf{P}(d^*,b^*)^{-1} \mathbf{Y} / N
\]
(7)
The hyperparameter values \( a^*, d^* \) and \( b^* \), obtained by procedure 2, are appropriate initial values for minimising the log likelihood, whether (1) or (6). The latter has the advantage of only being dependent on two hyperparameters and so converges more quickly. There are two cases. In the first, all the hyperparameters are adjusted during the optimisation to converge on a nearby local minimum corresponding to the prior model with the required length-scale characteristic. In the second, the optimisation may fail to locate a suitable local minimum, when all the hyperparameters are adjusted. In the latter situation, \( d^* \) needs to be held constant during the optimisation. It may then be necessary to adjust manually the value of \( d^* \) and repeat the optimisation to obtain the prior model with the required length-scale characteristic.

6. APPLICATION TO DATA WITH GAPS

In this section, by exploiting the procedures presented in Sections 4 and 5, the Gaussian regression methodology of Sections 2 and 3 are applied to a data set of 5,000 points sampled at 1Hz (CATS Benchmark, 2004). It contains four gaps, specifically, the intervals, (981s-1000s), (1981s-2000s), (2981s-3000s), (3981s-4000s) and (4981s-5000s). When applying Gaussian regression to data with gaps, depending on the context, a single Gaussian process model with covariance function having more than one term or a multiple Gaussian process model may be required (Leithead et al 2005b). The data is shown in Fig. 2 (the grey line) together with its spectral density function in Fig. 3 (the grey line). The data has a component with length-scale longer than the gaps at frequencies less than 0.045Hz, a component with length-scale similar to the gaps at frequencies between 0.045Hz and 0.095Hz and a component with length-scale shorter than the gaps above 0.096Hz. Here, to extract each of the above components separately, a multiple Gaussian process model with three processes is employed.
second from the residues of the long length-scale prediction and the third from the residues of the combined long and medium length-scale prediction. The fast and memory efficient generalised Schur algorithm of Section 4 is used together with initialisation algorithm of Section 5. The hyperparameter values for the three components are $a=2.422 \times 10^4$ & $d=0.0038$, $a=83.6391$ & $d=0.0473$ and $a=55.962$ & $d=1.274$, respectively. The noise hyperparameter value is $n=35.9130$. The long length-scale component prediction and confidence intervals are shown in Fig. 2 (black lines). A typical section, from 2850s to 3150s, of the medium length-scale component prediction and confidence intervals are shown in Fig. 4 and a typical short section, from 2900s to 3100s, of the short length-scale component prediction and confidence intervals in Fig. 5. The spectral density functions for the three components are depicted in Fig. 3. In addition, the differences between the data and the predictions from the complete three Gaussian process model together with the confidence interval (grey lines) are shown in Fig. 6. As would be expected, the confidence interval is much wider during the gaps.

7. CONCLUSION

The application of Gaussian regression to time-series data analysis is examined. Through the use of models consisting of multiple independent Gaussian processes, the general methodology is extended such that the individual Gaussian processes are conditioned on the data subject to the condition that they remain independent. When applied to time-series data, separate components with different frequency scales can be extracted.

Fast and memory-efficient methods for the matrix manipulations required by the Gaussian regression methodology are discussed. A procedure to determine the Shur decomposition of Toeplitz-like matrices, a key issue, is presented. A procedure to ensure appropriate initialisation, when training the prior model, is also presented.

A multiple Gaussian process model is applied, using the above procedures, to extract separate components with different frequency scales from a 5,000-point time-series data set with gaps. The effectiveness of the methods is clear.

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