

Nonparametric Covariance Estimation for Longitudinal Data via Penalized Tensor Product Splines

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Abstract

With high dimensional longitudinal and functional data becoming much more common, there is a strong need for methods of estimating large covariance matrices. Estimation is made difficult by the instability of sample covariance matrices in high dimensions and a positive-definite constraint we desire to impose on estimates. A Cholesky decomposition of the covariance matrix allows for parameter estimation via unconstrained optimization as well as a statistically meaningful interpretation of the parameter estimates. Regularization improves stability of covariance estimates in high dimensions, as well as in the case where functional data are sparse and individual curves are sampled at different and possibly unequally spaced time points. By viewing the entries of the covariance matrix as the evaluation of a continuous bivariate function at the pairs of observed time points, we treat covariance estimation as bivariate smoothing.

Within regularization framework, we propose novel covariance penalties which are designed to yield natural null models presented in the literature for stationarity or short-term dependence. These penalties are expressed in terms of variation in continuous time lag and its orthogonal complement. We present numerical results and data analysis to illustrate the utility of the proposed method.

keywords: non-parametric, covariance, longitudinal data, functional data, splines, reproducing kernel Hilbert space

1 Introduction

An estimate of the covariance matrix or its inverse is required for nearly all statistical procedures in classical multivariate data analysis, time series analysis, spatial statistics and, more recently, the growing field of statistical learning. Covariance estimates play a critical role in the

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performance of techniques for clustering and classification such as linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), factor analysis, and principal components analysis (PCA), analysis of conditional independence through graphical models, classical multivariate regression, prediction, and Kriging. Covariance estimation with high dimensional data has recently gained growing interest; it is generally recognized that there are two primary hurdles responsible for the difficulty in covariance estimation: the instability of sample covariance matrices in high dimensions and a positive-definite constraint we wish estimates to obey.

Prevalent technological advances in industry and many areas of science make high dimensional longitudinal and functional data a common occurrence, arising in numerous areas including medicine, public health, biology, and environmental science with specific applications including fMRI, spectroscopic imaging, gene microarrays among many others, presenting a need for effective covariance estimation in the challenging situation where parameter dimensionality p is possibly much larger than the number of observations, n .

We consider two types of potentially high dimensional data: the first is the case of functional data or times series data, where each observation corresponds to a curve sampled densely at a fine grid of time points; in this case, it is typical that the number of time points is larger than the number of observations. The second is the case of sparse longitudinal data where measurement times may be almost unique yet sparsely distributed within the observed time range for each individual in the study. In this case, the nature of the high dimensionality may not be a consequence of having more measurements per subject than the number of subjects themselves, but rather because when pooled across subjects, the total number of unique observed time points is greater than the number of individuals. Several approaches have been taken in effort to overcome the issue of high dimensionality in covariance estimation. Regularization improves stability of covariance estimates in high dimensions, particularly in the case where the parameter dimensionality p is much larger than the number of observations n . Regularization of the covariance matrix and its Cholesky decomposition has been explored extensively through various approaches including banding, tapering, kernel smoothing, penalized likelihood, and penalized regression; see citetpourahmadi2011covariance for a comprehensive overview.

To overcome the hurdle of enforcing covariance estimates to be positive definite, several have considered modeling various matrix decompositions including variance-correlation decomposition, spectral decomposition, and Cholesky decomposition. The Cholesky decomposition has received particular attention, as it which allows for a statistically meaningful interpretation as well as an unconstrained parameterization of elements of the covariance matrix. This parameterization allows for estimation to be accomplished as simply as in least squares regression. If we assume that the data follow an autoregressive process with (possibly) heteroskedastic errors, then the two matrices comprising the Cholesky decomposition, the Cholesky factor (which diagonalizes the covariance matrix) and diagonal matrix itself, hold the autoregressive coefficients and the error variances, respectively.

In longitudinal studies, the measurement schedule could consist of targeted time points or could consist of completely arbitrary (random) time points. If either the measurement schedule

has targeted time points which are not necessarily equally spaced or if there is missing data, then we have what is considered incomplete and unbalanced data. If the measurement schedule has arbitrary or almost unique time points for every individual so that at a given time point there could be very few or even only a single measurement, we must consider how to handle what we consider as sparse longitudinal data. We view the response as a stochastic process with corresponding continuous covariance function and the generalized autoregressive parameters as the evaluation of a continuous bivariate function at the pairs of observed time points rather than specifying a finite set of observations to be multivariate normal and estimating the covariance matrix. This is advantageous because it is unlikely that we are only interested in the covariance between pairs of observed design points, so it is reasonable to approach covariance estimation in a way that allows us to obtain an estimate of the covariance between two measurements at any pair of time points within the time interval of interest.

Through the Cholesky decomposition, we formulate covariance estimation as a penalized regression problem and propose novel covariance penalties designed to yield natural null models presented in the literature. By transforming the axes of the design points, we express these penalties in terms of two directions: the lag component and the additive component and characterize the solution coefficient function in terms of a functional ANOVA decomposition. Some have side-stepped the issue of high dimensionality by prescribing simple parametric models for the elements of the Cholesky decomposition. ?, Pourahmadi [1999], and Pourahmadi and Daniels [2002] have elicited stationary parametric models for the generalized autoregressive coefficients, letting the GARPs depend only on the distance between two time points. To induce the structural simplicity of such stationary models with the flexibility of a nonparametric approach, we penalize all functional components but that corresponding to the lag component so that the set of null models is comprised of stationary models. Huang et al. [2007] follow the heuristic argument presented in Pourahmadi [1999] that the generalized autoregressive parameters are monotone decreasing in as lag increases and set off-diagonal elements of either the covariance matrix or the Cholesky factor corresponding to large lags to zero. Rather than shrinking element of the Cholesky factor to zero after particular value of l , we choose to enforce structure of the Cholesky factor such that the null models coincide with parsimonious models commonly used in time series analysis and with simple parametric models proposed in the nonparametric covariance estimation literature.

The rest of the paper is organized as follows: Chapter 2 summarizes the general penalized estimation approach and introduces the transformed design coordinates and penalties for stationarity and non-monotonicity. Chapter 3 presents a detailed discussion of optimization and computational issues. Chapter 4 presents a simulation study and a real example to examine the performance of our methods as well as other proposed estimators. Chapter 5 concludes with discussion and future work.

2 Covariance estimation: a review

The following chapter presents a review of approaches to parsimoniously modelling covariance matrices. We focus on methods based on regularization and generalized linear modeling perspec-

tives, which are concerned with constraining the parameter space of covariance matrices so as to reduce its dimension, making estimation a non-Sisyphian endeavor. The generalized linear model (GLM) framework (Nelder and Wedderburn's (1972)) merges numerous seemingly disconnected approaches to model the mean of a distribution, and can accommodate many types of including normal, probit, logistic and Poisson regressions, survival data, and log-linear models for contingency tables. The key to the power of the GLM paradigm is the use of a link function to induce unconstrained reparameterization for the mean of a distribution, and hence the ability to reduce the dimension of the parameter space via modelling the covariate effect additively by increasing the number of parameters gradually one at a time corresponding to inclusion of each covariate. The extension of the GLM has lead to large class of models including nonparametric and generalized additive models, Bayesian GLM, and generalized linear mixed models. See (Hastie and Tibshirani, 1990), (Dey et al., 2001), (McCulloch and Searle, 2001). An analogous framework for modelling covariance matrices facilitates further developments in covariance estimation from the Bayesian, nonparametric and other paradigms.

Estimation of the covariance matrix is fundamental to the analysis of multivariate data, and the most commonly used estimator is the sample covariance matrix, S . While it is both positive-definite and an unbiased estimator of Σ , it is unstable large dimension M . Approaches rooted in decision theory yield stable estimators which are scalar multiples of the sample covariance matrix and known (Dempster, 1969) to distort the eigenstructure of Σ , unless p/n is small. A vast and growing literature on the problem of efficient estimation of the covariance matrix of a normal distribution has focused on either correcting this distortion in the eigenstructure and/or reducing the number of parameters to be estimated (Stein, 1975; Lin and Perlman, 1985; Yang and Berger, 1994; Daniels and Kass, 1999; Champion, 2003; Wong, Carter and On the other hand, in the literature of applied statistics, particularly for repeated measure data, there is a growing tendency to pick a stationary covariance matrix, such as compound symmetry and autoregression of order one with few parameters from a growing menu provided by the popular software packages (Zimmerman and Nunez-Anton, 2001). Of course, if the selected covariance structure is far from the truth, then the estimated covariance matrix could have considerable bias.

The sample covariance matrix S used in virtually all multivariate techniques is unbiased and positive-definite. While it is also computationally convenient, is not parsimonious, and in high dimensions, is unstable. Given a sample of size N Y_1, \dots, Y_N , from an M -dimensional Normal distribution with mean μ and covariance matrix Σ , the sample covariance matrix

$$S = (N - 1)^{-1} \sum_{i=1}^N (Y_i - \bar{Y}) (Y_i - \bar{Y})' \quad (1)$$

is a straightforward estimator of the $\frac{M(M+1)}{2}$ parameters of the unstructured covariance matrix Σ . The number of parameters of $\Sigma = [\sigma_{ij}]$ grows quadratically in the dimension M , and the parameters must satisfy the positive-definiteness constraint

$$v' \Sigma v = \sum_{i,j=1}^M v_i v_j \sigma_{ij} \geq 0 \quad (2)$$

for all $v \in \mathbb{R}^M$. Together, these hurdles make parsimoniously modeling covariance matrices a great challenge in Statistics and its areas of application.

in the literature of applied statistics for longitudinal data, there is a strong tendency to pick a stationary covariance matrix for characterizing the covariance structure. Typical choices are simple models which depend on a small number of parameters such as compound symmetry and autoregressive models of order k , where k is small. While they are very easy to handle computationally, selection of the parametric covariance structure is a challenge even for the experts, and model misspecification can lead to considerably biased estimates. To strike a balance between the variability of the sample covariance matrix and the bias of the estimated structured covariance matrix, it is prudent to rely on the data to formulate structures for the unknown underlying dependence in the data.

Alternately, several have proposed applying nonparametric methods directly to elements of the sample covariance matrix or a function of the sample covariance matrix. Diggle and Verbyla (1998) introduced a nonparametric estimator obtained by kernel smoothing the sample variogram and squared residuals. Yao, Mueller, and Wang applied a local linear smoother to the sample covariance matrix in the direction of the diagonal and a local quadratic smoother in the direction orthogonal to the diagonal to account for the presence of additional variation due to measurement error. [REVIEW 2009 WU AND POURAHMADI METHOD: banding the sample covariance matrix. Under the assumption of short range dependency, they show that their estimator converges to the true covariance matrix for a broad class of nonlinear processes.] The estimates yielded by these approaches, however, are not guaranteed to be positive definite.

2.1 Estimated structured (parametric) covariances

2.2 Shrinkage estimators based on the sample covariance matrix

2.2.1 Shrinking the spectrum and the correlation matrix

2.2.2 Ledoit-Wolf shrinkage estimator

2.2.3 Penalized likelihood approach

2.2.4 Elementwise shrinkage

Another way to induce parsimony is by applying a shrinkage operator elementwise to the sample covariance matrix.

2.2.5 tapering/banding estimators

2.2.6 thresholding the sample covariance matrix

For $\lambda > 0$, a thresholding operator $s_\lambda(z) : \Re \rightarrow \Re$ satisfies

- $s_\lambda(z) \leq z$;
- $s_\lambda(z) = 0$ for $|z| \leq \lambda$;
- $|s_\lambda(z) - z| \leq \lambda$.

Shrinkage and thresholding estimators can be viewed as the solution to the problem of minimizing a penalized quadratic loss function, and since the thresholding operator is applied elementwise to the sample covariance S , these optimization problems are univariate. A generalized thresholding estimator $s_\lambda(z)$ is the solution to

$$s_\lambda(z) = \arg \min_{\sigma} \left[\frac{1}{2} (\sigma - z)^2 + J_\lambda(\sigma) \right] \quad (3)$$

For detailed discussion of the connection between penalty functions and the resulting thresholding rules, see Antoniadis and Fan [2001]. Soft thresholding results from minimizing 3 using the lasso penalty, $J_\lambda = \lambda|\sigma|$, which corresponds to thresholding rule

$$s_\lambda(z) = \text{sign}(\sigma) (\sigma - \lambda)_+ . \quad (4)$$

2.2.7 Tuning parameter selection for element-wise shrinkage estimators

The performance of any regularized estimator depends heavily on the quality of tuning parameter selection. The Frobenius is a natural measure of the accuracy of an estimator; it quantifies the sum over the unique elements of Σ of the the first term in ??,

$$\|\hat{\Sigma}^\lambda - \Sigma\|^2 = \left(\sum_{i,j} (\hat{\sigma}_{ij}^\lambda - \sigma_{ij})^2 \right)^{1/2} \quad (5)$$

If Σ were available, one would choose the value of the tuning parameter λ which minimizes ??. In practice, one tries to first approximate the risk, or

$$E_\Sigma \left[\|\hat{\Sigma}^\lambda - \Sigma\|^2 \right],$$

and then choose the optimal value of λ . As in regression methods, cross validation and a number of its variants have become popular choices for tuning parameter selection in covariance estimation, though unanimous agreement on which precise procedure is optimal is fleeting. K -fold cross validation requires first splitting the data into folds $\mathcal{D}_1, \mathcal{D}_2, \dots, \mathcal{D}_K$. The value of the tuning parameter is selected to minimize

$$\text{CV}_F(\lambda) = \arg \min_{\lambda} K^{-1} \sum_{k=1}^K \|\hat{\Sigma}^{(-k)} - \tilde{\Sigma}^{(k)}\|_F^2, \quad (6)$$

where $\tilde{\Sigma}^{(k)}$ is the unregularized estimator based on based on \mathcal{D}_k , and $\hat{\Sigma}^{(-k)}$ is the regularized estimator under consideration based on the data after holding \mathcal{D}_k out. Using this approach, the size of the training data set is approximately $(K-1)N/K$, and the size of the validation set is approximately N/K (though these quantities are only relevant when subjects have equal numbers of observations). For linear models, it has been shown that cross validation is asymptotically consistent is the ratio of the validation data set size over the training set size goes to 1. See Shao [1993]. This result motivates the reverse cross validation criterion, which is defined as follows:

$$\text{rCV}_F(\lambda) = \arg \min_{\lambda} K^{-1} \sum_{k=1}^K \|\hat{\Sigma}^{(k)} - \tilde{\Sigma}^{(-k)}\|_F^2, \quad (7)$$

where $\tilde{\Sigma}^{(-k)}$ is the unregularized estimator based on based on the data after holding out \mathcal{D}_k , and $\hat{\Sigma}^{(k)}$ is the regularized estimator under consideration based on \mathcal{D}_k .

TODO: introduce bootstrap risk estimator methods here - See ?, section 2.2.1

2.3 (Generalized) linear models for covariance estimation

2.3.1 A review of linear models and generalized linear models for covariance matrices

While systematic and data-based modeling of covariance matrices is hampered by the positive-definiteness constraint and high-dimensionality, similar though simpler obstacles in modeling the mean vector μ (first moments) of the distribution of a random vector $Y = (y_1, \dots, y_M)'$ has been handled quite successfully in the framework of regression analysis, leading to the powerful theory of generalized linear models (GLM). The success of GLM in handling variety of continuous and discrete data is mainly due to relying on a link function $g(\cdot)$ and a linear predictor $g(\cdot) = X\beta$ to induce unconstrained parameterization and reduce the parameter space dimension simultaneously. Since the covariance matrix of a random vector Y , defined by $\Sigma = E(Y - \mu)(Y - \mu)$, is a mean-like parameter, one would like to exploit the idea of GLM along with the experience and progress in fitting the mixed-effects and time series models in developing a systematic, data-based procedure for covariance matrices.

The areas of time series analysis (Klein, 1997) and variance components (Searle, Casella and McCulloch, 1992, Chap. 2) are among the oldest in dealing with modeling covariance matrices using covariates implicitly and explicitly, respectively. In a sense, they provide the much needed core methods and ideas. In fact, time series techniques based on spectral and Cholesky decompositions provide suitable tools for handling the awkward positivedefiniteness constraint on a stationary covariance matrix (function). However, unlike modeling the mean vector where a link function acts component-wise on the vector μ , link functions for covariance matrices cannot act componentwise since positive-definiteness is a simultaneous constraint on all entries of a matrix. Not surprisingly, because of the complicated structure of a general covariance matrix, the most successful modeling

approaches need to rely on decomposing a covariance matrix into its “variance” and “dependence” components. The idea of regression and its diagnostic techniques work well for the logarithm of the variances, but their analogues need to be developed for the more complicated dependence components. The three major methods for producing such pairs, i.e. the variance-correlation, spectral (eigenvalue) and the Cholesky decompositions of several covariances are reviewed in Section 2. However, the latter being less familiar is described next for a single covariance matrix

2.3.2 Linear models for covariance

Gabriel (1962) was among the first to implicitly parameterize a multivariate normal distribution in terms of entries of the precision matrix Ω^{-1} . Dempster (1972) who recognized the entries of $\Sigma^{-1} = (\sigma^{ij})$ as the canonical parameters of the exponential family of normal distributions with mean zero and unknown covariance matrix Σ :

$$\log f(Y, \Sigma^{-1}) = -\frac{1}{2} \text{tr} \Sigma^{-1} (Y'Y) + \log |\Sigma|^{-1/2} - M \log \sqrt{\pi}$$

Soon thereafter, the simple structures of time series and variance components models motivated Anderson [1973] to define the class of linear covariance models:

$$\Sigma = \sum_{i=1}^q \alpha_i U_i \quad (8)$$

where the U_i s are known symmetric matrices and the α_i s are unknown parameters, restricted to ensure that Σ is positive definite. This class of models is general enough to include all linear mixed effects models as well as certain time series and graphical models. In, for q large enough, any covariance matrix admits representation of the form ??, since one can decompose every covariance matrix as

$$\Sigma = \sum_{i=1}^M \sum_{j=1}^M \sigma_{ij} U_{ij}, \quad (9)$$

where U_{ij} is an $M \times M$ matrix with a 1 in the (i, j) position, and zeros everywhere else. Despite the convenience of parameterization, the positive definite constraint 2 makes estimation an arduous task.

Inducing sparsity by setting certain elements of the covariance matrix or its inverse to zero is a common approach to reducing the dimensionality of a covariance structure. Inspection of model 8 and the covariance parameterization given in 9 makes it easy to see that this can be achieved by eliminating certain U_{ij} from the covariates in the linear covariance model. On the extreme end of the sparsity spectrum is the case of independent observations and Σ is diagonal, eliminating all U_{ij} from the linear model covariates for $i \neq j$. Connection between the linear covariance model and other models for covariance discussed in previous sections can be established if we consider intermediary cases, such as classes of stationary moving average (MA) and autoregressive (AR)

models introduced in the early times series literature. The $MA(q)$ model corresponds to a banded covariance matrix, setting

$$\sigma_{ij} = 0 \quad \text{for } |i - j| > q, \quad (10)$$

while the $AR(p)$ model corresponds to a banded inverse:

$$\sigma^{ij} = 0 \quad \text{for } |i - j| > p. \quad (11)$$

Of course, there are the nonstationary analogues to these classes of models, some of which were discussed in Section ???. We will review others which are related to antedependence models and Gaussian graphical models. Random variables y_1, \dots, y_M , which correspond to observation times t_1, \dots, t_M , with multivariate normal joint distribution said to be p^{th} -order antedependent or $AD(p)$ Gabriel [1962] if y_t and y_{t+s+1} are independent given the intervening values y_{t+1}, \dots, y_{t+s} for $t = 1, \dots, p$ and all $s \geq p$. A random vector $Y = (y_1, \dots, y_p)$ is $AD(p)$ if and only if its covariance matrix satisfies 11. Closely connected are the classes of variable order AD models and varying order, varying coefficient autoregressive models in which the coefficients and order of antedependence depend on time.

2.3.3 Log-linear covariance models

The constraint on the α_i s in 8 was eliminated with the introduction of log-linear covariance models; see Chiu et al. [1996]. For a general covariance matrix having spectral decomposition

$$\Sigma = P \Lambda P', \quad (12)$$

its matrix logarithm, denoted $\log \Sigma$, and defined by $\log \Sigma = P \log \Lambda P'$ is a symmetric matrix with unconstrained entries taking values on \mathbb{R} . A log-linear model for Σ may be written as

$$\log \Sigma = \sum_{i=1}^q \alpha_i U_i, \quad (13)$$

where the U_i s are as before in 8 and the α_i s are now unconstrained. The α_i s, however, now lack statistical interpretation since $\log \Sigma$ is a highly nonlinear operation. But for diagonal Σ , $\log \Sigma = \text{diag}(\sigma_{11}, \dots, \sigma_{MM})$, and model 13 reduces to modeling of heterogeneous variances, which has been extensively studied. Detailed presentation is given in ?, ?m and in references therein.

2.3.4 GLMs

To satisfy the positive-definiteness constraint, methods have been developed and applied to certain reparameterizations of the covariance structure. Chiu, Leonard, and Tsui modeled the matrix logarithm of the covariance matrix. Early nonparametric work using the spectral decomposition of the covariance matrix included that of Rice and Silverman (1991) which discussed smoothing and smoothing parameter choice for eigenfunction estimation for regularly-spaced data. Staniswalis and Lee (1998) extended kernel-based smoothing of eigenfunctions to functional data observed

on irregular grids. However, when the data are sparse in the sense that there are few repeated within-subject measurements and measurement times are quite different from subject-to-subject, approximation of the functional principal component scores defined by the Karhunen-Loeve expansion of the stochastic process by usual integration is unsatisfactory and requires numerical quadrature. Many have explored regression-based approaches using the Spectral decomposition, framing principal components analysis as a least-squares optimization problem. Among many others, Zou, Hastie and Tibshirani (2006) imposed penalties on regression coefficients to induce sparse loadings. [REVIEW THE METHODS OF HUANG, KAUFMAN, YAO HERE]

We adopt the approach based on the Cholesky decomposition. The modified Cholesky decomposition (MCD) has received much attention in the covariance estimation literature, as it ensures positive-definite covariance estimates, and, unlike the spectral decomposition whose parameters follow an orthogonality constraint, the Cholesky decomposition are unconstrained and have an attractive statistical interpretation as particular regression coefficients and variances. The Cholesky decomposition is similar to the spectral decomposition in that Σ is diagonalized by a lower triangular matrix T :

$$T\Sigma T' = D,$$

where the nonredundant entries of T are unconstrained and more meaningful statistically than those of the orthogonal matrix of the spectral decomposition. The matrix T is constructed from the regression coefficients when y_t is regressed on its predecessors:

$$y_t = \sum_{j=1}^{t-1} \phi_{t,j} y_j + \epsilon_t, \quad (14)$$

where the (t, j) entry of T is $\phi_{t,j}$, the negatives of the regression coefficients and the (t, t) entry of D is $\sigma_t^2 = \text{var}(\epsilon_t)$, the innovation variance. A schematic view of the components of a covariance matrix obtained through successive regressions (Gram-Schmidt orthogonalization procedure) is given in Table 2. Since the $\phi_{i,j}$ s are regression coefficients, it is evident that for any unstructured covariance matrix these and the log innovation variances are unconstrained, in the sequel they are referred to as the generalized autoregressive parameters (GARP) and innovation variances (IV) of Y or γ (Pourahmadi, 1999, 2000). Interestingly, this regression approach reveals the equivalence of modeling a covariance matrix to that of dealing with a sequence of $p - 1$ varying-coefficient and varying-order regression models. Consequently, one can bring the entire regression machinery to the service of the unintuitive task of modeling covariance matrices. Stated differently, the framework above is similar to that of using increasing order autoregressive models in approximating the covariance matrix or the spectrum of a stationary time series.

The covariance matrix Σ of a zero-mean random vector $Y = (y_1, \dots, y_m)'$ has the following unique modified Cholesky decomposition (Newton, 1988)

$$T\Sigma T' = D, \quad (15)$$

where T is a lower triangular matrix with 1's as its diagonal entries and $D = \text{diag}(\sigma_1^2, \dots, \sigma_m^2)$ is a diagonal matrix. An attractive feature of this decomposition is that unlike the entries of Σ , the

subdiagonal entries of T and the log of the diagonal elements of D , $\log(\sigma_m^2)$, $t = 1, \dots, m$, are not constrained. This permits one to impose structures on the unconstrained parameters without worrying about the resulting estimator not satisfying the positive-definiteness constraint. Denote estimators of T and D in 17 by \hat{T} and \hat{D} , which may be obtained by fitting linear models or some other structural models; then an estimator of Σ given by $\Sigma = \hat{T}^{-T} \hat{D} \hat{T}^{-T}$ is guaranteed to be positive-definite. From this perspective, covariance modeling can be considered an extension of generalized linear models McCullagh and Nelder [1989]. Factoring Σ as in 17 provides a link function $g(\Sigma) = (T, \log(D))$ where $\log(D) = \text{diag}(\log(\sigma_1^2), \dots, \log(\sigma_m^2))$. Parametric, non-parametric, or Bayesian models may then be applied to the unconstrained entries of T and $\log(D)$. Whereas other decompositions are permutation-invariant, the interpretation of the regression model induced by the MCD assumes a natural (time) ordering among the variables in Y .

immediately leads to the modified Cholesky decomposition 15. It also can be used to clarify the close relation between the decomposition (2) and the time series ARMA models in that the latter is means to diagonalize a Toeplitz covariance matrix, for details see Pourahmadi (2001, Sec. 4.2.5).

In sharp contrast, the fact that the lower triangular matrix T in the Cholesky decomposition of a covariance matrix Σ is unconstrained makes it ideal for nonparametric estimation. Wu and Pourahmadi (2003) have used local polynomial estimators to smooth the subdiagonals of T . For the moment, denoting such estimators of T and D in (2) by \hat{T} and \hat{D} , an estimator of Σ given by $\Sigma = \hat{T}^{-1} \hat{D} \hat{T}^{-1'}$ is guaranteed to be positive-definite. Although one could smooth rows and columns of T , the idea of smoothing along its subdiagonals is motivated by the similarity of the regressions in (3) to the varying-coefficients autoregressions (Kitagawa and Gersch, 1985, 1996; Dahlhaus, 1997):

$\sum_{j=0}^m$

$$f_{j,p}(t/p) y_{t_j} = \sigma_p(t/p) \epsilon_t, \quad t = 0, 1, 2, \dots, M, \quad (16)$$

where $f_{0,p}(\cdot) = 1$, $f_{j,p}(\cdot)$, $1 \leq j \leq m$, and ϵ_t are continuous functions on $[0, 1]$ and ϵ_t is a sequence of independent random variables each with mean zero and variance one. This analogy and comparison with the matrix T for stationary autoregressions having constant entries along subdiagonals suggest taking the subdiagonals of T to be realizations of some smooth univariate functions:

$$\phi_{t,t-j} = f_{j,p}(t/p), \quad \sigma_t = \sigma_p(t/p).$$

The details of smoothing and selection of the order m of the autoregression and a simulation study comparing performance of the sample covariance matrix to smoothed estimators are given in Wu and Pourahmadi (2003). Due to the closer connection between entries of T and the family of regression (3), it is conceivable that some of the entries of T could be zero or close to it. Smith and Kohn (2002) have used a prior that allows for zero entries in T and have obtained a parsimonious model for Σ without assuming a parametric structure. Similar results are reported in Huang, Liu and Pourahmadi (2004) using penalized likelihood with L_1 -penalty to estimate T for Gaussian data.

Alternatively, one can view T as a bivariate function,

Several others have considered this approach to covariance estimation; Kaufman et al. [2008] assume a stationary process, restricting covariance estimates to a specific class of functions. They as well as Huang, Liu, and Liu Huang et al. [2007] follow the heuristic argument presented by Pourahmadi [1999] that $\phi_{t,t-l}$ is monotone decreasing in l and set off-diagonal elements of either the covariance matrix or the Cholesky factor corresponding to large lags to zero. As in Huang et al. [2007], Kaufman et al. [2008], and Yao et al. [2005], we treat covariance estimation as a function estimation problem where the covariance matrix is viewed as the evaluation of a smooth function at particular design points.

including Bickel and Levina [2008] and Huang et al. [2006] have proposed nonparametric estimators of a specific covariance matrix (or its inverse) rather than the parameters of a covariance function.

Yao et al. [2005] do not utilize the Cholesky parameterization, and their estimates are not guaranteed to be positive definite. We combine the advantages of bivariate smoothing as in Yao et al. [2005] with the added utility of the Cholesky parameterization in Huang et al. [2007]; in doing so, we present a flexible and coherent approach to covariance estimation, while simultaneously we ensuring positive definiteness of estimates. Rather than shrinking element of the Cholesky factor to zero after a particular value of l , we choose to softly enforce monotonicity in l by using a hinge penalty as in the work of Tibshirani et al. [2011].

3 The Cholesky Decomposition and the MLE for Σ

Let $Y = (y_1, y_2, \dots, y_m)'$ denote a mean zero random vector with variance-covariance matrix Σ , which we can think of as the time-ordered measurements on one subject in a longitudinal study. To present a comprehensive overview our estimation procedure, we begin with the representation of the covariance matrix, Σ , in terms of its Cholesky decomposition. Decomposing Σ in such a way allows for both an unconstrained parameterization and statistically meaningful interpretation of covariance parameters. For any positive definite matrix Σ , there exists a unique lower triangular matrix T with diagonal entries equal to 1 which diagonalizes Σ :

$$T\Sigma T^T = D \quad (17)$$

The convenient statistical interpretation of the parameters of the covariance matrix then comes if we consider, for $t = 2, \dots, m$, regressing y_t on its predecessors y_1, \dots, y_{t-1} , letting

$$y_i = \sum_{j=1}^{i-1} \phi_{ij} y_j + \sigma_i \epsilon_i, \quad (18)$$

where $\text{var}(\epsilon_i) = \sigma_i^2$. If we take the i - j th element T to be $-\phi_{ij}$ for $j < i$, and take the i th diagonal entry of D to be $\text{var}(\epsilon_i) = \sigma_i^2$, a vectorized expression for Model 18 is given by

$$\epsilon = TY. \quad (19)$$

and taking covariances on both sides of (??), we see that T and D satisfy 17. Immediately, we have that $\Sigma^{-1} = T'D^{-1}T$. The regression coefficients $\{\phi_{ij}\}$ are referred to as the *generalized autoregressive parameters* (GARPs), and the $\{\sigma_{ij}\}$ are referred to as the *innovation variances* (IVs.) Assuming that Y follows a multivariate normal distribution, the loglikelihood function

$\ell(Y, \Sigma)$ satisfies

$$-2\ell(Y, \Sigma) = \log |\Sigma| + Y'\Sigma Y \quad (20)$$

From 17, we have that

$$|\Sigma| = |D| = \prod_{i=1}^m \sigma_i^2$$

and

$$\Sigma^{-1} = T'D^{-1}T.$$

Thus, 20 can be written in terms of the prediction errors and their variances of the non-redundant entries of (T, D) :

$$\begin{aligned} -2\ell(Y, \Sigma) &= \log |D| + Y'T'D^{-1}TY \\ &= \sum_{i=1}^m \log \sigma_i^2 + \sum_{i=1}^m \frac{\epsilon_i^2}{\sigma_i^2}, \end{aligned} \quad (21)$$

where $\epsilon_1 = y_1$ and $\epsilon_i = y_i - \sum_{j=1}^{i-1} \phi_{ij}y_j$. Maximum likelihood estimation or any of its penalized variants may then be employed to obtain estimates of T and D .

Unlike many of those before who have used the Cholesky decomposition as a means of modeling Σ , we allow observed time points to be individual-specific and not necessarily regularly spaced. Let Y_1, \dots, Y_N denote a random sample of mean zero vectors of longitudinal measurements taken on N subjects having common covariance structure Σ . We allow subject i to have observation vector $y_i = (y_{i1}, \dots, y_{i,m_i})'$ with corresponding vector of observation times $(t_{i1}, \dots, t_{i,m_i})'$. Accommodating the subject-specific sample sizes and measurement times requires merely adding a subscript, and Model 18 becomes

$$y_{ij} = \sum_{k=1}^{j-1} \phi_{ijk} y_{ik} + \sigma_{ij} \epsilon_{ij}, \quad (22)$$

where ϕ_{ijk} is the autoregressive coefficient corresponding to the pair of measurements observed at time t_{ij} and t_{ik} . A vectorized representation of Model 22 can be obtained as before by adding the necessary parameters to T and D .

Table 1: Ideal shape of repeated measurements.

		Occasion					
		1	2	...	t	...	m
Unit	1	y_{11}	y_{12}	...	y_{1t}	...	y_{1m}
	2	y_{21}	y_{22}	...	y_{2t}	...	y_{2m}
	\vdots	\vdots	\vdots		\vdots		\vdots
	i	y_{i1}	y_{i2}	...	y_{it}	...	y_{im}
	\vdots	\vdots	\vdots		\vdots		\vdots
	N	y_{N1}	y_{N2}	...	y_{Nt}	...	y_{Nm}

Table 2: Autoregressive coefficients and prediction error variances of successive regressions.

y_1	y_2	y_3	...	y_{m-1}	y_m
1					
ϕ_{21}	1				
ϕ_{31}	ϕ_{32}	1			
\vdots	\vdots		\ddots		
\vdots	\vdots			\ddots	
ϕ_{m1}	ϕ_{m2}	$\phi_{m,m-1}$	1
σ_1^2	σ_1^2	σ_{m-1}^2	σ_m^2

$$\begin{bmatrix} 1 & & & & \\ -\phi_{21} & 1 & & & \\ -\phi_{31} & -\phi_{32} & 1 & & \\ \vdots & & & \ddots & \\ -\phi_{m1} & -\phi_{m2} & \dots & -\phi_{m,m-1} & 1 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_m \end{bmatrix} \quad (23)$$

TODO: here, conclude with our view of the GARPs and IVs as functions, but allude to how this differs from the stationary approach of Pourahmadi and successive regressions by relaxing the stationarity assumption and viewing T as a continuous bivariate function. Move all the remaining details after this to Chapter 2. Removing the restriction that subjects having common covariance

structure also share common, equally-spaced observation times encourages a functional representation of the parameters defining the Cholesky decomposition of Σ . Rather than a vector of longitudinal data points, we view the random vectors Y_i and $\epsilon_i = (\epsilon_{i1}, \dots, \epsilon_{i,m-i})'$ as discrete renditions of the stochastic processes: $Y(t)$ and $\epsilon(t)$. We assume $Y(t)$ has covariance function $G(t, s)$ and that $\epsilon(t)$ follows a zero mean Gaussian white noise process with unit variance. Under mild assumptions regarding the behaviour of Y , then $G(t, s)$ satisfies some smoothness conditions, where smoothness is defined in terms of square integrability of certain derivatives. We view the entries of Σ as values of G evaluated at the distinct pairs of within-subject observed time points. If we

consider the Cholesky decomposition of Σ within such functional context, it is natural to extent the same notion to the elements of T and D . We view the GARPs $\{\phi_{ijk}\}$ and innovation variances as the evaluation of the smooth functions $\phi(t, s)$ and $\sigma^2(t)$ at observed time points, where

$$\phi_{ijk} = \phi(t_{ij}, t_{ik}), \quad t_{ik} < t_{ij}$$

and

$$\sigma_{ij}^2 = \sigma^2(t_{ij}).$$

With this definition of ϕ and σ^2 , Model 22 becomes

$$y(t_{ij}) = \sum_{k=1}^{j-1} \phi(t_{ij}, t_{ik}) y(t_{ik}) + \sigma(t_{ij}) \epsilon(t_i) \quad i = 1, \dots, N, \quad (24)$$

Our formulation transforms the task of estimating a covariance matrix is to estimating the function $\phi(t, s)$ (and $\sigma(t)$) using bivariate (univariate) smoothing. Like other nonparametric situations, we make no assumption about the functional form of ϕ other than that ϕ is smooth, with smoothness defined in terms of square integrability of certain derivatives. Our proposed method for covariance estimation defines a flexible, general framework which makes all of the existing techniques for penalized regression accessible for the seemingly far different task of estimating a covariance matrix.

To add to the interpretability of our proposed models, we propose a rotation of the (t, s) axes:

$$\begin{aligned} l &= t - s \\ m &= \frac{t + s}{2} \end{aligned}$$

The l axis, the “lag” between time points t and s is of special interest within the context of covariance modeling. The class of isotropic covariance functions M is isotropic are defined as those functions $G(t, s) = G(|t - s|)$ that depend on time points t and s only through the Euclidean distance $|t - s|$ between them. Isotropic covariance functions obey some notion of parsimony, so it is convenient to apply regularized estimation to ϕ in terms of the transformed points (l, m) . Along with this class of functions, others have proposed parsimonious models for the elements of the Cholesky decomposition in terms of the difference between Re-expressing ϕ in terms of these new arguments, our goal is to estimate

$$\phi^*(l, m) = \phi^*\left(s - t, \frac{1}{2}(s + t)\right) = \phi(s, t) \quad (25)$$

Rather than imposing structure on the unconstrained values of $\phi(s, t)$, we instead consider a rotation of the axes of the input space and re-express ϕ in terms of the transformed coordinates

$$\begin{bmatrix} l \\ m \end{bmatrix} = \begin{bmatrix} s - t \\ \frac{(s+t)}{2} \end{bmatrix}$$

$$\begin{aligned} \phi(s, t) &= \phi^*\left(s - t, \frac{s + t}{2}\right) \\ &= \phi^*(l, m) \end{aligned}$$

While our framework allows for estimation of the autoregressive coefficient function and the innovation variance function via any nonparametric regression setup, we focus on two primary approaches for representing ϕ and σ . First, we assume that ϕ belongs to a reproducing kernel Hilbert space, \mathcal{H} and employ the smoothing spline methods of Kimeldorf and Wahba (see Kimeldorf and Wahba [1971] and Wahba [1990] for comprehensive presentation.) To enhance the statistical interpretability of model parameters, we decompose ϕ into functional components similar to the notion of the main effect and the interaction terms in classical analysis of variance. We adopt the smoothing spline analogue of the classical ANOVA model proposed by Gu (see Gu [2013]), and estimation is achieved through similar computational strategies.

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