Semiparametric Ridge Regression for Longitudinal Data

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Abstract: This paper considers an extension of the linear mixed model, called semiparametric mixed effects model, for longitudinal data, when multicollinearity is present. To overcome this problem, a new mixed ridge estimator is proposed while the nonparametric function in the semiparametric model is approximated by the kernel method. The proposed approach integrates ridge method into the semiparametric mixed effects modeling framework in order to account for both the correlation induced by repeatedly measuring an outcome on each individual over time, as well as the potentially high degree of correlation among possible predictor variables. The asymptotic normality of the exhibited estimator is established. To improve efficiency, the estimation of the covariance function is accomplished using an iterative algorithm. Performance of the proposed estimator is compared through a simulation study and analysis of CD4 data.

Keywords: Kernel, Longitudinal Data, Mixed Effect, Ridge Regression, Semiparametric.

Mathematics Subject Classification (2010): 62J07, 62620.
1. Introduction

Longitudinal data frequently arise in biological and economic applications. A major difficulty in the analysis of longitudinal data is that the data are subject to within subject correlation among repeated measurements over time. In recent years, various traditional methods for longitudinal data have been developed. However, mixed effect models and semiparametric models are popularly applied. In this paper, we consider the following semiparametric mixed effects model

\[ Y_i(t_{ij}) = X_i^\top(t_{ij})\beta + g(t_{ij}) + Z_i^\top(t_{ij})b_i + \varepsilon_i(t_{ij}), \]  

where \( Y_i(t_{ij}) \) is the response for the \( i \)th subject at time point \( t_{ij} \), \( \beta = (\beta_1, \ldots, \beta_p)^\top \) is a \( p \times 1 \) vector of regression coefficients associated with the covariates \( X_i(t_{ij}) \); \( g(t_{ij}) \) is an unknown twice differentiable smooth function of time; the \( b_i \) are i.i.d., unobservable \( q \times 1 \) vectors of the random effects associated with covariates \( Z_i(t_{ij}) \) with mean zero and covariance matrix \( D_i \); and the \( \varepsilon_i(t_{ij}) \), independent of \( b_i \), is random error with \( E\{\varepsilon_i(t_{ij})\} = 0 \). Without loss of generality, we assume every \( t_{ij} \) is scaled into the interval \([0, 1]\). Similar to Fan and et al. (2007), we assume \( \text{Var}\{\varepsilon_i(t_{ij})\} = \sigma^2(t_{ij}) \), which is a nonparametric smooth function, but the correlation function between \( \varepsilon_i(t_{ij}) \) and \( \varepsilon_i(t_{ik}) \) has a parametric form, \( \text{corr}\{\varepsilon_i(t_{ij}), \varepsilon_i(t_{ik})\} = \rho(t_{ij}, t_{ik}, \theta) \), where \( \rho(t_{ij}, t_{ik}, \theta) \) is a positive definite function of \( t_{ij} \) and \( t_{ik} \), and \( \theta \) is an unknown parameter vector. We assume both the random effects and the errors are normally distributed and we have a random sample of \( n \) subjects with the \( i \)th subject having \( n_i \) observations over time and total observation of \( N = \sum_{i=1}^n n_i \).

In the mixed effects model, random component takes care the correlation among observations from the same subject, [see Fitzmaurice and et al. (2004) and Laird and Ware (1982)]. Since the parametric assumption in this model is not always adequate, it is of interest to model the time effect nonparametrically while accounting for the correlation within the same subject. In such cases, the semiparametric models are widely used in the longitudinal studies. Related works include Fan and Li (2004), Hu and et al. (2004) and Lin and Ying (2001). Model (1.1) is a natural extension of linear mixed models and semiparametric models called semiparametric mixed effect model that uses parametric fixed effects to present the covariate effects and an arbitrary smooth function to model the time effect to account for the within subject correlation using random effects.

The parametric component provides a simple summary of covariates effects which are of main scientific interest, while the baseline function is included for flexibility. With both parametric and nonparametric components, the proposed model is more flexible than the traditional linear model. Zeger and Diggle (1994) used a semiparametric random intercept model to analyze the CD4 cell numbers in HIV
seroconverters, where nonparametric function is estimated by backfitting method. Our work is an extension to their model. Indeed, we consider a more general class of mixed effects models with kernel estimator of nonparametric function.

In addition of proposing more flexible model (1.1), we consider the problem of multicollinearity of predictor variables and estimation in the proposed model. Ridge regression (RR), also known as Tikhonov regularization [see Tikhonov (1943)], is a well-known penalized regression approach to handling multiple colinear predictor variables that involves adding a regularization term to the least squares equation in order to derive parameter estimates in the context of an ill-conditioned or singular design matrix [see Hoerl and Kennard (1970a, b)]. The resulting shrinkage estimates, while biased, offer improved prediction accuracy, that is, reduced prediction variance, and thus may be preferable in settings with a large number of highly correlated independent variables, in which unique least squares solutions are not tenable. Recent applications of RR to longitudinal data include, for example, Zhang and Horvath (2006), Malo and et al. (2008), and Eliot and et al. (2011). In the present paper, we extend RR to the correlated response setting in which a single outcome of interest is measured repeatedly over time at potentially unevenly spaced time intervals. In the case of uncorrelated or minimally correlated predictor variables, mixed effects models with person specific random intercept and slopes terms can be applied to account for the within person correlation in making inferences about association. Here we integrate RR and the mixed effects modeling frameworks in order to account both for the correlation induced by repeatedly measuring the outcome on each individual over time, as well the potential high degree of correlation among potential predictor variables.

We begin in Section 2 by providing a brief background on kernel estimation of nonparametric function while proposed a new estimator, which we term the mixed ridge (MR) estimator, for longitudinal data. Further, its asymptotic normality is provided. In Section 3, an iterative algorithm is provided to calculate the estimator. A simulation study to evaluate the performance and application to real data are then provided in Sections 4. We conclude your paper in section 5.

2. Estimation procedure

Denote $Y_i = (Y_i(t_{i1}), \ldots, Y_i(t_{in_i}))^\top$, $X_i$, $Z_i$, $\varepsilon_i$ and $t_i$ similarly. The model (1.1) can be presented as

$$Y_i = X_i^\top \beta + g(t_i) + Z_i^\top b_i + \varepsilon_i,$$

where $g(t_i) = (g(t_{i1}), \ldots, g(t_{in_i}))^\top$. Let $V_i = Z_iD_iZ_i^\top + \Sigma_i$ be the $n_i \times n_i$ covariance matrix of $Y_i$ and $\Sigma_i = A_iR_i(\theta)A_i$ be the $n_i \times n_i$ working covariance matrix.
of \( \varepsilon_i \), where \( A_i = \text{diag}(\sigma(t_{i1}), \ldots, \sigma(t_{in_i})) \) and \( R_i(\theta) \) is the correlation matrix of \( \varepsilon_i \) with \((j,k)\) element equaling \( \rho(t_{ij}, t_{ik}, \theta) \). Under normality assumption of error term and random effects,

\[
Y_i \sim N(X_i \beta + g(t_i), V_i). \tag{2.2}
\]

Let \( \mu_Y(t_{ij}) = E\{Y_i(t)|t = t_{ij}\} \); \( \mu_X(t_{ij}) \) defined equivalently. It is evident that \( \mu_Y(t_{ij}) = \mu_X(t_{ij})\beta + g(t_{ij}) \). This together with equation (2.2) yields

\[
Y_i - \mu_Y(t_i) \sim N([X_i - \mu_X(t_i)]^T \beta, V_i).
\]

Further, denoting \( Y = (Y_1^T, \ldots, Y_n^T)^T \), and \( X, \varepsilon \) similarly and \( Z = \text{diag}(Z_1^T, \ldots, Z_n^T) \), we have matrix notation of model (1.1) as

\[
Y = X^T \beta + g(t) + Z^T b + \varepsilon,
\]

where \( g(t) = (g(t_1)^T, \ldots, g(t_n)^T) \) and \( b = (b_1^T, \ldots, b_n^T)^T \) is \((n \times q)\) vector of random effects with mean zero and covariance matrix \( D = \text{diag}(D_1, \ldots, D_n) \). Let \( V = ZDZ^T + \Sigma \) be the \( N \times N \) block diagonal covariance matrix of \( \varepsilon \) and \( \Sigma \) be the \( N \times N \) block diagonal covariance matrix of \( \varepsilon \).

Further, define \( Y_i = Y_i - \mu_Y(t_i) \), \( \mu_Y(t_i) = (\mu_Y(t_{i1}), \ldots, \mu_Y(t_{in_i}))^T \); \( X_i \) and \( \mu_X(t_i) \) similarly. Finally, for matrix notation, we have \( Y = (Y_1^T, \ldots, Y_n^T)^T \) and \( X = (X_1^T, \ldots, X_n^T)^T \).

A weighted least squares (WLS) criterion for \( \beta \) is

\[
l(\beta) = \sum_{i=1}^{n} (Y_i - X_i^T \beta)^T V_i^{-1} (Y_i - X_i^T \beta).
\]

the term \( l(\beta) \) cannot be directly used in statistical inference because it contains unknown functions \( \mu_Y(\cdot), \mu_X(\cdot) \). We employ the kernel smoother to estimate them, and the estimators are respectively defined as

\[
\hat{\mu}_X(t) = \sum_{i=1}^{n} \sum_{j=1}^{n_i} \omega_{ij} X_i(t_{ij}) , \quad \hat{\mu}_Y(t) = \sum_{i=1}^{n} \sum_{j=1}^{n_i} \omega_{ij} Y_i(t_{ij}),
\]

where \( \omega_{ij} = K_h(t_{ij} - t)/\sum_{k=1}^{n} \sum_{l=1}^{n_k} K_h(t_{kl} - t) \), \( h \) is a bandwidth, \( K_h(\cdot) = K(\cdot/h) \) and \( K(\cdot) \) is a kernel function.

Therefore, an estimator \( \hat{l}(\beta) \) of \( l(\beta) \) can be obtained by substituting \( \hat{\mu}_Y(t) \) and \( \hat{\mu}_X(t) \) of \( l(\beta) \) with \( \tilde{\mu}_Y(t) \) and \( \tilde{\mu}_X(t) \), that is

\[
\hat{l}(\beta) = \sum_{i=1}^{n} (\tilde{Y}_i - \tilde{X}_i^T \beta)^T V_i^{-1} (\tilde{Y}_i - \tilde{X}_i^T \beta),
\]

where \( \tilde{Y}_i = Y_i - \tilde{\mu}_Y(t_i) \), \( \tilde{\mu}_Y(t_i) = (\tilde{\mu}_Y(t_{i1}), \ldots, \tilde{\mu}_Y(t_{in_i}))^T \); \( \tilde{X}_i \) and \( \tilde{\mu}_X(t_i) \) similarly defined.
Ridge regression, designed specifically to handle correlated predictors, involves introducing a shrinkage penalty $\lambda$ to the WLS, then the weighted ridge regression (WRR) estimator of $\beta$ is the minimizer of the objective function

$$l^*(\beta) = \widehat{l}(\beta) + \lambda \beta^T \beta,$$

the WRR estimator is then defined as

$$\widehat{\beta}_{MR} = \arg \min_\beta \{ (\hat{Y} - \hat{X}\beta)^T V^{-1} (\hat{Y} - \hat{X}\beta) + \lambda \beta^T \beta \}$$  \hspace{1cm} (2.3)

Further, the best linear unbiased estimator (BLUE) of the random effects $b_i$ may be proceeded by calculating their conditional expectations given $Y_i$ while estimating $\beta$ by $\widehat{\beta}_{MR}$. This gives

$$\hat{b}_i = E[b_i|Y_i] = D_i Z_i^T V_i^{-1} (\hat{Y}_i - \hat{X}_i^T \widehat{\beta}_{MR}) = D_i Z_i^T V_i^{-1} (Y_i - X_i^T \widehat{\beta}_{MR} - \hat{g}(t_i)).$$

Fan and Li (2001) suggested the GCV to select the tuning parameter $\lambda$, the GCV statistic is defined by

$$GCV(\lambda) = \frac{\text{RSS}(\lambda)/n}{(1 - \text{tr}(d(\lambda))/n)^2},$$

where $\text{RSS}(\lambda) = (\hat{Y} - \hat{X}^T \widehat{\beta}_{MR})^T V^{-1} (\hat{Y} - \hat{X}^T \widehat{\beta}_{MR})$ and $d(\lambda) = \hat{X}(\hat{X}^T V^{-1} \hat{X} + \lambda I)^{-1} \hat{X}^T V^{-1} + Z D Z^T (I - \hat{X} [(\hat{X}^T V^{-1} \hat{X} + \lambda I)^{-1} \hat{X}^T V^{-1}])$. We select $\hat{\lambda} = \arg \min_{\lambda} \text{GCV}(\lambda)$.

In the following, we establish the limiting distribution of the WRR estimator. The Theorem 2.1 concerning the kernel method is given in Lin and Carroll (2001). We quote it here to ease comparison with properties of the MR method given in Theorem 2.2.

**Theorem 2.1.** Suppose that $h \propto n^{-\alpha}$, $1/5 \leq \alpha \leq 1/3$ and $n \rightarrow \infty$ and define

$$\hat{X} = X = \lim_{n \rightarrow \infty} \frac{\partial \hat{g}(t; \beta)}{\partial \beta}.$$

Then $\widehat{\beta}_K$ converges in distribution:

$$\sqrt{n}(\widehat{\beta}_{\text{kernel}} - \beta + h^2 b_{\text{kernel}}(\beta, g)/2) \overset{D}{\rightarrow} N(0, V_{\text{kernel}}).$$
where

\[ b_{\text{kernel}}(\beta, g) = E\{\hat{X}^TV^{-1}\hat{X}\}^{-1}E\{\hat{X}^TV^{-1}g^{(2)}(t)\}, \]  
\[ V_{\text{kernel}} = E\{\hat{X}^TV^{-1}\hat{X}\}^{-1}E\{(Z_1 - Z_2)^T\Sigma(Z_1 - Z_2)\}E\{\hat{X}^TV^{-1}\hat{X}\}^{-1}. \]

Here \( \hat{X} = (X - \mu_X(t)) \), \( \Sigma = \text{var}(Y|X, t) \), \( Z_1 = V^{-1}\hat{X} \), \( Z_2 = (Z_2^1, \ldots, Z_2^n) \) with

\[ Z_2^i = \left(\sum_{k=1}^m \sum_{l=1}^m E(\hat{X}^kV^{kl}|t^i)\right) f_j(t^i), \]

and \( V^{kl} \) denotes the \((k, l)\) entry of \( V^{-1} \).

**Theorem 2.2.** Under the assumptions of Theorem 2.1, the mixed ridge estimator \( \hat{\beta}_{MR} \) converges in distribution:

\[ \sqrt{n} \left\{ \hat{\beta}_{MR} - R(\lambda)(\beta + h^2b_{\text{kernel}}(\beta, g)/2) \right\} \xrightarrow{D} N(0, R(\lambda)V_{\text{kernel}}R^T(\lambda)). \]

### 3. E-M Algorithm

Whereas, improving the efficiency of regression coefficients are related to estimation of the covariance function, the solution is found by an iterative algorithm between \( \beta, b_i, g(t) \) and inverse of the estimated covariance matrix \( V \). The proposed algorithm is an extention of E-M algorithm with a structured covariance matrix of random errors. We apply the Newton–Raphson method to minimize equations (2.3) and get the updating formula

\[ \begin{align*}
\hat{\beta}_{MR}^{[r+1]} &= \left[ \sum_{i=1}^n \hat{X}_i^TV_i^{-1[r]}\hat{X}_i + \lambda I \right]^{-1} \left[ \sum_{i=1}^n \hat{X}_i^TV_i^{-1[r]}\hat{Y}_i \right], \\
\hat{\theta}^{[r+1]}(t_{ij}) &= \hat{\mu}_Y(t_{ij}) - \hat{\mu}_X(t_{ij})\hat{\beta}_{MR}^{[r+1]}, \\
\hat{\sigma}^{[r+1]}(t_{ij}) &= D_iZ_i^TV_i^{-1[r]}(\hat{Y}_i - \hat{X}_i^T\hat{\beta}_{MR}^{[r+1]}),
\end{align*} \]  

(3.7)

Hence, we get the following iterative algorithm:

**Step 0:** Set \( r = 0 \). Let \( \hat{D}_i^{[r]} = I \), \( \hat{\sigma}^{2[r]}(t) = 1 \) and \( \hat{\theta}^{[r]} = 1 \).

**Step 1:** Set \( r = r + 1 \). Update \( \hat{\beta}_{MR}^{[r+1]}, \hat{\theta}^{[r+1]}(t_{ij}) \) and \( \hat{\sigma}^{[r+1]}(t_{ij}) \) by the computed formulas (3.7) based on current values of \( \hat{V}^{[r]} = \text{diag}({\hat{V}_1^{[r]}, \ldots, \hat{V}_n^{[r]}}) \) where \( \hat{V}_i^{[r]} = Z_iD_i^{[r]}Z_i^T + \hat{\Sigma}_i^{[r]}, \hat{\Sigma}_i = \hat{\Lambda}_iR_i(\hat{\theta})\hat{\Lambda}_i, \hat{\Lambda}_i = \text{diag}(\hat{\sigma}(t_{i1}), \ldots, \hat{\sigma}(t_{ini})) \) and \( R_i(\theta) \) is the correlation matrix of \( \varepsilon_i \) with \((j, k)\) element equaling \( \rho(t_{ij}, t_{ik}, \hat{\theta}) \).

**Step 2:** Update \( \hat{D}_i^{[r]}, \hat{\sigma}^{2[r]}(t) \) and \( \hat{\theta}^{[r]} \).

At this step, the ML estimator of \( D_i \) would be

\[ \hat{D}_i^{[r]} = n_i^{-1}\hat{\gamma}_i^{[r]}\hat{\gamma}_i^{[r]T}. \]
The kernel estimator of \( \sigma^2 \) is
\[
\hat{\sigma}^2[r] = \frac{\sum_{i=1}^{n_i} \sum_{j=1}^{n_i} \hat{r}_{ij}^2 K_h(t - t_{ij})}{\sum_{i=1}^{n_i} \sum_{j=1}^{n_i} K_h(t - t_{ij})},
\]
where \( \hat{r}_{ij} = Y_i(t_{ij}) - X_{i}^{\top}(t_{ij})\hat{\beta}[r] - Z_{i}^{\top}(t_{ij})\hat{b}[r] - \hat{g}[r](t_{ij}) \). To construct the estimator of \( \theta \), we adopt the quasi-likelihood approach. By the quasi-likelihood approach, the estimator of \( \theta \) is defined by
\[
\hat{\theta} = \arg\max_{\theta} \left( -\frac{1}{2} \sum_{i=1}^{n} \{ \log |R_i(\theta)| + \hat{b}^{\top}_i \hat{A}^{-1}_i R^{-1}_i(\theta) \hat{A}^{-1}_i \hat{b}_i \} \right).
\]

Step 3: Repeat Steps 1 and 2 until the selected covariates converge to a stable value.

4. Illustrations

4.1 Simulation studies

A simple simulation study is conducted to characterize the relative performances of mixed ridge regression and the usual mixed effects modeling approach in the context of multiple, correlated predictors. To achieve different degrees of collinearity, the explanatory variables are generated using the following formula
\[
x_{ik} = (1 - \gamma^2)^{\frac{1}{2}}\omega_{ik} + \gamma^2\omega_{ip}, \quad i = 1, \ldots, n = 50, \quad k = 1, \ldots, p = 5, \quad (4.8)
\]
where \( \omega_{ik} \) are independent and generated from a standard normal distribution, \( \gamma \) is specified so that the correlation between any two explanatory variables is given by \( \gamma^2 \). Four different set of correlations corresponding to \( \gamma = 0.70, 0.80, 0.90 \) and 0.99 are considered. For the nonparametric component in (1.1), we select a smooth function of the form \( g(t_{ij}) = 2\sin(2\pi t_{ij}) \). We further assume \( n_i = 4 \) measurements for each subject \( i \) and simulate data from the following semiparametric mixed model
\[
Y_i(t_{ij}) = x_{1,i}(t_{ij})\beta_1 + x_{2,i}(t_{ij})\beta_2 + x_{3,i}(t_{ij})\beta_3 + x_{4,i}(t_{ij})\beta_4 + x_{5,i}(t_{ij})\beta_5 + g(t_{ij}) + b_i + \varepsilon_i(t_{ij}), \quad (4.9)
\]
where \( b_i \) independently follow normal distribution \( N(0, \sigma_b^2) \), where \( \sigma_b^2 = 0.25 \). The true value of \( \beta \) was taken to be \( \beta^T = (0.5, 1, 1.5, 2, 0.1, 0.2) \). The time \( t_{ij} \) is generated from the \( U(0,1) \) distribution. The random error process \( \varepsilon_i(t) \) is taken to be a Gaussian process with mean 0, variance function \( \sigma^2(t) = \exp(\frac{t}{12}) \) and AR(1) correlation structure \( \text{corr}(\varepsilon_i(s), \varepsilon_i(t)) = \rho^{|t-s|} \) for \( s \neq t \), where \( \rho = 0.9 \) to capture strong correlation errors.
We use the Epanechnikov kernel function \( K(u) = 0.75(1-u^2)_+ \). To investigate the impact on the performance of two methods under a misspecified correlation structure, we compare the performance of \( \hat{\beta}_{\text{kernel}} \) and \( \hat{\beta}_{\text{MR}} \) using the exchangeable working correlation structure \((\text{kernel} - I)\) or \((\text{MR} - I)\) when the true correlation structure is \(\text{AR}(1)\) \((\text{kernel} - C)\) or \((\text{MR} - C)\). For each of the estimators \( \hat{\beta}_{\text{kernel}} \) and \( \hat{\beta}_{\text{MR}} \), its estimation accuracy is measured by the mean squared error \((\text{MSE})\) defined by

\[
\text{MSE} = (\hat{\beta} - \beta)^T (\hat{\beta} - \beta).
\]

The simulation results for \(\text{MSE}\) of the proposed methods are presented in Table 2. Table 1 reports the empirical biases and standard deviations \((\text{SDs})\) of the estimated \(\beta\) from the kernel and backfitting methods. We can take the following observations:

(i) Mixed ridge method outperforms mixed method in terms of the \(\text{MSE}\) criterion, even for the cases of misspecified correlation structure.

(ii) Mixed ridge estimator has smaller bias and SD in all cases than the mixed estimator. Hence, our proposed method becomes more stable and efficient.

(iii) Furthermore, as correlation among predictors increases, the performance of mixed modeling decreases more rapidly than the mixed ridge model in terms of the biases, SDs and \(\text{MSEs}\) criterion. This result is more dramatic at extreme levels of correlation \((\gamma = 0.99)\).

### 4.2 CD4 data analysis

We now apply the semiparametric mixed model to the longitudinal CD4 cell count data through the proposed methods. In this data set, there are a total of 2,376 CD4 measurements from 369 subjects available. The first objective of this analysis is to characterize the population average time course of CD4 decay while accounting for the following additional predictor variables: smoking (packs per day); recreational drug use (yes or no); numbers of sexual partners; and depression symptoms as measured by the CESD scale (larger values indicate increased depressive symptoms). The analysis was conducted on square root transformed CD4 numbers whose distribution is more nearly Gaussian. We refer to Zeger and Diggle (1994) and Wang et al (2005) for more detailed descriptions of the data.

Since there seems to exist a positive correlation among responses from the same patient, we need to incorporate a correlation structure into the estimation scheme. Following Zeger and Diggle (1994), it is found that the compound symmetry
covariance matrix fitted the data reasonably well. The estimated correlation is $\rho = 0.509$.

To facilitate choosing the bandwidth $h$, we adopt the approach of Fan and Li (2004). $\hat{\sigma}^2(t)$ is a one dimensional kernel regression of the squared residuals over time. we estimate $h = 0.02$ and $h_1 = 0.015$. We use bootstrap resampling to get the SD of estimators.

The estimates of the parameters in the model are presented in Table 3. Based on the results, we see that the mixed estimator has larger SD than the mixed ridge estimator. Age plays little role. The effects of smoking and depression are found to be significant, whereas the other three effects are insignificant at level 0.05, which are similar to Wang et al (2005) except that the effect of sex partner is significant in their analysis.
Table 2: Mean square error based on 500 replications.

<table>
<thead>
<tr>
<th>Methods</th>
<th>$\gamma = 0.70$</th>
<th>$\gamma = 0.80$</th>
<th>$\gamma = 0.90$</th>
<th>$\gamma = 0.99$</th>
</tr>
</thead>
<tbody>
<tr>
<td>MR-C</td>
<td>0.0079</td>
<td>0.0118</td>
<td>0.0238</td>
<td>0.2103</td>
</tr>
<tr>
<td>MR-I</td>
<td>0.0087</td>
<td>0.0128</td>
<td>0.0258</td>
<td>0.2704</td>
</tr>
<tr>
<td>kernel-C</td>
<td>0.0081</td>
<td>0.0121</td>
<td>0.0249</td>
<td>0.2871</td>
</tr>
<tr>
<td>kernel-I</td>
<td>0.0087</td>
<td>0.0129</td>
<td>0.0261</td>
<td>0.2919</td>
</tr>
</tbody>
</table>

Table 3: Regression coefficient estimates(SD) in the analysis of the CD4 data.

<table>
<thead>
<tr>
<th>methods</th>
<th>Mixed Ridge</th>
<th>Mixed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.0208(0.0021)</td>
<td>0.0212(0.0021)</td>
</tr>
<tr>
<td>Smoking</td>
<td>0.5808(0.0080)</td>
<td>0.5941(0.0082)</td>
</tr>
<tr>
<td>Drug</td>
<td>0.4582(0.0166)</td>
<td>0.5350(0.0194)</td>
</tr>
<tr>
<td>Sex partner</td>
<td>0.0597(0.0024)</td>
<td>0.0585(0.0024)</td>
</tr>
<tr>
<td>Depression</td>
<td>-0.0531(0.0009)</td>
<td>-0.0532(0.0009)</td>
</tr>
</tbody>
</table>

Discussion and Results

In this paper, we consider a more flexible model called semiparametric mixed effects model and described an extension and application of ridge regression for longitudinal data with multicollinearity problem. We proposed a new estimator to use when data sets may have correlated variables and within subject effects. The proposed ridge estimator combines the flexiblity of nonparametric assumptions, usefulness of hierarchical linear models and ridge methodology. To improve efficiency for regression coefficients, the estimation of the covariance function is integrated in the iterative algorithm. As expected, the mixed ridge estimation results in coefficients with smaller biases, variances and MSE than the mixed model even for the cases of misspecified correlation structure. Furthermore, as correlation among predictors increases, the performance of mixed modeling decreases more rapidly than the mixed ridge model. There were the results obtained from numerical studies.

References


