Fence method for nonparametric small area estimation

Jiming Jiang, Thuan Nguyen and J. Sunil Rao

Abstract

This paper considers the problem of selecting nonparametric models for small area estimation, which recently have received much attention. We develop a procedure based on the idea of fence method (Jiang, Rao, Gu and Nguyen 2008) for selecting the mean function for the small areas from a class of approximating splines. Simulation results show impressive performance of the new procedure even when the number of small areas is fairly small. The method is applied to a hospital graft failure dataset for selecting a nonparametric Fay-Herriot type model.

Key Words: Fay-Herriot Model; Fence method; Nonparametric model selection; Penalized spline; Small area estimation.

1. Introduction

Small area estimation (SAE) has received increasing attention in recent literature. Here the term small area typically refers to a population for which reliable statistics of interest cannot be produced due to certain limitations of the available data. Examples of small areas include a geographical region (e.g., a state, county, municipality, etc.), a demographic group (e.g., a specific age × sex × race group), a demographic group within a geographic region, etc. In absence of adequate direct samples from the small areas, methods have been developed in order to “borrow strength”. Statistical models, especially mixed effects models, have played important roles in SAE. See Rao (2003) for a comprehensive account of various methods used in SAE.

While there is extensive literature on inference about small areas using mixed effects models, including estimation of small area means which is a problem of mixed model prediction, estimation of the mean squared error (MSE) of the empirical best linear unbiased predictor (EBLUP; see Rao 2003), and prediction intervals (e.g., Chatterjee, Lahiri and Li 2007), model selection in SAE has received much less attention. However, the importance of model selection in SAE has been noted by prominent researchers in this field (e.g., Battese, Harter and Fuller 1988, Ghosh and Rao 1994). Datta and Lahiri (2001) discussed a model selection method based on computation of the frequentist’s Bayes factor in choosing between a fixed effects model and a random effects one in this case is equivalent to testing the following one-sided hypothesis $H_0: \sigma_u^2 = 0$ vs $H_1: \sigma_u^2 > 0$. Note that, however, not all model selection problems can be formulated as hypothesis testing. Fabrizi and Lahiri (2004) developed a robust model selection method in the context of complex surveys. Meza and Lahiri (2005) demonstrated the limitations of Mallows’ $C_p$ statistic in selecting the fixed covariates in a nested error regression model (Battese, Harter and Fuller 1988), defined as $y_{ij} = x_{ij}' \beta + u_i + e_{ij}$, $i = 1, ..., m$, $j = 1, ..., n_i$, where $y_{ij}$ is the observation, $x_{ij}$ is a vector of fixed covariates, $\beta$ is a vector of unknown regression coefficients, and $u_i$’s and $e_{ij}$’s are the same as in the model above considered by Datta and Lahiri (2001). Simulation studies carried out by Meza and Lahiri (2005) showed that the $C_p$ method without modification does not work well in the current mixed model setting when the variance $\sigma_u^2$ is large; on the other hand, a modified $C_p$ criterion developed by these latter authors by adjusting the intra-cluster correlations performs similarly as the $C_p$ in regression settings. It should be pointed out that all these studies are limited to linear mixed models, while model selection in SAE in a generalized linear mixed model (GLMM) setting has never been seriously addressed.

Recently, Jiang et al. (2008) developed a new strategy for model selection, called fence methods. The authors noted a number of limitations of the traditional model selection strategies when applied to mixed model situations. For example, the BIC procedure (Schwarz 1978) relies on the effective sample size which is unclear in typical situations of SAE. To illustrate this, consider the nested error regression model introduced above. Clearly, the effective sample size is not the total number of observations $n = \sum_{i=1}^{m} n_i$, neither is proportional to $m$, the number of small areas unless all the $n_i$ are equal and fixed. The fence methods avoid such
limitations, and therefore are suitable to mixed model selection problems, including linear mixed models and GLMMs. The basic idea of fence is to build a statistical fence to isolate a subgroup of what are known as the correct models. Once the fence is constructed, the optimal model is selected from those within the fence according to a criterion which can incorporate quantities of practical interest. More details about the fence methods are given below.

The focus of this paper is nonparametric models for SAE. These models have received much recent attention. In particular, Opsomer, Breidt, Claeskens, Kauermann and Ranalli (2007) proposed a spline-based nonparametric model for SAE. The idea is to approximate an unknown nonparametric small-area mean function by a penalized spline (P-spline). The authors then used a connection between P-splines and linear mixed models (Wand 2003) to formulate the approximating model as a linear mixed model, where the coefficients of the splines are treated as random effects. Consider, for simplicity, the case of univariate covariate. Then, a P-spline can be expressed as

\[ f(x) = \beta_0 + \beta_1 x + \ldots + \beta_p x^p + \gamma_1 (x - \kappa_1)^p + \ldots + \gamma_q (x - \kappa_q)^p, \]  

where \( p \) is the degree of the spline, \( q \) is the number of knots, \( \kappa_j, 1 \leq j \leq q \) are the knots, and \( x_j = x_{(j+1)}/2 \). Clearly, a P-spline is characterized by \( p, q \), and also the location of the knots. Note that, however, given \( p, q \), the location of the knots can be selected by the space-filling algorithm implemented in R [cover.design()]. But the question how to choose \( p \) and \( q \) remains. The general "rule of thumb" is that \( p \) is typically between 1 and 3, and \( q \) proportional to the sample size, \( n \), with 4 or 5 observations per knot (Ruppert, Wand and Carroll 2003). But there may still be a lot of choices given the rule of thumb. For example, if \( n = 200 \), the possible choices for \( p \) range from 40 to 50, which, combined with the range of 1 to 3 for \( q \), gives a total of 33 choices for the P-spline. Our new adaptive fence method offers a data-driven approach for choosing \( p \) and \( q \) for the spline-based SAE model.

The rest of the paper is organized as follows. The fence methods are described in section 2. In section 3 we develop an adaptive fence procedure for the nonparametric model selection problem. In section 4 we demonstrate the finite sample performance of the new procedure with a series of simulation studies. In section 5 we consider a real-life data example involving a dataset from a medical survey which has been used for fitting a Fay-Herriot model (Fay and Herriot 1979). Some technical results are deferred to the appendix.

2. Fence methods

As mentioned, the basic idea of fence is to construct a statistical fence and then select an optimal model from those within the fence according to certain criterion of optimality, such as model simplicity. Let \( Q_M = Q_M(y, \theta_M) \) be a measure of lack-of-fit, where \( y \) represents the vector of observations, \( M \) indicates a candidate model, and \( \theta_M \) denotes the vector of parameters under \( M \). Here by lack-of-fit we mean that \( Q_M \) satisfies the basic requirement that \( E(Q_M) \) is minimized when \( M \) is a true model, and \( \theta_M \) is a true parameter vector under \( M \). Then, a candidate model \( M \) is in the fence if

\[ \hat{Q}_M \leq \hat{Q}_{M^*} + c_n \hat{\sigma}_{M^*,\hat{M}^*}, \]  

where \( \hat{Q}_M = \inf_{\theta \in \Theta} Q_M, \Theta_{M^*} \) being the parameter space under \( M, \hat{M} \) is a model that minimizes \( \hat{Q}_M \) among \( M \in M^* \), the set of candidate models, and \( \hat{\sigma}_{M^*,\hat{M}^*} \) is an estimate of the standard deviation of \( \hat{Q}_M - \hat{Q}_{M^*} \). The constant \( c_n \) on the right side of (2) can be chosen as a fixed number (e.g., \( c_n = 1 \)) or adaptively (see below).

The calculation of \( \hat{Q}_M \) is usually straightforward. For example, in many cases \( \hat{Q}_M \) can be chosen as the negative log-likelihood, or residual sum of squares. On the other hand, the computation of \( \hat{\sigma}_{M^*,\hat{M}^*} \) is quite challenging. Sometimes, even if an expression can be obtained for \( \hat{\sigma}_{M^*,\hat{M}^*} \), its accuracy as an estimate of the standard deviation cannot be guaranteed in a finite sample situation. Jiang, Nguyen and Rao (2009) simplified an adaptive fence procedure proposed by Jiang et al. (2008). For simplicity, we assume that \( M^* \) contains a full model, \( M_f \), of which each candidate model is a submodel. It follows that \( \hat{M} = M_f \). In the simplified adaptive procedure, the fence inequality (2) is replaced by

\[ \hat{Q}_M - \hat{Q}_{M^*} \leq c_n, \]  

where \( c_n \) is chosen adaptively as follows. For each \( M \in M^* \), let \( p^*(M) = P^*\{M_M(c) = M\} \) be the empirical probability of selection for \( M \), where \( M_M(c) \) denotes the model selected by the fence procedure based on (3) with \( c_n = c \), and \( P^* \) is obtained by bootstrapping under \( M_f \). For example, under a parametric model one can estimate the model parameters under \( M_f \) and then use a parametric bootstrap to draw samples under \( M_f \). Suppose that \( B \) samples are drawn, then \( p^*(M) \) is simply the sample proportion (out of a total of \( B \) samples) that \( M \) is selected by the fence procedure based on (3) with the given \( c_n \). Let \( p^* = \max_{M \in M^*} p^*(M) \). Note that \( p^* \) depends on \( c_n \). Let \( c_n^* \) be the \( c_n \) that maximizes \( p^* \) and this is our choice. Jiang et al. (2008) offers the following explanation of the motivation behind adaptive fence. Suppose that there is a true model among the candidate models, then, the optimal model is the one from which the data is generated, and
therefore should be the most likely given the data. Thus, given \( c_n \), one is looking for the model (using the fence procedure) that is most supported by the data or, in other words, one that has the highest (posterior) probability. The latter is estimated by bootstrapping. Note that although the bootstrap samples are generated under \( M_f \), they are almost the same as those generated under the optimal model. This is because the estimates corresponding to the zero parameters are expected to be close to zero, provided that the parameter estimators under \( M_f \) are consistent. One then pulls off the \( c_n \) that maximizes the (posterior) probability and this is the optimal choice.

There are two extreme cases corresponding to \( c_n = 0 \) and \( c_n = \infty \) (i.e., very large). Note that if \( c_n = 0 \), then \( p^* = 1 \). This is because when \( c_n = 0 \) the procedure always chooses \( M_f \). Similarly, if there is a unique simplest model (e.g., model with minimum dimension), say, \( M_* \), then \( p^* = 1 \) for very large \( c_n \). This is because, when \( c_n \) is large enough, all models are in the fence, hence the procedure always chooses \( M_* \), if simplicity is used as the criterion of optimality for selecting the model within the fence. These two extreme cases are handled carefully in Jiang et al. (2008) and Jiang et al. (2009). However, as noted by Jiang et al. (2008), the procedures to handle the extreme cases, namely, the screen tests and baseline adjustment/threshold checking, are rarely needed in practice. For example, in most applications there are a large number of candidate variables, and it is believed that only a small subset of them are important. This means that the optimal model is neither \( M_n \) nor \( M_f \). Therefore, there is no need to worry about the extreme cases, and the procedures to handle these cases can be skipped. In most applications a plot of \( p^* \) against \( c_n \) is W-shaped with the peak in the middle corresponding to \( c_n \).

The left plot of Figure 2 provides an illustration. This is a plot of \( p^* \) against \( c_n \) for the example discussed in section 5. The plot shows the typical “W” shape, as described, and the peak in the middle corresponds to where the optimal \( c_n \), i.e., \( c_n \) is.

Jiang et al. (2009) established consistency of the simplified adaptive fence and studied its finite sample performance.

3. Nonparametric SAE model selection

For the simplicity of illustration we consider the following SAE model:

\[
y_{ij} = f(X_{ij}) + B_i u_i + e_{ij}, \quad i = 1, \ldots, m,
\]

where \( y_{ij} \) is an \( n_i \times 1 \) vector representing the observations from the \( i^{th} \) small area; \( f(X_{ij}) = [f(x_{ij})]_{1 \leq i \leq n_i} \) with \( f(x) \) being an unknown (smooth) function; \( B_i \) is an \( n_i \times b \) known matrix; \( u_i \) is a \( b \times 1 \) vector of small-area specific random effects; and \( e_{ij} \) is an \( n_i \times 1 \) vector of sampling errors. It is assumed that \( u_i, e_{ij}, i = 1, \ldots, m \) are independent with \( u_i \sim N(0, G_i), G_i = G_i(\phi), \) and \( e_{ij} \sim N(0, R), R_i = R_i(\theta), \) \( \theta \) being an unknown vector of variance components. Note that, besides \( f(X_{ij}) \), the model is the same as the standard “longitudinal” linear mixed model (e.g., Laird and Ware 1982, Datta and Lahiri 2000).

The approximating spline model is given by replacing \( f(x) \) by \( f(x) \) in (1), where the coefficients \( \beta \)’s and \( \gamma \)’s are estimated by penalized least squares, i.e., by

\[
\text{minimizing } |y - X\beta - Z\gamma|^2 + \lambda |\gamma|^2,
\]

where \( y = (y_{ij})_{1 \leq i \leq m} \), the \( (i, j)^{th} \) row of \( X \) is \( (1, x_{ij}, \ldots, x_{ij}^p) \), the \( (i, j)^{th} \) row of \( Z \) is \( (x_{ij} - \kappa, \ldots, x_{ij} - \kappa)_q, i = 1, \ldots, m, j = 1, \ldots, n_i, \) and \( \lambda \) is a penalty, or smoothing, parameter. To determine \( \lambda \), Wand (2003) used the following interesting connection to a linear mixed model. To illustrate the idea, let us consider a simple case in which \( B_i = 0 \) (i.e., there is no small-area random effects), and the components of \( e_{ij} \) are independent and distributed as \( N(0, \tau^2) \). If the \( \gamma \)’s are treated as random effects which are independent and distributed as \( N(0, \sigma^2) \), then the solution to (5) are the same as the best linear unbiased estimator (BLUE) for \( \beta \), and the best linear unbiased predictor (BLUP) for \( \gamma \), if \( \lambda \) is identical to the ratio \( \tau^2/\sigma^2 \). Thus, the value of \( \lambda \) may be estimated by the maximum likelihood (ML), or restricted maximum likelihood (REML) estimators of \( \sigma^2 \) and \( \tau^2 \) (e.g., Jiang 2007). However, there has been study suggesting that this approach is biased towards undersmoothing (Kauermann 2005). Consider, for example, a special case in which \( f(x) \) is, in fact, the quadratic spline with two knots given by (10). (Note that this function is smooth in that it has a continuous derivative.) It is clear that, in this case, the best approximating spline should be \( f(x) \) itself with only two knots, i.e., \( q = 2 \) (of course, one could use a spline with many knots to “approximate” the two-knot quadratic spline, but that would seem very inefficient in this case). However, if one uses the above linear mixed model connection, the ML (or REML) estimator of \( \sigma^2 \) is consistent only if \( q \to \infty \) (i.e., the number of appearances of the spline random effects goes to infinity). The seeming inconsistency has two worrisome consequences: (i) the meaning of \( \lambda \) may be conceptually difficult to interpret; (ii) the behavior of the estimator of \( \lambda \) may be unpredictable.

The fence method offers a natural approach to choosing the degree of the spline, \( p \), the number of knots, \( q \), and the smoothing parameter, \( \lambda \) at the same time. Note, however, a major difference from the situations considered in Jiang et al. (2008) and Jiang et al. (2009) in that the true underlying model is not among the class of candidate models, i.e., the approximating splines (1). Furthermore, the
role of \( \lambda \) in the model should be made clear: \( \lambda \) controls the degree of smoothness of the underlying model. A natural measure of lack-of-fit is \( Q_M = |y - X\hat{\beta} - Z\hat{\gamma}|^2 \). However, \( \hat{Q}_M \) is not obtained by minimizing \( Q_M \) over \( \beta \) and \( \gamma \) without constraint. Instead, we have \( \hat{Q}_M = |y - X\hat{\beta} - Z\hat{\gamma}|^2 \), where \( \hat{\beta} \) and \( \hat{\gamma} \) are the solution to (5), and hence depends on \( \lambda \). The optimal \( \lambda \) is to be selected by the fence method, together with \( p \) and \( q \), as described below.

Another difference is that there may not be a full model among the candidate models. Therefore, the fence inequality (3) is replaced by the following:

\[
\hat{Q}_M - \hat{Q}_{\hat{M}} \leq c_n, \tag{6}
\]

where \( \hat{M} \) is the candidate model that has the minimum \( \hat{Q}_M \). We use the following criterion of optimality within the fence which combines model simplicity and smoothness. For the models within the fence, choose the one with the smallest \( q \); if there are more than one such models, choose the model with the smallest \( p \). This gives the best choice of \( p \) and \( q \). Once \( p, q \) are chosen, we choose the model within the fence with the largest \( \lambda \). Once again, note that \( \lambda \) is part of the model \( M \) that is selected (or “estimated”) by the fence method. The tuning constant \( c_n \) is chosen adaptively using the simplified adaptive procedure of Jiang et al. (2009), where parametric bootstrap is used for computing \( p^* \) (see section 2).

The following theorem is proved in Appendix. For simplicity, assume that the matrix \( W = (XZ) \) is of full rank. Let \( P_{q^{-1}} = I_n - P_w \), where \( n = \sum_{i=1}^m n_i \) and \( P_w = W(W'W)^{-1}W' \).

**Theorem.** Computationally, the above fence procedure is equivalent to the following: (i) first use the (adaptive) fence to select \( p \) and \( q \) using (6) with \( \lambda = 0 \) and \( \hat{Q}_M = y'P_{q^{-1}}y \) (see Lemma below), and same criterion as above for choosing \( p, q \) within the fence; (ii) let \( M_0 \) denotes the model corresponding to the selected \( p \) and \( q \), find the maximum \( \lambda \) such that

\[
\hat{Q}_{M_0,\lambda} - \hat{Q}_M \leq c_n, \tag{7}
\]

where for any model \( M \) with the corresponding \( X \) and \( Z \), we have

\[
\hat{Q}_{M_0,\lambda} = |y - X\hat{\beta}_\lambda - Z\hat{\gamma}_\lambda|^2, \\
\hat{\beta}_\lambda = (X'X)^{-1}X'y, \\
\hat{\gamma}_\lambda = \lambda^{-1}(I + \lambda^{-1}Z'Z)^{-1}Z'y - X\hat{\beta}_\lambda, \\
X'X = X'X - \lambda^{-1}X'Z(I + \lambda^{-1}Z'Z)^{-1}Z'X, \\
X'\hat{\gamma}_\lambda = X'y - \lambda^{-1}X'Z(I + \lambda^{-1}Z'Z)^{-1}Z'y,
\]

and \( c_n^* \) is chosen by the adaptive fence procedure described in section 2 (\( V_\lambda \) is defined below but not directly needed here for the computation because of the last two equations).

Note that in step (i) of the Theorem one does not need to deal with \( \lambda \). The motivation for (7) is that this inequality is satisfied when \( \lambda = 0 \), so one would like to see how far \( \lambda \) can go. In fact, the maximum \( \lambda \) is a solution to the equation \( \hat{Q}_{M_0,\lambda} - \hat{Q}_M = c_n^* \). The purpose of the last two equations is to avoid direct inversion of \( V_\lambda = I_n + \lambda^{-1}ZZ' \), whose dimension is equal to \( n \), the total sample size. Note that \( V_\lambda \) does not have a block diagonal structure because of \( ZZ' \), so if \( n \) is large direct inversion of \( V_\lambda \) may be computationally burdensome.

The proof of the Theorem requires the following lemma, whose proof is given in Appendix.

**Lemma.** For any \( M \) and \( y \), \( \hat{Q}_{M,\lambda} \) is an increasing function of \( \lambda \) with \( \inf_{\lambda>0} \hat{Q}_{M,\lambda} = \hat{Q}_M \).

### 4. Simulations

We consider an extension of the Fay-Herriot model (Fay and Herriot 1979) in a nonparametric setting. The model can be expressed as

\[
y_i = f(x_i) + v_i + e_i, \quad i = 1, ..., m, \tag{8}
\]

where \( v_i, e_i, i = 1, ..., m \) are independent such that \( v_i \sim N(0, A), e_i \sim N(0, D) \), where \( A \) is unknown but the sampling variance \( D_i \) is assumed known. The main difference from the traditional Fay-Herriot model is \( f(x) \), where \( f(x) \) is an unknown smooth function.

For simplicity we assume \( D_i = D, 1 \leq i \leq m \). Then, the model can be expressed as

\[
y_i = f(x_i) + e_i, \quad i = 1, ..., m, \tag{9}
\]

where \( e_i \sim N(0, \sigma^2) \) with \( \sigma^2 = A + D \), which is unknown. Thus, the model is the same as the nonparametric regression model.

We consider three different cases that cover various situations and aspects. In the first case, Case 1, the true underlying function is a linear function, \( f(x) = 1 - x, 0 \leq x \leq 1 \), hence the model reduces to the traditional Fay-Herriot model. The goal is to find out if fence can validate the traditional Fay-Herriot model in the case that it is valid. In the second case, Case 2, the true underlying function is a quadratic spline with two knots, given by

\[
f(x) = 1 - x + x^2 - 2(x - 1)^2 + 2(x - 2)^2, \quad 0 \leq x \leq 3 \tag{10}
\]

(the shape is half circle between 0 and 1 facing up, half circle between 1 and 2 facing down, and half circle between 2 and 3 facing up). Note that this function is smooth in that it has a continuous derivative. Here we intend to investigate whether the fence can identify the true underlying function in the “perfect” situation, i.e., when \( f(x) \) itself is a spline. The last case, Case 3, is perhaps the most practical situation,
in which no spline can provide a perfect approximation to \( f(x) \). In other words, the true underlying function is not among the candidates. In this case \( f(x) \) is chosen as 

\[
0.5 \sin(2\pi x), \quad 0 \leq x \leq 1,
\]

which is one of the functions considered by Kauermann (2005).

We consider situations of small or medium sample size, namely, \( m = 10, 15 \) or \( 20 \) for Case 1, \( m = 30, 40 \) or \( 50 \) for Case 2, and \( m = 10, 30 \) or \( 50 \) for Case 3. The covariate \( x_i \) are generated from the Uniform \([0, 1]\) distribution in Case 1, and from Uniform \([0, 3]\) in Case 2; then fixed throughout the simulations. Following Kauermann (2005), we let \( x_i \) be the equidistant points in Case 3. The error standard deviation \( \sigma \) in (9) is chosen as 0.2 in Case 1 and Case 2. This value is chosen such that the signal standard deviation in each case is about the same as the error standard deviation. As for Case 3, we consider three different values for \( \sigma, 0.2, 0.5 \) and 1.0. These values are also of the same order as the signal standard deviation in this case.

The candidate approximating splines for Case 1 and Case 2 are the following: \( p = 0, 1, 2, 3, \) \( q = 0 \) and \( p = 1, 2, 3, q = 2, 5 \) (so there are a total of 10 candidates). As for Case 3, following Kauermann (2005), we consider only linear splines (i.e., \( p = 1 \)); furthermore, we consider the number of knots in the range of the “rule of thumb” (i.e., roughly 4 or 5 observations per knot; see section 1), plus the intercept model \( (p = q = 0) \) and the linear model \( (p = 1, q = 0) \). Thus, for \( m = 10, q = 0, 2, 3; \) for \( m = 30, q = 0, 6, 7, 8; \) and for \( m = 50, q = 0, 10, 11, 12, 13. \)

Table 1 shows the results based on 100 simulations under Case 1 and Case 2. As in Jiang et al. (2009), we consider both the highest peak, that is, choosing \( c_n \) with the highest \( p^* \), and 95% lower bound (L.B.), that is, choosing a smaller \( c_n \) corresponding to a peak of \( p^* \) in order to be conservative, if the corresponding \( p^* \) is greater than the 95% lower bound of the \( p^* \) for any larger \( c_n \) that corresponds to a peak of \( p^* \). It is seen that performance of the adaptive fence is satisfactory even with the small sample size. Also, it appears that the confidence lower bound method works better in smaller sample, but makes almost no difference in larger sample. These are consistent with the findings of Jiang et al. (2009).

Table 2 shows the results for Case 3. Note that, unlike Case 1 and Case 2, here there is no optimal model (an optimal model must be a true model according to our definition). So, instead of giving the empirical probabilities of selecting the optimal model, we give the empirical distribution of the selected models in each case. It is apparent that, as \( \sigma \) increases, the distribution of the models selected becomes more spread out. A reverse pattern is observed as \( m \) increases. The confidence lower bound method appears to perform better in picking up a model with splines. Within the models with splines, fence seems to overwhelmingly prefer fewer knots than more knots.

<table>
<thead>
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<th>Sample Size</th>
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<th>( m = 30 )</th>
<th>( m = 50 )</th>
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<td>( p, q )</td>
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<td>(1, 0)</td>
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<td>Confidence L.B.</td>
<td>(0, 0)</td>
<td>20</td>
<td>(0, 0)</td>
</tr>
<tr>
<td></td>
<td>(1, 0)</td>
<td>13</td>
<td>(1, 0)</td>
</tr>
<tr>
<td></td>
<td>(1, 2)</td>
<td>59</td>
<td>(1, 6)</td>
</tr>
<tr>
<td></td>
<td>(1, 3)</td>
<td>8</td>
<td>(1, 7)</td>
</tr>
</tbody>
</table>

Table 2 Nonparametric model selection - Case 3. Reported are empirical distributions, in terms of percentage, of the selected models.
Note that the fence procedure allows us to choose not only $p$ and $q$ but also $\lambda$, (see section 3). In each simulation we compute $\hat{\beta} = \hat{\beta}_p$ and $\hat{\gamma} = \hat{\gamma}_q$, given below (7), based on the $\lambda$ chosen by the adaptive fence. The fitted values are calculated by (1) with $\beta$ and $\gamma$ replaced by $\hat{\beta}$ and $\hat{\gamma}$, respectively. We then average the fitted values over the 100 simulations. Figure 1 shows the average fitted values for the three cases ($m = 10, 30, 50$) with $\sigma = 0.2$ under Case 3. The true underlying function values, $f(x_i) = 0.5 \sin(2\pi x_i)$, $i = 1, ..., m$ are also plotted for comparison.

5. A real-life data example

We consider a dataset from Morris and Christiansen (1995) involving 23 hospitals (out of a total of 219 hospitals) that had at least 50 kidney transplants during a 27 month period (Table 3). The $y_i$'s are graft failure rates for kidney transplant operations, that is, $y_i =$ number of graft failures/$n_i$, where $n_i$ is the number of kidney transplants at hospital $i$ during the period of interest. The variance for graft failure rate, $D_i$, is approximated by $(0.2)(0.8)/n_i$, where 0.2 is the observed failure rate for all hospitals. Thus, $D_i$ is assumed known. In addition, a severity index $x_i$ is available for each hospital, which is the average fraction of females, blacks, children and extremely ill kidney recipients at hospital $i$. The severity index is considered as a covariate.

Table 3 Hospital data from Morris and Christiansen (1995)

<table>
<thead>
<tr>
<th>Area</th>
<th>$y_i$</th>
<th>$x_i$</th>
<th>$D_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.302</td>
<td>0.112</td>
<td>0.055</td>
</tr>
<tr>
<td>2</td>
<td>0.140</td>
<td>0.206</td>
<td>0.053</td>
</tr>
<tr>
<td>3</td>
<td>0.203</td>
<td>0.104</td>
<td>0.052</td>
</tr>
<tr>
<td>4</td>
<td>0.333</td>
<td>0.168</td>
<td>0.052</td>
</tr>
<tr>
<td>5</td>
<td>0.347</td>
<td>0.337</td>
<td>0.047</td>
</tr>
<tr>
<td>6</td>
<td>0.216</td>
<td>0.169</td>
<td>0.046</td>
</tr>
<tr>
<td>7</td>
<td>0.156</td>
<td>0.211</td>
<td>0.046</td>
</tr>
<tr>
<td>8</td>
<td>0.143</td>
<td>0.195</td>
<td>0.046</td>
</tr>
<tr>
<td>9</td>
<td>0.220</td>
<td>0.221</td>
<td>0.044</td>
</tr>
<tr>
<td>10</td>
<td>0.205</td>
<td>0.077</td>
<td>0.044</td>
</tr>
<tr>
<td>11</td>
<td>0.209</td>
<td>0.195</td>
<td>0.042</td>
</tr>
<tr>
<td>12</td>
<td>0.266</td>
<td>0.185</td>
<td>0.041</td>
</tr>
<tr>
<td>13</td>
<td>0.240</td>
<td>0.202</td>
<td>0.041</td>
</tr>
<tr>
<td>14</td>
<td>0.262</td>
<td>0.108</td>
<td>0.036</td>
</tr>
<tr>
<td>15</td>
<td>0.144</td>
<td>0.204</td>
<td>0.036</td>
</tr>
<tr>
<td>16</td>
<td>0.116</td>
<td>0.072</td>
<td>0.035</td>
</tr>
<tr>
<td>17</td>
<td>0.201</td>
<td>0.142</td>
<td>0.033</td>
</tr>
<tr>
<td>18</td>
<td>0.212</td>
<td>0.136</td>
<td>0.032</td>
</tr>
<tr>
<td>19</td>
<td>0.189</td>
<td>0.172</td>
<td>0.031</td>
</tr>
<tr>
<td>20</td>
<td>0.212</td>
<td>0.202</td>
<td>0.029</td>
</tr>
<tr>
<td>21</td>
<td>0.166</td>
<td>0.087</td>
<td>0.029</td>
</tr>
<tr>
<td>22</td>
<td>0.173</td>
<td>0.177</td>
<td>0.027</td>
</tr>
<tr>
<td>23</td>
<td>0.165</td>
<td>0.072</td>
<td>0.025</td>
</tr>
</tbody>
</table>

Ganesh (2009) proposed a Fay-Herriot model for the graft failure rates. as follows: $y_i = \beta_0 + \beta_j x_i + v_i + e_i$, where the $v_i$’s are hospital-specific random effects and $e_i$’s are sampling errors. It is assumed that $v_i, e_i$ are independent with $v_i \sim N(0, \lambda)$ and $e_i \sim N(0, \lambda)$. Here the variance $\lambda$ is unknown. Based on the model Ganesh obtained credible intervals for selected contrasts. However, inspections of the raw data suggest some nonlinear trends, which raises the question on whether the fixed effects part of the model can be made more flexible in its functional form.

To answer this question, we consider the Fay-Herriot model as a special member of a class of approximating spline models discussed in section 3. More specifically, we assume

$$y_i = f(x_i) + v_i + e_i, \quad i = 1, ..., m, \quad (11)$$

where $f(x)$ is an unknown smooth function and everything else are the same as in the Fay-Herriot model. We then consider the following class of approximating spline models:

$$\hat{f}(x) = \beta_0 + \beta_1 x + ... + \beta_p x^p + \gamma_1 (x - \kappa_1)_{+}^p + ... + \gamma_q (x - \kappa_q)_{+}^p \quad (12)$$

with $p = 0, 1, 2, 3$ and $q = 0, 1, 2, 3, ... (p = 0 \text{ is only for } q = 0)$. Here the upper bound 6 is chosen according to the “rule-of-thumb” (because $m = 23, \text{ so } m/4 = 5.75$). Note that the Fay-Herriot model corresponds to the case $p = 1$ and $q = 0$. The question is then to find the optimal model, in terms of $p$ and $q$, from this class.

We apply the adaptive fence method described in section 3 to this case. Here to obtain the bootstrap samples needed for obtaining $c^*_n$, we first compute the ML estimator under the model $M$, which minimizes $Q_M = y' P_{W^*} y$ among the candidate models [i.e., (12); see Theorem in section 3], then draw parametric bootstrap samples under model $M$ with the ML estimators treated as the true parameters. This is reasonable because $M$ is the best approximating model in terms of the fit, even though under model (11) there may not be a true model among the candidate models. The bootstrap sample size is chosen as 100.

The fence method selects the model $p = 3$ and $q = 0$, that is, a cubic function with no knots, as the optimal model. To make sure that the bootstrap sample size $B = 100$ is adequate, we repeated the analysis 100 times, each time using different bootstrap samples (recall in the adaptive fence one needs to draw bootstrap samples in order to determine $c^*_n$, so the question is whether different bootstrap samples lead to different results of model selection). All results led to the same model: a cubic function with no knots (even though the bootstrap-derived intermediate quantities, such as $p^*$ and $c^*_n$, varied across bootstraps). We also ran the data analysis using $B = 1,000$, and selected model remained the same. Thus, it appears that the bootstrap sample size $B = 100$ is adequate. The left figure of Figure 2 shows the plot of $p^*$ against $c_n$ in the adaptive fence model selection.
A few comparisons are always helpful. Our first comparison is to fence itself but with a more restricted space of candidate models. More specifically, we consider (12) with the restriction to linear splines only, i.e., \( p = 1 \), and knots in the range of the “rule of thumb”, i.e., \( q = 4, 5, 6 \), plus the intercept model \( (p = q = 0) \) and the linear model \( (p = 1, q = 0) \). In this case, the fence method selected a linear spline with four knots (i.e., \( p = 1, q = 4 \)) as the optimal model. The value of \( \lambda \) corresponding to this model is approximately equal to 0.001. The plot of \( \rho^* \) against \( c_n \) for this model selection is very similar to the left figure of Figure 2, and therefore omitted. In addition, the right figure of Figure 2 shows the fitted values and curves under the two models selected by the fence from within the different model spaces as well as the original data points.

A further comparison can be made by treating (11) as a generalized additive model (GAM) with heteroscedastic errors. A weighted fit can be obtained with the amount of smoothing optimized by using a generalized cross-validation (GCV) criterion. Here the weights used are \( w_i = 1/(A + D_i) \) where the maximum likelihood estimate for \( A \) is used as a plug-in estimate. Recall that the \( D_i \)’s are known. This fitted function is also overlayed in the right figure of Figure 2. Notice how closely this fitted function resembles the restricted space fence fit.

To expand the class of models under consideration by GCV-based smoothing, we used the BRUTO procedure (Hastie and Tibshirani 1990) which augments the class of models to look at a null fit and a linear fit for the spline function; and embeds the resulting model selection (i.e., null, linear or smooth fits) into a weighted backfitting algorithm using GCV for computational efficiency. Interestingly here, BRUTO finds simply an overall linear fit for the fixed effects functional form. While certainly an interesting comparison, BRUTO’s theoretical properties for models like (11) have not really been studied in depth.

Finally, as mentioned in section 3, by using the connection between P-spline and linear mixed model one can formulate (12) as a linear mixed model, where the spline coefficients are treated as random effects. The problem then becomes a (parametric) mixed model selection problem, hence the method of Jiang et al. (2009) can be applied. In fact, this was our initial approach to this dataset, and the model we found was the same as the one by BRUTO. However, we have some reservation about this approach, as explained in section 3.
6. Concluding remarks

Although the focus of the current paper is nonparametric SAE model selection, our method may be applicable to spline-based mixed effects model selection problems in other areas, for example, in the analysis of longitudinal data (e.g., Wang 2005).

In the case where a true model exists among the candidate models, such as Cases 1 and 2 in section 4, consistency of the proposed fence model selection method can be established in the same way as in Section 3 of Jiang et al. (2009) (although the result of the latter paper does not directly apply). However, practically, the situation that nonparametric modeling is most useful is when a true model does not exist, or is not among the candidates, such as Case 3 in section 4. In this case, no result of consistency can be proved, of course. It remains unclear what is a desirable asymptotic behavior to study in the latter case.

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Appendix

1. Proof of Lemma. Write $g(\lambda) = \hat{Q}_{M,\lambda}$. It can be shown (detail omitted) that $g'(\lambda) = 2\lambda y' B_x A_x B_y y$, where $A_x = B'(W'W + \lambda BB')^{-1} B$, $B_x = W(W'W + \lambda BB')^{-1} B$ with $B' = (0 I_q)$ and $W = (X Z)$. Hence $g'(\lambda) \geq 0$ for $\lambda > 0$. Also $\hat{Q}_{M,\lambda} \to \hat{Q}_M$ as $\lambda \to 0$.

2. Proof of Theorem. Consider the fence inequality

$$
\hat{Q}_{M,\lambda} - \hat{Q}_{M,\bar{\lambda}} \leq c_n \tag{A.1}
$$

where $(\bar{M}, \bar{\lambda})$ minimizes $\hat{Q}_{M,\lambda}$. Also consider the fence inequality using $\hat{Q}_{M,\lambda} = y' P_{W'y} y$, which is

$$
\hat{Q}_M - \hat{Q}_{M,\lambda} \leq c_n. \tag{A.2}
$$

By Lemma, we must have $\bar{\lambda} = 0$, and $\bar{M} = \bar{M}$. It follows, again by Lemma, that for the same $c_n$, (A.2) holds if and only if (A.1) holds for some $\lambda$. Therefore, the models within the fence, in terms of $p$ and $q$, are the same under both procedures. It is then easy to see, according to the selection criterion, that the same model $M_0 = M_0(c_n)$, in terms of $p$ and $q$, will be selected under both procedures for the given $c_n$. It then follows that the $c_n^*$ selected using the adaptive procedure will be the same under both procedures. Then, once again using the above argument, the optimal model $M_0^*$, in terms of $p$ and $q$, will be the same under both procedures.

The formulae below (7) can be derived using the expressions of BLUE and BLUP (e.g., Jiang 2007, §2.3.1) and the following identity (e.g., Sen and Srivastava 1990, page 275): If $U$ is $n \times q$ and $V$ is $q \times n$, then $(P + UV)^{-1} = P^{-1} - P^{-1} U (I_q + VP^{-1} U)^{-1} VP^{-1}$ so long as the inverses exist.

References


