Optimal designs for regression models with autoregressive errors

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Abstract

In the one-parameter regression model with AR(1) and AR(2) errors we find explicit expressions and a continuous approximation of the optimal discrete design for the signed least square estimator. The results are used to derive the optimal variance of the best linear estimator in the continuous time model and to construct efficient estimators and corresponding optimal designs for finite samples.

Keywords: linear regression, correlated observations, signed measures, optimal design, BLUE, continuous autoregressive model

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1. Introduction

Consider a linear regression model

\[ y_j = \theta^T f(t_j) + \epsilon_j \quad (j = 1, \ldots, N), \]

(1.1)

where \( \theta \in \mathbb{R}^m \) is a vector of unknown parameters, \( f(t) = (f_1(t), \ldots, f_m(t))^T \) is a vector of linearly independent functions defined on some interval, say \([A, B]\), and \( \epsilon_1, \ldots, \epsilon_N \) are random errors with \( \mathbb{E}[\epsilon_j] = 0 \) for all \( j = 1, \ldots, N \) and covariances \( \mathbb{E}[\epsilon_j \epsilon_k] = \rho(t_j - t_k) \). It is well known that the use of optimal or efficient designs yields to a reduction of costs by a statistical inference with a minimal number of experiments without losing any accuracy. Optimal design theory has been studied intensively for the case when errors are uncorrelated using tools from convex optimization theory, see Pukelsheim (2006), but the design problem in the case of dependent data is substantially harder because the corresponding optimization problems are usually non-convex. Most authors use asymptotic arguments to construct optimal designs, which do not solve the problem of non-convexity, see for example Sacks and Ylvisaker (1966, 1968); Bickel and Herzberg (1979); Näther (1985a); Zhigljavsky et al. (2010); Dette et al. (2015). Some optimal designs for the location model (in this case the optimization problems are in fact convex) and for a few one-parameter linear models have been discussed in Boltze and Näther (1982); Näther (1985a,b); Pázmán and Müller (2001) and Müller and Pázmán (2003) among others. Recently, for multi-parameter models, Dette et al. (2013) determined a necessary condition for the optimality of (asymptotic) designs for least squares estimation. Dette et al. (2014) studied
nearly universally optimal designs, while Dette et al. (2016) constructed new matrix-weighted estimators with corresponding optimal designs, which are very close to the best linear unbiased estimator with corresponding optimal designs. Although these results are promising, they rely on certain structural assumptions on the covariance kernel. For example, Dette et al. (2013) assume that the regression functions in model (1.1) are eigenfunctions of an integral operator associated with the covariance kernel of the error process and Dette et al. (2016) assume that the covariance kernel is triangular, see Mehr and McFadden (1965) for an exact definition. While these results cover the frequently used AR(1)-process as error structure, they are not applicable in models with autoregressive error processes of larger order.

The goal of the present paper is to give first insights in the optimal design problem for linear regression models with autoregressive error processes. We concentrate on a one-parameter linear regression model with an AR(1) and AR(2)-error process. In Section 2 we will introduce a signed least squares estimator and consider approximate designs on the design space \( \mathcal{T} = \{t_1, \ldots, t_N\} \), where the weights are not necessarily non-negative. We determine the optimal (signed) approximate design for signed least squares estimation, such that the signed least squares estimator has the same variance as the weighted least squares estimator based on observations at the experimental conditions \( t_1, \ldots, t_N \). In Section 3 we consider the one-parameter linear regression model with autoregressive errors of order 1 and study the asymptotic behavior of the signed least squares estimator with corresponding optimal design as the sample size tends to infinity. Section 4 is devoted to the case of an AR(2)-error process, where the situation is substantially more complicated. Finally, the results are illustrated on several numerical examples.

2. Various least squares estimators

For estimating \( \theta \), we use the following two estimators: the best linear unbiased estimator (BLUE)

\[
\hat{\theta}_{\text{BLUE},N} = (X^T\Sigma^{-1}X)^{-1}X^T\Sigma^{-1}Y
\]

and the signed least squares estimator (SLSE)

\[
\hat{\theta}_{\text{SLSE},N} = (X^T S X)^{-1}X^T S Y,
\]

where \( X = (f_i(t_j))_{j,i=1}^{N,m} \) is the design matrix of size \( N \times m \), \( S \) is an \( N \times N \) diagonal matrix with entries +1 and \(-1\) on the diagonal and \( \Sigma = (\rho(t_i - t_j))_{i,j=1}^{N} \) is the covariance matrix of observations. If \( S \) is the \( N \times N \) identity matrix, then SLSE coincides with the ordinary least squares estimator (LSE). The covariance matrix of the BLUE and the SLSE are given by

\[
\text{Var}(\hat{\theta}_{\text{BLUE},N}) = (X^T\Sigma^{-1}X)^{-1},
\]

\[
\text{Var}(\hat{\theta}_{\text{SLSE},N}) = (X^T S X)^{-1}(X^T S \Sigma S X)(X^T S X)^{-1},
\]

respectively. Throughout this paper we concentrate on the one-parameter regression model

\[
y_j = \theta f(t_j) + \epsilon_j,
\]

(2.2)
and remark that an extension to the multi-parameter model (1.1) could be performed following the discussion in Dette et al. (2016). A design on the (fixed) design space \( T = \{t_1, \ldots, t_N\} \) is an arbitrary discrete signed measure of the form \( \xi = \{t_1, \ldots, t_N; w_1, \ldots, w_N\} \), where \( w_i = s_i p_i, \quad s_i \in \{-1, 1\}, \quad p_i \geq 0, \quad i = 1, \ldots, N, \) and \( \sum_{i=1}^N p_i = 1 \). The variance of the SLSE for the design \( \xi \) is given by

\[
D(\xi) = \text{Var}(\hat{\theta}_{\text{SLSE},N}) = \sum_{i=1}^N \sum_{j=1}^N \rho(t_i - t_j) w_i w_j f_i f_j / \left( \sum_{i=1}^N w_i f_i^2 \right)^2, \tag{2.3}
\]

where we use the notation \( f_i = f(t_i) \) throughout this paper. The optimal design problem consists in the minimization of this expression with respect to the weights \( w_1, \ldots, w_N \) assuming that the observation points \( t_1, \ldots, t_N \) are fixed. Despite the fact that the functional \( D \) in (2.3) is not convex as a function of \( w_1, \ldots, w_N \), the problem of determining the optimal weights can be easily solved by a simple application of the Cauchy-Schwarz inequality. The proof of the following lemma is given in Dette et al. (2016); see also Theorem 5.3 in Nather (1985a), where this result was proved in a slightly different form.

**Lemma 2.1.** Assume that the matrix \( \Sigma = (\rho(t_i - t_j))_{i,j=1,\ldots,N} \) is positive definite and \( f_i \neq 0 \) for all \( i = 1, \ldots, N \). Then the optimal weights \( w_1^*, \ldots, w_N^* \), minimizing the expression (2.3) are given by

\[
w_i^* = e_i^T \Sigma^{-1} f / f_i; \quad i = 1, \ldots, N, \tag{2.4}
\]

where \( f = (f_1, \ldots, f_N)^T, \quad e_i = (0, \ldots, 0, 1, 0, \ldots, 0)^T \in \mathbb{R}^N \) is the \( i \)-th unit vector. Moreover, for the design \( \xi^* = \{t_1, \ldots, t_N; w_1^*, \ldots, w_N^*\} \) with weights (2.4) we have \( D(\xi^*) = D^* \), where \( D^* = 1/(f^T \Sigma^{-1} f) \) is the variance of the BLUE.

Note that the optimal weights in Lemma 2.1 are not uniquely defined. In fact, they can always be multiplied by a non-zero constant without changing their optimality. In the following discussion we will consider the case where the points \( t_i \) are given by the equidistant points on the interval \([A, B]\) and the sample size \( N \) tends to infinity. Heuristically the BLUE converges in this case to the BLUE in the continuous time model, where the full trajectory of the stochastic process can be observed. Note that for any finite \( N \) the SLSE with the optimal weights defined in Lemma 2.1 has the same variance as the BLUE.

Further we study the asymptotic properties of the SLSE and the optimal weights \( w_i^* \) defined in (2.4) as the sample size increases. In many cases we will be able to approximate an \( N \)-point design \( \xi = \{t_1, \ldots, t_N; w_1^*, \ldots, w_N^*\} \) with optimal weights defined in (2.4) by a signed measure (an approximate design) of the form

\[
\xi(dt) = P_A \delta_A(dt) + P_B \delta_B(dt) + p(t) dt, \tag{2.5}
\]

where \( \delta_A(dt) \) and \( \delta_B(dt) \) are Dirac-measures concentrated at the point \( A \) and \( B, \) respectively, and \( p(\cdot) \) is a density function (not necessarily non-negative) on the interval \([A, B]\). Approximate designs of the from (2.5) are easier to understand and analyze than discrete designs of the form \( \xi = \{t_1, \ldots, t_N; w_1^*, \ldots, w_N^*\}, \) and we will illustrate in Sections 3 and 4 the derivation of the
limits in the case of autoregressive error processes of order one and two, respectively.
As already mentioned in the introduction the AR(1) process corresponds to a triangular kernel and could also be treated with methodology developed in Dette et al. (2016). We discuss it here because for this case the arguments are simpler than for the AR(2) process. In fact, for the AR(2) error process the derivation of asymptotically optimal weights $w_1^*, \ldots, w_N^*$ of the form (2.4) as the sample size tends to infinity is substantially harder.

3. Autoregressive errors of order one

Consider the regression model (1.1) with $N$ equidistant points
\[ t_j = A + (j - 1)\Delta, \quad (j = 1, \ldots, N) \]
on the interval $[A, B]$, where $\Delta = (B - A)/(N - 1)$. Assume that the errors $\epsilon_1, \ldots, \epsilon_N$ in (2.2) satisfy the discrete AR(1) equation
\[ \epsilon_j - a\epsilon_{j-1} = z_j \]
for some $0 < a < 1$, where $\epsilon_1 \sim N(0, \sigma^2)$ and $z_2, \ldots, z_N$ are Gaussian independent identically distributed random variables with mean 0 and variance $\sigma^2_z = (1 - a^2)\sigma^2$. Without loss of generality, we assume $\sigma^2 = 1$.

Remark 3.1. Note that discrete AR(1) processes (3.2) are often considered for the parameter $-1 < a < 1$. For the subsequent discussion we need a continuous real-valued analogue, say $\{\epsilon(t)\}_{t \in [A, B]}$, of the discrete AR(1) error process, which is only available in the case $0 < a < 1$; see Chan and Tong (1987). The corresponding process with drift is denoted by $y(t) = \theta f(t) + \epsilon(t)$, $t \in [A, B]$. For $-1 < a < 0$ the discrete AR(1) process (3.2) does not have a continuous real-valued analogue and therefore in this case the limiting behavior of our estimators and designs is much harder to understand.

It is also worthwhile to mention that the autocovariance function of errors $\epsilon_1, \ldots, \epsilon_N$ is given by
\[ \mathbb{E}[\epsilon_j \epsilon_k] = \rho(t_j - t_k) = e^{-\lambda|t_j - t_k|} = e^{\lambda t_j}e^{-\lambda t_k} \quad \text{if } t_j \leq t_k, \]
where $\lambda = -\ln(a)/\Delta$. Thus, if $a \in (0, 1)$, the AR(1) error process has a triangular covariance kernel in the sense of Mehr and McFadden (1965), and the results of Dette et al. (2016) are applicable. In the following discussion we provide a different derivation of the asymptotically optimal weights, because the arguments will be useful for the discussion of an AR(2) error process in Section 4.

For an AR(1) error process, the inverse of the covariance matrix $\Sigma = (\rho(t_i - t_j))_{i,j=1}^N$ is given by the tridiagonal matrix
\[
\Sigma^{-1} = \frac{1}{S} \begin{pmatrix}
1 & k_1 & 0 & 0 & \cdots \\
k_1 & k_0 & k_1 & 0 & \cdots \\
0 & k_1 & k_0 & k_1 & 0 \\
\vdots & \ddots & \ddots & \ddots & \ddots \\
0 & k_1 & k_0 & k_1 & 0 \\
0 & 0 & k_1 & 1
\end{pmatrix},
\]
where \( k_0 = 1 + a^2 = 1 + e^{-2\lambda \Delta} \), \( k_1 = -a = -e^{-\lambda \Delta} \), \( S = 1 - a^2 = 1 - e^{-2\lambda \Delta} \) and \( \lambda = -\ln(a)/\Delta \).

Recalling the definition of the optimal weights \( w_i^*, i = 2, \ldots, N - 1 \), in (2.4) we have
\[
Sw_i^* f(t_i) = k_1 f_i - k_0 f_i + k_1 f_{i+1} = (1 + a^2) f_i - a f_{i-1} - a f_{i+1} = a(2f_i - f_{i-1} - f_{i+1}) + (a - 1)^2 f_i.
\]

We now assume that \( \lambda = -\ln(a)/\Delta \) is fixed and \( \Delta = (B - A)/(N - 1) \to 0 \). Since \( S(\Delta) = S'(0)\Delta + o(\Delta) \) with \( S'(0) = 2\lambda \) and \( a = 1 - \lambda \Delta + o(\Delta) \), we obtain
\[
w_i^* f(t_i) = \frac{\Delta}{S(\Delta)} a(2f_i - f_{i-1} - f_{i+1}) + (a - 1)^2 f_i \Delta = \frac{1}{S'(0)[-f''(t_i) + \lambda^2 f(t_i)\Delta + o(\Delta)].
\]

Thus, we have \( \frac{w_i^*}{\Delta} = \frac{1}{2\lambda f(t_i)}[-f''(t_i) + \lambda^2 f(t_i)] + O(\Delta) \). Therefore, for small \( \Delta \), the discrete signed measure \( \{ t_2, \ldots, t_{N-1}; w_2^*, \ldots, w_{N-1}^* \} \) is approximated by the continuous signed measure with density
\[
p(t) = -\frac{1}{2\lambda f(t)}(f''(t) - \lambda^2 f(t)). \tag{3.3}
\]

Now we consider the weights at the boundary points. For the left boundary weight, we obtain
\[
w_1^* f(t_1) = f_1 + k_1 f_2 = \frac{\Delta}{S(\Delta)} f_1 - a f_2 = \frac{\Delta}{S(\Delta)} \left[ f_1 - f_2 + \frac{f_2 - a f_2}{\Delta} \right] = \frac{1}{S'(0)[-f'(t_1) - a'(0)f(t_1)] + O(\Delta).
\]

Since \( t_1 = A \), for small \( \Delta \), we have \( w_1^* \approx P_A \), where
\[
P_A = \frac{1}{f(A)S'(0)}(-f'(A) - a'(0)f(A)) = \frac{1}{2\lambda f(A)}(-f'(A) + \lambda f(A)). \tag{3.4}
\]

Similarly, for the right boundary weight, we obtain
\[
w_N^* f(t_N) = f_N + k_1 f_{N-1} = \frac{\Delta}{S(\Delta)} f_N - a f_{N-1} = \frac{1}{S'(0)[f'(t_N) - a'(0)f(t_{N-1})] + O(\Delta).
\]

Since \( t_N = B \), for small \( \Delta \), we have \( w_N^* \approx P_B \), where
\[
P_B = \frac{1}{f(B)S'(0)}(f'(B) - a'(0)f(B)) = \frac{1}{2\lambda f(B)}(f'(B) + \lambda f(B)). \tag{3.5}
\]

Summarizing, we have proved the following result.

**Proposition 3.1.** Consider the one-parameter regression model (2.2) with AR(1) errors of the form (3.2), where \( 0 < a < 1 \) and \( f(\cdot) \) is a twice continuously differentiable function such that \( f(t) \neq 0 \) for all \( t \in [A, B] \). For large \( N \), the optimal discrete SLSE (defined in Lemma 2.1) is approximated by the continuous SLSE
\[
\hat{\theta} = D^*(P_A f(A)g(A) + P_B f(B)g(B) + \int_A^B p(t)f(t)g(t)dt) \tag{3.6}
\]
where \( D^* = \left( P_A f^2(A) + P_B f^2(B) + \int_A^B p(t)f^2(t)dt \right)^{-1} \), and \( p(t) \), \( P_A \) and \( P_B \) are defined in (3.3), (3.4) and (3.5), respectively. For this approximation, we have

\[
D^* = \lim_{N \to \infty} \text{Var}(\hat{\theta}_{\text{SLSE},N}),
\]

i.e. \( D^* \) is the limit of the variances (2.3) of the optimal discrete SLSE designs as \( N \to \infty \).

Throughout the following discussion we call a triple \((p, P_A, P_B)\) containing a (signed) density \( p \) and two weights \( P_A \) and \( P_B \), an approximate design for the continuous SLSE defined in (3.6).

**Remark 3.2.** Observing the discussion in the second part of Remark 3.1 it is reasonable to compare Proposition 3.1 with Theorem 2.1 in Dette et al. (2016). Note that the expressions for the optimal signed density \( p(\cdot) \) and optimal weights \( P_A \) and \( P_B \) at boundary points are particular cases of the general formulae

\[
p(t) = -\frac{1}{f(t)} \left[ h'(t) \right]'P_A = \frac{1}{f(A)v(A)q'(A)} \left[ f(A)u'(A) - f'(A) \right]P_B = \frac{h'(B)}{f(B)v(B)q'(B)}
\]

with \( u(t) = e^{\lambda t} \) and \( v(s) = e^{-\lambda s} \), where \( q(t) = u(t)/v(t) \) and \( h(t) = f(t)/v(t) \). Indeed, we easily see that \( h(t) = f(t)e^{\lambda t}, h'(t) = f'(t)e^{\lambda t} + f(t)\lambda e^{\lambda t}, q'(t) = 2\lambda e^{2\lambda t}, h'(t)/q'(t) = f'(t)e^{-\lambda t} + f(t)\lambda e^{-\lambda t} \) and, consequently,

\[
p(t) = -\frac{1}{f(t)e^{-\lambda t}}(f'(t)e^{-\lambda t} + f(t)\lambda e^{-\lambda t})' = -\frac{f''(t)e^{-\lambda t} - \lambda f''(t)e^{-\lambda t} + f'(t)\lambda e^{-\lambda t} - f(t)\lambda^2 e^{-\lambda t}}{f(t)e^{-\lambda t}} = -\frac{1}{2\lambda f(t)}(f''(t) - \lambda^2 f(t)),
\]

as desired. Similarly, we have

\[
P_A = \frac{1}{f(A)e^{-2\lambda^2 2\lambda^2 \lambda}} \left[ \frac{f(A)\lambda e^{\lambda A}}{e^{\lambda A}} - f'(A) \right] = \frac{1}{2\lambda f(A)} \left( -f'(A) + \lambda f(A) \right)
\]

\[
P_B = \frac{f'(B)e^{\lambda B} + f(B)\lambda e^{\lambda B}}{f(B)e^{-\lambda B^2 2\lambda B^2}} = \frac{1}{2\lambda f(B)} \left( f'(B) + \lambda f(B) \right).
\]

4. **Autoregressive errors of order two**

In this section we assume that the observations in model (2.2) are taken at \( N \) equidistant points of the form (3.1) and that the errors \( \epsilon_1, \ldots, \epsilon_N \) satisfy the discrete AR(2) equation

\[
\epsilon_j - a_1 \epsilon_{j-1} - a_2 \epsilon_{j-2} = z_j,
\]

where \( z_j \) are Gaussian independent identically distributed random variables with mean 0 and variance \( \sigma_z^2 = \sigma^2(1 + a_2)((1 - a_2^2) - a_1^2)/(1 - a_2) \). Here we make a usual assumption that (4.1) defines the AR(2) process for \( j \in \{ \ldots, -2, -1, 0, 1, 2, \ldots \} \) but we only take the values such that \( j \in \{ 1, 2, \ldots, N \} \). Note that the AR(2) process is often considered for parameters \( a_1 \) and
There are three different forms of the autocovariance function (note that we assume throughout $y$ by $\varepsilon$ expressions for the optimal weights $w$ on the autocovariance function $W$ of the form $\rho^{(2)}(t) = e^{-\lambda |t|} \left\{ \cos(q|t|) + \frac{\lambda}{q} \sin(q|t|) \right\}$, where $\lambda > 0$, $q > 0$, and
\[
\rho^{(3)}(t) = e^{-\lambda |t|} (1 + \lambda |t|),
\]
where $\lambda > 0$, $\lambda > 0$, and $\lambda > 0$, $q > 0$, and
\[
\rho^{(3)}(t) = e^{-\lambda |t|} (1 + \lambda |t|),
\]
where $\lambda > 0$, $q > 0$, and
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\]
where $\lambda > 0$, $q > 0$, and
\[
\rho^{(3)}(t) = e^{-\lambda |t|} (1 + \lambda |t|),
\]
where $\lambda > 0$. From formulas (11)–(13) in He and Wang (1989) we obtain that the corresponding three forms of the autocovariances of the discrete AR(2) process (4.1) are:

\[
r_k^{(1)} = \mathbb{E}[\epsilon_j \epsilon_{j+k}] = C p_k^1 + (1-C)p_k^2, \quad C = \frac{(1-p_1^2)p_1}{(1-p_1^2)p_1 - (1-p_2^2)p_2}, \tag{4.4}
\]

where $j \geq 0$, $p_1 \neq p_2$, $0 < |p_1|, |p_2| < 1$, 

\[
r_k^{(2)} = p^k (\cos(bk) + C \sin(bk)), \quad C = \cot(b) \frac{1-p^2}{1+p^2}, \tag{4.5}
\]

where $0 < p < 1$, $0 < b < 2\pi$ and $b \neq \pi$, and 

\[
r_k^{(3)} = p^k (1+kC), \quad C = \frac{1-p^2}{1+p^2}, \tag{4.6}
\]

where $0 < |p| < 1$. We determine approximations for the optimal weights $w_i^*$ in Lemma 2.1 for the three different types of autocovariance functions. All results are summarized in Theorem 4.1 below. The proof is somewhat similar (but more difficult) to the derivation above presented for the AR(1) errors.

**Theorem 4.1.** Consider the one-parameter model (2.2) such that the errors follow the AR(2) equation. Assume that $f(\cdot)$ is a four times continuously differentiable and $f(t) \neq 0$ for all $t \in [A, B]$. Define the following constants depending on the form of the autocovariance function $r_k$. If $r_k$ is of the form (4.4), set

\[
\lambda_1 = -\frac{\ln(p_1)}{\Delta}, \quad \lambda_2 = -\frac{\ln(p_2)}{\Delta}, \quad \tau_0 = \lambda_1^2 \lambda_2, \quad \tau_2 = \lambda_1^2 + \lambda_2^2, \quad \beta_1 = \lambda_1 + \lambda_2, \quad \beta_0 = \lambda_1 \lambda_2, \\
\gamma_1 = \lambda_1^2 + \lambda_1 \lambda_2 + \lambda_2^2, \quad \gamma_0 = \lambda_1 \lambda_2 (\lambda_1 + \lambda_2), \quad s_3 = 2\lambda_1 \lambda_2 (\lambda_1 + \lambda_2).
\]

If $r_k$ is of the form (4.5), set

\[
\lambda = -\frac{\ln(p)}{\Delta}, \quad q = -\frac{b}{\Delta}, \quad \tau_0 = (\lambda^2 + q^2)^2, \quad \tau_2 = 2(\lambda^2 - q^2), \quad \beta_1 = 2\lambda, \quad \beta_0 = \lambda^2 + q^2, \\
\gamma_1 = (3\lambda^2 - q^2), \quad \gamma_0 = 2\lambda (\lambda^2 + q^2), \quad s_3 = 4\lambda (\lambda^2 + q^2).
\]

If $r_k$ is of the form (4.6), set

\[
\lambda = -\frac{\ln(p)}{\Delta}, \quad \tau_0 = \lambda^4, \quad \tau_2 = 2\lambda^2, \quad \beta_1 = 2\lambda, \quad \beta_0 = \lambda^2, \quad \gamma_1 = 3\lambda^2, \quad \gamma_0 = 2\lambda^3, \quad s_3 = 4\lambda^3.
\]

For large $N$, the optimal discrete SLSE (defined in Lemma 2.1) can be approximated by the continuous SLSE

\[
\hat{\theta} = D^* (Q_B f(B)y'(B) - Q_A f(A)y'(A) + P_A f(A)y(A) + P_B f(B)y(B) + \int_A^B p(t) f(t)y(t) dt)
\]

where

\[
D^* = \left( Q_B f(B)f'(B) - Q_A f(A)f'(A) + P_A f^2(A) + P_B f^2(B) + \int_A^B p(t) f^2(t) dt \right)^{-1}.
\]
For this approximation, we have $D^* = \lim_{N \to \infty} \text{Var}(\hat{\theta}_{SLSE,N})$, i.e. $D^*$ is the limit of the variance (2.3) of the optimal discrete SLSE design as $N \to \infty$. Here the quantities $p(t)$, $Q_A$, $Q_B$, $P_A$ and $P_B$ in the continuous SLSE are defined by

$$p(t) = -\frac{1}{s_3 f(t)} (\tau_2 f''(t) - \tau_0 f(t) - f'''(t)), \quad (4.7)$$

$$P_A = \frac{1}{s_3 f(A)} (f'''(A) - \gamma_1 f'(A) + \gamma_0 f(A)),$$

$$P_B = \frac{1}{s_3 f(B)} (-f'''(B) + \gamma_1 f'(B) + \gamma_0 f(B)),$$

$$Q_A = \frac{1}{s_3 f(A)} (f''(A) - \beta_1 f'(A) + \beta_0 f(A)),$$

$$Q_B = \frac{1}{s_3 f(B)} (f''(B) + \beta_1 f'(B) + \beta_0 f(B)). \quad (4.8)$$

5. Examples

5.1. Approximations of the discrete SLSE

Consider the one-parameter model with $f(t) = t^\alpha$ and AR(1) errors. The design space is an interval $[A, B]$ such that $f(t) \neq 0$ for all $t \in [A, B]$. Then the optimal discrete design for the SLSE is approximated by a design of the form (2.5), where the density $p(t)$, and the weights $P_A$ and $P_B$ are defined by

$$p(t) = -\frac{1}{2\lambda} (\alpha(\alpha - 1)t^2 - \lambda^2), \quad P_A = \frac{1}{2\lambda} (-\alpha A^{-1} + \lambda), \quad P_B = \frac{1}{2\lambda} (\alpha B^{-1} + \lambda).$$

In Table 1 we display values of $p(t)$, $P(A)$ and $P_B$ for several exponents $\alpha$ and also for the regression function $f(t) = e^t$. For example, if $f(t) = e^t$ we observe that $P_A$ is positive for $\lambda > 1$ and negative for $0 < \lambda < 1$, $P_B$ is positive for $\lambda > 0$, $p(t)$ is positive for $\lambda > 1$ and negative for $\lambda \in (0, 1)$. For large $\lambda$, the contribution of observations at the interval $(A, B)$ to the continuous SLSE is significant. For the location model $f(t) = 1$, we can see that $P_B = P_B = 1/2$ and $p(t) = \lambda/2$. This implies that for small $\lambda$ the contribution of observations at boundary points to the continuous SLSE is large and the contribution of observations at the interval $(A, B)$ to the continuous SLSE is small. For large $\lambda$, the contribution of observations at the interval $(A, B)$ to the continuous SLSE is essential.

Next we consider the same models with an AR(2) error process. If $f(t) = t^\alpha$ then SLSE is approximated by the continuous SLSE of the form (2.5), where

$$p(t) = -\frac{1}{s_3} (\tau_2 \alpha(\alpha - 1)t^2 - \tau_0 - \alpha(\alpha - 1)(\alpha - 2)(\alpha - 3)t^4),$$

$$P_A = \frac{1}{s_3} (\alpha(\alpha - 1)(\alpha - 2)A^{-3} - \gamma_1 \alpha A^{-1} + \gamma_0), \quad P_B = \frac{1}{s_3} (-\alpha(\alpha - 1)(\alpha - 2)B^{-3} + \gamma_1 \alpha B^{-1} + \gamma_0), \quad Q_A = \frac{1}{s_3} (\alpha(\alpha - 1)A^{-2} - \beta_1 \alpha A^{-1} + \beta_0), \quad Q_B = \frac{1}{s_3} (\alpha(\alpha - 1)B^{-2} + \beta_1 \alpha B^{-1} + \beta_0).$$

Note that signs of $p(t)$, $Q_A$, $Q_B$, $P_A$ and $P_B$ depend on the form of the autocovariance function and its parameters. For the form (4.6), we provide values of $p(t)$, $Q_A$, $Q_B$, $P_A$ and $P_B$ for several functions $f(t)$ in Table 2. The other cases can be obtained similarly and are not displayed for the sake of brevity.
Table 1: The function $p(t)$ and the weights $P_A$ and $P_B$ of the continuous SLSE for several functions $f(t)$ and an AR(1) error process.

<table>
<thead>
<tr>
<th>$f(t)$</th>
<th>$P_A$</th>
<th>$P_B$</th>
<th>$p(t)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1$</td>
<td>$\frac{1}{2}$</td>
<td>$\frac{1}{2}$</td>
<td>$\frac{1}{4}$</td>
</tr>
<tr>
<td>$t$</td>
<td>$\frac{1}{2} - \frac{3}{4\lambda}$</td>
<td>$\frac{1}{2} + \frac{3}{4\lambda}$</td>
<td>$\frac{\lambda}{4}$</td>
</tr>
<tr>
<td>$t^2$</td>
<td>$\frac{1}{2} - \frac{3}{2\lambda}$</td>
<td>$\frac{1}{2} + \frac{3}{2\lambda}$</td>
<td>$\frac{\lambda}{4} - \frac{1}{\lambda^2}$</td>
</tr>
<tr>
<td>$t^3$</td>
<td>$\frac{1}{2} - \frac{9}{4\lambda} + \frac{3}{\lambda^2}$</td>
<td>$\frac{1}{2} + \frac{9}{4\lambda} - \frac{3}{\lambda^2}$</td>
<td>$\frac{\lambda}{4} - \frac{3}{\lambda^2}$</td>
</tr>
<tr>
<td>$t^4$</td>
<td>$\frac{1}{2} - \frac{3}{4\lambda} + \frac{3}{\lambda^2}$</td>
<td>$\frac{1}{2} + \frac{3}{4\lambda} - \frac{3}{\lambda^2}$</td>
<td>$\frac{\lambda}{4} - \frac{6}{\lambda^2} + \frac{6}{\lambda^4}$</td>
</tr>
<tr>
<td>$e^t$</td>
<td>$\frac{1}{2} - \frac{3}{4\lambda} + \frac{1}{\lambda^3}$</td>
<td>$\frac{1}{2} + \frac{3}{4\lambda} - \frac{1}{\lambda^3}$</td>
<td>$\frac{\lambda}{4} - \frac{1}{\lambda^2} + \frac{\lambda}{4\lambda^3}$</td>
</tr>
</tbody>
</table>

For example, if $f(t) = e^t$ we can see that both $P_A$ and $Q_A$ are positive for all $\lambda \neq 1$, $P_B$ is positive for $\lambda > 0.5$ and negative for $\lambda \in (0, 0.5)$, $p(t)$ is positive for $\lambda > \sqrt{2}$ and negative for $\lambda \in (0, \sqrt{2})$. For large $\lambda$, the contribution of observations at the interval $(A, B)$ to the continuous SLSE is notable. For the location model $f(t) = 1$, we can see that $P_A = P_B = 1/2$, $Q_A = Q_B = 1/(4\lambda)$ and $p(t) = \lambda/4$. This implies that for small $\lambda$ the contribution of observations at boundary points to the continuous SLSE is very large and the contribution of observations at the interval $(A, B)$ to the continuous SLSE is small. For large $\lambda$, the contribution of observations at the interval $(A, B)$ to the continuous SLSE is essential.

<table>
<thead>
<tr>
<th>$f(t)$</th>
<th>$P_A$</th>
<th>$P_B$</th>
<th>$p(t)$</th>
<th>$Q_A$</th>
<th>$Q_B$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1$</td>
<td>$\frac{1}{2}$</td>
<td>$\frac{1}{2}$</td>
<td>$\frac{1}{4}$</td>
<td>$\frac{1}{4\lambda}$</td>
<td>$\frac{1}{4\lambda}$</td>
</tr>
<tr>
<td>$t$</td>
<td>$\frac{1}{2} - \frac{3}{4\lambda}$</td>
<td>$\frac{1}{2} + \frac{3}{4\lambda}$</td>
<td>$\frac{\lambda}{4}$</td>
<td>$\frac{1}{4\lambda} - \frac{1}{2\lambda^2}$</td>
<td>$\frac{1}{4\lambda} + \frac{1}{2\lambda^2}$</td>
</tr>
<tr>
<td>$t^2$</td>
<td>$\frac{1}{2} - \frac{3}{2\lambda}$</td>
<td>$\frac{1}{2} + \frac{3}{2\lambda}$</td>
<td>$\frac{\lambda}{4} - \frac{1}{\lambda^2}$</td>
<td>$\frac{1}{4\lambda} - \frac{1}{\lambda^2} + \frac{2\lambda^2}{\lambda^3}$</td>
<td>$\frac{1}{4\lambda} + \frac{3}{2\lambda^2}$</td>
</tr>
<tr>
<td>$t^3$</td>
<td>$\frac{1}{2} - \frac{9}{4\lambda} + \frac{3}{\lambda^2}$</td>
<td>$\frac{1}{2} + \frac{9}{4\lambda} - \frac{3}{\lambda^2}$</td>
<td>$\frac{\lambda}{4} - \frac{3}{\lambda^2}$</td>
<td>$\frac{1}{4\lambda} - \frac{3}{2\lambda^2} + \frac{3}{2\lambda^3}$</td>
<td>$\frac{1}{4\lambda} + \frac{3}{2\lambda^2} + \frac{3}{2\lambda^3}$</td>
</tr>
<tr>
<td>$t^4$</td>
<td>$\frac{1}{2} - \frac{3}{4\lambda} + \frac{3}{\lambda^2}$</td>
<td>$\frac{1}{2} + \frac{3}{4\lambda} - \frac{3}{\lambda^2}$</td>
<td>$\frac{\lambda}{4} - \frac{6}{\lambda^2} + \frac{6}{\lambda^4}$</td>
<td>$\frac{1}{4\lambda} - \frac{6}{\lambda^2} + \frac{3}{4\lambda^3}$</td>
<td>$\frac{1}{4\lambda} + \frac{3}{2\lambda^2} + \frac{3}{2\lambda^3}$</td>
</tr>
<tr>
<td>$e^t$</td>
<td>$\frac{1}{2} - \frac{3}{4\lambda} + \frac{1}{\lambda^3}$</td>
<td>$\frac{1}{2} + \frac{3}{4\lambda} - \frac{1}{\lambda^3}$</td>
<td>$\frac{\lambda}{4} - \frac{1}{\lambda^2} + \frac{\lambda}{4\lambda^3}$</td>
<td>$\frac{1}{4\lambda} - \frac{1}{2\lambda^2} + \frac{1}{4\lambda^3}$</td>
<td>$\frac{1}{4\lambda} + \frac{1}{2\lambda^2} + \frac{1}{4\lambda^3}$</td>
</tr>
</tbody>
</table>

5.2. Practical implementation

Suppose that the $N$ equidistant points defined in (3.1) are the potential observation points. Let $K + 2$ be the number of observations actually taken in the experiment and that we want to construct a discrete design, which can be implemented in practice. If $K$ is small and $N$ is large, then efficient designs and corresponding estimators for the model (2.2) can be derived from the continuous approximations, which have been developed in the previous sections.

In Dette et al. (2016) a procedure with a good finite sample performance is proposed. It consists of a slight modification of the SLSE given in (2.1) and a discretization of the density $p(t)$ defined in (3.3) for AR(1) errors and (4.8) for AR(2) errors. To be precise consider a continuous SLSE with weights at the points $A$ and $B$ (the end-points of the interval $[A, B]$), which correspond
to the masses \( P_A \) and \( P_B \) and, for the AR(2) errors, \( Q_A \) and \( Q_B \) as well. We thus only need to approximate the continuous part of the design, which has a density on \((A, B)\), by a \( K \)-point design with equal masses.

We assume that the density \( p(\cdot) \) is not identically zero on the interval \((A, B)\). Define \( \varphi(t) = \kappa |p(t)| \) for \( t \in (A, B) \) and choose the constant \( \kappa \) such that \( \int_A^B \varphi(t)\,dt = 1 \), that is, \( \kappa = 1/\int_A^B |p(t)|\,dt \). Denote by \( F(t) = \int_A^t \varphi(s)\,ds \) the corresponding cumulative distribution function. As \( K \)-point design we use a \( K \)-point approximation to the measure with density \( \varphi(t) \), that is \( \bar{\xi}_K = \{t_{1,K}, \ldots, t_{K,K}; 1/K, \ldots, 1/K\} \), where \( t_{i,K} = R(F^{-1}(i/(K + 1))) \) \( i = 1, 2, \ldots, K \). Here \( R(t) \) is the operator of rounding a number \( t \) towards the set of points defined by (3.1); that is, points \( R(F(i/(K + 1))) = t_{i,K} := A + (\nu_i - 1)\Delta \). For given \( i, \nu_i \) is defined from

\[
|F(i/(K + 1)) - A + (\nu_i - 1)\Delta| = \min\{|F(i/(K + 1)) - A + (j - 1)\Delta|; \quad j = 1, \ldots, N\}.
\]

If \( p(t) = 0 \) on a sub-interval of \([A, B]\) and \( F^{-1}(i/(K + 1)) \) is not uniquely defined then we choose the smallest element from the set \( R(F^{-1}(i/(K + 1))) \) as \( t_{i,K} \). Also we define \( s_{i,K} = \text{sign}(p(t_{i,K})) \) and obtain from the representation of the continuous SLSE for AR(1) errors in Proposition 3.1 a reasonable estimator with corresponding design. To be precise, \( y_1, \ldots, y_{K+2} \) should be observed at experimental conditions \( A, t_{1,K}, t_{2,K}, \ldots, t_{K,K}, B \), respectively, and the parameter \( \theta \) has to be estimated by the following modified SLSE

\[
\hat{\theta}_{K+2} = D_{K+2} \left( P_A f(A)y_A + P_B f(B)y_B + \frac{B - A}{\kappa K} \sum_{i=1}^K s_{i,K} f(t_{i,K}) y_i \right),
\]

where

\[
D_{K+2} = \left( P_A f^2(A) + P_B f^2(B) + \frac{B - A}{\kappa K} \sum_{i=1}^K s_{i,K} f^2(t_{i,K}) \right)^{-1}.
\]

It follows from the discussion of the previous paragraph that \( \text{Var}(\hat{\theta}_{K+2}) \approx D^* \), where \( D^* \) is defined in (3.6). Similarly, the modified SLSE for AR(2) errors is defined by

\[
\hat{\theta}_{K+2} = D_{K+2} \left( Q_B f(B)y'(B) - Q_A f(A)y'(A)
+ P_A f(A)y_A + P_B f(B)y_B + \frac{B - A}{\kappa K} \sum_{i=1}^K s_{i,K} f(t_{i,K}) y(t_{i,K}) \right)
\]

(4.9)

where

\[
D_{K+2} = \left( Q_B f(B)f'(B) - Q_A f(A)f'(A) + P_A f^2(A) + P_B f^2(B) + \frac{B - A}{\kappa K} \sum_{i=1}^K s_{i,K} f^2(t_{i,K}) \right)^{-1}.
\]

Note that the expression in (4.9) contains the derivatives \( y'(A) \) and \( y'(B) \) of the observed process \( \{y(t)\}_{t \in [A, B]} \). If these derivatives are not available then we recommend to make two additional observations at the points \( A + \Delta \) and \( B - \Delta \) and to replace the derivatives by their
approximations \((y_{A+\Delta} - y_A) / \Delta\) and \((y_B - y_{B-\Delta}) / \Delta\). Thus, we replace the estimator (4.9) by the weighted least squares estimator (WLSE)

\[
\tilde{\theta}_{K+4} = (X^T W X)^{-1} X^T W Y,
\]

where \(Y = (y_A, y_{A+\Delta}, y_{t_1, K}, \ldots, y_{K, K}, y_{B-\Delta}, y_B)^T\) and the matrix \(W\) is defined by

\[
W = \text{diag}\left\{ \frac{P_A}{2} + \frac{Q_A}{\Delta}, \frac{P_A}{2} - \frac{Q_A}{\Delta}, \frac{B - A}{\kappa K}, \ldots, \frac{s_{K, K}}{\kappa K}, \frac{B - A}{\kappa K}, \frac{P_B}{2} - \frac{Q_B}{\Delta}, \frac{P_B}{2} + \frac{Q_B}{\Delta} \right\}.
\]

Note that the variance of \(\tilde{\theta}_{K+4}\) is given by \(\text{Var}(\tilde{\theta}_{K+4}) = (X^T W X)^{-1}(X^T W S W X)(X^T W X)^{-1}\).

5.3. Practical performance

Consider the regression model (2.2) with \(f(t) = 1, [A, B] = [0, 1]\) and AR(2) errors. Suppose that \(N = 101\) so that \(t_i = i/100, i = 0, 1, \ldots, N,\) are potential observation points. We also assume that the autocorrelation function \(r_k\) is of the form (4.6) with \(\lambda = 1\). We investigate the design \(\xi_{K+2}\) with \((K + 2)\) points \(0, t_{1, K}, t_{2, K}, \ldots, t_{K, K}\) and the design \(\xi_{K+4}\) with \((K + 4)\) points \(0, 0.01, t_{1, K}, t_{2, K}, \ldots, t_{K, K}, 0.99, 1\). The points \(t_{1, K}, t_{2, K}, \ldots, t_{K, K}\) are shown in the second column of Table 3. In this table we also display the variances of the WLSE \(\tilde{\theta}_{K+4}\), defined by (4.11), the LSE \(\hat{\theta}_{\text{lse}, K+2}\) based on the design \(\xi_{K+2}\) and the BLUE \(\hat{\theta}_{\text{blue}, K+2}\) and \(\hat{\theta}_{\text{blue}, K+4}\) for the designs \(\xi_{K+2}\) and \(\xi_{K+4}\), respectively. Let \(\hat{\theta}_{\text{blue}}\) denote the BLUE based on 101 observations at the points \(\{\frac{i}{100} | i = 0, \ldots, 100\}\), then we observe \(0.80158449 = \text{Var}(\hat{\theta}_{\text{blue}}) \approx D^* = 0.8\), which is in agreement with Theorem 4.1. We also observe \(\text{Var}(\hat{\theta}_{\text{blue}, K+4}) \approx \text{Var}(\hat{\theta}_{\text{blue}})\) and \(\text{Var}(\hat{\theta}_{\text{blue}, K+2}) \approx \text{Var}(\hat{\theta}_{\text{blue}})\) showing the importance of taking one additional observation at each boundary point \(A\) and \(B\). Note that the proposed estimator \(\tilde{\theta}_{K+4}\) defined in (4.11) is nearly as accurate as the BLUE \(\hat{\theta}_{\text{blue}, K+4}\) at the same points and that the LSE \(\hat{\theta}_{\text{lse}, K+2}\) is about 10 – 15% worse than the BLUE.

Table 3: The variances of the LSE, the WLSE defined by (4.11) and the BLUE for designs with \(K + 2\) and \(K + 4\) points. \(f(t) = 1, [A, B] = [0, 1]\), \(N = 101\), the autocovariance structure is given by (4.6) with \(\lambda = 1\), which yields \(D^* = 0.80000\) and \(\text{Var}(\hat{\theta}_{\text{blue}}) = 0.80158449\).

<table>
<thead>
<tr>
<th>(K)</th>
<th>(t_{1, K}, \ldots, t_{K, K})</th>
<th>(\text{Var}(\hat{\theta}_{\text{lse}, K+2}))</th>
<th>(\text{Var}(\hat{\theta}_{K+4}))</th>
<th>(\text{Var}(\hat{\theta}_{\text{blue}, K+2}))</th>
<th>(\text{Var}(\hat{\theta}_{\text{blue}, K+4}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.33, 0.67</td>
<td>0.914</td>
<td>0.80170</td>
<td>0.82663</td>
<td>0.80158714</td>
</tr>
<tr>
<td>3</td>
<td>0.25, 0.5, 0.75</td>
<td>0.921</td>
<td>0.80165</td>
<td>0.82022</td>
<td>0.80158533</td>
</tr>
<tr>
<td>4</td>
<td>0.2, 0.4, 0.6, 0.8</td>
<td>0.925</td>
<td>0.80162</td>
<td>0.81681</td>
<td>0.80158484</td>
</tr>
<tr>
<td>5</td>
<td>0.17, 0.33, 0.5, 0.67, 0.83</td>
<td>0.928</td>
<td>0.80161</td>
<td>0.81443</td>
<td>0.80158466</td>
</tr>
</tbody>
</table>

As a second example, consider the regression model (2.2) with \(f(t) = t^2, [A, B] = [0.1, 1.1]\) and AR(2) errors. Suppose that \(N = 101\) so that \(t_i = 0.1 + i/100, i = 0, 1, \ldots, N,\) are potential observation points. We also assume that the autocorrelation function \(r_j\) is of the form (4.6) with \(\lambda = 2\). We investigate the design \(\xi_{K+2}\) with \((K + 2)\) points \(0.1, t_{1, K}, t_{2, K}, \ldots, t_{K, K}, 1.1\) and the design \(\xi_{K+4}\) with \((K + 4)\) points \(0.1, 0.11, t_{1, K}, t_{2, K}, \ldots, t_{K, K}, 1.09, 1.1\). The non-trivial points
are shown in the second column of Table 4. In the other columns we display the variances of the different estimators introduced in the previous paragraph. We observe, similarly to the previous example, $0.37055791 = \text{Var}(\hat{\theta}_{\text{BLUE}}) \approx D^* = 0.36543$ which is again in line with Theorem 4.1. Note also $\text{Var}(\hat{\theta}_{\text{BLUE},K+4}) \equiv \text{Var}(\hat{\theta}_{\text{BLUE}})$ and the estimator $\hat{\theta}_{\text{BLUE},K+2}$ without the two additional observations at the boundary is not efficient. Again the proposed estimator $\tilde{\theta}_{K+4}$ is nearly as accurate as the BLUE at the same points but the LSE $\hat{\theta}_{\text{LSE},K+2}$ is dramatically worse than the BLUE.

Table 4: The variances of the LSE, the WLSE and the BLUE for designs with $K+2$ and $K+4$ points. $f(t) = t^2$, $[A, B] = [0.1, 1.1]$, $N = 101$ and the autocovariance is given by (4.6) with $\lambda = 2$, which yields $D^* = 60000/164189 \cong 0.36543$ and $\text{Var}(\hat{\theta}_{\text{BLUE}}) = 0.37055791$.

<table>
<thead>
<tr>
<th>$K$</th>
<th>$t_{1,K}, \ldots, t_{K,K}$</th>
<th>$\text{Var}(\theta_{\text{LSE},K+2})$</th>
<th>$\text{Var}(\theta_{K+4})$</th>
<th>$\text{Var}(\theta_{\text{BLUE},K+2})$</th>
<th>$\text{Var}(\theta_{\text{BLUE},K+4})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.14, 0.22</td>
<td>0.723</td>
<td>0.40218</td>
<td>0.53175</td>
<td>0.37079053</td>
</tr>
<tr>
<td>3</td>
<td>0.12, 0.17, 0.27</td>
<td>0.751</td>
<td>0.40204</td>
<td>0.52509</td>
<td>0.37072082</td>
</tr>
<tr>
<td>4</td>
<td>0.12, 0.15, 0.20, 0.30</td>
<td>0.783</td>
<td>0.40176</td>
<td>0.52089</td>
<td>0.37068565</td>
</tr>
<tr>
<td>5</td>
<td>0.12, 0.14, 0.17, 0.22, 0.33</td>
<td>0.818</td>
<td>0.40139</td>
<td>0.51689</td>
<td>0.37065785</td>
</tr>
</tbody>
</table>

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References


Näther, W., 1985b. Exact design for regression models with correlated errors. Statistics 16, 479–484.


