

# Best intention sequential designs in clinical trial studies

Valerii Fedorov  
Andrey Pepelyshev  
Luc Pronzato  
Anatoly Zhigljavsky



St. Petersburg  
June 27, 2009

Response is given by

$$y = \theta_0 + \theta_1 x + \theta_2 x^2 + \varepsilon, \quad x \in [-1, 1]$$

Our aim is to estimate  $x^* = -\frac{\theta_1}{2\theta_2}$

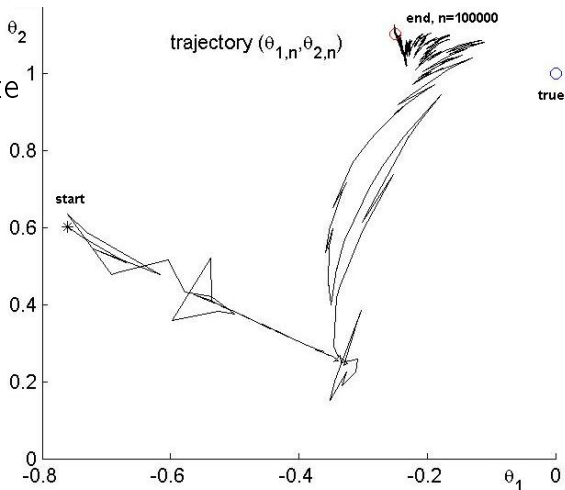
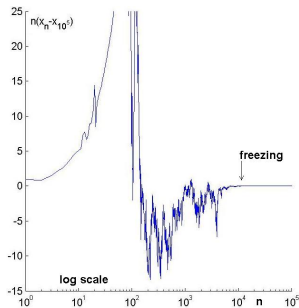
Best intention design procedure

- initial (equidistant) design  $x_1, \dots, x_k$ ,  $k$  is small
- in the loop  $n = k, k + 1, \dots$ 
  - $\theta_n = (X_n^T X_n)^{-1} X_n^T Y_n$  is LSE of  $\theta$ ,  $Y_n = (y_1, \dots, y_n)^T$
  - $x_{n+1} = -\frac{\theta_{1,n}}{2\theta_{2,n}}$  is the next design point

Trajectories for model  $\theta_0 + \theta_1 x + \theta_2 x^2$ 

$x_n \rightarrow x_0 \neq x^*$   
with rate  $\frac{1}{n}$  and freeze

$\theta_{i,n} \xrightarrow{\frac{1}{n}} \theta_{i,0} \neq \theta_i^*$



Consider two parameter model

$$y = \theta_1 x + \theta_2 x^2 + \varepsilon, \quad x \in [-1, 1]$$

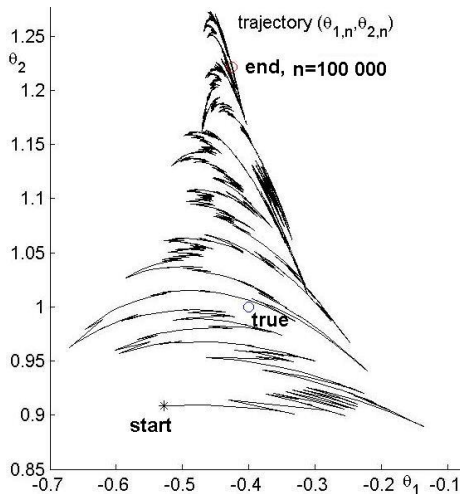
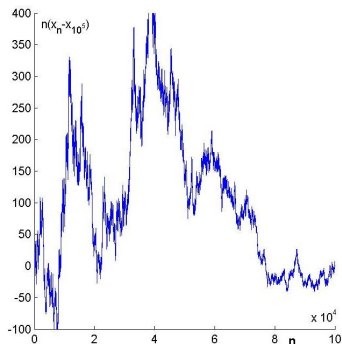
Best intention design procedure

- $x_n \rightarrow x^*$  if  $\theta_1^* = 0$
- $x_n \rightarrow x_0 \neq x^*$  if  $\theta_1^* \neq 0$

# Trajectories for model $\theta_1 x + \theta_2 x^2$

$$x_n \xrightarrow{\frac{1}{n}} x_0 \neq x^*$$

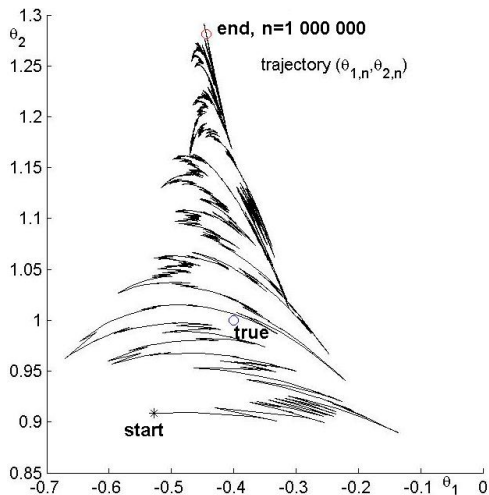
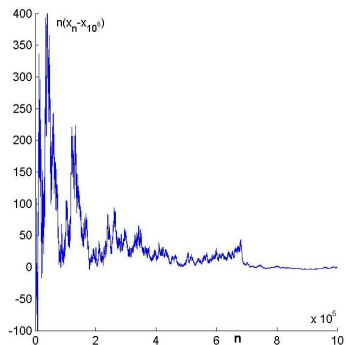
$$\theta_{i,n} \xrightarrow{\frac{1}{n}} \theta_{i,0} \neq \theta_i^*$$



# Long trajectories for model $\theta_1 x + \theta_2 x^2$

$$x_n \xrightarrow{\frac{1}{n}} x_0 \neq x^*$$

$$\theta_{i,n} \xrightarrow{\frac{1}{n}} \theta_{i,0} \neq \theta_i^*$$



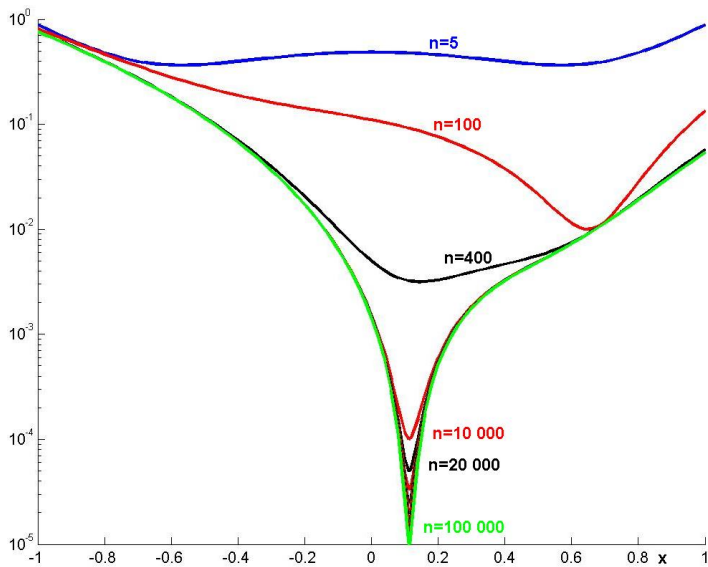
# Estimation of response

$$\eta(x, \theta) = \theta^T f(x)$$

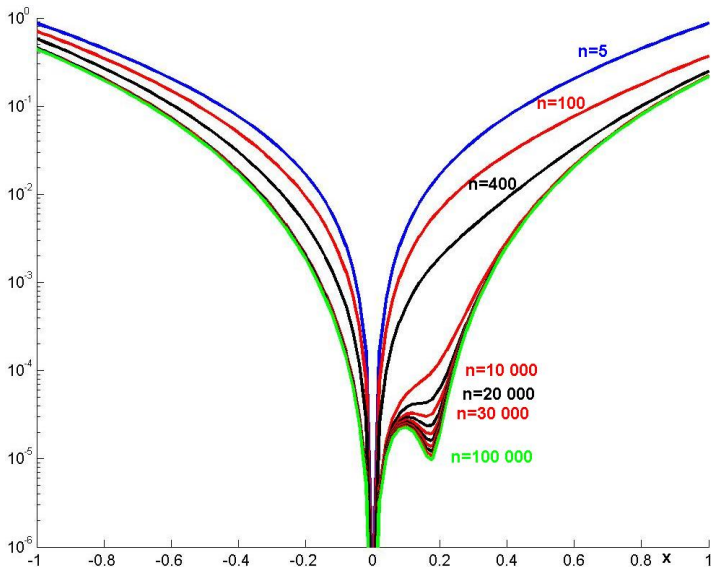
$$\text{Var}[\eta(x, \hat{\theta})] = d(x, \xi_n) = f^T(x) M^{-1}(\xi_n) f(x)$$

$$M(\xi_n) = \sum_{i=1}^n f(x_i) f^T(x_i)$$

$$\xi_n = \{x_1, \dots, x_n\}$$

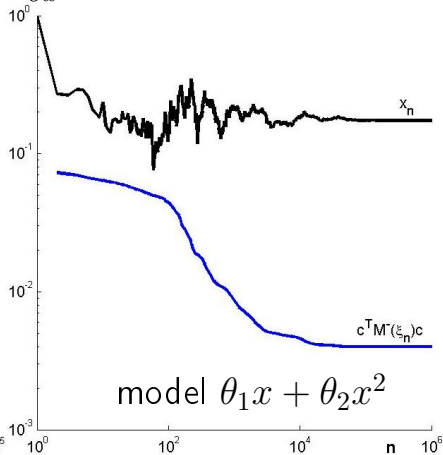
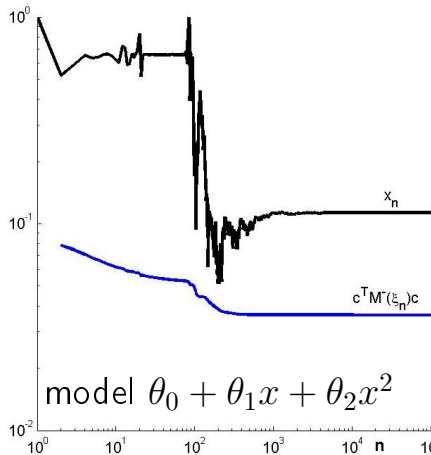
$d(x, \xi_n)$  for the model  $\theta_0 + \theta_1 x + \theta_2 x^2$ 



$d(x, \xi_n)$  for the model  $\theta_1 x + \theta_2 x^2$ 

# Variance of estimate of $x^*$

$$\text{Var}[x_n] = c^T M^{-1}(\xi_n) c, \quad c = \left. \frac{\partial f}{\partial x} \right|_{x=x^*}$$



# Recurrent formula for LSE

$M(\xi_n)$  grows linearly as  $n \rightarrow \infty$

Let  $Q_n = (M(\xi_n)/n)^{-1}$

- $x_{n+1} = -\frac{\theta_{1,n}}{2\theta_{2,n}}$  and observe  $y_{n+1}$
- $\theta_{n+1} = \theta_n + \frac{1}{n} \frac{Q_n f(x_{n+1})}{1 + f(x_{n+1})^T Q_n f(x_{n+1})} (y_{n+1} - \theta_n^T f(x_{n+1}))$
- $Q_{n+1} = Q_n + \frac{Q_n}{n} - \frac{1 + 1/n}{n} \cdot \frac{Q_n f(x_{n+1}) f^T(x_{n+1}) Q_n}{1 + f^T(x_{n+1}) Q_n f(x_{n+1})}$

# Bozzin-Zarrop approach

Model

$$y(t) = \phi^T(t)\theta^o + \varepsilon(t) = \theta_1^o u(t-1) + \theta_2^o u^2(t-1) + \varepsilon(t)$$

Stochastic approximation,  $\gamma(t)$  behaves like  $1/t$

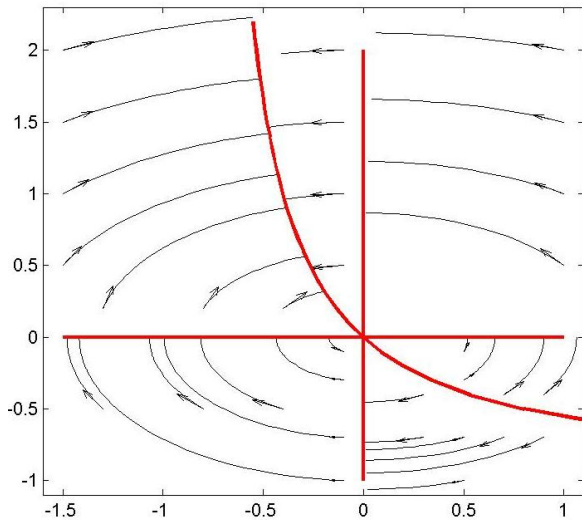
$$\theta(t) = \theta(t-1) + \gamma(t)\phi(t-1)(y(t) - \phi^T(t-1)\theta(t-1))$$

Associated differential equation

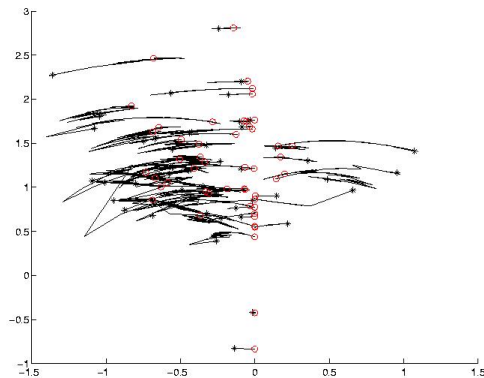
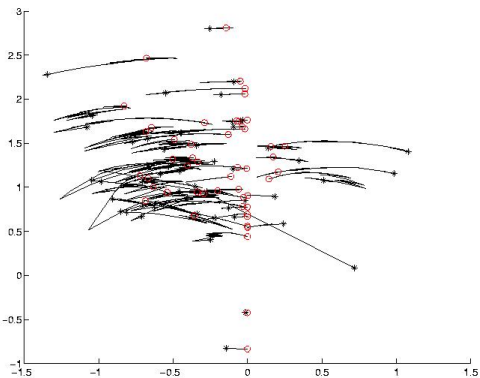
$$\frac{d}{d\tau}\theta_D(\tau) = G(\theta_D(\tau))(\theta^o - \theta_D(\tau))$$

$$G(\theta) = \mathbb{E}(\phi(t)\phi^T(t)) = \begin{pmatrix} u^2 & u^3 \\ u^3 & u^4 \end{pmatrix}$$

# Trajectories of differential equation



# 50 trajectories of LSE (left) and SA (right)



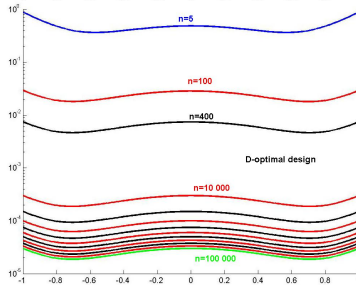
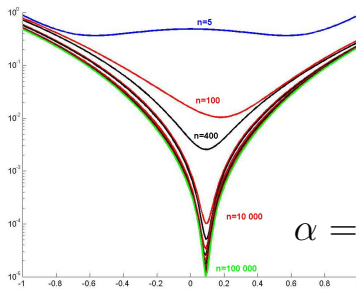
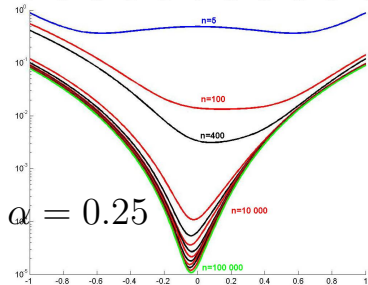
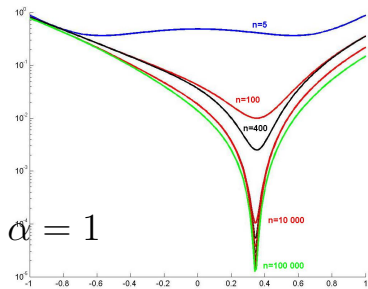
# How to modify the procedure to improve

- $D$ -optimal design  $\{-1, 0, 1\}$ ,  
put points at boundary points for large  $n$ ,  
i.e. try doses with low efficacy or high toxicity
- control the rate of convergence

$$\tilde{x}_k = \begin{cases} x_k & |x_k - \tilde{x}_{k-1}| \geq \frac{1}{k^\alpha} \\ x_k - \frac{1}{k^\alpha} & \tilde{x}_{k-1} - \frac{1}{k^\alpha} < x_k < \tilde{x}_{k-1} \\ x_k + \frac{1}{k^\alpha} & \tilde{x}_{k-1} < x_k < \tilde{x}_{k-1} + \frac{1}{k^\alpha} \end{cases}$$

$$\tilde{\xi}_n = \{\tilde{x}_1, \dots, \tilde{x}_n\}$$

consistent if  $\alpha < 0.25$

$$d(x, \tilde{\xi}_n) \text{ for the model } \theta_0 + \theta_1 x + \theta_2 x^2$$




$c^T M^{-1}(\tilde{\xi}_n) c$  for the model  $\theta_0 + \theta_1 x + \theta_2 x^2$ 
