

# Confidence sets for optimal factor levels of a response surface

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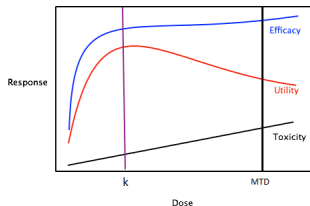


# Outline

- 1 Introduction
- 2 Our method
- 3 Extensions to other models
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Dose response for efficacy and safety.

- Low doses, small efficacy; High doses, safety problem.
- CUI combines efficacy and safety into one response function.
- CUI is almost always unimodal.

## Model specification

$$Y = f(\mathbf{x}, \boldsymbol{\theta}) + \epsilon$$

- $\epsilon \sim N(0, \sigma^2)$
- $f(\mathbf{x}, \boldsymbol{\theta}) = \mathbf{z}(\mathbf{x})^T \boldsymbol{\theta}$
- $\mathbf{x} = (x_1, \dots, x_q)^T$ ,  $\boldsymbol{\theta} = (\theta_1, \dots, \theta_p)^T$
- a constraint covariate region  $\chi$
- $\mathbf{k} = \mathbf{k}(\boldsymbol{\theta})$  is a maximum point of  $f(\mathbf{x}, \boldsymbol{\theta})$  in  $\chi$

## Problem

Suppose  $(Y_1, \mathbf{x}_1), (Y_2, \mathbf{x}_2), \dots, (Y_n, \mathbf{x}_n)$  are  $n$  observations, we want to construct a  $(1 - \alpha)$  level confidence set for  $\mathbf{k}$ .

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## Method given by Rao (1973)

The  $(1 - \alpha)$  conservative confidence set for  $\mathbf{k}$  is given by

$$\mathbf{C}_R(\mathbf{Y}) = \{\mathbf{k}(\boldsymbol{\theta}) \in \chi : \boldsymbol{\theta} \in C_{\boldsymbol{\theta}}\}$$

where  $C_{\boldsymbol{\theta}}$  is a  $(1 - \alpha)$  level confidence set for  $\boldsymbol{\theta}$ .

A choice of  $C_{\boldsymbol{\theta}}$

$$C_{\boldsymbol{\theta}} = \{\boldsymbol{\beta} : (\hat{\boldsymbol{\theta}} - \boldsymbol{\beta})^T (\mathbf{X}^T \mathbf{X}) (\hat{\boldsymbol{\theta}} - \boldsymbol{\beta}) \leq p \hat{\sigma}^2 f_{p, \nu}^{\alpha}\}.$$

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## Theorem (Neyman, 1937)

Suppose random observation  $\mathbf{Y}$  has distribution  $h(\mathbf{y}; \gamma)$ , where  $\gamma$  is the unknown parameter. Let  $\mathbb{B}$  and  $\Omega$  be the parameter space and sample space, respectively. For each  $\gamma_0 \in \mathbb{B}$ , let  $A(\gamma_0) \subset \Omega$  be the acceptance set of a size  $\alpha$  test of  $H_0 : \gamma = \gamma_0$ . For each  $\mathbf{Y} \in \Omega$ , define a set  $\mathbf{C}(\mathbf{Y}) \subset \mathbb{B}$  by  $\mathbf{C}(\mathbf{Y}) = \{ \gamma_0 : \mathbf{Y} \in A(\gamma_0) \}$ . Then the random set  $\mathbf{C}(\mathbf{Y})$  is a  $(1 - \alpha)$  level confidence set for  $\gamma$ .

A  $(1 - \alpha)$  level acceptance set for testing  $H_0 : \mathbf{k} = \mathbf{k}_0$

$$A(\mathbf{k}_0) = \{\mathbf{Y} : f(\mathbf{k}_0, \hat{\boldsymbol{\theta}}) - f(\mathbf{x}, \hat{\boldsymbol{\theta}}) \geq -c(\mathbf{k}_0) \sqrt{v(\mathbf{k}_0, \mathbf{x}, \hat{\boldsymbol{\theta}})}, \forall \mathbf{x} \in \mathcal{X}\},$$

where  $v(\mathbf{k}_0, \mathbf{x}, \hat{\boldsymbol{\theta}})$  is the estimated variance of  $f(\mathbf{k}_0, \hat{\boldsymbol{\theta}}) - f(\mathbf{x}, \hat{\boldsymbol{\theta}})$  and  $c(\mathbf{k}_0)$  is chosen such that

$$P\{\mathbf{Y} \in A(\mathbf{k}_0)\} = 1 - \alpha.$$

Computation of  $c(\mathbf{k}_0)$

- Analytical method (for univariate simple and quadratic linear functions)
- Simulation method

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A  $(1 - \alpha)$  level confidence set for  $k$

$$\begin{aligned}\mathbf{C}_E(\mathbf{Y}) &= \{\mathbf{k}_0 \in \chi : \mathbf{Y} \in A(\mathbf{k}_0)\} \\ &= \{\mathbf{k}_0 \in \chi : f(\mathbf{k}_0, \hat{\boldsymbol{\theta}}) - f(\mathbf{x}, \hat{\boldsymbol{\theta}}) \geq -c(\mathbf{k}_0) \sqrt{v(\mathbf{k}_0, \mathbf{x}, \hat{\boldsymbol{\theta}})}, \forall \mathbf{x} \in \chi\}.\end{aligned}$$

## A by-product

Substitute  $c_0 = \sqrt{pF_{p,\nu}^\alpha}$  for  $c(\mathbf{k}_0)$ , then we get a conservative solution

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## The function of set $\mathbf{C}_0$

- Conservative confidence set for  $\mathbf{k}$ , i.e., confidence level is larger than  $(1 - \alpha)$ .
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# GLMs

## Confidence set for a maximum point $k$ of $E(Y)$

Suppose we have the generalized linear model

$$g[E(Y)] = f(\mathbf{x}, \boldsymbol{\theta}),$$

where the link function  $g$  is strictly (increasing) monotone and differentiable.

Convert the GLMs problem to LMs problem

$$\operatorname{argmax}_{\mathbf{x} \in \mathcal{X}} E(Y) \iff \operatorname{argmax}_{\mathbf{x} \in \mathcal{X}} f(\mathbf{x}, \boldsymbol{\theta})$$

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# Cox-Proportional hazard model

Confidence set for a minimum point of  $h(t, \mathbf{x})$

Suppose we have the proportional hazard model

$$h(t, \mathbf{x}) = \lambda(t) \exp(f(\mathbf{x}, \boldsymbol{\theta})).$$

The interest is in constructing a confidence set for a minimum point of  $h(t, \mathbf{x})$ .

Convert to LM problem

$$\operatorname{argmin}_{\mathbf{x} \in \mathcal{X}} h(t, \mathbf{x}) \iff \operatorname{argmin}_{\mathbf{x} \in \mathcal{X}} f(\mathbf{x}, \boldsymbol{\theta}) \iff \operatorname{argmax}_{\mathbf{x} \in \mathcal{X}} f(\mathbf{x}, -\boldsymbol{\theta})$$

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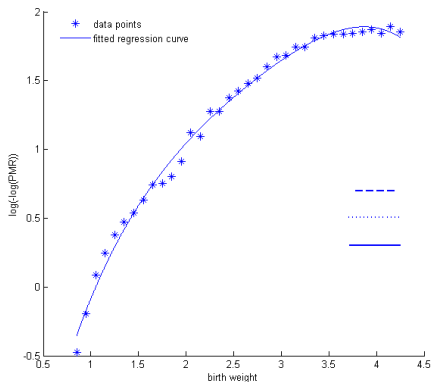
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## Example 1

The transformed perinatal mortality rate (PMR)  
 $Y = \log(-\log(PMR))$  and birth weight (BW)  $x = BW$  of white infants at 35 different levels of  $x$  studied by Selvin (1998).

**Table:** Perinatal mortality rate data for white infants

| x    | Y       | x    | Y      | x    | Y      | x    | Y      | x    | Y      |
|------|---------|------|--------|------|--------|------|--------|------|--------|
| 0.85 | -0.4761 | 1.55 | 0.6340 | 2.25 | 1.2771 | 2.95 | 1.6751 | 3.65 | 1.8351 |
| 0.95 | -0.1950 | 1.65 | 0.7391 | 2.35 | 1.2771 | 3.05 | 1.6830 | 3.75 | 1.8437 |
| 1.05 | 0.0849  | 1.75 | 0.7551 | 2.45 | 1.3731 | 3.15 | 1.7429 | 3.85 | 1.8527 |
| 1.15 | 0.2464  | 1.85 | 0.8042 | 2.55 | 1.4241 | 3.25 | 1.7429 | 3.95 | 1.8722 |
| 1.25 | 0.3791  | 1.95 | 0.9128 | 2.65 | 1.4775 | 3.35 | 1.8114 | 4.05 | 1.8437 |
| 1.35 | 0.4715  | 2.05 | 1.1204 | 2.75 | 1.5165 | 3.45 | 1.8269 | 4.15 | 1.8939 |
| 1.45 | 0.5364  | 2.15 | 1.0919 | 2.85 | 1.6018 | 3.55 | 1.8351 | 4.25 | 1.8527 |



The three 95% confidence sets:

$$\mathbf{C}_E(\mathbf{Y}) = [3.75, 4.21],$$

$$\mathbf{C}_0(\mathbf{Y}) = [3.72, 4.25],$$

$$\mathbf{C}_c(\mathbf{Y}) = [3.72, 4.25].$$

## Example 2

### 5FU+VM26 combination experiment (Stablein et al., 1983)

| Treatment levels |             | Days of survival        |
|------------------|-------------|-------------------------|
| 5FU(mg/kg)       | VM26(mg/kg) |                         |
| 0.0              | 0.00        | 8,9(2),10(5)            |
| 0.0              | 9.71        | 10,13(5),14(2)          |
| 0.0              | 19.40       | 8,10,13,14(4),15        |
| 0.0              | 25.90       | 9,14(4),15(3)           |
| 35.6             | 9.71        | 13,14(3),15(3),17       |
| 48.5             | 4.85        | 9,13(2),14(3),15(2)     |
| 48.5             | 19.40       | 14(2),15(2),16(4)       |
| 97.1             | 0.00        | 8(2),10,11,12(2),14,16  |
| 97.1             | 3.56        | 8,9(2),11(2),13(2),16   |
| 97.1             | 9.71        | 8,10,11,16(2),17(2),18  |
| 97.1             | 25.9        | 16(3),17,18(3),19       |
| 194.0            | 0.00        | 10, 13(6),14            |
| 194.0            | 4.85        | 11(2),14(3),16,17       |
| 194.0            | 19.40       | 8,14,16,20(4),21        |
| 259.0            | 0.00        | 9,11,12(3),13(3)        |
| 259.0            | 9.71        | 16(2),17,18(2),19(2),20 |

The number in the parentheses indicates the number of animals dead on that day.



## Model fitting

- $x_1 = (5FU - 130)/130$ ,  $x_2 = (VM26 - 13)/13$
- $h(t, \mathbf{x}) = \lambda(t) \exp(f(\mathbf{x}, \boldsymbol{\theta}))$
- $f(\mathbf{x}, \boldsymbol{\theta}) = \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_2^2 + \theta_5 x_1 x_2$
- $\chi = \{x_1, x_2 : x_1^2 + x_2^2 = 1\}$

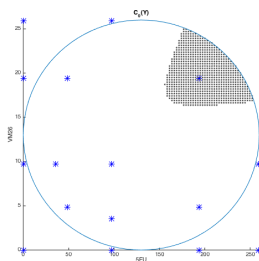


Figure: Confidence set  
 $C_0(Y)$

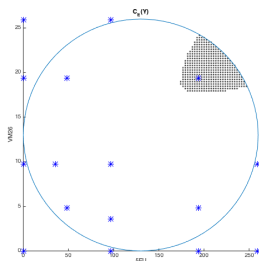


Figure: Confidence set  
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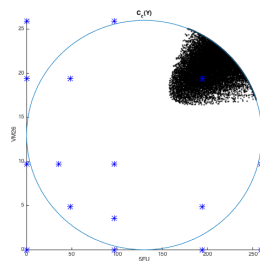


Figure: Confidence set  
 $C_R(Y)$

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## Conclusion

The confidence set  $\mathbf{C}_E(\mathbf{Y})$  is always smaller than  $\mathbf{C}_0(\mathbf{Y})$  and  $\mathbf{C}_R(\mathbf{Y})$ . Hence it is recommended to always use the confidence set  $\mathbf{C}_E(\mathbf{Y})$ .

## Future works

- Construction of a confidence set for the optimal factor levels of a function of a more general form.
- Construction of a confidence set by inverting acceptance sets in different forms, such as

$$A(\mathbf{k}_0) = \left\{ \mathbf{Y} : f(\mathbf{k}_0, \hat{\boldsymbol{\theta}}) - f(\mathbf{x}, \hat{\boldsymbol{\theta}}) \geq -c(\mathbf{k}_0)\hat{\sigma}, \forall \mathbf{x} \in \chi \right\}.$$

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*Thanks!*

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