

Design of experiments

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Session 1

Introduction

- Why experimental design

Factorial design

- Design matrix
- Model equation = coefficients
- Residual
- Response contour

Session 2

Factorial design

- Research problem
- Design matrix
- Model equation = coefficients
- Degrees of freedom
- Predicted response
- Residual
- ANOVA
- R^2
- Response contour

Session 3

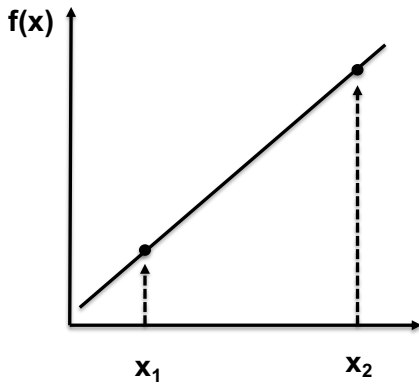
Composite designs

Second order models

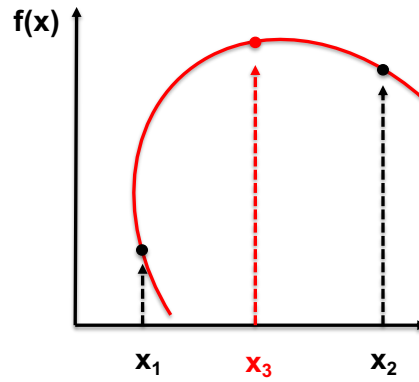
Stationary points

Higher order models

First order



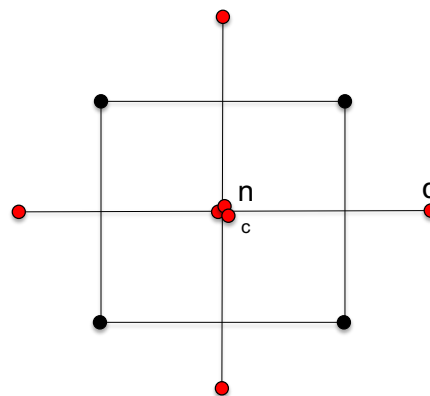
Second order



Optimization designs

Second order models through

- Center points
- Axial points
- Different designs



Central composite designs

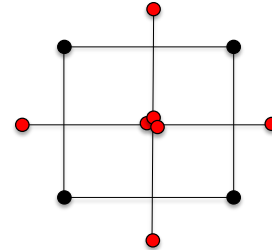
Center points

- Pure error (lack of fit)
- Curvature

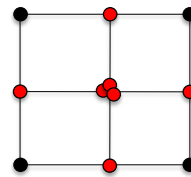
Axial points

- Quadratic terms

Spherical design
 $\alpha > 1$



Cuboidal design
 $\alpha = 1$



Some alternatives

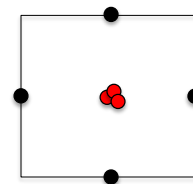
Center points

- Pure error (lack of fit)
- Curvature

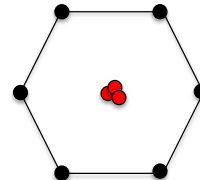
Axial points

- Quadratic terms

Box Behnken design



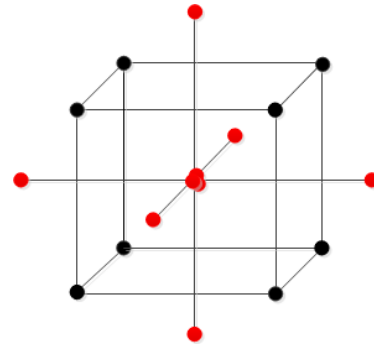
Doehlert design



Optimization designs

Things to consider when choosing a design

- Pure error (lack of fit)
- Estimated error distribution
- Area of operability
- Control over factor levels



Models

Factorial designs

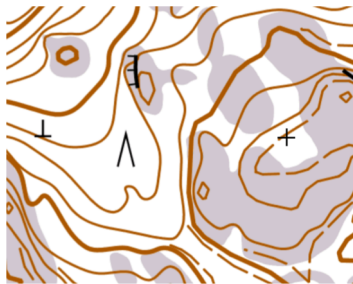
- Main effects
- Main effects + interactions

Optimization designs

- Main effects + interactions + quadratic terms
- $y = \beta_0 + \beta_i x_i + \beta_j x_j + \beta_{ij} x_i x_j + \dots + \beta_{jj} x_j^2 + \varepsilon$

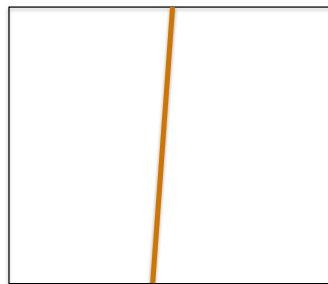
Models

Complicated vs. simple function?



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vs.



→ Start far enough to create variation, but close enough to use a simple function

Design matrix

With two factors

Factorial
Axial
Center points

N:o	x ₁	x ₂	x ₁₂	x ₁₁	x ₂₂
1	-1	-1	1		1
2	1	-1	-1		1
3	-1	1	-1		1
4	1	1	1		1
5	-α	0	0		0
6	α	0	0		0
7	0	-α	0		α ²
8	0	α	0		α ²
9	0	0	0		0
10	0	0	0		0
11	0	0	0		0

Research problem

A central composite design was performed for a tire tread compound and tire abrasion index was measured as a response

- Two factors x_1 and x_2
- Axial distance 1.633
- N:o of center points 4

Variable	Variable levels				
x_1	-1.633	-1	0	1	1.633
x_2	-1.633	-1	0	1	1.633

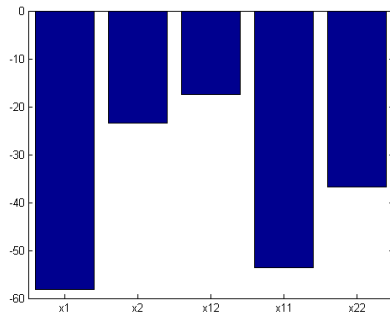
Myers et al., Response Surface Methodology, 3rd ed., 2009, 275.

Design matrix

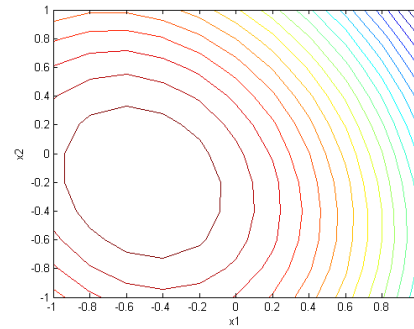
	N:o	x_1	x_2	x_{12}	x_{11}	x_{22}	y
Factorial	1	-1	-1	1	1	1	270
	2	1	-1	-1	1	1	270
	3	-1	1	-1	1	1	310
	4	1	1	1	1	1	240
Axial	5	-1.633	0	0	2.667	0	550
	6	1.633	0	0	2.667	0	260
	7	0	-1.633	0	0	2.667	520
	8	0	1.633	0	0	2.667	380
Center points	9	0	0	0	0	0	520
	10	0	0	0	0	0	290
	11	0	0	0	0	0	580
	12	0	0	0	0	0	590

Model

Unrefined coefficients

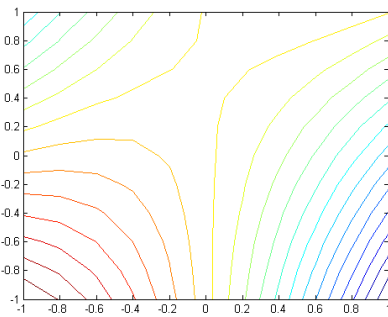


Contour

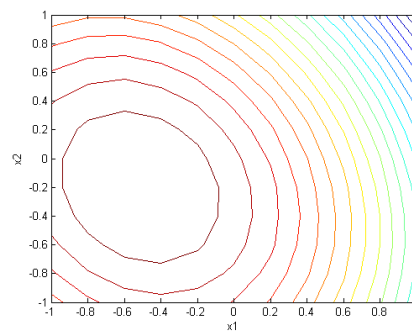


Quadratic models

Can show stationary points



Saddle point



Maximum/minimum

Quadratic models

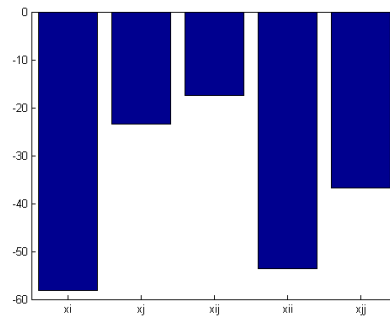
Stationary point can be described

Quadratic regression equation

$$y = \beta_0 + \beta_i x_i + \beta_j x_j + \beta_{ij} x_i x_j + \dots + \beta_{jj} x_j^2 + \varepsilon$$

Derivation $\frac{\partial \hat{y}}{\partial x_i} = \frac{\partial \hat{y}}{\partial x_j} = 0$ results in

$$\left. \begin{aligned} \beta_i + \beta_{ij} x_j + 2\beta_{ii} x_i &= 0 \\ \beta_j + \beta_{ij} x_i + 2\beta_{jj} x_j &= 0 \end{aligned} \right\} \begin{bmatrix} x_i & x_j \end{bmatrix}$$



Quadratic models

For determining a stationary point

$\hat{y} = b_0 + \mathbf{x}'\mathbf{b} + \mathbf{x}'\mathbf{B}\mathbf{x}$ where

$$\mathbf{x}' = [x_1 \quad x_2 \quad \dots \quad x_k], \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_k \end{bmatrix}, \quad \text{and } \mathbf{B} = \begin{bmatrix} b_{11} & b_{12}/2 & \dots & b_{1k}/2 \\ & b_{22} & \dots & b_{2k}/2 \\ & & \ddots & \vdots \\ \text{sym.} & & & b_{kk} \end{bmatrix}$$

→ location and character

Quadratic models

Stationary point location

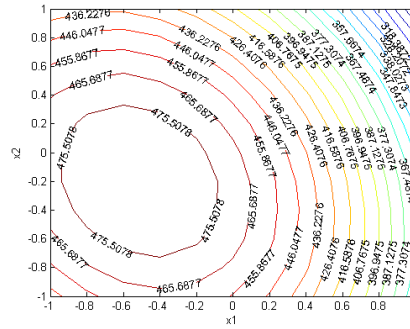
$$\frac{\partial \hat{y}}{\partial \mathbf{x}} = \mathbf{b} + 2\mathbf{B}\mathbf{x} = 0$$

$$\mathbf{x}_s = -\frac{1}{2}\mathbf{B}^{-1}\mathbf{b}$$

From the previous example

$$\mathbf{x}_s = \begin{bmatrix} x_1 & x_2 \end{bmatrix} = \begin{bmatrix} -0.5 & -0.2 \end{bmatrix}$$

$$\hat{y}_s = 485.8$$



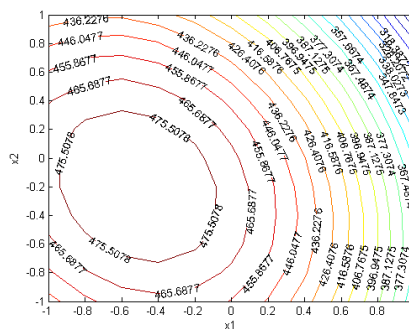
Quadratic models

Stationary point character

$$\mathbf{B} = \begin{bmatrix} b_{11} & b_{12}/2 & \dots & b_{1k}/2 \\ & b_{22} & \dots & b_{2k}/2 \\ & & \ddots & \vdots \\ sym. & & & b_{kk} \end{bmatrix}$$

Eigenvalues ($\lambda_1, \lambda_2, \dots, \lambda_k$)

- all $< 0 \rightarrow$ maximum
- all $> 0 \rightarrow$ minimum
- mixed in sign \rightarrow saddle point



$$\begin{cases} \lambda_1 = -57.3 \\ \lambda_2 = -33.0 \end{cases}$$

Research problem

A researcher wanted to maximize the yield of carbohydrates during an extraction process. She performed a total of 17 experiments based on a central composite design ($\alpha = 1$) with three variables and three center points. Determine a regression model and use it to optimize yield.

Variable	min	max
Temp	150	190
Time	30	180
L/S ratio	4	6

Session 3

Composite designs

Second order models

Stationary points

Nomenclature

Center point

Axial point / star point

Stationary point

Saddle point

Minimum

Maximum