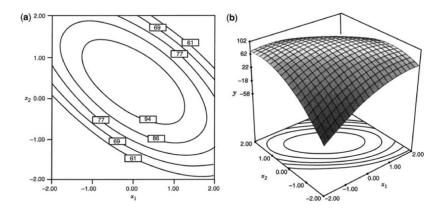
# Response Surface Methodology: Optimizing Second-Order Models

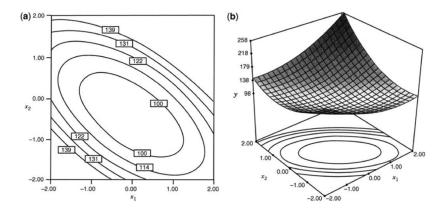
BIOE 498/598 PJ

Spring 2022

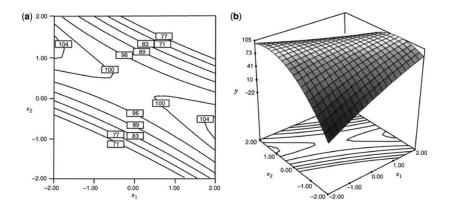
### Second-order response surfaces: Maximum



### Second-order response surfaces: Minimum



### Second-order response surfaces: Saddle Point



## Finding the response stationary point

The general second-order linear model is

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{j=1}^k \sum_{i=1}^{j-1} \beta_{ij} x_i x_j.$$

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We can rewrite this using matrix notation:

$$y = b_0 + \mathbf{x}^\mathsf{T} \mathbf{b} + \mathbf{x}^\mathsf{T} \mathbf{B} \mathbf{x}$$

$$b_0 = \beta_0, \quad \mathbf{b} = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_k \end{pmatrix}, \quad \mathbf{B} = \begin{pmatrix} \beta_{11} & \beta_{12}/2 & \cdots & \beta_{1k}/2 \\ & \beta_{22} & \cdots & \beta_{2k}/2 \\ & & \ddots & \vdots \\ \text{sym} & & & \beta kk \end{pmatrix}$$

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$$y = 3 - 0.3x_1 + x_2 + 1.2x_1^2 - 0.4x_1x_2$$
  
$$b_0 = 3, \quad \mathbf{b} = \begin{pmatrix} -0.3\\1 \end{pmatrix}, \quad \mathbf{B} = \begin{pmatrix} 1.2 & -0.2\\-0.2 & 0 \end{pmatrix}$$

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Solving for where the derivative equals zero:

$$\mathbf{b} + 2\mathbf{B}\mathbf{x}_s = \mathbf{0} \Rightarrow \mathbf{x}_s = -\frac{1}{2}\mathbf{B}^{-1}\mathbf{b}$$

What is the response at the stationary point?

$$y_s = b_0 + \mathbf{x}_s^{\mathsf{T}} \mathbf{b} + \mathbf{x}_s^{\mathsf{T}} \mathbf{B} \mathbf{x}_s$$
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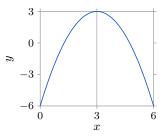
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Imagine a downward facing parabola

$$y = 3 - (x - 3)^2$$

The argmax is  $x_s = 3$  with response

$$y_s = 3 - (3 - 3)^2$$
  
= 3 - 0<sup>2</sup>.



# Chemical Process Example (Myers 2016)

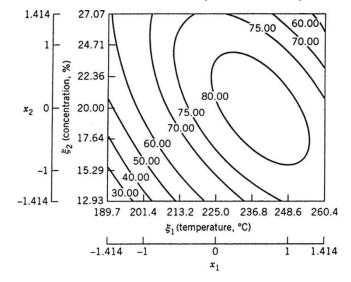
Observation	А		В		
	Temperature (°C) $\xi_1$	Conc. (%) $\xi_2$	$x_1$	<i>x</i> <sub>2</sub>	у
1	200	15	-1	-1	43
2	250	15	1	-1	78
3	200	25	-1	1	69
4	250	25	1	1	73
5	189.65	20	-1.414	0	48
6	260.35	20	1.414	0	76
7	225	12.93	0	-1.414	65
8	225	27.07	0	1.414	74
9	225	20	0	0	76
10	225	20	0	0	79
11	225	20	0	0	83
12	225	20	0	0	81

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 $y = 79.75 + 10.18x_1 + 4.22x_2 - 8.50x_1^2 - 5.25x_2^2 - 7.75x_1x_2$ 

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$$b_0 = 79.75, \quad \mathbf{b} = \begin{pmatrix} 10.12\\ 4.22 \end{pmatrix}, \quad \mathbf{B} = \begin{pmatrix} -8.50 & -3.875\\ -3.875 & -5.25 \end{pmatrix}$$

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=  $-\frac{1}{2} \begin{pmatrix} -0.1773 & 0.1309 \\ 0.1309 & -0.2871 \end{pmatrix} \begin{pmatrix} 10.12 \\ 4.22 \end{pmatrix}$   
=  $\begin{pmatrix} 0.6264 \\ -0.0604 \end{pmatrix}$ 

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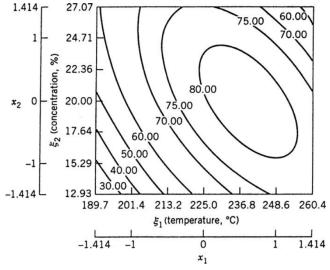
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$$\label{eq:constraint} \begin{split} \text{Temperature} &= 225 + 25 x_{1,s} = 225 + 25 (0.6264) = 240^\circ \text{C} \\ \text{Concentration} &= 20 + 5 x_{2,s} = 20 + 5 (-0.0604) = 19.7\% \end{split}$$

Visual confirmation of stationary point



Temperature =  $240^{\circ}$ C

Concentration = 19.7%

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  - ▶ All  $\lambda_i < 0 \rightarrow \text{maximum}$
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  - Indeterminate signs  $\rightarrow$  saddle point
- ▶ In the previous example,  $\lambda_1 = -11.0769$  and  $\lambda_2 = -2.6731$ , so  $\mathbf{x}_s$  is an argmax.

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The response anywhere can be defined in terms of the **canonical vector**  ${\bf w}$  an a diagonal matrix of eigenvalues  ${\bf \Lambda}$ ,

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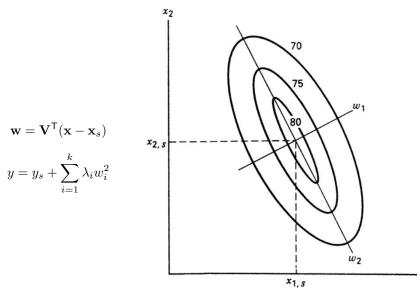
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or, more simply,

$$y = y_s + \sum_{i=1}^k \lambda_i w_i^2$$



x1