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Least squares

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Courtesy: Fred Pighin and J.P. Lewis, SIGGRAPH 2007 Course

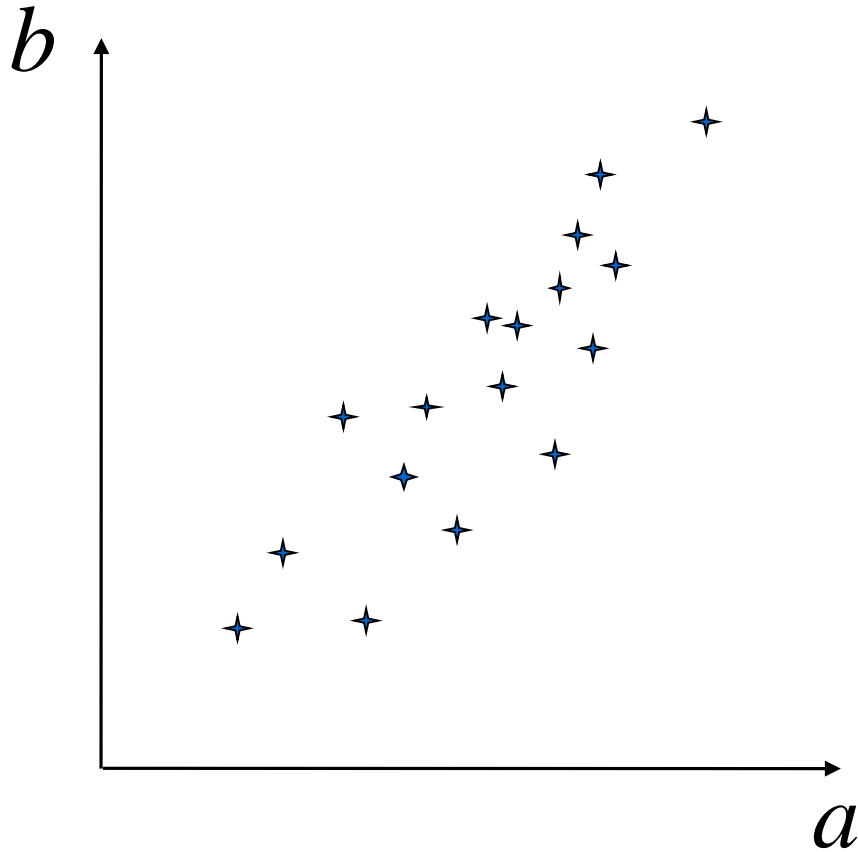
Outline

- Linear regression
- Geometry of least-squares
- Discussion of the Gauss-Markov theorem

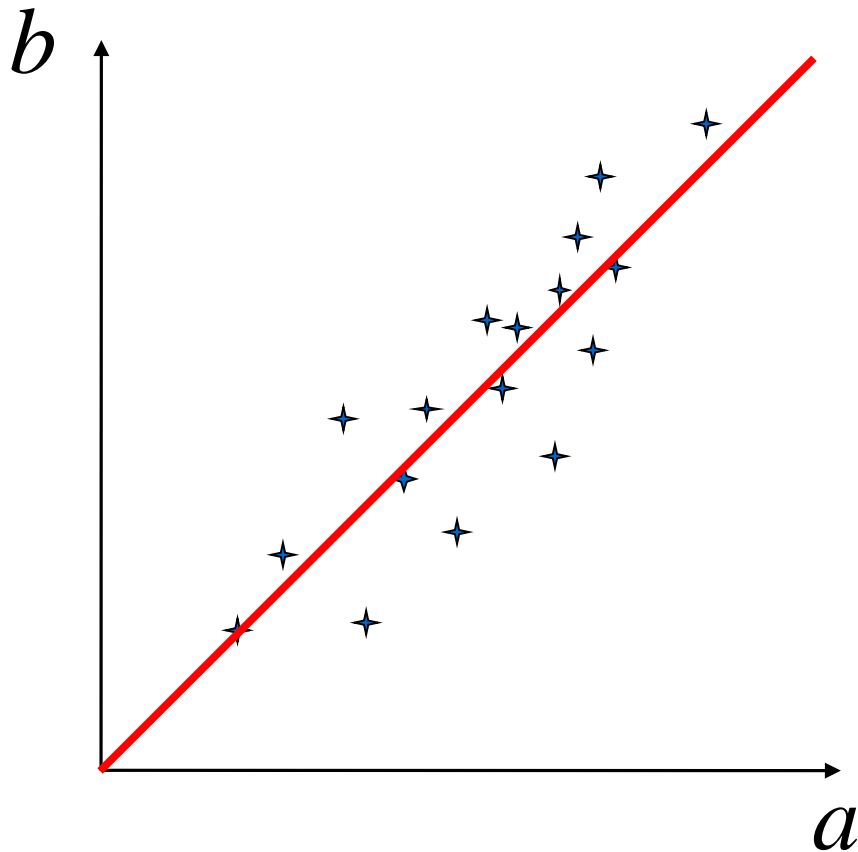
One-dimensional regression



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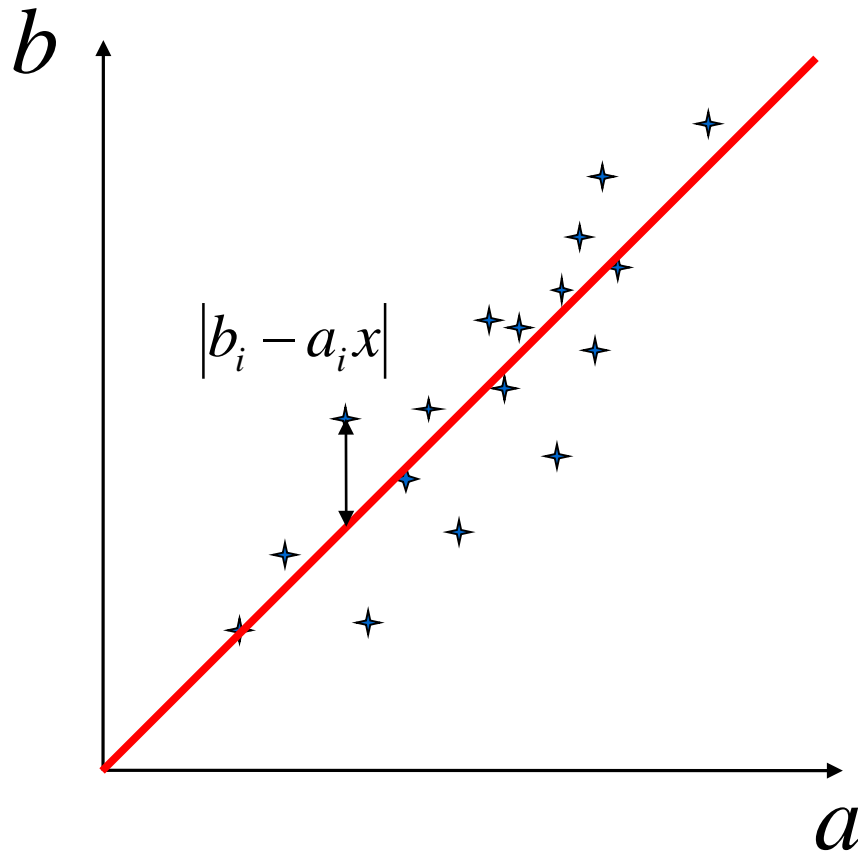
One-dimensional regression



Find a line that represent the
"best" linear relationship:

$$b = ax$$

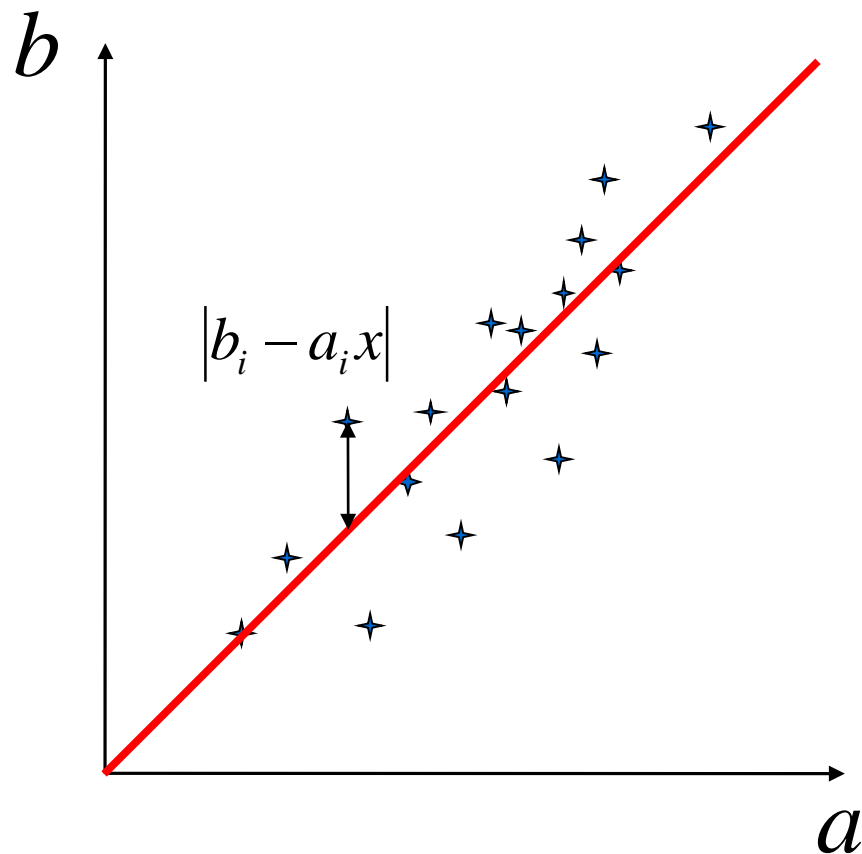
One-dimensional regression



- Problem: the data does not go through a line

$$e_i = b_i - a_i x$$

One-dimensional regression



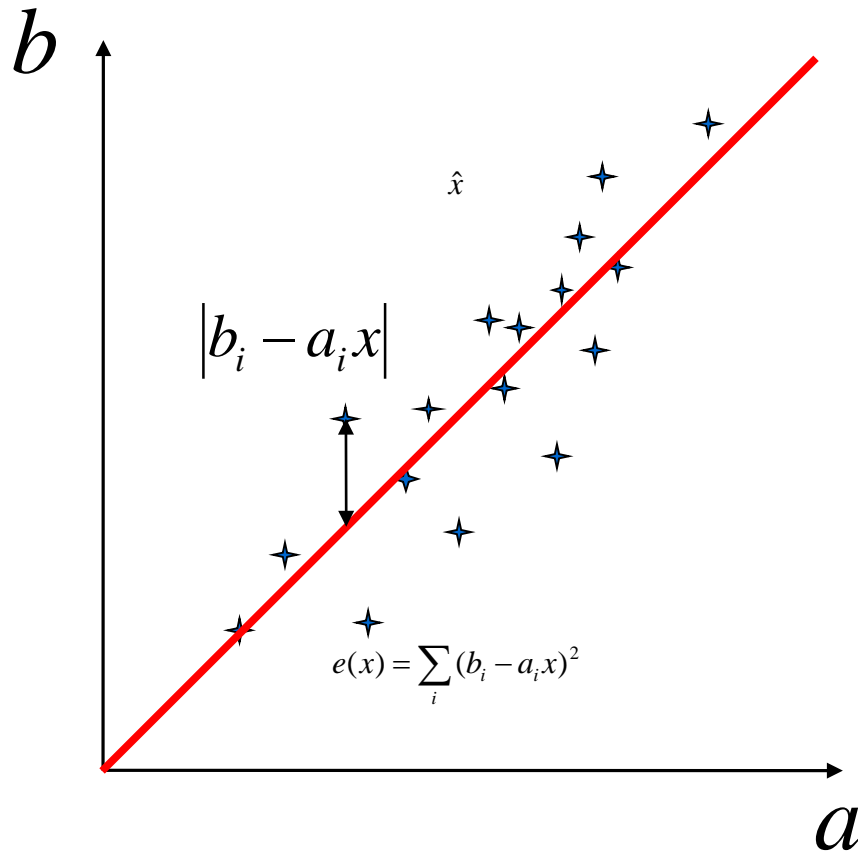
- Problem: the data does not go through a line

$$e_i = b_i - a_i x$$

- Find the line that minimizes the sum:

$$\sum_i (b_i - a_i x)^2$$

One-dimensional regression



- Problem: the data does not go through a line

$$e_i = b_i - a_i x$$

- Find the line that minimizes the sum:

$$\sum_i (b_i - a_i x)^2$$

- We are looking for that minimizes

Least squares example



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There are 3 mountains u , y , z that from one site have been measured as 2474 m, 3882 m, and 4834 m. But from u , y looks 1422 m taller and the z looks 2354 m taller, and from y , z looks 950 m taller. Set up the overdetermined system.

$$A\mathbf{x} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ -1 & 1 & 0 \\ -1 & 0 & 1 \\ 0 & -1 & 1 \end{bmatrix} \begin{bmatrix} u \\ y \\ z \end{bmatrix} \sim \begin{bmatrix} 2474 \\ 3882 \\ 4834 \\ 1422 \\ 2354 \\ 950 \end{bmatrix} = \mathbf{b}$$

Want to minimize $\|A\mathbf{x} - \mathbf{b}\|_2$

Approaches to solve $Ax \approx b$

- Normal equations-quick and dirty
- QR- standard in libraries uses orthogonal decomposition
- SVD - decomposition which also gives indication how linear independent columns are
- Conjugate gradient - no decompositions, good for large sparse problems

Matrix notation

Using the following notations

$$\mathbf{a} = \begin{bmatrix} a_1 \\ \vdots \\ a_n \end{bmatrix} \quad \text{and} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ \vdots \\ b_n \end{bmatrix}$$

we can rewrite the error function using linear algebra as:

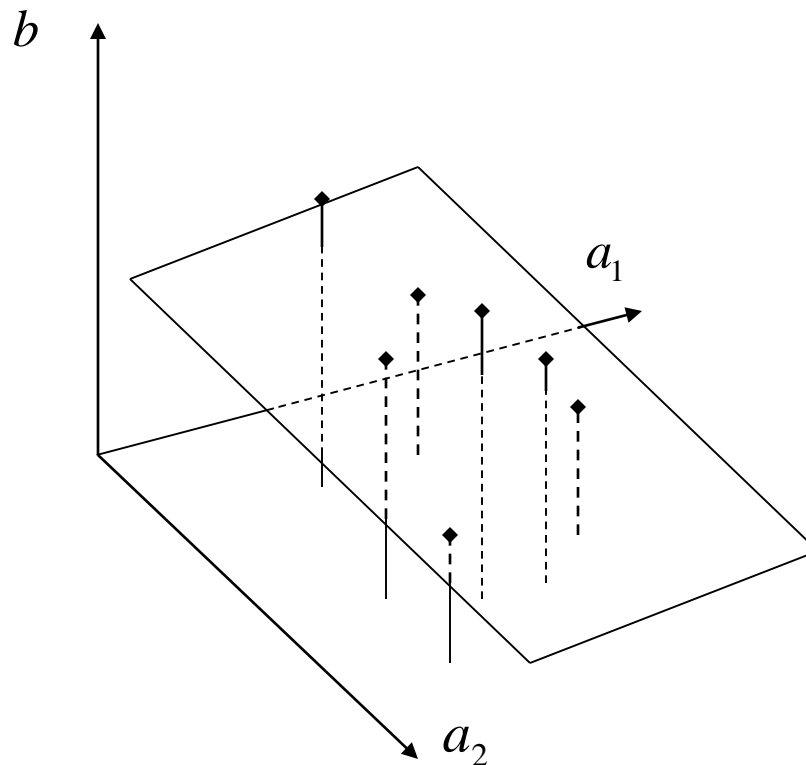
$$\begin{aligned} e(x) &= \sum_i (b_i - a_i x)^2 \\ &= (\mathbf{b} - x\mathbf{a})^T (\mathbf{b} - x\mathbf{a}) \end{aligned}$$

$$e(x) = \|\mathbf{b} - x\mathbf{a}\|^2$$

Multidimensional linear regression

Using a model with m parameters

$$b = a_1x_1 + \dots + a_mx_m = \sum_j a_jx_j$$



Multidimensional linear regression

Using a model with m parameters

$$b = a_1x_1 + \dots + a_mx_m = \sum_j a_jx_j$$

and n measurements

$$e(\mathbf{x}) = \sum_{i=1}^n (b_i - \sum_{j=1}^m a_{i,j}x_j)^2$$

$$= \left\| \mathbf{b} - \begin{bmatrix} \sum_{j=1}^m a_{i,j}x_j \end{bmatrix} \right\|^2$$

$$e(\mathbf{x}) = \|\mathbf{b} - \mathbf{Ax}\|^2$$

Matrix representation



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$$\begin{aligned} \mathbf{b} - \mathbf{Ax} &= \begin{bmatrix} b_1 \\ \vdots \\ b_n \end{bmatrix} - \begin{bmatrix} \overset{\text{parameter 1}}{\downarrow} a_{1,1} & \dots & a_{1,m} \\ \vdots & & \vdots \\ a_{n,1} & \dots & a_{n,m} \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \\ &= \begin{bmatrix} b_1 - (a_{1,1}x_1 + \dots + a_{1,m}x_m) \\ \vdots \\ b_n - (a_{n,1}x_1 + \dots + a_{n,m}x_m) \end{bmatrix} \end{aligned}$$

measurement n

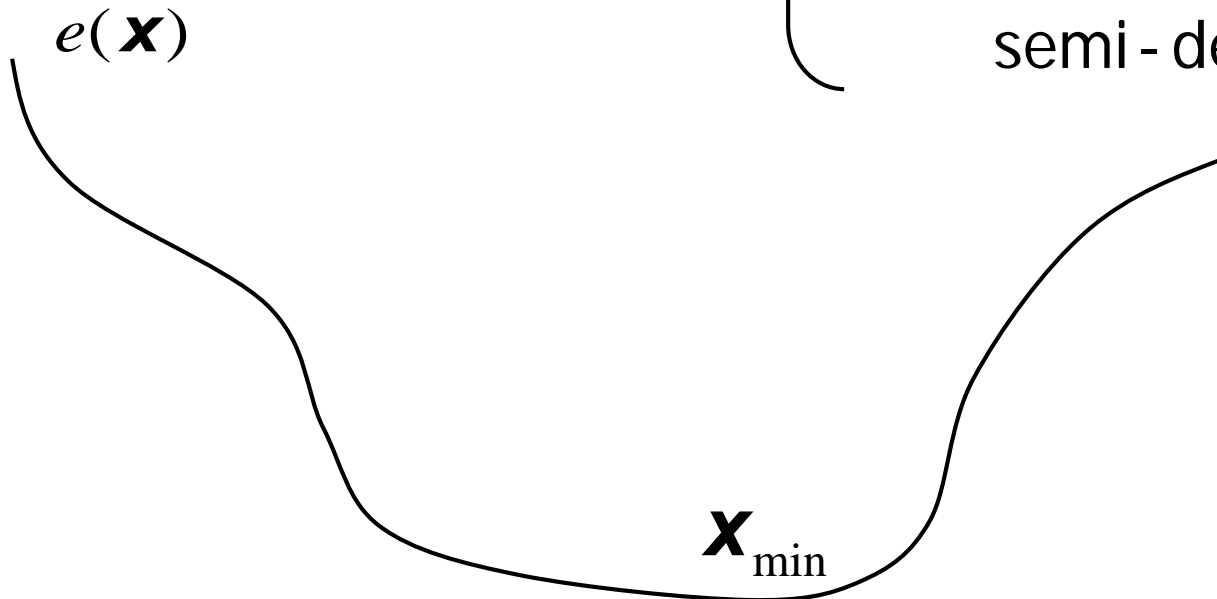
Minimizing $e(\mathbf{x})$

\mathbf{x}_{\min} minimizes $e(\mathbf{x})$ if

$e(\mathbf{x})$ is flat at \mathbf{x}_{\min}
 $\nabla e(\mathbf{x}_{\min}) = \mathbf{0}$

$e(\mathbf{x})$ does not go down
around \mathbf{x}_{\min}

$H_e(\mathbf{x}_{\min})$ is positive
semi-definite



Positive semi-definite



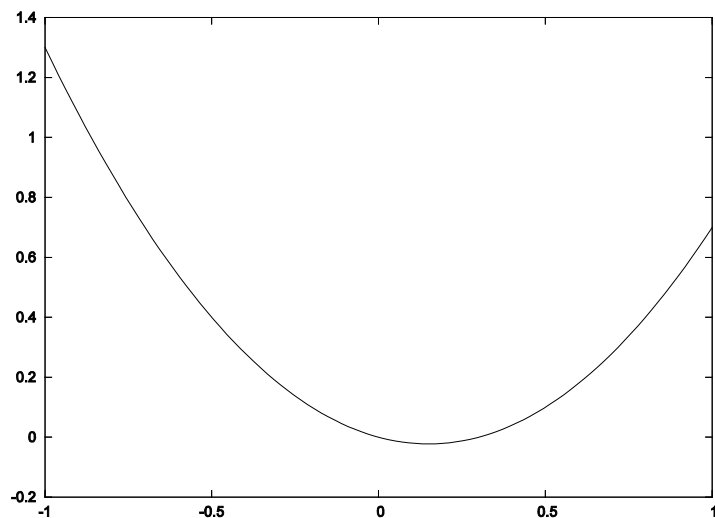
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A is positive semi - definite

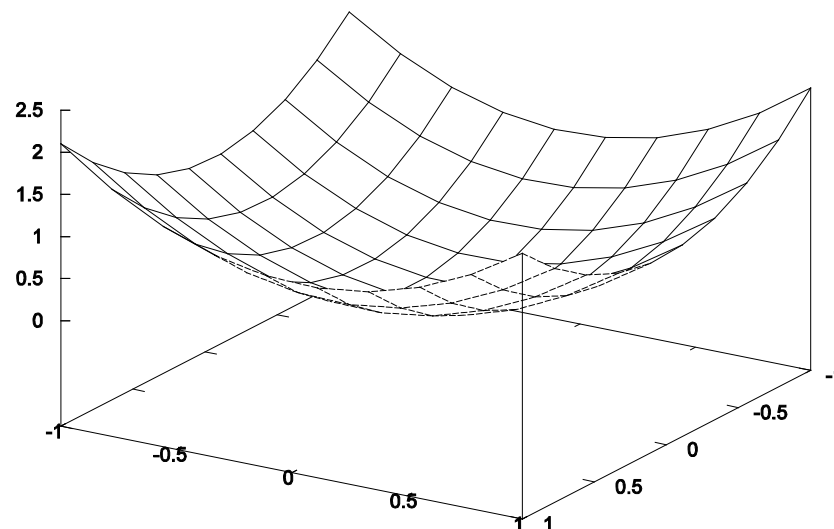


$$\mathbf{x}^T \mathbf{A} \mathbf{x} \geq 0, \text{ for all } \mathbf{x}$$

In 1-D



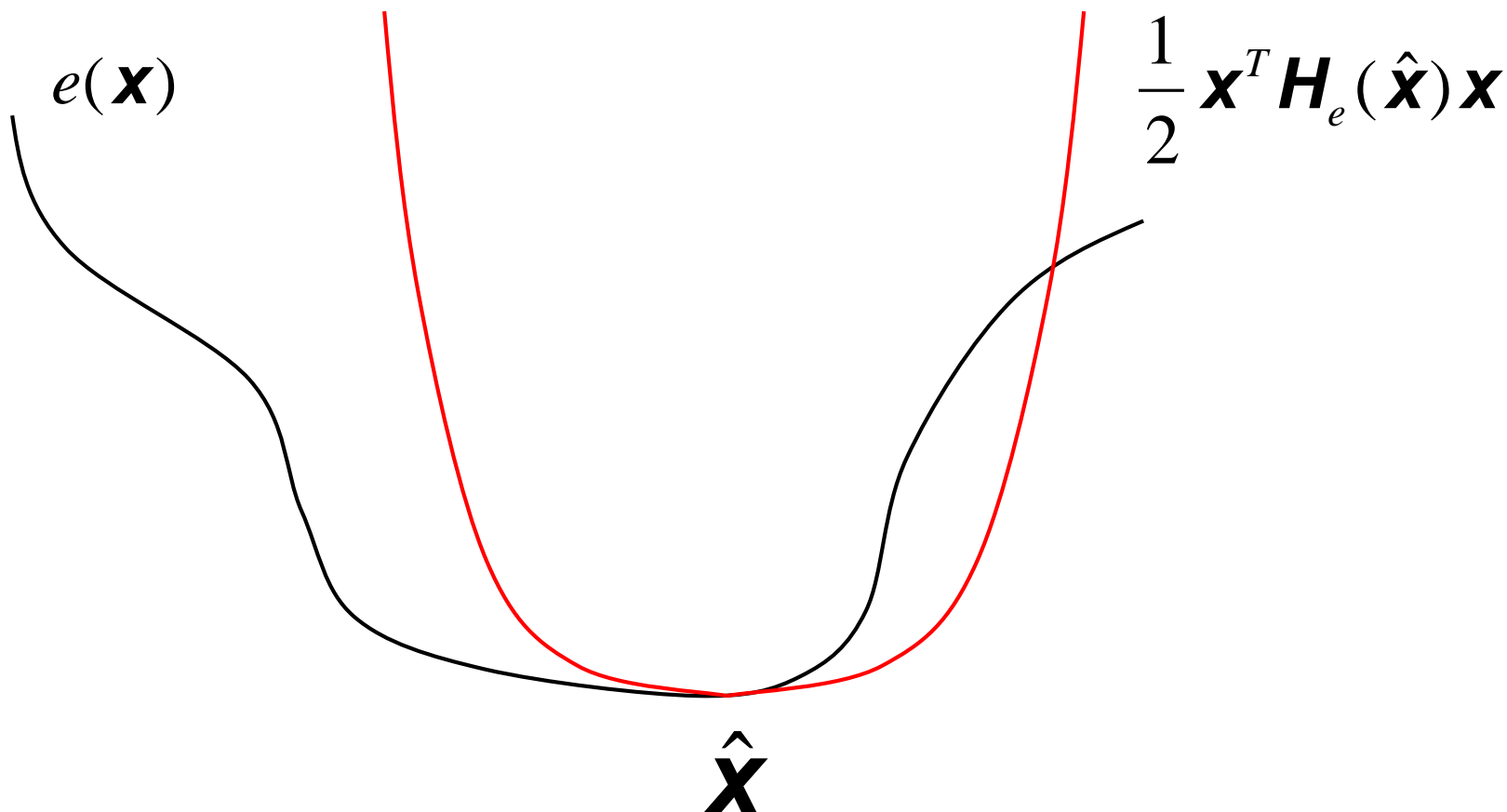
In 2-D



Minimizing $e(\mathbf{x})$



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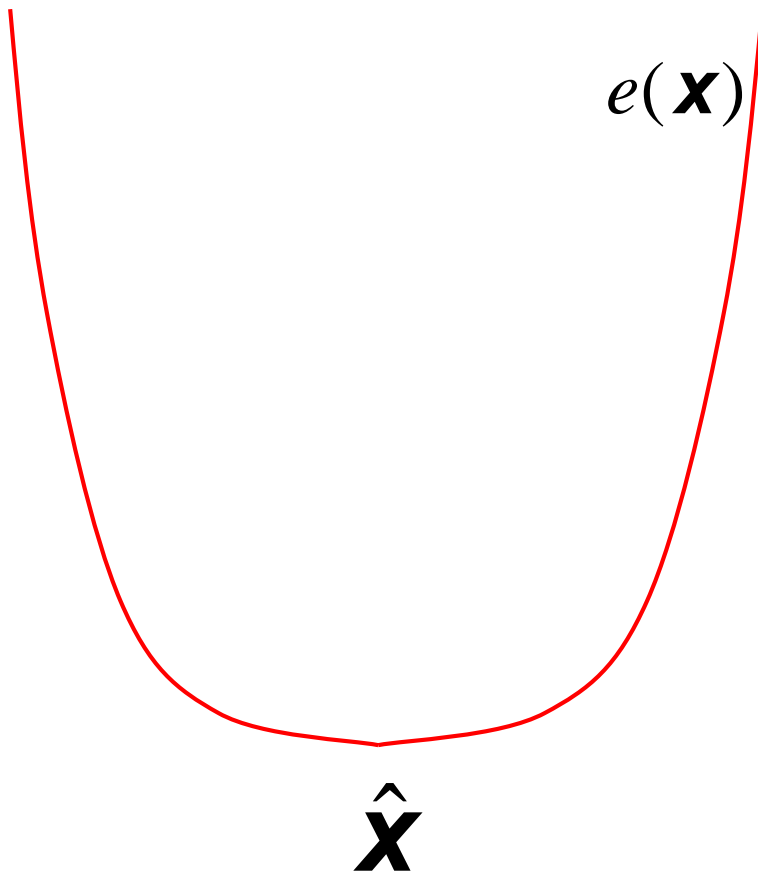


Minimizing $e(\mathbf{x}) = \|\mathbf{b} - \mathbf{Ax}\|^2$



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$$e(\mathbf{x}) = \frac{1}{2} \mathbf{x}^T \mathbf{H}_e(\hat{\mathbf{x}}) \mathbf{x}$$



Minimizing $e(\mathbf{x}) = \|\mathbf{b} - \mathbf{Ax}\|^2$

$\hat{\mathbf{x}}$ minimizes $e(\mathbf{x})$ if

$$\mathbf{A}^T \mathbf{A} \hat{\mathbf{x}} = \mathbf{A}^T \mathbf{b}$$

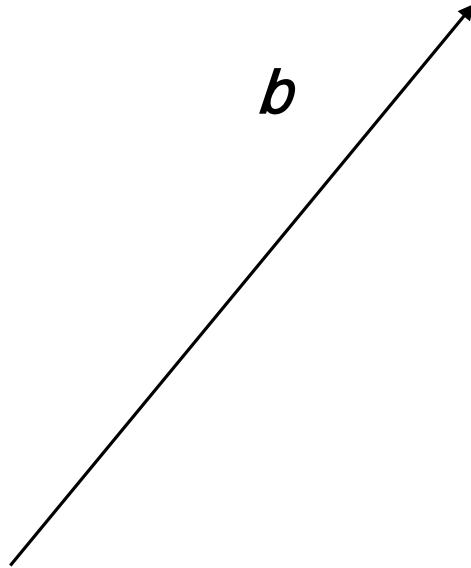
The *normal equation*

$2\mathbf{A}^T \mathbf{A}$ is positive
semi - definite

Always true

Geometric interpretation

- **b** is a vector in R^n

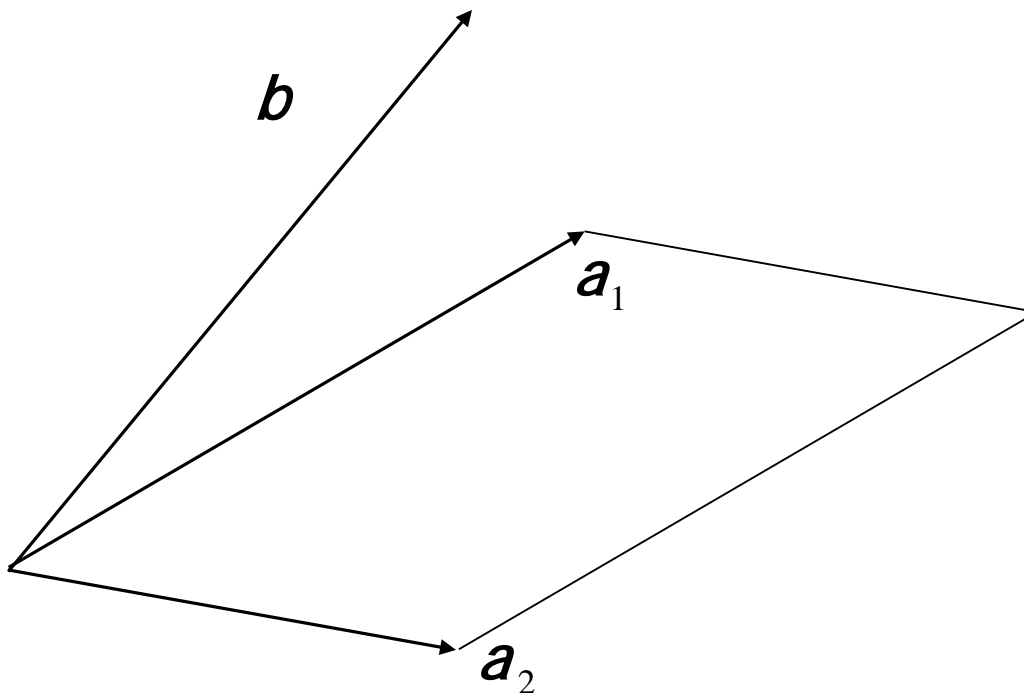


Geometric interpretation



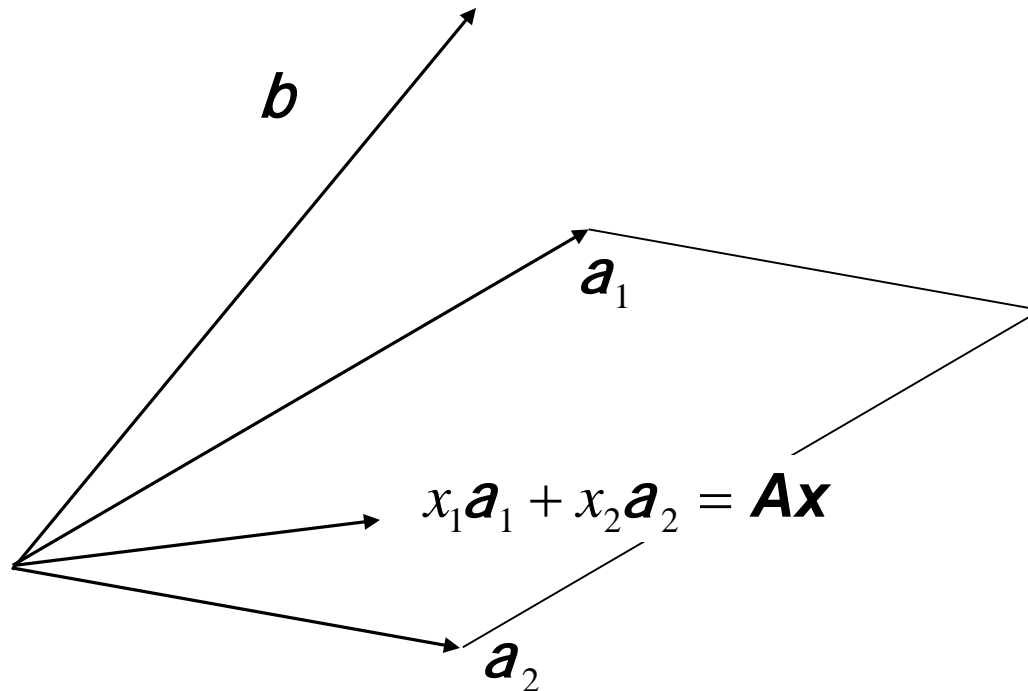
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- \mathbf{b} is a vector in \mathbb{R}^n
- The columns of \mathbf{A} define a vector space $\text{range}(\mathbf{A})$



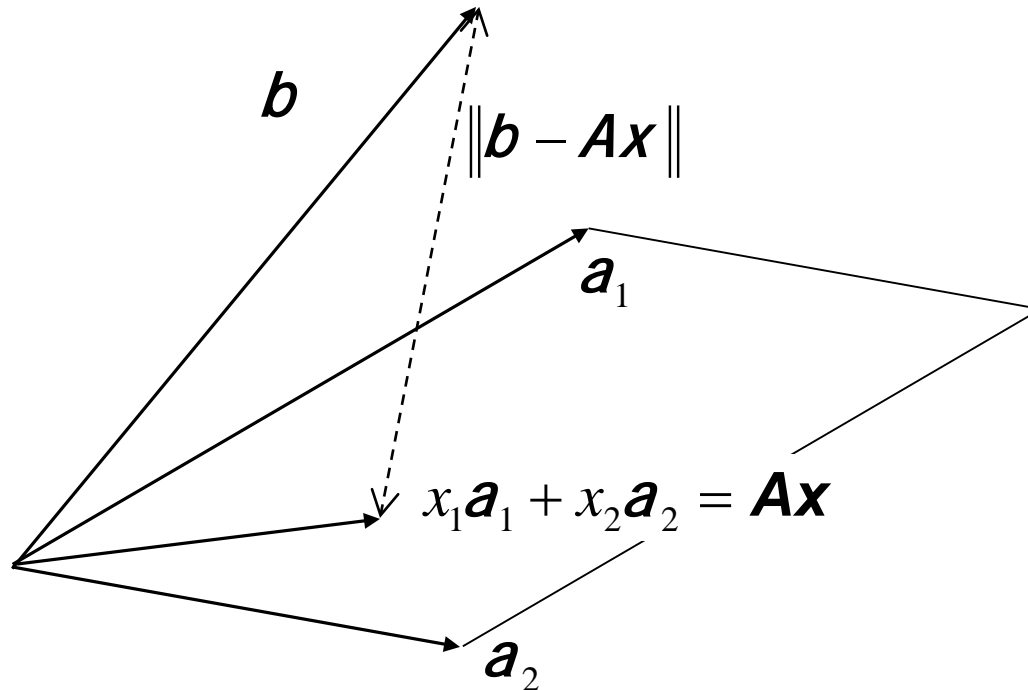
Geometric interpretation

- \mathbf{b} is a vector in \mathbb{R}^n
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- \mathbf{Ax} is an arbitrary vector in $\text{range}(\mathbf{A})$



Geometric interpretation

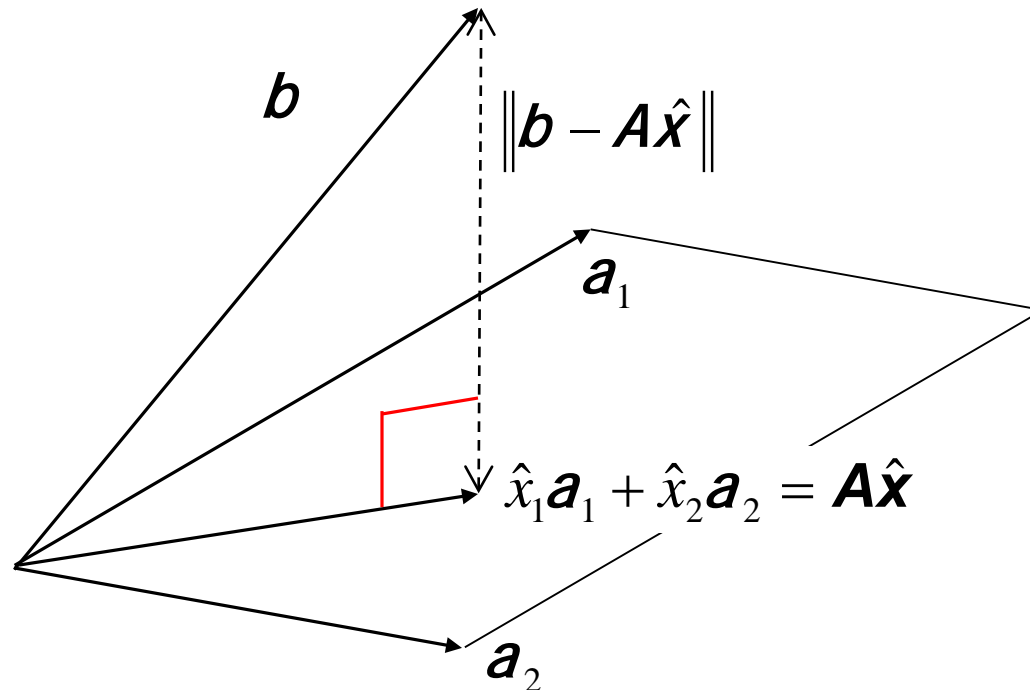
- \mathbf{b} is a vector in \mathbb{R}^n
- The columns of \mathbf{A} define a vector space $\text{range}(\mathbf{A})$
- \mathbf{Ax} is an arbitrary vector in $\text{range}(\mathbf{A})$



Geometric interpretation

- $A\hat{x}$ is the orthogonal projection of b onto $\text{range}(A)$

$$\Leftrightarrow A^T(b - A\hat{x}) = 0 \Leftrightarrow A^T A\hat{x} = A^T b$$



The normal equation: $\mathbf{A}^T \mathbf{A} \hat{\mathbf{x}} = \mathbf{A}^T \mathbf{b}$



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The normal equation: $\mathbf{A}^T \mathbf{A} \hat{\mathbf{x}} = \mathbf{A}^T \mathbf{b}$



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- **Existence:** has always a solution

$$\mathbf{A}^T \mathbf{A} \hat{\mathbf{x}} = \mathbf{A}^T \mathbf{b}$$

The normal equation: $\mathbf{A}^T \mathbf{A} \hat{\mathbf{x}} = \mathbf{A}^T \mathbf{b}$



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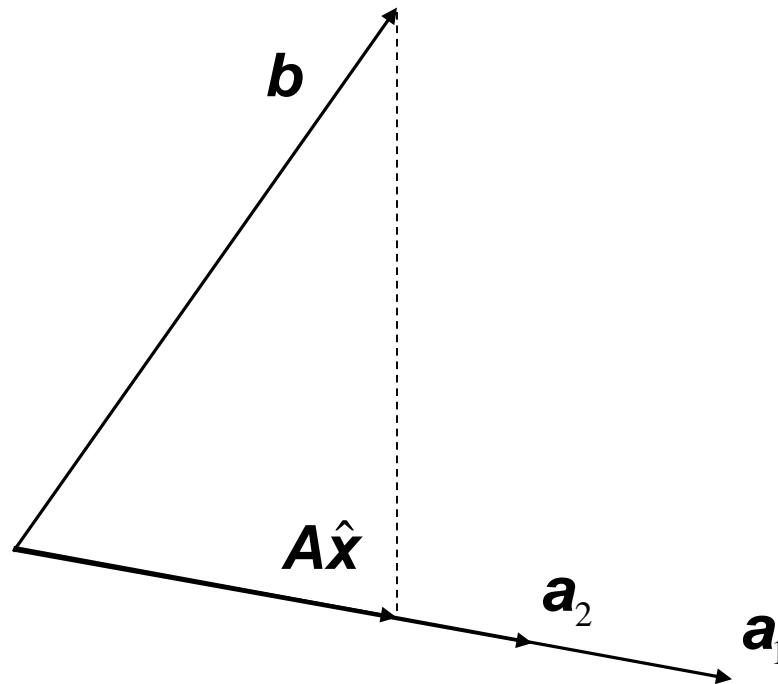
- **Existence:** $\mathbf{A}^T \mathbf{A} \hat{\mathbf{x}} = \mathbf{A}^T \mathbf{b}$ has always a solution
- **Uniqueness:** the solution is unique if the columns of \mathbf{A} are linearly independent

The normal equation: $\mathbf{A}^T \mathbf{A} \hat{\mathbf{x}} = \mathbf{A}^T \mathbf{b}$

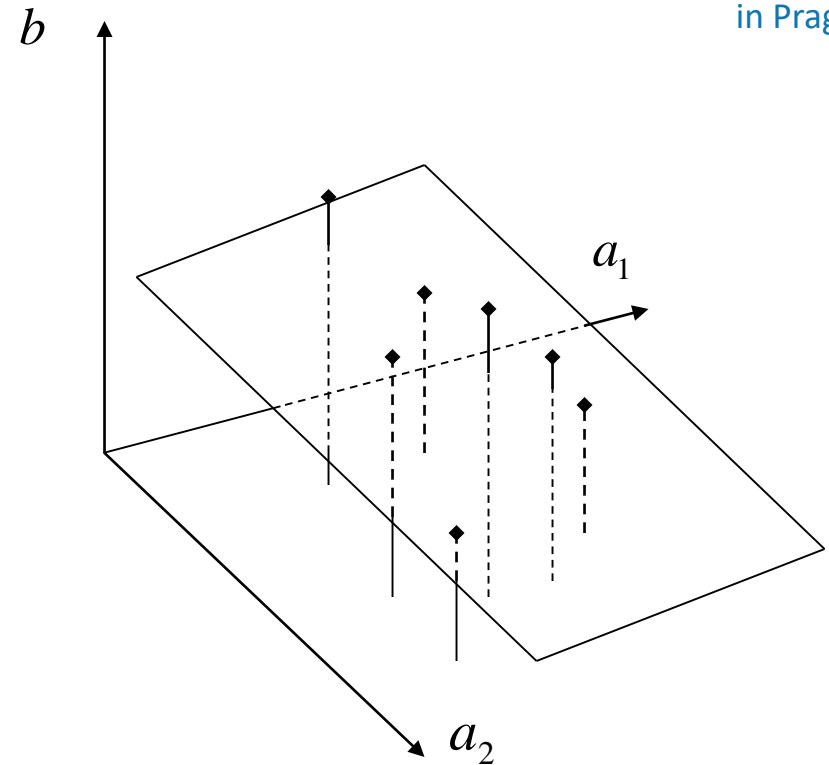


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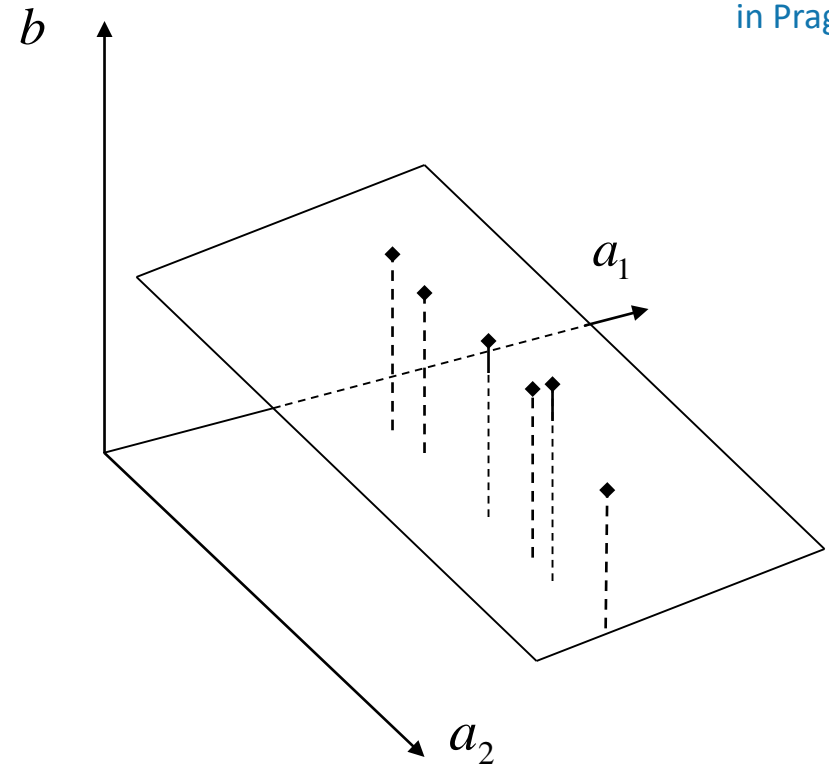
- **Existence:** $\mathbf{A}^T \mathbf{A} \hat{\mathbf{x}} = \mathbf{A}^T \mathbf{b}$ has always a solution
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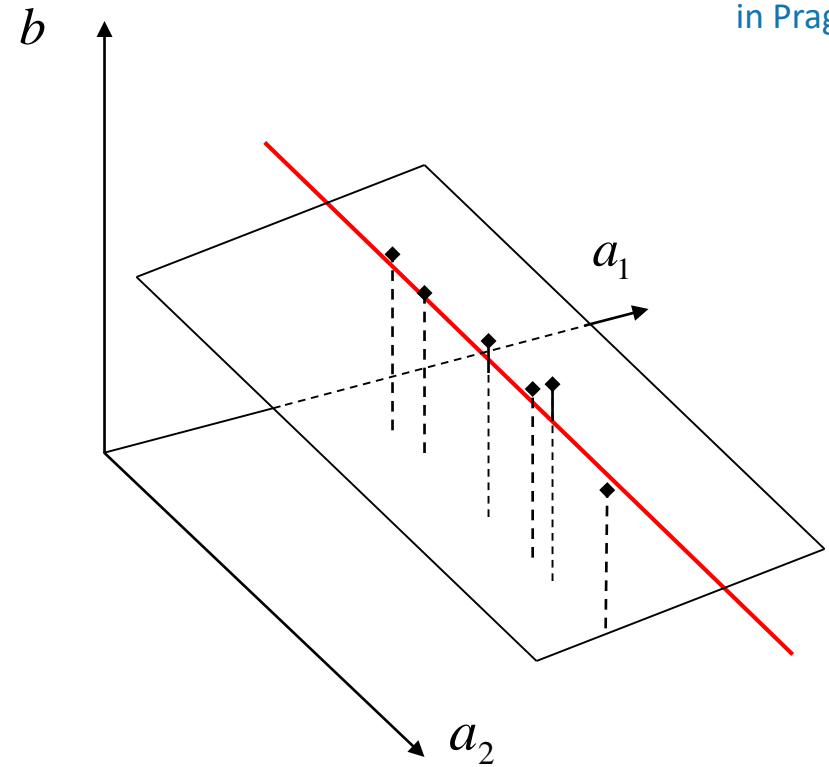
Under-constrained problem



Under-constrained problem

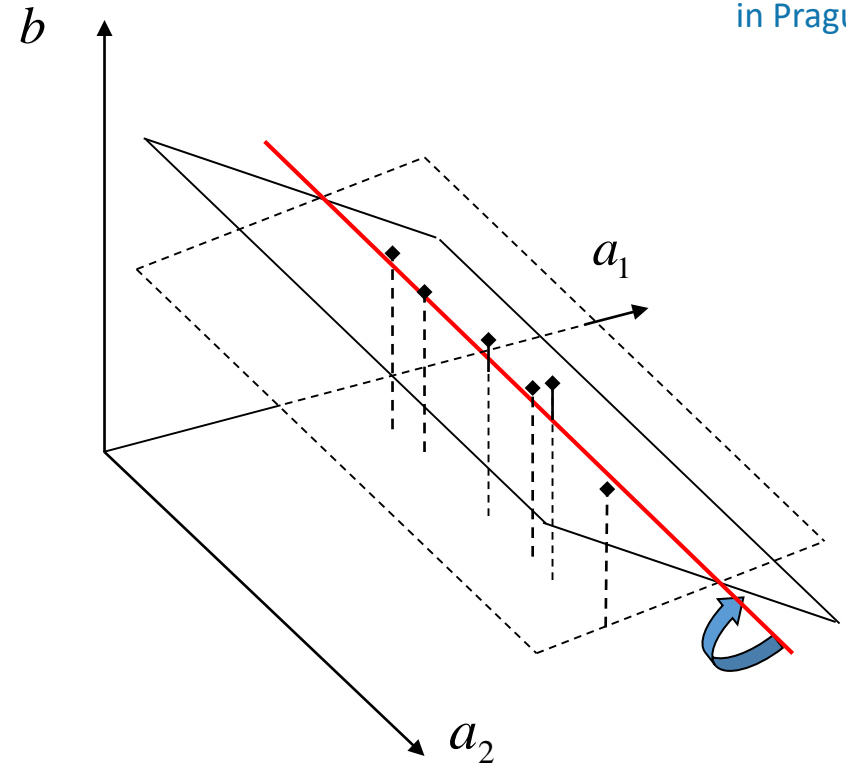


Under-constrained problem



Under-constrained problem

- Poorly selected data
- One or more of the parameters are redundant

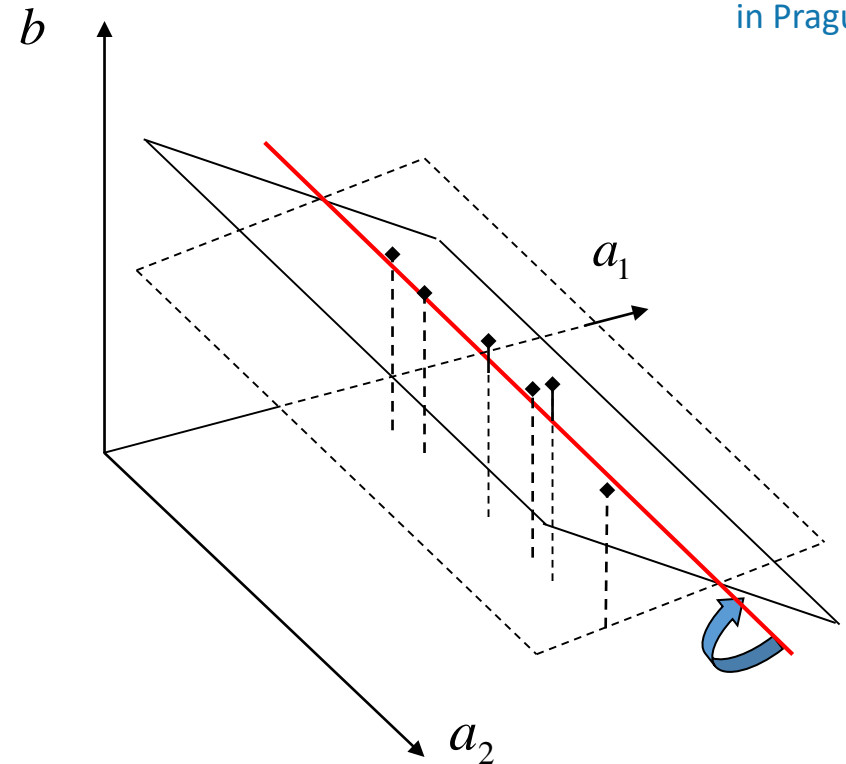


Under-constrained problem

- Poorly selected data
- One or more of the parameters are redundant

Add constraints

$$\mathbf{A}^T \mathbf{A} \mathbf{x} = \mathbf{A}^T \mathbf{b} \text{ with } \min_{\mathbf{x}} \|\mathbf{x}\|$$



How good is the least-squares?

- Optimality: the Gauss-Markov theorem

Let $\{b_i\}$ and $\{x_j\}$ be two sets of random variables and define:

$$e_i = b_i - a_{i,1}x_1 - \dots - a_{i,m}x_m$$

If A1: $\{a_{i,j}\}$ are not random variables,

A2: $E(e_i) = 0$, for all i ,

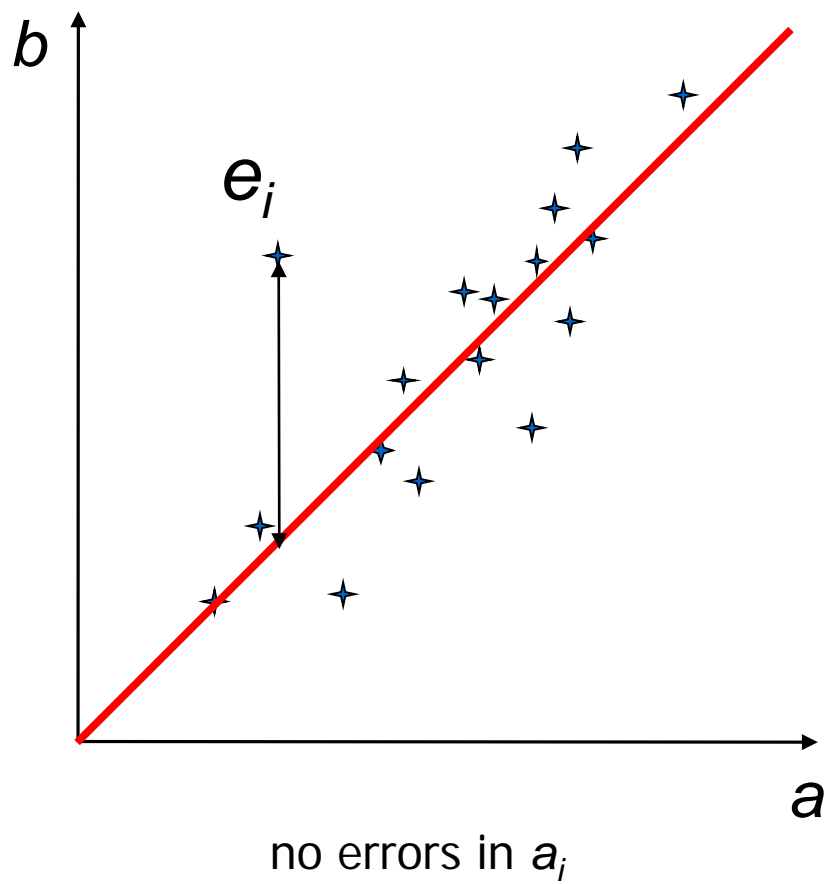
A3: $\text{var}(e_i) = \sigma$, for all i ,

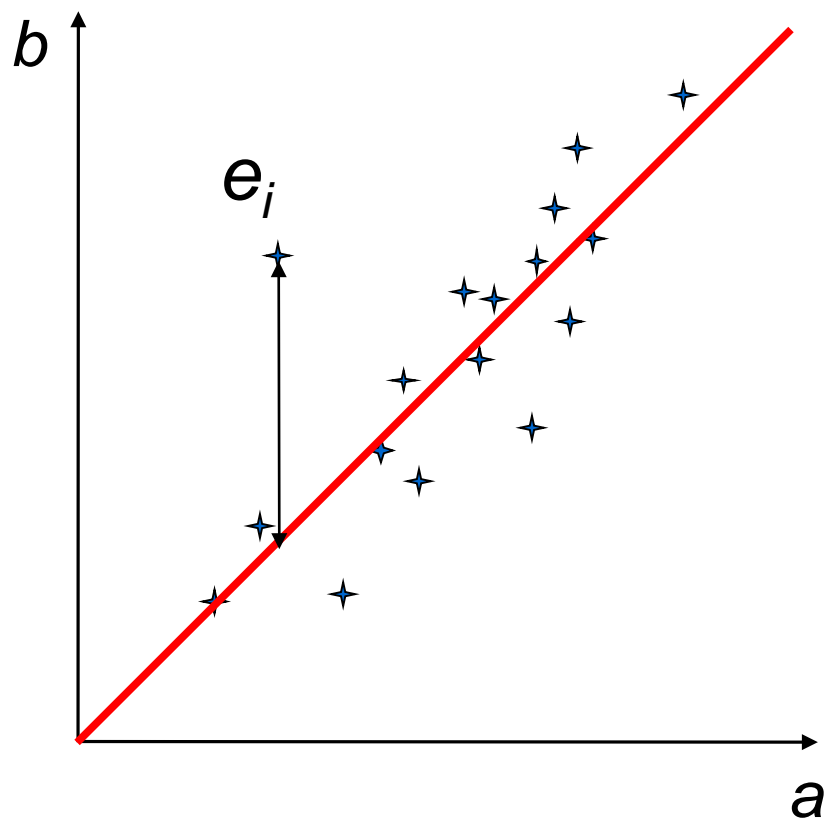
A4: $\text{cov}(e_i, e_j) = 0$, for all i and j ,
is the

Then

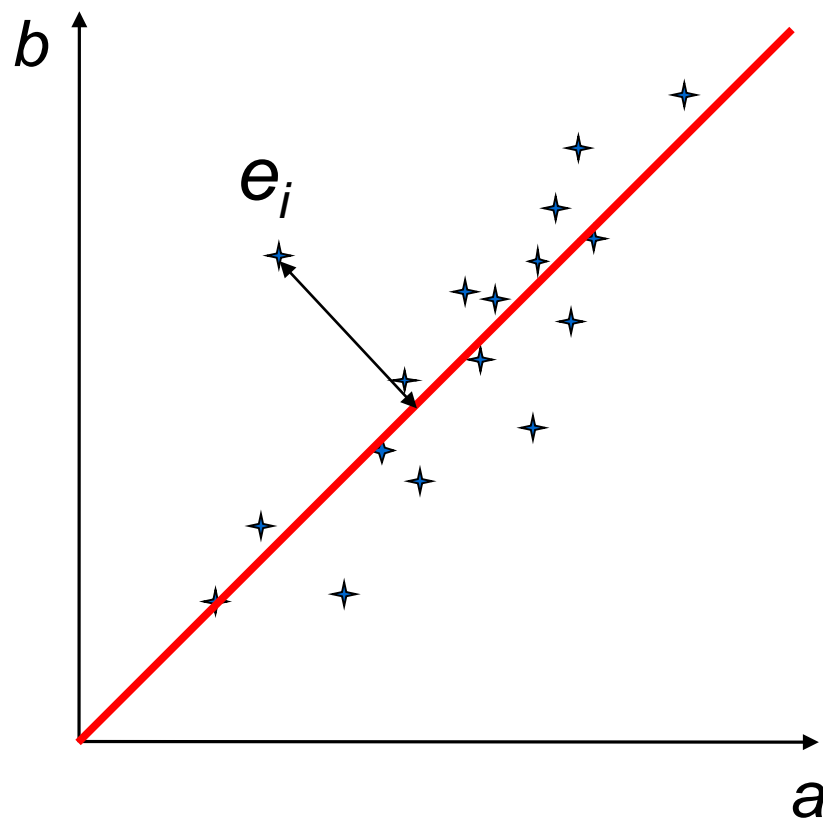
best unbiased linear estimator

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \sum e_i^2$$

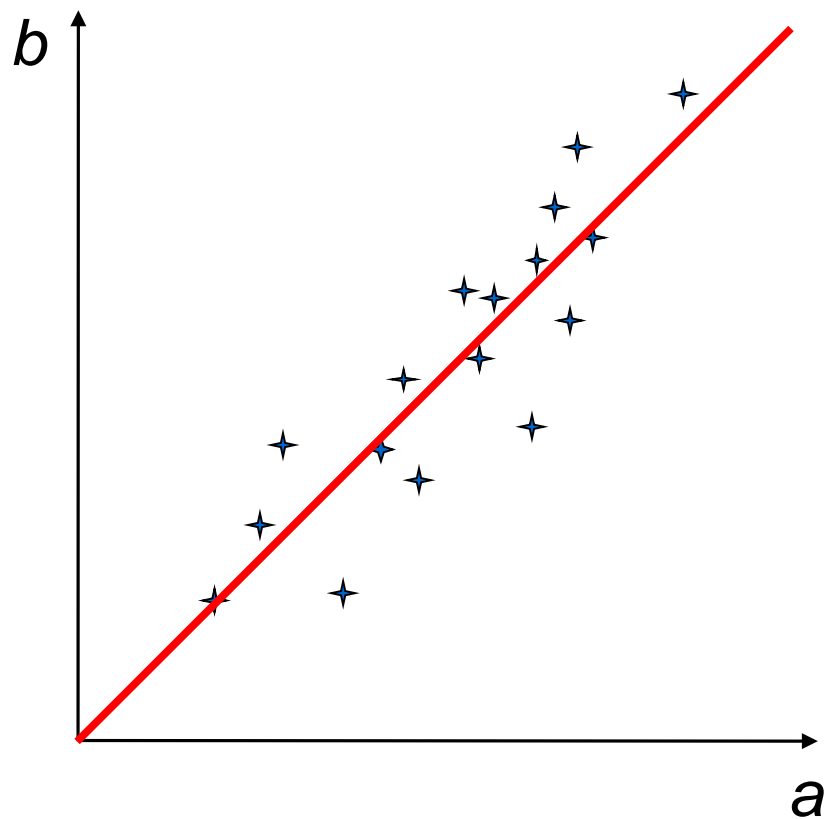


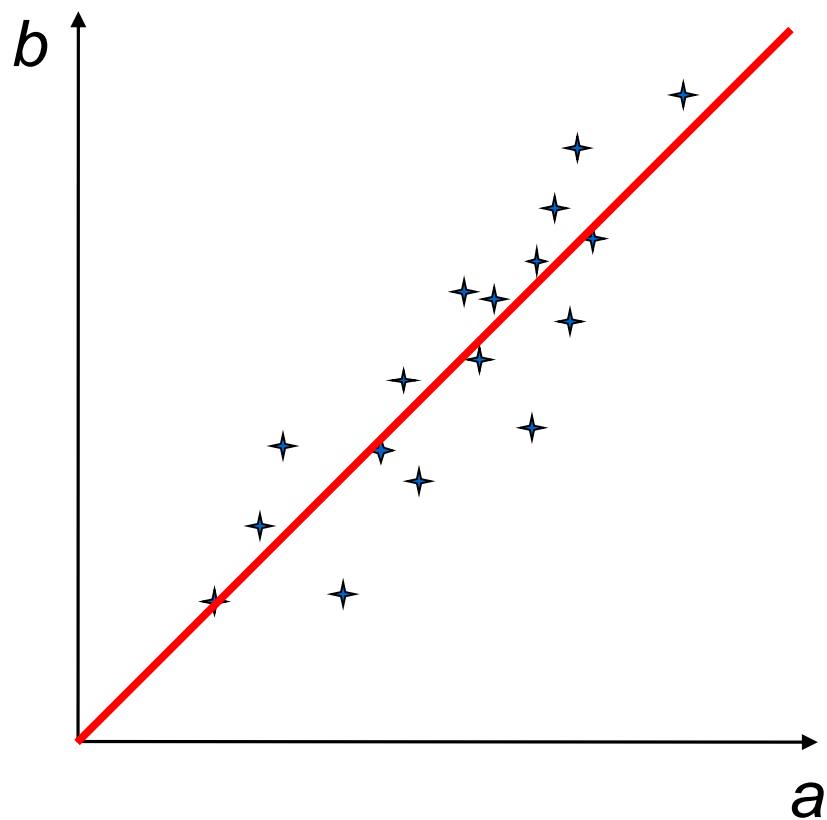


no errors in a_i

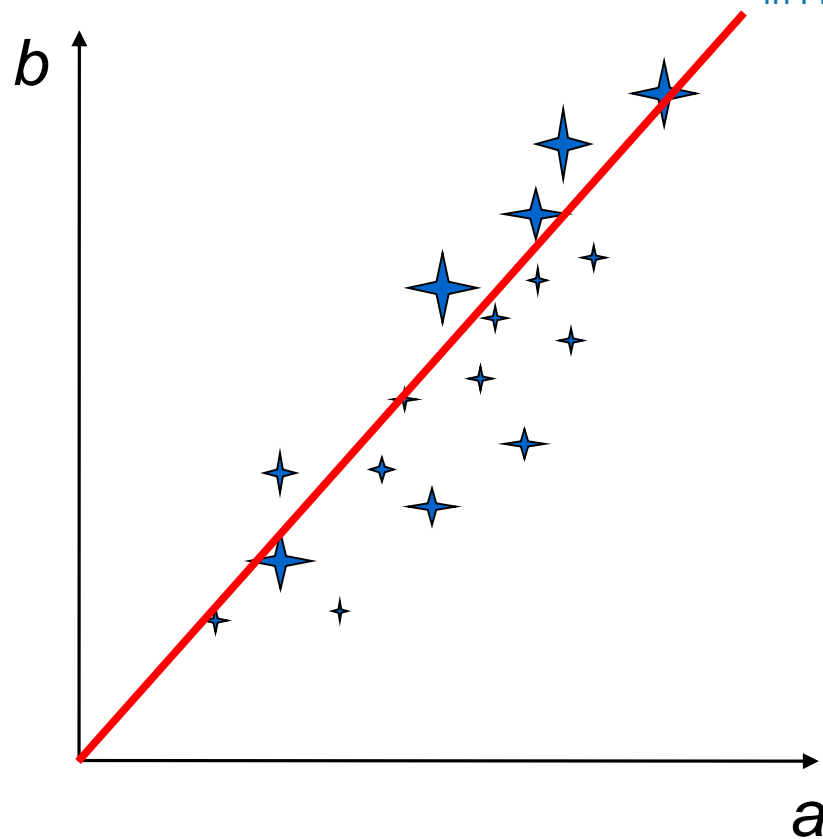


errors in a_i

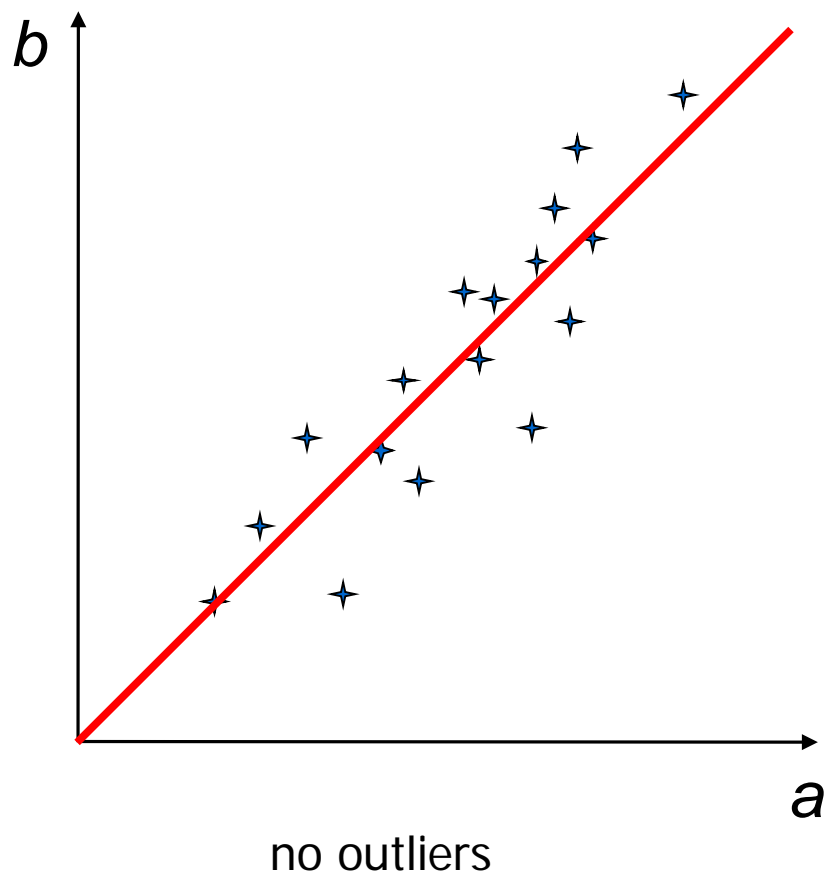


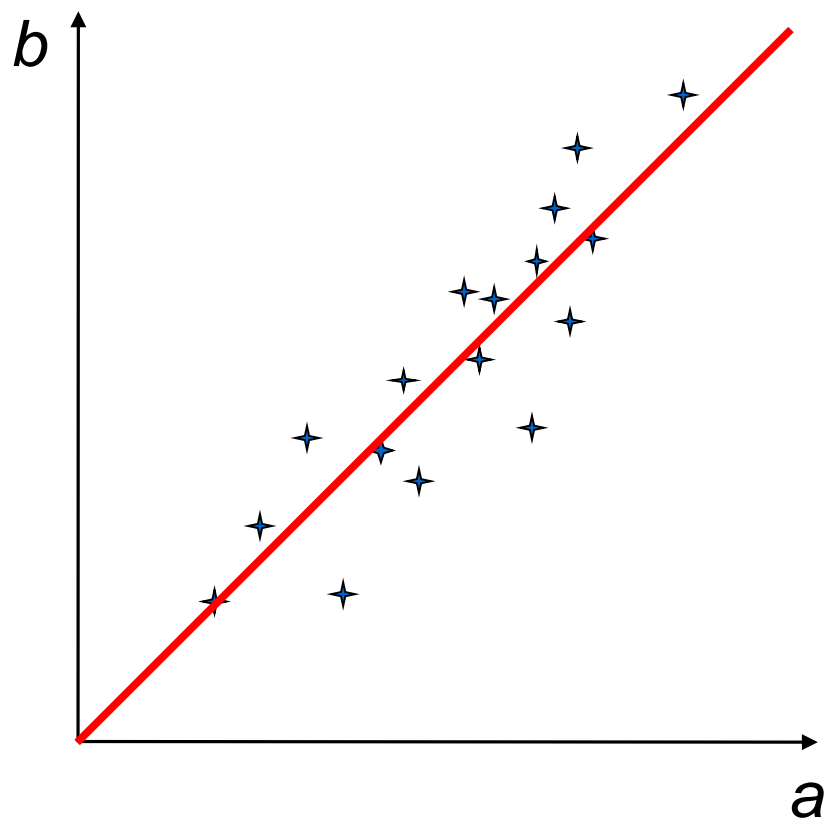


homogeneous errors

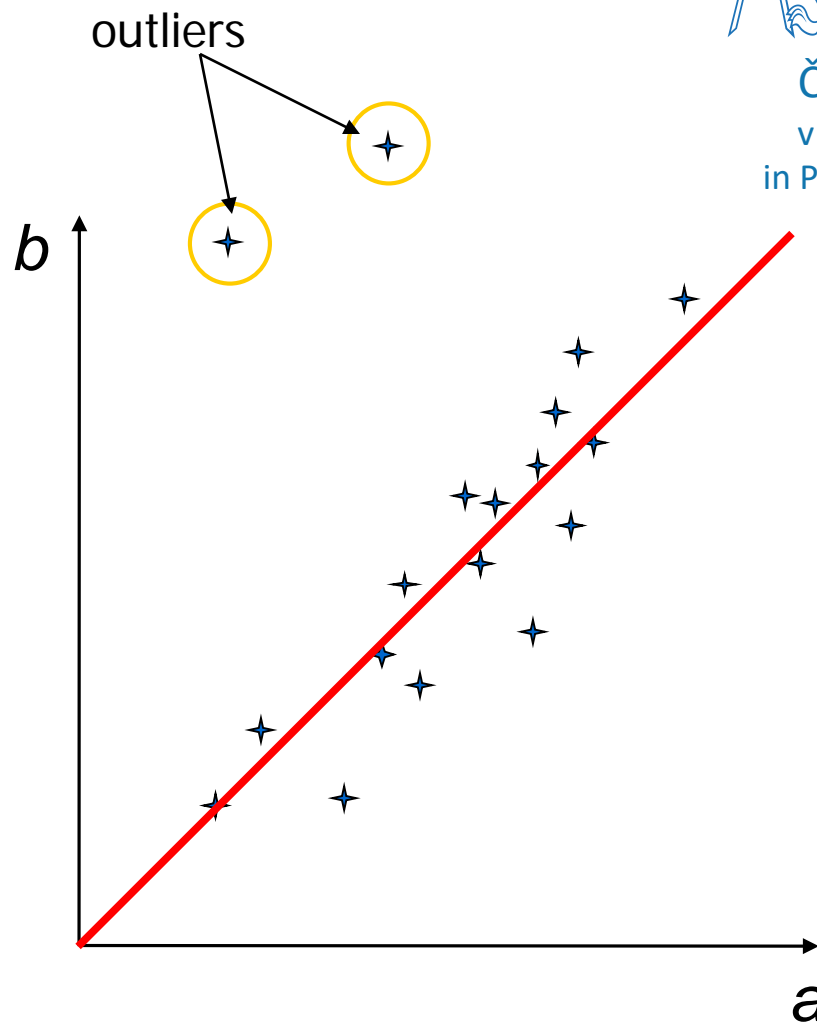


non-homogeneous errors





no outliers



outliers