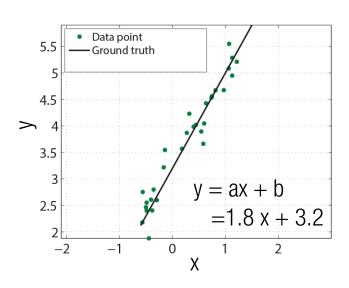
Linear least squares: $\min_{\mathbf{x}} \left\| \mathbf{A}\mathbf{x} - \mathbf{b} \right\|^2$

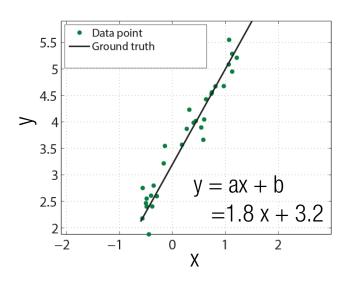


Linear least squares:

$$\min_{\mathbf{x}} \|\mathbf{A}\mathbf{x} - \mathbf{b}\|^{2} = \min_{\mathbf{x}} (\mathbf{A}\mathbf{x} - \mathbf{b})^{\mathsf{T}} (\mathbf{A}\mathbf{x} - \mathbf{b})$$

$$= \min_{\mathbf{x}} \mathbf{x}^{\mathsf{T}} \mathbf{A}^{\mathsf{T}} \mathbf{A} \mathbf{x} - 2 \mathbf{b}^{\mathsf{T}} \mathbf{A} \mathbf{x} - \mathbf{b}^{\mathsf{T}} \mathbf{b}$$

$$= \min_{\mathbf{x}} \mathbf{x}^{\mathsf{T}} \mathbf{A}^{\mathsf{T}} \mathbf{A} \mathbf{x} - 2 \mathbf{b}^{\mathsf{T}} \mathbf{A} \mathbf{x}$$



Linear least squares:

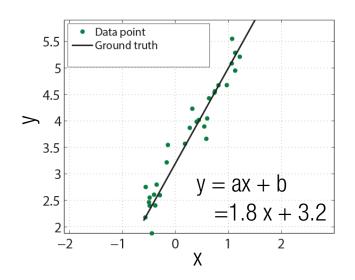
$$\min_{\mathbf{x}} \|\mathbf{A}\mathbf{x} - \mathbf{b}\|^{2} = \min_{\mathbf{x}} (\mathbf{A}\mathbf{x} - \mathbf{b})^{\mathsf{T}} (\mathbf{A}\mathbf{x} - \mathbf{b})$$

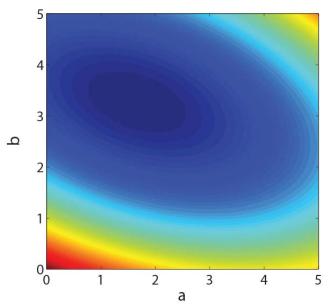
$$= \min_{\mathbf{x}} \mathbf{x}^{\mathsf{T}} \mathbf{A}^{\mathsf{T}} \mathbf{A} \mathbf{x} - 2 \mathbf{b}^{\mathsf{T}} \mathbf{A} \mathbf{x} - \mathbf{b}^{\mathsf{T}} \mathbf{b}$$

$$= \min_{\mathbf{x}} \mathbf{x}^{\mathsf{T}} \mathbf{A}^{\mathsf{T}} \mathbf{A} \mathbf{x} - 2 \mathbf{b}^{\mathsf{T}} \mathbf{A} \mathbf{x}$$

Error:

$$E = \mathbf{x}^{\mathsf{T}} \mathbf{A}^{\mathsf{T}} \mathbf{A} \mathbf{x} - 2 \mathbf{b}^{\mathsf{T}} \mathbf{A} \mathbf{x}$$





Linear least squares:

$$\min_{\mathbf{x}} \|\mathbf{A}\mathbf{x} - \mathbf{b}\|^{2} = \min_{\mathbf{x}} (\mathbf{A}\mathbf{x} - \mathbf{b})^{\mathsf{T}} (\mathbf{A}\mathbf{x} - \mathbf{b})$$

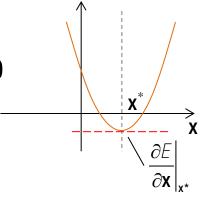
$$= \min_{\mathbf{x}} \mathbf{x}^{\mathsf{T}} \mathbf{A}^{\mathsf{T}} \mathbf{A} \mathbf{x} - 2 \mathbf{b}^{\mathsf{T}} \mathbf{A} \mathbf{x} - \mathbf{b}^{\mathsf{T}} \mathbf{b}$$

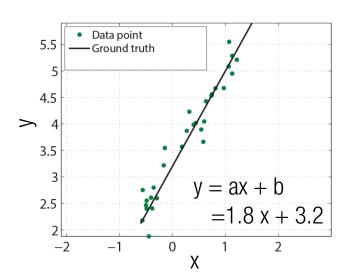
$$= \min_{\mathbf{x}} \mathbf{x}^{\mathsf{T}} \mathbf{A}^{\mathsf{T}} \mathbf{A} \mathbf{x} - 2 \mathbf{b}^{\mathsf{T}} \mathbf{A} \mathbf{x}$$

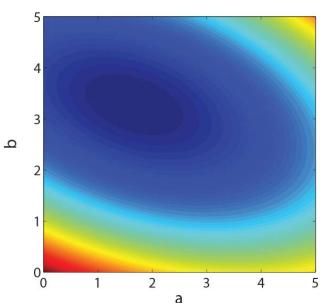
$$E = \mathbf{x}^{\mathsf{T}} \mathbf{A}^{\mathsf{T}} \mathbf{A} \mathbf{x} - 2 \mathbf{b}^{\mathsf{T}} \mathbf{A} \mathbf{x}$$

Condition for the solution:

$$\left. \frac{\partial E}{\partial \mathbf{x}} \right|_{\mathbf{x}^*} = 2\mathbf{A}^\mathsf{T} \mathbf{A} \mathbf{x} - 2\mathbf{A}^\mathsf{T} \mathbf{b} = \mathbf{0}$$







Linear least squares:

$$\min_{\mathbf{x}} \|\mathbf{A}\mathbf{x} - \mathbf{b}\|^{2} = \min_{\mathbf{x}} (\mathbf{A}\mathbf{x} - \mathbf{b})^{\mathsf{T}} (\mathbf{A}\mathbf{x} - \mathbf{b})$$

$$= \min_{\mathbf{x}} \mathbf{x}^{\mathsf{T}} \mathbf{A}^{\mathsf{T}} \mathbf{A} \mathbf{x} - 2 \mathbf{b}^{\mathsf{T}} \mathbf{A} \mathbf{x} - \mathbf{b}^{\mathsf{T}} \mathbf{b}$$

$$= \min_{\mathbf{x}} \mathbf{x}^{\mathsf{T}} \mathbf{A}^{\mathsf{T}} \mathbf{A} \mathbf{x} - 2 \mathbf{b}^{\mathsf{T}} \mathbf{A} \mathbf{x}$$

Error:

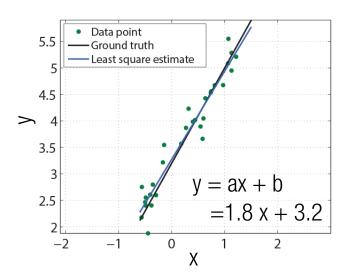
$$E = \mathbf{x}^{\mathsf{T}} \mathbf{A}^{\mathsf{T}} \mathbf{A} \mathbf{x} - 2 \mathbf{b}^{\mathsf{T}} \mathbf{A} \mathbf{x}$$

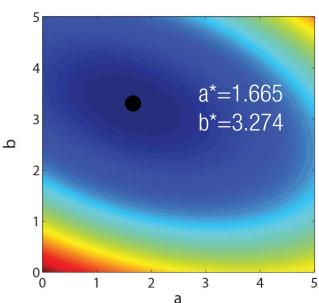
Condition for the solution:

$$\left. \frac{\partial E}{\partial \mathbf{x}} \right|_{\mathbf{x}^*} = 2\mathbf{A}^\mathsf{T} \mathbf{A} \mathbf{x} - 2\mathbf{A}^\mathsf{T} \mathbf{b} = \mathbf{0}$$



$$\mathbf{x}^* = \left(\mathbf{A}^\top \mathbf{A}\right)^{-1} \mathbf{A}^\top \mathbf{b}$$





Nonlinear least squares:

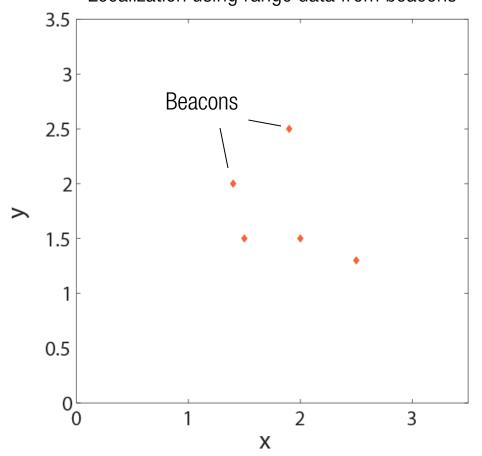
$$\min_{\mathbf{x}} \| \mathbf{f}(\mathbf{x}) - \mathbf{b} \|^2 = \min_{\mathbf{x}} (\mathbf{f}(\mathbf{x}) - \mathbf{b})^{\mathsf{T}} (\mathbf{f}(\mathbf{x}) - \mathbf{b})$$
$$= \min_{\mathbf{x}} \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - \mathbf{b}^{\mathsf{T}} \mathbf{b}$$
$$= \min_{\mathbf{x}} \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x})$$

Nonlinear least squares:

$$\min_{\mathbf{x}} \| \mathbf{f}(\mathbf{x}) - \mathbf{b} \|^{2} = \min_{\mathbf{x}} (\mathbf{f}(\mathbf{x}) - \mathbf{b})^{\mathsf{T}} (\mathbf{f}(\mathbf{x}) - \mathbf{b})$$

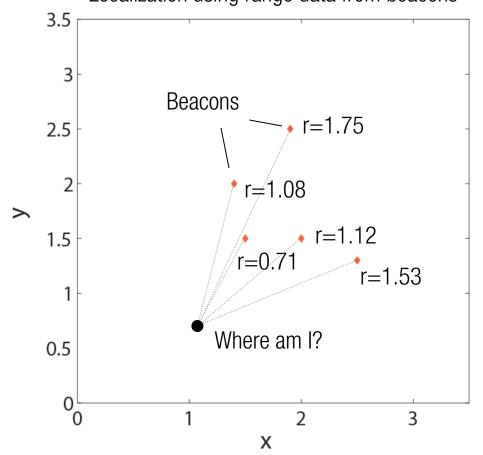
$$= \min_{\mathbf{x}} \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - \mathbf{b}^{\mathsf{T}} \mathbf{b}$$

$$= \min_{\mathbf{x}} \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x})$$



Nonlinear least squares:

$$\min_{\mathbf{x}} \| \mathbf{f}(\mathbf{x}) - \mathbf{b} \|^2 = \min_{\mathbf{x}} (\mathbf{f}(\mathbf{x}) - \mathbf{b})^{\mathsf{T}} (\mathbf{f}(\mathbf{x}) - \mathbf{b})$$
$$= \min_{\mathbf{x}} \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - \mathbf{b}^{\mathsf{T}} \mathbf{b}$$
$$= \min_{\mathbf{x}} \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x})$$

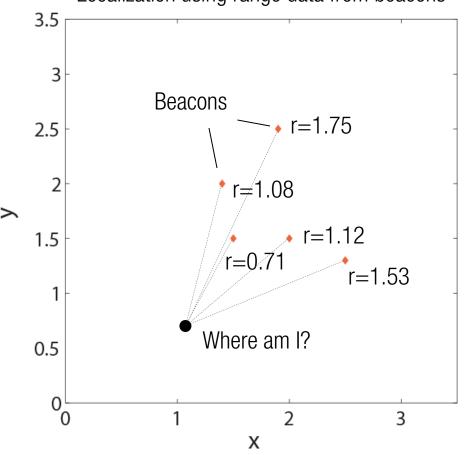


Nonlinear least squares:

$$\min_{\mathbf{x}} \| \mathbf{f}(\mathbf{x}) - \mathbf{b} \|^2 = \min_{\mathbf{x}} (\mathbf{f}(\mathbf{x}) - \mathbf{b})^{\mathsf{T}} (\mathbf{f}(\mathbf{x}) - \mathbf{b})$$
$$= \min_{\mathbf{x}} \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - \mathbf{b}^{\mathsf{T}} \mathbf{b}$$
$$= \min_{\mathbf{x}} \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x})$$

Error:

$$E = \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x})$$



Nonlinear least squares:

$$\min_{\mathbf{x}} \| \mathbf{f}(\mathbf{x}) - \mathbf{b} \|^2 = \min_{\mathbf{x}} (\mathbf{f}(\mathbf{x}) - \mathbf{b})^{\mathsf{T}} (\mathbf{f}(\mathbf{x}) - \mathbf{b})$$
$$= \min_{\mathbf{x}} \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - \mathbf{b}^{\mathsf{T}} \mathbf{b}$$
$$= \min_{\mathbf{x}} \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x})$$

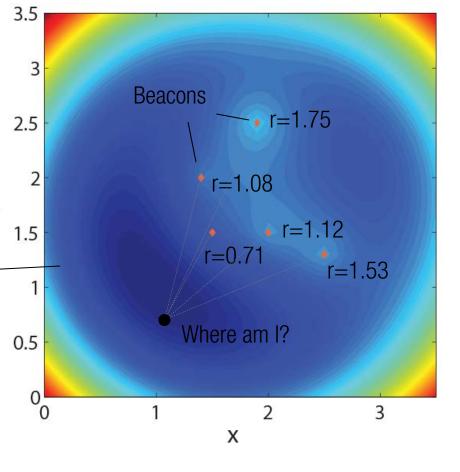
Error:

$$E = \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x})$$

$$E = \mathbf{S}^{\mathsf{T}}\mathbf{S}$$

where
$$\mathbf{S} = \begin{bmatrix} \sqrt{(u_1 - x)^2 + (v_1 - y)^2} \\ \vdots \\ \sqrt{(u_5 - x)^2 + (v_5 - y)^2} \end{bmatrix} - \begin{bmatrix} r_1 \\ \vdots \\ r_5 \end{bmatrix}$$
 0.5

Example:



Nonlinear least squares:

$$\min_{\mathbf{x}} \| \mathbf{f}(\mathbf{x}) - \mathbf{b} \|^2 = \min_{\mathbf{x}} (\mathbf{f}(\mathbf{x}) - \mathbf{b})^{\mathsf{T}} (\mathbf{f}(\mathbf{x}) - \mathbf{b})$$
$$= \min_{\mathbf{x}} \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - \mathbf{b}^{\mathsf{T}} \mathbf{b}$$
$$= \min_{\mathbf{x}} \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x})$$

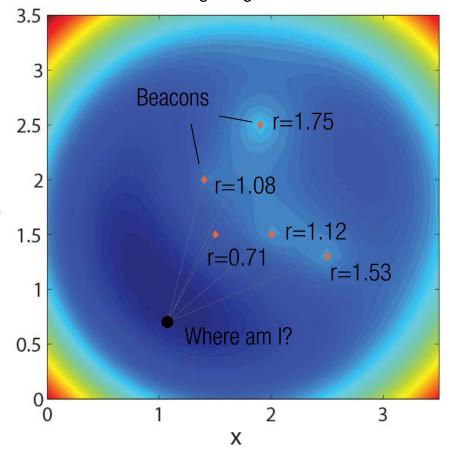
Error:

$$E = \mathbf{f}(\mathbf{x})^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2\mathbf{b}^{\mathsf{T}} \mathbf{f}(\mathbf{x})$$

Condition for the solution:

$$\left. \frac{\partial E}{\partial \mathbf{x}} \right|_{\mathbf{x}^*} = 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{b} = \mathbf{0}$$

where
$$\frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial \mathbf{f}_1}{\partial \mathbf{x}_1} & \cdots & \frac{\partial \mathbf{f}_1}{\partial \mathbf{x}_n} \\ \vdots & & \vdots \\ \frac{\partial \mathbf{f}_m}{\partial \mathbf{x}_1} & \cdots & \frac{\partial \mathbf{f}_m}{\partial \mathbf{x}_n} \end{bmatrix}$$
: Jacobian matrix

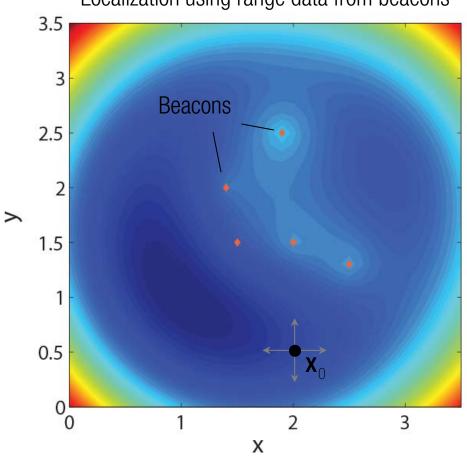


$$\left. \frac{\partial E}{\partial \mathbf{x}} \right|_{\mathbf{x}^*} = 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{b} = \mathbf{0}$$
 (1)

Objective:

Given \mathbf{x}_0 , move \mathbf{x} such that $\mathbf{f}(\mathbf{x}) < \mathbf{f}(\mathbf{x}_0)$.





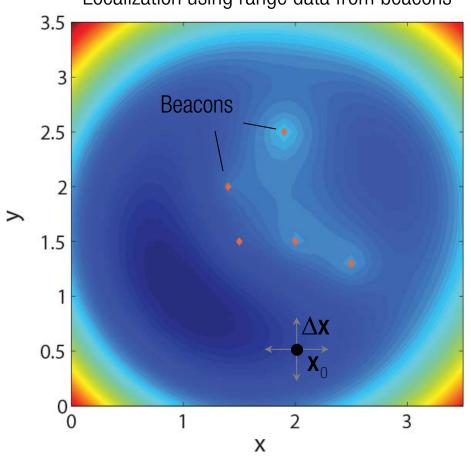
$$\left. \frac{\partial E}{\partial \mathbf{x}} \right|_{\mathbf{x}^*} = 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{b} = \mathbf{0}$$
 (1)

Objective:

Given \mathbf{x}_0 , move \mathbf{x} such that $\mathbf{f}(\mathbf{x}) < \mathbf{f}(\mathbf{x}_0)$.

Taylor expansion around **x**:

$$f(x + \Delta x) \approx f(x) + \frac{\partial f(x)}{\partial x} \Delta x$$



$$\left. \frac{\partial E}{\partial \mathbf{x}} \right|_{\mathbf{x}^*} = 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{b} = \mathbf{0}$$
 (1)

Objective:

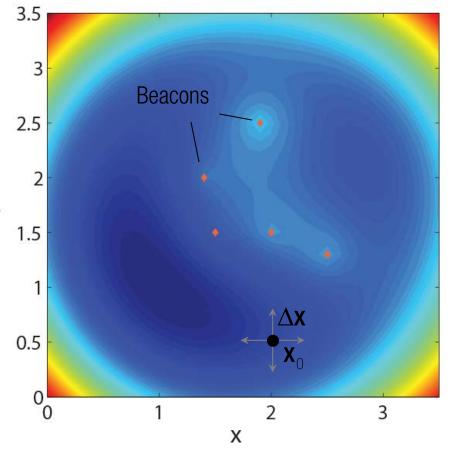
Given \mathbf{x}_0 , move \mathbf{x} such that $\mathbf{f}(\mathbf{x}) < \mathbf{f}(\mathbf{x}_0)$.

Taylor expansion around **x**:

$$f(x + \Delta x) \approx f(x) + \frac{\partial f(x)}{\partial x} \Delta x$$

Plugging into Equation (1):

$$\left. \frac{\partial E}{\partial \mathbf{x}} \right|_{\mathbf{x}^*} = 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \left(\mathbf{f}(\mathbf{x}) + \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} \Delta \mathbf{x} \right) - 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{b} = \mathbf{0}$$



$$\left. \frac{\partial E}{\partial \mathbf{x}} \right|_{\mathbf{x}^*} = 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{b} = \mathbf{0}$$
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Given \mathbf{x}_0 , move \mathbf{x} such that $\mathbf{f}(\mathbf{x}) < \mathbf{f}(\mathbf{x}_0)$.

Taylor expansion around **x**:

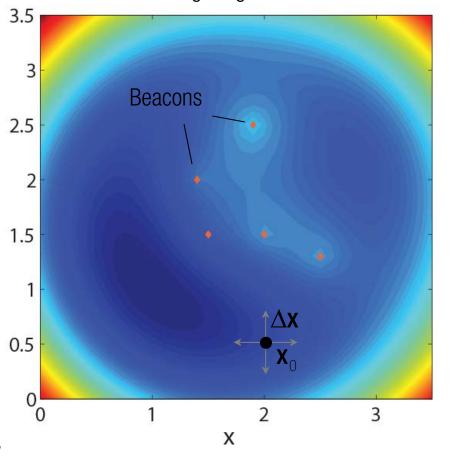
$$f(x + \Delta x) \approx f(x) + \frac{\partial f(x)}{\partial x} \Delta x$$

Plugging into Equation (1):

$$\left. \frac{\partial E}{\partial \mathbf{x}} \right|_{\mathbf{x}^*} = 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \left(\mathbf{f}(\mathbf{x}) + \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} \Delta \mathbf{x} \right) - 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{b} = \mathbf{0}$$

$$\longrightarrow \frac{\partial f(\mathbf{x})^{\top}}{\partial \mathbf{x}} \frac{\partial f(\mathbf{x})}{\partial \mathbf{x}} \Delta \mathbf{x} = \frac{\partial f(\mathbf{x})^{\top}}{\partial \mathbf{x}} (\mathbf{b} - \mathbf{f}(\mathbf{x}))$$

Note that $\mathbf{A}^{\mathsf{T}}\mathbf{A}\mathbf{x} = \mathbf{A}^{\mathsf{T}}\mathbf{b}$ for linear least squares.



$$\left. \frac{\partial \mathcal{E}}{\partial \mathbf{x}} \right|_{\mathbf{x}^*} = 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{f}(\mathbf{x}) - 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{b} = \mathbf{0}$$
 (1)

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Given \mathbf{x}_0 , move \mathbf{x} such that $\mathbf{f}(\mathbf{x}) < \mathbf{f}(\mathbf{x}_0)$.

Taylor expansion around **x**:

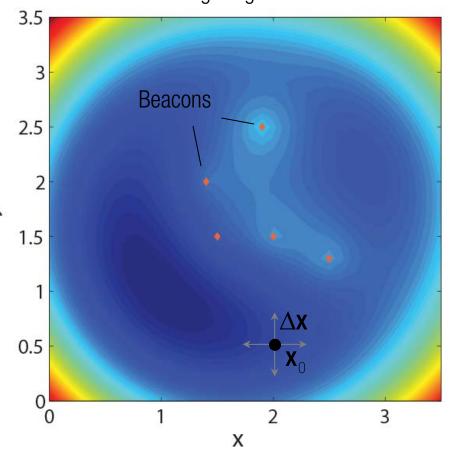
$$f(x + \Delta x) \approx f(x) + \frac{\partial f(x)}{\partial x} \Delta x$$

Plugging into Equation (1):

$$\left. \frac{\partial E}{\partial \mathbf{x}} \right|_{\mathbf{x}^*} = 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \left(\mathbf{f}(\mathbf{x}) + \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} \Delta \mathbf{x} \right) - 2 \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \mathbf{b} = \mathbf{0}$$

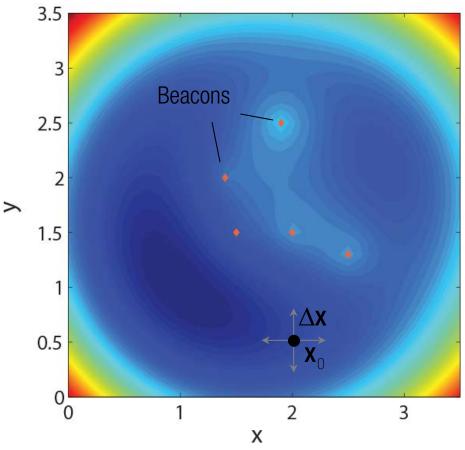
$$\longrightarrow \frac{\partial f(x)}{\partial x}^{\top} \frac{\partial f(x)}{\partial x} \Delta x = \frac{\partial f(x)}{\partial x}^{\top} (b - f(x))$$

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \Delta \mathbf{x}$$
where $\Delta \mathbf{x} = \left(\frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\top} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}\right)^{-1} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\top} (\mathbf{b} - \mathbf{f}(\mathbf{x}))$



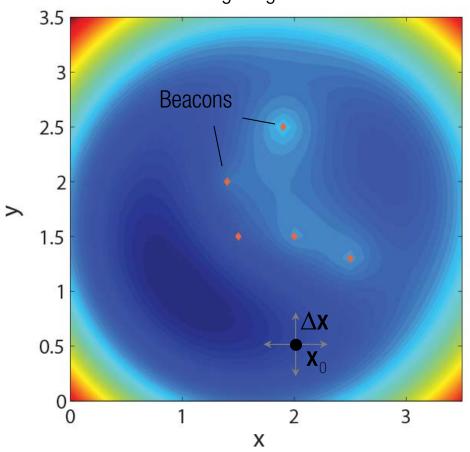
$$\mathbf{x}_{k+1} = \mathbf{x}_k + \Delta \mathbf{x}$$
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$$\mathbf{x}_{k+1} = \mathbf{x}_k + \Delta \mathbf{x}$$
where $\Delta \mathbf{x} = \left(\frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\top} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}\right)^{-1} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\top} \left(\mathbf{b} - \mathbf{f}(\mathbf{x})\right)$

$$\mathbf{f}(x,y) = \begin{bmatrix} \sqrt{(U_1 - X)^2 + (V_1 - y)^2} \\ \vdots \\ \sqrt{(U_5 - X)^2 + (V_5 - y)^2} \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} r_1 \\ \vdots \\ r_5 \end{bmatrix}$$



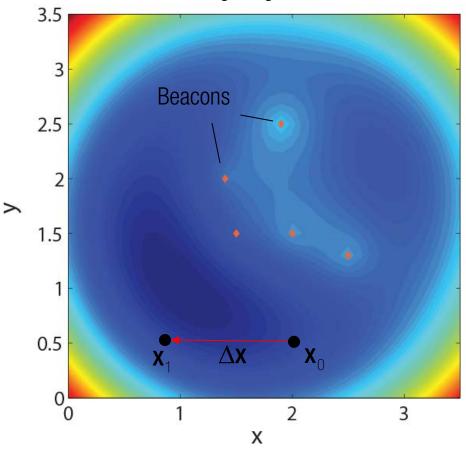
$$\mathbf{x}_{k+1} = \mathbf{x}_k + \Delta \mathbf{x}$$
where $\Delta \mathbf{x} = \left(\frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}\right)^{-1} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \left(\mathbf{b} - \mathbf{f}(\mathbf{x})\right)$

$$\mathbf{f}(x,y) = \begin{bmatrix} \sqrt{(U_1 - x)^2 + (V_1 - y)^2} \\ \vdots \\ \sqrt{(U_5 - x)^2 + (V_5 - y)^2} \end{bmatrix} \qquad \mathbf{b} = \begin{bmatrix} r_1 \\ \vdots \\ r_5 \end{bmatrix}$$

$$\frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} = \begin{bmatrix} \frac{u_1 - x}{\sqrt{(u_1 - x)^2 + (v_1 - y)^2}} & \frac{v_1 - y}{\sqrt{(u_1 - x)^2 + (v_1 - y)^2}} \\ \frac{u_5 - x}{\sqrt{(u_5 - x)^2 + (v_5 - y)^2}} & \frac{v_5 - y}{\sqrt{(u_5 - x)^2 + (v_5 - y)^2}} \end{bmatrix}$$

Jacobian matrix





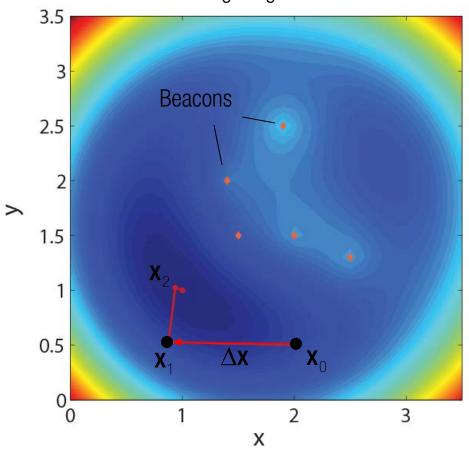
$$\mathbf{x}_{k+1} = \mathbf{x}_k + \Delta \mathbf{x}$$
where $\Delta \mathbf{x} = \left(\frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}\right)^{-1} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\mathsf{T}} \left(\mathbf{b} - \mathbf{f}(\mathbf{x})\right)$

$$\mathbf{f}(x,y) = \begin{bmatrix} \sqrt{(U_1 - x)^2 + (V_1 - y)^2} \\ \vdots \\ \sqrt{(U_5 - x)^2 + (V_5 - y)^2} \end{bmatrix} \qquad \mathbf{b} = \begin{bmatrix} r_1 \\ \vdots \\ r_5 \end{bmatrix}$$

$$\frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} = \begin{bmatrix} \frac{u_1 - x}{\sqrt{(u_1 - x)^2 + (v_1 - y)^2}} & \frac{v_1 - y}{\sqrt{(u_1 - x)^2 + (v_1 - y)^2}} \\ \frac{u_5 - x}{\sqrt{(u_5 - x)^2 + (v_5 - y)^2}} & \frac{v_5 - y}{\sqrt{(u_5 - x)^2 + (v_5 - y)^2}} \end{bmatrix}$$

Jacobian matrix

Example:
Localization using range data from beacons



$$\mathbf{x}_{k+1} = \mathbf{x}_k + \Delta \mathbf{x}$$
where $\Delta \mathbf{x} = \left(\frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\top} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}\right)^{-1} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\top} (\mathbf{b} - \mathbf{f}(\mathbf{x}))$

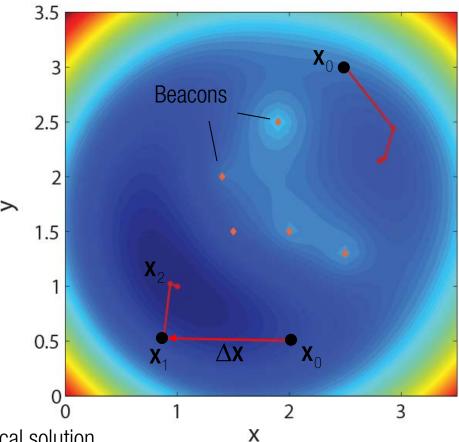
$$\mathbf{f}(x,y) = \begin{bmatrix} \sqrt{(u_1 - x)^2 + (v_1 - y)^2} \\ \vdots \\ \sqrt{(u_5 - x)^2 + (v_5 - y)^2} \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} r_1 \\ \vdots \\ r_5 \end{bmatrix}$$

$$\frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} = \begin{bmatrix} \frac{u_1 - x}{\sqrt{(u_1 - x)^2 + (v_1 - y)^2}} & \frac{v_1 - y}{\sqrt{(u_1 - x)^2 + (v_1 - y)^2}} \\ \frac{u_5 - x}{\sqrt{(u_5 - x)^2 + (v_5 - y)^2}} & \frac{v_5 - y}{\sqrt{(u_5 - x)^2 + (v_5 - y)^2}} \end{bmatrix}$$

Jacobian matrix

Example:

Localization using range data from beacons



A different initialization converges to a different local solution.

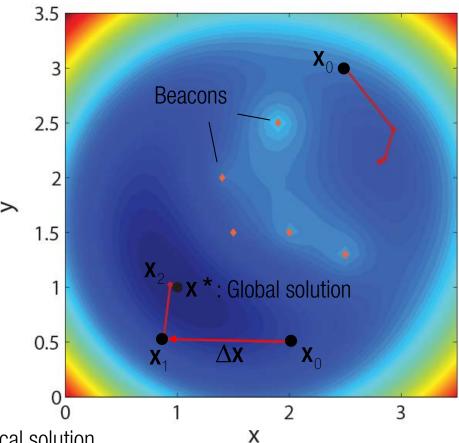
$$\mathbf{x}_{k+1} = \mathbf{x}_k + \Delta \mathbf{x}$$
where $\Delta \mathbf{x} = \left(\frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\top} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}\right)^{-1} \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}^{\top} (\mathbf{b} - \mathbf{f}(\mathbf{x}))$

$$\mathbf{f}(x,y) = \begin{bmatrix} \sqrt{(U_1 - X)^2 + (V_1 - y)^2} \\ \vdots \\ \sqrt{(U_5 - X)^2 + (V_5 - y)^2} \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} r_1 \\ \vdots \\ r_5 \end{bmatrix}$$

$$\frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} = \begin{bmatrix} \frac{u_1 - x}{\sqrt{(u_1 - x)^2 + (v_1 - y)^2}} & \frac{v_1 - y}{\sqrt{(u_1 - x)^2 + (v_1 - y)^2}} \\ \frac{u_5 - x}{\sqrt{(u_5 - x)^2 + (v_5 - y)^2}} & \frac{v_5 - y}{\sqrt{(u_5 - x)^2 + (v_5 - y)^2}} \end{bmatrix}$$

Jacobian matrix

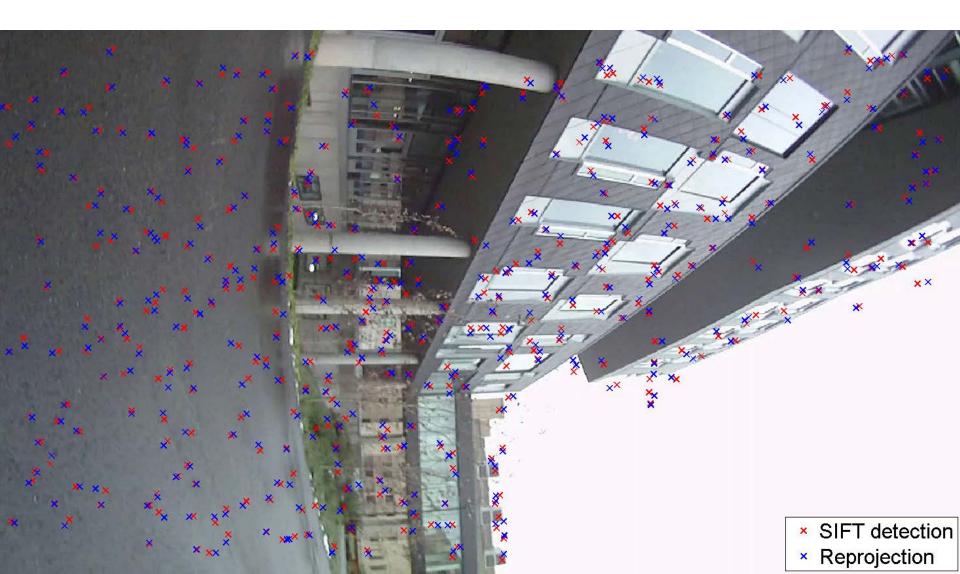
Example:
Localization using range data from beacons



A different initialization converges to a different local solution.

Geometric Refinement

Before Bundle Adjustment



Geometric Refinement

After Bundle Adjustment

