

Linear regression with one input

$$\langle x^{(1)}, y^{(1)} \rangle \dots \langle x^{(m)}, y^{(m)} \rangle$$

Training set

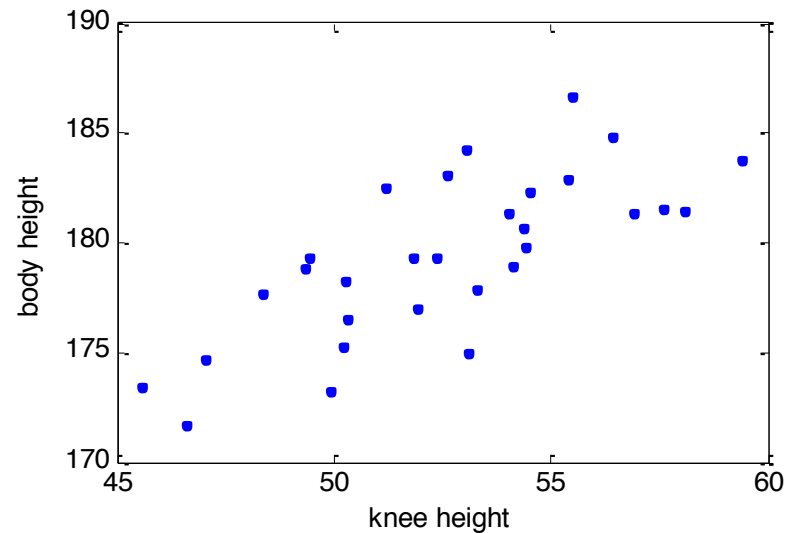
Learning algorithm?

Test input

x

„Hypothesis“
 h

Prediction



Hypothesis

$$h_{\theta}(x) = \theta_0 + \theta_1 \cdot x$$

Parameters?

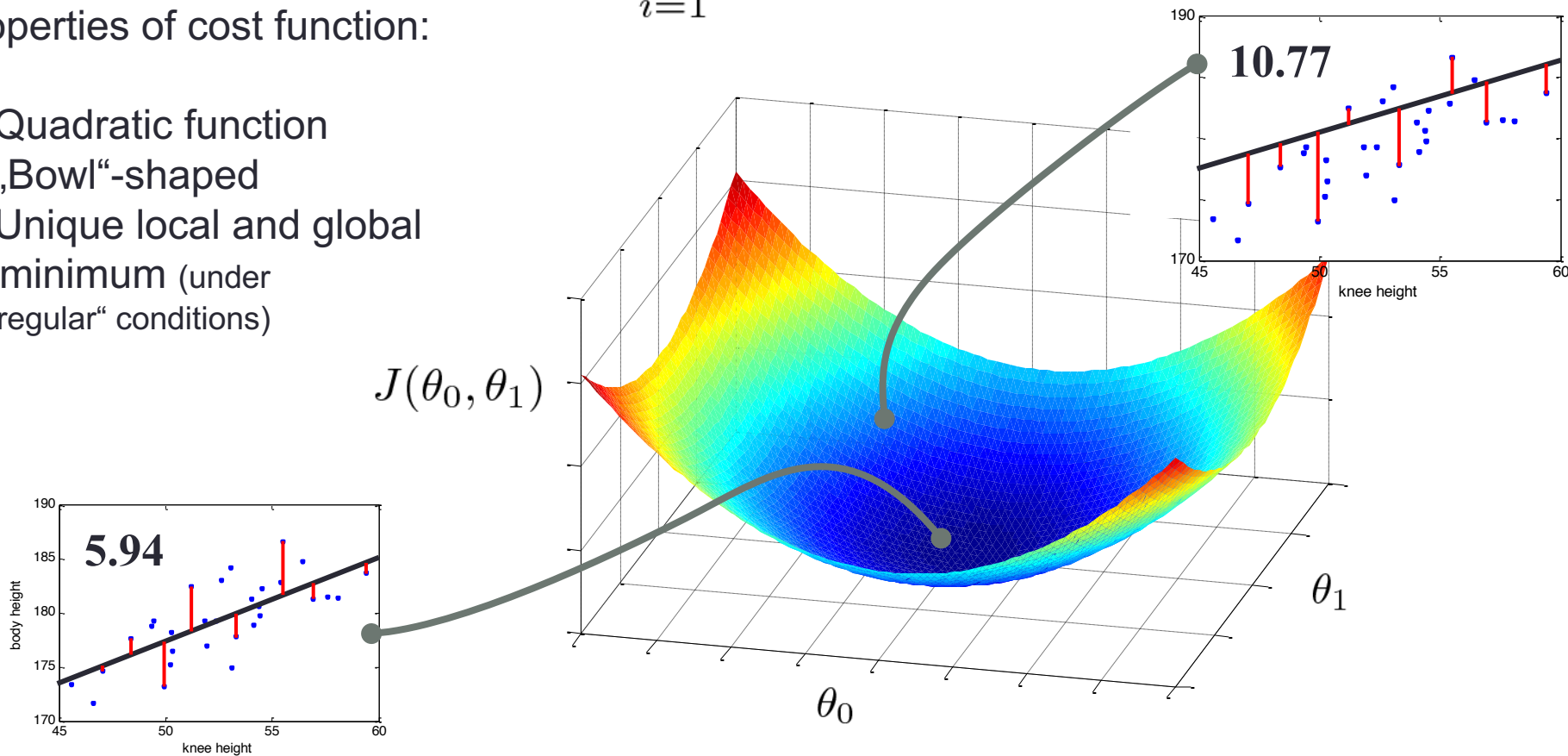
$$\theta = (\theta_0, \theta_1)$$

Cost function illustrated

$$J(\theta_0, \theta_1) = \frac{1}{m} \sum_{i=1}^m \left(h_{\theta} \left(x^{(i)} \right) - y^{(i)} \right)^2$$

Properties of cost function:

- Quadratic function
- „Bowl“-shaped
- Unique local and global minimum (under „regular“ conditions)



Linear hypothesis

- Hypothesis (one input):

$$h_{\theta}(x) = \theta_0 + \theta_1 \cdot x$$

- Hypothesis (multiple input features):

$$h_{\theta}(\mathbf{x}) = \theta_0 + \theta_1 \cdot x_1 + \cdots + \theta_n \cdot x_n$$

Example: $h(x) = 50 + 0.5 \cdot \text{kneeheight} + 0.3 \cdot \text{armspan} + 0.1 \cdot \text{age}$

- More compact notation:

$$h_{\theta}(\mathbf{x}) = \mathbf{x}^T \boldsymbol{\theta}$$

$$\mathbf{x} = \begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{pmatrix} \quad \boldsymbol{\theta} = \begin{pmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_n \end{pmatrix}$$

Introduce $x_0 = 1$
Why? Notation convenience!

Matrix and vector notation

	Knee Height	Arm span	Age	Height
x_0	x_1	x_2	x_3	y
1	50	166	32	171
1	56	172	17	175
1	52	174	62	168

$$\mathbf{X} = \begin{pmatrix} 1 & 50 & 166 & 32 \\ 1 & 56 & 172 & 17 \\ 1 & 52 & 174 & 62 \end{pmatrix}$$

$$\mathbf{y} = \begin{pmatrix} 171 \\ 175 \\ 168 \end{pmatrix}$$

$$\mathbf{x}^{(i)} = \begin{pmatrix} x_0^{(i)} \\ x_1^{(i)} \\ \vdots \\ x_n^{(i)} \end{pmatrix}$$

features of i 'th training example
 $(n+1) \times 1$

$$\mathbf{X} = \begin{pmatrix} \text{---} (\mathbf{x}^{(1)})^T \text{---} \\ \text{---} (\mathbf{x}^{(2)})^T \text{---} \\ \vdots \\ \text{---} (\mathbf{x}^{(m)})^T \text{---} \end{pmatrix}$$

design matrix
 $m \times (n+1)$

$$\mathbf{y} = \begin{pmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(m)} \end{pmatrix}$$

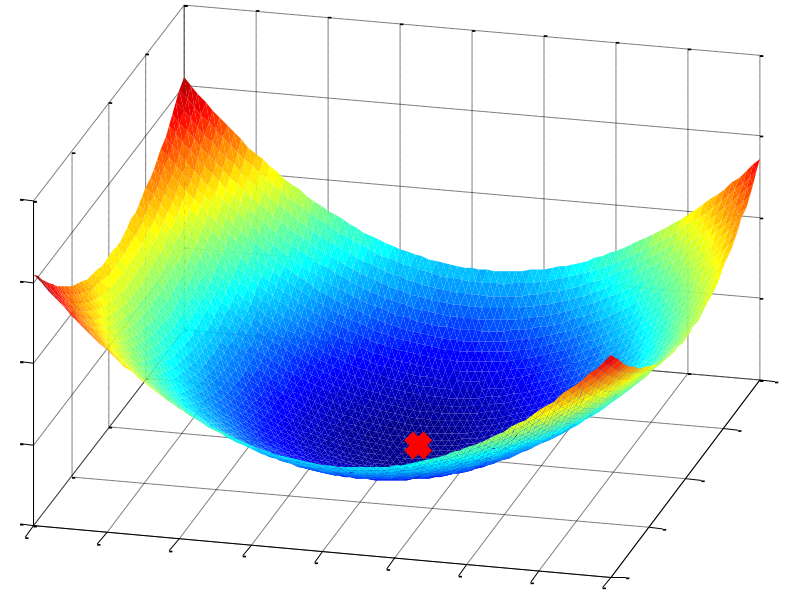
output/target vector
 $m \times 1$

Analytical solution

- Set all partial derivatives of cost function $J(\boldsymbol{\theta}) = 0$
- Solving system of linear equations yields:

$$\boldsymbol{\theta}^* = \underbrace{\left(\mathbf{X}^T \mathbf{X} \right)^{-1} \mathbf{X}^T}_{\text{Moore-Penrose Pseudoinverse of } \mathbf{X}} \mathbf{y}$$

Moore-Penrose Pseudoinverse of \mathbf{X}



\mathbf{X} ... design matrix
 \mathbf{y} ... output/target vector

- *Note: This analytical solution requires that columns of \mathbf{X} are linearly independent („regular“ conditions)*

Non-linear (quadratic) fit

x	y
0.01	-0.27
-1.22	2.63
0.17	-0.13
...	...

$$\phi_0 = 1 \quad \phi_1 = x \quad \phi_2 = x^2$$

$$\Phi = \begin{pmatrix} 1 & 0.01 & 0.01^2 \\ 1 & -1.22 & (-1.22)^2 \\ 1 & 0.17 & (0.17)^2 \\ \vdots & & \end{pmatrix} \quad \mathbf{y} = \begin{pmatrix} -0.27 \\ 2.63 \\ -0.13 \\ \vdots \end{pmatrix}$$

*design matrix with
non-linear features*

Hypothesis: $h_{\boldsymbol{\theta}}(\boldsymbol{\phi}) = \theta_0 + \theta_1 \cdot \phi_1 + \theta_2 \cdot \phi_2$

Optimal parameters: $\boldsymbol{\theta}^* = \left(\Phi^T \Phi \right)^{-1} \Phi^T \mathbf{y}$