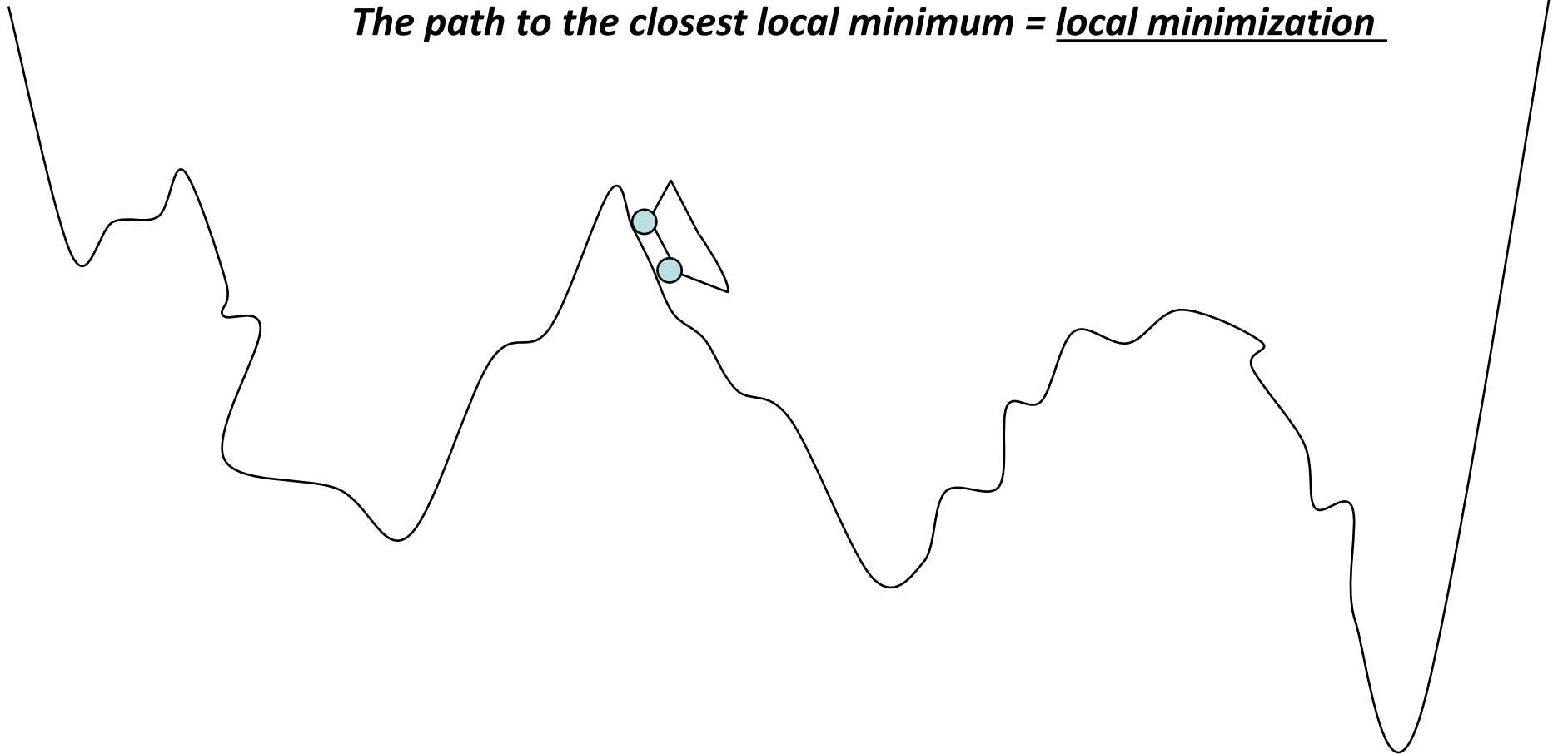


Optimization methods

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DTU

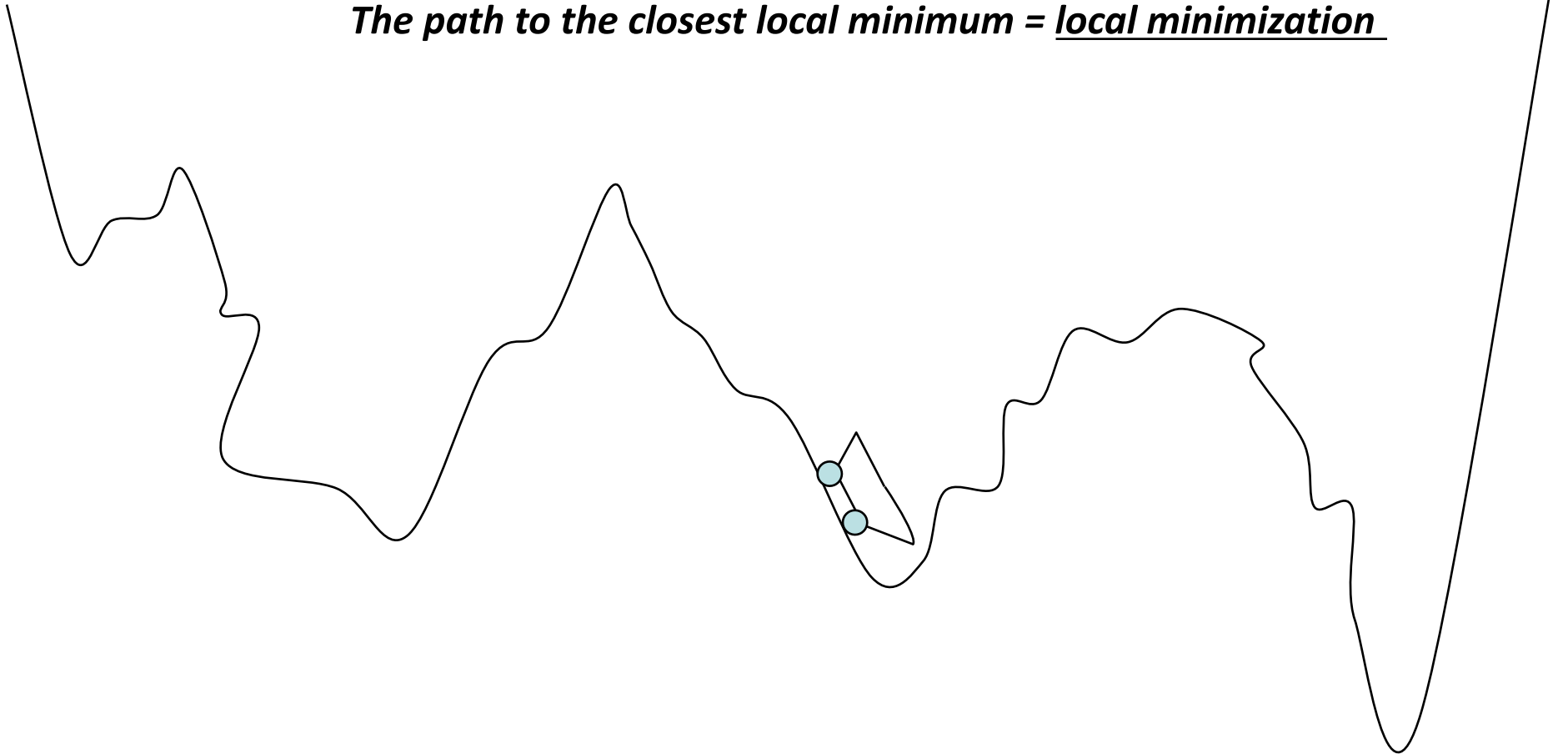
Minimization

The path to the closest local minimum = local minimization

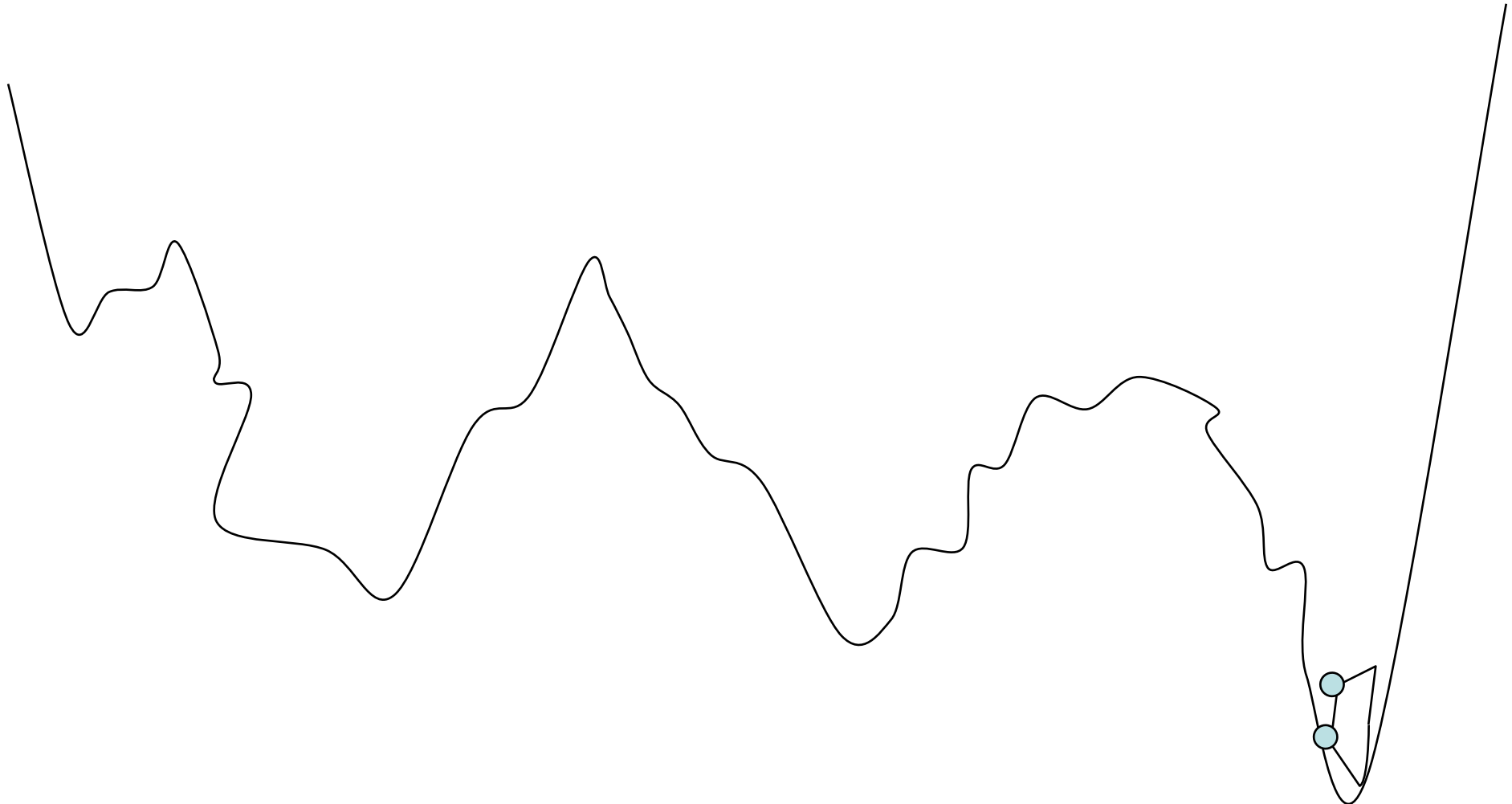


Minimization

The path to the closest local minimum = local minimization



Minimization



The path to the global minimum

Outline

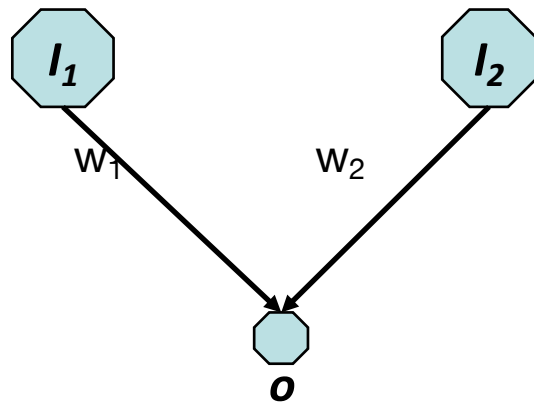
- Optimization procedures
 - Gradient descent
 - Monte Carlo

Linear methods. Error estimate

Linear function

$$o = I_1 \cdot w_1 + I_2 \cdot w_2$$

$$E = \frac{1}{2} \cdot (o - t)^2$$

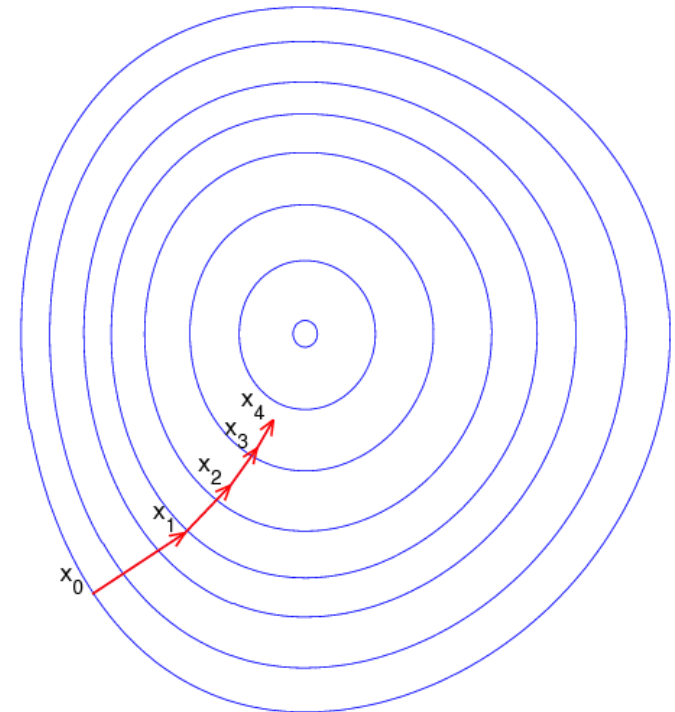


Gradient descent (from wikipedia)

Gradient descent is based on the observation that if the real-valued function $F(x)$ is defined and differentiable in a neighborhood of a point a , then $F(x)$ decreases fastest if one goes from a in the direction of the negative gradient of F at a . It follows that, if

$$b = a - \varepsilon \cdot \nabla F(a)$$

for $\varepsilon > 0$ a small enough number, then $F(b) < F(a)$



Gradient descent (example)

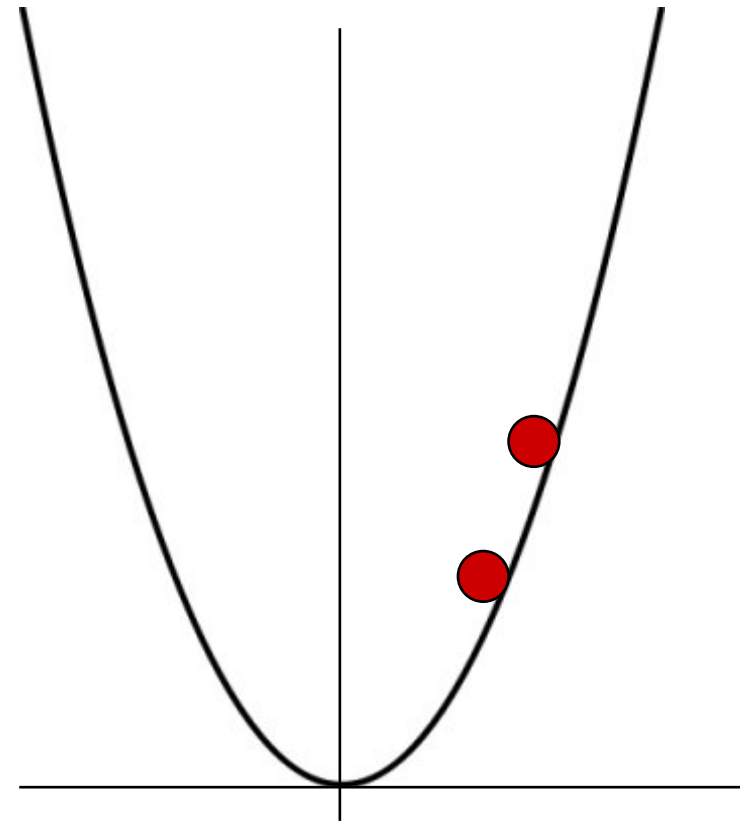
$$F(x) = x^2$$

$$\frac{\partial F}{\partial x} = 2 \cdot x$$

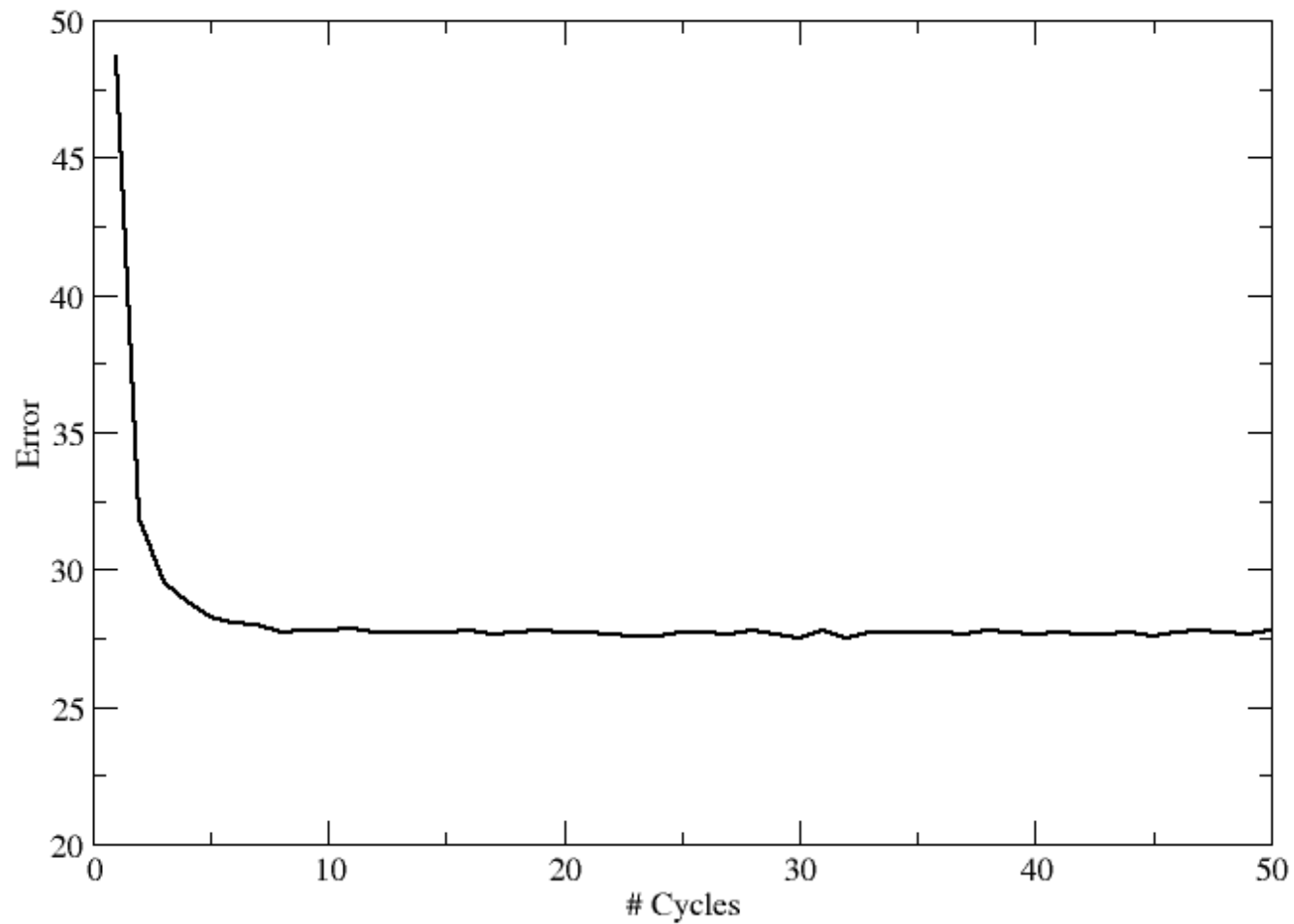
$$a = 2$$

$$F(a) = 4$$

$$b = a - \varepsilon \cdot \nabla F(a) = 2 - 0.1 \cdot 2 \cdot 2 = 1.6$$



Gradient descent



Gradient descent

Weights are changed in the opposite direction of the gradient of the error

$$w'_i = w_i + \Delta w_i$$

$$\Delta w_i = -\varepsilon \cdot \frac{\partial E}{\partial w_i}$$

$$E = \frac{1}{2} \cdot (O - t)^2$$

$$\frac{\partial E}{\partial w_i} = \frac{\partial E}{\partial O} \cdot \frac{\partial O}{\partial w_i}$$

$$\frac{\partial E}{\partial O} = (O - t)$$

$$\frac{\partial O}{\partial w_i} = ?$$

Gradient descent (Linear function)

Weights are changed in the opposite direction of the gradient of the error

$$E = \frac{1}{2} \cdot (O - t)^2$$

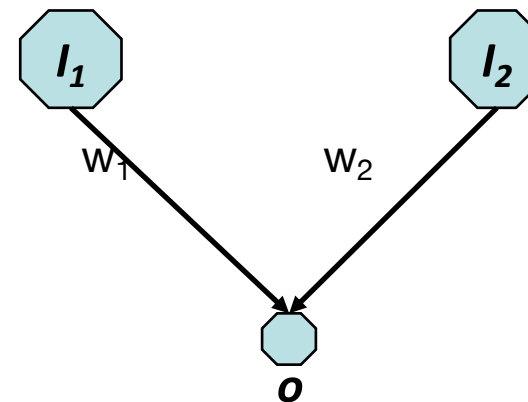
$$O = \sum_i I_i \cdot w_i$$

$$\frac{\partial E}{\partial w_i} = \frac{\partial E}{\partial O} \cdot \frac{\partial O}{\partial w_i}$$

$$\frac{\partial E}{\partial w_i} = (O - t) \cdot \frac{\partial O}{\partial w_i} = ?$$

Linear function

$$O = I_1 \cdot w_1 + I_2 \cdot w_2$$



Gradient descent

Weights are changed in the opposite direction of the gradient of the error

$$E = \frac{1}{2} \cdot (O - t)^2$$

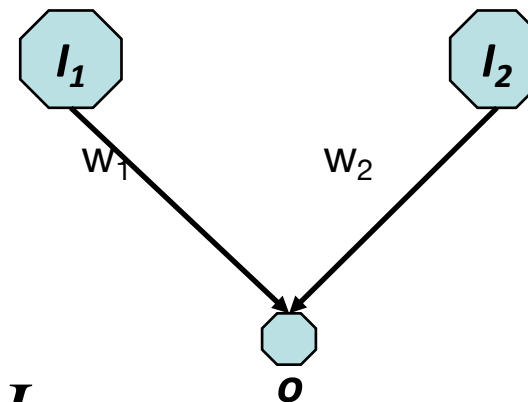
$$O = \sum_i I_i \cdot w_i$$

$$\frac{\partial E}{\partial w_i} = \frac{\partial E}{\partial O} \cdot \frac{\partial O}{\partial w_i}$$

$$\frac{\partial E}{\partial w_i} = (O - t) \cdot \frac{\partial O}{\partial w_i} = (O - t) \cdot I_i$$

Linear function

$$o = I_1 \cdot w_1 + I_2 \cdot w_2$$



Gradient descent. Example

Weights are changed in the opposite direction of the gradient of the error

$$w'_i = w_i + \Delta w_i$$

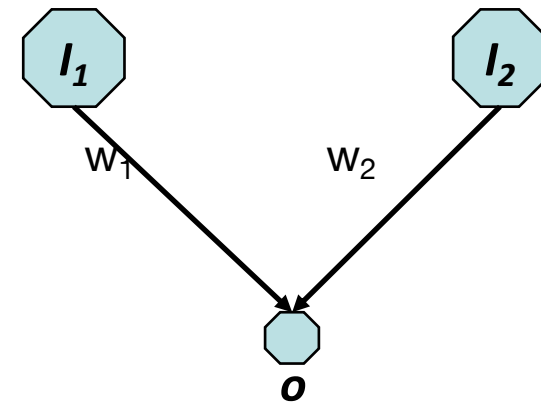
$$E = \frac{1}{2} \cdot (O - t)^2$$

$$O = \sum_i w_i \cdot I_i$$

$$\Delta w_i = -\varepsilon \cdot \frac{\partial E}{\partial w_i} = -\varepsilon \cdot ??$$

Linear function

$$O = I_1 \cdot w_1 + I_2 \cdot w_2$$



Gradient descent. Example

Weights are changed in the opposite direction of the gradient of the error

$$w'_i = w_i + \Delta w_i$$

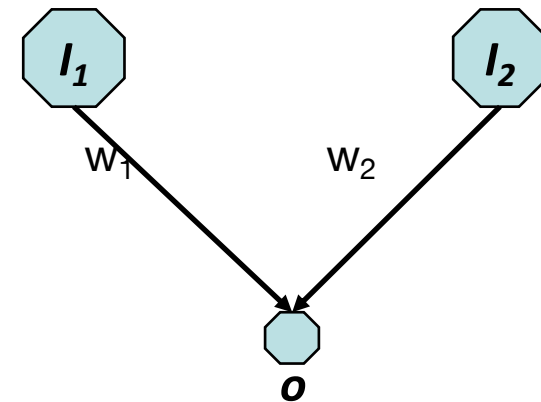
$$E = \frac{1}{2} \cdot (O - t)^2$$

$$O = \sum_i w_i \cdot I_i$$

$$\Delta w_i = -\varepsilon \cdot \frac{\partial E}{\partial w_i} = -\varepsilon \cdot (O - t) \cdot I_i$$

Linear function

$$O = I_1 \cdot w_1 + I_2 \cdot w_2$$



Gradient descent. Doing it your self

Weights are changed in the opposite direction of the gradient of the error

$$w'_i = w_i + \Delta w_i$$

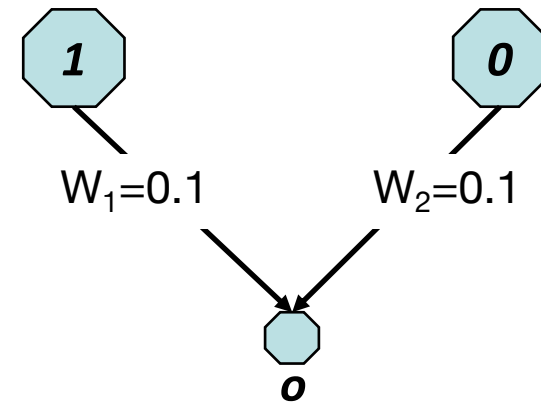
$$E = \frac{1}{2} \cdot (O - t)^2$$

$$O = \sum_i w_i \cdot I_i$$

$$\Delta w_i = -\varepsilon \cdot \frac{\partial E}{\partial w_i} = -\varepsilon \cdot (O - t) \cdot I_i$$

Linear function

$$O = I_1 \cdot w_1 + I_2 \cdot w_2$$



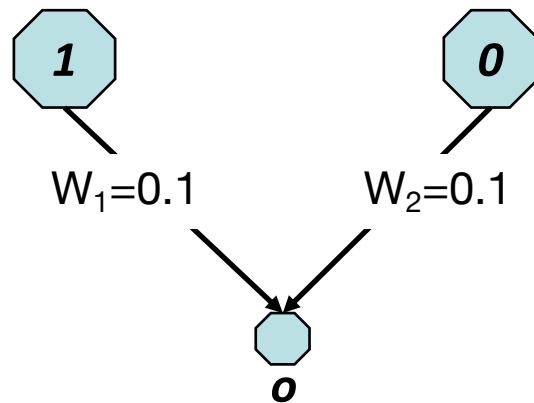
What are the weights after 2 forward (calculate predictions) and backward (update weights) iterations with the given input, and has the error decrease (use $\varepsilon=0.1$, and $t=1$)?

Fill out the table

What are the weights after 2 forward/backward iterations with the given input, and has the error decrease (use $\epsilon=0.1$, $t=1$)?

Linear function

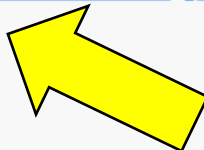
$$O = I_1 \cdot w_1 + I_2 \cdot w_2$$



itr	W1	W2	O
0	0.1	0.1	
1			
2			

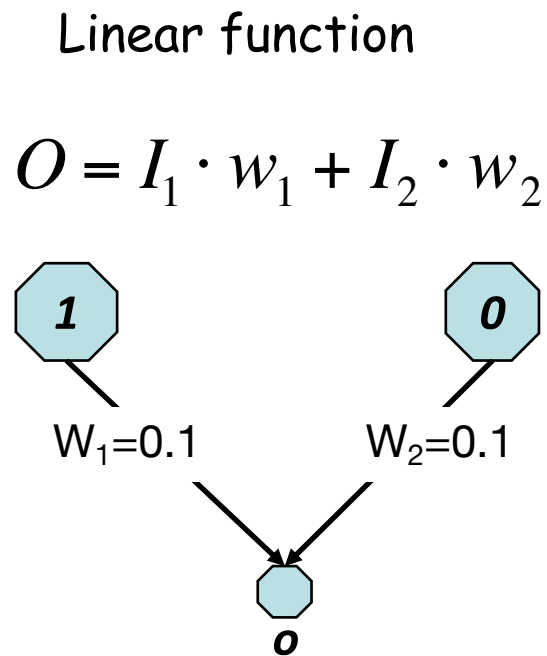
Fill out the table

	Data redundancy reduction algorithms (Hobonim1 and Hobonim2). [PDF] .
10.00 - 10.45 "Recorded"	Optimization procedures - Gradient decent, Monte Carlo Optimization procedures [PDF] GD handout
10.45 - 11.00	Break



Fill out the table

What are the weights after 2 forward/backward iterations with the given input, and has the error decrease (use $\epsilon=0.1$, $t=1$)?



itr	W1	W2	O
0	0.1	0.1	0.1
1	0.19	0.1	0.19
2	0.27	0.1	0.27