



UNIVERSITY OF TECHNOLOGY  
IN THE EUROPEAN CAPITAL OF CULTURE  
CHEMNITZ

# Neurocomputing

Linear regression

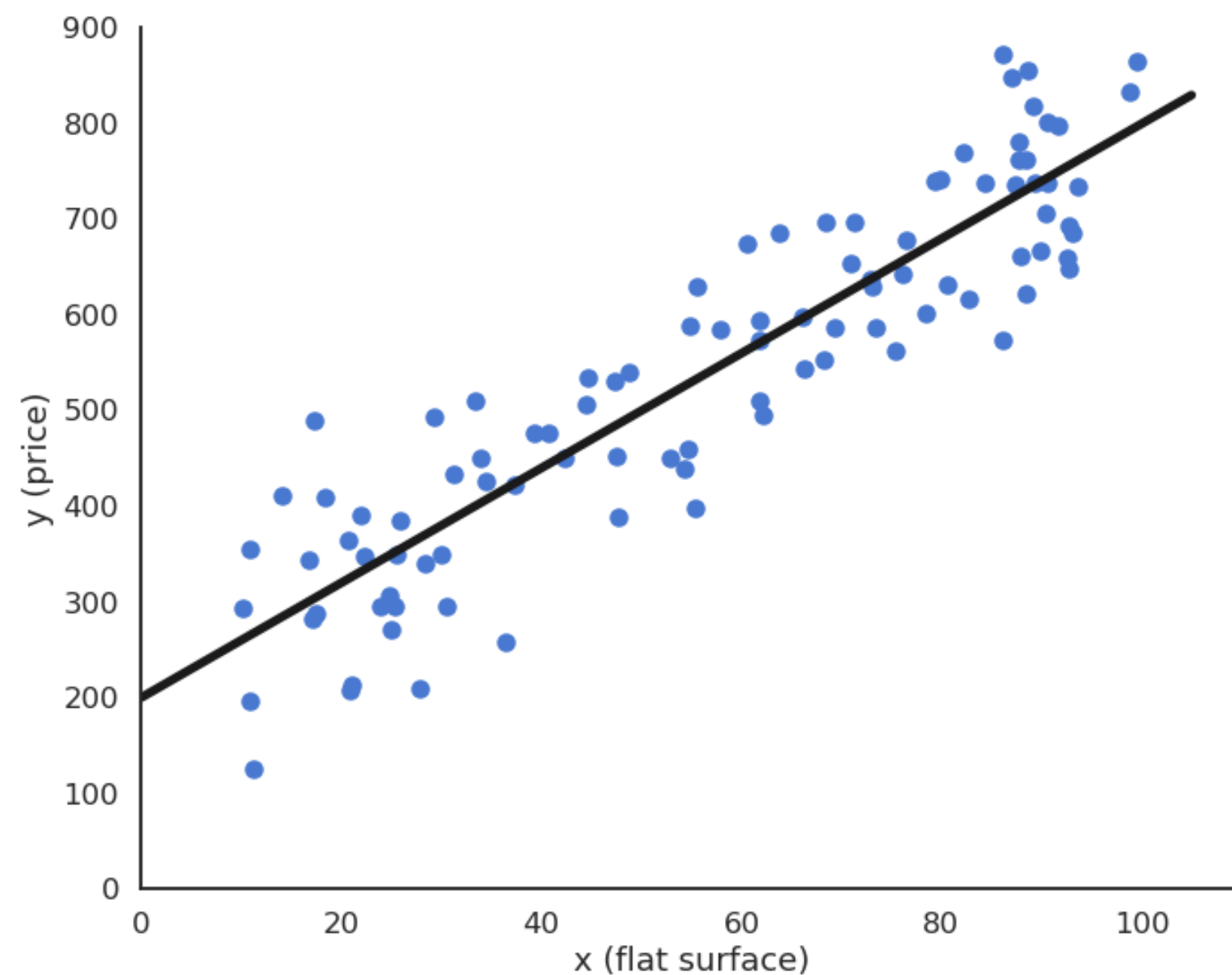
Julien Vitay

Professur für Künstliche Intelligenz - Fakultät für Informatik

<https://tu-chemnitz.de/informatik/KI/edu/neurocomputing>

# 1 - Linear regression

# Linear regression

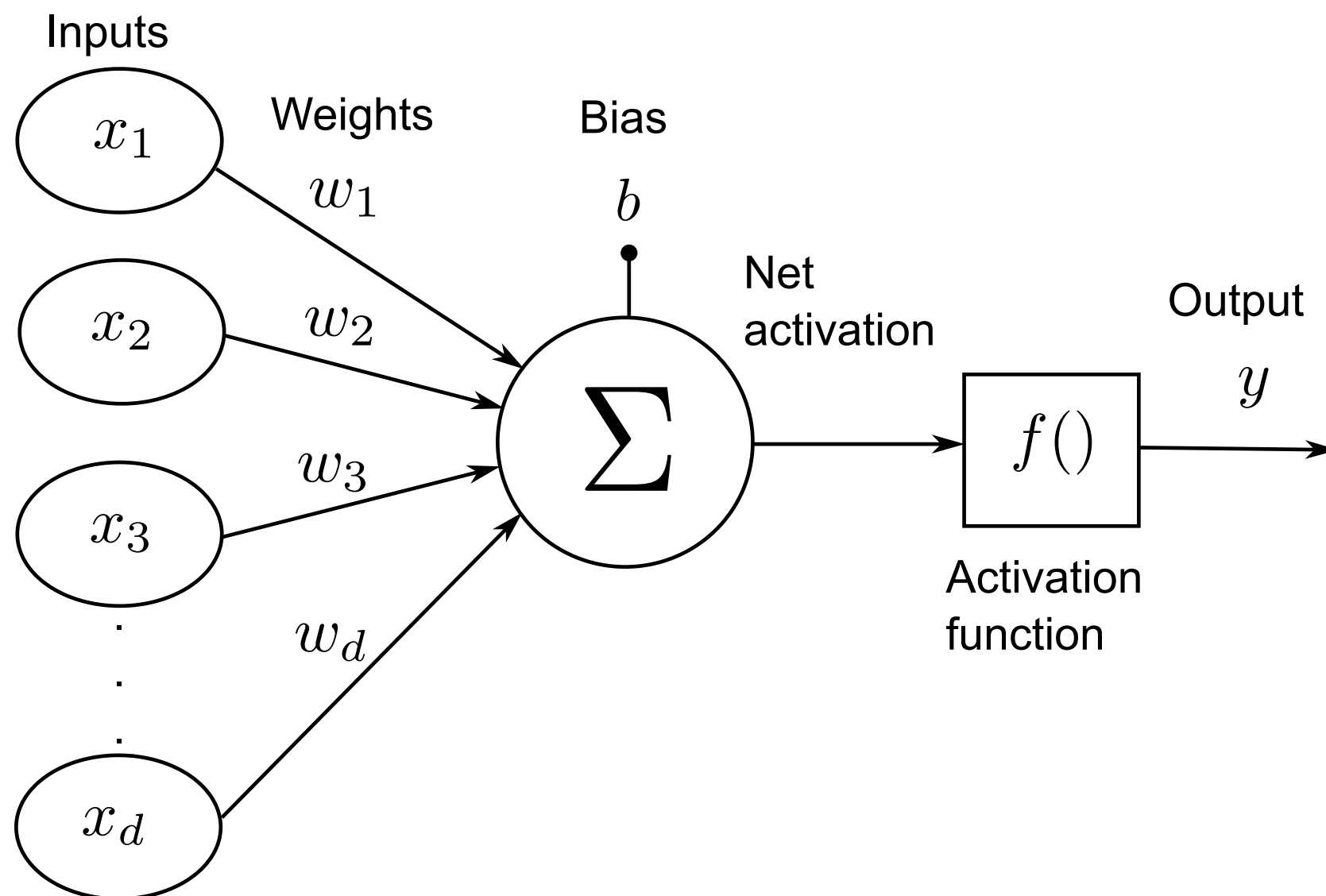


- We have a training set of  $N$  examples  $\mathcal{D} = (x_i, t_i)_{i=1..N}$ .
- In **linear regression**, we want to learn a linear model (hypothesis)  $y$  that is linearly dependent on the input  $x$ :

$$y = f_{w,b}(x) = w x + b$$

- The **free parameters** of the model are
  - the slope  $w$ ,
  - the intercept  $b$ .
- The data  $\mathcal{D} = (x_i, t_i)_{i=1..N}$  is given (fixed).

# Linear regression



- Mathematical model:

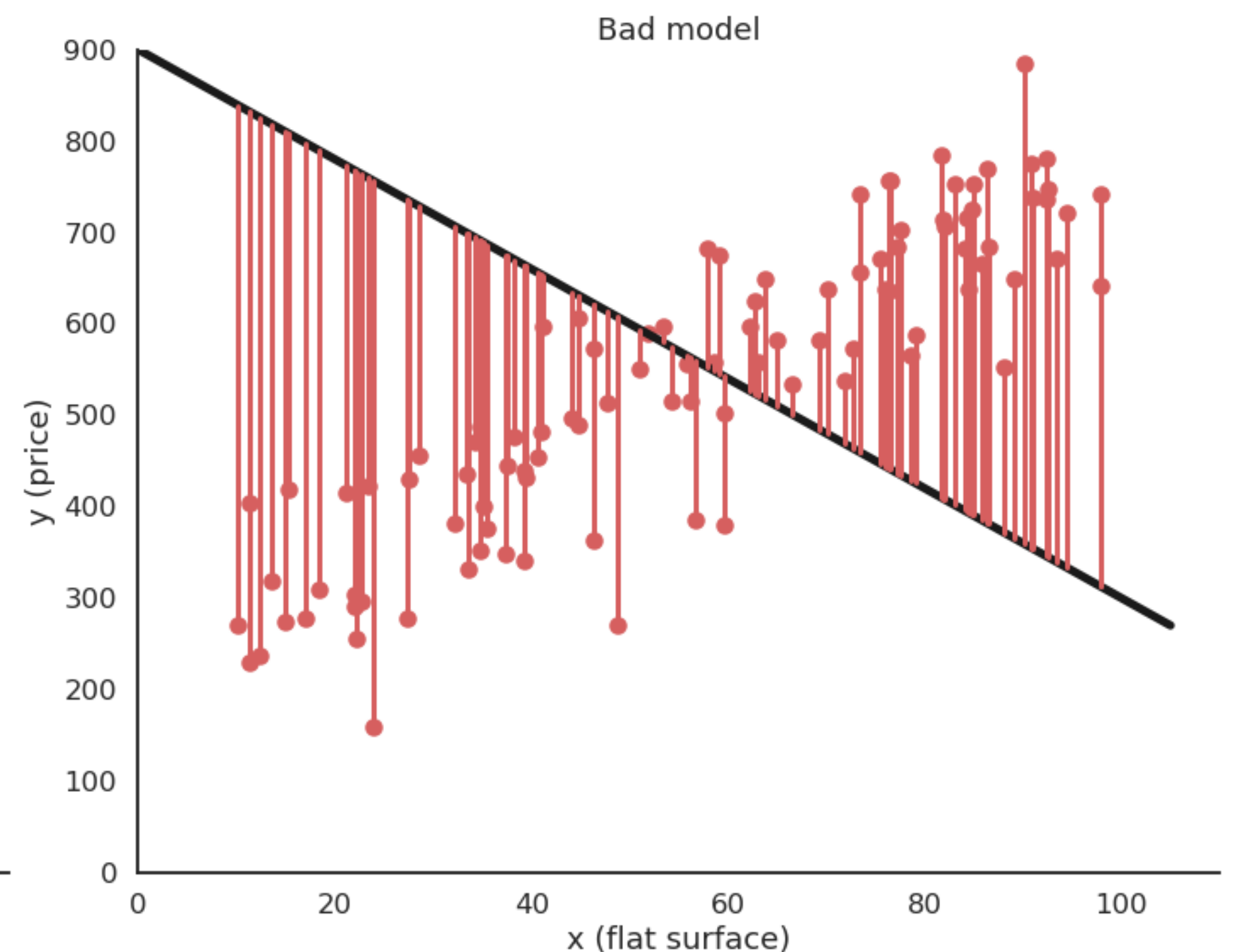
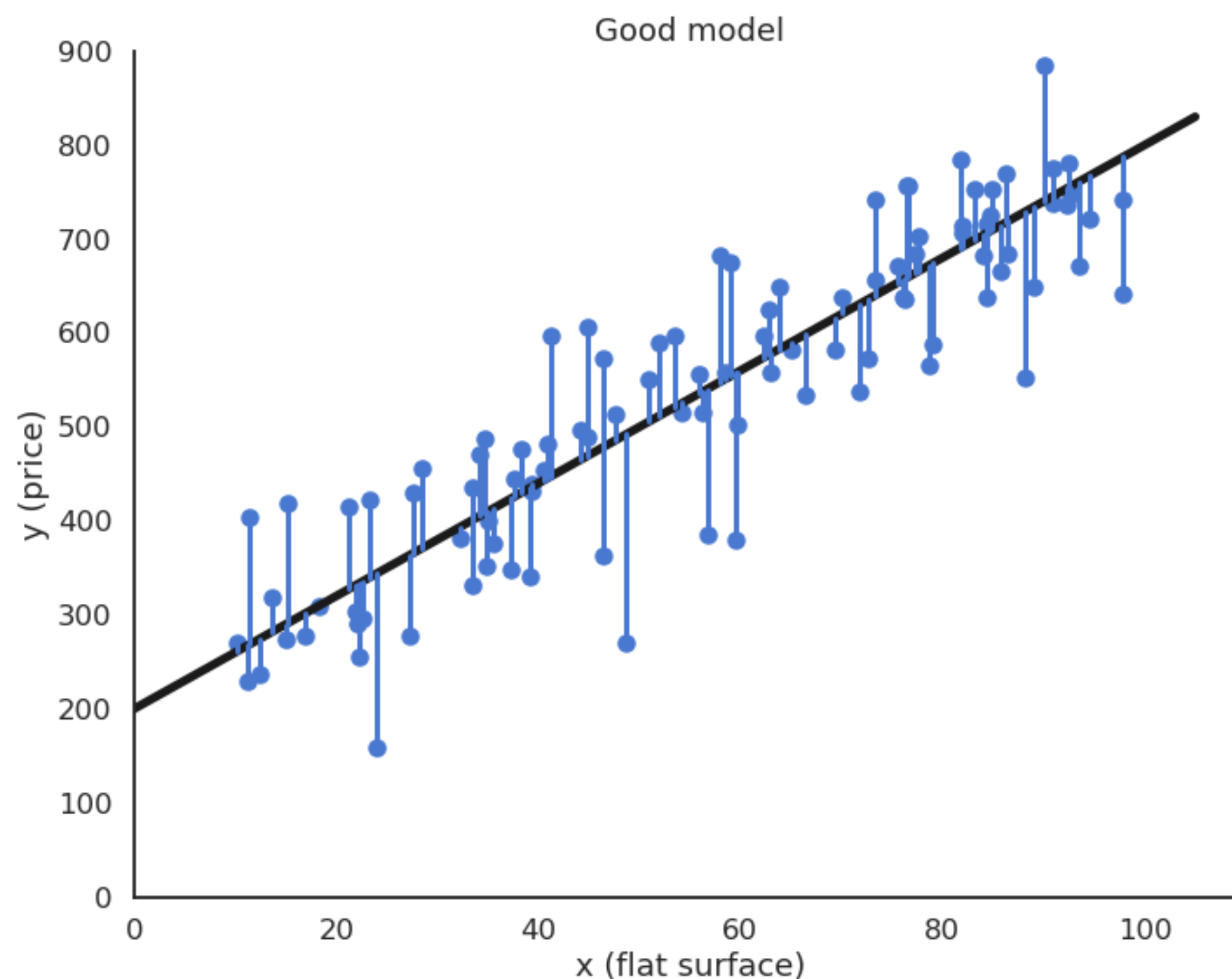
$$y = f_{w,b}(x) = w x + b$$

- This corresponds to a single artificial neuron  $y$  with:
  - one input  $x$ ,
  - one weight  $w$ ,
  - one bias  $b$ ,
  - a **linear** activation function.
- We will see that this generalizes to multiple inputs and outputs.

# Linear regression

- The goal of the linear regression (or least mean squares - LMS) is to minimize the **mean square error** (mse) between the targets and the predictions.
- It is defined as the mathematical expectation of the quadratic error over the training data:

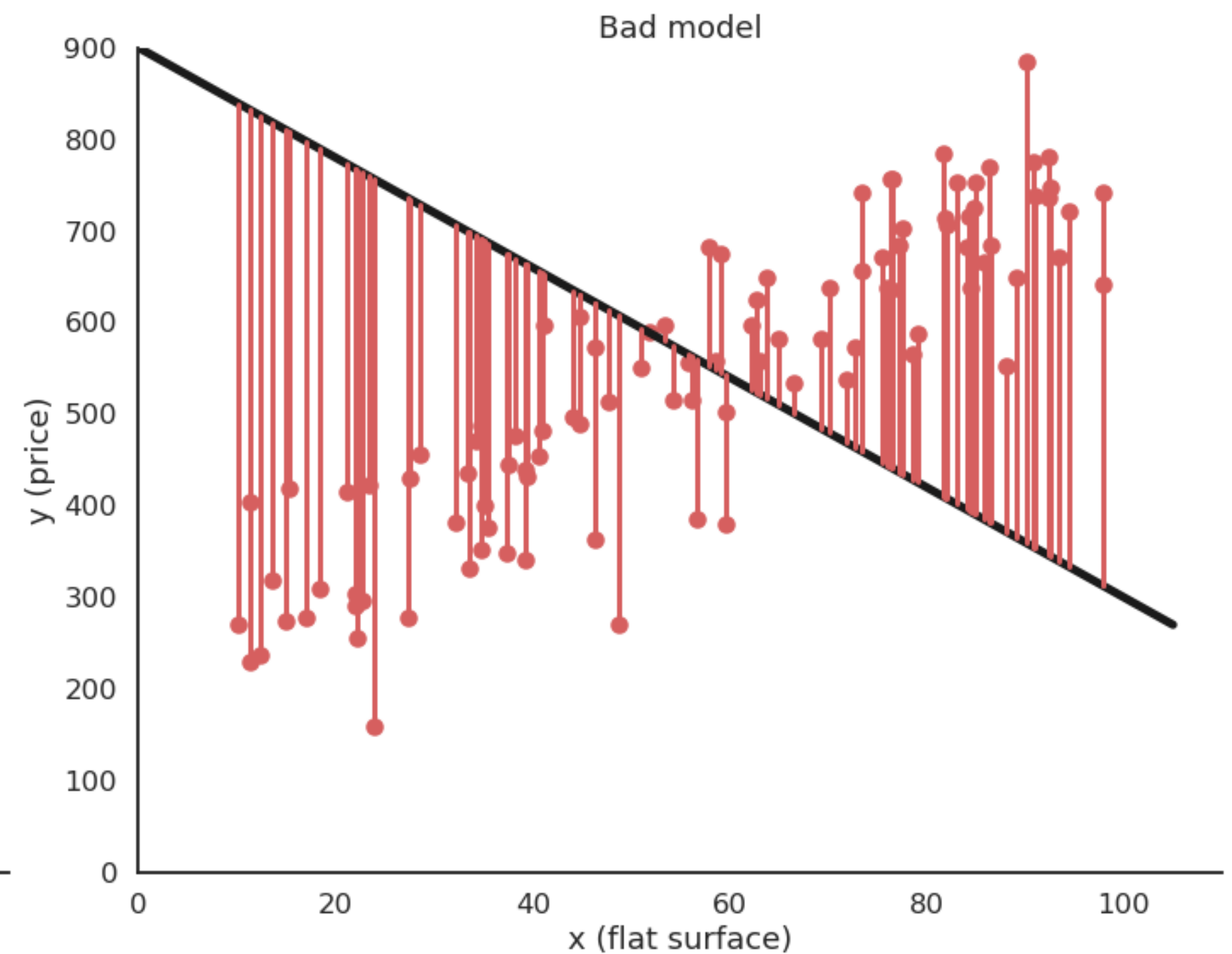
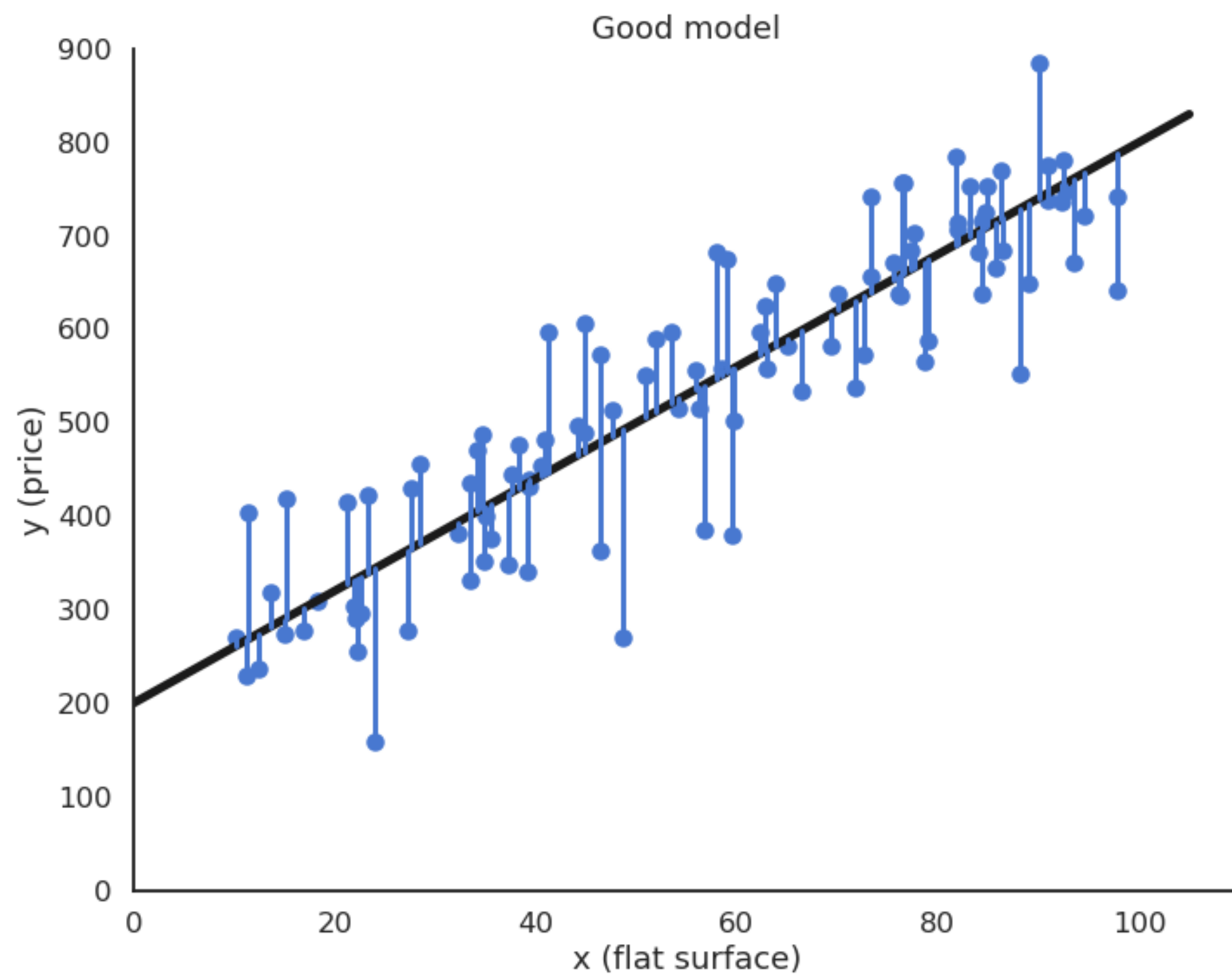
$$\mathcal{L}(w, b) = \mathbb{E}_{x_i, t_i \in \mathcal{D}} [(t_i - y_i)^2]$$



# Linear regression

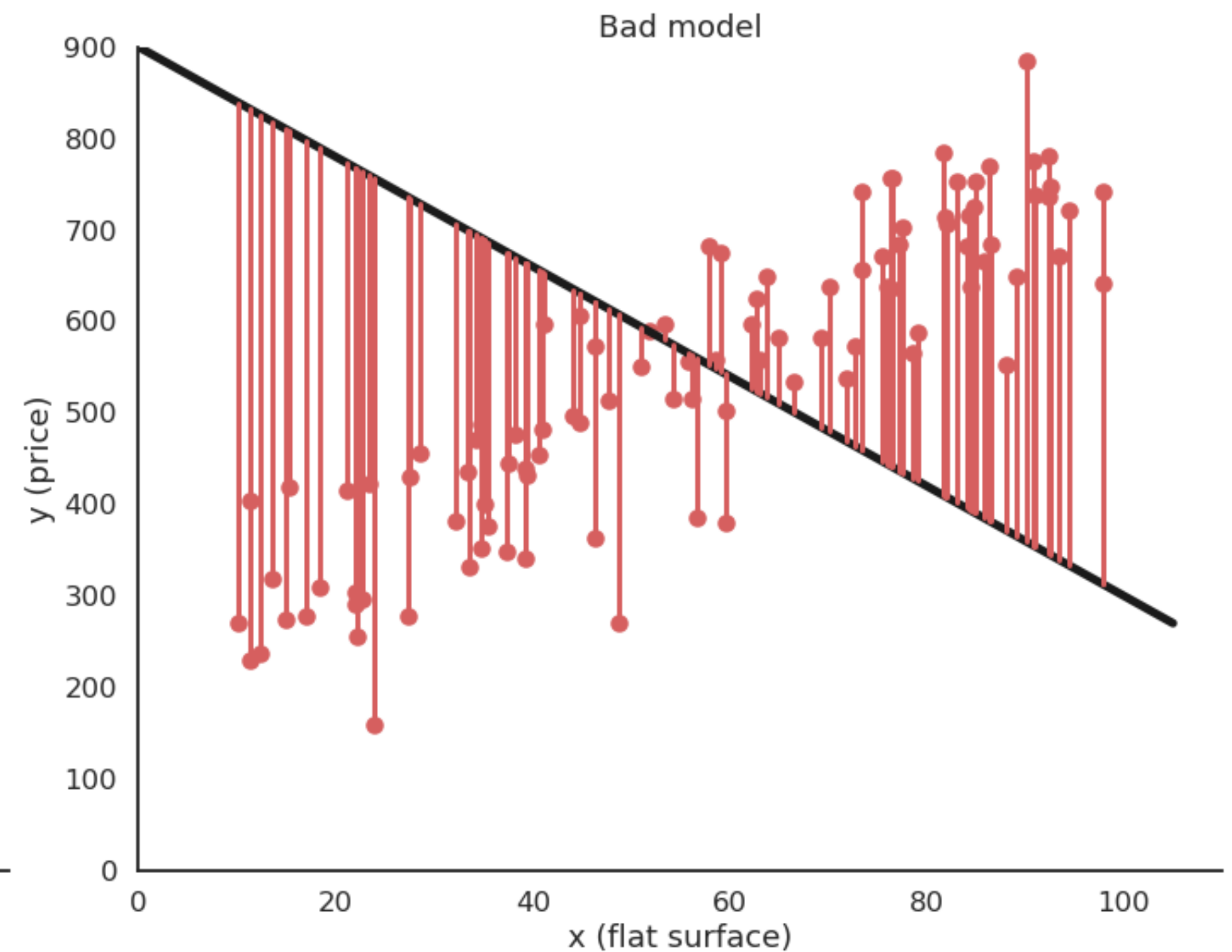
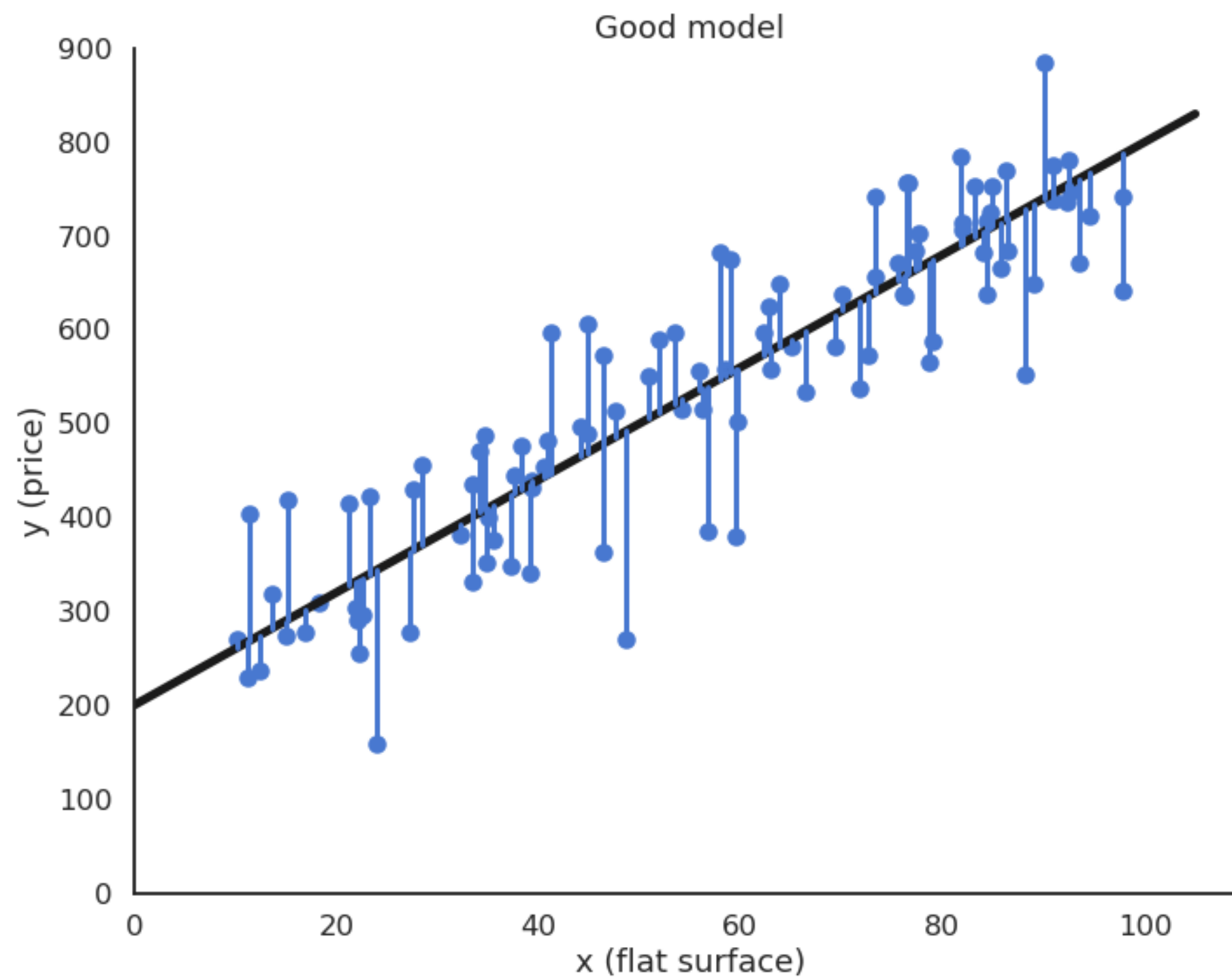
- As the training set is finite and the samples i.i.d (independent and identically distributed), we can simply replace the expectation by a sampling average:

$$\mathcal{L}(w, b) = \frac{1}{N} \sum_{i=1}^N (t_i - y_i)^2$$



# Linear regression

- The minimum of the mse is achieved when the **prediction**  $y_i = f_{w,b}(x_i)$  is equal to the **ground truth**  $t_i$  for all training examples.
- In other words, we want to minimize the **residual error** of the model on the data.
- It is not always possible to obtain the global minimum (0) but the closer, the better.



# Gradient descent for linear regression

- We search for  $w$  and  $b$  which minimize the mean square error:

$$\mathcal{L}(w, b) = \frac{1}{N} \sum_{i=1}^N (t_i - y_i)^2$$

- We will apply *gradient descent* to iteratively modify estimates of  $w$  and  $b$ :

$$\Delta w = -\eta \frac{\partial \mathcal{L}(w, b)}{\partial w}$$

$$\Delta b = -\eta \frac{\partial \mathcal{L}(w, b)}{\partial b}$$



# Gradient descent for linear regression

- Let's search for the partial derivative (gradient) of the quadratic error with respect to  $w$ :

$$\frac{\partial \mathcal{L}(w, b)}{\partial w} = \frac{\partial}{\partial w} \left[ \frac{1}{N} \sum_{i=1}^N (t_i - y_i)^2 \right]$$

- Partial derivatives are linear, so the derivative of a sum is the sum of the derivatives:

$$\frac{\partial \mathcal{L}(w, b)}{\partial w} = \frac{1}{N} \sum_{i=1}^N \frac{\partial}{\partial w} (t_i - y_i)^2$$

- This means we can compute a gradient for each training example instead of for the whole training set (see later the distinction batch/online):

$$\frac{\partial \mathcal{L}(w, b)}{\partial w} = \frac{1}{N} \sum_{i=1}^N \frac{\partial}{\partial w} l_i(w, b) \quad \text{with} \quad l_i(w, b) = (t_i - y_i)^2$$

# Gradient descent for linear regression

- The individual loss  $l_i(w, b) = (t_i - y_i)^2$  is the composition of two functions:
  - a square error function  $g_i(y_i) = (t_i - y_i)^2$ .
  - the prediction  $y_i = f_{w,b}(x_i) = w x_i + b$ .
- The **chain rule** tells us how to derive such composite functions:

$$\frac{df(g(x))}{dx} = \frac{df(g(x))}{dg(x)} \times \frac{dg(x)}{dx} = \frac{df(y)}{dy} \times \frac{dg(x)}{dx}$$

- The first derivative considers  $g(x)$  to be a single variable.
- Applied to our problem, this gives:

$$\frac{\partial}{\partial w} l_i(w, b) = \frac{\partial g_i(y_i)}{\partial y_i} \times \frac{\partial y_i}{\partial w}$$

# Gradient descent for linear regression

- The square error function  $g_i(y) = (t_i - y)^2$  is easy to differentiate w.r.t  $y$ :

$$\frac{\partial g_i(y_i)}{\partial y_i} = -2 (t_i - y_i)$$

- The prediction  $y_i = w x_i + b$  also w.r.t  $w$  and  $b$ :

$$\frac{\partial y_i}{\partial w} = x_i$$

$$\frac{\partial y_i}{\partial b} = 1$$

- The partial derivative of the individual loss is:

$$\frac{\partial l_i(w, b)}{\partial w} = -2 (t_i - y_i) x_i$$

$$\frac{\partial l_i(w, b)}{\partial b} = -2 (t_i - y_i)$$

# Gradient descent for linear regression

- This gives us:

$$\frac{\partial \mathcal{L}(w, b)}{\partial w} = -\frac{2}{N} \sum_{i=1}^N (t_i - y_i) x_i$$

$$\frac{\partial \mathcal{L}(w, b)}{\partial b} = -\frac{2}{N} \sum_{i=1}^N (t_i - y_i)$$

- Gradient descent is then defined by the learning rules (absorbing the 2 in  $\eta$ ):

$$\Delta w = \eta \frac{1}{N} \sum_{i=1}^N (t_i - y_i) x_i$$

$$\Delta b = \eta \frac{1}{N} \sum_{i=1}^N (t_i - y_i)$$

# Least Mean Squares (LMS) - Ordinary Least Squares (OLS)

- LMS is a **batch** algorithm: the parameter changes are computed over the whole dataset.

$$\begin{cases} \Delta w = \eta \frac{1}{N} \sum_{i=1}^N (t_i - y_i) x_i \\ \Delta b = \eta \frac{1}{N} \sum_{i=1}^N (t_i - y_i) \end{cases}$$

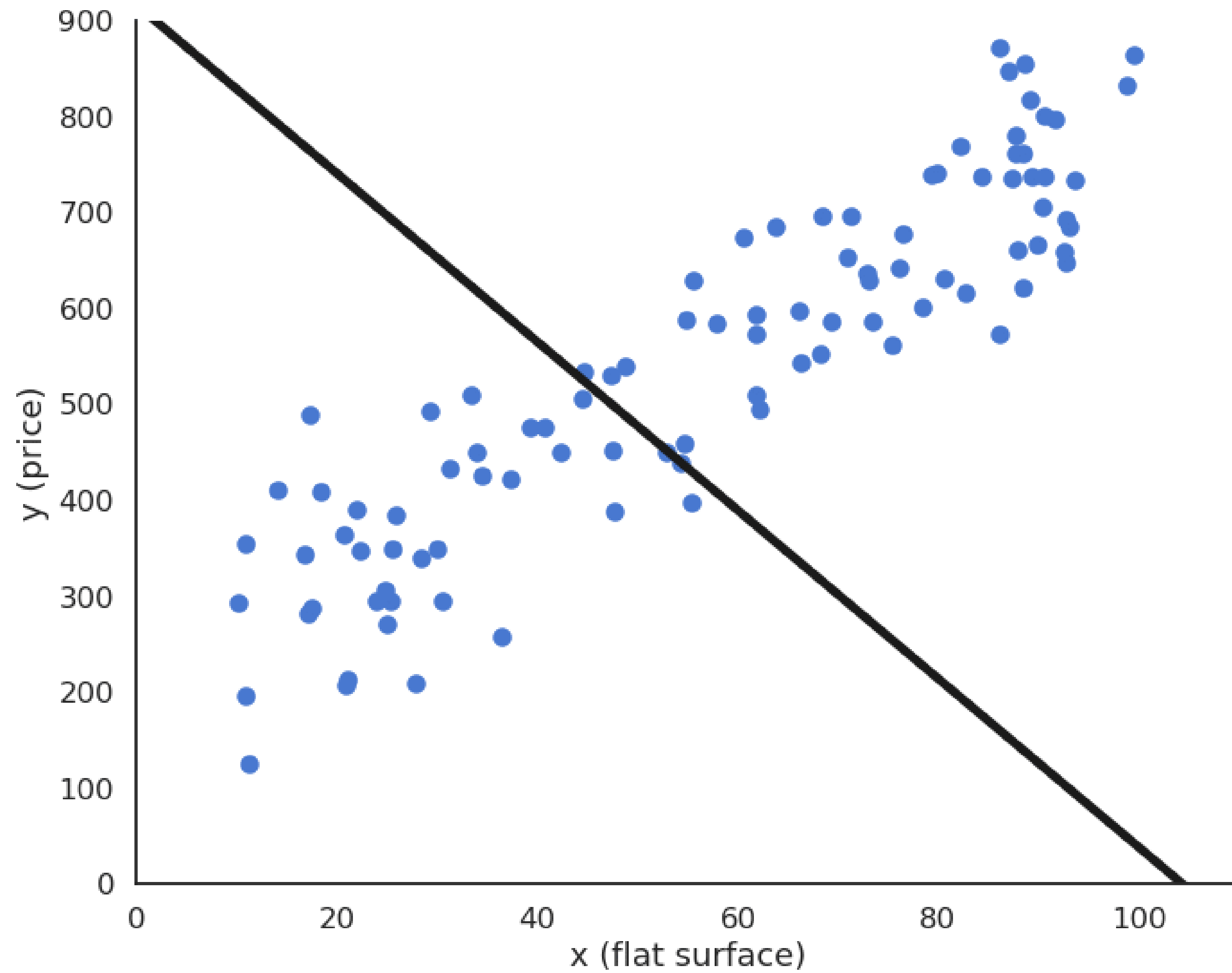
- The parameter changes have to be applied multiple times (**epochs**) in order for the parameters to converge.
- One can stop when the parameters do not change much, or after a fixed number of epochs.



## Least Mean Squares algorithm

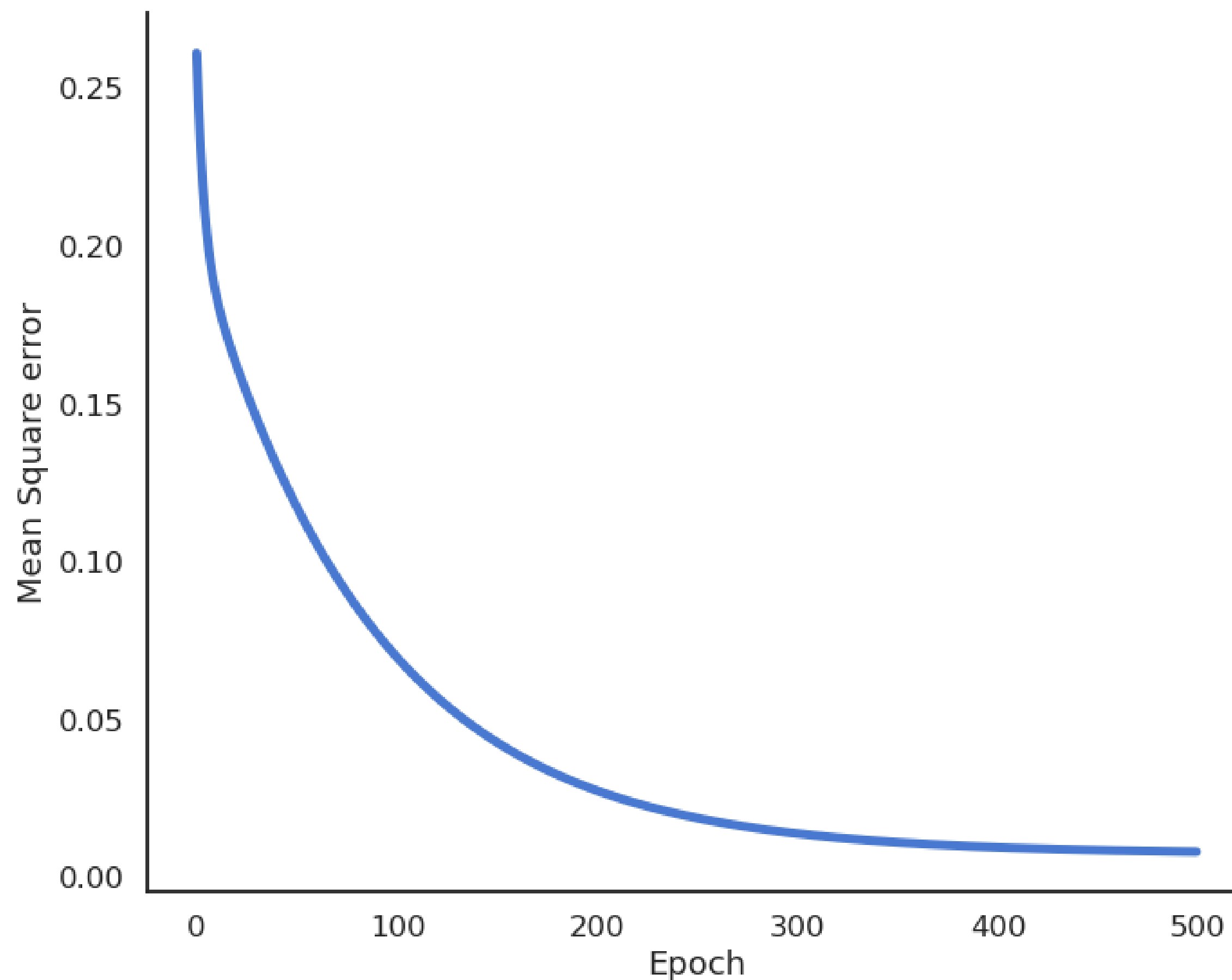
- $w = 0$  ;  $b = 0$
- **for** M epochs:
  - $dw = 0$  ;  $db = 0$
  - **for** each sample  $(x_i, t_i)$ :
    - $y_i = w x_i + b$
    - $dw = dw + (t_i - y_i) x_i$
    - $db = db + (t_i - y_i)$
  - $\Delta w = \eta \frac{1}{N} dw$
  - $\Delta b = \eta \frac{1}{N} db$

## Least mean squares in action



# Least mean squares

- During learning, the **mean square error** (mse) decreases with the number of epochs but does not reach zero because of the noise in the data.



# Delta learning rule: Online version of LMS

- LMS is very slow, because it changes the weights only after the whole training set has been evaluated.

$$\begin{cases} \Delta w = \eta \frac{1}{N} \sum_{i=1}^N (t_i - y_i) x_i \\ \Delta b = \eta \frac{1}{N} \sum_{i=1}^N (t_i - y_i) \end{cases}$$



## Online version of LMS : delta learning rule

- $w = 0$  ;  $b = 0$
- **for** M epochs:
  - **for** each sample  $(x_i, t_i)$ :
    - $y_i = w x_i + b$
    - $\Delta w = \eta (t_i - y_i) x_i$
    - $\Delta b = \eta (t_i - y_i)$

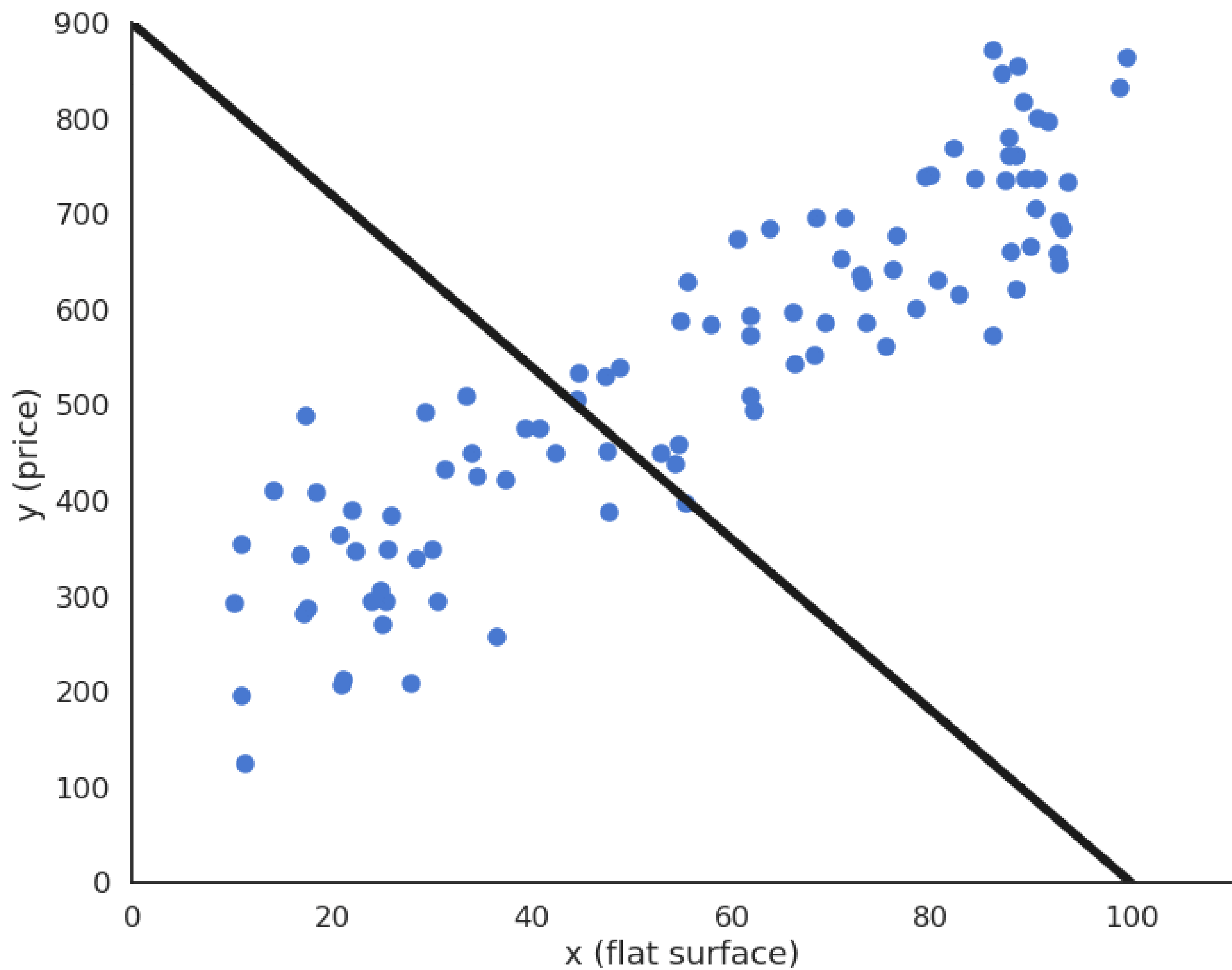
- It is also possible to update the weights immediately after each example using the **delta learning rule**:

$$\begin{cases} \Delta w = \eta (t_i - y_i) x_i \\ \Delta b = \eta (t_i - y_i) \end{cases}$$

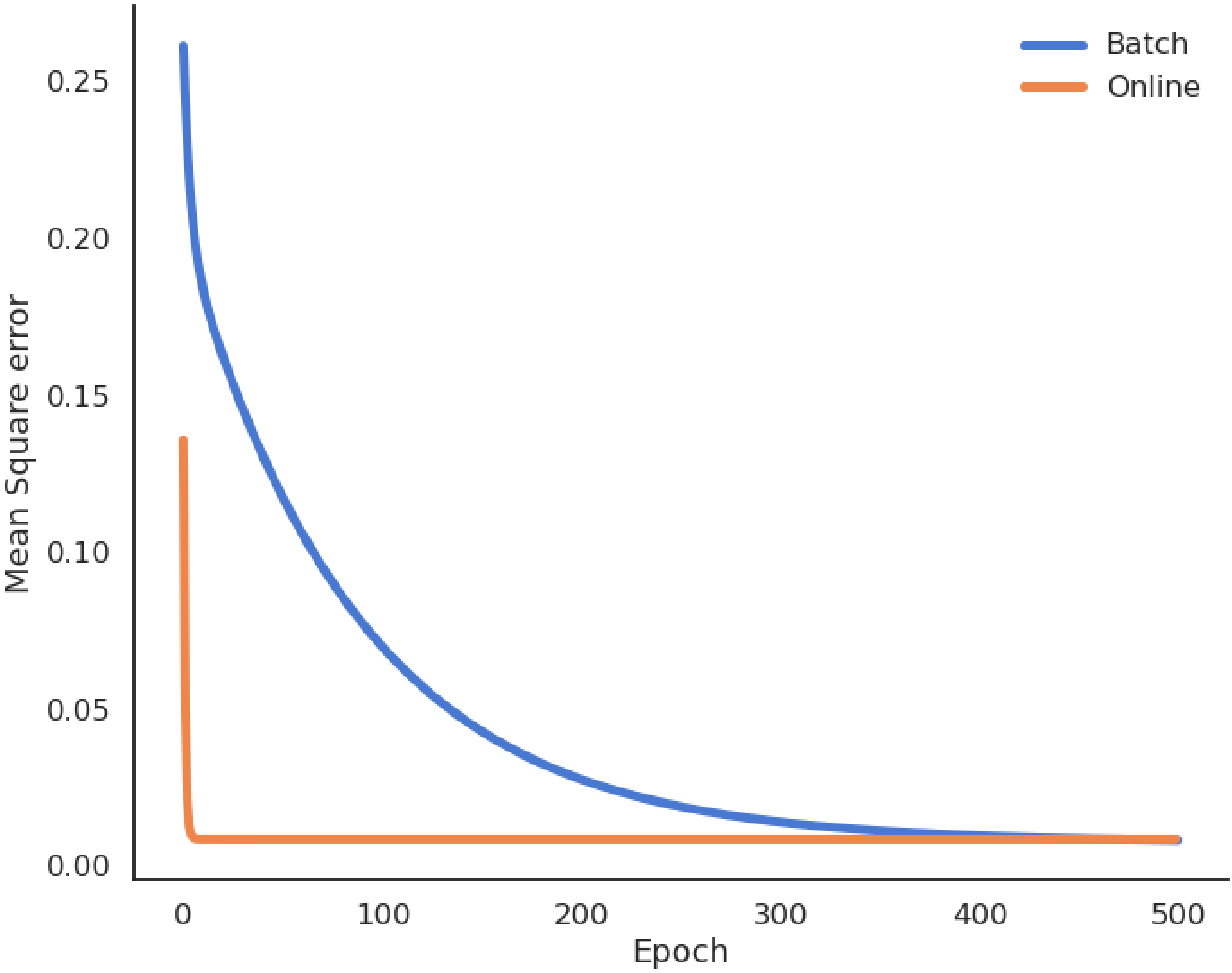
- The batch version is more stable, but the online version is faster: the weights have already learned something when arriving at the end of the first epoch.



# Delta learning rule in action (same learning rate!)



# Delta learning rule



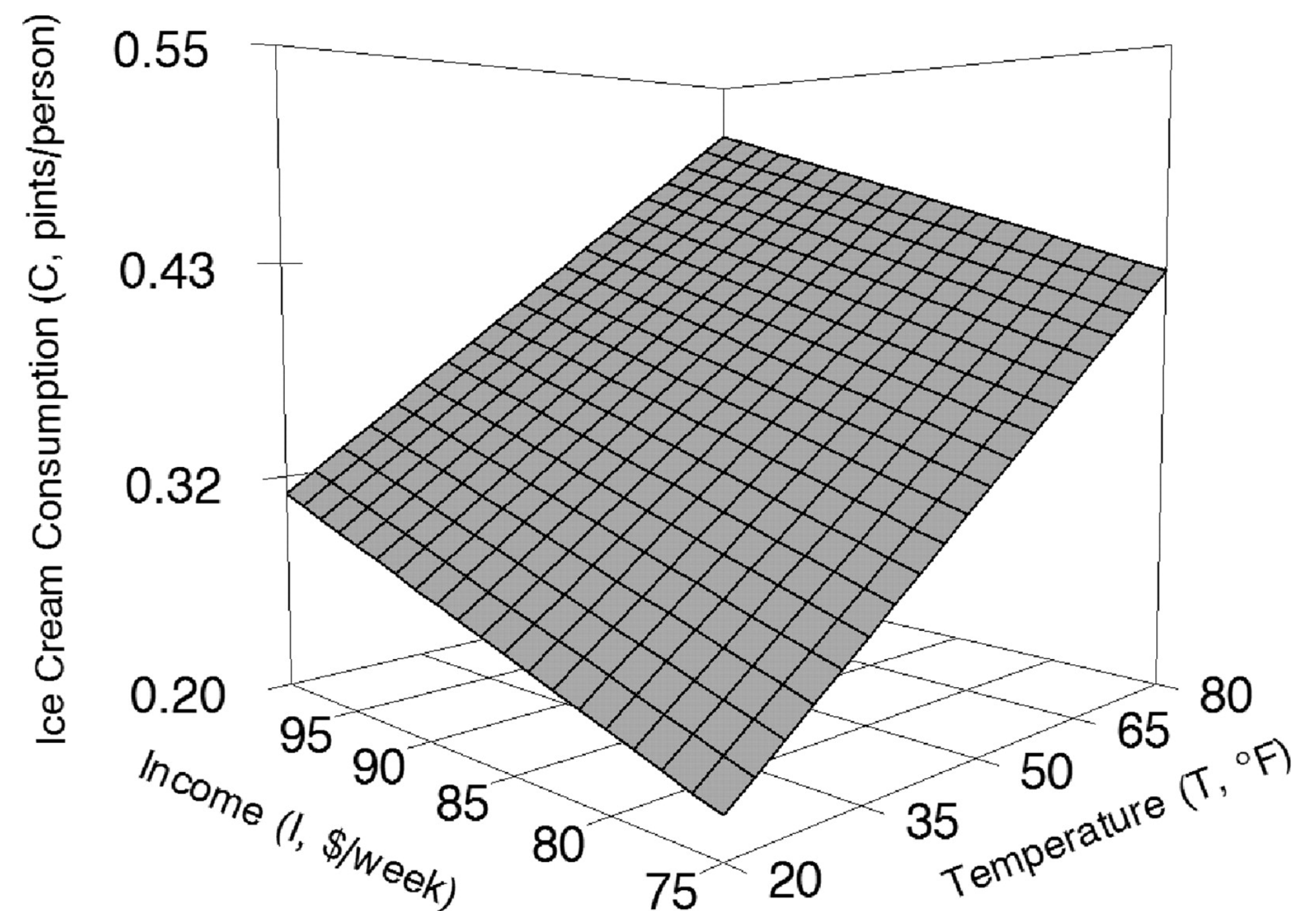
## 2 - Multiple linear regression

# Multiple linear regression

- The key idea of linear regression (one input  $x$ , one output  $y$ ) can be generalized to multiple inputs and outputs.
- **Multiple Linear Regression** (MLR) predicts several output variables based on several explanatory variables or **features**:

$$\begin{cases} y_1 = w_1 x_1 + w_2 x_2 + b_1 \\ y_2 = w_3 x_1 + w_4 x_2 + b_2 \end{cases}$$

- All we have is some samples: we want to know the best model for the data.

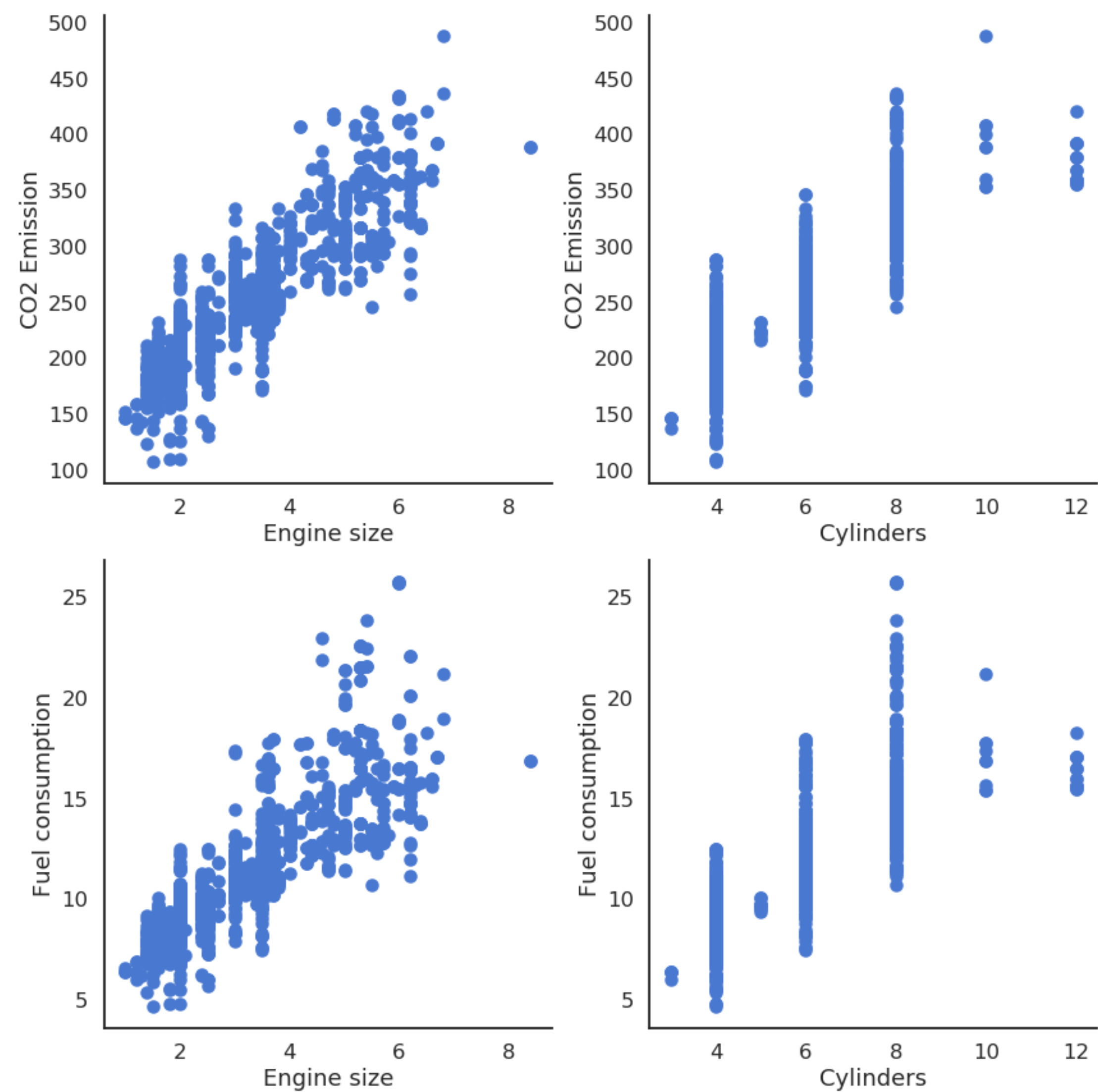


# MLR example: fuel consumption and CO2 emissions

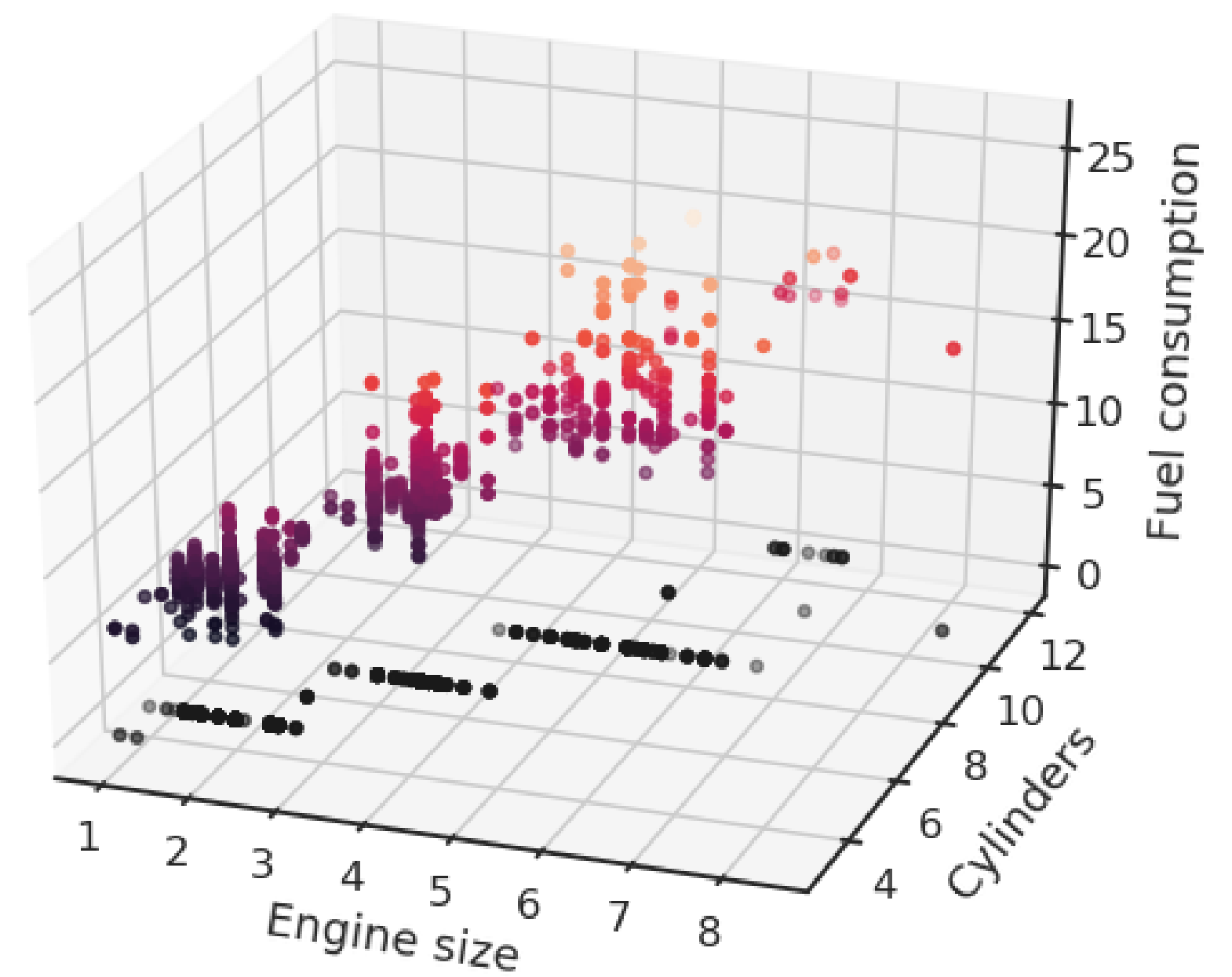
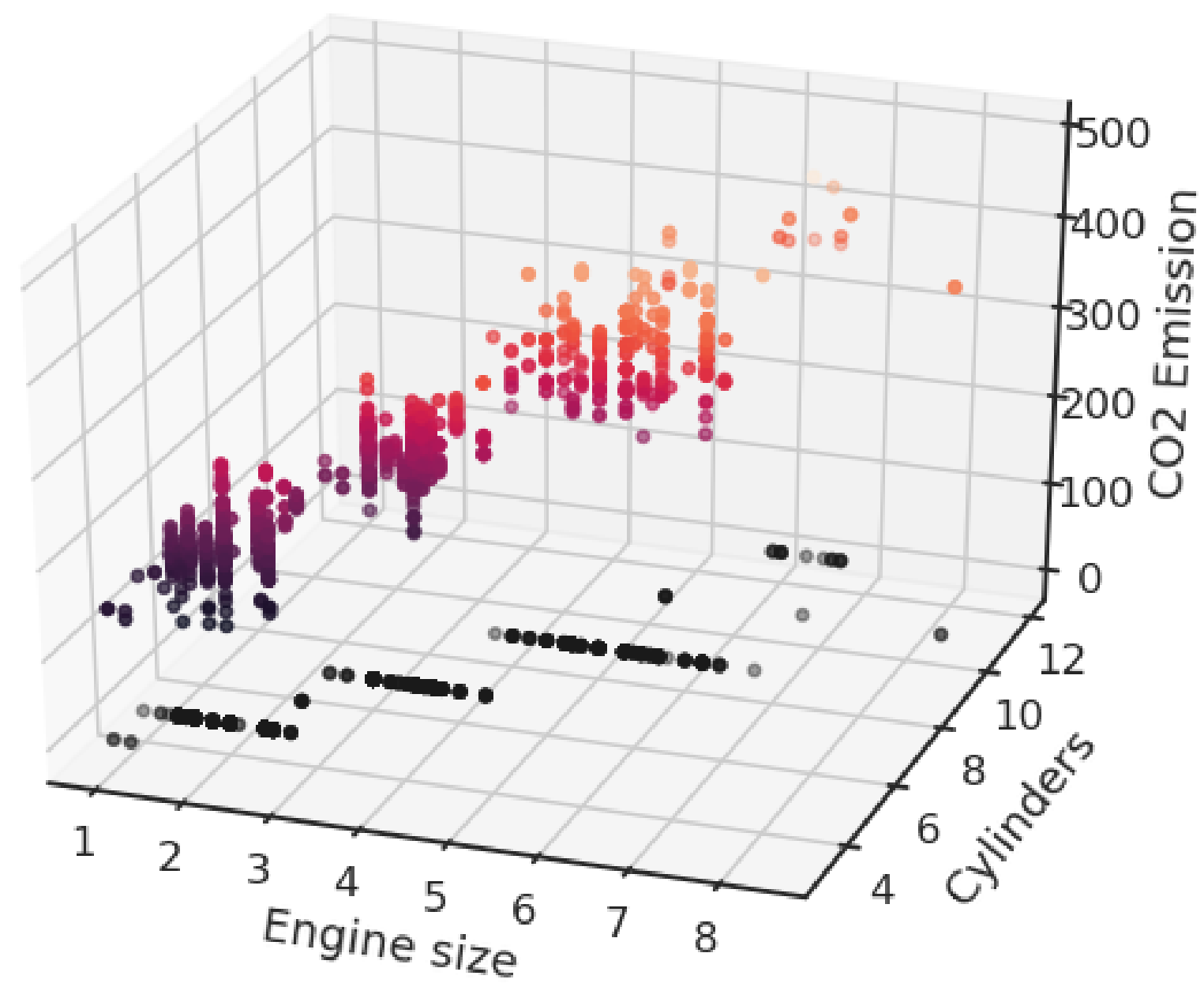
- Let's suppose you have 13971 measurements in some Excel file, linking engine size, number of cylinders, fuel consumption and CO2 emissions of various cars.
- You want to predict fuel consumption and CO2 emissions when you know the engine size and the number of cylinders.

Engine size	Cylinders	Fuel consumption	CO2 emissions
2	4	8.5	196
2.4	4	9.6	221
1.5	4	5.9	136
3.5	6	11	255
3.5	6	11	244
3.5	6	10	230
3.5	6	10	232
3.7	6	11	255
3.7	6	12	267
...	...	...	...

# MLR example: fuel consumption and CO2 emissions



## MLR example: fuel consumption and CO2 emissions



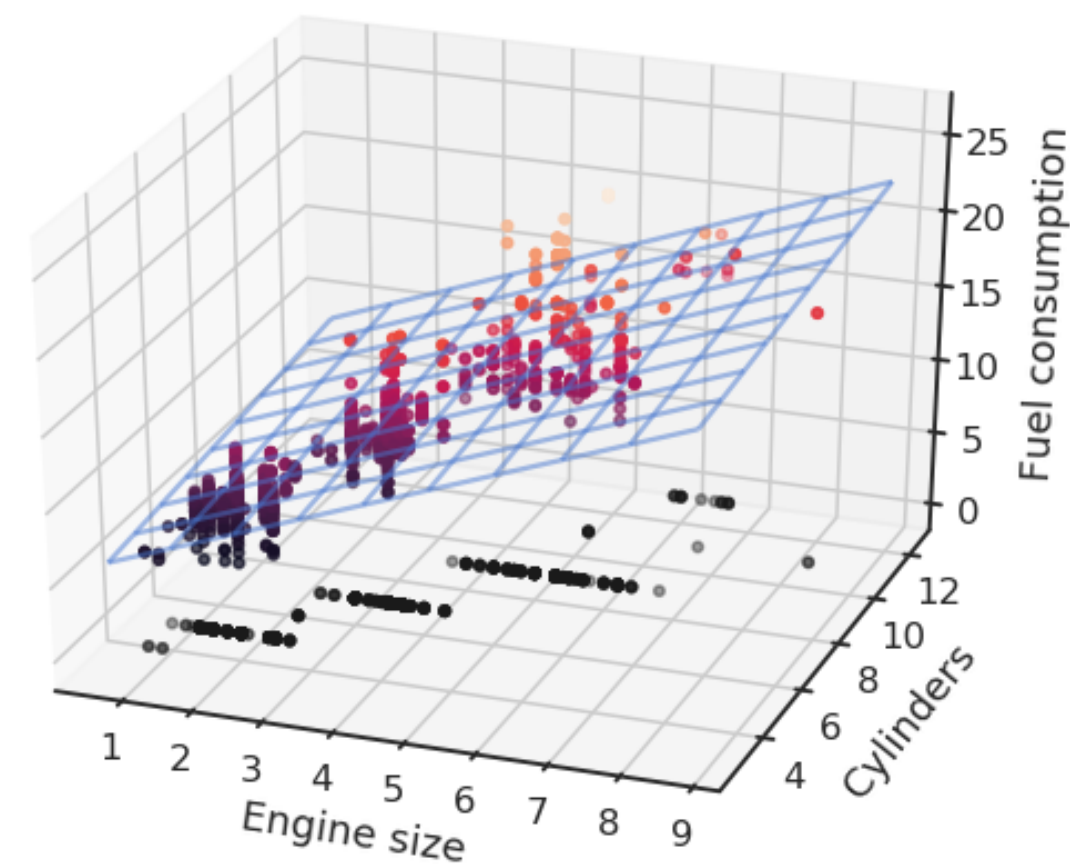
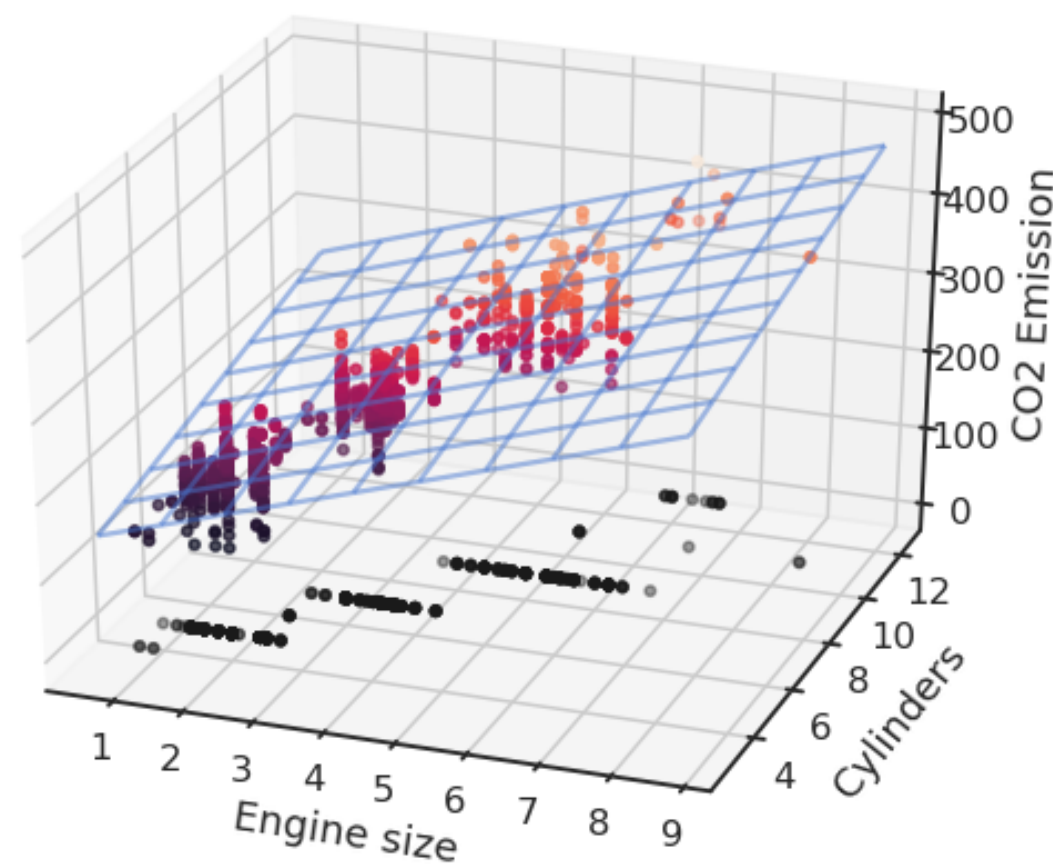


# MLR example: fuel consumption and CO2 emissions

- Noting the variables  $x_1, x_2, y_1, y_2$ , we can define our MLR problem:

$$\begin{cases} y_1 = w_1 x_1 + w_2 x_2 + b_1 \\ y_2 = w_3 x_1 + w_4 x_2 + b_2 \end{cases}$$

and use the least mean squares method to obtain the value of the parameters.



- Note: using the Python library `scikit-learn` (<https://scikit-learn.org>), this is done in two lines of code:

```
1 from sklearn.linear_model import LinearRegression
2 reg = LinearRegression().fit(X, y)
```



# Multiple linear regression

- The system of equations:

$$\begin{cases} y_1 = w_1 x_1 + w_2 x_2 + b_1 \\ y_2 = w_3 x_1 + w_4 x_2 + b_2 \end{cases}$$

can be put in a matrix-vector form:

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} w_1 & w_2 \\ w_3 & w_4 \end{bmatrix} \times \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$$

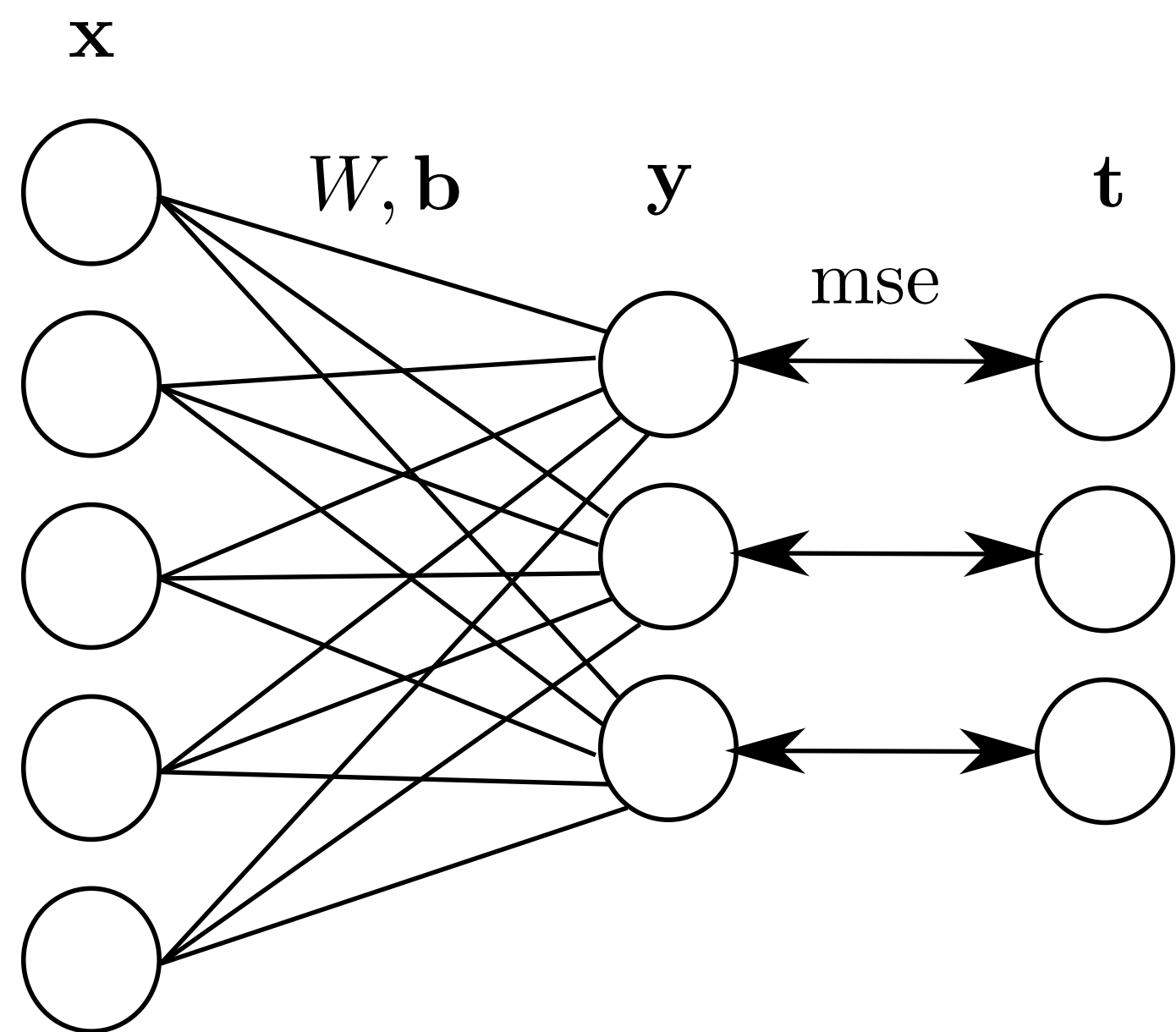
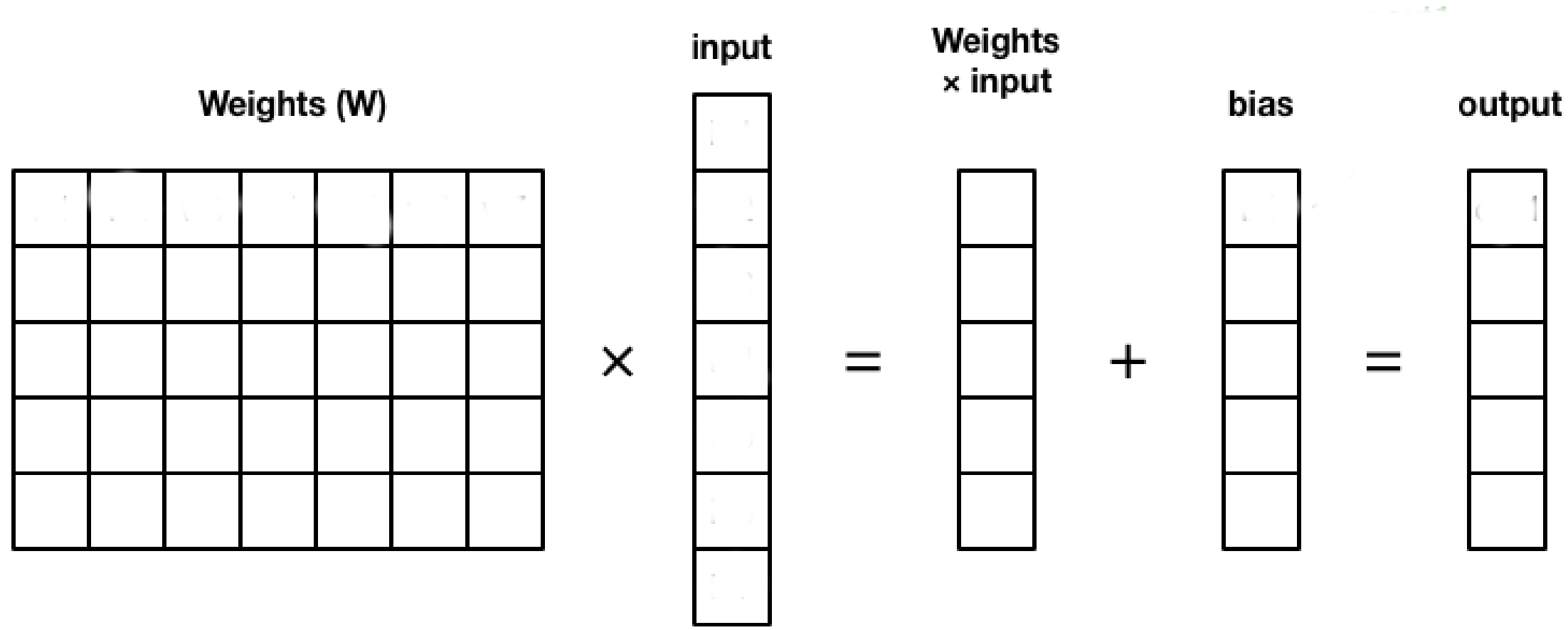
- We simply create the corresponding vectors and matrices:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad \mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} \quad \mathbf{t} = \begin{bmatrix} t_1 \\ t_2 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \quad W = \begin{bmatrix} w_1 & w_2 \\ w_3 & w_4 \end{bmatrix}$$

- $\mathbf{x}$  is the input vector,  $\mathbf{y}$  is the output vector,  $\mathbf{t}$  is the target vector.
- $W$  is called the **weight matrix** and  $\mathbf{b}$  the **bias vector**.

$$\mathbf{y} = f_{W,\mathbf{b}}(\mathbf{x}) = W \times \mathbf{x} + \mathbf{b}$$

# Multiple linear regression



- The model is now defined by:

$$\mathbf{y} = f_{W,\mathbf{b}}(\mathbf{x}) = W \times \mathbf{x} + \mathbf{b}$$

- The problem is exactly the same as before, except that we use vectors and matrices instead of scalars:  $\mathbf{x}$  and  $\mathbf{y}$  can have any number of dimensions, the same procedure will apply.
- This corresponds to a **linear neural network** (or linear perceptron), with one **output neuron** per predicted value  $y_i$  using the linear activation function.

## Multiple linear regression

- The mean square error still needs to be a scalar in order to be minimized. We can define it as the squared norm of the error **vector**:

$$\min_{W, \mathbf{b}} \mathcal{L}(W, \mathbf{b}) = \mathbb{E}_{\mathcal{D}}[\|\mathbf{t} - \mathbf{y}\|^2] = \mathbb{E}_{\mathcal{D}}[(t_1 - y_1)^2 + (t_2 - y_2)^2]$$

- In order to apply gradient descent, one needs to calculate partial derivatives w.r.t the weight matrix  $W$  and the bias vector  $\mathbf{b}$ , i.e. **gradients**:

$$\begin{cases} \Delta W = -\eta \nabla_W \mathcal{L}(W, \mathbf{b}) \\ \Delta \mathbf{b} = -\eta \nabla_{\mathbf{b}} \mathcal{L}(W, \mathbf{b}) \end{cases}$$

- Some more advanced linear algebra becomes important to know how to compute these gradients:

<https://web.stanford.edu/class/cs224n/readings/gradient-notes.pdf>

# Multiple linear regression

- We search the minimum of the mse loss function:

$$\min_{W, \mathbf{b}} \mathcal{L}(W, \mathbf{b}) = \mathbb{E}_{\mathcal{D}}[||\mathbf{t} - \mathbf{y}||^2] \approx \frac{1}{N} \sum_{i=1}^N ||\mathbf{t}_i - \mathbf{y}_i||^2 = \frac{1}{N} \sum_{i=1}^N l_i(W, \mathbf{b})$$

- The individual loss function  $l_i(W, \mathbf{b})$  is the squared  $\mathcal{L}^2$ -norm of the error vector, what can be expressed as a dot product or a vector multiplication:

$$l_i(W, \mathbf{b}) = ||\mathbf{t}_i - \mathbf{y}_i||^2 = \langle \mathbf{t}_i - \mathbf{y}_i \cdot \mathbf{t}_i - \mathbf{y}_i \rangle = (\mathbf{t}_i - \mathbf{y}_i)^T \times (\mathbf{t}_i - \mathbf{y}_i)$$

- Remember:

$$\mathbf{x}^T \times \mathbf{x} = \begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix} \times \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = x_1 x_1 + x_2 x_2 + \dots + x_n x_n = \langle \mathbf{x} \cdot \mathbf{x} \rangle = ||\mathbf{x}||_2^2$$

# Multiple linear regression

- The chain rule tells us in principle that:

$$\nabla_W l_i(W, \mathbf{b}) = \nabla_{\mathbf{y}_i} l_i(W, \mathbf{b}) \times \nabla_W \mathbf{y}_i$$

- The gradient w.r.t the output vector  $\mathbf{y}_i$  is quite easy to obtain, as it a quadratic function of  $\mathbf{t}_i - \mathbf{y}_i$ :

$$\nabla_{\mathbf{y}_i} l_i(W, \mathbf{b}) = \nabla_{\mathbf{y}_i} (\mathbf{t}_i - \mathbf{y}_i)^T \times (\mathbf{t}_i - \mathbf{y}_i)$$

- The proof relies on product differentiation  $(f \times g)' = f' g + f g'$ :

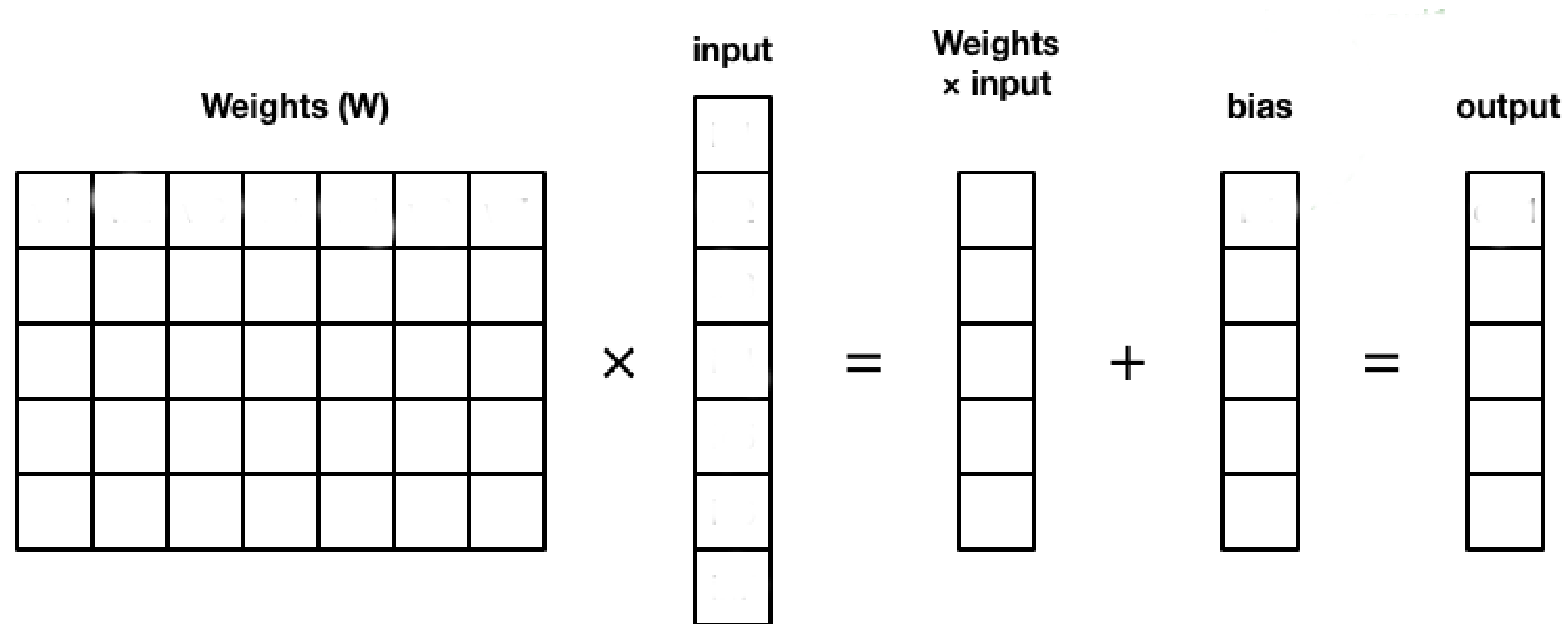
$$\nabla_{\mathbf{y}_i} (\mathbf{t}_i - \mathbf{y}_i)^T \times (\mathbf{t}_i - \mathbf{y}_i) = (\nabla_{\mathbf{y}_i} (\mathbf{t}_i - \mathbf{y}_i)) \times (\mathbf{t}_i - \mathbf{y}_i) + (\mathbf{t}_i - \mathbf{y}_i) \times \nabla_{\mathbf{y}_i} (\mathbf{t}_i - \mathbf{y}_i)$$

$$= -(\mathbf{t}_i - \mathbf{y}_i) - (\mathbf{t}_i - \mathbf{y}_i)$$

$$= -2 (\mathbf{t}_i - \mathbf{y}_i)$$

**Note:** We use the properties  $\nabla_{\mathbf{x}} \mathbf{x}^T \times \mathbf{z} = \mathbf{z}$  and  $\nabla_{\mathbf{z}} \mathbf{x}^T \times \mathbf{z} = \mathbf{x}$  to get rid of the transpose.

# Multiple linear regression



- The “problem” is when computing  $\nabla_W \mathbf{y}_i = \nabla_W (W \times \mathbf{x}_i + \mathbf{b})$ :
  - $\mathbf{y}_i$  is a vector and  $W$  a matrix.
  - $\nabla_W \mathbf{y}_i$  is then a Jacobian (matrix), not a gradient (vector).
- Intuitively, differentiating  $W \times \mathbf{x}_i + \mathbf{b}$  w.r.t  $W$  should return  $\mathbf{x}_i$ , but it is a vector, not a matrix...
- The gradient (or Jacobian) of  $l_i(W, \mathbf{b})$  w.r.t  $W$  should be a matrix of the same size as  $W$  so that we can apply gradient descent:

$$\Delta W = -\eta \nabla_W \mathcal{L}(W, \mathbf{b})$$

# Multiple linear regression

- We already know that:

$$\nabla_W l_i(W, \mathbf{b}) = -2 (\mathbf{t}_i - \mathbf{y}_i) \times \nabla_W \mathbf{y}_i$$

- If  $\mathbf{x}_i$  has  $n$  elements and  $\mathbf{y}_i$   $m$  elements,  $W$  is a  $m \times n$  matrix.
- Remember the outer product between two vectors:

$$\mathbf{u} \times \mathbf{v}^T = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} \begin{bmatrix} v_1 & v_2 & v_3 \end{bmatrix} = \begin{bmatrix} u_1 v_1 & u_1 v_2 & u_1 v_3 \\ u_2 v_1 & u_2 v_2 & u_2 v_3 \\ u_3 v_1 & u_3 v_2 & u_3 v_3 \\ u_4 v_1 & u_4 v_2 & u_4 v_3 \end{bmatrix}.$$

- It is easy to see that the outer product between  $(\mathbf{t}_i - \mathbf{y}_i)$  and  $\mathbf{x}_i$  gives a  $m \times n$  matrix:

$$\nabla_W l_i(W, \mathbf{b}) = -2 (\mathbf{t}_i - \mathbf{y}_i) \times \mathbf{x}_i^T$$

## Example

- Let's prove it element per element:

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = W \times \mathbf{x} + \mathbf{b} = \begin{bmatrix} w_1 & w_2 \\ w_3 & w_4 \end{bmatrix} \times \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$$

$$l(W, \mathbf{b}) = (\mathbf{t} - \mathbf{y})^T \times (\mathbf{t} - \mathbf{y}) = \begin{bmatrix} t_1 - y_1 & t_2 - y_2 \end{bmatrix} \times \begin{bmatrix} t_1 - y_1 \\ t_2 - y_2 \end{bmatrix} = (t_1 - y_1)^2 + (t_2 - y_2)^2$$

- The Jacobian w.r.t  $W$  can be explicitly formed using partial derivatives:

$$\nabla_W l(W, \mathbf{b}) = \begin{bmatrix} \frac{\partial l(W, \mathbf{b})}{\partial w_1} & \frac{\partial l(W, \mathbf{b})}{\partial w_2} \\ \frac{\partial l(W, \mathbf{b})}{\partial w_3} & \frac{\partial l(W, \mathbf{b})}{\partial w_4} \end{bmatrix} = \begin{bmatrix} -2(t_1 - y_1)x_1 & -2(t_1 - y_1)x_2 \\ -2(t_2 - y_2)x_1 & -2(t_2 - y_2)x_2 \end{bmatrix}$$

- We can rearrange this matrix as an outer product:

$$\nabla_W l(W, \mathbf{b}) = -2 \begin{bmatrix} t_1 - y_1 \\ t_2 - y_2 \end{bmatrix} \times \begin{bmatrix} x_1 & x_2 \end{bmatrix} = -2(\mathbf{t} - \mathbf{y}) \times \mathbf{x}^T$$



# Multiple linear regression

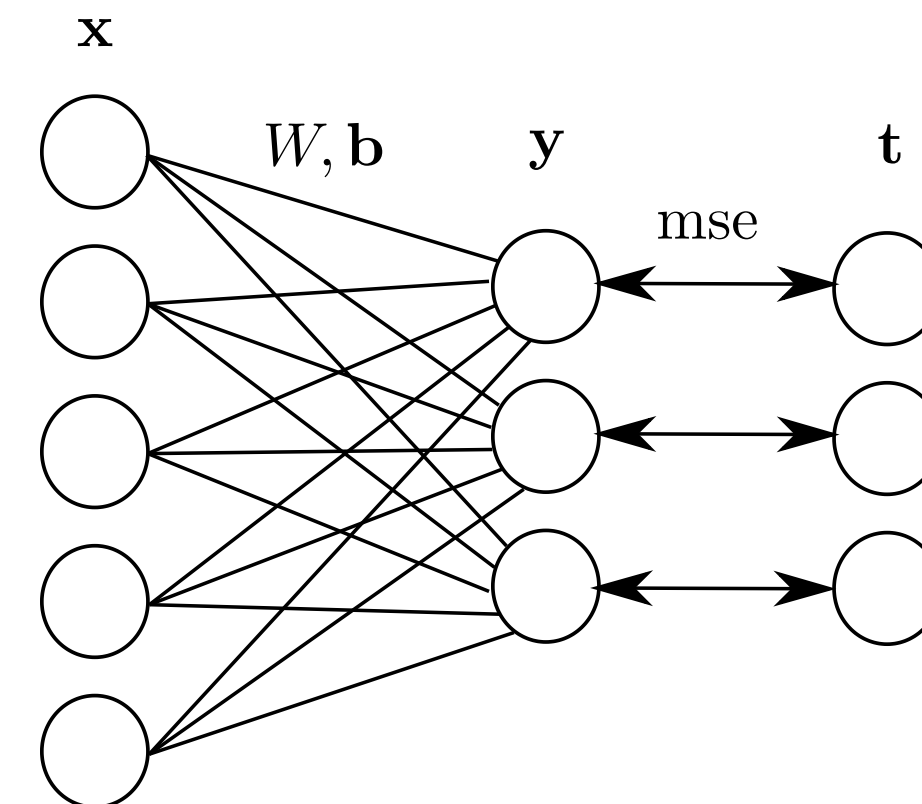
- Batch version (**least mean squares**):

$$\begin{cases} \Delta W = \eta \frac{1}{N} \sum_{i=1}^N (\mathbf{t}_i - \mathbf{y}_i) \times \mathbf{x}_i^T \\ \Delta \mathbf{b} = \eta \frac{1}{N} \sum_{i=1}^N (\mathbf{t}_i - \mathbf{y}_i) \end{cases}$$

- Online version (**delta learning rule**):

$$\begin{cases} \Delta W = \eta (\mathbf{t}_i - \mathbf{y}_i) \times \mathbf{x}_i^T \\ \Delta \mathbf{b} = \eta (\mathbf{t}_i - \mathbf{y}_i) \end{cases}$$

- The delta learning rule is always of the form:  $\Delta w = \eta \times \text{error} \times \text{input}$ . Biases have an input of 1.

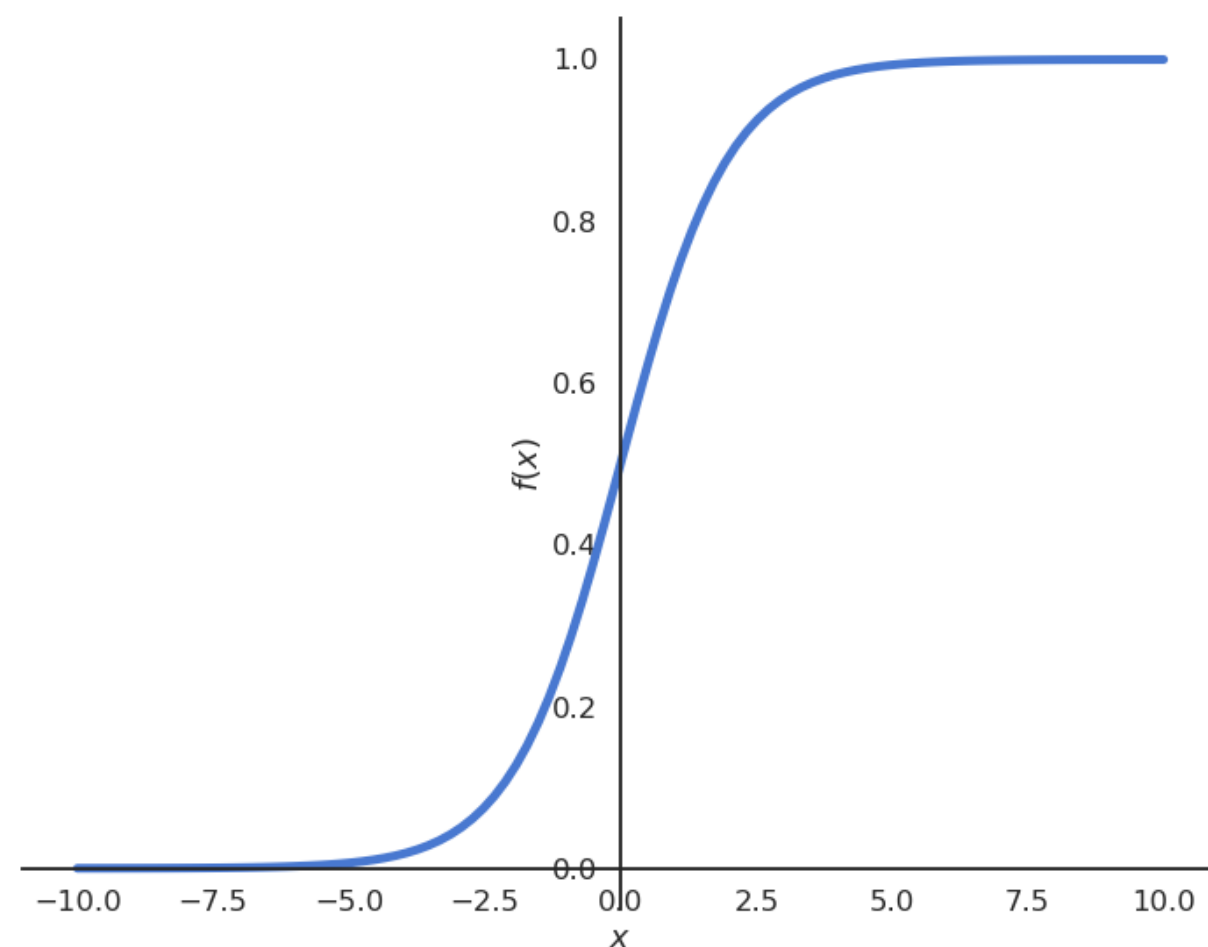


- This is completely equivalent to having one learning rule per parameter:

$$\begin{cases} \Delta w_1 = \eta (t_1 - y_1) x_1 \\ \Delta w_2 = \eta (t_1 - y_1) x_2 \\ \Delta w_3 = \eta (t_2 - y_2) x_1 \\ \Delta w_4 = \eta (t_2 - y_2) x_2 \end{cases} \quad \begin{cases} \Delta b_1 = \eta (t_1 - y_1) \\ \Delta b_2 = \eta (t_2 - y_2) \end{cases}$$

## 3 - Logistic regression

# Logistic regression



- Let's suppose we want to perform a regression, but where the outputs  $t_i$  are bounded between 0 and 1.
- We could use a logistic (or sigmoid) function instead of a linear function in order to transform the input into an output:

$$y = \sigma(w x + b) = \frac{1}{1 + \exp(-w x - b)}$$

- The logistic function

$$\sigma(x) = \frac{1}{1 + \exp(-x)}$$

has the nice property that

$$\sigma'(x) = \sigma(x) (1 - \sigma(x))$$

# Logistic regression

- We can perform a logistic regression with the same online LMS method as in the linear case:

$$l_i(w, b) = (t_i - \sigma(w x_i + b))^2$$

- The partial derivative of the individual loss is easy to find using the chain rule:

$$\frac{\partial l_i(w, b)}{\partial w} = 2 (t_i - y_i) \frac{\partial}{\partial w} (t_i - \sigma(w x_i + b))$$

$$= -2 (t_i - y_i) \sigma'(w x_i + b) x_i$$

- The non-linear transfer function  $\sigma(x)$  adds its derivative into the gradient:

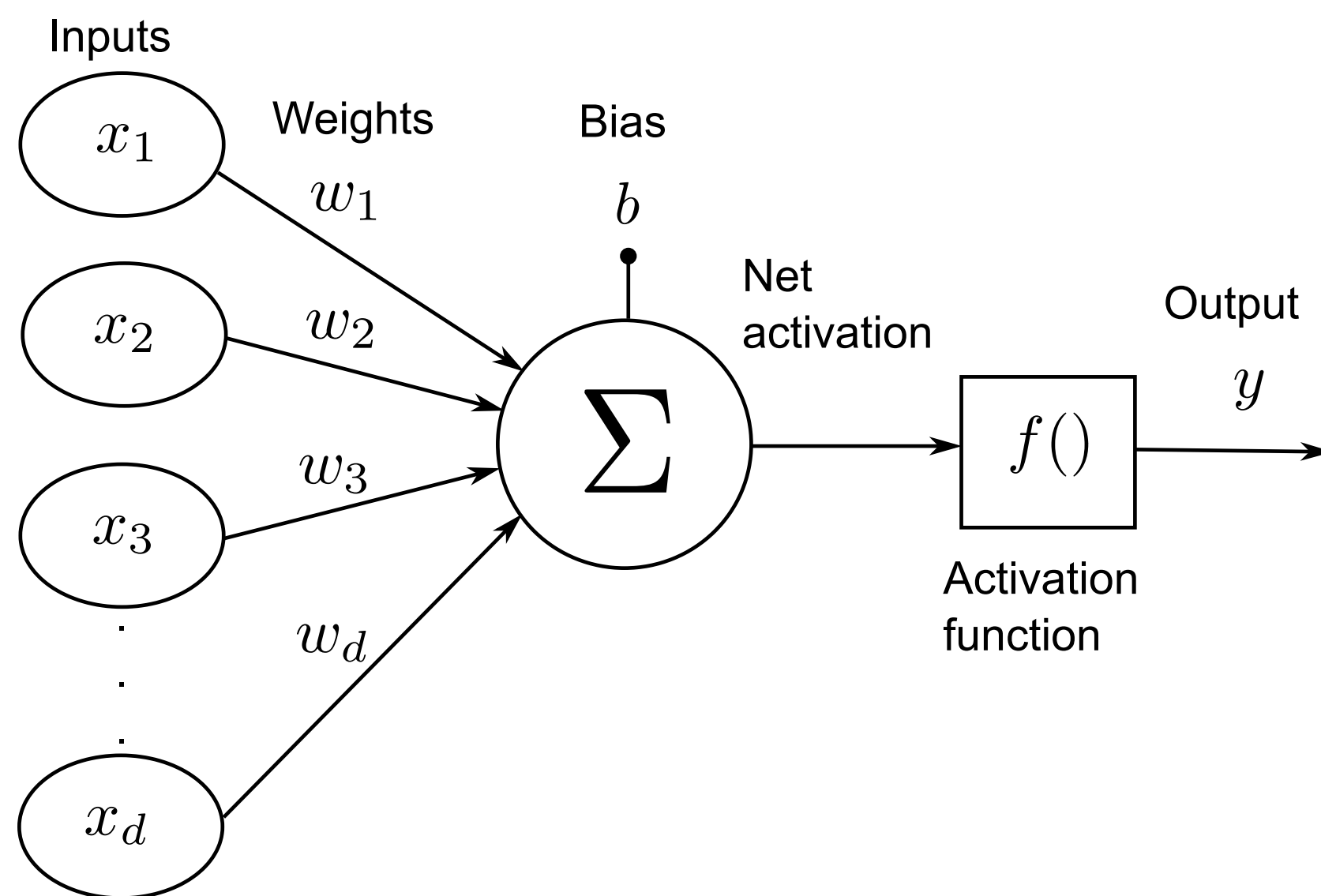
$$\Delta w = \eta (t_i - y_i) \sigma'(w x_i + b) x_i$$

- With the property  $\sigma'(x) = \sigma(x) (1 - \sigma(x))$ , it even becomes:

$$\Delta w = \eta (t_i - y_i) y_i (1 - y_i) x_i$$

so we do not even need to compute the derivative!

# Logistic regression



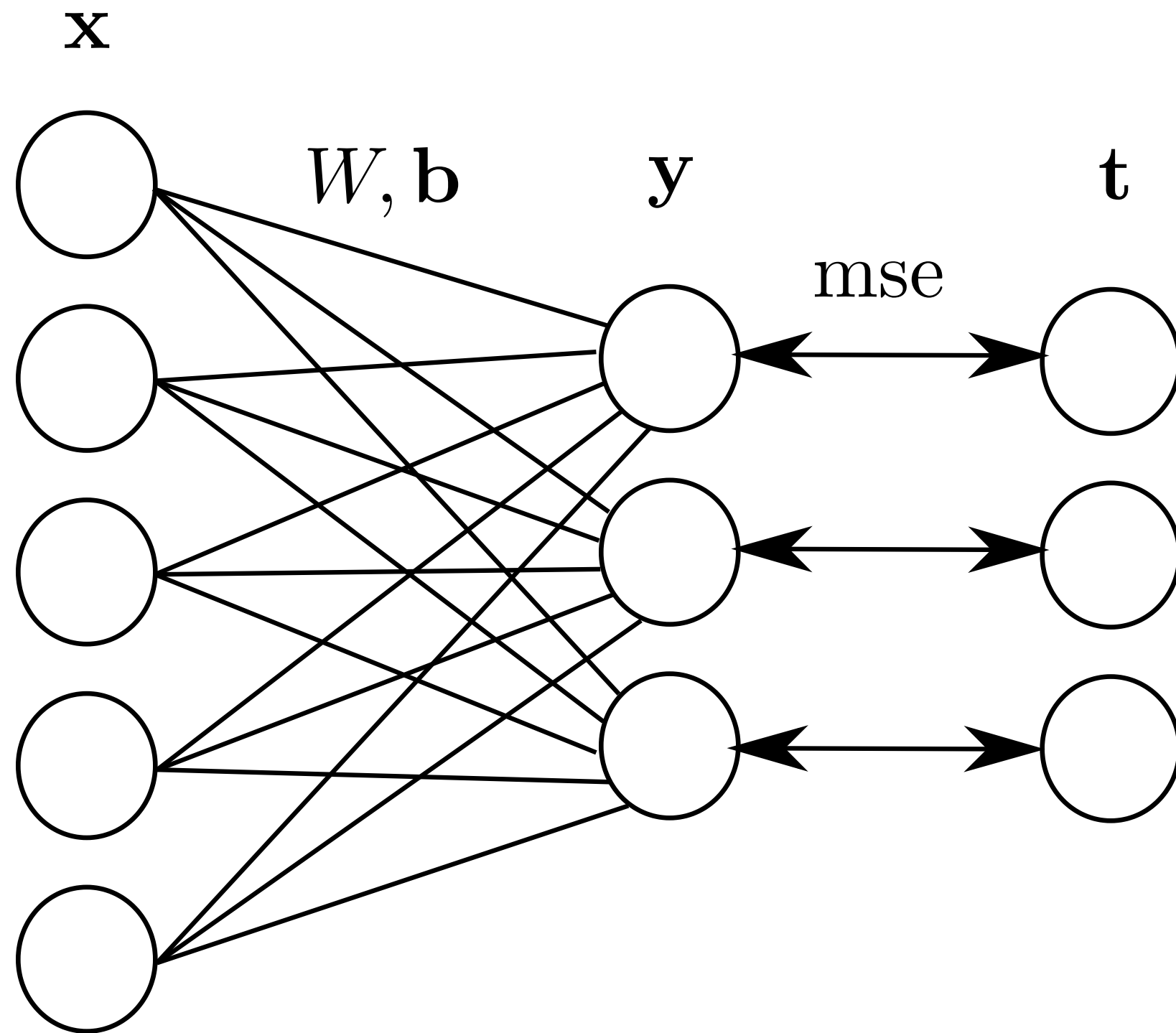
- Model:

$$y = \sigma(w x + b) = \frac{1}{1 + \exp(-w x - b)}$$

- The delta learning rule in case of logistic regression is:

$$\begin{cases} \Delta w = \eta (t_i - y_i) y_i (1 - y_i) x_i \\ \Delta b = \eta (t_i - y_i) y_i (1 - y_i) \end{cases}$$

# Generalized form of the delta learning rule



- Model:

$$\mathbf{y} = f(W \times \mathbf{x} + \mathbf{b})$$

- Loss function (mse):

$$\mathcal{L}(W, \mathbf{b}) = \mathbb{E}_{\mathbf{x}, \mathbf{t} \in \mathcal{D}} [\|\mathbf{t} - \mathbf{y}\|^2]$$

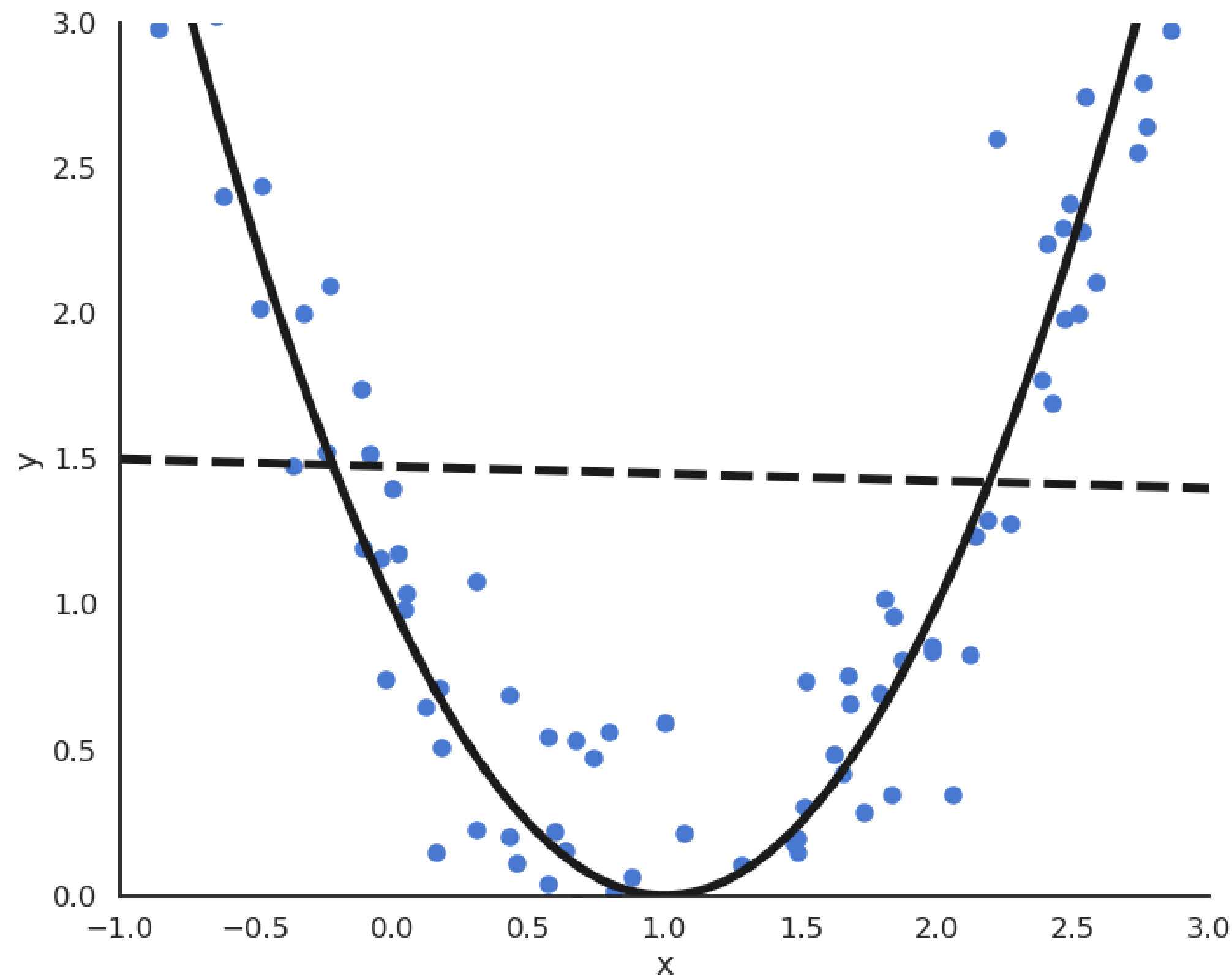
- Delta learning rule:

$$\begin{cases} \Delta W = \eta [(\mathbf{t} - \mathbf{y}) \odot f'(W \times \mathbf{x} + \mathbf{b})] \times \mathbf{x}^T \\ \Delta \mathbf{b} = \eta (\mathbf{t} - \mathbf{y}) \odot f'(W \times \mathbf{x} + \mathbf{b}) \end{cases}$$

- $\odot$  denotes element-wise multiplication, i.e.  $(\mathbf{t} - \mathbf{y}) \odot f'(W \times \mathbf{x} + \mathbf{b})$  is also a vector.
- In the linear case,  $f'(x) = 1$ .
- One can use any non-linear function, e.g hyperbolic tangent  $\tanh()$ , ReLU, etc.
- Transfer functions are chosen for neural networks so that we can compute their derivative easily.

## 4 - Polynomial regression

# Polynomial regression



- The functions underlying real data are rarely linear plus some noise around the ideal value.
- In the figure, the input/output function would be better modeled by a second-order polynomial (or higher):

$$y = f_{\mathbf{w},b}(x) = w_1 x + w_2 x^2 + b$$



# Polynomial regression

- Model:

$$y = f_{\mathbf{w},b}(x) = w_1 x + w_2 x^2 + b$$

- We can transform the input into a vector of coordinates:

$$\mathbf{x} = \begin{bmatrix} x \\ x^2 \end{bmatrix} \quad \mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}$$

- The problem becomes:

$$y = \langle \mathbf{w} \cdot \mathbf{x} \rangle + b = \sum_j w_j x_j + b$$

- We can simply apply multiple linear regression (MLR) to find  $\mathbf{w}$  and  $b$ :

$$\begin{cases} \Delta \mathbf{w} = \eta (t - y) \mathbf{x} \\ \Delta b = \eta (t - y) \end{cases}$$

# Polynomial regression

- This generalizes to polynomials of any order  $p$ :

$$y = f_{\mathbf{w},b}(x) = w_1 x + w_2 x^2 + \dots + w_p x^p + b$$

- We create a vector of powers of  $x$  (called **polynomial features**):

$$\mathbf{x} = \begin{bmatrix} x \\ x^2 \\ \dots \\ x^p \end{bmatrix} \quad \mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ \dots \\ w_p \end{bmatrix}$$

- And apply multiple linear regression (MLR) to find  $\mathbf{w}$  and  $b$ :

$$\begin{cases} \Delta \mathbf{w} = \eta (t - y) \mathbf{x} \\ \Delta b = \eta (t - y) \end{cases}$$

- Non-linear problem solved! The only unknown is which order for the polynomial matches best the data.
- One can perform regression with any kind of parameterized function using gradient descent.

## **5 - A bit of learning theory**

# What matters during training?

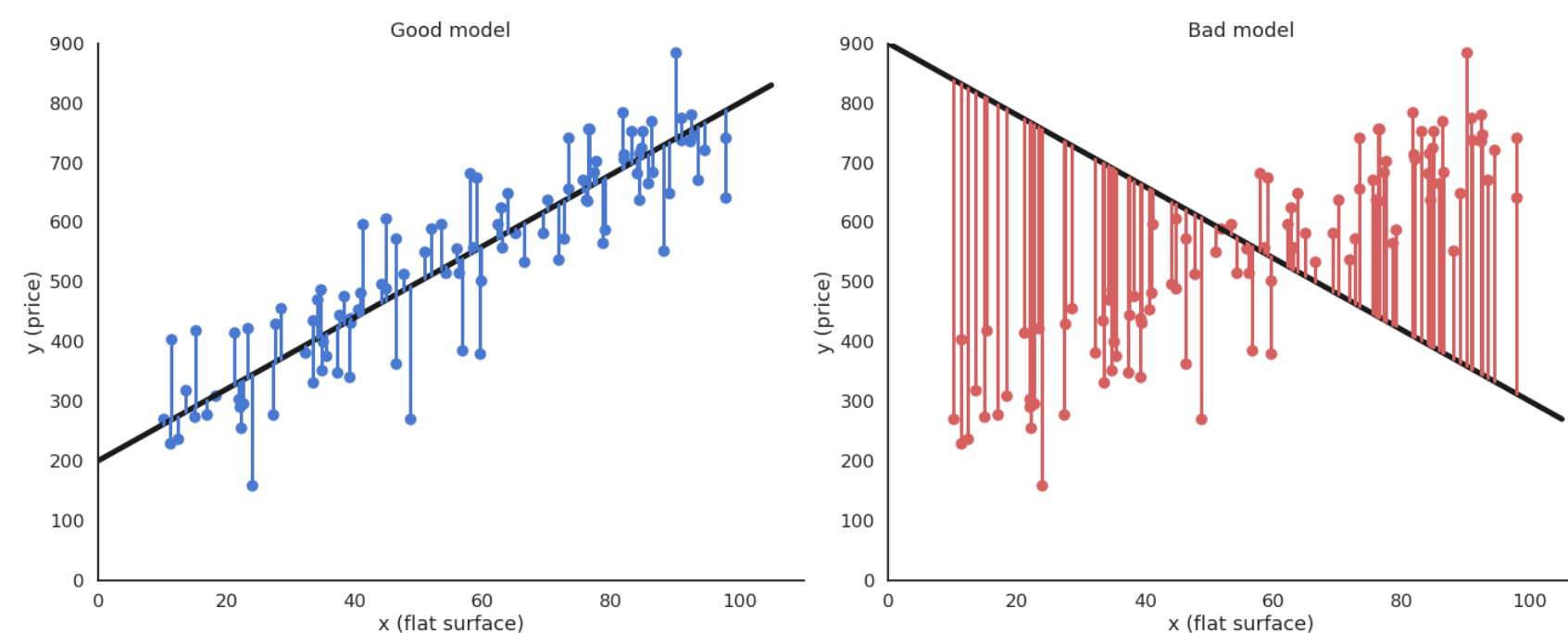
- Before going further, let's think about what we have been doing so far. We had a bunch of data samples  $\mathcal{D} = (x_i, t_i)_{i=1..N}$  (the **training set**) and we decided to apply a (linear) model on it:

$$y_i = w x_i + b$$

- We then minimized the mean square error (mse) on that training set using gradient descent. At the end of learning, we can measure the **residual error** of the model on the data:

$$\epsilon_{\mathcal{D}} = \frac{1}{N} \sum_{i=1}^N (t_i - y_i)^2$$

- We get a number, for example 0.04567. Is that good?

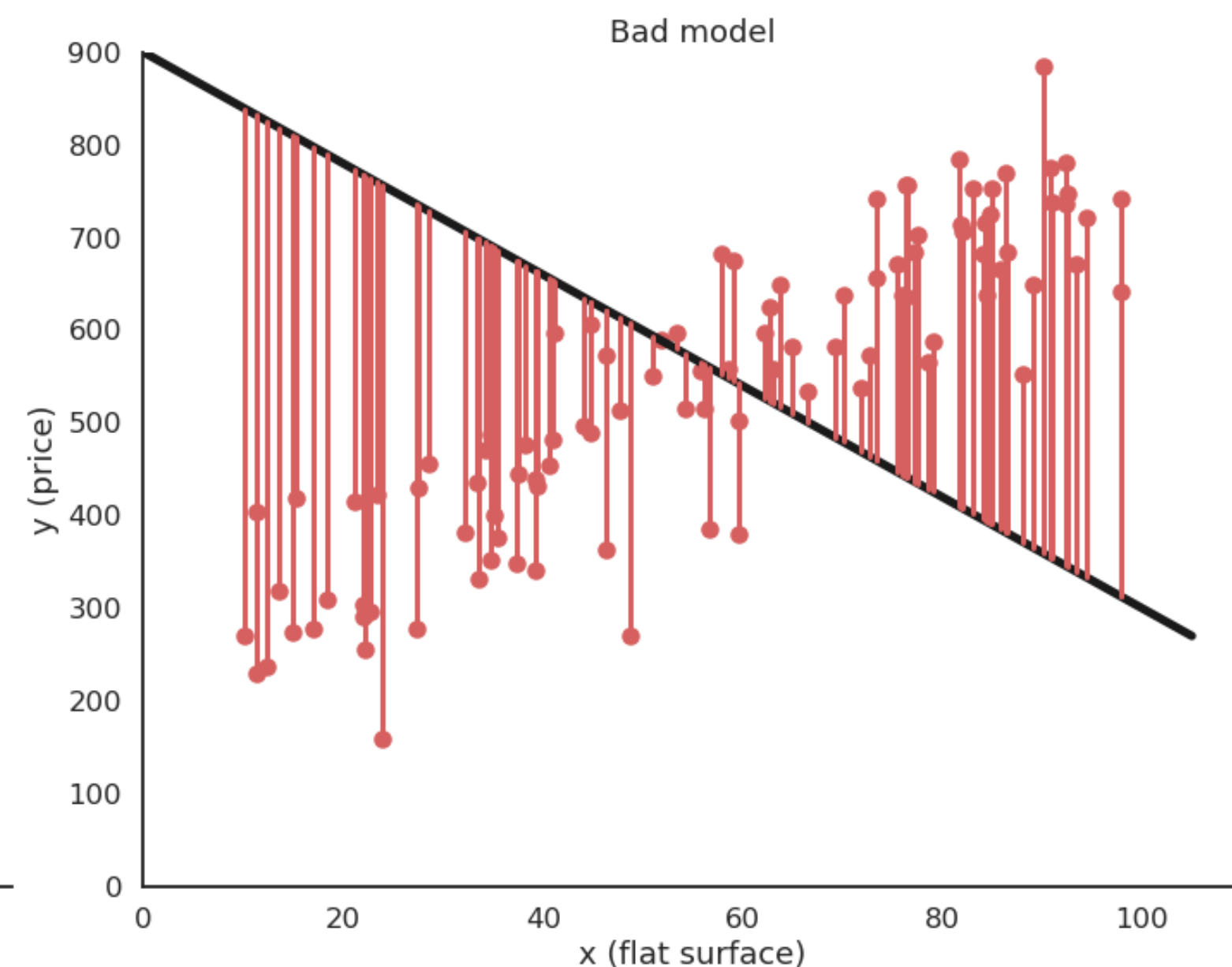
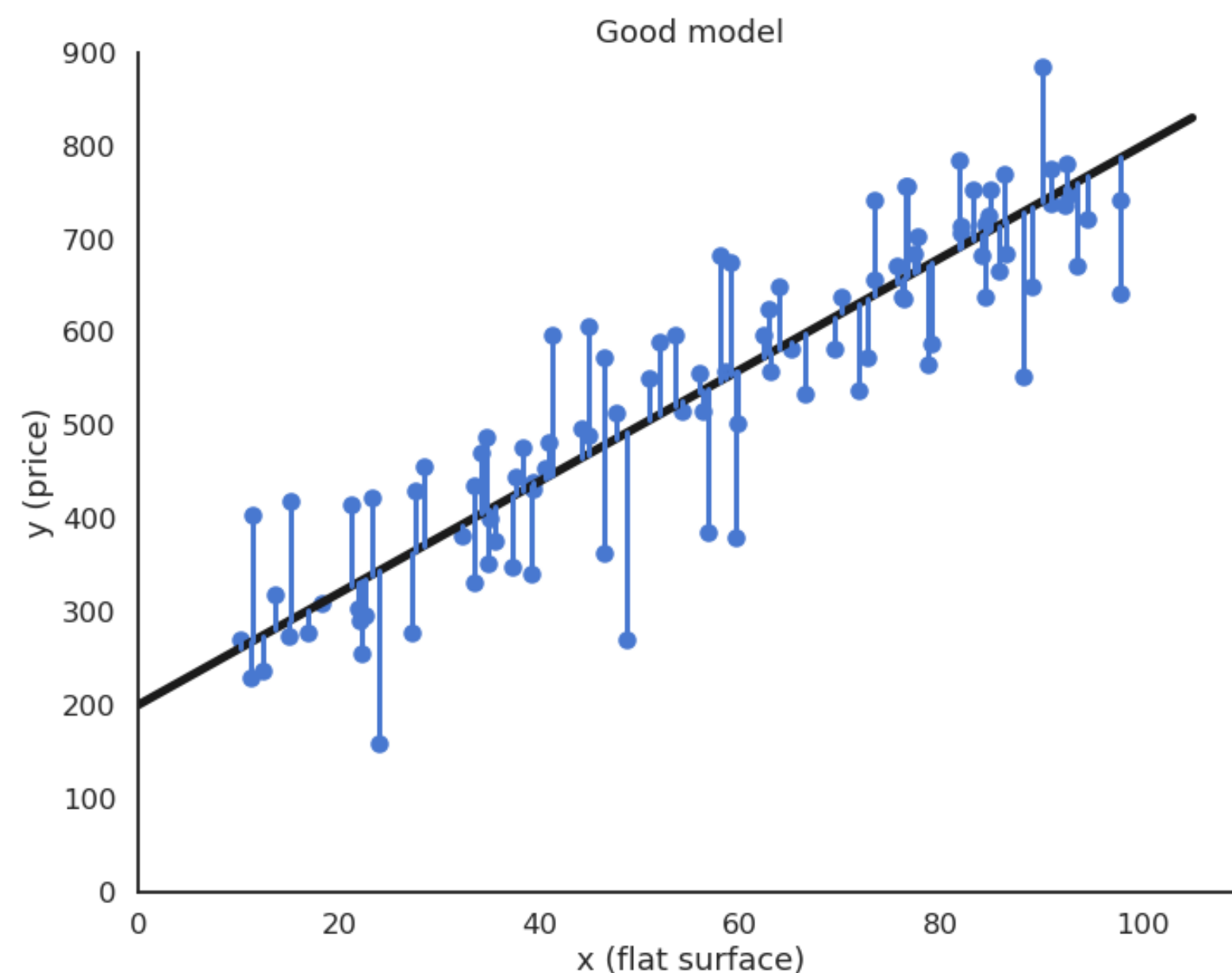


# Regression error

- The **mean square error** mse is not very informative, as its value depends on how the outputs are scaled:

$$\epsilon_{\mathcal{D}} = \frac{1}{N} \sum_{i=1}^N (t_i - y_i)^2$$

- If you multiply both the data  $t$  and the prediction  $y$  by 10, the residual error will be 100 times higher, without any change to the quality of the model.

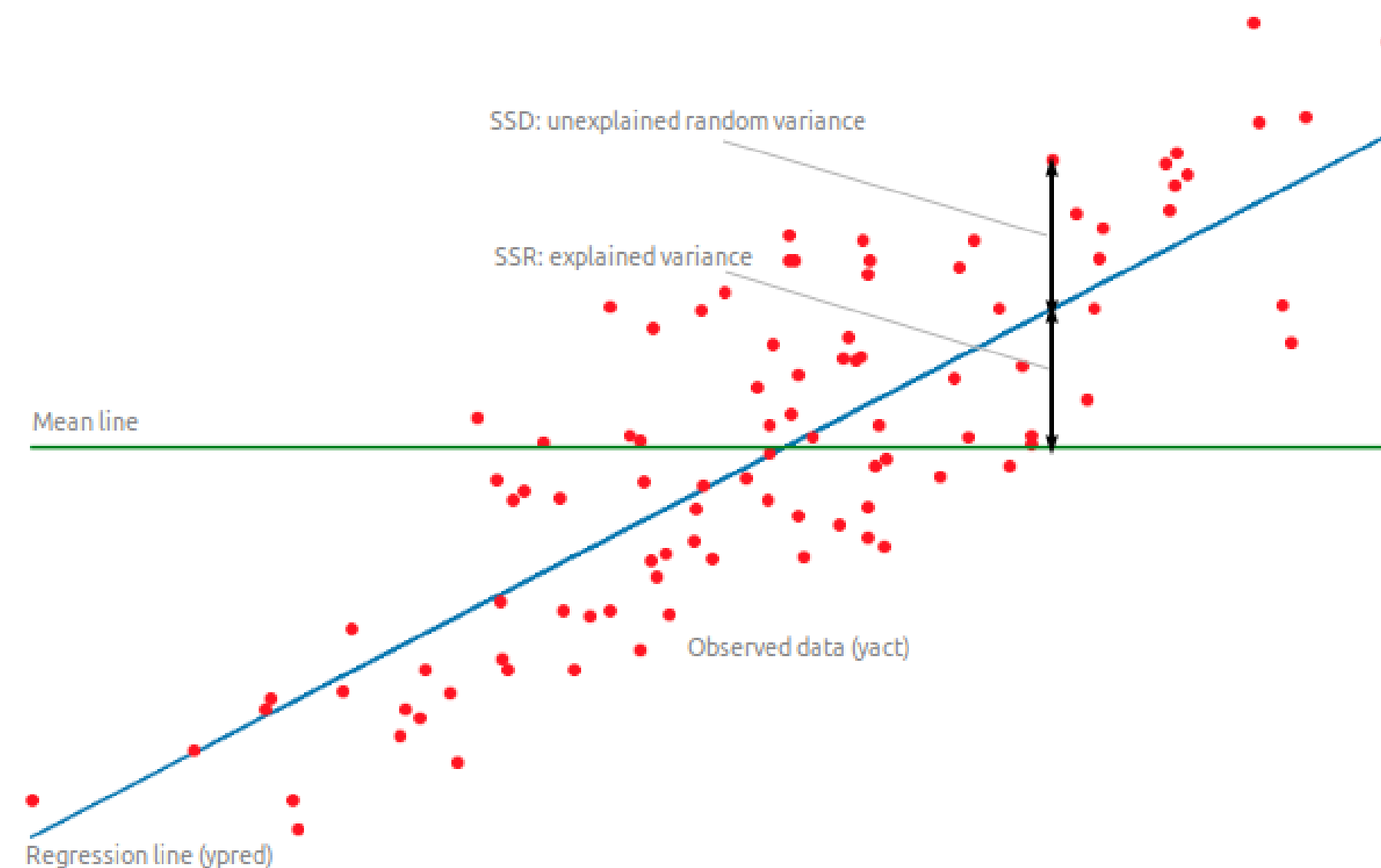


# Coefficient of determination

- The **coefficient of determination**  $R^2$  is a rescaled variant of the mse comparing the variance of the residuals to the variance of the data around its mean  $\hat{t}$ :

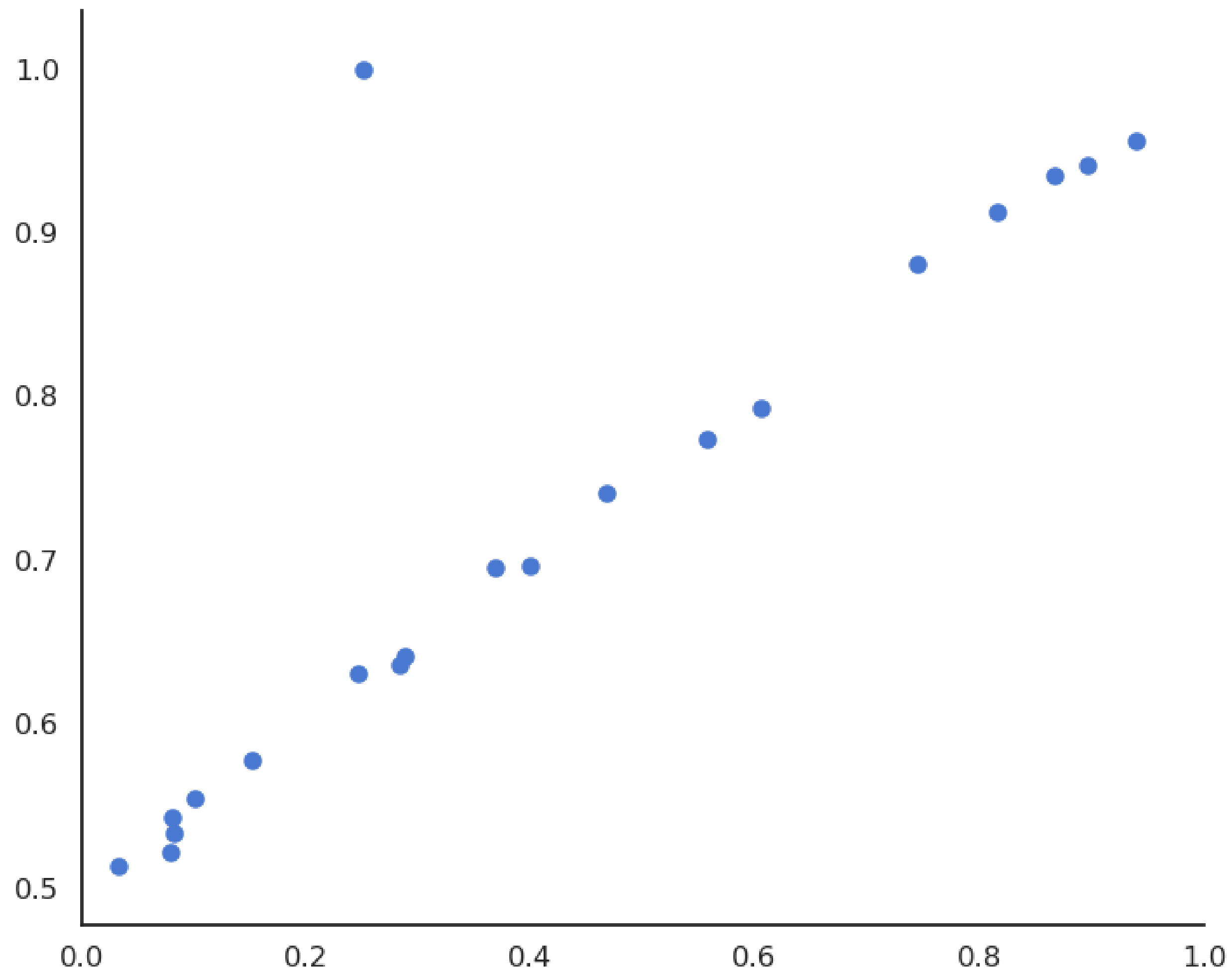
$$R^2 = 1 - \frac{\text{Var}(\text{residuals})}{\text{Var}(\text{data})} = 1 - \frac{\sum_{i=1}^N (t_i - y_i)^2}{\sum_{i=1}^N (t_i - \hat{t})^2}$$

- $R^2$  should be as close from 1 as possible. For example, if  $R^2 = 0.8$ , we can say that the **model explains 80% of the variance of the data**.



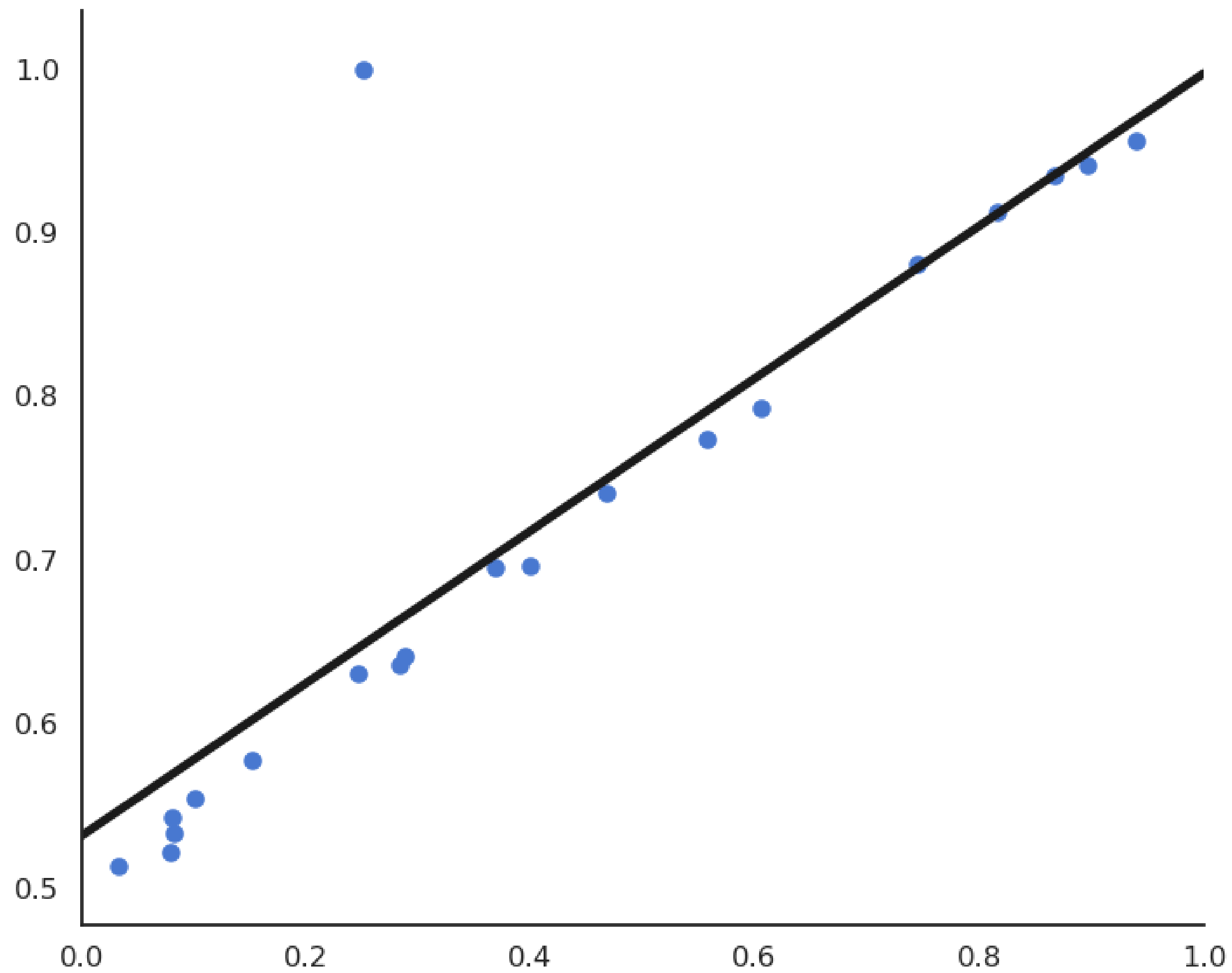
# Sensibility to outliers

- Suppose we have a training set with one **outlier** (bad measurement, bad luck, etc).



# Sensibility to outliers

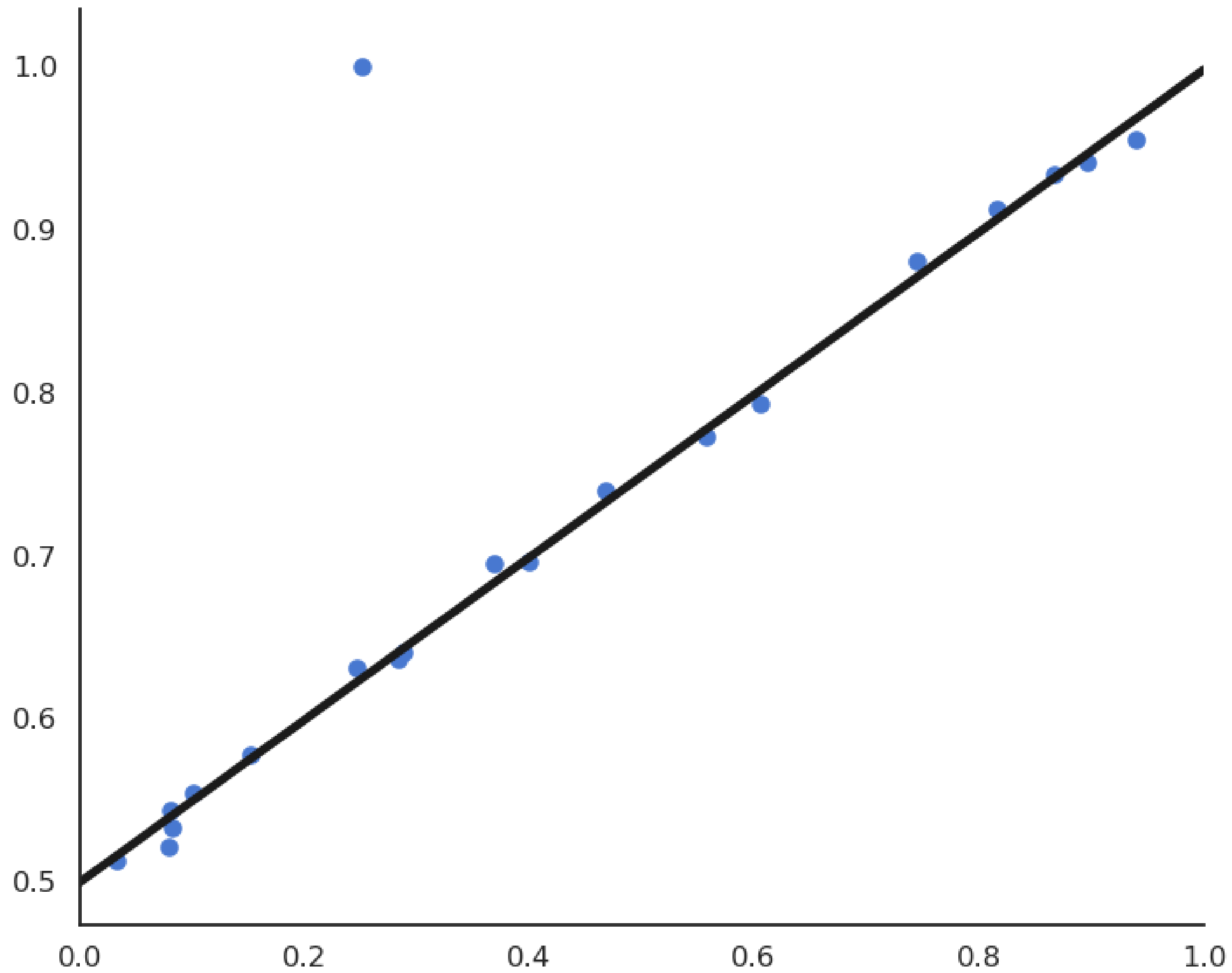
- LMS would find the minimum of the mse, but it is clearly a bad fit for most points.



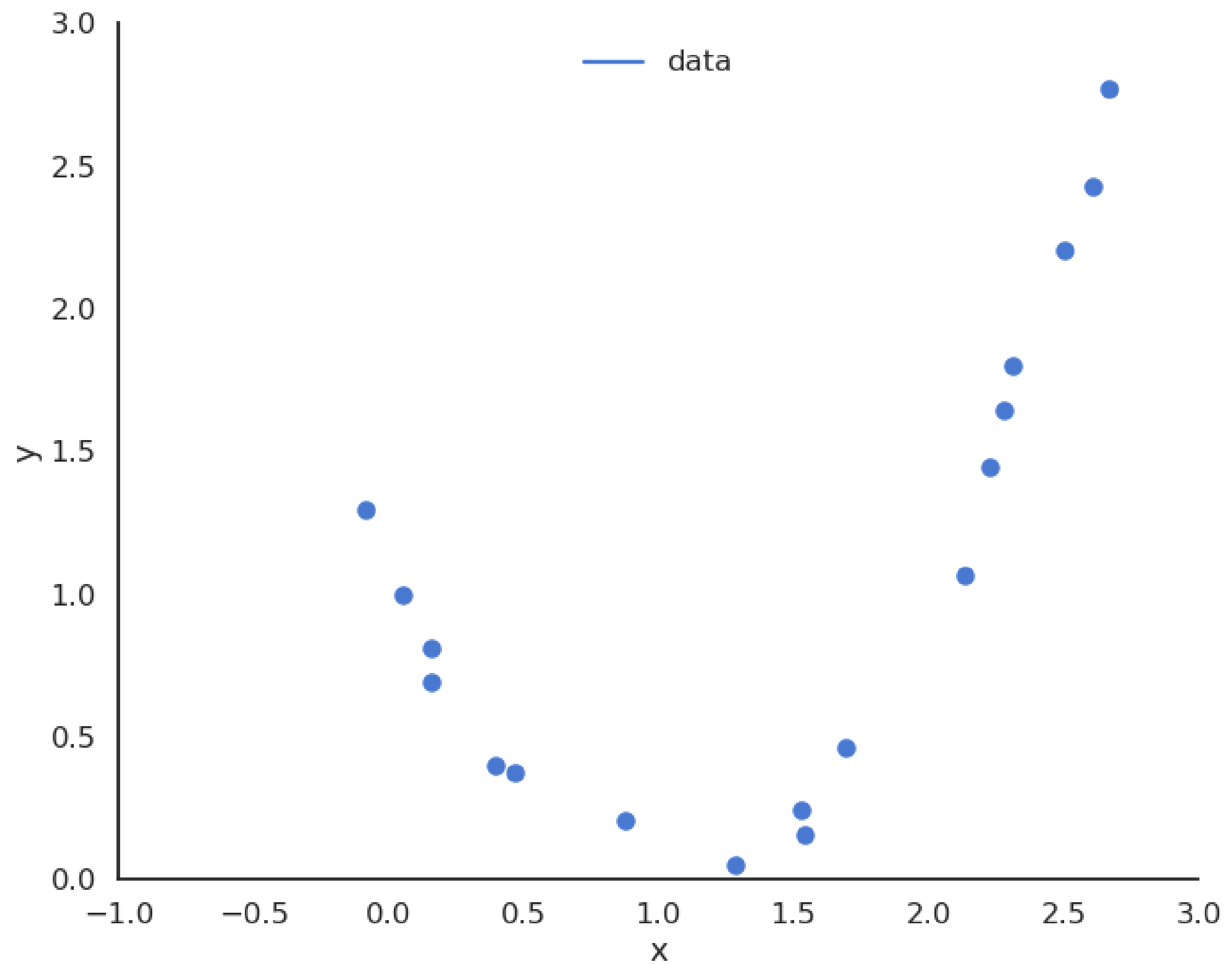


# Sensibility to outliers

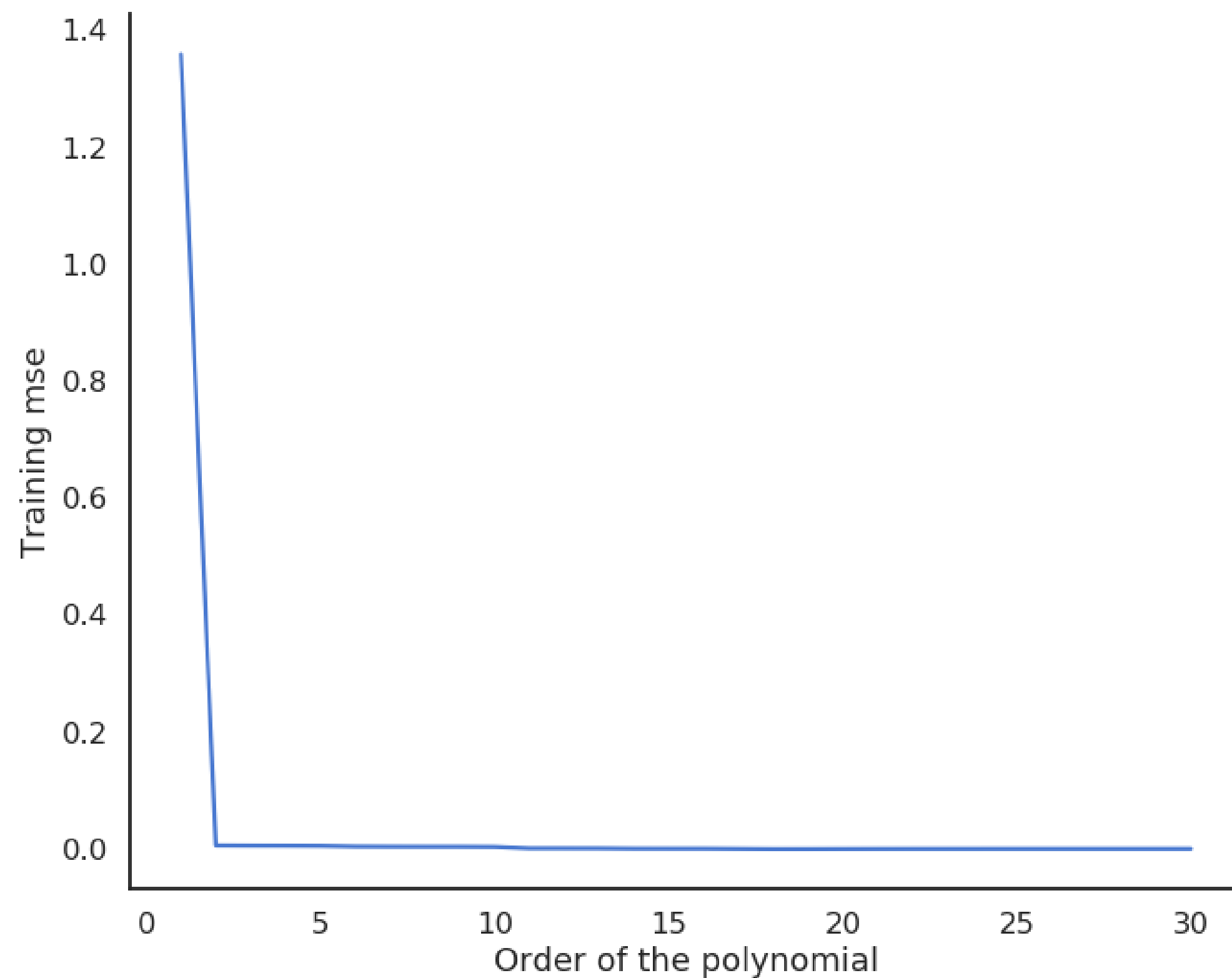
- This model feels much better, but its residual mse is higher...



# Polynomial regression



# Polynomial regression



- When only looking at the residual mse on the training data, one could think that the higher the order of the polynomial, the better.
- But it is obvious that the interpolation quickly becomes very bad when the order is too high.
- A **complex** model (with a lot of parameters) is useless for predicting new values.
- We actually do **not** care about the error on the training set.
- We care about **generalization**.

# Cross-validation

- Let's suppose we dispose of  $m$  models  $\mathcal{M} = \{M_1, \dots, M_m\}$  that could be used to fit (or classify) some data  $\mathcal{D} = \{x_i, t_i\}_{i=1}^N$ .
- Such a class could be the ensemble of polynomes with different orders, different algorithms (NN, SVM) or the same algorithm with different values for the hyperparameters (learning rate, regularization parameters...).
- The naive and **wrong** method to find the best hypothesis would be:



## Wrong method!

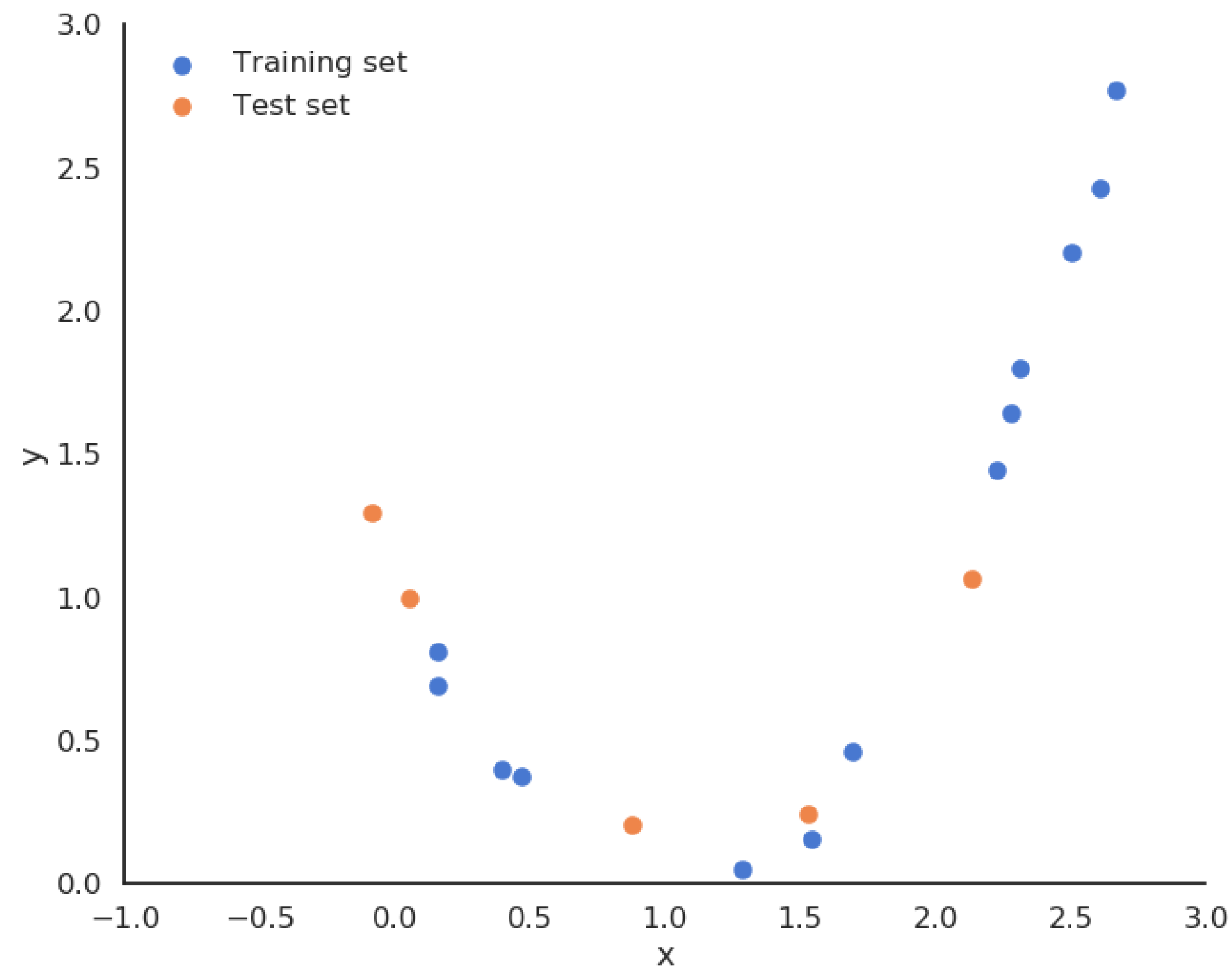
- For all models  $M_i$ :
  - Train  $M_i$  on  $\mathcal{D}$  to obtain an hypothesis  $h_i$ .
  - Compute the training error  $\epsilon_{\mathcal{D}}(h_i)$  of  $h_i$  on  $\mathcal{D}$ :

$$\epsilon_{\mathcal{D}}(h_i) = \mathbb{E}_{(\mathbf{x}, t) \in \mathcal{D}} [(h_i(\mathbf{x}) - t)^2]$$

- Select the hypothesis  $h_i^*$  with the minimal training error :  $h_i^* = \operatorname{argmin}_{h_i \in \mathcal{M}} \epsilon_{\mathcal{D}}(h_i)$

- This method leads to **overfitting**, as only the training error is used.

# Cross-validation: training and test sets



- The solution is randomly take some samples out of the training set to form the **test set**.
- Typical values are 20 or 30 % of the samples in the test set.
- Method:
  1. Train the model on the training set (70% of the data).
  2. Test the performance of the model on the test set (30% of the data).
- The test performance will better measure how well the model generalizes to new examples.

# Simple hold-out cross-validation



## Algorithm

- Split the training data  $\mathcal{D}$  into  $\mathcal{S}_{\text{train}}$  and  $\mathcal{S}_{\text{test}}$ .
- For all models  $M_i$ :
  - Train  $M_i$  on  $\mathcal{S}_{\text{train}}$  to obtain an hypothesis  $h_i$ .
  - Compute the empirical error  $\epsilon_{\text{test}}(h_i)$  of  $h_i$  on  $\mathcal{S}_{\text{test}}$ :

$$\epsilon_{\text{test}}(h_i) = \mathbb{E}_{(\mathbf{x}, t) \in \mathcal{S}_{\text{test}}} [(h_i(\mathbf{x}) - t)^2]$$

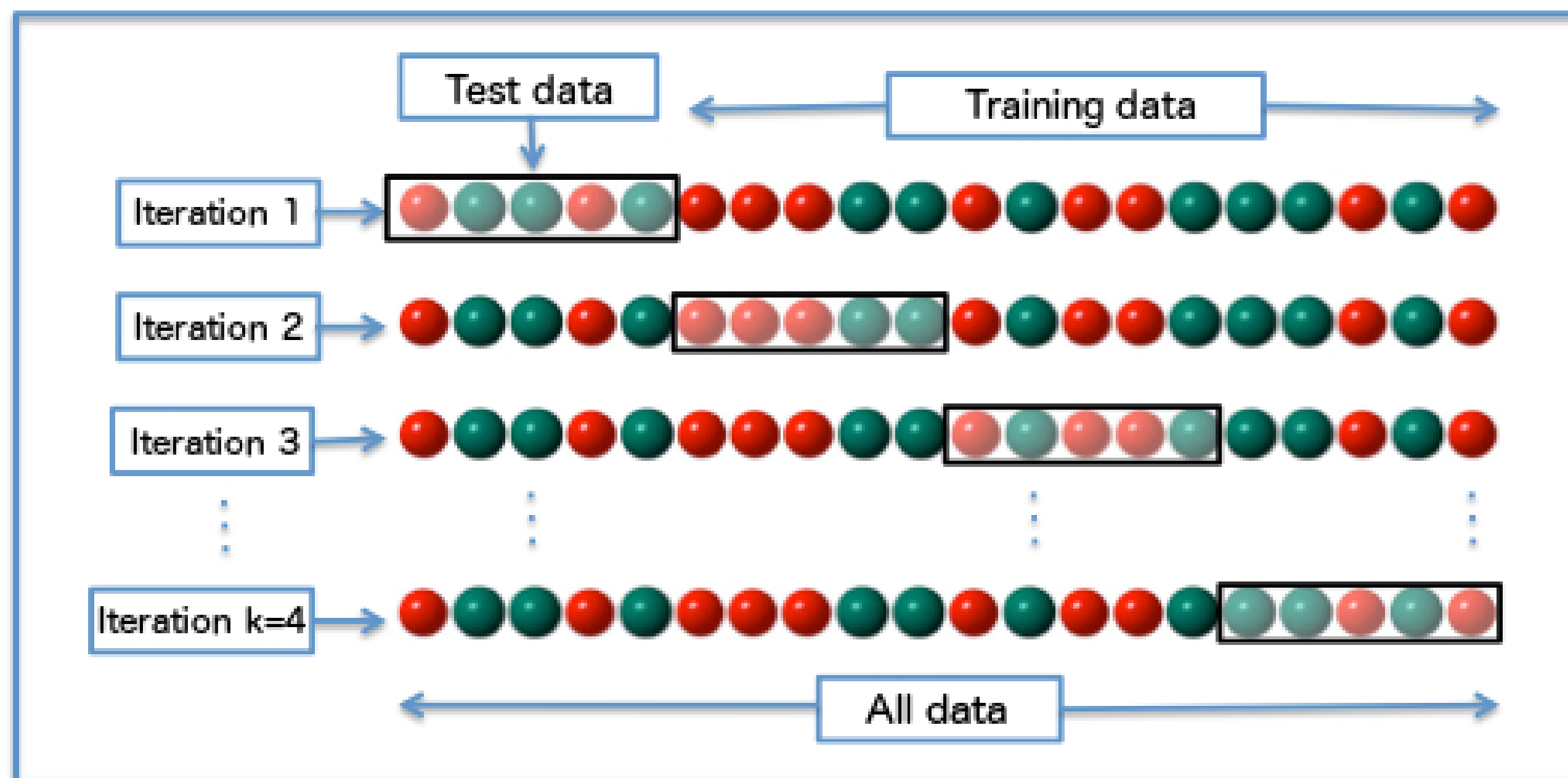
- Select the hypothesis  $h_i^*$  with the minimal empirical error :  $h_i^* = \operatorname{argmin}_{h_i \in \mathcal{M}} \epsilon_{\text{test}}(h_i)$

- Disadvantages:
  - 20 or 30% of the data is wasted and not used for learning. It may be a problem when data is rare or expensive.
  - The test set must be representative of the difficulty of the training set (same distribution).

# k-fold cross-validation

- **Idea:**

- build several different training/test sets with the same data.
- train and test each model repeatedly on each partition.
- choose the hypothesis that works best on average.



# k-fold cross-validation



## Algorithm

- Randomly split the data  $\mathcal{D}$  into  $k$  subsets of  $\frac{N}{k}$  examples  $\{\mathcal{S}_1, \dots, \mathcal{S}_k\}$
- For all models  $M_i$ :
  - For all  $k$  subsets  $\mathcal{S}_j$ :
    - Train  $M_i$  on  $\mathcal{D} - \mathcal{S}_j$  to obtain an hypothesis  $h_{ij}$
    - Compute the empirical error  $\epsilon_{\mathcal{S}_j}(h_{ij})$  of  $h_{ij}$  on  $\mathcal{S}_j$
  - The empirical error of the model  $M_i$  on  $\mathcal{D}$  is the average of empirical errors made on  $(\mathcal{S}_j)_{j=1}^k$

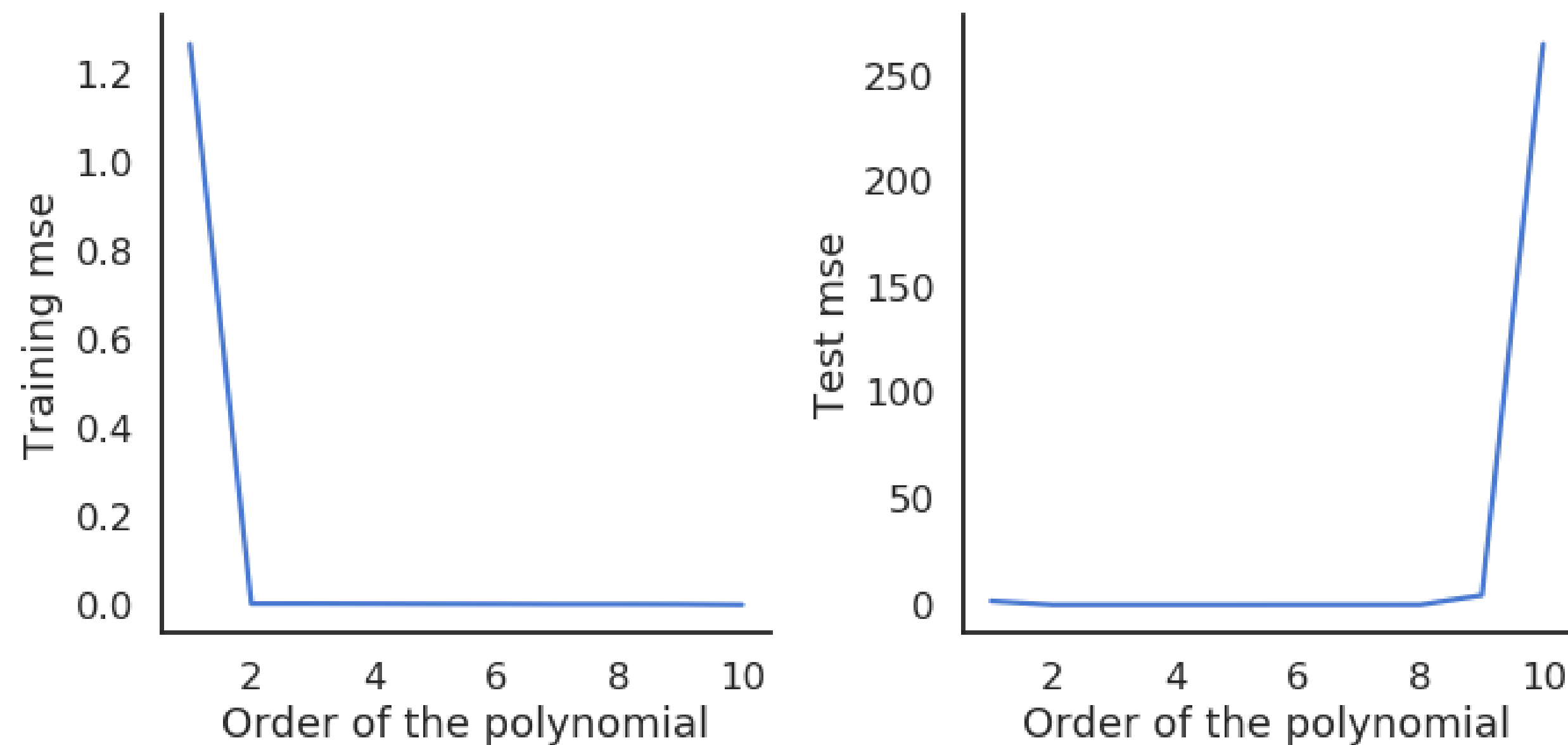
$$\epsilon_{\mathcal{D}}(M_i) = \frac{1}{k} \cdot \sum_{j=1}^k \epsilon_{\mathcal{S}_j}(h_{ij})$$

- Select the model  $M_i^*$  with the minimal empirical error on  $\mathcal{D}$ .

- In general  $k = 10$ . Extreme cases take  $k = N$ : **leave-one-out cross-validation**.
- k-fold cross-validation works well, but needs a lot of repeated learning.

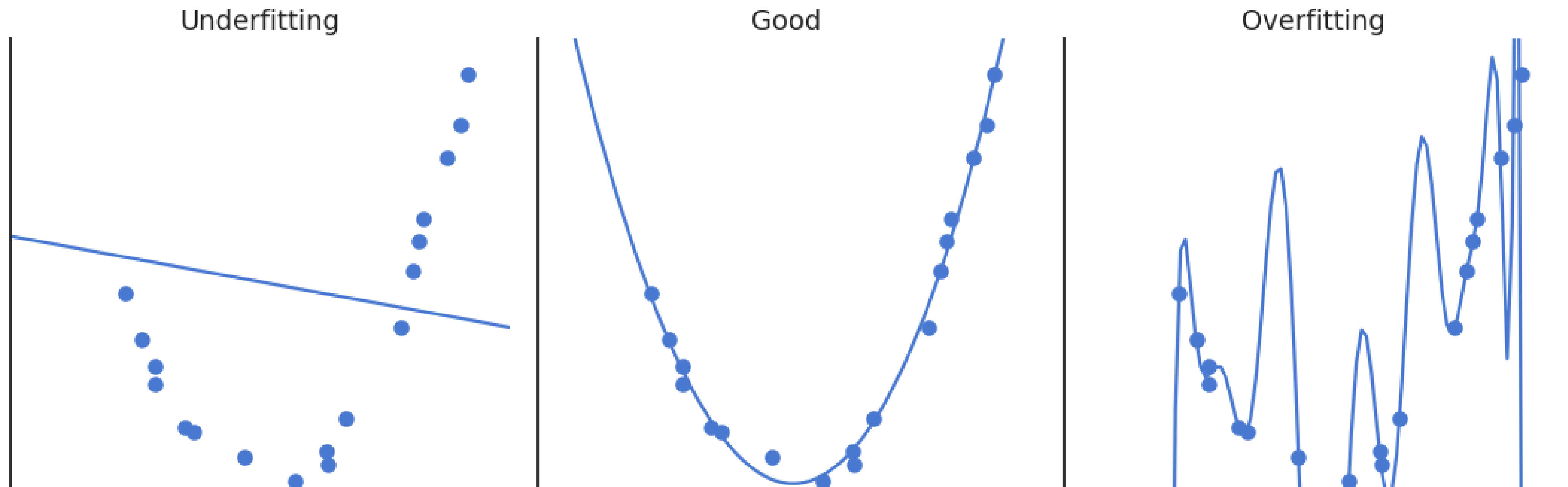


# Training and test errors



- While the training mse always decrease with more complex models, the test mse increases after a while.
- This is called **overfitting**: learning by heart the data without caring about generalization.
- The two curves suggest that we should chose a polynomial order between 2 and 9.

# Underfitting / Overfitting



- A model not complex enough for the data will **underfit**: its training error is high.
- A model too complex for the data will **overfit**: its test error is high.
- In between, there is the right complexity for the model: it learns the data correctly but does not overfit.

# What does complexity mean?

- In polynomial regression, the complexity is related to the order of the polynomial, i.e. the number of coefficients to estimate:

$$y = f_{\mathbf{w},b}(x) = \sum_{k=1}^p w_k x^k + b$$

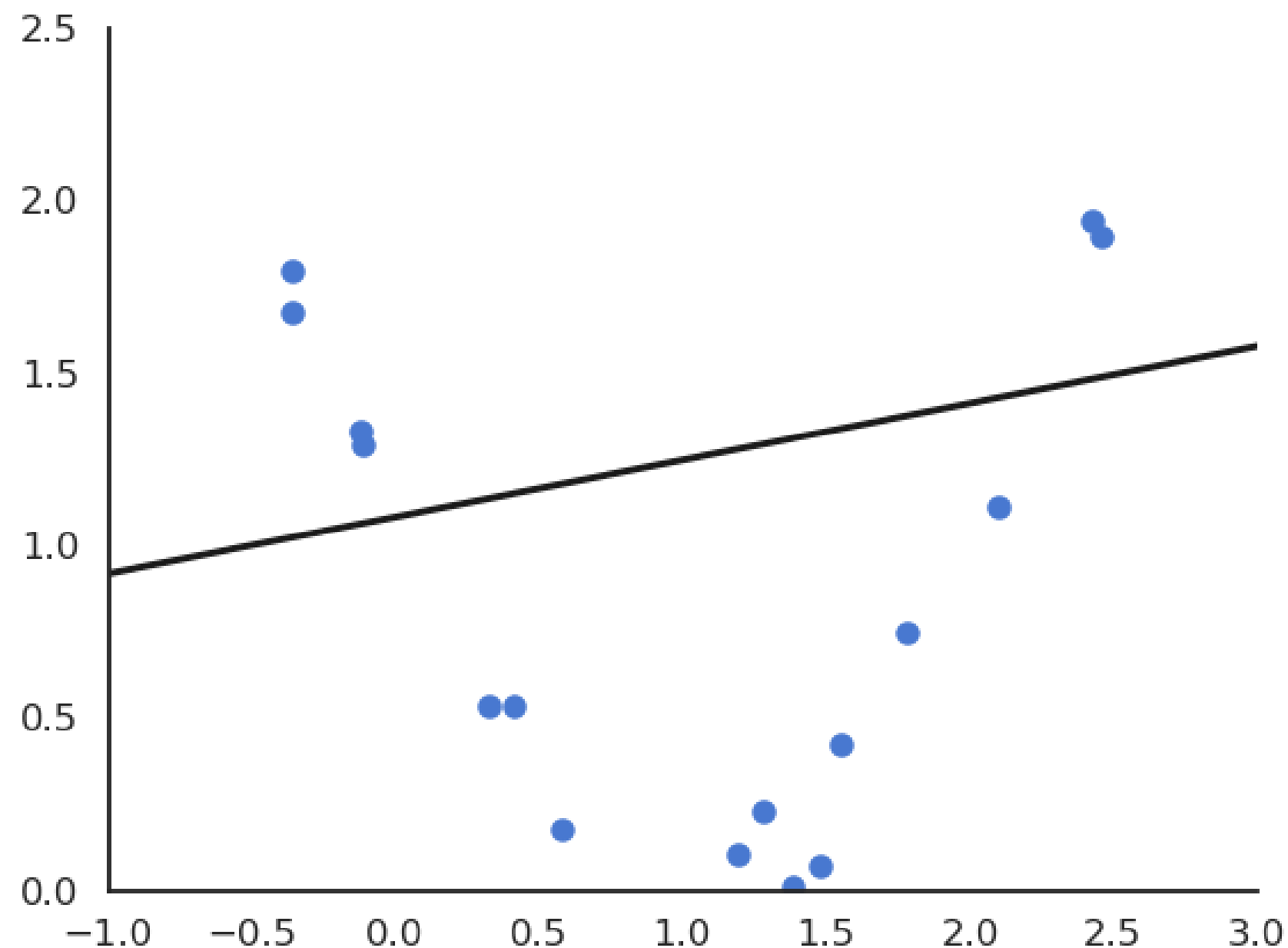
$$\mathbf{x} = \begin{bmatrix} x \\ x^2 \\ \dots \\ x^p \end{bmatrix} \quad \mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ \dots \\ w_p \end{bmatrix}$$

- A polynomial of order  $p$  has  $p + 1$  unknown parameters (**free parameters**): the  $p$  weights and the bias.
- Generally, the **complexity of a model** relates to its **number of free parameters**:
  - **The more free parameters, the more complex the model is, the more likely it will overfit.**

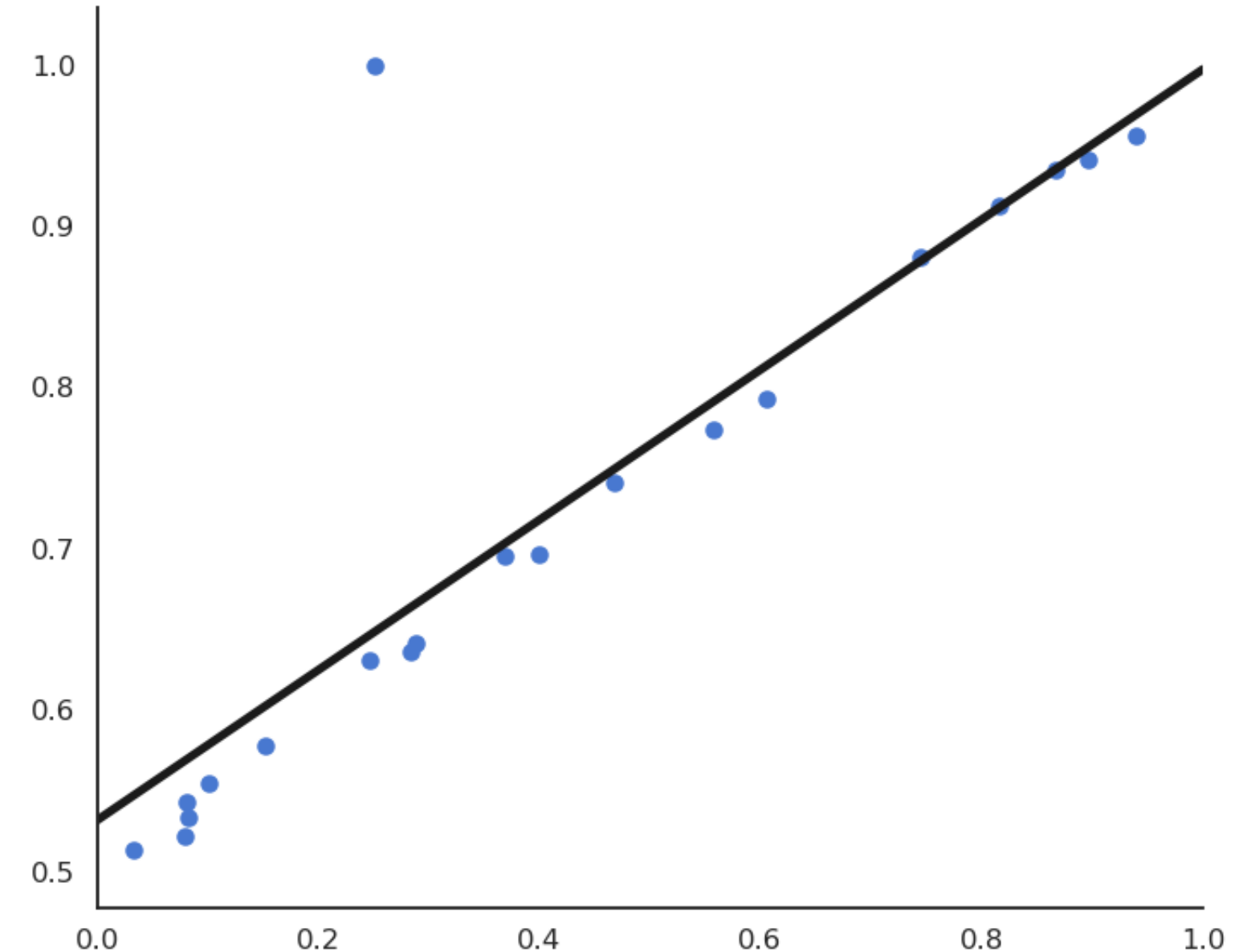
## 6 - Regularized regression

# Linear regression can either underfit or overfit depending on the data

## Underfitting

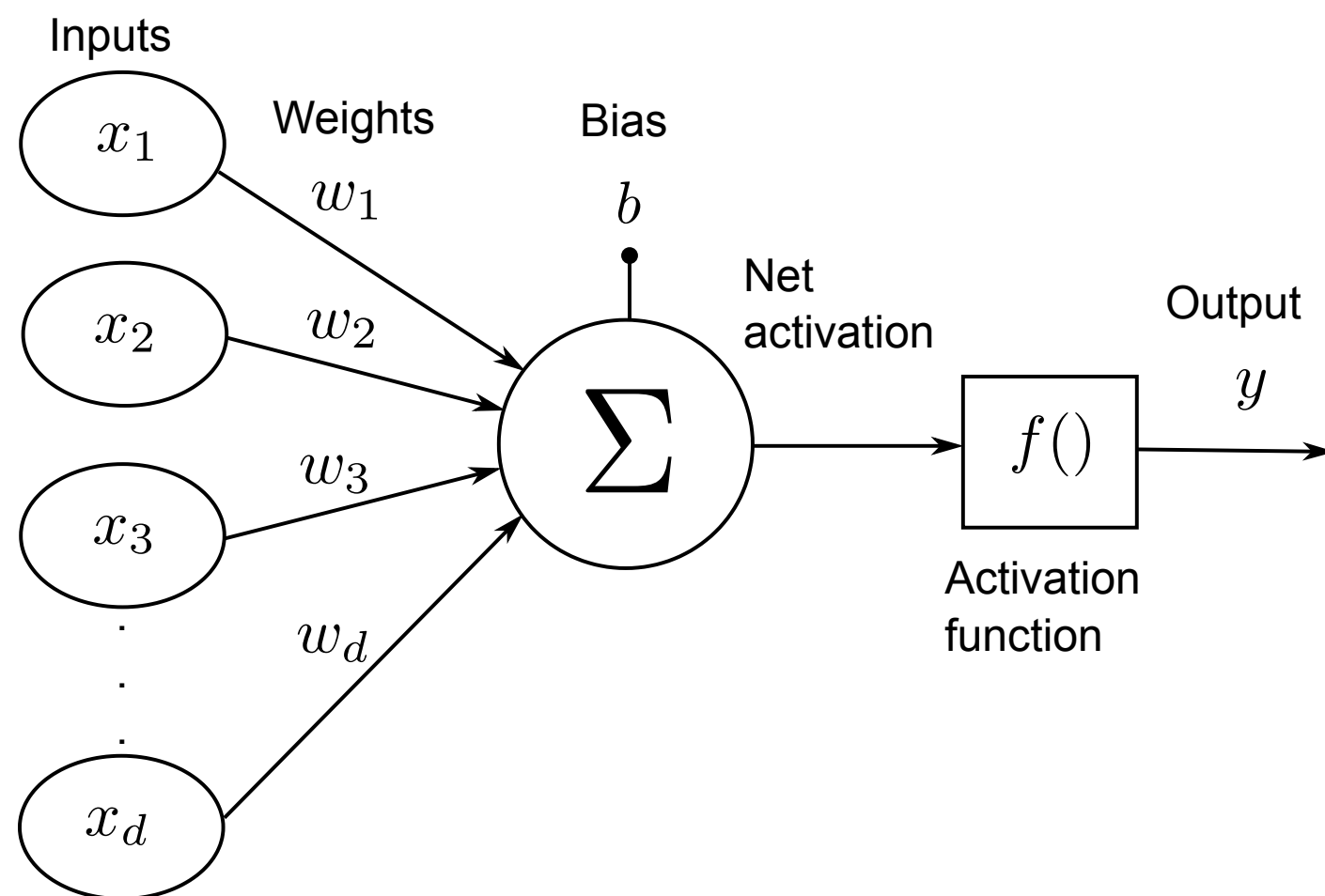


## Overfitting



- When linear regression **underfits** (both training and test errors are high), the data is not linear: we need to use a **neural network**.
- When linear regression **overfits** (the test error is higher than the training error), we would like to **decrease its complexity**.

# Complexity of a linear regression



- The problem is that the number of free parameters in linear regression only depends on the number of inputs (dimensions of the input space).

$$y = \sum_{i=1}^d w_i x_i + b$$

- For  $d$  inputs, there are  $d + 1$  free parameters: the  $d$  weights and the bias.

- We must find a way to reduce the complexity of the linear regression without changing the number of parameters, which is impossible.
- The solution is to **constrain** the values that the parameters can take: **regularization**.
- Regularization reduces the variance at the cost of increasing the bias.

## L2 regularization - Ridge regression

- Using **L2 regularization** for linear regression leads to the **Ridge regression** algorithm.
- The individual loss function is defined as:

$$l_i(\mathbf{w}, b) = (t_i - y_i)^2 + \lambda ||\mathbf{w}||^2$$

- The first part of the loss function is the classical **mse** on the training set: its role is to reduce the **bias**.
- The second part minimizes the L2 norm of the weight vector (or matrix), reducing the variance:

$$||\mathbf{w}||^2 = \sum_{i=1}^d w_i^2$$

- Deriving the regularized delta learning rule is straightforward:

$$\Delta w_i = \eta ((t_i - y_i) x_i - \lambda w_i)$$

- Ridge regression is also called **weight decay**: even if there is no error, all weights will decay to 0.

# L1 regularization - LASSO regression

- Using **L1 regularization** for linear regression leads to the **LASSO regression** algorithm (least absolute shrinkage and selection operator).
- The individual loss function is defined as:

$$l_i(\mathbf{w}, b) = (t_i - y_i)^2 + \lambda |\mathbf{w}|$$

- The second part minimizes this time the L1 norm of the weight vector, i.e. its absolute value:

$$|\mathbf{w}| = \sum_{i=1}^d |w_i|$$

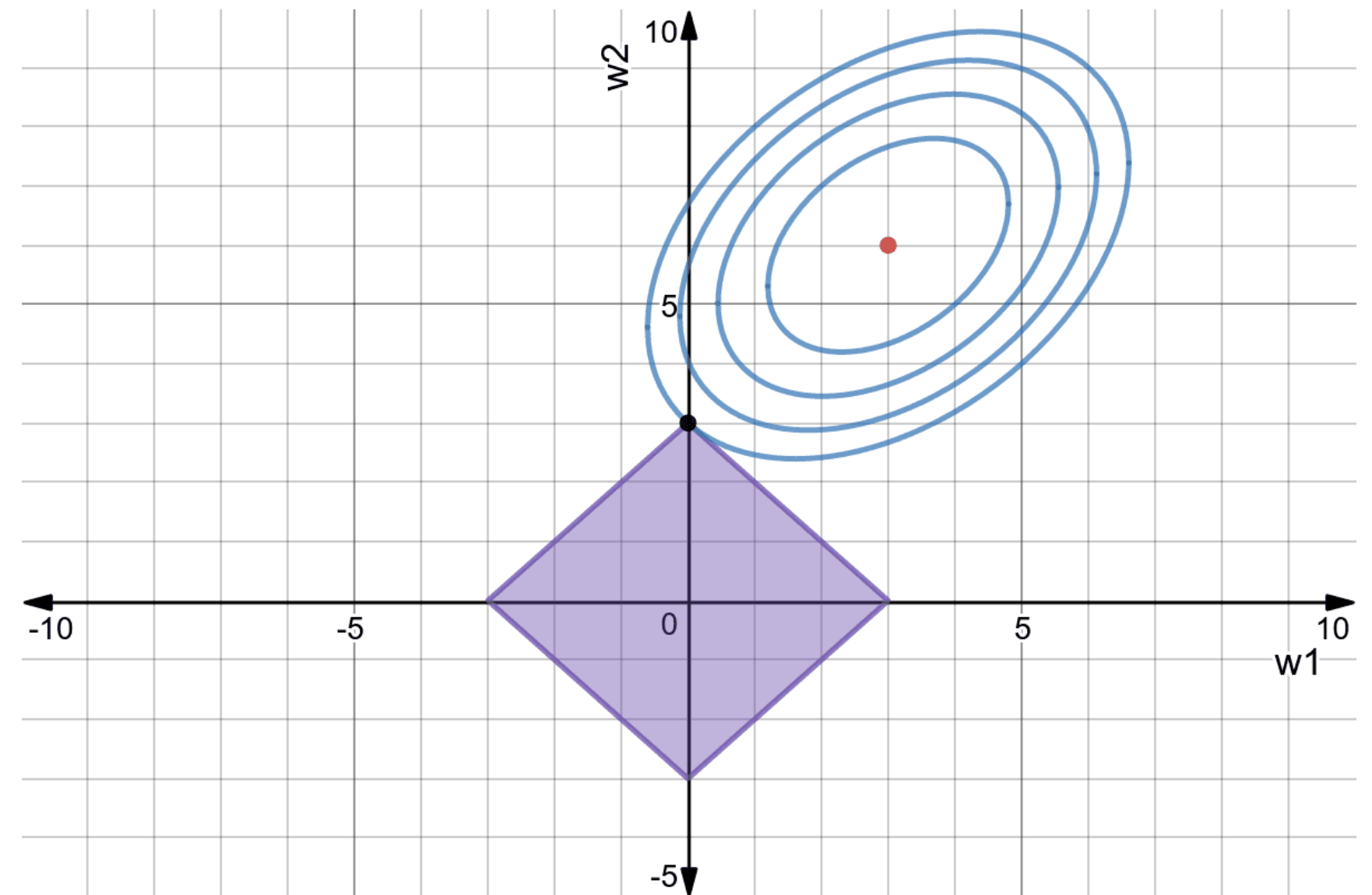
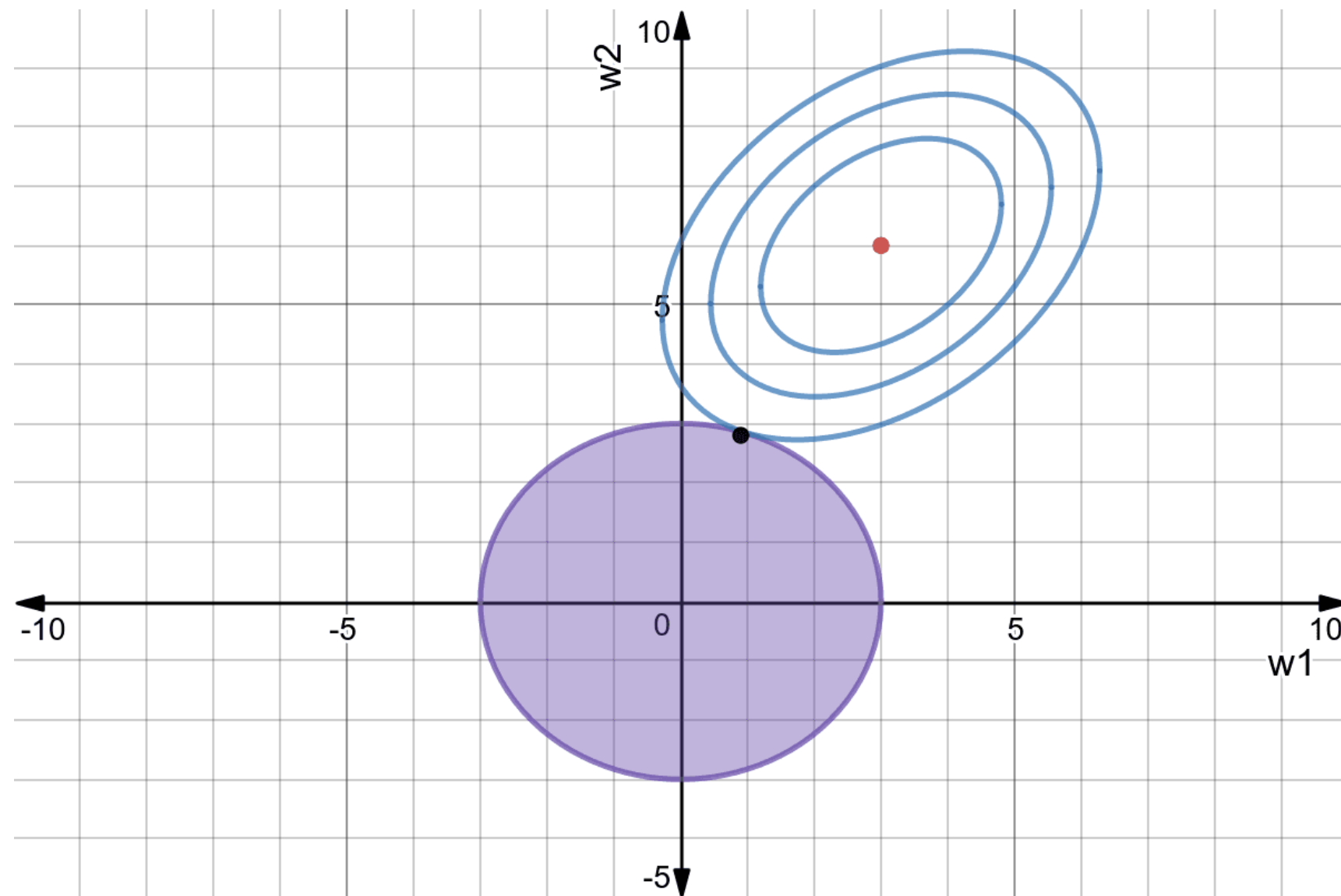
- Regularized delta learning rule with LASSO:

$$\Delta w_i = \eta ((t_i - y_i) x_i - \lambda \text{sign}(w_i))$$

- **Weight decay** does not depend on the value of the weight, only its sign. Weights can decay very fast to 0.



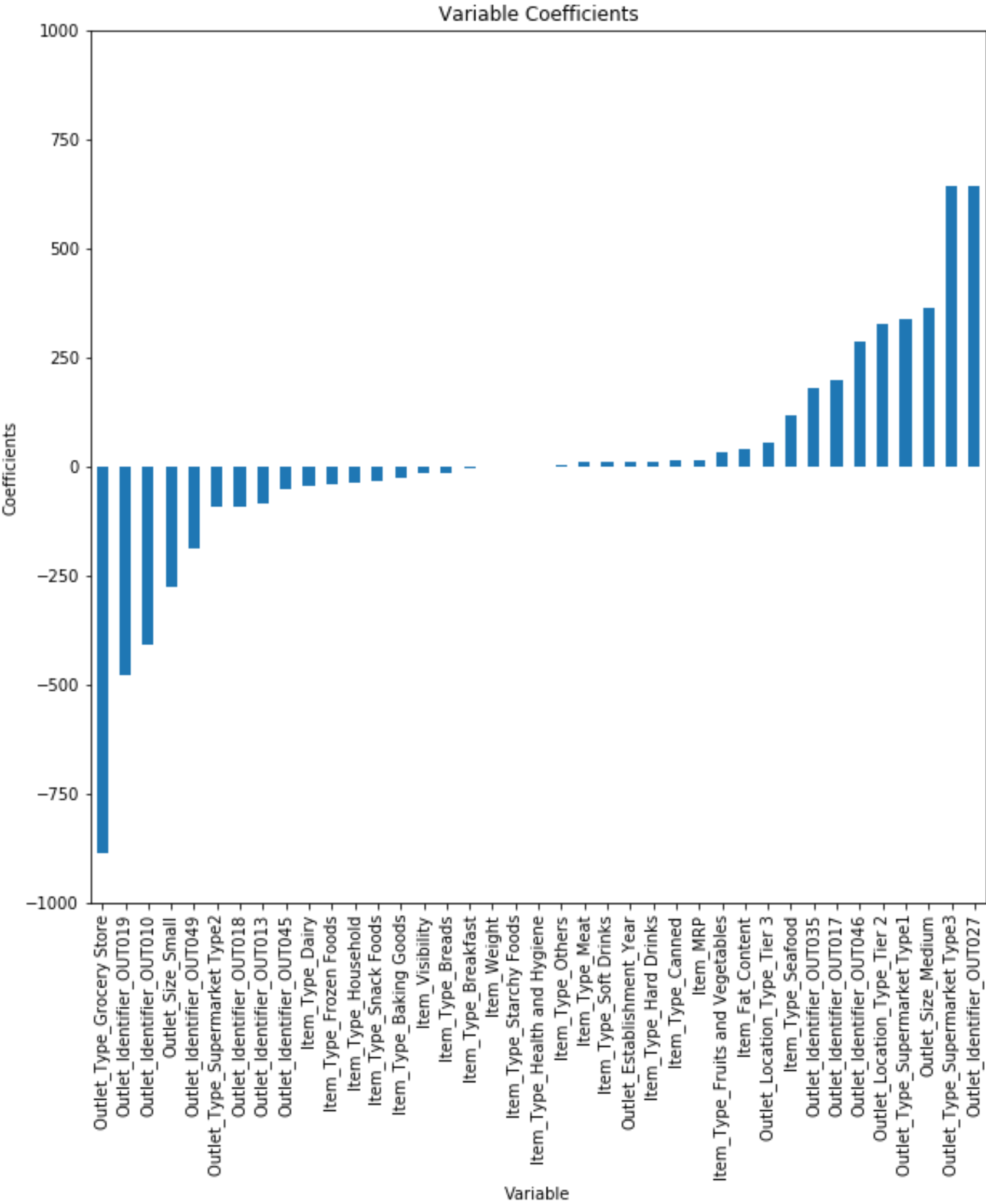
# Ridge and Lasso regression



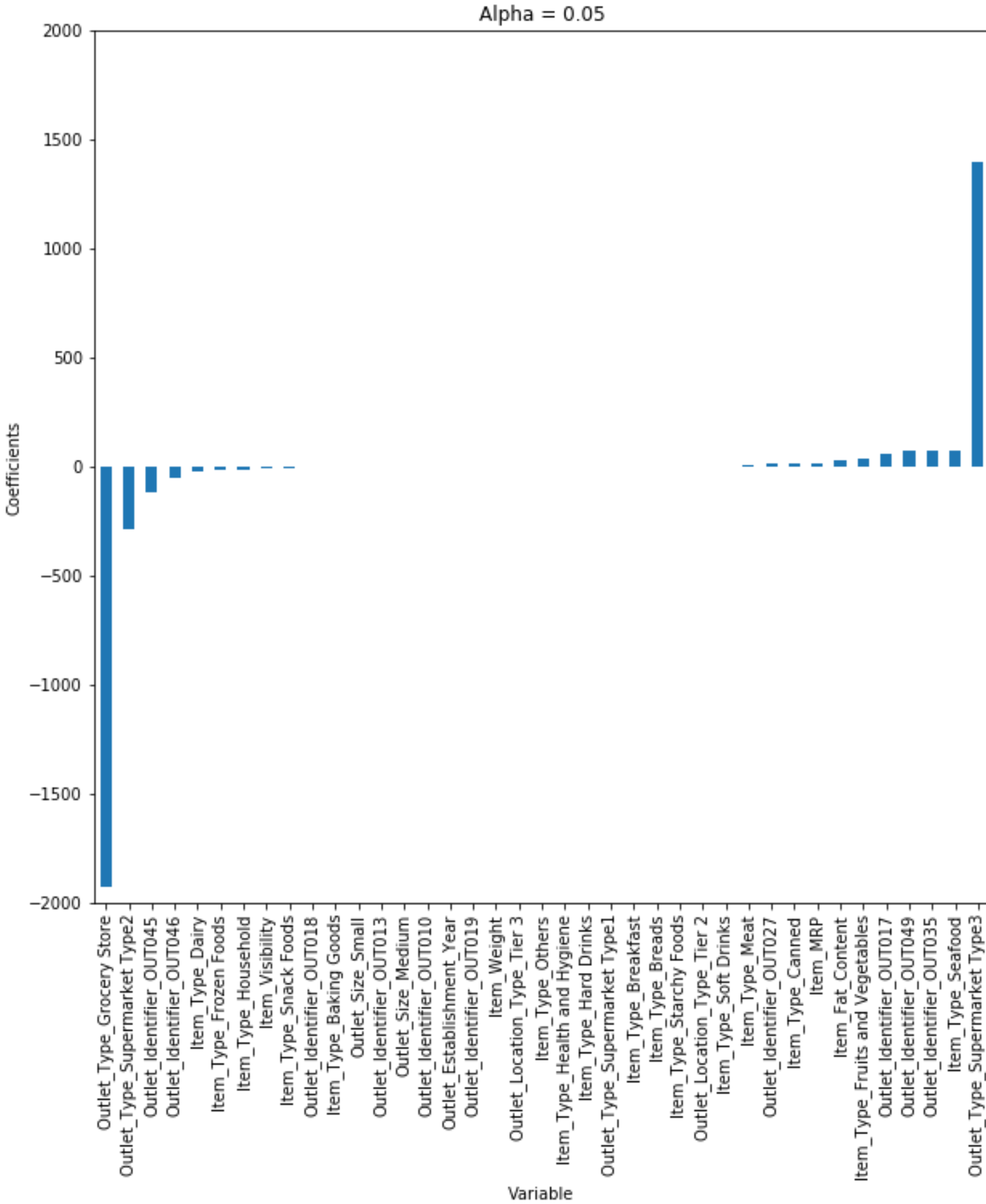
- **Ridge regression** finds the smallest value for the weights that minimize the mse.
- **LASSO regression** tries to set as many weight to 0 as possible (sparse code).
- Both methods depend on the **regularization parameter**  $\lambda$ . Its value determines how important the regularization term should.
- Regularization introduce a **bias**, as the solution found is **not** the minimum of the mse, but reduces the variance of the estimation, as small weights are less sensible to noise.

- LASSO allows **feature selection**: features with a zero weight can be removed from the training set.

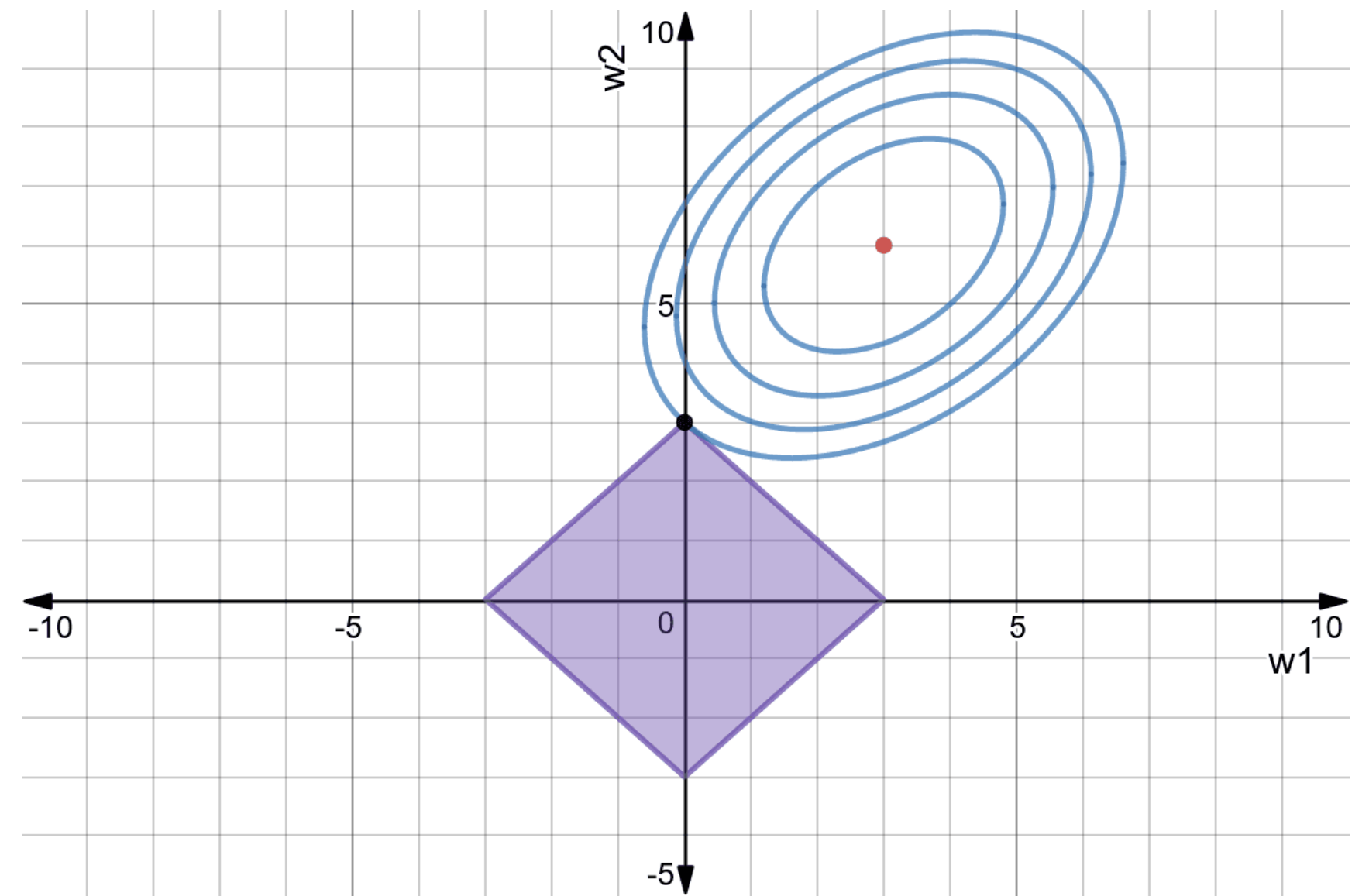
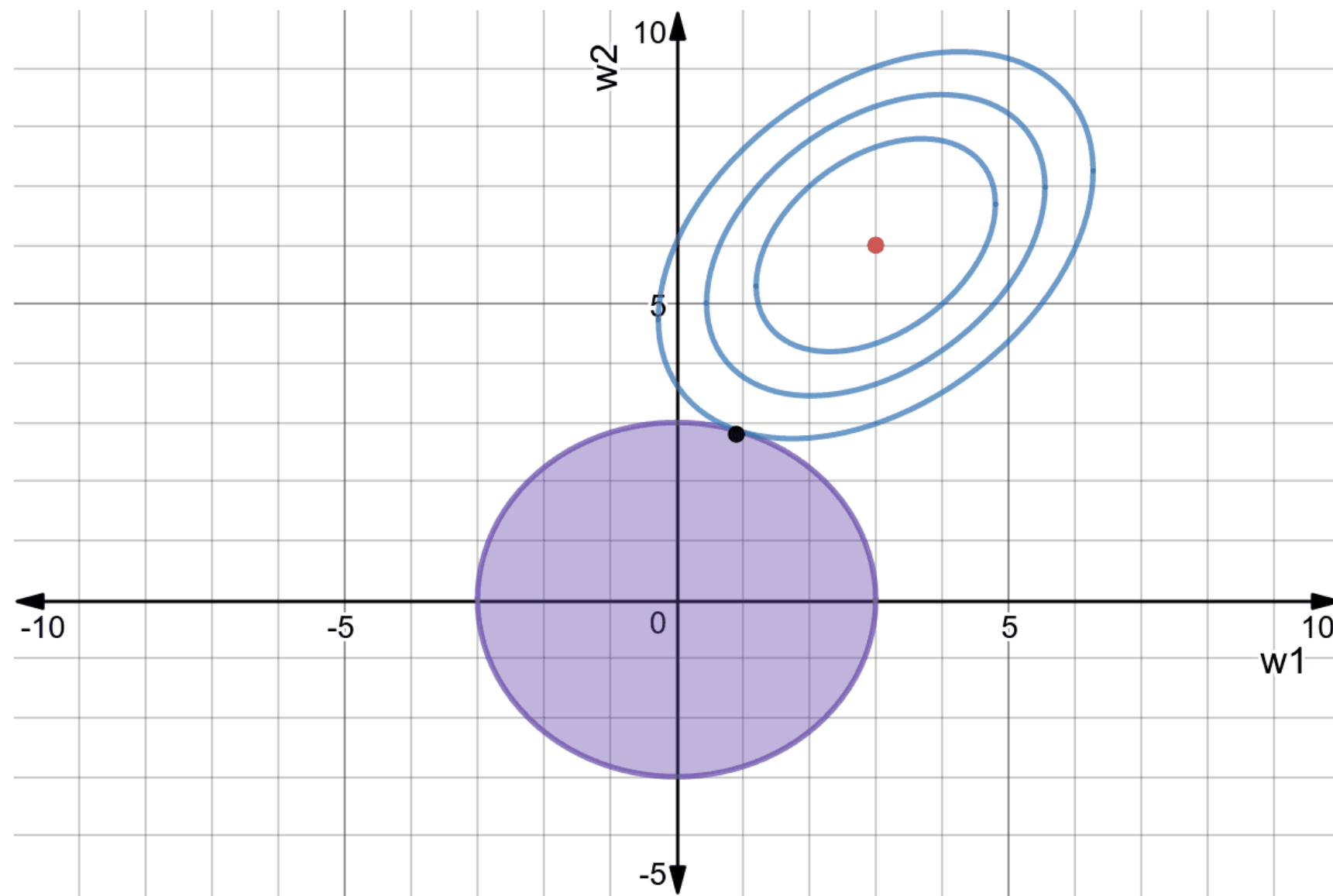
## Linear regression



## LASSO



# L1+L2 regularization - ElasticNet



- An **ElasticNet** is a linear regression using both L1 and L2 regression:

$$l_i(\mathbf{w}, b) = (t_i - y_i)^2 + \lambda_1 |\mathbf{w}| + \lambda_2 ||\mathbf{w}||^2$$

- It combines the advantages of Ridge and LASSO, at the cost of having now two regularization parameters to determine.