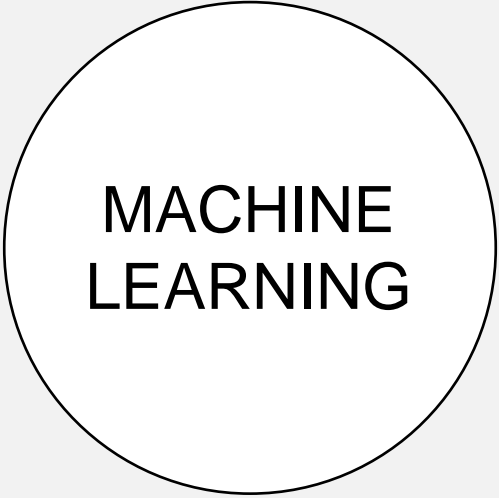
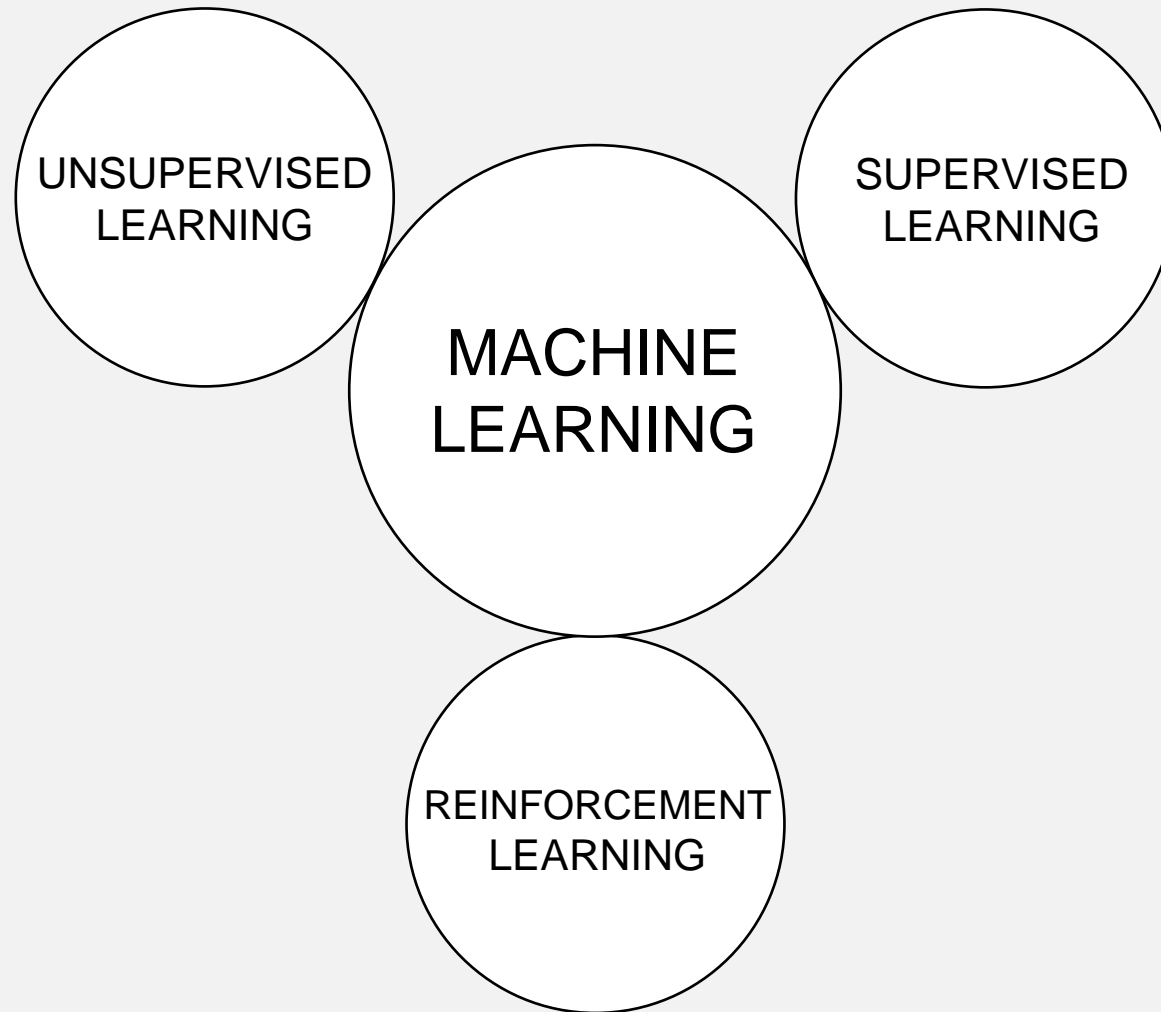


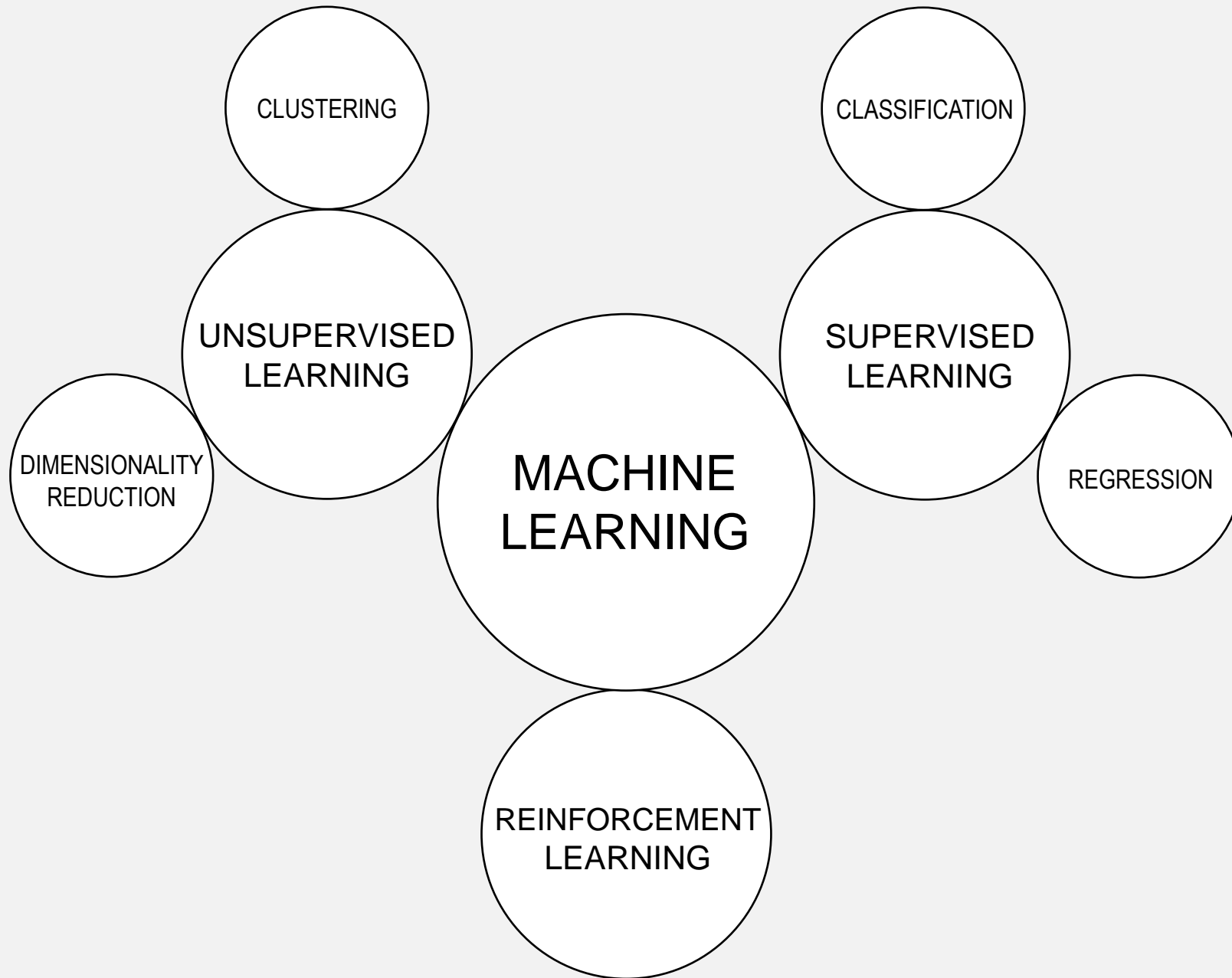
# REGRESSION

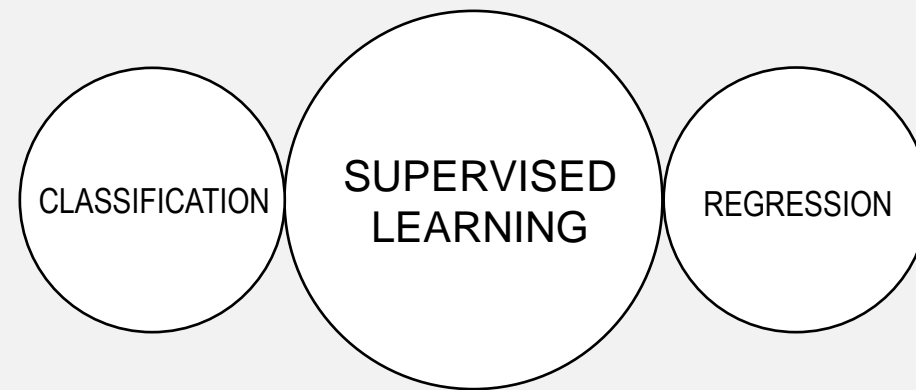
Lecture 8  
MALI, 2024



# MACHINE LEARNING





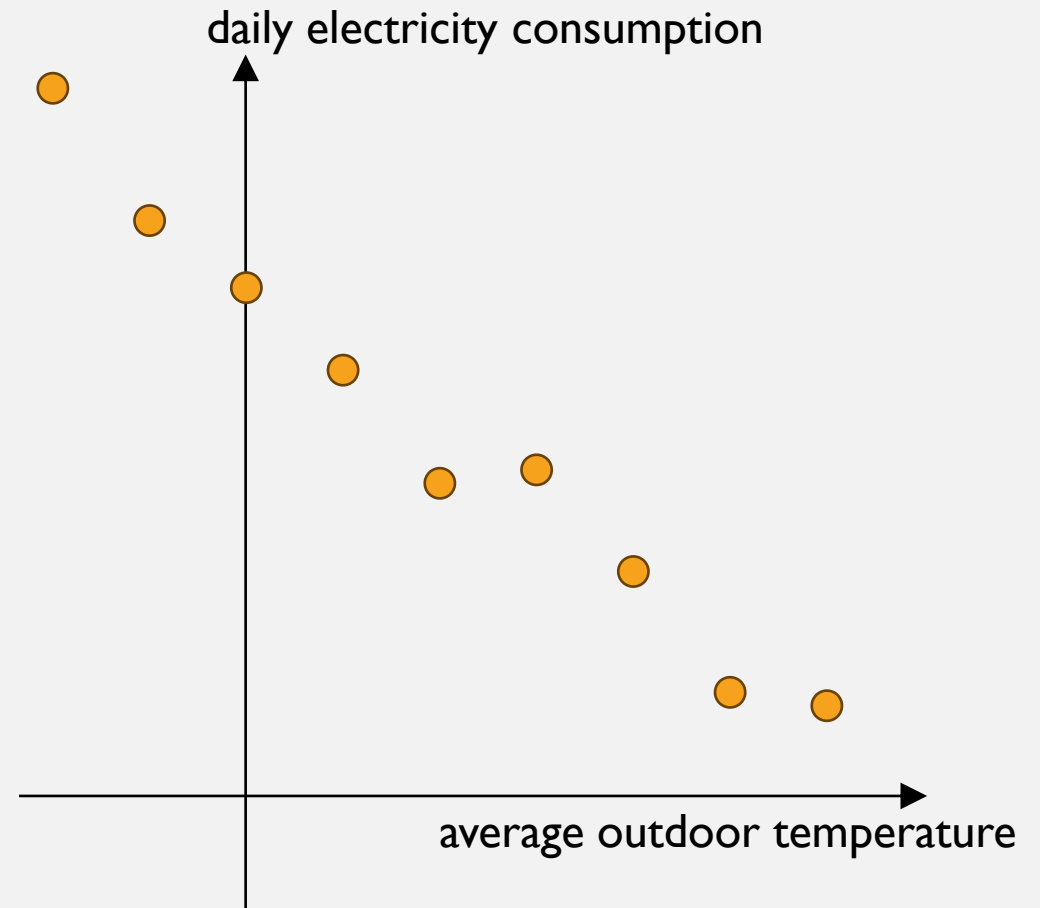


# REGRESSION

- Linear regression
- Performance metrics
- Polynomial regression
- Regularization

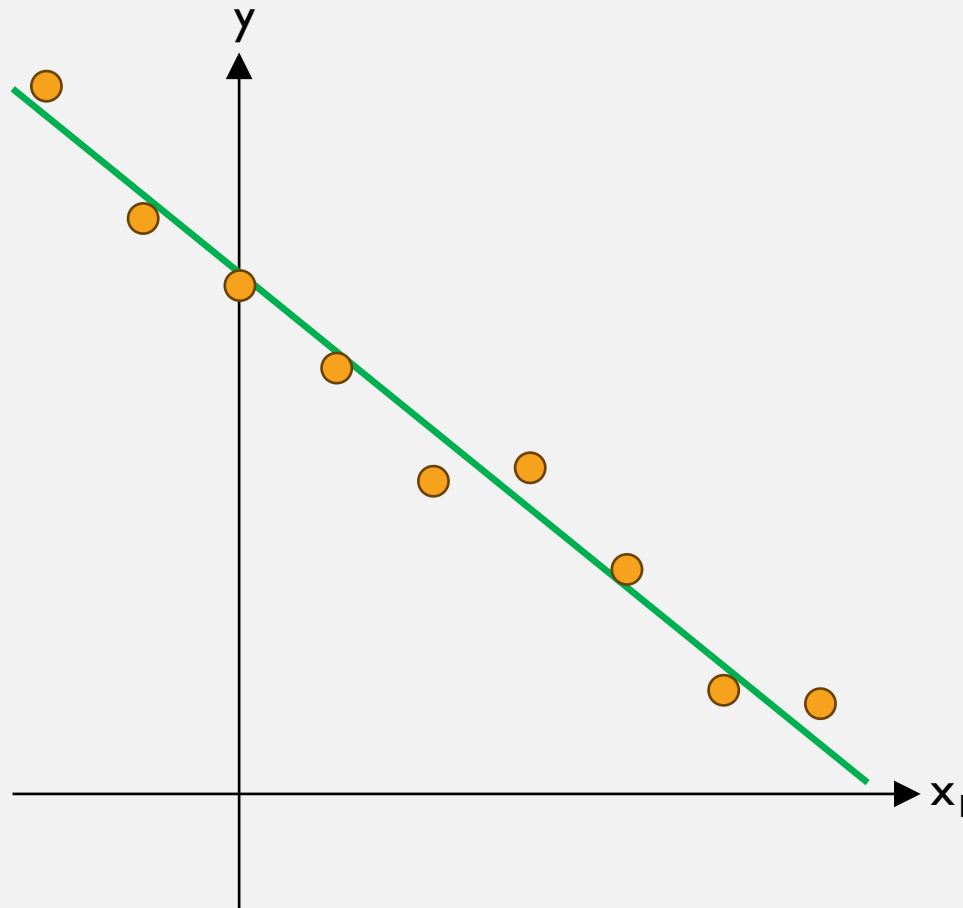
# REGRESSION

average outdoor temperature (°C)	daily electricity consumption (kWh)
-10	46.5
-5	37.9
0	33.2
5	27.5
10	20.3
15	21.1
20	14.2
25	6.3
30	5.6



# REGRESSION

$x_1$	$y$
$\theta_0 + -10 \times \theta_1 \approx$	46.5
$\theta_0 + -5 \times \theta_1 \approx$	37.9
$\theta_0 + 0 \times \theta_1 \approx$	33.2
$\theta_0 + 5 \times \theta_1 \approx$	27.5
$\theta_0 + 10 \times \theta_1 \approx$	20.3
$\theta_0 + 15 \times \theta_1 \approx$	21.1
$\theta_0 + 20 \times \theta_1 \approx$	14.2
$\theta_0 + 25 \times \theta_1 \approx$	6.3
$\theta_0 + 30 \times \theta_1 \approx$	5.6





# FINDING THETA'S

## FINDING THETA'S

$$\text{SSE} = \sum_i (y^{(i)} - \hat{y}^{(i)})^2 = \sum_i (y^{(i)} - \theta^T x^{(i)})^2$$

minimize  $\rightarrow$  take the derivative wrt. all  $\theta$ 's and set equal to zero:

$$\frac{\partial}{\partial \theta_j} \text{SSE} = \frac{\partial}{\partial \theta_j} \sum_i (y^{(i)} - \theta^T x^{(i)})^2 = 2 \sum_i (y^{(i)} - \theta^T x^{(i)}) x_j^{(i)} = 0$$

summarize in matrix form:

$$2\mathbf{X}^T(\mathbf{X}\boldsymbol{\theta} - \mathbf{y}) = 0$$

## FINDING THETA'S

$$\theta = (X^T X)^{-1} X^T y$$

$$X = \begin{bmatrix} 1 & -10 \\ 1 & -5 \\ 1 & 0 \\ 1 & 5 \\ 1 & 10 \\ 1 & 15 \\ 1 & 20 \\ 1 & 25 \\ 1 & 30 \end{bmatrix} \quad y = \begin{bmatrix} 46.5 \\ 37.9 \\ 33.2 \\ 27.5 \\ 20.3 \\ 21.1 \\ 14.2 \\ 6.3 \\ 5.6 \end{bmatrix} \quad X^T = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ -10 & -5 & 0 & 5 & 10 & 15 & 20 & 25 & 30 \end{bmatrix}$$

$$X^T X = \begin{bmatrix} 9 & 90 \\ 90 & 2400 \end{bmatrix} \quad (X^T X)^{-1} = \begin{bmatrix} \frac{8}{45} & -\frac{1}{150} \\ -\frac{1}{150} & \frac{1}{1500} \end{bmatrix}$$

$$(X^T X)^{-1} X^T = \begin{bmatrix} \frac{11}{45} & \frac{19}{90} & \frac{8}{45} & \frac{13}{90} & \frac{1}{9} & \frac{7}{90} & \frac{2}{45} & \frac{1}{90} & -\frac{1}{45} \\ \frac{1}{75} & \frac{1}{100} & \frac{1}{150} & \frac{1}{300} & 0 & \frac{1}{300} & \frac{1}{150} & \frac{1}{100} & \frac{1}{75} \end{bmatrix}$$

$$\theta = (X^T X)^{-1} X^T y = \begin{bmatrix} 33.72 \\ -1.009 \end{bmatrix}$$

$x_i$	$y$
-10	46.5
-5	37.9
0	33.2
5	27.5
10	20.3
15	21.1
20	14.2
25	6.3
30	5.6

in practice, the pseudoinverse is computed using SVD

# REGRESSION

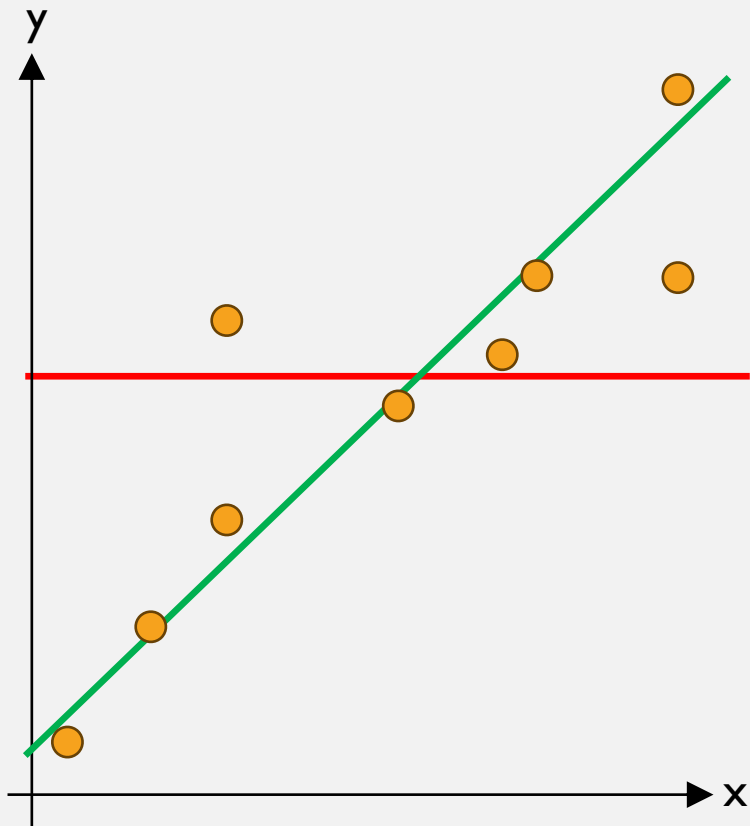
- Linear regression
- **Performance metrics**
- Polynomial regression
- Regularization

## SSE AND FRIENDS

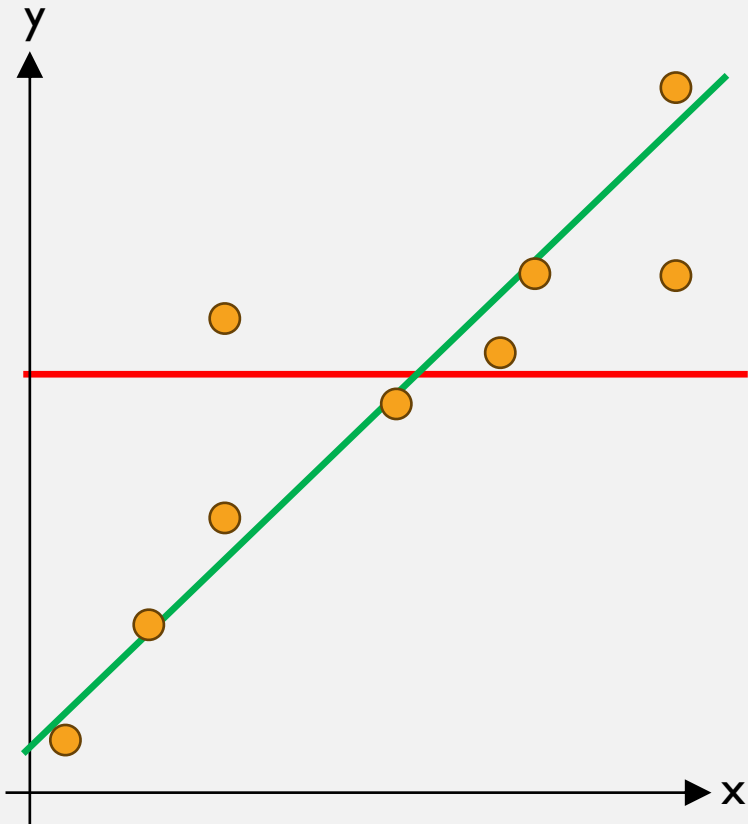
- The smaller the SSE, the better the model ...

... so what should we use as our performance metric?

# SSE AND FRIENDS



# SSE AND FRIENDS

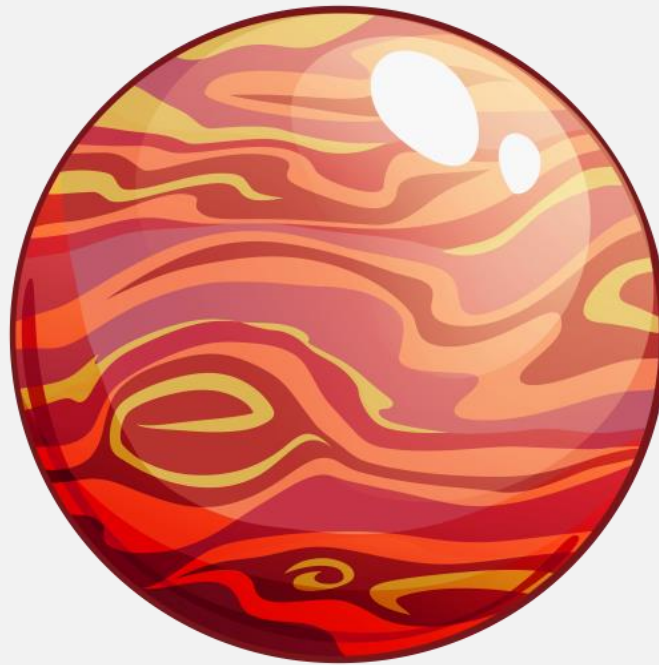


$$SST = \sum_i (y^{(i)} - \bar{y})^2 \quad \text{total deviation from mean}$$

$$SSE = \sum_i (y^{(i)} - \hat{y}^{(i)})^2 \quad \text{explained part}$$

$$SSR = \sum_i (\hat{y}^{(i)} - \bar{y})^2 \quad \text{unexplained part}$$

## CODE EXAMPLE



*Jupyter Notebook* **Regression - Hitters**

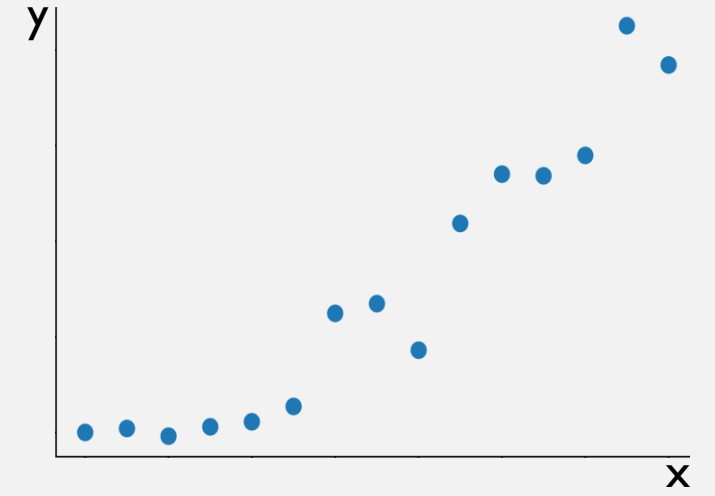
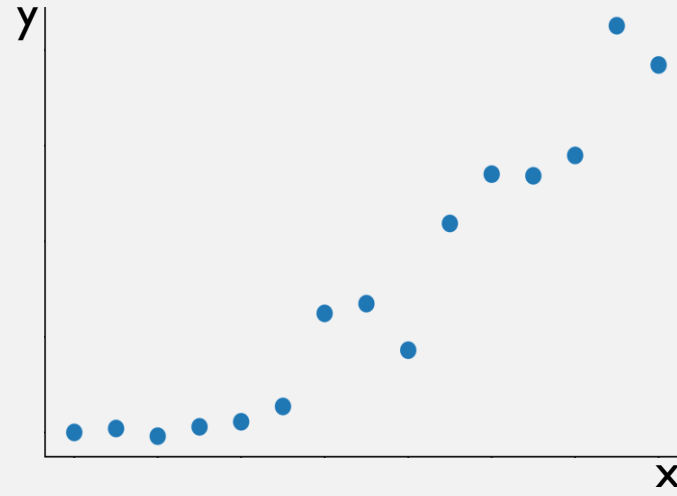
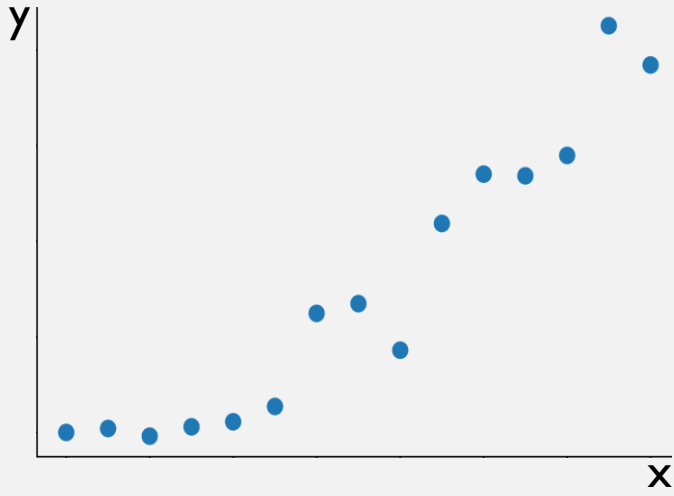


# REGRESSION

- Linear regression
- Performance metrics
- **Polynomial regression**
- Regularization

# POLYNOMIAL REGRESSION

# UNDERFITTING AND OVERFITTING



# REGRESSION

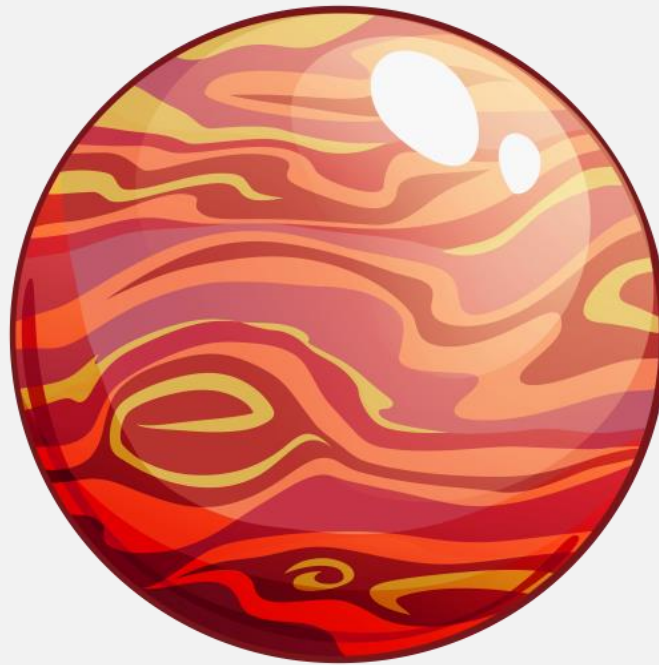
- Linear regression
- Performance metrics
- Polynomial regression
- **Regularization**

# REGULARIZATION

# THE OPTIMAL REGULARIZATION PARAMETER

# RIDGE VS LASSO REGRESSION

## CODE EXAMPLE



*Jupyter Notebook* **Regression - Hitters**



