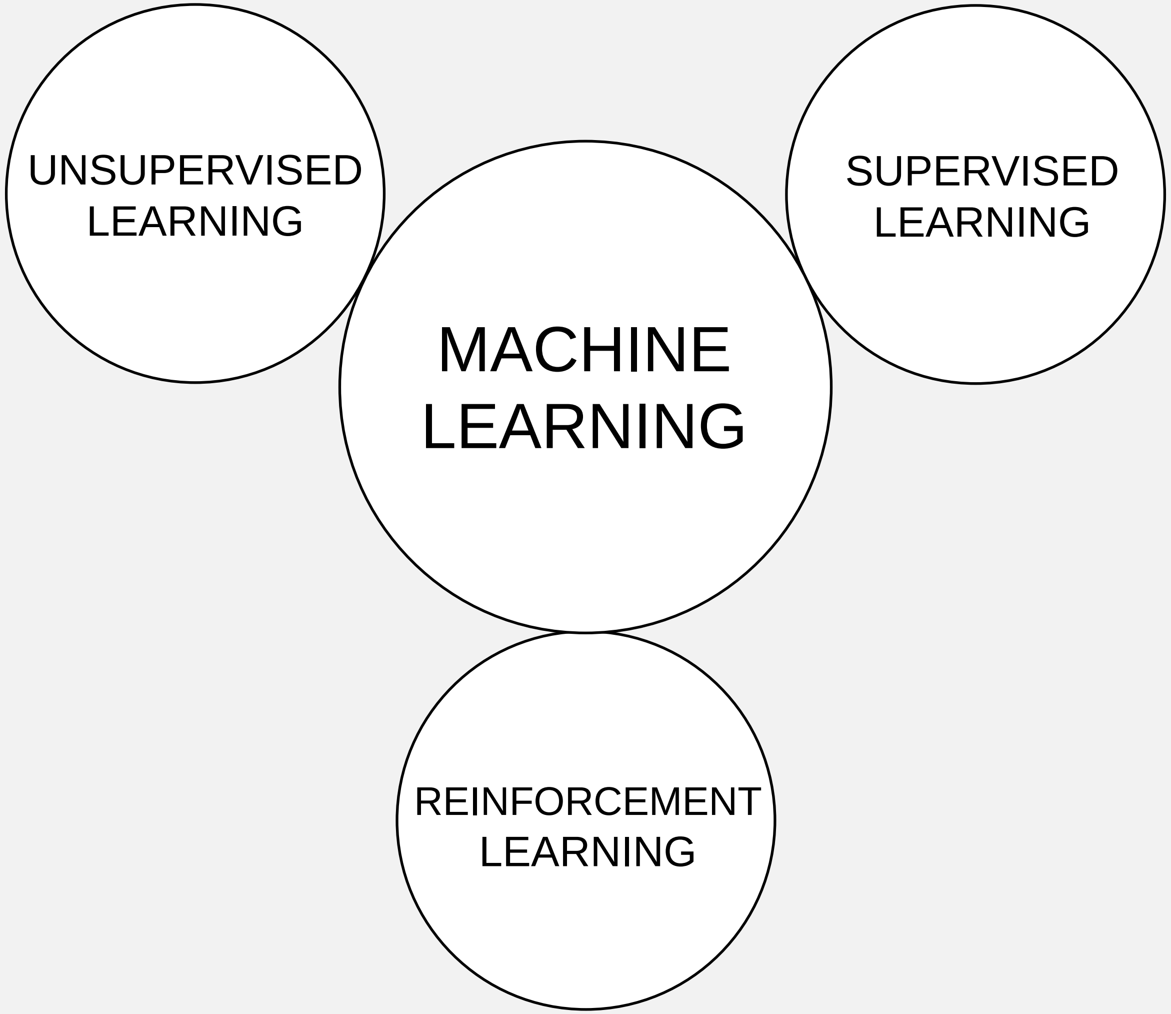
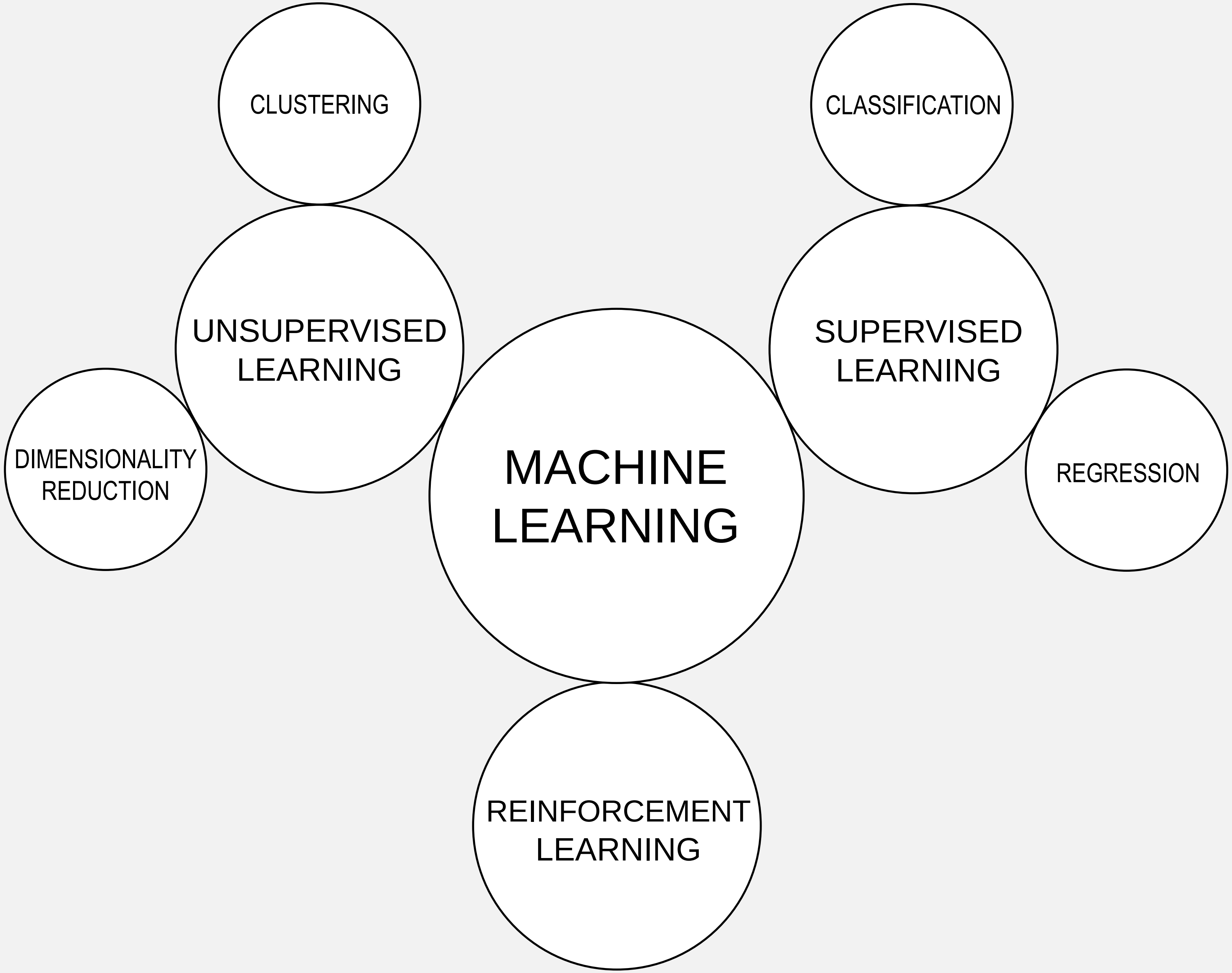
REGRESSION

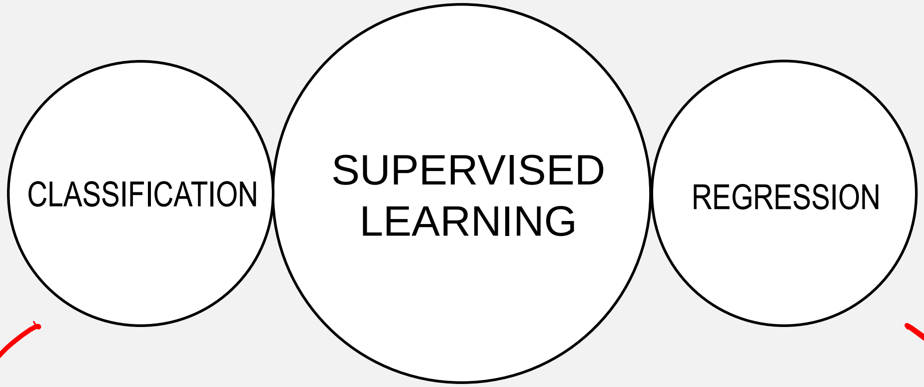
Lecture 8

MAL1, 2024

MACHINE LEARNING


UNSUPERVISED LEARNING
MACHINE LEARNING
SUPERVISED LEARNING
REINFORCEMENT LEARNING


CLUSTERING
CLASSIFICATION
UNSUPERVISED LEARNING
SUPERVISED LEARNING
DIMENSIONALITY REDUCTION
MACHINE LEARNING
REGRESSION
REINFORCEMENT LEARNING



response variable is a class

response variable is a number

REGRESSION

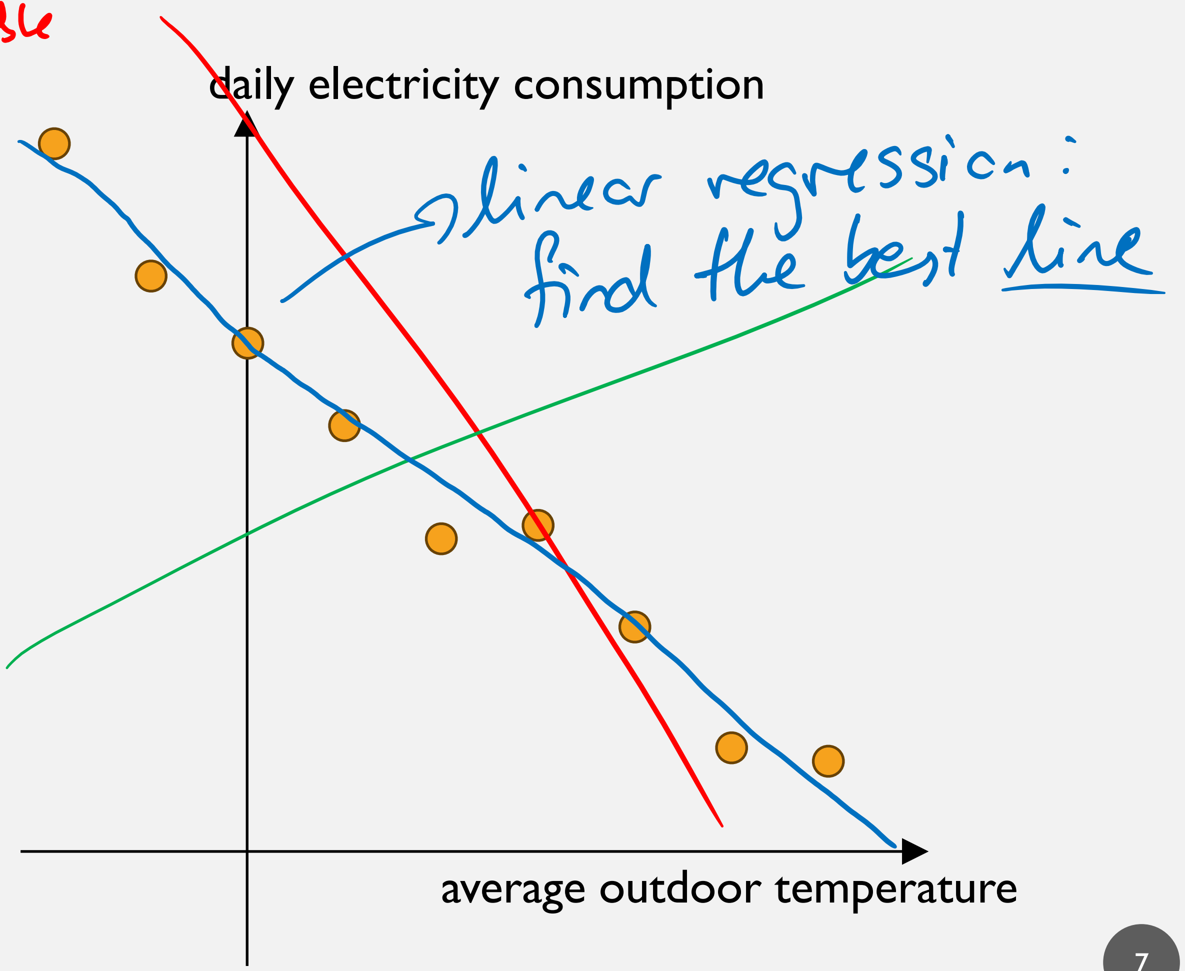
- Linear regression
- Performance metrics
- Polynomial regression
- Regularization

REGRESSION

feature

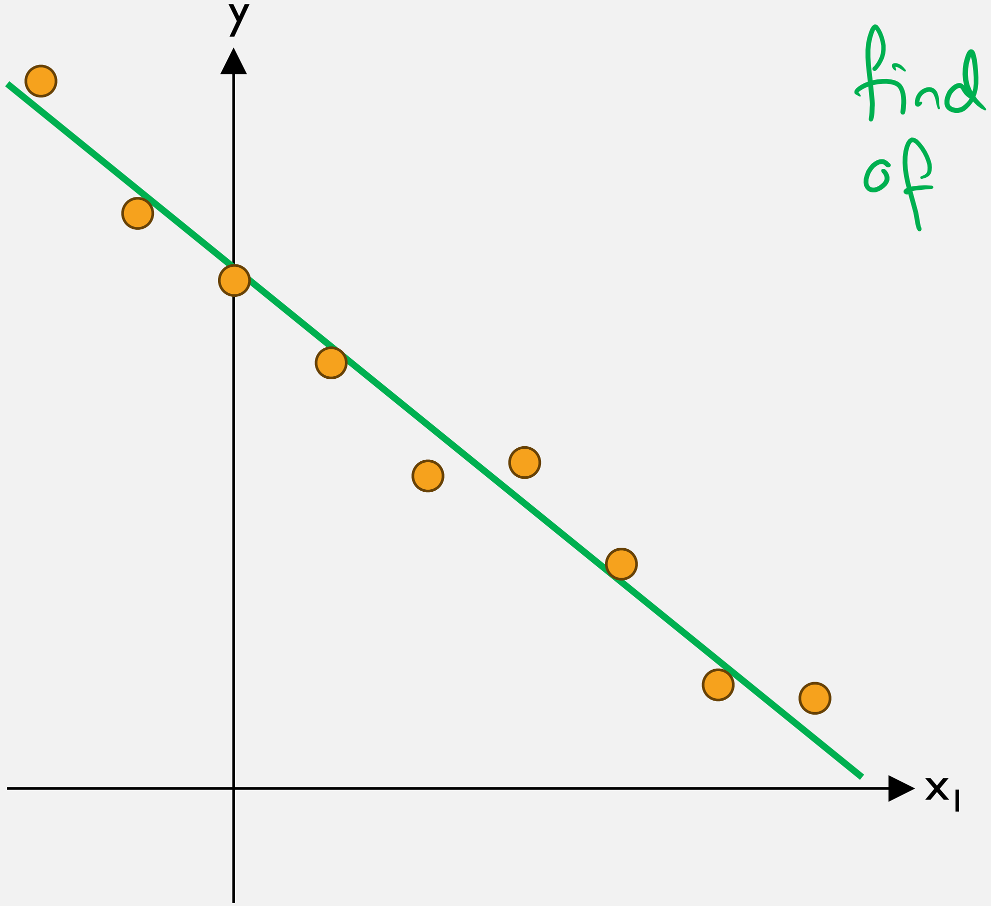
response variable

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



with $\hat{y} = \theta_0 + \theta_1 x_1$

find the "best" values of θ_0 and θ_1

$$\underbrace{\theta_0 = 33.72 \quad \theta_1 = -1.009}$$

finding these numbers

= training the model

FINDING THETA'S

$$\hat{y} = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \dots\dots\dots = \underbrace{\boldsymbol{\theta}^T \mathbf{x}}_{\text{matrix form}}$$

prediction

features

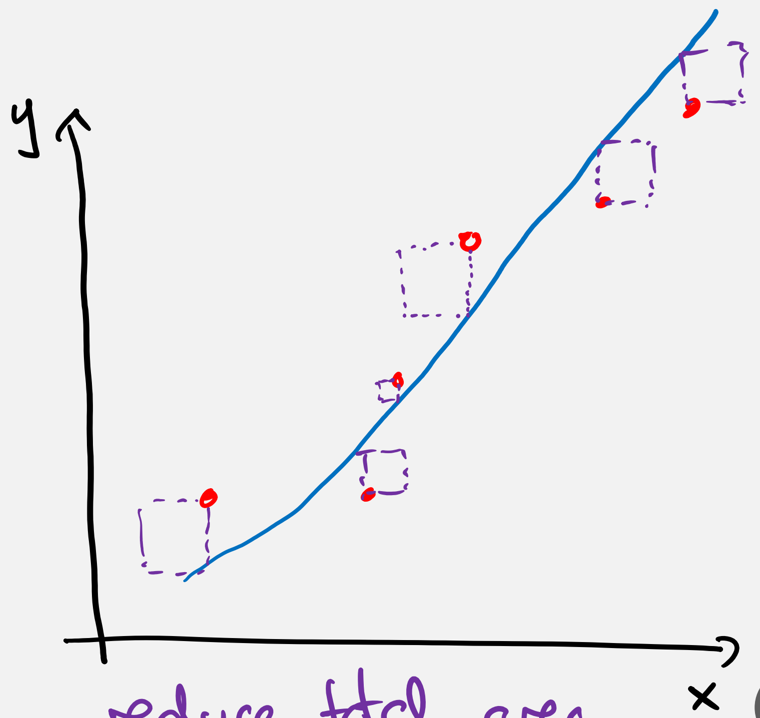
The best line reduces the error

$$SSE = \sum_i \left(y^{(i)} - \hat{y}^{(i)}\right)^2$$

sum of squared errors

observations

prediction



reduce total area

FINDING THETA'S

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

minimize → take the derivative wrt. all θ's and set equal to zero:

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

summarize in matrix form:

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

$$X^T X \theta = X^T y$$

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

FINDING THETA'S

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

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

$$\boldsymbol{X}^T = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ -10 & -5 & 0 & 5 & 10 & 15 & 20 & 25 & 30 \end{bmatrix}$$

$$\boldsymbol{X}^T\boldsymbol{X} = \begin{bmatrix} 9 & 90 \\ 90 & 2400 \end{bmatrix}$$

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

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

$$\boldsymbol{\theta} = \overbrace{(\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T}^{\text{pseudoinverse}}\boldsymbol{y} = \begin{bmatrix} 33.72 \\ -1.009 \end{bmatrix} \begin{matrix} \leftarrow \theta_0 \\ \leftarrow \theta_1 \end{matrix}$$

X matrix

y vector

x_0	x_1	y
1	-10	46.5
1	-5	37.9
1	0	33.2
1	5	27.5
1	10	20.3
1	15	21.1
1	20	14.2
1	25	6.3
1	30	5.6

dummy feature to match θ_0

$O(n^2)$ time instead of $O(n^3)$

in practice, the pseudoinverse is computed using SVD

REGRESSION

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SSE AND FRIENDS

- The smaller the SSE, the better the model …

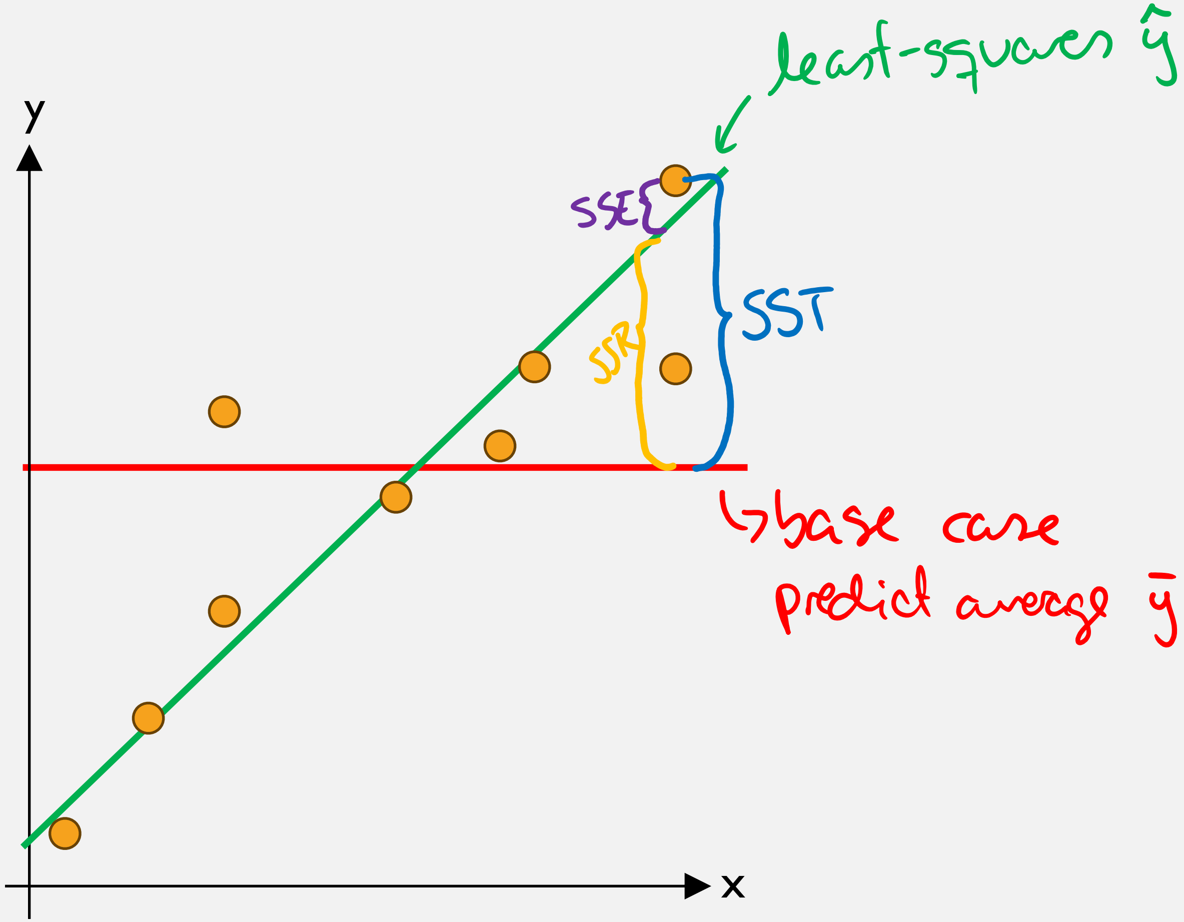
but SSE depends on # data points

$$MSE = \frac{1}{n} SSE$$ (mean squared error)

but MSE depends on scale of response variable

… so what should we use as our performance metric?

SSE AND FRIENDS



total

$$SST = \sum (y_i - \bar{y})^2$$

(total sum of squares)

unexplained part

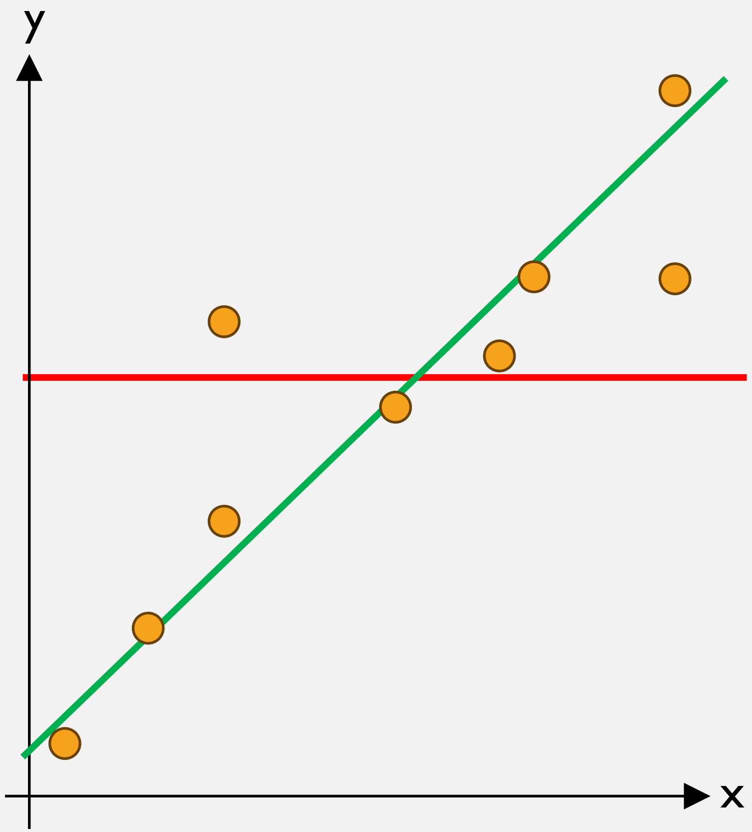
$$SSE = \sum (y_i - \hat{y}_i)^2$$

$$SSR = \sum (\hat{y}_i - \bar{y})^2$$

explained part

(sum of squares due to regression)

SSE AND FRIENDS



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

$$\text{SSE} = \sum_i \left(y^{(i)} - \hat{y}^{(i)}\right)^2$$ unexplained part

$$\text{SSR} = \sum_i \left(\hat{y}^{(i)} - \bar{y}\right)^2$$ explained part

performance metric

$$r^2 = \frac{SSR}{SST} = \frac{\text{"explained"}}{\text{"total"}}$$

the amount of variance the model is able to explain

$r^2 \leq 1 \rightarrow$ perfect predictive model

CODE EXAMPLE

Jupyter Notebook **Regression - Hitters**

REGRESSION

- Linear regression
- Performance metrics
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POLYNOMIAL REGRESSION

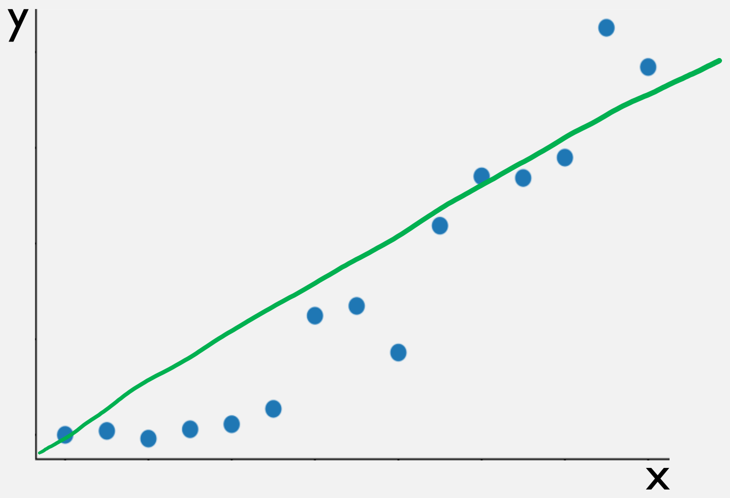
$$\hat{y} = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \dots$$

$x^2, x^3, \dots$ are just new features

$$X = \begin{bmatrix} 1 & x & x^2 & x^3 \\ 1 & x & x^2 & x^3 \\ 1 & x & x^2 & x^3 \\ 1 & x & x^2 & x^3 & \cdots \\ 1 & x & x^2 \\ 1 & x \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

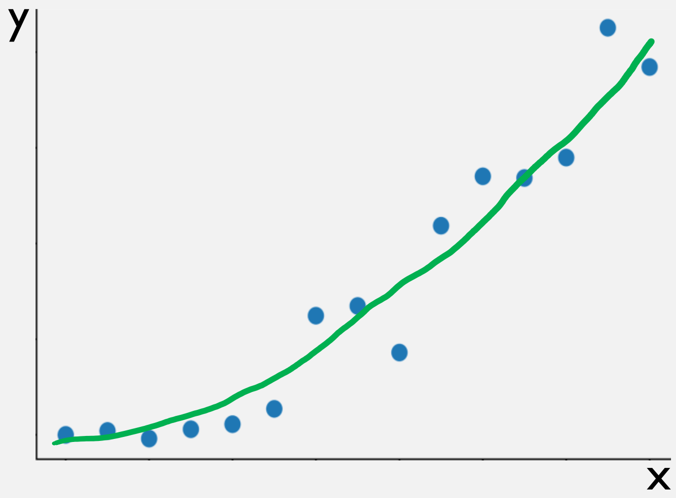
may be a good idea
– depending on underlying relationship

UNDERFITTING AND OVERFITTING



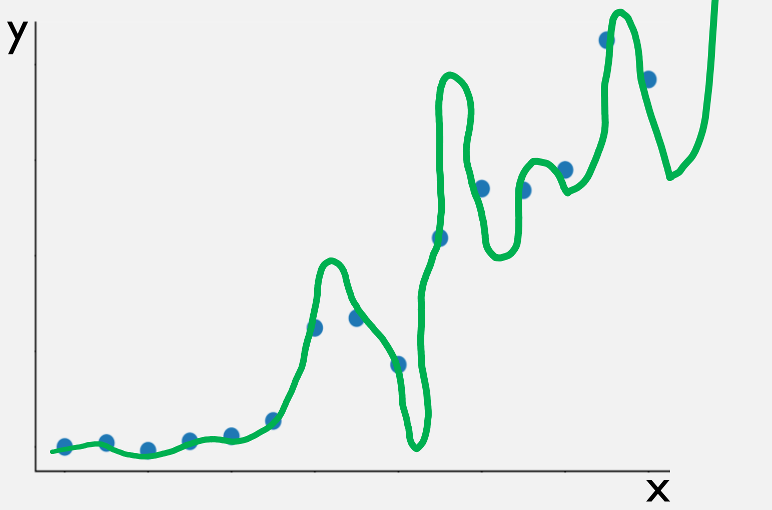
underfitting

high bias
low variance



sweet spot

bias-variance
trade-off



overfitting

low bias
high variance

Bias = "Inability to learn from data"
Variance = "Reliance on data"

REGRESSION

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REGULARIZATION

Tool to avoid overfitting

Idea: Penalize large coefficient

regularization parameter

loss function $\mathcal{L} = MSE + \alpha R(\theta)$

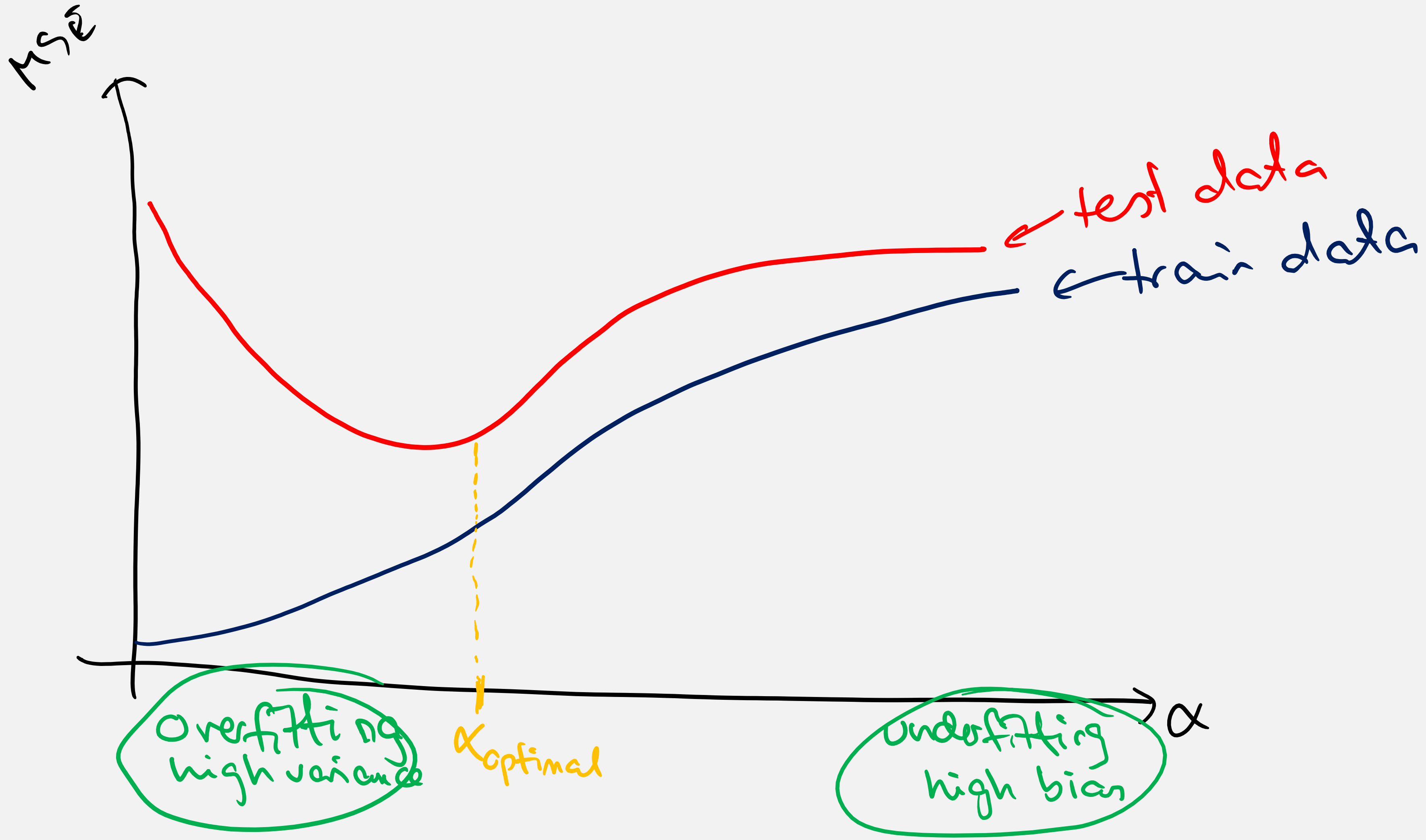
penalty function of θ

common choices for R

$R(\theta) = \sum \theta_i^2$ "L_2 regularization": Ridge regression

$R(\theta) = \sum |\theta_i|$ "L_1 regularization": Lasso regression

THE OPTIMAL REGULARIZATION PARAMETER



RIDGE VS LASSO REGRESSION

Ridge

Drives coefficients to small values overall

Lasso

Drives certain coefficients to zero

→ builtin feature selection

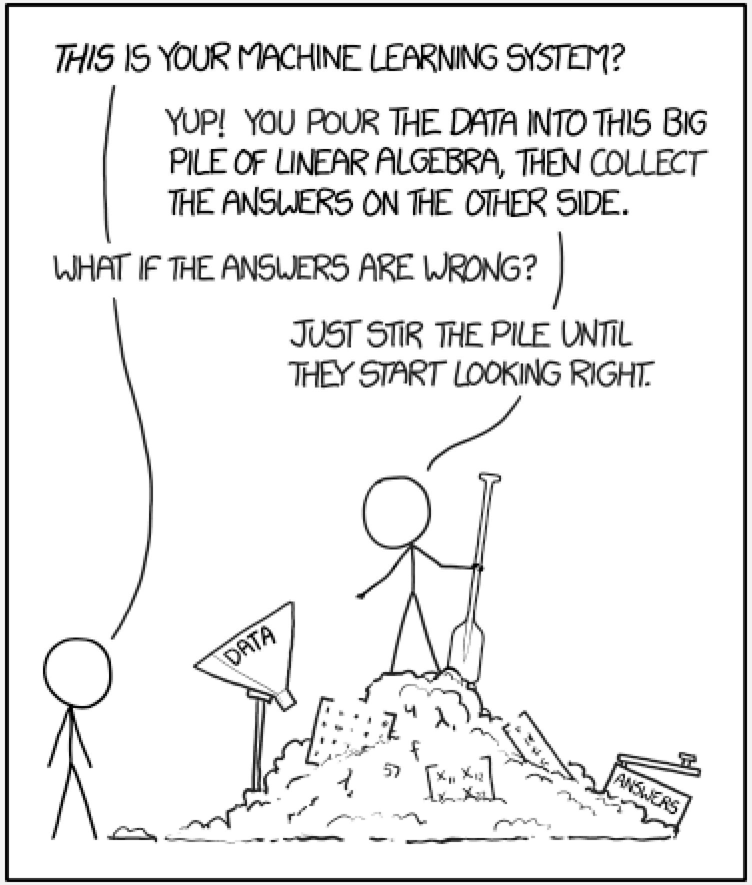
Elastic net

Combination

penalty ~ β · Lasso + (1 − β) · Ridge

CODE EXAMPLE

Jupyter Notebook **Regression - Hitters**


THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS