

Introduction to intelligent systems

# *Machine learning*

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# Overview

- ➊ Machine learning problems
- ➋ Machine learning algorithms
- ➌ Linear regression
- ➍ Generalization
- ➎ Tasks

## Feedback group

- David Svane-Petersen
- Yuxuan Zhang
- sebastian vargr
- Peter Vestereng Larsen

## Learning objectives

- I Types of machine learning problems.
  - I Generalization: Training and test error.
  - II Linear regression. Model, parameters, and cost function.
- 
- I Understand the concepts and definitions, and know their application. Reason about the concepts in the context of an example. Use correct technical terminology.
  - II As above plus: Read, manipulate, and work with technical definitions and expressions (mathematical and Python code). Carry out practical computations. Interpret and evaluate results.

## Machine learning problems

# Machine learning problems

## Categorization of learning problems

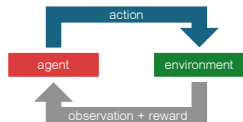
**Unsupervised** Learn function that describes the structure in data



**Supervised** Learn function that maps input to output to optimize cost



**Reinforcement** Learn a function (policy) that maps inputs to actions to optimize cumulative reward



## Unsupervised learning

Learn a function that describes the structure in a data set

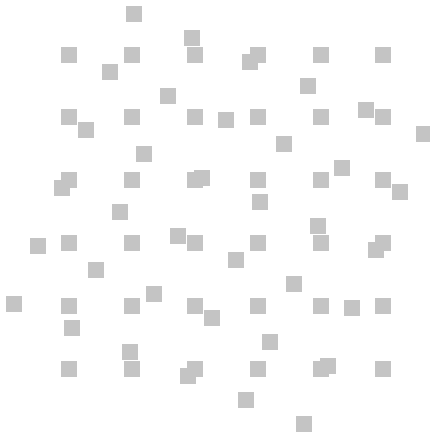
**Clustering** Find a way to group data points into meaningful components

**Dimensionality reduction** Find a lower-dimensional representation of the data

**Anomaly detection** Find data points that deviate from “normal” behaviour

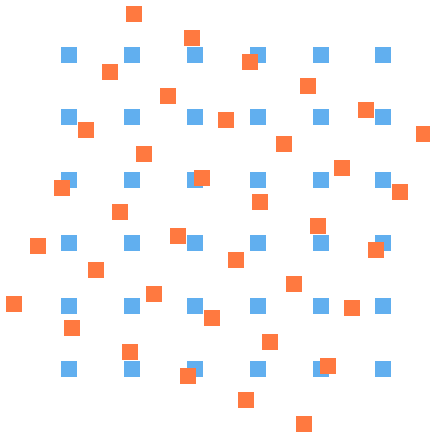


## Unsupervised learning: Discover patterns in data

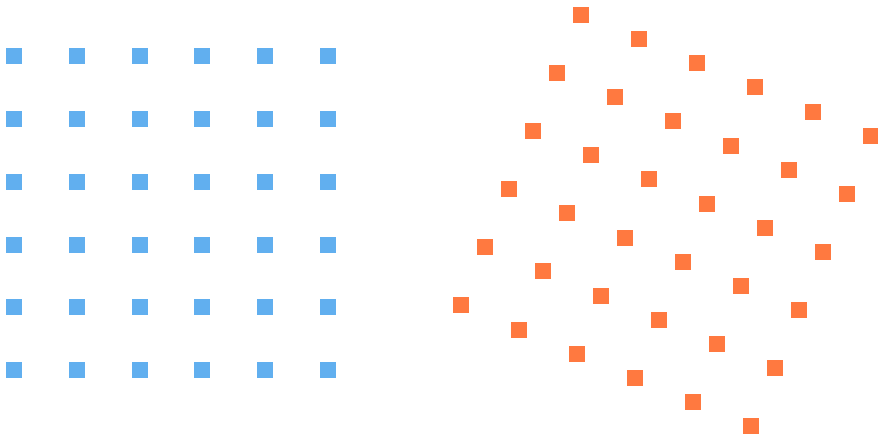




## Unsupervised learning: Discover patterns in data



## Unsupervised learning: Discover patterns in data



## Supervised learning

Learn a function that maps an input to an output to optimize a cost

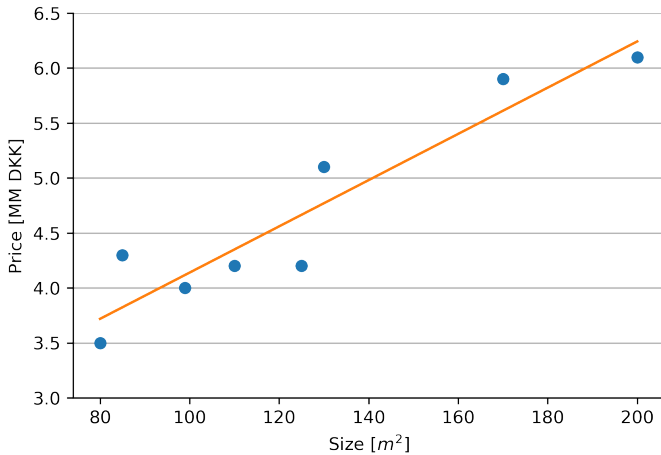
**Regression** Outputs are continuous variables

**Classification** Outputs are discrete classes

**Ranking** Output is a ranking of the data objects



## Supervised learning: House price prediction



## Reinforcement learning

Learn a function (policy) that maps inputs to actions to optimize cumulative reward

Evaluation vs. control

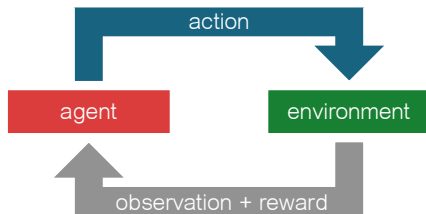
**Passive** Evaluate the future reward for a given policy

**Active** Estimate the optimal policy by exploration

Observability of the environment

**Full** Agent knows the state of the environment

**Partial** Agent must learn a representation of the environment



## Exercise: What is human learning?

Is human learning best characterized as

- Unsupervised learning
- Supervised learning
- Reinforcement learning

(If you think the answer is somehow obvious, see if you can come up with an argument against)

# Machine learning algorithms

# Machine learning algorithms

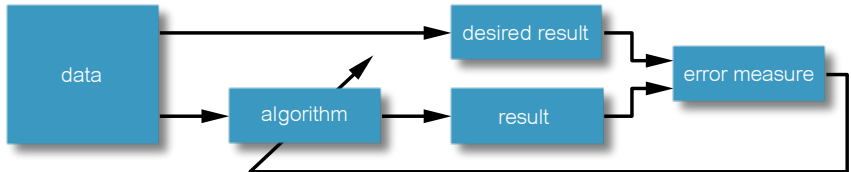
## Machine learning

- Algorithm with tunable parameters
- Takes in some data and produces some output
- Measure error between algorithm's output and the desired output
- Tune parameters to minimize error

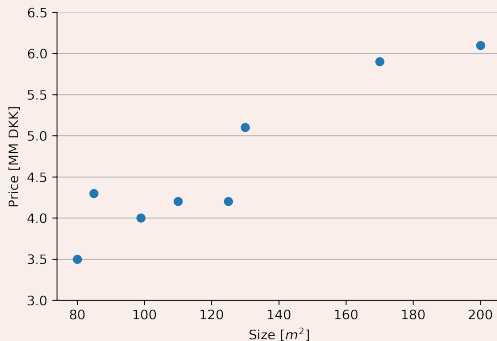
Goal: Generalization = good performance on future/unseen data



## Machine learning algorithms

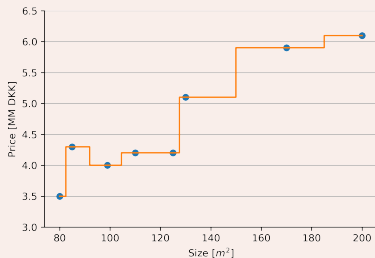
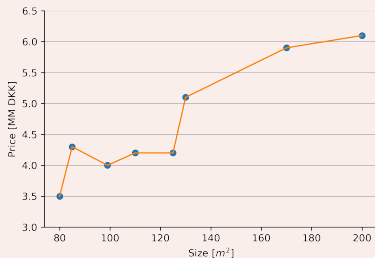
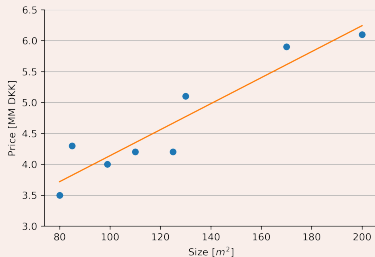
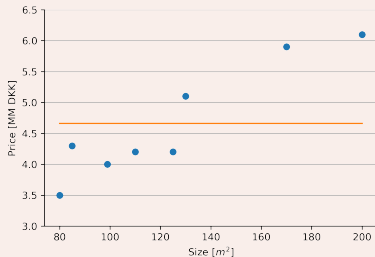


## Exercise: Price of a 150 $m^2$ house



- What would you expect the price of a 150  $m^2$  house to be?
- Discuss which “algorithm” you used to come up with your answer

## Exercise: House price regression



- Which of the above regression curves is best?
- Discuss how you could define a criteria for which is “best”

## House price regression

Possible criteria for a good regression line

**Fit** the observed data well

**Robust** to small changes in the data

**Generalize** to (unseen) future data

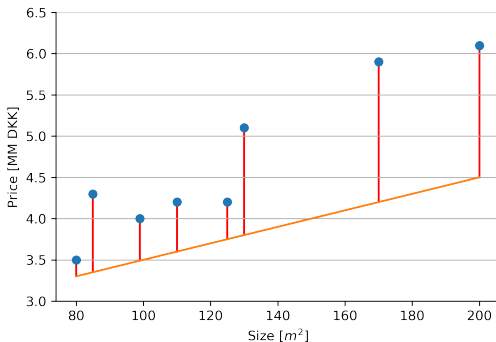
## Linear regression

## Linear regression

- Regression line:  $f(x) = ax + b$
- Error: Squared distance between data and regression line

$$E = \sum_{n=1}^N (y_n - f(x_n))^2$$

- Find values of  $a$  and  $b$  to minimize  $E$

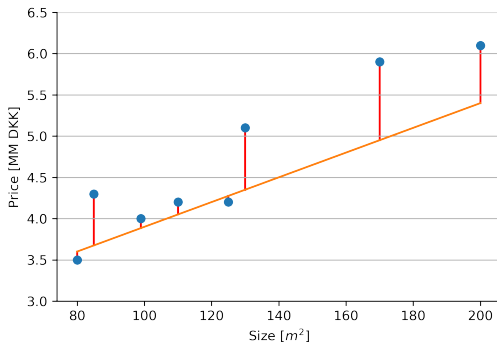


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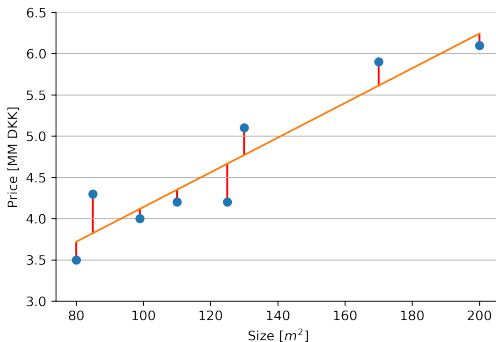


## Linear regression

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## Exercise: Least squares regression

Solve the least square regression problem by minimizing the error

- Differentiate the error measure wrt. the parameters  $a$  and  $b$
- This gives you two equations in two unknowns to solve

Problem specification

- Data

$$x = \{80, 85, 99, 110, 125, 130, 170, 200\}$$

$$y = \{3.5, 4.3, 4, 4.2, 4.2, 5.1, 5.9, 6.1\}$$

- Regression function

$$f(x) = ax + b$$

- Error measure

$$E = \sum_{n=1}^N (y_n - f(x_n))^2$$

### Some useful definitions

$$\bar{x} = \sum_{n=1}^N x_n = 999$$

$$\bar{y} = \sum_{n=1}^N y_n = 37.3$$

$$\overline{xy} = \sum_{n=1}^N x_n y_n = 4914.5$$

$$\overline{x^2} = \sum_{n=1}^N x_n^2 = 136951$$

## Solution: Equation for $a$

Differentiate wrt.  $a$  and equate to zero

$$E = \sum_{n=1}^N (y_n - f(x_n))^2 = \sum_{n=1}^N (y_n - ax_n - b)^2$$

$$\frac{dE}{da} = \sum_{n=1}^N -2(y_n - ax_n - b)x_n$$

$$= -2 \sum_{n=1}^N y_n x_n + 2a \sum_{n=1}^N x_n^2 + 2b \sum_{n=1}^N x_n$$

$$= -2\overline{xy} + 2a\overline{xx} + 2b\bar{x} = 0$$

$$\Rightarrow \underline{\overline{xx} \cdot a + \bar{x} \cdot b = \overline{xy}}$$

### Some useful definitions

$$\bar{x} = \sum_{n=1}^N x_n = 999$$

$$\bar{y} = \sum_{n=1}^N y_n = 37.3$$

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$$\overline{xx} = \sum_{n=1}^N x_n^2 = 136951$$

## Solution: Equation for $b$

Differentiate wrt.  $b$  and equate to zero

$$E = \sum_{n=1}^N (y_n - f(x_n))^2 = \sum_{n=1}^N (y_n - ax_n - b)^2$$

$$\frac{dE}{db} = \sum_{n=1}^N -2(y_n - ax_n - b)$$

$$= -2 \sum_{n=1}^N y_n + 2a \sum_{n=1}^N x_n + 2Nb$$

$$= -2\bar{y} + 2a\bar{x} + 2Nb = 0$$

$$\Rightarrow \underline{\bar{x} \cdot a + N \cdot b = \bar{y}}$$

### Some useful definitions

$$\bar{x} = \sum_{n=1}^N x_n = 999$$

$$\bar{y} = \sum_{n=1}^N y_n = 37.3$$

$$\overline{xy} = \sum_{n=1}^N x_n y_n = 4914.5$$

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## Solution: Two equations in two unknowns

Two equations

$$\overline{xx} \cdot a + \bar{x} \cdot b = \overline{xy}$$

$$\bar{x} \cdot a + N \cdot b = \bar{y}$$

In matrix notation

$$\begin{bmatrix} \overline{xx} & \bar{x} \\ \bar{x} & N \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \overline{xy} \\ \bar{y} \end{bmatrix}$$

### Some useful definitions

$$\bar{x} = \sum_{n=1}^N x_n = 999$$

$$\bar{y} = \sum_{n=1}^N y_n = 37.3$$

$$\overline{xy} = \sum_{n=1}^N x_n y_n = 4914.5$$

$$\overline{xx} = \sum_{n=1}^N x_n^2 = 136951$$

## Solution by substitution

Solve for  $b$  in eq. (B)

$$b = \frac{\bar{y} - \bar{x} \cdot a}{N}$$

Insert in eq. (A)

$$\bar{x}\bar{x} \cdot a + \bar{x} \cdot \underbrace{\frac{\bar{y} - \bar{x} \cdot a}{N}}_b = \bar{x}\bar{y}$$

and solve for  $a$

$$\begin{aligned} a &= \frac{N \cdot \bar{x}\bar{y} - \bar{x} \cdot \bar{y}}{N \cdot \bar{x}\bar{x} - \bar{x}^2} \\ &= \frac{8 \cdot 4914.5 - 999 \cdot 37.3}{8 \cdot 136951 - 999^2} \approx \underline{0.0210} \end{aligned}$$

Insert, and solve for  $b$

$$b = \frac{37.3 - 999 \cdot 0.0210}{8} \approx \underline{2.04}$$

### Equations

$$(A) \quad \bar{x}\bar{x} \cdot a + \bar{x} \cdot b = \bar{x}\bar{y}$$

$$(B) \quad \bar{x} \cdot a + N \cdot b = \bar{y}$$

### Constants

$$\bar{x} = 999$$

$$\bar{y} = 37.3$$

$$\bar{x}\bar{y} = 4914.5$$

$$\bar{x}\bar{x} = 136951$$

## Solution by solving matrix equation in Python

Two equations in matrix notation

$$\begin{bmatrix} \overline{xx} & \bar{x} \\ \bar{x} & N \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \overline{xy} \\ \bar{y} \end{bmatrix}$$

```
>>> N, x, y, xy, xx = 8, 999, 37.3, 4914.5, 136951
```

```
>>> X = np.array([[xx, x], [x, N]])
```

```
>>> print(X)
```

```
[[136951  999]
 [ 999    8]]
```

```
>>> y = np.array([xy, y])
```

```
>>> print(y)
```

```
[4914.5  37.3]
```

```
>>> a, b = np.linalg.solve(X, y)
```

```
>>> print(f'a = {a:.3}, b = {b:.3}')
```

```
a = 0.021, b = 2.04
```

### Some useful definitions

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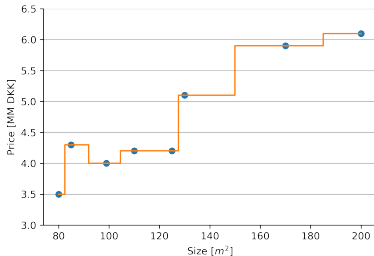
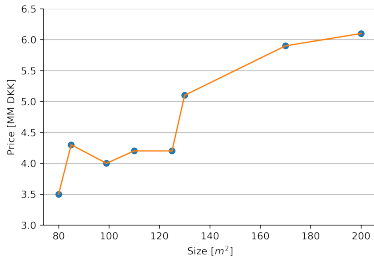
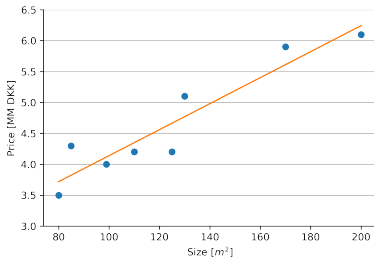
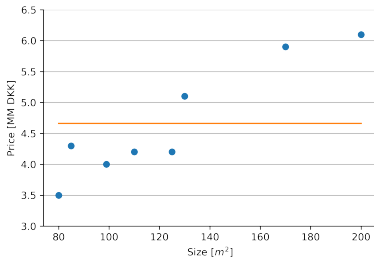
$$\overline{xy} = \sum_{n=1}^N x_n y_n = 4914.5$$

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## Generalization

## House price regression: Generalization

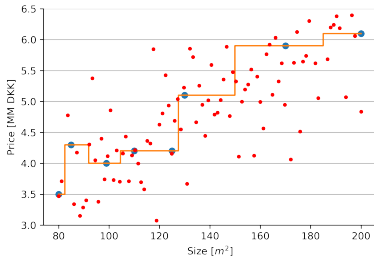
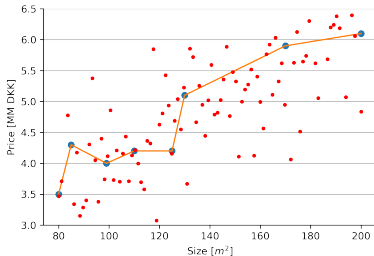
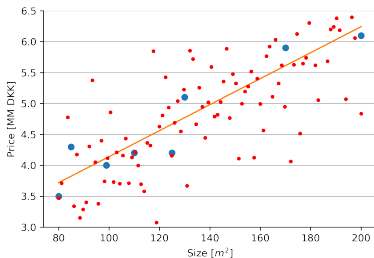
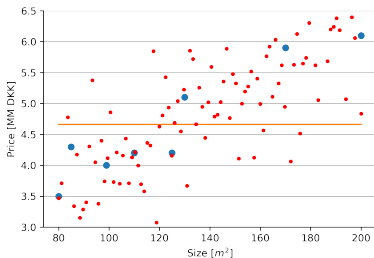
- If we knew future house prices, we could measure generalization error





## House price regression: Generalization

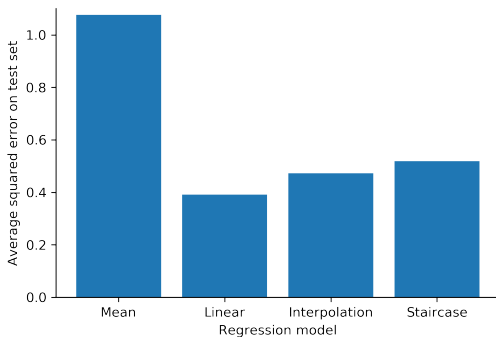
- If we knew future house prices, we could measure generalization error



## House price regression: Generalization

Generalization error / out-of-sample error

- Average error on future data

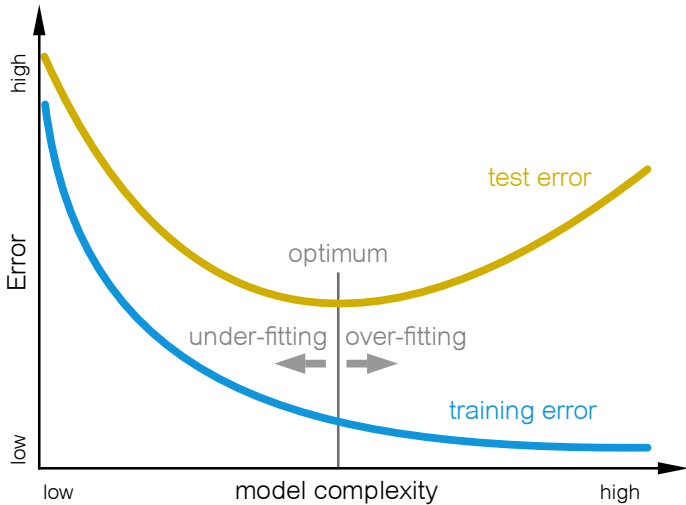


But, of course, we don't actually have access to future data

## Cross-validation

- We only have access to a finite data sample
- Split the data sample into two parts called the *training set* and the *test set*
- Fit the models using the training set
- Evaluate and compare model performance on the test set

## Model complexity



## Tasks

## Tasks for today

### Tasks today

1. Work through the *regression complexity* notebook  
06-RegressionComplexity.ipynb

### Today's feedback group

- David Svane-Petersen
- Yuxuan Zhang
- sebastian vargr
- Peter Vestereng Larsen