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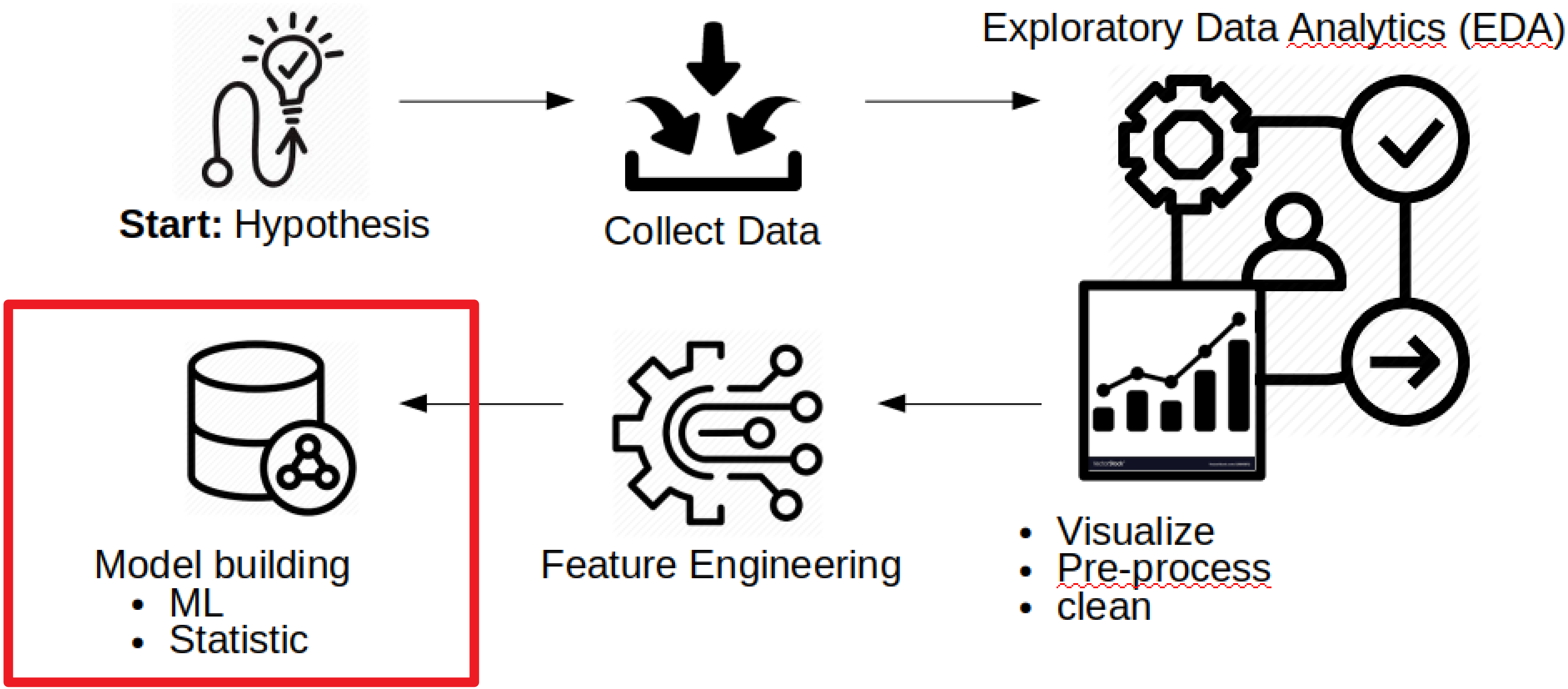
Machine Learning I

Introduction and Overview

Machine Learning I



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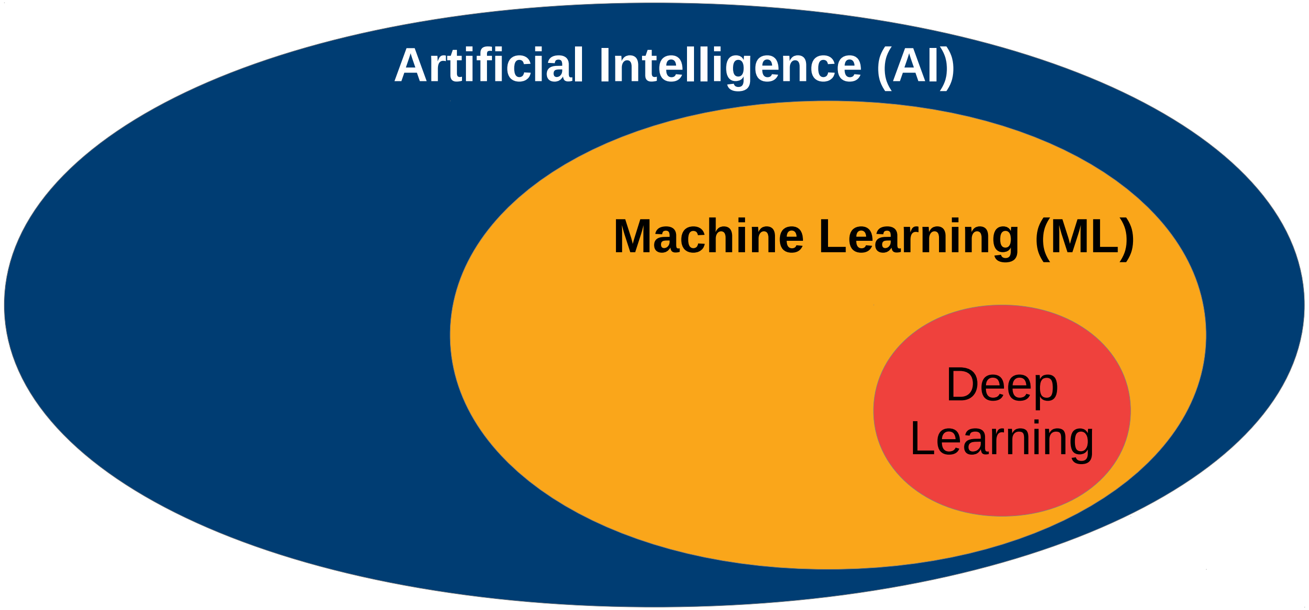
Outline

- Introduction to ML
  - Basic Definitions an Terminology
    - Supervised Learning
    - Generalization and Overfitting
    - Unsupervised Learning

Introduction to ML

Research and Application Fields



Introduction to ML

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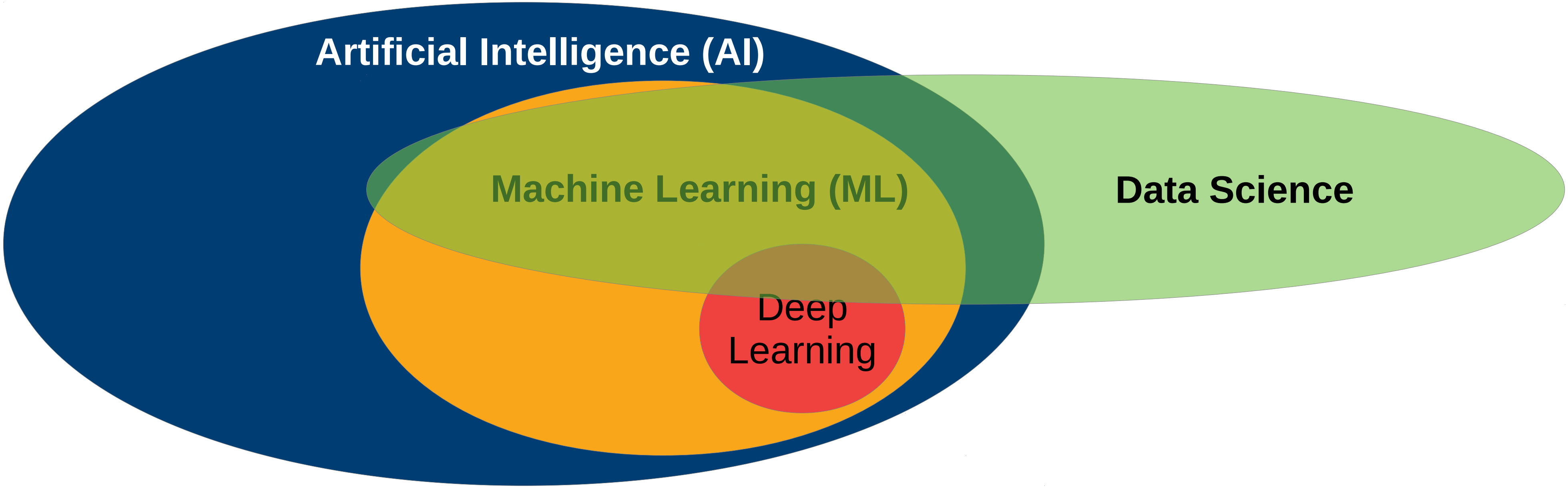
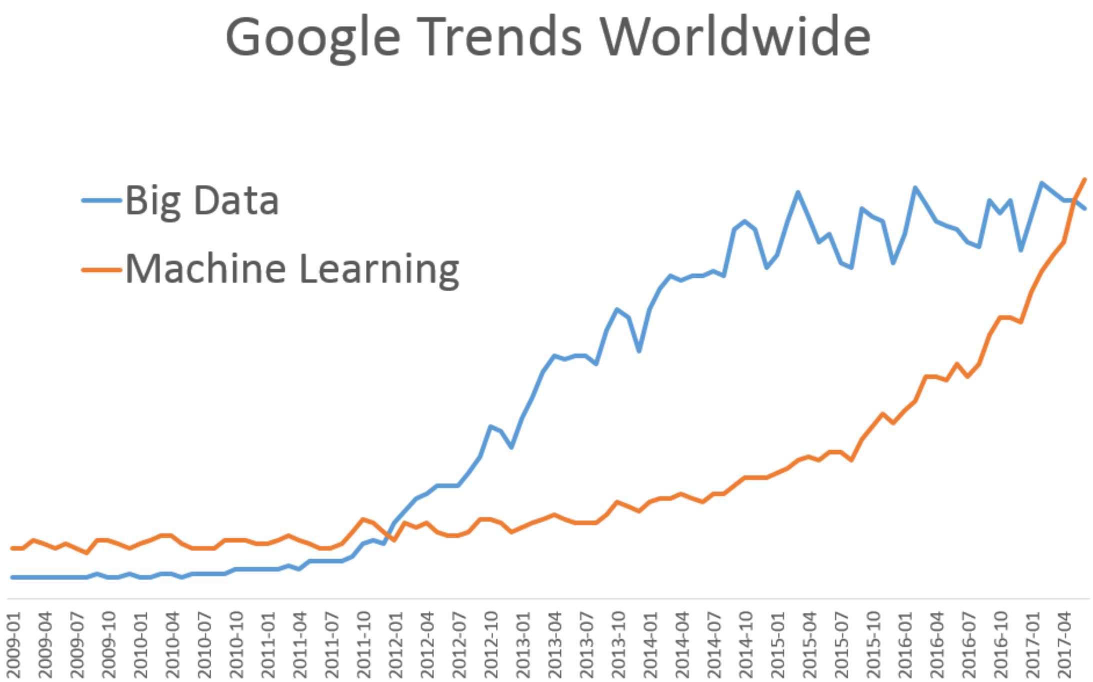
Research and Application Fields



The ML Hype


Google Trends Worldwide
Big Data
Machine Learning
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2009-04
2009-07
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Basic Types of Machine Learning Algorithms

Supervised Learning

Unsupervised Learning

Reinforcement Learning

Introduction to ML

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Basic Types of Machine Learning Algorithms

Supervised Learning

Unsupervised Learning

Reinforcement Learning

- Labeled data
- Direct and quantitative evaluation

- Learn model from „ground truth“ examples
- Predict unseen examples

Introduction to ML

Supervised Learning

Basic Notation:

Data is given as tuples

$$(X, Y) := \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$$

Where X is the actual **data** (sample) and y the associated **label.**

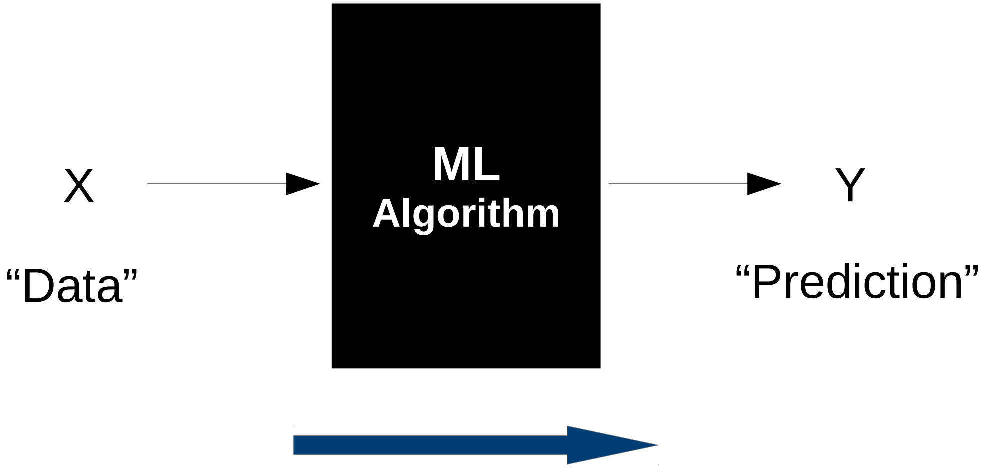
For most ML algorithms **(many Deep Learning algorithms are an exception)**

$$x_i \in \mathbb{R}^n, y_i \in \mathbb{R}$$

The data has to be represented as vectors and the labels are scalars.

Introduction to ML

Supervised Learning as a Black Box



ML algorithms "learns" ***mapping*** from input to output by example tuples

Introduction to ML

Supervised Learning: Example: Classification

ML

"coffee mug"

X: Image

Classification: Y discrete
semantic class label

ML algorithms "learns" ***mapping*** from input to output by example tuples

Introduction to ML

Supervised Learning: Example: Classification

X: Image

Vector

ML

“coffee mug”

Scalar

Classification: Y discrete
semantic class label

ML algorithms “learns” ***mapping*** from input to output by example tuples

Function f(x) → y

Introduction to ML

Supervised Learning: Example: Classification

X: Image

ML

Y: {“coffee mug”, “non coffee mug}

Supervised Learning: Example: Classification

X: Image

pixel by pixel →

$$\begin{pmatrix} 5 \\ 8 \\ 15 \\ 23 \\ 21 \\ 30 \\ 28 \\ \ldots \\ 5 \end{pmatrix}$$

$$X \in \mathbb{R}^n$$

→ **ML** →

Y': {-1,1} $Y' \in \mathbb{R}$

1: “coffee mug”,
-1: “non coffee mug

Introduction to ML

Supervised Learning: Example: Classification

ML Model: function *f* separating mugs from rest

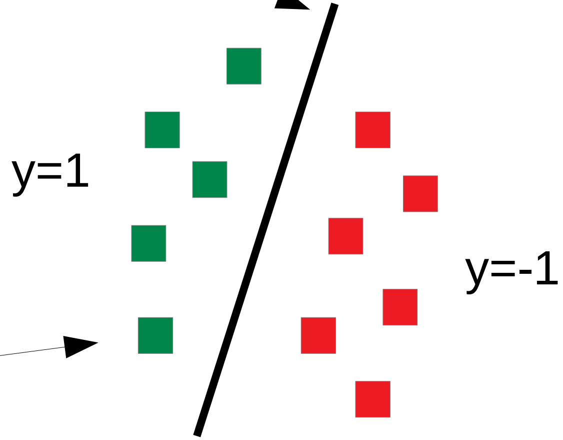
X

$$\begin{pmatrix} 5 \\ 8 \\ 1 \\ 5 \\ 2 \\ 3 \\ 0 \\ 2 \\ 8 \\ \ldots \\ 5 \end{pmatrix}$$

$X \in \mathbb{R}^n$

ML

Y': {-1,1}



$X \in \mathbb{R}^n$

Introduction to ML

Supervised Learning: Example: Classification

LEARNING: approximate „best“ *f* for the given data

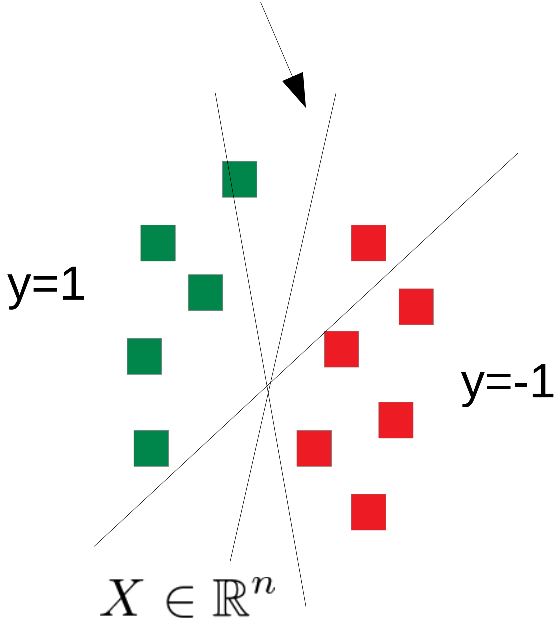
X

$$\begin{pmatrix} 5 \\ 8 \\ 1 \\ 5 \\ 2 \\ 3 \\ 0 \\ 2 \\ 8 \\ \dots \\ 5 \end{pmatrix}$$

$X \in \mathbb{R}^n$

ML

Y’: {-1,1}



Supervised Learning: Example: Classification

LEARNING: optimization problem:

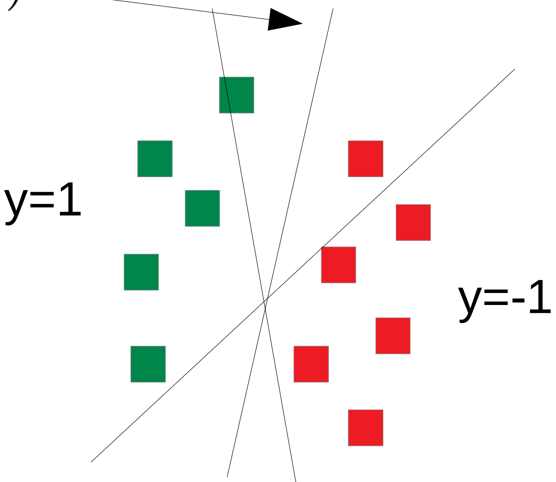
$$min(\|f(X,Y),Y'\|)$$

X

$(5, 8, 1, 5, 2, 3, 0, 2, 8, \dots, 5)^T$

$X \in \mathbb{R}^n$

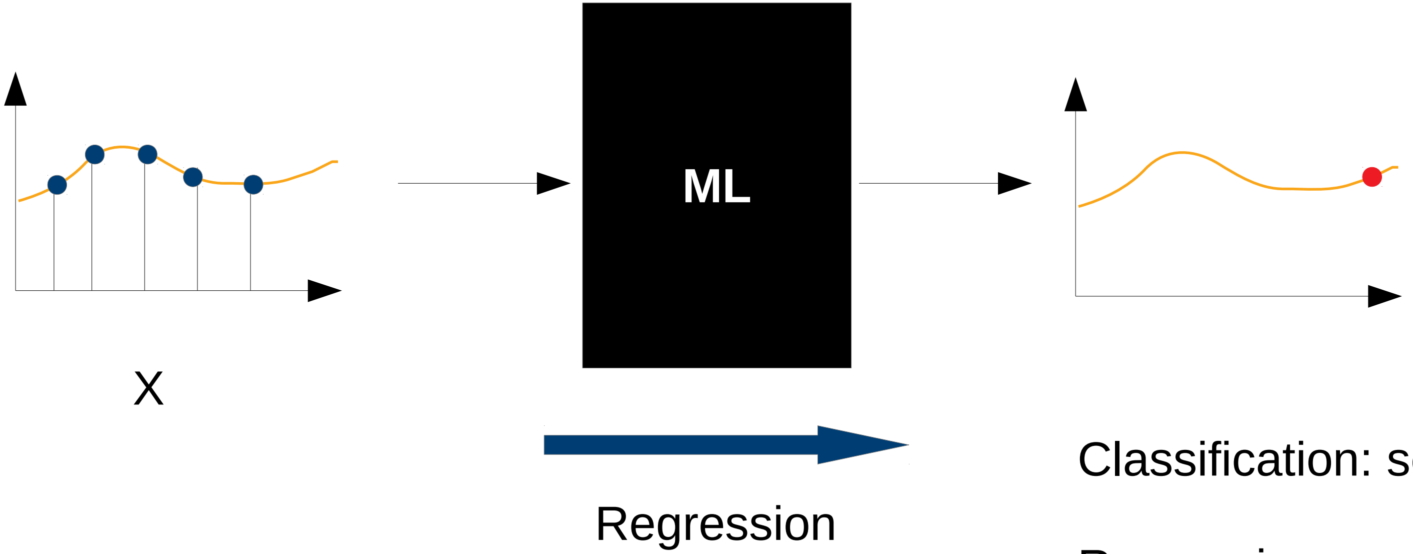
→ **ML** → Y': {-1,1}



$X \in \mathbb{R}^n$

Introduction to ML

Supervised Learning: Example: Regression



Y is **continuous**

Classification: separation function

Regression: continuous mapping
→ harder problem

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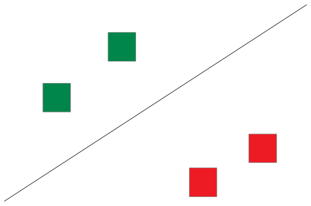
Challenges of Supervised Learning

- Not only need data – also need to have Y → human annotation
  - Getting “enough” labeled data is expensive
  - Sometimes impossible

UNDERFITTING

$$min(\|f(X,Y),Y'\|)$$



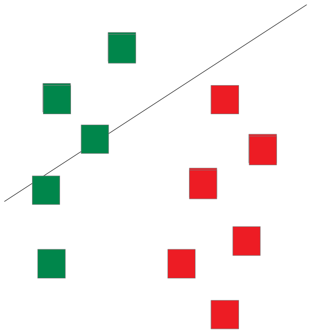
Training model
On little data

Challenges of Supervised Learning

- Not only need data – also need to have Y → human annotation
  - Getting “enough” labeled data is expensive
  - Sometimes impossible

UNDERFITTING

$$min(\|f(X,Y),Y'\|)$$



→ bad sampling
Of the data distribution

Introduction to ML

Challenges of Supervised Learning

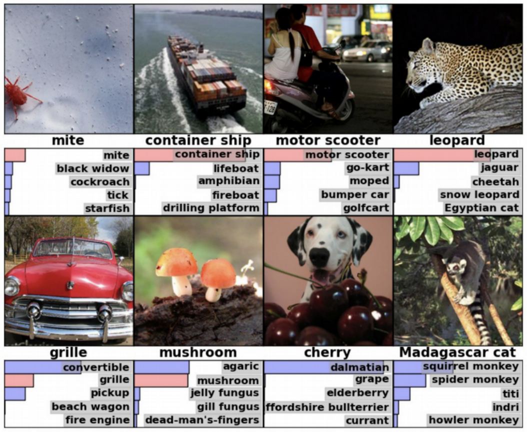
- Not only need data – also need to have Y → human annotation
  - Getting “enough” labeled data is expensive
  - Sometimes impossible

ImageNet Challenge

Example:

IMAGENET

- 1,000 object classes (categories).
- Images:
  - 1.2 M train
  - 100k test.



Introduction to ML

Challenges of Supervised Learning

- Not only need data – also need to have Y → human annotation
  - Getting “enough” labeled data is expensive
  - Sometimes impossible

Example:

CITYSCAPES DATASET

Introduction to ML

Challenges of Supervised Learning

- Not only need data – also need to have Y → human annotation
  - Getting “enough” labeled data is expensive
  - Sometimes impossible
- Training data is **only a sample:** prediction must work on **all data** → **generalization**

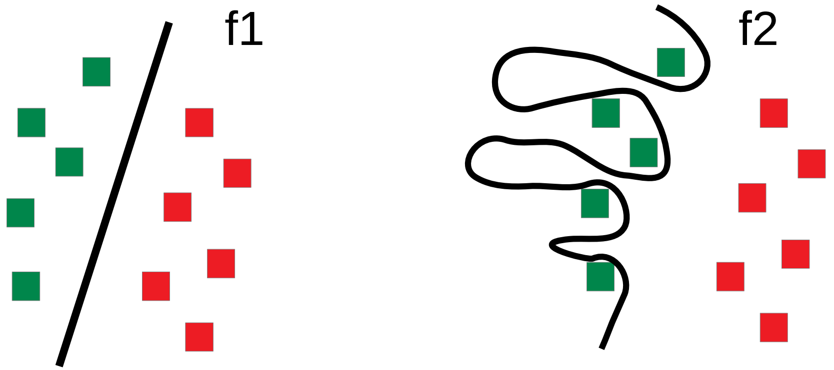
Introduction to ML

Challenges of Supervised Learning

- Training data is **only a sample:** prediction must work on **all data** → **generalization**

Which model is better?

$$min(\|f(X,Y),Y'\|)$$



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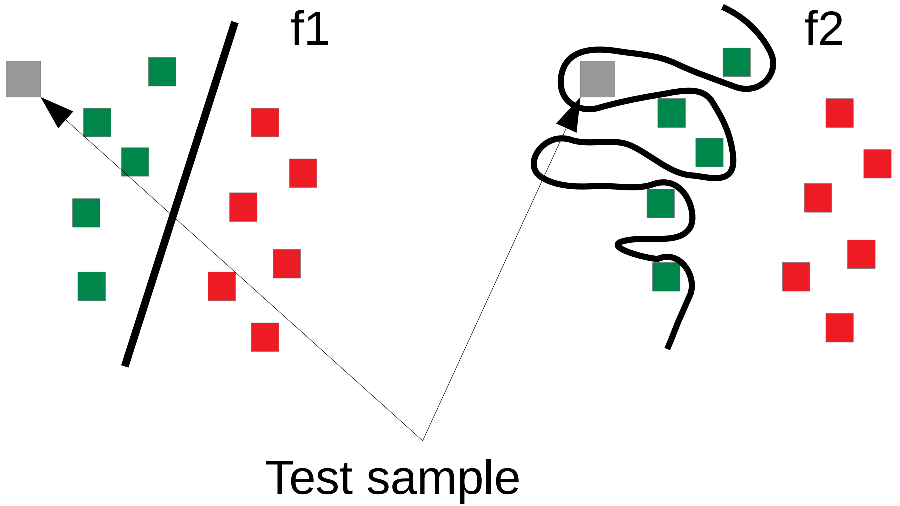
Challenges of Supervised Learning

- Training data is **only a sample:** prediction must work on **all data** → **generalization**

Which model is better?

$$min(\|f(X,Y),Y'\|)$$



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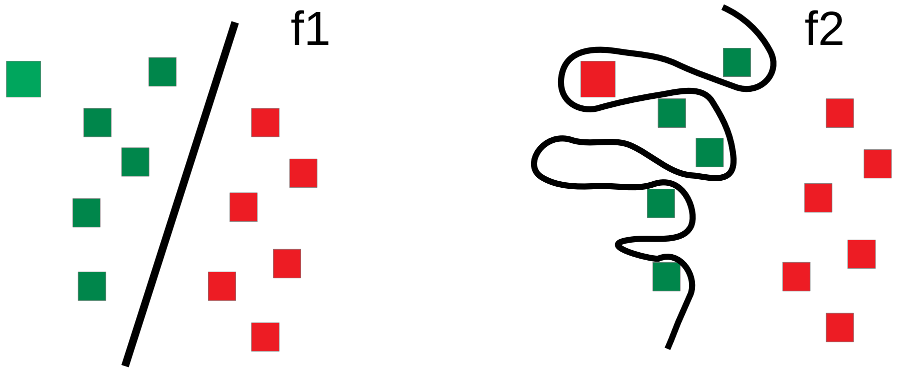
Challenges of Supervised Learning

- Training data is **only a sample:** prediction must work on **all data** → **generalization**

OVERFITTING

Model “to close” to train data

Very likely to happen in practice.
→ we need to work against this...



Introduction to ML

Data Preparation: Split into Train, Test, and Validate

A basic technique (we will learn more later) to at least detect overfitting is to split the available data into two or three subsets:

- Use unbiased **test set** for final evaluation of a model
- Use **train set** for model training
- **Validation set** (part of train set) can be used to optimize hyper parameters of the model

Caution: sets must be unbiased! (→ random sampling)
In practice it can be hard to guarantee clean train/test sets:
e.g. how to treat possible variance different data sources?
→ statistical analysis needed!

Introduction to ML

Basic evaluation (more techniques to come)

Train error: measure of how well the model predicts the given labels

$$Err_{train} := \frac{1}{|X_{train}|} \sum_{x_i \in X_{train}} |f(x_i) - y_i|$$

low train error is the necessary condition for a "good" model

Test error: **same as train error: low test error is the sufficient condition**

$$Err_{test} := \frac{1}{|X_{test}|} \sum_{x_i \in X_{test}} |f(x_i) - y_i|$$

Introduction to ML

Basic Types of Machine Learning Algorithms

Supervised Learning

Unsupervised Learning

Reinforcement Learning

- NO Labeled data
- NO Direct and quantitative evaluation

- Explore structure of data

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Unsupervised Learning

Data without “labels” $(x_1, x_2, \ldots, x_n)$

- **Clustering**
- **Outlier Detection (e.g. Defect or Intrusion detection)**

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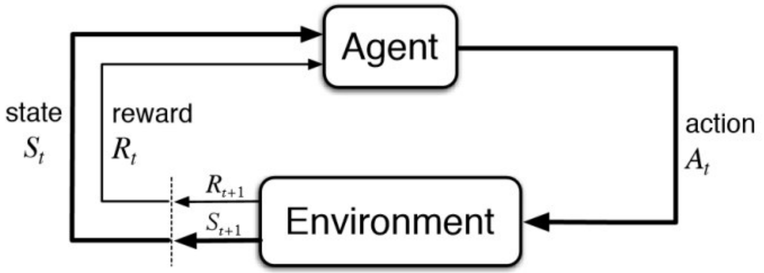

- Learning decisions in an interactive environment
- State ↔ Action learning
- Game playing and robotics
- Hardly use in Data Science

ML in Python

Libraries used in this lecture:

Introduction in this week‘s lab

… introduction in Block 8