

Machine Learning 1 – Fundamentals

Inductive Learning

Prof. Dr. J. M. Zöllner, M.Sc. Nikolai Polley, M.Sc. Marcus Fechner

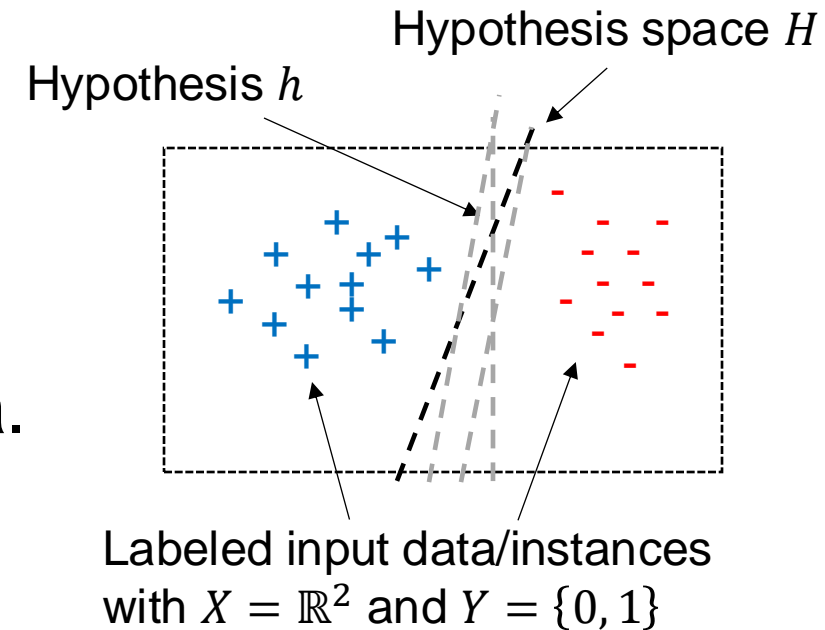


Learning System – Basics

- Every machine learning method requires data from an input space X
- An input instance $x_i \in X$ consists of attributes $x_i = \begin{pmatrix} x_{i1} \\ \vdots \\ x_{im} \end{pmatrix}$
- All input instances should be mapped to the solution space Y
 - Often classification or regression tasks
 - For a true/false classification, $Y = \{0, 1\}$
- **Assumption:** There exists a target function $t : X \rightarrow Y$, which can map all instances $x_i \in X$ perfectly to the solution space Y
 - t is unknown
 - The number of all possible input instances x_i is usually extremely high

Learning System

- A hypothesis h is an „arbitrary“ mapping $h: X \rightarrow Y$
- The hypothesis space H , consists of all possible $h \in H$, which can be represented by the model
- **Goal:** The machine learning method should find the best hypothesis $h \approx t$ in the large hypothesis space, that best fits the observed data.



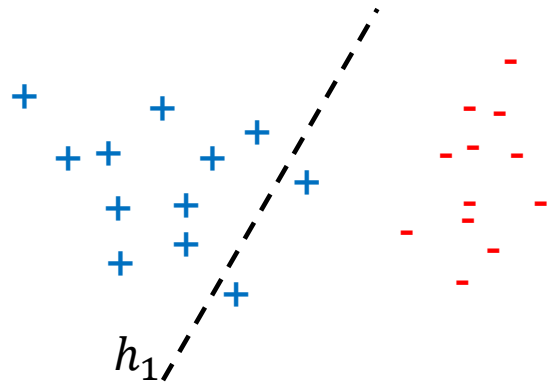
Learning System

■ Consistent

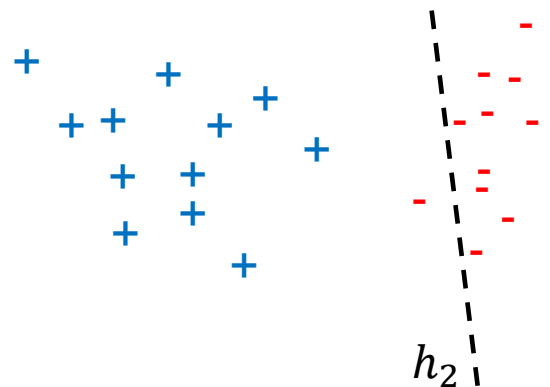
- No negative examples are classified positive **all negative**

■ Complete

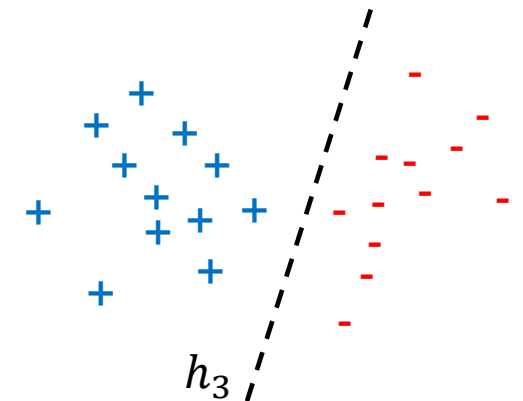
- All positive examples are classified positive **all positive**



Consistent hypothesis h_1
(not complete)



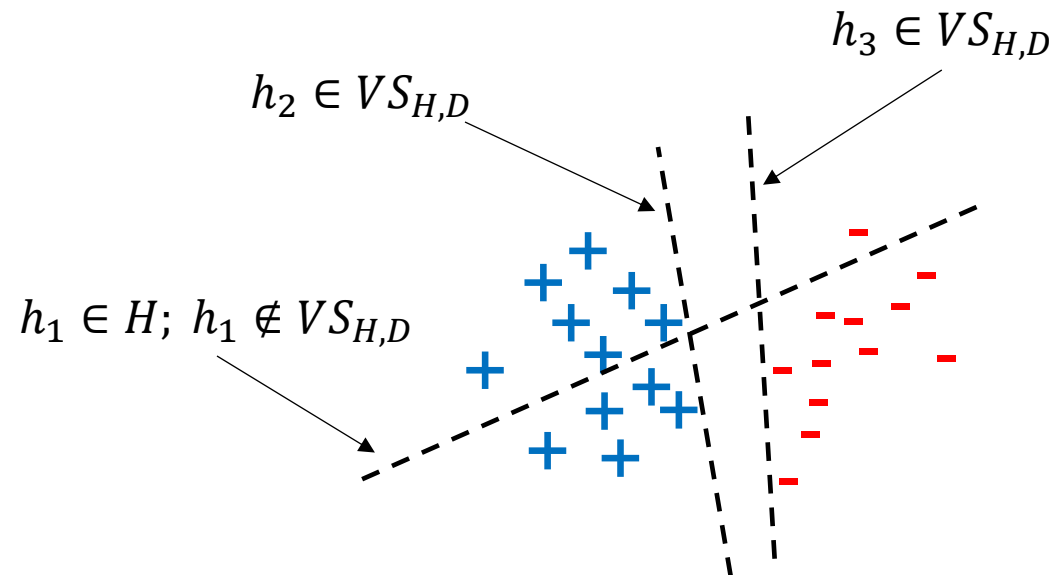
Complete hypothesis h_2
(not consistent)



Complete and consistent
hypothesis h_3

Version Space

- **Definition:** The version space $VS_{H,D}$, with respect to the hypothesis space H and the set of training examples D , is the subset of hypotheses of H that are **consistent and complete** with the training examples in D .



What is Induction? 归纳法

- Inductive reasoning is a method of reasoning in which a **general principle** is derived from a body of **specific observations**.

- Example:

„Socrates is a human being“, „Socrates is mortal“, „Caesar is a human being“,
„Caesar is mortal“

=> „All human beings are mortal.“

- **Definition:** Given a body of specific observations D . Hypothesis h follows inductively from D and prior knowledge B if ...

$$B \cup h \mapsto D, B \nrightarrow D, B \cup D \nrightarrow \neg h$$

- **Caution:** Individual examples can be derived from hypotheses, but not the other way around!

What is Deduction? 演绎法

- Deductive reasoning is a method of reasoning that starts with a **general principle** and examines the possibility to reach a **specific, logical conclusion**.
 - Uses mainly prior knowledge.
 - „All humans are mortal.“, „Socrates is a human being.“
 \Rightarrow „Sokrates is mortal.“
- **Definition:** From a set of principles A , B follows \Leftrightarrow There is a sequence of principles, from which B follows.

■ Examples:

$$\frac{A, A \rightarrow B}{B}$$

Modus Ponens

$$\frac{\forall x P(x)}{P(a)}$$

Instantiation

Induction vs. Deduction

添加两种方法的对比表格 (gpt)

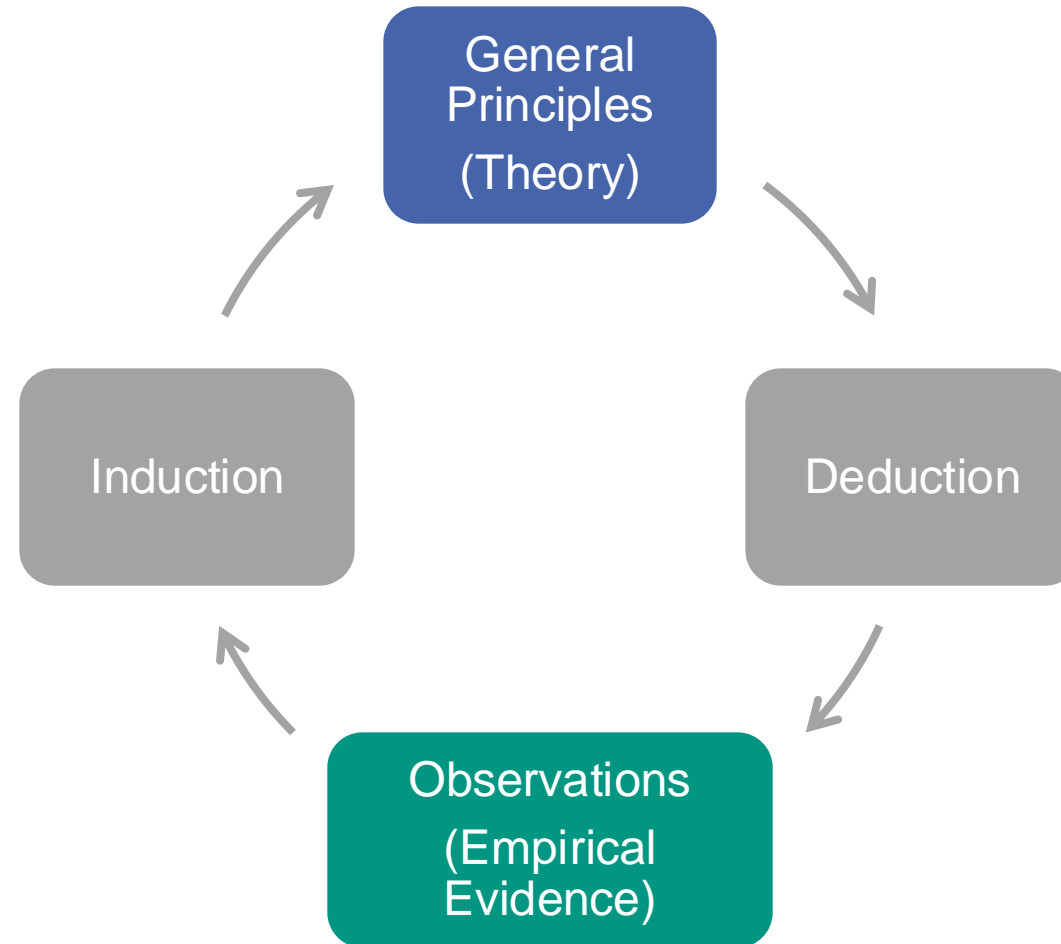
Induction

- Truth-expanding
(generation of new hypotheses)
- Basic approach based on the so-called inductive learning hypothesis
- Plausibility
- Very widespread learning approach
 - (based on a biological approach; makes living beings capable of surviving)

Deduction

- Truth-preserving
(Deriving new rules / facts)
- Logical Conclusion
- Correctness

Induction vs. Deduction



Inductive Learning Hypothesis

■ Challenge:

- The dimensionality of input space X is often very high
 - Example: Input instances are "normal" 8-bit RGB images with a size of 20×20 pixels
 - Space X contains $\dim(X) = (256 * 256 * 256)^{20*20} \approx 10^{2900}$ different images
 - There are 10^{80} atoms in the universe
- Target function t is unknown

■ Solution:

- Create dataset $D \subseteq X$
- Create loss function $\ell(t, h)$, which estimates the distance of a hypothesis h to the target function t .
- Learn hypothesis h for which ℓ is minimal

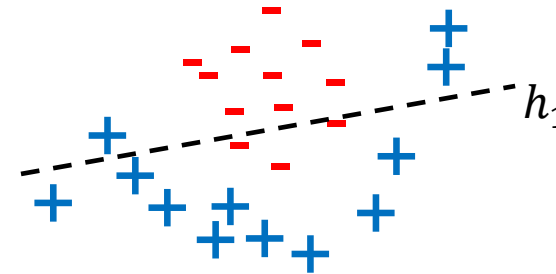
Inductive Learning Hypothesis

- **Definition:** Any hypothesis h that approximates the target function t well enough over a sufficiently large set of training instances $x_i \in D$ will also approximate the target function t well over unknown examples.
- If a learning system makes good predictions even on unknown data, we call this **generalization**.

那些从训练数据中学到的假设或规则，能够适用于尚未见过的测试数据。

Hypothesis Space and Version Space

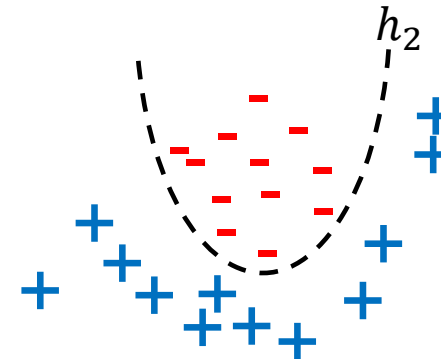
- Problems with models with small hypothesis space
 - The hypothesis space H_{lin} of a linear model contains only linear hypotheses.
 - In [example 1](#), there is no consistent and complete linear hypothesis.
 - Version space $VS_{H,D} = \emptyset$
 - Target function t not included in H_{lin} !
- Model with larger hypothesis space required, e.g. space of polynomials H_{pol} .
 - See [example 2](#)
 - Are models with infinite hypothesis space always best?



Example 1:

Linear hypothesis space H_{lin} does not contain a **consistent** and **complete** hypothesis to map the target function.

$$h_1 \in H_{lin}$$



Example 2:

Polynomial hypothesis space H_{pol} contains the target function.

$$h_2 \notin H_{lin}$$

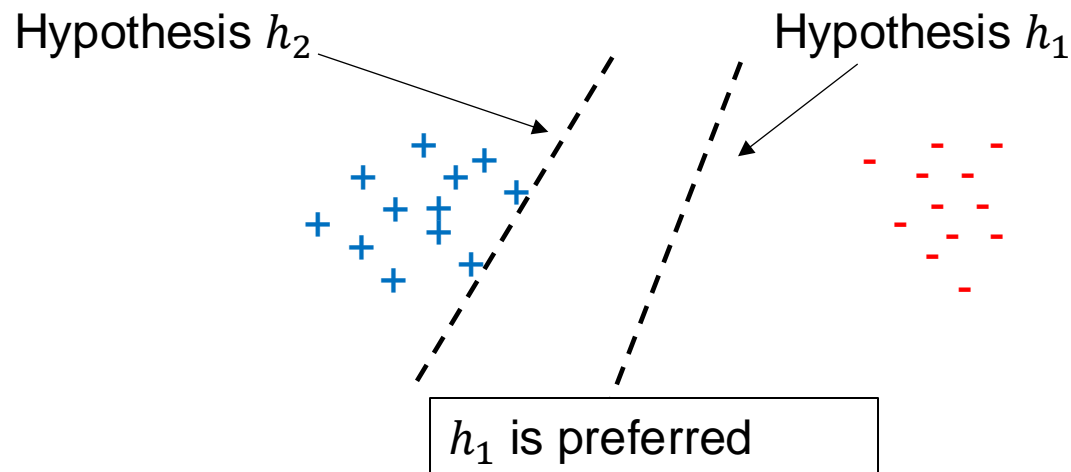
$$h_1, h_2 \in H_{pol}$$

Inductive Bias

- What does "Sufficiently large number of training instances" mean?
 - The number of training examples required correlates with the size of the hypothesis space $|H|$ of a model
 - Constrain the hypothesis space of a model by means of prior assumptions, but keep $h \approx t$ in the reduced hypothesis space
- **Inductive bias:**
 - Set of assumptions or prior knowledge that a learning system incorporates to generalize from data
 - Certain hypotheses are preferred over other hypotheses in the hypothesis space
- All machine learning techniques have an inductive bias to facilitate an efficient learning process and generalization
 - Different methods have different biases

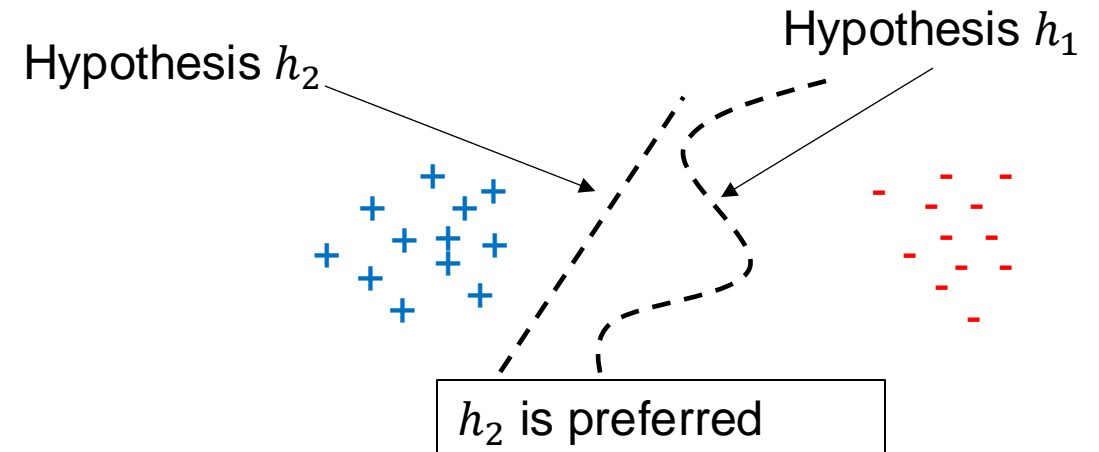
Typical Inductive Biases

- The hypothesis that maximizes the distance between input instances of different classes is preferred. (See SVM in later lecture)



- If a simple hypothesis and a complex hypothesis both minimize the loss function, the simpler hypothesis is preferred. (See Occam's Razor)

奥卡姆剃刀原则



Next Lecture

■ Learning theory

- Deepen the concepts addressed in this lecture and demonstrate them with examples.
- More fundamentals about machine learning