

"Multimedia II" kann im Master entweder als **Multimedia**veranstaltung oder als **Datenbank**veranstaltung („Datenbanken und Informationssysteme“) eingebracht werden

Gilt seit SS 2011

## Zusatzmaterial

- 2-01c Ergänzung – Ableitungsregeln
- 2-01d Ergänzung - Mathematische Grundlagen
  - 2.2 Matrix-Vektor Multiplikation
  - 2.3 Ableitungsregeln und mehrdimensionale Ableitung

# Was ist ein Ingenieur?

# 1 Introduction

## SS 19 – Machine Learning and Computer Vision

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[www.multimedia-computing.{de,org}](http://www.multimedia-computing.{de,org})



# Outline

- Why has machine learning become a must to know for computer science students?
- What is a well-defined learning problem?
- An example: *learning to play checkers*
- What questions should we ask about Machine Learning?

- Massive data available
  - Everything has become digital, is measured and collected
- Massive compute power available
- Progress in algorithms and theory in the past decades
  - big data analysis or mining

Three examples for machine learning:

- Data mining: using historical data to improve decisions
  - medical records → medical knowledge
- Software applications we can't program by hand
  - autonomous driving, speech recognition
- Customizing programs/services (=“reading” the user)
  - Amazon, Facebook, Google learns your preference in order to place profitable ads
  - Sensing homes learn to save energy

# Typical Data Mining Task

Given:

- 9714 patient records each describing a pregnancy and birth
- Each patient record contains 215 features

Learn to predict:

- Classes of future patients at high risk for Emergency Cesarean Section

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Data:

<i>Patient103</i> time=1	<i>Patient103</i> time=2	...	<i>Patient103</i> time=n
Age: 23	Age: 23		Age: 23
FirstPregnancy: no	FirstPregnancy: no		FirstPregnancy: no
Anemia: no	Anemia: no		Anemia: no
Diabetes: no	Diabetes: YES		Diabetes: no
PreviousPrematureBirth: no	PreviousPrematureBirth: no		PreviousPrematureBirth: no
Ultrasound: ?	Ultrasound: abnormal		Ultrasound: ?
Elective C-Section: ?	Elective C-Section: no		Elective C-Section: no
Emergency C-Section: ?	Emergency C-Section: ?		<b>Emergency C-Section: Yes</b>
...	...		...

Blutarmut

- One of 18 learned rules:

If No previous vaginal delivery, and  
Abnormal 2nd Trimester Ultrasound, and  
Malpresentation at admission  
Then Probability of Emergency C-Section is 0.6

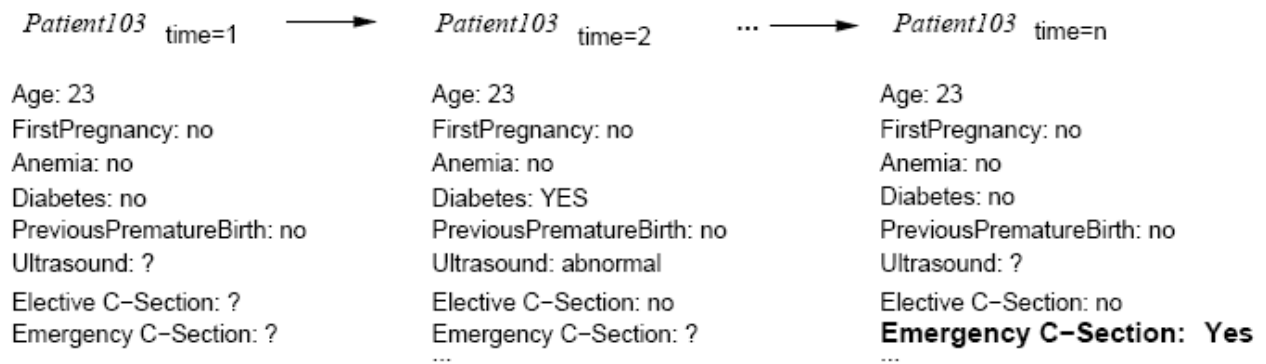
- Over training data:

$26/41 = .63$

- Over test data:

$12/20 = .60$

Data:





## Data:

*Customer103:* (time=t0)

Years of credit: 9  
Loan balance: \$2,400  
Income: \$52k  
Own House: Yes  
Other delinquent accts: 2  
Max billing cycles late: 3  
Profitable customer?: ?

*Customer103:* (time=t1)

Years of credit: 9  
Loan balance: \$3,250  
Income: ?  
Own House: Yes  
Other delinquent accts: 2  
Max billing cycles late: 4  
Profitable customer?: ?

...

*Customer103:* (time=tn)

Years of credit: 9  
Loan balance: \$4,500  
Income: ?  
Own House: Yes  
Other delinquent accts: 3  
Max billing cycles late: 6  
**Profitable customer?: No**

Rules learned from data:

...

...

...

```
If Other-Delinquent-Accounts > 2 and  
    Number-Delinquent-Billing-Cycles > 1  
Then Profitable-Customer? == No  
    [Deny Credit Card application]
```

```
If Other-Delinquent-Accounts == 0, and  
    (Income > $30k) OR (Years-of-Credit > 3)  
Then Profitable-Customer? == Yes  
    [Accept Credit Card application]
```

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## Customer purchase behavior:

*Customer103:* (time=t0)

Sex: M  
Age: 53  
Income: \$50k  
Own House: Yes  
MS Products: Word  
Computer: 386 PC  
Purchase Excel?: ?

...

*Customer103:* (time=t1)

Sex: M  
Age: 53  
Income: \$50k  
Own House: Yes  
MS Products: Word  
Computer: Pentium  
Purchase Excel?: ?

...

...

*Customer103:* (time=tn)

Sex: M  
Age: 53  
Income: \$50k  
Own House: Yes  
MS Products: Word  
Computer: Pentium  
**Purchase Excel?: Yes**

...

Today: Your browser and your cell phone apps collect the necessary data

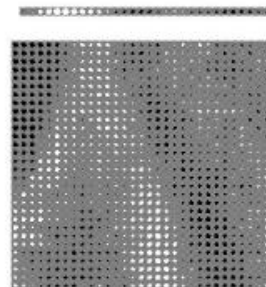
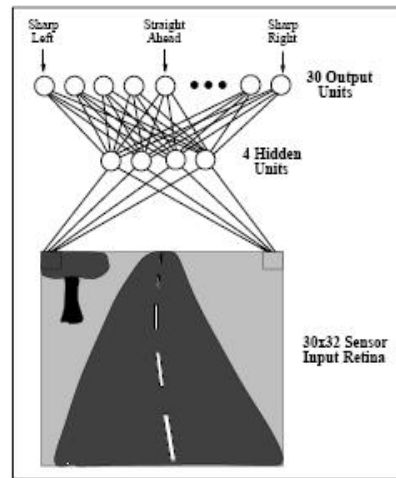
# Too Difficult to Program by Hand

ALVINN [Pomerleau] drives 70 mph on highways

1989



Camera resolution:  
30 x 32



Output:  
1 of 30 steering commands

Query:

Result:



## Machine Learning. (Mcgraw-Hill International Edit) (Taschenbuch)

von [Tom M. Mitchell](#) (Autor) "Ever since computers were invented, we have wondered whether they might be made to learn ..." [\(mehr\)](#)

★★★★★ (5 Kundenrezensionen)

**Statt:** EUR 67,95

**Jetzt:** EUR 67,45 **Kostenlose Lieferung.** [Siehe](#)

[Details.](#)

**Sie sparen:** EUR 0,50 (1%)

Source:  
[www.amazon.de](http://www.amazon.de)

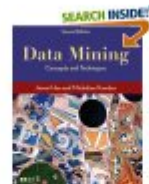
## Kunden, die diesen Artikel gekauft haben, kauften auch:



[Data Mining. Practical Machine Learning Tools and Techniques \(Morgan Kaufmann Series in](#)



[Foundations of Statistical Natural Language Processing](#) von Christopher D. Manning



[Data Mining. Concepts and Techniques \(Morgan Kaufmann Series in Data Management](#)



[Pattern Recognition and Machine Learning \(Information Science and Statistics\) von](#) Christopher M. Bishop



[An Introduction to Support Vector Machines. And Other Kernel-based Learning Methods](#)

## Data collection & machine learning is everywhere

- Cars, cell phones, browser, apps
- Data mining, big data analysis, AI
- Robotics
- .... What else?

## Opportunity for tomorrow

- Learn across mixed-media
- Learn across multiple internal databases, plus the web and newsfeeds

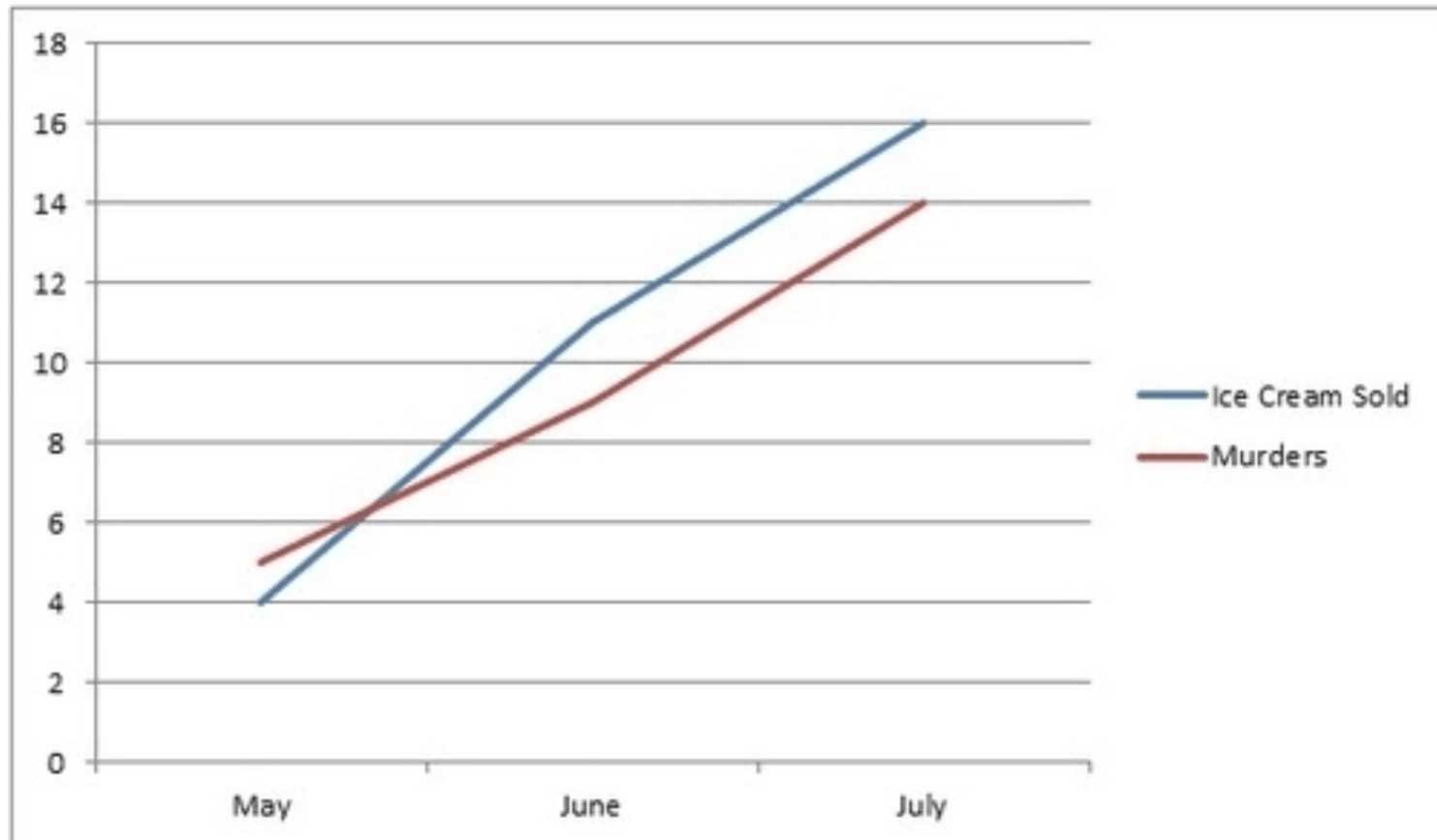
- Learn by active experimentation (Reinforcement Learning)
- Cumulative, lifelong learning
- Programming languages with learning as integral part?
- Explainable AI

## Challenges

- Free will
- Privacy
- “Skynet” (Terminator)
- Absurd correlations

# Absurd Correlation – Example 1

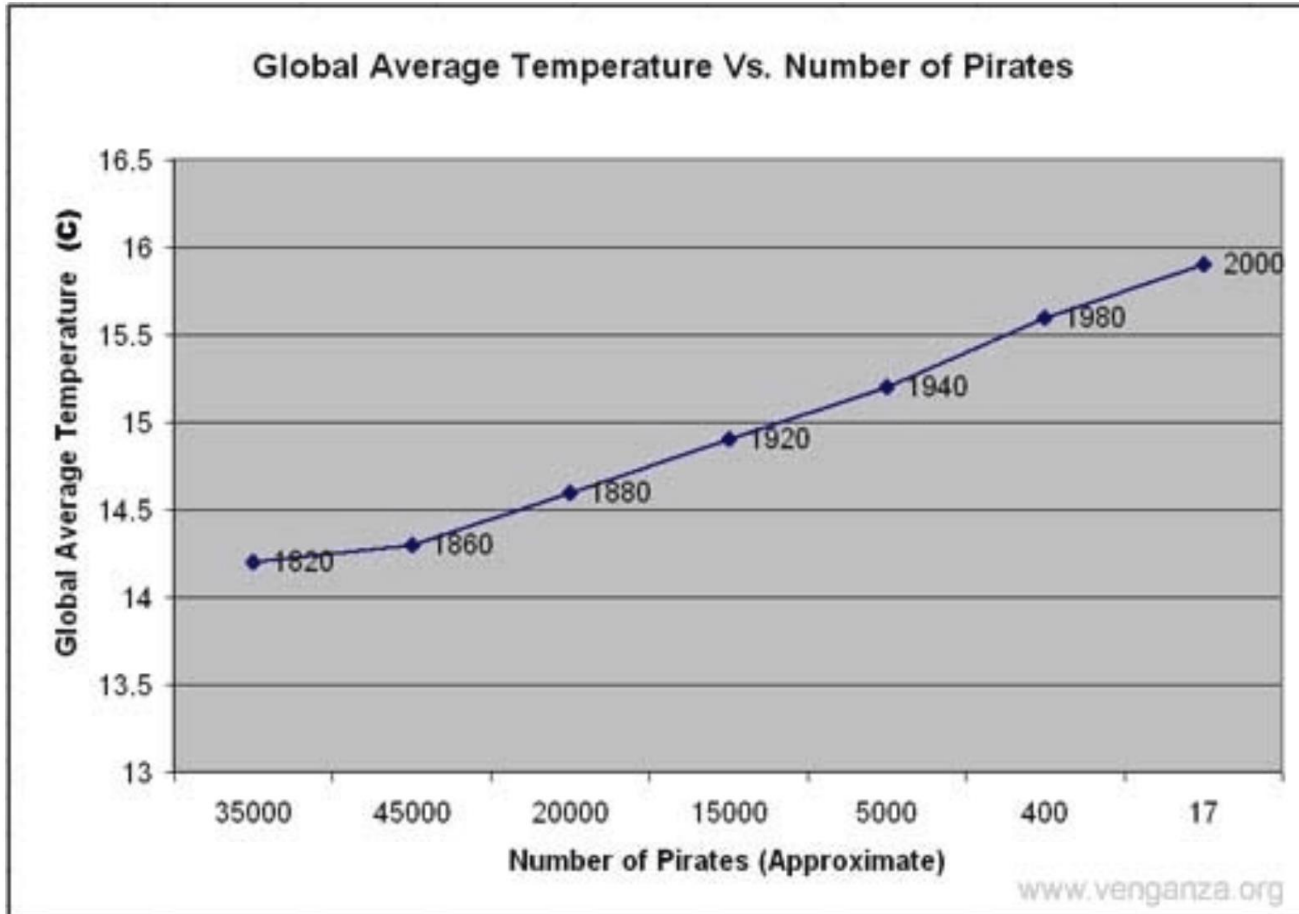
## 1. Ice cream consumption leads to murder.



*badpsychologyblog.org*

# Absurd Correlation – Example 2

## 2. A pirate shortage caused global warming.



- Artificial intelligence
- Bayesian methods
- Computational complexity theory
- Control theory
- Information theory
- Philosophy
- Psychology and neurobiology
- Statistics
- ...



# What is the Learning Problem?

# What is the Learning Problem?

Learning = Improving with experience at some task:

- Improve over task  $T$ ,
- with respect to performance measure  $P$ ,
- based on experience  $E$ .

E.g., Learn to play checkers:

- $T$ : Play checkers,
- $P$ : % of games won in world tournament,
- $E$ : opportunity to play against oneself.

# Examples of Task $T$ (1)

- Classification
  - e.g., an instance is described by feature  $\mathbf{x} \in \mathbb{R}^n$ , then
    - a)  $f(\mathbf{x}): \mathbb{R}^n \rightarrow \{1, \dots, k\}$  or
    - b)  $P(\mathbf{x}): \mathbb{R}^n \rightarrow \{p_1, \dots, p_k\}$  mit  $\sum_{i=1}^k p_i = 1$ ,  $p_i \geq 0$  und  $\mathbf{p} \in \mathbb{R}^k$ .
- Classification with missing inputs
  - Must learn a set of functions
- Regression

Approximate some function  $f^*(\mathbf{x}): \mathbb{R}^n \rightarrow \mathbb{R}$

  - e.g., by  $f(\mathbf{x}; \boldsymbol{\theta}): \mathbb{R}^n \rightarrow \mathbb{R}$ .  
 $\boldsymbol{\theta}$  are the parameters that are learned

- Transcription
  - Transcribe the information in some relatively unstructured representation into a discrete textual form
  - E.g., OCR, speech recognition
- Machine Translation
  - Convert a sequence of symbols in one language into a sequence of symbols in another language.
  - E.g., translate from French to English
- Anomaly detection

- Structured output
  - Any task where the output data is some data structure with important relationships between the different output elements.
  - E.g. image captioning, parse tree, bounding boxes, transcription and translation
- Synthesis and sampling
- Imputation of missing values
- Denoising
- Density estimation

- $T$ : Play checkers
- $P$ : Percent of games won in world tournament

Questions we will address in the following:

- What experience?
- What exactly should be learned?
- How shall it be represented?
- What specific algorithm to learn it?

# Type of Training Experience

- Direct or indirect?
  - Problem of credit assignment
    - Direct: E.g., set of board states with correct moves
    - Indirect: E.g., set of actual games played (all moves) with final outcome
- Teacher or not?
  - Everything given, oracle, or play against oneself? (= All given, can ask questions, or autonomous exploration)

A problem: is training experience representative of performance goal?

- How representative is your training data?
  - Common assumption: Training and test data are i.i.d

→ What type of knowledge should be learned?

Input: set of legal board states

- **ChooseMove:** *Board* → Move ??
  - Starting point: Learn to choose best move among legal moves
- **V:** *Board* →  $\mathbb{R}$  ??
  - Generate the successor states produced by every legal move. Then use *V* to choose the best successor state and therefore best legal move.



- If  $b$  is a final board state that is won, then  $V(b) = 100$
- If  $b$  is a final board state that is lost, then  $V(b) = -100$
- If  $b$  is a final board state that is drawn, then  $V(b) = 0$
- If  $b$  is not a final state in the game, then  $V(b) = V(b')$ , where  $b'$  is the best final board state that can be achieved starting from  $b$  and playing optimally until the end of the game.

This gives correct values, but is not operational.

- What does 'not operational' mean?
- Why?
- Should  $V(b)$  only take on three values?



# Choose Representation for Target Function

Many options:

- Collection of rules?
- Neural network?
- Polynomial function of board features?
- ...
- **Linear regression**

$$\hat{V}(b) = w_0 + w_1 \cdot bp(b) + w_2 \cdot rp(b) + w_3 \cdot bk(b) + w_4 \cdot rk(b) + w_5 \cdot bt(b) + w_6 \cdot rt(b)$$

- $bp(b)$ : number of black pieces on board  $b$
- $rp(b)$ : number of red pieces on  $b$
- $bk(b)$ : number of black kings on  $b$
- $rk(b)$ : number of red kings on  $b$
- $bt(b)$ : number of red pieces threatened by black (i.e., which can be taken on black's next turn)
- $rt(b)$ : number of black pieces threatened by red

$$\hat{V}(b) = \sum_{i=0}^6 w_i \cdot f_i(b) \quad \text{with} \quad f_0 = 1$$

- $f_1(b) := bp(b)$ : number of black pieces on board  $b$
- $f_2(b) := rp(b)$ : number of red pieces on  $b$
- $f_3(b) := bk(b)$ : number of black kings on  $b$
- $f_4(b) := rk(b)$ : number of red kings on  $b$
- $f_5(b) := bt(b)$ : number of red pieces threatened by black (i.e., which can be taken on black's next turn)
- $f_6(b) := rt(b)$ : number of black pieces threatened by red

# Obtaining Training Examples

Training examples:

$$\mathbf{D} = \{ \langle b, V_{train}(b) \rangle \}$$

- $V(b)$ : the true target function
- $\hat{V}(b)$ : the learned function
- $V_{train}(b)$ : the training value

One rule for estimating training values:

- $V_{train}(b) := \hat{V}(\text{Successor}(b))$

↑  
Use current value function  
to refine data

## Note

- Only the results of complete games are available (won, lost, draw)
- Need to assign values to the intermediate board states
- Above is just one simple approach that has proven to be successful
- $\text{Successor}(b) :=$  next board state following  $b$  for which it is again the program's turn to move (i.e., the board state following the program's move and the opponent's response).

# What Means 'Best Fit'?

Common Error Function:

- MSE = Mean Squared Error (value)
- LMS = Least Mean Squares (algorithm)
- LSE = Least Squared Error (result)

$$E = \frac{1}{|\text{training examples}|} \sum_{\langle b, V_{train}(b) \rangle \in \mathbf{D}} \left( V_{train}(b) - \hat{V}(b) \right)^2 \rightarrow \min$$

# Choose Weight Tuning Rule

## LMS Weight update rule:

Do repeatedly:

- Select a training example  $\langle b, V_{train}(b) \rangle$  at random from **D**

1. Compute  $error(b)$ :

$$error(b) = V_{train}(b) - \hat{V}(b)$$

2. For each board feature  $f_i$ , update weight  $w_i$ :

$$w_i \leftarrow w_i + c \cdot f_i \cdot error(b)$$

- $c$  is some small constant, say 0.1, to moderate the rate of learning

Consider the following cases:

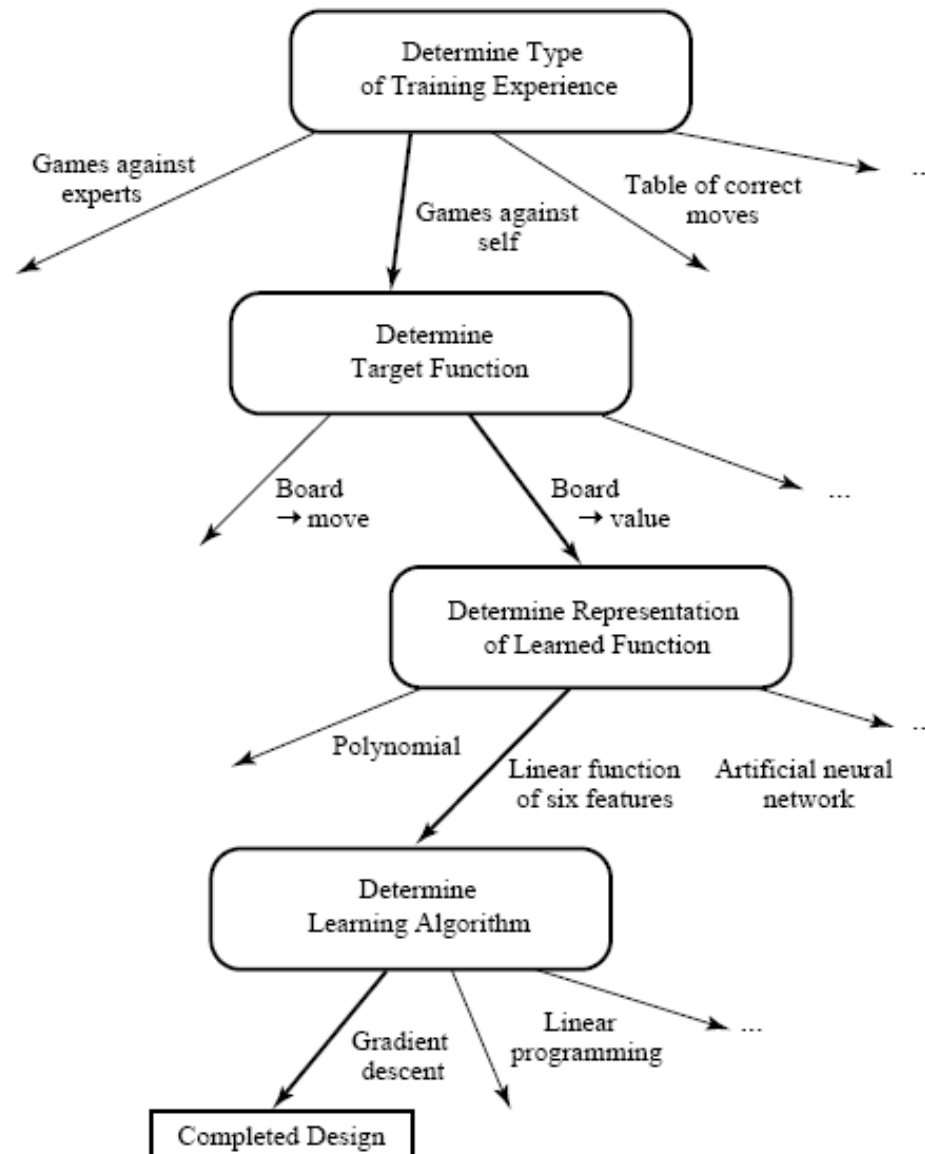
Case 1:  $error(b) == 0$

Case 2:  $error(b) > 0$

Case 3:  $error(b) < 0$

Why LMS? → Exercise

# Design Choices





- What algorithms can approximate functions well (and when)?
- How does number of training examples influence accuracy?
- How does the complexity of the hypothesis representation impact it?
- How does noisy data influence accuracy?
- What are the theoretical limits of learnability?
- How can prior knowledge of the learner help?
- What clues can we get from biological learning systems?
- How can systems alter their own representations?