# Outline

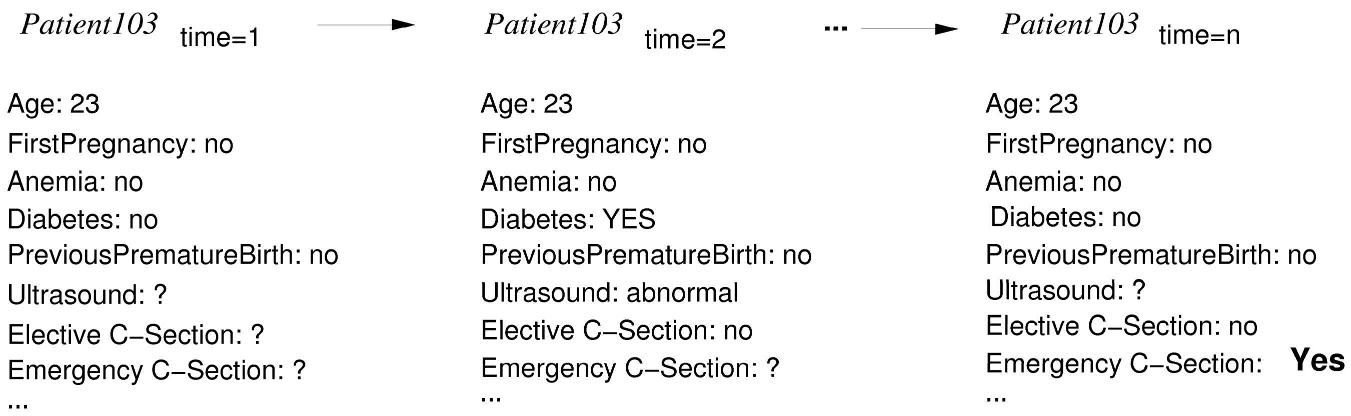
- What is a well-defined learning problem?
- An example: learning to play checkers
- What questions should we ask about Machine Learning?

# Why Machine Learning

- New kind of capability for computers
  - Database mining
    - medical records → medical knowledge
  - Self customizing programs
    - learning newsreader
  - Applications we can't program by hand
    - autonomous driving
    - speech recognition
- Understand human learning and teaching
- Time is right
  - Recent progress in algorithms and theory
  - Growing flood of online data
  - Computational power is available
  - Budding industry

# Rule and Decision Tree Learning

Data:



*Patient103* time=1

Age: 23
FirstPregnancy: no
Anemia: no
Diabetes: no
PreviousPrematureBirth: no
Ultrasound: ?
Elective C–Section: ?
Emergency C–Section: ?
...

*Patient103* time=2

Age: 23
FirstPregnancy: no
Anemia: no
Diabetes: YES
PreviousPrematureBirth: no
Ultrasound: abnormal
Elective C–Section: no
Emergency C–Section: ?
...

...

*Patient103* time=n

Age: 23
FirstPregnancy: no
Anemia: no
Diabetes: no
PreviousPrematureBirth: no
Ultrasound: ?
Elective C–Section: no
Emergency C–Section: **Yes**
...

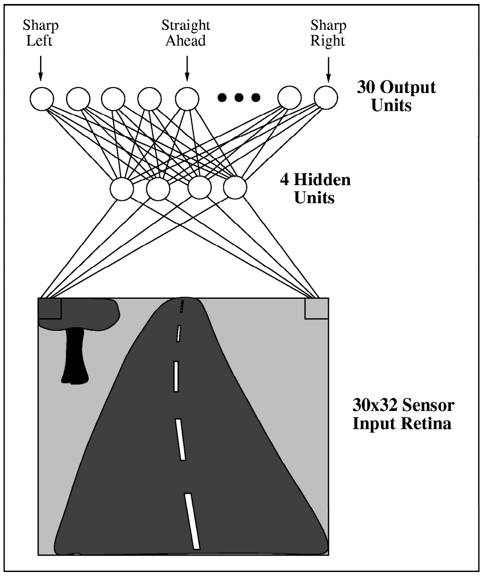
Learned rule:

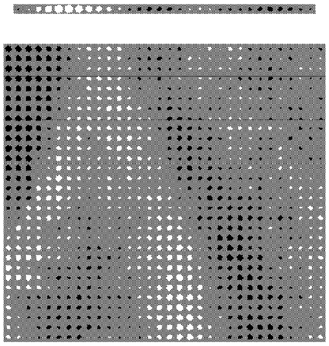
```
If   No previous vaginal delivery, and
     Abnormal 2nd Trimester Ultrasound, and
     Malpresentation at admission, and
     No Elective C-Section
Then Probability of Emergency C-Section is 0.6

 Training set: 26/41 = .634
 Test set: 12/20 = .600
```

# Neural Network Learning

ALVINN [Pomerleau] drives 70 mph on highways





# Relevant Disciplines

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

# 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 self

# Learning to Play Checkers

- $T$: Play checkers
- $P$: Percent of games won in world tournament
- 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?
- Teacher or not?

A problem: is training experience representative of performance goal?

# Choose the Target Function

- $ChooseMove : Board \rightarrow Move$ ??
- $V : Board \rightarrow \Re$ ??
- ...

# Possible Definition for Target Function $V$

- 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 a 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

# Choose Representation for Target Function

- collection of rules?
- neural network ?
- polynomial function of board features?
- ...

# A Representation for Learned Function

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

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

# Obtaining Training Examples

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

One rule for estimating training values:

- $V_{train}(b) \leftarrow \hat{V}(Successor(b))$

# Choose Weight Tuning Rule

**LMS Weight update rule:**

Do repeatedly:

- Select a training example $b$ at random

  1. Compute the $error(b)$ for this training example:

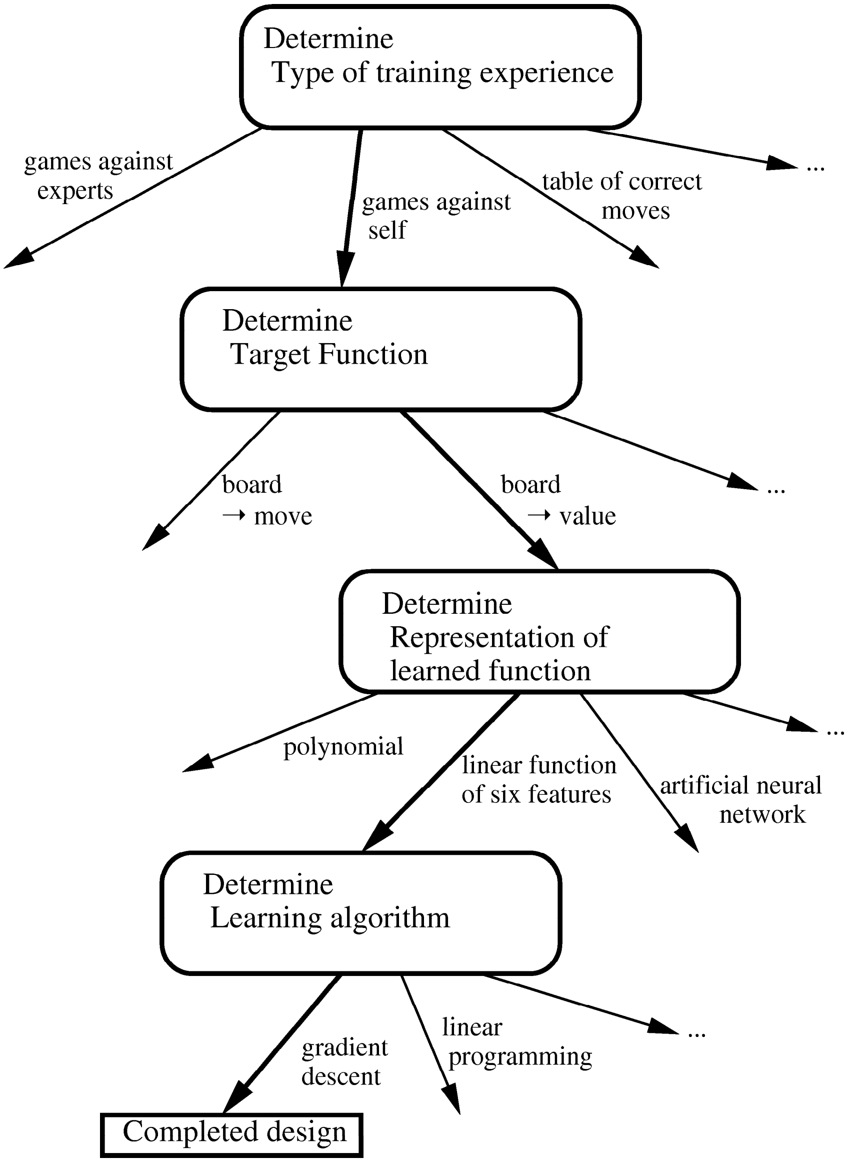
  $$error(b) = V_{train}(b) - \hat{V}(b)$$

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

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

$c$ is some small constant, say 0.5, to moderate the rate of learning

# Design Choices


Determine
Type of training experience
games against experts
games against self
table of correct moves
...
Determine
Target Function
board → move
board → value
...
Determine
Representation of learned function
polynomial
linear function of six features
artificial neural network
...
Determine
Learning algorithm
gradient descent
linear programming
...
Completed design

# Some Issues in Machine Learning

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