Outline

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

Why Machine Learning

- Recent progress in algorithms and theory
- Growing flood of online data
- Computational power is available
- Budding industry

Three niches 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
- **Self customizing programs**
  - Newsreader that learns user interests

Typical Datamining Task

Data:

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

Datamining Result

Data:

Patient103 time=1 → *Patient103* time=2 ... → *Patient103* time=n

Patient103 time=1	*Patient103* time=2	*Patient103* 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: ?	**Emergency C−Section: Yes**
...	...	...

Datamining Result

One of 18 learned rules:

- If No previous normal 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: $12/20 = .60$

Credit Risk Analysis

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
...

Credit Risk Analysis

Rules learned from synthesized 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

Other Prediction Problems: Customer purchase behavior

Customer103: (time=t0)	*Customer103:* (time=t1)	...	*Customer103:* (time=tn)
Sex: M	Sex: M		Sex: M
Age: 53	Age: 53		Age: 53
Income: $50k	Income: $50k		Income: $50k
Own House: Yes	Own House: Yes		Own House: Yes
MS Products: Word	MS Products: Word		MS Products: Word
Computer: 386 PC	Computer: Pentium		Computer: Pentium
Purchase Excel?: ?	Purchase Excel?: ?		**Purchase Excel?: Yes**
...	...		...

Other Prediction Problems: Customer retention

Customer103: (time=t0)

Sex: M
Age: 53
Income: $50k
Own House: Yes
Checking: $5k
Savings: $15k
Current−customer?: yes

Customer103: (time=t1)

Sex: M
Age: 53
Income: $50k
Own House: Yes
Checking: $20k
Savings: $0
Current−customer?: yes

...

Customer103: (time=tn)

Sex: M
Age: 53
Income: $50k
Own House: Yes
Checking: $0
Savings: $0
Current−customer?: No

Other Prediction Problems: Process optimization

Product72: (time=t0)

Stage: mix
Mixing−speed: 60rpm
Viscosity: 1.3
Fat content: 15%
Density: 2.8
Spectral peak: 2800
Product underweight?: ??
...

Product72: (time=t1)

Stage: cook
Temperature: 325
Viscosity: 3.2
Fat content: 12%
Density: 1.1
Spectral peak: 3200
Product underweight?: ??
...

...

Product72: (time=tn)

Stage: cool
Fan−speed: medium
Viscosity: 1.3
Fat content: 12%
Density: 1.2
Spectral peak: 3100
Product underweight?: Yes
...

ALVINN [Pomerleau] drives 70 mph on highways

Problems Too Difficult to Program by Hand

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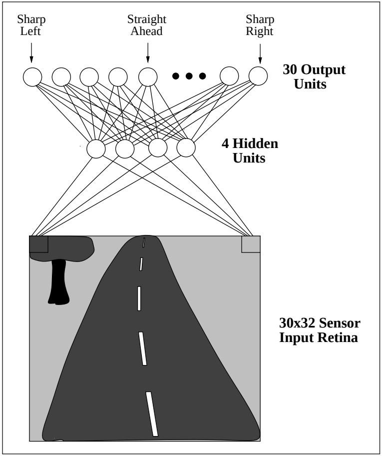


Software that Customizes to User

Where Is this Headed?

- **Today: tip of the iceberg**
  - First-generation algorithms: neural nets, decision trees, regression ...
  - Applied to well-formated data
  - Budding industry
- **Opportunity for tomorrow: enormous impact**
  - Learn across full mixed-media data
  - Learn across multiple internal databases, plus the web and newsfeeds
  - Learn by active experimentation
  - Learn decisions rather than predictions
  - Cumulative, lifelong learning
  - Programming languages with learning embedded?

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.
- Example - 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 it is NOT operational

Choose Representation for Target Function

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

A Representation for Learned Function

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

- $bp(b)$: 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

Obtaining Training Examples

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

One rule for estimating training values:

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

Choose Weight Tuning Rule

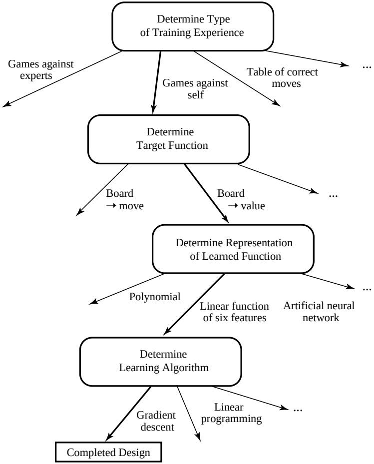
LMS Weight update rule:

Do repeatedly:

- Select a training example b at random
  1. Compute $error(b)$:
  $$error(b) = V_{train}(b) - \hat{V}(b)$$
  2. For each board feature f_i, update weight w_i:
  $$w_i \leftarrow w_i + \lambda \cdot f_i \cdot error(b)$$

λ, the rate of learning is some small constant, say 0.1.

Design Choices



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7. What clues can we get from biological learning systems?
8. How can systems alter their own representations?