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
 - $-\,\mathrm{medical}\xspace$ records \rightarrow 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:

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

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

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

Credit Risk Analysis

Data:

Customer103: (time=t0)	Customer103: (time=t1)	Customer103: (time=tn)
Years of credit: 9	Years of credit: 9	Years of credit: 9
Loan balance: \$2,400	Loan balance: \$3,250	Loan balance: \$4,500
Income: \$52k	Income: ?	Income: ?
Own House: Yes	Own House: Yes	Own House: Yes
Other delinquent accts: 2	Other delinquent accts: 2	Other delinquent accts: 3
Max billing cycles late: 3	Max billing cycles late: 4	Max billing cycles late: 6
Profitable customer?: ?	Profitable customer?: ?	Profitable customer?: No

Rules learned from synthesized data:

Other-Delinquent-Accounts > 2, and		
Number-Delinquent-Billing-Cycles > 1		
n Profitable-Customer? = No		
[Deny Credit Card application]		
Other-Delinquent-Accounts = 0, and		
(Income > \$30k) OR (Years-of-Credit > 3)		
Profitable-Customer? = Yes		
[Accept Credit Card application]		

Other Prediction Problems

...

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**

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**

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

...

Problems Too Difficult to Program by Hand

ALVINN [Pomerleau] drives 70 mph on highways







Software that Customizes to User



http://www.wisewire.com

Where Is this Headed?

Today: tip of the iceberg

- First-generation algorithms: neural nets, decision trees, regression ...
- Applied to well-formated database
- 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 $\mathbf{x} = \mathbf{x}$

- 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

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

- 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:

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

LMS Weight update rule:

Do repeatedly:

- \bullet 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 :

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

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

Design Choices



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?