Machine Learning Lecture 1: Introduction

What is Machine Learning?

- Building machines that automatically *learn* from experience
  - Sub-area of artificial intelligence
- (Very) small sampling of applications:
  - Detection of fraudulent credit card transactions
  - Filtering spam email
  - Autonomous vehicles driving on public highways
  - Self-customizing programs: Web browser that learns what you like and seeks it out
  - Applications we can't program by hand: E.g., speech recognition

What is Learning?

- Many different answers, depending on the field you're considering and whom you ask
  - Artificial intelligence vs. psychology vs. education vs. neurobiology vs. …

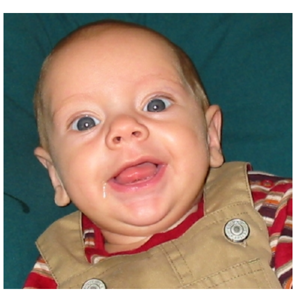
Does Memorization = Learning?

- Test #1: Thomas learns his mother's face

Memorizes:



But will he recognize:

Thus he can generalize beyond what he's seen!

Does Memorization = Learning? (cont'd)

- Test #2: Nicholas learns about trucks

Memorizes:


But will he recognize others?

- So learning involves **ability to generalize** from labeled examples
- In contrast, memorization is trivial, especially for a computer

What is Machine Learning? (cont'd)

- When do we use machine learning?
  - Human expertise does not exist (navigating on Mars)
  - Humans are unable to explain their expertise (speech recognition; face recognition; driving)
  - Solution changes in time (routing on a computer network; driving)
  - Solution needs to be adapted to particular cases (biometrics; speech recognition; spam filtering)
- In short, when one needs to generalize from experience in a non-obvious way

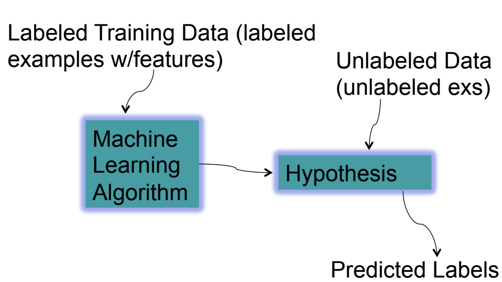
What is Machine Learning? (cont'd)

- When do we *not* use machine learning?
  - Calculating payroll
  - Sorting a list of words
  - Web server
  - Word processing
  - Monitoring CPU usage
  - Querying a database
- When we can definitively specify how all cases should be handled

More Formal Definition of (Supervised) Machine Learning

- Given several *labeled examples* of a *concept*
  - E.g., trucks vs. non-trucks (binary); height (real)
- Examples are described by *features*
  - E.g., number-of-wheels (int), relative-height (height divided by width), hauls-cargo (yes/no)
- A machine learning algorithm uses these examples to create a *hypothesis* that will *predict* the label of new (previously unseen) examples

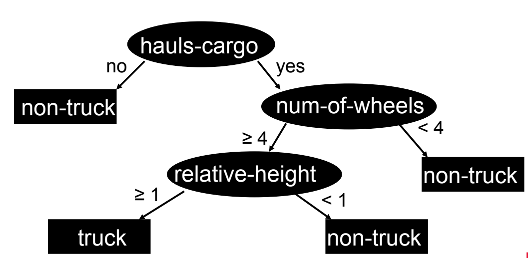
Machine Learning Definition (cont'd)



- Hypotheses can take on many forms

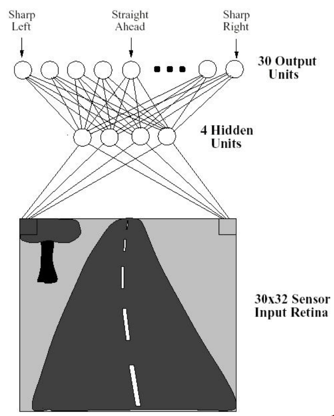
Hypothesis Type: Decision Tree

- Very easy to comprehend by humans
- Compactly represents if-then rules



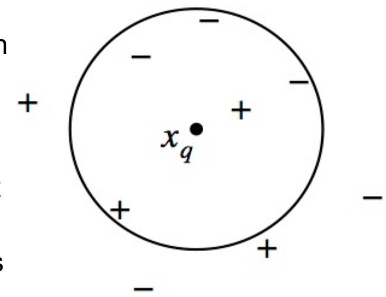
Hypothesis Type: Artificial Neural Network

- Designed to simulate brains
- “Neurons” (pro-cessing units) communicate via connections, each with a numeric weight
- Learning comes from adjusting the weights



Hypothesis Type: *k*-Nearest Neighbor

- Compare new (unlabeled) example x_q with training examples
- Find k training examples most similar to x_q
- Predict label as majority vote



Other Hypothesis Types

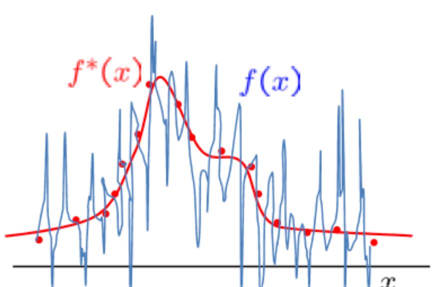
- Support vector machines
  - A major variation on artificial neural networks
- Bagging and boosting
  - Performance enhancers for learning algorithms
- Bayesian methods
  - Build probabilistic models of the data
- Many more

Variations

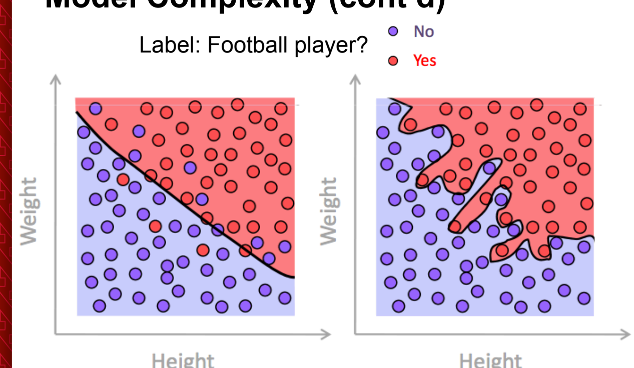
- Regression: real-valued labels
- Probability estimation
  - Predict the probability of a label
- Unsupervised learning (clustering, density estimation)
  - No labels, simply analyze examples
- Semi-supervised learning
  - Some data labeled, others not (can buy labels?)
- Reinforcement learning
  - Used for e.g., controlling autonomous vehicles
- Missing attributes
  - Must some how estimate values or tolerate them
- Sequential data, e.g., genomic sequences, speech
  - Hidden Markov models
- Outlier detection, e.g., intrusion detection
- And more …

Issue: Model Complexity

- Possible to find a hypothesis that perfectly classifies all training data
  – But should we necessarily use it?



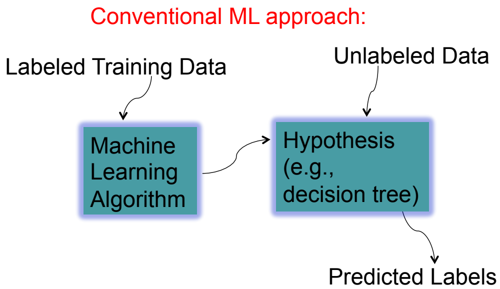
Model Complexity (cont’d)



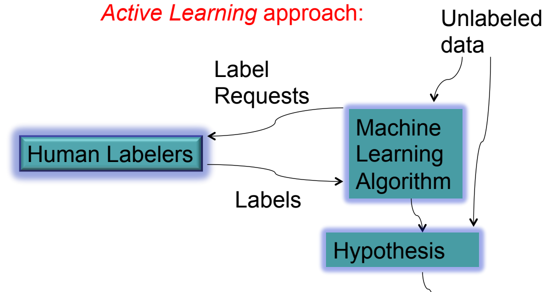
➔To generalize well, need to balance ***accuracy*** with ***simplicity***

Issue: What If We Have Little Labeled Training Data?

- E.g., billions of web pages out there, but tedious to label



What If We Have Little Labeled Training Data? (cont'd)



- Label requests are on data that ML algorithm is unsure of

Machine Learning vs Expert Systems

- Many old real-world applications of AI were *expert systems*
  - Essentially a set of if-then rules to emulate a human expert
  - E.g. "If medical test A is positive and test B is negative and if patient is chronically thirsty, then diagnosis = diabetes with confidence 0.85"
  - Rules were extracted via interviews of human experts

Machine Learning vs Expert Systems (cont'd)

- ES: Expertise extraction tedious; ML: Automatic
- ES: Rules might not incorporate intuition, which might mask true reasons for answer
- E.g. in medicine, the reasons given for diagnosis x might not be the objectively correct ones, and the expert might be unconsciously picking up on other info
- ML: More “objective”

Machine Learning vs Expert Systems (cont'd)

- ES: Expertise might not be comprehensive, e.g. physician might not have seen some types of cases
- ML: Automatic, objective, and data-driven
  - *Though it is only as good as the available data*

Relevant Disciplines

- Artificial intelligence: Learning as a search problem, using prior knowledge to guide learning
- Probability theory: computing probabilities of hypotheses
- Computational complexity theory: Bounds on inherent complexity of learning
- Control theory: Learning to control processes to optimize performance measures
- Philosophy: Occam’s razor (everything else being equal, simplest explanation is best)
- Psychology and neurobiology: Practice improves performance, biological justification for artificial neural networks
- Statistics: Estimating generalization performance

More Detailed Example: Content-Based Image Retrieval

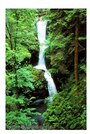
- Given database of hundreds of thousands of images
- How can users easily find what they want?
- One idea: Users query database by image *content*
  - E.g., "give me images with a waterfall"

Content-Based Image Retrieval (cont'd)

- One approach: Someone annotates each image with text on its content
  - Tedious, terminology ambiguous, may be subjective
- Another approach: *Query by example*
  - Users give examples of images they want
  - Program determines what's common among them and finds more like them

Content-Based Image Retrieval (cont'd)

User's Query



System's Response

User feedback

Yes

Yes

Yes

NO!

Content-Based Image Retrieval (cont'd)

- User's feedback then labels the new images, which are used as more training examples, yielding a new hypothesis, and more images are retrieved

How Does The System Work?

- For each pixel in the image, extract its color + the colors of its neighbors

- These colors (and their relative positions in the image) are the features the learner uses (replacing, e.g., number-of-wheels)
- A learning algorithm takes examples of what the user wants, produces a hypothesis of what's common among them, and uses it to label new images

Conclusions

- ML started as a field that was mainly for research purposes, with a few niche applications
- Now applications are very widespread
- ML is able to automatically find patterns in data that humans cannot
- However, still very far from emulating human intelligence!
- Each artificial learner is task-specific