Introduction to Machine Learning

CS307 --- Fall 2022

Course Overview

General Information for CS307

- **Where:** online
- **When:** Mon 8:00-11:00am
- **Instructor:** Vincent Ng
  - **Temporary office hours:** Mon after class on Zoom
- **Teaching Assistant:** Nhat Chung
  - **Office hours:** TBD
- **Private communication with course staff outside office hours:**
  - Via Piazza: create a private post with "Instructors" as the recipient (if you want both of us to read it) or our name as the recipient if you want only one of us to read it

General Information for CS307

- **Canvas**
- **Homework submission:** Gradescope
  https://www.gradescope.com
- **Class Discussion and Announcements:** Piazza
  http://piazza.com/fulbright.edu.vn/fall2022/cs307/home

Recommended Text:

Machine Learning.
Tom M. Mitchell, McGraw Hill, 1997.
Artificial Intelligence: A Modern Approach (2^{nd}/3^{rd} edition)
Russell and Norvig, Prentice-Hall, Inc., 2003/2010.

Prerequisites:

CS102 Algorithms
MATH202 Discrete Mathematics
MATH205 Probability
Ability to program in C++, Java, or Python
Familiarity with the big-O notation
Knowledge of propositional and first-order logic
Elementary knowledge of probability theory

Tentative Grading Policy:

~6 Assignments	30%
Term project	12%
2 Midterms	32%
Final exam	26%

Course Policies

Collaboration policy

assignments should be done individually

term project can be done in a group of two

need to turn in one solution/program per group

Late assignment submission policy

one day late (10% penalty)

two days late (30% penalty)

no assignments accepted if more than two days late

What is Machine Learning?

- T. Mitchell
  - Any computer algorithm that lets the system perform a task more effectively or more efficiently than before.
- H. Simon
  - Learning denotes changes in the system that are adaptive in the sense that they enable the system to do the task or tasks drawn from the same population more efficiently and more effectively the next time.

The ability to perform a task in a situation which has never been encountered before (Learning = Generalization)

Why Study Machine Learning?

- **Lots of (very exciting) applications**

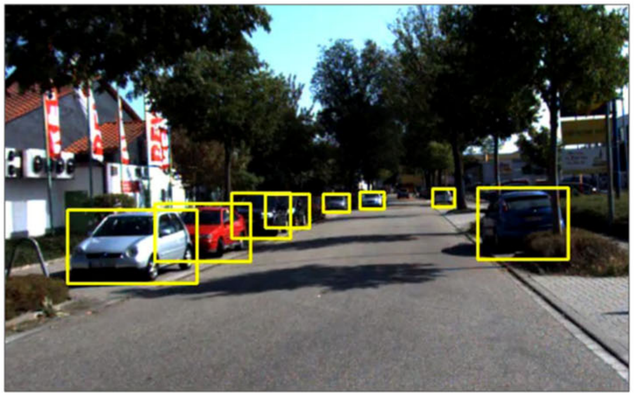
  Emergence of (semi-)intelligent autonomous systems in society

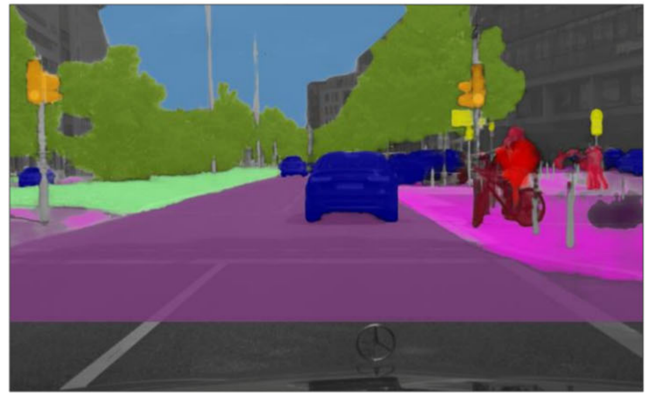
  --- Self-driving cars and trucks. Autonomous drones. Virtual assistants. Fully autonomous trading systems. Assistive robotics.

- **Shift of AI research from academic to real-world**

  --- Enabled by qualitative change in the field, driven in part by "Deep Learning" & Big Data.

DEEP LEARNING FOR SELF-DRIVING CARS





Note labeling!

Statistical model (neural net) trained on >1M images;
Models with > 500K parameters
Requires GPU power

(Mobileye 2016; Nvidia 2016)

 9

Real-time tracking of environment (360 degrees/ 50+m) and decision making.

10

Reasons for Accelerated Progress in Recent Years

--- deep learning / deep neural nets

success is evidence in support of the "hardware hypothesis"

(need to get near brain compute power; Moravec)

core neural net ideas from mid 1980s

needed: several orders of magnitude increase
in computational power and data

Aside:

(1) *This advance was not anticipated/predicted at all.*
by 2000, almost all AI/ML researchers had moved away from neural nets… changed around 2011/12.
(2) Algorithmic advances still provided larger part of speedups than hardware. Core algorithmic concept from 1980s but *key additional advances since*.

+ BIG DATA!

Reasons for Accelerated Progress in Recent Years

--- crowd-sourced human data --- *machines need to understand our conceptualization of the world.* E.g. vision for self driving cars trained on 100,000+ images of labeled road data.

--- engineering teams (e.g. IBM's Watson) strong commercial interests at a scale never seen before in our field

An AI arms race

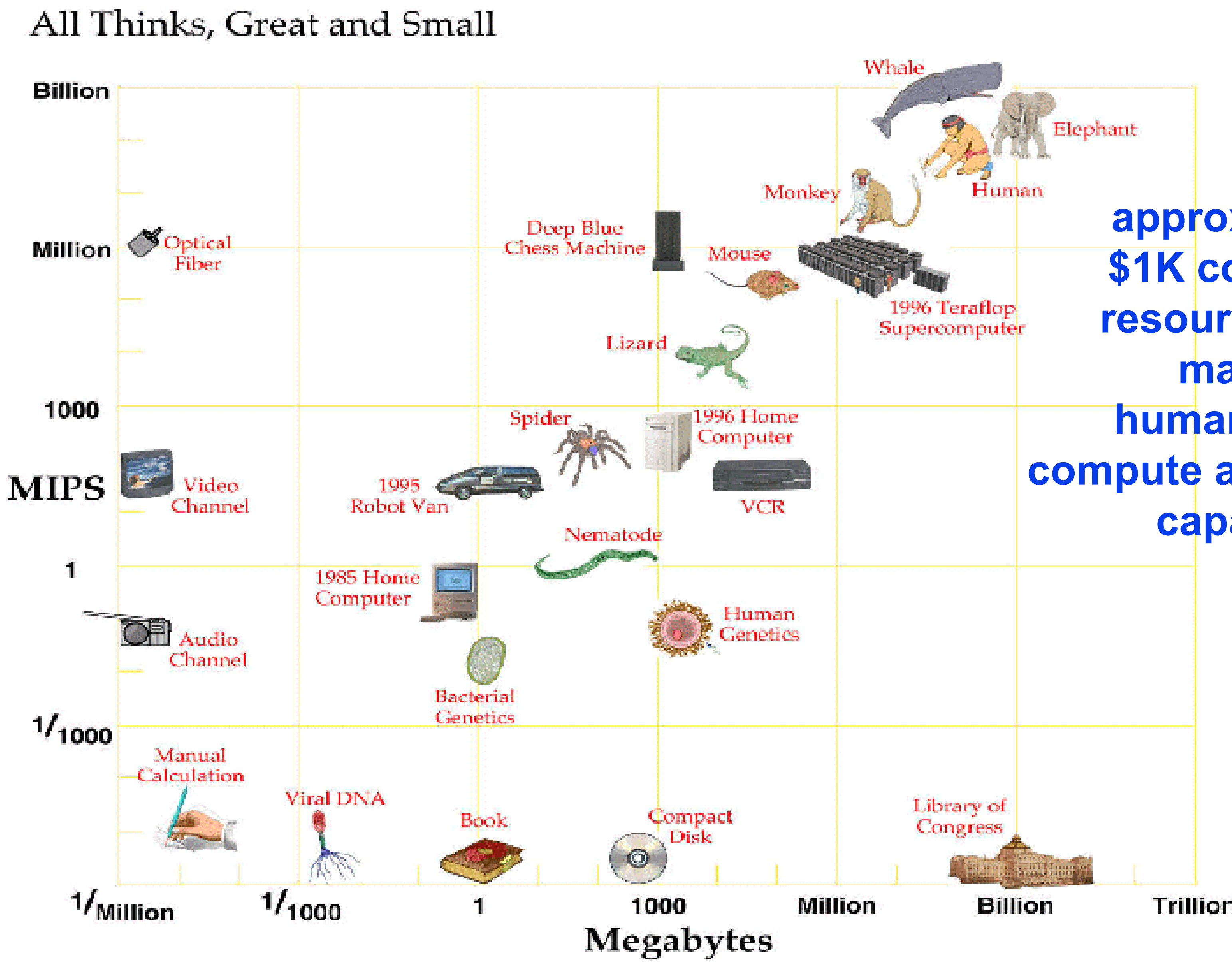
--- Investments in AI systems are being scaled-up by an order of magnitude (to billions).

Google, Facebook, Baidu, IBM, Microsoft, Tesla etc. ($2B+)

+ military ($19B proposed)

Computer vs. Brain

Processing Speed



approx. 2030 $1K compute resources will match human brain compute and storage capacity

Memory

Machine Learning Enabled Machine Perception

--- *machine perception* is starting to work (finally!)

systems are starting to *"hear"* and *"see"* after 50+ yrs of research

--- dramatic change: lots of AI techniques (reasoning, search, reinforcement learning, planning, decision theoretic methods) were developed assuming perceptual inputs were "somehow" provided to the system. But, e.g., robots could not really see or hear anything…

(e.g. *2005* Stanley car drove around *blind*; developers were told "don't bother putting in a camera" --- Thrun, Stanford

Our systems are finally becoming "grounded in (our) world."

Already: super-human face recognition (Facebook)

super-human traffic sign recognition (Nvidia)

Why Study Machine Learning?

- **Computer systems with new capabilities**
  - **Develop systems that are too difficult or impossible to construct manually**
  - **Develop systems that can automatically adapt and customize themselves to the needs of the individual users through experience**
  - **Discover knowledge and patterns in databases, database mining**

Why Study Machine Learning?

- **The most important of the 12 IT skills that employers can't say no to**
  - "As companies work to build software such as spam filtering and fraud-detection applications that seek patterns in jumbo-size data sets, some observers are seeing a rapid increase in the need for people with machine-learning knowledge, or the ability to design and develop algorithms and techniques to improve computers' performance"
  - "It's not just the case for Google. There are lots of applications that have big data sizes, which creates a fundamental problem of how you organize the data"

Why Study Machine Learning?

- **Understand human and biological learning**

- **Time is right**
  - **Initial algorithms and theory in place**
  - **Growing amounts of on-line data**
  - **Computational power available**

Some Other Applications

- Natural language understanding
- Computer vision
- Computational biology
- Medical informatics
- Astronomy

Ambiguity Resolution

<u>Word selection</u>

Can I have a peace of cake ?   piece

<u>Word sense disambiguation</u>

...Nissan Car and truck plant is …

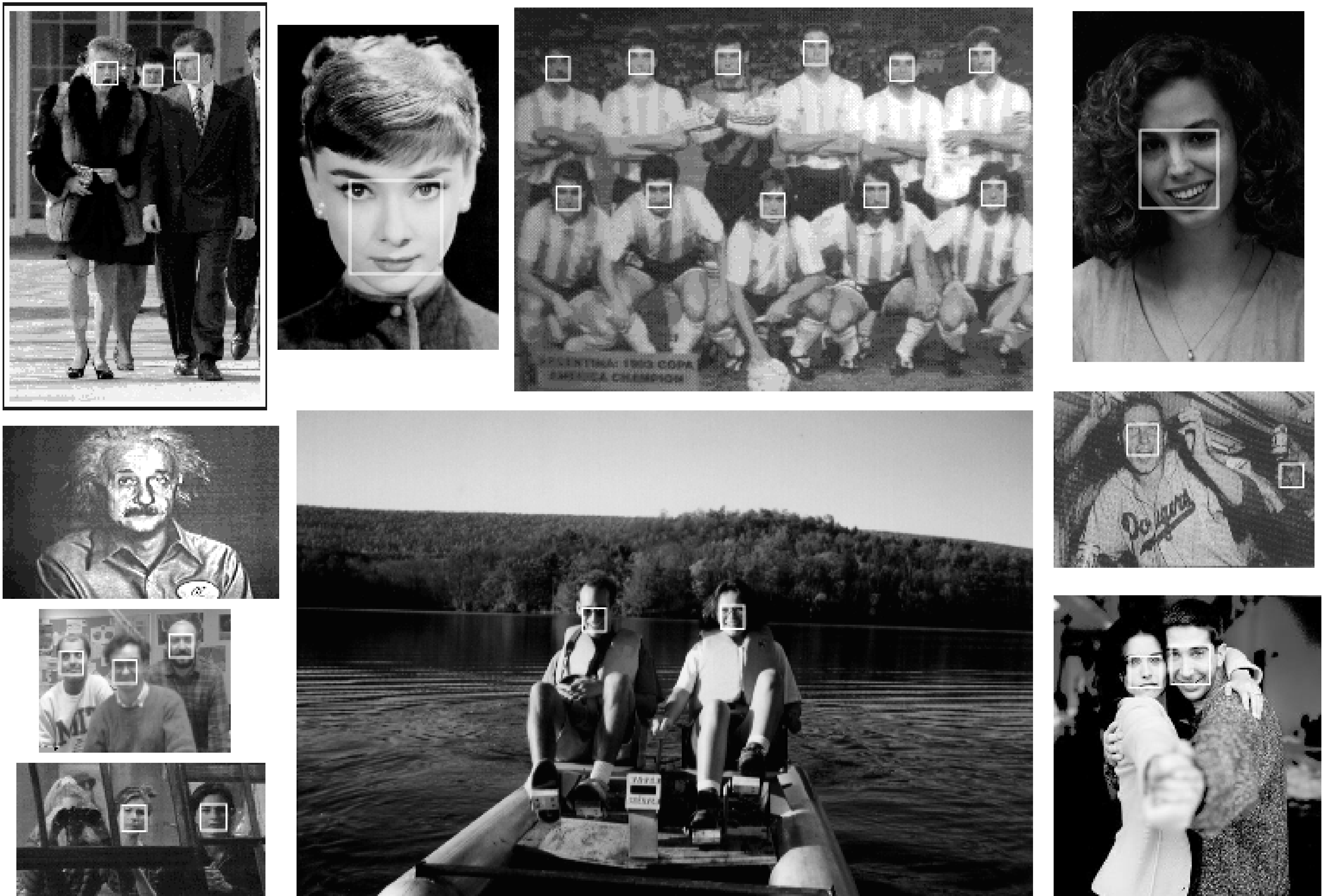
…divide life into plant and animal kingdom

<u>Preposition phrase attachment</u>

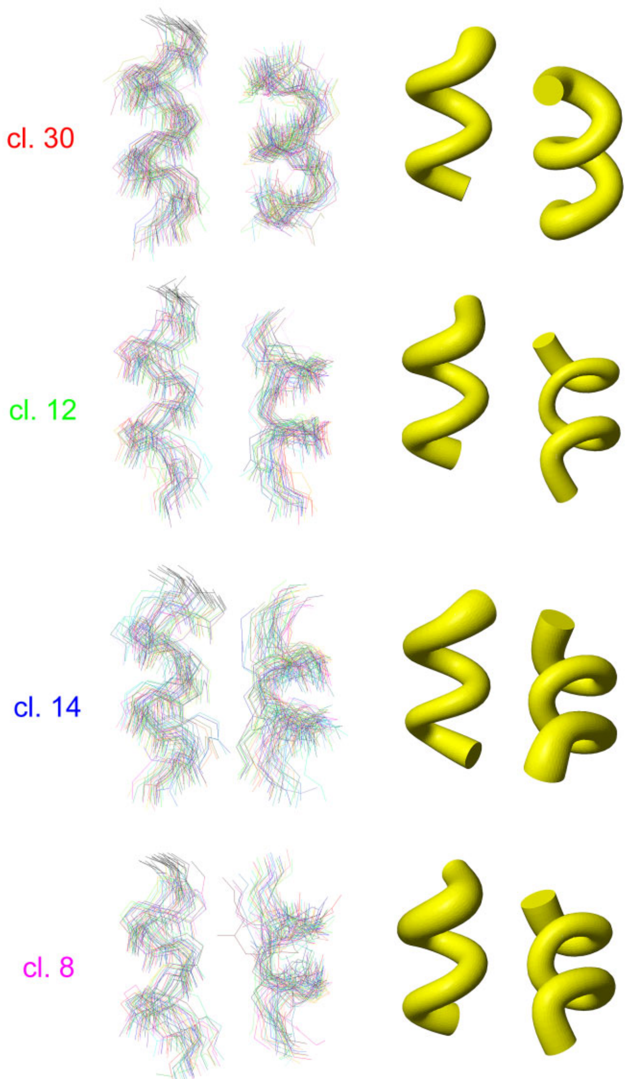
Buy a car with a steering wheel (his money)

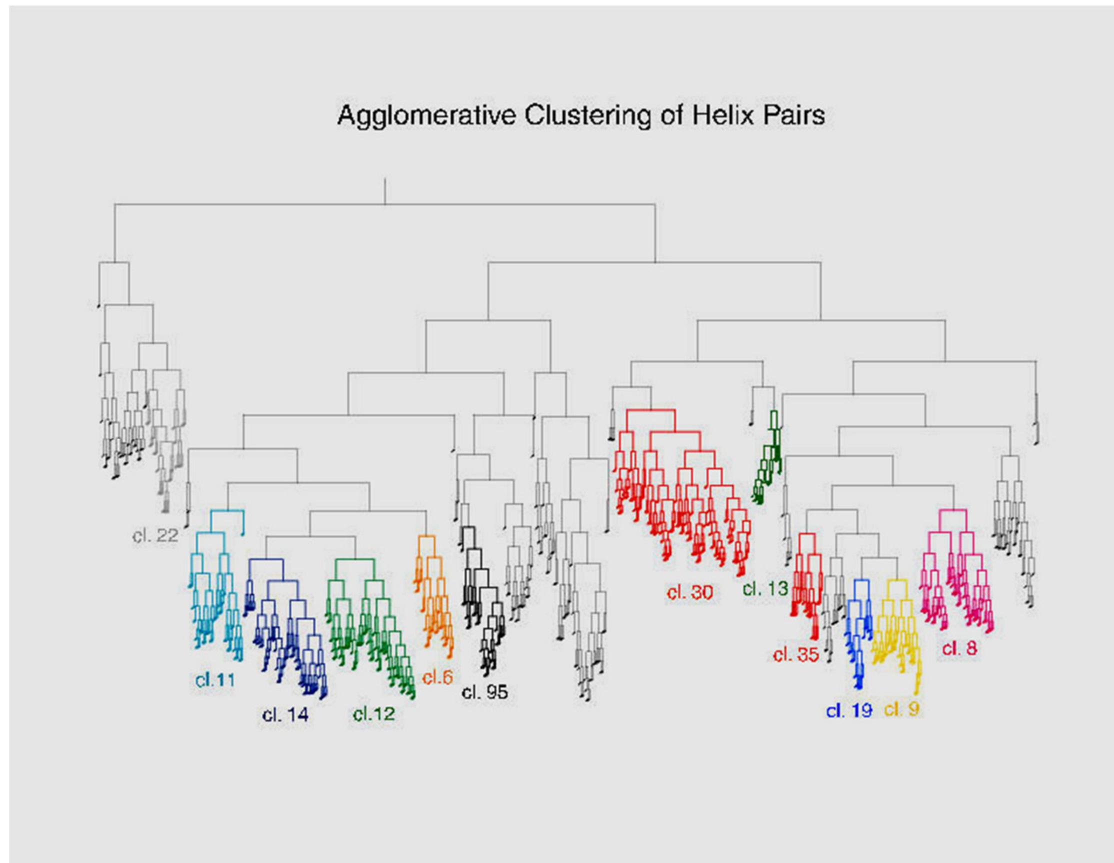
<u>Pronoun resolution</u>

The dog bit the kid. He was taken to a vet (hospital)

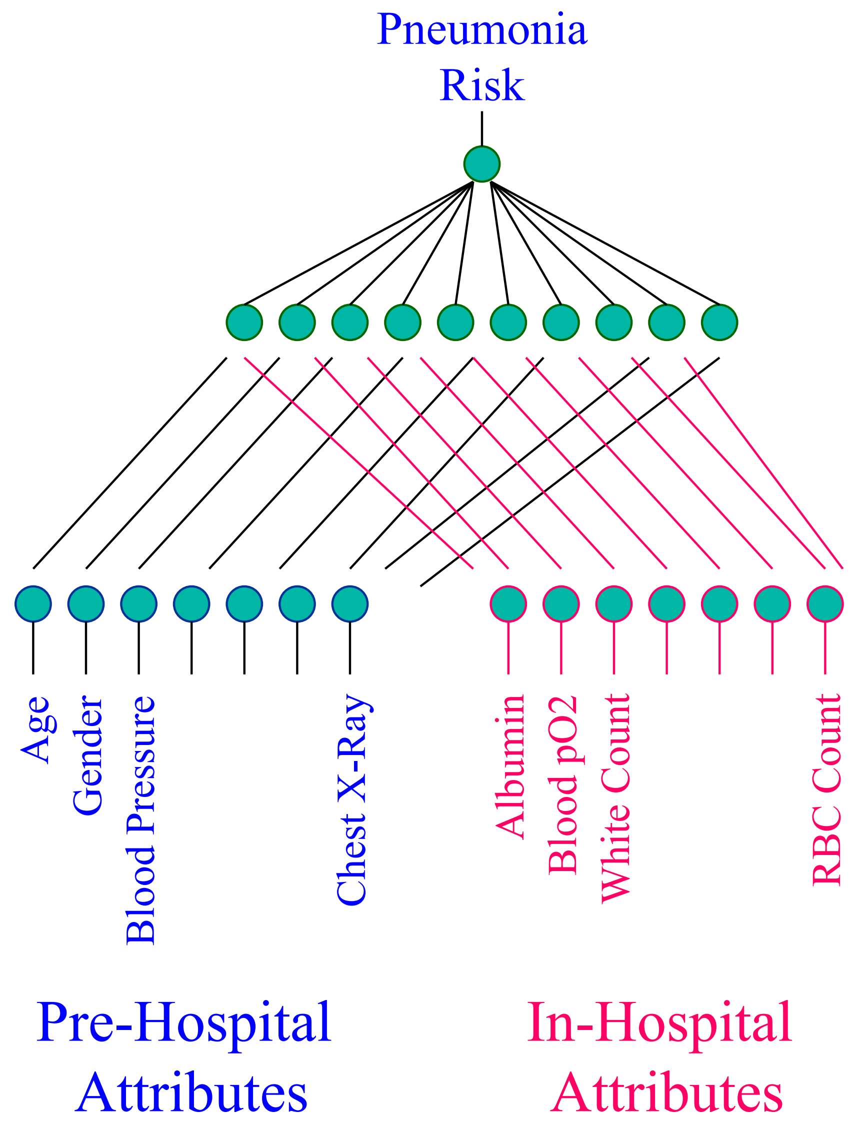


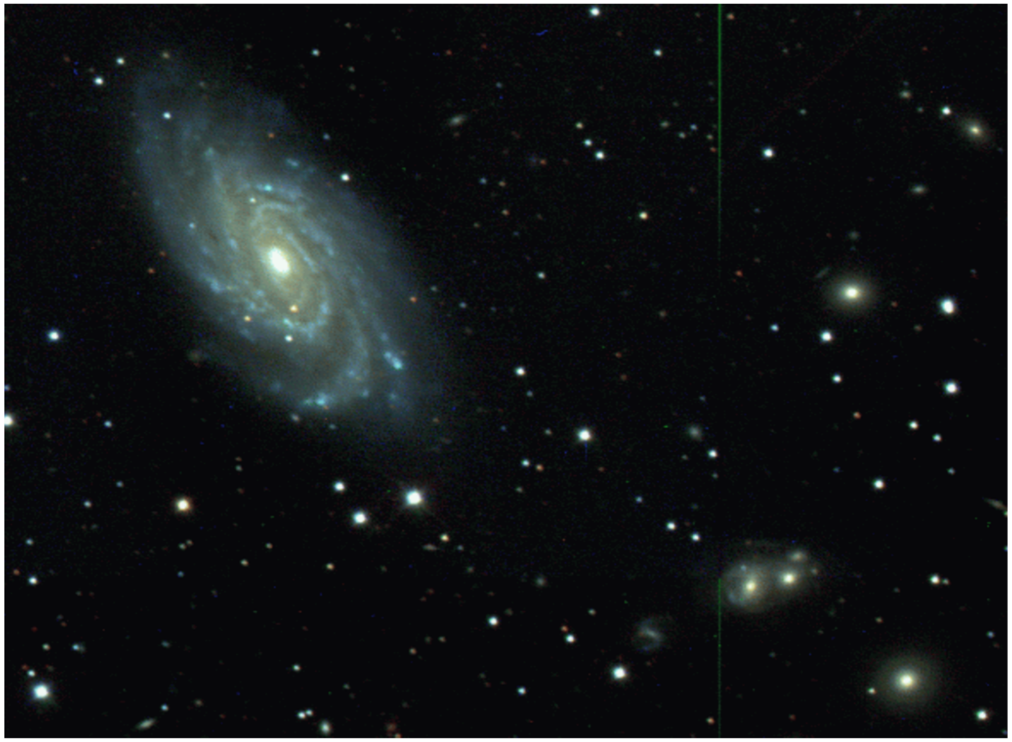
Protein Folding

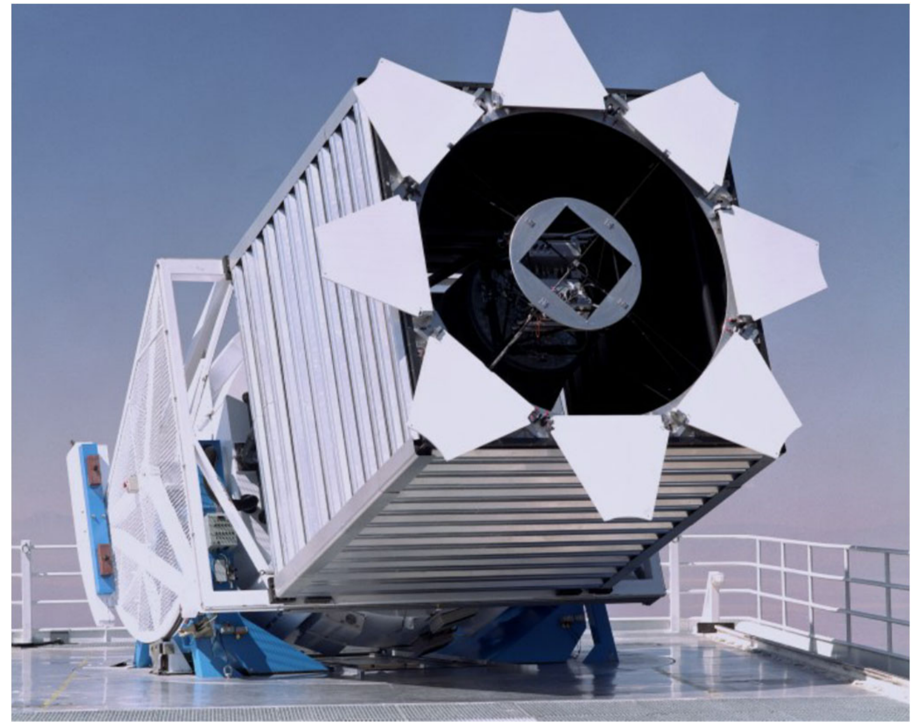


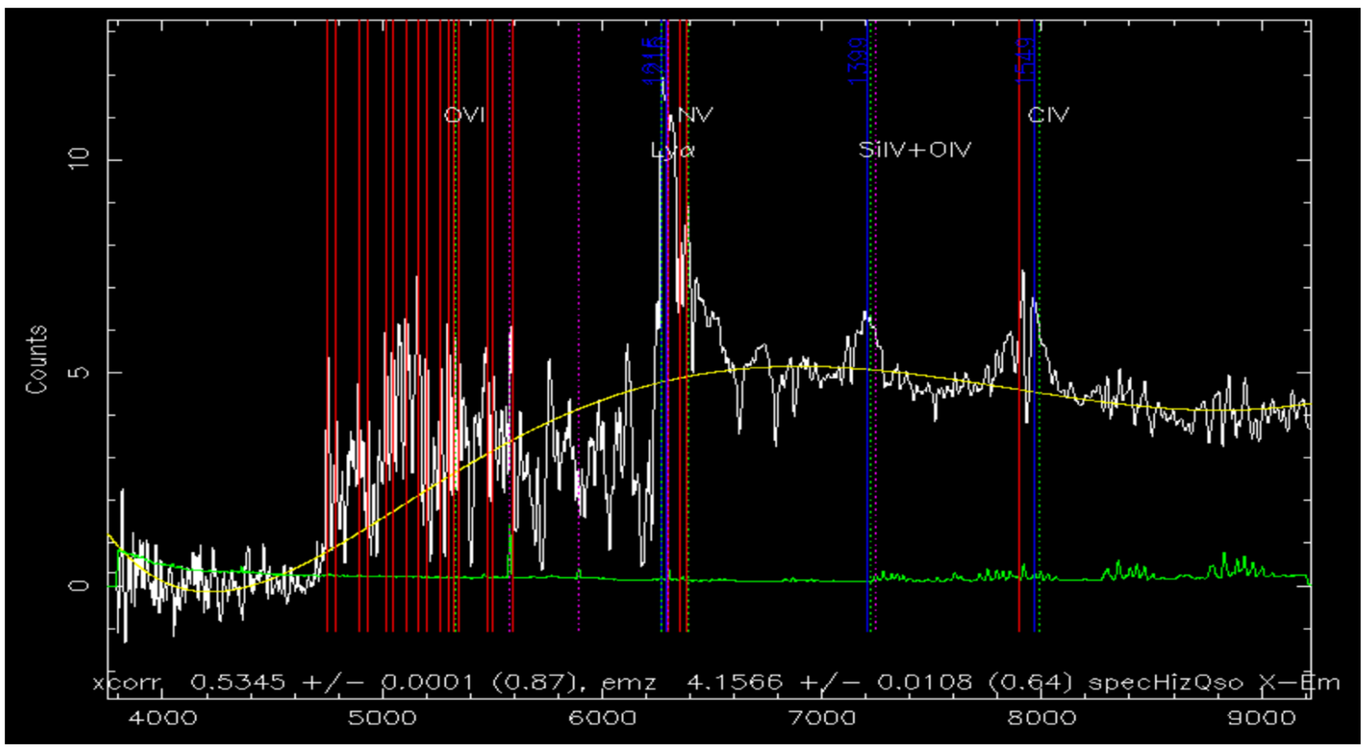


Pneumonia Risk Prediction








1215
1399
1549
OVI
NV
CIV
Lyα
SiIV+OIV
Counts
10
5
0
xcorr 0.5345 +/− 0.0001 (0.87), emz 4.1566 +/− 0.0108 (0.64) specHizQso X−Em
4000
5000
6000
7000
8000
9000

Even More Applications

- Speech processing
  - Building a speech recognizer
- Computer security
  - Detecting intrusion, worms, anomaly
- Software engineering
  - Software testing, automated analysis of software artifacts

Work in Machine Learning

- Makes use of:
  - Probability and Statistics, Linear Algebra
- Related to:
  - Philosophy, Psychology, Neurobiology, Linguistics
- Has applications in:
  - AI (Natural Language; Vision; Planning; HCI)
  - Computer Science (Compilers; Systems; databases)

Course Overview

- **Introduction to machine learning**
- **Supervised learning models and methods**: Decision trees, neural networks, nearest-neighbor algorithms, Bayesian learning, hidden Markov models
- **Unsupervised learning**: Clustering
- **Reinforcement learning**: Markov Decision Processes, temporal difference learning, Q-learning
- **General techniques**: Feature selection, cross-validation, maximum likelihood estimation, gradient descent, expectation-maximization

Goal

- Understand the principles underlying the design of existing learning algorithms so that we can
  - understand when to use which learner
  - understand why a learner makes certain mistakes
  - understand how to improve
- We don't just want to be users of machine learning software

Types of Supervised Learning Problems

- Regression: learning to predict a continuous/real value
  - tomorrow's stock price, driving, playing tennis
- Classification: learning to predict a discrete value from a predefined set of values
  - whether tomorrow's market will go up or down, whether people will like a movie or not

Example: Dog or Cat?

target concept

- How does a child learn to distinguish a dog and a cat?

Training:

Training examples (or instances) → Learner → Function

(Our Goal)

Learner: human, machine

machine → Learning algorithm

Function (a.k.a. hypothesis concept description)

Special names:
classifier (if discrete)
regressor (if continuous)

Input: examples
Output: class

Training set

(picture of animal1, dog)
(picture of animal2, cat)
(picture of animal3, cat)
……….

represented as a set of features/attributes

label/class (provided by teacher)

Evaluating a Classifier / Regressor

- How does a child learn to distinguish a dog and a cat?

Testing:

Test examples
(or instances) → hypothesis

Test set

(picture of animal101, ?)
(picture of animal102, ?)
(picture of animal103, ?)
……….

represented as a set of
features/attributes

predictions

(picture of animal101, dog)
(picture of animal102, cat)
(picture of animal103, cat)
……….

true labels

(picture of animal101, dog)
(picture of animal102, dog)
(picture of animal103, dog)
……….

Evaluation Issues

- Should test set be the same as training set?
  - Rote learning: memorization
  - Inductive learning: generalize from training examples

- Learning curves
  - show how performance on test data varies with amount of training data

Inductive Learning

- All learning can be seen as learning the representation of a function.
- **Inductive learning**: system tries to induce a "general rule" from a set of observed instances.
- **Supervised learning**: learning algorithm is given the correct value of the function for particular inputs, and changes its representation of the function to try to match the information provided by the feedback.
- An **example** or **instance** is a pair $(x, f(x))$, where x is the input and $f(x)$ is the output of the function applied to x.

Another Example: Enjoying Sport?

Example	Sky	Air Temp	Humidity	Wind	Water	Forecast	Enjoy Sport
0	Sunny	Warm	Normal	Strong	Warm	Same	**Yes**
1	Sunny	Warm	High	Strong	Warm	Same	**Yes**
2	Rainy	Cold	High	Strong	Warm	Change	**No**
3	Sunny	Warm	High	Strong	Cool	Change	**Yes**

- Each **training instance**, *x*, is a *day*, described by the **attributes** or **features** *Sky*, *AirTemp*, *Humidity, Wind, Water, Forecast,* and the **class attribute** *EnjoySport*
- Goal: learn **target concept**, *f*: *day* → {yes, no}

Inductive Learning

- **Given:** collection of examples

- **Return:** a function h (*hypothesis*) that approximates f (*target concept*).

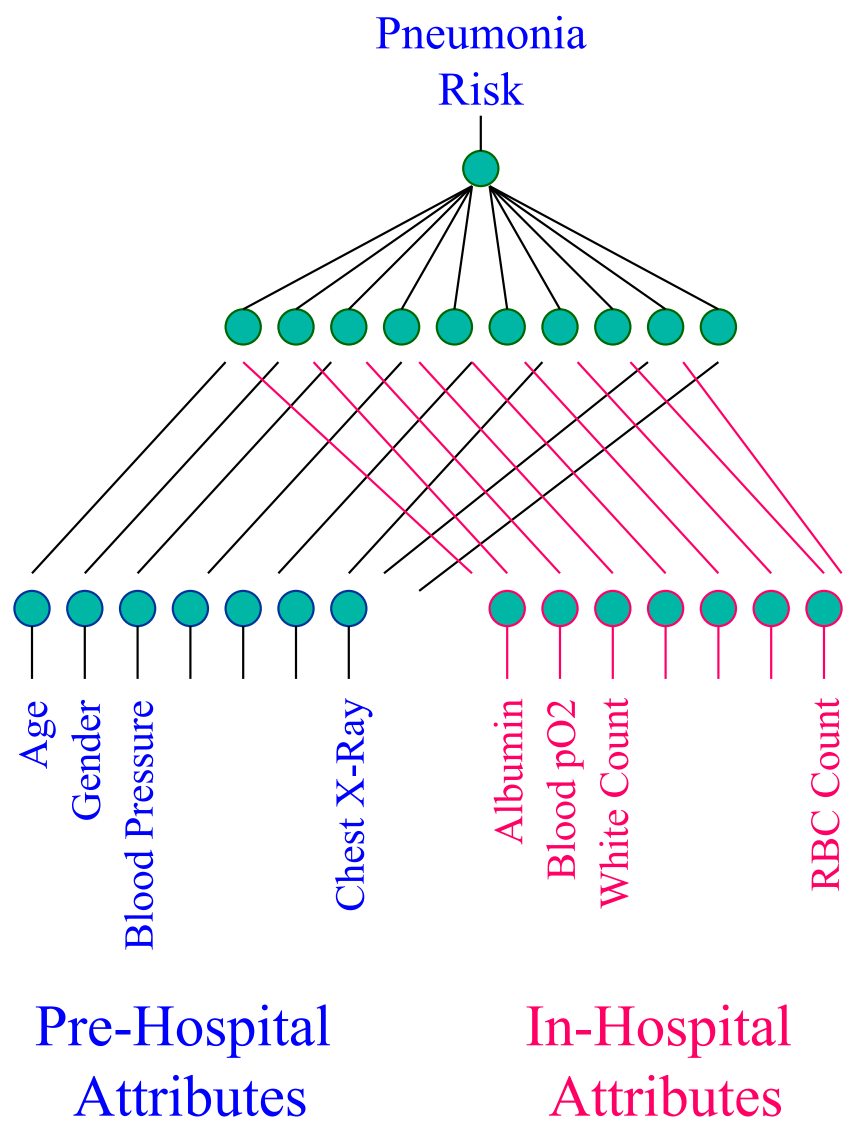
- **Assumptions for Inductive Learning Algorithms:**
  - The training sample represents the population
  - The input features permit discrimination

Three Major Paradigms in Machine Learning

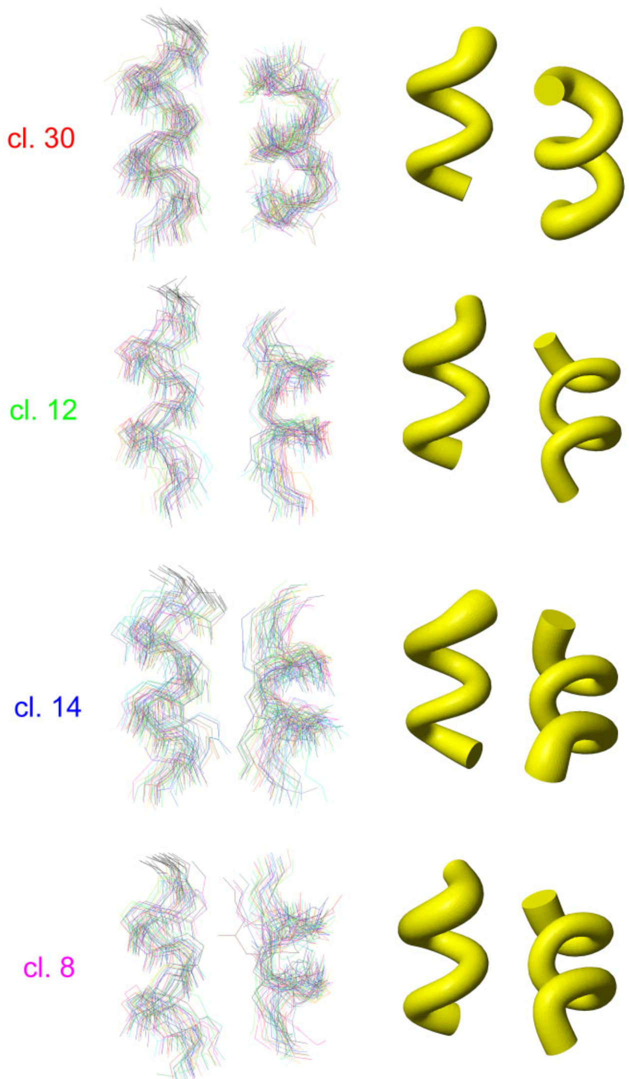
- **Supervised learning**
- **Unsupervised learning**
- **Reinforcement learning**

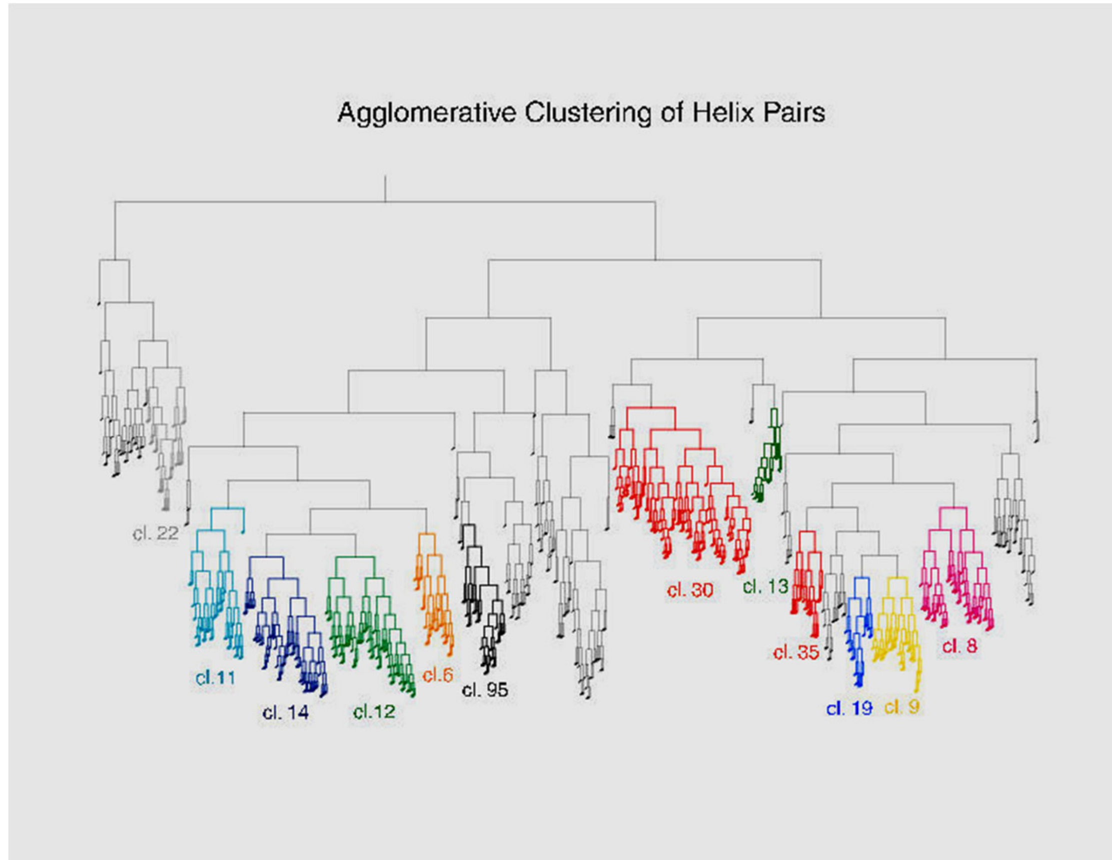
Example Task: Pneumonia Risk Prediction

- Teacher provides feedback
  - Use labeled examples to build predictive models
- Well-defined learning task
  - can determine how well learner has mastered target concept, e.g., by plotting a learning curve



Example Task: Protein Folding

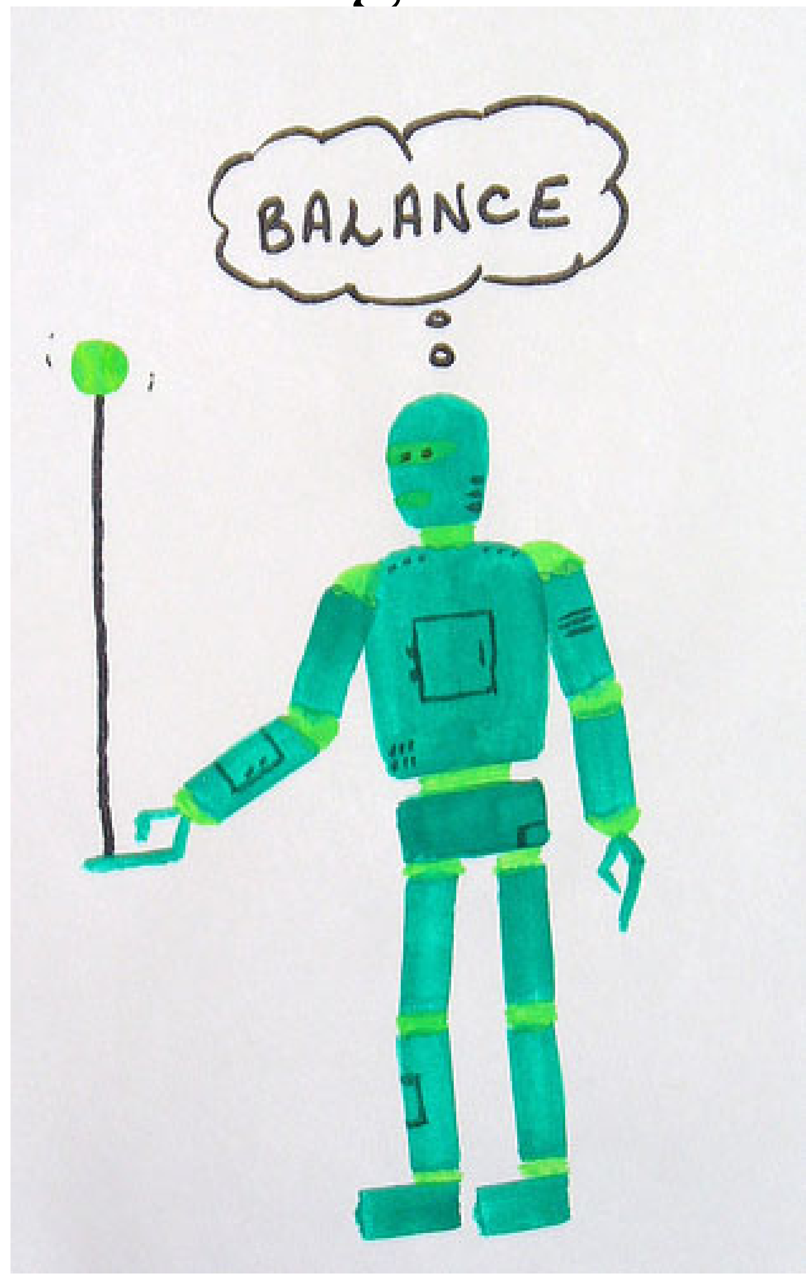




- Learn from unlabeled examples
- Task not necessarily well-defined
  - E.g., data from Wal-Mart

Example Task: Pole Balancing

- Well-defined learning task
- No teacher provides feedback
  - but there is implicit, delayed feedback during learning



Machine Learning is not Magic

- Machine learning is about learning **patterns** (i.e., **statistical regularities**) in data
  - Resembles human learning in the sense that humans learn patterns from experience
  - There is nothing to learn if there are no patterns in your data
  -
- You should have seen learning algorithms in your linear algebra and numerical methods courses (e.g., linear least squares)