CS269: Machine Learning Theory
Lecture 1: Course Introduction

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University of California, Los Angeles

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What is machine learning?

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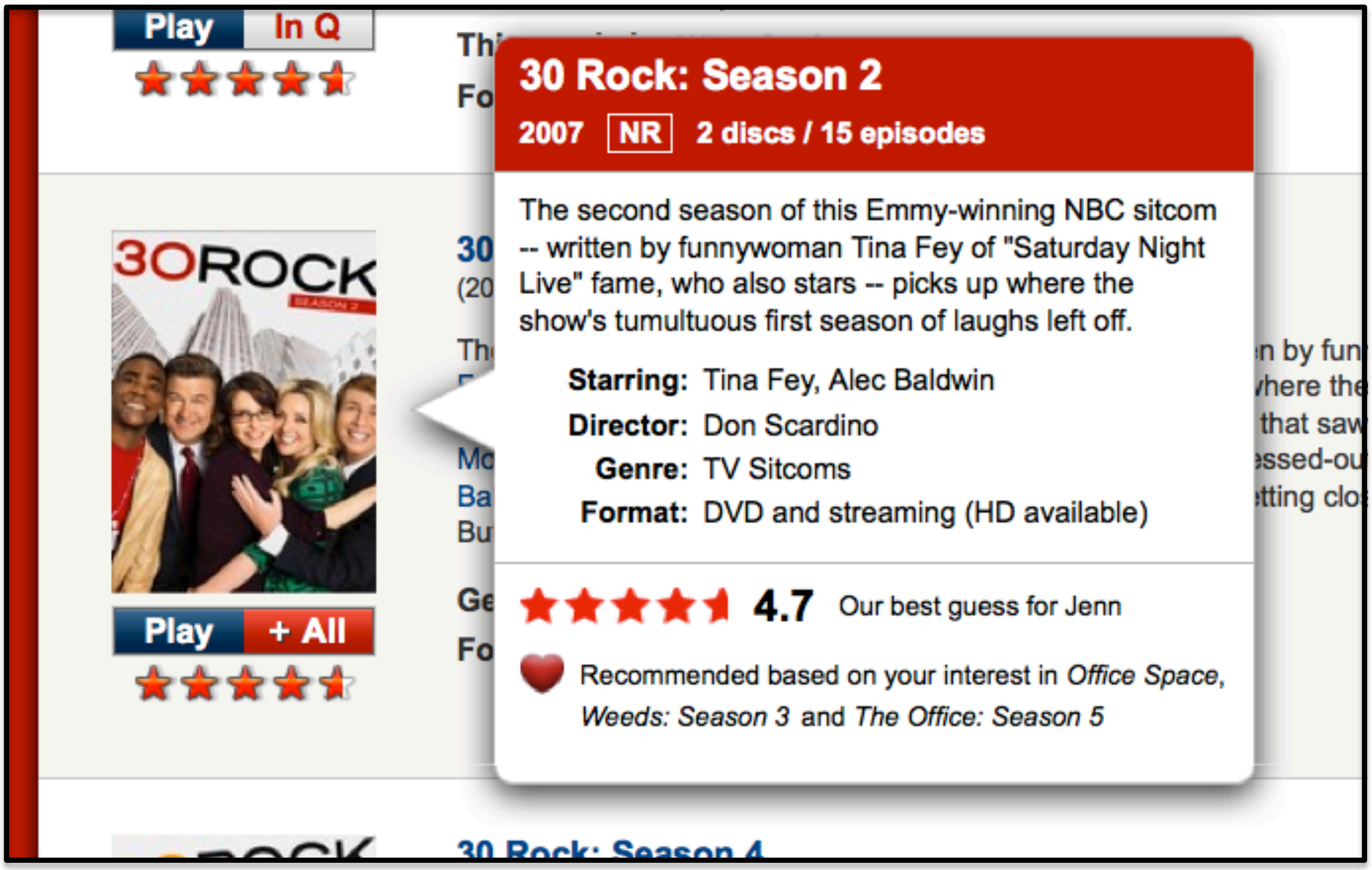
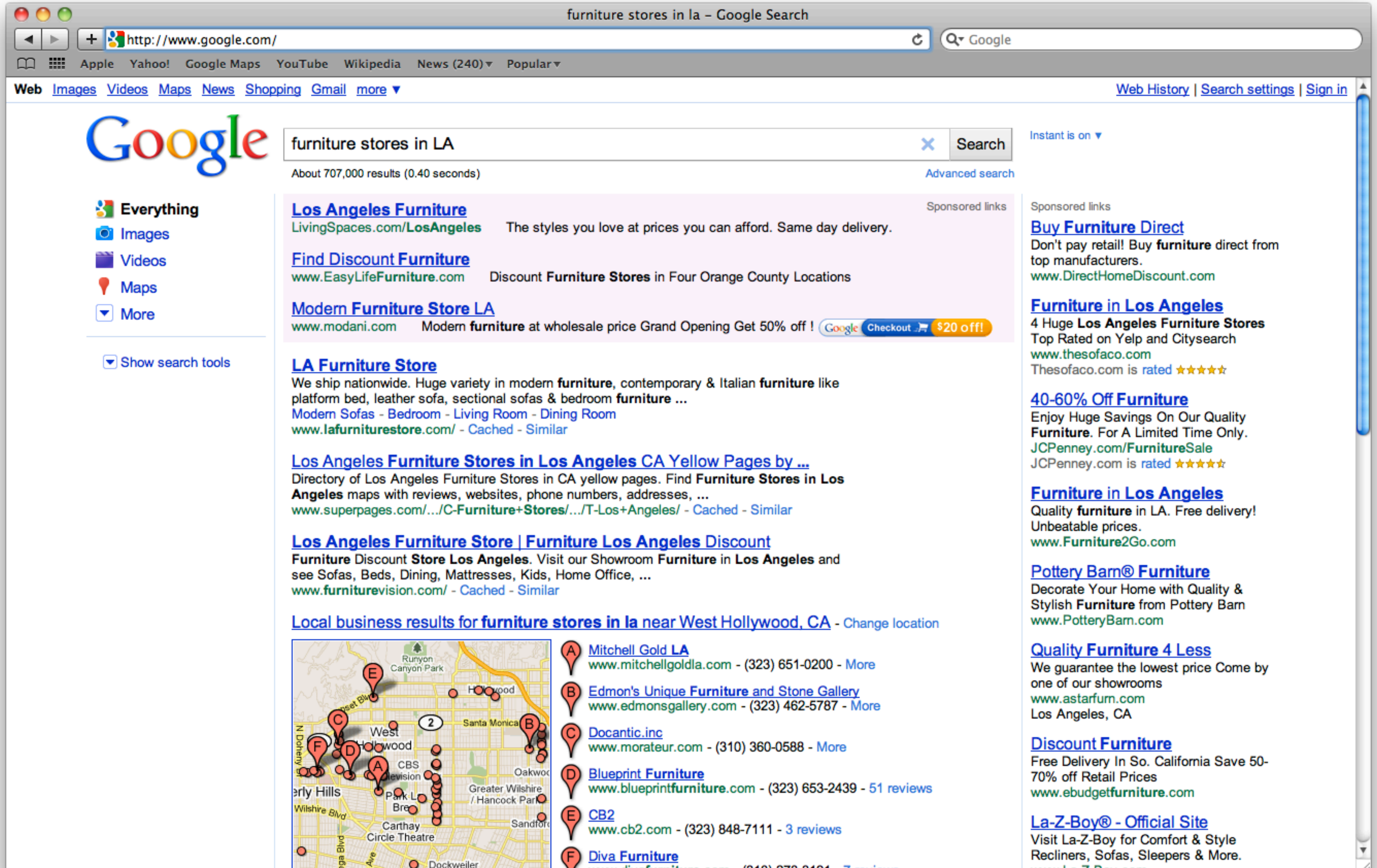
Machine learning is the study of how to use past observations or experience to automatically and efficiently learn to make better predictions or choose better actions in the future

Movie Recommendations



Click Prediction



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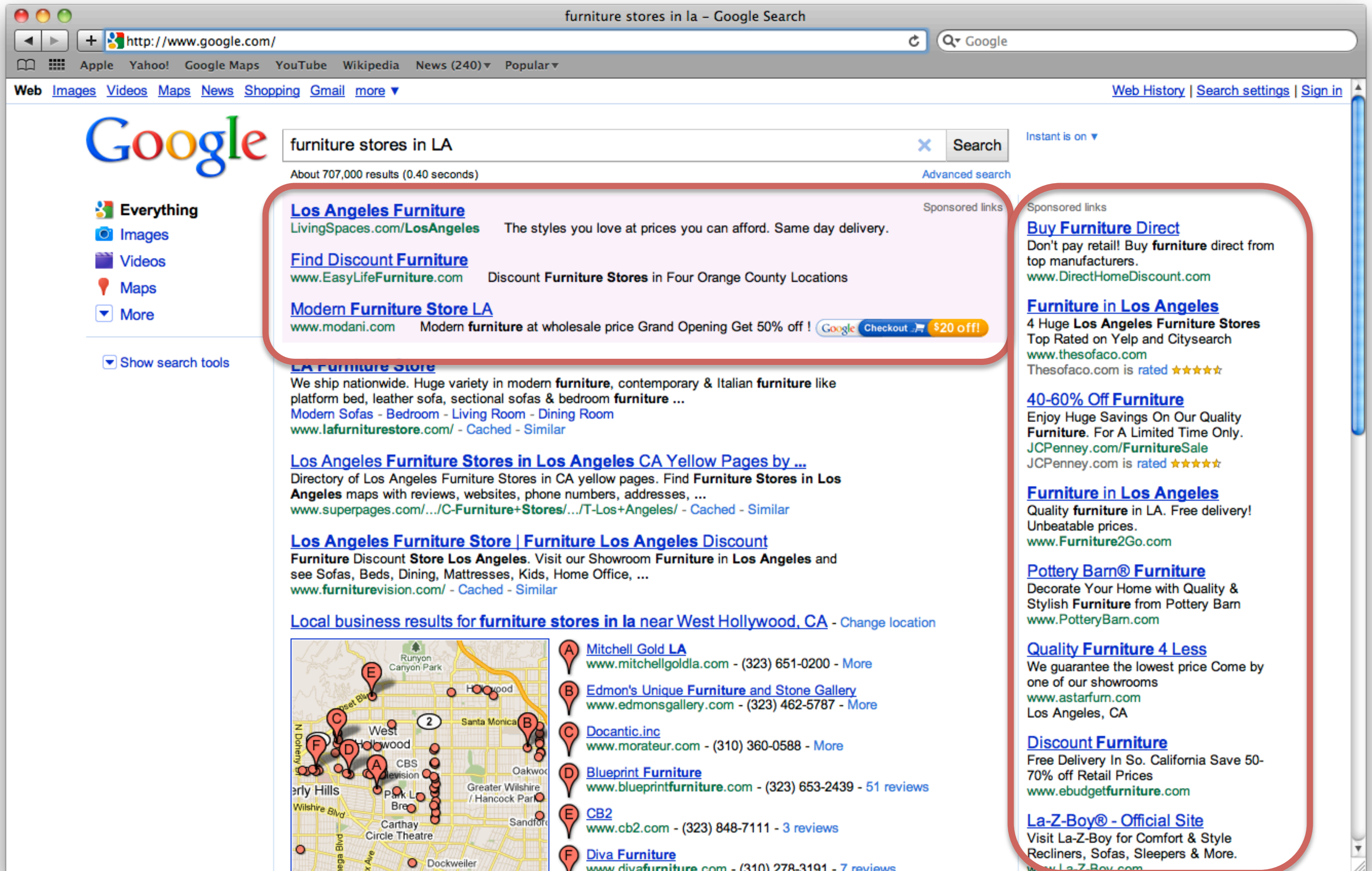
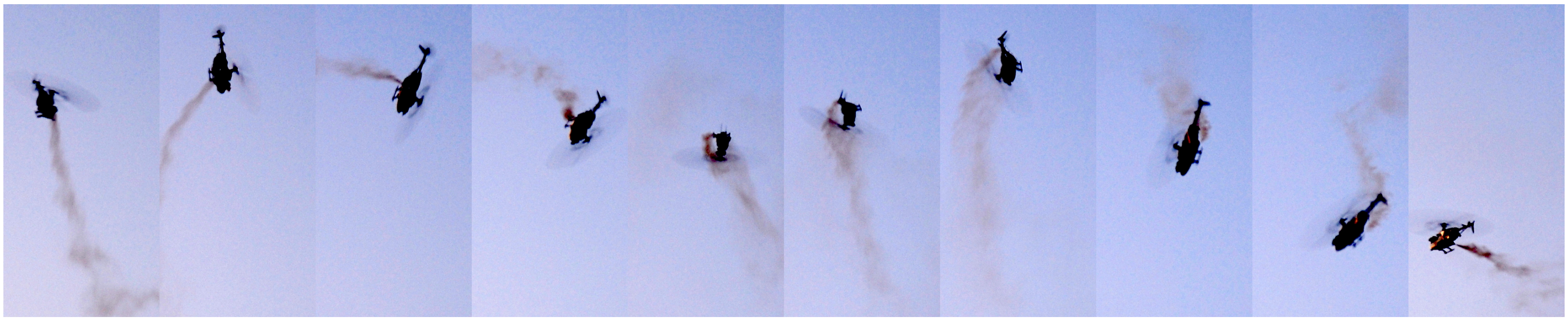


Autonomous Flight

Helicopter rolls:



Helicopter flips:

Other Examples

- Medical diagnosis
- Handwritten character recognition
- Customer segmentation (marketing)
- Document segmentation (classifying news)
- Spam filtering
- Weather prediction and climate tracking
- Gene prediction
- Face recognition

Spam Prediction

We are given a set of labeled email messages

To: Jenn Wortman Vaughan
From: Jeff Vaughan
Subject: Plans for tonight ✔

To: Jenn Wortman Vaughan
From: Bob Smith
Subject: V14GR4 4 U ✖

To: Jenn Wortman Vaughan
From: Jens Palsberg
Subject: Meeting ✔

Spam Prediction

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To: Jenn Wortman Vaughan
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Subject: V14GR4 4 U ✗

To: Jenn Wortman Vaughan
From: Jens Palsberg
Subject: Meeting ✓

Goal is to predict labels of new messages that arrive

To: Jenn Wortman Vaughan
From: NIPS Committee
Subject: Paper decision ?

A Classification Problem

First we need a way to represent the data…

“Jenn”	“269”	“Viagra”	Known Sender	Spelling Bad	Spam?
1	1	0	0	1	0
1	0	0	1	0	0
0	0	1	0	0	1
0	0	0	0	1	1
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"feature vector"

"label"

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Then we need a reasonable set of prediction rules…

- Disjunctions (spam if not known or not "269")
- Thresholds (spam if "Jenn"+"269"+known < 2)

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"concept class" or "function class" or "hypothesis class"

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"prediction rule" or "hypothesis" or "concept"

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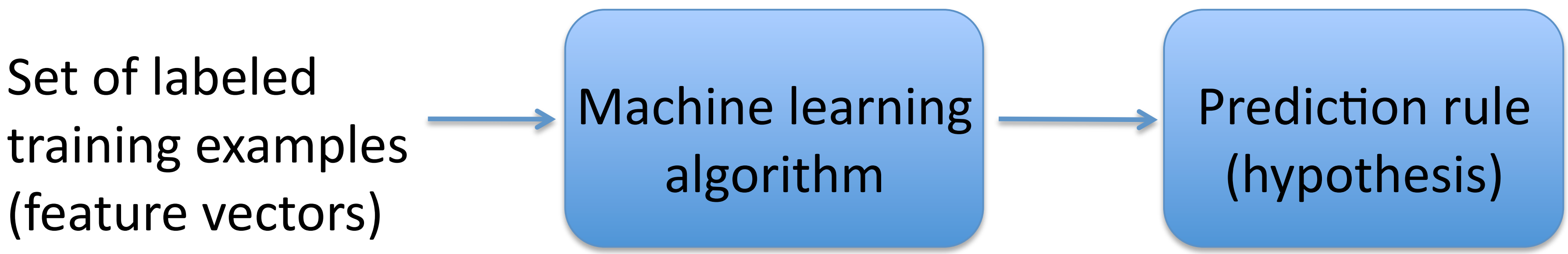
Finally, we need an algorithm…

Typical Classification Problem



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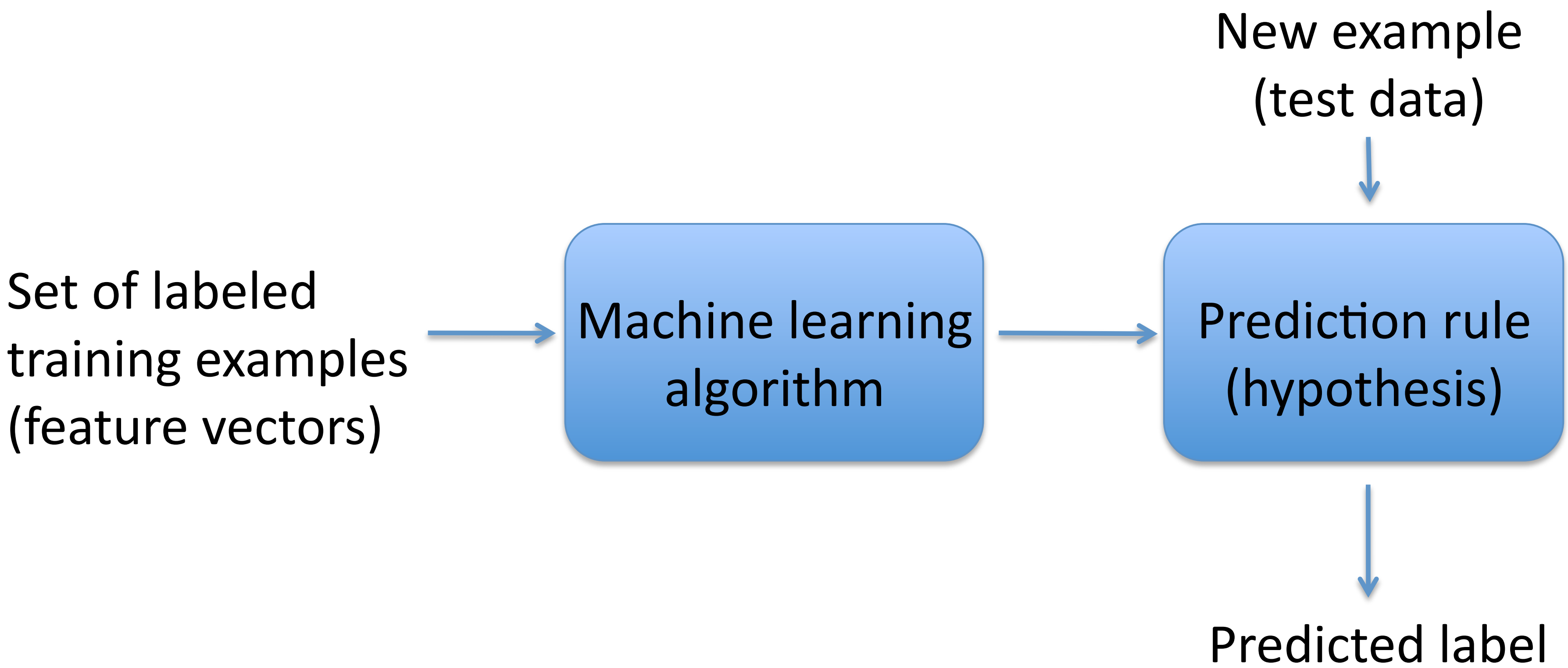

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What if there are no clear training and test sets?

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The goal is now to update the prediction rule over time while making as few mistakes as possible

Other Learning Settings

- Unsupervised learning (clustering)
- Semi-supervised learning
- Active learning
- Reinforcement learning

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This generates intuition useful for algorithm design

Questions We Ask

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- How much prior information or domain knowledge do we need to learn effectively?
- Are simpler hypotheses always better? Why?
- How should we trade off the standard notions of efficiency (time, space) with data efficiency?

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2. Online learning in adversarial settings, including the expert advice model and online convex optimization
3. Some of learning theory's success stories, including boosting and support vector machines
4. New research directions

Things We Will NOT Cover

- Implementation tricks
- Feature design
- Particular application domains (NLP, vision, robotics, search, etc.)
- Commercial uses of machine learning

… but you are welcome to explore some of these topics as part of your final projects

Grading

- Grades will be based on three components
  - 40% homework (two assignments, 20% each)
  - 20% participation (including preparation of scribe notes)
  - 40% final projects (including an in-class presentation and a written report)

Homework Policies

- Discussing homework problems with other students is ok, but you must write up your own answers and list your collaborators

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- Homework submitted up to 24 hours late will be penalized 25% (e.g., 80/100 goes to 55/100)
- No homework will be accepted more than 24 hours late

Scribe Notes

- In place of a textbook, lecture notes will be made available on the course website
- One pair of students will be responsible for preparing notes for each lecture
- Notes must be prepared using the LaTeX template

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If class is on…	A draft is due…	Revisions are due…
Monday	Wednesday, 2pm	Next Wednesday, 2pm
Wednesday	Friday, 2pm	Next Friday, 2pm

Final Projects

Option 1: Conduct a small research project

- Tackle an open theoretical problem
- Design and analyze your own learning model
- Implement and empirically evaluate algorithms that we study in class

Option 2: Read and synthesize a collection of papers

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Projects may be done individually or in small groups and include a presentation and a write-up of results

Logistical Loose Ends

- This is a four unit course
- This course does count toward AI majors/minors
- PTEs will be given out as soon as space opens up, with priority given to students who come to class
- Auditors are welcome as long as there is space – please reserve seats for students who are enrolled

One Last Note on Logistics…

All of this information and more is available on the course website:

http://www.cs.ucla.edu/~jenn/courses/F10.html

Check it often!

Models of Learning

Models of Learning

- A learning model must specify several things
  - What are we trying to learn?
  - What kind of data is available?
  - How is the data presented to the learner?
  - What type of feedback does the learner receive?
  - What is the goal of the learning process?

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  - What are we trying to learn?
  - What kind of data is available?
  - How is the data presented to the learner?
  - What type of feedback does the learner receive?
  - What is the goal of the learning process?
- To provide valuable insight, a learning model must be robust to minor variations in its definition

The Consistency Model

- **Definition:** We say that algorithm *A* learns concept class *C* in the consistency model if given a set of labeled examples *S*, *A* produces a concept $c \in C$ consistent with *S* if one exists and states that none exists otherwise.

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- **Definition:** We say that a class C is learnable in the consistency model if there exists an efficient algorithm A that learns C.

Example: Monotone Conjunctions

Guitar	Fast beat	Male singer	Acoustic	New	Liked
1	0	0	1	1	1
1	1	1	0	0	0
0	1	1	0	1	0
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- Find all of the variables that are true in every positive example.
- Let h be the conjunction of these variables.
- Output h if it is consistent with the negative example; otherwise, output none.

Example: DNFs

Guitar	Fast beat	Male singer	Acoustic	New	Liked
1	0	0	1	1	1
1	1	1	0	0	0
0	1	1	0	1	0
1	0	1	1	0	1
1	0	0	0	1	0

DNF = the set of all disjunctions of conjunctions

Trivial to learn in the consistency model!

What is wrong with this model?

Towards Generalizability

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$$\mathrm{err}(h) = \Pr_{x \sim D}[h(x) \neq c(x)]$$

- **Goal:** Find h such that the probability that $\mathrm{err}(h)$ is large is small – h is probably approximately correct

Towards Generalizability

"Approximately" quantified by accuracy parameter ε

- Don't have enough data to learn c perfectly
- Instead require that $\mathrm{err}(h) \leq \varepsilon$

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"Probably" quantified via confidence parameter δ

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Allow number of examples to depend on $1/\varepsilon$ and $1/\delta$

The PAC Model

- **Definition:** An algorithm A PAC-learns a concept class C by a hypothesis class H if for any $c \in C$, for any distribution D over the input space, for any $\varepsilon > 0$ and $\delta > 0$, given access to a polynomial number of examples drawn i.i.d. from D and labeled by c, A outputs a function $h \in H$ such that with probability at least 1- δ, err(h) $\leq \varepsilon$.

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- **Definition:** C is efficiently PAC-learnable by H if there exists an efficient algorithm A that PAC-learns C by H.