Algorithmic Aspects of Machine Learning

COMPSCI 590.7 Fall 2015

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Basic Info

- Webpage (course materials, related papers):
  http://www.cs.duke.edu/courses/fall15/compsci590.7/
- Contact me:
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- Email List:
  You are already on the list if you registered.
  Send me an email otherwise.

Basic Info

- **Expect to see (and do) Proofs.**
- Homework:
  ~3 problem sets, due 2 weeks after posted in class.
  Discussions allowed but *must acknowledge*.
- Final Project:
  Form groups of size 2-3, ~1 month.
  Can be original research or literature survey.

Lecture 1:Machine Learning Basics

Machine Learning Basics

- What do we want “machines” to learn?
- How do we know machines have learned?
- What guarantees can we hope to get?
- What tools do we have?

What do we want machines to learn?

Example: Dogs vs Cats

https://www.kaggle.com/c/dogs-vs-cats

Input: Many images with labels (cat or dog)

Goal: Given new image, decide cat or dog.

Example: Netflix

Input: Movie ratings from users

Goal: Recommend new movies for users

Example: Community Finding

Input: List of friends

Goal: Find “communities”

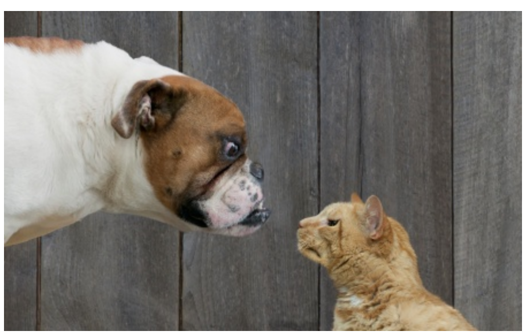
Supervised vs Unsupervised

- Input: (data, label)
- Output: Function f
- Hope:f(data) = label

- Input: data
- Output: “structure”
- Hope: explain and predict

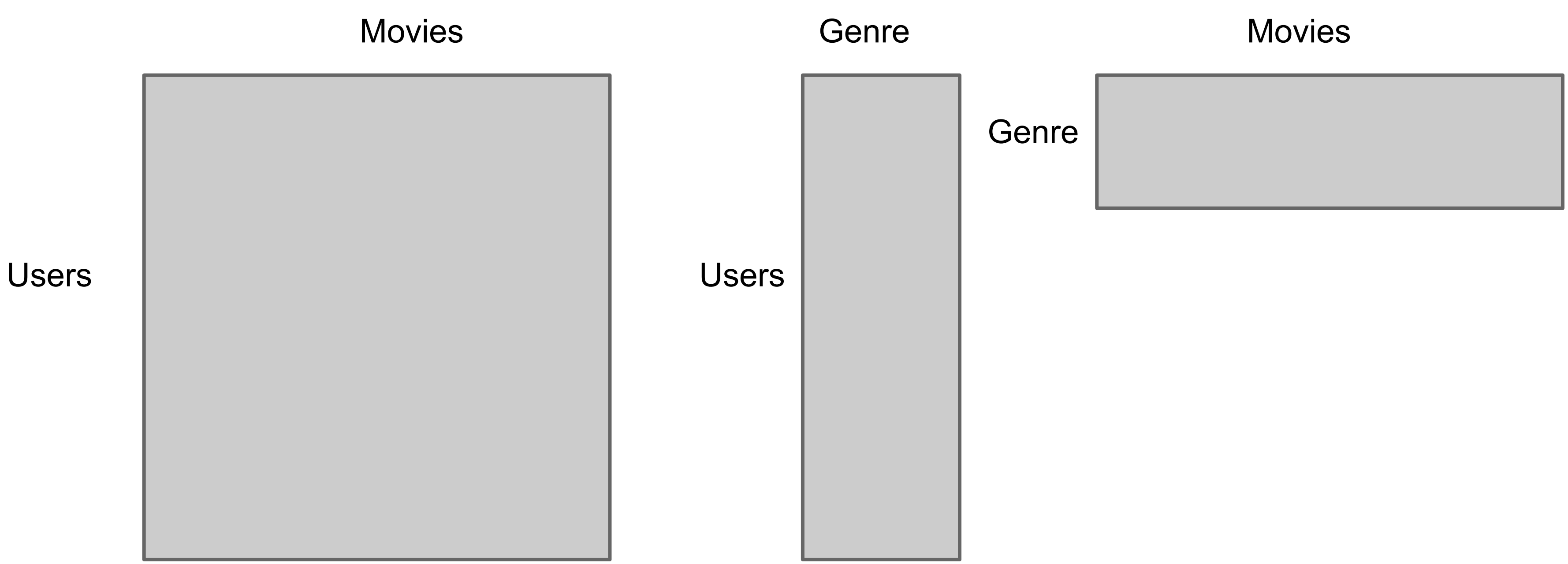
Supervised

Unsupervised



Example of Structure

- Movies have different genres.
- Users like different genres.
- Learning ~ Find the genres of movies and users
- To recommend
  - determine what genres the user likes
  - recommend a good movie in that genre.



Example of Structure: Probabilistic Models

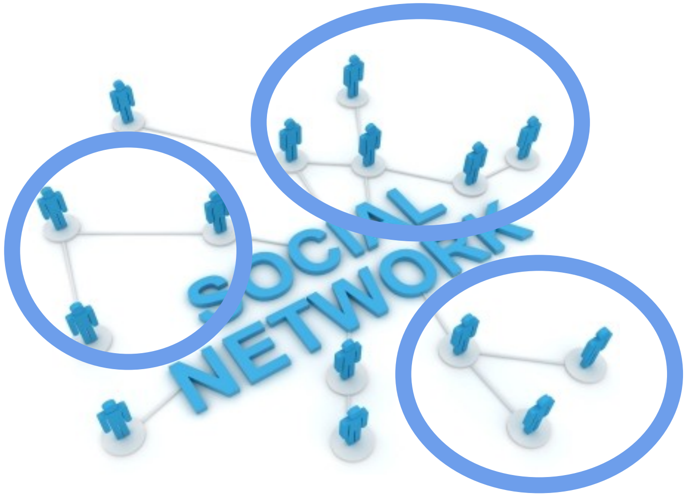
- People are in different communities
- Same community ⇒ Higher probability p to know each other
- Different community ⇒ Lower probability q to know each other
- Learning ~ Find out which groups of people are in the same community

Probablistic Models

Given: Data

Assumption: Data is generated from a class of distributions(“model”)

Learning ~ Finding parameters of the model



Connection

MNIST: Given images recognize digits.

Unsupervised: Given images, cluster similar images

Unsupervised Learning ⇒ features for Supervised Learning

How do we know machines have learned?

(General approach: Give an exam)

Human Learning, Machine Learning

- Take a course
- Understand the course material
- Take an exam

Goal of Exam: If the students understood the material, do well in exam.

- Get training examples
- Learn a *hypothesis*
  - maps input to labels
- Test on new examples

Goal of Test: If the hypothesis is good, do well in test samples.

What is a good hypothesis?

Ways to fail an exam

- Do not understand examples given in class
  (Make many mistakes on training samples)
- Only memorize the basic examples
  (Come up with a complicated hypothesis)

Good hypothesis = Simple + Do well on training

PAC Learning

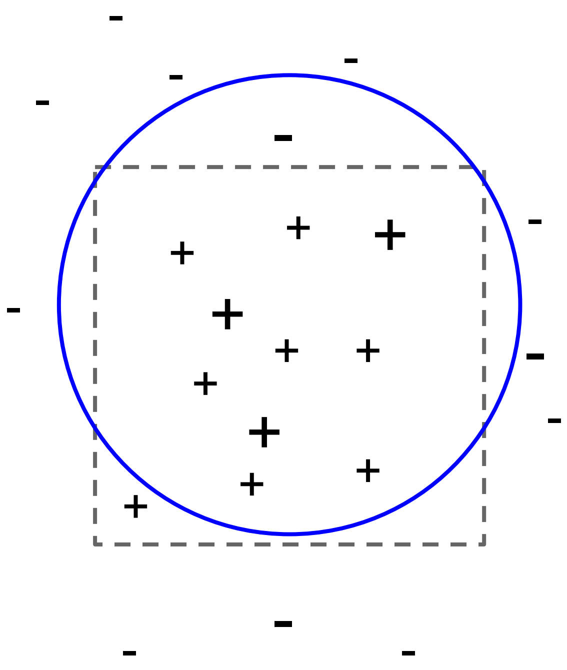
[Valiant 1984] For a concept class C, for any distribution D on data points, given samples

$$(x,y): x \sim D,\ y = c(x) \text{ for fixed } c \text{ in } C$$

an algorithm PAC learns the concept class if with probability $1-\delta$ the algorithm outputs a function f such that

$$\Pr_{x \sim D}[f(x) = c(x)] \geq 1 - \epsilon$$

Example



- Concept Class: Boxes
- Get samples and labels
- f may not be a box
- Tested on new samples

Generalization

If f is “simple”, doing well on the *current* samples guarantees good performance on *future* samples.

Exams for Unsupervised Learning

Make (probabilistic) predictions

What other movies do this user like?

What other people do this user know?

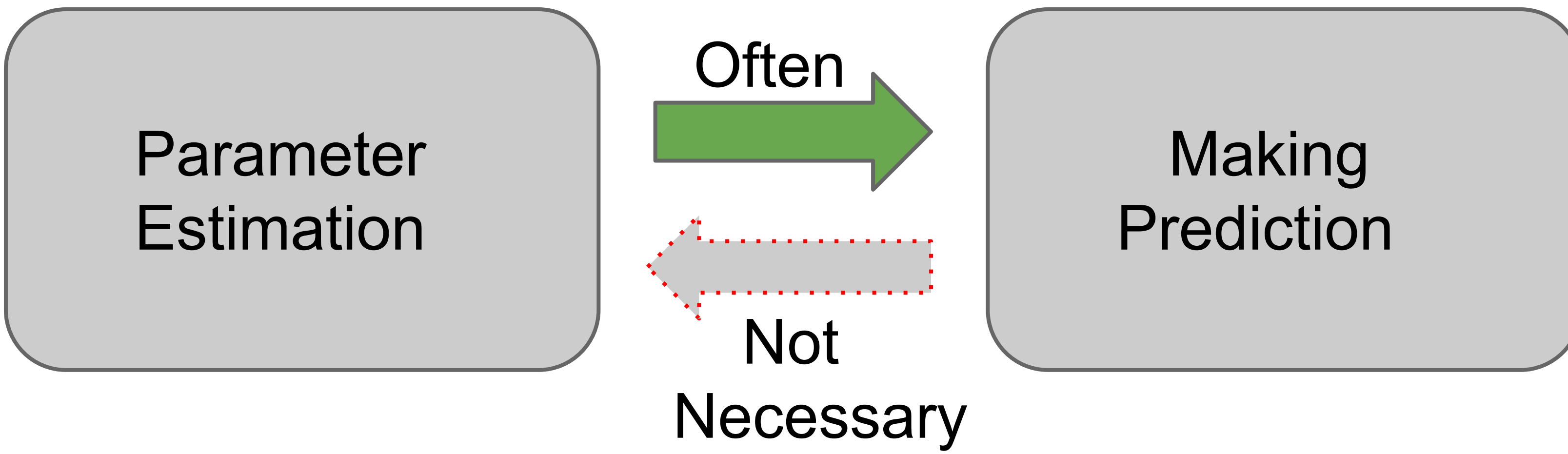
Generalization
If the model is "simple", explaining the *current* samples guarantees good prediction on *future* samples.

Alternative Guarantees

- Parameter Estimation:
  - Estimate parameters of the model
    - (what movies are comedies, who are in same community…)
  - Assumes the model is “correct”.
  - Easier to work with, often see in this course
- Maximum Likelihood Estimation:
  - Find the parameters that are best at explaining data
  - Only hope to do as well as the “best model”
  - Still restrict to the model (like restricting f ~ box)

All models are wrong, but some are useful.

Learning Parameters vs Making Predictions



- Has a well-defined model.
- Easy to explain/interpret.
- Concise representation.

- More robust to model mismatch
- More efficient algorithms.
- Often what we really want

What guarantees can we hope to get?

(and why do we care about guarantees?)

Why do we want guarantees?

- Understand why learning works (or not work)
  - Does the algorithm work with high dimension/high noise/…?
- Make sound conclusions
  - “I tried to find a good set of parameters but failed”
  - vs. “If there is a good set of parameters I’ll find it”
- Design better algorithms
  - Can I tweak the algorithm if data is not ideal?
  - Get new ideas by different way of thinking.

What we are not likely to do

- PAC learning for many problems
  - intersection of halfplanes
  - 2 layer “neural network”
- Learn many functions even with specific distribution
  - Learning parities with noise...
- Maximum Likelihood for many problems
  - mixture of Gaussians,
  - topic models

The Hope

Natural Instance

Reasonable Model
Reasonable Assumptions

Machine Learning Problem (worst case, for every...)

Example: Netflix

Input: Movie ratings from users

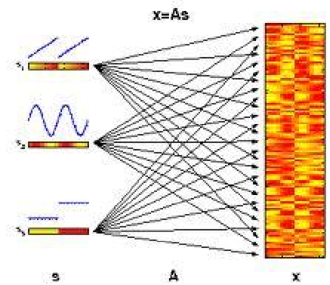
Goal: Recommend new movies for users

Natural Instances

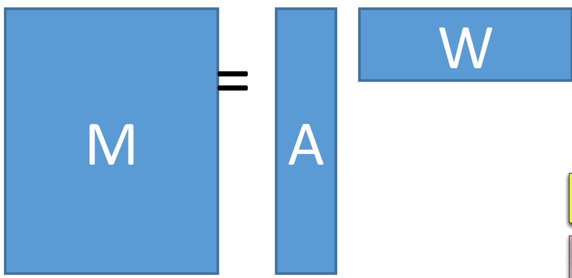
- Models are not perfect, but they can work
  - Breaking movies into genres is not perfect, but allows reasonable commendation
- Natural instances are often easier
  - People usually have a preference over different genres, ...
- “What is natural” is the hard problem
  - We will see examples later in the course.

What we will see

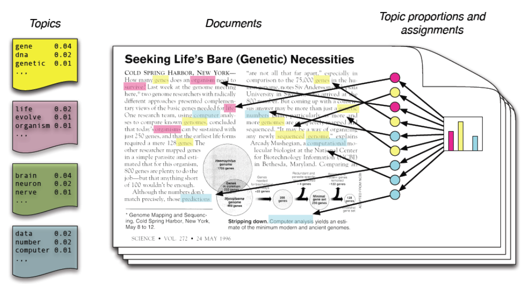
Social Network



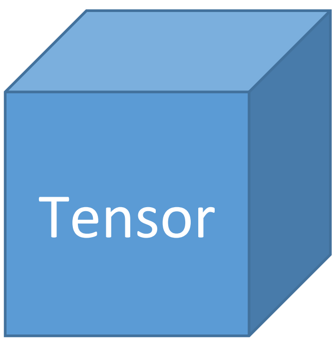
Independent Component Analysis



Matrix Factorization



Topic Models

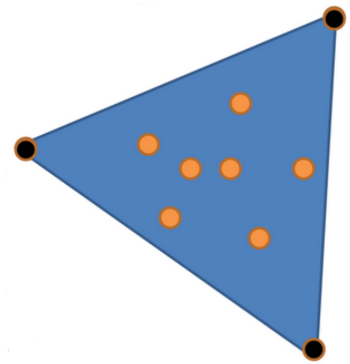


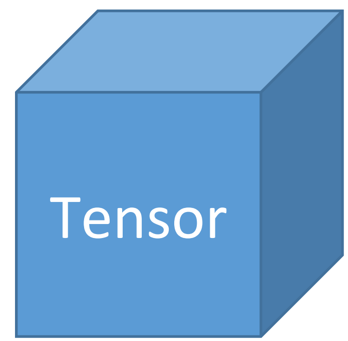
Tensor Methods

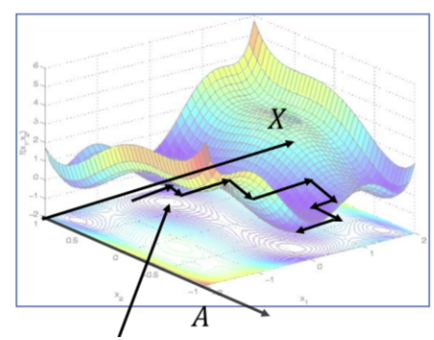
What tools do we have?

Tools

- Geometry
  - Nonnegative constraints
  - Finding extreme points
- Linear Algebra
  - Spectral methods
  - Tensor decomposition
- Optimization
  - use convex programs (LP, SDP) in learning
  - optimize a nonconvex function
- Hope: Will have more tools!







Schedule

- Nonnegative Matrix Factorization and Topic Models (~4 lectures)
- Spectral Clustering (~2 lectures)
- Tensor Decompositions (~5 lectures)
- (Non-convex) Optimization (~5 lectures)
- Matrix Completion (~4 lectures)