Course overview and general classes of problems

Hal Daumé III

CS 726: Machine Learning

1 September 2011

Course Background

What is this course about?

- Finding (and exploiting) patterns in data
- Replacing “human writing code” with “human supplying data”
  - ⇒ System figures out what the person wants based on examples
  - ⇒ Need to abstract from “training” examples to “test” examples
  - ⇒ Most central issue in ML: *generalization*

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Why is machine learning so cool?

- Broad applicability
  - Finance, robotics, vision, machine translation, medicine, etc.
- Close connection between theory and practice
- Open field, lots of room for new work
- `http://www.computerworld.com/action/article.do?command=viewArticleBasic&articleId=9026623`

Course Goals

By the end of the semester, you should be able to:

- Look at a problem and identify if ML is an appropriate solution
- If so, identify what types of algorithms might be applicable
- Apply those algorithms
- Conquer the world

In order to get there, you will need to:

- Do a lot of math (calculus, linear algebra, probability)
- Do a fair amount of programming
- Work hard (this is a 3-credit class)

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I try to take your comments seriously!
(but some things won't change...)

Topics Covered

- Supervised learning: learning with a teacher
- Unsupervised learning: learning without a teacher
- Complex settings: learning in a complicated world

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  - Structured prediction
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- Complex settings: learning in a complicated world
  - Time-series models
  - Structured prediction
  - Semi-supervised learning
  - Large-scale learning
- Not a zoo tour!
- Not an introduction to tools!
- You will learn how these techniques work and how to implement them.

Syllabus

http://hal3.name/courses/2011F_ML/

On Reading and Responsibilities. . .

Reading: I expect you to do it!

(but most are $\leq$ 12 pages, all are $\leq$ 20)

Online book draft (minus the figures) linked off the web page. (Extra credit for bugs!)

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Class time is for:

- Discussing questions from the reading
  - There are questions in the margins: be prepared to answer them
- Discussing homework assignments
  - Some questions are starred: these will be presented in class
- Me providing an insider's view

Requirements and Grading

Programming projects: 27%

Written homeworks: 18%

Midterm exam: 25%
Final “practical” exam: 25%

Class/Piazza participation: 5%

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- Three total
- Teams of at most three
- May be 48 hours late, at 50% mark down

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- Canned or your choice, teams
- Presentations during the final slot

Class/Piazza participation: 5%

Grading, continued...

Grading complaints

- Not allowed after one week

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How should you spend your time?

- 3 hours in class
- 2 hours reading
- 2 hours on written assignments
- 2 hours on programming projects

Things that irk me. . . aka: I'm only human!

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  Please read the class mailing list and come to class!

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(See HW00 for your opportunity to respond!)

Things you need to do now!

Complete Homework 00

- Due 6 Sep (that's Tuesday!, by beginning of class)
- Submit in `.pdf` format *only* using handin

Complete the first reading

- See syllabus
- Due by class Tuesday (I mean it!)
- Some parts of the web page are password protected!

Sign up to get mails

- Subscribe to the Piazza group.
- But be sure to actually read it!

Read the web page!

Now, on to some real content. . .

(but first, questions?)

Classification

- How would you write a program to distinguish a picture of me from a picture of someone else?

- How would you write a program to determine whether a sentence is grammatical or not?

- How would you write a program to distinguish cancerous cells from normal cells?

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Data ("weather" prediction)

Example dataset:

Class	**Outlook**	**Temperature**	**Windy?**
Play	Sunny	Low	Yes
No play	Sunny	High	Yes
No play	Sunny	High	No
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Three principle components:

1. Class label
2. Features
3. Feature values

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A *labeled* dataset is a collection of (x, y) pairs

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Task:

Class	**Outlook**	**Temperature**	**Windy?**
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Predict the class for this "test" example"

Requires us to **generalize** from the training data

Data (face recognition)

Class	Image
Avrim	
Avrim	
Avrim	
Avrim	

Class	Image
Tom	
Tom	
Tom	
Tom	

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What is a good *representation* for images?

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What is a good *representation* for images? Pixel values?

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What is a good *representation* for images? Pixel values? Edges?

Ingredients for classification

Whole idea: Inject *your* knowledge into a learning system

Sources of knowledge:

1. Feature representation
2. Training data: labeled examples
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3. Model
   - No single learning algorithm is always good ("no free lunch")
   - Different learning algorithms work with different ways of representing the learned classifier
   - When the data has nothing to say, which model is better
   - Typically requires some control over generalization

More on generalization later. . .

Regression

Regression is like **classification**, except the labels are real values.

Example applications:

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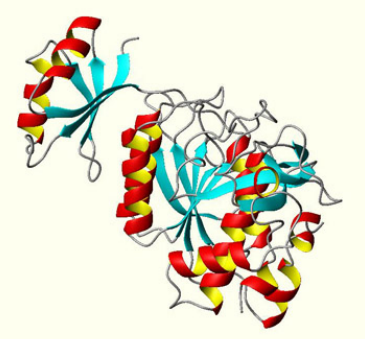

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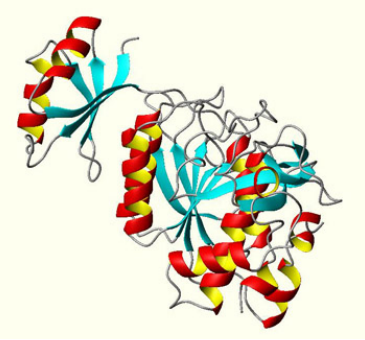

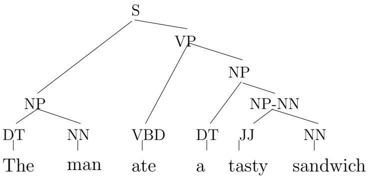

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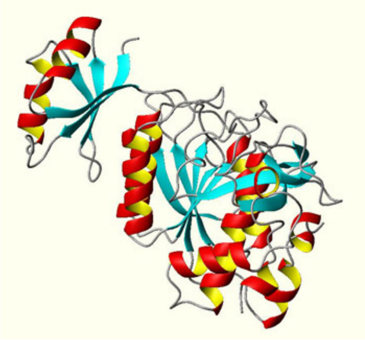

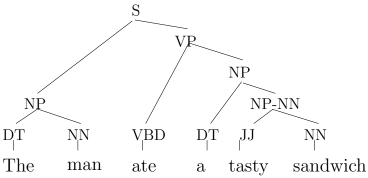

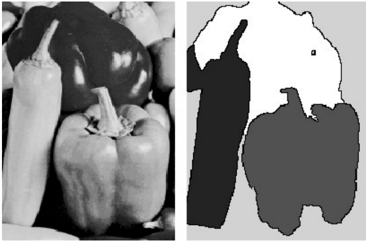

Unsupervised learning: Clustering

Two styles of clustering

1. Clustering into distinct components

2. Hierarchical clustering

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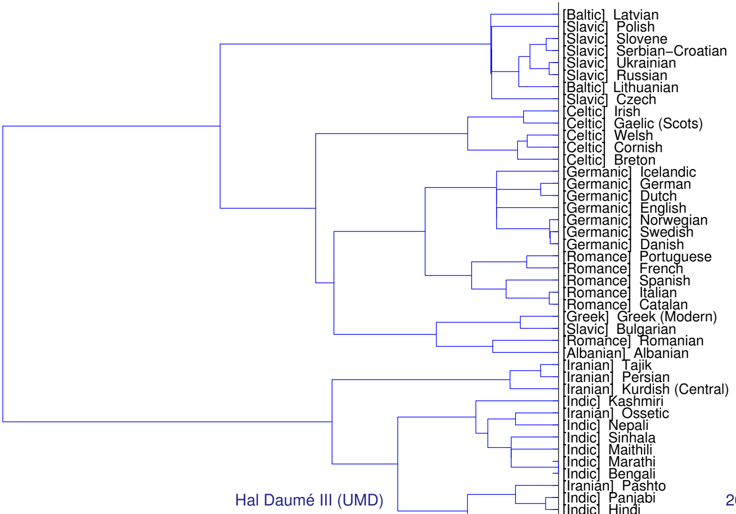
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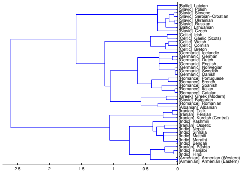

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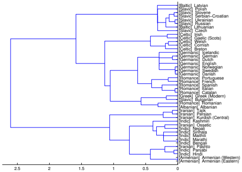

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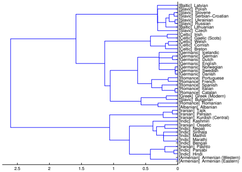
   - What is important?
   - How will we use this?



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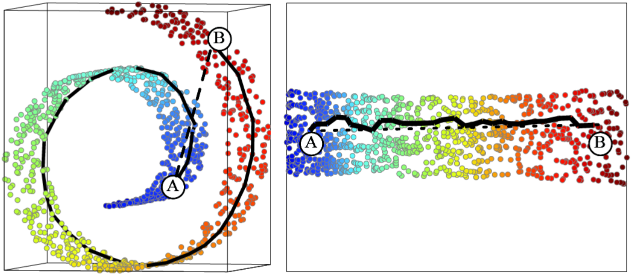

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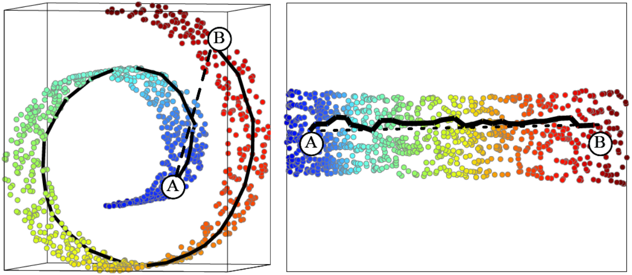

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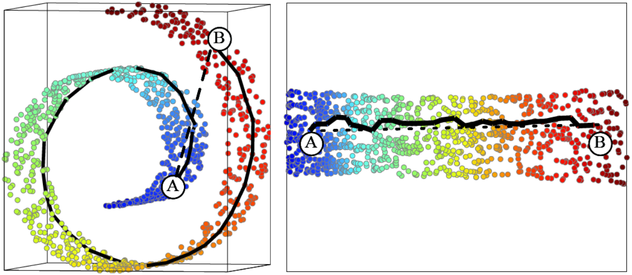

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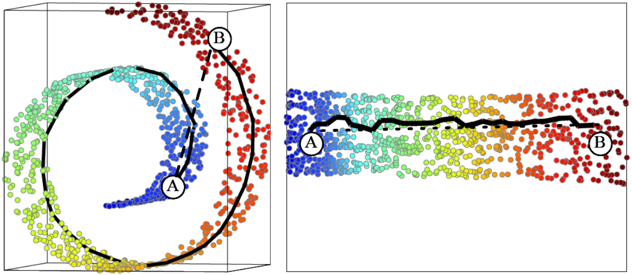

- Usually, replace “two” with “d” and “three” with “D” for $d \ll D$
- Useful for visualization (when $d \in \{2, 3\}$)
- Also useful for finding good representations for input to classifiers

Reinforcement learning

- Reinforcement learning is the penultimate ML problem
- It is “ML-hard”
- Unlike classification, regression and unsupervised learning, RL does not recieve examples
- Rather, it gathers experience by interacting with the world
- RL problems always include time as a variable

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  Example problems:

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  3. Taxi driving
- Key trade-off is exploration versus exploitation

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The *goal* of the agent is to take a sequence of actions so as to maximize its sum of rewards.

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- A state space that defines the *world* that our *agent* inhabits
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If you want to learn about RL, take AI

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Statistics makes heavy use of probability theory.

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It all started with a lady drinking tea. . .

History of ML?

- Initial attempts at object recognition [Rosenblatt, 1958]
- Learning to play checker [Samuel, 1959, 1963]
- Rosenblatt can't learn XOR [Minsky & Pappert, 1969]
- Symbolic learning, spectroscopy [Winston, 1975; Buchanan 1971]
- Backpropagation for neural nets [Werbos, 1974; Rummelhart, 1986]
- PAC model of learning theory [Valiant, 1984]
- Optimization enters machine learning [Bennett & Mangasarian, 1993]
- Kernel methods for non-linearity [Cortes & Vapnik, 1995]
- Machine learning behind day-to-day tasks [2005ish]
- Machine learning takes over the world [2010ish]