Class overview and intro to ML

Subhransu Maji

CMPSCI 689: Machine Learning

20 January 2015
Course background

- What is the course about?
  - Finding (and exploiting) patterns in data
  - Replacing “humans writing code” with “humans 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”
What is the course about?

- Finding (and exploiting) patterns in data
- Replacing “humans writing code” with “humans 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”

Why is machine learning so cool?

- Broad applicability
  - Finance, robotics, vision, machine translation, medicine, etc
  - Close connections between theory and practice
  - Open area, lots of room for new work
Course goals
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
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-unit course)
Topics covered
Topics covered

- Supervised learning: learning with a teacher
Topics covered

- Supervised learning: learning with a teacher
- Unsupervised learning: learning without a teacher
Topics covered

- Supervised learning: learning with a teacher
- Unsupervised learning: learning without a teacher
- Complex settings: learning in a complicated world
  - Time-series models
  - Structured prediction
  - Semi-supervised learning
  - Large-scale learning
Topics covered

- Supervised learning: learning with a teacher
- Unsupervised learning: learning without a teacher
- 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
Requirements and grading

- Weekly homework assignments: 20%

- Mini-projects: 45%

- Project: 30%

- Class/forum participation: 5%
Requirements and grading

- Weekly homework assignments: 20%
  - About 12 in total, graded at 0, 0.5 or 1
  - Completed individually
  - May not be late at all

- Mini-projects: 45%

- Project: 30%

- Class/forum participation: 5%
Requirements and grading

- **Weekly homework assignments: 20%**
  - About 12 in total, graded at 0, 0.5 or 1
  - Completed individually
  - May not be late at all

- **Mini-projects: 45%**
  - Three in total
  - Completed individually (but can be discussed with others)
  - May be 48 hours late, at 50% mark down

- **Project: 30%**

- **Class/forum participation: 5%**
Weekly homework assignments: **20%**
- About 12 in total, graded at 0, 0.5 or 1
- Completed individually
- May not be late at all

Mini-projects: **45%**
- Three in total
- Completed individually (but can be discussed with others)
- May be 48 hours late, at 50% mark down

Project: **30%**
- Canned or your choice, teams of two or more
- Proposal, presentation (or poster), report

Class/forum participation: **5%**
Who should take this course?

- Is this the right course for you?
  - Do you have all the pre-requisites?
    - good math and programming background
  - Balance of theory vs. practice. Other courses being offered:
    - 589 - Machine learning (but focus on applications)
    - 688 - Probabilistic graphical models (we will cover this only briefly)

- Still not sure?
  - talk to me after class

- Wait listed?
  - Will decide on a case by case basis
Course logistics

- **My office hours:** Tue 2:15-3:15 CS 142 (or by appointment)
- **TA:** Xiaojian Wu
  - TA office hours: TBD
- **Course website:** [http://www-edlab.cs.umass.edu/~smaji/cmpsci689/](http://www-edlab.cs.umass.edu/~smaji/cmpsci689/)
  - Class slides, homework assignments will be posted here
  - Check regularly for announcements
- **Moodle** for homework submission
  - Also a place for discussions
- **Edlab** for computational support (and MATLAB)
  - You may buy a student license of MATLAB for 100$
Finish homework 00
- Due 22 Jan (that’s *Thursday!* before class)
- Submit in `.pdf` format *only* via *moodle*
  - Those who are not yet on moodle may email me

Get started on p 0
- Intro to MATLAB programming
- Set up accounts on Edlab (if you don’t have MATLAB)
  - Will not be graded

Complete the first reading

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?
Classification

- How would you write a program to distinguish a picture of me from a picture of someone else?
  - Provide examples pictures of me and pictures of other people and let a classifier learn to distinguish the two.

- How would you write a program to determine whether a sentence is grammatical or not?
  - Provide examples of grammatical and ungrammatical sentences and let a classifier learn to distinguish the two.

- How would you write a program to distinguish cancerous cells from normal cells?
  - Provide examples of cancerous and normal cells and let a classifier learn to distinguish the two.
Data (“weather” prediction)

- Example dataset:

<table>
<thead>
<tr>
<th>Class</th>
<th>Outlook</th>
<th>Temperature</th>
<th>Windy?</th>
</tr>
</thead>
<tbody>
<tr>
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Data ("weather" prediction)

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- Three principal components
Data ("weather" prediction)

- Example dataset:

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- Three principal components
  1. Class label (aka "label", denoted by $y$)
Data ("weather" prediction)

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Three principal components

1. Class label (aka "label", denoted by $y$)
2. Features (aka "attributes")
Data ("weather" prediction)

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Three principal components

1. Class label (aka “label”, denoted by $y$)
2. Features (aka “attributes”)
3. Feature values (aka “attribute values”, denoted by $x$)
Data ("weather" prediction)

- Example dataset:

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- Three principal components
  1. Class label (aka “label”, denoted by $y$)
  2. Features (aka “attributes”)
  3. Feature values (aka “attribute values”, denoted by $x$)
    - Feature values can be binary, nominal or continuous
Data ("weather" prediction)

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Three principal components

1. Class label (aka "label", denoted by $y$)
2. Features (aka "attributes")
3. Feature values (aka "attribute values", denoted by $x$)
   - Feature values can be binary, nominal or continuous

A labeled dataset is a collection of $(x, y)$ pairs
Data ("weather" prediction)

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Task:

Predict the class of this “test” example

<table>
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<th>Class</th>
<th>Outlook</th>
<th>Temperature</th>
<th>Windy?</th>
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<tbody>
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<td>???</td>
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### Data (“weather” prediction)

- **Example dataset:**

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- **Task:**

- **Predict the class of this “test” example**
- **Requires us to generalize from the training data**
### Data (face recognition)

<table>
<thead>
<tr>
<th>Class</th>
<th>Image</th>
<th>Class</th>
<th>Image</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avrim</td>
<td><img src="image1" alt="Image" /></td>
<td>Tom</td>
<td><img src="image2" alt="Image" /></td>
</tr>
<tr>
<td>Avrim</td>
<td><img src="image3" alt="Image" /></td>
<td>Tom</td>
<td><img src="image4" alt="Image" /></td>
</tr>
<tr>
<td>Avrim</td>
<td><img src="image5" alt="Image" /></td>
<td>Tom</td>
<td><img src="image6" alt="Image" /></td>
</tr>
<tr>
<td>Avrim</td>
<td><img src="image7" alt="Image" /></td>
<td>Tom</td>
<td><img src="image8" alt="Image" /></td>
</tr>
</tbody>
</table>
What is a good representation for images?
What is a good representation for images? Pixel values?
What is a good *representation* for images? Pixel values? Edges?
Ingredients for classification
Ingredients for classification

- **Whole idea:** *Inject your* knowledge into a learning system
Ingredients for classification

- **Whole idea:** Inject your knowledge into a learning system
- **Sources of knowledge:**
  1. Feature representation
  2. Training data: labeled examples
  3. Model
Whole idea: *Inject your knowledge into a learning system*

**Sources of knowledge:**

1. Feature representation
   - Not typically a focus of machine learning
   - Typically seen as “problem specific”
   - However, it’s hard to learn from bad representations

2. Training data: labeled examples

3. Model
Ingredients for classification

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

- **Sources of knowledge:**
  1. Feature representation
     - Not typically a focus of machine learning
     - Typically seen as “problem specific”
     - However, it’s hard to learn from bad representations
  2. Training data: labeled examples
     - Often expensive to label lots of data
     - Sometimes data is available for “free”
  3. Model
Ingredients for classification

- **Whole idea:** Inject *your* knowledge into a learning system
- **Sources of knowledge:**
  1. Feature representation
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     - However, it’s hard to learn from bad representations
  2. Training data: labeled examples
     - Often expensive to label lots of data
     - Sometimes data is available for “free”
  3. Model
     - No single learning algorithm is always good ("no free lunch")
     - Different learning algorithms work with different ways of representing the learned classifier
Regression
Regression is like classification except the labels are real valued
Regression

- **Regression** is like **classification** except the **labels are real valued**

- Example applications:
Regression

- **Regression** is like **classification** except the **labels are real valued**

- **Example applications:**
  - Stock value prediction
Regression

- **Regression** is like **classification** except the **labels are real valued**

- **Example applications:**
  - Stock value prediction
  - Income prediction
Regression

- **Regression** is like **classification** except the **labels are real valued**

- **Example applications:**
  - Stock value prediction
  - Income prediction
  - CPU power consumption
Regression

- Regression is like classification except the labels are real valued

- Example applications:
  - Stock value prediction
  - Income prediction
  - CPU power consumption
  - Your grade in CMPSCI 689
Structured prediction
Structured prediction
Structured prediction

Being played in Australia tri-series one-day international cricket match can be a Sunday Super Sunday. Australia and India will face each host in Melbourne. The first match Australia beat England by three wickets with a superb debut of bonus points. The hands of the one-day series in India before Australia lost 0-2 in the four-Test series. After the end of the third Test draw India captain Mahendra Singh Dhoni was also announced his retirement from Test cricket. Now is not the right day of Test cricket whiles Dhoni color jersey will be anxious to show his usual self.

The dog chased the black cat.
Structured prediction

Being played in Australia tri-series one-day international cricket match can be a Sunday Super Sunday. Australia and India will face each host in Melbourne. The first match Australia beat England by three wickets with a superb debut of bonus points. The hands of the one-day series in India before Australia lost 0-2 in the four-Test series. After the end of the third Test draw India captain Mahendra Singh Dhoni was also announced his retirement from Test cricket. Now is not the right day of Test cricket whiles Dhoni color jersey will be anxious to show his usual self.

The dog chased the black cat.
Two types of clustering

1. Clustering into distinct components

2. Hierarchical clustering
Unsupervised learning: Clustering

- Two types of clustering
  1. Clustering into distinct components
  2. Hierarchical clustering
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   - How many clusters are there?

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- Two types of clustering
  1. Clustering into distinct components
    - How many clusters are there?
    - What is important? Person? Expression? Lighting?
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- North American birds
- Perching birds
- Jays, magpies, crows

http://vision.ucsd.edu/~gvanhorn/
Two types of clustering

1. Clustering into distinct components
   - How many clusters are there?
   - What is important? Person? Expression? Lighting?

2. Hierarchical clustering
   - What is important?
   - How will we use this?
Often data that is *really* two dimensional is *embedded* in a higher dimensional space, sometimes warped

Task is to *recover* the true geometry of the underlying data
Often data that is really two dimensional is embedded in a higher dimensional space, sometimes warped

Task is to recover the true geometry of the underlying data

- Usually, replace “two” with $d$ and “three” with $D$ for $d << D$
- Useful for visualization (when $d = 2$ or $3$)
- Also useful for finding good representations for input to classifiers
Unlike classification, regression and unsupervised learning, RL does not receive examples.

Rather, it gathers experience by interacting with the world.

RL problems always include time as a variable.

Example problems:

1. Chess
2. Robot control
3. Taxi driving

Key trade-off is exploration versus exploitation.
Reinforcement learning: general setting
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- A (simple) reinforcement learning problem is defined by:
  - A state space that defines the world that our agent inhabits
  - A set of actions that an agent can take in any state
  - The reward the agent gets for reaching some particular state
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Trivia: UMass played a significant role in advancing RL.
Why do we care about math?!

- Calculus and linear algebra
  - Techniques for finding maxima/minima of functions
  - Convenient language for high dimensional data analysis
- Probability
  - The study of the outcomes of repeated experiments
  - The study of the plausibility of some event
- Statistics:
  - The analysis and interpretation of data
- Statistics makes heavy use of probability theory
Recall, statistics is the analysis and interpretation of data.

In machine learning, we attempt to generalize from one “training” data set to general “rules” that can be applied to “test” data.

How is machine learning different from statistics?
1. Stats care about the model, we care about predictions.
2. Stats care about model fit, we care about generalization.
3. Stats tries to explain the world, we try to predict the future.
Why do we care about probability & statistics?

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And 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 [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]
Slide credits

- These content of slides are adapted from the machine learning course taught by Hal Daume’s at University of Maryland, College Park
- The figure on the hierarchical clustering of birds is from Grant Van Horn’s webpage http://vision.ucsd.edu/~gvanhorn/ (Take a look at the page for an interactive version)