CMSC 422: Machine Learning

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01 Sep 2015

Course Background

What is this course about?

- Finding (and exploiting) patterns in data
- Replacing “human writing code” with “human supplying data”
  - $\Rightarrow$ System figures out what the person wants based on examples
  - $\Rightarrow$ Need to abstract from “training” examples to “test” examples
  - $\Rightarrow$ 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. . .)

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- 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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- Not an introduction to tools!

- You will learn how these techniques work and how to implement them.

Syllabus

On Piazza, linked from

`http://hal3.name/`

Reading: I expect you to do it!

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

Online book draft (missing some figures) linked off the web page.

(Extra credit for new/unique bugs submitted or *fixed* on GitHub!)

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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 / labs
  - On each homework you must answer a “what didn’t you understand” question
- Me providing an insider’s view

Things you need to do now!

Complete Homework 00

- Due 08 Sep (that's next Tuesday!, by 8:00a)
- Submit using handin

Complete the first reading

- See syllabus
- Due by class Thursday (I mean it!)

Sign up to get mails

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

Read the Piazza course description information!

Now, on to some real content. . .

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- Training/testing

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- 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
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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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Predict the class for this "test" example"

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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

Ingredients for classification

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

Sources of knowledge:

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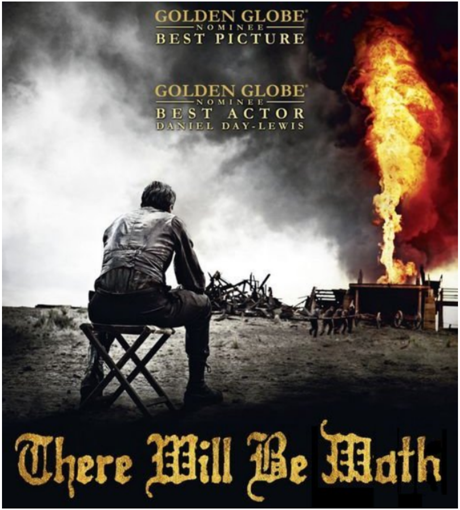
   - No single learning algorithm is always good ("no free lunch")
   - Different learning algorithms work with different ways of representing the learned classifier
   - When the data has nothing to say, which model is better
   - Typically requires some control over generalization

More on generalization later. . .

Why do we care about math?!

- **Calculus and linear algebra:**
- **Probability:**
- **Statistics:**



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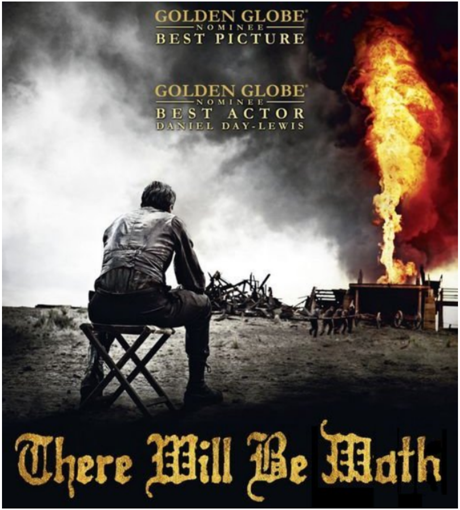

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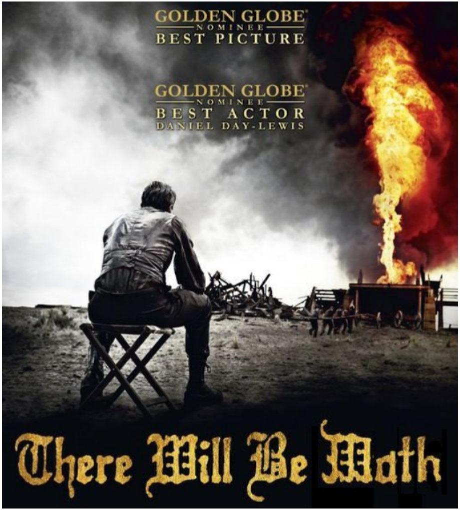

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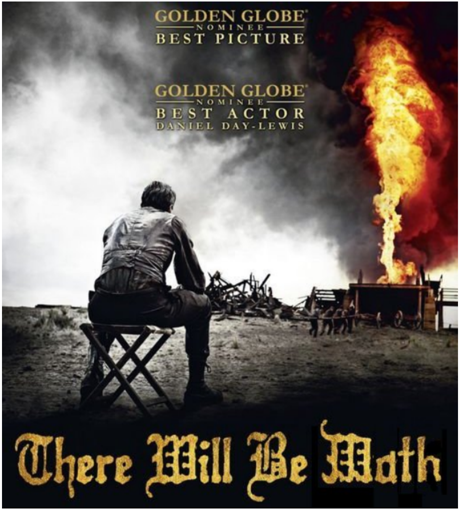

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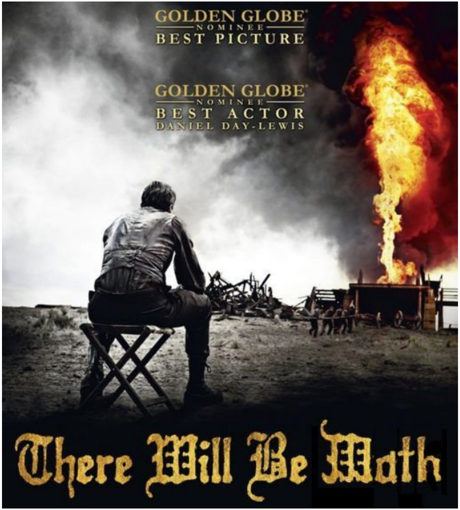

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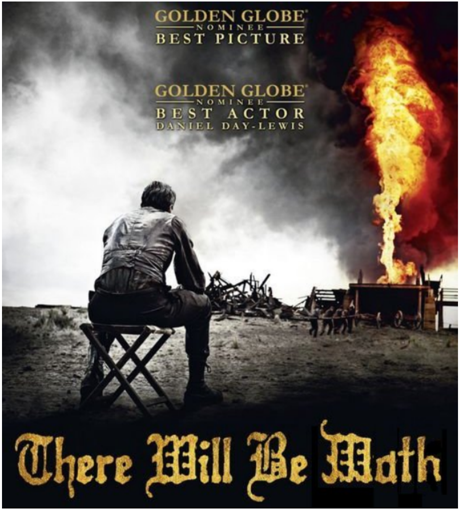
  1. The analysis and interpretation of data



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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]
- Neural networks and the biggest come-back ever [2013ish]