CSC 503/SENG 474
Data Mining

Nishant Mehta

Data Mining

- What is Data Mining?
  - Data Mining is roughly about finding patterns in large data sets. Data mining as a term has its origins more from the database community. A related term is “Knowledge discovery in databases”. Things like exploratory data analysis fit better within data mining than machine learning.
- Many of the tools are similar to tools from machine learning, but the purpose is somewhat different. Data Mining typically is more about obtaining some understanding/knowledge
- Draws from statistics, machine learning, and databases

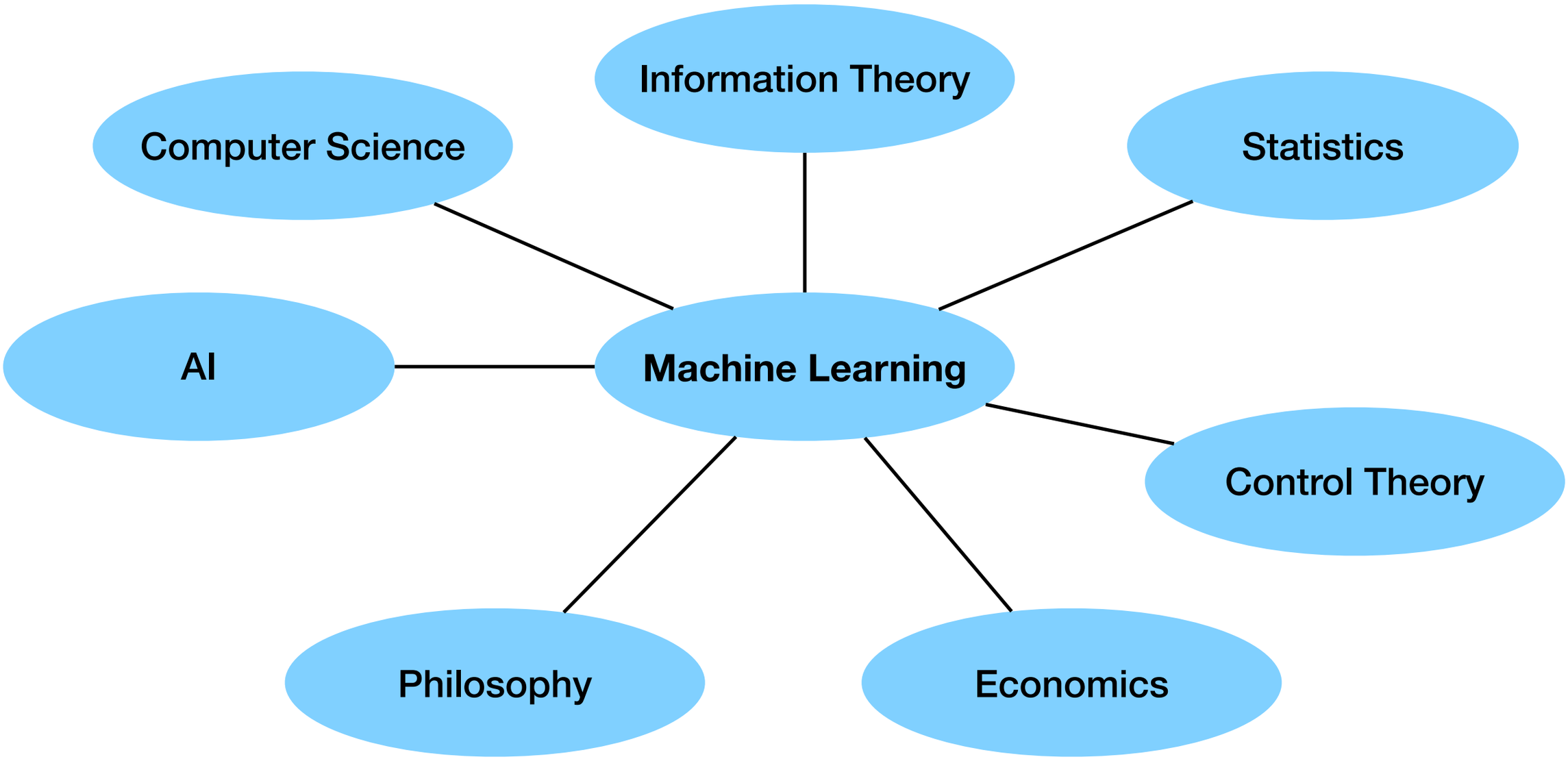
Machine Learning

- Machine learning is more about performing well on some learning task, as measured by minimizing prediction error. There can be a pattern, but we might not care about having some compact description of it. Prediction error is everything.

- There is a tremendous amount of overlap between statistics and machine learning. The label “statistician” or “machine learning person” says more about the types of problems you care about and how you study those problems.

- Things like reinforcement learning and online learning (especially against adversarial opponents) fit better with machine learning than data mining

Connections to other fields



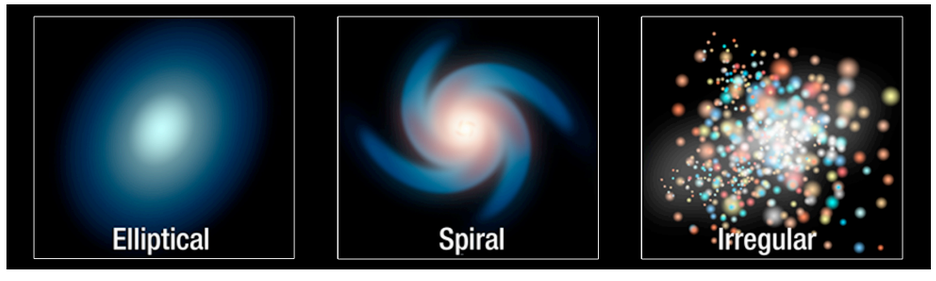
Motivation for Machine Learning

- A lot of tasks that are tedious or less interesting to humans could be handled by machines

- Some tasks are too challenging for humans. Why?

- Patterns are too hard to find (spotting forgeries)

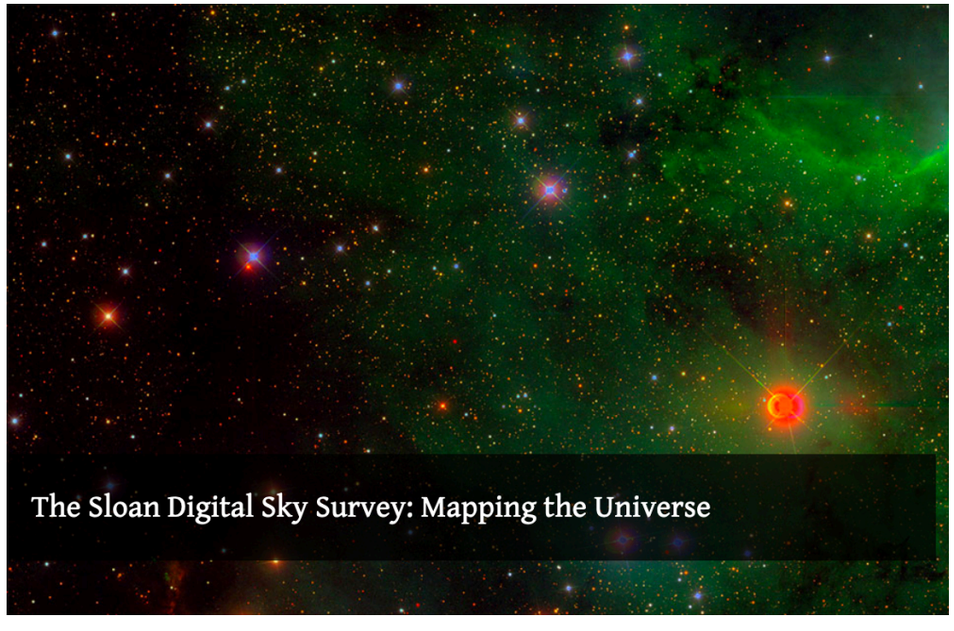
- Volume of data is too large (classify all galaxies present in a telescope capture of the sky)



The new tool in the art of spotting forgeries: artificial intelligence

Instead of obsessing over materials, the new technique takes a hard look at the picture itself – specifically, the thousands of tiny individual strokes that compose it

▲ Johannes Vermeer's Girl with a Pearl Earring, circa 1665. Photograph: Mauritshuis, The Hague



Anti-motivation for machine learning

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- The machines will take over and eliminate us
- *OR* the machines will take over and we will not even be worthy of consideration; so, we'll exist but simply be irrelevant and live at the whimsy of the machines

Anti-motivation for ~~machine learning~~ artificial intelligence

- The machines will take over and eliminate us
- *OR* the machines will take over and we will not even be worthy of consideration; so, we'll exist but simply be irrelevant and live at the whimsy of the machines
- BUT, Machine Learning is about excelling at particular tasks, while AI is about getting general, problem-solving agents
- A deep philosophical question: In the short-term, the pros might outweigh the cons. In the long term:

I think that is the single biggest existential crisis that we face and the most pressing one.

Formally…

A computer program is said to learn from experience *E* with respect to some class of tasks *T* and performance measure *P*, if its performance at tasks in *T*, as measured by *P*, improves with experience *E*.

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- Class of tasks?
  - Handwriting classification, face recognition, product recommendations, predicting stock prices, playing checkers/Go/Starcraft
- Performance measure?
  - Accuracy, Percentage of Games won
- Experience?
  - Data!

Examples of Learning

Task	Performance Measure	Experience
Classifying images of cats and dogs 	Percent of images in test set that are correctly classified	Training set of images with ground truth (i.e. correct) classifications
Playing Go 	Percent of games won against opponents	Records of previous games between humans, as well as playing practice games with itself

Three main types of machine learning

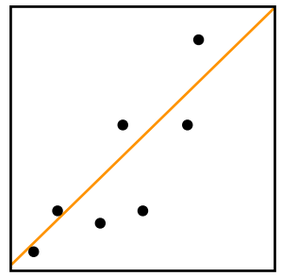
- Supervised learning
  - Prediction: Classification, Regression
- Unsupervised learning
  - Clustering, Density Estimation
- Reinforcement learning
  - Playing Games

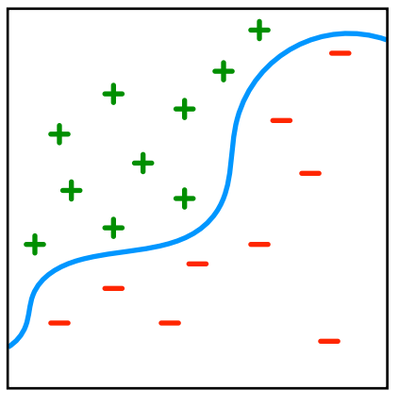
Three main types of machine learning

Supervised Learning

- Prediction tasks, like classification and regression

- Input: a training set consisting of labeled examples consisting of both
  - *input features* describing the example
  - a special feature we are trying to predict, the *class label* (classification) or *target* (regression)



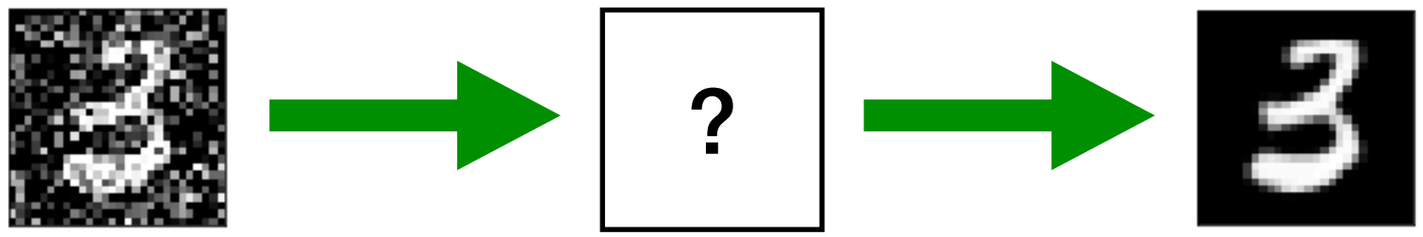


- Goal: learn (and output) a hypothesis that accurately predicts the label given the input features

Three main types of machine learning

Unsupervised Learning

- Input: a training set of examples (without labels)
- Goal: find a new representation of the data
- Examples:
  - Clustering: Group each example into one of *k* clusters
  - Density estimation: Model the underlying probability distribution that generates the data
  - Auto-encoding: Find new representation of input example to approximately reconstruct original example



Three main types of machine learning

Reinforcement Learning

- More on this later. Be sure do to the first assigned reading (Chapter 1 of Mitchell)

Real-world example of supervised learning

- You go into a coffee shop and want to predict whether or not the barista will make a good espresso.

- Suppose that you've collected some features about previous baristas and the resulting expresso quality

Baristas

Homo Hipstericus

Hat

Hipster glasses

Hipster mustache

Tattoo

Homo Hipstericus

Generalization

Hipster	Australian	Sleepy	Espresso Label
No	Yes	No	**Good**
No	No	No	**Bad**
Yes	No	No	**Good**
No	Yes	Yes	**Bad**
No	Yes	No	**Good**

Let’s infer a rule.

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Also, being a hipster also seems to result in a good espresso.

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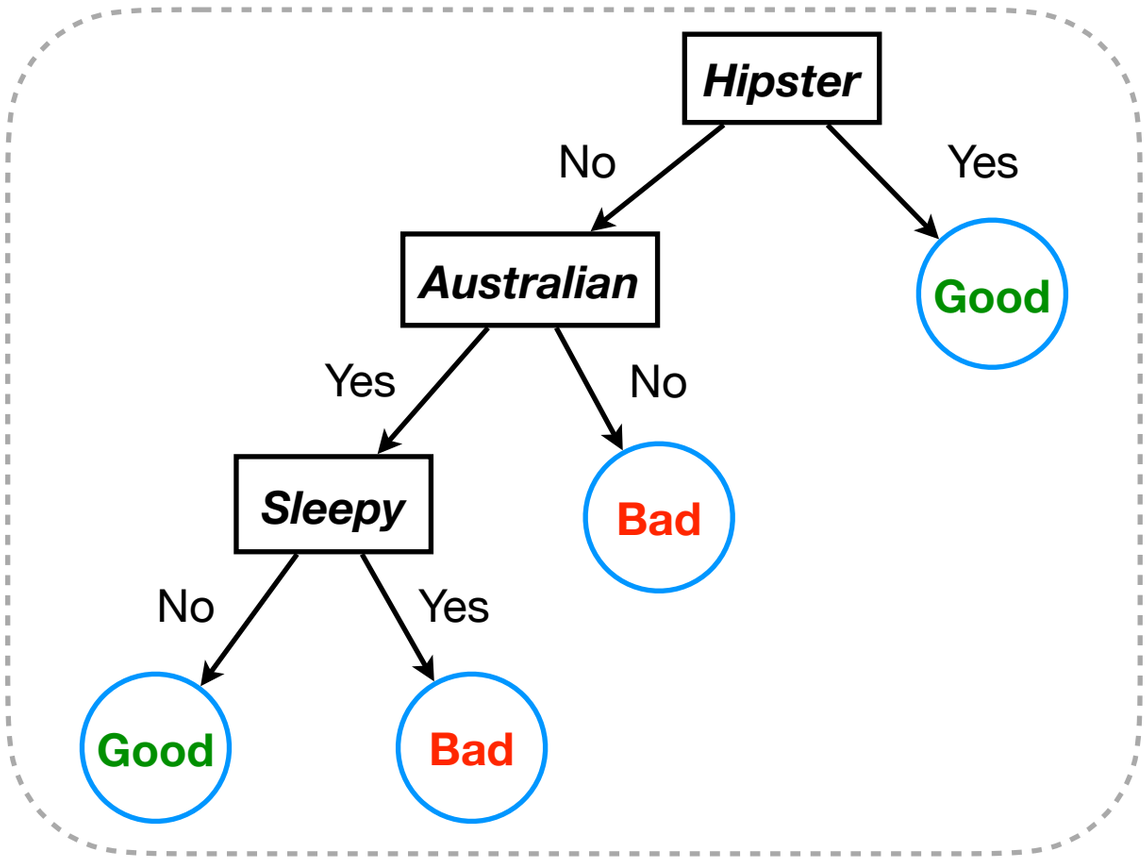
Let's infer a rule.

It looks like being a not-sleepy Australian is sufficient for making a good espresso.

Also, being a hipster also seems to result in a good espresso.

A not-sleepy non-Australian that is not a hipster seems to make a bad espresso.



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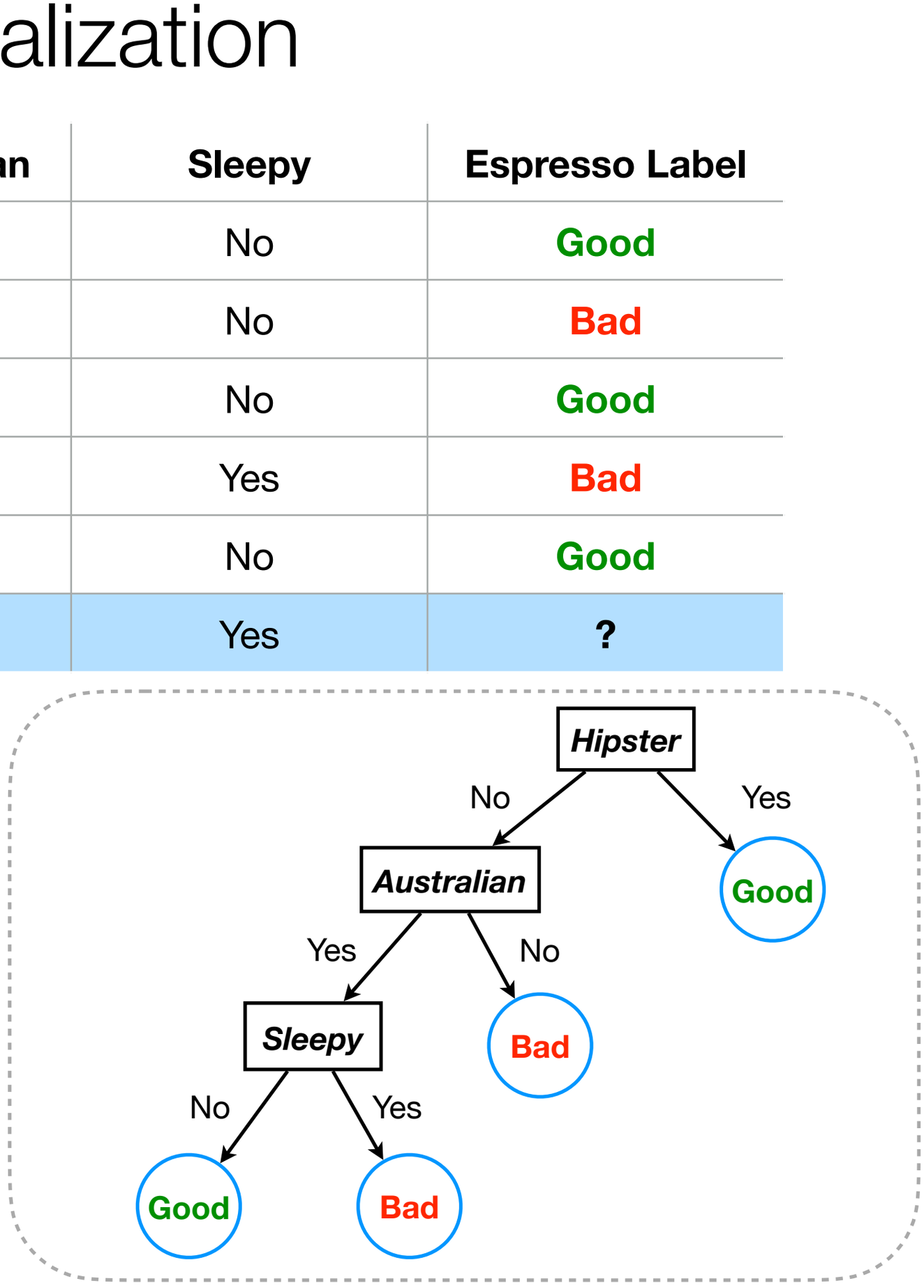
Yes	Yes	Yes	**?**

How about this espresso?

Our classifier predicts **Good**

But we are *generalizing*

(we never saw this example before)



Data can be noisy

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What if we are missing the feature “Australian” and we run into this barista?

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What if we are missing the feature “Australian” and we run into this barista?

For the same features, we have conflicting labels! This is a noisy label situation.

How to predict?

Data can be noisy

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How to predict?

Idea: Go with the class label which seems more likely, conditional on the features.

Predict Good

Course webpage

- https://web.uvic.ca/~nmehta/data_mining_fall2023

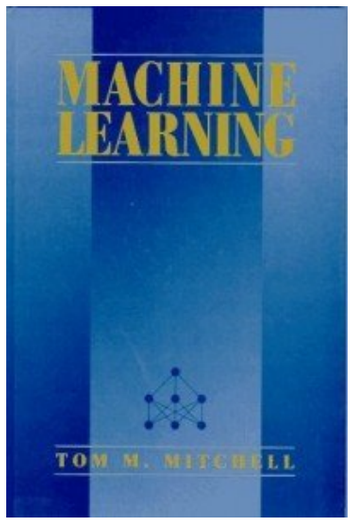
- I'll update this webpage frequently, so check it often. On the webpage, you can find:
  - The schedule, including planned topics
  - Required readings and some optional readings
  - Lecture slides and written notes

This course is math-intensive

- We'll use statistics
  - We'll take expectations and play with conditional probability.
- We'll use calculus (rarely integration though):
  - We'll often take gradients of univariate functions
- We'll use linear algebra: linear algebra review
  - We'll multiply matrices and vectors
  - We'll see singular values and eigenvalues of matrices
- All this will combined with programming; you'll implement math-based algorithms in Python (or your favorite language)

Textbooks

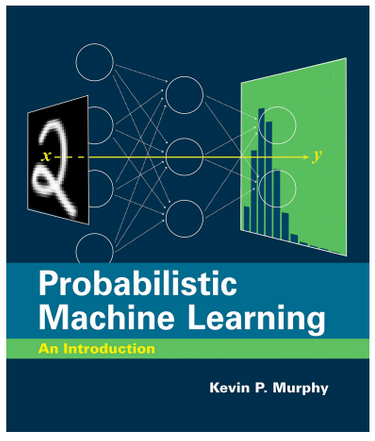
- Many required readings will be from:



Machine Learning
Tom Mitchell. McGraw Hill (1997)

- Yes, that's right, 1997. However, this is still THE best book for an introduction to machine learning

- Another book you could use is:



Probabilistic Machine Learning: An Introduction
Kevin Murphy. MIT Press (2022)

- A lot of the topics we cover are also in this book.

Grading

Undergrads

- 3 Assignments: 30% total
- Midterm: 20%
- Final exam: 25%
- Project: 25%

Grad students

- 2 Assignments: 20% total
- Midterm: 20%
- Final exam: 25%
- Project: 25%
- Advising an undergrad group: 10%

The Project

- The project is a major component of the course
- This is a group project. Each group is of between 4 to 6 people. It is better to have a group of 6, in case any group member drops the course.
- This is a machine learning course, so everyone working in a group needs to have a machine learning contribution (e.g. one person cannot have the sole task of gathering data).

The Project

- Initial Proposal - *Friday, Sept 22nd*
- Group Formation - *Friday, Sept 29th*
- Formal Proposal - *Monday, Oct 16th*
- Progress Report - *Monday, Nov 13th*
- Final Presentation - *tentatively Nov 24th, Nov 28th, and Dec 1st*
- Final Report - *Monday, Dec 4th*

TAs and Labs

- The TAs are Yibo Liu, Yifeng Bie, and Andrea Nguyen
- The labs will be based on Jupyter Notebooks
- Tentative plan: first lab on Monday, September 18th