Admin

- **EVERYONE**: sign in (separate sheets for registered and waitlist)

- **Waitlist**: come to either lab (1:15pm or 3pm)

- **Registered**: must come to your assigned lab section unless you have found someone to switch with you (email me ASAP if that’s the case)

- We are looking for 1 person to switch from B to A
Outline for January 23

• Welcome + what is Machine Learning (ML)?

• Examples of ML

• Syllabus highlights

• ML terminology

• Notation for this class

• First algorithm: K-nearest neighbors
Outline for January 23

- Welcome + what is Machine Learning (ML)?
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- First algorithm: K-nearest neighbors
Discuss with a Partner

• Introduce yourselves

• Come up with your own definition of “Machine Learning”

• How is Machine Learning different from or similar to:
  – Statistics
  – Data mining
  – Psychology of learning
What is Machine Learning?

• “Machine Learning is the study of methods for programming computers to learn.”

-Tom Dietterich
What is Machine Learning?

- “Machine Learning is the study of methods for programming computers to learn.”

  - Tom Dietterich

- “Machine Learning seeks to answer the question: ‘How can we build computer systems that automatically improve with experience, and what are the fundamental laws that govern all learning processes?’ ”

  - Tom Mitchell
Why would we want ML?
Why would we want ML?

1) No human experts

Example: predicting failure points for new machines

Adapted from “Machine Learning” by Tom Dietterich
Why would we want ML?

1) No human experts
   Example: predicting failure points for new machines

2) Human experts cannot explain expertise
   Example: cannot explain exactly what a handwritten “2” looks like

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   Example: predicting the stock market

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2) Human experts cannot explain expertise
   Example: cannot explain exactly what a handwritten “2” looks like

3) Phenomena change rapidly
   Example: predicting the stock market

4) Customization for each user
   Example: program that adapts to each user’s speech

Adapted from “Machine Learning” by Tom Dietterich
ML and related fields

• **Statistics**: understanding phenomenon that generated the data
ML and related fields

• **Statistics**: understanding phenomenon that generated the data

• **Data Mining**: find patterns in data that are understandable to humans

Adapted from “Machine Learning” by Tom Dietterich
ML and related fields

- **Statistics**: understanding phenomenon that generated the data

- **Data Mining**: find patterns in data that are understandable to humans

- **Psychology of learning**: understand the mechanisms behind how humans learn

Adapted from “Machine Learning” by Tom Dietterich
One more definition of ML

**Traditional Programming**

- Data → Computer → Output
- Program

**Machine Learning**

- Data → Computer → Program
- Output
One more definition of ML

**Traditional Programming**

- Data → Computer → Output
- Program → Computer

**Machine Learning**

- Data → Computer → Program
- Output → Computer

Function

---

Slide credit: Jessica Wu
Source: Pedro Domingos
Outline for January 23

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Classic examples of ML

- Email filtering (spam vs. not-spam)

<table>
<thead>
<tr>
<th>From: <a href="mailto:cheapsales@buystuffromme.com">cheapsales@buystuffromme.com</a></th>
<th>From: Alfred Ng</th>
</tr>
</thead>
<tbody>
<tr>
<td>To: <a href="mailto:ang@cs.stanford.edu">ang@cs.stanford.edu</a></td>
<td>To: <a href="mailto:ang@cs.stanford.edu">ang@cs.stanford.edu</a></td>
</tr>
<tr>
<td>Subject: Buy now!</td>
<td>Subject: Christmas dates?</td>
</tr>
<tr>
<td><strong>Deal of the week! Buy now!</strong> Rolex watches - $100 Medicine (any kind) - $50 Also low cost M0rgages available.</td>
<td>Key Andrew, Was talking to Mom about plans for Xmas. When do you get off work. Meet Dec 22? Alf</td>
</tr>
</tbody>
</table>

Images: Wikipedia, Matouš Havlena
Classic examples of ML

- Email filtering (spam vs. not-spam)
  - From: cheapsales@buystuffromme.com
    To: ang@cs.stanford.edu
    Subject: Buy now!
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    Medicine (any kind) - $50
    Also low cost mortgages available.
  - From: Alfred Ng
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    Alf

- Handwriting recognition (digits in a check)

Images: Wikipedia, Matouš Havlena
A classic example of a task that requires machine learning:
It is very hard to say what makes a 2
Classic examples of ML

- Tumor detection (benign vs. malignant)

Modern examples of ML

Self-driving cars are in our present and future

AlphaGo: plays humans never thought of

Images: Scientific American
Modern examples of ML

• Speech-to-text
• Machine translation
• Image caption generation
• Image generation from caption
• ....
Modern examples of ML

- Algorithms that learn how to create

*Image-to-Image Translation with Conditional Adversarial Nets (Nov 2016)*
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  https://www.cs.swarthmore.edu/~smathieson/teaching/s19/

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Learning Goals

• First part of the semester: focus on understanding and implementing algorithms
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• Later on: using powerful libraries (i.e. TensorFlow, Keras, etc)
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• Throughout: hypothesis development, algorithm selection, interpretation of results, iteration, conclusions
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• Throughout: hypothesis development, algorithm selection, interpretation of results, iteration, conclusions

• Language: Python3, will use numpy/scipy throughout
Topics (tentative)

- ML terminology and notation
- K-nearest neighbors
- Decision Trees
- Linear regression
- Logistic regression
- Naïve Bayes
- Ensemble methods
- Support vector machines
- Unsupervised learning
- Dimensionality reduction
- Clustering
- Neural networks
- CNNs
- GANs
- Gaussian mixture models
- Special topics in deep learning
- ML and ethics
Different Backgrounds

- Prerequisite: CS35

- CS66 could be first or last upper-level course

- May or may not have linear algebra, statistics, probability, etc

- May or may not have taken AI, computer vision, bioinformatics, NLP, etc
There will be math!

- Modern machine learning relies heavily on statistics and probability
- Our textbook is more stats-oriented, but we will not be coding in R
- Supplementary readings with CS focus
There will be math!

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THE ELEMENTS OF STATISTICAL LEARNING
Trevor Hastie, Robert Tibshirani, and Jerome Friedman

An Introduction to Statistical Learning
Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani
Course Components

• Labs (roughly 8-9 total): 35%

• Midterms (2 in-lab, week 6 and week 13): 40% (20% each)

• Final project: 15% (includes an oral presentation and “lab notebook”)

• Participation: 10%
My Expectations

• Come to class (M/W/F) and lab (W), and actively participate during both
  – Email me if you will be absent from class
  – If you are sick, do not come to class!

• Complete the weekly reading *before* lab (except this week)

• Come to office hours (Mon. 12:30-2pm, Fri. 1-3pm)
  – Occasional meetings outside of office hours are okay (keep the class size in mind)

• Post questions on Piazza
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<thead>
<tr>
<th>WEEK</th>
<th>DAY</th>
<th>ANNOUNCEMENTS</th>
<th>TOPIC &amp; READING</th>
<th>LABS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Jan 21</td>
<td>MLK Day - NO CLASS</td>
<td><strong>Introduction to Machine Learning</strong></td>
<td></td>
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<tr>
<td></td>
<td>Jan 23</td>
<td></td>
<td>• Machine learning terminology</td>
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<tr>
<td></td>
<td>Jan 25</td>
<td></td>
<td>• Notation</td>
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<td>• K-nearest neighbors</td>
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<td></td>
<td><strong>Reading:</strong></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>• <strong>Machine Learning</strong> by Tom Dietterich in Nature Encyclopedia of Cognitive Science (skim Sections 4-7)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• ISL: Sections 2.1, 2.2 (focus on 2.1 and pg. 39-42)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• (optional) ISL: Chapter 1</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>• (optional) <strong>The Discipline of Machine Learning</strong> by Tom Mitchell</td>
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(Note: you are responsible for reading the entire syllabus on the course webpage)
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6. Email: allow 24 hours for a response (more during weekends)

7. Piazza: should be used for all content/logistics questions
Participation

What counts as participation?

- Asking and answering questions in class (very important!)
  - Raise your hand (because some people are more/less comfortable shouting out answers)
  - Will call on groups, but only after giving you a few minutes to think out loud in pairs
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  – Switching “driver” and “navigator” frequently (at least every 30 min)
  – Discussing details instead of just trying to get to the end of the lab
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• Attending office hours

Sometimes participation goes too far…

• Try to avoid dominating class discussion, office hours, Piazza, pair-programming, etc
Academic Integrity

Discussing ideas and approaches to problems with others on a general level is fine (in fact, we encourage you to discuss general strategies with each other), but you should never read anyone else's code or let anyone else read your code.

• No code from online
• No code from students who took this course previously
Class Deans

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📍 Office: Parrish 130

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Black Cultural Center
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📍 Black Cultural Center Main
📍 Parrish Hall 122

Michelle D. Ray
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Dean’s Office
✉ mray2@swarthmore.edu
📞 (610) 680-5299
📍 Parrish Hall 116
Disability Services

https://www.swarthmore.edu/academic-advising-support/welcome-to-student-disability-services

Registering with the Student Disability Service

Please contact the Student Disability Services staff at studentdisabilityservices@swarthmore.edu, call Monica Vance at 610-328-7358, or Jenna Rose at 610-690-5538 to arrange an intake appointment. We are happy to hold initial appointments for incoming students by phone. If at all possible, please submit documentation of your disability in advance so that we can review it prior to talking with you. We recommend that you contact us as early as possible since some accommodations (e.g., electronic books, interpreters, etc.) can take a several weeks to arrange. We want to be sure that your needs are met in time for classes.
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Machine learning terminology

• One common style of machine learning is *classification*

• Goal: separate examples into two or more *classes* or *categories* (*discrete* setting)
Example: the classic bagel v. dog challenge

How can we distinguish between similar objects?

Images: veriy.com
Machine learning terminology

• Another common ML task is *regression*

• In this case the output or *response variable* is *continuous*
Machine learning terminology

- Another common ML task is regression

- In this case the output or response variable is continuous

Example: modeling house price as a function of size, location, year built, etc
Machine learning terminology

• *Supervised learning*: we have information about the output or response variable
  – (can be easier for the computer to learn the function between input and output)

• *Unsupervised learning*: data is unlabeled (no output/class information)
  – Note: there may not be an output to learn
Machine learning terminology

- **Training**: usually involves the program learning from many *examples* (in the supervised setting we know the “answer” or *label* and are using this to learn)

- **Testing**: program predicts output/label for new examples without using their labels
Machine learning terminology

- **Training**: usually involves the program learning from many *examples* (in the supervised setting we know the “answer” or *label* and are using this to learn)

- **Testing**: program predicts output/label for new examples without using their labels

*Caveat*: not all ML problems decompose into training and testing!
Learning System

- Learning is about **generalizing** from training data
- What does this **assume** about training and test set?

![Training data](apples_and_bananas)
![Test set](apples_and_bananas)
![Training data](apples_and_bananas)

Not always the case, but we’ll often assume it is!
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ML Notation

\[ X = \begin{bmatrix} x_1 \\ \vdots \\ x_i \end{bmatrix} \]

input/observations

\[ P = \text{# features} \]

(site, location, year built)

\[ n = \text{# data points} \]

\( X_{\text{train}} = \text{training data (75-80\%)} \)

\( X_{\text{test}} = \text{test data (20-25\%)} \)

\( X = \text{representative example} \)
\[ Y = \text{label/output/class} \]

\[ \ell = \# \text{ of classes} \]

\[
\begin{array}{c}
\text{discrete:} \\
Y = \begin{bmatrix}
\vdots \\
0 \\
\vdots
\end{bmatrix}
\end{array}
\]

\[ Y \in \mathbb{R}^n \]

\[ \text{continuous:} \quad Y \in \mathbb{R}^n \]

\[ \text{example: house price} \]

\[ \text{price} + \Delta \text{ in m} \]
Example

\[ Y = \begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix}, \quad \hat{Y} = \begin{bmatrix} 0 & 1 & 0 & 1 \end{bmatrix} \]

truth \hspace{2cm} prediction

Accuracy = \frac{1}{5} \left( 1 + 0 + 1 + 1 + 0 \right) = \frac{3}{5}