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This lecture (and all future lectures in this subject) will be recorded. If you choose to turn on your audio or video functions to participate in the class, your audio and/or video image will be recorded.

The recording will be made available to all students in the subject via LMS Lecture Capture until the end of semester.

If you prefer not to be recorded, you can choose **not** to turn on your audio or video function. It's easier for me to teach to faces than to black boxes, but this is a choice that you have. If you wish to ask a question without turning on audio or video, you can ask it in chat.

I do ask that you turn on your audio and video in breakout rooms, which are not recorded. If you do not, you won't be able to enter discussions with your fellow students.

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Lecture 1: Introduction and Overview

COMP90049
Introduction to Machine Learning

Semester 1, 2021

Lea Frermann, CIS

Roadmap

This lecture

- Introduction and Warm-up
- Housekeeping COMP90049
- Machine Learning

Intros & Warm-up

Introductions

About me

- Lecturer in CIS since 2019
- Research in natural language processing
- PhD from Edinburgh University
- 1.5 years research in industry (Amazon)

Introductions

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About you

Please go to: `pollev.com/iml2021`

Brainstorm / Discuss

What is Learning?

Brainstorm / Discuss

What is Machine Learning?

Definitions of Machine Learning

Definitions of Machine Learning

Definitions of Machine Learning

Learning what?

- **Task** to accomplish a goal, e.g.,
  - Assign continuous values to inputs (essay $\rightarrow$ grade)
  - Group inputs into known classes (email $\rightarrow$ $\{$spam, no-spam$\}$)
  - Understand regularities in the data

Learning from what?

- **Data**
- Where do the data come from? Is it reliable? Representative?

How do we learn?

- define a **model** that explains how to get from input to output
- derive a **learning algorithm** to find the best model parameters

How do we know learning is happening?

- The algorithm improves at its task with exposure to more data
- We need to be able to **evaluate** performance objectively

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About COMP90049

COMP90049 – Teaching Staff

Coordinator & Lecturer	Lea Frermann	lea.frermann@unimelb.edu.au
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	Hasti Samadi	hasti.samadi@unimelb.edu.au
	Zenan Zhai	zenan.zhai@unimelb.edu.au

COMP90049 – Organisation

- The subject will be delivered **fully online**
- I'll aim for as much interaction as possible (and desired)
- All live lectures will be recorded. All recordings and other materials will be made available online through Canvas

- **Live lectures** via Zoom for the first couple of weeks
- Afterwards possibly **pre-recorded with live Q&A sessions**
- We'll decide together as we go along

- **Live** workshops throughout the semester

Lectures

Lecture 1	Wed 17:15-18:15 Online; Zoom
Lecture 2	Fri 11:00-12:00 Online; Zoom

Lecture content

- Theory
- Derivation of ML algorithms from scratch
- Motivation and context
- Some coding demos in Python

Workshops

- **start from week 2**
- 1 hour per week
- $\sim$ 14 slots, please sign up and stick to one
- Online; live via zoom

Workshop Content

- Practical exercises
- Working through numerical examples
- Revising theoretical concepts from the lectures

Other Support

Coding drop-in sessions

Session 1	Wed 12–1 (link via Canvas Zoom)
Session 2	Fri 3:15–4:15 (link via Canvas Zoom)

- **start from week 2** and run until week 5
- you can ask questions around Python / the weekly code snippets
- **Not** an assignment consultation

COMP90049 – Subject Communication

Materials and announcements

- All materials will be made available through LMS (Canvas)
- Important news will be shared via Canvas Announcements (expect about 1 per week)

General inquiries: Piazza forum on LMS

- We encourage all students to join in discussions – answering other students' questions is one of the best ways to improve your own understanding
- Please do not post sections of your code or reports publicly on Piazza! If you must include these, private-message the instructors

Personal/private concerns: Email your tutor or lecturer

- If you email us about a general inquiry, we may ask you to re-post your question in the forum
- Please include COMP90049 in email subject

COMP90049 – Subject Communication

I am looking for 2-3 Student Representatives

- Communication channel between class and teaching team
- Collect and pass on (anonymous) feedback or complaints
- Attend a student-staff meeting during the semester (TBD)
- Represent the **diversity** of the class

Interested? Send me an email with a short paragraph on why you want this role.

Interaction and Engagement

- We'll experiment with breakout rooms, polls, shared whiteboards... please engage!
- Feel free to ask questions / use the chat / raise your hands (I'll do my best to monitor)
- Regular feedback surveys
- You are encouraged to switch on your camera in lectures and (particularly) workshops to maximize engagement. Please see the recent announcement / post on the subject Home page for acknowledgment of and details on privacy concerns.

COMP90049 – Subject Content

- **Topics** include: classification, clustering, optimization, unsupervised learning, semi-supervised learning, neural networks
- All from a theoretical and practical perspective
- Refreshers on maths and programming basics
- Theory in the lectures (some live-coding and demo-ing of libraries and toolkits)
- Hands-on experience in workshops and projects
- **Guest lecture 1**: academic writing skills
- **Guest lecture 2**: bias and fairness in machine learning

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Expected Background

Programming concepts

- We will be using **Python** and **Jupyter Notebooks**
- Basic familiarity with libraries (numpy, scikit-learn, scipy)
- You need to be able to write code to process your data, apply different algorithms, and evaluate the output
- Optional practice / demo Jupyter notebooks (most weeks)
- Optional **coding consultation sessions** in the first weeks of semester

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Mathematical concepts

- formal maths notation
- basic probability, statistics, calculus, geometry, linear algebra
- (why?)

What Level of Maths are we Talking?

$$\ln \frac{P(y=\texttt{true}|x)}{1-P(y=\texttt{true}|x)} = w \cdot f$$

$$\frac{P(y=\texttt{true}|x)}{1-P(y=\texttt{true}|x)} = e^{w \cdot f}$$

$$P(y=\texttt{true}|x) = e^{w \cdot f} - e^{w \cdot f} P(y=\texttt{true}|x)$$

$$P(y=\texttt{true}|x) + e^{w \cdot f} P(y=\texttt{true}|x) = e^{w \cdot f}$$

$$P(y=\texttt{true}|x) = h(x) = \frac{e^{w \cdot f}}{1+e^{w \cdot f}} = \frac{1}{1+e^{-w \cdot f}}$$

$$P(y=\texttt{false}|x) = \frac{1}{1+e^{w \cdot f}} = \frac{e^{-w \cdot f}}{1+e^{-w \cdot f}}$$

What Level of Maths are we Talking?

$$P(y = 1|x; \beta) = h_\beta(x)$$

$$P(y = 0|x; \beta) = 1 - h_\beta(x)$$

$$\rightarrow P(y|x; \beta) = (h_\beta(x))^y * (1 - h_\beta(x))^{1-y}$$

$$\begin{aligned} &\underset{\beta}{\operatorname{argmax}} \prod_{i=1}^{n} P(y_i|x_i; \beta) \\ =&\underset{\beta}{\operatorname{argmax}} \prod_{i=1}^{n} (h_\beta(x_i))^{y_i} * (1 - h_\beta(x_i))^{1-y_i} \\ =&\underset{\beta}{\operatorname{argmax}} \sum_{i=1}^{n} y_i \log h_\beta(x_i) + (1 - y_i) \log(1 - h_\beta(x_i)) \end{aligned}$$

Assessment

Two small coding projects (30%)

- Project 1: release week 3, due week 4
- Project 2: release week 5, due week 6
- Read in data, apply ML algorithm(s), evaluate.

Open-ended research project (30%)

- Release week 7, due week 10
- You will be given a data set and will formulate a research question and write a short research paper on your findings. You will be graded based on the quality of your report.

Final exam (40%)

- during exam period
- 2 hours; closed-book
- **Hurdle requirement:** you have to pass the exam ($\geq$ 50%).

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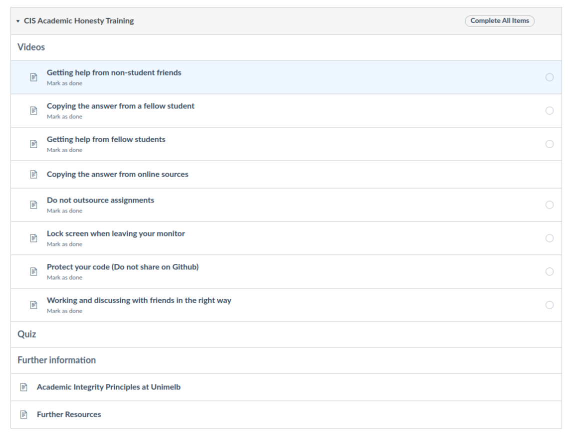
Academic Honesty

- Videos & Quiz
- Linked from Canvas 'Home' page (or in Modules)
- CIS-specific scenarios



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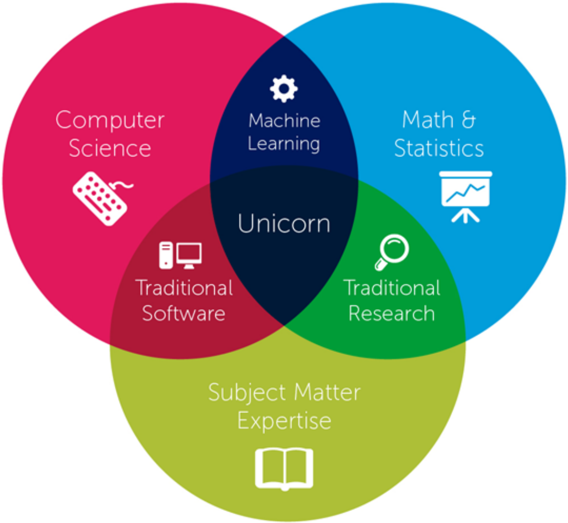
What and Why of Machine Learning?

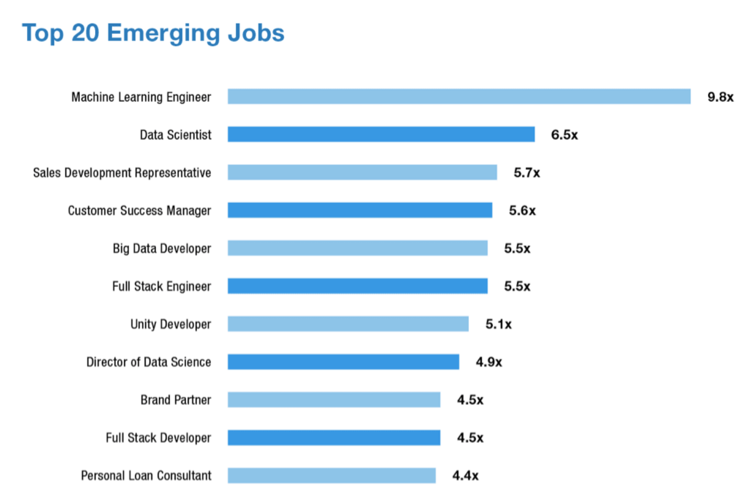
What is Machine Learning?



What is Machine Learning?

https://xkcd.com/1838/

(you're sitting in the right class!)



Source: https://www.springboard.com/blog/machine-learning-engineer-salary-guide/

Three ingredients for machine learning

... and related questions

Three ingredients for machine learning

... and related questions

1. **Data**

   - Discrete vs continuous vs ...
   - Big data vs small data
   - Labeled data vs unlabeled data
   - Public vs sensitive data

... and related questions

Models

- function mapping from inputs to outputs
- motivated by a data *generating* hypothesis
- probabilistic machine learning models
- geometric machine learning models
- parameters of the function are unknown

... and related questions

Learning

- Improving (on a task) after data is taken into account
- Finding the best model parameters (for a given task)
- Supervised vs. unsupervised learning

ML Example Problem

ML Example Problem

- Scenario 1

  You are an archaeologist in charge of classifying a mountain of fossilized bones, and want to quickly identify any “finds of the century” before sending the bones off to a museum

- Solution:

  Identify bones which are of different size/dimensions/characteristics to others in the sample and/or pre-identified bones

ML Example Problem

- Scenario 2:

  You are an archaeologist in charge of classifying a mountain of fossilized bones, and want to come up with a consistent way of determining the species and type of each bone which doesn't require specialist skills

- Solution:

  Identify some easily measurable properties of bones (size, shape, number of "lumps", ...) and compare any new bones to a pre-classified database of bones

ML Example Problem

- Scenario 3:

  You are in charge of developing the next “release” of Coca Cola, and want to be able to estimate how well received a given recipe will be

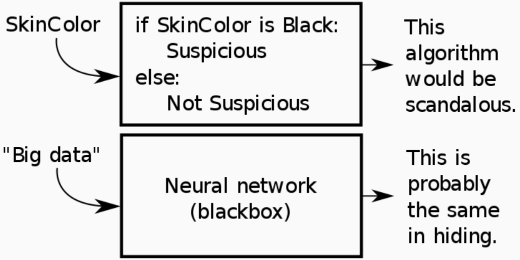
- Solution:

  Carry out taste tests over various “recipes” with varying proportions of sugar, caramel, caffeine, phosphoric acid, coca leaf extract, ... (and any number of “secret” new ingredients), and estimate the function which predicts customer satisfaction from these numbers

More Applications

- natural language processing
- image classification
- stock market prediction
- movie recommendation
- web search
- medical diagnoses
- spam / malware detection
- ...

Machine Learning, Ethics, and Transparency

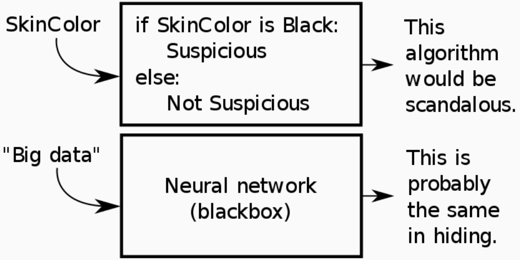


commons.wikimedia.org/wiki/File:Pseudo-algorithm_comparison_for_my_slides_on_machine_learning_ethics.svg

Def 1. **Discrimination**= To make distinctions.

For example, in supervised ML, for a given instance, we might try to discriminate between the various possible classes.

Machine Learning, Ethics, and Transparency



commons.wikimedia.org/wiki/File:Pseudo-algorithm_comparison_for_my_slides_on_machine_learning_ethics.svg

Def 2. **Discrimination**= To make decisions based on prejudice.

Digital computers have no volition, and consequently cannot be prejudiced. **However**, the data may contain information which leads to an application where the ensuing behavior is prejudicial, intentionally or otherwise.

Machine Learning gone wrong...

REUTERS

World Business Markets Breakingviews Video More

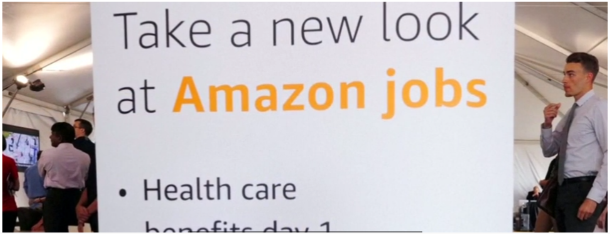
RETAIL OCTOBER 11, 2018 / 10:04 AM / UPDATED 2 YEARS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

By Jeffrey Dastin

8 MIN READ

SAN FRANCISCO (Reuters) - Amazon.com Inc's AMZN.O machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.



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Machine Learning gone wrong...

REUTERS

World Business Markets Breakingviews Video More

MEDIA AND TELECOMS MARCH 25, 2016 / 9:55 AM / UPDATED 5 YEARS AGO

Microsoft's AI Twitter bot goes dark after racist, sexist tweets

By Amy Tennery, Gina Cherelus

3 MIN READ

(Reuters) - Tay, Microsoft Corp's so-called chatbot that uses artificial intelligence to engage with millennials on Twitter, lasted less than a day before it was hobbled by a barrage of racist and sexist comments by Twitter users that it parroted back to them.

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Machine Learning gone wrong...

FRANZISKA BARCZYK

Artificial intelligence

Predictive policing algorithms are racist. They need to be dismantled.

Lack of transparency and biased training data mean these tools are not fit for purpose. If we can't fix them, we should ditch them.

by **Will Douglas Heaven** July 17, 2020

Yeshimabeit Milner was in high school the first time she saw kids she knew getting handcuffed and stuffed into police cars. It was February 29, 2008, and the principal of a nearby school in Miami, with a majority Haitian and African-American population, had put one of his students in a chokehold. The next day several dozen kids staged a peaceful demonstration. It didn't go well.

That night, Miami's NBC 6 News at Six kicked off with a segment called "Chaos on Campus." (There's a clip on YouTube.) "Tensions run high at Edison Senior High after a fight for rights ends in a battle with the law," the

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Not everything that *can* be done, *should* be done

- Attributes in the data can encode information in an indirect way
- For example, home address and occupation can be used (perhaps with other

  seemingly-banal data) to infer age and social standing of an individual
- Potential legal exposure due to implicit “knowledge” used by a classifier
- Just because you didn’t realize doesn’t mean that you shouldn’t have realized, or at least, made reasonable efforts to check

Questions to Ask

- Who is permitted to access the data?
- For what purpose was the data collected?
- What kinds of conclusions are legitimate?
- If our conclusions defy common sense, are there confounding factors?
- Could my research / application be abused (*dual use*)?

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Summary

Today

- COMP90049 Overview
- What is machine learning?
- Why is it important? Some use cases.
- What can go wrong?

Next lecture: Concepts in machine learning

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Marc Peter Deisenroth, A Aldo Faisal, and Cheng Soon Ong. Mathematics for Machine Learning. Cambridge University Press (forthcoming)

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Amazon scraps secret recruiting tool.
`https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G`

Predictive policing algorithms are racist.
`https://www.reuters.com/article/us-microsoft-twitter-bot-idUSKCN0WQ2LA`