Lecture 1: Introduction and Overview

COMP90049
Introduction to Machine Learning

Semester 2, 2022

Lida Rashidi, CIS

Acknowledgement: Lea Frermann

Roadmap

This lecture

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

Intros & Warm-up

Introductions

About Lida

- Lecturer in CIS since 2019
- Researcher in CIS since 2017 - Graph Mining and Information Retrieval
- PhD from the University of Melbourne
- 5 years of research in academia

About Joseph

- Lecturer in CIS since 2022
- Researcher in CIS since 2020 - Deep Learning for Neuroscience
- PhD from Queensland University of Technology
- 20 years of Army service in technical roles and 10 years of real estate industry experience

Introductions

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About you

Please go to: `pollev.com/comp90049`

Brainstorm / Discuss

What is Learning?

Brainstorm / Discuss

What is Machine Learning?

Definitions of Machine Learning

Some proposed definitions...

"The computer automatically learns something"

"Statistics, plus marketing"

" ... how to construct computer programs that automatically improve with experience .... A computer program is said to learn from experience ... if its performance ... improves with experience... "
Mitchell [1997, pp. xv-17]

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Definitions of Machine Learning

"We are drowning in information, but we are starved for knowledge"

John Naisbitt, Megatrends

Our definition of Machine Learning

> automatic extraction of **valid, novel, useful** and **comprehensible knowledge** (rules, regularities, patterns, constraints, models, ...) from arbitrary sets of data

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

About COMP90049

COMP90049 – Teaching Staff

Coordinator & Lecturer1	Lida Rashidi	rashidil@unimelb.edu.au
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	Jiayang Ao	jiayanga@student.unimelb.edu.au
	Chunhua Liu	chunhua@student.unimelb.edu.au
	Kazi Adnan	kazi.adnan@unimelb.edu.au

COMP90049 – Organisation

This subject is offered in **dual delivery** mode

- The lectures are **on campus** and **live-streamed** (and recorded)
- Workshops are either **on campus** or **live via Zoom**
- All live lectures will be recorded. All recordings and other materials will be made available online through Canvas
- Please tell us about your experience on dual delivery. **Your feedback is most welcome!**
- Most lectures are **live streamed** through Lecture Capture
- A few of the lectures will be **pre-recorded with live Q&A sessions**

Lectures

Lecture 1	Wed 17:15-18:15 Arts West West Wing-B101 (Kathleen Fitzpatrick Theatre)
Lecture 2	Thu 14:15-15:15 Sidney Myer Asia Ctr-B02 (Carrillo Gantner Theatre)

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
- $\sim$ 10 slots, please sign up and stick to one
- Online workshops are live via zoom and In-person workshops will be on campus

Workshop Content

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

Other Support

Coding drop-in sessions

Session 1	Tuesday 11:00–12:00 (link via Canvas Zoom)
Session 2	Friday 14:15–15:15 (link via Canvas Zoom)

- **start from week 2** and run for the first half of semester
- you can ask questions around Python / the weekly code snippets
- **Not** an assignment consultation

Assignment consultations

- 1-2 sessions per assignment for clarification. Usually half a week to a week before submission.

Possible Maths consultations

- Depends on your feedback, will survey you in week 3
- Clarify mathematical concepts (probability, optimization, ...)

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COMP90049 – Subject Communication I

For general questions

- **Default:** Post on the **Piazza** discussion board
- **Backup option 1:** Email the head tutor (Hasti) or your tutor
- **Backup option 2:** Email the lecturer

Piazza

- Actively engage by **asking and answering** questions. Peer teaching is the most effective way of learning!
- (Of course no assignment solutions should be given away. Doing – or asking for – this is academic misconduct.)

Personal/private concerns: Email head tutor or lecturer, e.g.,

- With specific assignment questions
- With private or personal concerns
- Constructive feedback, always very welcome!
- Please include COMP90049 in email subject

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COMP90049 – Subject Communication II

We need 2 or 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.

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**: Industry talk with focus on bias and fairness in machine learning

COMP90049 – Intended Learning Outcomes

- Understand elementary mathematical concepts used in machine learning
- Derive machine learning models from first principles
- Design, implement, and evaluate machine learning systems for real-world problems
- Identify the correct machine learning model for a given real-world problem

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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?

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

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

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

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

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

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

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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 2, due week 3
- Project 2: release week 5, due week 6
- Jupyter notebooks; 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;
- **Hurdle requirement:** you have to pass the exam ($\geq$ 50%).

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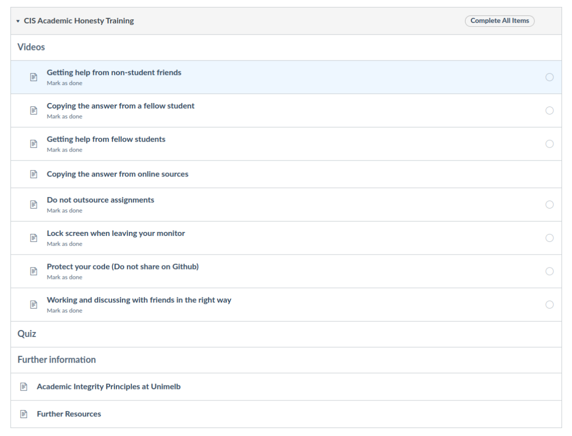
Academic Honesty

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



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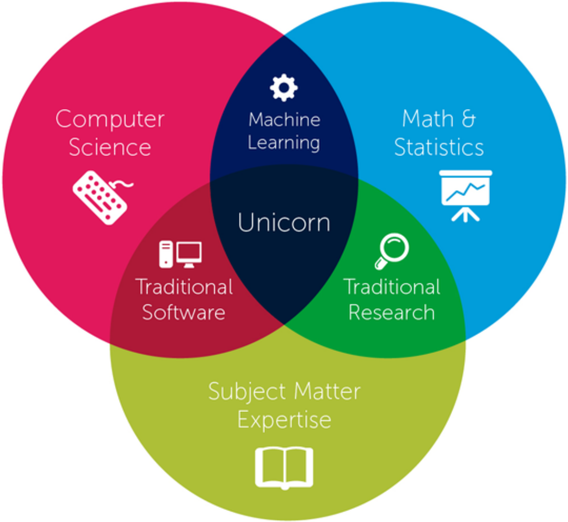
What and Why of Machine Learning?

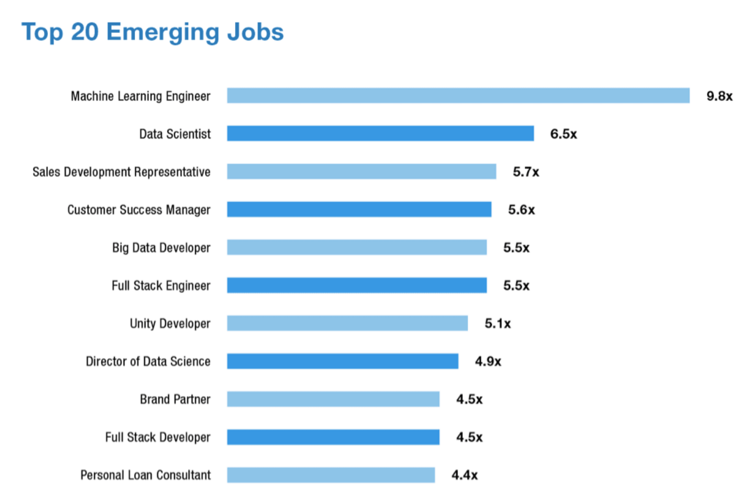
What is Machine Learning?



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

Three ingredients for machine learning

... 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

Three ingredients for machine learning

... 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

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CLUSTERING/OUTLIER DETECTION

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 2:

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SUPERVISED CLASSIFICATION ;

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

- 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

REGRESSION

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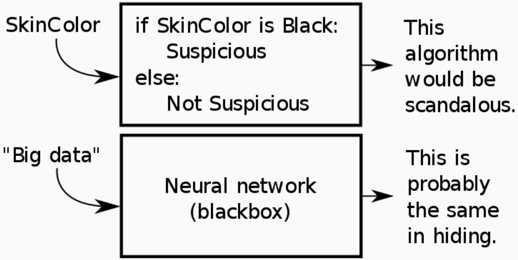
More Applications

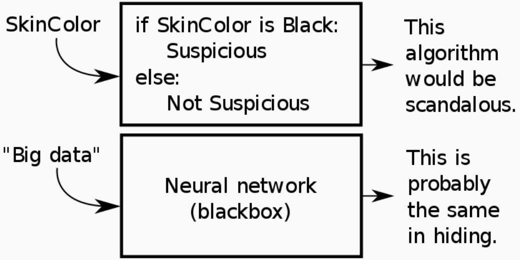
- natural language processing
- image classification
- stock market prediction
- movie recommendation
- web search
- medical diagnoses
- spam / malware detection
- ...



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.



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

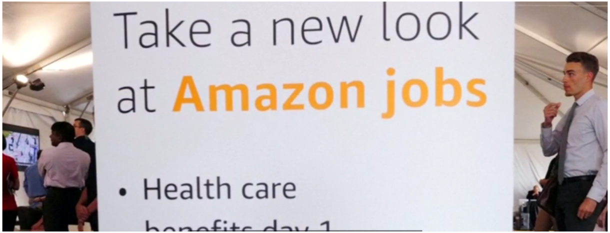
RETAIL OCTOBER 11, 2018 / 10:04 AM / UPDATED 2 YEARS AGO

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...

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Tech

Facial recognition to 'predict criminals' sparks row over AI bias

24 June 2020

A US university's claim it can use facial recognition to "predict criminality" has renewed debate over racial bias in technology.

Harrisburg University researchers said their software "can predict if someone is a criminal, based solely on a picture of their face".

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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

References i

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Tom Mitchell. Machine Learning. McGraw-Hill, New York, USA (1997).

Microsoft's AI robot goes dark.
https://www.reuters.com/article/us-microsoft-twitter-bot-idUSKCN0WQ2LA

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

Predictive policing algorithms are biased.
https://www.bbc.com/news/technology-53165286