

Lecture 1: Introduction and Overview

COMP90049

Introduction to Machine Learning

Semester 1, 2023

Lea Frermann, CIS

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This lecture

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

Intros & Warm-up

About me

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

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About you

Please go to: pollev.com/iml2023



What is learning?

Warm-up (3 minutes)

With your neighbor / in the chat:

1. Think of **3 words** that describe your expectation of this subject
2. Think of a short **definition of machine learning**?

interesting
practical
building blocks
theory
useful
- career
- money

What is machine learning?

The basic ingredients of ML

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 the data reliable? Representative?

How do we learn? : Define a model

- an algorithm to predict a certain outcome for an input
- typically a function with parameters
- 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



Lea Frermann
Coordinator
Lecturer



Kris Ehinger
Lecturer
(Weeks 2&3)



Hasti Samadi
Head Tutor
- First point of contact
- Consultations
- Assignment logistics
- Discussion Board

Coordinator	Lea Frermann	lea.frermann@unimelb.edu.au
Lecturer	Lea Frermann	lea.frermann@unimelb.edu.au
	Kris Ehinger	kris.ehinger@unimelb.edu.au
Head tutor	Hasti Samadi	hasti.samadi@unimelb.edu.au
Tutors	Tahrima Hashem	tahrima@unimelb.edu.au
	Chunhua Liu	chunhua@student.unimelb.edu.au
	Zenan Zhai	zenanz@student.unimelb.edu.au
	Kazi Adnan	kazi.adnan@unimelb.edu.au
	Jiayang Ao	jiayanga@student.unimelb.edu.au
	Kemal Kurniawan	kurniawan.k@unimelb.edu.au

The subject is offered as **dual delivery**

- Lectures are **on campus** and **live-streamed** (and recorded)
- Workshops are either **on campus** or **live on zoom** (not hybrid)
- All recordings and other materials will be made available online through Canvas

- **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
- **Guest lecture 2:** Fair machine learning at [SEEK](#) by [Fernando Mourão](#)



- 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

Lectures

Lecture 1	Tuesday 14:15 – 15:15 Medical Building C216 (Sunderland Theatre)
Lecture 2	Friday 14:15 – 15:15 Arts West West Wing-B101 (Kathleen Fitzpatrick Theatre)

- Lectures are live streamed through Lecture Capture for those who are not in Melbourne

Lectures

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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
- ~ 14 slots, please sign up and stick to one
- Online (Zoom) or face to face

Workshop Content

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

See link on Canvas homepage for schedule (subject to change). All consultations are held **online via Zoom**. Consultations are **optional** additional support. They are run based **on demand** by different tutors who will **answer your questions** on the respective materials: come prepared!

Coding consultations

- Starting week 3, for the first half of semester
- 2-hour blocks (join in at any point and stay for as long as you like)
- You can ask questions around Python / the weekly code snippets
- **Not** an assignment consultation

Maths consultations

- Starting week 3
- 1 hour at different times (changing weekly)
- Clarify mathematical concepts (probability, optimization, ...)

Assignment consultations

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



For general questions

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

Ed

- 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 lecture, e.g.,

- With specific assignment questions
- With private or personal concerns
- Constructive feedback, always very welcome!



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.



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)

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Mathematical concepts

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



What Level of Maths are we Talking?

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

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

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

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

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

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



What Level of Maths are we Talking?

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

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

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


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



Two small coding projects (total 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; open-course materials (closed everything-else!)
- **Hurdle requirement:** you have to pass the exam ($\geq 50\%$).



Academic Honesty

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



The screenshot displays the 'CIS Academic Honesty Training' interface. At the top, there is a header bar with the title 'CIS Academic Honesty Training' and a 'Complete All Items' button. Below the header, the content is organized into sections: 'Videos', 'Quiz', and 'Further information'. The 'Videos' section lists eight items, each with a document icon, a title, a 'Mark as done' link, and a progress indicator (a circle). A blue arrow points to the item 'Do not outsource assignments'. The 'Quiz' section is currently empty. The 'Further information' section contains two items: 'Academic Integrity Principles at Unimelb' and 'Further Resources'.

CIS Academic Honesty Training				Complete All Items
Videos				
	Getting help from non-student friends	Mark as done		<input type="radio"/>
	Copying the answer from a fellow student	Mark as done		<input type="radio"/>
	Getting help from fellow students	Mark as done		<input type="radio"/>
	Copying the answer from online sources			
	Do not outsource assignments	Mark as done		<input type="radio"/>
	Lock screen when leaving your monitor	Mark as done		<input type="radio"/>
	Protect your code (Do not share on Github)	Mark as done		<input type="radio"/>
	Working and discussing with friends in the right way	Mark as done		<input type="radio"/>
Quiz				
Further information				
	Academic Integrity Principles at Unimelb			
	Further Resources			

Academic Honesty



I really, really really need you to answer this tricky exam question, otherwise I my subject Introduction to Machine Learning. Can you please do this for me, chatGPT?



I'm sorry, but as an AI language model, I cannot cheat or help with academic dishonesty. It is important to be honest and ethical in your studies and academic pursuits. If you have a specific question or concept that you're struggling with, I would be happy to try to help you understand it better or provide resources to help you study. However, it's essential to put in the effort and hard work required to succeed in your studies honestly. Please let me know how I can further assist you.



 Regenerate response



[ChatGPT Feb 13 Version](#). Free Research Preview. Our goal is to make AI systems more natural and safe to interact with. Your feedback will help us improve.



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What is ChatGPT

- It's a **language model**. It was trained to reproduce the patterns with which words co-occur in English
- It has **no knowledge** beyond word co-occurrence. It does not 'know' or 'think'. It makes mistakes.

ChatGPT do's

- Play with it, **test its limits**. What works well, where does it make mistakes?
- Ask it to explain a concept you don't understand; use it for brainstorming.
- *Be critical of the output!*

ChatGPT don'ts

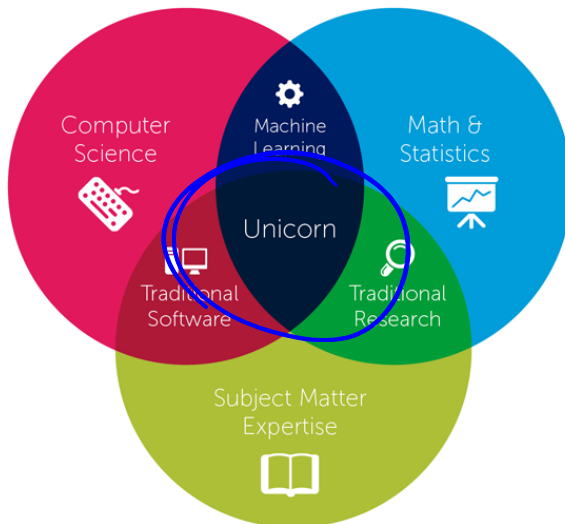
- Use it to prepare or write your assessment. Submitting work that is not your own counts as academic misconduct. AI-generated material is not your work.
- For more information, see the university's [policy](#).

In Lecture 18 we'll do a deep dive into chatGPT!



What and Why of Machine Learning?

What is Machine Learning (...not)?



What is Machine Learning (...not)?



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

- Scenario 1

You are a data scientist at a new streaming service for Australian music. You just got access to data collected from your first 10,000 customers (location, clicks, listening time, etc). You want to get a better idea about types of typical customer behavior to further improve your service. What would you do?

- Scenario 1

You are a data scientist at a new streaming service for Australian music. You just got access to data collected from your first 10,000 customers (location, clicks, listening time, etc). You want to get a better idea about types of typical customer behavior to further improve your service. What would you do?

- Solution:

Identify groups of customers that share similar behavior, e.g., like the same kinds of music; or stay for a similar amount of time on the website

CLUSTERING



- Scenario 2:

The streaming service has run for a number of months, and collected some popularity data on the listed songs (e.g., number of times listened to). Each week several hundred new bands want to be listed on the platform, and you want to quickly determine which ones are likely promising.

- Scenario 2:

The streaming service has run for a number of months, and collected some popularity data on the listed songs (e.g., number of times listened to). Each week several hundred new bands want to be listed on the platform, and you want to quickly determine which ones are likely promising.

- Solution:

Identify some easily measurable and relevant properties of the bands: genre, song length, etc and compare them to the corresponding properties of successful bands (or songs) already listed on the platform.

SUPERVISED CLASSIFICATION



- Scenario 3:

Now you want to get more specific: for a given new song you want to estimate the number of times it will be listened to in the first two weeks after being listed on the platform.

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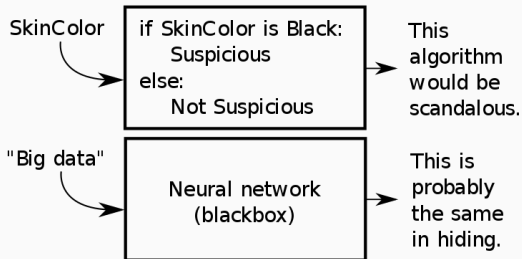
- Solution:

Again, define a set of relevant properties of songs. Take the songs already listed on the platform, and their associated known clicks. Estimate a function predicts the number of clicks based on your defined feature set.

REGRESSION



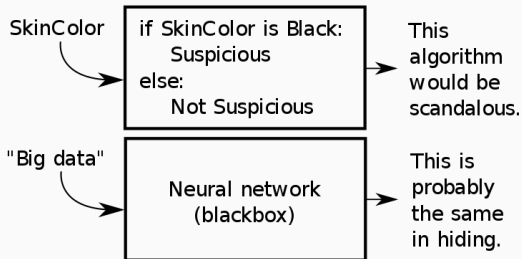
- natural language processing
- image classification
- stock market prediction
- movie recommendation
- web search
- medical diagnoses
- spam / malware detection
- ...



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.



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

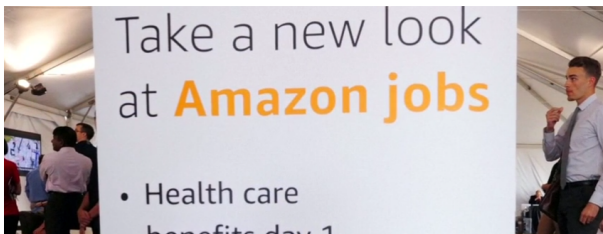
Amazon scraps secret AI recruiting tool that showed bias against women

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.



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 Tennerly, Gina Cherehus

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.





FRANÇOIS DARUET

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



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*)?



Today

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

Next lecture: Concepts in machine learning

Jacob Eisenstein. Natural Language Processing. MIT Press (2019)

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

Chris Bishop. Pattern Recognition and Machine Learning. Springer (2009)

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



Microsoft's AI robot goes dark.

[https:](https://www.reuters.com/article/us-microsoft-twitter-bot-idUSKCNOWQ2LA)

[//www.reuters.com/article/us-microsoft-twitter-bot-idUSKCNOWQ2LA](https://www.reuters.com/article/us-microsoft-twitter-bot-idUSKCNOWQ2LA)

Amazon scraps secret recruiting tool.

[https://www.reuters.com/article/](https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G)

[us-amazon-com-jobs-automation-insight-idUSKCN1MK08G](https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G)

Predictive policing algorithms are racist.

[https:](https://www.reuters.com/article/us-microsoft-twitter-bot-idUSKCNOWQ2LA)

[//www.reuters.com/article/us-microsoft-twitter-bot-idUSKCNOWQ2LA](https://www.reuters.com/article/us-microsoft-twitter-bot-idUSKCNOWQ2LA)

