Course introduction

Mitko Veta, Federica Eduati

Eindhoven University of Technology
Department of Biomedical Engineering

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Why machine learning?

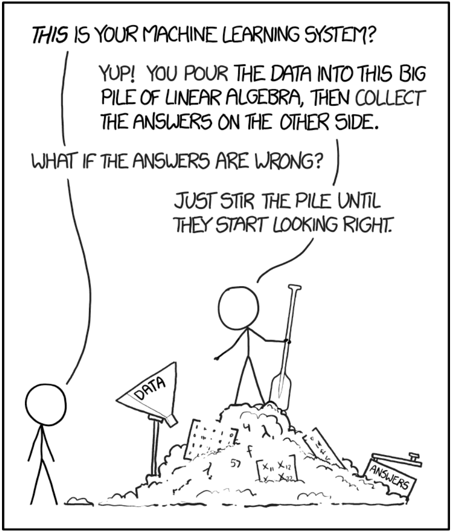


Figure source: xkcd.com

Historical perspective

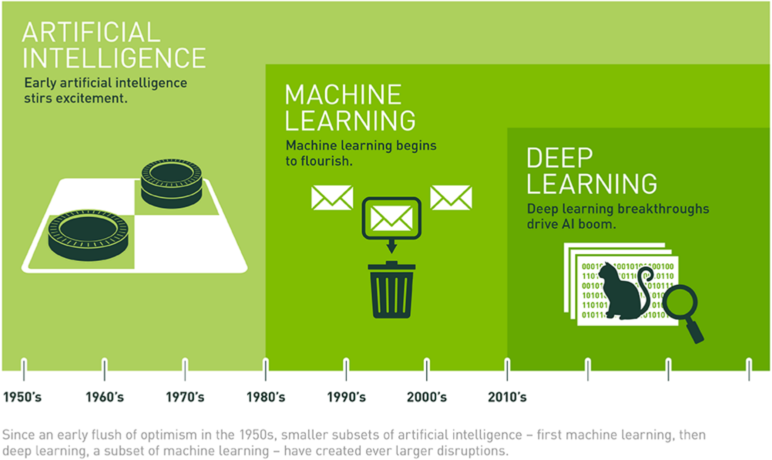


Figure source: nvidia.com

Historical perspective

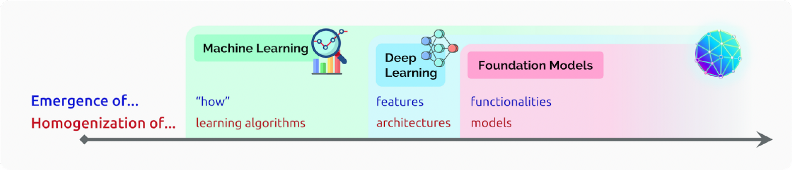
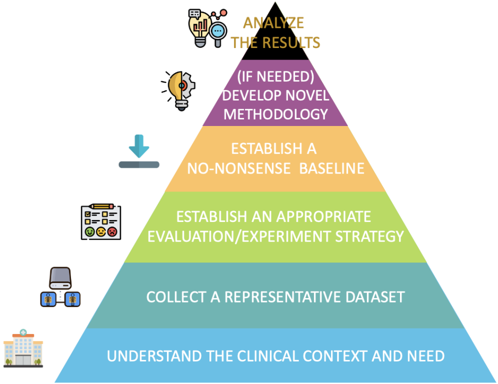


Fig. 1. The story of AI has been one of increasing *emergence* and *homogenization*. With the introduction of machine learning, *how* a task is performed emerges (is inferred automatically) from examples; with deep learning, the high-level features used for prediction emerge; and with foundation models, even advanced functionalities such as in-context learning emerge. At the same time, machine learning homogenizes learning algorithms (e.g., logistic regression), deep learning homogenizes model architectures (e.g., Convolutional Neural Networks), and foundation models homogenizes the model itself (e.g., GPT-3).

Figure source: Bommasani et al. "On the Opportunities and Risks of Foundation Models", arxiv.org/abs/2108.07258

Training machine learning models for medical image analysis

Also holds for other ML applications



Topics covered in the course

- Week 1: Machine learning fundamentals (Mitko Veta)
- Week 2: Linear models (Federica Eduati)
- Week 3: Deep learning I (Mitko Veta)
- Week 4: Deep learning II (Mitko Veta)
- Week 5: SVM, random forests (Federica Eduati)
- Week 6: Unsupervised machine learning (Federica Eduati)
- Week 7: Transformers (Mitko Veta & Federica Eduati), Explainable AI (Francesca Grisoni)

Weeks 1-6 lecture and practical. Week 7 only lecture. Week 8 (the week before the exam weeks) has no lecture or practical.

The course in a nutshell

- Assessment
  - 65% written exam
  - 25% practicals
  - 10% reading assignment
  - 0% **mandatory** Python self-assessment quiz in the first week
- GitHub repository used for material dissemination
- Canvas used for communication and submissions/grading
- Lecture schedule in My Timetable and on GitHub

Study materials

- Main guidance: lecture slides and practicals
- Books
  - **Deep Learning**, Ian Goodfellow and Yoshua Bengio and Aaron Courville
  - **The elements of Statistical Learning**, Trevor Hastie, Robert Tibshirani, Jerome Friedman
- Specific chapters and additional material (such as papers) are referenced in the lecture slides

Lecture slides and practicals in GitHub

Lectures

#	Date	Title	Slides
1	04/Sep	Machine learning fundamentals	~~intro , slides, extended~~
2	11/Sep	Linear models	~~slides~~
3	18/Sep	Deep learning I	~~slides~~
4	25/Sep	Deep learning II	~~slides, transformers intro~~
5	02/Oct	Support vector machines, random forests	~~slides~~
6	09/Oct	Unsupervised machine learning	~~slides~~
7	16/Oct	Transformers, Explainable AI	~~slides, explainable AI slides~~
8	23/Oct	*No lecture*	-
🔺	30/Oct	*Exam*	Example exam

Practical assignments

#	Date	Title	Exercises
1	06/Sep	Machine learning fundamentals I	exercises
2	11/Sep	Machine learning fundamentals II	exercises
3	18/Sep	Linear models	exercises
4	25/Sep	Deep learning I	exercises
5	02/Oct	Deep learning II	exercises in Google Colab
6	09/Oct	Support vector machines, random forests	exercises
7	16/Oct	*Catch up week!* 🍅	-

Submission in Canvas

Practical work — 25% of total

- Practical work week 1 (Machine learning fundamentals I)
  Due 17 Sep at 23:59 | 10 Pts
- Practical work week 2 (Machine learning fundamentals II)
  Due 24 Sep at 23:59 | 10 Pts
- Practical work week 3 (Linear models)
  Due 1 Oct at 23:59 | 10 Pts
- Practical work week 4 (Deep learning I)
  Due 8 Oct at 23:59 | 10 Pts
- Practical work week 5 (Deep learning II)
  Due 15 Oct at 23:59 | 10 Pts
- Practical work week 6 (Support vector machines, random forests)
  Due 25 Oct at 23:59 | 10 Pts

Self-assessment — 0% of total

- Python self-assessment
  Due 10 Sep at 23:59 | 4 Pts
- Self-reflection report on the use of large language models
  Due 25 Oct at 23:59

Reading assignment — 10% of total

- Paper review
  Due 25 Oct at 23:59 | 10 Pts
- Paper selection
  Due 27 Sep at 23:59

Final exam — 65% of total

- Final exam (grading only)
  65 Pts

Practicals

- Work done in groups of up to 5 students
- Distributed as Python notebooks
- Deliverables
  - Python functions and/or classes (.py files) that implement basic functionalities (e.g. a k-NN classifier)
  - A **single** Python notebook that contains the experiments, visualization of results and answer to the questions and math problems.

Practicals

- The assessment rubric for the practicals can be found in the handouts for week 1
- Instructions to setup the environment are in GitHub
- Two teaching assistants will be present during the practicals
- You are encouraged to use Canvas Discussion to ask general questions

Reading assignment

- Each group selects a paper with following criteria
  - Describes an application of Machine Learning to a Medical Imaging or Computational Biology problem
  - Recently published (after 2018)
  - Published in a high-quality journal
  - On a topic that you find interesting and want to learn more about
  - More information on the GitHub page

Reading assignment

- Use the "paper selection" assignment to discuss paper selection with us (propose a list)
- Write a review (800 words) with:
  - Summary of the application domain of the paper
  - Summary of the used (Machine Learning) methodology and evaluation metrics
  - Discussion of strong and weak points of the methodology and evaluation metrics
  - Suggestion of alternative methodology, evaluation metrics and ideas for improvement

Exam

- One example exam available in Canvas (more exams will not be available)
- (Usually) 13 questions $\times$ 5 points
  - Each question can contain multiple sub-questions
  - Open answers or multiple choice + open answers
  - For certain questions, the grading of the open answer sub-questions may be conditioned on correctly answering the corresponding multiple-choice sub-questions