Artificial Intelligence
Advanced Topics in AI & ML

Introduction. Course logistics and syllabus. Deep Learning and Neural Nets

Aleksandr Petiushko

ML Research

SOFIA UNIVERSITY

Content

Content

Content

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Intro

About the lecturer[1]

- Aleksandr Petiushko, PhD in theoretical CS (2016)
- Lecturer in Lomonosov MSU / MIPT for Machine Learning, Computer Vision, Deep Learning Theory, Python for an ML Researcher since 2019
- Former Huawei Chief Scientist (Scientific Expert), AIRI Director of Key Research Programs (Leading Scientific Researcher)
- Currently at Nuro, leading the ML Research

[1] Homepage: `https://petiushko.info/`

Intro

Time to introduce yourselves: what are your hobbies, motivation in ML, etc.: please go into “**Module 1 Students Introduction**” thread

Sofia Plagiarism Policy

- It covers parts "*sourced from AI*"
  - Please read the "**Sofia Plagiarism Policy**" thread
  - **First offense**: students need to rewrite assignment
  - **Second offense**: students fail the course
  - **Third offense**: students re to be withdrawn from their program

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  - It can produce very different information in comparison to the source used to ask question (e.g., book chapter)

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- Only the answers with some non-trivial arguments that contradict the initial post will be considered as graded ones

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- Preliminary grading scale:

Grade	Percent accumulated
A	90-100 %
B	75-89 %
C	60-74 %

Late Submission Policy

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- It means that if you're **7 days late** than no need to submit: you'll get **0 score** anyway.

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Unless:

- A student has a serious medical condition, and this condition is validated by a hospital or licensed California physician (in English)
- The Student contacts in time Student Services (student.services@sofia.edu) and describes the situation and provides all the needed proofs
- The student notifies in time our chair (Donna Dulo) and Professor about the situation with the confirmation from Student Services

Github

- Course page: `https://github.com/fatheral/sofia-aiml-2024`
- The professor's lectures will be uploaded there

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Natural Intelligence (human)

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Artificial Intelligence

- (Strong) The same as natural intelligence, but computer is instead of human
- (**Weak**) Algorithm which is able to train using the input data in order to do tasks afterward — instead of human

What is Machine Learning

In 1959 Arthur Samuel introduced the term “machine learning” into scientific use.

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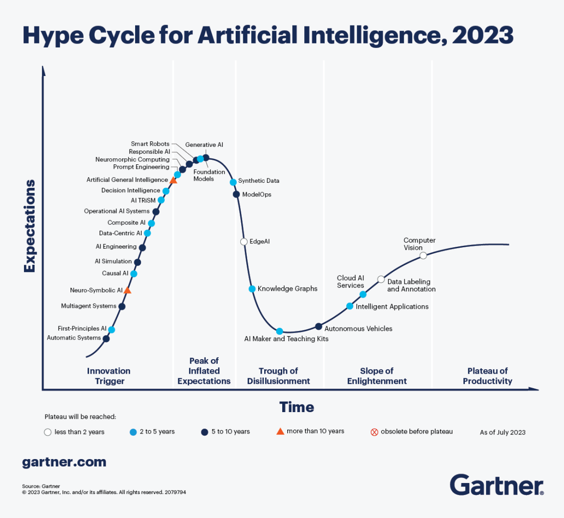
In 1997 Tom M. Mitchell introduced more formal definition of a machine learning algorithm.

Formal definition

A **computer program** is said **to learn** from examples E for some set of problems T and a quality metric P if its performance on problems from T, as measured by P, is improved by using examples E.

Broad concepts: AI Hype Cycle[2]



[2] www.gartner.com

Course content

- Deep Learning and Neural Nets
- Generative AI: Generative Adversarial Networks
- Generative AI: Diffusion
- Transformers: encoders and decoders
- LLMs: BERT, GPT
- Applications: Computer Vision
- Applications: Speech Recognition
- Multi-tasking
- Multi-modality
- Interpretability and Explainability
- Embodied AI: Self-Driving
- AI Ethics
- Robust ML

Deep Learning[3] and Neural Nets

- Neural Net (NN): a (usually!) non-linear function mapping a (usually) multi-dimensional input to some output (which can be of the same dimension, or a bigger/smaller one)

[3] Deep Learning Classical Book

Deep Learning[3] and Neural Nets

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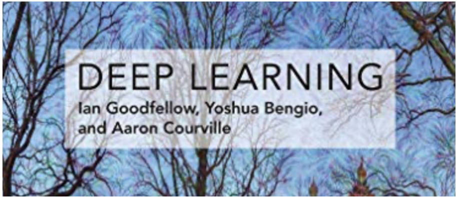
- Most common NN atomic operations: addition, multiplication, scalar non-linearity, aggregation/normalization
- Deep Learning: a NN consisting of more 2 layers of atomic operations (that's why deep) and the corresponding procedure of the training ("learning") it weights using back propagation process



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- Suppose we have m objects $\Rightarrow$ can construct training dataset X^m
- On top of that representation (usually a *linear*) a classifier is learned (e.g., SVM): $a(w, X^m) = \operatorname{sign} g(x, w) = \operatorname{sign}\langle x, w \rangle$

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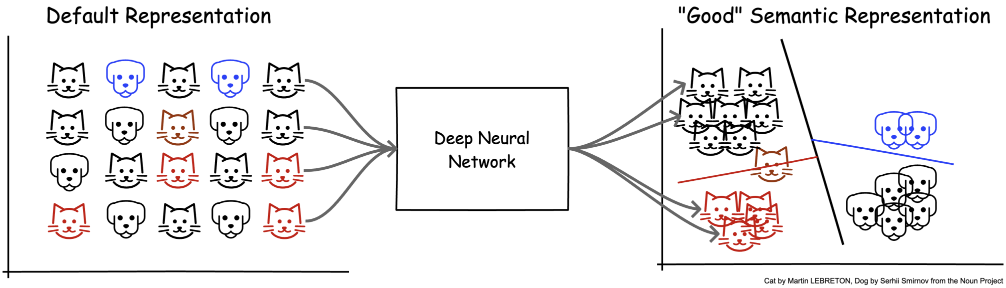
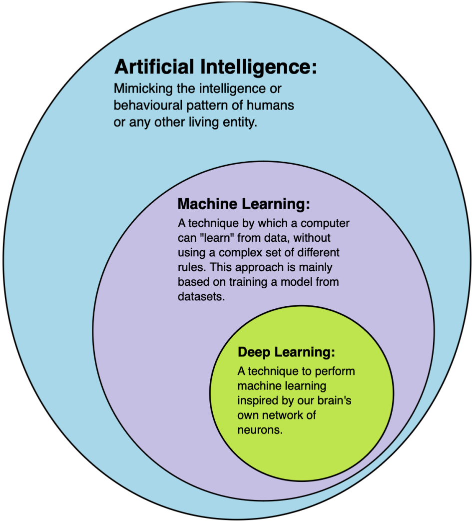
- Sometimes the initial features $x \in X$ are not suited enough for this task
- For this purpose, additional mapping h from X into some additional representation space $R \subseteq \mathbb{R}^N$: $h : X \to R$
- The learning of this additional mapping h is called **Representation Learning**

Representation spaces illustration[4]



[4] Image credit: blog.fastforwardlabs.com

AI vs ML vs DL[5]



[5] Wiki

Deep Learning History I[6]

1943	McCulloch & Pitts	introduced MCP Model, which is considered as the ancestor of Artificial Neural Model.
1949	Donald Hebb	considered as the father of neural networks, introduced Hebbian Learning Rule, which lays the foundation of modern neural network.
1958	Frank Rosenblatt	introduced the first perceptron, which highly resembles modern perceptron.
1974	Paul Werbos	introduced Backpropagation
1980	Teuvo Kohonen	introduced Self Organizing Map
	Kunihiko Fukushima	introduced Neocogitron, which inspired Convolutional Neural Network
1982	John Hopfield	introduced Hopfield Network
1985	Hilton & Sejnowski	introduced Boltzmann Machine
1986	Paul Smolensky	introduced Harmonium, which is later known as Restricted Boltzmann Machine
	Michael I. Jordan	defined and introduced Recurrent Neural Network

[6] On the Origin of Deep Learning

Deep Learning History II[7]

1990	Yann LeCun	introduced LeNet, showed the possibility of deep neural networks in practice
1997	Schuster & Paliwal	introduced Bidirectional Recurrent Neural Network
	Hochreiter & Schmidhuber	introduced LSTM, solved the problem of vanishing gradient in recurrent neural networks
2006	Geoffrey Hinton	introduced Deep Belief Networks, also introduced layer-wise pretraining technique, opened current deep learning era.
2009	Salakhutdinov & Hinton	introduced Deep Boltzmann Machines

- 2011: AlexNet — the first neural net winning the ImageNet challenge
- 2017: Invention of Transformer, the main architecture of LLM
- 2022: Invention of ChatGPT

[7] On the Origin of Deep Learning

More details on DL History and NN Architectures

Please read two links below:

- Deep Learning in a Nutshell: Core Concepts
- Deep Learning in a Nutshell: History and Training

Takeaway notes

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1. Please go through all the materials of **Module 0**
2. Please introduce yourself and complete the **Assignment 1**
3. Deep Learning is responsible for the most of the AI success today!
4. Let's get our journey started!

Thank you!