

AI and Linguistic Studies

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AI and Linguistic Studies

- **What is AI?**
- Machine Learning
- Natural Language Processing
- Large Language Models
- GPT and ChatGPT
- LLMs and AI in Education
- AI and University Education
- Citizen Morphosis
- Artificial General Intelligence

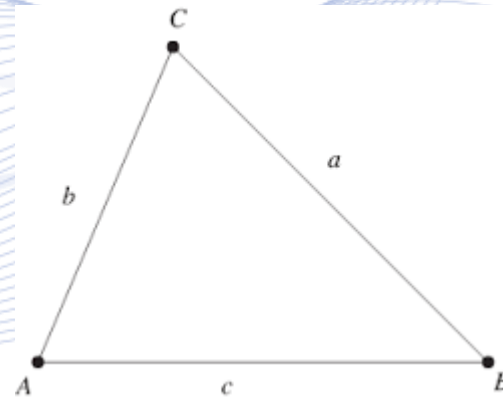
What is AI?

- ***AI Science and Engineering*** (AISE) is the interdisciplinary, scientific study and engineering of ***Artificial Systems*** that mimic and/or surpass ***human intelligence*** in information analysis and ***human interaction*** with the world.
- Core AISE disciplines are:
 - Classical (Symbolic) ***Artificial Intelligence*** (AI),
 - ***Machine Learning*** (ML).

Symbolic AI

Concepts and ideas (ιδέες).

- Concepts are specific mental constructs residing in our mind (brain?) that refine and abstract ideas.
- Examples: 'Triangle', 'Freedom', 'Love'.
- **Concept definition:** Triangle consists of three points connected by 3 straight line segments.



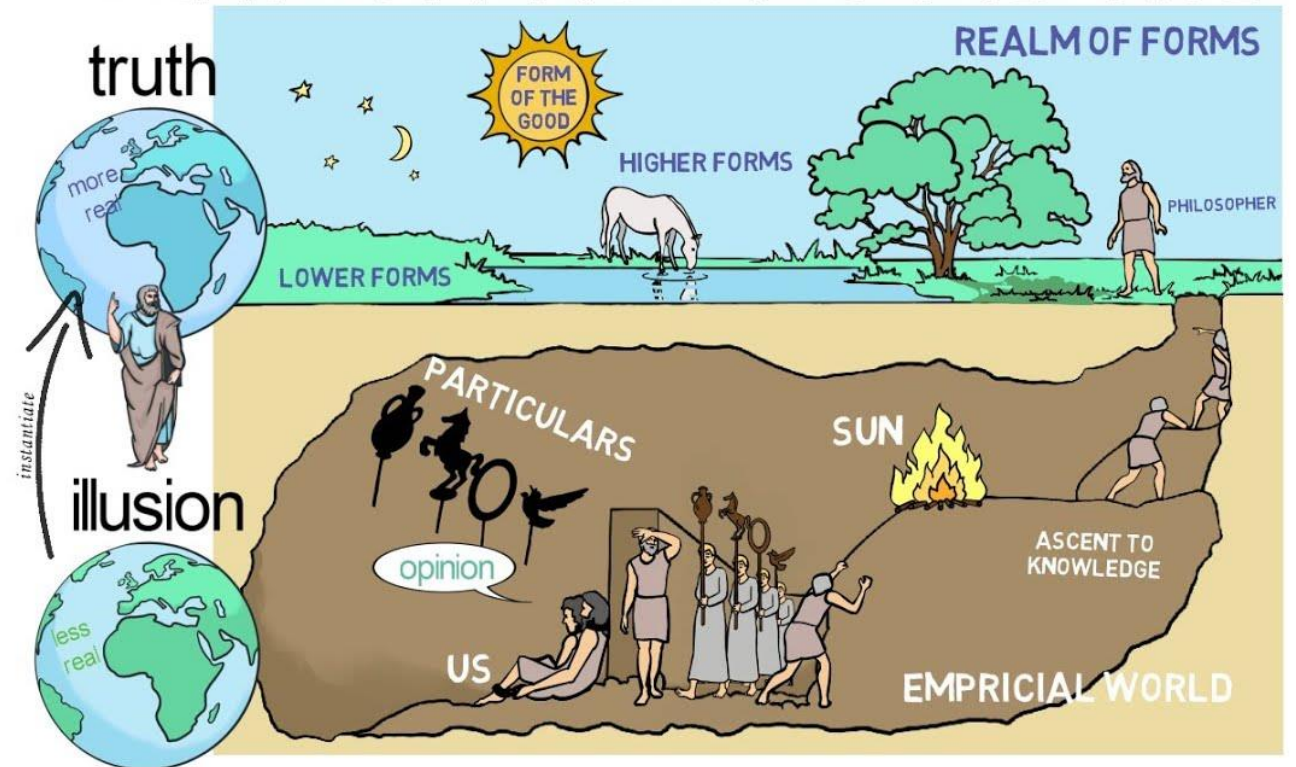
Triangle.

Symbolic AI

Ideas in Philosophy.

- Plato's cave.
- **Idealism**: reality is a reflection of ideas.
- **Materialism**: ideas are shadows of matter on itself (brain).

PLATO'S ANALOGY OF THE CAVE



Symbolic AI

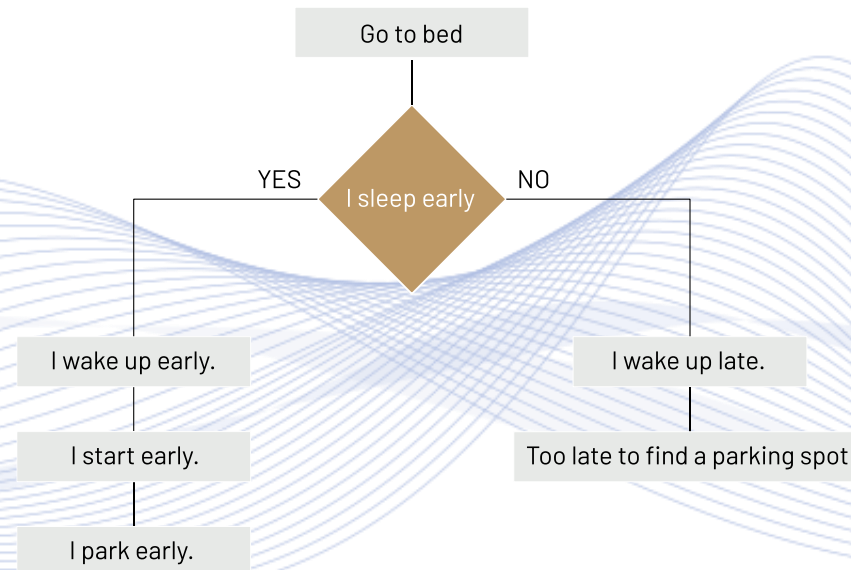
- ***Symbolic AI*** operates on concepts and their relations through ***logic*** and ***search***.
- It mimics and simulates high-level human intelligence and ***reasoning***.
- ***Reasoning*** is one of the most complex brain activities.
- ***Symbolic AI*** employs Mathematical Logic.

Symbolic AI

- Examples:

‘If somebody has high fever and coughs, she/he has flu.’

‘If I turn left, I may enter the opposite lane.’



- Symbolic AI failed to deliver!***

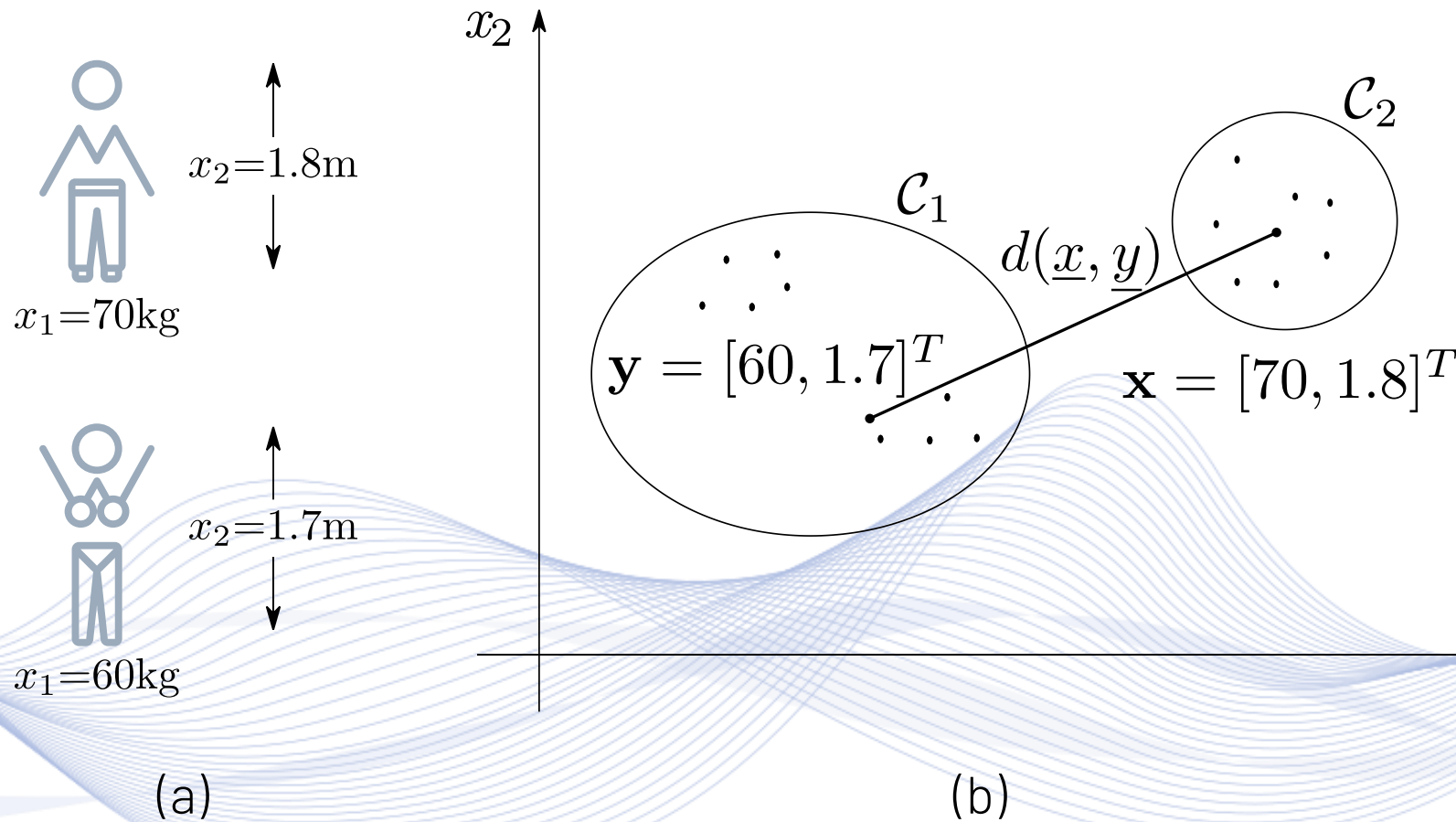
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Machine Learning

- ***Data***: measured quantities related to nature and/or human activities.
- ***Data are primarily numbers*** representing object characteristics (***features***).
- ***Measured in bits.***
- ***Data can be organized in vectors.***

Machine Learning



Measuring humans and producing their weight and height vectors.

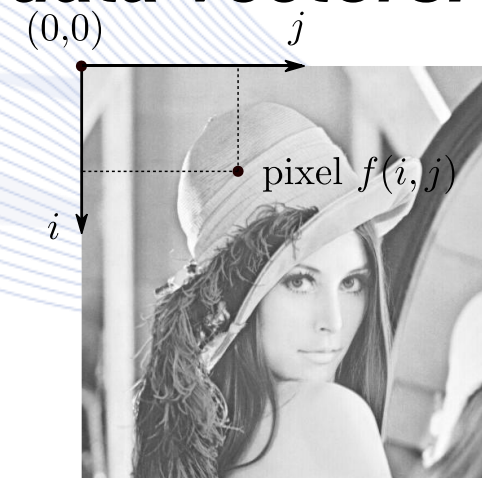
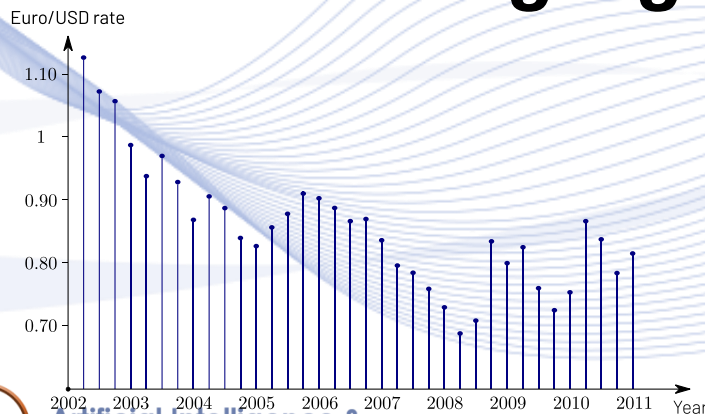
Machine Learning

Data can have *spatiotemporal structure*:

- 1D temporal signals, e.g., music
- 2D spatial signals: images
- Data features can be represented by **vectors**:

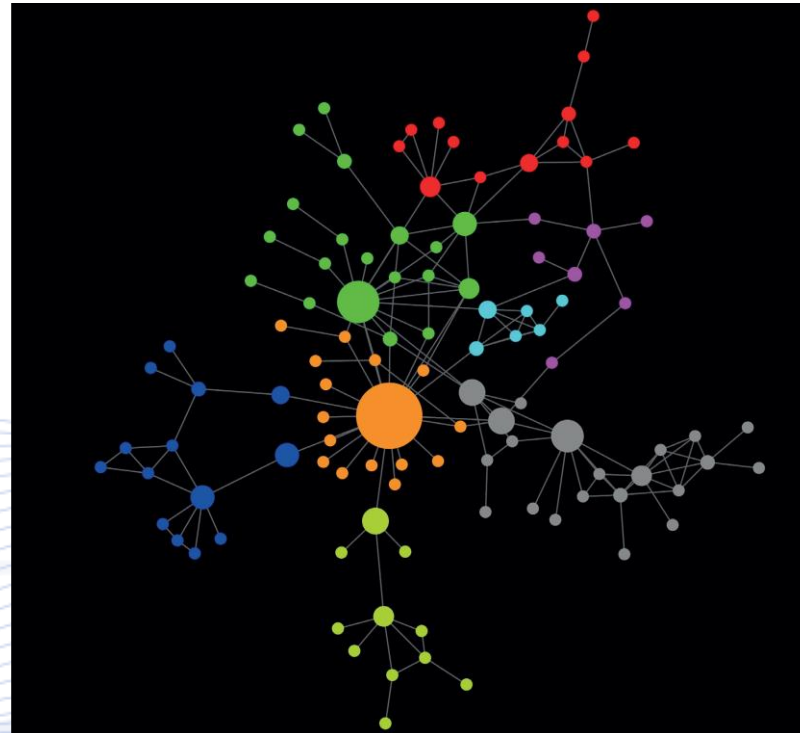
$$\mathbf{x}^T = [x_1, x_2, \dots, x_n].$$

Machine Learning algorithms learn from data vectors.



Machine Learning

- Graphs can represent relations of historical actors.



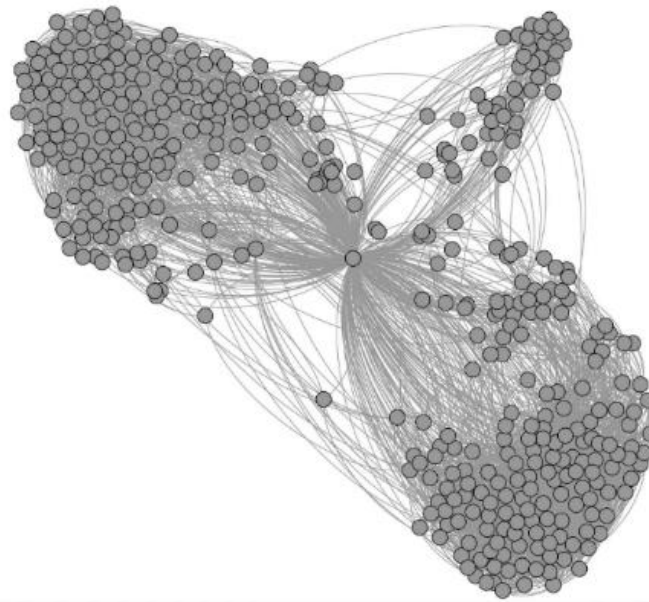
Clusters of the Byzantine nobility in the civil war period 1321-1328 AD.

Machine Learning



Citizen communities (graphs)

- Citizens are graph nodes connected by relations (graph edges):
 - friendship, political affiliation, etc.



Facebook friendship graph.

Generative AI



Machine Learning Algorithms that learn data and produce new data.

- ***Large Language Models***
 - Text production
- ***Generative Adversarial Networks, Diffusion Models***
 - Multimedia content creation (images, video, audio, computer graphics)



GAN-generated video.

AI and Linguistic Studies

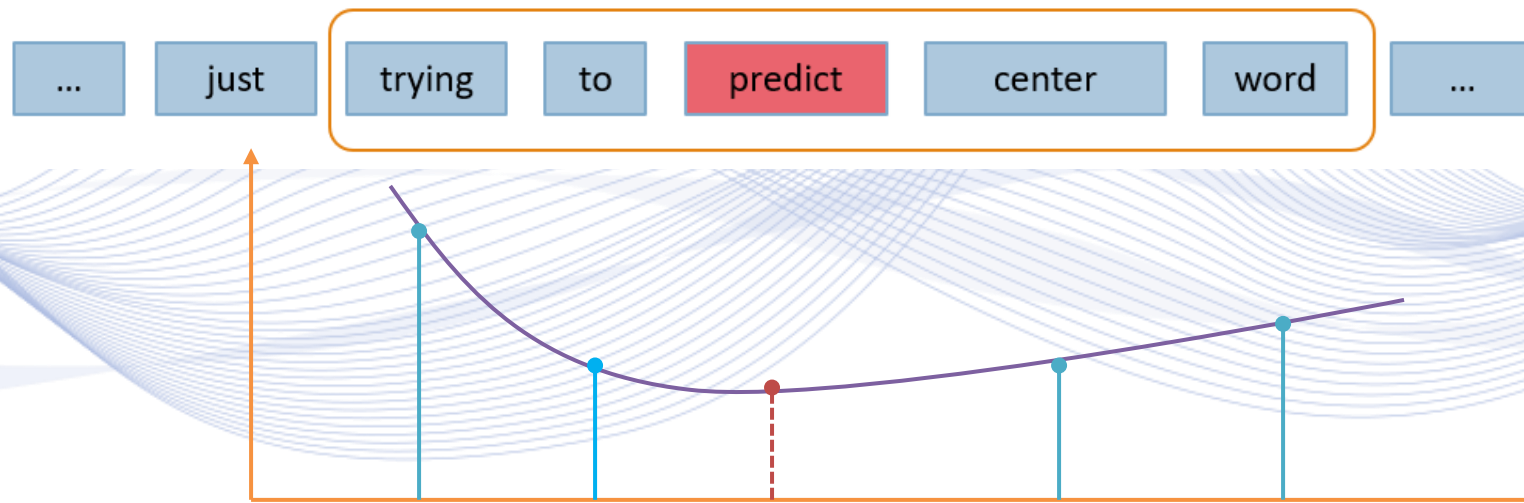
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Natural Language Processing

Word embeddings: Word2Vec (example)

Two-layer NN trained to reconstruct linguistic context of words.

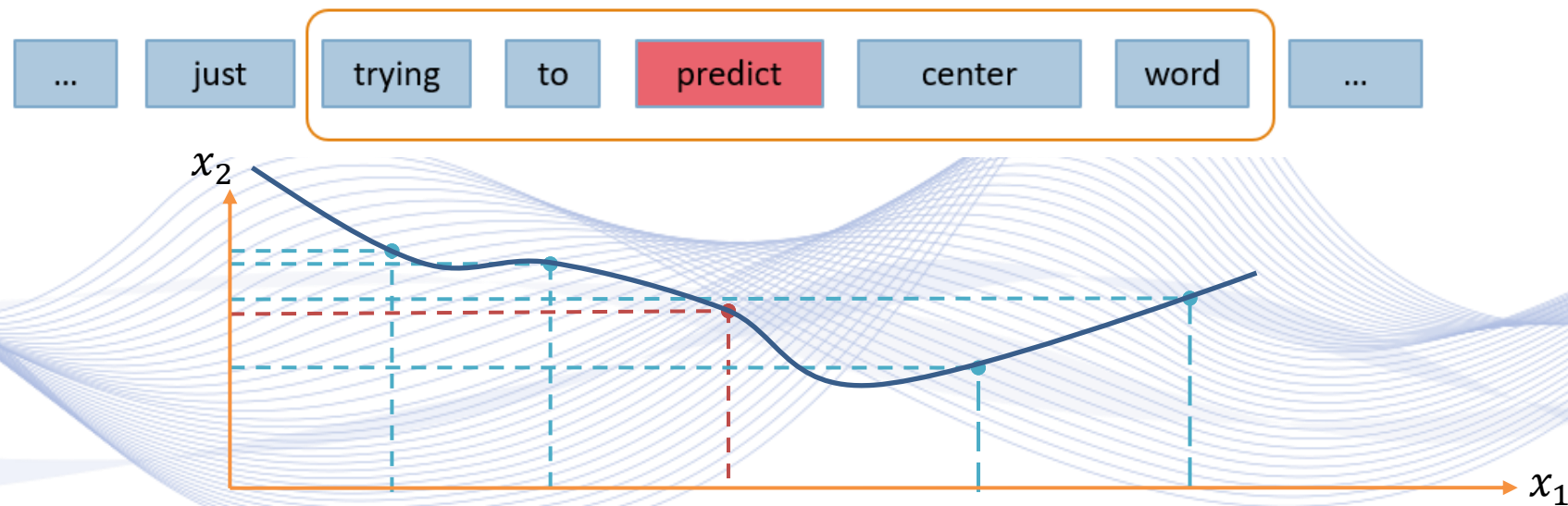
- Training is performed with pairs of context-target words.
- 2 training variations.



Natural Language Processing

Visualization of word prediction in 2D space

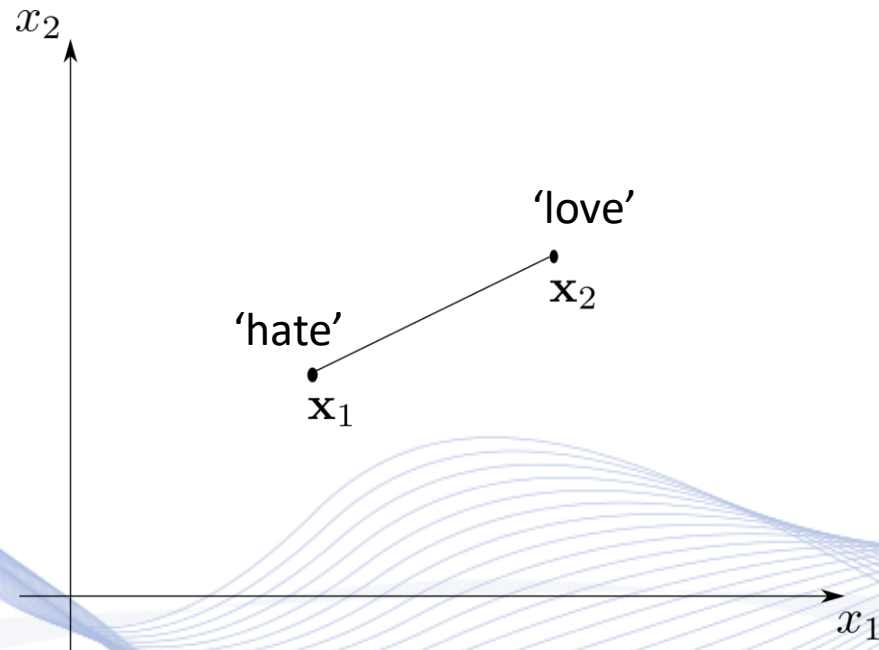
A sentence can be visualized as a curve in the vectorial space over time, connecting all its word embeddings.



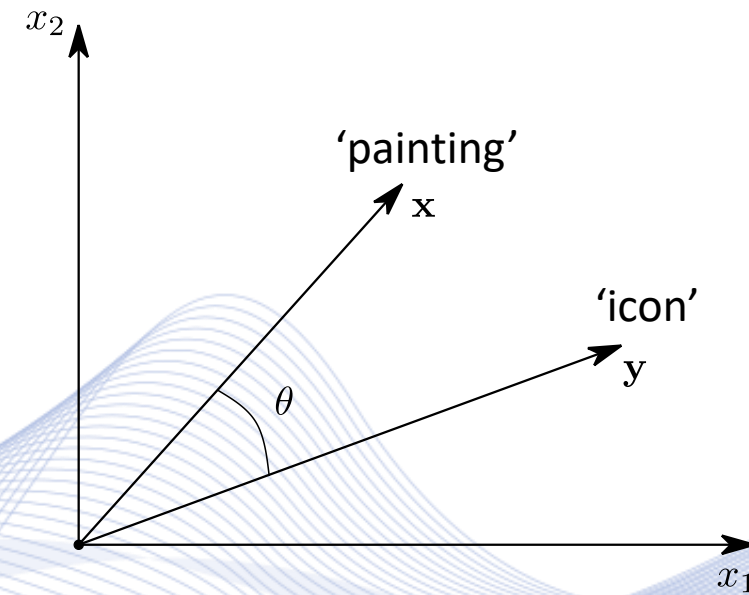
Word trajectory in a 2D vectorial space $[x_1, x_2]$.

Natural Language Processing

Vectors representing words

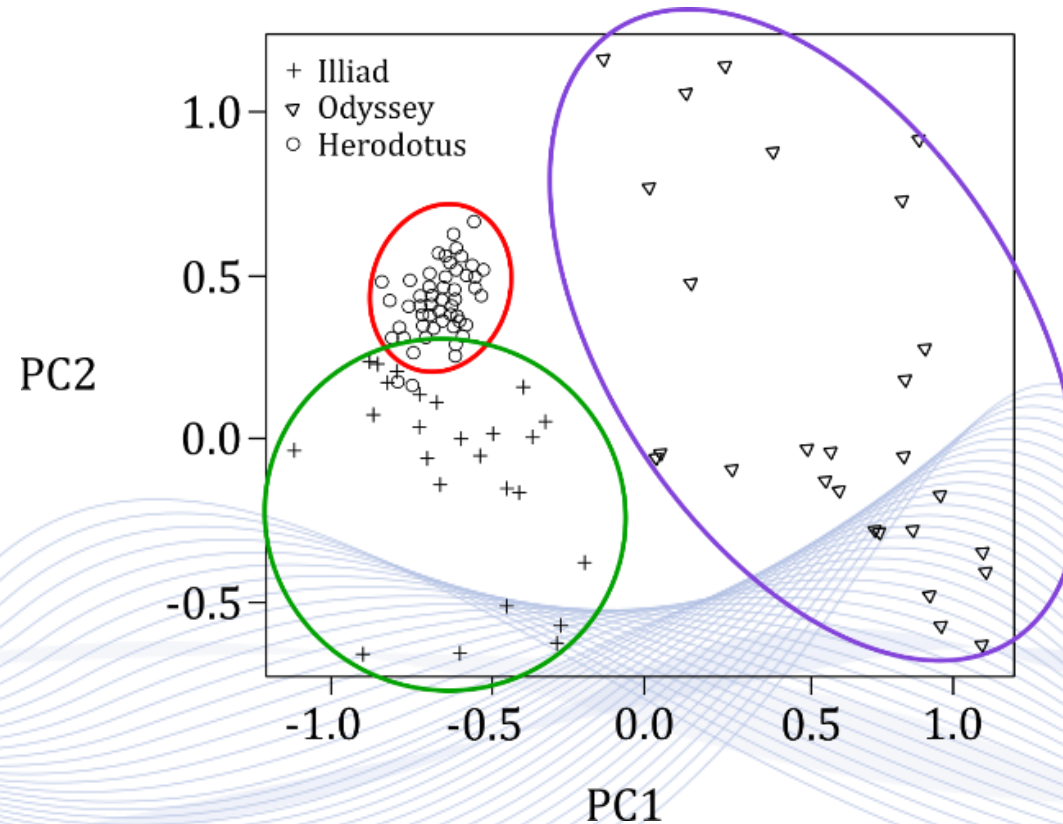


Distance between two words.



Semantic similarity between two words.

Natural Language Processing



Representing texts by vectors:

Principal component analysis of Homer's Iliad and Odyssey.

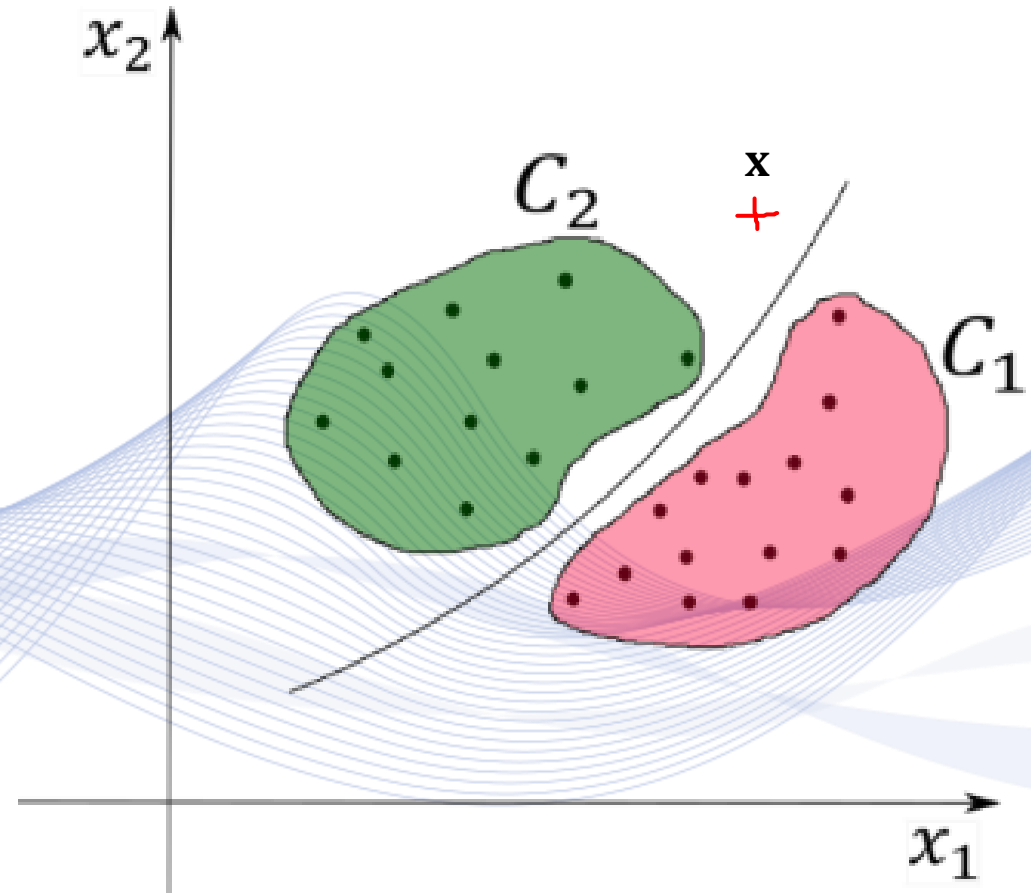
Natural Language Processing

Text Classification

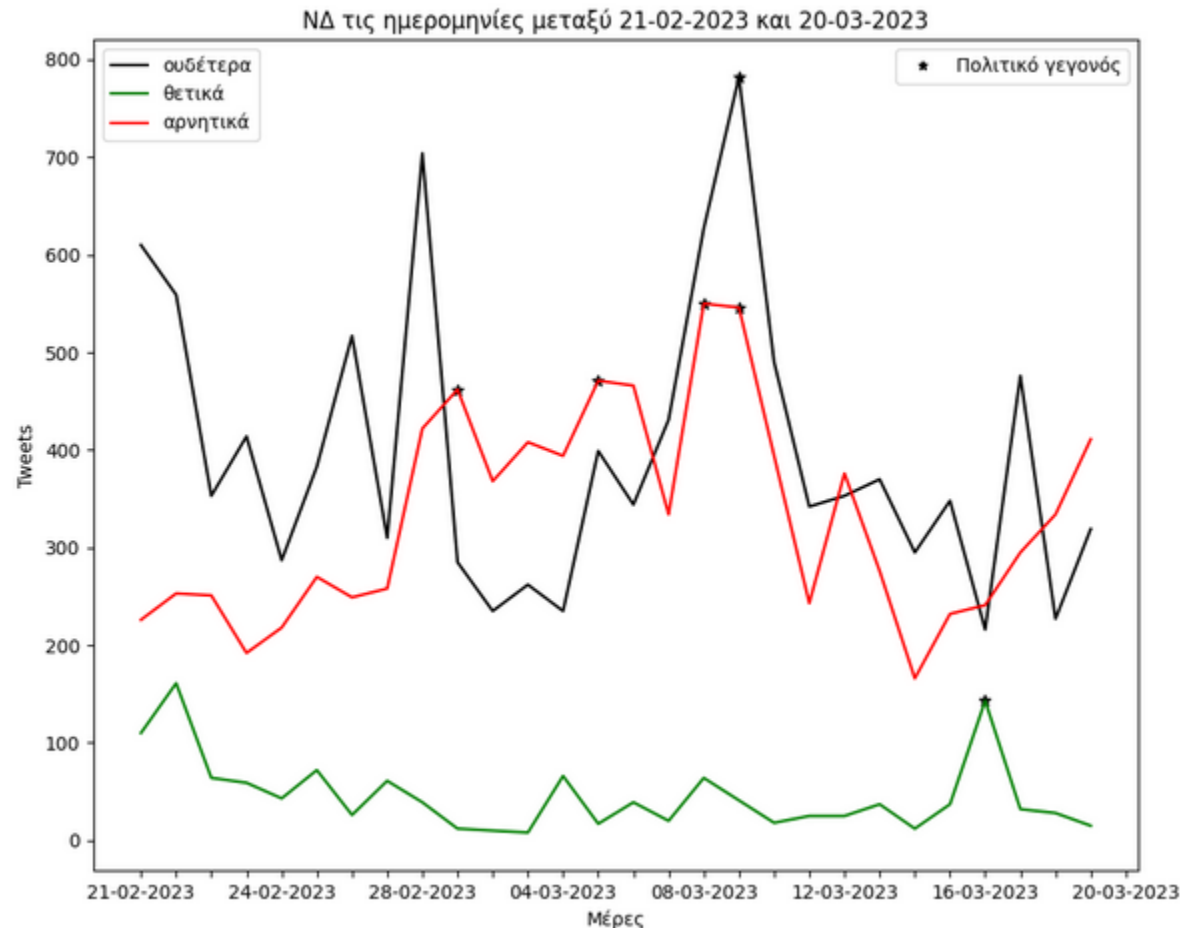
- Does text x belong to class C_1 or class C_2 ?

Examples:

- Text sentiment analysis
 - Is the text 'sad' or 'joyful'?
- Author recognition
 - Is this Epistle authored by St. Paul or not.



Natural Language Processing



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Large Language Models

- ChatGPT is a **Large Language Model (LLM)** that is fine-tuned from a **Generative Pre-Trained Transformer-3.5 (GPT-3.5)** LLM series, produced by OpenAI.
- An LLM is a **Deep Neural Network (DNN)** trained to generate smooth text similar to the human-generated one.
- The fine-tuning of the GPT-3.5 is performed using supervised and reinforcement learning with human feedback [OPE2023].

Large Language Models



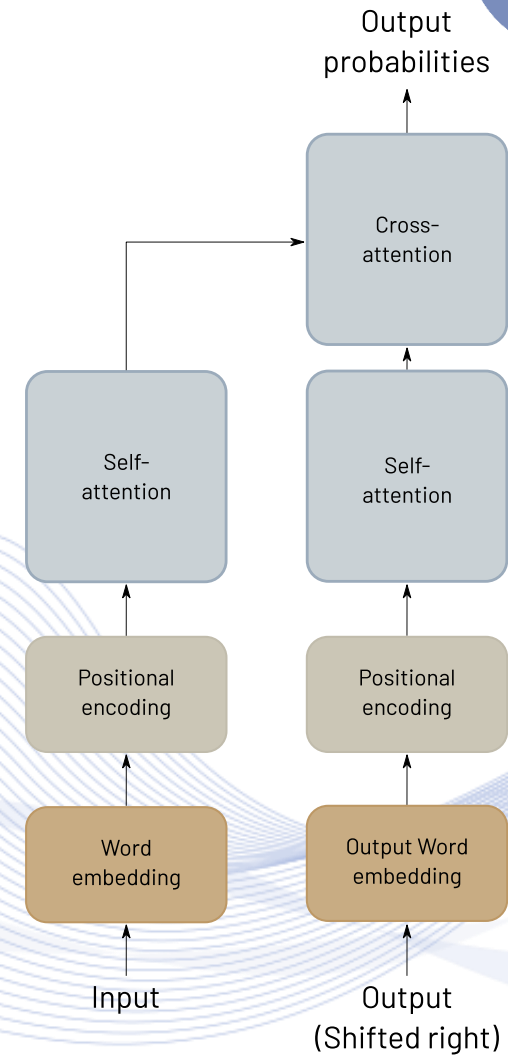
The building blocks of LLMs are [AJI2023] :

- **Tokenization:** transforming a text in a series of tokens, e.g.,:
 - *sub-words, words.*
- Text compression, in order to minimize the size of the encoded token, while retaining the ability to represent well text sequences.
- **Vector embedding:** Token representation by vectors capturing their semantic meaning in a high-dimensional space.
- Vector embeddings are processed by the NN and are learned during the training.

Large Language Models

Transformers provide data representations based on statistical correlations of input elements (NLP tokens).

- They comprise of the **encoder** and **decoder**.
- **Self-attention** weighs the importance of input or output tokens.
- **Cross-attention** cross-correlates input and output tokens.

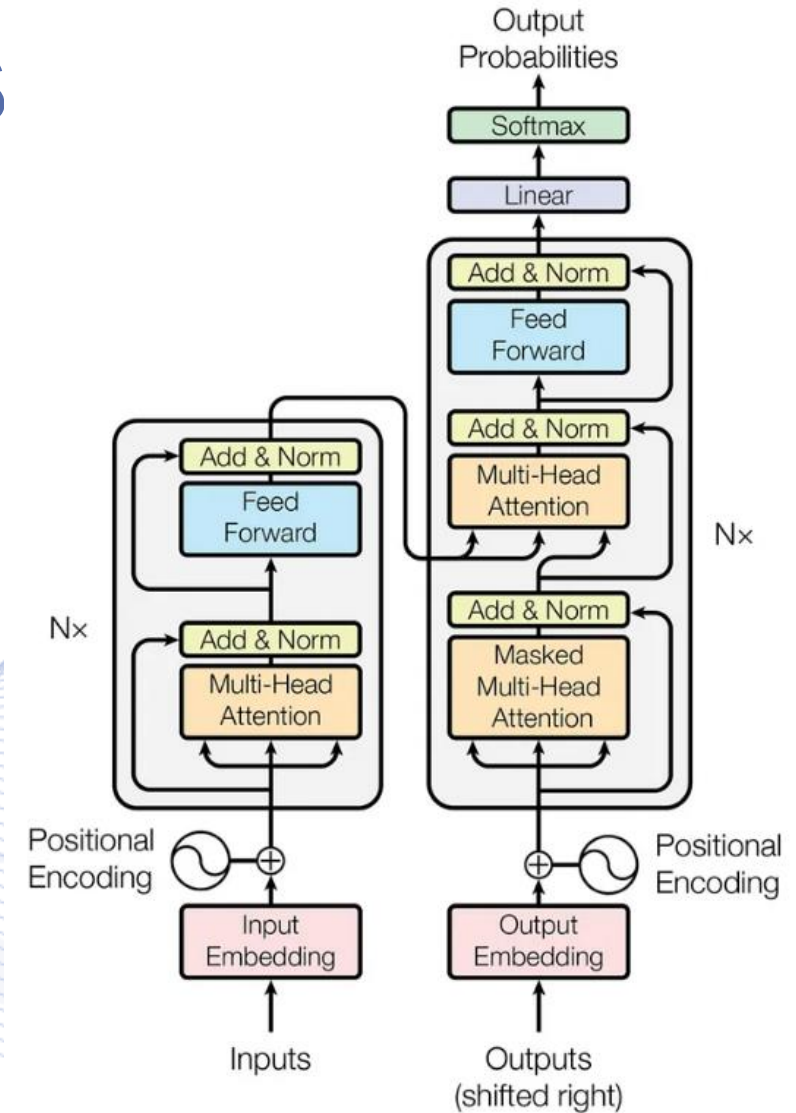


Transformer architecture.

Large Language Models

Transformers

- **Transformers** comprise of the encoder and decoder and use the self-attention mechanism to weigh the importance of input elements [VAS2017].
- GPT-3.5 is a fine-tuned model of the GPT-3, which is a Transformer DNN.



Transformer architecture [VAS2017].

Large Language Models

LLM training and text production example:

- LLMs' reply to the query '***What is the capital of Spain?***' would be '***Madrid***' rather than '***death penalty***', since:
- a) they encountered this semantic association (Spain, Madrid, capital) too many times in their training corpora.
- b) the learned association (Spain, country) helps them disambiguate the meaning of the query word 'capital'.
- ***Such statistical associations may occasionally be out of context, or semantically wrong or completely fabricated.***

Large Language Models

LLM training and text production:

- LLMs search for text patterns and correlations in huge amounts of training data and produce statistically probable output (text).
- They become increasingly better in learning word predictions and relations.
- This is an essential feature in outputting smooth 'human-like' text.
- ***Is Language all we need?***

Large Language Models

LLMs have high expressive and abstraction power.

They are mathematical functions

$$y = f(\mathbf{x}; \theta)$$

that learn parameters θ from labeled training text data (\mathbf{x}, \mathbf{y}) .

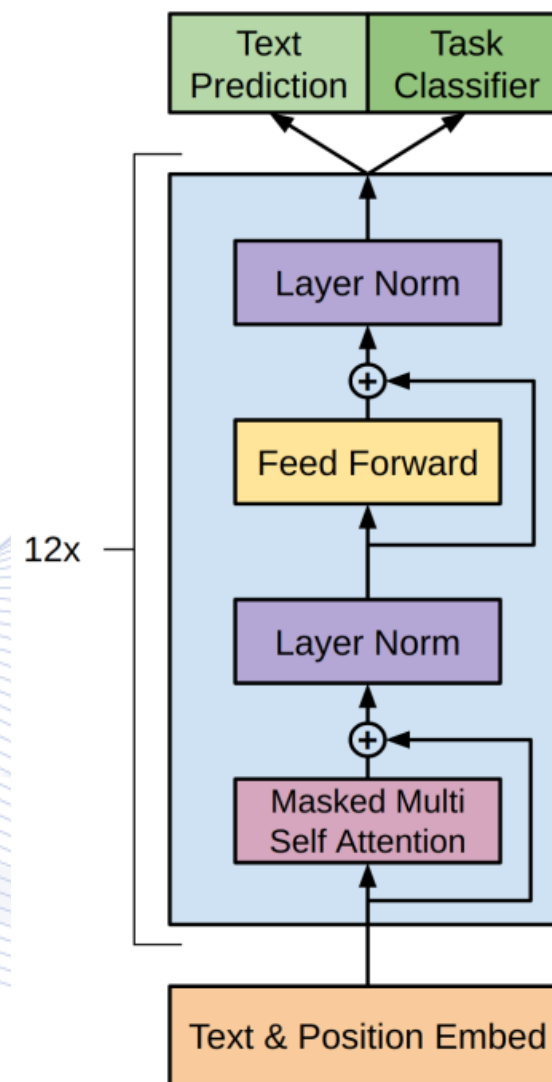
- Their power is in the ***huge number*** of parameters in θ .
- ***Special case of Generative AI.***
- Huge expressive and abstraction power compared to classical linguistic approaches.
- Non-explainable operation (so far).

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GPT

- The **Generative Pre-Trained Transformer (GPT)** is a **decoder-only Transformer** model that generates one token at a time [RAD2018].
- Semi-supervised training:
 - a) Unsupervised pre-training.
 - b) Supervised fine-tuning.



GPT architecture [RAD2018].

GPT Training stages

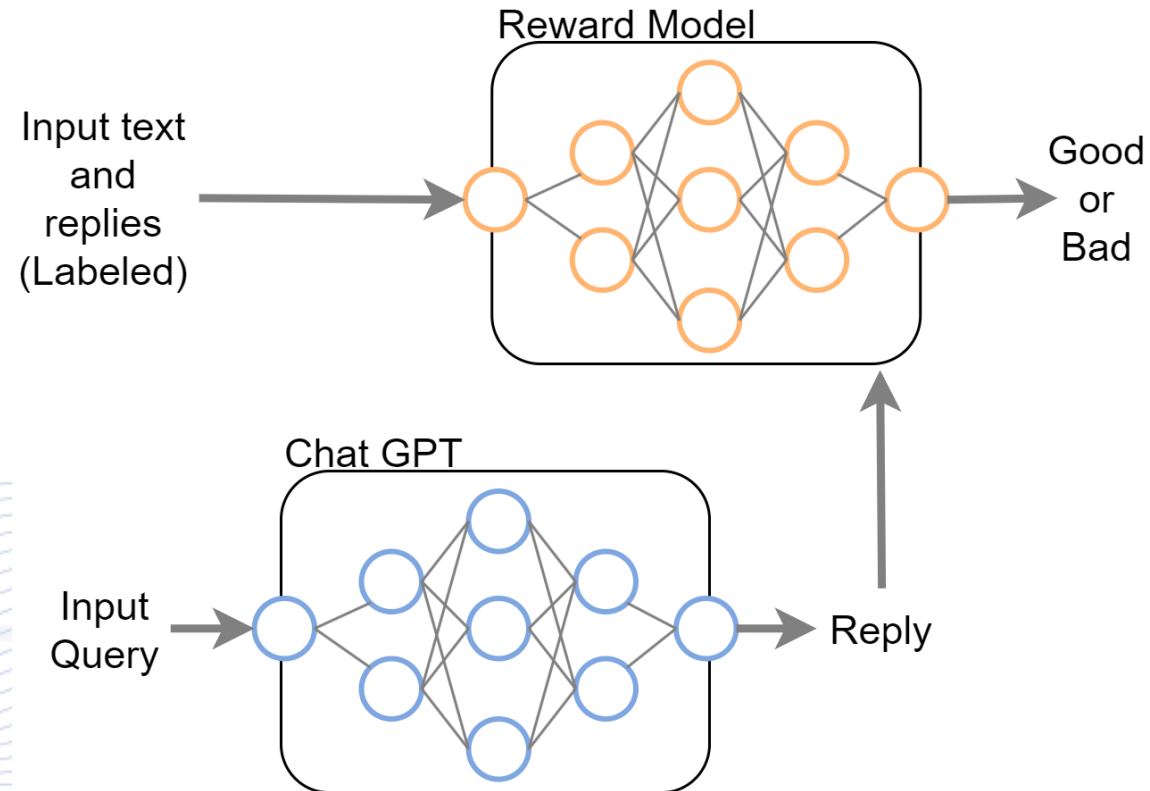
Unsupervised Pre-training stage:

- *Training dataset:* BooksCorpus [ZHU2015].
- *Objective:* Standard language modelling [RAD2018].

Fine-tuning stage:

- *Training dataset:* a labelled dataset corresponding to the fine-tuning task
- *Objective:* GPT model parameters adaptation to the supervised target task and language modelling [RAD2018].

ChatGPT Reward Model



ChatGPT fine tuning methodology.

GPT-4

- GPT-4 is a large multimodal model

Input: Both images and text

Output: Text

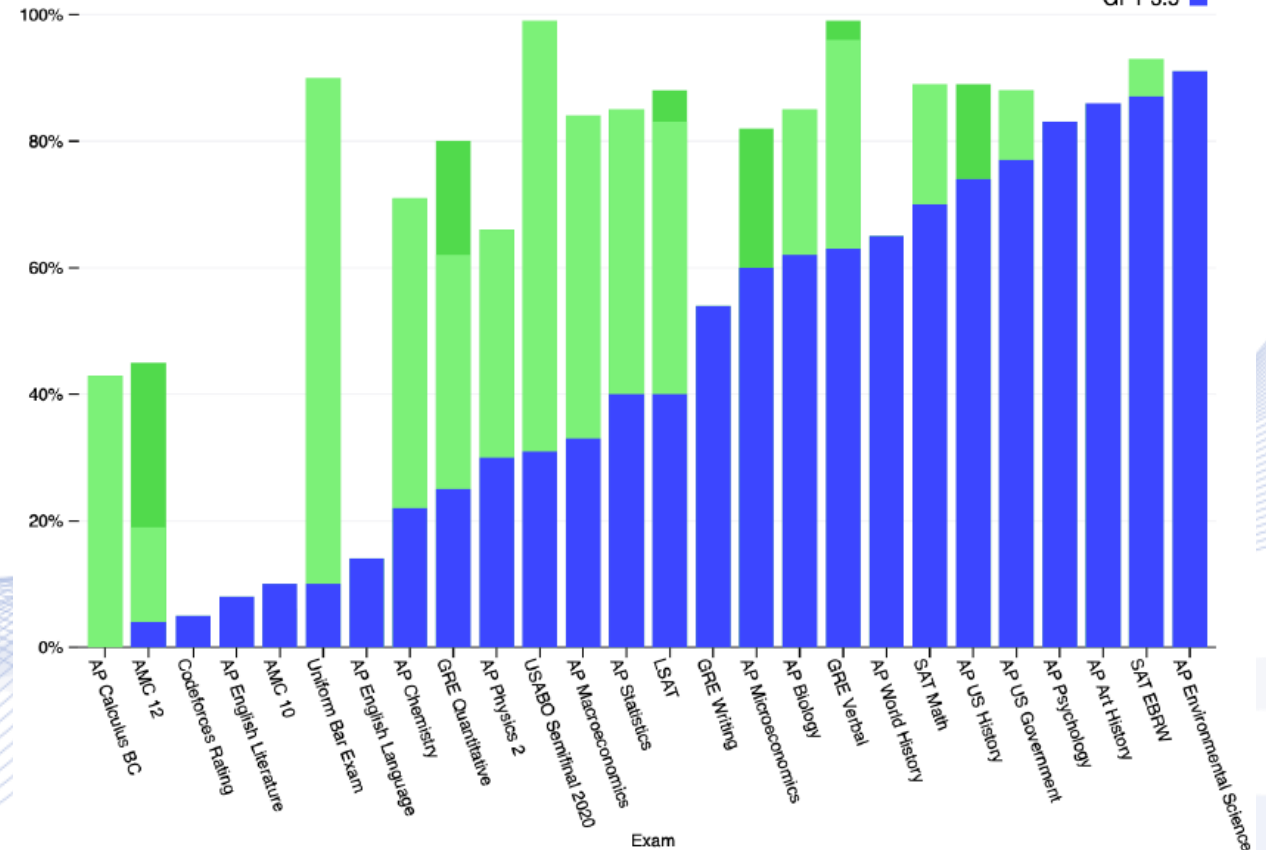
- Trained on next word prediction using public and licensed data.
- Fine-tuned through ***Reinforcement Learning with Human Feedback*** (RLHF) in order to align the models output with the user's intent [OP2023].
- Models capabilities originate from the pre-training process and not the RLHF [OP2023].

GPT-4

- GPT-4 exhibits human-level performance on various professional and academic benchmarks [OP2023].

Exam results (ordered by GPT 3.5 performance)

Estimated percentile lower bound (among test)



GPT performance on academic and professional exam [OP2023].

GPT-4 Capabilities

	GPT-4 Evaluated few-shot	GPT-3.5 Evaluated few-shot	LM SOTA Best external LM evaluated few-shot	SOTA Best external model (incl. benchmark-specific tuning)
MMLU [49] Multiple-choice questions in 57 subjects (professional & academic)	86.4% 5-shot	70.0% 5-shot	70.7% 5-shot U-PaLM [50]	75.2% 5-shot Flan-PaLM [51]
HellaSwag [52] Commonsense reasoning around everyday events	95.3% 10-shot	85.5% 10-shot	84.2% LLaMA (validation set) [28]	85.6 ALUM [53]
AI2 Reasoning Challenge (ARC) [54] Grade-school multiple choice science questions. Challenge-set.	96.3% 25-shot	85.2% 25-shot	85.2% 8-shot PaLM [55]	86.5% ST-MOE [18]
WinoGrande [56] Commonsense reasoning around pronoun resolution	87.5% 5-shot	81.6% 5-shot	85.1% 5-shot PaLM [3]	85.1% 5-shot PaLM [3]
HumanEval [43] Python coding tasks	67.0% 0-shot	48.1% 0-shot	26.2% 0-shot PaLM [3]	65.8% CodeT + GPT-3.5 [57]
DROP [58] (F1 score) Reading comprehension & arithmetic.	80.9 3-shot	64.1 3-shot	70.8 1-shot PaLM [3]	88.4 QDGAT [59]
GSM-8K [60] Grade-school mathematics questions	92.0%* 5-shot chain-of-thought	57.1% 5-shot	58.8% 8-shot Minerva [61]	87.3% Chinchilla + SFT+ORM-RL, ORM reranking [62]

Performance of GPT-4 on
academic benchmarks
[OP2023].

GPT-4 Limitations

GPT-4 suffers from the same limitations as the previous GPT models [OP2023]:

- Hallucinations.
- Bias in its output text.
- Lack knowledge past 2021 and doesn't learn from its experience.
- There is still a risk of generating harmful advice, buggy code and inaccurate information. This risk has been reduced compared to older models through additional signal in the RLHF.

ChatGPT Capabilities

ChatGPT *text processing* capabilities:

- **Translation:** chatGPT performs well translating in English [BAN2023].
- **Summarization:** Adequate results (similar to GPT3). However, it is outperformed by SOTA works [BAN2023].
- **Question Answering:** Near perfect scores [BAN2023].
- **Sentiment Analysis:** It outperforms supervised SOTA works [SCA2022] and zero-shot multilingual LLM [CAH2022] (evaluation metric: F1 score) [BAN2023].

ChatGPT Capabilities

- **Dialogue tasks:** ChatGPT generates high quality fluent human-like responses [BAN2023].
- **Misinformation detection:** ChatGPT detected misinformation at 92% and 73.33% accuracy on covid-scientific and covid-social datasets, containing scientific and social claims related to Covid-19 accordingly [BAN2023].
- **Code understanding and generation:** ChatGPT achieved higher score on the LinkedIn Python skills assessment than 85% of humans [CFTE].

ChatGPT Limitations

- ChatGPTs responses sometimes sound plausible, while they are ***incorrect or nonsensical*** [OPE2023].
- ChatGPT responses are sensitive to tweaks in input phrasing and prompt repetition [OPE2023].
- Training data bias causes ***excessively verbose responses*** and overuse of certain phrases [OPE2023].
- In translation, it still lacks excellent ability to successfully translate English in other languages [BAN2023].

ChatGPT Limitations

- In the case of an ambiguous query, the model **guesses *what the user intended to say***, rather than ask for clarifying questions [OPE2023].
- ChatGPT sometimes responds to ***harmful instructions or outputs biased answers***.
 - The Moderation API is used to flag certain types of unsafe content [OPE2023].
- ChatGPT has a limited understanding of ***low-resource languages***, due to low training data volume [BAN2023].

ChatGPT Limitations

ChatGPT hallucinations

- Reward functions can induce ChatGPT into hallucinating facts, rather than admitting ignorance.
- Hallucinations can become even more serious when ***human-in-the-loop*** LLM retraining or fine-tuning is employed.
- Users can trigger hallucinated replies, e.g., that ‘the Pope is a pop singer’, as the LLM thinks it maximizes its reward.

ChatGPT Limitations

ChatGPT hallucinations

- Humans make such judgement errors as well:
 - Sensory illusions, wild children's imagination.
- The human mind creates ***mental images*** of the world that map reality, yet are completely artificial, real, but different from reality.
- ***Arts can be considered as a form of creative expressed hallucination.***

ChatGPT Limitations

ChatGPT hallucinations

- In principle, **Generative AI fabricates imaginary outputs.**
- They may deviate from the training data and ‘common human sense’.
- Depending on their **social use**, we can call them Art or Fake data or Hallucinations.

ChatGPT: Questionmarks

- ***Does ChatGPT have access to external resources? No.***
 - Yet, if suitably trained ChatGPT can provide lots of factual information.
 - If not, what is its ***knowledge storage capacity?***
- ***Should LLMs have access to external resources? Yes.***
 - Knowledge graphs? Algebraic computations (Symbolic Algebra)?
 - This combination has great potential, e.g., in search.

ChatGPT: Questionmarks

- ***Can LLMs provide hints on how human memory works?***
 - Associative memories, Hopfield networks.
 - CNNs can store some training data information.
 - Transformer-based LLMs are based on ***statistical associations***.
- ***Relation between human imagination and ChatGPT hallucination?***
 - Kids are particularly good at fabricating facts or stories.

ChatGPT: Questionmarks

- ***Does ChatGPT have explicit reasoning mechanisms?***
 - No, it has been trained as a pure language model.
 - However, its replies ***show*** some reasoning capabilities.
- ***'Text is all we need' to learn reasoning?***
 - Language/text contain many examples of reasoning.
 - Reasoning as a result of learning-by-examples?
 - ***If proven, it is a Nobel-level breakthrough.***
 - It can reconcile Machine Learning and Symbolic AI.

ChatGPT: Questionmarks

Does ChatGPT have explicit reasoning mechanisms?

- Humans learn from their mothers, relatives, and peers how to think, based on countless everyday discussions.
- An eventual LLM ‘inference by example’ capacity may hint towards ways that ***humans learn to think.***

ChatGPT: Questionmarks

Causal, approximate reasoning?

- LLM output (statistical event cross-association):
‘It has repeatedly been observed (or better, has been found in the literature) that plants thrive, when the sun shines’.
- Causal argumentation:
‘Plants thrive when the sun shines, because they use sunlight in their photosynthesis’.

ChatGPT Questionmarks

- ***Do LLM/ChatGPT have abstraction mechanisms?***
 - Their internal structure and functionalities are unknown.
 - Clustering and concept creation? Rule creation?
- ***Can ChatGPT provide explicit language modelling?***
 - Derivation of ***grammar and syntax rules.***
- ***ChatGPT explainability?***

ChatGPT Questionmarks

- ***Do LLMs/ChatGPT have affect?***
 - Absolutely not in the human sense.
 - Yet, it is a disgrace that they can create such an impression to unsuspecting public, when texting like 'I love you'.
 - Machines are very good in understanding certain affect signals, e.g., ***facial expressions***.

LLM criticism

- *'Human intelligence can work well with few data'* (Chomsky, 2023) [CHO2023]: **completely wrong**.
- The contrary is true: both machine and human learning require massive training, in terms of data, architecture complexity and energy needs.
- ***Is it possible that similar laws govern both machine and human learning?***

LLM criticism

Criticism:

- *'Current LLMs have many deficiencies',*
- *'They do just massive plagiarism',*
- *'They know nothing about particular domains',*
- *'They are not multimodal, e.g., supporting visual perception' (except GPT-4).*
- **Completely wrong claims.** LLMs are only at the start. Great advances are expected.
- Such nihilistic criticism is similar to the ill-fated criticism of Rosenblatt's perceptron by Minsky and Papert that led to the AI winter at the end of the 1960s.

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LLMs and AI in Education

ChatGPT opportunities.

- LLMs can be used as a new education tool with massive impact in education.
- We have to research how to best use it.
- Its interaction with other teaching modes must be researched.
- Can it be used to trigger creative thinking, while speeding up tedious processes?

LLMs and AI in Education

IT and AI opportunities in education.

- What is the impact of IT and AI in teaching Mathematics?
- What is the impact of LLMs in teaching languages?
- What is the impact of Deep Arts in Arts Schools?
- What is the **long-term impact of IT and AI** in human memory?
- Will brain be 'restructured' to be, e.g., devoted more to thinking tasks than to memory?
- Can we observe such findings from historical records?

LLMs and AI in Education

UNESCO guidelines [MIA2023].

- Promote inclusion, equity, linguistic and cultural diversity.
- Protect human agency.
- Monitor and validate GenAI systems for education.
- ***Develop AI competencies including GenAI-related skills for learners.***
- Build capacity for teachers and researchers to make proper use of GenAI.
- Promote plural opinions and plural expressions of ideas.
- Test locally relevant application models and build a cumulative evidence base.
- Review long-term implications in intersectoral and interdisciplinary manner.

- ***Less than 10% of 450 schools/universities had policies on GenAI (2023).***

LLMs and AI in Education

Restrictive/regulated use of LLMs in education.

- Plagiarism tools to detect LLM-produced documents.
- Extreme caution when examining student projects
 - ***Very effort-intensive on Professors and students.***
- Extra caution in distance learning environments.
 - ***Return to old close student-Professor relations.***
- Imposition of minimal age to use LLM tools.

ChatGPT in Education

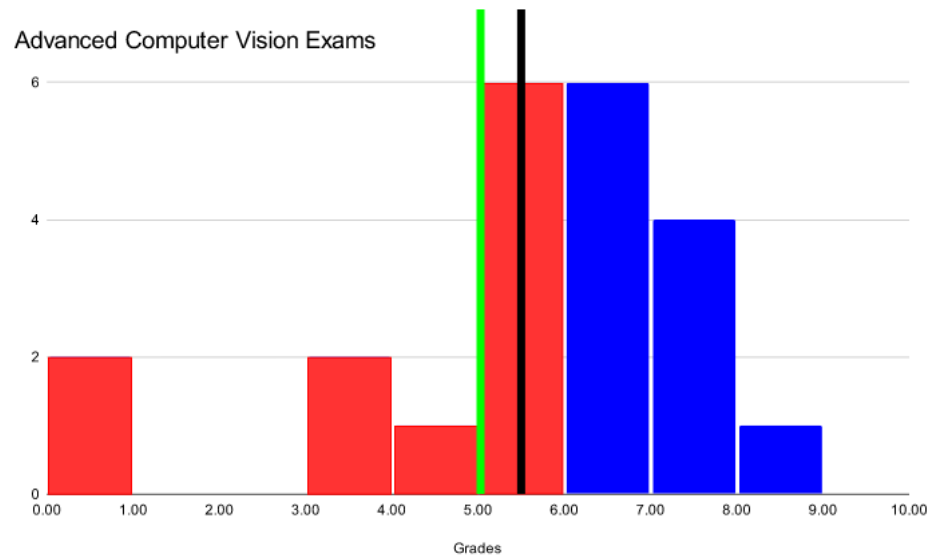
- ChatGPT can change the way we search and retrieve information.
- It has the capacity to help students reply to scientific questions.
- ChatGPT changes:
 - student project execution and examination.
 - educational exams.

ChatGPT in Education

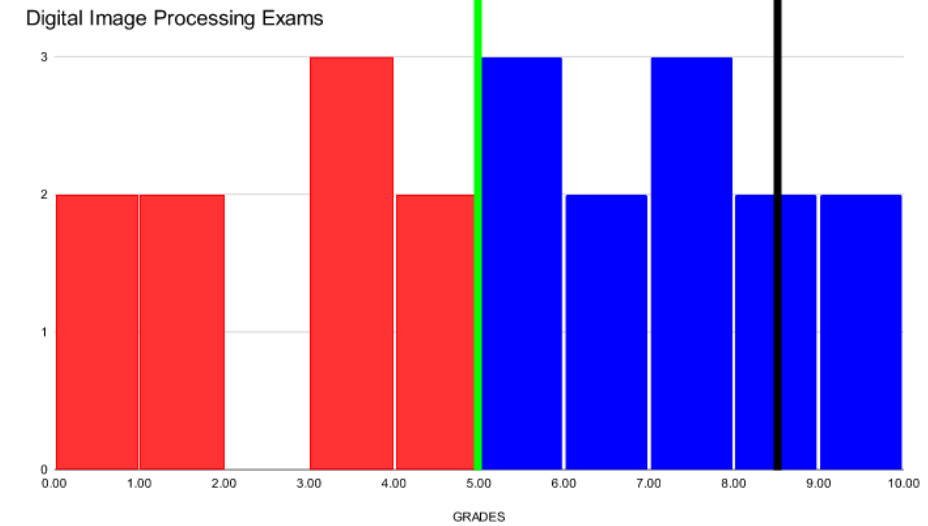
‘Scientific’ capacity of ChatGPT:

- Good at replying factual questions on known topics.
- It has certain capacity to reply mathematical questions.
- It can solve programming exercises very well (e.g., in Python).
- ***Currently, it can neither process nor output diagrams and figures.***

ChatGPT in Education



— Mean Value of student grades(N=22)
— ChatGPT Grade



— Mean Value of student grades(N=21)
— ChatGPT Grade

ChatGPT in CS/ECE exams: very good score in mathematical questions.

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AI and University Education

- Currently, the Humanities face the greatest pressure from LLMs and AI.
- The **mathematization of classical subjects** (e.g., Linguistics, Sociology) has advanced significantly.
- Alternative? Creation of departments for '**Philological/Linguistic Engineering**' or '**Social Engineering**' in Science/Engineering Schools.

AI and University Education

Is the combination of Liberal studies and AI doable?

- The distinction between Humanities and Natural Sciences/Engineering persists in most countries.
- Women prefer Humanities than Natural Sciences/Engineering.
 - Only 25-30% of engineers are women.

AI and University Education

The distinction between Humanities and Natural Sciences/Engineering has deep historical roots.

- Humanities were meant to be for the gentry (ruling class) [BER1946].
- They are very old disciplines.
- Emphasis on character rather than knowledge:
 - ‘καλός κ’ αγαθός’ (in Ancient Greece)
 - Liberal education of ‘Piano and French’ style.

AI and University Education

The distinction between Humanities and Natural Sciences/Engineering has deep historical roots.

- Natural Sciences/Engineering are much younger (16-19th centuries).
- They facilitated the industrial revolution.
- They are much closer to profit making and bourgeois ideology.

AI and University Education

Does the distinction between Humanities and Natural Sciences/Engineering have biological roots?

Contrasting arguments:

- There is no evidence that women are worse than men in mathematics.
- Women tend to have inclination to humanities, even if they do well in Mathematics (D. Kimura).
- Most people do not perform well in both linguistic and mathematical tests.

Exception: Few people are excellent in all disciplines.

AI and University Education

New Language Theory and Linguistic Methodologies

- **Understanding of LLM performance.**
- Development of new methodologies in Linguistic studies
 - Complement grammar, syntax, etymology etc.
- Teaching of this new theory and methodology.
- ***We are just at the start!***

AI and University Education

Past experience: from Humanities to Mathematics

- Transition from Aristotelian Logic to Mathematical Logic
 - Boolean Algebra and (19th century)
 - Foundations of Computers (mid 20th century)
- Mathematical Logic is essential tool in Symbolic AI (1960-1980)
- **Too bad Symbolic AI failed to deliver so far.**

AI and University Education

Creation of Departments for '*Mind and Social Science and Engineering*' in Schools of Arts and Humanities.

- Groundbreaking proposal.
- *Departments of Digital Humanities* is another good solution.
- The exact name or form is not important, as long as it serves the transfer of mathematical and programming skills to arts and humanities students.

AI and University Education

Alternatives:

- Introduction of 2-3 obligatory Mathematics and Computer Science courses in each Liberal Discipline.
- Double BSc/MSc degrees 'X+AI'
 - X: any Liberal Discipline (major).
 - AI minor

AI and University Education

Essential CS courses for AI education (minor in Liberal Studies):

- Mathematical Analysis
- Linear Algebra
- Probabilities and Statistics
- Signals and Systems
- Programming
- Machine Learning/Pattern Recognition
- Neural Networks
- Natural Language Processing.

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Citizen Morphosis

Information and Knowledge Society

- Information society: exponential increase of data/information, linear increase of knowledge.
- Knowledge society: exponential increase of knowledge?
- AI, IT and ***citizen morphosis*** are our only hope to have a smooth transition from the current Information Society to a Knowledge Society.
- Else, humanity may face a catastrophic social implosion, if proven unable to advance and pass knowledge to new generations (see ***start of Medieval Times***).

Citizen Morphosis

Citizen morphosis (rather than education) emphasizes the need for conscious citizens:

- with ***critical thinking, communication precision skills, imagination, and emotional intelligence;***
- being able to understand, adapt, and ultimately harness the tremendous new technological and economic possibilities and employment prospects.
- Such a level of education is sought after today in many job positions internationally.

Citizen Morphosis

Major overhaul of education at all levels to master knowledge development and uptaking needs.

- The need for such education permeates all levels of education and all social strata.
- A ***1/3-2/3 society***, where 1/3 of the population understands and benefits from scientific progress, while the remaining 2/3 lags, being impoverished and technophobic, is simply not sustainable.
- Need to educate women, minorities and Global South to improve the global education level.

Citizen Morphosis

The ***basic AI and IT concepts*** are simple and can be taught at all educational levels:

- Data clustering, similarity, classification etc.
- Educational readjustment for their teaching by ***rearranging the curriculum of Mathematics and Informatics.***
- A (partial) mathematization of education is inevitable.
- It is not certain that it is feasible, given the traditional separation of the sciences and the humanities.

Citizen Morphosis

- ***Classical studies*** are also an ideal tool for developing critical thinking and precision.
- They provide a solid basis for ***Ethics, Legal and Social Implications*** (ELSI) knowledge.

AI and Linguistic Studies

- What is AI?
- Machine Learning
- Natural Language Processing
- Large Language Models
- GPT and ChatGPT
- LLMs and AI in Education
- AI and University Education
- Citizen Morphosis
- **Artificial General Intelligence**

Artificial General Intelligence

Is AGI the next step after LLMs?

- A deeper understanding of LLM operation is needed.
- The exact GPT4 architecture and parameters (transformer network weights) are a well-kept corporate secret.
- A deep LLM functionality understanding would be difficult, even if LLMs were open, due to their immense complexity.
- Neuroscience did not advance enough to understand brain and human intelligence.

Artificial General Intelligence

Is AGI the next step after LLMs?

- Most probably AGI will be VERY different from human intelligence.
 - Airplanes are different than birds, yet they obey the same laws of Physics.
- The physical substrate of AI and human intelligence is very different.
 - Robots have very limited but different physical intelligence.
 - Things may change by developing biological robots.
- ***Life evolution by-design*** than through physical selection.
- Massive ***human-machine symbiosis*** at various levels.

Artificial General Intelligence

Is AGI the next step after LLMs?

- Will AGI be any different from human intelligence from a behavioral point of view that is worth talking about?
- Today ***too many*** commoners cannot make the difference.
- The phenomenon is intensified by:
 - Lack of proper education.
 - Access of machines remotely.
 - Unwise claims and behavior of AI agents to the general public, e.g.,:
 - AI hallucinations being misunderstood as imagination.
 - False claims of sentiments (internal affect states) by machines.

Artificial General Intelligence

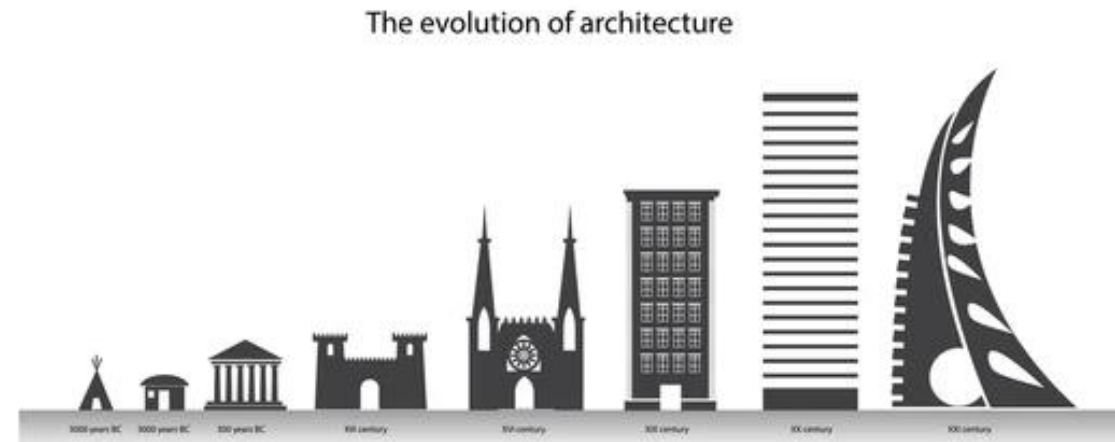
Layman's technophobia

- ***Fear of the unknown*** as commoners cannot understand AI.
- Machines appear to be intelligent and possibly better at that than the humans themselves.
- They are ***massively better*** in certain tasks, e.g., computations, memory/retrieval.
- Machines appear to be ***sentient***.
- Humans are awed by ChatGPT 'intelligence' much more than by other Generative AI methods, e.g., Deep Arts.
- ***Any technophobia can be socially destructive.***

Artificial General Intelligence

Scientific technophobia

- Very recent trend: scientists fearing the unknown.



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Parable: AI and the tower of Babel.

Artificial General Intelligence

Can AI be stopped or delayed?

- *AI is the response of humanity to a global society and physical world of ever-increasing complexity.*
- The physical and social complexity increase processes are ***very deep and seeming relentless.***
- *AI is a blessing, but it can become a curse.*
- Political, ethical, and regulatory concerns cannot and should not stop AI research [FUT2023].
- Scientific technophobia leads nowhere [NYT2023].

Artificial General Intelligence

Can AI be stopped or delayed?

- ***AI research can and should become more open, democratic, scientific and ethical.***
- Simple AI regulatory examples:
 - AI system registry,
 - Clear indication that somebody converses with a machine.
- AI deployment should be regulated and can be temporarily delayed.
 - Geopolitical aspects must be dealt by international cooperation.

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Q & A

Thank you very much for your attention!

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