AI, Large Language Models and University Education

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Artificial Intelligence & Information Analysis Lab

Large Language Models, ChatGPT and University Education

- Introduction
- Large Language Models
- GPT
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- Limitations
- ChatGPT and University Education
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Introduction

- 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.

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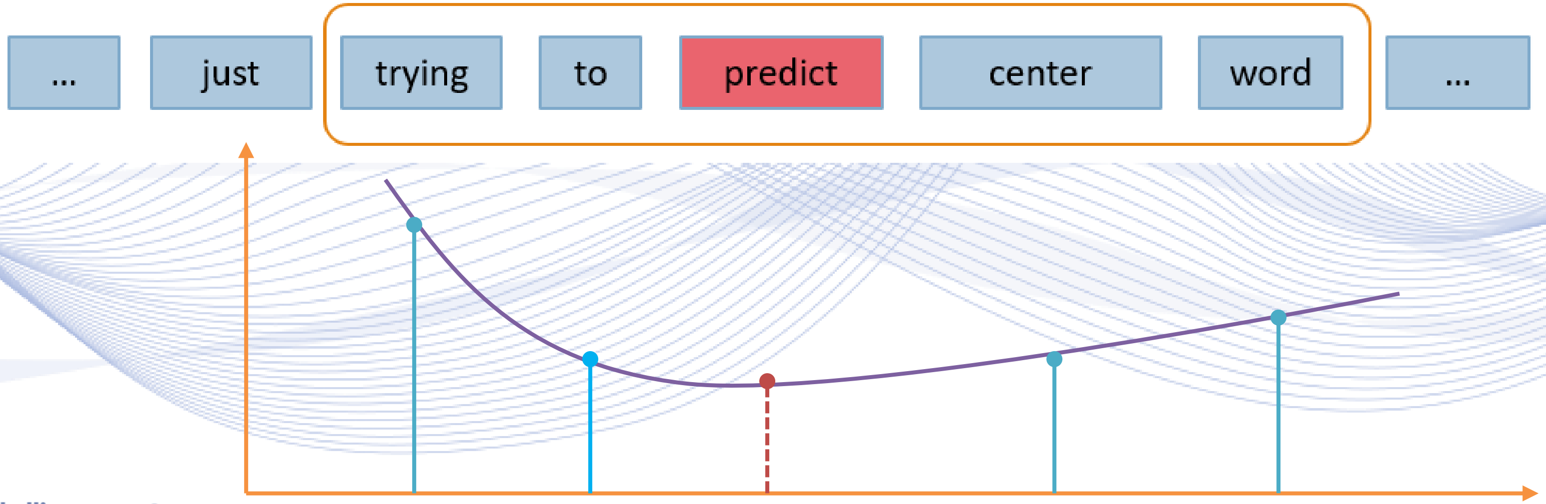
Large Language Models

Word embeddings: ***Word2Vec*** (example)

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

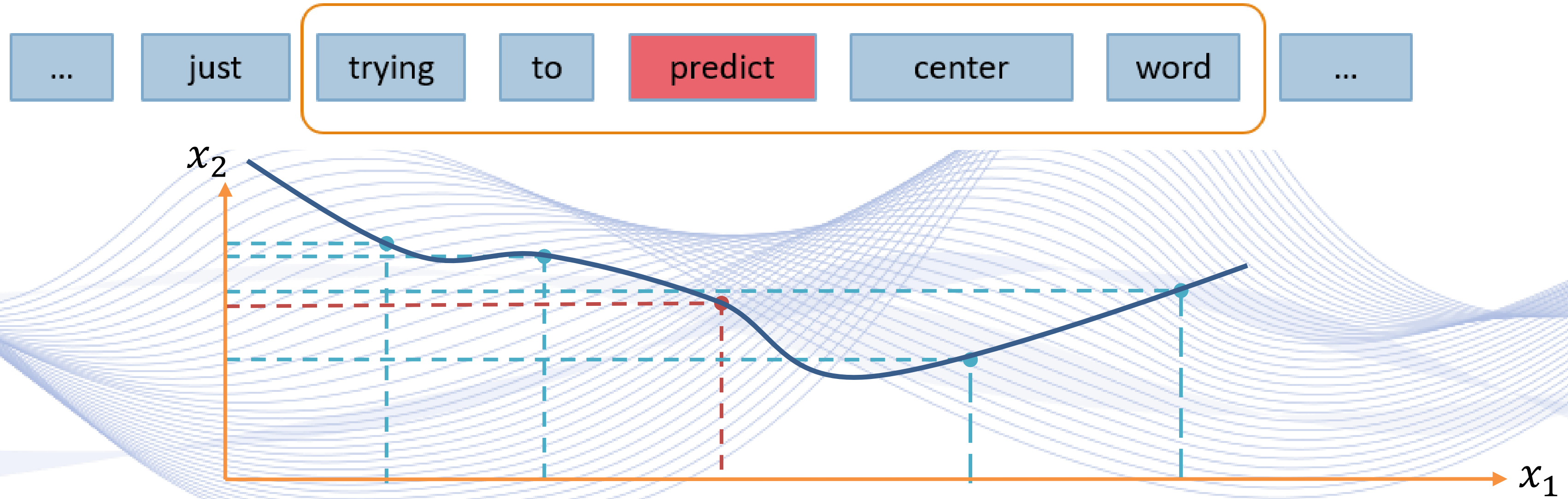
- Training is performed with pairs of context-target words.
- 2 training variations.



Word embeddings

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.

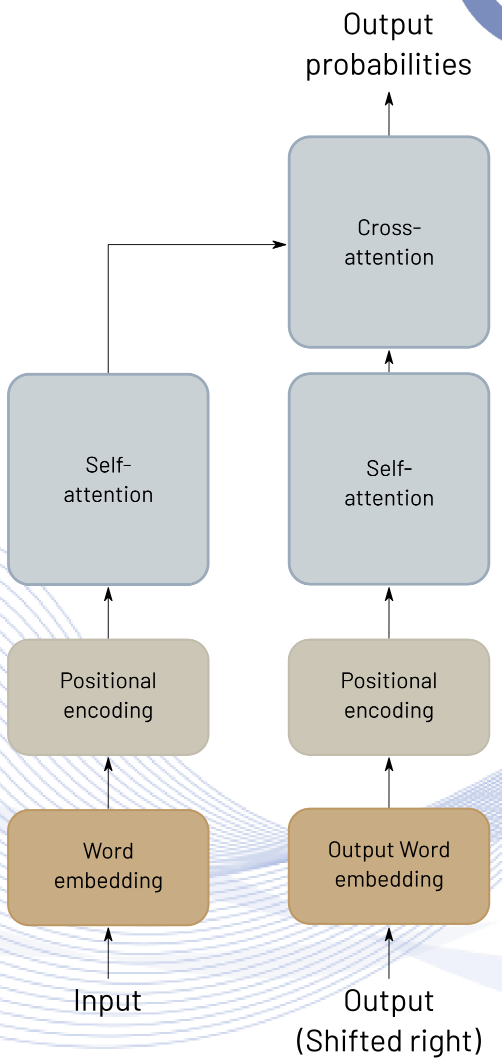


Word trajectory in a 2D vectorial space $[x_1, x_2]$.

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.

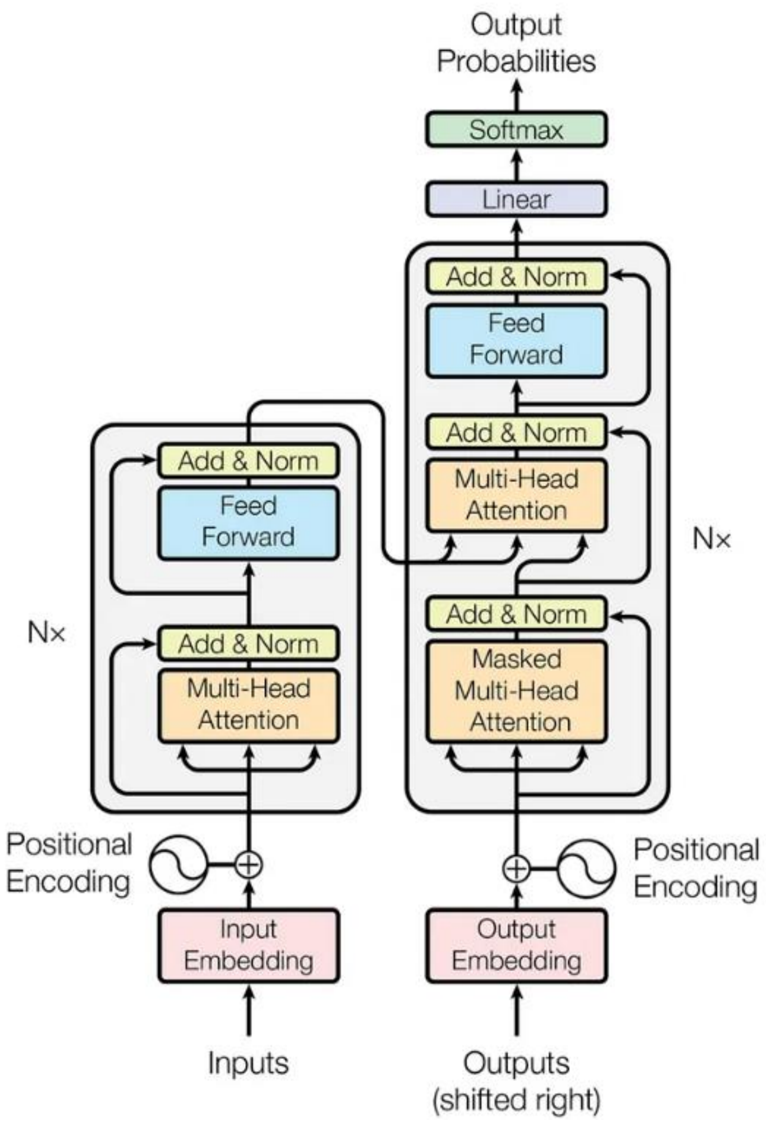


Transformer architecture.

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.

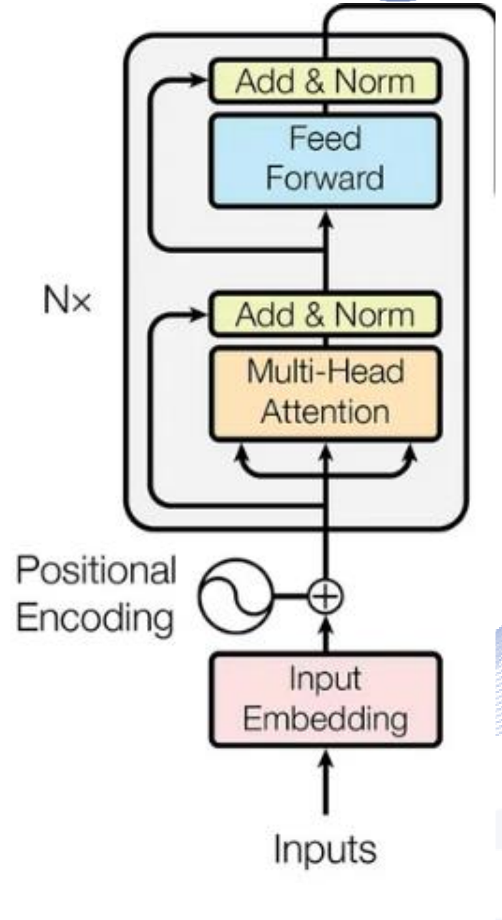


Transformer architecture [VAS2017].

Large Language Models

The ***transformer encoder*** processes the input sequence using two sub-layers [VAS2017]:

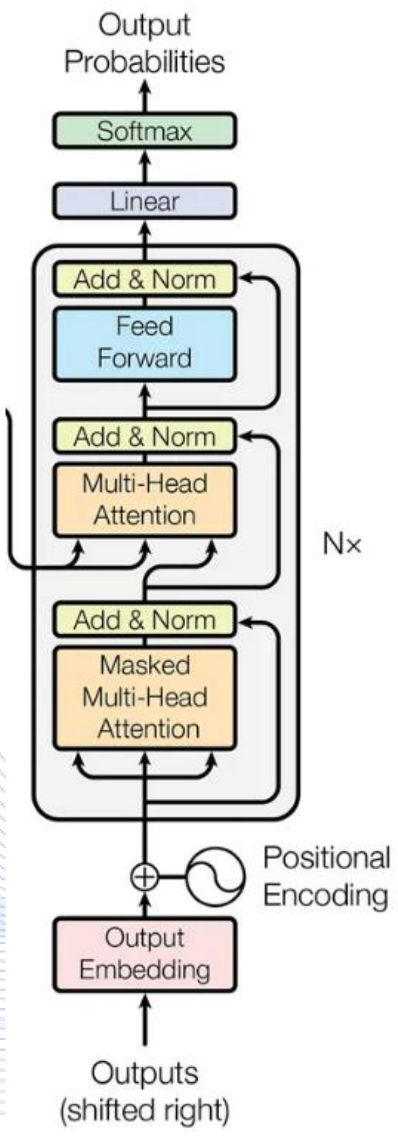
- ***Multi-head self-attention mechanism***: It attends to different parts of the sequence in parallel, inferring meaning and context.
- ***Position-wise fully connected feed-forward network***: Two linear transformations with a RELU activation in between applied to each position independently [VAS2017].



Transformer encoder [VAS2017].

Large Language Models

- The ***transformer decoder*** has an extra multi-head ***cross-attention*** sub-layer of attention, between the two sub-layers of the encoder layer.
- It outputs the probability of each vocabulary token.
- In the multi-head ***cross-attention*** sub-layer the key-value pairs $\mathbf{K}, \mathbf{V}$ are obtained from the encoder output.



Transformer decoder.

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.

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.***

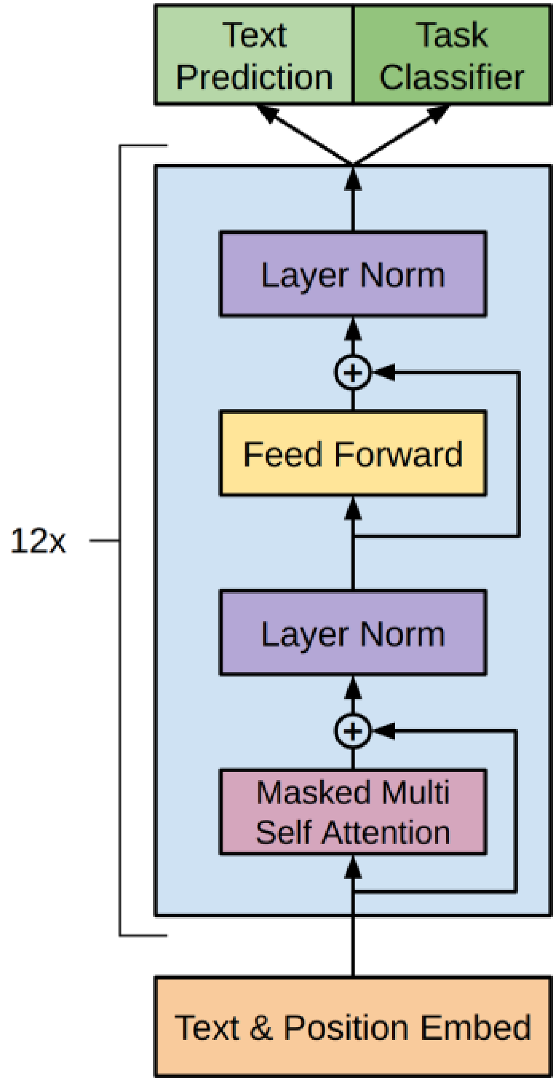
GPT

- 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].

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GPT Training stages

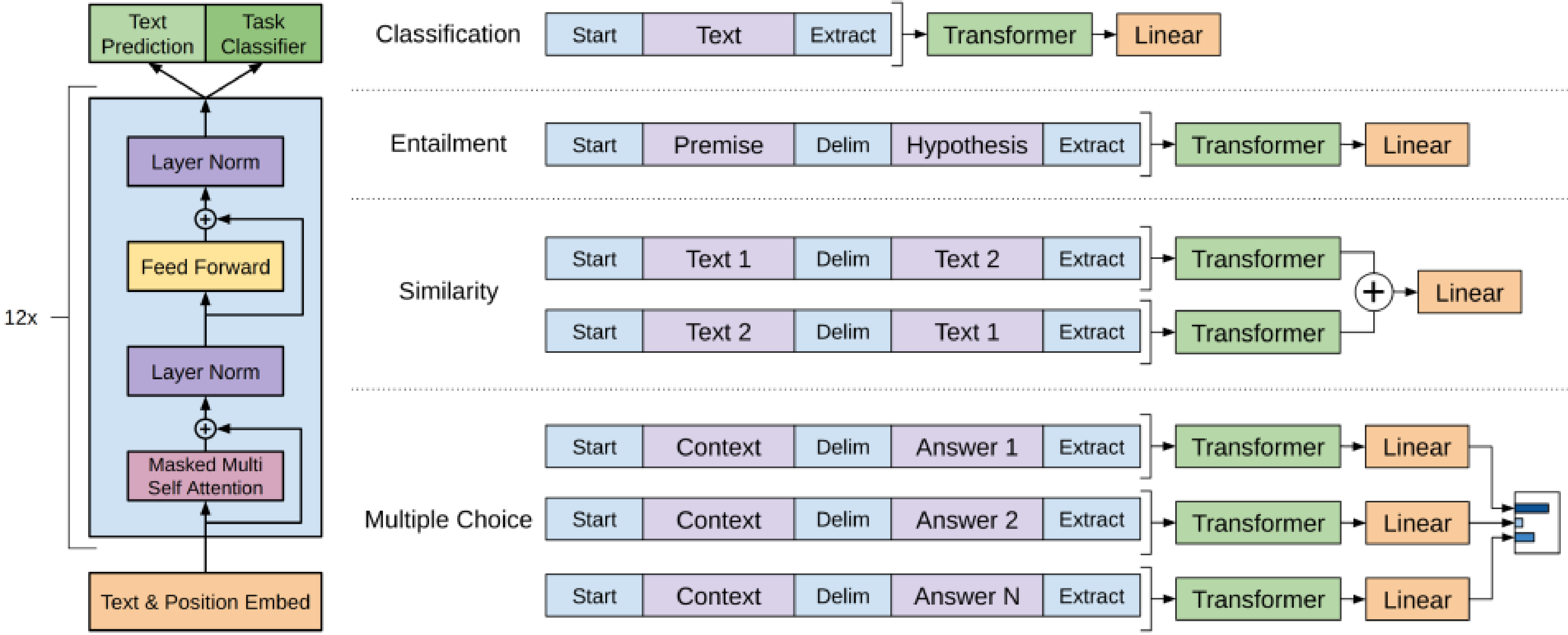
Unsupervised Pre-training stage:

- *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].

GPT



GPT architecture of GPT model (left). Input for GPT fine-tuning to perform various tasks (right) [RAD2018].

GPT-2

- GPT-2 is larger than the first GPT model [RAD2019]:
  - GPT: 117 million parameters, GPT-2: 1.5 billion parameters.

- GPT-2 employs ***zero-shot learning***.
- Special tasks (text translation, question answering, etc.) can be framed in the same way as language modelling.
- WebText training dataset (internal OpenAI corpus) was used with emphasis on document quality.

GPT-2

- ***Zero-shot learning***: GPT model input is: a) a task description b) prompt.
- Example: *Translate English to French* (task description), *cheese* (prompt).

- ***One-shot learning***: GPT model input is: a) task description and b) a single task example (from the training dataset).
- ***Few-shot learning***: GPT model input is: a) task description and b) few task examples (from the training dataset).

GPT-3

- GPT-3 is a Transformer DNN with the same design and architecture as GPT-2 [BRO2020].
- It is an autoregressive model generating a continuation of an input sequence of tokens.
- ***GPT-3 has 10 times bigger parameter set compared to GPT-2***:
  - 175 billion parameters, 96 attention layers.
  - Each layer has 96 heads. Each head is 128-dimensional.

- GPT-3 is trained on batches of size 3.2 million token.

GPT-3

- After the pretraining stage GPT-3 (in contrast to GPT-2), applies in-context learning to address fine-tuning issues [BRO2020]:
  - E.g., too many required data, overfitting.

- Training dataset comprises:
  - Common Crawl (filtered) [COM2023], WebText2 [ALE2019].
  - Books1, Books2 [JAR2020], Wikipedia [BRO2020].

GPT-4

- GPT-4 is a large multimodal model

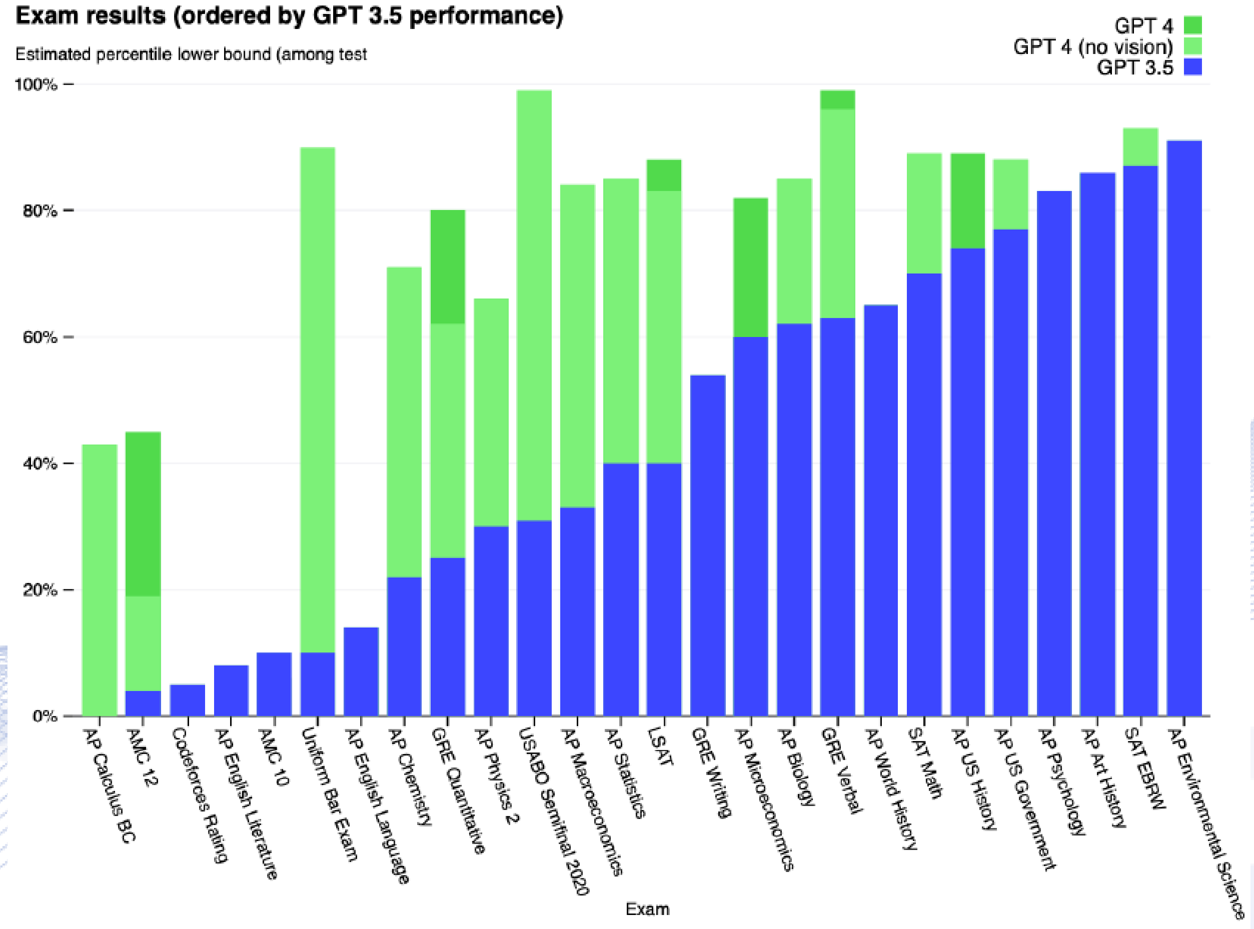
Input: Both images and text

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].



GPT performance on academic and professional exam [OP2023].

GPT-4 Capabilities

- Visual inputs
- Steerability
- Significantly reduced hallucinations
- Improved safety and alignment
- Improved mathematical reasoning
- Strong performance in many languages.

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].

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GPT-4 Limitations

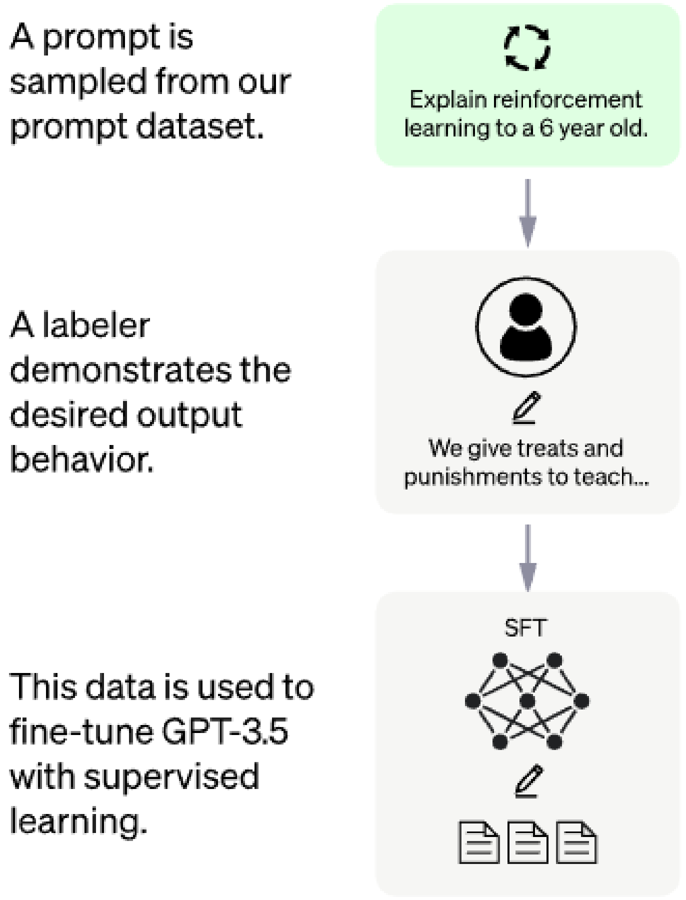
GPT-4 suffers from the same limitations as the previous GPT models [OP2023]:

- 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 – Fine-Tuning

A pre-trained 3rd generation GPT DNN for language tasks is acquired.

- Step 1: Fine-tune the pre-trained GPT DNN on a labelled dataset [OPE2023].

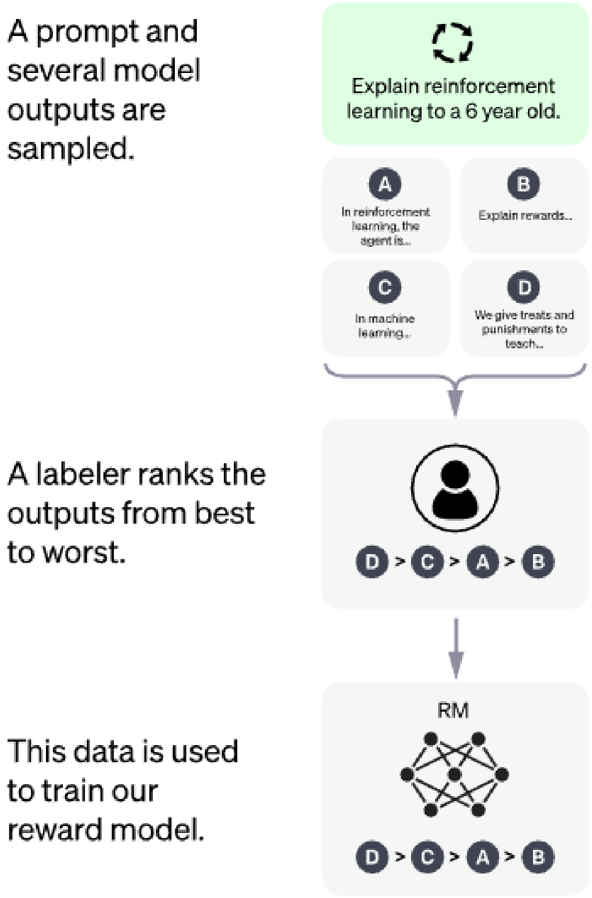


ChatGPT fine-tuning (step 1) [OPE2023].

ChatGPT – Fine-Tuning

- Step 2: A reward model is trained with a scalar output.
- The output quantifies how good was the response of the fine-tuned GPT to a given prompt.

- ***Human-in-the-loop*** through ***Reinforcement Learning from Human Feedback*** (***RLHF***).



Step 2 of ChatGPT fine-tuning: reward model training [OPE2023].

ChatGPT – Fine-Tuning

ChatGPT reward model:

- It is trained on a dataset of responses returned by the fine-tuned GPT-3 for a given prompt [OPE2023].
- For each prompt, the fine-tuned GPT outputs four responses according to a decoding strategy by sampling responses with the highest probability.
- The responses are labelled by a reward proportional to the quality of each output.
- Non-toxic and factual responses are given a higher reward.

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 Reasoning

- Despite performing well on certain reasoning tasks, ChatGPT is unreliable, as ***its responses are inconsistent*** [BAN2023].
  - Its reasoning evaluation was performed via question answering.
- ChatGPT has acceptable performance in deductive, abductive, temporal, causal and analogical reasoning [BAN2023].
- ChatGPT has weakness in inductive, spatial, mathematical, non-textual semantic and multi-hop reasoning [BAN2023].

ChatGPT Reasoning

Categories	Testset	Results
Deductive	ENTAILMENTBANK bAbI	28/30
Inductive	CLUTRR	13/30
Abductive	αNLI	26/30
Mathematical	Math	13/30
Temporal	Timedial (formatted)	26/30
Spatial	SpartQA StepGame (hard) StepGame (diagonal) StepGame (clock-direction)	12/30 7/30 11/20 5/20
Common sense	CommonsenseQA Pep-3k (Hard)	27/30 28/30
Causal	E-Care	24/30
Multi-hop	hotpotQA	8/30
Analogical	Letter string analogy	30/30

ChatGPT results on reasoning tasks [BAN2023].

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

- There are concerns and limitations due to lack of controllability and knowledge grounding in ChatGPT responses [BAN2023].

- ChatGPT fails in basic reasoning for recommendations.
  - It fails to answer correctly 66% of the time [BAN2023].

ChatGPT Limitations

ChatGPT hallucinations

- Statistical token associations may occasionally be out of context, or semantically wrong or completely fabricated.
- LLM training optimizes an ***objective function*** (or ***reward***) for a certain task.
- ***AI alignment problem***: a misaligned AI system may optimize some objective function, but not necessarily the intended one.
- Alternatively, an aligned AI system may get stuck in local minima and work sub-optimally.

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.

ChatGPT in Education

- ChatGPT can change the way we search and retrieve information.
- It has the capacity to help students reply to scientific questions.

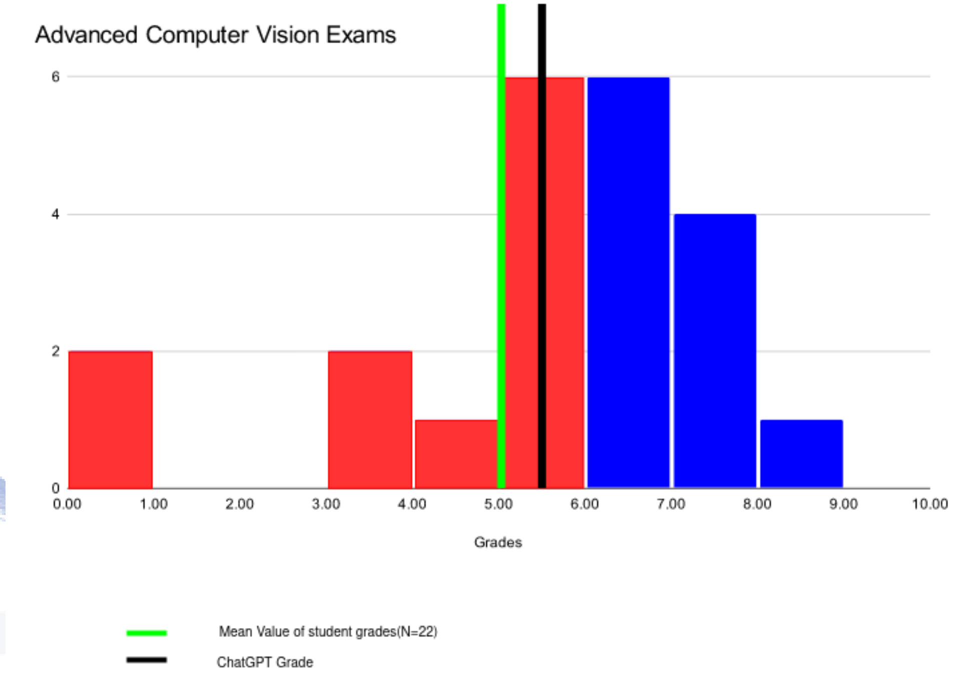
- ChatGPT changes:
  - student project execution and examination.
  - educational exams.

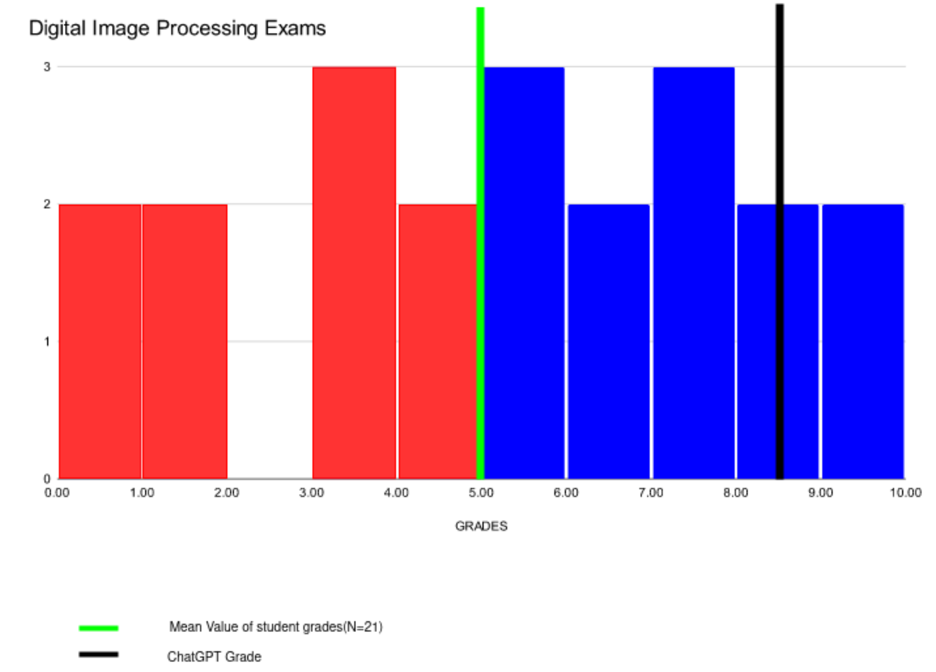
ChatGPT in Education

‘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





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

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ChatGPT in Education

ChatGPT and Mathematics:

- It can solve mathematical questions.
  - Complex numbers, Z/Fourier transform properties.
- Replies tend to be verbose.
- It fails on some simple mathematical questions
  - It cannot always handle well reasoning with negative numbers.

    Question: He asked me to give 2 Euros. I gave him 3; how much I owe him?

    ChatGPT: You owe him 1 Euro.

ChatGPT in Education

- ChatGPT in CS/ECE programming exercises: excellent scores (10/10).

Here is a Python code that implements the functionality you specified:

python Copy code

```python
import random

def find_mean(numbers):
    """Finds the mean value of a list of numbers"""
    return sum(numbers) / len(numbers)

def moving_average(signal, window_size):
    """Applies the moving average filter of size 'window_size' on a signal"""
    filtered_signal = []
    for i in range(len(signal) - window_size + 1):
        filtered_signal.append(find_mean(signal[i:i+window_size]))
    return filtered_signal

# Test the code
numbers = [random.randint(1, 100) for i in range(3)]
print("Random numbers:", numbers)
print("Mean value of the numbers is:", find_mean(numbers))

signal = [random.randint(1, 100) for i in range(10)]
print("Random signal:", signal)
print("Filtered signal with window size 3:", moving_average(signal, 3))
```

ChatGPT programming: arithmetic mean and 1D moving average filter routines in Python.

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.

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 then 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 halucinations being misunderstood as imagination.
  - False claims of sentiments (internal affect states) by machines.

Artificial General Intelligence

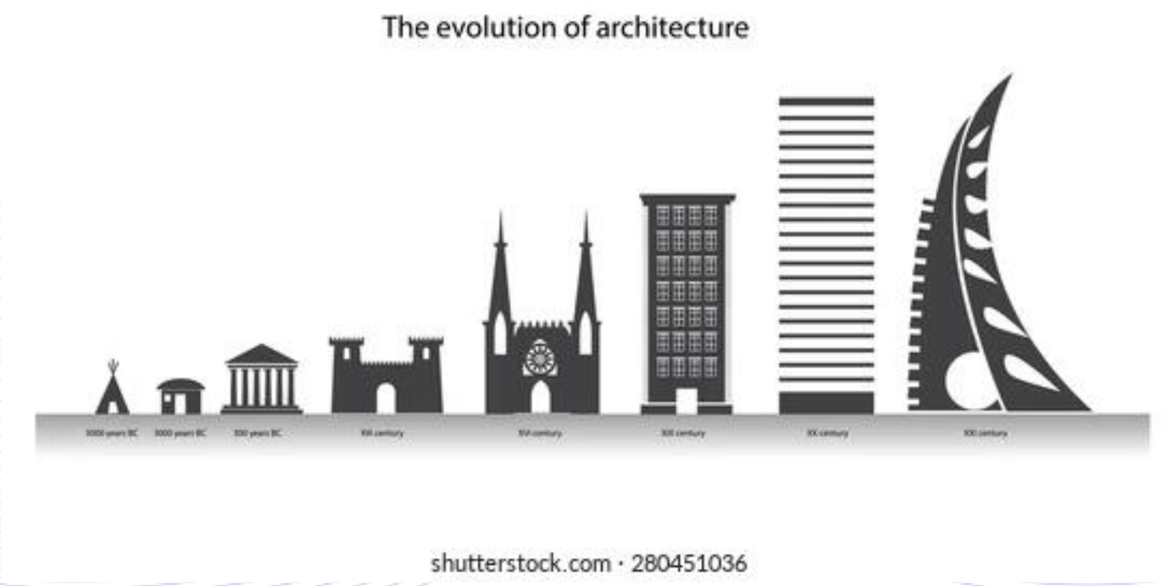
Layman's technophobia

- ***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.



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.

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 University Education

Changes will be drastic and will come very soon.

Schools of 'Information Science and Engineering' with departments of:

- Computer Science/Informatics,
- Mathematics
- Computer Engineering
- Artificial Intelligence Science and Engineering
- Internet/Web Science.

AI and University Education

AI Science and Engineering: A new scientific discipline?

- CSE spawning new disciplines ***through specialization***:
  - Web science
  - Data science
  - AI Science and Engineering.
- New scientific methodologies are not ***necessarily*** essential.
- Poor terminology?
- Past experience: ***Physics spawning Engineering disciplines***
  - Electrical Engineering, Mechanical Engineering.

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

- 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

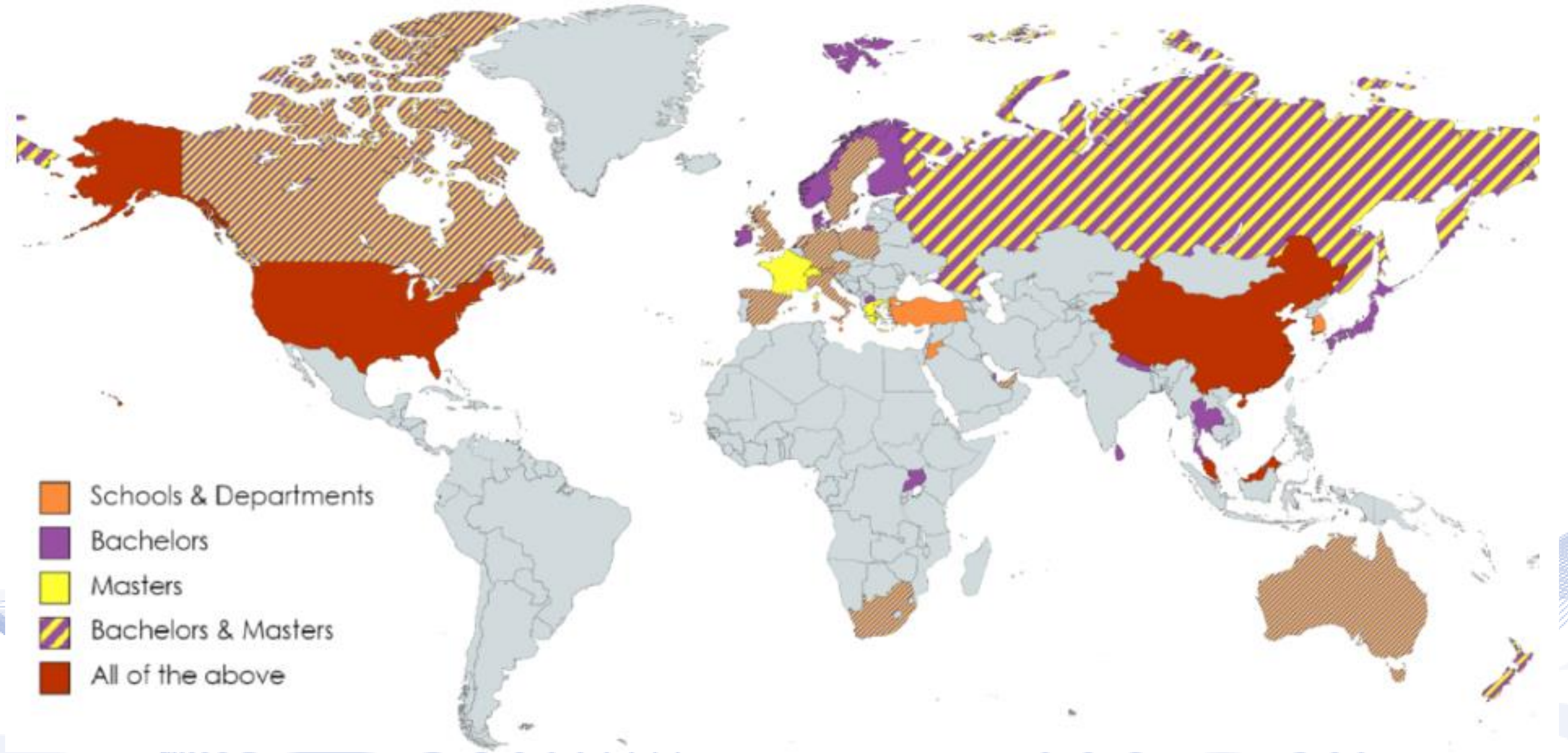
Creation of departments for '***Bio-Science and Engineering***' in Schools of Health Sciences, including:

- Biomedical Engineering, Genetic Engineering and Systems Biology.

Mandatory inclusion of Mathematics and Computer Science courses in all disciplines without exception.

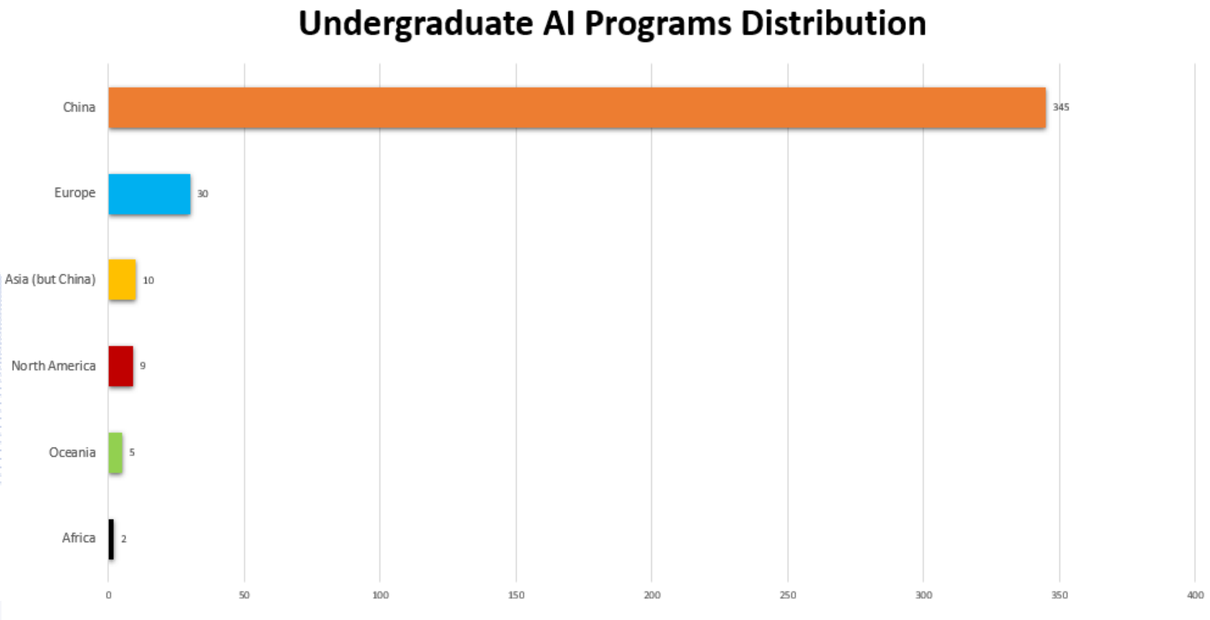
- Simply, one (poor) course in Statistics does not meet the current needs.
- Mandatory courses on AI ***Ethics, Legal and Social Implications*** (ELSI) in all ECE, EE, CS and CSE Curricula.
- It is already partly underway.

University Education on AI

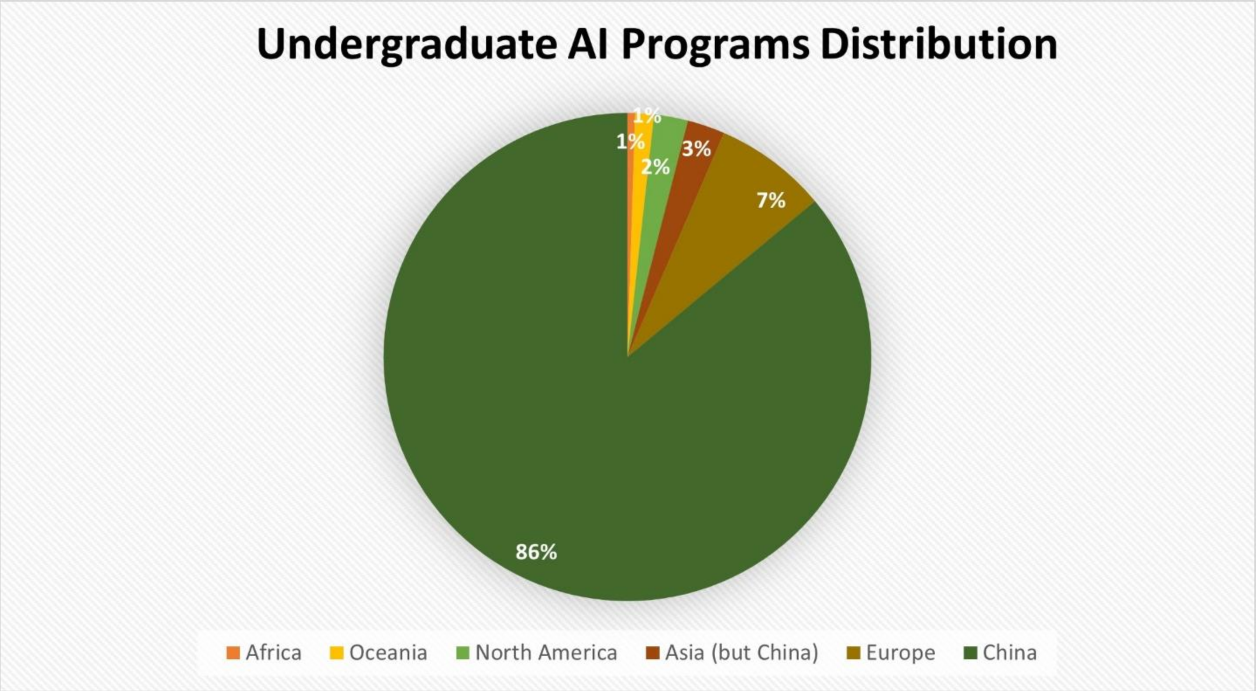


Countries that offer AI studies.

University Education on AI

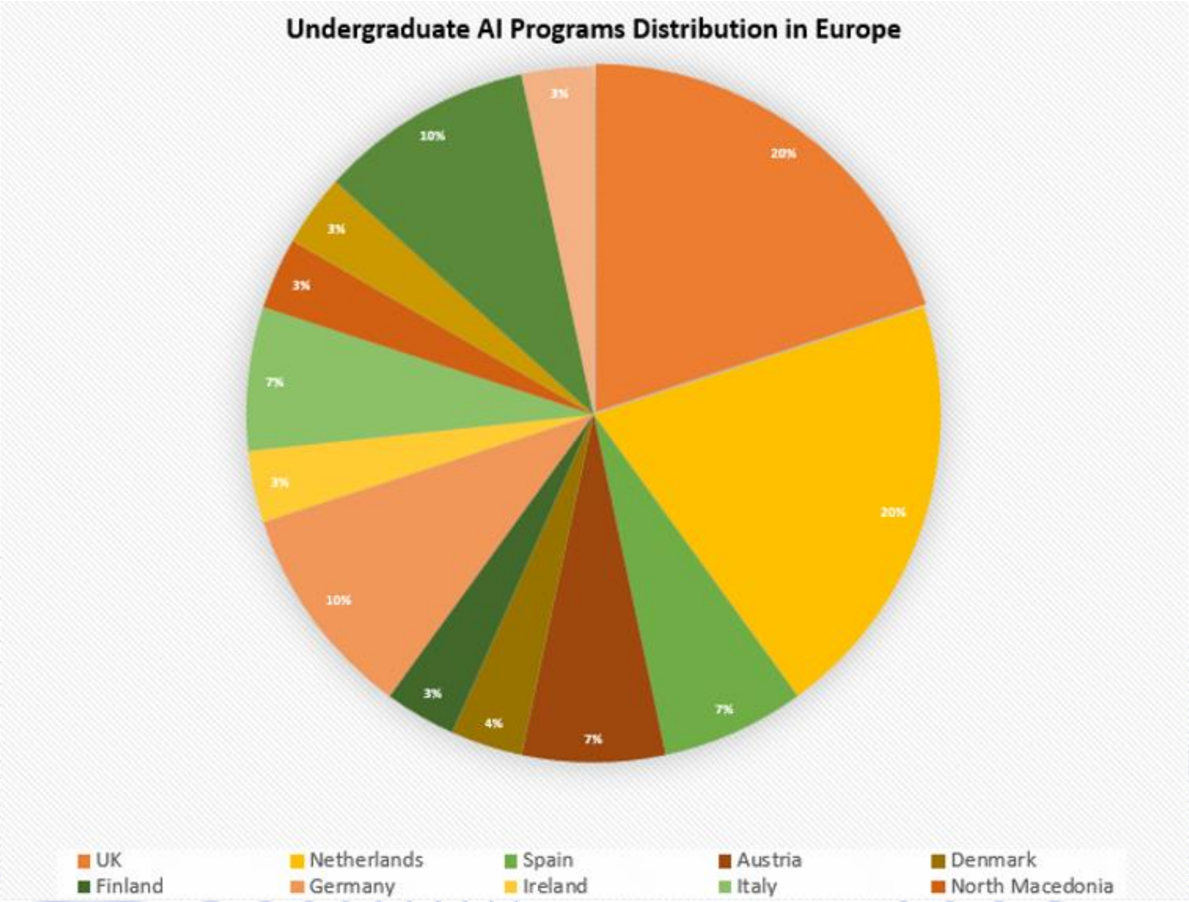


Number of undergraduate AI programs worldwide.



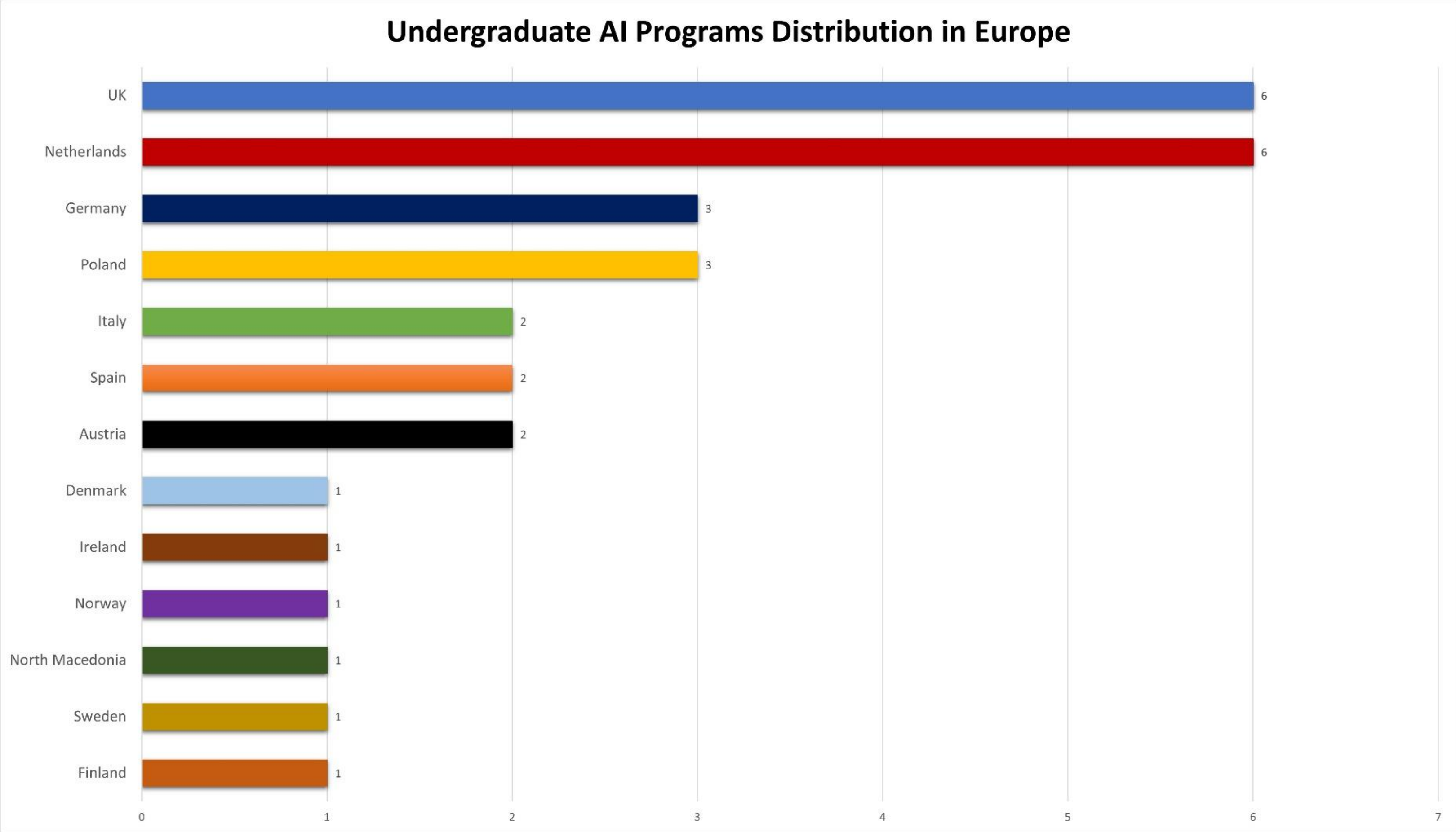
Global distribution of undergraduate AI studies.

University Education on AI



Distribution of undergraduate AI programs in Europe.

University Education on AI



Geographical distribution of AI undergraduate programs in Europe.

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Q & A

Thank you very much for your attention!

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