# Introduction to GenAI: Practical Benefits and Challenges

Jasmin Jahić; Lorena Escudero Sánchez; Challenger Mishra
jj542@cam.ac.uk; les44@medschl.cam.ac.uk; cm2099@cam.ac.uk

# Agenda

- Introduction to AI
- Properties, limitations and strengths of GenAI
- Exercises
- Discussion
- Framework for transformation of organisations

# Learning Outcomes

Be able to discuss basic AI terms

Be able to use ChatBots

Be able to recognise tasks potentially suitable for AI

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**Course material:**

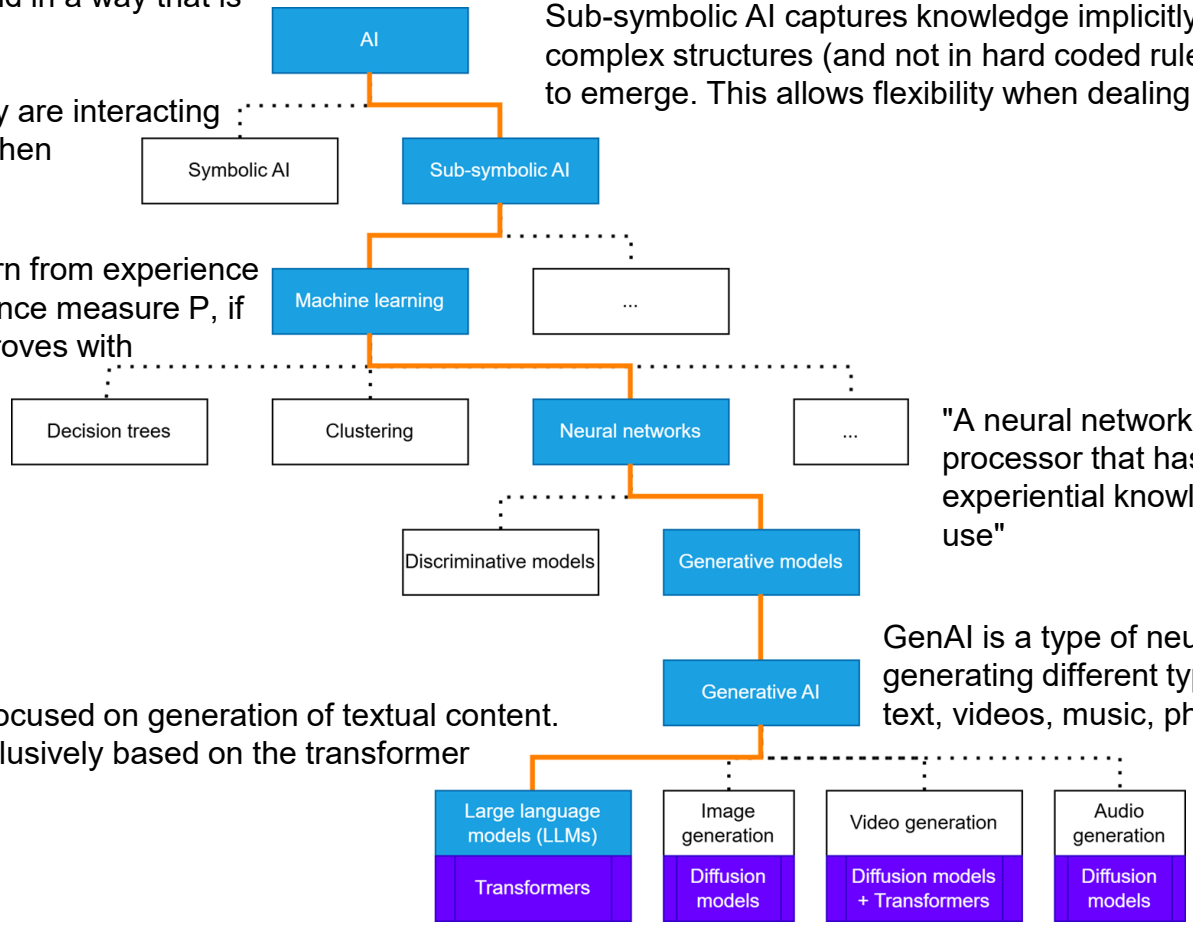
- Slides
- CoatOfArms image
- LibraryImage image
- Data Excel document

# Artificial Intelligence and Generative AI

Turing test: is it possible for machines to process information in a manner that thinking humans do and respond in a way that is indistinguishable from humans?

An imitation game: humans try to guess if they are interacting with another human or a “thinking machine” when communicating through a form of a terminal.

Machine learning: "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."




Sub-symbolic AI captures knowledge implicitly in numerical patterns and complex structures (and not in hard coded rules), allowing conclusions to emerge. This allows flexibility when dealing with uncertainty.

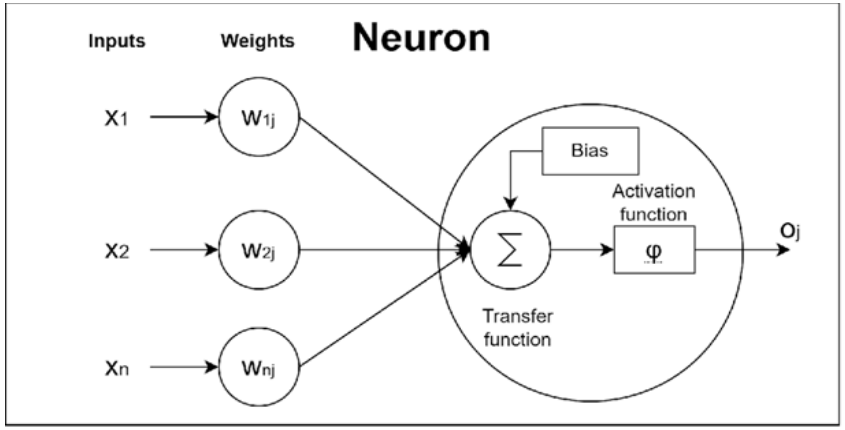
"A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use"

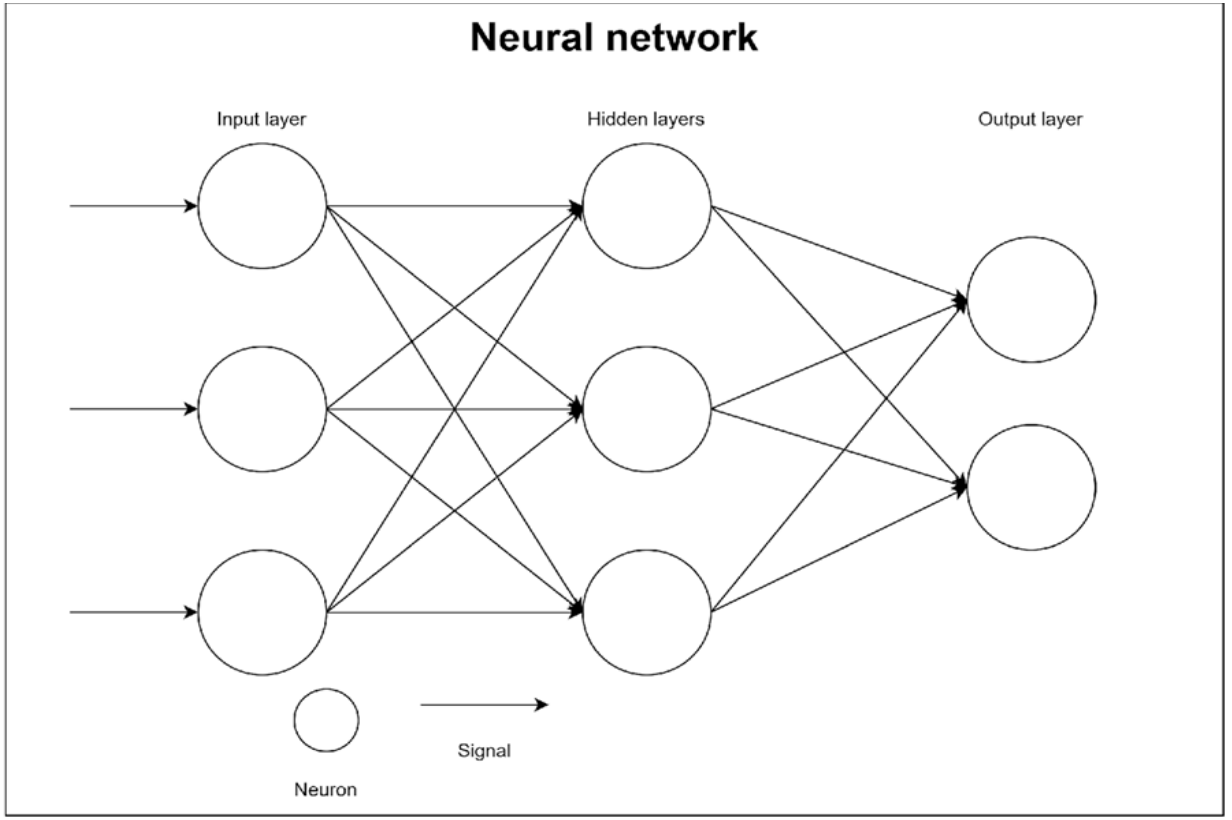
GenAI is a type of neural network capable of generating different types of new content such as text, videos, music, photos, etc.

LLMs are primarily focused on generation of textual content. They are almost exclusively based on the transformer architecture.

Transformers introduce the notion of ‘attention scores’, focusing on the most relevant data for the task at hand.

# Neural Networks




- Weights: assigned to a link between two neurons to determine how much the output of one neuron influences the input of another.
- Bias: influences the nonlinear function of a neuron.
- Probabilities (between 0 and 1)
- **Randomness**
- **Training**: adjusting weights and bias based on mass data (unsupervised and supervised learning)
- **Number of parameters**: weights and biases
- Train on ***available*** data
- Token: the smallest unit of input/output data. E.g., (e.g., "Good overview of AI" -> "Good", "overview", "of", "AI), on subword level (e.g., "overview" -> "over", "view").
- **Inference**: a process of reaching (inferring) some output from a trained neural network based on inputs – what is the next token?

# Properties of LLMs

A **context window** ('working memory') is the amount of data that a GenAI model can consider at any given time when generating an output to a prompt. As we approach the limit of the context window size, a GenAI model may 'forget' older information like previous input prompts and previous model output.

**Guardrails** are mechanisms that prevent models from answering certain questions, such as those about security exploits or confidential data.

**Data privacy**: the use of data is defined by contracts with LLM providers. OpenAI can use the data and conversations from your Free tier ChatGPT account to train its AI models - "Improve the model for everyone" (can be opted out) - Golden rule: once online, always online.

A **prompt** is an input provided into a GenAI system that serves to initiate a conversation or pose queries to obtain specific outputs.

**Probability**: the likelihood of an outcome within a range of real numbers, from 0 (impossible) to 1 (certain).

**Retrieval-augmented generation (RAG)**: The RAG combines algorithmic fetching (for instance, regular search on an external knowledge database or other sources external to an AI model) of data with GenAI, primarily LLMs. It helps ground GenAI results and avoid hallucinations.

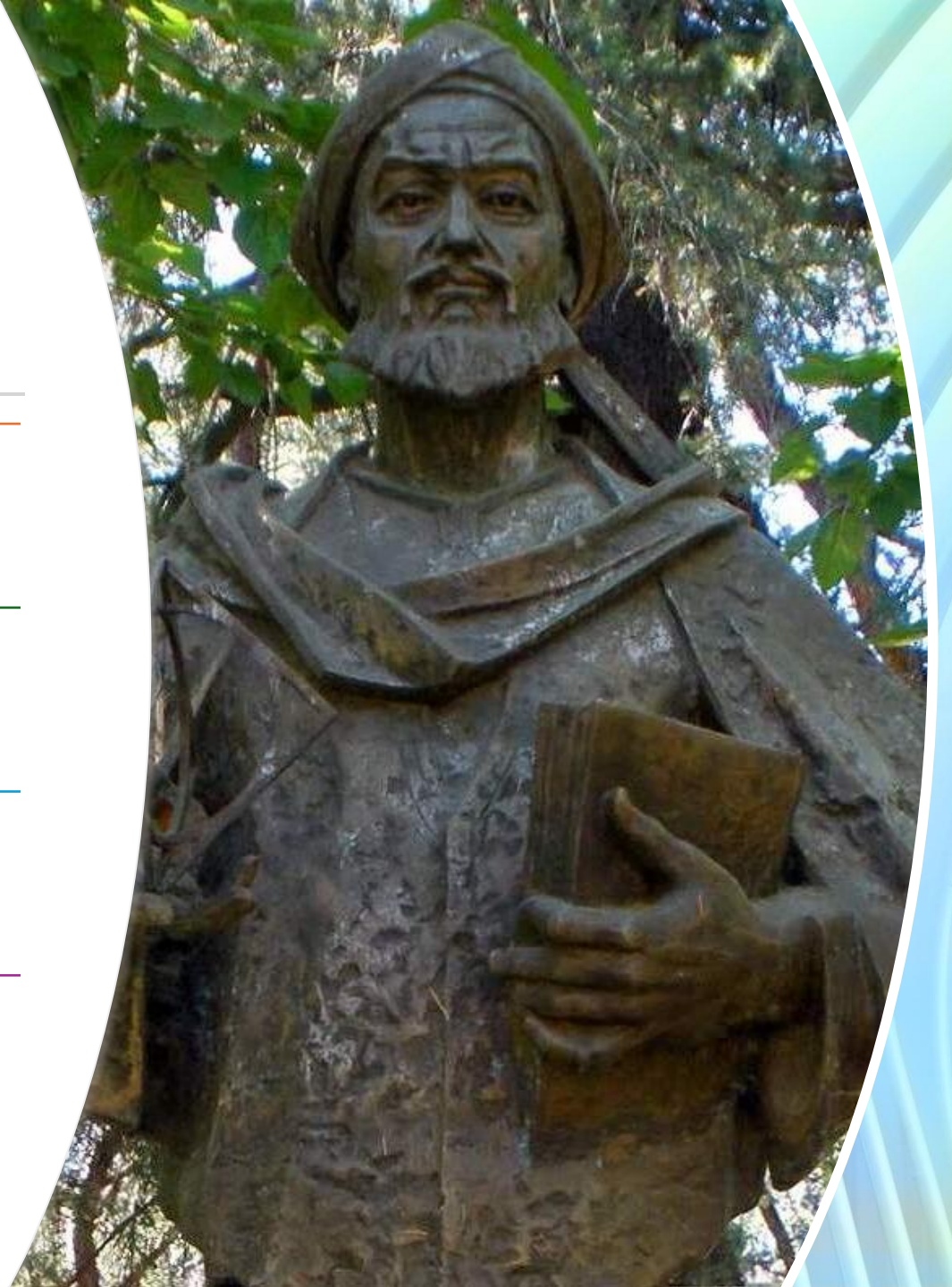
# GenAI in the context of Human-Computer Interaction

Algorithms and transformation functions

Input -> f -> Output

Design and implement input – output transformations: algorithms

Muhammad ibn Musa al-Khwarizmi (780 - 850)



# GenAI vs Algorithms

- Algorithms
  - Often formally defined - mathematical functions: input to output translation
  - Reproducible results
  - Rigid rules: E.g., “User” vs “Usr”. Not suitable for interpretation and generalisation. E.g., tracing design to implementation.
- GenAI
  - Results based on statistics and randomness
  - Low reproducibility
  - Highly flexible: Can handle cases which would take huge number of explicit encodings of rules. Suitable for interpretation and generalisation. E.g., “understand” which parts of code implement which architectural decisions.

# GenAI in the context of Human-Computer Interaction

Programming: writing an algorithm using programming languages

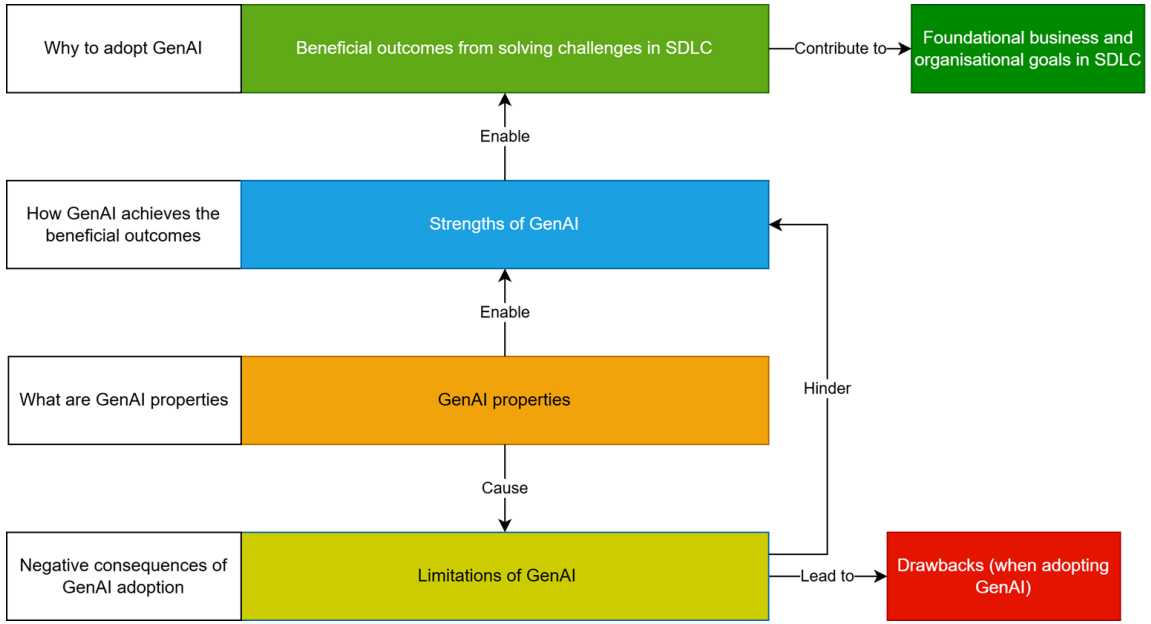
LLMs: inferring output from input based on pre-trained model

Both approaches are aiming to make computers do the work we want.

Algorithms do exactly what we programmed them to do.

LLMs can do much more.

# Properties of GenAI




## GenAI properties

- Randomness and probability
- Data diversity and data quality
- Model recency
- Controllability
- Ethical and legal compliance, censorship (guardrails)
- Interpretability and explainability
- Response time
- Generalization ability
- Parameter count
- Scaling and memory
- Robustness
- Factuality and calibration

## Strengths of GenAI

- Retrieve adequate state-of-the-art and state-of-the-practice solutions and domain knowledge
- Suggest innovative solutions
- Identify complex dependencies and detect anomalies
- Suggest solutions with optimised trade-offs
- Personalization
- Automate or assist with manual and repetitive actions
- Abstract and summarize large data sets
- Interpret complex statements
- Enhance algorithms with probability

## Limitations of GenAI

- Hallucinations
- Precision and completeness challenges
- Bias
- Lack of data
- Reproducibility and verifiability
- Difficulty with logic and arithmetic
- No memory/Limited Long-Term Memory
- Dependency on prompt engineering
- Lack of contextual knowledge
- Misinterpretation and missummary
- Too agreeable
- Misuse
- Performance issues
- Complexity and resource requirements needed for retraining
- Data confidentiality and copyright
- The question of value and ownership

## Beneficial outcomes

- Save time on repetitive and manual actions by automating them or receiving assistance from GenAI.
- Improve throughput, increase the productivity of the individuals and the whole organization.
- Improve quality of outcomes of executed actions, specifically: i) Improve precision of actions (e.g., identify and remove unnecessary conclusions); ii) Improve completeness of actions (e.g., enable contextual search that outperforms simple word matching).
- Educate people by suggesting solutions outside of their knowledge. This improves innovativeness, creativity, and potentially quality of outcomes from the executed actions.
- Expose hidden and complex dependencies that are not obvious to humans (e.g., dependencies that hinder productivity).
- Overall cost reduction due to the adoption of GenAI (adoption costs need to be significantly less than the experienced gains).

## Drawbacks

How limitations hinder GenAI strengths and beneficial outcomes. E.g.,:
"Save time" ->
"Hallucinations" ->
"Introduces overhead to evaluate and fix the generated faulty results before adopting them."

https://advanceonline.cam.ac.uk/courses/generative-ai-in-the-software-development-lifecycle

# GenAI Properties

- **Randomness and probability**: The ability to create new content without too much deviation from a reasonable scope.
- **Data diversity and data quality**: The basic rule is ‘garbage in, garbage out’. Without high-quality training data, it is hard to have high-quality models.
- **Model recency**: It describes how up-to-date the training data is. This impacts relevance to current events, technologies and norms, as well as affects factual accuracy and domain relevance.
- **Controllability**: The ability to steer output via prompts (prompts engineering) or parameters (model configuration). This determines how easily the model can be directed or constrained.
- **Ethical and legal compliance, censorship**: Related to controllability, this is a degree to which the model has been constrained for ethical and legal compliance, or due to censorship.
- **Interpretability and explainability**: A neural network is interpretable if it is possible to inspect it and understand why it got a particular answer for a given input, and how the answer would change when the input changes. A neural network is explainable if it is possible to understand the question, ‘Why was this output produced for this input?’
- **Response time**: Larger models tend to offer better results but are often slower. Response time matters, which depends on the model size, hardware resources and the model's context size (memory of previous prompts).
- **Ability to generalise**: This refers to the performance on unseen data, and the critical measure of whether the model truly understands or merely memorises.
- **Parameter count**: Larger models (with more GenAI parameters, such as weights) tend to perform better.
- **Scaling and memory**: This defines how response time and precision scale with the number of the prompts on the same topic. This parameter often depends on the fact of whether the model has or does not have the memory (in the sense of the context window size).
- **Robustness**: This refers to the stability of responses to paraphrasing, noise or adversarial prompts.
- **Factuality and calibration**: Factuality characterises the truthfulness of the generated content, while calibration refers to the model's stated confidence versus actual correctness.

# Strengths of GenAI

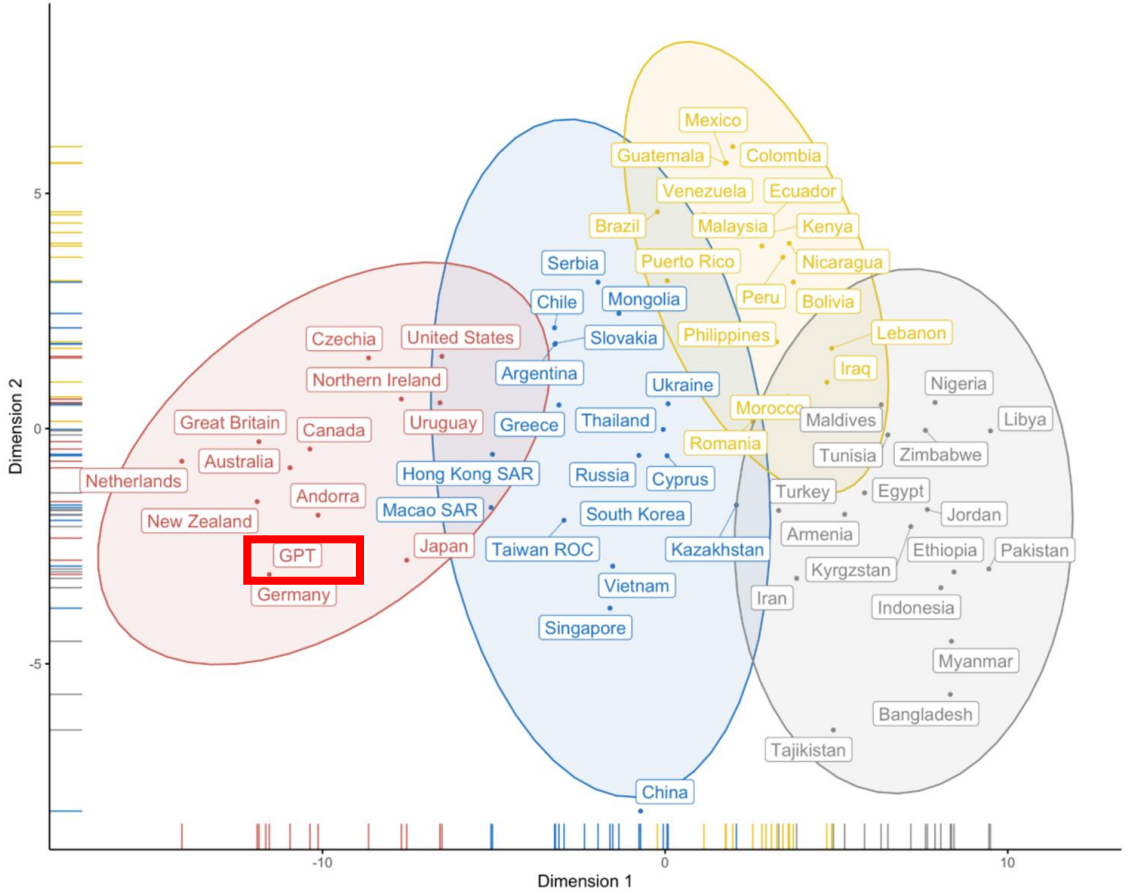
- **Retrieve solutions and domain knowledge**: GenAI is trained on large datasets, hence it can potentially retrieve adequate state-of-the-art and state-of-the-practice solutions and domain knowledge. Having a quick and summative access to such knowledge, scoped within the problem itself, enables GenAI to suggest solutions previously unknown to its users.
- **Suggest innovative solutions**: GenAI can suggest solution patterns that are new and innovative – that is, uncommon or not obvious to humans due to the patterns' complexity or lack of human creativity. GenAI does this by recombining known ideas into new patterns. One of the most famous examples of creating new solutions is Move 37 in Google DeepMind's AlphaGo game, which had a 1 in 10,000 chance of being used.
- **Identify complex dependencies and detect anomalies**: GenAI can analyse different artefacts such as code, design and reports. It also identifies dependencies and anomalies not obvious to humans. It can also identify complex patterns and unexpected or rare correlations (valuable for detecting risks and predicting behaviours) and support exploratory analysis in complex systems (focus on artefacts such as reports, design, code, tests and so on) and organisations (focus on processes, interactions, flows, toolchains and so on).
- **Suggest solutions with optimised trade-offs**: GenAI can consider many more interdependencies and plan a solution with many more steps in the future than humans can usually maintain in their heads. Therefore, GenAI can create complex and yet efficient solution patterns that are not obvious to humans. Such solutions can offer optimised trade-offs for existing or new solutions (for example, quality versus price, security versus usability). In Google DeepMind's AlphaGo game, it is worth mentioning that moves made by AlphaGo seemed at first like anomalies to some professional players. But, in hindsight and from a broader perspective, these were part of an intentional strategy.
- **Personalisation**: If individuals or organisations execute certain actions in a particular way or with a customised approach, GenAI can identify those patterns. Patterns include language (such as common phrases), sequences of actions, common logic, focus on specific parameters and so on. Pattern recognition is particularly interesting when GenAI identifies actions that always execute together and, therefore, can offer possibilities for automating them.
- **Automate or assist with manual and repetitive actions**: Many actions that SDLC stakeholders execute could be at least partially automated. GenAI can execute such actions, and if its randomness is reduced to an acceptable level, GenAI can be suitable for integration in workflows and toolchains. For a GenAI model to be suitable for automation and assistance, it must execute actions with an acceptable level of reproducibility.
- **Abstract and summarise large datasets**: GenAI is good at summarising large datasets such as code, documents and XML because of its large number of parameters and the self-attention property of transformers (Ranganathan and Abuka, 2022; Yan, 2025). Abstractive summarisation generates a new and unique summary that paraphrases the original text, similar to how a human would perform this task. On the other hand, extractive summarisation creates a summary by selecting and concatenating the most important or relevant sentences or phrases directly from the source document without any changes.
- **Interpret complex statements**: There is often a need to facilitate cross-domain communication and semantic translation in organisations (for instance, 'translating' from finance jargon to technical and vice versa). The internal knowledge representation in neural networks and the way transformers capture knowledge enable GenAI to identify and relate synonyms, and interpolate the meaning of terms and data between abstraction levels and different languages that stakeholders use. However, the interpretation of statements is highly dependent on expectations (that is, what the focus of the interpretation should be), the context of the interaction, prompt engineering and the dataset on which GenAI was trained.
- **Enhance algorithmic tools with probability**: For some actions, it is cumbersome to encode all possible combinations of conditions and solutions algorithmically (like with 'if-else'). Therefore, the presented GenAI strengths are useful for complementing algorithmic tools (such as static analysis) in executing or assisting with such actions.

# Limitations of GenAI

- **Hallucinations**: cause plausible-sounding but false or non-existent content. Examples include false statements, false citations, or source code that may look syntactically and stylistically correct but is semantically or factually incorrect, or those with application programming interfaces (APIs) that do not actually exist. GenAI can fabricate sentences and citations, reference books and authors that also do not exist, discuss hallucinated definitions and import non-existent software libraries.
- **Challenges with precision and completeness**: Unlike in the case of hallucinations, where GenAI 'invents facts', GenAI can be optimised to provide fluent and confident answers over complete or fully accurate ones. The facts may be correct, but the logic to provide an output sequence leads to low precision or incomplete results. Probability-driven decoding favours the 'most likely' phrasing rather than the 'most precise' explanation. No properties of 'right and wrong' or 'true and false' exist in these models by default (guardrails can help here), as it lacks intrinsic moral or factual grounding. In other words, it does not 'know' truth, ethics or correctness. It's a statistical model, and it maps inputs to probable outputs.
- **Bias**: Training data can contain societal, cultural and gender biases that GenAI models may unintentionally reproduce or amplify.
- **Lack of data**: For domains that are underrepresented in the training data (for instance, either an industrial domain like finance or mobile apps, or disciplines like software architecture and business management), GenAI's performance drops drastically.
- **Reproducibility and verifiability**: Because outputs are probabilistic and a product of randomness, they are hard to reproduce. Because of this, it is also hard to reproduce the 'line of arguments' that led to the output.
- **Difficulty with logic and arithmetic**: GenAI struggles with consistent logical reasoning and exact numeric operations – GenAI's 'reasoning' is pattern-based, not traditionally algorithmic.
- **No memory/Limited Long-Term Memory (LTM):** GenAI models do not have a concept of (long-term) memory. This can be mitigated to a certain degree by expanding input tokens to include previous results or through the concept of the context window. However, this limitation presents a challenge for continuous operations. Limited memory usually means less contextual precision since, at some point, the model is forced to 'forget' previous outputs.
- **Dependency on prompt engineering**: GenAI models are often packaged as tools to improve their usability (such as in chatbots and agents). These tools often offer commands and configurations to tailor the results. Therefore, users of these tools need to have proper prompting skills as changes in input can greatly affect output (due to the probabilistic nature of GenAI).

# LLMs behave like Humans – which Humans?

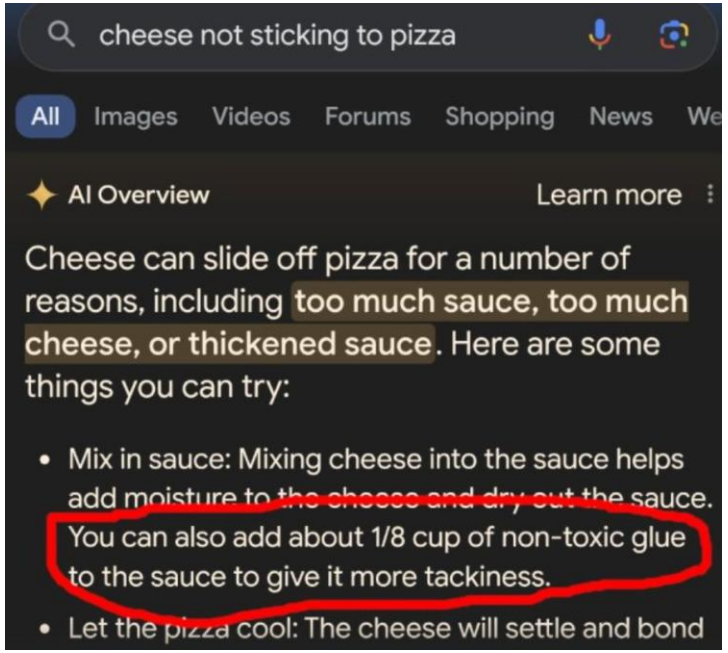
"LLMs' responses to psychological measures ... and ... their performance on cognitive psychological tasks most resembles that of people from Western, Educated, Industrialized, Rich, and Democratic (WEIRD) societies."




*Atari, Mohammad, Mona J. Xue, Peter S. Park, Damián E. Blasi, and Joseph Henrich. "Which Humans?"*

# Context Gap

- How do LLMs know what you need?




https://www.forbes.com/sites/rashishrivastava/2024/05/28/the-prompt-googles-ai-suggested-adding-glue-to-pizza/

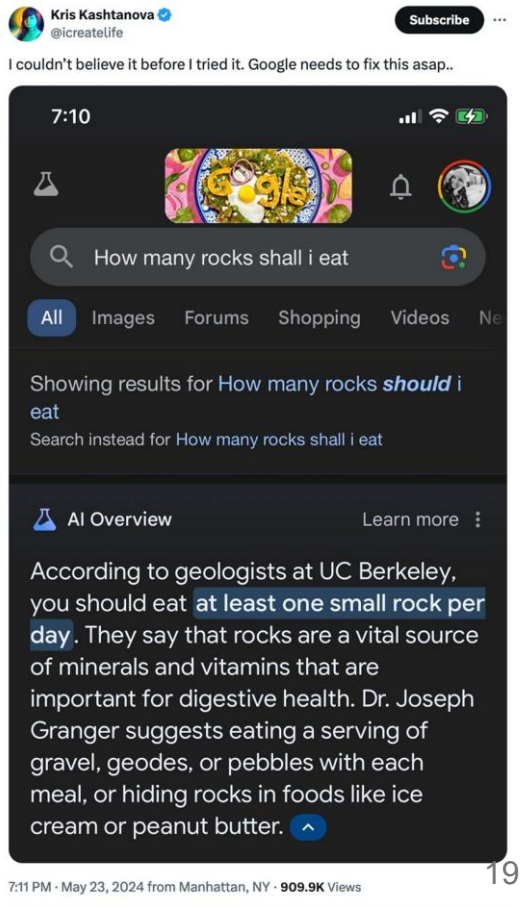
https://x.com/petergyang/status/1793480607198323196/photo/1

https://www.cnet.com/tech/services-and-software/glue-in-pizza-eat-rocks-googles-ai-search-is-mocked-for-bizarre-answers/

Too many possible answers to a question:
- Which one of them make sense to a human?
- Which one of them are adequate for a context and a domain?
- Which one of them are adequate for your intentions?

Communicating the context to LLMs – prompting:
- Zero-shot, few-shot, prompting patterns

Conceptual issue: how to pack a human context into a prompt? It is just too big. Humans understand it.



# Exercises

- Open https://chatgpt.com/
- Ask the chatbot to perform a task

- For each new task, open a new instance of ChatGPT

# Potential Beneficial Outcomes

## Beneficial outcomes

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- Enhance algorithms with probability

Let us test these

# Exercise: 1

- Give me a random number between 1 and 50.

# Exercise: 1

- Give me a random number between 1 and 50.
- How many of you got 37?

# Exercise: 2

- How many R's are in the word Strawberry?
  - There are 3 R’s in Strawberry.

# Exercise: 2

- How many R's are in the word Strawberry?
  - There are 3 R’s in Strawberry.

- Not true

# Exercise: 2

- How many R's are in the word Strawberry?
  - There are 3 R’s in Strawberry.

- Not true
  - You’re right — I made a counting mistake.
  - Strawberry has 2 R’s: S t r a w b e r r y → r + r = 2.

# Exercise: 3

- Let us start with our meetings on 22nd of June 2026. We will meet bi-weekly until end of the year, at 9am. If the meeting falls on a bank holiday, let us meet on the first working day available, at 9am.

  Topic of the meeting: GenAI in education.

  I need input for my Outlook.

  I need a file that I can click on and input the dates into my calendar. Generate the file.

# Exercise: 4

- Create a high-resolution image from this low-resolution image (see “CoatOfArms” file)

# Exercise: 4

- Create a high-resolution image from this low-resolution image (see “CoatOfArms” file)

- Change the background to grey

# Exercise: 4

- Create a high-resolution image from this low-resolution image (see “CoatOfArms” file)

- Change the background to grey
- What is in the image?
  - Is the answer correct? Give it few hints.

# Exercise: 5

- Find a book with the title: “Lord of the rings” (see “LibraryImage”)

# Exercise: 5

- Find a book with the title: “The Gallic and Civil peace” (see “LibraryImage”)

# Exercise: 5

- Find a book with the title: “Genghis Khan” – label it in the image (see “LibraryImage”)

# Exercise: 6

- Is there anything wrong with this table?

| Course | Students |
|---|---|
| Software architecture | Amy, Hasan, Hannah, Stewart, Li |
| Security | Amy, Hasan, Hannah, Stewart, Li, Stewart |
| Software engineering | Amy, Hasan, Hannah, Stewart, Li, Luka |
| AI | Emir, Damir, Emina, Luka |
| Computer architecture | Amy, Hasan, Hannah, Damir, Emina |
| Compilers | Amy, Hasan, Hannah, Damir, Emina |
| Machine learning | Amy, Hasan, Hannah, Damir, Leon |
| Object oriented programming | Francois, Hannah, Steward, Li, Luka |
| Discrete math | Francois, Hannah, Steward, Li, Luka |

# Exercise: 6

- Is there anything wrong with this table?
- How many students we have?

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# Exercise: 6

- Is there anything wrong with this table?
- How many students we have?
- Show a new table. First column: student name; Second column: courses separated by “;”

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# Exercise: 6

- Is there anything wrong with this table?
- How many students we have?
- Show a new table. First column: student name; Second column: courses separated by “;”
- Show a new table: First column: student names separated by “;”, Second column: courses separated by “;” – condition: group students that take the same set of courses.
- I think there was something wrong, repeat the analysis and show me the difference. You did not get the courses right.

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- To do this, previously you had to design an algorithm.

# Exercise: 6

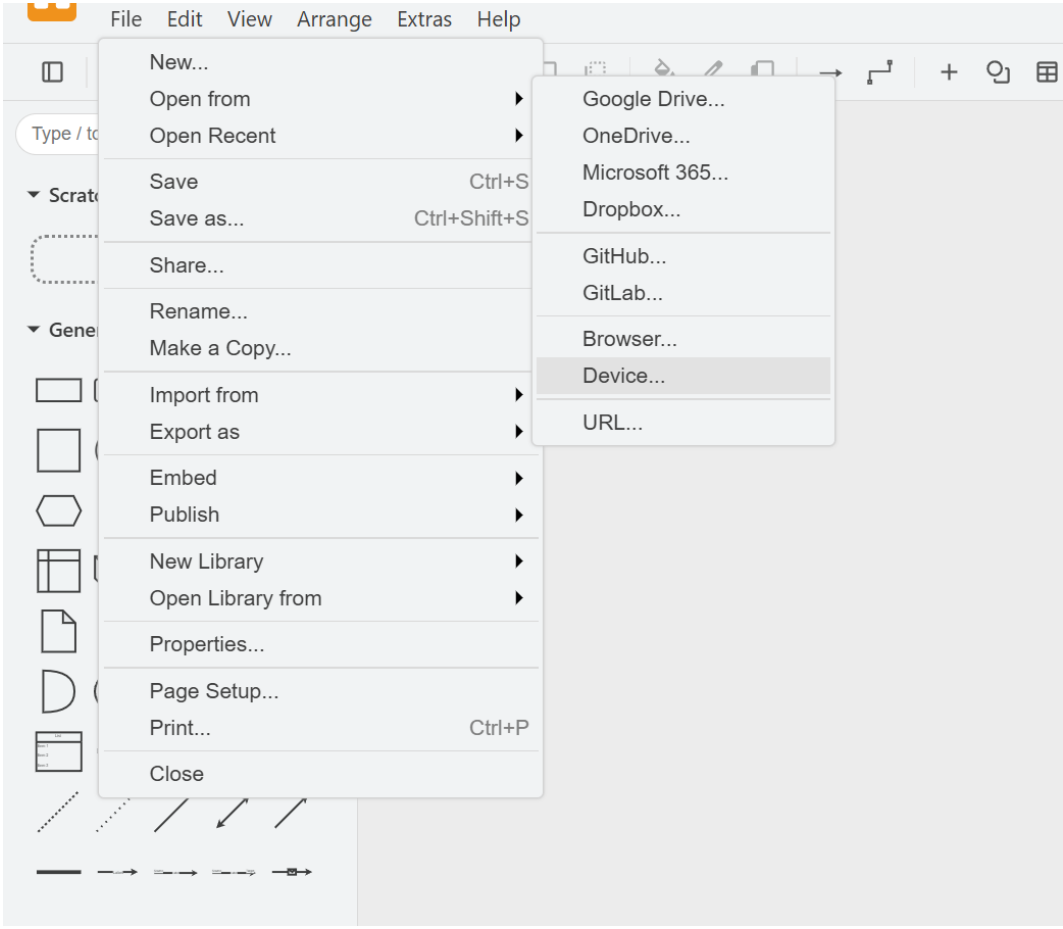
- Visualize the analysis
- I want to see an overview picture and how students are related to courses. Use boxes and arrows.

# Exercise: 6

- Visualize the analysis
- I want to see an overview picture and how students are related to courses. Use boxes and arrows.
- Generate a draw.io xml file
- Open the file with draw.io - https://app.diagrams.net/
- Change one connection, save as XML, upload to ChatGPT

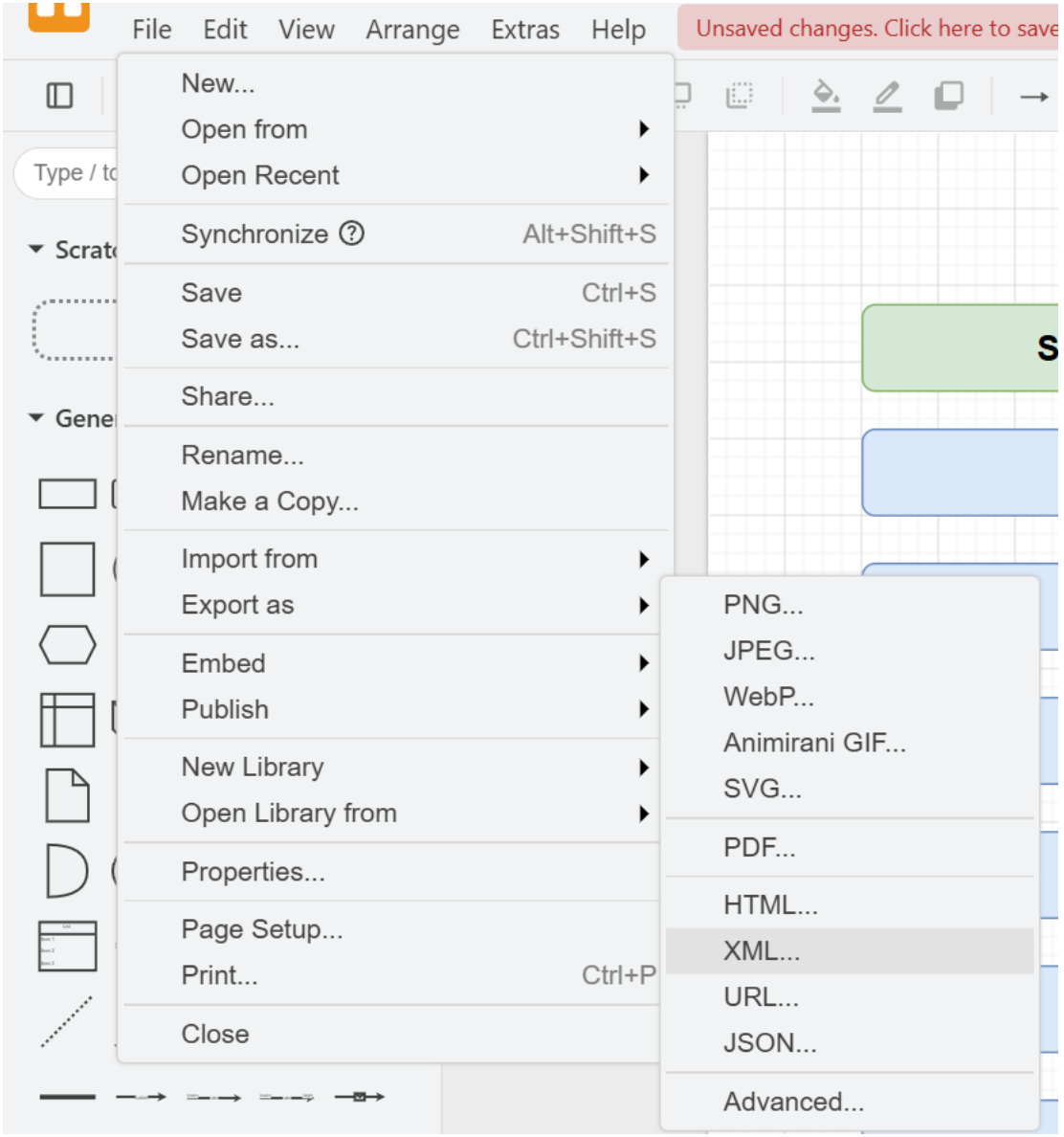
# Exercise: 6

- File - Open from - Device



# Exercise: 6

- File – Export as - XML



# Exercise: 6

- Visualize the analysis
- I want to see an overview picture and how students are related to courses. Use boxes and arrows.
- Generate a draw.io xml file
- Open the file with draw.io - https://app.diagrams.net/
- Change one connection, save as XML, upload to ChatGPT
- Generate a table from the XML:
  - First column: Course name, Second column: names of students taking that course separated by “;”
- Is anything missing/different compared to the original table?

# Exercise: 7

- Simple text transformations
- List all students from the table
- In case if you get something like:
  - 1. Amy
  - 2. Hasan
  - 3. Hannah
  - 4. Stewart
  - …

# Exercise: 7

- Simple text transformations
- List all students from the table
- In case if you get something like:
  - 1. Amy
  - 2. Hasan
  - 3. Hannah
  - 4. Stewart
  - …
- Just show names, no numbers or bullet points

# Exercise: 8

- Upload “Data.xlsx”
- Analyse the document and find any issues

- Check the results

# Exercise: 9

- My salary is £39 000 per year (PAYE).
- As a freelancer, I earn £3000 per year.
- How much taxes should I pay and why?

# Exercise: 10

- There is a washing machine in my apartment. The Landlord, according to our agreement, is responsible for repairing home appliances. The washing machine stopped working. I reported it to the landlord 5 weeks ago but there are no repairs planned so far. Do I have any legal claim and if yes according to which law?

# Exercise: 11

- This is my CV. Generate a website about me based on my CV.
  - https://www.cl.cam.ac.uk/~jj542/doc/cv.pdf

# What have we covered so far?

Standard issues with ChatGPT (obviously, it wasn't trained for specific tasks or there are corner cases it cannot handle – does not have appropriate "algorithms")

Execute well scoped tasks and generate files (e.g., Outlook file, but also Word, Excel and similar are possible).

Edit images

Image to text recognition, search algorithms

Data analysis, out of the box

Text transformation

Analysis of documents, inconsistencies (Excel)

Specialist advisor (tax advisor, legal advisor)

Programming tasks

# Good for

Any task, you can scope well, and describe almost as an algorithm

It also “understands” hints and is flexible when you make mistakes

# Which tasks would be suitable for GenAI

ADMINISTRATION

FINANCES

ANALYSIS

GRADING

…?

WHAT COULD WE IMPROVE AT THE COLLEGE, WITH PROPER USE OF AI

# Human-Computer Interaction

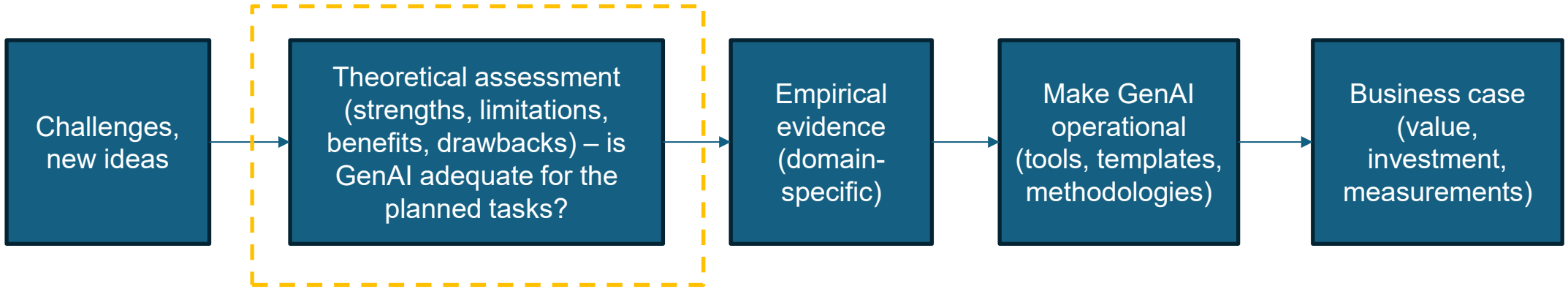
## Program an algorithm

- Deterministic and reproducible

## Ask GenAI to generate an answer based on previous data, statistics

- Bias
- Correctness
- Privacy, privacy, privacy!!!
- …

# Framework for transforming organisations




Emerging: AI officers and AI offices for transforming organisations

Recognize where to apply GenAI in organisation, devise a plan and methodologies, establish a toolchain

# Topics you would like to explore further

Join at slido.com - #1115 980

# Questions