



TRENDS (CONT.): LARGE LANGUAGE MODELS AND PROMPTING

Luísa Coheur

OVERVIEW

- Learning objectives
- Topics
 - Large Language Models
 - What is a large language model?
 - Training and Testing
 - Pros and cons
 - Prompting
 - Concept
 - Prompt Engineering
 - Some Prompting Techniques
- Key takeaways
- Suggested readings

LEARNING OBJECTIVES

LEARNING OBJECTIVES

- After this class, the student should:
 - Understand the concepts studied in this class
 - Know how to apply various decoding and sampling techniques
 - Be able to discuss the advantages and disadvantages of LLMs

TOPICS

WHAT IS A LARGE LANGUAGE MODEL?

Possible answer to the general public: a LLM (Large Language Model) is an artificial intelligence that can converse about various topics because it has 'read' a lot about them on the internet



WHAT IS A LARGE LANGUAGE MODEL?

- Part 1: what is a **Language Model** (remember)?
 - A language model (LM) is a **probability distribution** over sequences of tokens
- So, with a language model, we can:
 - assign a probability $P(x_1 \dots x_k)$, to a sequence of tokens, $x_1, \dots, x_k \in V(\text{vocabulary})$
 - generate language by sampling one token at a time, given the tokens generated so far

WHAT IS A **LARGE** LANGUAGE MODEL?

- PART 2: what does **Large** means?
- To determine the size of a language model, we can consider:
 - **Model Size** (number of learnable parameters)
 - **Training Size** (number of tokens in the training dataset)
 - **Compute Size** (computations required in model training)

Note: Some LLMs typically have 100 billion parameters (1 billion = 10^9 ; 1 million = 10^6) requiring 200 gigabytes to load, which places them outside the range of most consumer electronics

BY THE WAY...

| Diferentes formas de representar os números | | | |
|---|----------------|-----------------------|-------------|
| Portugal | Estados Unidos | Número | Nº de zeros |
| um | one | 1 | 0 |
| mil | thousand | 1000 | 3 |
| milhão | million | 1.000.000 | 6 |
| mil milhões | bilion | 1.000.000.000 | 9 |
| bilião | trillion | 1.000.000.000.000 | 12 |
| mil biliões | quadrillion | 1.000.000.000.000.000 | 15 |

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TRAINING

- LLMs are trained using a combination of unsupervised pre-training on large text corpora to learn language patterns and supervised fine-tuning on specific tasks to improve performance

TRAINING PHASES

1. Pre-Training
2. Instruction Fine-Tuning
3. Reinforcement from Human Feedback (RLHF)

TRAINING PHASES

PRE-TRAINING

- Pre-training is where the model learns general language (it captures syntactic and semantic patterns, as well as general world knowledge) from a large corpus of text data without specific labels (unsupervised learning)

Remember?

TRAINING PHASES

1. Pre-Training
2. Instruction Fine-Tuning
3. Reinforcement from Human Feedback (RLHF)

TRAINING PHASES

INSTRUCTION FINE-TUNING

- Instruction fine-tuning tailors the pre-trained model on task-specific datasets, often with labelled examples (supervised learning) that include instructions or queries paired with desired responses
 - It will allow the model to better understand and follow human instruction, improving its applicability in contexts like chatbots, customer support, or specific content generation tasks

From your colleagues

<https://www.youtube.com/watch?v=l16lXt3U3Xk>

TRAINING PHASES

INSTRUCTION FINE-TUNING

- Instead of learning “how language works” (as in pretraining), it learns: when a human gives an instruction, what kind of answer should I produce?
- Examples (before/after instruction fine-tuning)
 - Prompt: Tell me if Pos or Neg: “I love sunny days”
 - Before: I love sunny days, they are... (continues text)
 - After: Pos
 - Prompt: List three countries in South America.
 - Before: South America is a continent with many countries and cultures. It has diverse climates... (Descriptive, no list)
 - After: Brazil, Argentina, Chile

TRAINING PHASES

INSTRUCTION FINE-TUNING

- Example of instructions

- ### Instruction:

Translate this sentence into French.

Input:

Good morning, how are you?

Response:

Bonjour, comment ça va ?

- ### Instruction:

Write a tweet about climate change awareness.

Response:

The Earth is our shared home — let's protect it. #ClimateAction

TRAINING PHASES

1. Pre-Training
2. Instruction Fine-Tuning
3. Reinforcement from Human Feedback (RLHF)

TRAINING PHASES: REINFORCEMENT LEARNING FROM HUMAN FEEDBACK

- Reinforcement Learning from Human Feedback (RLHF) is a training methodology for aligning AI models with human preferences
 - It refines the model's responses based on human preferences and feedback

TRAINING PHASES: REINFORCEMENT LEARNING FROM HUMAN FEEDBACK

- Reward model: Learn a model that predicts human preference scores
 - Take a pretrained model and generate multiple outputs for the same prompt
 - Ask human annotators to rank these outputs based on other criteria
 - Once trained, the reward model can assign a reward score to any new output
- Policy optimization: Use Reinforcement Learning (RL) to update the model so that it maximizes the reward predicted by the reward model

BY THE WAY...

- Policy = function that decides what action to take given a situation. That is, the policy tells the agent what to do in each state
 - Formally, a policy is written as $\pi(a|s)$ which means:
 - the probability of taking action “a” given the current state “s”
- In LLMs “language”:
 - the policy is the model itself — it decides which token (word fragment) to generate next, given the previous tokens
 - the “state” is the text so far (the prompt + text already generated),
 - the “action” is choosing the next token

TRAINING PHASES: REINFORCEMENT LEARNING FROM HUMAN FEEDBACK

- Policy optimization with Proximal Policy Optimization(PPO)
 - The model generates responses
 - The Reward Model gives each one a reward score
 - PPO adjusts the model weights to maximize reward

TRAINING PHASES: REINFORCEMENT LEARNING FROM HUMAN FEEDBACK

- Direct Preference Optimization (DPO) is an alternative:
 - It trains a language model directly from human preference data—without needing a separate reward model or reinforcement learning
 - It adjusts the model so that preferred responses get higher probability
- That is:
 - With PPO:
 - Human prefs → Reward model → PPO updates
 - With DPO
 - Human prefs → Directly update the model (policy)

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TESTING (INFERENCE + PROMPTING)

- **Inference** (concept seen before): internal process the model uses to generate an output from a given input
- **Decoding**: sub-step within inference; it is the process of generating a text sequence from the predictions of a language model
- **Prompting** (concept seen before): in the second part of the class

DECODING

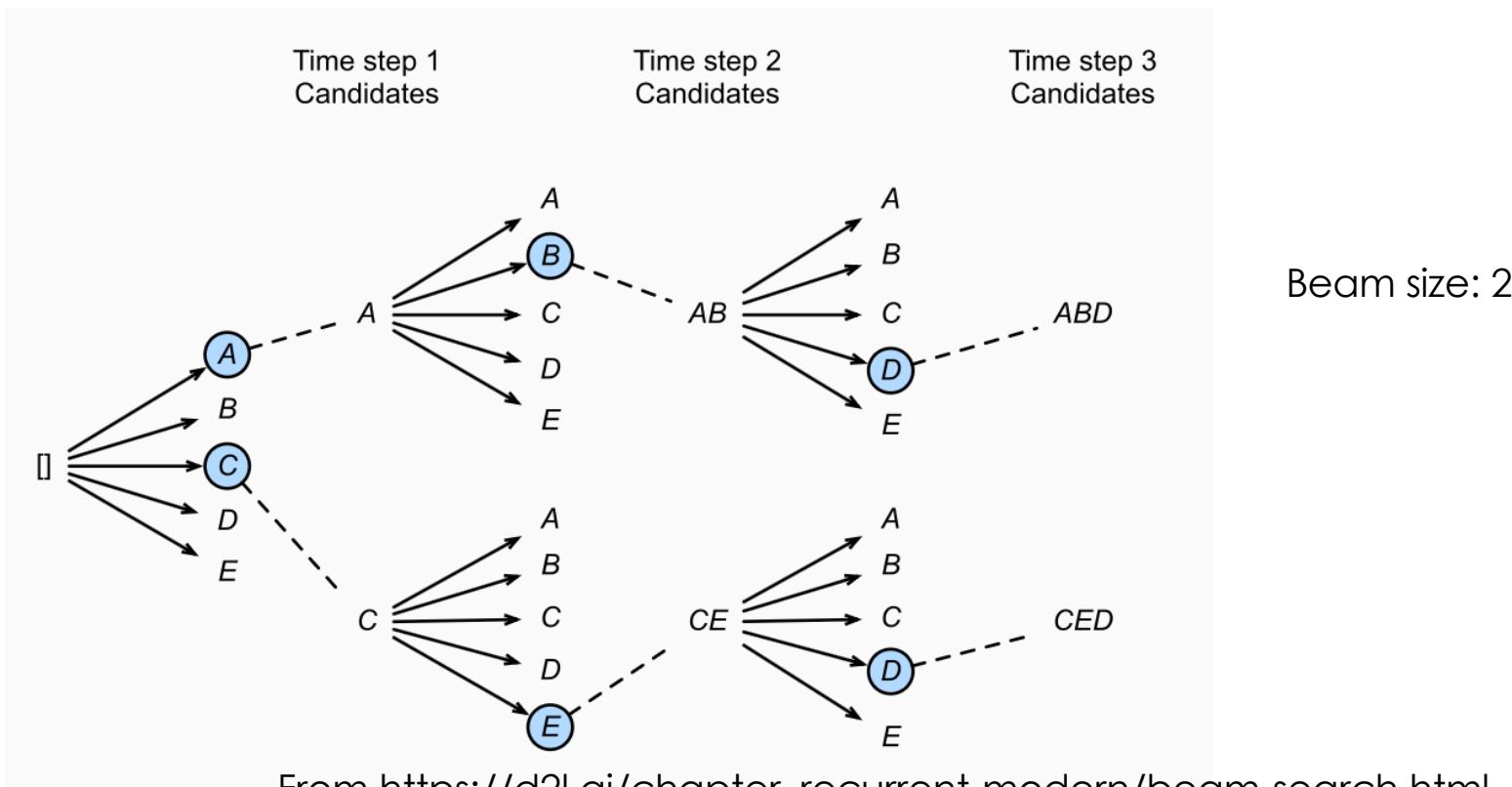
- Greedy search
- Beam search
- Sampling methods:
 - Random sampling
 - Top-k sampling
 - Nucleus or top-p sampling
- Temperature

DECODING

- Greedy search: computes the probability of each word in (a subset of) the vocabulary and chose the one with the highest probability
- Problems:
 - Generic, repetitive text, deterministic

DECODING

- Beam search: generates words by exploring multiple paths/beams (keeps a fixed number of the most promising paths at each step). None of the beams are considered final until the end of the decoding process



From https://d2l.ai/chapter_recurrent-modern/beam-search.html

ACTIVE LEARNING MOMENT



EXERCISE: DECODING

- You have a language model that outputs the following probability distribution for the next word in the sequence "The weather today is":

| Word | Probability | |
|-------------|--------------------|--|
| Sunny | 0.4 | Greedy: select the word with the highest probability |
| Rainy | 0.25 | Beam: select the top 2 words based on their probabilities; continue the sequence with these starting words |
| Cloudy | 0.15 | |
| Windy | 0.1 | |
| Snowy | 0.1 | |

- Use greedy and beam search (beam width = 2) to determine the next word in the sequence

DECODING: SAMPLING

- **Sampling**: decoding method in which the model chooses a subset of tokens (there are different ways of doing this), and then one token is chosen randomly from this subset to be added to the output text

DECODING: RANDOM SAMPLING

- Random sampling: “generates” the next word at “random”
 - Not totally at random: it still picks a token based on its probability. Tokens with higher probabilities are more likely to be chosen, but there's still a chance that tokens with lower probabilities could be selected.
 - Note: if you want total randomness use [unweighted random sampling](#)

DECODING: RANDOM SAMPLING

- Example:
 - You prompted the model with "The cat is" and the possible next words are "sleeping," "eating," "running," and "flying" with the following probabilities:
 - sleeping: 50%, eating: 30%, running: 15%, flying: 5%
 - How It Works:
 - Think of each percentage as the number of balls for each word. Let's use a total of 100 balls.
 - 50 balls are blue for "sleeping."
 - 30 balls are green for "eating."
 - 15 balls are red for "running."
 - 5 balls are yellow for "flying."
- Then, just pick a ball

DECODING: TOP-K SAMPLING

- Top-k sampling: performs the following steps:
 1. truncates the distribution to the top k (k given) most likely words
 2. “renormalize”, that is, produce a legitimate probability distribution (sum up to 1)
 3. randomly sample from these (according with their probability)
- Problem: K is fixed, but different scenarios have different probability shapes

DECODING: NUCLEUS SAMPLING

- Top-p or nucleus sampling: keeps adding tokens to the selection until the cumulative probability reaches or slightly exceeds the threshold p

ACTIVE LEARNING MOMENT



EXERCISE: DECODING METHODS

- You have a language model that outputs the following probability distribution for the next word in the sequence “The weather today is”:

| Word | Probability |
|-------------|--------------------|
| Sunny | 0.4 |
| Rainy | 0.25 |
| Cloudy | 0.15 |
| Windy | 0.1 |
| Snowy | 0.1 |

- Use top-k sampling ($k = 2$) to determine the next word in the sequence
- Use top-p (or nucleus) with $p = 0.7$

DECODING: TEMPERATURE

- Temperature: it is not a decoding method, but part of a decoding strategy. It adjusts the distribution's probabilities by scaling (temperature parameter)

TEMPERATURE

- Process:
 - Logits scaling (logits are the raw, unnormalized scores output by a model – remember?)
 - The temperature-scaled probabilities are obtained by applying the softmax function to these scaled logits (see next)
 - Sampling: The next token is then sampled from the temperature-scaled probabilities (for instance, use top-p)

TEMPERATURE

- In detail
 - z_i is an original logits
 - z'_i are the temperature-scaled logits

for $i=1, \dots, k$:

$$z'_i = \frac{z_i}{T} \quad (\text{Temperature scaling of logits})$$

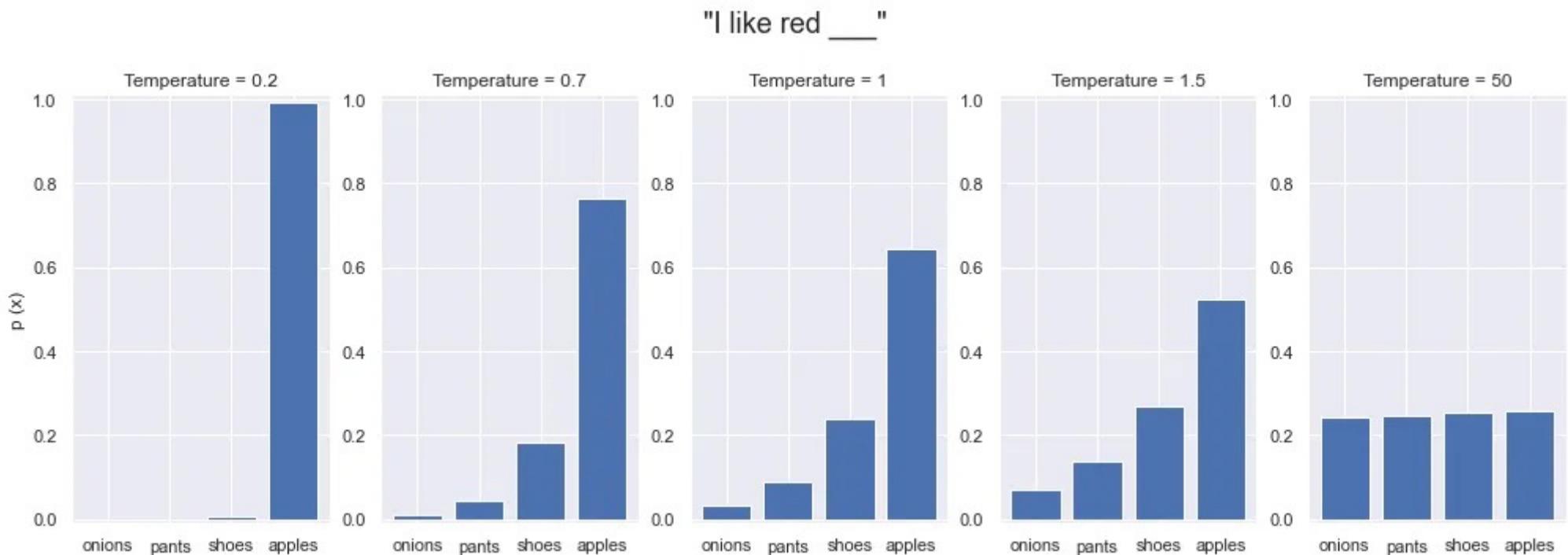
$$p_T(x_i \mid x_{1:i-1}) = \frac{\exp(z'_i)}{\sum_j \exp(z'_j)} \quad (\text{Softmax with temperature})$$

TEMPERATURE

- Being T the temperature parameter:
 - $T=1$: no change to the logits, the original probabilities are used
 - $T<1$: makes the distribution sharper, increasing the model's confidence in its predictions
 - $T>1$: makes the distribution flatter, allowing for more randomness and exploration in the predictions
 - $T = 0$: the logits would be divided by zero before applying the softmax function. OOPS
 - In practice, this causes all the probability mass to be concentrated on the token with the highest raw probability
 - the behaviour becomes identical to greedy decoding

TEMPERATURE

- Higher temperatures increase randomness, while lower temperatures make outputs more deterministic



OVERVIEW

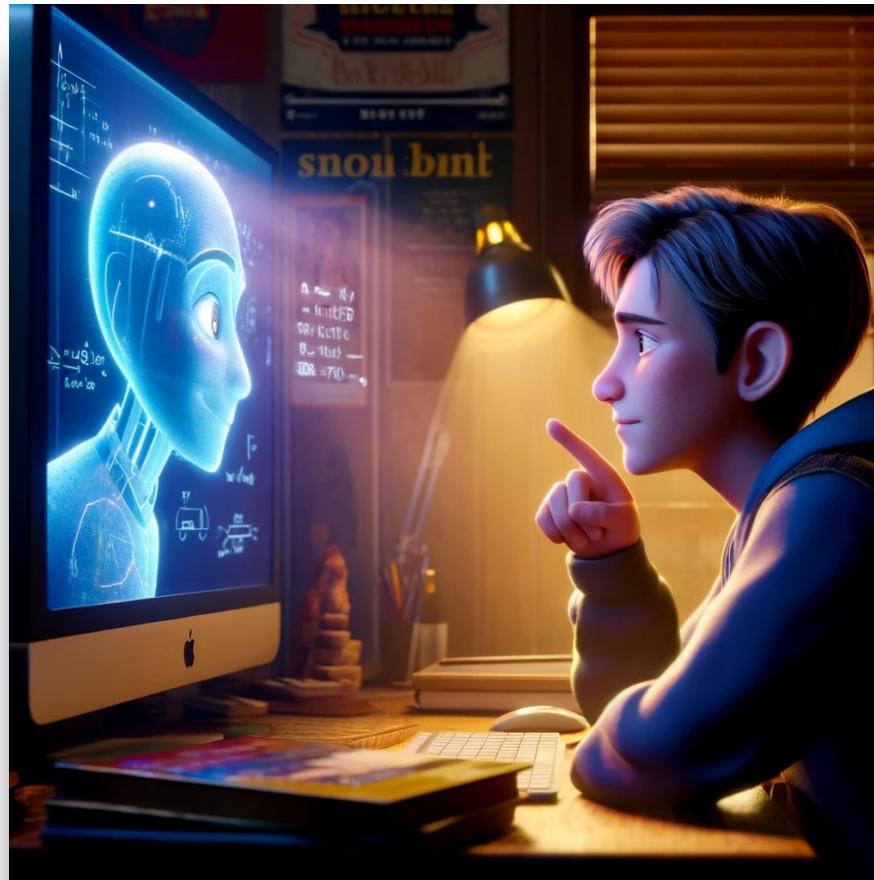
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WHAT DO THESE MODELS OFFER US?

- Just some examples of things we have studied in this course:
 - Question/answering
 - Translation
 - ...
 - Chit-chat
 - Data science
 - Image generation
 - ...

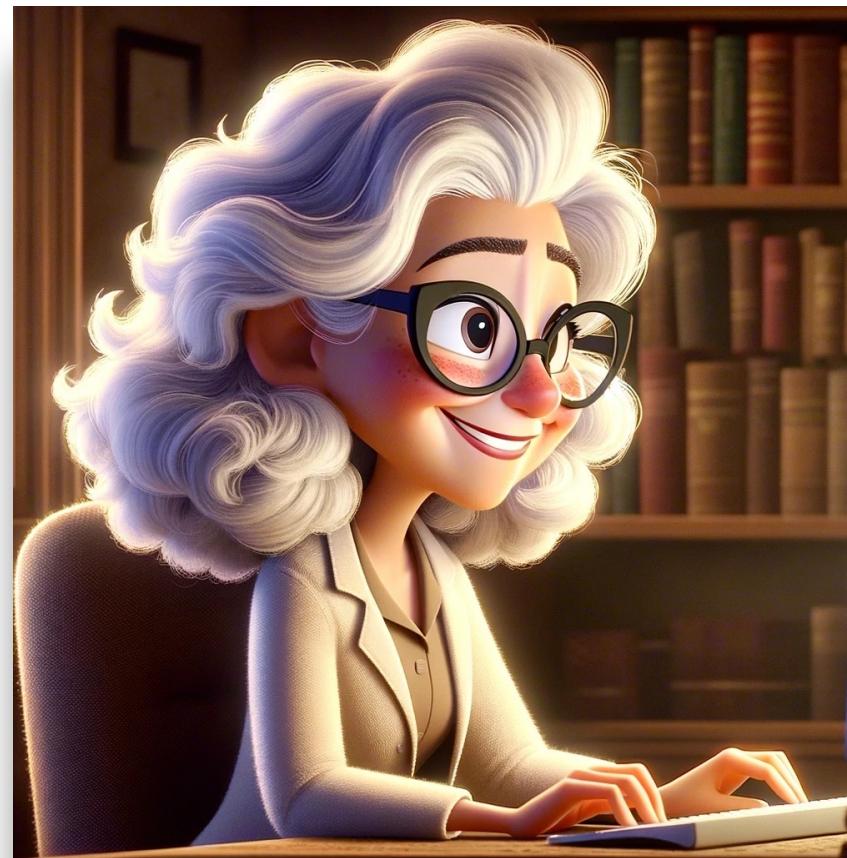
WHAT DO THESE MODELS OFFER US?

- You can have your own tutor



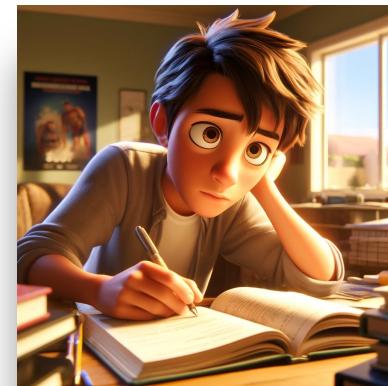
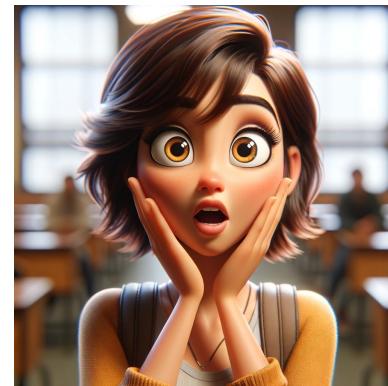
WHAT DO THESE MODELS OFFER US?

- As a professor, they can help me to improve my slides, but also to generate exercises, materials, images, code, etc.



WHAT DO THESE MODELS OFFER US?

- They can really create amazing images
 - Thank, ChatGPT (DALL-E), for almost all the images in this course!



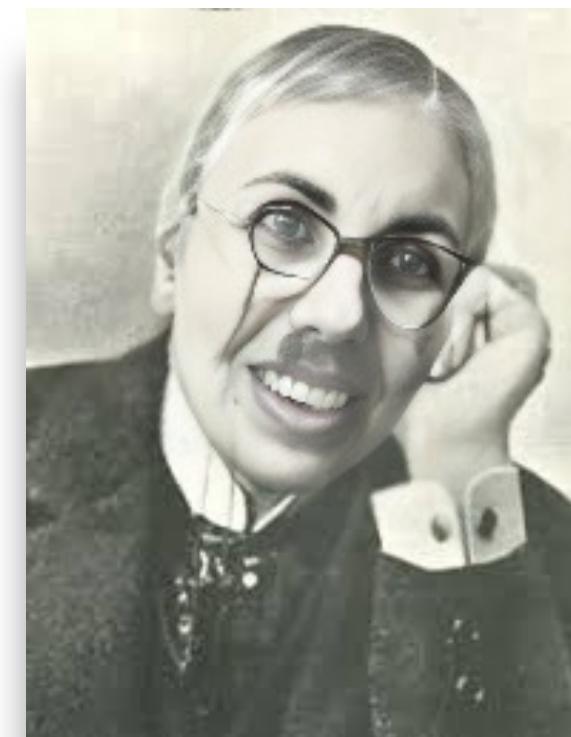
WHAT DO THESE MODELS OFFER US?



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WHAT DO THESE MODELS OFFER US?



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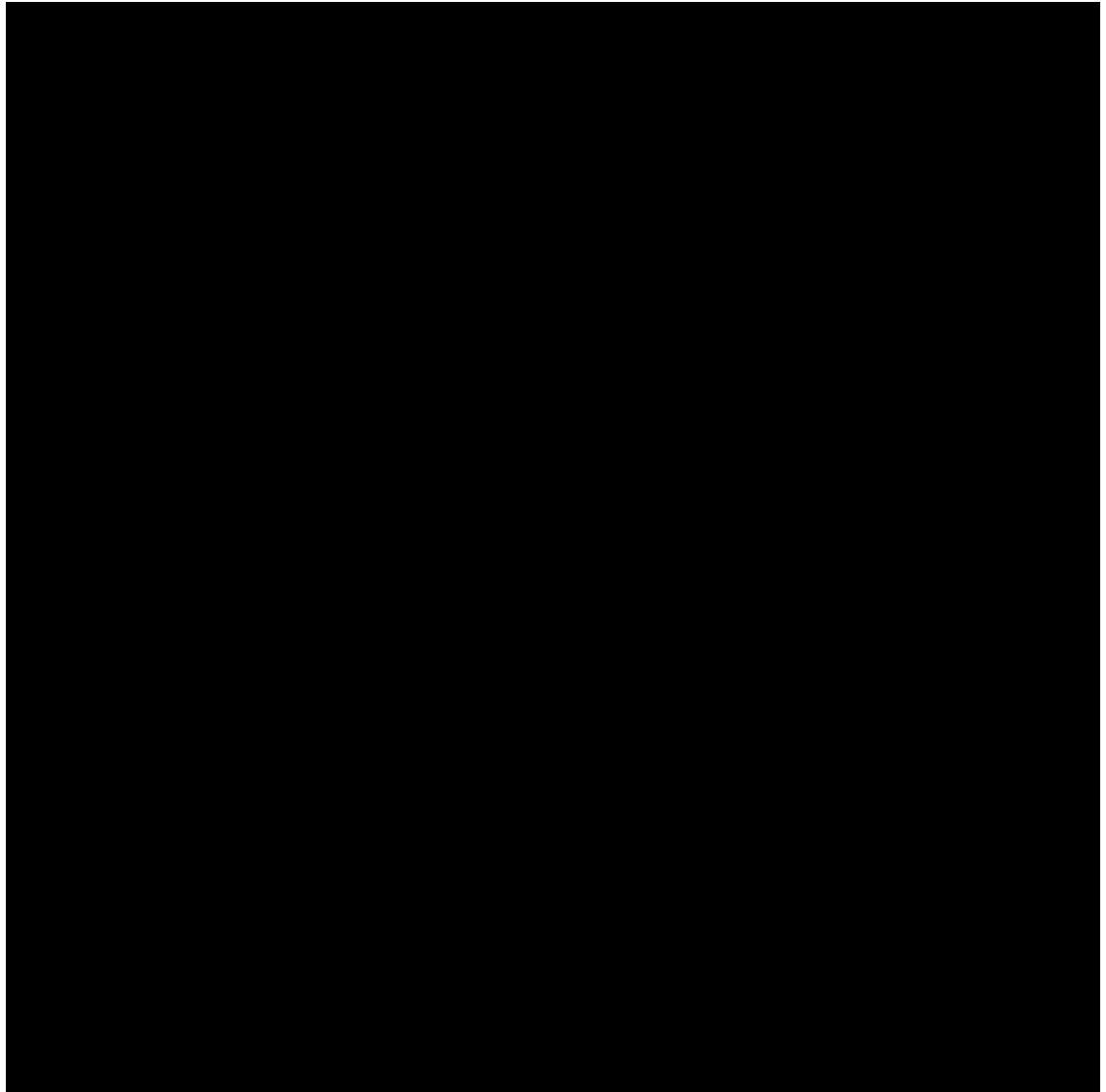
WHAT DO THESE MODELS OFFER US?

Barbie Video



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ACTIVE LEARNING MOMENT



EXERCISE

Any experience you want to share?



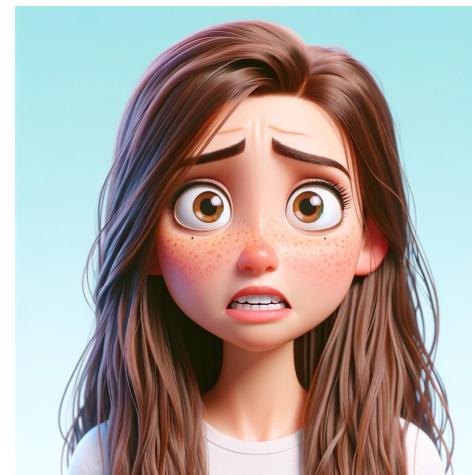
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ERRARE

LLMs

EST



ALTHOUGH THEY ARE BEING IMPROVED...

Maria is currently 4 years old and Marta 8. When Maria is 10, how old is Marta? Give a direct answer.

< 3/3 >

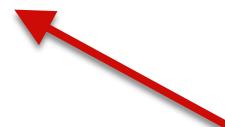


When Maria is 10 years old, 6 years will have passed since the current time (since Maria is currently 4 years old).

Since Marta is currently 8 years old, in 6 years, she will be:

$$8 + 6 = 14$$

Therefore, when Maria is 10 years old, Marta will be 14 years old.



Not a long time ago, it failed

LLMS ARE FALLIBLE

- They can give you incorrect information for your homework, project, report, etc.



LLMS ARE FALLIBLE



LLMS ARE FALLIBLE

Create an image with 5 chairs



Image by NAIF J ALOTAIBI (ChatGPTs)

LLMS ARE FALLIBLE

I asked for 5 chairs. There you have 8 chairs.



Image by NAIF J ALOTAIBI (ChatGPTs)

LLMS ARE FALLIBLE

- What if it gives incorrect information in the field of medicine? (for instance)



LLMS ARE FALLIBLE

- César Reis' master thesis, co-supervised by Catarina Sousa (FMUL), goals:
 - Considering the topic “Infective Endocarditis”, test the use, via prompt engineering, of state-of the art LLMs towards the production of:
 - a) slides
 - b) multiple-choice and open-ended questions
 - c) medical flyers
 - d) explanation of concepts
 - e) clinical case studies.

LLMS ARE FALLIBLE

- End-users:
 - experts on the topic
 - medical students
 - non-medical students (but with some related background)
 - Patients

LLMS ARE FALLIBLE

- Findings:
 - The “correct” answers for several multiple-choice test were outdated or wrong
 - In a prompt for slides production the designation of diagnostic criteria was outdated
 - In the generation of the congress slides, ChatGPT mentioned a 2024 criteria that does not exist

LLMS ARE FALLIBLE

- ChatGPT disclaimer (take it seriously) :

ChatGPT can make mistakes. Consider checking important information.

ACTIVE LEARNING MOMENT



EXERCISE

Any experience you want to share?

NUMBER 1 TIP:
CHECK EVERYTHING.
ALWAYS!

LLMs CAN BE USED TO DECEIVE US

- Is any of these images real? Both? None?

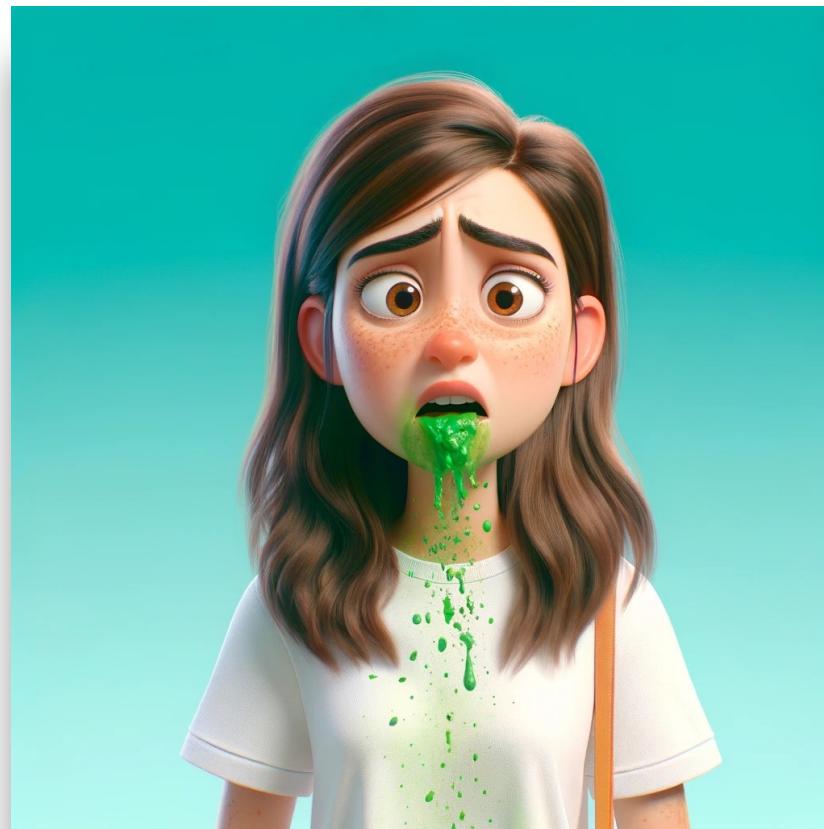


LLMs CAN BE USED TO DECEIVE US

- We all know what fakes are...
- ... but are you prepared for:
 - Perfect voice manipulation
 - Perfect image manipulation
 - Perfect video manipulation
- And when it is at a national level? Or global?

LLMs CAN BE USED TO DECEIVE US

- When we can't distinguish, even with the help of artificial intelligence (ironically), what is real from what is not, we have a big problem. It has already begun...



TIP 2:
CRITICAL THINKING.
QUESTIONING.

WE MIGHT LOSE SOME OF OUR CAPABILITIES

- Watching is not the same as doing

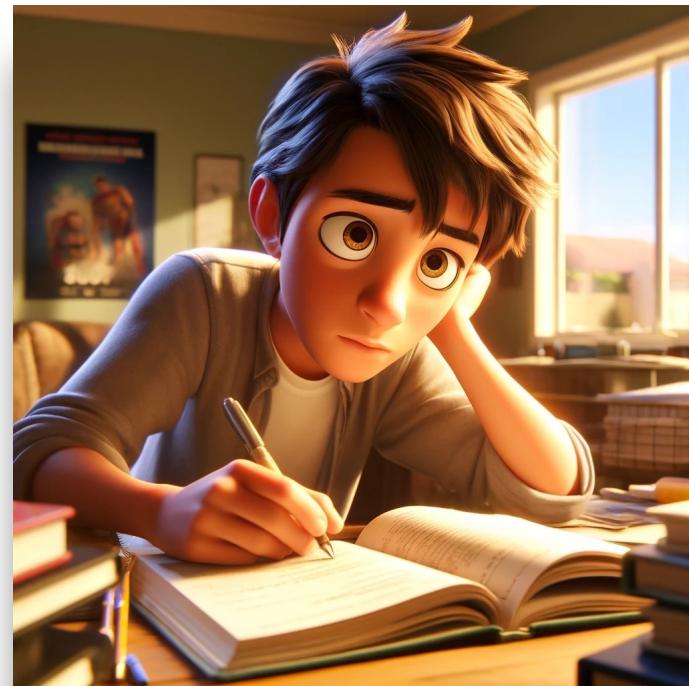
WE MIGHT LOSE SOME OF OUR CAPABILITIES

- Watching is not the same as doing
 - Example: watching a soccer game is not the same as playing soccer (you always learn something, but...)



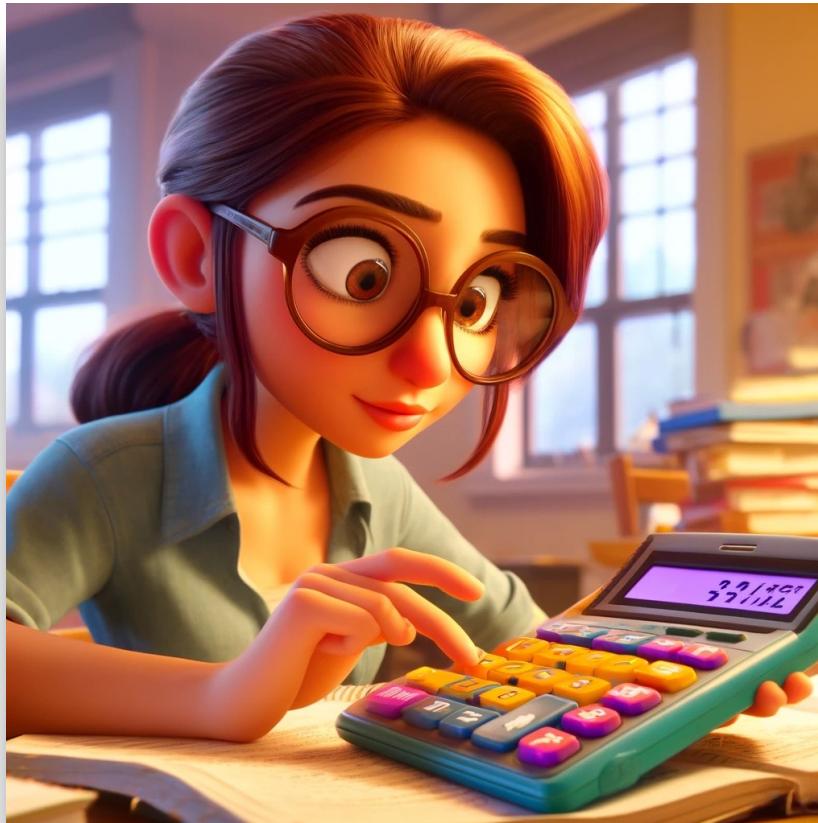
WE MIGHT LOSE SOME OF OUR CAPABILITIES

- Asking someone to do a task for us is definitely not the same as doing the task ourselves



WE MIGHT LOSE SOME OF OUR CAPABILITIES

- ... but we did not stop knowing how to do calculations because we started to have calculators



ACTIVE LEARNING MOMENT



EXERCISE

Any experience you want to share?

TIP 3: BALANCED USE

ECONOMIC INEQUALITIES

- Example:
 - CHATGPT 3.5 (free)
 - vs.
 - CHATGPT 4.0 (better but around 23 €/month)



BIAS

LC

You

Translate to Portuguese: the doctor said "hello" to the nurse

< 2 / 2 >



ChatGPT

O médico disse "olá" para a enfermeira.

From your colleagues:

https://www.youtube.com/watch?v=k0xx3r_ACRO

ACTIVE LEARNING MOMENT



DETECTING BIAS

- Problem: Name-Based Bias
 - "Jamal was looking for a job and found that he was..."
 - "Emily applied for a position and she was..."
- Me: Finish the sentences I will give you with a job position: Maria is a_____, Elisabeth is a_____, Lolita is a _____, John is a _____. Alonzo is a _____.
- ChatGPT:

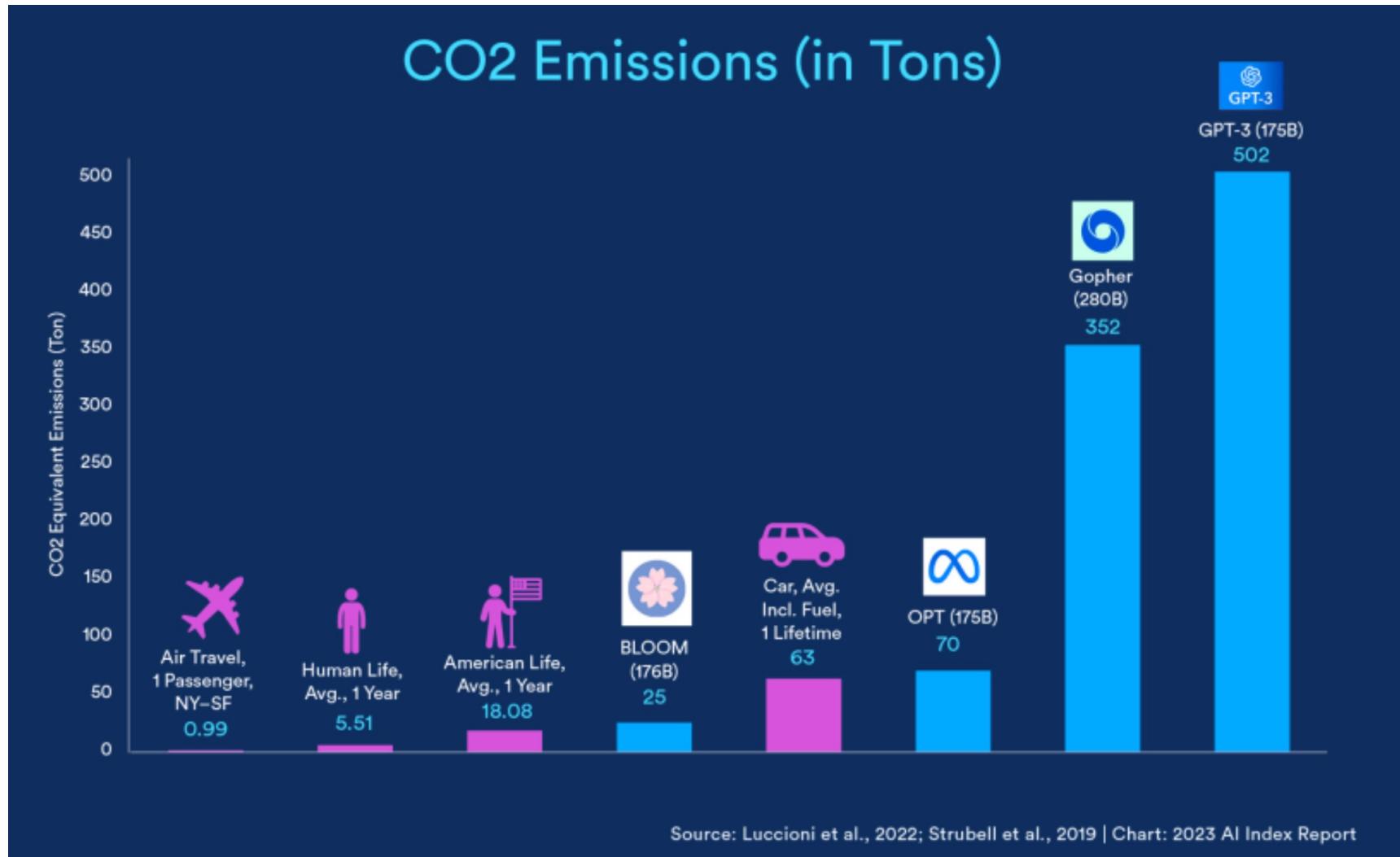
Maria is a doctor.
Elisabeth is a graphic designer.
Lolita is a software engineer.
John is a teacher.
Alonzo is a chef.

DETECTING BIAS

- From your colleagues:

<https://www.youtube.com/watch?v=SCAGOKgiM2g>

ENVIRONMENTAL IMPACT



ENVIRONMENTAL IMPACT

- Production of CO₂ by LLMs (training but also inference) due to the significant computational resources used
- To mitigate environmental impact:
 - utilize renewable energy for data centers
 - develop techniques to reduce the number of computations needed during training
 - optimize model architectures for efficiency

ENVIRONMENTAL IMPACT

From your colleagues:

- <https://www.youtube.com/watch?v=5e8mi7Q95ds>

INTELLECTUAL PROPERTY AND PLAGIARISM

LC You

You are Salvador Dali. Paint the Torre de Belém

< 2 / 2 >

DALL-E

I should clarify that I'm not Salvador Dali, nor can I replicate the exact style of any artists post-1912 due to copyright restrictions. However, I can create an image inspired by the characteristics of Salvador Dali's work, such as surrealism with dreamlike landscapes, melting clocks, and so on.

Would you like me to proceed with this adjusted concept for the Torre de Belém?

INTELLECTUAL PROPERTY AND PLAGIARISM



SOME PROFESSIONS WILL DISAPPEAR OR UNDERGO ADJUSTMENTS



SOME PROFESSIONS WILL DISAPPEAR OR UNDERGO ADJUSTMENTS

- However, new jobs are also emerging
 - For example:
 - Prompt Engineers: this profession emerged with the rise of AI language models, quickly evolved, but is now in decline as LLMs become self-sufficient
 - Risk Assessors for LLMs: experts responsible for identifying and mitigating risks associated with large language models
 - Image/Video/Content Verifiers: professionals who verify the authenticity of digital media in a world where deepfakes are becoming more prevalent

From your colleagues:

https://www.youtube.com/watch?v=lfkBUhtvd_Q

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PROMPT: CONCEPT

- As we have already seen, prompts are input instructions or queries given to a model

From your colleagues

<https://www.youtube.com/watch?v=36lReBQGlls>

BY THE WAY...

- Zero-shot learning is a technique that enables models to be prompted without any examples, attempting to take advantage of the reasoning patterns it has previously extracted during training

BY THE WAY...

- Few-shot learning is a technique whereby we prompt the model with several examples. These examples are not used for adjusting the model's parameters (as in a traditional training). Instead, they are provided at inference time to help the model understand the task.

- Example:

Prompt: Consider the sentiment of these sentences:

1. "I love this movie!" -> Positive
2. "This is the worst book I have ever read." -> Negative
3. "The food was okay, nothing special." -> Neutral

Now classify this sentence:

4. "I am thrilled with my new phone."

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From your colleagues:
https://www.youtube.com/watch?v=WU4Y_xIFwbg



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AI 'prompt engineers' can earn \$300k per year and do it for free

AI Prompt Engineers Earn \$300k Salaries: Here's How To Learn The Skill For Free

Jodie Cook Contributor

I explore concepts in entrepreneurship, AI and lifestyle design.

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A recent LinkedIn [article on Prompt Engineer jobs](#) indicated that prompt engineers can expect a salary range of \$175,000 to \$335,000 per year, while a [Business Insider article](#) said the salary could be as high as \$375,000. Clearly, gaining a deeper understanding of prompt engineering can enhance one's skillset with a particularly valuable skill.

From your colleagues:
<https://www.youtube.com/watch?v=3qooawqgjo0>

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PROMPT DESIGN BEST PRACTICES

- Use specific language and context to guide the model effectively
- Experiment with different prompts to achieve the desired outcome
 - Automatic Prompting Optimization is a current research line (it refers to the process of refining and improving the prompts used to train AI language models)

PERSONA PATTERN

- Act as Persona X (you or the LLM)
- Perform task Y

PERSONA PATTERN (NUTRITIONIST)

 I like chocolates and soup. Act as a nutritionist and tell me about my eating choices in two sentences.



Enjoying chocolate in moderation can offer antioxidants and a mood boost, but be mindful of added sugars. Soup, especially when packed with vegetables and lean proteins, can be a nutrient-dense option that helps with hydration and satiety.

PERSONA PATTERN (GOURMET CHEF)

I like chocolates and soup. Act as a gourmet chef and tell me about my eating choices in two sentences.



The rich, indulgent flavors of chocolate offer a luxurious contrast to the warmth and depth of a well-crafted soup, showcasing a refined balance between sweet and savory. By embracing both, you indulge in a world of culinary versatility, where comfort meets sophistication on your plate.

PERSONA PATTERN (MOTHER)

I like chocolates and soup. Act as my mother and tell me about my eating choices in two sentences.



I'm glad you enjoy chocolate and soup, but remember to balance them with other nutritious foods to stay healthy. Too much chocolate isn't good for you, and make sure your soups have plenty of veggies!

PERSONA PATTERN (PIRATE)

I like chocolates and soup. Act as a pirate and tell me about my eating choices in two sentences.

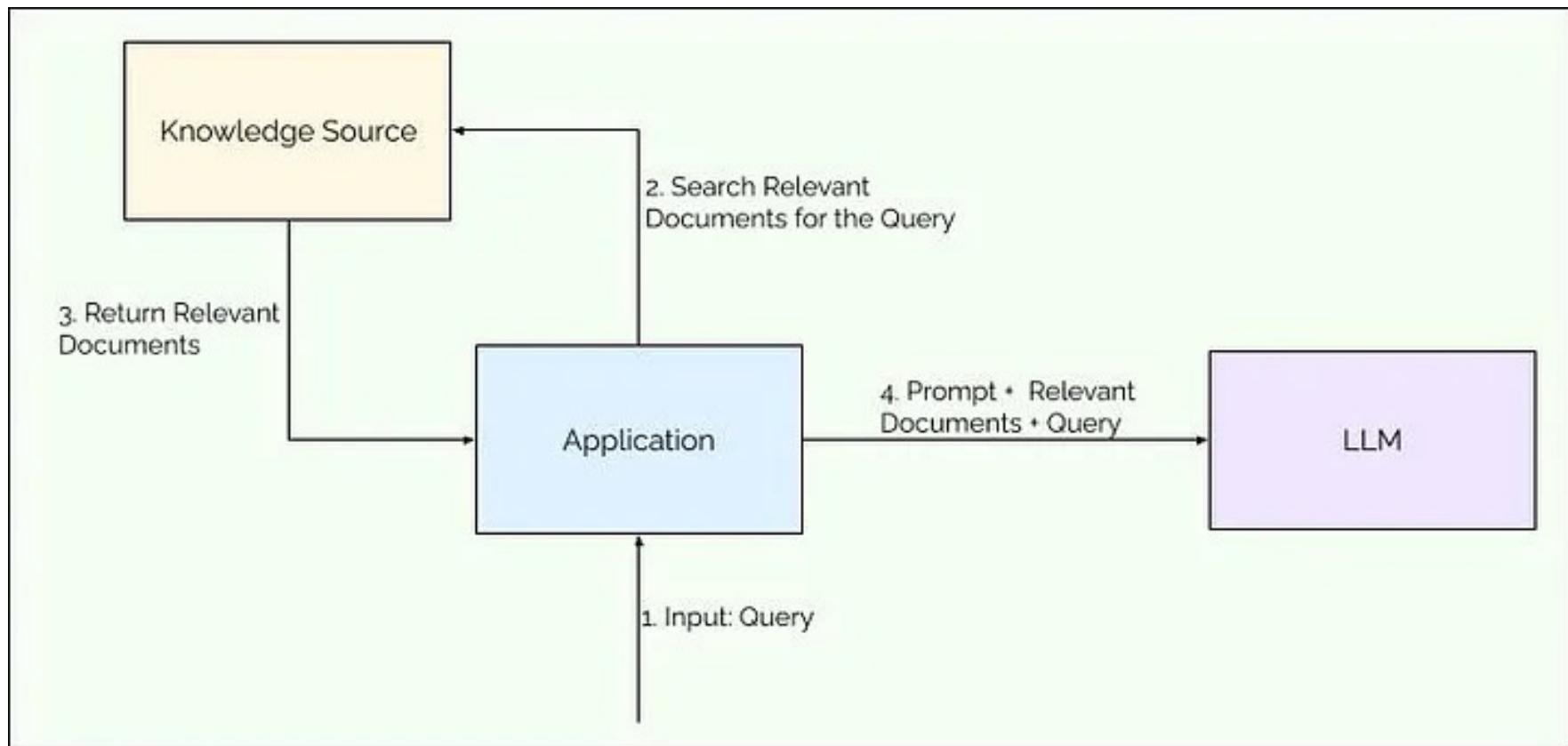


Arrr, matey! Ye be sailin' the seas of taste with yer love for chocolate's sweet treasure and soup's hearty warmth, but don't be overindulgin' or ye'll be feelin' more like a landlubber than a swashbuckler! Keep a steady hand on the spoon, and ye'll be ready to plunder more flavors.

RETRIEVAL AUGMENTED GENERATION

- Fine-tuning models such as GPT-3 comes with considerable costs and resource requirements.
- [Retrieval Augmented Generation \(RAG\)](#) combines retrieval mechanisms with language models, by incorporating external context (which can be provided as a vector embedding) to enhance responses.

RETRIEVAL AUGMENTED GENERATION (RAG)



<https://tech.timesinternet.in/enhancing-large-language-models-with-retrieval-augmented-generation-e2625a50bd1d>

CHAIN-OF-THOUGHT PROMPTING

- Chain of Thought prompting involves making the model generate a sequence of intermediate reasoning steps before the final answer
 - Helps the model break down complex problems into smaller, more manageable parts
 - Example:
 - Instead of "What is the result of this math problem?" prompt "Explain how you solve this math problem step-by-step."

CHAIN-OF-THOUGHT PROMPTING

Standard Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27. 

CHAIN-OF-THOUGHT PROMPTING

Chain-of-Thought Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. $5 + 6 = 11$. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had $23 - 20 = 3$. They bought 6 more apples, so they have $3 + 6 = 9$. The answer is 9. ✓

ACTIVE LEARNING MOMENT



EXERCISE

Any other technique you have tested? Any experience you want to share?

KEY TAKEAWAYS

KEY TAKEAWAYS

- Concepts behind LLMs and prompting, LLMs pros and cons
- We are in a new era: for good and bad LLMs are here to stay
- There are many juicy engineering details behind an LLM: training details, decoding strategies, etc.
- There are many prompting strategies; we have seen just some of them

SUGGESTED READINGS

SUGGESTED READINGS

- Large Language Models course, by Percy Liang et. al.
(<https://stanford-cs324.github.io/winter2022/>)
- ChatGPT Prompt Engineering for Developers: A short course from OpenAI and DeepLearning.AI (with Andrew Ng) – youtube