

# LECTURE 2: MACHINE LEARNING AND LLMS



DEPARTMENT OF MANAGEMENT  
AARHUS UNIVERSITY

10 SEPTEMBER 2025

MAGNUS BENDER  
ASSISTANT PROFESSOR



# TUTORIALS

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## 1. Quick recap on last week's tutorial



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# TUTORIALS

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1. Quick recap on last week's tutorial
2. Outlook on this week's tutorial
  - Topic:  
Python basics and data types
  - Recommended:  
Complete the Datacamp courses
    - ▶ Introduction to Python for Developers
    - ▶ Intermediate Python for Developers

# TODAY'S LECTURE

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Today at 11:33 AM

Please complete the sentence: A Large Language ...

Ol gpt-oss:120b  
Thought for less than a second ✓  
A Large Language Model is an artificial-intelligence system that has been trained on massive amounts of text data so it can understand, generate, and manipulate human-like language across a wide variety of tasks.

Follow up

- ↳ How are large language models trained?
- ↳ What are some common applications of large language models?
- ↳ What are the main limitations or challenges of using them?
- ↳ How do they differ from earlier AI models or from smaller language models?
- ↳ What ethical considerations should we keep in mind with large language models?

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# TODAY'S LECTURE

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- Central question:  
„How to answer a prompt?“

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# TODAY'S LECTURE

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- Central question:  
„How to answer a prompt?“
- Steps and terms
  1. ChatBot
  2. Artificial Intelligence
  3. Large Language Model
  4. Machine Learning

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# TODAY'S LECTURE

---

- Central question:  
„How to answer a prompt?“
- Steps and terms
  1. ChatBot
  2. Artificial Intelligence
  3. Large Language Model
  4. Machine Learning
- ➔ Important insights on capabilities and limits of AI

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# WHY TODAY'S LECTURE?

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- Public discourse on LLMs and the future of AI is full of *bullshit* claims

# WHY TODAY'S LECTURE?

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- Public discourse on LLMs and the future of AI is full of *bullshit* claims

#	Faulty claim (presented as a quote)
1	"AI will replace all human workers within the next decade."
2	"When an AI says it 'feels' something, it really experiences emotions."
3	"A single AI system can understand any domain it reads about, just like a human expert."
4	"If an AI is trained on a massive dataset, it becomes unbiased."
5	"AI can predict the future with near-perfect accuracy."
6	"All AI systems are self-learning and need no human supervision after deployment."
7	"If an AI passes a Turing test, it is truly intelligent."
8	"AI can replace doctors and make flawless medical diagnoses on its own."
9	"AI will inevitably become hostile and try to 'take over the world.'"

gpt-oss:120b asked for „(faulty) claims about AI“

# WHY TODAY'S LECTURE?

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- Your future manager reads it and believes most of it. A true story...

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# WHY TODAY'S LECTURE?

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# WHY TODAY'S LECTURE?

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- Your future manager reads it and believes most of it. A true story...
- In your future jobs, you will have to help people understand what AI, LLMs, and Machine Learning **can** and **cannot** do
- Knowing how they work is the only way. We have to **demystify LLMs and the terms around it**.

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# BACK TO THE TOPIC

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Respond to a prompt.



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# THE PROBLEM

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# THE PROBLEM

---

- Input

# THE PROBLEM

---

- Input
  - Any type of (textual) prompt.
  - Freely written by a human

# THE PROBLEM

---

- Input
  - Any type of (textual) prompt.
  - Freely written by a human
- Response

# THE PROBLEM

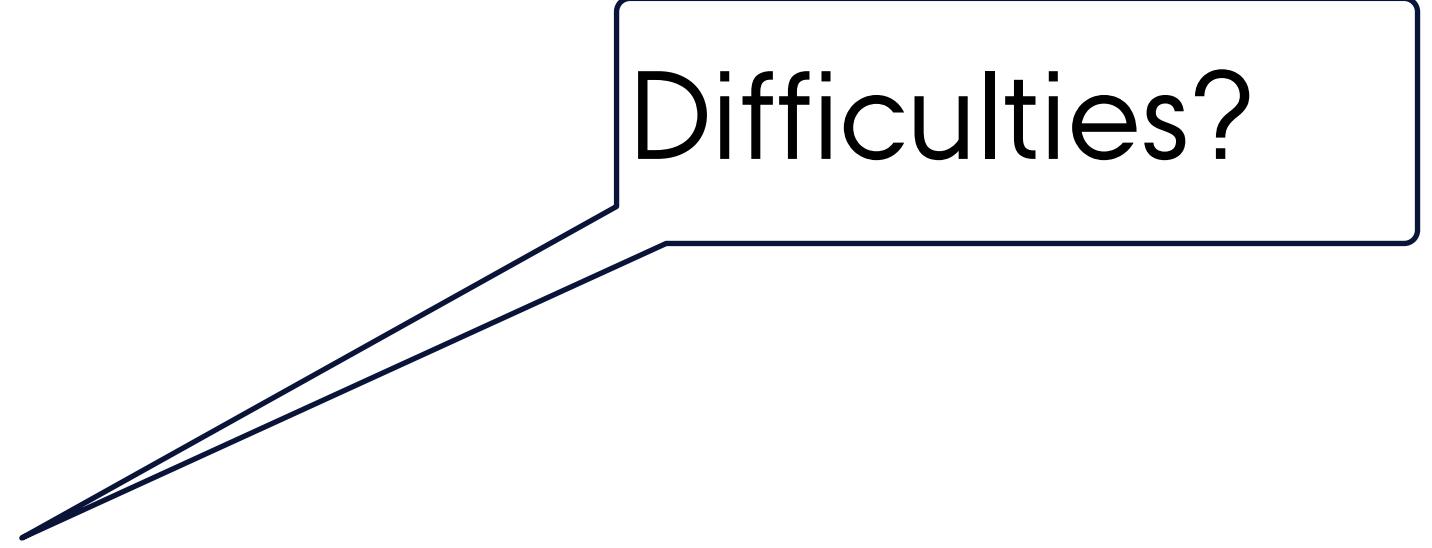
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  - Any type of (textual) prompt.
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  - Any type of textual response
  - Automatically generated by the „system“

# THE PROBLEM

---

- Input
  - Any type of (textual) prompt.
  - Freely written by a human
- Response
  - Any type of textual response
  - Automatically generated by the „system“
- Difficulties



Difficulties?

# THE PROBLEM

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- Input
  - Any type of (textual) prompt.
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- Response
  - Any type of textual response
  - Automatically generated by the „system“
- Difficulties
  - No prior knowledge about input, topic, ...



Difficulties?

# THE PROBLEM

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- Input
  - Any type of (textual) prompt.
  - Freely written by a human
- Response
  - Any type of textual response
  - Automatically generated by the „system“
- Difficulties
  - No prior knowledge about input, topic, ...
  - *High quality* of response expected



Difficulties?

# A FIRST TRY

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# A FIRST TRY

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Today at 3:06 PM

Good morning



Ol gpt-oss:120b

Thought for less than a second ▾

Good morning! ☀ I hope your day is off to a great start. How can I help you today?



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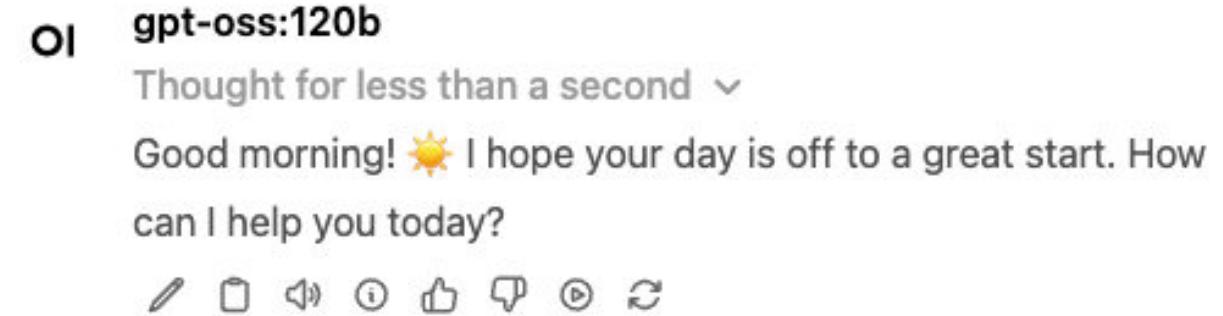
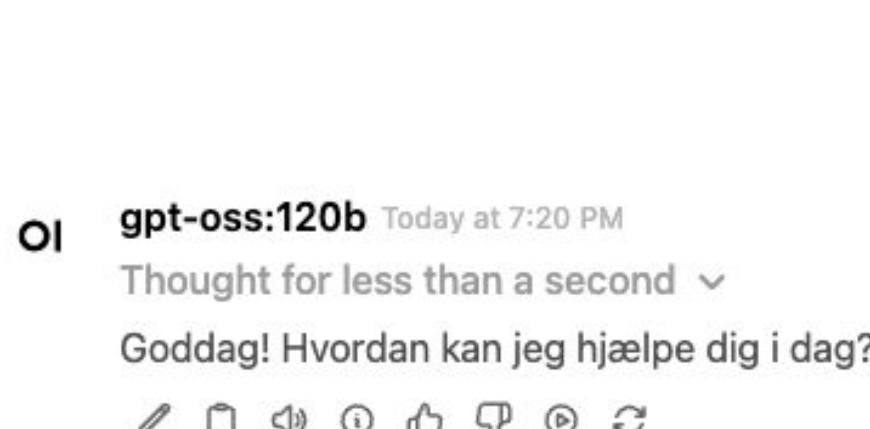
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# A FIRST TRY

---



# A FIRST TRY

---

Goddag

Ol gpt-oss:120b Today at 7:20 PM  
Thought for less than a second ^

"User says "Goddag" which is Danish/Norwegian/Swedish for "Good day". Likely they are greeting. We respond in same language. Maybe ask how we can help."

Goddag! Hvordan kan jeg hjælpe dig i dag?

Today at 3:06 PM  
Good morning

Ol gpt-oss:120b  
Thought for less than a second ^  
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# A FIRST TRY

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Goddag

Today at 3:06 PM

Good morning



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Good morning! ☀ I hope your day is off to a great start. How can I help you today?



if prompt == „Good morning“:

respond(„Good morning! ☀ I hope your day is off to a great start. How can I help you today?“)

else if prompt == „Goddag“:

respond(„Goddag! Hvordan kan jeg hjælpe dig i dag?“)

else if ...

# ARTIFICIAL INTELLIGENCE

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Arrange the terms: ChatBot, Artificial Intelligence, Large Language Model

# CHATBOT

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# CHATBOT

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- Responds to prompts

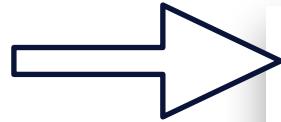
# CHATBOT

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- Responds to prompts
- More than just *generate text*

# CHATBOT

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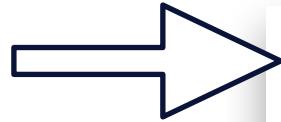
Thought for 1 seconds ^

"The user asks: "What is Aarhus BSS?" Likely they refer to Aarhus Business School? Actually Aarhus BSS stands for Aarhus Business School? Let's think: Aarhus BSS is part of Aarhus University, Denmark. BSS stands for Business and Social Sciences. It's a faculty within Aarhus University offering programs in business, economics, social sciences. So answer: it's a faculty, its history, programs, research, campuses, etc. Provide overview. Maybe also mention that BSS stands for Business and Social Sciences, includes Business School, Department of Business and Management, Department of Economics and Business Economics, etc. Also mention location, international orientation, rankings. Provide details. "

- Responds to prompts
- More than just *generate text*
  1. Analyzes prompt and decides about next step → „Thinking“

# CHATBOT

---



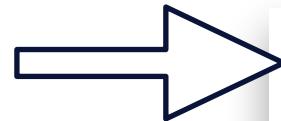
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- Responds to prompts
- More than just *generate text*
  1. Analyzes prompt and decides about next step → „Thinking“
  2. Possibly does a web search

# CHATBOT

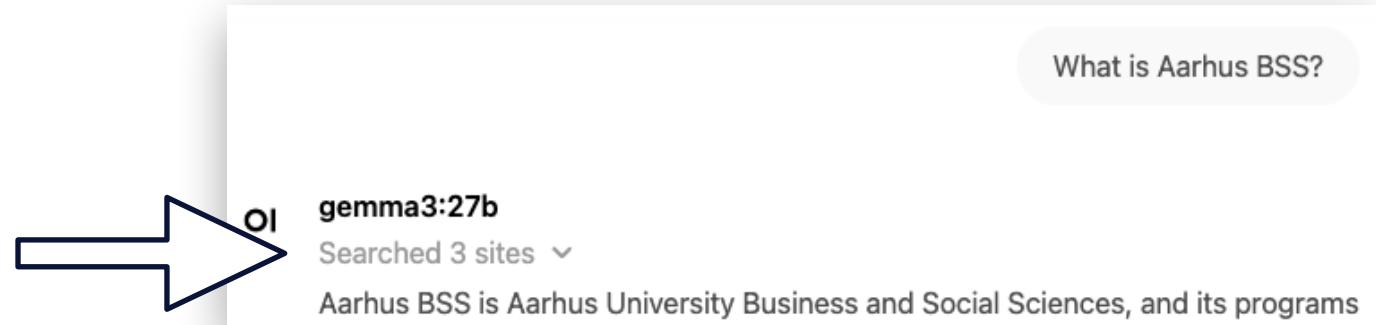
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Thought for 1 seconds ^

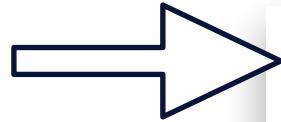
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- Responds to prompts
- More than just *generate text*
  1. Analyzes prompt and decides about next step → „Thinking“
  2. Possibly does a web search
  3. Analyzes results of web search



# CHATBOT

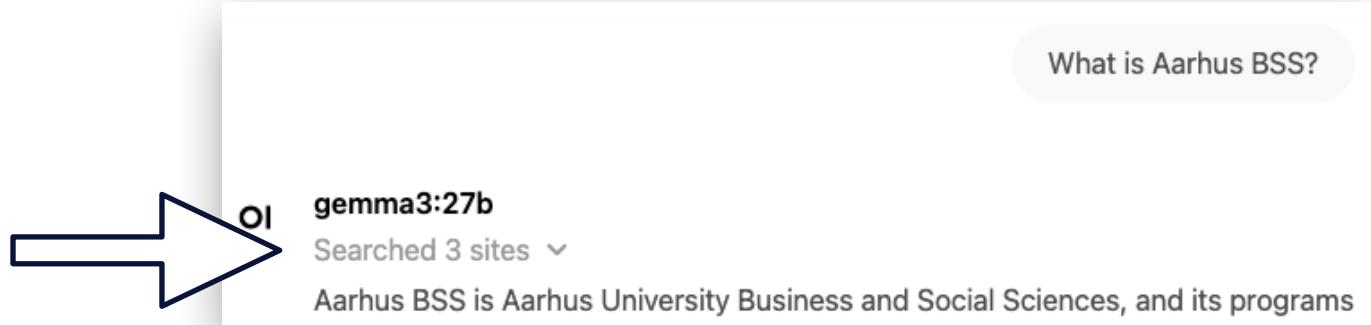
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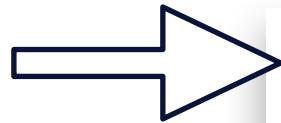
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- Responds to prompts
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  1. Analyzes prompt and decides about next step → „Thinking“
  2. Possibly does a web search
  3. Analyzes results of web search
  4. Generates response



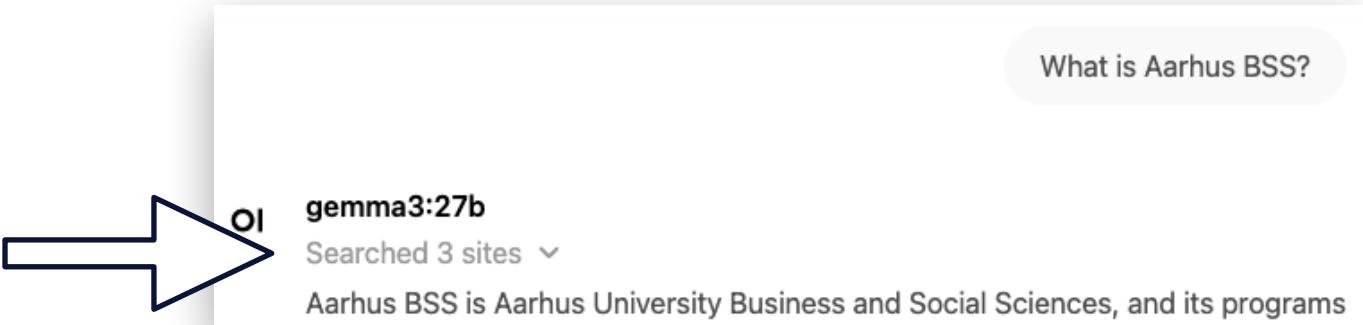
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- More than just *generate text*
  1. Analyzes prompt and decides about next step → „Thinking“
  2. Possibly does a web search
  3. Analyzes results of web search
  4. Generates response
- Backend by a Large Language Model, e.g., GPT, LLama, Gemma, ...



ChatBot	Models
ChatGPT	<ul style="list-style-type: none"><li>• GPT 5</li><li>• GPT 4o</li><li>• ...</li></ul>
Gemini	<ul style="list-style-type: none"><li>• 2.5 Flash</li><li>• 2.5 Pro</li><li>• ...</li></ul>

# ARTIFICIAL INTELLIGENT AGENTS

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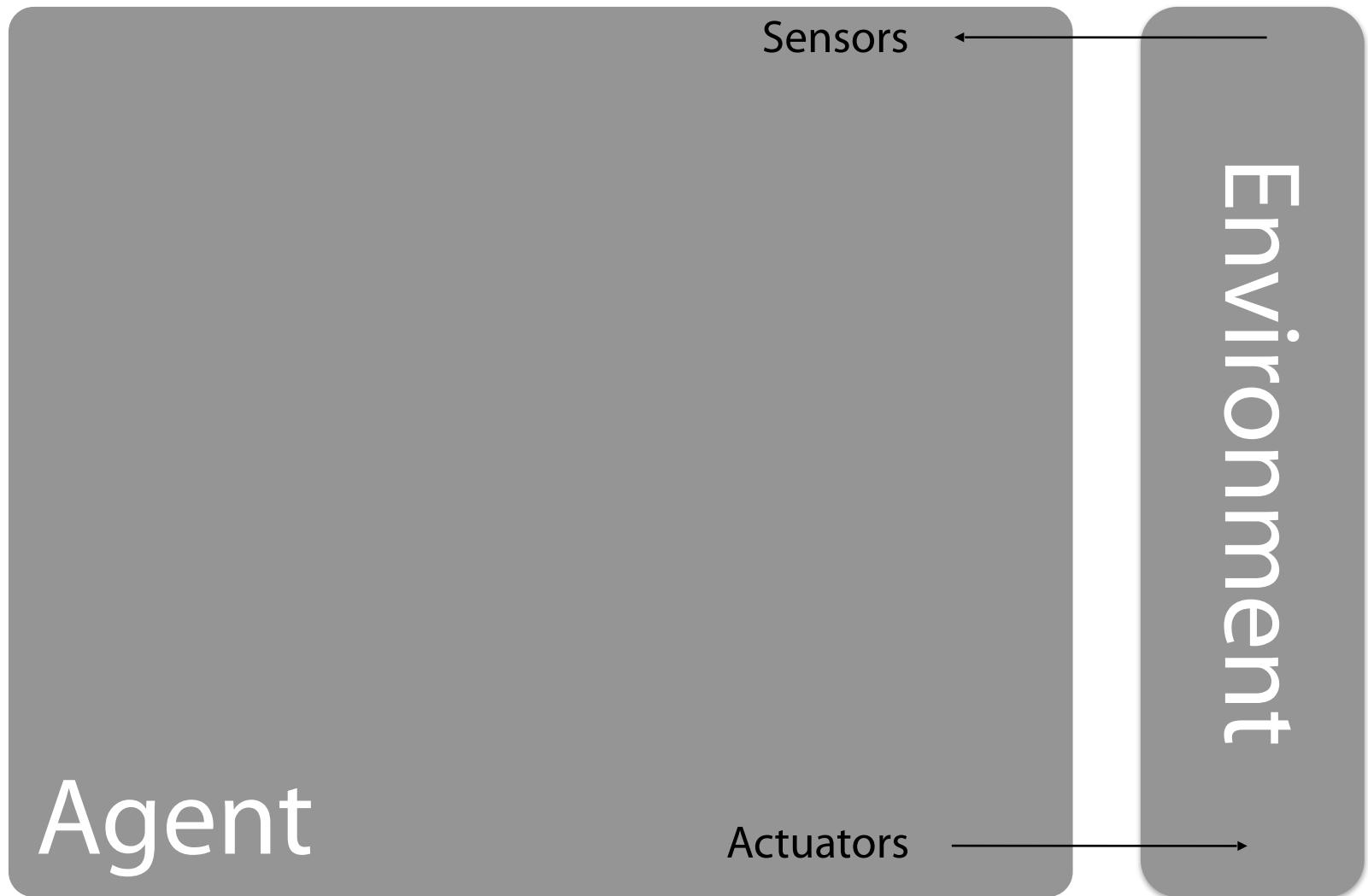
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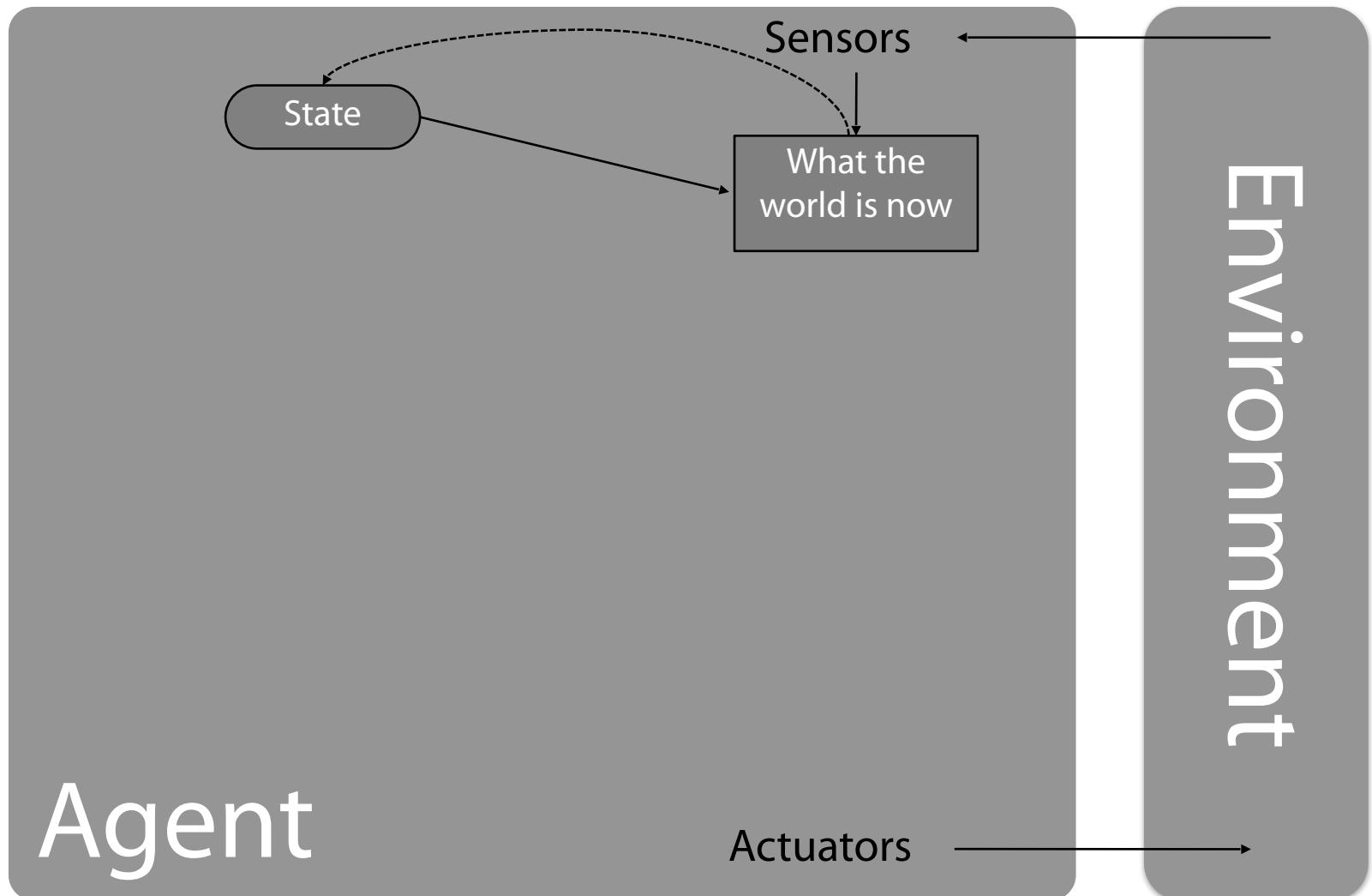
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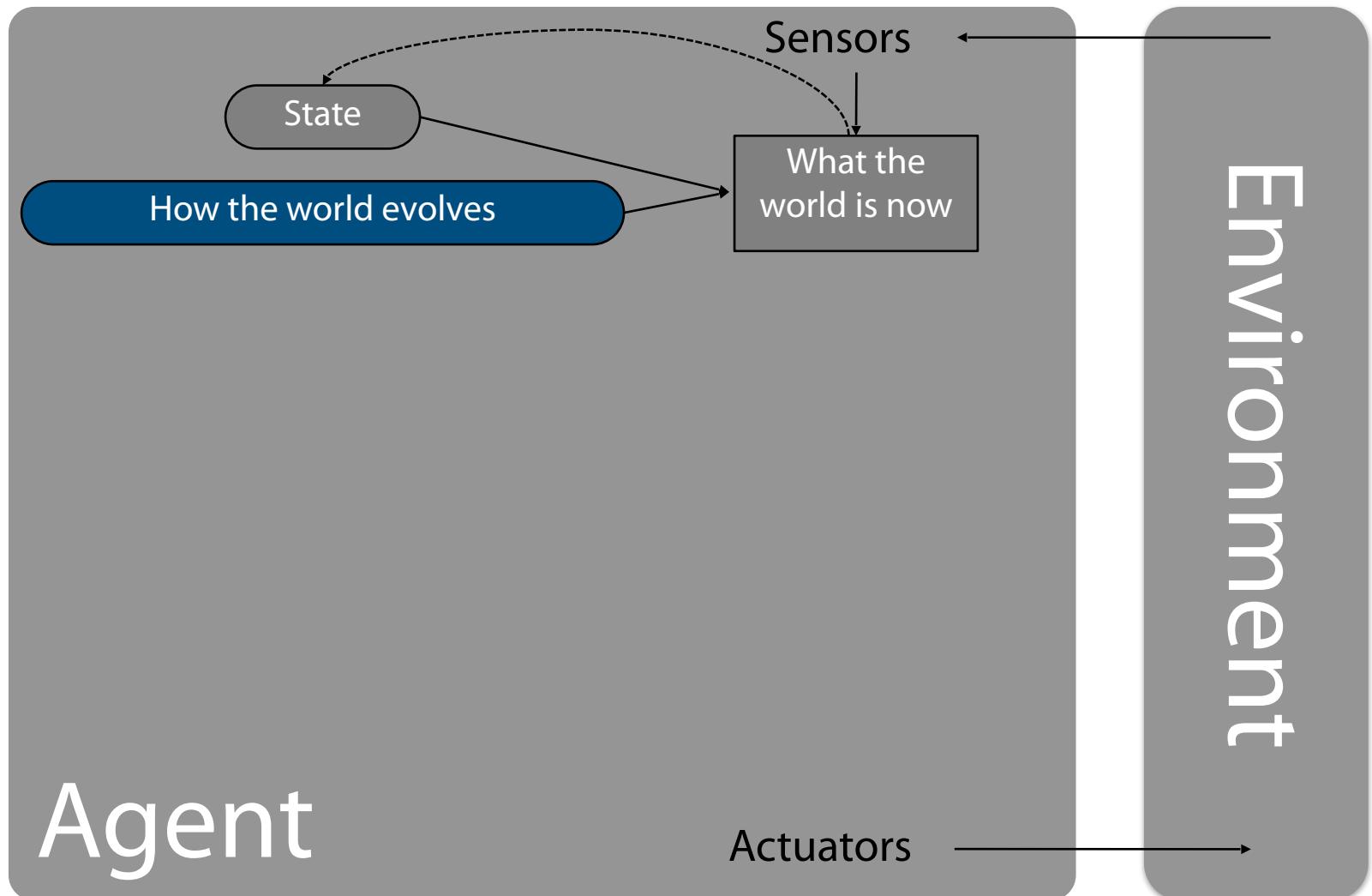
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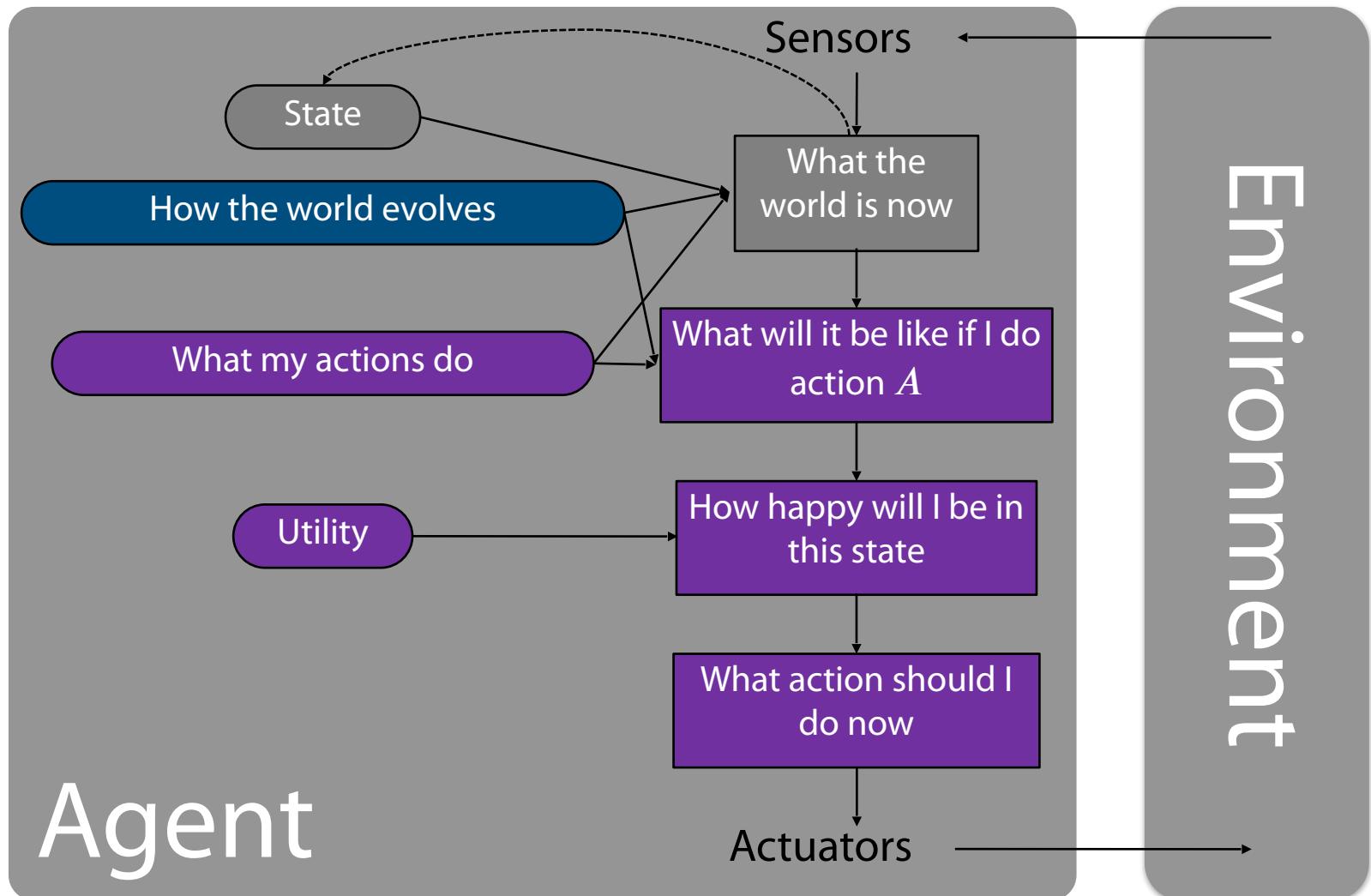


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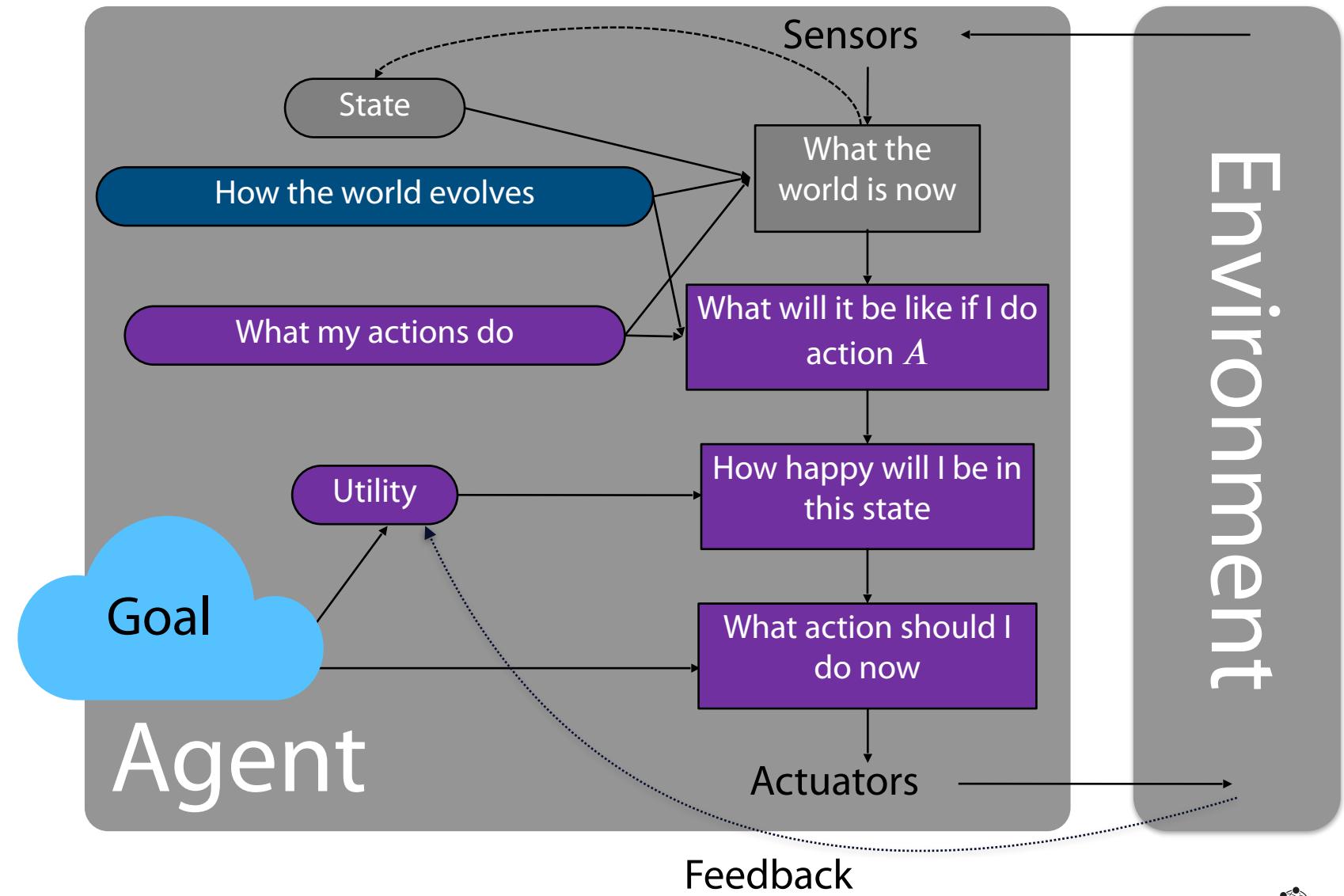
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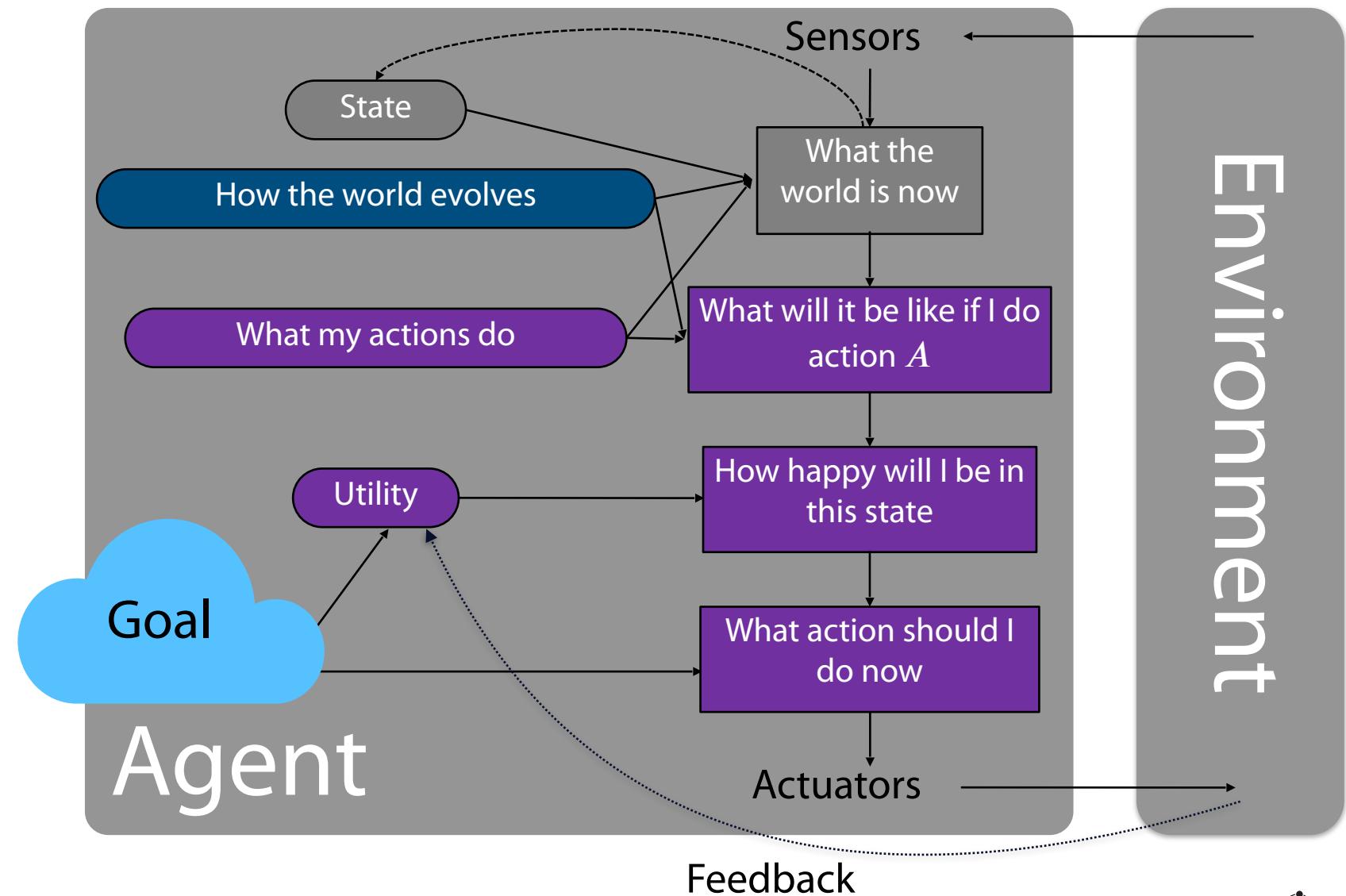


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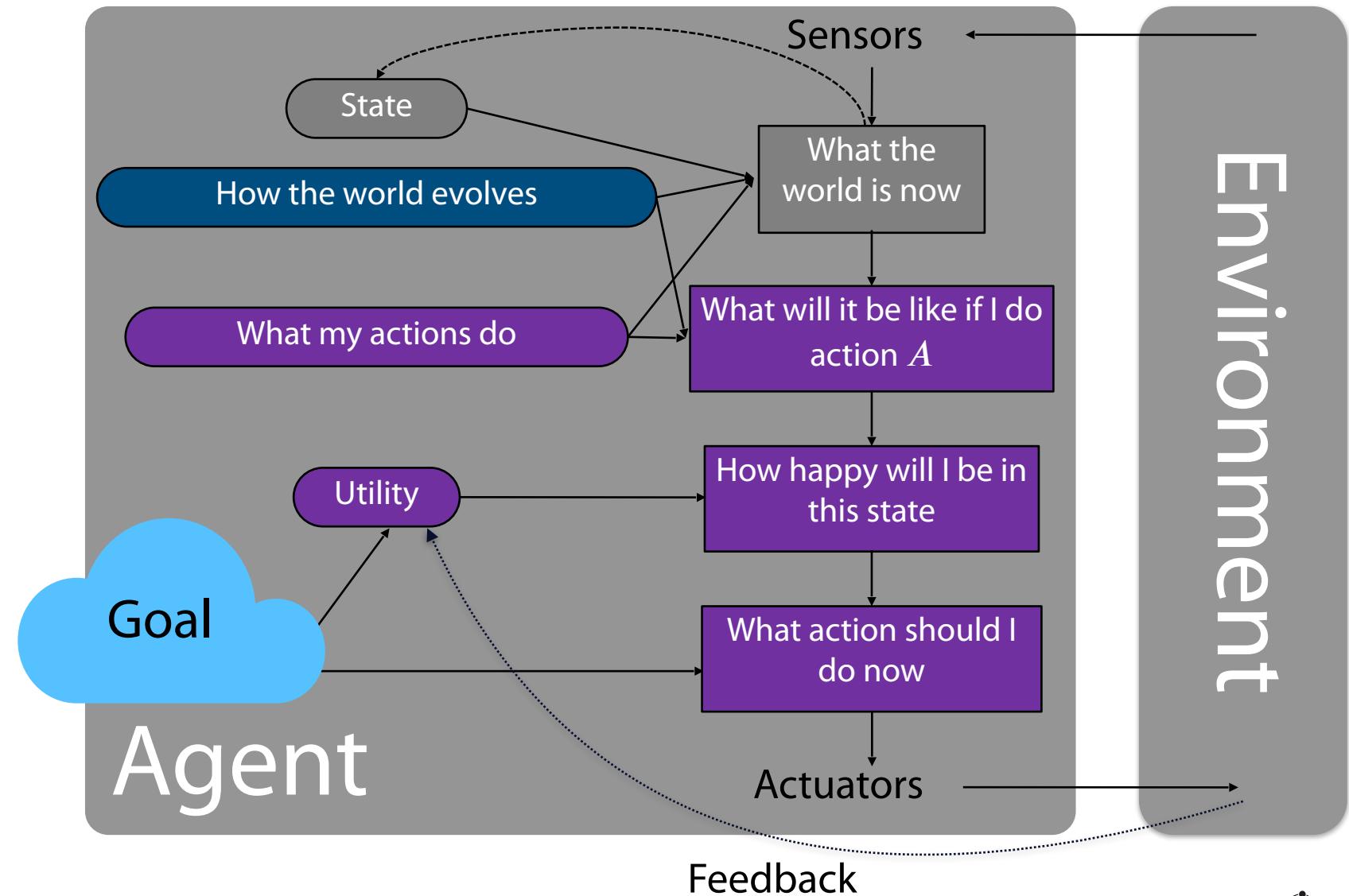
# ARTIFICIAL INTELLIGENT AGENTS

- Intelligent systems, but not necessarily *intelligent* in a human sense



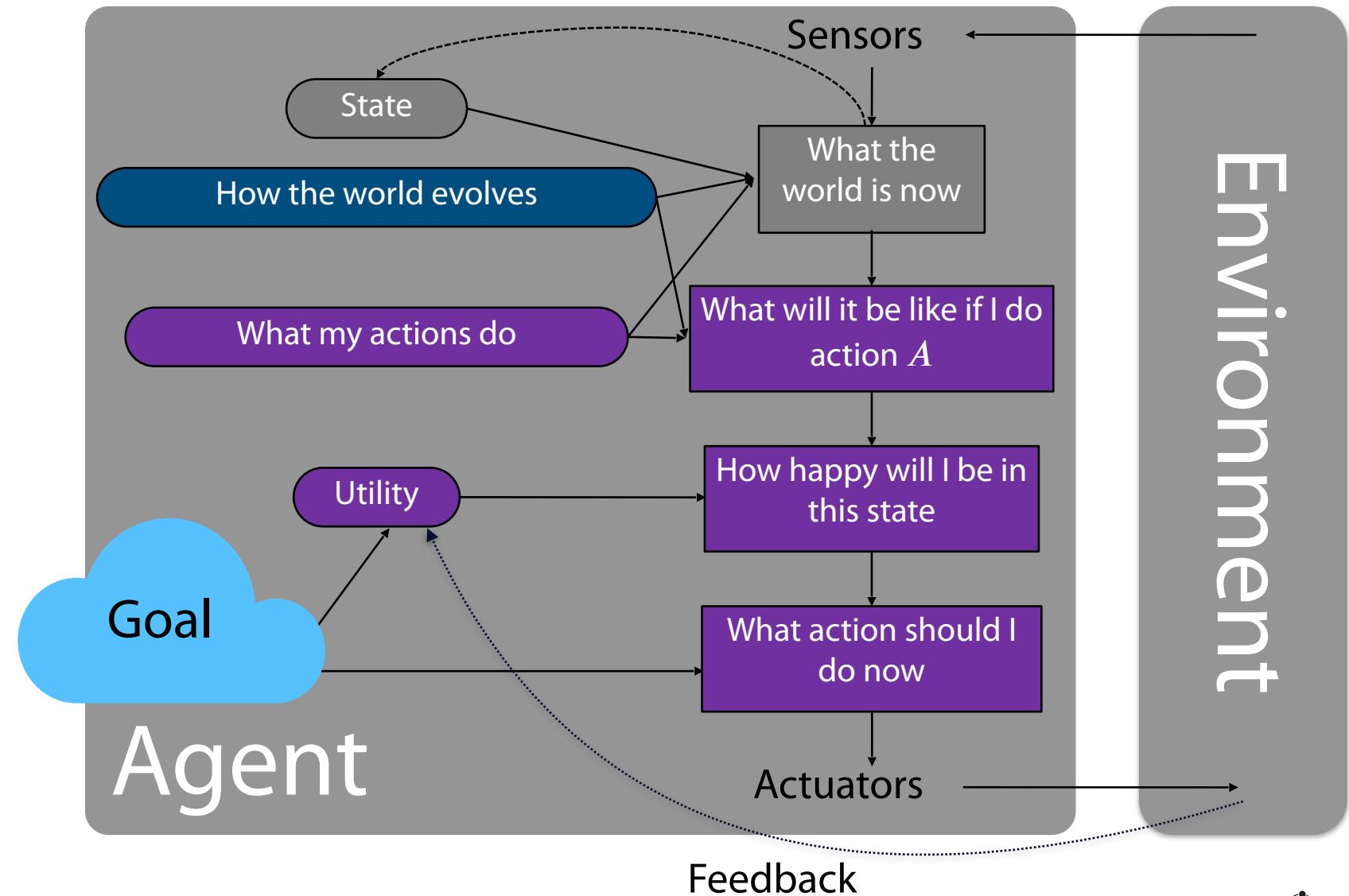
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- Intelligent systems, but not necessarily *intelligent* in a human sense
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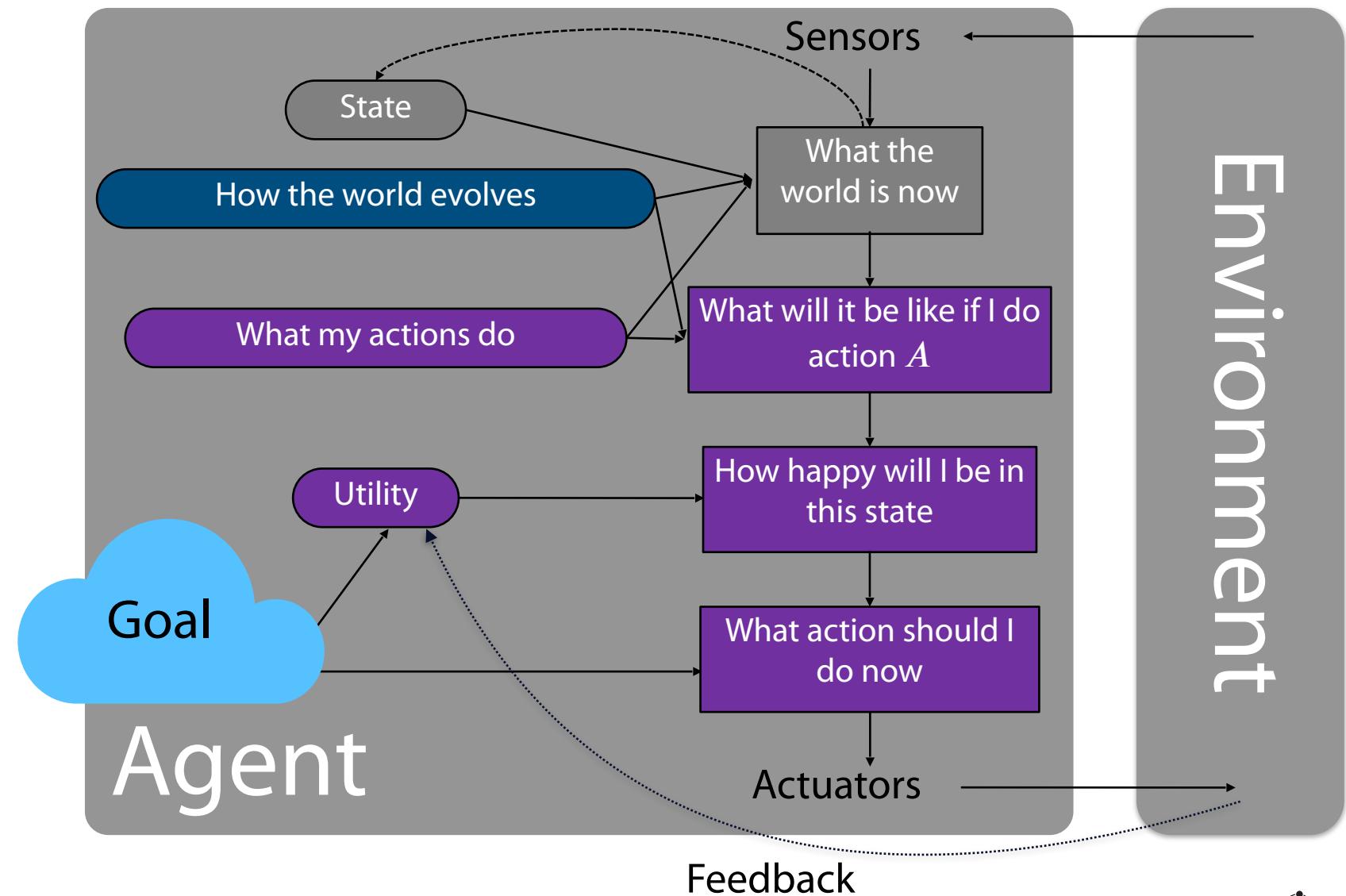
# ARTIFICIAL INTELLIGENT AGENTS

- Intelligent systems, but not necessarily *intelligent* in a human sense
- Agents
  - ... have goals



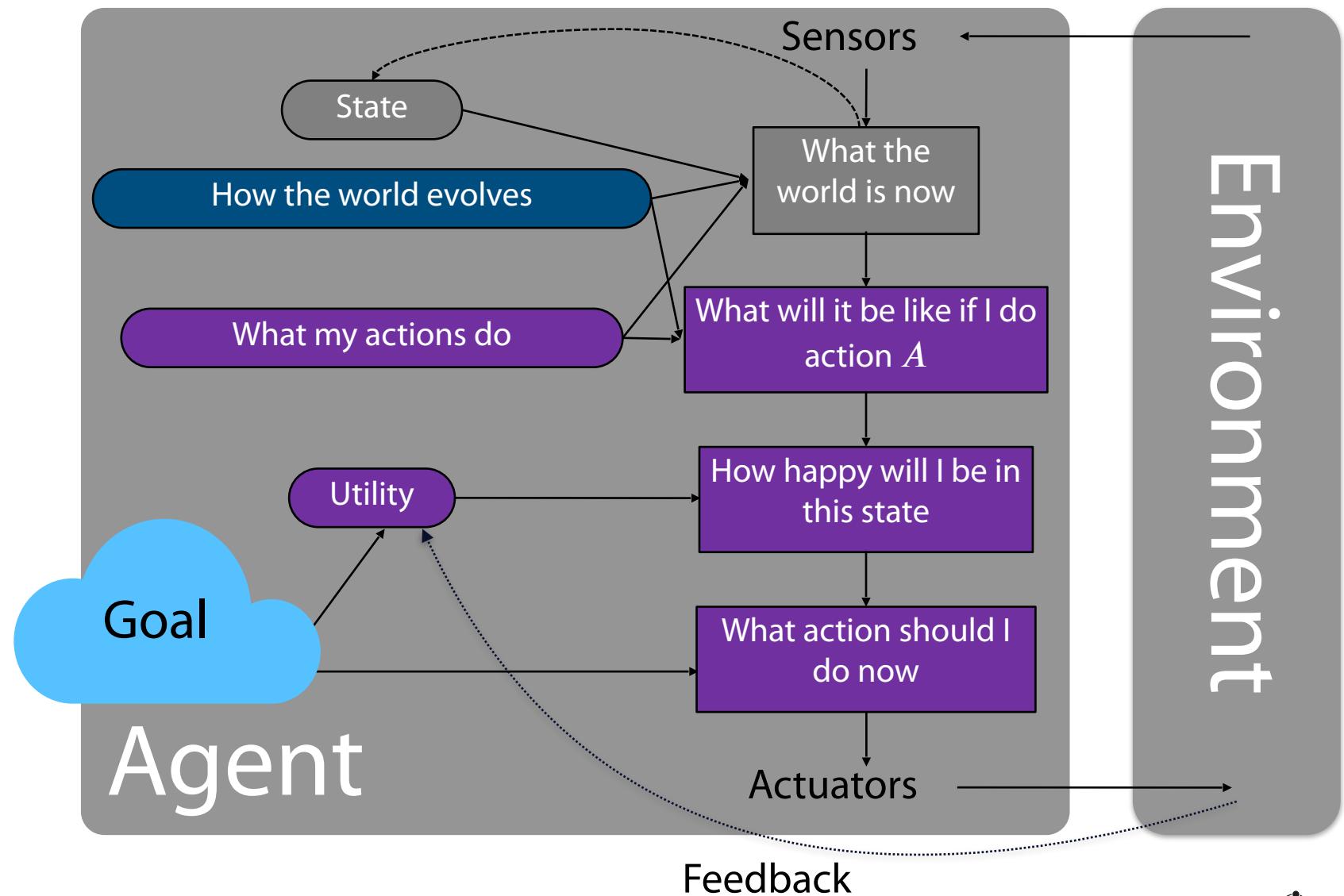
# ARTIFICIAL INTELLIGENT AGENTS

- Intelligent systems, but not necessarily *intelligent* in a human sense
- Agents
  - ... have goals
  - ... have a perception of their environment (sensors)



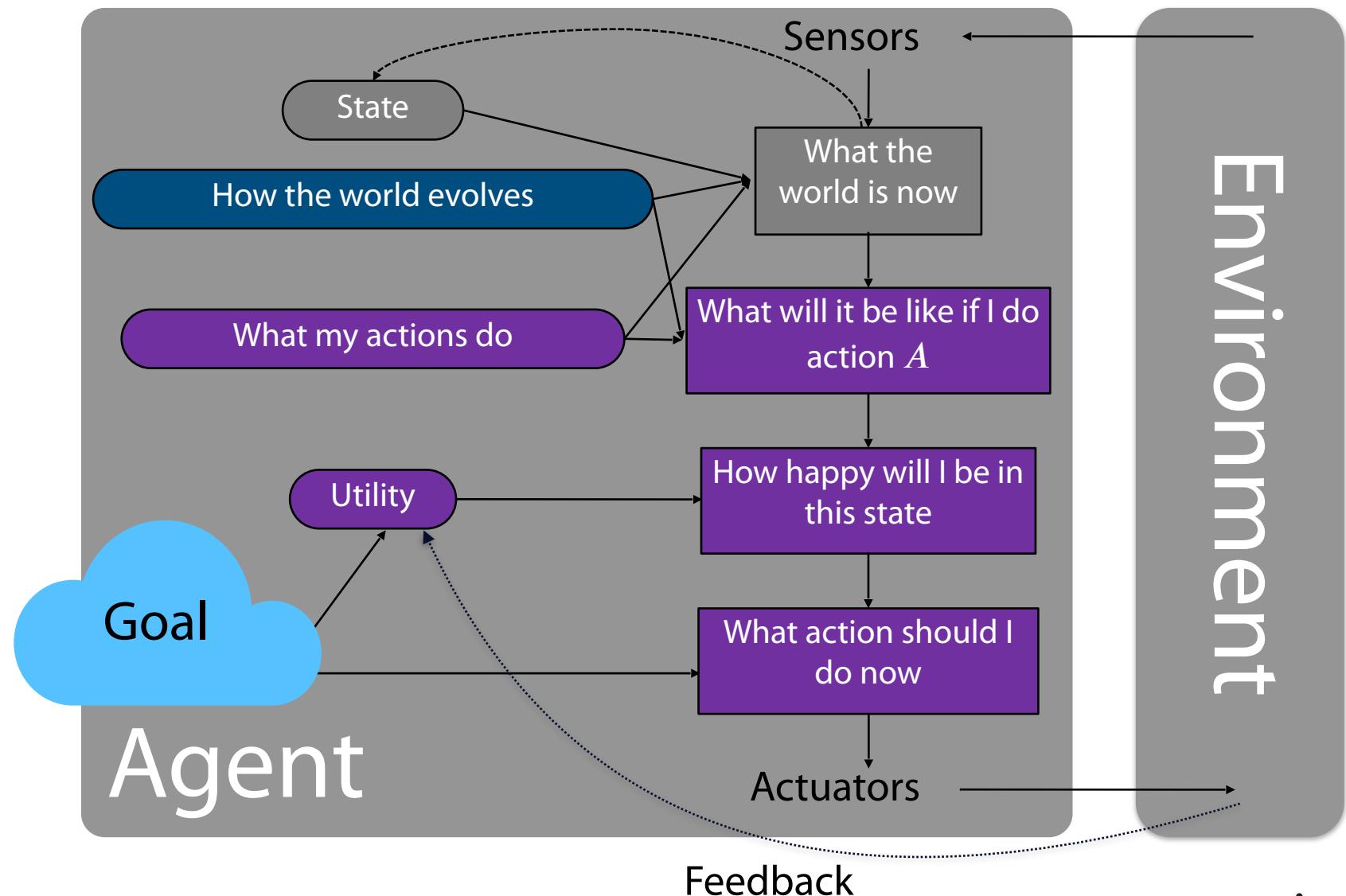
# ARTIFICIAL INTELLIGENT AGENTS

- Intelligent systems, but not necessarily *intelligent* in a human sense
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  - ... have a perception of their environment (sensors)
  - ... can change their environment (actuators)



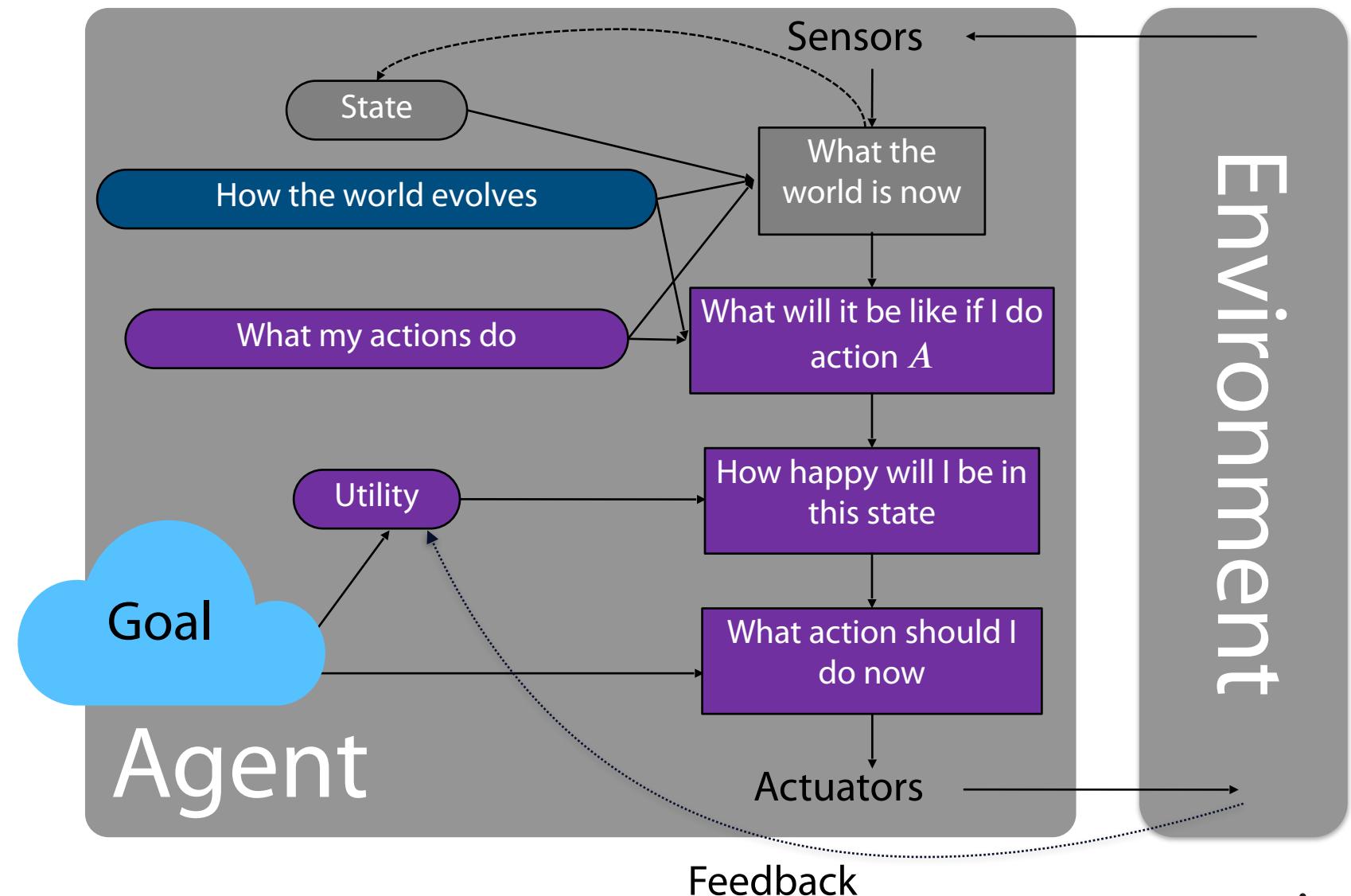
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  - ... can change their environment (actuators)
  - ... plan their actions



# ARTIFICIAL INTELLIGENT AGENTS

- Intelligent systems, but not necessarily *intelligent* in a human sense
- Agents
  - ... have goals
  - ... have a perception of their environment (sensors)
  - ... can change their environment (actuators)
  - ... plan their actions
  - ... update theirs goals → learn during runtime



# HOW TO ANSWER A PROMPT?

---

- Prompt
  - „Please complete the sentence: A Large Language ...“

Today at 11:33 AM

Please complete the sentence: A Large Language ...

Ol gpt-oss:120b  
Thought for less than a second ▾  
A Large Language Model is an artificial-intelligence system that has been trained on massive amounts of text data so it can understand, generate, and manipulate human-like language across a wide variety of tasks.

Follow up

↳ How are large language models trained?  
↳ What are some common applications of large language models?  
↳ What are the main limitations or challenges of using them?  
↳ How do they differ from earlier AI models or from smaller language models?  
↳ What ethical considerations should we keep in mind with large language models?



+  Web Search  Code Interpreter  

# HOW TO ANSWER A PROMPT?

---

- Prompt
  - „Please complete the sentence: A Large Language ...“
- Consists of two parts:
  1. Task: „Please complete the sentence:“
  2. Data: „A Large Language ...“

Today at 11:33 AM

Please complete the sentence: A Large Language ...

OL gpt-oss:120b

Thought for less than a second ▾

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✍ 📁 🔍 ⓘ ⌘ ⌘ ⌘ ⌘

Follow up

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# HOW TO ANSWER A PROMPT?

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- Prompt
  - „Please complete the sentence: A Large Language ...“
- Consists of two parts:
  1. Task: „Please complete the sentence:“
  2. Data: „A Large Language ...“
- Analysis of prompt to identify task and execution of task on data can be done with the help of an LLM

Today at 11:33 AM

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OL gpt-oss:120b

Thought for less than a second ▾

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- Consists of two parts:
  1. Task: „Please complete the sentence:“
  2. Data: „A Large Language ...“
- Analysis of prompt to identify task and execution of task on data can be done with the help of an LLM

The screenshot shows a conversational AI interface. The user prompt is "Please complete the sentence: A Large Language ...". The AI response is as follows:

gpt-oss:120b  
Thought for less than a second ^

"The user asks: "Please complete the sentence: A Large Language ...". They want to complete the sentence. Likely they want to finish the phrase "A Large Language Model ..." Possibly they want to fill in the blank. Could be "A Large Language Model is a type of AI that ...". We need to respond with a continuation. Probably produce a sentence: "A Large Language Model is a type of artificial intelligence that processes and generates human-like text based on massive amounts of data." That's a natural completion.

Thus answer: "A Large Language Model ..." Provide a sentence."

A Large Language Model is an artificial-intelligence system that has been trained on massive amounts of text data so it can understand, generate, and manipulate human-like language across a wide variety of tasks.

Below the AI response, there are several small icons for interacting with the message, including a pen, a reply arrow, a speaker, and a delete icon. At the bottom of the interface, there is a "Send a Message" input field and a row of buttons for "Web Search" and "Code Interpreter", along with microphone and speaker icons.

# LARGE LANGUAGE MODELS

---

Hands on the field of Natural Language  
Processing



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10 SEPTEMBER 2025

MAGNUS BENDER  
ASSISTANT PROFESSOR



# PREDICT *REASONABLE* WORDS

---



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ASSISTANT PROFESSOR



# PREDICT *REASONABLE WORDS*

---

Let's guess words!

„The red \_\_\_ rolled down the hill.“

# PREDICT *REASONABLE WORDS*

---

Let's guess words!

„The red \_\_\_ rolled down the hill.“

Menti „Word  
Cloud“

# PREDICT *REASONABLE* WORDS

---

## Let's guess words!

„The red \_\_\_ rolled down the hill.“

- What do we infer from context?
  - It must be a noun, referencing a rollable object
  - It is probably something that is typical of this situation.
- What could \_\_\_ be, but is probably not??

Menti „Word Cloud“

# WHY ARE LLMS SO GOOD? "SELF ATTENTION"

---

Let's guess words again! (heads up: more tricky!)

„The cat drank the milk because it was \_\_\_\_.“

# WHY ARE LLMS SO GOOD? "SELF ATTENTION"

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„The cat drank the milk because it was \_\_\_\_.“

- Popular choices:
  - „**hungry**“, „**thirsty**“
  - „**delicious**“, „**cold**“

Menti „Word  
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# WHY ARE LLMS SO GOOD? "SELF ATTENTION"

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„The cat drank the milk because it was \_\_\_\_.“

- Popular choices:
  - „**hungry**“, „**thirsty**“
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- The definite article „it“ can refer to:
  - „**the cat**“
  - „**the milk**“

Menti „Word  
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Menti „Word  
Cloud“

# WHY ARE LLMS SO GOOD? "SELF ATTENTION"

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Let's guess words! (heads up: more tricky!)

# WHY ARE LLMS SO GOOD? "SELF ATTENTION"

---

Let's guess words! (heads up: more tricky!)

Menti  
„Ranking“

# WHY ARE LLMS SO GOOD? "SELF ATTENTION"

---

Let's guess words! (heads up: more tricky!)

The **cat** drank the **milk** because it was **hungry**, because it had been ...

The **cat** drank the **milk** because it was **delicious**, because it had been ...

Menti  
„Ranking“

# WHY ARE LLMS SO GOOD? "SELF ATTENTION"

---

Let's guess words! (heads up: more tricky!)

The **cat** drank the **milk** because it was **hungry**, because it had been ...  
... out hunting all night.

The **cat** drank the **milk** because it was **delicious**, because it had been ...  
... in the fridge all night.

Menti  
„Ranking“

# WHY ARE LLMS SO GOOD? "SELF ATTENTION"

---

Let's guess words! (heads up: more tricky!)

The **cat** drank the **milk** because it was **hungry**, because it had been ...

... out hunting all night.

→ Cause for **cat** being **hungry**

The **cat** drank the **milk** because it was **delicious**, because it had been ...

... in the fridge all night.

→ Cause for **milk** being **delicious**.

Menti  
„Ranking“

# DEMO: COMPLETE THE SENTENCE

---

Interactive token builder

Model:  Load

Start of sentence:  Go

The cat drank the milk (20.74%) , (20.15%) the (27.87%) dog (55.28%) ate (32.92%) the (96.91%) cat (54.13%) , (96.29%) and (73.20%) the (91.18%) bird (38.22%) ate (39.09%) the (99.16%) dog (98.36%) , (88.95%) The ( fish 15.69% , (25.73%) the (46.50%) dog (98.24%) , (96.95%) and (98.09%) the (99.79%) bird (99.11%) are (61.90%)

History

Log

- ✓ generation complete (model stopped)
- deepseek-r1:8b loaded ✓
- ✓ generation complete (model stopped)
- llama3.2:1b loaded ✓
- ✓ generation complete (model stopped)

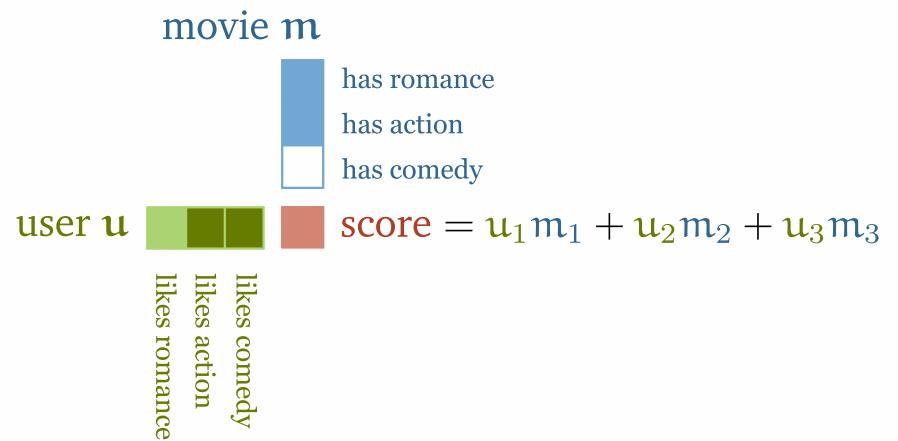
fish 15.69%  
chicken 8.70%  
bird 4.22%  
cake 3.40%  
ice 1.40%  
cookies 0.94%  
bread 0.76%  
pizza 0.70%  
soup 0.57%

# SELF-ATTENTION

---

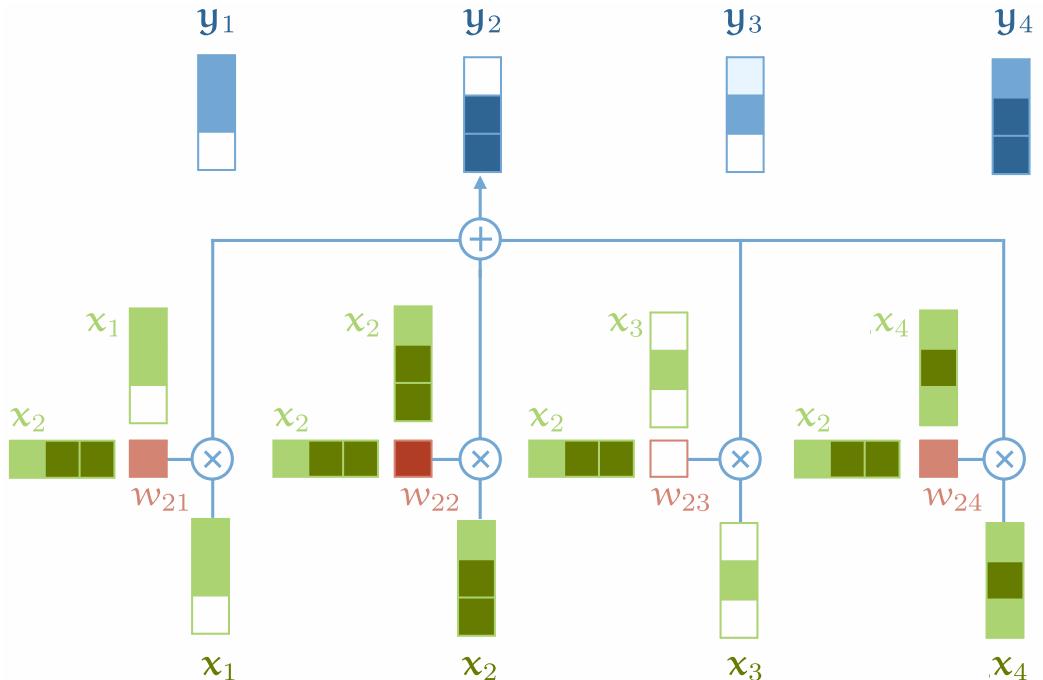
# SELF-ATTENTION

---



# SELF-ATTENTION

- Transformation of one sequence of vectors  $x_1, x_2, \dots, x_i$  (representing words) to another sequence of vectors  $y_1, y_2, \dots, y_i$



movie  $m$

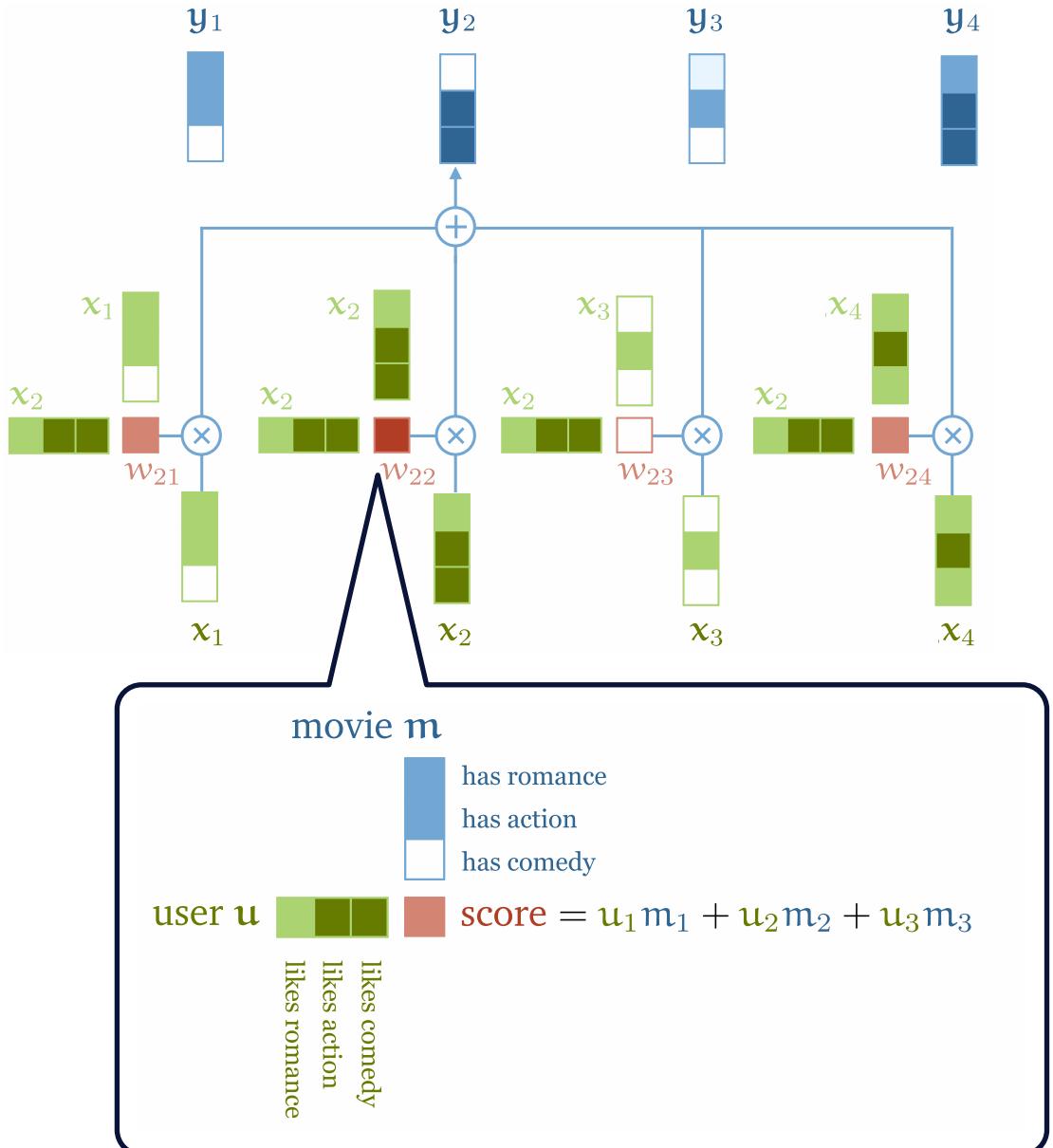
has romance  
has action  
has comedy

user  $u$   score =  $u_1 m_1 + u_2 m_2 + u_3 m_3$

likes comedy  
likes action  
likes romance

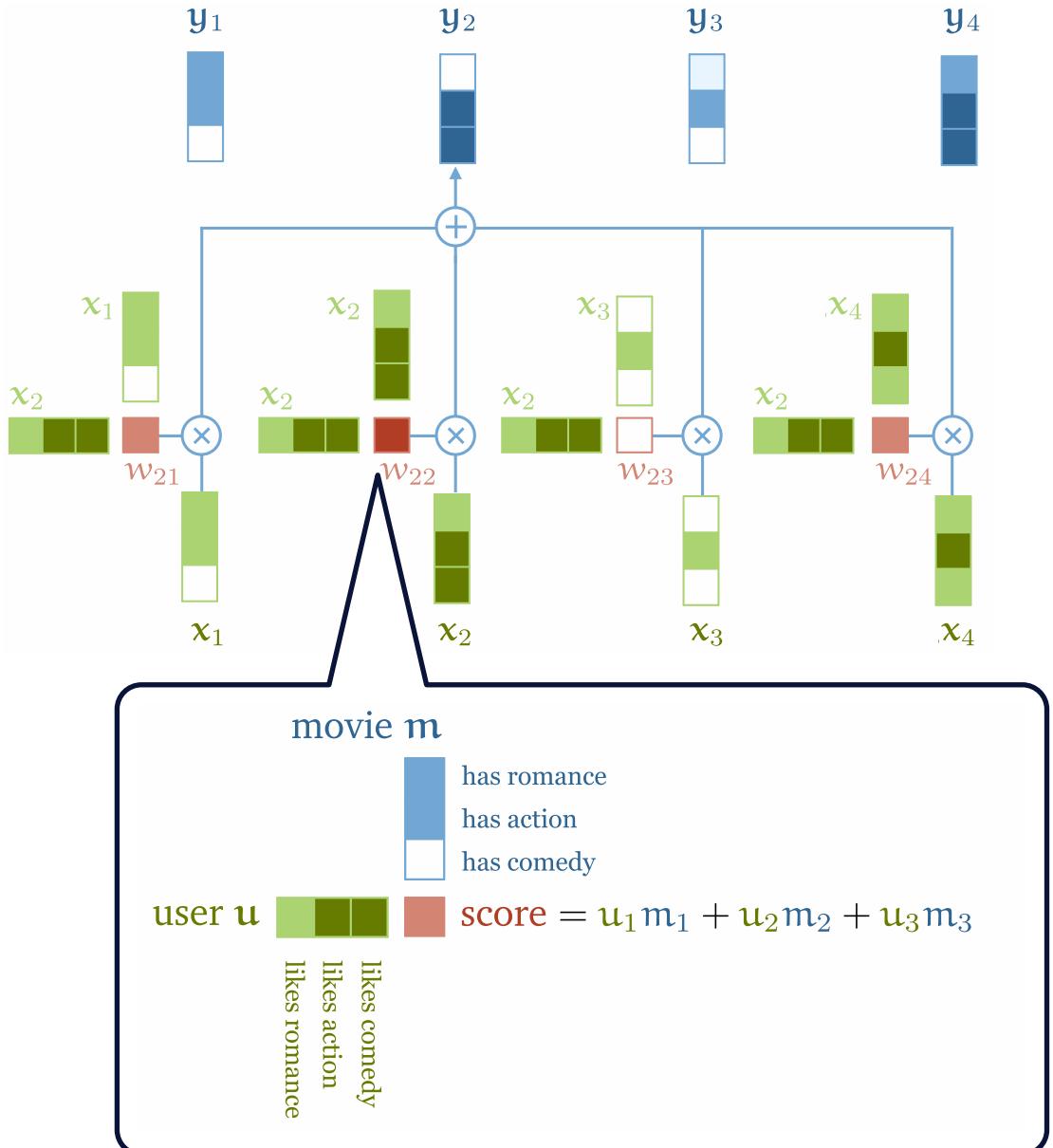
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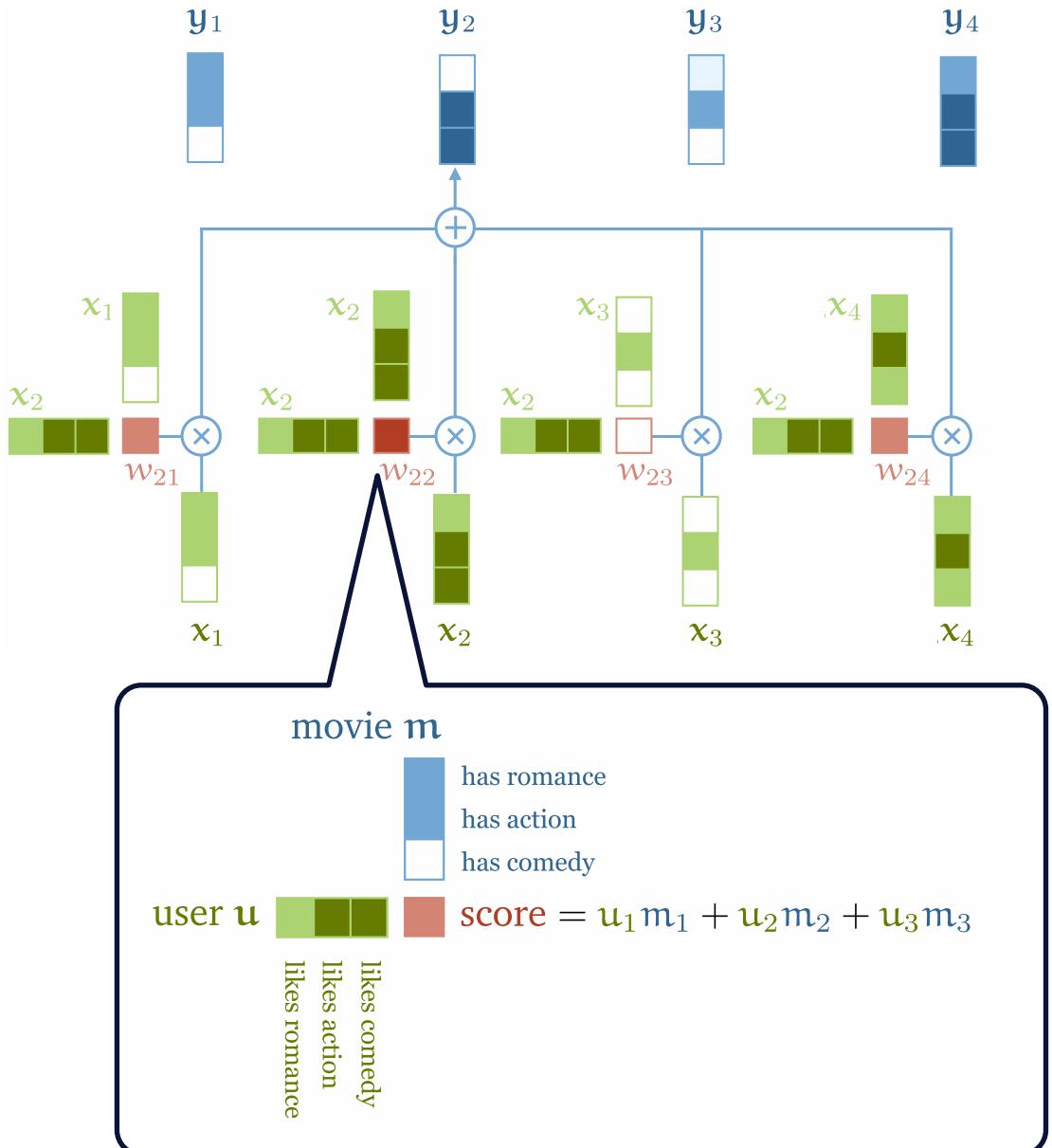
# SELF-ATTENTION

- Transformation of one sequence of vectors  $x_1, x_2, \dots, x_i$  (representing words) to another sequence of vectors  $y_1, y_2, \dots, y_i$ 
  - Emphasize important parts



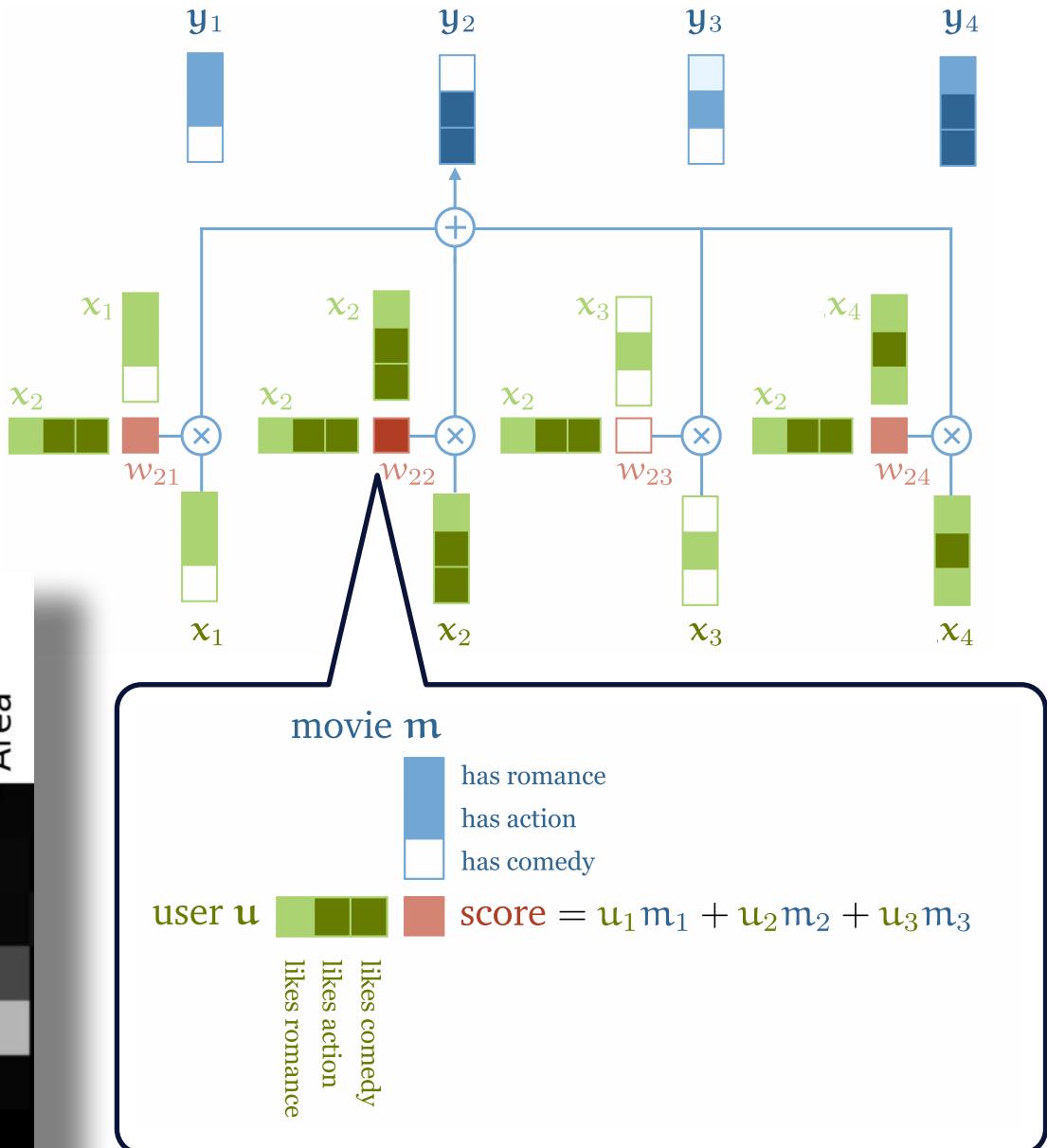
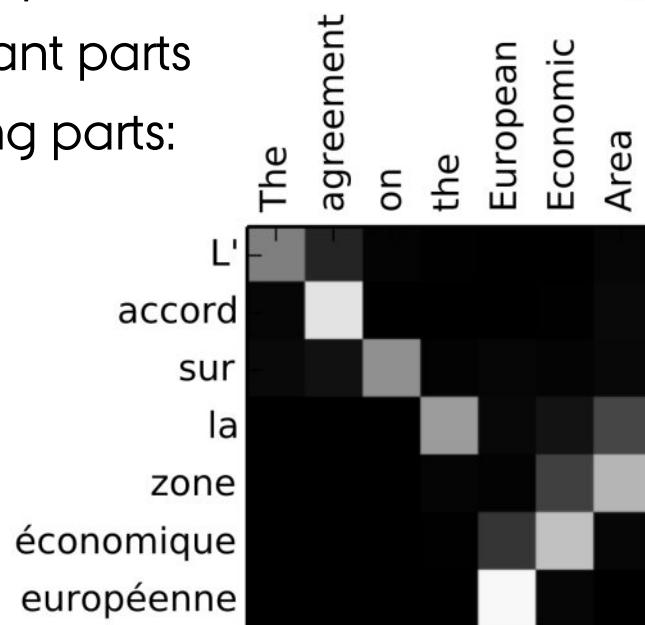
# SELF-ATTENTION

- Transformation of one sequence of vectors  $x_1, x_2, \dots, x_i$  (representing words) to another sequence of vectors  $y_1, y_2, \dots, y_i$ 
  - Emphasize important parts
  - Fade-out less important parts



# SELF-ATTENTION

- Transformation of one sequence of vectors  $x_1, x_2, \dots, x_i$  (representing words) to another sequence of vectors  $y_1, y_2, \dots, y_i$ 
  - Emphasize important parts
  - Fade-out less important parts
  - Identify corresponding parts:



# INTERMEDIATE SUMMARY: CONDITIONAL PROBABILITIES, GIVEN SURROUNDING WORDS

---

We can think of context as giving us

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We can think of context as giving us

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- Of all the possible words in the world, which could be there?
- More importantly, which cannot?

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and a **probable** space:

- Which words are the more likely?

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Formally, these are all probabilities (where the impossible ones have a probability of 0.0)

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We can think of context as giving us

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- Of all the possible words in the world, which could be there?
- More importantly, which cannot?

and a **probable** space:

- Which words are the more likely?

Internally an LLMs use vectors representing words.  
How to get these?

Formally, these are all probabilities (where the impossible ones have a probability of 0.0)

# TRANSFORMER LANGUAGE MODELS

---

Let's get technical: The Transformer architecture of  
LLMs



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# WORDS AS VECTORS

---



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Tomas Mikolov, Kai Chen, Greg  
Corrado, Jeffrey Dean, „Efficient Estimation of  
Word Representations in Vector Space“, 2013



# WORDS AS VECTORS

---

- Represent the meaning of words in vectors

# WORDS AS VECTORS

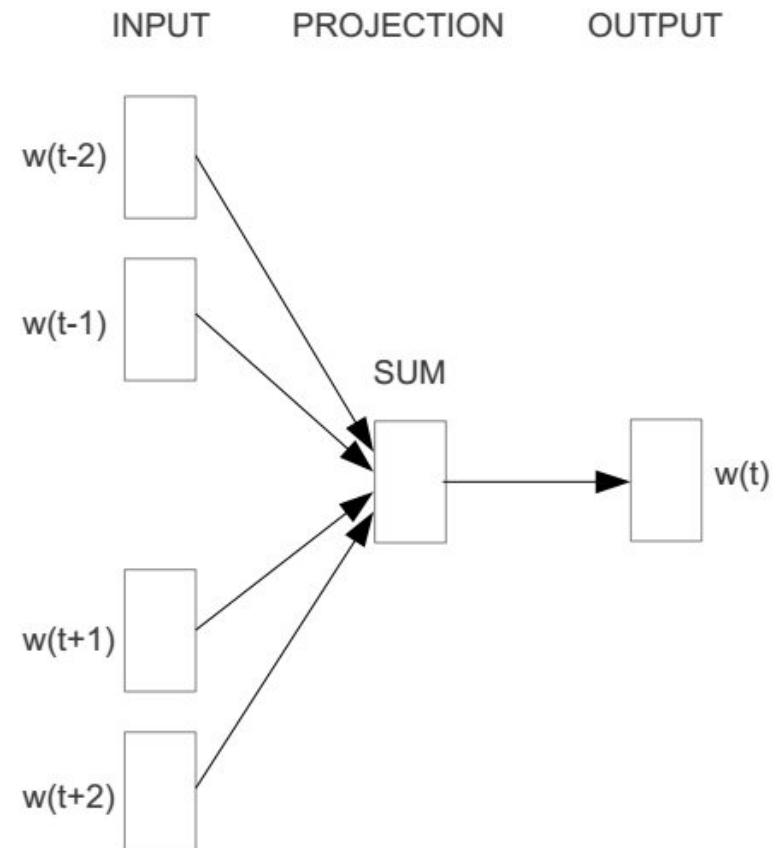
---

- Represent the meaning of words in vectors
- Example:

# WORDS AS VECTORS

---

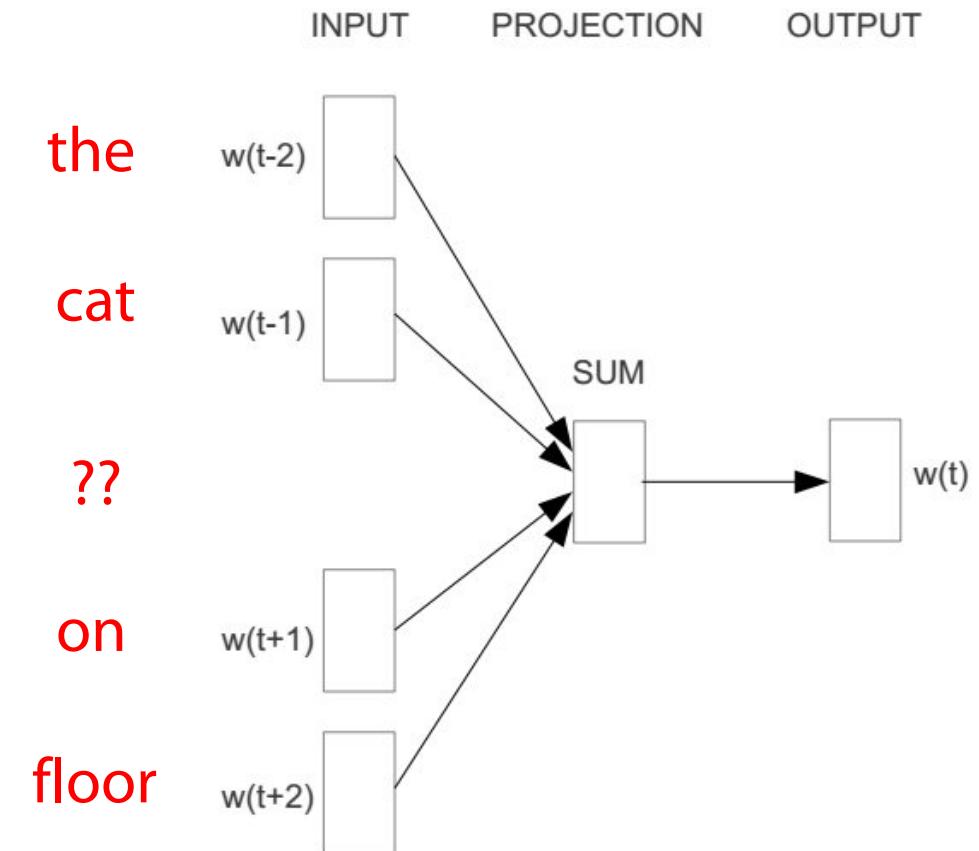
- Represent the meaning of words in vectors
- Example:
  - Continuous Bag of Words (CBOW) from the so-called Word2Vec approach



# WORDS AS VECTORS

---

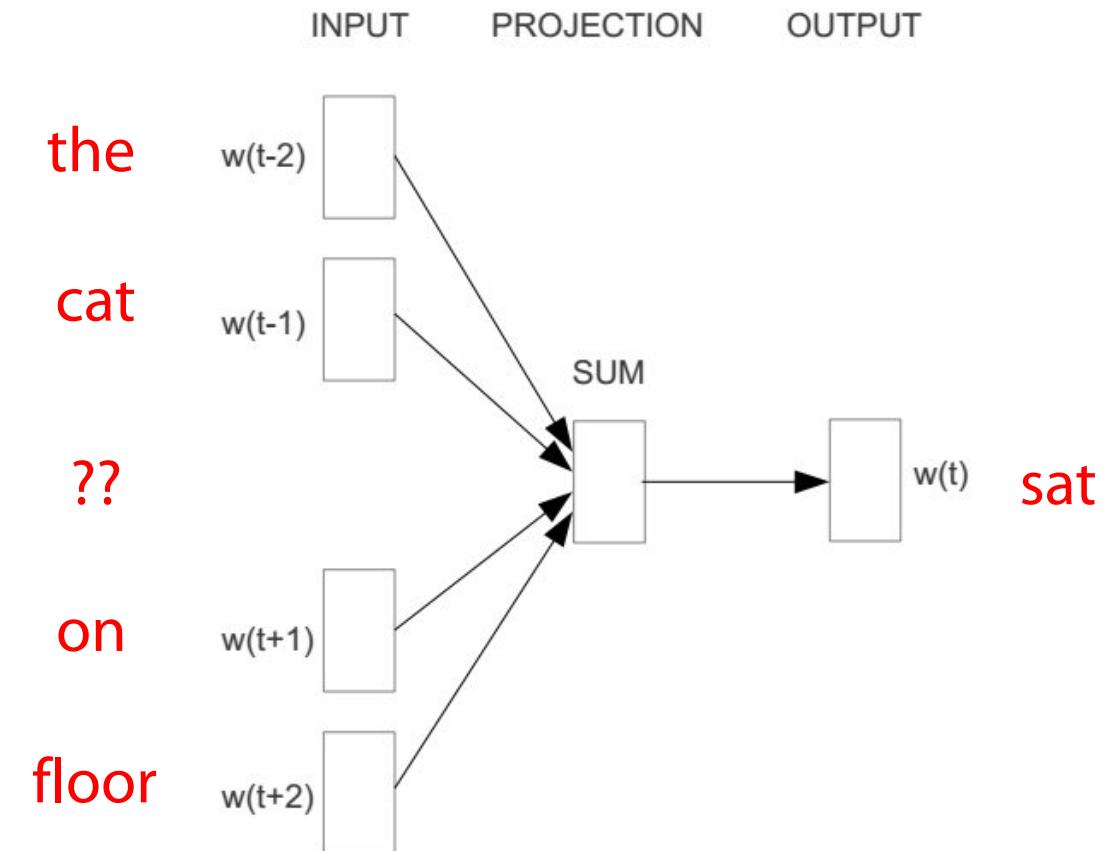
- Represent the meaning of words in vectors
- Example:
  - Continuous Bag of Words (CBOW) from the so-called Word2Vec approach
  - Use a window of words to predict the middle word



# WORDS AS VECTORS

---

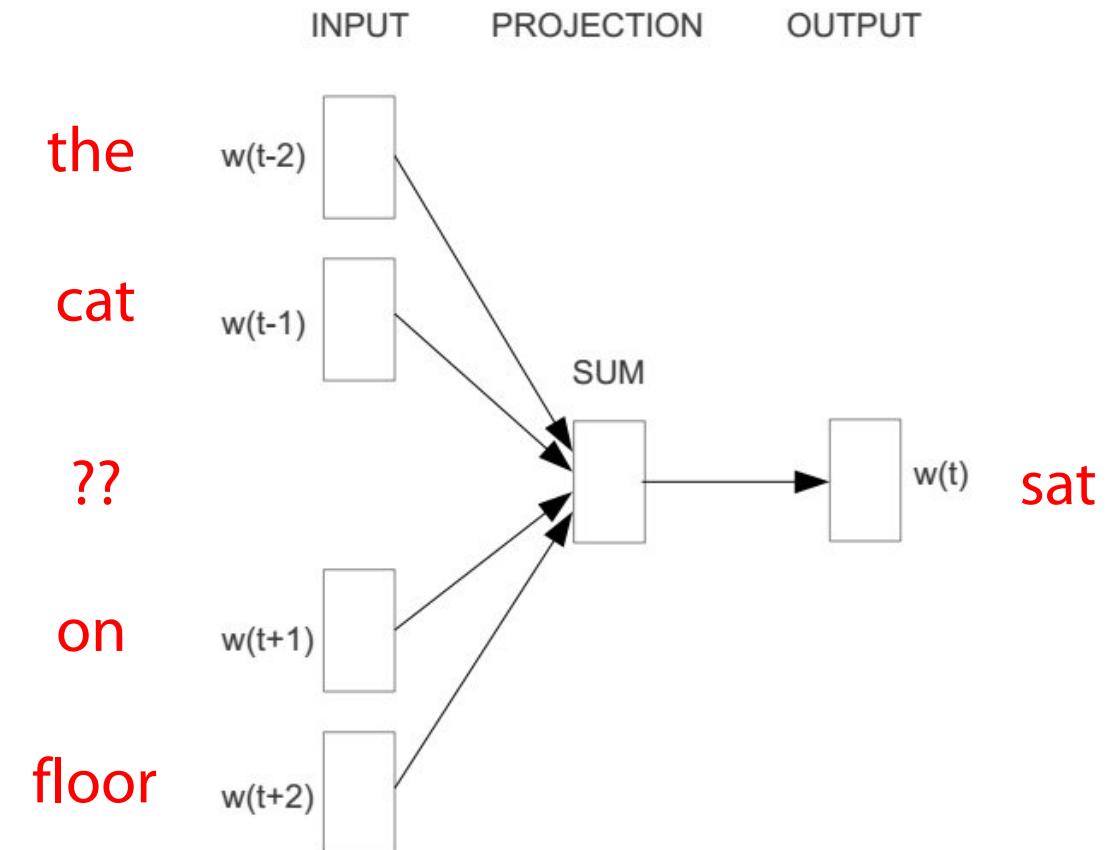
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# WORDS AS VECTORS

---

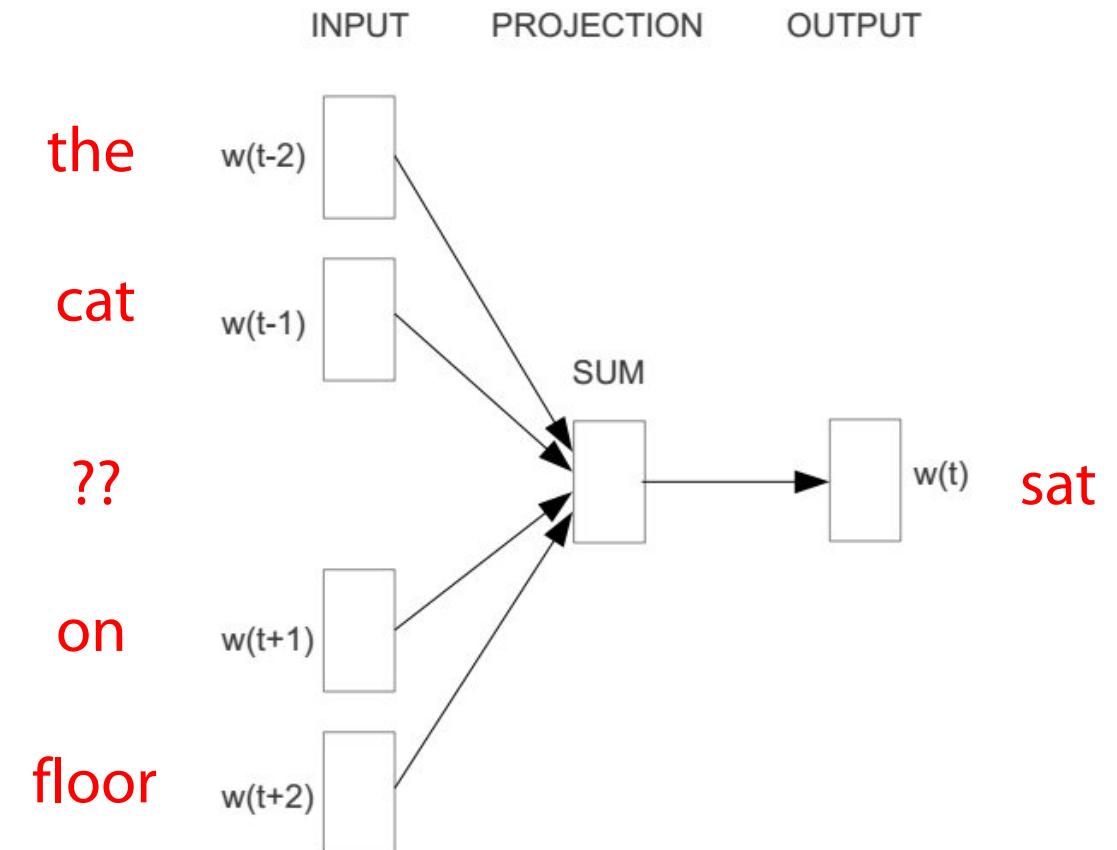
- Represent the meaning of words in vectors
- Example:
  - Continuous Bag of Words (CBOW) from the so-called Word2Vec approach
  - Use a window of words to predict the middle word
- Generally:
  - A vector representing a word (or token) is called an embedding



# WORDS AS VECTORS

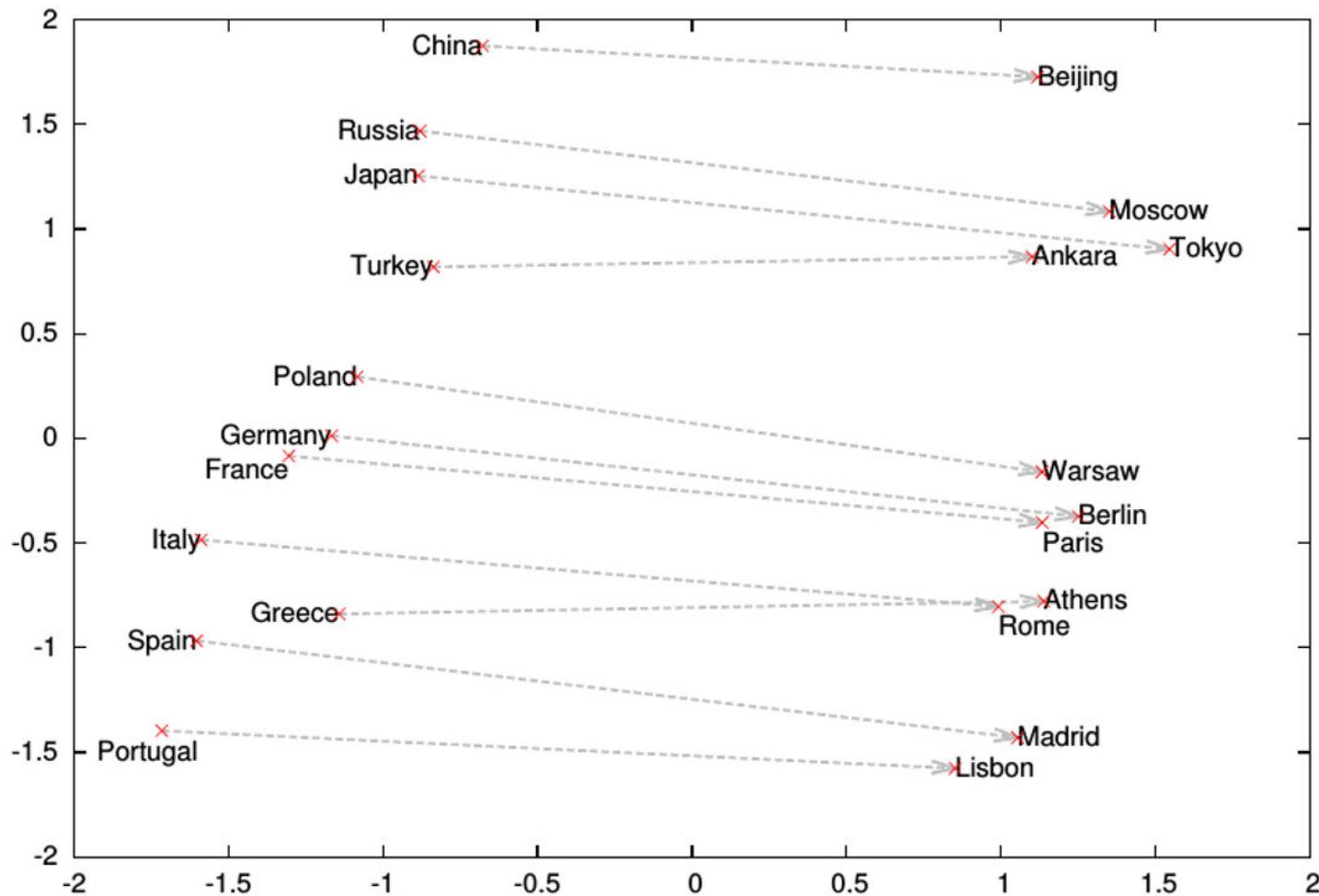
---

- Represent the meaning of words in vectors
- Example:
  - Continuous Bag of Words (CBOW) from the so-called Word2Vec approach
  - Use a window of words to predict the middle word
- Generally:
  - A vector representing a word (or token) is called an embedding
  - Embeddings are trained/ crafted to represent words as vectors useful for the current use-case!



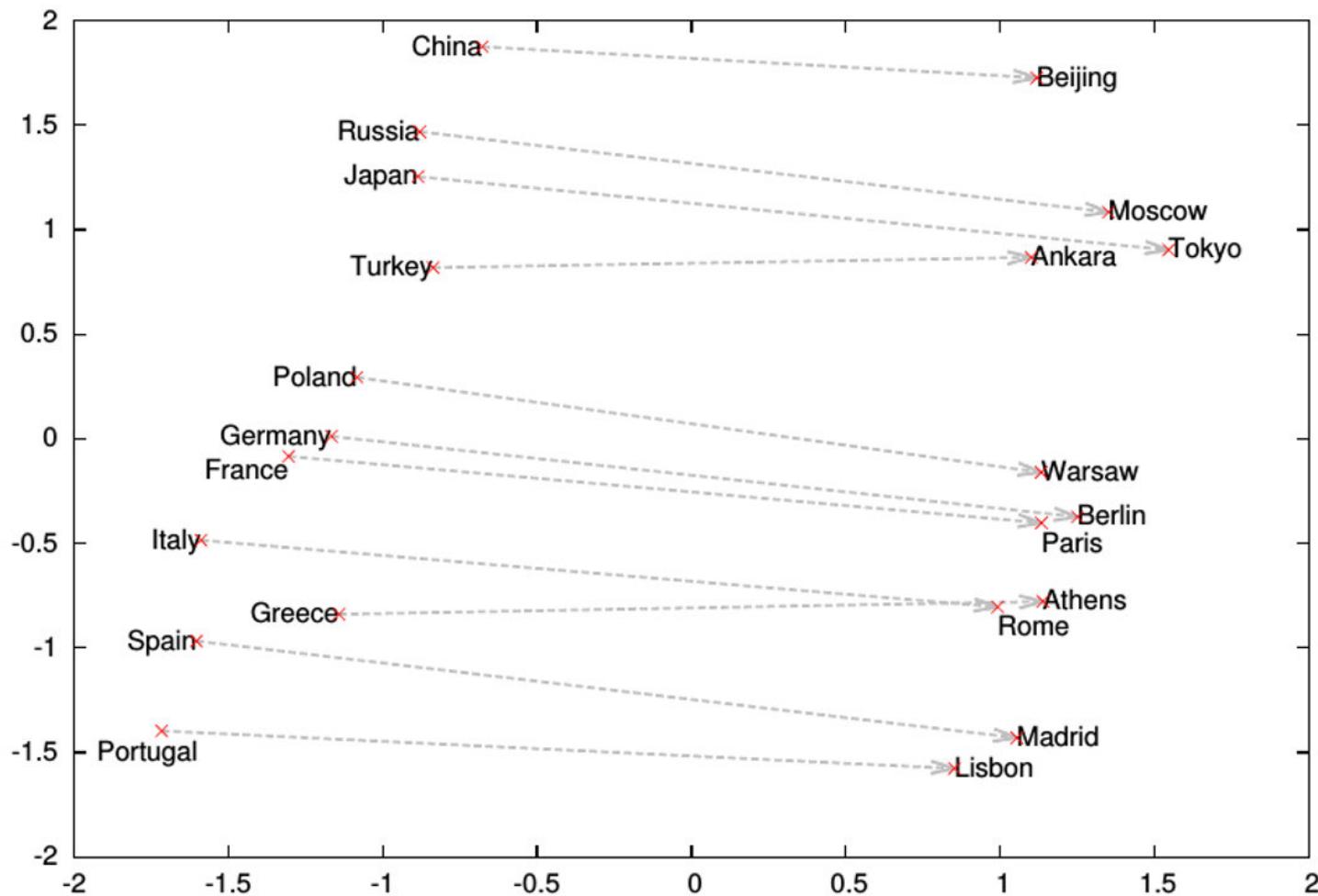
# EXAMPLE: WORD2VEC

---



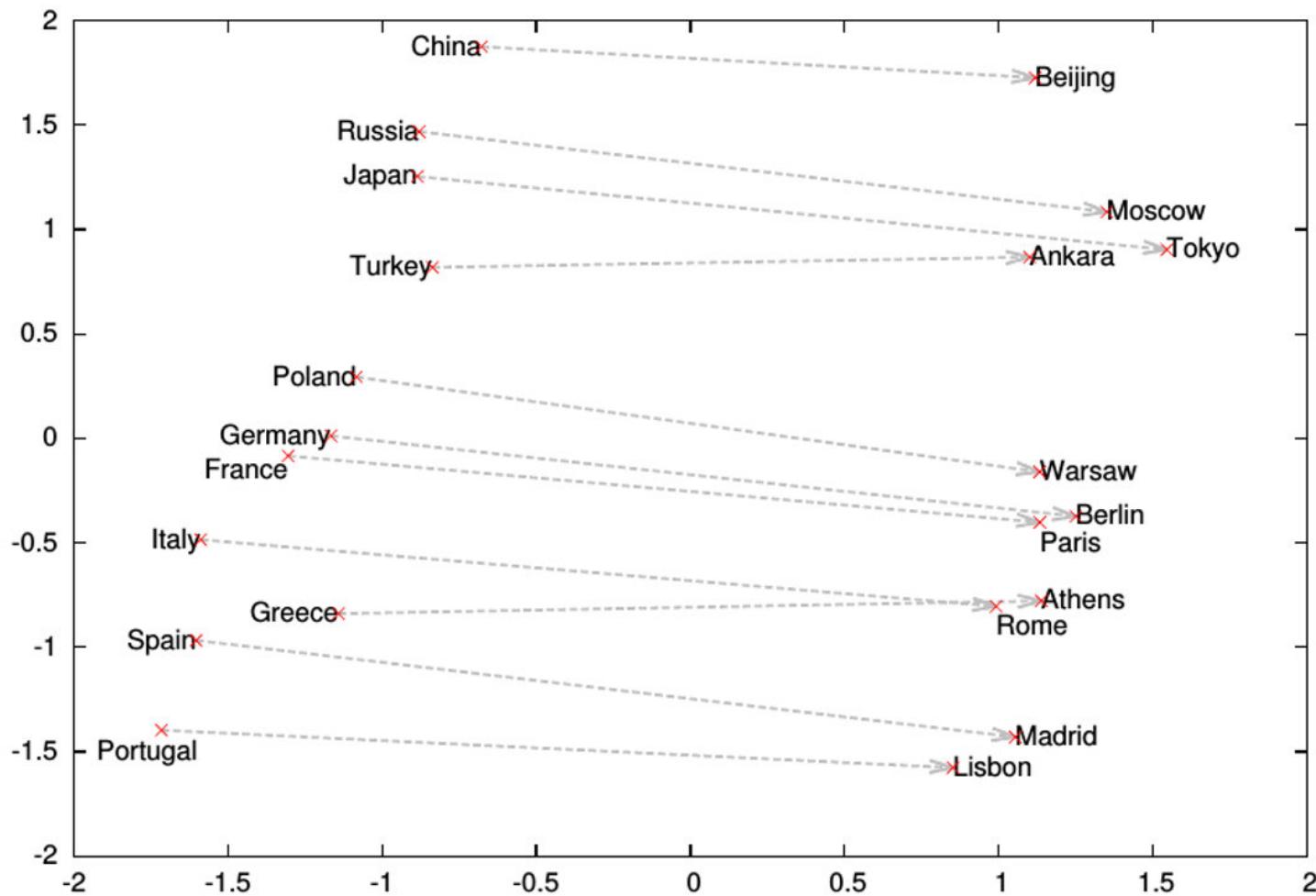
# EXAMPLE: WORD2VEC

- Known vectors (positions) for:



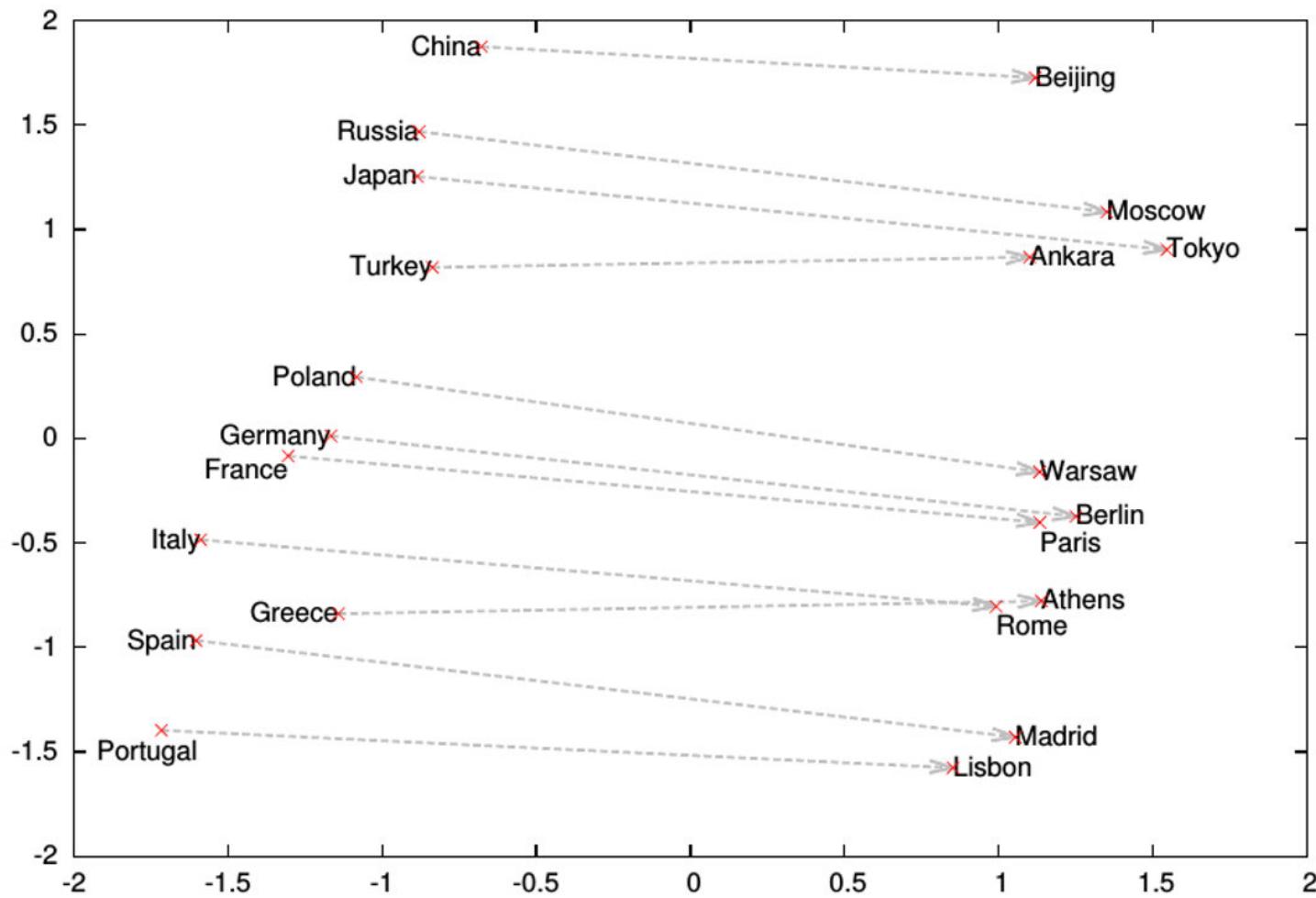
# EXAMPLE: WORD2VEC

- Known vectors (positions) for:
  - Man
  - Woman
  - King



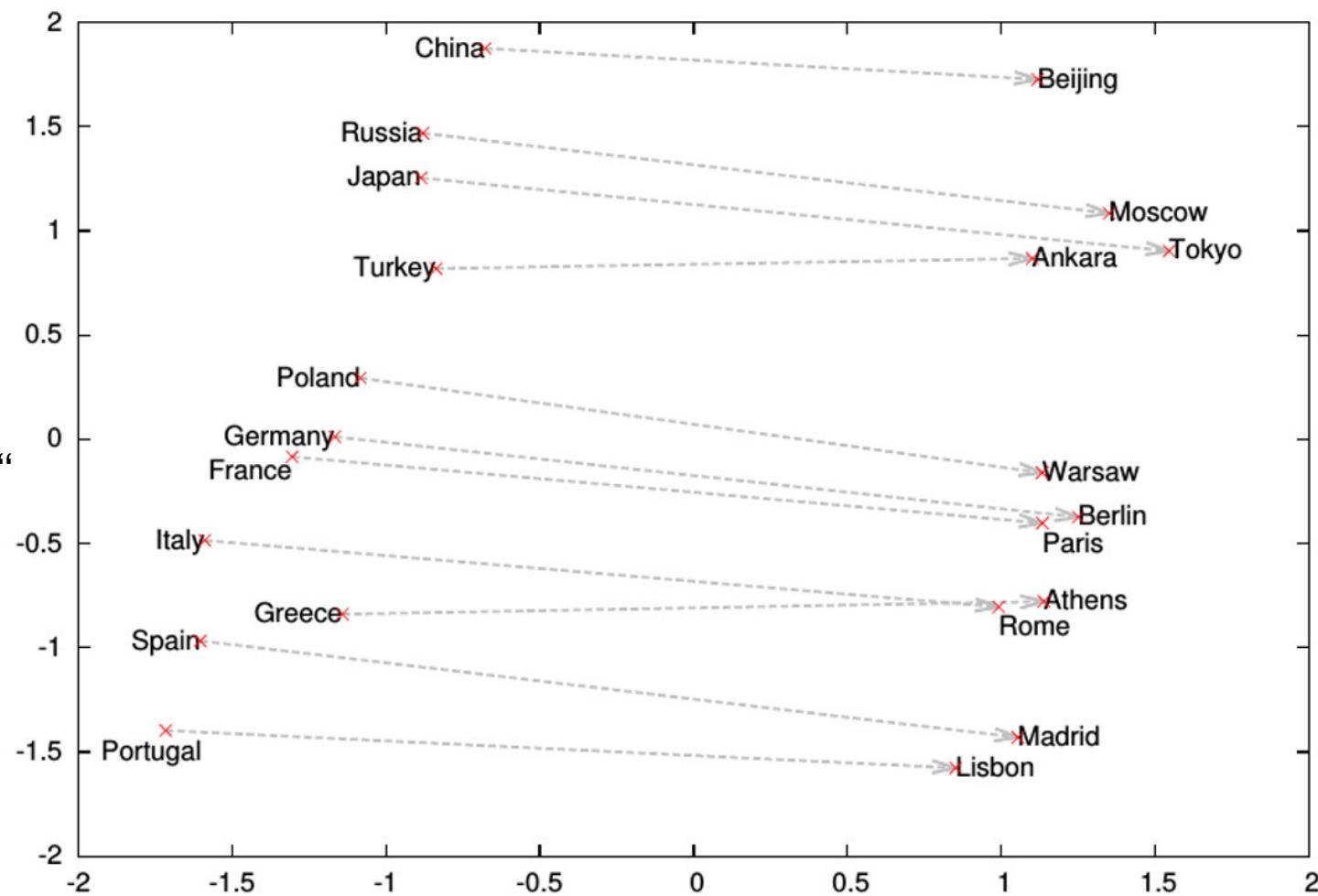
# EXAMPLE: WORD2VEC

- Known vectors (positions) for:
  - Man
  - Woman
  - King
- Known vectors (differences) for:
  - Man → Woman



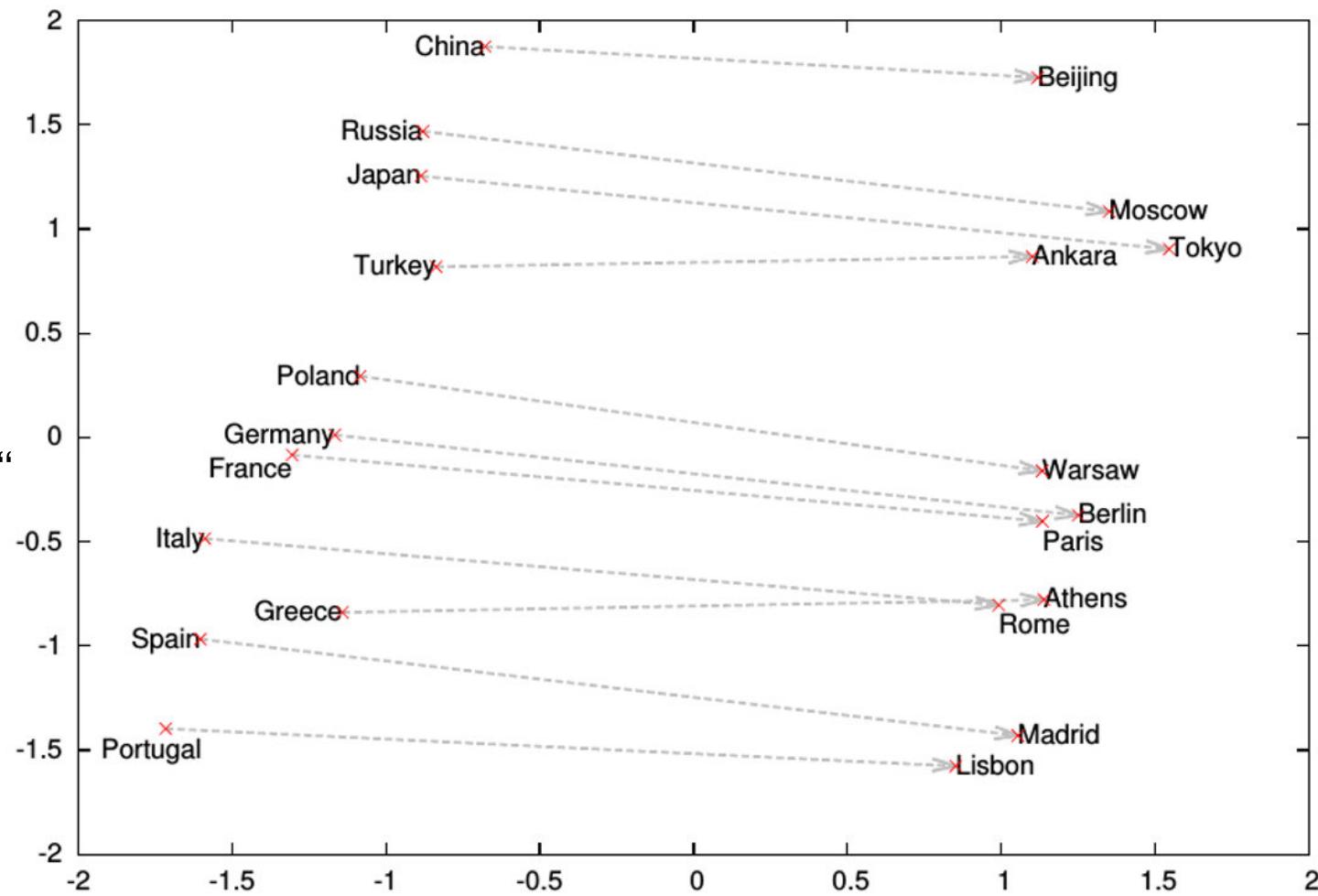
# EXAMPLE: WORD2VEC

- Known vectors (positions) for:
  - Man
  - Woman
  - King
- Known vectors (differences) for:
  - Man → Woman
- What is the corresponding word for „King“ in the relation „Man → Woman“
  - King → ?



# EXAMPLE: WORD2VEC

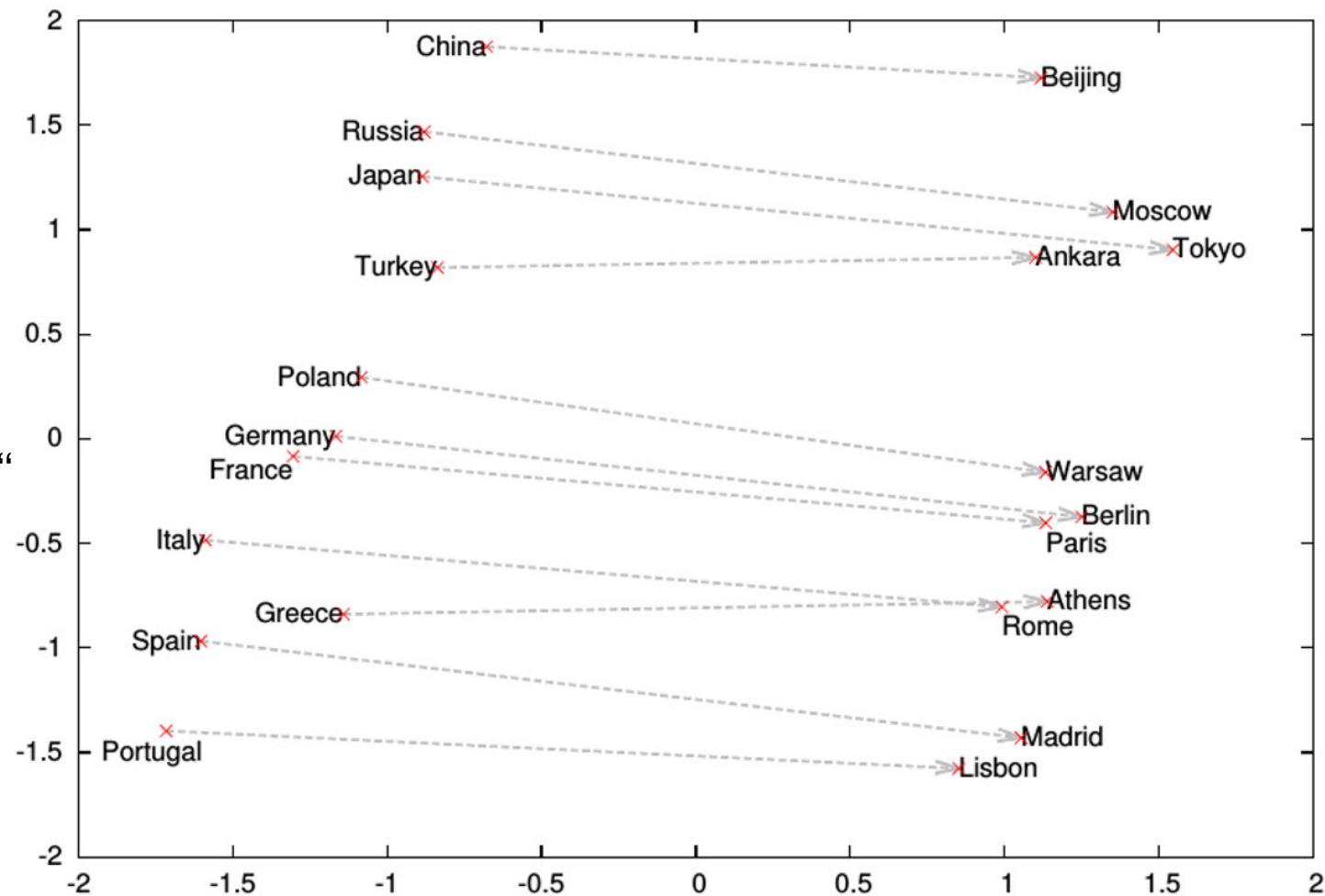
- Known vectors (positions) for:
  - Man
  - Woman
  - King
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  - Man → Woman
- What is the corresponding word for „King“ in the relation „Man → Woman“
  - King → ?
  - King - Man + Woman = Queen



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- Known vectors (differences) for:
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  - King → ?
  - King - Man + Woman = Queen

Representing words by vectors in a multi-dimensional vector space



# LLMS DO THE SAME

---

- We said „A word is represented by a vector“

# LLMS DO THE SAME

---

- We said „A word is represented by a vector“
- But what to do with special names or very uncommon words

# LLMS DO THE SAME

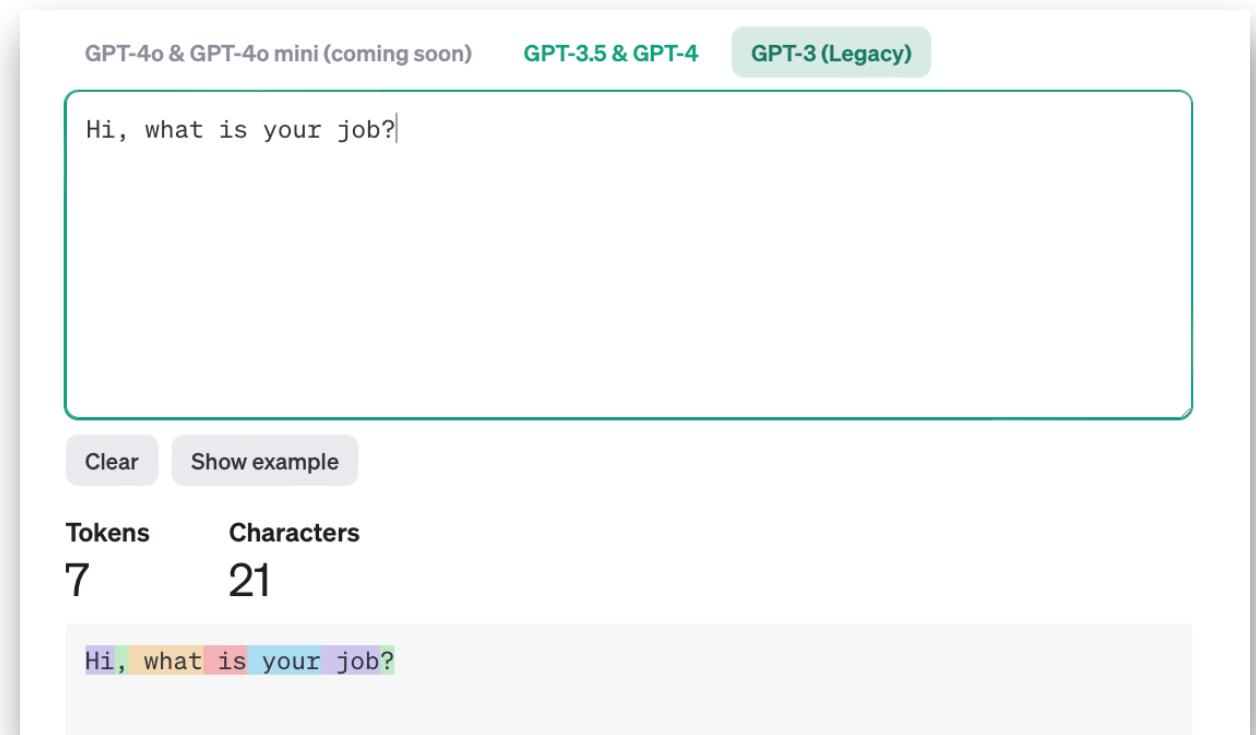
---

- We said „A word is represented by a vector“
- But what to do with special names or very uncommon words
  - Less common „barrel“
  - Name „Aarhus“
  - Typo „cllass“

# LLMS DO THE SAME

---

- We said „A word is represented by a vector“
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  - Less common „barrel“
  - Name „Aarhus“
  - Typo „cllass“
- Words are split into tokens
  - Each token may represent a full word, a part of it, or only one character or symbol.



The screenshot shows the OpenAI Tokenizer interface. At the top, there are three tabs: "GPT-4o & GPT-4o mini (coming soon)", "GPT-3.5 & GPT-4", and "GPT-3 (Legacy)". The "GPT-3.5 & GPT-4" tab is selected. Below the tabs, the input text "Hi, what is your job?" is entered into a text area. Below the text area, there are two buttons: "Clear" and "Show example". Further down, the token statistics are displayed: "Tokens" (7) and "Characters" (21). At the bottom, the input text is shown again, with each word and punctuation mark highlighted with a different color: "Hi, what is your job?".

<https://platform.openai.com/tokenizer>

# LLMS DO THE SAME

---

- We said „A word is represented by a vector“
- But what to do with special names or very uncommon words
  - Less common „barrel“
  - Name „Aarhus“
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- Words are split into tokens
  - Each token may represent a full word, a part of it, or only one character or symbol.
- LLM is able to get any sequence of text as input and to create any sequence, too.

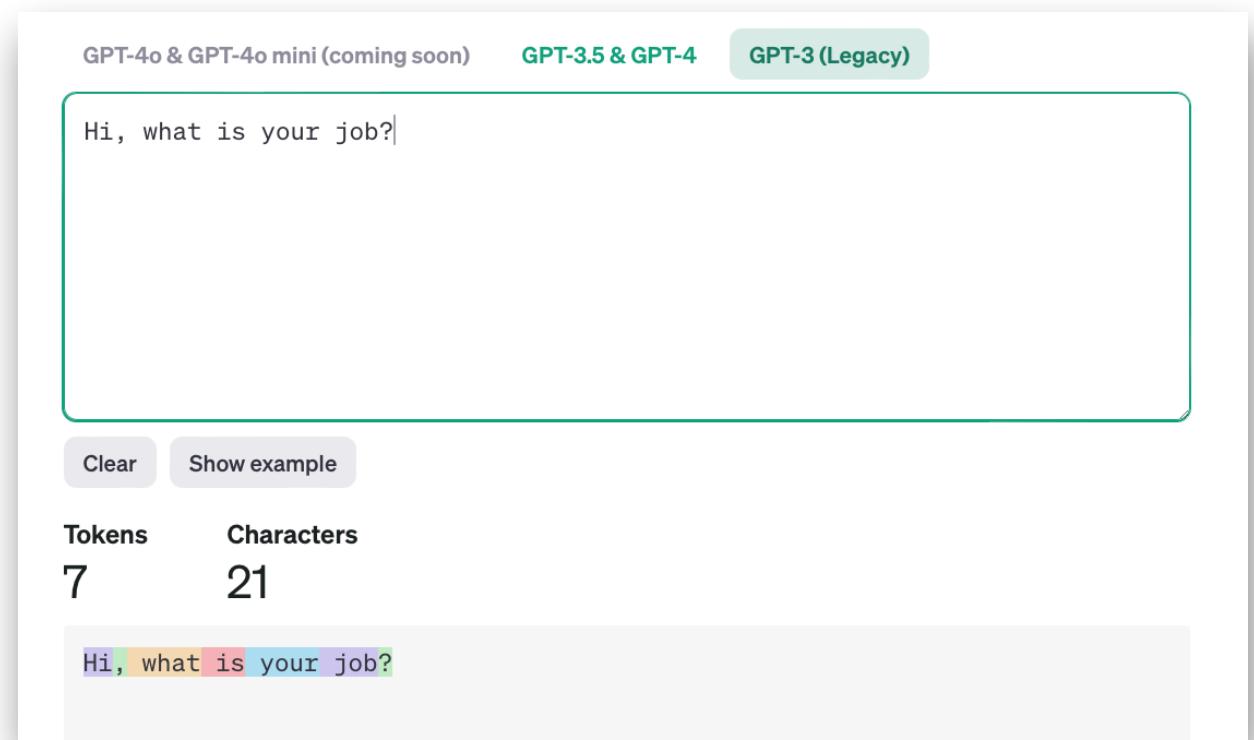
The screenshot shows a web-based tokenizer interface. At the top, there are three tabs: "GPT-4o & GPT-4o mini (coming soon)", "GPT-3.5 & GPT-4", and "GPT-3 (Legacy)". The "GPT-3.5 & GPT-4" tab is selected. Below the tabs, a text input field contains the sentence "Hi, what is your job?". A large green button is positioned below the input field. Below the button, there are two sets of metrics: "Tokens" (7) and "Characters" (21). At the bottom, a color-coded bar shows the tokens for the input text: "Hi" (green), " " (light blue), "w" (orange), "a" (red), "t" (pink), " " (light blue), and "y" (purple).

<https://platform.openai.com/tokenizer>

# LLMS DO THE SAME

---

- We said „A word is represented by a vector“
- But what to do with special names or very uncommon words
  - Less common „barrel“
  - Name „Aarhus“
  - Typo „cllass“
- Words are split into tokens
  - Each token may represent a full word, a part of it, or only one character or symbol.
- LLM is able to get any sequence of text as input and to create any sequence, too.
  - The outputs are again vectors representing tokens which are transformed to their corresponding word or character.



The screenshot shows the OpenAI Tokenizer interface. At the top, there are three tabs: "GPT-4o & GPT-4o mini (coming soon)", "GPT-3.5 & GPT-4", and "GPT-3 (Legacy)". The "GPT-3.5 & GPT-4" tab is selected. Below the tabs, a text input field contains the sentence "Hi, what is your job?". Below the input field, there are two buttons: "Clear" and "Show example". Further down, the text is analyzed into tokens and characters. The "Tokens" section shows the number 7, and the "Characters" section shows the number 21. Below this, the input text is shown again, but each word and punctuation mark is highlighted with a different color: "Hi" (green), " " (orange), "what" (red), " " (pink), "is" (blue), " " (purple), "your" (green), " " (orange), "job" (red). The entire screenshot is framed by a green border.

Tokens	Characters
7	21

<https://platform.openai.com/tokenizer>

# DEMO: TOKEN

---

„Hej, jeg bor i en by, og jeg har en 1-0-0-m-<sup>2</sup> stor by-g-ning, ...“

- No token representing the word „bygning“
- Model groups multiple tokens, representing substrings to form the word „bygning“

## Interactive token builder

Model:

qwen3:4b



Load

Start of sentence:

Hej, jeg bor i

Go

Hej, jeg bor i en (31.80%) ▾ by (43.08%) ▾ , (37.04%) ▾  
og (51.80%) ▾ jeg (93.43%) ▾ har (56.30%) ▾ en (63.00%) ▾  
1 (37.27%) ▾ 0 (30.02%) ▾ 0 (49.88%) ▾ 0 (40.10%) ▾ m (29.92%) ▾  
^ (75.96%) ▾ stor (6.48%) ▾ by (16.78%) ▾ g (97.33%) ▾  
ning (99.96%) ▾ , (48.24%) ▾ der (41.59%) ▾ er (63.50%) ▾  
1 (34.63%) ▾ 0 (60.29%) ▾ 0 (66.17%) ▾

History

Log

✓ generation complete (model stopped)  
qwen3:4b loaded ✓

# DEMO: TOKEN

---

„Hej, jeg bor i en by, og jeg har en 1-0-0-m-<sup>2</sup> stor by-g-ning, ...“

- No token representing the word „bygning“
- Model groups multiple tokens, representing substrings to form the word „bygning“
- Thus, possible to represent any word by letters and efficient to represent common words by their token.

## Interactive token builder

Model:

qwen3:4b



Load

Start of sentence:

Hej, jeg bor i

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Hej, jeg bor i en (31.80%) ▾ by (43.08%) ▾ , (37.04%) ▾  
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History

Log

✓ generation complete (model stopped)  
qwen3:4b loaded ✓

# TRANSFORMER BASED LLM

---

## A Large Language Model



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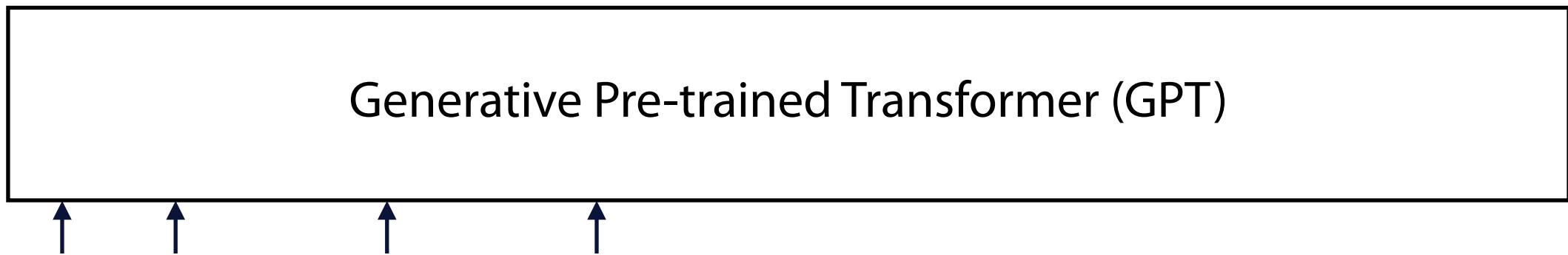
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ASSISTANT PROFESSOR



# TRANSFORMER BASED LLM

---



A Large Language Model



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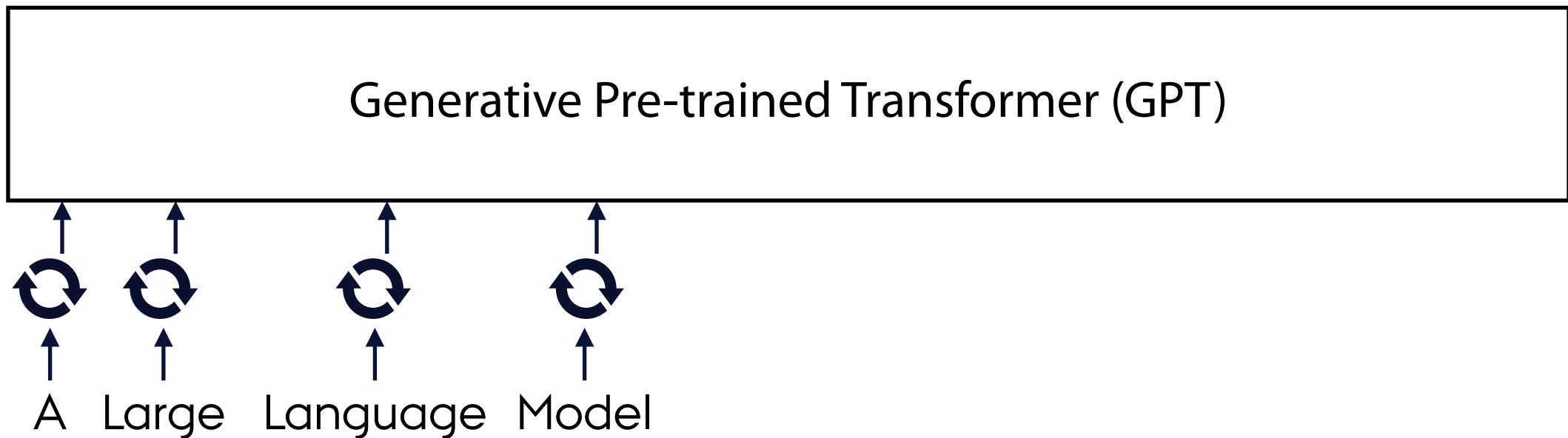
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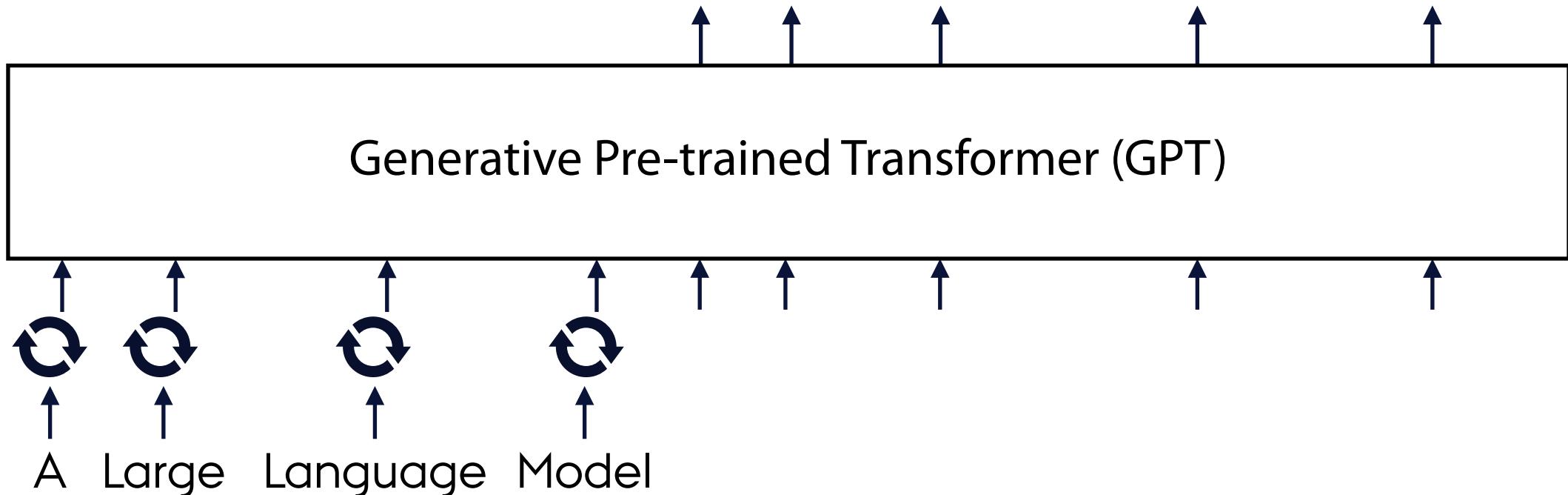
# TRANSFORMER BASED LLM

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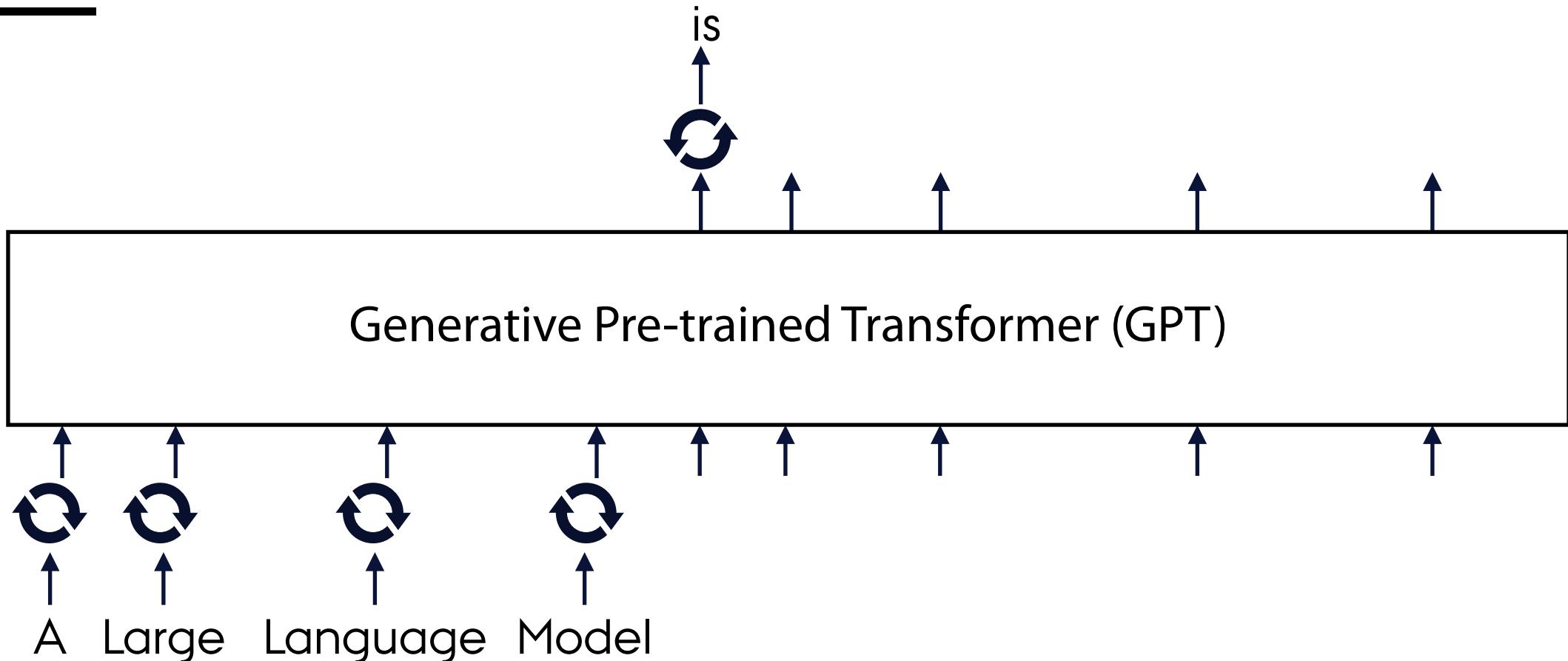
# TRANSFORMER BASED LLM

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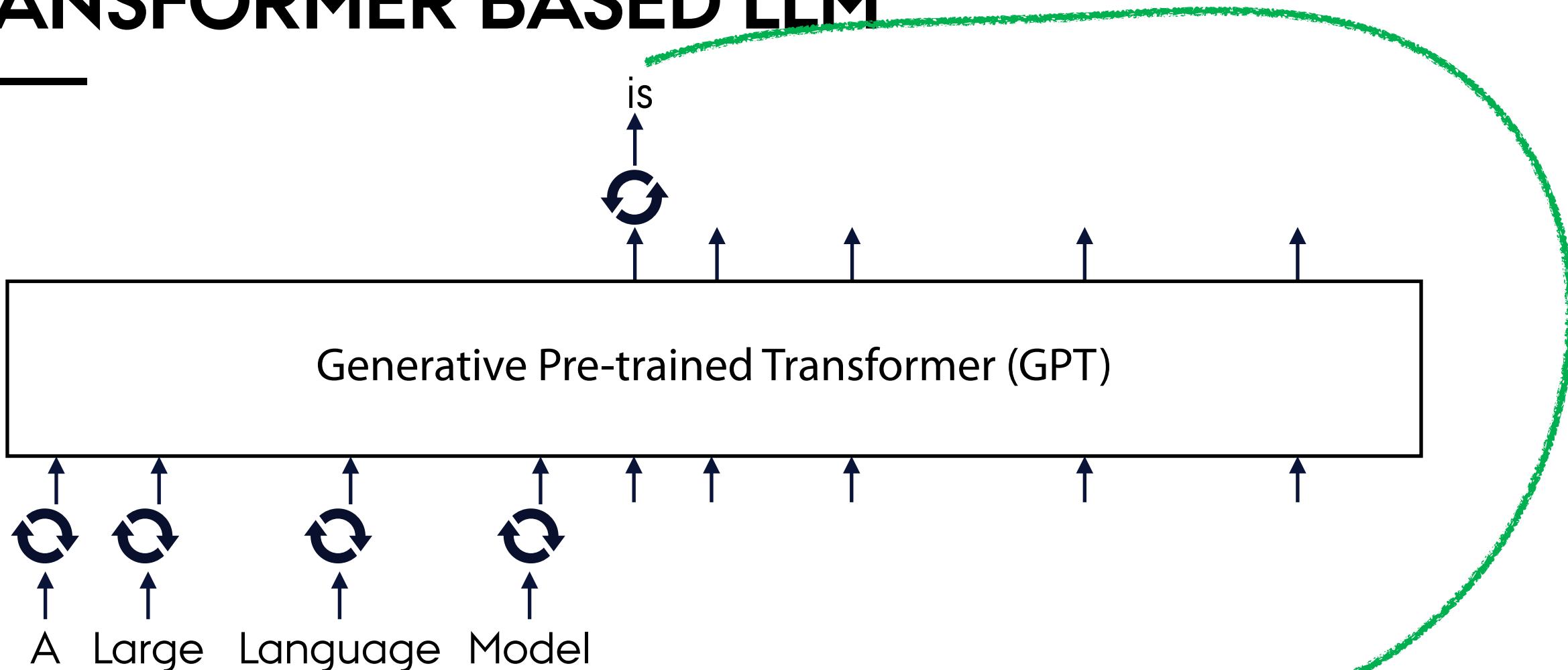
# TRANSFORMER BASED LLM

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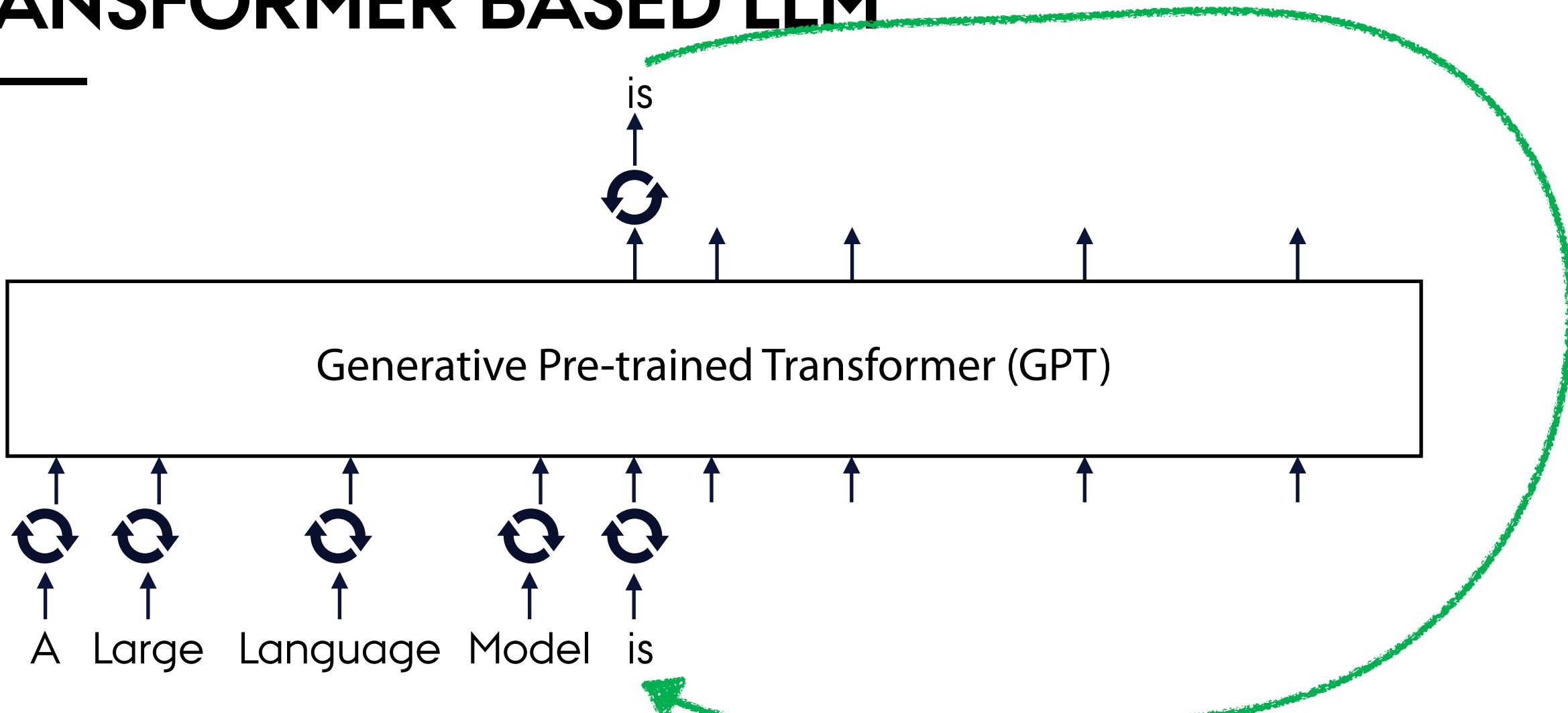
# TRANSFORMER BASED LLM

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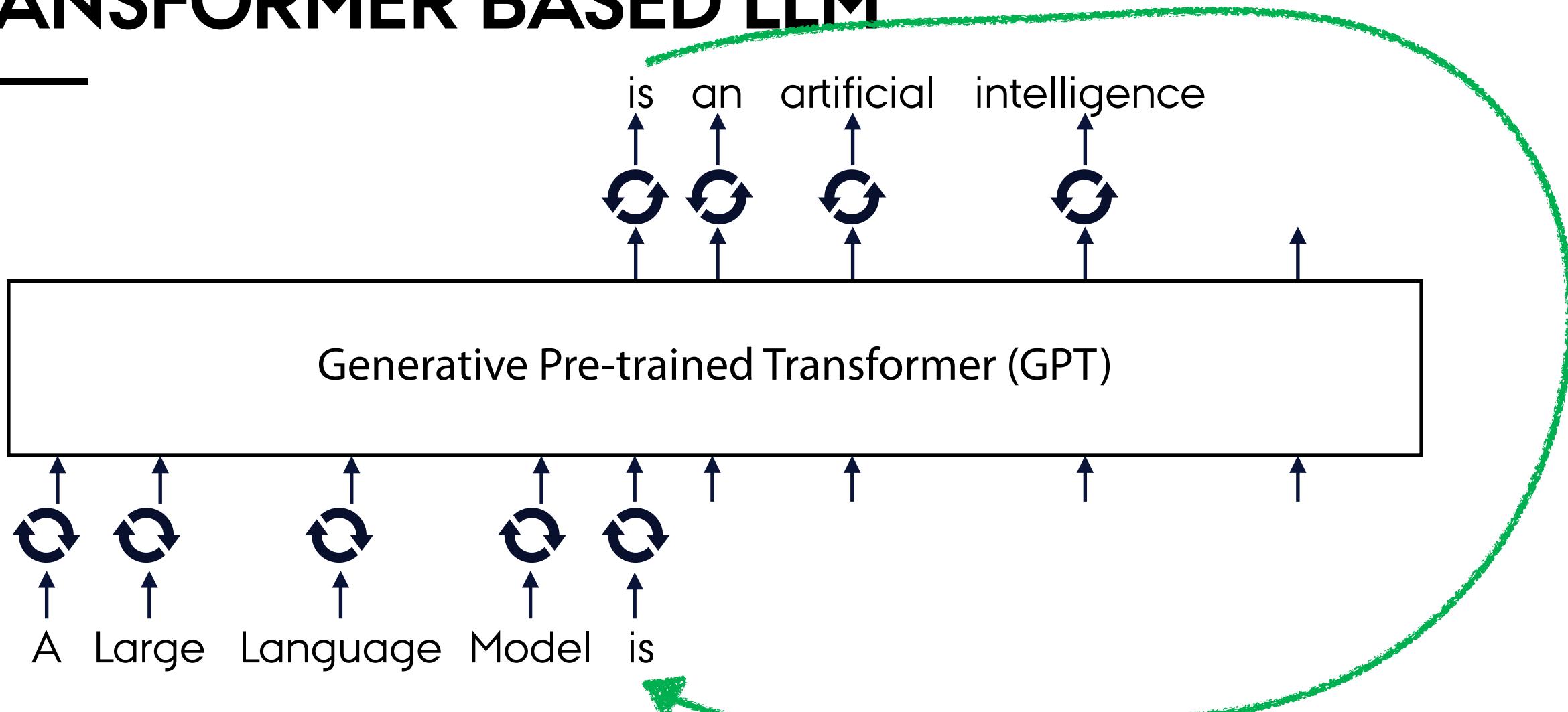


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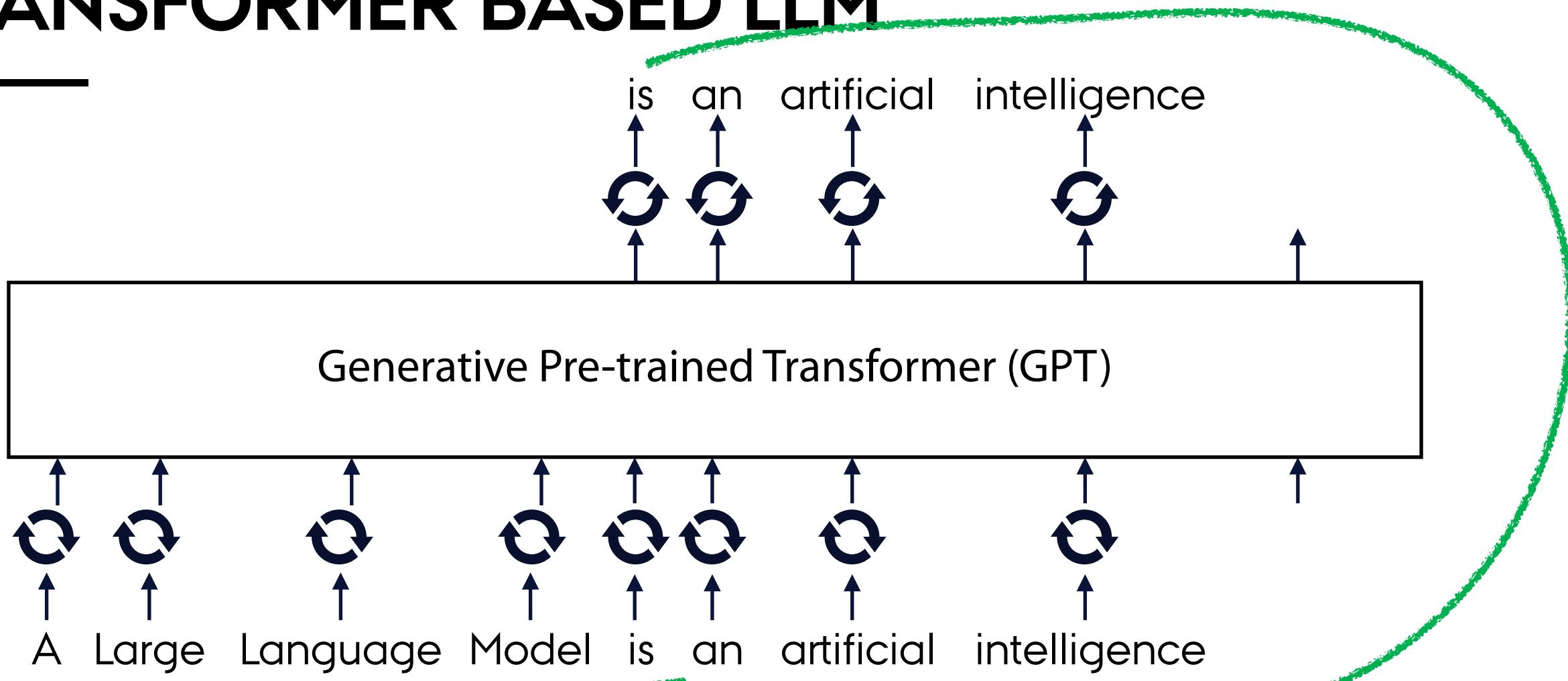
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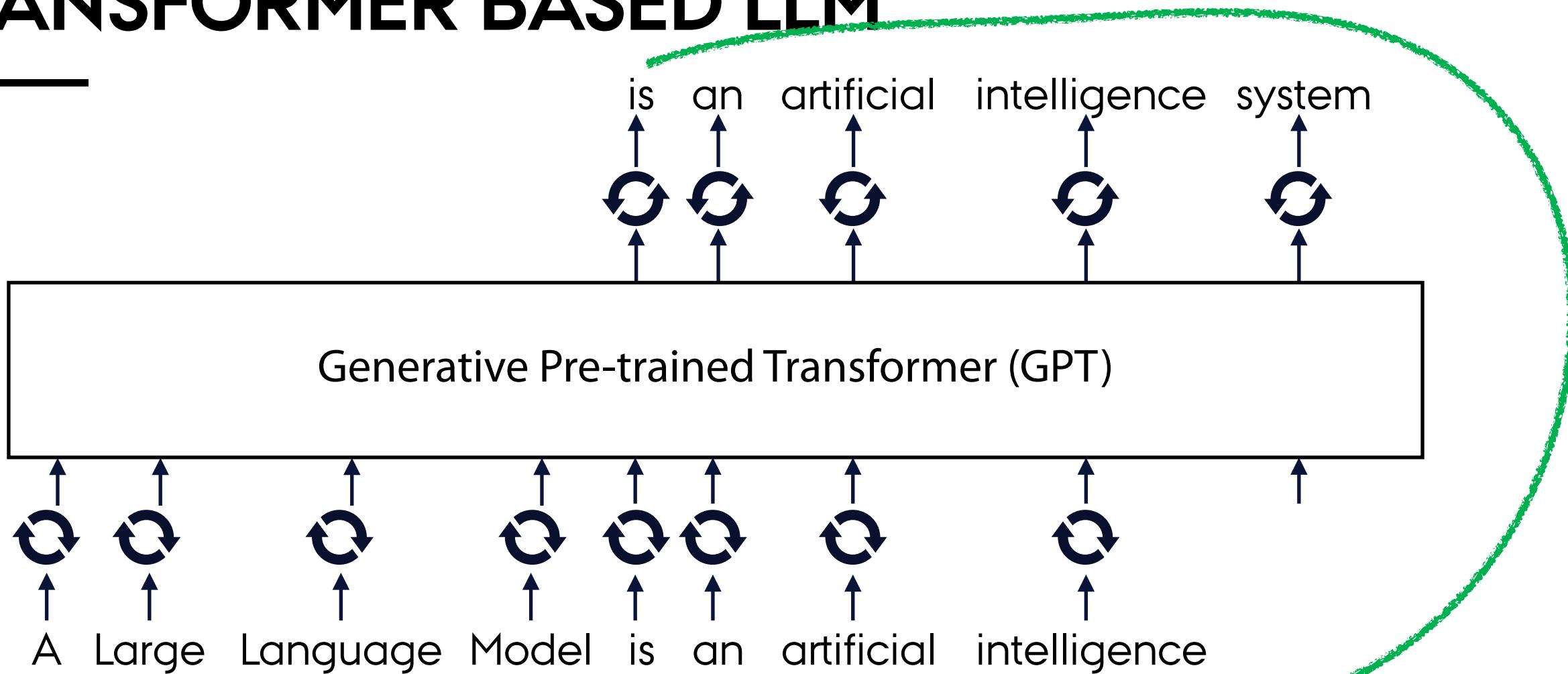
# TRANSFORMER BASED LLM



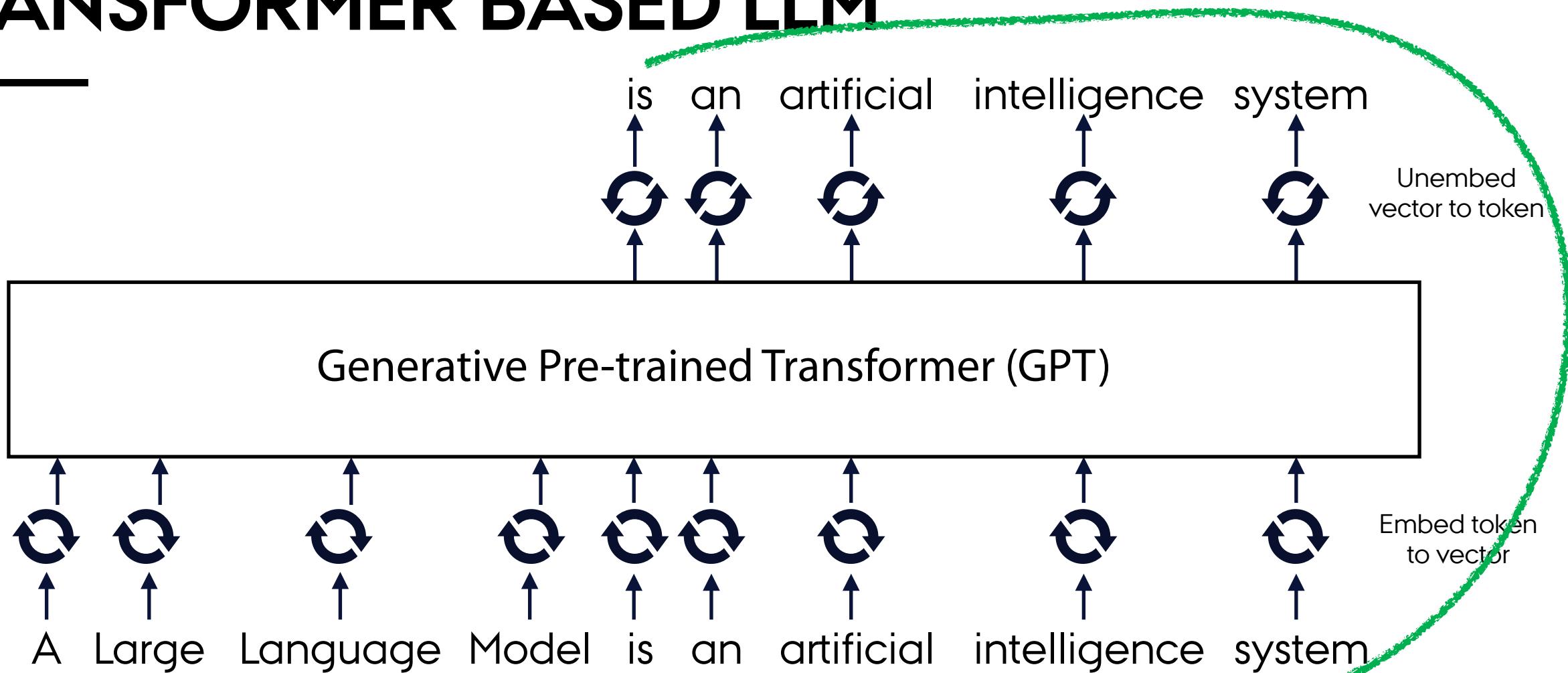
# TRANSFORMER BASED LLM



# TRANSFORMER BASED LLM



# TRANSFORMER BASED LLM



# GENERATIVE PRE-TRAINED TRANSFORMER (GPT)

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Radford et al., "Improving Language Understanding by Generative Pre-Training", **2018**  
Radford et al., "Language Models are Unsupervised Multitask Learners", **2019**  
Brown et al., "Language Models are Few-Shot Learners", **2020**



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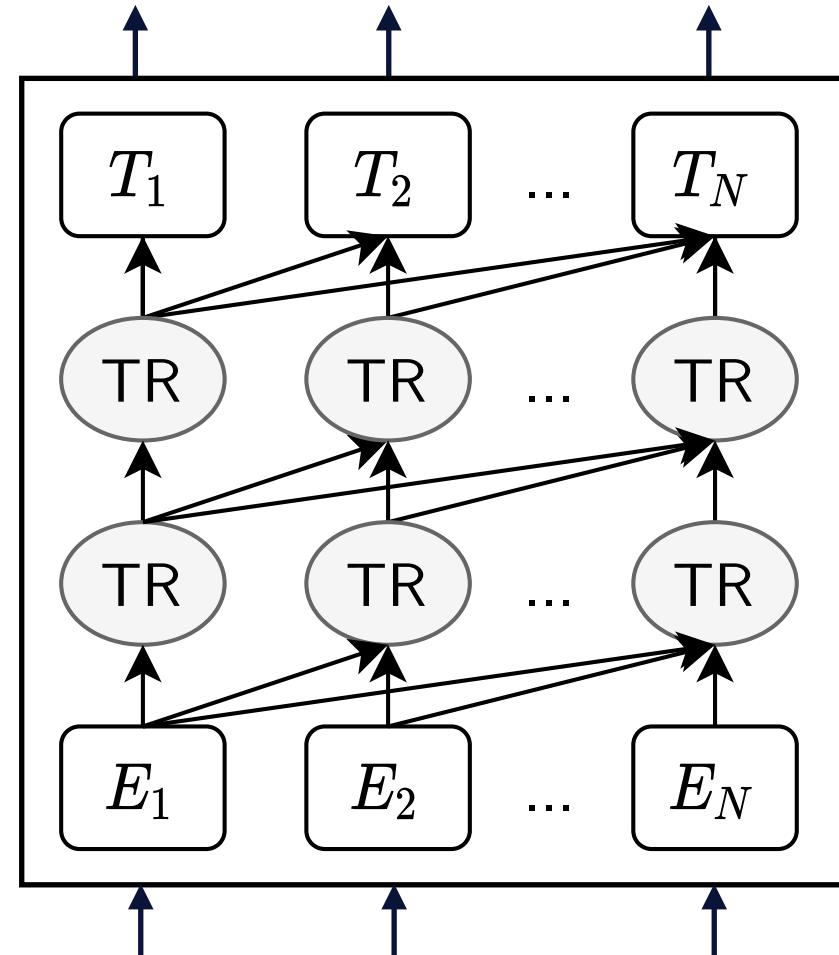
MAGNUS BENDER  
ASSISTANT PROFESSOR



# GENERATIVE PRE-TRAINED TRANSFORMER (GPT)

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- Internal view of the GPT block we had on last slide



Radford et al., "Improving Language Understanding by Generative Pre-Training", 2018

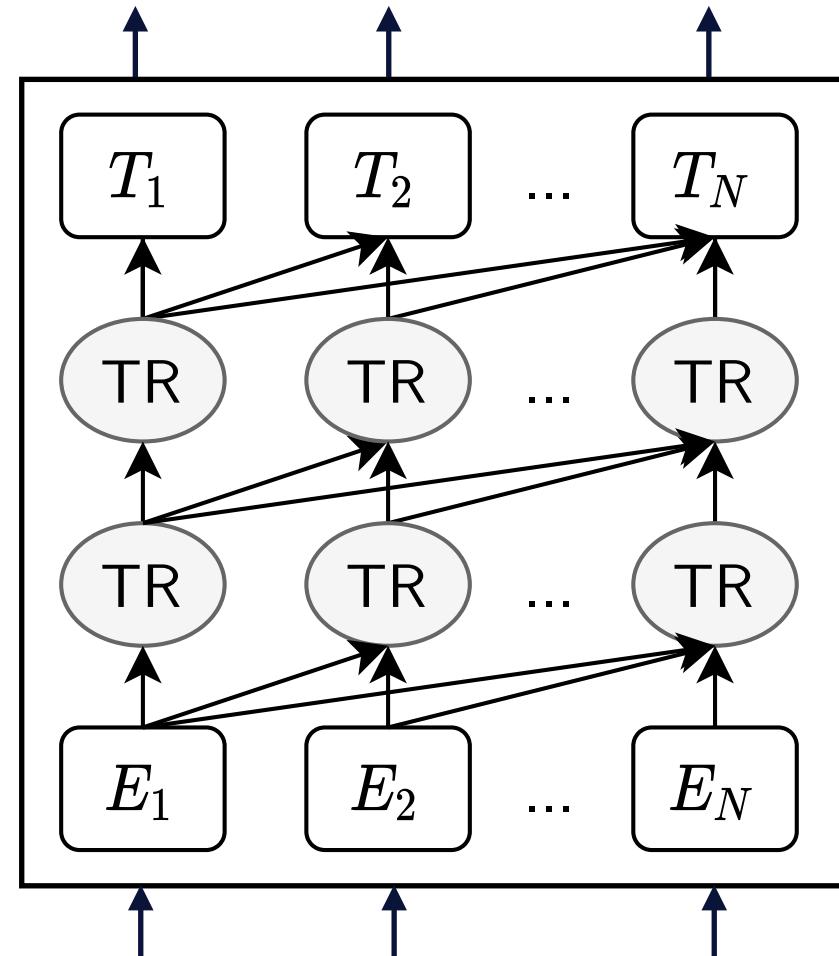
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- Multiple so-called *transformer blocks* (TR) one after another per token

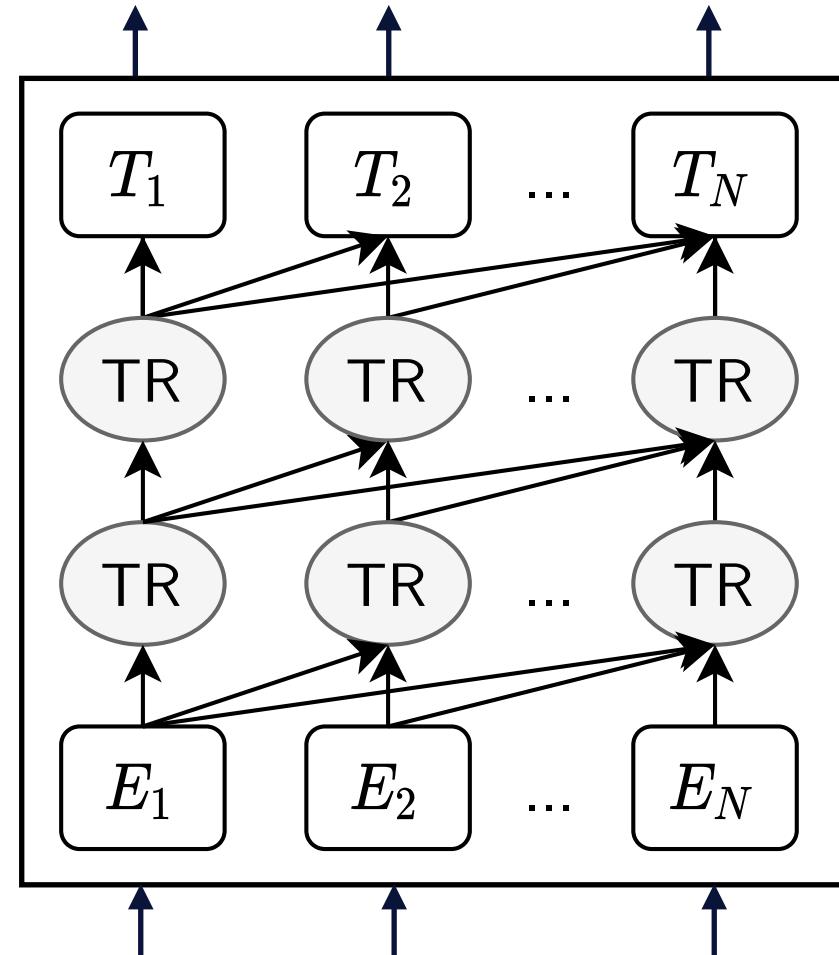


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# GENERATIVE PRE-TRAINED TRANSFORMER (GPT)

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- Internal view of the GPT block we had on last slide
- Multiple so-called *transformer blocks* (TR) one after another per token
  - Attention used in each TR



Radford et al., "Improving Language Understanding by Generative Pre-Training", 2018

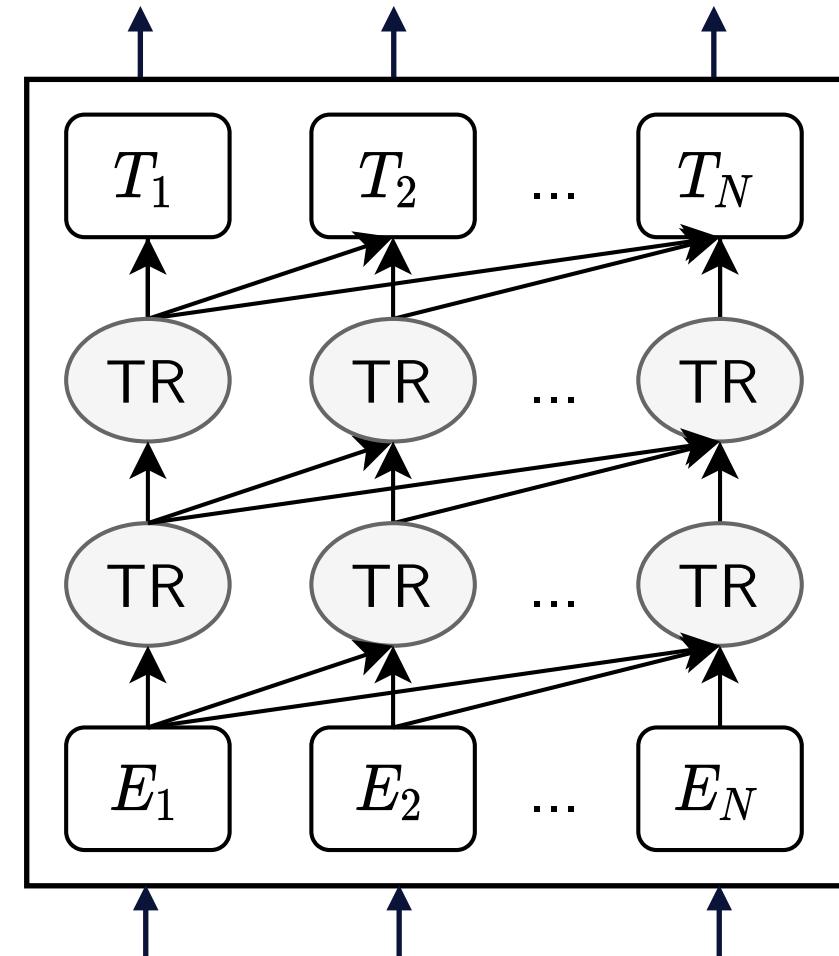
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- Internal view of the GPT block we had on last slide
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  - Left-to-right connections between blocks → Focus on generation of text



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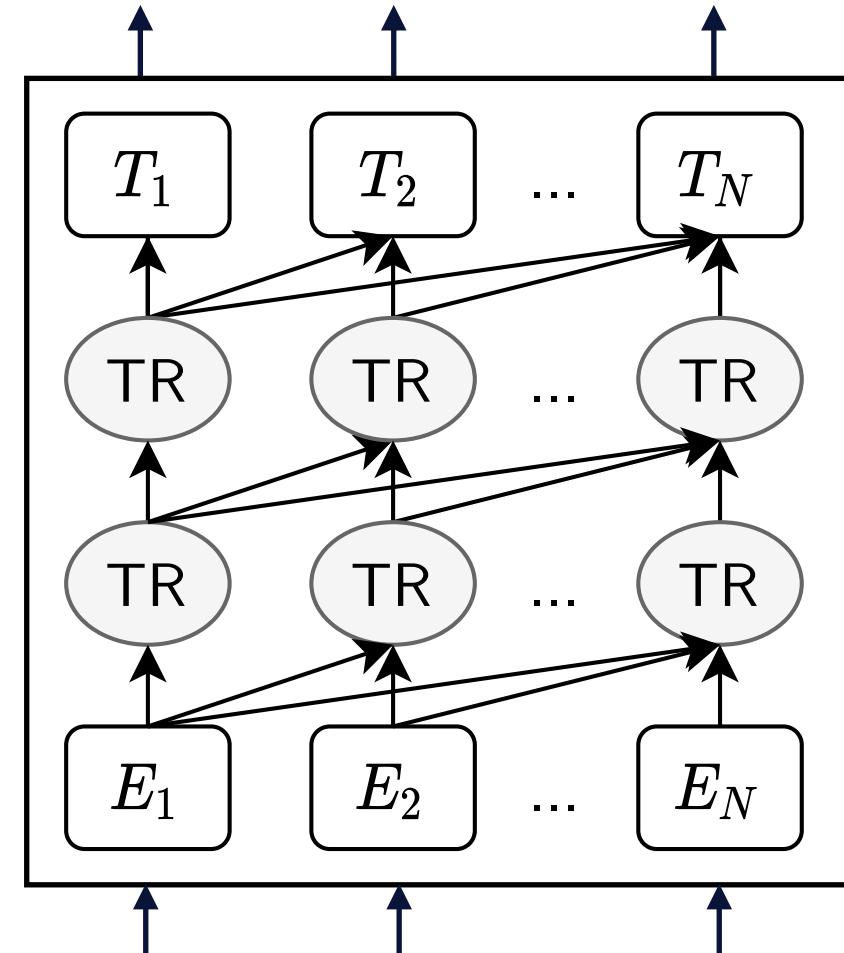
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# GENERATIVE PRE-TRAINED TRANSFORMER (GPT)

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- Internal view of the GPT block we had on last slide
- Multiple so-called *transformer blocks* (TR) one after another per token
  - Attention used in each TR
  - Left-to-right connections between blocks → Focus on generation of text

How to get the statistical values → so-called *weights* in each TR block



Radford et al., "Improving Language Understanding by Generative Pre-Training", 2018  
Radford et al., "Language Models are Unsupervised Multitask Learners", 2019  
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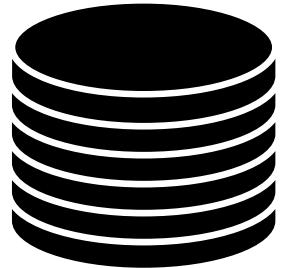
# MACHINE LEARNING

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How to obtain the statistical values used by the model?

# MACHINE LEARNING

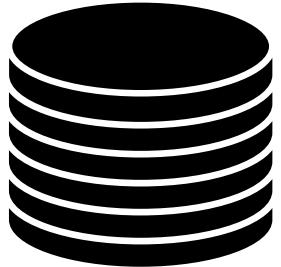
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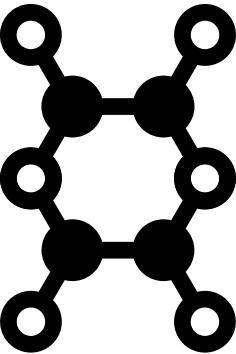
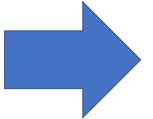
Training data  
(input and  
desired output)

# MACHINE LEARNING

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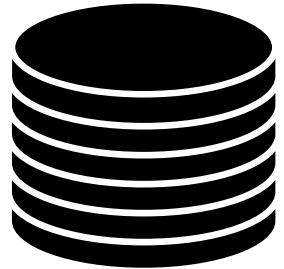
Training data  
(input and  
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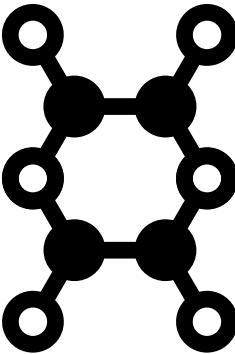
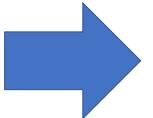
Training

# MACHINE LEARNING

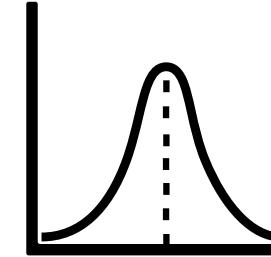
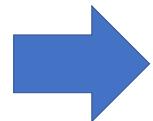
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Training data  
(input and  
desired output)



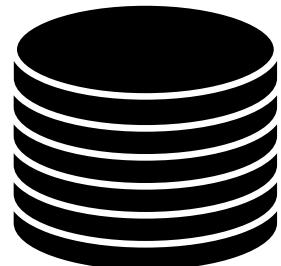
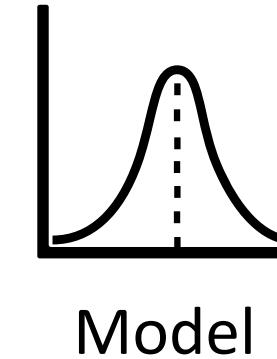
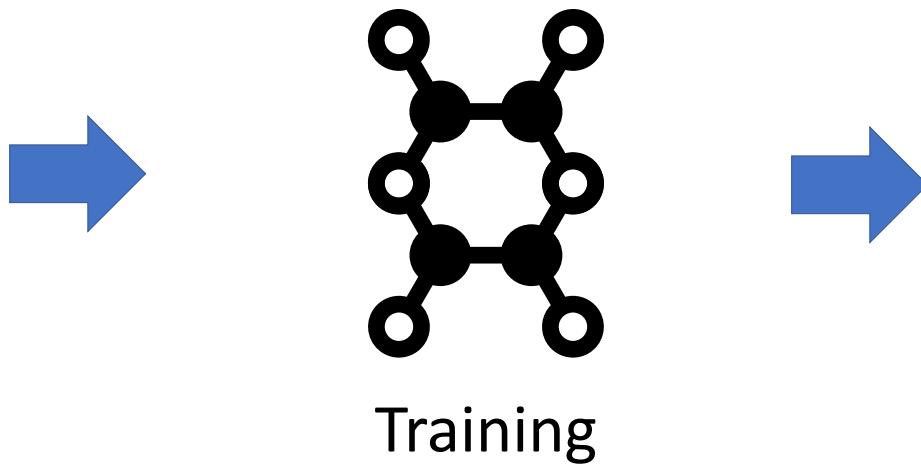
Training



Model

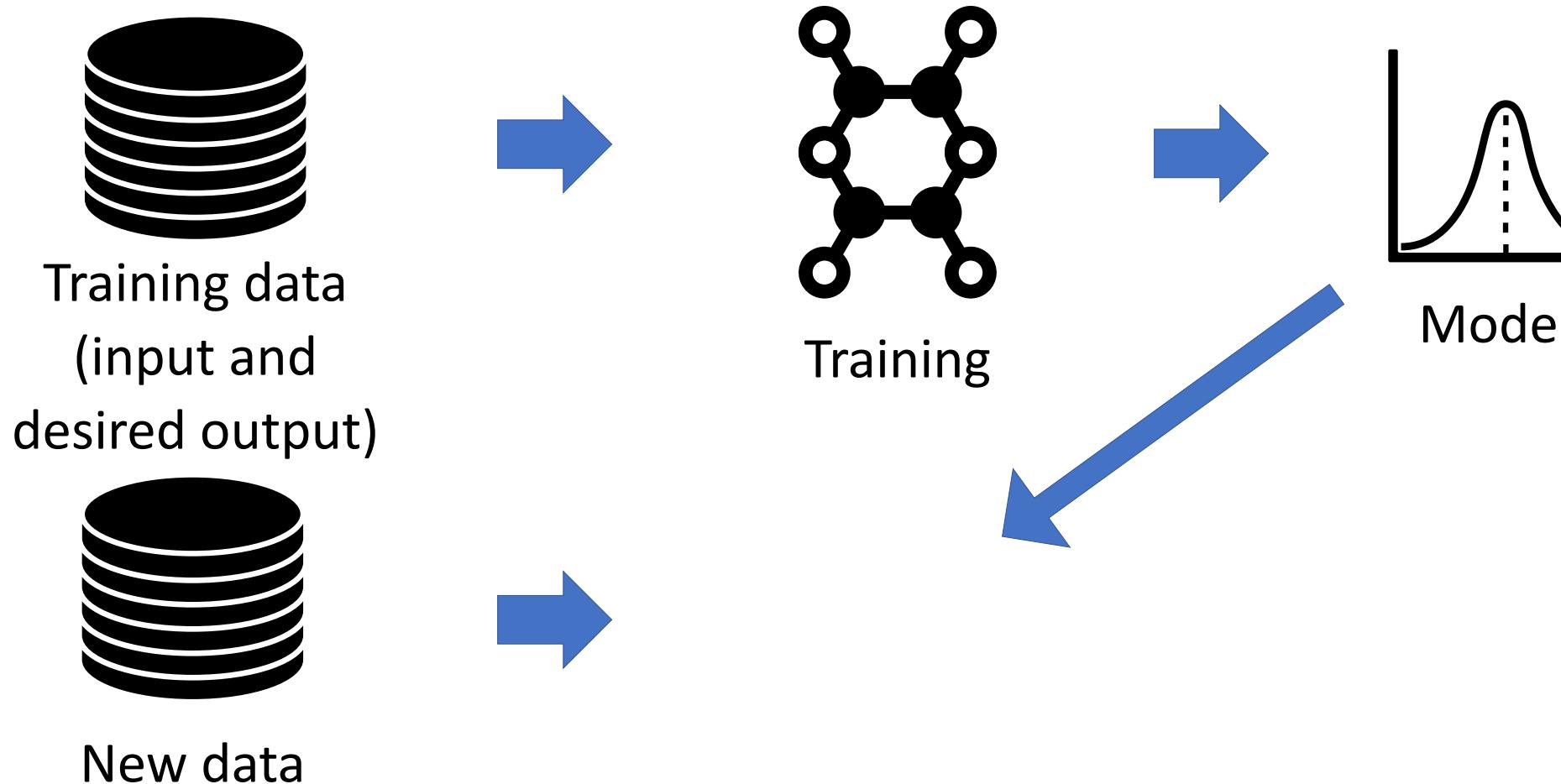
# MACHINE LEARNING

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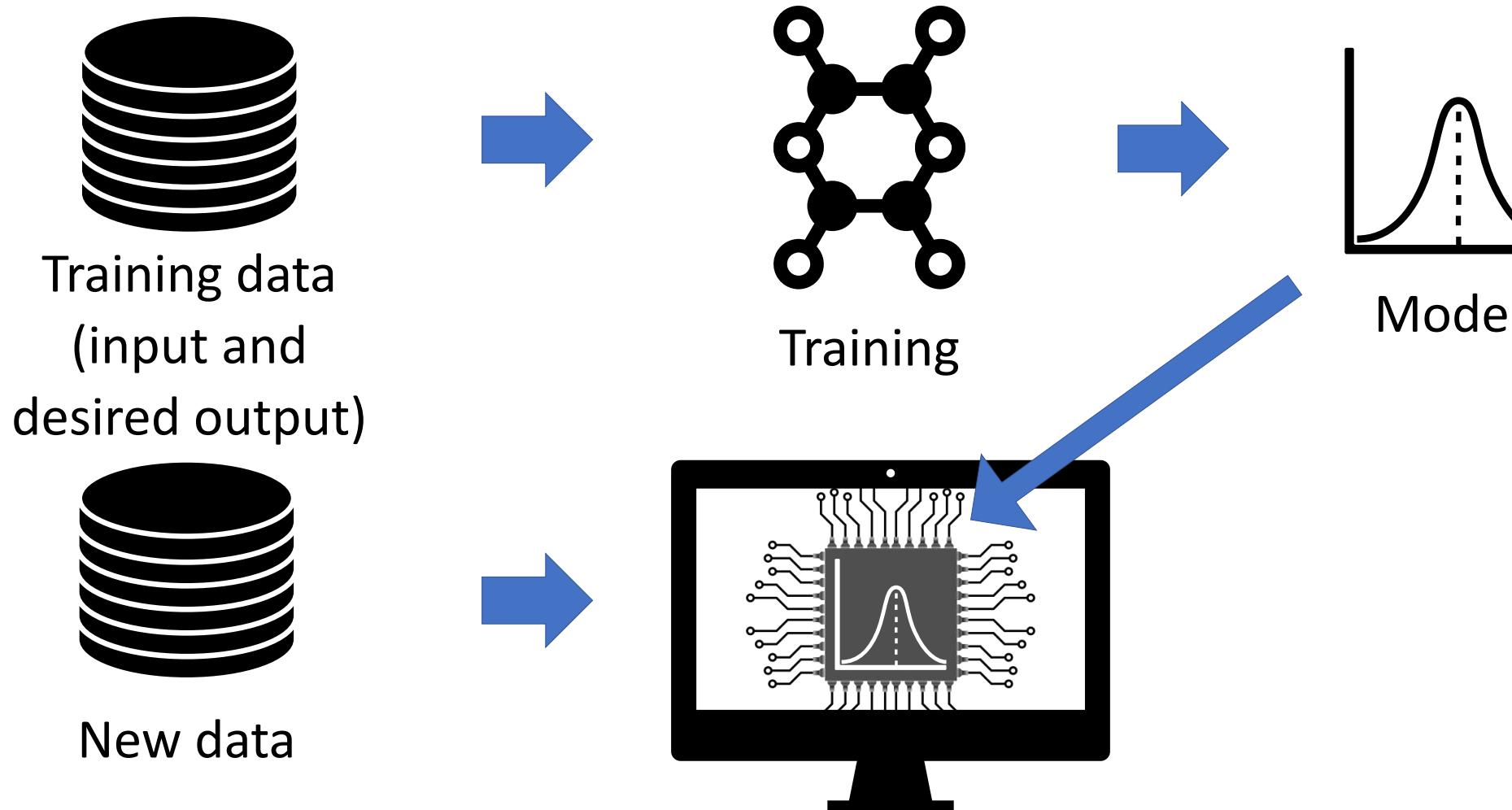
# MACHINE LEARNING

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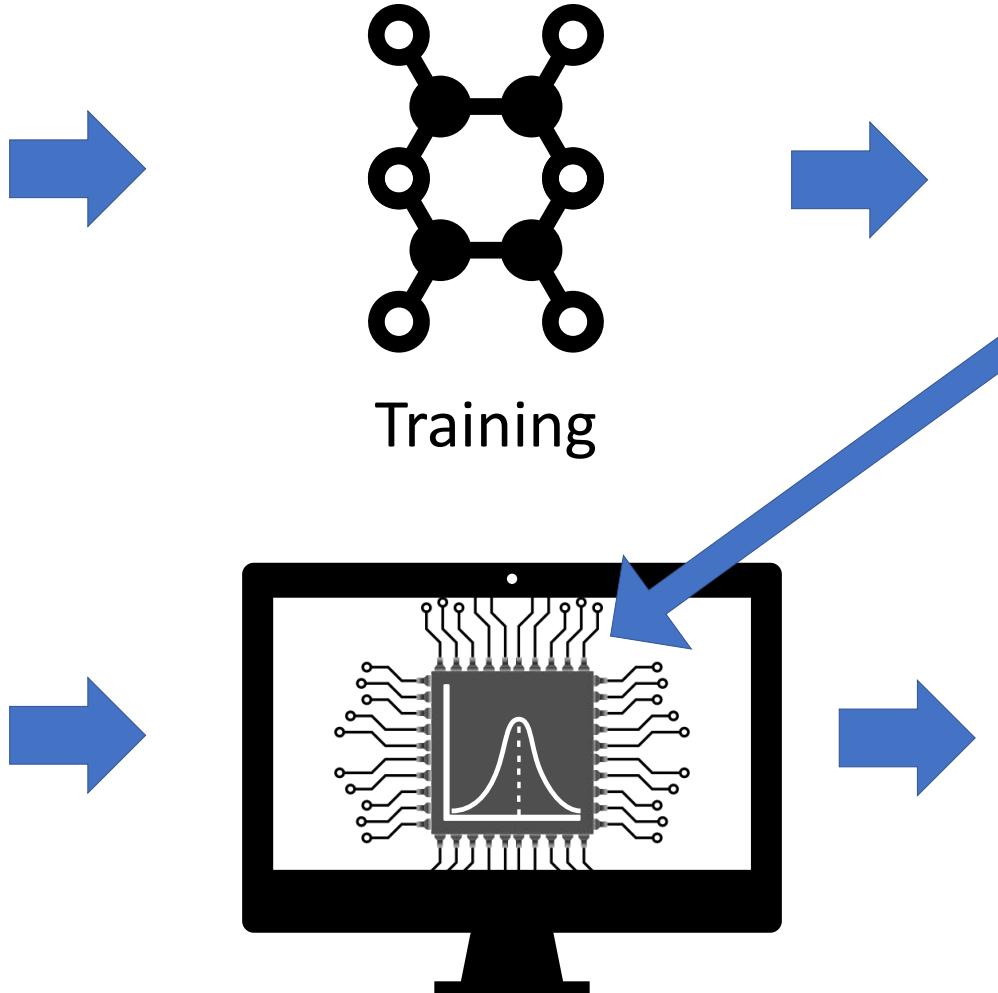
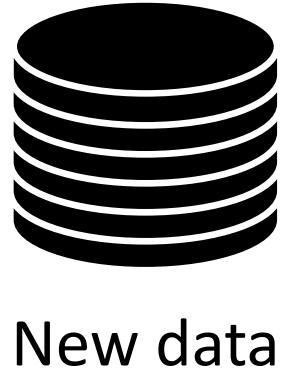


# MACHINE LEARNING

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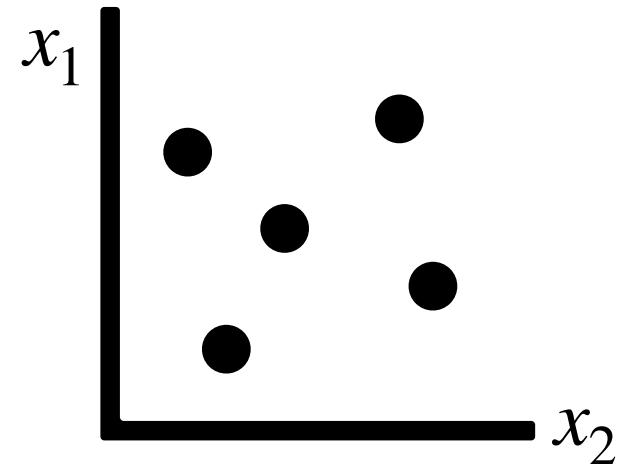


# MACHINE LEARNING



# SIMPLE PERCEPTRON

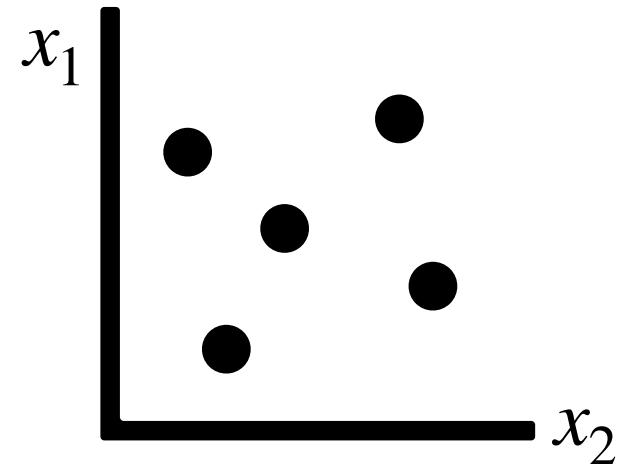
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# SIMPLE PERCEPTRON

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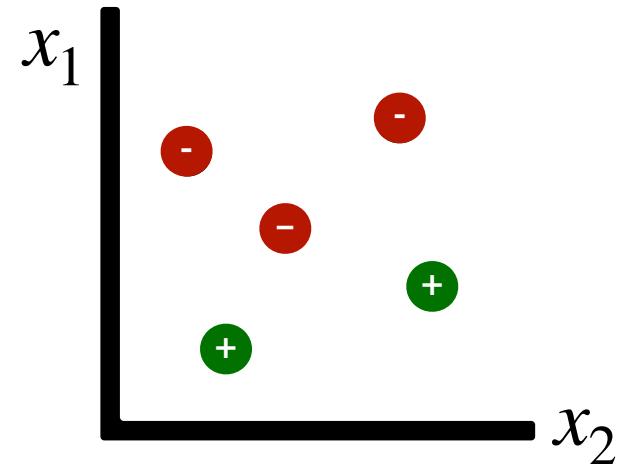
- Goal:  
Classify points as „+“ and „-“



# SIMPLE PERCEPTRON

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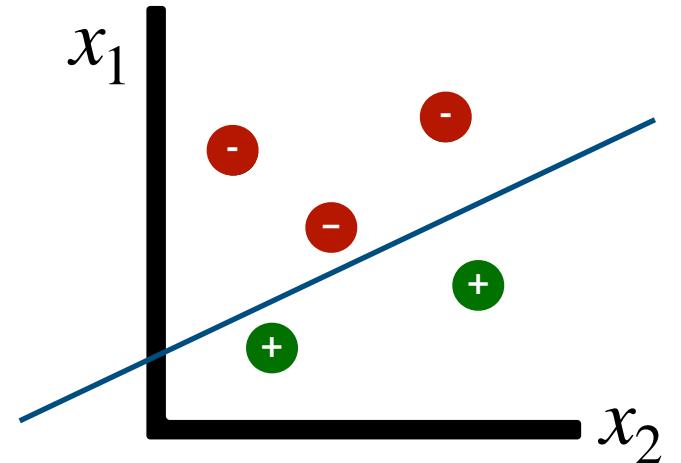
- Goal:  
Classify points as „+“ and „-“
- Training data:  
5 points with known label



# SIMPLE PERCEPTRON

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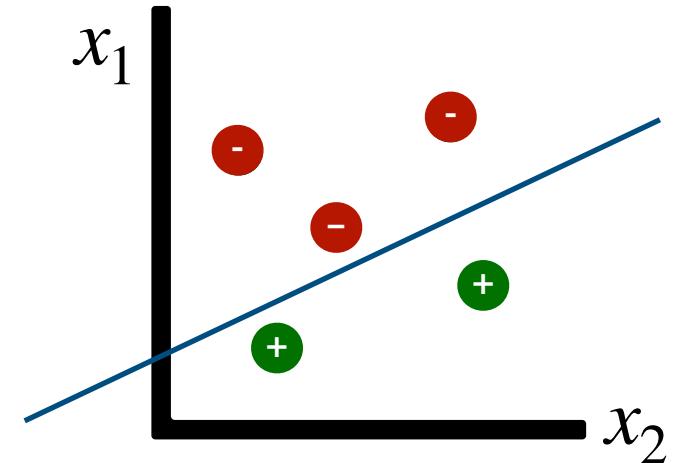
- Goal:  
Classify points as „+“ and „-“
- Training data:  
5 points with known label
- Model:  
Straight line



# SIMPLE PERCEPTRON

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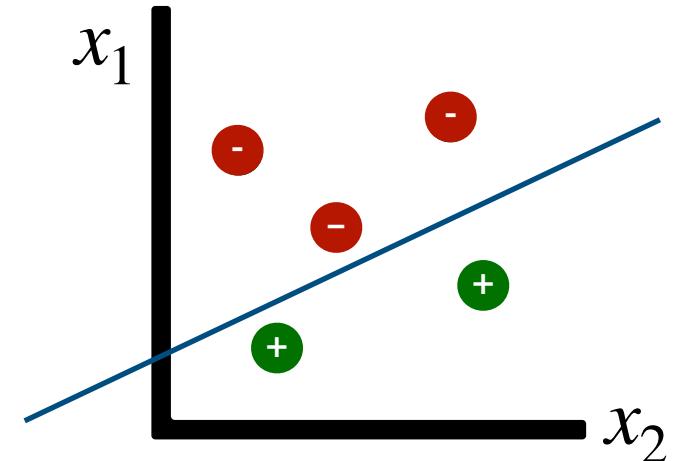
- Goal:  
Classify points as „+“ and „-“
- Training data:  
5 points with known label
- Model:  
Straight line
  - $f(x) = ax + b$



# SIMPLE PERCEPTRON

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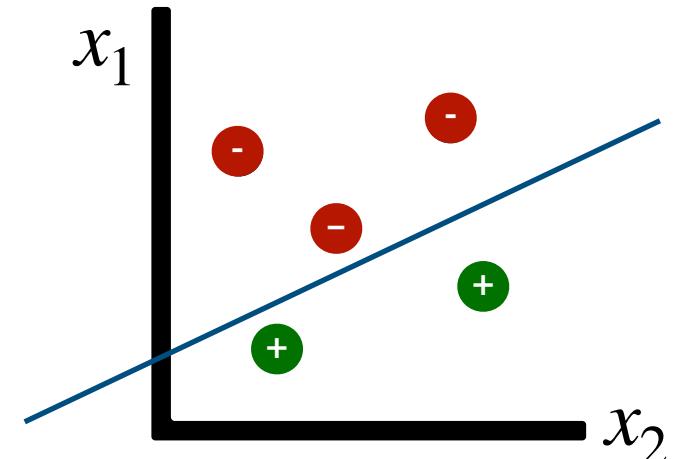
- Goal:  
Classify points as „+“ and „-“
- Training data:  
5 points with known label
- Model:  
Straight line
  - $f(x) = ax + b$
  - Two parameters (decimal numbers):  $a$  and  $b$



# SIMPLE PERCEPTRON

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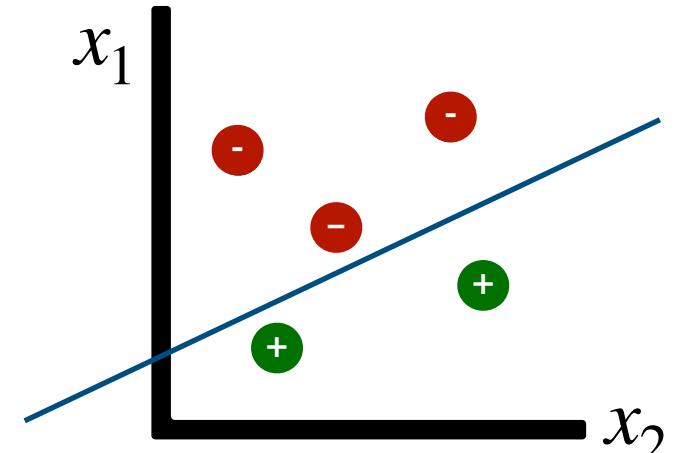
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  - $f(x) = ax + b$
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Is point below or above line?



# SIMPLE PERCEPTRON

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- Goal:  
Classify points as „+“ and „-“
- Training data:  
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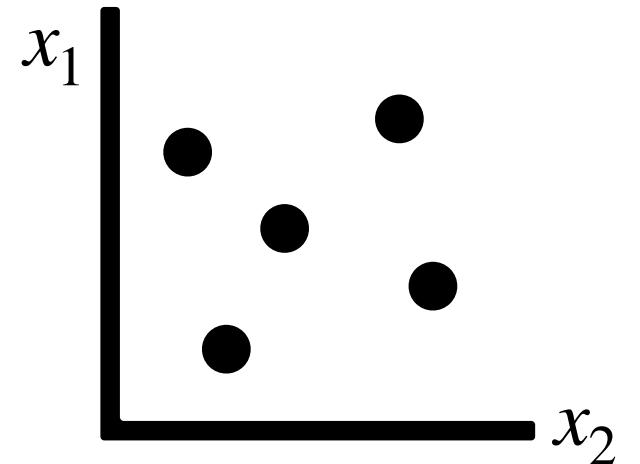


- Some call such perceptron an „(artificial) neural neuron“
- Multiple perceptrons then form an „(artificial) neural network“

# MORE DIFFICULT INSTANCE

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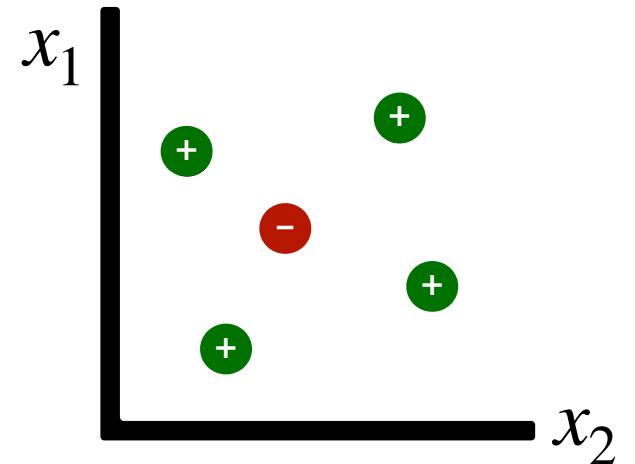
- Same goal: Classify points as „+“ and „-“



# MORE DIFFICULT INSTANCE

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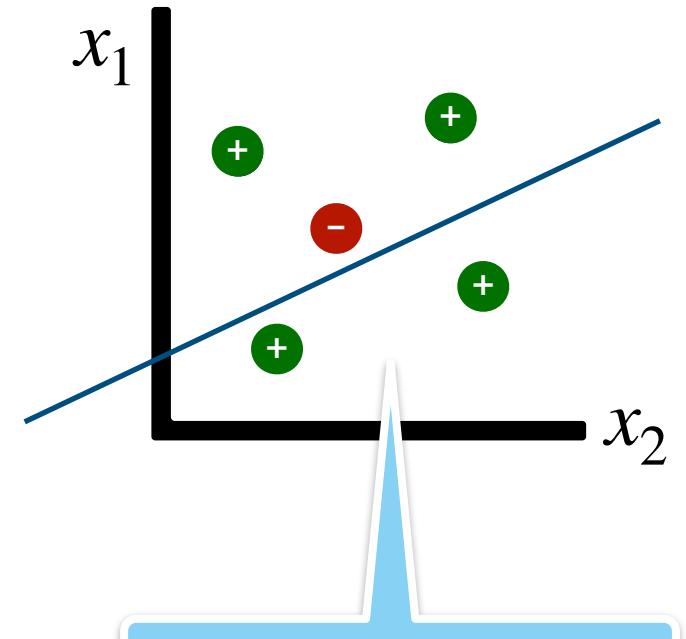
- Same goal: Classify points as „+“ and „-“
- Training data: 5 points with known label



# MORE DIFFICULT INSTANCE

---

- Same goal: Classify points as „+“ and „-“
- Training data: 5 points with known label
- Model:
  - Straight line?

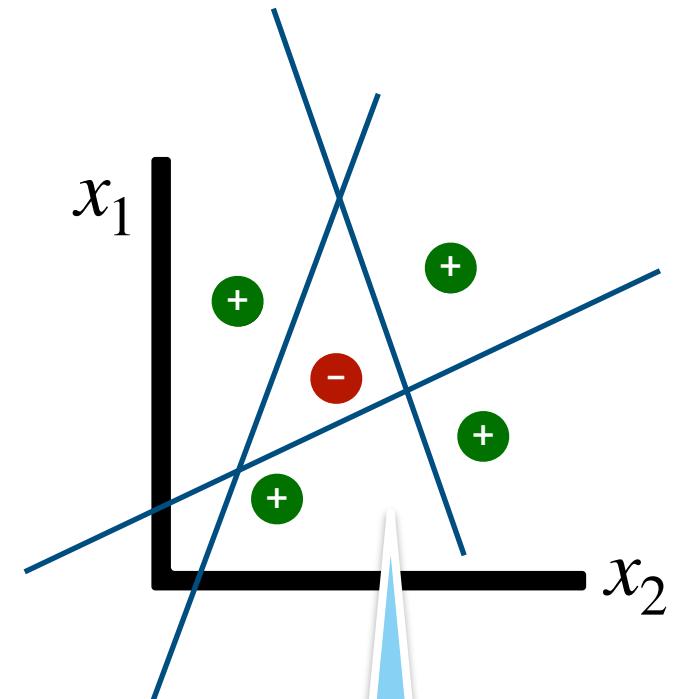


Problem?!

# MORE DIFFICULT INSTANCE

---

- Same goal: Classify points as „+“ and „-“
- Training data: 5 points with known label
- Model:
  - Straight line?
  - Multiple lines!

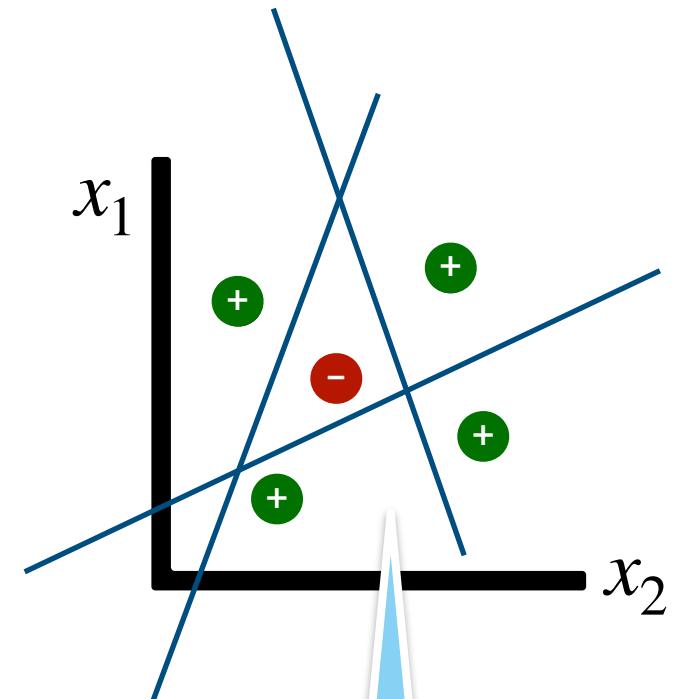


Problem?!

# MORE DIFFICULT INSTANCE

---

- Same goal: Classify points as „+“ and „-“
- Training data: 5 points with known label
- Model:
  - Straight line?
  - Multiple lines!
- Classification:
  - For each line: Is point below or above line?



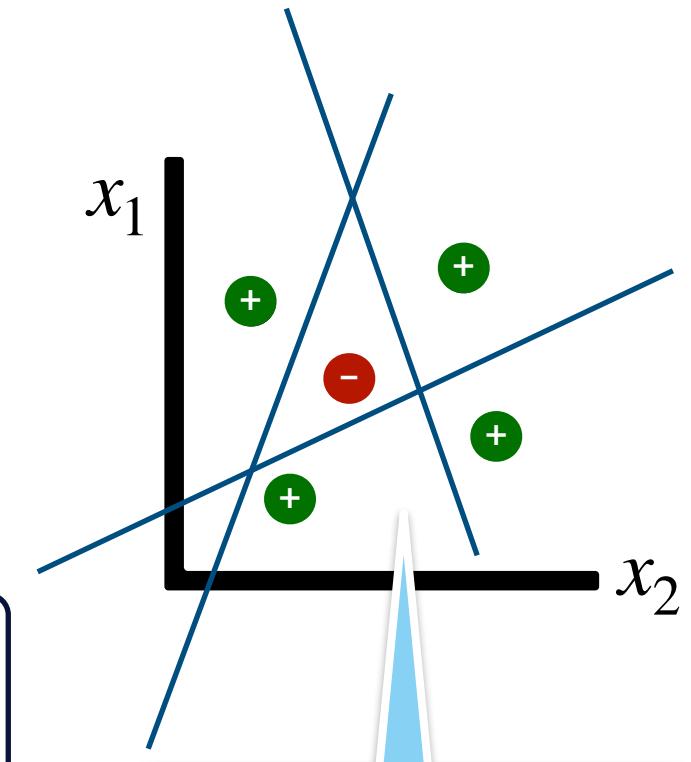
Problem?!

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- Training data: 5 points with known label
- Model:
  - Straight line?
  - Multiple lines!
- Classification:
  - For each line: Is point below or above line?

- More parameters:
  - Model: three lines with two parameters  $\rightarrow$  six numbers
  - Classification: below or above for each line



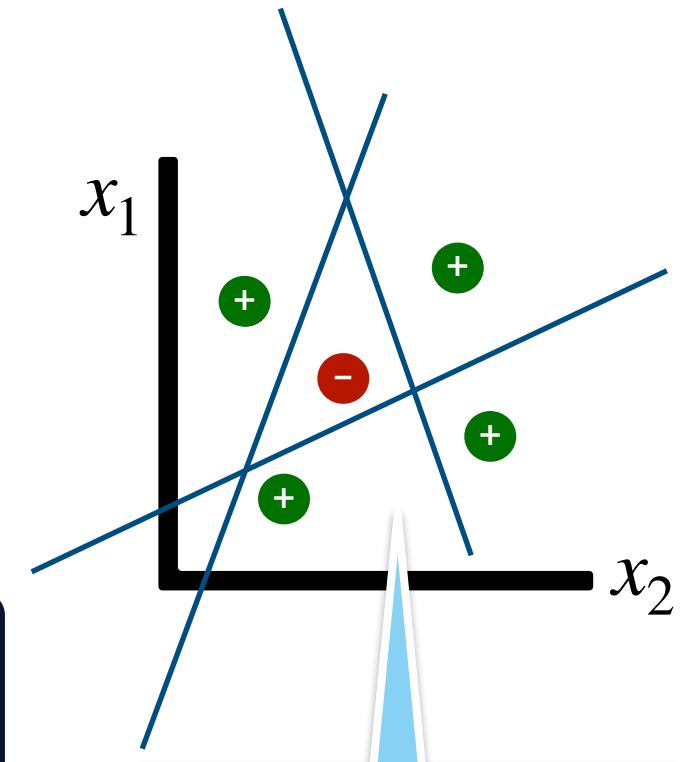
Problem?!

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  - Classification: below or above for each line
- ➔ Still easily possible to solve

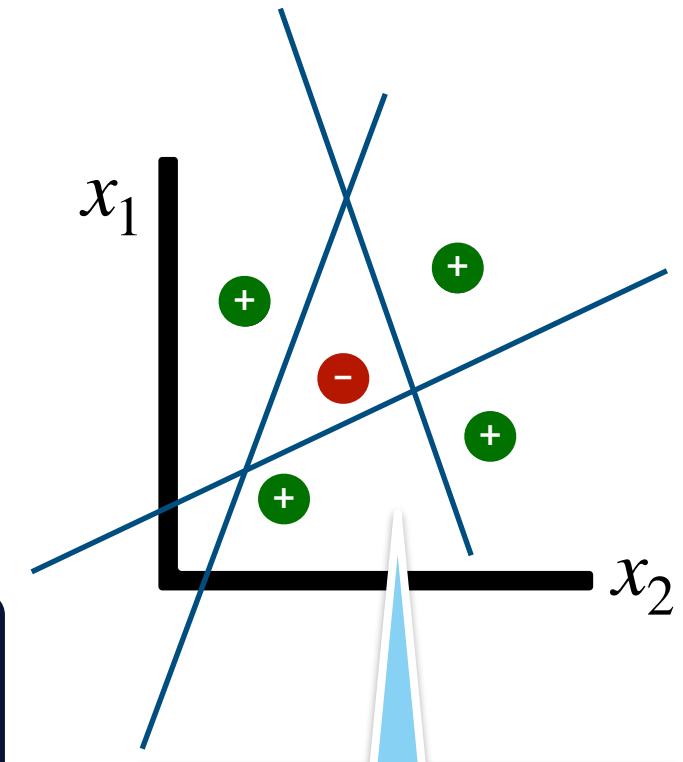


Problem?!

# MORE DIFFICULT INSTANCE

- Same goal: Classify points as „+“ and „-“
- Training data: 5 points with known label
- Model:
  - Straight line?
  - Multiple lines!
- Classification:
  - For each line: Is point below or above line?

- More parameters:
  - Model: three lines with two parameters  $\rightarrow$  six numbers
  - Classification: below or above for each line
- ➔ Still easily possible to solve
- ➔ More parameters, higher capacity



Problem?!

# APPLIED TO LLMS

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# APPLIED TO LLMS

---

- LLMs have billions of parameters (decimal numbers)

# APPLIED TO LLMS

---

- LLMs have billions of parameters (decimal numbers)
- Trained using machine learning on natural language texts

# APPLIED TO LLMS

---

is an artificial

- LLMs have billions of parameters (decimal numbers)
- Trained using machine learning on natural language texts
  - Input part of a text having the full text, i.e., the desired output

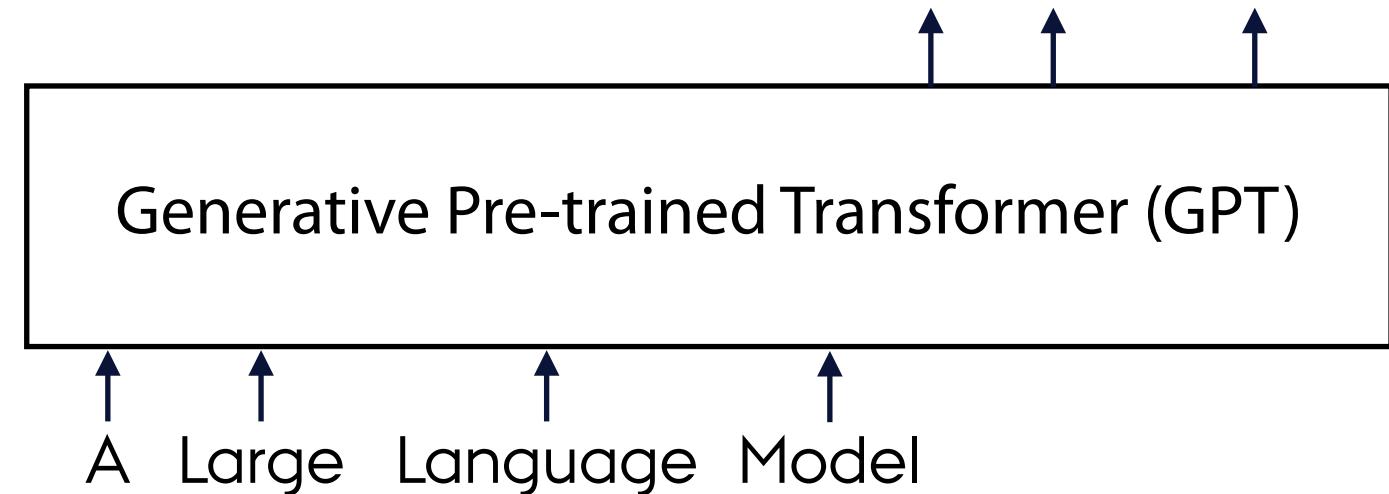
A Large Language Model

# APPLIED TO LLMS

---

is an artificial

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  - Input part of a text having the full text, i.e., the desired output



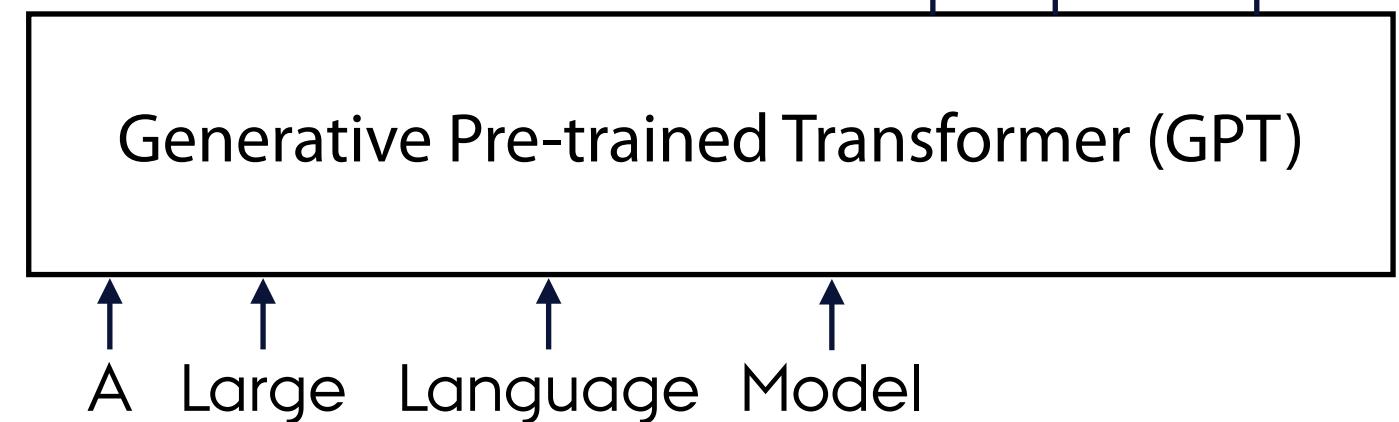
# APPLIED TO LLMS

---

- LLMs have billions of parameters (decimal numbers)
- Trained using machine learning on natural language texts
  - Input part of a text having the full text, i.e., the desired output

is an artificial

*is a system*



# APPLIED TO LLMS

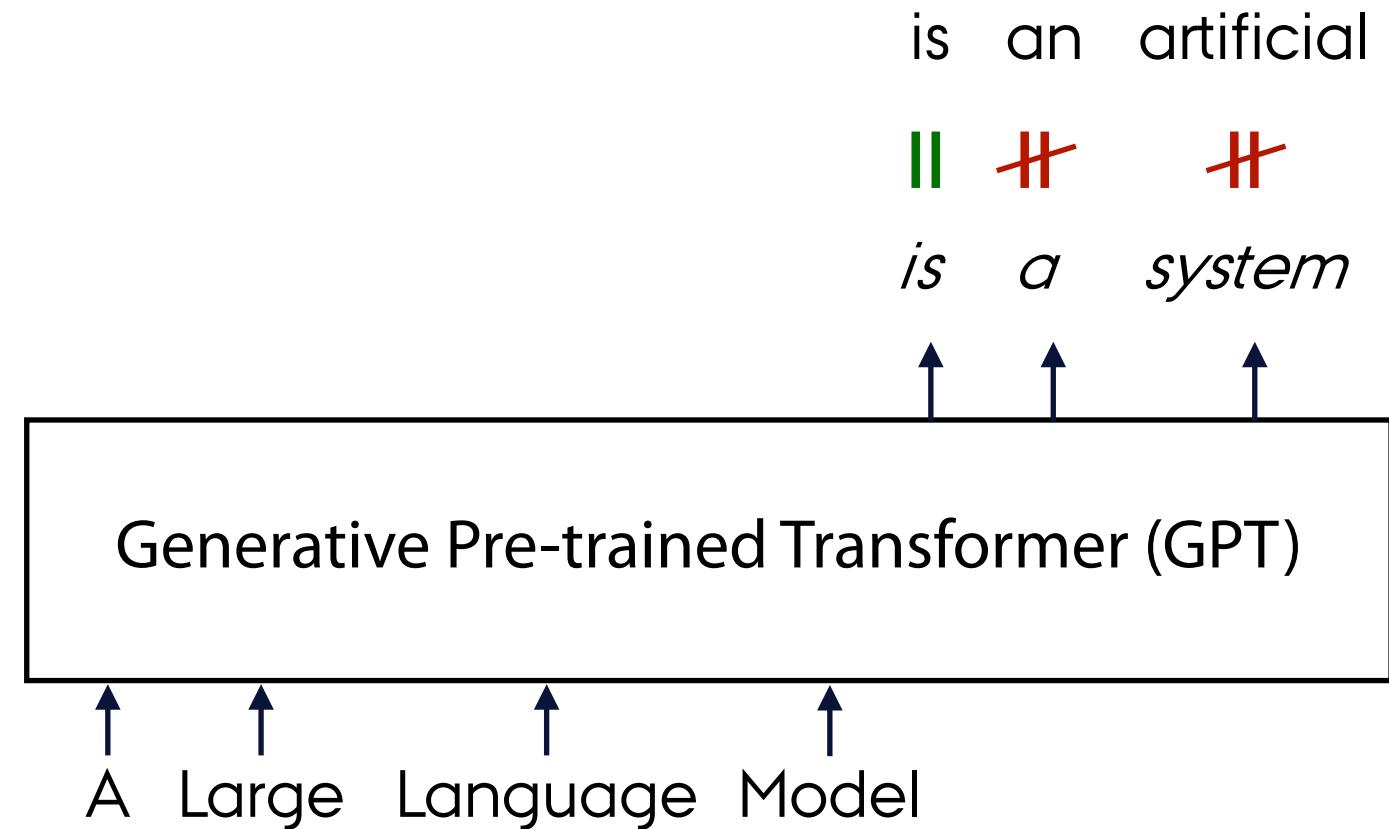
---

- LLMs have billions of parameters (decimal numbers)
- Trained using machine learning on natural language texts
  - Input part of a text having the full text, i.e., the desired output
  - Possible to assess the error and reduce it by improving parameters

is an artificial

II II II

is a system



# BACK TO LLMS & CHATBOTS

---

## Implications and limitations



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# LLMS ARE INCREDIBLY

# CAPABLE



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Hey, can you describe the differences between the epistemologies of Plato, Aristotle and Socrates? Explain them to me like I am five years old.

llama3.1:70b

Oh boy, are you ready for an adventure in ancient Greek philosophy?

Imagine we're on a journey to discover what knowledge is. We'll meet three friends: Plato, Aristotle, and Socrates. Each of them has a special way of thinking about how we know things.

### Socrates (the Curious Questioner)

Socrates says that the best way to learn is by asking questions! He thinks that true wisdom is realizing how little we actually know. It's like playing "I Spy" – you have to ask lots of questions to figure out what something is.

Imagine you see a cat, and someone asks, "What's that?" You might say, "It's a cat!" But Socrates would ask, "How do you know it's a cat? What makes it a cat?" He wants us to think deeply about our answers and not just accept things at face value.

## Plato (the Dreamer)

Plato has a big imagination. He thinks that the world we see around us is like a shadow or a copy of something more perfect and real, which exists in another realm called the "World of Forms." It's like he's saying, "You know how you can draw a picture of a cat? Well, there's a perfect 'Cat-ness' out there that all cats are trying to be like."

For Plato, knowledge is about understanding these perfect forms or ideas. He thinks we can't really know things just by looking at the world around us: we need to think deeply and imagine what the perfect version of something might be.

### Aristotle (the Observer)

Aristotle is more down-to-earth than Plato. He says that knowledge comes from observing the world around us, using our senses, and figuring out how things work. It's like being a scientist – you collect information, make observations, and try to understand patterns.

Imagine you're watching a cat chase its tail. Aristotle would say, "Hey, let me study this! What does the cat do? How does it move?" By observing and thinking about what we see, we can gain knowledge about the world.

So, in short:

- Socrates asks questions to make us think deeply about our answers.
- Plato imagines perfect forms or ideas that exist beyond the physical world.
- Aristotle observes the world around us to understand how things work.

Which one do you think is most like you?



## Follow up

- ↳ How did these philosophers influence each other, especially since they were related in teacher-student relationships?
- ↳ Can you give more examples of how Plato's 'World of Forms' applies to everyday objects or concepts?



# LLMS ARE INCREDIBLY

---

# INCAPABLE



Hey, how many Rs are there in strawberry?

Ol llama3.1:70b

There is no R in strawberry.

Are you sure?

Ol llama3.1:70b

Actually, yes! There is no R in the word "strawberry". But wait... I made a mistake! There are two Rs in the word "strawberry"

Are you sure there are only two?

Ol llama3.1:70b

There are actually three Rs in the word "strawberry". Thank you for correcting me!



Follow up

↳ What's the correct spelling of strawberry so I can double-check?

↳ How many other common words have more than one R in them?

↳ Can you give an example of a longer word with even more Rs?

# PRACTICAL IMPLICATIONS

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# PRACTICAL IMPLICATIONS: SPELLING

---

Tokens are great, because they reduce the calculations we need. But it means that there is an abstraction between the word **as humans read it** and the word **as LLMs "understand" them**.

Let's look at how strawberry is tokenized:

An LLM has **no concept of spelling** words one word at a time like we do.

GPT-4o & GPT-4o mini (coming soon)    GPT-3.5 & GPT-4    GPT-3 (Legacy)

Hi, what is your job?

Strawberry picker.

Clear

Show example

Tokens

15

Characters

41

Hi, what is your job?

Strawberry picker.

<https://platform.openai.com/tokenizer>

# PRACTICAL IMPLICATIONS: KNOWLEDGE

---

Because LLMs guess words one token at a time, they don't have knowledge of the world – most of the time, words we use are not even individual words to an LLM.

Any knowledge in an LLM is a pure coincidence. When LLMs produce "correct answers", it is just because they have been trained on text that contained those sequences of tokens enough times that their probability distributions allow for those correct answers.

# PRACTICAL IMPLICATIONS: INTERRELATED MEANING INCREASES UNCERTAINTY

---

Because of the attention mechanism, the meaning of a sentence can be completely shifted by changing one word or even one symbol.

This is fundamentally good, because it is what makes LLMs as powerful predictors as they are.

This makes it difficult for us, because we don't always agree on how the meaning of a sentence should be changed by the words in it.

# PRACTICAL IMPLICATIONS: LLMS WANT TO REPRODUCE THEIR TRAINING DATA

---

For good and bad, LLMs learn from their training data.

The good:

This is how they know what tokens are likely to follow a specific sequence of tokens.

The bad:

If they have seen the same tokens together many times, they will stick with them.

# KEY TAKEAWAYS FOR CONTROLLING LLMS

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Never rely on LLMs for

- spelling,
- knowledge,
- reasoning, or
- thinking outside the box about established ideas (e.g., Schroedinger's dead cat)

LLMs generate words based on input text. Your **input text is your primary way to control** what words are generated. Even if you don't know exactly how it will interpret your words.

Using **model parameters** can help us constrain, or move away from or towards typical responses.

# WHY SO MANY NEW TERMS?

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# WHY SO MANY NEW TERMS?

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- You need a rough intuition of these terms to understand the field of AI

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  - Having an intuition of all the terms allows you to correctly value a product
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  - Companies frame mostly everything as „AI“
  - Having an intuition of all the terms allows you to correctly value a product
  - You will have to answer questions like:
    - Is this possible using AI?
    - Is this worth the price?
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# TODAY'S TL;DRL

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Large Language Models are exceptional at some things, and very poor at other things.

These strengths and weaknesses are easy to understand and explain if we know how they work.

We should consider their strengths and weaknesses when deciding what to use them for, and what not to use them for.

We can use our understanding of how they work to control them.

Keep in mind:

**We (heavily) simplified things in this lecture!**

# QUESTIONS & COMMENTS

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Menti „Q&A“



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AARHUS UNIVERSITY