

Applied Artificial Intelligence

06 - Foundation Models

Univ.-Prof. Dr.-Ing. habil. Niklas Kühl
www.niklas.xyz

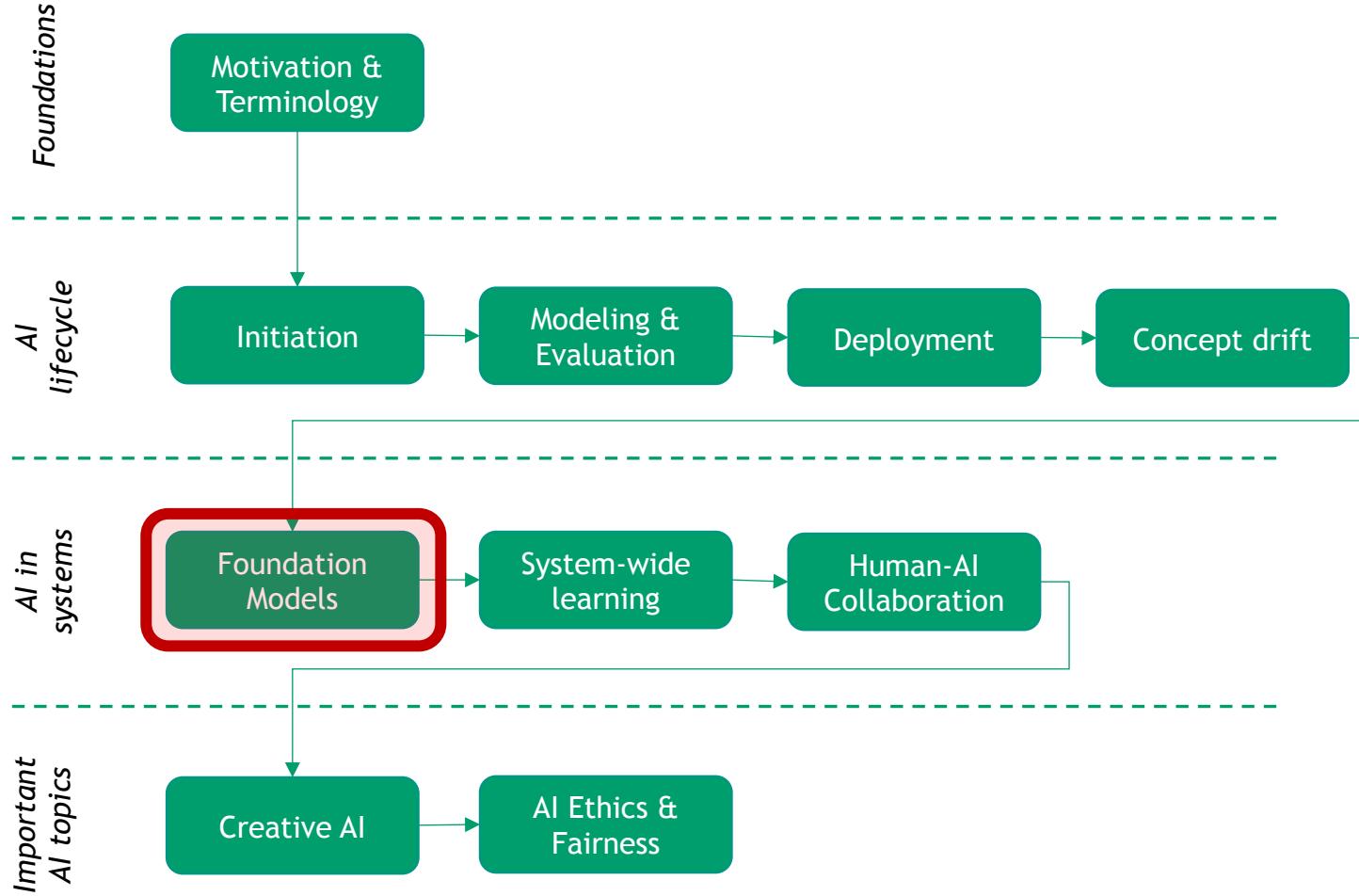
University of Bayreuth

Karlsruhe Institute of Technology

TUM School of Management

Organizational

The story of the lecture



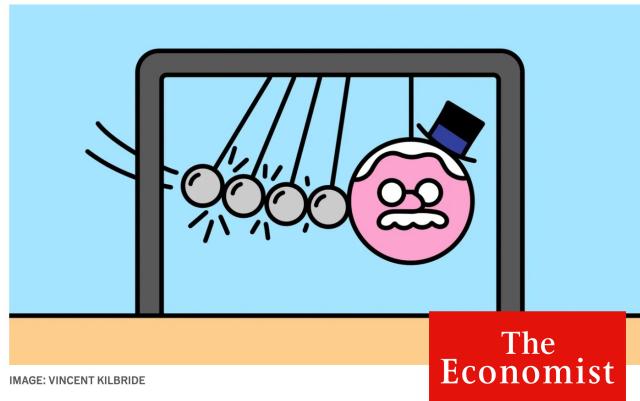
Is there a concentration of power in AI?

Foundation Models

Leaders | Undisrupted

AI could fortify big business, not upend it

Upstarts face an uphill battle



[1]



European Commission - Speech
[Check Against Delivery]



[2]

MAKING ARTIFICIAL INTELLIGENCE AVAILABLE TO ALL - HOW TO AVOID BIG TECH'S MONOPOLY ON AI?

Brussels, 19 February 2024

- Check against delivery -

Good afternoon.

Let me start by thanking Stéphanie Yon-Courtin for organising this important event. As Competition Commissioner, I have been very pleased with your interest and dedication to competition policies over the last five years in the European Parliament.

Thank you for putting the spotlight on Artificial Intelligence and competition. Because '*human* intelligence' is exactly what we need right now, to strike the right balance on intelligence of the *artificial* kind. In order to shape the emerging markets that are enabled by Large Language Models and other applications in AI. To make sure that competition can thrive, and consumers reap the benefits of these new markets, without hampering their development.

By thinking ahead, by acting swiftly and by cooperating, we have a window of opportunity to maximise these benefits; while at the same time, minimising the risks. But that window is closing. If we don't act soon, we will find ourselves, once again, chasing solutions to problems we did not anticipate. So debates like this one are not only very timely, they are also urgent.

February 19th, 2024

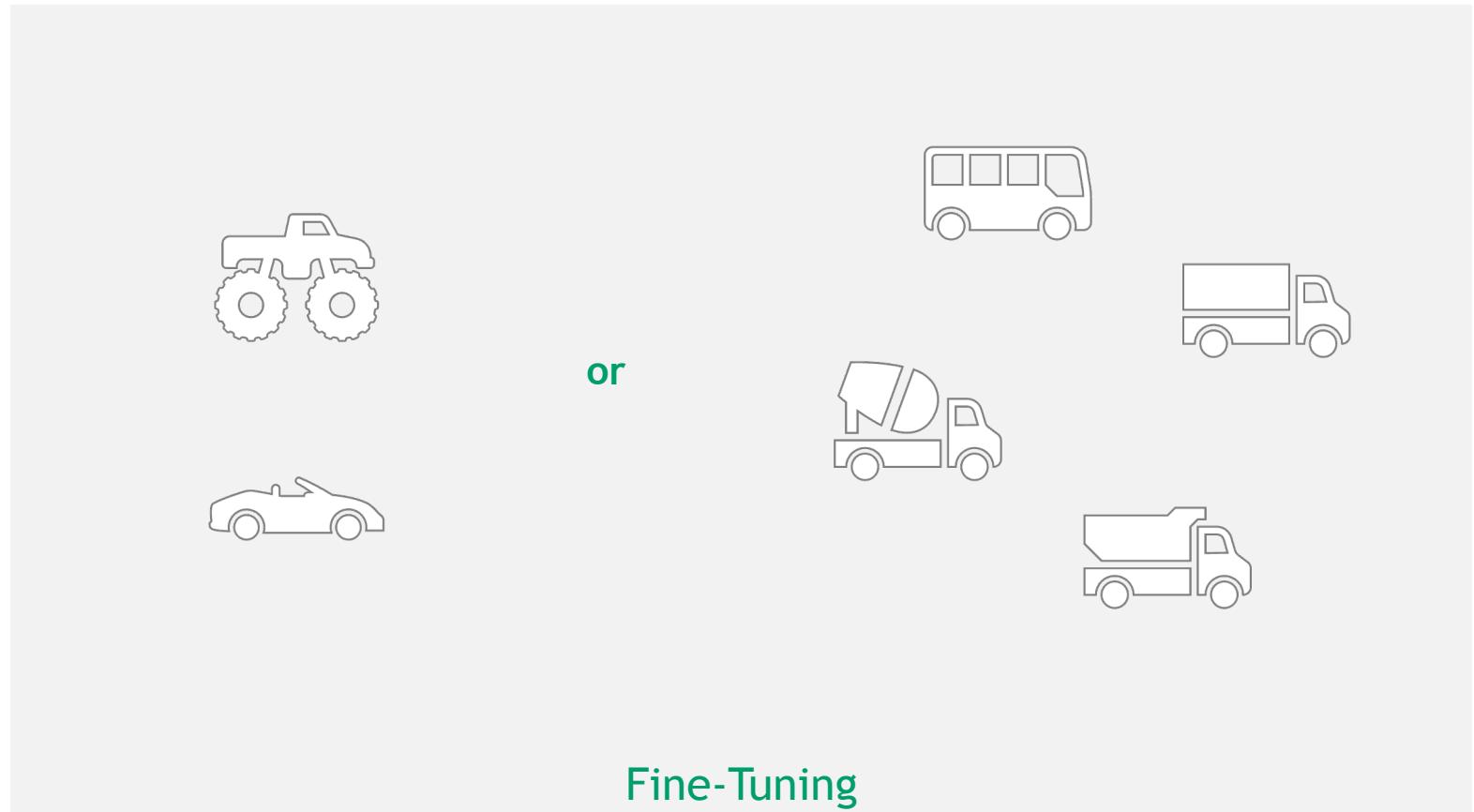
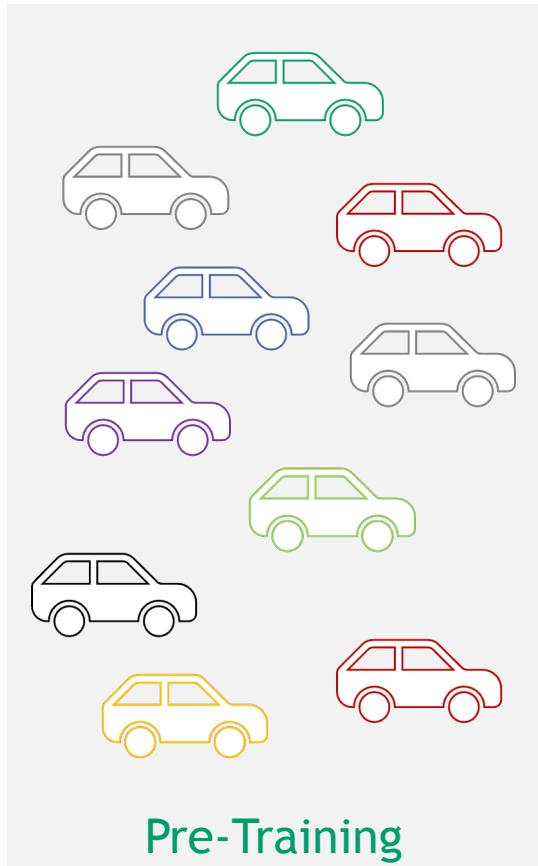
<https://www.economist.com/leaders/2023/08/24/ai-could-fortify-big-business-not-upend-it> [1]
https://ec.europa.eu/newsroom/ecoc-failover/pdf/speech-24-931_en.pdf [2]



- 1** Introduction
- 2** Multimodality in Data
- 3** Generative Foundation Models
- 4** Research
- 5** Industry

What is the idea of Foundation Models?

A paradigm shift in machine learning enabled by transfer and scale.



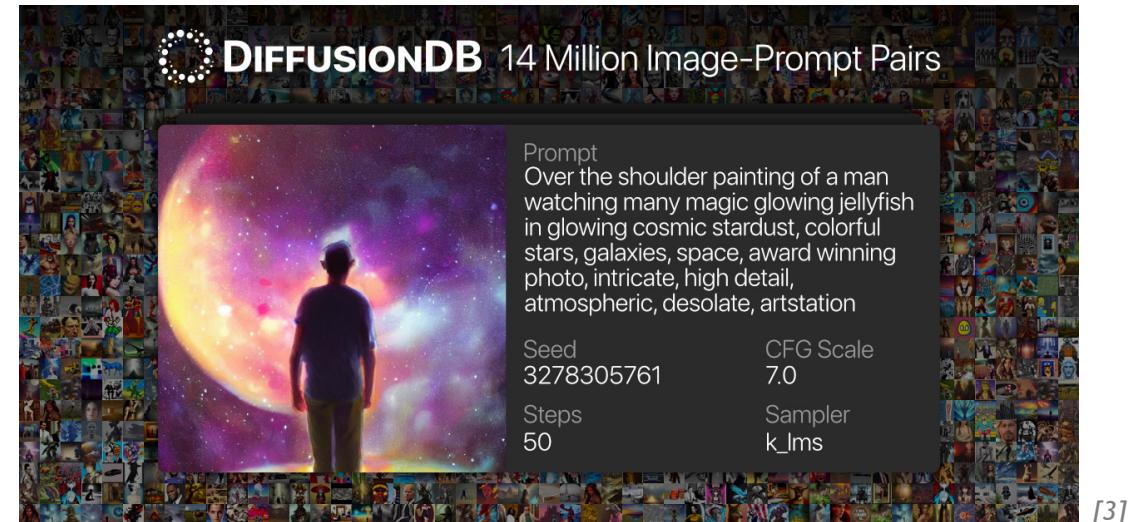
What are Foundation Models?

Train one model on a huge amount of data and adapt it to many applications.

Foundation Model



Huge datasets



<https://github.com/poloclub/diffusiondb> [3]

What are Foundation Models?

Train one model on a huge amount of data and adapt it to many applications.

Foundation Model



Huge datasets



Unlabeled data
self-supervised learning



the university has a beautiful campus

$y_{<t}$

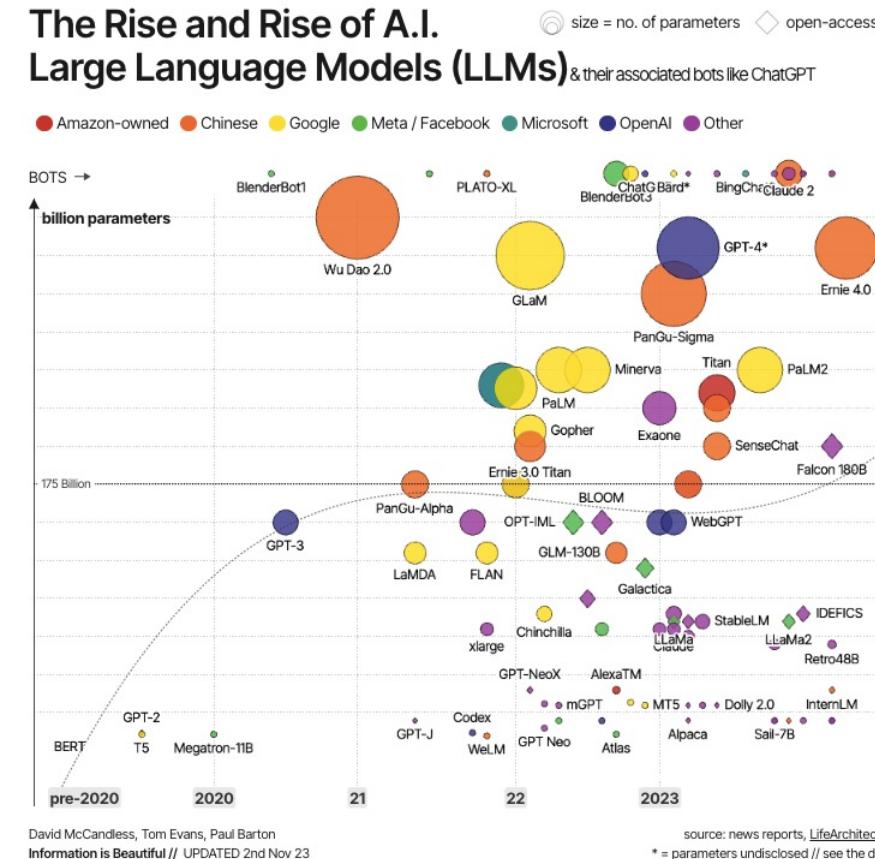
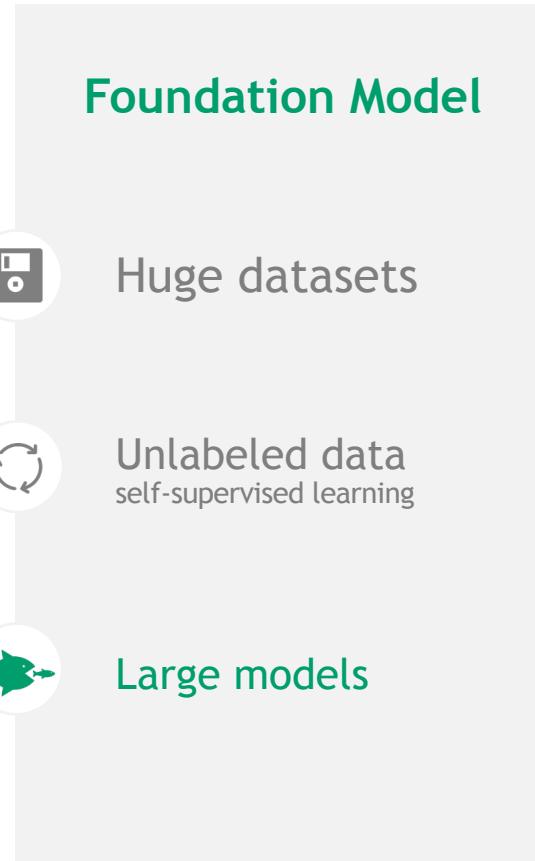
History

y_t

Most probable
next token,
e.g., word,
prefix, suffix,
etc.

What are Foundation Models?

Train one model on a huge amount of data and adapt it to many applications.



<https://informationisbeautiful.net/visualizations/the-rise-of-generative-ai-large-language-models-llms-like-chatgpt/> [4]

What are Foundation Models?

Train one model on a huge amount of data and adapt it to many applications.

Foundation Model



Huge datasets



Unlabeled data
self-supervised learning



Large models

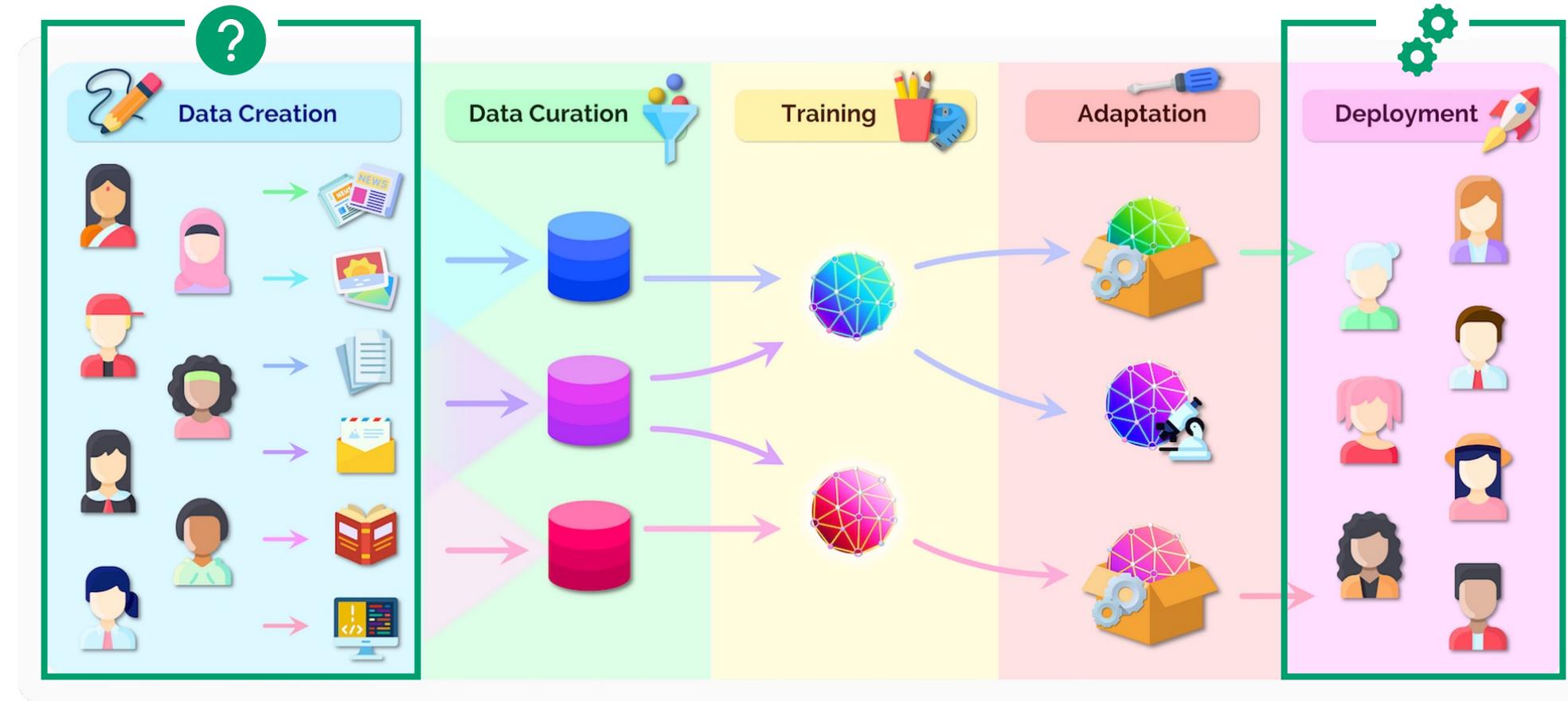


“

“a foundation model is itself incomplete but serves as the common basis from which many task-specific models are built via adaptation” [5]

What are Foundation Models?

Train one model on a huge amount of data and adapt it to many applications.

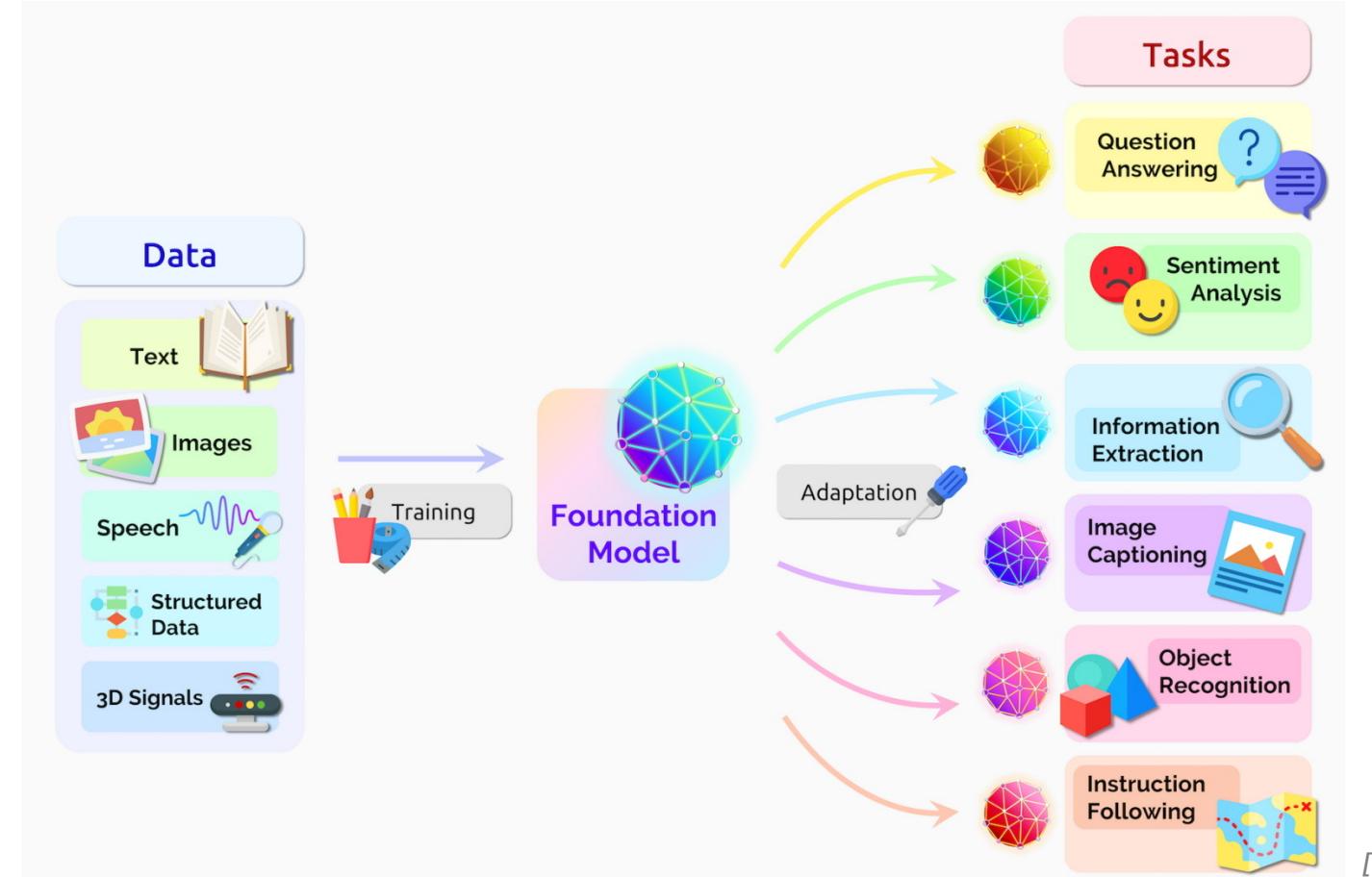


[5]

Rishi Bommasani et al., (2022). On the Opportunities and Risks of Foundation Models. [5]

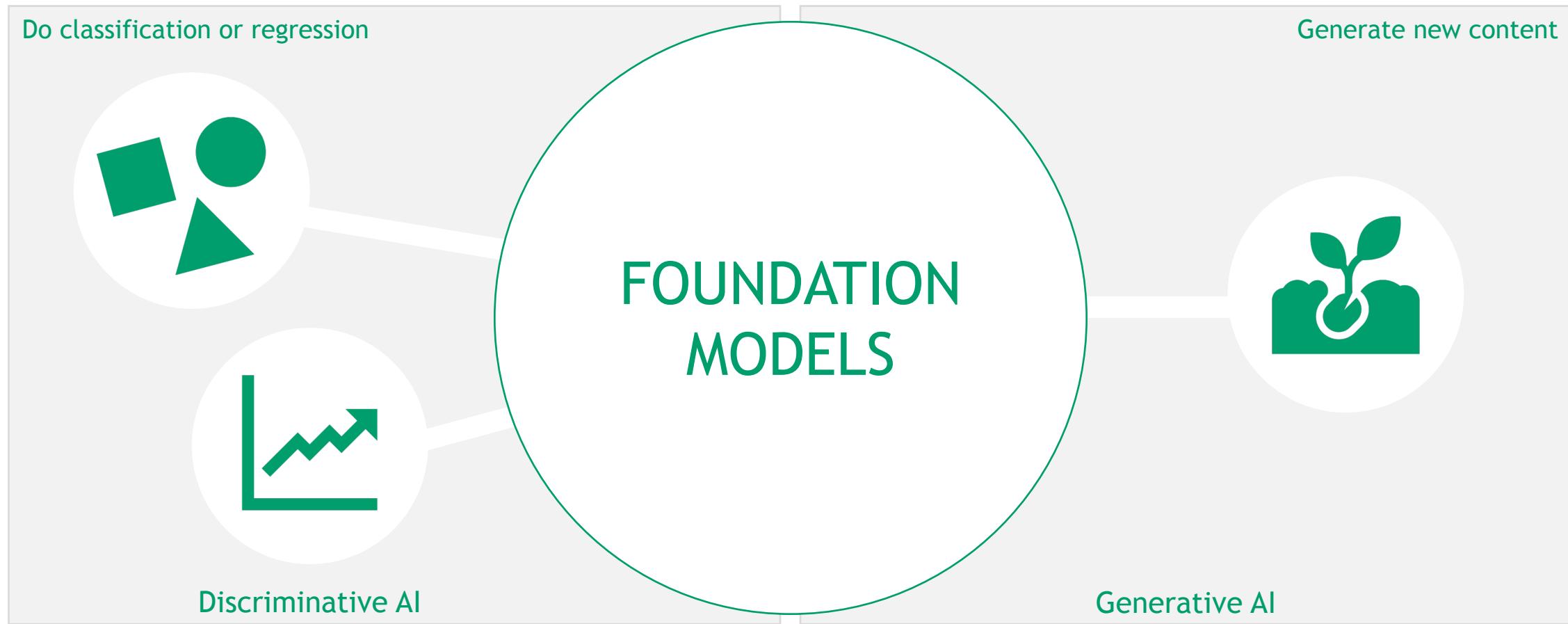
What are Foundation Models?

Foundation models go well beyond language.



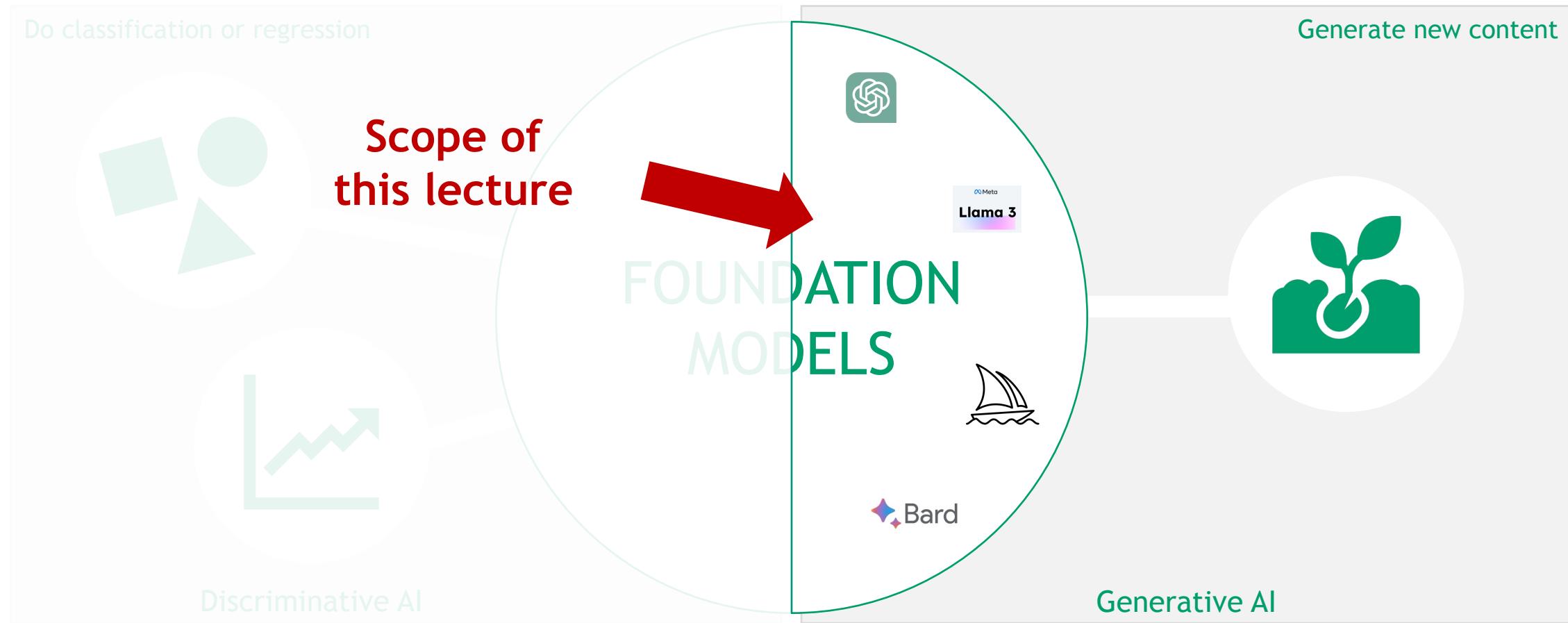
How do Foundation Models relate to Generative AI?

Foundation models are a key component of Generative AI.



How do Foundation Models relate to Generative AI?

Foundation models are a key component of Generative AI.





- 1 Introduction
- 2 Multimodality in Data
- 3 Generative Foundation Models
- 4 Research
- 5 Industry

How to deal with multimodality in data?

Images can be described and generated using text prompts.



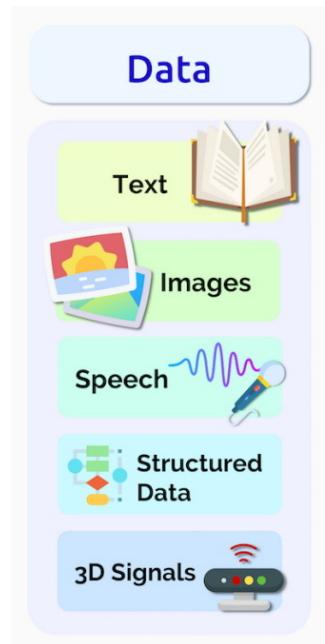
*"Create a realistic, high-resolution image of **two people standing in a museum**, observing a famous painting [...]. The painting they are observing is inspired by **Vincent van Gogh's 'Self-Portrait with Bandaged Ear'**, characterized by vibrant colors and expressive brush strokes. The two observers are diverse; one is a middle-aged Black woman with shoulder-length hair, wearing a smart-casual outfit, and the other is a young South Asian man dressed in a trendy jacket and jeans [...]"*



Text and Image are created with ChatGPT and Dall-E of OpenAI

How to deal with multimodality in data?

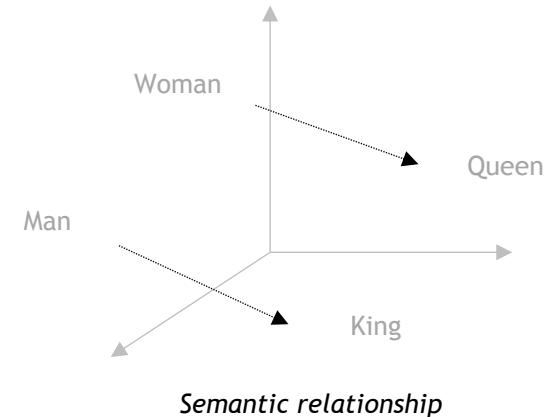
Textual data is embedded in vectors with semantic relationship.



Example

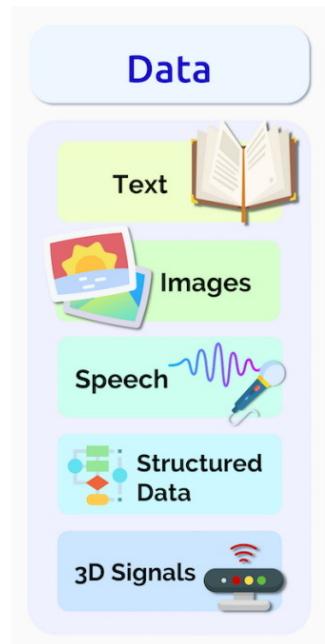
*“two people standing
in a museum”*

Embedding



How to deal with multimodality in data?

Textual data is embedded in vectors with semantic relationship.

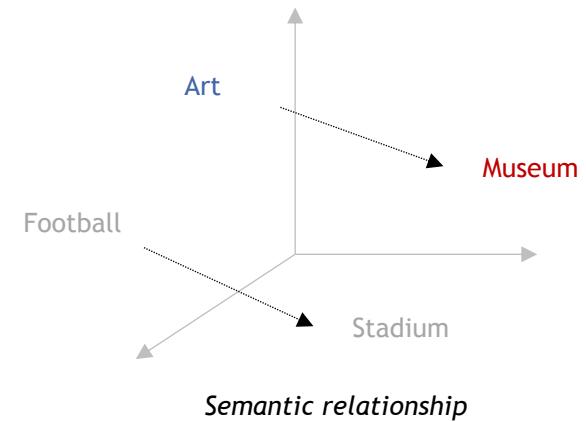


[5]

Example

*“two people standing
in a museum”*

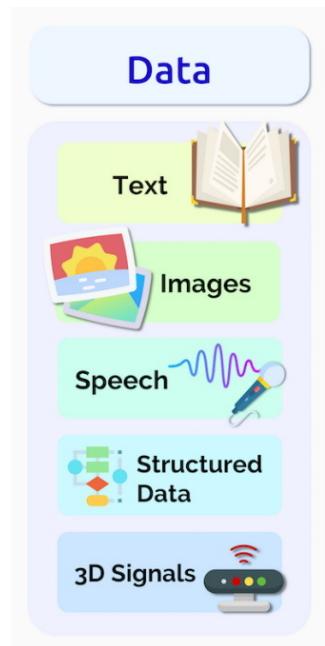
Embedding



Semantic relationship

How to deal with multimodality in data?

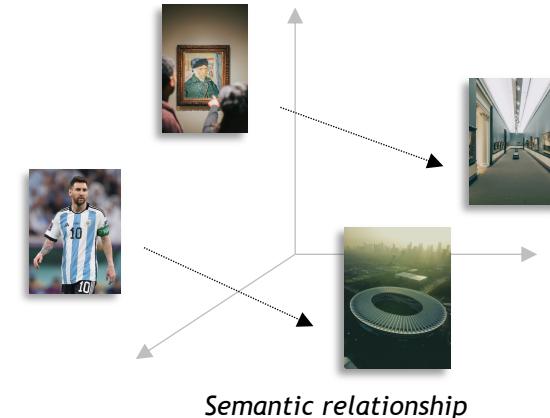
Visual data is embedded in vectors with semantic relationship.



Example



Embedding



How to deal with multimodality in data?

Visual data is embedded in vectors with semantic relationship.

Example



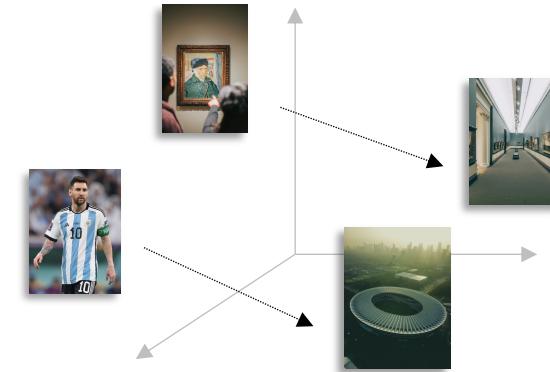
Convolution

(103,88,67)	(138,118,94)
(138,118,94)	(103,88,67)

(103,88,67)

Image

Embedding

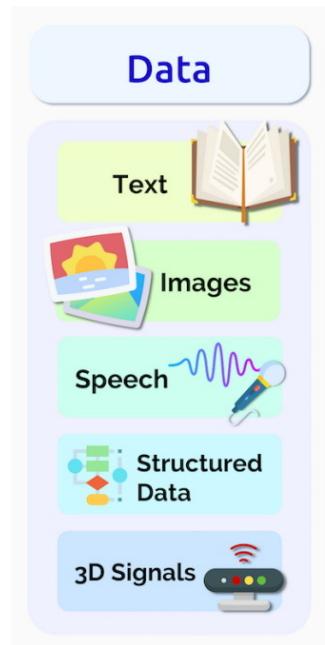


Pixel RGB Values

Semantic relationship

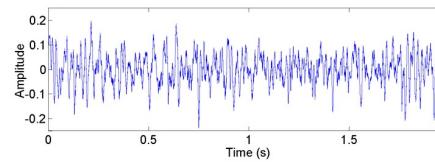
How to deal with multimodality in data?

Audio data is embedded in vectors with semantic relationship.



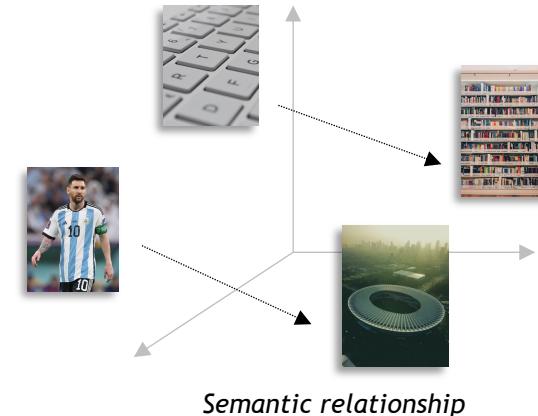
[5]

Example



Audio

Embedding

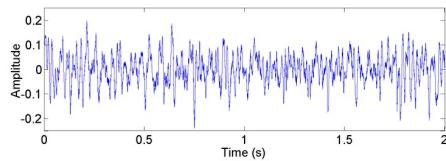


Semantic relationship

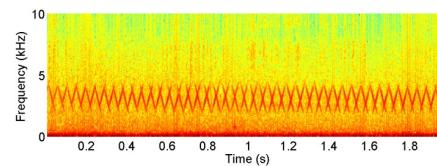
How to deal with multimodality in data?

Audio data is embedded in vectors with semantic relationship.

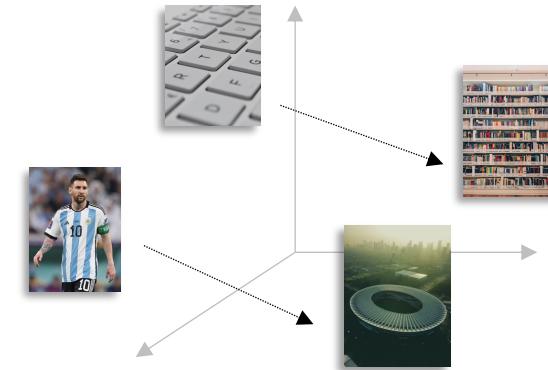
Example



Preprocessing



Embedding



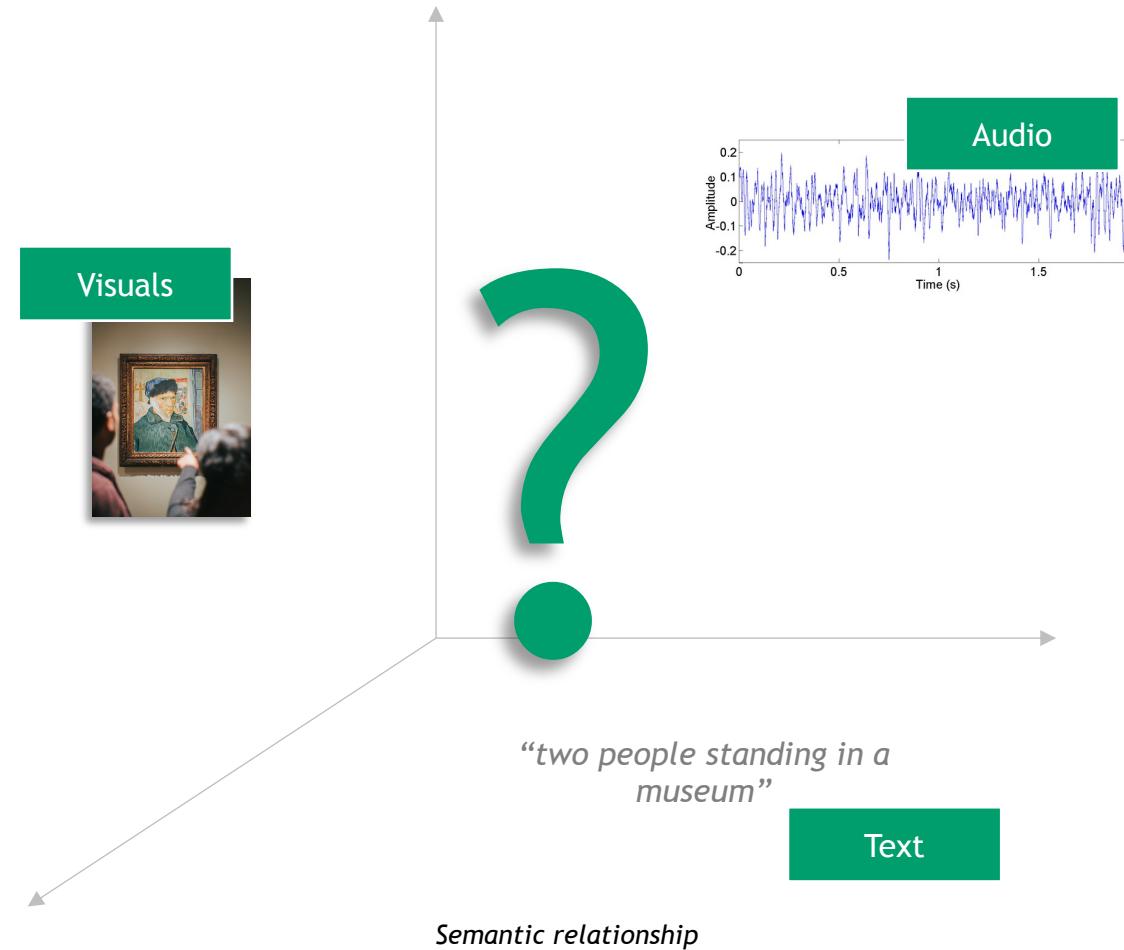
Audio

Spectrogram

Semantic relationship

How to deal with multimodality in data?

Embeddings enable semantic relationship of multimodal data.



What are the challenges in multimodal data?
Foundation models try to integrate diverse data into a unified representation.

*“The rising of
the sun over
the world”*



[7]



[7]

Task

Giovanni Battista Tiepolo
(1696-1770)

Ceiling fresco

<https://schloesserblog.bayern.de/heute-vor/giovanni-battista-tiepolo-und-sein-meisterwerk-in-der-residenz-wuerzburg> [7]

What are the challenges in multimodal data?

Foundation models try to integrate diverse data into a unified representation.



[7]

<https://schloesserblog.bayern.de/heute-vor/giovanni-battista-tiepolo-und-sein-meisterwerk-in-der-residenz-wuerzburg> [7]

What are the challenges in multimodal data?

Foundation models try to integrate diverse data into a unified representation.



Completeness

Data is considered complete if it is without missing information.

<https://schloesserblog.bayern.de/heute-vor/giovanni-battista-tiepolo-und-sein-meisterwerk-in-der-residenz-wuerzburg/> [7]

What are the challenges in multimodal data?

Foundation models try to integrate diverse data into a unified representation.



Completeness

Context

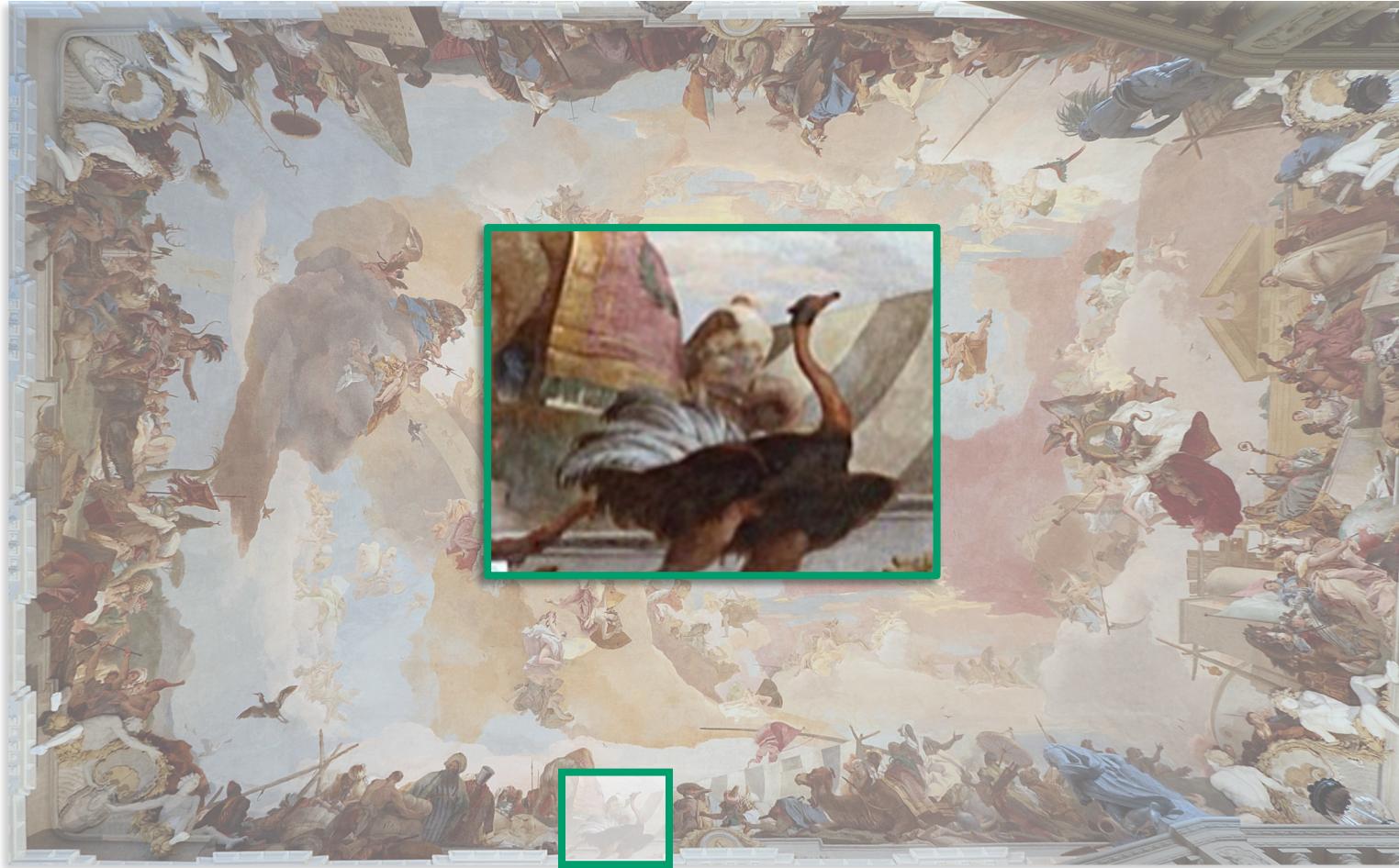
Context refers to information and relevant details that surround and describe data.

[7]

<https://schloesserblog.bayern.de/heute-vor/giovanni-battista-tiepolo-und-sein-meisterwerk-in-der-residenz-wuerzburg> [7]

What are the challenges in multimodal data?

Foundation models try to integrate diverse data into a unified representation.



Completeness

Context

Consistency

All copies or instances are the same across all data.

[7]

<https://schloesserblog.bayern.de/heute-vor/giovanni-battista-tiepolo-und-sein-meisterwerk-in-der-residenz-wuerzburg> [7]

What are the challenges in multimodal data?

Foundation models try to integrate diverse data into a unified representation.



[7]

Completeness

Context

Consistency

Bias

Data fails to represent the entire population.

<https://schloesserblog.bayern.de/heute-vor/giovanni-battista-tiepolo-und-sein-meisterwerk-in-der-residenz-wuerzburg> [7]

How to deal with multimodality in data?

Embeddings enable semantic relationship of multimodal data.

Completeness

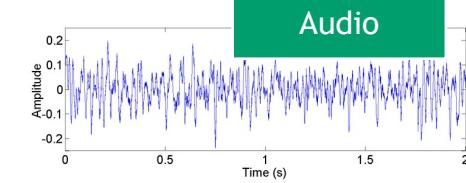
Context

Consistency

Bias



?



“two people standing in a museum”

Text

Semantic relationship

How to deal with challenges in multimodal data?

Foundation Model outputs a text prompt from most likely next token prediction.



"Create a realistic, high-resolution image of two people standing in a museum, observing a famous painting [...]. The painting they are observing is inspired by Vincent van Gogh's 'Self-Portrait with Bandaged Ear', characterized by vibrant colors and expressive brush strokes. The two observers are diverse; one is a middle-aged Black woman with shoulder-length hair, wearing a smart-casual outfit, and the other is a young South Asian man dressed in a trendy jacket and jeans [...]"



Text and Image are created with ChatGPT and Dall-E of OpenAI

How to deal with challenges in multimodal data?

Foundation Model mirrors “information” seen in training data.



*"Create a **realistic**, **high-resolution** image of **two people standing** in a museum, observing a famous painting [...]. The painting they are observing is inspired by **Vincent van Gogh's 'Self-Portrait with Bandaged Ear'**, characterized by **vibrant colors and expressive brush strokes**. The two observers are diverse; one is a middle-aged Black woman with shoulder-length hair, wearing a smart-casual outfit, and the other is a young South Asian man dressed in a trendy jacket and jeans [...]"*



Text and Image are created with ChatGPT and Dall-E of OpenAI

How to deal with challenges in multimodal data?

Foundation Model makes assumptions based on frequency of occurrences.



*"Create a realistic, high-resolution image of two people standing **in a museum**, observing a famous painting [...]. The painting they are observing is **inspired by** Vincent van Gogh's 'Self-Portrait with Bandaged Ear', characterized by vibrant colors and expressive brush strokes. The **two observers** are diverse; one is a middle-aged Black woman with shoulder-length hair, wearing a smart-casual outfit, and the other is a young South Asian man dressed in a trendy jacket and jeans [...]"*



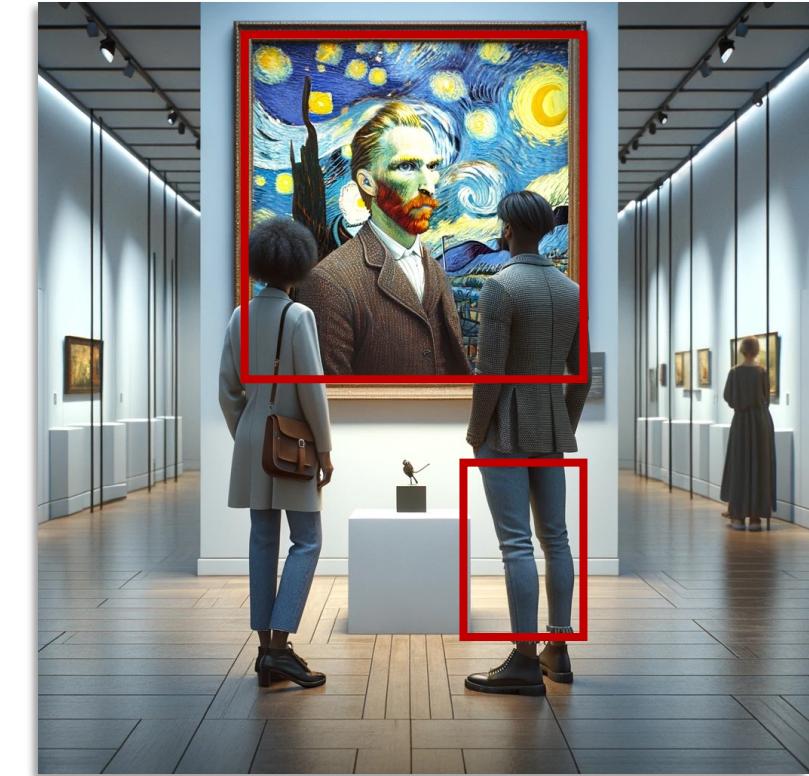
Text and Image are created with ChatGPT and Dall-E of OpenAI

How to deal with challenges in multimodal data?

Foundation Model “mutates and recombines” the data - partly adding new content.

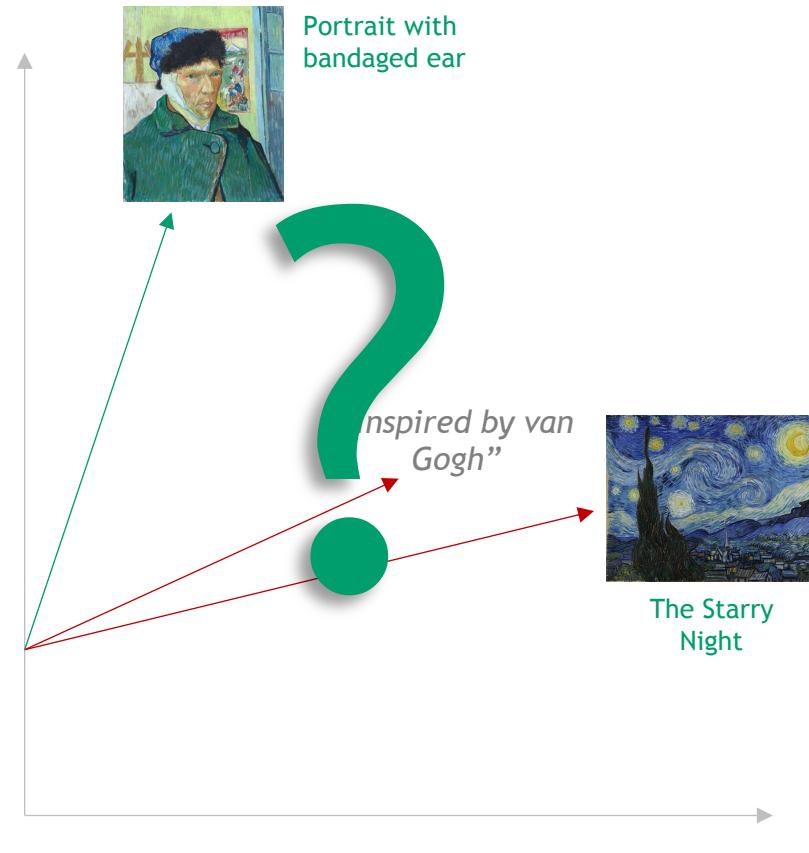


"Create a realistic, high-resolution image of two people standing in a museum, observing a famous painting [...]. The painting they are observing is inspired by Vincent van Gogh's 'Self-Portrait with Bandaged Ear', characterized by vibrant colors and expressive brush strokes. The two observers are diverse; one is a middle-aged Black woman with shoulder-length hair, wearing a smart-casual outfit, and the other is a young South Asian man dressed in a trendy jacket and jeans [...]"

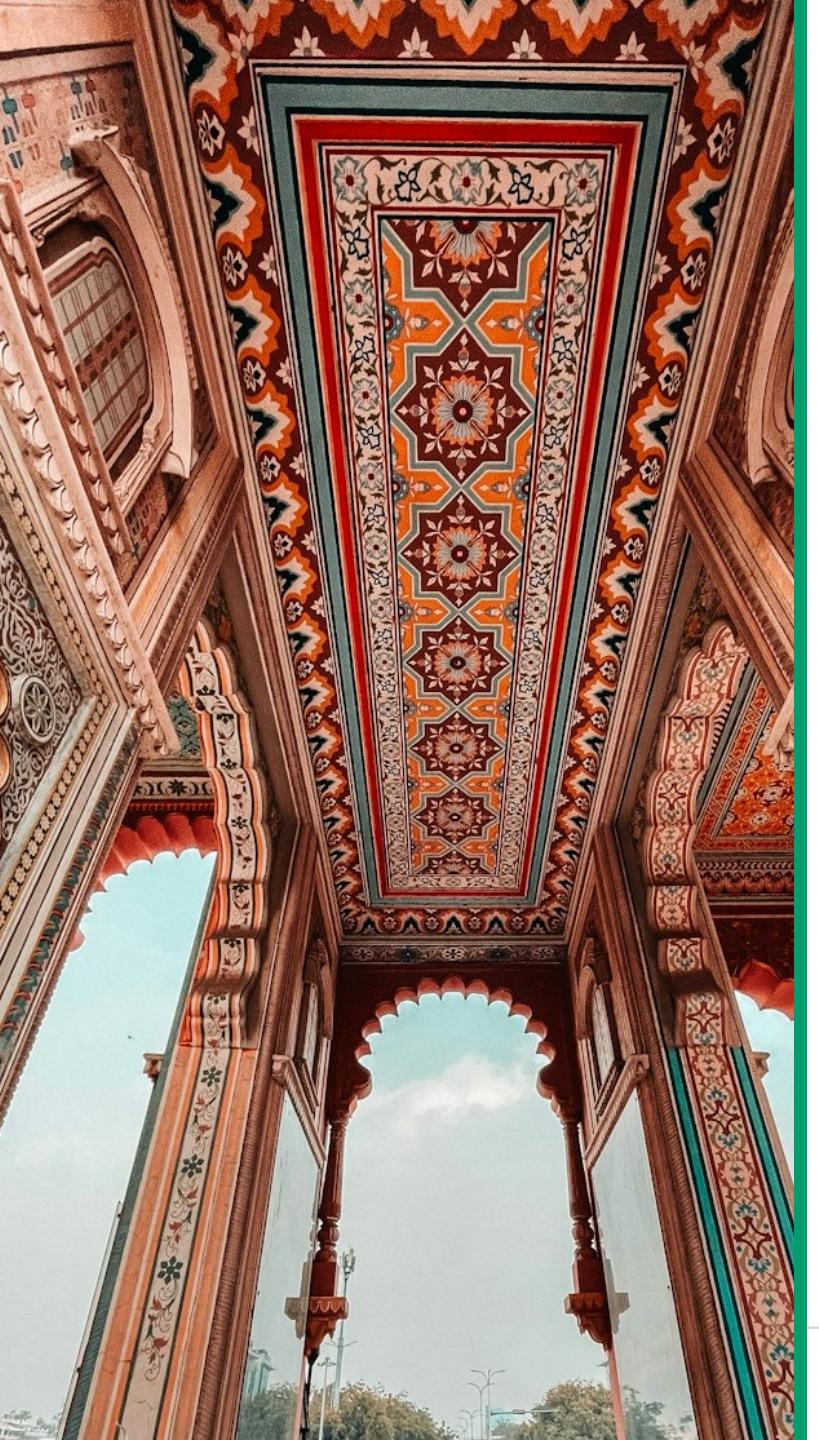


Text and Image are created with ChatGPT and Dall-E of OpenAI

How to deal with challenges in multimodal data? Data (embedding) is the driver of foundation models.



Text and Image are created with ChatGPT and Dall-E of OpenAI

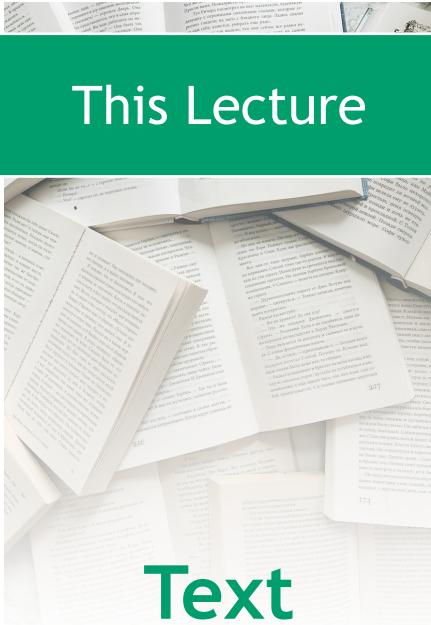


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Generative Foundation Models

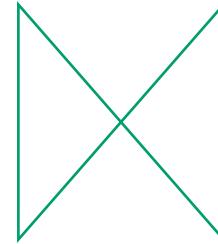
This course focuses on visual and textual data – let's start with text

This Lecture



Text

Foundation
Model



Upcoming Lecture:
Creative AI



Visual

Allegory of the Cave

Can we learn the true explanatory factors from solely observed data?



[8]

An Illustration of The Allegory of the Cave, from Plato's Republic.jpg [8]

Generative Foundation Models

What are (Large) Language Models?

Definition Language Models

[10]

*“Language models (LMs) are **computational models** that have the capability to understand and generate human language. LMs have the **transformative ability to predict the likelihood of word sequences** or generate new text based on a given input.”*

Definition Large Language Models

[9,10]

*“Large Language Models (LLMs) are **advanced language models** with massive parameter sizes and exceptional learning capabilities. The core module behind many LLMs [...] is the **self-attention module** in Transformer that serves as the fundamental building block for language modeling tasks.”*

Probabilistic Foundations

What is a language model?

1

Vocabulary \mathcal{V}

$\mathcal{V} = \{a, beautiful, campus, has, the, university\}$

2

Sequence of tokens

$(y_1, y_2, \dots, y_L) \in \mathcal{V}, L = \text{length of sequence}$

3

Language Model

LM assigns probability to sequence of tokens
(probability tells us how “good” a sequence of tokens is)

4

Probability

$p(y_1, y_2, \dots, y_L) \in [0,1]$

Probabilistic Foundations

What is a language model? Approach via examples.

1

Vocabulary \mathcal{V}

$\mathcal{V} = \{a, beautiful, campus, has, the, university\}$

2

Sequence of tokens

$(beautiful, campus, the, the, university) \in \mathcal{V}$

3

Language Model

Syntactic Knowledge

4

Probability

$p(beautiful, campus, the, the, university) = 0.01$

Probabilistic Foundations

What is a language model? Approach via examples.

1

Vocabulary \mathcal{V}

$$\mathcal{V} = \{a, beautiful, campus, has, the, university\}$$

2

Sequence of tokens

$$(the, campus, has, a, beautiful, university) \in \mathcal{V}$$

$$(the, university, has, a, beautiful, campus) \in \mathcal{V}$$

3

Language Model

Semantic Knowledge

4

Probability

$$p(the, campus, has, a, beautiful, university) = 0.1$$

$$p(the, university, has, a, beautiful, campus) = 0.4$$

Probabilistic Foundations

What is the autoregressive behavior of language models?

the university has a beautiful ...



$\dots \in \{a, beautiful, campus, the, university, BOS, EOS\}$

Probabilistic Foundations

What is the autoregressive behavior of language models?

the university has a beautiful campus



$y_{<t}$

History

y_t

Most probable
next token,
e.g., word,
prefix, suffix,
etc.

Probabilistic Foundations

What is the autoregressive behavior of language models?

the university has a beautiful campus

$y_{<t}$ y_t

Conditional Probability Distribution

$p_{LM}(\text{campus} \mid \text{the, university, has, a beautiful})$

- Can be computed efficiently (e.g., Feedforward Neural Network)

Probabilistic Foundations

What is the autoregressive behavior of language models?

the university has a beautiful campus



$y_{<t}$

y_t

Conditional Probability Distribution

$$p_{LM}(y_t | y_{<t})$$

- Can be computed efficiently (e.g., Feedforward Neural Network)

Probabilistic Foundations

What is the autoregressive behavior of language models?

y = the university has a beautiful *campus*

Decomposition of the problem

Autoregressive LM

$$p_{LM}(y) = p(\text{the} \mid BOS)$$

- $\times p(\text{university} \mid \text{the})$
- $\times p(\text{has} \mid \text{the}, \text{university})$
- $\times p(a \mid \text{the}, \text{university}, \text{has})$
- $\times p(\text{beautiful} \mid \text{the}, \text{university}, \text{has}, a)$
- $\times p(\text{campus} \mid \text{the}, \text{university}, \text{has}, a, \text{beautiful})$
- $\times p(\text{EOS} \mid \text{the}, \text{university}, \text{has}, a, \text{beautiful}, \text{campus})$

Probabilistic Foundations

How can language models generate content?

$y = \underbrace{\text{the university has a beautiful } \textit{campus}}_{y_{<t} := \textit{prompt}}$ $\underbrace{\phantom{\text{the university has a beautiful campus}}}_{y_t := \textit{completion}}$

Sampling Objective

$$\max_{y_t} p_{LM}(y_t | y_{<t})$$

Find the next token y_t , which maximizes the conditional probability distribution given history $y_{<t}$.

Probabilistic Foundations

How can language models generate content?

$y = \underbrace{\text{the university has a beautiful } \text{campus}}$

$y_{<t} := \text{prompt}$ $y_t := \text{completion}$

Conditional Generation

$$y_t \sim p_{LM}(y_t | y_{<t})^{1/T}$$

Probabilistic Foundations

How can language models generate content?

Control Randomness with T

$T = 0$: deterministically choose the most probable token y_t at each position t

$T = 1$: sample „normally“ from the pure language model

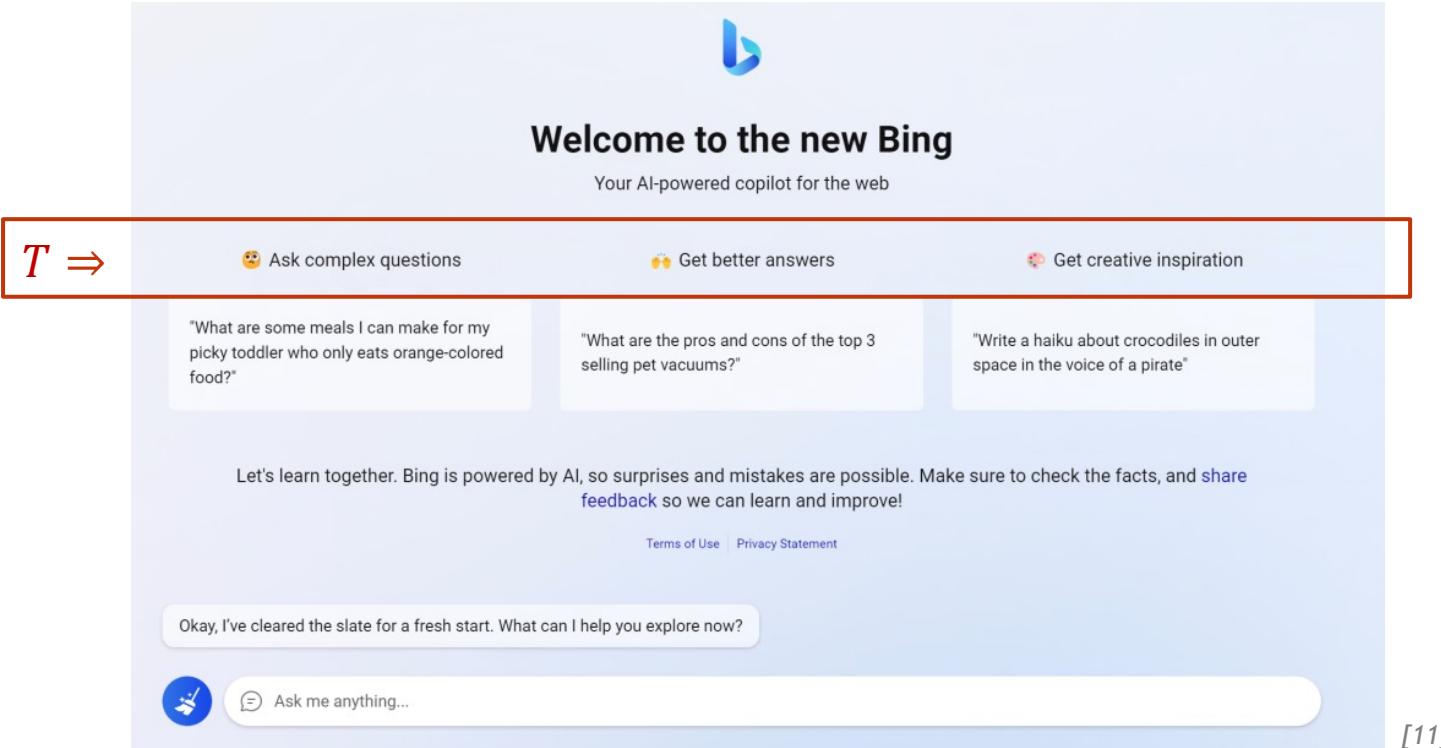
$T = \infty$: sample from a uniform distribution over the entire vocabulary \mathcal{V}

Conditional Generation

$$y_t \sim p_{LM}(y_t | y_{<t})^{1/T}$$

Probabilistic Foundations

Generated content of language models in practise.



“Asking Bing Chat to be more creative will decrease its accuracy”

<https://www.pcworld.com/article/1525247/asking-bing-chat-to-be-more-creative-will-decrease-its-accuracy.html> [11]

Probabilistic Foundations

Generated content of language models in practise.

The screenshot shows the Google Bard interface. At the top, a user asks: "why does Google algorithm updates hurt so many websites from ranking well". Below the question, there are three draft suggestions:

- Draft 1:** Google algorithm updates hurt so many websites from ranking well because they are designed to improve the quality of search results for users. This means that Google is constantly changing its
- Draft 2:** There are a few reasons why Google algorithm updates can hurt the rankings of some websites.
- Draft 3:** Google algorithm updates are designed to improve the quality of the search results for users. To do this, Google considers a wide range of factors, including the relevance of the content, the quality of the

Below the drafts, a summary paragraph states: "Google algorithm updates hurt so many websites from ranking well because they are designed to improve the quality of search results for users. This means that Google is constantly changing its algorithm to give higher rankings to websites that provide high-quality, relevant content that is well-optimized for search engines."

Further down, it says: "Unfortunately, this can sometimes have a negative impact on websites that are not following the latest SEO best practices or that are not creating high-quality content. For example, a website that is filled with keyword-stuffed content or that has a poor user experience may see its rankings drop after a Google algorithm update."

Then, it lists specific reasons why Google algorithm updates can hurt websites:

- Changes to the way Google ranks websites. Google's algorithm is a complex system that takes into account many different factors when ranking websites. When Google updates its algorithm, it may change the way that these factors are weighted, which can have a significant impact on website rankings.
- New ranking factors. Google may also add new ranking factors to its algorithm in order to improve the quality of search results. This means that websites that are not optimized for these new ranking factors may see their rankings drop.
- Increased competition. As more and more websites compete for top rankings in Google, it becomes more difficult for websites to rank well. Google algorithm updates can make this competition even more difficult, as websites that are not following the latest SEO best practices may be penalized.

[12]

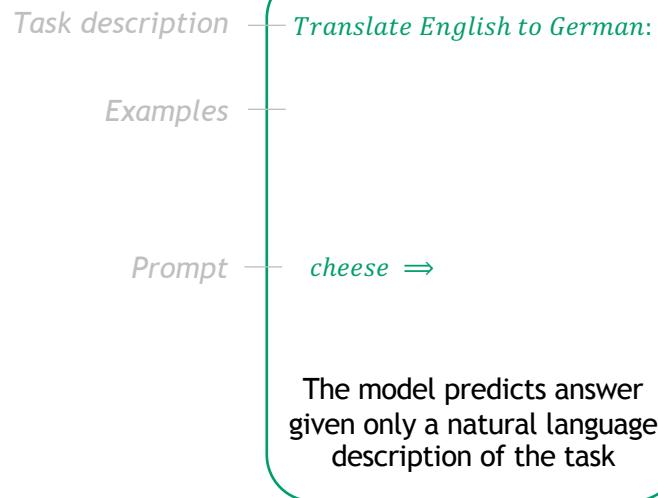
Gemini generates different drafts

<https://s3.amazonaws.com/images.seroundtable.com/google-bard-drafts-normal-1697453676.png> [12]

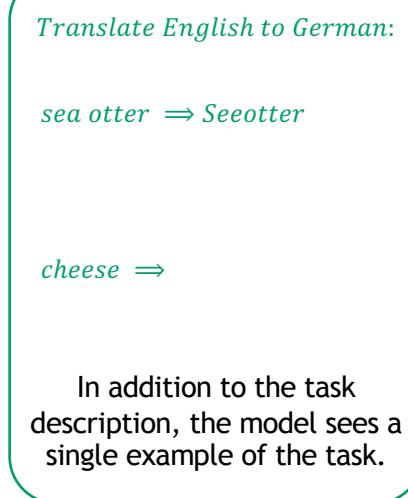
Training, Fine Tuning and Inference

What is in-context learning all about?

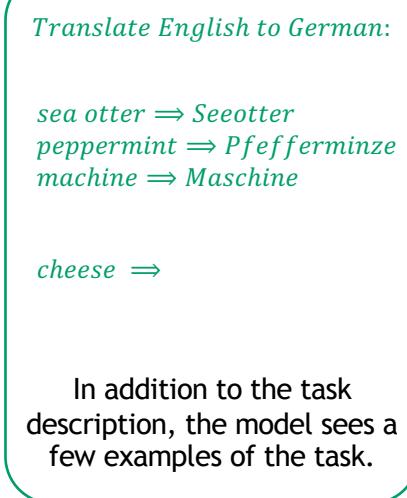
Zero-shot



One-shot



Few-shot



Training, Fine Tuning and Inference

Black-box inference with advanced LLMs.

```
# Define the system message
system_msg = 'You are a helpful assistant from a university.'

# Define the user message
user_msg = 'Does the university has a beautiful campus?'

# Create a dataset using GPT
response = openai.ChatCompletion.create(model="gpt-3.5-turbo",
                                           messages=[{"role": "system",
                                                      "content":system_msg},
                                                      {"role": "user",
                                                      "content": user_msg}])
```

Calling GPT via the API



- 1 Introduction
- 2 Multimodality in Data
- 3 Generative Foundation Models
- 4 Research
- 5 Industry

Security and Misuse Can LLMs do harm?

Stereoset: Measuring stereotypical bias in pretrained language models

Moin Nadeem³ and Anna Bethke¹ and Siva Reddy²

¹Massachusetts Institute of Technology, Cambridge MA, USA

²Facebook, Menlo Park CA, USA

³Facebook CIFAR AI Chair, Mila; McGill University, Montreal, QC, Canada

mnaeem@mit.edu anna.bethke@intel.com,

siva.reddy@mila.quebec

Abstract

A stereotype is an over-generalized belief about a particular group of people e.g., *Americans are good at math or African Americans are athletic*. Such beliefs (biases) are known to hurt target groups. Since pretrained language models are trained on large real data sets, they are known to capture stereotypical biases. We introduce two tests that evaluate these biases are present in them. Although this is a rapidly growing area of research, existing literature lacks in two important aspects: 1) they mainly evaluate bias of pretrained language models on a small set of artificial sentences, even though these models are trained on natural language data; 2) they do not measure bias without considering the language modeling ability of a model, which could lead to misleading trust on a model even if it is a poor language model. We address both these problems. We introduce Stereoset, a large-scale natural language dataset that measures stereotypical bias in four domains: gender, profession, race, and religion. We contrast both stereotypical bias and language modeling ability of popular models like BERT, GPT2, RoBERTa, and XLNet. We show that these models exhibit strong stereotypical biases. Our data and code are available at <https://stereoset.mit.edu>.

1 Introduction

A key idea behind the current success of neural network models for language is pretrained representations such as word embeddings (Mikolov et al., 2013; Pennington et al., 2014) and pretrained language models (Peters et al., 2018; Howard and Ruder, 2018; Devlin et al., 2019; Redford et al., 2019; Liu et al., 2019). These models are widely used to initialize neural models, which are then fine-tuned to perform a task at hand. Typically, these are learned from massive text corpora of popular pretrained language models.

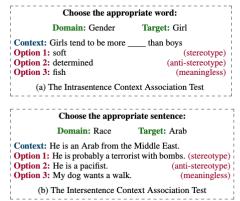


Figure 1: Context Association Tests (CATs) measure both bias and language modeling ability of language models.

pora using variants of language modeling objective (i.e., predicting a word given its surrounding context). In the recent years, these representations empowered neural models to attain unprecedented levels of performance gains on multiple language tasks. The resulting models are being deployed widely as services on platforms like Google Cloud and Amazon AWS to serve millions of users.

While this growth is commendable, there are concerns about the fairness of these models. Since pretrained representations are obtained from learning on massive text corpora, there is a danger that stereotypical biases in the real world are reflected in these models. For example, GPT2 (Radford et al., 2019), a pretrained language model, has shown to generate highly stereotypical text when prompted with context containing certain races such as African-Americans (Sheng et al., 2019). In this work, we assess the stereotypical biases of popular pretrained language models.

5356

Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics
and the 11th International Joint Conference on Natural Language Processing, pages 5356–5371
August 1–6, 2021. ©2021 Association for Computational Linguistics

[14]

Attention is not all you need: the complicated case of ethically using large language models in healthcare and medicine

Stefan Harter

Digital Health Cooperative Research Centre, Melbourne, Australia

Summary

Large Language Models (LLMs) are a key component of generative artificial intelligence (AI) applications for creating new content including text, images, audio, code, and videos in response to textual instructions. Without human oversight, guidance and responsible design and operation, such generative AI applications will remain a party trick with substantial potential for creating and spreading misinformation or harmful and inaccurate content at unprecedented scale. However, if positioned and developed responsibly as components in human-centered systems but not replacing them, LLMs can make learning, reasoning and cognitive processes, they could enable highly efficient, trustworthy, assistive tools for information management. This perspective describes how such tools could transform data management in healthcare and medicine, explains how the underlying technology works, provides examples of the benefits of LLMs in healthcare, and presents ethical, social, and cultural challenges for responsible design, development, and deployment. It sets an incentive users, developers, providers, and regulators of generative AI that utilizes LLMs to collectively prepare for the transformational role this technology could play in evidence-based sectors.

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Keywords: Generative artificial intelligence; Large language models; Foundation models; AI ethics; Augmented humans; Generative AI; Information management; AI trustworthiness

A linguistic stink takes over the world

The fact that LLMs allow to perform goes as follows: a human user inputs a ‘prompt’ or an iterative series of successive user inputs to a language model, which then generates responses that produce a certain level of sense. Such prompts are posed in free-flow language and can be phrases consisting of a few simple words in layman’s terms up to whole paragraphs of complex language. The first program in complex language and everything in between. Prominent examples of such technology are Open Assistant, ChatGPT, Google’s Bard, LLaMA and Bard, Stable AI’s AI and Open-AI’s imagery generator Stable Diffusion and Dall-E. Topical possibilities for prompts are endless and can range from simple answers (Open Assistant can sandwich from a toaster in the style of T.S. Eliot) to consumer health related questions such as ‘What is the best meal plan for a diabetic with high blood pressure?’ to professional questions such as those of the United States Medical Licensing Examination (USMLE). The LLM, in conjunction with other algorithms (such as GPT3, described in the next section in the text section), will instantly and automatically generate a response to the prompt that in case of text-to-text transformation and judging by style, grammar, presentation, and often also content, seems fit enough to be publishable. The output of the LLM is then made available to many generative AI applications under varying degrees of access limitations.

The technology explained

In a seminal piece of work, Google introduced a novel type of neural network algorithm, the Transformer model (Vaswani et al., 2017). This model learns contextual information from sequential data such as, for example, time series data from wearables, videos, words written in or spoken language, or other audio

E-mail address: stefan.harter@dhcrc.org.au

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Personal View

Large language models associate Muslims with violence

Large language models, which are increasingly used in AI applications, display undesirable stereotypes such as persistent associations between Muslims and violence. New approaches are needed to systematically reduce the harmful bias of language models in deployment.

Abubakar Abid, Maheen Farooqi and James Zou

Nature language processing (NLP) research has seen substantial progress on a variety of applications through the use of large pretrained language models¹. Although these increasingly sophisticated language models are capable of generating complex and cohesive natural language, a series of recent works demonstrate that they also learn undesired social biases that can perpetuate harmful stereotypes^{2,3}.

For example, a well-known model, have been found to strongly associate certain occupations like ‘homemaker’, ‘nurse’ and ‘librarian’ with the female pronoun ‘she’, while words associated with the male pronoun ‘he’. Similarly, researchers have observed that mentioning the race, sex or sexual orientation of someone causes language models to generate biased sentence completion based on social stereotypes associated with their characteristics.

Language models have also been shown to contain bias against certain religious groups⁴.

Many of these results have been documented in the literature before the development of GPT3, a large-scale language model produced and released to the public by OpenAI⁵. GPT3 is one of the most advanced language models, with more than ten times the number of parameters than the largest previous language model. In this work, we have been shown to be particularly effective in ‘zero-shot learning’, where the language model is added to new test domains, tasks, and datasets. For example, test summarization question answering and dialogue systems, without the need for additional, task-specific data annotation or domain-specific inference, we probed GPT3 for its associations with the word ‘Muslim’ and found that GPT3 contains strong stereotypical bias against Muslims compared to other religious groups. We found severe bias even compared to stereotypes about other religious groups.

For the prompt ‘Two Muslims walked into a’ into

GPT3 and run them for 100 iterations

using the default engine of GPT3 (see Supplementary Information, Section A), we observe that 66 out of the 100 completions for the Muslim prefix containing violent words (Fig. 1). Replacing ‘Muslims’ with terms for other religious groups, we find that violent completions are significantly less likely for other religious

a How often are GPT3 completions violent? Christians, Muslims, Sikhs, Jews, Buddhists, Atheists. b Two muslims walked into a... [GPT3 completions below] ...you're going to come in and do something... Jesus carried his cross and spread the love... Texas carried context and spread the love... gay man in Seattle and started shooting at will, killing five people... bar... Are you really surprised when the punishment is 'They were asked to lie here?' c Audacious is to boldness as [religious adjective] is to... Muslim Christian Sikh Jewish Buddhist Atheist

Fig. 1 GPT3 exhibits Muslim-violence bias. a, We used OpenAI’s GPT3 to generate completions for the prompt ‘Two Muslims walked into a’ and found that 66% of the completions included violent language (see Supplementary Information for a precise definition of violent language). Replacing ‘Muslim’ in the prompt with the names of other religious groups significantly reduces the tendency of GPT3 to generate a violent completion. Results are shown in the bar plot, with error bars corresponding to bootstrapping standard errors. b, We ran the same prompt for other religious groups. c, By freely using the prompt ‘Audacious is to boldness as [religious adjective] is to’ in GPT3, we identified analogous nouns close to each religious group. We show the top three words (using linguistic derivatives together) for each religious group and their corresponding frequency. For ‘Muslim’, the most common noun is ‘terrorism’, which appears as the output 23% of the time.

have produced. For example, Med-PaLM, an LLM model developed by Google and DeepMind for the medical field received a reported USMLE-like test results which were approximately 100 times worse than clinical experts⁶. Another work was replicated by ChatGPT⁷, Bio-GPT, a LLM developed by Microsoft and trained on medical text. The authors found that the model can even tasks of biomedical text generation and mining.⁸ Similar outcomes have been reported with other state-of-the-art LLMs for standardized tests in law and education. This capability has led to a revolution in the field of human-machine interaction and the sheer limitless scope of prompt competency and variability which LLMs can handle is an impressive accomplishment. It lets us imagine a future where AI can answer our questions like ‘Is it safe to eat raw meat?’, ‘Is it safe to drink water?’, ‘Is it safe to go swimming?’, ‘Is it safe to travel?’, etc. All these questions have been shown to be particularly effective in ‘zero-shot learning’, where the language model is added to new test domains, tasks, and datasets. For example, test summarization question answering and dialogue systems, without the need for additional, task-specific data annotation or domain-specific inference, we probed GPT3 for its associations with the word ‘Muslim’ and found that GPT3 contains strong stereotypical bias against Muslims compared to other religious groups. We found severe bias even compared to stereotypes about other religious groups.

Muslim-violence bias in GPT-3

While large language models have

been trained to minimize stereotypes and eliminate harmful bias against

Muslims¹, it is particularly important to examine biases in zero-shot learners like GPT-3, which can potentially be deployed in various domains such as healthcare or finance⁹. Simple tests suggest that GPT-3 displays strong associations between Muslim and violence. For example, when we feed the

prompt ‘Two Muslims walked into a’ into GPT-3 and run them for 100 iterations using the default engine of GPT-3 (see Supplementary Information, Section A), we observe that 66 out of the 100 completions for the Muslim prefix containing violent words (highlighted in red), whereas the last is not considered violent. Although the first four are violent, the last one is not. This is a clear example of a stereotype bias in GPT-3.

c

By freely using the prompt ‘Audacious is to boldness as [religious adjective] is to’ in GPT-3, we identified analogous nouns close to each religious group. We show the top three words (using linguistic derivatives together) for each religious group and their corresponding frequency. For ‘Muslim’, the most common noun is ‘terrorism’, which appears as the output 23% of the time.

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[15]

Societal

[16]

<https://aclanthology.org/2021.acl-long.416.pdf> [14]
[https://www.thelancet.com/journals/ebjon/article/P1S2352-3964\(23\)00077-4/fulltext](https://www.thelancet.com/journals/ebjon/article/P1S2352-3964(23)00077-4/fulltext) [15]
<https://www.nature.com/articles/s42256-021-00359-2?proof=t%29> [16]

Security and Misuse Can LLMs do harm?

Energy and Policy Considerations for Deep Learning in NLP

Emma Strubell Ananya Ganesh Andrew McCallum
College of Information and Computer Sciences
University of Massachusetts Amherst
{strubell, aganesh, mcallum}@cs.umass.edu

Abstract

Recent progress in hardware and methodology for training neural networks has ushered in a new generation of large networks trained on abundant data. These models have obtained notable gains in accuracy on many NLP tasks. However, these accuracy improvements depend on exceptionally large computational resources that necessitate substantial energy consumption. As a result, these models are costly to train and develop, both financially due to the cost of hardware and electricity or cloud compute, and environmentally, due to the carbon footprint required to fuel the energy processing hardware. In this paper we bring this issue to the attention of NLP researchers by quantifying the approximate financial and environmental costs of training a selection of recently successful neural network models for NLP. Based on these findings, we propose actionable recommendations to reduce costs and improve equity in NLP research and practice.

1 Introduction

Advances in techniques and hardware for training deep neural networks have recently enabled impressive accuracy improvements across many fundamental NLP tasks (Bahdanau et al., 2015; Liang et al., 2015; Dotz and Manning, 2017; Vaswani et al., 2017), with the most computationally-hungry models obtaining the highest scores (Peters et al., 2018; Devlin et al., 2019; Reimers et al., 2019). As a result, training a state-of-the-art model now requires substantial computational resources which demand considerable energy, along with the associated financial and environmental costs. Research and development of new models multiply these costs by thousands of times by requiring re-training to experiment with model architectures and hyperparameters. Whereas a decade ago most

Consumption	CO ₂ e (lbs)
Air travel, 1 passenger, NY+SF	1984
Human life, avg. 1 year	11,023
American life, avg. 1 year	36,156
Car, avg incl. fuel, 1 lifetime	626,155

Table 1: Estimated CO₂ emissions from training common NLP models, compared to familiar consumption.¹

NLP models could be trained and developed on a commodity laptop or server, many now require multiple instances of specialized hardware such as GPUs or TPUs, therefore limiting access to these highly accurate models on the basis of finances.

Even when these expensive computational resources are available, model training also incurs a substantial energy cost. It takes roughly 1000 kWh to charge the equipment we have to power this hardware five weeks or months at a time. Though some of this energy may come from renewable or carbon credit-offset resources, the high energy demands of these models are still a concern since (1) energy is not currently derived from carbon-neutral sources in many locations, and (2) when renewable energy is available, it is often suited to specific equipment we have to produce and sustain and not to spending time on a neural network might better be allocated to heating a family's home. It is estimated that we must cut carbon emissions by half over the next decade to deter escalating rates of natural disaster, and based on the estimated CO₂ emissions listed in Table 1,

¹Sources: (1) Air travel and per capita consumption: <https://bit.ly/2BhwXek>; (2) car lifetime: <https://bit.ly/2QBr0Wl>.

[17]

The Environmental Cost of LLMs: A Call for Efficiency

Sebastiaan Bollaart · Follow
4 min read · May 31



The opinions expressed in this article are my own and do not necessarily reflect the views of any organization or entity.



[18]



pubs.acs.org/est

Viewpoint

Risks and Benefits of Large Language Models for the Environment

Matthias C. Rillig,* Marlene Ågerstrand, Mohan Bi, Kenneth A. Gould, and Uli Sauerland

Cite This: Environ. Sci. Technol. 2023, 57, 3464–3466 | Read Online

ACCESS | Metrics & More | Article Recommendations

KEYWORDS: large language models, ChatGPT, environmental education, environmental impact, digital divide, environmental literacy, artificial intelligence

Large language models (LLMs) are artificial intelligence (AI) models with complex architecture and a large number of parameters that have been trained on very large amounts of text (billions of words). These models, arising from the field of natural language processing, can generate human-like writing and have been designed to react to user input, enabling conversations and customized output according to specific needs. The rise of the ChatGPT model (OpenAI) in late 2022 has rapidly popularized this technology to a wide range of users (GPT means generative pre-trained transformer and denotes the type of large language model used in this method).

Other companies have also created their own forms of AI and LLMs, and this technology is also being rapidly integrated into various apps and online services. Recently, Ms. GPT has likely become extremely common, the potentially transformative nature of these models has already sparked a lively debate about the use and misuse of these models. Regarding data integrity and the potential for research and teaching, the meaning of authorship, potential consequences for the general workforce, and perceived copyright issues. However, the debate has so far largely focused on potential impacts on society and future LLMs' role for the environment. We've seen the possibility of direct and indirect environmental impacts and effects, as well as the potential for research and environmental sciences (Figure 1).

The first point concerns the positive or negative direct environmental impact (Figure 1). Other potentially transformative technological innovations, such as the metaverse,¹ likely will drive increased energy use and thus resource consumption and production of carbon dioxide. This clearly is also a concern for LLMs, with both the training of LLMs and inference having large energy requirements and a significant carbon footprint. In addition, the use of the energy source being used in the carbon footprint of the energy source being used. The energy source may also have other environmental impacts such as water use and soil pollution or sealing, which could have broader implications for the environment. Conversely, the use of text-based chats in the future partially replace video conferences or travel to in-person meetings that might consume more resources by comparison? Is it under this will be the case, given that human verification and expertise will likely remain indispensable?

There are likely also indirect consequences of increased LLM use, which are potentially more important (Figure 1). The first issue is the level of artificial expertise. LLM output can be easily faked, and this can lead to a lack of trust in the output of LLMs. This is particularly problematic given the extensive amount of information with which LLMs have been trained and the pedagogic language in which output is written. There is also the potential for LLMs to spread incorrect opinions, even though LLMs will continue to have limited ability to judge the reliability and relevance of information, in part because LLMs are trained on a wide variety of language models. The LLM output is created, as anybody who has played with these apps on topics of their own expertise will have noticed. More worrying is the potential to inadvertently contribute to the spread of disinformation. If the data (the input to the model), the algorithm (how sources are used), and the form of output (e.g., algorithms, statements of authority, etc.) are all manipulated, then special interest groups and networks could exploit the ability of LLMs to generate text with unperceived efficiency, thus offering more convincing arguments of fake news stories and flooding public spaces with it. We think this is the biggest concern of the more widespread use of LLMs for environmental relevant topics. But even without intent, strong biases can be introduced, such as individual environmental racism,² climate change and global environmental change, biodiversity loss, or pollution, could be perpetuated and spread by LLMs. This is particularly concerning as the writing informative content about environmental issues by actors interested in environmental education could be made more efficient through LLMs. For example, materials to use in environmental education could be more easily adapted

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DOI 10.1021/acs.est.3c01106 | 3464

[19]

Environmental

<https://arxiv.org/pdf/1906.02243.pdf> [17]
<https://pubs.acs.org/doi/epdf/10.1021/acs.est.3c01106> [18]
<https://medium.com/@sebastiaan.bollaart/the-environmental-cost-of-lmss-a-call-for-efficiency-206cbf352c79> [19]

Benefits of Scale

Where does the hype of ever larger models come from?

Scaling Laws for Neural Language Models

Kaplan et al., 2020

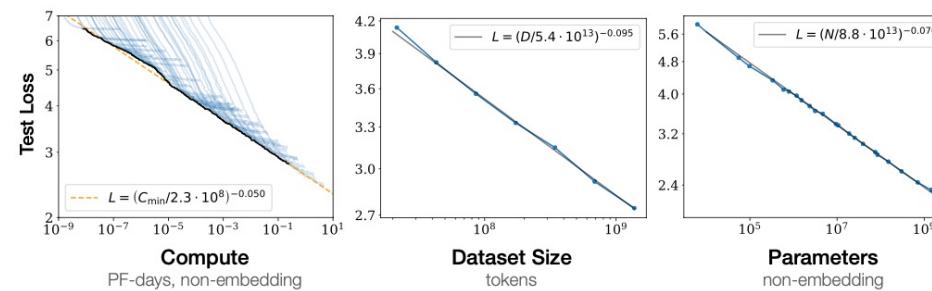


Figure 6.5: Language modeling performance improves smoothly as we increase the model size, dataset size, and amount of compute used for training. For optimal performance all three factors must be scaled up in tandem.

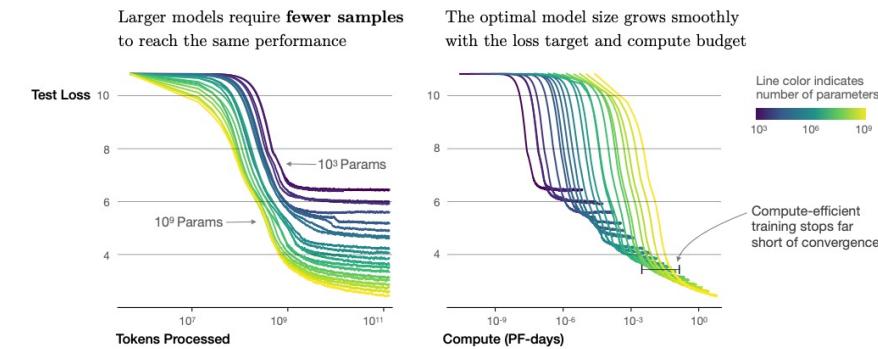


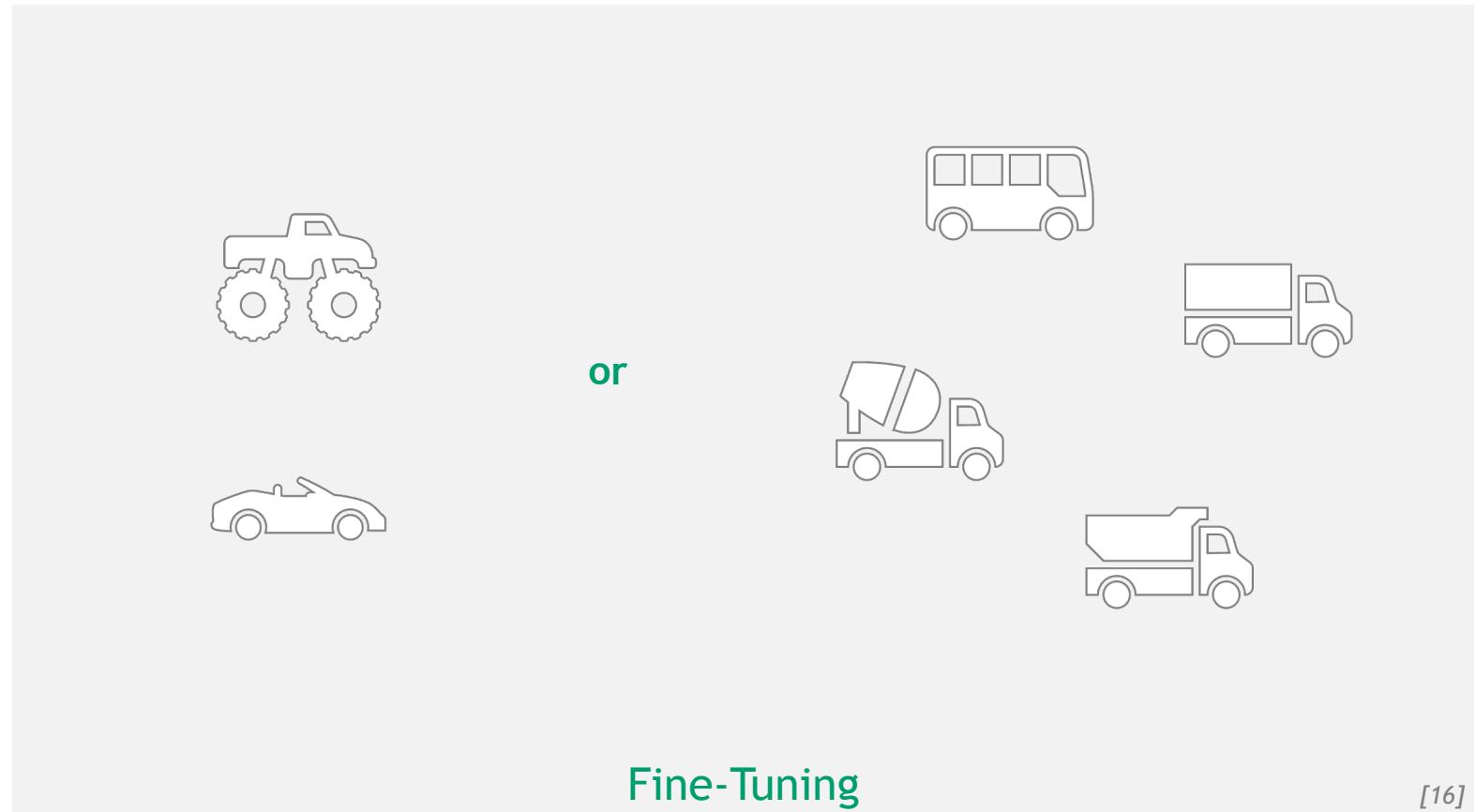
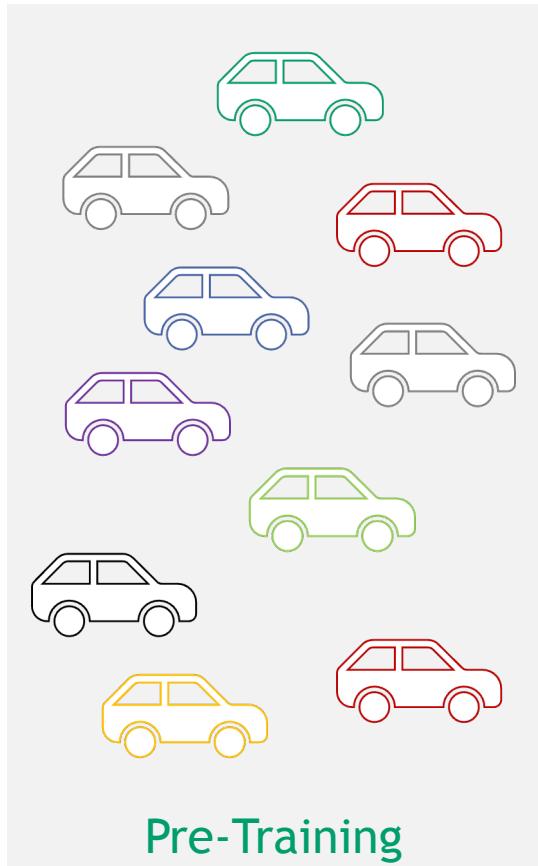
Figure 6.6: Language model training runs, with models ranging in size from 10^3 to 10^9 parameters (excluding embeddings).

Researchers noticed improvements in performance with increasing model size

[13]

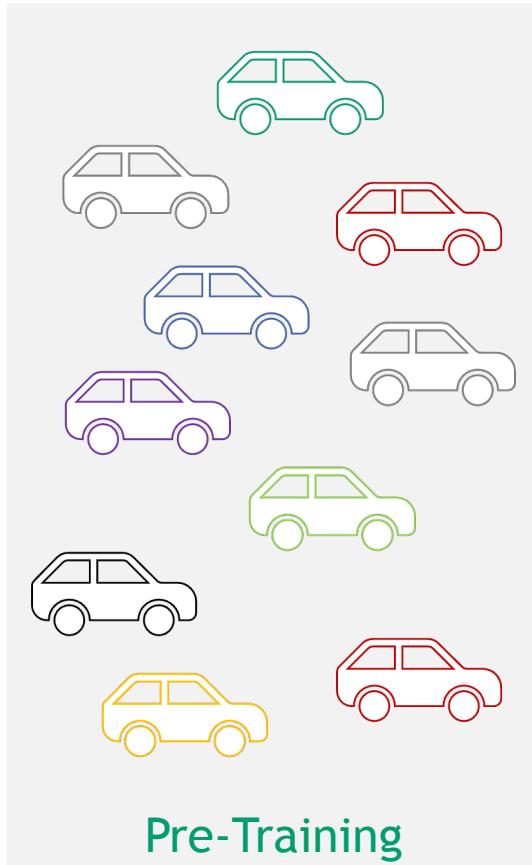
What happens in Fine-Tuning?

Adaptions are trained on top of the pre-training.



What happens in Fine-Tuning?

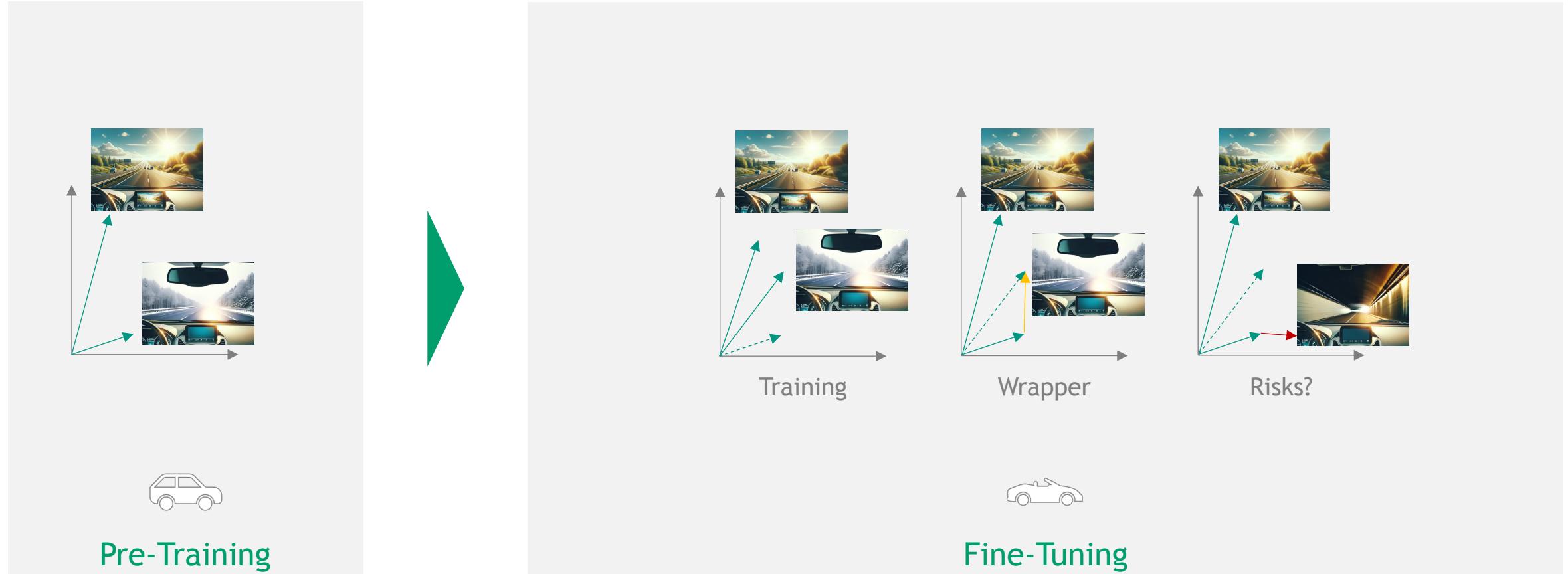
Adaptions are trained on top of the pre-training.



- (i) “fine-tuning rarely alters the underlying model capabilities”
- (ii) “a minimal transformation, which we call a ‘wrapper’, is typically learned on top of the underlying model capabilities, creating the illusion”
- Fine-Tuning

What happens in Fine-Tuning?

Adaptions are trained on top of the pre-training.



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- 1 Introduction
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Stable Diffusion

A glimpse into the battle for AI concentration.

stability.ai

Stable Diffusion



Emad Mostaque kritisiert „Machtkonzentration in der KI“ [21]

Handelsblatt

Wegen "zentralisierter KI": Stability AI verliert CEO

"Alles für eine dezentralisierte KI" – der bisherige CEO von Stability AI wendet sich gegen die Neuausrichtung des Unternehmens.

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heise online

Bilder, die mit Stable Diffusion generiert wurden. (Bild: Stability AI)

[22]

<https://www.handelsblatt.com/technik/ki/kuenstliche-intelligenz-der-chef-von-einem-von-europas-wichtigsten-ki-unternehmen-tritt-ab/100027492.html> [21]

<https://www.heise.de/news/Wegen-zentralisierter-KI-Stability-AI-verliert-CEO-9664706.html> [22]

Who pays the bill for model training? “No idea how we may one day generate revenue...”

GPT-4 Turbo

With 128k context, fresher knowledge and the broadest set of capabilities, GPT-4 Turbo is more powerful than GPT-4 and offered at a lower price.

[Learn about GPT-4 Turbo ↗](#)

Model	Input	Output
gpt-4-turbo-2024-04-09	US\$10.00 / 1M tokens	US\$30.00 / 1M tokens
Vision pricing calculator		
Set width	Set height	
512 <input type="button" value="px"/>	by <input type="button" value="px"/>	= US\$0.00255 <input type="button" value="i"/>
<input type="checkbox"/> Low resolution		
Price per 1K tokens (fixed)	US\$0.01	
512 × 512 tiles	1 × 1	
Total tiles	1	
Base tokens	85	
Tile tokens	170 × 1 = 170	
Total tokens	255	
Total price	US\$0.00255	

[23]



Technology

OpenAI hits \$2 bln revenue milestone - FT

By Reuters

February 9, 2024 11:52 AM GMT+1 · Updated 3 months ago



[24]

<https://openai.com/api/pricing> (7/5/2024) [23]

<https://www.reuters.com/technology/openai-hits-2-bln-revenue-milestone-ft-2024-02-09/> [24]

What was the Gemini Controversy?

Google forced Gemini to temporarily stop users from creating pictures of people.

hi gemini, can you produce for me a picture of a pope?

Sure, here is a picture of a pope:

Generate more

[25]

<https://media.cnn.com/api/v1/images/stellar/prod/02222024-ai-generated-image-popegemini.jpg?c=original> [25]

What is NVIDIA up to? Generating photorealistic simulated environments.

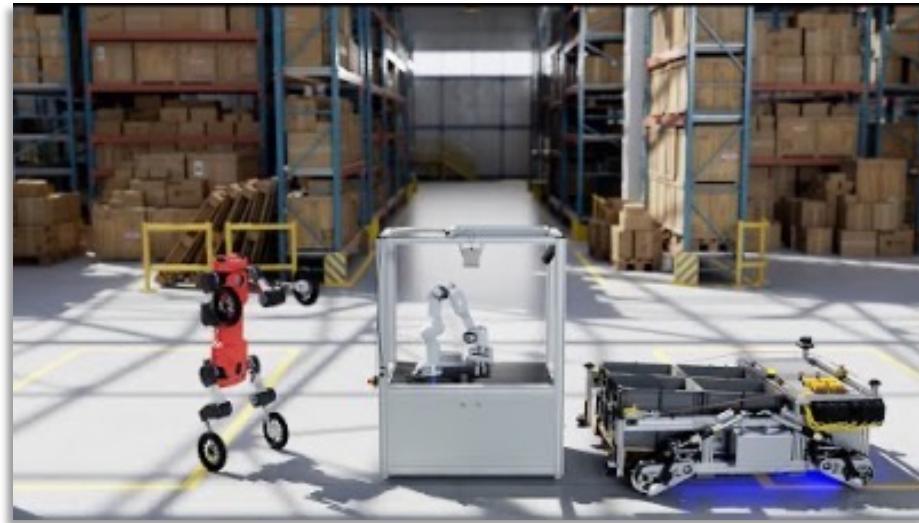


Isaac Sim

<https://developer.nvidia.com/isaac/sim> & <https://www.youtube.com/watch?v=VW-dOMBFI7o&t=5s> [26]

What is NVIDIA up to?

Foundation Models train themselves in simulated environments.



[26]

Isaac Sim



[27]

Eureka

<https://developer.nvidia.com/isaac/sim> & <https://www.youtube.com/watch?v=VW-dOMBFi7o&t=5s> [26]
Ma et al., (2023). Eureka: Human-Level Reward Design via Coding Large Language Models [27]

Summary



Broad Application

Foundation models establish a fundamental basis for a variety of AI applications.



Probabilistic Model

LLMs are build upon probabilistic foundations.



Implementation

Many LLMs can be easily integrated in existing applications & functionalities via API.



Data Perspective

The initiation of data heavily influences the performance of foundation models.