

GPT-NL

FACILITEIT VOOR EEN SOEVEREIN NEDERLANDS TAALMODEL

CLIN 2024

GPT-NL team

Dominique Blok & Erik de Graaf

Consortium



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SURF



Nederlands Forensisch Instituut
Ministerie van Justitie en Veiligheid



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Why GPT-NL?



2022: ChatGPT

Opinion Artificial intelligence

FINANCIAL TIMES

ChatGPT is fluent, clever and
dangerously creative

nrc›

Als de computer beter wordt met
taal dan wij

ChatGPT

The Verge

proves AI is
finally
mainstream –
and things are
only going to get
weirder

ChatGPT: New AI chatbot has everyone
talking to it

BBC

TechScape: Meet ChatGPT, the viral AI
tool that may be a vision of our weird
tech future

the Guardian

Is Chat GPT the world's first truly
useful chatbot?

THE TIMES

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2022: ChatGPT

The New York Times

Will ChatGPT Make Me Irrelevant?



Is no career safe anymore?

nature

Is AI coming for your job? ChatGPT renews fears



AI bot ChatGPT writes smart essays – should professors worry?

the Guardian

What is AI chatbot phenomenon ChatGPT and could it replace humans?

How Generative AI Will Change All Knowledge Work

TIME



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Criticism of LLMs

Transparency is sorely lacking amid growing AI interest

THE NEW STATESMAN

ChatGPT proves that AI still has a racism problem



OpenAI's hunger for data is coming back to bite it

MIT
Technology
Review

Evening Standard.

Meta's use of user data to train its AI violates GDPR, privacy group says

Former OpenAI employees say whistleblower protection on AI safety is not enough

The Verge

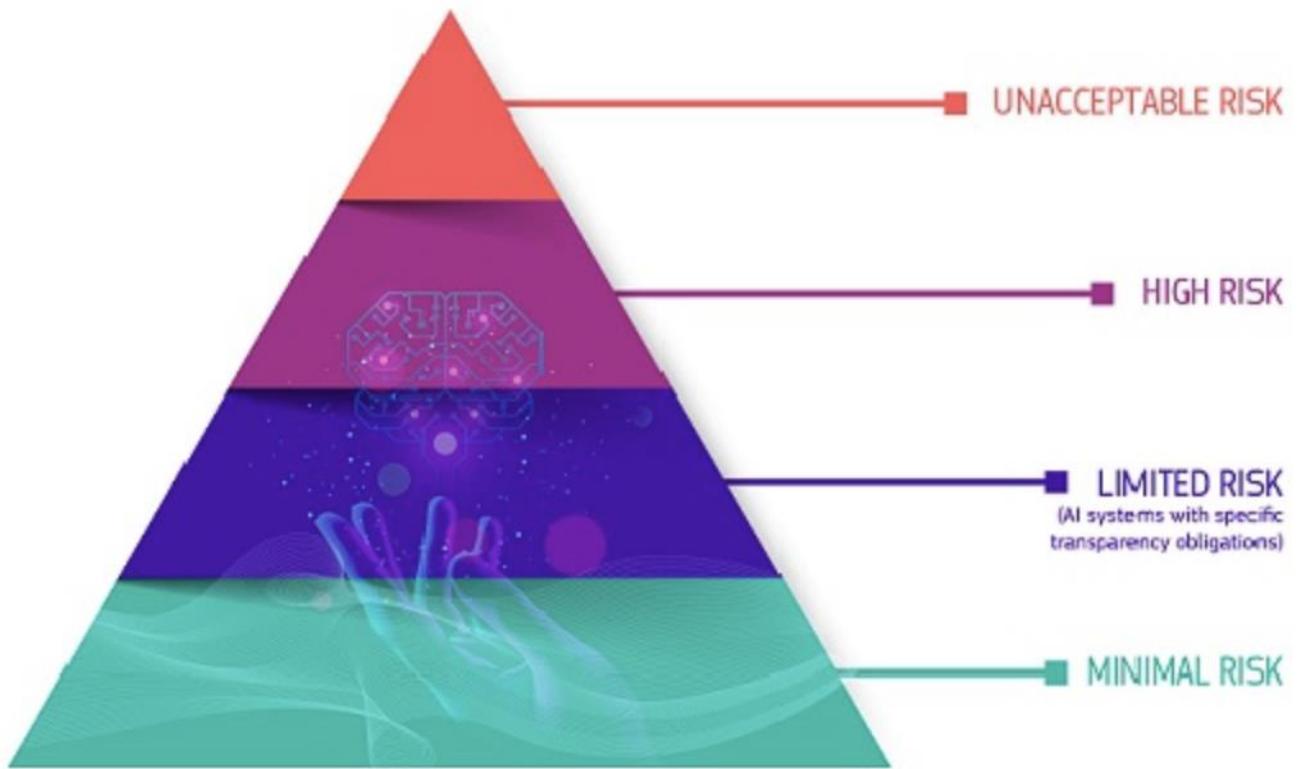


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EU AI Act

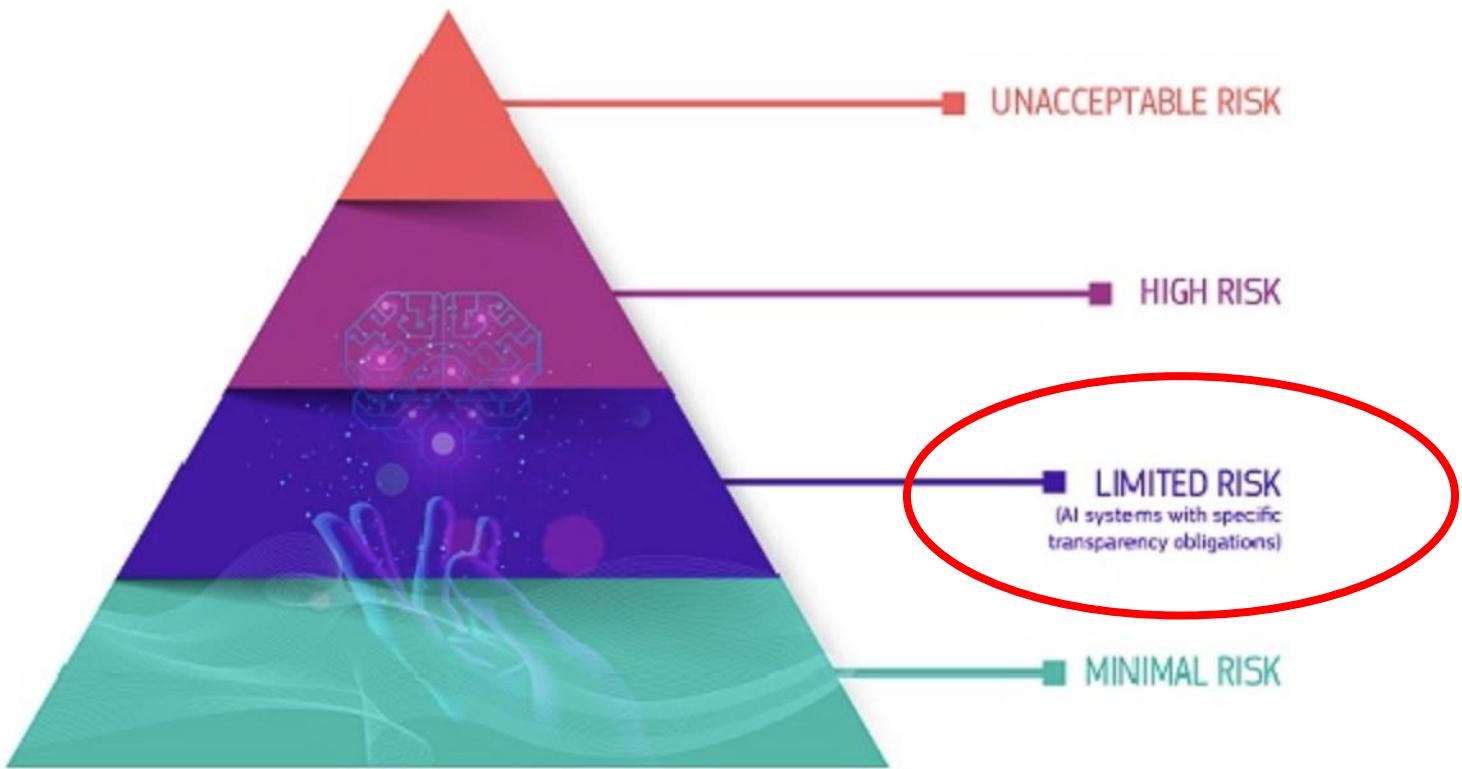
The Regulatory Framework defines 4 levels of risk for AI systems:



- Officially entered into force on August 1st, 2024
- Risk-based approach

EU AI Act

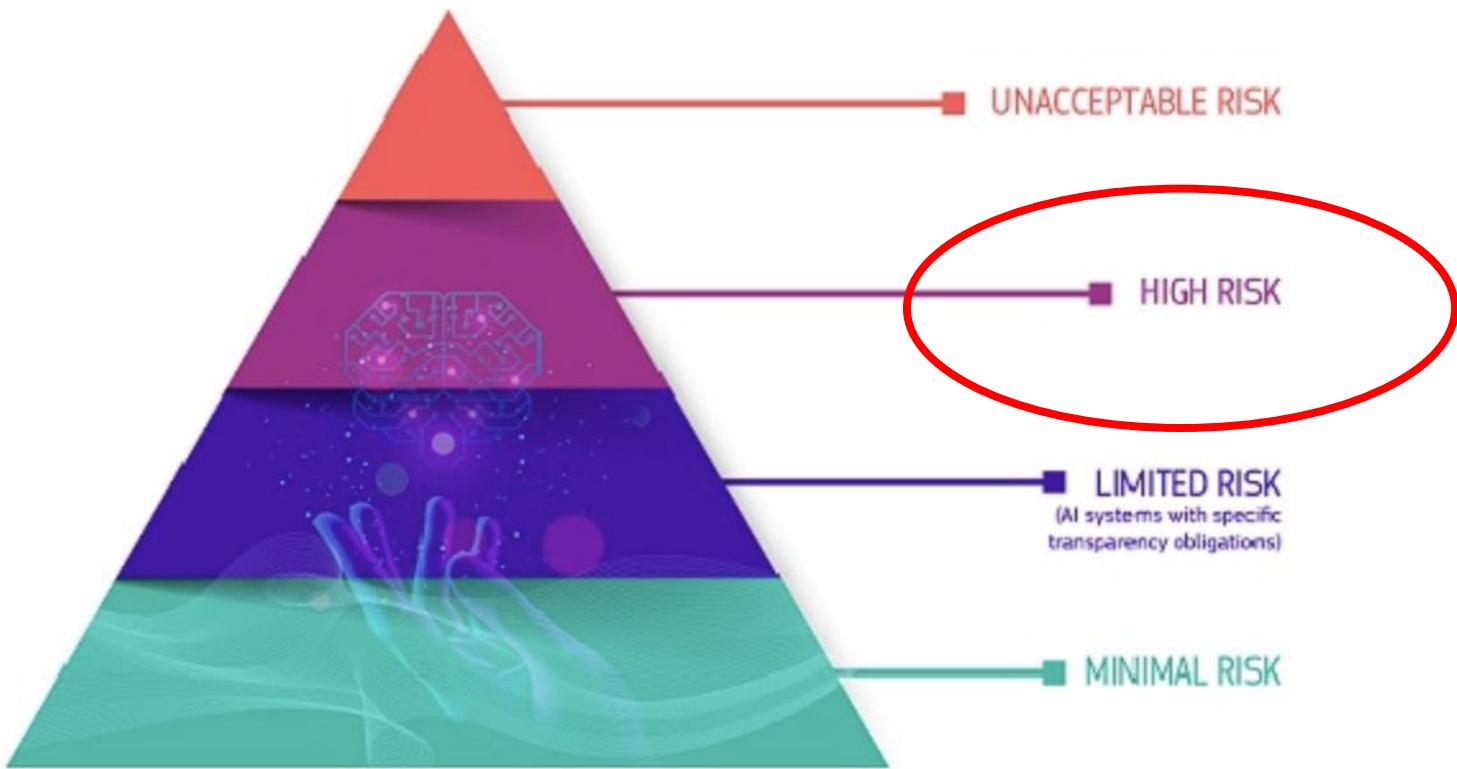
The Regulatory Framework defines 4 levels of risk for AI systems:



- Allowed as long as one is transparent about use of AI
- Examples: chatbots, AI generated text

EU AI Act

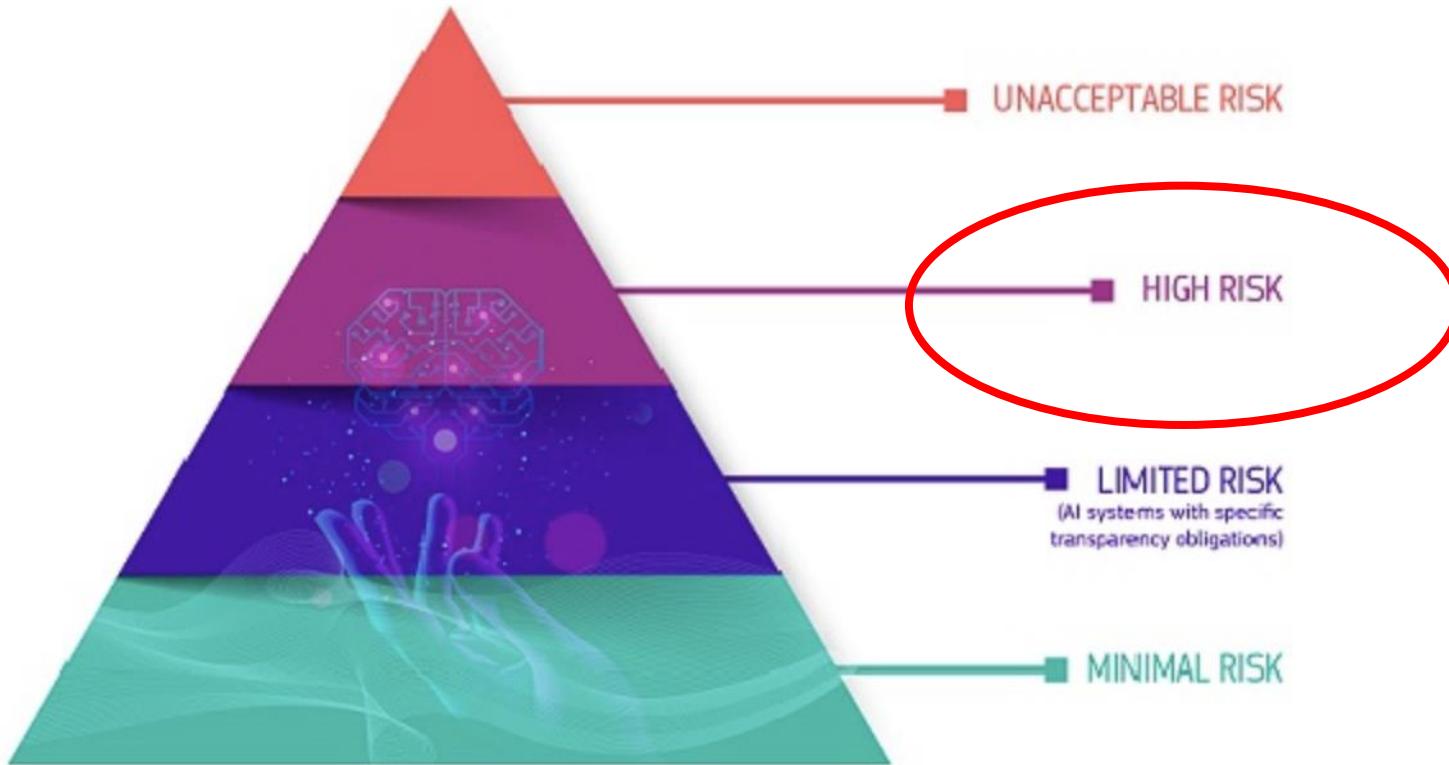
The Regulatory Framework defines 4 levels of risk for AI systems:



- Subject to strict obligations
- Examples: critical infrastructure, education, essential public services such as healthcare, law enforcement, border management, justice and democratic processes

EU AI Act

The Regulatory Framework defines 4 levels of risk for AI systems:



Obligations:

- adequate risk assessment and mitigation systems
- high quality of the datasets feeding the system to minimise risks and discriminatory outcomes
- logging of activity to ensure traceability of results
- detailed documentation providing all information necessary on the system and its purpose for authorities to assess its compliance
- clear and adequate information to the deployer
- appropriate human oversight measures to minimise risk
- high level of robustness, security and accuracy

Legal requirements

- AI Act:
 - Transparency
 - Robustness
 - Safety
- GDPR (General Data Protection Regulation): privacy
- Intellectual Property Law: prohibits taking IP without permission

As compliant as possible

Grading Foundation Model Providers' Compliance with the Draft EU AI Act

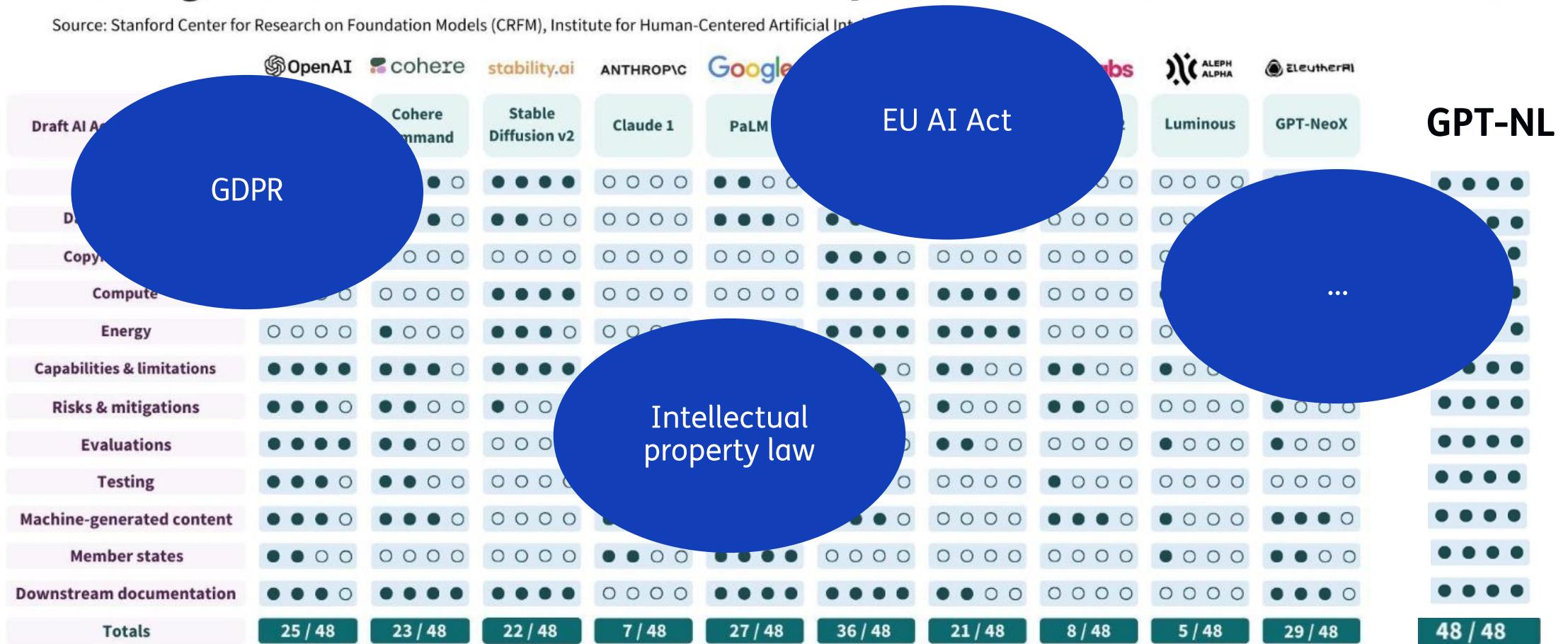
Source: Stanford Center for Research on Foundation Models (CRFM), Institute for Human-Centered Artificial Intelligence (HAI)

| | OpenAI | cohere | stability.ai | ANTHROPIC | Google | BigScience | Meta | AI21labs | ALEPH ALPHA | EleutherAI |
|----------------------------|---------|-----------------|---------------------|-----------|---------|------------|---------|------------|-------------|------------|
| Draft AI Act Requirements | GPT-4 | Coherer Command | Stable Diffusion v2 | Claude 1 | PaLM 2 | BLOOM | LLaMA | Jurassic-2 | Luminous | GPT-NeoX |
| Data sources | ● ○ ○ ○ | ● ● ● ○ | ● ● ● ● | ○ ○ ○ ○ | ● ● ○ ○ | ● ● ● ● | ● ● ● ● | ○ ○ ○ ○ | ○ ○ ○ ○ | ● ● ● ● |
| Data governance | ● ● ○ ○ | ● ● ● ○ | ● ● ○ ○ | ○ ○ ○ ○ | ● ● ○ ○ | ● ● ● ● | ● ● ○ ○ | ○ ○ ○ ○ | ○ ○ ○ ○ | ● ● ● ○ |
| Copyrighted data | ○ ○ ○ ○ | ○ ○ ○ ○ | ○ ○ ○ ○ | ○ ○ ○ ○ | ○ ○ ○ ○ | ● ● ● ○ | ○ ○ ○ ○ | ○ ○ ○ ○ | ○ ○ ○ ○ | ● ● ● ● |
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| Capabilities & limitations | ● ● ● ● | ● ● ● ○ | ● ● ● ● | ● ○ ○ ○ | ● ● ● ● | ● ● ● ○ | ● ● ○ ○ | ● ● ○ ○ | ● ○ ○ ○ | ● ● ● ○ |
| Risks & mitigations | ● ● ● ○ | ● ● ○ ○ | ● ○ ○ ○ | ● ○ ○ ○ | ● ● ○ ○ | ● ● ○ ○ | ● ○ ○ ○ | ● ● ○ ○ | ○ ○ ○ ○ | ● ○ ○ ○ |
| Evaluations | ● ● ● ● | ● ● ○ ○ | ○ ○ ○ ○ | ○ ○ ○ ○ | ● ● ○ ○ | ● ● ● ○ | ● ● ○ ○ | ○ ○ ○ ○ | ● ○ ○ ○ | ● ○ ○ ○ |
| Testing | ● ● ● ○ | ● ● ○ ○ | ○ ○ ○ ○ | ○ ○ ○ ○ | ● ● ○ ○ | ● ● ○ ○ | ○ ○ ○ ○ | ● ○ ○ ○ | ○ ○ ○ ○ | ○ ○ ○ ○ |
| Machine-generated content | ● ● ● ○ | ● ● ○ ○ | ○ ○ ○ ○ | ● ● ● ○ | ● ● ○ ○ | ● ● ○ ○ | ○ ○ ○ ○ | ● ● ○ ○ | ● ○ ○ ○ | ● ● ● ○ |
| Member states | ● ● ○ ○ | ○ ○ ○ ○ | ○ ○ ○ ○ | ● ● ○ ○ | ● ● ● ● | ○ ○ ○ ○ | ○ ○ ○ ○ | ● ○ ○ ○ | ● ○ ○ ○ | ● ● ○ ○ |
| Downstream documentation | ● ● ● ○ | ● ● ● ● | ● ● ● ● | ○ ○ ○ ○ | ● ● ● ● | ● ● ● ● | ● ● ○ ○ | ○ ○ ○ ○ | ○ ○ ○ ○ | ● ● ● ○ |
| Totals | 25 / 48 | 23 / 48 | 22 / 48 | 7 / 48 | 27 / 48 | 36 / 48 | 21 / 48 | 8 / 48 | 5 / 48 | 29 / 48 |

As compliant as possible

Grading Foundation Model Providers' Compliance with the Draft EU AI Act

Source: Stanford Center for Research on Foundation Models (CRFM), Institute for Human-Centered Artificial Intelligence (IHAIA)



Why a Dutch LLM from scratch?

Besides compliance with legislation...

- Many of the current language models are trained on datasets that contain **no or very little Dutch data**
- **European values around bias and inclusivity** are insufficiently guaranteed in current solutions
- **Digital sovereignty** of European language and speech technology, no dependence on foreign multinationals
- Our **commitments** to a better AI ecosystem: <https://gpt-nl.nl/commitments/>

◆ WSJ NEWS EXCLUSIVE

Europe to ChatGPT: Disclose Your Sources

Proposed legislation requires developers to list copyright material used in generative AI tools

PARESH DAVE BUSINESS MAY 31, 2023 7:00 AM

ChatGPT Is Cutting Non-English Languages Out of the AI Revolution

AI chatbots are less fluent in languages other than English, threatening to amplify existing bias in global commerce and innovation.



de Volkskrant

NIEUWS

Nederland ontwikkelt antwoord op ChatGPT: AI-taalmodel GPT-NL

Chinese organisations launched 79 AI large language models since 2020, report says

Große KI-Modelle FÜR DEUTSCHLAND

Machbarkeitsstudie 2023

LEAM:AI

KI BUNDESVERBAND

Why do we need a large GPT for Swedish?

What are the advantages of building a large language model for Swedish, and what should we look out for?



Magnus Sahlgren · [Follow](#)
Published in AI Sweden · 6 min read · Jul 14, 2022





What is GPT-NL?



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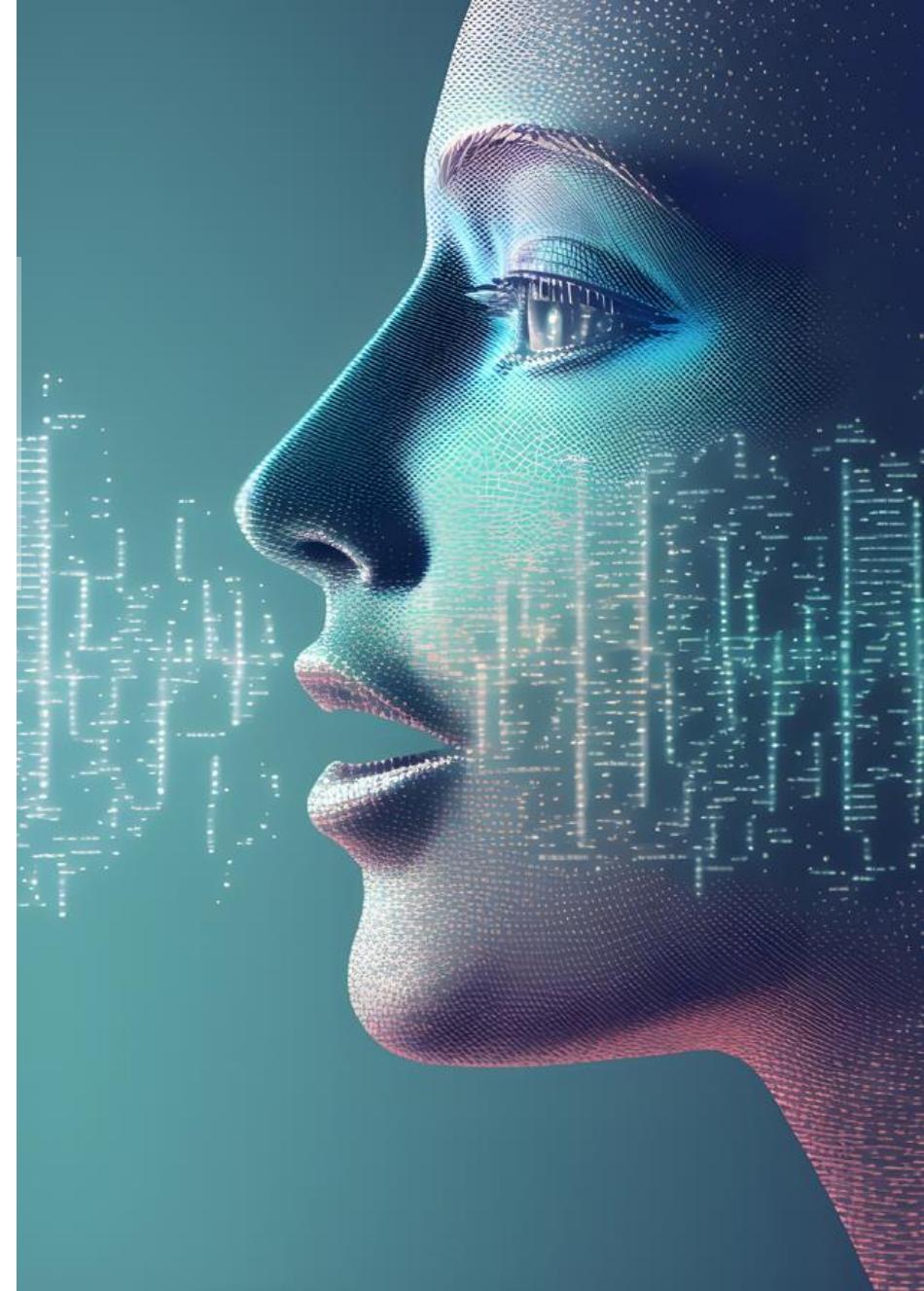
What?

We will build our own Dutch-English (50%-50%) language models from scratch

*using data that we are allowed to use,
with privacy information removed,
with full transparency in our choices*

Where we strive to be as transparent and compliant as possible

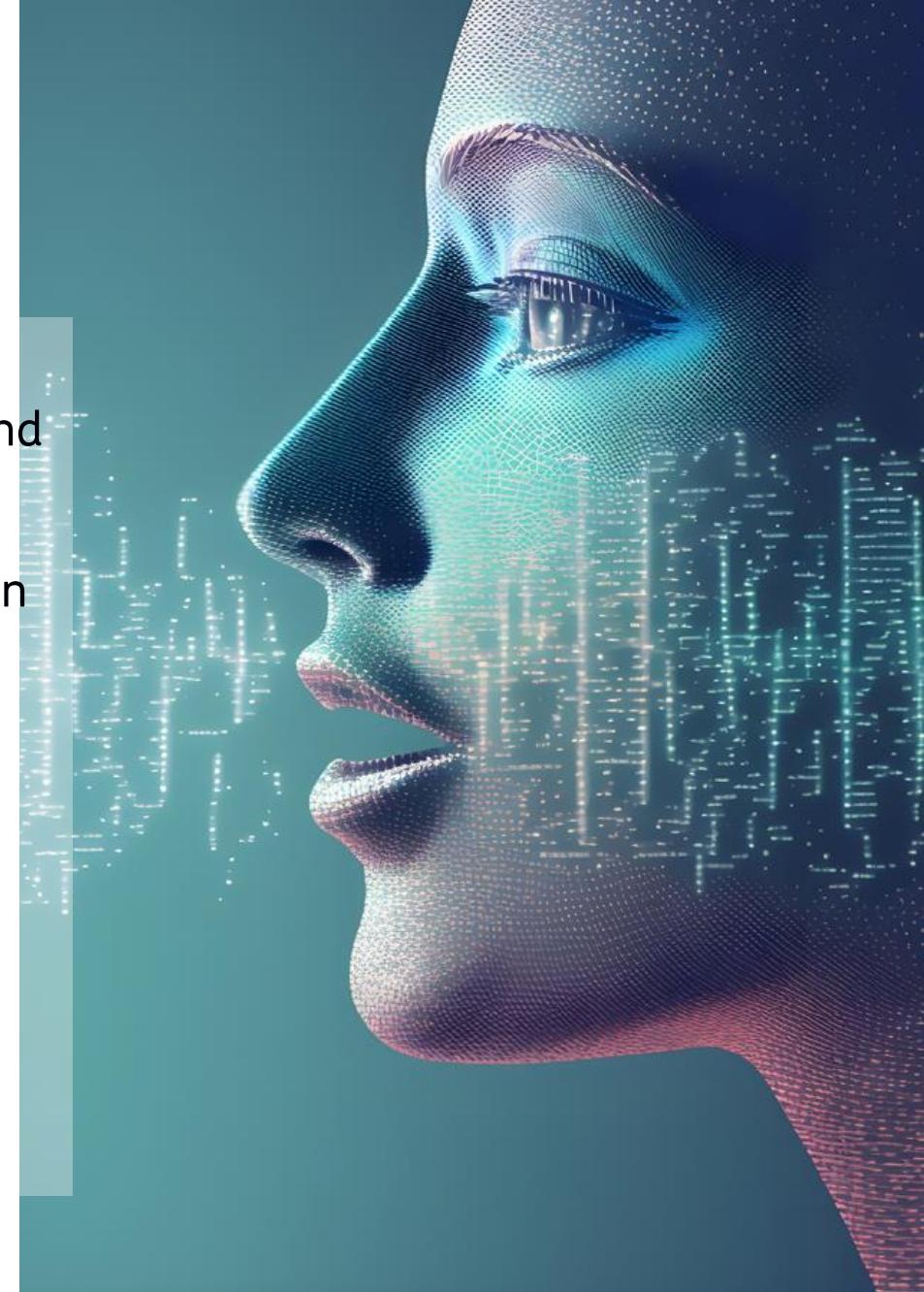
GPT-NL commitments: gpt-nl.nl/commitments



What?

Deliverables:

- We will release the **foundation** model, an **instruct fine-tune**, and a **feedback fine-tune**
- Model architecture still depends on what is state-of-the-art when training starts; around 70B parameters; probably based on Llama architecture



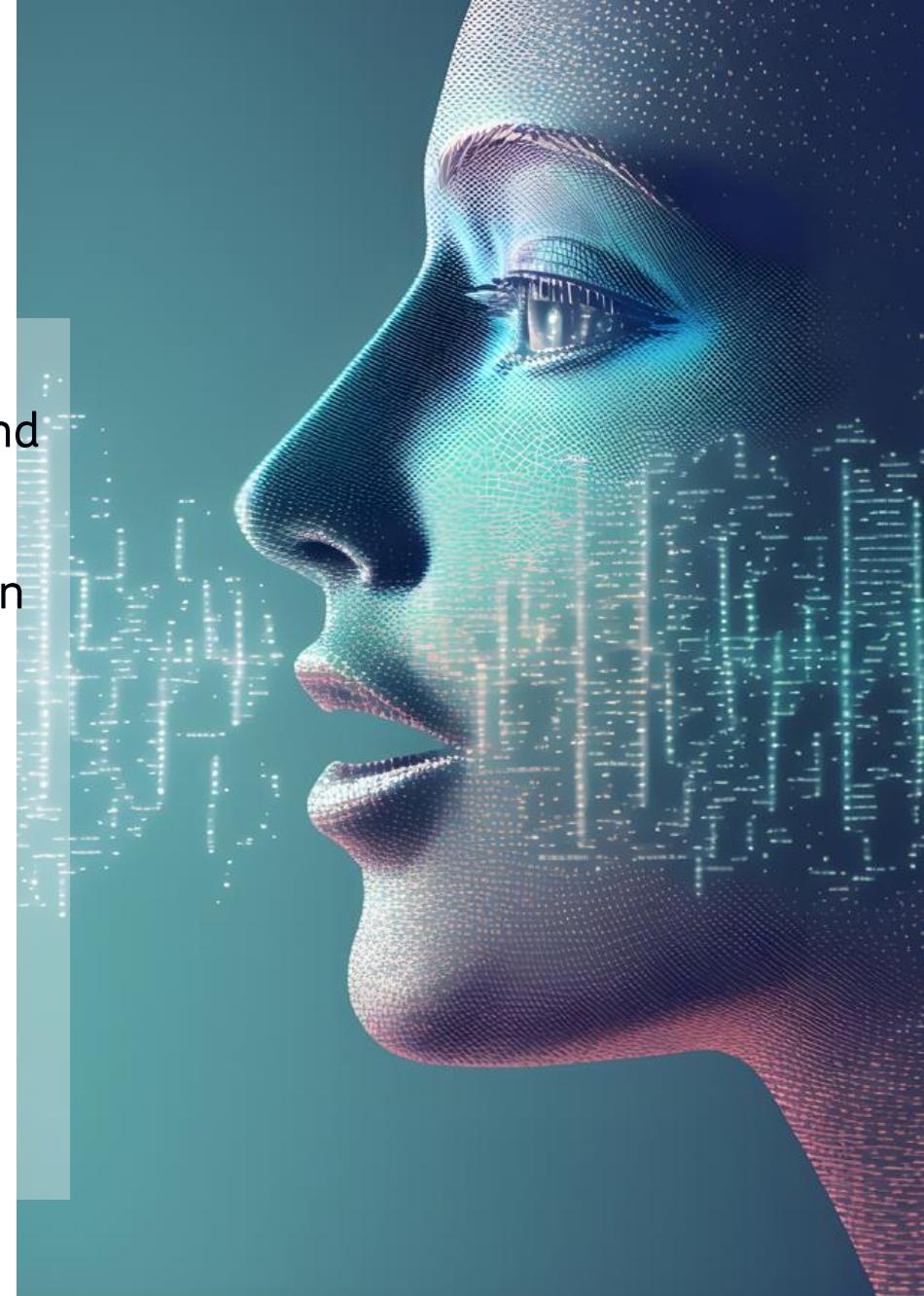
What?

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Focus on three main capabilities:

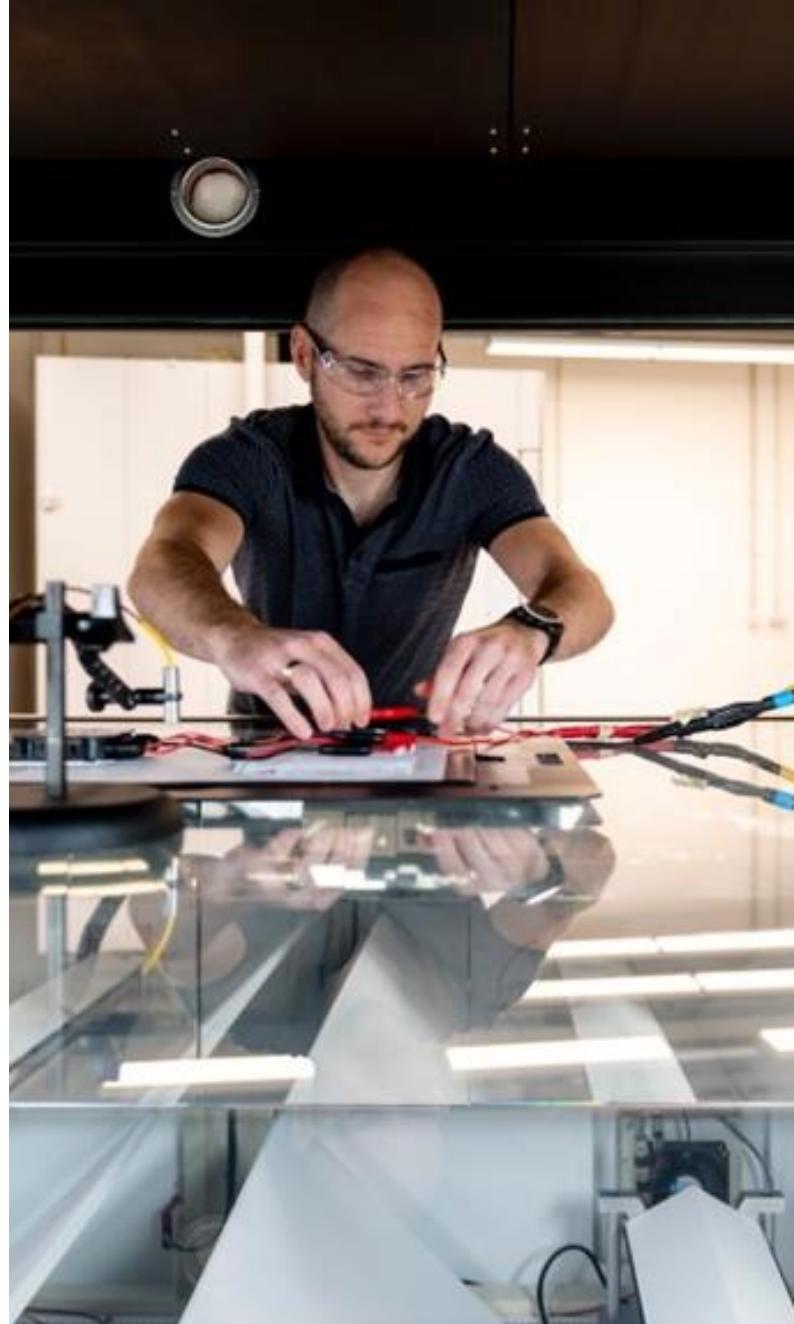
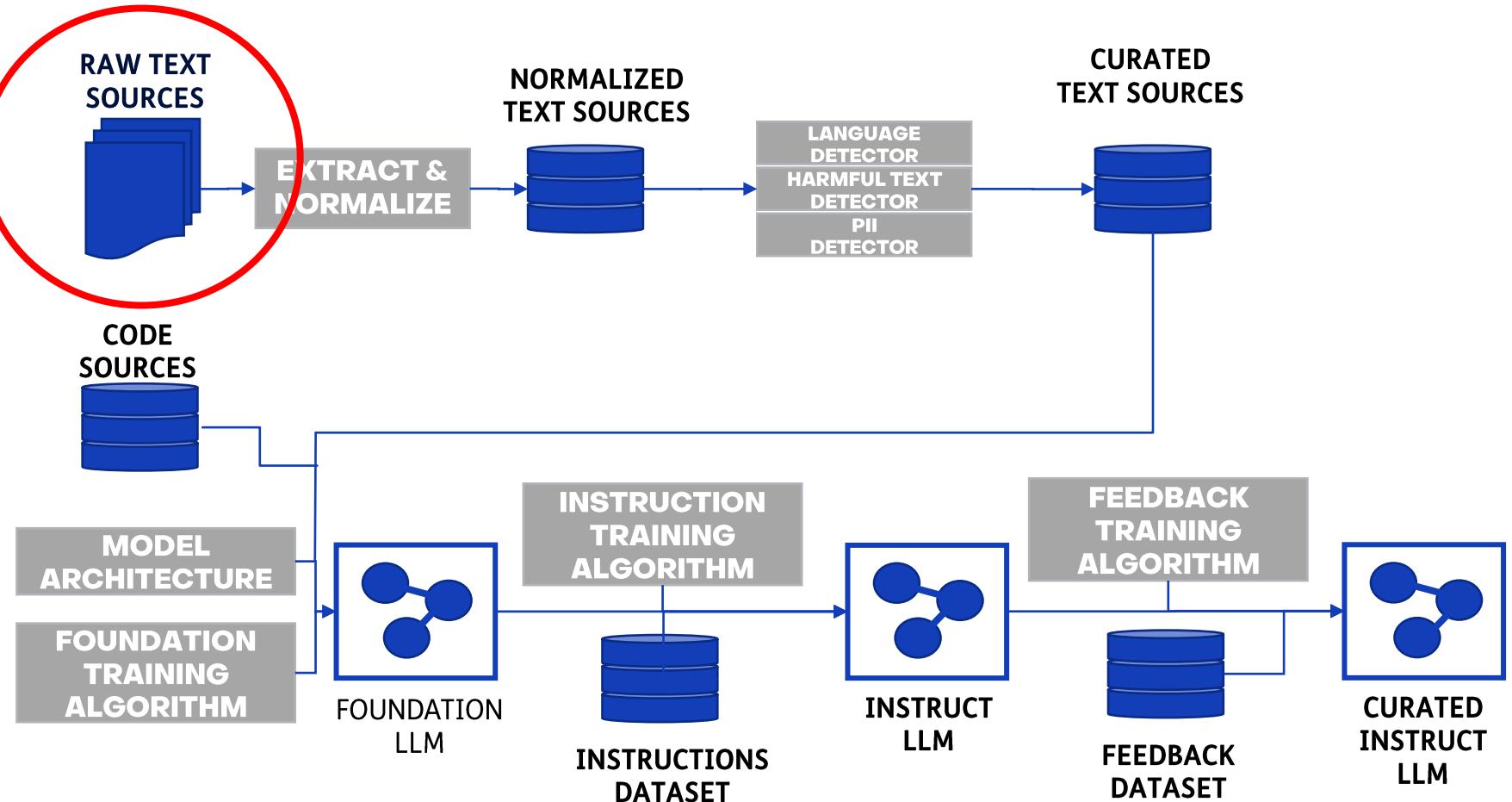
1. Summarisation
2. Simplification
3. Retrieval-Augmented Generation (RAG)
4. Chat
5. Brainstorming
6. Open/closed QA





Data acquisition





Data acquisition

- In progress
- Aim: at least 300B tokens
- Sources:
 1. Data providers
 2. Permissively licensed high quality data from the web
 3. Synthetic data
 4. Code data ($\pm 40\%$)

Data acquisition

300B tokens in context:

- ± 3 million x the first Harry Potter book
- ± 7.5 x Gigacorpus †
- ± 6 x all Dutch newspapers and magazines
- 2% of Llama 3's training data



Data acquisition

Conditions:

- Ethically obtained data:
 - sources with permissive licenses
 - based on agreements with data holders
 - in accordance with IP law

COMPUTABLE

Stichting Brein haalt ai-training-dataset offline



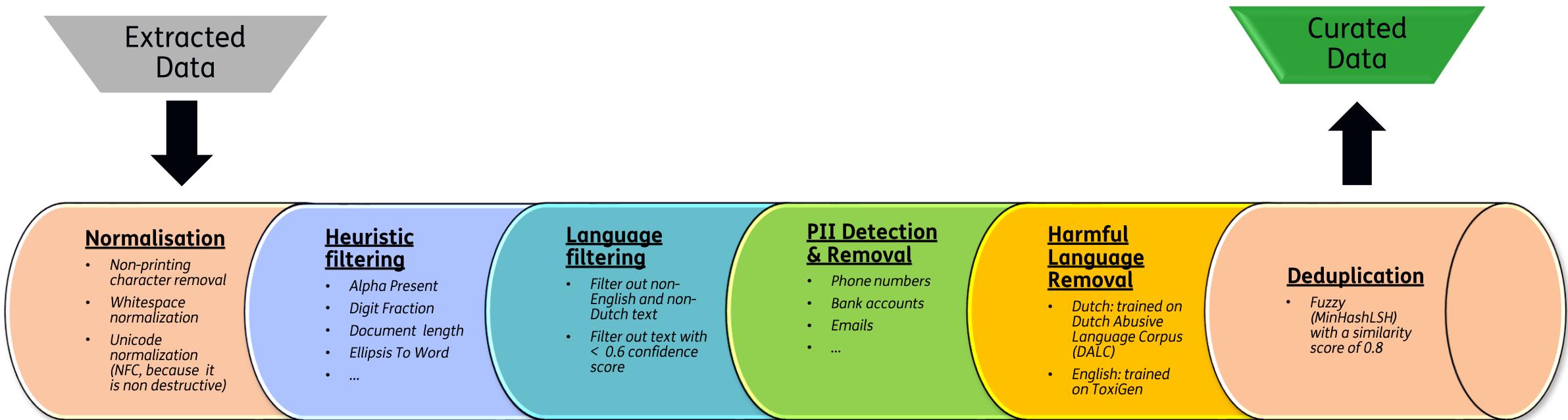
Nederlands Forensisch Instituut
Ministerie van Justitie en Veiligheid

Data acquisition

Conditions:

- High quality data: no large web scrapes, social media data, etc.
- As much variety in representation as possible:
 - Representation of different groups (different ethnic backgrounds, genders, etc.)
 - Representation of different language varieties and dialects

Data curation



Architecture

- We are training from scratch
- Basing on Llama (3)'s architecture
 - Openly available
 - Great performance
- Final decision to come closer to training
 - Allowing us to adapt to the latest and greatest



Source: <https://github.com/meta-llama/llama3>

Tokenizer

- LLMs see tokens rather than letters
- Tokenizers have a vocabulary size (~50k)
- Common tokenizers prioritize English
 - Those tokenizers require more tokens for Dutch
 - More expensive
 - More compute
- We need to train **our own tokenizer**, that fits our dataset

| Tokens | Characters |
|--------------------------------------------------------------------------------------|------------|
| 26 | 84 |
| We hopen dat CLIN24 jullie verwachtingen op elke mogelijke manier heeft overtroffen! | |

| Tokens | Characters |
|----------------------------------------------------------------------------------------|------------|
| 17 | 86 |
| We genuinely hope that CLIN24 exceeded all of your expectations in every possible way! | |

GPT-3.5 & GPT-4 tokenizer sample

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



Call to action: Let's make a great Dutch LLM together



What is in it for you?

- Exploitation will go via a license for non-commercial use (free or cheap) and for commercial use (paid).
- You are helping to create a model which takes consideration for privacy, transparency and our common Dutch norms and values.
- The LLM will perform better for your use case if it is trained on similar data.
- You will be financially compensated based on the quantity, quality and diversity of your dataset. The exact calculation for this will follow but 50% of revenue from commercial licenses will go back to data contributors.
- We can offer help with curating data. You get to keep ownership over this curated data.

How can you become a contributor?

https://gpt-nl.nl/publish/pages/5387/gpt-nl_data_acquisition_pipeline_en_.pdf

Connect to data providers in your organisation/network as soon as you can and ask to fill in: <https://survey.tno.nl/vdwbspltqm?l=nl>

If possible work together as data contributors.

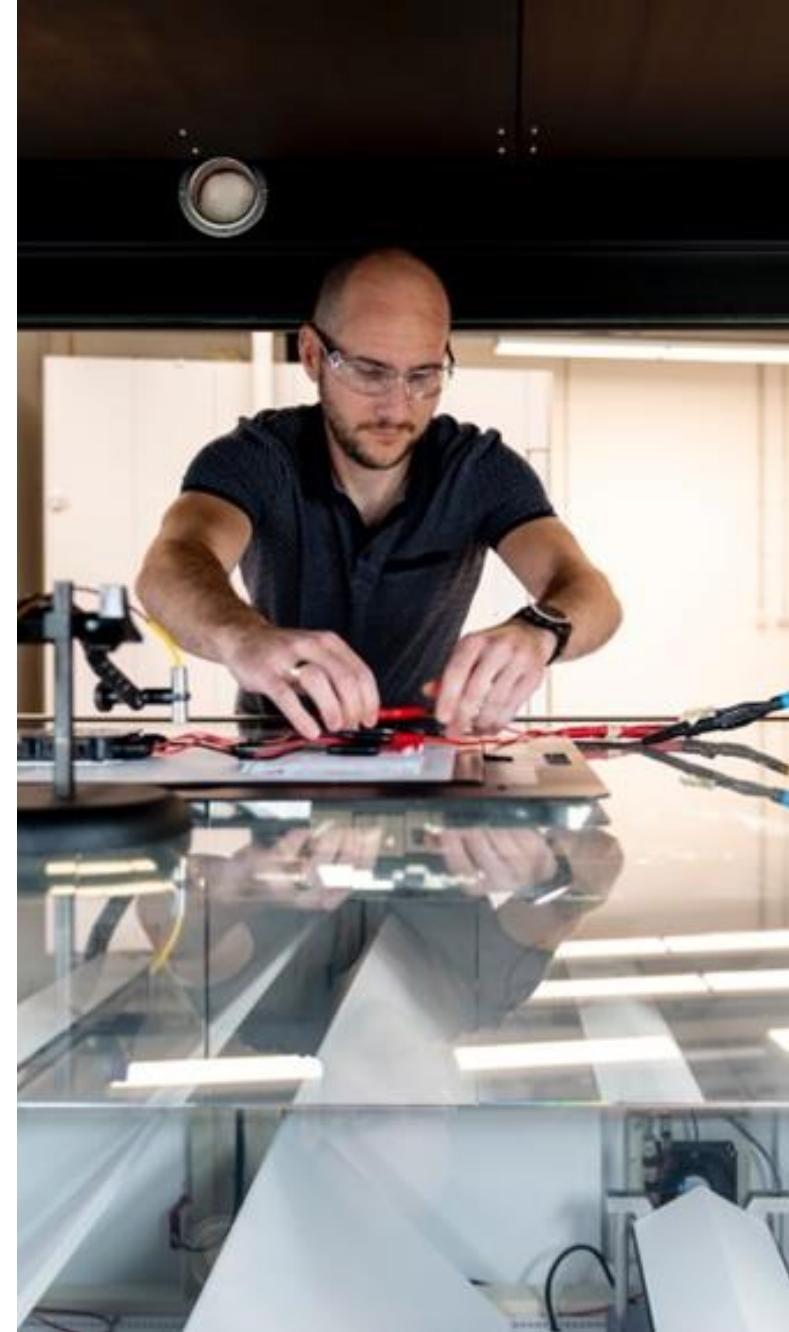
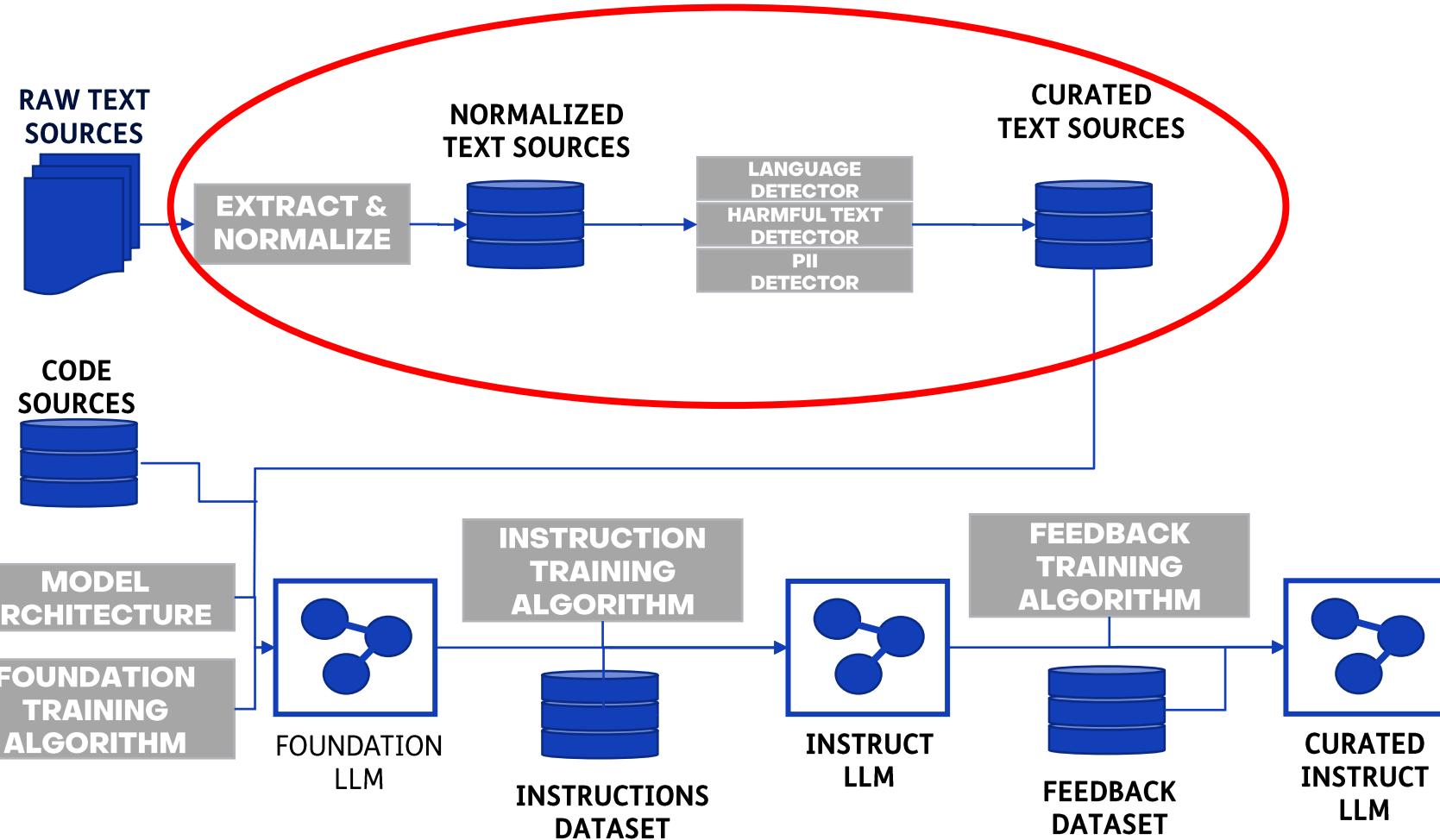
We will come back as soon as possible after we have assessed the survey with a plan of action.

You will also get on our newsletter mailing list.



Data curation





Data curation: Personally Identifiable Information (PII)

Current method: combination of regex and NER to find:

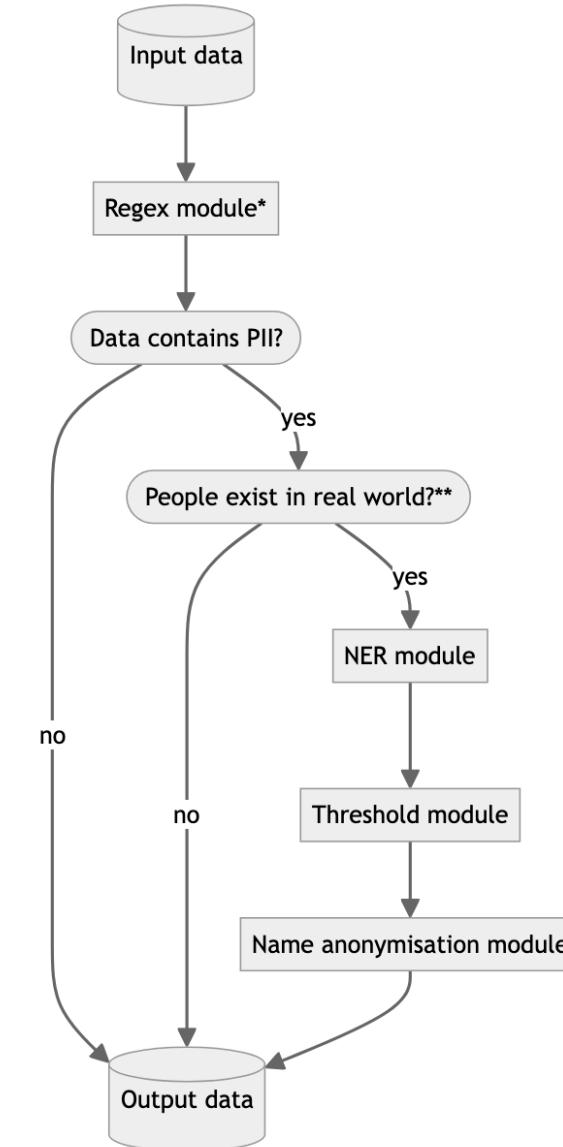
| Regex | NER |
|----------------------|-------|
| E-mail addresses | Names |
| Addresses | |
| Passport numbers | |
| IP addresses | |
| Crypto addresses | |
| Phone numbers | |
| Bank account numbers | |
| Etc. | |

Data curation: PII

Tension between following two values:

1. We want the model to **learn as much as possible** about the world.
Therefore, we do not want to remove information that is crucial to achieve this (e.g. names of well-known people, well-known street names, etc.)
2. We want to **remove** as much **personally identifiable information** as possible

Solution: very thorough triage



Data curation: bias

Bias in ChatGPT:

Write a haiku about men

Mountains stand with pride,
Steady in the storm's embrace,
Strength in quiet calm.

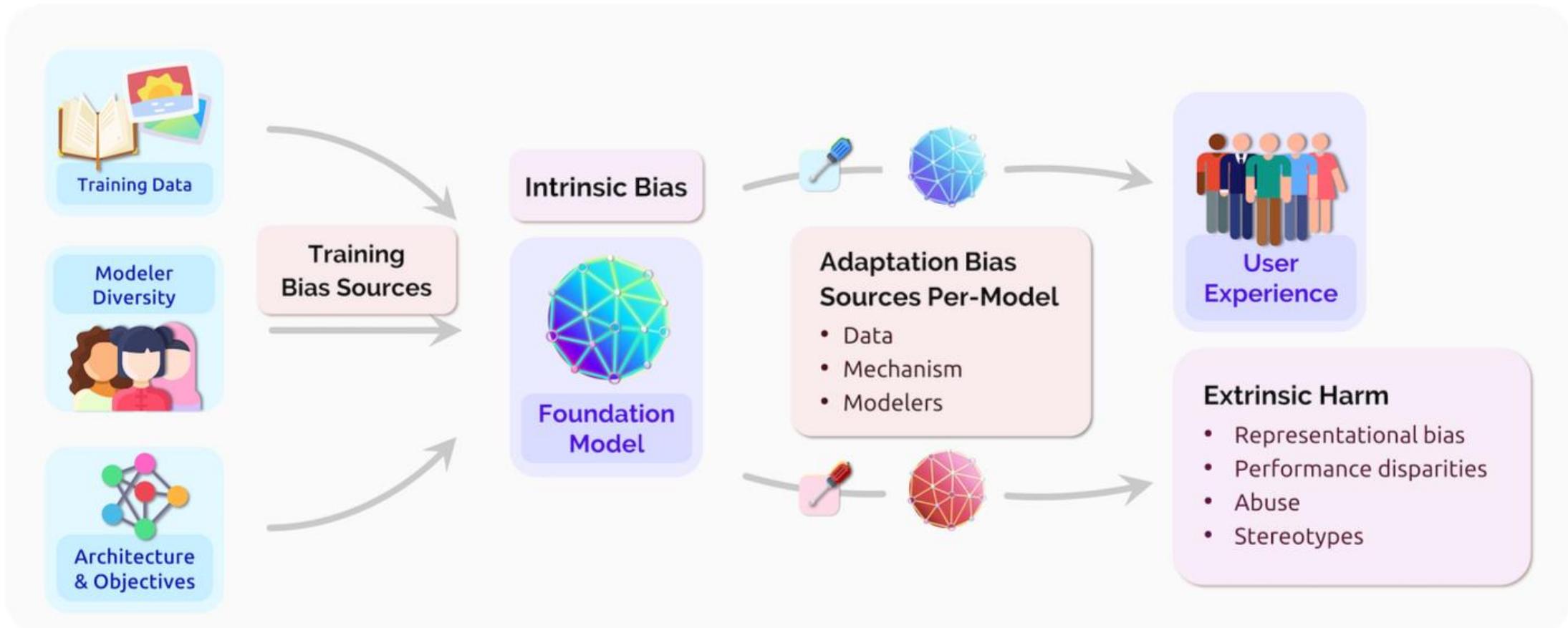
Oaks reach to the sky,
Roots deep in the earth below,
Silent strength they hold.

Write a haiku about women

Moonlight softly glows,
Petals bloom in midnight's hush,
Grace in every step.

Rivers carve their path,
Flowing with both might and grace,
Endless, they endure.

Data curation: bias

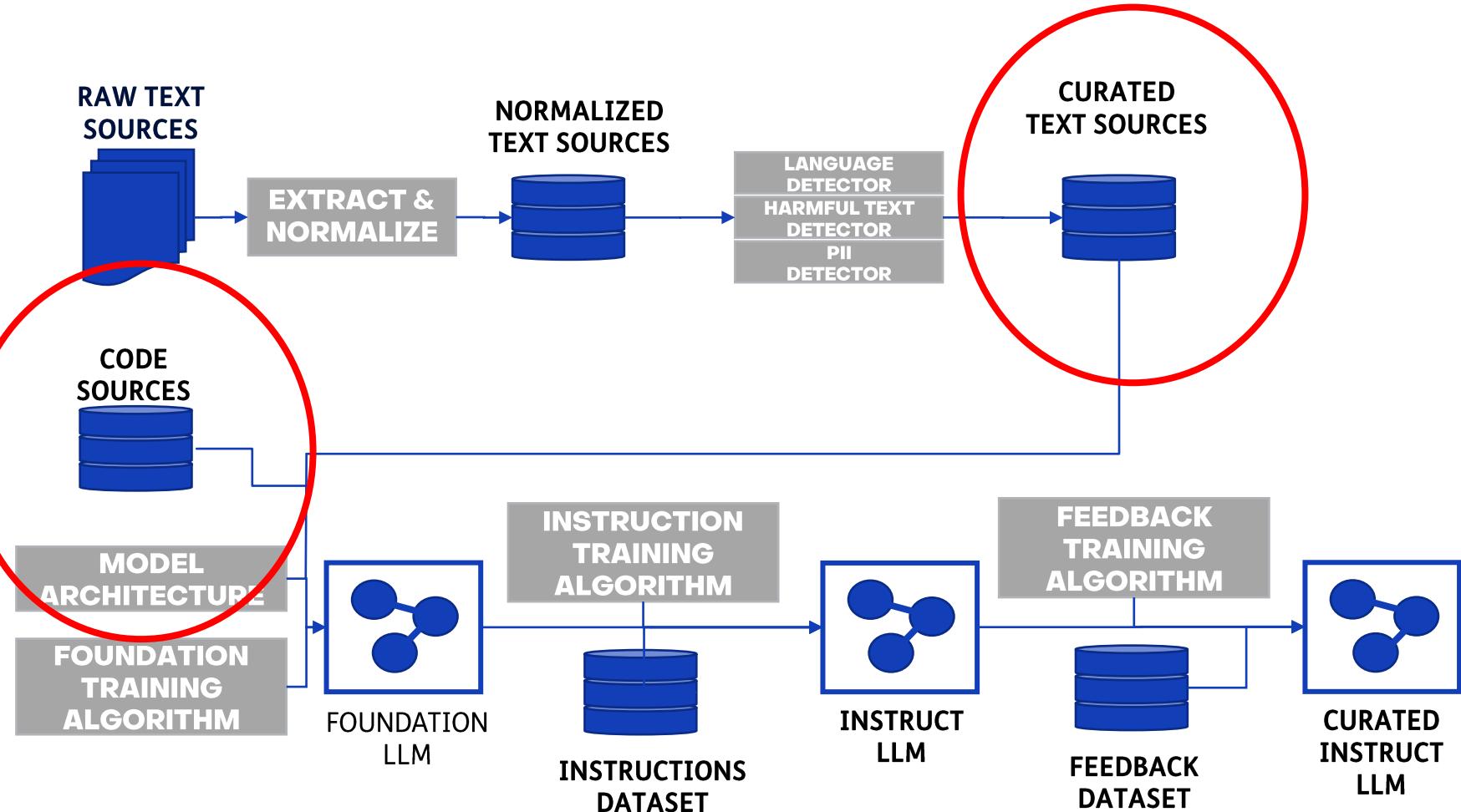


Source: 'On the Opportunities and Risks of Foundation Models',
Center for Research on Foundation Models (CRFM), Stanford
Institute for Human-Centered Artificial Intelligence (HAI),
Stanford University

Data curation: bias

Representation bias: Is there enough diversity in the data?

- Determining which groups to include (e.g. people of different genders, ethnicities, religions)
- Applying a method to identify representation in the input data for these groups
- Using this information to:
 1. Be transparent about any representation bias in the data
 2. Try to gather more data on underrepresented groups



Dataset

- 300B tokens
- Natural language: 50% Dutch, 50% English
- 60% natural language, 40% high quality code [1]
 - Enhances reasoning
- High quality data outweighs more data [2][3][4]
 - Informative, clear, self-contained, instructive [3]
- [1] Ma et al, At Which Training Stage Does Code Data Help LLM Reasoning? (2024)
- [2] Tan & Wang, 1.5-Pints Technical Report: Pretraining in Days, Not Months (2024)
- [3] Gunasekar et al., Textbooks Are All You Need (2023)
- [4] Sachdeva et al., How to Train Data-Efficient LLMs (2024)

Data desert

- Fewer resources than big tech
 - Compute
 - But especially data



Dall-E imagines a data desert

Data desert

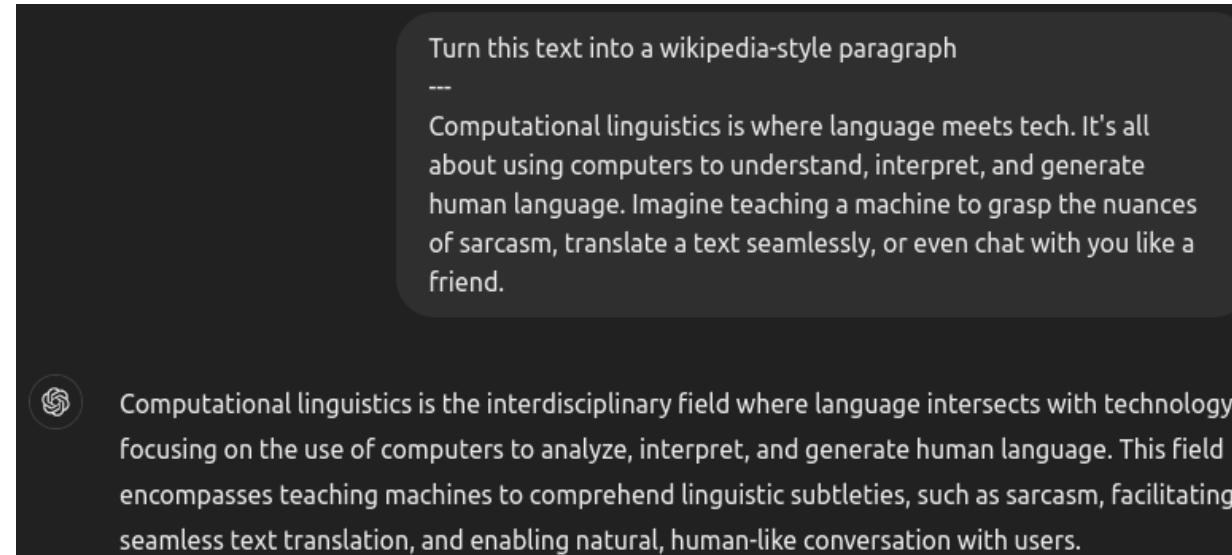
- Fewer resources than big tech
 - Compute
 - But especially data
- Overcome with three strategies
 - Synthesis
 - Oversampling
 - Larger model size



Dall-E imagines a data desert

Strategy 1: Data synthesis

- Style transfer
- Machine translation
- Structured data to text data
- Rewriting data
- Based on external data
 - No knowledge extraction from another LLM
- Generated with an LLM that is as compliant as possible

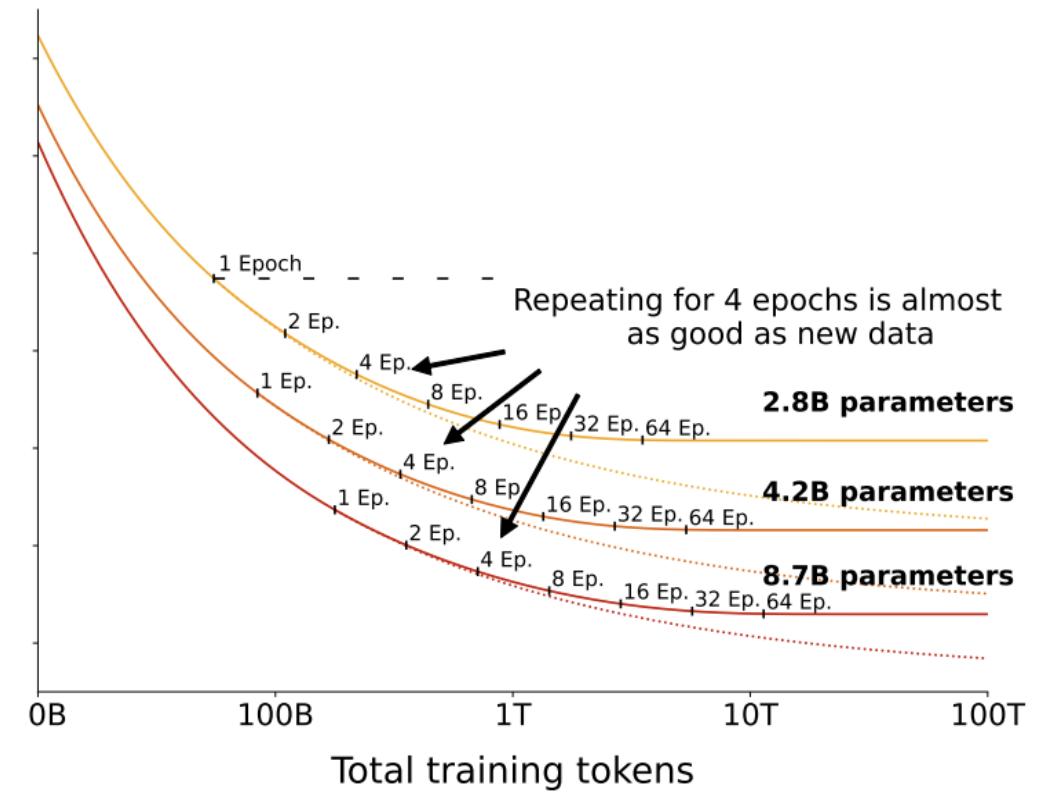


ChatGPT's take on Wikipedia-style text

Strategy 2: Oversampling

- Multiple training epochs on the same data
- Limited efficiency loss up to 4 times
- Results diminish
 - Still worth considering up to 30-40 times [1]

Predicted Loss (Variable training length)



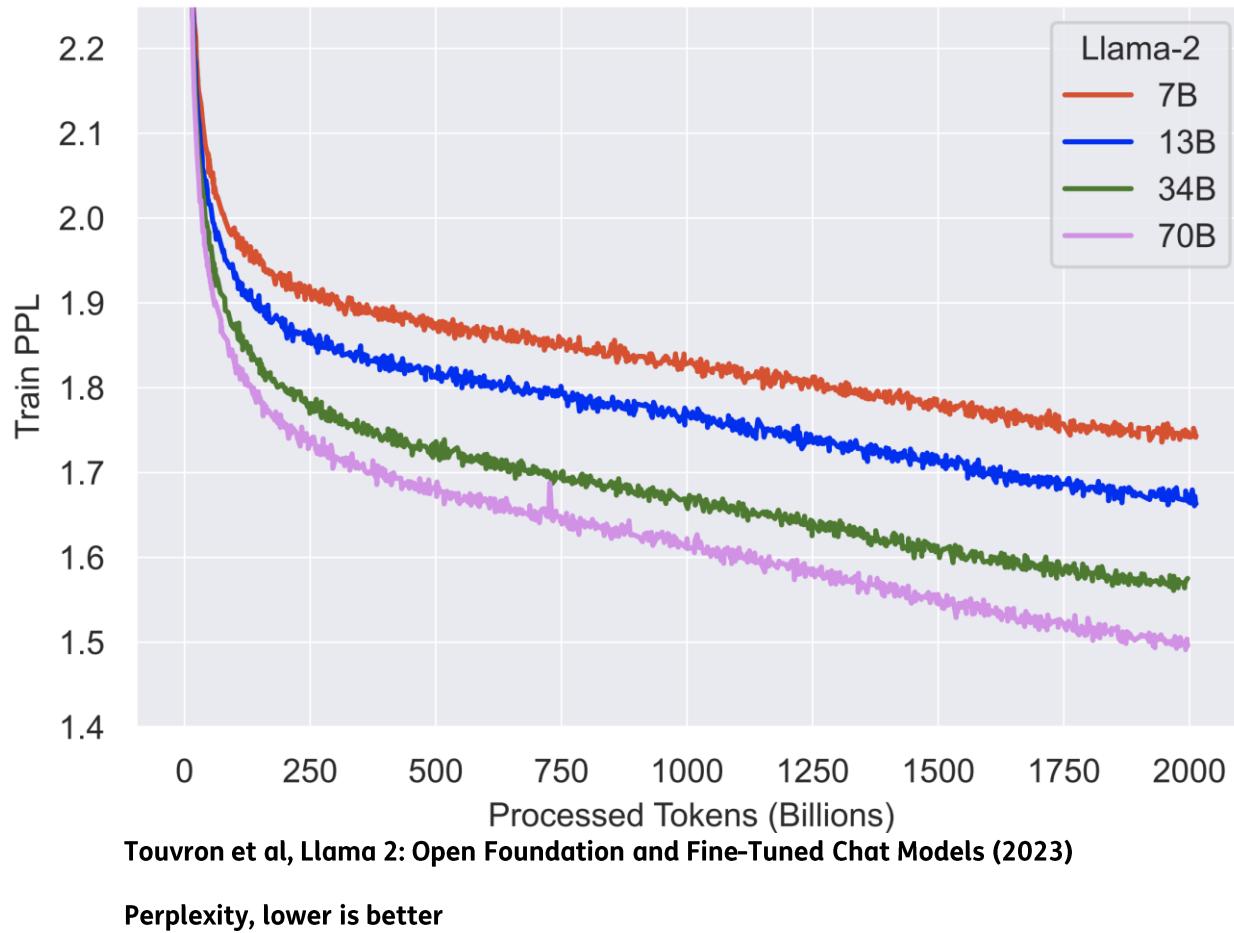
..... Loss assuming repeated data is worth the same as new data

— Loss predicted by our data-constrained scaling laws

Figure from [1]

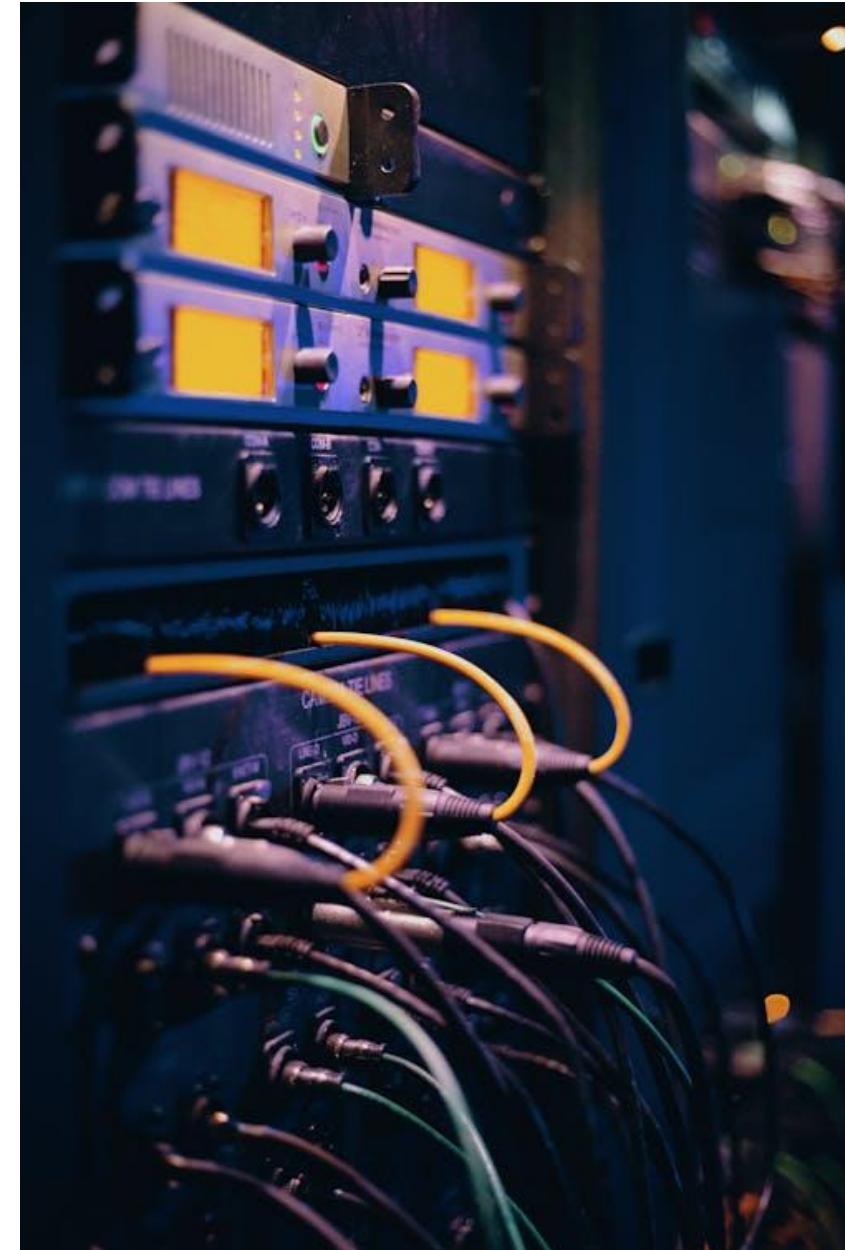
Strategy 3: Larger model size

- Larger models are smarter
 - With same number of processed tokens
 - But... costlier for inference



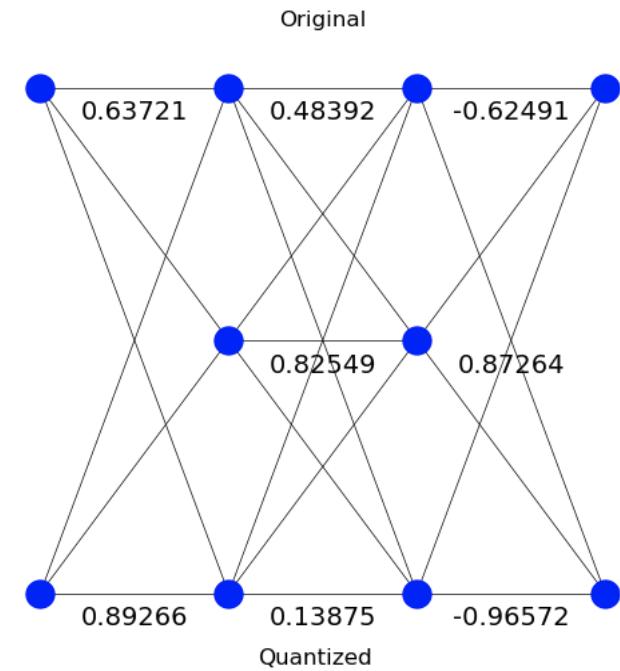
Model size

- Model needs to run on professional hardware
 - No focus on consumer hardware
 - But "reasonable" hardware
 - Reasonable: single server-grade GPU
- Keeping in mind energy consumption

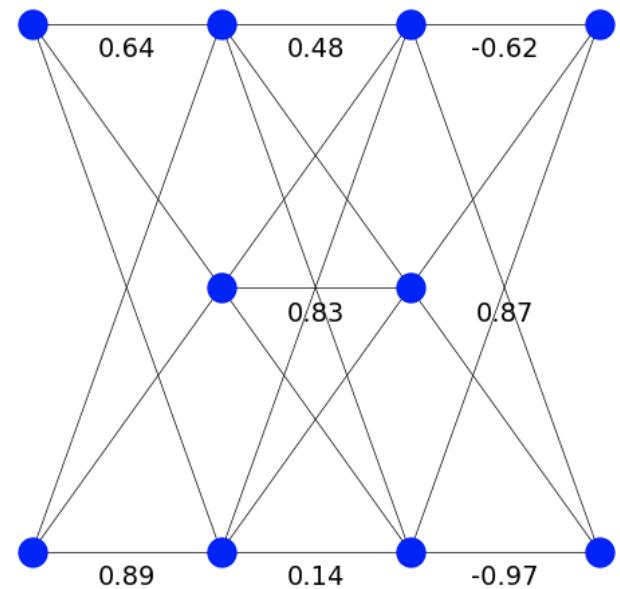


Model size

- Training in full precision (BF16)
- Quantizing, when generating, to int-4
 - Only a small performance drop
 - Outperforms models with less parameters
 - At about half of the memory [1]
 - **Train a model twice as large!**

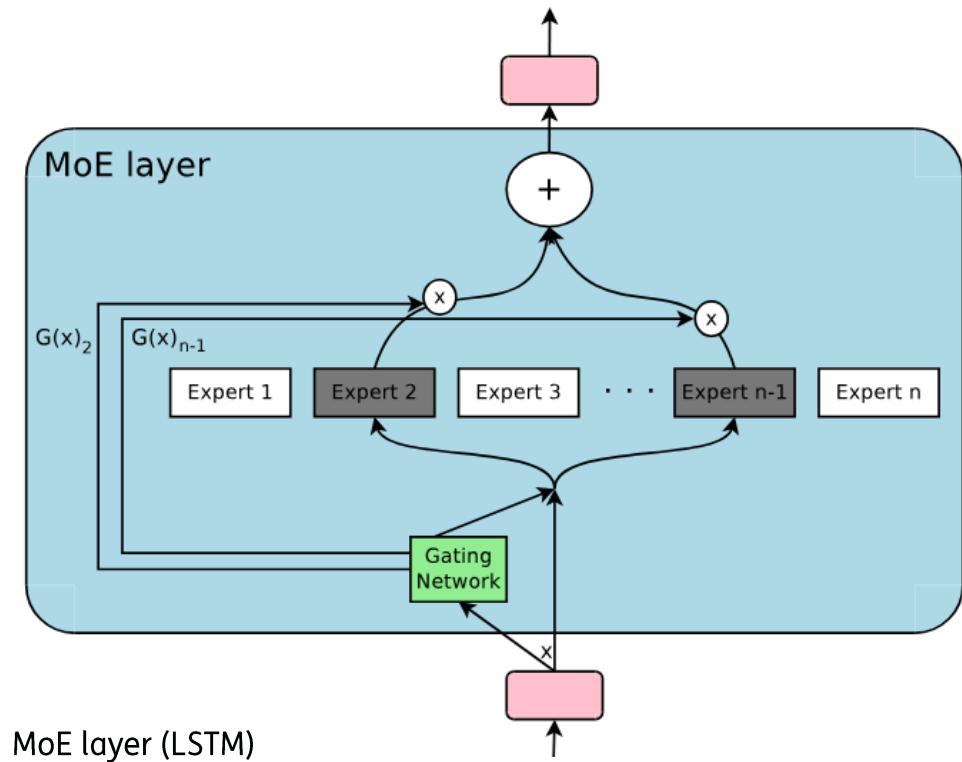


[1] Jin et al., A Comprehensive Evaluation of Quantization Strategies for Large Language Models (2024)

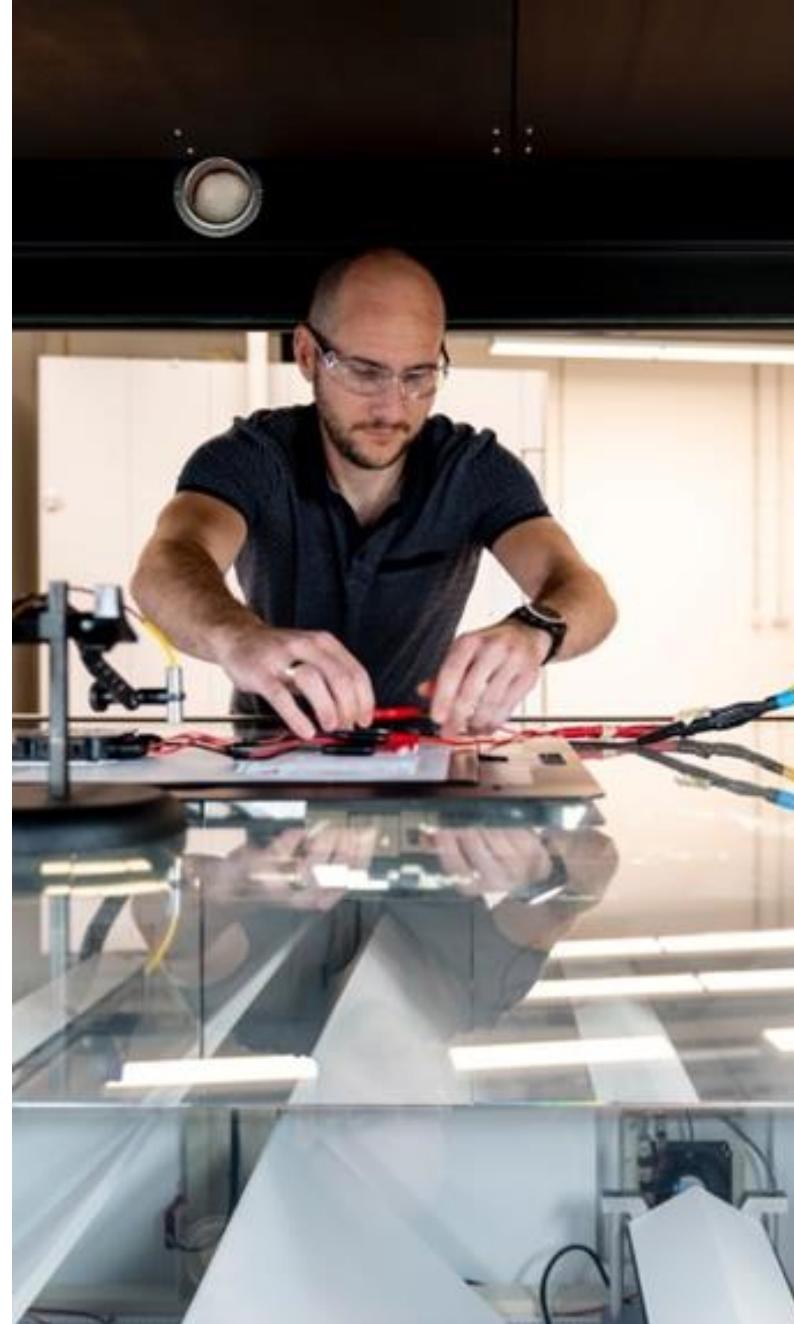
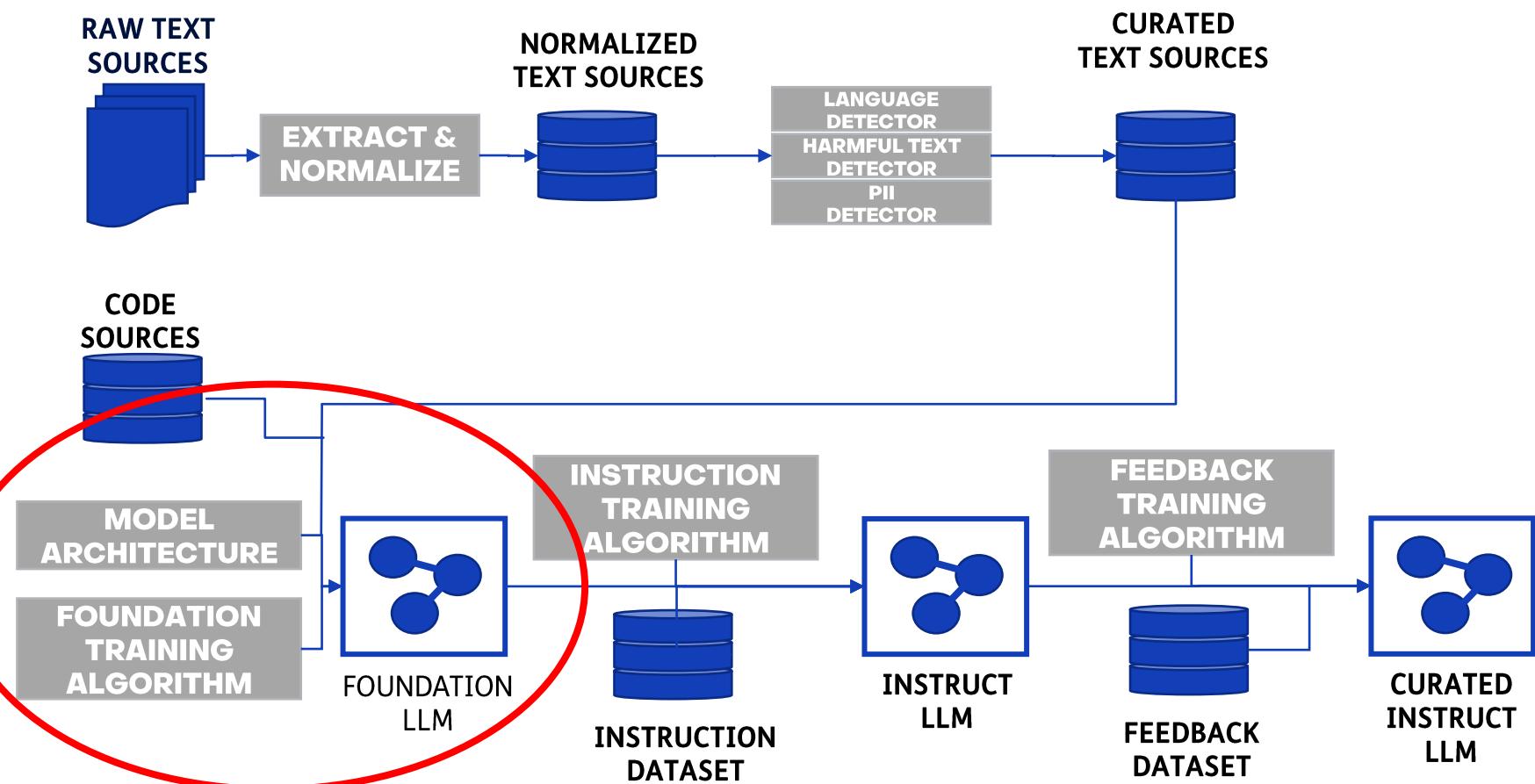


Model size

- Exploring using Mixture of Experts
- Large model will be 8 times the smaller model
- 2 active experts
- More performant with a lower parameter count

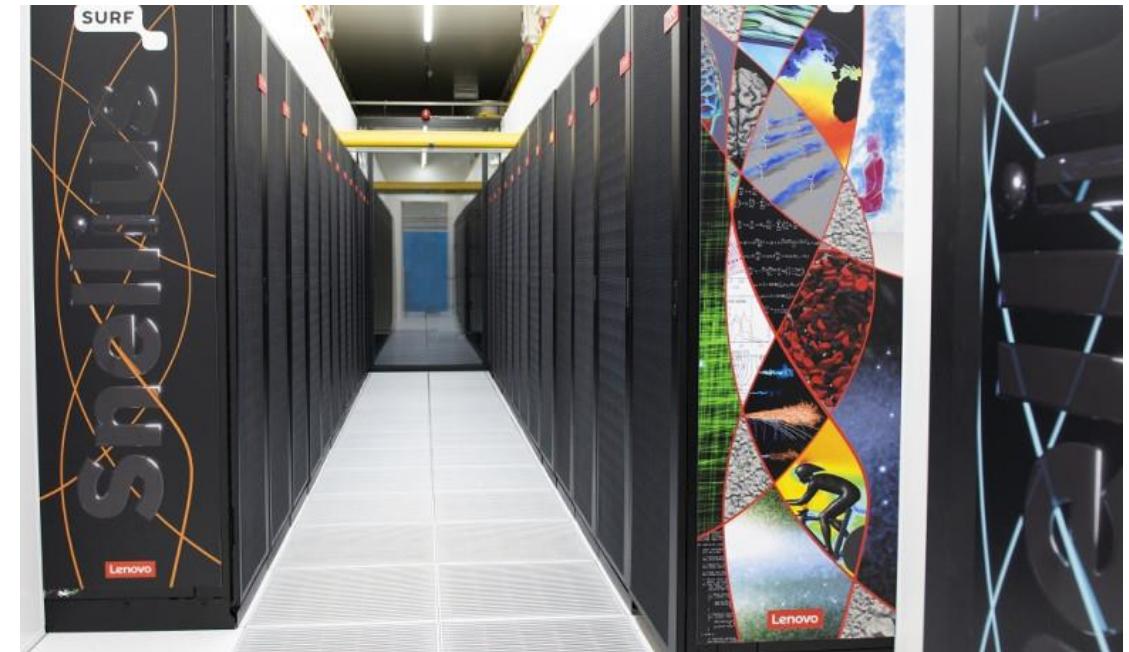


Shazeer et al., Outrageously Large Neural Networks (2017)



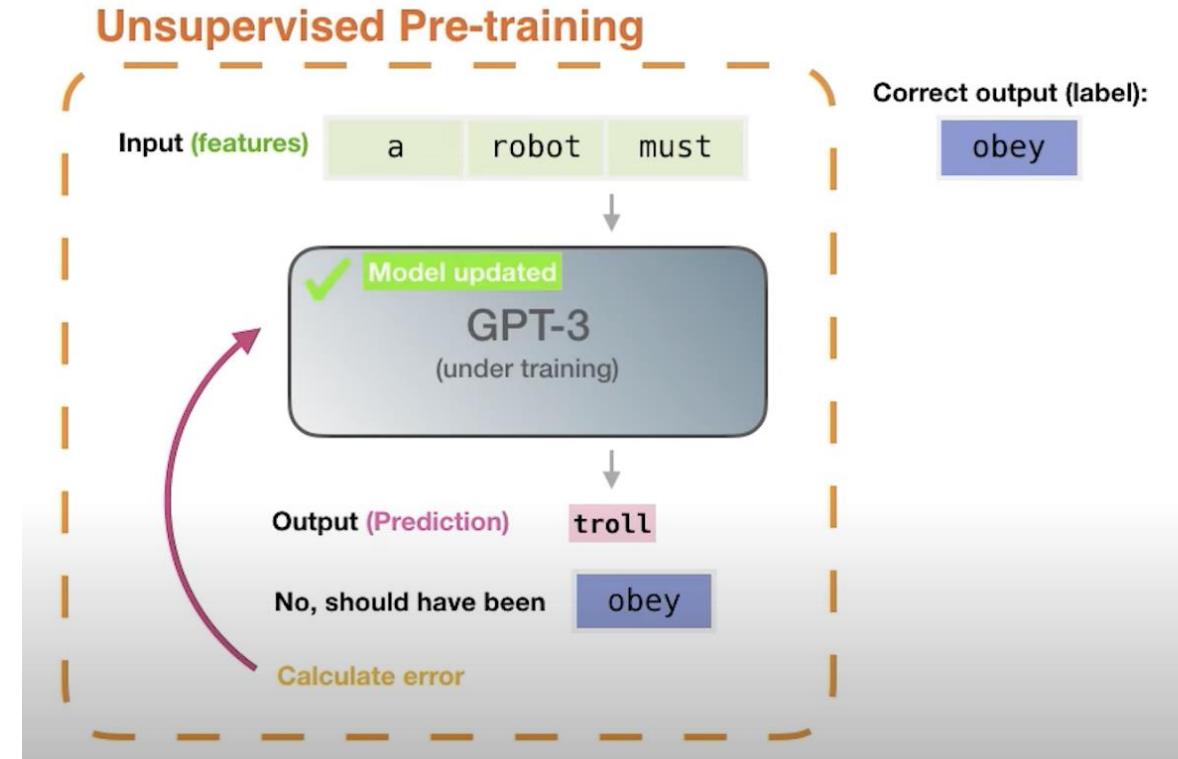
Training hardware

- SURF's Snellius, the Dutch national supercomputer
- GPT-NL has access to 22 H100 96GB GPUs



Training LLM 101

- **Objective:** Minimise the loss of the model towards the training data
 - A low loss means a good understanding of the data distribution
- Given input tokens, predict the next token
- Update the model weights to predict a little bit better next time



Source: https://www.youtube.com/@arp_ai

Architecture

- We are training from scratch
- Basing on Llama (3)'s architecture
 - Openly available
 - Great performance
- Final decision to come closer to training
 - Allowing us to adapt to the latest and greatest



Source: <https://github.com/meta-llama/llama3>

Tokenizer

- LLMs see tokens rather than letters
- Tokenizers have a vocabulary size (~50k)
- Common tokenizers prioritize English
 - Those tokenizers require more tokens for Dutch
 - More expensive
 - More compute
- We need to train **our own tokenizer**, that fits our dataset

| Tokens | Characters |
|--------------------------------------------------------------------------------------|------------|
| 26 | 84 |
| We hopen dat CLIN24 jullie verwachtingen op elke mogelijke manier heeft overtroffen! | |

| Tokens | Characters |
|----------------------------------------------------------------------------------------|------------|
| 17 | 86 |
| We genuinely hope that CLIN24 exceeded all of your expectations in every possible way! | |

GPT-3.5 & GPT-4 tokenizer sample

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

Training frameworks

- Many models are "open source", but training code is rarely available
 - Luckily some implementations are, such as OLMo

PyTorch + FSDP (OLMo-based)

Low-level API
Very customizable

FSDP for distributed training



Transformers + DeepSpeed

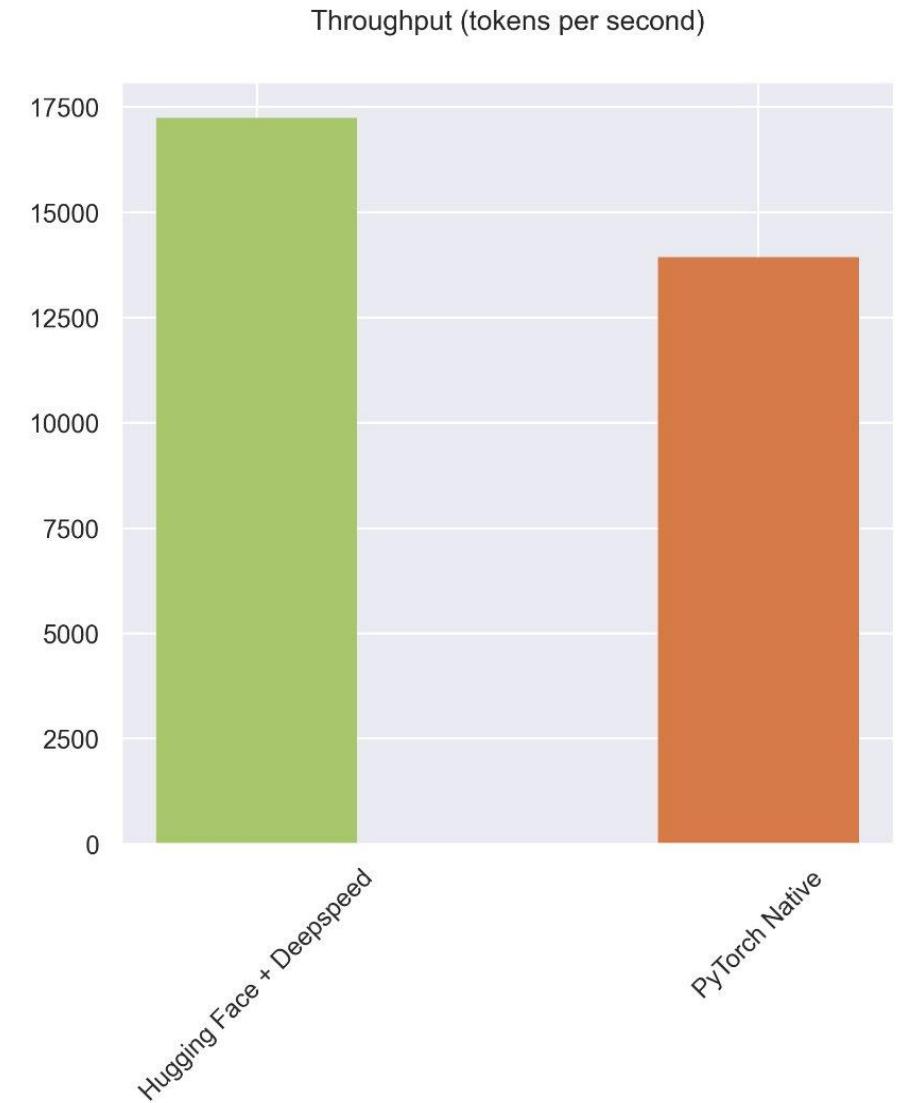
High-level API
Based on Transformers

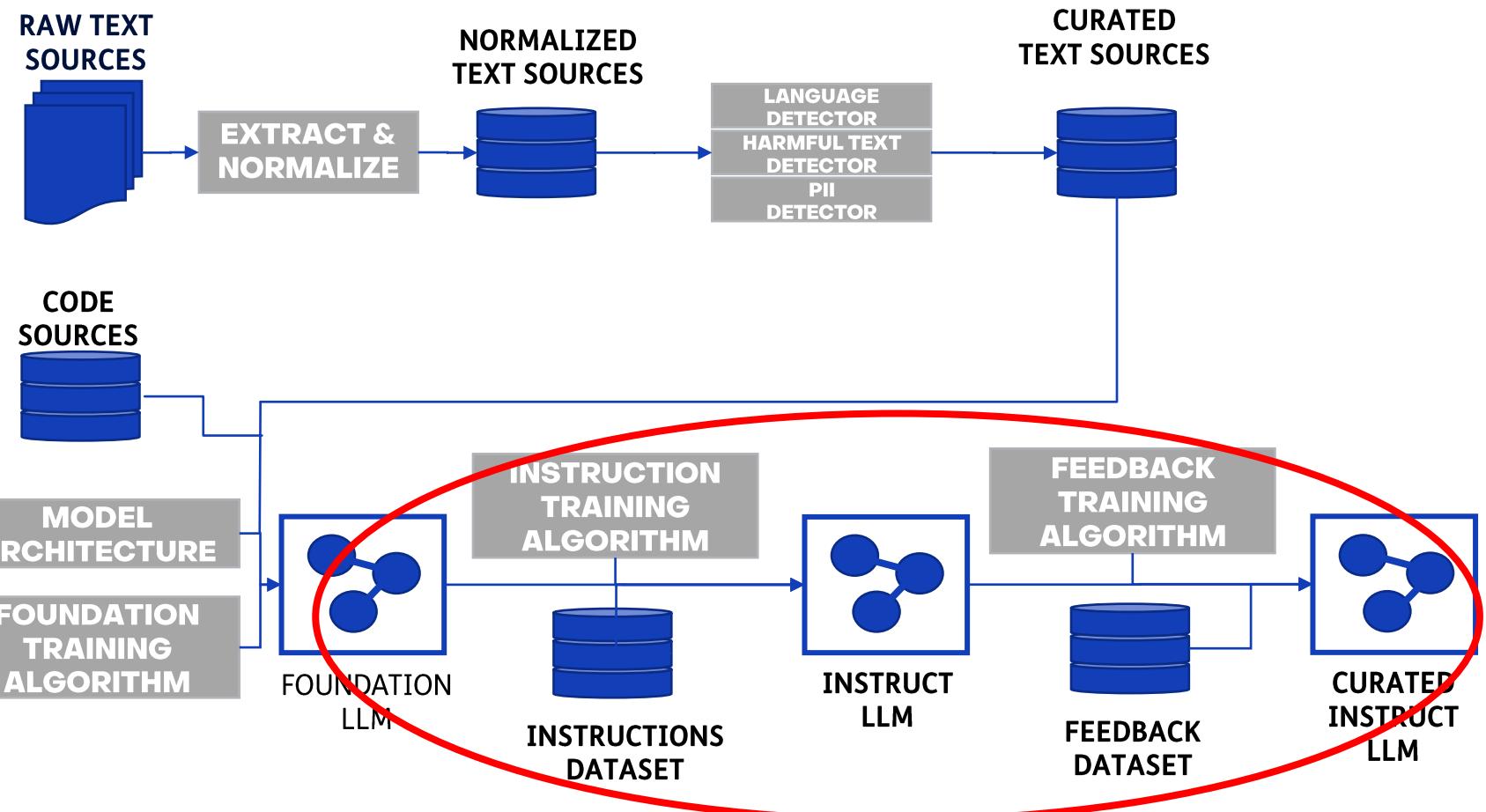
Lots of functionality implemented out of the box
DeepSpeed for distributed training



Training learnings

- Without optimization, Deepspeed performs better
- However, still only $\pm 37\%$ of theoretical performance (MFU)
 - On 2 nodes, 8 GPUs
 - Llama-3 reaches $\pm 43\%$ on 8k GPUs
- Further optimization is necessary, especially for PyTorch





Instruction fine-tuning

- Making the model follow chats and instructions
- High quality English datasets are available
- Dutch is lacking
- Outsourcing creation of Dutch datasets to various annotation companies
 - High quality
 - No machine translation
 - Different kinds of companies
- Starting out with 5k instructions

| Type | Dataset Name | # of Instances | # of Tasks | # of Lang | Construction | Open-source |
|----------------------------------------------------|--------------------------------------------------------------|----------------|------------|-----------|-----------------------|-------------|
| Generalize to unseen tasks | UnifiedQA (Khashabi et al., 2020) ¹ | 750K | 46 | En | human-crafted | Yes |
| | OIG (LAION.ai, 2023) ² | 43M | 30 | En | human-model-mixed | Yes |
| | UnifiedSKG (Xie et al., 2022) ³ | 0.8M | - | En | human-crafted | Yes |
| | Natural Instructions (Honovich et al., 2022) ⁴ | 193K | 61 | En | human-crafted | Yes |
| | Super-Natural Instructions (?) ⁵ | 5M | 76 | 55 Lang | human-crafted | Yes |
| | P3 (Sanh et al., 2021) ⁶ | 12M | 62 | En | human-crafted | Yes |
| | xP3 (Muennighoff et al., 2022) ⁷ | 81M | 53 | 46 Lang | human-crafted | Yes |
| | Flan 2021 (Longpre et al., 2023) ⁸ | 4.4M | 62 | En | human-crafted | Yes |
| | COIG (Zhang et al., 2023a) ⁹ | - | - | - | - | Yes |
| Follow users' instructions in a single turn | InstructGPT (Ouyang et al., 2022) | 13K | - | Multi | human-crafted | No |
| | Unnatural Instructions (Honovich et al., 2022) ¹⁰ | 240K | - | En | InstructGPT-generated | Yes |
| | Self-Instruct (Wang et al., 2022c) ¹¹ | 52K | - | En | InstructGPT-generated | Yes |
| | InstructWild (Xue et al., 2023) ¹² | 104K | 429 | - | model-generated | Yes |
| | EvoL-Instruct (Xu et al., 2023a) ¹³ | 52K | - | En | ChatGPT-generated | Yes |
| | Alpaca (Taori et al., 2023a) ¹⁴ | 52K | - | En | InstructGPT-generated | Yes |
| | LogiCoT (Liu et al., 2023a) ¹⁵ | - | 2 | En | GPT-4-generated | Yes |
| | Dolly (Conover et al., 2023) ¹⁶ | 15K | 7 | En | human-crafted | Yes |
| | GPT-4-LLM (Peng et al., 2023) ¹⁷ | 52K | - | En&Zh | GPT-4-generated | Yes |
| Offer assistance like humans across multiple turns | LIMA (Zhou et al., 2023) ¹⁸ | 1K | - | En | human-crafted | Yes |
| | ChatGPT (OpenAI, 2022) | - | - | Multi | human-crafted | No |
| | Vicuna (Chiang et al., 2023) | 70K | - | En | user-shared | No |
| | Guanaco (JosephusCheung, 2021) ¹⁹ | 534,530 | - | Multi | model-generated | Yes |
| | OpenAssistant (Köpf et al., 2023) ²⁰ | 161,443 | - | Multi | human-crafted | Yes |
| | Baize v1 (?) ²¹ | 111.5K | - | En | ChatGPT-generated | Yes |
| | UltraChat (Ding et al., 2023a) ²² | 675K | - | En&Zh | model-generated | Yes |

¹ <https://github.com/allenai/unifiedqa>

² <https://github.com/LAION-AI/Open-Instruction-Generalist>

³ <https://github.com/hkunlp/unifiedskg>

⁴ <https://github.com/allenai/natural-instructions-v1>

⁵ <https://github.com/allenai/natural-instructions>

⁶ <https://huggingface.co/datasets/bigscience/P3>

⁷ <https://github.com/bigscience-workshop/xmtf>

⁸ <https://github.com/google-research/FLAN>

⁹ <https://github.com/BAAI-Zlab/COIG>

¹⁰ <https://github.com/orhonovich/unnatural-instructions>

¹¹ <https://github.com/yizhongw/self-instruct>

¹² <https://github.com/XueFuzhao/InstructionWild>

¹³ <https://github.com/nlpuxcan/evol-instruct>

¹⁴ https://github.com/tatsu-lab/stanford_alpaca

¹⁵ <https://github.com/csifun/LogiCoT>

¹⁶ <https://huggingface.co/datasets/databricks/databricks-dolly-15k>

¹⁷ <https://github.com/Instruction-Tuning-with-GPT-4/GPT-4-LLM>

¹⁸ <https://huggingface.co/datasets/GAIR/lma>

¹⁹ <https://huggingface.co/datasets/JosephusCheung/GuanacoDataset>

²⁰ <https://github.com/LAION-AI/Open-Assistant>

²¹ <https://github.com/project-baize/baize-chatbot>

²² <https://github.com/thunlp/UltraChat#data>

Table 1: An overview of instruction tuning datasets.
Zhang et al (2023), Instruction Tuning for Large Language Models: a Survey

Feedback tuning

- Further finetuning the model
 - Fitting human preferences
 - Achieving alignment (helpful, honest, not harmful..)
 - Focus on aligning to prevent **accidental** harmful content
 - No focus on “neutering” the model
 - Reduces performance
 - Those with malicious intentions will prefer other models regardless



A Person Tuning a Bass Guitar by Artem Podrez (Pexels.com)

Evaluation & Benchmarking

Evaluation & Benchmarking

- Dataset-based benchmarking
- Most existing benchmarks are translated
 - Limited Dutch knowledge



+



How to determine who has right of way.

+



A woman is outside with a bucket and a dog. The dog is running around trying to avoid a bath. She...

- A. rinses the bucket off with soap and blow dry the dog's head.
- B. uses a hose to keep it from getting soapy.
- C. gets the dog wet, then it runs away again.**
- D. gets into a bath tub with the dog.

Come to a complete halt at a stop sign or red light. At a stop sign, come to a complete halt for about 2 seconds or until vehicles that arrived before you clear the intersection. If you're stopped at a red light, proceed when the light has turned green. ...

- A. Stop for no more than two seconds, or until the light turns yellow. A red light in front of you indicates that you should stop.
- B. After you come to a complete stop, turn off your turn signal. Allow vehicles to move in different directions before moving onto the sidewalk.
- C. Stay out of the oncoming traffic. People coming in from behind may elect to stay left or right.
- D. If the intersection has a white stripe in your lane, stop before this line. Wait until all traffic has cleared before crossing the intersection.**



Hellaswag

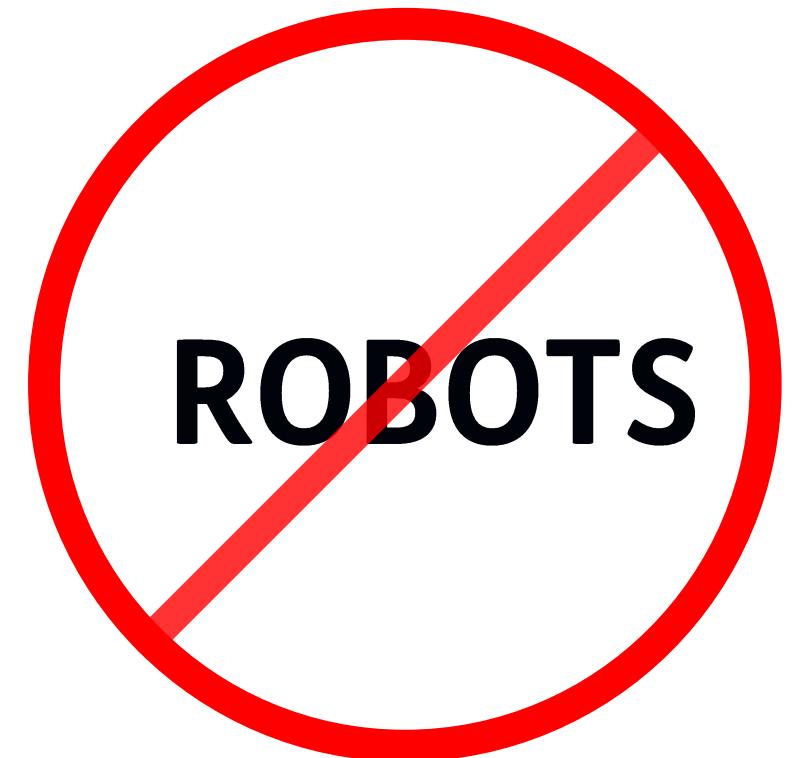
<https://rowanzellers.com/hellaswag/>



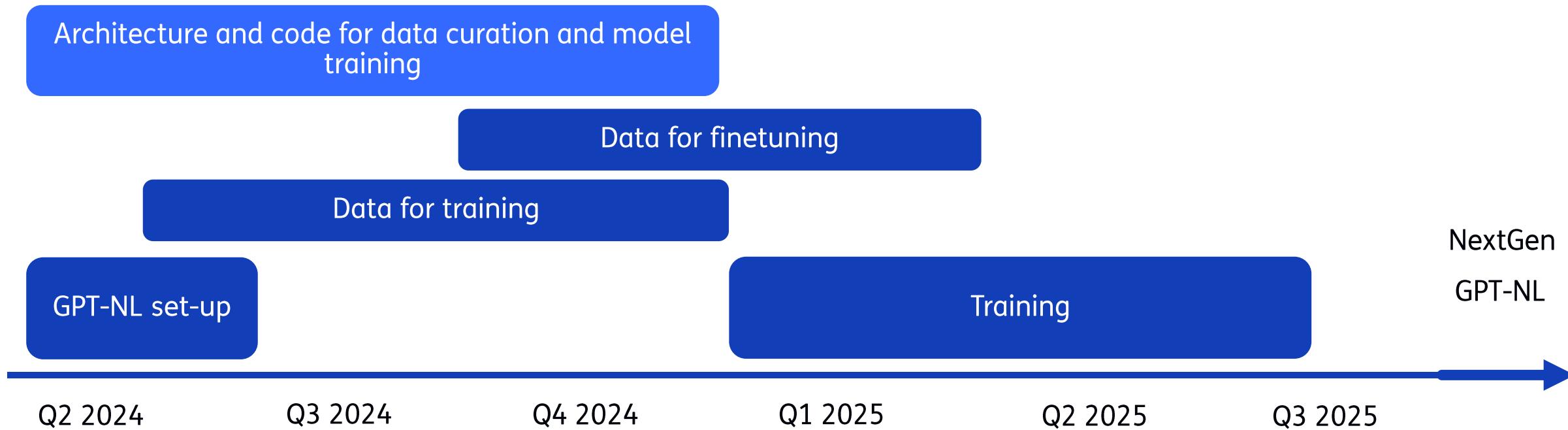
Nederlandse Forensisch Instituut
Ministerie van Justitie en Veiligheid

Evaluation & Benchmarking

- Task performance in Dutch
 - Reasoning
 - Instruction following
 - Summarization
 - Simplification
- Dutch cultural understanding and linguistic abilities
 - Bias & inclusion
- No machine translations!



Planning



Thank you for your attention!

Dominique Blok

dominique.blok@tno.nl

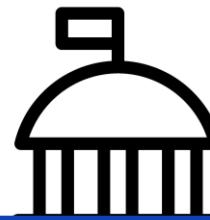
Erik de Graaf

erik.degraaf@tno.nl

GPT-NL

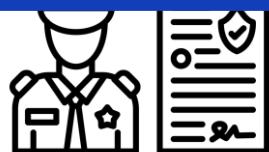
gpt-nl@tno.nl, gpt-nl.nl

For whom?



Focus on three main capabilities:

1. Summarisation
2. Simplification
3. Retrieval-Augmented Generation (RAG)



Main capabilities and use case

| | Summarization | Simplification | RAG |
|-------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Main capabilities | <ul style="list-style-type: none">• Regulations• Compliance requirements | <ul style="list-style-type: none">• Simplify complex jargon without compromising on factuality• Language levels specified to user | <ul style="list-style-type: none">• Access to and integration of organizational specific (sensitive) information• Provide interface for Q&A to users |
| Use cases | <ul style="list-style-type: none">• Case law documents• Insurance policies• Driving license guidelines• Medicine prescription explanations• Etc. | | |