Promoting Open Science in times of Artificial Intelligence: Do we grasp the interplay? (a self-reflecting case study of two current projects¹)



Probabilistic modeling of token sequences: Data converted into 'probabilities of occurrence of tokens'

Training data: large body of information from a variety of sources (freely and openly available on the Internet). Not entirely known to the user (modified subsequently through RLHF).

Innovations? • • • Curron Data differing "What is ՆԱԼԼԵԼՈԼ the 'Theory of relativity'?" from the practice mainstream?

Result containing



Prompt

The greater the data prominence, the higher the probability of occurrence.



(reliable) knowledge.

Marie Alavi,

Julia Priess-

Buchheit

have revolutionized the field

machines to understand and gen

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demystify tokens in LLMs, unra

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Nicolaus Wilder,

AND RESEARCH QUALITY

K:KIWA

Black box (stochastic parrot): Probabilistic Modeling of Token Sequences Searching for associations between tokens, predicting the probabilities of token sequences based on the context provided by previous tokens and generating outputs based on the tokens' statistical and probabilistic nature.

Promoting OS with RI and RE as umbrella concepts influencing data occurence





Using LLMs based on **Probabilistic Modeling of Token Sequences**

- Which data is used for training and probabilistic modeling of token sequences?
- What are the operational mechanisms of a LLM (cf. "black box")?
- Are certain **RI and RE principles** (such as accountability, interpretability, factuality, explainability, safety, reliability, traceability, etc.) **compatible** with LLM functionality?
- How can we ensure RI and RE principles at the intersection of AI and OS without lowering the online prominence of OS data?



Probabilistic Modeling of Token Sequences:

- The parameter for weighting probabilities is the **quantitative** prominence of available data
- prominent data: widely available online, easily discoverable, frequently repeated, cited, referenced, reviewed, edited, widely disseminated 3)

On the best way with OS:

Achieving data prominence involves factors such as **open** access publishing, open data repositories etc.

Training (of LLM) and prediction functionality require large online data to follow linguistic rules (Estimates: GPT-4 trained on 13 trillion tokens - ca. 10 trillion words 4).

RI, RE & OS

These RI/RE principles and IP rights make OS (reliable) data under-represented for Al training:

- Transparent and open sharing, collaboration, building on existing data and
- **preprint archives** reduce the likelihood of redundant studies
- Peer review assessing originality, validity, and significance of a study limits publishing similar study
- Protecting **Data Privacy** and **Confidentiality**, preventing unauthorized access
- Prioritizing quality over quantity: prevention of salami publication, re-publishing etc.
- Safeguarding/witholding data from harm or misuse (ethical need)
- Utilising Intellectual Property Rights to limit access

OS sources will not suffice to train a proper LLM.

How can we deal responsibly with these fundamentally different logics? Three perspectives:

At the intersection of OS and LLMs,

- end users must be aware of the different logics, principles and limitations in order to use LLMs with a critical and reflective approach in the scientific process.
- developers must be sensibilised to the principles of good research practices and reinforce these responsibly in the training processes.
- research community must reflect on its own processes and principles in light of these developments and readjust them if necessary.

Promoting OS as widely as possible could overcome the current under-representation, thereby refining the quality of knowledge that is freely accessible.

References: (1) AI-based assistance system for higher education (Project HAnS) and NERQ_OS findings; (2) Base Models: Standard pre-trained LLMs like ChatGPT (in distinction to RAG-Enhanced or Fine-Tuned LLMs); (3) Karamolegkou, A., Li, J., Zhou, L. & Anders Søgaard (2023). Copyright Violations and Large Language Models. In Procee-dings of the 2023 Conference on Empirical Methods in Natural Language Processing, p. 7403–7412, Singapore. Association for Computational Linguistics.; (4) Schreiner, A. (2023, July 11). GPT-4 architecture, datasets, costs and more leaked. the decoder. https://the-decoder.com/gpt-4-architecture-datasets-costs-and-more-leaked/