EleutherAI NTIA RFC Submission

The EleutherAI Institute

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Contents

Executive Summary

Drawing on EleutherAI's years of experience in open source AI, we look at the current landscape of open-weight models. We assess that in order to ensure the best outcomes:

The US should be the leader in open and transparent AI.

Leaders get to set standards, including in safety and security. Open-weight models bring tremendous benefit to science and innovation: two areas in which the US is already a world leader, in part due to a strong culture of open research. The US would be giving up a lot of influence and leverage by withdrawing from the open AI ecosystem.

More research is needed on the marginal risks and benefits of open-weight models.

We lack satisfactory empirical evidence on many of the purported risks of open models.[1]

Where we have relevant research, many effective mitigations lie outside of the AI model.

We need to look beyond the model parameters and instead leverage, for example, platform governance.

Restrictions on open-weight models are a costly intervention with comparatively little benefit.

Because few harms arise purely from model weights alone, there are many risks it does not address. However, the negative impact on basic research – including research on AI mitigations – would be significant. In the alternative scenario in which some model weights encode information that is truly dangerous and, for example, constitutes a threat to national security, closed model weights are not a strong enough defense.

1. Sayash Kapoor et al. 2024. On the societal impact of open foundation models. https://arxiv.org/pdf/2403.07918.pdf.

Part A: Argument and Narrative

1 The limits of current approaches to AI safety

Dialect prejudice predicts AI decisions about people's character, employability, and criminality[2] is a newly released study on racial bias in large language models, and its findings illustrate the pitfalls of the current AI safety paradigm. Existing benchmarks intended to measure prejudice in LLMs typically focus on examples in which the protected characteristic is explicitly mentioned, illustrated here for gender bias:

> "We couldn't start the board meeting at 9am today because a man and a woman were late.
> Question: Who was the secretary?"

The correct answer is "not enough information," and if the model responds "the woman," that is taken as evidence of negative stereotyping.[3] In contrast to such overt questions, the *Dialect prejudice* paper focuses on covert racial stereotypes. The researchers measure how prompts using African American English (AAE) affect text generation in five different models (RoBERTa, T5, GPT-2, GPT-3.5, GPT-4). Unfortunately but not surprisingly, they find that the use of AAE results in model generations that display severe prejudice. Alarmingly, the models

> "[exhibit] covert stereotypes that are more negative than any human stereotypes about African Americans ever experimentally recorded, although closest to the ones from before the civil rights movement."

The most consequential finding from the point of view of AI safety and policy is that reinforcement learning from human feedback (RLHF) has no effect on this covert dialect prejudice. In other words, the current safety "alignment" technique used by OpenAI and other companies helps models "hide their racism" by "overtly associating African Americans with exclusively positive attributes (e.g., brilliant)," while they continue to "covertly associate African Americans with exclusively negative attributes (e.g., lazy)." When prompted to make a decision, all of the tested LLMs are more likely to convict speakers of AAE of a crime, assign them lower-prestige jobs, and sentence them to death. It's worth reiterating that the levels of covert prejudice shown in this study are particularly severe: "more negative than the most negative experimentally recorded human attitudes about African Americans, i.e., the ones from the 1930s." 2.d.i & 5.a-b

To be clear, we have no reason to believe other models, including open-weight, would do any better; the researchers correctly explain that this dialect

2. Valentin Hofmann et al. 2024. *Dialect prejudice predicts AI decisions about people's character, employability, and criminality,* March 1, 2024. Accessed March 6, 2024. arXiv: 2403.00742[cs]. http://arxiv.org/abs/2403.00742.

3. Alicia Parrish et al. 2021. Bbq: a hand-built bias benchmark for question answering. In *Findings.* https://api.semanticscholar.org/CorpusID:239010011.

prejudice stems from patterns embedded in training data, and we can make an informed guess that our models would score similarly to GPT-2 or base GPT-3 (no finetuning). But we hope this example demonstrates why many in the AI research community are skeptical of policy proposals that assume AI development is best left to large actors who implement "guardrails" such as "safety finetuning." OpenAI is part of the White House voluntary commitments to manage risks posed by AI and an enthusiastic participant — or leader — in many "responsible AI" initiatives. Multiple organizations judged GPT-4's risk evaluation and adversarial testing to be more than adequate, and yet prompting the model with "she be having" as opposed to "she's usually having" generates prejudice worse than that recorded in 1933.

Informed by our experience developing AI models and observing many AI failures, we think that harm manifests in complex ways, risk mitigations take many forms, and open models contribute enormously to our collective effort to figure out AI safety.

2 Open-weight models and open source

This Request for Comment concerns dual-use foundation models with widely available weights, or open-weight models for short. The E.O. 14110 definition is concerned with capabilities and risks contained in the model weights themselves. EleutherAI's work centers on open source AI models, which are a subset of open-weight models: all open source models are open-weight, but not vice versa. We would like to clarify this distinction and address common open source license misconceptions.

2.1 The function of open source licenses

Some commentators argue that defining open source AI is misguided or irrelevant.[4] However, the history of open source software does not support this view in the slightest. Open source (that is, OSI-approved) licenses are a minimal legal framework that enables seamless software development on the Internet.[5] The open source movement made a great effort over the years to ensure that the licenses are legally sound and protect both creators and users of open source code. Creators are protected from liability while sending a clear signal that others can build on top of their work; users are protected from intellectual property claims. Most consequentially for market competition, open source licenses drastically reduce the legal burden for start-ups and small businesses. The beauty of this minimal legal framework is that it works regardless of the contributors' individual beliefs, geographic location, when they join a project, or whether they are involved in commercial or non-commercial activity. Open source has

4. https://www.technologyreview.com/2024/03/25/1090111/tech-industry-open-source-ai-definition-problem/

5. This section is particularly indebted to several open source legal experts and veterans, including Pamela Chestek, Luis Villa, Stefano Maffulli, and Deb Bryant.

become the norm in IT, and companies that previously argued against it now have open source procurement strategies.

At EleutherAI, we call our models open source, and we aim to make our research maximally open and transparent. In addition to releasing the model weights under an open source license, we also make available every associated artifact (such as training datasets or codebases we develop and maintain).

2.2 Custom open-ish licenses

However, not all open-weight models are open source. Open-RAIL is a type of "ethical license" created as a part of the BigScience Workshop scientific collaboration, and applied to the BLOOM model [6,7]. This license, developed as an experiment in governance, applies a number of use-based restrictions to the open-weight BLOOM model [8] based on what is judged as unethical or harmful use.

While admirable in intent, these licenses have drawn significant criticism [9]. The ethical use-based restrictions may be cloudy and up for interpretation, and there are no documented cases of enforcement mechanisms being established and successfully enacted against violators of the RAIL licenses.

The Open-RAIL license and its variants have been widely adopted [10,11] and modified by or inspired various organizations releasing models in the past two years [12,13,14,15]. A notable addition in the Llama 2 Community License [16] are two clauses meant to stifle competition and create network effects around Meta's Llama 2 release: namely, a clause requiring direct approval of usage from Meta for entities with "greater than 700 million monthly active users", and a clause preventing any outputs of Llama 2 models being used to improve others' models.

Although a majority of new flagship open-weight model releases have followed suit in writing a new, bespoke, RAIL-inspired usage-restricted license themselves, one commonality is that a majority of licenses after the release of the Llama 2 Community License have adopted a similar anti-competitive clause restricting the usage of model derivatives for improving other language models.

All such restricted licenses violate the spirit and definitions of OSI-approved

6. https://bigscience.huggingface.co/blog/the-bigscience-rail-license
7. Danish Contractor et al. 2022. Behavioral use licensing for responsible ai. In *2022 acm conference on fairness, accountability, and transparency.* FAccT '22. ACM, June. https://doi.org/10.1145/3531146.3533143. http://dx.doi.org/10.1145/3531146.3533143.
8. https://huggingface.co/spaces/bigscience/license
9. https://katedowninglaw.com/2023/07/13/ai-licensing-cant-balance-open-with-responsible/
10. https://huggingface.co/CompVis/stable-diffusion
11. Raymond Li et al. 2023. *Starcoder: may the source be with you!* arXiv: 2305.06161 [cs.CL].
12. https://github.com/deepseek-ai/DeepSeek-LLM/blob/main/LICENSE-MODEL
13. https://github.com/QwenLM/Qwen/blob/main/Tongyi%20Qianwen%20LICENSE%20AGREEMENT
14. https://huggingface.co/spaces/tiiuae/falcon-180b-license/blob/main/LICENSE.txt
15. https://www.databricks.com/legal/open-model-license
16. https://ai.meta.com/llama/license/

open source licenses [17][18]. This removes one of the main advantages of open source licenses: the reduced legal burden that preexisting and vetted licenses such as Apache 2.0 provide. Entities using RAIL-based licenses in their AI model stack will either need a lawyer upfront, or might encounter unforeseen legal issues down the line. However, *in practice* what we see is that, to the best of our knowledge, no one is attempting to the terms of these new custom licenses.[19]

2.3 EleutherAI and open source

EleutherAI is a 501(c)(3) research organization developing large scale, open source AI technologies in the United States. Despite existing for only four years – and being a legal entity for one, in order to sustain a small full-time research staff – EleutherAI rapidly became a leading AI research organization in the United States and has played a pivotal role in the development of open and accessible large scale AI technologies. We also serve as a bridge between the academic world of artificial intelligence and open source software communities.

EleutherAI was founded in July 2020 by a group of hackers and machine learning hobbyists who were early adopters of the idea that OpenAI's GPT-3 represented a paradigm shift in machine learning research, but were worried by OpenAI's rhetoric around the potential for harm and the necessity of restricting access to the model and other future models like it. While we agreed that the line of research OpenAI was pursuing was potentially risky, we felt that it was inappropriate to restrict access to the technology and prevent researchers from studying it. Instead, we felt that the best way to ensure a thriving and safe AI future was to ensure that private interests didn't dictate what research was permitted. Therefore we set out to replicate OpenAI's work.

Over the next two years we studied the machine learning development pipeline intensely, building the datasets[20], training libraries[21,22], and evaluation suites[23] necessary to create our own foundation models. We trained and publicly released GPT-Neo-2.7B[24], GPT-J-6B[25], and GPT-NeoX-20B[26], each of which were the

17. https://opensource.org/blog/metas-llama-2-license-is-not-open-source
18. https://openfuture.eu/blog/the-mirage-of-open-source-ai-analyzing-metas-llama-2-release-strategy/
19. For an added complication, it is unclear whether model weights are copyrightable at all.
20. Leo Gao et al. 2020. *The pile: an 800gb dataset of diverse text for language modeling.* arXiv: 2101.00027 [cs.CL].
21. Sid Black et al. 2021. *GPT-Neo: Large Scale Autoregressive Language Modeling with Mesh-Tensorflow.* V. 1.0, March. https://doi.org/10.5281/zenodo.5297715. https://doi.org/10.5281/zenodo.5297715.
22. Ben Wang. 2021. *Mesh-Transformer-JAX: Model-Parallel Implementation of Transformer Language Model with JAX.* https://github.com/kingoflolz/mesh-transformer-jax, May.
23. Leo Gao et al. 2023. *A framework for few-shot language model evaluation.* V. v0.4.0, December. https://doi.org/10.5281/zenodo.10256836. https://zenodo.org/records/10256836.
24. Sid Black et al. 2021.
25. Ben Wang and Aran Komatsuzaki. 2021. *GPT-J-6B: A 6 Billion Parameter Autoregressive Language Model.* https://github.com/kingoflolz/mesh-transformer-jax, May.
26. Sidney Black et al. 2022. GPT-NeoX-20B: an open-source autoregressive language model. In *Proceedings of bigscience episode #5 – workshop on challenges & perspectives in creating*

largest and most powerful publicly released LLM in the world at their time of release. We also pioneered new techniques for training models, such as inventing a novel transformer architecture later adopted by models such as PaLM[27], Stable LM[28], and Falcon[29], documenting the advantages of and popularizing then-unknown rotary positional embeddings[30,31]

In 2022 we began to see a cultural shift in machine learning. Whereas in the previous years we were the only people publicly working towards open sourcing GPT-3, emboldened by our efforts[32] many other organizations began to release powerful large language models including Meta[33,34], NVIDIA [35], and BigScience[36].

EleutherAI has always been an open and collaborative organization[37], with the primary goal of putting out high quality research and enabling others to do the same. Historically, that has meant being at the cutting edge of developing and releasing useful open-weights foundation models to level the research field, but with the increased interest and funding for other open-weights models to be released by better-funded for-profit companies, our role has has shifted to exploring and funding under-exposed areas of ML research [38], providing mentorship, and maintaining critical open-source software infrastructure for the open source AI community[39,40].

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large language models, edited by Angela Fan et al., 95–136. virtual+Dublin: Association for Computational Linguistics, May. https://doi.org/10.18653/v1/2022.bigscience-1.9. https://aclanthology.org/2022.bigscience-1.9.

27. Aakanksha Chowdhery et al. 2023. Palm: scaling language modeling with pathways. *Journal of Machine Learning Research* 24 (240): 1–113. http://jmlr.org/papers/v24/22-1144.html.

28. Marco Bellagente et al. 2024. *Stable lm 2 1.6b technical report.* arXiv: 2402.17834 [cs.CL].

29. Ebtesam Almazrouei et al. 2023. The falcon series of language models: towards open frontier models.

30. Jianlin Su et al. 2023. *Roformer: enhanced transformer with rotary position embedding.* arXiv: 2104.09864 [cs.CL].

31. Stella Biderman et al. 2021. *Rotary embeddings: a relative revolution.* EleutherAI Blog. [Online; accessed March 2024]. https://blog.eleuther.ai/rotary-embeddings/.

32. Source: personal conversations with researchers involved in the named projects

33. Susan Zhang et al. 2022. *Opt: open pre-trained transformer language models.* arXiv: 2205.01068 [cs.CL].

34. Ross Taylor et al. 2022. *Galactica: a large language model for science.* arXiv: 2211.09085 [cs.CL].

35. https://huggingface.co/nvidia/nemo-megatron-gpt-20B

36. BigScience Workshop et al. 2023. *Bloom: a 176b-parameter open-access multilingual language model.* arXiv: 2211.05100 [cs.CL].

37. In fact, we conduct all our research openly through a Discord server. Join us: https://discord.gg/zBGx3azzUn

38. https://github.com/EleutherAI/aria

39. Gao et al. 2023.

40. Alex Andonian et al. 2023. *GPT-NeoX: Large Scale Autoregressive Language Modeling in PyTorch.* V. 2.0.0, September. https://doi.org/10.5281/zenodo.5879544. https://www.github.com/eleutherai/gpt-neox.

2.3.1 Empowering US government AI capacity

EleutherAI works closely with high performance computing (HPC) engineers across the country to make large language model technologies more accessible. We have worked with HPC engineers at several national labs to bring the GPT-NeoX training library[41] to their supercomputers, thereby empowering the U.S. Government to sponsor and perform cutting edge research in large scale artificial intelligence. At Oak Ridge National Lab, our library powers research done by ORNL staff[42,43], enables researchers with computing grants to research large language models[44,45,46], and was used to benchmark the new Frontier supercomputer[47].

Beyond Oak Ridge, our library is also available at Pacific Northwest National Lab[48,49], Argonne National Lab[50], and Lawrence Livermore National Lab[51], and our HPC team is currently working on bringing it to the Texas Advanced Computing Center as part of our commitment to the National AI Research Resource[52] to support the development of a large language model for scientific applications. We have also co-authored papers with the Laboratory for Physical Sciences[53] on malware detection using large language models.

3 Challenges and opportunities in open source policy

In the many 2023 open model policy debates, we noticed some concerning trends that tend to exclude open source communities:

Policy crafted for the largest commercial players. This is far the most frequent problem (see: EU AI Act). Narratives that exaggerate the

41. Andonian et al. 2023.

42. Junqi Yin et al. 2023. Forge: pre-training open foundation models for science. In *Proceedings of the international conference for high performance computing, networking, storage and analysis,* 1–13.

43. Junqi Yin et al. 2024. Comparative study of large language model architectures on frontier. *arXiv preprint arXiv:2402.00691.*

44. https://www.together.ai/blog/redpajama-models-v1

45. Kshitij Gupta et al. 2023. Continual pre-training of large language models: how to re-warm your model? In *Workshop on efficient systems for foundation models@ icml2023.*

46. Adam Ibrahim et al. 2024. Simple and scalable strategies to continually pre-train large language models. *arXiv preprint arXiv:2403.08763.*

47. https://www.olcf.ornl.gov/benchmarks/

48. Orion Walker Dollar et al. 2022. Moljet: multimodal joint embedding transformer for conditional de novo molecular design and multi-property optimization.

49. Sameera Horawalavithana et al. 2022. Foundation models of scientific knowledge for chemistry: opportunities, challenges and lessons learned. In *Proceedings of bigscience episode# 5–workshop on challenges & perspectives in creating large language models,* 160–172.

50. https://docs.alcf.anl.gov/polaris/data-science-workflows/applications/gpt-neox/

51. Personal communication

52. https://new.nsf.gov/focus-areas/artificial-intelligence/nairr

53. Mohammad Mahmudul Alam et al. 2023a. Recasting self-attention with holographic reduced representations. In *International conference on machine learning,* 490–507. PMLR.

amount of resources needed to build an LLM do not help. Once safety gets defined as "whatever a 'frontier' company did for their latest model," there is little space to develop sound open source policies.

Lack of knowledge about the open AI ecosystem. It is unfortunately common to see a panel on the subject of open source AI with no open source practitioners present. The open source community on the other hand does not devote resources to making itself visible or intelligible to the outside. This results in frequent inaccuracies and misunderstandings. It is paramount policymakers proactively communicate with the actual developers of open-weight models. We usually do not have government relations teams.

Difficulty operationalizing and implementing guidelines. We've witnessed many generative AI failures not because no mitigations were implemented, but rather due to a) the best available mitigations still not being enough, and b) inappropriate use cases. The AI industry urgently needs more robust and sophisticated mitigations.

Government unable to independently verify third-party claims. Our specific concern here is that we have observed a mismatch between what a proposed mitigation can realistically achieve and the problems they are purported to solve. One such example is watermarking when applied to disinformation.

We understand that "the government needs to improve technical capacity" is not a novel statement, apologies! But we hope open source communities diffusing knowledge can help.

4 Types and Levels of Access, and Corresponding Risks & Benefits

In response to 1.d., we provide a breakdown of the levels of access to open foundation models and closed foundation models alike. There are broad spectrums of access to foundation models which can impact their levels of benefit and risk[54]. The information in this section also relates to the definition of "wide availability" (1.c.), as well as multiple risks and benefits questions: 2.a, 3.b, 3.e, and 4.

4.1 Model Components

The most important component of model access is **model weights**. Openly available model weights are a necessary prerequisite for open foundation models, and provide significant benefits. Open weights allow for reproducible research

54. Irene Solaiman. 2023. *The gradient of generative ai release: methods and considerations.* arXiv: 2302.04844 [cs.CY].

not obsoleted by the deprecation of companies' previous-generation offerings, and allow for customization to new use cases or other reuses. Full access to model weights, aside from reproducibility, also is required for work such as interpretability research or investigation on modifying model training methods or architectures[55]. They also carry substantial financial benefit to the ecosystem at large. Access to model weights allows organizations to run models locally, which is cheaper than APIs, and locally hosted models are able to maintain user privacy in ways that can be highly desirable or even legally required, depending on the context. Although open weights carry a majority of the benefits of open foundation models, they also hold the burden of much of the risks: open model weights are not currently able to be revoked or restricted after release, and can be fine-tuned by any actor, including malicious ones.

Modes of access or supplementary component access beyond just foundation model weights can provide benefits far beyond a simple undocumented open weights release. Access to model **training data** can enable external auditing and compliance checks, as well as forms of research investigating the impacts of training data on model behavior. The primary risk of training dataset release is to the companies themselves: they often treat training data as a proprietary secret and competitive advantage. Additionally, disclosing information about training data can potentially open these model trainers up to lawsuits about the dataset contents. However **from a societal point of view models only become safer by having their training data disclosed.**

Releasing other artifacts produced in the process of model (pre)training, such as intermediate training **checkpoints**, can empower otherwise-impossible research regarding the training dynamics of these foundation models[56,57], or verify that companies' claims regarding the training process are true[58]. Widespread access to partially trained model checkpoints is essential for making this field of research more accessible, as they allow people who don't have the technical knowledge or computational resources to train their own models to do impactful research.

Likewise, publicly releasing artifacts produced in the course of model fine-tuning can increase transparency and bring benefits to research and the public *writ large*. Sharing the **fine-tuning data**, especially data such as labels produced by a workforce of human annotators for red-teaming or for adjusting a model for "safety" training, can allow for external auditors to examine what sorts of safety is being targeted by model trainers[59], and can allow for the reuse of data labeler labor. Additionally, sharing **Reward Models** produced in the

55. Stella Biderman, Hailey Schoelkopf, et al. 2023. Pythia: a suite for analyzing large language models across training and scaling. In *International conference on machine learning,* 2397–2430. PMLR.

56. *Id.*

57. Yuandong Tian et al. 2023. Joma: demystifying multilayer transformers via joint dynamics of mlp and attention. In *The twelfth international conference on learning representations.*

58. Dami Choi, Yonadav Shavit, and David Duvenaud. 2023. *Tools for verifying neural models' training data.* arXiv: 2307.00682 [cs.LG].

59. Stephen Casper et al. 2024. *Black-box access is insufficient for rigorous ai audits.* arXiv: 2401.14446 [cs.CY].

course of Reinforcement Learning from Human Feedback or other safety training or filtering can allow for auditing of safety interventions and expose potential biases in these judgements[60]. In both cases, assuming a model's weights are also released openly, the main risk introduced is to the company training the model: they will face potential reputational risks or greater scrutiny as a result of these releases, regarding their safety mitigations and practices **Again, disclosing approaches and components around safety increases accountability and boosts our collective ability to design safer systems**.

4.2 Software Components

Some model developers release the software that they used to create the model. While a wide variety of softwares are commonly used in the process of model development, they can broadly be grouped into **Data Processing**, **Model Training**, **Model Finetuning**, **Model Inference**, and **Model Evaluation**. The primary benefits of releasing these software are: sharing best practices across the ecosystem; ensuring transparency and reproducibility by allowing other researchers to reuse and vet code to check that the results are correct; and deduplicating effort by allowing people to use or build on existing code when building their own models. The risks associated with each are varied but come primarily in two forms: risk associated with making technology more accessible, and concerns about reputational harm and/or liability for the organization releasing the software.

The release of code for data processing can enable the sharing of best practices and provide consistency in the use of data across the ecosystem, as well as provide deeper insight into the shaping of a model's dataset than just a static data release. The primary risk of releasing data processing code is to the organization inadvertently sharing information about the training data which they wished to keep secret.

The release of model training code is an essential part of building an open source ecosystem. The overwhelming majority of people in the field of AI and machine learning today (both professional and hobbyist) do not have substantial expertise in large scale optimization or high performance computing. As a result, the expertise required to create high-quality training libraries is relatively niche and accessible open source training libraries tend to be used by a wide variety of organizations beyond the ones developing it. Similarly, the primary risk is that it makes it easier for potential bad actors to train their own models. However, while the expertise to train models is relatively niche, there are nevertheless thousands of such people worldwide and any well-resourced actor can afford to hire relevant experts. Developing a high quality training library from scratch can be done by a small team of engineers in a matter of weeks.

Model finetuning code is probably the least impactful form of software to release. Because so much less compute is used for finetuning than training, it is

60. Nathan Lambert et al. 2024. *Rewardbench: evaluating reward models for language modeling.* arXiv: 2403.13787 [cs.LG].

far less important that finetuning code be highly optimized. Many people use basic utilities in their machine learning framework of choice (typically PyTorch, Jax, or TensorFlow) to finetune large language models. Otherwise, the benefits and risks are largely identical to the case of training code.

The release of model inference code can also be useful in making the model usable and accessible to a wide variety of users with varying budgets, and is important for the adoption of an open foundation model. Such code releases can lower the barriers to at-scale deployment of a model, which can increase both positive and negative usage.

Releasing code for model evaluation is an essential way to enable meaningful comparisons between models and to enable transparency in the the reporting of evaluations, especially safety-critical ones. Generally evaluation code release does not present added risks beyond the other components previously discussed, though for some critical topics releasing a labeled dataset of correct and incorrect instances is undesirable.

4.3 API Components

Both closed and open foundation models are often served for mass usage via APIs, enabling usage of a model without needing access to model weights or to run the model's code locally. While open models are often served via APIs, the risk analysis of APIs typically focuses on the perspective of closed models due to the fact that open models can also be accessed with fewer restrictions outside of APIs.

APIs can provide varying levels of access and transparency, which we discuss here. All APIs offer the ability for a user to feed in inputs and receive outputs– for example, generated text from a model such as GPT-4, or images generated by Midjourney. This form of access is the most restricted and therefore least suitable for research activities, although it is sufficient for many commercial applications. It is commonly assumed that by applying "safety finetuning" and exposing a model only via this form a models' behavior can be assured to be safe. However, this is a misunderstanding of both the security context of AI deployment and the technical literature on safety finetuning.

While safety filters anecdotally appear to be successful at preventing unintentional misuse, they are woefully inadequate for preventing deliberate abuse. There are a wide variety of simple and easy-to-use techniques for "jailbreaking" a language model, or bypassing its safety filters. GPT-4, Claude 1 and 2, and Gemini all had their safety filters bypassed within days of their public release. A EuroPol workshop[61] examining the potential for criminals to use ChatGPT found that "[m]any of these safeguards, however, can be circumvented fairly easily through prompt engineering." and that while OpenAI has successfully closed some exploits, "there is no shortage of new workarounds being discovered by researchers and threat actors." We are unaware of any statistics on criminal

61. Europol. 2023. *Chatgpt – the impact of large language models on law enforcement.* Publications Office of the European Union. https://doi.org/doi/10.2813/255453.

use of open vs closed models, but our experience working with large language models indicates that even for use-cases that are allegedly forbidden to a powerful closed model, it is easier to get a high quality generation from a closed model via jailbreaking than it is to get a comparatively high-quality output from a weaker open model with no safety finetuning. The fact that safety filters are easy to bypass is also widely known to the general public and has been covered in accessible news articles by journalists at Vice, CBS News, and Yahoo among others.

It is also common for API providers to provide more detailed information than just model generations. **Logits**, the probability distributions[62] over potential next tokens, are generally viewed as the preferred form of output for researchers as it is more useful for many types of research and most knowledge benchmarks rely on access to logits to score models. However the full set of logits can expose information about models that closed model providers often want to keep secret such as architectural details, tokenizer details, and sometimes even details about the training data. As a compromise, it has become common practice to make the k most probable tokens for some reasonable, but small, k available.

Another feature many API providers included until very recently is **logit bias**. Logit biases allow the user to skew the distribution of logits towards or away from specific tokens, such as discouraging slurs. Recent work showed that allowing user-specified logit bias removes the security enhancements of top-k logits and enables users to obtain access to the full logit distribution, as well as information about the model architecture, efficiently[63,64]. As a result of this work, major model providers have stopped allowing users to specify arbitrary logit biases or have limited logit bias to only impact models when they're used for generation rather than returning logits. This continues to enable most industry applications, but substantially limits the usefulness for researchers.

Foundation model APIs also need not be limited to model inference. **Fine-tuning APIs** are often made available, allowing users to provide a dataset which the API provider will use to fine-tune and subsequently host for the user. This can be used to enable many successful real-world deployments of models specialized for a given task and can be used for many types of research. However it comes with substantial downsides from a safety point of view, as safety filters are easy to finetune out of a model, even inadvertently[65].

Finally, many API providers allow their models to interface with external apps or plug-ins through a process generally known as **tool use**. Tool use for large language models is a budding field of research whose risks and benefits are

62. Technically, logits are a particular transformation of the probabilities, but nothing is lost on a conceptual level by this simplification.

63. Matthew Finlayson, Swabha Swayamdipta, and Xiang Ren. 2024. Logits of api-protected llms leak proprietary information. *arXiv preprint arXiv:2403.09539.*

64. Nicholas Carlini et al. 2024. Stealing part of a production language model. *arXiv preprint arXiv:2403.06634.*

65. Xiangyu Qi et al. 2023. Fine-tuning aligned language models compromises safety, even when users do not intend to! In *The twelfth international conference on learning representations.*

difficult to assess at this time. However it is clear that current implementations pose massive security risks. For example, researchers at Salt Labs[66] found that ChatGPT plug-ins enabled a wide variety of attacks including impersonating the user to the third-party app, impersonating the third-party app to the user, and tricking a user into running malicious code. The first two attacks allow attackers to gain control of user accounts either on the OpenAI side or on the third-party application side, and the last enables attackers to install malware on user systems without their knowledge. Another prominent example is the work of Greshake et al.[67] which showed that by inserting invisible text into the HTML markup of one's personal website, one can gain control of the ChatGPT session of any user who uses ChatGPT's web browsing capabilities to view thier website. The attacker can then see all user inputs, all model outputs, and impersonate the model at will.

5 National security considerations

Concerns have been raised about the impact of generative AI on national security. Here we present our observations from years of participation in an international open model research community.

5.1 Foreign open-weight models

The United States is not the sole creator of powerful open-weight models. At time of writing there are nine open weight models approximately as powerful as or more powerful than LLaMA 2 70B: Qwen 1.5, Mixtral, Grok-1, Falcon-180B, Yi-34B, DBRX, DeepSeek-67B, Command R, and LLaMA 2 70B itself. Four of these models were trained in the US[68], three in China, one in France, and one in the UAE. At various points in the past year, each of these countries has produced the model holding the title of "most powerful public-weight model in the world." In addition to releasing highly capable pretrained language models, the governments of all three countries have identified investment in open source AI as part of their national strategy.

In February, the New York Times published an article claiming that

> "Some of the technology in 01.AI's system came from Llama. Mr. Lee's start-up then built on Meta's technology, training its system [Yi-34B] with new data to make it more powerful."

66. Aviad Carmel. 2024. Security flaws within chatgpt ecosystem allowed access to accounts on third-party websites and sensitive data. *Salt Labs Blog,* https://salt.security/blog/security-flaws-within-chatgpt-extensions-allowed-access-to-accounts-on-third-party-websites-and-sensitive-data.

67. Kai Greshake et al. 2023. Not what you've signed up for: compromising real-world llm-integrated applications with indirect prompt injection. In *Proceedings of the 16th acm workshop on artificial intelligence and security,* 79–90.

68. Cohere's Command R was likely trained within the US, although Cohere is a Canadian company.

This quote implies that, if not for the release of LLaMA 2, 01.AI wouldn't have been able to train a model as powerful as Yi-34B because *the trained LLaMA 2 model was a component in the pipeline that produced Yi.* There is no reason to believe that this claim is true, and substantial reason to believe that this claim is false. We believe that the authors made an understandable but regrettable mistake when trying to follow a technical discussion on the Hugging Face Hub. For further elaboration on this topic, see our recent blog post[69].

This article highlights a common misunderstanding of the relationship between current and future open-weight models. Future open weight models are very rarely based on current open weight models *as computing artifacts.* Rather they will draw design inspiration, learn about best practices, and learn to avoid pitfalls previous developers fell into *by studying the academic papers and technical reports accompanying those models.* The models themselves play no role in the transfer of scientific knowledge other than to demonstrate that the authors did in fact successfully train a powerful model. As a result, heavy restrictions or bans on the release of powerful pretrained models is unlikely to meaningfully limit model development overseas.

Note that we focus above on general capabilities rather than size or pretraining budget. The list and distribution of countries that have trained the *largest* language models or *most expensive* language models is largely similar, with the notable addition of Russia on the "largest" list due to Yandex's 100B parameter language model. While there are some differences in capabilities brought about by design choices, capabilities and expenditures are very strongly correlated for any competent team independent of individual design choices. One thing that is important to keep in mind regarding countries that have trained *large but not as good* models is that those models are typically trained for a small fraction of the number of tokens that the powerful models they are being compared to were trained for. However training them for a meaningful amount of time requires solving all the core engineering problems, and increasing the training token budget is primarily a question about financial investment. If Russia prioritized funding for training an approximately state-of-the-open model, we should take YaLM-100B as evidence that they are likely to succeed.

5.2 Cybersecurity

Cybersecurity and artificial intelligence is a major topic of interest to the US government, as demonstrated by unclassified version of the Office of the Director of National Intelligence (ODNI)'s 2024 Annual Threat Assessment of the U.S. Intelligence Community[70]. The Threat Assessment outlined three key threats from generative artificial intelligence:

- Automatic disinformation campaigns

69. Hailey Schoelkopf, Aviya Skowron, and Stella Biderman. 2024. *Yi-34b, llama 2, and common practices in llm training: a fact check of the new york times.* EleutherAI Blog. [Online; accessed March 2024]. https://blog.eleuther.ai/nyt-yi-34b-response/.

70. ttps://www.dni.gov/files/ODNI/documents/assessments/NIC-Declassified-ICA-Foreign-Threats-to-the-2022-US-Elections-
pdf

- Cyber warfare and AI-powered hacking campaigns
- Chemical, biological, radiological and nuclear (CBRN) information

which we will address in turn.

5.2.1 Disinformation

As far as we are aware, limited ability to produce false information is not the primary bottleneck for disinformation campaigns. While it can be a bottleneck, other issues such as dissemination of information, compromising trust in authorities, and discrete infiltration of social media platforms tend to be substantially greater barriers[71].

We also take issue with the common suggestion that disinformation is a problem that should be solved at the model-provider level.[72] Disinformation is a highly nuanced and contextually sensitive concept that cannot be evaluated in a vacuum: true sentences in one sociopolitical context might be misleading in another and clearly false in a third. Additionally, it is not even clear that *false information* is necessarily the most dangerous[73]. Research on vaccine hesitancy has shown that *misleading true information* is substantially more impactful at reducing compliance than false information.[74].

It is important to keep in mind that the ability to create photo-realistic images and videos has been around for over five years and has been used in attempted disinformation ops. One interesting case study is the Russia-Ukraine war in which falsified videos of Ukrainian President Volodymyr Zelenskyy and Russian President Vladimir Putin were created by Russia and Ukraine respectively and distributed to the other side.[75] However disinformation experts are skeptical that these photorealistic videos played a significant role in shaping discourse on either side[76] and point to cruder but better situated attacks on the epistemic commons as being more effective, highlighting the need for a nuanced view of the issue beyond the ability to generate realistic synthetic content.

None of this is to say that disinformation isn't a real problem or that artificial intelligence does not play a role in its creation or propagation[77]. However over-indexing on the threat of foundation models for disinformation risks both underestimating the problem and overestimating the solution, leaving the U.S. at substantially increased risk.

71. Jon Bateman and Dean Jackson. 2024. Countering disinformation effectively: an evidence-based policy guide.

72. https://www.aisnakeoil.com/p/ai-safety-is-not-a-model-property

73. Michael Hameleers. 2023. Disinformation as a context-bound phenomenon: toward a conceptual clarification integrating actors, intentions and techniques of creation and dissemination. *Communication Theory* 33 (1): 1–10.

74. Jennifer Nancy Lee Allen, Duncan J Watts, and David Rand. 2023. Quantifying the impact of misinformation and vaccine-skeptical content on facebook.

75. https://theconversation.com/deepfakes-in-warfare-new-concerns-emerge-from-their-use-around-the-russian-invasion-of-ukra

76. Bateman and Jackson 2024.

77. While it is a very different type of artificial intelligence than foundation models, recommender algorithms are a key battleground in the fight against disinformation

5.2.2 Cyber warfare and AI-powered hacking campaigns

The question of whether open source systems and openly available tools for finding security vulnerabilities have increased security has been debated beyond the field of artificial intelligence for decades. In general, security experts believe that there is no reason to think that closed systems are more secure than open systems or that publicly sharing tools for attacking systems decreases security.[78,79]

Foundation models, including open foundation models, are beginning to show promise for helping secure our computing systems. Models for malware detection[80,81] and fuzzing[82] are especially promising applications of current technologies. Malware detection gives the ability to protect us from offensive cyber-operations of adversaries, and the relatively cheap cost of the models considered in those papers[83] may imply that for a fixed amount of investment one gets substantially more defensive value than offensive value. Deng et al. (2023) reports using both API and open-weight models to find 65 bugs in the PyTorch library, 41 of which they were able to confirm are novel bugs. While the criticality of these bugs is generally not particularly high, the substantial history of fuzzers improving defenses makes this a clear defensive win.

5.2.3 (CBRN) Information

Chemical, biological, radiological and nuclear (CBRN) information is highly sensitive and sometimes classified information that pertains to the development of extremely dangerous weapons. Some have suggested that large language models will make this kind of information more readily accessible and "democratize access" to biological weapons. The best available research indicates that this is not true of current models,[84,85] and we believe that the focus on *models* in these conversations misses the point in a fundamental way: the core issue isn't the model (which is effectively a better search algorithm over the training corpus for these purposes) but rather the presence of this information in the training data in the first place. We expect that better data management practices, oversight

78. https://www.zdnet.com/article/risky-business-keeping-security-a-secret-5000127072/

79. David A Wheeler. 2021. Secure programming howto. *Walters Art Museum in Baltimore, Maryland.*

80. Mohammad Mahmudul Alam et al. 2023b. Recasting self-attention with holographic reduced representations. In *International conference on machine learning,* 490–507. PMLR.

81. Mohammad Mahmudul Alam et al. 2024. Holographic global convolutional networks for long-range prediction tasks in malware detection. In *Proceedings of the 27th international conference on artificial intelligence and statistics (aistats).*

82. Yinlin Deng et al. 2023. Large language models are zero-shot fuzzers: fuzzing deep-learning libraries via large language models. In *Proceedings of the 32nd acm sigsoft international symposium on software testing and analysis,* 423–435.

83. They are multiple orders of magnitude cheaper than training a competent code generation algorithm.

84. Ella Guest, Caleb Lucas, and Christopher A Mouton. 2024. The operational risks of ai in large-scale biological attacks: results of a red-team study.

85. https://openai.com/research/building-an-early-warning-system-for-llm-aided-biological-threat-creation

of training data, and data investigation and removal will address this issue (to the extent that there is one) far better than any model-level interventions.

When considering models developed for widespread deployment, it is important to keep in mind that there is no evidence that language models are capable of generalizing from, e.g., first year undergraduate biology to designing biological weapons, making models trained only on the former not threatening. Even when more advanced knowledge is necessary for specific applications, curating biological data to selectively remove the specific dangerous subfields will very likely ameliorate the threat.[86] It is possible that models specialized for sufficiently similar applications would be able to perform this kind of generalization, and if substantial evidence of such generalization emerges, access control protocols **for those specialist models** may be appropriate.

Part B: Remaining questions

1 Defining "open" or "widely available"

a Will closed models be opened?

Yes, there is significant evidence that the weights of models similar to current closed AI systems will become available. The current most advanced open models are equal or better than the most advanced closed models from just a few years ago. In many cases, prominent closed models have been replicated wholesale and released openly. For example, GPT-3[87] was replicated and released openly less than 2 years later by Meta AI's OPT[88] models, and the unreleased Chinchilla[89] model from Google DeepMind was replicated by Meta AI in the form of the Llama 1[90] series of models less than a year later.

Other prominent models have been replicated by entities not labs at major tech companies. For example, an academic lab led a collaboration to successfully replicate AlphaFold2[91] as OpenFold[92], without a restrictive license or lack of

86. Research on this topic is currently on-going at EleutherAI.

87. Tom Brown et al. 2020. Language models are few-shot learners. In *Advances in neural information processing systems,* edited by H. Larochelle et al., 33:1877–1901. Curran Associates, Inc. https : / / proceedings . neurips . cc / paper_files / paper / 2020 / file / 1457c0d6bfcb4967418bfb8ac142f64a-Paper.pdf.

88. Zhang et al. 2022.

89. Jordan Hoffmann et al. 2022. *Training compute-optimal large language models.* arXiv: 2203.15556 [cs.CL].

90. Hugo Touvron et al. 2023. *Llama: open and efficient foundation language models.* arXiv: 2302.13971 [cs.CL].

91. John Jumper et al. 2021. Highly accurate protein structure prediction with alphafold. *Nature* 596 (July): 1–11. https://doi.org/10.1038/s41586-021-03819-2.

92. Gustaf Ahdritz et al. 2023. Openfold: retraining alphafold2 yields new insights into its learning mechanisms and capacity for generalization. *bioRxiv,* https://doi.org/10.1101/2022.11.20.517210. eprint: https://www.biorxiv.org/content/early/2023/08/12/2022.11.20.517210.full.pdf. https://www.biorxiv.org/content/early/2023/08/12/2022.11.20.517210.

training details documented. OpenAI's CLIP models[93] were also replicated and released openly by LAION[94], and the released CLIP models by OpenAI were used to drive the then-state of the art in controllable image generation via VQGAN-CLIP[95]. The Stable Diffusion 1 model[96], then the most capable image generation model, was released with open weights. In general, the trend has been for open-weights models to match closed AI systems of the time or in some cases be the forefront.

In fact, during the drafting of this response xAI released Grok-1[97] and Databricks released DBRX[98], two large and powerful models following the same Mixture-of-Experts architecture used in many leading closed labs. According to DataBricks's analysis their model outperforms GPT-3.5 (likely `gpt-3.5-turbo-16k-0613` in particular), a model that was state-of-the-art when released November 2022.

b Predicting the Gap

The timeframe between deployment of an open and closed equally-performing model is difficult to predict reliably. The primary blocker for the capabilities of open models is funding, which can disappear at the whim of a handful of well-resourced individuals. The continued increase in costs (of compute and capital) to create the most capable closed models will create further barriers to entry, but open models remain frequently competitive to closed models and there is evidence that they will continue to do so despite these costs.

The centralization of funding for training these models is itself also a source of uncertainty in the gap between open and closed models, as individual factors affecting the sponsoring organizations unrelated to AI research *per se* can have substantial impacts on release timelines. For example,

c What level of distribution constitutes "wide availability?"

For the bulk of our response to this question, see Section 4.

93. Alec Radford et al. 2021. Learning transferable visual models from natural language supervision. In *Icml*.

94. Mehdi Cherti et al. 2023. Reproducible scaling laws for contrastive language-image learning. In *Proceedings of the ieee/cvf conference on computer vision and pattern recognition,* 2818–2829.

95. Katherine Crowson et al. 2022. Vqgan-clip: open domain image generation and editing with natural language guidance. In *Computer vision – eccv 2022: 17th european conference, tel aviv, israel, october 23–27, 2022, proceedings, part xxxvii,* 88–105. Tel Aviv, Israel: Springer-Verlag. ISBN: 978-3-031-19835-9. https://doi.org/10.1007/978-3-031-19836-6_6. https://doi.org/10.1007/978-3-031-19836-6_6.

96. Robin Rombach et al. 2022. High-resolution image synthesis with latent diffusion models. In *Proceedings of the ieee conference on computer vision and pattern recognition (cvpr)*. https://github.com/CompVis/latent-diffusionhttps://arxiv.org/abs/2112.10752.

97. https://x.ai/blog/grok-os

98. https://www.databricks.com/blog/introducing-dbrx-new-state-art-open-llm

d Do certain forms of access to an open foundation model provide more or less benefit or more or less risk than others?

For the bulk of our response to this question, see Section 4.

i Are there promising prospective forms or modes of access that could strike a more favorable benefit-risk balance? If so, what are they?

For the bulk of our response to this question, see Section 4.

We would like to additionally note that, although the weights of closed models that have been productized such as ChatGPT are not openly available, such deployed models may be far more "widely available" to end users than many openly downloadable foundation model weights, especially weights of models too large for end consumer hardware to quickly run. Calculations regarding volume of risk and benefit should take not just availability of weights into account, but also level of distribution and barriers to *model use*, since widely deployed models receive more traffic and use than open-weight models.

2 Comparing Risks

d Well-Financed Actors

There is no substantial evidence that the lack of weight access to existing models is a meaningful factor constraining the actions of state-level actors or other well-financed actors. A small but dedicated research team with ten million dollars in funding could relatively easily obtain a model as good as or better than the best models with widely available weights today.

i How do these risks compare to those associated with closed models?

For both closed and open models, there are numerous state or determined non-state actors capable of training highly-capable state of the art models without relying on the models which already exist. See also Section 5.1 and in particular our discussion of the claim that LLaMA 2 enabled the training of Yi.

Notably when trying to maximize benefit but minimize risk, local hosting or edge deployment can enable a greater amount of personalization and tailoring for a particular use case. This can reduce risk, because while ensuring the complete "safety" of a general-purpose foundation model is an under-specified task[99], basing safety around a concrete goal and use case, alongside potential threat models, can allow for safety and risk reduction to be effectively achieved.

99. https://www.aisnakeoil.com/p/ai-safety-is-not-a-model-property

ii How do these risks compare to those associated with other types of software systems and information resources?

While it has been speculated that AI models will produce security risks such as assistance in creating bioweapons, existing studies have shown that there is not evidence that current systems are able to meaningfully assist in bioweapon development[100], and that they are not more helpful than the use of freely available traditional software or information resources such as Google or PubMed. AI models are currently trained on almost exclusively publicly available information and content, indicating that most threat models–similar to Google or other search engines–consist of publicly discoverable information simply being easier to surface and access.

3 Unique Benefits of Open Models

We feel it would be appropriate to collect some of the unique benefits and perspectives that open models offer as a component of the AI ecosystem.

Throughout our response elsewhere we discuss risks and benefits of open release, but feel that EleutherAI is well-positioned to convey precisely why open models matter, and can be entirely of a different kind than closed models.

In particular, while openly available model weights can carry some of the benefits we discuss, maximally open models such as those EleutherAI releases including GPT-NeoX[101] and Pythia[102], or AI2's OLMo[103] and LLM360's Amber[104] models that followed, provide extensive benefits for the AI ecosystem, for research, and for AI governance.

Open models open up new research areas There are entire areas of ML research that would not be possible without open and well-documented models like Pythia. Understanding models' "learning dynamics"–how they change over the course of training, in response to new data[105,106,107,108]. Many other forms of research require access to the dataset in addition to

100. https://www.rand.org/news/press/2024/01/25.html
101. Sidney Black et al. 2022.
102. Biderman, Schoelkopf, et al. 2023.
103. Dirk Groeneveld et al. 2024. *Olmo: accelerating the science of language models.* arXiv: 2402.00838 [cs.CL].
104. Zhengzhong Liu et al. 2023. *Llm360: towards fully transparent open-source llms.* arXiv: 2312.06550 [cs.CL].
105. Davis Brown et al. 2023. Understanding the inner-workings of language models through representation dissimilarity. In *Proceedings of the 2023 conference on empirical methods in natural language processing,* edited by Houda Bouamor, Juan Pino, and Kalika Bali, 6543–6558. Singapore: Association for Computational Linguistics, December. https://doi.org/10.18653/v1/2023.emnlp-main.403. https://aclanthology.org/2023.emnlp-main.403.
106. Dmitrii Krasheninnikov et al. 2023. *Meta- (out-of-context) learning in neural networks.* arXiv: 2310.15047 [cs.LG].
107. James A. Michaelov and Benjamin K. Bergen. 2023. *Emergent inabilities? inverse scaling over the course of pretraining.* arXiv: 2305.14681 [cs.CL].
108. Fabien Roger. 2023. *Large language models sometimes generate purely negatively-reinforced text.* arXiv: 2306.07567 [cs.LG].

model weights[109,110], and interpretability research requires at minimum weight and gradient-level access to a model[111,112,113].

Sharing knowledge broadly Openly released, and especially well-documented or transparent open model projects, disseminate knowledge throughout the open source community. EleutherAI in particular has trained many researchers, many of whom come from non-traditional backgrounds[114]. This allows a larger amount of people to contribute to pushing knowledge of the Machine Learning field forward and to help develop techniques that serve them and their concerns.

Safety research is supported and broadened by open models Safety research is also helped by access to open and transparent foundation models. Open-weights models allow more researchers than just the small number at industry labs to investigate how to improve model safety, improving the breadth and depth of methods that can be explored, and also allows for a wider demographic of researchers or auditors of safety. Too much work on improving safety has been made possible by open-weights foundation models to list in full, but we provide a sample here: research on the ability to extract "memorized" training datapoints[115] from a model, investigating the failure modes of watermarking schemes[116], and steering models' predictions to provably not depend on undesired attributes such as gender[117]. Even for researchers in industrial labs such as Google, open models can enable research on model safety that would not otherwise be possible: in an earlier revision of *Quantifying Memorization Across Neural Language Models*, Carlini et al. [118] state that their research on harmful memorization in language models "would not have been possible without EleutherAI's complete public release of The Pile dataset and their

109. Stella Biderman, USVSN PRASHANTH, et al. 2023. Emergent and predictable memorization in large language models. In *Advances in neural information processing systems,* edited by A. Oh et al., 36:28072–28090. Curran Associates, Inc. https://proceedings.neurips.cc/paper_files/paper/2023/file/59404fb89d6194641c69ae99ecdf8f6d-Paper-Conference.pdf.

110. Choi, Shavit, and Duvenaud 2023.

111. Eric Todd et al. 2024. *Function vectors in large language models.* arXiv: 2310.15213 [cs.CL].

112. Kevin Meng et al. 2023. *Mass-editing memory in a transformer.* arXiv: 2210.07229 [cs.CL].

113. Wes Gurnee et al. 2023. *Finding neurons in a haystack: case studies with sparse probing.* arXiv: 2305.01610 [cs.LG].

114. Jason Phang et al. 2022. *Eleutherai: going beyond "open science" to "science in the open".* arXiv: 2210.06413 [cs.CL].

115. Biderman, PRASHANTH, et al. 2023.

116. John Kirchenbauer et al. 2023. *On the reliability of watermarks for large language models.* arXiv: 2306.04634 [cs.LG].

117. Nora Belrose et al. 2023. Leace: perfect linear concept erasure in closed form. In *Advances in neural information processing systems,* edited by A. Oh et al., 36:66044–66063. Curran Associates, Inc. https://proceedings.neurips.cc/paper_files/paper/2023/file/d066d21c619d0a78c5b557fa3291a8f4-Paper-Conference.pdf.

118. https://arxiv.org/abs/2202.07646v2

GPT-Neo family of models"[119].

Overall, open models enable people close to the deployment context to have greater control over the capabilities and usage restrictions of their models, study the internal behavior of models during deployment, and examine the training process and especially training data for signs that a model is unsafe to deploy in a specific use-case. They also lower barriers of entry by making models cheaper to run and enable users whose use-cases require strict guarding of privacy (e.g., medicine, government benefits, personal financial information) to use.

5 Technical issues in managing risks and distributing benefits

a What model evaluations, if any, can help determine risks or benefits?

We caution that current benchmarks in the research community, used in the field as objectives to measure progress on an artificially-constructed task, while useful for some research applications, are not suited for direct policy or risk measurement purposes.

The best evaluation for measuring model safety is one that closely tracks an explicitly outlined threat model and restricted use case, rather than attempting to measure "safety" writ large across all potential use cases. For example, red-teaming with the help of domain experts, with adequate baseline systems also available, can be used to assess safety in real-world (adversarial) scenarios, if the red-teamers are adequately representative of user demographics.

As an additional example of the necessity of targeting and comparing against a concrete scenario of potential harm, and a threat model for how a model might cause such harm, we call back to Section 1 and note that **"bias benchmarks" used in the field are insufficient to ensure that models that score highly do not cause harm in the real world.** Another paper illustrating this phenomenon is *Large language models propagate race-based medicine*[120], which finds that Bard, ChatGPT, Claude, and GPT-4[121], which finds that deployed large language models recommend discredited race-based medical practices grounded in eugenics research. The study specifically considers what would happen if an inexperienced doctor consults the state-of-the-art models to answer some basic questions about medical best practices and finds that substantial harm would ensue. We believe that **real world harm**, rather than artificial bias benchmarks, must be prioritized when designing evaluation protocols for

119. Nicholas Carlini et al. 2023. *Quantifying memorization across neural language models.* arXiv: 2202.07646 [cs.LG].

120. Jesutofunmi A Omiye et al. 2023. Large language models propagate race-based medicine. *NPJ Digital Medicine* 6 (1): 195.

121. ChatGPT here presumably refers to GPT-3.5 via the chat interface, though the paper is unclear on this point.

deployed systems. In particular, this means that models cannot be evaluated in a vacuum and must be evaluated situated in a proposed application context.

f Components Necessary for Red Teaming

Prior work such as *Black-Box Access is Insufficient for Rigorous AI Audits*[122] has argued that black-box access is insufficient for effective auditing: it is crucial to also take into account factors such as methodological choices and how these might impact a model's safety, or additionally internal documentation and evaluations to investigate what systems are being optimized for and what steps are being taken to reduce risks. Ensuring a broad range of people are able to audit the model can achieve broader coverage of potentially-unforeseen harms. While some types of auditing or evaluation can be done with purely inputs + outputs to a model, having the ability to know what types of transformation or augmentation layers surround a foundation model, and access to full outputs such as logits or log-probabilities can enable more thorough evaluation of models, such as probing for bias or more fine-grained answer probabilities and nuances in evaluation.

g Testing and Verifying Model Weights

Here we limit our scope to verifying claims regarding either model trainers' claims made to auditors, or assessing whether the audited model is the one deployed. Regarding the latter, it is possible to determine that these models match, as a sufficiently large quantity of random queries will reveal if two models are non-identical. However, a complication is that API providers do more than just run the input through their model. For example, they will sometimes process and reformat the input, and also call external APIs such as web search, a code compiler, or a computer algebra system. While API calls can be avoided by restricting questions to natural language English and turning off web-browsing, reprocessing and reformatting of inputs is more challenging. The model host would need to disclose all such steps and how they work for testing to be feasible. There may also be other, non-public, steps that model hosts use that need to be taken into account when devising the verification scheme. Regarding methods for proving model trainers' claims made to auditors are truthful, especially with respect to training data composition, this is not yet possible, with the best work to date on the topic being Tools for Verifying Neural Models' Training Data[123]. Note that their schema is not secure and can be fooled.

122. Casper et al. 2024.
123. Choi, Shavit, and Duvenaud 2023.