Large language models shape and are shaped by society: A survey of arXiv publication patterns

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Abstract

There has been a steep recent increase in the number of large language model (LLM) papers, producing a dramatic shift in the scientific landscape which remains largely undocumented through bibliometric analysis. Here, we analyze 388K papers posted on the CS and Stat arXivs, focusing on changes in publication patterns in 2023 vs. 2018–2022. We analyze how the proportion of LLM papers is increasing; the LLM-related topics receiving the most attention; the authors writing LLM papers; how authors' research topics correlate with their backgrounds; the factors distinguishing highly cited LLM papers; and the patterns of international collaboration. We show that LLM research increasingly *focuses on societal impacts*: there has been an 18× increase in the proportion of LLM-related papers on the Computers and Society sub-arXiv, and authors newly publishing on LLMs are more likely to focus on applications and societal impacts than more experienced authors. LLM research is also *shaped by social dynamics*: we document gender and academic/industry disparities in the topics LLM authors focus on, and a US/China schism in the collaboration network. Overall, our analysis documents the profound ways in which LLM research both shapes and is shaped by society, attesting to the necessity of sociotechnical lenses.

1 Introduction

The number of LLM papers is increasing steeply [1, 2]. Due to the rapidly changing scientific landscape, many basic bibliometric trends remain undocumented. Addressing this gap, we analyze 388K papers posted on the CS and Stat arXivs to answer six questions, focusing in particular on trends since the beginning of 2023:

1. **How is the proportion of LLM papers changing? (§3.1)** We extend findings from prior work by showing not only that there is a steep recent increase in LLM publications (a 12× increase in the proportion of papers mentioning "large language models" in title or abstract in 2023 relative to the same period in 2022), but also that *the fastest growing topics and keywords* in the arXiv sample are LLM-related.

2. **What topics are LLM papers focusing on? (§3.2)** We create an ontology of 35 LLM-related topics and use this to classify 13,774 LLM papers through May 2023. We find that the fastest-growing topics cover the empirical capabilities of LLMs and the societal implications thereof: for example, the fastest growing topic is "Applications of LLMs/ChatGPT", which has increased by a factor of 8×. Similarly, the sub-arXiv with the largest (18×) increase in its proportion of LLM papers is Computers and Society, attesting to the broader social impact of these models.

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3. **Who is writing LLM papers? (§3.3)** Academic institutions account for a much larger share of LLM publications than industry institutions (and this becomes even more pronounced in 2023), but a small number of industry institutions produce a large number of papers.

4. **Do LLM authors with different backgrounds tend to focus on different topics? (§3.4)** Authors from different backgrounds tend to focus on different topics. We document a gender gap in the topics LLM authors study: papers with a majority of predicted-female author names are 3× more likely to study bias and fairness, for example. There are also academic/industry differences: papers with industry-affiliated authors are more likely to study model efficiency and pretraining. Papers led by authors who are newcomers to LLMs are more likely to discuss societal impacts and applications (e.g., privacy, education, law), while experienced LLM authors work more on improving model performance and evaluating them on existing tasks (e.g., information retrieval, summarization).

5. **What distinguishes highly cited LLM papers? (§3.5)** Larger, industry-affiliated teams are more likely to write highly cited LLM papers. Papers with only industry affiliations have 2.5× higher odds of being above the 95th citation percentile compared to papers with only academic affiliations. Papers with more than 10 authors have 13.4× higher odds of being above the 95th citation percentile compared to papers with two or fewer authors.

6. **What are the patterns of collaboration? (§3.6)** We analyze the network of collaborations between the 20 institutions writing the most LLM papers, all of which are either American or Chinese. We document a US-China schism: pairs of institutions which frequently collaborate are almost exclusively based in the same country. An exception to this is Microsoft, which collaborates frequently with academic institutions from both countries. We also find that while both academic-academic and academic-industry collaborations are common, collaborations across multiple industry institutions are rare.

Overall, our analysis documents two ways in which LLMs are increasingly entwined with society. First, LLM research increasingly *focuses on societal impacts* — from novel positive applications to societal harms like misinformation and bias. This shift is driven in part by a surge of new authors who are writing LLM papers for the first time. Second, LLM research is profoundly shaped by *social dynamics*. The topics that LLM authors focus on depend on their backgrounds, as evidenced by the gender and industry/academic disparities we reveal. This suggests that the research directions the scientific community prioritizes will be shaped by who gets to do LLM research in the first place. Similarly, the US-China divide in the collaboration network is a social dynamic which is likely to continue to shape the nature of LLM research. Overall, LLMs both *shape and are shaped by* social dynamics, and are thus best understood by sociotechnical, not purely technical, approaches.

2 Methods

We summarize our data and methods here and provide full details in Appendix A; Table 1 lists the fields we use in our analysis. Our primary dataset consists of 388K papers posted on the CS and Stat arXivs between January 1, 2018 and May 26, 2023. Following past ML survey papers [3–6], we identify an analysis subset of 13,774 LLM-related papers whose title or abstract contains at least one of an interpretable set of keywords (§A.2): the specific keywords we use are {language model, foundation model, BERT, XLNet, GPT-2, GPT-3, GPT-4, GPT-Neo, GPT-J, ChatGPT, PaLM, LLaMA}.

We define several fields for each paper in this subset. In defining all these fields, we both follow procedures used in past work as closely as possible and also conduct manual audits to assess the reliability of our annotations; however, there remain inherent limitations in how these fields are defined, as we discuss fully in Appendix A. We assigned each paper a topic (§A.3) by applying a clustering algorithm to semantic embeddings of the paper abstracts [7, 8], then labeled the clusters using a combination of LLM annotation and manual annotation; the labels are somewhat subjective, though we

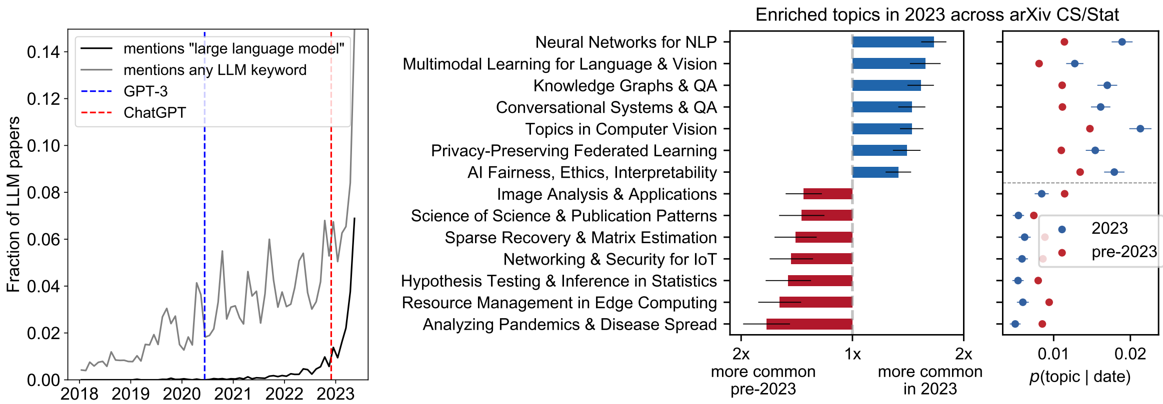
	Field Name	Field Description
About LLMs? (§A.2)	mentions keyword	1 if paper title or abstract contains an LLM-related keyword from the list {language model, foundation model, BERT, XL-Net, GPT-2, GPT-3, GPT-4, GPT-Neo, GPT-J, ChatGPT, PaLM, LLaMA}, 0 otherwise
Topics (§A.3)	sub-arXiv	name of subarXiv paper belongs to
	topic	name of topic generated from topic model
Affiliations (§A.4)	academic	1 if paper has ≥ 1 academic affiliation with ≥ 10 LLM papers, 0 otherwise
	industry	1 if paper has ≥ 1 industry affiliation with ≥ 10 LLM papers, 0 otherwise
Gendered names (§A.5)	majority predicted female	1 if at least half of gendered author names on a paper are predicted female, 0 if fewer than half of gendered author names are predicted female, undefined if no predictions
Citations (§A.6)	citation percentile	citation percentile among papers published in same year

Table 1: A summary of data fields used in our analyses. Further details in §2 and Appendix A.

verified that they are reasonable by examining 25 papers per cluster. We computed two separate topic clusterings for the LLM-related papers (comprising 35 LLM-related topics like "Prompts & In-Context Learning") and the full set of CS/Stat papers (comprising 100 broader topics like "Deep Learning Theory"). We annotated papers for whether their authors had academic or industry affiliations (§A.4). Each paper also has a *sub-arXiv*: papers on arXiv must select one primary category, such as Artificial Intelligence (cs.AI) or Computation and Language (cs.CL). We also annotated each paper for whether at least half of its authors' names are predicted to be gendered female (§A.5).[1] Finally, for all LLM-related papers, we pulled citation data from Semantic Scholar and defined the *citation percentile* for each paper as its citation count percentile rank relative to papers published in the same year (§A.6).

Throughout the paper, we perform analyses comparing how frequently a paper topic occurs in one group compared to another: for example, how much more frequently a paper topic occurs in industry papers compared to non-industry papers, or in pre-2023 papers compared to 2023 papers. These analyses rank topics by the ratio $\frac{p(\text{topic} \mid \text{group 1})}{p(\text{topic} \mid \text{group 2})}$ and report the k topics with the highest and lowest ratios, which we refer to as the *enriched* topics for each group. We plot the ratio and include errorbars which are 1.96× the standard error on a risk ratio. We separately plot the numerator and denominator of each ratio and report 1.96× the Bernoulli standard error.

[1] While name-gender associations have been widely applied to study gender disparities in bibliometrics and elsewhere [9–21], this approach has important limitations [18, 19, 22, 23]. In particular, it fails to accurately reflect non-binary authors and authors whose gender does not match the majority association with their name, and its performance varies by name origin: for example, it often fails to yield any prediction for East Asian names. Our gender-related analyses ought thus be regarded as applying only to authors who are not members of these groups, an important caveat; in particular we observe that a large fraction of East Asian names remain unclassified in our data (though overall we have predictions for 61% of author names and 92% of papers). To acknowledge the inherent limitations of name-gender inference, we refer to the classified categories throughout the text as *predicted* female and *predicted* male, following previous work [24]. In spite of these limitations, we believe it is important to attempt to systematically document gender disparities in the study of LLMs due to anecdotal evidence suggesting these disparities may be pronounced [25], as well as previous academic research documenting gender differences in scholarly authorship, in views on social implications of computing, and in social and ethical issues more generally [10, 14–17, 21, 26–29]. See §A.5 for a full discussion of these points and more details of methodology and robustness checks.



(a) (b)

Figure 1: The proportion of LLM papers has increased rapidly in 2023. Figure 1a: The light gray line shows the proportion of arXiv CS/Stat papers which mention any LLM keyword (as defined in Table 1), and the black line shows the proportion which mention the specific phrase "large language model." Figure 1b: The fastest growing topics across all of CS/Stat pertain to LLMs. Left: Enrichment ratios of $\frac{p(\text{topic} \mid \text{paper published in 2023})}{p(\text{topic} \mid \text{paper published in 2018–2022})}$. Blue topics are enriched in papers in 2023, red topics are enriched in papers pre-2023. Right: The fraction of papers on each topic pre-2023 and in 2023.

3 Results

3.1 How is the proportion of LLM papers changing?

LLM papers account for an increasing fraction of arXiv submissions. Figure 1a shows that the fraction of CS/Stat papers which are LLM-related has grown steeply in 2023, up to 15% of all submissions; the fraction is 2× higher than the same time period in 2022. When only counting papers that mention the specific phrase "large language model" in title or abstract, the trend steepens, with a 12× increase since 2022 up to 7% of all CS/Stat submissions. These trends are consistent with previous findings that raw counts of LLM papers have increased steeply [1–3].

The fastest growing topics and keywords pertain to LLMs. We identified the fastest-growing paper topics among all CS/Stat submissions. We rank topics by comparing their frequency in 2023 to their frequency from 2018–2022, i.e., by evaluating the ratio $\frac{p(\text{topic} \mid \text{published in 2023})}{p(\text{topic} \mid \text{published in 2018–2022})}$. Figure 1b shows the topics with the largest and smallest values of this ratio.

The most striking finding is that the four fastest-growing topics all pertain to LLMs: "Neural Networks for NLP" (1.7× more common in papers published in 2023 compared to papers publishd pre-2023), "Multimodal Learning for Language & Vision" (1.6×), "Knowledge Graphs & QA"[2] (1.5×), and "Conversational Systems & QA" (1.4×). In fact, 16 out of the top 20 cited papers in 2023 fall into these top four categories (e.g., [34–37]). Interest is also growing in trustworthy AI, including "Privacy-Preserving Federated Learning" and "AI Fairness, Ethics, and Interpretability." Other topics are falling in popularity, such as "Analyzing Pandemics & Disease Spread," consistent with the reduced urgency around COVID-19.

In addition to identifying the fastest-growing topics, we also identify the fastest-growing keywords: i.e., the keywords most likely to be used in 2023 vs. in 2018–2022, filtering for unigrams and bigrams which occur in at least 100 abstracts. We rank keywords using the analogous quantity for the ratio used to rank topics — i.e., $\frac{p(\text{keyword} \mid \text{paper published in 2023})}{p(\text{keywork} \mid \text{paper published in 2018–2022})}$. Table S1 presents the top 50 enriched keywords, revealing similar results to the topic-based analysis: many of the fastest-growing keywords directly address LLMs, or related topics like generative AI and text-to-image models.

[2]QA: Question Answering. Many of these papers are now using LLMs, e.g. [30–33].

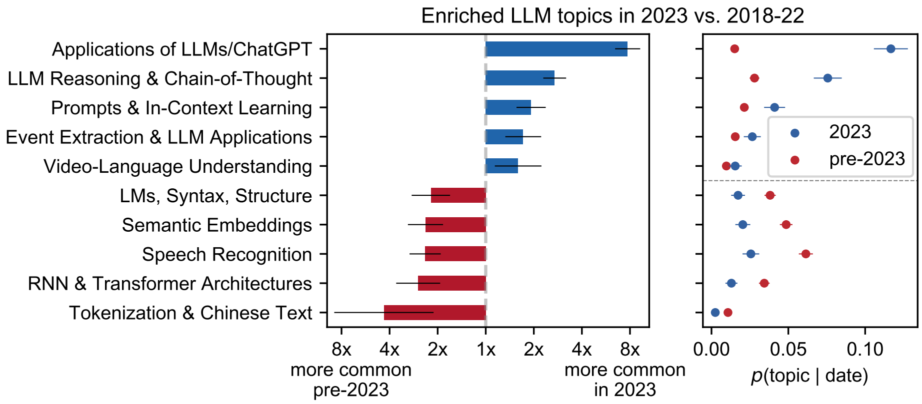


Figure 2: The fastest growing LLM research topics in 2023. LLM papers are increasingly focused on new applications and prompting methods, while papers on linguistic syntax and model architecture are becoming less common. Left: Enrichment ratios given by $\frac{p(\text{topic}|\text{posted in 2023})}{p(\text{topic}|\text{posted pre-2023})}$. Blue topics are more common in 2023, red topics are more common pre-2023. Right: Topic frequencies pre-2023 and since 2023.

3.2 What topics are LLM papers focusing on?

LLM topic clusters cover a broad range of sub-fields. Table S2 presents a list of the 35 LLM topics, with paper counts per cluster. We caution that the topic names do not perfectly describe all papers in a cluster, because some clusters cover multiple related themes and the names must be succinct. Nevertheless, many intuitive topics emerge, covering model architectures, translation, summarization, speech recognition, ChatGPT, pretraining, vision-language models, protein LMs, healthcare, stereotyping & bias, and code generation. The largest topics are "Multilingual LMs & Low-Resource Languages" ($N = 804$), "Efficiency & Compression" (779), "Vision-Language Models" (766), "Speech Recognition" (730), and "NLP for Healthcare" (596).

The fastest-growing LLM topics cover their capabilities and societal applications. The total number of LLM papers has risen quickly in 2023, and some topics have contributed more to this growth than others. We rank the 35 topics by how frequently they occur in 2023 LLM papers compared to pre-2023 LLM papers: i.e., $\frac{p(\text{topic} \mid \text{LLM paper, published in 2023})}{p(\text{topic} \mid \text{LLM paper, published pre-2023})}$. Figure 2 plots results. By far the fastest growing topic is on "Applications of LLMs/ChatGPT", which has risen from 1.4% of LLM papers in 2018–2022 to 11% in 2023, an 8× increase. This cluster of papers spans a broad range of topics, from empirical studies of LLMs on applied tasks (e.g., [38–41]) to discussions of societal applications of ChatGPT (e.g., [42–45]) to ethical arguments (e.g., [46–50]). The next two fastest-growing topics — "LLM Reasoning & Chain-of-Thought" and "Prompts & In-Context Learning" — also focus on recent advances in LLMs, but with more emphasis on studying benchmark performance under different prompting strategies (e.g. [51–55]). On the other hand, the "RNNs & Transformer Architectures" topic is shrinking, consistent with the convergence around a few, widely-used models rather than unique task-specific architectures; the "Semantic Embeddings" topic is also shrinking, possibly because few-shot prompting LLMs have become a popular alternative to embeddings.

The Computers and Society sub-arXiv has the fastest-growing proportion of LLM-related papers. We rank sub-arXivs by how quickly their proportion of LLM papers is increasing, i.e., according to the ratio $\frac{p(\text{paper is about LLMs}|\text{paper on sub-arXiv, published in 2023})}{p(\text{paper is about LLMs}|\text{paper on sub-arXiv, published pre-2023})}$. Computers and Society (cs.CY) ranks first: its proportion of papers which are about LLMs has increased by 18× compared to pre-2023 (15% vs. 0.8%). Topics range widely, including the impacts of LLMs on education [56–58],

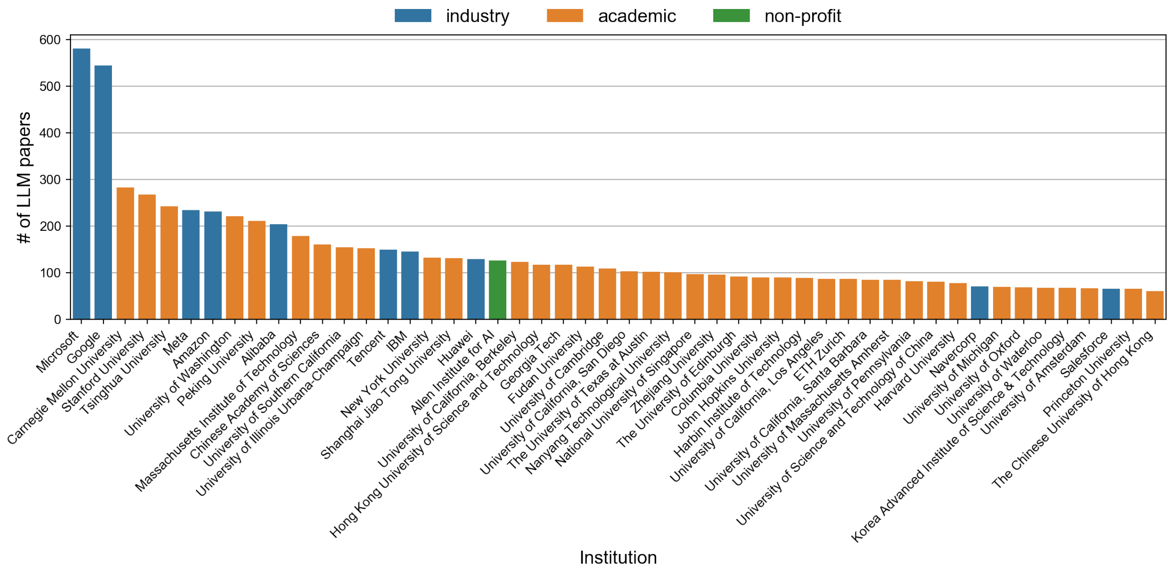


Figure 3: The 50 institutions with the most LLM papers. Most are academic, but there are several large industry players, with Microsoft and Google producing by far the most papers.

ethics and safety [59, 60], and legal considerations [61–63]. Software Engineering (cs.SE) has also seen a 7× increase in the proportion of papers about LLMs (rising to 14%), consistent with the growth of interest in LLMs for program generation (e.g. [64–68]). Other sub-arXivs with rapid growth include Robotics, HCI, Cryptography, and Computer Vision, reflecting the many applied domains of CS which LLMs are impacting.

Overall, a striking trend in LLM papers emerges consistently across both the topic and sub-arXiv analyses: LLMs are no longer confined to NLP research, but have broken into a number of other fields, as researchers increasingly discuss new applications and societal implications of these models.

3.3 Who is writing LLM papers?

Most LLM papers are published by academic institutions, but industry institutions play a significant role. To understand what type of institutions produce the most LLM research, we consider the 282 institutions that have published at least 10 LLM papers. Of these, we identified 243 (86.2%) as academic, 34 (12.1%) as industry, and 5 (1.8%) falling outside these categories. There were 11,915 LLM papers for which we identified at least one email address. Of these, 7,699 (64.6%) were produced by at least one of these 243 academic institutions and 2,904 (24.4%) by at least one of these 34 industry institutions. (These numbers underestimate the total percentage of papers written by academic and industry institutions, since we only identified institutions that produced at least 10 LLM papers.) As illustrated in Figure 3, a handful of industry institutions produce many of the LLM papers. Also note that the ratio of academic LLM papers to industry LLM papers is higher in 2023 than before 2023 (see Table 2), suggesting that recent growth in LLM papers may be driven especially by increasing academic interest.

Most LLM papers have majority predicted-male author names. We find that most papers are written by teams with majority predicted-male author names (see Table 2), and that this trend holds for both papers written before 2023 and in 2023. We stress that our results apply only to authors with gendered names identified by the packages, and in particular should not be taken to apply to

	2018–2022	2023
Academic institutions with $\geq$ 10 LLM papers	0.636	0.693
Industry institutions with $\geq$ 10 LLM papers	0.259	0.193
Majority predicted-female author names	0.175	0.166
1 author	0.038	0.049
2-5 authors	0.701	0.604
6-9 authors	0.222	0.278
10+ authors	0.040	0.069

Table 2: Proportion of papers written by different authorship groups for papers published 2018–2022 and in 2023. The proportions for 'Academic' and 'Industry' are calculated in the subset of papers for which we were able to identify at least one email address. In this subset, our reported proportions are lower bounds, since we only identify academic and industry institutions with at least 10 papers (see §A.4). Similarly, the proportions for 'Majority predicted-female author names' are calculated in the subset of papers for which we obtained an estimate for the fraction of predicted-female author names (see §A.5) and exclude papers with no predicted-male or predicted-female author names.

authors with East Asian names (§2 and §A.5 further discuss this point).

LLM papers are mostly written by middle-sized teams. We find that a large majority of LLM papers are written by teams with between 2 and 9 authors (see Table 2). Table 2 also suggests that recent LLM papers, those published in 2023, may be more likely to come from a single author or from a larger team (though both proportions remain small). In §3.5 we show that the number of authors on a paper correlates with how often that paper is cited.

3.4 Do authors with different backgrounds study different LLM topics?

Having described LLM paper topics (§3.2) and LLM author backgrounds (§3.3), we analyze the connection between the two: that is, do LLM authors of different backgrounds focus on different topics?

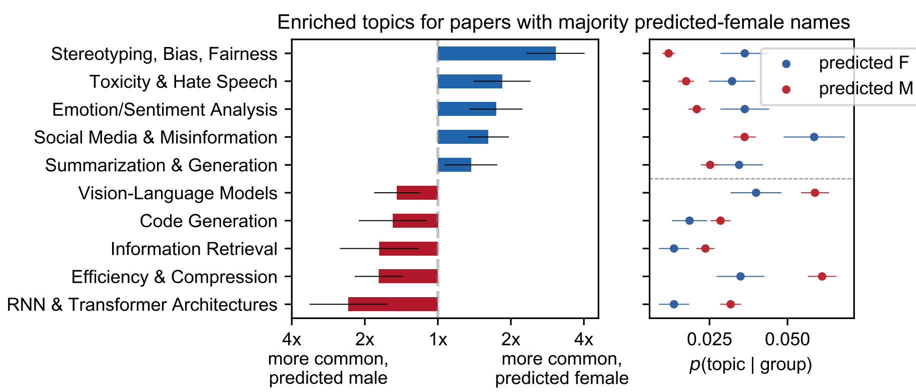


Figure 4: Topics which occur most disproportionately among majority-predicted-female or majority-predicted-male LLM papers. Left: Topics are sorted by $\frac{p(\text{topic}|\text{majority of author names are predicted female})}{p(\text{topic}|\text{majority of author names are predicted male})}$, excluding papers with no gendered author names. Blue bars correspond to topics which are more likely to occur among majority-predicted-female papers, and red bars to topics which are more likely to occur among majority-predicted-male papers. Right: Topic frequencies by predicted group.

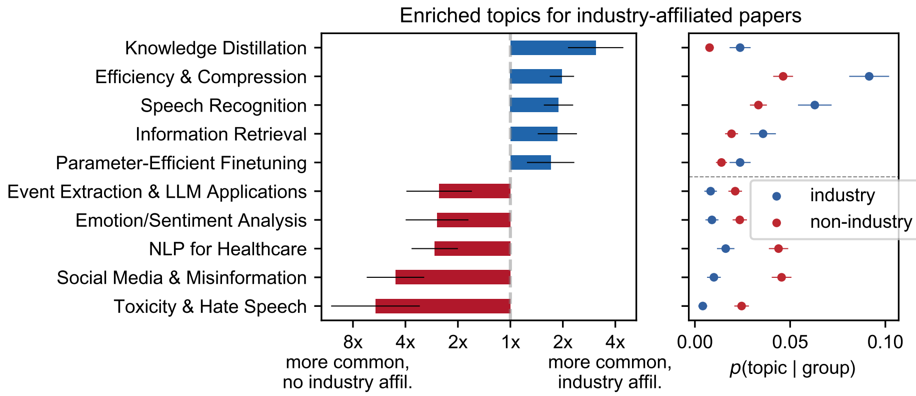


Figure 5: Topics which occur most disproportionately among industry vs. non-industry papers. Left: Topics are sorted by $\frac{p(\text{topic}|\geq 1 \text{ industry affiliation})}{p(\text{topic}|\text{no industry affiliation})}$, excluding papers with no inferred affiliations. Blue bars correspond to topics which are more likely to occur among papers with an industry affiliation, and red bars to topics which occur more frequently among papers without an industry affiliation. Right: Topic frequencies by group.

Paper topics correlate with predicted author gender. Figure 4 presents the topics which occur most disproportionately among LLM papers where the majority of author names are predicted female vs. male. The topic most disproportionately common among majority-predicted-female papers is "Stereotyping, Bias, Fairness", followed by "Toxicity and Hate Speech"; the topic most disproportionately common among majority-predicted-male papers is "RNN & Transformer Architectures", followed by "Efficiency & Compression". These results remain largely robust across multiple name classification packages and classification hyperparameters but we reiterate that they apply only to authors with gendered names identified by the packages, and in particular should not be taken to apply to authors with East Asian names; see §2 and §A.5 for further discussion.

Nonetheless, the finding of gender disparities in which LLM topics are studied — for example, that authors with predicted female names are more likely to focus on topics like bias and fairness — has important implications in light of the underrepresentation of women in computing (and the low proportion of predicted female names we observe; Table 2). If LLM topics of study correlate with author demographics like gender, and the population of LLM authors is demographically skewed, the topics which receive the most attention may not reflect the interests of society as a whole, which is concerning given the increasingly broad societal impacts of LLMs.

Industry papers focus on different topics. Figure 5 illustrates topics that are more likely in papers with industry affiliations. These include methodological, efficiency-oriented contributions on knowledge distillation, fine-tuning, and compression, as well as applications like speech recognition and information retrieval. In contrast, papers without an industry affiliation are more likely to focus on applications like toxicity, social media, misinformation, and healthcare. (Figure S1 plots enriched topics for academic-affiliated papers. It is not precisely the inverse of Figure 5 because papers can have both academic and industry affiliations, but illustrates similar trends.)

Experienced LLM authors study model training and NLP tasks; authors newly entering the field study applied & inter-disciplinary topics. Among LLM papers written in 2023, we study how topic choice differs by authors who are new to LLMs vs. experienced with them. We define an *experienced* author as someone who has co-authored an LLM paper between 2018-2022 and in 2023, and a *new* LLM author as someone whose first LLM paper was in 2023. We then take all

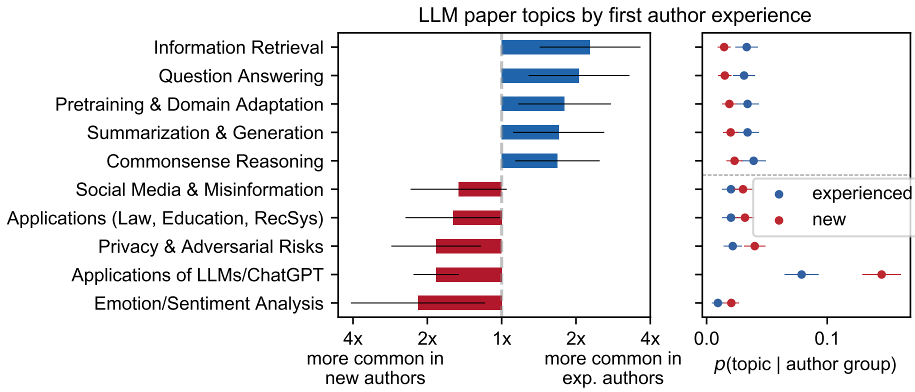
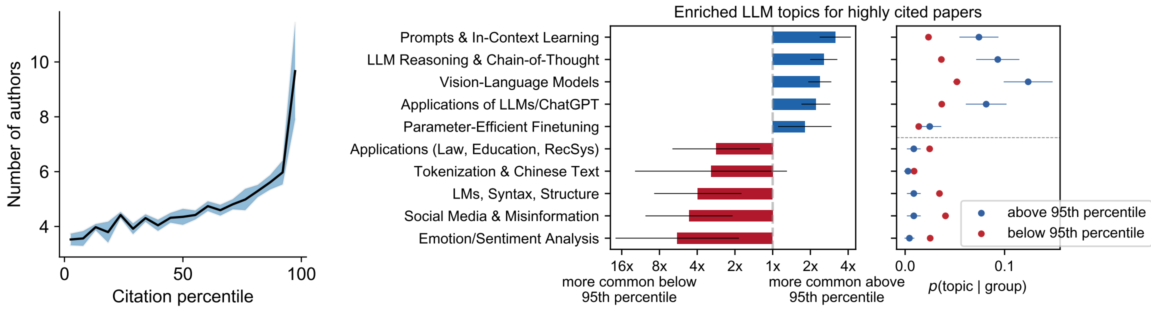


Figure 6: Topics of LLM papers written in 2023 vary with researcher experience. Authors who have written an LLM paper before 2023 (blue) are now writing papers about LLMs for NLP tasks and LLM training. Papers by authors who are new to LLMs in 2023 (red) focus more on societal applications. For this analysis, papers are coded according only to the experience level of their first author; Figure S2 shows results when coding papers by their last authors.

LLM papers written in 2023, code them according to whether their first author is experienced or new, and compute enrichment ratios of $\frac{p(\text{topic}|\text{published in 2023, experienced first author})}{p(\text{topic}|\text{published in 2023, new first author})}$. The top 5 enriched and unenriched topics are displayed in Figure 6 (Figure S2 gives an analogous version for last authors, surfacing similar trends).

Of the 3,238 LLM papers in our dataset from 2023, 1,384 (43%) are first-authored by experienced LLM authors and 1,854 by new LLM authors. Papers by experienced LLM authors are about twice as likely as papers by new authors to address classical NLP tasks like information retrieval, question answering, text summarization, and commonsense reasoning. On net, these five topics account for a smaller fraction of LLM papers in 2023 than before (Table S2), but they are receiving continued interest from authors who have previously worked in the field. Many of these papers use in-context learning to repurpose LLMs for existing tasks, e.g., prompting models with retrieved passages to improve question answering [69–71] or using LLMs to improve both generation and evaluation of open-ended text, such as for text summarization [72–74]. Also, notably, the two fastest-growing topics from Figure 2 that focus more on methods than applications are more common in experienced researchers: "Prompts & In-Context Learning" and "LLM Reasoning & Chain-of-Thought" are respectively 1.5× and 1.3× more likely in papers by experienced authors. There remains a strong coalition of experienced authors who focus on training and evaluating LLMs and applying them within NLP.

On the other hand, authors who are new to LLMs are writing more about applications: for example, 15% of papers by this group fall in the "Applications of LLMs/ChatGPT" topic, which is also the fastest-growing LLM paper topic overall. New LLM authors are more likely to discuss the societal implications of LLMs for topics like education, law, and misinformation, and are using the models for tasks like legal reasoning, social media analysis, and emotion/sentiment detection. Previous papers have outlined the many possibilities that LLMs may create for computational social scientists [75–78], and these data confirm that LLMs are reaching a new crop of authors who are working on society-facing applications. Other enriched topics for new LLM authors are interdisciplinary, such as "Privacy & Adversarial Risks" (1.9×), "Video-Language Understanding" (1.4×), and "Vision-Language Models" (1.4×), reflecting that many new-to-LLM authors may arise from other sub-fields of CS. To further investigate the backgrounds of recent LLM authors, we analyze the publication histories of authors publishing LLM papers in 2023 §B.1. We find that these LLM authors are more likely to have published in certain sub-arXivs, including Computation and Language (cs.CL), but also several other



(a) (b)

Figure 7: Characteristics of highly cited LLM papers. Figure 7a: Highly cited papers have larger author teams. This trend is especially pronounced for the top citation percentiles. Shaded regions show 1.96× the standard error on the mean. Figure 7: Enrichment ratios of $\frac{p(\text{topic}|\text{above 95th citation percentile})}{p(\text{topic}|\text{below 95th citation percentile})}$. Blue topics are enriched in papers above the 95th citation percentile, red topics are enriched in papers below the 95th citation percentile. Right: The fraction of papers on each topic among papers which are above the 95th citation percentile and below the 95th citation percentile.

applied fields of CS: Software Engineering (cs.SE), Multimedia (cs.MM), and Social and Information Networks (cs.SI), for examples. Overall, we conclude that new LLM authors from diverse fields are disproportionately contributing to the growth of research on applications, while experienced authors continue to focus on improvements to model training, prompting, and existing NLP tasks.

3.5 What distinguishes highly cited LLM papers?

We analyze the characteristics of highly cited LLM papers, as measured using *citation percentile* (i.e., the paper's citation percentile among papers published in the same year; see §A.6 for details). Overall, highly cited LLM papers have three characteristics: (1) larger author teams, (2) industry affiliations, and (3) the presence of certain topics.

Highly cited papers have larger author teams. As shown in Figure 7a, papers with higher citation percentiles have larger author teams, and this trend is particularly pronounced for the most highly cited papers. Papers with more than 10 authors have 13.4× higher odds of being above the 95th citation percentile than papers with two or fewer authors.[3]

Industry papers are more likely to be highly cited. Papers with only industry-affiliated authors have 3.2× the odds of being above the 95th citation percentile compared to papers with only academic-affiliated authors, and papers with both industry and academic affiliated authors have 1.8× the odds of being above the 95th citation percentile compared to papers with only academic-affiliated authors. This gap persists when controlling for number of authors: papers with only industry affiliations still have 2.5× higher odds of being above the 95th citation percentile compared to papers with only academic-affiliated authors, and papers with both industry and academic affiliations have 1.4× higher odds of being above the 95th citation percentile compared to papers with only academic-affiliated authors.

Citations vary by paper topic. We identify the most highly cited LLM paper sub-topics, with papers labeled by our LLM-specific 35-topic model. We rank topics using the ratio $\frac{p(\text{topic}|\text{above 95th citation percentile})}{p(\text{topic}|\text{below 95th citation percentile})}$, and Figure 7 displays results. The top two topics are "Prompts & In-Context Learning" (3.2× more

[3] To quantify the effect of author team size and industry/academic affiliation on citations, we run a logistic regression where the dependent variable is whether the paper is above the 95th percentile, and the independent variables are author team size and whether the paper has an academic affiliation, an industry affiliation, or both; we remove papers with neither an academic nor industry affiliation. As in §3.3, we conduct this analysis on papers which have either an academic or industry affiliation with an institution which has published at least 10 LLM papers.

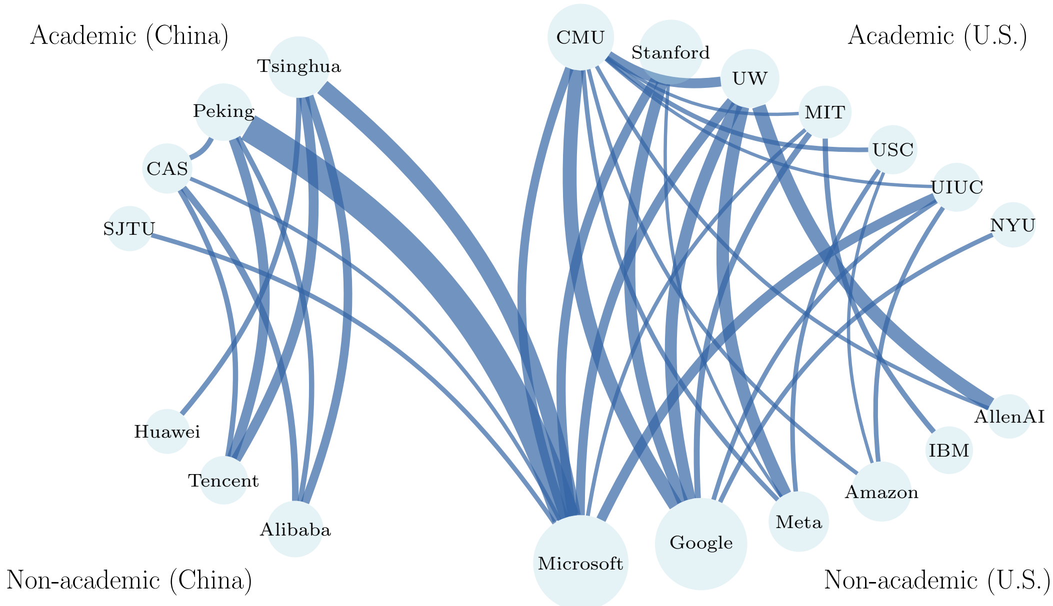


Figure 8: The 20 institutions with the most LLM papers and their pairwise collaborations. Node area is proportional to number of papers, and edge width is proportional to number of collaborations between nodes (for visual clarity, we show only edges corresponding to ≥ 5 collaborations). Note the central position of Microsoft, which collaborates with academic institutions across the U.S. and China.

common in highly cited papers) and "LLM Reasoning & Chain-of-Thought" (2.6×), which focus on new methods for LLMs. The next two enriched topics are "Vision-Language Models" (2.4×), in which highly cited papers present new results and architectures for multi-modal tasks [36, 79, 80], and "Applications of LLMs/ChatGPT" (2.2×), in which highly cited papers cover a broad set of emerging results and implications [81, 82]. We note the concordance between the topics with high citation percentiles and the topics growing fastest in 2023 (Figure 2). As one might expect, the LLM topics which are growing the fastest overall are also likely to include highly-cited papers.

3.6 What are the patterns of collaboration?

We examine which institutions tend to collaborate (co-author papers), focusing in particular on patterns of academic/industry and international collaboration.

Academic-academic and academic-industry collaborations are both frequent, while industry-industry collaborations are rare. We consider collaborations among those institutions with at least 10 LLM papers. There are 1,291 papers produced by a collaboration between at least two of these academic institutions, and 1,456 by at least one of these academic institutions and one of these industry institutions, while there were only 48 by a collaboration between at least two of these industry institutions.

Collaborations between American and Chinese institutions are relatively rare. In Figure 8, we present the network of the 20 institutions that produced the most LLM papers in our dataset, where edges indicate the number of collaborations between two institutions. All of these institutions are either Chinese or American. The network suggests little collaboration between the U.S. and China with the exception of Microsoft, which collaborates with institutions in both countries.

4 Related work

There have been several recent reviews on impacts and applications of LLMs; some cover many domains [83–85] and some are domain-specific (e.g., education [77, 86, 87]; healthcare [88–91]; law [92, 93]; code generation [94–96]; recommender systems [97]; social science [56, 75, 98]). These papers survey different use cases of LLMs, from tasks in computer science research to on-the-ground use by the general public. In general, these papers differ from our work in that they do not attempt to systematically describe bibliometric trends like those we analyze. Beyond LLMs, there have been many other bibliometric analyses on paper topics, author characteristics, and citation networks [9, 10, 14, 16, 17, 20, 21, 99–111]. This papers differ from our own because they do not focus on LLMs specifically.

More closely related to our work are two recent papers which present some bibliometric analysis of LLM research [1, 2]. Liu et al. [2] identify 194 arXiv papers mentioning ChatGPT; they show that most of these papers are recent, and provide the distribution of sub-arXivs to which they were submitted. Similar to [83], they compose a manual taxonomy of the different applications which researchers are using ChatGPT for, and list prospective opportunities and limitations. Zhao et al. [1] show that usage of the phrases "language model" and "large language model" has increased rapidly on arXiv, similar to our Figure 1a. Beyond this result, their paper orients more towards NLP practitioners: they provide a detailed list of released LLMs, review known aspects of these models' training & architecture details, and compile the results of some of these models on language, reasoning, and alignment benchmarks.

Most similar to our work, Fan et al. [3] analyze 5,752 LLM papers from Web of Science (WoS), published from Jan 2017 – Feb 2023. They fit a topic model, analyze co-citations between topics, and examine collaboration networks. Our work is different and complementary in several important ways. First, our primary focus of study is the *recent* shift in LLM publication patterns, and as such many of our analyses compare papers from 2023 to those from 2018-2022; in contrast, Fan et al. focus on describing their entire study window of the last six years. Second, we rely on arXiv data, not WoS data, yielding better coverage of preprints which is essential for studying recent trends. Finally, we analyze additional research questions: e.g., how author characteristics affect topic choice (§3.4) and which topics are highly cited (§3.5).

5 Discussion

We conduct a bibliometric analysis of the dramatic LLM-related shift in the scientific landscape, analyzing papers posted on the CS and Stat arXivs. We assess how the proportion of LLM papers is increasing; the topics which LLM papers are focusing on; who is writing LLM papers; how LLM authors' research topics correlate with their backgrounds; the factors distinguishing highly cited LLM papers; and the patterns of collaboration.

Our analysis has limitations. First, much of our work focuses on changes in the first half of 2023, a relatively short time period. LLM literature is evolving quickly, and seasonal trends may also affect our results (for example, the timing of major NLP conferences affects the sample) so future work should examine how the findings reported here evolve on updated samples. Second, our analyses rely on imperfect labels — e.g., the topic of a paper and whether it is LLM-related, the paper's citation percentile, whether an author's name is predicted to be gendered, and whether authors have an academic/industry affiliation. All these variables are, for reasons we document in §2 and Appendix A, potentially observed with both bias and noise. In all cases, we carefully considered whether the benefits of analyzing these variables outweighed the imperfections in inferring them, but these caveats should be kept in mind.

Overall, we show that LLM research both *shapes and is shaped by society*: it both increasingly focuses on societal impacts, and is also deeply shaped by social dynamics like gender disparities and the US/China schism in the collaboration network. An important implication of these findings is that LLMs must be analyzed with a sociotechnical, not a purely technical, lens, substantiating calls in recent work [112–116]. We need practitioners with diverse disciplinary expertise to assess the complex societal impacts of LLMs on domains from education to medicine to law. Beyond disciplinary diversity, our results imply that increasing *demographic* diversity among LLM researchers is also a pressing need. LLMs increasingly affect us all, but the scientists studying them do not represent us all equally. We provide evidence that this non-representativeness affects scientific research: specifically, we show that the topics LLM authors prioritize correlate with their backgrounds. For example, in light of our finding that there are gender disparities in topics studied, we find it plausible that a larger fraction of LLM papers would focus on bias and fairness if the LLM author population were less gender-skewed. The social impacts of LLMs are more likely to be positive if the scientists who study them represent diverse backgrounds and views.

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References

[1] Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, Yifan Du, Chen Yang, Yushuo Chen, Zhipeng Chen, Jinhao Jiang, Ruiyang Ren, Yifan Li, Xinyu Tang, Zikang Liu, Peiyu Liu, Jian-Yun Nie, and Ji-Rong Wen. A Survey of Large Language Models, June 2023. arXiv:2303.18223 [cs].

[2] Yiheng Liu, Tianle Han, Siyuan Ma, Jiayue Zhang, Yuanyuan Yang, Jiaming Tian, Hao He, Antong Li, Mengshen He, Zhengliang Liu, Zihao Wu, Dajiang Zhu, Xiang Li, Ning Qiang, Dingang Shen, Tianming Liu, and Bao Ge. Summary of ChatGPT/GPT-4 Research and Perspective Towards the Future of Large Language Models, May 2023. arXiv:2304.01852 [cs].

[3] Lizhou Fan, Lingyao Li, Zihui Ma, Sanggyu Lee, Huizi Yu, and Libby Hemphill. A Bibliometric Review of Large Language Models Research from 2017 to 2023, April 2023. arXiv:2304.02020 [cs].

[4] Kenneth Peng, Arunesh Mathur, and Arvind Narayanan. Mitigating dataset harms requires stewardship: Lessons from 1000 papers. *Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks*, 1, December 2021.

[5] Su Lin Blodgett, Solon Barocas, Hal Daumé III, and Hanna Wallach. Language (Technology) is Power: A Critical Survey of "Bias" in NLP. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5454–5476, Online, July 2020. Association for Computational Linguistics.

[6] Anjalie Field, Su Lin Blodgett, Zeerak Waseem, and Yulia Tsvetkov. A Survey of Race, Racism, and Anti-Racism in NLP. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 1905–1925, Online, August 2021. Association for Computational Linguistics.

[7] Zihan Zhang, Meng Fang, Ling Chen, and Mohammad Reza Namazi Rad. Is Neural Topic Modelling Better than Clustering? An Empirical Study on Clustering with Contextual Embeddings for Topics. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3886–3893, Seattle, United States, July 2022. Association for Computational Linguistics.

[8] Maarten Grootendorst. BERTopic: Neural topic modeling with a class-based TF-IDF procedure, March 2022. arXiv:2203.05794 [cs].

[9] Molly M King, Carl T Bergstrom, Shelley J Correll, Jennifer Jacquet, and Jevin D West. Men Set their Own Cites High: Gender and Self-citation Across Fields and Over Time. *Socius*, 3, 2017.

[10] Jevin D West, Jennifer Jacquet, Molly M King, Shelley J Correll, and Carl T Bergstrom. The Role of Gender in Scholarly Authorship. *Public Library of Science One (PLOS One)*, 8(7):e66212, 2013.

[11] Emma Pierson. Outnumbered but Well-spoken: Female Commenters in the New York Times. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, pages 1201–1213, 2015.

[12] Ian Van Buskirk, Aaron Clauset, and Daniel B Larremore. An Open-source Cultural Consensus Approach to Name-based Gender Classification. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 17, pages 866–877, 2023.

[13] Serina Chang and Kathleen McKeown. Automatically inferring gender associations from language. *EMNLP*, 2019.

[14] Emma Pierson. In Science, it Matters that Women Come Last. *FiveThirtyEight [ABC News]*, 2014.

[15] Cassidy R Sugimoto, Chaoqun Ni, Jevin D West, and Vincent Larivière. The Academic Advantage: Gender Disparities in Patenting. *Public Library of Science One (PLOS One)*, 10(5):e0128000, 2015.

[16] Jordan D Dworkin, Kristin A Linn, Erin G Teich, Perry Zurn, Russell T Shinohara, and Danielle S Bassett. The Extent and Drivers of Gender Imbalance in Neuroscience Reference Lists. *Nature Neuroscience*, 23(8):918–926, 2020.

[17] Yang Yang, Tanya Y Tian, Teresa K Woodruff, Benjamin F Jones, and Brian Uzzi. Gender-diverse Teams Produce More Novel and Higher-impact Scientific Ideas. *Proceedings of the National Academy of Sciences*, 119(36):e2200841119, 2022.

[18] Junming Huang, Alexander J Gates, Roberta Sinatra, and Albert-László Barabási. Historical Comparison of Gender Inequality in Scientific Careers Across Countries and Disciplines. *Proceedings of the National Academy of Sciences*, 117(9):4609–4616, 2020.

[19] Luke Holman, Devi Stuart-Fox, and Cindy E Hauser. The Gender Gap in Science: How Long Until Women are Equally Represented? *Public Library of Science Biology (PLOS Biology)*, 16(4):e2004956, 2018.

[20] Y Samuel Wang, Carole J Lee, Jevin D West, Carl T Bergstrom, and Elena A Erosheva. Gender-based Homophily in Collaborations Across a Heterogeneous Scholarly Landscape. *Public Library of Science One (PLOS One)*, 18(4):e0283106, 2023.

[21] Vincent Larivière, Chaoqun Ni, Yves Gingras, Blaise Cronin, and Cassidy R Sugimoto. Bibliometrics: Global Gender Disparities in Science. *Nature*, 504(7479):211–213, 2013.

[22] Jeffrey W. Lockhart, Molly M. King, and Christin Munsch. Name-based demographic inference and the unequal distribution of misrecognition. *Nature Human Behaviour*, pages 1–12, April 2023. Publisher: Nature Publishing Group.

[23] Helena Mihaljević, Marco Tullney, Lucía Santamaría, and Christian Steinfeldt. Reflections on Gender Analyses of Bibliographic Corpora. *Frontiers in Big Data*, 2, 2019.

[24] Kamil Wais. Gender prediction methods based on first names with genderizer. *R J.*, 8(1):17, 2016.

[25] Eliza Strickland and Glenn Zorpette. The AI Apocalypse: A Scorecard. *Institute of Electrical and Electronics Engineers Spectrum (IEEE Spectrum)*, 2023.

[26] Emma Pierson. Demographics and Discussion Influence Views on Algorithmic Fairness. *arXiv preprint arXiv:1712.09124*, 2017.

[27] M Fumagalli, Roberta Ferrucci, F Mameli, Sara Marceglia, S Mrakic-Sposta, Stefano Zago, Claudio Lucchiari, D Consonni, F Nordio, G Pravettoni, et al. Gender-related Differences in Moral Judgments. *Cognitive Processing*, 2010.

[28] Maurice Jakesch, Zana Buçinca, Saleema Amershi, and Alexandra Olteanu. How Different Groups Prioritize Ethical Values for Responsible AI. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, pages 310–323, 2022.

[29] Allison Koenecke, Eric Giannella, Robb Willer, and Sharad Goel. Popular Support for Balancing Equity and Efficiency in Resource Allocation: A Case Study in Online Advertising to Increase Welfare Program Awareness. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 17, pages 494–506, 2023.

[30] Zhifeng Li, Yifan Fan, Bowei Zou, and Yu Hong. UFO: Unified Fact Obtaining for Commonsense Question Answering, May 2023. arXiv:2305.16048 [cs].

[31] Ehsan Doostmohammadi, Tobias Norlund, Marco Kuhlmann, and Richard Johansson. Surface-Based Retrieval Reduces Perplexity of Retrieval-Augmented Language Models, July 2023. arXiv:2305.16243 [cs].

[32] Xiaomeng Ma, Lingyu Gao, and Qihui Xu. ToMChallenges: A Principle-Guided Dataset and Diverse Evaluation Tasks for Exploring Theory of Mind, May 2023. arXiv:2305.15068 [cs].

[33] Zhihong Shao, Yeyun Gong, Yelong Shen, Minlie Huang, Nan Duan, and Weizhu Chen. Enhancing Retrieval-Augmented Large Language Models with Iterative Retrieval-Generation Synergy, May 2023. arXiv:2305.15294 [cs].

[34] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and Efficient Foundation Language Models. *arXiv preprint arXiv:2302.13971*, 2023.

[35] OpenAI. GPT-4 Technical Report, 2023.

[36] Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. BLIP-2: Bootstrapping Language-Image Pre-training with Frozen Image Encoders and Large Language Models. 2023.

[37] Yejin Bang, Samuel Cahyawijaya, Nayeon Lee, Wenliang Dai, Dan Su, Bryan Wilie, Holy Lovenia, Ziwei Ji, Tiezheng Yu, Willy Chung, et al. A multitask, multilingual, multimodal evaluation of chatgpt on reasoning, hallucination, and interactivity. *arXiv preprint arXiv:2302.04023*, 2023.

[38] Sunhao Dai, Ninglu Shao, Haiyuan Zhao, Weijie Yu, Zihua Si, Chen Xu, Zhongxiang Sun, Xiao Zhang, and Jun Xu. Uncovering ChatGPT's Capabilities in Recommender Systems, May 2023. arXiv:2305.02182 [cs].

[39] Lei Zhang, Yuge Zhang, Kan Ren, Dongsheng Li, and Yuqing Yang. MLCopilot: Unleashing the Power of Large Language Models in Solving Machine Learning Tasks, April 2023. arXiv:2304.14979 [cs].

[40] M. Z. Naser, Brandon Ross, Jennier Ogle, Venkatesh Kodur, Rami Hawileh, Jamal Abdalla, and Huu-Tai Thai. Can AI Chatbots Pass the Fundamentals of Engineering (FE) and Principles and Practice of Engineering (PE) Structural Exams?, April 2023. arXiv:2303.18149 [cs].

[41] Minje Choi, Jiaxin Pei, Sagar Kumar, Chang Shu, and David Jurgens. Do LLMs Understand Social Knowledge? Evaluating the Sociability of Large Language Models with SocKET Benchmark, May 2023. arXiv:2305.14938 [cs].

[42] Reza Hadi Mogavi, Chao Deng, Justin Juho Kim, Pengyuan Zhou, Young D. Kwon, Ahmed Hosny Saleh Metwally, Ahmed Tlili, Simone Bassanelli, Antonio Bucchiarone, Sujit Gujar, Lennart E. Nacke, and Pan Hui. Exploring User Perspectives on ChatGPT: Applications, Perceptions, and Implications for AI-Integrated Education, June 2023. arXiv:2305.13114 [cs].

[43] Ishika Joshi, Ritvik Budhiraja, Harshal Dev, Jahnvi Kadia, M. Osama Ataullah, Sayan Mitra, Dhruv Kumar, and Harshal D. Akolekar. ChatGPT – a Blessing or a Curse for Undergraduate Computer Science Students and Instructors?, May 2023. arXiv:2304.14993 [cs].

[44] Meredith Ringel Morris. Scientists' Perspectives on the Potential for Generative AI in their Fields, April 2023. arXiv:2304.01420 [cs].

[45] Krishna Kumar. Geotechnical Parrot Tales (GPT): Harnessing Large Language Models in geotechnical engineering, June 2023. arXiv:2304.02138 [physics].

[46] Leon Derczynski, Hannah Rose Kirk, Vidhisha Balachandran, Sachin Kumar, Yulia Tsvetkov, M. R. Leiser, and Saif Mohammad. Assessing Language Model Deployment with Risk Cards, March 2023. arXiv:2303.18190 [cs].

[47] David Gray Widder and Richmond Wong. Thinking Upstream: Ethics and Policy Opportunities in AI Supply Chains, March 2023. arXiv:2303.07529 [cs].

[48] Atoosa Kasirzadeh. ChatGPT, Large Language Technologies, and the Bumpy Road of Benefiting Humanity, April 2023. arXiv:2304.11163 [cs].

[49] Alejo Jose G. Sison, Marco Tulio Daza, Roberto Gozalo-Brizuela, and Eduardo C. Garrido-Merchán. ChatGPT: More than a Weapon of Mass Deception, Ethical challenges and responses from the Human-Centered Artificial Intelligence (HCAI) perspective, April 2023. arXiv:2304.11215 [cs].

[50] Sunder Ali Khowaja, Parus Khuwaja, and Kapal Dev. ChatGPT Needs SPADE (Sustainability, PrivAcy, Digital divide, and Ethics) Evaluation: A Review, April 2023. arXiv:2305.03123 [cs].

[51] Wei-Lin Chen, Cheng-Kuang Wu, and Hsin-Hsi Chen. Self-ICL: Zero-Shot In-Context Learning with Self-Generated Demonstrations, May 2023. arXiv:2305.15035 [cs].

[52] Shivanshu Gupta, Matt Gardner, and Sameer Singh. Coverage-based Example Selection for In-Context Learning, May 2023. arXiv:2305.14907 [cs].

[53] Xingchen Wan, Ruoxi Sun, Hootan Nakhost, Hanjun Dai, Julian Martin Eisenschlos, Sercan O. Arik, and Tomas Pfister. Universal Self-adaptive Prompting, May 2023. arXiv:2305.14926 [cs].

[54] Jennifer Hu and Roger Levy. Prompt-based methods may underestimate large language models' linguistic generalizations, May 2023. arXiv:2305.13264 [cs].

[55] Jennifer D'Souza, Moussab Hrou, and Sören Auer. Evaluating Prompt-based Question Answering for Object Prediction in the Open Research Knowledge Graph, June 2023. arXiv:2305.12900 [cs, math].

[56] Evangelos Pournaras. Science in the Era of ChatGPT, Large Language Models and AI: Challenges for Research Ethics Review and How to Respond, May 2023.

[57] Cecilia Ka Yuk Chan and Wenjie Hu. Students' Voices on Generative AI: Perceptions, Benefits, and Challenges in Higher Education, April 2023. arXiv:2305.00290 [cs].

[58] Felix Dobslaw and Peter Bergh. Experiences with Remote Examination Formats in Light of GPT-4, March 2023. arXiv:2305.02198 [cs].

[59] Emilio Ferrara. Should ChatGPT be Biased? Challenges and Risks of Bias in Large Language Models, April 2023. arXiv:2304.03738 [cs].

[60] Sourojit Ghosh and Aylin Caliskan. ChatGPT Perpetuates Gender Bias in Machine Translation and Ignores Non-Gendered Pronouns: Findings across Bengali and Five other Low-Resource Languages, May 2023. arXiv:2305.10510 [cs].

[61] Peter Henderson, Xuechen Li, Dan Jurafsky, Tatsunori Hashimoto, Mark A. Lemley, and Percy Liang. Foundation Models and Fair Use. *SSRN Electronic Journal*, 2023.

[62] Hanlin Li, Nicholas Vincent, Stevie Chancellor, and Brent Hecht. The Dimensions of Data Labor: A Road Map for Researchers, Activists, and Policymakers to Empower Data Producers. In *2023 ACM Conference on Fairness, Accountability, and Transparency*, pages 1151–1161, June 2023. arXiv:2305.13238 [cs].

[63] Zihao Li. The Dark Side of ChatGPT: Legal and Ethical Challenges from Stochastic Parrots and Hallucination, April 2023. arXiv:2304.14347 [cs].

[64] Zhuokui Xie, Yinghao Chen, Chen Zhi, Shuiguang Deng, and Jianwei Yin. ChatUniTest: a ChatGPT-based automated unit test generation tool, May 2023. arXiv:2305.04764 [cs].

[65] Chao Liu, Xuanlin Bao, Hongyu Zhang, Neng Zhang, Haibo Hu, Xiaohong Zhang, and Meng Yan. Improving ChatGPT Prompt for Code Generation, May 2023. arXiv:2305.08360 [cs].

[66] Yuwei Zhang, Ge Li, Zhi Jin, and Ying Xing. Neural Program Repair with Program Dependence Analysis and Effective Filter Mechanism, May 2023. arXiv:2305.09315 [cs].

[67] Vijayaraghavan Murali, Chandra Maddila, Imad Ahmad, Michael Bolin, Daniel Cheng, Negar Ghorbani, Renuka Fernandez, and Nachiappan Nagappan. CodeCompose: A Large-Scale Industrial Deployment of AI-assisted Code Authoring, May 2023. arXiv:2305.12050 [cs].

[68] Priyanshu Gupta, Avishree Khare, Yasharth Bajpai, Saikat Chakraborty, Sumit Gulwani, Aditya Kanade, Arjun Radhakrishna, Gustavo Soares, and Ashish Tiwari. GrACE: Generation using Associated Code Edits, May 2023. arXiv:2305.14129 [cs].

[69] Ori Ram, Yoav Levine, Itay Dalmedigos, Dor Muhlgay, Amnon Shashua, Kevin Leyton-Brown, and Yoav Shoham. In-Context Retrieval-Augmented Language Models, January 2023. arXiv:2302.00083 [cs].

[70] Weijia Shi, Sewon Min, Michihiro Yasunaga, Minjoon Seo, Rich James, Mike Lewis, Luke Zettlemoyer, and Wen-tau Yih. REPLUG: Retrieval-Augmented Black-Box Language Models, May 2023. arXiv:2301.12652 [cs].

[71] Zhengbao Jiang, Frank F. Xu, Luyu Gao, Zhiqing Sun, Qian Liu, Jane Dwivedi-Yu, Yiming Yang, Jamie Callan, and Graham Neubig. Active Retrieval Augmented Generation, May 2023. arXiv:2305.06983 [cs].

[72] Tianyi Zhang, Faisal Ladhak, Esin Durmus, Percy Liang, Kathleen McKeown, and Tatsunori B. Hashimoto. Benchmarking Large Language Models for News Summarization, January 2023. arXiv:2301.13848 [cs].

[73] Yang Liu, Dan Iter, Yichong Xu, Shuohang Wang, Ruochen Xu, and Chenguang Zhu. G-Eval: NLG Evaluation using GPT-4 with Better Human Alignment, May 2023. arXiv:2303.16634 [cs].

[74] Mingqi Gao, Jie Ruan, Renliang Sun, Xunjian Yin, Shiping Yang, and Xiaojun Wan. Human-like Summarization Evaluation with ChatGPT, April 2023. arXiv:2304.02554 [cs].

[75] Caleb Ziems, William Held, Omar Shaikh, Jiaao Chen, Zhehao Zhang, and Diyi Yang. Can Large Language Models Transform Computational Social Science?, April 2023. arXiv:2305.03514 [cs].

[76] Hong Shen, Tianshi Li, Toby Jia-Jun Li, Joon Sung Park, and Diyi Yang. Shaping the Emerging Norms of Using Large Language Models in Social Computing Research, July 2023. arXiv:2307.04280 [cs].

[77] Enkelejda Kasneci, Kathrin Sessler, Stefan Küchemann, Maria Bannert, Daryna Dementieva, Frank Fischer, Urs Gasser, Georg Groh, Stephan Günnemann, Eyke Hüllermeier, Stepha Krusche, Gitta Kutyniok, Tilman Michaeli, Claudia Nerdel, Jürgen Pfeffer, Oleksandra Poquet,

Michael Sailer, Albrecht Schmidt, Tina Seidel, Matthias Stadler, Jochen Weller, Jochen Kuhn, and Gjergji Kasneci. ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103:102274, April 2023.

[78] Christopher Michael Rytting, Taylor Sorensen, Lisa Argyle, Ethan Busby, Nancy Fulda, Joshua Gubler, and David Wingate. Towards Coding Social Science Datasets with Language Models, June 2023. arXiv:2306.02177 [cs].

[79] Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily L Denton, Kamyar Ghasemipour, Raphael Gontijo Lopes, Burcu Karagol Ayan, Tim Salimans, Jonathan Ho, David J Fleet, and Mohammad Norouzi. Photorealistic text-to-image diffusion models with deep language understanding. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh, editors, *Advances in Neural Information Processing Systems*, volume 35, pages 36479–36494. Curran Associates, Inc., 2022.

[80] Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, Roman Ring, Eliza Rutherford, Serkan Cabi, Tengda Han, Zhitao Gong, Sina Samangooei, Marianne Monteiro, Jacob L Menick, Sebastian Borgeaud, Andy Brock, Aida Nematzadeh, Sahand Sharifzadeh, Mikoł aj Bińkowski, Ricardo Barreira, Oriol Vinyals, Andrew Zisserman, and Karén Simonyan. Flamingo: a visual language model for few-shot learning. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh, editors, *Advances in Neural Information Processing Systems*, volume 35, pages 23716–23736. Curran Associates, Inc., 2022.

[81] Sébastien Bubeck, Varun Chandrasekaran, Ronen Eldan, Johannes Gehrke, Eric Horvitz, Ece Kamar, Peter Lee, Yin Tat Lee, Yuanzhi Li, Scott Lundberg, et al. Sparks of artificial general intelligence: Early experiments with gpt-4. *arXiv preprint arXiv:2303.12712*, 2023.

[82] Rishi Bommasani, Drew A Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, et al. On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*, 2021.

[83] Rishi Bommasani, Drew A. Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S. Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, Erik Brynjolfsson, Shyamal Buch, Dallas Card, Rodrigo Castellon, Niladri Chatterji, Annie Chen, Kathleen Creel, Jared Quincy Davis, Dora Demszky, Chris Donahue, Moussa Doumbouya, Esin Durmus, Stefano Ermon, John Etchemendy, Kawin Ethayarajh, Li Fei-Fei, Chelsea Finn, Trevor Gale, Lauren Gillespie, Karan Goel, Noah Goodman, Shelby Grossman, Neel Guha, Tatsunori Hashimoto, Peter Henderson, John Hewitt, Daniel E. Ho, Jenny Hong, Kyle Hsu, Jing Huang, Thomas Icard, Saahil Jain, Dan Jurafsky, Pratyusha Kalluri, Siddharth Karamcheti, Geoff Keeling, Fereshte Khani, Omar Khattab, Pang Wei Koh, Mark Krass, Ranjay Krishna, Rohith Kuditipudi, Ananya Kumar, Faisal Ladhak, Mina Lee, Tony Lee, Jure Leskovec, Isabelle Levent, Xiang Lisa Li, Xuechen Li, Tengyu Ma, Ali Malik, Christopher D. Manning, Suvir Mirchandani, Eric Mitchell, Zanele Munyikwa, Suraj Nair, Avanika Narayan, Deepak Narayanan, Ben Newman, Allen Nie, Juan Carlos Niebles, Hamed Nilforoshan, Julian Nyarko, Giray Ogut, Laurel Orr, Isabel Papadimitriou, Joon Sung Park, Chris Piech, Eva Portelance, Christopher Potts, Aditi Raghunathan, Rob Reich, Hongyu Ren, Frieda Rong, Yusuf Roohani, Camilo Ruiz, Jack Ryan, Christopher Ré, Dorsa Sadigh, Shiori Sagawa, Keshav Santhanam, Andy Shih, Krishnan Srinivasan, Alex Tamkin, Rohan Taori, Armin W. Thomas, Florian Tramèr, Rose E. Wang, William Wang, Bohan Wu, Jiajun Wu, Yuhuai Wu, Sang Michael Xie, Michihiro Yasunaga, Jiaxuan You, Matei Zaharia, Michael Zhang, Tianyi Zhang, Xikun Zhang, Yuhui Zhang, Lucia Zheng, Kaitlyn Zhou, and Percy Liang. On the Opportunities and Risks of Foundation Models, July 2022. arXiv:2108.07258 [cs].

[84] Chen Ling, Xujiang Zhao, Jiaying Lu, Chengyuan Deng, Can Zheng, Junxiang Wang, Tanmoy Chowdhury, Yun Li, Hejie Cui, Xuchao Zhang, Tianjiao Zhao, Amit Panalkar, Wei Cheng, Haoyu Wang, Yanchi Liu, Zhengzhang Chen, Haifeng Chen, Chris White, Quanquan Gu, Jian Pei, Carl Yang, and Liang Zhao. Domain Specialization as the Key to Make Large Language Models Disruptive: A Comprehensive Survey, July 2023. arXiv:2305.18703 [cs].

[85] Shukang Yin, Chaoyou Fu, Sirui Zhao, Ke Li, Xing Sun, Tong Xu, and Enhong Chen. A Survey on Multimodal Large Language Models, June 2023. arXiv:2306.13549 [cs].

[86] Tariq Alqahtani, Hisham A. Badreldin, Mohammed Alrashed, Abdulrahman I. Alshaya, Sahar S. Alghamdi, Khalid bin Saleh, Shuroug A. Alowais, Omar A. Alshaya, Ishrat Rahman, Majed S. Al Yami, and Abdulkareem M. Albekairy. The emergent role of artificial intelligence, natural learning processing, and large language models in higher education and research. *Research in Social and Administrative Pharmacy*, June 2023.

[87] Debby R. E. Cotton, Peter A. Cotton, and J. Reuben Shipway. Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, 0(0):1–12, March 2023. Publisher: Routledge _eprint: https://doi.org/10.1080/14703297.2023.2190148.

[88] Yiqiu Shen, Laura Heacock, Jonathan Elias, Keith D. Hentel, Beatriu Reig, George Shih, and Linda Moy. ChatGPT and Other Large Language Models Are Double-edged Swords. *Radiology*, 307(2):e230163, April 2023. Publisher: Radiological Society of North America.

[89] Malik Sallam. The Utility of ChatGPT as an Example of Large Language Models in Healthcare Education, Research and Practice: Systematic Review on the Future Perspectives and Potential Limitations, February 2023. Pages: 2023.02.19.23286155.

[90] Michael Wornow, Yizhe Xu, Rahul Thapa, Birju Patel, Ethan Steinberg, Scott Fleming, Michael A. Pfeffer, Jason Fries, and Nigam H. Shah. The Shaky Foundations of Clinical Foundation Models: A Survey of Large Language Models and Foundation Models for EMRs, March 2023. arXiv:2303.12961 [cs].

[91] Shubo Tian, Qiao Jin, Lana Yeganova, Po-Ting Lai, Qingqing Zhu, Xiuying Chen, Yifan Yang, Qingyu Chen, Won Kim, Donald C. Comeau, Rezarta Islamaj, Aadit Kapoor, Xin Gao, and Zhiyong Lu. Opportunities and Challenges for ChatGPT and Large Language Models in Biomedicine and Health, June 2023. arXiv:2306.10070 [cs, q-bio].

[92] Zhongxiang Sun. A Short Survey of Viewing Large Language Models in Legal Aspect, March 2023. arXiv:2303.09136 [cs].

[93] Jaromir Savelka, Kevin D. Ashley, Morgan A. Gray, Hannes Westermann, and Huihui Xu. Explaining Legal Concepts with Augmented Large Language Models (GPT-4), June 2023. arXiv:2306.09525 [cs].

[94] Daoguang Zan, Bei Chen, Fengji Zhang, Dianjie Lu, Bingchao Wu, Bei Guan, Wang Yongji, and Jian-Guang Lou. Large Language Models Meet NL2Code: A Survey. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7443–7464, Toronto, Canada, July 2023. Association for Computational Linguistics.

[95] Frank F. Xu, Uri Alon, Graham Neubig, and Vincent Josua Hellendoorn. A systematic evaluation of large language models of code. In *Proceedings of the 6th ACM SIGPLAN International Symposium on Machine Programming*, MAPS 2022, pages 1–10, New York, NY, USA, June 2022. Association for Computing Machinery.

[96] Yichen Xu and Yanqiao Zhu. A Survey on Pretrained Language Models for Neural Code Intelligence, December 2022. arXiv:2212.10079 [cs].

[97] Wenqi Fan, Zihuai Zhao, Jiatong Li, Yunqing Liu, Xiaowei Mei, Yiqi Wang, Jiliang Tang, and Qing Li. Recommender Systems in the Era of Large Language Models (LLMs), July 2023. arXiv:2307.02046 [cs].

[98] Danica Dillion, Niket Tandon, Yuling Gu, and Kurt Gray. Can AI language models replace human participants? *Trends in Cognitive Sciences*, 27(7):597–600, July 2023. Publisher: Elsevier.

[99] Janvijay Singh, Mukund Rungta, Diyi Yang, and Saif M Mohammad. Forgotten Knowledge: Examining the Citational Amnesia in NLP. *arXiv preprint arXiv:2305.18554*, 2023.

[100] Vinodkumar Prabhakaran, William L Hamilton, Dan McFarland, and Dan Jurafsky. Predicting the rise and fall of scientific topics from trends in their rhetorical framing. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1170–1180, 2016.

[101] Ashton Anderson, Dan Jurafsky, and Dan McFarland. Towards a computational history of the acl: 1980-2008. In *Proceedings of the ACL-2012 Special Workshop on Rediscovering 50 Years of Discoveries*, pages 13–21, 2012.

[102] Bas Hofstra, Vivek V Kulkarni, Sebastian Munoz-Najar Galvez, Bryan He, Dan Jurafsky, and Daniel A McFarland. The diversity–innovation paradox in science. *Proceedings of the National Academy of Sciences*, 117(17):9284–9291, 2020.

[103] David Jurgens, Srijan Kumar, Raine Hoover, Dan McFarland, and Dan Jurafsky. Measuring the evolution of a scientific field through citation frames. *Transactions of the Association for Computational Linguistics*, 6:391–406, 2018.

[104] Stephan Risi, Mathias W Nielsen, Emma Kerr, Emer Brady, Lanu Kim, Daniel A McFarland, Dan Jurafsky, James Zou, and Londa Schiebinger. Diversifying history: A large-scale analysis of changes in researcher demographics and scholarly agendas. *Plos one*, 17(1):e0262027, 2022.

[105] Heather Piwowar, Jason Priem, Vincent Larivière, Juan Pablo Alperin, Lisa Matthias, Bree Norlander, Ashley Farley, Jevin West, and Stefanie Haustein. The state of oa: a large-scale analysis of the prevalence and impact of open access articles. *PeerJ*, 6:e4375, 2018.

[106] Benjamin M Althouse, Jevin D West, Carl T Bergstrom, and Theodore Bergstrom. Differences in impact factor across fields and over time. *Journal of the American Society for Information Science and technology*, 60(1):27–34, 2009.

[107] Jevin D West, Theodore C Bergstrom, and Carl T Bergstrom. The eigenfactor metricstm: A network approach to assessing scholarly journals. *College & Research Libraries*, 71(3):236–244, 2010.

[108] Aaron Clauset, Daniel B Larremore, and Roberta Sinatra. Data-driven predictions in the science of science. *Science*, 355(6324):477–480, 2017.

[109] Samuel F Way, Allison C Morgan, Daniel B Larremore, and Aaron Clauset. Productivity, prominence, and the effects of academic environment. *Proceedings of the National Academy of Sciences*, 116(22):10729–10733, 2019.

[110] Samuel F Way, Allison C Morgan, Aaron Clauset, and Daniel B Larremore. The misleading narrative of the canonical faculty productivity trajectory. *Proceedings of the National Academy of Sciences*, 114(44):E9216–E9223, 2017.

[111] Samuel F Way, Daniel B Larremore, and Aaron Clauset. Gender, productivity, and prestige in computer science faculty hiring networks. In *Proceedings of the 25th international conference on world wide web*, pages 1169–1179, 2016.

[112] Seth Lazar and Alondra Nelson. Ai safety on whose terms?, 2023.

[113] Dan Hendrycks, Mantas Mazeika, and Thomas Woodside. An overview of catastrophic ai risks. *arXiv preprint arXiv:2306.12001*, 2023.

[114] Statement on ai harms and policy. *The Conference on Fairness, Accountability, and Transparency (FAccT) Executive Committee*, 2023.

[115] Alexander Einarsson, Andrea Lynn Azzo, and Kristian Hammond. Toward a safety science in artificial intelligence.

[116] Q Vera Liao and Ziang Xiao. Rethinking model evaluation as narrowing the socio-technical gap. *arXiv preprint arXiv:2306.03100*, 2023.

[117] Colin B. Clement, Matthew Bierbaum, Kevin P. O'Keeffe, and Alexander A. Alemi. On the Use of ArXiv as a Dataset, April 2019. arXiv:1905.00075 [physics].

[118] Team Kaggle. Leveraging ML to Fuel New Discoveries with the arXiv Dataset, August 2020.

[119] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, May 2019. arXiv:1810.04805 [cs].

[120] Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations, March 2018. arXiv:1802.05365 [cs].

[121] Rodney Kinney, Chloe Anastasiades, Russell Authur, Iz Beltagy, Jonathan Bragg, Alexandra Buraczynski, Isabel Cachola, Stefan Candra, Yoganand Chandrasekhar, Arman Cohan, Miles Crawford, Doug Downey, Jason Dunkelberger, Oren Etzioni, Rob Evans, Sergey Feldman, Joseph Gorney, David Graham, Fangzhou Hu, Regan Huff, Daniel King, Sebastian Kohlmeier, Bailey Kuehl, Michael Langan, Daniel Lin, Haokun Liu, Kyle Lo, Jaron Lochner, Kelsey MacMillan, Tyler Murray, Chris Newell, Smita Rao, Shaurya Rohatgi, Paul Sayre, Zejiang Shen, Amanpreet Singh, Luca Soldaini, Shivashankar Subramanian, Amber Tanaka, Alex D. Wade, Linda Wagner, Lucy Lu Wang, Chris Wilhelm, Caroline Wu, Jiangjiang Yang, Angele Zamarron, Madeleine Van Zuylen, and Daniel S. Weld. The Semantic Scholar Open Data Platform, January 2023. arXiv:2301.10140 [cs].

[122] Wikipedia. Large language model, July 2023. Page Version ID: 1163529235.

[123] Hongjin Su, Weijia Shi, Jungo Kasai, Yizhong Wang, Yushi Hu, Mari Ostendorf, Wen-tau Yih, Noah A. Smith, Luke Zettlemoyer, and Tao Yu. One Embedder, Any Task: Instruction-Finetuned Text Embeddings, May 2023. arXiv:2212.09741 [cs].

[124] Leland McInnes, John Healy, and James Melville. UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction, September 2020. arXiv:1802.03426 [cs, stat].

[125] Suzanna Sia, Ayush Dalmia, and Sabrina J. Mielke. Tired of Topic Models? Clusters of Pretrained Word Embeddings Make for Fast and Good Topics too! In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1728–1736, Online, November 2020. Association for Computational Linguistics.

[126] Laure Thompson and David Mimno. Topic Modeling with Contextualized Word Representation Clusters, October 2020. arXiv:2010.12626 [cs].

[127] Dominika Tkaczyk. New Methods for Metadata Extraction from Scientific Literature, October 2017. arXiv:1710.10201 [cs].

[128] Zara Nasar, Syed Waqar Jaffry, and Muhammad Kamran Malik. Information extraction from scientific articles: a survey. *Scientometrics*, 117(3):1931–1990, December 2018.

[129] Lucía Santamaría and Helena Mihaljević. Comparison and benchmark of name-to-gender inference services. *PeerJ Computer Science*, 4:e156, July 2018. Publisher: PeerJ Inc.

[130] Ferhat Elmas. gender-guesser. 2016.

[131] Stacy Conkiel. How to Benchmark Against a Subject Area. `https://www.altmetric.com/blog/how-to-benchmark-against-a-subject-area/`.

[132] Ke Chen, Gordon Wichern, François G. Germain, and Jonathan Le Roux. Pac-HuBERT: Self-Supervised Music Source Separation via Primitive Auditory Clustering and Hidden-Unit BERT, April 2023. arXiv:2304.02160 [cs, eess].

[133] Nicolas Jonason and Bob L. T. Sturm. Exploring Softly Masked Language Modelling for Controllable Symbolic Music Generation, May 2023. arXiv:2305.03530 [cs, eess].

[134] Xingchen Song, Di Wu, Binbin Zhang, Zhendong Peng, Bo Dang, Fuping Pan, and Zhiyong Wu. ZeroPrompt: Streaming Acoustic Encoders are Zero-Shot Masked LMs, May 2023. arXiv:2305.10649 [cs, eess].

[135] Ibrahim Malik, Siddique Latif, Raja Jurdak, and Björn Schuller. A Preliminary Study on Augmenting Speech Emotion Recognition using a Diffusion Model, May 2023. arXiv:2305.11413 [cs, eess].

[136] Zhepei Wang, Cem Subakan, Krishna Subramani, Junkai Wu, Tiago Tavares, Fabio Ayres, and Paris Smaragdis. Unsupervised Improvement of Audio-Text Cross-Modal Representations, May 2023. arXiv:2305.01864 [cs, eess].

[137] Yuwei Zhang, Zhi Jin, Zejun Wang, Ying Xing, and Ge Li. SAGA: Summarization-Guided Assert Statement Generation, May 2023. arXiv:2305.14808 [cs].

[138] Yinfang Chen, Huaibing Xie, Minghua Ma, Yu Kang, Xin Gao, Liu Shi, Yunjie Cao, Xuedong Gao, Hao Fan, Ming Wen, Jun Zeng, Supriyo Ghosh, Xuchao Zhang, Chaoyun Zhang, Qingwei Lin, Saravan Rajmohan, and Dongmei Zhang. Empowering Practical Root Cause Analysis by Large Language Models for Cloud Incidents, May 2023. arXiv:2305.15778 [cs].

[139] Canwen Xu, Julian McAuley, and Penghan Wang. Mirror: A Natural Language Interface for Data Querying, Summarization, and Visualization. In *Companion Proceedings of the ACM Web Conference 2023*, pages 49–52, April 2023. arXiv:2303.08697 [cs].

[140] Mohammad Shahmeer Ahmad, Zan Ahmad Naeem, Mohamed Eltabakh, Mourad Ouzzani, and Nan Tang. RetClean: Retrieval-Based Data Cleaning Using Foundation Models and Data Lakes, March 2023. arXiv:2303.16909 [cs].

[141] Francisco Romero, Caleb Winston, Johann Hauswald, Matei Zaharia, and Christos Kozyrakis. Zelda: Video Analytics using Vision-Language Models, May 2023. arXiv:2305.03785 [cs].

A Supplementary Methods

A.1 Data

Using code from [117], we pulled metadata for all 2.1M articles submitted to arXiv as of 26 May 2023. The metadata includes arXiv ID, author list, title, abstract, submission date, and arXiv subject categories. We subsetted the data to include only papers that list at least one CS or Stat subarXiv, and we downloaded PDF full-texts from Kaggle [118] for all papers from Apr 2007 through 26 May 2023, leaving 556K submissions. For all analyses unless otherwise specified, we further subset the data to only include papers since the start of 2018, resulting in 388K papers. (We chose 2018 to roughly align with the growing use of representations from pretrained language models, like BERT and ELMo [119, 120].) We then apply PDF-to-text conversion to produce plaintext files for each paper [117]. To study influential papers and citation networks, we also pulled citation data using the Semantic Scholar API [121] for the ∼14K LLM papers described below.

A.2 Identifying LLM-related papers

Consistent with past ML survey papers [3–6], we composed an analysis subset of LLM papers by searching for an interpretable set of keywords. Since we are interested in characterizing temporal trends, we chose a broad set of terms; in particular, we wanted to capture relevant papers *before* modern instruction-tuned LLMs, to better trace the shifts since these recent models' emergence. As such, we include terms like "language model" and "BERT", which have been in use for longer than "large language model" (see Figure 1a). The complete keyword list consists of {language model, foundation model, BERT, XLNet, GPT-2, GPT-3, GPT-4, GPT-Neo, GPT-J, ChatGPT, PaLM, LLaMA}[4], and 13,774 papers since 2018 contain at least one of them in their title or abstract. The specific models on the keyword list were taken from the collection on Wikipedia [122] as of June 2023, but we removed the long tail of models for which there are < 10 hits (e.g., Chinchilla, LaMDA, Galactica) or many false positives (e.g., OPT, Claude, BLOOM – for which there are many hits entirely unrelated to NLP). We inspected 50 paper abstracts which mention one of these less-common architectures and found that all of them mention at least one other keyword on our list, so we expect minimal reduction to recall as a result of removing these long-tail keywords.

A.3 Topic modeling

Several of our analyses rely on paper topic annotations, for example to identify sub-areas that are receiving increased research attention. We followed a modern topic modeling approach, using semantic embeddings followed by dimensionality reduction and clustering. More specifically, we adopted the following workflow (closely resembling that of [7]): (1) embed paper abstracts in a 768-dimensional space using the open source INSTRUCTOR-XL model [123]; (2) apply PCA to reduce dimensionality to $n = 200$ components, which explain ∼90% of the embedding variance; (3) apply UMAP [124] to further transform the data into 2D-space while preserving local structure; (4) cluster the papers in 2D space using k-means or agglomerative clustering (discussed below); (5) assign an informative topic name to each cluster. We map clusters to topics one-to-one, as is standard [7, 8], and we refer to them interchangeably. Recent work [7, 8, 125, 126] shows that this embedding-based approach presents a more accurate and efficient alternative to other methods, such as LDA.

Clustering (step 4) varied slightly for the full set and the LLM subset: for the full set of 388K CS/Stat papers we used k-means with 100 clusters, and for the subset of 13,774 LLM papers we used Ward agglomerative clustering with 35 clusters. While Ward and k-means yielded highly similar results (adj. Rand index > 0.6), we preferred Ward for its improved adaptability to uneven cluster sizes; k-means, however, was the only method that scaled and yielded plausible results for the full paper set. Choosing the cluster count k required manual tuning to ensure that clusters were neither

[4]We ignore case for "language model" and "foundation model," and enforce case for the other keywords.

too broad nor overly redundant. For example, with $k = 30$ clusters in the broad LLM subset, papers about language model stereotyping were in the same cluster as papers about predicting hate speech, while with $k = 40$ there were multiple thematically similar clusters about low-resource languages, so we settled on $k = 35$.

The final step of annotating clusters has previously been done by constructing a TF-IDF matrix and identifying the enriched terms that distinguish the cluster from others [7, 8]. In this approach, the researcher is left to manually synthesize the over-represented terms into succinct topic titles. Though intuitive, the process of converting papers to terms and then terms to topic names adds an unnecessary step; instead, we prompt an LLM (`gpt-3.5-turbo-16k`) to use a sample of the cluster's paper titles and abstracts and, from those, directly assign a succinct cluster name. We performed a final manual pass by looking at samples of 25 papers per cluster to ensure that (a) the papers are thematically coherent and (b) the topic title is suitable (and we edited the titles for clarity/brevity, as necessary).

A.4 Identifying industry and academic affiliations

Since author affiliations are rarely available in arXiv metadata, we extract affiliations by searching for regular expressions in paper full-texts, a common approach for metadata extraction in bibliometrics [127, 128]. Specifically, many papers list author emails in the full-text, and we search for them with high precision by designing regexs to match the "`@`" symbol and appropriate surrounding text in the paper's first 100 lines[5]. We conduct a manual audit of 100 papers to verify that all the extracted strings are author emails, and that the 22 papers *without* any extracted emails indeed do not obviously list emails in the manuscript. Overall, 86.4% of the LLM paper subset has at least one extracted email. Based on a manual audit of 50 papers, we did not observe that papers missing emails over-represent any particular type of affiliation.

Using the list of emails associated with each paper, we labeled each paper depending on whether it has (1) an academic affiliation and (2) an industry affiliation. (Some papers may have both academic and industry affiliations and others may have none.) To perform this annotation, we extracted the domain name (e.g., 'cornell.edu') from each email. We then combined domain names that correspond to the same institution using a semi-automated approach. Furthermore, for all domains d with at least 10 papers in our entire arXiv dataset, we mapped all domains s that are subdomains of d to d (e.g., $s =$'cs.cornell.edu'$\mapsto d =$'cornell.edu'). We also manually identified groups of domains with at least 10 LLM papers (e.g., 'fb.com' and 'meta.com'). Finally, among the 282 remaining domains with at least 10 LLM papers, we manually identified academic domains and industry domains.

A.5 Analysis of gendered names

We study how LLM paper topics vary depending on whether author names are predicted to be gendered female or male. This method of using name-gender associations is widely applied to study gender disparities both in bibliometrics and more broadly [9–21] because it is difficult to scale other approaches to large datasets. It is important to note that this method has limitations — in particular, it will yield misleading results for non-binary authors or authors whose gender does not match that commonly associated with their name, and its accuracy and coverage also varies by name origin: in particular, it has been found to be less reliable for East Asian authors [18, 19, 129]. In spite of these limitations, we believe it is important to document gender disparities in the study of LLMs because of previous evidence suggesting these disparities are pronounced [25], as well as previous academic research documenting gender differences in publication patterns and in opinions on ethical and social issues [10, 14–17, 21, 26–29].

We predict whether names are commonly gendered male or female using the open-source package nomquamgender [12], which has been shown to achieve similar performance to paid services. We leave names unclassified if the uncertainty exceeds the default threshold of 0.1, which assigns a prediction to 61% of author names on LLM papers. 19% of author names on LLM papers which have a prediction

[5]We use two regexs, to match two possible formats: `author@domain.xyz` and {`author1,author2,`$\cdots$}`@domain.xyz`.

are predicted female. For each paper, we compute the fraction of names with a prediction that are predicted female, which we refer to as the *predicted female fraction*: for example, for a paper with 3 predicted male author names, 2 predicted female author names, and 1 unclassified author name, the predicted female fraction would be $2/(2 + 3) = 0.4$. 8% of LLM papers have no name-gender predictions; we omit these papers from our analysis of topic differences, analyzing the remaining 92% of papers. Consistent with prior work, we observe that a large fraction of East Asian names remain unclassified [18, 19]; all our results on gender disparities thus ought to be interpreted as applying only to authors without East Asian names, an important caveat in this analysis.

We compare papers with predicted female fraction ≥ 0.5 to papers with predicted female fraction < 0.5, referring to these papers as "majority predicted female" and "majority predicted male" respectively. We confirm that our results remain similar across multiple gendered name inference packages (comparing the results from [12] to those from [130]); across multiple uncertainty thresholds for inference; and across multiple thresholds for binarizing the gendered female fraction.

A.6 Citation counts

For each of the LLM papers, we pull data on the paper's citing and cited references from the Semantic Scholar API [121] (this includes all references, not just those in the LLM papers). We quantify how well a paper is cited using its *citation percentile* metric, which measures the percentile rank of a paper's number of citations compared to all other LLM papers published in the same year. Percentile-based metrics for citations are commonly used in bibliometric analysis [131]; comparing to papers with the same publication year accounts for the fact that older papers will naturally tend to have higher citation counts. Semantic Scholar caps the number of tracked citations at 10,000 per paper; only 3 papers in our subset are above this threshold, so it does not meaningfully affect our results.

B Supplementary Results

Table S1: The 50 most disproportionately-used keywords (including unigrams & bigrams) in arXiv CS/Stat paper abstracts in 2023 vs. 2018–2022.

Keyword	$\frac{p(\text{keyword} \mid \text{after 2023})}{p(\text{keyword} \mid \text{before 2023})}$
`chatgpt`	249.540
`2023`	74.497
`generative ai`	53.800
`models llms`	42.965
`llms`	42.103
`llm`	39.469
`stable diffusion`	21.853
`chain thought`	21.774
`image diffusion`	21.716
`large language`	19.793
`latent diffusion`	17.170
`foundation models`	16.079
`text prompts`	13.477
`ai generated`	12.888
`diffusion models`	10.771
`diffusion model`	9.581
`foundation model`	9.283
`prompting`	8.832
`nerfs`	8.494
`context learning`	8.429
`denoising diffusion`	8.378
`prompts`	8.337
`prompt learning`	8.140
`models clip`	7.492
`text prompt`	7.440
`diffusion based`	7.398
`text guided`	7.371
`diffusion probabilistic`	7.340
`trained vision`	7.054
`al 2022`	6.901
`demonstrated remarkable`	6.572
`prompt`	6.317
`sam`	6.105
`gpt`	6.062
`generative pre`	6.021
`codex`	5.983
`instruction following`	5.689
`nerf`	5.629
`clip model`	5.569
`field nerf`	5.288
`based diffusion`	5.233
`huggingface`	5.159
`retrieval augmented`	5.151
`contrastive language`	5.121
`efficient fine`	5.087
`3d aware`	5.066
`dall`	5.057
`neural radiance`	5.051
`neural operator`	5.018
`valuable insights`	4.988

Table S2: **LLM paper topics that have grown (or shrunk) the most in 2023 compared to 2018-2022.** p-values computed with a χ^2 test. Topics were assigned and labeled using our neural topic modeling approach described in the methods.

Topic	N	$\frac{p(\text{topic}\mid 2023)}{p(\text{topic}\mid \text{pre-2023})}$	$p(\text{topic} \mid 2023)$	$p(\text{topic} \mid \text{pre-2023})$	p-value
Applications of LLMs/ChatGPT	537	7.74	0.117	0.015	5.7e-150
LLM Reasoning & Chain-of-Thought	540	2.70	0.076	0.028	4.4e-34
Prompts & In-Context Learning	358	1.92	0.041	0.021	1.0e-09
Event Extraction & LLM Applications	249	1.72	0.027	0.015	4.8e-05
Video-Language Understanding	152	1.60	0.015	0.010	8.1e-03
Code Generation	362	1.59	0.037	0.023	2.7e-05
Vision-Language Models	766	1.48	0.074	0.050	1.9e-07
NLP for Healthcare	596	1.26	0.051	0.041	1.2e-02
Parameter-Efficient Finetuning	196	1.24	0.017	0.013	2.1e-01
Applications (Law, Education, RecSys)	329	1.17	0.027	0.023	2.3e-01
Privacy & Adversarial Risks	396	1.16	0.032	0.028	2.1e-01
Chemistry & Protein LMs	166	1.10	0.013	0.012	6.5e-01
Information Retrieval	297	1.06	0.023	0.021	7.1e-01
Stereotyping, Bias, Fairness	214	1.02	0.016	0.015	9.8e-01
Summarization & Generation	371	0.95	0.026	0.027	7.4e-01
Dialogue & Conversational AI	500	0.90	0.033	0.037	3.3e-01
Pretraining & Domain Adaptation	384	0.88	0.025	0.029	3.4e-01
Knowledge Distillation	150	0.88	0.010	0.011	5.9e-01
Text Generation & Robotics	548	0.84	0.035	0.041	9.3e-02
Commonsense Reasoning	499	0.79	0.030	0.038	3.3e-02
Efficiency & Compression	779	0.77	0.046	0.060	3.4e-03
Text Classification & OOD Generalization	182	0.75	0.011	0.014	1.4e-01
Multilingual LMs & Low-Resource Languages	804	0.66	0.042	0.063	6.8e-06
Question Answering	432	0.64	0.022	0.034	5.3e-04
Machine Translation	243	0.60	0.012	0.019	4.5e-03
Social Media & Misinformation	538	0.60	0.026	0.043	1.3e-05
Emotion/Sentiment Analysis	332	0.59	0.016	0.027	5.1e-04
Toxicity & Hate Speech	272	0.56	0.012	0.022	7.1e-04
Creative Generation (Music, Poetry)	85	0.48	0.003	0.007	3.0e-02
Named Entity Recognition	206	0.47	0.008	0.017	2.8e-04
LMs, Syntax, Structure	458	0.45	0.017	0.038	9.8e-09
Semantic Embeddings	578	0.42	0.020	0.049	3.6e-12
Speech Recognition	730	0.42	0.026	0.061	2.7e-15
RNN & Transformer Architectures	404	0.38	0.013	0.034	4.1e-10
Tokenization & Chinese Text	121	0.23	0.002	0.011	1.7e-05

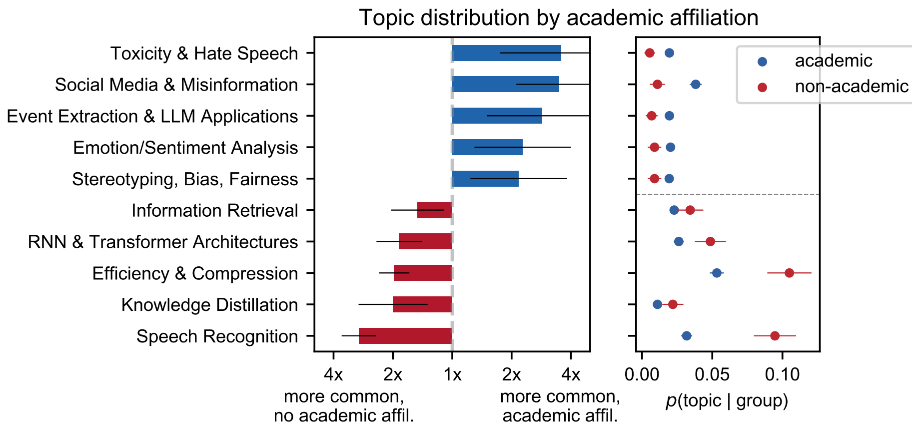

Figure S1: Topics which occur most disproportionately among academic vs. non-academic papers. Left: The horizontal axis plots the ratio $\frac{p(\text{topic}|\geq 1 \text{ academic affiliation})}{p(\text{topic}|\text{no academic affiliation})}$, excluding papers with no inferred affiliations. Blue bars correspond to topics which are more likely to occur among papers with an academic affiliation, and red bars to topics which occur more frequently among papers without an academic affiliation; we plot the 5 topics with the most extreme skews. Right: Topic frequencies by group.

B.1 Enriched sub-arXivs in LLM authors

See Figure S3 and Table S3.

Recent authors of LLM papers publish most in NLP, but also in related applied fields. To further characterize the authors publishing LLM papers in 2023, we study which *other* academic fields these authors publish in (excluding their LLM papers because we analyze these elsewhere). We compared two sets of authors: 1) active LLM authors, i.e., all authors with at least one LLM paper in 2023 and at least one other non-LLM paper (9,213 authors), and 2) similarly prolific non-LLM authors, i.e., a group of authors who (i) have never written an LLM paper, (ii) have also published a paper in 2023, and (iii) are sampled to have a matched distribution of paper counts as the LLM author set. We focus on active LLM authors (i.e., those who have published an LLM paper in 2023) because our focus is on recent changes in publication patterns. We use sub-arXivs as a proxy for an author's academic field, and for each sub-arXiv, we compare the fractions of active LLM and non-LLM authors who have ever published in that sub-arXiv, *excluding* the LLM papers themselves. This analysis assesses which *other* fields active LLM authors publish in when excluding their recent work on LLMs. To ensure enough data for meaningful comparisons, we only include sub-arXivs in which $\geq 2\%$ of all authors have published.

Figure S3 plots results, with sub-arXivs sorted by $\frac{p(\text{has published in sub-arXiv}|\text{LLM author in 2023})}{p(\text{has published in sub-arXiv}|\text{non-LLM author})}$. Unsurprisingly, we find the largest ratios in the "Computation and Language" and "Information Retrieval" sub-arXivs, with 52% and 17% of LLM authors having published in those categories, respectively, compared to 17% and 6% of other authors. This result confirms that a majority of LLM authors have previous experience with NLP. However, we also find large enrichments of active LLM authors in sub-arXivs corresponding to applied fields, such as "Sound", "Software Engineering", "Databases", "Multimedia" "Social and Information Networks", and "Human-Computer Interaction" (full list in Table S3). For concrete examples, authors who have published in the "Sound" sub-arXiv are now using LLMs for music [132, 133] and speech analysis [134–136], authors from "Software Engineering" are using LLMs for program generation and repair [68, 137, 138], and authors from "Databases" are using LLMs for database queries and retrieval [139–141]. In contrast, LLM authors are strongly unen-

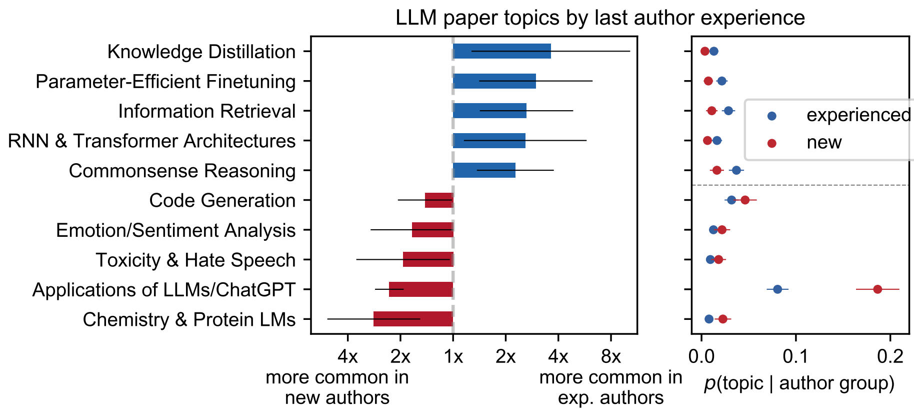

Figure S2: Topics of LLM papers written in 2023 vary with researcher experience. This is an analogous plot to Figure 6, except papers are coded according to whether their last author has written about LLMs before 2023 (“experienced”, blue) or not (“new”, red).

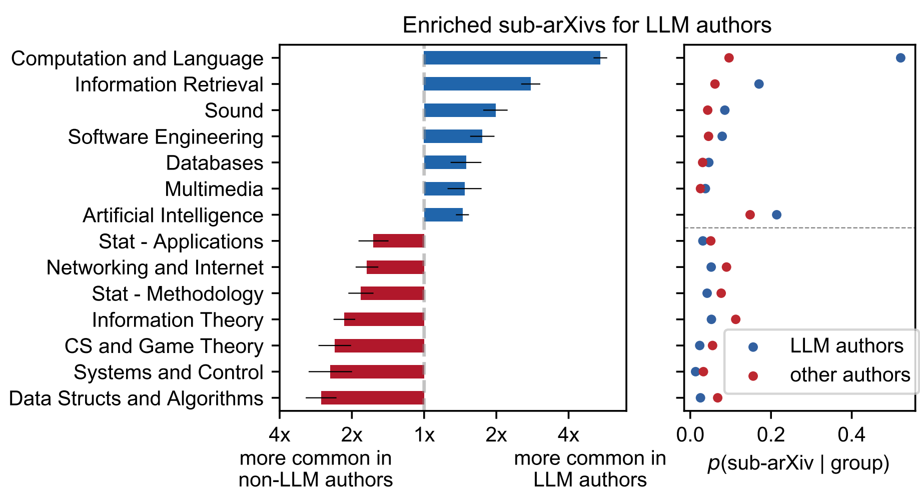

Figure S3: LLM authors enrich for having published in sub-arXivs related to NLP, as well as several other applied fields which now use LLMs; they are strongly unenriched for theoretical sub-arXivs. Left: enrichment ratios of $\frac{p(\text{has published in sub-arXiv}|\text{LLM author})}{p(\text{has published in sub-arXiv}|\text{non-LLM author})}$, excluding all LLM papers. Blue sub-arXivs are enriched for LLM authors, red sub-arXivs are enriched for a publication count-matched sample of other authors. Right: The fraction of LLM (or non-LLM) authors who have previously published in a given sub-arXiv, again excluding LLM papers themselves.

riched for theoretical sub-arXivs like "Stat – Methodology" and "Information Theory", and computer systems-related sub-arXivs like "Networking and Internet" and "Systems and Control". We conclude that while most active LLM authors have prior experience with language systems, a significant fraction of them are entering from other applied fields. This accords with the rise of LLM-enabled applications outside of traditional NLP that we describe in §3.2.

Table S3: **Sub-arXivs that 2023 LLM authors are enriched for publishing in, excluding their LLM papers.** Sub-arXivs are sorted by how much more likely an LLM author from 2023 is to have published in that sub-arXiv compared to a publication count-matched non-LLM author. Sub-arXivs are displayed only if $\geq 2\%$ of authors, overall, have published in them; p-values computed with a χ^2 test. We use "sub" as short-hand for sub-arXiv.

sub-arXiv	$\frac{p(\text{sub}\mid\text{LLM author})}{p(\text{sub}\mid\text{non-LLM author})}$	p(sub | LLM author)	p(sub | non-LLM author)	p-value
Computation and Language	5.43	0.52	0.10	0.0e+00
Information Retrieval	2.78	0.17	0.06	3.0e-118
Sound	1.98	0.09	0.04	1.2e-31
Software Engineering	1.75	0.08	0.05	2.4e-21
Databases	1.49	0.05	0.03	9.6e-08
Multimedia	1.47	0.04	0.03	3.4e-06
Artificial Intelligence	1.44	0.21	0.15	4.6e-31
Social and Info. Networks	1.40	0.10	0.07	1.2e-11
Human-Computer Interaction	1.26	0.09	0.07	5.5e-06
Computers and Society	1.24	0.08	0.06	4.7e-05
Computer Vision	1.06	0.46	0.43	1.8e-04
Machine Learning	1.02	0.53	0.52	1.0e-01
Cryptography and Security	0.98	0.12	0.13	5.3e-01
Neural Computing	0.92	0.04	0.05	2.4e-01
Hardware Architecture	0.88	0.02	0.02	1.9e-01
Robotics	0.75	0.11	0.15	8.0e-15
Distributed Computing	0.71	0.07	0.10	6.6e-12
Graphics	0.67	0.02	0.03	1.9e-05
Stat - ML	0.65	0.09	0.14	3.3e-25
Multiagent Systems	0.64	0.03	0.04	8.1e-08
Comp. Eng, Finance, and Sci	0.62	0.02	0.03	4.4e-06
Stat - Applications	0.62	0.03	0.05	3.0e-11
Networking and Internet	0.58	0.05	0.09	1.6e-23
Stat - Methodology	0.55	0.04	0.08	1.7e-23
Information Theory	0.47	0.05	0.11	9.3e-50
CS and Game Theory	0.42	0.02	0.06	1.9e-28
Systems and Control	0.41	0.01	0.03	2.9e-18
Data Structs and Algorithms	0.37	0.03	0.07	1.0e-42