# Topics, Authors, and Networks in Large Language Model Research: Trends from a Survey of 17K arXiv Papers

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# **ABSTRACT**

Large language model (LLM) research is dramatically impacting society, making it essential to understand the topics and values it prioritizes, the authors and institutions driving it, and its networks of collaboration. Due to the recent growth of the field, many of these fundamental attributes lack systematic description. We gather, annotate, and analyze a new dataset of 16,979 LLM-related arXiv papers, focusing on changes in 2023 vs. 2018-2022. We show that LLM research increasingly focuses on societal impacts: the Computers and Society sub-arXiv has seen 20× growth in its proportion of LLM-related papers in 2023. This change is driven in part by an influx of new authors: a majority of 2023 papers are first-authored by researchers who have not previously written an LLM-related paper, and these papers focus particularly on applications and societal considerations. While a handful of companies hold outsize influence, academia publishes a much larger fraction of papers than industry overall, and this gap widens in 2023. LLM research is also being shaped by social dynamics: there are gender and academic/industry differences in the topics authors prioritize, and a stark U.S./China schism in the collaboration network. Overall, our analysis documents how LLM research both shapes and is shaped by society, attesting to the necessity of sociotechnical lenses; we discuss implications for researchers and policymakers.

# **KEYWORDS**

large language models, bibliometrics, science of science, sociotechnical systems, collaboration networks

#### 1 INTRODUCTION

Large language model (LLM) research is having an enormous impact on society, driving deployments in high-stakes domains and drawing regulatory attention from governments around the globe [5, 36, 46, 57, 68, 72]. Given the impact of this research, it is pressing to understand the topics and values it prioritizes, the authors and institutions driving it, and its networks of collaboration. However, due to the explosive recent growth of the field [63, 121], information on all these attributes is lacking. Addressing this, we conduct a comprehensive bibliometric analysis of a new dataset of 16,979 LLM-related papers<sup>1</sup> posted to arXiv from Jan. 1, 2018 through

Sep. 7, 2023; we annotate this dataset with an ontology of 40 LLM-related topics. Our data and code are publicly available,<sup>2</sup> and are designed so that the data can be easily updated and re-analyzed at future timepoints. We study five questions, focusing in particular on trends since the beginning of 2023:

- (1) What topics are LLM papers prioritizing? (§3.1) 2023 has seen a striking growth of LLM papers focusing on societal applications and impacts: for example, the Computers and Society sub-arXiv has grown more than any other sub-arXiv in its proportion of LLM papers, by a factor of 20×. The fastest-growing topic within LLM research is "Applications of LLMs/ChatGPT," which has grown 8× in 2023. Simultaneously, as research has centralized around a few models (e.g., GPT-4, LLaMA), there has been reduced emphasis on bespoke, task-specific architectures.
- (2) Who is writing LLM papers? (§3.2) Perhaps surprisingly given that public discourse around LLMs largely focuses on a few companies, academic institutions account for a much larger fraction of the total LLM research volume than industry (Figure 1). This trend becomes even more pronounced in 2023, in part due to the increased output of the top-producing Chinese universities. Among industry institutions, those receiving the most press coverage are not always the most prolific: for example, OpenAI is not in the top 50 institutions by paper count.
- (3) Do LLM authors with different backgrounds tend to prioritize different topics? (§3.3) LLM authors are not a representative sample of the general population. If author backgrounds influence the LLM topics they prioritize, it suggests, worryingly, that the highly skewed population of LLM authors may prioritize topics which do not reflect the priorities of society writ large. Substantiating this concern, we document a gender gap in the topics LLM authors study: papers with a majority of predicted-female author names are more than twice as likely to study bias, harms, and hate speech, for example. There are also academic/industry differences: papers with industry-affiliated authors are more likely to study model efficiency, while academic papers are more likely to study societal impacts (misinformation, hate speech, bias) and domain-specific applications (law, healthcare). Also, much of the surge in work on applications has

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<sup>&</sup>lt;sup>1</sup>To trace changes over time prior to the most recent wave of instruction-tuned chatstyle models, we use a broad search criterion including older terms like "BERT" and "language model." In the text, we refer to this entire set of papers as LLM-related,

though not every paper in the set adheres to the most recent conception of a "large language model."

<sup>&</sup>lt;sup>2</sup>https://github.com/rmovva/LLM-publication-patterns-public

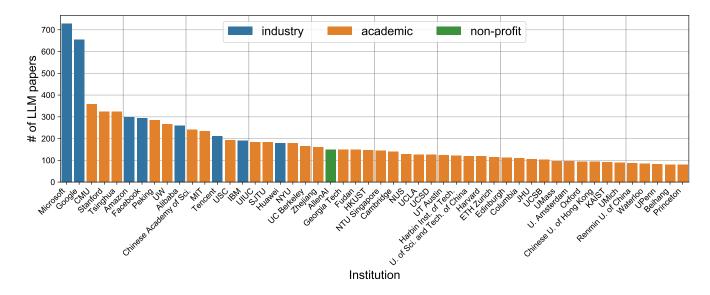


Figure 1: The 50 institutions with the most LLM papers. Most are academic, but there are several large industry players, with Microsoft and Google producing by far the most papers. While academia is more prolific, industry papers are more highly cited, as we document below.

been driven by newcomers to LLM research. Over 60% of 2023 LLM papers are first-authored by researchers writing about LLMs for the first time, and they've focused especially on ChatGPT.

- (4) What distinguishes highly-cited papers? (§3.4) To better understand the prevailing values of LLM research, we study the topics and characteristics of highly-cited papers. In addition to papers that report on capable new models, application-oriented *evaluations* have become a frequent subject of highly-cited work (*e.g.*, studies of accuracy on medical challenge problems). On average, papers by larger, industry-affiliated author teams garner more citations.
- (5) What are the patterns of collaboration? (§3.5) Previous research has warned of the harms of an "AI arms race," where companies or countries compete, rather than collaborate, to develop AI as quickly as possible [37]. 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 U.S./China schism: pairs of institutions which frequently collaborate are almost exclusively based in the same country. An exception to this is Microsoft, which collaborates with both American and Chinese universities. Within countries, we also find that while academic-academic and academic-industry collaborations are common, collaborations between multiple industry institutions are rare.

Overall, our analysis documents two ways in which LLMs are increasingly entwined with society, with clear implications for researchers and policymakers. 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, suggesting the value of frameworks and educational resources which reduce barriers-to-entry and promote good practice in LLM research. The growing societal impacts of LLMs attest to the necessity of regulatory attention, interdisciplinary collaboration, and careful translational work to ensure these impacts are positive. 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, and implies that it is pressing to expand opportunity and diversify the research community to ensure that the topics it prioritizes represent a broad swath of society rather than a nonrepresentative few. We also document a U.S./China divide in the collaboration network, substantiating concerns about AI-related competition between the two countries [12, 35]. Overall, our analysis reveals profound ways in which LLMs both shape and are shaped by society, 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 418K papers posted on the CS and Stat arXivs between January 1, 2018 and September 7, 2023. Following past ML survey papers [4, 23, 26, 78], we identify an analysis subset by searching for a list of keywords in paper titles or abstracts. Keyword search has the benefits of transparency, simplicity, and consistency with past work, but also has caveats; see §A.2 for further details. Our keyword list surfaces 16,979 papers; the specific terms we include are {language model, foundation model, BERT, XLNet, GPT-2, GPT-3, GPT-4, GPT-Neo, GPT-J, ChatGPT, PaLM, LLaMA}.

	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, XLNet, GPT-2, GPT-3, GPT-4, GPT-Neo, GPT-J, ChatGPT, PaLM, LLaMA}, 0 otherwise
Topics (§A.3)	sub-arXiv topic	name of subarXiv paper belongs to name of topic generated from topic model
Affiliations (§A.4)	academic industry	1 if paper has $\geq 1$ academic affiliation with $\geq 10$ LLM papers, 0 otherwise 1 if paper has $\geq 1$ industry affiliation with $\geq 10$ LLM papers, 0 otherwise
Gendered names (§A.5)	majority predicted female	1 if at least half a paper's authors' names predicted female, 0 if fewer than half are predicted female, undefined if no predictions
Citations (§A.6)	citation percentile	citation percentile among papers published in same 3-month interval

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 tracked a paper's primary *sub-arXiv* designation, such as Artificial Intelligence (cs.AI) or Computation and Language (cs.LG). For more fine-grained labels, we assigned each paper a topic (§A.3) by applying a clustering algorithm to semantic embeddings of the paper abstracts [31, 120], then titled the clusters using a combination of LLM annotation and manual annotation; though topic titles can be subjective, we verified that they reasonably describe the clusters by examining 25 papers per cluster. We computed two separate topic clusterings for the LLM-related papers (comprising 40 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 list academic or industry affiliations (§A.4). We also annotated each paper for whether at least half of its authors' names are predicted to be gendered female (§A.5).3 Finally, for all LLM-related papers, we pulled citation data from Semantic Scholar, and defined the citation percentile for each paper as the percentile of its citation count relative to papers from the same 3-month window (§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 their *enrichment ratios*  $\frac{p(\text{topic} \mid \text{group 1})}{p(\text{topic} \mid \text{group 2})}$ , and we present results by displaying the 5 topics with both the highest and lowest ratios. For each of these 10 topics, we plot their ratios with 1.96× risk ratio standard error CIs; separately, we plot the numerator and denominator of each ratio with 1.96× Bernoulli SE CIs.

#### 3 RESULTS

Past work has shown that the raw count of LLM papers has risen steeply [23, 63, 121]. These trends replicate on our arXiv corpus: LLM-related papers are accounting for a larger fraction of the arXiv, up to 12% of all CS/Stat submissions in Q2 2023 (Figure S1). So far in 2023, 2.4× as many papers are LLM-related compared to the same range in 2022. Moreover, we find that compared to *all other topics* in computer science (Figure S2) and *all words/bigrams* mentioned in paper abstracts (Table S1), LLM- & generative AI-related topics and terms are growing fastest. LLMs are having sweeping impacts on computer science research, and we dissect these ongoing changes by studying the topics, authors, and institutions that are accounting for them.

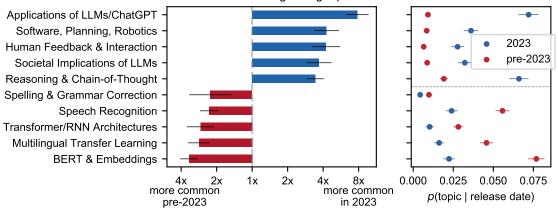
# 3.1 What topics are LLM papers focusing on?

LLM topic clusters cover a broad range of sub-fields. Table S2 presents a list of the 40 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 names must be succinct. Nevertheless, many intuitive topics emerge, covering model architecture, robotics, search, summarization, speech recognition, ChatGPT, vision-language models, healthcare, natural sciences, stereotyping & bias, and code generation. The largest topics are "Efficiency & Performance" (N = 987), "BERT & Embeddings" (955), "Speech Recognition" (742), "NLP for Healthcare" (697), and "Pretrained LMs & Text Classification" (674).

The fastest-growing LLM topics cover their capabilities and societal applications. The total number of LLM papers has risen quickly in 2023, but some topics have contributed more to this growth than others. We rank the 40 topics by how frequently they occur in 2023 LLM papers compared to pre-2023 LLM papers: i.e.,  $\frac{p(\text{topic} \mid \text{published in 2023})}{p(\text{topic} \mid \text{published pre-2023})}.$  Figure 2 plots results. The fastest-growing

 $<sup>^3\</sup>mathrm{While}$  name-gender associations have been widely applied to study gender disparities in bibliometrics and elsewhere [19, 38, 39, 49, 54, 80, 81, 95, 101, 104, 105, 113], this approach has important limitations [39, 65, 69]. 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, a large fraction of East Asian names remain unclassified in our data, though overall we have predictions for 60% 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 [103]. In spite of these limitations, we believe it is important to attempt to systematically document gender disparities LLM research due to anecdotal evidence suggesting these disparities may be pronounced [93], as well as previous work documenting gender differences in academic literature, in views on social implications of computing, and in social and ethical issues more generally [19, 27, 40, 51, 54, 80, 82, 95, 105, 113]. See §A.5 for full discussion of these points and more details of methodology and robustness checks.





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

topic is by far "Applications of LLMs/ChatGPT", which has risen from 0.9% of LLM papers in 2018–2022 to 7% in 2023, an  $8\times$  increase. This cluster of papers spans a broad range of topics and overlaps thematically with "Societal Implications of LLMs" (4× growth). Collectively, these topics span empirical studies of LLMs on applied tasks, e.g., [8, 13, 76, 117], discussions of societal applications of ChatGPT [42, 52, 71, 73], and ethical arguments [14, 48, 92, 106]. The next two fastest-growing topics - "Software, Planning, Robotics" and "Human Feedback & Interaction" — hint further at applications. The former includes papers on two promising use cases of recent models, code generation and robotics, while the latter topic concerns the growing role of user feedback and HCI in developing useful language systems. On the other hand, the "BERT & Embeddings" topic is shrinking, consistent with prompt-based, few-shot models now replacing fine-tuned BERT systems. Many papers in this shrinking topic also study internal model representations, which may be less common now that intermediate activations and token-level probabilities are inaccessible from widely-used closed-source models like ChatGPT. Topics on transformers, multilingual models, and language correction are also shrinking; LLMs may have rendered some of this architecture-/task-specific research less relevant, due to the broad proliferation of fewer, performant models.

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  $\frac{p(\text{paper is about LLMs}|\text{paper on sub-arXiv \& published in 2023})}{p(\text{paper is about LLMs}|\text{paper on sub-arXiv & published pre-2023})}$  (Figure S3). Computers and Society (cs.CY) ranks first, with a ratio of 20x: in 2023, 16% of its papers are about LLMs, compared to just 0.8% pre-2023. Topics range widely, including the impacts of LLMs on education, e.g., [6, 17, 83], ethics and safety [25, 29, 92], and legal considerations [36, 58, 59]. Software Engineering (cs.SE) has also seen a 6× increase in the proportion of papers about LLMs (rising

to 19%), consistent with the growth of interest in LLMs for program generation, e.g., [33, 74, 109, 119]. Other sub-arXivs with rapid growth include HCI (a  $10\times$  increase up to 10%), Robotics, 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 and have broken into a number of other fields, as researchers increasingly discuss new applications and societal implications of these models.

# 3.2 Who is writing LLM papers?

A large (and growing) majority of LLM papers are published by academic institutions. To understand what type of institutions produce the most LLM research, we consider the 280 academic and 41 industry institutions that have published at least 10 LLM papers.<sup>4</sup> Out of the 14,179 papers with at least one extracted affiliation, 11,627 (82.0%) were written by one of these 321 institutions. Of these, 9,937 (85.5%) were written by at least one of the 280 academic institutions and 3,774 (32.5%) were written by at least one of the 41 industry institutions. As illustrated in Figure 1, the most prolific institutions are Microsoft and Google, and Amazon, Meta, and Alibaba are also in the top 10. However, overall, industry institutions account for a relatively small fraction of research output; rather, a long tail of universities produce the vast majority of LLM papers. Moreover, academia's LLM research output has grown faster in 2023 than industry's (Table 2), leading to an even starker ratio of academic paper count to industry paper count (3.3× in 2023 vs. 2.3× pre-2023). Part of this increase appears to be a result of higher output from the top 10 Chinese academic institutions, which account for 16.1% of LLM papers in 2023 vs. 12.7% pre-2023 ( $p < 10^{-6}$ ,  $\chi^2$  test), while the top 10 U.S. universities have remained at ~17% (p = 0.36). Despite their widely-used and studied models, OpenAI is notably absent

<sup>&</sup>lt;sup>4</sup>Eight institutions were not clearly academic or industry, *e.g.*, nonprofits and government labs. AllenAI was the only such institution in the top 100 producers.

**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 on the subset of papers which we were able to link to at least one of the 321 institutions with  $\geq$  10 LLM papers (see §A.4). Papers with no extracted affiliation or with rare affiliations were excluded from these statistics. Similarly, the proportions for 'Majority predicted-female author names' are calculated on the subset of papers with at least one name-gender prediction (see §A.5). 'Top 10' refers to the ten most prolific institutions in the U.S. and China.

	2018-2022	2023
≥ 1 academic affiliation	83.5%	88.9%
≥ 1 industry affiliation	35.8%	26.6%
top 10 academic institution, U.S.	17.5%	16.8%
top 10 academic institution, China	12.7%	16.1%
majority predicted-female names	17.5%	16.1%
1 author	3.4%	5.0%
2-5 authors	69.6%	59.0%
6-9 authors	22.8%	28.0%
10+ authors	4.1%	8.0%

from the list of the 50 most prolific institutions, perhaps concording with their reputation for research secrecy [34, 102].

Most LLM papers have majority predicted-male author names. Over 80% of papers are written by teams with majority predicted-male author names (Table 2), and this trend does not change in 2023. Academic-only author teams are more likely to be majority predicted-female than industry-only teams are (19.1% vs. 12.0%,  $p < 10^{-7}$ ), with industry-academic collaborations in-between (14.6%). We stress that results from name-gender inferences have caveats, and in particular should not be taken to apply to authors with East Asian names (see §2 and §A.5).

LLM papers are mostly written by middle-sized teams. A large majority of LLM papers are written by teams with between 2 and 9 authors (Table 2). In 2023, median author count has increased from 4 to 5, and the percentage of  $\geq$ 10-author teams has nearly doubled to 8.0%. An exception to the trend of larger teams is the small but significant increase in solo-authored papers, from 3.4% of LLM submissions pre-2023 up to 5.0% in 2023 ( $p < 10^{-6}$ ).

In 2023, a majority of first authors are new to LLMs. To what extent are new researchers responsible for the growth of LLM research? We code all authors according to whether they had already written an LLM paper prior to 2023; we define experienced authors as those who wrote an LLM paper between 2018-2022, while new authors are those whose first LLM paper was in 2023. 5 Of the 6,427 papers from 2023, 3,948 (61.4%) had new first authors, 2,519 (39.2%) had new last authors, and 1,490 (23.2%) had teams entirely composed of new authors (i.e., none of their authors had written an LLM-related paper prior to 2023). These statistics indicate that newcomer authors and

author teams account for a substantial fraction of the recent growth in LLM literature. In §3.3, we show that contributions from these new authors lean towards particular subtopics.

# 3.3 Do authors with different backgrounds study different LLM topics?

Having described LLM paper topics (§3.1) and LLM author backgrounds (§3.2), we analyze the connection between the two: that is, do LLM authors of different backgrounds focus on different topics?

Paper topics correlate with predicted author gender. Figure S4 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 "Biases & Harms," followed by "Toxicity & Hate Speech"; the topic most disproportionately common among majority-predicted-male papers is "Transformer/RNN Architectures," followed by "Visual Foundation Models." These trends remain robust across multiple name classification packages and classification hyperparameters, though we reiterate the potential for specific types of errors (see §2 and §A.5).

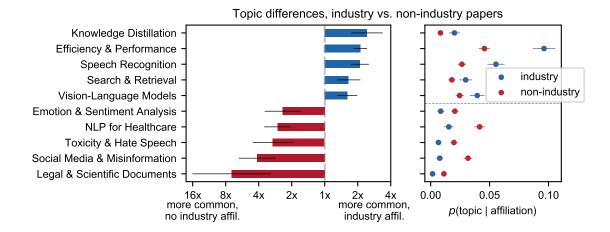
The finding of gender disparities in which LLM topics are studied — for example, that authors with predicted female names are more likely to focus on topics like bias and harms — has important implications in light of the underrepresentation of women in computing (and the low proportion of predicted female names we observe; Table 2). Because 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 3 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 speech recognition and search. In contrast, papers without an industry affiliation (i.e., academic-only papers) are more likely to focus on applications like legal document analysis, toxicity detection, social media data, and healthcare. (Figure S5 plots enriched topics for academic-affiliated papers. It is not precisely the inverse of Figure 3 because papers can have both academic and industry affiliations, but illustrates similar trends.) Interestingly, we find academic and majority-predicted-female teams tend to focus on similar topics: three of the top five enriched topics (bias, toxicity, and social media) are shared across majority-predicted-female papers and academic papers, and the correlation in enrichment ratios across all topics is also statistically significant (Spearman  $\rho = 0.46$ , p = 0.003).

First-time author teams study applications, while experienced authors study core NLP tasks. Among LLM papers written in 2023, we study how topic choice differs by author experience level. We compare the 1,490 papers from 2023 written by author teams with no experienced co-authors (i.e., authors who have not co-authored an LLM paper from 2018-22) to the 4,937 papers from 2023 written by teams with at least one experienced co-author. In Figure 4, we dis-

play the most and least enriched topics sorted by  $\frac{p(\text{topic}|2023\ \&\ \text{only new authors})}{p(\text{topic}|2023\ \&\ \geq\ 1\ \text{experienced author})}$ 

<sup>&</sup>lt;sup>5</sup>Authors are matched using their names as entered on arXiv. It is possible that this mis-estimates the fraction of first-time authors, due to imperfect linkage across papers.



**Figure 3:** Topics which occur most disproportionately among industry (blue) vs. non-industry (red) 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. Right: Topic frequencies by group.

Figures S6 and S7 offer analogous versions when only considering the experience level of the paper's first and last author respectively, surfacing similar trends.

Strikingly, all five enriched topics for papers written by new author teams center on diverse society-facing applications across domains like education, finance, and misinformation ([18, 44, 47, 53, 66, 84, 100, 112], inter alia). Many of these papers also fall within the fastest-growing topics overall ("Applications of LLMs/ChatGPT" and "Societal Implications of LLMs"), indicating that new authors are contributing to the rapid growth in these areas. On the other hand, 2023 papers by teams with an experienced co-author lean towards methodological innovations for training and prompting LLMs (those topics are also growing in 2023, albeit not as fast as more applied ones). Experienced authors also focus on re-purposing LLMs towards core NLP tasks like information retrieval and commonsense knowledge, e.g., retrieval-augmented question answering [41, 85, 90] or LLM-based generation and evaluation of open-ended text, such as for text summarization [28, 64, 118]. These findings on author experience point to emergent areas of specialization, underscoring the importance of collaboration (§3.5).

# 3.4 What distinguishes highly-cited LLM papers?

Past work has studied highly-cited papers as clarifying exemplars of a field's values [3, 55]. We perform a similar analysis of LLM-papers using citation counts from Semantic Scholar (see §A.6).

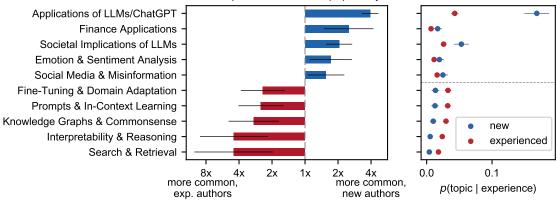
In 2023, top-cited papers emphasize model performance and applied evaluations. We qualitatively analyze the 50 LLM papers with the most citations so far in 2023. Applications of ChatGPT and multimodal vision-language models are the most common topics, accounting for 12 and 9 papers respectively. As in ML more broadly [3], papers that report on new models usually prioritize accuracy, efficiency, and/or generalization as values. However, specific to the LLM literature, evaluation (rather than new models/methods)

has become a primary contribution of several top-cited LLM papers. These papers identify specific applications or vulnerabilities of LLMs and design new datasets to study them, often releasing these data. For example, [77] evaluates GPT-4 on medical challenge problems, [32] evaluates ChatGPT against human experts across domains, [30] compares ChatGPT against humans for social media annotation, [70] assesses detectability of LLM-generated fake news, and [2] studies hallucinations. Most such papers are grounded in values of societal relevance and real-world deployability, suggesting more attention towards these values than traditional ML [3].

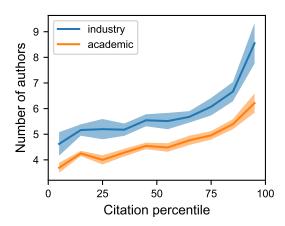
To extend our qualitative analysis, we examine LLM topics which are most and least enriched among papers in the top 10% (decile) of citations (Figure S8). Since older papers have had more time to accrue citations, we map a paper's raw citation count to its *citation percentile*, comparing only to other papers from the same 3-month interval (§A.6 for details). Consistent with our qualitative analysis, enriched topics in the top citation decile include "Vision-Language Models" and "Visual Foundation Models," as well as techniques for improving performance like "Reasoning & Chain-of-Thought" and "Prompts & In-Context Learning." Interestingly, the 5 topics which are *least* enriched among the top citation decile include several societal-impact topics which predicted-female and academic teams are more likely to write about, including "Social Media & Misinformation" and "Toxicity & Hate Speech."

Citations increase with author count, especially for very-large teams. Papers with higher citation percentiles have larger author teams (Figure 5): papers in the top decile have a mean of 8.2 authors (median 6), compared to a mean of 4.9 authors overall (median 4) and a mean of 3.5 authors in the bottom decile (median 3). The trend is particularly pronounced at the highest citation percentiles: the top 2% of papers have a mean author count of 14.0 (median 7), due in part to a few papers with outlier author counts that have accrued many citations (>50 authors, e.g. [5, 7, 9, 60]).





**Figure 4:** Topics of 2023 LLM papers vary with researcher experience. Teams of authors who are all new to LLMs (blue; no LLM co-authors prior to 2023) write disproportionately about applications and societal implications, while author teams with an experienced author (red; co-authored an LLM paper before 2023) write more about methods and core NLP tasks.



**Figure 5: Highly cited papers are written by larger teams.** This trend is especially pronounced for the top citation percentiles. Shaded regions show 1.96× the standard error on the mean.

Industry papers receive more citations. While academic institutions account for a larger number of papers (Table 2), industry papers are better-cited. Industry and academic papers account for a similar fraction of the total citation count across all papers, despite the fact that there are 2.6× as many academic papers. The median industry paper receives 3 more citations and has a 6.4% higher citation percentile than the median academic paper. Papers with only industry affiliations are 2.3× as likely to be in the top citation decile as papers with only academic affiliations. This is not simply due to larger industry author teams: controlling for author count, industry-only papers remain 1.9× as likely to be in the top decile than academic-only papers. The specific industry institutions with the most top-decile papers are generally the most prolific overall, though there are some exceptions: DeepMind and OpenAI rank

15th and 22nd respectively despite falling outside the top 50 when ranked by overall paper count, suggesting an outsize per-paper impact. Figure S9 plots top-cited paper count against total paper count systematically for all top institutions.

# 3.5 What are the patterns of collaboration?

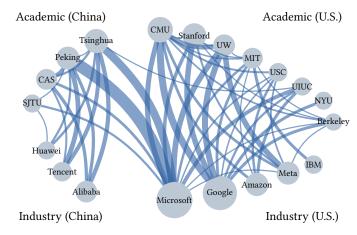
We examine which institutions tend to co-author papers together, focusing in particular on patterns of academic/industry and international collaboration.

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 2,250 papers produced by a collaboration between at least two of these academic institutions, and 2,084 by at least one of these academic institutions and one of these industry institutions, while there were only 104 by a collaboration between at least two of these industry institutions.

Collaborations between American and Chinese institutions are relatively rare. In Figure 6, we present the network of the 20 institutions that produced the most LLM papers in our dataset, all of which are either Chinese or American. An edge between two institutions indicates that at least five papers resulted from a collaboration between them. 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 [5, 62, 114] and others are domain-specific (*e.g.*, education [1, 11, 46]; healthcare [86, 89, 98, 108]; law [88, 96]; code generation [110, 111, 116]; recommender systems [24]; social science [16, 83, 122]). 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



**Figure 6:** Collaborations between the 20 institutions with the most LLM papers. Node area is proportional to number of papers and edge width to number of collaborations between nodes (we show only edges corresponding to  $\geq 5$  collaborations). Microsoft uniquely collaborates with academic institutions across the U.S. and China.

differ from our work in that they do not attempt to systematically describe bibliometric trends like those we analyze.

More closely related to our work are three recent papers which present some bibliometric analysis of LLM research [23, 63, 121]. Liu et al. [63] identify 194 arXiv papers mentioning ChatGPT, and compile a distribution of sub-arXivs that these papers were submitted to. Related to [5], they offer a taxonomy of different applications which researchers are using ChatGPT for. Zhao et al. [121] show that usage of the phrases "language model" and "large language model" has increased rapidly on arXiv, and then provide a practitioneroriented review of the architecture, training, and benchmarking details of several widely-used models. Fan et al. [23] 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 rather than WoS, yielding better coverage of preprints, which are essential to study recent trends. Finally, we analyze additional research questions: e.g., how author characteristics affect topic choice (§3.3) and which topics are highly cited (§3.4).

#### 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. Focusing in particular on trends since the beginning of 2023, we document 1) the topics LLM papers are prioritizing; 2) the authors and institutions writing LLM papers; 3) how author background correlates with the topics they prioritize; 4) the factors distinguishing highly cited LLM papers; and 5) the networks of collaboration.

Our analysis has limitations. First, much of our work focuses on changes in the first nine months 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 U.S./China schism in the collaboration network. This substantiates calls in recent work to analyze LLMs with a sociotechnical, not a purely technical, lens [20, 22, 37, 56, 61]. Our analysis has four practical implications for researchers and policymakers:

- (1) Onboard first-time authors. We find that the majority of authors writing LLM papers in 2023 have never done so before, suggesting the value of resources designed to onboard newcomers to the field. Examples would include tutorials at conferences; online educational resources; and frameworks to lower the barrier-to-entry for model training and deployment. Resources which reduce the probability of errors are also valuable, since past work has shown that when ML methods become much more widely used, errors become more common as well [45].
- (2) Facilitate interdisciplinary collaboration. We find both an influx of authors from different backgrounds, and a rise of applications of LLMs to specific (and often high-stakes) domains like law, medicine, and education. Both of these trends suggest that interdisciplinary collaboration — between domain experts and LLM experts, for example — will be essential. Funders, conferences, and journals can all incentivize this in their calls for proposals and papers.
- (3) Diversify the community of LLM authors. LLMs increasingly affect us all, but the scientists studying them do not represent us all equally. We show that this non-representativeness affects research: specifically, the topics LLM authors prioritize correlate with their backgrounds. Diversifying the author population is pressing if we want LLM research to reflect the priorities of society as a whole.
- (4) Where common goals exist, facilitate cross-country and cross-industry cooperation. Our analysis reveals a pronounced lack of collaboration between the U.S. and China, and between industry teams, substantiating concerns about the potential for destructive competition [12, 37]. While institutions may sometimes have incentives or values which make collaboration impossible, where common ground can be found, efforts to create consensus around avoiding risky or unethical uses of AI [115] are valuable.

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#### A APPENDIX: SUPPLEMENTARY METHODS

#### A.1 Data

We downloaded the latest release of arXiv metadata from Kaggle [43] in September, including all papers posted to the arXiv through 7 September 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 further subset the data to only include papers since the start of 2018, resulting in 418K papers. (We chose 2018 to roughly align with the growing use of representations from pretrained language models, like BERT and ELMo [15, 79].) We downloaded PDF full-texts for all these papers, available from a GCP bucket jointly hosted by Kaggle and arXiv [43]. We then apply PDFto-text conversion to produce plaintext files for each paper using the pdftotext Python tool. To study influential papers, we also pulled citation data using the Semantic Scholar API [50] for the 16,979 LLM papers described below. Our repository includes documented code snippets for each of these steps, so future timepoints of arXiv data will also be easy to annotate.

# A.2 Identifying LLM-related papers

Consistent with past ML survey papers [4, 23, 26, 78], 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 intentionally chose a broad set of terms; in particular, we wanted to capture relevant papers before modern instruction-tuned, chat-style LLMs, to better answer research questions about changes over time. As such, we include terms like "language model" and "BERT," which have been in use for longer than "large language model." 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, and 16,979 papers since 2018 contain at least one of them in their title or abstract. Besides "language model" and "foundation model," we chose the specific model keywords by referencing Wikipedia's page for LLMs as of July 2023 [107]. We removed the long tail of models for which there are < 10hits (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. We refer to this entire set of 16,979 papers as "LLM-related papers" and sometimes abbreviate to "LLM papers," though note that not every paper in this set may adhere to the most recent (and evolving) conception of a "large language model."

# 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 [120]): (1) embed paper abstracts in a 768-dimensional space using the open source INSTRUCTOR-XL model [94]; (2) apply PCA to reduce dimensionality to n=200 components, which explain ~90% of the embedding variance; (3) apply UMAP [67] 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 [31, 120], and we refer to them interchangeably. Recent work [31, 91, 97, 120] 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 418K CS/Stat papers we used k-means with 100 clusters, and for the subset of 16,979 LLM papers we used Ward agglomerative clustering with 40 clusters. While Ward and k-means yielded highly similar results (adjusted 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 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 = 50 there were multiple thematically similar clusters about low-resource languages, so we settled on k = 40.

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 [31, 120]. 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-4 through the OpenAI API as of 15 Sep 2023) to use a sample of the cluster's paper titles and abstracts and, from those, directly assign a succinct cluster name. In many cases, these names were either too long, not specific enough, or overly specific. We performed a 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 [75, 99]. Specifically, many papers list author emails in the full-text, and we search for them with high precision by designing regexs to match the "e" symbol and appropriate surrounding text<sup>7</sup> in the paper's first 100 lines. We conduct a manual audit of 100 papers to verify that all the extracted strings are author emails, and that the papers without any extracted emails indeed do not obviously list emails in the manuscript. Overall, 86% of the LLM paper subset has at least one extracted email, which drops to 83% after removing

 $<sup>^6\</sup>mathrm{We}$  ignore case for "language model" and "foundation model," and enforce case for the other keywords.

 $<sup>^7</sup>We$  use two regexs, to match two possible formats: author@domain.xyz and {author1,author2,...}@domain.xyz.

uninformative domains such as gmail.com. 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 s to s (e.g., s = 'cs.cornell.edu' s s 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 329 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 [19, 38, 39, 49, 54, 80, 81, 95, 101, 104, 105, 113] 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 [38, 39, 87]. 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 [93], as well as previous academic research documenting gender differences in publication patterns and in opinions on ethical and social issues [19, 27, 40, 51, 54, 80, 82, 95, 105, 113].

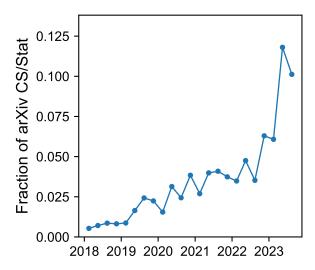
We predict whether names are commonly gendered male or female using the open-source package nomquamgender [101], which has been shown to achieve similar performance to paid services. We leave names unclassified if the uncertainty exceeds the default threshold of 0.1, which assigns a prediction to 60.1% of author names on LLM papers. 18.5% of author names on LLM papers which have a prediction 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 namegender 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 [38, 39]; 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  $\geq 0.5$  to papers with predicted female fraction < 0.5, referring to these papers

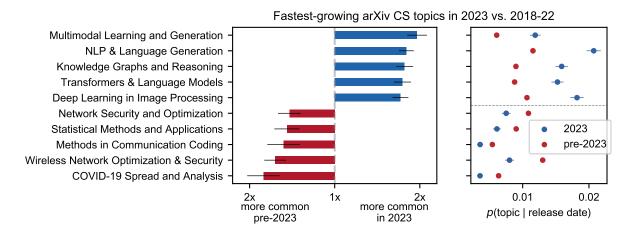
as "majority predicted female" and "majority predicted male" respectively. We confirm that our results remain similar across multiple gendered name inference packages (comparing the results from [101] to those from [21]); across multiple uncertainty thresholds for inference; and across multiple thresholds for binarizing the gendered female fraction.

#### A.6 Citation counts

For each of the LLM papers, we pull its citation count from the Semantic Scholar API [50], reflecting the number of times another paper has cited it (note that this includes all references, not just those by other LLM papers). Because papers in 2018, for example, have had more time to accrue citations than papers from 2022, we avoid using raw citation counts. Instead, we compute each paper's 3month citation percentile: that is, the percentile of its citation count comparing only to other papers released during the same 3-month interval, so e.g. a paper from 2020-02-15 would be compared only to papers from 2020-01-01 through 2020-03-31. Percentile-based metrics for citations are commonly used in bibliometric analysis [10]. Each paper is mapped to one of 22 intervals: [2018-01-01, 2018-04-01], ..., [2023-04-01, 2023-07-01]. We exclude papers from the most recent 3-month interval, leaving 15,147 papers in this analysis. Note that 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.



**Figure S1:** The overall incidence of LLM-related papers has increased substantially in the last few years, up to over 10% of all arXiv CS/Stat submissions since the second quarter of 2023. Papers are identified as LLM-related if their title or abstract contains one of the following keywords: {language model, foundation model, BERT, XLNet, GPT-2, GPT-3, GPT-4, GPT-Neo, GPT-J, ChatGPT, PaLM, LLaMA}.



**Figure S2:** The fastest-growing and shrinking topics out of all 100 annotated topics on the CS/Stat arXivs. All of the top four topics involve multimodal models, NLP, and LLMs. These results suggest that LLMs have grown quickly not only in terms of absolute statistics, but also relative to all other growing topics within CS research.

**Table S1:** The 50 most disproportionately-used keywords (including unigrams & bigrams) in arXiv CS/Stat paper abstracts in 2023 vs. 2018–2022. Most of the keywords relate to LLMs, though some terms also relate to Segment Anything (SAM) and multimodal text-image models (e.g., CLIP). Keywords that never appear prior to 2023 are excluded.

Keyword	$\frac{p(\text{keyword} \text{post-2023})}{p(\text{keyword} \text{pre-2023})}$
2023	189.4
llama	188.6
chatgpt	179.8
like chatgpt	132.6
llm based	80.8
segment model	73.1
models 11ms	57.4
llms	54.4
11m	46.4
stable diffusion	44.1
model llm	43.0
image diffusion	41.2
cot	41.1
llms demonstrated	35.6
llms shown	35.6
generative ai	35.4
chain thought	29.5
foundation models	23.9
large language	21.5
text prompts	16.0
diffusion models	12.4
foundation model	12.2
latent diffusion	12.1
diffusion model	11.3
tuned models	11.1
prompt engineering	11.0
underscores	9.9
valuable insights	9.8
underscore	9.8
models clip	9.6
denoising diffusion	9.6
prompts	8.1
instruction following	8.1
text guided	7.9
ai generated	7.9
text prompt	7.7
context learning	7.6
prompting	7.6
open vocabulary	7.4
sam	7.2
diffusion based	7.0
gpt	7.0
prompt	6.8
nerfs	6.6
demonstrated remarkable	6.6
models gpt	6.6
hallucinations	6.5

Table S2: Topics in the LLM literature that have grown and shrunk the most in 2023, compared to 2018-2022. p-values computed with a  $\chi^2$  test. The 40 topics were assigned and labeled using our neural topic modeling approach described in the methods. Topics are sorted by  $\frac{p(\text{topic}|\text{since-}2023)}{p(\text{topic}|\text{pre-}2023)}$ .

Торіс	N	$\frac{p(\text{topic} \text{since-2023})}{p(\text{topic} \text{pre-2023})}$	p(topic   since-2023)	<i>p</i> (topic   pre-2023)	<i>p</i> -value
Applications of LLMs/ChatGPT	560	7.84	0.072	0.009	3.7e-109
Software, Planning, Robotics		4.28	0.036	0.008	2.1e-37
Human Feedback & Interaction		4.24	0.028	0.007	1.2e-28
Societal Implications of LLMs		3.69	0.032	0.009	3.0e-29
Reasoning & Chain-of-Thought		3.45	0.066	0.019	2.7e-55
Visual Foundation Models	270	3.28	0.028	0.009	1.4e-22
Finance Applications	110	1.83	0.009	0.005	1.8e-03
Vision-Language Models	504	1.72	0.040	0.023	4.9e-10
Applications & Benchmark Evals	336	1.64	0.026	0.016	4.6e-06
Fine-Tuning & Domain Adaptation	364	1.62	0.028	0.017	3.1e-06
Video & Multimodal Models	437	1.56	0.033	0.021	2.5e-06
Natural Sciences		1.43	0.021	0.015	2.1e-03
Privacy & Adversarial Risks		1.43	0.038	0.027	3.2e-05
Code Generation	408	1.42	0.029	0.021	4.3e-04
Audio & Music Modeling	119	1.41	0.009	0.006	7.3e-02
Prompts & In-Context Learning	418	1.22	0.028	0.023	4.9e-02
NLP for Healthcare	697	1.20	0.046	0.038	1.4e-02
Interpretability & Reasoning	315	1.09	0.020	0.018	4.6e-01
Biases & Harms	448	1.01	0.027	0.026	9.3e-01
Legal & Scientific Documents	179	0.91	0.010	0.011	6.1e-01
Entity Extraction & RecSys	435	0.87	0.023	0.027	1.9e-01
Translation & Low-Resource	433	0.81	0.022	0.027	4.1e-02
Knowledge Graphs & Commonsense	492	0.80	0.025	0.031	2.0e-02
Efficiency & Performance	987	0.73	0.047	0.065	4.1e-06
Summarization & Evaluation		0.69	0.014	0.020	3.8e-03
Dialogue & Conversational AI		0.68	0.023	0.035	5.4e-05
Datasets & Benchmarks		0.66	0.011	0.016	3.7e-03
Search & Retrieval		0.63	0.015	0.023	1.5e-04
Question Answering & Retrieval		0.61	0.026	0.042	3.7e-08
Social Media & Misinformation	458	0.56	0.018	0.032	2.8e-08
Text Generation	424	0.54	0.016	0.030	2.5e-08
Emotion & Sentiment Analysis	347	0.53	0.013	0.025	2.9e-07
Knowledge Distillation	169	0.53	0.006	0.012	3.4e-04
Pretrained LMs & Text Classification	674	0.52	0.025	0.049	3.3e-14
Toxicity & Hate Speech		0.51	0.011	0.021	8.7e-07
Spelling & Grammar Correction	132	0.44	0.004	0.010	1.1e-04
Speech Recognition		0.43	0.024	0.056	1.4e-22
Transformer/RNN Architectures		0.36	0.010	0.028	8.7e-15
Multilingual Transfer Learning	587	0.35	0.016	0.046	2.1e-24
BERT & Embeddings	955	0.29	0.022	0.077	3.2e-50

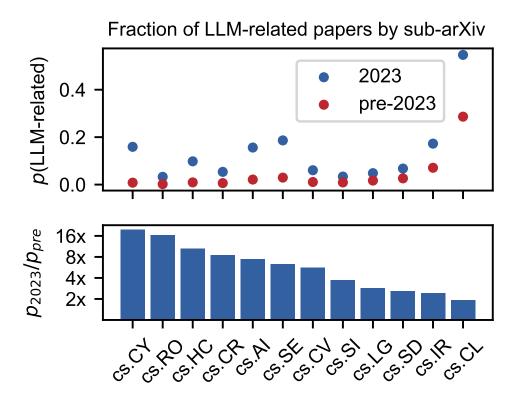
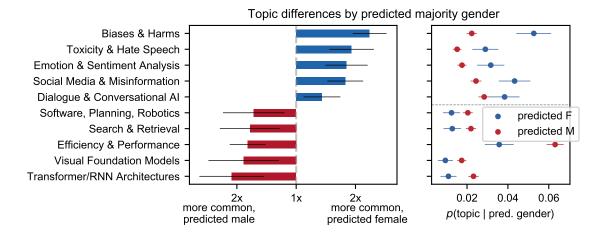
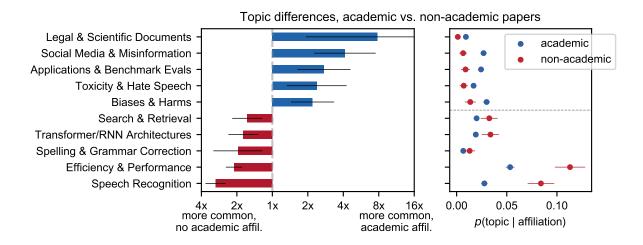


Figure S3: Sub-arXivs which have grown the most in their fraction of LLM papers. Top:  $p(\text{LLM-related} \mid \text{sub-arXiv}, 2023)$  is in blue, while  $p(\text{LLM-related} \mid \text{sub-arXiv}, 2018-22)$  is in red. Bottom: sub-arXivs are sorted by the ratio of these two quantities, representing how much more likely, in 2023, a random paper in the sub-arXiv concerns language models. Computers and Society (cs.CY) displays the most extreme shift: 16% of its papers are LLM-related in 2023, compared to less than 1% in 2018-2022. Other sub-arXivs with at least 10% of LLM-related papers and significant growth in 2023 include Human-Computer Interaction (cs.HC), Artificial Intelligence (cs.AI), Software Engineering (cs.SE), and Information Retrieval (cs.IR). Despite an already-high rate of LLM papers before 2023, it is striking that over half (55%) of papers in Computation and Language (cs.CL) released in 2023 concern LLMs.



**Figure S4:** Topics that occur disproportionately according to a paper's predicted majority author gender. 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 S5:** 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.

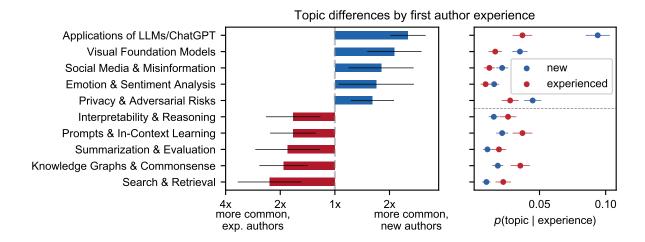
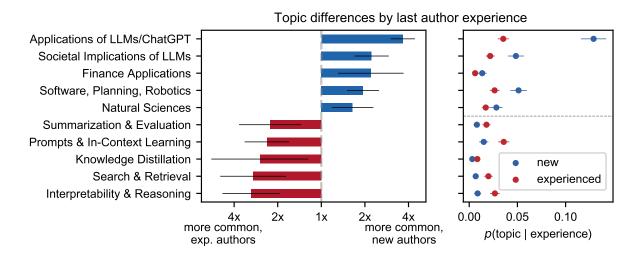


Figure S6: Topics of LLM papers written in 2023 vary with first author experience. This is an analogous plot to Figure 4, except papers are coded only according to whether their **first author** has written about LLMs before 2023 ("experienced", red) or not ("new", blue).



**Figure S7:** Topics of LLM papers written in 2023 vary with last author experience. This is an analogous plot to Figure 4, except papers are coded only according to whether their **last author** has written about LLMs before 2023 ("experienced", red) or not ("new", blue).

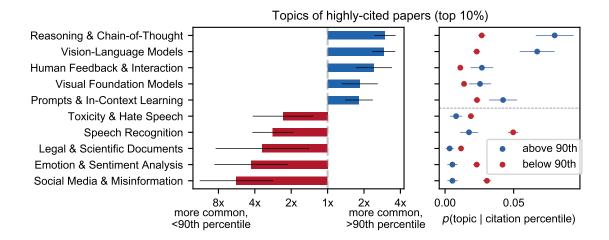
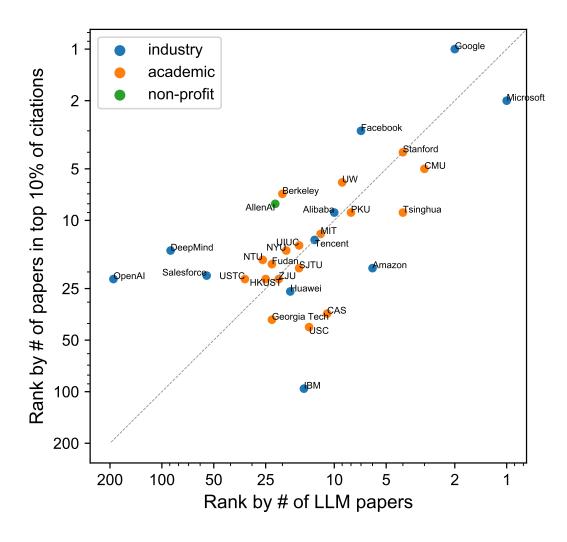


Figure S8: Highly-cited papers often report on new models and improved performance. To adjust for paper release date, citation counts are mapped to percentiles, only comparing to other papers released in the same 3-month window. Bar plot displays the ratio  $\frac{p(\text{topic}|\text{above 90th percentile})}{p(\text{topic}|\text{below 90th percentile})}$ . Dot plot displays the frequency of the topic in the highly-cited (blue) and not highly-cited (red) groups.



**Figure S9:** Top-contributing LLM institutions ranked by either total LLM paper count (x-axis) or number of LLM papers with a top 10% citation count (y-axis). Institutions above the diagonal have relatively more high-impact papers than total papers, while institutions below the diagonal have relatively more total papers than high-impact papers. Institutions that are either in the top 25 by total count or top 25 by top-decile count are included in this plot, yielding 30 institutions. Notably, OpenAI and DeepMind do not publish as frequently as other institutions, but they have many high-impact papers. Other outliers from the diagonal include AllenAI and UC Berkeley (above the diagonal), and Amazon and IBM (below).