NLLG Quarterly arXiv Report 06/23: What are the most influential current AI Papers?

Steffen Eger, Christoph Leiter, Jonas Belouadi Ran Zhang, Aida Kostikova, Daniil Larionov, Yanran Chen, Vivian Fresen Natural Language Learning Group (NLLG), https://nl2g.github.io/

Abstract

The rapid growth of information in the field of Generative Artificial Intelligence (AI), particularly in the subfields of Natural Language Processing (NLP) and Machine Learning (ML), presents a significant challenge for researchers and practitioners to keep pace with the latest developments. To address the problem of information overload, this report by the Natural Language Learning Group at Bielefeld University focuses on identifying the most popular papers on arXiv, with a specific emphasis on NLP and ML. The objective is to offer a quick guide to the most relevant and widely discussed research, aiding both newcomers and established researchers in staying abreast of current trends. In particular, we compile a list of the 40 most popular papers based on normalized citation counts from the first half of 2023. We observe the dominance of papers related to Large Language Models (LLMs) and specifically ChatGPT during the first half of 2023, with the latter showing signs of declining popularity more recently, however. Further, NLP related papers are the most influential (around 60% of top papers) even though there are twice as many ML related papers in our data. Core issues investigated in the most heavily cited papers are: LLM efficiency, evaluation techniques, ethical considerations, embodied agents, and problem-solving with LLMs. Additionally, we examine the characteristics of top papers in comparison to others outside the top-40 list (noticing the top paper's focus on LLM related issues and higher number of co-authors) and analyze the citation distributions in our dataset, among others.

1 Introduction

In an era of ever-accelerating information flow, staying abreast of the overwhelming flood of data and research output is an intimidating task. This holds true especially in the context of the current large public interest (and even hype) surrounding Generative AI, with papers disseminated in ever shorter time intervals. This report, published by the Natural Language Learning Group (https://nl2g.github.io/) at Bielefeld University, aims to alleviate the information overload problem, even if only by a small extent, by identifying the currently most popular papers on the arXiv (https://arxiv.org/), especially focusing on the AI subfields natural language processing (NLP) and machine learning (ML) as some of the most vividly discussed research areas, including in mainstream media. Our intention is to give practitioners, incomers, and users of AI, from related and non-related fields (e.g., the social sciences or digital humanities) a quick guide on the most popular and presumably most relevant papers in order to better and (more) quickly grasp current developments.

We place particular emphasis on exploring arXiv,¹ given its status as a comprehensive and extremely popular pre-print repository. Notably, arXiv's expedited publication process provides a distinct advantage over traditional conferences and journals, ensuring that the latest research becomes readily available to the scientific community at a much faster pace.

This report is structured as follows. In Section 2, we outline our methodology, which is entirely straightforward: we select papers from arXiv from the first half of the year 2023 and sort them by normalized citation counts. In Section 3, we show and discuss the list of the 40 most popular papers — in terms of normalized citation counts — from our arXiv dataset. In Section 4, we provide an analysis of our arXiv dataset relating to citation distributions, arXiv categories involved, characteristics of top papers, and popularity of 'hype' concepts such as ChatGPT and large language models (LLMs) over time. In Section 5, we conclude.

Among our key findings are that: (i) NLP, once a niche area of research, is now considerably more influential than ML in terms of the citations it attracts: even though there are twice as many ML papers in our datasets, ~60% of the most highly cited papers are from NLP; (ii) LLM and ChatGPT related papers have clearly dominated the first half of 2023, but especially ChatGPT is now on the decline; (iii) the efficient open-source model LLaMA from Meta AI is the relatively and absolutely most cited paper in our dataset, leaving behind the larger and properietary ChatGPT and GPT-4.

Our code and data is available from https://github.com/NL2G/Quaterly-Arxiv.

2 Methodology

To identify the most influential papers from the AI subfields NLP and ML, we used the following methodology.

Dataset name	Size	Time period	# Primary Categories
arxiv-0623	20,843	01/01/2023-06/31/2023	123
arxiv-0623-top40	40	01/01/2023- $06/31/2023$	5

Table 1: Elementary statistics on our two released datasets. Size is the number of papers in each dataset; the last column gives the number of distinct primary arXiv categories our papers are assigned to.

1. **Data Retrieval from arXiv**: We collect all papers from 01/01/2023 to 06/31/2023 belonging to the arXiv categories cs.CL (computation and language) and cs.LG (machine learning) using a Python arXiv API.² Our retrieval time is **July, 29, 2023** (which is important,

¹Our report is similar to a 'conference report' as a popular form of science communication, e.g., https://www.romanklinger.de/blog-assets/2023-05-12/eacl2023-conf-report.pdf. But instead of focusing on conferences, we focus on arXiv for multiple reasons: among others, (i) in an age of rapid developments, conferences and journals are too slow and often lagging behind recent developments; (ii) as everyone who regularly submits to NLP/ML conferences knows, conferences also suffer from low reviewing quality, with junior and non-expert reviewers abounding. Instead, we focus on citations (even though these are not unproblematic themselves) as a form of large-scale crowd voting.

²ArXiv papers may belong to several categories. We only require that one of the involved categories be one of the two indicated.

 $^{^3}$ We did not include cs.AI (without cs.LG or cs.CL) but we note that our top-40 list would have looked very

because citation counts are constantly in flux). ArXiv papers can be updated anytime; we take the date of the first submission of a paper to arXiv as its publication date.

2. **z-score calculation:** For each paper, we extract its citation count, as a measure of popularity and arguably importance [1], from Semantic Scholar https://www.semanticscholar.org/. Since papers published at different time points may naturally have different citation counts (e.g., older papers have higher chance of being cited than very novel papers), we calculate a normalized citation count by determining how many standard deviations a paper is above the mean of citations of all papers published in the same week (Sunday-Saturday). This is the so-called z-score of Newman [23]:

$$z_t = \frac{c_t - mean(\mathbf{c}(t))}{std(\mathbf{c}(t))}$$

for a paper published in week t with citation count c_t ; $\mathbf{c}(t)$ is the list of citation counts of all papers published in week t. If a paper lies several standard deviations above the mean (for all papers published in the same week), it can be considered excellent for its class. For example, in a normal distribution, only about 16% of data points lie one standard deviation above the mean value. As will be seen below, our top papers lie at least 9–12 standard deviations above the mean.⁴

3. Manual Evaluation The published date on arXiv might differ from the actual first publication/release/submission date of a paper, e.g., when the authors upload the paper much later to arXiv. Thus, we conduct a manual evaluation to verify if a paper genuinely appeared the first time as indicated by its arXiv release time stamp. If the paper was available earlier, we remove it from consideration.

Steps 1 and 2+3 above result in two distinct datasets that we release with this report. We refer to them as arxiv-0623 and arxiv-0623-top40, respectively. Table 1 gives elementary statistics on each of them.

3 Top N papers

Table 2 showcases the top 20 papers extracted according to the methodology described in Section 2. We make several interesting observations:

- 13 out of 20 (65%) of papers have cs.CL as their prime arXiv category (note that authors of papers may wish to indicate as many additional categories as they desire). cs.LG is the prime category 3 times, followed by cs.CV (computer vision; 2 times) and cs.CR (cryptography) and cs.AI (1 time each).
- The absolute citation counts vary drastically, with 14 as lowest number in our top-20 list for a paper published in very late May (*Large Language Models are not Fair Evaluators* [30]) and 874 as highest numbers for the LLaMA paper [28] published in late February. The relative citation counts vary from 12 standard deviations above the mean to 28 standard deviations above the mean.

similar with our without the cs.AI requirement. In particular, all top-40 papers would have remained the same — also note that many cs.AI papers are still included in our dataset, see below.

⁴Our approach of identifying top papers in arXiv via the zscore is similar to [11].

No.	Title	Cat.	Link	Week	Cit	z-score
1	LLaMA: Open and Efficient Founda-	cs.CL	http://arxiv.org/abs/2302.	9	874	28.051
2	tion Language Models GPT-4 Technical Report	cs.CL	13971v1 http://arxiv.org/abs/2303.	11	509	25.382
3	PaLM 2 Technical Report	cs.CL	08774v3 http://arxiv.org/abs/2305.	20	82	25.182
4	Sparks of Artificial General Intelli-	cs.CL	10403v1 http://arxiv.org/abs/2303.	12	354	24.302
	gence: Early experiments with GPT-4		12712v5			
5	PaLM-E: An Embodied Multimodal Language Model	cs.LG	http://arxiv.org/abs/2303. 03378v1	10	164	21.225
6	QLoRA: Efficient Finetuning of Quantized LLMs	cs.LG	http://arxiv.org/abs/2305.	21	30	19.944
7	Segment Anything	cs.CV	http://arxiv.org/abs/2304.	14	165	18.548
8	Judging LLM-as-a-judge with MT-	cs.CL	http://arxiv.org/abs/2306.	23	21	17.916
9	Bench and Chatbot Arena A Multitask, Multilingual, Multimodal Evaluation of ChatGPT on Reasoning,	cs.CL	05685v2 http://arxiv.org/abs/2302. 04023v2	6	214	16.819
10	Hallucination, and Interactivity A Survey of Large Language Models	cs.CL	http://arxiv.org/abs/2303.	13	169	16.594
11	Visual Instruction Tuning	cs.CV	18223v11 http://arxiv.org/abs/2304.	16	89	15.277
	_		08485v1			
12	Tree of Thoughts: Deliberate Problem Solving with Large Language Models	cs.CL	http://arxiv.org/abs/2305. 10601v1	20	49	14.968
13	Voyager: An Open-Ended Embodied Agent with Large Language Models	cs.AI	http://arxiv.org/abs/2305. 16291v1	21	21	13.860
14			http://arxiv.org/abs/2302.	6	175	13.716
15	How Close is ChatGPT to Human Experts? Comparison Corpus, Evalua-		http://arxiv.org/abs/2301. 07597v1	3	94	13.712
16	tion, and Detection Extracting Training Data from Diffusion Models	cs.CR	http://arxiv.org/abs/2301.	5	97	13.596
17	Large Language Models are not Fair Evaluators	cs.CL	http://arxiv.org/abs/2305.	22	14	13.352
18	HuggingGPT: Solving AI Tasks with ChatGPT and its Friends in Hugging	cs.CL	http://arxiv.org/abs/2303. 17580v3	13	129	12.614
19	Face A Watermark for Large Language Models	cs.LG	http://arxiv.org/abs/2301.	4	76	12.481
20	DetectGPT: Zero-Shot Machine- Generated Text Detection using Probability Curvature	cs.CL	http://arxiv.org/abs/2301. 11305v2	4	76	12.481

Table 2: Papers, their prime category, arXiv link, week of first arXiv submission, citation count (as of 07/29/2023) and z-score. **Top 20 papers** according to z-score among all arxiv-0623 papers.

No.	Title	Cat.	Link	Week	Cit	z-score
21	Mastering Diverse Domains through World Models	cs.AI	http://arxiv.org/abs/2301. 04104v1	2	59	12.238
22	Augmented Language Models: a Survey	cs.CL	http://arxiv.org/abs/2302. 07842v1	7	79	12.079
23	A Comprehensive Survey on Pretrained Foundation Models: A History from BERT to ChatGPT	cs.AI	http://arxiv.org/abs/2302. 09419v3	7	79	12.079
24	ImageBind: One Embedding Space To Bind Them All	cs.CV	http://arxiv.org/abs/2305. 05665v2	19	39	11.966
25	Muse: Text-To-Image Generation via Masked Generative Transformers	cs.CV	https://arxiv.org/abs/2301. 00704	1	111	11.692
26	T2I-Adapter: Learning Adapters to Dig out More Controllable Ability for Text-to- Image Diffusion Models	cs.CV	http://arxiv.org/abs/2302. 08453v2	7	76	11.609
27	Is ChatGPT a General-Purpose Natural Language Processing Task Solver?	cs.CL	http://arxiv.org/abs/2302. 06476v2	6	145	11.328
28	SemEval-2023 Task 2: Fine-grained Multilingual Named Entity Recognition (Multi-CoNER 2)	cs.CL	http://arxiv.org/abs/2305. 06586v2	19	36	11.024
29	Mathematical Capabilities of ChatGPT	cs.LG	http://arxiv.org/abs/2301. 13867v2	5	79	11.016
30	The Flan Collection: Designing Data and Methods for Effective Instruction Tuning	cs.AI	http://arxiv.org/abs/2301. 13688v2	5	78	10.873
31	The False Promise of Imitating Proprietary LLMs	cs.CL	http://arxiv.org/abs/2305. 15717v1	21	16	10.480
32	The RefinedWeb Dataset for Falcon LLM: Outperforming Curated Corpora with Web Data, and Web Data Only	cs.CL	http://arxiv.org/abs/2306. 01116v1	22	11	10.421
33	Distilling Step-by-Step! Outperforming Larger Language Models with Less Train- ing Data and Smaller Model Sizes	cs.CL	http://arxiv.org/abs/2305. 02301v2	18	26	10.387
34	Video-LLaMA: An Instruction-tuned Audio-Visual Language Model for Video Understanding	cs.CL	http://arxiv.org/abs/2306. 02858v3	23	12	10.136
35	InstructBLIP: Towards General-purpose Vision-Language Models with Instruction Tuning	cs.CV	http://arxiv.org/abs/2305. 06500v2	19	33	10.083
36	PandaGPT: One Model To Instruction- Follow Them All	cs.CL	http://arxiv.org/abs/2305.	21	15	9.804
37	ChatGPT is not all you need. A State of the Art Review of large Generative AI models	cs.LG	http://arxiv.org/abs/2301. 04655v1	2	46	9.459
38	Theory of Mind May Have Spontaneously Emerged in Large Language Models	cs.CL	http://arxiv.org/abs/2302.	5	68	9.440
39	mPLUG-Owl: Modularization Empowers Large Language Models with Multimodal- ity	cs.CL	http://arxiv.org/abs/2304. 14178v1	17	34	9.377
40	Otter: A Multi-Modal Model with In- Context Instruction Tuning	cs.CV	http://arxiv.org/abs/2305. 03726v1	18	23	9.146

Table 3: Papers, their prime category, arXiv link, week of first arXiv submission, citation count (as of 07/29/2023) and z-score. **Papers 21-40** according to z-score among all arxiv-0623 papers.

- The four dominating papers can be seen as technical reports on **LLM foundations models**, including LLaMA [28] (the paper with the highest z-score), PaLM 2 [2], and GPT4 (represented twice; once as an OpenAI publication without dedicated authors focusing on technical details [24] and once by a group of Microsoft researchers focused on extensive evaluation [6], both published at around the same time). A "Survey of Large Language Models" [32] (rank 10 in our list) published in late March and already updated 11 times further indicates the popularity of diverse LLMs.
- While not all being technical reports or surveys, the vast majority of top papers are centered around LLMs (at least 18 out of 20, i.e., 90%). Exceptions are two papers from the computer vision domain (ranks 7 and 13).
- It is interesting that LLaMA [28], a set of **efficient** (and open-source) foundation language models, dominates overall. This hints at the importance of efficiency for LLMs in general, both from an environmental perspective but possibly even more so from a practical perspective, as the LLaMA models can still be fine-tuned even by researchers with a 'modest' GPU endowment [19]. Efficiency is further represented by QLoRA [8], submitted to arXiv in late May, which discusses efficient fine-tuning of quantized LLMs.
- Three top papers [3, 16, 27] (ranks 9, 15 and 18) are specifically centered around **ChatGPT** (arguably as the originator of the new LLM hype [20]) and particularly discuss its *evaluation* including failure cases. The paper [27] uses ChatGPT to solve AI tasks by querying huggingface.
- Two further top papers (ranks 12 and 14) explore **problem solving with LLMs**, one using external tools [25] and one using reasoning strategies [31].
- Using LLMs for evaluation is discussed in the two papers [30, 33] (ranks 8 and 17), one for evaluating open-ended dialogue and one discussing biases of evaluation with LLMs. Both papers are much more recent, being published in late May and early June.
- Two papers [9, 29] (ranks 5 and 13) discuss **embodied agents** that can interact with the real world, making use of LLMs.
- Two papers [17, 22] (ranks 19 and 20) can be seen as particularly discussing the **ethical aspects** of detecting LLM generated text (e.g., for spotting misleading AI generated content or to detect cheating in educational contexts) and watermarking AI generated text, i.e., embedding signals in automatically generated text that allow its algorithmic detection. Both papers were published early on, in late January.
- Finally, the exceptions in our top 20 list are two computer vision papers. The Segment Anything paper [18] by Meta AI Research provides a dataset for image segmentation. The paper [7] discusses privacy of image diffusion models such as DALL-E 2 (which can be considered the analogues of LLMs in the computer vision domain). A further computer vision paper introduces a multimodal framework called LLaVA [21], building on top of GPT4.
- Recently, there has been a debate whether AI/NLP has become more negative, i.e., whether papers tend to report more negatively regarding ongoing research (e.g., outline limitations and failure cases) [5, 4]. In our top-20 list, only two papers (10%) could be considered critique

papers, namely [30], which focuses on and uncovers biases in LLMs as evaluation models, and [7], which criticizes lack of privacy of diffusion models, allowing to retrieve private information from the training data. In the top-40 list, there are two additional negative papers, i.e., [12] which disputes the mathematical capabilities of ChatGPT, and [15], which challenges whether distillation in which a smaller student LLM is trained on the outputs of a larger properietary LLM such as ChatGPT is really effective. A few papers are partly negative, highlighting some limitations, such as [3]. Overall, the most popular papers are (currently) thus positive regarding the development and abilities of recent LLMs.

Table 3 gives analogous papers with rank 21 to 40. We refrain from an in-depth analysis as above. The papers have a similar scope, however, with 11 out of 20 (55%) having cs.CL as primary category and 13 out of 20 (65%) having a variant of LLM in their title (language models, ChatGPT, GPT, etc.). Interestingly, the list of papers with ranks 21-40 contain quite a few **multimodal** approaches such as text-to-image generation models, and relatively more so than the list of papers with ranks 1-20.

4 Analysis

We now briefly perform a few further analyses on our corpus (not only arxiv-0623-top40 but also arxiv-0623) in order to better understand recent developments.

How many citations and standard deviations are there per week? Figure 1 gives the mean citation counts of papers belonging to three primary categories (cs.CL, cs.LG, and all others) over time. We observe that:

- citations tend to decrease over time (as is expected; more recent papers cannot yet have been cited so frequently), with, on average, decisively fewer than 2 citations per paper starting from May for all three arXiv categories
- cs.CL attracts (considerably) more citations than cs.LG and the aggregation of all other involved primary categories
- February has been the month with the most impactful papers in cs.CL, especially week 6 (e.g., Toolformer [25] and ChatGPT analysis [3] submitted to arXiv) and week 9 (e.g., LLaMA [28] submitted)

Detailed results including overall standard deviations are also give in Table 4. Standard deviations are particularly large in weeks 1, 6, 8-13.

How many arXiv categories (scientific subfields) are involved? Our dataset arxiv-0623 comprises 20,843 papers submitted to arXiv between 01/01/2023 and 06/31/2023 with at least one of the indicated categories given as cs.CL or cs.LG. As NLP and ML affect all aspects of life nowadays, we would expect that these papers do not only originate from either ML or NLP. Indeed, we find that our 20,843 papers are assigned to 123 different primary arXiv categories. We give detailed statistics on those 19 primary categories occurring at least 100 times in Table 5. Overall, the most frequent 19 primary categories are made up of 5 top level categories, namely: cs (computer science), stat (statistics), eess (electrical engineering and systems science), math (mathematics)

Week Number	Week Date	Mean	Std	Mean cs.CL	Mean cs.LG	Mean Rest
1	01-01/01-07	2.208	9.305	3.164	1.175	2.787
2	01-08/01-14	1.759	4.677	1.714	1.852	1.703
3	01-15/01-21	2.029	6.707	4.110	1.707	1.452
4	01-22/01-28	1.942	5.934	2.318	1.729	2.084
5	01-29/02-04	2.144	6.977	4.314	1.417	2.290
6	02 - 05/02 - 11	2.647	12.566	7.578	1.464	2.036
7	02-12/02-18	1.900	6.383	3.368	1.181	2.112
8	02 - 19/02 - 25	2.158	9.813	3.617	1.321	2.618
9	02-26/03-04	2.651	31.063	10.496	0.983	1.426
10	03-05/03-11	1.688	7.647	3.734	1.442	1.224
11	03-12/03-18	2.191	19.967	7.901	0.947	1.196
12	03-19/03-25	1.930	14.487	6.117	0.764	1.286
13	03-26/04-01	2.197	10.052	5.688	1.104	1.485
14	04-02/04-08	1.743	8.802	3.380	0.744	1.761
15	04-09/04-15	1.680	6.175	4.000	0.585	1.692
16	04 - 16/04 - 22	1.692	5.715	3.093	0.957	1.471
17	04-23/04-29	1.174	3.501	2.368	0.704	1.020
18	04-30/05-06	0.885	2.418	1.320	0.633	0.718
19	05-07/05-13	0.869	3.187	1.162	0.378	1.024
20	05-14/05-20	0.641	3.231	1.204	0.270	0.431
21	05-21/05-27	0.496	1.479	0.550	0.485	0.405
22	05-28/06-03	0.334	1.023	0.494	0.251	0.306
23	06-04/06-10	0.276	1.157	0.474	0.162	0.260
24	06-11/06-17	0.338	1.674	0.449	0.405	0.192
25	06-18/06-24	0.309	3.861	0.331	0.481	0.123
26	06-25/07-01	0.257	2.163	0.228	0.173	0.354

Table 4: Mean number of citations, over all papers including standard deviations, and for the primary categories cs.CL, cs.LG and the remaining categories.

Mean Citation Counts

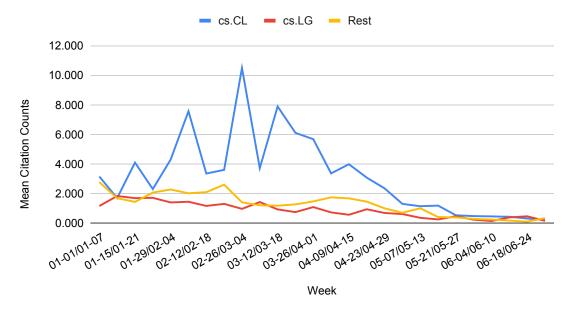


Figure 1: Mean number of citations over weeks for different arXiv categories.

and quant-ph (quantum physics).⁵ The five most frequent fine-grained categories are cs.LG, cs.CL, cs.CV (computer vision), stat.ML (statistics, machine learning) and cs.AI (artificial intelligence).

A pie chart of the distribution of primary categories is shown in Figure 2. cs.LG is the largest category, almost 40% of papers have it as its primary category. cs.CL is only about half the size (but dominates the top-40 papers as discussed above). Other primary categories (outside of the top 5 categories) are about the same size as cs.CL.

What distinguishes top papers from other papers? We use the tool of [13] based on the log-likelihood ratio test [10] to determine unusually frequent words in our top-40 papers arxiv-0623-top40 vs. all other papers. Among the top-10 most distinctive unigrams are chatgpt, gpt-4, modalities, visual, zero-shot. Among the top bigrams are language models, large language, models (llms), wide range. The singular most important trigram is large language models. Conversely, words that characterize papers outside the top-40 the best are jargon referring to an older deep learning era such as learning, neural, deep, network, neural network, machine learning, etc. While this characterization is very simplistic (it certainly does not satisfy to publish a paper on LLMs to obtain high citation numbers), it is nonetheless insightful.

Top-40 papers also have way more authors on average (11.8, with a standard deviation of 19.5) compared to the remaining papers (4.5 with a standard deviation of 3.2). Part of the effect could be trivial: more authors can increase self-citation counts (an arguably at least partly unethical

⁵ArXiv does unfortunately not include the humanities or social sciences directly.

Category	Occurrences
cs.LG	8127
cs.CL	4966
cs.CV	1670
stat.ML	859
cs.AI	455
eess.IV	414
cs.CR	304
cs.IR	288
cs.RO	285
cs.SD	265
math.OC	214
eess.AS	212
eess.SP	201
cs.HC	148
cs.NE	143
eess.SY	134
cs.SE	127
quant-ph	125
cs.CY	111

Table 5: All primary categories given in our arXiv dataset whose occurrence exceeds 100. ArXiv categories are described here: https://arxiv.org/category_taxonomy.

practice [26]). On the other hand, more fundamental research may require a larger author list and industry may also produce papers with a higher number of authors.

What are the most important key words of the top-40 papers? We plot a wordcloud of the top-40 papers (see Figure 3). To do so, we use KeyBERT [14] to identify the 5 most important tri-grams from the title and abstract of each paper. Then we filter out a manually selected list of unimportant words and lemmatize each word. Finally, we use the python library wordcloud⁶ for plotting. Here the focus of current research into ever larger models becomes apparent again, with phrases such as trillion token, 175b, large scale and large language model. The keywords publicly available also show a focus on non-proprietary data and models.

How popular are LLMs over time in our arXiv dataset? While we have seen that LLMs are the dominating theme in the top-40 paper list, we wonder how the popularity of LLMs and ChatGPT have developed over time in our complete arXiv dataset arxiv-0623. To this end, we query the keywords "LLMs" and "ChatGPT" in our dataset over time and flag a paper as relevant if it contains the keywords in its title or abstract.⁷

Figure 4 shows the results. Both keywords were not very relevant in early 2023, less than 2% of papers contained them in January. The ChatGPT curve increases until late March (6% of all papers). Starting from mid-April, LLMs become the more popular keyword. ChatGPT

 $^{^6 {\}tt https://github.com/amueller/word_cloud}$

⁷We lowercase abstracts and titles, and we look for the keywords "llm(s)" and "large language model(s)" for LLM; for ChatGPT, we look for "chatgpt" and "chat-gpt".

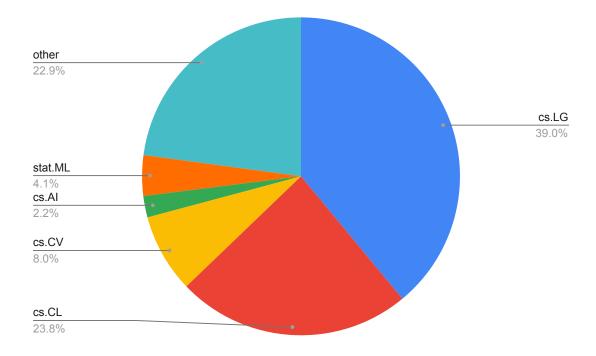


Figure 2: Pie chart of distribution of main categories in our dataset.

as a keyword declines since then, while LLMs spike in the week of 05/21 (which marks 2023's camera-ready submission deadline for the popular NLP conference ACL https://www.aclweb.org/portal/content/acl-2023-call-papers) with almost 12% of papers containing it; we assume that many accepted ACL papers (with LLMs as a topic) were posted to arXiv right after the camera-ready deadline. Since then, LLMs seem to be declining as a keyword, also — even though this could just be an artefact of the conference deadline.

5 Conclusion

We have examined arXiv papers related to the categories cs.CL and cs.LG over the first half of 2023. First, we sorted papers according to their normalized citation counts, finding that LLM related papers clearly dominate. Within LLMs, the most popular current issues center around: efficiency, LLM based evaluation, ethical aspects, embodied agents and problem solving with LLMs (only slightly less prominent are multimodal approaches encompassing language and other modalities such as images, with at least 8 papers within the top-40). We have also looked at, among others: (i) what characteristics top papers have relative to papers outside the top-40 list in terms of number of authors and vocabulary, (ii) the distributions of citations in our dataset, and (iii) the popularity of ChatGPT, which 'caused' the current hype surrounding LLMs in late 2022, and LLMs over time. We hope that our investigation is beneficial not only to newcomers and outsiders to the field of NLP and ML (of which there are seemingly very many nowadays, given how popular the fields have

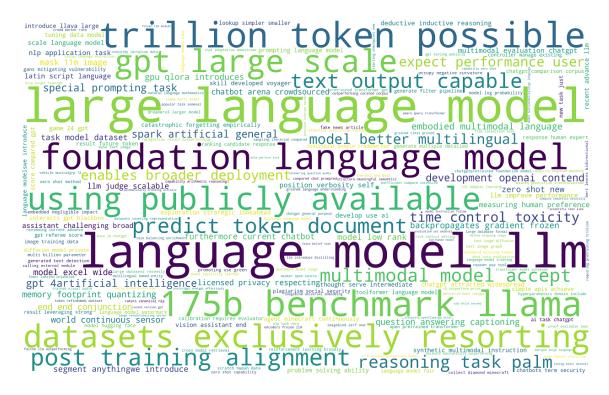


Figure 3: Wordcloud based on the top-40 papers.

become [34]), providing quick links to useful starting literature, but also to established researchers and their doctoral students.

In the future, we want to regularly update the current report to see how tastes shift over time, examine our arXiv datasets arxiv-0623 and arxiv-0623-top40 in much more depth, and include further arXiv categories related to AI fields (e.g., cs.CV, stat.ML, cs.AI) into our datasets, among others.

Limitations

Limitations of our approach include the following. First of all, science tools like SemanticScholar or GoogleScholar make quite a few mistakes in correctly attributing citations. While we did not study this in depth, we note for example that LLaMA (our top paper) has 874 citations according to SemanticScholar (July 29, 2023) but only 710 citations according to GoogleScholar, a relative difference of $\frac{164}{874} = 18.7\%$. The paper with fewest citations in our top 20 list [30] has 14 citations (July 29, 2023) according to SemanticScholar but only 9 citations according to GoogleScholar, a relative difference of $\frac{5}{14} = 35.7\%$. While we do think that our rankings are relatively reliable, such deviations may naturally bias our selection of papers, assumedly with higher uncertainty for low citation papers. Secondly, focusing particularly on highly cited papers may induce a bias towards these papers similar to that of a self-fulfilling prophecy or preferential attachment. Thirdly, our focus

ChatGPT + LLMs Popularity

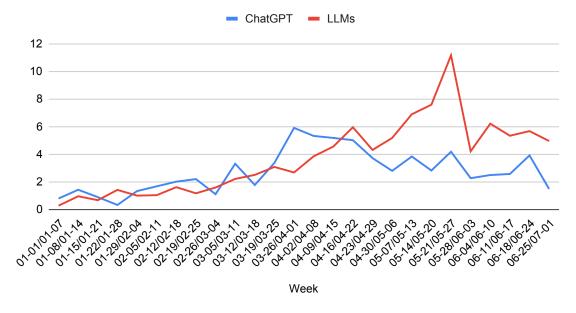


Figure 4: Popularity of ChatGPT and LLMs (in percentage of papers having the words in their abstracts or titles) over time in our dataset.

on weekly citation averages may have unexpected effects: for example, a younger paper with more citations could be ranked below an older paper with fewer citations, for example, if that older paper was published in a week with fewer average citations (e.g., in the early weeks of January where research, and other human activity, is typically less productive, at least in relevant parts of the world, due to preceding holiday activities). Finally, some authors and research groups, potentially more traditional ones, may refrain from submitting their papers to arXiv, despite its otherwise high popularity particularly in the computer science community (see exponential submission growth rates of arXiv submission numbers in the last decades https://info.arxiv.org/help/stats/2021_by_area/index.html). Papers from such authors or groups will not be part of our dataset and analysis.

Our limitations must be kept in mind when interpreting our results.

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