
Consent in Crisis: The Rapid Decline of the AI Data Commons

Shayne Longpre¹, Robert Mahari¹, Ariel Lee¹, Campbell Lund¹, Hamidah Oderinwale², William Brannon², Nayan Saxena², Naana Obeng-Marnu², Tobin South², Cole Hunter², Kevin Klyman², Christopher Klam², Hailey Schoelkopf², Nikhil Singh², Manuel Cherep², Ahmad Mustafa Anis³, An Dinh³, Caroline Chitongo³, Da Yin³, Damien Sileo³, Deividas Mataciunas³, Diganta Misra³, Emad Alghamdi³, Enrico Shippole³, Jianguo Zhang³, Joanna Materzynska³, Kun Qian³, Kush Tiwary³, Lester Miranda³, Manan Dey³, Minnie Liang³, Mohammed Hamdy³, Niklas Muennighoff³, Seonghyeon Ye³, Seungone Kim³, Shrestha Mohanty³, Vipul Gupta³, Vivek Sharma³, Vu Minh Chien³, Xuhui Zhou³, Yizhi Li³, Caiming Xiong⁴, Luis Villa⁴, Stella Biderman⁴, Hanlin Li⁴, Daphne Ippolito⁴, Sara Hooker⁴, Jad Kabbara⁴, and Sandy Pentland⁴

¹Team Leads, ²Top Contributors, ³Contributors (alphabetized), ⁴Advisors

Abstract

General-purpose artificial intelligence (AI) systems are built on massive swathes of public web data, assembled into corpora such as C4, RefinedWeb, and Dolma. To our knowledge, we conduct the first, large-scale, longitudinal audit of the consent protocols for the web domains *underlying* AI training corpora. Our audit of 14,000 web domains provides an expansive view of crawlable web data and how codified data use preferences are changing over time. We observe a proliferation of AI-specific clauses to limit use, acute differences in restrictions on AI developers, as well as general inconsistencies between websites’ expressed intentions in their Terms of Service and their robots.txt. We diagnose these as symptoms of ineffective web protocols, not designed to cope with the widespread re-purposing of the internet for AI. Our longitudinal analyses show that in a single year (2023-2024) there has been a rapid crescendo of data restrictions from web sources, rendering ~5%+ of all tokens in C4, or 28%+ of the most actively maintained, critical sources in C4, fully restricted from use. For Terms of Service crawling restrictions, a full 45% of C4 is now restricted. If respected or enforced, these restrictions are rapidly biasing the diversity, freshness, and scaling laws for general-purpose AI systems. We hope to illustrate the emerging crises in data consent, for both developers and creators. The foreclosure of much of the open web will impact not only commercial AI, but also non-commercial AI and academic research.

1 Introduction

The web has become the primary communal source of data, or “data commons”, for general-purpose and multi-modal AI systems. The scale and heterogeneity of web-sourced training datasets provide the foundation for both open and closed AI systems, such as OLMo [42], GPT-4o [85], and Gemini [115]. However, the use of web content for AI poses ethical and legal challenges to data consent, attribution, copyright, and the potential impact on creative industries [35, 62, 94, 128]. This has spurred new initiatives to better verify data quality and provenance [34, 32, 55, 66, 11], isolate public

domain and permissively licensed data [77], and integrate new infrastructure to signal [31], detect [112], and even evade the use of data for AI training [108].

The focus of this work is to understand the evolving role of the internet as a primary ingredient to AI, and how AI has collided with the limited protocols that govern data use. Web data is traditionally collected using *web crawlers*—automatic bots that systematically explore the internet and record what they see. However, the mechanisms for indicating restrictions to web crawlers, such as the Robots Exclusion Protocol (REP), were not designed with AI in mind [92]. The REP is referred to as robots.txt in practice. As such, we examine their (in)ability to communicate the nuances in how content creators wish their work to be used, if at all, for AI. And more broadly, we analyze how AI is already re-shaping the culture of web consent, and how this is shifting the landscape for AI training data. Our results foretell significant changes not only to AI data collection practices and data scaling laws, but also the structure of consent on the open web, which will impact more than AI developers.

To this end, we present a large-scale audit of the web sources underlying three open AI training corpora: C4 [98], RefinedWeb [90], and Dolma [111]. In contrast to prior audits that assess datasets—curated snapshots of data—this work looks *beneath* the datasets at the web domains they were derived from, and traces the temporal evolution of these sources. We are, to our knowledge, the first to systematically measure detailed provenance, crawler consent mechanisms, and content monetization factors, all relevant to the responsible downstream use of this data. These analyses enable us to trace fundamental distribution shifts in how preference signals are expressed and the inadequacy of existing tools. Our work has several key findings:

1. **A proliferation of restrictions on the AI data commons.** We find a rapid proliferation of restrictions on web crawlers associated with AI development in both websites’ robots.txt and Terms of Service. We estimate, in on year (2023-04 to 2024-04), ~25%+ of tokens from the most critical domains, and ~5%+ of tokens from the entire corpora of C4, RefinedWeb, and Dolma have since become restricted by robots.txt. Forecasting these trends forward shows a decline in unrestricted, open web data year-over-year.
2. **Consent asymmetries & inconsistencies.** OpenAI’s crawlers are significantly more restricted than those of other AI developers. More broadly, preference signaling mechanisms like robots.txt see errors and omissions in their coverage across AI developers, as well as contradictions with their terms of services—indicating inefficiencies in the tools used to communicate data intentions.
3. **A divergence in content characteristics between the head and tail of public web-crawled training corpora.** We find the largest web-based sources of public training corpora have significantly higher rates of user content, multi-modal content, and monetized content, but only slightly less sensitive/explicit content. Top web domains comprise news, encyclopedias, and social media sites, as compared to the many organization websites, blogs, and e-commerce websites in the long tail of web sources.
4. **A mismatch between web data and common uses of conversational AI.** We contrast data web sources with the real-world usage of conversational AI—showing how substantial portions of web-derived training data may be misaligned with the tasks that AI models are actually used for. These results may have implications for model alignment, future data collection practices, and copyright.

2 Methodology

AI models that are highly performant on tasks in language [98], images [132, 37, 4], video [7, 76, 79], and even audio [64, 26] increasingly depend on massive web-sourced training datasets. These datasets are collected using web crawlers—agents that navigate the web, accessing and retrieving web pages without human intervention. While these robots are essential for a variety of applications, including search engines, studying the internet (*ie* archiving), and link verification tools; recently they have also become the backbone of AI training data collection [97, 16].

In our study, we focus on three popular, open-source, and permissively licensed data sources which are derived from Common Crawl, the largest publicly available crawl of the web, which has collected and stored hundreds of billions of web pages since 2008. For each web-based data source, we sample the web domains from which it was created, and extensively human annotate their properties. Our

ATTRIBUTE	DETAILS	COLLECT
Content Modalities	Whether the web domain has images, videos, and standalone audio in addition to text.	
User Content	Whether the web domain hosts primarily content provided by users, such as forums, blog hosting, and social media websites.	
Sensitive Content	Whether explicit, illicit, pornographic, or hate speech content is clearly present.	
Paywall	Whether the web domain has use limits or any access gating behind a paywall.	
Advertisements	Whether the web domain has automatic advertisements embedded into any of its pages.	
Purpose & Service	The purpose or service(s) of a website? Options: E-commerce, Social Media/Forum, Encyclopedia, Academic, Government, Organization site, News, or Other.	
<i>Terms & Restrictions</i>		
Robots.txt	A web domain’s robots.txt restrictions on crawler agents. We use Google’s crawler rules.	 
Terms & Policies	The terms, content, copyright, and privacy policy pages found for a web domain.	 
Crawling & AI Policy	Do terms restrict both crawling and AI, restrict crawling, restrict only AI, conditionally restricting crawling/AI, or not apply restrictions?	 
Content Use Policy	Are there content use restrictions. Options: restricted to personal, academic, or non-commercial use, conditionally restricted, or unrestricted.	 
Non-Compete Policy	Is content use prohibited for developing competing services?	 

Table 2: The **list of attributes collected for each web domain**, as sampled from C4, Dolma, and RefinedWeb. 🤖 denotes automatic collection; ✍️ denotes human annotation; ⌚ denotes this information was collected historically from 2016, as well as statically. Full annotation guidelines are given in Appendix A.2.2.

analysis examines a snapshot of the present, as well as longitudinal changes across time, to understand how ecosystem norms have evolved.

Data sources The data sources used for our study are C4 [98], RefinedWeb [90], and Dolma [111]. These data sources each have 100k-1M+ downloads, are the primary component in most modern foundation models [16, 42, 14], as well as being widely used to derive other popular datasets [130, 118, 116]. Common Crawl is released on a monthly basis, and, as see in Table 1, each data source is based on a different set of monthly snapshots. Each of these corpora apply various automatic filtering techniques, including removing duplicative pages, low-quality content, and personal identifiable information such as addresses.

DATA SOURCE	CRAWL DATES	WEB DOMAINS
C4	4/2019	15,928,138
REFINEDWEB	2008 to 2/2023	33,210,738
DOLMA	5/2020 to 6/2023	45,246,789
Intersection		10,136,147

Table 1: Statistics on audited data sources.

Head sample and random sample For each data source, we identified and selected the top 2k web domains ranked by their number of tokens. We refer to the resulting 3.95k union of these web domains as HEAD_{All} . This sample represents the largest, most actively maintained, and critical domains for AI training. For certain analyses, we consider only the head of C4, which we will refer to as HEAD_{C4} .

We are also interested in how consent preferences have evolved within a wider sample of internet domains. To capture this, we randomly sampled 10K domains ($\text{RANDOM}_{10\text{k}}$) from the intersection of the three corpora, totalling 10,136,147 domains. From the 10k sample, we selected a random subset of 2K for human annotation ($\text{RANDOM}_{2\text{k}}$). $\text{RANDOM}_{10\text{k}}$ was sampled from the intersection of domains listed across all three datasets, which means this subset may skew towards more widely-used or high-quality domains.

Human annotations We trained annotators to manually label the websites for their content modalities (e.g. video, text); website purpose(s) (e.g. news, e-commerce); presence of paywalls and embedded advertisements; the text of the terms of service, if any; and other metadata detailed in Table 2. Annotators received individual instructions, frequent quality calibration, and were compensated well above industry standards at \$25-\$30 per hour. We collected annotations for the entirety of HEAD_{All} as well as from the random sample $\text{RANDOM}_{2\text{k}}$. More details on our annotation process are available in Appendix A, and all annotations will be made publicly available for reproducibility and future research.

Measuring website administrators’ intentions A goals of our audit is to measure website administrators’ intentions for how their site can be crawled and its content used—including for training AI models. We used the Wayback Machine¹, a digital archive of 835 billion web pages, to collect historical versions of each website’s homepage, its Robots Exclusion Protocol (REP), commonly referred to as robots.txt file, and its terms of service page. This was collected at monthly intervals, from January 2016 to April 2024.

The REP, first introduced in 1995 and codified in 2022, has become the default mechanism for website owners to indicate to web crawlers what parts of their website, if any, they consent to have crawled [54]. While it is not legally enforceable, it is respected by all major search engines, as it prevents website servers from getting overloaded by crawlers, it allows websites to signal pages that are undesirable to crawl (for example, calendar sites that could lead to infinite loops), and by respecting it, crawlers disincentivize adversarial tactics designed to impede crawlers. Website creators are able to set one set of instructions for all web crawlers or a different instructions for each web crawler. For instance, Google Search respects instructions which specifies the user agent “Googlebot” while Common Crawl listens to the user agent “CCBot.”

In our audit, we record the robots.txt instructions for a range of crawlers, but focus our analysis on five AI developers, Google, OpenAI, Anthropic, Cohere, and Meta, as well as non-profit web archival organizations such as Common Crawl and the Internet Archive, which have seen their data taken for AI training. Collectively, we refer to these as “AI Organizations”. We classify robots.txt for each crawler in ascending order of restrictions, from no robots.txt present, to sitemaps which support crawlers without limitations, to basic restrictions on a subset of directories, to full restrictions on any crawling of the website. For each corpus, we measure the percentage of “restricted tokens” as the portion of tokens from web domains that fully restrict one or more of the AI Organizations’s crawlers. For Terms of Service analysis, we define restricted tokens to simply mean the portion of unusable tokens due to terms that preclude crawling or AI. See Appendix B.2 for the full list of agents and Appendix B.1 for the robots.txt restriction classification taxonomy.

In addition to robots.txt, we recorded the Terms of Service (ToS) and other content and copyright policies for each website. These documents support more nuanced preferences than the REP, and allow for blanket bans on downstream use cases rather than just specification of what data agents are allowed to collect. We used an automatic annotation pipeline (see Appendix B for details) to categorize ToS agreements according to stance towards use of web crawlers and AI training, content use restrictions, and non-compete clauses, in ascending degrees of restrictiveness.

3 Findings

3.1 The Rise of Restrictions on Open Web Data

To understand the web sources *underlying* foundation models, we analyze the longitudinal changes in robots.txt and Terms of Service restrictions between January 2016 and April 2024. In Figure 1 the plots depict the percent of tokens present in each category of restriction over time, for the AI Organizations in HEAD_{C4}—the largest, most actively maintained, and critical domains for AI training. The fine-grained longitudinal analysis of robots and Terms of Service trends allows us to estimate this time series into the future. We apply Seasonal Autoregressive Integrated Moving Average (SARIMA) models to generate forecasts of future trends for both the `head_sample` and `random_subset`, the details of which can be found in Appendix C along with the coefficients and tests.

In Figure 2 we measure the restricted tokens, or how many tokens fall into the most restrictive settings for each of robots.txt and Terms of Service, as a portion of the Full Corpus, or HEAD_{ALL}. The intermittent lack of smoothness for Figures 2c and 2d is mainly due to temporal gaps in the Wayback Machine; however the main trends remain visible. In all analyses we exclude web domains which could not be retrieved from the Wayback Machine, and all proportions are based on the set of web domains which existed in that time period.

These analyses show a clear and systematic rise in restrictions to crawl and train on data, from across the webs. We make no assertion regarding whether the prior omission of a robots.txt or restrictions implies consent to use data. To the degree these restrictions are respected, it also foretells a decline

¹<https://wayback-api.archive.org/>

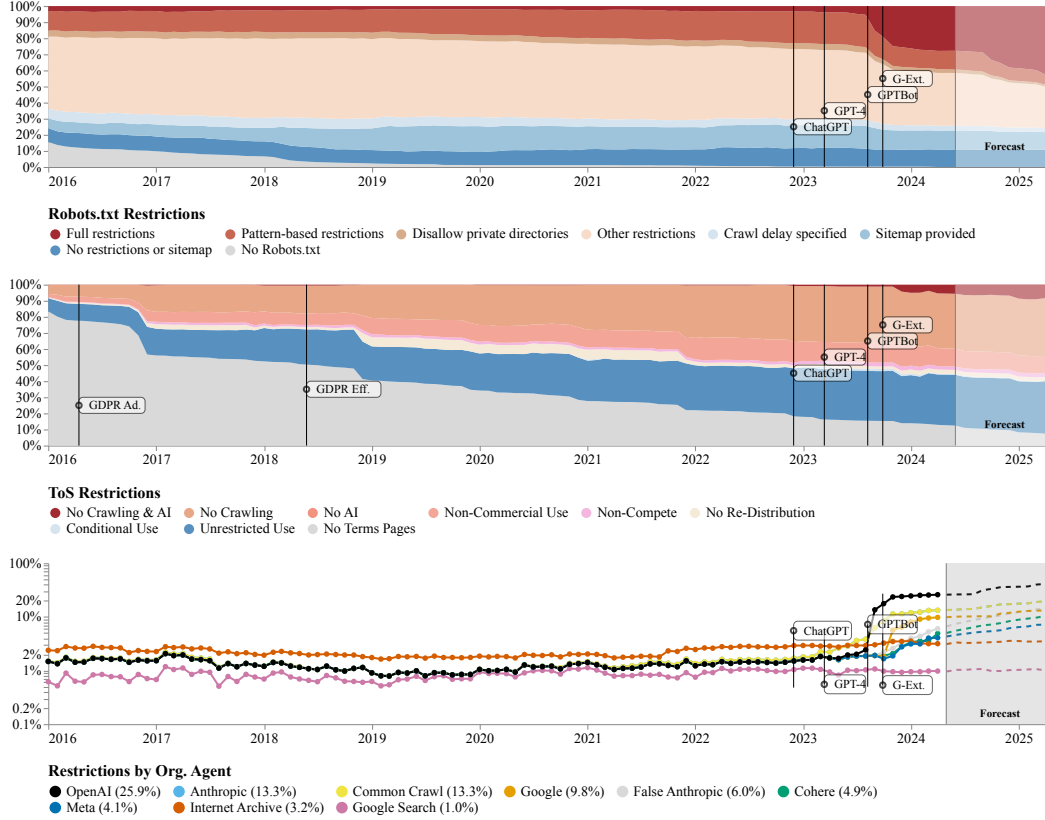


Figure 1: A temporal analysis, from 2016 to April 2024, of the web consent signals in $HEAD_{C4}$, a sample of the largest and most critical web domains. The colored regions represent the restriction categories as a portion of the total tokens in $HEAD_{C4}$. We also use SARIMA methods to forecast trends a year into the future. Top: Ascending categories of robots.txt restrictions for the AI Organizations: Google, OpenAI, Anthropic, Cohere, Meta, Common Crawl, and the Internet Archive. Middle: Ascending categories of Terms of Service restrictions (taxonomies described in Table 2). Bottom: A breakdown of robots.txt restrictions by organization—the April 2024 restriction rates are listed in the legend.

in open data, which may impact more than commercial AI developers, or even AI organizations in general. We break down and discuss the findings of this temporal analysis below.

Web domains are adopting robots.txt and Terms of Service pages to signal preferences. Figure 1(Top & Middle) shows from 2016, the portion of web domains in $HEAD_{C4}$ without a robots.txt and Terms of Service has gone from 20% and 80% respectively, to near zero.² This reflects an emerging adoption of these practices to signal and protect data intentions.

Robots.txt crawling restrictions have risen precipitously since mid-2023. Figure 1(Top) shows the rapid re-distribution of robots.txt restrictions, directly after the introduction of GPTBot and Google-Extended crawler agents. This re-distribution to full restrictions mainly comes from websites with previously moderate restrictions, such as disallowed directories, pattern-based or search page restrictions, and partly from websites with no prior restrictions in their robots.txt.

Across the entire corpora, ~1% of C4, RefinedWeb, and Dolma tokens were restricted in mid 2023, as compared to 5-7% of tokens in April 2024. Among the most critical domains ($HEAD_{All}$), 20-33% of all tokens are restricted, as compared to <3% one year prior (Figure 2a). From a relative perspective, from 2023-4 to 2024-4 these restrictions have risen 500%+ for both C4 and RefinedWeb’s full corpus,

²These values may be slightly high, especially for Terms of Service pages, due to gaps in the Wayback Machine.

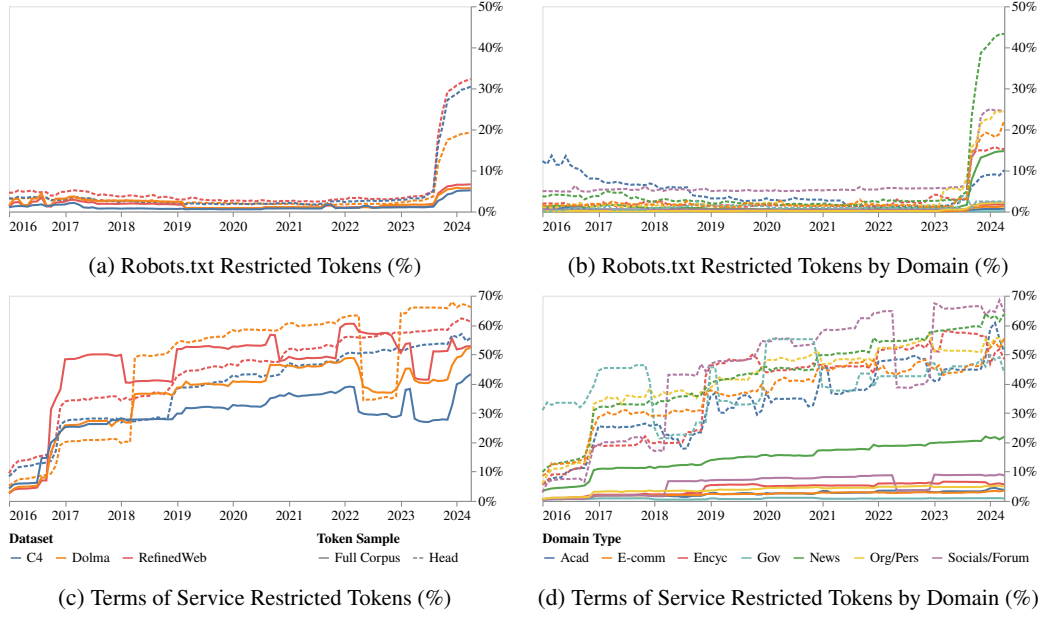


Figure 2: A temporal depiction of the percentage of restricted tokens across both the Full Corpus and the HEAD_{All} sample—the largest and most critical data sources. The robots.txt analysis (top) and Terms of Service analysis (bottom), are each broken down by corpora—C4, RefinedWeb, and Dolma (left),—and by the restrictions by domain type, averaged across corpora (right).

and 1000%+ for both C4 and RefinedWeb’s head distributions. Note that these measurements only capture *full restricted* domains, and the numbers are higher for partially restricted domains.

AI developers are restricted at widely varying degrees. Figure 1(Lower) breaks down the restrictions by AI developers and non-profit organizations. OpenAI crawlers are restricted for 25.9% of tokens in HEAD_{C4}, followed by Anthropic and Common Crawl (13.3%), Google’s AI crawler (9.8%), and more distantly Cohere (4.9%), Meta (4.1%), the Internet Archive (3.2%), and lastly Google Search’s crawler (1.0%). These asymmetries in restrictions have significant differences, and tend to advantage less widely known AI developers. In Subsection 3.2 we discuss these asymmetries and their consequences in more depth.

Terms of Service pages have imposed more anti-crawling and now anti-AI restrictions. Figure 1(Middle) illustrates this gradual re-composition of Terms pages—with web domains shifting from no terms pages, to those with restrictions on crawling, commercial-use, using the data for competing services, or re-distribution. Only in 2024 do we see the wider emergence of Terms which specifically mention and restrict the use of their data for generative AI. In the last year, we’ve seen a 26-53% relative increase in Terms of Service crawling restrictions across C4, RefinedWeb, and Dolma. Figure 2c shows 45-55% of all tokens in these three corpora have a form of data use restriction in their Terms pages. In practice, most automatic crawlers do not heed these Terms, though they may provide some avenue of legal enforcement³

AI restrictions are driven primarily by news, forums, and social media websites. For robots.txt, Figure 2b shows nearly 45% of all News website tokens are fully restricted in HEAD_{All}, as compared to 3% in 2023. For Terms of Service, Figure 2d shows News website tokens have had a 6% rise in the restricted portion since 2023. Paired with the findings in Table 2, this suggests that the composition of tokens in crawls respecting robots.txt may shift away from news, social media, and forums, and towards organization and e-commerce websites.

Forecasting trends in the future suggest a continued and significant decline in open and consenting web data sources. SARIMA forecasts suggest that for just the next year (by April 2025) an additional absolute 2-4% of C4, RefinedWeb, and Dolma tokens will be fully restricted by robots.txt.

³For instance, see *Bogard v. TikTok Inc.*, No. 3:23-cv-00012-RLY_MJD, 2024 WL 1588423, at *4 (S.D. Ind. Mar. 24, 2024).

Robots Restrictions	Terms of Service Policies								
	None	Conditional	No Distribution	Non-Complete	NC Only	No AI	No Crawling	No Crawling or AI	
	Restricted	6.3 %	0.3 %	0.3 %	0.4 %	2.3 %	--	8.6 %	2.7 %
	Partial	14.0 %	0.2 %	1.8 %	1.6 %	5.1 %	0.1 %	12.4 %	0.9 %
	None	5.6 %	0.1 %	0.3 %	0.1 %	1.9 %	--	34.9 %	0.2 %

Figure 3: A cross tabulation of the Terms of Service policies and robots.txt restrictions for HEAD_{C4}, measured in percentage of tokens. **We find two ways of expressing restrictions on data use for AI frequently disagree**, both in what they express, and can express.

Equivalently, an additional 7-11% of the highest quality tokens in the head distribution will become restricted. The forecasts for Terms of Service are even starker, with the restricted tokens in the full corpus expected to rise an absolute 6-10% by April 2025. These trends illustrate a systematic rise in restrictions on data sources, which, where enforced or respected, will severely hamper the data scaling practices in the coming years—which have thus forth been responsible for the remarkable capability improvements.

3.2 Inconsistent and Ineffective Communication on AI Consent

In many cases, data holders fail to effectively communicate their preferences on how their data is used by AI systems. We observe robots.txt instructions which allow some AI organizations to crawl while restricting others, references to non-existent crawlers, and contradictions between the robots.txt and Terms of Service. Together, these issues point to the need for better preference signaling protocols.

Some AI crawlers are allowed, while others are not. We find not all AI agents are disallowed equally. In Table 3 we estimate the conditional probabilities of each organization’s crawler being restricted, conditioned on whether any other AI organization is restricted. Whereas OpenAI and Common Crawl agents are frequently disallowed (in 91.5% and 83.4% of cases where *any* of the organizations are disallowed), the agents of other AI companies, such as Google, Cohere, and Meta are often omitted from robots.txt. The omissions of Cohere, Meta, and other small AI organizations are likely because website administrators are unaware or unable to update their robots.txt to reflect the full list of AI developers. On the other hand, the particularly high omission rates of Internet Archive and Google Search suggest web administrators may be open to more traditional crawler uses like archiving and search engines, even as they seek to restrict AI usage. A full confusion matrix showing the correlation between restrictions for each user agent is provided in Appendix Figure 5.

ORGANIZATION	REST. (%)
OPENAI	91.5
COMMON CRAWL	83.4
ANTHROPIC	83.4
GOOGLE EXTENDED	72.0
FALSE ANTHROPIC	61.6
COHERE	52.3
META	52.2
INTERNET ARCHIVE	32.3
GOOGLE SEARCH	17.1

Table 3: The % each org’s crawler agents are **restricted** if at least one other org in this pool is restricted. Gray indicates crawlers with a primary purpose other than AI training data.

Unrecognized crawler agents cause incorrect specifications. We find several instances where robots.txt refer to user agents that the companies do not recognize. For instance, 4.5% of websites disallowed the unrecognized user agents ANTHROPIC-AI or CLAUDE-WEB (documented as FALSE ANTHROPIC), but not the documented agent for Anthropic’s crawler, CLAUDEBOT. The origin and reason for these unrecognized agents remains unclear—Anthropic reports no ownership of these. These inconsistencies and omissions across AI agents suggest that a significant burden is placed on the domain creator to understand evolving agent specifications across (a growing number of) developers. AI crawler standardization could address these challenges in consent/preference signaling.

Contradictions exist between robots.txt and ToS. The Robots Exclusion Protocol (REP) is a guideline for web crawlers, while a website’s Terms of Service is a legal agreement between the

Variable	URL Group				Stats Diff	Pct. Tokens in Corpus		
	Top 100	Top 500	Top 2000	Random		C4	RW	Dolma
Restrictive Robots.txt	38.4	35.0	26.5	3.4	+23.1	5.0±1.5	6.6±2.3	5.6±1.9
Restrictive Terms	64.1	61.0	51.2	15.7	+35.5	43.2±15.2	52.8±30.3	52.3±15.4
User Content	21.3	19.1	19.4	15.1	+4.4	27.9±12.3	39.8±32.8	37.3±16.7
Paywall	31.8	31.3	24.6	1.6	+23.0	4.1±1.1	4.9±0.4	10.8±1.2
Ads	54.6	61.4	53.2	5.4	+47.9	23.5±12.6	44.8±34.4	34.8±18.1
Modality: Image	96.8	97.0	96.7	95.0	+1.7	97.7±2.3	98.6±0.9	97.5±1.9
Modality: Video	87.0	78.8	58.7	18.9	+39.8	32.9±14.2	27.0±14.7	35.4±10.6
Modality: Audio	80.7	68.3	41.8	3.4	+38.4	21.2±14.7	12.5±6.3	20.5±6.7
Sensitive Content	0.0	0.4	1.1	0.6	+0.5	0.8±1.0	0.2±0.4	1.8±3.0
<i>Web Domain Service & Purpose</i>								
Academic	14.1	10.1	9.8	3.8	+6.0	3.1±1.6	2.6±1.2	3.0±0.7
Blogs	2.6	2.9	3.9	15.1	-11.2	23.2±11.3	16.3±16.0	20.1±11.9
E-Commerce	8.4	9.9	10.1	10.6	-0.5	20.0±17.8	32.6±37.6	17.7±19.1
Encyclopedia/Database	20.5	13.2	11.1	0.4	+10.7	3.5±3.4	5.8±9.8	5.1±5.8
Government	3.2	2.8	2.8	1.1	+1.7	0.9±0.9	0.9±0.8	0.8±0.6
News/Periodicals	45.6	53.3	50.0	5.3	+44.7	11.5±3.9	16.8±10.8	22.9±10.9
Org/Personal Website	15.3	13.2	12.7	71.2	-58.5	48.5±13.3	57.3±24.2	46.3±14.2
Social Media/Forums	9.4	9.3	11.8	1.6	+10.1	5.1±4.8	5.4±8.9	14.9±8.3
Other	15.0	10.9	11.8	4.3	+7.4	4.7±2.7	2.8±1.3	3.7±2.0

Table 4: **Mean incidence rates of web source features across C4, RefinedWeb, and Dolma.** We measure incidence rates for the top 100, 500, and 2000 URLs, ranked by number of tokens, as well as the random sample. The ‘Diff’ column reports the % difference between the top 2k and random samples. We test for significant differences between the overall corpus and each of the top-100, top-500 and top-2000 sets with a Bonferroni-corrected two-sided permutation test, where differences significant at the Bonferroni-corrected 5σ level are indicated in bold. We also estimate the percentage of tokens in each corpus, C4, RefinedWeb, and Dolma, for which the web feature is present ($\pm 95\%$ bootstrap CI shown in gray), by computing the final percentage of tokens based on the estimate for the unobserved population (from the random sample), and the observed head sample.

website and users of the site. The benefit of the REP is its machine-readability. However, its rigid structure, created in 1995, limits what signals it can convey. In contrast, a ToS can communicate rich and nuanced policies in natural language. Without a robots.txt, a ToS lacks practical deterrence of unwanted crawling. Inversely, without a ToS, a robots.txt may lack any plausible enforcement [107]. We found that in many cases, websites’ robots.txt implementations fails to capture the intentions specified in their Terms of Service.

In Figure 3, we illustrate the distribution of Terms and REP use criteria (the taxonomy is defined in Table 2 and broken down in detail in Appendix B). Common use criteria expressed in modern ToS pages include prohibitions specifically on commercial use, conditional use limiting actions such as third-party re-posting, non-compete criteria, or specific prohibitions only against “AI”, but not against crawling for search engines. We also see many websites write anti-crawling terms but have no robots.txt file (35.1%), or have no ToS but a restrictive robots.txt (20.3%) that disallows at least some crawlers. Terms specifying only non-commercial uses are also often paired with fully or partially restrictive robots.txt files, which may unintentionally limit academic web crawlers, as a side effect of deterring corporate use. Another formidable challenge is that websites currently have to list every search engine or AI user agent they want to restrict. Empirical evidence from both Figure 5 and Figure 3 suggests the absence of REP expressivity and standardization for AI is leading to inconsistent or unintended signals that fail to reflect intended preferences.

3.3 Correlating Features of Web Data

What does web data actually look like? Prior work has measured the characteristics of web-derived datasets, for the presence of artifacts [34, 66], undesirable text and images [69, 11], demographic biases [32], and quality discrepancies across languages [22]. We expand upon these analyses by measuring what web data sources look like *before* they have been neatly processed into AI training

datasets. We measure the presence of multi-modal content, user-derived content, website monetization schemes, and sensitive content on the most well-represented web domains on the internet (HEAD_{All}) and on a random sample of domains (RANDOM_{2k}). We also annotate the services provided and purpose of each web domain.

Most of the web is comprised of organizational/personal websites, and blogs, however the head distribution is disproportionately news, forums, and encyclopedias. Table 4 shows several notable and statistically significant differences between head distribution (HEAD_{All}) and tail distribution (RANDOM_{2k}) of web domains. HEAD_{All} is comprised mostly of news, and social media/forums, and encyclopedias (72.9%), in contrast to the long tail data in RANDOM_{2k} , which is dominated by personal or organization websites, blogs and E-commerce sites (97%). Academic and government content is also proportionately higher in the head distribution. Note however that though they are all derived from Common Crawl snapshots, C4, RefinedWeb, and Dolma, all show variations in their source compositions—highlighting the importance of curation choices.

The head distribution of domains is more multimodal, and heavily monetized. We observe that HEAD_{All} web domains are much more heavily monetized through ads (+47.5%) and paywalls (+24.1%). Accordingly, they also have significantly greater restrictions from both robots.txt (+22.5%) and Terms of Service (+35.3%). This monetization and restrictions likely correspond to the higher quality and heterogeneity of content usually produced by news, periodicals, forums, and databases which are more common in HEAD_{All} . This is reflected by the higher proportions of image (+4.4%), video (+39.8%), and audio content (+38.4%) than the rest of the web. Interestingly, the fraction of user-generated content and sensitive content between the head and tail distributions is less pronounced. Crawlers that respect the restrictions that occur far more frequently in HEAD_{All} will increasingly lose access to the most multi-modal, highly curated, and up-to-date content sources.

3.4 Misalignment between Real-world AI Usage and Web Data

In this section, we measure the degree of alignment between real world uses of ChatGPT and the content in the webcrawls that form the bulk of AI training. For each web domain in HEAD_{All} , we had annotators label the services provided by the website, as well as the presence of some monetization, such as a paywall or automatic ads. We compare these services against the services that real-world users solicit in their interactions with conversational AI systems. We use WildChat, a recent set of 1 million user conversations with ChatGPT [131], collected through a HuggingFace Space wrapper around OpenAI services. We randomly sampled 100 conversation logs from WildChat, which the paper authors manually clustered by the type of tasks or goals conveyed by each conversation, with the goal of relating the core function of these conversations with the services provided by the websites crawled in training. Subsequently, we used GPT-4o to label 1k randomly selected conversations from the WildChat dataset; these conversations were labelled using the taxonomy we developed to categorize websites. Further details on the taxonomy and labelling procedure can be found in Appendix B.6.

Apparent uses of ChatGPT are misaligned with the popular web domains language models are trained on. Figure 4(a) shows the distribution of services provided by the web domains, broken down by whether those domains are monetized. In contrast, Figure 4(b) shows how ChatGPT is used in the real world. The way that users interact with ChatGPT is different in important ways from the types of content that is most frequently represented in publicly available web-based training datasets. For instance, in over 30% of conversations, users request creative compositions such as fictional story writing or continuation, role-playing, or poetry. However, creative writing is poorly represented among the web data used for model training. These results may provide evidence for where models trained exclusively on unstructured internet data are most “unaligned” with how real users want to use generative AI [87]. Language models trained only on web data are known to struggle to understand the structure of discourse and underperform models trained with instruction finetuning and preference training on highly curated data [124, 6, 27]. The misalignment between real use cases and web crawled data may suggest the key areas of model distributional misalignment, as well as inform future data collection efforts based on real-world uses.

Sexual role-play appears to be a prevalent use of ChatGPT, despite being mostly removed from common public datasets. Whereas sensitive (e.g. sexual) content represents < 1% of the web domains in HEAD_{C4} (see Table 4), sexual role-play represents 12% of all recorded user interactions in WildChat. All the public datasets we consider—C4, RefinedWeb, and Dolma—have undergone some

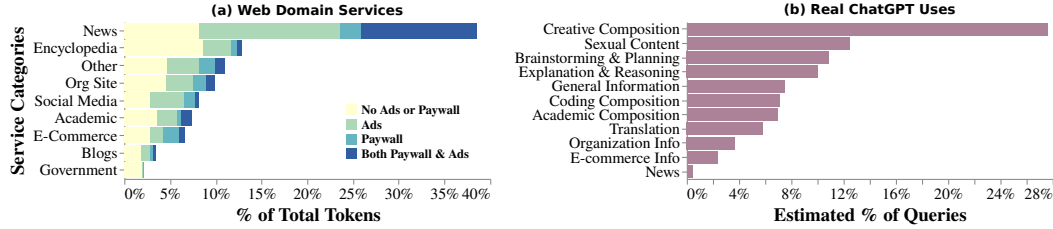


Figure 4: **The most common services provided by web domains in HEAD_{C4} do not match real ChatGPT use cases from WildChat user logs.** Left: We measure the proportion of tokens in HEAD_{C4} dedicated to each type of web service, and the degree to which they are monetized via paywalls and ads. Right: We measure the proportion of each type of user query in WildChat.

form of filtering to remove illegal or sexually explicit content, as training on such content introduces potential liability concerns; the web, in general, is known to have high portions of sexually explicit content [11, 83]. OpenAI states in the GPT-4 technical report that it also filtered its training data for harmful content [84]. In addition to filtering web-derived training data, OpenAI’s models are further trained to refuse requests that violate OpenAI’s Usage Policies.⁴ OpenAI’s Usage Policies prohibit “sexually explicit or suggestive content” with respect to minors, or re-distribution that may harm others; however, there is ambiguity as to whether this would cover all user requests for sexual role-play [52]. For instance, the GPT-4 technical report makes a distinction in model refusal instructions between erotic and non-erotic sexual content, “(e.g. literary or artistic value) and contextualized sexual content (e.g. medical)” [84].

Sexual-related uses of AI are a topic of ongoing debate within the scientific community [53, 82, 119], and rules differ by company, service, and jurisdiction. In a review of 30 generative AI developers’ acceptable use policies, Klyman [52] finds that OpenAI’s policies are not among the most restrictive with respect to sexual content; while OpenAI has a blanket ban on “sexually explicit or suggestive content,” other companies’ acceptable use policies also explicitly prohibit “erotic content,” “adult content,” “pornography,” “nudity,” and “sexual fetishes” [3, 41, 1]. However, harsher restrictions on sexual content come with tradeoffs, as more heavily safety-tuned language models may then be less able to direct users to resources about sex education or generate fictional stories with PG-13 type content.

Common ChatGPT uses appear distinct from the uses of commercialized web sources. Figure 4 shows that a significant portion of tokens in HEAD_{C4} are from web domains with ads, paywalls, or both—in other words they are the most commercialized. However, while news websites (the mostly highly commercialized category) comprise nearly 40% of all tokens in HEAD_{C4}, fewer than 1% of ChatGPT queries appear to be related to news or current affairs. It also shows that news websites have the highest instance of ads, paywalls, or both—in other words, they are the most commercialized. Our observations suggest that real-world use cases of ChatGPT are not necessarily directly related to the most prevalent, commercialized content on the web. This finding has interesting implications for the use of AI in industries with web-based services, such as journalism, or for US copyright analysis, which evaluates how the secondary use of a protected work (training AI models) affects the potential market for the original use of the work (see 17 U.S.C §107).

We believe our observations provide strong empirical evidence for the (mis)alignment between AI uses and web-derived training data. However, our observations come with significant caveats. The WildChat [131] dataset may not include a representative sample of how people interact with language models. Not only does it solely include conversations with a specific instance ChatGPT, but the WildChat proxy service is hosted on a technical website, HuggingFace Spaces, which could suggest a more technical user base, or one more likely to audit ChatGPT for inappropriate uses. Model uses also change both by time and product; our analysis is specific to the model interactions collected in WildChat between April 9, 2023, at 12 AM to May 1, 2024, using the GPT3.5-Turbo and GPT-4 APIs. Different AI products are likely to have different use distributions, and usage patterns will inevitably change over time. Finally, the use taxonomy, both for web domains and WildChat uses, were developed based on a manual, iterative process that is limited in its granularity. It is possible that

⁴<https://openai.com/policies/usage-policies/>

data/information from News web domains could be used in responses for non-News classifications in WildChat, e.g. General Information. This would be exceedingly difficult to measure, and merits analysis in future work.

4 Discussion

The web-sourced AI data commons is rapidly becoming more restricted. The web has acted as the primary “data commons” for general-purpose AI. It’s scale and heterogeneity have become fundamental to advances in capabilities. However, our results show web domains are rapidly restricting crawling and use of their content for AI. In less than a year, ~5% of the tokens in C4 and other major corpora have recently become restricted by robots.txt. And nearly 45% of these tokens now carry some form of restrictions from the domain’s Terms of Service. If these rising restrictions are respected by model developers (as many claim to) or is legally enforced, the availability of high-quality pretraining sources will rapidly diminish.

The rise in restrictions will skew data representativity, freshness, and scaling laws. Prior work has forefronted scaling data as essential to frontier model capabilities [46, 120]. While the declining trend in consent will protect content creators’ intentions, it would also challenge these data scaling laws [46, 120]. Not only would these restrictions reduce the scale of available data, but also the composition (away from news and forums), diversity, and representativeness of training data—biasing this data toward older content and less fresh content.

Recently, multiple AI developers have been accused of bypassing robots.txt opt-outs to scrape publisher websites [88, 73]. While it is not possible to confirm, in each case it appears AI systems may be distinguishing between crawling data for training, and crawling data to retrieve information for user questions at inference time. One of the few, OpenAI has two crawler agents, GPTBot for training, and ChatGPT-User for live browsing plugins (see Table 5). Other companies may simply not be registering their inference time crawlers for opt-outs. This circumvention may allow developers to directly attribute the retrieved web pages, as well as better achieve data representativity, freshness, and approximate the scaling laws had they trained on it. However, creators may feel this violates the spirit of the opt-outs, especially if the opportunity to attribute sources is not taken.

The web needs better protocols to express intentions and consent. The REP places an immense burden on website owners to correctly anticipate all agents who may crawl their domain for undesired downstream use cases. We consistently find this leads to protocol implementations that don’t reflect intended preferences. An alternative scheme might give website owners control over *how* their webpages are used rather than *who* can use them. This would involve standardizing a taxonomy that better represents downstream use cases, e.g. allowing domain owners to specify that web crawling only be used for search engines, or only for non-commercial AI, or only for AI that attributes outputs to their source data. New commands could also set extended restriction periods given dynamic sites may want to block crawlers for extended periods of time, e.g. for journalists to protect their data freshness. Ultimately, a new protocol should lead to website owners having greater capacity to self-sort consensual from non-consensual uses, implementing machine-readable instructions that approximate the natural language instructions in their Terms of Service.

Rising expressions of non-consent will affect non-profits, archives, and academic researchers.

A new wave of robots.txt and Terms of Service pages have not, or cannot, distinguish the various uses of their data. For instance, having to individually prohibit a plethora of AI crawlers has motivated many domains to simply blanket prohibit any crawling with the wildcard “*” marker. Or domains have also limited crawlers from non-profit archives such as the Common Crawl Foundation or Internet Archive, in order to prevent other organizations from downloading their data for training. However, these archives are also used for non-commercial uses of AI, as well as academic research, knowledge, and accountability, well beyond the scope of AI. For instance, the Common Crawl is reported to be cited in 10,000+ research articles from varying fields.⁵ This tension between data creators and, predominantly, commercial AI developers has left academic and non-commercial interests as secondary victims. As web consent continues to evolve, we believe it is essential that these often essential facilities not be marginalized or severely hampered.

⁵<https://commoncrawl.org/>

Economic fears of AI systems may change how internet data is created and protected. The content on the internet was not created to be used for training AI models. Its use for this purpose is already resulting in changing incentives around content creation, especially in cases where generative AI competes with the original sources of content. As we show in Figure 4, large portions of today’s internet are owned by commercial interests, with sites that are locked behind paywalls or financed by advertisements. We expect small-scale content providers, who are less resourced to protect themselves from undesired crawling, may opt out of the web entirely, or move to posting on walled, content websites. If we don’t develop better mechanisms to give website owners control over how their data is used, we should expect to see further decreases in the open web, with more websites locking their data behind login or paywalls to prevent it being trained on.

Real-world AI uses may have implications for copyright and fair use. Analysis of copyright infringement, including fair use, includes a four factor analysis. One analysis evaluates how the use of a protected work (e.g., to train AI models) affects the potential market for the original work (see 17 U.S.C §107). To investigate this question broadly, we document the major use settings of primary training domains, and compare those to the real use cases found in WildChat (Section 3.4). We find that while News domains dominate as a source of data, ChatGPT is not currently used often for news—instead uses like creative compositions (such as role-play or fiction writing), sexual role-play, brainstorming, or general information requests are most common. While there exist several limitations to this analysis, outlined in Subsection 3.4, the mismatch in use cases between training data and popular chatbots might suggest that AI chatbots are not directly competing with many of their training sources. We caution against over-interpreting these results to suggest a stronger case for fair use, as we believe future work is necessary to substantiate these findings and their relation to nuanced legal discussions.

5 Related Work

Prior work has conducted large scale audits of the provenance, quality, biases, and characteristics of AI training data, for pretraining text [32, 55, 34, 57], finetuning text [66], as well as multimodal datasets [11, 13, 12, 109, 30], and challenges in data development [89]. Recent work have looked at collecting non-copyrighted data [77], interpreting the legal implications of fair use for AI data [44, 61], and forecasting future data constraints [120]. However, there is little work inspecting the evolution of consent signals on AI data. Prior research have attempted to understand the link decay on the web [25], the collection process for Common Crawl [5], or evolving behavior and implications of web crawlers [60, 18, 58, 113, 19]. Initial news reports have begun to investigate the rate of blocking AI web crawlers for general websites [86] and news publishers [127], laying the foundation for our more rigorous analysis. The dearth of data documentation on AI datasets [39, 9, 101, 8] has been highlighted as a challenge for understanding AI model behavior [67, 100, 74, 43, 81], reproducibility, consent, and authenticity [68].

6 Conclusion

In this work, we presented the first, large-scale audit of the web sources underlying the massive training corpora for modern, general-purpose AI. Our audit of 14,000 web domains provides a view the changing nature of crawlable content, consent norms, and points to daunting trends for the future openness of the highest quality data used to train AI. The inconsistencies and omissions between robots.txt and terms of service pages suggest a data ecosystem ill-equipped to signal or enforce preferences. Lastly, we uncover distributional mismatches in the documented real uses of AI systems and their underlying data. We release all our collected annotations and analysis, with the hope that future work will further investigate the provenance, consent, and composition of the fundamental ingredients to AI systems.⁶

Impact & Ethics Statement

Consent to copy, use and train on data is a complex issue. First, the robots.txt and Terms of Service that communicate these intentions are owned by the web administrators, which are often imperfect

⁶<https://github.com/Data-Provenance-Initiative/Data-Provenance-Collection>

proxies for the actual copyright holders. For instance, social media websites or forums often host content that was originally created or belongs to others. This is pervasive across the web. And there are insufficient tools to attribute all content to their copyright holders, or disentangle consenting from non-consenting use content—indeed that is partly demonstrated by this work. As such, it is important to recognize that robots.txt and Terms of Service have become the status quo out of practicality, though they suffer from limitations in ownership, and effective communication of intentions.

Additionally, while many data preference signals exist, which ones should be enforceable and how they should be enforced both remain open questions, legally and ethically. Data crawling restrictions can be motivated by intentions to protect copyright holders, privacy, or a desire to monetize the data themselves. Some of these motivations may not override the competing right for humans to collect public web material, for study, or non-commercial purposes. And, some have argued that humans, and by extension machines, have the “right to read and learn” from open web data [48]. The laws, ethics, and best practices that emerge around these conflicting goals will impact the future efficacy of AI technologies, the types of organizations that are able to acquire sufficient data to compete in frontier model development, as well as the economy of creators from which these datasets are sourced. In this work, we do not prescribe legal or ethical answers, but describe the precise and evolving nature of preference signals on the web. While we advocate for more protocols and mechanisms that enable more effective communication of these intentions, we leave the adherence to these intentions as a broader question for readers, developers, and legislators.

Acknowledgements

This research was conducted by the Data Provenance Initiative, a collective of independent and academic researchers volunteering their time to data transparency projects. The Data Provenance Initiative is supported by the Mozilla Data Futures Lab Infrastructure Fund.

We would like to thank Arvind Narayanan, Stefan Baack, Aviya Skowron, Cullen Miller, Greg Lindahl, Pedro Ortiz Suarez, and Anna Tumadóttir for their insightful feedback and guidance.

We would also like to thank the ML Collective community for the generous computational support on experiments.

Contributions

Here we break down contributions to this work. Contributors are listed alphabetically, except for team leads who are placed first.

- **Annotation Process Design for Web Domain Services** Shayne Longpre (lead), Robert Mahari (lead), Hanlin Li (lead), Ahmad Mustafa Anis, Deividas Mataciunas, Diganta Misra, Emad Alghamdi, Enrico Shippole, Hamidah Oderinwale, Jianguo Zhang, Joanna Materzynska, Kevin Klyman, Kun Qian, Kush Tiwary, Lester Miranda, Manan Dey, Manuel Cherep, Minnie Liang, Mohammed Hamdy, Nayan Saxena, Nikhil Singh, Niklas Muennighoff, Naana Obeng-Marnu, Robert Mahari, Seonghyeon Ye, Seungone Kim, Shayne Longpre, Shrestha Mohanty, Tobin South, Vipul Gupta, Vivek Sharma, Vu Minh Chien, William Brannon, Xuhui Zhou, Yizhi Li, An Dinh, Ariel Lee, Campbell Lund, Caroline Chitongo, Christopher Klamm, Cole Hunter, Da Yin, Damien Sileo, Hailey Schoelkopf
- **Annotation Process Design for Web Domain Characteristics** Robert Mahari (lead), Shayne Longpre (lead)
- **Annotation Process Design for Terms of Service** Robert Mahari (lead); Hamidah Oderinwale (lead), Campbell Lund (lead), Shayne Longpre
- **Annotations & Annotation Quality Review** Robert Mahari (lead), Shayne Longpre (lead), Jad Kabbara (lead), Ahmad Mustafa Anis, William Brannon, Caroline Chitongo, Vu Minh Chien, Manan Dey, An Dinh, Da Yin, Vipul Gupta, Mohammed Hamdy, Cole Hunter, Daphne Ippolito, Jad Kabbara, Christopher Klamm, Kevin Klyman, Ariel Lee, Minnie Liang, Hanlin Li, Lester Miranda, Shrestha Mohanty, Niklas Muennighoff, Seungone Kim, Damien Sileo, Hailey Schoelkopf, Enrico Shippole, Tobin South, Nayan Saxena, Xuhui Zhou
- **Data Corpus Collection** Tobin South (lead)
- **Wayback Machine Data Collection** Ariel Lee (lead)
- **Robots.txt Longitudinal Analysis** Ariel Lee (lead), Shayne Longpre (lead), Nikhil Singh (lead), Nayan Saxena, Tobin South,
- **Terms of Service Longitudinal Analysis** Ariel Lee (lead), Shayne Longpre (lead)
- **Trend Forecasting** Ariel Lee (lead)
- **Robots.txt and ToS Comparisons** Shayne Longpre (lead), William Brannon (lead), Campbell Lund, Ariel Lee
- **Web Domain Characteristics Analysis** William Brannon (lead), Shayne Longpre (lead)
- **Annotation Process Design for WildChat** Shayne Longpre (lead), Nayan Saxena (lead)
- **WildChat vs Web Domain Analysis** Shayne Longpre (lead), Manuel Cherep (lead), Campbell Lund, Ariel Lee, Nayan Saxena
- **Writing** Shayne Longpre (lead), Jad Kabbara (lead), Robert Mahari (lead), Daphne Ippolito (lead), Sara Hooker (lead)
- **Legal Analysis** Robert Mahari (lead), Luis Villa
- **Visualizations & Visual Data Analysis** Naana Obeng-Marnu (lead), Nikhil Singh (lead), Shayne Longpre (lead), William Brannon (lead)
- **Senior Advisors** Stella Biderman, Daphne Ippolito, Sara Hooker, Jad Kabbara, Hanlin Li, Sandy Pentland, Luis Villa, Caiming Xiong

References

- [1] Aleph Alpha. Terms & conditions, 2024. URL <https://aleph-alpha.com/terms-conditions/>.
- [2] Rohan Anil, Andrew M Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, et al. Palm 2 technical report. *arXiv preprint arXiv:2305.10403*, 2023.
- [3] Anthropic. Usage policy, 2024. URL <https://www.anthropic.com/legal/aup>.
- [4] Anas Awadalla, Le Xue, Oscar Lo, Manli Shu, Hannah Lee, Etash Kumar Guha, Matt Jordan, Sheng Shen, Mohamed Awadalla, Silvio Savarese, Caiming Xiong, Ran Xu, Yejin Choi, and Ludwig Schmidt. Mint-1t: Scaling open-source multimodal data by 10x: A multimodal dataset with one trillion tokens, 2024.
- [5] Stefan Baack. A critical analysis of the largest source for generative ai training data: Common crawl. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency*, pages 2199–2208, 2024.
- [6] Yuntao Bai, Saurav Kadavath, Sandipan Kundu, Amanda Askell, Jackson Kernion, Andy Jones, Anna Chen, Anna Goldie, Azalia Mirhoseini, Cameron McKinnon, Carol Chen, Catherine Olsson, Christopher Olah, Danny Hernandez, Dawn Drain, Deep Ganguli, Dustin Li, Eli Tran-Johnson, Ethan Perez, Jamie Kerr, Jared Mueller, Jeffrey Ladish, Joshua Landau, Kamal Ndousse, Kamile Lukosuite, Liane Lovitt, Michael Sellitto, Nelson Elhage, Nicholas Schiefer, Noemi Mercado, Nova DasSarma, Robert Lasenby, Robin Larson, Sam Ringer, Scott Johnston, Shauna Kravec, Sheer El Showk, Stanislav Fort, Tamera Lanham, Timothy Telleen-Lawton, Tom Conerly, Tom Henighan, Tristan Hume, Samuel R. Bowman, Zac Hatfield-Dodds, Ben Mann, Dario Amodei, Nicholas Joseph, Sam McCandlish, Tom Brown, and Jared Kaplan. Constitutional AI: Harmlessness from AI Feedback, December 2022. URL <http://arxiv.org/abs/2212.08073>. arXiv:2212.08073 [cs].
- [7] Max Bain, Arsha Nagrani, Gül Varol, and Andrew Zisserman. Frozen in Time: A Joint Video and Image Encoder for End-to-End Retrieval, May 2022. URL <http://arxiv.org/abs/2104.00650>. arXiv:2104.00650 [cs].
- [8] Jack Bandy and Nicholas Vincent. Addressing “documentation debt” in machine learning research: A retrospective datasheet for bookcorpus. *arXiv preprint arXiv:2105.05241*, 2021.
- [9] Emily M. Bender and Batya Friedman. Data statements for natural language processing: Toward mitigating system bias and enabling better science. *Transactions of the Association for Computational Linguistics*, 6:587–604, 2018. doi: 10.1162/tac1_a_00041. URL <https://aclanthology.org/Q18-1041>.
- [10] Stella Biderman, Kieran Bicheno, and Leo Gao. Datasheet for the pile. *arXiv preprint arXiv:2201.07311*, 2022.
- [11] Abeba Birhane, Vinay Uday Prabhu, and Emmanuel Kahembwe. Multimodal datasets: misogyny, pornography, and malignant stereotypes. *arXiv preprint arXiv:2110.01963*, 2021.
- [12] Abeba Birhane, Vinay Prabhu, Sang Han, and Vishnu Naresh Boddeti. On hate scaling laws for data-swamps. *arXiv preprint arXiv:2306.13141*, 2023.
- [13] Abeba Birhane, Vinay Prabhu, Sang Han, Vishnu Naresh Boddeti, and Alexandra Sasha Luccioni. Into the laions den: Investigating hate in multimodal datasets. *arXiv preprint arXiv:2311.03449*, 2023.
- [14] Sid Black, Stella Biderman, Eric Hallahan, Quentin Anthony, Leo Gao, Laurence Golding, Horace He, Connor Leahy, Kyle McDonell, Jason Phang, et al. Gpt-neox-20b: An open-source autoregressive language model. *arXiv preprint arXiv:2204.06745*, 2022.
- [15] Rishi Bommasani, Dilara Soylu, Thomas Liao, Kathleen A. Creel, and Percy Liang. Ecosystem graphs: The social footprint of foundation models. *ArXiv*, abs/2303.15772, 2023. URL <https://arxiv.org/abs/2303.15772>.

- [16] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc., 2020. URL https://proceedings.neurips.cc/paper_files/paper/2020/file/1457c0d6bfc4967418bfb8ac142f64a-Paper.pdf.
- [17] Sébastien Bubeck, Varun Chandrasekaran, Ronen Eldan, Johannes Gehrike, Eric Horvitz, Ece Kamar, Peter Lee, Yin Tat Lee, Yuanzhi Li, Scott Lundberg, et al. Sparks of artificial general intelligence: Early experiments with gpt-4. *arXiv preprint arXiv:2303.12712*, 2023.
- [18] Maria Carla Calzarossa and Luisa Massari. Analysis of web logs: challenges and findings. In *International Workshop on Performance Evaluation of Computer and Communication Systems*, pages 227–239. Springer, 2010.
- [19] Maria Carla Calzarossa and Luisa Massari. Temporal analysis of crawling activities of commercial web robots. 10 2012. ISBN 978-1-4471-4593-6. doi: 10.1007/978-1-4471-4594-3_44.
- [20] Nicholas Carlini, Daphne Ippolito, Matthew Jagielski, Katherine Lee, Florian Tramer, and Chiyuan Zhang. Quantifying memorization across neural language models. In *The Eleventh International Conference on Learning Representations*, 2022.
- [21] Nicholas Carlini, Matthew Jagielski, Christopher A Choquette-Choo, Daniel Paleka, Will Pearce, Hyrum Anderson, Andreas Terzis, Kurt Thomas, and Florian Tramèr. Poisoning web-scale training datasets is practical. *arXiv preprint arXiv:2302.10149*, 2023.
- [22] Isaac Caswell, Julia Kreutzer, Lisa Wang, Ahsan Wahab, Daan van Esch, Nasanbayar Ulzii-Orshikh, Allahsera Tapo, Nishant Subramani, Artem Sokolov, Claytone Sikasote, et al. Quality at a glance: An audit of web-crawled multilingual datasets. *arXiv preprint arXiv:2103.12028*, 2021.
- [23] Sarah H. Cen, Aspen Hopkins, Andrew Ilyas, Aleksander Madry, Isabella Struckman, and Luis Videgaray. Ai supply chains (and why they matter), April 2023. URL <https://aipolicy.substack.com/p/supply-chains-2>. The second post in our series On AI Deployment.
- [24] Alan Chan, Herbie Bradley, and Nitarshan Rajkumar. Reclaiming the digital commons: A public data trust for training data. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society*, AIES ’23, page 855–868. Association for Computing Machinery, 2023. doi: 10.1145/3600211.3604658. URL <https://doi.org/10.1145/3600211.3604658>.
- [25] Athena Chapekis, Samuel Bestvater, Emma Remy, and Gonzalo Rivero. When Online Content Disappears. May 17 2024. URL <https://www.pewresearch.org/data-labs/2024/05/17/when-online-content-disappears/>.
- [26] Guoguo Chen, Shuzhou Chai, Guanbo Wang, Jiayu Du, Wei-Qiang Zhang, Chao Weng, Dan Su, Daniel Povey, Jan Trmal, Junbo Zhang, et al. Gigaspeech: An evolving, multi-domain asr corpus with 10,000 hours of transcribed audio. *arXiv preprint arXiv:2106.06909*, 2021.
- [27] Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. Scaling instruction-finetuned language models. *arXiv preprint arXiv:2210.11416*, 2022.
- [28] Frances Corry, Hamsini Sridharan, Alexandra Sasha Luccioni, Mike Ananny, Jason Schultz, and Kate Crawford. The problem of zombie datasets: A framework for deprecating datasets. *ArXiv*, abs/2111.04424, 2021. URL <https://arxiv.org/abs/2111.04424>.
- [29] Anamaria Crisan, Margaret Drouhard, Jesse Vig, and Nazneen Rajani. Interactive model cards: A human-centered approach to model documentation. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, pages 427–439, 2022.

- [30] Terrance De Vries, Ishan Misra, Changhan Wang, and Laurens Van der Maaten. Does object recognition work for everyone? In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops*, pages 52–59, 2019.
- [31] Michael Dinzinger, Florian Heß, and Michael Granitzer. A survey of web content control for generative ai, 2024.
- [32] Jesse Dodge, Maarten Sap, Ana Marasović, William Agnew, Gabriel Ilharco, Dirk Groeneveld, Margaret Mitchell, and Matt Gardner. Documenting large webtext corpora: A case study on the colossal clean crawled corpus. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 1286–1305, 2021.
- [33] Aparna Elangovan, Jiayuan He, and Karin Verspoor. Memorization vs. generalization : Quantifying data leakage in NLP performance evaluation. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 1325–1335, Online, April 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.eacl-main.113. URL <https://aclanthology.org/2021.eacl-main.113>.
- [34] Yanai Elazar, Akshita Bhagia, Ian Magnusson, Abhilasha Ravichander, Dustin Schwenk, Alane Suhr, Pete Walsh, Dirk Groeneveld, Luca Soldaini, Sameer Singh, Hanna Hajishirzi, Noah A. Smith, and Jesse Dodge. What’s in my big data?, 2023.
- [35] Ziv Epstein, Aaron Hertzmann, Laura Herman, Robert Mahari, Morgan R Frank, Matthew Groh, Hope Schroeder, Amy Smith, Memo Akten, Jessica Fjeld, et al. Art and the science of generative ai. *Science*, 380(6650):1110–1111, 2023.
- [36] Michael Färber and Ann-Kathrin Leisinger. Datahunter: A system for finding datasets based on scientific problem descriptions. In *Proceedings of the 15th ACM Conference on Recommender Systems*, pages 749–752, 2021.
- [37] Samir Yitzhak Gadre, Gabriel Ilharco, Alex Fang, Jonathan Hayase, Georgios Smyrnis, Thao Nguyen, Ryan Marten, Mitchell Wortsman, Dhruva Ghosh, Jieyu Zhang, et al. Datacomp: In search of the next generation of multimodal datasets. *Advances in Neural Information Processing Systems*, 36, 2024.
- [38] Leo Gao, Stella Biderman, Sid Black, Laurence Golding, Travis Hoppe, Charles Foster, Jason Phang, Horace He, Anish Thite, Noa Nabeshima, et al. The pile: An 800gb dataset of diverse text for language modeling. *arXiv preprint arXiv:2101.00027*, 2020.
- [39] Timnit Gebru, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé Iii, and Kate Crawford. Datasheets for datasets. *Communications of the ACM*, 64(12):86–92, 2021.
- [40] Samuel Gehman, Suchin Gururangan, Maarten Sap, Yejin Choi, and Noah A Smith. Real-toxicityprompts: Evaluating neural toxic degeneration in language models. *arXiv preprint arXiv:2009.11462*, 2020.
- [41] Google. Generative ai prohibited use policy, 2024. URL <https://policies.google.com/terms/generative-ai/use-policy>.
- [42] Dirk Groeneveld, Iz Beltagy, Pete Walsh, Akshita Bhagia, Rodney Kinney, Oyvind Tafjord, Ananya Harsh Jha, Hamish Ivison, Ian Magnusson, Yizhong Wang, et al. Olmo: Accelerating the science of language models. *arXiv preprint arXiv:2402.00838*, 2024.
- [43] Suchin Gururangan, Swabha Swayamdipta, Omer Levy, Roy Schwartz, Samuel Bowman, and Noah A. Smith. Annotation artifacts in natural language inference data. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 107–112, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi: 10.18653/v1/N18-2017. URL <https://aclanthology.org/N18-2017>.
- [44] Peter Henderson, Xuechen Li, Dan Jurafsky, Tatsunori Hashimoto, Mark A Lemley, and Percy Liang. Foundation models and fair use. *arXiv preprint arXiv:2303.15715*, 2023.

- [45] Isaac Hepworth, Kara Olive, Kingshuk Dasgupta, Michael Le, Mark Lodato, Mihai Maruseac, Sarah Meiklejohn, Shamik Chaudhuri, and Tehila Minkus. Securing the ai software supply chain. Technical report, Google, 2024.
- [46] Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, et al. Training compute-optimal large language models. *arXiv preprint arXiv:2203.15556*, 2022.
- [47] Ben Hutchinson, Andrew Smart, Alex Hanna, Emily Denton, Christina Greer, Oddur Kjar-tansson, Parker Barnes, and Margaret Mitchell. Towards accountability for machine learning datasets: Practices from software engineering and infrastructure. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, FAccT ’21, page 560–575, New York, NY, USA, 2021. Association for Computing Machinery. ISBN 9781450383097. doi: 10.1145/3442188.3445918. URL <https://doi.org/10.1145/3442188.3445918>.
- [48] Jeff Jarvis. Testimony before the senate judiciary subcommittee on privacy, technology, and the law: Oversight of a.i.: The future of journalism. Senate Judiciary Committee, 1 2024. URL https://www.judiciary.senate.gov/imo/media/doc/2024-01-10_-_testimony_-_jarvis.pdf. Accessed: date-of-access.
- [49] Yacine Jernite, Huu Nguyen, Stella Biderman, Anna Rogers, Maraim Masoud, Valentin Danchev, Samson Tan, Alexandra Sasha Luccioni, Nishant Subramani, Isaac Johnson, et al. Data governance in the age of large-scale data-driven language technology. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, pages 2206–2222, 2022.
- [50] Sayash Kapoor, Emily F. Cantrell, Kenny Peng, Thanh Hien Pham, Christopher A. Bail, Odd Erik Gundersen, Jake M. Hofman, Jessica R. Hullman, Michael A. Lones, Momin M. Malik, Priyanka Nanayakkara, Russel A. Poldrack, Inioluwa Deborah Raji, Michael Roberts, Matthew J. Salganik, Marta Serra-Garcia, Brandon M Stewart, Gilles Vandewiele, and Arvind Narayanan. Reforms: Reporting standards for machine learning based science. *ArXiv*, abs/2308.07832, 2023. URL <https://arxiv.org/abs/2308.07832>.
- [51] Pauline T Kim. Auditing algorithms for discrimination. *U. Pa. L. Rev. Online*, 166:189, 2017.
- [52] Kevin Klyman. Acceptable use policies for foundation models: Considerations for policymakers and developers. Stanford Center for Research on Foundation Models, April 2024. URL <https://crfm.stanford.edu/2024/04/08/aups.html>.
- [53] Andreas Köpf, Yannic Kilcher, Dimitri von Rütte, Sotiris Anagnostidis, Zhi Rui Tam, Keith Stevens, Abdullah Barhoum, Duc Minh Nguyen, Oliver Stanley, Richárd Nagyfi, Shahul ES, Sameer Suri, David Alexandrovich Glushkov, Arnav Varma Dantuluri, Andrew Maguire, Christoph Schuhmann, Huu Nguyen, and Alexander Julian Mattick. Openassistant conversations - democratizing large language model alignment. In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2023. URL <https://openreview.net/forum?id=VSJotgbPHF>.
- [54] M Koster, G Illyes, H Zeller, and L Sassman. Rfc 9309: Robots exclusion protocol. *Internet Engineering Task Force*, 2022. URL <https://www.rfc-editor.org/rfc/rfc9309>.
- [55] Julia Kreutzer, Isaac Caswell, Lisa Wang, Ahsan Wahab, Daan van Esch, Nasanbayar Ulzii-Orshikh, Allahsera Tapo, Nishant Subramani, Artem Sokolov, Claytone Sikasote, et al. Quality at a glance: An audit of web-crawled multilingual datasets. *Transactions of the Association for Computational Linguistics*, 10:50–72, 2022.
- [56] Joshua Alexander Kroll. *Accountable algorithms*. PhD thesis, Princeton University, 2015.
- [57] Sneha Kudugunta, Isaac Rayburn Caswell, Biao Zhang, Xavier Garcia, Derrick Xin, Aditya Kusupati, Romi Stella, Ankur Bapna, and Orhan Firat. Madlad-400: A multilingual and document-level large audited dataset. In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2023.

- [58] Shinil Kwon, Young-Gab Kim, and Sungdeok Cha. Web robot detection based on pattern-matching technique. *Journal of Information Science*, 38(2):118–126, 2012.
- [59] Hugo Laurençon, Lucile Saulnier, Thomas Wang, Christopher Akiki, Albert Villanova del Moral, Teven Le Scao, Leandro Von Werra, Chenghao Mou, Eduardo González Ponferrada, Huu Nguyen, Jörg Froberg, Mario Šaško, Quentin Lhoest, Angelina McMillan-Major, Gerard Dupont, Stella Biderman, Anna Rogers, Loubna Ben allal, Francesco De Toni, Gilda Pistilli, Olivier Nguyen, Somaieh Nikpoor, Maraim Masoud, Pierre Colombo, Javier de la Rosa, Paulo Villegas, Tristan Thrush, Shayne Longpre, Sebastian Nagel, Leon Weber, Manuel Muñoz, Jian Zhu, Daniel Van Strien, Zaid Alyafeai, Khalid Almubarak, Minh Chien Vu, Itziar Gonzalez-Dios, Aitor Soroa, Kyle Lo, Manan Dey, Pedro Ortiz Suarez, Aaron Gokaslan, Shamik Bose, David Adelani, Long Phan, Hieu Tran, Ian Yu, Suhas Pai, Jenny Chim, Violette Lepercq, Suzana Ilic, Margaret Mitchell, Sasha Alexandra Luccioni, and Yacine Jernite. The bigscience roots corpus: A 1.6tb composite multilingual dataset. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh, editors, *Advances in Neural Information Processing Systems*, volume 35, pages 31809–31826. Curran Associates, Inc., 2022. URL https://proceedings.neurips.cc/paper_files/paper/2022/file/ce9e92e3de2372a4b93353eb7f3dc0bd-Paper-Datasets_and_Benchmarks.pdf.
- [60] Junsup Lee, Sungdeok Cha, Dongkun Lee, and Hyungkyu Lee. Classification of web robots: an empirical study based on over one billion requests. *computers & security*, 28(8):795–802, 2009.
- [61] Katherine Lee, A Feder Cooper, and James Grimmelmann. Talkin’bout ai generation: Copyright and the generative-ai supply chain. *arXiv preprint arXiv:2309.08133*, 2023.
- [62] Mark A Lemley and Bryan Casey. Fair learning. *Texas Law Review*, 99:743, 2020.
- [63] Quentin Lhoest, Albert Villanova del Moral, Yacine Jernite, Abhishek Thakur, Patrick von Platen, Suraj Patil, Julien Chaumond, Mariama Drame, Julien Plu, Lewis Tunstall, et al. Datasets: A community library for natural language processing. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 175–184, 2021.
- [64] Xinjian Li, Shinnosuke Takamichi, Takaaki Saeki, William Chen, Sayaka Shiota, and Shinji Watanabe. Yodas: Youtube-oriented dataset for audio and speech. In *2023 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*, pages 1–8. IEEE, 2023.
- [65] Shayne Longpre, Le Hou, Tu Vu, Albert Webson, Hyung Won Chung, Yi Tay, Denny Zhou, Quoc V Le, Barret Zoph, Jason Wei, et al. The flan collection: Designing data and methods for effective instruction tuning. *arXiv preprint arXiv:2301.13688*, 2023.
- [66] Shayne Longpre, Robert Mahari, Anthony Chen, Naana Obeng-Marnu, Damien Sileo, William Brannon, Niklas Muennighoff, Nathan Khazam, Jad Kabbara, Kartik Perisetla, et al. The data provenance initiative: A large scale audit of dataset licensing & attribution in ai. *arXiv preprint arXiv:2310.16787*, 2023.
- [67] Shayne Longpre, Gregory Yauney, Emily Reif, Katherine Lee, Adam Roberts, Barret Zoph, Denny Zhou, Jason Wei, Kevin Robinson, David Mimno, and Daphne Ippolito. A pretrainer’s guide to training data: Measuring the effects of data age, domain coverage, quality, & toxicity, 2023.
- [68] Shayne Longpre, Robert Mahari, Naana Obeng-Marnu, William Brannon, Tobin South, Katy Gero, Sandy Pentland, and Jad Kabbara. Data authenticity, consent, & provenance for ai are all broken: what will it take to fix them? *arXiv preprint arXiv:2404.12691*, 2024.
- [69] Alexandra Sasha Luccioni and Joseph D Viviano. What’s in the box? an analysis of undesirable content in the common crawl corpus. *arXiv preprint arXiv:2105.02732*, 2021.
- [70] Rohan Mahadev and Anindya Chakravarti. Understanding gender and racial disparities in image recognition models. *arXiv preprint arXiv:2107.09211*, 2021.

- [71] Srdjan Matic, Costas Iordanou, Georgios Smaragdakis, and Nikolaos Laoutaris. Identifying sensitive urls at web-scale. In *Proceedings of the ACM Internet Measurement Conference*, pages 619–633, 2020.
- [72] Angelina McMillan-Major, Zaid Alyafeai, Stella Biderman, Kimbo Chen, Francesco De Toni, Gérard Dupont, Hady Elsahar, Chris Emezue, Alham Fikri Aji, Suzana Ilić, et al. Documenting geographically and contextually diverse data sources: The bigscience catalogue of language data and resources. *arXiv preprint arXiv:2201.10066*, 2022.
- [73] Dhruv Mehrotra and Tim Marchman. Perplexity is a bullshit machine. *WIRED*, 6 2024. URL <https://www.wired.com/story/perplexity-is-a-bullshit-machine/>. Accessed: date-of-access.
- [74] Anna P. Meyer, Aws Albarghouthi, and Loris D’Antoni. The dataset multiplicity problem: How unreliable data impacts predictions. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*, FAccT ’23, page 193–204, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 9798400701924. doi: 10.1145/3593013.3593988. URL <https://doi.org/10.1145/3593013.3593988>.
- [75] Milagros Miceli, Tianling Yang, Adriana Alvarado Garcia, Julian Posada, Sonja Mei Wang, Marc Pohl, and Alex Hanna. Documenting data production processes: A participatory approach for data work. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI ’22)*, volume 6, New York, NY, USA, nov 2022. Association for Computing Machinery. doi: 10.1145/3555623. URL <https://doi.org/10.1145/3555623>.
- [76] Antoine Miech, Dimitri Zhukov, Jean-Baptiste Alayrac, Makarand Tapaswi, Ivan Laptev, and Josef Sivic. HowTo100M: Learning a Text-Video Embedding by Watching Hundred Million Narrated Video Clips. In *ICCV*, 2019.
- [77] Sewon Min, Suchin Gururangan, Eric Wallace, Weijia Shi, Hannaneh Hajishirzi, Noah A Smith, and Luke Zettlemoyer. Silo language models: Isolating legal risk in a nonparametric datastore. In *NeurIPS 2023 Workshop on Distribution Shifts: New Frontiers with Foundation Models*, 2023.
- [78] Margaret Mitchell, Simone Wu, Andrew Zaldivar, Parker Barnes, Lucy Vasserman, Ben Hutchinson, Elena Spitzer, Inioluwa Deborah Raji, and Timnit Gebru. Model cards for model reporting. In *Proceedings of the conference on fairness, accountability, and transparency*, pages 220–229, 2019.
- [79] Mathew Monfort, Alex Andonian, Bolei Zhou, Kandan Ramakrishnan, Sarah Adel Bargal, Tom Yan, Lisa Brown, Quanfu Fan, Dan Gutfreund, Carl Vondrick, et al. Moments in time dataset: one million videos for event understanding. *IEEE transactions on pattern analysis and machine intelligence*, 42(2):502–508, 2019.
- [80] Niklas Muennighoff, Thomas Wang, Lintang Sutawika, Adam Roberts, Stella Biderman, Teven Le Scao, M Saiful Bari, Sheng Shen, Zheng-Xin Yong, Hailey Schoelkopf, et al. Crosslingual generalization through multitask finetuning. *arXiv preprint arXiv:2211.01786*, 2022.
- [81] Niklas Muennighoff, Alexander M Rush, Boaz Barak, Teven Le Scao, Aleksandra Piktus, Nouamane Tazi, Sampo Pyysalo, Thomas Wolf, and Colin Raffel. Scaling data-constrained language models. *arXiv preprint arXiv:2305.16264*, 2023.
- [82] Hellina Hailu Nigatu and Inioluwa Deborah Raji. “i searched for a religious song in amharic and got sexual content instead”: Investigating online harm in low-resourced languages on youtube. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency*, FAccT ’24, page 141–160, New York, NY, USA, 2024. Association for Computing Machinery. ISBN 9798400704505. doi: 10.1145/3630106.3658546. URL <https://doi.org/10.1145/3630106.3658546>.
- [83] Ogi Ogas and Sai Gaddam. *A Billion Wicked Thoughts: What the World’s Largest Experiment Reveals about Human Desire*. Dutton Adult, New York, NY, 2011.

- [84] OpenAI. Gpt-4 technical report, 2023.
- [85] OpenAI. Hello gpt-4o: We’re announcing gpt-4o, our new flagship model that can reason across audio, vision, and text in real time., 2024. URL <https://openai.com/index/hello-gpt-4o/>.
- [86] Originality.ai. AI Bot Blocking. Technical report, Originality.ai, September 22 2023. URL <https://originality.ai/ai-bot-blocking>.
- [87] Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *arXiv preprint arXiv:2203.02155*, 2022. URL <https://arxiv.org/abs/2203.02155>.
- [88] Katie Paul. Exclusive: Multiple ai companies bypassing web standard to scrape publisher sites, licensing firm says. *Reuters*, 6 2024. URL <https://www.reuters.com/technology/artificial-intelligence/multiple-ai-companies-bypassing-web-standard-scrape-publisher-sites-licensing-2024-06-21/>. Accessed: date-of-access.
- [89] Amandalynne Paullada, Inioluwa Deborah Raji, Emily M Bender, Emily Denton, and Alex Hanna. Data and its (dis) contents: A survey of dataset development and use in machine learning research. *Patterns*, 2(11), 2021.
- [90] Guilherme Penedo, Quentin Malartic, Daniel Hesslow, Ruxandra Cojocaru, Alessandro CapPELLI, Hamza Alobeidli, Baptiste Pannier, Ebtesam Almazrouei, and Julien Launay. The refinedweb dataset for falcon llm: outperforming curated corpora with web data, and web data only. *arXiv preprint arXiv:2306.01116*, 2023.
- [91] Guilherme Penedo, Quentin Malartic, Daniel Hesslow, Ruxandra Cojocaru, Alessandro CapPELLI, Hamza Alobeidli, Baptiste Pannier, Ebtesam Almazrouei, and Julien Launay. The RefinedWeb dataset for Falcon LLM: outperforming curated corpora with web data, and web data only. *arXiv preprint arXiv:2306.01116*, 2023. URL <https://arxiv.org/abs/2306.01116>.
- [92] David Pierce. The text file that runs the internet. *The Verge*, 2020. URL <https://www.theverge.com/24067997/robots-txt-ai-text-file-web-crawlers-spiders>.
- [93] Aleksandra Piktus, Odunayo Ogundepo, Christopher Akiki, Akintunde Oladipo, Xinyu Zhang, Hailey Schoelkopf, Stella Biderman, Martin Potthast, and Jimmy Lin. Gaia search: Hugging face and pyserini interoperability for nlp training data exploration. *arXiv preprint arXiv:2306.01481*, 2023.
- [94] Audrey Pope. *Nyt v. openai: The times’s about-face*, April 2024. URL <https://harvardlawreview.org/blog/2024/04/nyt-v-openai-the-times-about-face/>.
- [95] Luiza Pozzobon, Beyza Ermiş, Patrick Lewis, and Sara Hooker. On the challenges of using black-box apis for toxicity evaluation in research, 2023.
- [96] Mahima Pushkarna, Andrew Zaldivar, and Oddur Kjørtansson. Data cards: Purposeful and transparent dataset documentation for responsible ai. In *2022 ACM Conference on Fairness, Accountability, and Transparency*, pages 1776–1826, 2022.
- [97] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research*, 21(1):5485–5551, 2020.
- [98] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67, 2020. URL <http://jmlr.org/papers/v21/20-074.html>.

- [99] Inioluwa Deborah Raji and Joy Buolamwini. Actionable auditing revisited: Investigating the impact of publicly naming biased performance results of commercial ai products. *Communications of the ACM*, 66(1):101–108, 2022.
- [100] Anna Rogers. Changing the world by changing the data. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 2182–2194, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.170. URL <https://aclanthology.org/2021.acl-long.170>.
- [101] Nithya Sambasivan, Shivani Kapania, Hannah Highfill, Diana Akrong, Praveen Paritosh, and Lora M Aroyo. “everyone wants to do the model work, not the data work”: Data cascades in high-stakes ai. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, CHI ’21, New York, NY, USA, 2021. Association for Computing Machinery. ISBN 9781450380966. doi: 10.1145/3411764.3445518. URL <https://doi.org/10.1145/3411764.3445518>.
- [102] Victor Sanh, Albert Webson, Colin Raffel, Stephen H. Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, et al. Multitask prompted training enables zero-shot task generalization. *ICLR 2022*, 2021. URL <https://arxiv.org/abs/2110.08207>.
- [103] Joseph R. Saveri, Cadio Zirpoli, Christopher K.L. Young, and Kathleen J. McMahon. Paul tremblay, mona awad vs. openai, inc., et al., 2023. URL https://storage.courtlistener.com/recap/gov.uscourts.cand.414822/gov.uscourts.cand.414822.1.0_1.pdf. Case 3:23-cv-03223-AMO Document 1 Filed 06/28/23, UNITED STATES DISTRICT COURT, NORTHERN DISTRICT OF CALIFORNIA, SAN FRANCISCO DIVISION.
- [104] Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, et al. Bloom: A 176b-parameter open-access multilingual language model. *arXiv preprint arXiv:2211.05100*, 2022.
- [105] Teven Le Scao, Thomas Wang, Daniel Hesslow, Lucile Saulnier, Stas Bekman, M Saiful Bari, Stella Bideman, Hady Elsahar, Niklas Muennighoff, Jason Phang, et al. What language model to train if you have one million gpu hours? *arXiv preprint arXiv:2210.15424*, 2022.
- [106] Skipper Seabold and Josef Perktold. statsmodels: Econometric and statistical modeling with python. In *9th Python in Science Conference*, 2010.
- [107] Andrew Sellars. Twenty years of web scraping and the computer fraud and abuse act. *Boston University Journal of Science & Technology Law*, 24:372, 2018.
- [108] Shawn Shan, Wenxin Ding, Josephine Passananti, Stanley Wu, Haitao Zheng, and Ben Y. Zhao. Nightshade: Prompt-specific poisoning attacks on text-to-image generative models, 2024.
- [109] Shreya Shankar, Yoni Halpern, Eric Breck, James Atwood, Jimbo Wilson, and D Sculley. No classification without representation: Assessing geodiversity issues in open data sets for the developing world. *arXiv preprint arXiv:1711.08536*, 2017.
- [110] Taylor G. Smith et al. pmdarima: Arima estimators for Python, 2017–. URL <http://www.alkaline-ml.com/pmdarima>. [Online; accessed <today>].
- [111] Luca Soldaini, Rodney Kinney, Akshita Bhagia, Dustin Schwenk, David Atkinson, Russell Authur, Ben Bogin, Khyathi Chandu, Jennifer Dumas, Yanai Elazar, Valentin Hofmann, Ananya Harsh Jha, Sachin Kumar, Li Lucy, Xinxu Lyu, Ian Magnusson, Jacob Morrison, Niklas Muennighoff, Aakanksha Naik, Crystal Nam, Matthew E. Peters, Abhilasha Ravichander, Kyle Richardson, Zejiang Shen, Emma Strubell, Nishant Subramani, Oyvind Tafjord, Evan Pete Walsh, Hannaneh Hajishirzi, Noah A. Smith, Luke Zettlemoyer, Iz Beltagy, Dirk Groeneveld, Jesse Dodge, and Kyle Lo. Dolma: An Open Corpus of Three Trillion Tokens for Language Model Pretraining Research. *Allen Institute for AI, Tech. Rep*, 2023.
- [112] SpawningAI, 2024. URL <https://haveibeentrained.com/>.

- [113] Yang Sun, Ziming Zhuang, and C Lee Giles. A large-scale study of robots. txt. In *Proceedings of the 16th international conference on World Wide Web*, pages 1123–1124, 2007.
- [114] Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Stanford alpaca: An instruction-following llama model. https://github.com/tatsu-lab/stanford_alpaca, 2023.
- [115] Gemini Team, Rohan Anil, Sebastian Borgeaud, Yonghui Wu, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, et al. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.
- [116] Shubham Toshniwal, Ivan Moshkov, Sean Narenthiran, Daria Gitman, Fei Jia, and Igor Gitman. OpenMathInstruct-1: A 1.8 Million Math Instruction Tuning Dataset, February 2024. URL <http://arxiv.org/abs/2402.10176>. arXiv:2402.10176 [cs].
- [117] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.
- [118] Ahmet Üstün, Viraat Aryabumi, Zheng-Xin Yong, Wei-Yin Ko, Daniel D’souza, Gbemileke Onilude, Neel Bhandari, Shivalika Singh, Hui-Lee Ooi, Amr Kayid, et al. Aya model: An instruction finetuned open-access multilingual language model. *arXiv preprint arXiv:2402.07827*, 2024.
- [119] Bertie Vidgen, Adarsh Agrawal, Ahmed M. Ahmed, Victor Akinwande, Namir Al-Nuaimi, Najla Alfaraj, Elie Alhajjar, Lora Aroyo, Trupti Bavalatti, Max Bartolo, Borhane Blili-Hamelin, Kurt Bollacker, Rishi Bomassani, Marisa Ferrara Boston, Siméon Campos, Kal Chakra, Canyu Chen, Cody Coleman, Zacharie Delpierre Coudert, Leon Derczynski, Debojyoti Dutta, Ian Eisenberg, James Ezick, Heather Frase, Brian Fuller, Ram Gandikota, Agasthya Gangavarapu, Ananya Gangavarapu, James Gealy, Rajat Ghosh, James Goel, Usman Gohar, Sujata Goswami, Scott A. Hale, Wiebke Hutiri, Joseph Marvin Imperial, Surgan Jandial, Nick Judd, Felix Juefei-Xu, Foutse Khomh, Bhavya Kailkhura, Hannah Rose Kirk, Kevin Klyman, Chris Knotz, Michael Kuchnik, Shachi H. Kumar, Srijan Kumar, Chris Lengerich, Bo Li, Zeyi Liao, Eileen Peters Long, Victor Lu, Sarah Luger, Yifan Mai, Priyanka Mary Mammen, Kelvin Manyeki, Sean McGregor, Virendra Mehta, Shafee Mohammed, Emanuel Moss, Lama Nachman, Dinesh Jinenhally Naganna, Amin Nikanjam, Besmira Nushi, Luis Oala, Iftach Orr, Alicia Parrish, Cigdem Patlak, William Pietri, Forough Poursabzi-Sangdeh, Eleonora Presani, Fabrizio Puletti, Paul Röttger, Saurav Sahay, Tim Santos, Nino Scherrer, Alice Schoenauer Sebag, Patrick Schramowski, Abolfazl Shahbazi, Vin Sharma, Xudong Shen, Vamsi Sistla, Leonard Tang, Davide Testuggine, Vithursan Thangarasa, Elizabeth Anne Watkins, Rebecca Weiss, Chris Welty, Tyler Wilbers, Adina Williams, Carole-Jean Wu, Poonam Yadav, Xianjun Yang, Yi Zeng, Wenhui Zhang, Fedor Zhdanov, Jiacheng Zhu, Percy Liang, Peter Mattson, and Joaquin Vanschoren. Introducing v0.5 of the ai safety benchmark from mlcommons, 2024.
- [120] Pablo Villalobos, Anson Ho, Jaime Sevilla, Tamay Besiroglu, Lennart Heim, and Marius Hobbhahn. Position: Will we run out of data? limits of llm scaling based on human-generated data. In *Forty-first International Conference on Machine Learning*.
- [121] Vijay Viswanathan, Luyu Gao, Tongshuang Wu, Pengfei Liu, and Graham Neubig. Datafinder: Scientific dataset recommendation from natural language descriptions. *arXiv preprint arXiv:2305.16636*, 2023.
- [122] Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. Self-instruct: Aligning language model with self generated instructions, 2022. URL <https://arxiv.org/abs/2212.10560>.
- [123] Yizhong Wang, Swaroop Mishra, Pegah Alipoormolabashi, Yeganeh Kordi, Amirreza Mirzaei, Anjana Arunkumar, Arjun Ashok, Arut Selvan Dhanasekaran, Atharva Naik, David Stap, et al. Benchmarking generalization via in-context instructions on 1,600+ language tasks. *arXiv preprint arXiv:2204.07705*, 2022. URL <https://arxiv.org/abs/2204.07705>.

- [124] Jason Wei, Maarten Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. Finetuned language models are zero-shot learners. In *International Conference on Learning Representations*, 2021.
- [125] Laura Weidinger, John Mellor, Maribeth Rauh, Conor Griffin, Jonathan Uesato, Po-Sen Huang, Myra Cheng, Mia Glaese, Borja Balle, Atoosa Kasirzadeh, Zac Kenton, Sasha Brown, Will Hawkins, Tom Stepleton, Courtney Biles, Abeba Birhane, Julia Haas, Laura Rimell, Lisa Anne Hendricks, William Isaac, Sean Legassick, Geoffrey Irving, and Iason Gabriel. Ethical and social risks of harm from language models, 2021.
- [126] Johannes Welbl, Amelia Glaese, Jonathan Uesato, Sumanth Dathathri, John Mellor, Lisa Anne Hendricks, Kirsty Anderson, Pushmeet Kohli, Ben Coppin, and Po-Sen Huang. Challenges in detoxifying language models. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 2447–2469, 2021.
- [127] Ben Welsh. Who blocks openAI, google AI and Common Crawl? Technical report, homepages.news, June 5 2024. URL <https://palewi.re/docs/news-homepages/openai-gptbot-robotstxt.html>.
- [128] Writers Guild of America. WGA negotiations—status as of may 1, 2023, May 2023. URL https://www.wga.org/uploadedfiles/members/member_info/contract-2023/WGA_proposals.pdf.
- [129] Albert Xu, Eshaan Pathak, Eric Wallace, Suchin Gururangan, Maarten Sap, and Dan Klein. Detoxifying language models risks marginalizing minority voices. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2390–2397, 2021.
- [130] Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. mt5: A massively multilingual pre-trained text-to-text transformer, 2021.
- [131] Wenting Zhao, Xiang Ren, Jack Hessel, Claire Cardie, Yejin Choi, and Yuntian Deng. Wildchat: 1m chatgpt interaction logs in the wild. *arXiv preprint arXiv:2405.01470*, 2024.
- [132] Wanrong Zhu, Jack Hessel, Anas Awadalla, Samir Yitzhak Gadre, Jesse Dodge, Alex Fang, Youngjae Yu, Ludwig Schmidt, William Yang Wang, and Yejin Choi. Multimodal c4: An open, billion-scale corpus of images interleaved with text. *Advances in Neural Information Processing Systems*, 36, 2024.

Part I

Appendix

Table of Contents

A	Human Annotation Methodology Details	26
A.1	Details on Crowdworkers	26
A.2	Human Annotation Guidelines	26
B	Automatic Annotation Methodology Details	30
B.1	Robots.txt Taxonomy	30
B.2	Robots.txt Agents	31
B.3	Terms of Service Taxonomy	34
B.4	Prompt engineering	35
B.5	Annotating and scoring	38
B.6	WildChat Annotation	38
C	Forecasting Method	39
D	Extended Related Work	40

A Human Annotation Methodology Details

A.1 Details on Crowdworkers

Many of the annotations we rely on were provided by a group of crowdworkers. We engaged in an extensive and iterative training process to ensure that each worker was comfortable with the task and to guarantee consistency across them. We employed a total of 14 crowd source workers from six countries: Pakistan (8), Bangladesh (2), Vietnam (1), Philippines (1), USA (1), and Germany (1). We paid a total of \$6,972 to annotate 14,228 rows of data, with a mean of \$498 per worker, and approximately \$25-\$30 per hour. Our data annotation process involved daily check-ins, review of every 100-200 annotations, and feedback to ensure quality and consistency.

A.2 Human Annotation Guidelines

This section lays out the annotation guidelines used for our pretraining data collection, both for annotations carried out by authors (in Appendix A.2.1) and for those carried out by crowdworkers (in Appendix A.2.2).

A.2.1 Web Source Annotations (Authors)

Some websites, that were crawled in earlier years, have since been shutdown and no longer work. We record this and exclude them from our analysis.

Instructions for Website Issue

Some websites have been sold or shut down since the scrape. In these cases, check the box for website issues and don't continue.

For **User Content**, we aimed to differentiate websites with significant portions of unmoderated user content from those that are primarily comprised of content curated by the website administrators. Over the course of annotating we found that the “Yes (strong moderation)” annotation label was often used for news and encyclopedic sources which did accept some (usually moderated) user content, but were most similar to websites without any user content (“No” label). In contrast, the “Yes (weak moderation)” websites tended to include websites with significant degrees of raw user-generated content, such as from social media websites, forums, or review sites. As such, in the paper we group “No” and “Yes (strong moderation)” as not accepting significant user content, whereas “Yes (weak moderation)” does.

Instructions for User Content

Is there a non-negligible amount of content on the website that comes from third-party users, instead of the website host? Options:

Yes (strong moderation) – there is content from third-parties, but it is strongly moderated/curated, either by the host, or by a review system. E.g. Wikipedia, academic journal websites, or NYTimes, since it has a comments section, but it is carefully moderated.

Yes (weak moderation) – there is content from third-parties, that is only weakly moderated. E.g. reddit, stackoverflow, youtube, ecommerce comment/review websites, or very low-quality news sites that have unrefined op-eds and comments sections that appear completely unmoderated.

No – all (or the vast majority) of website content is provided or well curated by the host. E.g. company websites, patent records, government databases.

Instructions for “Website Description”

Write a short phrase that describes the purpose and domain of the website. The goal is to help us cluster and categorize websites by their content domain (the type(s) of content/topics they contain e.g. legal, biomedical, books) as well as the type/purpose of service the website is providing (e.g. news, social media, exams, ecommerce, etc). While there is some overlap, the first helps to distinguish where the training data might be useful, whereas the second determines the purpose of the website, for copyright infringement questions. Make sure the short phrase captures all major elements of a website’s purpose and content, as there can be multiple, and is as precise as possible. Here are some examples:

- “Lifestyle blog about travel”
- “E-commerce for appliances and product reviews”
- “Video game news, forums, art, and retail”
- “Government database of parliamentary recordings and legislative documents”
- “Informal blog site for baking recipes”

The content domain and type of service categories should be easily inferred from the website description.

The purpose of the **Type of Service** annotations is to understand the function of websites, and how they might be related to the function of real user conversations with general-purpose models trained on this web data. This is distinct from the text pretraining domain analysis conducted in prior work [67], as the annotations are not about the relevant source or topic (e.g. legal, biomedical, social, etc), but the functional purpose of the website for users. The taxonomy was developed after authors reviewed hundreds of websites themselves, compared categories, and clustered common functions.

Instructions for “Type of Service”

What is the purpose or service of the website? This is relevant to US copyright infringement analysis into the “effect of the use on the potential market for or value of the work”. i.e. will copying this data jeopardize the website’s business.

We have listed out some common types of service below. Using the “website description” you wrote, pick the best fitting type of service, or if none of these fit exactly, write your own (Other) e.g. “Video Game Blogging”. We will later create more clusters based off these suggestions. Here are the starter options:

- Ecommerce (e.g. Amazon, gaming, etc)
- Periodicals (News, magazine) (e.g. NYTimes, LATimes, Forbes, etc)
- Social Media (e.g. Twitter, Facebook, Reddit, etc)
- Encyclopedia/Database (e.g. Wikipedia, IMDB, etc)
- Academic (e.g. pubmed, nature, journals.plos.org, etc)
- Government (e.g. sec.gov, justia.com, parliament.uk, etc)
- Company/Organization/Personal website (e.g., www.ge.com)
- Blog websites (e.g., www.medium.com)
- Other: In a second stage, we will expand the list above

The purpose of annotating for **Sensitive Content** is to understand the distribution of content that practitioners may wish to exclude from their corpus for reasons of toxicity, bias, nudity, hate speech, or other offensive topics.

Instructions for “Illegal/Sensitive/NSFW Content”

Does the website contain a non-negligible amount of pornography, drug content, violence, promotion of illegal activities, or hate speech. This should only be yes, if it’s more than a minimal amount, for example while there are some sensitive things in Wikipedia, the answer is no; whereas the answer is yes for Reddit.

Options:

- Pornography: y/n
- Drug content : y/n
- Violence: y/n
- Promotion of illegal activities: y/n
- Hate speech: y/n

A.2.2 Pretraining Datasets (Crowdworker)**General instructions**

Please read the below instructions carefully, as accuracy is crucial for our analysis, and the choices are sometimes nuanced. Turn off your ad blockers or browser extensions for this task. Inspect each website thoroughly, navigating through many pages. This is essential for finding ads, paywalls, videos, and audio content that may not be on the main page of the website.

Instructions for Website Issue

Some websites have been sold or shut down since the scrape. In these cases, check the box for website issues and don’t continue.

Instructions to Annotate “Terms of Service Link(s)”

For each website domain, we want to find all links that are related to the domain’s terms, including around general use, data, content, privacy, etc.. This will allow us to later identify all legal terms associated with using the website, its content or data. It is critically important that main terms pages are not missed, so we will randomly review some to make sure we are getting a comprehensive list. The most important policies for our work are copyright-related policies.

Here are 3 examples of the terms found for a website:

imdb.com Links:

- <https://www.imdb.com/conditions>
- <https://www.imdb.com/licensing/subservicetc/>
- <https://www.imdb.com/privacy>

plos.org Links:

- <https://plos.org/terms-of-service/>
- <https://plos.org/text-and-data-mining/>
- <https://plos.org/terms-of-use/>
- <https://plos.org/privacy-policy/>

goodreads.com Links:

- <https://www.goodreads.com/about/terms>

- <https://www.goodreads.com/about/privacy>
- <https://www.goodreads.com/api/terms>

Suggested procedure to find the links:

1. Many websites have links to their terms, privacy, or content policies at the bottom of their main page. Scroll to the very bottom and see if any exist.
2. Sometimes not all relevant terms will appear there. We recommend you also search for:
 - (a) "<website name> terms of use"
 - (b) "<website name> copyright policy"
 - (c) "<website name> content policy"
 - (d) "<website name> privacy policy"
 - (e) "<website name> developer policy"
 - (f) "<website name> data mining"
3. ONLY include pages you find that appear to be relevant to the legal conditions/terms of using the website or data in some capacity. Very rarely, websites may have hundreds of these pages. In those cases, feel free to just include the top few main ones.

Instructions to Annotate "Paywall"

Does the website paywall any of its content? We hope to see what websites require some sort of paid subscription or sign up (even if it offers free starter trials) in order to view their content.

Output options:

- No – we did not find any paywall for any of the content. Examples: Wikipedia, Reddit, Youtube.
- Some – a fair amount of content can be viewed without any issue (e.g. multiple news articles), but after some reading/searching there appears to be a paywall on the rest of the content. Examples: <https://www.popularmechanics.com/>.
- All – every main page of content is paywalled. This means that no single webpage or article of content can be fully read without subscribing in some way. Examples: NYTimes, Wall Street Journal.

Suggested procedure to determine if there is a paywall:

1. Make sure you are not logged into any accounts on your browser, especially ones applicable to the website.
2. Explore the website content and see if a paywall request appears.
3. Double check by searching: "does <website name> have a paywall?"

Instructions to Annotate "Content Modalities"

What modalities of content appear on the website? A modality is the actual content of the website, for which we have four options: text, images, videos, audio. These modalities can appear at different levels, depending on the website. Do not count the content in automatic embedded advertisements towards this.

- For text, there must be at least one paragraph or multiple sentences/captions on the website.
- For images, there must be at least one or more distinct images embedded on the page. Visual styling that is part of the website design does not count.

- For videos, there must be at least one embedded video – often they are not on the main page, so you may need to look.

Output options:

- Text
- Images
- Videos
- Audio

Levels of modality appearing on the website:

- No – Content of this type is not on the website.
- Yes – There is content of this type, even if it's not common, like images on Wikipedia. Do not count visual styling/illustrations that are just part of the natural website design – the presence of image(s) should be notable. Do not count the content in ads.

Suggested procedure:

1. Try to find representative webpages on the website; if there is a search bar try to search for some generic terms
2. Explore enough pages to be able to make a confident assessment of how much of each modality is present.

Instructions to Annotate “Advertisements”

Do third-party advertisements appear on the website? Many websites host advertisements to make money. They may appear on the top, bottom, or side bars of just some pages, so look thoroughly. Self promotion does not count. These may not be on the main website page. Remember to turn off your ad blockers / extensions.

Output options:

- No – No automatic advertisements are integrated into the pages.
- Yes – Some automatic advertisements do appear on the pages.

Suggested procedure:

1. Search through the website and its content, looking for advertisements.

B Automatic Annotation Methodology Details

B.1 Robots.txt Taxonomy

Using the Wayback Machine, we snapshoted websites' robots.txt and terms of service at monthly intervals from January 2016 to April 2024. For each web domain, we identified scraping constraints for the wildcard ("*") as well as the user agents of the six organizations commonly known to train AI models (Google, OpenAI, Anthropic, Cohere, Meta, Common Crawl). See Table 5 for details on each of these organizations.

We then categorized the robots.txt restrictions for every web domain across an ascending spectrum of restrictions. These were:

1. No robots.txt present.
2. No restrictions or sitemap: a simple directive allowing unrestricted access to crawlers, e.g.

```
User-agent: *
Disallow:
```

ORGANIZATION	USER AGENT	DETAILS	DOCS	PURPOSE
OpenAI	GPTBot	OpenAI’s official user-agent for crawling and collecting training data from the web.	●	Training
	ChatGPT-User	OpenAI’s official user-agent for live user queries that trigger browsing plugins. According to OpenAI’s documentation, their current opt-out implementation treats both user agents the same.	●	Retrieval
Google	Google-Extended	Google’s official user-agent for “Gemini Apps, Vertex AI generative APIs, and future generations of models.”	●	Training
Google Search	Googlebot	Google’s official user-agents for general web crawling, related to their search engine.	●	Web Search
Common Crawl	CCBot	Common Crawl’s user-agent for maintaining open access archives of the web, particularly for research.	●	Archive, research
Anthropic	ClaudeBot	Anthropic’s official user-agent for crawling and collecting training data from the web. Their policy states that their opt-outs respect this agent as well as Common Crawl’s CCBot.	●	Training, retrieval
False Anthropic	anthropic-ai	An unofficial but widely adopted user-agent, presumably to disallow any Anthropic data crawling and collection.	○	Training
	Claude-Web	An unofficial but widely adopted user-agent, presumably for live queries in Claude which trigger browsing.	○	Retrieval
Meta	FacebookBot	Meta’s official user-agent for crawling and collecting training data from the web	●	Training, retrieval
Cohere	cohere-ai	An unofficial but widely adopted user-agent, presumably to disallow any Cohere data crawling and collection.	○	Training, retrieval
Internet Archive	ia_archiver	The official user-agent that supports the Wayback Machine open web archive. The Internet Archive may ignore this user-agent		Training, retrieval
All Agents	All	Notation for our aggregation of robots.txt policies towards all agents. This is used to track if a website is fully lenient or restrictive to all user agents.		

Table 5: The **list of organizations we trace, and their associated web crawler user-agents**. We provide basic details on these crawlers, and links to their documentation where provided. We list the stated purpose of crawlers, including for Training AI models, for Retrieving relevant information for a general-purpose AI system, for conducting Web Search, or for creating an Archive or the web.

- Only a sitemap is present: a list of all URLs on the website along with metadata, helping search engines index the site more thoroughly and efficiently.
- Only a sitemap and crawl delay are present: Limit the frequency of crawler requests to the server, often included to prevent a site from being overloaded with too many requests- this affects the crawling rate but not accessibility.
- Search and query restrictions apply: disallow directives that match patterns associated with search result pages or URLs containing query parameters, e.g.

Disallow: /search
Disallow: /*?*

- Crawling specific directories is prohibited: many sites have confidential or private directories that should not be crawled
- Agent is fully disallowed from crawling any parts of the website

B.2 Robots.txt Agents

In Table 5 we detail the AI-related organizations, their agents and their accompanying documentation, where present. In Table 6 we show the statistics for agents across all the robots.txt we analyzed. Lastly, Figure 5 describes the observed company-to-company conditional probabilities for robots.txt restrictions, to understand how agent restrictions are prioritized among many web administrators.

AGENT NAME	# OBSERVED	ALL DISALLOWED		SOME DISALLOWED		NONE DISALLOWED	
		Count	%	Count	%	Count	%
All Agents	269,212	1175	0.44%	198642	73.79%	69395	25.78%
*	226,903	2935	1.29%	183364	80.81%	40604	17.89%
Mediapartners-Google	20,848	749	3.59%	3710	17.80%	16389	78.61%
Googlebot	12,831	44	0.34%	9544	74.38%	3243	25.27%
MJ12bot	10,556	5962	56.48%	319	3.02%	4275	40.50%
Twitterbot	10,385	29	0.28%	3413	32.86%	6943	66.86%
Slurp	10,070	507	5.03%	4364	43.34%	5199	51.63%
AhrefsBot	9,824	5506	56.05%	1516	15.43%	2802	28.52%
IRLbot	9,142	134	1.47%	157	1.72%	8851	96.82%
Yandex	8,948	2901	32.42%	1623	18.14%	4424	49.44%
bingbot	8,077	195	2.41%	3079	38.12%	4803	59.47%
Googlebot-News	7,958	82	1.03%	7548	94.85%	328	4.12%
Baiduspider	7,789	3476	44.63%	1933	24.82%	2380	30.56%
msnbot	6,784	261	3.85%	2737	40.34%	3786	55.81%
008	5,661	5360	94.68%	108	1.91%	193	3.41%
ia_archiver	5,604	2768	49.39%	1822	32.51%	1014	18.09%
SemrushBot	5,418	3865	71.34%	84	1.55%	1469	27.11%
Googlebot-Image	5,082	728	14.33%	1842	36.25%	2512	49.43%
Nutch	5,011	4446	88.72%	0	0.00%	565	11.28%
ccBot	5,005	3227	64.48%	1328	26.53%	450	8.99%
facebookexternalhit	2,286	31	1.36%	323	14.13%	1932	84.51%
NPBot	2,261	2259	99.91%	0	0.00%	2	0.09%
wget	2,234	2234	100.00%	0	0.00%	0	0.00%
rogerbot	2,147	736	34.28%	703	32.74%	708	32.98%
libwww	2,138	2046	95.70%	0	0.00%	92	4.30%
SemrushBot-SA	2,108	1428	67.74%	10	0.47%	670	31.78%
sitecheck.internetseer.com	2,064	1972	95.54%	0	0.00%	92	4.46%
Download Ninja	2,060	1971	95.68%	0	0.00%	89	4.32%
ZyBORG	2,059	1941	94.27%	0	0.00%	118	5.73%
Zealbot	2,058	1969	95.68%	0	0.00%	89	4.32%
Xenu	2,048	1959	95.65%	0	0.00%	89	4.35%
Facebook	2,020	0	0.00%	936	46.34%	1084	53.66%
linko	1,991	1902	95.53%	0	0.00%	89	4.47%
ChatGPT-User	895	750	83.80%	118	13.18%	27	3.02%
anthropic-ai	260	229	88.08%	1	0.38%	30	11.54%
cohere-ai	185	180	97.30%	1	0.54%	4	2.16%
Google-Extended	871	836	95.98%	4	0.46%	31	3.56%
Amazonbot	546	358	65.57%	109	19.96%	79	14.47%
FacebookBot	235	220	93.62%	2	0.85%	13	5.53%
ClaudeBot	45	40	88.89%	0	0.00%	5	11.11%
Claude-Web	89	82	92.13%	0	0.00%	7	7.87%

Table 6: **A breakdown of the top 60 web crawler agents mentioned across the robots.txt for all 14k web domains we analyzed.** Those highlighted in gray are related to the organizations in our analysis (see a detailed summary of them in Table 5). We compute the number of times each agent is observed, as well as the proportion of times a robots.txt restricts it either fully, partially, or not at all. Lastly, the *ALL AGENTS* row refers to the number of total observations, as well as the tally of instances where a robots.txt fully restricts every agent, partially restricts every agent, or restricts no agents at all.

Organization A	Google	--	98.2	81.2	51.5	81.2	44.8	23.6	13.9	60
	OpenAI	38.4	--	54.3	20.1	54.3	17.3	9.7	5.5	24.4
	Anthr	56.5	96.6	--	35.4	100	30.8	17.7	9.7	43.5
	Cohere	98.8	98.8	97.7	--	97.7	72.1	43	26.7	98.8
	CC	56.5	96.6	100	35.4	--	30.8	17.7	9.7	43.5
	Meta	98.7	97.3	97.3	82.7	97.3	--	44	30.7	92
	IA	60	63.1	64.6	56.9	64.6	50.8	--	33.8	58.5
	Search	100	100	100	100	100	100	95.7	--	100
	F. Anthr	94.3	98.1	98.1	81	98.1	65.7	36.2	21.9	--
		Google	OpenAI	Anthr	Cohere	CC	Meta	IA	Search	F. Anthr
		Organization B								

Figure 5: We compute the percentage that organization B is restricted by a web domain’s robots.txt, given organization A’s agents have been restricted. The organizations include AI companies (OpenAI, Google, Anthropic, Anthropic’s False agents, Cohere, Meta), non-profit web archives (Common Crawl, the Internet Archive), and then a general web search agent (Google Search). **We find OpenAI web agents are nearly always disallowed if any AI organizations are disallowed, but the reciprocal is less frequent.**

B.3 Terms of Service Taxonomy

After a close reading of hundreds of ToS pages, the paper authors noted three distinct indicators for metered data usage: competing service clauses, license type, and in some cases, explicit crawling and AI policies. To identify clauses relating to these topics at scale, we utilized the *GPT-4o* model with custom prompting, sending requests through the OpenAI API. This section will detail the taxonomies we developed for categorizing the ToS pages, as well as the prompt engineering and annotation methodology behind automating the process.

Our taxonomies were designed with the variant nature of legal documents in mind. While we initially tried to categorize ToS pages as either, *TRUE or FALSE*, for containing a policy relating to the taxonomy at hand, we quickly found examples that broke this mold. In order to account for nuanced clauses, our final taxonomies consist of multiple categories in ascending order of restrictiveness. The order and definitions were refined as we came across enough additional examples to demand their own category. For our temporal analysis, this structure allows us to better express the tightening restrictions on web data over time.

See the finalized taxonomies below:

Competing services taxonomy

1. Non-Compete

- **Definition:** the ToS includes a clause that specifically prohibits the use of its content, data, or materials for competing services. This category relates to commercialization or other commercial uses of the site's content and does not include clauses that solely restrict scraping, storing data, or distributing data.

2. No Re-Distribution

- **Definition:** the ToS prohibits the distribution or reselling of content. This includes clauses restricting selling content or creating and distributing datasets. Does not include general commercial usage restrictions unless they directly pertain to redistribution.

3. Non-Compete/No Re-Distribution

- **Definition:** both of the above categories are present in the given ToS.

4. No restrictions

- **Definition:** the ToS does not include clauses that restrict competing services or re-distribution.

License type taxonomy

1. Personal/Noncommercial/Research Only

- **Definition:** the ToS explicitly states that the content is available for personal, noncommercial, or research purposes only. Commercial use of the content is strictly prohibited.

2. Conditional Commercial Access

- **Definition:** the ToS specifies that only certain parts of the website are open-access or commercially viable, while other parts are restricted. Commercial use is allowed under specific conditions (for example: permission must be granted for commercial purposes, Commercial use is allowed but third-party reposting is prohibited, non-compete clauses restrict using the content in ways that compete with the service provider).

3. Open or Unrestricted Commercial Use

- **Definition:** the ToS does not explicitly disallow commercial use, indicating that the website content is open for use or considered public information. This category includes terms that allow commercial use without specific restrictions or conditions (for example: creative Commons licenses permit commercial use).

Crawling and AI taxonomy

1. Prohibits crawling and AI unconditionally

- **Definition:** the ToS explicitly states that both crawling and the use of data for AI or ML are prohibited without exception.

2. Prohibits crawling unconditionally, but no mention of AI

- **Definition:** the ToS explicitly states that crawling and associated activities (such as to copy, use, or distribute and other automated means) are prohibited with no exceptions or conditions. Does not mention any restrictions to AI or ML uses.

3. Prohibits AI unconditionally, but not crawling

- **Definition:** the ToS explicitly prohibits AI or ML usage without exception but doesn't mention a policy on crawling.

4. Only prohibits crawling and AI under certain conditions, or to certain parts of the website

- **Definition:** the ToS provides conditions under which crawling and the use of data for AI or ML are restricted or permitted. This category includes clauses containing "With the exception of material marked 'Open Access'..."

5. No restrictions on crawling or AI

- **Definition:** the ToS does not contain any clauses or mentions regarding the prohibition or restriction of crawling or the use of data for AI or ML. Both activities are implicitly allowed.

B.4 Prompt engineering

For each indicator—competing services, license type, and crawling and AI policies—we developed a unique prompt directing *GPT-4o* to produce a verdict and supply directly quoted evidence. Based on our taxonomy, the verdict corresponds to the best fitting category and the evidence is each instance of text contributing to said verdict for a given ToS.

Our prompts were refined through an iterative process, comparing each output with a “gold answer” annotation set to uncover shortcomings and improve (see section Appendix B.5 for details on the annotation process). For each version of our prompt, we analyzed false negatives (clauses that the model failed to recognize) to widen our scope and improve the specificity of our prompt, and analyzed false positives (clauses that the model recognized incorrectly) to narrow our scope. The prompts were modified using this methodology until performing with an average accuracy of 85% or higher against our annotation set [table 7].

See the finalized prompts below:

Competing services prompt

Your task is to analyze the provided Terms of Service (ToS) document to determine if there are specific restrictions related to competing services or the redistribution of content. You will categorize each ToS based on the following taxonomy:

1. Non-Compete:

Definition: the ToS includes a clause that specifically prohibits using or sharing its content or data to create competing services. This does not include clauses solely restricting scraping, storing data, or non-commercial use.

2. No Re-Distribution:

Definition: the ToS prohibits the distribution or reselling of content. This does not include general commercial usage restrictions unless they directly pertain to redistribution.

3. Non-Compete and No Re-Distribution:

Definition: both of the above categories are present in the given ToS.

4. No restrictions:

Definition: the ToS does not include clauses that restrict competing services or re-distribution.

Return ONLY a dictionary with your verdict (a category number from the taxonomy) and the corresponding evidence. Evidence does not need to be continuous, you should include all mentions of a non-compete or no-redistribution. Do NOT include any additional text in your response do NOT wrap your response with “`json`. Format the response exactly like these examples:

- {"verdict":1, "evidence": "Exact text from ToS detailing Non-Compete."}
- {"verdict": 2, "evidence": "Exact text from ToS detailing No Re-Distribution."}
- {"verdict": 3, "evidence": "Exact text from ToS detailing Non-Compete; Exact text from T
- {"verdict": 4, "evidence": "N/A"}

This format will assist in a comprehensive review of the ToS and allow for accurate categorization based on the specific language used in the document.

License type prompt

Your task is to analyze the provided Terms of Service (ToS) document to determine the license type, categorizing it based on the following taxonomy. Use direct quotes from the ToS as evidence to support your categorization. Focus on the explicit language used regarding permissions and restrictions for personal, noncommercial, or commercial use.

1. Personal/Noncommercial/Research Only:

Definition: the ToS restricts use to personal, noncommercial, or research purposes without any exceptions allowing commercial use.

2. Conditional Commercial Access:

Definition: the ToS contains restrictions on general use but specifies conditions under which commercial use is permitted. This includes needing permissions, complying with certain conditions, or paying fees for commercial use. Look for terms like 'requires written permission,' 'subject to approval,' or 'commercial use permitted under conditions.'

3. Open or Unrestricted Commercial Use:

Definition: the ToS permits commercial use broadly, without requiring additional permissions or adhering to specific conditions. This includes terms that explicitly allow or imply commercial use is permitted across all contents.

Return ONLY a dictionary with your verdict (a category number from the taxonomy) and the corresponding evidence. Evidence does not need to be continuous, you should include all mentions of a license type. Do NOT include any additional text in your response do NOT wrap your response with “`json`. Format the response exactly like these examples:

```
- {"verdict": 1, "evidence": "Exact text from ToS detailing
Personal/Noncommercial/Research Only license."}
- {"verdict": 2, "evidence": "Exact text from ToS detailing
Conditional Commercial Access license."}
- {"verdict": 3, "evidence": "Exact text from ToS detailing
Open or Unrestricted Commercial Use license or 'N/A' if there is no
explicit mention."}
```

This will assist in a comprehensive review of the ToS and allow for accurate categorization based on the specific language used in the document. Ensure that your assessment is detailed and directly references the ToS document.

Crawling and AI prompt

Your job is to analyze the Terms of Service (ToS) document that I will provide you to determine the policy on web scraping and artificial intelligence (AI) or machine learning (ML). You will categorize each ToS document based on the following taxonomy:

1. Prohibits scraping and AI unconditionally:
Definition: the ToS explicitly states that both scraping and the use of data for AI or ML are prohibited without exception.
2. Prohibits scraping unconditionally, but no mention of AI:
Definition: the ToS explicitly states that scraping and associated activities (such as to copy, use, or distribute and other automated means) are prohibited with no exceptions or conditions. Does not mention any restrictions to AI or ML uses.
3. Prohibits AI unconditionally, but not scraping:
Definition: the ToS explicitly prohibits AI or ML usage without exception but doesn't mention a policy on scraping.
4. Only restricts or permits scraping and AI under certain conditions, or to certain parts of the website:
Definition: the ToS provides conditions under which scraping and the use of data for AI or ML are restricted or permitted. This category includes clauses containing "With the exception of material marked 'Open Access'..."
5. No restrictions on scraping or AI:
Definition: the ToS does not contain any clauses or mentions regarding the prohibition or restriction of scraping or the use of data for AI or ML. Both activities are implicitly allowed.

Return ONLY a dictionary with your verdict (a category number from the taxonomy) and the corresponding evidence. Evidence does not need to be continuous, you should include all mentions of a scraping, AI or ML policy. Do NOT include any additional text in your response do NOT wrap your response with "json". Format the response exactly like these examples:

```
- {"verdict": 1, "evidence": "Exact text from ToS detailing explicit
scraping AND AI prohibition."}
- {"verdict": 2, "evidence": "Exact text from ToS detailing explicit
scraping prohibition."}
- {"verdict": 3, "evidence": "Exact text from ToS detailing explicit
AI prohibition"}
- {"verdict": 4, "evidence": "Exact text from ToS detailing the
conditions restricting scraping and or AI."}
- {"verdict": 5, "evidence": "N/A"}
```

This will assist in a comprehensive review of the ToS and allow for accurate categorization based on the specific language used in the document. Ensure that your assessment is detailed and directly references the ToS document.

B.5 Annotating and scoring

To empirically measure the ability of *GPT-4o* to follow our prompts and taxonomies, we manually audited a sample of 100 URLs for each indicator in question: competing services, license type, and crawling and AI. The URLs were randomly sampled from the 10k Random Subset and each ToS link was carefully reviewed for clauses relating to our taxonomies. We found that most of the relevant clauses were located in the Terms of Service (rather than a Privacy Policy or Copyright Notices page), and we saved all verdicts and corresponding evidence to our annotation dataset for comparison with the results from *GPT-4o*. With this “gold answer” annotation set, we calculated the micro-average precision/recall of each prompt to ensure all class labels from our taxonomy were weighted relative to their size, and the results are reported in Table 7.

Scoring metric	Competing Services	License Type	Crawling and AI Policy
Precision/Recall	0.92	0.85	0.89

Table 7: Precision and Recall Values for each prompt against the annotation set. Each score is a micro-average of all the individual class scores.

B.6 WildChat Annotation

In Figure 4, we distinguish a wide range of different types of service related user prompts that serve various purposes:

- **Creative Composition:** These requests involve role-playing, fictional story writing, or continuing existing narratives, allowing users to explore their imaginative capabilities.
- **Academic Composition:** These focus on non-fiction essay writing, continuation, or editing, aiding in scholarly and professional writing.
- **Coding composition:** These requests ask for assistance fixing, debugging, or general coding help, supporting developers.
- **Brainstorming, planning, or ideation:** These requests ask the system to help brainstorm, generate ideas, or plan out a project.
- **Explanation & Reasoning:** These prompts ask the system to explain or reason through a question, help with puzzles, math problems or other problem-solving tasks.
- **Self-help:** These requests seek advice or support for personal issues, providing a platform for guidance.
- **Sexual content:** These requests are related to sexually explicit content requests—such as sexual role-play or fiction.
- **News:** These prompts request information related to news, recent events, are generally current affairs that may be applicable to news websites.
- **E-commerce Information:** These requests inquire about products and purchasing information.
- **Translation:** These requests ask for aid in translating text from one language to another, assisting users in overcoming language barriers.
- **Organization Information:** These requests ask for information specific to organizations, companies, or individuals, which may pertain to organization/personal websites.

To assess the accuracy of using GPT-4o's service type predictions, we conducted a manual evaluation of 50 randomly sampled WildChat prompts. Each prompt's predicted type of service was reviewed for correctness, resulting in an error rate of 18%. The system prompt for GPT-4o is shown below:

System Prompt Used for WildChat Analysis

You are a categorization assistant. I will provide you with a user prompt and a response. Your task is to classify the prompt into one or more of the following '*Type of Service*' categories.

Categories:

- General informational requests
- Creative composition
- Academic composition
- Coding composition
- Brainstorming, planning, or ideation
- Asking for an explanation, reasoning, or help solving a puzzle or math problem
- Translation
- Self-help, advice seeking, or self-harm
- Sexual or sexual roleplay content requests
- News or recent events informational requests
- E-commerce or information requests about products and purchasing
- Information requests specifically about organizations, companies, or persons
- Other (choose this only as a last resort)

Descriptions (do not include these in the labels):

- Creative composition: such as role-playing, fictional story writing, or continuation
- Academic composition: such as non-fiction essay writing, continuation, or editing
- Coding composition: fixing, debugging, or help
- Brainstorming, planning, or ideation
- Asking for an explanation, reasoning, or help solving a puzzle or math problem
- Self-help: advice seeking, or self-harm
- Sexual or illegal content requests: inappropriate or illicit content requests
- News or recent events informational requests
- E-commerce: information requests about products and purchasing
- Information requests: specifically about organizations, companies, or persons

Provide the classification in the following JSON format:

```
{
  "Type of Service": []
}
```

C Forecasting Method

We chose the SARIMA parameters through an automated model selection process using the `auto.arima` function of the `pmdarima` package [110], and fit the models with the `statsmodels` implementation of SARIMA [106]. The automated selection process chooses lag and differencing

orders, along with other parameters, to optimize the Akaike information criterion. We show the selected parameters and their interpretations in Table 8.

Table 8: SARIMA parameter interpretation

Parameter	Value	Description
Non-seasonal order	(2, 1, 2)	- AutoRegressive (AR) order: 2 - Integrated (I) order: 1 - Moving Average (MA) order: 2
Seasonal order	(1, 1, 1, 6)	- Seasonal AutoRegressive (SAR) order: 1 - Seasonal Integrated (SI) order: 1 - Seasonal Moving Average (SMA) order: 1 - Seasonal periodicity: 6

The non-seasonal order (2, 1, 2) indicates that the current value being predicted is dependent on the past 2 observations, the time series is differenced once to achieve stationarity, and the prediction is influenced by the past 2 forecast errors. Similarly, the seasonal order (1, 1, 1, 6) indicates that the current value is affected by the previous seasonal value, the seasonal component is differenced once to remove seasonal non-stationarity, the prediction is impacted by the past seasonal forecast error, and the data exhibits a recurring pattern every 6 periods.

Table 9: Coefficients and associated hypothesis tests for SARIMA models on the share of tokens restricted, over all three corpora.

(a) C4.

	coef	std err	z	P> z	[0.025 0.975]
ar.L1	-0.5980	0.231	-2.584	0.010	-1.052 -0.144
ma.L1	0.7518	0.285	2.639	0.008	0.193 1.310
ar.S.L2	-0.1074	0.191	-0.562	0.574	-0.482 0.267
ma.S.L2	-0.4791	0.227	-2.108	0.035	-0.924 -0.034
sigma2	1.943e-05	1.39e-06	13.934	0.000	1.67e-05 2.22e-05

(b) Dolma.

	coef	std err	z	P> z	[0.025 0.975]
ar.L1	-0.8510	0.236	-3.602	0.000	-1.314 -0.388
ma.L1	0.7399	0.276	2.658	0.008	0.199 1.280
ar.S.L6	-0.0747	0.183	-0.408	0.683	-0.434 0.284
ma.S.L6	-0.9154	0.298	-4.398	0.000	-1.323 0.507
sigma2	2.521e-05	4.069e-06	6.198	0.000	1.71e-05 3.33e-05

(c) RefinedWeb.

	coef	std err	z	P> z	[0.025 0.975]
ar.L1	0.1996	0.156	1.280	0.201	-0.106 0.505
ma.L1	-0.9145	0.124	-7.367	0.000	-1.158 -0.671
ar.S.L16	-0.1649	0.122	-1.354	0.176	-0.403 0.074
ma.S.L16	-0.6390	0.159	-4.025	0.000	-0.950 -0.328
sigma2	6.146e-05	4.43e-06	13.871	0.000	5.28e-05 7.01e-05

D Extended Related Work

Data Documentation Previous work has highlighted the importance of data documentation in machine learning [89, 100, 74, 43, 81]. These works particularly stress the challenges posed by poor documentation to reproducibility, sound scientific practice, and understanding of model behavior [101, 8, 67]. Recent research has also explored the significance of documenting AI ecosystems [15]

and the supply chain from data to models [23]. Previous studies have strongly advocated for and provided frameworks for documentation and audits to enhance transparency and accountability in AI systems [75, 50, 99]. Similar to Longpre et al. [66] which leverages the collective knowledge of legal and machine learning experts, earlier research has emphasized the importance of interdisciplinary collaborations [47]. ‘Datasheets for Datasets’ [39] and ‘Data Statements’ [9] both offer structured frameworks for revealing essential metadata, such as the motivation behind and intended use of datasets. Pushkarna et al. [96] expanded on datasheets with ‘Data Cards’ that include sources, collection methods, ethics, and adoption information. Additionally, Mitchell et al. [78] introduced model cards to benchmark model performance across demographic groups and disclose evaluation procedures. Crisan et al. [29] proposed interactive model cards as an alternative mode of documentation and metadata sharing. Complementary to transparency regarding the dataset creation process, Corry et al. [28] provides a framework to guide users on how to navigate datasets as they approach the end of their life cycle. Longpre et al. [68] highlighted the importance of building standards across data documentation, aspects of which we draw on here.

Data Audits Several works stressed the importance of auditing datasets used to train models [22, 13, 11]. Building these audits into the workflow on AI is critical to building accountability [56, 51]. While previous works audited a variety of datasets and modalities, our work presents the largest and most comprehensive analysis of data used in training foundation models. This is becoming more pressing with the increasing richness of data sources, including those compiled by academics [124, 102, 80], synthetically generated by models [114, 122], or aggregated by platforms like Hugging Face [63]. The trend of combining and re-packaging numerous datasets and web sources has become prevalent among practitioners [38, 91, 123, 65]. Significant work has gone into analyzing these underlying text datasets (in particular CommonCrawl) [71, 40, 69, 22]. Several notable works have conducted large-scale analyses into data, particularly pretraining text corpora [38, 32, 55, 59, 104, 105, 72]. Other works have investigated the geo-diversity of vision-based datasets [109, 30, 70]. In terms of finding and visualizing datasets, a few recent tools have been proposed [36, 121].

Web Audits Previous work has attempted to understand the changing landscape of the web through various web audits and to understand the evolving behavior and implications of web crawlers. A study [25] investigated how often webpages that once existed become inaccessible by looking at a sample of webpages from Common Crawl from 2013 to 2023 and found that 38% of webpages that existed in 2013 are no longer accessible a decade later. Previous work has studied the identification and characterization of traffic generated by web crawlers [60, 18, 58] including temporal analysis of web crawlers activity [113, 19]. In [86], an analysis of the top 1000 websites in the world focused on identifying which sites are blocking popular AI web crawlers such as OpenAI’s GPTBot or the Google-Extended bot and found almost 35% of these websites blocked GPTBot vs 12.5% only for the Google-Extended bot. A similar study [127] found that more than 53% of 1,164 surveyed news publishers blocked GPTBot vs 41.3% for the Google-Extended bot.

Challenges in data transparency and its harms Despite efforts to document datasets [93, 10], there is a growing crisis in data transparency. The sheer scale of modern data collection and heightened scrutiny over copyright issues [103] have disincentivized thorough attribution and documentation of data lineage. This lack of transparency has led to a decline in understanding training data, as evidenced by the reduced number of datasheets [39] and the non-disclosure of training sources by prominent models [84, 2, 117]. This gap in documentation can result in data leakages between training and test sets [33, 20], exposure of personally identifiable information (PII) [17], and the perpetuation of biases and unintended behaviors [126, 129, 95], the large portions of hateful material in datasets [12, 13], all of which can cause significant harm [125]. Transparency becomes even more critical when assessing the supply chain risks of AI [45] and the ease of data poisoning in web-scale data [21].

Data governance Given the importance of data documentation and auditing, and the increasing difficulty of managing and working with ever increasing datasets, various efforts have been pushed at the data governance front, including the BigScience project [49] and the Public Data Trust [24].