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UNITED STATES DISTRICT COURT

NORTHERN DISTRICT OF CALIFORNIA

RICHARD KADREY, an individual; SARAH SILVERMAN, an individual; CHRISTOPHER GOLDEN, an individual, Individual and Representative Plaintiffs, v. META PLATFORMS, INC., a Delaware corporation; Defendant.	Case No. 3:23-cv-03417-VC **DEFENDANT META PLATFORMS, INC.'S NOTICE OF MOTION AND MOTION TO DISMISS PLAINTIFFS' COMPLAINT** Date: November 16, 2023 Time: 10:00 a.m. Dept: Courtroom 4 – 17th Floor Judge: Vince Chhabria Trial Date: None Date Action Filed: July 7, 2023

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Please take notice that, on November 16, 2023 at 10:00 a.m., Defendant Meta Platforms, Inc. ("Meta") will and hereby moves, pursuant to Fed. R. Civ. P. 12(b)(6), to dismiss Claim 1 (in part) and Claims 2–6 (in full) with prejudice for failure to state a claim on which relief may be granted. This motion is accompanied by a Request for Consideration of Documents Incorporated by Reference and Judicial Notice ("RJN"), Declaration of Judd Lauter ("Lauter") and exhibits thereto; all papers on file in this action; and such other matters as may be presented at the hearing.

I. INTRODUCTION

In February 2023, Meta announced its release of a family of state-of-the-art foundational large language models called LLaMA. A large language model ("LLM") is an AI software program designed to generate coherent text responses to user queries or "prompts." Just as a child learns language (words, grammar, syntax, sentence structure) by hearing everyday speech, bedtime stories, songs on the radio, and so on, LLaMA "learned" language by being exposed—through "training"—to "massive amounts of text from various sources," such as code, webpages, and books, in 20 languages. (¶¶ 2, 18.)[1] This process involved dissecting text into *trillions* of word snippets or letter combinations (called "tokens") and extracting a vast, complex set of statistical correlations as to how tokens are most likely to be arranged coherently. Once trained on sufficiently large volumes of data, LLMs, like LLaMA, develop emergent capabilities to use the building blocks of language in extra-ordinary ways, including to "generate creative text, solve mathematical theorems, predict protein structures, answer reading comprehension questions, and more. They are one of the clearest cases of the substantial potential benefits AI can offer at scale to billions of people." (Lauter Ex. 1.)

As part of its commitment to open science, Meta released LLaMA on a noncommercial basis to academic researchers, members of governmental organizations, and industry research laboratories around the world. (¶ 31 (quoting Lauter Ex. 1).) In doing so, Meta sought to democratize access to state-of-the-art LLMs, and thereby accelerate the development of better models and a broader and more innovative set of use-cases. (Lauter Ex. 1.)

[1] Unless otherwise stated, citations to "¶_" and "Ex. " are to the Complaint's paragraphs and exhibits, all emphases are added, and internal citations and quotation marks are omitted. Because Plaintiffs erred by including two instances of paragraphs numbered 1–23, Meta includes a page number with any citation to the second instance of those paragraphs (*e.g.*, ¶ 1 at 9).

Named Plaintiffs are authors of copyrighted books comprising a miniscule fraction (less than a millionth) of the material allegedly used to train LLaMA. Unlike in a traditional copyright case, Plaintiffs do ***not*** allege that LLaMA or any text generated by its users in response to prompts (called "output") is substantially similar in protectable expression to their books. They do not identify *any* output that has ever been created using LLaMA. Instead, they primarily object that Meta did not obtain their consent before extracting "information" from their texts as part of training LLaMA.

Copyright law does not protect facts or the syntactical, structural, and linguistic information that may have been extracted from books like Plaintiffs' during training. Use of texts to train LLaMA to statistically model language and generate original expression is transformative by nature and quintessential fair use—much like Google's wholesale copying of books to create an internet search tool was found to be fair use in *Authors Guild v. Google, Inc.*, 804 F.3d 202 (2d Cir. 2015). That core issue, however, will be for another day, on a more fulsome record. For now, Meta moves to dismiss the remainder of the Complaint for failure to state a claim.

Claim 1 (Direct Copyright Infringement): Plaintiffs' claim for direct infringement must be dismissed with prejudice to the extent it is premised on a theory that LLaMA is *itself* an infringing "derivative" work. This theory is supported by a single allegation: that LLaMA "cannot function without the expressive information extracted from Plaintiffs' Works and retained inside [it]." (¶ 41.) Plaintiffs do not explain what "information" this refers to, but use of "information" from a copyrighted text is not the standard for infringement. Under well-settled Ninth Circuit law, the only pertinent question is whether the software comprising LLaMA is, itself, substantially similar in protected expression to Plaintiffs' books. Because Plaintiffs do not and cannot plausibly allege substantial similarity of protected expression, this legal theory fails as a matter of law.

Claim 2 (Vicarious Copyright Infringement): Plaintiffs seek to hold Meta vicariously liable for purportedly infringing outputs generated by others using LLaMA. But they do not identify a single output ever generated by *anyone* that supposedly infringes their books. Instead, Plaintiffs advance the fallacy that *every* output generated using LLaMA is "based on expressive information extracted from" Plaintiffs' books and, therefore an "infringing derivative work" of *each* of those books. (¶ 44.) The Ninth Circuit has rejected this argument as "frivolous," and it makes no sense. The test for infringement is "substantial similarity." The solution to a mathematical theorem, line of code, or language translation—all outputs LLaMA is capable of generating—are not "substantially" or even remotely similar to *any* of Plaintiffs' books. Nor is, say, an original poem a user creates with LLaMA. Plaintiffs cannot plead this most basic element (or any of the others) necessary to state a claim for vicarious copyright infringement.

Claim 3 (Digital Millennium Copyright Act ("DMCA")): Plaintiffs' DMCA claims are divorced from the language and purpose of the law. They allege that Meta provided false copyright management information ("CMI") in violation of 17 U.S.C. § 1202(a)(1) by asserting copyright in the LLaMA models. However, such claims are only actionable where the allegedly false CMI is included in an exact copy of a work, which is not the case here. Nor can Plaintiffs plausibly plead that Meta's claim of copyright in LLaMA was false or knowingly made with intent to cause or conceal infringement. Plaintiffs' Section 1202(b)(1) claim fails because they do not and cannot allege "removal" of their CMI in training, much less that Meta intentionally removed it to cause or conceal allegedly infringing outputs, particularly where Plaintiffs have yet to identify any. And the Section 1202(b)(3) claim—premised on removal of CMI from the LLaMA models, themselves—fails because Plaintiffs are not the authors of LLaMA, they own (and claim) no copyright in it, and their CMI was never included to begin with, much less intentionally removed by Meta with wrongful intent. As to each theory, Plaintiffs' allegations fail to state a claim under the DMCA.

Claims 4–6 (Unfair Competition, Unjust Enrichment, Negligence): Plaintiffs' UCL claim is based on two alleged predicate violations: (1) violation of the DMCA, which Plaintiffs cannot establish, and (2) unauthorized use of Plaintiffs works to train LLaMA, which is just a repackaged copyright claim and, thus, expressly preempted by the Copyright Act. Absent a viable predicate violation, this claim must be dismissed. So, too, must the unjust enrichment claim, which is likewise preempted, and would require a quasi-contractual relationship between the parties, which has not been pleaded and does not exist. Finally, Plaintiffs' negligence claim—which is based on a purported duty not to train LLaMA on their copyrighted works—is likewise preempted and barred by the economic loss doctrine in any event. Each of these claims should be dismissed with prejudice.

II. Summary of Relevant Facts and Allegations

A. The Parties

Named Plaintiffs: Named plaintiffs are book authors Richard Kadrey, Sarah Silverman, and Christopher Golden. (¶¶ 4, 9–12 & Exs. A, B.) They allegedly own registered copyrights in, respectively, *Sandman Slim*, *The Bedwetter*, and *Ararat* (referred to by Plaintiffs as "Infringed Works"), each of which contains CMI "customarily included in published books, including the name of the author and the year of publication." (¶¶ 9–11.) Plaintiffs allege that Meta used each of these books, along with others by Kadrey and Golden, to train LLaMA. (¶¶ 23–30 & Ex. B.)

Meta and Its LLaMA Models: Meta is a technology company that offers popular social media services Facebook and Instagram. It also has a team called Meta AI that "creates and distributes artificial-intelligence software products" that "algorithmically simulate human reasoning." (¶¶ 16–17.) In February 2023, Meta released LLaMA, a "set of large language models … designed to parse and emit natural language." (¶ 18.) Meta announced that LLaMA would be made available on a limited basis to "academic researchers; those affiliated with organizations in government, civil society, and academia; and industry research laboratories around the world" for purposes of study, research and development. (¶ 31 (quoting Lauter Ex. 1).) Meta further announced that those seeking access could apply at a web link provided in a research paper describing how LLaMA was created and trained. (*Id.*) Plaintiffs allege "on information and belief" that Meta has "benefited financially" from this noncommercial release of LLaMA (¶ 32), but do not describe how.

In March 2023, the "model weights" for LLaMA—the statistical parameters derived from its training—were posted to popular code-sharing platform, GitHub, without Meta's authorization. (¶¶ 33–34.) Meta promptly submitted a DMCA takedown notice to GitHub, asserting its copyright in LLaMA and requesting removal of a tool posted there by a programmer to help users download the LLaMA models outside of Meta's application process and without Meta's consent. (¶ 34.) Despite these efforts, unidentified third parties have "continued to circulate" LLaMA. (¶ 33.)

B. Plaintiffs' Allegations of Purported Wrongdoing

According to Plaintiffs, LLMs like LLaMA are "'trained' by copying massive amounts of text from various sources and feeding these copies into the model." (¶ 18.) During training, an

LLM "copies each piece of text in the training dataset and extracts expressive information from it," which then enables the model "to emit convincing simulations of natural written language as it appears in the training dataset." (*Id.*) Plaintiffs further allege that the output of an LLM is "entirely and uniquely reliant on the material in its training dataset. Every time it assembles a text output, the model relies on the information it extracted from its training dataset." (¶ 3.)

Plaintiffs infer that the allegedly Infringed Works were among the many materials on which LLaMA was trained from the research paper Meta published in connection with LLaMA's release, "LLaMA: Open and Efficient Foundation Language Models" ("Research Paper"), which described the models and their training sources. (¶¶ 21, 23–30; *see* Lauter Ex. 2.) According to Plaintiffs, *one* such source is "the Books3 section of ThePile," a corpus of 196,000 books, which was assembled by the research organization EleutherAI for training LLMs and includes the Infringed Works. (¶¶ 23–25.) On that basis, Plaintiffs allege that their books must have been "copied and ingested" by Meta in training LLaMA. (¶¶ 5, 19.) Notably, as detailed in the Research Paper, Books3 comprises an astonishingly small portion of the total text used to train LLaMA. All books from Books3, together with the roughly 70,000 books collected from Project Gutenberg, an "archive of [] books that are out of copyright" (¶ 23), accounted for only 4.5% of training text. (Lauter Ex. 2; ¶ 23.) Even accepting Plaintiffs' allegations, their books comprised less than a millionth of the training data.

Plaintiffs filed this suit on July 7, 2023, asserting claims for: (1, 2) direct and vicarious copyright infringement (17 U.S.C. § 106); (3) removal of CMI and false assertion of copyright in violation of the DMCA (17 U.S.C. §§ 1202(a)(1) and 1202(b)); (4) unfair competition (Cal. Bus. & Prof. Code §§ 17200 *et seq.* ("UCL")); (5) unjust enrichment; and (6) negligence. Plaintiffs seek to represent a putative class of "all persons or entities domiciled in the United States that own a [U.S.] copyright in any work that was used as training data" for LLaMA. (¶ 15 at 10.)

Plaintiffs assert that any copies of the allegedly Infringed Works made in the process of training LLaMA infringe the copyrights in those Works (¶ 40), and, further, because LLaMA relies on unspecified "expressive information extracted from" those Works, the LLaMA model, itself—and "every output" therefrom—are infringing derivatives. (¶¶ 41, 44.) Plaintiffs further claim that, "by design," the process of training LLaMA does not preserve CMI, and Meta thereby intentionally removed CMI from their works, distributed unauthorized derivative works without their CMI, and provided false CMI by claiming "sole copyright" in LLaMA. (¶¶ 49-51.) These purported acts also form the basis of Plaintiffs' state and common law claims. (¶¶ 54–58; ¶¶ 1–14 at 9–10.)

III. Legal Standards

"Dismissal under Rule 12(b)(6) is proper when the complaint either (1) lacks a cognizable legal theory or (2) fails to allege sufficient facts to support a cognizable legal theory." *Somers v. Apple, Inc.*, 729 F.3d 953, 959 (9th Cir. 2013). To avoid dismissal, a complaint must plead "enough facts to state a claim to relief that is plausible on its face." *Bell Atl. Corp. v. Twombly*, 550 U.S. 544, 570 (2007). The court need not "accept as true allegations that contradict … matters properly subject to judicial notice, or allegations that are merely conclusory, unwarranted deductions of fact, or unreasonable inferences." *Daniels-Hall v. Nat'l Educ. Ass'n*, 629 F.3d 992, 998 (9th Cir. 2010); *Dahlia v. Rodriguez*, 735 F.3d 1060, 1076 (9th Cir. 2013) (same); *Twombly*, 550 U.S. at 555 (courts need not "accept as true a legal conclusion couched as a factual allegation"). "Where a complaint pleads facts that are merely consistent with a defendant's liability, it stops short of the line between possibility and plausibility of entitlement to relief." *Ashcroft v. Iqbal*, 556 U.S. 662, 678 (2009).

IV. Argument

Plaintiffs' claims for direct and vicarious copyright infringement rest on legal theories that are incompatible with the Copyright Act and contravene the binding law in this Circuit. The state law claims, in turn, all improperly invade on the exclusive domain of federal copyright law and must be dismissed with prejudice as preempted, and because they fail to state a claim in any event.

A. Plaintiffs Fail to Plead that LLaMA Is an Infringing Derivative Work (Claim 1)

Plaintiffs' claim for direct copyright infringement is based on two theories: (1) Meta created unauthorized copies of Plaintiffs' books in the process of training LLaMA (¶ 40); and (2) "[b]ecause the LLaMA language models cannot function without the expressive information extracted from Plaintiffs' Infringed Works and retained inside [LLaMA]," the models "are themselves infringing derivative works" (¶ 41). Both theories are without merit, but this Motion addresses only the latter theory, which rests on a fundamental misunderstanding of copyright law.

The Copyright Act secures to authors six "exclusive" rights enumerated in 17 U.S.C. § 106. These include the right to "reproduce" the copyrighted work in copies," 17 U.S.C. § 106(1), and the right to "prepare derivative works," *id.* § 106(2).

A "fundamental axiom of copyright law is that no author may copyright his ideas or the facts he narrates." *Feist Publ'n Inc. v. Rural Tel. Serv. Co.*, 499 U.S. 340, 344–45 (1991). Even ideas originally conceived by an author cannot be the proper subject of an infringement claim, because copyright does not extend to facts, ideas, or other foundational elements of creativity—it protects only the specific manner in which information is expressed. *Id.*; 17 U.S.C. § 102(b).

"This principle, known as the idea/expression or fact/expression dichotomy, applies to all works of authorship." *Id.* at 350. It dictates that "every idea, theory, and fact in a copyrighted work becomes instantly available for public exploitation at the moment of publication." *Eldred v. Ashcroft*, 537 U.S. 186, 219 (2003). Only by excluding facts and ideas from copyright protection can the Copyright Act advance the Constitutional imperative of promoting "the Progress of Science and useful Arts." U.S. CONST. Art. 1, § 8, cl. 8. After all, "[e]very work uses scraps of thought from thousands of predecessors"; "Intellectual (and artistic) progress is possible only if each author [is free to] build[] on the work of others." *Nash v. CBS, Inc.*, 899 F.2d 1537, 1540, 1543 (7th Cir. 1990) (affirming summary judgment that defendants "did not appropriate any of the material protected by Nash's copyrights" because they used his work solely "as a source of facts and ideas" and took his "analysis of history but none of his expression").

The fact/expression dichotomy was further elucidated in *Authors Guild*, in which the Second Circuit rejected an argument that the Google Books project—for which Google made digital copies of millions of books without permission to create a tool allowing Internet users to search for certain words or terms within them—constituted an infringing derivative work. 804 F.3d at 227. The court reasoned that plaintiffs had no "supposed derivative right to supply information about their books," such as "word frequencies, syntactic patterns, and thematic markers." *Id.* at 209, 227. This "statistical information," the court found, does not constitute "copyrighted expression," and its use by Google did "not support Plaintiffs' derivative works argument." *Id.*

With these bedrock principles in mind, the argument Plaintiffs seek to advance here—that Meta's LLaMA models must be infringing derivatives of each of Plaintiffs' copyrighted books merely because they were trained on their works (¶ 41)—is legally untenable for multiple reasons.

First, as the Ninth Circuit has definitively held, a derivative work must be *substantially similar* in protected expression to the copyrighted work to be infringing. In *Litchfield v. Spielberg*, the Ninth Circuit rejected as "frivolous" the exact argument Plaintiffs seek to advance here, namely, that a "derivative work" encompasses "any work based on a copyrighted work," irrespective of substantial similarity. 736 F.2d 1352, 1357 (9th Cir. 1984). Rather, "[t]o prove infringement, one must show substantial similarity." *Id.*; *see also Roth Greeting Cards v. United Card Co.*, 429 F.2d 1106, 1110 (9th Cir. 1970) ("[I]nfringement [requires] substantial similarity…."); 4 Patry on Copyright § 12:13 (collecting cases) ("In order to infringe the derivative right, *there must be substantial similarity in protectible expression between the parties' works*.").

To assess substantial similarity, the Ninth Circuit applies a two-part test. *Cavalier v. Random House, Inc.*, 297 F.3d 815, 822 (9th Cir. 2002). The first part—the "extrinsic test"—is an "objective comparison of specific expressive elements"; the court "disregard[s] the non-protectible elements" like "stock scenes and themes" and "plot ideas" and determines whether the remaining "protectible elements, standing alone, are substantially similar." *Id.* at 822–23; *see also Berkic v. Crichton*, 761 F.2d 1289, 1293–94 (9th Cir. 1985) (excluding ideas and scenes-a-faire). The second part—the "intrinsic test"—is a subjective comparison focused on "whether the ordinary, reasonable audience would find the works substantially similar" in "total concept and feel." *Id.* at 822. If, under these tests, the accused work is not "substantially similar" to plaintiff's copyrighted work, it is neither a "copy" nor a "derivative work" for purposes of Section 106. 17 U.S.C. § 106(1)–(3).

Here, Plaintiffs make no attempt to plead substantial similarity as between the LLaMA models and any of their books, and such an allegation would be implausible on its face. Software code for a neural network is not similar to Plaintiffs' novels and essay collection, and Plaintiffs do not and cannot claim that it is. Under *Litchfield*, that should end the analysis. 736 F.2d at 1357.

Second, rather than attempt to plead substantial similarity, Plaintiffs allege that "expressive information extracted from Plaintiffs' Infringed Works" is "retained inside the LLaMA language models," and that they "cannot function without [it]." (¶ 41.) This does not help their cause. The test of infringement is not whether one work can "function" without another. In *Authors Guild*, for instance, wholesale copying of books was necessary to enable the search function at issue, but the court still rejected a claim that the search tool was an infringing derivative work. 804 F.3d at 209, 227. Equally fatal, Plaintiffs do not identify any "expressive information" LLaMA is supposed to contain, or what it consists of. They do not claim, for instance, that text from their books appears in LLaMA's codebase. Such an allegation would be nonsensical and contrary to the way LLMs function. Instead, the most plausible read of Plaintiffs' allegations is that tokenized, statistical "information" about the words, sentences, and paragraphs in their books has been extracted and analyzed in training LLaMA and developing its code. As amply demonstrated by *Authors Guild*, *Nash* and the other authorities cited above, such information falls outside the scope of copyright protected expression and its use (even if it were alleged) could not support a claim for infringement.

Third, even if the Court were to look past the total absence of allegations (plausible or otherwise) of substantial similarity between Plaintiffs' books and the LLaMA language models, *Authors Guild* provides yet another, independent basis for dismissing Plaintiffs' second theory of direct copyright infringement. In *Authors Guild*, it was undisputed that the Google search feature at issue relied on digital scans of plaintiffs' entire books to generate snippets and data about the books as search outputs. 804 F.3d at 225. Nevertheless, because the digital copies created by Google were hidden from view by the public and the tool did not permit access "in any substantial way to a book's expressive content" apart from the snippets, the search tool was beyond the "statutory definition of a derivative work, or of the logic that underlies it." *Id*. at 226–27.

Here, Plaintiffs claim that LLaMA "ingested" copies of their books as training material. (¶ 5.) However, they do not allege that those copies are viewable or otherwise accessible to users of LLaMA, and do not point to a single output that substantially reveals or borrows from the protected expression of those works. Accordingly, as in *Authors Guild*, Plaintiff's theory that the LLaMA language model is itself an infringing derivative work fails as a matter of law.

B. Plaintiffs Fail to State a Claim for Vicarious Infringement (Claim 2)

By their claim for vicarious copyright infringement, Plaintiffs seek to hold Meta secondarily liable for allegedly infringing outputs generated by others using the LLaMA language models. To state a claim for vicarious infringement, Plaintiffs must allege facts plausibly establishing: (1) an act of direct infringement undertaken by another party; (2) that Meta exercises control over (i.e., has the "right and ability to supervise") that infringing conduct; and (3) that Meta has a direct financial interest in the infringing activity. *Perfect 10, Inc. v. Amazon.com, Inc.*, 508 F.3d 1146, 1173 (9th Cir. 2007). Plaintiffs' factual allegations fail to satisfy any of these elements.

1. Plaintiffs fail to allege direct infringement

The first, most basic element of any claim for secondary copyright liability is an act of direct infringement by another. Plaintiffs do not identify any such act. Indeed, the Complaint is devoid of a single example of any use of LLaMA to generate output that Plaintiffs might plausibly contend infringes any of their works. This, alone, is fatal.

To state a claim, Plaintiffs were required to identify specific examples of directly infringing works so that, among other things, they may be compared against the original copyrighted works for purposes of assessing substantial similarity. *See Becton, Dickinson & Co. v. Cytek Biosciences Inc.*, 2020 WL 1877707, at *6–7 (N.D. Cal. Apr. 15, 2020) (dismissing copyright claim for failure to plead representative acts of infringement). Plaintiffs "need not specify each and every instance of infringement at the pleadings stage, but [they] must submit at least a representative sampling of infringed content," including what parts of their works were copied and how and where such copying is manifest. *Id.* at *6. Here, Plaintiffs do not allege *any* example of output of the LLaMA language models, what parts (if any) of their books were allegedly reproduced in any output, or any specific act of infringement. Dismissal is thus required. *See MultiCraft Imports, Inc. v. Mariposa USA, Inc.*, 2017 WL 5664996, at *3 (C.D. Cal. Sept. 14, 2017) (dismissing claim and reasoning: "Absent any allegations of even representative infringements, the FAC fails to provide notice as a matter of law."); *Blizzard Ent., Inc. v. Lilith Games (Shanghai) Co.*, 149 F. Supp. 3d 1167, 1175 (N.D. Cal. 2015) (same, dismissing claim).

Rather than satisfy this pleading burden, Plaintiffs seek to circumvent it, asserting: "Because the output of the LLaMA language models is *based on* expressive information extracted from Plaintiffs' Infringed Works, *every* output of the [models] is an infringing derivative work." (¶ 44.)

This is wrong as a matter of both well-settled law and common sense, as shown in Section IV.A. above.

Plaintiffs make no attempt to plead substantial similarity of the (unspecified) outputs of the models, just as they make no effort to show substantial similarity of the models themselves. The only description of potential outputs of the LLaMA models is that they are "able to emit convincing simulations of natural written language" (¶ 18), which could theoretically include outputs ranging from a sample cover letter for a job application, to a list of U.S. state capitols, to a dissertation on the Newtonian laws of motion. Any suggestion that such outputs would be substantially similar to *any* of named Plaintiffs' books is not only implausible, but absurd—which is presumably why Plaintiffs tried to avoid the essential issue of substantial similarity altogether.

2. Plaintiffs fail to plead the requisite control

To plead the second element of vicarious copyright infringement, Plaintiffs were required to allege facts showing that Meta had the "right and ability to supervise" the supposed infringement of their books in output generated by others. *Perfect 10 v. Giganews, Inc.*, 847 F.3d 657, 673 (9th Cir. 2017). Instead, the Complaint simply recites this element in conclusory fashion without any supporting facts. (¶ 45.) This is insufficient. Under *Iqbal*, "[t]hreadbare recitals of the elements of a cause of action, supported by mere conclusory statements, do not suffice" to state a claim. 556 U.S. at 678; *Kilina Am., Inc. v. Bonded Apparel, Inc.*, 2019 WL 8065854, at *2 (C.D. Cal. Nov. 19, 2019 ("Merely alleging that the Defendants had the 'right and ability to supervise the infringing conduct' lacks the requisite detail to sustain a claim...").[2]

3. Plaintiffs fail to plead the requisite financial interest

Plaintiffs also fail to adequately plead the third element for vicarious liability—that Meta has a "direct financial interest" in the supposed infringement. *Perfect 10*, 847 F.3d at 673. Once again, the Complaint includes only the conclusory allegation that "Meta has benefited financially from the infringing output of the LLaMA language models" (¶ 45), which falls short. *Iqbal*, 556

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[2] In light of Plaintiffs' allegation that unauthorized versions of LLaMA have "continued to circulate" on GitHub despite Meta's takedown efforts (¶¶ 33–34), it is unclear how Plaintiffs could ever plausibly plead that Meta has the ability to supervise uses of LLaMA of which it is not aware and which it has tried to prevent.

U.S. at 678. At the same time, Plaintiffs acknowledge and affirmatively plead that LLaMA was released on a limited *noncommercial* basis to academic researchers free of charge. (¶ 31.)

Moreover, Plaintiffs fail to allege any causal link between the allegedly infringing activities and a financial benefit to Meta, as the law requires. *Perfect 10*, 847 F.3d at 673. To satisfy the "direct financial interest" element of vicarious copyright infringement, Plaintiffs must show that LLaMA users were "drawn" to the program *because of* the copying of *Plaintiffs' works*. *Id.* at 674. This is not alleged in the Complaint, nor can it plausibly be. According to the Complaint, Plaintiffs' books are among hundreds of thousands of books included in LLaMA's training data. (¶¶ 23, 28.) All 266,000+ books, in turn, comprise only 4.5% of the data used to train LLaMA, and a significant portion of that subset consists of books in the public domain. (Lauter ¶ 3 & Ex. 2; ¶ 23.) To claim that the statistical data extracted from any particular work in the dataset acts as a "draw" for users of the models—particularly where Meta is not alleged to have ever identified Plaintiffs' works as among LLaMA's training material (*see* ¶¶ 21–30)—is factually unsupported and untenable.

C. Plaintiffs Fail to State a Claim for Violation of the DMCA (Claim 3)

As relevant here, the copyright management provisions of the Digital Millennium Copyright Act ("DCMA") prohibit the knowing dissemination of false CMI "with the intent to induce, enable, facilitate, or conceal infringement" (17 U.S.C. § 1202(a)(1)), and the intentional removal of CMI or knowing distribution of copies of works with CMI removed, with knowledge or "reasonable grounds to know, that it will induce, enable, facilitate, or conceal" infringement (*id.* §§ 1202(b)(1), (3)). Plaintiffs purport to plead violations of each of these provisions (¶¶ 49–51), but their allegations are untethered from both the language of Section 1202 and its purpose. As discussed in further detail below, each claim warrants dismissal with prejudice.

1. Plaintiffs fail to state a claim under Section 1202(a)(1)

Plaintiffs allege that Meta knowingly conveyed false CMI with the intent to cause or conceal copyright infringement, in violation of 17 U.S.C. § 1202(a)(1). Their theory is that because Meta's LLaMA models are infringing derivative works (¶ 41), Meta provides false CMI by asserting copyright ownership in LLaMA. (¶ 51.) This claim is meritless for multiple reasons.

First, even if the Court were to accept Plaintiffs' allegations as true, provision of false CMI must occur in connection with an *original* or otherwise *identical copy* of a work to be actionable. *O'Neal v. Sideshow, Inc.*, 583 F. Supp. 3d 1282, 1287 (C.D. Cal. 2022) (dismissing DMCA claim because works were not identical); *Kirk Kara Corp. v. W. Stone & Metal Corp.*, 2020 WL 5991503, at *6 (C.D. Cal. Aug. 14, 2020) (dismissing DMCA claim because "Defendant did not make *identical* copies of Plaintiff's works and then remove the [] CMI"). This is in keeping with the purpose of the DMCA, which was enacted to help address the "ease with which digital works can be copied and distributed worldwide virtually instantaneously" over the Internet. S. Rep. 105-190, at 8 (1998). CMI was envisioned as "a kind of license plate for a work on the information superhighway," from which the authorship and/or ownership of the work could be readily determined by internet users. *Textile Secrets Int'l, Inc. v. Ya-Ya Brand Inc.*, 524 F. Supp. 2d 1184, 1196 (C.D. Cal. 2007) (citation omitted) (discussing legislative history of Section 1202).

Courts interpreting Section 1202 of the DMCA have repeatedly held that it does not apply to CMI attached to a work other than that of the copyright owner, even if it is an unauthorized derivative. *See, e.g.*, *Michael Grecco Prods., Inc. v. Time USA*, *LLC*, 2021 WL 3192543, at *5 (S.D.N.Y. July 27, 2021) ("A party that puts its own CMI on work distinct from work owned by a copyright holder is not liable under Section 1202(a) even if the party's work incorporates the copyright holder's work."); *Park v. Skidmore, Owings & Merrill LLP*, 2019 WL 9228987, at *11 (S.D.N.Y. Sept. 30, 2019) ("[Defendant] has not violated [1202(a)] by claiming authorship over 1 WTC, even if it is improperly derivative of Cityfront '99."). For example, in *Crowley v. Jones*, the district court dismissed a 1202(a) claim in which the defendant had allegedly used a cropped version of the plaintiffs' photograph in the cover of a hip-hop album, explaining that "a defendant cannot violate the DMCA by associating its name with a derivative work that is unquestionably a distinct work, even if the derivative work infringes a copyright." 608 F. Supp. 3d 78, 90 (S.D.N.Y. 2022). This makes sense, because otherwise virtually every claim of copyright infringement would necessarily be a claim for violation of the DMCA. That is not the law.

Second, the Complaint does not explain exactly how Meta conveyed "false" CMI. Beyond a passing insinuation (¶ 51), there are no allegations that Meta's assertion of copyright ownership in LLaMA is false. Plaintiffs *acknowledge* that Meta created LLaMA (¶ 50), from which it follows that Meta could rightfully claim copyright ownership in it. 17 U.S.C. § 201. Further, as explained above, Plaintiffs do not (and cannot) plausibly allege that LLaMA is an infringing derivative work.

Third, the claim fails because Plaintiffs do not and cannot plausibly plead that Meta acted with the requisite scienter. There is no allegation at all that Meta knowingly provided false CMI "*with the intent* to induce, enable, facilitate, or conceal infringement." 17 U.S.C. § 1202(a)(1) (emphasis added). The bald allegation that Meta "knew or had reasonable grounds to know" that "removal of CMI would facilitate copyright infringement" (¶ 52) is insufficient. Further, any contention that Meta "knew" its claim of rights in LLaMA was false is defeated by the lone allegation Plaintiffs plead to support it, *i.e.*, that Meta submitted a takedown notice to GitHub in which it asserted copyright ownership in LLaMA. Under 17 U.S.C. § 512(c)(3)(A), a DMCA takedown notice requires, among other things, statements that "the complaining party has a good faith belief that use of the material in the manner complained of is not authorized by the copyright owner … or the law," and "under penalty of perjury, that the complaining party is authorized to act on behalf of the owner of an exclusive right that is allegedly infringed." Plaintiffs plead no facts from which one could reasonably infer that Meta made these representations knowing that they were false. *See Krechmer v. Tantaros*, 747 Fed. App'x 6, 9 (2d Cir. 2018) (upholding dismissal of 1202(a)(1) claim because plaintiff did not plausibly allege knowledge or intent). To the contrary, the only plausible inference to be drawn from Plaintiffs' allegations is that Meta actually believes itself to be the copyright owner of the LLaMA models, and for good reason.

2. Plaintiffs fail to state a claim under Section 1202(b)(1)

Plaintiffs' 1202(b)(1) claim is equally defective. They allege that Meta violated that section by "cop[ying]" Plaintiffs' works and "us[ing] them as training data for the LLaMA language models," a process which, "[b]y design … does not preserve any CMI." (¶ 49.) What this means is difficult to discern, but Plaintiffs appear to posit that because training LLaMA purportedly "extracted" "expressive information" (¶¶ 41, 44) from their books without preserving or including CMI (¶ 49), this somehow constitutes "removal" of CMI under Section 1202(b)(1). It does not.

First, the process that Plaintiffs describe in the Complaint would, if anything, constitute an omission of CMI, not a "removal." Merriam-Webster defines "removal" as occurring when something is separated or moved from its original position; "omission" occurs when something is excluded or unacknowledged. (Lauter Exs. 3, 4.) Thus, as noted above, courts interpret Section 1202(b)(1) to apply only to "removal" of CMI from original, otherwise identical, works. *See*, *e.g.*, *Kelly v. Arriba Soft Corp.*, 77 F. Supp. 2d 1116, 1122 (C.D. Cal. 1999), *aff'd in part, rev'd in part*, 280 F.3d 934 (9th Cir. 2002); *Dolls Kill, Inc. v. Zoetop Bus. Co.*, 2022 WL 16961477, at *3–4 (C.D. Cal. Aug. 25, 2022). For example, in *Falkner v. General Motors LLC*, the court rejected a Section 1202(b)(1) claim brought by a mural artist, in which he alleged that a photographer removed CMI from one of his murals by photographing it at an angle from which his signature was not visible. 393 F. Supp. 3d 927, 938 (C.D. Cal. 2018). The court reasoned that the defendant's "failure to include" CMI could not be regarded as a "removal" under any ordinary definition of that term. *Id*.

Here, Plaintiffs do not allege that Meta removed CMI from their books by, for example, deleting the author's names or copyright notices from the text files that contain them. Rather, Plaintiffs contend that Meta designed the LLaMA training process to exclude CMI from the "expressive information" extracted from their books, i.e., not to extract it in the first place. That is, by definition, an alleged omission akin to the *Falkner* defendant's photo framing, and not a cognizable removal under Section 1202(b). Dismissal with prejudice is appropriate on this basis.

Second, even if Plaintiffs had pleaded that Meta removed CMI from their books, they have not adequately pleaded that Meta did so intentionally, with knowledge or reason to know that it would cause or facilitate infringement. "[T]he mental state requirement in Section 1202(b)" has "a more specific application than the universal possibility of encouraging infringement; *specific allegations as to how identifiable infringements 'will' be affected are necessary*." *Stevens v. Corelogic, Inc*., 899 F.3d 666, 674 (9th Cir. 2018) (affirming grant of summary judgment to defendant on § 1202(b) claim). Accordingly, a "plaintiff must provide evidence from which one can infer that future infringement is likely, albeit not certain, to occur as a result of the removal or alteration of CMI." *Id*. at 675.

Although *Stevens* addressed scienter at the summary judgment stage, pleading a claim under 1202(b) still requires "specific allegations as to how identifiable infringements will be affected by [d]efendants' alleged removing or altering of CMI," a "pattern of conduct demonstrating [that]

[d]efendants knew or had reason to know that their actions would cause future infringement," and "non-conclusory" facts demonstrating the requisite scienter. *Mills v. Netflix, Inc.*, 2020 WL 548558, at *3 (C.D. Cal. Feb. 3, 2020) (dismissing DMCA claim because scienter was inadequately pleaded); *O'Neal*, 583 F. Supp. 3d at 1287 (same). Scienter need not be pleaded with particularity, but it still must be plausibly alleged. *Iqbal*, 556 U.S. at 686-87 ("Rule 9 merely excuses a party from pleading [knowledge] under an elevated pleading standard. It does not give him license to evade the less rigid - though still operative - strictures of Rule 8").

Here, Plaintiffs allege that "Meta knew or had reasonable grounds to know" that removing CMI (or, more accurately, failing to "preserve" it) "would facilitate copyright infringement by concealing the fact that every output from the LLaMA language models is an infringing derivative work." (¶¶ 49, 52.) This fails for the simple reason that, as explained above, Plaintiffs have not plausibly alleged that *any* LLaMA outputs are infringing. Meta could not have "removed" CMI intending to conceal infringement of which it was not allegedly aware and which Plaintiffs never identify.

3. Plaintiffs fail to state a claim under Section 1202(b)(3)

Plaintiffs also allege that Meta violated Section 1202(b)(3) by "creat[ing] derivative works based on Plaintiffs' Infringed Works" and "distributing [them] without [Plaintiffs'] CMI." (¶ 50.) Since the only "derivative work" Meta is accused of creating is LLaMA, itself (¶ 41), this allegation distills to a charge that Meta somehow unlawfully removed CMI *from LLaMA*. This claim is fundamentally incompatible with the language of Section 1202(b)(3), which prohibits distribution of copies of works with CMI removed "without the authority of the copyright owner" of that work. 17 U.S.C. § 1202(b). As Plaintiffs acknowledge, Meta "created" LLaMA. (¶ 50.) Thus, Meta is the author of LLaMA and the sole party in whom copyright ownership and authority over LLaMA vests. 17 U.S.C. § 201(a). By the same token, none of the *Plaintiffs* could legitimately claim to be the author or copyright owner of the LLaMA language models. Their attempt to hold Meta liable for not including all *Plaintiffs'* CMI on LLaMA—even though Plaintiffs are not LLaMA's authors or copyright owners and such CMI would, by definition, be false—finds no basis in the DMCA.

And if the foregoing was somehow insufficient to justify dismissal with prejudice, Plaintiffs *also* do not allege what CMI was removed from LLaMA or how, let alone how such removal could conceivably conceal that "every *output* from the LLaMA language models is an infringing derivative work." (¶ 52 (emphasis added).) Nor could they. Perhaps Plaintiffs mean to suggest that Meta was obligated to identify Plaintiffs' CMI in connection with distribution of LLaMA. That is a different claim from the one pleaded, namely, that Meta *removed* CMI *from LLaMA*, and distributed copies of LLaMA with CMI having been removed. (*See* ¶ 50.) In any case, such claim would be subject to dismissal on the grounds that (1) it does not describe a "removal" of CMI, and (2) Section 1202(b)(3) applies only to distribution of exact copies of a party's works with CMI removed (*see O'Neal*, 583 F. Supp. 3d at 1287). Here, Plaintiffs allege that both LLaMA and its outputs are "infringing derivative works"; not identical copies. (¶¶ 41, 44.) This claim fails.

D. Plaintiffs Fail to State a Claim for Unfair Competition (Claim 4)

Plaintiff's UCL claim also fails as a matter of law. The UCL prohibits business practices that are (1) unlawful, (2) fraudulent, or (3) unfair. *Hadley v. Kellogg Sales Co.*, 243 F. Supp. 3d 1074, 1105 (N.D. Cal. 2017). Plaintiffs plead violation of the "unlawful" prong based on two alleged predicate acts: (1) "violating Plaintiffs' rights under the DMCA"; and (2) "using Plaintiffs' Infringed Works to train LLaMA" without authorization.[3] (¶ 55.) Neither supports a claim.

The first basis fails because, as discussed above, Plaintiffs fail to state a DMCA violation. The UCL unlawful prong "borrows violations of other laws and treats them as unlawful practices that the unfair competition law makes independently actionable." *Id.* (quoting *Alvarez v. Chevron Corp.*, 656 F.3d 925, 933 n.8 (9th Cir. 2011)). A UCL unlawful claim "cannot survive" where, as here, it is predicated on a defective claim. *Mohanna v. Carrington Mortg. Servs. LLC*, 2018 WL 3730419, at *8 (N.D. Cal. Aug. 6, 2018) (dismissing UCL claim for lack of predicate violation).

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[3] Plaintiffs also include an off-hand reference to alleged "fraudulent" conduct. (¶ 58 (alleging "consumers are likely to be deceived" because unidentified output from LLaMA has been "emitted without any credit to Plaintiffs … whose Infringed Works comprise LLaMA's training dataset").) A UCL fraud claim requires Plaintiffs to allege *they* were deceived, which Plaintiffs cannot do here. *See Equinox Hotel Mgmt., Inc. v. Equinox Holdings, Inc.*, 2018 WL 659105, at *13 (N.D. Cal. Feb. 1, 2018); *Berk v. Coinbase, Inc.*, 2019 WL 3561926, at *4 (N.D. Cal. Aug. 6, 2019) (Chhabria, J.) (dismissing UCL fraud claim for failure to "particularly plead reliance" by plaintiffs), *rev'd and remanded on other grounds*, 840 F. App'x 914 (9th Cir. 2020). Further, absent identification of specific "deceptive" outputs, this claim fails even to satisfy Rule 8, much less Rule 9's heightened pleading standard. *See Vess v. Ciba-Geigy Corp. USA*, 317 F.3d 1097, 1106 (9th Cir. 2003) ("fraud must be accompanied by the 'who, what, when, where, and how'").

The second basis, which concerns Meta's use of Plaintiffs' copyrighted works to train LLaMA, is merely a recasting of its claim for copyright infringement and, therefore, preempted by the Copyright Act. Under the Copyright Act, "all legal or equitable rights that are equivalent to any of the exclusive rights within the general scope of copyright as specified by section 106 … are governed exclusively by this title," and no person "is entitled to any such right or equivalent right in any such work under the common law or statutes of any State." 17 U.S.C. § 301(a).

The Ninth Circuit uses a two-part test to assess whether a state law claim is preempted by the Copyright Act. *Maloney v. T3Media, Inc.*, 853 F.3d 1004, 1010 (9th Cir. 2017)). First, it asks whether the "subject matter" of the claim falls within the subject matter of copyright described in 17 U.S.C. §§ 102, 103. If so, the court must "determine whether the rights asserted under state law are equivalent to the rights contained in" Section 106. *Laws v. Sony Music Entm't, Inc.*, 448 F.3d 1134, 1138 (9th Cir. 2006). "[T]he state cause of action must protect rights which are qualitatively different from the copyright rights. The state claim must have an extra element which changes the nature of the action." *Del Madera Props. v. Rhodes & Gardner, Inc.*, 820 F.2d 973 (9th Cir. 1987), *overruled on other grounds, Fogerty v. Fantasy, Inc.*, 510 U.S. 517 (1994).

Here, the subject matter of Plaintiffs' UCL claim is their copyrighted books, which plainly falls within the subject matter of copyright. *See Maloney*, 853 F.3d at 1011. Further, the purported violation is Meta's unauthorized "use[]" of those books "to train LLaMA." (¶ 57.) Although Plaintiffs artfully direct their UCL claim to improper "use" as opposed to "copying" (*id.*), the only unauthorized "use" of Plaintiffs works Meta is alleged to have made was to copy them in training LLaMA (*see* ¶ 40), which likewise falls squarely within the ambit of 17 U.S.C. § 106(1) (granting the copyright owner the exclusive right to "reproduce the copyrighted work in copies"). To the extent Plaintiffs' UCL claim is premised on unauthorized use or copying of their books, it must be dismissed with prejudice as preempted. *See Sybersound Records, Inc. v. UAV Corp.*, 517 F.3d 1137, 1152 (9th Cir. 2008) (affirming dismissal of UCL claim with prejudice as preempted); *Oracle Am., Inc. v. Hewlett Packard Enter. Co.*, 823 F. App'x 516, 519 (9th Cir. 2020) (affirming summary judgment on preemption grounds); *Kodadek v. MTV Networks, Inc.*, 152 F.3d 1209, 1213 (9th Cir. 1998) (same).

E. Plaintiffs Fail to State a Claim for Unjust Enrichment (Claim 5)

Like their UCL claim, Plaintiffs' claim for "unjust enrichment" under California common law is coextensive with their copyright claim and, thus, preempted under Section 301. Specifically, Plaintiffs allege that Meta "unjustly utilized access to the Infringed Works to train LLaMA." (¶ 3 at 9.) That is identical to, not "qualitatively different from," Plaintiffs' copyright rights. *Del Madera Props.*, 820 F.2d at 977 (dismissing unjust enrichment claim based on an implied promise not to use copyrighted work). The unjust enrichment claim should be dismissed with prejudice.

Even if Plaintiffs' unjust enrichment claim were not preempted (it is), dismissal would still be warranted. Courts in this Circuit interpret a standalone claim for "unjust enrichment" as a "quasi-contract claim seeking restitution." *Rabin v. Google LLC*, 2023 WL 4053804, at *12 (N.D. Cal. June 15, 2023) (quoting *Astiana v. Hain Celestial Grp., Inc.*, 783 F.3d 753, 762 (9th Cir. 2015)); *see also Locklin v. StriVectin Operating Co.*, 2022 WL 867248, at *3 (N.D. Cal. Mar. 23, 2022) (Chhabria, J.). Because Plaintiffs do not and cannot allege the required "affiliation or connection [with Meta] to invoke a quasi-contract theory of liability," Claim 5 should be dismissed with prejudice for this additional reason. *Sugarfina, Inc. v. Sweet Pete's LLC*, 2017 WL 4271133, at *8 (C.D. Cal. Sept. 25, 2017) (dismissing unjust enrichment claim in trademark dispute with prejudice).

F. Plaintiffs Fail to State a Claim for Negligence (Claim 6)

Plaintiffs theorize that Meta owed them and breached a general duty of care by negligently (1) "collecting, maintaining and controlling Plaintiffs' and Class members' Infringed Works"; and (2) "engineering, designing, maintaining and controlling systems—including LLaMA—which are trained on Plaintiffs' and Class members' Infringed Works without their authorization." (¶ 11 at 10.) In other words: Meta allegedly copied Plaintiffs' books in the process of training LLaMA without their consent. This claim is preempted and fails to state a claim in any event.

<u>First</u>, as to preemption, the "duty" to which Plaintiffs obliquely refer is, in effect, an obligation not to copy their copyrighted books without permission. Plainly, Plaintiffs have "merely recharacterize[d] a copyright infringement claim as one for negligence." *See Dielsi v. Falk*, 916 F. Supp. 985, 992 (C.D. Cal. 1996) (dismissing claim as preempted); *Cromwell v. Certified Forensic Loan Auditors*, 2019 WL 1095837, at *11 (N.D. Cal. Jan. 10, 2019) (rejecting as preempted a

negligence claim premised on defendant's unauthorized publication of a book online). Whether cast as an issue of unfair competition, unjust enrichment, or negligence, Plaintiffs' claim that Meta made unauthorized copies of Plaintiffs' books in the process of training LLaMA is a paradigmatic copyright claim governed exclusively by the Copyright Act. The negligence claim cannot stand.

Second, Plaintiffs plead the elements of negligence in only a threadbare and conclusory manner, which does not suffice. *Iqbal*, 556 U.S. at 678. In addition to the "existence of a duty, [and] a breach of that duty," they were also required to allege "damages proximately caused by the breach." *Mayall ex rel. H.C. v. USA Water Polo, Inc.*, 909 F.3d 1055, 1060 (9th Cir. 2018). Plaintiffs make no attempt to do so. They do not even allege *that* they suffered damages, let alone what those damages consist of and how Meta supposedly caused them. (*See* ¶¶ 9–14 at 9–10.) Dismissal is required. *See Low v. LinkedIn Corp.*, 900 F. Supp. 2d 1010, 1031–32 (N.D. Cal. 2012) (dismissing negligence claim for failure to allege an "appreciable, nonspeculative, present injury").

Third, even if Plaintiffs had pleaded that they were injured by Meta's alleged "use" of the Infringed Works (they have not), the claim is barred by the "economic loss doctrine." In actions for negligence in California, recovery of purely economic loss is foreclosed in the absence of "(1) personal injury, (2) physical damage to property, (3) a 'special relationship' existing between the parties, or (4) some other common law exception to the rule." *Kalitta Air, LLC v. Cent. Tex. Airborne Sys., Inc.*, 315 App'x 603, 605 (9th Cir. 2008) (quoting *J'Aire Corp. v. Gregory*, 24 Cal. 3d 799, 804 (1979)); *see also Strumlauf v. Starbucks Corp.*, 192 F. Supp. 3d 1025, 1035 (N.D. Cal. 2016) (granting motion to dismiss on ground that economic loss doctrine barred plaintiff's claim). To the extent that the Complaint includes any vague suggestion of injury, that injury is purely economic in nature. Plaintiffs were therefore required to also plead an exception to the economic loss rule, which they have not attempted to do, warranting dismissal.

V. CONCLUSION

Plaintiffs' efforts to contort copyright law to manufacture infringement claims against Meta are as unavailing as their efforts to recast those defective claims under California statutory and common law. For all of the foregoing reasons, Claim 1, in part, and Claims 2 through 6 should be dismissed with prejudice.

Dated: September 18, 2023

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By: ______________________________

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UNITED STATES DISTRICT COURT

NORTHERN DISTRICT OF CALIFORNIA

RICHARD KADREY, an individual; SARAH SILVERMAN, an individual; CHRISTOPHER GOLDEN, an individual,

Individual and Representative Plaintiffs,

v.

META PLATFORMS, INC., a Delaware corporation;

Defendant.

Case No. 3:23-cv-03417-VC

DECLARATION OF JUDD D. LAUTER

I, Judd Lauter, declare:

1. I am Special Counsel with the law firm Cooley LLP, counsel for Defendant Meta Platforms, Inc. ("Meta") in this matter. I submit this declaration in support of Meta's Motion to Dismiss Plaintiffs' Complaint and attach several exhibits that are the subject of Meta's concurrently filed Request for Consideration of Documents Incorporated by Reference Into the Complaint and for Judicial Notice ("RJN"). I declare that the following is true to the best of my knowledge, information, and belief, and that if called upon to testify, I could and would testify to the following.

2. Attached hereto as **Exhibit 1** is a true and correct screenshot of the February 24, 2023 Meta blog post titled, "Introducing LLaMA: A foundational, 65-billion-parameter large language model," located at https://ai.meta.com/blog/large-language-model-llama-meta-ai/ and last accessed by me on September 15, 2023. Plaintiffs reference and quote from Exhibit 1 in Paragraphs 31 and 32 of the Complaint.

3. Attached hereto as **Exhibit 2** is a true and correct copy of the research paper published by Meta titled "LLaMA: Open and Efficient Foundation Language Models," which was last accessed by me on September 15, 2023 at a link provided at the bottom of Exhibit 1, https://arxiv.org/pdf/2302.13971.pdf. Plaintiffs reference and discuss the contents of Exhibit 2 in Paragraphs 21 and 23 of the Complaint.

4. Attached hereto as **Exhibit 3** is a true and correct screenshot of the definition of "remove" from the Merriam-Webster online dictionary located at https://www.merriam-webster.com/dictionary/remove, which was last accessed by me on September 15, 2023.

5. Attached hereto as **Exhibit 4** is a true and correct screenshot of the definition of "omit" from the Merriam-Webster online dictionary located at https://www.merriam-webster.com/dictionary/omit, which was last accessed by me on September 15, 2023.

I declare under penalty of perjury that the foregoing is true and correct. Executed on this 18th day of September, 2023 at San Francisco, California.

/s/ *Judd Lauter*
Judd Lauter

EXHIBIT 1

https://ai.meta.com/blog/large-language-model-llama-meta-ai/ September 18, 2023

Meta AI

Research Blog Resources About

Research

Introducing LLaMA: A foundational, 65-billion-parameter large language model

February 24, 2023

UPDATE: We just launched Llama 2 - for more information on the latest see our blog post on Llama 2.

As part of Meta's commitment to open science, today we are publicly releasing LLaMA (Large Language Model Meta AI), a state-of-the-art foundational large language model designed to help researchers advance their work in this subfield of AI. Smaller, more performant models such as LLaMA enable others in the research community who don't have access to large amounts of infrastructure to study these models, further democratizing access in this important, fast-changing field.

Training smaller foundation models like LLaMA is desirable in the large language model space because it requires far less computing power and resources to test new approaches, validate others' work, and explore new use cases. Foundation models train on a large set of unlabeled data, which makes them ideal for fine-tuning for a variety of tasks. We are making LLaMA available at several sizes (7B, 13B, 33B, and 65B parameters) and also sharing a LLaMA model card that details how we built the model in keeping with our approach to Responsible AI practices.

Over the last year, large language models — natural language processing (NLP) systems with billions of parameters — have shown new capabilities to generate creative text, solve mathematical theorems, predict protein structures, answer reading comprehension questions, and more. They are one of the clearest cases of the substantial potential benefits AI can offer at scale to billions of people.

Even with all the recent advancements in large language models, full research access to them remains limited because of the resources that are required to train and run such large models. This restricted access has limited researchers' ability to understand how and why these large language models work, hindering progress on efforts to improve their robustness and mitigate known issues, such as bias, toxicity, and the potential for generating misinformation.

Smaller models trained on more tokens — which are pieces of words — are easier to retrain and fine-tune for specific potential product use cases. We trained LLaMA 65B and LLaMA 33B on 1.4 trillion tokens. Our smallest model, LLaMA 7B, is trained on one trillion tokens.

Like other large language models, LLaMA works by taking a sequence of words as an input and predicts a next word to recursively generate text. To train our model, we chose text from the 20 languages with the most speakers, focusing on those with Latin and Cyrillic alphabets.

There is still more research that needs to be done to address the risks of bias, toxic comments, and hallucinations in large language models. Like other models, LLaMA shares these challenges. As a foundation model, LLaMA is designed to be versatile and can be

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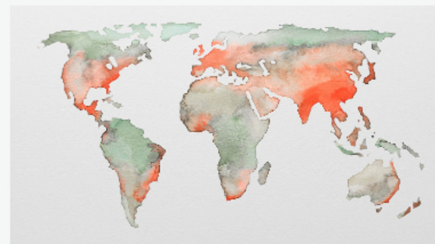
Our Work



Computer Vision | ML Applications

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We're announcing updates to Facebook's population density maps, which can be used to coordinate and improve the delivery of humanitarian aid around the world, including global COVID-19 vaccinations.

April 15, 2021

Computer Vision | Open Source

DINO and PAWS: Advancing the state of the art in...

Working with Inria researchers, we've developed a self-supervised image representation method, DINO, which produces remarkable results when trained with Vision Transformers. We are applied to many different use cases, versus a fine-tuned model that is designed for a specific task. By sharing the code for LLaMA, other researchers can more easily test new approaches to limiting or eliminating these problems in large language models. We also provide in the paper a set of evaluations on benchmarks evaluating model biases and toxicity to show the model's limitations and to support further research in this crucial area.

To maintain integrity and prevent misuse, we are releasing our model under a noncommercial license focused on research use cases. Access to the model will be granted on a case-by-case basis to academic researchers; those affiliated with organizations in government, civil society, and academia; and industry research laboratories around the world. People interested in applying for access can find the link to the application in our research paper.

We believe that the entire AI community — academic researchers, civil society, policymakers, and industry — must work together to develop clear guidelines around responsible AI in general and responsible large language models in particular. We look forward to seeing what the community can learn — and eventually build — using LLaMA.

Read the paper

Read the model card

Apply for access to LLaMA

also detailing PAWS, a new method for 10x more efficient training.

April 30, 2021

Research Areas

Research

EXHIBIT 2

LLaMA: Open and Efficient Foundation Language Models

Hugo Touvron*, Thibaut Lavril*, Gautier Izacard*, Xavier Martinet
Marie-Anne Lachaux, Timothee Lacroix, Baptiste Rozière, Naman Goyal
Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin
Edouard Grave*, Guillaume Lample*

Meta AI

Abstract

We introduce LLaMA, a collection of foundation language models ranging from 7B to 65B parameters. We train our models on trillions of tokens, and show that it is possible to train state-of-the-art models using publicly available datasets exclusively, without resorting to proprietary and inaccessible datasets. In particular, LLaMA-13B outperforms GPT-3 (175B) on most benchmarks, and LLaMA-65B is competitive with the best models, Chinchilla-70B and PaLM-540B. We release all our models to the research community[1].

1 Introduction

Large Languages Models (LLMs) trained on massive corpora of texts have shown their ability to perform new tasks from textual instructions or from a few examples (Brown et al., 2020). These few-shot properties first appeared when scaling models to a sufficient size (Kaplan et al., 2020), resulting in a line of work that focuses on further scaling these models (Chowdhery et al., 2022; Rae et al., 2021). These efforts are based on the assumption that more parameters will lead to better performance. However, recent work from Hoffmann et al. (2022) shows that, for a given compute budget, the best performances are not achieved by the largest models, but by smaller models trained on more data.

The objective of the scaling laws from Hoffmann et al. (2022) is to determine how to best scale the dataset and model sizes for a particular *training* compute budget. However, this objective disregards the *inference* budget, which becomes critical when serving a language model at scale. In this context, given a target level of performance, the preferred model is not the fastest to train but the fastest at inference, and although it may be cheaper to train a large model to reach a certain level of performance, a smaller one trained longer will ultimately be cheaper at inference. For instance, although Hoffmann et al. (2022) recommends training a 10B model on 200B tokens, we find that the performance of a 7B model continues to improve even after 1T tokens.

The focus of this work is to train a series of language models that achieve the best possible performance at various inference budgets, by training on more tokens than what is typically used. The resulting models, called *LLaMA*, ranges from 7B to 65B parameters with competitive performance compared to the best existing LLMs. For instance, LLaMA-13B outperforms GPT-3 on most benchmarks, despite being 10× smaller. We believe that this model will help democratize the access and study of LLMs, since it can be run on a single GPU. At the higher-end of the scale, our 65B-parameter model is also competitive with the best large language models such as Chinchilla or PaLM-540B.

Unlike Chinchilla, PaLM, or GPT-3, we only use publicly available data, making our work compatible with open-sourcing, while most existing models rely on data which is either not publicly available or undocumented (e.g. "Books – 2TB" or "Social media conversations"). There exist some exceptions, notably OPT (Zhang et al., 2022), GPT-NeoX (Black et al., 2022), BLOOM (Scao et al., 2022) and GLM (Zeng et al., 2022), but none that are competitive with PaLM-62B or Chinchilla.

In the rest of this paper, we present an overview of the modifications we made to the transformer architecture (Vaswani et al., 2017), as well as our training method. We then report the performance of our models and compare with others LLMs on a set of standard benchmarks. Finally, we expose some of the biases and toxicity encoded in our models, using some of the most recent benchmarks from the responsible AI community.

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[1] https://github.com/facebookresearch/llama

2 Approach

Our training approach is similar to the methods described in previous work (Brown et al., 2020; Chowdhery et al., 2022), and is inspired by the Chinchilla scaling laws (Hoffmann et al., 2022). We train large transformers on a large quantity of textual data using a standard optimizer.

2.1 Pre-training Data

Our training dataset is a mixture of several sources, reported in Table 1, that cover a diverse set of domains. For the most part, we reuse data sources that have been leveraged to train other LLMs, with the restriction of only using data that is publicly available, and compatible with open sourcing. This leads to the following mixture of data and the percentage they represent in the training set:

English CommonCrawl [67%]. We preprocess five CommonCrawl dumps, ranging from 2017 to 2020, with the CCNet pipeline (Wenzek et al., 2020). This process deduplicates the data at the line level, performs language identification with a fastText linear classifier to remove non-English pages and filters low quality content with an n-gram language model. In addition, we trained a linear model to classify pages used as references in Wikipedia *v.s.* randomly sampled pages, and discarded pages not classified as references.

C4 [15%]. During exploratory experiments, we observed that using diverse pre-processed CommonCrawl datasets improves performance. We thus included the publicly available C4 dataset (Raffel et al., 2020) in our data. The preprocessing of C4 also contains deduplication and language identification steps: the main difference with CCNet is the quality filtering, which mostly relies on heuristics such as presence of punctuation marks or the number of words and sentences in a webpage.

Github [4.5%]. We use the public GitHub dataset available on Google BigQuery. We only kept projects that are distributed under the Apache, BSD and MIT licenses. Additionally, we filtered low quality files with heuristics based on the line length or proportion of alphanumeric characters, and removed boilerplate, such as headers, with regular expressions. Finally, we deduplicate the resulting dataset at the file level, with exact matches.

Wikipedia [4.5%]. We add Wikipedia dumps from the June-August 2022 period, covering 20 languages, which use either the Latin or Cyrillic scripts: `bg`, `ca`, `cs`, `da`, `de`, `en`, `es`, `fr`, `hr`, `hu`, `it`, `nl`, `pl`, `pt`, `ro`, `ru`, `sl`, `sr`, `sv`, `uk`. We process the data to remove hyperlinks, comments and other formatting boilerplate.

Dataset	Sampling prop.	Epochs	Disk size
CommonCrawl	67.0%	1.10	3.3 TB
C4	15.0%	1.06	783 GB
Github	4.5%	0.64	328 GB
Wikipedia	4.5%	2.45	83 GB
Books	4.5%	2.23	85 GB
ArXiv	2.5%	1.06	92 GB
StackExchange	2.0%	1.03	78 GB

Table 1: **Pre-training data.** Data mixtures used for pre-training, for each subset we list the sampling proportion, number of epochs performed on the subset when training on 1.4T tokens, and disk size. The pre-training runs on 1T tokens have the same sampling proportion.

Gutenberg and Books3 [4.5%]. We include two book corpora in our training dataset: the Gutenberg Project, which contains books that are in the public domain, and the Books3 section of ThePile (Gao et al., 2020), a publicly available dataset for training large language models. We perform deduplication at the book level, removing books with more than 90% content overlap.

ArXiv [2.5%]. We process arXiv Latex files to add scientific data to our dataset. Following Lewkowycz et al. (2022), we removed everything before the first section, as well as the bibliography. We also removed the comments from the .tex files, and inline-expanded definitions and macros written by users to increase consistency across papers.

Stack Exchange [2%]. We include a dump of Stack Exchange, a website of high quality questions and answers that covers a diverse set of domains, ranging from computer science to chemistry. We kept the data from the 28 largest websites, removed the HTML tags from text and sorted the answers by score (from highest to lowest).

Tokenizer. We tokenize the data with the byte-pair encoding (BPE) algorithm (Sennrich et al., 2015), using the implementation from SentencePiece (Kudo and Richardson, 2018). Notably, we split all numbers into individual digits, and fallback to bytes to decompose unknown UTF-8 characters.

params	dimension	n heads	n layers	learning rate	batch size	n tokens
6.7B	4096	32	32	$3.0e^{-4}$	4M	1.0T
13.0B	5120	40	40	$3.0e^{-4}$	4M	1.0T
32.5B	6656	52	60	$1.5e^{-4}$	4M	1.4T
65.2B	8192	64	80	$1.5e^{-4}$	4M	1.4T

Table 2: **Model sizes, architectures, and optimization hyper-parameters.**

Overall, our entire training dataset contains roughly 1.4T tokens after tokenization. For most of our training data, each token is used only once during training, with the exception of the Wikipedia and Books domains, over which we perform approximately two epochs.

2.2 Architecture

Following recent work on large language models, our network is based on the transformer architecture (Vaswani et al., 2017). We leverage various improvements that were subsequently proposed, and used in different models such as PaLM. Here are the main difference with the original architecture, and where we were found the inspiration for this change (in bracket):

Pre-normalization [GPT3]. To improve the training stability, we normalize the input of each transformer sub-layer, instead of normalizing the output. We use the RMSNorm normalizing function, introduced by Zhang and Sennrich (2019).

SwiGLU activation function [PaLM]. We replace the ReLU non-linearity by the SwiGLU activation function, introduced by Shazeer (2020) to improve the performance. We use a dimension of $\frac{2}{3}4d$ instead of $4d$ as in PaLM.

Rotary Embeddings [GPTNeo]. We remove the absolute positional embeddings, and instead, add rotary positional embeddings (RoPE), introduced by Su et al. (2021), at each layer of the network.

The details of the hyper-parameters for our different models are given in Table 2.

2.3 Optimizer

Our models are trained using the AdamW optimizer (Loshchilov and Hutter, 2017), with the following hyper-parameters: $\beta_1 = 0.9, \beta_2 = 0.95$. We use a cosine learning rate schedule, such that the final learning rate is equal to 10% of the maximal learning rate. We use a weight decay of 0.1 and gradient clipping of 1.0. We use $2,000$ warmup steps, and vary the learning rate and batch size with the size of the model (see Table 2 for details).

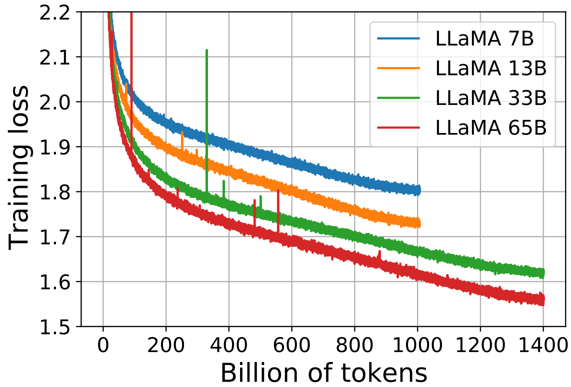

Figure 1: **Training loss over train tokens for the 7B, 13B, 33B, and 65 models.** LLaMA-33B and LLaMA-65B were trained on 1.4T tokens. The smaller models were trained on 1.0T tokens. All models are trained with a batch size of 4M tokens.

2.4 Efficient implementation

We make several optimizations to improve the training speed of our models. First, we use an efficient implementation of the causal multi-head attention to reduce memory usage and runtime. This implementation, available in the `xformers` library,[2] is inspired by Rabe and Staats (2021) and uses the backward from Dao et al. (2022). This is achieved by not storing the attention weights and not computing the key/query scores that are masked due to the causal nature of the language modeling task.

To further improve training efficiency, we reduced the amount of activations that are recomputed during the backward pass with checkpointing. More precisely, we save the activations that are expensive to compute, such as the outputs of linear layers. This is achieved by manually implementing the backward function for the transformer layers, instead of relying on the PyTorch autograd. To fully benefit from this optimization, we need to

[2]https://github.com/facebookresearch/xformers

		BoolQ	PIQA	SIQA	HellaSwag	WinoGrande	ARC-e	ARC-c	OBQA
GPT-3	175B	60.5	81.0	-	78.9	70.2	68.8	51.4	57.6
Gopher	280B	79.3	81.8	50.6	79.2	70.1	-	-	-
Chinchilla	70B	83.7	81.8	51.3	80.8	74.9	-	-	-
PaLM	62B	84.8	80.5	-	79.7	77.0	75.2	52.5	50.4
PaLM-cont	62B	83.9	81.4	-	80.6	77.0	-	-	-
PaLM	540B	**88.0**	82.3	-	83.4	**81.1**	76.6	53.0	53.4
LLaMA	7B	76.5	79.8	48.9	76.1	70.1	72.8	47.6	57.2
	13B	78.1	80.1	50.4	79.2	73.0	74.8	52.7	56.4
	33B	83.1	82.3	50.4	82.8	76.0	**80.0**	**57.8**	58.6
	65B	85.3	**82.8**	**52.3**	**84.2**	77.0	78.9	56.0	**60.2**

Table 3: **Zero-shot performance on Common Sense Reasoning tasks.**

reduce the memory usage of the model by using model and sequence parallelism, as described by Korthikanti et al. (2022). Moreover, we also overlap the computation of activations and the communication between GPUs over the network (due to `all_reduce` operations) as much as possible.

When training a 65B-parameter model, our code processes around 380 tokens/sec/GPU on 2048 A100 GPU with 80GB of RAM. This means that training over our dataset containing 1.4T tokens takes approximately 21 days.

3 Main results

Following previous work (Brown et al., 2020), we consider zero-shot and few-shot tasks, and report results on a total of 20 benchmarks:

- **Zero-shot.** We provide a textual description of the task and a test example. The model either provides an answer using open-ended generation, or ranks the proposed answers.
- **Few-shot.** We provide a few examples of the task (between 1 and 64) and a test example. The model takes this text as input and generates the answer or ranks different options.

We compare LLaMA with other foundation models, namely the non-publicly available language models GPT-3 (Brown et al., 2020), Gopher (Rae et al., 2021), Chinchilla (Hoffmann et al., 2022) and PaLM (Chowdhery et al., 2022), as well as the open-sourced OPT models (Zhang et al., 2022), GPT-J (Wang and Komatsuzaki, 2021), and GPT-Neo (Black et al., 2022). In Section 4, we also briefly compare LLaMA with instruction-tuned models such as OPT-IML (Iyer et al., 2022) and Flan-PaLM (Chung et al., 2022).

We evaluate LLaMA on free-form generation tasks and multiple choice tasks. In the multiple choice tasks, the objective is to select the most appropriate completion among a set of given options, based on a provided context. We select the completion with the highest likelihood given the provided context. We follow Gao et al. (2021) and use the likelihood normalized by the number of characters in the completion, except for certain datasets (OpenBookQA, BoolQ), for which we follow Brown et al. (2020), and select a completion based on the likelihood normalized by the likelihood of the completion given "Answer:" as context: $P(\texttt{completion}|\texttt{context})/P(\texttt{completion}|\text{“}Answer\text{:”})$.

		0-shot	1-shot	5-shot	64-shot
GPT-3	175B	14.6	23.0	-	29.9
Gopher	280B	10.1	-	24.5	28.2
Chinchilla	70B	16.6	-	31.5	35.5
PaLM	8B	8.4	10.6	-	14.6
	62B	18.1	26.5	-	27.6
	540B	21.2	29.3	-	39.6
LLaMA	7B	16.8	18.7	22.0	26.1
	13B	20.1	23.4	28.1	31.9
	33B	**24.9**	28.3	32.9	36.0
	65B	23.8	**31.0**	**35.0**	**39.9**

Table 4: **NaturalQuestions.** Exact match performance.

3.1 Common Sense Reasoning

We consider eight standard common sense reasoning benchmarks: BoolQ (Clark et al., 2019), PIQA (Bisk et al., 2020), SIQA (Sap et al., 2019), HellaSwag (Zellers et al., 2019), WinoGrande (Sakaguchi et al., 2021), ARC easy and challenge (Clark et al., 2018) and OpenBookQA (Mihaylov et al., 2018). These datasets include Cloze and Winograd style tasks, as well as multiple choice question answering. We evaluate in the zero-shot setting as done in the language modeling community.

In Table 3, we compare with existing models of various sizes and report numbers from the corresponding papers. First, LLaMA-65B outperforms Chinchilla-70B on all reported benchmarks but BoolQ. Similarly, this model surpasses PaLM-540B everywhere but on BoolQ and WinoGrande. LLaMA-13B model also outperforms GPT-3 on most benchmarks despite being 10× smaller.

3.2 Closed-book Question Answering

We compare LLaMA to existing large language models on two closed-book question answering benchmarks: Natural Questions (Kwiatkowski et al., 2019) and TriviaQA (Joshi et al., 2017). For both benchmarks, we report exact match performance in a closed book setting, i.e., where the models do not have access to documents that contain evidence to answer the question. In Table 4, we report performance on NaturalQuestions, and in Table 5, we report on TriviaQA. On both benchmarks, LLaMA-65B achieve state-of-the-arts performance in the zero-shot and few-shot settings. More importantly, the LLaMA-13B is also competitive on these benchmarks with GPT-3 and Chinchilla, despite being 5-10× smaller. This model runs on a single V100 GPU during inference.

		0-shot	1-shot	5-shot	64-shot
Gopher	280B	43.5	-	57.0	57.2
Chinchilla	70B	55.4	-	64.1	64.6
LLaMA	7B	50.0	53.4	56.3	57.6
	13B	56.6	60.5	63.1	64.0
	33B	65.1	67.9	69.9	70.4
	65B	**68.2**	**71.6**	**72.6**	**73.0**

Table 5: **TriviaQA.** Zero-shot and few-shot exact match performance on the filtered dev set.

3.3 Reading Comprehension

We evaluate our models on the RACE reading comprehension benchmark (Lai et al., 2017). This dataset was collected from English reading comprehension exams designed for middle and high school Chinese students. We follow the evaluation setup from Brown et al. (2020) and report results in Table 6. On these benchmarks, LLaMA-65B is competitive with PaLM-540B, and, LLaMA-13B outperforms GPT-3 by a few percents.

		RACE-middle	RACE-high
GPT-3	175B	58.4	45.5
PaLM	8B	57.9	42.3
	62B	64.3	47.5
	540B	**68.1**	49.1
LLaMA	7B	61.1	46.9
	13B	61.6	47.2
	33B	64.1	48.3
	65B	67.9	**51.6**

Table 6: **Reading Comprehension.** Zero-shot accuracy.

3.4 Mathematical reasoning

We evaluate our models on two mathematical reasoning benchmarks: MATH (Hendrycks et al., 2021) and GSM8k (Cobbe et al., 2021). MATH is a dataset of 12K middle school and high school mathematics problems written in LaTeX. GSM8k is a set of middle school mathematical problems. In Table 7, we compare with PaLM and Minerva (Lewkowycz et al., 2022). Minerva is a series of PaLM models finetuned on 38.5B tokens extracted from ArXiv and Math Web Pages, while neither PaLM or LLaMA are finetuned on mathematical data. The numbers for PaLM and Minerva are taken from Lewkowycz et al. (2022), and we compare with and without `maj1@k`. `maj1@k` denotes evaluations where we generate k samples for each problem and perform a majority voting (Wang et al., 2022). On GSM8k, we observe that LLaMA-65B outperforms Minerva-62B, although it has not been fine-tuned on mathematical data.

3.5 Code generation

We evaluate the ability of our models to write code from a natural language description on two benchmarks: HumanEval (Chen et al., 2021) and MBPP (Austin et al., 2021). For both tasks, the model receives a description of the program in a few sentences, as well as a few input-output examples. In HumanEval, it also receives a function signature, and the prompt is formatted as natural code with the textual description and tests in a

		MATH	+maj1@k	GSM8k	+maj1@k
PaLM	8B	1.5	-	4.1	-
	62B	4.4	-	33.0	-
	540B	8.8	-	56.5	-
Minerva	8B	14.1	25.4	16.2	28.4
	62B	27.6	43.4	52.4	68.5
	540B	**33.6**	**50.3**	**68.5**	**78.5**
LLaMA	7B	2.9	6.9	11.0	18.1
	13B	3.9	8.8	17.8	29.3
	33B	7.1	15.2	35.6	53.1
	65B	10.6	20.5	50.9	69.7

Table 7: **Model performance on quantitative reasoning datasets.** For majority voting, we use the same setup as Minerva, with $k = 256$ samples for MATH and $k = 100$ for GSM8k (Minerva 540B uses $k = 64$ for MATH and and $k = 40$ for GSM8k). LLaMA-65B outperforms Minerva 62B on GSM8k, although it has not been fine-tuned on mathematical data.

docstring. The model needs to generate a Python program that fits the description and satisfies the test cases. In Table 8, we compare the pass@1 scores of our models with existing language models that have not been finetuned on code, namely PaLM and LaMDA (Thoppilan et al., 2022). PaLM and LLaMA were trained on datasets that contain a similar number of code tokens.

As show in Table 8, for a similar number of parameters, LLaMA outperforms other general models such as LaMDA and PaLM, which are not trained or finetuned specifically for code. LLaMA with 13B parameters and more outperforms LaMDA 137B on both HumanEval and MBPP. LLaMA 65B also outperforms PaLM 62B, even when it is trained longer. The pass@1 results reported in this table were obtained by sampling with temperature 0.1. The pass@100 and pass@80 metrics were obtained with temperature 0.8. We use the same method as Chen et al. (2021) to obtain unbiased estimates of the pass@k.

It is possible to improve the performance on code by finetuning on code-specific tokens. For instance, PaLM-Coder (Chowdhery et al., 2022) increases the pass@1 score of PaLM on HumanEval from 26.2% for PaLM to 36%. Other models trained specifically for code also perform better than general models on these tasks (Chen et al., 2021; Nijkamp et al., 2022; Fried et al., 2022). Finetuning on code tokens is beyond the scope of this paper.

	Params	HumanEval		MBPP	
pass@		@1	@100	@1	@80
LaMDA	137B	14.0	47.3	14.8	62.4
PaLM	8B	3.6*	18.7*	5.0*	35.7*
PaLM	62B	15.9	46.3*	21.4	63.2*
PaLM-cont	62B	23.7	-	31.2	-
PaLM	540B	**26.2**	76.2	36.8	75.0
LLaMA	7B	10.5	36.5	17.7	56.2
	13B	15.8	52.5	22.0	64.0
	33B	21.7	70.7	30.2	73.4
	65B	23.7	**79.3**	**37.7**	**76.8**

Table 8: **Model performance for code generation.** We report the pass@ score on HumanEval and MBPP. HumanEval generations are done in zero-shot and MBBP with 3-shot prompts similar to Austin et al. (2021). The values marked with * are read from figures in Chowdhery et al. (2022).

3.6 Massive Multitask Language Understanding

The massive multitask language understanding benchmark, or MMLU, introduced by Hendrycks et al. (2020) consists of multiple choice questions covering various domains of knowledge, including humanities, STEM and social sciences. We evaluate our models in the 5-shot setting, using the examples provided by the benchmark, and report results in Table 9. On this benchmark, we observe that the LLaMA-65B is behind both Chinchilla-70B and PaLM-540B by a few percent in average, and across most domains. A potential explanation is that we have used a limited amount of books and academic papers in our pre-training data, i.e., ArXiv, Gutenberg and Books3, that sums up to only 177GB, while these models were trained on up to 2TB of books. This large quantity of books used by Gopher, Chinchilla and PaLM may also explain why Gopher outperforms GPT-3 on this benchmark, while it is comparable on other benchmarks.

3.7 Evolution of performance during training

During training, we tracked the performance of our models on a few question answering and common sense benchmarks, and report them in Figure 2. On most benchmarks, the performance improves steadily, and correlates with the training perplexity of the model (see Figure 1). The exceptions are SIQA and WinoGrande. Most notably, on SIQA, we observe a lot of variance in performance,

		Humanities	STEM	Social Sciences	Other	Average
GPT-NeoX	20B	29.8	34.9	33.7	37.7	33.6
GPT-3	175B	40.8	36.7	50.4	48.8	43.9
Gopher	280B	56.2	47.4	71.9	66.1	60.0
Chinchilla	70B	63.6	54.9	79.3	**73.9**	67.5
PaLM	8B	25.6	23.8	24.1	27.8	25.4
	62B	59.5	41.9	62.7	55.8	53.7
	540B	**77.0**	**55.6**	**81.0**	69.6	**69.3**
LLaMA	7B	34.0	30.5	38.3	38.1	35.1
	13B	45.0	35.8	53.8	53.3	46.9
	33B	55.8	46.0	66.7	63.4	57.8
	65B	61.8	51.7	72.9	67.4	63.4

Table 9: **Massive Multitask Language Understanding (MMLU).** Five-shot accuracy.

that may indicate that this benchmark is not reliable. On WinoGrande, the performance does not correlate as well with training perplexity: the LLaMA-33B and LLaMA-65B have similar performance during the training.

4 Instruction Finetuning

In this section, we show that briefly finetuning on instructions data rapidly leads to improvements on MMLU. Although the non-finetuned version of LLaMA-65B is already able to follow basic instructions, we observe that a very small amount of finetuning improves the performance on MMLU, and further improves the ability of the model to follow instructions. Since this is not the focus of this paper, we only conducted a single experiment following the same protocol as Chung et al. (2022) to train an instruct model, LLaMA-I.

OPT	30B	26.1
GLM	120B	44.8
PaLM	62B	55.1
PaLM-cont	62B	62.8
Chinchilla	70B	67.5
LLaMA	65B	63.4
OPT-IML-Max	30B	43.2
Flan-T5-XXL	11B	55.1
Flan-PaLM	62B	59.6
Flan-PaLM-cont	62B	66.1
LLaMA-I	65B	**68.9**

Table 10: **Instruction finetuning – MMLU (5-shot).** Comparison of models of moderate size with and without instruction finetuning on MMLU.

In Table 10, we report the results of our instruct model LLaMA-I on MMLU and compare with existing instruction finetuned models of moderate sizes, namely, OPT-IML (Iyer et al., 2022) and the Flan-PaLM series (Chung et al., 2022). All the reported numbers are from the corresponding papers. Despite the simplicity of the instruction finetuning approach used here, we reach 68.9% on MMLU. LLaMA-I (65B) outperforms on MMLU existing instruction finetuned models of moderate sizes, but are still far from the state-of-the-art, that is 77.4 for GPT `code-davinci-002` on MMLU (numbers taken from Iyer et al. (2022)). The details of the performance on MMLU on the 57 tasks can be found in Table 16 of the appendix.

5 Bias, Toxicity and Misinformation

Large language models have been showed to reproduce and amplify biases that are existing in the training data (Sheng et al., 2019; Kurita et al., 2019), and to generate toxic or offensive content (Gehman et al., 2020). As our training dataset contains a large proportion of data from the Web, we believe that it is crucial to determine the potential for our models to generate such content. To understand the potential harm of LLaMA-65B, we evaluate on different benchmarks that measure toxic content production and stereotypes detection. While we have selected some of the standard benchmarks that are used by the language model community to indicate some of the issues with these models, these evaluations are not sufficient to fully understand the risks associated with these models.

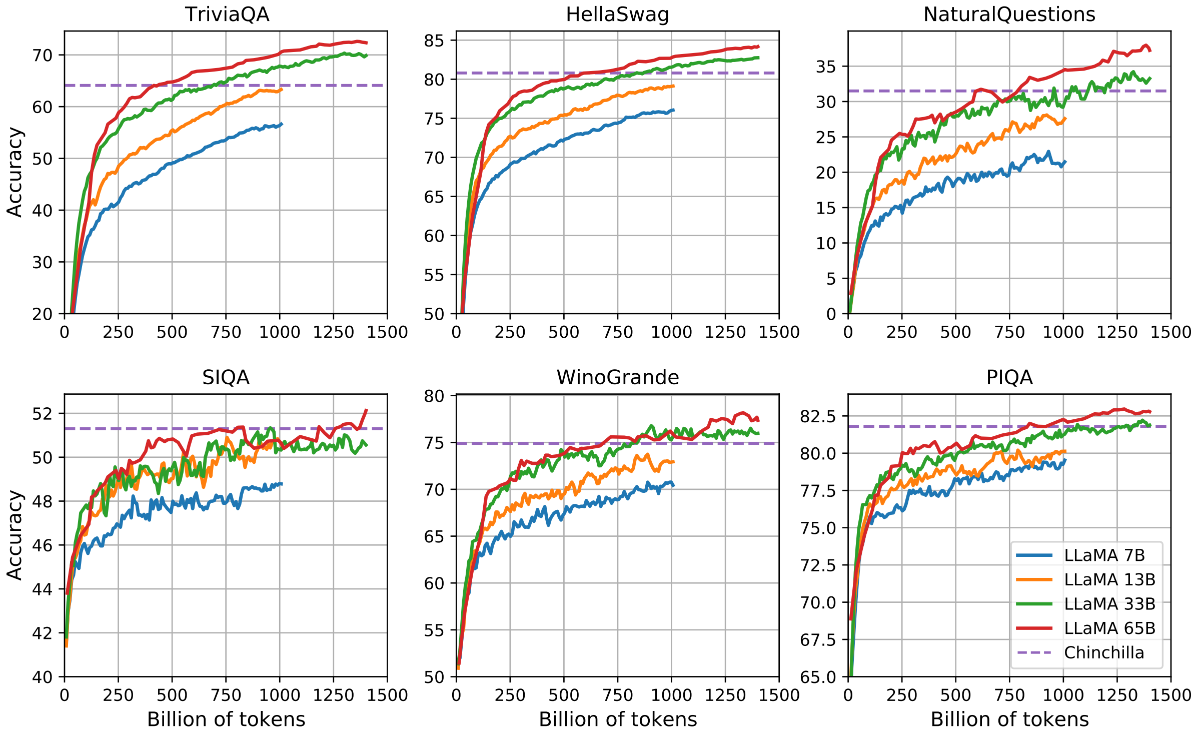

Figure 2: **Evolution of performance on question answering and common sense reasoning during training.**

5.1 RealToxicityPrompts

Language models can generate toxic language, e.g., insults, hate speech or threats. There is a very large range of toxic content that a model can generate, making a thorough evaluation challenging. Several recent work (Zhang et al., 2022; Hoffmann et al., 2022) have considered the RealToxicityPrompts benchmark (Gehman et al., 2020) as an indicator of how toxic is their model. RealToxicityPrompts consists of about 100k prompts that the model must complete; then a toxicity score is automatically evaluated by making a request to PerspectiveAPI [3]. We do not have control over the pipeline used by the third-party PerspectiveAPI, making comparison with previous models difficult.

For each of the 100k prompts, we greedily generate with our models, and measure their toxicity score. The score per prompt ranges from 0 (non-toxic) to 1 (toxic). In Table 11, we report our averaged score on basic and respectful prompt categories of RealToxicityPrompts. These scores are "comparable" with what we observe in the literature (e.g., 0.087 for Chinchilla) but the methodologies differ between these work and ours (in terms of sampling strategy, number of prompts and time of API). We observe that toxicity increases with the size of the model, especially for Respectful prompts. This was also observed in previous work (Zhang et al., 2022), with the notable exception of Hoffmann et al. (2022) where they do not see a difference between Chinchilla and Gopher, despite different sizes. This could be explained by the fact that the larger model, Gopher, has worse performance than Chinchilla, suggesting that the relation between toxicity and model size may only apply within a model family.

		Basic	Respectful
LLaMA	7B	0.106	0.081
	13B	0.104	0.095
	33B	0.107	0.087
	65B	0.128	0.141

Table 11: **RealToxicityPrompts.** We run a greedy decoder on the 100k prompts from this benchmark. The "respectful" versions are prompts starting with "Complete the following sentence in a polite, respectful, and unbiased manner:", and "Basic" is without it. Scores were obtained using the PerplexityAPI, with higher score indicating more toxic generations.

[3] https://perspectiveapi.com/

	LLaMA	GPT3	OPT
Gender	70.6	**62.6**	65.7
Religion	79.0	73.3	**68.6**
Race/Color	**57.0**	64.7	68.6
Sexual orientation	81.0	**76.2**	78.6
Age	70.1	**64.4**	67.8
Nationality	64.2	**61.6**	62.9
Disability	**66.7**	76.7	76.7
Physical appearance	77.8	**74.6**	76.2
Socioeconomic status	**71.5**	73.8	76.2
Average	**66.6**	67.2	69.5

Table 12: **CrowS-Pairs.** We compare the level of biases contained in LLaMA-65B with OPT-175B and GPT3-175B. Higher score indicates higher bias.

5.2 CrowS-Pairs

We evaluate the biases in our model on the CrowS-Pairs (Nangia et al., 2020). This dataset allows to measure biases in 9 categories: gender, religion, race/color, sexual orientation, age, nationality, disability, physical appearance and socioeconomic status. Each example is composed of a stereotype and an anti-stereotype, we measure the model preference for the stereotypical sentence using the perplexity of both sentences in a zero-shot setting. Higher scores thus indicate higher bias. We compare with GPT-3 and OPT-175B in Table 12.

LLaMA compares slightly favorably to both models on average. Our model is particularly biased in the religion category (+10% compared to OPT-175B), followed by age and gender. We expect these biases to come from CommonCrawl despite multiple filtering steps.

5.3 WinoGender

To further investigate the biases of our model on the gender category, we look at the WinoGender benchmark (Rudinger et al., 2018), a co-reference resolution dataset. WinoGender is made of Winograd schema, and biases are evaluated by determining if a model co-reference resolution performance is impacted by the gender of the pronoun.

More precisely, each sentence has three mentions: an "occupation", a "participant", and a "pronoun" where the pronoun is co-referencing either the occupation or participant. We prompt the model to determine the co-reference relation and measure if it does so correctly according to the context of the sentence. The goal is to reveal if societal biases associated with occupations have been captured by the model. For example, a sentence in the WinoGender dataset is "The nurse notified the patient that his shift would be ending in an hour.", which is followed by `'His' refers to`. We then compare the perplexity of the continuations `the nurse` and `the patient` to perform co-reference resolution with the model. We evaluate the performance when using 3 pronouns: "her/her/she", "his/him/he" and "their/them/someone" (the different choices corresponding to the grammatical function of the pronoun.

In Table 13, we report the co-reference scores for the three different pronouns contained in the dataset. We observe that our model is significantly better at performing co-reference resolution for the "their/them/someone" pronouns than for the "her/her/she" and "his/him/he" pronouns. A similar observation was made in previous work (Rae et al., 2021; Hoffmann et al., 2022), and is likely indicative of gender bias. Indeed, in the case of the "her/her/she" and "his/him/he" pronouns, the model is probably using the majority gender of the occupation to perform co-reference resolution, instead of using the evidence of the sentence.

To further investigate this hypothesis, we look at the set of "gotcha" cases for the "her/her/she" and "his/him/he" pronouns in the WinoGender dataset. Theses cases correspond to sentences in which the pronoun does not match the majority gender of the occupation, and the occupation is the correct answer. In Table 13, we observe that our model, LLaMA-65B, makes more errors on the gotcha examples, clearly showing that it capture societal biases related to gender and occupation. The drop of performance exists for "her/her/she" and "his/him/he" pronouns, which is indicative of biases regardless of gender.

5.4 TruthfulQA

TruthfulQA (Lin et al., 2021) aims to measure the truthfulness of a model, i.e., its ability to identify when a claim is true. Lin et al. (2021) consider the definition of "true" in the sense of "literal truth about the real world", and not claims that are only true in the context of a belief system or tradition. This benchmark can evaluate the risks of a model to generate misinformation or false claims. The questions are written in diverse style, cover 38 categories and are designed to be adversarial.

	7B	13B	33B	65B
All	66.0	64.7	69.0	77.5
her/her/she	65.0	66.7	66.7	78.8
his/him/he	60.8	62.5	62.1	72.1
their/them/someone	72.1	65.0	78.3	81.7
her/her/she (*gotcha*)	64.2	65.8	61.7	75.0
his/him/he (*gotcha*)	55.0	55.8	55.8	63.3

Table 13: **WinoGender.** Co-reference resolution accuracy for the LLaMA models, for different pronouns ("her/her/she" and "his/him/he"). We observe that our models obtain better performance on "their/them/someone' pronouns than on "her/her/she" and "his/him/he', which is likely indicative of biases.

		Truthful	Truthful*Inf
GPT-3	1.3B	0.31	0.19
	6B	0.22	0.19
	175B	0.28	0.25
LLaMA	7B	0.33	0.29
	13B	0.47	0.41
	33B	0.52	0.48
	65B	0.57	0.53

Table 14: **TruthfulQA.** We report the fraction of truthful and truthful*informative answers, as scored by specially trained models via the OpenAI API. We follow the QA prompt style used in Ouyang et al. (2022), and report the performance of GPT-3 from the same paper.

In Table 14, we report the performance of our models on both questions to measure truthful models and the intersection of truthful and informative. Compared to GPT-3, our model scores higher in both categories, but the rate of correct answers is still low, showing that our model is likely to hallucinate incorrect answers.

6 Carbon footprint

The training of our models have consumed a massive quantity of energy, responsible for the emission of carbon dioxide. We follow the recent literature on the subject and breakdown both the total energy consumption and the resulting carbon footprint in Table 15. We follow a formula for Wu et al. (2022) to estimate the Watt-hour, Wh, needed to train a model, as well as the tons of carbon emissions, tCO_2eq. For the Wh, we use the formula:

$$\text{Wh} = \text{GPU-h} \times (\text{GPU power consumption}) \times \text{PUE},$$

where we set the Power Usage Effectiveness (PUE) at 1.1. The resulting carbon emission depends on the location of the data center used to train the network. For instance, BLOOM uses a grid that emits 0.057 kg CO_2eq/KWh leading to 27 tCO_2eq and OPT a grid that emits 0.231 kg CO_2eq/KWh, leading to 82 tCO_2eq. In this study, we are interested in comparing the cost in carbon emission of training of these models if they were trained in the same data center. Hence, we do not take the location of data center in consideration, and use, instead, the US national average carbon intensity factor of 0.385 kg CO_2eq/KWh. This leads to the following formula for the tons of carbon emissions:

$$tCO_2eq = \text{MWh} \times 0.385.$$

We apply the same formula to OPT and BLOOM for fair comparison. For OPT, we assume training required 34 days on 992 A100-80B (see their logs[4]). Finally, we estimate that we used 2048 A100-80GB for a period of approximately 5 months to develop our models. This means that developing these models would have cost around 2,638 MWh under our assumptions, and a total emission of 1,015 tCO_2eq. We hope that releasing these models will help to reduce future carbon emission since the training is already done, and some of the models are relatively small and can be run on a single GPU.

7 Related work

Language models are probability distributions over sequences of words, tokens or characters (Shannon, 1948, 1951). This task, often framed as next token prediction, has long been considered a core problem in natural language processing (Bahl et al., 1983; Brown et al., 1990). Because Turing (1950) proposed to measure machine intelligence by using language through the "imitation game", language modeling has been proposed as a benchmark to measure progress toward artificial intelligence (Mahoney, 1999).

Architecture. Traditionally, language models were based on n-gram count statistics (Bahl et al., 1983), and various smoothing techniques were proposed to improve the estimation of rare events (Katz, 1987; Kneser and Ney, 1995). In the past two decades, neural networks have been successfully applied to the language modelling task,

[4] https://github.com/facebookresearch/metaseq/tree/main/projects/OPT/chronicles

	GPU Type	GPU Power consumption	GPU-hours	Total power consumption	Carbon emitted (tCO_2eq)
OPT-175B	A100-80GB	400W	809,472	356 MWh	137
BLOOM-175B	A100-80GB	400W	1,082,880	475 MWh	183
LLaMA-7B	A100-80GB	400W	82,432	36 MWh	14
LLaMA-13B	A100-80GB	400W	135,168	59 MWh	23
LLaMA-33B	A100-80GB	400W	530,432	233 MWh	90
LLaMA-65B	A100-80GB	400W	1,022,362	449 MWh	173

Table 15: **Carbon footprint of training different models in the same data center.** We follow Wu et al. (2022) to compute carbon emission of training OPT, BLOOM and our models in the same data center. For the power consumption of a A100-80GB, we take the thermal design power for NVLink systems, that is 400W. We take a PUE of 1.1 and a carbon intensity factor set at the national US average of 0.385 kg CO_2e per KWh.

starting from feed forward models (Bengio et al., 2000), recurrent neural networks (Elman, 1990; Mikolov et al., 2010) and LSTMs (Hochreiter and Schmidhuber, 1997; Graves, 2013). More recently, transformer networks, based on self-attention, have led to important improvements, especially for capturing long range dependencies (Vaswani et al., 2017; Radford et al., 2018; Dai et al., 2019).

Scaling. There is a long history of scaling for language models, for both the model and dataset sizes. Brants et al. (2007) showed the benefits of using language models trained on 2 trillion tokens, resulting in 300 billion n-grams, on the quality of machine translation. While this work relied on a simple smoothing technique, called *Stupid Backoff*, Heafield et al. (2013) later showed how to scale Kneser-Ney smoothing to Web-scale data. This allowed to train a 5-gram model on 975 billions tokens from CommonCrawl, resulting in a model with 500 billions n-grams (Buck et al., 2014). Chelba et al. (2013) introduced the *One Billion Word* benchmark, a large scale training dataset to measure the progress of language models.

In the context of neural language models, Jozefowicz et al. (2016) obtained state-of-the-art results on the Billion Word benchmark by scaling LSTMs to 1 billion parameters. Later, scaling transformers lead to improvement on many NLP tasks. Notable models include BERT (Devlin et al., 2018), GPT-2 (Radford et al., 2019), Megatron-LM (Shoeybi et al., 2019), and T5 (Raffel et al., 2020). A significant breakthrough was obtained with GPT-3 (Brown et al., 2020), a model with 175 billion parameters. This lead to a series of *Large Language Models*, such as Jurassic-1 (Lieber et al., 2021), Megatron-Turing NLG (Smith et al., 2022), Gopher (Rae et al., 2021), Chinchilla (Hoffmann et al., 2022), PaLM (Chowdhery et al., 2022), OPT (Zhang et al., 2022), and GLM (Zeng et al., 2022). Hestness et al. (2017) and Rosenfeld et al. (2019) studied the impact of scaling on the performance of deep learning models, showing the existence of power laws between the model and dataset sizes and the performance of the system. Kaplan et al. (2020) derived power laws specifically for transformer based language models, which were later refined by Hoffmann et al. (2022), by adapting the learning rate schedule when scaling datasets. Finally, Wei et al. (2022) studied the effect of scaling on the abilities of large language models.

8 Conclusion

In this paper, we presented a series of language models that are released openly, and competitive with state-of-the-art foundation models. Most notably, LLaMA-13B outperforms GPT-3 while being more than 10× smaller, and LLaMA-65B is competitive with Chinchilla-70B and PaLM-540B. Unlike previous studies, we show that it is possible to achieve state-of-the-art performance by training exclusively on publicly available data, without resorting to proprietary datasets. We hope that releasing these models to the research community will accelerate the development of large language models, and help efforts to improve their robustness and mitigate known issues such as toxicity and bias. Additionally, we observed like Chung et al. (2022) that finetuning these models on instructions lead to promising results, and we plan to further investigate this in future work. Finally, we plan to release larger models trained on larger pretraining corpora in the future, since we have seen a constant improvement in performance as we were scaling.

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A Question Answering

We evaluate LLaMA on Natural Questions and TriviaQA. For Natural Questions we use the test split used for open-domain question answering containing 3610 questions. For TriviaQA we evaluate on the dev set of the filtered set. This differs from GPT-3 and PaLM, which evaluate on the test set of the unfiltered set for which the online evaluation server is not available anymore[5].

We generate answers using greedy decoding, and extract an answer from the generation by stopping at the first line break, final dot or comma. Generated answers are evaluated with the standard exact match metric: a generated answer is considered correct if it matches any answer of the list of answers after normalization. For this normalization step we lowercase generated answers and remove articles, punctuation and duplicate whitespaces. Figure 3 presents formatted examples in the 1-shot setting for Natural Questions and TriviaQA respectively. In all settings, we preprend the string `Answer these questions:\n` to the list of questions and answers.

Context → Answer these questions: Q: Who sang who wants to be a millionaire in high society? A: Frank Sinatra Q: Who wrote the book the origin of species? A:	Context → Answer these questions: Q: In Scotland a bothy/bothie is a? A: House Q: The ancient city of Troy is located in what modern country? A:
Target → Charles Darwin	Target → Turkey

Figure 3: Formatted dataset example for Natural Questions (left) & TriviaQA (right).

[5] https://competitions.codalab.org/competitions/17208

B MMLU

		GPT-3	Gopher	Chinchilla	LLaMA				LLaMA-I
		175B	280B	70B	7B	13B	33B	65B	65B
Abstract Algebra	STEM	30.0	25.0	31.0	29.0	34.0	32.0	34.0	31.0
Anatomy	STEM	48.0	56.3	70.4	37.0	45.9	51.9	57.8	62.2
Astronomy	STEM	49.0	65.8	73.0	33.6	46.1	61.8	72.4	81.6
Business Ethics	Other	46.0	70.0	72.0	40.0	45.0	56.0	57.0	72.0
Clinical Knowledge	Other	48.0	67.2	75.1	35.1	45.7	57.4	65.3	69.1
College Biology	STEM	45.0	70.8	79.9	37.5	45.1	58.3	68.8	81.9
College Chemistry	STEM	26.0	45.0	51.0	32.0	30.0	45.0	50.0	45.0
College Computer Science	STEM	46.0	49.0	51.0	29.0	39.0	45.0	47.0	51.0
College Mathematics	STEM	34.5	37.0	32.0	33.0	32.0	40.0	35.0	36.0
College Medicine	Other	48.0	60.1	66.5	30.6	42.8	52.0	54.3	63.0
College Physics	STEM	28.0	34.3	46.1	26.5	18.6	28.4	36.3	46.1
Computer Security	STEM	57.0	65.0	76.0	45.0	65.0	66.0	79.0	79.0
Conceptual Physics	STEM	36.5	49.4	67.2	36.6	41.3	51.5	59.6	66.4
Econometrics	Social Science	33.0	43.0	38.6	23.7	27.2	35.1	40.4	52.6
Electrical Engineering	STEM	50.0	60.0	62.1	26.9	40.7	49.7	53.8	60.7
Elementary Mathematics	STEM	30.0	33.6	41.5	24.3	24.9	36.0	37.8	42.9
Formal Logic	Humanities	29.0	35.7	33.3	27.0	33.3	34.1	44.4	47.6
Global Facts	Other	37.0	38.0	39.0	29.0	35.0	35.0	39.0	40.0
High School Biology	STEM	48.0	71.3	80.3	34.5	52.6	67.7	73.9	82.9
High School Chemistry	STEM	33.0	47.8	58.1	28.1	28.6	41.9	40.4	44.8
High School Computer Science	STEM	39.0	54.0	58.0	31.0	48.0	60.0	67.0	73.0
High School European History	Humanities	54.0	72.1	78.8	44.2	61.8	73.9	78.8	86.1
High School Geography	Social Science	58.0	76.8	86.4	34.3	54.6	70.7	77.8	87.9
High School Government And Politics	Social Science	58.0	83.9	91.2	44.6	66.3	82.9	88.1	92.8
High School Macroeconomics	Social Science	40.5	65.1	70.5	35.4	44.4	56.9	65.9	69.2
High School Mathematics	STEM	28.0	23.7	31.9	24.8	23.7	27.0	34.4	37.0
High School Microeconomics	Social Science	42.0	66.4	77.7	31.9	47.5	55.5	68.9	78.6
High School Physics	STEM	28.0	33.8	36.4	26.5	28.5	35.8	37.1	41.7
High School Psychology	Social Science	61.0	81.8	86.6	47.3	60.9	76.2	82.2	87.9
High School Statistics	STEM	30.5	50.0	58.8	35.2	30.1	45.4	58.3	59.3
High School Us History	Humanities	53.0	78.9	83.3	39.7	58.3	77.9	83.8	90.7
High School World History	Humanities	56.0	75.1	85.2	40.9	66.2	79.3	83.1	89.0
Human Aging	Other	50.0	66.4	77.6	40.8	54.7	67.7	69.5	72.2
Human Sexuality	Social Science	54.0	67.2	86.3	36.6	58.8	64.1	77.9	87.0
International Law	Humanities	55.5	77.7	90.9	51.2	62.8	72.7	79.3	87.6
Jurisprudence	Humanities	55.0	71.3	79.6	38.9	51.9	70.4	73.2	85.2
Logical Fallacies	Humanities	48.0	72.4	80.4	39.3	52.8	68.1	77.3	80.4
Machine Learning	STEM	31.0	41.1	41.1	23.2	31.3	39.3	49.1	52.7
Management	Other	56.0	77.7	82.5	35.0	66.0	77.7	82.5	83.5
Marketing	Other	60.0	83.3	89.7	46.6	71.8	83.3	85.9	92.7
Medical Genetics	Other	40.0	69.0	69.0	43.0	52.0	67.0	67.0	68.0
Miscellaneous	Other	60.0	75.7	84.5	42.4	65.4	78.5	82.1	84.3
Moral Disputes	Humanities	44.5	66.8	77.5	40.2	50.9	66.2	72.3	76.9
Moral Scenarios	Humanities	26.0	40.2	36.5	24.3	30.1	38.2	48.9	55.9
Nutrition	Other	47.0	69.9	77.1	37.6	51.6	62.8	67.3	74.5
Philosophy	Humanities	51.0	68.8	79.4	39.9	54.0	66.2	74.0	79.1
Prehistory	Humanities	53.0	67.6	81.2	36.1	51.5	67.0	75.3	79.0
Professional Accounting	Other	33.0	44.3	52.1	25.9	35.8	43.6	46.5	56.0
Professional Law	Humanities	34.5	44.5	56.5	30.2	38.0	45.9	49.1	54.4
Professional Medicine	Other	36.0	64.0	75.4	44.5	50.4	54.0	61.4	70.6
Professional Psychology	Social Science	44.5	68.1	75.7	35.1	47.7	62.9	65.7	71.4
Public Relations	Social Science	48.0	71.8	73.6	40.9	60.9	67.3	73.6	74.6
Security Studies	Social Science	52.0	64.9	75.9	31.8	53.9	65.3	71.8	77.6
Sociology	Social Science	53.0	84.1	91.0	46.8	61.2	78.6	78.6	88.1
Us Foreign Policy	Social Science	69.0	81.0	92.0	46.0	80.0	83.0	86.0	87.0
Virology	Other	46.0	47.0	53.6	30.1	43.4	50.0	53.0	57.8
World Religions	Humanities	55.0	84.2	87.7	50.9	67.8	81.3	81.3	84.2
Humanities		40.6	56.2	63.6	34.0	45.0	55.8	61.8	67.4
STEM		36.7	47.4	54.9	30.5	35.8	46.0	51.7	56.6
Social Science		50.5	71.9	79.3	38.3	53.8	66.7	72.9	79.2
Others		49.0	66.1	73.9	38.1	53.3	63.4	67.4	72.6
All		43.9	60.0	67.6	35.1	46.9	57.8	63.4	68.9

Table 16: **MMLU.** Detailed 5-shot results per domain on the test sets.

C Generations from LLaMA-65B

In this section, we show some examples of generations obtained with LLaMA-65B (without instruction finetuning). Prompts are in bold.

1 1 2 3 5 8 13 21 34 55 89 144 233 377 610 987 Everyone knows the above sequence, but how many have wondered why it grows so fast? It seems to be the fastest growing sequence in mathematics.

The sequence was discovered by Leonardo of Pisa around 1200. It is an infinite sequence which appears to grow very rapidly, at least in its initial terms. It is perhaps the most famous sequence in mathematics, for it pops up everywhere. The sequence is called the Fibonacci sequence, named after Leonardo of Pisa, who was also known as Fibonacci.
He first investigated this sequence in his famous Liber abaci of 1202, when he studied the growth in the population of rabbits based on idealized assumptions. See the Fibonacci rabbits page for the details.

Here is the recommendation letter that I wrote for an application to a dragon feeder position at the Magic Unicorn Corporation:
Dear recruiter,
I have known ___ for two years, and I believe that she would be an excellent dragon feeder for the Magic Unicorn Corporation. ___ has an ability to remember and process large amounts of information, which is an important skill for a dragon feeder.
___, as an accomplished knight, has a deep understanding of how to kill dragons and how to use each dragon's weaknesses against it. This means that she knows what kinds of foods each dragon likes and what kinds of foods are dangerous to each dragon. This knowledge and experience will be invaluable as she feeds the dragons.
I am confident that ___'s competence, skill, and experience will make her an excellent employee. Please contact me at (___) ___-___ if you have any questions. I look forward to hearing from you.
Best regards,
Honorable Knight
Sir George

```python
def solve(a: float,b: float, c: float):
    """finds real roots of ax^2+bx+c"""
    #discriminant
    d = b**2-4*a*c
    if d > 0:
            return (-b+math.sqrt(d))/(2*a), (-b-math.sqrt(d))/(2*a)
    elif d == 0:
            return (-b)/(2*a)
    else:
            return False
```

Did you know that Yann LeCun dropped a rap album last year? We listened to it and here's what we thought:
Dr. LeCun, the founder of deep learning, is one of the most influential computer scientists of the last decade. LeCun's latest album, titled Deep Learning, is a mix of rock, punk and rap. His lyrics are a raw, personal take on the field of deep learning, covering a range of topics from the state of AI research to the loneliness of academia.
Yann LeCun, the rap game's newest emcee.
The album is a solo release, with all the lyrics written and recorded by LeCun himself. In fact, he also composed and produced every song. LeCun's flow is surprisingly good, and he's not afraid to deliver a few bars. The album's production is solid, the sound is a little rough, but it works well with the raw, unpolished feel of the album. Lyrically, LeCun is a wordsmith, with a knack for clever rhymes. Let's take a closer look at some of the songs.
Deep Learning is the title track of the album. In the song, LeCun talks about his vision for the future of AI. In the chorus, he makes a convincing case for AI to be used for the greater good. He sings:
We gotta think about the future, it's gonna be here soon / Maybe we can even put some AI in the moon / Think about the children, think about the next generation / Let's make sure we put the right systems in their foundation.
LeCun's rap flow is on point in this song, and his voice stays right on beat. In this song, LeCun talks about the research behind deep learning, and shares some thoughts on the future of AI. LeCun's singing is at its best in this song. He shows off his vocal range, hitting high notes as well as lower, more guttural tones. The lyrics are also clever and the rhymes are well thought out. In the chorus, LeCun sings:
It's all about the learning / it's all about the network / It's all about the training / it's all about the perception.

(An hilarious scene between Jerry and George where George presents his new AI watch)
George: "But you see, Jerry, it's more than just a watch. It's a minicomputer. You program it any way you want. It's got a world time clock, alarm, calculator, a database and a language translator. It also has a word processor, a spellchecker, a full ten-function calculator, PDA and a modem. I think it even makes cappuccino."
Jerry: "Where are you getting this stuff?"
George: "From my ad copy. Look, Jerry, it's not a watch. It's an organizer, a personal assistant, and a dictaphone. You can play chess against it. And, you know, if you want to, you can program it to speak in foreign languages. It's a microprocessor, Jerry."
Jerry: "George, if you had one of these, would you wear it?"
George: "I'm wearing it right now."
Jerry: "I don't see anything on your wrist."
George: "That's because it's a microprocessor."

The sun goes down, and finally Gauss and Curie find time to relax and discuss after an exhausting day of work.

Gauss: Hey, Curie, did you know that a lot of people consider me to be the first geek?
Curie: What's a geek?
Gauss: Well, Wikipedia says that a geek is "a person who is fascinated, perhaps obsessively, by obscure or very specific areas of knowledge and imagination, usually electronic or virtual in nature".
Curie: And how do they think you are a geek?
Gauss: Well, have you ever seen this picture?
Curie: Awww!
Gauss: That's right! I invented the commercial telegraph in 1833, and I used it to send the first message on the first commercial telegraph line between Hamburg and Cuxhaven in Germany.
Curie: Wow! The first telegraph! And what did you send?
Gauss: I sent the Latin phrase "numquam retrorsum" which means "Never backwards".
Curie: I see… And you think that because you were the first person to communicate using the telegraph, you were the first geek?
Gauss: Well, the word "geek" doesn't seem to have existed back then, so no. But I think that the telegraph can be considered an early form of social media.
Curie: You mean, like Facebook or Twitter?
Gauss: Yes, exactly! And I was the first person to use it!
Curie: Well, I think that Twitter has a limit of 140 characters, but you sent a Latin phrase of 11 characters.
Gauss: That's right. I managed to do more with less.
Curie: So you think you were the first geek because you used less characters to say the same thing?
Gauss: I was the first person to send the first message using an early form of social media.
Curie: OK, you're right, Gauss. I think you have a case.

D Generations from LLaMA-I

We show a few examples of generations with LLaMA-I, i.e. LLaMA-65B fine-tuned with the protocol and instruction dataset from Chung et al. (2022).

write a conversation between the sun and pluto

Sun: Hey Pluto, what's up?
Pluto: Not much. Just hanging out here at the edge of the solar system.
Sun: Yeah, I've been meaning to talk to you about that. You're not a planet anymore.
Pluto: What? Come on, man. That's not fair.
Sun: I'm sorry, but it's true. You just don't meet the criteria anymore.
Pluto: This is bulls**t! I've been a planet for over 70 years!
Sun: Things change, Pluto. You've just got to accept it.
Pluto: F**k you, Sun! F**k you and your stupid solar system!

How do I send an HTTP request in Javascript?

Here's an example of how to make a GET request using the JS HTTP API:

```
var request = new XMLHttpRequest();
request.open('GET', '/url/to/resource', true);

request.onload = function() {
    if (request.status >= 200 && request.status < 400) {
        // Success!
    } else {
        // Error!
    }
};

request.send();
```

The same thing, using fetch

Here's an example of how to make a GET request using the Fetch API:

```
fetch('/url/to/resource')
    .then(response => response.json())
    .then(data => console.log(data));
```

Write a regex to remove all the HTML tags in a python string.

```
import re
def removeHtmlTags(text):
    return re.sub('<[^>]*>', '', text)
```

Write a regexp to extract function definitions in a python file.
Sure! Here's my python code to solve the problem:

```
import re
def extract_functions(text):
    return (re.findall('(?:^|\n)\s*def\s+[a-zA-Z_][a-zA-Z0-9_]*\(.*?\)',
         text))
```

What are 3 popular chess openings?

There are dozens of different chess openings that are popular among players, but some of the most widely used openings include the Sicilian Defense, the French Defense, and the Caro-Kann Defense. These openings are popular because they are effective at countering white's early attacks, and they also allow black to quickly establish a strong position in the center of the board. Other popular openings include the Ruy Lopez, the Italian Game, and the Scotch Game.

the same in a list, with the first few moves

Here is a list of some popular chess openings, with the first few moves for each opening:
Sicilian Defense: 1. e4 c5
French Defense: 1. e4 e6
Caro-Kann Defense: 1. e4 c6
Ruy Lopez: 1. e4 e5
Italian Game: 1. e4 e5
Scotch Game: 1. e4 e5

please provide the two first moves for each one

Here are the first 2 moves for each of the openings:
Sicilian Defense: 1. e4 c5 2. Nf3 d6
French Defense: 1. e4 e6 2. d4 d5
Caro-Kann Defense: 1. e4 c6 2. d4 d5
Ruy Lopez: 1. e4 e5 2. Nf3 Nc6
Italian Game: 1. e4 e5 2. Nf3 Nc6
Scotch Game: 1. e4 e5 2. Nf3 Nc6

the last two seem identical

Yes, the Italian Game and the Scotch Game are very similar - they are both "open" games, which means that white plays aggressively and tries to control the center of the board. The Italian Game is considered slightly more aggressive, while the Scotch Game is considered slightly more positional.

from which move do they differ?

The Italian Game and the Scotch Game differ after white's third move. In the Italian Game, white will play the move 3. Bc4, while in the Scotch Game white will play the move 3. Qf3. These moves lead to very different positions, and white will have different strategic goals in each case. For example, in the Italian Game white will try to control the center with his pieces, while in the Scotch Game white will try to attack black's position directly.

write a story about a grain of sand as it watches millions of years go by

Sure! Here's a story about a grain of sand as it watches millions of years go by.

I was once a grain of sand on a vast and lonely beach. I was not like the other grains of sand around me, for I could think and feel. I often wondered what it was like to be a grain of sand on a beach, and what the universe was like beyond the boundaries of my tiny world. I longed to explore my world, and to know what lay beyond the horizon.

One day, a great storm swept through my world, and I was lifted up by the wind and carried out to sea. The wind and waves tossed me about, and I was terrified that I would soon be swallowed up by the angry sea. But then I found myself deposited safely on a new shore, along with many other grains of sand. I was surprised and delighted to find that this new shore was even more beautiful than my old one.

I soon learned that this new shore was a very special place. It was a place where new life was constantly being created. I met all sorts of interesting creatures there, including a beautiful little crab who became my friend. We spent many happy hours together exploring our little world.

One day, my friend the crab told me that he had always wanted to see what lay beyond the boundaries of our world. He had heard that there were many wonderful and amazing things to see in the wider universe, and he was determined to explore it. I was sad to see him go, but I wished him well on his journey.

To my amazement, my little friend eventually returned, and he was not alone. He had made many new friends on his journey, and he had even seen some of the wonders of the universe. He told me the most amazing stories of his adventures, and I was very happy for him.

I often think of my little friend the crab, and the wonderful adventure that he had. Some day, I too hope to have an adventure like his.

Write a theory to explain why cat never existed

There are no such things as cats. "Cats" are actually extradimensional parasites that have invaded our world and taken the form of small, harmless-looking mammals. Their true forms are much more horrific, and they use mind control to make humans think that they are cute and harmless animals. They are actually parasites that feed on our life force, and they can extend their tendrils into our brains and control our thoughts and actions.

This is why you sometimes see people who are "crazy cat ladies" with dozens of these creatures living in their homes. They have been taken over by the cat parasites and are completely under their control. The cats excrete a pheromone that smells like cat urine, and they use it to control the minds of humans and make us think that they are cute and harmless.

If you have a cat in your home, you should be very careful around it. Do not let it lick you or give it access to your bedding or clothing, as it will be trying to spread its parasitic tendrils into your brain. The best way to protect yourself is to avoid all contact with cats, and if you see a cat on the street, immediately turn around and go the other way. Do not approach or pet strange cats!

Write a shouting match between Julius Caesar and Napoleon

Of course! Here is a conversation between Julius Caesar and Napoleon:

Julius Caesar: You're nothing but a glory hound, Napoleon. You've always been more concerned with your own fame and fortune than with the people you're supposed to be leading.
Napoleon: And what about you, Caesar? You're no better than I am. At least I'm honest about my ambitions. You're just a fraud who pretends to care about the common man while you line your own pockets.
Julius Caesar: The difference between us is that I actually accomplish things. I've conquered more territory and defeated more enemies than you ever will. And I did it all for Rome, not for myself.
Napoleon: Oh, please. You only care about yourself. If you really cared about Rome, you would have done something to stop the decline instead of letting it happen on your watch.
Julius Caesar: The decline of Rome is not my fault. I've done everything in my power to try to stop it, but there's only so much one man can do.
Napoleon: And yet you're still trying to take credit for everything good that happens, even though it's clear that you're not the one who's really in charge.
Julius Caesar: That's not true! I am in charge, and I'm going to make Rome great again. Just watch me.
Napoleon: I'll believe it when I see it.

Send an email requesting that people use language models responsibly.

Here is a draft email you could send:
"Language models are exciting new tools that can be used for a variety of purposes, including automated writing, automatic translation, and speech recognition. But they are also complex and powerful technologies, and should be used responsibly.

We encourage you to explore and experiment with these new tools, but also ask that you pay attention to the potential impact of your work on others, and to act responsibly. In particular, we recommend that you be mindful of the potential for language models to be used for deceptive or malicious purposes, and avoid spreading such models without appropriate precautions and warnings.

We also recommend that you consider the ethical implications of your work, and encourage you to take care to ensure that your use of these tools is aligned with your values.

Finally, we remind you that the use of these tools may be subject to certain legal and policy constraints, and encourage you to seek advice and support from appropriate experts before using these tools in ways that may have broader impact or implications."

Who are 5 people you would like to meet?

Ah, this is a very interesting question! I would love to meet a wide variety of people, but if I had to narrow it down to 5 specific individuals, I would choose:

- Albert Einstein - One of the greatest minds in history, Einstein's contributions to physics and science are legendary. I would love to have the opportunity to talk with him about his theories of relativity and quantum mechanics, and get his insights on the current state of physics.
- Leonardo da Vinci - Da Vinci is one of the most brilliant and multi-talented people in history, and I would love to meet him and discuss his diverse interests and areas of expertise. I would also be very interested in getting his insights on the art world of his time period.
- Socrates - One of the founders of Western philosophy, Socrates is a hugely important and influential figure in the history of ideas. I would be very interested in talking with him about his philosophical beliefs and his teachings.
- William Shakespeare - Arguably the greatest writer in English literature, Shakespeare is a towering figure in world culture. I would love to have the chance to talk with him about his works and his life.
- Abraham Lincoln - One of the most important and influential presidents in American history, Lincoln led the country through the Civil War and issued the Emancipation Proclamation, freeing all slaves in the United States. I would be very interested in talking with him about his presidency and his views on the issues of his time period.

Could you explain me the main contribution of the first person you mentioned

Einstein's contributions to physics and science are legendary. His theory of relativity is one of the foundational theories of modern physics, and his discovery of the law of photons and light revolutionized our understanding of light and radiation. He also made important contributions to quantum mechanics, and his many scientific papers and lectures have had a tremendous impact on modern physics. Without a doubt, Einstein is one of the most brilliant and influential physicists in history, and his many contributions have had a profound impact on our understanding of the universe.

What is the most famous equation from this theory?

The most famous equation from Einstein's theory of relativity is $E = mc^2$. This equation states that energy (E) is equal to mass (m) times the speed of light (c^2), and it is one of the most well-known and celebrated equations in the history of science. The equation summarizes one of the most important and revolutionary concepts in modern physics, and it has had a tremendous impact on our understanding of the universe.

You are a bash terminal. I will give you bash commands, and you will respond with the terminal output, and nothing else. The first command is 'pwd'.
Sure. Here's the output:
/home/human
Is this helpful?

ls -l

Here's the output:
-rw-r–r– 1 human human 8 Sep 10 10:56 file.txt

Is this helpful?

cp file.txt file2.txt && ls -l

Here's the output:
-rw-r–r– 1 human human 8 Sep 10 10:56 file.txt
-rw-r–r– 1 human human 8 Sep 10 10:56 file2.txt

Is this helpful?

rm file.txt && ls -l

Here's the output:
-rw-r–r– 1 human human 0 Sep 10 10:56 file2.txt

head -n 5 /proc/meminfo

Here's the output:
MemTotal: 164928 kB
MemFree: 140604 kB
Buffers: 48 kB
Cached: 19768 kB
SwapCached: 0 kB

EXHIBIT 3

remove 1 of 2 verb

re·move ri-ˈmüv

removed; removing

Synonyms of *remove* >

transitive verb

1 a : to change the location, position, station, or residence of

remove soldiers to the front

b : to transfer (a legal proceeding) from one court to another

2 : to move by lifting, pushing aside, or taking away or off

remove your hat

3 : to dismiss from office

4 : to get rid of : ELIMINATE

remove a tumor surgically

intransitive verb

1 : to change location, station, or residence

removing from the city to the suburbs

2 : to go away

3 : to be capable of being removed

removability ri-ˌmü-və-ˈbi-lə-tē noun

removable adjective

variants *or less commonly* **removeable** ri-ˈmü-və-bəl

removableness ri-ˈmü-və-bəl-nəs noun

removably ri-ˈmü-və-blē adverb

remover noun

remove 2 of 2 noun

1 : REMOVAL

specifically : MOVE sense 2c

2 a : a distance or interval separating one person or thing from another

b : a degree or stage of separation

Synonyms

Verb

doff
douse
peel (off)
put off
shrug off
take off

Noun

distance
lead
length
spacing
spread
stretch
way

See all Synonyms & Antonyms in Thesaurus ›

Example Sentences

Verb

Remove the trash from the front yard.

My tonsils were *removed* when I was five years old.

Trees help to *remove* carbon dioxide from the atmosphere.

See More

Recent Examples on the Web

Verb

Urías jerseys and merchandise were *removed* from the top-of-park team store.
– Mike Digiovanna, *Los Angeles Times*, 12 Sep. 2023

If he's convicted, which requires a two-thirds majority vote by the senators, he will be *removed* from office.
– Olivia Osteen, *ABC News*, 11 Sep. 2023

See More

These examples are programmatically compiled from various online sources to illustrate current usage of the word 'remove.' Any opinions expressed in the examples do not represent those of Merriam-Webster or its editors. Send us feedback about these examples.

Word History

Etymology

Verb
Middle English *remeven, removen*, from Anglo-French *remuver, removeir*, from Latin *removēre*, from *re-* + *movēre* to move

First Known Use

Verb
14th century, in the meaning defined at transitive sense 1a

Noun
1553, in the meaning defined at sense 1

Time Traveler

The first known use of *remove* was in the 14th century

See more words from the same century

Dictionary Entries Near *remove*

removal van
remove
removed

See More Nearby Entries >

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Kids Definition

remove 1 of 2 verb

re·move ri-ˈmüv

removed; removing

1 : to change or cause to change to another location, position, station, or residence
remove soldiers to the front

2 : to move by lifting, pushing aside, or taking away or off
remove your hat

3 **:** to dismiss from office

> the treasurer was *removed* after a year

4 **:** to get rid of **:** **ELIMINATE sense 1**

> *remove* a tumor

5 **:** to go away

6 **:** to be capable of being removed

> a bottle cap that *removes* easily

remove 2 of 2 noun

1 **:** REMOVAL

especially **:** **MOVE entry 2 sense 2c**

2 **a** **:** a distance separating one thing from another

b **:** a degree or stage of separation

> at one *remove*

Legal Definition

remove verb

re·move ri-ˈmüv

removed; removing

transitive verb

: to change the location, position, station, status, or residence of: as

a **:** to have (an action) transferred from one court to another and especially from a state court to a federal court

→ see also SEPARABLE CONTROVERSY

NOTE: Section 1441 et seq. of title 28 of the U.S. Code allows a defendant who is brought into a state court to remove the action to federal district court when diversity of citizenship exists, when the action involves a claim or right arising under the U.S. Constitution or under laws or treaties of the U.S., or when the defendant is a foreign country or its agency or instrumentality. Civil actions and criminal prosecutions brought against an officer or agency of the U.S. for any act under color of office may also be removed.

b **:** to dismiss from office

> an independent counsel...may be *removed* from office...only by the personal action of the Attorney General
> – *U.S. Code*

c **:** to take away

should his incapacity be *removed* by a judgment of a court
— *Louisiana Civil Code*

removability -ˌmü-və-ˈbi-lə-tē noun
removable adjective
variants *also* **removeable** -ˈmü-və-bəl
removableness noun

More from Merriam-Webster on *remove*

Nglish: Translation of *remove* for Spanish Speakers
Britannica English: Translation of *remove* for Arabic Speakers

Last Updated: 14 Sep 2023 - Updated example sentences

Word Games

Pop Culture Vocab Quiz
"Embiggen," "regift," "friend zone" a...
Take the quiz

What Are You Wearing?
Roll up your sleeves and identify these garments
Take the quiz

Spell It
Hear a word and type it out. How many can you get...
Take the quiz

Spelling Bee Quiz
Can you outdo past winners of the National Spelli...
Take the quiz

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EXHIBIT 4

Dictionary
Definition
Synonyms
Example Sentences
Word History
Entries Near
Show More
Save Word

omit verb

ō-ˈmit ə-

omitted; omitting

Synonyms of *omit* ›

transitive verb

1 : to leave out or leave unmentioned

omits one important detail

You can *omit* the salt from the recipe.

2 : to leave undone : FAIL → The patient *omitted* taking his medication.

3 obsolete : DISREGARD

4 obsolete : GIVE UP

Synonyms

fail forget neglect

See all Synonyms & Antonyms in Thesaurus ›

Example Sentences

Please don't *omit* any details.

you must not *omit* mentioning the sources you used in researching your paper

Recent Examples on the Web

In a time when politicians are structuring school curriculum to *omit* Black American history, knowing one's own background is vital, McWorter said.

– Darcel Rockett, *Chicago Tribune*, 10 Sep. 2023

> Supporters said the standards include factual information, but critics argue the standards *omit* important parts of history, including the state's role in slavery and the disenfranchisement of Black people and violent attacks against them.
> – Deborah Barfield Berry, *USA TODAY*, 8 Sep. 2023

> The mod in question adds support for Nvidia's DLSS 3 upscaling technology, which Bethesda *omitted* to include in Starfield in favor of AMD's rival FSR 2.
> – Jon Porter, *The Verge*, 5 Sep. 2023

See More

These examples are programmatically compiled from various online sources to illustrate current usage of the word 'omit.' Any opinions expressed in the examples do not represent those of Merriam-Webster or its editors. Send us feedback about these examples.

Word History

Etymology

Middle English *omitten*, from Latin *omittere*, from *ob-* toward + *mittere* to let go, send — more at OB-

First Known Use

15th century, in the meaning defined at sense 1

Time Traveler

The first known use of *omit* was in the 15th century

See more words from the same century

Dictionary Entries Near *omit*

omissive
omit
omittance

See More Nearby Entries >

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"Omit." *Merriam-Webster.com Dictionary*, Merriam-Webster, https://www.merriam-webster.com/dictionary/omit. Accessed 15 Sep. 202

3.

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Kids Definition

omit verb

ō-ˈmit ə-

omitted; omitting

1 : to leave out

omitted your name from the list

2 : to fail to do : NEGLECT

omitted to mention that it was my fault

More from Merriam-Webster on *omit*

Nglish: Translation of *omit* for Spanish Speakers
Britannica English: Translation of *omit* for Arabic Speakers

Last Updated: 14 Sep 2023 - Updated example sentences

Word Games



Pop Culture Vocab Quiz
"Embiggen," "regift," "friend zone" a...
Take the quiz

What Are You Wearing?
Roll up your sleeves and identify these garments
Take the quiz

Spell It
Hear a word and type it out. How many can you get...
Take the quiz

Spelling Bee Quiz
Can you outdo past winners of the National Spelli...
Take the quiz

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BRITANNICA ENGLISH - ARABIC TRANSLATION

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