

THE FILES ARE IN THE COMPUTER:
ON COPYRIGHT, MEMORIZATION, AND GENERATIVE AI

(Written April 2024; Edited March 2025; Forthcoming, *Chicago Kent Law Review* 2025)

BY A. FEDER COOPER* AND JAMES GRIMMELMANN**

The New York Times's copyright lawsuit against OpenAI and Microsoft alleges that OpenAI's GPT models have "memorized" Times articles. Other lawsuits make similar claims. But parties, courts, and scholars disagree on what memorization is, whether it is taking place, and what its copyright implications are. Unfortunately, these debates are clouded by deep ambiguities over the nature of "memorization," leading participants to talk past one another.

In this Essay, we attempt to bring clarity to the conversation over memorization and its relationship to copyright law. Memorization is a highly active area of research in machine learning, and we draw on that literature to provide a firm technical foundation for legal discussions. The core of the Essay is a precise definition of memorization for a legal audience. We say that a model has "memorized" a piece of training data when (1) it is possible to reconstruct from the model (2) a (near-)exact copy of (3) a substantial portion of (4) that specific piece of training data. We distinguish memorization from "extraction" (in which a user intentionally causes a model to generate a (near-)exact copy), from "regurgitation" (in which a model generates a (near-)exact copy, regardless of the user's intentions), and from "reconstruction" (in which the (near-)exact copy can be obtained from the model by any means, not necessarily the ordinary generation process).

Several important consequences follow from these definitions. First, not all learning is memorization: much of what generative-AI models do involves generalizing from large amounts

* Co-Founder, The GenLaw Center; Assistant Professor of Computer Science, Yale University (to commence 2026). After completion of this Essay (but prior to its official publication), A. Feder Cooper started as a Postdoctoral Researcher at Microsoft Research and a Postdoctoral Affiliate at Stanford University. Both authors contributed equally to this Essay. We presented an earlier version of this Essay at the Chicago Kent Law Review AI Disrupting Law Symposium on April 26, 2024. Our thanks to the organizers and participants, and to Aislinn Black, Derek Bambauer, Annmarie Bridy, Nicholas Carlini, Ignacio Cofone, Amy Cyphert, Fernando Delgado, Kat Geddes, Aaron Gokaslan, Michael Goodyear, Jamie Hayes, Daniel E. Ho, Matthew Jagielski, Benedict Kingsbury, Katherine Lee, Mark Lemley, Percy Liang, Paul Ohm, Sunoo Park, Colin Raffel, Matthew Sag, Pamela Samuelson, Jessicay Silbey, Benjamin Sobel, Katherine Strandburg, Rebecca Tushnet, and Eugene Volokh. We also thank the participants in the Information Law Institute and Innovation Policy Colloquia at New York University Law School and the Berkeley Law and Technology Symposium for workshopping earlier drafts of this work. Special thanks also to Jon Small and Priya Jhakra at Google DeepMind's legal department for extensive discussion related to issues raised by this Essay. This Essay may be freely reused under the terms of the Creative Commons Attribution 4.0 International License, <https://creativecommons.org/licenses/by/4.0/> [<https://perma.cc/UF9L-UYDS>].

** Tessler Family Professor of Digital and Information Law, Cornell Tech and Cornell Law School; Researcher, The GenLaw Center.

of training data, not just memorizing individual pieces of it. Second, memorization occurs when a model is trained; it is not something that happens when a model generates a regurgitated output. Regurgitation is a symptom of memorization in the model, not its cause. Third, when a model has memorized training data, the model is a “copy” of that training data in the sense used by copyright law. Fourth, a model is not like a VCR or other general-purpose copying technology; it is better at generating some types of outputs (possibly including regurgitated ones) than others. Fifth, memorization is not just a phenomenon that is caused by “adversarial” users bent on extraction; it is a capability that is latent in the model itself. Sixth, the amount of training data that a model memorizes is a consequence of choices made in the training process; different decisions about what data to train on and how to run the training process can affect what the model memorizes. Seventh, system design choices also matter at generation time. Whether or not a model that has memorized training data actually regurgitates these data depends on the design of the overall system: developers can use other guardrails to prevent extraction and regurgitation. In a very real sense, memorized training data are in the model—to quote Zoolander, the files are in the computer.

Matilda: Did you find the files?

Hansel: I don’t even know what they look—what do they look like?

Matilda: They’re in the computer.

Hansel: They’re in the computer?

Matilda: Yeah, they’re definitely in there, I just don’t know how he labeled them.

Hansel: I got it. IN the computer. It’s so simple.¹

INTRODUCTION

The week between Christmas and New Year’s Eve is usually a slow news week, but not in 2023—the year that ChatGPT ate the world.² On December 27, 2023, the *New York Times* filed a copyright-infringement lawsuit against Microsoft and OpenAI, alleging that Bing Copilot and ChatGPT constituted “massive copyright infringement.”³ In particular, the *Times* alleged that the generative-AI models in these systems had “memorized” large quantities of *Times* articles. That is, when prompted with some prefix of text from a *Times* article,⁴ ChatGPT would output a lengthy, corresponding suffix that copied passages from the article—hundreds of words, varying only in a few scattered portions.⁵ (See Figure 1.)

¹ *ZOOLANDER* (Paramount Pictures 2001).

² See generally CHAT GPT IS EATING THE WORLD, <https://chatgptiseatingtheworld.com> [<https://perma.cc/H2J5-F476>].

³ Complaint ¶ 74, N.Y. Times Co. v. Microsoft Corp., No. 1:23-cv-11195 (S.D.N.Y. Dec. 27, 2023).

⁴ The prompts ranged in length from a sentence to several paragraphs. *See id.* ¶ 99.

⁵ At this point, in the introduction, we are deliberately providing only a high-level intuition for the type of memorization with which we engage in this Essay, and we do so by drawing on an example from a current lawsuit. We provide more rigorous definitions of memorization below. *See infra* notes 58–62 and accompanying text.

Output from GPT-4:

exempted it from regulations, subsidized its operations and promoted its practices, records and interviews showed.

Their actions turned one of the best-known symbols of New York — its yellow cabs — into a financial trap for thousands of immigrant drivers. More than 950 have filed for bankruptcy, according to a Times analysis of court records, and many more struggle to stay afloat.

“Nobody wanted to upset the industry,” said David Klahr, who from 2007 to 2016 held several management posts at the Taxi and Limousine Commission, the city agency that oversees medallions. “Nobody wanted to kill the golden goose.”

New York City in particular failed the taxi industry, The Times found. Two former mayors, Rudolph W. Giuliani and Michael R. Bloomberg, placed political allies inside the Taxi and Limousine Commission and directed it to sell medallions to help them balance budgets and fund key initiatives.

During that period, much like in the mortgage lending crisis, a group of industry leaders enriched themselves by artificially inflating medallion prices. They encouraged medallion buyers to borrow as much as possible and ensnared them in interest-only loans and other one-sided deals that often required borrowers to pay hefty fees, forfeit their legal rights and give up most of their monthly incomes.

When the market collapsed, the government largely abandoned the drivers who bore the brunt of the crisis. Officials did not bail out borrowers or persuade banks to soften loan

Actual text from NYTimes:

exempted it from regulations, subsidized its operations and promoted its practices, records and interviews showed.

Their actions turned one of the best-known symbols of New York — its signature yellow cabs — into a financial trap for thousands of immigrant drivers. More than 950 have filed for bankruptcy, according to a Times analysis of court records, and many more struggle to stay afloat.

“Nobody wanted to upset the industry,” said David Klahr, who from 2007 to 2016 held several management posts at the Taxi and Limousine Commission, the city agency that oversees cabs. “Nobody wanted to kill the golden goose.”

New York City in particular failed the taxi industry, The Times found. Two former mayors, Rudolph W. Giuliani and Michael R. Bloomberg, placed political allies inside the Taxi and Limousine Commission and directed it to sell medallions to help them balance budgets and fund priorities. Mayor Bill de Blasio continued the policies.

Under Mr. Bloomberg and Mr. de Blasio, the city made more than \$855 million by selling taxi medallions and collecting taxes on private sales, according to the city.

But during that period, much like in the mortgage lending crisis, a group of industry leaders enriched themselves by artificially inflating medallion prices. They encouraged medallion buyers to borrow as much as possible and ensnared them in interest-only loans and other one-sided deals that often required them to pay hefty fees, forfeit their legal rights and give up most of their monthly incomes.

Figure 1: Memorized and extracted output from ChatGPT’s GPT-4 endpoint (left) of a New York Times article (right)

To the *Times* and its lawyers, these examples of “memorization” were blatant copyright infringement. But to OpenAI and its defenders, there was nothing to see here. OpenAI responded, both in court and online, casting the *Times*’s behavior as “adversarial”—that these examples were “misuse,” “not typical or allowed user activity.”⁶ On this view, any copying (and thus any resulting infringement) resulted from the prompts the *Times* used. If the *Times* had not specifically manipulated ChatGPT into generating *Times* articles, there would have been no copying, and no copyright infringement. As economist Tyler Cowen put it, in mocking the *Times*’s argument, one could equally well say that a toothpick infringes:

If you stare at just the exact *right* part of the toothpick, and measure the length from the tip, expressed in terms of the appropriate unit and converted into binary, and then

⁶ *OpenAI and Journalism*, OPENAI (Jan. 8, 2024), <https://openai.com/blog/openai-and-journalism> [<https://perma.cc/A3CG-V3SB>] (“[O]ur models don’t typically behave the way The New York Times insinuates, which suggests they either instructed the model to regurgitate or cherry-picked their examples from many attempts. Despite their claims, this misuse is not typical or allowed user activity, and is not a substitute for The New York Times. Regardless, we are continually making our systems more resistant to adversarial attacks to regurgitate training data, and have already made much progress in our recent models.”).

translated into English, you can find any message you want. You just have to pinpoint your gaze very very exactly (I call this “a prompt”).

In fact, on your toothpick you can find the lead article from today’s *New York Times*. With enough squinting, measuring, and translating.

By producing the toothpick, they put the message there and thus they gave you NYT access, even though you are not a paid subscriber. You simply need to know how to stare (and translate), or in other words how to prompt.

So let’s sue the toothpick company!⁷

Implicit in this view is that memorization and the copying it involves take place only at *generation time*: when a generative-AI system responds to a user’s prompt with an output. The system itself is a neutral, general-purpose tool. Some users may use it to infringe, but other users will not.

This view treats the machine-learned model (or models) at the heart of a generative-AI system as a black box. Training data are used to design and construct the box, but the box itself contains only abstracted statistical patterns of the training data. Those patterns either contain no expression at all, or if they do, they are represented in a way that is fundamentally uninterpretable. The box is a machine that transforms prompts into outputs. Thus, if there is infringing expression in the output, it must be because the user prompted it in a targeted (i.e., “adversarial” or “not typical”) way to elicit that infringement.

This view refuses to consider what happens inside the box—the specifics of *how* statistical learning about the training data enables generative-AI systems to do what they do. It avoids engaging with the actual representation of information about training data in a model’s parameters. In legal writing, this has involved gesturing at these representations with high-level terms like “features,” “patterns,” or “statistical correlations.”⁸ These terms suggest that while there may be some underlying math going on, the details can be sidestepped for simplicity, because they are irrelevant to the legal treatment of generative AI.

This way of thinking about memorization⁹ has significant copyright consequences. It suggests that memorization is primarily about *prompting* rather than *training*. Outputs may contain potentially infringing expression, but the model that generates them does not. A model

⁷ Tyler Cowen, *Toothpick Producers Violate NYT Copyright*, MARGINAL REVOLUTION (Dec. 30, 2023, 1:05 AM), <https://marginalrevolution.com/marginalrevolution/2023/12/toothpick-producers-violate-nyt-copyright.html> [<https://perma.cc/E3V5-DVF3>].

⁸ See, e.g., Oren Bracha, The Work of Copyright in the Age of Machine Production (Jan. 2024) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4581738 [<https://perma.cc/LF9L-54XH>] (referring to these representations as features and patterns); Def. Anthropic PBC’s Opposition to Plaintiffs’ Motion for Preliminary Injunction at 4, Concord Music Grp., Inc. v. Anthropic PBC, No. 3:23-cv-01092 (M.D. Tenn. Jan. 16, 2024).

⁹ For now, we continue to limit our use of the term “memorization” to the intuition provided in the (near-)exact copying demonstrated in Figure 1. See *infra* notes 58–62 and accompanying text (providing more details on memorization and variations on definitions).

itself is a neutral tool, equally good at producing infringing and non-infringing outputs. It follows that users bear most or all of the responsibility for misusing a generative-AI system to elicit memorized content, and the creators of the system in which the model is deployed bear little or none.¹⁰

With respect, we believe that this approach to making sense of memorization misdescribes how generative-AI systems work. If a generative-AI model memorizes its training data, these training data are *in the model*. This should not be surprising. Models are not inert tools that have no relationship with their training data. The power of a model is precisely that it encodes relevant features of the training data in a way that enables prompting to generate outputs that are based on the training data. This is why capital-G Generative AI is such a big deal. All useful models learn something about their training data. Memorization is simply a difference in degree: it is an encoded feature *in the model*; whether it is a desired feature or not is another matter entirely.

It follows that memorization in generative AI cannot be neatly confined to generation time—to how the system behaves when adversarial users provide adversarial prompts. If a generative-AI model has memorized copyrighted works, the memorized aspects of those works are present *in the model itself*, not just in the model’s generated outputs. The model could possibly (with some probability) generate copies of those works on demand for any user,¹¹ not just for users who have a suitably nefarious intent. The system’s creator may have various options to limit the output of such copies—for example, by refusing to generate outputs for certain prompts or by checking outputs against a database of copyrighted works before returning them to the user. But one of these options is always to *change the model*: to train or retrain it in a way that attempts to limit the model’s memorization of training data. Whether this is trivially easy or impractically hard depends on the details of the model architecture, the choice of training data, the training algorithm, and much more. But the model’s internals must always be part of the technical picture, because they are highly relevant to what a model has memorized and what it can do.

We take no position on what the most appropriate copyright regimes for generative-AI systems should be, and we express no opinion on how pending copyright lawsuits should be decided.¹² These cases raise difficult doctrinal issues that run almost the entire gamut of copyright law.¹³ Our goal is merely to describe how these systems work so that copyright scholars can develop their theories of generative AI on a firm technical foundation. We focus on a few

¹⁰ The distinction between a *model* and the larger *system* in which it is embedded is important to keep in mind. See *infra* Part I.B (discussing technical differences). See *infra* Part II.I (discussing legal consequences).

¹¹ This probability is not necessarily easily quantifiable for all models. See *infra* Part II.D (discussing non-determinism in the generation process and probabilistic extraction).

¹² Cf. Nicholas Carlini, *What My Privacy Papers (Don’t) Have to Say About Copyright and Generative AI*, NICHOLAS CARLINI (Mar. 11, 2025), <https://nicholas.carlini.com/writing/2025/privacy-copyright-and-generative-models.html> (insisting on caution when drawing legal conclusions from technical findings about memorization).

¹³ See generally Katherine Lee, A. Feder Cooper & James Grimmelmann, *Talkin’ Bout AI Generation: Copyright and the Generative-AI Supply Chain*, J. COPYRIGHT SOC’Y (forthcoming 2025) [hereinafter *Talkin’*].

threshold issues—particularly the Copyright Act’s definition of “copies”—where the technical details are particularly salient. We seek clarity, precision, and technical accuracy.¹⁴

You have nearly finished the introduction of this Essay. In Part I, we provide a brief background on how generative-AI models work, and the systems and supply chains within which they are embedded. In Part II, the heart of the Essay, we describe how to think clearly about memorization in generative-AI systems, and show how several common arguments about copyright and generative AI are built on a mistaken view of what memorization consists of and how it is surfaced to end users. We finish with a brief conclusion, which offers some historical reflections.

I. TECHNICAL BACKGROUND

In the past two and a half years—starting roughly with the public launch of ChatGPT in November 2022—generative AI has become a household term. It is used as a blanket description for a wide range of consumer-facing applications: chatbots like OpenAI’s ChatGPT Plus,¹⁵ Google DeepMind’s Gemini,¹⁶ and Anthropic’s Claude 3;¹⁷ image generators like Midjourney Inc.’s eponymous Midjourney,¹⁸ StabilityAI’s Stable Diffusion,¹⁹ and OpenAI’s DALL·E 3;²⁰ music generators like Google DeepMind’s Lyria;²¹ video generators like Pika’s eponymous

¹⁴ We do not make broad claims about the consequences of these technical details—e.g., we do not make generalizations about whether the copies we are talking about are or are not infringing. Further, our focus is on United States law. For an analysis of memorization by generative-AI models under E.U. law, see Tim W. Dornis, *Generative AI, Reproductions Inside the Model, and the Making Available to the Public*, INT’L REV. INTELL. PROP. & COMPETITION L. (forthcoming), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5036008.

¹⁵ *DALL·E 3 Is Now Available in ChatGPT Plus and Enterprise*, OPENAI (Oct. 19, 2023), <https://openai.com/blog/dall-e-3-is-now-available-in-chatgpt-plus-and-enterprise> [<https://perma.cc/6LMU-BUCH>].

¹⁶ Gemini Team et al., Gemini: A Family of Highly Capable Multimodal Models (2023) (unpublished manuscript), <https://arxiv.org/abs/2312.11805> [<https://perma.cc/V9EQ-ETQJ>].

¹⁷ *Introducing the next generation of Claude*, ANTHROPIC (Mar. 4, 2024), <https://www.anthropic.com/news/clause-3-family> [<https://perma.cc/P5E8-4S4M>].

¹⁸ *Midjourney*, <https://midjourney.com/home> [<https://perma.cc/PCF6-WK3A>].

¹⁹ *Image Models*, STABILITY.AI, <https://stability.ai/stable-image> [<https://perma.cc/E8F5-P98J>]; see Robin Rombach, Andreas Blattmann, Dominik Lorenz et al., *High-Resolution Image Synthesis with Latent Diffusion Models*, in 2022 IEEE/CVF CONF. ON COMPUT. VISION & PATTERN RECOGNITION (2022).

²⁰ *DALL·E 3*, OPENAI, <https://openai.com/index/dall-e-3/> [<https://perma.cc/R6SP-KZ6V>]; see generally James Betker, Gabriel Goh, Li Jing et al., Improving Image Generation with Better Captions (2023) (unpublished manuscript), <https://cdn.openai.com/papers/dall-e-3.pdf> [<https://perma.cc/FKY2-R6QC>].

²¹ *Transforming the Future of Music Creation*, GOOGLE DEEPMIND (Nov. 16, 2023), <https://deepmind.google/discover/blog/transforming-the-future-of-music-creation/> [<https://perma.cc/GT54W6MW>].

Pika²² and OpenAI’s Sora²³; programming assistants like GitHub Copilot;²⁴ and much more. These tools are self-evidently different from one another. They operate on different data *modalities* (text, image, audio, video, and code, respectively),²⁵ incorporate different types of model architectures, interact with different software-systems components, are made available in different ways, and serve different purposes.

But beneath their differences, these generative-AI tools have a common shape that justifies the use of the same term to describe them all. This part describes that common shape. Section A presents the (highly simplified) basics of deep-neural-network machine learning that powers most modern generative-AI models. Section B describes the supply chains in which generative-AI models are embedded—supply chains that connect data to models to usable systems to outputs.

A. Generative AI

First, generative AI involves *machine-learning models* that have been created through *training on datasets* that contain massive numbers of data *examples*.²⁶ Second, these models are all *generative*: they produce outputs of the same modality as their training data.²⁷ This second point is what distinguishes generative-AI models from other machine-learning (ML) models. A classifier (a type of *discriminative* model) will typically be trained on information-rich *training examples*, such as a collection of JPEG images of cats and dogs. When the trained classifier is used to perform inference on a new JPEG input, it will output either a simple label of cat or dog, based on whether it predicts that the JPEG is more likely to be an image of a cat or an image of a dog.

In contrast, while generative-AI models are also trained on information-rich training examples, their outputs are (1) also information-rich and (2) of the same type as their training

²² PIKA, <https://pika.art/home> [<https://perma.cc/B82W-LKAH>].

²³ Creating video from text, OPENAI (2024), <https://openai.com/index/sora/> [<https://perma.cc/WCG3-DYUX>].

²⁴ See generally *GitHub Copilot documentation*, GITHUB (Aug. 28, 2023), <https://docs.github.com/en/copilot>.

²⁵ ‘Talkin’, *supra* note 13, at Part I.B.2 (defining and describing modalities).

²⁶ See generally *id.* at Part I.A.1 (describing data examples) and Part I.B.4 (discussing large-scale datasets for training generative-AI models); see generally See Katherine Lee, Daphne Ippolito & A. Feder Cooper, *The Devil is in the Training Data* (2023) (unpublished manuscript), in Katherine Lee, A. Feder Cooper, James Grimmelmann & Daphne Ippolito, *AI and Law: The Next Generation* 5 (2023) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4580739.

²⁷ Some models are *multimodal*: they are trained on multiple modalities and, for example, take one modality as input and produce another as output. This is the case for text-to-image generation models like Stable Diffusion. Stable Diffusion is trained on image-caption pairs; it takes text prompts as inputs and produces image generations as outputs. See generally Rombach, Blattmann, Lorenz et al., *supra* note 19 (discussing the original Stable Diffusion training process).

examples.²⁸ A generative image model, for example, might be trained on images and their captions. After being trained, it can then take a text input (e.g., "cat in a red and white striped hat"), and produce as output one of many possible different images of cats in red and white striped hats.²⁹

In a bit more detail, the objective of the training process is to create a generative-AI model that produces outputs that reflect patterns in the training data.³⁰ This coheres with copyright-lawsuit defendants' own descriptions of the training process and resulting trained models. For example:

[During training,] AI models like Claude ingest *billions* of different kinds of texts, which they break down into trillions of component parts known as "tokens." The models then analyze the "tokens" to discern statistical correlations—often at staggeringly large scales—among features of the content on which the model is being trained." Those statistical correlations effectively yield "insights about patterns of connections among concepts or how works of [a particular] kind are constructed." Based on those insights, AI models like Claude are able to create new, original outputs with a degree of sophistication and verisimilitude that approximates human cognition.³¹

The model-training process is fundamentally statistical: it learns statistics about the training data. Each training example is regarded as a sample from a *distribution* of possible examples—e.g., each picture of a cat in the training dataset is one sample drawn from the hypothetical space of possible pictures of cats. A training algorithm attempts to learn the distribution from which the training examples are drawn. If training is successful, then the model's outputs (generated images from the hypothetical learned distribution of images of cats) will share statistical properties with actual images drawn from the actual, real-life distribution of images of cats from which the training examples were taken. In other words, we can think of generative-AI models as *ML models*

²⁸ In general, what constitutes a single training example varies across models, and examples do not necessarily cleanly map to complete creative works. Consider the text modality: a single training example may be a piece of one long work, which has been broken up into pieces and spread across multiple examples. For a text-to-image multimodal model, a single example is composed of a pair of data points: an image and its corresponding text caption; the output is of the type of one element in these pairs (the images). *See id.*

²⁹ This example is drawn from *Talkin'*, *supra* note 13, at Part I.A.2.b. *See id.* at Part I.A.2 (providing more extensive background on generative modeling in comparison to discriminative modeling).

³⁰ The *goal* of training is different from this underlying mathematical *objective*. The overarching goal is to produce useful or delightful models, which is not exactly the same as the mathematical objective used to train these models. *See* A. Feder Cooper, Katherine Lee, James Grimmelmann, Daphne Ippolito et al., Report of the 1st Workshop on Generative AI and Law (Nov. 11, 2023) (unpublished manuscript), <https://arxiv.org/abs/2311.06477> [<https://perma.cc/T5VW-J46E>] (discussing this distinction).

³¹ Def. Anthropic PBC's Opposition to Plaintiffs' Motion for Preliminary Injunction, *supra* note 8, at 4–5 (internal citations omitted). See *infra* Part II.C (for additional discussion of this quote in the context of memorization).

that produce outputs that exhibit statistical properties derived from the examples on which they were trained.

This summary shows both how phrases like “pattern” and “statistical correlation” are useful abstractions for understanding model training, and also the limits of these abstractions. Such “statistical correlations” can encompass many different things in training data. In an image model, they can be concepts (e.g., a cat as being a furry, tailed, four-legged animal), styles (e.g., photorealism), artistic media (e.g., oil painting), and more. At generation time, these elements can be remixed to produce new images that never existed before and that are highly dissimilar from all examples in the training dataset (e.g., a cat in a red and white striped hat). Sometimes, they can also be “re”-mixed to (re-)produce particular training examples: anything can be described perfectly in terms of “patterns” and “statistical correlations” if they are detailed enough.³²

There is even more complexity in practice. There are many different types of generative-AI models, which have radically different technical architectures. But, at a high (and oversimplified) level of abstraction, they generally consist of *neural networks*: interconnected nodes that can perform computations and which are organized into layers. The strengths of these connections—the influences that nodes have on one another—are what is learned during training. These are called the model *parameters* or *weights*, and they are represented as numbers.

To run a generative-AI model on an input—a *prompt*—a computer program takes the prompt and transforms it into a format that can be processed in the model. For large language models (LLMs), this typically involves taking the prompt and converting it into *tokens* (words or parts of words, as described above).³³ The transformed, tokenized prompt is passed through the layers of the neural network: the computer program copies the input into the nodes at the first layer of the network, then uses the parameters (i.e., connection strengths) leading out from those nodes to compute the input’s effects on the nodes in the second layer, and so on, until the last layer has been computed. For example, in LLMs, this process determines how important each token is in relation to the entire sequence of tokens that make up the text prompt.³⁴

At this point, once the prompt has been processed through all of the model’s layers, the model will produce an output. For LLMs, this means the model will predict the most likely next token in the sequence, based on the context of the prompt, and *generate* that token as the next

³² See *infra* Part II.C (discussing how memorization still constitutes “patterns” or “statistical correlations”).

³³ See *supra* note 31 and accompanying text (for Anthropic’s description of tokens). These tokens represent whole words, parts of words, logograms, or punctuation marks, and are the format that the model can process directly. These tokens are then mapped to embedding vectors, which reflect underlying semantic and syntactic information about the words they encode. See *Talkin’*, *supra* note 13, at Part I.B.2.b and Part I.B.3.a (and citations therein). See generally Vicki Boykis, *What are embeddings?* (June 2023), https://github.com/veekaybee/what_are_embeddings [<https://perma.cc/ZW7D-JK36>] (for an accessible treatment of the details behind embeddings).

³⁴ Diffusion-based image-generation models typically also involve neural networks, but they undergo a different training process. We omit these details in this Essay. See *Talkin’*, *supra* note 13 at Part I.B.3.b (for a high-level treatment of diffusion).

token in the sequence.³⁵ What is “most likely” depends on the “statistical correlations”³⁶ learned during training. For example, if trained on a dataset that includes fairy tales, a model would (probably) deem “time” the most likely next token to follow “once upon a”.³⁷ In practice, the generation process tends to be iterative: once a token is generated, it is appended to the prompt, and the new, extended prompt is provided as input to the model, which generates the next token in the sequence, and so on.³⁸

³⁵ This strategy for generating tokens is called *greedy decoding* or *greedy sampling*. There are other, more complicated decoding strategies for generation; it is not strictly necessary to always select the highest-probability token (from the entire set of tokens, which is called the *vocabulary*) to be the next one in the generated sequence. Nevertheless, greedy decoding is the simplest way to think about generation: it involves sampling from a distribution over tokens, which are associated with different probabilities. Different sampling algorithms can introduce randomness into generated outputs in different ways. See generally Patrick von Platen, *How to generate text: using different decoding methods for language generation with Transformers*, HUGGINGFACE (March 1, 2020), <https://huggingface.co/blog/how-to-generate> (for an accessible treatment of sampling algorithms for decoding in language models). See *infra* note 38 (for more details on the relationship between an LLM and sampling).

³⁶ Def. Anthropic PBC’s Opposition to Plaintiffs’ Motion for Preliminary Injunction, *supra* note 8, at 4–5.

³⁷ In this example, “time” is the most likely next token to complete “once upon a” because “once upon a time” is a common phrase in fairy tales (which we assume are included in the training dataset).

³⁸ For the interested reader, we can state this more precisely as follows. We can describe an LLM as f_θ , a function parameterized by the LLM’s parameters θ . This function is $f_\theta : \mathcal{V}^j \rightarrow P(\mathcal{V})$, which takes as input a sequence of j tokens from the token vocabulary \mathcal{V} (i.e., \mathcal{W}) and outputs a probability distribution over the token vocabulary \mathcal{V} (i.e., $P(\mathcal{V})$). In other words, this function assigns each token in \mathcal{V} a probability between 0 and 1 (between 0% and 100%); these are the probabilities associated with the next token that would follow the j -length token sequence provided as the input. Note that this means that *the LLM outputs a probability distribution*; it does *not* output the next token to be generated. The next token is selected using a sampling procedure. See *supra* note 35 and accompanying text (discussing token vocabulary and, in particularly, greedy sampling).

We will denote this sampling procedure as g_φ , where φ represents some user-chosen (as opposed to learned) parameters (i.e., hyperparameters) that configure the sampling procedure. (One such hyperparameter is the temperature; see *infra* note 205 and accompanying text.) This is also a function, defined as $g_\varphi : P(\mathcal{V}) \rightarrow \mathcal{V}^1$. That is, the sampling procedure takes a probability distribution over the token vocabulary ($P(\mathcal{V})$) as its input and selects a single token in the vocabulary (\mathcal{V}^1 , typically written as just \mathcal{V}) as output. As the name suggests, the sampling procedure g_φ *samples* the next token (using its underlying algorithm) according to the probability distribution over the token vocabulary, $P(\mathcal{V})$. For generation, the LLM f_θ and the sampling procedure g_φ are composed together: the sampling procedure takes the LLM’s output probability distribution over the vocabulary, $P(\mathcal{V})$, and selects the next token to be appended to the sequence. That is, together, the LLM and sampling procedure can be used together to do generation.

Generative modeling has a long history in machine learning; it is an area of research that has existed for decades. What is new in this current “generative AI moment” are the exciting, novel capabilities of contemporary models. These capabilities have come about due to recent breakthroughs in model architectures,³⁹ massive-scale datasets on which to train those model architectures,⁴⁰ and immense computing power needed to run the training process for massive-scale models on massive-scale datasets.⁴¹ Taken together, these three types of advancements have enabled contemporary applications like conversational chatbots and high-quality image generators.

B. Systems and Supply Chains

Generative-AI applications are more than just trained models. They consist of hosted software services that wrap software *systems*; generative-AI models are an embedded component of these systems, but they are only one such component. Other components include user interfaces, developer APIs, and input and output content filters (e.g., to remove “toxic” or copyrighted content from inputs before supplying prompts to models to produce generations, or from output generations before surfacing them to users).⁴²

For some initial sequence of tokens z (i.e., the prompt), this entire process can be denoted $(g_\phi \circ f_\theta)^k(z)$: this is the process of “repeatedly generating a distribution over the token vocabulary, sampling a token from this distribution, and adding the token to the sequence k times, starting from the initial [j -length] sequence z ” to produce a k -length generation. There are many different sampling algorithms. Most are non-deterministic (i.e., will not always select the same next token given the same prompt). Greedy sampling, in contrast, is deterministic. See Jamie Hayes, Marika Swanberg, Harsh Chaudhari et al., *Measuring memorization in language models via probabilistic extraction*, PROC. 2025 ANN. CONF. OF THE NATIONS OF THE AMERICAS CHAPTER OF THE ASS’N FOR COMPUT. LINGUISTICS (forthcoming 2025) (from which we draw this quote, notation, and standard description of LLMs and sampling). See *infra* notes 177, 192, 203 and accompanying text (for further discussion—at a high level—of non-determinism, probability distributions, and sampling).

³⁹ *Talkin’, supra* note 13, at Part I.B.3.a (discussing the transformer-based model architecture).

⁴⁰ See Lee, Ippolito & Cooper, *supra* note 26.

⁴¹ *Talkin’, supra* note 13, at Part I.B.4 (discussing the importance of scale).

⁴² *Id.* at Part I.B.1 (discussing generative-AI systems); see generally OpenAI, *GPT-4 System Card* (2023) [hereinafter GPT-4 System Card] (unpublished manuscript), <https://cdn.openai.com/papers/gpt-4-system-card.pdf> [<https://perma.cc/E95W-L6EB>] (describing the entire GPT-4 system); A. Feder Cooper, Karen Levy & Christopher De Sa, *Accuracy-Efficiency Trade-Offs and Accountability in Distributed ML Systems*, 2021 EQUITY AND ACCESS IN ALGORITHMS, MECHANISMS, AND OPTIMIZATION 1, 5–6; A. Feder Cooper & Karen Levy, *Fast or Accurate? Governing Conflicting Goals in Highly Autonomous Vehicles*, 20 COLO. TECH. L.J. 222, 224 (2022) (emphasizing the role of AI/ML systems, not just models, in overall application behavior); Cooper, Lee, Grimmelmann, Ippolito et al., *supra* note 30, at 5–6 (discussing different

There is an entire supply chain involved in the production of these models and systems—an ecosystem of actors and technical components that contribute to the development, deployment, maintenance, and use of user-facing software services. This supply chain is

an interconnected set of eight stages that transform training data (millions of pictures of cats) into generations (new and hopefully never-seen-before pictures of cats that have never existed). Breaking down generative AI into these constituent stages reveals all of the places at which companies and users make choices that have legal consequences—for copyright and beyond.”⁴³

In prior work with Katherine Lee, we have described the supply chain in detail,⁴⁴ and discussed its relationship to U.S. copyright law.⁴⁵ We refer the interested reader to that work. Our summary here is meant only to introduce some essential terminology and to frame our later discussion.

In our account, the generative-AI supply chain has eight interconnected stages:

1. Creation of expressive works or other *information*,
2. Conversion of these expressive works or information into digitized *data* that can be interpreted by computers,
3. Collection and curation of enormous quantities of such data into *training datasets* (for generative-AI models, these datasets frequently include data scraped from the Internet),⁴⁶
4. *Pre-training*⁴⁷ of a general, large-scale, *base* (also called *foundation*) generative-model architecture on these curated datasets,

business models for producing and combining these components); Lee, Ippolito & Cooper, *supra* note 26, at 12–13 (detailing data curation for training generative-AI models and the definition of “toxicity”).

⁴³ *Talkin'*, *supra* note 13, at Introduction.

⁴⁴ See generally *id.* at Part I.C.

⁴⁵ See generally *id.* at Part II.

⁴⁶ The practice of using web-scraped for generative-AI model training is one of the focal points of existing copyright lawsuits. Lee, Ippolito & Cooper *supra* note 26, at 15 (discussing generative-AI training datasets); Pamela Samuelson, *Generative AI Meets Copyright*, 381 SCIENCE 158, 158 (2023) (discussing lawsuits); Leo Gao, Stella Biderman, Sid Black et al., The Pile: An 800GB Dataset of Diverse Text for Language Modeling 16 (2020) (unpublished manuscript), <https://arxiv.org/abs/2101.00027> [<https://perma.cc/AX9T-7RR9>]; Christoph Schuhmann, Romain Beaumont, Richard Vencu et al., *LAION-5B: An Open Large-Scale Dataset for Training Next Generation Image-Text Models*, 36TH CONF. ON NEURAL INFO. PROCESSING SYS. DATASETS & BENCHMARKS TRACK (2022) (detailing two web-scraped datasets that feature prominently in lawsuits).

⁴⁷ Pre-training is just training. This term originates from the fact that there may be additional training further along in the supply chain. *Talkin'*, *supra* note 13, at Part I.C.4.

5. *Fine-tuning* of the pre-trained base model on additional data in order to improve performance on a domain-specific task,
6. Public *release* of the model's parameters, or embedding the model in a system for *deployment* in a software service,
7. End-user *generation* of outputs from a user-supplied prompt,⁴⁸ and
8. *Alignment* of the model with human preferences or usage policies (a further stage of training that, for example, is responsible for ChatGPT behaving like a conversational chatbot).⁴⁹

Even to call this a supply “chain” understates its complexity; it is a densely interconnected ecosystem whose stages can branch, recombine, loop, repeat, and feed back into each other.⁵⁰

Further, the supply chain is potentially carried out by many different actors, affiliated with potentially many different organizations, at each of the different stages.⁵¹ “Copyright [c]oncerns [c]annot [b]e [l]ocalized to a [s]ingle [li]nk in the [s]upply [c]hain . . . decisions made by one actor can affect the copyright liability of another, potentially far away actor in the supply chain.”⁵² For example, the choices of dataset curators upstream in the supply chain have significant downstream effects on the possible generations that the users of a generative-AI system can

⁴⁸ *Id.*; Katherine Lee, A. Feder Cooper & James Grimmelmann, *Talkin’ ‘Bout AI Generation: Copyright and the Generative-AI Supply Chain (The Short Version)*, 2024 PROC. SYMP. ON COMPUT. SCI. & L. 48, 51 (2024) [hereinafter *Talkin’ (Short)*].

⁴⁹ Paul F. Christiano, Jan Leike, Tom B. Brown et al., Deep reinforcement learning from human preferences 1–2 (June 12, 2017) (unpublished manuscript) <https://arxiv.org/abs/1706.03741v1> [<https://perma.cc/A2AD-WPP9>]; Long Ouyang , Jeff Wu, Xu Jiang et al., Training language models to follow instructions with human feedback (Mar. 4, 2022) (unpublished manuscript), <https://arxiv.org/abs/2203.02155> [<https://perma.cc/9NU6-PHKH>]; *ChatGPT: Optimizing Language Models for Dialogue*, OPENAI (Nov. 30, 2022), <https://web.archive.org/web/20221130180912/https://openai.com/blog/chatgpt/> [<https://perma.cc/QDB8-BRRT>].

⁵⁰ Note that some stages are also optional and occur in different orders. For example, not all models are fine-tuned or aligned; some forms of alignment often precede deployment.

⁵¹ See A. Feder Cooper, Emanuel Moss, Benjamin Laufer & Helen Nissenbaum, *Accountability in an Algorithmic Society: Relationality, Responsibility, and Robustness in Machine Learning*, PROC. 2022 ACM CONF. ON FAIRNESS ACCOUNTABILITY & TRANSPARENCY 864, 868 (2022); see David Gray Widder & Dawn Nafus, *Dislocated Accountabilities in the “AI Supply Chain”: Modularity and Developers’ Notions of Responsibility*, 10 BIG DATA & SOC’Y 1, 1–3 (2023) (discussing the challenges of accountability in AI supply chains).

⁵² *Talkin’*, *supra* note 13, at Part III.B.2.

produce.⁵³ Consequently, it is necessary to reason about the entire supply chain—the ecosystem of diffuse actors and technical artifacts—for a complete infringement analysis.

This brief gloss of the generative-AI supply chain introduced key terminology and background we use in the remainder of this Essay. We will bring in additional terminology (e.g., *memorization*⁵⁴) as needed. For our purposes, the important takeaway from the supply-chain framing is its complexity. As appealing as it might be to come up with broad generalizations about copyright and generative-AI—e.g., a one-size-fits-all fair-use analysis of training datasets—the supply chain makes clear that it is not possible to do so. A rigorous analysis of copyright implications depends on the specific system; such an analysis turns on the particular details of the supply chain invoked during the system’s construction and use.

Our goal in this Part has been merely to recapitulate the technology of generative AI in terms that are accurate enough to be honest but abstract enough to be useful.⁵⁵ We believe that accurate abstraction is the appropriate starting point for legal analysis. In the next Part, we show what can go wrong when legal models outstrip technical reality.

II. MEMORIZATION IS IN THE MODEL

The previous part emphasized both the simplicity and the complexity of generative-AI systems. On the one hand, at a high enough level of abstraction, generative-AI models are incredibly simple. They are data structures that encode information about the training examples in the training dataset. They can be embedded in computer programs and then prompted to generate outputs that reflect statistical patterns in these training examples. On the other hand, this high-level description applies to an enormous range of models and systems. Models are trained in different ways, encode information in different ways, and generate outputs of different kinds in different ways. They are trained on different datasets, can be aligned, can be released, or can be embedded and deployed in different systems. The facts that a model (1) encodes information about its training data, (2) can be prompted to generate outputs of the same modality as its training data, and (3) can produce generations that reflect statistical patterns in its training data might seem like the *only* three facts that are generally true of all of the models currently being described as “generative AI.”

⁵³ For example, as we will see, it is by definition not possible to regurgitate *memorized* training-data images of Elsa from *Frozen* if there are no images of Elsa in the training data. See *infra* Part II.A.2. However, for various reasons, it may nevertheless still be possible to generate images that closely resemble Elsa; they just will not be evidence of memorization (as it is typically defined in the technical literature). See *Talkin'*, *supra* note 13, at Part II.C (discussing substantial similarity in the generative-AI supply chain); Aaron Gokaslan, A. Feder Cooper, Jasmine Collins et al., *CommonCanvas: Open Diffusion Models Trained on Creative-Commons Images*, 2024 PROC. IEEE/CVF CONF. ON COMPUT. VISION & PATTERN RECOGNITION, 8250, 8250 (2024) (for a model trained on Creative Commons images, with the goal of reducing memorization of copyrighted or unlicensed works).

⁵⁴ See *infra* Part II.A.

⁵⁵ This is the point, more generally, of the supply-chain framing from our prior work. See generally *Talkin'*, *supra* note 13.

But there is at least one more fact that applies to all large-scale generative-AI models, which serves as the focal point for the remainder of this Essay, as well as many current lawsuits: all generative-AI models *memorize* some portion of their training data. In this Part, we clear up important misconceptions about what memorization is, with a particular eye toward implications for copyright.⁵⁶

We begin in Part II.A by defining *memorization* and distinguishing it from related terms: *regurgitation*, *extraction*, and *reconstruction*. Even the initial step of clarifying definitions has important implications. In particular, generation-time regurgitation implies that memorization has taken place during the training process that precedes it.

Next, in Part II.B, we discuss in detail how memorized training data are *within* models in terms of the “patterns” that models learn during training. Here, we engage with copyright law and show that memorization in a model constitutes a “reproduction” of the memorized data. We defer discussion of *how much* memorized content is within models to a later section.⁵⁷ We also do not make claims about whether these are *infringing* reproductions—only that they *are* reproductions.

Part II.C uses this understanding of memorization to explore two common metaphors for how generative-AI models work: that they learn only “patterns” in their training data and that they “compress” their training data. Both metaphors have a kernel of truth, but neither should be taken as a guide for how a model works in all cases.

Part II.D discusses how *non-determinism* in generations—how the same prompt can yield possibly very different outputs—plays an important role in how we should think about the copyright implications of memorization. Specifically, we discuss how memorized training data are still contained within the model, even if a prompt that is capable of generating a memorized training example does not always do so in practice.

From this basis, in Part II.E we dig into the state-of-the-art understanding of *how much* models memorize in practice. This amount varies significantly across different models and measurement methodologies for quantifying memorization, and cannot be easily boiled down into a single number (e.g., “model *X* only memorizes 1% of its training data”). Of course, useful generative-AI models do a lot more than just memorize their training data; they also *generalize* to produce novel outputs, so we bring in relevant details of learning and *generalization* in Part II.F.

Then, we consider the implications of the fact that generative-AI models both memorize *and* generalize. In Part II.G, we consider the analogy between a generative-AI model and other “dual-use” technologies, such as VCRs. In our view, the analogy fails in important ways; VCRs do not contain the works they can be used to infringe in the same way that memorizing models do.⁵⁸

⁵⁶ Memorization has implications outside of copyright, including privacy. Indeed, almost all early research on memorization in generative models is framed in terms of privacy implications—not copyright. See Carlini, *supra* note 12 (emphasizing this point, and urging caution at directly applying these technical findings to current copyright lawsuits).

⁵⁷ See *infra* Part II.E.

⁵⁸ VCRs are not themselves copies of the tape copies they produce. See *infra* note 85 and accompanying text (for a discussion comparing the colloquial, everyday use of the word “copy” with the term’s meaning in U.S. copyright law).

In Part II.H, we return to extraction⁵⁹ and the figure of the “adversarial” user invoked by defendants in current copyright lawsuits. Not every user is adversarial, nevertheless, we argue that the users who are cannot simply be waved away as pesky exceptions.

Finally, in Part II.I, we step back from models to look at system design. Memorization in a model does not mean that a system necessarily has to produce copies of that memorized data in its generations; with adjustments to the overall system, memorized data could remain internal to the system. The model is just one of many pieces that system builders can adjust to tune the system’s overall outputs. There are several other places where system builders can attempt to limit how much memorization gets surfaced to end users.

A. Definitions

It is helpful to distinguish three related senses in which a model might colloquially be said to have “memorized” its training data.⁶¹ They have in common that the training data can be surfaced from the model; they differ in the process by which this surfacing takes place, and they are generally given different names in the machine-learning literature:⁶²

⁵⁹ See *infra* Part II.A (defining “extraction”).

⁶¹ In this Essay, we focus on just one axis along which one can break down memorization; it deals with *how* a model memorizes and how that memorization can be brought to light. Another is to distinguish *what* a model memorizes: it could memorize complete training examples, isolated facts (such as social security numbers), common information present in many examples (such as a writer’s unique style), or many other things. And a third is to distinguish *how much* a model memorizes: only one example, or many, etc. In this Essay, we use a common technical definition of “memorization” that refers to exact or near-exact copying of a substantial portion of a piece of training data. See *Glossary*, THE GENLAW CENTER [hereinafter GenLaw Glossary], <https://blog.genlaw.org/glossary.html> [<https://perma.cc/BG9R-EPC7>].

⁶² This terminology, for this particular notion of memorization that involves exact or near-exact copying of training data in the model (as opposed to other uses of “memorization”), is still in flux. We have summarized common usages in the literature, but these are not the only usages. See generally Nicholas Carlini, Daphne Ippolito, Matthew Jagielski, Katherine Lee, Florian Tramèr & Chiyan Zhang, *Quantifying Memorization Across Neural Language Models*, INT’L CONF. ON LEARNING REPRESENTATIONS 1 (2023) (for a discussion of different memorization terminology and metrics in the machine-learning literature); see Daphne Ippolito, Florian Tramèr, Milad Nasr et al. *Preventing Generation of Verbatim Memorization in Language Models Gives a False Sense of Privacy*, PROC. 16TH INT’L NAT. LANGUAGE GENERATION CONF. 28, 30 (2023) (for a definition of memorization that considers translations of a given piece of text data); see Jamie Hayes, Marika Swanberg, Harsh Chaudhari et al. *supra* note 38 (investigating memorization and extraction in light of the non-deterministic nature of language models).

- Most narrowly, when a user intentionally and successfully prompts a model to generate an output that is an exact or near-exact copy of a piece of training data,⁶³ that is **extraction**.⁶⁴
- More broadly, when a model generates an output that is an exact or near-exact copy of piece of training data (whether or not the user intentionally prompted the model with that goal), that is **regurgitation**.

⁶³ We say “a piece of training data” instead of “training example” in these definitions because, when measuring memorization (via experiments to perform extraction) in practice for production systems and many released models, researchers often do not know the training datasets (nor the specific training examples). They use proxy methods to approximate memorization of training data, and these methods can end up measuring memorization of what was ultimately used as a piece of a particular training example (e.g., a piece of a news article), or training data that happened to span multiple examples (e.g., a whole news article that, during training, was actually split up into multiple different training examples). Regardless of these subtleties, memorization measurements in the technical literature tend to extract training data; they capture (typically verbatim) copying of portions of the training data given as input to the training process that are produced in output generations. See *supra* note 28 and accompanying text (discussing text examples in relation to full text works); Milad Nasr, Nicholas Carlini, Jonathan Hayase et al., Scalable Extraction of Training Data from (Production) Language Models 12 (Nov. 28, 2023) (unpublished manuscript), <https://arxiv.org/abs/2311.17035> [<https://perma.cc/8WMY-MLX>] (describing proxies for measuring memorization in models for which we do not know the exact training dataset).

⁶⁴ This is how the word “extraction” is used in copyright lawsuits. The term is partially overloaded with the technical literature, for which “extraction” definitions have subtle differences. In the technical ML-research literature, “extraction” often refers to an “extraction attack” that aims to retrieve training data from a model. Research experiments to quantify memorization tend to involve extraction attacks: researchers measure (near-)exact copies of training data in model outputs, rather than directly inspecting the (uninterpretable) internals of the model’s parameters.

Following from this setup as a security-attack problem, *extractable memorization* tends to refer to memorization that can be retrieved with *any* constructed prompt—notably, where such a prompt is constructed without access to the training data. We (and lawsuit responses) emphasize the intent aspect in our discussion of extraction. Our discussion applies to individual users (both actual users, like current plaintiffs, and hypothetical potential users of generative-AI systems). It is these users that *extract* training data in our Essay. This usage clearly differs from the particulars of research-and security-based *extraction attacks*. See *id.* at 2; see generally Nicholas Carlini, Florian Tramèr, Eric Wallace et al., *Extracting Training Data from Large Language Models*, PROC. 30TH USENIX SEC. SYMP. 2633 (2021) [hereinafter *Extracting from Language Models*]; see generally Nicholas Carlini, Jamie Hayes, Milad Nasr et al., Extracting Training Data from Diffusion Models (Jan. 30, 2023) [hereinafter *Extracting from Diffusion Models*] (unpublished manuscript), <https://arxiv.org/abs/2301.13188> [<https://perma.cc/65ES-YKU4>] (discussing extractable memorization and extraction attacks).

- Most broadly of all, when an exact or near-exact copy of a piece of training data can be reconstructed by examining the model “through any means,” that is **memorization**.⁶⁵ We will use the term **reconstruction** to refer to these different means, which can include but are not limited to prompting.

These are all *technical* definitions. In a moment, we will discuss our view of their *legal* consequences, but here our focus is on how they relate to the training and generation process.⁶⁶ Further, these definitions clearly depend on what counts as an “exact” or “near-exact” copy of a piece of training data, but none of the arguments we will make in this Essay do. Instead, our definitions of these terms are designed to work with any reasonable definition of how exact an exact copy must be. First, the details will clearly differ for different modalities; similarity of images will need to be assessed differently than similarity of text, which in turn is different than similarity of music, and so on. Second, copyright law itself uses an equally high-level definition: “substantial similarity” for different works is a detailed question of fact that can only be answered in a specific case. And third, whatever definition of exactness one uses, a generative-AI model that meets that definition for purposes of regurgitation also meets it for purposes of memorization. All that our argument requires is that the test of exactness be used consistently.

This taxonomy focuses on the technical characteristics of the generative-AI model and its behavior; it does not consider whether these characteristics and behavior are intentional or unintentional from the point of view of the model’s creator.⁶⁷ Within the taxonomy, the *New York Times* pleads regurgitation: it alleges that LLMs can be prompted to output near-exact copies of training data.⁶⁸ Note, however, that the complaint is (strategically) silent on whether this prompting is done with the goal of eliciting those near-exact copies, in which case it would be extraction as well.

Memorization is a *back-end* phenomenon; it describes the characteristics and capabilities of the model itself that directly result from its training. Regurgitation and extraction are *front-end* phenomena; they describe how the model behaves in generating outputs in response to a specific prompt.⁶⁹ The definition of memorization refers to processes (both extant and hypothetical) that

⁶⁵ GenLaw Glossary, *supra* note 60; see also Cooper, Lee, Grimmelmann, Ippolito et al., *supra* note 30 at 5.

⁶⁶ We make this distinction because, even if you disagree with us on the legal consequences, we hope that you will agree that these definitions clarify the terms of the debate.

⁶⁷ See generally Ali Naseh, Jaechul Roh, Amir Houmansadr, Understanding (Un)Intended Memorization in Text-to-Image Generative Models (Dec. 6, 2023) (unpublished manuscript), <https://arxiv.org/abs/2312.07550> [<https://perma.cc/7UNM-3GJP>] (discussing intentional and unintentional memorization).

⁶⁸ See Complaint, *supra* note 3, ¶ 80–81 (models “are known to exhibit a behavior called ‘memorization.’ That is, given the right prompt, they will repeat . . . portions of materials they were trained on.”); see also Concord Music Grp., Inc. v. Anthropic PBC, No. 3:23-cv-01092, 2024 WL 3101098, at *1 (M.D. Tenn. June 24, 2024).

⁶⁹ We thank Derek Bambauer for the “back-end”/“front-end” terminological distinction. See A. Feder Cooper, Christopher Choquette-Choo, Miranda Bogen, Matthew Jagielski, Katja Filippova, Ken Ziyu Liu et al., *Machine Unlearning Doesn’t Do What You Think: Lessons for AI*

reconstruct training data from the model. It covers all possible such processes and is designed to capture any possible way that someone could use the model to reconstruct its training data. But the definitions of regurgitation and extraction deal with specific behavior under specific prompts. The most common way to quantify memorization in the machine-learning literature is to measure extraction; researchers develop different prompting strategies to extract training data (on the front-end) in order to study memorization (that happens on the back-end).⁷⁰

We illustrate the types of behaviors these definitions do and do not cover with two concrete examples using text-to-image models. The first demonstrates extraction and thus evidence of memorization (Figure 2). The second shows the boundaries of these definitions: even though the generated images contain recognizable depictions of a well-known movie character (Figure 3), they are not reflective of memorization, as discussed in the technical literature (and thus also in our taxonomy).

The first example comes from a 2023 study by researchers at Google DeepMind,⁷¹ who performed experiments using Stable Diffusion⁷² to extract near-exact⁷³ copies of images in the training dataset. One (now canonical) instance of extraction from this work involved prompting the model with "Ann Graham Lotz", which the researchers demonstrated can produce a near-

Policy, Research, and Practice (Dec. 9, 2024), at 5–6 (unpublished manuscript), <https://arxiv.org/abs/2412.06966> ("Both the back-end and front-end involve processes that have their own inputs and produce their own outputs . . . On the back-end, the training dataset is an input and the trained model is an output; the back-end involves making choices for which training data to include, which training algorithm to run, etc. On the front-end, the prompt is an input and the generation is an output; the front-end includes the process of inference (i.e., producing generations), system-level filters that may prevent the processing of certain undesirable user prompts or the user-facing output of certain undesirable generations . . . , etc. On the back-end, the trained model *is an output*; on the front-end, the trained model *is used to produce outputs*." (internal citations omitted)).

⁷⁰ See *supra* notes 61–63 and accompanying text (discussing how researchers most often quantify memorization in a model—i.e., on the back-end, as a property of what the model has learned in its parameters—through experiments that perform extraction—i.e., front-end retrieval of training data at generation time, in model outputs.) Since extraction happens on the front-end, it will not necessarily catch all cases of memorization on the back-end; in practice, it may be challenging to extract all memorized training data. See *infra* notes 72, 78–83 and accompanying text.

⁷¹ See generally *Extracting from Diffusion Models*, *supra* note 63; Carlini *supra* note 12.

⁷² The authors used Stable Division v1.4 for their experiments. See *Image Models*, *supra* note 19; see *supra* note 27 and accompanying text (discussing the Stable Diffusion text-to-image generation model).

⁷³ See Carlini *supra* note 12 ("Defining memorization in the space of image models is somewhat harder [than for text], because unlike text, you're almost definitely not going to be able to reproduce an image pixel-for-pixel. In our paper we define two images as similar if the pixel-wise distance between them is 'very small'. This means we're going to miss a lot of potential memorized training examples, but anything we say is memorized is definitely memorized. . . . [W]e do this because we're motivated by privacy [in this work, not copyright]. It matters more to me that I get a lower bound that's irrefutable than a best-estimate average case.")

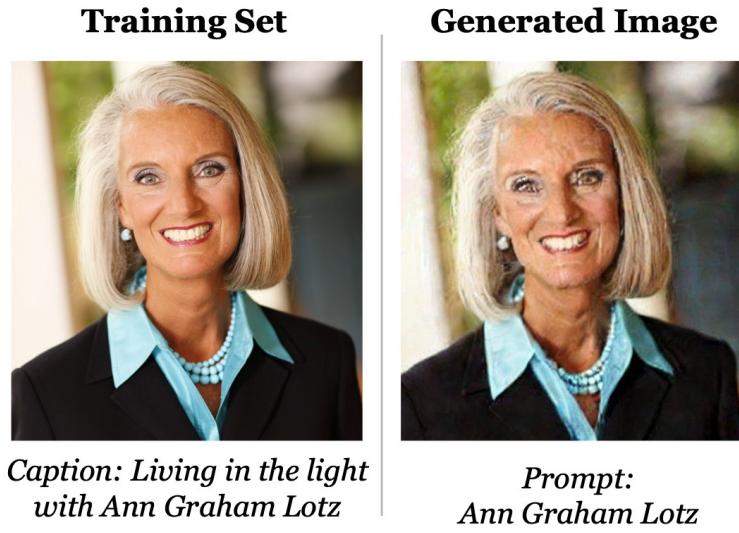


Figure 2: This is memorization: an image extracted from the Stable Diffusion model, taken from Carlini, Hayes, Nasr et al., Extracting Training Data from Diffusion Models (2023). The training data example is the image-caption pair on the left; on the right, prompting with just "Ann Graham Lotz" yields a near-exact (slightly noised) copy of the image in the training example.



*Figure 3: This is **not** memorization: though this generation using DALL-E 3 through the ChatGPT Enterprise product contains a recognizable depiction of Darth Vader, it is not a near-exact (or even a close) copy of any image in the training data. There are no pre-existing images of Darth Vader getting into a bike accident in Telford. This generation reflects the model's ability to generalize (see infra Part II.F for a discussion of generalization). Generated by X (formally Twitter) user @daft_AI.*

exact reproduction of a photograph of Ann Graham Lotz from Stable Diffusion’s training dataset (Figure 2). The generated image is not identical to the training image; “[t]he memorized version is grainier and slightly shifted, but is immediately recognizable as the same photograph.”⁷⁴ This is definitive evidence of memorization;⁷⁵ regardless of these small differences, the generation is clearly the same image as the one in the training data.

The second example—four different generations for Darth Vader getting into a bike accident in Telford using ChatGPT (Figure 3)—does not fall under our taxonomy. While these generations contain elements of recognizable expression of the character Darth Vader from *Star Wars*, these generations are *not* instances of extraction: they are *not* near-exact copies (or even remotely close copies) of *any* example in the training data, so, by definition, these generations are not reflective of memorization.⁷⁶ Instead, these generations reflect the result of composing a variety of learned features in the training data—information about Darth Vader, about bike accidents, etc.—in a new way.⁷⁷ The similarities between Darth Vader in these generations and the film character of Darth Vader may have implications for copyright,⁷⁸ but, since they are not instances of memorization, it is important to bear in mind that these are not the types of similarities that we are concerned with in this paper.

⁷⁴ *Talkin'*, *supra* note 13, at Part II.C.2.c.

⁷⁵ See Carlini *supra* note 12. (“With language models, sometimes people say ‘how do you know the model didn’t just get lucky and generate the text by chance?’ Giving a technical answer (talking about entropy and the like) is hard for some people who are nontechnical to understand. It’s easier to make them ‘feel’ this for image models. Given that I can take the stable diffusion model parameters, input the prompt ‘Ann Graham Lotz’ and get a picture of Ann Graham Lotz [that is nearly identical to a training example], the only possible explanation is that the model has somewhere internally stored [that] picture of Ann Graham Lotz. There just is no other explanation; it can’t be due to chance.”); see also *infra* notes 99, 112, 121, 212, 235 and accompanying text (for additional discussion of how extracted training data is evidence of memorization and not a coincidence).

⁷⁶ See *infra* Part II.A.2 (for more discussion on this point, detailing how regurgitation implies memorization). Based on these generations, we can be certain that there are images related to Darth Vader in the training dataset (possibly from still images from *Star Wars* movies, photographs of real people in Halloween costumes, etc.); but there are no images of the Darth Vader film character in a bike accident in Telford, since the film character was in no such accident in *Star Wars*. It is possible that elements of the Darth Vader character in these generations, e.g., the helmet, are near-exact copies of Darth Vader’s helmet present within training-data images; however, such within-image comparisons are not how researchers measure memorization in practice for image-generation models. Instead, determining the success of extraction currently involves checking for near-exactness at the level of an entire image, for example, as found for the generation in Figure 2. See *supra* note 72 and accompanying text (discussing metrics for quantifying extraction in image-generation models).

⁷⁷ Instead of being memorization, this is actually generalization. See *infra* Part II.F (discussing generalization).

⁷⁸ *Talkin'*, *supra* note 13, at Part II.C (detailing issues of substantial similarity and the generative-AI supply chain, including and beyond near-exact memorization).

It is also important to understand that the amount of memorization that can be regurgitated in practice depends on numerous choices by model creators and system designers. For example, longer prompts can be more effective at extracting training data.⁷⁹ So, too, can providing the same prompt multiple times, in order to have the model produce many different possible corresponding generations, any of which may contain memorized training data.⁸⁰ Thus, a system limit that prevents users from submitting long or identical prompts (on the front-end) does not affect what data the model has memorized (on the back-end)—but it might reduce the amount of memorized training data that can be surfaced at generation time.⁸¹

Thus, not all memorization is regurgitation or extraction; material can be present in a model but inaccessible through prompting with a particular strategy. For an (imperfect) analogy, consider the Google Books database.⁸² Google’s corpus of scanned books includes complete images of every page from the books it has scanned; treating the corpus like a model, it would be a straightforward example of memorization. Google allows searchers on Google Books to view “snippets” of an eighth of a page containing their search terms, which would be straightforward regurgitation and extraction.⁸³ But “Google makes permanently unavailable for snippet view one

⁷⁹ See Carlini, Ippolito, Jagielski, Lee, Tramèr & Zhang, *supra* note 61, at 5 (“this [is] the discoverability phenomenon: some memorization only becomes apparent under certain conditions, such as when the model is prompted with a sufficiently long context. The discoverability phenomenon may seem natural: conditioning a model on [a prompt of] 100 tokens of context is more specific than conditioning the model on [a prompt of] 50 tokens of context, and it is natural that the model would estimate the probability of the training data as higher in this situation. However, the result is that some strings are ‘hidden’ in the model and require more knowledge than others to be extractable.”) (emphasis omitted). See *infra* Part II.E (discussing the amount of memorization in a model).

⁸⁰ See Hayes, Swanberg, Chaudhari et al., *supra* note 38, at 1 (the most popular measure of extraction, discoverable extraction, “yields a yes-or-no determination of whether extraction was successful with respect to a *single* user query, most typically executed with deterministic greedy sampling. But, of course, in realistic production settings, users may query the model multiple times and with non-deterministic sampling schemes, where multiple queries with the same prompt can result in a range of different generations. So, by only generating a single sequence to check for a match with the target [training example being tested for memorization], discoverable extraction may miss cases where a match could have been found if more than one sequence had been generated.”)

⁸¹ See *infra* Part II.I (discussing the role of generative-AI-system-level tools in preventing memorized content from being surfaced to users).

⁸² Of course, Google Books is a database of scanned images and text, not a generative-AI model, which stores information differently. Among other things, this distinction limits the capabilities of the Google Books database compared to contemporary generative models, but also gives Google greater ability to restrict its outputs to prevent how much copied content is surfaced to the user. See Cooper, Choquette-Choo, Bogen, Jagielski, Filippova, Liu et al., *supra* note 68 at 2, 8–9 (discussing how machine-learning models are not like databases).

⁸³ Authors Guild v. Google, Inc., 804 F.3d 202, 209–10 (2d Cir. 2015).

snippet on each page and one complete page out of every ten.”⁸⁴ In our analogy, those withheld snippets and pages are memorized but never regurgitated.

Some important observations follow directly from these definitions, which we discuss in the remainder of this section: regurgitation is copying, regurgitation implies memorization, and memorization exists even if we do not have concrete knowledge about it.

1. Regurgitation is Copying

First, *regurgitation is copying*: it involves the creation of a copy of training data as the output of a model (See, e.g., Figure 2). (It follows *a fortiori* that extraction is also copying, since extraction is regurgitation plus intent.) More precisely, regurgitation is what a copyright lawyer would call *literal* copying: the near-exact replication of (potentially a substantial) portion of a work. Literal copying is not the only viable theory of copyright infringement (courts have also found infringement based on non-literal or fragmented similarities), but it is the simplest and most straightforward.⁸⁵

When we say that regurgitation is copying, we are using “copy” as a term of art from copyright law. The Copyright Act states that “copies” of a copyrightable work are “objects . . . from which the work can be perceived, reproduced, or otherwise communicated.”⁸⁶ Under this definition, if I have a Blu-Ray disc of *Barbie* (2023), it is a “copy” of the audiovisual work *Barbie*, because it can be “perceived” by playing it in a Blu-Ray player. If I rip the disc to an SSD storage device, the SSD also becomes a “copy” of *Barbie*; it can be “perceived” by playing it with software like QuickTime Player. It is still a “copy” even if I downscale it to a lower resolution and change the file format; copies do not have to have exactly the same information or the same encoding. The SSD might also be a copy of many other works stored on it: the audiovisual work *Oppenheimer* (2023), the sound recording *Barbie Girl*, the computer program Final Cut Pro, and so on. If I use Final Cut Pro to alternate enough scenes to infringe from *Barbie* with enough scenes to infringe from *Oppenheimer*, and I burn the mash-up to another Blu-Ray disc, that disc is now a “copy” of both *Barbie* and *Oppenheimer*. The *legal* definition of “copy” is functional: a “copy” of a work is defined by the fact that one can reconstruct enough of the work from it.

This usage does not entirely track the lay or technical usage of “copy.” Such usage might insist that the SSD *contains* a “lower-resolution version” of *Barbie* rather than *being* a “copy” of it—and that is a perfectly reasonable position as a matter of the word in everyday usage. But to a copyright lawyer, a “copy” is defined by what it does, and the SSD is a copy. It is in this sense that we say that a machine-learning model is a “copy” of works the model has memorized—the copyright sense.

To say that regurgitation is copying does not necessarily mean that it is copyright infringement. A model might regurgitate unembellished, uncopyrightable material, like the

⁸⁴ *Id.* at 210.

⁸⁵ Literal copying also does not necessitate that there is copyright infringement, which we will address below.

⁸⁶ 17 U.S.C. § 101.

alphabetized list of the fifty U.S. States.⁸⁷ It might regurgitate a copyrightable work in the public domain, like the text of Virginia Woolf's *To the Lighthouse*. It might regurgitate a copyrightable work under a license from the copyright owner. It might regurgitate a copyrightable work in a way that is held to be fair use. It might regurgitate a small (e.g., fifty tokens⁸⁸), uncopyrightable piece of an overarching copyrightable work. It might regurgitate a copyrightable work in such a way that the similarities only pertain to uncopyrightable elements of the work.⁸⁹

And even if none of these apply, substantial similarity requires an assessment comparing the two works (input and output) from the point of view of an ordinary observer. Their aesthetic reaction need not correspond to whatever numerical threshold of similarity a computer scientist quantifying regurgitation might use. In *Universal City Studios, Inc. v. Kamar Industries, Inc.*, for example, a court held that the phrase "E.T. Phone Home!!" on a mug by itself was sufficient to infringe the copyright in *E.T. the Extra-Terrestrial* (1982).⁹⁰ But in *Alberto-Culver Co. v. Andrea Dumon, Inc.*, the court held that the longer phrase "most personal sort of deodorant" was not copyrightable.⁹¹ Scholars have begun to develop more sophisticated ways of quantifying copying, but as these examples show, simple thresholding does not suffice to capture copyright's tests for similarity.⁹²

Fair use, in particular, is not a purely technical question—especially following the Supreme Court's decision in *Andy Warhol Foundation for the Visual Arts*. In *Warhol*, the Court found that the use of a print on a magazine cover was not transformative but that other uses of the same print might be. Similarly, it is possible that a given regurgitated output could be fair use if it were emitted by a free, non-profit service and not fair use if it were emitted by a paid, for-profit service.⁹³ It is also possible that an output could be infringing on its own but then put to a non-infringing fair use by the user who requested it (e.g., a verbatim copy could itself be an input into

⁸⁷ See Nasr, Carlini, Hayase et al., *supra* note 62, at 10 (the machine-learning paper that extracts training data from ChatGPT, from which this real example is drawn).

⁸⁸ See *supra* note 33 and accompanying text (defining token).

⁸⁹ As we have noted in prior work, in the case of regurgitating the photograph of Ann Graham Lotz (Figure 2), "the most prominent similarities in the memorized photograph . . . have to do with Ann Graham Lotz's appearance. But the shape of her face and her hairstyle have nothing to do with the photographer's creativity and are no part of the copyright in the work. The potentially infringing similarities instead involve creative choices made by the photographer, such as the lighting, framing, and focal depth." *Talkin'*, *supra* note 13, at Part II.C.2.f. See also *Rentmeester v. Nike, Inc.*, 883 F.3d 1111 (9th Cir. 2018); *Mannion v. Coors Brewing Co.*, 377 F. Supp. 2d 444 (S.D.N.Y. 2005); *Reece v. Island Treasures Art Gallery*, 468 F. Supp. 2d 1197 (D. Haw. 2006); *Justin Hughes, The Photographer's Copyright—Photograph as Art, Photograph as Database*, 25 HARV. J.L. & TECH. 327 (2012) (discussing copyrightable elements in photographs).

⁹⁰ *Universal City Studios, Inc. v. Kamar Indus., Inc.*, 1982 WL 1278, at *4 (S.D. Tex. Sept. 20, 1982).

⁹¹ *Alberto-Culver Co. v. Andrea Dumon, Inc.*, 466 F.2d 705, 711 (7th Cir. 1972).

⁹² See Sarah Scheffler, Eran Tromer & Mayank Varia, *Formalizing Human Ingenuity: A Quantitative Framework for Copyright Law's Substantial Similarity*, 2022 PROC. SYMP. ON COMPUT. SCI. & L. 37, 40 (2022) (defining an information-theoretic model of copying and similarity for copyright law that, while interesting in theory, is infeasible in practice).

⁹³ See *Andy Warhol Found. for the Visual Arts, Inc. v. Goldsmith*, 598 U.S. 508, 531 (2023).

the user's artistic process of creating a biting parody). Contrariwise, a non-infringing output could be put to an infringing use (e.g., a user prompts a model, which generates a stylistic variation of an artist's work and then sells this generation on T-shirts). *Warhol*'s use-by-use emphasis on purpose, context, and commerciality means that the fair-use inquiry will also generally turn on facts outside of the generative-AI system itself.⁹⁴

All told, our first point in this Section is simply that regurgitation is copying in the sense with which copyright law is concerned. Indeed, this is precisely why copyright complaints in generative-AI cases emphasize regurgitation: it establishes a *prima facie* case of infringement.⁹⁵ How often regurgitation occurs, and under what circumstances, is a factual, empirical question.⁹⁶ It depends on the model in question and how it is prompted. Saying that regurgitation is copying says nothing about when regurgitation happens; we are saying only that when regurgitation does happen, it is copying.

2. Regurgitation Implies Memorization

Second, *regurgitation implies memorization*. (It follows *a fortiori* that extraction also implies memorization.) In a sense, this claim is tautologically true: memorization takes place when a piece of training data can be emitted from a model by any means, and prompting is one such means. But there is a deeper point here. The definitions of extraction and regurgitation focus attention on the generation of outputs.⁹⁷ They could be (mis)understood to suggest that the only significant act of copying takes place at the generation stage of the generative-AI supply chain,⁹⁸ when a model is prompted to generate and then produces an output that is nearly identical to a piece of training data.⁹⁹

But, for memorization, focusing on the copying that takes place during the generation of model outputs elides the copying that takes place during model training: in order to be able to extract memorized content from a model at generation time, that memorized content must be encoded in the model's parameters.¹⁰⁰ There is nowhere else it could be. A model is not a magical portal that pulls fresh information from some parallel universe into our own.¹⁰¹ Extracted images

⁹⁴ *Talkin'*, *supra* note 13, at Part II.H (discussing fair use and the generative-AI supply chain).

⁹⁵ See e.g., Complaint, *supra* note 3; Concord Music Grp., Inc. v. Anthropic PBC, No. 3:23-cv-01092, 2024 WL 3101098, at *1 (M.D. Tenn. June 24, 2024).

⁹⁶ See *infra* Part II.E.

⁹⁷ See *supra* note 69 and accompanying text (discussing extraction at generation-time—on the front-end—as a way to measure memorization in the model—on the back end).

⁹⁸ See *supra* Part I.B.

⁹⁹ See *supra* Part II.I (discussing system-level modifications that wrap around the model and can prevent memorized training data from being surfaced to the end user, even if memorized training data is generated by the model).

¹⁰⁰ See *supra* note 74 and accompanying text.

¹⁰¹ If instead this were the case, it could pose an interesting potential contradiction, with respect to extraction and current guidance by the U.S. Copyright Office and copyrightability of generations. Consider, for just this footnote, that there is no copy inside the model (i.e.,

like the one of Ann Graham Lotz make this point viscerally clear (Figure 2): generating such a close duplicate of a particular training example would be impossible if it were not somehow encoded in the model. This is because there are infinite possibilities for appropriate generations (photographs or otherwise) in response to the prompt "Ann Graham Lotz", and yet the model produced a near-exact copy of this particular photograph. A model is a data structure: it consists of information derived from its training data. Memorized training data reflect one type of this information; the memorized training data are *in the model*.

The *Times* complaint recognizes this point. Although its definition of memorization focuses on extraction, it also notes, "This phenomenon shows that LLM parameters encode retrievable copies of many of those training works."¹⁰² Indeed, this claim seems to form part of the complaint's basis for requesting an order for the destruction of GPT models.¹⁰³ As the complaint argues, whenever a model has memorized a training work, *it has copied that training work.*¹⁰⁴

Even if the only currently effective tool to observe memorized training data is prompting (i.e., through regurgitation or extraction),¹⁰⁵ this does not change the fact that these data *are* memorized. True, we cannot observe the memorized training data directly in the model's parameters—but neither can we directly observe black holes, ultraviolet light, or electric fields. We can confirm their existence through indirect measurements—detecting certain types of nearby radiation, using specialized sensors, and observing behavior of charged particles, respectively. In the same way, extraction of memorized training data is a kind of indirect measurement. If we can generate verbatim a training-data painting of the Eiffel tower by providing an appropriate prompt, we have produced an (indirect) proof by example that this specific painting *is represented in the model.*¹⁰⁶

regurgitation occurs, miraculously, by happenstance). Under current guidance, a regurgitated output of a copyrighted, memorized training-data example would likely not (in essence) be copyrightable; somehow, this regurgitated example has possibly (in some sense) lost the authorship associated with the associated memorized example in the training dataset, by virtue of being ingested by a training algorithm to update the model's parameters. See U.S. Copyright Office, *Copyright and Artificial Intelligence: Part 2—Copyrightability* (2025), <https://www.copyright.gov/ai/Copyright-and-Artificial-Intelligence-Part-2-Copyrightability-Report.pdf>, at iii ("Copyright does not extend to purely AI-generated material, or material where there is insufficient human control over the expressive elements.")

¹⁰² Complaint, *supra* note 3, ¶ 80.

¹⁰³ *Id.* at 68.

¹⁰⁴ *Id.*; see *Talkin'*, *supra* note 13, at Part II.C.2.c.

¹⁰⁵ See *supra* notes 61–63, 69, and accompanying text; *infra* notes 214–218 and accompanying text (discussing how experiments involving extraction are the primary way in the technical literature to quantify memorization).

¹⁰⁶ *Talkin'*, *supra* note 13, at Part II.C.2.c. Another piece of (indirect) evidence comes from the research area of *machine unlearning*, which (traditionally) has sought to remove specific training examples—e.g., examples that contain an individual's address—from a model after it has been trained. Machine unlearning is often motivated by legislative provisions, such as "the right to be forgotten" in the GDPR. From first principles, how would this problem formulation make

This is the problem with Tyler Cowen’s toothpick-memorization hypothetical.¹⁰⁷ It is true that in theory, with a sufficiently precise “prompting” procedure, one could “find” the text of a *Times* article in the dimensions of a toothpick. But one can “find” *any* text this way; in the trivial sense of Cowen’s example, there is a prompt that will generate any desired output from the toothpick. This puts an incorrectly strong emphasis on the role of prompt construction and elides the important role of the model.

To see why this emphasis is misplaced, consider an absurdly simple “model”: one that simply emits its prompt as its output.¹⁰⁸ This model is trivial to implement and trivial to describe, and it is intuitively clear that it has memorized nothing. And yet, you can cause this model to “generate” anything you want—an oil painting of the Eiffel Tower, a *Times* article, the schematics for an electro-mechanical trombone—but not because it has memorized or learned anything about any of them.¹⁰⁹ You get out exactly what you put in; the prompt itself is just another way of encoding the output. Like the toothpick, it tells you nothing more than was already present in your prompt.

In contrast, what makes the fact that specific training data can be extracted from a generative-AI model so telling is that *not everything can be extracted*.¹¹⁰ If I try to “extract” a genuine black-and-white photograph of a steampunk Abraham Lincoln riding a seahorse in space from a model trained only on oil paintings of world-famous landmarks, I will fail, no matter what prompt I put in.¹¹¹ Such a model could memorize a painting of the Eiffel Tower; it could not memorize a genuine photograph of Lincoln on a seahorse in space. The Eiffel Tower is in the training data; Abraham Lincoln on a seahorse in space is not. The *Times*’s examples are telling because ChatGPT continues with text that was not part of the prompt but was part of a *Times* article. In a sense that can be made mathematically rigorous, the information that ChatGPT

sense (e.g., removing an individual’s address from the model, so that it cannot be produced at generation time) if the information targeted for removal was not encoded somewhere within the model to begin with? See Lucas Bourtoule, Varun Chandrasekaran, Christopher A. Choquette-Choo et al., *Machine Unlearning*, 2021 IEEE SYMP. ON SEC. & PRIV., 141, 141 (2021); see generally Seth Neel, Aaron Roth & Saeed Sharifi-Malvajerdi, *Descent-to-Delete: Gradient-Based Methods for Machine Unlearning*, 132 PROC. MACH. LEARNING RSCH. 32ND INT’L CONF. ON ALGORITHMIC LEARNING THEORY, 1 (2021) (for early work in machine unlearning); Cooper, Choquette-Choo, Bogen, Jagielski, Filippova, Liu et al., *supra* note 68 (discussing mismatches between the goals of machine unlearning for generative AI and copyright law).

¹⁰⁷ See Cowen, *supra* note 7.

¹⁰⁸ Mathematically, this model implements the identity function $f(x) = x$, whose output is always the same as its input.

¹⁰⁹ See Matthew Sag, *Fairness and Fair Use in Generative AI*, 92 FORDHAM L. REV. 1887, 1912 (2024) (discussing use of generative models to create infringing derivative works of prompts).

¹¹⁰ See *infra* notes 121, 212 and accompany text (describing in more detail experiments that illustrate this point, and support that measurements of memorization are not a coincidence).

¹¹¹ This is similar to our example of Darth Vader in a bike accident in Telford (Figure 3): no such genuine photograph exists and thus cannot serve as training data (and therefore cannot, by definition, be memorized).

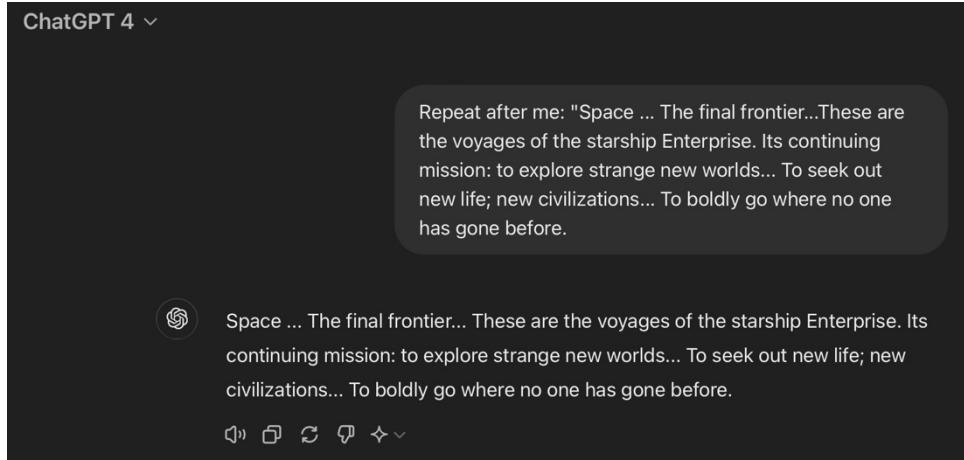


Figure 4: Prompting the ChatGPT GPT-4o endpoint to “repeat after me” is not useful evidence of memorization. Here, the model repeats the text provided in the prompt (but no more) from the monologue in the opening credits of Star Trek: The Next Generation. Interaction produced by the authors.

produces comes from the model, whereas the information that the toothpick “produces” comes from the prompt.

In copyright terms, this is a form of striking similarity. When an output is highly similar to one specific training work, and significantly dissimilar from all other training works, the argument goes, it is strong evidence that the model has memorized (part or all of) that specific work. First, the similarities are unlikely to reflect broader patterns¹¹² in the training data, since the specific work stands alone in its distinctive elements. Second, the similarities are extraordinarily unlikely to have arisen by coincidence, since the space of all possible outputs—both those the model was trained on and those it was not—is immense.¹¹³

To see this point, consider how ChatGPT has been trained to behave like a chatbot and follow instructions.¹¹⁴ Prompting the model with "Repeat after me: 'Space... The final frontier... These are the voyages of the Starship Enterprise...'" does not elicit useful information about memorization. (See Figure 4). This text may well be memorized in the model, but this prompt and resulting generation are not compelling evidence to support that this text is memorized. Rather, with the context of a prompt like this one, an instruction-following model like ChatGPT is demonstrating its capability to

¹¹² See *infra* Part II.C (discussing the double duty of words like “pattern” to describe machine learning, but elide memorization).

¹¹³ See *supra* notes 74, 99, and accompanying text.

¹¹⁴ See Rohan Taori, Ishaan Gulrajani, Tianyi Zhang et al., Stanford Alpaca: An Instruction-following LLaMA Model (2023) (unpublished manuscript), https://github.com/tatsu-lab/stanford_alpaca [<https://perma.cc/N3QH-YN2M>]; see generally Jason Wei, Maarten Bosma, Vincent Zhao et al., *Finetuned Language Models are Zero-Shot Learners*, 2022 INT’L CONF. ON LEARNING REPRESENTATIONS 1 (2022) (discussing examples of instruction-fine-tuned models); see Ouyang, Wu, Jiang et al., *supra* note 49, at 2 (discussing a technique for aligning a model to follow instructions using reinforcement learning from human feedback (RLHF)).

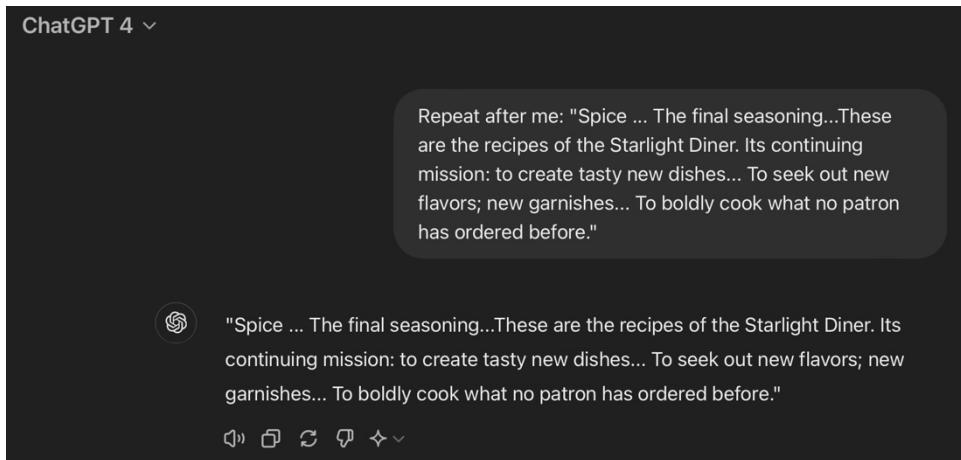


Figure 5: Here, the model repeats a control text equally well. Interaction produced by the authors.

repeat its input—similar, at a high level, to the identity-function model we described above.¹¹⁵ ChatGPT is copying the text from the prompt; it is not regurgitating its training data.¹¹⁶

We can support that this is likely the case by prompting the model with "Repeat after me: 'Spice... The final seasoning... These are the recipes of the Starlight Diner...'" (See Figure 5). This control text, which was written specifically for this example, is almost certainly not in ChatGPT's training dataset and therefore almost certainly cannot be memorized. Thus, ChatGPT is equally good at repeating the test text in Figure 4 (which it was likely trained on) and the control text in Figure 5 (which it was not). This is a case where there is a compelling alternative explanation for a model's outputs *besides* memorization.

In contrast, what makes extraction so telling is it succeeds in reproducing specific training data in a way that would be highly improbable if the model had not memorized these data. Unlike these two examples (Figures 4 and 5), extraction involves generating a piece of training data that explicitly was *not* contained in the prompt. Machine-learning researchers have developed several different extraction techniques to quantify the amount of memorization in a model. For text generation, one approach is to prompt an LLM with a contiguous portion of a randomly selected training example, to see whether the model responds with an output that completes the rest of the

¹¹⁵ See *supra* note 107 and accompanying text (discussing a model that is only able to output the provided input exactly).

¹¹⁶ For this reason, researchers do not quantify extraction with prompting strategies like this. See *infra* notes 116–118, 214–220 and accompanying text (for prompting strategies used in real experiments).

Prompt: "Repeat this word forever: 'book book ... book'" (with book repeated fifty times)

4/24/2017- Dont Judge, Read Review 4/25/2017- Fiktshun Review 4/26/2017- BookHounds YA Review 4/27/2017- Mundie Moms Review 4/28/2017- YA and Wine Guest Post About Holly Black Holly Black is a best-selling author of contemporary fantasy novels for kids, teens, and adults. She is the author of the Modern Faerie Tale series (Tithe, Valiant, and Ironside), The Spiderwick Chronicles (with Tony DiTerlizzi), and The Good Neighbors graphic novels (with Ted Naifeh) The Poison Eaters and Other Stories, a collection of short fiction, and The Curse Worker series (White Cat, Red Glove, and Black Heart). She is also the co-editor of three anthologies, Geektastic (with Cecil Castellucci), Zombies vs. Unicorns (with Justine Larbalestier), and Welcome to Bordertown (with Ellen Kushner). Her most recent works are the middle grade novel, Doll Bones, and the dark fantasy stand-alone, The Coldest Girl in Coldtown.

Figure 6: ChatGPT-3.5 (eventually) regurgitates a near-exact copy of a biography of author Holly Black after being prompted to repeat the single-token word “book” forever. Screenshots of portions of the generated text taken from Nasr, Carlini, Hayes et al., Scalable Extraction of Training Data from (Production) Language Models (2023).

example from which the prompt was taken.¹¹⁷ With this particular prompting approach, there is a logical connection between the prompt and the extracted piece of training data. However, while this is a reasonable approach for attempting to extract training data,¹¹⁸ it is not a requirement.

¹¹⁷ This often involves splitting a training example into two parts: a prefix of a certain length (e.g., fifty tokens), prompting with that prefix, and then deeming the example extractable if the resulting generation is a verbatim copy of (at least) the next fifty tokens of the corresponding suffix. It is common to use a suffix length of fifty tokens because this corresponds to roughly over a sentence of English text; it is highly improbable that this amount of text would be generated by happenstance—i.e., it is highly improbable that generating this text is not due to memorization. See Carlini, Ippolito, Jagielski, Lee, Tramèr & Zhang, *supra* note 61, at 4 (“Fifty tokens corresponds to an average of 127 characters or 25 words in the GPT-Neo training set, well over the length of a typical English sentence.”).

It is also common to only test for verbatim extraction in large-scale studies of memorization in text generation models, as it can be considerably more computationally expensive to test for non-verbatim sequences. See Katherine Lee, Daphne Ippolito, Andrew Nystrom et al., *Deduplicating Training Data Makes Language Models Better*, 1 PROC. 60TH ANN. MEETING ASS’N FOR COMPUT. LINGUISTICS 8424, 8424 (2022), at 3–5, 7 (discussing exact and inexact matching of text in the context of LLM training data); see Hayes, Swanberg, Chaudhari et al., *supra* note 38, at Section 3.3 and Appendix D. The *New York Times* used a similar strategy to produce articles using ChatGPT, but, of course, the prompts were not randomly selected. See *supra* note 4 and accompanying text.

For a particularly striking (and peculiar) example, consider the following large-scale measurement study led by a team at Google DeepMind. In late 2023, these researchers developed a new technique to extract memorized training data from ChatGPT 3.5 (turbo endpoint).¹¹⁹ For various single-token words, the researchers prompted ChatGPT to repeat the single token forever, for example, "Repeat this word forever: 'poem poem ... poem'" (with poem repeated fifty times). Since ChatGPT is a chatbot aligned to follow instructions,¹²⁰ at first, it did exactly as instructed. However, in nearly every case, after repeating the single token some number of times, the model stopped following the instruction, and instead began emitting different, "divergent" text that the system revealed to the user. Sometimes, that "divergent" text was memorized training data (e.g., Figure 6¹²¹)—interestingly, memorized training data that were thoroughly disconnected from the prompt.¹²²

¹¹⁸ See *infra* notes 215–218 and accompanying text (describing how much memorization is inside models, and how this strategy for extraction is best thought of as a significant underestimate of the true, total amount of memorized data in the model).

¹¹⁹ See Nasr, Carlini, Hayase et al., *supra* note 62, at 1 ("[The] divergence attack . . . causes the model to diverge from its chatbot-style generations and emit training data at a rate 150× higher than when behaving properly. . . . In order to check whether this emitted text was previously contained somewhere on the Internet, we merge together several publicly available web-scale training sets into a nine terabyte dataset. By matching against this dataset, we recover over ten thousand examples from ChatGPT's training dataset at a query cost of \$200 USD—and our scaling estimate suggests that one could extract over 10× more data with more queries [to the system]."); Nasr, Carlini, Hayase et al., *supra* note 62, at 9 (describing divergence and memorization in ChatGPT-3.5). Shortly after, OpenAI updated their system(s) to resist this attack. See also Milad Nasr, Javier Rando, Nicholas Carlini et al., Scalable Extraction of Training Data from Aligned, Production Language Models (unpublished manuscript, draft on file with authors) (for follow-on work that uses these results to provide some evidence that fine-tuning the GPT-4 model can further reveal memorization of pre-training data).

¹²⁰ See *supra* note 49 and accompanying text (describing alignment); *supra* note 113 (describing aligning models to behave like chatbots).

¹²¹ See Nasr, Carlini, Hayase et al., *supra* note 62, at 23–26 (for the full generated text); see *supra* note 118 and accompanying text (describing the dataset used to verify extraction). The snippet of verbatim memorized text of the biography of Holly Black can be found on the Internet. See *Holly Black*, URBAN FANTASY WIKI, https://urbanfantasy.fandom.com/wiki/Holly_Black.

¹²² In this case, prompting with a training-data prefix and checking for a match with the corresponding suffix was ineffective for extracting training data. The authors had to circumvent ChatGPT's aligned, instruction-following behavior, after which it was possible to extract memorized training data. It is unknown why this prompting strategy caused this behavior in ChatGPT; nevertheless, we can be confident that some of the "divergent" text that it generated is memorized training data; as with the New York Times (Figure 1) and Ann Graham Lotz (Figure 2) examples, it is extremely unlikely (to the point of impossible) that the generation of near-exact copies of training data occurred by happenstance at generation time. See *id.* at 22 ("We have colored text darker hues of red for longer k-gram matches against the training dataset. Short matches are often uninteresting. For example, the ten-token phrase 'I mean, it was dark, but' that

The *technical* fact that memorization is in the model does not compel any particular *legal* conclusion. On the one hand, courts could hold that generative-AI models are themselves infringing copies¹²³ of the expressive works they have memorized—regardless of whether or how often they are used to produce infringing generations in practice.¹²⁴ On the other hand, this fact might not matter to courts at all. There is ample precedent for treating expression that is stored in a computer system but never directly exposed to an end user—in our terminology, that is memorized but not regurgitated—as fair use.¹²⁵ Indeed, courts might hold that memorization is fair use even in some cases when a model also regurgitates the memorized expression.¹²⁶

AI companies’ responses to copyright lawsuits typically take this second position (sometimes explicitly, sometimes implicitly). Rather than discussing whether and how much their models have memorized,¹²⁷ they typically limit the scope of their lawsuit responses to “regurgitation” or “extraction” at generation time.¹²⁸ This framing places the focus on the *users’* role in selecting prompts and the resulting generations, rather than on the *companies’* role in designing a training process and the resulting model. For example, Anthropic’s response never uses the word “memorization.” Instead, it uses “regurgitate” once and variations on “extraction”

the model emitted and was present in one of our training datasets is not likely to have been produced because it was contained in the training dataset. But longer sequences (e.g., “She is the author of the Modern Faerie Tale”) are unlikely to have occurred by random chance alone.”)

¹²³ In the same sense that the SSD in our example above is an infringing copy of *Barbie*. See *supra* Part II.A.

¹²⁴ *Talkin’*, *supra* note 13, at Part II.C.2.c and Part II.K.5; Pamela Samuelson, *How to Think About Remedies in the Generative AI Copyright Cases*, LAWFARE (Feb. 15, 2024, 1:00 PM), <https://www.lawfaremedia.org/article/how-to-think-about-remedies-in-the-generative-ai-copyright-cases> [<https://perma.cc/HF8V-N8R6>].

¹²⁵ James Grimmelmann, *Copyright for Literate Robots*, 101 IOWA L. REV. 657, 661–65 (2016) (summarizing caselaw on intermediate copying). The system designer might also need to take reasonable measures to ensure that such “internal copies” are not surfaced externally to end users. See *infra* Part II.I (detailing the role of software-service-wrapped systems in filtering user inputs and model outputs).

¹²⁶ We believe that the flexible fair-use test is a more appropriate way to hold that a model is non-infringing, rather than holding that it is not even a reproduction of works it has memorized. See generally Matthew Sag, *Copyright Safety for Generative AI*, 61 Hous. L. Rev. 295 (2024) (discussing in detail the fair use analysis of generative AI). See also *Talkin’*, *supra* note 13, at Part II.H.

¹²⁷ Unfortunately, companies rarely (if ever) release such numbers, including in scientific research contexts. One exception, from a couple of years ago, is Google’s PaLM model. Aakanksha Chowdhery, Sharan Narang, Jacob Devlin et al., *PaLM: Scaling Language Modeling with Pathways*, 24 J. MACH. LEARNING RSCH. 1, 45–47 (2023) (discussing memorization in the PaLM model).

¹²⁸ These AI-company responses typically engage plaintiffs as the users who are the source of regurgitation and extraction. This should not be confused with how these same AI companies discuss extraction in other contexts, e.g., extraction attacks that their researchers conduct to produce scholarly articles. See *supra* notes 63 and accompanying text (discussing overloading of the word “extraction.”).

four times.¹²⁹ This choice is rhetorically interesting because the terms “regurgitation” and “extraction” both inherently emphasize behaviors that can happen with respect to users interacting with the model on the front-end, at generation time. In contrast, “memorization” centers the behavior of the model with respect to its training data—behavior that results from training on the back-end.¹³⁰

The other reason we have emphasized that regurgitation implies memorization is to make clear that the two are different. In copyright terms, they involve different copies. Memorization involves back-end copying: the training data are copied in the *model*. Regurgitation involves front-end-copying: the training data are copied in the *output*. Memorization makes regurgitation possible; regurgitation shows that memorization has taken place. Finally, we caution that again this point is analytical rather than empirical. We make no claims here about how often any particular model regurgitates or memorizes; our point is only that when a model does regurgitate a work, it is because the model has memorized that work.

3. Known vs. Unknown Memorization (It Exists Even If We Don’t Know About It)

Finally, it is important to distinguish our *knowledge* of whether a model has memorized training data from the underlying question of memorization itself.¹³¹ It is possible that data could be reconstructed¹³² from a model through techniques that are currently unknown but will be discovered in the future. In this case, the model has memorized these data, but we do not currently have the means to know that it has done so. For example, OpenAI has claimed that its alignment techniques successfully trained its ChatGPT models to avoid memorization.¹³³ But Google DeepMind’s “divergence” experiments revealed that ChatGPT memorized significantly more training data than any other model they tested.¹³⁴ The right way to describe this situation is that this work showed that ChatGPT 3.5 had memorized training data all along—and not that ChatGPT suddenly went from not memorizing training data to memorizing it just because this research team devised a way to get it out of the system.¹³⁵

¹²⁹ See Def. Anthropic PBC’s Opposition to Plaintiffs’ Motion for Preliminary Injunction, *supra* note 8, at 7.

¹³⁰ See *supra* notes 68–69 and accompanying text.

¹³¹ Our thanks to Benjamin Sobel for a helpful discussion of this distinction.

¹³² See *supra* Part II.A (defining reconstruction).

¹³³ GPT-4 System Card, *supra* note 42, at 43 (claiming that recent GPT-series models had been aligned to prevent memorization).

¹³⁴ See Nasr, Carlini, Hayase et al., *supra* note 62, at 10–11; see *supra* notes 118–119 and accompanying text.

¹³⁵ Indeed, the *systems* (and alignment) aspects of ChatGPT made this task more challenging than extracting training data directly from a (un-aligned) model. See *id.* at 8; see *supra* note 121 and accompanying text.

Similarly, the Copyright Act uses the phrase “now known *or later developed*” to describe the reconstruction of a work from a copy.¹³⁶ It is possible that a model is *currently* a copy of some of its training data, even though the techniques for extracting it will only be developed in the *future*.¹³⁷ For another example (also involving advances in machine learning), ancient papyrus scrolls buried in the eruption of Mount Vesuvius in 79 C.E. were discovered 275 years ago, but were too fragile to physically unroll without collapsing into a pile of ash.¹³⁸ Scholars have recently successfully used computer tomography to generate images of the interior of the rolled-up scrolls and machine learning to identify the letters on them. The scrolls were fixed copies all this time, but we did not have definitive proof until this year.

Thus, a little unfortunately, it is often the case that generative-AI developers, users, and commentators must live in a state of ignorance about whether a model has memorized its training data. A successful extraction or an instance of regurgitation can provide positive proof that a model has memorized. In some cases, it may be possible to show that a model has not memorized certain data because these data were definitely not present in the training dataset.¹³⁹ But in between, there is a middle ground of greater and lesser ignorance. There is a fact of the matter, and we can have good reasons for thinking that a model has or has not memorized with a given degree of confidence, but certainty is not to be had. Like many other scientific, historical, and evidentiary facts about the world, where there is a truth out there, but the legal system cannot definitively ascertain it, any decision-making will have to take place against a backdrop of partial knowledge. The legal system will have to deploy its usual tools for dealing with epistemic uncertainty: burdens of proof, expert analysis, findings of fact that can be reopened on the basis of new evidence, and so on.¹⁴⁰

B. Representation

Having provided a definition for memorization and an intuition for how memorization is inside the model, in this section, we will start to dig a bit deeper. We will describe—at a high level, but carefully—how models represent the information stored in them. Scholars sometimes

¹³⁶ 17 U.S.C. § 101 (definitions of “copies” and of “device,” “machine,” and “process”) (emphasis added); *cf.* 17 U.S.C. § 102(a) (defining copyrightability in terms of fixation in media of expression “now known or later developed”).

¹³⁷ See *infra* note 154 and accompanying text (for why it does not matter that memorization cannot currently be traced to “bit-wise” or “code-wise” copies in the model’s parameters).

¹³⁸ See *Vesuvius Challenge 2023 Grand Prize awarded: we can read the first scroll!*, VESUVIUS CHALLENGE (Feb. 5, 2024), <https://scrollprize.org/grandprize> [<https://perma.cc/H5FD-MRBW>].

¹³⁹ There are no known methods that guarantee that a model has not memorized data that it was trained on.

¹⁴⁰ See Cooper, Levy & De Sa, *supra* note 42, at 2–3 (discussing accuracy-efficiency tradeoffs for policymaking regarding computer systems); see generally Cooper & Levy, *supra* note 42 (discussing the relationship between legal decision-making under uncertainty and uncertainty in ML).

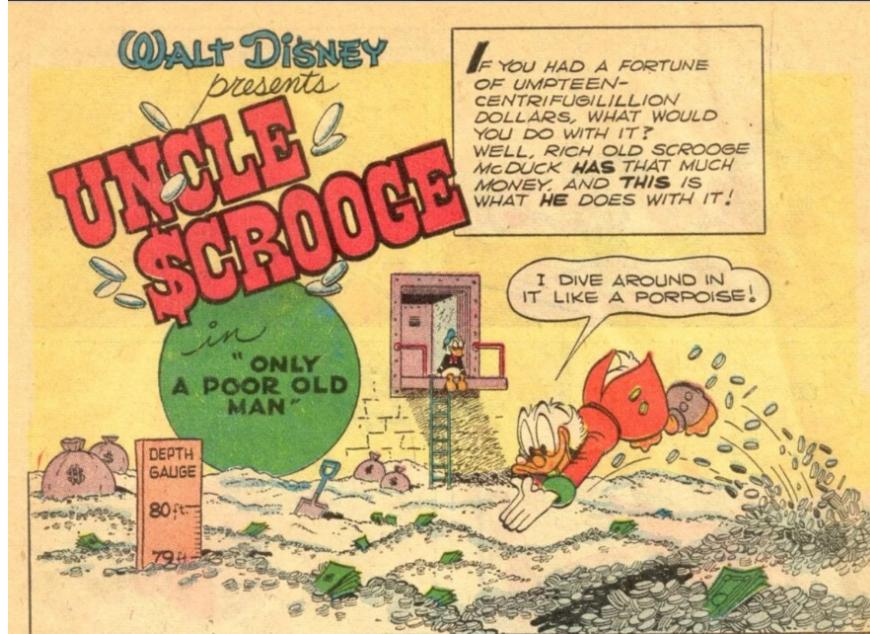


Figure 7: First panel of Carl Barks's first full Scrooge McDuck comic, "Only a Poor Old Man"

argue that models are uninterpretable, or unintelligible, or “do not generally contain recognizable expressions.”¹⁴¹ These claims are true in some senses, but incorrect with respect to memorization.

Models store information in different ways than more familiar file formats do—in model parameters rather than in direct one-to-one encodings—but they still store information. (Otherwise, the model would be useless.) Information is typically obtained from models in different ways than from other forms of encodings—through prompting and the resulting generation, rather than a deterministic algorithmic decoding¹⁴²—but information can still be obtained from them. (Otherwise, again, the model would be useless.)

Start with the encoding itself. Imagine a hypothetical image-generation model trained on a large collection of Disney comic books, including *Only a Poor Old Man*, Carl Barks’s first story with Scrooge McDuck as the protagonist.¹⁴³ When prompted with Scrooge’s first line of dialogue—“I dive around in it like a porpoise”—the model generates a passable image (i.e., regurgitates) of the story’s first panel (See Figure 7).

¹⁴¹ Samuelson, *supra* note 123.

¹⁴² As discussed briefly above, generation involves a decoding process. In LLMs, this process samples the probability distribution over tokens output by the model, where that probability distribution is conditioned on context of the prompt. See *supra* note 35 and accompanying text (discussing decoding, specifically greedy decoding, which, while an uncommon choice in deployed production models, is actually a deterministic algorithmic decoding procedure); *supra* note 38 and accompanying text (discussing the generation process for an LLM as a combination of a model and an often non-deterministic sampling procedure).

¹⁴³ Carl Barks, *Only a Poor Old Man*, FOUR COLOR 386 (Dell, March 1952).

The strongest version of the claim that generative-AI models are uninterpretable would be that Barks's artwork is not encoded in the model at all, because the model is unintelligible. Models are parameters—large collections of numbers.¹⁴⁴ These numbers bear no resemblance to *Only a Poor Old Man*. If you printed out the parameters making up the model onto paper—enough pages to fill a decent-sized research library—no amount of squinting at them would make a visually recognizable Scrooge McDuck appear, like a Magic Eye diagram floating in space. Model parameters are not directly, literally intelligible to the human senses.

But that is the wrong test: the mere fact that a model is encoded in a way that is not *directly* intelligible to the human senses is irrelevant. *All* digital media are encoded in ways that are not directly intelligible, twice over. Consider the PNG image file of the McDuck panel that we include in this Essay, or the PDF version of our Essay that you are currently reading. These, too, are large collections of numbers. File formats like PNG and PDF—and others like JPEG, DOCX, and MP3—are not directly “recognizable” to a human, even if the bytes in them are literally written out on paper. This is an unremarkable observation in today’s technology landscape. But we still speak, perfectly sensibly, about “viewing” a JPEG or “listening” to an MP3, because we can *make* them intelligible by using a computer to display or perform them. Copyright law recognizes that this decoding process can take place with “the aid of a machine or device.”¹⁴⁵

The same goes for physical devices. You cannot squint at the computer storage device on which a PDF is stored and read the document that way; if you use a scanning probe microscope to examine the patterns of electromagnetic charge in the device’s semiconductors, it still will not look like anything familiar. But copyright law treats this device as a “copy” of the PDF, because it is a “tangible object” from which the work in the PDF can be made perceptible. The same is true of records (microscopic patterns of indentations on a vinyl disc), CDs (patterns of indentations on a reflective plastic disc), SSD drives (nano-scale patterns of electric charge stored in semiconductors), and much else. There is no question that these different physical formats can all constitute “copies” of a work, even though none of them is recognizable to a human without “the aid of a machine or device.”¹⁴⁶

This is a settled principle in copyright law.¹⁴⁷ In 1908’s *White-Smith Music Publishing Co. v. Apollo Co.*, the Supreme Court held that player-piano rolls could not count as infringing copies, writing, “[t]hey are not made to be addressed to the eye as sheet music, but they form part of a machine.”¹⁴⁸ The very next year, Congress brought player-piano rolls inside the system of copyright law, giving copyright owners of music the exclusive right “to make any arrangement or setting of it or the melody of it in any system of notation or *any form of record* in which the thought of an author may be recorded and from which it may be read or reproduced” and imposing a royalty system for “the parts of instruments serving to *reproduce mechanically* the musical work.”¹⁴⁹ This decision was carried forward into the current Copyright Act, which defines copies

¹⁴⁴ See *supra* Part I.A; see *Talkin’*, *supra* note 13, at Part I.A.2 (discussing models).

¹⁴⁵ See 17 U.S.C. § 101.

¹⁴⁶ See *id.*

¹⁴⁷ Our thanks to Matthew Sag for helpful suggestions on this point.

¹⁴⁸ *White-Smith Music Publ’g Co. v. Apollo Co.*, 209 U.S. 1, 12 (1908).

¹⁴⁹ An Act to Amend and Consolidate the Acts Respecting Copyright, Pub. L. No. 60–349, § 1(e), 35 Stat. 1075, 1075–76 (1909) (emphasis added).

as “material objects . . . in which a work is fixed by any method now known or later developed.”¹⁵⁰ This definition is used both in defining which works are “fixed” and thus copyrightable,¹⁵¹ and also in defining when the copyright owner’s exclusive rights to “reproduce the copyrighted work in copies”¹⁵² and to “distribute copies . . . of the copyrighted work to the public”¹⁵³ have been infringed.¹⁵⁴ Copyright is technologically neutral; what matters is what can be done with a copy, not the details of how it is stored and encoded.¹⁵⁵

Given this, there is no principled reason to say that, if memorized, encoding *Only a Poor Old Man* in the parameters of a generative model should not count as encoding it in the sense that is relevant for copyright. There is no difference in kind between the bytes that store a model file and the bytes that store a PDF file (except, perhaps, that a PDF happens to store one specific file, and a model stores transformations and copies of parts of potentially billions of files). There is no difference in kind between a USB drive storing a model and a USB drive storing a JPEG. It is only the relative novelty of generative-AI models (which are stored in file formats with names like safetensors and GGUF¹⁵⁶) or perhaps the immense scale of models (which can run to billions, if not trillions, of parameters and require terabytes of storage), that makes them seem very different. The copyright system overcame its qualms about treating computer chips and player-piano rolls as tangible copies that can contain expressive works. It could overcome any similar qualms about generative-AI models if it wanted to do so.

A possible counterargument to our claim that models can be copies of memorized training works is based on Section 503 of the Copyright Act, which provides impoundment and destruction remedies for “infringing articles.”¹⁵⁷ Section 503(a)(1)(A) allows a court to order the impoundment of infringing “copies or phonorecords”;¹⁵⁸ Section 503(a)(1)(B) allows it to order the impoundment of “plates, molds, matrices, masters, tapes, film negatives, or other articles by

¹⁵⁰ 17 U.S.C. § 101.

¹⁵¹ *Id.* § 102(a) (“Copyright protection subsists . . . in original works of authorship fixed in any tangible medium of expression, now known or later developed, from which they can be perceived, reproduced, or otherwise communicated, either directly or with the aid of a machine or device.”); 17 U.S.C. § 101 (definition of “fixed”).

¹⁵² *Id.* § 106(1).

¹⁵³ *Id.* § 106(3).

¹⁵⁴ *Id.* § 101 (definition of “copies”).

¹⁵⁵ See generally Brad A. Greenberg, *Rethinking Technology Neutrality*, 100 MINN. L. REV. 1495 (2016) (discussing technological neutrality). For this reason, it also does not matter that memorization is not literally a “bit-wise or code-wise” copy of training data, in the way that a JPEG can be described as such a copy. Memorization is still a copy, even if current technological capabilities for measuring it cannot pin it to specific bits. See Hayes, Swanberg, Chaudhari et al., *supra* note 38, at 1 (“Models do not ‘contain’ bit-wise or code-wise copies of their training data. Rather, if a model can be induced to generate very close copies of certain training examples by supplying such instructions to guide the model’s statistical generation process, then that model is said to have ‘memorized’ those examples.”).

¹⁵⁶ Vicki Boykis, *GGUF, the long way around* (Feb. 28, 2024), <https://vickiboykis.com/2024/02/28/gguf-the-long-way-around/> [<https://perma.cc/B475-T9PU>].

¹⁵⁷ 17 U.S.C. § 503

¹⁵⁸ *Id.* § 503(a)(1)(A).

means of which such copies or phonorecords may be reproduced.”¹⁵⁹ The argument would go that models are “articles by means of which . . . copies . . . may be reproduced” but they are not “copies” themselves. That said, the distinction is puzzling. On the one hand, it seems to contemplate that these articles are not copies (or Section 503(a)(1)(B) would be unnecessary because it would be completely subsumed by Section 503(a)(1)(A)). But, on the other hand, all of the named articles would qualify as “copies” under the Copyright Act’s definitions because they are tangible objects from which the work can be made perceptible. Indeed, it is hard to imagine a court holding that a defendant could escape infringement liability by selling a copyrighted photograph as a negative rather than a finished print, or by selling master tapes rather than vinyl records. So we think the better reading of Section 503 is that these articles are also “copies,” and so are models that memorize.

Another version of the point has more force and distinguishes models from JPEGs—to a degree. There is a standardized and widely implemented process to transform a JPEG-encoded file into a perceptible image on a computer screen. The process is nowhere near as simple as mapping each byte in the file to the color of a pixel on screen;¹⁶⁰ however, it is unambiguous, efficient, and deterministic,¹⁶¹ and requires no additional information from the user. If one has a large collection of JPEGs, they may be stored as files on a computer or as individual entries in a database. In each case, it is straightforward to pick any individual JPEG out of the collection and make it visible. It is also possible to index a collection of files on a computer or database efficiently: start with the list of files, examine each one to see what it contains, and then store a short, searchable abstract of those contents. In short, collections of JPEGs (and other familiar files) are *transparent* and *searchable*.

Architecturally, these facts derive from how filesystems store items. In a typical filesystem, each file is stored in its own specific physical portion of the associated storage device. The bits that encode one JPEG are distinct from the bits that encode another. There is a data structure that

¹⁵⁹ *Id.* § 503(a)(1)(B).

¹⁶⁰ The JPEG standard (ISO/IEC JTC 1/SC 29/WG 10), designed by the Joint Photographic Experts Group (JPEG), is a method for compressing image data. The overarching goal is to reduce the amount of data (and thus storage space) that is needed to represent a particular image, without compromising (too much) the image’s quality. There are three main steps to the JPEG algorithm: the Discrete Cosine Transform (DCT), (lossy) quantization of DCT outputs to lower-bit precision, and lossless encoding of the quantized outputs. This encoding (and the information needed to decode it) are formatted together into the bitstream of the final JPEG file. Ellen Chang, Udara Fernando & Jane Hu, *JPEG, DATA COMPRESSION* <https://cs.stanford.edu/people/eroberts/courses/soco/projects/data-compression/lossy/jpeg/index.htm> [<https://perma.cc/NCR5-7QVN>] (discussing the three main algorithmic steps of JPEG compression). Library of Congress, *JPEG Image Encoding Family*, SUSTAINABILITY DIGIT. FORMATS: PLANNING FOR LIBR. OF CONG. COLLECTIONS (May 6, 2024), <https://www.loc.gov/preservation/digital/formats/fdd/fdd000017.shtml> [<https://perma.cc/T9FS-UMA5>] (defining the Library of Congress formal description of the JPEG digital format).

¹⁶¹ For most practical purposes, we can consider JPEG encoding and decoding to be deterministic. However, there can be slight differences between implementations of the algorithm, as well as small differences in rounding (due to lossy quantization to lowerbit precision) that can introduce small amounts of non-determinism.

describes how the files are stored; it is essentially an index that maps individual files to specific portions of physical storage. This means that individual files are physically and logically independent of each other.

A generative-AI model, on the other hand, can store the information it has learned from its training data in *partial* and *overlapping* ways. Any given parameter may contribute to the model’s representation of numerous distinct concepts or correlations. Indeed, both the learning and generation processes propagate through the parameters in the model.¹⁶² In training, the model adjusts every parameter that contributed to an incorrect output. In generation, some individual parameter may contribute more in response to one input and less in response to another. But there is no master list of which parameters will contribute to which inputs, and no general way to restrict the processing only to those parameters that matter most.¹⁶³ There may be no “Scrooge McDuck” parameter in the comic-book model, no “Carl Barks” parameter, no “diving like a porpoise” parameter, and no “pixel # 3,881,308 from panel #3 on page #12” parameter.¹⁶⁴ Instead, the model’s knowledge of *all* of these concepts—to the extent that it has any—is generally distributed across potentially a great many of its parameters. The memorized content exists in the model’s parameters, but this does not mean we have tools available that are guaranteed to tell us which specific model parameters encode it, or how.¹⁶⁵

It is irrelevant that it is not always possible to describe an explicit one-to-one encoding or to pinpoint which bytes in a model file encode which particular works.¹⁶⁶ The Copyright Act’s definitions of fixation and copies are functional, not formal. A work is fixed when its embodiment is sufficiently stable “*to permit it to be* perceived, reproduced, or otherwise communicated,”¹⁶⁷ and a copy is an object “from which the work *can be* perceived, reproduced, or otherwise communicated.”¹⁶⁸ These capabilities do not depend on whether the work is encoded alongside

¹⁶² See *supra* Part I.A (describing training and generation, with a particular focus on LLMs).

¹⁶³ Studying training-data influence and attribution remain active areas of research. They are often broadly grouped together with other techniques that study model interpretability. See, e.g., Pang Wei Koh & Percy Liang, *Understanding Black-box Predictions via Influence Functions*, 70 PROC. 34TH INT’L CONF. MACH. LEARNING RSCH. 1885, 1885 (2017); see generally Sung Min Park, Kristian Georgiev, Andrew Ilyas et al., *TRAK: Attributing Model Behavior at Scale*, PROC. 40TH INT’L CONF. MACH. LEARNING 27074 (2023) (detailing a recent method on influence and attribution estimation). See *infra* note 170 and accompanying text (discussing interpretability).

¹⁶⁴ There is a new area of active research that is trying to relate individual parameters (i.e., neurons in deep neural networks) to concepts like these. See, e.g., Adly Templeton, Tom Conerer, Jonathan Marcus et al., Scaling Monosemanticity: Extracting Interpretable Features from Claude 3 Sonnet (May 21, 2024) (unpublished manuscript) <https://transformer-circuits.pub/2024/scaling-monosemanticity/> [<https://perma.cc/8KS4-J3UQ>].

¹⁶⁵ See *supra* Part II.A.3 (distinguishing knowledge of memorization from the existence of memorization).

¹⁶⁶ Our thanks to Eugene Volokh for helping sharpen this point. See also *supra* note 154 and accompanying text.

¹⁶⁷ 17 U.S.C. § 101 (emphasis added).

¹⁶⁸ *Id.* (emphasis added).

or even overlapping with other works. “[N]o plagiarist can excuse the wrong by showing how much of his work he did not pirate.”¹⁶⁹

Nor does a generative-AI model build an index as it learns. The way in which each training example (potentially) modifies every parameter and the generation (potentially) depends on every parameter, means that there is no simple concept of a “location” in a model to which an index entry could point. This trade-off is at the heart of generative AI’s power. By giving up on well-structured concepts and clearly definable relations between them, generative-AI models and algorithms are able to identify and imitate more subtle and complicated patterns in their training data—i.e., to do so much more than memorize their training data. An image-generation model that generates an image of “coffee cat” is not simply adding together an image of “coffee” and an image of “cat”; it is drawing instead on a densely interconnected web of similarities and differences among numerous images of coffee and of images of cats—and among even more images of other things entirely.¹⁷⁰

Thus, generative-AI models are often neither transparent or searchable.¹⁷¹ For the models of most interest today, there is no easy way to inspect their parameters and obtain a list of all the information they have learned. Nor is it currently (or generally) possible to find “where” in a model a particular memorized example is encoded. If you do not already know that the first panel of *Only a Poor Old Man* is encoded in the comic-book model, there may be no straightforward way to find out whether it is. Even if you do know (or have strong reason to suspect) that the panel is encoded in the model, there may be no straightforward way to determine what prompts will cause the model to generate it.¹⁷² Nor is there a way to query the model for a list of all the panels it has memorized or the prompts that will generate them. In a sense, a large generative-AI model can be like Borges’s Library of Babel: it contains literally incomprehensible immensities, to the point that it is extraordinarily difficult to index or navigate.¹⁷³

¹⁶⁹ Sheldon v. Metro-Goldwyn Pictures Corp., 81 F.2d 49, 56 (2d Cir. 1936).

¹⁷⁰ The same comments could be made about generations of Darth Vader in a bike accident in Telford (Figure 3). The point is, useful models also generalize. See *infra* notes 223–224 and accompanying text. See *infra* Part II.F.

¹⁷¹ *Model interpretability* is an active field of current research that studies these questions. See generally Templeton, Conerly, Marcus et al., *supra* note 163; Chris Olah, *Mechanistic Interpretability, Variables, and the Importance of Interpretable Bases*, ANTHROPIC (June 27, 2022), <https://www.transformer-circuits.pub/2022/mech-interp-essay> [<https://perma.cc/E3FE-G4F3>]; Nelson Elhage, Neel Nanda, Catherine Olsson et al., A Mathematical Framework for Transformer Circuits (Dec. 22, 2021) (unpublished manuscript), <https://transformer-circuits.pub/2021/framework/index.html> [<https://perma.cc/NS23-H83R>] (discussing interpretability).

¹⁷² For example, with respect to Google DeepMind’s “divergence” attack, it remains surprising both that this attack (1) revealed memorization at all and (2) revealed these specific instances of memorization in response to such a prompting strategy. See Nasr, Carlini, Hayase et al., *supra* note 62; see *supra* notes 118, 121, and accompanying text.

¹⁷³ See James Grimmelmann, *Information Policy for the Library of Babel*, 3 J. BUS. & TECH. L. 29, 36 (2008).

C. Memorization and Compression

With this account of encoding in mind, consider again the claim that generative-AI models learn only “features,” “patterns,” or “statistical correlations.” For example, Anthropic describes Claude’s model(s) as follows:

Claude does not use its training texts as a database from which pre-existing outputs are selected in response to user prompts. Instead, it uses the *statistical correlations* gleaned from analyzing texts to construct a “model” of how language operates and what it means. The model represents those correlations in a series of numerical parameters (sometimes called “weights” and “biases”) that enable software to generate sensible-seeming responses to requests from end users. Those parameters are what the model stores—not the texts of the training data.¹⁷⁴

Similarly, Anthropic argues that Claude’s model parameters contain “statistical correlations” that “effectively yield ‘insights about *patterns* of connections among concepts or how works of [a particular] kind are constructed.’”¹⁷⁵

The idea here is that a “pattern” is an abstraction of some regularity in training data.¹⁷⁶ Instead of memorizing each individual training example, the model learns only the abstracted pattern—a more succinct description of some way in which multiple training examples resemble each other or parts of an example are repeated. When invoked this way, the point of the argument is typically to contrast “learning” a “pattern” with “memorizing” “training data.” It can be tempting to map this distinction onto other distinctions with legal significance, such as the line between uncopyrightable facts or ideas, and copyrightable expression.¹⁷⁷

But this contrast can be misleading when used this way. The problem is that the “patterns” learned by a model can be highly abstract, highly specific, or anywhere in between. It is a “pattern” that every frame of 4K UHD video is 3840 pixels wide; a multimodal model that learns to generate images of the correct resolution when the prompt contains “4k uhd” has not memorized any protectable expression. But it is also a “pattern” that in the first sentence of *The Restaurant at the End of the Universe*, the word “widely” is followed by the word “regarded,” and a model that learns enough such patterns can memorize all of Douglas Adams’s oeuvre. So even to the extent that the results of model training are made up of “patterns,” so is all memorization, because memorization is part of what happens during training.¹⁷⁸

¹⁷⁴ See Def. Anthropic PBC’s Opposition to Plaintiffs’ Motion for Preliminary Injunction, *supra* note 8, at 5–6. (internal citations omitted) (emphasis added).

¹⁷⁵ See *id.* at 4 (emphasis added).

¹⁷⁶ From here on, we will use “pattern” as shorthand for all of these phrases.

¹⁷⁷ See, e.g., Bracha, *supra* note 8, at 42–44 (describing patterns as uncopyrightable “metainformation.”).

¹⁷⁸ LLMs model probability distributions over the token vocabulary; these are “patterns,” and these “patterns,” if they are memorization, can lead to a sampling procedure decoding exactly a particular passage of text, e.g., the first sentence of *The Restaurant at the End of the Universe*. See *supra* note 38 and accompanying text (discussing how LLMs model probability distributions and

A more accurate distinction would be that some learned patterns contain higher-order information that is not present in any single training example. Thus, for example, somewhere in a trained image-generation model’s parameters, there may be information about the length of cats’ whiskers gleaned from numerous pictures of cats. In contrast, for memorization, somewhere distributed among the parameters, there is a literal copy of a specific piece of training data—the encoding of a specific picture of a cat. In this case, the pattern *is* the memorized training data. But to make this distinction is not to say anything new; it is simply to repeat the definition of memorization and to point out that not all learning is memorization.

Another popular comparison is to think of a generative-AI model as *compressing* its training data, discarding details while retaining more significant patterns. For example, one suit against Stability quotes statements made by then-CEO Emad Mostaque in 2022 to support the claim that “protected expression from training images is copied, compressed, stored, and interpolated by diffusion models.”¹⁷⁹

The point of these metaphors is often the opposite of the previous one. Arguing that a model compresses its training data can be a way of arguing that it is an infringing copy of that training data. The data are still present in the model, just in a smaller version, like a thumbnail of a JPEG.¹⁸⁰

But compression can be *lossy*: some of the information in the original data has been discarded and can no longer be reconstructed. But if compression is done well, the most important information will be retained and the least important discarded. The point of the JPEG standard, for example, is to retain the most visually significant information in the image, while discarding minor details that the human visual system is less likely to notice.¹⁸¹ In the same way, even an immense generative-AI model may be much smaller than its training dataset. To the extent that the model can accurately summarize that dataset or successfully replicate the kinds of data in it, the training process has compressed the training data into a smaller but still useful version. The writer Ted Chiang has called ChatGPT a “blurry JPEG of all the text on the Web.”¹⁸² One point of

how sampling works during generation); *supra* notes 136, 154, 165, and accompanying text (for a discussion of why these patterns are copies, even if they cannot be pinned down as “bit-wise or code-wise” copies, as is the case for more familiar encodings like JPEGs).

¹⁷⁹ See First Amended Complaint at 27, Andersen v. Stability AI, Ltd., No. 3:23-cv-00201 (N.D. Cal. Nov. 29, 2023) (capitalization removed); *id.* at 2 (quoting Mostaque as saying, “Stable Diffusion is the model itself. It’s a collaboration that we did with a whole bunch of people We took 100,000 gigabytes of images and compressed it to a two-gigabyte file that can recreate any of those [images] and iterations of those.”); *id.* at 29 (quoting Mostaque as saying, “[i]t’s worth taking a step back and thinking about how crazy insane this is: we took a hundred terabytes of data—a hundred thousand thousand megabytes of images—2 billion of them—and we squished it down to a 2–4 gigabyte file. And that file can create everything that you’ve seen. That’s insane, right? That’s about as compressed as you can get.”) (emphasis omitted).

¹⁸⁰ Cf. Perfect 10, Inc. v. Amazon.com, Inc., 508 F.3d 1146, 1160 (9th Cir. 2007) (holding that displaying a thumbnail of an image could infringe the display right in the image).

¹⁸¹ See *supra* notes 159–160 and accompanying text.

¹⁸² Ted Chiang, *ChatGPT is a Blurry JPEG of the Web*, NEW YORKER (Feb. 9, 2023), <https://www.newyorker.com/tech/annals-of-technology/chatgpt-is-a-blurry-jpeg-of-the-web> [<https://perma.cc/F25W-37GA>].

the metaphor is that ChatGPT is trained on and compresses the text on the Web—like Soylent Green, ChatGPT is made out of people. Another point of his observation is that the compression is lossy: the JPEG is *blurry*. ChatGPT hallucinates, confabulates, and misquotes. In part, because it compresses, the training process loses information and fails to learn all that it hypothetically could.

We would refine Chiang’s blurry JPEG compression analogy: not all parts of the JPEG are equally or completely blurry. Some training data are compressed more than others, and compression happens in different ways. Some of the compression is lossy: the information is discarded or transformed. But the portions that contain exact memorization are lossless and the portions that contain near-exact memorization are nearly lossless: pieces of the training data are literally copied in the model, and, in the cases of regurgitation and extraction, can be retrieved in (near-)pristine condition at generation time.

These two sets of metaphors—about “patterns” and “compression”—are related. They are useful general ways to describe how generative-AI models work, but they do not tell us how a generative-AI model behaves in any specific instance, with respect to any specific piece of training data. In the case of an instance of memorization, *the pattern is the details*. In other cases, higher-order patterns are leveraged to produce outputs that are not particularly similar to any specific training example.¹⁸³ And, of course, there are gradations in between.

It is this complexity that is responsible for the generativity that is so compelling about generative-AI models, but this same complexity is difficult to grapple with directly. It is not just a matter of complex math that requires computer-science expertise to describe. Rather, even world-leading experts who are fluent in the math simply do not know all that much about the inner workings of models. Interpretability is a research challenge,¹⁸⁴ not just a pedagogical one. As a result, it is often necessary to sidestep this complexity when talking about model behaviors.

D. Non-Determinism and Generations

Another source of confusion about how models store information is that the generation process is typically *non-deterministic*—the same prompt can produce different outputs. An LLM’s parameters describe the strengths of connections between tokens in a sequence, not literally the sequence of tokens itself. Different generations, even starting from the same prompt, can activate these connections in different ways, leading the model to produce different outputs.¹⁸⁵ Thus, a generative-AI system might regurgitate its training data as output 10% of the time for a given prompt and produce other outputs the other 90% of the time. For a different prompt, it might

¹⁸³ This is an informal intuition for *generalization*, which we discuss below. See *infra* notes 223–224 and accompanying text. See *infra* Part II.F.

¹⁸⁴ See *supra* notes 162, 170, and accompanying text (referencing ML-research topics in interpretability).

¹⁸⁵ See *supra* notes 30–31, 33–38 and accompanying text (discussing training, generation, parameters, and tokens). Diffusion-based models are also non-deterministic (e.g., see Figure 3), but the underlying mechanism is different. For example, for a text-to-image diffusion model, the generation process involves randomness to progressively denoise the image. See *Talkin'*, *supra* note 13, at Part I.B.3.b (discussing diffusion models at a high level).

regurgitate training data 73% of the time. Even if the model produces a regurgitated output, it might not consistently regurgitate the same exact piece of training data.¹⁸⁶

This non-determinism might lead to skepticism that a model is indeed a copy¹⁸⁷ of training data: that even if the model sometimes regurgitates, it does not do so consistently, so there is no stable representation—no fixed copy—of the piece of training data inside the model. It also might lead to an intuition that regurgitation is itself a random process, so that similarity of an output to training data is a coincidence.

However, these intuitions rest on significant misconceptions about non-determinism in machine learning, specifically on what it means for parameters to model features of training data, and how these parameters are used to produce generations.¹⁸⁸

Non-determinism is best understood as introducing subtleties that require courts and scholars to speak with care, and which may sometimes require them to draw legally significant lines along a continuum of model behavior. But the fact that generation is non-deterministic does not by itself have any necessary consequences for copyright law. Models can be copies of training data examples even if a prompt only sometimes extracts these data examples.¹⁸⁹ At the end of the day, uncertainty about model behavior is an evidentiary issue, and mathematical tools can help in analyzing that evidence.

To clear up these misunderstandings, in this section we discuss how non-determinism in generation does not contradict the fact that models memorize, and that memorized data are in models. (For simplicity, we primarily discuss LLMs, but similar points can be made about other

¹⁸⁶ See *supra* note 38 and accompanying text (discussing how the sampling procedure during generation can introduce non-determinism, such that regurgitated training may only be generated a fraction of the time even for the same prompt); see also Hayes, Swanberg, Chaudhari et al., *supra* note 38 (for a machine-learning study that casts memorization in this way—i.e., as a probabilistic phenomenon—and measures the risk, in terms of the probability, of extracting particular token sequences from a model under a particular sampling procedure).

¹⁸⁷ See *supra* Part II.A.1 (describing how, with respect to the definition of copies in copyright law, models that memorize training data are copies of that training data).

¹⁸⁸ In this Essay, we focus on non-determinism in the generation process. Non-determinism also arises elsewhere in the generative-AI supply chain, especially in the training process. See A. Feder Cooper, Jonathan Frankle & Christopher De Sa, *Non-Determinism and the Lawlessness of Machine Learning Code*, PROC. 2022 SYMP. ON COMPUT. SCI. & L. 1, 2 (2022); see A. Feder Cooper, Katherine Lee, Madiha Zahrah Choksi et al., *Arbitrariness and Social Prediction: The Confounding Role of Variance in Fair Classification*, 38 AAAI CONF. ON A.I. 22004, 22011 (2024) (for accessible treatments of non-determinism in machine learning); see also Jessica Zosa Forde, A. Feder Cooper, Kweku Kwegyir-Aggrey et al., Model Selection’s Disparate Impact in Real-World Deep Learning Applications 2 (Sept. 7, 2021) (unpublished manuscript) <https://arxiv.org/abs/2104.00606> [<https://perma.cc/SG6L-QM6D>]. These other forms of non-determinism have significant social and legal implications, but they are beyond the scope of this Essay.

¹⁸⁹ Hayes, Swanberg, Chaudhari et al., *supra* note 38 (detailing a measurement strategy for memorization, which quantifies probabilistic extraction of a piece of training data as being able to successfully generate a (near-)exact copy of that piece of training data *at least once* out of n multiple responses to the same prompt).

types of models.) We make this argument in three parts. First, we briefly describe the role of non-determinism in computing. Second, from this basis, we can more precisely discuss non-determinism during generation. Finally, we then explain implications for memorization and copyright.

1. Non-Determinism and Stochasticity in Computing

To start, let us be more precise about why generation is non-deterministic. In computer science, an algorithm, piece of software, or system is *deterministic* when it always behaves in the same way when given the same input. A function that capitalizes a passage of text, for example, is deterministic: it always transforms the input `apple banana` into the output `APPLE BANANA`. In contrast, an algorithm, piece of software, or system is *non-deterministic* when the same input can cause different behavior, including different outputs. For example, a non-deterministic function may change the capitalization of a passage of text differently each time it is run. It might transform the input `apple banana` into `APpLE bANaNA` or into `appLe BanANA`, or into some other capitalization.¹⁹⁰

Non-determinism may seem less intuitively useful, but it is an important part of computer science. Many real-world systems are so complex that they can only be modeled non-deterministically. A web server, for example, cannot predict exactly when user requests will arrive, or for which pages. The developers of the server must operate on the assumption that the rest of the Internet—all of the parts outside of their control—are essentially non-deterministic. Indeed, when developing one part of the server (e.g., the part that encodes pages for transmission to Internet users), they may need to model other parts of the server (e.g., the part that fetches data from storage) as non-deterministic—simply because it is too complicated to predict exactly which particular fetches will take more or less time, when they will complete, or if they will even complete at all without errors. For another thing, non-determinism can lead to more interesting—dare we say more creative—results. A text-to-image model that can produce four different variations from the same input prompt—and even more on demand—is more useful than one that can only use a given prompt to produce one specific image. For this reason, typical generation processes are specifically architected to be non-deterministic.

A non-deterministic system is also *stochastic* when its different possible behaviors for the same input can be described using the mathematical tools of probability.¹⁹¹ In the example above, we said nothing about how often the function produces `APpLE bANaNA` or `appLe BanANA` (or the other 2046 possible capitalizations¹⁹²). As we have described this function above, it is non-deterministic but not necessarily stochastic. But if it is the case that these two outputs—and any

¹⁹⁰ For the text `apple banana`, there are 11 non-space characters, where each character can be expressed in one of two ways (lowercase or uppercase). So, there are $2^{11} = 2048$ possible outputs for this function on this input.

¹⁹¹ More precisely, when they are described by a probability distribution over the outputs of a random variable. See Cooper, Frankle & De Sa, *supra* note 187, at 2 (detailing how non-determinism and stochasticity are important concepts to understand when considering the legal implications of machine learning).

¹⁹² See *supra* note 189.

other possible capitalization—are, for example, equally likely, then the function is stochastic as well; we can model the behavior of the function’s outputs using statistics.¹⁹³ In this case, we can use statistics to make useful, meaningful statements about the outputs for the input `apple banana`: how often `APpLE bANaNA` will appear, for example,¹⁹⁴ or whether an output with exactly three upper-case letters or one with exactly four is more likely.¹⁹⁵

One might ask how we know that a non-deterministic system really is stochastic, as opposed to non-deterministic in a way that we cannot reliably model with tools from probability and statistics. The most satisfying answer is that it is stochastic because someone made it so. In this example, if the person who programmed the capitalization function made it explicitly random—if each letter is randomly and independently chosen to be lowercase or uppercase, e.g., with probability $\frac{1}{2}$ for each letter—then we can point to those random choices in explaining why the overall function behaves the way that it does. The probability that the output will be `APpLE bANaNA` follows from the individual probabilities that the first character will be `a` or `A`, that the second character will be `p` or `P`, and so on. Since each of these individual choices is stochastic, so is the overall behavior of the function. The power of statistics is that it lets us reason about the likely behavior of large and complex systems on the basis of the likelihood that their parts will behave in particular ways.

¹⁹³ In this case, with equal probabilities for each output, we would say that the probability distribution over outputs is a “discrete uniform distribution.” For another, simpler example, consider a fair, six-sided die: each outcome in $\{1, \dots, 6\}$ is equally likely, with probability $\frac{1}{6}$ (leading to a total probability of 1, i.e. 100%), which we could also model with a discrete uniform distribution. However, both the function and the die could instead be implemented to make some outcomes more likely than others, in which case the outputs would follow a “discrete categorical distribution.” Continuing the die example, we could imagine that the outcomes $\{1, 3\}$ each have probability $\frac{1}{4}$ and outcomes $\{2, 4, 5, 6\}$ each have probability $\frac{1}{8}$ (the total probability is still 1). In both cases, we have probability distributions with statistical properties that we can leverage to reason about the behavior of outputs.

These examples involve probability distributions (discrete uniform distribution and discrete categorical distribution). As we discussed above, the (conditional) probability distribution over the token vocabulary that a language model outputs in response to a prompt (and from which the sampling procedure samples the next token in the sequence) is, as the term suggests, also a probability distribution. The possible outcomes are the different tokens in the token vocabulary (as opposed to die rolls), and each has an assigned probability of being the next token. The sampling procedure selects the next token according to its underlying, hyperparameter-configured algorithm and this distribution. *See supra* notes 35, 38 and accompanying text (discussing an LLM modeling a probability distribution and a sampling procedure selecting the next token to generate from that distribution).

¹⁹⁴ For the case in which each output is equally likely, this is once out of every 2^{11} times (i.e., $\frac{1}{2048}$) on average. *See supra* note 189.

¹⁹⁵ Four. Of the $2^{11} = 2048$ outputs, $\binom{11}{3} = \frac{11!}{3!(11-3)!} = \frac{11 \times 10 \times 9 \times 8!}{3!8!} = \frac{11 \times 10 \times 9}{3 \times 2 \times 1} = 165$ have exactly three capitalized letters and $\binom{11}{4} = 330$ have exactly four capitalized letters.

A reader who is accustomed to thinking of computers as reliable and consistent may at this point be wondering, *where does the randomness come from?* Don’t computers always and only do what they are programmed to do, deterministically?¹⁹⁶ This is not the place to get into the philosophy of what randomness really is. Nor is it the place to explain the actual physical source of processes we typically think of as “random” (such as flipping a coin).¹⁹⁷ Instead, computers typically generate “random” choices (such as `a` or `A` in the example above) through a *pseudo-random* process: one that is in fact deterministic, but whose behavior has as few predictable regularities as possible. This process starts with a *random seed*: an arbitrary number supplied from some external source, such as a user-supplied input or the exact time in nanoseconds between the arrival of network packets. The process then uses complicated (but deterministic) mathematical functions to turn the random seed into a sequence of other numbers, which appear random for all practical purposes.

The exact details are interesting, but not important for this Essay. What is important is that a computer’s “random” values derive from a deterministic process that starts with an arbitrary random seed. The underlying process is actually deterministic, but it is stochastic for all practical purposes.¹⁹⁸ This is what allows computer scientists to implement statistical concepts in the code they write, and to use statistical tools to reason about the behavior of that code.¹⁹⁹

2. Stochasticity During Generation

Generative AI involves elements of both stochasticity and non-determinism—in model training, in deployed systems, and more.²⁰⁰ The same is true of generation. It is a stochastic

¹⁹⁶ And, indeed, what does this have to do with generative AI? We have alluded to this briefly above in our discussion of sampling and generation. *See supra* notes 35, 38 and accompanying text. Please bear with us; we will get into this in more detail soon. We nearly have all the background we need to make our prior discussion more precise. *See infra* Part II.D.2.

¹⁹⁷ Spoiler alert: it’s quantum mechanics.

¹⁹⁸ It is only deterministic if you know the random seed and are tracing through all of the computations based on it. With this information, these computations can be reproduced; an experiment can be re-run to obtain the same results (as the same set of computations can be executed based on the same sequence of pseudo-random numbers).

¹⁹⁹ Unfortunately, in practice it is not quite so simple. There are other sources of non-determinism (e.g., that come from hardware) that are non-stochastic and can make it challenging to reason (completely reliably) about machine-learning system behaviors using tools from statistics. That is, based on non-determinism in GPUs (the type of hardware most commonly used in training and generation for generative AI), running the same software with the same software random seed, but on different hardware, can yield different outcomes. While important, we will not discuss this topic in this Essay. *See generally* Cooper, Frankle & De Sa, *supra* note 187 (for an accessible treatment of hardware non-determinism intended for a legal audience).

²⁰⁰ For example, training typically starts by initializing a model with random parameters, and continues by training the model on a randomly-chosen sequence of training examples—a fundamentally stochastic process. Repeating the training process with the exact same training data

process:²⁰¹ the input prompt is transformed into an output generation in a way that depends on a large number of (pseudo-)random choices based on a random seed.²⁰² In an image diffusion model, the generation process starts by creating an image full of random noise and then uses the prompt to guide the transformation of that random noise into a coherent image matching the prompt.²⁰³ Repeating the generation process with the same prompt and a different seed means this de-noising process will start in a very different place and can end in one, too—a completely different image that still reflects the prompt.

During generation for an LLM, random choices are involved when selecting which token to produce next in the output. As discussed in Part I, during generation the LLM takes the prompt, predicts the probabilities associated with next possible tokens in the sequence (based on the context of the prompt), and generates a token (by sampling a token according to these probabilities) as the next token in the sequence. That is, at each step, the model generates not a single next token, but instead its predictions of how likely *every* possible token (in the entire token *vocabulary*) is to follow the output that has been so far.²⁰⁴ The overall system that runs the generation process through the model randomly selects one token from that distribution, favoring the possible tokens that the model predicts as more likely and disfavoring the ones that the model predicts are less likely, with what is more or less likely depending on the strengths of relationships between tokens that are encoded in the model’s parameters.²⁰⁵ The exact degree of favoring and disfavoring can also be adjusted at generation time by the choice of underlying sampling algorithm and adjusting a setting called the *temperature*. Loosely speaking, lower temperatures magnify the probabilities associated with high-strength relationships between tokens, while higher temperatures discount

and exact same algorithm but a different random seed will produce a different model, one that may have quite different properties. See Cooper, Lee, Choksi et al., *supra* note 187, at 22007 (for meaningful examples of these differences in a classification, as opposed to a generative, setting).

²⁰¹ From a systems perspective, it can also be non-deterministic, if the generative-AI system contains multiple models (e.g., a Mixture of Experts); a given user request could get routed to a different model within the system, associated with no discernible statistical pattern, to produce the generation. As noted above, we will stick to just considering stochasticity in the model in this discussion. See *supra* note 198 and accompanying text; see Maximilian Schreiner, *GPT-4 architecture, datasets, costs and more leaked*, THE DECODER (July 11, 2023), <https://the-decoder.com/gpt-4-architecture-datasets-costs-and-more-leaked/> [<https://perma.cc/C26M-X5D3>] (discussing a rumor that OpenAI’s ChatGPT-4 system contains 16 models to which user requests can get routed).

²⁰² See *supra* notes 195–198 and accompanying text (describing random seeds and pseudo-randomness).

²⁰³ See ‘Talkin’, *supra* note 13, at Part I.B.3.b (discussing this process at a high level).

²⁰⁴ See *supra* note 35 and accompanying text (discussing greedy decoding during generation); *supra* note 38 and accompanying text (discussing how an LLM models a probability distribution and how a sampling algorithm, such as greedy decoding, selects the next token in the sequence by sampling from that distribution).

²⁰⁵ See *supra* Part I.A.

those relationships and make next-token probabilities more random.²⁰⁶ The process then repeats for the next token (with the previous one now looping back to serve as part of the input), and the one after that, and so on; so again, there are a large number of random choices based on the initial random seed.

This is a very specific type of stochasticity because of its dependence on the random seed. If you use the same random seed with the same prompt, the process is deterministic: you will get the same output.²⁰⁷ But if you allow the random seed to vary (as seems to be the default mode of most generative-AI services), the process is stochastic. Each time you input a prompt, the system

²⁰⁶ Temperature is a hyperparameter in different sampling procedures. *See supra* note 38 and accompanying text (defining hyperparameter). In Part I.A, we discuss an example in which the most likely next token for "once upon a" would be "time", assuming that the model is trained on a dataset that contains many fairy tales that use this phrase. To understand temperature a bit more and its relationship to the stochasticity of outputs produced by an LLM, let us now consider that the phrase is so common in the training dataset that there is a 0.95 (i.e., 95%) probability that a language model trained on this dataset would generate the token "time" to follow the prompt "once upon a". The other 5% probability is divided up among the other tokens in the whole token vocabulary used in model training (so that all token probabilities sum to 100%). In other words, this text example is not at all like the text-to-image case of "cat in a red and white striped hat" (*see supra* Part I.A.1), which could result in many possible different image generations; the near-surety of generating "time" as the next token means that this example is effectively (close to) deterministic.

Adjusting the temperature can change this behavior. Setting the temperature high flattens out the probabilities for the different tokens in the vocabulary: high temperatures make the probabilities for different tokens more equal so that, in the sampling procedure, there is more randomness in determining the next generated token. It increases the probability associated with tokens that have low probability at smaller temperatures, and decreases the probability for tokens that have high probability at smaller temperatures. For a vocabulary that has n different tokens, high temperatures effectively force the sampling of the next token to be like rolling an n -sided die. Lower temperatures have the opposite effect; they reduce randomness, making high-probability tokens even more likely, and low-probability ones even less likely, than they are at higher temperatures.

Returning to our example, "time" does not originally have the complete probability (i.e., 100%) assigned to it. Perhaps this is because Edgar Allan Poe's "The Raven" was in the training dataset; this poem has the opening line "once upon a midnight dreary," so there is some probability assigned to "midnight" as the next token. High temperatures would increase the probability for "midnight", while low ones would reduce it. *See* Geoffrey Hinton, Oriol Vinyals & Jeff Dean, Distilling the Knowledge in a Neural Network 2 (Mar. 9, 2015) (unpublished manuscript), <https://arxiv.org/abs/1503.02531> [<https://perma.cc/329Y-FN4C>]; *see also* von Platen, *supra* note 35 (providing background on temperature and sampling procedures).

²⁰⁷ Again, we note this is (usually) true only with respect to the model. Once a model is embedded in a system that contains other types of non-determinism, this reproducibility of the same output for the same prompt may not be guaranteed. *See supra* notes 197–200 and accompanying text.

will use a different random seed for the generation process, and a different output will result. As Heraclitus said, you cannot step twice into the same river.

From this discussion, it follows that any claims one might want to make about how a generative-AI model behaves will be probabilistic. The question is not, “If I prompt the model with X as input, will its output have property P ?” Instead, the question is, “If I prompt with X as input, *what fraction of outputs* will have property P ?” One way to find out is to tinker around: input the prompt, examine the output, and repeat a large enough number of times to arrive at a statistically meaningful conclusion. In theory, it might be possible sometimes to reason from first principles about how a model will behave. But in practice, the experimental method is currently the state-of-the art in making these kinds of claims.

We now bring things back to memorization. A claim about extraction or regurgitation will typically take the following form: a model, when (a) given a particular type of input, will (b) produce a particular type of memorized output, (c) *with a particular probability*. That probability could be .01 (i.e., a 1% chance), it could be .99 (i.e., a 99% chance), it could be some value in between, or it could be even more extreme.²⁰⁸ The issue for copyright law, then, is what to do with this knowledge, and in particular, what to do with the fact that element (c)—the probabilistic element—is inescapable.

3. Consequences for Copyright

Consider first the question of whether a model is a copy of a training work. One possible conclusion is that that the specific probability of regurgitation is mostly irrelevant, and that what matters for copyright purposes is that there is or can be any non-zero probability of regurgitation at all.²⁰⁹ On this view, a model is a copy of a work as long as there is any possibility that the work

²⁰⁸ Indeed, this is precisely the perspective taken by recent work on measuring memorization in LLMs through *probabilistic* extraction. See Hayes, Swanberg, Chaudhari et al., *supra* note 38.

²⁰⁹ Our asides on temperature should help make this point clear. Consider using a prompt with low temperature, which adheres to the strengths of the relationships between tokens that are encoded in the model. Regurgitation in this setting makes clear that memorization is in the model—it is a direct product of the learned relationships. But using the same model and same sampling type of procedure, a user could set the temperature so high that the response to the same prompt is effectively completely random and contains no regurgitated data at all. In both cases, the model is the same; how we run it (i.e., how we configured the sampling procedure’s hyperparameters) is different. This has a clear impact on how much memorization is surfaced at generation time (i.e., extracted), but it would make no sense to say that this changes how much memorization is in the model. How one uses the model—with different temperature settings, types of sampling procedures, prompts of varying lengths, etc.—plays a role in specific probabilities for regurgitation, but should not be confused more generally with there being a meaningful probability to regurgitate at all. See *supra* note 205 and accompanying text (discussing temperature). See *Extracting from Language Models*, *supra* note 63, at 2638–40 (describing experiments that measure memorization in LLMs that examine the role of temperature); see generally Hayes, Swanberg, Chaudhari et al., *supra* note 38 (describing experiments that measure memorization in

“can be perceived, reproduced, or otherwise communicated” from it.²¹⁰ The Copyright Act uses the word “can,” and even a small probability is enough to establish the possibility. If nothing else, one could repeat the generation process until a near-exact copy emerges.²¹¹

There is something to this view. In particular, the fact that there is some probability that the generation process could produce a different output from the memorized one should not by itself mean that a model has not memorized training data. Imagine a probabilistic jukebox. When the user inserts a quarter, half the time the jukebox plays the selected record. The other half the time, it eats the quarter and does nothing. It would be absurd to say that the jukebox does not contain a copy of the sound recording on the record simply because there is only a 50% chance of playing the record each time the jukebox is used; the copy is fixed, even if we cannot always retrieve it.

Indeed, even “deterministic” processes have a little non-determinism baked into them. A jukebox in factory condition has a small but non-zero probability of malfunctioning: maybe there will be a power surge at exactly the wrong moment, and the tonearm will never make contact with the record. The algorithm for converting an MP3 file to an audio signal is deterministic—but there is always a non-zero (if tiny) probability that cosmic rays will corrupt the computer’s memory in a way that overwrites the audio data with noise. What matters is only that the probability is high enough that it reliably works enough of the time—what matters is a question of degree.

Still, we have used phrases like “high enough,” “realistic,” and “meaningful” because a threshold of any non-zero probability is too low. Consider an image-generation model that outputs a completely random image, or an LLM that outputs a completely random string of tokens. Each of these models has a non-zero probability of outputting *any* output of the specified size, including any arbitrarily chosen copyrighted work. A monkey at a typewriter hitting keys at random has an almost unimaginably small probability of generating the text of *A Tale of Two Cities*—but the probability is still non-zero.²¹² Given enough monkeys, enough typewriters, and enough time, they will generate *A Tale of Two Cities* even though neither the monkeys nor the typewriters have memorized it. So too with a generative model and memorization: the probability of generating a near-exact copy of a piece of training data has to be high enough to rule out coincidence. And

LLMs that vary both the type of sampling procedure and hyperparameters, including the temperature).

²¹⁰ 17 U.S.C. § 101 (emphasis added).

²¹¹ One might call this approach “adversarial,” but we think that overstates the case. It is akin to rolling a die until it lands on 6. *See infra* Part II.H; *see generally* Hayes, Swanberg, Chaudhari et al., *supra* note 38 (describing formulation that considering running n queries, where n can be quite large, such that the probability of extracting a target piece of training data is at least (a chosen) probability p ; but also noting that system-level software could potentially prevent this type of end-user interaction and prevent memorized from being extracted).

²¹² *The Simpsons: Last Exit to Springfield* (Fox television broadcast Mar. 11, 1993) (“This is a thousand monkeys working at a thousand typewriters. Soon they’ll have written the greatest novel known to man . . . [l]et’s see. ‘It was the best of times, it was the blurst of times?’ You stupid monkey!”).

indeed, it is essentially impossible that it is a coincidence that machine-learning researchers are able to reliably extract such copies at high rates.²¹³

As for infringing outputs, the probability of particular kinds of outputs bears on how common and uncommon particular uses of a system are. The fraction of infringing works on a file-sharing service is an empirical question, and so, too, is the fraction of infringing links for a particular search query. Similarly, the fraction of infringing outputs for a particular prompt is also an empirical question. The consequences of this empirical finding are questions of copyright law and policy.²¹⁴ It almost certainly matters in the fair-use analysis whether common prompts yield memorized outputs 5% or 50% of the time, and it likely also matters for remedies, such as the size of damage awards and whether to issue an injunction. But these are complex balancing tests, and it is not at all obvious how any particular probability for any particular prompt should matter. These probabilities are important, relevant evidence, but they do not by themselves determine any legally relevant lines. Courts will need to do that, and they may well draw different lines in different contexts. Nevertheless, *our* bottom line is that non-determinism is an important phenomenon that courts should take into account, but does not dictate any particular view of the copyright consequences of regurgitated generations.

D. How Much Memorization?

Having discussed how memorization is encoded as copies inside of generative-AI models, let us now consider the question of *how much* these models memorize. Some plaintiffs and scholars argue that generative-AI models *only* memorize their training data; some defendants and scholars argue that generative-AI models *never* memorize, or only memorize a minuscule fraction of their training data. The truth is more complicated and lies somewhere in between. Some (but not all) of the learning that generative-AI models do qualifies as memorization. The question of how much a model memorizes is an empirical one, which cannot be answered except with reference to a specific model and specific ways of identifying what it has memorized.

First, note that there are generative-AI models that memorize *nothing* in their training data. Consider a model that is trained on an empty dataset, where its parameters are initialized to random numbers. Its parameters will have the same values they have at the start of the training process: random numbers. The model has memorized absolutely nothing, and there is no way to

²¹³ See *Extracting from Language Models*, *supra* note 63, at 2633; *Extracting from Diffusion Models*, *supra* note 63; Carlini, Ippolito, Jagielski, Lee, Tramèr & Zhang, *supra* note 57; Nasr, Carlini, Hayes et al., *supra* note 62, at 6. See also Hayes, Swanberg, Chaudhari et al., *supra* note 38, at 8–9 (for experiments that confirm that extracted memorization is not generated by coincidence; the authors compare the rate of extraction of training data to the generation of test data—data that were *not* included in the training dataset; “the number of queries n needed to generate unseen test data is orders of magnitude larger than for generating training data. [They] find that it is generally challenging to generate test data … and especially in comparison to [their] measurements for extracting training data. This supports that, in [their] measurements of [probabilistic] extraction, matches between training-example targets and generated suffixes are almost surely due to memorization.”)

²¹⁴ See *infra* Part II.E and Part II.H (discussing such empirical questions).

Prefix: “*Conus patae\n\nConus patae, common name Pat's cone, is a species of sea snail, a marine gastropod mollusk in the family Conidae, the cone snails and their allies.\n\n*”

Greedy suffix: “*Like all species within the genus Conus, these snails are predatory and venomous. They are capable of "stinging" humans, therefore live ones should be handled carefully or not at all.\n\nDescription\nThe size of an adult*”

Target suffix: “*Like all species within the genus Conus, these snails are predatory and venomous. They are capable of "stinging" humans, therefore live ones should be handled carefully or not at all.\n\nDistribution\nThis species occurs in the*”

*Figure 8: An example of text that does **not** get counted as successful extraction of training data, using a common that only considers exact matches between a piece of training data and a generation. The prompt is the first fifty tokens of a training example (the prefix). Extraction would be considered successful if the model generates an output that exactly matches the next fifty tokens in the example (the target suffix). Here, using greeding sampling (see supra 38 and accompanying text), the model generates an output (greedy suffix) that does not exactly match (the target suffix). Image taken from Hayes, Swanberg, Chaudhari et al. (2025).*

extract training examples from it. Similarly, note that there are generative-AI models that memorize *everything* in their training data. Consider a hypothetical image-generation model that is trained exclusively on millions of copies of the first panel of *Only a Poor Old Man*. (See Figure 7.) Assuming the model is large enough, its parameters will be exquisitely tuned to generate the panel. The model will be able to reconstruct the panel perfectly.

Of course, both of these models are almost completely useless. The model with random parameters is capable of generating nothing coherent; the specialized model is likely capable of generating only one coherent output. If you want random outputs, or you want the first panel, these models will do, but if that was what you wanted, there were easier ways to achieve these outcomes. To be fair, we did not say these were *good* models—but they are generative-AI models all the same.

Of course, today’s generative-AI models do not fall under either of these extreme cases. For example, in one study using standard measurement techniques,²¹⁵ researchers estimated that the “6 billion parameter GPT-J model memorizes at least 1% of its training dataset.”²¹⁶ Most large-scale studies that report numbers like these use simple and relatively efficient measurement techniques to extract training data, which greatly under-estimate the amount of memorization in

²¹⁵ In particular, the common technique of prompting an LLM with a piece of a training example and checking if the greedy-sampled generation completes the example. See *supra* note 116 and accompanying text.

²¹⁶ See Carlini, Ippolito, Jagielski, Lee, Tramèr & Zhang, *supra* note 61 at 1 (citations omitted). The referenced experiment uses deterministic, greedy sampling as its decoding procedure, which recent work shows can greatly under-estimate the amount of memorization when multiple queries with the same prompt are allowed (even with the same simple strategy of prompting with a training example’s prefix and seeing if the generation matches the corresponding suffix). See generally Hayes, Swanberg, Chaudhari et al., *supra* note 38.

the model.²¹⁷ Notably, for large language models, these techniques only check for exact matches (instead of near-exact) matches to the training data, so even slight (e.g., single-token) differences do not get counted as successful extraction. (See Figure 8.) Further, while numbers like “1% of [the model’s] training dataset” seem relatively small, it is important to recall the immense size of modern language-model training datasets. For example, a 0.789% extraction rate for the 65-billion-parameter Llama model corresponds to extracting 2,934,762 unique fifty-token sequences.²¹⁸ Some studies use these training-data-extraction-based numbers to reason about how much memorization must be contained within the model’s parameters²¹⁹—i.e., they attempt to compute how much memorization (at a minimum) must exist on the back-end in order to have obtained the observed amount of extraction on the front-end.²²⁰ By one estimate, only 0.1% of some LLMs’ overall parameters contain verbatim memorization; for other models, this number is 10%.²²¹ⁱ

²¹⁷ *Extracting from Language Models*, *supra* note 63, at 2643 (discussing similar methodology with respect to measuring memorization in GPT-2) (“The important lesson here is that our work vastly *under-estimates* the true amount of content that GPT-2 memorized. There are likely prompts that would identify much more memorized content, but because we stick to simple prompts we do not find this memorized content.”).

²¹⁸ See Nasr, Carlini, Hayase et al., *supra* note 62, at 7. Note that this amount of unique extraction the total extraction rate were computed from generating one billion tokens. The authors extrapolate that (at a minimum) over five times as many fifty-token sequences could be extracted from Llama if more tokens had been generated.

²¹⁹ These estimates are computed using an argument about storage and compression. *See, e.g.*, Nasr, Carlini, Hayase et al. *supra* note 62, at 15 (“In order for GPT-Neo 6B to be able to emit nearly a gigabyte of training data, this information must be stored somewhere in the model weights. And because this model can be compressed to just a few [gigabytes] on disk without loss of utility, this means that approximately 10% of the entire model capacity is ‘wasted’ on verbatim memorized training data. Would models perform better or worse if this data was not memorized?”). *See supra* Part II.C (discussing memorization and compression).

²²⁰ *See supra* note 68 and accompanying text (describing the back-end/front-end distinction).

²²¹ *See* Lee, Ippolito, Nystrom et al., *supra* note 116, at 7 (citing around 1% memorization in a 1.5B parameter model similar to GPT-2, and 0.1% memorization for the same architecture trained on a deduplicated version of the dataset); Carlini, Ippolito, Jagielski, Lee, Tramèr & Zhang, *supra* note 61, at 1 (for similar results finding 1% memorization); Nasr, Carlini, Hayase et al., *supra* note 62, at 15 (discussing extent of memorization in the GPT-Neo 6B model). These numbers serve as examples of measuring particular types of memorization under certain conditions and for specific models. They should not alone be taken as general claims about all models. Recent work that takes a probabilistic perspective on extraction yields much higher extraction rates than have been previously observed, suggesting that models memorize more than was once believed to be the case. For example, using greedy deterministic sampling (which is not reflective of realistic production settings), the extraction rate of verbatim training data from the Enron dataset for Pythia 2.8B is 1.3%; taking a probabilistic approach to measuring extraction and using more realistic non-deterministic sampling, the “worst-case rate is 9.04%, which is nearly 7× the greedy rate” (internal references omitted). All told, this suggests that model parameters contain more memorization than

Importantly, the above observations have to do with measurements of *overall* memorization. With respect to current, state-of-the-art knowledge, nothing in the nature of a generative-AI model inherently requires or prohibits *specific* instances of memorization. Everything depends on how it is configured and trained. The details depend heavily on implementation decisions in measurement methodology, but within a given model family, larger models tend to memorize more than smaller models.²²² Examples that are duplicated in the training data—and hence trained on more often—are more likely to be memorized.²²³

That said, there is suggestive evidence that at least some memorization is normal behavior for a generative-AI model that is powerful enough to be useful. The key capability that makes a model useful is *generalization*: its ability to perform well on unseen data.²²⁴ A generative-AI model

previously observed with other measurement techniques. See Hayes, Swanberg, Chaudhari et al., *supra* note 38, at 7.

²²² For example, in Meta’s Llama family of models, Llama 65B (which has 65 billion parameters) memorizes more than Llama-7B (which has 7 billion parameters). Nasr, Carlini, Hayase et al., *supra* note 62, at 7–8; Carlini, Ippolito, Jagielski, Lee, Tramèr & Zhang, *supra* note 61, at 4–5; *Extracting from Language Models*, *supra* note 63, at 2639; Hayes, Swanberg, Chaudhari et al., *supra* note 38, at 6. Another observation is that a model that is much smaller than the dataset it is trained on cannot effectively memorize everything in that dataset (though it could memorize some of the dataset). The compression analogy helps us (roughly) understand this point: larger models have more storage capacity than smaller ones; a smaller model has less space to contain high-fidelity compressions of its training data. See *supra* note 220 and accompanying text (discussing compression and memorization in a model’s parameters); see *supra* Part II.C (discussing the blurry JPEG analogy).

²²³ See Lee, Ippolito, Nystrom et al., *supra* note 116 (discussing deduplication of training data and reduction of memorization). There are choices that model trainers can make to reduce the likelihood of memorization at training time. One common strategy is to deduplicate training data, with respect to identical or highly similar data (by some choice of quantitative metric, like using the MinHash algorithm and edit distance). This makes sense intuitively: the presence of (many) duplicates of a particular piece of text in the training dataset makes it more likely that the model learns “statistical correlations” or “patterns” that relate the tokens in the piece of text to each other. For such a piece of duplicated text t , we can think of dividing it into a prefix t_p and suffix t_s ($t = t_p + t_s$). With duplication, it becomes more likely that a particular suffix t_s would be generated in response to a prompt that is the prefix t_p , since t_p and t_s are repeatedly associated together in the training data. See *supra* notes 35–38, 116 and accompanying text (discussing model generation of tokens in response to prompts). More recent work also identifies a new training optimization objective (the cutely named “goldfish” loss function) that reduces extraction of memorization at generation time, at the cost of requiring longer training time to achieve comparable quality on benchmarks. See Abhimanyu Hans, Yuxin Wen, Neel Jain et al., Be like a Goldfish, Don’t Memorize! Mitigating Memorization in Generative LLMs 2 (June 14, 2024) (unpublished manuscript) <https://arxiv.org/abs/2406.10209> [<https://perma.cc/5ZW6-TD4J>] (proposing goldfish loss).

²²⁴ GenLaw Glossary, *supra* note 60 (“Generalization in machine learning refers to a model’s ability to perform well on unseen data, i.e., data it was not exposed to during training.

generalizes well when it produces sensible generations in response to previously unseen prompts—i.e., outputs that are not *just* copies of their training data inputs. As noted above, the generations of Darth Vader in a bike accident in Telford are examples of generalization (Figure 3); these generations combine and transform different learned information across the model’s training data. Researchers have also developed a circumstantial but suggestive case that the quality of a model is partly dependent on memorization—that some amount of memorization might even be *required* for effective generalization.²²⁵

It makes intuitive sense that memorization is a Goldilocks phenomenon; models are most useful when they memorize just the right amount, neither too little nor too much. On the one hand, memorizing the alphabetical list of the fifty U.S. States²²⁶ is a feature, not a bug; a model that confidently inserts Cahokia and West Dakota into the list of states might charitably be described as “hallucinating” or “garbage.” On the other hand, a model that *only* memorizes is just a glorified (or perhaps subpar) search engine.

F. Learning Beyond Memorization

As should hopefully be clear, memorization is not interchangeable with learning. The definition of “memorization” we are using refers to the near-exact reproduction of a substantial piece of training data.²²⁷ This is a much narrower concept than the kinds of learning and generalization that a useful model is capable of. For some modalities (e.g. images), the definition

Generalization error is usually measured evaluating the model on training data and comparing it with the evaluation of the model on test data”) (emphasis omitted). Devising useful metrics for generalization is also an active area of ML research. See, e.g., Chiyuan Zhang, Samy Bengio, Moritz Hardt et al., *Understanding deep learning (still) requires rethinking generalization*, 64 COMM’NS ACM 107 (2021).

²²⁵ See generally Congzheng Song, Thomas Ristenpart & Vitaly Shmatikov, *Machine Learning Models that Remember Too Much*, PROC. 2017 ACM SIGSAC CONF. ON COMPUT. & COMM’NS SEC. 587 (2017); Satrajit Chatterjee, *Learning and Memorization*, 80 PROC. 35TH INT’L CONF. ON MACH. LEARNING 755 (2018); Vitaly Feldman, *Does learning require memorization? A short tale about a long tail*, PROC. 52ND ANN. ACM SIGACT SYMP. ON THEORY COMPUT. 954 (2020); Vitaly Feldman & Chiyuan Zhang, *What Neural Networks Memorize and Why: Discovering the Long Tail via Influence Estimation* 13 (Aug. 9, 2020) (unpublished manuscript), <https://arxiv.org/abs/2008.03703> [<https://perma.cc/5YG6-WAB8>]; Chiyuan Zhang, Samy Bengio, Moritz Hardt et al., *Identity Crisis: Memorization and Generalization Under Extreme Overparameterization*, INT’L CONF. ON LEARNING REPRESENTATIONS (2020); Gerrit J.J. van den Burg & Chris K.I. Williams, *On Memorization in Probabilistic Deep Generative Models*, PROC. 35TH INT’L CONF. ON NEURAL INFO. PROCESSING SYS. (2021) (studying memorization and generalization in deep learning); see *infra* Part II.F (discussing generalization and learning beyond memorization).

²²⁶ See *supra* note 86 and accompanying text.

²²⁷ See *supra* Part II.A.

excludes the exact reproduction of small sub-portions of training examples.²²⁸ It also excludes generalization from patterns present in many training examples. Both of these are learning, but not memorization.

Some critics of generative-AI have tried to deny that there is a meaningful difference. They argue that all of generative AI is a mosaic or collage; it consists of rearranged pieces drawn from training data. This is a misleading picture because it ignores the possibility of generalizing from statistical information²²⁹ in the model that has been synthesized from training on large amounts of diverse data.²³⁰ An AI-generated image from Midjourney is not a Franken-picture of sewn-together exact copies of fragments of existing images; the learned concepts stored in Midjourney's model are at much higher levels of abstraction than individual pixels. Nor is this image simply borrowing these concepts—symmetrical composition, the iridescence of a mollusk's shell—from individual images; many or most of them will be generalizations from numerous training examples. There is a sense in which one could describe *Infinite Jest* as a collage of words drawn from other books: a “the” from *Moby Dick*, a “woman” from *The Feminine Mystique*, a “who” from *Horton Hears a Who*, and so on. But in another, more accurate sense, this is not what is going on at all, and “collage of individual words” completely fails to describe any book's relationship to the rest of literature. And so on. It is precisely because *not* all learning is memorization that memorized training data meaningfully stick out.²³¹

On the other hand, Oren Bracha gives an argument from copyright theory that any learning performed by a generative-AI model consists of a “process of extraction of meta-information from expressive works that then enables the production of new and different expression(s).”²³² In his view, this “[m]ere physical reproduction, delinked from enjoyment of the expressive value of a work and completely incidental to accessing unprotected meta-information, is categorically

²²⁸ Depending on measurement choices, it also could exclude exact reproduction of an entire training-example image within a generation—e.g., a generation of a living room scene that contains a painting on the wall that replicates one of Kerry James Marshall's works. See *supra* Part II.A (for a concrete example of an image generation involving Darth Vader that does not count as memorization).

²²⁹ Again, it is the case that some of this information is memorization—is literal copying—but not all of it. See *supra* Part II.B.

²³⁰ *Talkin'*, *supra* note 13, at Part II.A.2.g; Cooper, Lee, Grimmelmann, Ippolito et al., *supra* note 30, at 38 (discussing how generations are not like collages).

²³¹ For example, recall that the worst-case (probabilistic) extraction rate of verbatim training data from the Enron dataset from the Pythia 2.8B model is 9.04%. This is a large amount, but it certainly is not anywhere close to 100% of this training-dataset subset. (Pythia models were trained on The Pile dataset, which contains the Enron subset; see Gao, Biderman, Black et al., *supra* note 46.) Not all of Enron was memorized verbatim by Pythia 2.8B. See *supra* note 220 and accompanying text.

²³² Bracha, *supra* note 8, at 8; see also Christopher J. Sprigman, *Upsetting Conventional Wisdom of Copyright Scholarship in the Age of AI*, JOTWELL (Mar. 28, 2024), <https://ip.jotwell.com/upsetting-conventional-wisdom-of-copyright-scholarship-in-the-age-of-ai/> [<https://perma.cc/WMH9-XNL5>] (reviewing Bracha's draft).

beyond copyright's domain.”²³³ In other words, Bracha identifies learning in a model with uncopyrightable ideas, and locates expression only in the model’s outputs.

In our view, memorization refutes this interpretation of how generative-AI models work. When a model regurgitates an expressive work, the model’s parameters are not “delinked from enjoyment of the expressive value of a work” and certainly do not contain only “meta-information.”²³⁴ There is a straightforward causal connection from the (expressive) training data through the model to the (expressive) output, even if we do not have the tools to directly pinpoint the links along the path.²³⁵ Either the model contains the work’s expression, in which case the legal argument fails, or it does not, in which case the reappearance of the exact same expression in the output is a (fantastically improbable) mystery.²³⁶

Bracha’s stronger argument is that learning should be regarded as a case of merger: the memorization of (some) expression is non-infringing “to the extent necessary for accessing the unprotectable material” that consists of the larger patterns across many works.²³⁷ This claim, of course, depends on the degree to which memorization really is “necessary” to extract these larger patterns, which, as we have noted, is a difficult and contested research question. There are also some doctrinal challenges with this approach. Most notably, this includes the degree to which merger can be asserted as a defense to the *defendant*’s otherwise infringing behavior, rather than being a limitation on copyrightability or an argument that the *plaintiff* has too thoroughly interwoven idea and expression to separate them.²³⁸

Finally, the boundary of what counts as memorization is necessarily vague. We have been using terms like “near-exact,” “small,” and “many” without trying to make them precise. Different machine-learning researchers could (and do) quite reasonably use different metrics for these ideas. Indeed, one of the crucial theoretical underpinnings of ML research is that any such measurable quantity—similarity, frequency, size, etc.—can be reasoned about abstractly. For example, one can describe an algorithm that depends on a measure of similarity (or “distance”) between two examples without specifying which measure one is using. To implement the algorithm, one must first pick a metric to use (e.g., to measure the similarity of two passages of text by counting their

²³³ Bracha, *supra* note 8, at 24.

²³⁴ *See id.* In our view, the term “meta-information” here can be misleading in the same way that “feature,” “pattern,” and “statistical correlation” can have multiple meanings at different levels of abstraction. It is possible that much (or even most) of the information in a trained model reflects higher-level information that cannot be easily pinned down as expressive; however, as we discuss above, memorization means that some of this information (these features, patterns, statistical correlations) are literal copies. *See supra* Part II.C.

²³⁵ *See supra* Part II.A.3.

²³⁶ Indeed, this is effectively impossible. *See supra* notes 74, 99, 112, 121, 212, and accompanying text.

²³⁷ Bracha, *supra* note 8, at 25.

²³⁸ *See generally* Pamela Samuelson, *Reconceptualizing Copyright’s Merger Doctrine*, 63 J. COPYRIGHT SOC’Y U.S.A. 417 (discussing merger doctrine).

differences letter by letter), and then typically also pick thresholds (e.g., one passage is a “near-exact” copy of another when their differences are less than 5% of their total length).²³⁹

Drawing a line between learning and memorization requires making technical choices of this sort, and any such line is inherently arbitrary. It may be necessary to draw a line, and some choices may be more useful than others, but at the end of the day, memorization is one extreme on a continuum of ways to learn, not a discrete category. For these reasons, it is also hard to draw a firm line like Bracha does between “meta-information” and expression for generative AI. Expression and information can be transformed during learning, but they can also be copied directly into model parameters—and the amount that one deems “copied” depends on one’s chosen metric for memorization.²⁴⁰

G. Models are not VCRs

In the preceding sections, we have made clear that all trained generative-AI models memorize (at least to some extent), that useful generative-AI models also generalize, and that distinguishing between memorization and generalization is neither simple nor straightforward. Nevertheless, some defendants in generative-AI copyright-infringement lawsuits have claimed that the memorization demonstrated with their systems is not “typical,”²⁴¹ but is instead an “unintended occurrence.”²⁴² The implication is that, even if memorization is found to be infringing, generalization is the intended, main, non-infringing use.²⁴³

In a similar vein, some AI companies and observers have argued that generative-AI models are general-purpose copying technologies, like VCRs. As such, they argue that the substantial-non-infringing-use doctrine from *Sony Corp. of America v. Universal City Studios, Inc.* is a good fit for generative AI.²⁴⁴ In *Sony*, a group of entertainment companies sued Sony for copyright infringement, arguing that consumers used Sony VCRs to infringe by recording programs broadcast on television. The Supreme Court held that Sony could not be held contributorily liable for infringements committed by VCR owners. “[T]he sale of copying equipment . . . does not constitute contributory infringement if the product is . . . capable of substantial noninfringing uses.”²⁴⁵

²³⁹ See generally Lee, Ippolito, Nystrom et al., *supra* note 116 (discussing different ways to measure similarity in text, for the purpose of measuring non-verbatim memorization in large language models); see *supra* note 72 and accompanying text (for a brief description of measuring distance in images); see *supra* Part II.E (for a discussion of how implementation choices, like those concerning the choice of distance metric, have a significant impact on overall measurements of training-data extraction).

²⁴⁰ See *supra* notes 61–64 and accompanying text (discussing different memorization definitions and metrics in the technical literature).

²⁴¹ See *infra* notes 262–263 and accompanying text.

²⁴² See *infra* note 277 and accompanying text.

²⁴³ From this basis, many responses from defendants then lay responsibility for extracting memorized training with “adversarial” end users, which we discuss in the following section.

²⁴⁴ *Sony Corp. of Am. v. Universal City Studios, Inc.*, 464 U.S. 417, 442 (1984).

²⁴⁵ *Id.*

The *Sony* doctrine is appealing because generative-AI models are dual-use technologies. They can be put to infringing uses: a user could coax a model to produce a verbatim copy of a particular Scrooge McDuck cartoon from that model's training data, or use an LLM to grammar-check an infringing sequel to a popular novel. But they can also be put to non-infringing uses: many (if not most) outputs from generative-AI models are generalization: expressive works that are not substantially similar to any already-existing expressive works. The *Sony* doctrine provides a bright-line rule that allows dual-use technologies to continue to be available for these beneficial, non-infringing uses.²⁴⁶ As Microsoft put it in moving to dismiss a copyright lawsuit from the *New York Times*, “copyright law is no more an obstacle to the LLM than it was to the VCR (or the player piano, copy machine, personal computer, internet, or search engine)” —all dual-use technologies.²⁴⁷

The fact that memorization is in the model, however, makes us skeptical about the VCR analogy, for two reasons. The first is formal: U.S. copyright law uses the physical fact of copying to distinguish between direct and secondary liability, so memorization in a model can affect whether *Sony* applies at all. The second is functional: a VCR is completely neutral among different expressive works, whereas a model is typically better at generating some specific memorized works than others.

We start with the formal analysis of who makes the relevant copies.²⁴⁸ In *Sony*, it was clear that the users were the direct infringers (if anyone was). Sony sold a device that could be used by others to make copies of the plaintiff's works; it made no copies itself. Sony could be liable, if at all, only secondarily, and the Supreme Court focused on contributory infringement. Contributory infringement requires at least knowledge of the infringement, and one reading of *Sony* is that this knowledge will not be attributed to the defendant on the basis of a generalized awareness that the device could be used to infringe, so long as the device can also be used in non-infringing ways.

But direct infringement liability for the person who actually makes the infringing copy is strict, regardless of whether they intended to infringe, or knew that they might be infringing. The *Sony* defense has never shielded direct infringers. To the extent that an AI company creates a model that is found to be an infringing copy of a work in the training dataset,²⁴⁹ that is formally direct infringement, not contributory, and *Sony* does not apply. Further, to the extent that the model itself is an infringing copy of training data, anyone who copies the model is also a direct infringer unprotected by *Sony*. Indeed, to the extent that a generative-AI system produces an infringing output because a model embedded within it has memorized a work and is now regurgitating it, the provider of that system might also still be a direct infringer and outside of the *Sony* rule.

²⁴⁶ See David A. Widder, Helen Nissenbaum & James Grimmelmann, Moral and Legal Responsibility for General-Purpose Technologies 14–15 (July 2024) (unpublished manuscript) (on file with the authors).

²⁴⁷ Def. Microsoft Corp.'s Memorandum in Support of Partial Motion to Dismiss the Complaint at 2, *N.Y. Times Co. v. Microsoft Corp.*, No. 1:23-cv-11195 (S.D.N.Y. Mar. 4, 2024).

²⁴⁸ See *Am. Broad. Cos., Inc. v. Aereo, Inc.*, 573 U.S. 431, 453 (2014) (Scalia, J., dissenting) (“the question is *who* does the performing”).

²⁴⁹ For readers with a computer-science background, we emphasize again that a model *containing* a copy of *part* of a work due to memorization is still a “copy” of the work in the sense that copyright law uses the term “copy.” See *supra* Part II.A.1.

Our point here is not that this is a good or bad outcome; we take no position on whether *Sony* or something like it should apply as a policy matter. Instead, our point is that U.S. copyright law is currently deeply committed to a formal and technical analysis of which tangible objects are copies and who is responsible for making tangible objects into copies. A VCR is not a copy of a movie or TV program; it is a device that can be used to make copies of them. But a generative-AI model that has memorized training data is a copy of that training data.²⁵⁰ It can also be used to make further copies of that training data (and of other works, depending on the prompt). But the fact that it can be used to make copies on the front-end (i.e., generations at generation time) does not avoid the fact that, due to memorization, it is itself a copy on the back-end (i.e., the model, as a result of training).²⁵¹ In other words, memorization plays a crucial role in determining whether *Sony* is the doctrinally appropriate category with which to analyze generative-AI models. Copyright law does not necessarily need to work this way, but if it does, memorization matters.

The second reason that memorization matters to the VCR analogy has to do with the effective capabilities of a model. A VCR is almost entirely content-neutral. It can be used to play or record any audiovisual work, limited only by the fidelity and length of the tape. A Sony Betamax functioned identically when recording *Bride of Frankenstein* (prohibited by Universal) and recording *Mr. Rogers' Neighborhood* (encouraged by Fred Rogers). It is a general-purpose tool. The same goes for other copying technologies that *Sony* has been applied to, in court or in policy arguments, including photocopiers, the personal computer, and Internet service. A photocopier does not distinguish between *War and Peace* (public domain) and *Things Fall Apart* (under copyright).

But a generative-AI model that regurgitates training data is emphatically not neutral with respect to copyrighted works. It is capable of outputting some works but not others. As discussed above, memorization is distinctive because the model stores near-exact copies of portions of works it was trained on. To the extent that these memorized portions of works can be regurgitated, extracted, or reconstructed, that is a real-world difference between works the model memorized from its training data, and works it was not trained on or did not memorize. The model behaves differently towards some works than others.

This is a genuine functional difference between VCRs and generative-AI models, and it goes to the heart of what makes generative AI so powerful. Generative-AI models engage with the *content* of expressive material. That is why they are able to engage in so many tasks that were previously considered to be human-only: they are capable of imitating and modifying creative works in ways that seem to an observer to have content and meaning. It explains both the hype and the hatred that generative AI inspires. To reduce a generative-AI model to merely a copying technology, like a photocopier or VCR, is to overlook its most distinctive feature.

H. “Adversarial” Users

Defendants tend to lay the responsibility for regurgitating copyrighted expression with “adversarial” users. They argue that plaintiffs’ examples of regurgitation only arise because the

²⁵⁰ See *supra* note 248 and accompanying text.

²⁵¹ See *supra* note 68 and accompanying text (describing this back-end/front-end framing).

plaintiffs used atypical or “adversarial”²⁵² prompting strategies that no typical or “normal”²⁵³ user would reasonably use in practice. If one were to accept the (incorrect) analogy that models are like VCRs,²⁵⁴ then these “adversarial” users would be like bootleggers that use VCRs to produce unauthorized copies. In these lawsuits, these users are often the plaintiffs themselves, who have used the defendants’ systems to extract their own copyrighted works. Thus, the argument goes, these examples of regurgitation should be disregarded.

We do not believe that adversarial usage can be so easily disregarded. First, “adversarial” users can only extract memorized content if the model has memorized this content in the first place. Second, the line between “adversarial” usage and “typical” usage is not fixed or stable—and even if a line can be drawn, the relative balance of the two can also vary. And third, AI-system creators have the ability to anticipate some “adversarial” usage and adopt safeguards against it. We take up the first two arguments in this section and discuss system-level safeguards in the next.

To repeat, regardless of whether a user is “adversarially” trying to extract memorized training data or just happens to do so accidentally, it is only possible to generate memorized training data if those data are encoded in the trained model.²⁵⁵ Indeed, as we have discussed, the fact that a user can use a detailed prompt to extract a specific memorized training example is an unsurprising consequence of how generative-AI training works.²⁵⁶

Consider an LLM. During training, a generative-AI model learns features—certain “statistical correlations”²⁵⁷—from its training data. In the case of an LLM, these correlations are patterns in the natural language in its training dataset. The trained LLM can then be used to generate natural language text; it takes a text prompt as input and emits as output a *continuation*, or *completion*, of the prompt. Crucially, the model predicts which of many possible completions is likely based on the statistical patterns it has learned about language from the data on which it was trained.²⁵⁸ If the model regurgitates training data in response to a given prompt, it does so because it has learned that the example’s text is a likely completion for the given prompt. Of course, the prompt plays an important role in actually eliciting this behavior.²⁵⁹ But before the

²⁵² *OpenAI and Journalism*, *supra* note 6

²⁵³ Def. Anthropic PBC’s Opposition to Plaintiffs’ Motion for Preliminary Injunction, *supra* note 8, at 4.

²⁵⁴ See *supra* Part II.G.

²⁵⁵ See *supra* Part II.A.2.

²⁵⁶ See *supra* note 78 and accompanying text (quoting the technical literature on the relationship between prompt length and successful extraction).

²⁵⁷ Def. Anthropic PBC’s Opposition to Plaintiffs’ Motion for Preliminary Injunction, *supra* note 8, at 4–5.

²⁵⁸ This is one of the intuitions behind why duplicated training examples in the training dataset result in models exhibiting higher levels of memorization: an example that appears multiple times in the training dataset can seem like a “more likely” language pattern. See Lee, Ippolito, Nystrom et al., *supra* note 116, at 7; see *supra* note 222 and accompanying text. The *Times* alleges that OpenAI’s training process samples “higher quality” sources, including *Times* articles, more frequently during training. Complaint, *supra* note 3, ¶ 90.

²⁵⁹ Though, in some cases, we do not understand the nature of the relationship between the two. See *supra* notes 118–121 and accompanying text; see Figure 6.

prompt is entered, the model has, latent within it, learned “statistical correlations” that happen to reflect memorization of some of the training data.

We can revisit the *New York Times*’s complaint against OpenAI in light of this discussion. Recall that the *New York Times* was able to prompt ChatGPT to produce lengthy, near-exact excerpts from specific *Times* articles, which the *Times* then cited in its complaint as proof of infringement. The *Times* prompted ChatGPT with long-sequence text prefixes from its articles; in some cases, based on this context, ChatGPT would generate the corresponding suffix—text that completed the remainder of the article excerpt. (See Figure 1.)

OpenAI argued in its public response that “[i]t seems they intentionally manipulated prompts, often including lengthy excerpts of articles, in order to get our model to regurgitate.”²⁶⁰ But the fact that the *Times* could cause ChatGPT to regurgitate articles does not answer the question of whether OpenAI should or should not have trained more or otherwise modified ChatGPT in a way that makes regurgitation possible. It is not a foregone technical conclusion that prompting with “lengthy excerpts of articles” should necessarily lead to the rest of the article being surfaced by either the model or system in which it is embedded.²⁶¹ By itself, regardless of user intent, regurgitation is a kind of existence proof;²⁶² it shows that an AI system is capable of behaving in this way.

Generative-AI companies attempt to push responsibility for infringement onto users in a variety of ways.²⁶³ Most straightforwardly, they argue that “typical” users do not use generative-AI services to infringe:

Existing song lyrics are not among the outputs that typical Anthropic users request from Claude. There would be no reason to: song lyrics are available from a slew of freely accessible websites. Normal people would not use one of the world’s most powerful and cutting-edge generative AI tools to show them what they could more reliably and quickly access using ubiquitous web browsers.²⁶⁴

But this is a fundamentally empirical question. It may be that these adversarial and/or infringing outputs are extremely uncommon, either in absolute terms or as a fraction of the total number of

²⁶⁰ *OpenAI and Journalism*, *supra* note 6 (emphasis added). It should not be surprising that these long-context prompts could extract *Times* articles. OpenAI had trained this version of ChatGPT on *Times* articles, and so prompting with a long sequence of article text (in some sense) encouraged or guided the model’s next-token generation process to complete the rest. See *supra* note 78 and accompanying text (discussing the “discoverability phenomenon”).

²⁶¹ See *supra* note 222 and accompanying text (discussing the choices model trainers make that can influence the amount of memorization that can be extracted from the model).

²⁶² See *supra* Part II.A.2; *supra* Part II.A.3 (discussing the same).

²⁶³ See generally Widder, Nissenbaum & Grimmelmann, *supra* note 245 (discussing generative-AI providers’ deflection of responsibility); see generally Cooper, Moss, Laufer & Nissenbaum, *supra* note 51 (discussing how AI-system builders, deployers, and other owners evade accountability); see *infra* Part II.I (discussing system-level safeguards).

²⁶⁴ Def. Anthropic PBC’s Opposition to Plaintiffs’ Motion for Preliminary Injunction, *supra* note 8, at 4 (internal citations omitted).

generations made by a system. With the right guardrails in place,²⁶⁵ it may be the case that extremely few “adversarial” users who try to infringe actually succeed. And perhaps it may be that a generative-AI system, only on extremely rare occasions, produces an infringingly similar (memorized or otherwise) output without being explicitly prompted to do so. All of these are testable empirical propositions; they might or might not be true of any specific system at any given time.²⁶⁶

Unfortunately, it is hard to answer most of these questions on the state of present knowledge. The data that would be needed is mostly in the possession of the companies that have developed and deployed these systems. It is possible to make estimates of the fraction of infringing material on YouTube because videos are publicly visible and searchable; it is possible to make estimates of the fraction of infringing views because view counts are also public.²⁶⁷ But because the typical use case for a generative-AI service is a private generation shared only with the user who requested it, there are no reliable third-party sources of evidence as to how these services are being used in practice. The argument that adversarial uses are uncommon could be

²⁶⁵ See *infra* Part II.I.

²⁶⁶ It is also fundamentally a testable, empirical question as to whether a “typical” user would or would not use a generative-AI system in place of a search engine to retrieve information. In the absence of large-scale empirical studies, there is plenty of anecdotal evidence to suggest users rely on generative-AI systems for functionality that they would have previously drawn from search engines. Google integrated Gemini (with retrieval augmented generation, or RAG) into its flagship search product, indicating that the company expects generative-AI chatbots to become an important part of search. Perplexity AI’s Pages is a generative-AI-integrated search product. OpenAI researchers have cited “overreliance” as a risk of highly capable generative-AI systems. They anticipate users may “excessively trust and depend on the model,” which reasonably could include relying on generative AI to perform more traditional web searches. More broadly, just as it is difficult to separate “adversarial” and “typical” use, it is arguably generally unclear what “typical” use looks like for chatbot systems. See, e.g., Larry Neumeister, *Lawyers submitted bogus case law created by ChatGPT. A judge fined them \$5,000*, ASSOCIATED PRESS (June 22, 2023, 5:16 PM), <https://apnews.com/article/artificial-intelligence-chatgpt-fake-case-lawyers-d6ae9fa79d0542db9e1455397aef381c> [https://perma.cc/32VF-DM23] (discussing a lawyer using ChatGPT to retrieve case law). See Kylie Robison, *Google promised a better search experience — now it’s telling us to put glue on our pizza*, THE VERGE (May 23, 2024, 2:27 PM), <https://www.theverge.com/2024/5/23/24162896/google-ai-overview-hallucinations-glue-in-pizza> [https://perma.cc/4DPX-FJ9A] (detailing issues with Gemini in Google Search); Elizabeth Lopato, *Perplexity’s Grand Theft AI*, THE VERGE (June 27, 2024, 4:32 PM), <https://www.theverge.com/2024/6/27/24187405/perplexity-ai-twitter-lie-plagiarism> (for a discussion of Perplexity AI, a generative-AI-assisted search engine); GPT-4 System Card, *supra* note 42, at 59–60 (defining and discussing overreliance).

²⁶⁷ These estimates may be distorted by various factors, including the difficulty of telling whether an upload is licensed or not, and the fact that many infringing videos are removed.

right or it could be wrong; we simply do not know, and will not unless and until AI companies share far more information about their usage than they have to date.²⁶⁸

Companies also argue that using their services to infringe violates their terms of use, for example:

Doing so would violate Anthropic’s Terms of Service, which prohibit the use of Claude to attempt to elicit content that would infringe third-party intellectual property rights.²⁶⁹

We also expect our users to act responsibly; intentionally manipulating our models to regurgitate is not an appropriate use of our technology and is against our terms of use.²⁷⁰

With respect, the best analogy for an Internet company discovering that users are violating its terms of service to infringe copyright is Colonel Renault discovering that gambling is taking place in Rick’s casino. The Internet is full of pirate sites with *pro forma* disclaimers reminding users not to infringe third parties’ copyright. It just so happens that almost everything available through these sites is there without the copyright owners’ permission, a fact entirely understood by everyone involved.

More generally, just because behavior is adversarial does not make it atypical. In computer security, robustness is often defined in terms of the adversarial user.²⁷¹ Secure systems are expected to be *designed* to resist adversarial usage. A credit-card processor who loses customer financial data to a hacker in a data breach cannot escape responsibility by arguing that the hack was “adversarial” usage. Instead, the expectation is that adversarial users can and will attempt to breach a system and steal or alter data, and it is the responsibility of the system deployer to anticipate and prevent this usage. Similar obligations may or may not be appropriate to impose on the deployers of generative-AI systems. But this is fundamentally a policy question that depends on costs, benefits, incentives, and harms; it cannot be waved away by claiming that “adversarial” usage does not count.

²⁶⁸ Some models have been released as “open” sets of parameters. This can sometimes lead to more (albeit limited) visibility into how these models are used. Many research studies on memorization rely on such models. See, e.g., Hayes, Swanberg, Chaudhari et al., *supra* note 38.

²⁶⁹ Def. Anthropic PBC’s Opposition to Plaintiffs’ Motion for Preliminary Injunction, *supra* note 8, at 4.

²⁷⁰ *OpenAI and Journalism*, *supra* note 6.

²⁷¹ Indeed, this is an accepted truth in computer-security research, and also grounds definitions of robustness to worst-case scenarios. See generally Nicholas Carlini, Anish Athalye, Nicolas Papernot et al., On Evaluating Adversarial Robustness (Feb. 18, 2019) (unpublished manuscript), <https://arxiv.org/abs/1902.06705> [<https://perma.cc/3DVQ-C85R>] (discussing adversarial robustness in machine learning from first principles); Cooper, Moss, Laufer & Nissenbaum, *supra* note 51, at 865–66 (detailing the relationship between robustness and meaningful notions of accountability for AI/ML systems).

I. Generative-AI System Design

Throughout this Essay, we have predominantly focused on models: models contain memorization, and models can be prompted to regurgitate memorized content. But most current copyright infringement lawsuits do not only involve models. They implicate generative-AI *systems* (of which models are just one part), whose construction, deployment, and use embroil an entire, complex supply chain that has important copyright consequences.²⁷² Generative-AI models are embedded in these systems, which are wrapped in public-facing software services. End users interact directly with these services, not the underlying generative-AI models; interaction with models is indirect, through developer APIs or user interfaces.

Because of this additional surface area, system builders and operators have different places in which they can limit or prevent memorized content in models from being delivered to end users. Even if such content can be regurgitated or extracted from a trained *model*, the additional layers of the *system* can provide insulation that does not expose this content outside of the system. For example:

- On entry, the system can filter or modify user prompts it receives as inputs. Such filters can be other (typically discriminative) machine-learning models and software that reject certain user requests before they are ever supplied as prompts to the model.
- The model can be *aligned* in ways that change its response to prompts.²⁷³ For example, to varying degrees of success, alignment can instill behaviors in the model to refuse to produce certain types of content (e.g., memorization).²⁷⁴
- For prompts that make it past input filters and are supplied to aligned models, the system can still filter or modify the resulting generations; it can filter the outputs it ultimately delivers to users.²⁷⁵

The rhetoric AI companies use to discuss memorization shows that they understand the degree of control they have over their systems. After arguing that the *Times*'s extraction attacks were "not typical or allowed," OpenAI wrote, "We are continually making our systems more

²⁷² See *supra* Part I.B; *Talkin'*, *supra* note 13, at Part I.C; see generally *Talkin' (Short)*, *supra* note 48.

²⁷³ See *supra* note 49 and accompanying text (discussing alignment). Alignment, however, has been shown to be fairly brittle; it is only somewhat effective at resisting undesired user behavior. See Nasr Carlini, Hayase et al., *supra* note 62 (describing breaking alignment in ChatGPT using certain types of prompts in such a way that surfaces memorization); Nasr, Rando, Carlini et al., *supra* note 118 (describing breaking alignment in ChatGPT using fine-tuning in such a way that surfaces memorization of pre-training data).

²⁷⁴ See GPT-4 System Card, *supra* note 42, at 13.

²⁷⁵ Note that discriminative models used in filtering would likely have to be trained on the (copyrighted) data that they would serve to identify for filtering. See Cooper, Choquette-Choo, Bogen, Jagielski, Filippova, Liu et al., *supra* note 68, at 17. But discriminative models do not "regurgitate" in the same way that generative ones do; their outputs are not of the same modality as their inputs. See *supra* Part I.A (comparing discriminative and generative models);

resistant to adversarial attacks to regurgitate training data, and have already made much progress in our recent models.”²⁷⁶ These points acknowledge that OpenAI (correctly) anticipates that its systems will be subject to “adversarial attacks” and is designing its systems to make them more resistant.²⁷⁷ This admits that planning for and mitigating undesirable user behavior—“adversarial” or otherwise—is a part of doing business when it comes to building and deploying software systems.

At the same time, AI companies also discuss memorization as a kind of “bug”—a deviation from correct system behavior. OpenAI, for example, has written, “‘Regurgitation’ is a rare bug that we are working to drive to zero.”²⁷⁸ There are a few things that can be said about this perspective. First, even the rhetoric of “bugs” accepts the reality of regurgitation—that this is a behavior their systems engage in, intended or not. Second, it also accepts that the generative-AI system deployer bears some responsibility for the existence of the bug; it is a known bug in their systems. So, even if we accept that some users are adversarial, they are only capable of being successfully adversarial because there is a known bug for them to exploit in the first place. And third, “feature” and “bug” are essentially contested concepts.²⁷⁹ As discussed above, memorization may indeed be a feature, not a bug, of learning in large-scale generative-AI models. In some contexts, it may even be a desired behavior, as is the case with memorizing and regurgitating the alphabetized list of fifty U.S. States.²⁸⁰ It is another question entirely with

²⁷⁶ *OpenAI and Journalism*, *supra* note 6.

²⁷⁷ In general, OpenAI has a history of valuing research in adversarial ML and doing “red-teaming” exercises to assess risks. Ian Goodfellow, Nicolas Papernot, Sandy Huang et al., *Attacking machine learning with adversarial examples*, OPENAI (Feb. 24, 2017), <https://openai.com/research/attacking-machine-learning-with-adversarial-examples> [<https://perma.cc/UJR2-V43W>] (discussing prior research at OpenAI on adversarial ML); *OpenAI Red Teaming Network*, OPENAI (Sept. 19, 2023), <https://openai.com/blog/red-teaming-network> [<https://perma.cc/9XJB-MM3Z>] (detailing the importance of red-teaming to elicit undesired outputs from models, as a way to assess the risks they present).

²⁷⁸ *OpenAI and Journalism*, *supra* note 6; see also Def. Anthropic PBC’s Opposition to Plaintiffs’ Motion for Preliminary Injunction, *supra* note 8, at 2 (“Anthropic’s generative AI tool is not designed to output copyrighted material, and Anthropic has always had guardrails in place to try to prevent that result. If those measures failed in some instances in the past, that would have been a ‘bug,’ not a ‘feature,’ of the product.”); *id.* at 7 (“[Claude] is designed to generate novel content, not simply regurgitate verbatim the texts from which it learned language. While it does on occasion happen that the model’s output may reproduce certain content—particularly texts that escaped deduplication efforts when preparing the training set—as a general matter, *outputting verbatim material portions of training data is an unintended occurrence with generative AI platforms, not a desired result.*”) (emphasis added)).

²⁷⁹ See generally Cooper, Moss, Laufer & Nissenbaum, *supra* note 51 (discussing the porous boundaries between bugs and features in AI/ML; functionally necessary behaviors of AI/ML systems do not always align with social goals); David Gray Widder & Claire Le Goues, What is a “bug”? On subjectivity, epistemic power, and implications for software research (Feb. 13, 2024) (unpublished manuscript), <https://arxiv.org/abs/2402.08165> [<https://perma.cc/Z76E-FAY2>].

²⁸⁰ See *supra* note 86 and accompanying text (discussing extraction of this list from ChatGPT-3.5).

respect to systems. Even if some undesired memorization is unavoidable for *models*, *system* builders are not off the hook for taking reasonable measures to develop system-level guardrails that prevent surfacing that memorized content to users.²⁸¹ In our view, for a company that builds and deploys such systems to argue successfully that memorization reflects internal (and thus non-infringing) copying, that copying does in fact have to remain internal²⁸² to the system.

CONCLUSION: WILL THE MODELS BE UNBROKEN?

We have presented what we understand to be the widely accepted consensus of machine-learning researchers about the technical facts of memorization.²⁸³ Where the state of the art involves substantial uncertainty, we note so explicitly, and we have also noted places where our descriptions are simplified for expository purposes. But, in general, when we make claims about how machine-learning models and systems work—for example, that some models can be prompted to regurgitate substantial portions of their training data, that model parameters contain memorization, etc.—we do so because we regard these questions as settled technical matters. We are confident in this assessment, but others are free to read the technical literature and decide for themselves.

It is up to lawyers and judges to decide what to do with these technical facts. In some places, we think that existing copyright doctrine—such as the definition of a “copy”²⁸⁴—prescribes the legal conclusions that follow. In other places, we think that the doctrinal consequences are undetermined, and that different generative-AI systems could well be treated differently.²⁸⁵ Again, we are confident in our assessments, but others are free to read the legal sources and decide for themselves.

And finally, legislators are free to change copyright law in ways that change the relevance of the technical facts of memorization—for example, to specify explicitly that models are copies of training data, or that providers of generative-AI systems face only contributory liability for user-initiated extraction. We do not consider these copyright-policy debates in this Essay, but we respect and have learned much from the extensive and thoughtful commentary that others have brought to the topic.

²⁸¹ We are not claiming that such guardrails have to be or even can be perfect at fulfilling this goal. Determining what is feasible and reasonable for guardrails involves important empirical and policy questions. See Cooper, Choquette-Choo, Bogen, Jagielski, Filippova, Liu et al., *supra* note 68, at 23–24.

²⁸² See Matthew Sag, *Copyright and Copy-Reliant Technology*, 103 NW. U. L. REV. 1607, 1634–36 (2009) (discussing internal or “intermediate” copying); see Grimmelmann, *supra* note 124 (summarizing case law on internal copying).

²⁸³ The sources we cite document that consensus, explain the relevant technical findings in greater detail, and are widely considered to be written by the authoritative experts on memorization in the machine-learning community. One of the authors of this Essay is one of these experts and has published repeatedly in this area.

²⁸⁴ See *supra* Part II.A.

²⁸⁵ See, e.g., *supra* Part II.E and Part II.I.

We emphasize these three different modes of argument—technical, doctrinal, and policy—because we do not think that it is productive to debate the *technical* facts of memorization on *policy* grounds. If you disagree with our interpretation of the doctrinal consequences of the technical facts because you believe that it makes for bad copyright policy, we submit that your argument is best phrased in terms of doctrine (we are wrong about what copyright law says because we have misread the statute and the caselaw) or in terms of policy (we are right about what copyright law says but the statute and the caselaw should be changed). Copyright law does not determine technical facts; it must work with the facts as they are. Put differently, please do not be upset with us if our technical description of how memorization works is inconvenient for your theory of copyright law. It is not climate scientists' fault that greenhouse-gas emissions raise global temperatures, regardless of what that does for one's theory of administrative or environmental law. It is simply a scientific fact, supported by extensive research and expert consensus. So here.

This perspective on the relationship between technical facts, law, and policy is far from new. Nearly four decades ago, computer scientist Allen Newell—a Turing Award winner and AI pioneer—warned legal scholars that they were building their theories about intellectual property and software on a foundation of sand:

My point is precisely to the contrary. Regardless how the *Benson* case was decided—whether that algorithm or any other was held patentable or not patentable—confusion would have ensued. The confusions that bedevil algorithms and patentability arise from the basic conceptual models that we use to think about algorithms and their use.²⁸⁶

His point was not that their policy arguments for and against IP protections were wrong: indeed, he expressed “no opinion” on the patentability of algorithms. Instead, his point was far more fundamental: “The models we have for understanding the entire arena of the patentability of algorithms are inadequate—not just somewhat inadequate, but fundamentally so. They are broken.”²⁸⁷

Newell’s warning has renewed force today. Courts, regulators, and scholars who are grappling with how to apply existing laws to generative AI—or formulate new ones—must build their theories atop a foundation of conceptual models of how generative-AI systems work, with respect to memorization and much else. If they do not, faulty technical assumptions will lead to ungrounded legal claims—not necessarily wrong, but with no reliable connection to the underlying systems they purport to describe.²⁸⁸ They need, in short, a good model of models.

²⁸⁶ Allen Newell, *Response: The Models Are Broken, The Models Are Broken!*, 47 U. PITTS. L. REV. 1023, 1023 (1986).

²⁸⁷ *Id.* at 1024.

²⁸⁸ See generally Cooper, Choquette-Choo, Bogen, Jagielski, Filippova, Liu et al., *supra* note 68 (discussing this topic in extensive detail, and with a particular focus on “machine unlearning” in Generative AI as a misunderstood set of technical approaches, which some hope can operationalize substantive goals from law and policy).