

BUILDING AND USING GENERATIVE MODELS UNDER US COPYRIGHT LAW

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Advancements in artificial intelligence (AI) have made it possible to generate new text, code, pictures, and music.² Users have described the results as “pure magic.”³ The popularity and capability of these tools have prompted reams of speculation about how they will transform society.

These new tools are powered by machine learning (ML) techniques. Machines “learn” by digesting millions of example sentences, software functions, pictures, or songs. The tools then use the accumulated “knowledge” to generate new works. For copyright

¹ Author is a Partner at Taylor English Duma LLP. “Building and Using Generative Models Under US Copyright Law,” Volume 18 Rutgers Bus. L.R. No. 2 (2023). All rights reserved. The author wishes to thank Garrett Hostetter, BYU Law School class of 2023 for his feedback and research assistance.

² Bernard Marr, *Beyond ChatGPT: 14 Mind-Blowing AI Tools Everyone Should Be Trying Out Now*, FORBES (Feb. 28, 2023, 2:31 AM), <https://www.forbes.com/sites/bernardmarr/2023/02/28/beyond-chatgpt-14-mind-blowing-ai-tools-everyone-should-be-trying-out-now/?sh=305066b97a1b> (previewing AI tools for text generation (ChatGPT and Murf), art creation (DALL-E 2 and Stable Diffusion2), video creation (Lumen5, Gen1, and Deep Nostalgia), music generation (Soundraw and Podcastle), and other creative works (Looka)); KELVIN CHAN AP, *What can ChatGPT maker’s new AI model GPT-4 do?*, ABC NEWS (Mar. 15, 2023, 9:35 AM), <https://abcnews.go.com/International/wireStory/chatgpt-makers-new-ai-model-gpt-4-97881867> (previewing Chat GPT-4); Christopher Tozzi, *GitHub Copilot vs. Amazon CodeWhisperer*, ITPRO TODAY (Jan. 26, 2023), <https://www.itprotoday.com/development-techniques-and-management/github-copilot-vs-amazon-codewhisperer-what-developers-need> (comparing two software AI tools); Alex Hughes, *Midjourney: The gothic AI image generator challenging the art industry*, SCIENCE FOCUS (Feb. 7, 2023, 4:40PM), <https://www.sciencefocus.com/future-technology/midjourney/> (describing a popular AI art generator).

³ Jim Carroll, “*The Nearest Thing To Magic Can Now Emerge In Moments!*”, JIM CARROLL (Sept. 12, 2022), <https://jimcarroll.com/2022/09/daily-inspiration-the-nearest-thing-to-magic-can-now-emerge-in-moments/>; Yanir Seroussi, *ChatGPT is transformative AI*, Yanir Seroussi (Dec. 11, 2022), <https://yanirseroussi.com/2022/12/11/chatgpt-is-transformative-ai/>; User (@u/devdef), REDDIT (Jan. 5, 2021, 7:55 PM), https://www.reddit.com/r/computervision/comments/krennw/openai_text2image_model_is_pure_magic/; All About AI, *Midjourney V4 - Image to Image: Pure Magic*, YOUTUBE (Nov. 8, 2022), https://www.youtube.com/watch?v=tQ_-NADMGcg.

purposes, much of the ML training is accomplished using copies of millions of different works as inputs to the learning process. Almost all of these works are copyrighted.

Machine learning is not new. Its theoretical foundations were established in the 1960s and working systems were created in the 1980s and 1990s. What is new is *scale* and *quality*. Scientists have harnessed the increasing capability of computers and the explosion of digital content to create software programs that rival humans in the ability to generate pictures, text, or music. Earlier AI technologies produced outputs that were clearly mechanical. In contrast, these new tools appear to be so smart that some people incorrectly describe what they do as if they were human and have human intentions and motivations.

ML applications are meant to produce wholly new outputs—but sometimes the applications reproduce fragments, or even whole copies, of works used in training. This raises important questions about copyright infringement. Further, even if outright copying does not occur, these ML applications can generate works that recall the style of specific authors and artists, causing worries that ML may outcompete and replace human creators.

Predictably, this new use of copyrighted material has already prompted lawsuits.⁴ Whenever new uses of copyrighted works emerge, fights for control follow. Copyright holders unsurprisingly want to be paid for the use of their works to build these ML models.

This article addresses the legal issues associated with building and using ML models from a technology-first perspective. It explains machine learning models, how they are trained, and how they generate new works. It then analyzes the applicable law,

⁴ See *Doe v. GitHub Inc.*, No. 3:22-CV-06823 (N.D. Cal. filed Nov. 3, 2022); *Anderson v. Stability.*, No. 3:23-CV-00201 (N.D. Cal. filed Jan. 13, 2023); *Getty Images, Inc. v. Stability AI, Inc.*, No. 1:23-CV-00135-UNA (D. Del. filed Feb. 3, 2023).

comparing and contrasting machine learning with the technologies examined in previous cases, finding that the case law strongly supports the conclusion that building and using generative ML models is either outside the scope of copyright or is a fair use.

1. A Primer on Machine Learning

One of the features of the US legal system is that the law is never analyzed in a vacuum. Legal opinions start by discussing the relevant facts of a case. Based on these facts, legal principles from previous cases are applied using logic and analogy, extending the law to new circumstances.⁵

Applying copyright law to machine learning should follow the same process. Unfortunately, most legal analyses in this area are incomplete or inaccurate in their descriptions of how ML models are made and used. These unsteady factual foundations have resulted in incorrect analogies and analyses in both lawsuits and law review articles.⁶

This section aims to provide an accurate and easily understandable description of the mechanics of machine learning. This foundation will then be used in later sections to analyze and apply relevant legal principles.

⁵ Roscoe Pound, *Hierarchy of Sources and Forms in Different Systems of Law*, 7 TUL. L. REV. 475, 482-87 (1933) (“Principles do not attach any definite detailed legal results to any definite, detailed states of fact. . . . [They] are authoritative starting points for legal reasoning, employed continually and legitimately where cases are not covered or are not fully . . . covered by rules in the narrower sense.”).

⁶ Getty Images, Inc. v. Stability AI, Inc., No. 1:23-CV-00135-UNA, at *12 (D. Del. filed Feb. 3, 2023), <https://fingfx.thomsonreuters.com/gfx/legaldocs/byvrlkmwnve/GETTY%20IMAGES%20AI%20LAWSUIT%20complaint.pdf> (“Stability AI encodes the images, which involves creating smaller versions of the images that take up less memory. Separately, Stability AI also encodes the paired text.”).

Building and Training Machine Learning Models

The creation of a generative machine learning tool involves two phases. The first phase is the training of a “model.” The second phase is using the “model” to make new outputs, such as new sentences, pictures, or code. These phases need to be examined separately because training and generation happen at different times, usually by different parties, and they involve different outputs.

Two Analogies for ML Training

One persistent misunderstanding some people have is how ML applications can recreate familiar objects. These people think of a machine learning model as just a complicated type of storage that saves everything it sees and then brings forth bits and pieces of memorized material to mash together into a collage.⁷ In contrast, the power of machine learning is that it helps the computer identify meaningful correlations that are too attenuated or esoteric to be expressed by software developers. In other words, the model isn’t memorizing the copyrightable expression in an input. Rather, it is evaluating and recording factual relationships between different elements of the expression.

Before diving into the mechanics of ML training, there are two analogies that may be helpful in developing a mental model of how ML training works: the art inspector and the law student. Both of these analogies illustrate the mechanics of model training, but in slightly different ways.

The Art Inspector

⁷ See, e.g., *Anderson v. Stability*, No. 3:23-CV-00201, at *3 (N.D. Cal. filed Jan. 13, 2023) (describing Stable Diffusion as “merely a complex collage tool.”).

Imagine a newly hired art inspector given the job of examining every painting in the Louvre. This inspector has no background or experience in art and so has no preconceived ideas about art (what's beautiful or repugnant) or what is significant about any particular painting (what makes a Picasso a Picasso).

Lacking any guidance, the inspector studies each painting by measuring everything about it, such as the number of brushstrokes, paint thickness, average space between brushstrokes, size of the painting, and the thickness of lines. He includes *every* piece of information he can—the age of the painter, the date the painting was made, and in which corner the artist signed their name. The inspector measures aspects of the paintings that seem bizarrely random or unimportant, such as the number of consonants in the artist's name and the relationship between colors that are six inches apart. He is meticulous in his approach. Nothing is left untouched in the exhaustive analysis. Everything is recorded in the inspector's database.

As the inspector studies each painting, he tries to make his job more interesting by turning each measurement into a guessing game. Before he makes each measurement, he tries to predict what the answer will be, using the information he has gathered already. "How many brushstrokes are in this painting?" he wonders. "Well, it's a Rembrandt from the middle third of his career. I'd guess... 84 brushstrokes per square inch." The inspector then checks the measurement and records how good his prediction was before moving on to the next measurement and the next prediction. When the inspector begins to play, his answers are usually wrong. But as he takes more and more measurements, his predictions are increasingly correct.

After studying thousands (or millions) of paintings, the inspector is the world's foremost authority on validating paintings. He is regularly asked his opinion as to whether various newly-discovered paintings are legitimate. His ability to pinpoint which artist created a painting and to predict other things about each painting is unparalleled. Where before, the inspector took the artist's name and information to predict the measurements of their paintings, now the inspector uses the measurements to predict the painter.

The Law Student

When a student begins law school, they are frequently told that their job isn't just to learn the law—their job is to learn how to “think like a lawyer.” As a result, legal teaching is structured differently than many other types of professional training. Learning the rules isn't enough; they must learn how to apply the law to new situations.

One common way of teaching legal reasoning is the *case method*. The case method involves studying judicial decisions, or cases, in order to understand the legal principles and rules that govern a particular area of law. Rather than simply memorizing legal rules and statutes, students learn to analyze and apply the law through a close examination of real-life legal disputes.

In practice, law students are given a set of facts, usually from a court decision, and then asked to analyze the legal issues raised. They look at the relevant laws, the arguments made by the parties, and the reasoning behind the decision. By examining the evidence and arguments, students develop their own understanding of the legal principles at play.

Law professors usually pair the case method with the Socratic method. In the Socratic method, the professor asks questions instead of providing answers. As the law

students struggle to imitate previous “correct” answers to similar questions, they begin to derive legal principles from the various scenarios. The professor provides feedback—validation of a correct analysis, or correction of a wrong answer—which the students then use to further refine their understanding.

When the time comes for the exam, a successful law student is able to take a hypothetical situation and generate a new analysis that nevertheless incorporates the correct principles, even though the student was never *explicitly* taught which principles to use. The student may not have a specific reason to weigh one factor over another, emphasize certain facts, or avoid certain arguments. She just knows, based on evaluation of example cases, how courts have weighted various facts and principles in the past.

In contrast, imagine a second student who attempts to master the material by memorizing all the facts and holdings from every case discussed in class. This second student does well when asked to describe the facts and holding of an important case, but fails to apply the principles of the law to new situations.

In short, the successful law student has a mental model of how the law is “supposed” to work based upon her analysis of the many cases studied during the class. Unlike the second student who just memorized facts, she can predict how courts would analyze new facts and new situations. She has learned to “think like a lawyer.”

Examining the Two Analogies

Training an ML model is similar to the processes of the art inspector and the law student. In both cases, the basic steps are the same: *receive* an example; *predict* the relationship between the different elements of the example; *check* the result, and *adjust* to

improve future predictions. Those commonalities apply to the mechanical process performed by a computer during model training. However, there are some individual points from each analogy worth emphasizing.

The art inspector analogy is better at showing how ML models start with a clean slate. Before models are trained they are literally filled with random data. All associations that come out of ML applications were learned by observation. The art inspector's measurement of small, random details is also closer to the fixed process that occurs during ML training. But though the art inspector recorded and saved all his measurements (inputs), what is actually recorded during ML training is instead the changing probabilities associated with different inputs.

The law student analogy is better at showing how unifying principles are the product of inference. Just like the law student is never explicitly taught the correct legal principles, ML training processes are not instructed what any of their inputs "mean." Instead, the "meaning" that is observed in an ML application is actually a complex probability function with millions or billions of parameters.

The law student analogy also demonstrates how direct memorization of inputs is actually antithetical to the goals of model training. Avoiding direct memorization is so important that ML training processes almost universally involve removing part of the training information to force the model to engage in the inference process. This is sometimes referred to as "masking" or "dropout." Failure to hide or remove information during training makes models unusable.

The danger in the law student analogy is that it makes the ML application easier to anthropomorphize. The process of training is not creative or selective. The ML models do not “think” or analogize. All the “learning” that occurs within the ML application is simply the rote construction or use of massively complex probability functions.

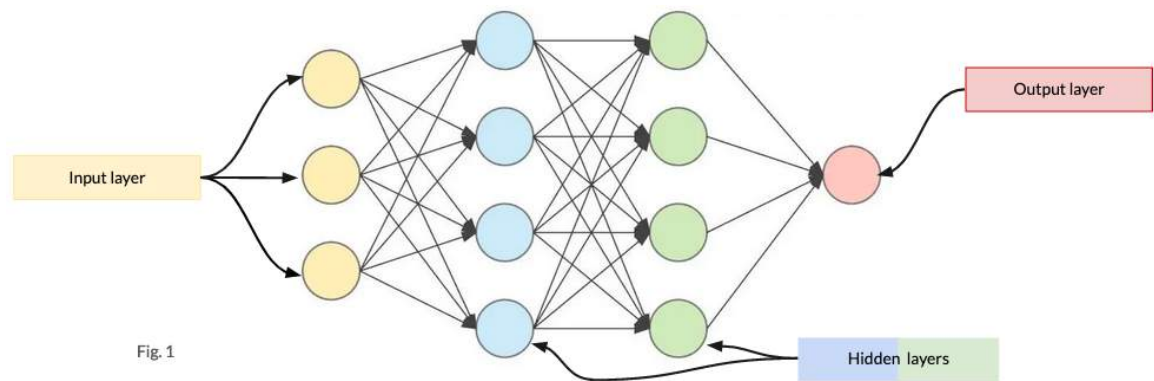
The Training Process

With these analogies in mind, we can examine how the same steps—receive, guess, check, adjust—are used to train an ML model. However, while the steps are conceptually similar to the mental processes of the art inspector and the law student, they are turned into a mechanical process that can be repeatedly performed by a computer.

Creating a “Brain”: the Architecture of Machine Learning Models

Because computers do not have brains and senses like humans, the first step is to create a logical “brain”—a structure that can receive and process input. This structure is sometimes referred to as the “architecture” of the ML application.

To build a model, a data scientist begins by defining a logical structure for processing inputs to create outputs. Each part of the training process corresponds to a different part of the structure. These structures—initially inspired by the interconnections between brain cells—are called “neural networks.” There are many different types of neural networks, but they share three general structures: an input layer, one or more “hidden” layers, and an output layer. These layers are made up of “nodes”—logical structures where values are temporarily stored and computation can occur. These nodes are highly interconnected by logical paths to other nodes. A stylized illustration is shown in Fig. 1.



This stylized figure has three nodes in the input layer, eight nodes in two hidden layers, and one node in the output layer. Different ML applications can have different numbers of nodes in each layer and can have many different types of interconnections.

The Input Layer (Receive)

The input layer of a neural network is where the data is provided to the model. It is similar to the art inspector viewing a painting or the law student reading a case.

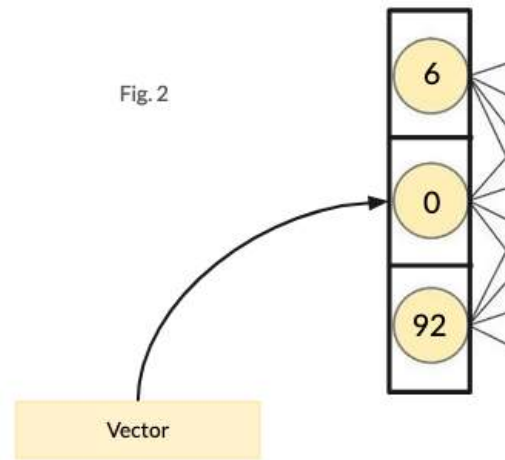
Unlike humans, who can process whole pictures or cases at a time, computers are more limited. Each node in the input layer has a memory designed to receive a single element of the input data. The goal of the input layer is to provide a uniform representation of the raw data that the model will use to make predictions.

As humans, we might think about these inputs as representing the pixels in an image or words on a page. However, from the computer's point of view, the input is just a list of numerical values called a "vector." For example, in a model that processes images, each node in the input layer just gets a number. Depending on the application, the number could represent the brightness of one part of an individual pixel. In a model that processes text,

each node in the input layer might receive a value that represents a word or character. See Fig. 2.

The Hidden Layers (Predict)

The hidden layers in a neural network are where the majority of the processing occurs in an ML application. These layers are called “hidden” because the data that is processed within them is not directly observable from the inputs or outputs of the model. The hidden layers contain a series of interconnected nodes, each of which performs a mathematical calculation on the inputs received from the previous layer. After performing the calculation, the node can pass forward the same value, a changed value, or nothing at all.



Each hidden node has an associated “weight” that changes the probability that a value will be changed or passed on. The weight corresponds to the model’s “best guess” as to how the inputs should be used. See Fig. 3.

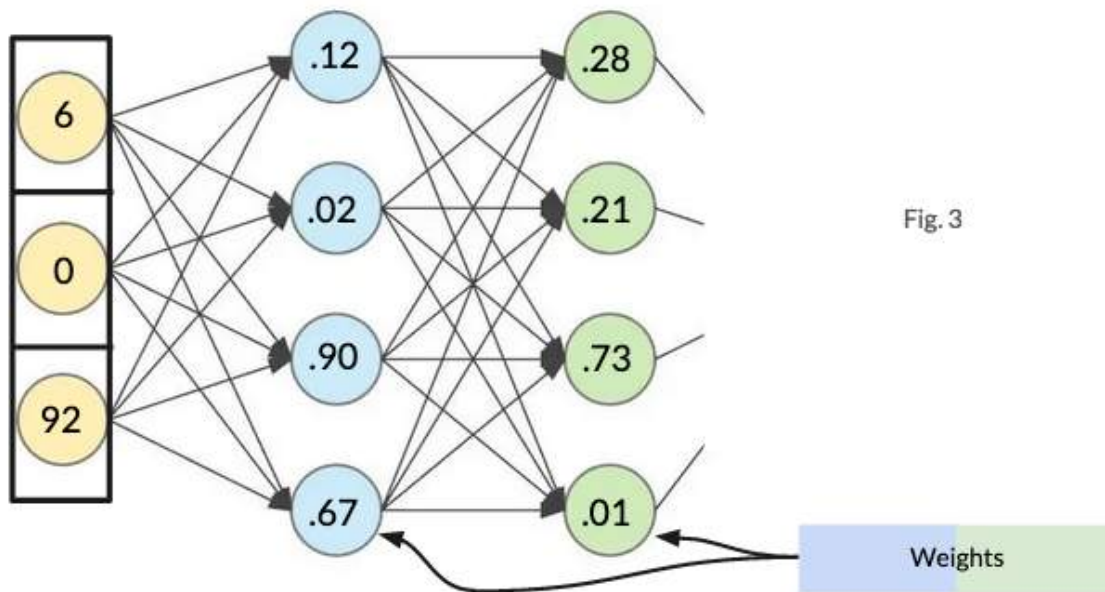


Fig. 3

Similar to the art inspector, scientists have no idea what information will end up being important for the evolution of the neural network. In the past, data scientists tried to identify specific “features” of the input data that they would provide to the neural network. However, isolating the right features took time, was error-prone, and didn’t work as well. The current trend is simply to provide *all* of the data to the neural network and let the computer identify which correlations are useful. As a result, the correlations developed during the training process can be unexpected.

For example, in one application called “neural style transfer,” some layers have been found to correspond to elements of an artist’s style (like the number of brushstrokes, heaviness of lines, use of color) and other layers have been found to correspond to the large shapes and patterns in the image—what we would think of as the “content.” The neural style transfer application generates a new output image by taking the “style” layers from a first

picture and the “content” layers from a second picture and using them together. See Fig. 4.



Fig. 4

Despite the identification of these correlations, neither the “style” nor the content of an image is saved as part of the model during training. Like the law student that extracts principles taught in court cases, the model has extracted correlations that, to humans, resemble certain artistic styles.

Applying this more concretely to the functioning of a real ML application, a common use of neural style transfer applications is to render pictures as if they had the unique brushwork of Vincent van Gogh. However, to perform this function, it would be counterproductive to save the brushstroke pattern for any existing van Gogh painting—none of the brushstrokes would fit a different image. Instead, it appears that one or more layers of the neural style transfer model contain a function that spreads out, moves, or changes the input values associated with each pixel in a way that creates a result that, to humans, resembles the brushwork style of van Gogh.

For humans might describe the process of creating a painting with van Gogh-style brushwork as “applying each color in a thick, contoured slab of paint.” But for a model, this instruction might say like “for every pixel of blue, adjust the blue values of all surrounding pixels by an amount corresponding to this equation.” It involves none of the

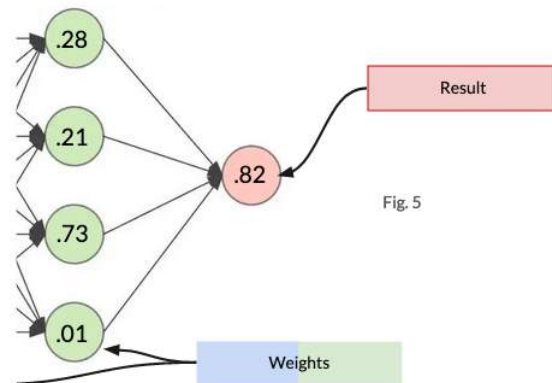
creativity and judgment that a human artist would need to use to apply the technique. Instead, it is “just” an evolved probability function that is literally inhuman in its complexity. Stable Diffusion, a modern model for processing and generating images, has 890 million parameters. GPT3, a model for understanding natural language, has 175 billion. Each parameter can be thought of as a conditional probability associated with one possible state of the neural network.

The Output Layer (Check)

The output of the hidden layers are then passed to the output layer, where the final result is provided. Just as with the input layers, the ML application doesn’t “know” what the output represents. Like the input, it is just a vector of numbers. See Fig. 5.

How the result is interpreted is up to the human user. For example, the example value .82 in Fig. 5 could be interpreted as a classification (“there is an 82% chance this email is spam”), a recommendation (“if you liked this show, there is an 82% chance you might also like...”), or in the case of generative AI, one

part of a pixel value of a new picture (change the blue in this output pixel to 82% of its maximum value) or the next word of a new sentence (the number .82 corresponds to the word “elephant”).



Update the Weights (Adjust)

During training, every input has a known correct output (or possible output, if there are multiple correct possibilities). The result is compared with the correct output and the weights in the neural network are adjusted a tiny bit so that the next time the model receives a similar input, it will be more likely to provide a similar answer.

Try Again (Repeat)

This same process is then repeated. After processing and recording the predicted probabilities over the millions of provided examples, the application builds a comprehensive statistical picture of the range of possible answers for any given input and the likelihood of each answer. In many cases, the same inputs are re-used in different rounds of training to see if there are any further statistical correlations that can be learned from each example.

A portion (10-20%) of the input examples are never used as training inputs but are instead saved as a “testing” set. The testing set is never used as part of the training. The application receives the training input, predicts the output, and checks it against a known correct answer. However, the differences between the prediction and the correct answer are never used to adjust the weights in the model. Instead, the performance of the model is evaluated by using these never-used inputs as a barometer for how good the model’s predictions have become.

At some point, the model's predictions stop improving. At that point, training is complete. The only way to further improve the model’s prediction is to provide more example inputs for training. As more examples are used in the training process, the

resulting model has a better, more coherent picture of the interrelated probabilities required to process the inputs “correctly.”

Defining the “Model”

In computer science terms, the interconnected network of weighted nodes is equivalent to a program—a very complicated program. **Training is the process of iteratively “evolving” the neural network’s probabilities so it can emulate running a computer program that produces the correct outputs for each input.**

The “model,” respectively, is the combination of the neural network design and the weights. **It is a set of numbers and equations that encode statistical probabilities about the inputs that have been processed during training.**

If a person were to save a well-trained model to disk and examine it, what that person would see would be a gigantic matrix of numbers—the learned weights associated with the nodes in the hidden layers. The model would not directly contain any copies of its source inputs, even in compressed form.

It is hard to say exactly what any single probability within the model represents. However, they provide a very detailed statistical picture of the collective experience of humanity when it comes to the inputs. In other words, the model doesn’t really record knowledge about any single input. Instead, it records knowledge about what makes an image a *picture* as opposed to a bunch of noise, or what makes a bunch of words a *story* or an *article* instead of a bunch of gibberish. Or more specifically, what makes a song a “pop song from the 80s” as opposed to an “aria.” And because humanity has embedded so much

implicit knowledge in words, pictures, and songs, these models can appear quite “intelligent.”

The knowledge embedded within the model is “latent”, in the sense that it is hidden, but unexpressed knowledge.. The logical landscape of this hidden knowledge—what concepts are “close together” or “far apart,” and in which ways, is sometimes called the “latent domain.”

Overtraining and Memorization

There is one specific type of training failure that is significant for copyright purposes: overtraining. If training continues beyond the level where the guesses stop improving, the probabilities associated with a specific input can get pinned to a specific output. The model still does not directly include its source inputs, but it has effectively “memorized” instructions for re-creating one or more inputs in response to a particular prompt. So while the model would not contain copies of the training works, it could nevertheless reproduce them if provoked to do so.

Overtraining and memorization is not the desired output of an ML model—it is a type of failure that scientists work to avoid. The desired outcome is a model that has encoded enough probabilities, that like the successful law student, it can respond effectively to novel inputs. An overtrained model is like the second law student that memorized the assigned cases but never learned to generalize. In other words, reproducing works is neither necessary nor desirable in machine learning.

In practice, overtraining in commercial models ranges from uncommon to extremely rare. For example, GitHub estimates that its CoPilot model for generating source

code includes a copied snippet longer than about 150 characters approximately 1% of the time.⁸ Researchers studying the model for the Stable Diffusion image generator were able to make the model reproduce copies of about one hundred source images, only 0.0003% of the input training set.⁹ And even then, those reproductions were hardly accessible. To find those reproductions, researchers concentrated on images that were duplicated hundreds of times in the dataset and then reconstructed the exact known parameters used to train the model for those duplicated images. Even with this head start, they still had to generate hundreds of *possible* duplicates and then use a specialized process to find the reported matches.

Inference and Generation Using Machine Learning Models

Once an ML model is trained, it can be applied to a task. Using an ML model is almost exactly the same as training an ML model. The difference is that there is no “Adjust” phase of the process. In use, the ML application *receives* the input and makes the same types of measurements as it would for any other input. It then uses the hidden layers with their trained weights to *predict* the output. However, once the prediction has been provided

⁸ *Does GitHub CoPilot copy code from the training set?*, COPILOT: FEATURES (last visited Mar. 15, 2023), <https://github.com/features/copilot> (“Our latest internal research shows that about 1% of the time, a suggestion may contain some code snippets longer than ~150 characters that matches the training set. Previous research showed that many of these cases happen when GitHub Copilot is unable to glean sufficient context from the code you are writing, or when there is a common, perhaps even universal, solution to the problem.”).

⁹ NICHOLAS CARLINI, ET AL., EXTRACTING TRAINING DATA FROM DIFFUSION MODELS (2023), available at <https://arxiv.org/abs/2301.13188>. On page 6 the authors state that they studied the 350,000 most-duplicated images in the dataset and identified a total of 109 duplicated images, or 0.00031 percent. Taken as a percentage of the 5.85 billion images in the entire dataset, the identified percentage of duplicates found is 0.0000000018%.

to the output layer, the process is finished. The prediction is simply interpreted by the application and then returned as the result.

In general, there are two ways in which these ML results are used: *inference* and *generation*.

Inference

Inference refers to the process of using a trained model to make predictions or decisions based on new, previously unseen data. An ML application used for inference can usually be thought of as categorizing the newly-seen input in some way. This categorization can be interpreted as a classification, a prediction, or a recommendation. Thinking back to the art inspector, the inspector's ability to identify the artist associated with paintings he had never seen before is an example of inference. Because inference does not create a new work, it does not implicate copyright law.

Generation

Generation, on the other hand, refers to the process of creating *new* content, data, or outputs. Generation often involves models designed for tasks like natural language processing, image synthesis, or music composition.

Generative ML applications are usually designed to produce outputs of the same type as the inputs. For instance, a generative model trained on text data may be used to generate new text, such as sentences, paragraphs, or even entire articles. A model trained on images may be used to create new images. However, there is no inherent restriction forcing ML applications to generate outputs of the same type as their inputs. For example, some generative systems can take an image as an input and return a textual description of

the input, whereas other generative systems can take a textual description of a scene and return an image providing a rendering of the scene described by the user.

Just like inference, the generation process relies on the statistical patterns learned from the training data to create a predicted output. This output is returned as the result (or as part of the result). This is analogous to the law student's ability to create a new, coherent legal analysis based on the principles and lessons she derived from her case studies.

The difference between the law student and the ML application, however, is that the law student uses her intelligence and creativity to generate her answers, whereas an ML application has neither intelligence nor creativity. What the ML application does have is *context* and *randomness*.

Context

Taking the example of text, scientists have known since the 1960s that it was possible to construct sentences by analyzing a bunch of writing, finding which words tend to follow each other, and then repeatedly picking out the next word with the highest probability.

Humans instinctively perform this kind of analysis. For example, if someone was asked to predict the next word in the sentence "It was a dark and stormy _____," almost everyone would respond with the word "night." Sometimes there are a number of possible "next words," such as in the sentence "The wizard raised his _____." Some people might predict the next word might be "wand," "staff," or "hand."

When scientists tried to get computers to imitate humans, however, they quickly figured out that just choosing the most probable next word resulted in sentences that were

trite, ungrammatical, and repetitive. The difference was that the computer was only considering the single preceding word. Humans take into account all the words in the sentence, as well as the millions of words of context accumulated throughout our lives.

The logical way to improve the quality of the sentences created was to use more context when determining the most probable next word. Instead of only looking at the immediately preceding word, the computer could look at the two preceding words, the three immediately preceding words, or more. Nevertheless, using more than about five words of context usually resulted in systems that were too big to run on the computers of the time.

In the past fifteen years, however, the storage and processing capabilities of computers and networked computer systems have grown exponentially. As of the writing of this article, state-of-the-art text generation systems are able to take in about fifty typewritten pages of context when determining what word to generate next.¹⁰ Scientists have also identified methods (called “attention”) of helping the model adaptively use different parts of its provided context to improve generation.

Randomness

The second ingredient in generation is randomness. Scientists have discovered that one ingredient that makes humans creative is the element of surprise. Humans don’t always

¹⁰ GPT-4 Technical Report, <https://arxiv.org/abs/2303.08774>, What is the difference between the GPT-4 models? <https://help.openai.com/en/articles/7127966-what-is-the-difference-between-the-gpt-4-models>, OpenAI’s GPT-4 is a safer and more useful ChatGPT that understands images, <https://the-decoder.com/open-ai-gpt-4-announcement/> (“The context length of GPT-4 is limited to about 8,000 tokens, or about 25,000 words. There is also a version that can handle up to 32,000 tokens, or about 50 pages....”).

use the highest probability outputs. We vary how we express ourselves in order to produce different effects on readers or viewers.

To emulate this tendency in humans, data scientists building generative ML applications include a parameter (frequently called “temperature”) that is interpreted as a probability that the model should choose a slightly lower-probability path for a part of its output. For example, a temperature of 0.7 could mean that there is a 70% chance that the highest probability path will be used when generating an output, and there is a 30% chance that one of the lower probability paths will be taken instead.

The “temperature” used in an application does not correspond to any physical or logical law. It is a heuristic, derived over time and observation, that causes ML applications to seem more “human” in their outputs. Many ML applications allow users to control the temperature used for a particular generation. This allows a human using the ML application the ability to guide the course of generation by using or constraining the level of randomness affecting the output.

Controlling the Generation

Despite the use of limited randomness as part of the generative process, the output of an ML model is not random. A human using the ML application typically describes what should be generated and/or provides other inputs that are used to initialize and guide the generative process. These inputs are usually referred to as the “prompt.”

The ML application takes the prompt and analyzes it as if it were an input. It then uses the analyzed prompt to identify a place in the latent domain to focus on when running the generative process. That is why when a user provides "cute purple dinosaur" into an

image generator, the application returns images of a cute purple dinosaur, not a motorcycle or a cloud. Further, the more information that is given within the prompt, the more control is exerted over the output.

The practice of developing a prompt that will give the desired output is sometimes referred to as “prompt engineering.” Prompt engineering is actually an exploration through the latent space of the model—the probabilistic landscape of ideas and meanings—to match the generated expression to the author’s or artist’s conception. The goal of the author is to develop the exact set of inputs—images, words, and options—that will lead to the generation of the desired output.

2. Building Machine Learning Models Under US Copyright Law

There is no question of the importance of training material, including copyrighted material, for building cutting-edge ML systems. Using more training material results in better models, and better models mean better outputs. The leading ML models available today leverage billions of individual training examples, almost all of which are copyrighted. And yet, there is nothing improper with this usage. A comparison of cases and authorities with the actual mechanics of ML training suggests that in most cases, inputting copyrighted works into an ML model is a fair use, if it implicates copyright at all.

The Hypothetical

This is best observed by analyzing the training and distributing process of an actual ML model. This section will evaluate arguments for copyright infringement using the example of a “Stable Diffusion” model, as used in an ML-based image generation service,

to show that all uses of copyrighted material are either outside copyright's scope, de minimis, or covered by the "fair use" doctrine.

Stable Diffusion is a generative deep learning model that was released in 2022. It is designed to convert text descriptions provided by a user into images that match the artist's intent. It was trained using 5 billion images with matching text downloaded from websites on the Internet. Many of these images are commercially licensed.

Although this hypothetical uses real facts and is similar to real cases, it doesn't directly correspond to any one particular case. More details about those specific cases are available on the Internet. The applicable facts for this article are these: The training for the ML model was performed by a German university with funding from a for-profit UK-based company that has a United States affiliate. A copy of the model is provided by the German university to the U.S. entity. The U.S. company uses the model to generate images, for itself and for others. A copyright holder sues the U.S. entity for copyright infringement in the United States.

Threshold Questions—Does Copyright Even Apply to the Training Process?

Before evaluating whether building the model is a fair use, it's necessary to consider whether copyright even applies. The two specific issues for this question are 1) whether the training and import of the model is importation of material legally generated abroad, and 2) whether the copying of the image into the input during the training process is subject to limitations under 17 U.S.C. 117.

Importation of Information Legally Generated Abroad

One feature of the international race to create large ML models is that much of the training takes place in jurisdictions like India, the United Kingdom, and Germany. This is no accident. Unlike the United States, these countries (and others) have statutorily declared that using material for the purposes of ML training is not covered by copyright.

Specifically, both the UK¹¹ and Germany allow the reproduction of copyrighted works for non-commercial Text and Data Mining (TDM). As stated in the German Act:^{12 13}

§ 60d on Text and Data Mining:

(1) It is permitted to make reproductions to carry out text and data mining . . . for scientific research purposes in accordance with the following provisions.

(2) Research organisations are authorized to make reproductions. ‘Research organisations’ means universities, research institutes, and other establishments conducting scientific research if they:

1. pursue non-commercial purposes,
2. reinvest all their profits in scientific research or
3. act in the public interest based on a state-approved mandate.

The authorization under sentence 1 does not extend to research organisations cooperating with a private enterprise which exerts a certain degree of influence on the research organization and has preferential access to the findings of its scientific research.

¹¹ Copyrights, Designs and Patents Act, (1988) § 29A, (1) (UK)

(1) The making of a copy of a work by a person who has lawful access to the work does not infringe copyright in the work provided that—

(a) the copy is made in order that a person who has lawful access to the work may carry out a computational analysis of anything recorded in the work for the sole purpose of research for a non-commercial purpose, and

¹² Urheberrechts-Wissensgesellschafts-Gesetz [Law on Copyright and Related Rights], Sep. 7, 2017, RGBI I at 3346, (Ger.), available at https://www.gesetze-im-internet.de/englisch_urhg/englisch_urhg.html (English translation).

¹³ An earlier version of this paper included an incorrect translation. The text and accompanying analysis has been updated accordingly. Thanks to Alex J. Champandard for highlighting the error.

(4) Those authorised in accordance with subsections (2) and (3) and pursuing non-commercial purposes may make reproductions made pursuant to subsection (1) available to the following persons:

1. a specifically delimited circle of persons for their joint scientific research and
2. individual third persons for the purpose of monitoring the quality of the scientific research.

The making available to the public must be terminated as soon as the joint scientific research or the monitoring of the quality of the scientific research has been concluded.

[. . .]

(6) Rightholders are authorised to take necessary measures to prevent the security and integrity of their networks and databases being put at risk on account of reproductions made in accordance with subsection (1).

The German TDM exception is for research organizations, which may include the German nonprofit, depending on whether the influence from funding from the UK entity is less than the required degree of influence. But assuming this is met, the generation of the model in Germany would be lawful, as the TDM exception would cover the initial copying necessary to train the model. An evaluation of the German TDM rule by the EU's Policy Department for Citizens' Rights and Constitutional Affairs concluded:¹⁴

The exception covers the acts of reproduction necessary for undertaking TDM.... It is worth noting that German law does not impose a “lawfully accessed source” requirement as France does. Also, it does not limit the source materials that can be mined to “text and data included or associated with scientific writings”. With regard to databases, their reproduction is being qualified as constituting “normal use”.¹⁵

¹⁴ *THE EXCEPTION FOR TEXT AND DATA MINING (TDM) IN THE PROPOSED DIRECTIVE ON COPYRIGHT IN THE DIGITAL SINGLE MARKET - LEGAL ASPECTS* (Feb. 2018), [https://www.europarl.europa.eu/RegData/etudes/IDAN/2018/604941/IPOL_IDA\(2018\)604941_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/IDAN/2018/604941/IPOL_IDA(2018)604941_EN.pdf).

¹⁵ *Id.* at 18. The German TDM exception also allows for the creation and limited distribution of a “corpus,” (e.g., source materials that were normalized, structured and categorized). However, as the model creation process does not create a corpus, this provision is inapplicable.

If the creation of the model is *per se* lawful in Germany, then importation of the model into the US might be allowed under *Kirtsaeng v. John Wiley & Sons, Inc.*, 568 U.S. 519.

Kirtsaeng involved a dispute between a student (Kirtsaeng) and an academic textbook publisher (Wiley). Wiley assigned the rights to publish, print, and sell foreign editions of its English language textbooks abroad to its wholly-owned subsidiary, Wiley Asia. The books were sold at low prices in Thailand, where Kirtsaeng bought them, and then shipped to the United States where he re-sold them for a profit.

Wiley filed a lawsuit against Kirtsaeng, claiming that his unauthorized importation and resale of its books was an infringement of its exclusive right to distribute and prohibit importation. However, Kirtsaeng argued that the “first sale” doctrine permitted the importation and resale of the books as they were “lawfully made” and acquired legitimately.

The District Court and Second Circuit held that the “first sale” doctrine does not apply to goods manufactured abroad. The U.S. Supreme Court reversed, finding that any works “subject to protection under this title” included works “without regard to the nationality or domicile of the author,” and that any works “first published” in any nation that had signed a copyright treaty with the U.S. could be considered “lawfully made under [the Copyright Act].”¹⁶

Kirtsaeng is usually cited relative to the first sale doctrine under copyright law. However, the court’s holding is not limited to first sale only. The court said that the

¹⁶ *Id.*

exclusive right of distribution under copyright “is by its terms “[s]ubject to” the various doctrines and principles contained in §§107 through 122”¹⁷ which specifically apply to all works “lawfully made under this title” - which includes Berne signatories like Germany.¹⁸

The German university’s actions under the German TDM exception meet this standard of “lawfulness.”¹⁹ The text of the exception emphasizes that the University’s behavior “**is deemed lawful** and therefore cannot be prohibited by the rightsholder.” Principles of comity suggest that US courts give heed to German copyright law when it is applicable, as here, to determine whether a particular copy was lawfully made.

In *Kirtsaeng*, the importation of the textbooks was lawful because the publisher’s exclusive rights in those copies of the books had been exhausted. In contrast, the German TDM exception excludes the creation of the model from copyright altogether. The similarity is that in both *Kirtsaeng* and in this hypothetical, the use of the material “cannot be prohibited” by the rightsholder.²⁰

Limitations on Exclusive Rights in Computer Programs

Putting aside the German TDM exception, a second hurdle is the possible application of 17 U.S.C. 117(a) to the copyrighted input material. 17 U.S.C. 117 of the United States Copyright law lays out exceptions to the exclusive rights of the copyright owner. The original text of this section confirmed the application of copyright to software, stating that the Act did not give the owner of a copyright in a software work “any greater

¹⁷ *Kirtsaeng v. John Wiley & Sons, Inc.*, 568 U.S. 519, 524, 133 S. Ct. 1351, 1355 (2013).

¹⁸ *Id.*

¹⁹ *Kirtsaeng v. John Wiley & Sons, Inc.*, 568 U.S. 519, 530, 133 S. Ct. 1351, 1358 (2013).

²⁰ German TDM exception.

or lesser rights" when used in conjunction with a machine.²¹ In 1980, this section was amended to better address computer technology, following the recommendations of the National Commission on the New Technological Uses of Copyrighted Works (CONTU).²² One of the changes was the addition of section 117(a)(1). Section 117 states in relevant part:

(a) Making of Additional Copy or Adaptation by Owner of Copy.— Notwithstanding the provisions of section 106, it is not an infringement for the owner of a copy of a computer program to make or authorize the making of another copy or adaptation of that computer program provided:

- (1) that such a new copy or adaptation is created as an essential step in the utilization of the computer program in conjunction with a machine and that it is used in no other manner....

Two immediate questions present themselves. First, whether a digital copy of a work, like the images used to train Stable Diffusion, is a "computer program," and 2) whether a person that downloads a copy of an image from a website is an "owner" of that copy.

Digital Works as Computer Programs

Many people naturally draw a distinction between a computer program and a computer file due to the common use of these terms. However, the definition in section 117 is not so limited. It defines a computer program as "a set of statements or instructions to be used directly or indirectly in a computer in order to bring about a certain result." It may seem surprising to some, but this definition includes digital media files.

²¹ Pub. L. 94-553, title I, §101, 90 Stat. 2546 (1976) (codified at 17 U.S.C. §117).

²² NAT'L COMM'N ON NEW TECH. USES OF COPYRIGHTED WORKS, PB85-225621, FINAL REPORT OF THE NATIONAL COMMISSION ON THE NEW TECHNOLOGICAL USES OF COPYRIGHTED WORKS (CONTU Rep.) (1978) at 12.

When we think about an image or a song on our computer, we usually don't pay attention to the distinction between how a file is encoded and the copyrighted work itself. However, the files we use on our computer are not the work, just as a compact disk is not the same as the music *on* the compact disk.

Turning specifically to images, when a person views an image on a computer, the image they are viewing consists of individually controlled pixels on the computer screen that create the pattern of light and color we recognize as a picture. This is the "certain result" envisioned by the statute. We are likely familiar with many of the common file extensions, such as .jpg and .png. Two image files with different extensions may result in identical images being placed on the screen, but the process followed by the computer is different for every type of file.

Each different type of image file contains a different type of instructions that are interpreted by the computer processor to understand how to control the pixels in the screen to create the desired output. These are the "set of statements or instructions to be used directly or indirectly in a computer" to bring about the result (the showing of the picture).

These instructions are usually converted to a binary format for ease of use on a computer—but not always. One type of image format (.ps, for "Postscript") consists only of human-readable instructions that tell the computer how to draw the desired image on the screen.

Because image files have "a set of statements or instructions" that is used by a computer to bring about "a certain result," image files—like all digital media—fit the statutory definition of a "computer program."

Ownership of a “Copy” of a Work

One limitation of 117(a) is that its application is limited to “the owner of a copy of a computer program.” Most standard computer programs, like Microsoft Word or Mozilla Firefox, are licensed, not sold. Each download or installation is preceded by an “End User License Agreement” screen laying out the terms of use under the copyright owner’s license.

However, the situation is different for the content available on websites. There is no license agreement for each file retrieved from a website and no opportunity for meaningful offer and acceptance. By design, people put content on the Internet so that users and automated processes can receive copies of the website contents and view them on their computer. As explained, this process requires the computer to implement the file “instructions” and thereby create an individual copy of the work.

The reproduction of these copyrighted works is by design. Copyright owners have the option to not put their content on the Internet or to impose controls like password-protecting certain files. Copyright owners forgo these protections knowing that, absent controls that limit access, Internet websites are designed to automatically provide copies of all requested files. Websites provide these files even before humans are able to perceive

the results or agree to any purported terms of use. Copyright owners *intend* this transfer to occur.²³ Without it, no one would be able to view their website.²⁴

Therefore, the most common occurrence when placing content on the Internet is that a copy is automatically provided to any person or agent wanting to receive a copy. This copy is provided by the copyright owner or an authorized licensee for use on a computer to read or view the copy. This transfer may not involve a monetary payment, but website owners usually expect to benefit in other ways. This expected benefit may take the form of advertising revenue, brand improvement, future sales, or even just increased recognition.²⁵ Under common-law principles, a good given for free with the expectation of

²³ Kernal Records Oy v. Mosley, 794 F. Supp. 2d 1355, 1364 (S.D. Fla. 2011) (quoting Getaped.com, Inc. v. Cangemi, 188 F. Supp. 2d 398, 402 (S.D.N.Y. 2002)) (“Consequently, when a website goes live, the creator loses the ability to control either duplication or further distribution of his or her work. A webpage in this respect is indistinguishable from photographs, music files or software posted on the web - all can be freely copied. Thus, when a webpage goes live on the Internet, it is distributed and ‘published.’”); *see also* Playboy Enters. v. Russ Hardenburgh, 982 F. Supp. 503, 513 (N.D. Ohio 1997) (plaintiffs violated the copyright holder’s publishing right by moving password protected images onto a publicly accessible webpage). *Playboy* makes clear that if a copyright owner forgoes protecting their works by making them publicly available, then they’ve consented to individual copying. *Id.*

²⁴ There is a standard, called robots.txt, that requests that automated Internet agents refrain from downloading certain files or requesting the contents of particular URLs. Most automated Internet agents respect this standard, but compliance is optional. The content still remains available for download at any time. *See* Google Search Central, *Robots FAQs*, GOOGLE SEARCH CENTRAL (last updated Feb. 20, 2023), <https://developers.google.com/search/docs/crawling-indexing/robots/robots-faq>; Field v. Google, 412 F. Supp. 2d 1106, 1113 (D. Nev. 2006).

²⁵ *See, e.g.,* True Freight Logistics LLC v. Glob. Tranz Enters., No. CV-18-01472-PHX-JGZ, 2019 U.S. Dist. LEXIS 237148, at *10 (D. Ariz. Jan. 9, 2019)(Getting traffic sent to a company’s website was part of a “party’s reasonably expected benefits of the bargain.”).

benefit can still be a “sale.”²⁶ Accordingly, the recipient of the copy is the owner of *that copy* of the copyrighted work.²⁷

The recipient’s ownership of this single copy of the work doesn’t significantly undermine the exclusive rights of the copyright owner. The recipient doesn’t own the *copyright* in the work. The recipient receives no rights to reproduce, sell, or distribute the work. The one exception are the rights granted under section 117, which include the right to make a copy if doing so is an essential step in the utilization of the work on a computer.

Under this analysis, the use of retrieved material for the limited purpose of ML model training is one of the few situations that fit squarely into the confines of section 117(a)(1). The individual who accesses copyrighted work online obtains a limited ownership in that work, which they can copy if it is essential in utilizing a work on a computer. Since ML models qualify as “computer programs,” and inputting copyrighted works is necessary for them to function, then ML training on copyrighted works is outside the scope of the exclusive rights granted under copyright law.

²⁶ “Defendant was offering complimentary drinks to its patrons. Nonetheless, it was not offering these drinks out of any sense of hospitality or charity. Defendant runs a casino, and the complimentary drinks were offered as an incentive to patrons to gamble, and therefore enhance defendant’s business.” *Levondosky v. Marina Assocs.*, 731 F. Supp. 1210, 1212 (D.N.J. 1990).

²⁷ *Hamer v. Sidway*, 124 N.Y. 538, 546 (Ct. App. N.Y. 1891) (“Consideration means not so much that one party is profiting as that the other **abandons some legal right in the present or limits his legal freedom of action in the future as an inducement** for the promise of the first.”) (emphasis added). In *Hamer* an uncle promised to give ownership of pecuniary property (\$5,000) to his nephew if he would abstain from certain activities until he was twenty-one. Though the uncle gained no monetary or tangible benefit, the court held that it was a valid contract. *Id.* at 551. Corbin on Contracts supports this saying that “there are innumerable transactions, even including many that are called commercial, in which the promisor receives nothing of economic advantage, the promisor receives no “benefit” that is measurable with money or even with other things of value.” 2 Corbin on Contracts § 5.9 (2022).

Capitol Records, LLC v. ReDigi Inc., 934 F. Supp. 2d 640 is not to the contrary. The *ReDigi* case dealt with resale of digital goods. In the circumstance described above, however, the transaction is between the copyright holder and an immediate recipient. *ReDigi* likely restricts the ability of the recipient to resell any of the content received over the Internet—but it does not prohibit first-party interaction.

The Application of Copyright to Building the Model

But what if a court were to incorrectly hold that ML training was covered by copyright law? Under that assumption, every use of the copyrighted material—even if it is shared with a machine rather than other persons—would presumptively violate the copyright owner’s exclusive right to reproduce a work under section 106 of the Copyright Act.²⁸

Separate, but related to the training issue, is whether the completed product (the “trained” model) would also violate copyright law through its outputs. If the model output closely resembles a copyrighted work in the training dataset, it could constitute infringement by either being a derivative work, if not a complete reproduction.²⁹ Though separate problems, the question for both of these issues is the same: whether these acts are excused as fair use under section 107.

The Fair Use Standard

The fair use doctrine is designed to balance the protection that copyright law grants to owners with the greater public good and to encourage creativity, education, and free speech.³⁰ This doctrine allows for the use of copyrighted materials without the permission of the owner for specific purposes such as criticism, comment, news reporting, teaching,

²⁸ 17 U.S.C. §106 (“the owner of copyright under this title has the exclusive rights to do and to authorize any of the following:(1) to reproduce the copyrighted work in copies or phonorecords; (2) to prepare derivative works based upon the copyrighted work....”).

²⁹ *Id.*

³⁰ Authors Guild, Inc. v. HathiTrust, 755 F.3d 87, 95 (2d Cir. 2014) (“*there* are important limits to an author's rights to control original and derivative works. One such limit is the doctrine of “fair use,” which allows the public to draw upon copyrighted materials without the permission of the copyright holder in certain circumstances.”).

scholarship, or research.³¹ The determination of whether a particular use is considered fair use is decided on a case-by-case basis and is a combination of law and fact.³² There is no automatic assumption of fair use. Fair use is an affirmative defense, with the defendant bearing the burden of proof.³³

Fair use is evaluated based on four factors: 1) the purpose and character of the use; 2) the nature of the copyrighted work; 3) the amount or substantiality of the portion used; and 4) the effect of the use on the potential market or value of the work.³⁴ Courts have also considered whether a particular use advances the public purpose of encouraging the creation of new works.³⁵

The Purpose and Character of the Use

Regarding the first factor of fair use, the purpose and character of the use, several aspects of ML training are directly relevant to the inquiry. These are: 1) the use is transformative; 2) the use is limited to “reading” the work; 3) the work is only used for making measurements and recording facts about the content; and 4) the use is for a research purpose.

³¹ See e.g., *Folsom v. Marsh*, 9 F. Cas. 342, 344, F. Cas. No. 4901 (C.C.D. Mass. 1841) (criticism and comment); *Nunez v. Caribbean Int'l News Corp.*, 235 F.3d 18, 25 (1st Cir. 2000) (publishing copyrighted images for new reporting); *Cambridge Univ. Press v. Patton*, 768 F. 3d 1232, 1242 (11 Cir. 2014); *Authors Guild, Inc. v. HathiTrust*, 755 F.3d 87, 95 (2d Cir. 2014) (scholarship); *Sony Comp. Entertainment, Inc. v. Connectix Corp.*, 203 F.3d 596, 599-601 (9th Cir. 2000) (using copyrighted software for reverse engineering, i.e. “research.”).

³² *Harper & Row, Publs. v. Nation Enters.*, 471 U.S. 539, 560 (1985).

³³ *Am. Geophysical Union v. Texaco Inc.*, 60 F. 3d 913, 918 (2d Cir. 1994).

³⁴ *Authors Guild, Inc. v. HathiTrust*, 755 F.3d 87, 96 (2d Cir. 2014).

³⁵ *Id.* at 94 (quoting *Campbell v. Acuff-Rose Music, Inc.*, 510 U.S. 569, 575 (1994)) (“for fair use of copyrighted materials has been thought necessary to fulfill copyright's very purpose, “to promote the Progress of Science and useful Arts....”); see also U.S. Const., Art. I, § 8, cl. 8. (“To promote the Progress of Science and useful Arts, by securing for limited Times to Authors and Inventors the exclusive Right to their respective Writings and Discoveries.”).

The Use in ML Training is Transformative

The primary consideration relevant to the character and use of the work is whether the use of the work is transformative. The concept of transformative use comes from the 1994 Supreme Court decision in *Campbell v. Acuff-Rose Music*.³⁶ In *Campbell*, the Supreme Court described “transformative” use as being the key element underlying the first fair use factor:

The central purpose of this investigation is to see, in Justice Story’s words, whether the new work merely “supersede[s] the objects” of the original creation, or instead adds something new, with a further purpose or different character, altering the first with new expression, meaning, or message; it asks, in other words, whether and to what extent the new work is “transformative.”³⁷

The leading cases regarding computer-driven transformation of works are *Authors Guild, Inc. v. HathiTrust*³⁸ and the related case *Authors Guild v. Google*.³⁹ The factual background of these two cases is similar: the Authors Guild sued HathiTrust and Google for copyright infringement because of the defendants’ mass digitization of books. HathiTrust, a digital library consortium, created its digital copies for preservation, for accessibility for visually impaired users, and to create a search index. Google created Google Book search to facilitate researchers in locating relevant information. Users could search across books for specific words and phrases and then see a “snippet view” with the search result highlighted.

³⁶ *Campbell v. Acuff-Rose Music, Inc.*, 510 U.S. 569, 586, 114 S. Ct. 1164, 1175 (1994).

³⁷ *Id.* at 579.

³⁸ *Authors Guild, Inc. v. HathiTrust*, 755 F.3d 87, 97 (2d Cir. 2014).

³⁹ *Authors Guild, Inc. v. Google, Inc.*, 804 F.3d 202, 217 (2d Cir. 2015).

In these cases, there were two accused processes: 1) the creation of a digital copy of the books for the purposes of creating a search index, and 2) the distribution of whole or partial copies to users. Since the process of training an ML model does not result in distribution, the relevant portion for our purposes is the creation of the digital copy for indexing.

In the *Authors Guild* cases, digitization was accomplished by “mak[ing] a digital scan of each book, extract[ing] a machine-readable text, and creat[ing] an index of the machine-readable text of each book.”⁴⁰ The end result was a search index enabling users to find content within the books more effectively as well as research new types of questions.⁴¹

With regard to the creation of the search index, the *Hathitrust* court said:

[We] conclude that the creation of a full-text searchable database is a quintessentially transformative use.... the result of a word search is different in purpose, character, expression, meaning, and message from the page (and the book) from which it is drawn. Indeed, we can discern little or no resemblance between the original text and the results of the [defendant’s] full-text search.⁴²

The *Google* court further elaborated on the transformative nature of the search index by highlighting the new statistical research tools that it made possible:

[The] purpose of Google's copying of the original copyrighted books is to make available significant information about those books, permitting a searcher to identify those that contain a word or term of interest, as well as those that do not include reference to it. In addition, through the ngrams tool, Google allows readers to learn the frequency of usage of selected words in the aggregate corpus of published books in different historical periods. We have no doubt that the purpose of this copying is the sort of

⁴⁰ *Authors Guild v. Google, Inc.*, 804 F.3d 202, 208 (2d Cir. 2015).

⁴¹ *Id.*

⁴² *Authors Guild, Inc. v. HathiTrust*, 755 F.3d 87, 97 (2d Cir. 2014).

transformative purpose described in *Campbell* as strongly favoring satisfaction of the first factor.⁴³

The *Authors Guild* cases are not alone. Many other courts looking at similar fact patterns have found the same. For example, in *A.V. v. iParadigms, LLC*, the court found that the copying and archiving of student papers is permissible when aimed at detecting and preventing plagiarism rather than capturing expressive content. In *Perfect 10 v. Amazon.com, Inc.*, the court ruled that Google's copying of Internet content to make it searchable was considered transformative as it turned the image into a “pointer” directing the user to a source of information. Similarly, in *Kelly v. Arriba Soft Corp.*, the court ruled that copying to produce exact replicas of artistic works displayed in thumbnail form on the internet was transformative as it was unrelated to any aesthetic purpose and was aimed at facilitating searches.

Just like the building of a search index is a “quintessentially transformative use,” so too is the building of an ML model. The result of the machine-based processing is a product with wholly different purposes, capabilities, and uses. There is no way in which an ML model could be mistaken for any of its training inputs. The mass of statistical probabilities that make up a generative ML model are so different from the training material that there is no question it is “different in purpose, character, expression, meaning, and message”⁴⁴ from any (or all) of the works that were used as input.

Also significant is that ML models, like the search index in the *Authors Guild* cases, records information *about* the works used for training, not any of the expression contained

⁴³ *Authors Guild v. Google, Inc.*, 804 F.3d 202, 217 (2d Cir. 2015).

⁴⁴ *Authors Guild, Inc. v. HathiTrust*, 755 F.3d 87, 97 (2d Cir. 2014).

within the works themselves. And, just like the search index in *Google*, ML models allow people to perform new types of research and discover new correlations.

The Use in ML Training is Limited to “Reading” the Work

One persistent misunderstanding is the perception that the ML training process makes repeated or derivative copies of each work used as input.⁴⁵ There is also the perception that the model somehow “stores” the works used for training within the model. Both of these perceptions are incorrect.

As described relative to the “receive” part of ML training, there is only one copy of the work needed for training: the initial copying of the work into the input layer of the ML model. This is the process by which the model “reads” the input in order to perform the training process. Reading (or viewing) a work, including on or by a computer, has been repeatedly found to be fair use.

⁴⁵ See Benjamin L.W. Sobel, *Artificial Intelligence’s Fair Use Crisis*, 41 COLUM. J.L. & ARTS 45, 48 (2017) (These “training data” often comprise thousands of unauthorized copies of copyrighted works, which are reduplicated and modified countless more times throughout the training process.”); *id.* at 62 (“Once an input dataset has been compiled, it may be copied, emulated, and re-copied thousands of times during the learning process.”); U.S. PAT. & TRADEMARK OFF., PUBLIC VIEWS ON ARTIFICIAL INTELLIGENCE AND INTELLECTUAL PROPERTY POLICY (2020) (saying that ML “functions by ingesting copyright works” which results in “mass digitization.”).

Courts do not seem to have an incorrect notion of ML, rather they often have no notion at all. See *Carpenter v. McDonald’s Corp.*, 580 F. Supp. 3d 512, 516 (N.D. Ill. 2022) (describing ML simply as “a form of artificial intelligence.”); *Performance Pricing, Inc. v. Google, Inc.*, No. 2:07cv432, 2009 U.S. Dist. LEXIS 77538, at *5 fn. 3 (E.D. Tex. Aug. 28, 2009) (describing ML as “a type of computational algorithm which is derived by other algorithms.”). *But see* *Ocean Tomo, LLC v. Patentratings, LLC*, 375 F. Supp. 3d 915, 956 (N.D. Ill. 2019) (“At a high level, machine learning tools attempt to discern patterns within data, but with no pre-conceived concepts or requirements as to the structure of these data. Machine learning uses an iterative process, in which the system initially forecasts an outcome based on combinations of input variables. The system then determines the errors of its forecasts, and adjusts accordingly, iterating until these error terms are minimized.”).

For most of history, the idea that receiving or reading a work might implicate a copyright owner's exclusive rights would have seemed absurd.⁴⁶ The exclusive rights granted to the copyright owner only address the means of reproduction and distribution. They do not include the right to read the work, which has been and still is unrestricted.⁴⁷ This is consistent with the overriding purpose of the patent and copyright clause of the U.S. Constitution: "to promote the Progress of Science and useful Arts."⁴⁸ The widespread dissemination of knowledge is the underlying policy purpose for all copyright law.⁴⁹

It is instructive to compare the exclusive audiovisual rights granted to copyright owners under 17 U.S.C. 106(4)-(6). These subsections address the rights of public display, performance, and broadcast. Even though it is receiving the work that drives demand, the

⁴⁶ See Jessica Litman, *The Exclusive Right to Read*, 13 CARDOZO ARTS & ENT. L.J. 29, 34 (1994) ("Ninety years later, the U.S. copyright law is even more technical, inconsistent and difficult to understand; more importantly, it touches everyone and everything....Most of us can no longer spend even an hour without colliding with the copyright law. Reading one's mail or picking up one's telephone messages these days requires many of us to commit acts that the government's Information Infrastructure Task Force now tells us ought to be viewed as unauthorized reproductions or transmissions.")); Jessica Litman, *Readers' Copyright*, 58 J. COPYRIGHT SOC'Y U.S.A. 325 (2010) ("Copyright gives no exclusive rights to control private performance or display.⁸⁰ What you do with a book, movie, or sound recording in your living room is not copyright infringement, even if your copy is pirated. Private performance and display is simply off limits. (That isn't because copyright owners didn't ask for private performance and display rights - they did. But nobody took those demands seriously, I think, because at some level everyone understood that the freedom to read and enjoy material without the copyright police looking over your shoulder is an interest that copyright law has respected and should protect.").

⁴⁷ Jessica Litman, *Lawful Personal Use*, 85 TEX. L. REV. 1871, 1882 (2007) ("copyright . . . left reading, listening, and viewing unconstrained.").

⁴⁸ U.S. CONST., Art. I, § 8, cl. 8.

⁴⁹ *Twentieth Century Music Corp. v. Aiken*, 422 U.S. 151, 156 (1975) ("Creative work is to be encouraged and rewarded, but private motivation must ultimately serve the cause of promoting broad public availability of literature, music, and the other arts.... 'The sole interest of the United States and the primary object in conferring the monopoly,' this Court has said, 'lie in the general benefits derived by the public from the labors of authors.'"); *Cambridge Univ. Press v. Patton*, 769 F.3d 1232, 1237 (11th Cir. 2014) ("These boundaries must be drawn carefully in order to assure that copyright law serves its intended purpose, which is to promote the creation of new works for the public good by providing authors and other creators with an economic incentive to create.").

exclusive rights granted under the law are focused on the making available of the work, not its reception.

It is only with the advent of computers that reading has been brought within the ambit of copyright owners' control due to the fact that at least one transient copy (sometimes referred to as a "RAM copy") is technically required for any user to perceive or use a work on a computer.

A few widely-criticized decisions, mostly in the Ninth Circuit, have found that the RAM copy is enough to support a charge of copyright infringement.⁵⁰ In contrast, most scholars and courts have found that there is a fair use right to receive and "read" a work, even if that reading necessarily involves creating a copy.⁵¹

⁵⁰ *MAI Sys. Corp. v. Peak Comput., Inc.*, 991 F.2d 511, 519 (9th Cir. 1993) ("However, since we find that the copy created in the RAM can be 'perceived, reproduced, or otherwise communicated,' we hold that the loading of software into the RAM creates a copy under the Copyright Act."); *MDY Indus., LLC v. Blizzard Entm't, Inc.*, 629 F.3d 928, 938 (9th Cir. 2010) ("The parties agree that when playing WoW, a player's computer creates a copy of the game's software in the computer's random access memory ("RAM"), a form of temporary memory used by computers to run software programs. This copy potentially infringes unless the player (1) is a licensee whose use of the software is within the scope of the license or (2) owns the copy of the software."); *see also* *Vault Corp. v. Quaid Software Ltd.*, 847 F.2d 255, 260 (5th Cir. 1988) ("the act of loading a program from a medium of storage into a computer's memory creates a copy of the program."). As for criticism *see* 2 Nimmer on Copyright § 8.08 ("However, it is submitted above that *MAI v. Peak* itself wrongly concluded in favor of liability.").

⁵¹ At one point courts considered RAM copies to be copyright infringement but they now view it as an "implied license" when "the copyright holder knows of the use and encourages it." *Field v. Google*, 412 F. Supp. 2d 1106, 1116 (D. Nev. 2006). The purpose of publishing content on the Internet is for people to view it, and no one can view it unless their computer makes a copy. *Ticketmaster L.L.C. v. RMG Techs., Inc.*, 507 F. Supp. 2d 1096, 1105 (C.D. Cal. 2007) ("[C]opies of webpages [are] stored automatically in a computer's cache or random access memory ("RAM") upon a viewing of the webpage."). Copyright owners expect and want these copies to be made. *Field* 412 F. Supp. 2d at 1114. The leading case on this is *Sony Corp. of America v. Universal City Studios, Inc.*, 464 U.S. 417 (1984). *See also* *Fox Broad. Co. v. Dish Network L.L.C.*, 747 F.3d 1060 (9th Cir. 2013); *Recording Indus. Ass'n of Am. v. Diamond Multimedia Sys., Inc.*, 180 F.3d 1072 (9th Cir. 1999).

See James Grimmelman, *Copyright for Literate Robots*, 101 IOWA L. REV. 657, 659 (2016) (quoting Jessica Litman, *Lawful Personal Use*, 85 TEX. L. REV. 1871, 1882 (2007)) ("In a world of books and other pre-digital technologies, 'copyright . . . left reading, listening, and viewing unconstrained.'"); Jessica Litman, *Lawful Personal Use*, 85 TEX. L. REV. 1871, 1897–903 (2007) (listing many examples of day-to-

*Sony Corp. of Am. v. Universal City Studios, Inc.*⁵² is instructive. The case centered around Sony's Betamax video cassette recorder (VCR), which allowed users to record television programs for later viewing, a practice known as "time-shifting." Universal City Studios, along with other movie studios, sued Sony, arguing that the VCR facilitated copyright infringement by enabling users to record copyrighted television programs without authorization. The plaintiffs sought monetary damages and an injunction to stop the production and sale of Betamax VCRs.

The Supreme Court, in a 5-4 decision, ruled in favor of Sony, stating that noncommercial home use of the VCR to record television programs for later viewing is fair use. Although time-shifting required making a copy of a copyrighted work, it was non-infringing because the purpose was to allow the users to receive the work at the time of their choosing—not distribution, publishing or performance.⁵³

This fair use "right to read" is illustrated by the use of a web browser to read online materials. Just by opening a webpage, people request copyrighted works from the owners

day private copying that violate the strict language of the copyright statute, yet are protected as fair use); Aaron Perzanowski & Jason Schultz, *Copyright Exhaustion and the Personal Use Dilemma*, 96 MINN. L. REV. 2067, 2086–2092 (2012) (defending personal uses as fair use, including the right to read); C. Edwin Baker, *First Amendment Limits on Copyright*, 55 VAND. L. REV. 891, 904 (2002) ("The expressive liberty protected by the First Amendment encompasses copying as a way of receiving or preserving personal access"); Jed Rubenfeld, *The Freedom of Imagination: Copyright's Constitutionality*, 112 YALE L.J. 1, 38 (2002) ("Because it protects the freedom of imagination, the First Amendment directly protects not only speakers, but readers, viewers, and *listeners* as well.") (emphasis added); Diane Leenheer Zimmerman, *Is There a Right to Have Something to Say? One View of the Public Domain*, 73 FORDHAM L. REV. 297, 326 (2004) ("Speech requires... some ability to acquire such content and certainly the privilege of using it.").

⁵² *Sony Corp. of Am. v. Universal City Studios, Inc.*, 464 U.S. 417 (1984).

⁵³ *Id.* at 449 ("time-shifting merely enables a viewer to see such a work which he had been invited to witness in its entirety free of charge, the fact that the entire work is reproduced, does not have its ordinary effect of militating against a finding of fair use."). The defendants in *Sony* brought substantial evidence that the copyright holders wanted users to make copies, if necessary to view their works. *Id.* at 445 (Fred Rogers, copyright holder of *Mister Rogers' neighborhood* testified that "he had absolutely no objection to home taping for noncommercial use and expressed the opinion that it is a real service to families to be able to record children's programs and to show them at appropriate times.").

and make a RAM copy on their computer in order to perceive the work. This happens millions of times every day. It has never been questioned whether ordinary web browsing is fair use. Any attempt to sue end users for making an incidental, necessary copy of a work, freely provided by the owner in response to a web request, would be quickly and easily disposed of as non-infringing.

Courts have noted and emphasized that this type of copying is fair use. “[M]erely by accessing a webpage, an Internet user acquires the ability to make a copy of that webpage.”⁵⁴ Like software, “copies of webpages [are] stored automatically in a computer’s cache or random access memory (“RAM”) upon a viewing of the webpage.”⁵⁵ Yet this copying is non-infringing, because, there is an “implied license” to make copies when “the copyright holder knows of the use and encourages it.”⁵⁶

The use of copyrighted materials as input to an ML model is exactly the same as the use of copyrighted materials as input to a web browser. Both recipients receive a copy of the work and view it by loading it into memory so that it can be processed by the computer. The only difference is that in the web browser, it is a human doing the viewing and in ML training, it is the machine that “views” the data.⁵⁷

ML Model Training is Limited to Making Measurements and Recording Facts

⁵⁴Getaped.com, Inc. v. Cangemi, 188 F. Supp. 2d 398, 402 (S.D.N.Y. 2002).

⁵⁵Costar Realty Info., Inc. v. Field, 737 F. Supp. 2d 496, 507 (S.D. Md. 2010).

⁵⁶Field v. Google, 412 F. Supp. 2d at 1115 (D. Nev. 2006); *see also id.* at 1114 (“Field knew that if he used the “no-archive” meta-tag on the pages of his site, Google would not provide “Cached” links for the pages containing his works. Field consciously chose not to use the “no-archive” meta-tag on his Website....When the pages containing Field’s copyright works were displayed in Google’s search results, they were automatically displayed with “Cached” links, as Field intended they would be.”).

⁵⁷To the extent that reading for personal edification is different than a machine “reading” for the purpose of generating a statistical model, courts have almost uniformly found that machine “reading” is fair use. *See generally* James Grimmelman, *Copyright for Literate Robots*, 101 Iowa L. Rev. 657, 659 (2016).

Also relevant to the first fair use factor is that ML training is limited to making measurements and recording facts. Because the outputs of ML applications *seem* so expressive, people mistakenly assume that ML applications copy creative expression from inputs and use the copied expression to generate derivative outputs.⁵⁸

Rather than copying any expression, however, the model training process records facts about the work. Think of the analogy of the art inspector taking every measurement possible—brushstrokes per square inch, correlations between colors six inches apart, and the number of syllables in the artist’s name. Facts *about* a work cannot be copyrighted and are not part of the expressive content of a work.⁵⁹

This distinction between factual and expressive content was made clear by *Feist Publications, Inc. v. Rural Telephone Service Co.*⁶⁰ In *Feist*, Rural Telephone Service Co. (Rural) created a telephone directory that included listings for its customers, while Feist Publications, Inc. (Feist) was a company that specialized in producing area-wide telephone directories. Feist used Rural’s listings without permission in its own directory, resulting in Rural suing Feist for copyright infringement.

⁵⁸ In *Doe v. GitHub Inc.*, the plaintiffs accuse the defendants of “distributing” the input code “to Copilot users as if it were created by Copilot.” No. 3:22-cv-06823, at *6 (N.D. Cal. filed Nov. 3, 2022). Although the plaintiff’s admitted that “Codex and Copilot do not retain copies of the materials they are trained on,” they argue that “[i]n practice, however, the Output is often a near-identical reproduction of code from the training data.” *Id.* at *15. Likewise, in *Anderson v. Stability AI LTD.*, the plaintiffs argue that “[t]hese ‘new’ images are based entirely on the Training Images and are derivative works of the particular images Stable Diffusion draws from when assembling a given output.” No. 3:23-cv-00201, at *3 (N.D. Cal. filed Jan. 13, 2023). This leads them to conclude that the AI tool “is merely a complex collage tool.” *Id.*

⁵⁹ “[C]opyright’s idea/expression dichotomy strikes a definitional balance between the First Amendment and the Copyright Act by permitting free communication of facts while still protecting an author’s expression. No author may copyright his ideas or the facts he narrates.” *Harper & Row, Publs. v. Nation Enters.*, 471 U.S. 539, 556 (1985) (internal citations omitted).

⁶⁰ 499 U.S. 340 (1991).

The key issue in the case was whether Rural's telephone directory was eligible for copyright protection. The Supreme Court held that the directory was not protected by copyright because it lacked the necessary originality and creativity. The *Feist* court emphasized that facts, such as names, addresses, and phone numbers, are not copyrightable because they are discovered rather than created, and thus do not meet the originality requirement. The court noted that *compilations* of facts may be copyrightable, but only those compilations that show sufficient human creativity.

Though similar to the phone books in *Feist*, ML training is even further from infringement in that the factual content recorded in the model is generated by the training process. In *Feist*, the factual content was directly copied from Rural's phone book. But in ML training, the statistical probabilities associated with each input are not part of the work at all. They are generated in response to the "predict" and "adjust" phases of the training process. This would be like if *Feist* recorded measurements such as the number of businesses associated with each letter, the correlation of phone numbers with names, and other similar facts, and then published those facts without publishing any part of the phone book itself. If the court was unwilling to find that straightforward facts violated copyright, then the argument for abstract and newly generated facts like the facts recorded in ML models is even stronger. Ultimately, whether abstract or straightforward, the rule remains that facts are not copyrightable.

Even viewing the model as a whole, the statistical measurements within a model are not selected due to any human creativity or judgment. It is the computer process that identifies correlations and records the facts. Moreover, humans are currently unable to even

understand the connection between any particular weight in the model and any fact observed during training.

One case that moves towards addressing “abstract facts”, is *New York Mercantile Exchange, Inc. v. IntercontinentalExchange, Inc* which focused on the issue of copyright protection for market settlement prices.⁶¹

New York Mercantile Exchange, Inc. (NYMEX) sued IntercontinentalExchange, Inc. (ICE), claiming that ICE had infringed on NYMEX's copyrights by republishing its market settlement prices without authorization. NYMEX argued that the settlement prices were original and creative works deserving of copyright protection.

The Second Circuit disagreed with NYMEX's argument. The court held that the settlement prices were not copyrightable because they were factual information and not original expressions. The court reasoned that the prices were determined by an objective process involving the exchange of bids and offers and thus did not possess the requisite level of creativity and originality required for copyright protection. Like the measurements taken as part of the ML training process, the bid and offer prices in *New York Mercantile* were independent facts, albeit difficult to extract, available for anyone to use.

As the *Feist* court noted:

[F]acts do not owe their origin to an act of authorship. The distinction is one between creation and discovery: The first person to find and report a particular fact has not created the fact; he or she has merely discovered its existence. To borrow from Burrow-Giles, one who discovers a fact is not its "maker" or "originator." The discoverer merely finds and

⁶¹ 497 F.3d 109 (2d Cir. 2007).

records. Census takers, for example, do not "create" the population figures that emerge from their efforts; in a sense, they copy these figures from the world around them.⁶²

Just like the census taker in the example given by the Supreme Court, the ML model records only facts in the form of statistical probabilities. These facts are available for anyone, or any process, to copy and use. And just as there is no copyrightable expression in a mechanistic set of measurements about a work, there is no expression copied *from* the work to make such a set of facts.

The Use in ML Training is a Research Purpose

The third consideration relevant to the character and use of the work is the special deference given to research purposes by the Copyright Act.⁶³ This consideration acknowledges the importance of promoting the progress of knowledge and fostering innovation, which are both key objectives of copyright law. When copyrighted material is used for research purposes, courts are more likely to find that it is fair use, as it supports the advancement of knowledge and serves the greater public good.

The facts developed and recorded in the model through the ML training process are a type of research output. Not only are the models a research topic in the computer science context, but the statistical insights encoded in ML models themselves have produced new

⁶² Feist Publ'ns, Inc. v. Rural Tel. Serv. Co., 499 U.S. 340, 347 (1991) (internal citations omitted).

⁶³ 117 U.S.C. §107 ("reproduction in copies...for purposes such as...teaching (including multiple copies for classroom use), scholarship, or research, is not an infringement of copyright.").

insights into domains like linguistics⁶⁴ and art history⁶⁵ Scientists writing in the journal *Nature* said:

AI can act as an instrument revealing properties of a physical system that are otherwise difficult or even impossible to probe. Humans then lift these insights to scientific understanding. Second, AI can act as a source of inspiration for new concepts and ideas that are subsequently understood and generalized by human scientists. Third, AI acts as an agent of understanding. AI reaches new scientific insight and — importantly — can transfer it to human researchers.⁶⁶

First Factor Arguments Against Fair Use

Some considerations under the first fair use factor weigh against a finding of fair use. The first is the commercial nature of much ML training activity. As described in the copyright statute, the purpose and character of the use includes “whether such use is of a commercial nature or is for nonprofit educational purposes.”⁶⁷ There is substantial legitimate academic and nonprofit activity that includes making ML models and generating

⁶⁴ Steven Piantadosi, *Modern language models refute Chomsky’s approach to language*, LINGBUZZ (Mar. 2023) <https://lingbuzz.net/lingbuzz/007180> (“Modern machine learning has subverted and bypassed the entire theoretical framework of Chomsky’s approach, including its core claims to particular insights, principles, structures, and processes. I describe the sense in which modern language models implement genuine theories of language, including representations of syntactic and semantic structure.”).

⁶⁵ Will Fenstermaker, *How Artificial Intelligence Sees Art History*, MET (Feb. 4, 2019), <https://www.metmuseum.org/perspectives/articles/2019/2/artificial-intelligence-machine-learning-art-authorship> (“Machine learning, he said, makes it possible to begin visualizing the diversity and complexity of artistic creation. . . . But by harnessing artificial intelligence, it’s possible to envision artworks that may have existed, based on our knowledge of artworks that we know to exist, and in that way gain a fuller, more complete understanding of visual culture.”); Ahmed Elgammal, *The Shape of Art History in the Eyes of the Machine*, 32 Thirty-Second AAAI Conf. A.I. 2183, 2183 (2018) (“[T]he machine can learn an internal representation encoding discriminative features through its visual analysis . . . he learned representations also consistently highlighted certain artists as the extreme distinctive representative of their styles, which quantitatively confirms art historian observations.”).

⁶⁶ Mario Krenn et al., *On scientific understanding with artificial intelligence*, 4 NATURE REV. PHYSICS 761, 761 (2022).

⁶⁷ 17 U.S.C. § 107(1).

content using them,⁶⁸ but in this hypothetical there is a clear commercial incentive for the ML activity.

As expressed by the Supreme Court in *Andy Warhol Foundation for the Visual Arts, Inc. v. Goldsmith et al.*, (“*Warhol*”)⁶⁹ “the first fair use factor instead focuses on whether an allegedly infringing use has a further purpose or different character, which is a matter of degree, and the degree of difference must be weighed against other considerations, like commercialism.”⁷⁰

In *Warhol*, Goldsmith took a photograph of Prince in 1981 and Warhol created a series of silkscreen prints of the photograph in 1984.⁷¹ The prints were part of Warhol's "Prince Series," which consisted of 40 portraits of Prince. Goldsmith argued that Warhol's prints infringed her copyright in the original photograph. She argued that the prints were "substantially similar" to the original photograph and as such were derivative of the original work.⁷²

The Andy Warhol Foundation argued that the prints were protected by fair use. The foundation argued that the prints were transformative because they had a different

⁶⁸ See, e.g. the machine learning category of arxiv.org, a repository of scholarly papers dealing with machine learning, at <https://arxiv.org/list/cs.LG/recent>.

⁶⁹ *Andy Warhol Foundation for the Visual Arts, Inc. v. Goldsmith et al.*, ___ U.S. ___, ___ S. Ct. ___ (2023), slip. op. available at https://www.supremecourt.gov/opinions/22pdf/21-869_87ad.pdf.

⁷⁰ *Id.* at 12, citing *Campbell v. Acuff-Rose Music, Inc.*, 510 U. S. 569, 579 (1994). But see *Google LLC v. Oracle Am., Inc.*, 141 S. Ct. 1183 (2021) (“There is no doubt that a finding that copying was not commercial in nature tips the scales in favor of fair use. But the inverse is not necessarily true, as many common fair uses are indisputably commercial. For instance, the text of §107 includes examples like “news reporting,” which is often done for commercial profit. So even though Google’s use was a commercial endeavor—a fact no party disputed, see 886 F. 3d, at 1197—that is not dispositive of the first factor....”)

⁷¹ *Warhol*, slip. op. at 3-4.

⁷² *Id.*, at 8-9, 11.

“meaning and message” than Goldsmith’s original photo and were used for a different purpose, and as such did not harm Goldsmith’s market for the original photograph.⁷³

The Supreme Court granted *certiorari* on the single issue of whether the first fair use factor weighed in favor of fair use in the specific circumstance of the Andy Warhol Foundation’s licensing of “Orange Prince” to Condé Nast for use in a magazine.⁷⁴ The *Warhol* court then found that AWF’s licensing of Orange Prince was not justified by the first fair use factor.⁷⁵

In general, commercial use of a derivative work makes a finding of fair use less likely. However, the distinctions between the works at issue in *Warhol* and how ML models are trained tends to reduce the significance of the commercial nature of some ML model building. As expressed by the *Warhol* court, “[t]he fair use provision, and the first factor in particular, requires an analysis of the specific “use” of a copyrighted work.”⁷⁶ The court found that only “AWF’s commercial licensing of Orange Prince” was unjustified, and in particular that the Court “expresses no opinion as to the *creation*... of the Prince Series works.”⁷⁷

In contrast, the differences between ML models and the works they are trained on are so stark that there is no reasonable comparison between them. The *Warhol* court found that both Orange Prince and Goldsmith’s original photograph were licensed for magazine covers, showing that the two works were substitutes in that market. However, an ML model

⁷³ *Id.* at 9-10.

⁷⁴ *Id.* at 11-12.

⁷⁵ *Id.* at 2.

⁷⁶ *Id.* at 20.

⁷⁷ *Id.* at 21 (emphasis added).

is not viewable or intelligible in the same way as the works used to train the model. For example, Goldsmith's photo could be an input to an ML training procedure, but the ML model trained in part on Goldsmith's photo could not be licensed to replace the original photo in any circumstance. It is conceivable that an image later generated using the model could possibly be infringing, but the model itself is distinct.

The First Fair Use Factor Weighs Heavily in Favor of Fair Use

For any (and all) of the reasons listed above, the use of copyrighted works for ML training leans heavily—almost decisively—in favor of fair use.

In the recent case *Google LLC v. Oracle America, Inc.*,⁷⁸ the Supreme Court highlighted the importance of transformativeness. In *Google v. Oracle*, Google exactly copied portions of Oracle's copyrighted source code. The copied source code had the same meaning and message. But the Supreme Court found that Google's use was transformative because of the way in which it drove the creation of new, independent works. "To the extent that Google used parts of the Sun Java API to create a new platform that could be readily used by programmers, its use was consistent with that creative 'progress' that is the basic constitutional objective of copyright itself."⁷⁹

Generative ML models are *much more* transformative than the copied source code at issue in *Google v. Oracle*. It is much more transformative than search indexes at issue in the *Authors Guild* cases, or any of the other cases that found fair use. People can and do use generative ML models to facilitate the almost unlimited generation of *new* works.

⁷⁸ *Id.*

⁷⁹ *Id.*

Generative ML models make artistic creation accessible to a broad portion of the population—and it is evident that new works are being created every hour of every day. This fulfills the “basic constitutional purpose” of copyright to an unprecedented degree.

The Nature of the Copyrighted Work

The second fair use factor is the nature of the copyrighted work. This factor does not influence the fair use analysis either way. None of the types of works that could be used for training receive any special favor or analysis. To the ML application, the exact type of content used for training is irrelevant; the model only sees a series of numbers. All types of works are treated equivalently. Thus this factor does not bear any weight in the analysis. This is especially true when, as here, the creative work is used for a transformative purpose.⁸⁰

The Amount or Substantiality of the Portion Used

The third factor in the fair use analysis is whether the amount of copying exceeded what was necessary and if it was excessive. There are no strict rules on how much of a copyrighted work can be copied while still being considered fair use.⁸¹ The permissible extent of copying depends on the purpose and character of the use. Excessive copying is copying anything "more" than what is reasonably “necessary.”⁸² In some cases, copying

⁸⁰ *Cariou v. Prince*, 714 F.3d 694, 710 (2d Cir. 2013) (quoting *Bill Graham Archives v. Dorling Kindersley Ltd.*, 448 F.3d 605, 612 (2d Cir. 2006)).

⁸¹ *Maxtone-Graham v. Burtchell*, 803 F.2d 1253, 1263 (2d Cir. 1986). “[T]he extent of permissible copying varies with the purpose and character of the use.” *Campbell*, 510 U.S. at 586-87. “The crux of the inquiry is whether “no more was taken than necessary.” *Id.* at 589.

⁸² *See Harper & Row v. Nation Enterprises*, 471 U.S. 539, (1985).

the entire work might be necessary, and in such instances, this factor doesn't weigh against a finding of fair use.

In the case of ML models, the purpose is to get as wide an exposure to different types of inputs as possible. Further, it isn't reasonable to view (or train on) just *part* of a picture or *part* of an article. The situation is similar to *Authors Guild, Inc. v. Hathitrust*. Just as it was reasonable in *Hathitrust* to read entire books to create a full-text index, using entire works is a reasonable way to train an ML model.⁸³ Since using the entire works is reasonably necessary to enable ML model training, the copying is not excessive. Accordingly, the third fair use factor does not incline the fair use analysis either way.

The Effect on the Market

The last factor in the fair use analysis is how the use affects the market for the original work. As with the first fair use factor, this factor weighs heavily in favor of fair use.

The fourth fair use factor properly addresses possible markets—but it does not include *all* the hypothetical markets that copyright holders could pursue. Those markets may exist, but the possible “market harm” is the extent to which the result of the copying serves as a substitute for the original work.⁸⁴ As stated by the Supreme Court in *Campbell v. Acuff-Rose Music*: “[T]he only harm to derivatives that need concern us, as discussed

⁸³ *Authors Guild v. Hathitrust* at 210.

⁸⁴ “Even when an entire copyrighted work was recorded, the District Court regarded the copying as fair use because there is no accompanying reduction in the market for plaintiff’s original work.” *Sony Corp. of Am. v. Universal City Studios, Inc.*, 464 U.S. 417, 425-26, 104 S. Ct. 774, 780 (1984); Fair use depends on “the likelihood that the parody may serve as a market substitute for the original”, *Campbell v. Acuff-Rose Music, Inc.*, 510 U.S. 569, 586, 114 S. Ct. 1164, 1175 (1994).

above, is the harm of market substitution.”⁸⁵ Taking the example of the *Warhol* court, both the Goldsmith photograph and the Warhol print were licensed for the same purpose—use in a magazine. Other possible uses, like display of the Prince Series in a museum, were not examined.

Trained ML models and ML applications are wholly different types of goods than the inputs that they trained on. There is no possible market substitution between the ML model and any particular input it is trained on. The ML model is useless as an artwork, song, poem, or as any other type of creative work. As described above, anyone looking at an ML model would only see a “gigantic matrix of numbers” inscrutable to any process but the ML application itself.⁸⁶

Even if a separate recognizable market for training ML models develops, it is hard to argue that training an ML model would have a significant effect on the market for any one particular work used in the model training. What matters in ML model training is volume. Models are trained on millions of works. The contribution of each individual work to the model weights is so small as to be nearly imperceptible, if it can be measured at all.

Using Copyrighted Works to Train an ML Model is Fair Use

From the analysis above, it becomes clear that ML training is “quintessential” fair use. When ML model training is examined with the correct factual background, the strength of its legality surpasses that of even the most obvious and well-known cases.

⁸⁵ *Campbell v. Acuff-Rose Music, Inc.*, 510 U.S. 569, 593, 114 S. Ct. 1164, 1178 (1994).

⁸⁶ *Supra*, “Defining the Model.” Also see . LeCun, “My take on Ali Rahimi’s “Test of Time” award talk at NIPS,” 2017, available at https://www2.isye.gatech.edu/~tzhao80/Yann_Response.pdf (“The engineering artifacts have almost always preceded the theoretical understanding”).

There is no need to posit a special exception for “fair learning”⁸⁷ to address ML model training. Existing case law convincingly makes the case that ML model training is fair use.

It is undisputed that copyrighted works are necessary for many types of ML training. But as stated by the *Feist* court, “[t]he primary objective of copyright is not to reward the labor of authors, but to promote the Progress of Science and useful Arts. To this end, copyright assures authors the right to their original expression, but encourages others to build freely upon the ideas and information conveyed by a work.”⁸⁸ This is what ML models enable people to do.

This analysis has been presented in the context of a hypothetical lawsuit against a generative image service using the Stable Diffusion model. The specifics of the German training location are tied to this hypothetical. All the analysis regarding fair use, however, has been agnostic to the type of input used to train the ML model. This is because ML models can’t see or appreciate the expression that is central to copyright. ML models are the classic “literate robot”⁸⁹—an automated process that courts have found to be fair use because the copyright-protected expression is never exposed to a human viewer.

3. Providing a Generative Service Using Machine Learning Models is Fair Use

The lawsuits against ML applications have targeted the training process as part of the complaint due to the copying that occurs as part of the training process.⁹⁰ But it is

⁸⁷ See, e.g., Lemley, Mark A. and Casey, Bryan, *Fair Learning*, 99 TEX. L. REV. 4 (2020).

⁸⁸ *Feist Publ'ns Inc.*, 499 U.S. at 349-50 (internal quotation marks and citations omitted).

⁸⁹ James Grimmelman, *Copyright for Literate Robots*, 101 IOWA L. REV. 657 (2016).

⁹⁰ “Stability scraped, and thereby copied over five billion images from websites as the Training Images used as training data for Stable Diffusion.” *Anderson v. Stability*, No. 3:23-cv-00201 (N.D. Cal. filed Jan.

typically not the *inputs* to ML models that are the real source of disputes, but the generative *outputs* that are the most concerning to artists and authors.⁹¹ The analysis of the generative aspects primarily revolves around two questions: first, if the output of the ML application is a reproduction or derivative work of one or more of the inputs, and second, if the output of the ML application implicates a copyright interest in one or more works used as inputs, then is providing the ML application itself inducing infringement.

Generating Content Using an ML Application

The threshold question for any copyright infringement is whether a particular copyrighted work has been copied. Looking specifically at the Stable Diffusion-based application from the hypothetical, there are two scenarios in which it is possible to generate works that would clearly infringe a particular copyrighted work.

Direct Reproduction of Inputs

The first scenario was discussed in the context of overtraining and memorization above.⁹² A group of AI researchers from Google, DeepMind, UC Berkeley, Princeton, and

13, 2023) at *15; “Stability AI has copied more than 12 million photographs from Getty Images’ collection, along with the associated captions and metadata, without permission from or compensation to Getty Images, as part of its efforts to build a competing business.” *Getty Images, Inc. v. Stability AI, Inc.*, No. 1:23-cv-00135-UNA (D. Del. filed Feb. 3, 2023) at *1.

⁹¹ “These resulting derived images compete in the marketplace with the original images. Until now, when a purchaser seeks a new image “in the style” of a given artist, they must pay to commission or license an original image from that artist.” *Anderson v. Stability* at *1; “Stability AI now competes directly with Getty Images by marketing Stable Diffusion and its DreamStudio interface to those seeking creative imagery....” *Getty Images, v. Stability AI* at *3; *see generally Artists decry use of AI-generated art*, THE INDEPENDENT (Dec. 10, 2022), available at “<https://www.independent.co.uk/news/world/americas/ai-art-lensa-magic-avatar-b2242891.html>.”

⁹² *Supra* at “Overtraining and Memorization.”

ETH Zurich developed a process by which they could extract almost visually identical copies of one hundred nine of the inputs used in the Stable Diffusion dataset.⁹³

It is instructive, however, to understand the process used by the researchers to extract these matches. For the images extracted from Stable Diffusion, the researchers had preexisting knowledge of exactly how the ML model was trained. They selected the 350,000 most duplicated images in the dataset—i.e., the images most likely to suffer from overtraining—and the exact terms associated with those images in the model.⁹⁴ With this inside knowledge, they prompted the generation of five hundred images for each of the 350,000 target images using exactly matching terms—175 million total generated images.⁹⁵ Each of these 175 million images was inspected by an automated process for similarity to the target image.⁹⁶ The result was the production of one hundred nine successfully visually similar images-- an extremely minor occurrence, about three percent.⁹⁷ Not only that, but to even retrieve, or “discover” that this replication occurred, required immense effort and searching. With some understatement, the researchers commented that successfully extracting duplicated images from Stable Diffusion was “computationally expensive.”⁹⁸

⁹³ Nicholas Carlini, et al., *Extracting Training Data from Diffusion Models*, arxiv.org, (2023) (The researchers were also able to force a different application using a much smaller dataset (60,000 images) to regenerate about 1250 of its inputs by retrying the process a million times and comparing every generated image to every input).

⁹⁴ *Id.* at 5.

⁹⁵ *Id.*

⁹⁶ *Id.* at 4.

⁹⁷ Keep in mind that this was done using a dataset of the most duplicated images. If the process were repeated with the other images used by the model, we would expect the number to be much smaller, perhaps even non-existent. Again, scenarios where duplication becomes a possibility, known as “overtraining,” are avoided by ML designers.

⁹⁸ *Id.* at 5.

One reason why it was so difficult to find duplicated images is because the “duplicates” were not identical to the inputs. Though very similar, the duplicates were “degraded”, meaning they had noise or trivial differences distinguishing them from the inputs.

Thus, while direct reproduction of inputs due to memorization is possible, it is generally rare. Researchers have been able to provoke models to generate outputs similar to inputs,⁹⁹ but direct copying is also unlikely to be the goal of users due to the degraded form of the outputs. If anyone wanted a pristine copy of an image (or any other type of input), they would simply make a copy, rather than use an ML application to generate a poor reproduction.¹⁰⁰

Finally, direct reproduction becomes more unlikely and more difficult as ML models get trained on more inputs, and the training sets are filtered to remove duplicate inputs. The larger and more diverse the training set, the greater the capability and likelihood that a model will generate wholly new works.

⁹⁹ In the case of generative text applications, recent experiments have found that they may be more likely to reproduce portions of their inputs. As with generative image models this is likely the result of inadvertent overtraining due to the duplication of inputs in the training set. See, e.g., Henderson et al., *Foundation Models and Fair Use*, available at <https://deliverypdf.ssrn.com/delivery.php?ID=394013103113027029124025108118071109050063050068079069007115006009071030107023119009034102098026110059062000090125091003002065045007060077040003019098086127108048012022119125003087001010029004085015086093100100085079001026010066006098025065012020&EXT=pdf>. Updated training methods that avoid duplicated would likely make the reproduction of inputs less likely.

¹⁰⁰ Intent doesn’t matter for copyright infringement. However, the likelihood of a course of action is relevant to the fair use analysis.

Character Copyright

The second scenario has to do with copyrighted characters. Recognition of characters as independently copyrightable works emerged in 1930 with the case of *Nichols v. Universal Pictures*.¹⁰¹ In *Nichols*, the Second Circuit Court of Appeals denied protection to the plaintiff's characters because they were not "distinctly delineated" but rather poorly developed. The characters, a Jewish gentleman and the poor Irish Catholic girl he loved, were considered mere 'prototypes.' Judge Hand stated that the less developed a character is, the less copyrightable it becomes.¹⁰² In denying the copyrightability of the poorly-developed characters at issue in *Nichols*, the court left open the possibility that well-delineated characters could be copyrighted separate from any of the works in which they appear. Later courts applying this test found that the character of Tarzan was found to be "sufficiently delineated" and protected by copyright.¹⁰³ Similarly, Superman's character was deemed well-delineated due to its original literary expressions and incidents, thus deserving copyright protection.¹⁰⁴

In the context of images, reproductions of well-known characters in new, independently created situations have been found to infringe a character's copyright. In *Walt Disney Productions v. Air Pirates*,¹⁰⁵ the court examined a series of comic books that depicted famous Disney characters engaging in counter-cultural activities, including

¹⁰¹ 45 F.2d 119 (2d Cir. 1930), cert. denied, 282 U.S. 902 (1931).

¹⁰² *Nichols v. Universal Pictures Corp.*, 45 F.2d 119, 121 (2d Cir. 1930).

¹⁰³ *Burroughs v. Metro-Goldwyn-Mayer, Inc.*, 683 F.2d 610 (2d Cir. 1982).

¹⁰⁴ *Detective Comics, Inc. v. Burns Publications*, 111 F.2d 432; 434 (2d Cir. 1940).

¹⁰⁵ 581 F.2d 751 (9th Cir. 1978).

promiscuity and drug use.¹⁰⁶ These unauthorized comic books parodied and subverted the wholesome image of the Disney characters, which led to the legal dispute over copyright infringement. The court held that the Disney characters were copyrightable, and that the copyright was infringed, based on the grounds that the comic-book characters had distinctive "physical as well as conceptual qualities" that was "likely to contain some unique elements of expression."

Unlike every other type of copyrighted work recognized by the courts, copyrighted characters are not limited to a single expression. As a consequence, people using ML applications can create new works that show well-known, possibly copyrighted characters, in new situations. This is a particular risk for image-generating ML applications, because it seems likely that just as an ML model learns to emulate a van Gogh painting, it might learn to generate a facsimile of a cartoon character like Superman or Iron Man. Even though the model would likely never reproduce an existing image of the character, producing new scenes with "old" characters might be infringing because of the visually distinctive markings that are associated with these types of characters. Because of this possibility, the question now becomes whether providing these technologies would "induce infringement."¹⁰⁷

¹⁰⁶ *Id.* at 753.

¹⁰⁷ For simplicity, this article assumes that an image incorporating a copyrighted character would be infringing. Nevertheless, an image that included a character might still be fair use for other reasons specific to that work.

The Significant Noninfringing Uses of ML Applications

The analysis of whether a product might induce the infringement of another's copyright is driven by whether the product has "significant noninfringing uses" and whether the product is marketed to users as a means to infringe copyright.

The "significant noninfringing uses" doctrine originated from *Sony Corp. v. Universal City Studios* discussed above.¹⁰⁸ In *Sony*, the accused product was Sony's Betamax video cassette recorder (VCR). It was undisputed by both sides in *Sony* that Sony's VCRs were capable of making infringing copies of movies or other material. However, the court found that if a product had substantial noninfringing uses, the manufacturer would not be liable for contributory copyright infringement. In the case of the VCR, making copies for private, non-commercial use was sufficient.¹⁰⁹ The Court reasoned that stifling the distribution of products with legitimate uses would impede technological progress and undermine the goals of copyright law—to promote the progress of science and useful arts.

In *MGM Studios v. Grokster*,¹¹⁰ the Supreme Court clarified the doctrine by introducing the concept of "inducement" to the analysis of secondary liability. The *Grokster* Court held that even if a technology has substantial noninfringing uses, its

¹⁰⁸ 464 U.S. 417 (1984).

¹⁰⁹ "The question is thus whether the Betamax is capable of commercially significant non-infringing uses. In order to resolve that question, we need not explore all the different potential uses of the machine and determine whether or not they would constitute infringement. Rather, we need only consider whether on the basis of the facts as found by the District Court a significant number of them would be non-infringing. "Moreover, in order to resolve this case we need not give precise content to the question of how much use is commercially significant.", *Sony Corp. of Am. v. Universal City Studios, Inc.*, 464 U.S. 417, 442, 104 S. Ct. 774, 789 (1984).

¹¹⁰ 545 U.S. 913 (2005).

distributor may still be liable for copyright infringement if the service actively induces users to infringe copyrights.

In the context of generative ML applications, the primary purpose (and the primary use) is the generation of new works. Compare with copy machines, which have significant noninfringing uses even though they are designed to make it easy to copy things.

In contrast, generative ML is defined by its ability to *generate* new things; it is a poor copyist. While it is possible to generate infringing works using such applications, the overwhelming majority of users generate original art, original text, or original code. This is not just a “significant noninfringing purpose,” it is in furtherance of the purposes of copyright. Assuming marketing consistent with the generative aspect of generative ML, there should be no secondary liability on the part of a party hosting a generative ML service, even if it can possibly be used to create possibly-infringing works.

Generating Works “In the Style of” Particular Artists

One of the most controversial aspects of generative ML models is the ability to create works “in the style of” a known artist.¹¹¹ Prompts that include specific artists’ names can generate works that are strongly reminiscent of that artist’s style. These ML-generated works can and likely do compete with the original artists in the marketplace.¹¹²

¹¹¹ See, e.g., *‘In the style of’: why AI art needs to address named artists as prompts*, BYTESIDE, available at <https://www.byteside.com/2022/09/ai-art-named-artists-monet-picasso-rutkowski/>; *Is A.I. Art Stealing from Artists?*, THE NEW YORKER, available at <https://www.newyorker.com/culture/infinite-scroll/is-ai-art-stealing-from-artists>.

¹¹² See, e.g., “Stability AI Competes Commercially with Getty Images,” *Getty Images, Inc. v. Stability AI, Inc.*, at *15 (D. Del. filed Feb. 3, 2023).

The difficulty for artists is that “style,” standing alone, has not generally been found to be copyrightable.¹¹³ That said, style is not completely divorced from expression. Courts have found that a copied “style” is more likely to indicate that one work was copied from another. For example in *Steinberg v. Columbia Pictures*,¹¹⁴ the court said: “Even at first glance, one can see the striking stylistic relationship between the posters, and since style is one ingredient of ‘expression,’ this relationship is significant.” However, this statement was in the context of both works being substantially similar, meaning that courts only consider style if the works are first substantially similar enough to be considered substitutes. For example, in *Steinberg* the court first noted that “[b]oth illustrations represent a bird's eye view across the edge of Manhattan.... Both depict approximately four city blocks in detail and become increasingly minimalist as the design recedes into the background.”¹¹⁵ After observing this substantial similarity, only then did the court consider style: “Both use the device of a narrow band of blue wash across the top of the poster to represent the sky, and both delineate the horizon with a band of primary red.”¹¹⁶ In other

¹¹³ “[o]f course, the idea of animal styled duffle bags would not be protectible under copyright law.”, *Wildlife Express Corp. v. Carol Wright Sales, Inc.*, 418 F.3d 502, 510 (7th Cir. 1994); “Our decision does not grant license to copyright a musical style or “groove.””, (*Williams v. Gaye*, 895 F.3d 1106, 1138 (9th Cir. 2018)); “[Plaintiff] wants to copyright a style...., and no sensible reading of the 1976 Act permits that step.... [The accused work] Liza does, however, convey an impression similar to Mara's....[By] contending that Liza infringes the Mara copyright, [Plaintiff] demonstrates that its claim embraces an aesthetic style rather than a precise set of features.”, *Pivot Point Int’l v. Charlene Prods., Inc.*, F. Supp. 2d 828 (N.D. Ill. 2001) (decision upheld on remand); *but see Jacobs v. Robitaille*, 406 F. Supp. 1145, (D.N.H. 1976) (holding that copying “style” may result in unfair competition).

¹¹⁴ *Steinberg v. Columbia Pictures Indus.*, 663 F. Supp. 706 (S.D.N.Y. 1987).

¹¹⁵ *Id.* at 712.

¹¹⁶ *Id.* See also *Ford Motor Co. v. B & H Supply, Inc.*, 646 F. Supp. 975 (D. Minn. 1986) (describing the similar “style” as an element in finding two works substantially the same).

words, there must be substantial similarity, not just a similarity in “style,” to find that one work infringes another.

When separated from specific copied elements between two works, the concept of “style” has been found to lie more in the realm of an *idea* than an expression. For example, the court in *Dave Grossman Designs v. Bortin*¹¹⁷ stated:

The law of copyright is clear that only specific expressions of an idea may be copyrighted, that other parties may copy that idea, but that other parties may not copy that specific expression of the idea or portions thereof. For example, Picasso may be entitled to a copyright on his portrait of three women painted in his Cubist motif. Any artist, however, may paint a picture of any subject in the Cubist motif, including a portrait of three women, and not violate Picasso's copyright so long as the second artist does not substantially copy Picasso's specific expression of his idea.¹¹⁸

This distinction matters because from a copyright perspective, the relevant market—fourth fair use factor—is the market for a *particular work*, not for an artist's work *in general*.¹¹⁹ The case law is clear: the copying of an artist's distinctive style in the context of a new image is not an infringement of the artist's copyright in any particular work.¹²⁰ Looking at other types of works, doing things “in the style of” another artist is even more attenuated. There is no copyrightable interest in the written style of a particular author, nor of the general style of a musical artist. There must always be specific copied expression. Thus, ML applications that generate new works “in the style of” a particular artist are not

¹¹⁷ *Dave Grossman Designs, Inc. v. Bortin*, 347 F. Supp. 1150 (N.D. Ill. 1972).

¹¹⁸ *Id.* at 1156.

¹¹⁹ “[W]hen a commercial use amounts to mere duplication of the entirety of an original, it clearly “supersede[s] the objects,” *Folsom v. Marsh*, supra, at 348, of the original and serves as a market replacement for it, making it likely that cognizable market harm to the original will occur.” *Campbell v. Acuff-Rose Music, Inc.*, 510 U.S. 569, 591, 114 S. Ct. 1164, 1177 (1994).

¹²⁰ An artist or author may have causes of action other than copyright, including trademark liability or potential right of publicity claims. However, those are not the focus of this article.

infringing—and to the extent that the result is the generation of new works, images “in the style of” another artist further copyright’s overall purpose.

4. Conclusion

There are many discussions of how ML—especially generative ML—will change society and the law. The effects of machine learning and ML applications are sure to create upheaval. As the applications of machine learning continue to expand and evolve, it is crucial for legal frameworks to adapt and ensure that innovation is not stifled while still maintaining the core objectives of copyright law—promoting the progress of arts and sciences while protecting the rights of creators.

By delving into the fundamentals of machine learning, including the training process and the generation of new works, this analysis drew parallels and distinctions between ML and previously scrutinized technologies in the context of copyright law.... While this article has focused on image-generating ML tools, the analysis applies to all the various types of generative AI. The case law overwhelmingly supports the conclusion that constructing and utilizing generative ML models is allowable under US copyright law.