Diffusing the Creator: Attributing Credit for Generative AI Outputs

Donal Khosrowi
Institut für Philosophie, Leibniz Universität Hannover
donal.khosrowi@philos.uni-hannover.de

Finola Finn
Institut für Philosophie, Leibniz Universität Hannover
finola.finn@philos.uni-hannover.de

Elinor Clark
Institut für Philosophie, Leibniz Universität Hannover
elinor.clark2@gmail.com

ABSTRACT

The recent wave of generative AI (GAI) systems like Stable Diffusion that can produce images from human prompts raises controversial issues about creatorship, originality, creativity and copyright. This paper focuses on creatorship: who creates and should be credited with the outputs made with the help of GAI? Existing views on creatorship are mixed: some insist that GAI systems are mere tools, and human prompters are creators proper; others are more open to acknowledging more significant roles for GAI, but most conceive of creatorship in an all-or-nothing fashion. We develop a novel view, called CCC (collective-centered creation), that improves on these existing positions. On CCC, GAI outputs are created by collectives in the first instance. Claims to creatorship come in degrees and depend on the nature and significance of individual contributions made by the various agents and entities involved, including users, GAI systems, developers, producers of training data and others. Importantly, CCC maintains that GAI systems can sometimes be part of a co-creating collective. We detail how CCC can advance existing debates and resolve controversies around creatorship involving GAI.

CCS CONCEPTS

• **Applied computing** → Arts and humanities; • **Social and professional topics** → Computing / technology policy; • **Computing methodologies** → Artificial intelligence; Computer vision.

KEYWORDS

Generative AI, image synthesis, credit attribution, creatorship, collective-centered, ethics, copyright

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1 INTRODUCTION

The recent proliferation of generative AI systems (GAI) that competently produce text, images and other outputs from human prompts (e.g., Stable Diffusion, DALL-E2, ChatGPT) has attracted considerable attention from the public, media, regulators and academics. Central points of contention range from safety and responsibility in regard to offensive or untruthful outputs to disruptive potentials of GAI for labor markets and education systems [21, 36, 43, 63, 70, 74]. In the space of creative visual production, GAI has been especially controversial, radically 'democratizing' creative production by allowing unskilled users to generate high-quality imagery, and raising questions about creativity, intellectual property, plagiarism, illegitimate scraping of training data, censorship and so on [22, 26, 32, 33, 60]. Two particularly contentious questions stand out. First, the *creativity question*: do GAI systems produce genuinely novel and/or creative outputs? Second, the *creatorship question*: who should be credited with the production of these outputs? Should human prompters receive all the credit, while GAI systems are mere tools, akin to a sophisticated brush? And what about developers who built the systems, or producers of training data?

Unsurprisingly, both questions are difficult to answer and deeply entangled. The creativity question hinges on both facts and values, e.g., facts about the production process and value-judgments about what constitutes a genuinely creative or original achievement. Issues of creativity and originality are inherently controversial and reasonable disagreement will often persist [4, 7, 12, 18, 24, 34, 41, 59, 64, 72]. The creatorship question is similarly challenging, also turning on value-judgments, and requiring that we can trace the origin of specific outputs [4, 19, 20, 27, 37, 38].

Even so, we argue that significant progress on the creatorship question is possible by drawing on a recent view we have developed in a very different space: scientific discovery involving AI [13]. There, we proposed a collective-centered view (CC), which insists that discoveries are made by collectives, and that credit for discovery should be distributed within the collective according to the nature and significance of specific contributions. Importantly, this view permits that AI systems can be part of a discovering collective, making contributions that can be comparable in significance to human contributions.

Here, we develop a sibling to this view, called the CCC (collective-centered creation) view, that applies to GAI. CCC maintains that issues of creatorship are not all-or-nothing: different agents and entities, i.e., GAI systems, human prompters, creators of training data and others, can each make important contributions to an output and attributions of credit hinge on the nature and significance of the contributions made. Detailing CCC, we argue that it is an attractive option for addressing creatorship in a systematic way. It reinforces existing arguments from the public debate, e.g., that scraping imagery from the web to train models without creators'

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consent and acknowledgment is problematic [11, 67, 73]. And it generates novel intuitions: such as whether a human prompter or GAI system has a stronger claim to co-creatorship depends on several features of what role they played in producing an output. For instance, a casual user, Jake, who uses a generic prompt like 'cute cat' may not have strong creatorship claims, but a more involved user like Jo, who pursues a specific aim and iteratively refines her prompts to meet her goals, might. Creatorship, on the CCC view, is hence a matter of degree: you can be more or less of a creator, depending on several finer-grained variables that track what role you played in producing an output.

Despite considerable utility, CCC also has important limitations: it is not a tool to definitively settle creatorship issues and disputes. These will often be irreducibly controversial for the value-judgments they hinge on or because details on how outputs were produced remain inaccessible. Equally, CCC does not seek to resolve practical downstream questions, such as how to award copyright to large collectives or how specific contributions should be rewarded (e.g. through payment). Rather, CCC *informs* attempts to address such issues by providing a general framework that facilitates efforts to clarify creatorship in a systematic way, by offering a rich conceptual machinery that helps structure our reasoning and locate sources of disagreement.

We proceed as follows. *Section 2* introduces GAI systems and surveys the existing debate for prominent views on creatorship. *Section 3* develops CCC, explaining its conceptual resources. *Section 4* draws on toy cases to map out how CCC addresses creatorship questions and shows how it can reinforce existing intuitions as well as articulate new ones. *Section 5* concludes.

2 GAI & CREATORSHIP: THE STATE OF PLAY

2.1 Generative AI

GAI includes a broad array of systems and system architectures, which are unified functionally by their ability to generate potentially novel outputs (e.g., text, images, video, etc.) when given some prompt. Here, we focus only on generative visual AI systems that allow a user to generate images from text, image and other inputs, such as OpenAI's DALL-E2, Stability.ai's Stable Diffusion, Midjourney and related systems. Unlike earlier systems based on generative adversarial networks [28, 53], many recent GAI systems are based on encoder-decoder deep neural network (DNN) architectures and involve diffusion models as decoders [54, 56]. Glossing over further details, we emphasize that most GAI systems now offer various parameters that allow users to steer image synthesis; permit a combination of text and image prompts for conditioning (e.g., image-to-image, inpainting); and allow supplementary tools like ControlNet to afford even finer-grained user control over outputs, e.g., to precisely determine the pose of a person [75]. Given their accessibility, cost-effectiveness and impressive abilities, millions of users now employ GAI on a daily basis to produce tailor-made imagery that caters to their needs [23, 31, 57].

2.2 Existing views on creatorship

On the heels of this growing popularity, the last year has seen a surge of debate amongst users, commentators, academics and technologists about a range of questions relating to creatorship, originality and the ethics of GAI. Some of these questions are familiar, while others are novel responses to unprecedented aspects of GAI. Here, we provide an overview of the most influential views expressed thus far concerning whether GAI systems meet the conditions for creatorship[1] and, if so, how much credit they are due. Often drawing on earlier theories of authorship and creative agency in literature, cinema, photography and so on, a number of proposals have been put forward.

Referring to AI's lack of agency and intentional autonomy, Hertzmann [34] and McCormack et al. [50] assert that these systems are not creative agents and, as such, cannot be credited as creators. A lack of physiological vision and subsequent understanding have also been flagged as precluding machines' ability to create [17]. Some legal scholars have made similar assertions, with Ginsburg et al. [27] and earlier skeptics (see [40] for overview) arguing that machines do not show genuine creativity and therefore do not qualify for copyright, as they only operate within the predetermined limits of programming or user instruction. A recent decision of the Committee on Publication Ethics builds on these stances, asserting that AI cannot be named as an author on their publications due to being non-legal entities that cannot be held accountable [15]. Other legal scholars simply do not present GAIs as a creator or engage seriously with that question [10], presumably because intellectual property law does not allow copyright or patents to be granted to nonhuman entities. Coming from a philosophy of art and aesthetics perspective, Anscomb [4] sees AI as deserving some credit as a contributor but not as an authorial creative agent, due to lack of intention and knowledge-how.

Such views lead some to conclude that AI is merely a tool. Hertzmann, for example, presents AI as yet another tool for art production [34], and OpenAI has also framed DALL-E2 in this light, saying it is a "powerful creative tool" that "extends creativity" [52]. Their blog promotes the responses of artists who describe using DALL-E2 as like "a musician playing an instrument" or taking up "a paint brush" that must be "guided by the artist" [51]. It seems a significant portion of GAI users agree [2, 55], as well as some of the wider public who tend to give more credit to people using AI for assistance than to people who use other people for assistance in creating art [37].

In stark contrast, some claim that GAI can be a creator and heavily downplay human involvement. This view is taken by some developers of GAI systems that, they claim, autonomously create novel art [19, 42] using skill, appreciation and imagination [14]. While this stance is less often applied to the GAI we discuss here, AI systems are increasingly acknowledged as generating "truly creative works" [29, p.173]. Based on this belief, some legal scholars suggest a reworking of the requirements for copyright that would allow the threshold of originality to include some AI-generated works [29, 40].

A third type of view focuses on the notion of collaboration [46], emphasizing that GAI systems are increasingly capable of making unique contributions to the production of visual outputs. Some creatives feel GAI is their "collaborator" [51] and has autonomy,

[1] Some literature we discuss predates current-generation GAI and targets broader issues of *authorship* or defining the *artist*. While there may be subtle conceptual differences between authorship, the role of the artist and creatorship, we assume here that the views we review map onto creatorship, regardless of such differences.

leading to new forms of authorship [47]; a view that is often echoed in the public discourse, such as in social media groups, where many users describe collaborative relationships with GAI [1, 16, 66].

Among the menu of options, collaborative views seem the most plausible, but we also think that they say too little on how credit may be distributed amongst collaborators, with the most direct suggestions made by legal scholars Benhamou and Andrijevic [10], albeit solely with a view to copyright and without consideration of the AI's role. Scholars such as McCormack et al. [50] have agreed that "[a]uthors have a responsibility to accurately represent the process used to generate a work, including the labour of both machines and other people" [50, p.13], and Anscomb asserts that AI might deserve some of the credit for the production of artworks [4]. But how could we go about ascertaining the need for this credit in individual cases, and then apportioning it? As Epstein et al. [20] and Jago and Carroll [37] suggest, people are vulnerable to allocating credit based on questionable criteria, such as anthropomorphicity, so there is a need to understand and communicate different contributors' involvement on conceptually firmer grounds. Inadequate attributions of credit not only raise moral problems (e.g., unjust miscrediting), but also have economic and social consequences, affecting how we value works and who benefits from them [37]. Moreover, credit allocation is important for the public's ability to interpret and understand works [9, 38].

In the spirit of related approaches, such as Jenkins and Lin's proposals for determining credit for AI-generated text [38], the CCC view we develop here maintains that GAI can be part of a co-creating collective, but also provides a richer framework that helps us better understand different agents' and entities' roles within a collective. Let us outline our earlier CC view proposed in the context of scientific discovery, and explain how it can be adapted to GAI.

3 THE CCC VIEW: FROM DISCOVERY TO CREATION

Scientists now routinely use AI systems to make scientific discoveries. A celebrated case is AlphaFold 2.0 [39], an AI system that can predict the structure of never-before-synthesized proteins with impressive accuracy; something that takes significant human efforts in any single case, and could not be achieved at scale without systems like AlphaFold. An important question here is whether these systems are making discoveries, or whether they are merely sophisticated tools, like electron microscopes.

Existing theories of scientific discovery have often been agent-centered [68]: they focus on picking out a central discoverer who is responsible for a discovery. However, in the case of discovery involving AI, these views fail to neatly identify such a discoverer, as neither the AI nor the human scientists have strong enough claims to the title alone. Responding to this challenge, we have proposed the collective-centered view (CC) of scientific discovery [13]. Centrally, CC maintains that discoveries are made by *collectives*: a potentially large and diverse set of actors and entities that all make important contributions to discovery. Depending on various finer-grained variables, CC allows that AI systems, too, can be part of a discovering collective and make significant contributions that should be appropriately recognized.

The creatorship question regarding GAI presents an analogous credit distribution problem. Often, neither the GAI systems, human prompters nor producers of training data alone are neatly identified as *the* creator. But each of these agents and entities, among others, can make important contributions to an output[2]. Here, we adapt our earlier CC view to the creation of visual outputs using GAI to make progress on understanding the role of various agents and entities and, in turn, the issue of creatorship.

On our adapted CCC (collective-centered creation) view, the very starting question 'who is the creator?' is misleading: creation is a collective achievement, and credit distribution depends on the nature and significance of the contributions made. Specifically, CCC maintains that for most cases of creation using visual GAI:

- There is ***no clear single creator*** who can be credited with an output.
- A ***collective of actors and entities*** all made important contributions to an output.
- Credit for this output should be ***distributed between these contributors*** according to the nature and significance of the contributions made.

CCC, of course, is not the first view to emphasize that artistic (and literary) production often takes the format of co-creation or co-production. But contra existing views, CCC does not aim at offering neat, principled categorizations between different subgroups of agents, e.g. authors, creators, contributors, assistants [4, 6, 8, 9, 25, 35, 46, 48]. While we agree that making such distinctions can be sensible (as they help organize, negotiate and appraise contributions to artistic creation in professional and public discourse), we also think that any such categorizations should be grounded in a conceptually richer analysis that tracks important primary features of contributors and their contributions, especially regarding GAI. CCC, then, starts bottom-up, by first analyzing which of these features matter for determining inclusion in a co-creating collective. Pencils and hard drives won't make the cut – not because we say so, but because they don't score highly on relevant criteria. CCC hence provides conceptual machinery that specifies the sorts of considerations we should entertain when seeking to clarify creatorship and locate our disagreements.

Let us elaborate several features that CCC uses to inform who may be included in a co-creating collective and how credit may be distributed. The features we outline here are continuous with existing debates on creatorship [5, 6, 8, 9, 25, 35, 38, 48, 50], and while we do not insist that these features are ultimately the right ones, or only ones, to focus on, we consider them productive starting points for developing a systematic approach to dealing with GAI's growing role in creative production.

3.1 Relevance/(Non-)redundancy and Control

The first two features to help clarify creatorship come as a bundle: relevance and non-redundancy track what difference a contribution makes to an output. They are causal-counterfactual notions: to determine how relevant or (non-)redundant a contribution X is to an output Y, we must answer the counterfactual question: 'take X away, what would the output Y have looked like?' If a contribution

[2] We assume that creatorship questions are pertinent if some significant output has been produced. Importantly, we assume that *whether* an output has significance is settled (largely) independently of the criteria we outline. We also focus only on primary outputs delivered by GAI. Users may further transform these, which can change users' standing as creators for these downstream products.

is not relevant, or relevant but highly redundant, Y will remain the same. For instance, if Jo and Jake produce a painting of a cat on a mat, where Jo does all the painting and Jake's role is to hand Jo the brushes as she requests them, we might think that Jake is not terribly relevant and can be made redundant. Take Jake away, and the output would have been the same, either because Jo gets the brushes herself, or because someone else fills in for Jake. By contrast, consider Jerome, who takes a more active role in suggesting what brush could be the right one to achieve a certain texture. Jo and Jerome engage in a symbiotic relationship, with Jerome asking questions, making suggestions, adding interpretations and so on. Jerome's involvement, let us imagine, makes a difference to the output: the painting would be different if Jerome wasn't there, and it might be difficult to replace Jerome. Jerome hence scores more highly for relevance/non-redundancy. Lastly, consider Jake making a solo attempt to produce an image of a 'cat on a mat' using Stable Diffusion. Take away his access to the system, and Jake would have failed to produce the image, for lack of relevant skills. Generally, the more relevant and non-redundant a contribution, the stronger the claim for candidacy in a co-creating collective.

A second feature that is closely related to relevance and non-redundancy is control [71]. Control tracks how precisely and robustly an agent or entity can steer or maintain an output. Intuitively, control may seem to involve intention, but we render it as a deflationary notion that only requires that an agent or entity has causal powers to make an output be a certain way rather than another. Consider Jo, who iteratively refines her prompts to precisely get the image she wants. Jo exerts a high degree of control and can thus stake a strong claim to creatorship. By contrast, consider again Jake, who casually prompted Stable Diffusion with 'cat on a mat'. Does Jake exhibit control? Not necessarily. Diffusion models begin synthesis from quasi-random noise patterns that are determined by a seed number, which can change from prompt to prompt. Importantly, one and the same prompt can yield dramatically different outputs depending on the seed [62]. So, Jake might have ended up with an entirely different image if the seed had been different. Jake, in this case, doesn't exercise much control if he is happy with whatever output he gets. There is no back-and-forth interaction, like in Jo's iterative endeavour, where Jake works against the randomness of diffusion-based image synthesis to realize a specific result.

Two further points help fine-grain control. First, control can be dispositional in a way that relevance and non-redundancy are not: an individual does not always need to exert actual influence in order to exhibit control, but they must be able to if the need arises. Consider a variation of Jo's case where she is lucky to get the exact image she wants on the first try. We might still maintain that Jo exhibits control if it is true that she would have intervened (successfully) had the output diverged from her expectations. Similarly, we might say that Stable Diffusion exhibits control over an output if it would have robustly produced the same output even if Jake had tried to steer it towards another. Second, control is zero-sum: the less control a user exercises, the more control the GAI has. So, when clarifying control, we ask 1) how counterfactually robust an output's features are, and 2) due to who.

Relevance, redundancy and control are thorny concepts, as they all hinge on (appropriate) counterfactuals. Whether Jake would have been able to produce 'cat on a mat' without Stable Diffusion, for example, might depend on whether we ask for the exact pixel-by-pixel image or just something in the ballpark. But even if we have clear counterfactuals in mind, learning them empirically is also difficult, e.g. telling what Jo's painting would have looked like without Jerome's suggestions or whether Jo would have intervened if the GAI hadn't produced what she wanted right away. These challenges are not unique to CCC, however. They obtain in many areas, e.g. in legal reasoning, where we routinely assess what would have happened if people had acted differently. Difficult as these challenges may be in practice, considering relevance, (non-)redundancy and control is essential for distributing credit for creatorship.

3.2 Originality

Originality concerns how original a contribution is, i.e. whether it is novel in character and unique to the contributor. This is related to but different from the originality and significance of an output, which - as mentioned earlier - is not our focus here. Let us assume some recognizably original output is generated. A key question for clarifying creatorship is: whose *original* contributions helped achieve that output originality? A natural starting point is to look at users' text/image prompts. Suppose that there has never before existed an image of a Donald Trump-shaped cheese wheel rolling down a hill. A user's idea and intent to produce such an image and their formulating a prompt that corresponds to these would constitute an original contribution. By contrast, a generic prompt such as 'cute dog' would not score highly – many others have likely used similar prompts. But prompts are not all that is needed to make an image – a GAI system itself must be disposed in the right way to actually produce images that correspond well to user prompts. Specifically, the DNNs underlying existing GAI systems may make original contributions to the production of original outputs, when, at training, the systems latch onto text-image relationships in original ways, e.g. by learning novel representations and relationships between them that can be used to competently synthesize, for instance, what a Donald Trump-shaped cheese wheel rolling down a hill would look like. Here, a mere collage might not be enough: success is measured by whether the system made original connections that help synthesize a coherent visual entity that recognizably looks like 1) Donald Trump, 2) a cheese wheel and 3) like it is rolling down a hill.

Right away, one might insist that originality still ultimately comes from the user – after all, it was them who prompted the system in a certain, original way. But while coming up with the 'what' may often involve originality on the part of the user, concretizing the 'how' may also require originality on the part of a GAI system. This is best understood in cases where a user is unable to imagine how an image corresponding to their prompt could look. Take Jerome, who prompts Midjourney to produce an image encapsulating 'the abstract feeling of realizing that you didn't tell your parents that you loved them enough'. Here, Jerome might only learn about how this feeling could be visualized once he sees the output. If Jerome thinks it captures the feeling well, and there haven't been previous attempts to visualize the feeling with similar results, it seems like Midjourney, too, has made original contributions to producing the output.

Even so, one might wonder where, exactly, we could locate originality in GAI systems' contributions. For instance, one might insist that the computations performed by GAI systems are 'deterministic' or 'always the same', regardless of whether an output is original. To clarify, we don't claim that there is a mysterious originality property to be found (or not found) anywhere at the computational level. But – like in descriptions of human contributions where the type-level neural activation patterns might be indistinguishable between a truly creative and an unoriginal prompter – some token-level macro behaviors that GAI systems exhibit can nevertheless be usefully characterized by ascriptions of originality (e.g. learning a latent manifold that enables them to produce novel images or following a specific denoising trajectory towards a coherent rendition of an original output). We also do not claim that GAI systems are always or routinely original. GAI systems are prone to reproducing existing works, raising concerns about (near-)plagiarism [45, 69]. So, our suggestion is that, especially in cases where output originality cannot be fully and correctly accounted for by reference to human users, GAI systems may reasonably be described as making original contributions of their own which, in turn, can justify their inclusion in a co-creating collective.

3.3 Time/effort

Other things being equal, the more time and effort an agent or entity spends on furnishing a contribution, the stronger their claim to candidacy in a co-creating collective. Consider Jake again. Even if Jake's brush-handing contributions are not highly relevant and somewhat redundant, if Jo recruited Jake to assist for hundreds of hours, Jake may nevertheless have some claim to candidacy in a co-creating collective. Of course, time and effort are crude metrics. Spent inefficiently, they shouldn't count for much, such as when Jake takes a tedious, pointillist approach to making 'cat on a mat' with his ballpoint pen but the result is aesthetically unimpressive because he can't draw cats, neither with slow points nor with fast strokes. But while contemporary legal theories of creative value often avoid relying on sweat-of-the-brow metrics [29], we think that time and effort should nevertheless be considered as one among a variety of features that can ground claims to candidacy – especially in the realm of GAI usage [65]. In this context, time and effort are best understood as tracking the computational complexity and compute effort (e.g. FLOPs) involved in furnishing a contribution. While GAI systems are certainly faster than humans at producing images once trained, a wider view that puts the computational efforts going into training and inference into perspective can ground the claim that significant time and effort can be involved in furnishing GAI outputs.

3.4 Leadership and Independence

Leadership captures whether a contributor steered the production of an output with a specific intention in mind. For instance, Jo may have a concrete vision for an image, choose a particular method for the job, say Stable Diffusion, and pursue that vision by refining her prompts in a targeted way to realize a specific output. Jake, by contrast, may deploy a generic prompt like 'cat on a mat' and turn out happy with whatever result he gets. While there is intention involved, he does not exert a great deal of leadership. Leadership is closely related to control, i.e. the ability to precisely and robustly steer or maintain an output. Yet, while successful leadership often involves control, it differs from mere control in that it also involves intentions, e.g. identifying, setting and pursuing goals and directing available means to reach them.

Second, independence tracks whether a contributor depends on detailed guidance to furnish their contribution or whether they act in a more autonomous way. Jo and Jerome might be independent in that sense, both coming up with suggestions for what a painting could look like, discussing plans based on what they each think is best. Jake, by contrast, would not make independent contributions if his role is confined to handing Jo the brushes she requests.

While leadership and independence are important, they should not be overemphasized. For instance, leadership roles frequently fall on agents ready to disproportionally absorb credit, such as when a famed director's artistic vision is emphasized as key to achieving a significant work, but other agents' creative contributions that fill important blanks are left underrecognized. Nuancing the role of leadership and independence is especially relevant as GAI systems have a hard time exhibiting these features at levels comparable to humans. For lack of intentions, they cannot exhibit leadership but only control. Likewise, they cannot exhibit full-fledged forms of independence that humans can, e.g. changing a prompt to deliver a different, better output. However, GAI systems may still exhibit some thinner forms of independence at training that carries through to the ultimate outputs. Within the confines of a learning task defined by humans, DNNs must be sufficiently flexible to learn whatever there is to learn – and that is often the point of taking a machine learning approach. Weights and biases aren't hand-tuned by humans, and while humans write training algorithms and build system architectures, they do not fully determine what a system learns in particular (e.g. which representations), especially in unsupervised or self-supervised regimes. So, while GAI systems are not independent in the sense of 'choosing to do it their own way', and what they end up learning is still importantly shaped by human aims, leadership and oversight [4, 50], we maintain that GAI systems can nevertheless exhibit some forms of independence if what they learn and later draw on at inference is not fully determined by humans.

Zooming out, we see that the domain of leadership and independence is, for now, mostly reserved for humans. But we stress that leadership and independence don't get a project anywhere without someone or something following guidance and doing the work that's needed to realize an independently formed vision, which may involve plenty of relevance, non-redundancy, time and effort, as well as some originality and control on the part of GAI systems.

3.5 Directness

Finally, directness captures how directly a contribution is involved in producing an output. For instance, imagine cash-strapped Jo couldn't produce any paintings if it wasn't for her friend Jack, who provides her studio space rent-free. Jack's help is highly relevant and nonredundant, but not direct: his aid will support Jo, let us assume, in producing *whatever* paintings she wants to make and doesn't steer the form of any specific painting. Contrast this with Jerome, who is dialectically engaging with Jo at various points to co-shape their open-ended artistic endeavor. He is, therefore, both highly relevant and direct. Like Jerome, GAI systems can make direct contributions. The computations performed at inference directly generate the ultimate outputs at issue. To be clear, by 'direct' we don't mean to suggest that these contributions involve any kind of intentionality. Directness is a causal notion, not a mental one, and while direct contributions made by humans may often involve intentions, this is not a requirement for directness as we understand it.

Directness also plays a special role among the features CCC tracks: it modulates the extent to which other features matter for creatorship. Take the role of developers: without their efforts in building GAI systems, most users wouldn't be able to produce the images they do. But developers don't make direct contributions to the creation of specific images. Rather, their contributions primarily consist in building GAI systems that have the capacity to produce images. This is an important achievement but not to be conflated with the production of specific images, to which developers contribute only in an indirect, enabling way. So, despite developers' high causal relevance to the production of specific outputs, this relevance must be appropriately discounted by the low directness of their contributions. Similar considerations apply to other variables and agents, such as producers of training data or low-wage workers providing human feedback for reinforcement learning. Generally, then, the less direct a contribution is overall, the less strongly the other features that a contribution exhibits weigh in determining its significance.

3.6 Putting CCC together

Stepping back from individual criteria, let us look at how the framework functions as a whole. First, all the features that CCC tracks come in degrees: a contribution can be less or more relevant, exhibit stronger leadership, or little originality and so on. Second, none of the features are individually necessary or sufficient for claims to creatorship, no matter the degree to which they are present. Consider sufficiency: a GAI system can be highly relevant to producing an output, and yet be considered a mere tool if a user scores highly on leadership, control, originality and so on. Nor is any single feature always necessary: seasoned users don't need much time or effort for good results, though some features will seem essential in many cases (e.g. directness).

Second, it could be a concern that distinguishing between the features we sketched here is sometimes difficult (e.g. control and leadership). This is neither surprising, nor a problem, however. The broader themes CCC's concepts draw on, like causation, agency, and originality, have been subjects of study and controversy for centuries because they are complex and non-trivial. With artistic creation uniting these themes, it seems misguided to expect a finite list of distinct and razor-sharp conceptual ingredients that explain it neatly. CCC, then, doesn't raise but only encounters conceptual challenges, and these shouldn't distract us from further exploring CCC's descriptive and explanatory value.

Third, taken together, the features outlined here (and potentially others) form a basis for *candidacy* in a co-creating collective: if you exhibit none, or some but to low degrees, you won't get close to being a creator, but if you score highly on all, you should be considered a serious candidate. Within CCC's feature space, there will be many combinations that can ground strong claims to candidacy in very different ways. Importantly, though, CCC does not maintain that there is ever a sharp threshold to decide creatorship. To the contrary, it acknowledges substantial and often reasonable disagreement about creatorship questions, and only insists that creatorship is not all-or-nothing. CCC therefore invites us to work through attributions carefully, by providing a set of clearer criteria that help us locate and potentially resolve disagreement about creatorship. With these tenets in mind, let us proceed to explore what CCC can do for us in practice.

4 WHAT CCC CAN DO FOR YOU

4.1 CCC across the space of contenders

To show how CCC can be useful to make progress on understanding creatorship, we proceed as follows: first, we consider CCC's criteria mapped against possible contenders for creatorship, i.e. users, GAI systems and others, and comment on how each group may fare at a general level. We then focus specifically on the comparison between human prompters and GAI and discuss two cases that mark the ends of a credit distribution spectrum. Finally, we elaborate how CCC reinforces existing intuitions offered in the public discourse on creatorship questions, as well as generates novel claims about creatorship.

Let us begin by applying CCC's criteria to some of the most likely candidates: users, GAI systems, developers and producers of training data. As elaborated earlier, each of the features CCC tracks can be exhibited to different degrees, depending on concrete contextual details.

First, users can make less or more relevant/non-redundant contributions. Users can also spend lower or higher amounts of time and effort, and the originality of their contributions can vary from generic one-word prompts like 'banana' to highly engineered prompts pursuing specific objectives. Relatedly, they can exercise lower or higher degrees of control, leadership and independence when pursuing generic or more involved prompting projects. Finally, prompter contributions will always show directness, but to considerably varying degrees, e.g. through only generating a *kind* of image using a generic prompt like 'banana', or exhibiting high degrees of directness using targeted prompts.

Second, like users, GAI systems can make less or more relevant and non-redundant contributions. But they can only exhibit a certain degree of independence and cannot demonstrate leadership, for lack of intentions. However, if unchallenged by a user, they will exercise control in producing certain images rather than others, given a prompt. GAI systems' contributions always involve some and potentially a lot of compute time and effort; and they can be less or more original, e.g., depending on whether they draw on original connections made at training. Importantly, their contributions exhibit high directness: their computations literally make the specific images synthesized.

Third, as elaborated earlier, developers' contributions are always indirect. They do not make specific images, but rather enable their production. These contributions can exhibit less or more relevance and redundancy, but little specific control over particular outputs. Likewise, they may involve less or more time and effort, as well as varying degrees of originality, leadership and independence; but for lack of directness, these features are discounted: developers do not intend to produce any specific image; they only intend to build systems that can.

Lastly, producers of training data can make varied contributions to creation, too. There are two importantly different ways to conceptualize this group: first, as capturing *all* producers of *all* training data used to train a GAI system taken together. Second, as *specific* producers of *particular* training data tokens. On the wider construal, producers of training data make contributions that are highly relevant and somewhat non-redundant (e.g. there are more images on the web than large datasets like LAION-5B contain, but many images contained in LAION-5B are unique) but they exercise little control over the output. While they may, as a whole, exercise significant time and effort furnishing their contributions, scoring individually from low (Jack posting a photo of grass, which gets scraped and put into LAION-5B) to high (Jill's collected 10-year efforts in producing her published illustrations), and with some originality in the mix, their contributions display no leadership, independence or directness regarding any image produced with GAI (which is why there are concerns about scraping images without consent). These assessments can change importantly when we turn to specific producers of particular training data tokens. For instance, concerning relevance and redundancy, Jacinda's collected paintings of non-cheese things looking like they are made from cheese may play a crucial role in enabling a GAI system to produce 'Donald Trump-shaped cheese wheel rolling down a hill'.

We expand on further differences in regard to producers of specific training data later. For now, let us turn to explore more concrete theses that CCC can ground, focusing first on a comparison of human users and GAI systems.

4.2 Humans vs. GAI: A spectrum of creatorship

Can GAI systems be part of co-creating collectives? CCC suggests yes, for they may exhibit a number of important features and to significant enough degrees to merit candidacy. But how would credit for an output be allocated between human users and GAI systems? That depends crucially on the specific context. Let us offer two examples, which fall on opposite sides of a spectrum for how credit may be distributed. These examples will help us establish that GAI systems can have strong claims to creatorship; sometimes stronger than humans.

Consider Jake's 'cat on a mat' prompt again. Four images are generated (Figure 1), from which he chooses the first.

Figure 1: 'Cat on a mat, art', produced by Stable Diffusion.

How should we consider Jake's and Stable Diffusion's claims to credit here? CCC suggests that the GAI has a stronger claim than Jake. Jake typed in a generic prompt and did not contribute interestingly to the output beyond that. He did not have any concrete ideas regarding composition, palette, style, etc., and he wouldn't have been able to create any of these images without GAI.

Contrast this with Jill, an experienced visual artist working on campaign visuals for an environmental protection agency. She wants to create an image of a polluted ocean in the palm of a hand to correspond with key mission statements. Starting from a hand-drawn sketch, Jill refines her prompts, guiding the GAI through a series of many images, and exerting precise control, e.g., by using inpainting and ControlNet to pose the hand and steer the composition, until she gets an image that conforms to her concrete expectations. Jill already knew what image she wanted to create and could have created something similar by different means, say with Photoshop. In such a case, CCC can ground why Jill deserves a significant credit share and that GAI is more akin to a tool than a full-fledged creator on par with her.

CCC can capture the difference between these cases in a systematic fashion. Table 1 maps out Jill, Jake and Stable Diffusion against CCC's criteria. For simplicity, we use a qualitative coding as 'low' or 'high' to indicate the degree to which each feature tracked by CCC is realized. 'n/a' indicates that a feature doesn't apply in a case, e.g., because GAI systems do not have intentions necessary for leadership.

Table 1: Comparing contributors. SD is Stable Diffusion.

	Jill	SD1	Jake	SD2
Relevance	high	high	low	high
Non-redundancy	high	low	low	high
Control	high	low	low	high
Time/effort	high	high	low	high
Originality	high	high	low	low
Leadership	high	n/a	low	n/a
Independence	high	low	high	low
Directness	high	high	high	high

Table 1 encodes Jill's comparatively much stronger claim than Stable Diffusion (SD1). Jake, by contrast, loses out to Stable Diffusion (SD2) on several criteria, including relevance, redundancy, control and time/effort, so Stable Diffusion has a comparatively stronger claim than him. CCC can hence capture how creatorship and credit depend on a number of context-specific details and locate the roles of various agents and entities straddling full creator and mere tool, author or background furniture, rather than relying on rigid categories. This flexibility and ability to give insights into different situations, where our intuitions can vary widely and surprisingly, is at the heart of CCC – no agent or entity should be judged in or out at the outset, but instead should be allocated credit according to the specific contributions they make.

Nevertheless, there are some likely objections even against our moderate claim that GAI systems can be strong candidates for co-creating collectives and can sometimes play more significant roles than humans do. For instance, one could insist that GAI systems are not appropriate targets for credit as they are not making the right sorts of contributions to an output – they might be producing, but not creating. But taking this approach can raise problems. For instance, it can lead to credit and subsequent responsibility gaps (cf. [49, 58]), where the (human) creators established as forming a collective do not fully capture the credit for the output and allocating the concomitant responsibility is hindered by a lack of proper targets. While the visual 'cat on the mat' may be mundane and unoriginal, credit for this image, however little, must still be allocated somewhere. But if not to Jake, to who? Consider a variation of Jake's case, where instead of prompting Stable Diffusion, he asks his artistic friend, Jana, to help him make 'cat on a mat'. Jana looks at a range of other cat and mat pictures for inspiration, and drawing on experience and learned aesthetic norms, casually sketches some variants she expects Jake to like. Insisting that Jana should be allocated credit, while Stable Diffusion shouldn't, even though their contributions take a similar form, seems to be begging the question on who can be a creator and is thus not compelling. The intuition that Jake is not solely responsible for the creation of the 'cat on the mat' visuals is even stronger in cases where the output is in some way harmful, for example, if Jake inputs a prompt and, to his surprise, receives images filled with racist stereotypes. In this case, it seems implausible to allocate responsibility to Jake. So, until compelling arguments are offered that CCC misses additional criteria to negotiate creatorship, which can sustain principled distinctions between humans and machines, we maintain that GAIs can sometimes be considered parts of co-creating collectives.

4.3 CCC reinforces and generates intuitions

CCC can reinforce existing intuitions as well as generate new ones to advance ongoing debates. Existing controversy around the role of creators of training data is an important example. While common image datasets like LAION-5B are heavily populated with generic imagery, they also contain the works of dead and living artists who have spent considerable time and effort developing their works, and have not consented to their works being used to train GAI systems that 'appropriate' the capacity to generate imagery in their distinctive style. Many commentators and artists insist that something illegitimate is happening here [22, 32, 67] and CCC can reinforce such intuitions on independent grounds: in some cases, producers of training data may have claims to candidacy in a co-creating collective.

Take Jamal, who has spent years crafting his distinctive and acclaimed style as a digital artist. Jamal's images were scraped and a GAI trained on them is now capable of rendering images in Jamal's style. Jamal may reasonably complain that he is made worse off by GAI, as almost anyone can now freely produce imagery that looks like his, worsening his prospects of getting commissions and drowning out his distinctiveness in a sea of near-indistinguishable mimicry. Does Jamal have a claim to be considered a part of a co-creating collective for some outputs? CCC answers in the affirmative. Consider relevance and redundancy. Jamal's works are highly relevant and non-redundant to a GAI system's ability to produce outputs in his style – take them out from the training dataset, re-train the system, and the GAI wouldn't be able to reproduce his unique style. They may also involve high degrees of control: while Jamal didn't intend to effect specific results in a GAI user's outputs, the look of his works will co-determine what any GAI outputs prompted to mimic his style will look like – had his palette been warmer, the outputs would have been warmer, too. Contrast this with Jimmy, whose 27 generic pictures of his cat 'Mr Snuggles' posted on Instagram won't make a recognizable difference to any cat images produced with the help of GAI. Generally, the more specific a prompt is to a region of the latent manifold that's crucially shaped by a specific creator's works, the stronger the claim that creator has to credit for a GAI's output due to the relevance/non-redundancy and control involved.

What about the other criteria? We may assume that Jamal's contributions involved large amounts of time and effort in developing his style and producing his works. But while Jamal may have also exhibited plenty of leadership and independence in producing his oeuvre, his contributions to specific GAI outputs are not very *direct*: they are causally mediated by GAI systems. So, what should we conclude about Jamal's candidacy in a co-creating collective? We think that it is not implausible to consider Jamal a co-creator, albeit a distant one. Nevertheless, even a weak claim to co-creatorship may ground derivative claims, e.g., to be appropriately credited or asked for consent. Reasonably, Jamal may decline to be a co-creator on a diffuse number of prompting endeavors by people he doesn't know and whose values he may not share. Importantly, CCC makes clear that he may do so on grounds that are independent from concerns about intellectual property violations in scraping and using imagery for training GAI.

CCC also generates novel intuitions, for example, that GAI systems have the capacity to create *illusions of creatorship*. Specifically, users can be led to over credit themselves, despite having made only minimal contributions to an output - and CCC explains why. Consider Jake again, who might think he created 'cat on a mat', using Stable Diffusion as a mere tool. But Jake might be entirely unaware of how little control he exerted over the output if he does not have access to relevant counterfactuals, such as how the images would have looked if a different seed had been used, or if he had, equally randomly, prompted 'a mat with a cat on it' instead of 'cat on a mat'. Lacking such counterfactuals, Jake may understandably feel he exercised control to effect a specific output; but that feeling might be quite misleading. Users also lack information about the significance of others' contributions. Take training data. Jaden likes sci-fi and uses Midjourney to produce a striking image of 'a battlecruiser landing on a desert planet'. But no amount of intricate prompt-engineering would get him anywhere near that if not for the extensive amounts of aesthetically rich training data produced by concept artists over decades, contributions that may score highly on some of CCC's criteria. But for lack of access to relevant counterfactuals, e.g., realizing that without those contributions Jaden's battlecruiser image would have looked like a teenager's pencil drawing, and without considering the kinds of features CCC tracks and what other candidates for co-creatorship there might be, it can be easy for users to overestimate their role in creation processes. CCC can help dispel such overestimations and allow users to better understand their roles: if Jake would have been happy with many different outputs, his role is more akin to someone browsing a gallery of cat images and selecting one they like. That is a fine role to play, but different from being a creator, and we shouldn't worry about withholding credit when it is based on illusion.

4.4 CCC advances existing debates

Addressing the role of GAI, some have insisted that - in the name of transparency and authenticity - AI itself should not be credited with creatorship [15, 50]. But as others have argued in relation to the usage of ChatGPT [38], and we have demonstrated here in regards to visual outputs, failing to examine the role of GAI in fact hinders transparency and authenticity, obscuring the process of creation and the significance of different agents and entities involved. Many academics have called for the fair attribution of credit in the creation of GAI works [4, 20, 37, 50], but have not provided concrete recipes for doing so. Members of the public, too, have been asking and debating who should be able to claim creatorship of GAI outputs [1, 44]. CCC, as outlined here, responds to those demands. It provides a fine-grained framework that allows and encourages a more nuanced allocation of credit, accommodating the unique aspects of GAI-based creation, supporting some common intuitions and showing that GAI can in fact be a strong contender for creatorship claims.

In providing these findings, CCC addresses several problematic tendencies in the public discourse around GAI. Major differences persist in what people take to be the most compelling approach to attributing credit for GAI outputs – with some members of the public stating that the "typical structure people will be crediting will be a brilliant human on top and the AI as a facilitator, or a human-AI synergy", while others have assumed the lion's share will go to "the AI and its creators". Each side appears confident that their view is "obviously" what "most people" will take up [2]. CCC works to counter these assumptions by demonstrating the sheer complexity and diversity of credit attribution that uses of GAI bring about. It also shows that brittle analogies, which liken GAI systems to e.g. a pencil or AutoCAD, or flattening assertions that 'the history of art and technology has seen all this before', do little justice to the intricacies and novelties of GAI and its rapidly growing uptake across society [1, 16, 66].

In particular, CCC works against a popular tendency to over-hype the contributions of human users. Excited by the new possibilities that GAI offers, users often take credit for visual outputs with little to no acknowledgement of other agents involved in their creation – some going so far as to feel "we are becoming like small gods with those tools" [3, see also 55]. Academics in the public discourse have reinforced such hype, with Drew Hemment stating that "AI gives artists superpowers" [64]. As we have seen, CCC untangles agents' roles in the creative process facilitated by GAI, thereby aiding users to understand, negotiate and articulate the contribution they have made to final outputs.

CCC also helps challenge problematic narratives of GAI creatorship. For instance, tech companies have incentives to downplay their hand in the creation of users' individual outputs and to instead present GAI as a beneficial, innocuous tool. But the collective-driven nature of image synthesis that CCC emphasizes makes clear that such a framing is not always accurate. Describing GAI systems as mere tools may shift too much responsibility onto users; e.g., when GAI systems have built-in propensity to generate toxic imagery it seems odd to insist that problematic outputs are the result of inappropriate tool-use alone. CCC makes clear that developers, too, play relevant roles in the production of specific outputs, although only indirect ones that are mediated by the GAI systems they trained, fine-tuned and released. Attempts to push framings suggesting GAI systems are mere tools have already played out at significant scale in the negotiations surrounding the EU AI Act, in which the most dominant technology companies lobbied to push the act's regulatory obligations onto European providers (e.g. app developers whose products access GAIs through APIs) and users of their general AI models (including the likes of ChatGPT and Stable Diffusion), rather than taking accountability for potential damages themselves [30, 61]. In campaigning for this framing, tech company leaders and lobbyists have asserted "the balance of responsibility between users, deployers and providers... needs to be better distinguished" and that "giving the right responsibilities to the right actor in the AI value chain is key" (quoted in [61], pp.12-14). We agree in general, but not with their preferred distinctions. As CCC shows, understanding the roles played by users, developers and GAI systems themselves do not in fact liberate developers of responsibility. Their (indirect) hand in creatorship, and the accountability that comes with that, cannot be justifiably attributed to others further downstream.

Finally, CCC also informs and critically challenges existing scholarly and legal conceptualizations of creatorship. CCC shows that long-held expectations for how authorship and copyright should be attributed may now need reworking in the face of GAI. Copyright attributions, for example, usually aim to identify a small set of agents - but CCC suggests that perhaps copyright sometimes needs to be distributed more widely, even if doing so in practice can be extremely challenging. CCC also highlights the degree to which existing theories are not fully appropriate for these new technologies and the multi-layered processes of creation they entail, while also suggesting that earlier, more general understandings of creatorship may lack sufficient flexibility. Using all-or-nothing categorizations rather than gradations for roles such as artist, author, assistant, or contributor, for example, may obscure important contributions. In regard to GAI specifically, CCC responds to scholars' calls for the fair attribution of credit, offering a framework to dissect the creative process and distribute degrees of creatorship in a finer-grained way than existing work.

5 CONCLUSIONS

We have proposed the CCC (collective-centered creation) view as a systematic framework for addressing pressing questions about creatorship in the context of generative AI (GAI). At its core, CCC maintains that GAI systems can meet the bar for being included in a co-creating collective, challenging a wide range of views that have tended to downplay the role of GAI. Reinforcing collaborative views that have so far been lacking more concrete instruments to understand how creatorship and credit can be distributed, CCC also brings more nuance to creatorship debates: it insists that creatorship is gradual, not all-or-nothing, and informs concrete judgments by providing a rich conceptual machinery. We have shown how CCC can inform existing debates, by lending independent support to influential views, and by prompting us to consider new ways of thinking about creative production with GAI, be that in regard to the GAI's role itself or that of other candidates for co-creation, such as producers of training data. Taken together, CCC offers a flexible framework that can advance public, academic and legal debate as GAI is developed further, deployed more broadly, and as we, collectively, form a better understanding of our relationships with it. As indicated earlier, CCC is also limited in scope. It does not yield definitive judgments on creatorship issues in specific cases, nor does it insist that its criteria are the right ones, or the only ones that matter. CCC as sketched here is intended as a first, systematic conceptual contribution on questions of creatorship with GAI, but not as the final word on these issues. We hope that scholars from different fields will feel invited to contribute to the larger project of refining this type of approach, be that through technical contributions by computer scientists (e.g. efforts to permit more precise analyses of difference-making contributions, control, or originality); conceptual improvements made by art theorists, practitioners and philosophers to further detail CCC's conceptual machinery; or suggestions by legal scholars to make progress on understanding how CCC's tenets can be reconciled with existing legislation or inform the development of tailor-made law that encodes novel intuitions about creative visual production involving GAI.

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