# Creative ML Assemblages: The Interactive Politics of People, Processes, and Products

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Creative ML tools are collaborative systems that afford artistic creativity through their myriad interactive relationships. We propose using "assemblage thinking" to support analyses of creative ML by approaching it as a system in which the elements of people, organizations, culture, practices, and technology constantly influence each other. We model these interactions as "coordinating elements" that give rise to the social and political characteristics of a particular creative ML context, and call attention to three dynamic elements of creative ML whose interactions provide unique context for the social impact a particular system as: people, creative processes, and products. As creative assemblages are highly contextual, we present these as analytical concepts that computing researchers can adapt to better understand the functioning of a particular system or phenomena and identify intervention points to foster desired change. This paper contributes to theorizing interactions with AI in the context of art, and how these interactions shape the production of algorithmic art.

CCS Concepts: • **Social and professional topics**; • **Computing methodologies** → **Artificial intelligence**;

Additional Key Words and Phrases: creative AI, machine learning, art & technology, cultural studies, assemblage

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## 1 INTRODUCTION

Machine learning (ML) tools for performing creative tasks raise important questions about the social and material conditions of creativity. Regardless of medium, creative processes and artistic products are fundamentally social endeavors [17, 73]. They are reflections of the people involved (their knowledge, understanding of the world, and motivation) [16, 18, 74, 75, 136], shaped by the technologies artists can access [72, 84], and structured by the social and organizational arrangements in which artists are embedded and that influence reception of their work [132, 148, 165]. Put differently, a given creative ML context (in which an artist creatively employs ML/AI tools) is constituted by a myriad of interacting, socially situated and technological elements (e.g., developers, artists, training data, code, scholarly ML communities, and companies). While each individual element underscores the rich interactions shaping the context, the experiential work of creative ML



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is more than each element separately. Rather, it is more precise to say creative ML comprises the *interactions of all the elements together*. Thus, a theory that aids understanding of how distributed social and technical elements cohere in a given creative ML context supports analyses of the complex interactions influencing the production and reception of ML-mediated creativity.

In this paper, we argue the concept of *assemblage* can enrich examinations of creative ML tools, practices, and communities by providing a framework to shift away from treating these tools as mere technical objects [112] and identify how particular values and logics operate within an ML-art context, which can illuminate how these tools can be remade in ways that contest hegemonic power dynamics and better serve local communities of practice. The scholarly notion of assemblage is a way of understanding how a given phenomena is produced through the symbiotic interactions of different elements (see: [51, 99, 133]). In this work, assemblages are broadly defined by their *interactive structure*: the stable arrangement of disparate social, material, and discursive elements that cohere toward a greater purpose [50]. For example, a city is an assemblage of people, infrastructure, and policy that have been arranged to create a livable space [118]. Drawing on this understanding, creative ML can be studied as an assemblage by approaching it as a system in which the elements of people, organizations, culture, practices, and technology are constantly influencing each other. The dynamic relationships between interactive elements of a creative ML tool (e.g., choices made in developing a ML model, safety classifiers, collaboration norms and values, knowledge traditions informing interpretation of ML model outputs and artworks) give rise to its specific characteristics and how different communities make sense of that tool's creative possibilities. Here, what is important is not the mere naming of assemblage elements, but understanding their interdependent relationships through which "the particular form and structure of the assemblage constrains some activities and energizes others" [154, p. 92].

We propose three dynamic elements of creative ML that offer starting points to interrogate the energizing what, how, why, and when circumstances in which ML-mediated creativity happens:

- *People*: This element includes all stakeholders involved in the design, development, and reception of ML-mediated creative works, such as artists, engineers, researchers, and art audiences. The specific roles and responsibilities of these stakeholders will vary depending on the context and technologies employed.
- *Processes*: This element encompasses all aspects of the creative ML process, from artistic conceptualization to engagement with ML tools. The specific steps involved in this process will also vary depending on the context and technologies employed.
- *Products*: This element refers to the ML-mediated outcomes of creative processes, and may take many forms including visual art [61], fashion [141], music [108, 156, 157], and animation or motion design [127], among others. The specific forms these products can take are diverse and depend on the creative intentions, goals of the people involved, and how those relate to extant creative, technical, personal, or business evaluation criteria.

We developed this broadly generalizable people-process-product analytic through a methodological application of "assemblage thinking" (see [13, 23]), in alignment with prior analyses of algorithmic systems [168]. We reflexively and iteratively diagrammed [175] artistic and ML pipelines to situate how they are realized through various actors, materials, organizations, and ideas. While the configuration of these elements will vary by creative ML context (or may include other elements), they conceptually provide a minimum means to understand the enactment of ML-mediated creativity.

This research is motivated by the recognition that ML-mediated creativity arises from the unfolding actions and circulation of sociotechnical elements. HCI researchers have introduced methodologies for studying creative ML that draw on sociology of culture and Science and Technology Studies (STS) to conceptualize how creative ML practices reflect dynamic interactions between different knowledge communities with distinct values and traditions (see: [29, 132, 148]). These studies emphasize the need for computing research to account for the dynamic interactions that shape ML-mediated creativity without falling into technodeterministic accounts. We aim to further broaden approaches to studying creative ML tools, practices, and communities by offering:

(1) An analysis of specific ways the people-process-product facets interactively shape creative ML assemblages. We focus on three overarching findings: how hierarchies in ML-art communities broker the flow of different creative and technical resources (*people*); how artists creatively engage ML in ways that obscure or reveal its sociopolitical properties (*process*), and how the social dynamics of cultural criticism shape ML-art evaluation (*product*).
(2) A descriptive account of how assemblage thinking enriches analysis of ML-mediated creativity by examining the working interactions between many disparate social and technical elements. As we detail in our Discussion (Section 5), assemblage thinking strengthens HCI analyses of ML-art as it: (1) calls attention to how different sociotechnical elements co-function to shape local dynamics; (2) offers a method to examine distributed sensemaking within a particular context; (3) facilitates analysis of entangled social power dynamics; and (4) increases understanding of the contingent ways communities experience creative ML tools.
(3) An examination of one ML-art context through an assemblage lens: academic and professional ML communities. We were motivated to focus on this context as they provide a major forum for artist-researchers to share and promote their work, collaborate on projects, and educate future generations of ML experts. This context has also received less attention in the literature on ML-mediated creativity, particularly compared to community collectives and individual practice (e.g., [29, 32, 145]).

This study contributes to HCI literature on ML-mediated creativity as it suggests assemblage thinking as a generative lens to more deeply understand how the interactive structure of creative ML systems shapes its social impacts. For computing research broadly, assemblage thinking focuses researcher attention away from solely the code or technical functioning of a ML model to the broader sociotechnical influences through which the creative ML tool is produced and artworks are made in practice. Examining the relationships between the elements of an assemblage thus offers researchers a useful method to make sense of how their historically-specific arrangement shape a particular computing phenomenon (see: [124, 154, 179, 180]). In this way, approaching creative ML as an assemblage calls attention to the layered dynamics unappreciated when looking at one element in isolation. After introducing the people-process-product analytic (Section 4), we conclude with a discussion of the areas of work our findings extend, arguing for computing researchers to consider the dynamic politics shaping creative ML (Section 5).

## 2 BACKGROUND

The practice of ML in the arts has roots in different movements, traditions, and disruptions [161]. In this section, we briefly situate our analysis with respect to the rich history of art-and-technology communities and existing research on technological assemblages. Here, we synthesize related work to highlight the dynamic relationships and cultural politics between artists and institutions, and to which assemblage thinking calls attention. We also emphasize and foreground the entangled arrangements of *people*, *process*, and *products* elements that have always shaped art-and-technology. The contributions of our research complement and extend the work summarized, and emphasize the need for attention to the social power dynamics that shape ML-mediated creativity.

### 2.1 Entangled Knowledge Worlds: The Early Practice of Computer Technology in the Arts

The earliest "computer art," as it was known, was an experiment in creative process shaped by interdependent relationships between art and engineering worlds [164]. Research using *assemblage* to study art-and-technology communities uses "entanglement" as a metaphor for framing the interdependence of social and technical knowledge traditions to enact creativity (e.g., [33, 82, 130]), which we similarly employ.[1] In the 1960s, computer access was gated by major institutions that were guided by logics not readily attuned to the arts [83]. Mainframe computers filled entire rooms and were cost prohibitive save for corporations, universities, state and military agencies, and other well-funded institutions [83]. Multidisciplinary artists interested in accessing these computers used time-sharing and required collaboration with engineers to navigate the technical requirements of mainframe computing [93, 117], creating unexpected alliances with "potential to benefit engineers' employers in the form of commercial products and intellectual property, while simultaneously expanding artists' aesthetic visions and opportunities" [117, p. 7]. To further such creative explorations, in 1966, engineers Billy Klüver and Fred Waldhauer of Bell Labs, and artists Robert Rauschenberg and Robert Whitman founded the renowned non-profit *Experiments in Art and Technology* to increase access to new technologies and promote collaborations among artists, engineers, and scientists [88]. The organization believed such "collaborations could lead technology in directions more positive for the needs, desires, and pleasures of the individual" [88, n.p.], especially at a time in which public perceptions of technology were shaped against a backdrop of weapons and war [117]. Thereafter, numerous academic and professional communities formalized what would become key institutions in the art-and-technology space, including the *Leonardo* journal founded by painter and aeronautical engineer, Frank Malina, to enable communication among artists using technology in their art practice [103]. Such academic and professional institutions were interactive forces shaping broader discourses and technical knowledge about computer art through education, coordination, community dialogue, and idea sharing. These institutions thus became one interactive element forging — or *entangling* — disparate techniques and new ways of relating between art and engineering worlds.

Proponents of the burgeoning art-and-technology communities saw it as exceeding the mere production of artistic *products*, but to explore and redefine creative *processes* in alignment with other 1960s art trends, including minimalism, conceptualism, and land art [117]. The broader movement's aim to foster new creative processes is reflected in its numerous celebrated figures in music, video, and visual art reliant on corporate or university computing resources, including John Cage, Harold Cohen, Alison Knowles, Nam June Paik, and Lillian Schwartz, among others [94]. Yet, during this early computing era, mainstream art venues' interest and reception to computer art vacillated [79]. While landmark art shows in the late 1960s-early 1970s emphasized cultural interest — such as the 1968 "Cybernetic Serendipity: The Computer and the Arts" exhibit at the Institute of Contemporary Arts, London, and the 1970 exhibit "Information" at the Museum of Modern Art — computer art was typically shown and discussed separately from mainstream art [93]. Indeed, computer art often fostered hostility and resentment from art worlds: from dismissal to censorship to active aggression, including attacks on artists and computer sabotage [26, 117]. While mainstream art has never been free of complicated institutional funding and alliances, it was common for critics to attack art-and-technology movements as "polluting the art world" and artists as "amoral opportunists for collaborating with the stewards of the Cold War military-industrial complex" [117, p. 10]. Such

[1]This work often adapts STS scholar Karen Barad's conceptualization of entanglement (see [15, p.160] for a deeper discussion of this metaphor).

comments by fellow actors in art worlds underscore how different communities make sense of art-and-technology elements, and ascribe values to the broader assemblage as a whole.

The entanglements that shape art-and-technology communities are not fixed, but in flux, subject to external influence, disruption, and reformation. For instance, in the 1980s, computer art experienced a transformative shift shaped by technological innovation, companies, and academic and professional institutions. Personal computers increased access to easy-to-use artistic software that rendered "consumptive creativity...a hallmark of computer use" [125, p. 183], Global North countries established publicly funded institutions for digital media [55], and in 1974, the Association of Computing Machinery (ACM) held its first computer art show becoming another site to shape art-and-technology discourses, education, and idea sharing [66]. Foregrounding contemporary creative ML, artist-engineer collaborations continued to produce novel algorithms that explored questions about society and technology. For example, Harold Cohen continued to evolve his autonomous painting program *AARON* that he first developed in 1972 at Stanford's AI Lab (inspired by indigenous American petroglyphs and children's drawings) and iterated on through the 2010s (see Figure 1) [41]; and William Latham developed his 3D rendered *FormGrow/Mutator Generated Art* series (1992/1993) that depicts the imagined Darwinian evolution of an artificial life form [11], which he created on an IBM 3090 mainframe computer and exhibited at the 1992 ACM


Fig. 1. Untitled Computer Drawing, 1982, Harold Cohen. Presented by Michael Compton 1986. © Harold Cohen. Photo: Tate.

SIGGRAPH Art Show [67]. Rather than a linear, deterministic trajectory, the practice of technology in the arts arises from broader forces of social power and interactions among art and engineering worlds, including through academic and professional communities. This brief history underscores how art-and-technology communities are (re)assembled based on different movements, traditions, and disruptions. In the next section, we discuss how contemporary creative ML communities are dynamically (re)shaped through sociotechnical interactions.

### 2.2 Entangled Cultural Politics: Art-and-ML Communities

Contemporary creative ML tools are developed and realized through different stakeholders, organizations, and creative ideas. Akin to prior art-and-technology eras, ML-artist communities are an experiment in creative process [116] shaped by complex entanglements with differing knowledge and cultural systems [11]. Prior HCI scholarship describes the culture of ML-art worlds as ones that often reject dominant epistemologies in ML engineering, which are constrained by discourses of scientific progress and profit that inform the normative "goals and standards of researchers, engineers, and big corporations" [29, p. 12]. In contrast to dominant ML engineering perspectives, algorithms and data are not viewed as systems to complete tasks but as raw *material* in artists' creative processes [104]. Through this lens, ML artists manipulate the technical aspects of algorithms to grapple with their limitations [12] or offer artistic commentary on their inherent sociotechnical power dynamics [4, 29]. As such, ML-mediated creativity is constituted by artistic vision, computational resources, and the often complicated institutional partnerships that artists are reliant upon [11, 104].

Examining the entangled influences shaping creative ML as a field call attention to the what, how, why, and when circumstances that shape ML-mediated creativity. In the 2010s, advances in deep learning fostered interest from artists who began experimenting with the creative facets of new neural network algorithms developed by multinational tech companies [11, 117]. A pivotal moment for ML-art occurred with the 2015 release of the DeepDream software, which uses convolutional neural networks (CNNs) to create psychedelic images [122], a style coined "inceptionism" [123]. The new creative ML tool captured interest of different art worlds, as San Francisco's Gray Area Foundation for the Arts held an exhibit on DeepDream artworks in collaboration with Google Research [10], and the software was used as an image filter in American pop band Foster the People's music video for "Doing It for the Money" [78], which pushed creative ML onto a new global stage. Such highly public flashpoints in art-and-technology can draw in new financial and other resources that influence or reshape creative ML worlds, sub-worlds, and the social interactions or negotiations that occur between them.

Artistic and creative communities have influenced the development of creative ML, alongside corporate deep learning advancements. On social media, communities of artist-coders shared models, resources, and publicly experimented with deep neural networks, including now prominent ML-artists, such as Memo Atken, Sofia Crespo, Mario Klingemann, and Robbie Barrett, among others [11, p. 101]. As prior HCI work describes, these knowledge sharing norms are one interactive mechanism through which ML-artists re-appropriate ML models into new contexts [132, 148, 149]. This underscores the interdependent and complex relationship between ML-artists and conventional ML fields: "while [ML-artists] depend on the algorithms that are developed in academia and industry, they seek to express their freedom from the underlying constraints that result from the values of AI culture such as accuracy, productivity and performance" [29, p. 13]. "Hacking" creative ML tools is another disruptive negotiation influencing creative ML as a field. As technology companies released off-the-shelf image generators in the early 2020s (e.g. [3]), ML-artists began modifying OpenAI's CLIP model, a general-purpose image classifier, to experiment and develop new creative ML ensembles that furthered mainstream ML techniques and imaginations for new creative ML modalities [138]. Recent years have given rise to numerous off-the-shelf creative ML tools, including those employed for storytelling [6] and re-mixing and creating new media [114], such as music [156, 157] or visual arts [3, 160]. These tools have in turn given rise to new art-and-technology communities. For instance, the emergence of "promptism," an art movement involving the manipulation of computer-generated imagery [32, 92] and live ML art exhibitions (e.g., Prompt Battle [146]), underscore increasing enthusiasm towards text-to-image generators as an artistic medium.

The growth of creative ML is not without tension, however, particularly among some visual art communities concerned with how these technologies may threaten creative economies. In response, ML-art has been banned in certain online art communities [58] and media conventions [131]; and in December 2022, thousands of artists staged an online protest against AI-generated art on the popular image-sharing forum ArtStation [14]. An illustrator whose style appeared too similar to AI-generated art was kicked out of a public Internet forum [42], despite making their creative process transparent, including sharing "layered PhotoShop files, which AI couldn't create, and iterative designs" [37, n.p.]. Underlying this kind of collective push back against creative ML tools are myriad concerns about the conditions of creative production, including questions of consent and the ethical construction of ML system training data [59], professional displacement through technological unemployment [143], and philosophical questions of what constitutes creativity, such as whether the "formulaic approach" [40, n.p.] offered by generative ML models could supplant conceptual and transformational forms of creativity. The ever-shifting reception of creative ML in different communities underscores how a given ML-art context is influenced by shifting interdependencies across influential elements — including the development of ML techniques, people's relationships to institutions and resources, and broader sociopolitical and economic views. An assemblage approach to studying ML-mediated creativity is thus to recognize its contextual relationships with models, artists, engineers, ML techniques, and institutional infrastructures.

### 2.3 From ML Models to Creative ML Assemblages

Our research frames creative ML as an *assemblage* in which the entangled elements of people, organizations, culture, practices, and technology are constantly influencing each other. The scholarly notion of assemblage emphasizes the interdependent relationships between heterogeneous elements [51]. As Manuel Delanda [50, p. 5] defines it, assemblages are "wholes whose properties emerge from the interactions between parts." To help explain, an assemblage approach to a museum could conceive it as a network of relationships between people (e.g., staff, visitors, volunteers, donors), practices (e.g., collecting, curating, and interpreting objects), objects (e.g., paintings, sculptures, installations), and ideas (e.g., history, culture, colonialism) [21, 137, 172]. Importantly, assemblage theory prioritizes not the mere naming of elements, but the kinds of experiences and relationships their interaction energizes and constrains [154]. As Jasbir K. Puar [133, n.p.] notes, it is through these "relations of force, connection, resonance, and patterning" that things and concepts crystallize. The particular relationships that form between these interdependent assemblage elements are called "emergent properties" [50, p. 12] that collectively shape the sociopolitical characteristics and social impacts of a creative ML system in a particular context. For example, the experience and characteristics of a museum shift significantly based on the collection of objects, the ways they are displayed, and the curator's and visitors' interpretation of displayed objects [91]. An assemblage lens offers computing researchers a generative tool for recognizing how creative ML is similarly contingent; as with all creative assemblages, they are "not completed or stable constructions...[but] better conceived as temporary and provisional connective arrangements" [113, p. 37]. Thus, while the elements of a creative ML assemblage have cohesion, they are not rigid nor universally ordered. In other words, they can be reconfigured, whether that is by artists, technology builders, or social forces (e.g., markets and economic systems, creative or other industry logics, laws and regulation, new technologies).

*2.3.1 Use of Assemblage to Understand Creativity.* Prior research has employed assemblage thinking to theorize "the work" of creativity. Cameron Duff and Shanti Sumartojo [57, p. 2] offer a definition of creative assemblages: "a temporary mixture of heterogeneous material, affective and semiotic forces, within which particular capacities for creativity emerge, alongside the creative practices these capacities express." In other words, creativity and creative processes are a result of entangled interaction: "the interweaving of practices, technologies, institutions, authors, knowledge and issues" [174, p. 2]. In their analysis of art collaborations, Phillip Mar and Kay Anderson [113, p. 38] argue that creativity should be conceived "in terms of the working interactions between many parts of the collaborative assemblage (not just artists), [as these interactions]...evoke a more active sense of a 'creative assemblage' as something facilitative, a way of doing, of working between heterogenous entities." For example, Baptiste Caramiaux and Marco Donnarumma's [28] analysis of AI in body-based performance art finds that researcher-artists engage ML as a non-neutral tool to create performances with deeper critical and political considerations of the technology employed. This insight illustrates how creative acts are embedded in larger structures of co-creators that enable or constrain creative configurations [100, 102]. Creativity, thus, results from the co-functioning of different assemblage elements, including artists, the different communities or institutions they interact with, artistic practices, and social norms [113].

*2.3.2 Use of Assemblage and Related Concepts in HCI.* As ML-mediated creativity is constitutive of different social-technical facets [29, 121, 151, 162], it can be understood as an assemblage characterized by heterogeneous but co-functioning elements. Previous HCI studies have employed assemblage thinking as a methodology to explore algorithmic and machine learning systems and to better foreground the myriad external influences that shape the lived experiences and transformative possibilities of algorithmic and data-driven systems [9, 48, 168]. This includes research using assemblage to understand the "emergence and nourishment" of group creativity in HCI design [65] (see also: [46, 47]) and the creative practice of art bots [130]. Within this literature, the notion of assemblage offers research a way to make sense of how certain skills, practices, or sociotechnical relationships form. As Yu-Shan Tseng [168, p. 2] summarizes, "by focusing on the distributed nature of a given phenomenon, assemblage thinking understands algorithmic systems as gatherings and fallings-out of distributed relationships of users, programmers, machine learning algorithms, big data, digital infrastructures, governmental institutions, policy and cultural practices." In this way, assemblage thinking enables researchers to better examine computational systems within their social contexts [24, 63, 168], which shape the what, how, why, and when circumstances of creative ML.

Another strand of HCI examinations of ML-art draws on a complementary concept sometimes employed in assemblage research: *diffraction*. Diffraction is a metaphor for understanding how different knowledge traditions can intersect and overlap, and how they can produce new insights [15, 77]. For example, Helen Pritchard and Jane Prophet [132, p. 9] employed the concept of diffraction to study the work of code-based artists, finding that these artists draw knowledge from both mainstream art and new media art communities, leading to practices emerging 'between' the fields...that engage with what is excluded from both. Hugo Scurto et al. [148, p. 2] also drew on the concept of diffraction in their interviews with ML-artists, finding that these artists often re-conceive ML models as a "set of computational material possessing specific properties — rather than on what it is currently used for (e.g., a set of computational techniques contributing to socio-cultural discourses on artificial intelligence)." Pedro Sanches et al. [144] used diffraction to demonstrate how designers of ML tools can resist treating data-driven systems as neutral and objective, but rather as having multiple, situated meanings based on how people's lived experiences shapes their algorithmic sensemaking. While assemblage and diffraction are complementary and emphasize the importance of context and interconnectedness, a key distinction is in their focus. Diffraction is focused on the details of how a system works, while assemblage is more concerned with the overall interactive structure of a system or context. This research engages assemblage thinking to widen the scholarly view of ML-mediated creativity by focusing on three elements: people, processes, and products. This approach is well-suited to examining the distributed nature of algorithmic systems [7, 97], as it acknowledges the complex interactions between these elements.

## 3 METHODOLOGICAL APPROACH

We employed "assemblage thinking as a methodology" to examine the broader landscape of ML-mediated creativity. Assemblage methodologies vary in approach, but they are guided by several core epistemological commitments [13]:

(1) assemblages are characterized by multiplicity, meaning they are comprised of heterogeneous elements but can be treated as a stable entity [43, 51].
(2) assemblage elements fit together in dynamic, complex ways [50, 167].
(3) assemblages require labor to maintain them [175].
(4) assemblages are not final but can be reshaped in new ways [8].

In alignment with these epistemological commitments, we employed an iterative method of affinity mapping to define relevant elements, structures, values, and dynamics surrounding an ML-art context [109, 129]. The people-process-product analytic was derived from our analysis, which we document below. Three members of the research team met bi-weekly from October-December 2021 to create the initial affinity maps, followed by continued group discussion and weekly co-working refinement sessions from December 2021 to September 2022. Our reflexive approach to assemblage thinking helped us to identify and narrow down the relevant social and material elements of creative ML, taking time for independent and collective reflection. We also emphasized reflexive and auto-ethnographic discussion among the researchers (see: [28, 62]), who consisted of HCI, ML researchers, and cultural sociologists.

### 3.1 Author Positionality

Our team comprised researchers with a variety of academic and industrial disciplinary expertise, both within and complementary to creative ML pipelines. This includes authors with expertise in HCI, the sociology of Science and Technology, and the Sociology of Culture (with a substantive focus on visual arts, music, and film making). Three of the authors have expertise in machine learning, ML creativity, and responsible AI practice. In addition, three members of the research team also work in and support performing arts, music, and visual arts communities. Of these, one author previously worked for a graphic design studio managing the creative process and serves on the governing board of a digital art magazine of visual art, culture, and criticism in the U.S. South. A second author consults with performing arts institutions on their organizational structure and audience engagement; and a third author has contributed to art galleries dedicated to ML-art and organized workshops in creativity within the computer vision community. The research team relied on our scholarly, professional, and cultural experiences during the analysis, which was especially generative in discussing experiences with ML pipelines, creative sectors, and academic and professional ML organizations.

### 3.2 Initial Affinity Mapping: Stereotypical ML Pipelines and Creative Processes

Our first step was to visually map out the “sites and situations" [115] of a stereotypical ML pipeline and creative process to develop a relational understanding of ML-mediated creativity through an iterative and inductive analysis. In our experience, neither ML pipelines nor creative processes are truly linear in practice; thus we did not prioritize this format in our mappings. Our goal was to identify the kinds of major elements shaping these spaces: human actors (e.g., individuals and organizations), materials (e.g., code, art, models), discursive or symbolic drivers (e.g., values, logics), and sociopolitical or economic elements (e.g., access to resources, social inequalities) (see [39] for more on situational analysis).

**Stereotypical ML Pipelines.** Drawing on our research teams’ experience with ML pipelines, we began by listing the primary actors and structures related to ML tool development placing post-its on a digital whiteboard. These included those involved in training data, algorithms, computing resources, system outputs, companies, and individual stakeholders who build ML tools (e.g., technical and non-technical researchers, data scientists, engineers, product managers, and applied ethicists) and those who support their development (e.g. business executives or streams of funding). We then added in key actions or moments within *ML workflows*, including problem definition, dataset curation, data annotation/labeling, data processing, model development, and validation; *scale*, or the pace at which tools are developed and deployed.

Next, we discussed key cultural facets and impacts, including the *assumptions* or algorithmic logics built into systems; and the *ramifications* of ML tools across different domains, such as changes to behavior or social relationships of downstream stakeholders (e.g., users and non-users impacted by a system). Lastly, we discussed the webs of relations between the identified actors, discourses, and structures. This process, which is similar to what anthropologists Shore and Wright [176] identify as “studying through," allowed us to trace connections forward and backward to get a clearer picture of how these different elements cohere. For instance, we identified how corporate stakeholders who develop many large ML models currently hold a considerable power imbalance in the assemblage, owing to their significant control over much of the algorithm development and data governance; and how hegemonic ML pipeline may leave out or incorporate communities in problematic ways. This initial mapping process helped us to locate dominant people and processes that shape how a particular ML tool is developed.

**Stereotypical Creative Process.** We repeated this initial affinity mapping exercise for creative processes, listing the high-level actors and structures shaping creative ecologies. Given the heterogeneity of creative communities and fields, we did not strive to develop a totalizing account of all creative sectors or possible elements in creative industries, but focused on surfacing major elements common to art worlds [17, 165]. Again drawing on members of the research teams’ experience teaching in sociology of culture, their personal art practice, and prior work in creative industry, we listed stakeholders involved in the creation, promotion, viewing, and reception of creative work. While our goal was not to be granular in accounting for all possible stakeholders in every creative sector, we anchored our discussion to visual arts and film. In the context of visual arts, for example, the actors shaping artistic ecologies might include artists, commissioning agents, auction houses, individual buyers, sellers, grant funders, or art media. In the context of film, relevant actors include writers, directors, producers, cinematographers, set decorators, and distributors.

We also noted there are various materials and mediums that shape completed artworks; again the goal was not to document every possible medium, but recognize that many are employed. We then added in key moments of a stereotypical creative process. As these processes can be highly individual or vary by domain, we focused on high-level moments to capture reasonably generalizable aspects of what this looks like, including (1) *inspiration*, (2) *initial idea formation*, such as brainstorming, freewriting, experimental exploration, (3) *incubation* time for reflection on ideas, and (4) *elaboration*, such as prototyping, drafting, editing, revising.

We then added in key discursive and sociopolitical drivers shaping the creative process, including basic elements of creative workflows, from the gathering of resources to the actual implementation of the creation to render the creative product; and values like *vision, intuition, collaboration* and *technique*. Again, we discussed how the specifics within these processes may change based on the context. For instance, in filmmaking, the process comprises research and material collection, concept and shooting plan development, production, and post-production including editing and sound adjustment. Lastly, we discussed how social power relations shape the relationships between the various actors and entities we listed. We reflected on how these power relations may appear in

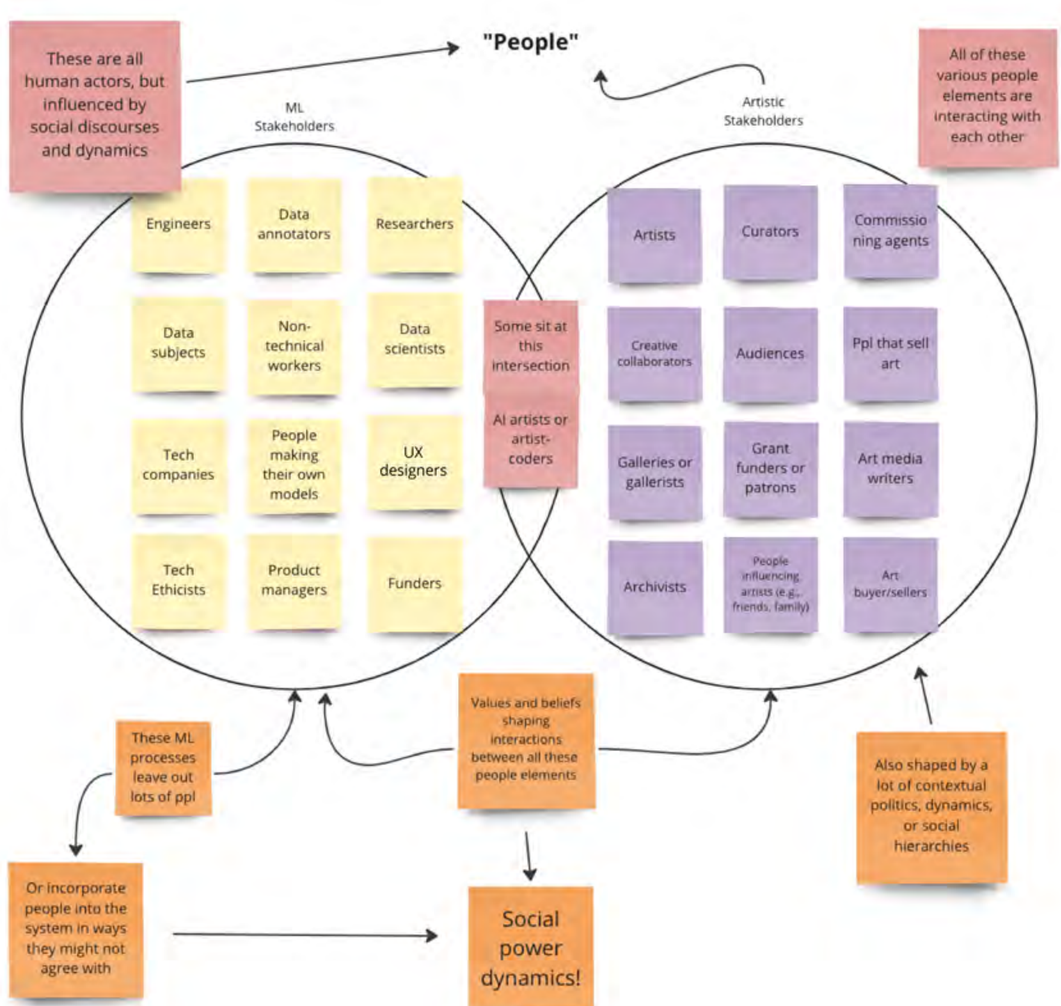


Fig. 2. Snapshot of a "messy" affinity map for the 'people' element of creative ML assemblages

overt ways (e.g., systematic exclusion from art shows, non-consensual forced inclusion in museums) or more subtle form (e.g., smaller signals of approval or disapproval by people in positions of social power).

### 3.3 Synthesizing our Affinity Maps: Identifying Commonalities and Gaps

After creating initial affinity maps of these separate domains, we analyzed themes, identifying commonalities and gaps between stereotypical ML pipelines and creative processes. Through this cross-analysis, we clustered similar elements and began to group these under three broad themes — human actors, actions/process, and outputs/artwork — each of which are influenced by social discourses or sociopolitical dynamics. At this stage, our process was still “messy" as we collaboratively rearranged key aspects of creative and ML processes in our affinity maps (see Figure 2 for a snapshot of one in-progress affinity map on “people").[2] In our discussions, we also identified gaps in creative ML pipelines and tensions in creative processes with respect to people, processes, and products, which led to discussions of how understanding the dynamics shaping these touch points might point to ways they could be reconfigured towards more equitable ends.

In our final stage of analysis we decided that given the variability across creative ML contexts, the elements of people, creative processes, and products were generalizable and flexible enough categories to reflect the basic elements of creative ML assemblages and offer entry points to interrogate the what, how, and why circumstances of ML-mediated creativity, while allowing other researchers to employ these in more specific ways relative to the creative ML context they are focused on. Next, we began to discuss each element in the context of academic and professional ML communities, drawing on positive and challenging personal experiences navigating these spaces as well as extant research. We elaborate on each of these elements, in the finding sections that follow.

### 3.4 Limitations

Although our work offers generative insights for thinking through key relational aspects of creative ML, it has limitations. While we focus on three key facets of creative ML assemblages — people, process, and product — the interactive elements of a particular creative ML assemblage may exceed the ones we discuss here. Accordingly, our analysis of creative ML assemblages is not comprehensive in the sense that it offers the final frame of analysis for all creative ML tools. This was also not our aim or motivation; nor what assemblage methodology affords. Assemblage thinking provides a frame or theoretical orientation that specifically intervenes in totalizing or grand theories. It also draws attention to how each creative ML tools must be examined within its wider social context and interaction with elements of that context. As such, the insights we offer here can support such analyses that endeavor to understand the relational dynamics of creative ML systems.

## 4 CREATIVE ML ASSEMBLAGES: INTERACTIVE POLITICS OF PEOPLE, PROCESSES, AND PRODUCTS

Creative ML is an assemblage that affords creativity through its myriad interactive relationships. Our analysis identified three key elements that interact to shape the sociopolitical politics and characteristics of creative ML assemblages: people, processes, and products. As assemblages are highly contextual, we frame these entangled elements as high-level analytical concepts that researchers can adapt to better understand the how, why, and when circumstances of creative ML tools or ML-mediated creativity. In what follows, we describe each element first within creative ML broadly and then illustrate within the context of academic and professional ML communities, drawing on HCI and related literature.

[2]Here, we include only one snapshot of our affinity mapping to illustrative our process.

### 4.1 People: Community Hierarchies and Logics Broker the Flow of Resources

*People* are a key entity of creative assemblages and include the various actors, communities, or organizations whose distributed arrangement shape the design and development of algorithmic artwork. Assemblage thinking encourages examination of how creative ML systems are located in wider social contexts (e.g., corporate labs, art galleries, university campuses) whose norms, procedures, and techniques influence the realization of computational creativity. Different communities of people are arranged in creative ML assemblages in ways that shape their agency and relationships to ML model development pipelines, sensemaking of an ML tool, and the resulting ML-mediated art. For example, the outputs of creative ML tools — and perhaps computational artifacts more broadly — are typically attributed to the artists who directly create the art piece or the ML researchers who developed the tool. However, a wide range of distributed communities influence the characteristics and performance of ML models with varying levels of agency and visibility.

Looking just at ML model pipelines, less visible *people* include artists whose work comprises training data (e.g., the LAION-5B dataset [147]); archivists or other actors in the art world who made decisions about the promotion and preservation of historical work shaping whose creative perspectives are reflected in ML models [90, 135]; people represented in text, image, audio, or visual data [128]; crowd workers, who prepare, annotate, or rate data [52, 126] in ways dictated by the interests, priorities, and values of others in greater positions of power [170]; or workers who maintain servers and data storage across geo-national boundaries [44]. From an assemblage lens, focusing on how *people* are distributed in creative ML reveals sociopolitical touch points where communities of people unite and part ways across different professions and geolocations with consequences for experiences of creative ML.

The hierarchical arrangement of communities of people in the development, governance, or use of creative ML sets an ethos of engagement for how and which ideas are mobilized in the assemblage. As Philip Mar and Kay Anderson [113] describe in their study of an art collective at Sydney's Museum of Contemporary Art, professional institutions are a *coordinating element* in maintaining creative assemblages. In particular, the hierarchical positions people occupy enable or hinder the exchange of creative ideas, deep learning techniques, and other resources that shape a given ML-art context. For instance, people entities who enact cultural "brokering" positions and work to bridge otherwise disconnected groups or ideas provide "a vision of options otherwise unseen" [27, p. 354]. For creative ML, cultural brokers are those who have access to- or are steeped in- different artistic and technical communities, and can facilitate the exchange of artistic ideas and resources across various creative ecologies.

The concept of cultural brokering points to how center/periphery social power dynamics mediate the flow of ideas and engineering techniques among people within creative ML assemblages and pattern friction. This insight draws attention to how social interactions render creative assemblages gendered, racialized, and shaped by other interlocking social categories of difference [34, 96, 133] that pattern people's experiences in the production and mobilization of creative ML resources. Therefore, "the work" of social inequality in dynamically shaping creative ML assemblages must not be overlooked. In sum, the topological configuration of *people* in a given ML-art context facilitates or constrains the exchange of resources used to foster ML-mediated creativity within and across different communities. To illustrate, we next describe how academic and professional ML communities function as "cultural brokers" in creative ML assemblages.

*4.1.1 Scholarly Communities as Power-laden "Cultural Brokers" in Creative ML Assemblages.* Academic and professional ML communities play a significant role in creative ML assemblages, acting as "cultural brokers" that set an ethos of engagement and impact artists' social capital and access to resources. These communities comprise a variety of individual and collective *people*, including students, faculty, independent or industry researchers, folks in reviewer or service roles, universities, and funders/sponsors. Academic and professional ML communities function not only through the coordinated exchange of ideas but also through other activities related to social capital, such as service work, workshop or conference coordination, socials, career and mentorship support. They enact their coordinating role through the circulation, generation, and promotion of ML knowledge, privileging conference proceedings and journal publications as brokered touch points.

Consider, for example, the hypothetical experience of an artist who is also an ML expert. This researcher-artist possesses deep knowledge of ML systems and leverages their technical knowledge in the artistic-technical process. This expertise allows them to contribute to the technical development of creative ML tools, which is extolled and financially rewarded in ML communities through competitions (e.g., [163]). This researcher-artist can also broker concepts and ideas between artistic and technical traditions, while enjoying the privilege of prestige in ML communities. This prestige may afford increased opportunities for lucrative employment, collaboration among other ML researchers, citation, and promoting their work in the form of ML research papers or open-source code. They might be invited to give talks in top-tier venues, surrounded by a growing clique of prominent ML researchers. These reputational privileges and connections provide a visible platform to present themselves — their story and their art. Similarly, a researcher-artist who is not necessarily an ML expert but who has associations with ML experts may benefit from access to professional ML circles — from increased access to computational resources to being professionally recognized in the ML community. In contrast, artists with limited access to high profile academic and professional communities, or ML artists who face resource, geographical, or financial barriers to participation, may miss well-deserved visibility and recognition for their work given the brokering function of academic communities. The assemblage lens highlights how the culture of the context energizes and constrains how people move through spaces with varying levels of agency. Within the current culture of academic and professional ML communities, people with technical ML expertise and relative access to resources can more easily navigate these spaces.

*4.1.2 Impacts of Scholarly"Cultural Brokers" on ML Knowledge Production.* In practice, academic and professional ML communities, particularly university faculty and departments, play an important coordinating role as brokers and maintainers of ML knowledge with ripple effects for who is represented in ML and how different research is received. As a field, machine learning is highly shaped by social inequality and social categories of difference. Only 22% of ML professionals across the globe are women [68]. Of the ML tenure track faculty at 15 top universities around the world, 67% are white and 14.3% are Asian; Black and Latino faculty have the smallest representation, of 0.6% and 0.8% respectively [177]. In this way, we should recognize academic and professional ML communities as a gendered and racialized "cultural broker" within the assemblage — meaning here that they reflect and rely on social inequalities in their function.

The same patterns of exclusion that structure global patterns of racial and gender representation in academic and professional ML communities shape reception of researchers' ideas. An examination of U.S. doctoral recipients across a thirty year period shows how contributions of scholars from historically marginalized genders and racial groups are more likely to produce novel scientific work, yet their work is frequently de-valued as outside normative discourses [86]; consequently, they often experience more professional friction compared to dominant (or overrepresented) social groups within scholarly communities. Numerous investigations and audits of ML communities have found systematic patterns of gender, racial, and sexuality-based discrimination [173, p. 10]. These patterns of inequality bear out in computational artefacts created by ML researchers that underpin popular ML models [25]. For example, creative ML datasets often have Western compositions [106, 140], or prioritize North American needs and experiences [105], which influence what a creative ML model can generate or output [134]. Given the dominant values of scale and fast pace research in the machine learning field [76], without meaningful attention from academic and professional ML communities, creative ML can amplify existing inequities and ring in new ethical concerns in computational creativity [107, p. 4].

*4.1.3 Conferences as Sites of "Cultural Brokering".* Conferences, workshops, and art shows also reflect important coordinating work that academic and professional ML communities perform. These events are highly visible touch points where differently situated communities interact. Developing and maintaining access to social power, which is gated by "cultural brokers," is a critical factor in how artists build reputations and become famous [120]. This is because successful exhibition, distribution, and promotion of artworks, depend on artists' relationships to galleries and other cultural institutions that can place work in front of viewing audiences [71].

Academic ML communities regularly host juried shows that afford reputational and resource privileges, including the Association for Computing Machinery, the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), and the Conference on Neural Information Processing Systems (NeurIPS). The social power dynamics influencing the machine learning field also pattern engagement at these events, which directly affect the promotion of certain ML artists and AI-art. For instance, art works submitted to an ML conference art gallery [61] or song contest [87] are often created by one or more artists with financial access to computational resources, such as graphical processing units (GPUs) or tensor processing units (TPUs). Well-resourced artists are likely to have connections to- or be- ML researchers affiliated with Global North R1 universities and/or top tech companies. These connections can also provide the advantage of being able to describe the computational principles behind their art in the form of conference papers, giving them further visibility in academic communities over artists with fewer scholarly resources or networking connections. In short, the dynamics shaping academic and professional ML communities pattern artists' access to consequential socio-political networks and creative ecologies.

### 4.2 Process: Criticality and Meaning-Making Through Creative Engagement with ML

The *process* aspect of creative ML assemblages concerns artistic engagement with ML, and is a key form of labour in these assemblages that shapes and is shaped by the exchange of ideas across creative, social, and technological communities. For example, the development or use of certain techniques signals group membership and draws boundaries around artistic communities [100, 101], but it can also rise to new conventions that other artists can build on [158]. While the creative process can be thought of as a literal process of "assembling" algorithmic art, assemblage thinking draws attention to how a given ML-art context holds together different creative and technical knowledge traditions and understandings of machine learning. These traditions and understandings can activate or deactivate power asymmetries within the assemblage. As such, the kind of relations that ML-mediated creative processes enact are shaped by broader cultural norms and reception to different types of engagement with ML models within a particular context [119, 155]. From an assemblage lens, focusing on creative processes calls attention to how different communities make sense of an ML tool's performance and outputs, which are often intentionally presented (explicitly or implicitly) as representing societal consensus. For ML-mediated creativity, engaging the value-laden representational power of creative ML tools can become a key source of inspiration [29], in alignment or against societal consensus.

Within creative ML assemblages, algorithms and data are mediums for artists' creative processes that they creatively and technically manipulate [104]. More specifically, ML-artists view models as *computational material* "whose raw properties, such as adaptive learning, model extrapolation, algorithmic exploration, or probabilistic uncertainty, can be crafted and experienced" [148, p. 2].

This computational material is a collaboratively laboured over effort with sociopolitical properties resulting from choices and interactions made by the particular algorithm's developers [70]. Three especially important ones are data collection, model training, and the testing and evaluation of the developed system. Training data are an essential element for the technical functioning of creative ML models that in part enact the artistic/aesthetic dimensions of creative products. ML models learn patterns, which are influenced by who or what is represented in training data and how they are represented [128]. The patterns ML models learn shape the system's performance and can lead to system outputs that enact a range of representational and cultural harms [134, 152]. Most ML datasets — including those for creative domains — disproportionately represent the culture, ideas, and artifacts predominant in eurocentric and Western contexts [53] and often reflect dominant discourses by embedding gendered and racialized stereotypes [169, 178]. Normative, Western discourses can be further inscribed into datasets through data labeling and annotation, such as the disproportionate labeling of queer identities as "toxic" [54]. These normative patterns in ML model development extend to datasets used for creative ML systems, including fashion [106, 141] and generative art datasets [159]. Datasets that intentionally shift these dominant gazes are rare; notable exceptions include the se-Shweshwe dataset of South African modern Shweshwe fashion dresses [111] and KaoKore dataset of pre-modern Japanese art facial expressions [166]. Consequently, creative ML tools often best reflect the people, culture, and beliefs of eurocentric and Western contexts, albeit in ways that still reflect social hierarchies.

Assemblage thinking draws attention to how ML-artists remix computational material through creative engagement, underscoring the fluidity of ML. The creative process is informed by artists' perspectives, criticality, and the meaning-making they enact through different techniques. As creative processes are collective and interactive [17], they can be analyzed through their position within a respective cultural ecology and its values [74]. As described in Section 4.1, the ways artists navigate ML-art worlds, and in particular academic and professional ML communities, are influenced by relational dynamics that often mirror broader social inequalities, group membership, and boundary-making. The kinds of social relations and commentary enacted through the ML-mediated creative processes can be analyzed similarly by examining and asking questions about its ethos. For example, through their creative process, does the artistic team identify potential sources of inequalities in the algorithms and data they employed as material? Do they intervene in those inequalities as part of their creative process (e.g., do they stimulate the production and exhibition of non-mainstream and non-Western creative approaches)? Or, to what extent do these creative processes reshape the dynamics within the local ML-art ecology? The answers to these questions will vary by context, but they offer insight into the what, how, and why circumstances in which ML-mediated creativity happens. For example, artists may cultivate new creative cultures [117], forge new ML techniques [138], or identify potential sources of inequalities in the algorithms and data they employ as material [12]. In the next section, we examine how such questions offer researchers different entry points for identifying what kinds of social relations are formed and enacted through an artist's creative process. To illustrate, we explore two ML-art pieces shown in the 2021 juried CVPR art show [61].

*4.2.1 Crafting Computational Material as a Social Mirror in Scholarly ML-art Competitions.* The Conference on Computer Vision and Pattern Recognition (CVPR) is a premier annual computer vision event, and since 2018, has hosted a juried art show. Computer vision techniques have long been entangled with the arts [11], particularly at academic and professional organizations [66]. In these shows, researcher-artists employ algorithms or ML models as material in their creative process. As algorithms have social and political properties [29], some artists manipulate these models to reveal and intervene in these properties as part of the creative process. ML-artists may employ

Fig. 3. Veiled woman holding vase, 2021.
© Nouf Aljowaysir. Photo: Courtesy of artist.

Fig. 4. Actor smoking hookah, 2021.
© Nouf Aljowaysir. Photo: Courtesy of artist.

artistic-technical processes to shift or creatively comment on an algorithm's representational performance as it relates to social inequalities, such as gender [95], race [19], disability [20], or colonialism [134]. For example, in her "Salaf" collection, ML artist Nouf Aljowaysir created a series of photographs motivated by frustration of the Western colonial gaze often enacted through AI failures. As Aljowaysir describes, she "construct[ed] her genealogical journey using two different voices: [her] own and an AI 'narrator'" [5, n.p]. She found generative ML models failed in recognizing the faces of Bedouin people, and rehearsed tired warfare stereotypes. The Bedouin are nomadic Arab tribes of Middle Eastern deserts. Using the U-2 Net model, she erased the stereotypical Orientalist images to create an "absent" dataset, and then trained the generative ML model StyleGAN2 on the absent dataset to signify the erasure of her ancestral memories. Her collection is a moving series of ML-generated photographs haunted by the absences of human figures (see Figures 3 and 4 for two photographs part of the winning Salaf collection). It was Aljowaysir's criticality towards the ways that creative ML tools often fails disproportionately for certain communities that inspired and shaped her creative process to rework ML models. Assemblage thinking draws attention to what and how we form relationships to ML-art and how that shapes the broader assemblage. For Aljowaysir, the creative process became an opportunity to give sociotechnical commentary on creative ML tools and to invite viewing audiences to imagine a future where ML models are designed to not reproduce structural inequalities, like Orientalism, that too often materialize in algorithms.

A way to employ assemblage thinking in the study of ML-mediated creativity is to understand how artists make sense of and engage the characteristics of the baseline ML model. For example, artists may use ML models to offer commentary on society and technology, or to imagine new social relations. In the work "Cyprus as AI Saw it in 1879: Perpetuating Colonialism," ML-artist Alexia Achilleos [2] created a series of photographs that explicitly incorporated historical accounts of colonialism. Achilleos fed textual descriptions from Sir. Samuel Baker's book *Cyprus as I Saw it 1879* into two AttnGAN Text-to-Image models: (1) a model trained on the popular Common Objects in Context (MS-COCO) dataset created in the U.S.; and (2) a model custom trained on data of Cypriot and Eastern Mediterranean landscapes. The final art piece contains an image from each model, which juxtaposes the colonialist gaze against generative image models of Cyprus that offer more and less resemblance to the Eastern Mediterranean landscape. Achilleos described how her creative process offered critical commentary on both Baker's Orientalist gaze and continued colonialism in digital and ML imagery [2]. The work was also exhibited as an installation at Electropixel 12 in Nantes, France. As a dynamic element of creative ML assemblages, the creative process energizes certain sociopolitical properties of ML models through artists' disassembling and reassembling of ML models. The creative *process* is thus an important, active force energizing the production and meaning-making of ML-art.

### 4.3 Products: Social Dynamics of Cultural Criticism Shape Evaluation of AI-art

*Creative products* refer to the algorithmic art outcomes of a creative ML system. While art may be made for personal or specific ends (e.g., a client commission), the dynamics of cultural criticism are a key way that power functions in creative ML assemblages and stabilize broader meanings ascribed to ML-mediated artworks. It is easy to assume the assessment of artistic products depends on objective or inherent quality, such as its technical finesse or novelty. However, cultural studies scholars have revealed how the concepts typically used to evaluate creative work are socially constructed and vary across evaluating audiences: peers, critics, or the general public. For example, peer assessment is often captured through prizes and awards [30, 139] or through the repetition of other artists' content [100]. Professional critics might communicate their assessment through the conferment of awards or harsh reviews [30]; and non-professional or public audiences signal approval (or disapproval) through sales or box office revenues [102]. Within a given ML-art context, whose judgements are disproportionately influential will be contextual.

An assemblage lens calls attention to the location and power of different evaluating audiences, and the knowledge traditions they draw upon. When peers evaluate their fellow artists' creative work, they tend to favor artworks by artists highly embedded in the same field [30], reflecting how evaluation preferences emanate from a core. Similarly in film, the existing social status and the experience of the filmmaking team influences their chances for an Academy Award nomination [139]. In contrast to peer assessment, when professional critics evaluate creative works. They perceive this as sign of novelty [30]. Assessments by professional critics are also influenced by sociological factors. Social categories of difference tend to pattern critics' assessment of artistic work. For example, analyses of book reviews have found that book critics mobilize gender, racial, and ethnic identifiers to make claims about a novel's authenticity, classify works into ethnic rather than more general literary genres, and identify talent [35, 36]. Phillipa Chong [35] identifies these evaluation practices as "reading difference" where critics assign differential value to literary works based on their classification of authors into racial, ethnic, or national categories. When public audiences evaluate creative works, they often value art that shares similarities with other contemporary works or those that are relatively consistent with an artist's established style. For visual arts, Stoyan V. Sgourev and Niek Althuizen [150] find public audiences only reward stylistic inconsistencies – differences in an artist's work compared to their previous work – for high-status artists. For these artists, audiences attribute stylistic inconsistencies as an expression of creativity. In contrast, stylistic inconsistencies in the work of artists with lower-status are not perceived in the same way. These insights underscore the multiple and mutable dynamics of creative judgements. As discussed above (Section 4.1), socio-historical patterns of inclusion/exclusion shape the degree to which one is embedded within a particular community and may influence creative processes (Section 4.2). Here, those patterns of embeddedness shape evaluation criteria that further mobilize the flow of certain ideas or discourses in a creative ML assemblage.

Creative judgements thus have a kinetic, rather than fixed, characteristic. Evaluation criteria change depending on the particular institutional arrangements – i.e., the role of art galleries, critical discourse, and educating institutions – and the political organization of artists within artistic movements [1, 142]. The sociopolitical conditions informing viewing audiences within a creative ML assemblage are thus essential coordinating elements to consider when examining artistic production and evaluation. To illustrate, we next focus on how dominant logics and trends in academic and professional ML communities shape evaluation of ML-art, focusing on the values and cultural priorities of the context.

*4.3.1 Whose Assessments? The Politics of Evaluating ML-art.* As ML-artists are embedded within particular artistic and ML communities, the logics of those communities shape the meaning-making and subsequent assessment of artworks. This reflects the "relations of exteriority" that characterize creative assemblages, where components of one assemblage may be disassembled and reassembled within and across creative assemblages [50]. Rather than give attention to qualitative evaluation criteria like transformative social commentary or group collaboration, there is a strong emphasis on quantifying creativity within ML as a field. For example, ML researchers have proposed to evaluate creative products, including painting, sculpture, and poetry, by quantifying the piece's level of creativity through metrics of 'novelty,' 'unexpectedness,' and 'influence' in art networks [60, 110, 153]. This speaks to a dominant ML logic that all relevant information about the social world can be found within training data. This is problematic regardless of tool, but in the context of creative ML, this logic is especially inattentive to how people experience and construct meaning from art works, where the social context, audience's knowledge, and expectations are constitutive factors. While creative ML algorithms may be able to recognize low-level features, such as color, brushstrokes, and frequency-related information, they remain ineffective in capturing emotive responses to an artistic style. While quantified assessments prop up a logic that creative judgements can be easily reduced to computational assessment, they also ignore major social factors shaping creative judgements, such as (1) artist prestige or embeddedness within an artistic community, (2) kinetic factors reshaping creative ecologies and their approach to creative judgements (e.g. the changing influence of institutional arrangements on evaluations), and (3) historical patterns of exclusion in terms of which artists are celebrated (e.g., pre-existing racial and ethnic inequalities) are seldom considered in quantitative evaluations.

Citational politics are an important coordinating element in shaping assessment within the academic and professional ML communities. Across scholarly disciplines, ML papers are among those most cited; and the most highly cited ML papers re-use or manipulate popular model architectures, such as Generative Adversarial Networks, and may not necessarily explore the possibility of lesser-known but relevant model architectures [45]. The preference given to a particular ML model does not necessarily mean that model is the "best;" rather model popularity is often patterned based on whether it is considered "state-of-the-art," which is a politically fraught phenomena and shapes the development and collective investment in certain kinds of algorithms. While having a high citation count affords professional prestige in scholarly circles, energy invested into particular ML models shapes what creative outputs are possible from those models, and how those artworks are assessed. Although most ML conferences have an anonymous review process, citations can potentially reveal influential authors associated with a paper, who may have promoted their artworks in different venues. Additionally, workshops at leading conferences often invite the most influential and often highly visible researchers to share their findings. Although this may have a positive impact on the number of participants in the workshop, the ideas and papers from ML scholars outside the mainstream may be side-lined. Unfortunately, many creativity-driven ML papers are only presented in creativity-focused workshops and not into main ML venues and thus garner less attention than other research topics. These knowledge politics shape ML scholarly conversations on creative assessment, which currently prioritize technical contributions and computational novelty over other dimensions of creativity.

## 5 DISCUSSION

In this paper, we have employed assemblage thinking to illustrate the people-process-product facets of creative ML assemblages. We structure our discussion into two sections, discussing the theoretical and methodological implications that assemblage thinking offers, highlighting how this approach could be applied in HCI and CSCW.

### 5.1 Creative ML as Entangled Interactions of Sociotechnical Elements

Our findings illuminate how creative ML is a collaborative effort in which the elements of people, organizations, culture, practices, and technology are constantly influencing each other. In our study, we unpacked three entangled touch points that enable creative ML and energize particular values and social conditions into being, focusing on the relational encounters between coder-artists, ML models, and viewing audiences in academic and professional ML communities. Rather than emphasize static understandings of creative ML as enacting a singular kind of effect in the world, we have sought to illustrate how ML-art spaces are patterned by numerous interacting forces. These forces include access to ML resources (Section 4.1), how conventional ML pipelines shaped by Global North logics (Section 4.2), and citational politics in academic communities (Section 4.3). These forces are dynamic and socially situated. As such, the sociopolitical characteristics of creative ML are not inherent nor fixed. Rather, they are produced through situated interactions between different socio-material actors, including patterns of inequality in the field of ML, scholarly and professional discourses, artists' creative motivations and vision, and ML techniques and artifacts.

However, creative ML is more than each element individually (developers, artists, code, scholarly communities, companies): it comprises the interactions of all elements together. By examining how (1) different communities broker resources and knowledge, (2) the creative process offers a way to remake the sociopolitical characteristics of computational material, and (3) cultural logics that influence the reception of ML-mediated art, it becomes clearer that creative ML is not just the algorithmic creation of engineers and artists, but is shaped by local community dynamics and sociohistorical forces that pattern daily life. The creative ML model is just one component in a broader apparatus that constrains and energizes how different people, ideas, and values move. Prior HCI work has critiqued how dominant discourses of art made "by AI" minimizes the creative and technical work that goes into creative ML [49] and how different communities conceive of ML as as a research discipline, raw material to be crafted in artistic practice, or a cultural object. Baptiste Caramiaux and Sarah Fdili Alaoui [29, p. 4], for instance, describe ML as a "cultural object stemming from a collective cultural history...built from culturally-curated data (e.g., images) and deployed within a socio-cultural context." These studies reframe AI in art practice as value-laden material with political and cultural impact.

Our study extends this work, further revealing how we cannot fully understand creative ML models if we study them as only a technical system, an artistic endeavor, or even a product to be sold. The relationships between the technical system and the social world are reciprocal and co-functioning [56]. Looking back to earlier art-and-technology movements enacted by engineering and art worlds (Sections 2.1 and 2.2), and the varied influence and reception these movements received is a reminder of how the social impacts of a given ML-art context is situated and local. As Caramiaux and Alaoui [29] also note, the field of ML-art has a complex relationship to conventional ML, as it is both reliant on its research advances and positions its values of creative exploration and questions of power in opposition to the conventional ML field. These points of friction shape the development of different creative ML spaces. The concept of assemblage enables understandings of ML-mediated creativity as constantly changing and enacted by a wide range of factors. The analytical shift from creative ML model to creative ML assemblage has important methodological implications for how to examine the social impacts of creative ML.

### 5.2 Methodological Implications of Assemblage Thinking

Central concerns in HCI analyses of ML-art center on how to conceptualize the fluid interactions and collaborations occurring through ML-mediated art practice [29, 31] and to what extent artists can critically appropriate ML models [31]. Hugo Scurto et al. [148] describe the technical and creative work of ML-artists as a practice of "intra-active machine learning," in which the creative process is an amalgam of different knowledge traditions and sociotechnical conditions. They emphasize that while the ways in which artists' blend techniques from different knowledge fields yields something distinctly new, engaging in these practices creates friction as ML-artists navigate institutions and practitioners with a different normative sense of ML materials and techniques. Assemblage thinking, while complementary to this prior work, widens HCI's analytical scope to enable examination of the ongoing processes through which people, organizations, culture, practices, and technology influence each other to shape a given ML-art context. Next, we discuss four ways assemblage thinking can support HCI research.

**Accounts of How Sociotechnical Elements Co-function in Creative ML:** Our research enriches understandings of creative ML by illustrating how assemblage thinking helps to interrogate the what, how, why, and when circumstances in which ML-mediated creativity happens. HCI scholars recognize that creative ML is a rapidly evolving space [31], and as different creative ML tools and modalities become more accessible, their integration into professional art and culture industries and existing tools – such as design [22], gaming [181], and stock photography [64] — will likely increase. The effects creative ML will have in different creative sectors in terms of labour, reshaping techno-creative practices, and the meanings ascribed to products made with these technologies will be influenced by numerous, entangled local and broader influences. Prior investigations reveal how emerging deep learning technologies that enable end-to-end automation of creative outputs — such as image, music, or video generators — can mechanize creative processes (e.g., [40, 80]) and manifest hegemonic power dynamics into creative products, such as sexism [38] and Orientalism [134], at scale. Understanding the logics and dynamics shaping the creation and reception of creative ML applications grows only more urgent. The people-process-product analytic we offer for engaging assemblage thinking is *contextually flexible*: these entangled elements apply to different creative ML applications, although the precise ways they crystallize depend on the context at hand. In this way, the people-process-product analytic offers a generative starting point to examine the social impacts of creative ML applications complementing the rich history of HCI explorations of creativity [69].

**Accounts of Distributed Sensemaking:** Our research underscores how assemblage thinking draws attention to how ML-mediated creativity emerges through collective and contingent interaction, and offers a powerful method to understand distributed sensemaking in ML-art. Accordingly, our findings extend HCI work on "distributed critique" in creative communities, which reflect how feedback regarding the design and interpretation of sociotechnical artifacts is a social process of sensemaking arising from the interactions of different communities [98]. Employing assemblage thinking to study people, creative processes, and creative products in ML-art contexts offers entry points to uncover the ongoing, collective sensemaking in a given ML-art context that is distributed across differently situated actors. Prior CSCW work has already examined ML-artists' sensemaking. For example, Caramiaux and Alaoui [29, p. 19] describe: "AI artists have a political voice that promotes the development of a necessary critical discourse on technology and AI and brings it to the general public." This suggests that ML-artists may have a different understanding of creative ML models than ML researchers, who may be more focused on the technical aspects of these models. Examining a ML-art context as an assemblage can help us to understand these different understandings of ML models and how they shape the generation, exchange, and reception of ML-art. In particular, the people-process-product analytic can provide entry points to consider relevant communities and their particular understandings. For example, we saw how artists and mainstream ML research communities can understand the properties and social impacts of ML models in significantly different ways, which shape engagement with (Section 4.2) and evaluation of (Section 4.3) creative ML models. By examining the different ways in which people make sense of ML models, we can gain insights into the social and political implications of ML-art.

**Accounts of Entangled Social Power Dynamics:** Assemblage thinking facilitates analysis of the entangled values and logics underpinning creative ML tools, practices, and communities. CSCW has long been concerned with understanding interdependent processes of change and emergence in computing. Steven J. Jackson et al. [89, p. 2] use the metaphor of *the knot* to describe the "multiple gatherings and entanglements through worlds of design, practice, and policy are brought into messy but binding alignment." Assemblage thinking provides a complementary framework to examine and trace how different human, technical, and discursive elements *become knotted*, and how social power dynamics flow within and across contexts. This analytical lens supports scholarly analyses of how the values and logics of a creative ML tool interact with the already existing values and logics of a creative industry. For example, ML applications enact social formations through their marking of social identities (e.g., gender, race, religion, sexuality) in data, which are reinforced through algorithmic logics of scale [81].

Assemblage thinking calls attention to the effects of knotted relations among forces in creative ML. For instance, ML researchers have designed algorithms to classify musical styles by gender relying on crowdsourced and algorithmically augmented data, suggesting there is a "female style" in music [171]. If certain gendered musical styles or features correlate with higher or lower revenues, already existing gender inequalities in the music industry may perpetuate. Assemblage thinking offers a method to understand how different components of an assemblage (e.g., algorithmic logics of data classification and essentialist data labeling) can be plugged into another assemblage (e.g., the music industry), in which its interactive effects differ (e.g., the unanticipated reinforcement of gender inequality). By examining the entangled values and logics underpinning these interactions, we can better understand the potential social and political implications of creative ML tools.

**Accounts for Developing Creative ML:** Assemblage thinking underscores the contingency of creative ML tools, and how they can be reformed with different logics and values. The people-process-product analytic offers starting points to help researchers interrogate the energizing what, how, why, and when circumstances in which ML-mediated creativity happens. Insights drawn from such analyses can point to opportunities for technology builders to reshape creative ML tools towards more equitable ends. To use Steven J. Jackson et al.'s [89] metaphor, the social power relations of a particular tool can *become unknotted*. For example, in our analysis, ML-artists drew upon their perspective and lived experience to critique the representational and cultural harms (e.g., demeaning stereotypes, erasure) that saw arising from conventional ML models and datasets (Section 4.2). As datasets are an important factor in the performance of a creative ML tool, curation of non-Western datasets is a critical mechanism to develop creative ML tools that meaningfully center non-Western art and aesthetics.

However, assemblage thinking also reveals the broader hierarchies in which ML tool components are situated (like ML datasets) and how bigger shifts are often necessary. While important, merely developing new datasets is not a panacea; as changing this one element is unlikely to radically transform the power dynamics shaping creative ML pipelines, which are also often driven by global logics of capitalism. As Anna Lauren Hoffman [85, p. 3550] describes simply increasing dataset representation is unlikely to shift power dynamics as shallow forms of "inclusion represents an ethics of social change that does not upset the social order." Certainly, the creation of more equitable ML datasets can help center historically marginalized voices and stories. Yet, other inequities will persist, such as restricted access to computational and data resources, or being disconnected from networks of ML artists. Remaking the relational dynamics of dominant ML pipelines requires more transformative action, which assemblage thinking can help illuminate without slipping into a myopic view.

## 6 CONCLUSION

We illustrate how creative ML can be understood as an assemblage by approaching it as a system in which the elements of people, organizations, culture, practices, and technology are constantly influencing each other. Through an analysis of key elements, we illuminate how assemblage thinking can strengthen HCI analyses of how creative ML is produced through relations of force, connection and patterning. However, our goal is not to merely draw attention to the interactive relationships that assemble and reassemble ML-art worlds. Rather, it is to offer a framework to understand how heterogeneous human, technical, and discursive elements cohere and give shape to creative ML systems.

For computing research broadly, assemblage thinking focuses researcher attention away from solely the code or technical functioning of a ML model to the broader sociotechnical influences through which the creative ML tool is produced and artworks are made in practice. While creativity and ML systems are collective phenomena, studying them through the lens of assemblage enables deeper understandings of the what, how, why, and when circumstances in which ML-mediated creativity happens. Assemblage thinking, with its emphasis on the "work" or labor of coordinating elements, thus helps researchers identify how particular values and logics operate within an ML-art context. Insights from these analyses can illuminate how creative ML tools can be made or remade in ways that uphold or contest hegemonic power dynamics. Assemblage thinking can thus be useful in designing transformative ML-art art futures.

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