# CG-art

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# CG-Art: Demystifying the Anthropocentric Bias of Artistic Creativity[1]

## Abstract

The possibility of algorithmic artistic creativity has been subject to criticism, raising doubts about the validity of the term computer-generated art (CG-art) as defined by Margaret Boden. Critics argue that, rather than a mere limitation of current technology, the creation of CG-art is inherently impossible, as art is considered a uniquely human capacity. However, recent cognitive science studies on artistic creativity suggest that such rejection of CG-art may stem from an anthropocentric bias. This chapter aims to convincingly argue that the dismissal of machines' creative artistic potential lacks support from recent advancements in computer science, with particular emphasis on providing an explanatory account of the functioning of Generative Adversarial Networks (GANs).

**Keywords:** CG-art; computer; art; creativity; algorithm

[1] An adapted version of this chapter was published in the article "CG-Art: Demystifying the Anthropocentric Bias of Artistic Creativity" (Arriagada, 2020).

## 3.1. Introduction

Artificial intelligence (AI) has developed exponentially since the beginning of the 21st century. Every day we are surprised by algorithms that allow machines to perform tasks once considered impossible. We receive shopping recommendations on Amazon and reminders of our agenda thanks to Google Assistant. Car company Tesla has invested millions in autonomous driving. Such examples continue to spread. In short, it seems that every time we exclude something from the domain of AI, researchers take it as a challenge to overcome. Though, all the tasks mentioned above are perceived as mechanical. Therefore, they can be mathematically modelled to be executed by a computer. Our common sense can project AI development in the distant future and imagine that it will be possible to perform any mechanical task by an application or computer program. However, can a machine create art? Is artistic creation a mathematically modellable task?

## 3.2. Creativity: Limit or Goal for CG-Art?

The scenario just described has led artists, philosophers, cognitive researchers and programmers to wonder if a machine has the potential to create. Thus far, computational creativity has established itself as a subfield within AI (Toivanen et al., 2019). Simon Colton and Geraint Wiggins (2012) define its research as: "the philosophy, science and engineering of computational systems which, by taking on particular responsibilities, exhibit behaviours that unbiased observers would deem to be creative" (p. 21).

The subject continues to be discussed since it requires a certain level of mathematical modelling of what we understand by creativity. As we saw in Chapter 2, Margaret Boden (2011) proposed the following definition of creativity: “the ability to come up with ideas or artefacts that are new, surprising, and valuable” (p. 29). Regarding artistic creativity, this chapter will demonstrate that precisely the *value* aspect of the definition is the most controversial when analysing creative algorithms. In due course, I shall return to this matter and endeavour to showcase that neglecting the significance of artistic computer creations disregards two crucial factors: the mechanical evaluation of artistic work and robotic embodiment. Both of these facets are explored in Section 3.4.

As pointed out in the preceding chapter, creative algorithms have undergone fruitful development thanks to Artificial Neural Networks (ANN) models. In particular, a subtype of these models, Generative Adversarial Networks (GAN), allowed the computer program AlphaGo to defeat Lee Sedol, considered the best human Go player in the world. This competition is used to show that GAN effectively created movements that seemed irrational to humans. Therefore, it is no longer absurd to argue that algorithms can create Go plays that are novel and surprising. Nevertheless, is this homologous to artistic creation? What about the aesthetic assessment of the creations of machines?

The fundamental point here is that Boden (2011) defined a particular type of art by joining the concepts of *creativity* and *computing*. Thus, CG-art is understood as “*the artwork results from some computer program being left to run by itself, with minimal or zero interference from a human being*” (p. 141). The use of algorithms to generate aesthetically pleasing output for human evaluation has produced numerous examples. One such example is the painting *Portrait of Edmond de Belamy*, an AI creation sold at Christie's in October 2018 (Still & d'Inverno, 2019). This piece, produced by a GAN, has gained widespread attention as the first AI artwork to be sold at auction.[2] While this claim is inaccurate—an auction at the Gray Area Foundation for the Arts in San Francisco in 2016 raised nearly $100,000 by selling twenty-nine CG artworks (Miller, 2019)—it has sparked questions about whether machines can create art.

In examining the history of CG-art, we encounter two notable examples: Harold Cohen's AARON and David Cope's EMI. Both projects were propelled by the dedicated efforts of their programmers to refine the underlying algorithms, while the software played a predominant role in the actual creation of the artwork. Nevertheless, the prevailing consensus holds that the creative output of AARON and EMI represents the authorial vision of Cohen and Cope, respectively, rather than that of the software itself. This critical issue will be thoroughly investigated in Section 3.6. Before delving into this topic, however, it is essential to gain an understanding of the nature of art and its differentiation from mathematical modelling, as perceived by the lay public.

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[2] For details, see Chapter 6.

## 3.3. Is Mystical Inspiration the Only Explanation for Artistic Creativity?

We have seen that a GAN can produce a novel and surprising play. However, a third characteristic is still lacking to meet Boden's definition of creativity: *value*. It is beyond the scope of this thesis to evaluate the value of AlphaGo's creations. The focus of this investigation is algorithms for generating art, so the value referred to here is aesthetic value. If it is already controversial to claim that AlphaGo produces plays, it is even more problematic to assert that machines can produce outputs of aesthetic value. On this point, scientist and artist Aaron Hertzmann (2018) notes:

> The concepts of art and inspiration are often spoken of in mystical terms, something special and primal beyond the realm of science and technology; it is as if only humans create art because only humans have "souls." Surely, there should be a more scientific explanation. (p. 1)

While rejecting the notion that a computer program can create art, Hertzmann prompts us to scrutinise our concept of art. I concur that many artists are hesitant to regard computer-generated outputs as authentic art. Nevertheless, their arguments ultimately rely on *talent* and *inspiration*, which are perceived as mystical qualities. The aim of this research is not to challenge many artists' mystical conceptions of art.[3]

[3] For a more comprehensive examination of mysticism and artistic creation in 20th century art, please consult *Mística y creación en el siglo XX: Tradición e innovación en la cultura europea* (Cirlot & Vega, 2013).

Rather, this investigation treats such views as matters of faith and, therefore, indefeasible.

Considering the above, next it will be investigated the aesthetic aspects of algorithms or machine creations. It must be pointed out that a straightforward objection to the lack of a mystical connection in CG-art is that it differs from human art. Thus, although human artists may choose to believe in mysticism, potential computer artists do not have to submit to this requirement. From this research perspective, it is much more productive to study the aesthetic value of CG-art without appealing to concepts such as *talent*.

## 3.4. The Aesthetic Value of CG-Art. Two Approaches: Human and Mechanical Evaluation

The subsequent sections will not delve into how CG-art can effectively generate novel and surprising works, as this can be achieved simply through random combinations. Therefore, this chapter will not elaborate on these issues. Instead, it is argued here that the most controversial aspect of CG-art is its aesthetic value. As a result, this chapter will demonstrate how CG-art satisfies this requirement through two approaches: one focusing on human evaluation and the other on machine evaluation.

### *3.4.1. Human Evaluation of the Aesthetic Value of CG-Art*

Recently, people's perceptions of CG-art have been evaluated. Researchers examined how human observers react to artworks generated by computers and humans in the article "Putting the Art in Artificial: Aesthetic Responses to Computer-Generated Art" (Chamberlain et al., 2018). The findings reveal a negative bias towards CG-art. As expected, the works in which CG-art exhibited plastic representational features were perceived as more artificial than abstract works.[4] Similarly, the observers valued imitations of brushstrokes and slight imperfections in CG artworks more highly.

Chamberlain et al. (2018) verified that this negative prejudice toward the aesthetic value of CG-art diminishes when the observer can see the production of the work. This led them to suggest that increasing the anthropomorphic characteristics of a robot could eliminate hostility towards CG-art. Indeed, a human observer seems to expect to see artists working on their artwork. The *black box* model, in which only the printed output of an algorithm can be seen, moves away from the current human vision of artistic creation. The simple fact of seeing a robotic arm painting on a canvas increases the observer's empathy. Chamberlain et al. postulate that this may result from the activation of mirror neurons in the human brain.

[4] For details, see Chapter 5.

If the *black box* nature of CG-art presents a challenge to its aesthetic value, it is worth considering how this challenge could be overcome. However, creating a robot as complex as those depicted in the TV series *Westworld* (2016) is not yet technologically possible. Nevertheless, this challenge can be addressed by presenting human works and CG-art to observers without revealing which is which. This issue is addressed explicitly in the article "CAN: Creative Adversarial Networks Generating 'Art' by Learning About Styles and Deviating from Style Norms" (Elgammal et al., 2017). The authors developed Creative Adversarial Networks (CAN), a modification of a GAN, which was optimised to be genuinely creative, rather than simply imitating human artistic styles (as explained in Section 3.4.2).

The findings in this study showed that humans assign a higher score to the CG-art created by CAN, surpassing a sample of Abstract Expressionism premiered at the Art Basel art show in 2016. The participants were asked to assign a score of 1 to 5 for the qualitative indicators of intentionality, visual structure, communication and inspiration. For this, the procedure already tested in a similar experiment conducted by researchers Leslie Snapper, Cansu Oranç, Angelina Hawley-Dolan, Jenny Nissel and Ellen Winner (2015) was used. In particular, subjects had to answer the following four questions:

> Q1: As I interact with this painting, I start to see the artist's intentionality: it looks like it was composed very intentionally.
>
> Q2: As I interact with this painting, I start to see a structure emerging.
>
> Q3: Communication: As I interact with this painting, I feel that it is communicating with me.

Q4: Inspiration: As I interact with this painting, I feel inspired and elevated. (Elgammal et al., 2017, p. 17)

As observed, no particular interest is in defining any of these qualitative aspects. This is because the experiment focuses on a functional measurement model. As mentioned above and discussed in Chapter 2, those blind tests are built on a modified Turing test. For this chapter, what is essential is that the experiment results surprisingly showed that CG-art scored higher than human art on every item (Elgammal et al., 2017). On this basis, it must be concluded that in a blind test, CG-art has aesthetic value for humans.

On the other hand, human-made art consistently receives aesthetic appreciation during its creation process. For example, human writers usually draught, correct, and modify their ideas as they go along until they finally consider that their writing meets their aesthetic-literary standards. This is an internal evaluation carried out by the artists on their products. So far, we have only discussed the external evaluation of CG-art performed by the human audience. Therefore, it is necessary to consider whether an algorithm aesthetically values its own art.

### *3.4.2. Mechanical Evaluation of the Aesthetic Value of CG-art*

When Harold Cohen wrote the computer program AARON, which he designed to produce art autonomously, he filtered the output that seemed aesthetically valuable to him. Since then, algorithms, particularly ANNs, have progressed significantly. As previously mentioned, the GAN subtype is currently the most widely used. In the following paragraphs, it will be demonstrated that GANs filter their products, discriminating between those that achieve aesthetic value and those that do not. In other words, GANs evaluate their performance in a way that is not supervised by humans. However, before discussing this, it is necessary to understand how a GAN works:[5]

> Generative Adversarial Network (GAN) has two sub networks, a generator and a discriminator. The discriminator has access to a set of images (training images). The discriminator tries to discriminate between "real" images (from the training set) and "fake" images generated by the generator. The generator tries to generate images similar to the training set without seeing these images. The generator starts by generating random images and receives a signal from the discriminator whether the discriminator finds them real or fake. (Elgammal et al., 2017, p. 5)

This dual model has an aesthetic assessment incorporated into it. In effect, when the *discriminator* (D) is deceived by the *generator* (G), the GAN reaches an aesthetic value similar to that of the original set of training images provided. Therefore, a GAN does not create new computer art styles but rather emulates human artistic styles. Fortunately, among the GANs exist a subtype, named creative adversarial networks (CANs), explicitly coded to move away from imitation and achieve authentic ANN-

[5] The following is a continuation of the brief description of these ANNs provided in Chapter 2, Section 2.4.2.

based creativity. Researchers Ahmed Elgammal, Bingchen Liu, Mohamed Elhoseiny, and Marian Mazzone (2017) explained that in this modification of the GAN, D gives G two signals: (a) classification of art or non-art, and (b) correspondence to a specific artistic style.[6] In this way, "the proposed CAN model generates images that can be characterised as novel and not emulating the art distribution, however, aesthetically appealing" (p. 13).

Therefore, the statement by Hertzmann (2018) that "unlike human artists, these systems do not grow or evolve over time" (p. 19) does not seem justifiable. A CAN is capable of creating and evaluating on its own. Therefore, these capabilities allow us to affirm that a CAN grows and evolves aesthetically.

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[6] The operation of a CAN is essentially a modified GAN designed to achieve three objectives: generating novel works, ensuring that the novelty of the work remains within acceptable limits, and increasing stylistic ambiguity (Elgammal et al., 2017). The CAN comprises two subnetworks: the *discriminator* (D) and the *generator* (G). D has access to a human art database with labels to distinguish the style of the samples (e.g., Renaissance, Baroque, Impressionism, Expressionism, etc.). G does not have access to this database. G aims to deceive D from a starting point of nothing and receives feedback in two aspects, two signals. The first signal that G receives from D is the classification of art or non-art. Moreover, G receives the signal indicating how difficult it was for D to classify the artwork into a specific style. The greater the difficulty D faced in classifying G's work, the more G deviates from the styles known to D. Therefore, the CAN creates art that goes beyond emulating known styles; it exhibits true creativity by deviating from them.

The described mechanical evaluation of the aesthetic value of CG-art can be related to the concept of *creative autonomy*, which Kyle E. Jennings has discussed in his article "Developing Creativity: Artificial Barriers in Artificial Intelligence" (2010). This author claims that the biggest challenge for AI developers is to demonstrate that their systems are more than an extension of their own human creativity. Thus, Jennings

> introduced the concept of creative autonomy, which requires that a system be able to evaluate its creations without consulting others, that it be able to adjust how it makes these evaluations without being explicitly told when or how to do so, and that these processes not be purely random (p. 499).

According to the above, creative autonomy will be guaranteed every time we face a CAN-based system. Still, this is also true for ANN-generated artworks employing GANs. Those cases can be considered emulation of styles. However, it must be noted that GAN's products can also be CG-art, just not a new style of art. For example, you can have a new GAN-made pop song. This song would be CG-art, even though the GAN emulates the human artistic style of pop music.[7]

Nevertheless, this issue still needs to be investigated because, although all GANs are autonomously creative, that does not imply that creative autonomy is exclusive to GANs. In this sense, Jukka M. Toivanen et al., in the article "Towards transformational creation of novel songs" (2019), have argued that a creative system

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[7] For details, see Chapter 7.

must contain an architecture with at least three elements: a generator, a discriminator, and "a meta-level control layer in which the system uses this system-internal feedback to modify its own constraints" (p. 5). The meta-level control layer could be the determining condition to decide if a system has creative autonomy. As we have seen, this condition will always be fulfilled in the case of GAN-based systems.

## 3.5. CG-Art and Society

Hertzmann (2018) asserts that the final criticism of CG-art is that art is a social activity and, as computers are not *social agents*, they cannot create art. We will briefly address this criticism with two responses that will be relevant for future analysis and development.

First, Hertzmann gives the impression of forgetting that he is discussing CG-art. While it is true that human-made art is social, in the terms stated by Hertzmann, this does not necessarily mean that CG-art must be social as well. By studying CG-art, we are not examining human art; rather, we are analysing algorithm-made art, and the ways in which algorithms relate are not well-studied, even in sociology. Therefore, it cannot be concluded from the perspective of this study that a computer cannot create art simply because it is not a social entity. This is based on the fact that an algorithm does not have the same kind of experience as a human. The point here is to determine whether a computer can create art, not whether it can create human art. The latter is currently not possible. However, it is possible that in the future, with an algorithm implanted in an anthropomorphised robot, social interactions may be achieved to fulfil this condition.

Nevertheless, there is no desire for CG-art to be considered human. Their ways of knowing and experiencing are different. In addition, CG-art is fundamentally based on Big Data, which is one of the most social things we have, as it reflects patterns of social behaviour. Therefore, it is not surprising that in blind tests, CG-art is valued aesthetically, as it is based on a small sample of Big Data. Indeed, it can be hypothesised that if we are optimistic and wait for the Big Data used by CG-art to be expanded, we will have aesthetic works never thought of by humans.

## 3.6. Collaboration. Authorship. Apprentice and Teacher. Codes and Laws

A final objection to CG-art is related to the authorship of the artworks. In this regard, Hertzmann (2018) points out:

> To date, there is a rich body of computer-generated art, and in all cases, the work is credited to the human artist (s) behind the tools, such as the authors or users of the software – and this might never change. (p. 2)

Many researchers indeed argue that the real authors of machine-generated artworks are the programmers of their code (e.g., Hertzmann, 2018, 2020; McCormack et al., 2019). However, from the perspective of this research, this is incorrect for the following two reasons.

First, and as Hertzmann himself recognises, human artistic work is social. Therefore, it involves many agents. There is no restriction that only one of them is considered an artist, as different agents can fulfil different artistic functions. Let me give an example to clarify this point. We have at least a director and actors collaborating artistically when a film is shot. Both functions hybridise and complement each other. We cannot say, for example, that the artwork *film* is the creation only of the director and not the actors. In effect, we say that the director fulfils the artistic function of *directing* and the actors of *acting*. In both cases, art has been produced and a film, which is an artwork in and of itself, has been created.

CG-art invites us to consider a new, more current art form that underlies collective creation. It can be argued that the programmer and the algorithm are the artists. I postulate this because the algorithm acts as a creative agent or colleague, unlike a tool, for example, a paintbrush or a musical instrument. Such a co-creative artistic aspect has recent examples in the musical field.[8] Thus, we can cite the album *Hello World* (2019), the first AI-human collaborated pop music record. This LP is a work of the human-AI duo called SKYGGE, a conceptual subjectivity representing the interaction between the French musician Benoit Carré and the Flow Machines software, an AI-assisted music composing system. In this respect, researcher Melissa Avdeeff (2019) has said:

> Regardless of the "intelligence" of AI, it is principally human-driven and consumed, and, as such, it will be human agents who ultimately guide its use and

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[8] For details, see Chapter 7.

> progress. SKYGGE's *Hello World* is a product of these new forms of production and consumption, and functions as a pivot moment in the understanding and value of human-computer collaborations. (p. 11)

According to Avdeeff, AI-human collaborations are currently in their early stages, and it is tempting to be intrigued by their novelty. However, it is crucial to seize the opportunity to study the value of these collaborations while they are still primarily human-driven. Full implementation of AI-creative autonomy will provide fewer aspects that can be used to understand these CG artworks aesthetically due to the *black box* issue previously mentioned.

Another example of artistic collaboration between human musicians and AI is *PROTO* (2019). This avant-garde LP is a joint work of artist Holly Herndon and AI Spawn. It is especially remarkable that Herndon herself created Spawn and taught it to sing (Hsu, 2019).[9]

Nevertheless, it is true that in other artistic disciplines different from music, the software is still considered a tool and not a collaborative agent. In this sense, researchers Anna Kantosalo and Sirpa Riihiaho (2019) have evaluated the human-computer co-creative processes of poetry writing. Similarly, researcher Anna Jordanous (2017) studied *Beyond the Fence* (2016), the first computer-generated musical. In both cases, the software has been perceived as a passive element. This is a shift away from the idea of co-authoring proposed here.

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[9] For details, see Chapter 7.

Second, I propose an analogy in which a creative algorithm is to its programmer as a human apprentice is to a human master. If we assume that human art is social, then we can understand that no artist has not had a teacher. This role of teacher can be exercised by an expert or by the life experiences of an artist. In the first case, a particular human being performs the task of teaching. In the second, there is no particular human being who performs the same task. Nevertheless, in both cases, the artwork is nurtured by prior learning.

CG-art is also founded on learning. Its teacher might be its programmer, another algorithm, a set of artworks, or the like. Learning from an agent does not prohibit CG-art from creating its own art. In the same way, human apprentices do not have to grant authorship of their work to their teachers. As researcher Arthur I. Miller mentions in his book *The Artist in the Machine: The World of AI-Powered Creativity* (2019), although Wolfgang Amadeus Mozart learned music thanks to his father, nobody considers Mozart's compositions his father's property. For Miller, the rise of the GANs will make this analogy increasingly clear between programmers and AI.

Additionally, machine learning (ML) fits the analogy of master and apprentice quite well. As computer scientist Lex Fridman (2019) points out, in ML, raw data requires a human expert's costly and inefficient role in extracting features that algorithms can work with. However, the Deep Learning (DL) approach is different. DL automates the feature extraction process, eliminating the need for human expertise. Instead, DL algorithms start their work with information that is much closer to raw data. This is why the author argues that in ML, the human expert is the teacher and the machine is the apprentice. Moreover, DL conforms to the concept of vicarious learning, which is based on observation.

Finally, there are criticisms of CG-art founded on the fact that an algorithm is a code and, therefore, cannot create because it follows rigid rules. Though, everything that exists follows inviolable rules. For example, neither CG-art nor a human artist can violate physical laws. That is a fundamental limitation for both types of art. In this regard, Murray Shanahan has said that "in principle, because the brain obeys the laws of physics, computers can do anything the brain can do" (as cited in Miller, 2019). However, we all follow a code of some kind. The computations performed by an algorithm are complex instructions initially written by programmers but then carried out by the algorithm itself as it learns. In the case of humans, we develop genetically according to our DNA, which is a code we are born with. Therefore, it is not a limitation for artists to respect physical laws and develop according to their genetic code. These criticisms seem worth investigating and explaining to the general public in order to clarify these points.

## 3.7. Conclusion

This chapter examined the relationship between computation and artistic creativity from both philosophical and scientific perspectives. It was argued that CG-art is a relatively new art form, and that many of its criticisms are based on an anthropocentric viewpoint. CG-art is not human art and is not intended to be such. It was demonstrated that CG artworks meet the aesthetic value criteria through human and mechanical evaluation. Furthermore, in blind tests, human observers have consistently found CG-art to be more creative than art created by humans. These conclusions cannot be coincidental, and something about CG-art must make it aesthetically pleasing to our senses. Building on these premises, the following chapter of this thesis will delve into the mechanical aspects of artistic creativity.

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