http://dx.doi.org/10.14236/ewic/EVA2019.22

Artificial Intelligence and Problems in Generative Art Theory

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In previous writing I've described what has arguably become the most widely cited theory of generative art. Based on notions from complexity science, and in particular Murray Gell-Mann and Seth Lloyd's notion of "effective complexity," I argue that generative art is not a subset of computer art. Rather, generative art turns on the use of autonomous systems and the artist ceding control to those systems. As part of this theory for generative art, I've introduced a series of problems. These are not problems in the sense that they require single correct solutions. Rather they are questions that the artist will consider when making a piece; that critics and historians will typically address in their analysis; and that insightful audience members will ponder. They are problems that typically offer multiple opportunities and possibilities. It is notable that, for the most part, these problems equally apply to both digital and non-digital generative art; to generative art past, present, and (it is believed) future; and to ordered, disordered, and complex generative art. In addition, these same problems or questions are generally trivial, irrelevant, or nonsensical when asked in the context of non-generative art. In a sense the applicability of these questions can cleanly divide art into generative art and non-generative art. More importantly, the exploration of these questions can illuminate the analysis and critique of generative art. More recently a new form of neural-network-based artificial intelligence called "deep learning" has appeared on the scene. Deep learning has been applied to digital art creation. In this paper I explore whether the problems in generative art noted above hold up well in this new artificial intelligence context for generative art. The conclusion reached is that our current complexity-based theory of generative art can easily assimilate the use of deep learning.

Art theory. Generative art. Neural networks. Inceptionism. Deep learning. Artificial intelligence. Complexity theory.

1. INTRODUCTION

In 2003 I wrote a paper that laid out the core ideas for a theory of generative art using notions from complexity science as a context (Galanter 2003). The key element was the idea that what is definitive about generative art isn't what it is, but rather how it is made. In particular, I suggested that generative art is created when an artist cedes some degree of control to an autonomous system that creates, or is, the art. Since its publication this paper has arguably served as the most frequently cited theory generative art theory in the literature. The often-quoted definition is:

> Generative art refers to any art practice where the artist uses a system, such as a set of natural language rules, a computer program, a machine, or other procedural invention, which is set into motion with some degree of autonomy contributing to or resulting in a completed work of art.

Beyond this definition a number of additional ideas were outlined. In particular, the notion of effective complexity was used as a framework for sorting various generative systems. The idea is that systems can vary in complexity, and while simple systems are typically either very highly ordered or very highly disordered, complex systems exhibit both order and disorder (Gell-Mann 1995). How this is applied to generative art systems is illustrated in figure 1. The move to a complexity-based context brings with it the opportunity to leverage concepts like emergence, connectionist agents, feedback, nonlinearity, deterministic chaos, self-organization, and so on.

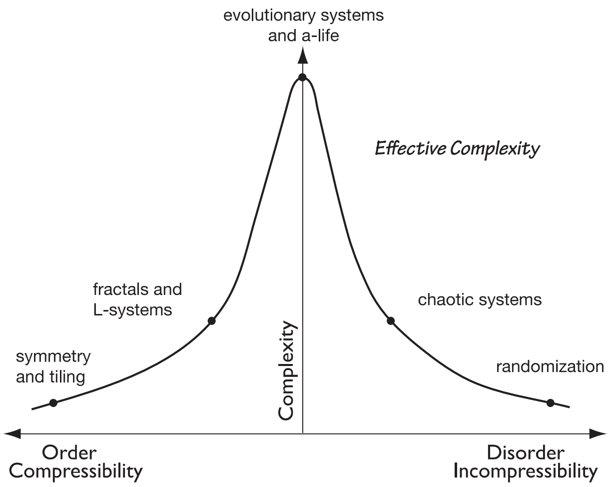

***Figure 1:** Generative art methods by effective complexity.*

There are additional implications offered by this theory. For example, generative art is not a subset of computer art, but rather it is technology agnostic. And indeed when one considers the ancient use of symmetry and tiling found inscribed on artefacts some 77,000 years old, it's clear that generative art is as old as art itself (Balter 2002).

Over the years I've refined and expanded this view of generative art. This has been thoroughly compiled in a recent chapter (Galanter 2016a). There it is noted, for example, that generative art only requires a weak form of autonomy, i.e. the sense that word is used in robotics. This avoids a number of philosophical complications that a stronger form of autonomy would invite.

In addition, some find it surprising that not all rule-based art is generative art. For example, some rules are suggestive but insufficient to determine a final design. Others are constraint rules that tell the artist what *not* to do, but again are not sufficient to fix a specific form.

1.1 Artificial neural networks and deep learning

In this same chapter the topic of artificial neural networks (or simply "neural networks") is briefly mentioned. Neural networks are inspired by nature's biological computer, the brain. Just as neurons establish networks where associations are created based on the strength of synapse connections, artificial neural networks use weighted virtual connections to associate various input patterns with corresponding output patterns.

Traditional neural networks typically have three layers. A layer of nodes for input data is widely connected to a middle "hidden" layer that gathers weighted sums. That middle layer is then connected to a layer of nodes that represent output values. A neural network "learns" by processing a body of input data and iteratively updating the network weights. Later, when presented with novel input, patterns in the input will result in patterns in the output based on previous learning.

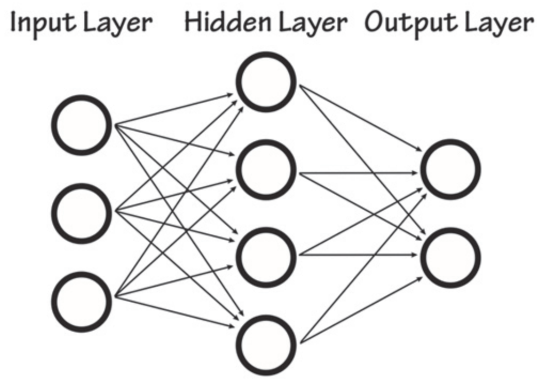

***Figure 2:** A very simple traditional neural network.*

Early typical practice was to limit the number of hidden layers to just one or two. Training neural networks with more layers, typically to attack more difficult problems, was found to be impractical. More layers, and more nodes, require gathering more training data to extract more complex patterns. In addition, the processing requirement for more nodes and more data increases exponentially due to the growing combinatorics of the connections.

More recently "deep learning" has overcome this perceived limitation. The need for data has been satisfied to some extent by the "big data" movement whereby large databases have been released for public use and access via the Internet. Of particular interest to artists are image databases of artworks that have been released by various museum and university initiatives. These can be used to learn art styles, and then modify new input images to produce output images exhibiting that style. In addition, the need for increased computation has been met by Moore's Law and recently affordable GPU-based computing clusters.

Deep learning systems now typically implement dozens of layers, and layer operations can include not only traditional weighted sums, but also the application of convolution matrices and other techniques. Some of the first art applications were explored by Google Research, resulting in a style and technique known as inceptionism (Mordvintsev et al. 2015).

2. PROBLEMS IN GENERATIVE ART THEORY

In the same chapter noted above I introduced a number of problems in generative art theory (Galanter 2016a). These are not problems requiring single correct solutions. Rather, these are problems that invite consideration by the artist when creating generative art; that theorists will want to consider in their analysis; and that well-informed audience members will want to ponder. These are problems that encourage multiple possibilities and opportunities.

It is posited that these problems generally apply to all forms of generative art including digital and non-digital forms, as well as past, present, and future work. But of equal importance, these same problems when applied to non-generative art can seem irrelevant, trivial, or even nonsensical.

The fact that this body of problems applies to all generative art, but *only* generative art, is a very good sign in terms of art theory. It means that this generative art theory isn't arbitrary or forced, but rather that it has content significance and consistency.

But how well will these problems capture new, previously unanticipated, forms of generative art? An analysis of the new forms of artificial intelligence-based generative art afforded by deep learning offers a strong test case. We can try to apply these problems in generative art theory to deep learning art. If they are found to be relevant rather than irrelevant, substantial rather than trivial, and sensible rather than not, this should reinforce overall confidence in the associated generative art theory.

In the remaining sections each of these problems is introduced, and then discussed in the context of generative and non-generative art. Then the problem is considered relative to AI-based generative art afforded by deep learning. Specific responses to the problem are not the point. The question is whether these problems are sensibly applicable to deep learning-based generative art at all. (The noted chapter presents a much more detailed treatment of these problems, but without the following consideration of AI-based generative art.)

2.1 The problem of authorship

Regarding generative art, the problem of authorship asks, "How do traditional views of authorship shift regarding credit, expression, and provenance?"

When first encountering digital generative art, a novice will frequently ask "Who is the artist, the human or the computer?" Many will reflexively answer that the programmer, i.e. the human, is the artist. This question is particularly sharp in that it resonates with a major vector in humanities discourse, that being poststructuralism and notions such as "the death of the author." Some might see digital generative art as the very embodiment of the shift of attention away from traditional views of the author.

In other writing I've introduced a point of view I've called "complexism." It is an attempt to reconcile the decades long "war" between the modernist culture of science and the postmodern culture of the humanities (Galanter 2016b). This is done by applying insights from complexity science in a cultural studies setting. In that critique I offer a theory of authorship that suggests when authorship would be most appropriately credited to the computer rather than the programmer. And, in fact, the example offered is a subset of deep learning-based generative art.

Whatever side one might take in the question of whether a computer can truly be considered an author, it's clear that it is a non-trivial and meaningful question. And the introduction of deep learning AI-based generative art only increases the importance of that question.

Compare this, for example, to the question "Who is the author of the Mona Lisa?" In the case of non-generative art the question is not a philosophical conundrum, it is merely a question of fact.

2.2 The problem of intent

The problem of intent asks, "Why is the artist working with and ceding control to generative systems?"

It was noted earlier that the category "generative art" is a reference to how the art was made, but it says nothing about why the artist chose to work that way. For example, John Cage, William Burroughs, and Ellsworth Kelly all used randomization to create art. But they did so for quite different reasons. Cage used randomization to put into practice a Zen attitude of non-judgement in aesthetic consideration. Burroughs, on the other hand, hoped to unleash the unconscious via randomization as a Dada-esque tactic. And Kelly's intent was to explore the creation of form through random erosion.

For some artists it is the generative system itself that is the topic of exploration. For others it is merely a means to some practical end. And still others are looking to exercise what I've called "truth to process" where a visible trace of the generative system is evident in the artefact (Galanter 2009b).

One common motivation among artists is to use generative systems to inject an element of surprise in their art making practice. Perhaps someday AI-based systems using deep learning will act as full-fledged studio collaborators.

But however used, and for whatever reason, deep learning systems clearly invite the question of intent common to all generative art practitioners. But asking why a non-generative artist uses generative systems is clearly nonsensical.

2.3 The problem of uniqueness

The problem of uniqueness asks, "Does it diminish the value of the art when unique objects can be mass-produced?"

Traditionally works of art have been treasured as unique and thus rare objects. Walter Benjamin offered a critique of once new art technologies for mechanical reproduction such as printmaking and photography. Benjamin declared such work to have a diminished "aura." Today digital media art and Internet distribution has allowed dematerialization to the point where duplication approaches zero cost.

Digital generative art introduces a completely new paradox. Rather than offering an endless supply of *copies*, it provides an endless supply of *original and unique* artefacts. The apparently oxymoronic phrase "mass-produced unique objects" in fact describes the reality of generative art. Some generative artists exercise this new paradigm so as to be in itself the content of the work.

Deep learning AI-based generative art can easily generate mass-produced unique objects, and in this respect is no different than previous forms of generative art.

2.4 The problem of authenticity

The problem of authenticity asks, "Given that it is in part created by an unemotional and unthinking system, is generative art really art at all?"

There are those who will insist that generative art is simply not art. A critique of this issue almost immediately engages what many consider a foundational art theory question, "What is art?"

In the realm of analytic philosophy there are a number of theories in this regard. They include:

- Art as representation
- Art as expression
- Art as significant form
- Art as experience
- Art as open concept via family resemblance (neo- Wittgensteinianism)
- Art as institution
- Art as historical definition

A discussion of these theories is beyond the scope of this paper, but at least some of them are more or less what everyday language would suggest. However, that's not to imply that carefully nuanced philosophic discussion is unnecessary (Carroll 1999).

Of these theories, the one most likely to be problematic with regard to authenticity, is "art as expression." This was an idea born of romanticism, a period when ascendant science seemed poised to dominate thinking about the world, and art was driven inward as a way to explore emotions and subjectivity.

If one's basis for art is the expression of feelings and emotions, it might seem obvious that generative systems without feelings and emotions cannot create art. One possible retort would be that the feelings and emotions being explored are those of the artist, and the generative system is used as a tool towards that end. A stronger response would reference other theories of art, and then make the point that expression does not have a monopoly on art making.

In the case of AI-based generative systems such as deep learning, this problem teases issues around sentience and consciousness. I'm unaware of artists currently claiming to have created conscious systems, but it seems to be only a matter of time before some artists will claim that their generative system is capable of expression in a way no different than found in human artists.

To underscore the obvious, non-generative art doesn't participate in the problem of authenticity. Human artists are assumed to be thinking and feeling agents.

2.5 The problem of dynamics

The problem of dynamics asks, "Must generative art change over time while being exhibited to an audience?"

This is a topic of debate among artists and critics. One type of generative art is that where the generative system is left behind in the studio, and the artwork's form is a fixed artefact. Another type is where the artwork *is* the generative system. As such the audience experiences the work as form that is not only changing over time, something that even a film does, but is also not predetermined and devoid of surprise after having been viewed a first time.

Generative art created by deep learning systems is mostly of the first type, but real-time dynamic generative art is also possible given adequate computational power.

In any case, by its very nature non-generative art does not enter into such discussions. And AI-based deep learning generative art clearly does.

2.6 The problem of postmodernity

The problem of postmodernity asks, "Is generative art an unavoidably postmodern approach to art?"

Of the problems noted here, the problem of postmodernity is perhaps the one that has a limited life expectancy. One can reasonably wonder whether the attitudes and issues around postmodernism will remain in current discourse in twenty or thirty years.

Similar to the problem of dynamics, the relationship between generative art and postmodernism is a topic of debate among artists and critics. In generative art some see the reification of post-structural issues regarding authorship. And artificial life inspired generative systems resonate with the concepts of simulacra and simulation offered by Baudrillard (1994).

But generative art can also be viewed as a response that reverses postmodernity's corrosive claims. By harnessing systems such as reaction-diffusion, evolution, artificial life, and other natural processes, generative art can rescue art from postmodernism's distain for formalism. Generative art can rescue truth and beauty from the nihilistic relativism and social construction of postmodernism.

Generative deep learning AI systems, by vaguely simulating natural neurology, participate in both of the above; they can build up or break down the influence of postmodernism on aesthetics as noted above.

Like generative art in general, AI-based generative art comfortably fits into this discourse. The vast majority of non-generative art, however, was practiced long before postmodernism arrived on the scene, and is largely irrelevant relative to that discourse.

2.7 The problem of locality, code and malleability

The problem of locality, code, and malleability asks, "Is the art in the object, the system, the code, or something else entirely?"

Digital generative art raises ontological issues as to where the art resides. But such debates are not limited to digital generative art. For his wall drawings Sol LeWitt would author construction directions, and then different assistants in different locations would follow those directions to install the drawing. (Such work is generative when execution of such directions has the potential of yielding non-identical instances.) Again one can ask where the art is. Is it in the paper instructions? Or is it in the text, and the paper copy is merely a representation of the text? Or is the art, in fact, the physical drawing on the wall?

With digital generative art there is an additional twist. Generative artists will sometimes make their code available, and arbitrary people can download it, modify it, and then run it to create their own variations. This problematises the traditional role of a heroic single artist creating a fixed masterpiece. Now where is the art? Is it the original artist's artefact? Is it the code? Is it the code as modified? Or is it the second artefact made by a second artist?

Reasonable people can disagree as to the answers here, but there is little doubt that there are questions in this realm relevant to all generative art. And indeed these same questions easily apply to AI-based generative art systems. But these considerations are irrelevant to non-generative art.

2.8 The problem of creativity

The problem of creativity asks, "Are generative systems creative? What is required to create a truly creative computer?"

The philosopher Margaret Boden has written that "Creativity is the ability to come up with ideas or artefacts that are new, surprising, and valuable" (Boden 2004). But few would want to argue that digital generative art systems, let alone non-digital systems, are capable of forming "ideas." But perhaps her allowance for artefacts would allow generative art systems to be considered creative.

A reasonable step in the direction of machine creativity in the arts would be the capability to discriminate between high- and low- quality art. For example, an evolutionary computing system could use such a capability as a fitness function. This would lead to an overall generative art system that modifies its own behaviour.

In previous writing I've taken a different tack than Boden (Galanter 2009a). The core idea is that the difference between a non-creative and creative system is the difference between a "complex system" and a "complex adaptive system." As noted previously, complex systems are those that exhibit features such as emergence, connectionist agents, feedback, nonlinearity, deterministic chaos, self-organization, and so on. Complex adaptive systems have these same features, but in addition they modify their structure or behaviour to maintain their integrity in response to changes in the environment. So, for example, a weather system is a complex system, but a beehive is a complex adaptive system.

There is more that can be said about this paradigm for creativity, but it's worth pointing out here that this approach avoids troublesome considerations regarding consciousness and awareness, and it can be extended beyond humans.

When it comes to non-generative art any creativity is credited to the artist and not the artist's brushes or pencils. But in the case of generative art, where the system surprises the artist it's reasonable to wonder whether the artist has contributed all of the creativity on display. And in the case of AI-based generative art systems the problem of creativity becomes even more relevant.

2.9 The problem of meaning

The problem of meaning asks, "Can and should generative art be about more than generative systems?"

One of the advantages of theorizing generative art as simply a way of making art is that it maximises artistic options. As noted in the problem of intent, the same generative system can have different meanings to different artists.

For some a generative system might simply be a pragmatic solution to a production need. For example, in animated filmmaking one might use an L-system-based generative tool for populating a forest scene with trees. This would be much easier, i.e. less expensive, than modelling hundreds of trees by hand. But the film itself would not be about generative art, or L-systems, or even trees.

However, some generative artworks are about generative systems and little more. For example, Haacke's Condensation Cube is a non-digital generative artwork. It is a clear, sealed, approximately 76 cm cube, with about a quarter of an inch of water in it. The water evaporates and then condenses on the walls of the cube. This creates ever-changing patterns of condensation and droplets that flow back to the bottom of the cube. The piece isn't merely about the patterns on the cube. It's actually about the generative system creating the patterns. Condensation Cube was originally titled Weather Cube, but Haacke changed the name to better reflect its literal function. It serves as a good example of the notion of "truth to process" mentioned earlier.

Similar to both digital and non-digital generative systems, deep learning AI-based generative art systems can be at both extremes. They can be about generativity, or not about generative systems at all, or something in between.

However, the question of whether generative art can be about more than generative systems is trivially irrelevant when asked in the context of non-generative art.

3. CONCLUSION

The goal here was to determine whether deep learning AI-based generative art would comfortably fit within generative art theory that is based on the artist ceding control to autonomous systems for the creation of art.

It was noted that a set of "problems" can be used in the discussion of generative art, and that these same problems can seem irrelevant, trivial, or even nonsensical when applied to non-generative art.

So these problems can serve a dual function. On the one hand they can invite a discussion for any given piece of generative art. In addition, the degree to which the problems are relevant to a given kind of art production method can indicate how appropriate it is to think of that method as a generative art system.

The ease with which those problems can be applied to deep learning AI-based artworks is strong confirmation that they fit within this paradigm for generative art. And in the analysis of deep earning Ai-based generative art no need to modify this current generative art theory was discovered along the way.

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