Complexity, Neuroaesthetics, and Computational Aesthetic Evaluation

Philip Galanter, BA, MFA
Department of Visualization, Texas A&M University, College Station, Texas, USA
e-mail: galanter@viz.tamu.edu

Abstract

Human artistic creativity typically includes a self-critical aspect that guides innovation towards a productive end. It seems likely that truly creative computers in the arts will require a similar ability to make aesthetic evaluations. Attempts to build such systems, however, have so far mostly failed.

Part of the challenge is understanding the actual mechanisms that underlie aesthetics as experienced by humans. To date scientific progress towards such understanding has been incomplete. Nevertheless some useful contributions include suggested theories from the field of evolutionary psychology, models of human esthetics from psychologists such as Arnheim, Berlyne, and Martindale, various empirical studies of human aesthetics, and a growing literature in the nascent field of neuroaesthetics.

A common thread found in all of the above is the notion of complexity as applied to the aesthetic perception of art objects and events. It is suggested here that notions of complexity regarding art have lagged the new paradigms offered by complexity science, and that a more contemporary conception of complexity can integrate and improve older theories of aesthetics. This may be where the path to improved computational aesthetic evaluation begins.

1. Introduction

In previous writing I have outlined the current challenges in evolutionary art practice. These include art theoretical issues such as the notion of “truth to process.” There is also the technical challenge of vastly increasing the complexification capacity of evolutionary systems by introducing multi-level emergence. The final challenge is very much related to this paper. It involves automating an aesthetic fitness function via computational aesthetic evaluation so that the need for human interaction is eliminated. [1, 2]

Typical industrial applications of evolutionary computing search a solution space optimizing a predefined fitness function, thus selecting superior candidates from the population. Because such a fitness function can be evaluated mechanically the system can run numerous generations without human intervention. Attempts to create objective fitness functions to judge aesthetics in have, for the most part, failed. And successful aesthetic fitness functions have tended to be for very specific needs and do not generalize well. [3] Because of this evolutionary systems for art and design typically have one or more humans judging each individual in the gene pool based on the aesthetic quality they find in the work. This creates a “fitness bottleneck” greatly limiting the number of generations that can run, which in turn limits the degree to which the art or design can evolve. [4]

Computational aesthetic evaluation remains a significant unsolved problem in the field of generative art. And the need for machine evaluation is broader than that required for evolutionary approaches. Just as artists and designers exercise critical aesthetic judgment in their creative work, it seems reasonable to think that a truly creative computer would require some form of self-critical functionality.

A problem quickly encountered when thinking about computational aesthetic evaluation is that of *human* aesthetic evaluation. A recurring theme in aesthetics is the balance of order and complexity. For example, it is this balance referred to in Coleridge’s notion of beauty as “unity in variety.” To pursue these issues scientifically we need a suitable understanding of complexity and order, as well as robust psychological models of human aesthetic experience.

2. Models of complexity

In a 1998 lecture by Feldman and Crutchfield at the Sante Fe Institute well over a dozen competing theories of complexity were presented. [5] But there are generally two families of complexity models. The first type of model defines complexity as being the opposite of order. The second type of model defines complexity as being a careful balance of order and disorder. Examples of both follow.

2.1 Shannon Information and Algorithmic Complexity

In 1948 Claude Shannon launched the field of information theory. [6] Shannon was interested in measuring and quantifying communication channels in terms of their capacity. His insight was the idea that the more “surprise” a channel presents the greater the amount of information delivered. In addition, the more information there is in the channel the less ordered it is, and the less it can be compressed without loss. In Shannon’s paradigm complexity is proportional to the amount of information. And so the more disordered a channel is the more complex it is.

For example, a channel that only delivers the letter “a” over and over again offers no surprise and delivers no information. It offers a high degree of order and can potentially be compressed to a single letter.

A channel that delivers typical English language sentences delivers quite a bit more information. But that information is still somewhat redundant and is not maximally surprising. For example, if the characters “elephan” come out of the channel one expects the next character to be a “t.”

The channel that has maximal information is the one that delivers entirely random characters. In such a channel every character matters and if a single one is lost it can’t be recovered based on the surrounding characters. A string of random characters cannot be compressed without loss and is maximally disordered.

Kolmogorov, Solomonoff, and Chaitin independently developed similar ideas in the context of computation. In their work algorithmic complexity is proportional to the size of the smallest program, including both code and data, that can execute a given algorithm. [7-9]

Similar to the above, a program that generates an infinite number of “a” characters can be very small. Such a program has very low algorithmic complexity. A program that delivers English language text will be larger, but can still take advantage of redundancies in the language to achieve some compression. A program that delivers an equal number of random characters will be larger still because there are no redundancies in strings of random characters.

In short, in the cases of both information theory and algorithmic complexity low complexity corresponds to both high degrees of order and compressibility. And high complexity corresponds to high degrees of disorder and incompressibility.

From this point of view the most complex music would be white noise and the most complex digital image would be random pixels. But to a listener all white noise sounds alike, and to a viewer all random pixel images look alike. Is this really what we mean when we speak of complexity in the arts?

2.1 Effective Complexity

With the advent of complexity science as a discipline, defining order and complexity has become much more problematic. But for many in the complexity science community the notion of complexity as presented above doesn’t square with our everyday experience. Arguably the most complex systems we encounter are other living organisms. And life requires both order maintaining integrity and persistence, and disorder allowing adaptation, change, and flexibility.

Murray Gell-Mann has proposed the notion of effective complexity, a quantity that is greatest when there is a balance of order and disorder such as that found in the biological world. [10] Unlike information and algorithmic complexity, effective complexity is not inversely proportional to order and compressibility. Rather both order and disorder contribute to complexity. (See figure 1).

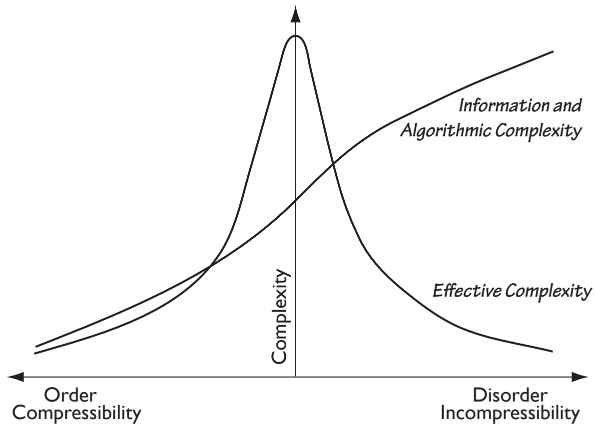

Figure 1

3. Psychological Models of Aesthetics

In considering human models of aesthetics researchers in the sciences have also invoked notions of complexity and its relationship to beauty.

3.1 Birkhoff's Aesthetic Measure and Information Aesthetics

The mathematician George David Birkhoff published a mostly speculative book in 1933 called "Aesthetic Measure." He proposed the formula M=O/C where M is the measure of aesthetic effectiveness, O is the degree of order, and C is the degree of complexity. Birkhoff notes, "The well known aesthetic demand for 'unity in variety' is evidently closely connected with this formula." [11]

But what is complexity? And what is order? It is sometimes forgotten that Birkhoff began with an explicit psychoneurological hypothesis. Birkhoff suggested that C and O are proxies for the effort required (complexity) and the tension released (order) as perceptual cognition does its work. But as a practical matter Birkhoff quantified complexity and order using counting operations appropriate to the type of work in question.

For some Birkhoff's formula seems to measure orderliness rather than beauty, and penalizes complexity in a rather unqualified way. [12]

I would suggest that Birkhoff intuitively equated complexity with disorder in a way consistent with the information theory and algorithmic complexity paradigm. And indeed, in an attempt to add conceptual and quantitative rigor, Max Bense and Abraham Moles restated Birkhoff's general concept in the context of Shannon's information theory creating the study of information aesthetics. [13, 14]

3.2 Daniel Berlyne and Arousal Potential

Daniel E. Berlyne was a psychologist widely noted for his work regarding physiological arousal and aesthetic experience as a neurological process. One of Berlyne's significant contributions is the concept of arousal potential and its relationship to hedonic response.

Arousal potential is a property of stimulus patterns and a measure of the capability of that stimulus to arouse the nervous system. Arousal potential has three sources; psychophysical properties such as very bright light; ecological stimuli such as survival threats like pain; and especially what Berlyne called collative effects. Collative effects are combined, comparative, context sensitive experiences such as “novelty, surprisingness, complexity, ambiguity, and puzzlingness.” Berlyne explicitly notes the correspondence between many of these collative effects and concepts from Shannon’s information theory. [15]

Berlyne proposes that the hedonic response, that is the aesthetic sense of pleasure and pain, is the result of separate and distinct reward and aversion systems. Each of these systems is made up of neurons. The firing thresholds of individual neurons will vary according to a Gaussian probability distribution, and so the number of neurons responding will increase as a Gaussian cumulative distribution. Berlyne further proposes that the reward system requires less arousal potential exposure to activate, but that when activated the aversion system will produce a larger response. (See figure 2.)

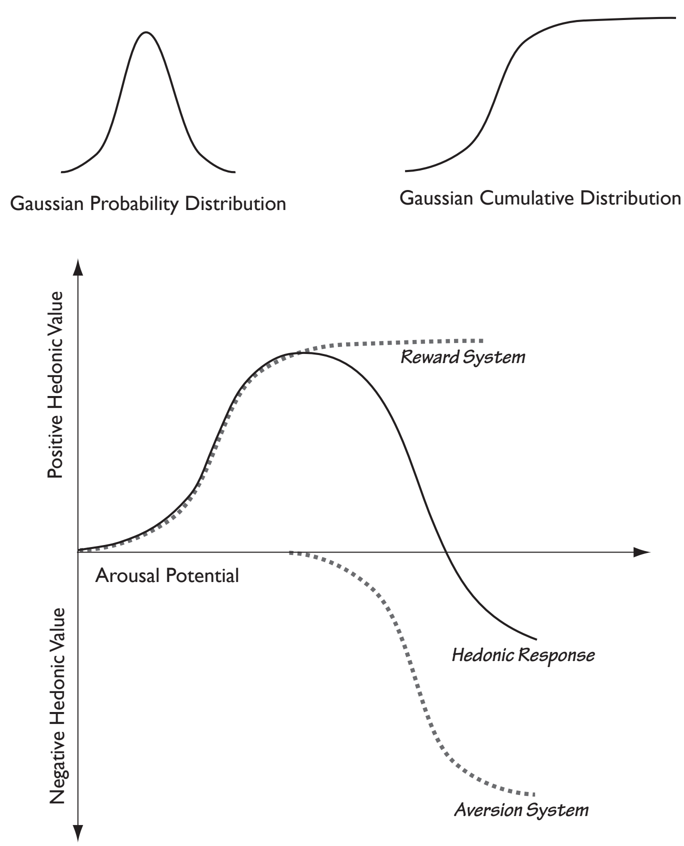

Figure 2

The result is the hedonic response as a summation of the positive reward system and the negative aversion system known as the Wundt curve. With no arousal potential there is a hedonic response of indifference. As more arousal potential is presented the hedonic response increases manifesting itself as a pleasurable experience. Beyond a certain point, however, the aversion system begins to activate. As the aversion system reaches higher levels of activation the hedonic response will lessen and eventually cross into increasing levels of pain.

For Berlyne increasing collative effects such as novelty and surprise also represent increasing complexity in the information theory sense. From this point of view works of only moderate information complexity maximize the hedonic response. This resonates with the intuitive artistic notion that audiences respond best to works that are not so static as to be boring, and yet also operate within learned conventions so as to not be experienced as chaotic. But this also means there is no obvious mapping of complexity to aesthetic value.

3.3 Colin Martindale, Prototypicality, and Neural Networks

Psychologist Colin Martindale published a series of experiments that seemed to contradict the arousal potential model of Berlyne. For some Berlyne's notion of collative effects was already problematic. Terms like novelty and complexity were slippery both in specification and mechanism.

But Martindale's primary critique was empirical. For example, contrary to Berlyne's model he found that psychophysical, ecological, and collative properties are not additive, nor can they be traded off. And much more often than not, empirically measured responses do not follow the inverted-U of the Wundt curve but rather are monotonically increasing. Finally, a number of studies showed that meaning, rather than pure sensory stimulation, is the primary determinant of aesthetic preference. [16-18] In a series of publications Martindale developed a natural neural network model of aesthetic perception that is much more consistent with experimental observation. [19-21]

Martindale first posits that neurons form nodes that accept, process, and pass on stimulation from lower to higher levels of cognition. Shallow sensory and perceptual processing tends to be ignored. It is the higher semantic nodes, the nodes that encode for meaning, that have the greatest strength in determining preference. However, should the work carry significant emotive impact the limbic system can become engaged and dominate the subjective aesthetic experience.

Nodes are described as specialized recognition units connected in an excitatory manner to nodes corresponding to superordinate categories. Nodes at the same level, however, will have a lateral inhibitory effect. Nodes encoding for similar stimuli will be physically closer together than unrelated nodes. And so nodes encoding similar and related exemplars will tend towards the centre of a semantic field. The result is that the overall nervous system will be optimally activated when presented an unambiguous stimulus that matches a prototypically specific and strong path up the neural hierarchy. (Martindale 1988b)

Martindale doesn't reference notions of complexity, but he does make Berlyne's appeal to information theory notions of complexity even more vulnerable. Martindale also introduces higher forms of cognition as important and frequently dominating aspects of aesthetic experience.

But it is hard to reconcile Martindale's neural prototypicality and high level cognition with known aesthetic experiences such as encounters with the sublime or the variety aspect of "unity in variety." Prototypicality would seem to shun variety and fall short of processing extraordinary sensation as pleasure.

4. A Neuroaesthetic Complexity Model

Neuroaesthetics is the study of the neurological bases for all aesthetic behavior including the arts. A fundamental issue in neuroaesthetics is fixing the appropriate level of inspection for a given question. It may be that the study of individual neurons will illuminate certain aspects of aesthetics. Other cases may require a systems view of various brain centers and their respective interoperation. [22]

In the realm of aesthetics Berlyne, Martindale, and Birkhoff somewhat anticipated the neuroaesthetic approach. Each, however, has significant problems.

Both Berlyne and Birkhoff treat order and complexity as opposites. This approach convolves complexity with disorder, and eliminates complexity as a direct predictor of aesthetic quality.

There is, however, another interpretation. The notion of Gell-Mann's effective complexity was previously mentioned. From that point of view complexity is a balance of order and disorder. Comparing Berlyne's Wundt curve with a plot of effective complexity versus order, it is notable that both peak in the middle. This suggests that positive hedonic response may be proportional to effective complexity. Effective complexity has, in a sense, the balance of order and disorder "built in." And the idea that extreme order under-stimulates and extreme disorder over-stimulates seems quite plausible.

Martindale's model of aesthetics is based on current thinking about neural networks and thus has an intrinsic connection to complexity theory. It engages the notion that masses of smaller entities can have local interactions that create emergent behavior at a larger scale. What it lacks is an explanation as to *why* a prototypical response should be experienced as pleasurable, and how it is that prototype-defying experiences like encounters with the sublime can nevertheless bring about intense aesthetic pleasure.

In response to these concerns, I am suggesting that in the context of aesthetics the information theory-based notion of complexity be abandoned in favor of effective complexity.

There is a plausible evolutionary basis for suggesting that effective complexity correlates well with aesthetic value. Effective complexity is maximized in the very biological systems that present us with our greatest opportunities and challenges. And so there is great survival value in having a sensory system optimized for the processing of such complexity.

And there is additional survival value in our experiencing such processing as being pleasurable. As in other neurological reward systems, pleasure directs our attention to where it is needed most. Reward systems for food and sex direct our activity towards important survival behaviors. In a similar way our aesthetic reward system encourages us to seek stimuli with high effective complexity content; the kind of stimuli associated with social interactions and the biological world.

This aesthetic reward system is suggested to be a low-level generic feature that operates throughout the entire nervous system. However, efficient processing in a given region is sufficient to trigger the reward system. This provides a corrective to Martindale's notion of prototypically. What is rewarded isn't matching prototypes per se, but rather the full and efficient exploitation of our complexity-tuned neural system. Matching prototypes just happens to be one of several ways to do that.

Because it operates in a distributed low-level manner, an aesthetic reward system can respond to various levels of cognitive abstraction. Full and efficient information processing by a system tuned for complexity is what is rewarded. So, for example, aesthetic pleasure could result from the efficient processing of complex meanings. But it could also result from the immersive preverbal experience of the sublime.

A widely distributed low-level aesthetic reward system might also explain why certain mathematical proofs, or chess moves, or philosophical arguments are said to have aesthetic value. Such experiences fully and efficiently engage some neural region, and this triggers the aesthetic reward system.

And so to summarize this model of neuroaesthetic complexity:

- Unlike information or algorithmic complexity, effective complexity comes with the balance of order and disorder, or expectation and surprise, built in.

- There is survival value in gathering as much information as possible short of being overstimulated.

- In terms of survival our most difficult transactions are those with other complex systems.

- So our nervous system evolved to optimally process information regarding other complex systems.

- And a reward system evolved to encourage us to fully utilize that capacity.

- Aesthetic pleasure is what that reward system feels like.

- The balance of unity and variety in aesthetics reflects our nervous system being tuned to process effective complexity.

The adoption of effective complexity as a guiding principle in aesthetics will not address all aspects of the computational aesthetic evaluation challenge. Nor will this model of a complexity-tuned, efficiency triggered, aesthetic reward system. But it seems plausible that they will advance the cause.

References

[1] Galanter, P., *Truth to Process – Evolutionary Art and the Aesthetics of Dynamism*, in *International Conference on Generative Art*. 2009, Generative Design Lab, Milan Polytechnic: Milan, Italy.

[2] Galanter, P., *The Problem with Evolutionary Art Is*, in *Applications of Evolutionary Computation, Pt Ii, Proceedings*, C. DiChio, et al., Editors. 2010, Springer-Verlag Berlin: Berlin. p. 321-330.

[3] Galanter, P., *Computational Aesthetic Evaluation: Past and Future*, in *Creativity and Computers*, J. McCormack and M. d'Inverno, Editors. in press, Springer: Berlin.

[4] Todd, P.M. and G.M. Werner, *Frankensteinian Methods for Evolutionary Music Composition*, in *Musical networks: Parallel distributed perception and performance*, N. Griffith and P.M. Todd, Editors. 1998, MIT Press/Bradford Books: Cambridge, MA.

[5] Feldman , D.P. and J. Crutchfield *A Survey of "Complexity Measures"*. 1998, Santa Fe Institute: Santa Fe.

[6] Shannon, C.E., *A mathematical theory of communication.* The Bell System Technical Journal, 1948. **27**(3): p. 379--423.

[7] Kolmogorov, A.N., *Three approaches to the quantitative definition of information.* Problems in Information Transmission, 1965. **1**: p. 1-7.

[8] Solomonoff , R.J., *A formal theory of inductive inference, Part I and Part II.* Information and Control, 1964. **7**: p. 1-22, 224-254.

[9] Chaitin, G.J., *On the length of programs for computing finite binary sequences* Journal of the ACM, 1966(13): p. 547-569.

[10] Gell-Mann, M., *What is complexity?* Complexity – John Whiley and Sons, 1995. **1**(1): p. 16-19.

[11] Birkhoff, G.D., *Aesthetic measure*. 1933, Cambridge, Mass.,: Harvard University Press. xii, 1 p., 2 l., 3-225, 1 p.

[12] Scha, R. and R. Bod, *Computationele Esthetica.* Informatie en Informatiebeleid, 1993. **11**(1): p. 54-63.

[13] Bense, M., *Aesthetica; Einführung in die neue Aesthetik*. 1965, Baden-Baden,: Agis-Verlag. 348 p.

[14] Moles, A.A., *Information theory and esthetic perception*. 1966, Urbana,: University of Illinois Press. 217.

[15] Berlyne, D.E., *Aesthetics and psychobiology*. 1971, New York,: Appleton-Century-Crofts. xiv, 336 p.

[16] Martindale, C., K. Moore, and J. Borkum, *Aesthetic Preference: Anomalous Findings for Berlyne's Psychobiological Theory.* The American Journal of Psychology, 1990. **103**(1): p. 53-80.

[17] Martindale, C., K. Moore, and K. Anderson, *The Effect Of Extraneous Stimulation On Aesthetic Preference.* Empirical Studies of the Arts, 2005. **23**(2): p. 83-91.

[18] Martindale, C., *Relationship of preference judgements to typicality, novelty, and mere exposure.* Empirical Studies of the Arts, 1988. **6**(1): p. 79-96.

[19] Martindale, C., *Cognition and consciousness*. The Dorsey series in psychology. 1981, Homewood, Ill.: Dorsey Press. xiii, 462 p.

[20] Martindale, C., *The pleasures of thought: A theory of cognitive hedonics.* Journal of Mind and Behavior, 1984. **5**(1): p. 49-80.

[21] Martindale, C., *Cognitive psychology : a neural-network approach*. 1991, Pacific Grove, California: Brooks/Cole Publishing Company. xxi, 282 p.

[22] Skov, M. and O. Vartanian, *Introduction - What is neuroaesthetics?*, in *Neuroaesthetics - Foundations and frontiers in aesthetics*, M. Skov and O. Vartanian, Editors. 2009, Baywood Pub.: Amityville, N.Y. p. iv, 302 p.