xCoAx 2019
Conference on Computation, Communication, Aesthetics & X
Milan, Italy

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Aesthetics of Uncertainty

Keywords
machine learning
art
uncertainty
aesthetics
aporia
uncanny

Machine learning has a tendency to reveal inconsistencies which have transversal relevance bridging computer science with art and the humanities. Rather than purely situations of inconsistency, discrepancy, or malfunction, Derrida's notion of aporia (Derrida 1993) describes uncertainty as a precondition of dialectics. Expanding on Derrida's line of thinking, this paper speculates that the internal frictions which can be found in artificial intelligence and machine learning systems may be understood in terms of a new kind of aesthetic informed by uncertainty.

1 INTRODUCTION

The cold calculation of computational processes may appear the epitome of certitude, yet there is an internal discord between the level of uncertainty in machine learning and its probabilistic approach (Pasquinelli 2019). While computation is itself deterministic, executing mathematical procedures, machine learning is a non-deterministic approach capable of producing unpredictable outcomes (Lehman et al. 2018). The tension between the certainty and uncertainty in machine learning divulges an aporetic sense of the uncanny (Freud 2003) in the process. The incongruity which arises in the outcomes of machine learning prompt a need for interpretation much closer to the humanistic approach of hermeneutics than the norms of computer science. Derrida argues that the exercise of freedom is predicated on aporia: moments of impasse, doubt and contradiction, which open up the imperative to act, to decide, to reason. Applying Derrida's line of thinking to the situations of aporia presented by machine learning, this paper speculates as to whether the indeterminacy entailed in the use of machine learning systems may contribute to an aesthetics of uncertainty. Developing this notion from the interplay between the predictive intentions of machine learning and the unpredictability at work in its use, this investigation asks how uncertainty may present itself as a guiding principle of aesthetic applications of machine learning.

2 UNCANNY MACHINERY

What one apprehends in machine learning-generated images is often a visualisation out of uncertainty. Looking closely at several such examples, this section develops an understanding of several aspects of uncertainty in machine learning and artificial intelligence.

2.1 A Face Which Resembles No One

Situations of uncertainty within content generated using machine learning are often accompanied by an element of the uncanny, a sense of indecision as to what to make of what one is experiencing. This first, intuitive sign of uncertainty signals an unresolved contradiction within the process. In computer vision systems, this often arises in the form of discrepancies between the particularities of human vision and visual processes performed by computers. For example, eigenpictures, introduced by Sirovich and Kirby in 1987, are images representing a set of basis features in a data set of images. Initially applied to recognition of faces, hence the term "eigenfaces", this approach entails performing principle component analysis on a dataset in order to reduce the amount of information necessary to perform facial identification. Generating a smaller set of images representing the most salient features in the dataset, eigenfaces facilitate facial recognition by creating a set of average images against which to compare inputs. Invoking the prefix, "eigen-", meaning "own" or "proper", in this case is itself fairly conflicted. It appears to conflate instantiations of faces with their salient parts. To claim an eigenface as one's own face or one's proper face would be difficult. Yet while an eigenface may appear blurry and imprecise to human viewers, it is nonetheless mathematically representative of part of an image dataset. For this reason, eigenfaces manifest a visible contradiction. Although they are reminiscent of the data used to create them, these uncertain images (Ekman et al. 2017) are not so much an "own" face as the condensed aspects of a face as defined from a crowd of other faces. In an eigenface, one encounters a composite face which is not passable as a human face, but which somehow exudes "facelike" qualities. This ghostly apparition arguably contains something of an essence of "faceness", yet an eigenface may conversely elicit a mild reaction of repulsion in viewers: recoiling from a face which resembles no one. Part of this rests on the fact that faces, in all their variability, are not that different from one another. It is paradoxically comforting and disturbing to see in these images that "we", in the grand sense of "humanity", are more similar than we tend to think. The overestimation of visual difference among bodies engrained and propped up by biology, culture and politics are in some senses disregarded by the procedure of producing these average images. But beyond our astonishment at creating a thing which projects a human likeness back at us, it is also horrifying not to find our own face in the looking glass. Am I represented in the dataset? What does an averaged face say about faciality? Have I been ensnared in an apparatus of capture, hooked by the face?

Fig. 1.
Eigenfaces by Jeremy Kun, 2011.

The eigenfaces produced by Jeremy Kun (Fig. 1.) visually pose questions to us, appearing as spectres of personages who emerge from and recede back into the darkness. While not intended themselves to be works of art, these images vacillate between the rationalism of calculation and the nuance of their haunting beauty. While the level of faciality instrumentalised (Parisi 2018) in facial recognition and generation algorithms is significant enough for it to be efficacious, there remains a significant gulf between the characteristics of algorithmically-analysed or generated faces and the representational norms culturally accepted as aesthetically desirable. These are procedural (Carvalhais 2016) faces, intended to be computed, not considered end-products in themselves. Yet the faces produced, even by relatively successful generative adversarial networks (GANs), inspire description as awkward, creepy, eerie, generally uncanny. The discrepancy between our expectations of what a face is or should be and that which is produced using current machine learning techniques grows narrower as machine learning systems become more effective, but as they do, it raises questions as to what is really at stake in such forms of representation. While there is a tendency to take great satisfaction in the failure of machine learning and artificial intelligence to compete with human ability, there are often equal levels of fear and elation when computers succeed in this pursuit. Even beyond the Turing test, there is a persistent inclination to consider the human the measure of machines. This lends itself to an inevitable uncanniness of finding such comparison inconclusive, not least due to the lack of a consistent metric, “human”, against which to compare, but also because at a certain point such measurements don’t return much information. In many ways, the questions posed by the outcomes of machine learning are merely a reflection of the questions posed through the process itself: the design of the methodology is dependent upon on the desired result, rather than the inverse. There is therefore a level of the uncanny in the practice of designing algorithms to replicate human traits before feigning surprise at their human resemblance.

2.2 Imaging Invisible Infrastructures

The uncertainty of machine learning and artificial intelligence also reveals itself in other ways beyond the uncanny discomfort of machinic representations. Uncertainty may also be found at other levels of machine learning systems, such as the degree of unknown factors within the vastness of high-level computational processes. For example, the proposition of apprehending a machine learning system in its entirety is astonishing in its own right. Kate Crawford and Vladan Joler’s *Anatomy of an AI System* (Fig. 2.) takes a comprehensive view of an apparatus which is otherwise far too amorphous, complex and colossal to fathom. What one encounters in using the Amazon Echo, they show, is only the tip of a very large iceberg. It seems the more one digs, the more one finds in excavating the hidden labour, data and planetary resources obscured behind the physical device itself. By taking meticulous account of all factors possible, even and especially those considered “externalities”, it is revealed how expansive a seemingly simple “smart” device is in actuality. It is only through taking an exhaustive perspective as Crawford and Joler do that one can grasp a sense of the monumental scale of such a system.

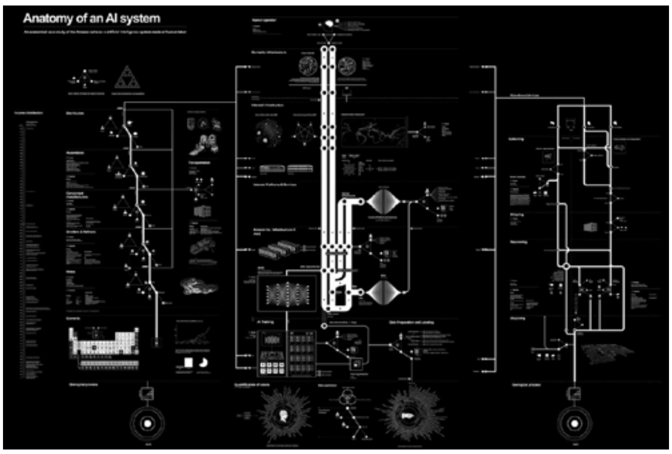

Fig. 2.
Anatomy of an AI System.
Diagram by Kate Crawford and Vladan Joler, 2018.

An especially compelling quality of *Anatomy of an AI System* is its wavering between certainty and uncertainty. On the one hand, it is demystifying in that it lays bare the kind of system that is often talked about in approximations, metaphor, unknowns and unknowables. In accounting for all parts of a seemingly immeasurable network of invisible, obscured or unknown infrastructure, the researchers unmask the beast at the same time as demonstrating its magnitude. The sheer volume of information, in itself clear, gives these diagrams a level of exposed opacity. It's worth noting that sharks are listed among the issues facing the submarine cable infrastructure which forms a part of the immense combined infrastructure behind the Amazon Echo (see Fig. 3.). This is due to electrical disturbances emanated by the undersea cable provoking them to attack the cable. One would hardly suspect from the household gadget's humble appearance that it is engulfed in a much larger assemblage aggravating sharks on the ocean floor, among its many other unforeseen consequences.

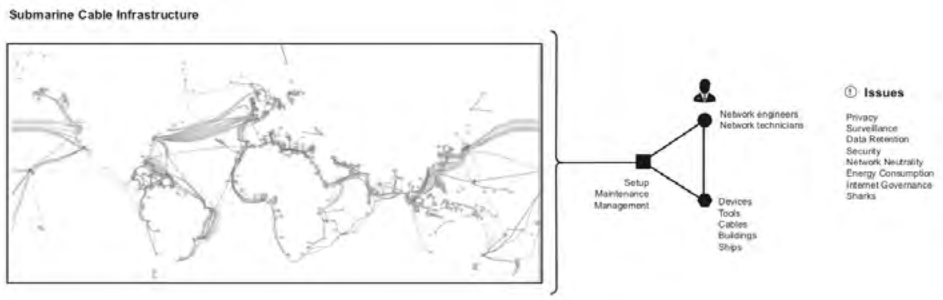

Fig. 3.
Anatomy of an AI System, detail.
Diagram by Kate Crawford and Vladan Joler, 2018.

3 AESTHETICS OF APORIA

The indeterminacy of machine learning systems opens up situations of aporia: moments of irresolution in what are expected to be exact procedures. Derrida describes aporia as a necessary condition for dialectics (Derrida 1993, 14), as it is uncertainty that necessitates decisiveness. Espen Aarseth writes of aporia (Aarseth 1997, 90-96) as a situation of inaccessibility or impasse, which then lends itself to epiphany. I differ as to my interpretation of the term aporia, defining it more in line with Derrida's usage, but I do find Aarseth's approach to reading relevant to the present investigation, as it emphasises that in situations when clarity is lacking, an interpretation must be made. If this is so, and uncertainty is a vital circumstance for the exercise of decision-making, could the uncertainty entailed in machine learning and artificial intelligence be considered productive of openings for aesthetic decision-making? Some of the most entrenched aspects of valuation in the appraisal of art are unsettled by machine learning encroaching into the artistic sphere. The issues of agency, autonomy and synthetic introspection evoked by generative machine learning algorithms act to undermine art world dogma regarding what art is or should be. For example, machine learning art challenges the art object's status as singular, individuated, scarce, original: *an object*. It also questions the notion of a work of art being a reflection of the intellect of its author, which in this case would be difficult to identify. Naming the algorithm as the author of an aesthetic artefact[1] fails to grasp the importance of the creation of the systems which in turn produce the artefact. Yet crediting a human or humans alone leaves out the significance machines, and machinic processes, played in the process. In the case of the eigenfaces which were examined previously, not only is there ambiguity in authorship, human, nonhuman or composite, but there is also confusion as to their subject. Eigenfaces are not windows into the interior world of the person whose face stares out at us. Artificially generated faces are not only simulacra (Baudrillard 2010), computational portraits without sitters, but they are practically non-representational. The generated face is a flat approximation of what a human may take to be the face of another human, not a representation of how computers interpret humans to be or to appear (Moura 2017). On the other hand, an artificially generated image bearing a resemblance to a face is no less a depiction of a face than traditional forms of images, such as photography, painting or drawing, which have only tangential relationships with the objects they are meant to depict.

1. As has been claimed by the group Obvious

4 CONCLUSIONS

Though often inconclusive and prone to irresolution, one may think of the aporetic openings (Anker 2009) revealed in the creative use of machine learning as contributing to the aesthetic properties of algorithmic media, rather than merely acting as discrepancies within their functionality. In lack of traditional criteria by which to adequately judge the products of machine learning, uncertainty may be viewed as a new conceptual approach to aesthetic qualities of artefacts produced using machine learning. The first example covered in this paper, eigenfaces showing averaged features from datasets of human faces (Kun 2011), offers insight into the ambiguity between the decisiveness of computation and the approximation of human vision through algorithmic approaches. The second example, Crawford and Joler's *Anatomy of an AI System*, zooms out to show the internal difficulties of taking part or a whole of a system. The indecision revealed in these situations of uncertainty are cause for reflection and re-evaluation if not a revaluation. If the distance between a face and not a face may be a matter of a single pixel for a computer (Su et al. 2019), we must consider whether our own, human aesthetic categories are equally flimsy. Rather than acting to establish new aesthetic categories in place of the old, an uncertain aesthetic may seek out blurriness, indecision and conflictedness as values. Such an ideology would champion irresolution in the face of imperatives to decide. What art and aesthetics do for artificial intelligence and machine learning is that they can reveal the irrationality found in technologies descended from rationalism. The digital image is dynamic and not merely an electronic version of a traditional, fixed image such as a painting or a printed photograph. Additionally, an image produced using machine learning is a part of a functional system, meaning that the generated image is inextricably linked to databases, processes and networks from which it emerges and within which it is situated. To more fully explore the aesthetic potential of machine learning, thus, it is essential to grasp its many internal uncertainties, not necessarily to resolve them, but to acknowledge the aporias they give access to as opportunities for new directions.

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