Re Sound Art Machines and Aesthetics

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Modelling an aesthetic experience through computational processes can be problematic for artistic expressions foregrounding the conceptual over the perceptual. Nevertheless, being able to judge aesthetic value and to generate accordingly, is evidently non-negotiable for the notion of an "art machine." Despite neuroscientific evidence (Berridge and Kringelbach 2015; Reybrouck et al 2018) that aesthetic appreciation is not a specific neural process concerned with aesthetic properties of a perceptual input, it is still customary to endorse the contrary and its natural corollaries: that there must be some objective mapping (a rule, a universal law) between perception and judgment, and that aesthetic judgment can be reduced to normative assessments of an art object's perceptual qualities. This fallacy, surprisingly widespread in creative AI endeavors, can often lead to single-factor explanations.

In the realm of "experimental aesthetics," instead, Leder and Nadal's (2014) posit that aesthetic judgement and aesthetic emotion are outputs of a recursive and complex network of connected stages in a continuous evaluation of an artwork. This model of information processing integrates perceptual, cognitive and affective accounts of the aesthetic experience, and it is modular, lending itself to countless variations. In it, one can distinguish two connected and inter-dependent circuits: an inner loop of continuous affective evaluation, comprising automatic and deliberate evaluation, and an outer loop which includes social interaction discourse, context and pre-classification.

Computational aesthetics in the sound realm has so far explored exclusively the automatic evaluation subnetwork, with particular focus on perceptual analyses. The music phenomenon per se, is based on different levels: a general domain level of the auditory system, a syntactical or prosodic level, and a culture-specific level. At a domain-general level, sound complexity (*e.g.*, spectral, temporal, etc.) is directly linked to information theory-based accounts of the music experience, an approach rooted in Birkhoff's (1933) "aesthetic measure," Bense's (1965) and Mole's (1973) "Information Aesthetics," Stiny and Gips' (1978) "Algorithmic Aesthetics," and Gell-Mann and Lloyds' (1996) "effective complexity." Complexity and entropy, however, are fundamentally different in music, where redundancy and repetition can be deliberately used as aesthetic features. For abstract art or music, conceptual complexity (Minissale 2012) might be more relevant than perceptual complexities. Similarly, dissonance is thought to be linked to unpleasant sensations, but there are many examples of music willingly employing it as an aesthetic signature. The same applies to design-based measures, such as contrast, unity in variety or symmetry.

The syntactical or prosodic level is normally informed by Gestalt theory, often combined with probability theory. According to Meyer (1956), for example, musical enjoyment is proportional to the level of agreement or violation of perceptual musical expectation (acquired, allegedly, through statistical learning). Narmour (1990) extended these concepts in his "Implication-Realization" (I-R) model of melodic expectation, which has been applied in music to generative (Brown et al 2015) and analytical (Potter et al 2007) tasks. However, in types of organized sound other than tonal, some of which have been described as "boring, formless and nonsense" (Priest 2013), the balance between expectation and novelty is often intentionally subverted for artistic reasons. "Prototypicality" (Martindale and Moore 1988) was proposed as a counter theory to Berlyne's

(1960) "arousal potential" but, to the author's knowledge, it has not been employed in a generative music context. Similarly, the "processing fluency" theory of aesthetic pleasure (Reber et al 2004), which maintains the notion of expectation insofar as familiarity is concerned, is still largely unexplored in the sound domain, except for "self-similarity" (Manaris et al 2005), one of the fluency variables.

Beyond the merits and issues that the above approaches might have when used in isolation, the most urgent agenda if one is to hope for truly engaging sound art machines is to address the lack of networked modularity between different automatic evaluation methods and to overcome single-factor explanations in the modelling of the aesthetic experience of music. Moreover, it is paramount to consider the role of context and social interaction discourse. For example, communities of sound art machines could exchange information and "experiences" about artworks, dynamically updating their beliefs about the context and the social value of the artifacts, which would in turn contribute to deriving online expectations. Affective computing could be leveraged to model the emotional state component of an aesthetic experience, while meta learning (Lemke 2015) and Bayesian program learning (Lake 2015) could be instead employed for tasks involving familiarity and the treatment of unseen classes of artworks. While the aim is not necessarily to reproduce, simulate or surrogate what is thought to be the human aesthetic experience, it is imperative to move beyond perceptual analyses of the aesthetic object, and towards the full potential of sound art machines.

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Biography

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