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Generation in Context: An Exploratory Method for Musical Enquiry

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ABSTRACT

This paper discusses a method, Generation in Context, for interrogating theories of music analysis and music perception. Given an analytic theory, the method consists of creating a generative process that implements the theory in reverse. Instead of using the theory to create analyses from scores, the theory is used to generate scores from analyses. Subjective evaluation of the quality of the musical output provides a mechanism for testing the theory in a contextually robust fashion. The method is exploratory, meaning that in addition to testing extant theories it provides a general mechanism for generating new theoretical insights. We outline our initial explorations in the use of generative processes for music research, and we discuss how generative processes provide evidence as to the veracity of theories about how music is experienced, with insights into how these theories may be improved and, concurrently, provide new techniques for music creation. We conclude that Generation in Context will help reveal new perspectives on our understanding of music.

1. INTRODUCTION

Generation in Context (GIC) is a novel research method for interrogating theories of music analysis and music perception. The method encompasses a framework for generating data, a technique for evaluating and analysing data, and a set of guidelines for experimental design. The method is rooted in the epistemology of situated cognition [1] which emphasises the importance of context in modelling perceptual phenomena.

The GIC method involves building a computational model of a music-analytical or music-perceptual theory, and inverting the model (from analytical to generative) to create new musical works. The characteristics of these new works can be assessed against outcomes predicted by the theories. This kind of reverse-engineering is sometimes referred to as analysis-by-synthesis [2]. Assessment of the outcomes can be made by the researchers or other informed listeners. Our formalised approach to this evaluation uses a variation of the Consensual Assessment Technique (CAT) developed by Teresa Amabile [3].

Music perception studies predominantly operate within a reductionist epistemology. This perspective advocates the reduction of confounding variables as a "cardinal rule" of experimental design, so that the inferences regarding the causes of observations may be drawn unambiguously [4]. A reductionist approach is, however, problematic when the phenomenon of interest is comprised of many interacting variables. We believe that music is such a complex phenomenon and also that our understandings and experiences of music composition, performance, listening, theory, and criticism provide complementary perspectives on music activity and perception. The GIC method advocates (and is designed to allow for) the use of models that take into account many musical elements, such as pitch, harmony, rhythm, tempo, and dynamics. It may also account for broader contextual matters such as musical style, cultural setting, and so on.

The GIC method seeks to support the understanding of music by bringing together the study of music perception and algorithmic composition. In summary our objectives are to: (i) Use algorithmic composition systems to interrogate theories of music perception, and (ii) Develop improved algorithmic compositional techniques by incorporating models of music perception.

The authors, along with colleagues in the Smart Music Research Group, have developed the GIC process for our collaborative research which will explore the development of new generative approaches to music making based on ideas from studies in music theory and music perception. We will outline some of our independent experiments that have lead us to develop the GIC method and discuss the its operations and implications in some detail.

2. EARLY EXPLORATIONS

Each of the members of our Smart Music Research Group have previously (to varying extents) explored how algorithmic music generation can be an effective method for music research. It is because of these positive experiences that we are working collaboratively to build on this approach.

Robert Davidson - Analysis and composition

A common strategy of composers, particularly since the work of John Cage, has been to explore ways of "finding" rather than "composing" music [5]. A number of tools have been developed to generate musical material that may be used as stimulus for composers; some of these are used regularly by some of the most prominent composers, including John Adams [6], Steve Reich [7] and many others. These composers use such systems to generate materials to survey and choose between (rather than adopting wholesale) music from algorithmic systems. This approach is exemplified by composers such as Larry Polansky or David Cope. Davidson has explored the extension of these systems into more intuitively-oriented material based on representations of music perception in order to generate a higher proportion of useful options for his musical expression. He has also extensively explored the use of found-object approaches using melody derived from spoken intonation in speech recordings [8] inspired by theories of the inherent musicality of speech prosody [20].

Toby Gifford & Andrew Brown - Multiple expectation 'Chimera'

The Chimera Architecture [9] is an abstract representation system that is the basis for a generative rhythmic improvisation system intended for use in ensemble contexts. This interactive software system learns in real time based on audio input from live performers. The analysis procedures do not yield a single scenario, but rather a collection of plausible scenarios with associated confidences. Analytical results are stored in a hierarchical structure that includes multiple scenarios allowing for abstracted and alternate interpretations of the current metrical context. The system draws upon this Chimera Architecture when generating a musical response. The Chimera Architecture was motivated by music perception research, particularly of Jackendoff [10] who proposed the parallel multiple analysis model, and Huron [11] who describes the competing concurrent representation theory. The generated rhythms are intended to have a particular ambiguity in relation to the music performed by other members of the ensemble. This ambiguity is controlled through alternate interpretations of the Chimera. A performance system, the Jambot, based on the Chimera Architecture has been used for a number of live performances.

Eugene Narmour - Modelling duration implications.

Narmour has constructed a generative model of melody that implements aspects of his Implication-Realisation theory. His express intent in doing so is to isolate the bottom-up processes of implication-realisation from top-down stylistic considerations, and also to isolate melodic pitch content from rhythm by generating isochronous melodies with notes of equal volume, the idea being to "see how far the bottom up model can be pushed". However, looking at the generated melodies from a different lens - that of their subjective musicality without regard to their experimental intent - has caused him to reflect that "In terms of algorithmic method, those who have applied prospectively oriented perceptual theories to generate automatic composition may discover that their results lack sufficient retrospective input necessary to produce a convincing output." For example, prospectively generating melodic pitches based on realisations and denials of expectation without any coding of retrospective stylistic input from final-state learning, (such as stylistic scale step) is likely to produce compositions with sequences little more convincing than if the prospectively oriented tones were randomly chosen.

Temperley - Statistical melodic construction

Temperley has explored music theory and cognition from a probabilistic perspective. About the possibility of generative processes to provide insights to the music researcher he remarks that: "Quite apart from the aesthetic value of stochastically generated music ... it might also be of interest in music cognition research. For example, if it turned out that stochastically generated hymn tunes were indistinguishable from real ones by competent listeners of the style, this might shed light on how musical styles are cognitively represented. However, the possibility of using stochastically generated music in experimental cognition research has not been much explored" [12].

Following up on these suggestions Temperley has experimented with the use of probabilistic principles of key and metre perception in stochastic melody generation. In reflection on the generated melodies, he notes that the outcomes lack global coherence, display a meandering quality, and do not display phrase boundaries and other higher-level features that would be expected of realistic melodies. Temperley sees a productive interaction between music analysis and generation, commenting that "Analytical modeling (key-finding, meter-finding, etc.) can be useful for generative processes, because it gives insight into the relationship between note patterns and underlying structures" [13].

Pearce & Wiggins - Modelling compositional style

In their study published in 2007, Pearce and Wiggins deployed a learning-based perceptual model of musical melodic listening. They generated melodies using the model and used human judges to compare the original and generated melodies. They concluded that the analysis by synthesis approach they undertook "proved fruitful in examining the generated melodies in the context of existing pieces in the style. It facilitated empirical examination of specific hypotheses about the models through detailed comparison of the generated and original melodies on several dimensions. It also permitted examination of objective features of the melodies which influenced the ratings and subsequent identification of weaknesses in the Systems and directions for improving them" [2:80]. Our GIC method draws significantly on this approach.

3. GENERATION AND REPRESENTATION

The central idea of the GIC method is to test analytic theories (either musicological or perceptual) by creating a computational model of the theory and running it in reverse. Generally speaking analytical theories of music will take as input a musical score or (increasingly often) a recording of a musical performance. The analysis is a process that reduces the musical surface into a higher-order representation. Generation is the opposite of analysis: it takes a higher-order representation and 'composes' the musical surface from it.

Perceptual models rely on predictive rules and assume the existence of unconscious cognitions and the automatic invocation of law-like processes. These deal with bottom-up primitives (e.g., feature extraction, event fusion, and correlated binding) as well as top-down complexes (e.g., function, grouping boundaries, statistical learning, and familial similarity). The challenge for generative models is to encode all these, thus formulating a meta-framework for perceptual models and a better explanation concerning how both musical perception and musical creativity stem from the same cortical network.

To follow the GIC method, the first step is to formalise the analytical procedure under investigation in order to construct a computational model of it. This in turn requires that the theory be formalisable, a strong requirement not readily met by most music analytic theories as they are presented. Performing this step in-and-of itself will yield insights into the theory, highlighting areas of inconsistency, vagueness, and subjectivity. In many cases it may be simply not possible to formalise fully the analytic procedure, and this is certainly a stumbling block for our method in that the computational model may not adequately represent the analysis procedure. However, one might ask, if a theory is not formalisable, to what extent is it really a theory?

There are computational benefits of formalisation, but also constraints. The theories need to be described in precise terms and even small elements of discretion or improvisation must be articulated (or else ignored). Generative systems require decisions about all musical elements. It is not possible to create a pitch list alone; such a list requires defaults for rhythms, duration, dynamic, and timbre. Thus the generative processes and a holistic contextual approach are complementary.

The digital media of computational systems provide a convenient match with the currently dominant statistical approaches to music cognition, such as those articulated by Huron & Temperley. While this complementarity is convenient for our approach, it is necessary to recognise that this might be problematic. A recursive feedback between description and evaluation could blind the researcher to other less convenient approaches and solutions.

4. CONTEXTUAL ROBUSTNESS

The algorithmic music process is a creative practice, as such it seeks to do more than validate or test a theory; it attempts to produce aesthetically valuable music. In doing so all musical dimensions need to be taken into account, in particular its situatedness. The cultural context in which the music will be heard and what function the music might play are taken into account. Musical experience exists in an ecology of influences, musical and non-musical, and the objective of the GIC method is to situate the music "in the wild" so as to assess its robustness.

It is important to remember that the distinctive activities of composing, listening, and performing all emanate from the same brain. Defining each as a separate domain is analytically convenient, but it does not represent reality. To compose is both to listen and to perform. Before choosing a specific notation a composer must imagine how aural conceptions sound when interpreted out loud. Thus the field of algorithmic composition must work to formulate unified theories that integrate the perceiving listener, the producing composer, and the performing musician. These musical activities take place in a context, or a situation, and for experimental results to be valid they need to take account of the setting.

In order for the method to be robust it needs to address issues of adaptation to context. We therefore employ the epistemology of situated cognition, which is a perspective on human thought that views knowledge as a dynamic combination of parallel influences, acknowledges the importance of context to understanding, and argues that perception is properly described as an interaction between the perceiver and the environment. From this perspective algorithmic composition is a natural tool for interrogating music perception theories since it allows for the modeling of music perception in a musically and culturally realistic setting. From a methodological perspective, the most salient tenet of situated cognition is the importance of modeling phenomena in their natural context [14] in order to understand how the algorithmic systems perform "in the wild" [15]. From this viewpoint we see algorithmic composition as distinct from analysis-by-synthesis. Analysis-by-synthesis has previously been used to validate a specific musical feature in isolation, and the generated music is tailored to this purpose, with an emphasis on the removal of confounding variables [16, 17, 2]. Algorithmic composition, by contrast, is primarily concerned with the creation of quality music. Our hypothesis is that the testing of musicological theories using algorithmic composition rather than analysis-by-synthesis will shed light on practical aspects of composition where analysis-by-synthesis fails to.

5. EVALUATION

In the GIC method the musicality of the output of algorithmic music systems is evaluated through a series of trials based on the Consensual Assessment Technique (CAT); a method for obtaining reliable subjective evaluations of creative work. In this technique, a panel of judges gives quantitative evaluations of the creative work according to a number of criteria. The judges are required to be domain experts in the creative field, and the evaluations are conducted independently by each judge. A statistical measure of the inter-judge agreement is then reinterpreted as a metric for the reliability of the collective subjective evaluations of the panel. In view of our goal to evaluate the compositional output of algorithmic music systems holistically (rather than assessing individual musical features in isolation) we consider this method to be appropriate. Pearce & Wiggins [2] used the technique to assess stylistic success as a dimension of evaluation. They found that the combination of quantitative and qualitative data yielded deeper insights into the compositional weaknesses of their models than would the quantitative data on its own. The GIC method uses a variation of CAT that incorporates a structured survey of qualitative evaluation that is guided by criteria for assessment of (human) compositions in an educational context, such as those of Swanwick & Tillman [18].

GIC departs from the scientific methodology in the sense that it embraces indirect evidence. Whereas a reductionist approach to studying music perception tends to isolate musical parameters such as melody, harmony and rhythm, the GIC methodology advocates a holistic approach to music analysis and to music perception, where parameters are studied in the context of realistic pieces of music. The motivation for utilising indirect evidence is two-fold. Firstly, to avoid the problems of artificial reductionism discussed above. Secondly, to provide a fertile source of new insights following the exploratory method of GIC.

The primary weakness of the GIC method is the flip-side of its strength: embracing indirect evidence weakens the incontrovertibility of the evidence. Two factors mitigate this weakness;

(i) This indirectness is compatible with Popper's view of science as a process of tentative falsification - in science one never obtains incontrovertible evidence confirming the truth or falsehood of a theory, but rather gathers a body of evidence in support of or discordant with a collection of competing theories, and chooses the theory that is least discordant [19]. The more direct the evidence, the sharper the evidence will be at narrowing down alternate theories. However this does not mean that indirect evidence is of no value.

(ii) This methodology is not intended to replace more traditional psychological experimental methodologies, but to complement them. Where more direct evidence is required, a different method should be applied. A strength of GIC is that it may provide insights that may be later verified more unambiguously by other means.

6. CONCLUSION

Interestingly, cognitive musicology has rarely employed algorithmic composition as an investigative tool. Rather, where computational models of music perception have been used to generate musical material (described as analysis-by-synthesis) they have tended to focus on individual musical parameters, and have not attempted to utilise other aspects of composition theory to create a complete musical work. We suggest that algorithmic composition provides a contextually rich environment for investigating theories of music perception and music analysis with less risk of artificial reductionism.

The GIC method combines the ideas discussed above (generation as the inverse of analysis, contextual robustness, and subjective evaluation) into a novel method for interrogating theories of music perception and music analysis. By formalising an analytic theory, inverting into a generative compositional model, and evaluating the output of the compositional model in a musically realistic context, the method provides an alternate mechanism for evaluating the theory. The method is exploratory in the sense that, in addition to providing a means for evaluating theories, we expect that application of this method will prove a fertile source of theoretical insights.

We believe that the introduction of this method provides a link between music theory, music cognition, and algorithmic music. By implementing computational models of music perception theories, and furthermore by implementing them as complete algorithmic composition systems (rather than a model of a particular musical feature) we suggest that these disparate fields of musical inquiry may be united, and the approach will have benefit for both fields. Judging success through consent of an expert listening panel allows for the complexity and context of realistic musical results to be taken into account.

In the future we will be exploring the potential of the GIC method to elaborate on the early experiments outlined above and to work toward building a computing system that assists music researchers and composers by enabling rapid exploration and generation of musical ideas and theories.

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