**7601 words**

**Introduction and Basic Premises**

My dissertation lies at the intersection of musicology, media studies, and critical data studies. The basic question generating my project is this: what can the history of digital music and music recommendation reveal about the values and ideological assumptions embedded in our present-day digital systems? One way to tell this history places its origin in the 1990s. 1994 marks the release of Ringo, the first music recommendation service; it is also the period when Music Information Retrieval (MIR) coalesced as a new interdisciplinary field. However, I plan to tell a longer and more detailed history — one reaching back to the cybernetic turn of the 1950s and its unlikely entanglement with the musical practices of the late-eighteenth century. My project will examine how music became thinkable in computational terms; the lasting influence of widespread, “benchmark” datasets; the ontology of the digital musical object; the systems of valuation underpinning recommendation systems; and, ultimately, the intimate relationship between music, early capitalism, and postmodernism in the digital age.

My dissertation rests on several premises. The first is an approach to “algorithmic opacity” — a challenge that many scholars and data activists cite as a key ethical concern of our age. These scholars argue that because algorithmic systems operate on unfathomably large, complex scales, they are difficult, if not impossible, to understand fully — even for the developers working on them. In response, one group of scholars, including figures such as Timnit Gebru, have developed auditing tools to promote algorithmic transparency.[[1]](#footnote-1) Yet others, like Louise Amoore, view algorithmic opacity as intractable. While she challenges developers to provide more transparency about their working processes, she draws on Feminist STS scholarship to argue that the opaque, partial accounts of these systems are still insightful and valuable in their own right. Despite their essential disagreement, however, both positions are relentlessly focused on the present — on solving problems of knowing and understanding within the current ecosystem. In contrast, I argue we will only grasp the principles that shape today’s digital culture if we understand the history of algorithmic systems. The datasets used in the 1990s and 2000s were relatively small and relied on rule-based programming. These two characteristics may make it easier to see how these systems parsed and processed data, in contrast to today’s big data systems which rely on unsupervised learning via neural networks.[[2]](#footnote-2) Yet present-day computing architecture often relies recursively on older, rules-based classification algorithms as part of their learning processes.[[3]](#footnote-3) Old infrastructures, and still older ideological assumptions, are built into our digital present.

My second premise rejects the increasingly widespread assertion that ML algorithms used to develop facial recognition or fraud detection technologies, applied in domains such as policing and credit scoring, are more important to account for than the algorithmic systems used for music recommendation. My project shows that music is far from an ancillary application of digital technologies, but instead has been fundamental to the conception and design of these systems from their earliest iterations. In computer science, scholars have pointed specifically to music recommendation as the ostensibly low-stakes domain that helped to validate their research. In fact, they have argued that whereas biased or faulty ML models used in the judicial process, for example, can produce immediate material harm, the worst outcome for a music recommender is that it suggests a suboptimal song.[[4]](#footnote-4) It is this dismissal of music’s importance I seek to challenge. I show how understanding the digital, informationalized musical object and how recommender systems query it gives us crucial insights into all ML. Music’s relatively low bandwidth requirements meant that it was the first cultural domain to be digitized on a large scale. How researchers digitized and then mobilized the digital musical object therefore provided nothing less than a blueprint for the subsequent digitization of all culture. From that perspective, musical data is not simply a case study, but rather offers an archaeology of digital culture. This status is not wholly surprising: music’s presence in the internet’s development is just the latest example of music deployed as a proof-of-concept for new technologies, new media forms, and new economic principles.

My third basic premise is the centrality of style in present-day ML systems. I show that the encounter between music and algorithmic systems is foreshadowed and illuminated by earlier discourses of style. In the 1950s, Leonard Meyer was one of the earliest music scholars to apply information theory to music. Key to his early theories were Markov chains — a random process in which the probability of what comes next is determined by what immediately comes before. A recurring motif in Meyer’s work is an understanding of style that is essentially probabilistic, reducible to a series of choices made within a set of constraints. He argued that theorists need to account for the totality of possibilities available to a composer, including the choices not made, the paths not taken.[[5]](#footnote-5) Within the fields of Artificial Intelligence (AI) and Machine Learning (ML), disciplinary shifts in the 1980s meant that the predictive capacity of models were favored over their interpretability.[[6]](#footnote-6) That is, when researchers found themselves choosing between a model that could give a better real-world prediction and a model that they could more-or-less fully understand, they chose the former. Increasingly both AI/ML researchers and Music Information Retrieval (MIR) researchers found the predictive capacities of Markov chains helpful to their work. Since music was central to the design and testing of early digital systems, Meyer’s application of Markov chains to musical contexts was subsequently replicated and applied (sometimes knowingly, sometimes not) in other areas of early ML research. In today’s systems, the popularity and widespread applications of large language models (LLMs) is one of the outcomes of this history.[[7]](#footnote-7) LLMs are fundamentally predictive engines: predicting what word comes next, what musical syntax comes next, what song comes next. These predictions are based on an informationalized conception of style-as-probability. For example, asking ChatGPT or Claude.ai to generate a poem in the style of Shakespeare relies on those models’ being able to generate words based on the probabilities of neighboring words within Shakespeare’s corpus. Similarly, asking an LLM to critique a paragraph for a college essay draws on a model’s normative understanding of the style of a college essay. In short, old questions of style — particularly the ways in which style discourse has often tried to harmonize qualitative and quantitative elements in cultural products — remain fundamental to AI models and algorithmic systems.

**Literature Review**

Recent musicological literature on digital music tends to focus on digital music’s effects on musical production in the present or recent past. Notable scholars in this field include David Arditi (2019, 2021), Georgina Born (2021, 2022, 2023), Eric Drott (2013, 2021, 2023), Paula Harper (2016, 2020, 2022), Tom Johnson (2018), Martin Scherzinger (2019), and Timothy Taylor (2024). In general, this scholarship borrows from social anthropology, and largely considers the new social mediations of digital music and its effect on cultural production. For instance, Taylor emphasizes how value drives cultural circulation, while Born’s ethnographies examine how digital affordances reshape artists’ work. Another related strain of this scholarship, represented by scholars such as Arditi, Drott, and Scherzinger, consider the economic effects of digital culture. Drott’s most recent book, *Streaming Music, Streaming Capital,* argues that music has been partially decommodified on music platforms. His central claim is that consumers now view music as a latent resource, there for the taking. Scherzinger’s work examines changing musical labor practices and outlines the legal history of digital music. David Arditi shows that music record companies continue to extract record profits, despite popular beliefs to the contrary. These companies generate revenue for the same track multiple times through a mix of subscription and licensing fees, leading to windfall profits.[[8]](#footnote-8),[[9]](#footnote-9) Other notable scholars in this area include Nick Srnick, who was the first to explicate “platform capitalism,” and Jeremey Wade Morris, who writes on digital curation, digital fandom, the rise of “infomediaries.” While my work is in dialogue with this scholarship, my main consideration is the historical development of digital music’s infrastructure — an absent element in nearly all of the above scholarship. Indeed, these scholars tend to view digital systems as more or less readymade, which allows them to theorize new forms of musical production and reception. This project is not primarily concerned with the experiences of present-day listeners and artists in “online” or digital spaces. Rather, I want to reveal the history of the material and conceptual structures that make these musical experiences possible, and the kind of musical object that our digital systems have created.

In addition to scholarship on music and recent digital culture, a lineage of research on the history of capitalism and cultural production is important for my project. Much recent scholarship in this area takes its inspiration from Fredric Jameson’s seminal essay, “Postmodernism, or, the Cultural Logic of Late Capitalism,” which argues that the era of financialization has made the cultural and economic spheres indistinguishable, while art objects and even capital itself share a surface-oriented, depthless aesthetic character. Sianne Ngai has been the most influential scholar to elaborate Jameson’s view in the web age, especially in her explication of “minor aesthetic categories” — the cute, the zany, the interesting, and the gimmick. She argues that these categories enact the major economic relations of late (digital) capitalism. But another strain of scholarship, which includes Mary Poovey and John Guillory, has provided a longer-duration history of the relationship between economics and aesthetics under changing capitalist regimes. Poovey’s early work explored how economics and aesthetics were once the same discipline, housed within moral philosophy and theories of taste. And at the same time John Guillory argued that aesthetics and economics are historically conjoined via the shared concept of “value.” My project is partly a response to these arguments about the history and theory of economics and aesthetics in advanced capitalist societies. I will argue that we cannot fully understand our own cultural moment without returning to some of the debates activated by early capitalism, especially those about value and representation.

Science and Technology Studies (STS) and Critical Data Studies form the third pillar of scholarship for my project. In particular, the foundational work of Mark Ackerman (2000); Wiebe Bijker (1995); Geoffery Bowker and Susan Leigh Star (1999), and Langdon Winner (1980) inform my project. Bowker and Star’s *Sorting Things Out* is especially important for its argument that classification systems function as infrastructure; this claim on its own helped create what we know as Critical Data Studies. Elaborating on this premise, Nick Seaver was among the first scholars to theorize algorithms as cultural forms, drawing attention to the social construction of algorithmic systems. However, most scholarship on data falls under the purview of data ethics. Some, such as Joy Buolamwini (2018, 2019); Timnit Gebru (2021); Melanie Mitchell (2021); and Inioluwa Deborah Raji (2020) are concerned with identifying and minimizing algorithmic bias. Here again, the problem of opacity is a recurrent concern, as in the work of Jenna Burrell (2016) and Morgan Ames (2018). Most recently, Alexander Campolo and Katia Schwerzmann have warned that the kind of opacity created by deep learning is enacting a new kind of authority, one that is harder to contest than more visible, traditional power structures.[[10]](#footnote-10) Conversely, Louise Amoore has been broadly critical of the dominant paradigm of algorithmic transparency, accountability, and explainability. In *Cloud Ethics*, she argues that algorithmic systems are dangerous because they foreclose alternative visions of the future by “condens[ing] multiple potential futures to a single output.”[[11]](#footnote-11) For her, the critical moment for deep learning algorithms is the moment of “aperture,” when the system takes billions of combinatorial possibilities latent in the data and condenses them into a single, seemingly objective output. Algorithmic systems, she claims, create the “bounded conditions” in which democracy functions. In contrast to Buolamwini, she points out that bias is essential for these systems to work at all; and that even the most unreasonable algorithmic output is rational according to the system’s ground truths and computational logic. Examining moments of “algorithmic madness” are moments where algorithms “give accounts of themselves,” thus revealing insight into a system’s logic.[[12]](#footnote-12) Most compellingly, she points out that algorithms are complex, contingent texts operating under shifting networks of authorship. She marks the late-eighteenth century as an analogous moment when ideas about authorship and literary practices were in flux. She asserts that one way to interpret algorithmic systems is by using the interpretive tools developed by humanities scholars, which is an idea I find compelling.

**Methods and Sources**

Many humanistic research projects on digital systems take the form of institutional ethnography (e.g. Florian Jaton (2021) and Nick Seaver (2022)). By contrast, my project is primarily historical and theoretical, focused on material infrastructures such as public benchmark datasets, patents, company records, conference proceedings, and personal blogs on music technology. Datasets I will discuss include GTZAN, the Million Song Dataset, Magnatagatune, and the 2004 ISMIR Genre dataset; music recommendation companies from the 2000s I intended to research include Pandora, Mood Logic, MusicBudda, Mubu, Cantametrix, MusicGenome, MongoMusic, and EchoNest. The Bancroft Library holds relevant archival material in its History of Science and Technology collection, while Standard and MIT (in particular the MIT Media Lab) keep paper archival records. While I intend to interview early pioneers in MIR — including Bob Sturm, Patti Maes, George Tzanetakis, Robert Gjerdingen, Jean-Julien Aucouturier, and Francois Pachet — I consider it important that this project is not primarily ethnographic. This stance is partly motivated by a frank skepticism of the limits of ethnographic research, limits partially outlined by Barbara and Karen Fields’ (2012) work on oral testimony and memory. It is undeniably important to gather these actors’ accounts of their work on early digital systems. Yet their reports are neither definitive nor exhaustive; ultimately, I am more interested in telling a story that accounts for a deeper, broader history of digital music.

**Chapter Outlines**

The introduction of my dissertation will consider the historical context of the late 1990s and early 2000s, framed in terms of tech utopianism, the myths that drive technological development, and the central place music occupies in both.

**Chapter One: Music, Information, and Computation**

Chapter One tells the story of how music became thinkable in computational terms. Key to this history are contemporary music theorists of eighteenth-century music, especially Leonard Meyer, Robert Gjerdingen, and Leonard Ratner, and later musicologists who were influenced by them, such as Roger Moseley. These scholars share a modular, digital conception of music that makes music amenable to computational procedures. Meyer thought of musical composition as an essentially probabilistic process, describable in the terms of information theory. I show that his vision of music became something like a foundational “ground truth” for later forms of musical computation and computational musicologies. “Ground truths” are what computational models learn or take to be true about the world. The ground truth concept is typically associated with the labeled training datasets used to design and test supervised ML models. However, scholars have recently invoked the concept to address the consequences of a simple fact: any computational research question must first be articulated in terms that a computer can apprehend and manage.[[13]](#footnote-13) In the case of something like MIR, nothing can be queried at all unless musical works are (re)conceived in computational terms. So it is not surprising that, when computational music research was in its nascent stage, MIR researchers borrowed, or independently developed, Meyer’s understanding of the musical object: a probabilistic vision of music that could be computed using techniques such as Markov chains.

One unremarked curiosity of early digital music databases and early attempts at AI music composition is the prominence of eighteenth-century music, particularly Mozart, in these databases and compositional models. In part, this peculiarity resulted from a distinctive strand of twentieth-century intellectual history. The view of Mozart popularized by German emigres in the postwar North American academy was markedly Romantic: writers such as Alfred Einstein portrayed Mozart’s oeuvre as a succession of elegant, organic musical wholes. In the 1950s and 1960s, however, two groups of music theorists began to contradict this view. On the one hand, as we have seen, theorists like Leonard Meyer at UChicago and his student Robert Gjerdingen conceived of eighteenth-century music in statistical, probabilistic terms. Shot through with the early language of Norbert Weiner’s cybernetics, this work applied a mathematical-universalist view to music. On the other hand, the group of musicologists around Leonard Ratner in Stanford emphasized the importance of the *ars combinatoria* — the quasi-mathematical art of combining and recombining already existing elements — across eighteenth-century musical practices. Ratner went on to champion what came to be known as topic theory: a way of listening to and analyzing music based on audible and interchangeable units of meaning.

The ideas of Meyer and Ratner rapidly took hold across the academy – especially in music-adjacent fields that could instrumentalize their computational models of music. In the 1990s, David Cope, a music researcher at UC Santa Cruz, built one of the earliest examples of AI composition software: EMI (Experiments in Music Intelligence). Cope first taught EMI how to create music in the style of Mozart, based on Ratner’s explication of the ars combinatoria in eighteenth-century compositional practice. But the late 1990s also witnessed the beginning of the dotcom boom; at this time, early music recommendation companies began poaching music scholars to help build their systems. Two notable examples are Nolan Gasser, who abandoned his PhD at Stanford to head Pandora’s Music Genome Project; and Meyer’s student Robert Gjerdingen, who briefly left his position at Northwestern to join MoodLogic as their Vice President.

These Chicago-Stanford views of music played a disproportionate role in the development of these digital systems. Ultimately, musicologists working on music recommendation found the newly formulaic conception of eighteenth-century music – and the audibility of these formulas – conveniently compatible with emerging computational systems. Moreover, they found that analogous strategies could be deployed for querying a more lucrative, but comparably formulaic musical object: the American popular song. Even as these companies grew and trained their models to query a wider variety of music, our digital systems retain powerful traces of eighteenth-century music, as reconceived by mid-twentieth-century academic music theorists.

**Chapter Two: The Database**

The second chapter explores how, once music was recast in these probabilistic terms, MIR researchers compiled pieces of music into databases. This chapter will outline the history of several early prominent, “benchmark” datasets and trace their lasting influence on MIR’s understanding of musical genre. Benchmark datasets are datasets intended to enable evaluation between different ML models. The basic premise is that if researchers test their various models using the same data, then ML models can be meaningfully compared.[[14]](#footnote-14) Today, some datasets are created explicitly as benchmark sets; historically, however, a dataset’s benchmark status tended to be conferred simply on account of its widespread use.

In the mid-1990s, creating musical databases was a difficult and time-consuming task. In general, these early databases tended to be small; they were labor-intensive to create and researchers encountered real storage and bandwidth constraints. By and large, MIR researchers found genre the most intuitive basis on which to organize these databases. But manually labeling tracks according to genre was challenging and time-consuming. One of the first tasks MIR tried to automate, then, was music genre recognition. Researchers tried to create models that could “listen to” and automatically classify music according to its genre. But in contrast to mainstream musicological understandings of genre — ones that usually take generic categories to be a kind of social contract, historically situated and contingent — MIR researchers proceeded as if genre could be assigned via measurable, quantitative features. Bound by the constraints of first-order logic necessary for rules-based classification systems (i.e. *if P, then Q*), MIR researchers applied what Lorraine Daston has called “thin rules” to these systems. Thin rules require a predicable, stable world that affords their rigid application.[[15]](#footnote-15) In MIR, the consequence of understanding genre via thin rules meant that genre narrowed into a small set of categories widely used by the American music industry in the mid-1990s.[[16]](#footnote-16) Moreover, these systems proceeded as if genre could be identified from the sonic surface, computable via a small set of extracted statistical features. This approach to computation meant that certain ground truths about both the musical object and genre came to be embedded in the infrastructures of these systems. One enduring legacy of these early datasets and their ground truths is that these systems replicated and magnified a rigid, somewhat idiosyncratic understanding of genre and musical similarity.

The first widely circulating, benchmark dataset was the GTZAN Dataset. Created in 2002 by George Tzanetakis, many MIR researchers found its size and scope just right: big enough to be robust, small enough to be manageable. Moreover, Tzanetakis was willing to share his dataset with anyone who asked for it, and it began circulating widely.[[17]](#footnote-17) Bob Sturm first identified the extent to which GTZAN and the 2004 ISMIR Genre Competition datasets in particular had spread. He later examined the GTZAN dataset more closely and found a startling number of problems with it. Sturm’s work inspired MIR researchers to create better standard datasets. Yet the GTZAN and 2004 ISMIR datasets continue to exert an influence, despite falling out of widespread use. Many subsequent datasets remain organized by genre, and many use either ten genre categories, like GTZAN, or six genre categories, like the 2004 ISMIR dataset.[[18]](#footnote-18) I will show that these datasets afforded deep-seated ideological assumptions beyond musical genre to spread, as well as show how this history contextualizes MIR’s shift to context-based recommendation.

**Chapter 3: The Digital Musical Object**

The third chapter considers the “digital musical object.” One widespread but overlooked question in research about music recommendation is what the digital musical object *is* and how we should understand it. By this I mean that researchers typically take for granted that there is a commensurability between “real-world” musical objects and an audio file’s extracted, aggregated datapoints. In today’s digital systems, music is made equivalent to quantifiable aspects of sound. This understanding obscures not only relationships we think of situated and “cultural,” but also intra-musical relationships that we might consider syntactical or semiotic. For example, how should (or could) these systems conceptualize and differentiate indigenous musics and the diasporic musics that stemmed from the same traditions? If digital systems are focused on sonic similarity, it is likely that distinct musical practices will be conflated. And while metadata could help distinguish between practices by reintroducing a kind of “extra-musical” commentary, even today, managing metadata remains a difficult and contested issue.[[19]](#footnote-19)

This chapter will argue that the digital musical object has undergone a process analogous to money in the late-eighteenth century. The outcome of this process is that musical data can now circulate freely and widely — and generate value. What Mary Poovey calls the “problematic of representation” in the history of money is useful here. She argues that the turn to paper money and the widespread use of credit in the early nineteenth century meant that a traditional understanding of monetary instruments as having a “literal relation to value” was undermined.[[20]](#footnote-20) The abstraction of diverse monetary instruments (bills of exchange, bank paper, checks, coins) allowed these multiple monetary “genres” to become equivalent and interchangeable. And, as James Thompson’s orthodox Marxist view emphasizes, it was this gradual abstraction of money that enabled its transformation from wealth into capital. Here, circulation is key. Money as an inert hoard is merely accumulated wealth, whereas “money in process” can generate surplus value.[[21]](#footnote-21) Likewise, in today’s digital spaces, numbers, in the form of data, have created a new kind of ur-commensurate object — one that required a massive project of abstraction before it could function.[[22]](#footnote-22) But siloed data is not particularly valuable on its own: value is generated through circulation in the model, or as data exchanged between systems. Money and data, I argue, have undergone parallel conceptual transformations at these peripheral or liminal moments in the history of capitalism. The first section of this chapter will consider the financialization of data in the 2000s. Nuancing Clive Humby’s well-known bon mot that “data is the new oil” and Drott’s conception of musical data as a latent resource, I argue that data is better understood as pure capital.

The second half of the chapter focuses more closely on musical data and the ontology of the digital musical object: how musical data lives in databases and how ML models understand them. My central claim is that, despite many Romantic legacies persisting in our ideas about music, our digital systems actually rely on something much closer to an eighteenth-century understanding of music: as meaningful sonic surface. MIR researchers assumed that identifiable characteristics could become known through statistical extractions from audio files — the machine-audible surface of the sound.

Topic theorists, such as Leonard Ratner and his student Wye J. Allanbrook, had long viewed music in this way. For them, musical topics — audible markers of musical meaning in the eighteenth century — lie on the surface of the music. A French Overture, a military march, a hunt: these meanings were immediately evident to eighteenth-century listeners, who were not required to look beyond them to discover hidden depths or decipher complex structures. MIR researchers’ basic conception of the digital musical object thus strikingly converged with contemporary music theorists’ view of music, and eighteenth-century European music in particular: music became modular, syntactical, and knowable through an audible surface. Crucially, on a practical level, this audible surface was more amenable to the computational technologies of MIR researchers than more nebulous conceptions of musical depth associated with musical Romanticism.

Moreover, because these early databases were mostly (if not exclusively) collections of Euro-American music, early music computational systems acquired a distinctly local view of what counts as a normal versus an unusual musical surface. These early computational systems were not only performative, they were also normative. Computational systems learned music from a small subset of Euro-American examples, which created the standard against which all other music would be compared. Despite the profoundly utopian, democratic, and cosmopolitan rhetoric of online culture, Euro-American ideas about musical ontology are embedded in its foundational infrastructures.

**Chapter Four: Evaluative Systems**

Chapter 4 takes up the issue of evaluation and considers what happens to data once it is gathered and sorted. In this chapter, I consider classification algorithms, one of the central planks of automatic music genre recognition. As Bowker and Star maintain, classification systems can act as infrastructure. The categories included in any classification system, along with its degree of granularity and flexibility, are decided early in the development of a classification algorithm. As Chapter Two will show, the systems used to classify musical genre tended to be based on the most popular genre labels used by the music industry. So, even as ML models grew in complexity and shifted from supervised to unsupervised learning processes, earlier classification algorithms continued to nest within these systems.[[23]](#footnote-23) The result, I show, is that the operation of classification systems became at once more obscure and more influential in music recommendation processes.

By the early 2010s, companies like EchoNest claimed to have moved beyond familiar musical genres as their starting point. For example, a snapshot of their website in 2012 emphasized that they had developed a ML model that scored “acoustic attributes” like “danceability,” “energy,” and “speechiness” as part of their recommendation process. These “attributes” amounted to aggregations of measurable acoustic data. As EchoNest explained, “danceability,” to take one example, comprised data about tempo, rhythm stability, beat strength, and overall regularity. It is notable, then, that the model calculated “danceability” by using more or less the same data that had once been used to generate more conventional genre classifications. A new classification system was merely overlaid onto these models, without erasing the older schemes. This meant that MIR researchers’ early, often contingent, choices invisibly persisted. Further, as we will see, to calculate an “acoustic attribute” was to make an inaugural assumption about what music is and what its most important or salient features are. And this aesthetic value system turned out to be inseparable from economic calculations, since the better the recommendations, the more profitable the company.

**Chapter Five: Aesthetic-Economic Entanglements**

In digital systems, “everything lies in a space.”[[24]](#footnote-24) In the context of music recommendation, ML models query pieces of music and place them in “similarity spaces.” Musics that are similar are clustered together, while hyperplanes delineate the boundaries of musical difference. This operation is predicated on first making all musical objects equivalent, understandable in quantified, numeric form.

As Steffen Mau has pointed out, the quantification of the social — the translation of social life into numerical data — allows virtually anything to be compared.[[25]](#footnote-25) And, in the case of music recommendation companies, it is in their best interest to create systems that could work with any kind of music.[[26]](#footnote-26) Quantifying music, then, transforms the musical object into something that uncannily resembles an economic one: an object where difference is bracketed, which allows it to circulate through systems as an anonymous equivalent. Except, if every object is fungible with any other, evaluative systems fail. These economic-digital objects require some differentiation. To accomplish this, systems unknowingly draw on historical discourses on beauty and taste. As Mary Poovey has described, eighteenth-century discourses on taste relied on an idea of discrimination as a process that both differentiated and evaluated objects.[[27]](#footnote-27) Thus at the very moment the musical object is transformed into a fungible musical-economic one, digital systems transform it back into a musical-aesthetic object.

Ultimately, I argue, digital systems’ entanglement with these economic- and aesthetic-musical objects complicate the very foundation of the originary division between those two spheres. Early political economists “sought to deny difference,” transforming every individual into homo economicus and mediated every exchange through the universal equivalent of money.[[28]](#footnote-28) In present-day digital systems, data is always-already universally equivalent, yet they rely on difference to function. In short, only an aesthetic conception of value allows these systems to operate. Counterintuitively, then, digital systems rely on the qualitative, “infinitely nuanced,” aesthetic object as the basis of their evaluations. Every digital commodity is an aesthetic commodity, built in digital music’s economic-aesthetic image.

In this chapter, I will examine Joseph Haydn’s symphonies and trace their aesthetic and economic entanglements at the liminal moments of early and late capitalism. On the one hand, Nicholas Mathew has shown how Haydn’s encounter with these new, early capitalist regimes left material traces on his work. In the late-eighteenth century, the introduction of public concert culture, burgeoning publishing infrastructure, and emerging copyright regimes created a new kind of aesthetic-economic object. On the other hand, Haydn’s music continues to reappear in early musical databases, with surprising frequency. I argue that Haydn’s music is, once again, encountering a moment where ideas about musical value are undergoing profound changes, resulting in a new kind of aesthetic-economic object. Ultimately, tracing Haydn’s music in emergent media environments provides crucial insights into the contested ways of knowing, understanding, and valuing music — or, all digital cultural forms.

**Conclusion: Digital Music and “New AI”**

The conclusion sketches the development of digital music and music recommendation after 2014. The early 2010s were a period of accelerated change in the history of computing. 2012 marks the point when convolutional neural networks (CNNs) became computationally viable on large scales and ushered in our current era of deep learning.[[29]](#footnote-29) In 2014, Spotify acquired EchoNest, whose technology catapulted Spotify to its dominant position in the digital music sphere. The most dramatic development has been the increasing reliance on unsupervised machine learning. Because unsupervised learning is based primarily on pattern recognition and clustering to label and organize data, old questions (and aporias) of musical style remain central to these systems.

When Robert Gjerdingen first explicated partimento schemas, he reintroduced a way of knowing music based on pattern recognition. He showed the extent to which the eighteenth-century musical corpus is littered with audible, schematic prototypes. Yet while these prototypes are integral to musical style, they don’t independently proxy it. Indeed, the usefulness of these schemata relied on their capacity to be integrated into nearly any stylistic context.

In unsupervised ML, models look across a much larger and more heterogeneous musical corpus. The recursive nature of neural networks, along with the immensity of present-day datasets, seems to allow some models to approximate a “deep” understanding of music — learning something closer to the situated, “thicker,” more ambiguous rules of music as we experience it. Yet they are relying on a strikingly similar strategy as laid out by Gjerdingen to learn and know music: recognizing patterns from the machine-audible musical surface. But whereas in the eighteenth century, composers understood style as a surface feature undergirded by the syntactical rules of musical language, digital systems invert this understanding. These systems backwards engineer a syntactical understanding of the musical object by querying the stylistic surface. Moreover, as Alexander Campolo and Katia Schwerzmann highlight, the way unsupervised systems rely on prototypes —creating composites from a multiplicity of examples — produces an “artificial naturalism” from the data. This naturalism makes it appear that “exemplary representations…emerge from the structure of the data itself.” [[30]](#footnote-30) But in reality, these exemplars often produce normative representations from the data that become nearly impossible to contest. In the context of music, I argue that computational systems are producing a normative view of musical style that is influencing both what music means today and what music is understood to be.

Bibliography

Ackerman, Mark S. “The Intellectual Challenge of CSCW: The Gap Between Social Requirements and Technical Feasibility.” *Human-computer interaction* 15, no. 2–3 (2000).

Allanbrook, Wye Jamison. *The Secular Commedia: Comic Mimesis in Late Eighteenth-Century Music.* Edited by Mary Ann Smart and Richard Taruskin. Berkeley, California: University of California Press, 2014.

Ames, Morgan G, and Massimo Mazzotti. *Algorithmic Modernity: Mechanizing Thought and Action, 1500-2000*. United Kingdom: Oxford University Press, 2023.

Amoore, Louise. *Cloud Ethics: Algorithms and the Attributes of Ourselves and Others.* Durham: Duke University Press, 2020.

Arditi, David. “Music Everywhere: Setting a Digital Music Trap.” *Critical sociology* 45, no. 4–5 (2019): 617–630.

Arditi, David. *Streaming Culture: Subscription Platforms and the Unending Consumption of Culture*. Emerald, 2021.

Barlow, John Perry. “A Declaration of the Independence of Cyberspace.” (1996)

Bijker, Wiebe E. *Of Bicycles, Bakelites, and Bulbs: Toward a Theory of Sociotechnical Change.* Cambridge, Mass: MIT Press, 1995.

Boltanski, Luc, and Eve Chiapello. *The New Spirit of Capitalism.* Translated by Gregory Elliott. New updated edition. London: Verso, 2018.

Born, Georgina. “Diversifying MIR: Knowledge and Real-World Challenges, and New Interdisciplinary Futures.” *Transactions of the International Society for Music Information Retrieval* 3, no. 1 (2020): 193–204.

Bowker, Geoffery. “How to Be Universal: Some Cybernetic Strategies, 1943-70.” *Social studies of science* 23, no. 1 (1993).

Bowker, Geoffrey C., and Susan Leigh Star. *Sorting Things out: Classification and Its Consequences.* Cambridge, Mass: MIT Press, 1999.

Campolo, Alexander, and Katia Schwerzmann. “From Rules to Examples: Machine Learning’s Type of Authority.” *Big data & society* 10, no. 2 (2023).

Cech, Tim, Ole Wegen, Daniel Atzberger, Rico Richter, Willy Scheibel, and Jürgen Döllner. “Standardness Fogs Meaning: A Position Regarding the Informed Usage of Standard Datasets.” *arXiv (Cornell University)* (2024).

Cope, David, and Douglas R. Hofstadter. *Virtual Music: Computer Synthesis of Musical Style.* Cambridge, Mass: MIT Press, 2001.

Corrêa, Débora C., and Francisco Rodrigues. “A Survey on Symbolic Data-Based Music Genre Classification.” *Expert systems with applications* 60 (2016).

Daston, Lorraine. *Rules: A Short History of What We Live by*Princeton, New Jersey: Princeton University Press, 2022.

Daston, Lorraine and Peter Galison. “The Image of Objectivity.” *Representations (Berkeley, Calif.)* 40, no. 40 (1992).

Dreyfus, Hubert L., and Stuart E. Dreyfus. “Making a Mind versus Modeling the Brain: Artificial Intelligence Back at a Branchpoint.” *Daedalus (Cambridge, Mass.)* 117, no. 1 (1988).

Drott, Eric. “Copyright, Compensation, and Commons in the Music AI Industry.” *Creative industries journal* 14, no. 2 (2021).

Drott, Eric. *Streaming Music, Streaming Capital*. 1st ed. Durham: Duke University Press, 2023.

Drott, Eric. “The End(s) of Genre.” *Journal of music theory* 57, no. 1 (2013).

Dyson, Esther. “A Magna Carta for the Knowledge Age.” (1994)

Foucault, Michel. *The Birth of Biopolitics: Lectures at the Collège de France, 1978-79.* Basingstoke [England] ; Palgrave Macmillan, 2008.

Gelbart, Matthew. *Musical Genre and Romantic Ideology: Belonging in the Age of Originality.* Oxford, United Kingdom: Oxford University Press, 2022.

Gjerdingen, Robert O. *A Classic Turn of Phrase: Music and the Psychology of Convention.* Philadelphia: University of Pennsylvania Press, 1988.

Gjerdingen, Robert O. “Partimento, Que Me Veux-Tu?” *Journal of music theory* 51, no. 1 (2007).

Gjerdingen, Robert O., and David Perrott. “Scanning the Dial: The Rapid Recognition of Music Genres.” *Journal of new music research* 37, no. 2 (2008).

Guillory, John. *Cultural Capital: The Problem of Literary Canon Formation.* Chicago: University of Chicago Press, 2013.

Harper, Paula. "Autoplaying, Unmuting, Attending: (Re)formatting the Twenty-First-Century Digital Sensorium." *Twentieth-Century Music* 19, no. 3 (2022).

Hayles, N. Katherine. *How We Became Posthuman: Virtual Bodies in Cybernetics, Literature, and Informatics.* Chicago: The University of Chicago Press, 1999.

Jameson, Fredric. *Postmodernism, or, The Cultural Logic of Late Capitalism.* Durham: Duke University Press, 1991.

Kang, Edward B. “Ground Truth Tracings (GTT): On the Epistemic Limits of Machine Learning.” *Big data & society* 10, no. 1 (2023).

Kelly, Kevin. *New Rules for the New Economy: 10 Radical Strategies for a Connected World.* New York, N.Y: Viking, 1998.

Kitchin, Rob. The Data Revolution: Big Data, Open Data, Data Infrastructures, and Their Consequences. Los Angelos, California: Sage Publications, 2014.

Kittler, Friedrich A. *Gramophone, Film, Typewriter.* Stanford, California: Stanford University Press, 1999.

Latour, Bruno. “Why Has Critique Run out of Steam? From Matters of Fact to Matters of Concern.” *Critical inquiry* 30, no. 2 (2004).

Lupker, Jeffrey A. T., and William J. Turkel. “Music Theory, the Missing Link Between Music-Related Big Data and Artificial Intelligence.” *Digital humanities quarterly* 15, no. 1 (2021).

Manovich, Lev. *The Language of New Media*Cambridge, Mass: MIT Press, 2001.

Mathew, Nicholas. *Haydn Economy: Music, Aesthetics, and Commerce in the Late Eighteenth Century.* Chicago: University of Chicago Press, 2022.

Marx, Karl. *Grundrisse*. Translated by Martin Nicolaus. Penguin Books, 2016.

Mau, Steffen. *The Metric Society: On the Quantification of the Social.* Cambridge, UK: Medford, MA, 2019.

McLuhan, Eric, and Frank Zingrone. *Essential McLuhan*. London: BasicBooks, 1997.

Meyer, Leonard. *Emotion and Meaning in Music.* Chicago: University of Chicago Press, 1957.

Meyer, Leonard. “Meaning in Music and Information Theory.” *The Journal of aesthetics and art criticism* 15, no. 4 (1957).

Meyer, Leonard. *Style and Music: Theory, History, and Ideology.* Philadelphia: University of Pennsylvania Press, 1989.

Milligan, Ian. *History in the Age of Abundance?: How the Web Is Transforming Historical Research*. 1st ed. Montreal [Quebec]: McGill-Queen’s University Press, 2019.

Mitchell, Melanie. “Why AI Is Harder Than We Think.” *arXiv (Cornell University)* (2021).

Monteiro, Eric et al. “Quantifying Quality: Towards a Post-Humanist Perspective on Sensemaking,” from *Living with Monsters? Social Implications of Algorithmic Phenomena, Hybrid Agency, and the Performativity of Technology*. Springer Verlag, 2018.

Mosco, Vincent. *The Digital Sublime: Myth, Power, and Cyberspace.* Cambridge, Mass: MIT Press, 2004.

Moseley, Roger. “Digital Analogies: The Keyboard as Field of Musical Play.” *Journal of the American Musicological Society* 68, no. 1 (2015).

Moseley, Roger. “Chopin’s Aliases.” *19th century music* 42, no. 1 (2018): 3–29.

Neer, Richard. “Connoisseurship and the Stakes of Style.” *Critical inquiry* 32, no. 1 (2005).

Pasquinelli, Matteo. *The Eye of the Master: A Social History of Artificial Intelligence.* London; Verso, 2023.

Pizelo, Samuel. “Games and the Rise of Systems Thinking: From Models to Machines.” *Representations (Berkeley, Calif.)* 165, no. 1 (2024): 92–119.

Poovey, Mary. “Aesthetics and political economy in the eighteenth century: the place of gender in the social constitution of knowledge,” from *Aesthetics and Ideology, edited by George Levine.* New Brunswick, N.J: Rutgers University Press, 1994.

Poovey, Mary. *A history of the modern fact: Problems of knowledge in the sciences of wealth and society*. University of Chicago Press, 1998.

Poovey, Mary. *Genres of the Credit Economy: Mediating Value in Eighteenth- and Nineteenth-Century Britain.* Chicago: University of Chicago Press, 2008.

Ratner, Leonard. "Ars Combinatoria: Chance and Choice” in Eighteenth-Century Music (1970).

Rehding, Alexander, Gundula Freuzer, Peter McMurrary, Sybille Krämer, and Roger Moseley. “Discrete/Continuous: Music and Media Theory after Kittler.” *Journal of the American Musicological Society* 70, no. 1 (2017): 221–256.

Scaringella, N., G. Zoia, and D. Mlynek. *Automatic Genre Classification of Music Content: A Survey*. *IEEE Signal Processing Magazine*. Vol. 23. New York: IEEE, 2006.

Scherzinger, Martin. “The Political Economy of Streaming,” in *The Cambridge companion to music in digital culture*, pp. 274-297. Cambridge University Press, 2019.

Schwartz, Peter, Peter Leyden, and Joel Hyatt. *The Long Boom: A Vision for the Coming Age of Prosperity.*  Reading, Mass: Perseus Books, 1999.

Seaver, Nick. “Attention Is All You Need: Humans and Computers in the Time of Neural Networks,” from *Scenes of Attention*, Columbia University Press, 2023.

Seaver, Nick. *Computing Taste: Algorithms and the Makers of Music Recommendation.* Chicago: The University of Chicago Press, 2022.

Siskin, Clifford, and William Warner. *This Is Enlightenment*. Chicago: University of Chicago Press, 2010.

Sturm, Bob. “A survey of evaluation in music genre recognition,” in Proceedings of Adaptive Multimedia Retrieval, Copenhagen, Denmark, 2012

Sturm, Bob. “The GTZAN Dataset: Its Content, its faults, their effects on evaluation, and future use,” *arXiv (Cornell University)* (2013).

Taylor, Timothy D. *Making Value: Music, Capital, and the Social*. Duke University Press, 2024.

Thompson, James. Models of Value: Eighteenth-Century Political Economy and the Novel. Durham: Duke University Press, 1996.

Turner, Fred. *From Counterculture to Cyberculture: Stewart Brand, the Whole Earth Network, and the Rise of Digital Utopianism.* Chicago: University of Chicago Press, 2006.

Tzanetakis, G., and P. Cook. “Musical Genre Classification of Audio Signals.” *IEEE transactions on speech and audio processing* 10, no. 5 (2002).

Wiener, Norbert. *Cybernetics, or, Control and Communication in the Animal and the Machine.* 2nd edition. New York: M.I.T. Press, 1961.

Winner, Langdon. “Do Artifacts Have Politics?” *Daedalus (Cambridge, Mass.)* 109, no. 1 (1980).

Wiggins, Chris, and Matthew L. Jones. *How Data Happened: A History from the Age of Reason to the Age of Algorithms*. WW Norton & Company, 2023.

1. Gebru, Timnit et al, "Datasheets for Datasets: Documentation to facilitate communication between dataset creators and consumers," 2021. [↑](#footnote-ref-1)
2. Unsupervised learning is when the model isn’t given pre-labeled data to learn from – it relies instead on finding patterns in the data and clustering output based on those patterns. The promise of unsupervised learning is that it is less biased than learning off humanly labeled datasets (the data can “speak for itself”) but the outputs are still verified by people. [↑](#footnote-ref-2)
3. Amoore, Louise, *Cloud Ethics* (Duke University Press, 2020), 10. [↑](#footnote-ref-3)
4. Ehsan, Upol et al, "Charting the sociotechnical gap in explainable ai: A framework to address the gap in xai," *Proceedings of the ACM on human-computer interaction* 7, no. CSCW1 (2023): 23 [↑](#footnote-ref-4)
5. Meyer, Leonard, *Style and Music* (University of Chicago Press, 1996); “Meaning in Music as Information Theory,” in The Journal of Aesthetics and Art Criticism (1957). [↑](#footnote-ref-5)
6. Wiggins, Chris, and Matthew L. Jones, *How data happened: A history from the age of reason to the age of algorithms*, (WW Norton & Company, 2023), 175-194. [↑](#footnote-ref-6)
7. LLM = ChatGPT, Claudi.ai [↑](#footnote-ref-7)
8. Arditi, David, "Music everywhere: Setting a digital music trap," *Critical Sociology* 45, no. 4-5 (2019): 617-630. [↑](#footnote-ref-8)
9. Arditi, David, *Streaming Culture: Subscription platforms and the unending consumption of culture*, (Emerald Publishing Limited, 2021). [↑](#footnote-ref-9)
10. Campolo, Alexander, and Katia Schwerzmann, "From rules to examples: Machine learning's type of authority," *Big Data & Society* 10, no. 2 (2023). 1-13. [↑](#footnote-ref-10)
11. Amoore, *Cloud Ethics,* 2. [↑](#footnote-ref-11)
12. Amoore, *Cloud Ethics*, 110. [↑](#footnote-ref-12)
13. Kang, Edward B, "Ground truth tracings (GTT): On the epistemic limits of machine learning." *Big data & society* 10, no. 1 (2023): 20539517221146122. [↑](#footnote-ref-13)
14. Sort of contested how well this works, though, since everyone splits the data into test/training differently. For more, see Cech, Tim et al., "Standardness Fogs Meaning: A Position Regarding the Informed Usage of Standard Datasets." *arXiv preprint arXiv:2406.13552* (2024). [↑](#footnote-ref-14)
15. Daston, Lorraine, *Rules: A short history of what we live by,* (Princeton University Press, 2022): 3. [↑](#footnote-ref-15)
16. Gjerdingen, Robert O., and David Perrott, "Scanning the dial: The rapid recognition of music genres," *Journal of new music research* 37, no. 2 (2008): 93-100. [↑](#footnote-ref-16)
17. Bob Sturm found that GTZAN was used in ~25% of MIR research between 2002-2011; see Sturm, Bob L. "A survey of evaluation in music genre recognition," in *International Workshop on Adaptive Multimedia Retrieval*, pp. 29-66. [↑](#footnote-ref-17)
18. Sturm, Bob L. "A survey of evaluation in music genre recognition," In *International Workshop on Adaptive Multimedia Retrieval*, pp. 29-66. [↑](#footnote-ref-18)
19. For more, see Kitchin, Rob, *The Data Revolution: Bit Data, Open Data, Data Infrastructures, and Their Consequences* (Sage, 2014). [↑](#footnote-ref-19)
20. Poovey, Mary, *Genres of the Credit Economy: Mediating Value in Eighteenth- and Nineteenth-Century Britain* (University of Chicago Press), 26. [↑](#footnote-ref-20)
21. Thompson, James, *Models of Value: Eighteenth-Century Political Economy and the Novel* (Duke University Press, 1996), 32. [↑](#footnote-ref-21)
22. See Mau, Steffen, *The Metric Society: On the Quantification of the Social* (John Wiley and Sons, 2019), 12. Argues that our social world has been reduced to numbers, making everything comparable. Today, everything is a “quantitative measurement of social phenomena;” and quantification “expresses phenomena, characteristics, or states of affairs in a general, abstract, and universally accessible language – that of mathematics.” [↑](#footnote-ref-22)
23. Amoore, *Cloud Ethics*, 10. [↑](#footnote-ref-23)
24. Seaver, Nick. "Everything lies in a space: cultural data and spatial reality." *Journal of the Royal Anthropological Institute* 27, no. S1 (2021): 43-61. [↑](#footnote-ref-24)
25. Mau, *The Metric Society*, 6. [↑](#footnote-ref-25)
26. Seaver, Nick, “Behind the Music Recommendation Curtain: *Computing Taste* with Nick Seaver,” interview by Allison Jerzak, *Musicology Now*, June 22, 2023, 6:15, https://musicologynow.org/behind-the-music-recommendation-curtain-computing-taste-with-nick-seaver/ [↑](#footnote-ref-26)
27. Poovey, Mary, “Aesthetics and Political Economy in the Eighteenth Century: The Place of Gender in the Social Constitution of Knowledge,” *in Aesthetics and Ideology*, ed. George Levine (New Brunswick, NJ: Rutgers University Press, 1994), 89 [↑](#footnote-ref-27)
28. Poovey, “Aesthetics and Political Economy in the Eighteenth Century: The Place of Gender in the Social Constitution of Knowledge,”), 90 [↑](#footnote-ref-28)
29. Jones and Wiggins, *How Data Happened*, 186-194. [↑](#footnote-ref-29)
30. Campolo and Schwerzmann, "From rules to examples,” 2. [↑](#footnote-ref-30)