The Classical Cadence as a Closing Schema: Learning, Memory, and Perception

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For Shannon

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There is a sequence of perceptions in the mind of a listener, measured inferentially in psychology. There is a sequence of events in the air or transmission cable, measured in physics. There is an operational schema, the "score" or a "piece of music," representing certain aspects of the psychological and physical events. Each of these sequences forms an interconnected system of signs. Each sign system is closely related to the others.

Joel E. Cohen

In the previous chapter, I reviewed contemporary accounts of the classical cadence articulated in the "New *Formenlehre*" tradition and then outlined the theories that account for the acquisition and mental representation of the most common cadence types associated with the late-eighteenth-century repertories of Haydn, Mozart, and Beethoven, paying particular attention to the cadential typology presented in William E. Caplin's treatise, *Classical Form*. Citing psychologist Eleanor Rosch's work on category formation, I argued that category systems for the classical cadence are psychologically relevant if they mirror the structure of attributes encountered in classical music that listeners are likely to learn and remember.[1] Following Robert Gjerdingen's schema-theoretic approach, I then suggested that listeners who are familiar with the classical style have internalized the most common cadence types as a flexible network of rival closing schemata.

For Rosch, models of category formation depend on the statistical properties of objects and events encountered in the external environment. For our purposes, this means that the acquisition and retention of a network of cadence types depends on the frequent occurrence of these patterns on the one hand, and on a listener's repeated exposure on the other.[2] Providing evidence in support of the former claim is thus the purpose of Part II.[3]

This chapter presents the representation scheme used throughout Part II. §3.1 considers the motivations for corpus studies in music research, and §3.2 presents the corpus of expositions from Haydn's string quartets and describes how it might be digitally encoded and stored. For the purposes of pattern discovery (Chapter 4), classification (Chapter 5), and prediction (Chapter 6), §3.3 represents the most pertinent features (or *viewpoints*) from the Haydn Corpus according to the *multiple viewpoints* framework developed by Darrell Conklin and Marcus Pearce. Using Gjerdingen's schema-theoretic approach as a guide, I then represent the "core" events of the classical cadence in §3.4 according to the chromatic scale degrees and melodic contours of the outer parts (which Gjerdingen calls the "two-voice framework"), a coefficient representing the strength of the metric position, and a vertical sonority, presented as a combination of vertical interval classes or chromatic scale degrees.[4]

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[1] Eleanor Rosch, "Principles of Categorization," in *Cognition and Categorization*, ed. E. Rosch and B. B. Lloyd (Hillsdale, NJ: Erlbaum, 1978), 252.

[2] Jean Mandler writes, "... repeated experiences and their internal representation lead to the phenomenon known as 'familiarity.' Because of the individual nature of experience, one person's 'familiar' organization can be another's chaos." "Categorical and Schematic Organization in Memory," in *Memory Organization and Structure*, ed. C. Richard Puff (New York, NY: Academic Press, 1979), 260.

[3] I leave the latter claim for Part III.

[4] Robert O. Gjerdingen, *Music in the Galant Style: Being an Essay on Various Schemata Characteristic of Eighteenth-Century Music* (New York: Oxford University Press, 2007), 142.

§3.1 Corpus Studies: Motivations

In the history of music scholarship, corpus studies are nothing new. As Gjerdingen noted in a recent issue of *Music Perception* devoted to corpus research, music historians have been collecting musical prints and manuscripts for centuries, with the word "corpus" gracing the titles of several scholarly editions.[5] But following the birth of modern computation and the proliferation of data in machine-readable formats, corpus studies have come to denote the collection and statistical analysis of large bodies of data,[6] typically using automated procedures made available by relatively recent advances in computer processing power.[7]

Computational corpus studies got their start in the early 1960s when linguists Henry Kučera and W. Nelson Francis created the first machine-readable corpus of American English at Brown University.[8] Compiled from five hundred samples of English-language text and consisting of over one million words, the *Brown Corpus* laid the groundwork for the study of natural languages using field-collected samples.[9] And as a consequence of innovations like optical character recognition (OCR), which automatically transcribes printed text into digital formats, natural language corpora using automatic transcription methods are now commonplace in language research.[10]

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[5] Robert O. Gjerdingen, ""Historically Informed" Corpus Studies," *Music Perception* 31, no. 3 (2014): 192.

[6] David Temperley and Leigh VanHandel, "Introduction to the Special Issue on Corpus Methods," *Music Perception* 31, no. 1 (2013): 1.

[7] Cory McKay and Ichiro Fujinaga, "Style-Independent Computer-Assisted Exploratory Analysis of Large Music Collections," *Journal of Interdisciplinary Music Studies* 1, no. 1 (2007): 64.

[8] Charles F. Meyer, *English Corpus Linguistics: An Introduction* (New York, NY: Cambridge University Press, 2002).

[9] Henry Kučera and W. Nelson Francis, *Computational Analysis of Present-Day American English* (Providence, RI: Brown University Press, 1967).

[10] Despite its relatively modest size relative to current language corpora—the Corpus of Contemporary American English is currently the largest corpus of American English at over 450 million words—the *Brown Corpus* remains a significant lexical resource in corpus linguistics. See, for example, Christopher D. Manning and Hinrich Schütze, *Foundations of Statistical Natural Language Processing* (Cambridge, MA: MIT Press, 1999).

In the 'data-rich' environment characterizing present-day scholarship,[11] interrelated subfields like corpus linguistics, computational linguistics, and natural language processing provide but three examples from the litany of emerging sub-disciplines witnessed over the past few decades. Fields like biology (computational biology, bioinformatics), psychology (cognitive science, artificial intelligence), and of course, music research (music information retrieval, empirical musicology) have all instituted encoding initiatives at one time or another, and all now borrow and share corpus-based methods quite freely.

And yet, despite the growth of corpus studies over the past few decades, both in the *Formenlehre* tradition and in the discipline at large, Markus Neuwirth has characterized the prevailing approach adopted by *Formenlehre* theorists as one based on what statistician David Fischer has called "intuitive statistics,"[12] with scholars frequently eschewing explicit statistical methods in favor of qualitative descriptions derived from empirical observation. Caplin states in the Introduction to *Classical Form*, for example, that "the account of classical form given here is a 'theory' only in an informal sense... Principles are derived from empirical observation and are largely descriptive. No attempt is made to ground the concepts in some broader system of mathematics, logic, cognition, or the like, and no proof is offered for the many assertions made."[13] Like Caplin, James Hepokoski and Warren Darcy also rely on empirical observation, characterizing *Elements of Sonata Theory* as a "research report, the product of our analyses of hundreds of individual movements by Haydn, Mozart, Beethoven, and many surrounding composers of the time (as well as later composers),"[14] but as Paul Wingfield points out, the

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[11] David Huron, "The New Empiricism: Systematic Musicology in a Postmodern Age," in *The 1999 Ernest Bloch Lectures* (University of California, Berkeley, 1999).

[12] Markus Neuwirth, "Recomposed Recapitulations in the Sonata-Form Movements of Joseph Haydn and his Contemporaries" (PhD Dissertation, Leuven University, 2013), 34.

[13] William E. Caplin, *Classical Form: A Theory of Formal Functions for the Instrumental Music of Haydn, Mozart, and Beethoven* (New York: Oxford University Press, 1998), 5.

[14] James Hepokoski and Warren Darcy, *Elements of Sonata Theory: Norms, Types, and Deformations in the Late-Eighteenth-Century Sonata* (New York: Oxford University Press, 2006), v.

authors fail to provide "a full account of the sample, complete descriptive statistics and an explanation of sampling methodology."[15]

With the drive toward digitization now in full swing, statistical methods provide powerful analytic tools, enabling the testing of *a priori* hypotheses for bodies of music that often far exceed the capacities of one scholarly lifetime,[16] and allowing the analyst to uncover empirical evidence that remains open to falsification and subsequent replication.[17] To be sure, according to David Huron, the impetus for corpus studies "is not merely some obsession with things numerical, or a kleptophilic compulsion to collect, but a proper moral imperative," where the desire for truth, knowledge, "and other good things" depends on the quality and quantity of the collected evidence.[18] Leonard Meyer summarizes this point nicely:

> Since all classification and all generalization about stylistic traits are based on some estimate of relative frequency, statistics are inescapable. This being so, it seems prudent to gather, analyze, and interpret statistical data according to some coherent, even systematic, plan… it would appear desirable to define as rigorously as possible what is to count as a given trait, to gather data about such traits systematically, and to collate and analyze it consistently and scrupulously—in short, to employ the highly refined methods and theories developed in the discipline of mathematical statistics and sampling theory.[19]

[15] Paul Wingfield, "Beyond 'Norms and Deformations': Towards a Theory of Sonata Form as Reception History," *Music Analysis* 27, no. i (2008): 141.

[16] Jonathan Wild, "A Review of the Humdrum Toolkit: UNIX Tools for Musical Research, created by David Huron," *Music Theory Online* 2.7 (1996).

[17] Gjerdingen has pointedly observed that music scholars "bandy about words like 'typical,' 'characteristic,' or 'standard' with the open confidence of embezzlers who, knowing that they alone keep the books, cannot imagine being called into account." "Defining a Prototypical Utterance," *Psychomusicology* 10, no. 2 (1991): 127. For a discussion of statistical methods in the *Formenlehre* tradition, see Neuwirth, "Recomposed Recapitulations," 25–67.

[18] David Huron, "On the Virtuous and the Vexatious in an Age of Big Data," *Music Perception* 31, no. 1 (2013): 5.

[19] Leonard B. Meyer, *Style and Music: Theory, History, and Ideology* (Philadelphia, PA: University of Philadelphia Press, 1989), 64.

But perhaps the most important motivation for corpus studies follows from the prevailing view in cognitive psychology that humans learn and comprehend complex, rule-governed structures like natural language merely by exposure during early development. If *implicit learning* is indeed the primary mechanism by which we acquire knowledge about the world around us, a representative sample of works in the classical style will serve as a proxy for the musical experiences of listeners situated in that style.[20] And so for those with sufficient exposure to the eighteenth-century instrumental repertories of Haydn and his contemporaries—whether deceased members of the Viennese courts or modern listeners who have immersed themselves in classical music—a detailed study of the recurrent patterns characterizing Haydn's string quartets is at once an inventory of part of their stylistic knowledge.[21] Thus, my hope is that examining a large number of cadences from a relatively narrow, historically limited corpus will provide a clearer view of the cadence types that characterize Haydn's compositional style, as well as provide empirical evidence for the kinds of closing patterns that listeners may learn implicitly.

§3.2 The Haydn Corpus

The Haydn Corpus consists of symbolic representations of 50 *sonata-form* expositions selected from Haydn's string quartets (1771–1803).[22] Table 3.1 presents the reference information, keys,

[20] Vasili Byros, "Meyer's Anvil: Revisiting the Schema Concept," *Music Analysis* 31, no. 3 (2012): 278.

[21] Robert O. Gjerdingen, "Courtly Behaviors," *Music Perception* 13, no. 3 (1996): 380–381.

[22] Music corpora exist in symbolic and audio formats. Symbolic representations include printed notes, scores, and text, and a number of encoding formats are now prevalent in the research community, including Musical Instrument Digital Interface (MIDI), Kern, and MusicXML, with software like Huron's *Humdrum Toolkit* (*The Humdrum Toolkit*, 1993, `music-cog.ohio-state.edu/Humdrum/index.html`), the *MidiToolbox* in Matlab (Tuomas Eerola and Petri Toiviainen, *MIDI Toolbox: MATLAB Tools for Music Research*, 2004), and Michael Cuthbert's *Music21* in Python providing frameworks for encoding and analysis ("music21: A Toolkit for Computer-Aided Musicology and Symbolic Music Data," in *11th International Society for Music Information Retrieval Conference* [2010], 637–642). For reviews of the *Humdrum Toolkit* and *Music21*, see Wild, "A Review of the Humdrum Toolkit: UNIX Tools for Musical Research, created by David Huron"; Dmitri Tymoczko, "Review of Michael Cuthbert, Music21: a Toolkit for Computer-aided Musicology (http://web.mit.edu/music21/)," *Music Theory Online* 19, no. 3 (2013).

Table 3.1: Reference information (Opus number, work, movement, measures), keys (case denotes mode), time signatures, and tempo markings for the exposition sections of each movement in the Haydn Corpus.

Excerpt	*Key*	*Time Signature*	*Tempo Marking*
Op. 17, No. 1, i, mm. 1–43	E	4/4	Moderato
Op. 17, No. 2, i, mm. 1–38	F	4/4	Moderato
Op. 17, No. 3, iv, mm. 1–26	E♭	4/4	Allegro molto
Op. 17, No. 4, i, mm. 1–53	c	4/4	Moderato
Op. 17, No. 5, i, mm. 1–33	G	4/4	Moderato
Op. 17, No. 6, i, mm. 1–73	D	6/8	Presto
Op. 20, No. 1, iv, mm. 1–55	E♭	2/4	Presto
Op. 20, No. 3, i, mm. 1–94	g	2/4	Allegro con spirito
Op. 20, No. 3, iii, mm. 1–43	G	3/4	Poco Adagio
Op. 20, No. 3, iv, mm. 1–42	g	4/4	Allegro molto
Op. 20, No. 4, i, mm. 1–112	D	3/4	Allegro di molto
Op. 20, No. 4, iv, mm. 1–49	D	4/4	Presto scherzando
Op. 20, No. 5, i, mm. 1–48	f	4/4	Allegro moderato
Op. 20, No. 6, ii, mm. 1–27	E	cut	Adagio
Op. 33, No. 1, i, mm. 1–37	b	4/4	Allegro moderato
Op. 33, No. 1, iii, mm. 1–40	D	6/8	Andante
Op. 33, No. 2, i, mm. 1–32	E♭	4/4	Allegro moderato
Op. 33, No. 3, iii, mm. 1–29	F	3/4	Adagio
Op. 33, No. 4, i, mm. 1–31	B♭	4/4	Allegro moderato
Op. 33, No. 5, i, mm. 1–95	G	2/4	Vivace assai
Op. 33, No. 5, ii, mm. 1–30	g	4/4	Largo
Op. 50, No. 1, i, mm. 1–60	B♭	cut	Allegro
Op. 50, No. 1, iv, mm. 1–75	B♭	2/4	Vivace
Op. 50, No. 2, i, mm. 1–106	C	3/4	Vivace
Op. 50, No. 2, iv, mm. 1–86	C	2/4	Vivace assai
Op. 50, No. 3, iv, mm. 1–74	Eb	2/4	Presto
Op. 50, No. 4, i, mm. 1–64	f♯	3/4	Allegro spirituoso
Op. 50, No. 5, i, mm. 1–65	F	2/4	Allegro moderato
Op. 50, No. 5, iv, mm. 1–54	F	6/8	Vivace
Op. 50, No. 6, i, mm. 1–54	D	4/4	Allegro
Op. 50, No. 6, ii, mm. 1–25	d	6/8	Poco Adagio
Op. 54, No. 1, i, mm. 1–47	G	4/4	Allegro con brio
Op. 54, No. 1, ii, mm. 1–54	C	6/8	Allegretto
Op. 54, No. 2, i, mm. 1–87	C	4/4	Vivace
Op. 54, No. 3, i, mm. 1–58	E	cut	Allegro
Op. 54, No. 3, iv, mm. 1–82	E	2/4	Presto
Op. 55, No. 1, ii, mm. 1–36	D	2/4	Adagio cantabile
Op. 55, No. 2, ii, mm. 1–76	f	cut	Allegro
Op. 55, No. 3, i, mm. 1–75	B♭	3/4	Vivace assai
Op. 64, No. 3, i, mm. 1–69	B♭	3/4	Vivace assai
Op. 64, No. 3, iv, mm. 1–79	B♭	2/4	Allegro con spirito
Op. 64, No. 4, i, mm. 1–38	G	4/4	Allegro con brio
Op. 64, No. 4, iv, mm. 1–66	G	6/8	Presto
Op. 64, No. 6, i, mm. 1–45	E♭	4/4	Allegretto
Op. 71, No. 1, i, mm. 1–69	B♭	4/4	Allegro
Op. 74, No. 1, i, mm. 1–54	C	4/4	Allegro moderato
Op. 74, No. 1, ii, mm. 1–57	G	3/8	Andantino grazioso
Op. 76, No. 2, i, mm. 1–56	d	4/4	Allegro
Op. 76, No. 4, i, mm. 1–68	B♭	4/4	Allegro con spirito
Op. 76, No. 5, ii, mm. 1–33	F♯	cut	Largo. Cantabile e mesto

time signatures, and tempo markings for each movement. The corpus spans much of Haydn's mature compositional style (Opp. 17–76), with the majority of the expositions selected from first movements (28) or finales (11), and with the remainder appearing in inner movements (ii: 8; iii: 3). All movements were downloaded from the KernScores database in the MIDI format and analyzed in Matlab.[23] To ensure that each instrumental part would qualify as monophonic—a pre-requisite for many of the analytical techniques that follow—all trills, extended string techniques, and other ornaments were removed.[24] Note velocities and durations were quantized exactly, and the tempo in beats-per-minute (bpm) for each movement was determined by score or convention (see the tempo markings in Table 3.1). Table 3.2 provides a few descriptives concerning the number of events in each movement for each instrumental part.

Most natural languages consist of a finite alphabet of discrete symbols (letters), combinations of which form words, phrases, and so on. As a result, the mapping between the individual letter or word encountered in a printed text and its symbolic representation in a computer database is essentially one-to-one. Music encoding is considerably more complex. Notes, chords, phrases, and the like are characterized by a number of different features, and so regardless of the unit of meaning, digital encodings of individual events must concurrently represent multiple properties of the musical surface. To that end, many symbolic formats encode standard music notation as a series of discrete event sequences in an $m \times n$ matrix, where m denotes the number of events in the symbolic representation, and n refers to the number of encoded features (e.g., chromatic pitch, onset time, rhythmic duration, etc.).

By way of example, Figure 3.1 presents the note matrix provided by the *MIDI Toolbox* for the first measure from the opening movement of Haydn's String Quartet in F, Op. 17/2. The columns of the note matrix refer to the following characteristics: (1) onset time, measured in

[23] `http://kern.ccarh.org/`.

[24] For events presenting extended string techniques (e.g., double or triple stops), I retained the note event in each part that preserved the voice leading both within and between instrumental parts.

Table 3.2: Descriptive statistics for the Haydn Corpus.

Instrumental Part	*N*	*M* (*SD*)	*Range*
Violin 1	14,506	290 (78)	133–442
Violin 2	10,653	213 (70)	69–409
Viola	9156	183 (63)	79–381
Cello	8463	169 (60)	64–326

Note. *N* refers to the number of note events, *M* denotes the mean rounded to the nearest integer, and *SD* represents the standard deviation, also rounded to the nearest integer.

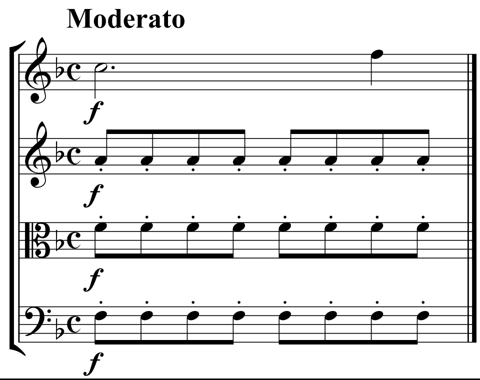
quarter-note beats; (2) duration in quarter-note beats; (3) instrumental part (or MIDI channel), with the instrumental parts ordered from 0–3 (beginning with the first violin); (4) pitch in semitones, where middle C (C_4) is 60; (5) velocity, which in MIDI nomenclature describes how quickly the key is pressed, and thus, how loudly the note is played (0–127); (6) onset time in seconds; and (7) duration in seconds.[25]

The note matrix is fairly self-explanatory, but two further comments are warranted here. First, when the movement begins on a metric downbeat, as does the example in Figure 3.1, the onset vector measured in quarter-note beats begins at 0 (and not 1). Second, as a consequence of the quantization step during pre-processing, the velocity vector in the note matrix does not vary, so this feature will be excluded from further discussion.

The *MIDI Toolbox* obtains the first five columns of the note matrix in Figure 3.1 from the note-event messages of the MIDI protocol, but the MIDI file also encodes meta events that represent more general features of the music, such as the key, tempo, meter, and time signature.[26] The tempo associated with the note matrix is 100 bpm, for example, so given the onset and duration vectors measured in quarter-note beats and the tempo provided by the

[25] Tuomas Eerola and Petri Toiviainen, "MIR in Matlab:The MIDI Toolbox," in *Proceedings of the 5th International Conference on Music Information Retrieval (ISMIR)* (2004), 22.

[26] Eleanor Selfridge-Field, ed., *Beyond MIDI: The Handbook of Musical Codes* (Cambridge, MA: MIT Press, 1997), 53.



Onset (beats)	Duration (beats)	MIDI channel	Pitch	Velocity	Onset (seconds)	Duration (seconds)
0	3	0	72	64	0	1.8
0	0.5	1	69	64	0	0.3
0	0.5	2	65	64	0	0.3
0	0.5	3	53	64	0	0.3
0.5	0.5	1	69	64	0.3	0.3
0.5	0.5	2	65	64	0.3	0.3
0.5	0.5	3	53	64	0.3	0.3
1	0.5	1	69	64	0.6	0.3
1	0.5	2	65	64	0.6	0.3
1	0.5	3	53	64	0.6	0.3
1.5	0.5	1	69	64	0.9	0.3
1.5	0.5	2	65	64	0.9	0.3
1.5	0.5	3	53	64	0.9	0.3
2	0.5	1	69	64	1.2	0.3
2	0.5	2	65	64	1.2	0.3
2	0.5	3	53	64	1.2	0.3
2.5	0.5	1	69	64	1.5	0.3
2.5	0.5	2	65	64	1.5	0.3
2.5	0.5	3	53	64	1.5	0.3
3	1	0	77	64	1.8	0.6
3	0.5	1	69	64	1.8	0.3
3	0.5	2	65	64	1.8	0.3
3	0.5	3	53	64	1.8	0.3
3.5	0.5	1	69	64	2.1	0.3
3.5	0.5	2	65	64	2.1	0.3
3.5	0.5	3	53	64	2.1	0.3

Example 3.1: Top: Haydn, String Quartet in F, Op. 17/2, i, m. 1. Bottom: Event representation provided by the *MIDI Toolbox*.

MIDI file, we can easily derive either of the onset and duration vectors in seconds shown in the right-most columns of the note matrix:

$$\mathtt{dur}_{\mathrm{sec}}(e_i) = \frac{\mathtt{dur}_{\mathrm{beats}}(e_i) \times 60}{\mathtt{bpm}(e_i)}$$

where event e_i refers to the i^{th} row of the note matrix.[27] The appeal of symbolic representations like this one is that they encode only the most important features, thereby requiring very little computer memory while remaining flexible enough to allow the researcher to derive any further features with relative ease. From the vector of chromatic pitches, for example, we could easily obtain a sequence of melodic contours or intervals for each instrumental part, or a vector of vertical intervals between one or more parts. If we also include information from the MIDI file's meta events (e.g., key and time signatures, tempo changes, etc.), we can derive vectors representing metric positions, scale degrees, variations in the onset and duration vectors measured in seconds, and so on.

Figure 3.1 also demonstrates a few limitations of the Haydn Corpus. Because the encoded representations were not aligned with selected performances, clock-time measures like those represented in columns six and seven reflect a metronomic interpretation of musical time that necessarily departs from the kinds of everyday encounters with this repertory we might hope to study. Ideally, we could align the encoded representations with performances, either by employing tempo-alignment algorithms, or by annotating an isochronous pulse at a given metrical level in the performance and then aligning the encoded representation to the obtained tempo curve, but such is the encoding bottleneck that time-aligned symbolic representations are exceedingly rare in the research community. What is more, as I mentioned in the previous section, the MIDI format does not distinguish between enharmonic equivalents—F♯ and G♭

[27] To obtain the corresponding values for the onset vector measured in seconds, one need only replace `dur` with `onset` in the equation.

are represented by the same numeric value (66). As a result, the encoded representation shown in the note matrix is too reductive to capture the entire pitch alphabet, and so distributional analyses for pitch-based features like pitch class or scale degree will generally be restricted to alphabets of 12 elements.[28]

§3.3 Representing Cadences with *Multiple Viewpoints*

Representation schemes like the one presented in Figure 3.1 roughly correspond to the *multiple viewpoints* framework first proposed by Darrell Conklin in the late 1980s, and later extended and refined by his student, Marcus Pearce.[29] Conklin's primary aim was to apply statistical modeling procedures from the machine learning and prediction of language to domains such as music, where events have a multidimensional structure.[30] Like the note matrix in Figure 3.1, the *multiple viewpoints* framework accepts sequences of musical events that typically correspond to individual notes as notated in a score. Each event e consists of a set of *basic attributes*—what I have up until this point been calling 'features'—and each attribute is associated with a *type*, τ, which specifies the properties of that attribute. The *syntactic domain* (or alphabet) of each type, $[\tau]$, denotes the set of all unique elements associated with that type, and each element of the

[28]John Snyder has been particularly critical of this limitation ("Entropy as a Measure of Musical Style: The Influence of A Priori Assumptions," *Music Theory Spectrum* 12, no. 1 [1990]: 121–160).

[29]Darrell Conklin, "Modelling and Generating Music Using Multiple Viewpoints," in *Proceedings of the First Workshop on Artificial Intelligence and Music* (St. Paul, MN, 1988), 125–137; Darrell Conklin, "Prediction and Entropy of Music" (MA Thesis, University of Calgary, 1990); Darrell Conklin and Ian H. Witten, "Multiple Viewpoint Systems for Music Prediction," *Journal of New Music Research* 24, no. 1 (1995): 51–73; Marcus T. Pearce and Geraint A. Wiggins, "Improved Methods for Statistical Modelling of Monophonic Music," *Journal of New Music Research* 33, no. 4 (2004): 367–385; Marcus T. Pearce, "The Construction and Evaluation of Statistical Models of Melodic Structure in Music Perception and Composition" (PhD Dissertation, City University, London, 2005); Marcus T. Pearce, Darrell Conklin, and Geraint A. Wiggins, "Methods for Combining Statistical Models of Music," in *Computer Music Modelling and Retrieval*, ed. U. K. Wiil (Heidelberg, Germany: Springer Verlag, 2005), 295–312.

[30]Conklin and Witten, "Multiple Viewpoint Systems for Music Prediction," 57-58. Since this chapter concerns classification and the following chapter concerns prediction, a discussion of the framework would seem more suitable in Chapter 4, but the relevance of *multiple viewpoints* systems to the symbolic representation of music is such that a review of the formalism will be more useful to us here. I refer the reader to Chapter 4 for a more detailed discussion of context models for music prediction and their application in the Haydn Corpus.

syntactic domain also maps to a corresponding set of elements in the *semantic domain*, $[\![\tau]\!]$. Following Conklin, attribute types appear here in typewriter font to distinguish them from ordinary text. For the twelve-tone chromatic scale, for example, the type `pitch class` would consist of the syntactic set, $\{0, 1, 2, \ldots, 11\}$, and the semantic set, {C,C♯/D♭,D,...,B}.[31]

Within this representation language, Conklin defines several distinct classes of type, but we will concern ourselves in what follows with just three: *basic*, *derived*, and *linked*.[32] Basic types are irreducible representations of the musical surface—that is, they cannot be derived from any other type. Thus, an attribute representing the sequence of chromatic pitches would serve as a basic type in Conklin's approach because it cannot be derived from a sequence of pitch classes, scale degrees, melodic intervals, or indeed, any other attribute. What is more, basic types represent every event in the corpus. For example, a sequence of melodic contours would not constitute a basic type because either the first or last events of the melody would receive no value.[33] Indeed, an interesting property of the set of n basic types for any given corpus is that the Cartesian product of the domains of those types determines the *event space* for the corpus, denoted by ξ:

$$\xi = [\tau_1] \times [\tau_2] \times \ldots \times [\tau_n]$$

Each event consists of an n-tuple in ξ—a set of values corresponding to the set of basic types that determine the event space. ξ therefore denotes the set of all representable events in the

[31] Note that in this example the semantic domain of pitch-class names is necessarily larger than the corresponding syntactic domain as a consequence of enharmonic equivalence, hence the appearance of two labels C♯ and D♭ for the value 1.

[32] For a review of *multiple viewpoints* systems, including a discussion of the viewpoint classes defined by Conklin and Pearce, see Conklin and Witten, "Multiple Viewpoint Systems for Music Prediction"; Pearce, "The Construction and Evaluation of Statistical Models of Melodic Structure in Music Perception and Composition," 49–79.

[33] In a melody of length n, a sequence of contours will necessarily be of length $n - 1$.

corpus.[34] To model a corpus of Bach chorales, Conklin identified six basic types: chromatic pitch (`pitch`), key signature (`keysig`), time signature (`timesig`), fermata (`fermata`), start time (`st`), and duration (`duration`).[35] With the exception of `fermata`, the MIDI format encodes all of these types either as note or meta events, and the *MIDI Toolbox* represents three of these types explicitly in its note matrix representation (see columns 1, 2, and 4 in Figure 3.1).

As should now be clear from the examples given above, derived types like pitch class, scale degree, and melodic interval do not appear in the event space but are derived from one or more of the basic types. Thus, for every type in the encoded representation there exists a partial function, denoted by Ψ, which maps sequences of events onto elements of type τ. The term *viewpoint* therefore refers to the function associated with its type, but for convenience both authors refer to viewpoints by the types they model.[36] The function is partial because the output may be undefined for certain events in the sequence (denoted by $\perp$). Again, viewpoints for attributes like melodic contour or melodic interval demonstrate this point, since either the first or last element will receive no value (i.e., it will be undefined).

Basic and derived types attempt to model the relations within attributes, but they fail to represent the relations *between* attributes. I argued in Chapter 2 that prototypical utterances are comprised of a cluster of co-occurring features, and the relations between those features could be just as significant as their presence (or absence). In isolation, the harmonic progression V–I does not provide sufficient grounds for the identification of a perfect authentic cadence, but the co-occurrence of that progression with $\hat{1}$ in the soprano, a six-four sonority preceding the

[34]Pearce, "The Construction and Evaluation of Statistical Models of Melodic Structure in Music Perception and Composition," 58–59.

[35]In the representation scheme outlined in his dissertation, Pearce expanded the list of basic types described by Conklin by omitting `fermata` and `timesig` and including rest duration (`deltast`), bar length (`barlength`), metric pulses (`pulses`), mode (`mode`), and phrasing (`phrase`). "The Construction and Evaluation of Statistical Models of Melodic Structure in Music Perception and Composition," 63.

[36]Pearce explains that for basic types, Ψ_τ is simply a projection function, thereby returning as output the same values it receives as input. Ibid., 59.

root-position dominant, or a trill above the dominant makes such an interpretation far more likely. Thus, linked viewpoints attempt to model correlations between attributes by calculating the cross-product of their constituent types.[37] We might hypothesize, for example, that the succession of scale degrees in the bass voice interacts with the chordal sonorities it supports, and a viewpoint linking these attributes measures this interaction explicitly.

§3.4 Viewpoint Selection

Taken together, basic, derived, and linked viewpoints form an elegant multiple viewpoints system for the representation and analysis of music. But how do we select the appropriate viewpoints for the representation of cadences in Haydn's string quartets? According to Gjerdingen's schema-theoretic approach, a cadence is best understood as an instance of bass-melody co-articulation. Gjerdingen represents the "core" events of the cadence by the scale degrees and melodic contours of the outer voices (i.e., the two-voice framework), a coefficient representing the strength of the metric position (strong, weak), and a sonority, presented using figured bass notation. Given the importance of melodic intervals in studies of recognition memory for melodies,[38] we might also add this attribute to Gjerdingen's list.

3.4.1 Note Events

Melodic Interval. The melodic interval of an event is represented as an integer by the attribute type `melint`. Given the chromatic pitch vector provided by the symbolic representation, which

[37] For readers familiar with David Lewin's *direct product* systems, a linked viewpoint models a *product type*. *Generalised Musical Intervals and Transformations* (New Haven, CT: Yale University Press, 1987), 1–15; Conklin and Witten, "Multiple Viewpoint Systems for Music Prediction," 12–13.

[38] See, for example, W. Jay Dowling, "The Importance of Interval Information in Long-Term Memory for Melodies," *Psychomusicology* 1 (1981): 30–49.

I will hereafter call `cpitch`, we derive a sequence of melodic intervals by the function:

$$\Psi\texttt{melint}(e_i) = \begin{cases} \perp & \text{if } i = 1, \\ \Psi\texttt{cpitch}(e_i) - \Psi\texttt{cpitch}(e_{i-1}) & \text{otherwise.} \end{cases} \tag{3.1}$$

Here, we obtain the distance between adjacent pitches as an integer, where ascending intervals are positive and descending intervals are negative.

Contour. The viewpoint `contour` reduces the information present in `melint` still further. Starting from the basic type `cpitch`, we derive a sequence of melodic contours from the function:

$$\Psi\texttt{contour}(e_i) = \begin{cases} -1 & \text{if } \Psi\texttt{cpitch}(e_i) < \Psi\texttt{cpitch}(e_{i-1}) \\ \texttt{0} & \text{if } \Psi\texttt{cpitch}(e_i) = \Psi\texttt{cpitch}(e_{i-1}) \\ 1 & \text{if } \Psi\texttt{cpitch}(e_i) > \Psi\texttt{cpitch}(e_{i-1}) \end{cases} \tag{3.2}$$

where all ascending intervals receive a value of 1, all descending intervals a value of −1, and all lateral motion a value of `0`. This viewpoint assumes all ascending motion is equivalent, whether by a semitone or an octave.

Scale Degree. I derived `melint` and `contour` from `cpitch`, but a viewpoint relating the chromatic pitches in each movement to a referential tonic pitch class cannot be obtained from the symbolic representation alone. In some studies, the referential tonic is determined from the opening key signature, resulting in scale-degree distributions that do not control for modulations or changes in modality.[39] Key-finding algorithms have also become more common in recent decades, allowing researchers to automatically identify the key of a passage with high

[39]Elizabeth Hellmuth Margulis and Andrew P. Beatty, "Musical Style, Psychoaesthetics, and Prospects for Entropy as an Analytic Tool," *Computer Music Journal* 32, no. 4 (2008): 68.

degrees of accuracy ($>90\%$).[40] Nevertheless, the lack of available annotated corpora indicating modulations and changes of mode makes testing these algorithms quite difficult.[41] To resolve these issues, I manually annotated the key, mode, modulations, and pivot boundaries for each movement in the corpus and then included the analysis in a separate text file to accompany the MIDI representation. Thus, every note event in the corpus was associated with the viewpoints `key` and `mode`. The vector of keys assumes values in the set {0,1,2,...,11}, where `0` represents the key of C, 1 represents C♯ or D♭, and so on. Passages in the major and minor modes receive values of `0` and 1, respectively.

To derive a viewpoint relating each chromatic pitch to a referential tonic, chromatic scale degree (or `csd`) maps `cpitch` to `key` and reduces the resulting vector of chromatic scale degrees modulo 12:

$$\Psi\texttt{csd}(e_i) = (\Psi\texttt{cpitch}(e_i) - \Psi\texttt{key}(e_i)) \mod 12 \tag{3.3}$$

The domain of `csd` consists of twelve distinct symbols numbered from `0` to 11, where `0` denotes the tonic, 7 the dominant, and so on.[42] Events located within the boundaries of a pivot were encoded in both keys. In a movement that modulates to the key of the dominant (e.g., from C to G), for example, the pitch class C appearing within the pivot would receive the values {0,7}, and the pitch class E would receive the values {4,9}.

[40] Joshua Albrecht and Daniel Shanahan, "The Use of Large Corpora to Train a New Type of Key-Finding Algorithm: An Improved Treatment of the Minor Mode," *Music Perception* 31, no. 1 (2013): 59–67.

[41] David Temperley and Elizabeth Marvin examined distributional approaches to key finding using a corpus of classical string quartets, and they only included the opening eight measures from each movement to ensure modulations would not affect the results ("Pitch-Class Distribution and the Identification of Key," *Music Perception* 25, no. 3 [2008]: 193–212). Nevertheless, Leigh VanHandel recently noted that in 58 of the 310 movements a modulation still took place within the first eight measures ("The Role of Phrase Location in Key Identification by Pitch Class Distribution," in *12th International Conference on Music Perception and Cognition and the 8th Triennial Conference of the European Society for the Cognitive Sciences of Music* [2012]).

[42] This viewpoint is quite common in corpus studies. See, for example, Margulis and Beatty, "Musical Style, Psychoaesthetics, and Prospects for Entropy as an Analytic Tool," 68; Pearce, "The Construction and Evaluation of Statistical Models of Melodic Structure in Music Perception and Composition," 71.

Metrical Strength. In Gjerdingen's view, a mental representation for a musical category is "likely in no particular key," and "may or may not have a particular meter."[43] For this reason, Gjerdingen generalizes across metric contexts by appealing to the *strength* of each event in the notated meter, which he characterizes as either strong or weak. Whether duple or triple, simple or compound, the internal organization of the meter is therefore largely irrelevant, as strong beats in one context are equivalent to strong beats in any other context. For our purposes, this approach greatly simplifies matters, since we would otherwise be forced to divide the corpus into its various metric conditions (e.g., $\frac{4}{4}$, $\frac{3}{4}$, $\frac{6}{8}$, etc.), examining each in isolation.

Many corpus studies determine the metric context inductively by using statistical procedures like autocorrelation, which classifies meters by finding periodicities in the note onset distribution.[44] By making minimal prior assumptions about the metric organization, this approach has the added benefit of distinguishing the perceptible meter from the notated time signature, which does not always accurately reflect the real metric organization.[45] Nevertheless, corpus studies of note onset distributions using the notated measure as a rigid framework provide convincing evidence that the time signature serves as a normative template for the representation of temporal information in Western notation. And thus, while note distributions derived from large symbolic corpora sometimes disregard significant variations in metric organization within an individual composition, they also capture large-scale differences between various metric contexts with great precision. To be sure, if the metric organization of music in say, common time, is to be understood as a mental representation acquired by implicit, statistical learning, then metric strength or stability (like tonal strength or stability) should arise out of

[43] Gjerdingen, *Music in the Galant style*, 453.

[44] Judith C. Brown, "Determination of the Meter of Musical Scores by Autocorrelation," *Journal of the Acoustical Society of America* 94, no. 4 (1993): 1953–1957; Petri Toiviainen and Tuomas Eerola, "Autocorrelation in Meter Induction: The Role of Accent Structure," *Journal of the Acoustical Society of America* 119, no. 2 (2006): 1164–1170.

[45] Grosvenor Cooper and Leonard Meyer, *The Rhythmic Structure of Music* (Chicago: The University of Chicago Press, 1960), 88.

distributional statistics, and the notated measure provides a useful starting point in this regard. Thus, in what follows, I consider the metric strength of note events in the corpus by first determining their position in the notated measure.

Just as `csd` relates the sequence of chromatic scale degrees in each movement to a particular key, a viewpoint representing metric position relates the sequence of note onset times to a particular time signature. The *MIDIToolbox* provides the basic type `onset`, which refers to the onset time of each event measured in quarter-note beats, and the basic type `timesig` indicates the number of quarter-note beats in the notated measure.[46] Six meters appear in the corpus—$\frac{4}{4}$, cut, $\frac{3}{4}$, $\frac{2}{4}$, $\frac{6}{8}$, and $\frac{3}{8}$—so the domain of `timesig` consists of four values: 1.5, 2, 3, and 4 quarter-note beats. In other words, each of these values represents one or more of the meters from the Haydn Corpus: $\frac{4}{4}$ and cut consist of 4 quarter-note beats, $\frac{3}{4}$ and $\frac{6}{8}$ consist of 3 quarter-note beats, and so on. To determine the metric position of each event in the corpus, the viewpoint `metricpos` reduces `onset` modulo `timesig` and adds 1 to the resulting sequence of metric positions to ensure that the downbeat in each measure = 1.

$$\Psi\texttt{metricpos}(e_i) = ((\Psi\texttt{onset}(e_i) \mod \texttt{timesig}(e_i)) + 1 \tag{3.4}$$

Thus, a note event falling on the 20$^{\text{th}}$ quarter note in a common-time movement would receive a value of 1 in `metricpos` because it falls on a downbeat in the notated measure $((20 \mod 4) + 1)$.

To this point I have only offered a method for determining the metric position of each event in the corpus. To determine the *strength* of each event in the notated meter, it might be useful to review a few working definitions for terms relating to metric organization that appear frequently in contemporary theory. If meter refers to nested layers of approximately equally spaced beats or pulses,[47] *metric strength* reflects the coincidence of these layers at multiple

[46]None of the excerpts in the Haydn Corpus feature a change of time signature during the movement.
[47]Harald Krebs, *Fantasy Pieces: Metrical Dissonance in the Music of Robert Schumann* (New York: Oxford

levels. And the greater the number of layers that align at a given moment, the greater its metric strength.[48] The precise cocktail of features responsible for the perception of meter is not yet known, though metric attending would seem to depend on isochronous patterns of accentuation resulting from changes in harmony, dynamics, rhythmic duration (agogic accents), and register, just to name a few.

Accent is a loaded term in music research. It generally refers to how events in a musical sequence draw attention to themselves;[49] to borrow a well-known expression from Grosvenor Cooper and Leonard Meyer, an accented event is "marked for consciousness."[50] In *A Generative Theory of Tonal Music*, Fred Lerdahl and Ray Jackendoff distinguish between three types of accent: 1) *phenomenal*, which refers to stressed or emphasized events in a continuous sequence; 2) *structural*, which refers to "points of gravity" in a phrase, such as a cadence; and 3) *metrical*, which refers to the strength of certain beats in a given metrical context. In their view, phenomenal accent "functions as a perceptual input to metrical accent," where "moments of stress in the raw signal serve as 'cues' from which the listener attempts to extrapolate a regular pattern of metrical accents."[51] Yonatan Malin would seem to agree, suggesting that phenomenal accents *generate* metrical layers when they recur at regular intervals. And like Lerdahl and Jackendoff, Malin characterizes phenomenal accents according to the usual cast of characters: dynamics, agogic accents, register, harmonic and textural change, the functional beginning of a unit, and so forth.[52]

University Press, 1999), 22.

[48]Yonatan Malin, *Songs in Motion: Rhythm and Meter in the German Lied* (New York: Oxford University Press, 2010), 39.

[49]Ibid., 41.

[50]Cooper and Meyer, *The Rhythmic Structure of Music*, 8.

[51]Fred Lerdahl and Ray Jackendoff, *A Generative Theory of Tonal Music* (Cambridge, Massachusetts: The MIT Press, 1983), 17.

[52]Malin, *Songs in Motion: Rhythm and Meter in the German Lied*, 41. Although I have only cited the contributions of twentieth-century theorists, these ideas have a long history in music theory. Lerdahl and Jackendoff's accent types recall Johann Philipp Kirnberger's *Akzenttheorie*, and Cooper and Meyer's off-cited expression that accented events are marked for consciousness is reminiscent of Johann Mattheson's description of events in

But perhaps the clearest cue to musical meter lies in the frequency-of-occurrence of note onsets within the notated measure. Caroline Palmer and Carol Krumhansl have noted, for example, that note onset distributions readily conform to theoretical accounts of the metric hierarchy for works in both duple and triple meters.[53] Thus, we might derive a measure of metric strength empirically by examining the distribution of note onsets in the notated measure for each meter in the corpus.[54]

Note events can appear in a range of metric positions within each measure. For movements in common or cut time in the Haydn Corpus, for example, note events appeared in 51 unique metric positions. To visualize each meter using a histogram, I have divided the notated measure into equal-sized bins, with the size of each bin corresponding to the duration of a 32nd note. Histograms typically display the number of note events in each bin, but this approach gives equal weight to each note event, regardless of duration. To resolve this issue, several recent corpus studies weighted pitch-class and scale-degree distributions by the rhythmic duration of each event, so I have also adopted that procedure here.[55]

Rather than weight the histogram for each meter by notated durations, which assumes durational equivalence across the corpus regardless of the underlying tempo,[56] I have elected to

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metrically strong positions as having an "inner content and emphasis." For a review of theories of accent, rhythm, and meter in music theory scholarship, see William E. Caplin, "Theories of Musical Rhythm in the 18th and 19th Centuries," in *The Cambridge History of Western Music Theory*, ed. Thomas Christensen (Cambridge, UK: Cambridge University Press, 2002), 657–694; Justin London, "Rhythm in Twentieth-Century Theory," in *The Cambridge History of Western Music Theory*, ed. Thomas Christensen (Cambridge, UK: Cambridge University Press, 2002), 695–725.

[53] Caroline Palmer and Carol L. Krumhansl, "Mental Representations for Musical Meter," *Journal of Experimental Psychology: Human Perception and Performance* 16, no. 4 (1990): 728–41.

[54] This approach also lends support to the claim that mental representations for various meters result from statistical learning, whereby metrically strong or stable events appear frequently at particular positions on the metric grid.

[55] The Krumhansl-Schmuckler key-finding algorithm provides one well-known example (*Cognitive Foundations of Musical Pitch* [New York, NY: Oxford University Press, 1990], 77-110).

[56] Snyder, "Entropy as a Measure of Musical Style: The Influence of A Priori Assumptions." To normalize note distributions across movements in different meters and tempi, Snyder also suggested weighting each note as a fraction of the duration of the entire piece (141).

weight each histogram using Richard Parncutt's model of *durational accent*, which maps the physical inter-onset interval (IOI) between events e_i and e_{i+1} to the phenomenal accent of note event e_i.[57] Following a number of experimental studies linking IOI with metrical accentuation, Parncutt's function assumes that the perceptual or durational accent for a given note event increases with the IOI that follows it. To account for limitations of auditory processing for very short ($<$ 50 ms) and very long ($>$1–2 s) IOIs, he also includes two free parameters, represented by k and τ in the equation below.

$$accent_{dur}(e_i) = \left[1 - exp\left\{\frac{-ioi(e_i)}{\tau}\right\}\right]^k$$

The function $accent_{dur}(e_i)$ denotes the durational accent of event e_i, exp is the natural exponential function, $ioi(e_i)$ refers to the IOI following event e_i, expressed in milliseconds, τ is the saturation duration, which is proportional to the duration of echoic memory, and k is the *accent index*, which accounts for the minimum discriminable IOI. Parncutt suggests that parameter values of $k = 2$ and $\tau = 500$ ms provide a good fit to experimental data, so I have retained those values here.[58]

Shown in Figure 3.1, the durational accent increases for small values of IOI and plateaus (or *saturates*) at around 2 s, when the IOI exceeds the duration of echoic memory. The further we move from right to left along the curve (i.e., the shorter the IOI between events), the greater the difference in accent between long and short IOIs. According to Parncutt, the shape of the curve therefore sharpens the difference between long and short events and renders metrical interpretations less ambiguous.[59]

Unfortunately, identifying physical IOIs between events in polyphonic textures is relatively

[57] Richard Parncutt, "A Perceptual Model of Pulse Salience and Metrical Accent in Musical Rhythms," *Music Perception* 11, no. 4 (1994): 409–464.
[58] Ibid., 426–433.
[59] Ibid., 431–432.

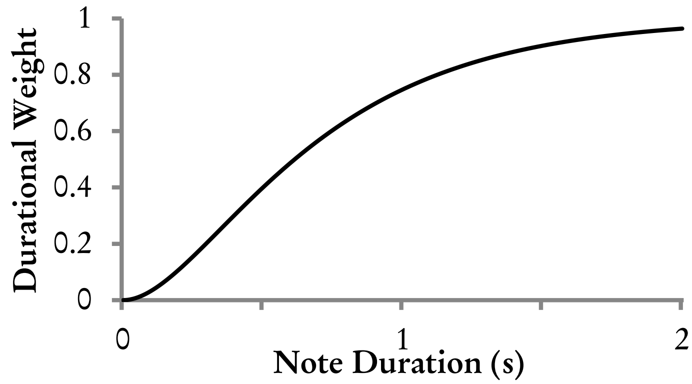


Figure 3.1: Durational weight plotted against note duration in seconds, reproduced from Figure 6 of Parncutt (1994), 431.

complex. Do we select the IOI between adjacent events within a given instrumental part, or within the entire texture? How do we account for effects of auditory streaming? To simplify matters, I have elected to treat note duration as a rough approximation of inter-onset interval, with the hope that the results obtained here will be replicated in subsequent analyses weighted by IOI.

Using Parncutt's model, I determined the durational salience of the note durations (measured in seconds) in each movement. To demonstrate the effect of weighting the note distributions by durational salience, Figure 3.2 presents bar plots of the distribution of the proportion of note onsets within the notated measure in $\frac{4}{4}$, with the plot on the left weighted by note count, and the plot on the right weighted by summing the durational accents in each metric position. The plot below presents the arithmetic difference between these two distributions, with positive values indicating a greater proportion of note events in the duration-weighted distribution. The plot on the left demonstrates that note onsets appeared prevalently at positions throughout the notated measure, but the duration-weighted distribution shown in the plot on the right indicates that longer durations appeared far more frequently in metrically strong positions, such as beats one and three. In fact, weighting the note distribution by durational accent clarified

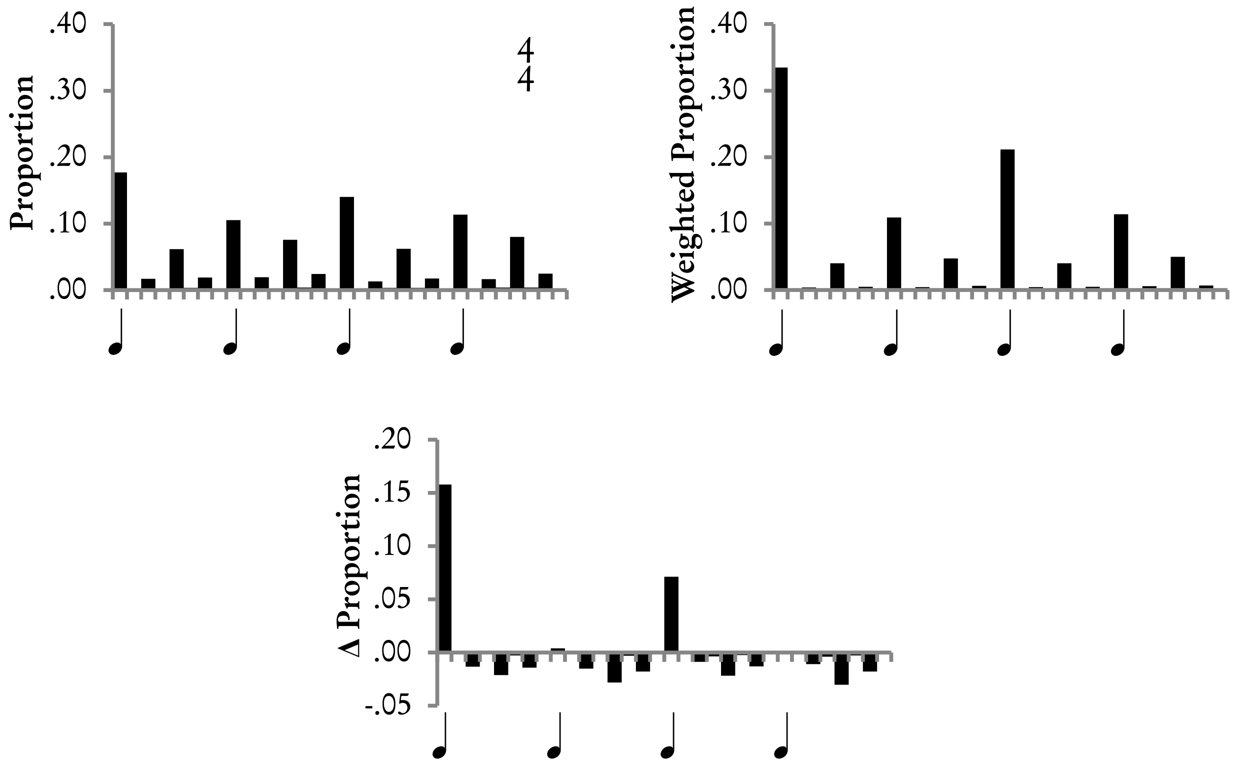


Figure 3.2: Top: Bar plots of the proportion of note onsets in each metric position within the notated measure in $\frac{4}{4}$, weighted by note count (left), or by summing the durational accents in each metric position (right). Bottom: Bar plot of the difference in the proportion of note onsets.

the metrical hierarchy just as Parncutt suggested, with the downbeat receiving the greatest proportion of durations at the level of the measure, followed by beat three at the half-note level, beats two and four at the quarter-note level, and so on.

From visual inspection alone, a four-level viewpoint of metric strength would seem to provide the best fit to the underlying distribution. But to select the optimum number of levels across all of the metric conditions, quantifying the degree of fit in each case, it might be useful to examine the statistical properties of the distribution more closely. If we conceptualize metric strength along a continuous scale, with strong or stable events at one end and weak or unstable events at the other, we might reorder the metric positions within the histogram from

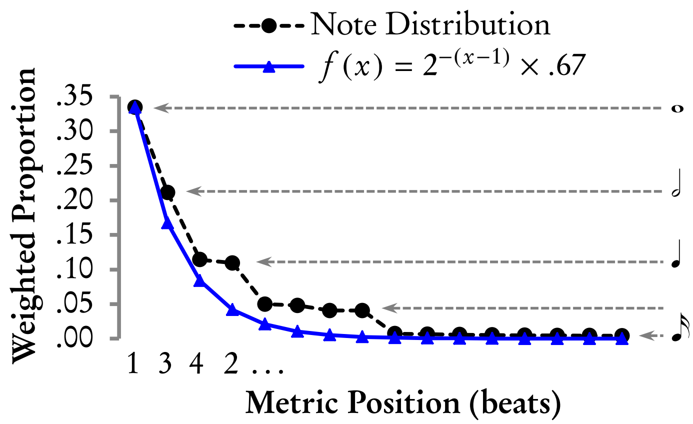


Figure 3.3: Line plot of the duration-weighted proportion of note onsets in $\frac{4}{4}$, ordered from most to least common. The right y-axis annotates the durational level reflected in the note distribution, which appears in dotted black. The exponential distribution (base 2) appears in blue (color).

most common to least common to reflect this scale. The black line in Figure 3.3 presents the most common sixteen metric positions from the duration-weighted note distribution shown in Figure 3.2.

Formally, the note onset distribution presented in Figure 3.3 is a discrete probability distribution, and it loosely conforms to the family of power laws used in linguistics to describe the frequency-of-occurrence of words in language corpora.[60] George Zipf noted, for example, that in many language corpora the frequency of any word is inversely proportional to its rank in the corpus.[61] According to Zipf's law, the most frequent word occurs twice as often as the second most frequent word, three times as often as the third most frequent word, and so on. In this case, however, the note onset distribution more closely resemblances an exponential function with base 2, where the most frequent metric position occurs twice as often as the second most frequent position and four times as often as the third most frequent position. The blue curve in Figure 3.3 visualizes the exponential function, $2^{-(x-1)} \times .67$, where x represents

[60]Manning and Schütze, *Foundations of Statistical Natural Language Processing*, 20–29.
[61]George Kingsley Zipf, *Human Behavior and the Principle of Least Effort* (Oxford, UK: Addison-Wesley, 1949).

the rank of each metric position according to its frequency in the distribution, $2^{-(x-1)}$ halves the proportion of note onsets as we ascend in rank (i.e., from left to right); and .67 ensures that the curve passes through the top-ranked position in this particular distribution.[62]

Nevertheless, the exponential function is not a perfect fit. If metric strength is to be conceived as a continuous exponential function, as I previously suggested, we would expect note onsets in the fourth-ranked metric position to appear half as often as those in the third-ranked position, but meter distributions like this one instead demonstrate a staircase effect, where each stair conforms to a different durational level within the metric hierarchy. In this case, the fourth-ranked position (beat two) appears almost as often as the third-ranked position (beat four) because both positions reflect the quarter-note durational level in $\frac{4}{4}$. From left to right, the next four positions in the distribution represent the eighth-note level, the next eight represent the sixteenth-note level, and the final sixteen positions represent the thirty-second-note level (not shown).

Given this staircase effect, one possible explanation for the close fit between the note distribution and the exponential curve with base 2 might be that the durational levels of the metric hierarchy in $\frac{4}{4}$ preserve the same 2:1 ratio from top to bottom (i.e., a whole note is double the duration of a half note, a half note is double the duration of a quarter note, etc.). And if a doubling of the durational level corresponds to a doubling of the proportion of note onsets in $\frac{4}{4}$, we could further hypothesize that the ratio represented between adjacent levels of any metric hierarchy should correspond to the ratio between stairs of the corresponding note onset distribution.

Bearing this assumption in mind, I have created a hypothetical note distribution for each meter that preserves the ratio between adjacent levels of the metric hierarchy. Table 3.2 presents

[62]To ensure this equation would fit *any* distribution, we could replace the constant .67 with $2(y_1)$, where y_1 refers to the most frequent (i.e., highest ranked) metric position in the measure.

Table 3.2: Levels of the metric hierarchy for each meter.

Metric Strength	$\frac{4}{4}$			$\frac{3}{4}$			$\frac{2}{4}$			$\frac{6}{8}$			$\frac{3}{8}$		
	Dur.	N[a]	w[b]	Dur.	N	w	Dur.	N	w	Dur.	N	w	Dur.	N	w
4	𝅝	1	32	𝅗𝅥.	1	24	𝅗𝅥	1	16	𝅗𝅥.	1	24	♩.	1	12
3	𝅗𝅥	1	16	♩	2	8	♩	1	8	♩.	1	12	♪	2	4
2	♩	2	8	♪	3	4	♪	2	4	♪	4	4	𝅘𝅥𝅯	3	2
1	♪	4	4	𝅘𝅥𝅯	6	2	𝅘𝅥𝅯	4	2	𝅘𝅥𝅯	6	2	𝅘𝅥𝅰	6	1
	𝅘𝅥𝅯	8	2	𝅘𝅥𝅰	12	1	𝅘𝅥𝅰	8	1	𝅘𝅥𝅰	12	1			
	𝅘𝅥𝅰	16	1												

[a] N refers to the number of metric positions within the notated measure for each level.
[b] w refers to the durational weight of each level, measured in 32nd notes.

the durational levels for each meter, starting with the 32nd note value. A measure in $\frac{4}{4}$ consists of six such levels, $\frac{3}{4}$, $\frac{2}{4}$, and $\frac{6}{8}$ consist of five levels, and $\frac{3}{8}$ consists of four. To create a hypothetical note distribution, we must first determine the proportion of note onsets for each level of the metric hierarchy. The column denoted by w represents the number of 32nd notes contained within each durational level. To find the proportion of note onsets associated with each level L, we need only divide the weight w at each level by the sum of the weights for that meter:

$$prop(L_i) = \frac{w_i}{\sum w}$$

w preserves the ratios between adjacent levels, and the function $prop$ ensures the resulting values in L sum to 1. In $\frac{4}{4}$, for example, the downbeat receives a durational weight of 32, and the sum of the weights in $\frac{4}{4}$ is 63, so the estimated proportion of note onsets associated with the metric downbeat is .51.

Unfortunately, these values assume each level consists of just one metric position; within the notated measure, however, the lower levels of the metric hierarchy feature multiple metric positions. As a result, if we were to assign each metric position the appropriate proportion using the equation above, the sum of the resulting values in the distribution would be greater than 1. To adjust these proportions such that they accommodate the number of metric positions N associated with each level, I multiply the values of N by the corresponding proportions in L and sum them, and then divide each L_i by this sum:

$$prop_{adj}(L_i) = \frac{L_i}{\sum(L \times N)}$$

Using the adjusted proportions from the equation above, we can assign a proportion to each metric position according to its membership in the metric hierarchy. I will hereafter refer to this procedure as the *proportions model*. Figure 3.4 presents the bar plots of the duration-weighted note distributions for each movement on the left in blue, with the distributions provided by the proportions model on the right in red. The majority of the movements in the Haydn Corpus were notated in common or cut time, so the top-left distribution represents over 20,000 note events. By comparison, only one movement was notated in $\frac{3}{8}$, so the bottom-left plot represents less than 1,000 note events.

I mentioned previously that Palmer and Krumhansl have already noted the degree to which note onset distributions conform to theoretical accounts of the metric hierarchy for each meter,[63] and the distributions on the left in Figure 3.4 replicate that finding. In fact, the frequency-of-occurrence of notes in the metric positions associated with each durational level corresponds exactly with the levels of metric strength found in Table 3.2 for *every* meter—the metric position associated with the level of the measure received the highest proportion of note onsets, the metric positions associated with the next lower level received the next highest

[63] Palmer and Krumhansl, "Mental Representations for Musical Meter."

proportions, and so on.

There are a number of statistical procedures for determining the degree of fit between the predicted distributions from the proportions model and the corresponding note distributions from the Haydn Corpus. In this instance, I have elected to describe the relationship using *linear regression*, which calculates a best-fit line that minimizes the error between the predicted estimates and the actual values found in the note distribution. To understand the regression estimates that appear in Figure 3.4, R^2 refers to the fit of the model, where a value of 1 indicates that the model accounts for all of the variance in the outcome variable (i.e., a perfectly linear relationship between the predictor and the outcome), and a value of 0 indicates that the model fails to account for any of the variance.

The distributions from the proportions model provide an excellent fit for the simple meters ($\frac{4}{4}$, $\frac{3}{4}$, and $\frac{2}{4}$), suggesting that the empirical distributions reflect the ratios between adjacent levels of the metric hierarchy. Nevertheless, the fixed 2:1 or 3:1 ratios characterizing each distribution in the proportions model are somewhat variable in the empirical distributions. In $\frac{4}{4}$, the model underestimated the proportion of durations for the most frequent metric positions (the downbeat and beat three), but overestimated the proportion of durations for the lowest levels of the hierarchy (the metric positions associated with the levels of the 16^{th} and 32^{nd} note). The same trend emerged in the $\frac{3}{4}$ distributions, where the model underestimated the proportion of durations at the downbeat and overestimated the proportion of durations at the level of the 16^{th} note and lower. Note, however, that the proportions model correctly predicted the 3:1 ratio between the dotted-half-note level and the quarter-note level in the note distribution—in both distributions, the proportion of durations at the downbeat was three times larger than the proportion of durations for metric positions at the quarter-note level.

In $\frac{2}{4}$, the proportions model predicted far smaller proportions at the eighth-note level than the empirical note distribution demonstrated. To be sure, the difference between the levels

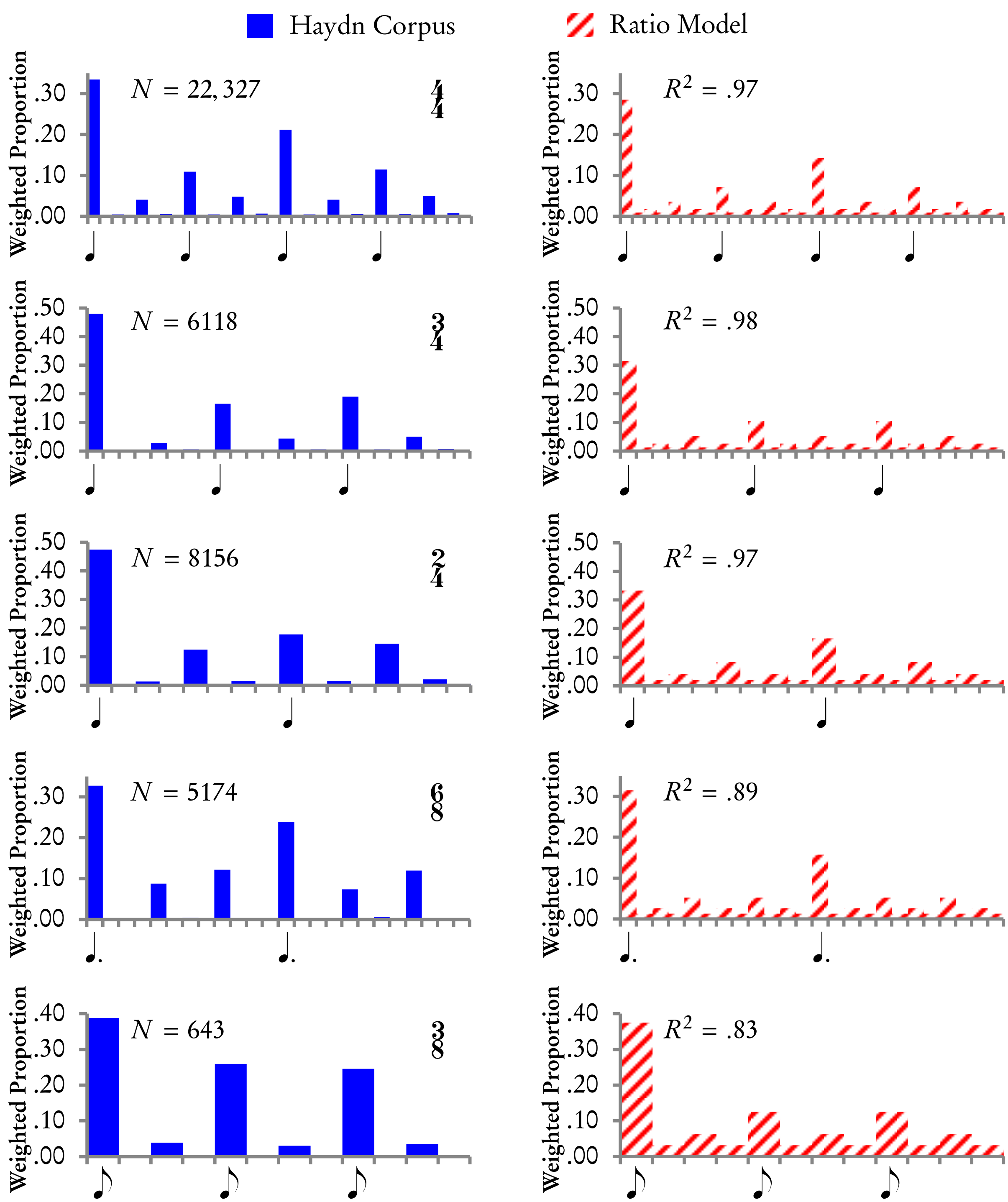


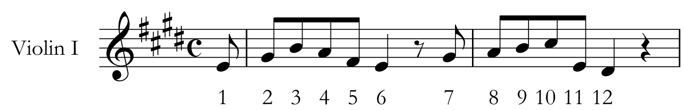
Figure 3.4: Left: Bar plots of the proportion of note onsets weighted by durational accent for movements in $\frac{4}{4}$, $\frac{3}{4}$, $\frac{2}{4}$, $\frac{6}{8}$, and $\frac{3}{8}$ (solid blue). N refers to the number of note onsets represented in each plot. Right: Bar plots of the proportion of note onsets predicted by the proportions model (dashed red). R^2 indicates model fit (color).

of the quarter note and eighth note are surprisingly small. If we were to derive a viewpoint of metric strength strictly from empirical observation, it would seem reasonable to assign the same value to the metric positions from these two durational levels. For the sake of consistency across all of the meters, however, I have elected to retain the theoretical metric hierarchy in $\frac{2}{4}$.

For the compound meters, the predicted models were less successful. In $\frac{6}{8}$, the second dotted quarter received a greater proportion of durations than the model predicted, just as we noted for the corresponding level from the $\frac{4}{4}$ distribution. The proportions model for $\frac{3}{8}$ suffered from the same limitation; in this case, the predicted 3:1 ratio between the levels of the dotted quarter and eighth note did not correspond with the ratio in the empirical distribution, where proportions for metric positions at the eighth-note level were much larger. In fact, the ratio between these two levels was less than 2:1 in the empirical distribution. Nevertheless, the small sample size for the $\frac{3}{8}$ distribution calls into question any similarities or differences we might observe between the model and the distribution.

Given the degree of fit between the empirical note distributions and the corresponding proportions models, a viewpoint of metric strength reflecting the coincidence of layers of nested periodicities appears well justified. Metric strength in this context is an ordinal viewpoint, where the value associated with each metric position represents the number of periodicities (or layers) it supports within the notated meter. Since meter minimally involves two or three layers,[64] a viewpoint representing four levels of metric strength should be sensitive enough to allow us to make subtler distinctions than a two- or three-level viewpoint would permit, while still being coarse enough to generalize across all five metric contexts. Shown in Table 3.2, level 4 represents the metric downbeat; level 3 represents the duple or triple subdivision of the measure; level 2 represents the next subdivision, which typically corresponds to the level of the

[64] Lerdahl and Jackendoff, *A Generative Theory of Tonal Music*, 19; Justin London, *Hearing in Time: Psychological Aspects of Musical Meter* (New York: Oxford University Press, 2004), 47.



	1	2	3	4	5	6	7	8	9	10	11	12
`melint`	⊥	4	3	-2	-3	-2	4	1	2	2	-9	-1
`contour`	⊥	1	1	-1	-1	-1	1	1	1	1	-1	-1
`strength`	1	4	1	2	1	3	1	4	1	2	1	3
`csd`	0	4	7	5	2	0	4	5	7	9	0	11

Figure 3.5: Top: First violin part from Haydn's String Quartet in E, Op. 17/1, i, mm. 1–2. Bottom: Viewpoint representation.

quarter or eighth note; and level 1 represents the lowest level of strength, which consists of all of the remaining metric positions across the measure.

3.4.2 Chord Events

To this point I have represented note events in the Haydn Corpus according to four viewpoints: melodic interval (`melint`), melodic contour (`contour`), chromatic scale degree (`csd`), and metric strength (`strength`). Figure 3.5 presents the viewpoint representation for the first violin part from the opening two measures of the first movement of Haydn's String Quartet in E, Op. 17/1. The appeal of this approach is that it represents each part in isolation, allowing us to consider the distinct roles these instrumental parts may play, both in the corpus at large, and in cadential contexts. Nevertheless, by treating the note event as the unit of analysis, this representation scheme can tell us nothing about the manifold ways in which these parts may interact. In short, it tells us nothing about the vertical sonorities that characterize this style.

Identifying events beyond the level of the note using inductive methods is a tremendous challenge. As a consequence, many analysts have elected to ignore the symbolic encoding entirely and instead annotate vertical sonorities using roman numerals, figured bass symbols,

Example 3.2: Top: Haydn, String Quartet in E, Op. 17/1, i, mm. 1–2. Bottom: Full expansion.

and the like. But in recent decades, several studies have attempted to derive principles of tonal harmony from symbolic corpora by constructing composite viewpoints of chord events from simpler viewpoints derived from note events.

The simplest procedure for deriving chord events from multi-voiced textures is to partition note events into simultaneities whenever all of the instrumental parts have the same onset time. Shown at the top of Example 3.2, all four instrumental parts feature the same onset time on six occasions in the first two measures. This approach works well for homo-rhythmic textures and simple species counterpoint, but it under-partitions more complex polyphony where common onset times may not coincide with the harmonic rhythm of the passage.[65] For this reason, many

[65]Darrell Conklin, "Representation and Discovery of Vertical Patterns in Music," in *Music and Artifical*

current music analysis software frameworks perform a *full expansion* of the symbolic encoding, which duplicates overlapping note events at every unique onset time.[66] Shown below in the same example, expansion results in the identification of ten unique onset times for which all four instrumental parts are present. With this method, we could model the resulting sequence of note combinations directly, or sample at regular metric intervals using what Conklin calls *threaded* viewpoints.

In previous publications, Conklin represented vertical sonorities by the melodic intervals between adjacent onset times in each instrumental part. Beginning with the cello part in Example 3.2, Conklin's method derives the vertical pattern $\langle 0, 0, 0, 3 \rangle$ between events 1 in 2. Ian Quinn and Panayotis Mavromatis have pointed out, however, that this approach hard-codes the ordering of the four parts when in principle, voices are permutable.[67] Swapping the alto and tenor voices in a vertical sonority would produce a complete different representation in Conklin's method, for example. As an alternative, Quinn developed a representation consisting of an ordered triple (S_1, S_2, I), where S_1 and S_2 are sets of intervals above the bass in semitones modulo the octave, and I is the melodic interval (again modulo the octave) from the first bass note to the second. He calls this representation a *voice-leading type*.[68]

The appeal of Quinn's representation is that the most common voice-leading types in a given corpus will have analogues in figured-bass nomenclature. Nevertheless, as a representation scheme for chord events, Quinn's voice-leading type is more promiscuous than traditional definitions of 'chord' would embrace. Whereas theorists tend to assign 'chordal' status only to

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Intelligence: Proc. ICMAI 2002, ed. Christina Anagnostopoulou, Miguel Ferrand, and Alan Smaill, vol. 2445 (Springer-Verlag, 2002), 3–4.

[66] Conklin, "Representation and Discovery of Vertical Patterns in Music," 4. In *Humdrum*, this technique is called *ditto*, while *Music21* calls it *chordifying*.

[67] Ian Quinn and Panayotis Mavromatis, "Voice-Leading Prototypes and Harmonic Function in Two Chorale Corpora," in *Mathematics and Computation in Music*, ed. Carlos Agon et al. (Heidelberg: Springer, 2011), 231.

[68] Ian Quinn, "Are Pitch-Class Profiles Really Key for Key," *Zeitschrift der Gesellschaft der Musiktheorie* 7 (2010): 151–163; Quinn and Mavromatis, "Voice-Leading Prototypes and Harmonic Function in Two Chorale Corpora." The ELVIS team at McGill University use the same method. For more details, see `http://elvisproject.ca/`.

those vertical sonorities featuring stacked intervals of a third, Quinn's voice-leading types make no distinction between chord tones and non-chord tones, consonant and dissonant intervals, or diatonic and chromatic scale degrees.[69] As a result, the syntactic domain (or alphabet) of voice-leading types is enormous. Thus, to adapt Quinn's method here, we need to reduce the syntactic domain such that the resulting viewpoint corresponds more closely with the figured bass symbols in Gjerdingen's schema-theoretic framework.[70]

The viewpoint *vertical interval class combination* (`vintcc`) models the vertical intervals in semitones modulo 12 between the lowest instrumental part b and the upper parts u from the basic type `cpitch`:

$$\Psi\texttt{vintcc}(e_{i_b}) = |\Psi\texttt{cpitch}(e_{i_b}) - \Psi\texttt{cpitch}(e_{i_u})| \mod 12 \tag{3.5}$$

If we only consider unique onsets that contain all four instrumental parts, the number of combinatorial possibilities is 12^3 (or 1728), but this procedure excludes combinations containing only one or two vertical interval classes.[71] By including unique onsets for combinations containing two, three, or four instrumental parts, the number of combinatorial possibilities increases to $13^3 - 1$ (or 2196), since the syntactic domain of each vertical interval class = $\{0, 1, 2, \ldots, \perp\}$.[72]

To reduce the syntactic domain of `vintcc` to a more reasonable number while retaining

[69] Quinn, "Are Pitch-Class Profiles Really Key for Key," 152.

[70] Ideally, we would reduce the syntactic domain to less than, say, 30 symbols, but given the number of combinatorial possibilities for three- and four-note chords, such a feat is staggeringly difficult to achieve. At present, the creation of an alphabet-reduction algorithm that identifies such a reduced set of chord classes is beyond the scope of this dissertation, but see Christopher W. White, "Some Statistical Properties of Tonality, 1650-1900" (PhD Dissertation, Yale University, 2013); Christopher W. White, "An Alphabet-Reduction Algorithm for Chordal n-Grams," in *Proceedings of the 4th International Conference on Mathematics and Computation in Music* (Springer, 2013), 201–212.

[71] I did not include onsets consisting of just one instrumental part under the assumption that such instances would not constitute chord events.

[72] I excluded the combination representing just one instrumental part from the calculation, $\langle \perp, \perp, \perp \rangle$. Again, $\perp$ indicates that the vertical interval class is undefined.

those combinations that approximate figured bass symbols, I have excluded note events in the upper parts that double the lowest instrumental part at the unison or octave, allowed permutations between vertical intervals, and excluded interval repetitions. Following Quinn, the assumption here is that both the precise location and repeated appearance of a given interval in the instrumental texture are inconsequential to the identity of the combination. Thus, by allowing permutations and excluding voice doublings of the lowest instrumental part, the major triads $\langle 4, 7, 0\rangle$ and $\langle 7, 4, 0\rangle$ would reduce to $\langle 4, 7, \perp\rangle$. Similarly, by eliminating repetitions, the chords $\langle 4, 4, 10\rangle$ and $\langle 4, 10, 10\rangle$ would reduce to $\langle 4, 10, \perp\rangle$. Using this procedure, the potential domain of `vintcc` reduces dramatically from 2196 to 232 unique vertical interval combinations, though the Haydn Corpus only contained 190 of the 232 possible combinations, reducing the domain yet further.

Unfortunately, `vintcc` does not represent voice-leading information, nor does it define each harmony in relation to an underlying tonic. Quinn's solution to the first limitation was to encode the melodic interval between successive events in the bass. Given the viewpoint `csd`, however, we may instead represent vertical sonorities as combinations of chromatic scale degrees. The viewpoint `csdc` includes the chromatic scale degrees derived from `csd` as combinations of two, three, or four instrumental parts. Here, the number of possibilities increases exponentially to $13^4 - 13^1$ (or 28, 548), since the cello part is now encoded explicitly in combinations containing all four parts.[73] Rather than treating permutable combinations as equivalent (e.g., $\langle 0, 4, 7, \perp\rangle$ and $\langle 4, 7, 0, \perp\rangle$), as we did in `vintcc`, it will also be useful to retain the chromatic scale degree in the lowest instrumental part in `csdc` and only permit permutations in the upper parts. Excluding voice doublings and permitting permutations in the upper parts reduces the potential domain of `csdc` to 2784, though in the Haydn Corpus the domain reduced yet further to 688 distinct

[73] As with `vintcc`, I excluded combinations representing less than two instrumental parts from the calculation (e.g., $\langle\perp, \perp, \perp, \perp\rangle$).

combinations.

§3.5 Conclusions

This chapter took a circuitous path through the Haydn Corpus. I began in §3.1 with a brief discussion of corpus studies in music research, and then in §3.2 presented the corpus of expositions from Haydn's string quartets and the representation scheme employed by the *MIDIToolbox*. Digital encodings of individual note or chord events typically represent multiple properties of the musical surface, so in §3.3 I adopted a multiple viewpoints framework to encode irreducible viewpoints like chromatic pitch (`cpitch`), note onset in beats (`onset`), metric position (`metricpos`), key (`key`), and mode (`mode`). From these basic types I then derived a number of other viewpoints in §3.4 to represent the "core" events of the classical cadence: melodic interval (`melint`), contour (`contour`), chromatic scale degree (`csd`), and strength (`strength`) to represent note events, and vertical interval class combination (`vintcc`) and chromatic scale degree combination (`csdc`) to represent chord events.

Armed with this representation scheme, I now apply a few common statistical methods to probe the corpus at large and consider whether cadences and other closing formulæ are indeed the most recurrent patterns in classical music. Thus, Chapter 4 attempts to reinforce the link between psychological stability and statistical frequency, providing distributional evidence in support of the view that cadences are among the most important event schemas in the tonal system.

Part III

Experimental Evidence: Twenty-First-Century Listeners

Bibliography

389-8, ISO. *Acoustics: Reference Zero for the Calibration of Audiometric Equipment—Part 8: Reference Equivalent Threshold Sound Pressure Levels for Pure Tones and Circumaural Earphones*. Technical Report. International Organization for Standardization, 2004.

Aarden, Bret. "Dynamic Melodic Expectancy." PhD Dissertation, The Ohio State University, 2003.

———. "Expectancy vs. Retrospective Perception: Reconsidering the Effects of Schema and Continuation Judgments on Measures of Melodic Expectancy." In *Proceedings of the 7th International Conference on Music Perception and Cognition*. Adelaide: Adelaide: Causal Productions, 2002.

Agawu, Kofi. "Concepts of Closure and Chopin's Opus 28." *Music Theory Spectrum* 9 (1987): 1–17.

Agmon, Eytan. "Functional Harmony Revisited: A Prototype-Theoretic Approach." *Music Theory Spectrum* 17, no. 2 (1995): 196–214.

Albrecht, Joshua, and Daniel Shanahan. "The Use of Large Corpora to Train a New Type of Key-Finding Algorithm: An Improved Treatment of the Minor Mode." *Music Perception* 31, no. 1 (2013): 59–67.

Anson-Cartwright, Mark. "Concepts of Closure in Tonal Music: A Critical Study." *Theory and Practice* 32 (2007): 1–18.

Attneave, Fred. "Transfer of Experience with a Class-Schema to Identification-Learning of Patterns and Shapes." *Journal of Experimental Psychology* 54, no. 2 (1957): 81–88.

Baayen, R. Harald, Doug J. Davidson, and Douglas M. Bates. “Mixed-Effects Modeling with Crossed Random Effects for Subjects and Items.” *Journal of Memory and Language* 59 (2008): 390–412.

Baayen, R. Harold. *languageR: Data Sets and Functions with "Analyzing Linguistic Data: A Practical Introduction to Statistics". R package version 1.4.*, 2012.

Baayen, R. Harold, and Petar Milin. “Analyzing Reaction Times.” *International Journal of Psychological Research* 3, no. 2 (2010): 12–28.

Bach, C. P. E. *Essay on the True Art of Playing Keyboard Instruments*. Translated by William Mitchell. New York: W. W. Norton & Co., Inc., 1949.

Baddeley, Alan. *Human Memory: Theory and Practice*. Hillsdale, NJ: Erlbaum, 1990.

Baeza-Yates, Ricardo, and Berthier Ribeiro-Neto. *Modern Information Retrieval*. New York, NY: ACM Press, 1999.

Bain, Jennifer. “Theorizing the Cadence in the Music of Machaut.” *Journal of Music Theory* 47, no. 2 (2003): 325–362.

Bar, Moshe. “The proactive brain: Using analogies and associations to generate predictions.” *Trends in Cognitive Sciences* 11, no. 7 (2007): 280–289.

Barr, Dale J., Roger Levy, Christoph Scheepers, and Harry J. Tily. “Random Effects Structure for Confirmatory Hypothesis Testing: Keep It Maximal.” *Journal of Memory and Language* 68 (2013): 255–278.

Barry, Barbara. “In Search of an Ending: Reframing Mahler’s Contexts of Closure.” *Journal of Musicological Research* 26, no. 1 (2007): 55–68.

Bartlett, Frederic C. *Remembering: A Study in Experimental and Social Psychology*. London, United Kingdom: Cambridge University Press, 1932.

Bartlett, James C., and Jay W. Dowling. “Scale Structure and Similarity of Melodies.” *Music Perception* 5, no. 3 (1988): 285–314.

Bates, D.M., M. Maechler, and B. Bolker. *lme4: Linear Mixed-Effects Models Using S4 Classes, (R package version 0.98.501) [computer software].*, 2011.

Bell, Timothy C., John G. Cleary, and Ian H. Witten. *Text Compression*. Englewood Cliffs, NJ: Prentice Hall, 1990.

Besson, Mireille, and Frédérique Faïta. "An Event-Related Potential (ERP) Study of Musical Expectancy: Comparison of Musicians with Nonmusicians." *Journal of Experimental Psychology: Human Perception and Performance* 21, no. 6 (1995): 1278–1296.

Bharucha, Jamshed, and Keiko Stoeckig. "Priming of Chords: Spreading Activation or Overlapping Frequency Spectra." *Perception and Psychophysics* 41, no. 6 (1987): 519–524.

Bharucha, Jamshed J. "Anchoring Effects in Music: The Resolution of Dissonance." *Cognitive Psychology* 16, no. 4 (1984): 485–518.

———. "Event Hierarchies, Tonal Hierarchies, and Assimilation: A Reply to Deutsch and Dowling." *Journal of Experimental Psychology: General* 113, no. 3 (1984): 421–425.

———. "MUSACT: A Connectionist Model of Musical Harmony." In *Proceedings of the Cognitive Science Society*. Hillsdale, NJ: Erlbaum Press, 1987.

———. "Music Cognition and Perceptual Facilitation: A Connectionist Framework." *Music Perception* 5, no. 1 (1987): 1–30.

Bharucha, Jamshed J., and Carol L. Krumhansl. "The Representation of Harmonic Structure in Music: Hierarchies of Stability as a Function of Context." *Cognition* 13 (1983): 63–102.

Bharucha, Jamshed J., and Keiko Stoeckig. "Reaction Time and Musical Expectancy: Priming of Chords." *Journal of Experimental Psychology: Human Perception and Performance* 12, no. 4 (1986): 403–410.

Bigand, Emmanuel. "More about the Musical Expertise of Musically Untrained Listeners." *Annals of the New York Academy of Sciences* 999 (2003): 304–312.

Bigand, Emmanuel, and Richard Parncutt. "Perceiving Musical Tension in Long Chord Sequences." *Psychological Research* 62 (1999): 237–254.

Bigand, Emmanuel, and Marion Pineau. "Global Context Effects on Musical Expectancy." *Perception and Psychophysics* 59, no. 7 (1997): 1098–1107.

Bigand, Emmanuel, François Madurell, Barbara Tillman, and Marion Pineau. "Effect of Global Structure and Temporal Organization on Chord Processing." *Journal of Experimental Psychology: Human Perception and Performance* 25, no. 1 (1999): 184–197.

Bigand, Emmanuel, Charles Delbé, Bénédicte Poulin-Charronnat, Marc Leman, and Barbara Tillmann. "Empirical Evidence for Musical Syntax Processing? Computer Simulations Reveal the Contribution of Auditory Short-Term Memory." *Frontiers in Systems Neuroscience* 8 (2014): 1–27.

Bigand, Emmanuel, Barbara Tillmann, Benedicte Poulin-Charronnat, and D. Manderlier. "Repetition Priming: Is Music Special?" *The Quarterly Journal of Experimental Psychology* 58A, no. 8 (2005): 1347–1375.

Bigand, Emmanuel, Benedicte Poulin, Barbara Tillmann, Francois Madurell, and D. A. D'Adamo. "Sensory Versus Cognitive Components in Harmonic Priming." *Journal of Experimental Psychology: Human Perception and Performance* 29, no. 1 (2003): 159–171.

Blombach, Ann. "Phrase and Cadence: A Study of Terminology and Definition." *Journal of Music Theory Pedagogy* 1 (1987): 225–251.

Bolton, Thaddeus L. "Rhythm." *The American Journal of Psychology* 6, no. 2 (1894): 145–238.

Boltz, Marilyn. "Perceiving the End: Effects of Tonal Relationships on Melodic Completion." *Journal of Experimental Psychology: Human Perception and Performance* 15, no. 4 (1989): 749–761.

Bowerman, Bruce L., and Richard T. O'Connell. *Linear Statistical Models: An Applied Approach*. Pacific Grove, CA: Duxbury, 1990.

Bregman, Albert S. *Auditory Scene Analysis: The Perceptual Organization of Sound*. Cambridge, MA: MIT Press, 1990.

Brower, Candace. "Memory and the Perception of Rhythm." *Music Theory Spectrum* 15, no. 1 (1993): 19–35.

Brown, Judith C. "Determination of the Meter of Musical Scores by Autocorrelation." *Journal of the Acoustical Society of America* 94, no. 4 (1993): 1953–1957.

Brown, Peter F., Vincent J. Della Pietra, Stephen A. Della Pietra, Jennifer C. Lai, and Robert L. Mercer. "An Estimate of an Upper Bound for the Entropy of English." *Computational Linguistics* 18, no. 1 (1992): 31–40.

Bubic, Andreja, D. Yves von Cramon, and Ricarda I. Schubotz. "Prediction, cognition and the brain." *Frontiers in Human Neuroscience* 4 (2010): 1–15.

Bugge, Esben Paul, Kim Lundsteen Juncher, Brian Søborg Mathiasen, and Jakob Grue Simonsen. "Using Sequence Alignment and Voting to Improve Optical Music Recognition From Multiple Recognizers." In *Proceedings of the 12th International Society for Music Information Retrieval Conference (ISMIR 2011)*, 405–410. 2011.

Bunton, Suzanne. "On-Line Stochastic Processes in Data Compression." PhD Dissertation, University of Washington, 1996.

———. "Semantically Motivated Improvements for PPM Variants." *The Computer Journal* 40, nos. 2/3 (1997): 76–93.

Burgoyne, John Ashley. "Stochastic Processes and Database-Driven Musicology." PhD Dissertation, McGill University, 2012.

Burnham, Scott. "Form." In *The Cambridge History of Western Music Theory*, edited by Thomas Christensen, 880–906. Cambridge: Cambridge University Press, 2002.

Burstein, Poundie. "Mid-section Cadences in Haydn's Sonata-Form Movements." *Studia Musicologica* 51, nos. 1-2 (2010): 91–107.

Burstein, Poundie L. "The Half Cadence and Other Such Slippery Events." *Music Theory Spectrum* 36, no. 2 (2014): 203–227.

Butler, David. "Describing the Perception of Tonality in Music: A Critique of the Tonal Hierarchy Theory and a Proposal for a Theory of Intervallic Rivalry." *Music Perception* 6, no. 3 (1989): 219–42.

Byros, Vasili. "Foundations of Tonality as Situated Cognition, 1730–1830." PhD Dissertation, Yale University, 2009.

———. "Meyer's Anvil: Revisiting the Schema Concept." *Music Analysis* 31, no. 3 (2012): 273–346.

Caplin, William E. *Classical Form: A Theory of Formal Functions for the Instrumental Music of Haydn, Mozart, and Beethoven*. New York: Oxford University Press, 1998.

———. “Harmonic Variants of the Expanded Cadential Progression.” In *A Composition as Problem II: Proceedings of the Second International Estonian Music Theory Conference*, edited by M. Humal, 49–71. Tallinn: Estonian Academy of Music, 2000.

———. “Harmony and Cadence in Gjerdingen’s "Prinner",” edited by Markus Neuwirth and Pieter Bergé, 17–57. Leuven, Belgium: Leuven University Press, 2015.

———. “Schoenberg’s ’Second Melody’, or, ’Meyer-ed’ in the Bass.” In *Communication in Eighteenth-Century Music*, edited by Danuta Mirka and Kofi Agawu, 160–186. Cambridge, UK: Cambridge University Press, 2008.

———. “Teaching Classical Form: Strict Categories versus Flexible Analyses.” *Tijdschrift voor Muziektheorie (Dutch Journal of Music Theory)* 18, no. 3 (2013): 119–135.

———. “The Classical Cadence: Conceptions and Misconceptions.” *Journal of the American Musicological Society* 57, no. 1 (2004): 51–118.

———. “The Classical Sonata Exposition: Cadential Goals and Form-Functional Plans.” *Tijdschrift voor muziektheorie (Dutch Journal of Music Theory)* 6, no. 3 (2001): 195–209.

———. “The "Expanded Cadential Progression": A Category for the Analysis of Classical Form.” *Journal of Musicological Research* 7 (1987): 215–257.

———. “Theories of Musical Rhythm in the 18th and 19th Centuries.” In *The Cambridge History of Western Music Theory*, edited by Thomas Christensen, 657–694. Cambridge, UK: Cambridge University Press, 2002.

———. “William Caplin Responds.” *Intersections: Canadian Journal of Music* 31, no. 1 (2010): 67–76.

Caplin, William E., James Hepokoski, and James Webster. *Musical Form, Forms, and Formenlehre: Three Methodological Reflections*. Edited by Pieter Bergé. Leuven, Belgium: Leuven University Press, 2009.

Carlsen, James C. “Some Factors Which Influence Melodic Expectancy.” *Psychomusicology* 1, no. 1 (1981): 12–29.

Carlsen, James C., Pierre I. Divenyi, and Jack A. Taylor. “A Prelimary Study of Perceptual Expectancy in Melodic Configurations.” *Bulletin of the Council for Research in Music Education* 22 (1970): 4–12.

Casella, Alfredo. *The Evolution of Music throughout the History of the Perfect Cadence*. London, UK: Chester, 1924.

Casey, Michael A., Remco C. Veltkamp, Masataka Goto, Marc Leman, Christophe Rhodes, and Malcolm Slaney. “Content-Based Music Information Retrieval: Current Directions and Future Challenges.” *Proceedings of the IEEE* 96, no. 4 (2008): 668–696.

Chuen, Lorraine, David Sears, and Stephen McAdams. “Psychophysiological Responses to Auditory Change.” *Psychophysiology*, 2016. doi:10.1111/psyp.12633.

Clark, Andy. “Whatever next? Predictive brains, situated agents, and the future of cognitive science.” *Behavioral and Brain Sciences* 36, no. 3 (2013): 1–73.

Cleary, John G., and W. J. Teahan. “Unbounded Length Contexts for PPM.” *The Computer Journal* 40, nos. 2/3 (1997): 67–75.

Cleary, John G., and Ian H. Witten. “Data Compression Using Adaptive Coding and Partial String Matching.” *IEEE Transactions on Communications* 32, no. 4 (1984): 396–402.

Clifford, Robert. “Perennial Questions.” *Tempo* 59, no. 234 (2005): 29–33.

Cohen, Barry H. *Explaining Psychological Statistics*. Hoboken, NJ: John Wiley & Sons, Inc., 2008.

Collins, Tom, Barbara Tillmann, Frederick S. Barrett, Charles Delbé, and Petr Janata. “A Combined Model of Sensory and Cognitive Representations Underlying Tonal Expectations in Music: From Audio Signals To Behavior.” *Psychological Review* 121, no. 1 (2014): 33–65.

Cone, Edward T. “Conversations with Roger Sessions.” *Perspectives of New Music* 4, no. 2 (1966): 29–46.

Conklin, Darrell. “Modelling and Generating Music Using Multiple Viewpoints.” In *Proceedings of the First Workshop on Artificial Intelligence and Music*, 125–137. St. Paul, MN, 1988.

———. “Prediction and Entropy of Music.” MA Thesis, University of Calgary, 1990.

Conklin, Darrell. "Representation and Discovery of Vertical Patterns in Music." In *Music and Artifical Intelligence: Proc. ICMAI 2002*, edited by Christina Anagnostopoulou, Miguel Ferrand, and Alan Smaill, 2445:32–42. Springer-Verlag, 2002.

Conklin, Darrell, and Ian H. Witten. "Multiple Viewpoint Systems for Music Prediction." *Journal of New Music Research* 24, no. 1 (1995): 51–73.

Cook, Nicholas. "Methods for Analysing Recordings." In *The Cambridge Companion to Recorded Music*, edited by Nicholas Cook, Eric Clarke, Daniel Leech-Wilkinson, and John Rink, 221–246. Cambridge: Cambridge University Press, 2009.

Cooper, Grosvenor, and Leonard Meyer. *The Rhythmic Structure of Music*. Chicago: The University of Chicago Press, 1960.

Corrigall, Kathleen A., and Laurel J. Trainor. "Musical Enculturation in Preschool Children: Acquisition of Key and Harmonic Knowledge." *Music Perception* 28, no. 2 (2010): 195–200.

Costa-Giomi, Eugenia. "Young Children's Harmonic Perception." *Annals of the New York Academy of Sciences* 999, no. 1 (2003): 477–484.

Cuddy, Lola L., Annabel J. Cohen, and D. J. K. Mewhort. "Perception of Structure in Short Melodic Sequences." *Journal of Experimental Psychology: Human Perception and Performance* 7, no. 4 (1981): 869–883.

Cuddy, Lola L., and Carole A. Lunney. "Expectancies Generated By Melodic Intervals: Perceptual Judgments of Melodic Continuity." *Perception and Psychophysics* 57, no. 4 (1995): 451–462.

Cudworth, Charles L. "Cadence Galante: The Story of a Cliché." *The Monthly Musical Record* 79 (1949): 176–178.

Curtis, Meagan E., and Jamshed J. Bharucha. "Memory and Musical Expectation for Tones in Cultural Context." *Music Perception* 26, no. 4 (2009): 365–375.

Cuthbert, Michael Scott, and Christopher Ariza. "music21: A Toolkit for Computer-Aided Musicology and Symbolic Music Data." In *11th International Society for Music Information Retrieval Conference*, 637–642. 2010.

Dack, James. "Sacred Music." In *The Cambridge Companion to Haydn*, edited by Caryl Clark. Cambridge: Cambridge University Press, 2005.

Darwin, Christopher J., and Michael T. Turvey. "An Auditory Analogue of the Sperling Partial Report Procedure: Evidence for Brief Auditory Storage." *Cognitive Psychology* 3 (1972): 255–267.

DiCiccio, Thomas J., and Bradley Efron. "Bootstrap Confidence Intervals." *Statistical Science* 11, no. 3 (1996): 189–228.

Diergarten, Felix. "'The True Fundamentals of Composition': Haydn's Partimento Counterpoint." *Eighteenth Century Music* 8, no. 1 (2011): 53–75.

Dietterich, Thomas G. "Approximate Statistical Tests for Comparing Supervised Classification Learning Algorithms." *Neural Computation* 10, no. 7 (1998): 1895–1923.

Dixon, Peter. "Models of Accuracy in Repeated-Measures Designs." *Journal of Memory and Language* 59 (2008): 447–456.

Dowling, W. Jay. "Scale and Contour: Two Components of a Theory of Memory for Melodies." *Psychological Review* 85, no. 4 (1978): 341–354.

———. "The Importance of Interval Information in Long-Term Memory for Melodies." *Psychomusicology* 1 (1981): 30–49.

Dowling, W. Jay, and Dane L. Harwood. *Music Cognition*. New York: Academic, 1986.

Downie, J. Stephen. "Evaluating a Simple Approach to Music Information Retrieval: Conceiving Melodic N-Grams as Text." PhD Dissertation, The University of Western Ontario, 1999.

———. "Music Information Retrieval." Chap. 7 in *Annual Review of Information Science and Technology*, edited by Blaise Cronin, 295–340. Medford, NJ: Information Today, 2003.

Duane, Ben. "Agency and Information Content in Eighteenth- and Early Nineteenth-Century String-Quartet Expositions." *Journal of Music Theory* 56, no. 1 (2012): 87–120.

———. "Texture in Eighteenth- and Early Nineteenth-Century String-Quartet Expositions." PhD Dissertation, Northwestern University, 2012.

Dunsby, Jonathan. “Schoenberg on Cadence.” *Journal of the Arnold Schoenberg Institute* 4, no. 1 (1980): 41–49.

Ebbinghaus, Hermann. *On Memory: A Contribution to Experimental Psychology*. New York: Teachers College, Columbia University, 1885/1913.

Eberlein, Roland. “A Method of Analysing Harmony, based on Interval Patterns or “Gestalten?” In *Music, Gestalt, and Computing*, edited by Marc Leman, 1317:225–236. Lecture Notes in Computer Science. Springer Berlin / Heidelberg, 1997.

Eberlein, Roland, and Jobst Fricke. *Kadenzwahrnehmung und Kadenzgeschichte: ein Beitrag zu einer Grammatik der Musik*. Frankfurt/M.: P. Lang, 1992.

Eerola, Tuomas. “The Dynamics of Musical Expectancy: Cross-Cultural and Statistical Approaches to Melodic Expectations.” PhD Dissertation, University of Jyväskylä, 2004.

Eerola, Tuomas, and Carol L. Krumhansl. “Real-Time Prediction of Melodies: Continuous Predictability Judgments and Dynamic Models.” In *Proceedings of the Seventh International Conference on Music Perception and Cognition*, edited by Catherine Stevens, Denis Burnham, Gary McPherson, Emery Schubert, and James Renwick, 473–476. Adelaide, Australia: Causal Productions, 2002.

Eerola, Tuomas, and Petri Toiviainen. *MIDI Toolbox: MATLAB Tools for Music Research*, 2004.

———. “MIR in Matlab:The MIDI Toolbox.” In *Proceedings of the 5th International Conference on Music Information Retrieval (ISMIR)*, 22–27. 2004.

Efron, Bradley, and Robert J. Tibshirani. *An Introduction to the Bootstrap*. London, UK: Chapman & Hall, 1993.

Egermann, Hauke, Marcus T. Pearce, Geraint A. Wiggins, and Stephen McAdams. “Probabilistic Models of Expectation Violation Predict Psychophysiological Emotional Responses to Live Concert Music.” *Cognitive, Affective, and Behavioral Neuroscience* 13, no. 2 (2013).

Escoffier, Nicolas, and Barbara Tillmann. “The Tonal Function of a Task-Irrelevant Chord Modulates Speed of Visual Processing.” *Cognition* 107, nos. 1070–1083 (2008).

Felsenstein, Joseph. *Inferring Phylogenies*. Sunderland, MA: Sinauer Associates, 2004.

Ferguson, George A., and Yoshio Takane. *Statistical Analysis in Psychology and Education*. Sixth. Toronto, ON: McGraw-Hill, 2005.

Fisher, Ronald A. *Statistical methods, experimental design, and scientific inference*. Oxford: Oxford University Press, 1990.

———. *The design of experiments*. 8th. New York, NY: Hafner Publishing Company, 1971.

Forster, Kenneth I., and Michael E. J. Masson. "Special Issue: Emerging Data Analysis." *Journal of Memory and Language* 59, no. 4 (2008): 387–556.

Fox, John, and Sanford Weisberg. *An R Companion to Applied Regression*. 2nd. Thousand Oaks, CA: Sage, 2011.

Fraisse, Paul. "Rhythm and Tempo." In *The Psychology of Music*, edited by Diana Deutsch, 149–180. New York: Academy Press, 1982.

Friston, Karl. "A theory of cortical responses." *Philosophical Transactions of the Royal Society, London, Series B* 360 (2005): 815–836.

———. "The free energy principle: a unified brain theory?" *Nature Reviews Neuroscience* 11 (2010): 127–138.

Garner, Wendell R. "Good Patterns Have Few Alternatives: Information Theory's Concept of Redundancy Helps in Understanding the Gestalt Concept of Goodness." *American Scientist* 58, no. 1 (1970): 34–42.

———. *The Processing of Information and Structure*. Potomac, MD: Lawrence Erlbaum, 1974.

Gascuel, Olivier. "A Note on Sattath and Tversky's, Saitou and Nei's, and Studier and Keppler's Algorithms for Inferring Phylogenies from Evolutionary Distances." *Molecular Biology and Evolution* 11, no. 6 (1994): 961–963.

Gati, Itamar, and Amos Tversky. "Weighting Common and Distinctive Features in Perceptual and Conceptual Judgments." *Cognitive Psychology* 16, no. 3 (1984): 341–370.

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

Gjerdingen, Robert O. “Categorization of Musical Patterns by Self-Organizing Neuronlike Networks.” *Music Perception* 7, no. 4 (1990): 339–370.

———. “Courtly Behaviors.” *Music Perception* 13, no. 3 (1996): 365–382.

———. “Defining a Prototypical Utterance.” *Psychomusicology* 10, no. 2 (1991): 127–139.

———. “"Historically Informed" Corpus Studies.” *Music Perception* 31, no. 3 (2014): 192–204.

———. “Learning Syntactically Significant Temporal Patterns of Chords: A Masking Field Embedded in an ART 3 Architecture.” *Neural Networks* 5 (1992): 551–564.

———. *Music in the Galant Style: Being an Essay on Various Schemata Characteristic of Eighteenth-Century Music*. New York: Oxford University Press, 2007.

———. “The Psychology of Music.” In *The Cambridge History of Western Music Theory*, edited by Thomas Christensen, 956–981. Cambridge: Cambridge University Press, 2002.

———. “Using Connectionist Models to Explore Complex Musical Patterns.” *Computer Music Journal* 13, no. 3 (1989): 67–75.

Gould, Stephen Jay. *Wonderful Life*. New York, NY: W. W. Norton & Company, 1989.

Green, Douglass M. *Form in Tonal Music: An Introduction to Analysis*. 2nd. New York: Holt, Rinehart / Winston, 1979.

Griffiths, Thomas L. “Manifesto for a New (Computational) Cognitive Revolution.” *Cognition* 135 (2015): 21–23.

Guthrie, David, Ben Allison, Wei Liu, Louise Guthrie, and Yorick Wilks. “A Closer Look at Skip-gram Modelling.” In *Proceedings of the 5th International Conference on Language Resources and Evaluation (LREC 06)*, 1222–1225. European Language Resources Association, 2006.

Halekoh, Ulrich, and Søren Højsgaard. “A Kenward-Roger Approximation and Parametric Bootstrap Methods for Tests in Linear Mixed Models – The R Package pbkrtest.” *Journal of Statistical Software* 59, no. 9 (2014).

Hankinson, Andrew. “Optical Music Recognition Infrastructure for Large-Scale Music Document Analysis.” PhD Thesis, McGill University, 2014.

Hansen, Niels Chr., and Marcus T. Pearce. "Predictive Uncertainty in Auditory Sequence Processing." *Frontiers in Psychology* 5 (2014): 1–17. doi:10.3389/fpsyg.2014.1052.

Hard, Bridgette M., Barbara Tversky, and David S. Lang. "Making Sense of Abstract Events: Building Event Schemas." *Memory and Cognition* 34, no. 6 (2006): 1221–1235.

Harter, Courtenay L. "Bridging Common Practice and the Twentieth Century: Cadences in Prokofiev's Piano Sonatas." *Journal of Music Theory Pedagogy* 23 (2009): 57–77.

Hatten, Robert. "Interpreting Deception in Music." *In Theory Only* 12, no. 5 (1992): 31–50.

Hawkins, Jeff, and Sandra Blakeslee. *On Intelligence*. New York, NY: Times Books, 2004.

Heider, Eleanor R. "Universals in Color Naming and Memory." *Journal of Experimental Psychology* 93, no. 1 (1972): 10–20.

Hepokoski, James, and Warren Darcy. *Elements of Sonata Theory: Norms, Types, and Deformations in the Late-Eighteenth-Century Sonata*. New York: Oxford University Press, 2006.

Hiller, Lejaren, and Ramon Fuller. "Structure and Information in Webern's Symphonie, Op. 21." *Journal of Music Theory* 11, no. 1 (1967): 60–115.

Hippel, Paul von. "Questioning a Melodic Archetype: Do Listeners Use Gap-Fill to Classify Melodies?" *Music Perception* 18, no. 2 (2000): 139–153.

Hubert, Lawrence. "Min and Max Hierarchical Clustering Using Asymmetric Similarity Measures." *Psychometrika* 38, no. 1 (1973): 63–72.

Huron, David. "On the Virtuous and the Vexatious in an Age of Big Data." *Music Perception* 31, no. 1 (2013): 4–9.

———. *Sweet Anticipation: Music and the Psychology of Expectation*. Cambridge, MA: MIT Press, 2006.

———. *The Humdrum Toolkit*, 1993. music-cog.ohio-state.edu/Humdrum/index.html.

———. "The New Empiricism: Systematic Musicology in a Postmodern Age." In *The 1999 Ernest Bloch Lectures*. University of California, Berkeley, 1999.

———. "Tone and Voice: A Derivation of the Rules of Voice-Leading from Perceptual Principles." *Music Perception* 19, no. 1 (2001): 1–64.

Huron, David, and Elizabeth Hellmuth Margulis. “Musical Expectancy and Thrills.” In *Handbook of Music and Emotion: Theory, Research, Applications*, edited by Patrick N. Juslin and John Sloboda, 575–604. Oxford, UK: Oxford University Press, 2010.

Huron, David, and Richard Parncutt. “An Improved Model of Tonality Perception Incorporating Pitch Salience and Echoic Memory.” *Psychomusicology* 12, no. 2 (1993): 154–71.

Hutchins, Sean, and Caroline Palmer. “Repetition Priming in Music.” *Psychology of Popular Media Culture* 1(S) (2011): 69–88.

Hyland, Anne. “Rhetorical Closure in the First Movement of Schubert’s Quartet in C Major: A Dialogue with Deformation.” *Music Analysis* 28, no. 1 (2009): 111–42.

Jackson, Roland. “Gesualdo’s Cadences: Innovation Set Against Convention.” In *Musicologia humana: Studies in honor of Warren and Ursula Kirkendale*, 275–289. Firenze, Italy: Leo S. Olschki, 1994.

Jaeger, T. Florian. “Categorical Data Analysis: Away from ANOVAs (Transformation or Not) and Towards Logit Mixed Models.” *Journal of Memory and Language* 59 (2008): 434–446.

James, William. *The Principles of Psychology*. 2 vols. New York: Holt, 1890.

Janata, Petr. “ERP Measures Assay the Difference of Expectancy Violation of Harmonic Contexts in Music.” *Journal of Cognitive Neuroscience* 7, no. 2 (1995): 153–164.

Janata, Petr, and D. Reisberg. “Response-Time Measures as a Means of Exploring Tonal Hierarchies.” *Music Perception* 6, no. 2 (1988): 161–172.

Janata, Petr, Jeffrey L. Birk, John D. Van Horn, Marc Leman, Barbara Tillmann, and Jamshed J. Bharucha. “The Cortical Topography of Tonal Structures Underlying Western Music.” *Science* 298 (2002): 2167–2170.

Johns, Donald. “On the Nature of Cadence.” In *Music in Performance and Society: Essays in Honor of Roland Jackson*, edited by John Koegel and Malcolm S. Cole, 393–410. Warren, MI: Harmonie Park, 1997.

Jonaitis, Erin, and Jenny Saffran. “Learning Harmony: The Role of Serial Statistics.” *Cognitive Science* 33 (2009): 951–968.

Justus, Timothy, and Jamshed Bharucha. "Modularity in Musical Processing: The Automaticity of Harmonic Priming." *Journal of Experimental Psychology: Human Perception and Performance* 27, no. 4 (2001): 1000–1011.

Kahana, Michael Jacob. *Foundations of Human Memory*. New York, NY: Oxford University Press, 2012.

Kim, Seung-Goo, June Sic Kim, and Chun Kee Chung. "The Effect of Conditional Probability of Chord Progression on Brain Response: An MEG Study." *PLoS ONE* 6, no. 2 (2011): 1–9. doi:10.1371/journal.pone.0017337.

Kloepper, Tobias H., and Daniel H. Huson. "Drawing Explicit Phylogenetic Networks and their Integration into SplitsTree." *BMC Evolutionary Biology* 8, no. 22 (2008). doi:10.1186/1471-2148-8-22.

Knopoff, Leon, and William Hutchinson. "Entropy as a Measure of Style: The Influence of Sample Length." *Journal of Music Theory* 27, no. 1 (1983): 75–97.

———. "Information Theory for Musical Continua." *Journal of Music Theory* 25, no. 1 (1981): 17–44.

Koch, Heinrich Christoph. *Introductory Essay on Musical Composition*. Translated by Nancy Kovaleff Baker. New Haven, CT: Yale University press, 1983.

Koelsch, Stefan, and Juul Mulder. "Electric Brain Responses to Inappropriate Harmonies During Listening to Expressive Music." *Clinical Neurophysiology* 113 (2002): 862–869.

Koelsch, Stefan, Schmidt Björn-Helmer Schmidt, and Julia Kansok. "Effects of Musical Expertise on the Early Right Anterior Negativity: An Event-Related Brain Potential Study." *Psychophysiology* 39 (2002): 657–663.

Koelsch, Stefan, Thomas Fritz, Katrin Schulze, David Alsop, and Gottfried Schlaug. "Adults and Children Processing Music: An fMRI Study." *NeuroImage* 25 (2005): 1068–1076.

Koelsch, Stefan, Tomas Gunter, Angela D. Friederici, and Erich Schröger. "Brain Indices of Music Processing: "Nonmusicians" Are Musical." *Journal of Cognitive Neuroscience* 12, no. 3 (2000): 520–541.

Koelsch, Stefan, Tobias Grossmann, Thomas C. Gunter, Anja Hahne, Erich Schröger, and Angela D. Friederici. "Children Processing Music: Electric Brain Responses Reveal Musical Competence and Gender Differences." *Journal of Cognitive Neuroscience* 15, no. 5 (2003): 683–693.

Koelsch, Stefan, Simone Kilches, Nikolaus Steinbeis, and Stefanie Schelinski. "Effects of Unexpected Chords and of Performer's Expression on Brain Responses and Electrodermal Activity." *PLoS ONE* 3, no. 7 (2008): 1–10.

Koelsch, Stefan, S. Jentschke, D. Sammler, and D. Mietchen. "Untangling Syntactic and Sensory Processing: An ERP Study of Music Perception." *Psychophysiology* 44, no. 3 (2007): 476–490.

Krebs, Harald. *Fantasy Pieces: Metrical Dissonance in the Music of Robert Schumann*. New York: Oxford University Press, 1999.

Krumhansl, Carol L. *Cognitive Foundations of Musical Pitch*. New York, NY: Oxford University Press, 1990.

Krumhansl, Carol L., Jamshed J. Bharucha, and Edward J. Kessler. "Perceived Harmonic Structure of Chords in Three Related Musical Keys." *Journal of Experimental Psychology: Human Perception and Performance* 8, no. 1 (1982): 24–36.

Krumhansl, Carol L., and Edward Kessler. "Tracing the Dynamic Changes in Perceived Tonal Organization in a Spatial Representation of Musical Keys." *Psychological Review* 89, no. 4 (1982): 334–368.

Kurby, Chistopher A., and Jeffrey M. Zacks. "Segmentation in the Perception and Memory of Events." *Trends in Cognitive Sciences* 12, no. 2 (2008): 72–79.

Kučera, Henry, and W. Nelson Francis. *Computational Analysis of Present-Day American English*. Providence, RI: Brown University Press, 1967.

Lamont, Alexandra, and Nicola Dibben. "Motivic Structure and the Perception of Similarity." *Music Perception* 18, no. 3 (2001): 245–274.

Larson, Steve. "Continuations as Completions: Studying Melodic Expectations in the Creative Microdomain Seek Well." In *Music, Gestalt, and Computing: Studies in Cognitive and Systematic Musicology*, edited by Marc Leman, 321–334. Berlin: Springer-Verlag, 1997.

Latham, Edward. "Drei Nebensonnen: Forte's Linear-Motivic Analysis, Korngold's Die Tote Stadt, and Schubert's Winterreise as Visions of Closure." *Gamut* 2, no. 1 (2009): 299–345.

Leino, Sakari, Elvira Brattico, Mari Tervaniemi, and Peter Vuust. "Representation of Harmony Rules in the Human Brain: Further Evidence From Event-Related Potentials." *Brain Research* 1142 (2007): 169–177.

Leman, Marc. "An Auditory Model of the Role of Short-Term Memory in Probe-Tone Ratings." *Music Perception* 17, no. 4 (2000): 481–509.

Lenth, Russell V. "lsmeans: Least-Squares Means. R package version 2.00-4.," 2014.

Lerdahl, Fred, and Ray Jackendoff. *A Generative Theory of Tonal Music*. Cambridge, Massachusetts: The MIT Press, 1983.

Lerdahl, Fred, and Carol L. Krumhansl. "Modeling Tonal Tension." *Music Perception* 24, no. 4 (2007): 329–66.

Lewin, David. *Generalised Musical Intervals and Transformations*. New Haven, CT: Yale University Press, 1987.

London, Justin. "Building a Representative Corpus of Classical Music." *Music Perception* 31, no. 1 (2013): 68–90.

———. *Hearing in Time: Psychological Aspects of Musical Meter*. New York: Oxford University Press, 2004.

———. "Rhythm in Twentieth-Century Theory." In *The Cambridge History of Western Music Theory*, edited by Thomas Christensen, 695–725. Cambridge, UK: Cambridge University Press, 2002.

Loui, Psyche. "Acquiring a New Musical System." PhD Dissertation, University of California, Berkeley, 2007.

Loui, Psyche, and David Wessel. "Harmonic Expectation and Affect in Western Music: Effects of Attention and Training." *Perception and Psychophysics* 69, no. 7 (2007): 1084–1092.

Loui, Psyche, Tineke Grent-'t Jong, Dana Torpey, and Marty Woldorff. "Effects of Attention on the Neural Processing of Harmonic Syntax in Western Music." *Cognitive Brain Research* 25 (2005): 678–687.

MacKay, David J. C. *Information Theory, Inference, and Learning Algorithms*. Cambridge, UK: Cambridge University Press, 2003.

Maess, Burkhard, Stefan Koelsch, Thomas C. Gunter, and Angela D. Friederici. "Musical Syntax is Processed in Broca's Area: An MEG Study." *Nature Neuroscience* 4, no. 5 (2001): 540–545.

Malin, Yonatan. *Songs in Motion: Rhythm and Meter in the German Lied*. New York: Oxford University Press, 2010.

Mandler, George. "Organization, Memory, and Mental Structures." In *Memory Organization and Structure*, edited by C. Richard Puff, 303–319. New York, NY: Academic Press, 1979.

Mandler, Jean M. "Categorical and Schematic Organization in Memory." In *Memory Organization and Structure*, edited by C. Richard Puff, 259–299. New York, NY: Academic Press, 1979.

Manning, Christopher D., and Hinrich Schütze. *Foundations of Statistical Natural Language Processing*. Cambridge, MA: MIT Press, 1999.

Margulis, Elizabeth Hellmuth. "A Model of Melodic Expectation." *Music Perception* 22, no. 4 (2005): 663–714.

———. "Aesthetic Responses to Repetition in Unfamiliar Music." *Empirical Studies of the Arts* 31, no. 1 (2013): 45–57.

———. "Melodic Expectation: A Discussion and Model." PhD Dissertation, Columbia University, 2003.

———. "Musical Repetition Detection Across Multiple Exposures." *Music Perception* 29, no. 4 (2012): 377–385.

———. "Surprise and Listening Ahead: Analytic Engagements with Musical Tendencies." *Music Theory Spectrum* 29, no. 2 (2007): 197–217.

Margulis, Elizabeth Hellmuth, and Andrew P. Beatty. "Musical Style, Psychoaesthetics, and Prospects for Entropy as an Analytic Tool." *Computer Music Journal* 32, no. 4 (2008): 64–78.

Margulis, Elizabeth Hellmuth, and William H. Levine. "Timbre Priming Effects and Expectation in Melody." *Journal of New Music Research* 35, no. 2 (2006): 175–182.

Marmel, Frédéric, and Barbara Tillmann. "Tonal Priming Beyond Tonics." *Music Perception* 26, no. 3 (2009): 211–221.

Marmel, Frédéric, Barbara Tillmann, and Charles Delbé. "Priming in Melody Perception: Tracking Down the Strength of Cognitive Expectations." *Journal of Experimental Psychology: Human Perception and Performance* 36, no. 4 (2010): 1016–1028.

Marmel, Frédéric, Barbara Tillmann, and W. Jay Dowling. "Tonal Expectations Influence Pitch Perception." *Perception & Psychophysics* 70, no. 5 (2008): 841–852.

Marsden, Alan. "Interrogating Melodic Similarity: A Definitive Phenomenon or the Product of Interpretation?" *Journal of New Music Research* 41, no. 4 (2012): 323–335.

Marston, Nicholas. "Review of William E. Caplin, Classical Form: A Theory of Formal Functions for the Instrumental Music of Haydn, Mozart, and Beethoven." *Music Analysis* 20, no. 1 (2001): 143–149.

Martin, Frederick N., and Craig A. Champlin. "Reconsidering the Limits of Normal Hearing." *Journal of the American Academy of Audiology* 11 (2000): 64–66.

Martin, Nathan John, and Julie Pedneault-Deslauriers. "The Mozartean Half Cadence." In *What is a cadence? Theoretical and Analytical Perspectives on Cadences in the Classical Repertoire*, edited by Markus Neuwirth and Pieter Bergé, 185–214. Leuven: Leuven University Press, 2015.

Matthews, Max V., John R. Pierce, and Linda A. Roberts. "Harmony and New Scales." In *Harmony and Tonality*, edited by Johan Sundberg, 59–84. Stockholm: Royal Swedish Academy of Music, publ. no. 54, 1987.

McAdams, Stephen. "Psychological Constraints on Form-Bearing Dimensions in Music." *Contemporary Music Review* 4 (1989): 181–198.

McAdams, Stephen, and Carolyn Drake. "Auditory Perception and Cognition." In *Stevens' Handbook of Experimental Psychology*, edited by Hal Pashler and Steven Yantis, vol. 1: Sensation and Perception, 397–452. New York: Wiley, 2002.

McAdams, Stephen, Bradley W. Vines, Sandrine Vieillard, Bennett K. Smith, and Roger Reynolds. "Influences of Large-Scale Form on Continuous Ratings in Response to a Contemporary Piece in a Live Concert Setting." *Music Perception* 22, no. 2 (2004): 297–350.

McKay, Cory, and Ichiro Fujinaga. “Style-Independent Computer-Assisted Exploratory Analysis of Large Music Collections.” *Journal of Interdisciplinary Music Studies* 1, no. 1 (2007): 63–85.

Meriam, Alan P. *The Anthropology of Music*. Evanston, IL: Northwestern University Press, 1964.

Meyer, Charles F. *English Corpus Linguistics: An Introduction*. New York, NY: Cambridge University Press, 2002.

Meyer, Leonard. “A Universe of Universals.” *The Journal of Musicology* 16, no. 1 (1998): 3–25.

Meyer, Leonard B. “Emotion and Meaning in Music.” PhD Dissertation, The University of Chicago, 1954.

———. *Emotion and Meaning in Music*. Chicago: University of Chicago Press, 1956.

———. *Explaining Music: Essays and Explorations*. Berkeley: University of California Press, 1973.

———. “Meaning in Music and Information Theory.” *The Journal of Aesthetics and Art Criticism* 15, no. 4 (1957): 412–424.

———. *Music, the arts, and ideas*. Chicago: The University of Chicago Press, 1967.

———. “Nature, Nurture, and Convention: The Cadential Six-Four Progression.” In *The Spheres of Music*, 226–263. Chicago: The University of Chicago Press, 2000.

———. *Style and Music: Theory, History, and Ideology*. Philadelphia, PA: University of Philadelphia Press, 1989.

———. *The Spheres of Music*. Chicago: The University of Chicago Press, 2000.

Mihaescu, Radu, Dan Levy, and Lior Pachter. “Why Neighbor-Joining Works.” *Algorithmica* 54, no. 1 (2009): 1–24.

Miles, Jeremy, and Mark Shevlin. *Applying Regression and Correlation*. London: Sage Publications, 2001.

Miller, George. “The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information.” *Psychological Review* 63 (1956): 81–97.

Minsky, Marvin. “A Framework for Representing Knowledge.” In *The Psychology of Computer Vision*, edited by P. H. Winston, 211–277. New York: McGraw-Hill, 1975.

Miranda, Robbin A., and Michael T. Ullman. "Double Dissociation Between Rules and Memory in Music: An Event-Related Potential Study." *Neuroimage* 38, no. 2 (2007): 331–345.

Mirka, Danuta. "Absent Cadences." *Eighteenth Century Music* 9, no. 2 (2012): 213–235.

Müllensiefen, Daniel, and Marc Pendzich. "Court Decisions on Music Plagiarism and the Predictive Value of Similarity Algorithms." *Musicae Scientiae* Discussion Forum 4B (2009): 257–295.

Müller, Mira, Lea Höfel, Elvira Brattico, and Thomas Jacobsen. "Aesthetic Judgments of Music in Experts and Laypersons—An ERP Study." *International Journal of Psychophysiology* 76 (2010): 40–51.

Moffat, Alistair. "Implementing the PPM Data Compression Scheme." *IEEE Transactions on Communications* COM-38, no. 11 (1990): 1917–1921.

Narmour, Eugene. "Analyzing Form and Measuring Perceptual Content in Mozart's Sonata K. 282: A New Theory of Parametric Analogues." *Music Perception* 13, no. 3 (1996): 265–318.

———. *Beyond Schenkerism*. Chicago: The University of Chicago Press, 1977.

———. *The Analysis and Cognition of Basic Melodic Structures: The Implication-Realization Model*. Chicago, IL: University of Chicago Press, 1990.

———. *The Analysis and Cognition of Melodic Complexity: The Implication-Realization Model*. Chicago, IL: University of Chicago Press, 1992.

Neely, James H. "Semantic Priming and Retrieval from Lexical Memory: Evidence for Facilitatory and Inhibitory Processes." *Memory & Cognition* 4, no. 5 (1976): 648–654.

———. "Semantic Priming and Retrieval from Lexical Memory: Roles of Inhibitionless Spreading Activation and Limited-Capacity Attention." *Journal of Experimental Psychology: General* 106, no. 3 (1977): 226–254.

Neisser, Ulric. *Cognition and Reality*. San Francisco: W. H. Freeman / Company, 1976.

———. *Cognitive Psychology*. New York, NY: Taylor & Francis, 1967/2014.

Nettheim, Nigel. "A Bibliography of Statistical Applications in Musicology." *Musicology Australia* 20 (1997): 94–106.

Neuwirth, Markus. "Fuggir la cadenza, or the Art of Avoiding Cadential Closure: Physiognomy and Functions of Deceptive Cadences in the Classical Repertoire." In *What is a Cadence? Theoretical and Analytical Perspectives on Cadences in the Classical Repertoire*, edited by Markus Neuwirth and Pieter Bergé, 117–156. Leuven, Belgium: Leuven University Press, 2015.

———. "Recomposed Recapitulations in the Sonata-Form Movements of Joseph Haydn and his Contemporaries." PhD Dissertation, Leuven University, 2013.

Noorden, Leon van. "Temporal Coherence in the Perception of Tone Sequences." PhD Dissertation, Institute for Perception Research, 1975.

Okada, Akinori. "An Asymmetric Cluster Analysis Study of Car Switching Data." In *Data Analysis: Studies in Classification, Data Analysis, and Knowledge Organization*, edited by Wolfgang Gaul, Otto Opitz, and Martin Schader, 495–504. Berlin, Germany: Springer Berlin Heidelberg, 2000.

Okada, Akinori, and Takeyoshi Iwamoto. "University Enrollment Flow Among the Japanese Prefetures." *Behaviormetrika* 23, no. 2 (1996): 169–185.

Omigie, Diana, Marcus T. Pearce, and Lauren Stewart. "Tracking of pitch probabilities in congenital amusia." *Neuropsychologia* 50 (2012): 1483–1493.

Omigie, Diana, Marcus T. Pearce, Victoria J. Williamson, and Lauren Stewart. "Electrophysiological correlates of melodic processing in congenital amusia." *Neuropsychologia* 51 (2013): 1749–1762.

Otsuka, Asuka, Shinya Kuriki, Noboru Murata, and Toshikazu Hasegawa. "Neuromagnetic Responses to Chords are Modified by Preceding Musical Scale." *Neuroscience Research* 60 (2008): 50–55.

Palmer, Caroline, and Carol L. Krumhansl. "Mental Representations for Musical Meter." *Journal of Experimental Psychology: Human Perception and Performance* 16, no. 4 (1990): 728–41.

Parncutt, Richard. "A Perceptual Model of Pulse Salience and Metrical Accent in Musical Rhythms." *Music Perception* 11, no. 4 (1994): 409–464.

———. *Harmony: A Psychoacoustical Approach*. Berlin: Springer-Verlag, 1989.

Parncutt, Richard, and Albert S. Bregman. "Tone Profiles Following Short Chord Progressions: Top-Down or Bottom-Up?" *Music Perception* 18, no. 1 (2000): 25–57.

Patel, Aniruddh D., Edward Gibson, Jennifer Ratner, Mireille Besson, and Phillip J. Holcomb. "Processing Syntactic Relations in Language and Music: An Event-Related Potential Study." *Journal of Cognitive Neuroscience* 10, no. 6 (1998): 717–733.

Pearce, Marcus T. "The Construction and Evaluation of Statistical Models of Melodic Structure in Music Perception and Composition." PhD Dissertation, City University, London, 2005.

Pearce, Marcus T., Darrell Conklin, and Geraint A. Wiggins. "Methods for Combining Statistical Models of Music." In *Computer Music Modelling and Retrieval*, edited by U. K. Wiil, 295–312. Heidelberg, Germany: Springer Verlag, 2005.

Pearce, Marcus T., Daniel Müllensiefen, and Geraint A. Wiggins. "The Role of Expectation and Probabilistic Learning in Auditory Boundary Perception: A Model Comparison." *Perception* 39 (2010): 1367–1391.

Pearce, Marcus T., and Geraint A. Wiggins. "Auditory Expectation: The Information Dynamics of Music Perception and Cognition." *Topics in Cognitive Science* 4 (2012): 625–652.

———. "Expectation in Melody: The Influence of Context and Learning." *Music Perception* 23, no. 5 (2006): 377–405.

———. "Improved Methods for Statistical Modelling of Monophonic Music." *Journal of New Music Research* 33, no. 4 (2004): 367–385.

Pearce, Marcus T., María Herrojo Ruiz, Selina Kapasi, Geraint A. Wiggins, and Joydeep Bhattacharya. "Unsupervised Statistical Learning Underpins Computational, Behavioural, and Neural Manifestations of Musical Expectation." *NeuroImage* 50 (2010): 302–313.

Peebles, Crystal. "The Role of Segmentation and Expectation in the Perception of Closure." Dissertation, Florida State University, 2011.

Pinkerton, Richard C. "Information Theory and Melody." *Scientific American* 194, no. 2 (1956): 77–86.

Piston, Walter. *Harmony*. Third. New York, NY: W. W. Norton & Company, 1962.

Plomp, Reinier, and Willem J. M. Levelt. “Tonal Consonance and Critical Bandwidth.” *Journal of the Acoustical Society of America* 38, no. 4 (1965): 548–560.

Posner, Michael I. “Empirical Studies of Prototypes.” In *Noun Classes and Categorization*, edited by Colette Craig, 53–61. Amsterdam: John Benjamin, 1986.

Potter, Keith, Geraint A. Wiggins, and Marcus T. Pearce. “Towards greater objectivity in music theory: Information-dynamic analysis of minimalist music.” *Musicae Scientiae* 11, no. 2 (2007): 295–324.

Poulin-Charronnat, Benedicte, and Emmanuel Bigand. “The Influence of Voice Leading on Harmonic Priming.” *Music Perception* 22, no. 4 (2005): 613–627.

Quené, Hugo, and Huub van den Bergh. “Examples of Mixed-Effects Modeling with Crossed Random Effects and with Binomial Data.” *Journal of Memory and Language* 59 (2008): 413–425.

Quinn, Ian. “Are Pitch-Class Profiles Really Key for Key.” *Zeitschrift der Gesellschaft der Musiktheorie* 7 (2010): 151–163.

———. “Fuzzy Extensions to the Theory of Contour.” *Music Theory Spectrum* 19, no. 2 (1997): 232–263.

———. “General Equal-Tempered Harmony (Introduction and Part I).” *Perspectives of New Music* 44, no. 2 (2006): 114–158.

———. “General Equal-Tempered Harmony: Parts 2 and 3.” *Perspectives of New Music* 45, no. 1 (2007): 4–63.

———. “Listening to Similarity Relations.” *Perspectives of New Music* 39, no. 2 (2001): 108–158.

Quinn, Ian, and Panayotis Mavromatis. “Voice-Leading Prototypes and Harmonic Function in Two Chorale Corpora.” In *Mathematics and Computation in Music*, edited by Carlos Agon, Moreno Andreatta, Gérard Assayag, Emmanuel Amiot, Jean Bresson, and John Mandereau, 230–240. Heidelberg: Springer, 2011.

Rameau, Jean-Phillippe. *Treatise on Harmony*. Translated by Phillip Gossett. New York: Dover, 1971. Originally published as *Traité l’harmonie* (Paris: Ballard, 1722).

Randel, Don. "Emerging Triadic Tonality in the Fifteenth Century." *The Musical Quarterly* 57, no. 1 (1971): 73–86.

Ratner, Leonard G. *Classic Music: Expression, Form, and Style*. New York: Schirmer Books, 1980.

———. *Harmony: Structure and style*. New York: McGraw-Hill, 1962.

Ratz, Erwin. *Einführung in die musikalische Formenlehre: Über Formprizipien in den Inventionen und Fugen J. S. Bachs und ihre Bedeutung für die Kompositionstechik Beethovens*. 3rd. Vienna: Universal, 1973.

Reber, Arthur S. "Implicit Learning and Tacit Knowledge." *Journal of Experimental Psychology: General* 118, no. 3 (1989): 219–235.

———. *Implicit Learning and Tacit Knowledge: An Essay on the Cognitive Unconscious*. Oxford: Oxford University Press, 1993.

———. "Implicit Learning of Artificial Grammars." MA Thesis, Brown University, 1965.

———. "Implicit Learning of Artificial Grammars." *Journal of Verbal Learning and Verbal Behavior* 6 (1967): 855–863.

———. "The Cognitive Unconscious: An Evolutionary Perspective." *Consciousness and Cognition* 1, no. 2 (1992): 93–133.

Richards, Mark. "Closure in Classical Themes: The Role of Melody and Texture in Cadences, Closural Function, and the Separated Cadence." *Intersections: Canadian Journal of Music* 31, no. 1 (2010): 25–45.

Rockstro, William S. "Cadence." In *Grove's Dictionary of Music and Musicians*, edited by J. A. Fuller Maitland, 1:434–441. London, 1908-1910.

Rockstro, William S., George Dyson, William Drabkin, Harold S. Powers, and Julian Rushton. *Cadence*, 2001.

Roese, Neal J., and Jeffrey W. Sherman. "Expectancy." In *Social Psychology: Handbook of Basic Principles*, 2nd, edited by Arie W. Kruglanski and E. Tory Higgins, 91–115. New York, NY: The Guilford Press, 2013.

Rohrmeier, Martin, and Ian Cross. "Statistical Properties of Tonal Harmony in Bach's Chorales." In *Proceedings of the 10th International Conference on Music Perception and Cognition (ICMPC)*, 619–627. Sapporo, Japan, 2008.

Rohrmeier, Martin, Patrick Rebuschat, and Ian Cross. "Incidental and Online Learning of Melodic Structure." *Consciousness and Cognition* 20 (2011): 214–222.

Rosch, Eleanor. "Cognitive Reference Points." *Cognitive Psychology* 7 (1975): 532–547.

———. "Principles of Categorization." In *Cognition and Categorization*, edited by E. Rosch and B. B. Lloyd, 28–48. Hillsdale, NJ: Erlbaum, 1978.

Rosch, Eleanor, and Carolyn B. Mervis. "Family Resemblances: Studies in the Internal Structure of Categories." *Cognitive Psychology* 7 (1975): 573–605.

Rosch, Eleanor H. "Natural Categories." *Cognitive Psychology* 4 (1973): 328–350.

Rosner, Burton, and Eugene Narmour. "Harmonic Closure: Music Theory and Perception." *Music Perception* 9, no. 4 (1992): 383–412.

Rothstein, William. *Phrase Rhythm in Tonal Music*. New York: Schirmer Books, 1989.

Rumelhart, David E. "Notes on a Schema for Stories." In *Representation and Understanding: Studies in Cognitive Science*, edited by Daniel G. Bobrow and Allan M. Collins, 211–236. New York: Academic Press, 1975.

———. "Schemata: The Building Blocks of Cognition." In *Theoretical Issues in Reading Comprehension*, edited by Rand J. Spiro, Bertram C. Bruce, and William F. Brewer, 33–58. Hillsdale, NJ: Erlbaum, 1980.

Rumelhart, David E., and Andrew Ortony. "The Representation of Knowledge in Memory." In *Schooling and the Acquisition of Knowledge*, edited by Richard C. Anderson, Rand J. Spiro, and William E. Mongague, 99–135. Hillsdale, NJ: Erlbaum, 1977.

Saitou, Naruya, and Masatoshi Nei. "The Neighbor-Joining Method: A New Method for Reconstructing Phylogenetic Trees." *Molecular Biology and Evolution* 4, no. 4 (1987): 406–425.

Sanguinetti, Giorgio. *The Art of Partimento: History, Theory, and Practice*. Oxford, UK: Oxford University Press, 2012.

Sattath, Shmuel, and Amos Tversky. "Additive Similarity Trees." *Psychometrika* 42, no. 3 (1977): 319–345.

Schank, Roger C., and Robert P. Abelson. *Scripts, Plans, Goals and Understanding: An Enquiry into Human Knowledge Structures*. Hillsdale, NJ: Erlbaum, 1977.

Schellenberg, E. Glenn. "Expectancy in Melody: Tests of the Implication-Realization Model." *Cognition* 58 (1996): 75–125.

———. "Simplifying the Implication-Realization Model of Melodic Expectancy." *Music Perception* 14, no. 3 (1997): 295–318.

Schellenberg, E. Glenn, Emmanuel Bigand, Benedicte Poulin-Charronnat, and Catherine Stevens. "Children's Implicit Knowledge of Western Music." *Developmental Science* 8, no. 6 (2005): 551–566.

Schmalfeldt, Janet. "Cadential Processes: The Evaded Cadence and the 'One More Time' Technique." *Journal of Musicological Research* 12, no. 1 (1992): 1–52.

———. *In the Process of Becoming: Analytic and Philosophical Perspectives on Form in Early Nineteenth-Century Music*. New York: Oxford University Press, 2011.

Schmuckler, Mark A. "Expectancy Effects in Memory for Melodies." *Canadian Journal of Experimental Psychology* 51, no. 4 (1997): 292–306.

———. "Expectation in Music: Additivity of Melodic and Harmonic Processes." PhD Dissertation, Cornell University, 1988.

———. "Expectation in Music: Investigation of Melodic and Harmonic Processes." *Music Perception* 7, no. 2 (1989): 109–150.

Schoenberg, Arnold. *Fundamentals of Musical Composition*. London: Faber & Faber, 1967.

———. *Harmonielehre*. Translated by Roy Carter. Berkeley and Los Angeles, CA: University of California Press, 1978.

———. *The Musical Idea and the Logic, Technique, and Art of Its Presentation*. Translated by Patricia Carpenter and Severine Neff. New York: Columbia University Press, 1995.

Sears, David. "The Perception of Cadential Closure." In *What is a Cadence? Theoretical and Analytical Perspectives on Cadences in the Classical Repertoire*, edited by Markus Neuwirth and Pieter Bergé, 251–283. Leuven: Leuven University Press, 2015.

Sears, David, William E. Caplin, and Stephen McAdams. "Perceiving the Classical Cadence." *Music Perception* 31, no. 5 (2014): 397–417.

Selfridge-Field, Eleanor, ed. *Beyond MIDI: The Handbook of Musical Codes*. Cambridge, MA: MIT Press, 1997.

Sethares, William A. "Consonace-Based Spectral Mappings." *Computer Music Journal* 22, no. 1 (1998): 56–72.

Shannon, Claude. "A Mathematical Theory of Communication." *Bell System Technical Journal* 27, no. 3 (1948): 379–423.

Shannon, Claude E. "Prediction and Entropy of Printed English." *Bell System Technical Journal* 30 (1951): 50–64.

Simons, M., H. Ney, and S. C. Martin. "Distant Bigram Language Modeling Using Maximum Entropy." In *Proceedings of the International Conference on Acoustics, Speech and Signal Processing*, 787–790. Washington, DC: IEEE Computer Society Press, 1997.

Simonton, Dean. "Computer Content Analysis of Melodic Structure: Classical Composers and Their Compositions." *Psychology of Music* 22, no. 1 (1994): 31–43.

———. "Melodic Structure and Note Transition Probabilities: A Content Analysis of 15,618 Classical Themes." *Psychology of Music* 12, no. 3 (1984): 3–16.

Sloboda, John A. *The musical mind: The cognitive psychology of music*. Oxford, UK: Oxford University Press, 1985.

Smith, Bennett K. "PsiExp: An Environment for Psychoacoustic Experimentation using the IRCAM Musical Workstation." *Paper presented at the Society for Music Perception and Cognition*, 1995, Berkeley, CA.

Sneath, Peter H. A., and Robert R. Sokal. *Numerical Taxonomy: The Principles and Practice of Numerical Classification*. San Francisco, CA: Freeman, 1973.

Snyder, Bob. *Music and Memory: An Introduction*. Cambridge, MA: The MIT Press, 2000.

Snyder, John L. "Entropy as a Measure of Musical Style: The Influence of A Priori Assumptions." *Music Theory Spectrum* 12, no. 1 (1990): 121–160.

Spitzer, Mark. "The Retransition as Sign: Listener-Oriented Approaches to Tonal Closure in Haydn's Sonata-form Movements." *Journal of the Royal Musical Association* 121, no. 1 (2000): 11–45.

Squire, Larry R. "Mechanisms of Memory." *Science* 232, no. 4758 (1986): 1612–1619.

Stefanowitsch, Anatol, and Stefan Th. Gries. "Collostructions: Investigating the Interaction of Words and Constructions." *International Journal of Corpus Linguistics* 8 (2003): 209–243.

Steinbeis, Nikolaus, Stefan Koelsch, and John A. Sloboda. "The Role of Harmonic Expectancy Violations in Musical Emotions: Evidence from Subjective, Physiological, and Neural Responses." *Journal of Cognitive Neuroscience* 18, no. 8 (2006): 1380–1393.

Studier, James A., and Karl J. Keppler. "A Note on the Neighbor-Joining Algorithm of Saitou and Nei." *Molecular Biology and Evolution* 5, no. 6 (1988): 729–731.

Takeuchi, Akinobu, Takayuki Saito, and Hiroshi Yadohisa. "Asymmetric Agglomerative Hierarchical Clustering Algorithms and Their Evaluations." *Journal of Classification* 24 (2007): 123–143.

Takumi, Satoshi, and Sadaaki Miyamoto. "Top-down vs Bottom-up Methods of Linkage for Asymmetric Agglomerative Hierarchical Clustering." In *International Conference on Granular Computing*, 459–464. IEEE, 2012.

Tan, Norma, Rita Aiello, and Thomas G. Bever. "Harmonic Structure as a Determinant of Melodic Organization." *Memory and Cognition* 9, no. 5 (1981): 533–539.

Tekman, Hasan Gürkan, and Jamshed J. Bharucha. "Implicit Knowledge Versus Psychoacoustic Similarity in Priming of Chords." *Journal of Experimental Psychology: Human Perception and Performance* 24, no. 1 (1998): 252–260.

Temperley, David. "Pitch-Class Distribution and the Identification of Key." *Music Perception* 25, no. 3 (2008): 193–212.

———. "Review of Music in the Galant Style." *Journal of Music Theory* 50, no. 2 (2006): 277–290.

Temperley, David. "What's Key for Key? The Krumhansl-Schmuckler Key-Finding Algorithm Reconsidered." *Music Perception* 17, no. 1 (1999): 65–100.

Temperley, David, and Leigh VanHandel. "Introduction to the Special Issue on Corpus Methods." *Music Perception* 31, no. 1 (2013): 1–3.

Tenenbaum, Joshua B., Charles Kemp, Thomas L. Griffiths, and Noah D. Goodman. "How to Grow a Mind: Statistics, Structure, and Abstraction." *Science* 331 (2011): 1279–1285.

Terhardt, Ernst. "Pitch, Consonance, and Harmony." *Journal of the Acoustical Society of America* 55 (1974): 1061–1069.

Terhardt, Ernst, Gerhard Stoll, and Manfred Seewann. "Algorithm for Extraction of Pitch and Pitch Salience from Complex Tonal Signals." *Journal of the Acoustical Society of America* 71, no. 3 (1982): 679–688.

———. "Pitch of Complex Signals According to Virtual-Pitch Theory: Tests, Examples, and Predictions." *Journal of the Acoustical Society of America* 71 (1982): 671–678.

Tillmann, Barbara, Jamshed J. Bharucha, and Emmanuel Bigand. "Implicit Learning of Tonality: A Self-organizing Approach." *Psychological Review* 107, no. 4 (2000): 885–913.

Tillmann, Barbara, and Emmanuel Bigand. "A Comparative Review of Priming Effects in Language and Music." In *Language, Vision and Music*, edited by Paul McKevitt, Seán Ó Nualláin, and Conn Mulvihill, 231–240. Amsterdam, John Benjamins, 2002.

———. "Global Context Effect in Normal and Scrambled Musical Sequences." *Journal of Experimental Psychology: Human Perception and Performance* 27, no. 5 (2001): 1185–1196.

———. "Musical Priming: Schematic Expectations Resist Repetition Priming." In *Proceedings of the 8th International Conference on Music Perception & Cognition*, edited by Scott D. Lipscomb, Richard Ashley, Robert O. Gjerdingen, and Peter Webster, 674–676. Adelaide, Australia: Causal Productions, 2004.

———. "Musical Structure Processing After Repeated Listening: Schematic Expectations Resist Veridical Expectations." *Musicae Scientiae*, 2010, 33–47.

Tillmann, Barbara, Emmanuel Bigand, and Francois Madurell. "Local versus Global Processing of Harmonic Cadences in the Solution of Musical Puzzles." *Psychological Research* 61 (1998): 157–174.

Tillmann, Barbara, Petr Janata, and Jamshed J. Bharucha. "Activation of the Inferior Frontal Cortex in Musical Priming." *Cognitive Brain Research* 16 (2003): 145–161.

Tillmann, Barbara, and Frédéric Marmel. "Musical Expectations Within Chord Sequences: Facilitation Due to Tonal Stability Without Closure Effects." *Psychomusicology* 23, no. 1 (2013): 1–5.

Tillmann, Barbara, and Bénédicte Poulin-Charronnat. "Auditory Expectations for Newly Acquired Structures." *The Quarterly Journal of Experimental Psychology* 63, no. 8 (2010): 1646–1664.

Tillmann, Barbara, Isabelle Peretz, Emmanuel Bigand, and Nathalie Gosselin. "Harmonic Priming in an Amusic Patient: The Power of Implicit Tasks." *Cognitive Neuropsychology* 24, no. 6 (2007): 603–622.

Tillmann, Barbara, Petr Janata, Jeffrey Birk, and Jamshed J. Bharucha. "The Costs and Benefits of Tonal Centers for Chord Processing." *Journal of Experimental Psychology: Human Perception and Performance* 29, no. 2 (2003): 470–482.

Tillmann, Barbara, Emmanuel Bigand, Nicolas Escoffier, and Philippe Lalitte. "The Influence of Musical Relatedness on Timbre Discrimination." *European Journal of Cognitive Psychology* 18, no. 3 (2006): 343–358.

Tillmann, Barbara, Petr Janata, Jeffrey L. Birk, and Jamshed J. Bharucha. "Tonal Centers and Expectancy: Facilitation or Inhibition of Chords at the Top of the Harmonic Hierarchy." *Journal of Experimental Psychology: Human Perception and Performance* 34, no. 4 (2008): 1031–1043.

Tirovolas, Anna, and Daniel J. Levitin. "Analysis of Empirical Articles in Music Perception." *Music Perception* 29, no. 1 (2011): 23–36.

Toiviainen, Petri, and Tuomas Eerola. "Autocorrelation in Meter Induction: The Role of Accent Structure." *Journal of the Acoustical Society of America* 119, no. 2 (2006): 1164–1170.

Toiviainen, Petri, and Carol L. Krumhansl. "Measuring and Modeling Real-Time Responses to Music: The Dynamics of Tonality Induction." *Perception* 32 (2003): 741–766.

Trainor, Laurel J., and Sandra E. Trehub. "Key Membership and Implied Harmony in Western Tonal Music: Developmental Perspectives." *Perception and Psychophysics* 56, no. 2 (1994): 125–132.

Tversky, Amos. "Features of Similarity." *Psychological Review* 84, no. 4 (1977): 327–352.

Tversky, Amos, and J. Wesley Hutchinson. "Nearest Neighbor Analysis of Psychological Spaces." *Psychological Review* 93, no. 1 (1986): 3–22.

Tymoczko, Dmitri. "Review of Michael Cuthbert, Music21: a Toolkit for Computer-aided Musicology (http://web.mit.edu/music21/)." *Music Theory Online* 19, no. 3 (2013).

Vallières, Michel. "Beginnings, Middles, and Ends: Perception of Intrinsic Formal Functionality in the Piano Sonatas of W. A. Mozart." PhD Dissertation, McGill University, 2011.

Vallières, Michel, Daphne Tan, E. Caplin William, and Stephen McAdams. "Perception of Intrinsic Formal Functionality: An Empirical Investigation of Mozart's Materials." *Journal of Interdisciplinary Music Studies* 3, nos. 1&2 (2009): 17–43.

VanHandel, Leigh. "The Role of Phrase Location in Key Identification by Pitch Class Distribution." In *12th International Conference on Music Perception and Cognition and the 8th Triennial Conference of the European Society for the Cognitive Sciences of Music*. 2012.

Venables, William N., and Brian D. Ripley. *Modern Applied Statistics with S*. New York: Springer, 2002.

Villarreal, Eduardo G.A., Elvira Brattico, Sakari Leino, Leif Østergaard, and Peter Vuust. "Distinct Neural Responses to Chord Violations: A Multiple Source Analysis Study." *Brain Research* 1389 (2011): 103–114.

Vos, Piet, and Dennis Pasveer. "Goodness Ratings of Melodic Openings and Closures." *Perception and Psychophysics* 64, no. 4 (2002): 631–639.

Vos, Piet G., and Jim M. Troost. "Ascending and Descending Melodic Intervals: Statistical Findings and Their Perceptual Relevance." *Music Perception* 6, no. 4 (1989): 383–396.

Ward, Joe H. “Hierarchical Grouping to Optimize an Objective Function.” *Journal of the American Statistical Association* 58, no. 301 (1963): 236–244.

Weber, Reinhard. “The Continuous Loudness Judgement of Temporally Variable Sounds with an "Analog" Category Procedure.” In *Fifth Oldenburg Symposium on Psychological Acoustics*, edited by A. Schick, J. Hellbruck, and R. Weber, 267–294. Oldenburg: BIS, 1991.

Weiser, Margaret. “Rating Cadence Stability: The Effects of Chord Structure, Tonal Context, and Musical Training.” PhD Dissertation, McMaster University, 1992.

Welch, Bernard L. “On the Comparison of Several Mean Values: An Alternative Approach.” *Biometrika* 38, nos. 3/4 (1951): 330–336.

West, Brady T., Kathleen B. Welch, and Andrzej T. Galecki. *Linear Mixed Models. A Practical Guide using Statistical Software*. Boca Raton: Chapman & Hall/CRC, 2007.

White, Christopher W. “An Alphabet-Reduction Algorithm for Chordal n-Grams.” In *Proceedings of the 4th International Conference on Mathematics and Computation in Music*, 201–212. Springer, 2013.

———. “Some Statistical Properties of Tonality, 1650-1900.” PhD Dissertation, Yale University, 2013.

Wild, Jonathan. “A Review of the Humdrum Toolkit: UNIX Tools for Musical Research, created by David Huron.” *Music Theory Online* 2.7 (1996).

Wingfield, Paul. “Beyond ‘Norms and Deformations’: Towards a Theory of Sonata Form as Reception History.” *Music Analysis* 27, no. i (2008): 137–177.

Witten, Ian H., and Timothy C. Bell. “The Zero-Frequency Problem: Estimating the Probabilities of Novel Events in Adaptive Text Compression.” *IEEE Transactions on Information Theory* 37, no. 4 (1991): 1085–1094.

Witten, Ian H., Leonard C. Manzara, and Darrell Conklin. “Comparing Human and Computational Models of Music Prediction.” *Computer Music Journal* 18, no. 1 (1992): 70–80.

Wright, James K., and Albert S. Bregman. “Auditory Stream Segregation and the Control of Dissonance in Polyphonic Music.” *Contemporary Music Review* 2 (1987): 63–92.

Yang, Albert C.-C, C.-K Peng, H.-W Yien, and Ary L. Goldberger. "Information Categorization Approach to Literary Authorship Disputes." *Physica A: Statistical Mechanics and its Applications* 329, nos. 3-4 (2003): 473–483.

Youngblood, Joseph. "Style as Information." *Journal of Music Theory* 2, no. 1 (1958): 24–35.

Zipf, George Kingsley. *Human Behavior and the Principle of Least Effort*. Oxford, UK: Addison-Wesley, 1949.

Ziv, Naomi, and Zohar Eitan. "Themes as Prototypes: Similarity Judgments and Categorization Tasks in Musical Contexts." *Musicae Scientiae* Discussion Form 4A (2007): 99–133.