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Musical Complexity and Top 40 Chart Performance

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Abstract

Radio airplay drives record sales and reflects the preferences of popular music consumers. Musical preference is a function of complexity and familiarity in a laboratory setting. Musical pattern recognition research evaluates the similarity of two melodies or rhythms. This project measures the musical complexity or self-dissimilarity of songs in the *Billboard* modern rock top 40 and relates it to their chart performance. For songs that show short-term and long-term popularity, complexity is positively correlated with overall chart performance.

Musical Complexity and Top 40 Chart Performance

The *Billboard* modern rock top 40 reflects the relative frequency of radio airplay among charted songs. Erdelyi (1940, as cited by North & Hargreaves, 1997a) found that radio airplay (i.e. plugging) "systematically *precedes* sales" (p. 88), implying that sales are driven by radio airplay. Therefore, the longer a song is in the charts and the higher it is ranked, the more money it potentially generates. In addition, the frequency of radio airplay reflects the preference of its listening audience. If this were not true, the audience would switch stations. Many research studies have shown the relationship between musical complexity and preference among subjects in a laboratory. This project tests the scope of these findings by correlating musical complexity to the performance of songs in the modern rock top 40.

Background

Many factors contribute to the perception of musical complexity. Finnas (1989) indicates that "Unusual harmonies and timbres, irregular tempi and rhythms, unexpected tone sequences and variations in volume, etc., make the music seem complex" (p. 6). Previous laboratory studies focusing on musical complexity and preference (Vitz, 1964; Simon & Wohlwill, 1968; McMullen, 1974a, 1974b; Heyduk, 1975; Steck & Machotka, 1975) measure or vary complexity in a musical stimulus by the number of different chords or pitches, percentage of major triads, level of synchopation, number of tones or bits of information per second, and melodic redundancy.

Research in musical pattern recognition (Rauterberg, 1992; Shmulevich & Povel, 1998; Shmulevich et. al., 2001) compares two compositions and judges their similarity for the purpose of database queries. These methods focus on the change in note pitch and duration so that

differences in key or tempo do not affect the query. This project uses similar techniques to evaluate the complexity within a song.

Brain research (Berlyne et. al., 1967; Birbaumer et. al., 1994) studies the effect of auditory complexity on the electroencephalogram (EEG) of participants. Subjects with popular music preferences are more sensitive to changes in rhythmic complexity.

Musical complexity, familiarity and preference

Vitz (1964) approaches the relationship between musical complexity and preference from the point of view of information theory. This presupposes humans can be viewed as information processing machines that require an optimal amount of information per unit time. Vitz (1964, pp. 176-177) supports this view citing previous work in attention research that defines the complexity of a stimulus as the deviation between expectation and perception that draws an organism's attention. He claims that this deviation is analogous to information in terms of information theory. Too much information leads to uncertainty and anxiety, while too little creates boredom. However, after perceiving the information, we process it thereby reducing its perceived complexity. This reduction in complexity leads to the notion that organisms have an optimal level of complexity.

Vitz (1964) uses a mathematical definition of information that measures the uncertainty in a musical situation. For instance, if the same note is played repeatedly, there is no uncertainty and therefore no complexity. However, if each note has the same likelihood of being played a maximum uncertainty and therefore maximum complexity is perceived. Vitz (1964) hypothesizes that an inverted U-shaped relationship exists between complexity and preference. He tests this by comparing subject preference ratings for a series of short compositions that vary

in the amount of information (or uncertainty) per note. In addition, Vitz (1964) varies the number

of tones per second and number of different pitches in the compositions.

Contrary to his hypothesis, Vitz (1964) found that as complexity increased, so did

preference, although it flattens out toward the higher end of complexity. One explanation is that

a high enough complexity level was not used in the experiment. He concludes that his results

"disconfirm … that the information formula was an adequate substitute for such general terms as

stimulus variability, complexity, change, etc." (Vitz, 1964, p. 182). In addition, he suggests that

his hypothesis should be weakened so that it states the human is a *variation* processing system

rather than an *information* processing system, hinting at the second order role of context and

relative complexity. Finally, Vitz indicates that it is unlikely that information per second should

be solely used to predict preference.

Simon and Wohlwill (1968) build on Vitz's (1964) work that showed context plays a role

in the relationship between complexity and preference. The most obvious difference between the

studies is that Simon and Wohlwill (1968) use "actual music passages as opposed to artificially

constructed note sequences" (p. 229). They found that musically trained subjects preferred the

highly complex pieces, while the untrained subjects showed a preference for highly or

moderately complex pieces. Their results somewhat support that subjects were more accepting of

repetition for more complex pieces.

McMullen (1974b) builds on research similar to Vitz (1964) that indicates the complexity

of a stimulus may be based on the "number of distinguishable elements … [and] the information

theory concept of redundancy" (p. 199). He therefore creates original compositions that vary in

the number of different notes, and in the redundancy as defined by the "degree of randomness"

(McMullen, 1974b, p. 199) in the composition. He holds the total number of notes, rhythm, and duration constant.

McMullen (1974a; 1974b) concludes that compositions containing a low or moderate number of notes and redundancy are preferred. Because complexity increases with the number of unique notes and decreases with redundancy, his results do not contradict the inverted U-shaped relationship.

Heyduk (1975) begins his argument by noting that early research on musical preference used general musical recordings that had not been created purposefully for the experiment. He identifies a weakness in previous work that almost exclusively used "stimulus materials that were clearly defined but did not combine the chordal, sequential, instrumental, and thematic characteristics of genuine aesthetic products adapted for experimental use" (Heyduk, 1975, p. 85).

Heyduk (1975) uses a broader definition of musical complexity, based on psychological complexity that represents all previous stimulus measures including "novelty, stimulus complexity, uncertainty, [and] arousal properties" (Heyduk, 1975, p. 84). In addition, Heyduk (1975) assumes that "experience with an event reduces its psychological complexity" (p. 84).

Heyduk (1975) describes the optimal complexity model provided by Walker (1973, as cited by Heyduk, 1975). In the optimal complexity model, the difference between the psychological complexity of a stimulus and an organism's optimal complexity level drives preference. As the stimulus approaches the optimal complexity, preference increases. As the stimulus becomes too complex or too simple, preference decreases.

Heyduk (1975) suggests that previous research indicating repetition of a stimulus increases preference is a special case of the optimal complexity model. If repetition decreases the

perceived complexity of a stimulus, then it can increase or decrease preference based on the optimal complexity of an organism.

Heyduk (1975) tests the hypothesis that "repeated exposure effects are a joint function of situational and individual factors" (p. 85). Specifically, he uses four especially composed piano solos that varied in the number of different chords, percentage of major triads, and level of synchopation. The compositions were intended to exhibit clear differences in complexity and form an ordered set. Initial complexity ratings given by subjects concurred with the intended complexity differences. Based on a subject's preference for the four compositions, Heyduk (1975) identifies the optimal complexity level and predicts the effect of repetition of a more complex or simpler composition. He found an inverted U-shaped relationship between complexity and preference. Heyduk's (1975) analysis suggests "the affective response of a subject to a musical composition was influenced by its proximity to the subject's preferred complexity level" (p. 88). In addition, Heyduk (1975) found that an individual's optimal complexity level helped predict their reaction to repetition of one composition. Heyduk (1975) states, "the information about an individual's optimal level gained from initial liking ratings was useful for predicting subsequent hedonic responses to repetition of an event with specific complexity" (pp. 88-89).

Steck and Machotka (1975) reexamine the inverted U-shaped relationship between stimulus complexity and preference, including information theory. They explore the possible effect of the context of complexity on musical preference. In line with previous research they use sequences of computer-generated tones (sine waves) to build compositions. Each composition varied in complexity by the number of tones per second. They remove any familiarity that the subjects might find in the music and also remove rhythm as a possible contributor to complexity.

Their most complex composition contains tone rates very near the maximum human capacity to distinguish them. Before judging a set of compositions for preference, subjects listen to two compositions that defined the set's range of complexity. Therefore, subjects had a context from which to judge.

Steck and Machotka (1975) found that subjects did indeed exhibit an inverted U-shaped relationship between complexity and preference for each set of compositions. However, because subjects not only judged a full distribution of complexity compositions, but also subintervals that contained overlapping ranges of complexity, it was possible to analyze the subject's absolute complexity preference. They found that an absolute complexity preference did not exist. In fact, subjects consistently preferred the same relative complexity for each set they judged. Therefore, Steck and Machotka (1975) claim, "preferences were *entirely* dependent on context, that is, that subjects who had a given point of preferred complexity on the full distribution had the same relative point on the subintervals" (p. 172). Therefore, "there is no 'natural' degree of complexity toward which a given subject will tend; there is, instead, a relative degree toward which the subject will repeatedly be attracted" (Steck & Machotka, 1975, p. 173).

Previous research in musical complexity and preference has implications for this project. Vitz (1964) found that his method of measuring complexity did not display the desired inverted U-shaped preference curve. Perhaps if greater levels of complexity were attained using multiple measures the relationship would exist. This project uses two measures of complexity with the hope that one or both of them will show a relationship with the performance of songs in the *Billboard* modern rock top 40. This project defines a different notion of melodic and rhythmic redundancy than McMullen (1974a, 1974b) and uses it to represent musical complexity. This is

done at the Gestalt level rather than examining the precise probabilities that were used previously to define expectation, uncertainty, and complexity.

The differences between musically trained and untrained subjects studied by Simon and Wohlwill (1968) does not play a role in this project. This project uses real songs from the modern rock genre to test the relationship between complexity and preference, and ignores the potential differences between musically trained and untrained populations. Instead, all listeners to this genre are grouped into one population.

Repetition as studied by Heyduk (1975) plays a role in this project because songs in the modern rock top 40 dominate radio airplay. However, because all of the songs considered for comparison in this project are in the top 40, this project expects that they receive comparable airplay and repetition. Therefore, the effect of repetition can be ignored as a small influencer of performance for this population of listeners and songs.

In this project, the context of complexity to which Steck and Machotka (1975) refer is the set of songs currently listed on *Billboard*'s modern rock top 40. This ranking is provided for the relative evaluation of songs within the "modern rock" genre and can be considered a musical context by the listeners. This project ignores the potential role of context imposed by individual radio stations or social groups, focusing exclusively on the *Billboard* rankings.

Pattern recognition and autocorrelation

Rauterberg (1992) theorizes that cognitive complexity is a function of "system complexity", "task complexity", and "behaviour complexity" (p. 296). Based on this assumption, he was able to test and validate the separate measures of complexity.

Schmulevich et. al. (2001) describe their system of comparing melodies. They begin by generating a pitch vector that contains the absolute pitch of every note in the score. Then, they

create a pitch difference vector that contains the relative change in pitch for every transition in the pitch vector. They define the "objective pitch error" (Schmulevich et. al., 2001, p. 29) between two melodies as the magnitude of the difference between the pitch difference vectors. The objective pitch error, *e*, for pitch difference vectors *u* and *v*, is defined as $e = \|u - v\|$. Because the equation only deals with the pitch changes, songs containing the same melody played in different keys will still be judges as identical.

Schmulevich et. al. (2001) indicate that total pitch error should be a function of objective pitch error and "perceptive pitch error" (p. 30). They illustrate how perceptual information about the current tonal context of a melody can affect the perceived melodic complexity. Therefore, their comparison of melodies includes this perceived pitch error as well.

Schmulevich and Povel (1998) report on three ways to measure rhythmic complexity. A later report (Schmulevich et. al., 2001) describes an implementation of rhythm pattern recognition. The authors begin by generating a vector of inter-onset intervals (IOI). An IOI is the time between the onset of a note and the onset of the following note. This provides an indication of note durations. Next, they create a "rhythm difference vector" (Schmulevich et. al., 2001, p. 24) that represents the relative change in note durations. The rhythm difference vector is computed by dividing each IOI by its previous IOI. Schmulevich et. al. (2001) state, "The rhythm error is defined as

$$e_r = \left(\sum_{j=1}^{n-1} \frac{\max(s_j, t_j)}{\min(s_j, t_j)} \right) - (n-1),$$

where *s* … represents the rhythm difference vector of the scanned rhythm pattern (of length *n*) and *t* … represent the rhythm difference vector of the target pattern" (p. 25). This method of

measurement does not distinguish between rhythms played at a different tempo and evaluates to zero when the rhythms are identical.

Leman (1995) describes the use of autocorrelation in determining the periodic nature of a signal. He first calculates the similarity between the original signal and a copy offset by one sample. He then repeats this step increasing the offset by one each time.

This project combines pattern recognition techniques described by Schmulevich et. al. (2001) and autocorrelation described by Leman (1995) to compute rhythmic and melodic complexity of a single song that can be compared between songs.

Brain research

Berlyne, et. al. (1967) use the desynchronization of an electroencephalogram (EEG) as an indicator of brain activity and attempt to correlate it to the frequency and complexity of simultaneous visual or auditory stimulus. They use an "orientation reaction (of which EEG desynchronization is a component)" (Berlyne et. al., 1967, p. 361) and compared it to the pitch of stimulus sine waves. Berlyne et. al. (1967) found that high and low frequencies received the most brain response and provide the possible explanation that "these are encountered less often and are thus more novel than intermediate frequencies" (p. 361). In addition, the brain response is greater for highly pleasant and unpleasant tones. They found that musical complexity measured as the number of simultaneous tones had no effect on brain activity.

Birbaumer et. al. (1994) record EEG activity from different parts of the scalp while subjects listen to music samples varying in melodic, rhythmic, and combined complexity. Overall, results show that the brain reacts similarly to periodic (low complexity) and stochastic (high complexity) music. However, the middle range melodies produce noticeably less activity on the prefrontal cortex. Subjects who prefer classical music to popular music maintain higher

brain activity, while those who prefer popular music show a decrease in activity for music that had weakly chaotic rhythm (medium complexity).

Studies that combine brain research with music listening have a bearing on the perception and cognition of sound. However, this project does not explicitly draw on it. One interpretation is that people who prefer popular music are more sensitive to changes in rhythm. Because the *Billboard* rankings ultimately depend on the preferences of people who prefer popular music, the results of this project may be compared to the findings of Birbaumer et. al (1994).

<center>*Rationale*</center>

This project correlates the rhythmic and melodic complexity of songs in the modern rock top 40 to their chart performance. Rhythmic and melodic complexity is compared to the number of weeks in the chart, average weekly change in position, peak ranking, and debut ranking. Theoretically, it takes longer for a more complex song to become too familiar and hence lose preference. Therefore, this project expects more complex songs to take a long gradual trajectory through the charts, while simpler songs take a short steep trajectory. Specifically, this project's hypotheses are that:

(1)   rhythmic and melodic complexity is positively correlated with number of weeks in the chart,

(2)   rhythmic and melodic complexity is negatively correlated with the weekly change in position, and

(3)   rhythmic and melodic complexity is not correlated with peak ranking or debut ranking.

Method

This project tests the implication of the inverted U-shaped relationship between complexity and preference on a larger scale. Instead of looking at individual subjects' preferences for specially designed compositions or computer generated tone sequences, this project examines the effect of musical complexity on a song's performance in the *Billboard* modern rock top 40.

Data

This project uses the weekly rankings of the *Billboard* modern rock top 40 for the first half of 1996 (Modern, 1996, January 6 – June 29). Each song present in the chart during this period was considered for membership in the dataset. Songs in the dataset met three criteria:

(1) The song entered and exited the chart during this time span,

(2) The song remained in the rankings for at least 10 weeks, and

(3) A MIDI file representing the song could be found on the Internet.

This project imposed these criteria so that all data is complete, substantial, and available, respectively. A minimum of ten weeks in the charts ensures a moderate level of short-term popularity. Meenaghan and Turnbull (1981, as cited by North & Hargreaves, 1997b) state, "Successful records moved through five stages in a typically 16 weeklong period between their release and final abandonment by the music industry" (p.280). Because this project could not locate MIDI files for all of the songs that fit the first two criteria, the songs exhibit another quality. It stands to reason that songs for which no MIDI file exists after six years did not sustain popularity during that time. Therefore, songs that meet the third criteria additionally show a level of long-term popularity. This project collected MIDI files (Alanis Morissette; Alice In Chains;

Foo Fighters; Garbage; Gin Blossoms; Jars of Clay; Presidents of The U.S.A.; Red Hot Chili

Peppers; Smashing Pumpkins; Tori Amos) for all ten songs that met the above criteria.

Measuring the complexity of a MIDI file

A MIDI file is a concise description of a song. Instead of containing sound samples that

represent how an audio speaker can reproduce the sounds, it contains a series of commands to a

MIDI synthesizer that generates the sounds. MIDI files can be thought of as musical scores that

do not use standard music notation. Instead of indicating the pitch and duration (quarter note,

eighth note, etc.), MIDI files contain specific commands that tell the synthesizer what

instruments are playing and when a note begins to play (note-on) and when it stops playing

(note-off). This project only deals with note-on commands that can be differentiated from the

rest because they begin with the prefix '9'. Ramsey (1999, pp. 4.21-4.23) provides the technical

details of MIDI.

A portion of this project includes the customization and enhancement of the midi player

software developed by König (1998). This previous program decodes MIDI files and sends the

individual commands to a MIDI synthesizer that plays the song. This project utilizes the

decoding provided by König, compiles a list of note-on commands sorted by onset time, and

computes the rhythmic and melodic complexity of the song.

MIDI files allow for very small differences in onset time. Therefore, notes that appear to

be played at the same time on a musical score may be played at slightly different times in a MIDI

file. This difference is usually imperceptible. However, it is necessary to deal with these small

deviations so that the representation vectors closely resemble the score notation on which the

complexity algorithms depend. This project accomplishes this by allowing only one note to turn

on within the duration of one-twelfth of a beat. For note-on commands that occur together within

this threshold, the lowest pitch was recorded for the melody. Therefore, a C-Major chord would be recorded as a C note in the melody. During a song, the music may stop and restart. If this duration is greater than 7 beats, it is ignored in the rhythmic pattern.

Melodic complexity

After the notes have been filtered to treat chords as notes and ignore long pauses, separate algorithms measurer the rhythmic and melodic complexity of the song. Both algorithms build on autocorrelation described by Leman (1995) and similarity algorithms described by Schmulevich (2001).

Beginning with the list of notes attained in the previous section, an absolute pitch vector, $P = \langle p_1, p_2, ..., p_n \rangle$, is created to contain an ordered list of pitches present in the song. The melodic complexity algorithm advances in several steps:

(1) The melody difference vector, $M = \langle m_1, m_2, ..., m_{n-1} \rangle$, is generated by finding the change in pitch between adjacent notes in p. Specifically, $m_i = p_{i+1} - p_i$.

(2) Subinterval pairs, $A_i = \langle a_{i1}, a_{i2}, ..., a_{i(n-i)} \rangle$ and $B_i = \langle b_{i1}, b_{i2}, ..., b_{i(n-i)} \rangle$ for $1 \le i \le n-1$, are created for every offset in M. Specifically, $a_{ij} = m_j$ (i.e. $A_i = \langle m_1, m_2, ..., m_{n-i} \rangle$) and $b_{ij} = m_{i+j-1}$ (i.e. $B_i = \langle m_i, m_{i+1}, ..., m_{n-1} \rangle$).

(3) The differences between subinterval pairs, A_i and B_i for $1 \le i \le n-1$, are stored in distance vectors, $D_i = \langle d_{i1}, d_{i2}, ..., d_{i(n-i)} \rangle$. Specifically, $d_{ij} = a_{ij} - b_{ij}$ (i.e. $D_i = \langle a_{i1} - b_{i1}, a_{i2} - b_{i2}, ..., a_{i(n-i)} - b_{i(n-i)} \rangle$).

(4) The total error vector, E_{tot}, is created as the concatenation of all subinterval distance vectors, D_i. Specifically, $E_{tot} = D_1 D_2 ... D_{n-1}$.

(5) The total error, E_{melody}, is calculated as the Euclidian length of E_{tot} and divided by the number of pitch changes. Therefore, the number of notes in a song does not affect its melodic complexity. Specifically, $E_{melody} = \|E_{tot}\|/(n-1)$.

Essentially, this algorithm compares every pitch change, m_i, to every other pitch change, m_j, calculating the standard deviation between each pair of pitch changes and dividing by the number of pitch changes. Two songs that repeat the same melody a different number of times are calculated to have the same internal melodic complexity. Tempo, rhythm, and key do not affect this measure.

Rhythmic complexity

Rhythmic complexity is computed in a way analogous to melodic complexity. Beginning with the original ordered list of notes, an absolute time vector, $T = \langle t_1, t_2, ..., t_n \rangle$, was created that contains an ordered list of note onset times in the song. The rhythmic complexity algorithm completes in several steps:

(1) The inter-onset interval vector, $O = \langle o_1, o_2, ..., o_{n-1} \rangle$, is generated by finding the difference between adjacent times in T. Specifically, $o_i = t_{i+1} - t_i$.

(2) The rhythm difference vector, $R = \langle r_1, r_2, ..., r_{n-2} \rangle$, represents the linear change between durations. Specifically, $r_i = \log_2(o_{i+1}/o_i)$. Calculating R in this way makes a doubling in duration equal to one and a halving of duration equal to negative one. For instance, a quarter note followed by a half note incurs a rhythm difference of one, while a quarter note followed by an eighth note incurs a difference of negative one.

(3) The following four steps are analogous to steps 2-5 in the melodic complexity

algorithm. Subinterval pairs, $A_i = \langle a_{i1}, a_{i2}, ..., a_{i(n-i-1)} \rangle$ and $B_i = \langle b_{i1}, b_{i2}, ..., b_{i(n-i-1)} \rangle$ for

$1 \leq i \leq n-2$, are created for every offset in R. Specifically, $a_{ij} = r_j$ (i.e.

$A_i = \langle r_1, r_2, ..., r_{n-i-1} \rangle$) and $b_{ij} = r_{i+j-1}$ (i.e. $B_i = \langle r_i, r_{i+1}, ..., r_{n-2} \rangle$).

(4) The differences between subinterval pairs, A_i and B_i for $1 \leq i \leq n-2$, are stored in

distance vectors, $D_i = \langle d_{i1}, d_{i2}, ..., d_{i(n-i-1)} \rangle$. Specifically, $d_{ij} = a_{ij} - b_{ij}$ (i.e.

$D_i = \langle a_{i1} - b_{i1}, a_{i2} - b_{i2}, ..., a_{i(n-i-1)} - b_{i(n-i-1)} \rangle$).

(5) The total error vector, E_{tot}, is created as the concatenation of all subinterval distance

vectors, D_i. Specifically, $E_{tot} = D_1 D_2 ... D_{n-1}$.

(6) The total error, E_{rhythm}, is calculated as the Euclidian length of E_{tot} and divided by the

number of pitch changes. Therefore, the number of notes in a song does not affect its

rhythmic complexity. Specifically, $E_{rhythm} = \|E_{tot}\| / (n-2)$.

This algorithm compares every rhythm change, r_i, to every other rhythm change, r_j, calculating

the standard deviation between them and dividing by the number of rhythm changes. Two songs

that repeat the same rhythm a different number of times are calculated to have the same rhythmic

complexity. Tempo, melody, and key do not affect this measure.

Results

This project included all ten songs that met the above selection criteria. Each song was

analyzed in terms of its rhythmic and melodic complexity and four performance factors: number

of weeks in the chart, average weekly change in position, peak ranking, and debut ranking.

Because the sample is so small, the complete data is available in Table 1. The correlations

between rhythmic and melodic complexity, and the four performance factors are shown in Table 2. With an alpha level of 0.01 (the likelihood of no correlation is less than 1%), the correlation between melodic complexity and number of weeks in the charts was statistically significant. The estimated magnitude (r^2) of this relationship is 0.52. In other words, approximately 52% of the explanation of chart longevity is associated with melodic complexity.

With an alpha level of 0.05, the correlation between rhythmic complexity and number of weeks in the charts, rhythmic complexity and peak ranking, and melodic complexity and average weekly change in position were statistically significant. The estimated magnitudes of these relationships are 0.35, 0.37, and 0.36, respectively.

Discussion

The results support the first hypothesis that rhythmic and melodic complexity is positively correlated with number of weeks in the chart. This supports the theory that complex songs maintain our interest longer that was partially confirmed by Simon and Wohlwill (1968).

Only melodic complexity supports the second hypothesis and appears to be negatively correlated to average weekly change in position. Therefore the hypothesis is partially confirmed.

Surprisingly, the third hypothesis is partially disconfirmed by the positive correlation between rhythmic complexity and peak ranking. Perhaps popular music listeners are showing their extra sensitivity to rhythmic complexity as described by Birbaumer et. al. (1994).

If the results of this study can be reproduced, the implication for record companies and bands in the modern rock genre is to consider the complexity of their music as a factor in how much money it generates. For songs that overcome the odds and show short-term popularity (ten weeks on the modern rock top 40 chart) and later show sustained long-term popularity (MIDI file exists after 6 years), complexity is associated with overall chart performance (i.e. longevity and

peak ranking). Future research may seek to show a causal relationship (i.e. complexity implies performance) by identifying songs that are initially pleasing or simple enough to be popular in the short-term and complex enough to maintain this popularity in the long-term.

Of course, this study only involved ten songs and a relatively short time span. More conclusive results may be obtained through a more expansive study. In addition, there may be other factors that have a more direct relationship with chart performance. Perhaps more notable artists perform the more complex songs. These artists have more freedom of expression than newcomers and rely on prior success to drive their current popularity. In this case, complexity should not be considered on its own to contribute to chart success. Future work may shed light on this possibility. Additionally, more popular songs may inspire enthusiasts to generate a more precise (and complex) MIDI representation, implying the inverted causal relationship between popularity and MIDI complexity.

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Table 1

Song Complexity Compared To Chart Performance

	Complexity		Chart Performance			
Title	Rhythmic	Melodic	Total Weeks	Average Change	Peak Ranking*	Debut Ranking*
Peaches	0.57	6.15	12	4.67	33	10
Heaven Beside You	0.53	9.65	18	3.83	35	1
Follow You Down	0.43	9.97	12	3.42	33	25
Only Happy When It Rains	0.34	10.15	19	2.58	25	7
Caught A Lite Sneeze	0.43	12.41	13	3.54	28	12
Ironic	0.86	13.83	21	3.71	40	4
Aeroplane	0.58	14.18	17	3.06	33	18
Flood	0.68	15.06	17	3.06	29	10
Zero	0.30	15.10	19	3.21	32	5
Big Me	1.81	23.14	23	2.87	38	9

Notes: Rankings are inverted (top rank = 40).

Table 2

Correlation Between Complexity and Chart Performance

Complexity	Rhythmic		Melodic	
	r	*t*	*r*	*t*
Total Weeks	0.59	2.04*	0.72	2.91**
Average Change	-0.17	-0.49	-0.60	-2.11*
Peak Ranking	0.61	2.18*	0.35	1.06
Debut Ranking	-0.11	-0.30	-0.08	-0.24

Notes: n = 10, * $p < 0.05$, ** $p < 0.01$