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A Comparative Analysis of Melodic Rhythm in Two Corpora of American Popular Music

Christopher Wm. White[a*], Joe Pater[b], and Mara Breen[c]

[a]*Department of Music, University of Massachusetts Amherst, USA;*
[b]*Department of Linguistics, University of Massachusetts Amherst, USA;*
[c]*Department of Psychology, Mount Holyoke College, South Hadley, USA*

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This paper compares two corpora of melodies drawn from pre-millennial and post-millennial American popular music, and identifies several notable differences in their use of rhythm. The pre-millennial corpus contains 80 melodies written between 1957–1997 (Tan, Lustig, and Temperley 2018), while the post-millennial corpus (compiled for this study) consists of 24 songs popular between 2015–2019. For both corpora, we analyzed 1) the distribution of note onsets within a measure; 2) the most-frequent four-note rhythms; and 3) the density of note onsets within measures. Our analyses indicated that the post-millennial melodies distribute notes more evenly throughout their measures, show a greater diversity of rhythms, and use greater note-onset density. However, we also found that individual songs re-used rhythmic cells with more internal consistency in the post-millennial dataset. We then analyze Lizzo's "Truth Hurts," a 2019 song (not included in the original analysis) that features many characteristics typical of our post-millennial corpus. We subject many of these features to a computationally-aided close reading, showing how these parameters can be used to support the song's formal and expressive designs.

Keywords: popular music; rhythm; meter; melody; corpus analysis; text

2010 Mathematics Subject Classification: 00A65; 62P15; 91E10; 94A17
2012 Computing Classification Scheme: Applied computing Sound and music computing

1. Introduction

In the last several decades, American popular music has undergone a number of stylistic shifts that distinguish it from previous popular genera. In particular, analyses of 20th-century popular music note a change in both the musical materials used in popular songs (Temperley (2018), Duinkler (2021), White and Quinn (2015)), as well as the styles of songs considered "mainstream" by influential compendia, in particular the Billboard charts (Burgoyne, Wild, and Fujinaga (2013), Sloan and Harding (2021)). Recent scholarship has argued that such changes in contemporary popular music are at least in part due to the increasing influence of rap and hip hop, especially in the way that melodic materials are conceived of and constructed (Barna (2019), Peres (2016), Duinkler (2020a), Duinkler (2020b)).

To investigate some aspects of this stylistic shift, this paper compares two popular-music corpora: 1) a corpus of 20th-century American popular-music melodies (Tan,

*Corresponding author. Email: cwmwhite@umass.edu

Lustig, and Temperley 2018), and 2) a new corpus of post-millennial melodies drawn from the five highest-ranked songs on the "Billboard Top 100" for each year, 2015–2019. We investigate aspects of the syllabic density, metric placement, and rhythmic motives in these repertoires; our analyses show that recent music does indeed contain greater syllabic density, that its accents are more evenly distributed throughout its measures, and that there is variation in how rhythmic motives are deployed in these two repertoires.

The following analyses are of an exploratory rather than experimental nature. In what follows, a series of approaches are outlined that will be useful to investigating the differences in melodic delivery between two corpora. However, the end results of this investigation are designed to be descriptive – to provide quantitative insights that complement broader musicological research into this repertoire. To that end, we begin this article with a series of quantitative analyses, focusing on five musical domains: where melodic onsets appear within measures, the density of these onsets, the way that onsets combine into recurrent rhythmic cells, the entropy associated with these parameters, and how these parameters are expressed in different musical genres. We then end this article by using the insights garnered from our computational approaches to analyze the events of Lizzo's "Truth Hurts", a song that gained widespread popularity in the United States in 2019 (yet was not included in our original corpus analysis). This analysis will allow us to connect the quantifiable aspects of our corpus analysis to post-millennial composition and expression, demonstrating how broader statistical changes might manifest in particular songs.

2. The Corpora

The corpus of 20th-century American popular-music melodies is drawn from the work of Tan, Lustig, and Temperley (2018), and consists of 80 melodies in quadruple meter from songs drawn from the Rolling Stone's "500 Greatest Songs of All Time." The corpus includes songs from 1955 to 1997 and represents its constituent melodies using pitch and scale degree information, as well as rhythmic/metric information. The latter is used in the following analyses, and includes the onset point for each pitch in each melody, indexed by the measure within the song. For this analysis, genres were associated with each song as well, with Spotify's (Spotify.com) genre labels used; when multiple genres were given, the most general designator was selected. Reflecting the relative size of each corpus, the earlier corpus included 16 genre designations, while the more recent corpus included 5.

The post-millennial corpus consists of the 25 songs that appear at the five-highest ranked positions on the Billboard Top 100 for each year between 2015 and 2019. Songs are annotated in Praat (Boersma and Weenink 2019) and contain multiple layers of pitch, and accent, information. To align with the the 20th-century corpus, only songs in quadruple meter were considered, which excluded 1 song from the analyses and yielded a final dataset of 24 songs. Downbeats and measures were identified by a) listening to the track to identify the metric levels associated with the tactus and measure, b) tagging the onsets of measures in the audio signal, and c) running an automated process that divided these measures into smaller pulses, continuing until the measure is divided into eighths. Designations of *tactus* were designed to gravitate around a comfortable tapping pulse of approximately 90-120 BPM (London 2004), and the *measure* was a grouping of these pulses into groups of four (as shown to be typical in American popular repertoires Temperley (2018); examples of these metric layers can be seen in Figure 9 and Figure 10). Text was then added to the Praat file in two layers. The first layer used the metric divisions place text along with the metric boundaries or to further divide the eighth-measure layer into quicker durations (this step roughly corresponds to transcribing a melody into metrically-aligned notation). The next microtimed layer aligned syllables with their exact onset in the sound signal. (Again, both layers can be seen in Figure 9 and Figure 10; this method is also similar to that of Adams (2008), Adams (2009)). All annotations were done by a research assistant, and checked by the authors, with disagreements resolved by group discussion. Again, genre labels were taken from Spotify. Example annotations can be seen in our analyses in Section 4, below, and a full list of the songs used can be found in our online supplement at the link below (NB: to be changed to author's website after review).

3. Quantitative Analyses

The following analyses will rely on five domains for the comparison of these two datasets: the metric profiles, the onset density, the rhythmic 4-grams, the entropy associated with several of these parameters, and the variations between genres. In what follows, we describe each of these approaches and their corresponding results in turn.

3.1. *Melodic-Metric Profiles*

A *melodic-metric profile* represents where melodic events fall within the measure. This approach tallies the relative proportion with which each melody's constituent note attacks fall at all points within a measure of 4/4. Only note onsets are used (i.e., this representation does not capture how long notes are held after their attack). Figure 1 shows the melodic metric profiles for both corpora, with all events averaged over all songs. Values are presented modulo 1: zero represents the downbeat, and subsequent points on the horizontal axis represent sixteenth notes (i.e., .125 is the measure's second eighth note, .5 is the measure's halfway point, .25 and .75 are the first and third quarter-note events, and so on). The melodic-metric profiles for both datasets' melodies follow the same basic contour, with more events occurring on the eighth-note pulse than on intervening sixteenth notes. Our post-millennial dataset is more evenly distributed – the eighth-note peaks are lower and the sixteenth-note valleys are shallower in post-millennial pop than in 20th-century pop and rock. This result suggests that more recent music makes more use of the quicker pulse than does 20th-century popular music.[1]

The melodic-metric profiles also suggest that more melodic events occur at the end of the measure in 20th-century American popular music than in our post-millennial dataset. Figure 2 shows that, in the 1955–1997 corpus, popular songs tend to have a high density of events in the fourth quarter of the measure relative to other beats; by contrast, in the post-millennial dataset, events are again distributed evenly. The high density of fourth-quarter events in the 20th-century pop and rock corpus likely reflects syncopations that anticipate the downbeat, which are characteristic of this style (Tan, Lustig, and Temperley 2018). Indeed, in 20th-century pop and rock, such anticipations underscore

[1] This is an interesting reversal of the trend noted in Tan, Lustig, and Temperley (2018), in which songs seem to use fewer offbeat sixteenth notes in the later decades in their corpus; they speculate this is because of an increase in average tempo in the later 20th century. However, on the one hand, this quickening of pulse in popular song is noted in recent hip-hop this music in Duinkler (2020a). On the other hand, the increase in quicker note values tracks with the centuries-long trend associated with the quickening metric values in Medieval and Renaissance vocal music identified in DeFord (2015). Such connections between tempo, rhythmic profile, and text provide an interesting line of future comparisons across styles. Indeed, there may be a potential connection between the use of the 16th-note pulse and a reduction of tempo in more rap- and hip-hop-influenced songs.

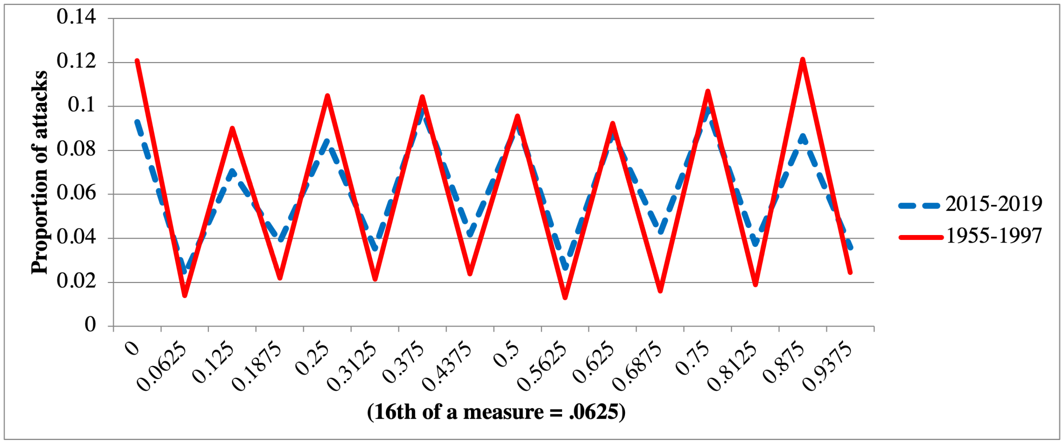

Figure 1. The melodic-metric profile for both corpora.

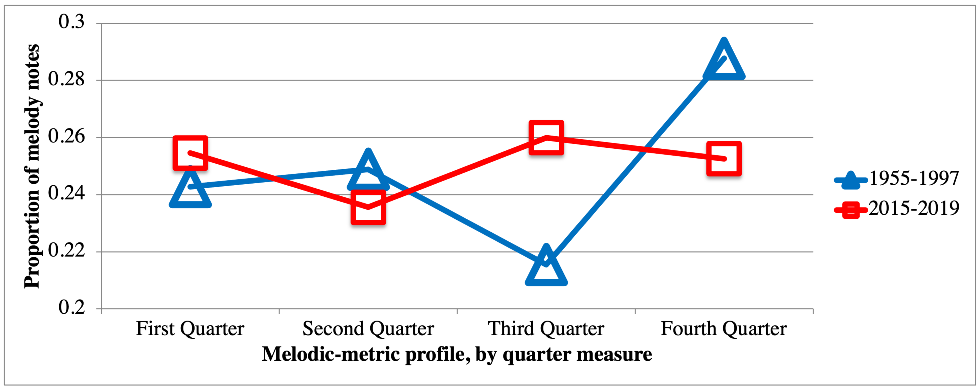

Figure 2. melodic-metric profiles for both corpora, compressed to quarter-measure components.

the primacy of the downbeat: highlighting an event with a syncopation draws a listener's attention to that event (Butler (2006); Temperley (1999)). A fourth-quarter spike is conspicuously absent from our corpus. The flatter distribution, then, not only shows a greater saturation of quicker pulses in this corpus, but also suggests that post-millennial melodies have a freer relationship to rhythm and meter. If attacks and syncopations are more evenly distributed throughout a measure in our dataset, this suggests less emphasis on downbeats overall.

3.2. *Density*

Table 1 shows several measurements of the density of songs within these two corpora. For these calculations, each corpus was divided into its constituent measures. Measures containing no events were removed, and the number of events within the remaining measures were tallied. (To align with the mid-century American corpus, metric (i.e., not microtimed) onset timings were used.) The first row averages the number of note onsets per measure in each corpus, while the second row shows the standard deviation of this mean, calculated as the mean of each individual song's standard deviation. (In other words, this latter calculation can be imagined as the amount of variation in note density one can expect within an individual piece in each corpus.) The third and fourth

Table 1. Analysis of rhythmic density in both corpora's melodies.

	Average onsets per measure (note density)	SD of mean density (between songs)	Most-dense events average z-scores	Least-dense events average z-scores
1955-1997	4.12	1.87	1.92	-1.66
2015-2019	7.19	2.91	2.04	-2.15

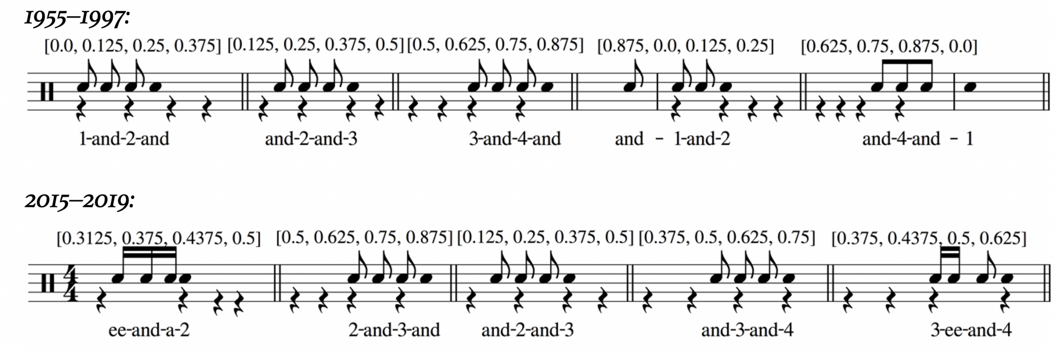

Figure 3. The five most-frequent 4-member rhythmic cells in the melodies of both corpora.

columns depict the extremes in note densities present within individual songs in each corpus. Here, the z-scores for each song's most- and least-dense measure was calculated. (A z-score is the number of standard deviations that separates a point in a distribution from that distribution's average, and can therefore be seen as representing how divergent one can expect a song's most/least dense measures to be.)

These metrics show that songs in the more recent corpus tend to have a greater overall density, and feature a wider array of densities within a single track. Not only are songs in the post-millennial corpus more dense on average, but there is a wider deviation around this average. Furthermore, the most- and least-dense moments in post-millennial songs tend to be further away from the song's average density than in the earlier corpus.

3.3. *Rhythmic 4-grams*

To describe some differences between the rhythmic figures used in each dataset, we isolated the most frequent 4-member rhythmic cells used in both corpora, or what we will call *rhythmic 4-grams*. These 4-grams consist of sequences of onsets modulo 4. Figure 3 shows the five most frequent of these events, represented in three ways: 1) as a 4-tuple of metrically-indexed values (following the same sixteenth-note-based indexes as the above melodic-metric profiles); 2) as note values within measures of 4/4 (with no value given to the final event, as its duration is unspecified within this approach); 3) as standard pedagogical syllables used to show metric position (numbers indicate the quarter pulse, "and's" indicate intervening eighth pulses, and "ee's" indicate sixteenth pulses).

Two large observations arise from this comparison. First – consistent with the contours of Figure 1 – most of the rhythms in Figure 3 favor the eighth-note pulse, but sixteenth notes are more prevalent in our post-millennial pop dataset. Second – consistent with the contours of Figure 2 – the rhythms drawn from the 20th-century rock and pop dataset emphasize the last eighth-note of the measure as well as the following downbeat, whereas the rhythms drawn from the post-millennial pop dataset fall on a wider variety of metric positions.

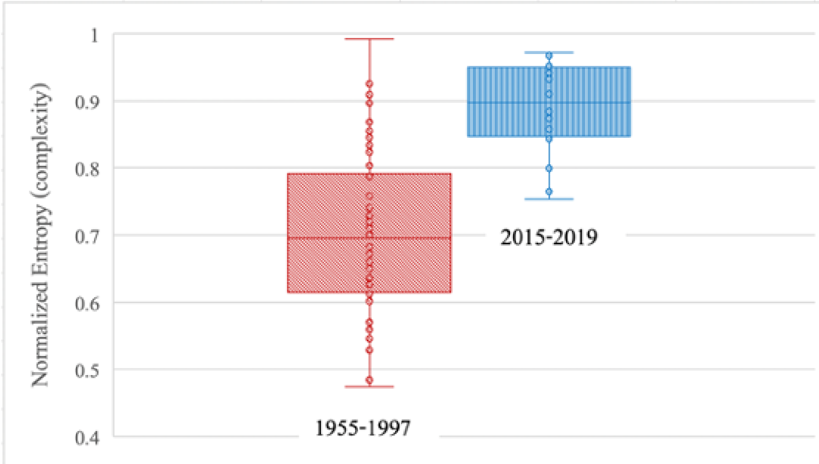

Figure 4. The normalized entropy (complexity) for the melodic-metric profiles distributions for both corpora.

3.4. *Entropy*

Entropy is a measurement of the how equally-distributed some set of probabilities is, with distributions dominated by a few very-frequent outcomes featuring lower entropies than those with many equally-possible outcomes. In a sense, entropy shows the complexity of a distribution: a situation with many equally likely outcomes is more difficult to predict – and therefore more complex – than a situation with fewer, highly determined outcomes. As shown in the denominator of Equation 1, the formula for entropy sums the logarithms of each event within a probability distribution ($\log(p(x_1))$) weighted by the overall amount that each event occurs ($p(x_i)$). Normalized entropy then represents an entropy measurement as a proportion of the maximum entropy, which – given that maximum entropy occurs when all events are equally probable – is the logarithm of the number of events ($\log(n)$). The resulting values is between 0 and 1, with 1 indicating a maximally complex (evenly distributed) distribution.

$$\eta_x = \frac{Entropy}{Entropy_{max}} = \frac{\sum_{i=1}^{n} \log p(x_i) p(x_i)}{\log(n)} \tag{1}$$

Normalized entropy was calculated for the distributions of onsets in each song's melodic-metric profile, as well as the distributions of each song's rhythmic 4-grams. Figure 4 shows the former using a box-and-whisker plot, with individual dots indicating each song's normalized entropy, boxes showing the two central quartiles, a line showing the mean, and the whiskers indicating the upper and lower boundaries of the distribution. The post-millennial corpus features higher entropies, an unsurprising result given that its average melodic-metric profile contained a more-even distribution of events. However, this chart also makes it clear that both datasets do indeed feature songs with divergent – and overlapping – levels of organization, but with post-millennial songs more likely to have a more-even distribution of note onsets throughout the measure.

Figure 5 similarly represents the normalized entropies of each piece's rhythmic 4-gram distributions. In this calculation, songs that use many different cells with roughly the same frequency receive a high normalized entropy, while songs that favor fewer cells and use them more frequently would receive lower complexity scores. By this metric, the

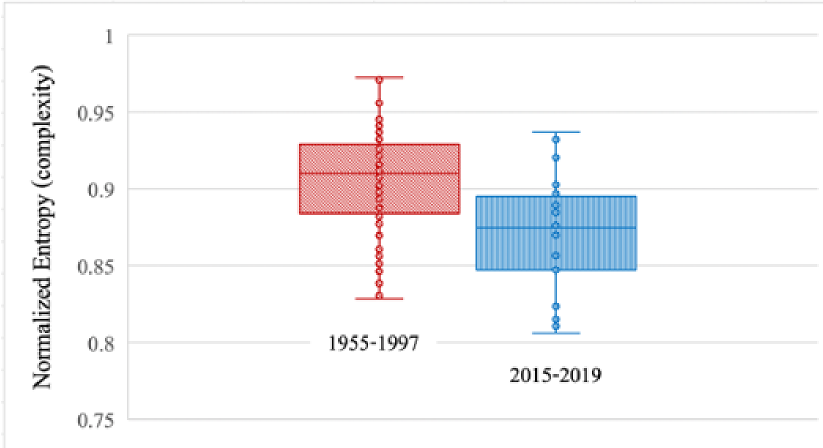

Figure 5. The normalized entropy (complexity) for the 4-gram distributions for both corpora.

post-millennial dataset features more rhythmic consistency than the 20th-century rock and pop corpus: individual pieces are more constrained in their rhythmic motives in the later corpus. This suggests that while pre-millennial pop might have a more standard rhythmic practice, individual post-millennial songs seem to be more internally consistent in their deployment of rhythmic motives. [2]

3.5. *Genre and Normalized Entropy*

Figures 6 and 7 explore some connections between genre and entropy. Figure 6 shows the normalized entropy of each song's melodic-metric profile, divided by genre and averaged. The red bars show the genres within the 1955-1997 corpus, ordered from left to right with descending values; blue bars show normalized entropy for the post-millennial corpus, ordered from left to right in ascending values. Reflecting the higher average normalized entropy discussed above, each genre within the latter corpus returns high (more-complex) assessments than the earlier corpus. Notably, different genres seem to contribute the largest amounts of complexity to the two corpora: while pop and funk are among the most complex in the earlier corpus, these two genres now contribute some of the lowest normalized entropies in the latter corpus. Additionally, blues and folk music have the highest normalized entropy within their melodic-metric profiles in the earlier corpus, while rap and trap music evince the most complexity in the post-millennial corpus. Figure 7 similarly divides the 4-gram normalized entropies used above genre for each corpus. Recall that complexity declined along this parameter within our post-millennial pop dataset compared to 20th-century rock and pop. This figure suggests that rap and trap music contribute most thoroughly to this decline. In other words, while these genres (genres unique to the post-millennial corpus!) contribute a greater diversity in the metric positions used by its melodic lines, they also use consistent rhythmic cells throughout

[2]These findings may be an example of what Abrams (forthcoming) identifies as the *Charleston Paradox*. The paradox involves repetitive rhythms that are uniformly distributed throughout a metric grid. For rhythms of this sort, notions of complexity that focus on the distribution of events within a measure will assess the rhythm as highly complex, while notions of complexity that focus on linear (event-to-event) prediction will assess the rhythm as very simple. While both domains of complexity often align in Western-European common-practice music (Temperley 2010) it is not at all obvious that this correlation should hold in the repertoires under current consideration.

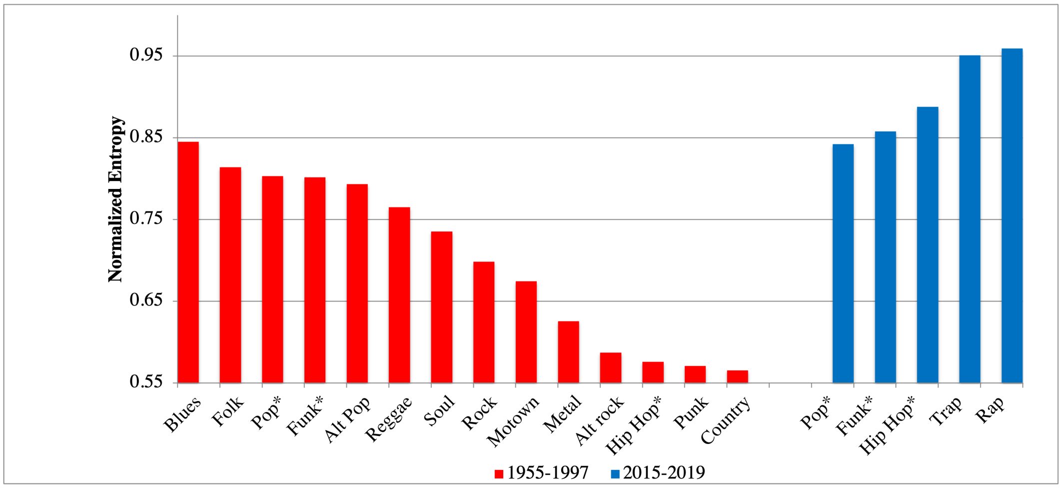

Figure 6. The average normalized entropy for rhythmic profiles for both corpora; asterisks show genres shared by both corpora

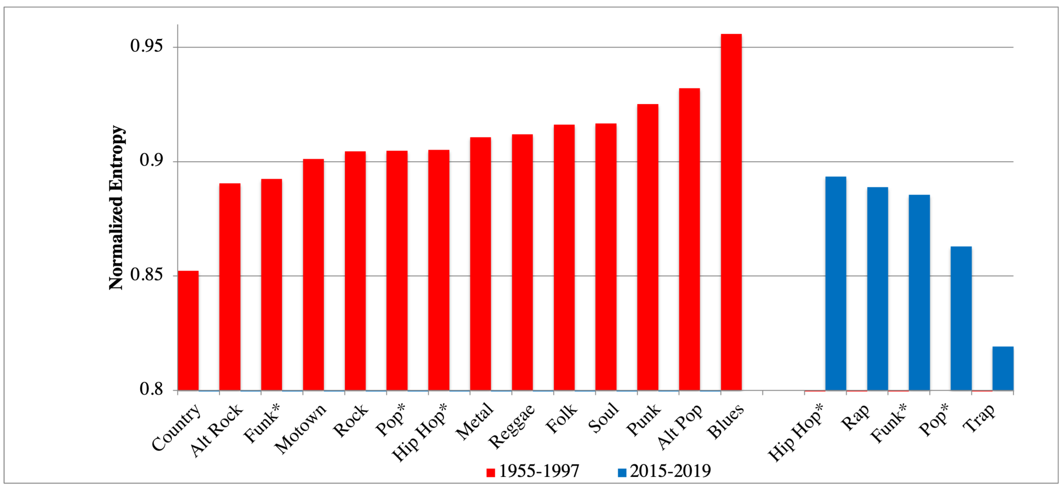

Figure 7. The average normalized entropy for rhythmic profiles for both corpora; asterisks show genres shared by both corpora

their songs.

3.6. *Discussion*

Within these quantitative analyses, we see a picture of earlier corpora exhibiting a greater preference to place melodic onsets on certain positions in the measure while more recent songs distribute melodic events more evenly throughout the measure. Specifically, melodic-metric profiles of the earlier corpus apportioned more of their probability distributions to eighth-note pulses and placed relatively more note onsets at the end of measures, the latter of which is likely connected to the preponderance of downbeat-oriented syncopations in that corpus. Both properties, therefore, suggest that melodies within the earlier repertoire emphasize traditionally stronger pulses – especially the downbeat – more than later popular songs. Furthermore, our analyses additionally showed that post-millennial melodies were also rhythmically more dense, hosting more notes per measure than pre-millennial melodies. However, we also noted that there exists a more constrained usage of rhythms within more recent songs: as shown by the within-song probability distributions of rhythmic 4-grams, individual songs are more likely to repeat the same rhythmic cells in the more-recent corpus than in the earlier corpus. Additionally, the changing generic constituencies of these corpora seem to suggest some provocative connections between corpora's differing rhythmic characteristics and the genres being represented therein. While all of the genres' melodic-metric profiles sport higher normalized entropy in the post-millennial corpus, two genera unique to the newer corpus – trap and rap – have the most complex average profiles. Similarly, these genres play a crucial role in the reduction of normalized entropy in the distribution of 4-grams in the post-millennial corpus. In others words, if these quantitative analyses suggest a shifting in rhythmic styles over time, part of this shift seems particularly connected to the trap and rap genres. More speculatively, these findings may also evidence these genres' increasing influence on post-millennial popular music. As much recent work has noted, recent popular music across genres has increasingly incorporated the spoken-word techniques of rap (Barna (2019), Duinkler (2020a), Duinkler (2020b), Peres (2016)). For instance, note that the funk and hip-hop genera are represented in both datasets; the higher and lower melodic entropy values and 4-gram entropy values, respectively, within the more recent incarnations of these genera may be the result of their increased usage of rap-influenced musical materials.

The data patterns describe trends present within these two corpora, and provide some provocative suggestions about the potential differences between 20th-century and 21st-century corpora. They also suggest directions along which an analysis of recent popular music might travel. In what follows, we invoke some of these analytical potentials, by subjecting a post-millennial song outside of our corpus to a close reading using computer-aided techniques inspired by our corpus analyses.

4. Computer-assisted analysis of Lizzo's "Truth Hurts"

After the song's original release in 2017, Lizzo re-released her single "Truth Hurts" to great popular success in 2019, with the song sitting at 13 on Billboard's Year-End chart for that year. The song appears to interact with many of this study's observations. Lizzo's words – their accents, relative speed, and metric placement – seem to steer this song, creating feelings of tension, motion, and resolution, yielding an infectious and confident drive to the overall track. Indeed, while finding a home on the pop charts, Spotify's genre tags include *pop*, *pop rap*, *rap*, and *trap queen*, and Billboard itself refers to the track as a "rap song" (Trust 2019). This song provides a central case of the tendencies outlined above: it is a rap/trap-influenced song that – being the 13th most popular song in 2019 – is a central example of American popular music of this era. To illustrate some ways that the general trends identified by the above corpus analyses might be used in an individual post-millennial song, we subject "Truth Hurts" to many of the same analytical techniques as used above (e.g., investigating aspects of the melody's rhythmic density and rhythmic 4-grams) and observe how the song manipulates these parameters for expressive and formal purposes. (The lyrics and formal annotations of "Truth Hurts" can be found in our Online Supplement.)

Table 2. Comparative rhythmic densities

	"Truth Hurts"	2015-2019	1955-1997
Normalized Entropy of melodic-metric profile	.89	.94 (median)	.51 (median)
Normalized Within-Song Entropy of rhythmic 4-Grams	.66	.87 (median)	.91 (median)
Average Rhythmic Density per measure	5.5 (SD = 2.2)	7.25 (SD = 2.91)	4.12 (SD = 1.87)

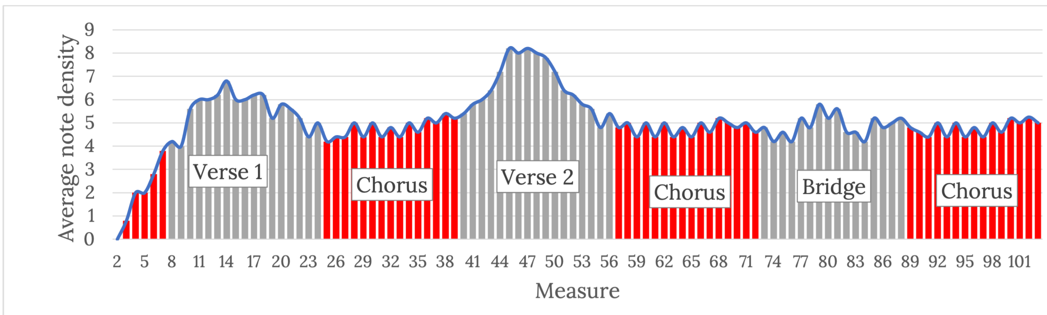

Figure 8. The changing rhythmic density throughout the melody of Lizzo's "Truth Hurts".

4.1. *Melodies Density and Normalized Entropies*

Table 2 shows the normalized entropies of the song's melodic-metric profile and its rhythmic 4-gram distribution. For comparison, the median values for both above-analyzed corpora are included as well: in both categories, "Truth Hurts" exhibits a value closer to the median of the post-millennial dataset than to the 20th-century dataset. The table also shows the song's average rhythmic density per measure, along with those of the two corpora. Notably, the average rhythmic density (and its standard deviation) sits between the two corpora, suggesting that this song's melody is not as dense as other comparably-popular post-millennial songs (for instance, it has much less dense texture than Lil Nas X's "Old Town Road," another 2019 hit).

Figure 8 represents density fluctuations within the form of "Truth Hurts." Here, each measure's value represents the average of that bar's density and densities of the prior and succeeding two measures. The figure illustrates how the variations in text density differentiate between verses and choruses, with the former noticeably more dense than the latter. The overall fluctuations of density additionally form a song-wide peak in verse 2, crafting a density trajectory that climaxes in verse 2 and dissipates into the following chorus.

Figure 8 additionally suggests local gradients in rhythmic density within this track, and Figure 9 and Figure 10 show two such instances, now using our corpus's metered and micro-timed representations to illustrate specific passages. As noted in the figures, the divisions of the top four layers show metric pulses, with the measure-long duration at the top being sequentially divided into shorter metric durations. The "metered text" layer aligns each syllable to the closest metric pulse, while the "micro-timed" band aligns syllables with their onset with the sound signal. While the above analyses use the metered-text band for their analyses, the microtimed layer will be useful in showing some subtle aspects of Lizzo's text delivery. (NB: Using this grid notation instead of Western

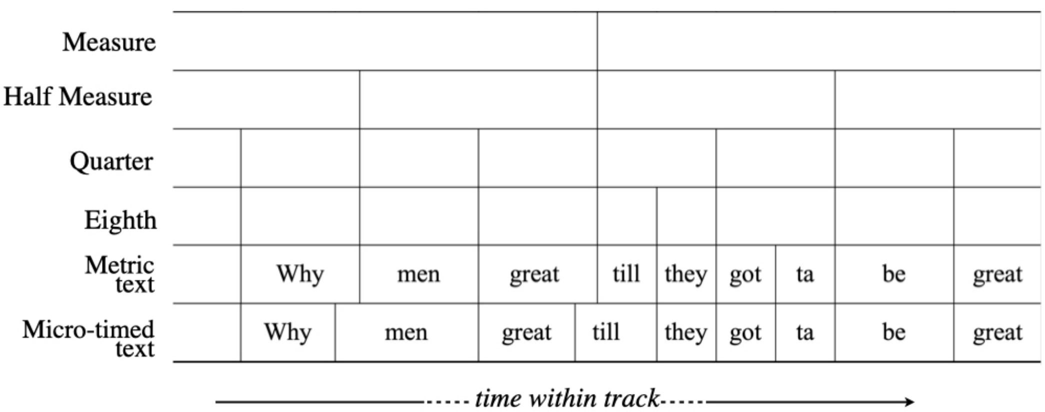

Figure 9. Metric and microtimed syllables beginning the chorus of ”Truth Hurts”.

staff notation is a conscious choice, as we believe our representation both captures the rhythmic variation under discussion in this repertoire, and also sidesteps representing a musical genre that is – arguably – not native to staff notation.)

First, consider Figure 9, which represents the beginning of song's chorus. As the phrase begins, Lizzo only uses single-syllable words, with each word lasting the same duration. (She additionally either drops or elides the "are" of "Why *are* men great" when fitting this mono-rhythmic pattern into the meter; the "omitted are", or *null copula*, would be a common feature of African-American English; see Erik and Bailey (1993). The next events double the declamation, fitting single-syllable words into quicker durations (i.e., "till they") while using the phrase's only two-syllable word ("gotta"). The phrase ends (with "be great") by shifting back to the opening's broader pace of declamation. The microtimed onsets similarly move from less-precise alignments to stricter alignments throughout the phrase, with "men" and "till" anticipating their respective metric pulses, while the remaining syllables begin relatively synchronously with the onset of metric pulses. Notably, several other parameters also support the phrase's trajectory. For instance, the text's consonants begin with a greater number of obstruent consonants (i.e., brighter, bursting consonants, like "t") being used mostly in the quicker section. Even within this short phrase, the melody's text and accompanying rhythm produce a trajectory that departs from and returns to its initial state.

Figure 10 shows a passage from verse 2, the song most-dense moment. While the earlier example's declamation created a denser texture by using quicker pulses, Lizzo now creates an increasingly "crammed" beat with suggestions of *metric grouping dissonances*, rhythmic groupings that conflict with the prevailing metric pulses (Krebs (1999), Butler (2006)). The two phrases preceding the music of the example mildly increase their respective syllabic density ("You tried to break my heart? Oh, that breaks my heart [11 syllables] / That you thought you ever had it, no, you ain't from the start" [14 syllables]), while occupying the same time duration. The next line (beginning with "Hey I'm glad" and ending with "hide this") increases to 16 syllables within the same duration, and is followed by a yet denser delivery (beginning with "No I'll" and ending with "side chick") at 17 syllables. These most-dense phrases pose a metric problem: Lizzo must perform a declamatory feat to accommodate the number of spoken syllables into the requisite window of time, momentarily subverting the expected metric subdivisions to do so.

This accommodation is illustrated in Figure 10's metric and microtimed layers. Both

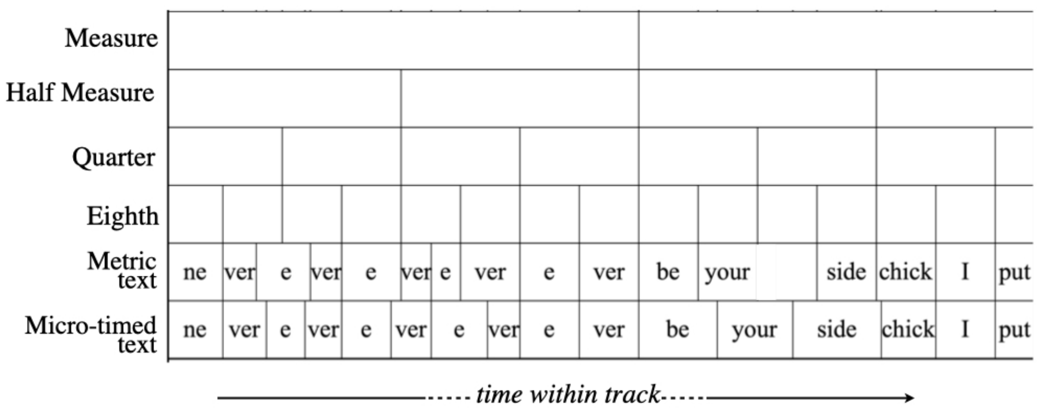

Figure 10. Metric and microtimed syllables in the most-dense portion of verse 2.

show the compression occurring in Lizzo's syllable delivery; however, the mircrotimed layer shows the rhythmic play underpinning this compression. There, Lizzo's string of "ever"s breaks the chain of eighth-measure durations preceding it, cutting into the previous "ver," and suggest a brief 3-against-2 dissonance with the eighth-measure layer. Overall, the microtimed layer allows for a nearly-even distribution of these ten syllables over the duration of this measure, something which would additionally suggest a 10-against-8 dissonance with the eighth-measure layer!

These two phrases, therefore, illustrate similar fluctuations of syllable delivery. However, taken together, these examples evidence a large-scale move from more disciplined and regular text declamations to a less-regular and more-syllabically-dense texture. The former example is representative of the chorus's texture, while the freedom and supersaturation of the latter occur in Lizzo's verses. In the context of this song, then, the prosodic looseness of the verses appear to aim toward the regularity of the choruses, creating a larger trajectory – if not a sense of goal orientation – within "Truth Hurts." Notably, this parallels the verse/chorus trajectories of 20th-century American rock. In the Loose-Verse-Tight-Chorus paradigm (Temperley 2018), the less-organized harmonic, melodic, and rhythmic material of verses "aims" toward the more strictly regulated/predictable material of choruses. Additionally, Lizzo's declamation is also reminiscent of the how rap musicians compose their verses and choruses, with the former being generally less rhythmically regular and more dense, and the latter being more regular and less dense (Ohriner 2019). In other words, "Truth Hurts" performs a broader trajectory that mimics both earlier popular music and contemporary rap styles, but instantiates that trajectory by picking aspects of both styles– through the prosodic declamation of the text (as in rap), while singing clear melodic phrases over traditional harmonies (as in 20th-century popular music). The effect, then, is a dramatic rhythmic push-and-pull of expressive rhythm and melodic density, a drama that relies upon the parameters that were identified by our corpus analysis as hallmarking post-millennial popular songs.

5. Conclusions and Future Directions

This brief study posits some suggestions about quantifiable ways that post-millennial American popular music may differ from its 20th-century counterpart. In particular, more recent music seems to use melodies whose notes are distributed more evenly both throughout the measure and throughout metric levels than in earlier music. This may suggest a different syncopation usage and less emphasis on downbeats in more recent music (Tan, Lustig, and Temperley 2018), and may also indicate quicker and denser rhythms used in post-millennial popular songs. We also found that there were greater fluctuations in the rhythmic density in more-recent melodies, and also noted that individual rhythmic cells are more often reused within the post-millennial corpus. Aligning with recent popular-music scholarship, we noted that these quantitative differences might evidence the increasing inclusion and influence of rap and rap-based genres in 21st-century popular music.

We then leveraged these quantitative observations to guide an analysis of Lizzo's 2019 hit single "Truth Hurts," both solidly post-millennial and categorized within rap and rap-adjacent genres. Overall, we showed that the song's melodic rhythms generally adhered to the trends identified in our earlier corpus analyses, and that its melody's rhythmic density was used to articulate the boundaries between formal sections within the song. Finally, a close reading of both the chorus's melody and the melody of the song's most-dense passage showed that density itself seemed to participate (if not communicate) the trajectory of the phrases, with short- and long-term melodic groupings showing a distinct motion between a less and greater states of density.

Importantly, this work has certain limitations: for one, our post-millennial corpus is somewhat limited in scope (being roughly a third the size of the 20th-century corpus), and certain parameters (e.g., tempo) are not considered in the present study. However, our study is designed to be exploratory. Our goals are to suggest connections between musicological research and the quantitative properties of these repertoires, to offer future directions for study, and encourage avenues for computational- and empirically-guided analyses of post-millennial popular music. In particular, our findings suggest that post-millennial popular music – likely due to the influence of spoken-word genres like rap – may be more reliant on melodic rhythms and the delivery of text for its musical expression and formal design than are earlier 20th-century popular songs. While this trend seems by no means ubiquitous, parameters associated with text delivery appear to be wielded alongside timbre, melodic pitch, and accompanimental harmony in the compositional palates of contemporary songwriters and producers. Indeed, our study suggests that by foregrounding more text- and rhythmic-based analyses of this repertoire, an analysis will not only account for salient musical materials, but may additionally acknowledge the cultural forces and generic influences that underpin this repertoire.

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Supplemental online material

Supplemental online material for this article can be accessed at `your-own-link`, and shows the songs used in the post-millennial corpus, along with the lyrics and form of Lizzo's "Truth Hurts." Temporary folder for review: https://drive.google.com/drive/folders/14jQgFS1mLpiYdTm5ogBzXHWY_vtlCO6o?usp=sharing

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