

A FEATURE-BASED APPROACH TO MODELING EXPERT MUSICAL INSIGHTS: THE MAX MARTIN COEFFICIENT

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ABSTRACT

We investigate the possibility of modeling musical composition and production styles using computationally extracted acoustical features and metadata. Specifically, we characterize the work of successful pop songwriter and producer Max Martin. Acoustic features from Martin’s catalog are broken down into timbre, pitch, intensity and rhythm categories. Metadata features include date of release, and Billboard Hot 100 chart peak position. Preliminary analyses provide early insights into trends over Martin’s career and suggest ways to compare his data to those of his music industry peers.

1. INTRODUCTION

Many fans of western popular music know the names Britney Spears, The Weeknd, Katy Perry, Taylor Swift, Pink, and Kelly Clarkson. What many don’t know is that all of these artists have had number-one Billboard songs written and produced by the same person. This person is Max Martin, a 45-year-old music industry stalwart who has achieved a level of success that far exceeds the recognition of his name. In fact, only two people have more Billboard Hot 100 number-one songwriting credits than Max Martin’s 21 songs: John Lennon (26 songs) and Paul McCartney (32 songs). Only long-time Beatles producer George Martin has more number-one production credits (23 songs to 21). While the Beatles are widely regarded as the most influential band of all time, Max Martin maintains relative anonymity. The phenomenon of Martin’s success has led to qualitative assessments by writers and music industry experts, who seek to identify the underlying attributes of Martin’s works that explain his commercial success [2,5].

Here we attempt to characterize Max Martin’s body of work using acoustic and metadata features extracted directly from audio of songs he has both written and produced. A longer-term goal of this work is to explore the possibility of modeling musical composition and production styles with computationally extracted features and metadata.

Category	Features
Timbre (short-term)	spectral flux mean, spectral flux std, spectral flux mean for 10 octave sub-bands
Pitch (long-term)	mean strength of 12 chromatic degrees, mode
Intensity (short-term)	high energy/low energy ratio
Rhythm (long-term)	pulse clarity mean, pulse clarity std tempo
Metadata (song-level)	# of writers, date of release Billboard peak

Table 1. Features extracted from song set, broken into five categories. Short-term timbre and intensity features used a 50-msec window with 50% overlap, while long-term pitch and rhythm features used a 5-sec window with 20% overlap. Metadata features comprised one value per song.

2. METHODS

2.1 Song Set

The present analysis considers 160 songs. All songs were written and produced by Max Martin. Songs were chosen after consulting Martin’s production discography on Wikipedia ¹. The final list includes every song that charted on the Billboard Hot 100 (61 songs), as well as those that did not chart but were included in the discography (99 songs).

2.2 Acoustical Features

A variety of acoustical features, summarized in Table 1, were extracted from the data using the MIR Toolbox for Matlab [3,4]. Short-term acoustical features used a 50-msec window with a 50% overlap. These included all timbral and intensity features. Long-term features were computed with a 5-sec window and a 20% overlap. These included all pitch and rhythm features.

2.3 Metadata Features

Billboard and Wikipedia were used to gather metadata (Table 1). We found that Billboard charts sometimes contained inconsistent peak positions for a given song. Therefore, in cases of conflicting information, we defaulted to the human-annotated Wikipedia information.

¹ https://en.wikipedia.org/wiki/Max_Martin_production_discography



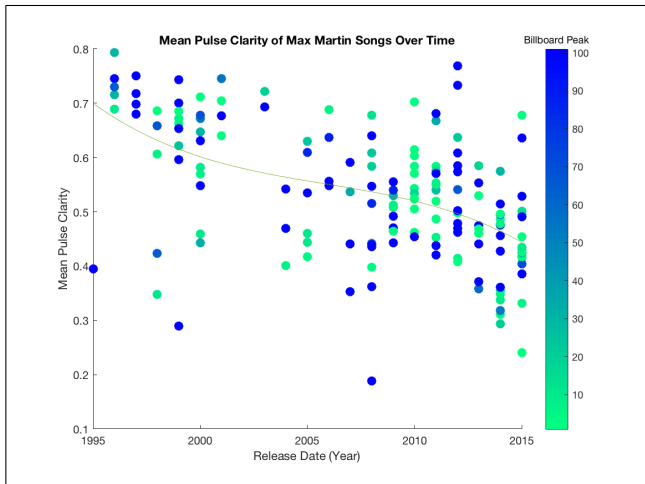


Figure 1. Mean pulse clarity values of Max Martin songs over time with a cubic regression line. The color denotes peak position on the Billboard Hot 100 charts. Songs that did not chart were given a value of 101.

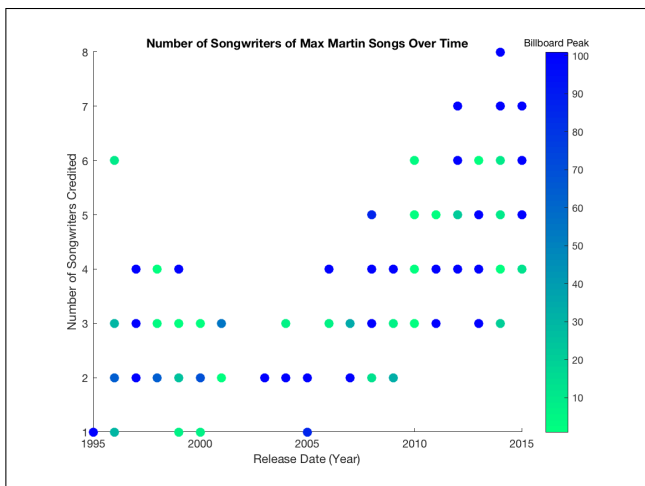


Figure 2. Number of songwriters credited on each song plotted by date of release. The color denotes peak position on the Billboard Hot 100 charts. Songs that did not chart were given a value of 101.

2.4 Analysis

Mean and standard deviation of each acoustical feature were computed on a per-song basis. These summary descriptors were then aggregated across songs along with one of the metadata features (number of writers), and orthogonalized using Principal Components Analysis (PCA).

3. PRELIMINARY RESULTS

We visualize representative acoustical and metadata features across songs. To assess changes in the features across Martin’s career, descriptors are plotted against song release date. For example, mean pulse clarity of songs over time is shown in Figure 1, while number of co-writers ver time is plotted in Figure 2. A cubic spline interpolation of pulse clarity shows a downward trend of this descriptor

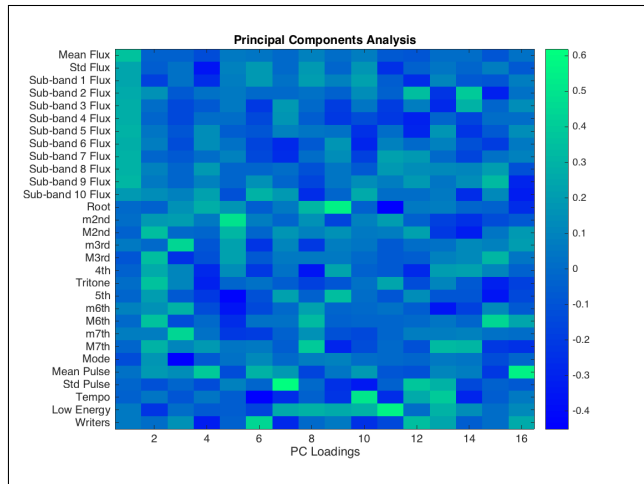


Figure 3. Loadings of the first 16 principal components (PC) plotted against each of the 30 features.

over time. Inspection of the plot also suggests an increase in variance of this descriptor over time, perhaps indicating that Martin has made more timbrally and rhythmically diverse music as his career has progressed. The increase in number of co-writers on each song over time may have contributed to this diversity, as more opinions, styles, and backgrounds were involved in the creative process.

Figure 3 shows the loadings of the first 16 PCs of features aggregated across songs, which explain 90% of the variance in the song set. Here we see that the component explaining the most variance comprises short-term timbral (flux) features, which draws comparisons to the “fullness” feature from past studies [1]. PC2 and PC3 appear to relate to specific scale degrees, with major-scale degrees in PC2 and minor degrees in PC3.

4. CONCLUSIONS

This work presents a first step toward computational modeling of an expert songwriter’s compositional and production style using acoustical features and metadata. Further analyses will reveal whether definitive insights about Martin’s work can be drawn from this approach.

As we seek to discover what *uniquely* characterizes Martin’s work, an important next step in this research will be the development of a control set of songs against which Max Martin’s work can be directly compared. This could include the catalogs of comparably successful fellow songwriters and producers, or songs that reached similar positions on Billboard simultaneously with Martin’s. Such analyses will also help us to interpret the characteristics of Martin’s work among larger-scale trends in songwriting and production, such as the possible end of the “Loudness Wars.”

5. ACKNOWLEDGEMENTS

We thank Charles Slomovitz at Shazam for providing useful insights and help in guiding the project.

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