60 Years of Pop Music on Spotify:
Exploring the Fluctuation of Audio Features

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Code available on GitHub: https://github.com/tamareliens/Data_Science_Exam.git

Abstract

In music, pop is a broad term used to describe songs that are popular in the mainstream. This study aims to identify what characteristics make pop music appealing to a wide audience and how those characteristics have changed over time. To get an insight into what audio features characterize songs in the pop genre, linear regression analyses and time series exploration will be performed on annotated Spotify data. For any song, Spotify provides metadata including information about scores for the features danceability, energy, instrumentalness, loudness, tempo and valence. The analysis did not show convincing linear relationships and decomposing the variables' time series into trend and seasonality did not reveal patterns in the data.

Keywords: pop music, Spotify audio features, linear regression, time series

1.Introduction

1.1 The Categorization of Genres

The categorization of music into different genres has been a topic of discussion for decades, among both scholars and critics. Back in 1982, Tagg divided music into the three categories that are still widely accepted as the overarching genres: traditional music, art music and popular music. Dividing those overarching genres into sub-genres is considered a more complicated and debatable task. According to Fabbri (1982), music genres are distinguished based on a set of social rules, which address 1) technical, 2) semiotic, 3) behavioral, 4) social and ideological, and 5) economical and juridical aspects of music. The technical rules of genre relate strictly to the content of the music. The semiotic aspect refers to what message or emotion is being communicated. The behavioral rules are determined by the appearance and behavior of the composers, performers and audience within the genre. Demographics and political affiliations of the people belonging to a music genre describe the social aspect of that genre. Lastly, the economical and juridical aspect consists of the laws and financial agreements supporting a genre (e.g., record contracts).

1.2 Change over time

Though exhaustive, Fabbri's (1982) definition does not consider that music genres change over time. The author emphasizes the restrictions of genres rather than their dynamic nature, which contradicts the experience of musicians and music consumers (Negus, 2013). Lena and Peterson (2008) studied the trajectories of various genres and demonstrated how cultural classifications of music change as a result of historical events and contextual factors. The researchers found the same developmental pattern for many different genres in music. Namely, over the course of their history, genres evolved from avant-garde (i.e. new, experimental music in a small group) to scene-based (i.e. creating a community), then to industry-based (i.e. primary organizational form is the industrial corporation), and eventually became traditionalist (i.e. great value is attached to preserving heritage and passing it on). More support for the dynamic nature of music genres comes from studies on American jazz (Lopes, 2002) and Italian *canzone d'autore* (Santoro, 2002).

1.3 What is 'pop'?

'Pop' is a good example of a dynamic genre. Looking up 'pop music' on the world wide web gives numerous definitions. Some describe pop as being an umbrella-genre covering many different kinds of genres (e.g. rock, country, rap) that are played by a broad audience[1]. Others consider pop to be a genre on its own, often assigning more specific characteristics to it, like having ‘repeated choruses’[2], ‘easy tunes’[3] or ‘electronic instruments’[4]. Likewise in academic research, where definitions of pop music vary by researcher and time period. For instance, Boyle et al. (1981) described pop as comprising all music experienced through the mass media, allowing for a variety of styles or subgenres. In contrast, Hatch and Millward described pop as “a body of music which is distinguishable from popular, jazz, and folk music” (1987, p. 1). Frith (2001) states that the music industry distinguishes pop from rock based on a more sociological difference of pop being single-based and aimed at teenagers while rock is ‘album-based music for adults’ (p. 95). However, an overlapping aspect of all definitions is that pop is popular music, i.e. music that is appealing to a wide audience at a given time.

1.4 The history of pop

But what was popular back in the days, might not be appealing to a wide audience today. To illustrate, The Beatles were considered a ‘mainstream’ band in the 1960s, but nowadays would be assigned to a more alternative music preference. In other words, the style of music categorized as pop has changed over time.

The origin of pop can be found in the invention of the electrical microphone in the 1930s, which made the amplification of voices and use of new vocal techniques possible (Frith, 2001). The microphone allowed singers to be heard over the sound of bands and orchestras. And more importantly, artists could now sing softly and express the intimacy of private conversation and love declarations in songs, both live and in the recording studio. The British musicologist Frith (2001) explains that the singer’s personality and emotions became more important than the instruments played or the composer’s sophisticated writing skills, which increased the need for simple, emotional songs.

In the 1950s, the advent of television and the rise of a teenage market in the United States and the United Kingdom laid the foundation for the modern version of pop performance and the idolization of pop stars. More and more pop groups emerged who appealed to teenagers because of their appearance and harmoniously sung emotional, relatable stories.

[1] https://www.damvibes.com/music-theory/pop-music-genre-definition-history/
[2] https://en.wikipedia.org/wiki/Pop_music#cite_note-8
[3] https://www.oxfordlearnersdictionaries.com/definition/english/pop-music
[4] https://www.macmillandictionary.com/dictionary/british/pop-music

In the late 1960s and early 70s, progressive pop branched from progressive rock as a subgenre of pop that seeked to deviate from pop music's conventional formula. Artists within progressive pop emphasized the importance of virtuosity and creativity and generally focused on concept-based albums that were expected to be heard and appreciated sitting down (Bennett, 2020). Examples of stylistic features from progressive pop are variations in rhythm and key and "experiments with larger forms" (Baaz & Palmberg, 2001, p. 49).

The late 70s and 80s were characterized by new wave music, which encompasses pop and rock-oriented styles using synthesizers and lighter melodies, compared to the established punk culture. The terms synth-pop, techno-pop and electro-pop are being used interchangeably referring to music primarily using synthesizers, drum machines and sequencers. Borthwick and Moy (2004) describe the genre as diverse but unified by a shared set of values that deviate from the playing styles, rhythms, and structures of rock music. Instead, the genre embraces "synthetic textures" and "robotic rigidity," often influenced by the limitations of the technology at the time, such as monophonic synthesizers (i.e. only able to play one note at a time) (Parker, 2009).

The last decades, pop music has been characterized by more uptempo songs, both suitable for the radio and night clubs. Pop aims to encourage dancing or incorporates rhythms that are dance-oriented in nature (Warner, 2003). Dance-pop emerged from dance and disco music and later evolved into electronic dance music (EDM).

1.5 Pop on Spotify

Today, we have access to music from all over the world courtesy of digital music services such as Spotify. The service contains over 80 million songs, over 11 million artists and thousands of different (sub)genres. Spotify's 'data alchemist' Glenn McDonald explains that genre categories are produced internally through both machine learning and data curators (Johnston, 2018). Psychoacoustic attributes, like danceability or degree of happiness, have been invented by curators and are aggregated over genres and evaluated for each song using machine learning. Data scientists or developers can collect data through Spotify's web API and gather, among other things, the metadata for albums, artists and tracks in specific playlists.[5]

[5] https://developer.spotify.com/documentation/web-api

1.6 The present study

The above outlined studies on genre categorization and the historical progression of pop aim to highlight the ignorance surrounding the mutability of the stylistic characteristics of pop music. The great collection of songs and metadata available on Spotify provides the opportunity to investigate how certain features have changed over decades. History has shown how pop music has evolved in various ways: from soft intimate love songs to electronic dance, from teenage stories to instrumental experiments, from simple progressions to rhythmic variations. Therefore, this study focuses on the features danceability, energy, loudness, instrumentalness, valence, mode and tempo.

2. Method

2.1 Data

Spotify's API was used to create a dataset containing 2263 songs. The songs come from 40 different playlists categorized within the genre pop, which have been generated by Spotify itself. In the selection of playlists, attention was paid to including songs from different decades, varying between the 60s and today. The names of the playlists and their index corresponding to the data scraping files can be found in Appendix A. The data was scraped between the 19th and 22d of May 2023, which is relevant since Spotify updates its playlists on a regular basis.

For this study, only the variables described in Table 1 were selected from the dataset (see Appendix B for the full list of variables). In the process of cleaning the data, tracks were filtered on whether one of the genres of the first artist is pop, because Spotify does not provide genres for individual tracks. This left only 1430 tracks, even though all tracks in the dataset came from pop playlists. Spotify also does not provide the release date of individual tracks, only for the albums they appear on.

Index	Variable	Description	Example Value
1	danceability	Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.	0.585

2	energy	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.	0.842
3	loudness	The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typically range between -60 and 0 db.	-5.883
4	mode	Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0.	0
5	instrumentalness	Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.	0.00686
6	valence	A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).	0.428
7	tempo	The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.	118.211
8	release_date_ album	The release date of the album the track is on.	1963-03-25

Table 1: Descriptions and example values for the variables in the dataset. The first 10 descriptions are directly derived from Spotify[6], while the other variables have been extracted indirectly and therefore have self-made descriptions and example values.

2.2 Analysis

The remaining dataset containing 1430 tracks will be used for the rest of the analysis. Due to the size of the dataset and the limited time available, only the release year of albums will be

[6] https://developer.spotify.com/documentation/web-api/reference/get-audio-features

considered, instead of the specific dates or months. First, linear regression analyses will be performed to examine whether there are linear relationships between the release year and the features of tracks. Then time series analysis including autocorrelation plotting and decomposition into trend and seasonality will be conducted to gain deeper understanding of potential patterns in the data.

3. Results

3.1 Linear regression

Linear regression analyses were performed to investigate whether there is a linear relationship between release year as predictor and danceability, tempo, mode, energy, instrumentalness, valence, and loudness as dependent variables. The output of each model is shown in Table 2.

Variable	R-squared	coefficient	t-value	P > | t |	F-statistic
danceability	0.03	0.001	6.000	0.000	36.00
tempo	0.00	0.002	0.042	0.967	0.001753
mode	0.00	-0.002	-2.215	0.027	4.905
energy	0.01	0.001	3.564	0.000	12.71
instrumentalness	0.00	-0.000	-1.488	0.137	2.214
valence	0.07	-0.004	-10.456	0.000	109.3
loudness	0.24	0.090	20.965	0.000	439.5

Table 2: Output of the linear regression models with release_year as predictor.

R-squared values can vary between 0 and 1 and indicate the amount of variance in each variable that can be explained by Release Year. Coefficient values represent the magnitude and direction of the linear relationship between a variable and Release Year. The t-value measures the ratio of the estimated coefficient to its standard error and assesses whether the coefficient is significantly different from zero. A larger absolute t-value indicates a stronger evidence against the null hypothesis of no linear relationship between the predictor and the

dependent variables. The corresponding p-value indicates the statistical significance of the coefficient. Lastly, The F-statistic tests the overall significance of the model by comparing the variability explained by the independent variable to the variability not explained by the model. A higher F-statistic and a lower p-value indicate a more significant relationship between Release Year and the dependent variables.
Based on the values in Table X, four of the variables are statistically significant. For Danceability, there is a very weak positive relationship with Release Year (coefficient = 0.001, t-value = 6.000, $p < 0.001$) and 3% of the variance in Danceability can be explained by a linear regression model with Release Year as predictor (R-squared = 0.03). Energy generates similar findings (coefficient = 0.001, t-value = 3.564, $p < 0.001$, R-squared = 0.01). For Valence, there is a very weak negative relationship with Release Year (coefficient = -0.004, t-value = -10.456, $p < 0.001$) and the model explained 7% of the variance. The Loudness model indicates a very weak positive relationship with Release Year (coefficient = 0.090, t-value = 20.965, $p < 0.001$) and the highest R-squared: the model explains 24% of the variance (R-squared = 0.24). Tempo, Mode and Instrumentalness are not statistically significant.

In general, the results of the linear regression models suggest that the relationship between Release Year and the various variables is hardly linear, if at all.

3.2 Time Series Analysis

Next to linear regression analyses, the temporal component of the data was further investigated by visualizing the variables over time, generating autocorrelations and decomposing the time series into trend and seasonality.

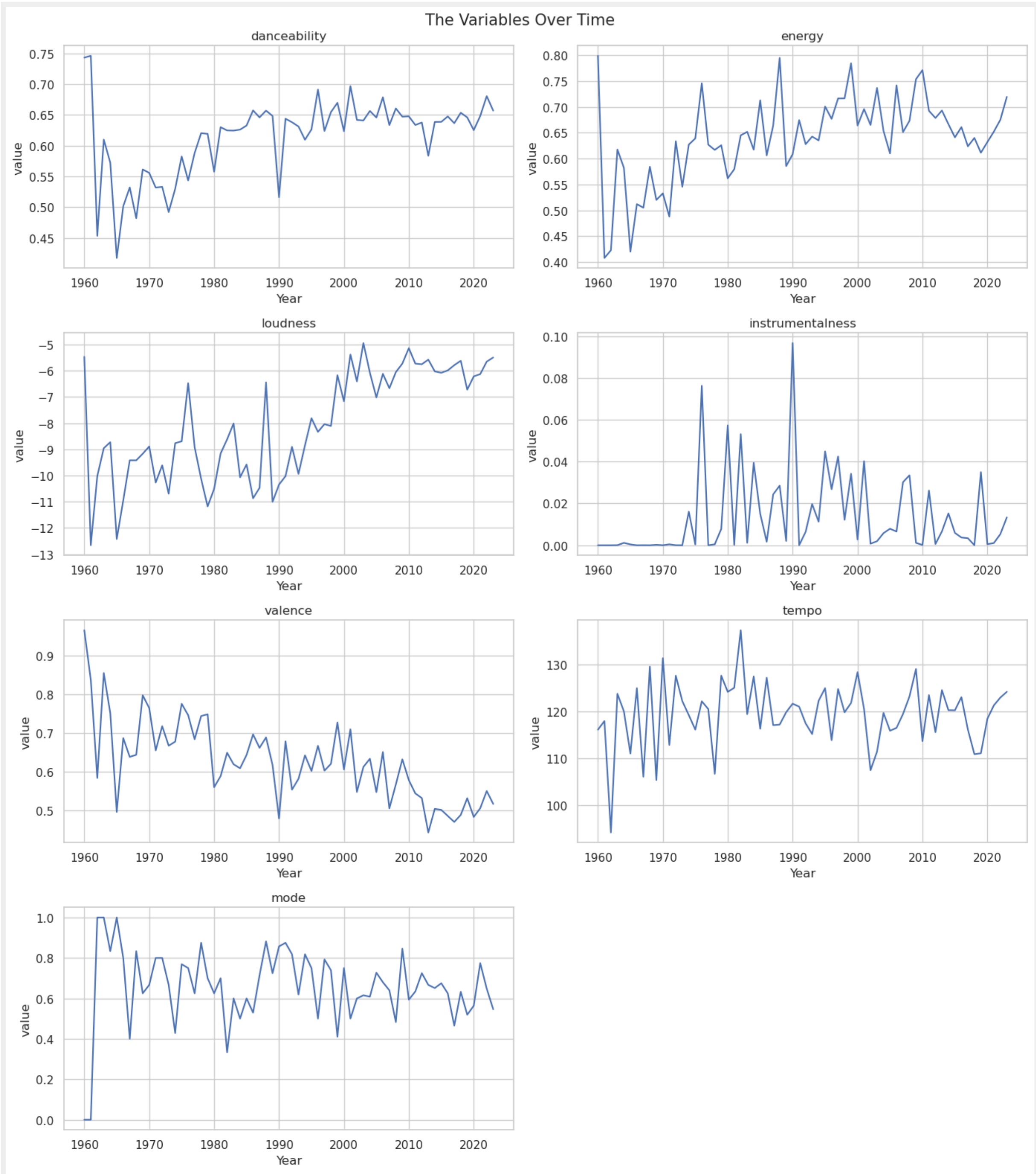

Figure 1: The variables plotted over time.

At first glance, the values for the various variables appeared to fluctuate greatly over the course of 64 years. The plots suggested that Valence and Mode might follow a negative trend, while Danceability, Energy and Loudness might follow a positive trend. Instrumentalness and Tempo do not seem to show a trend. Following, the autocorrelation functions (ACF) were plotted for each variable to provide insight into serial correlations in the data.

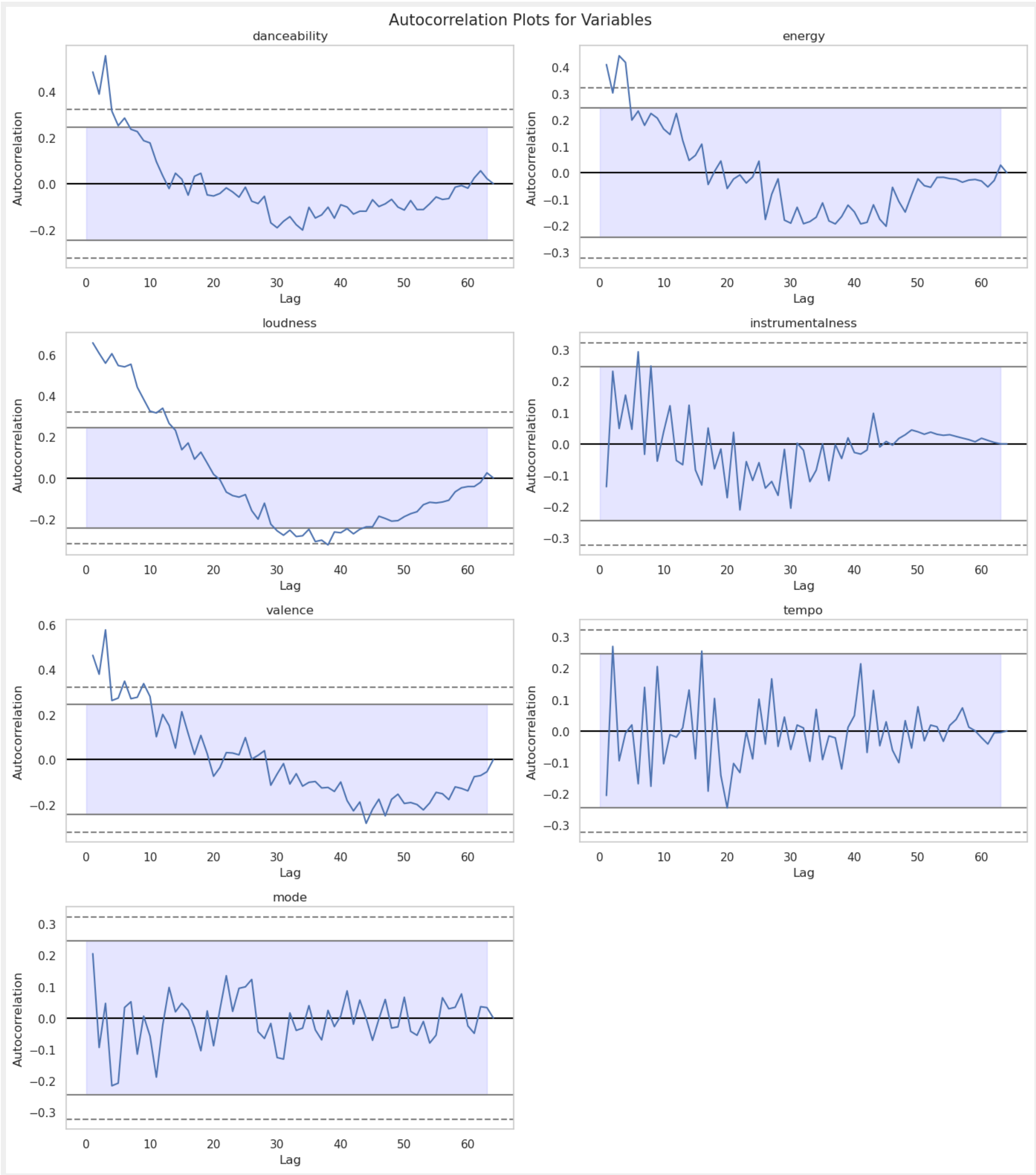

Figure 2: Autocorrelation plots for each variable.

The autocorrelation function plots in Figure 2 show the correlation between a variable's values at different time lags. In these plots, the lags represent the release years of songs. The y-axis represents the autocorrelation coefficient, whose values are statistically significant outside of the 95% confidence interval (the shaded blue region). Positive and significant values for the autocorrelation coefficient suggest a positive correlation between values in those years, and vice versa for negative values.

For Danceability, Energy, Tempo and Mode the plots indicated randomness or white noise in the data. Therefore, only the time series for Loudness, Instrumentalness and Valence were further decomposed into trend, seasonality and residuals using an additive model.

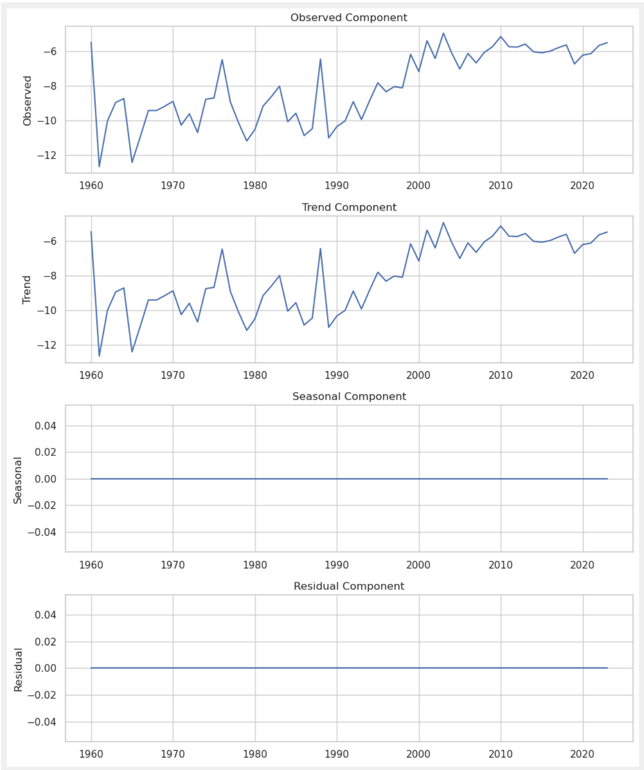

Figure 3: Decomposition of time series for Loudness. From top to bottom, the components shown are: observed, trend, seasonal and residuals.

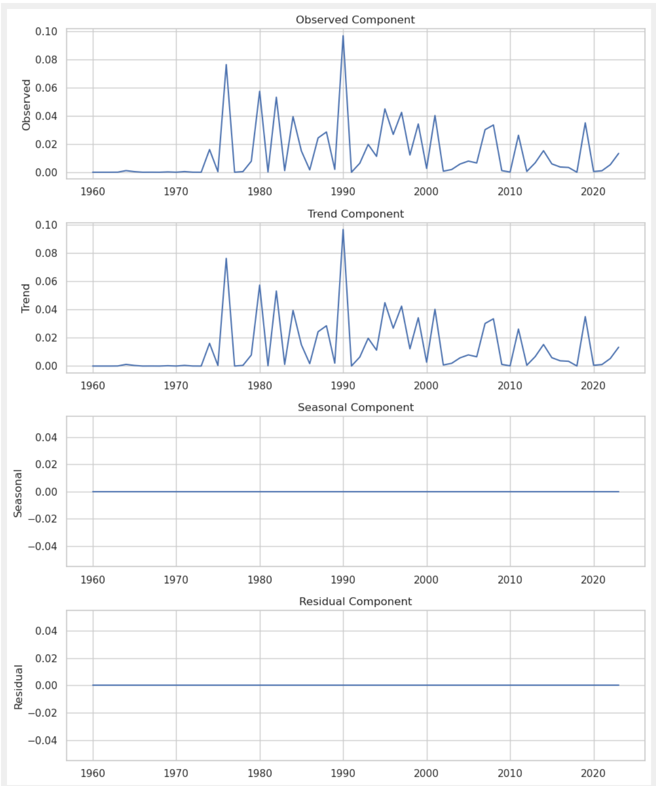

Figure 4: Decomposition of time series for Instrumentalness. From top to bottom, the components shown are: observed, trend, seasonal and residuals.

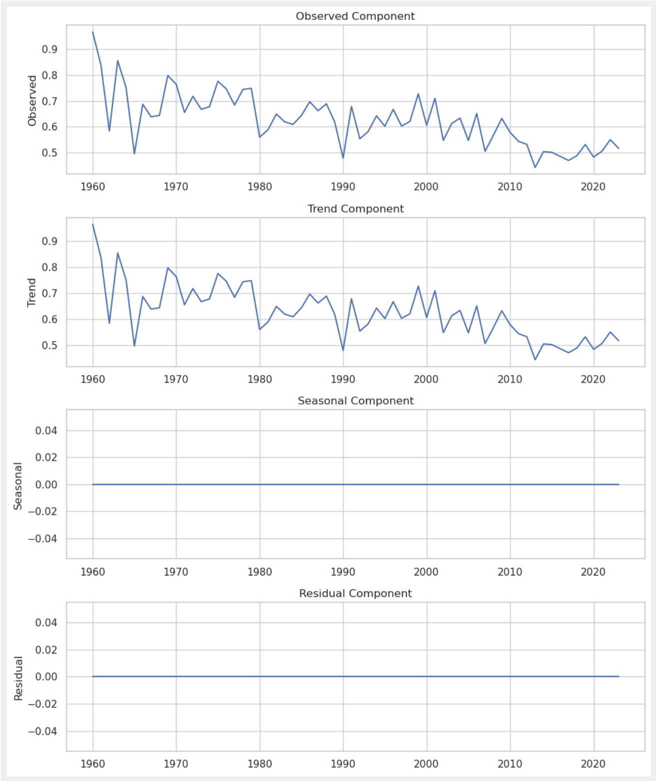

Figure 5: Decomposition of time series for Valence. From top to bottom, the components shown are: observed, trend, seasonal and residuals.

Figures 3, 4 and 5 show flat lines at y = 0 for both the seasonal and residual components for each of the variables, suggesting that there is no seasonality or residual patterns in the data. This could mean that the trend component captures all patterns in the data, but more likely there is a bug in the analysis.

4. Discussion

The present study aimed to explore the mutability of stylistic characteristics in pop music. The focus was on examining how certain features, namely danceability, energy, loudness, instrumentalness, valence, mode, and tempo, have changed over a period of over six decades. The linear regression models found significant relationships between release year and danceability, energy, valence and loudness. However, the very small sizes of the coefficients suggest that linear regression is not the best model to fit the data. After plotting the features over time and observing the autocorrelation plots, the time series for loudness, instrumentalness and valence were decomposed. The seasonality and residuals components could not explain patterns in the data for any of the three features.

Due to the exploratory nature of the analysis, there follows no direct conclusion from the above described findings. Moreover, a few limitations should be taken into account, including: the small size of the dataset, the fact that Spotify does not provide genre and release dates for individual tracks, and the restriction to annual lags instead of monthly. To conclude, future research is encouraged to continue the exploration by performing more tests and models, like exponential smoothing and ARIMA.

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Appendix A: The playlists used for data scraping

Index	**Name**	**URI**	**Number of Tracks**
0	Pop Party	spotify:playlist:37i9dQZF1DWXti3N4Wp5xy	150
1	Dance Pop Hits	spotify:playlist:37i9dQZF1DWZQaaqNMbbXa	148
2	Happy Pop Hits	spotify:playlist:37i9dQZF1DWVlYsZJXqdym	50
3	Women of Pop	spotify:playlist:37i9dQZF1DX3WvGXE8FqYX	75
4	Guilty Pleasures	spotify:playlist:37i9dQZF1DX4pUKG1kS0Ac	150
5	Soft Pop Hits	spotify:playlist:37i9dQZF1DWTwnEm1IYyoj	100
6	Internet Rewind	spotify:playlist:37i9dQZF1DWSPMbB1kcXmo	80
7	70s Party	spotify:playlist:37i9dQZF1DX1Hya1sRqqxI	150
8	80s Party	spotify:playlist:37i9dQZF1DX6xnkAwJX7tn	150
9	90s Party	spotify:playlist:37i9dQZF1DXdo6A3mWpdWx	150
10	Party Hits 2000s	spotify:playlist:37i9dQZF1DX7e8TjkFNKWH	150
11	Partyhits van de jaren 10	spotify:playlist:37i9dQZF1DWWylYLMvjuRG	150
12	60s Party	spotify:playlist:37i9dQZF1DX3AdAEX3vkB1	134
13	60s Pop Mix	spotify:playlist:37i9dQZF1EIgE4vw8UBiVo	50
14	70s Pop Mix	spotify:playlist:37i9dQZF1EIg0r197lDGql	50
15	80s Pop Mix	spotify:playlist:37i9dQZF1EIg0AuSxAydwd	50
15	90s Pop Mix	spotify:playlist:37i9dQZF1EIePiJCdjVKSH	50
17	Best of 00s Pop	spotify:playlist:37i9dQZF1DWUaThf8nMdW6	50

18	10s Pop Run	spotify:playlist:37i9dQZF1DX3PIAZMcbo2T	50
19	Today's Top Hits	spotify:playlist:37i9dQZF1DXcBWIGoYBM5M	50
20	Songs to Sing in the Car	spotify:playlist:37i9dQZF1DWWMOmoXKqHTD	100
21	Just Hits	spotify:playlist:37i9dQZF1DXcRXFNfZr7Tp	100
22	Easy 60s	spotify:playlist:37i9dQZF1DWZWYUuTGjjhE	80
23	Easy 70s	spotify:playlist:37i9dQZF1DWSWNiyXQAvbl	81
24	Easy 80s	spotify:playlist:37i9dQZF1DX6l1fwN15uV5	80
25	Easy 90s	spotify:playlist:37i9dQZF1DWV8xrpik0esU	80
26	Easy 00s	spotify:playlist:37i9dQZF1DX8j4KHUVrE2f	80
27	Easy 10s	spotify:playlist:37i9dQZF1DX7udthHrZCWz	80
28	The Pop Lounge	spotify:playlist:37i9dQZF1DXcQRnVXaCXYk	70
29	Mood Booster	spotify:playlist:37i9dQZF1DX3rxVfibe1L0	78
30	Sunny Day	spotify:playlist:37i9dQZF1DX1BzILRveYHb	75
31	Mega Hit Mix	spotify:playlist:37i9dQZF1DXbYM3nMM0oPk	75
32	Pop songs we can all scream	spotify:playlist:37i9dQZF1DX2KwEtNSejGe	100
33	Summer Throwback	spotify:playlist:37i9dQZF1DXd1MXcE8WTXq	80
34	Piano Ballads	spotify:playlist:37i9dQZF1DWVIzZt2GAU4X	75
35	Timeless Love Songs	spotify:playlist:37i9dQZF1DX7rOY2tZUw1k	100
36	Energiebooster: pop	spotify:playlist:37i9dQZF1DX0vHZ8elq0UK	150
37	The Ultimate Hit Mix	spotify:playlist:37i9dQZF1DWUZMtnnlvJ9p	143

38	Deep Dive: 70s Pop	spotify:playlist:37i9dQZF1DXbpLIJzuZ9tc	100
39	Deep Dive: 80s Pop	spotify:playlist:37i9dQZF1DX0mziTeNtU34	280

Appendix B: Descriptions of all variables in the dataset

Index	Variable	Description	Example Value
1	danceability	Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.	0.585
2	energy	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.	0.842
3	key	The key the track is in. Integers map to pitches using standard pitch class notation. E.g. 0 = C, 1 = C♯/D♭, 2 = D, and so on. If no key was detected, the value is -1. The range is -1 - 11.	9
4	loudness	The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typically range between -60 and 0 db.	-5.883
5	mode	Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0.	0

6	acousticness	A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.	0.00242
7	instrumentalness	Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.	0.00686
8	liveness	Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.	0.0866
9	valence	A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).	0.428
10	tempo	The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.	118.211
11	duration_ms	The duration of the track in milliseconds.	237040
12	time_signature	An estimated time signature. The time signature (meter) is a notational convention to specify how many beats are in each bar (or measure). The time signature ranges from 3 to 7 indicating time signatures of "3/4", to "7/4".	4

13	num_bars	The number of bars a track has. A bar (or measure) is a segment of time defined as a given number of beats.	96
14	num_sections	The number of sections a track has. Sections are defined by large variations in rhythm or timbre, e.g. chorus, verse, bridge, guitar solo, etc. Each section contains its own descriptions of tempo, key, mode, time_signature, and loudness.	8
15	num_segments	The number of segments a track has. Each segment contains a roughly consistent sound throughout its duration.	614
16	genres_artist	All genres the first artist of a track belongs to.	[‘baroque pop’, ‘classic rock’, ‘folk rock’, ‘pop’]
17	release_date_album	The release date of the album the track is on.	1963-03-25

Table X: Descriptions and example values for the variables in the dataset. The first 10 descriptions are directly derived from Spotify (https://developer.spotify.com/documentation/web-api/reference/get-audio-features), while the other variables have been extracted indirectly and therefore have self-made descriptions and example values.