Timbre & Sentiment Analysis

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1. Introduction

Music has been a channel for artists to express social sentiments for long, but the exact correlation in effect has not been unfolded. This data visualization project thus explores the correlation between music and news sentiment from 1920 to 2020. Specifically, the music timbre has been employed to quantify sounds.

2. Motivation

Music timbre is the tone color of a song, a medium for songwriters to deliver different emotions: a song marked with brightness is generally associated with elation and euphoric, whereas a song characterized by flatness is connected to melancholy and even ennui. To quantify timbre, EchoNest, a data analysis platform, employs 12 specially designed basis to capture different aspects of music timbre. While timbre 8 to 12 are more abstractly engineered, the first 4 timbres represent measurable audio concepts:

Timbre Basis	Explanation
TimbreAvg1	average loudness of the segment
TimbreAvg2	brightness
TimbreAvg3	more closely correlated to the flatness of a sound
TimbreAvg4	stronger attack

On the other hand, NLTK, a mainstreamed natural language processing toolkit with a massive pre-trained neural network at our disposal could help assign four scores to each sentence corresponding to four different emotions: *negative*, *neutral*, *positive*, and *compound*. This package helps convert words to sentiments.

With the two data analysis platform, we are particularly interested in the following:

1. How strong/weak a correlation do we have between each timbre and each sentiment? For example, could we expect a period with more negative sentiments to have music characterized by a flatter timbre?
2. Does the correlation change overtime? If the correlation is strong, is it strong consistently across the entire 90 years?

3. Data & Preprocessing

To maximize our usage and expression of temporal data, patterns need to be extracted as a part of data cleaning and preprocessing.

For the timbre dataset, the annual average of 12 features are computed and are given label of decades.

	decade	TimbreAvg1	TimbreAvg2	TimbreAvg3	TimbreAvg4
0	d00	44.322720	-0.007627	5.642236	1.093926
1	d10	48.034690	2.731672	15.971815	-2.353063
2	d20	34.464108	-97.556057	65.149260	7.411861
3	d30	34.137379	-106.199096	54.036186	1.357188
4	d40	35.551153	-85.922172	48.202446	2.311282

For NY Times news dataset, in each year, the sentiment scores of each sentence are computed, summed, and normalized, so that after processing each year contains 4 numbers corresponding to the proportion of emotion of type negative, neutral, positive, and compound.

	year	neg	neu	pos	compound
0	1920	0.079613	0.812051	0.075566	0.032770
1	1921	0.079852	0.823460	0.073893	0.022795
2	1922	0.078825	0.818973	0.074271	0.027931
3	1923	0.114978	0.823673	0.083444	-0.022095
4	1924	0.107314	0.822202	0.081600	-0.011115

4. Univariate Analysis

Correlation Between Timbres:

In order to confirm the relative independence between each timbre, we used a heat map to find the correlation coefficient between each pair of timbres. Timbre1 (loudness) & Timbre2 (brightness) appears to be the most highly correlated with a Correlation Coefficient of 0.56. Other Timbres appear to be relatively less correlated, which agrees with the API design of mapping audio into an independent basis.

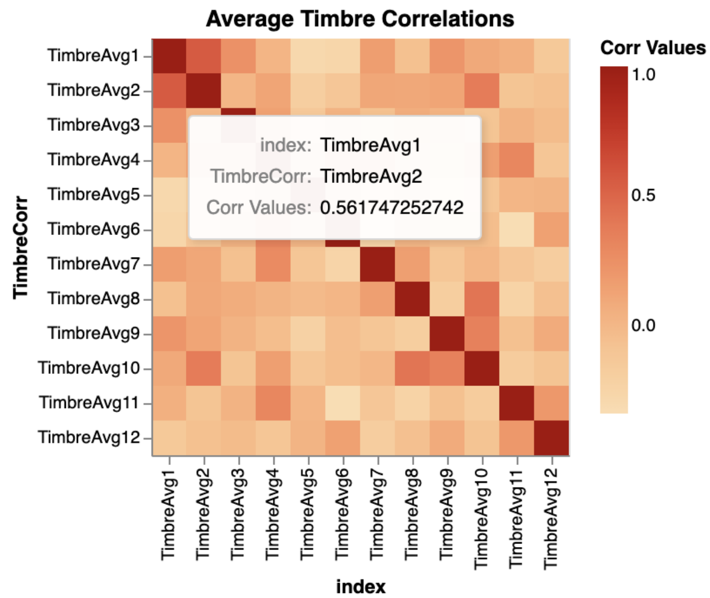

Image 1: Correlation Coefficient between each Music Timbre

Timbre Average by Decade:

TimbreAvg1 is consistently at the highest value across decades. TimbreAvg2 and TimbreAvg3 appears to have the opposite trend before the 80s and converge into a relatively uniform distribution as other timbres.

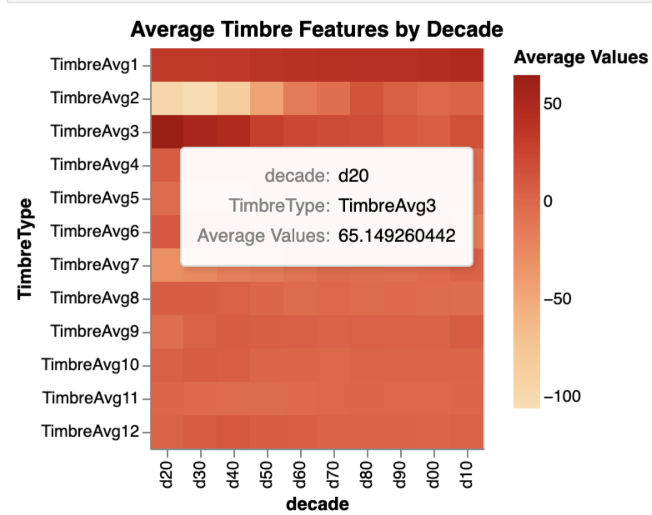

Image 2: Timbre Averages by Decade

Timbre Distribution Over Time:

Timbre1 (loudness)

The average loudness of popular music increased as time went on. That is probably due to the technological advancement in music production as well as devices.

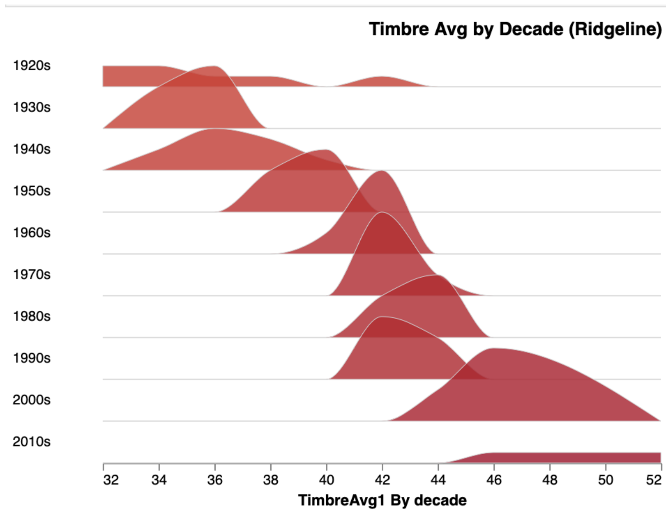

Image 3: Distribution of Timbre 1 (loudness) Over Time

<u>Timbre2 (brightness)</u>

Brightness of music showed a drastic change from negative value to positive values, which has stronger harmonic tones. This could be due to the advancement in music theory and the realization that certain harmonic combinations create more popular music (ex: Chainsmokers classic harmonic)

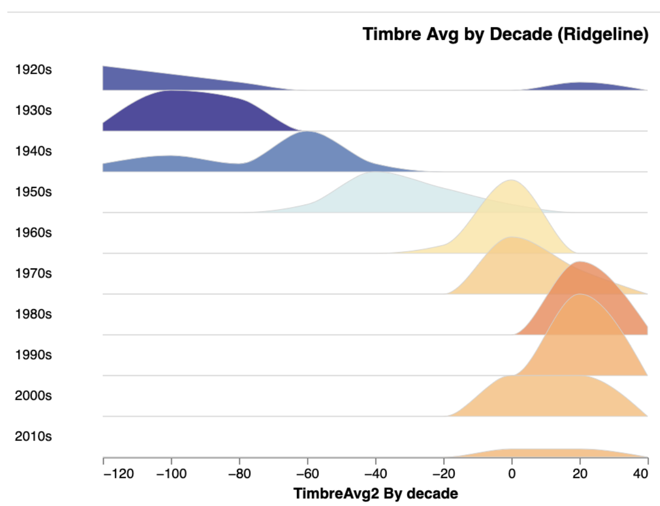

Image 4: Distribution of Timbre 2 (brightness) Over Time

<u>Timbre3 (flatness)</u>

On the other hand, the flatness of music went from a more spread out distribution to a leftward shift to lower positive values. A lower flatness indicates that music is moving away from resemblance to white noise and is instead taking on more peaks and resonant structure.

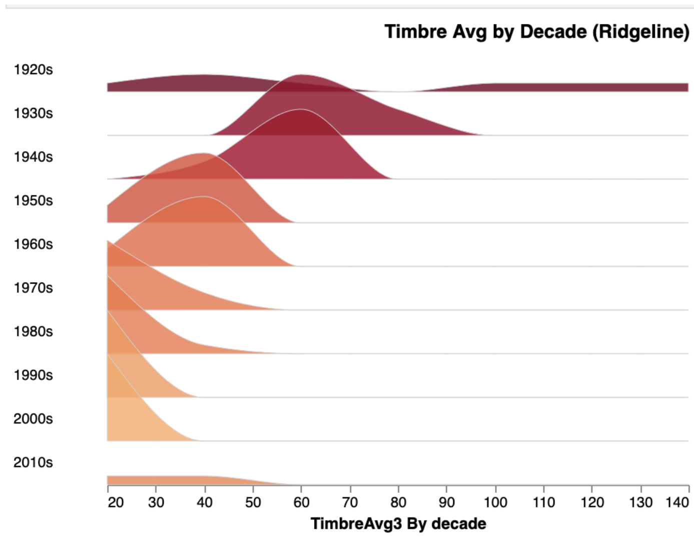

Image 5: Distribution of Timbre 3 (flatness) Over Time

<u>Timbre4 (attack)</u>

The attack of sound shows decreasing variance with the exception of 2010s. This means that popular music are unifying around the time it takes to rise from 0 volume to max volume.

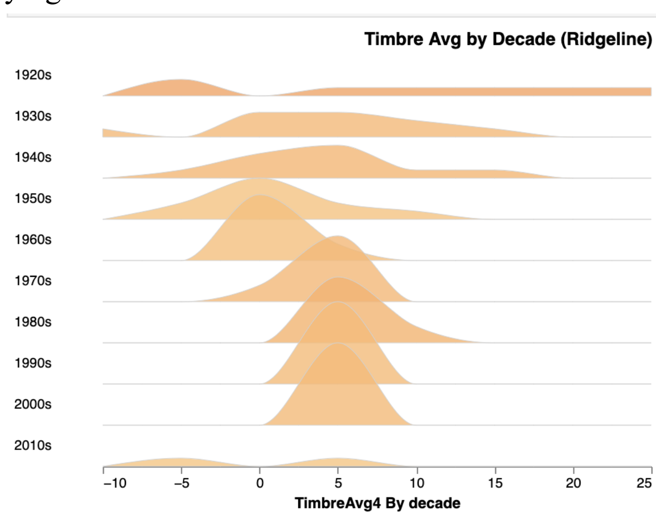

Image 6: Distribution of Timbre 4 (attack) Over Time

5. Insights & Conclusion

General Observation:

For most combinations, 1920s to 1940s (Jazz Age) contribute the most to respective positive/negative correlation. As time passes by, the strong correlation starts to vanish, which could be caused by the increasing complexity of society and multifariousness of modern zeitgeist.

Correlation between Timbre & Emotion:

- Negative Emotion:
  - Positive Correlation: Timbre3 (flatness): r = 0.72
  - Negative Correlation: Timbre2 (brightness): r = -0.74
- Positive Emotion:
  - Positive Correlation: Timbre6: r = 0.38
  - Negative Correlation: Timbre11: r = -0.33
- Neutral Emotion:
  - Positive Correlation: Timbre8 and Timbre10: r = 0.51
  - Negative Correlation: Timbre2 (brightness): r = -0.59

Conclusion:

1. There are strong correlations between specific timbre features and particular emotions, but some matches expectations (TimbreAvg 3 and Negative sentiment) while others defy intuitions (TimbreAvg2 and Positive sentiment).
2. The strong correlations are NOT consistent over decades; the correlation tapers as the world modernizes.

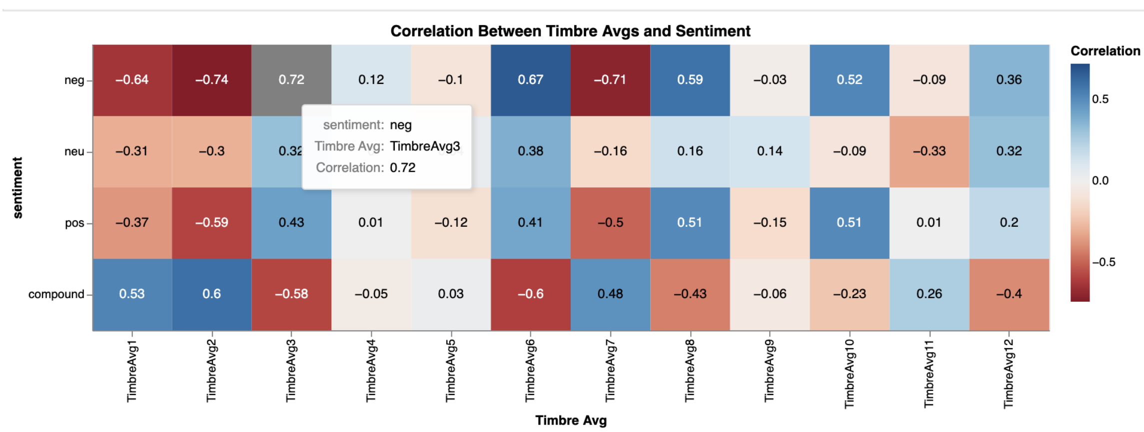

Image 7: Correlation between Timber and Sentiment

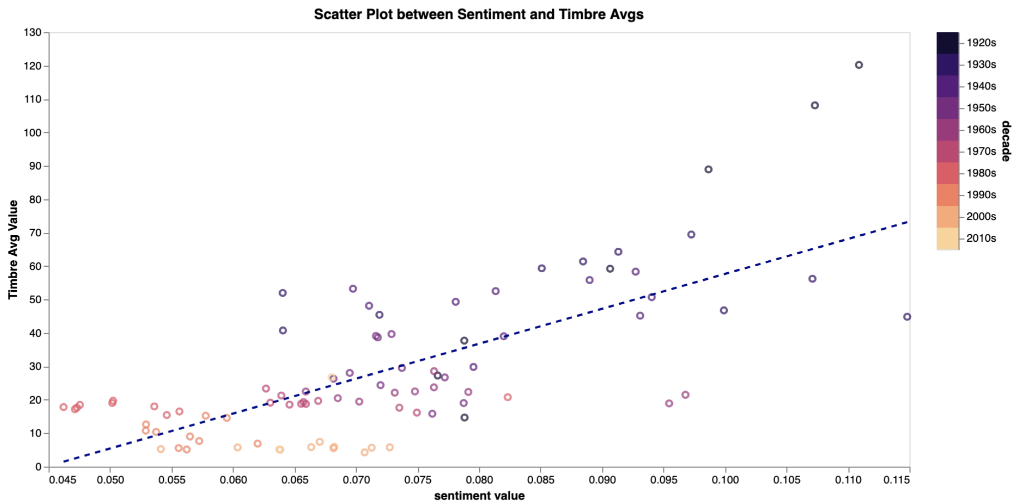

Image 8: Scatter Plot of Timbre 3 on Sentiment Value Over Time

Selecting a combination in Image 7 (top) shows the corresponding scatter plot fitted with a regression line underneath (bottom), and the bar on the right facilitates examining the trend by decades.

6. Visualization Techniques

Image 1 - Image 2: Heat Map

- Purpose of Image: compare quantitative values between two categorical variables
- Design Choice: continuous gradient with darker color representing higher values

Image 3 - Image 6: Ridgeline Plot

- Purpose of Image: showcase distribution shift of timbre over time
- Design Choice: darker warm tone color representing higher positive value and darker cool tone color representing lower negative value

Image 7: Heat Map

- Purpose of Image: compare correlation coefficient between 12 timbres and 4 types of emotions
- Design Choice: highly contrasting color to represent strong positive and negative correlations; combinations with low correlation coefficient are not marked with strong color to give strongly correlated combinations emphasis

Image 8: Scatter Plot

- Purpose of Image: scatter plot of timbre average against sentiment value with time shift expressed through color
- Design Choice: darker color represent older historical period to express shift in modernization

7. Future Scope

The capacity to demarcate different sentiments by music timbre has been plummeted over recent years. To discover the relationship between music and social sentiments, if there is any, it is thus necessary to look at other aspects of music, such as pitch modulations and the keys music pieces are written in.

It is worth noting that NLTK offers limited classification of social sentiment. To classify news messages to more nuanced emotions such as anger, anxiousness, or excitedness, other packages are required, such as the module Text2Emotion.

8. Works Cited

1. Schindler, Alexander, "Capturing the Temporal Domain in Echonest Features for Improved Classification Effectiveness", VL - 8382. https://www.researchgate.net/publication/266171053_Capturing_the_Temporal_Domain_in_Echonest_Features_for_Improved_Classification_Effectiveness
2. Full Github Repository: https://github.com/yangshengaa/dsc106-sp21-hw-group-bubbletea