

HARMONIC CO-OCCURENCE NETWORK | Exploring Musical Connections Through Network Analysis Atal Gupta | Kunj Jasoria | Vinit Singh

Undergraduate Research Showcase

Project completed as part of ES404 | Networks and Complex Systems Supervised by **Prof. Udit Bhatia**

MOTIVATION

Music, inherently complex and beautifully structured, carries patterns that often escape the naked ear. This project aims to unravel these hidden structures within and across different musical genres—rock, metal, classical, and jazz—by employing a novel approach using network analysis. By representing musical pieces as networks where nodes are pitch classes and edges represent temporal successions or harmonic relations, we delve deep into the architecture of music. This approach not only offers a quantitative method to compare and contrast genres but also provides a unique lens to view the dynamics of musical composition and evolution.

PROBLEM STATEMENT

Traditional music theory dissects melody, harmony, and rhythm separately, missing their interconnections across genres. We need a quantitative method to unveil music's network structures, bridging elements and genres. Our project applies network analysis to reveal pitch class relationships and temporal succession, revolutionizing musical composition

understanding.

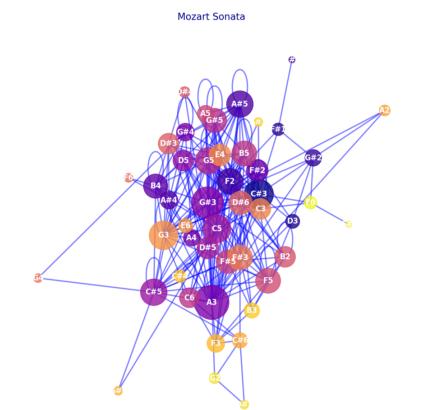


FIGURE 1 Harmonic Co-occurrence Network for Mozart Sonata

HOW THE NETWORK IS IMPOSED

The music is segmented into samples, capturing discrete snapshots for analysis. FFT for samples highlights top frequencies to extract dominant tones. Map dominant frequencies to MIDI numbers, providing standardized values for tones. Nodes are MIDI numbers and connect co-occurring numbers within samples to form edges. By combining sample networks into a unified graph representing the entire piece or pieces across genres. Thicken edges for repeated connections, indicating frequent occurrence of patterns.

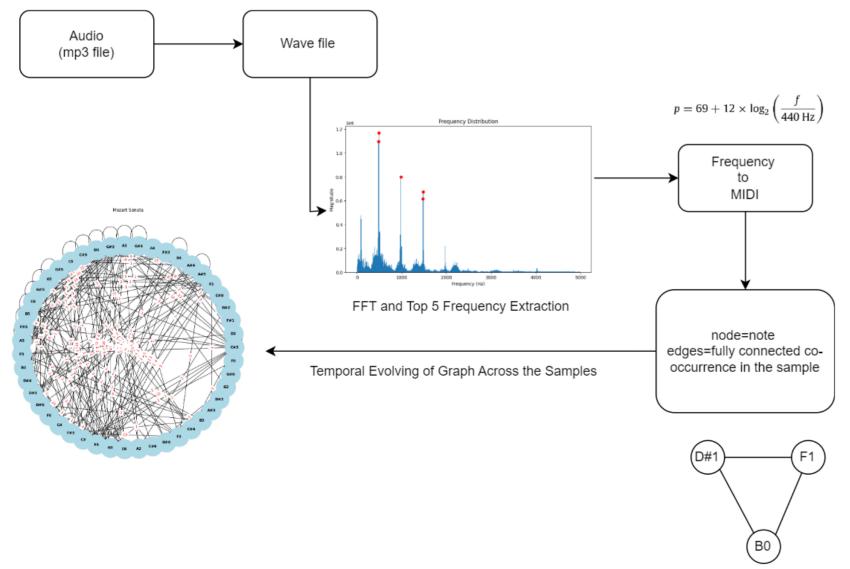


FIGURE 2 Audio file to HCN - Generation Process

MUSIC THEORY FOR PITCH DETECTION

Music theory helps understand the relationships between pitches and rhythms. Pitch detection, essential for music analysis, identifies the pitches in a sound. This process is crucial for transcribing audio into musical notation and has various applications in music technology.

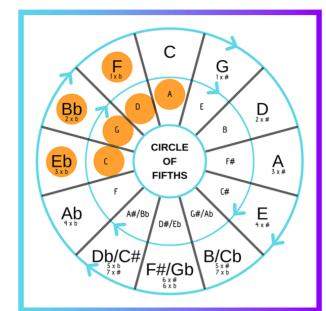


FIGURE 3 Musical Notes in Music Theory

MIDI (Musical Instrument Digital Interface) numbers are part of a standard protocol used to encode the pitch of musical notes for communication between electronic instruments and computers. Each MIDI number represents a specific pitch, with the number 69 corresponding to A4, tuned to 440 Hz. The pitch-to-MIDI number relationship is defined by the formula in figure 2. This ensures that a one-unit change in MIDI number equals a semitone step, enabling precise pitch representation across the audible spectrum from 20 Hz to 20 kHz.

EXPERIMENTS AND INFERENCES

HCN varies from power-law to heavy-tailed distribution

Out of 48 songs analyzed across various genres, 14 were found to exhibit a scale-free, power-law distribution, while the rest showed a tendency towards heavier-tailed distributions, deviating from the typical power-law behavior.

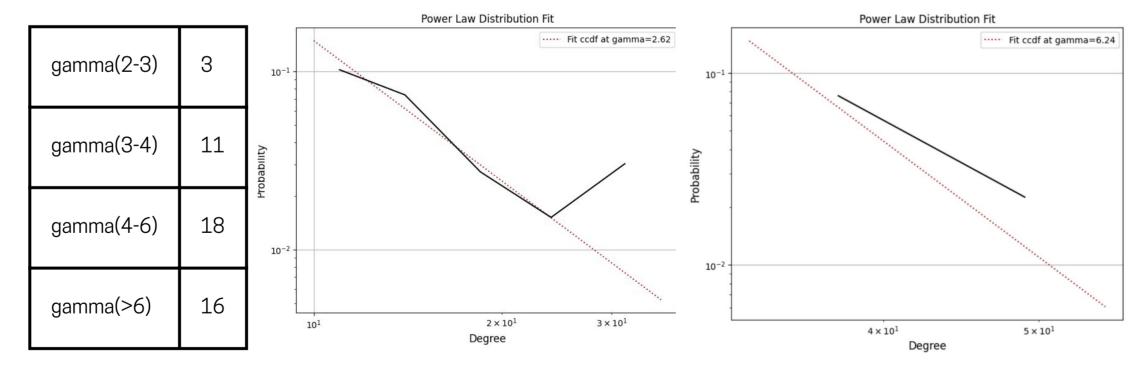


FIGURE 4 Overall Analysis for FIGURE 5 Degree Distribution of the HCN of gamma across 48 songs Miles Davis - move approx. following power-law

FIGURE 6 Degree Distribution of the HCN of Vassarlean deviating from power-law

Assortativity in Music Networks

The assortativity coefficients across the genres indicate varying levels of node similarity connecting to each other. For instance, the assortativity in rock, EDM, and metal tends to be negative (Rock: -0.042; Metal: -0.180; EDM: -0.173), suggesting that high-degree nodes tend to connect with low-degree nodes. This contrasts with more neutral values in classical and jazz music, indicating a less pronounced preference in node connections based on degree. This can be justified by the phenomenon that when a composer is creating a rhythm, there is a main note surrounded by subordinate notes. The occurrence of this pattern, which is less common, results in the disassortativeness in the music networks.

Sub-genre Detection through Louvain Community

Through Louvain community detection on various Harmonic Co-occurrence Networks (HCNs), it was discovered that certain communities recur consistently across songs of the same genre. Further analysis revealed that specific communities formed by songs of a particular genre represent distinct sub-genres within that genre.

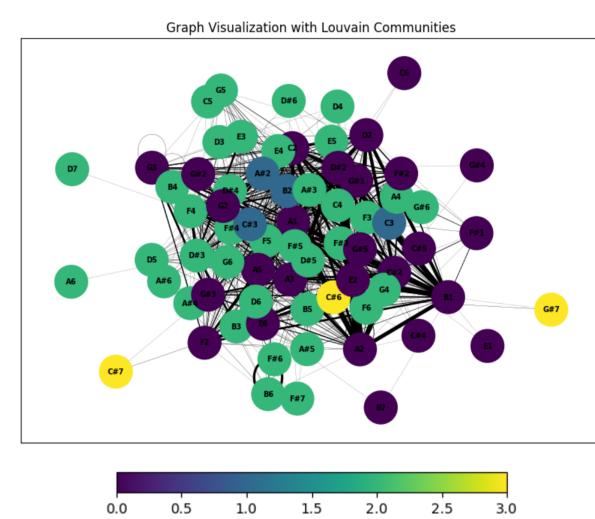


FIGURE 7 Louvain Community Detection on the HCN of Miles Davis - Move (Jazz)

Community 0 shows traits of progressive metal, marked by its complex structure and possible symphonic influences, featuring a broad spectrum of technical notes. Community 1 aligns with power metal, characterized by a mix of low and high pitches and sharp notes that suggest fast tempos and an anthemic style, potentially hinting at glam metal elements. Community 2 is indicative of death or black metal due to its focus on aggressive, dissonant harmonies and the use of extreme notes, reflecting the intensity of these sub-genres.

CONCLUSION AND FUTURE WORKS

- **Conclusive Insights**: Our study demonstrates the complex network structures in music, with genre-transcending patterns of connectivity and unique community arrangements. Assortativity analysis revealed a universal preference for diverse note connections, while community detection highlighted thematic consistencies within genres.
- **Expand Temporal Analysis**: Future research should focus on the temporal dynamics of musical networks, capturing their evolution throughout a piece.
- **Algorithmic Development**: Leverage these insights to craft algorithms capable of genre classification and new music generation that adheres to or subverts typical genre structures.
- **Music Therapy Application**: Investigate how the structural nuances of music influence its therapeutic impact, potentially enhancing music therapy practices.
- Enhanced Music Recommendation: Utilize network patterns to refine music recommendation systems, potentially revolutionizing how users discover music that aligns with their structural preferences.

References

[1] Xiao Fan Liu, Chi K. Tse, Michael Small, Complex network structure of musical compositions: Algorithmic generation of appealing music, Physica A: Statistical Mechanics and its Applications, Volume 389, Issue 1, 2010,

[2] Jeff Heaton (2023, April 19). Extract Musical Notes from Audio in Python with FFT [Video]. YouTube. https://www.youtube.com/watch?v=rj9N0iFLxWA

View Analysis

