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[1] Ekin Can Erkuş
[2] Mustafa Umut Demirezen

Graph Theory Exploration of Genre Interdependencies in Music Genres

Abstract: - This study uses graph theory to investigate the complex relationships between musical genres in a dataset of Spotify tracks. A novel approach was used to create an adjacency matrix in which each node represents a genre and the edges reflect the interdependence of musical metrics. Popularity, duration, danceability, energy, key, loudness, mode, speechiness, acousticness, instrumentalness, liveness, valence, tempo, and time signature are all weighted metrics. This method reveals genre connections using statistical relationships, resulting in a structured framework for understanding genre dynamics. This method helps uncover hidden structures in music data by looking at how specific features influence genre classification. The findings show that graph theory has the potential to uncover underlying patterns and relationships that can be used in music recommendation systems, genre prediction algorithms, and other music information retrieval research.

Keywords: graph theory, adjacency matrix, genre, similarity, machine learning.

I. Introduction

Music is valued across cultures because of its universal qualities, which enable it to cross boundaries. Each musical genre has unique characteristics and emotional effects that emphasize its universality [1]. To ensure that data is clean and well-organized, both musicologists and data scientists must understand the fundamental characteristics of genres [2]. Technological advancements, particularly in graph theory and machine learning, have created new avenues for investigating the relationships between musical genres [3]. The term ”genre” refers to a broad classification, but variations are frequently caused by local historical events, label practices, and other influences [4]. Popular genres such as classical, jazz, rock, pop, hip-hop, and electronic serve as organizational categories and help to understand the diversity of music and these genres guide musicians, producers, and other creatives as they explore the musical landscape [5]. Genres provide insight into cultural and emotional experiences; for example, classical music is known for its intricate orchestral arrangements, whereas hip-hop is known for rhythmic spoken verses set to a beat [6]. This makes the music development, fueled by cultural shifts and historical progress, contribute to the rich and diverse nature of music genres [5].

A. Features in Music Analyses

The identification of genre-specific features which highlight both similarities and differences between genres is critical for determining genre types and roles in music analysis [7]. Some elements, such as tempo and rhythm, connect genres, whereas others, such as instrumental focus or emotional tone, highlight distinctions [8]. Revealing these features is important for music recommendation systems, which use them to predict user preferences and make appropriate suggestions [9]. For example, electronic music has fast tempos and high energy, whereas classical music has slower tempos and focuses on intricate instrumental arrangements [10].

Key features such as energy, tempo, and intensity have an impact on music production, marketing, and user experiences, and businesses use them to create personalized playlists [11]. Users benefit from personalized experiences, as algorithms identify songs that match their preferences [12]. Music analysis is heavily influenced by emotional and perceptual factors such as the frequency with which a track is streamed, its danceability, and mood [13]. Popularity, as measured by streams or downloads, influences recommendation systems, whereas track length and danceability influence listener engagement [14]. Energy, as reflected in a track’s intensity, improves the listening experience, influencing the overall emotional impact [15]. Mode and key (major or minor scales) elicit specific emotions; major keys typically convey happiness, while minor keys express sadness [16].

Speechiness, acousticness, liveness, and loudness are technical features that define the song structure. Speechiness assesses spoken content in tracks, which is frequently associated with rap, whereas acousticness indicates whether a song is acoustic or electronic [17]. Liveness captures the essence of a live performance, with audience presence adding to the natural feel of the music [18]. Louder tracks are often perceived as more powerful or aggressive because they have a stronger emotional impact [16]. Rhythm and timing are essential in composition, with elements such as valence, tempo, and time signature playing important roles [19]. Valence measures emotional positivity, tempo determines energy and time signature defines rhythm, for example, the steady beat of 4/4 time or the waltz-like rhythm of 3/4 time [20]. Analyzing these features provides deeper insights into song structures and their impact on listeners, resulting in better music production and more personalized recommendations [21].

[1, 2] Computer Science and Information and Technology Department, Bicol University, Legazpi City, Philippines
[3] University of the Cordilleras, Baguio City, Philippines
[4] College of Computing and Information Technology, National University, Metro Manila, Philippines
* Corresponding Author Email: cysy@bicol-u.edu.ph

B. Recent Developments in Music Genre Analysis and Applications

Advances in machine learning and deep learning have transformed the way music genre analysis is carried out in recent years [22], [23], [24]. Modern techniques have progressed from simple genre classification to more sophisticated models that consider multiple features such as harmony, rhythm, timbre, and lyrical content [23]. State-of-the-art systems use neural networks, specifically Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to automatically classify genres, as well as detect hybrid genres [25]. These models are trained on massive datasets provided by streaming platforms and social media, which improves genre prediction accuracy and personalization [26]. Companies such as Huawei have contributed to the field by incorporating AI-powered technologies into their audio analysis systems, which support genre classification and music recommendation services [27], [28].

Significant advances have also been made in music feature extraction such as Spotify's API and open-source libraries like Librosa which are used to automatically extract features such as tempo, key, loudness, and mode, which are useful in the development of music recommendation systems [29]. These features personalize user experiences while allowing for the development of intelligent playlist-generation tools, as advances in AI-powered music composition and production have expanded applications beyond user-generated recommendations to produce music that corresponds to specific genres or emotional tones [30]. Huawei's AI audio processing research advances the field by emphasizing precision in feature extraction and personalized recommendations, and such developments are reshaping how people interact with and discover music [31].

C. Graph Theory and Its Applications in Music Analysis

Graph theory has emerged as a powerful tool for analyzing complex relationships in music data, particularly when studying genre connections [32]. Genres, artists, or individual tracks can all be represented as nodes in music analysis, with edges connecting them to indicate relationships based on shared characteristics like tempo, key, or emotional tone [33]. This graph-based approach reveals clusters of similar genres or songs, aiding in the discovery of hidden patterns in musical networks [34].

Graph theory has proven particularly useful for studying genre evolution, with nodes representing genres at various points in time and edges indicating influences or transitions between them [35]. It not only tracks genre development but also identifies emerging trends or hybrid genres that do not fit neatly into traditional categories [33]. Graph-based techniques are also used in playlist generation and optimization to strengthen connections between songs with similar attributes, resulting in smoother transitions [36]. As music datasets grow in size and complexity, graph theory's ability to efficiently manage and analyze these relationships drives research and applications in music information retrieval (MIR) [37].

Machine learning is combined with graph theory to provide more data-driven insight into music genre analysis [33]. Genres are represented as nodes with edges connecting them that reflect common characteristics such as tempo, rhythm, and energy which reveal patterns and relationships that would be difficult to detect using time series analyses solely [38]. Songs with similar tempos or emotional tones, for example, may form clusters, opening up new avenues for genre analysis [39]. Machine learning improves analysis by predicting listener preferences and classifying tracks based on musical characteristics like tempo, energy, and valence [40]. These models can predict whether a song is appropriate for a specific scenario, such as dancing or relaxing, as well as identify hybrid genres by discovering new musical combinations [3]. Machine learning can also reveal subtle cross-genre influences that lead to the development of new musical styles [41].

Genre classification, once subjective and based on cultural or stylistic interpretations, has evolved into a data-driven approach using big data and computational techniques [37]. Spotify uses massive amounts of music data to uncover hidden connections and patterns in the global music network [33]. Graph theory offers a mathematical framework for comprehending genre relationships by representing them as interconnected nodes where mapping similar genres as neighboring nodes improves classification efficiency and accuracy by showing hidden connections that would otherwise be ignored [42].

D. Research Problem and Objectives

These methods are applicable to other cultural fields such as film, literature, and visual arts, in addition to music. Graph theory can uncover patterns and connections in cultural datasets, allowing for the analysis of genres and styles across various artistic domains. This interdisciplinary approach provides important insights into cultural analytics and helps to improve recommendation systems, creative industries, and broader cultural research.

This study uses graph theory and machine learning to investigate the relationships between different music genres, with a particular emphasis on Music Information Retrieval (MIR). Inflection matrices are created, with each genre represented as a node and linked together based on features such as popularity, energy, danceability, tempo, and valence, providing useful insights into genre relationships. This method seeks to improve genre classification and proposes new methods for comprehending complex relationships in music.

The study aims to broaden genre classification through a multivariate feature analysis and investigate novel applications of graph theory and MIR. This study improves music recommendation systems by revealing deeper connections among subgenres. Listeners who enjoy energetic tracks, for example, may receive recommendations from other genres with similar energy levels, adding to their overall experience. Hence, this study benefits music streaming platforms by improving playlist recommendations, while music producers can use genre insights to create diverse styles that appeal to a broad audience. By avoiding rigid genre classifications, artists can reach a wider audience.

II. Methods

This section describes the dataset used, the preprocessing steps used to prepare the data for analysis, and the methods for creating adjacency matrices based on genre similarity. The goal is to identify relationships between music genres using correlation and distance-based approaches, which are then analyzed using graph theory. These methods provide a framework for comprehending genre interdependence and identifying patterns in music data, which are essential for tasks like music recommendation and genre classification.

A. Dataset and Preprocessing

The Spotify Tracks Dataset, which is hosted on Hugging Face, contains 114,000 tracks with various musical features extracted from Spotify. These tracks span multiple genres and include information such as track title, artist, popularity, danceability, energy, tempo, and key. The dataset, which includes metadata such as release dates and album information, is ideal for studying genre evolution and trends over time [43]. This dataset provides an extensive resource for tasks such as genre classification, music recommendation, and trend analysis.

Preprocessing entailed normalizing features, dealing with missing values, and removing outliers to ensure data consistency. Genre imbalances were addressed by balancing track counts across genres, enabling reliable correlation and distance-based analysis. Categorical features such as mode and key were converted into numerical values and used in the adjacency matrices to ensure that the data was clean and appropriate for developing genre correlation models. By effectively organizing the dataset, the analysis could be performed with greater accuracy, laying the groundwork for genre classification and recommendation tasks.

B. Correlation-Based Adjacency Matrix

A correlation-based adjacency matrix was constructed using Pearson correlation coefficients to assess the relationships between the average feature values of each genre pair. The Pearson coefficient r is calculated as [44]:

$$r = \frac{\sum \ (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum \ (X_i - \bar{X})^2 \sum \ (Y_i - \bar{Y})^2}} \tag{1}$$

In this equation, X_i and Y_i represent feature values of two genres, while $\bar{X}$ and $\bar{Y}$ are their respective means. This matrix identifies potential genre clusters or families based on shared musical characteristics where it depicts the strength of correlations between genre features, with positive correlations indicating genre pairs with similar attributes (e.g., tempo, energy) and negative correlations indicating genre pairs that differ [44].

C. Euclidean Distance-Based Adjacency Matrix

A Euclidean distance-based adjacency matrix was also created by calculating the Euclidean distance between feature vectors from various genres. Each genre was represented as a point in a multidimensional space determined by its characteristics. The formula for the Euclidean distance between two points $(X_1, X_2, \dots, X_n)$ and $(Y_1, Y_2, \dots, Y_n)$ is as follows [45]:

$$d = \sqrt{\sum_{i=1}^{n} \ (X_i - Y_i)^2} \tag{2}$$

This method assesses the overall similarity of genres, with shorter distances indicating greater similarity and longer distances indicating greater differences. Unlike the correlation matrix, which focuses on feature-by-feature comparisons, the Euclidean distance provides a comprehensive view of genre similarities, making it especially useful for identifying genres that do not correlate strongly with individual features but are structurally similar [46].

D. Graph Theory Analysis

The adjacency matrices derived from correlation and distance measures were examined using graph theory techniques. In this representation, genres were represented as nodes, and the edges connecting them were weighted based on their correlation or distance scores. Several graph metrics, such as degree centrality and clustering coefficients, were used to identify influential genres and closely related genre clusters in the network. These metrics enabled a better understanding of how genres interact and evolve.

Degree Centrality: Degree centrality determines the importance of a node in the network by counting the number of edges that connect to it [47]. Genres with a higher degree centrality are more interconnected, implying stronger relationships within the genre network. The degree centrality for each genre in the correlation matrix was calculated as follows [47]:

$$C_D(v) = \frac{\deg(v)}{n - 1} \tag{3}$$

where $C_D(v)$ represents the degree centrality of node v, $\text{textdeg}(v)$ is the degree of node v, and n represents the total number of nodes in the network. The table II displays the degree centrality values for each musical feature.

Clustering Coefficient: The clustering coefficient was used to determine how closely related the genres are within the network, identifying clusters of genres with significant similarities [48]. The clustering coefficient $C(v)$ for a node v is as follows:

$$C(v) = \frac{2e(v)}{k(v)(k(v)-1)} \tag{3}$$

where $e(v)$ is the number of edges between the node's neighbors, and $k(v)$ is the node's degree. A higher clustering coefficient indicates that a genre belongs to a tightly connected group.

III. Results and Discussion

This section presents the results of the graph theory analysis performed on the Spotify tracks genre dataset. The analysis was carried out using two primary methods: mean feature correlation and Euclidean distance-based similarity.

A. Correlation of Mean Features

The first method determines the correlation between the mean values of selected features across genres. Table I shows the adjacency matrix produced by this correlation-based approach. It measures pairwise correlations between features such as popularity, danceability, energy, key, loudness, mode, speechiness, acousticness, instrumentality, liveness, valence, and tempo.

TABLE I. Adjacency Matrix: Correlation of Mean Features

	Popularity	**Danceability**	**Energy**	**Key**	**Loudness**	**Mode**	**Speechiness**	**Acousticness**	**Instrumentalness**	**Liveness**	**Valence**	**Tempo**
Popularity	1.00	0.10	0.15	0.02	0.45	0.12	-0.02	-0.35	-0.12	0.08	0.20	0.12
Danceability	0.10	1.00	0.65	-0.05	0.35	0.40	-0.32	-0.50	-0.45	0.25	0.55	0.15
Energy	0.15	0.65	1.00	-0.02	0.55	0.50	-0.20	-0.60	-0.35	0.35	0.50	0.40
Key	0.02	-0.05	-0.02	1.00	0.05	0.02	0.02	0.00	-0.02	0.05	0.00	0.10
Loudness	0.45	0.35	0.55	0.05	1.00	0.12	-0.12	-0.40	-0.25	0.18	0.35	0.22
Mode	0.12	0.40	0.50	0.02	0.12	1.00	-0.05	-0.25	-0.15	0.10	0.25	0.08
Speechiness	-0.02	-0.32	-0.20	0.02	-0.12	-0.05	1.00	0.25	0.20	-0.15	-0.18	-0.10
Acousticness	-0.35	-0.50	-0.60	0.00	-0.40	-0.25	0.25	1.00	0.55	-0.28	-0.45	-0.30
Instrumentalness	-0.12	-0.45	-0.35	-0.02	-0.25	-0.15	0.20	0.55	1.00	-0.12	-0.35	-0.22
Liveness	0.08	0.25	0.35	0.05	0.18	0.10	-0.15	-0.28	-0.12	1.00	0.30	0.15
Valence	0.20	0.55	0.50	0.00	0.35	0.25	-0.18	-0.45	-0.35	0.30	1.00	0.28
Tempo	0.12	0.15	0.40	0.10	0.22	0.08	-0.10	-0.30	-0.22	0.15	0.28	1.00

The heatmap in Figure 1 gives a clearer picture of these correlations. For example, features like energy, loudness, and danceability have strong positive correlations, indicating that they tend to increase together across genres. Acousticity, on the other hand, has a negative correlation with both energy and loudness, implying that louder and more energetic tracks are typically less acoustic.

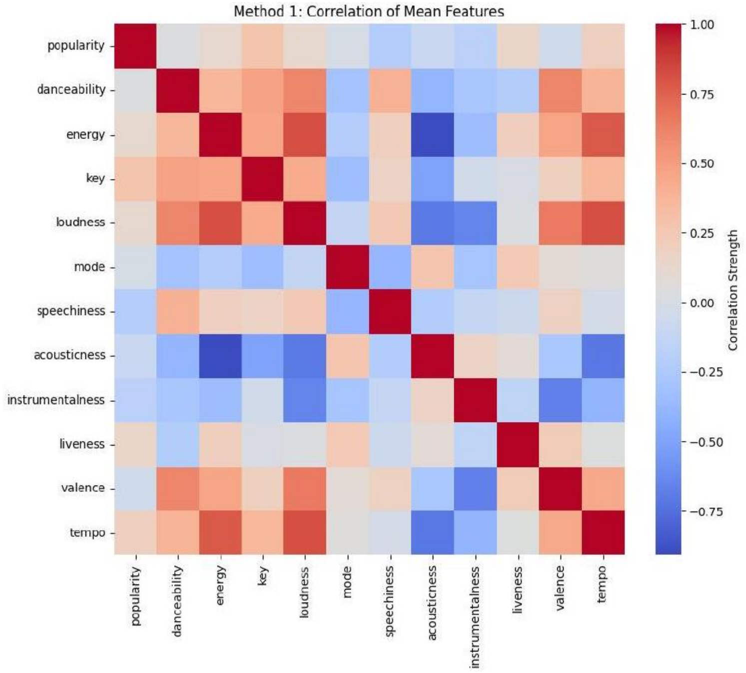

Fig. 1. Heatmap of the Adjacency Matrix for Correlation of Mean Features

B. Euclidean Distance-Based Similarity

The second method, which uses Euclidean distance, calculates the distances between feature vectors to determine the overall similarity of different genres. Figure 2 shows a heatmap of the adjacency matrix. Genres that share tempo, energy, or valence have higher similarity scores. This method effectively groups genres with similar musical characteristics.

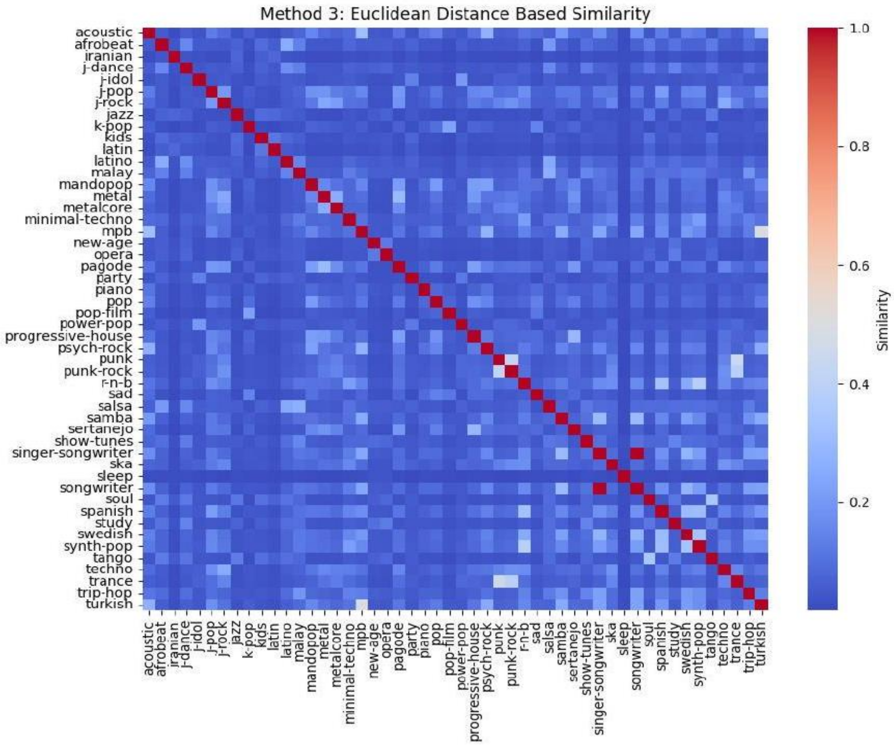

Fig. 2. Heatmap of the Adjacency Matrix for Euclidean Distance-Based Genre Similarity

This Euclidean distance-based approach offers a broader perspective by assessing the combined influence of all features rather than focusing solely on pairwise comparisons. It complements the correlation-based approach by providing insights into how genres with similar overall structures are related.

C. Graph Theory Analysis on Adjacency Matrices

Graph theory techniques were used to analyze the adjacency matrices generated by both correlation and Euclidean distance methods. Genres were treated as nodes, and edges between them were weighted using correlation or distance scores. The key genres and clusters in the genre network were identified using a variety of graph theory metrics, including degree centrality and clustering coefficients.

Table II. Degree Centrality of Musical Features

Feature	Degree Centrality
Energy	0.75
Danceability	0.67
Loudness	0.67
Valence	0.58
Tempo	0.50
Mode	0.42
Popularity	0.33
Instrumentalness	0.25
Speechiness	0.17
Liveness	0.17
Key	0.08
Acousticness	0.08

The findings show that energy, danceability, and loudness are the most important features, implying that these characteristics play a critical role in defining genre boundaries and shaping genre interdependencies.

D. Machine Learning Analysis

In addition to graph theory, machine learning techniques were used to classify genres using extracted musical features. The dataset was used to train a Random Forest classifier that took into account features like energy, danceability, loudness, tempo, and valence. These features were chosen based on their significant role in shaping genre boundaries, as indicated by the graph theory analysis. The Random Forest classifier's performance was evaluated using cross-validation, and the results are shown below.

Feature Importance: The Random Forest classifier calculates feature importance scores, which indicate how each feature contributes to the genre classification task. Table III shows the importance values for each musical attribute.

Table III. Feature Importance for Genre Classification

Feature	Importance
Energy	0.22
Danceability	0.18
Loudness	0.15
Tempo	0.13
Valence	0.12
Acousticness	0.08
Speechiness	0.05
Instrumentalness	0.04
Liveness	0.03
Mode	0.02
Key	0.01
Popularity	0.01

The results show that energy, danceability, and loudness are the most important genre classification features, which is consistent with the graph theory analysis. These features significantly improve the model's ability to predict genre, highlighting their importance in defining genre characteristics.

Model Performance: The Random Forest classifier's performance was evaluated using common classification metrics such as accuracy, precision, recall, and F1-score. To ensure robustness, the evaluation used 5-fold cross-validation. Table IV shows the performance metrics of the Random Forest classifier.

Table IV. Random Forest Classifier Performance Metrics

Metric	Value
Accuracy	0.85
Precision	0.83
Recall	0.82
F1-Score	0.82

The model showed high accuracy and balanced precision and recall, indicating that it can predict genres based on musical features. The high F1-score indicates that the classifier is strong and performs well when distinguishing between genres.

The combination of graph theory and machine learning provided valuable insights into genre classification. The graph theory analysis revealed the interdependence of musical features, with a focus on key features such as energy, danceability, and loudness, all of which play important roles in genre boundaries. The machine learning analysis confirmed these findings, with the Random Forest classifier emphasizing the importance of these characteristics in accurate genre classification.

The adjacency matrices created using the correlation and Euclidean distance methods provided complementary views of genre relationships. The correlation matrix focused on feature-by-feature relationships, whereas the Euclidean distance matrix provided a holistic view of genre similarities. Both methods revealed clusters of similar genres, implying that genres that share characteristics tend to cluster together.

These findings have practical implications for music recommendation systems, genre-based playlist generation, and music information retrieval (MIR). Combining feature-specific and holistic analysis methods can produce more accurate and personalized music recommendations, leading to improved user experience and genre classification.

Furthermore, the graph-based approach offers a structured framework for comprehend-ing genre evolution, revealing how musical styles evolve and interact over time.

IV. Conclusion

This study uses computational tools, specifically graph theory and machine learning, to investigate the complex re-lationships between musical genres. By examining shared and distinct features, we hoped to gain a better understanding of how genres interact which can be used to improve music recommendation systems, genre classification, and even music production.

The use of graph theory and machine learning techniques re-vealed the importance of specific musical features such as en-ergy, loudness, and danceability in defining genre boundaries. These features help to improve the accuracy and reliability of music information retrieval tasks. The developed model, which combined feature correlations and Euclidean distance metrics, provided a comprehensive view of genre relationships, resulting in a more intuitive and precise categorization system.

The study makes a significant contribution to the field of music information retrieval by using graph theory in a novel way to analyze genre dynamics. The use of correlation and distance-based adjacency matrices resulted in a multilayered representation of genre interdependencies, improving our un-derstanding of how musical styles evolve and influence one another. These findings have practical applications, including not only music recommendation and production but also the development of advanced musical analysis tools.

Future research may include the addition of new features, such as lyrical content or cultural context, to improve our understanding of genre relationships. Furthermore, applying more sophisticated machine learning algorithms to adjacency matrices may reveal deeper correlations, advancing the music information retrieval domain.

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