Methodology

A bipartite weighted graph (denoted as X) was constructed to model the "like" relationships between users and music genres, where nodes represent users and genres, and edges represent user-genre interactions weighted by their frequency.

From this bipartite graph, weighted projections were calculated to derive a unipartite network:

- **Genre-Genre Network (Z):** Nodes represent music genres, and weighted edges signify the degree of user overlap between genres (i.e., genres liked by the same users).

Using a graph projection algorithm, a genre-projected graph was created to derive edge weights based on the number of shared users. For each genre, connected genres and their respective weights were identified, and these connections were ranked in descending order of weight to highlight genre similarities.

Network measures such as degree centrality, betweenness centrality, and clustering coefficients were applied to both Y and Z to evaluate structural properties and highlight influential nodes or dense areas of interaction. To identify community structures, the Louvain algorithm was applied to Z, leveraging its efficiency for large datasets. The Louvain method grouped nodes into communities based on modularity optimisation, providing insights into distinct clusters of users with similar music preferences or closely related genres. Compared to the Girvan-Newman algorithm, Louvain's scalability made it more suitable for the size and complexity of the networks.

The results of this analysis, including the identification of key nodes, community structures, and their implications, are summarised in the following sections.

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Results

Similarity between Deezer's music genres

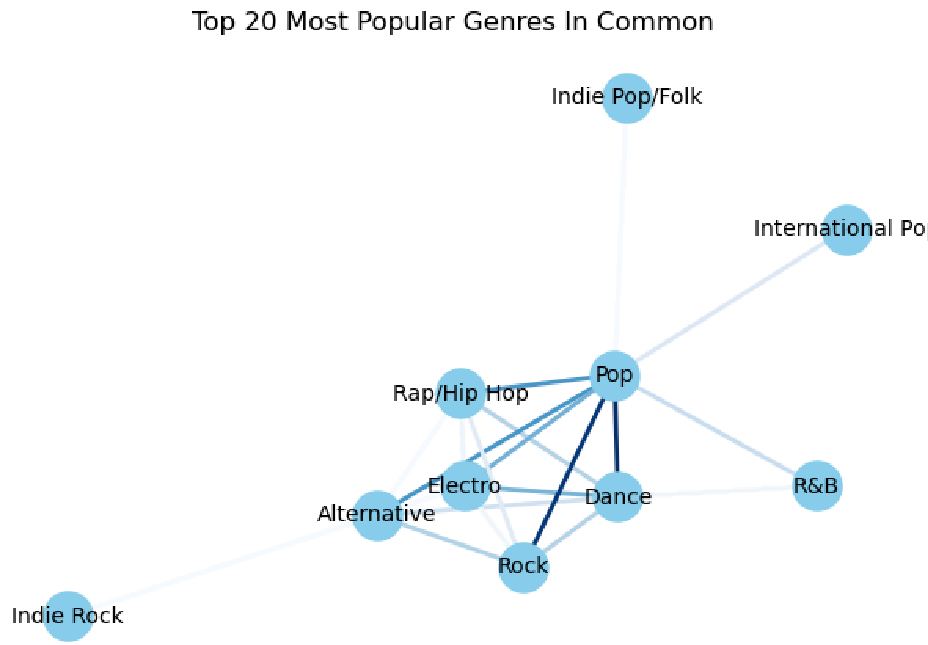

Figure 1 This node-link diagram illustrates the genres with the highest audience overlap. Each node represents a genre, while edges denote shared audience connections, with thicker and darker edges indicating stronger overlaps.

The strongest overlap in shared listeners was observed between Pop and Dance, as indicated by the dark blue line in Figure 1 and is substantiated by other network measures. This can be expected as both genres are widely recognised as popular mainstream categories.

Genre	Degree Centrality	Betweenness Centrality
Rock	1.0	0.0077
Pop	1.0	0.0077
Electro	1.0	0.0077
Films/Games	1.0	0.0077
Film Scores	1.0	0.0077
Indie Pop	0.9879	–
Indie Pop/Folk	0.9879	–
Dance	0.9879	0.0063
Metal	0.9879	0.0072
Hard Rock	0.9879	0.0063
Classical	–	0.0063
Rap/Hip Hop	–	0.0063

Table 1: Top 10 Genres with Highest Degree and Betweenness Centrality Score

Results from Table 1 identify Rock, Pop, Electro, Films/Games, and Film Scores as key genres in the genre-genre network, with a degree centrality score of one, signifying universal popularity as they share at least one listener with every other genre. These mainstream genres ensure the network is fully connected (Lambiotte & Ausloos, 2005) and exhibit the highest betweenness centrality scores, acting as bridges between diverse user preferences. By connecting niche genres to mainstream ones, they facilitate shared preferences across various user groups. For users, these genres serve as hubs for discovering related music, fostering cross-genre exploration. From a business perspective, understanding these relationships is essential, as they provide a baseline for recommendation systems. Striking a balance between familiar and exploratory content can drive user engagement and satisfaction.

Identifying Homogeneous groups of Genres

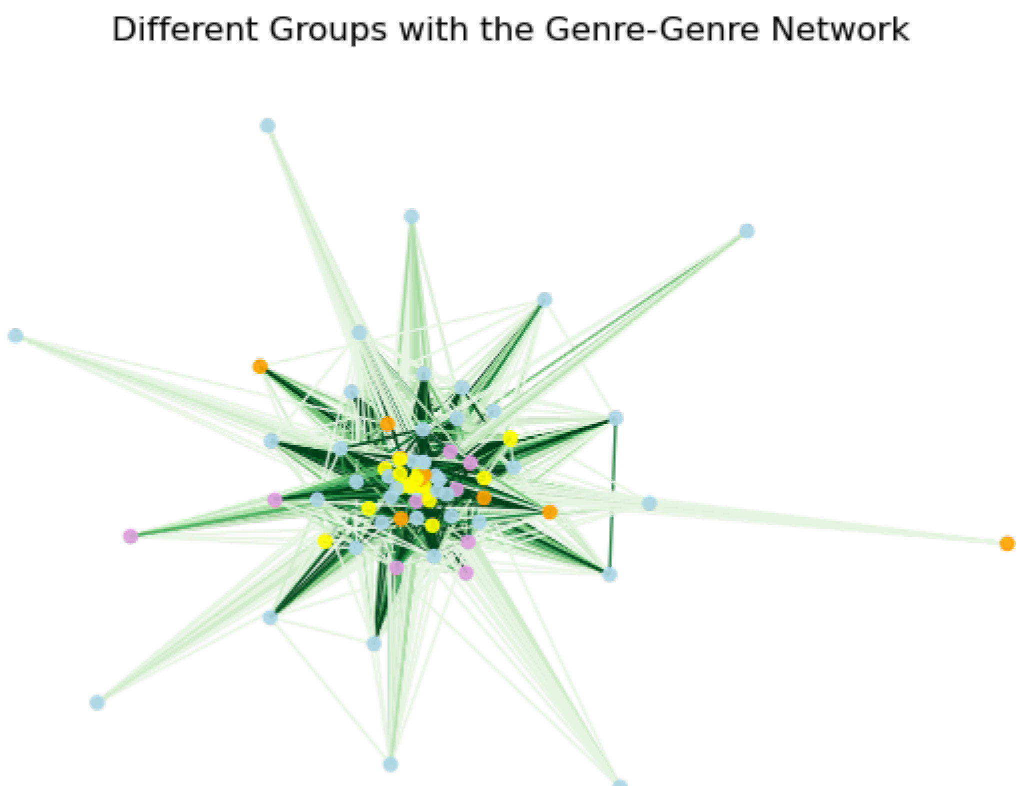

Figure 2 illustrates four distinct genre categories, each represented by a different node colours. The ties between nodes indicate the number of shared listeners, with the thickness of the edges corresponding to the degree of overlap.

The unipartite weighted genre-genre network, enriched with Louvain community detection, reveals four distinct genre categories, enhancing the understanding of user preferences. By clustering genres into communities, it becomes possible to identify broader trends in user behavior, such as shared listening patterns and cross-genre interests. Leveraging the genre-gren network (Z), Sonic can design a recommendation system that balances user preferences with opportunities for exploration. Recommending genres with high degree centrality and are widely popular, so high degree centrality, will have a board appela amongst users. It is a critical step to ensure that users engage with thte recommendation system and can encourage exploration gradually and promoting cross-genre discovery.

Category 1	**Category 2**	**Category 3**	**Category 4**
TV Soundtracks	R&B	Early Music	Grime
Kids & Family	Comedy	Bolero	Dirty South
Nursery Rhymes	Electro	Instrumental Jazz	East Coast
Film Scores	Trance	Urban Cowboy	Reggae
Game Scores	Folk	Spirituality & Religion	Dancehall/Ragga
Films/Games	Rock	Indie Rock	Dub
Soundtracks	Asian Music	Metal	Ska
Musicals	Rap/Hip Hop	Indie Pop	West Coast
Kids	Electro Hip Hop	Indian Music	Ranchera
	Pop	Indie Pop/Folk	
	Latin Music	Electric Blues	
	Electro Pop/Electro Rock	Hard Rock	
	Sports	Oldschool R&B	
	Dance	Traditional Country	
	Disco	Classic Blues	
	Alternative	Romantic	
	Techno/House	Chill Out/Trip-Hop	
	International Pop	Soul & Funk	
	Dubstep	Brazilian Music	
	Singer & Songwriter	Modern	
	Contemporary R&B	African Music	
	Dancefloor	Jazz Hip Hop	
		Blues	
		Country	
		TV shows & movies	
		Alternative Country	
		Classical Period	
		Delta Blues	
		Chicago Blues	
		Country Blues	
		Acoustic Blues	
		Bollywood	
		Rock & Roll/Rockabilly	
		Bluegrass	
		Baroque	
		Contemporary Soul	
		Opera	
		Old school soul	
		Jazz	
		Tropical	
		Classical	
		Indie Rock/Rock pop	
		Vocal Jazz	
		Old School	

Table 2: Genres can be classified into the following four categories

Social Influence on Music Genres

Genre	**Count**
Pop	8
Rock	6
Dance	5
Rap/Hip Hop	4
Electro	4
Techno/House	4
R&B	4
Alternative	4
Folk	4
Indie Pop/Folk	3
International Pop	3
Indie Rock	3
Contemporary R&B	3
Singer & Songwriter	3
Disco	2
Chill Out/Trip-Hop/Lounge	1
Instrumental Jazz	1
Electro Pop/Electro Rock	1
Latin Music	1
Jazz	1
Vocal Jazz	1
Country	1
Brazilian Music	1
Contemporary Soul	1
Alternative Country	1
Metal	1
Indie Rock/Rock Pop	1
Blues	1
Film Scores	1
Films/Games	1
Kids	1
East Coast	1
Reggae	1

Table 3: Genre Counts from Top 10 Popular Users

Highly connected individuals in the network favor mainstream genres like Pop, Rock, and Dance, reflecting their broad appeal. Duricic et al. (2021) confirm homophily in listening preferences among friends, though it remains unclear whether shared tastes drive connections or result from them. Understanding this interplay allows Sonic to design recommendation systems that integrate personal preferences with social influences for better engagement.

Business Recommendations:

The Louvain algorithm automatically clusters genres into distinct communities based on shared listener patterns. It removes the subjectivity involved in manual genre categorisation. The largest overlap between genres was with Pop and Dance at 10.78% shared listener, suggesting that from this list of genres identified by Deezer's, there are no redundant tags.

Defining key genres such as Rock, Pop, Electro, Film/Games, and Film Scores as anchors within the genre ecosystem offers valuable insights into the most influential and widely listened-to categories. Positioning music within these categories allows Sonic to establish strategic entry points that cater to both casual and dedicated listeners, making these genres particularly effective for engaging diverse audience segments.

Understanding the network enables Sonic's A&R team to strategically focus talent scouting on genre trends. Targeting high-centrality genres (e.g., Pop or Rock) maximises user reach and engagement, while identifying underserved areas reveals growth opportunities. By monitoring changes in shared listener overlaps, Sonic can anticipate market trends, foster innovation, and enhance platform engagement.

The identification of four main categories enables Sonic to visualise the music market more effectively, grouping similar genres for clearer positioning. Louvain clustering highlights overlaps in listener preferences, facilitating data-driven decisions on artist collaborations and market potential. Sonic can focus investments on central genres with broad appeal while leveraging bridging genres for cross-genre experimentation.

References

Lambiotte, R. and Ausloos, M., 2005. Uncovering collective listening habits and music genres in bipartite networks. *Physical Review E—Statistical, Nonlinear, and Soft Matter Physics*, *72*(6), p.066107.

Duricic, T., Kowald, D., Schedl, M. and Lex, E., 2021, November. My friends also prefer diverse music: homophily and link prediction with user preferences for mainstream, novelty, and diversity in music. In *Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining* (pp. 447-454).