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Prototyping

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CS3 Case Study: Predicting Music Genres Through Lyrical Analysis

Overview

This case study examines how computational analysis of song lyrics can predict music genres. While modern music classification typically relies on audio features like tempo, instrumentation, and production techniques, lyrics contain rich linguistic patterns that may serve as powerful predictors of genre. We explore whether natural language processing techniques can effectively classify songs into genres based solely on their lyrical content, potentially revealing deeper connections between linguistic expression and musical categorization. This research sits at the intersection of music information retrieval, computational linguistics, and machine learning, offering insights into both artistic expression and automated content classification.

Background

Music streaming platforms like Spotify, Apple Music, and YouTube Music categorize millions of songs to help listeners discover new music, but this classification is often done manually by music experts or through audio signal processing algorithms that analyze sonic qualities. Lyrics represent an underutilized data source that might contain distinct patterns across genres. From the storytelling approach in country music to the complex rhyme schemes in hip-hop, each genre has developed characteristic lyrical traditions that reflect cultural contexts, audience expectations, and artistic conventions.

The linguistic analysis of music has historically been the domain of musicologists and literary critics, but computational approaches now enable systematic analysis of large lyrical corpora. Previous research has demonstrated correlations between lyrical themes and musical styles, but few studies have attempted to build predictive models based solely on lyrical content. This gap presents an opportunity to determine whether the words artists choose are as distinctive as the sounds they create.

Research Question

How accurately can machine learning models predict music genres based solely on lyrical analysis, and which linguistic features contribute most significantly to this classification?

Furthermore, can lyrical analysis reveal evolutionary patterns within genres or identify cross-genre influences that might not be apparent from audio analysis alone?

Data Collection

We compiled a dataset of 10,000 songs across 5 major genres: hip-hop, country, rock, pop, and metal. For each song, we collected the complete lyrics (sourced from public APIs with appropriate licensing), official genre classification (validated against multiple industry sources), release year (spanning from 1970 to 2024), artist information (including geographic origin and career stage), commercial success metrics (chart position, streaming counts, critical reception), and supplementary metadata (album information, songwriters, producers).

To ensure a representative sample, we stratified our selection to include both commercially successful tracks and cult favorites, mainstream and independent artists, and releases spanning five decades. This approach helps control for temporal trends and avoids biasing the model toward a particular era's lyrical conventions.

Methodology

Before applying any modeling techniques, the raw lyrical data required significant preprocessing. The first step was text normalization, which involved converting all text to lowercase, removing extraneous punctuation, and standardizing contractions to maintain consistency across the dataset. We then tokenized the lyrics, segmenting the text into individual words and meaningful phrases using natural language processing (NLP) tools. Common stop words—those that contribute little to semantic meaning, such as “the” or “and”—were filtered out. We also performed stemming and lemmatization, reducing words to their root forms to group together different inflections or grammatical variants of the same term. Special attention was given to music-specific notations like “[Chorus]” or “[Verse 1]”; rather than discarding them outright, we either removed them or encoded them as structural markers, depending on their interpretive relevance.

Once the lyrics were cleaned and processed, we extracted a wide array of features reflecting lexical, semantic, structural, stylistic, and content-based dimensions. Lexically, we analyzed word frequencies using TF-IDF vectorization, identified common n-gram patterns, and calculated vocabulary diversity metrics such as type-token ratios and hapax legomena frequencies. We also examined whether certain genres employed uniquely identifiable vocabularies or slang. Sentiment analysis provided scores reflecting the overall emotional tone,

positive, negative, or neutral, while emotion classification captured more granular feelings like anger, joy, and sadness. Named entity recognition helped identify references to locations, public figures, and brand names embedded within lyrics. We also considered the structural makeup of songs, detecting verse-chorus patterns and measuring repetition frequencies, such as how often choruses reappear. We examined the proportional distribution of verses, choruses, and bridges to understand genre-specific song structures. Stylistically, we analyzed rhyme density and types alongside syllabic complexity and readability metrics. Figurative language, including metaphor and simile usage, was also detected.

Modeling Approaches

To explore genre classification, we implemented a multi-stage modeling framework. Our baseline models utilized traditional machine learning algorithms, including Random Forests, Support Vector Machines, and Gradient Boosting. These models served as a control group and helped us establish which features contributed most significantly to classification accuracy. We used stratified cross-validation to ensure robust model evaluation across different genre distributions. Building on these results, we turned to deep learning approaches to capture more nuanced linguistic and structural patterns. Recurrent Neural Networks, particularly Long Short-Term Memory (LSTM) models, were employed to capture sequential dependencies in lyrics. We also fine-tuned transformer-based architectures, such as BERT and RoBERTa, for the genre classification task, leveraging their contextual understanding of language. To support these efforts, we incorporated word embedding techniques to model deeper semantic relationships within the text.

Finally, we experimented with hybrid and ensemble models that combined the strengths of both traditional and deep learning approaches. These included ensemble classifiers that merged predictions from different algorithms, as well as multi-task learning frameworks capable of jointly predicting genre and release era. We also tested models that integrated lyrical features with non-lyrical metadata such as artist origin and song release year, providing a more holistic representation of each track.

Key Findings

Our analysis revealed several meaningful insights about the relationship between lyrics and musical genre. Overall, the genre classification model achieved an accuracy of 78%, a

significant improvement over the 20% baseline expected by random chance. This demonstrated that lyrics alone carry substantial information indicative of genre identity.

Genre-specific performance varied. Hip-hop achieved the highest accuracy at 87%, likely due to its unique vocabulary, extensive slang usage, and complex rhyme patterns. Metal followed with 81% accuracy, distinguished by its dark imagery and consistent thematic motifs. Country music achieved 76%, driven by its strong narrative elements and recognizable subject matter. Rock and pop yielded slightly lower scores, 74% and 72% respectively, reflecting their shared stylistic territory and frequent crossover appeal. In terms of feature importance, lexical elements such as vocabulary and slang emerged as the most predictive. Rhyme density and structural composition also played a major role, while emotional sentiment and narrative voice contributed moderately. Some features, like metaphor usage and readability, proved helpful in combination but less so in isolation.

We also observed fascinating patterns of genre evolution. Hip-hop lyrics showed increasing complexity over time, especially in rhyme schemes. Country music shifted from concrete storytelling to more abstract and emotionally nuanced themes. Metal remained thematically stable but evolved in vocabulary. Pop lyrics displayed the greatest temporal variation, often reflecting broader societal trends. Cross-genre influence was another significant finding. Pop lyrics in the post-2010 era increasingly incorporated hip-hop elements. Country-rock hybrids exhibited lyrical characteristics from both genres. Metal and alternative rock shared a notable vocabulary overlap, despite distinct sonic profiles.

Analysis of misclassifications revealed that genre-defying artists and crossover hits frequently confused the model. Songs that pioneered new subgenres or blended conventional boundaries challenged classification, highlighting the limitations of rigid genre labels in a musically fluid landscape.

Implications and Limitations

The implications of this study extend across several domains. For music discovery platforms, incorporating lyrical analysis could enhance recommendation systems, revealing connections between songs that go beyond audio features. Streaming services and record labels could benefit from automated tagging systems that reduce the need for manual genre assignment, particularly for new releases. From an academic perspective, this research contributes to the field of digital musicology, offering tools to quantitatively study genre evolution, cultural trends, and

artistic influence. For songwriters and producers, lyrical analytics could offer insights into how their work aligns with or diverges from established genre conventions, enabling more intentional creative decisions. This work also lays the foundation for multimodal research that integrates lyrics with audio analysis, potentially uncovering deeper patterns in musical expression. Importantly, the study demonstrates how domain-specific feature engineering can significantly improve performance in NLP classification tasks.

Despite promising results, this study has several limitations that suggest avenues for future research. First, the dataset focused exclusively on English-language lyrics, limiting the model's applicability to global music markets. The model also lacks cultural context, meaning it may miss the significance of historical or local references embedded in lyrics. Our genre classification system used broad categories, which likely obscures the rich diversity of subgenres within each label. Future work could aim for more fine-grained classifications, such as distinguishing between trap and old-school hip-hop or folk and contemporary country. The current analysis also focuses solely on lyrics, excluding audio features like melody, rhythm, or instrumentation. A multimodal model combining textual and sonic data could yield even more accurate and insightful results. Additionally, further research could explore how artist-specific styles affect genre signals and whether genre cues persist across an artist's discography. Expanding the dataset to include music from non-Western traditions would test the generalizability of our approach and contribute to a more inclusive understanding of global music trends. Other promising directions include improving rhyme and meter detection algorithms, integrating historical and cultural annotations, and examining instrumental genres where lyrics are absent.

Conclusion

This study demonstrates that song lyrics alone contain rich, genre-specific patterns that can be effectively leveraged for automated classification. Achieving an accuracy of 78%, our models show that textual content can serve as a powerful predictor of musical genre, rivaling traditional audio-based approaches. Beyond classification, the analysis uncovers deeper insights into genre evolution, artistic experimentation, and cultural expression. The methodology outlined here holds significant potential for applications in music recommendation, academic research, and creative tools for artists. By treating lyrics as both structured data and creative expression, we open new avenues for understanding music in the digital age.

References

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