**TITLE**

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ABSTRACT

KEYWORDS

MIR, GIR, MARSYAS, Machine Learning, Classification

1 Introduction & Motivation

Music, a universal language, intricately reflects the cultural and geographical contexts of its origins [1]. This paper seeks to use advanced data analysis techniques to uncover the geographic information embedded within music. With the foregoing field of data science and the increasing integration of artificial intelligence (AI) across disciplines [2], the combination of music and geography through advanced machine learning (ML) techniques is becoming more used [3]. This new way of viewing and categorizing data opens up more applications.

The integration of geographic data into music analysis is a known concept in Music Information Retrieval (MIR) [4]. This step involves the integration of geographic data into music analysis. Further, with the geographic data acquired, GIS principles such as clustering methods, provides a structured approach to unveil patterns and relationships within the intricate landscape of musical genres. This combination of geographic expertise and data science is an interesting combination.

At its core, this research seeks to unravel the intricate relationship between music and geography by using GIS techniques and data-driven methodologies. The main goal is to develop a robust framework that utilizes Machine Learning algorithms, such as CatBoost [5], and the MARSYAS framework [6] to accurately classify traditional, ethnic, or 'world' genre-based music. By doing so, this paper aims to contribute not only to the field of music classification but also to the broader discourse on how geographic nuances shape and define musical genres.

The significance of this study lies in its potential to provide an understanding of the geographical influences on music and of the methods used. Beyond the conventional categorization of genres, the research aims to capture the essence of geographic diversity within musical compositions. As a geography student, this work represents a bridge between traditional geographical analysis and the evolving landscape of Machine Learning, using a multidisciplinary approach to explore the cultural and spatial dimensions of music.

2. Literature Review

2.1 MIR (Music Information Retrieval)

Music Information Retrieval (MIR) represents a specialized field within information retrieval that focuses on the extraction, analysis, and organization of musical information from various sources. MIR encompasses a wide range of tasks, including music classification, genre identification, chord recognition, and recommendation systems. The overarching goal is to develop computational techniques that enable machines to understand, organize, and retrieve music-related data efficiently [7]. MIR has three different key tasks: **Information retrieval**, such as cover-sond identification, similarity measures or music recommendations, **Classification & estimation**, such as identification of performer, genre, or tempo. Lastly, **Sequence labeling**, such as optical music recognition (OMR), Melody extraction and Chord estimation [7]. It is seen that MIR is connected to geographic data in the tasks of information retrieval and classification & estimation. Geographic Information Retrieval (GIR) is also intertwined with the classification of music in a geographical context.

2.2 Geographic Information Retrieval (GIR) in Music

Geographic Information Retrieval (GIR) is a specialized field within information retrieval that focuses on extracting and organizing spatially relevant information from large datasets. In the context of GIR, the emphasis is on retrieving data based on geographic parameters, such as coordinates, place names, or spatial relationships. GIR uses processes such as ranking, georeferencing, indexing or evaluation [8] in order to get the geographic information needed. GIR is often coupled with unstructured text-based information such as Books, news articles and databases. In many cases, music is not considered as text-based information. But if we look closely at the structure of music, we can evaluate similarities between music and text-based information.

Exploring the parallels between textual and musical information reveals intriguing commonalities in how individuals perceive and process both forms of expression. Both text and music are powerful vehicles of emotion [9], functioning as complex channels through which human experiences are received and interpreted. While textual narratives have the power to trigger empathy, convey stories, and evoke feelings [10], music achieves a similar impact through its melodic and rhythmic elements. Both serve as conduits for emotional expression, tapping into the intricate realms of human sentiment and experience.

Ein Bild, das Text, Schrift, Reihe, Diagramm enthält.

Automatisch generierte Beschreibung

Figure 1: Information flow of music compared to text-based information (Part 1)

The ordered arrangement of information is another commonality between text and music. Textual information is structured through language, syntax, and semantics, creating a coherent narrative [11]. Similarly, music organizes sound patterns, melodies, and harmonies into a structured composition, guiding listeners through a sonic journey [12]. In essence, both text and music rely on the meticulous organization of elements to convey meaning and elicit specific responses.

Furthering the parallels, the processing of both text and music engages our sensory organs and activates similar neural pathways. Textual information is primarily accessed through the visual stimuli of reading, engaging the eyes and the corresponding brain regions [11]. The experience of music with hearing loss is similar to the experience of reading with vision loss. In a comparable manner, music, primarily an auditory experience, is processed through the ears, activating overlapping regions in the brain associated with auditory perception and emotional response [13].

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Automatisch generierte Beschreibung

Figure 2: Information flow of music compared to text-based information (Part 2)

Studying the connections between text and music can help us find geographic details in music. The way emotions, information organization, and our brain processes both text and music are similar.

2.2 MARSYAS and other feature extraction frameworks

The MARSYAS (MusicAl Research SYstem for Analysis and Synthesis) framework, a robust tool in music information retrieval (MIR), was developed by the Music Technology Group at Pompeu Fabra University. It is optimized for performance and user-friendly because it has a user-interface. Its creation is due to the need for a flexible and comprehensive platform capable of extracting complex audio features from music signals, enabling a deeper understanding and analysis of musical compositions [6].

The primary objective behind MARSYAS' development was to address the multifaceted challenges associated with music analysis. Traditional methods often fell short in capturing the richness of audio data, especially when dealing with complex musical genres and diverse instrumentation [6]. MARSYAS was designed as a solution to these limitations, aiming to provide researchers, musicians, and data scientists with a tool capable of not only processing audio signals but also uncovering nuanced patterns and features within them. The main advantages of MARSYAS are:

1. Extensive Feature Extraction: MARSYAS offers a comprehensive set of tools for extracting audio features. Its strength lies in its ability to capture a wide array of features, including spectral, temporal, and rhythmic components. This ability allows for a more nuanced representation of musical content, making it particularly suitable for diverse genres and complex compositions [14].

2. Modularity and Customization: One of the distinguishing features of MARSYAS is its modular design, enabling users to customize and adapt the framework to their specific analytical needs. This modularity facilitates the creation of tailored workflows, allowing researchers to focus on particular aspects of music analysis relevant to their study objectives [6].

3. Open-Source Nature: MARSYAS is an open-source framework that encourages collaboration and community-driven development. This characteristic encourages a continuous refinement of the tool, ensuring that it remains at the forefront of advancements in music analysis. Its open-source nature also makes it accessible to a broader audience, promoting transparency and reproducibility in research [6].

Various feature extraction toolboxes are available to analyze audio signals, each offering unique capabilities. Marsyas is just one among several options. Aubio, written in C++, stand out for its high-level feature extraction, including onset detection, beat tracking, and melody [15]. Essentia serves as a comprehensive workflow environment with both high and low-level features, facilitating audio input, preprocessing, and statistical analysis in C++ with Python bindings [16]. Librosa provides a Python API for feature extraction [17], while jAudio offers a Java-based standalone application with a GUI and CLI for batch processing [18]. Other tools also contribute to this type of application, each designed with specific focus and functionality.

In addition to these toolboxes, Spotify has also focused on music feature extraction using its own API. Leveraging the capabilities of its API, Spotify has developed methods for extracting various musical features that help analyze and categorize audio content within its platform. This initiative by Spotify further expands the range of tools available and demonstrates how industry leaders are actively engaged in advancing feature extraction techniques to improve music understanding and user experience [19].

2.4 CatBoost Classification

CatBoost, an advanced machine learning algorithm developed by Yandex, specializes in classification tasks and stands out in handling categorical features [5]. The algorithm constructs decision trees iteratively during the training process, emphasizing the correction of errors from previous iterations – a characteristic of gradient boosting [20]. A distinctive advantage of CatBoost lies in its seamless integration of categorical variables into the training workflow. Unlike many other algorithms, CatBoost eliminates the need for extensive preprocessing steps, simplifying the implementation process. This is particularly beneficial for practitioners seeking an efficient solution for real-world applications where datasets often comprise a mix of numerical and categorical features.

Python implementation of CatBoost is straightforward and aligns seamlessly with the broader ecosystem of data science libraries [5].

There are a few considerations to keep in mind. Cat-Boost's computational intensity, especially for larger datasets, can impact performance, even though a GPU training is possible [5]. Fine-tuning of hyperparameters may be necessary to achieve optimal results, although the algorithm often shows competitive performance with default settings.

2.4 Clustering methods

Clustering plays an important role in classification tasks. Clustering groups similar items or data points together to identify patterns or relationships based on shared characteristics. This can be manual (in a manual method) or with specialized algorithms such as DBScan. Clustering can be done with geographic data, such as defining the data into spatial categories such as regions or continents according to the UNN [21].

Advantages of human-made regional clusters lie in interpretability and alignment with established geographic boundaries, though they may oversimplify [22], particularly when organizing data into distinct human-made regional clusters, such as continents. Other than manually clustering, there is an option to automatically cluster the data. Automatic clustering is a process where a computer algorithm organizes data into distinct groups or clusters based on inherent similarities, without explicit instructions or predefined categories. An example is the DBScan (Density-Based Spatial Clustering of Applications with Noise), which is quite well-known and often used in geographically based algorithms.

DBScan identifies dense regions of data points in a space, separated by sparser areas. It works by defining clusters as continuous regions of high data point density, allowing for the automatic discovery of clusters with irregular shapes. DBScan categorizes points as core, border, or noise, making it robust in handling clusters of varying shapes and sizes while being resistant to outliers. This algorithm is particularly useful in situations where clusters have varying densities and when traditional methods may struggle to capture such complexities [23]. It is important that DBScan is only used for spatial clustering tasks.

As already mentioned, clustering will group similar items or data points together. This can be done with non-spatial data aswell. There are many different types of automatic clustering methods that take into account different characteristics and structures of the data. Examples include k-means algorithms, which are a type of partitioning clustering method. K-means works by dividing a dataset into a predetermined number of clusters, with each data point assigned to the cluster that has the nearest mean. This algorithm is known for its simplicity and efficiency in handling large datasets [20].

~~Another example is the hierarchical clustering, which involves creating a tree of clusters. It can be agglomerative, starting with individual data points as clusters and merging them iteratively, or divisive, starting with one cluster and dividing it into smaller ones. Hierarchical clustering results in a tree-like structure called a dendrogram, which illustrates the relationships between clusters. So, k-means is a partitioning algorithm known for simplicity and efficiency, while hierarchical clustering creates a tree-like structure that provides a detailed view of relationships within the data. The choice between them depends on the specific characteristics of the data and the goals of the analysis [24].~~

2.5 SMOTE

In scenarios where one class is significantly underrepresented, traditional machine learning algorithms may struggle to accurately learn patterns and make predictions for the minority class. SMOTE (Synthetic Minority Over-sampling Technique) is a resampling method used in machine learning to address class imbalance. It operates by generating synthetic examples of the minority class to balance the dataset, particularly beneficial when the minority class is underrepresented. SMOTE selects a data point from the minority class and creates synthetic instances along the line segments connecting it to its nearest neighbors. This technique helps prevent biased models that favor the majority class and enhances the performance of classifiers by providing a more balanced representation of the classes [25].

2.6 PCA

Another technique, Principal Component Analysis (PCA), is used for dimensionality reduction, helping in computational efficiency and pattern recognition. While SMOTE (see chapter 2.5) focuses on class balance, PCA complements it by simplifying the data structure. Principal Component Analysis (PCA) serves as a key dimensionality reduction technique in machine learning and data analysis. Its core function involves transforming complex datasets into a lower-dimensional space while retaining crucial information. This is achieved by identifying principal components, representing directions where variance in the data is maximized [26].

3. Research

Exploring the intersection of music and geography this study investigates the capability of tree-based machine learning, specifically utilizing the CatBoost algorithm, to accurately classify traditional, ethnic, or 'world' genre-based music. Western music is excluded from the data since western music influence is global. The study utilizes the MARSYAS framework for audio feature extraction, incorporating geographical clustering methods, such as manual clustering and DBScan, to reveal patterns within the data. Additionally, techniques like SMOTE and PCA are applied for data balancing and dimensionality reduction.

The goal is to contribute to the evolving landscape of music analysis by combining machine learning, audio feature extraction, and geographic clustering. The exploration of different methods aims to explore the complexity of music and to show that music is also within the domain of Geographic Information Retrieval (GIR).

4. Methods

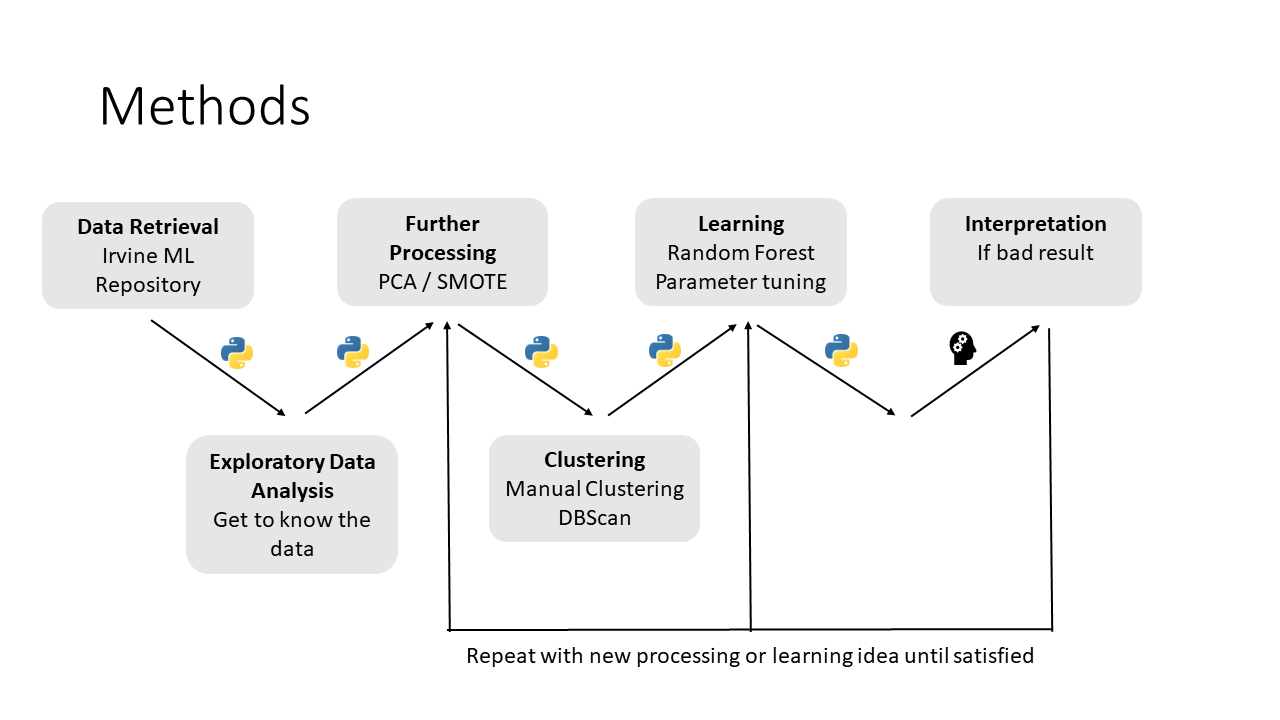
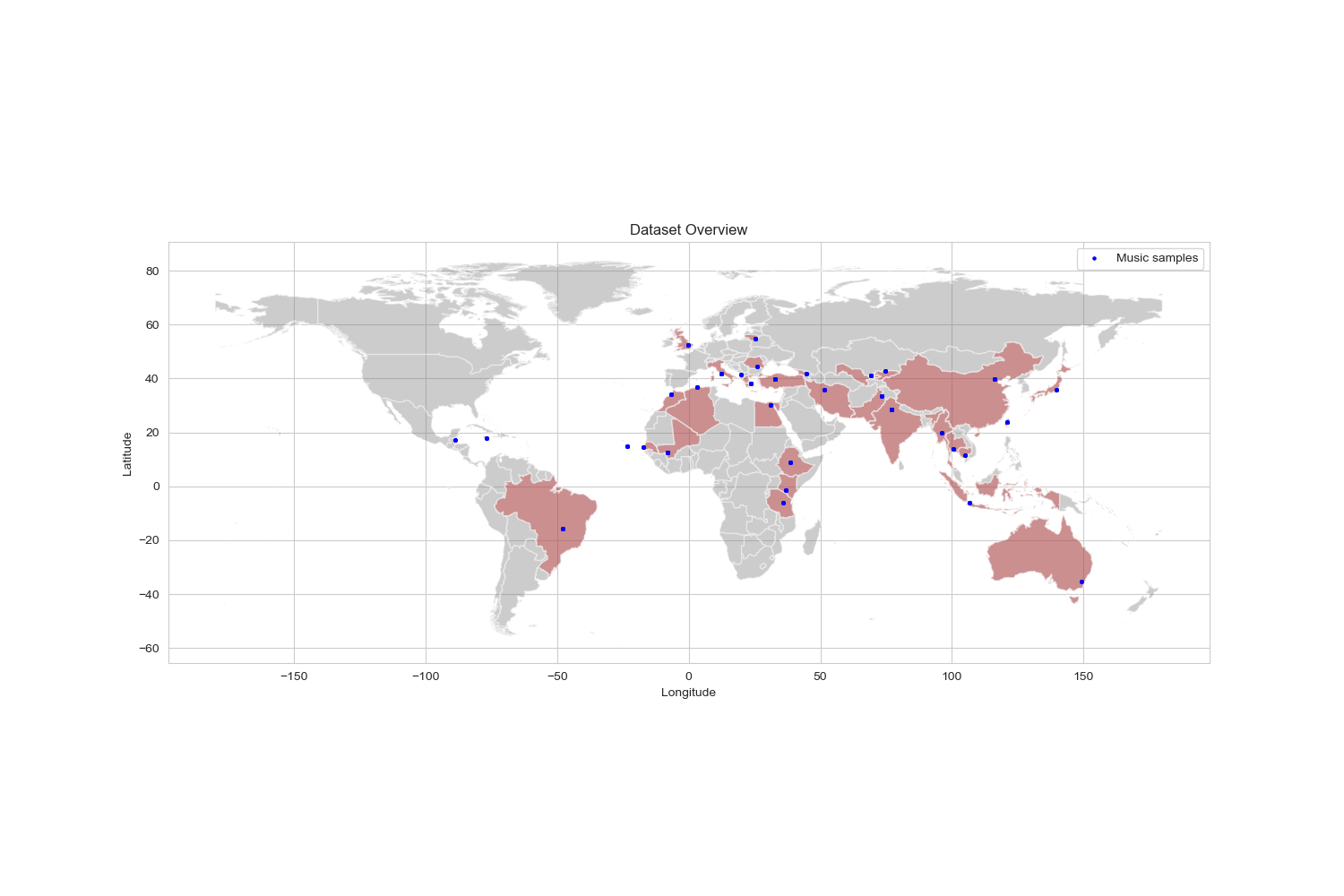


Figure 3: Overview of methods

The project unfolds through a series of systematic steps implemented in Python, aiming to elucidate the intricate relationship between music and geography. The first phase involves data retrieval from the Irvine Machine Learning Repository [27], providing the dataset for analysis.

The Dataset itself is about 1059 tracks long and covering 33 countries. Geographical information, specifically the origin of each track, is manually gathered from CD sleeve notes. In instances where the provided information is insufficient, additional sources are consulted. The precision of location data is constrained to the country of origin. Determination of the country of origin relies on the primary residence of the artist or artists, excluding tracks with ambiguous origin. The geographical point of origin is established as the latitude and longitude of each country's capital city (or the province of the area). Audio features are extracted from the wave files using the MARSYAS program (see Chapter 2.2).



**Figure 3: Geographical Overview of the Dataset [python]**

An exploratory data analysis (EDA) is done, to gain insights into the characteristics and distribution of the dataset. This analytical phase aims to enhance understanding by systematically examining the dataset's patterns and key features. Building on the insights gained from EDA, further processing is undertaken to refine the data. This includes adjustments to the data structure, utilizing Principal Component Analysis (PCA) for dimensionality reduction, and employing Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance.

The clustering phase includes both manual and automatic clustering. Manual clustering and DBscan aligns with predefined geographic regions, while K-means operates on the attributes and internal data structures to reveal latent patterns within the dataset. These three clustering methods are all used for later processing. The machine learning phase focuses on training the CatBoost algorithm on these 6 datasets: Three clustering methods each with PCA and SMOTE. Parameter tuning is performed to optimize the performance of the model, and cross-validation (CV) is used to evaluate its robustness. The results obtained from the machine learning model set the stage for an in-depth interpretation using various metrics such as accuracy, precision, recall and F1 score.

These steps were performed until the scores of the model results did not improve.

5. Results

**Chat GPT general statements:**

* Geographic Patterns Unveiled:

The analysis reveals discernible geographic patterns within the music dataset, shedding light on the influence of different regions on musical compositions.

* Nuanced Regional Characteristics:

Clustering methods expose nuanced regional characteristics, allowing for a more detailed exploration of the geographical diversity inherent in various music genres.

* Impact of Feature Attributes:

DBScan applied to feature attributes unveils intricate musical similarities, providing insights into the internal structures and commonalities within the dataset.

* CatBoost Classification Performance:

The machine learning model, CatBoost, demonstrates robust classification performance, showcasing its efficacy in accurately categorizing traditional, ethnic, and 'world' genre-based music.

* Iterative Refinement Enhances Insights:

The iterative refinement process proves instrumental in enhancing the overall understanding of geographic influences on music genres, ensuring the study evolves dynamically.

* Interpretation Metrics Illuminate:

Evaluation metrics, including accuracy, precision, recall, and F1 score, offer a comprehensive lens for interpreting the performance of the machine learning model across diverse geographic and musical contexts.

* Balancing Techniques Impact:

The application of SMOTE for class balancing and PCA for dimensionality reduction significantly impacts the overall effectiveness of the analysis, emphasizing the importance of careful preprocessing.

* Potential for Future Insights:
* The results provide a foundation for future exploration, suggesting avenues for additional research into the nuanced interplay between geography and music, particularly in the context of diverse cultural influences.
* Cross-Domain Insights:

The findings not only contribute to the field of music analysis but also offer potential cross-domain insights into the broader discourse of how geographical nuances shape and define creative expressions.

* Robust Framework for Further Studies:

The established framework, incorporating clustering, machine learning, and iterative refinement, serves as a robust foundation for further studies exploring the multifaceted relationships between geographic factors and music genres.

6.  Critical discussion

7.  Conclusion

8.  Suggestions for future work

**After an insi**

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The exploration of future research directions involves envisioning innovative applications of the MARSYAS framework, such as the implementation of an online platform. This platform could revolutionize user experiences by enabling real-time classification of uploaded music to specific geographic points, creating an interactive map interface. Not only would this implementation enhance user engagement, but it would also contribute to a deeper understanding of global music genre distribution. Such an online tool holds significant potential for music enthusiasts, researchers, and artists seeking insights into the geographic influences shaping their compositions.

Another prospective avenue for future work lies in adopting a more traditional, music-theoretical approach to analyze the structure of compositions. Prioritizing traditional music theory methodologies over machine learning, this approach would delve into chord progressions, musical scales, and rhythmic patterns. By doing so, researchers could gain a profound understanding of intrinsic musical elements defining genres, offering a complementary perspective to the data-driven analyses conducted in this study. This approach caters to scholars and practitioners valuing the richness of musical theory and aiming to explore genre classification from a more traditional standpoint.

Furthermore, researchers could extend the exploration of machine learning models by experimenting with different algorithms. Diversifying the techniques employed, including ensemble methods, neural networks, or hybrid models, could offer a more comprehensive evaluation of classification performance. Such an approach enables a thorough assessment of the strengths and limitations of various algorithms, contributing to the development of more robust models for music genre classification.

In essence, future research could take a multifaceted approach, encompassing the online implementation of the MARSYAS framework, a return to traditional music analysis methodologies, and an exploration of diverse machine learning models. These avenues collectively have the potential to broaden the scope of research, offering new insights into the complex relationship between music genres and geographic influences.

**Meine Idee:**

e.g. implementation of MARYAS framework online. A map which will classify your music automatically to a geographic point.

Or: A more into-the-music work which analyses the structure behind the music more traditionally and less with machine learning

Or. Try different ML-

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Appendix

MARSYAS framework kapitel

MARSYAS vs. Spotify's Music Classification Algorithms

While Spotify has developed sophisticated algorithms for music classification and recommendation, MARSYAS differentiates itself through its focus on audio feature extraction and its open-source design.

Feature Extraction Emphasis

MARSYAS places a strong emphasis on feature extraction, providing users with a comprehensive toolkit for capturing diverse aspects of audio content. This is particularly valuable when the goal is to uncover subtle nuances and patterns within music, contributing to a more detailed and nuanced analysis compared to algorithms primarily designed for classification or recommendation.

Customization and Modularity

Unlike proprietary algorithms employed by commercial platforms like Spotify, MARSYAS offers a high degree of customization and modularity. Users can tailor the framework to specific research questions or musical genres, allowing for a more flexible and adaptable approach. This is especially advantageous in academic or research settings where the focus may extend beyond mainstream music genres.

Open-Source Collaboration

The open-source nature of MARSYAS encourages collaboration and the continuous evolution of the framework. While Spotify's algorithms remain proprietary and closed, MARSYAS benefits from the collective input of a diverse community of researchers and developers. This collaborative environment contributes to ongoing improvements and ensures that the framework remains relevant and responsive to emerging trends in music analysis.

In conclusion, the MARSYAS framework's development was driven by a commitment to overcoming the limitations of traditional music analysis methods. Its strengths lie in extensive feature extraction, modularity, and open-source accessibility, positioning it as a valuable tool for in-depth music research. While Spotify's algorithms excel in their application for commercial music recommendation, MARSYAS offers a distinctive set of advantages for researchers seeking a more customizable and feature-centric approach to music analysis.