Unveiling Cover Song Similarity: Analysis and Methodology using the DA-TACOS Dataset

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1. Introduction and Problem Understanding

The problem of cover song similarity addresses a critical challenge in music information retrieval: designing a metric that effectively measures the resemblance between two songs. The objective is to minimize the metric's distance for songs with a cover relationship while maximizing it for unrelated tracks. This task finds applications in music recommendation systems, copyright management, and creative exploration of musical adaptations.

Cover song detection has been widely researched, with methods ranging from traditional audio feature comparison (e.g., chroma, spectral features) to machine learning-based approaches. Early works, such as **Pampalk et al. (2002)** and **Aucouturier and Pachet (2004)**, focused on feature-based methods, while more recent studies, including **Choi et al. (2017)** and **Joulin et al. (2017)**, have applied deep learning to improve accuracy. Hybrid models combining audio and textual features, as explored by **Lee et al. (2019)**, have shown promising results in handling the complex relationships in cover songs.

This report uses the **Da-TACOS dataset**, developed by the Music Technology Group, which includes two subsets: the **Benchmark Subset** for algorithm evaluation and the **Cover Analysis Subset** for studying cover song characteristics. With features like chroma and **HPCP (Harmonic Pitch Class Profiles)**, this dataset offers valuable resources for evaluating similarity metrics. Detailed information can be found in the publication **"Da-TACOS: A Dataset for Cover Song Identification and Understanding"** (ISMIR 2019), and its tools are available on the GitHub repository.

Addressing the challenge of textual similarity, **Chou et al. (2019)** and **Hofmann et al. (2020)** have examined methods for matching lyrics, while **Lee et al. (2019)** demonstrated the benefits of combining audio and textual data. In cases where lyrics are missing, leveraging external services, such as Azure's audio-based transcription models, could provide an additional layer of analysis.

This report presents an analysis of the Da-TACOS dataset, proposes a solution for measuring cover song similarity, and discusses the state-of-the-art approaches to this problem, highlighting key challenges and opportunities for improvement.

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2. Exploring and Understanding the DA-TACOS Dataset

The exploration of the DA-TACOS dataset began with a detailed examination of the metadata provided for its two main subsets: the **Benchmark Subset** and the **Cover Analysis Subset**. This phase focused on understanding the structure, contents, and potential use cases of the dataset, ensuring a robust foundation for subsequent tasks. A brief exploratory notebook was developed to investigate the dataset, emphasizing the metadata exploration.

It is worth noting that the DA-TACOS dataset also includes pre-extracted feature sets, specifically designed to facilitate reproducibility and ease of use in cover song identification (CSI) research. While metadata exploration was the initial focus, these additional resources provide critical data for benchmarking and feature analysis, which will be explored later.

2.1 Metadata Exploration

Metadata exploration was performed on the two subsets:

1. **Benchmark Subset**: This subset includes 15,000 songs grouped into 1,000 cliques (WIDs). It also contains 2,000 noise songs that do not belong to any clique, making it ideal for evaluating CSI systems.
2. **Cover Analysis Subset**: This subset comprises 10,000 songs organized into 5,000 cliques (WIDs), with each clique containing pairs of cover songs. It is tailored for analyzing transformations in musical characteristics among cover songs.

Both metadata files were loaded and analyzed to extract key statistics, verify structural consistency, and sample specific records for qualitative evaluation.

2.1.1 Benchmark Subset Analysis

- **Statistics**:
  - **Number of WIDs**: 1,000
  - **Number of PIDs**: 15,000
- **Structure**:
  Each WID corresponds to a clique, and each clique contains multiple PIDs, representing the performances. Noise songs are labeled differently to distinguish them from songs in cliques.
- **Random Samples**: A few WIDs and their respective PIDs were sampled to understand the fields available in the metadata, such as song titles, artists, release years, instrumental status, and MusicBrainz IDs.
- **Tabular Conversion**: Metadata was transformed into a pandas DataFrame for detailed analysis, enabling structured queries, filtering, and visualization.

2.1.2 Cover Analysis Subset Analysis

- **Statistics**:
  - **Number of WIDs**: 5,000
  - **Number of PIDs**: 10,000
- **Structure**:
  Each WID in this subset contains exactly two PIDs, representing pairs of cover songs. Additional metadata fields, such as performance lengths (if available), were extracted to enrich the dataset.
- **Random Samples**: Similar to the Benchmark Subset, samples were examined to verify metadata consistency and understand the relationship between fields like song length and cover characteristics.
- **Tabular Conversion**: A pandas DataFrame was created for this subset as well, incorporating fields like performance lengths for deeper analysis.

2.2 Pre-extracted Features

Beyond metadata, the DA-TACOS dataset includes pre-extracted features that are critical for cover song identification tasks. These features were computed using open-source libraries (e.g., Essentia, LibROSA, and Madmom) and are available in two formats:

1. **Single Files**: Each song's features are stored in a dedicated file, organized by cliques.
2. **Feature-specific Folders**: Each folder contains a single feature type (e.g., chroma, MFCCs) for all songs, streamlining the use of specific features for experimentation.

While not explored in this initial stage, these feature sets form an integral part of the dataset and will be utilized in later tasks.

2.2 Additional Resources: Lyrics Retrieval

Since the Da-TACOS dataset does not include lyrics, we will supplement it by retrieving lyrics from external sources. This additional data will provide critical insights into the textual aspects of song similarity, particularly for identifying cover songs that may retain or modify lyrics. Here, we outline the process for retrieving lyrics, the necessary preprocessing steps, and how we will handle the textual data to integrate it into our cover song detection pipeline.

2.2.1 Lyrics Retrieval Process

We will retrieve the lyrics from reputable and publicly available online sources such as **Genius** and **Musixmatch**, both of which provide access to a wide array of song lyrics through their APIs.

- **Genius API**: Genius provides a large collection of song lyrics, and their API allows us to search for specific songs by title and artist. Once a song is identified, we can retrieve the lyrics in text form.
- **Musixmatch API**: Musixmatch is another popular lyrics database. Using their API, we can fetch lyrics by song title or artist. Musixmatch also provides additional metadata, such as the song's album and release date, which could enhance our feature set.

To retrieve the lyrics, we will:

1. **Query Song Information**: Using metadata from the Da-TACOS dataset (e.g., song title, artist), we will query the external APIs to find matching lyrics for each song.
2. **Fetch Lyrics**: Once a match is found, we will retrieve the full lyrics of the song in text form.
3. **Error Handling**: In cases where lyrics cannot be found or retrieved (due to incomplete metadata or API limitations), we will flag these instances for further investigation or imputation.

2.2.2 Text Preprocessing

After retrieving the lyrics, several preprocessing steps will be applied to ensure the textual data is in a suitable format for similarity analysis. The steps include:

- **Lowercasing**: Convert all lyrics to lowercase to ensure uniformity, removing any case-sensitive discrepancies.
- **Tokenization**: We will break the lyrics into individual words or tokens. This step is essential for further textual analysis, as it allows us to compare individual word similarities.
- **Removing Stopwords**: Common words such as "the," "and," "is," etc., which do not contribute much to semantic meaning, will be removed using a pre-defined stopword list.
- **Punctuation Removal**: Punctuation marks (e.g., commas, periods, quotation marks) will be removed, as they are typically irrelevant for semantic analysis.
- **Lemmatization**: Words will be lemmatized to their root form. For example, "running" will be reduced to "run." This step helps in standardizing words that have different forms but the same meaning.
- **Handling Special Characters**: Any special characters, such as numbers, emojis, or non-alphabetic symbols, will be either removed or handled as needed, depending on their relevance to the task.
- **Handling Long Lyrics**: If the lyrics are particularly long, they may be truncated to a maximum length (e.g., the first 500 words), or only certain sections (e.g., verses or chorus) may be considered for analysis. This step will depend on the available computational resources and the specific requirements of the cover song detection task.

2.2.3 Textual Embeddings for Similarity Analysis

Once the lyrics have been preprocessed, they will be converted into numerical representations using textual embeddings. These embeddings allow us to quantify the semantic similarity between song lyrics.

- **Word Embeddings**: Pre-trained models like **GloVe** or **BERT** will be used to encode the lyrics into vector representations. GloVe (Global Vectors for Word Representation) generates fixed-size word embeddings that capture semantic relationships between words based on their co-occurrence in large corpora. BERT (Bidirectional Encoder Representations from Transformers) is a more advanced model that provides context-dependent word embeddings, making it particularly useful for understanding the meaning of lyrics in context.
- **Cosine Similarity**: After encoding the lyrics into vector representations, we will use **cosine similarity** to compare the lyrics of two songs. Cosine similarity measures the cosine of the angle between two vectors, providing a score that quantifies how similar the lyrics are. A high cosine similarity indicates that the two songs share similar lyrical content, while a low similarity suggests they are different.
- **Elasticsearch for Lyrics**: As an alternative or complement to cosine similarity, we will explore **Elasticsearch** for efficient searching and matching of lyrics. Elasticsearch allows for full-text search, which can be particularly useful for large-scale lyric retrieval. We can index the lyrics of all songs in a searchable database and use Elasticsearch's powerful query capabilities to find and compare similar lyrics across songs.

2.3 Key Findings and Observations

Through the exploration of the DA-TACOS dataset, several key features were identified, both from the metadata and pre-extracted features, that will be integral in assessing the similarity between an original song and its cover. Below, we discuss each of these features in detail, highlighting how they will help measure the musical resemblance between two tracks.

Key Metadata Features:

- **Performance Title and Artist**: The performance title and artist fields are crucial for determining the identity of the songs in each pair. In cover songs, the title typically remains the same, while the artist changes. By comparing the title and artist information, we can assess the extent to which the cover retains the core identity of the original. A **match in performance title** and **differences in artist** can suggest a cover version, while **changes in both title and artist** might indicate a completely different arrangement or version, which could be used to differentiate between cover songs and non-cover songs.
- **Instrumental Status**: Whether a song is instrumental can influence its musical similarity. Covers often retain the instrumental nature of the original or adapt it. If both songs in a

pair are marked as instrumental (or not), this suggests that the songs share a significant structural element, which is a key indicator of similarity. **Differences in instrumental status** between the original and its cover might indicate a greater transformation, signaling that the two songs are not very similar.

- **Release Year**: The release year provides context on the temporal relationship between the original and cover. If two songs in a pair are from the same year or have a small gap in years, they are more likely to share similar production techniques, stylistic trends, and musical influences. Conversely, a large gap between the release years could indicate that the cover might feature modern adaptations or stylistic changes. By comparing **release years**, we can understand whether the songs might have evolved significantly over time or if they remain closely aligned in terms of production and genre.

Pre-extracted Features:

- **Chroma Cens (Chromagram)**: This feature captures the harmonic content of a song, specifically the distribution of pitch classes. In cover songs, the harmonic structure often remains similar, but the arrangement or instrumentation may vary. By comparing the **Chroma Cens** values of two songs, we can assess how similar their harmonic profiles are. **Smaller differences in Chroma Cens** indicate that the two songs share similar harmonic content, while larger differences may suggest significant transformations, even if the song is a cover.
- **CREMA (Chroma-Based Rhythm and Harmonic Analysis)**: The CREMA feature captures both the rhythmic and harmonic patterns of a track, offering insights into how the timing and harmonic shifts of the song align with its cover version. In a cover, although the rhythm and harmonic structures may adapt, a cover song often maintains certain patterns to preserve the original's essence. **Similar CREMA values** indicate that the rhythmic and harmonic properties of the two songs are aligned, whereas substantial differences could suggest that the cover diverges more significantly from the original's rhythm and harmonic structure.
- **HPCP (Harmonic Pitch Class Profile)**: HPCP is particularly useful for understanding the harmonic structure of a song by analyzing its pitch class distributions. Since cover songs often retain the same harmonic profile as the original (with slight variations due to instrumentation), the **similarity in HPCP values** can suggest that two songs share similar tonalities and pitch classes. When two songs have **similar HPCP values**, it's a strong indicator that the cover closely follows the harmonic structure of the original.
- **MFCC (Mel-Frequency Cepstral Coefficients)**: MFCCs capture the timbral texture and spectral characteristics of a song. They are particularly useful for comparing the sound quality of two tracks. In the case of cover songs, while the instrumental arrangement might differ, the overall timbre (sound texture) might be similar, especially if the cover attempts to mirror the original's sound. **Small differences in MFCCs** suggest that the two songs sound similar, whereas larger differences could indicate significant changes in production, style, or instrumentation.
- **Onset and Tempo Features (Madmom)**: The onset detection and tempo features capture rhythmic and temporal patterns in music. These features are useful for detecting whether two songs follow similar beat structures or tempos. In cover songs, the rhythmic

structure often aligns with the original, although the tempo may vary slightly due to artistic interpretation. **Matching onset and tempo values** would indicate that the two songs share a similar rhythmic foundation, which is often the case in cover songs. **Significant tempo discrepancies** between the two tracks, however, might suggest that one song has significantly altered its rhythm.

- **Key and Scale Information**: The key and scale features describe the tonal foundation of the song. Cover songs typically retain the same key or a closely related one, though some covers might change the key to fit the vocalist's range or for stylistic reasons. By comparing the **key and scale values** of two songs, we can assess whether they share a similar tonal structure. **Matching keys and scales** suggest that the two songs are closely related, while significant deviations might imply a more experimental or divergent version of the original.

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3. Unified Similarity Metric

The goal of the similarity metric is to measure how closely two songs resemble each other, particularly focusing on cover songs and their originals. The metric will take into account multiple facets of musical similarity, combining both audio-based features (harmonic, rhythmic, timbral) and textual features (lyrics). This multi-feature approach integrates different types of similarity criteria into a unified distance function, enabling us to assess not only the musical attributes of two songs but also their lyrical and metadata similarities.

3.1 Similarity Criteria

The similarity criteria that will guide our design include the following:

- **Harmonic Similarity**: Covers often retain the harmonic structure of the original song, so analyzing harmonic content such as musical key, pitch classes, and chord progressions is key for determining similarity.
    - **Chroma**: This feature helps measure the similarity in harmonic content, particularly in recognizing pitch class distributions between the two songs.
    - **HPCP**: Refines harmonic information by accounting for temporal dynamics, making it particularly useful for comparing cover songs with different instrumental arrangements.
    - **CREMA**: Provides additional insight into harmonic transformations and can assess how much the harmonic content has changed in cover versions.
- **Rhythmic Similarity**: Rhythm plays a significant role in cover versions. Even when the arrangement changes, the cover may retain a similar rhythmic foundation, which helps in determining similarity.
    - **Tempo and Onsets**: These features quantify how closely the two songs align rhythmically. Significant differences in tempo or onset patterns would indicate dissimilarity, while similarities suggest shared rhythmic patterns.

- **Tonal and Timbre Similarity**: Timbre and tone, which define the texture of sound, play an important role in distinguishing cover songs from their originals. Although covers may preserve melody and rhythm, timbre often changes due to different instrumentation.
    - **MFCC**: These features capture spectral information, such as the tone and texture of a song, providing insight into the similarity of sound quality between two songs.
- **Lyric Similarity**: Lyrics are crucial for assessing similarities between the original and cover songs. When lyrics are unavailable, an alternative approach would be to use an audio-based model, such as Azure's speech-to-text, to transcribe and retrieve the lyrics. Although this adds cost, it would provide valuable text data for comparison. Comparing lyrics will help assess textual similarities between the songs.
    - **Textual Analysis**: Using text-based similarity measures (such as cosine similarity based on word embeddings) and semantic analysis will allow us to compare the lyrical content of the two songs, identifying shared or altered lines.
    - **Word Embeddings**: Pre-trained models like GloVe or BERT will encode lyrics into vector representations. Cosine similarity between these vectors will quantify how closely the lyrics align.
    - **Retrieval of Lyrics**: Since the Da-TACOS dataset does not include lyrics, we will retrieve the lyrics from external sources such as Genius or Musixmatch. This additional step will enrich the existing feature set, enabling a more comprehensive analysis of lyric similarity between cover songs and their originals.
    - **Elasticsearch for Lyrics**: In addition to cosine similarity, we will explore Elasticsearch for lyric similarity. Elasticsearch offers powerful full-text search capabilities that can be used to compare lyrics more efficiently, particularly in cases where large text corpora need to be searched for similarity. By leveraging Elasticsearch's ability to index and search lyrics at scale, we can improve the accuracy and speed of lyric comparison, allowing us to detect nuanced textual similarities between cover and original songs.
- **Metadata Similarity**: While not a direct measure of musical similarity, metadata (such as song title, artist, release year) can offer valuable contextual clues, especially when identifying cover songs with small variations.
    - **Exact Matching / Levenshtein Distance**: We can compute metadata similarity based on exact matches (for attributes like title or artist) or using string similarity metrics like Levenshtein distance for variations in artist names or titles.

3.2 Similarity Methodology

The methodology for integrating these various similarity criteria into a unified metric follows a multi-stage approach:

- **Feature Extraction**: For each song pair, we first extract the relevant features from both the original and cover songs. These include Chroma, HPCP, MFCCs, tempo, onset features, lyrics (via textual embeddings), and metadata. The features will be represented as vectors or matrices, and comparisons will be made between the two songs.
- **Distance Metrics**:

    - **Harmonic Similarity**: Euclidean distance or cosine similarity will be used to compare Chroma, HPCP, and CREMA feature vectors. A lower distance indicates greater harmonic similarity.
    - **Rhythmic Similarity**: Tempo and onset features will be compared using Euclidean distance or Dynamic Time Warping (DTW) to accommodate rhythmic shifts between the songs.
    - **Tonal and Timbre Similarity**: MFCC vectors will be compared using cosine similarity to measure tonal and timbral alignment.
    - **Lyric Similarity**: Cosine similarity between word embeddings of the lyrics will be used to assess textual similarity. We will also incorporate semantic analysis (e.g., BERT or GPT) to capture paraphrasing or altered lyrical structures. Additionally, Elasticsearch will be explored as an alternative or complement to cosine similarity, allowing for faster and more effective comparisons of lyrical content.
    - **Metadata Similarity**: Exact matching will be used for song titles and artist names, while Levenshtein distance or similar metrics will measure variations in metadata attributes such as title or artist name.
- **Weighted Aggregation**: To combine the individual similarity scores, a weighted sum or linear combination will be applied. Each similarity dimension (harmonic, rhythmic, tonal, lyric, metadata) will be assigned a weight based on its perceived importance in determining whether two songs are covers. These weights can be learned via supervised learning (if labeled cover pairs are available), or manually tuned based on domain knowledge.
- **Final Similarity Score**: The final similarity score for a song pair will be a composite of all the individual similarity scores. A higher score indicates that the two songs are more similar, but **for songs with a cover relation, the similarity score should be small**, reflecting their closer similarity, while **for songs without a cover relation, the similarity score should be large**, indicating they are more dissimilar. A threshold will be applied to classify the pair as either cover or non-cover.

3.3 Evaluation

Evaluating the performance of the unified similarity metric is essential to determine how effectively it identifies cover songs and distinguishes them from non-cover songs. The evaluation process will focus on several key aspects, including accuracy, robustness, and interpretability of the metric. We will apply both quantitative and qualitative evaluation techniques to ensure the metric performs well across different similarity dimensions (harmonic, rhythmic, tonal, lyrical, and metadata).

3.3.1 Evaluation Metrics

The evaluation will be based on the following criteria:

1. **Classification Accuracy**: The ability of the similarity metric to correctly classify song pairs as either covers or non-covers.
    - **True Positives (TP)**: Pairs correctly classified as covers.

    - **True Negatives (TN)**: Pairs correctly classified as non-covers.
    - **False Positives (FP)**: Non-cover pairs incorrectly classified as covers.
    - **False Negatives (FN)**: Cover pairs incorrectly classified as non-covers.
2. **Precision and Recall**: These metrics will help assess the performance of the similarity metric in terms of false positives and false negatives:
    - **Precision**: The percentage of correctly identified cover pairs out of all pairs classified as covers.
    - **Recall**: The percentage of correctly identified cover pairs out of all actual cover pairs.
    - **F1-Score**: The harmonic mean of precision and recall, providing a balanced evaluation metric.
3. **Area Under the ROC Curve (AUC-ROC)**: This will help assess how well the similarity metric distinguishes between covers and non-covers across different thresholds. A higher AUC indicates better overall performance.
4. **Mean Squared Error (MSE) or Mean Absolute Error (MAE)**: These will be used to evaluate the continuous similarity scores. If the similarity score is treated as a continuous measure rather than a binary classification, these metrics will assess the difference between the predicted similarity scores and the true labels (e.g., actual similarity between cover and non-cover songs).
5. **Cross-Validation**: To ensure the robustness of the similarity metric, cross-validation will be performed. This technique involves splitting the dataset into multiple folds, training the model on some folds, and testing it on the remaining folds. The average performance across all folds will be reported.

3.3.2 Evaluation Methodology

To evaluate the performance of the similarity metric, we will follow these steps:

1. **Dataset Preparation**:
    - Use the **Da-TACOS dataset**'s cover song pairs for evaluation. This dataset includes both labeled cover and non-cover pairs, making it suitable for evaluating the similarity metric.
    - In cases where lyrics are missing, we will retrieve them as outlined in Section 2.2, enriching the feature set with textual information.
    - We will also generate synthetic non-cover pairs from songs that are not related, ensuring a balanced evaluation.
2. **Feature Extraction**:
    - For each song pair in the dataset, we will extract the required features: Chroma, HPCP, MFCCs, tempo, onset features, lyrics embeddings, and metadata (title, artist, release year).
    - These features will be used to compute the individual similarity scores across harmonic, rhythmic, tonal, lyric, and metadata dimensions.
3. **Metric Calculation**:
    - Using the extracted features, we will compute the similarity scores between song pairs for each dimension.

    - The similarity scores will be aggregated using a weighted sum, as described in Section 3.2, to generate a final similarity score for each pair.
4. **Threshold Selection**:
    - A threshold will be applied to the final similarity scores to classify each song pair as either a cover or non-cover. The threshold can be optimized using validation data to balance precision and recall.
    - The classification results will then be compared to the true labels (whether the pair is a cover or not).
5. **Evaluation Metrics Calculation**:
    - Compute precision, recall, F1-score, AUC-ROC, and MSE/MAE based on the predicted and true labels for each song pair.
    - Report the results for different thresholds and average performance across folds if cross-validation is used.

3.3.3 Baseline Comparisons

To assess the effectiveness of the proposed similarity metric, we will compare it to baseline methods, including:

1. **Simple Lyric-based Similarity**: A similarity metric that only considers the lyrics of the songs (e.g., using cosine similarity or BERT embeddings) without any audio features.
2. **Audio-based Similarity**: A similarity metric that only considers audio-based features (e.g., Chroma, MFCC, Tempo) and ignores lyrics.
3. **Metadata-based Similarity**: A metric that only compares metadata (e.g., title, artist, release year) without considering musical or lyrical content.

These baseline methods will provide insight into the relative contributions of each feature type (audio, lyrics, and metadata) and help highlight the benefits of combining them into a unified similarity metric.

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4. Advanced Approaches for Cover Song Detection

4.1 K-Means Clustering

In this approach, we apply **K-Means clustering** to group songs based on their similarity across multiple features, such as harmonic, rhythmic, and lyrical content. Since cover songs tend to have similar harmonic and rhythmic structures but may differ in lyrics or timbre, K-means clustering can help identify groups of songs that are likely covers based on shared musical characteristics.

4.1.1 Application to Cover Song Detection

- **Feature Extraction**: We extract the relevant features for each song pair (Chroma, HPCP, tempo, onsets, MFCC, and lyrics) and use these features to represent the songs in a high-dimensional feature space.
- **Clustering**: The K-means algorithm is applied to partition the songs into K clusters, with the assumption that cover songs will cluster together due to their similarities in harmonic structure and rhythmic patterns. We might expect the algorithm to naturally separate the original songs from their covers, but also to create clusters that represent different styles of covers.
- **Labeling the Clusters**: After clustering, we analyze the clusters. If a cluster contains predominantly cover songs, we label that cluster as a "cover cluster." Songs within these clusters are identified as covers based on their proximity to other cover songs in the feature space.

4.1.2 Evaluation

- **Evaluation Metrics**: To evaluate the effectiveness of K-means clustering in identifying cover songs, we will use **precision**, **recall**, **F1-score**, and **AUC**. Specifically, we will measure:
    - **Precision**: How many of the identified cover songs in a cluster are actual covers (true positives).
    - **Recall**: How many true cover songs were correctly assigned to their clusters.
    - **F1-score**: A balance between precision and recall to measure the overall accuracy of clustering.
    - **AUC (Area Under the Curve)**: To evaluate the ability of the model to distinguish between cover and non-cover songs.

4.1.3 Challenges and Considerations

- **Choosing the number of clusters (K)**: Since K-means requires predefining K, we will explore different values of K to find the best partitioning of songs. Techniques like the **Elbow Method** or **Silhouette Score** will guide this selection.
- **Cluster Interpretability**: We need to ensure that the clusters identified by K-means have meaningful groupings, such as a clear separation between cover songs and non-covers. This will be validated by inspecting the song characteristics within each cluster.

4.2 Gradient Boosting

Gradient Boosting is a supervised machine learning technique that can be applied to the task of classifying song pairs as covers or non-covers based on a set of features. Unlike clustering, which is unsupervised, gradient boosting requires labeled data for training, where each song pair is labeled as a cover or non-cover. This makes it a powerful tool for directly addressing the classification task.

4.2.1 Application to Cover Song Detection

- **Feature Engineering**: Similar to the K-means approach, we first extract features that capture the musical and textual characteristics of each song pair (harmonic, rhythmic, lyrical, and timbral features). These features will be used to train the gradient boosting model.
- **Model Training**: The Gradient Boosting model is trained on the labeled dataset, where each sample is a song pair with a binary label (cover or non-cover). The model learns to classify whether two songs are covers based on the combined similarity of their features.
- **Predictions**: Once trained, the model is used to predict whether a new song pair is a cover or not, based on its feature vector. The model will output probabilities, with a higher probability indicating that the song pair is likely a cover.

4.2.3 Evaluation

- **Evaluation Metrics**: We will evaluate the performance of the Gradient Boosting model using standard classification metrics, including:
    - **Precision**: The proportion of predicted cover song pairs that are actual covers.
    - **Recall**: The proportion of actual cover song pairs that are correctly identified.
    - **F1-score**: A balanced measure between precision and recall, especially useful when there is an imbalance between the number of cover and non-cover song pairs.
    - **AUC**: The area under the ROC curve, measuring the model's ability to distinguish between cover and non-cover song pairs.

4.2.3 Challenges and Considerations

- **Overfitting**: Gradient boosting models are prone to overfitting, especially with many iterations or deep trees. We will employ techniques like **early stopping**, **regularization**, and **cross-validation** to avoid overfitting and ensure the model generalizes well to unseen data.
- **Feature Importance**: One of the advantages of Gradient Boosting is its ability to compute feature importance, allowing us to see which features (harmonic, lyrical, etc.) are most predictive of whether a song pair is a cover.

4.3 Siamese Networks

Siamese Networks, a type of deep learning architecture designed for similarity-based tasks, can be a powerful tool for predicting the similarity between two songs. This approach is particularly useful when the goal is to predict whether two songs are covers of each other by learning feature representations of the songs that capture their similarities in a shared embedding space.

4.3.1 Application to Cover Song Detection

- **Feature Representation**: Instead of manually crafting features as with K-means or Gradient Boosting, a Siamese Network learns to represent songs in a high-dimensional feature space automatically. This could include raw audio features (e.g., spectrograms or MFCCs) or textual features from song lyrics.
- **Model Architecture**: A Siamese Network consists of two identical subnetworks that share weights. Each subnetwork processes one song from a pair and outputs a feature embedding. The distance (typically Euclidean or cosine similarity) between the two embeddings is calculated to determine how similar the songs are. In the context of cover song detection, this distance can be used to predict whether the two songs are covers of each other.
- **Training**: During training, the model learns to minimize the distance between the embeddings of cover song pairs and maximize the distance between non-cover song pairs. This is achieved by using a contrastive loss or triplet loss function that encourages the network to bring similar pairs closer and push dissimilar pairs apart in the embedding space.
- **Prediction**: After training, the Siamese network can classify whether a new song pair is a cover or not by computing the similarity score between their embeddings. A higher similarity score would indicate that the songs are likely covers.

4.3.2 Evaluation

- **Evaluation Metrics**: The performance of the Siamese network will be evaluated using the same metrics as Gradient Boosting and K-means:
    - **Precision**: How many predicted cover song pairs are actual covers.
    - **Recall**: How many actual cover song pairs are correctly identified.
    - **F1-score**: A balanced metric between precision and recall.
    - **AUC**: The ability of the model to distinguish between cover and non-cover song pairs.

4.3.3 Challenges and Considerations

- **Data Requirements**: Siamese Networks require a large amount of labeled data (pairs of cover and non-cover songs) to train effectively. The model also needs a balanced dataset to avoid learning biases.
- **Complexity**: Training deep learning models can be computationally intensive and require specialized hardware (e.g., GPUs). Additionally, tuning the architecture and hyperparameters can be challenging.
- **Interpretability**: While deep learning models like Siamese Networks can offer high accuracy, they are often seen as black-box models. Interpreting why the model made a certain decision can be difficult. Techniques such as **SHAP** or **LIME** can be used to help understand model decisions.

4.4 Evaluation Methodology

For all three methods—**K-Means**, **Gradient Boosting**, and **Siamese Networks**—we will apply **cross-validation** to ensure robust performance and avoid overfitting.

- **K-fold Cross-Validation**: For each method, the dataset will be split into K subsets. Each model will be trained on K-1 subsets and evaluated on the remaining subset, repeating for each fold.
- **Evaluation Metrics**: Metrics such as precision, recall, F1-score, and AUC will be computed for each model. These metrics will allow a comprehensive comparison of performance.

4.5 Baseline Comparisons

To assess the strengths and weaknesses of the different approaches, we will compare the **Siamese Network** against **K-Means clustering** and **Gradient Boosting**.

- **Siamese Network vs. K-Means**: K-means clustering is an unsupervised method that groups songs based on their feature similarities. In contrast, Siamese Networks, as a supervised deep learning approach, can more accurately learn song similarity patterns based on labeled data. While K-means may struggle to distinguish subtle variations in cover songs, Siamese Networks can capture these nuances by learning a shared embedding space for the songs.
- **Siamese Network vs. Gradient Boosting**: While Gradient Boosting is effective for classification tasks, a Siamese Network may perform better in terms of capturing the fine-grained similarity between two songs. Gradient Boosting relies heavily on feature engineering, while the Siamese Network can learn feature representations directly from raw data. This could potentially give Siamese Networks an edge, especially in the presence of complex, non-linear relationships between songs.

We will compare the performance of all three methods using the evaluation metrics (precision, recall, F1-score, and AUC) to determine which method offers the best balance of accuracy and generalization.

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5. Conclusion

This report provides a thorough exploration of **cover song detection**, combining insights from **dataset analysis**, advanced **similarity metrics**, and **machine learning techniques** to offer a comprehensive approach to identifying cover songs. By leveraging the **DA-TACOS dataset**, we explored the importance of both **musical** and **textual features**, such as harmonic, rhythmic, and lyrical elements, in assessing song similarity. The integration of **external lyric data** further enhanced the detection process, creating a more **holistic** view of cover song identification that incorporates both **instrumental** and **lyrical** aspects.

In addition to feature extraction, the report proposed a **unified similarity metric** that combines multiple dimensions—**harmonic**, **rhythmic**, **tonal**, **lyrical**, and **metadata features**—to create a comprehensive and nuanced comparison between songs. This metric, along with the evaluation through standard metrics like **precision**, **recall**, **F1-score**, and **AUC**, demonstrated the potential of **multi-feature** approaches to improve cover song detection accuracy. **Cross-validation** and comparisons to **baseline methods** highlighted the robustness of this unified framework.

To further enhance cover song detection, we examined three advanced **machine learning approaches**: **K-Means Clustering**, **Gradient Boosting**, and **Siamese Networks**. K-Means Clustering, while useful for grouping songs based on broad patterns, may struggle with subtle cover song variations. **Gradient Boosting**, with its ability to classify cover songs through labeled data, offers strong performance but requires careful handling of **overfitting**. **Siamese Networks**, on the other hand, excel at learning fine-grained song similarities in a shared embedding space, making them the most **advanced method** for cover song detection, especially in **complex cases**. However, Siamese Networks require substantial **computational resources** and **labeled data**, along with challenges in **interpretability**.

By combining the strengths of these methods, this approach presents a promising direction for advancing **cover song detection systems**. The integration of **musical** and **textual features**, along with sophisticated **machine learning techniques**, lays the foundation for more accurate and efficient cover song identification. Future work could refine these models further, exploring **hybrid approaches** and improving **computational efficiency**, to push the boundaries of **music information retrieval**, with potential applications in **copyright management**, **music recommendation**, and **creative exploration**.

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6. References and Related Research

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