

# Breaking the Loop: Innovating Discovery on Spotify

## A Novel Recommendation Algorithm for Finding More Diverse Music



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### INTRODUCTION

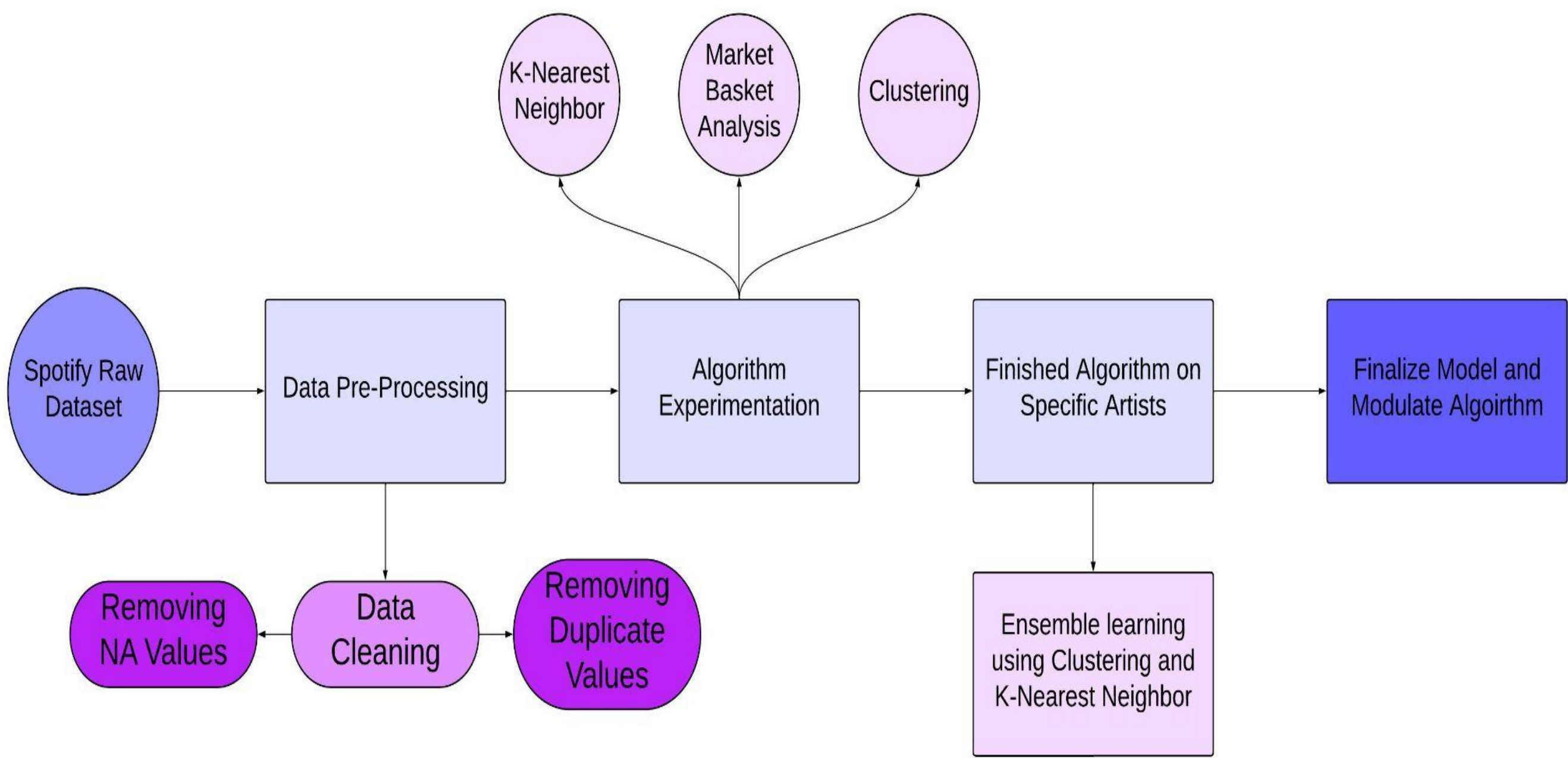
Spotify and various music streaming platforms often face criticism for its seemingly uninspired song recommendation algorithms. Paradoxically, these algorithms are not flawed due to a lack of precision but rather their excessive accuracy. Spotify's system operates on a **feedback loop** mechanism, meticulously identifying a user's preferences to suggest similar tracks. The desire to break away from habitual music selections and explore beyond accustomed genres, eras, or tastes becomes challenging. The algorithm's design, unfortunately, does not support this quest for musical discovery, forcing users to manually search for new songs. This project seeks to unveil an innovative approach to song recommendations, emphasizing the intrinsic attributes of the songs without the interference of user data in the outcomes.

### DATA

A Spotify dataset encapsulating 89,714 unique songs and 125 genres was used for this algorithm. Each song has 16 distinct attributes, ranging from duration of song to genre. Part of the pre-processing was to disregard redundant and non-predictive attributes, using a technique called *information gain*. After the non-predictive attributes were eliminated, only seven features remained: acousticness, danceability, energy, instrumentalness, liveness, speechiness, and valence. A description of each feature can be found in the figure below.

Attribute	Definition
Acousticness	A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
Danceability	Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.
Energy	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale.
Instrumentalness	Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content.
Genre	The genre in which the track belongs
Speechiness	Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value.
Valence	A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry.)

### PIPELINE



### ALGORITHMS

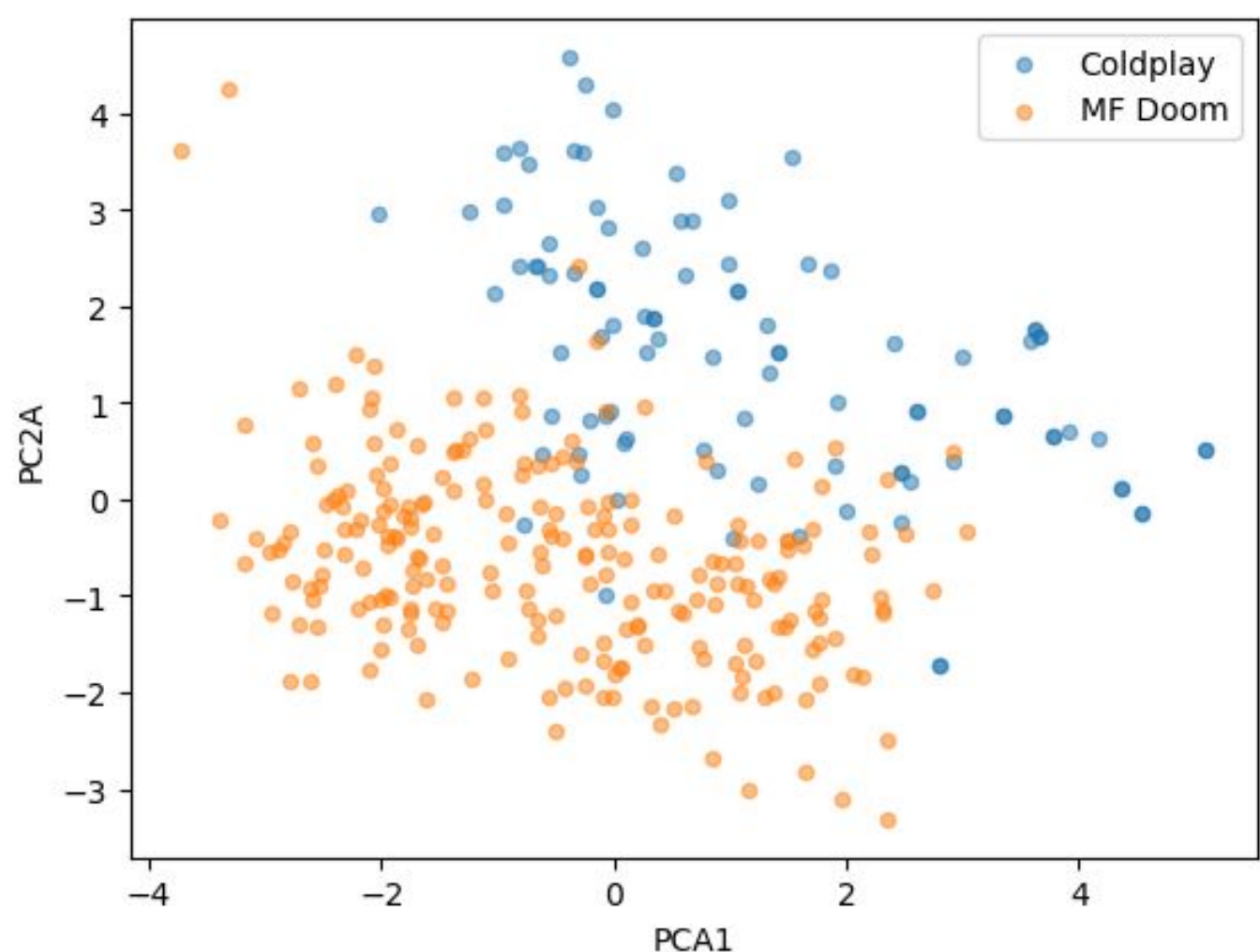


Fig. 1: Example of song clustering by attributes. Artists Coldplay and MF DOOM were chosen to show attribute disparity.

number of clusters      number of cases      centroid for cluster  $j$

$$\text{objective function} \leftarrow J = \sum_{j=1}^k \sum_{i=1}^n \|x_i^{(j)} - c_j\|^2$$

Distance function

Fig. 2: Using Euclidean distance (nearest neighbor) to find the closest songs based on selected attributes.

**Clustering** in machine learning is the process of grouping similar data points together based on their characteristics or features, without prior knowledge of group definitions. **Nearest neighbor** is an algorithm that classifies an unknown data point by assigning it the same category as the most similar data point in the training set, typically measured using Euclidean distance.

### RESULTS

Track Name	Cluster
Hymn for the Weekend	2
Christmas Lights	1
Yellow	2
Yellow	2
Green Eyes	0
Christmas Lights	1
The Scientist	0
Christmas Lights	1
Higher Power	2
Christmas Lights	1
Christmas Lights	1
Everyday Life	0

Non-Coldplay song closest to 'Green Eyes' by Coldplay: 'Infinity' by Jaymes Young  
Non-Coldplay song closest to 'Christmas Lights' by Coldplay: 'The Universal' by Blur  
Non-Coldplay song closest to 'Hymn for the Weekend' by Coldplay: 'Black Balloon' by The Goo Goo Dolls

Fig. 3: **Top** - Coldplay songs and their respective cluster. The top song from each cluster is isolated. **Bottom** - The closest non-Coldplay song to the top Coldplay song in each cluster.

Using both clustering and nearest neighbor, the algorithm first clusters the songs into three distinctive groups. Then, after finding the most representative song from each cluster, the algorithm utilizes nearest neighbor to find a song with the smallest *Euclidean distance* to each top song from each cluster. This combination technique is called **ensemble learning**.

### CONCLUSION

	P1	P2	P3	P4	P5	Total
<b>Experimental Algorithm</b>						
How many songs have you heard before?	0/3	0/3	1/3	1/3	0/3	<b>2/15</b>
How many artists have you heard of before?	2/3	1/3	1/3	3/3	1/3	<b>8/15</b>
How many songs do you like?	2/3	3/3	3/3	3/3	2/3	<b>13/15</b>
<b>Spotify's Algorithm</b>						
How many songs have you heard before?	2/3	2/3	3/3	3/3	3/3	<b>13/15</b>
How many artists have you heard of before?	2/3	3/3	3/3	3/3	3/3	<b>14/15</b>
How many songs do you like?	2/3	3/3	2/3	3/3	3/3	<b>13/15</b>

The survey revealed that the algorithm effectively recommended new music to participants, with only **2 out of 15** songs being previously recognized. Conversely, Spotify's algorithm predominantly offered familiar tracks, including Van Morrison's "Brown Eyed Girl" to three individuals. The tests did face limitations, however. Due to the (somewhat) limited scope of the 89,714 song dataset, it was difficult at times to find certain artists in the dataset, or artists that had three unique songs.