



# Moodify: A Mood Booster For The Soul

Ashish Singh, Rohan Shah, Sree Kiran Prasad Vadaga, Vidhya Sagar Reddy Kandi  
CSCE 676: Data Mining and Analysis by James Caverlee, Texas A&M University

## Problem Statement

Based on the songs the user listens to and their personal information, identify their mood (i.e., sad, depressed, anxious, happy, excited, etc.) and recommend songs having a similar theme to improve it.

## Motivation

As per CDC, mental health includes our emotional, psychological, and social well-being and affects how we think, feel, and act. Mental health can also have a negative impact on one's physical health. Interestingly, music plays a vital role for individuals in the age group mentioned earlier and studies show that adolescents listen to music for 2-3 hours each day, especially when they are feeling distressed. This correlation between music and suicide has caused many to blame music as the source.

## Related Work

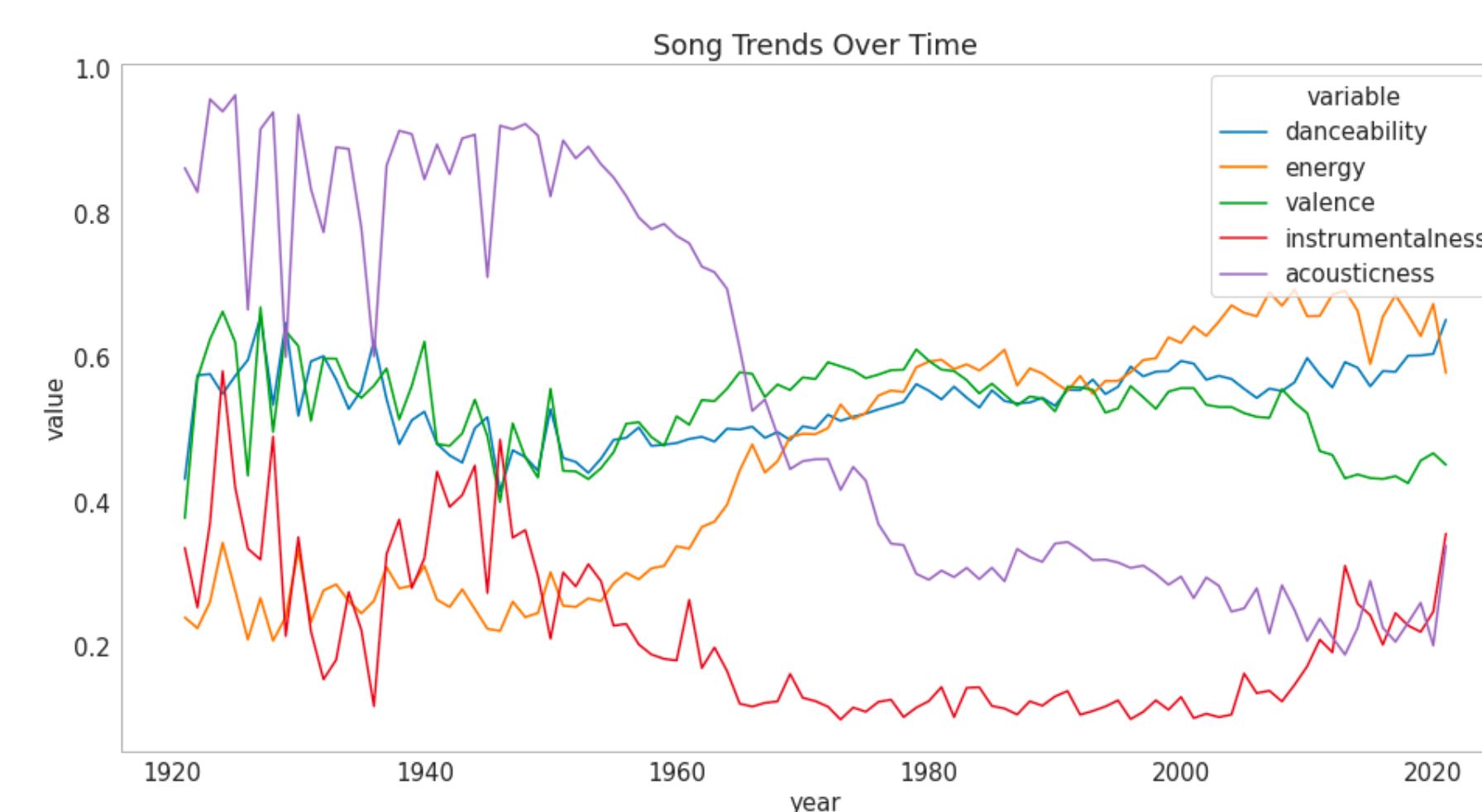
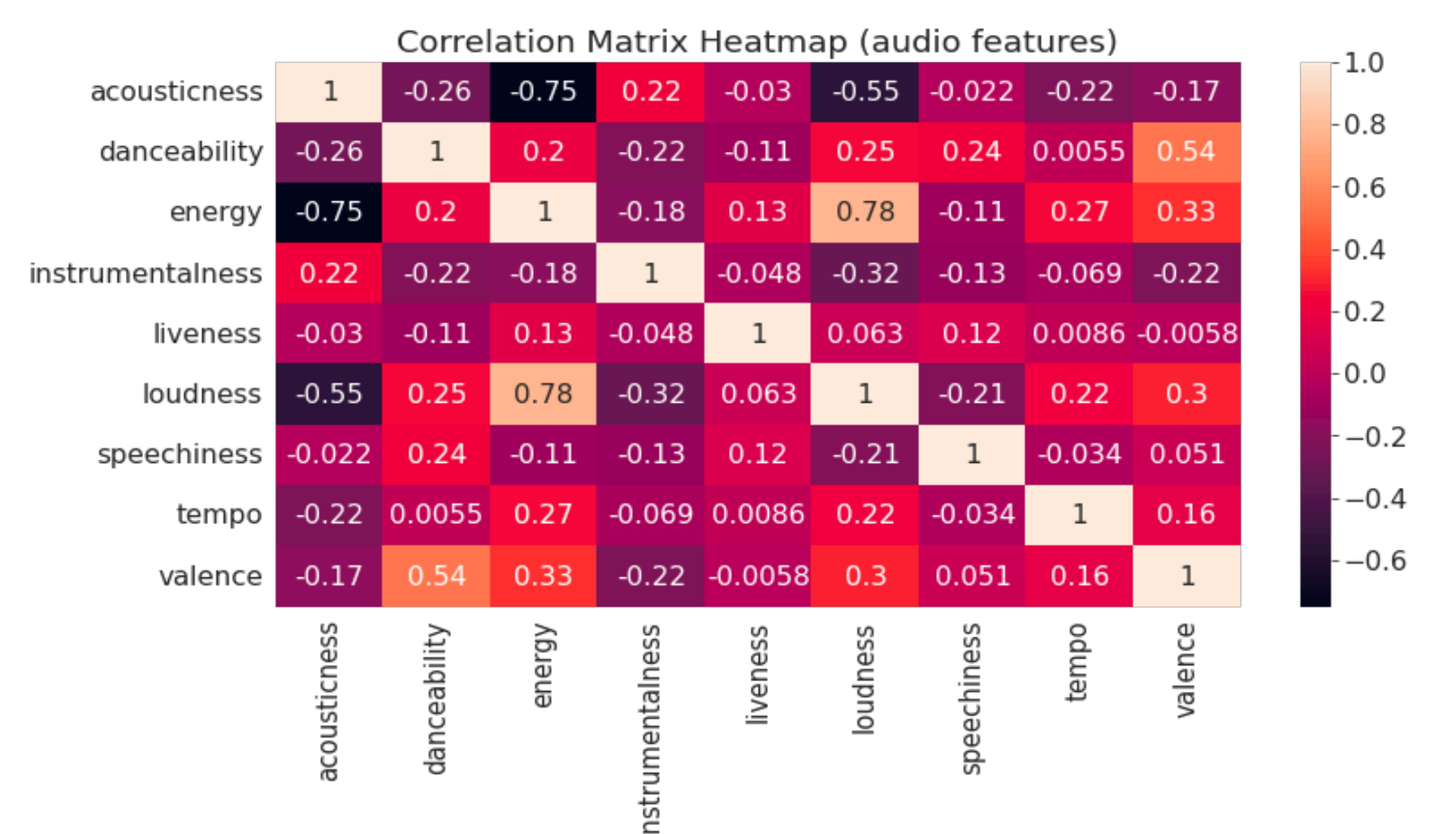
MRS are becoming more essential to help users find songs than before. Popular audio streaming providers such as Spotify and Apple Music accommodate the aim to limit the user's choice overload by providing the set of playlists under the “Mood” section. However, these playlists are more based on context rather than mood; whether it can be activity-based (e.g., Songs to Sing in The Car) or time-related events (e.g., Soft Morning). Moreover, these playlists are not personalized. They do not consider the user mood (e.g., current mood and desired mood) and user listening history (e.g., musical taste) to tailor the recommendation. Thus, creating a personalized affective MRS.

## Data Creation & Extraction

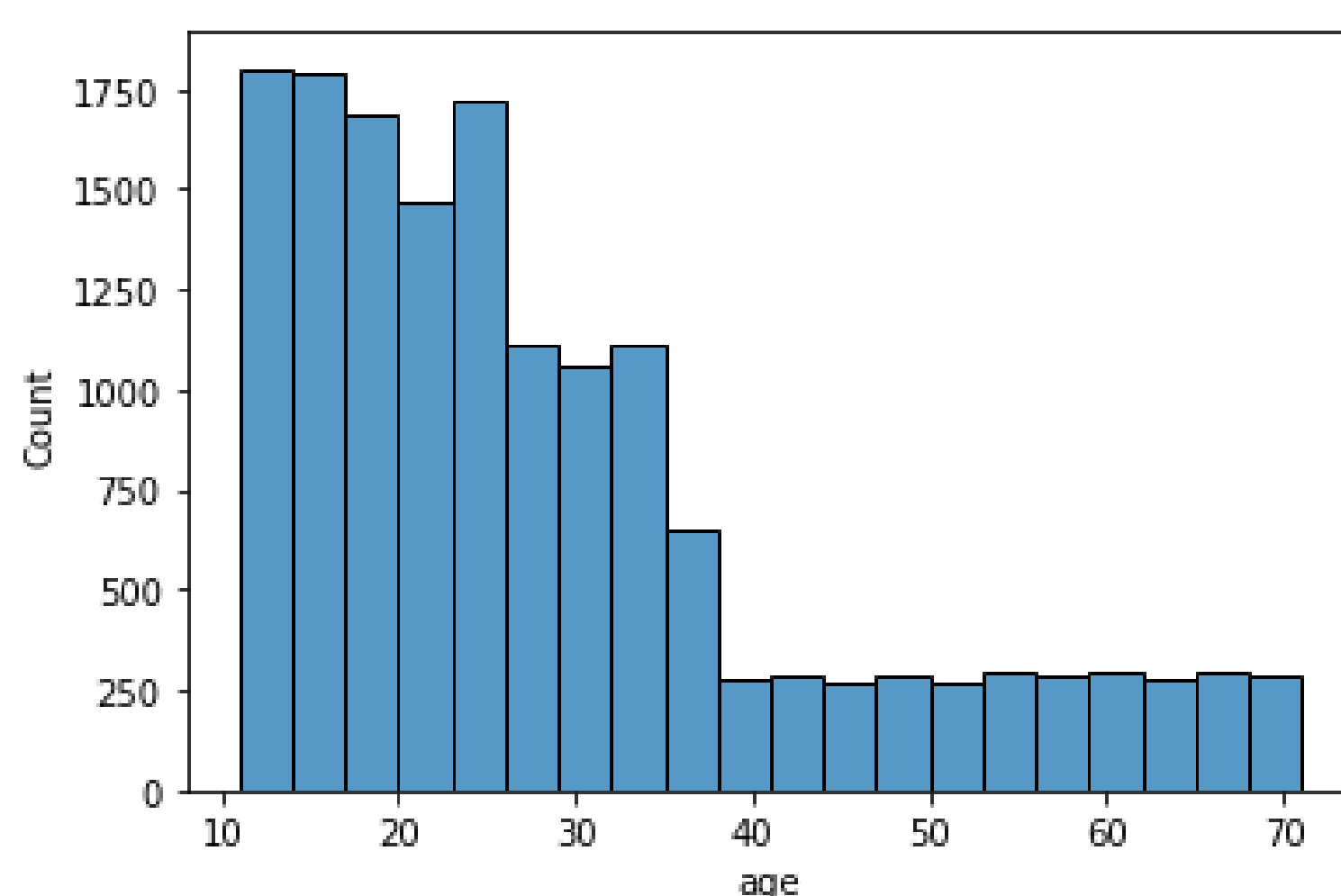
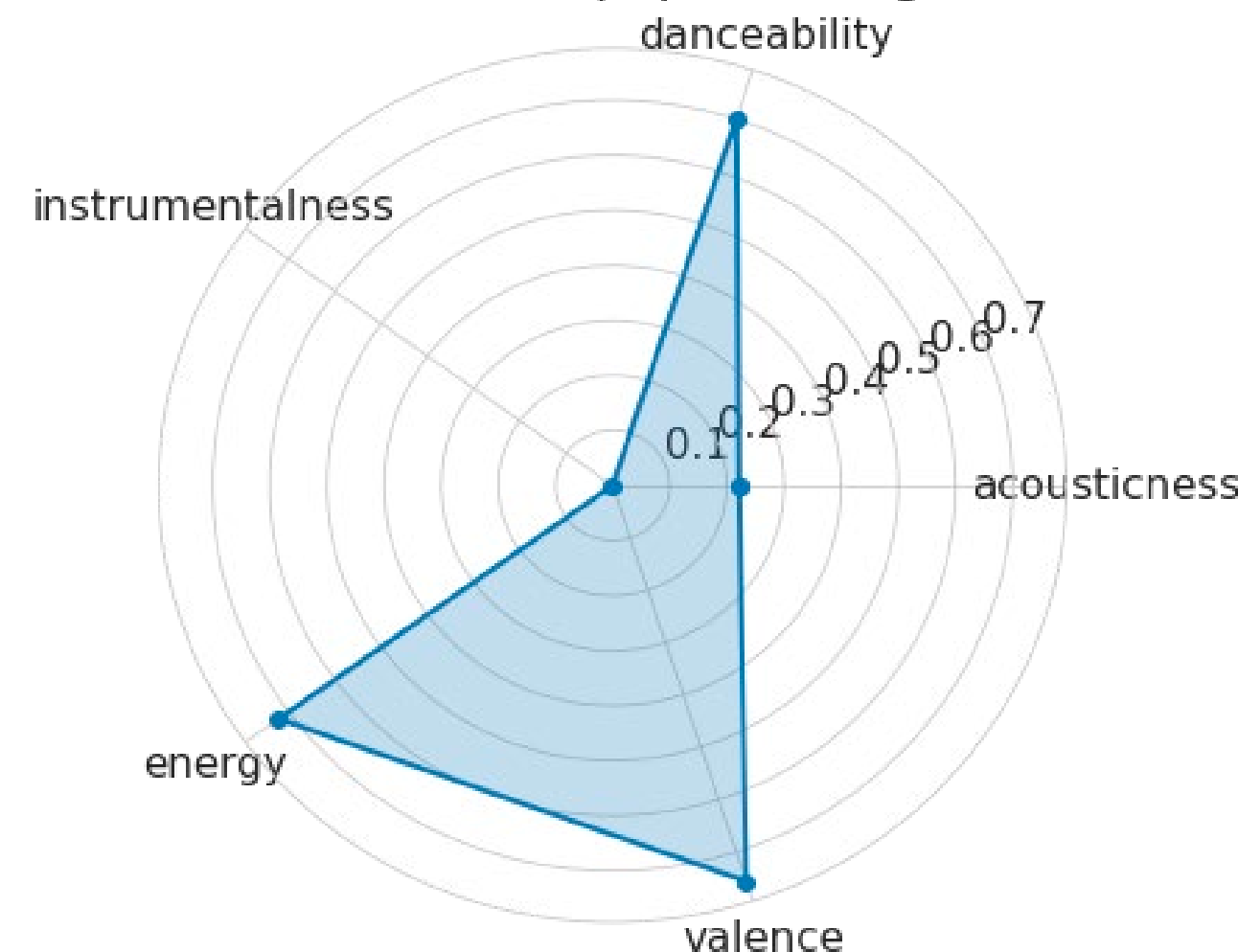
Our dataset includes the following:

1. Information about songs (such as song names, artist names, etc.) | 107,000 songs from Kaggle
2. Audio-based attributes and other metrics such as popularity associated with each song | Spotify Web API
3. Lyrics of each song | Web scraping & Genius API
4. User's personal information and user's playlist of songs | 65, 108 users from Kaggle and PPI randomly sampled using statistical data provided by Spotify

## Exploratory Data Analysis



Audio Features of the most popular song: drivers license



## Methodologies

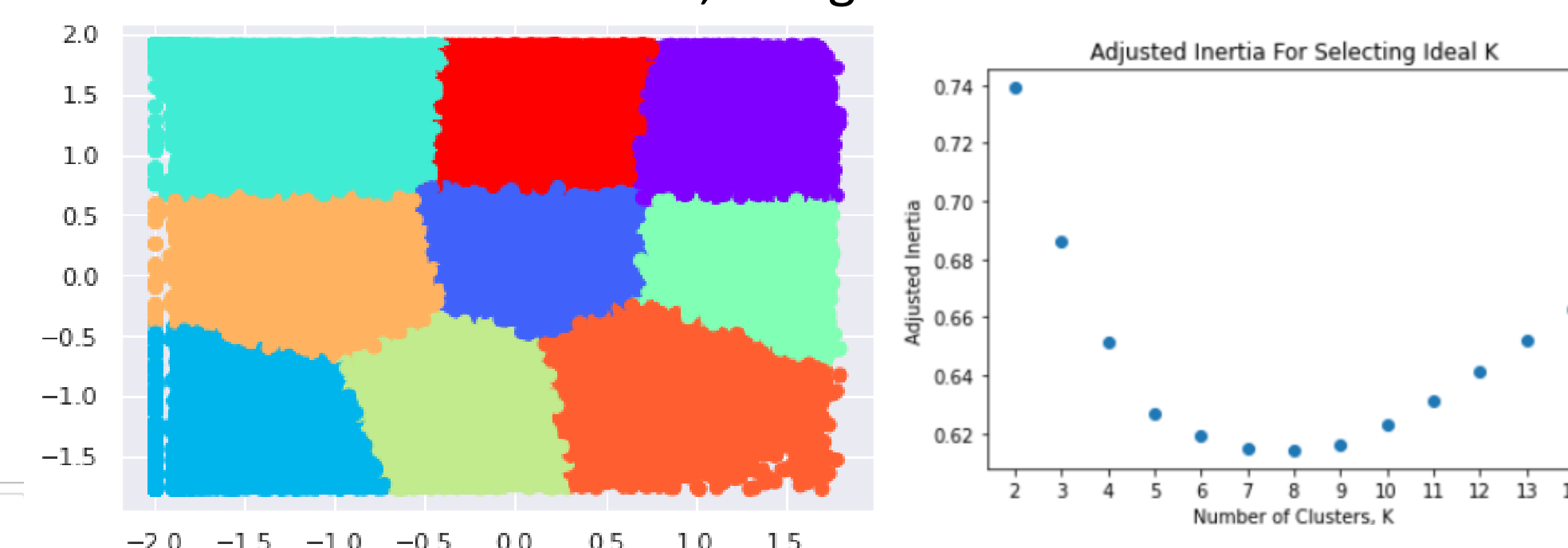
### Method 1: Rule Based Clustering

#### 1. Training

- Emotions reduced to a 2-D plane using Valence and Arousal (energy) metric.
- **Key Principles:** K-Means Clustering, Z-Transformation, Scaled Inertia, Jaccard Distance

#### 2. Testing

- K-fold cross-validation, using hit ratio metric



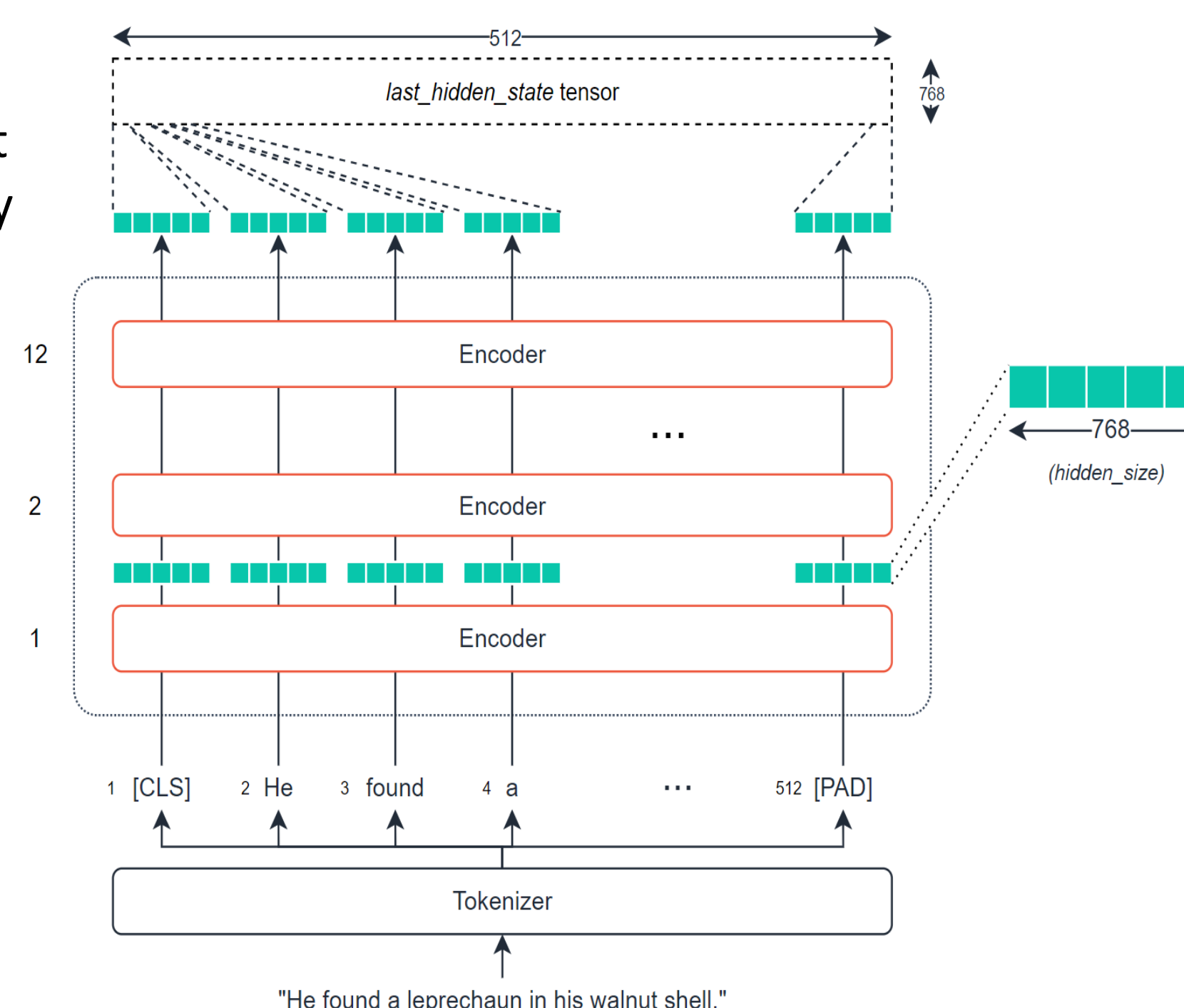
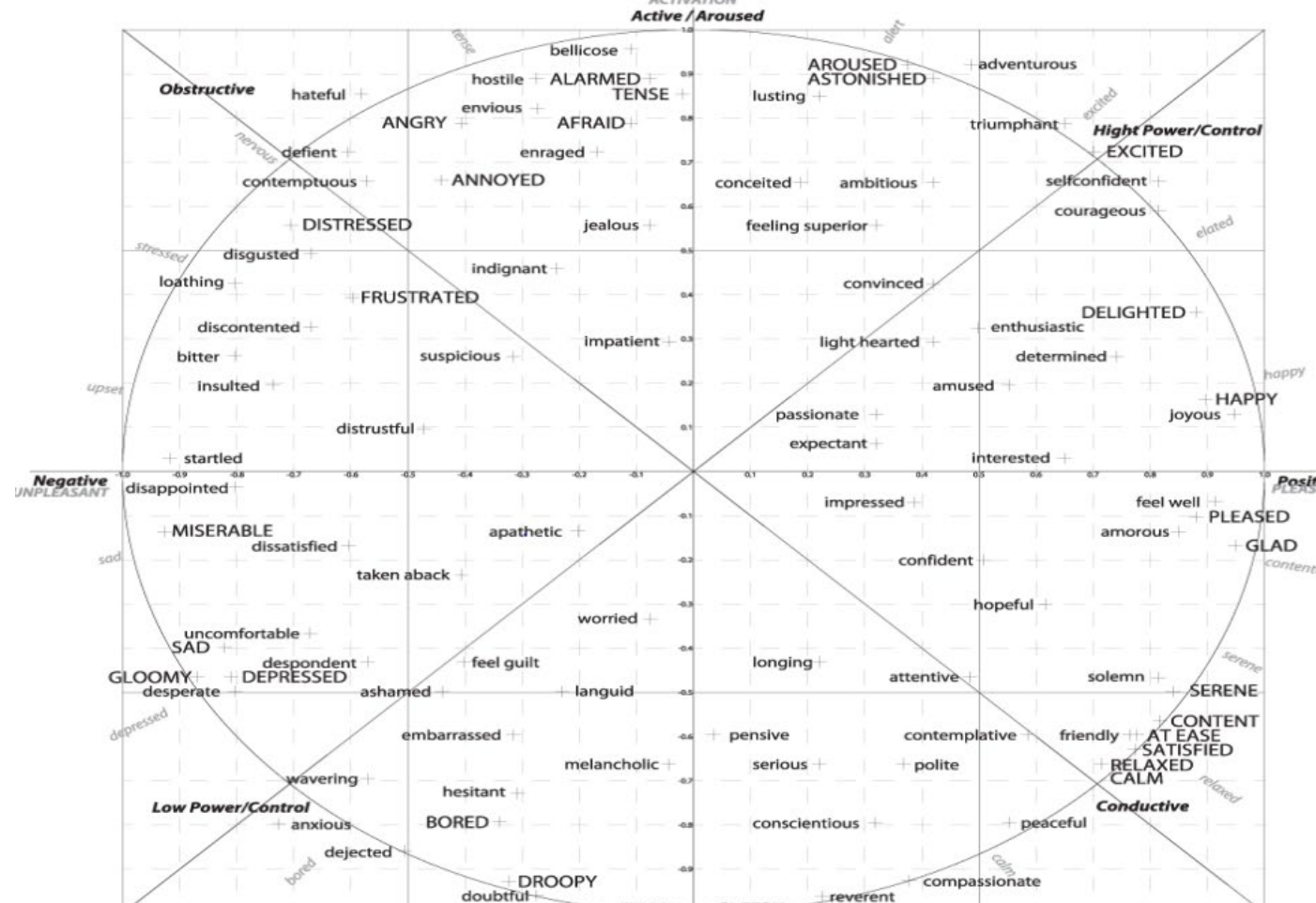
### Method 2: Embeddings With LightFM

The extracted lyrics and the user personal features are used to find the similar songs to the user's playlist and recommend the top songs based on the similarity score, sentiment and the user features.

#### Key Principles: BERT, NLP, LightFM, Cosine Similarity

#### Process Steps:

1. Lyrics Pre-processing: Tokenization, lowercase, and lemmatization
2. TFIDF vectorizer: TF IDF scores generated
3. Sentence embeddings: Using BERT sentence transformers
4. Interaction Matrix Creation: User-song interaction, Song-feature and User-feature matrices.



## Results & Conclusion

- Evaluation metric used: **Hit Ratio** (Fraction of users for which the correct answer is included in the recommendation list of length).
- NLP approach with sentence embedding and LightFM better compared to rule-based approach.

| Hit Ratio |            |             |  |
|-----------|------------|-------------|--|
| k-fold    | Rule based | NLP_LightFM |  |
| 3         | 0.00937455 | 0.01298997  |  |
| 4         | 0.0091876  | 0.01265489  |  |
| 5         | 0.0087009  | 0.01200471  |  |
| 6         | 0.0081203  | 0.01097543  |  |
| 7         | 0.0078765  | 0.01038677  |  |
| 8         | 0.0073089  | 0.00998766  |  |

|    | user_id                          | user_playlist | song       | similarity_score | Polarity  | Sentiment | recommended_song        | Rank |
|----|----------------------------------|---------------|------------|------------------|-----------|-----------|-------------------------|------|
| 9  | 84b0cd6e3fe13609af340bb7341d3487 | I Love You    | I Love You | 0.693975         | 0.733333  | 0.866667  | The Christmas Song      | 1    |
| 26 | 84b0cd6e3fe13609af340bb7341d3487 | Try           | Try        | 0.683918         | 0.251820  | 0.609674  | Heyma                   | 2    |
| 8  | 84b0cd6e3fe13609af340bb7341d3487 | I Love You    | I Love You | 0.682793         | 0.266176  | 0.535294  | Smiling Faces Sometimes | 3    |
| 7  | 84b0cd6e3fe13609af340bb7341d3487 | I Love You    | I Love You | 0.674626         | -0.013917 | 0.675482  | Detroit Rock City       | 4    |
| 3  | 84b0cd6e3fe13609af340bb7341d3487 | Hello!        | Hello!     | 0.513266         | 0.104246  | 0.561294  | This Year               | 5    |

3. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks (<https://arxiv.org/abs/1908.10084>)
4. Recommendation systems: Principles, methods & evaluation ([www.sciencedirect.com/science/article/pii/S1110866515000341](http://www.sciencedirect.com/science/article/pii/S1110866515000341))

## Future Work

1. Consider the genre of the songs and the artists for providing recommendations.
2. 3-D representation of emotions(+dominance vector) could be considered for clustering along with arousal and valence scores to find better clusters.
3. Matrix factorization could be used to generate the ground set (baseline) and recommendation models can be evaluated based on this metric.
4. Feedback loop could be incorporated into recommendations for serving better results.

### References:

- 1.Affective Music Recommender System (MRS): Investigating the effectiveness and user satisfaction of different mood inducement strategies
- 2.Thayer's arousal-valence emotion plane – ([https://www.researchgate.net/figure/Thayers-arousal-valence-emotion-plane\\_fig1\\_3458005](https://www.researchgate.net/figure/Thayers-arousal-valence-emotion-plane_fig1_3458005))