1 Method's Current Usage

1.1 Extracting User Influence from Ratings and Trust for Rating Prediction in Recommendations

Authors: Wenchuan Shi et al.
Published: Scientific Reports, 2020
Summary: This study integrates user reliability and popularity into the SVD framework for rating prediction. Reliability is derived from user rating spans, while popularity measures trust relationships. These factors are combined to create a user influence matrix, enhancing matrix factorization. The model improves prediction accuracy, outperforming state-of-the-art methods on datasets like FilmTrust and Epinions.
Takeaway: This approach demonstrates SVD's utility in uncovering user-item latent structures, inspiring my project to extract hidden patterns between tracks and features.

1.2 Non-negative Data-driven Mapping of Structural Connections with application to the neonatal brain

Authors: E. Thompson et al.
Published: NeuroImage, 2020
Summary: This study introduces a novel data-driven framework using Singular Value Decomposition (SVD) and Non-negative Matrix Factorization (NMF) for mapping neonatal brain connectivity. SVD reduces dimensionality in connectivity matrices derived from diffusion MRI, and NMF identifies interpretable, sparse, non-negative dimensions. These dimensions represent white matter tracts and their corresponding grey matter networks. The framework highlights structural connectivity patterns and cortical parcellations in neonatal brains, enabling insights into early neurodevelopment.
Takeaway: This approach demonstrates SVD's capacity for dimensionality reduction, inspiring its application in my music project to identify representative structures within music track features.

1.3 A Denoising Method for Seismic Data Based on SVD and Deep Learning

Authors: Guoli Ji & Chao Wang
Published: Applied Sciences, 2022
Summary: This study combines Singular Value Decomposition (SVD) with MobileNetV2 deep learning to denoise seismic data. SVD decomposes seismic data into dimensions,

distinguishing effective signals from noise based on right singular vectors (RSVs). Deep learning automates RSV classification into noise or signals, improving accuracy over manual methods. The method demonstrates superior noise attenuation compared to traditional SVD, preserving seismic signal integrity while suppressing Gaussian and intense amplitude noise.
Takeaway: This application of SVD highlights its ability to reduce noise in data, which might be helpful for my project to reduce noise before conducting other analysis like clustering.

2 My Experimentation

2.1 Goal

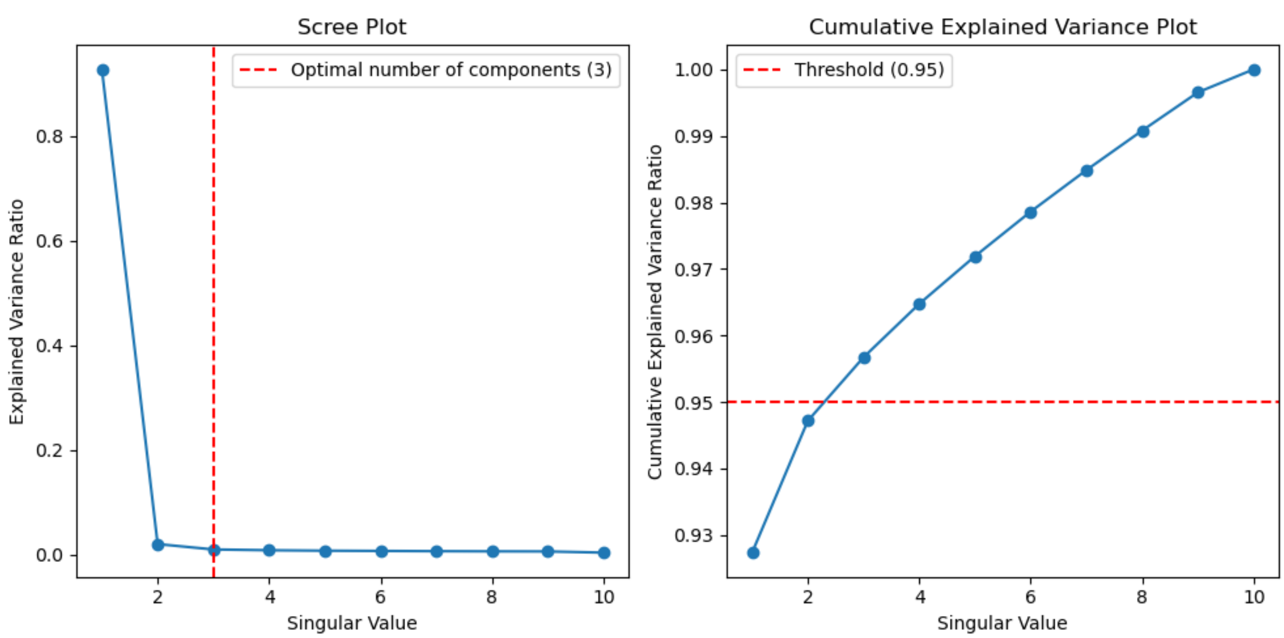
I conducted **singular value decomposition** with *PySpark* to reduce the dimensionality of music track features. The reduced features can be used for further analysis like clustering or visualization.

2.2 Challenges

1. **Interpretability**: The reduced dimensions are not easy to interpret, making it hard to understand the underlying structure of music track features.
2. **Outliers**: The outliers in the data may bias the dimension space, making it difficult to identify the true structure of the data.
3. **Distribution Visualization**: When exhibiting the distribution of tracks in the reduced dimension space, there is a potential pitfall: we can't directly use vectors in the U matrix to visualize the distribution; instead, we need to multiply U and s to get the reduced space.

2.3 Process

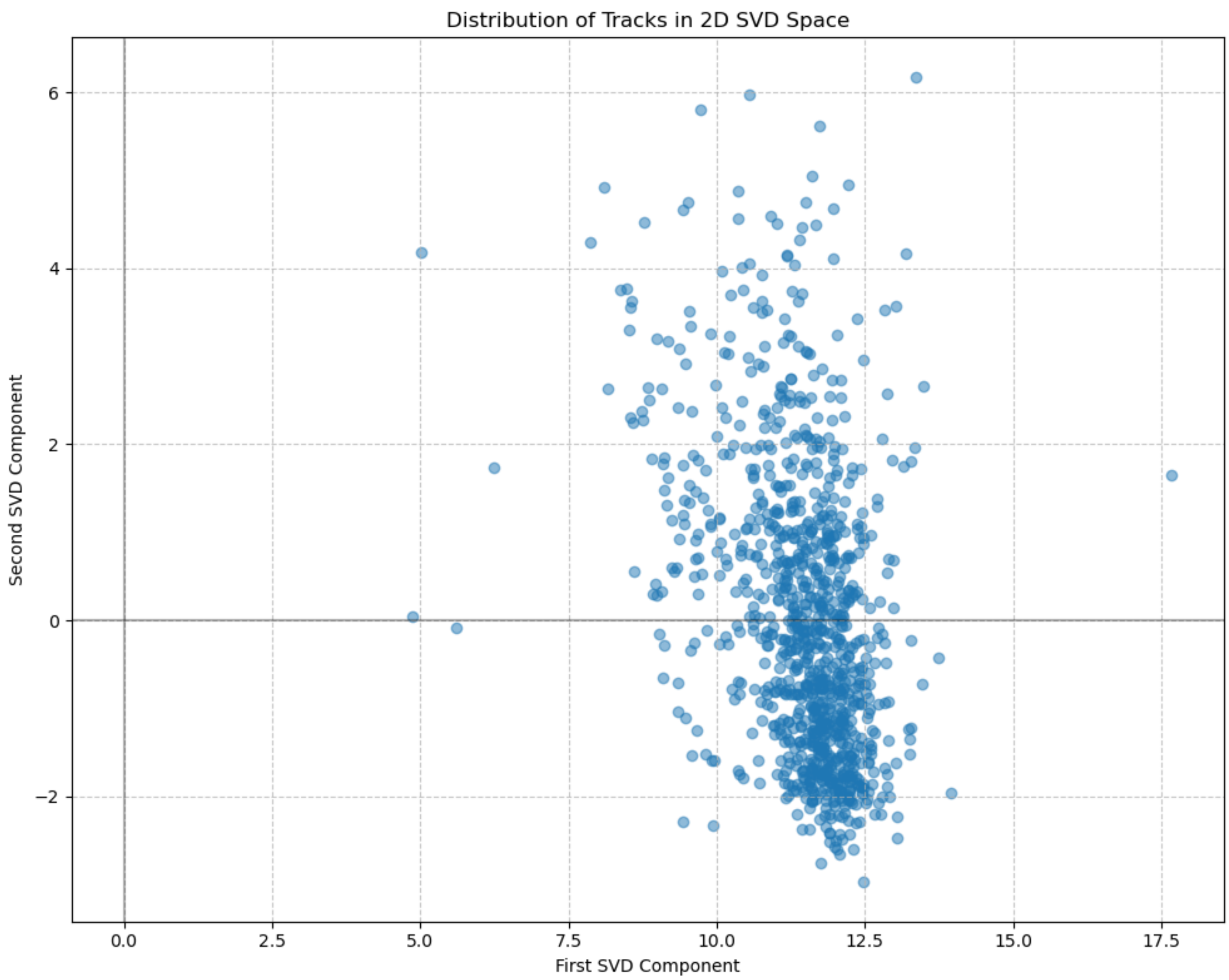
1. The SVD process was relatively straightforward. I first standardized the features to prepare them for SVD.
2. Then I used data-driven method to determine the number of dimensions to keep. According to the scree plot and explained variance, I chose the first 3 dimensions to keep.



3. Then I examined the dimensions through visualizations:

- **Distribution of tracks in the reduced feature space**: At beginning I used the first two dimensions in U matrix to visualize the distribution of tracks in the reduced dimension space.
- **Correlation between the original features and the reduced dimensions**: To understand these dimensions, I visualized the relationship between the original features and the reduced dimensions by visiting the right singular vectors V as a heatmap.

4. Through the scatter plot, I found a weird pattern: the first dimension has smaller range than the second one. This is not expected, as the first dimension should represent the most important information.
5. Thus I looked up online [visualization of SVD](), and found that in SVD, to visualize distribution, I should multiply U and s to get the reduced space. So I did this step to get the correct space visualization.
6. However, in the resulting space, I notice that the distribution is still narrow on the first dimension, with several outliers; while widely spread on the second dimension. This indicates that the current first dimension might not be the most important one, but biased by some outliers.



7. I further examined the outliers in the first dimension, and found that the outliers are actually *white noise*, which should not be included in our music analysis, and they just bias the dimension space.

```
+--------------------------------------------------------+
|name                                                    |
+--------------------------------------------------------+
|Sold                                                    |
|Baby White Noise                                        |
|Hush Little Pink Noise Baby - Loopable with No Fade     |
|Santa Claus Is Coming To Town                           |
|Baby Sleep Pink Noise                                   |
|Hair Dryer Sound on Low Power (White Noise)             |
|Pouring Rain with Pure Brown Noise - Loopable with no fade|
|White Noise Only (Loop)                                 |
|Skit - Happy New Year MAPARA!!!                         |
|Sleeping Hoover                                         |
+--------------------------------------------------------+
```

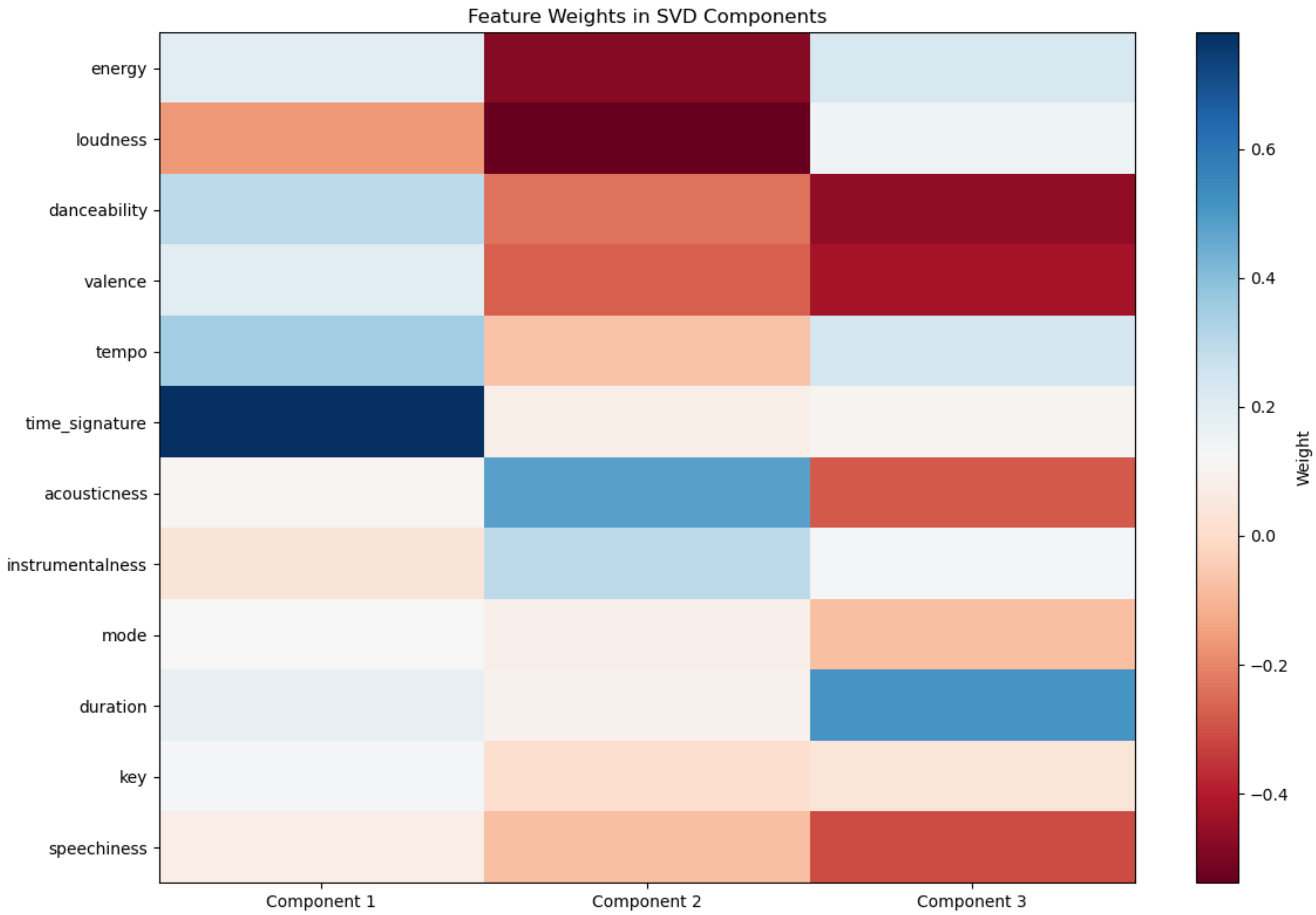
8. Therefore, in the later step, I should find a good way to identify white noise in the dataset and remove them.

Note

Previoiusly I also tried PCA, and in PCA, the white noise does not significantly bias the space as in SVD. This indicates that PCA might be more robust to my case than SVD.

3 Findings and Implications

According to discussion in the previous section, the first dimension in SVD is likely to be biased. Due to time constraints, I did not continue with further analysis using SVD. All my analysis that requires dimensionality reduction is based on PCA results.
Considering the consistency of the results between PCA and SVD (the first two dimensions of PCA and the second and third dimensions of SVD are basically the same), I derived the following conclusions based on the second and third dimensions of SVD:



Dimension 1 (1st in PCA, 2nd in SVD)

This dimension primarily captures the contrast between emotional intensity and acoustic properties.
Negative weights (red) are strongly associated with energy, danceability, loudness and valence, indicating an emphasis on energetic and pleasant qualities in music.
In contrast, positive weights (blue) on acousticness suggest an emphasize in acoustic or organic sound characteristics.
This dimension likely reflects a spectrum ranging from high-energy, electronically produced

music to softer, more acoustic styles. Tracks scoring low in dimension 1 typically being suitable for vibrant settings like parties or workouts.

Dimension 2 (2nd in PCA, 3rd in SVD)

The pattern on this dimension is not so clear as the previous one, but it likely captures the contrast between music that is speech- (like rap) or rythm-driven (like pop).
Speechiness has a significant negative contribution (red), indicating a preference for tracks with clear spoken content, such as podcasts or rap.
This dimension offers insights into the prominence of speech-driven music.

Summary

The decomposition of music features into important dimensions reveals distinct and relatively interpretable patterns in the dataset, where dimension 1 captures the raw intensity of music, and dimension 2 provides a contrast between speech- or rythm-driven tracks.
Together, these dimensions enable a deeper understanding of the underlying structure of music tracks, and can be used for further investigation like clustering or time series analysis.