*Diagrams are color coded – print in color on paper*

# klustr: a tool for dimensionality reduction and visualization of large audio datasets

**Lamtharn Hantrakul, Avneesh Sarwate**
MT Hauz
1065 Terrell St.
Georgia Tech Center for Music Technology
Atlanta, GA 30318

## ABSTRACT

We present *klustr*: a tool for automatic dimensionality reduction and 2D visualization of large audio datasets. The tool facilitates visual navigation and discovery of similar sounding samples in a collection, allowing musicians and researchers to quickly find sounds that are similar to one another based on perceptual features such as timbre. In this paper, we present a version of k*lustr* that is optimized for navigating drum samples typically found in pop, hip-hop and electronic music.

## 1. INTRODUCTION

From speech, images and sensor input, data from the natural world is often high dimensional. Instead of interacting directly with this high dimensional data however, a collection of audio sample is often instead organized using simple high-level descriptors, such as the type of sound e.g "vocal_shout". However, these labels are often not available, and when available, do not capture the nuances of relationships between sounds. In order to build relationships between samples at the timbre level, we must form representations drawn from the high dimensional audio data. These are typically in the form of STFT or MFCC features, but even these are in dimensions in the order of several thousands. This paper presents an approach of allowing users to navigate these relatively high dimensional features in 2D space.

Dimensionality reduction techniques are normally used for two purposes. Methods such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) are often used to extract key components that capture the distribution of the data using a smaller number of dimensions. This reduced data often yields better performance in classic machine learning algorithms such as Support Vector Machines (SVM) [1].

Alternatively, dimensionality reduction can be used to visualize representations learned by non-linear models such as neural networks. A highly popular stochastic dimensionality reduction algorithm called t-distributed neighbor embedding (TSNE) [2] has become the standard tool for visualizing embeddings learnt by deep convolutional neural networks [3]. TSNE is particularly adept at preserving spatial relationships in higher dimensions but in 2 or 3 dimensions. This enables researchers to grasp an intuition of their model's behavior and tune hyperparameters accordingly.

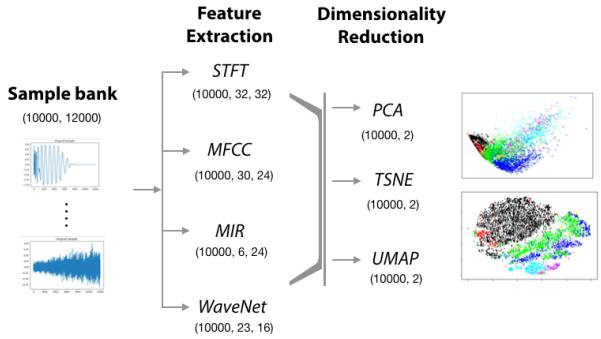



**Figure 1:** *klustr* pipeline

In this paper, we use these dimensionality reduction techniques to directly encode features into a 2 dimensional plane. Our purpose is not to find the best set of features for a classifier, nor to understand the internal representation of a neural network. Instead, we are attempting to take advantage of dimensionality reduction to generate a navigable 2D map where neighboring samples are similar in sounds e.g a raspy snare is located next to another gritty snare, but is further away from a kick drum. We highly recommend using the Python notebook linked at the end of this paper to see more plots and understand our data processing pipeline.

## 2. RELATED WORK

Navigable audio datasets, when labelled, are often presented to the user in an ontology of high level sound descriptors. AudioSet for example [4], divides two million hand annotated samples into categories such as "human sounds" and "sounds of things". The UrbanSound dataset uses tags such as "Mechanical" and "Music" sounds [5]. Alternatively, one can organize using features based from the audio signal itself.

In the domain of creating end-user interfaces that arrange large sound datasets in a 2D layout using audio features, Fried et al [6] used a two-step method to embed audio samples into a 2D grid. The authors first used a metric learning algorithm such as LDA to transform their feature space into a representation. Next, kernelized sorting is used to match samples to defined "tiles" on a grid. Given two sets A and B, the kernelized sorting algorithm can use the functions f(A) and f(B) to generate a mapping $A \rightarrow B$.

Many open-sourced projects have explored this 2D mapping. Two projects from Google Creative Lab take advantage of TSNE to create a fun-to-use 2D grid of bird sounds [7]. Another project called the *Infinite Drum Machine* mapped a collection of urban sounds into a 2D map and then colored them according to whether they were "kickdrum-like" or "snare-like" using clustering of STFT features [8]. Lastly, a recent Medium blog post outlines a comparison of various dimensionality reduction techniques used on short audio clips [9]. These projects are popular examples used in online media to demonstrate the usefulness of dimensionality reduction. However, to our knowledge, no industry tool exists that robustly implements these techniques for end-users to use on user-specified sample collections.

## 3. CONTRIBUTIONS

Our implementation of *Klustr* is based on work by Kyle McDonald [7] and Leon Fedden [9]. We extend their work by using a larger database of drum samples (approximately 10,000). Unlike these previous implementations, our ground truth for each sample is known. We scrape the tags included in sample bank filenames such as "kick_1.wav" and "real_tom.wav" to label the sound. This enables us to evaluate, to a certain extent, the quality of the clustering, separation and layout of samples on the 2D plot. We also experiment with novel techniques, notably UMAP (a dimensionality reduction method) [11] and the WaveNet architecture for extracting embeddings of audio files [12]. We optimize over all these combinations to find a recommended pipeline that can embed all 10,000 samples in 2D in approximately ~15 seconds using the CPU on a modern laptop.

## 4. ALGORITHM OVERVIEW AND DESCRIPTION

### 4.1 Extraction and Dimensionality Reduction Pipeline

Like Fried et al [6] we adopt a two step process. The first entails feature extraction from the audio file followed by a second step of dimensionality reduction. We standardize the length of all drum shots to the first 0.25 seconds at a sampling rate of 48kHz. This enables us to capture essential attack transients of different drum types, while keeping file sizes manageable. We use a collection of feature extraction methods:

- *Short Time Fourier Transform (STFT):* Window-size of 2048 and hop-size of 512
- *Mel Frequency Cepstral Coefficients (MFCC):* We selected the first 30 MFCC's
- *Hand-crafted MIR features*: RMSE, spectral centroid, spectral crest, spectral flux, spectral rolloff and zero crossing rate
- *Wavenet Autoencoder features*: We use the state-of-the-art WaveNet architecture to encode the samples into a compressed representation at the model bottle-neck and interpret this as the extracted "feature"

We then use a variety of dimensionality reduction techniques on these features:

- *Principal Component Analysis (PCA)*
- *T-distributed Stochastic Neighbor Embedding (TSNE)*
- *Uniform Manifold Approximation and Projection (UMAP)*

The pipeline and resulting dimensions at each step are summarized in figure 1.

### 4.2 Dataset

The dataset is composed of short "one-shot" drum samples typically found in sample libraries. The distribution of sounds is summarized in table 1.

| Drum | *Kick* | *Tom* | *Snare* | *Clap* | *Hi Hat* | *Ride* | *Crash* | Total |
|---|---|---|---|---|---|---|---|---|
| Samples | 5158 | 422 | 2546 | 1324 | 159 | 228 | 723 | 10,560 |

**Table 1:** Dataset of drum "one shots"

### 4.3 Unsupervised Clustering Feature Selection

We use unsupervised k-means clustering to first evaluate the set of features most useful for separating samples into different classes in high dimensional space (e.g MFCC = 30x24). We reason that features useful to high-dimensional clustering should be useful to the dimensionality reduction algorithm in grouping and separating samples into classes in lower 2 dimensional space.

To evaluate the clusters, e use the *silhouette coefficient* as our metric, which combines the mean intra-cluster distance (a) and mean nearest-cluster distance (b). Each sample receives a score computed by $(\boldsymbol{b} - \boldsymbol{a}) / \boldsymbol{max}(\boldsymbol{a}, \boldsymbol{b})$ and the average is computed for the class. Values close to 1.0 indicate good clustering while values near -1.0 indicate significant overlaps and wrongly assigned clusters [12]. To ensure initialization does not influence final clustering, we use three initialization methods to the k-means algorithm.

We also take advantage of our ground truth class labels and prior knowledge of 7 distinct clusters during initialization. Thus we can use *homogeneity, completeness* and *V-measure* scores to further evaluate unsupervised clustering. These measures calculate the quality of clustering when ground truth labels are known [12]. Scores closer to 1.0 indicate better performance.

| | STFT | MIR | MFCC | WaveNet |
|---|---|---|---|---|
| Silhouette | 0.246 | 0.140 | 0.192 | **0.278** |
| Homogeneity | **0.508** | 0.378 | 0.482 | 0.246 |
| Completeness | **0.439** | 0.302 | 0.362 | 0.184 |
| V-measure | **0.471** | 0.336 | 0.413 | 0.210 |

**Table 2:** Unsupervised k-means clustering with k=7

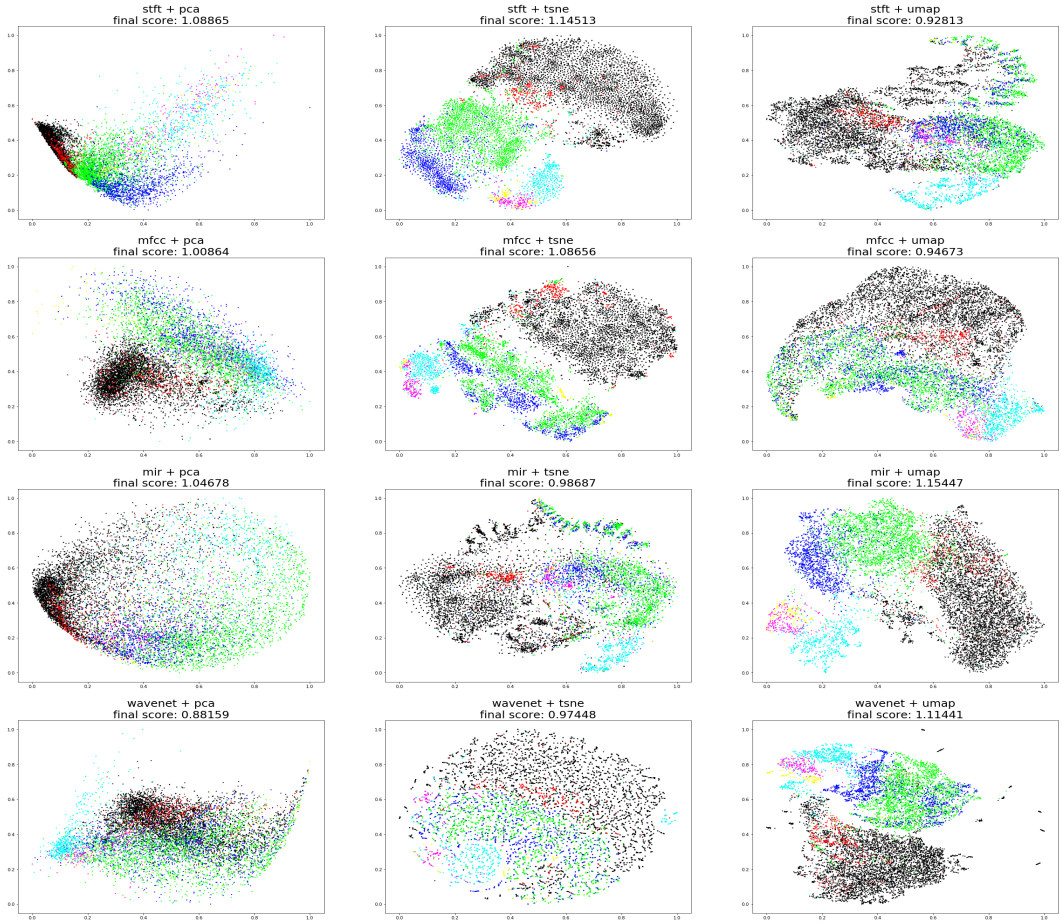



**Figure 2:** 2 dimensional plots using the defined features and chosen dimensionality reduction technique. All coordinates in X and Y are scaled from 0.0 – 1.0 for visual comparison. The final score is the quoted aggregate of both Silhouette score and Geometry scores.

These initial results suggest that STFT features are best for unsupervised clustering and should be used for dimensionality reduction in the second step. This because it yielded the highest homogeneity, completeness and v-score measures (0.508,0.439,0.471) and the second highest silhouette coefficient (0.246).

## 5. DIMENSIONALITY REDUCTION

We used the following parameters in each dimensionality reduction algorithm, note that both TSNE and UMAP first require a search over hyper-parameters to select the best 2D embedding:

- *PCA*: plot the first two principal components
- *TSNE:* perform a grid search over several perplexity and iteration values. *Perplexity* can be described as the algorithm's attention to spreading clusters out in space. *Iterations* refers to the number of iterations during stochastic optimization. Optimal combination was perplexity: 100 and iterations: 2000 (Appendix A)
- *UMAP:* perform a grid search over several *neighbor* and *distance* values. *Neighbors* is similar to perplexity above. *Distance* controls prioritizing an even spread of points (higher) vs more representative inter-point distances (smaller). Optimal combination was neighbors: 50 and distances: 0.5 (Appendix B)

## 6. RESULTS & EVALUATION

### 6.1 Silhouette Coefficient

The final results for different features and dimensionality reduction techniques are shown in figure 2.

| | PCA | TSNE | UMAP |
|---|---|---|---|
| **STFT** | **0.115** | **0.053** | -0.089 |
| **MFCC** | -0.010 | 0.034 | -0.048 |
| **MIR** | -0.035 | -0.062 | **0.124** |
| **WaveNet** | -0.102 | -0.065 | 0.059 |

**Table 3:** Silhouette coefficients for the 2D embedding

The silhouette coefficients for the embedding shown in figure 2 are presented in table 3. We note that in 2D, quick visual inspection shows that using TSNE and UMAP produce superior results to PCA.

We note however, that overall silhouette coefficients in 2D (table 3) are lower than the scores achieved on the original dimensionality (table 2). If this was a pure classification task, this suggests two variables is not sufficient to separate clusters. However, the plots show that the pipeline is still able to preserve important timbral relationships in 2D space for the purpose of *klustr.*

Most importantly, comparing figure 2 plots and table 3 reveals a significant downfall of using only silhouette coefficients as the evaluation metric. Note how the PCA+STFT combination in table 3 has a *higher* coefficient (0.115) than TSNE+STFT (0.053). This is because

the PCA plot contains *tight clusters* of samples which would in turn produce a high silhouette coefficient. However, from a user standpoint, the tight plot of PCA+STFT would be relatively more difficult to navigate compared to TNSE+STFT, which spaces the samples and clusters out further. The visually pleasing layout of TNSE+STFT, actually *impacts negatively* on the silhouette coefficient, due to samples that are further away from the mean of the class cluster. For this reason, we motivate a series of new metrics based on the geometry of the clusters and how they are positioned in 2D space. This is presented next.

### 6.2 Geometry Coefficient

Given that we are projecting drum samples in a 2D space, we want to evaluate our projections using metrics that explicitly account for visual spread of clusters. We thus motivate the following "Geometric scores" based on the convex hulls containing the points of a class:

- *Roundness:* We use the Polsby Popper Test [13] to calculate "roundness" of a class's projection. For a convex hull with area A and perimeter P this metric is defined as $4\pi A / P^2$. A "round" hull is associated with a more similar in shape to a circle (roundness has values (0, 1], with a circle having a value of 1).
- *Overlap:* This is the area of the union of convex hulls of classes divided by the sum of the areas of the hulls. An overlap close to 1.0
- is desirable, indicating we have no overlapping areas.

| | PCA | | TSNE | | UMAP | |
|---|---|---|---|---|---|---|
| | *Roundness* | *Overlap* | *Roundness* | *Overlap* | *Roundness* | *Overlap* |
| **STFT** | 0.674 | **0.275** | 0.823 | **0.240** | **0.834** | 0.183 |
| **MFCC** | 0.689 | 0.235 | 0.827 | 0.195 | 0.789 | 0.205 |
| **MIR** | **0.904** | 0.182 | **0.861** | 0.177 | 0.786 | 0.243 |
| **WaveNet** | 0.696 | 0.209 | 0.838 | 0.240 | 0.796 | **0.258** |

**Table 4:** Geometry-based metrics for the 2D embedding

Here we see that the roundness coefficient captures the visually pleasing and spaced layout of TSNE/UMAP embeddings compared to PCA embeddings. Although the MIR+PCA combination yields the highest roundness coefficient, this is counteracted by the poor performing silhouette coefficient in table 3 (-0.035) and table 2 (0.150)

### 6.3 Final score

By aggregating these metrics, we can find the best overall 2D mapping that accounts for cluster and visual quality. The 2D maps and final score are presented in figure 2 above the plot. The best performing combination is MIR+UMAP (1.15) and STFT+TSNE (1.14).

### 6.4 Discussion

Surprisingly, the handcrafted MIR features combined with UMAP produced the best plot according to our metric. This suggests that for short, percussive sounds, these MIR features produced the best separation of classes.

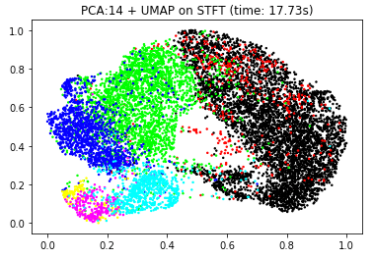
We believe the low performance of WaveNet features, despite its popularity in deep learning literature, is due to two reasons. Firstly, the weights in WaveNet were trained on melodic and pitched instrument sounds, not percussive sounds [11]. This would explain why STFT and MFCC features perform better than WaveNet features in 2D space. Secondly, WaveNet was trained for audio reconstruction, not classification. Thus the bottleneck features are an optimized representation for generating audio, which are not useful in 2D embeddings.

We also note that STFT features performed better than MFCC's overall, which makes sense since MFCC's are arguably more salient features for speech, not drum samples.

### 6.5 Optimizing for speed

Another important metric is speed. PCA is by far the fastest, allowing the embedding of new points without recalculating on an entirely new data set. UMAP is significantly faster than TSNE (grid search times of ~20 mins vs ~6 hours), but being a relatively new algorithm, is still not robust to certain datasets in high dimensions and hyper parameters (shown in Appendix C). We are unsure why this may be the case and at the time of writing, the publication documenting UMAP has yet to be published.

We propose a middle ground combining speed and plot quality by searching over various PCA dimensions followed by UMAP. We found the optimal plot with a final score of 1.16 could be achieved in ~17 seconds using a 2012 MacBook Pro on CPU using the first 14 PCA components and UMAP.




## 7. CONCLUSION

### 7.1 Optimal pipeline for *Klustr*

Our results show that a combination of STFT, PCA and UMAP yields the best 2D representation that optimizes for cluster and visual quality as well as time performance.

### 7.2 Future work

The current pipeline can be benchmarked with kernalized sorting and improved with outlier rejection before forming convex hulls in the calculation of geometric scores. Ideally, we would perform a user study with musicians to validate our metrics. We intend on using these findings in an application where users can "drag and drop" their sample library and preview samples by navigating through the 2D map.

## 8. REFERENCES

[1] Faruqe, Md Omar, and Md Al Mehedi Hasan. "Face recognition using PCA and SVM." *Anti-*

*counterfeiting, Security, and Identification in Communication, 2009. ASID 2009. 3rd International Conference on*. IEEE, 2009.

[2] Maaten, Laurens van der, and Geoffrey Hinton. "Visualizing data using t-SNE." *Journal of Machine Learning Research*9.Nov (2008): 2579-2605.

[3] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Advances in neural information processing systems*. 2012.

[4] Gemmeke, J. F., Ellis, D. P., Freedman, D., Jansen, A., Lawrence, W., Moore, R. C., ... & Ritter, M. (2017). Audio Set: An ontology and human-labeled dataset for audio events. In *IEEE ICASSP*.

[5] Salamon, Justin, Christopher Jacoby, and Juan Pablo Bello. "A dataset and taxonomy for urban sound research." *Proceedings of the 22nd ACM international conference on Multimedia*. ACM, 2014.

[6] Fried, Ohad, et al. "AudioQuilt: 2D Arrangements of Audio Samples using Metric Learning and Kernelized Sorting." *NIME*. 2014.

[7] "Bird Sounds". Accessed through https://experiments.withgoogle.com/ai/bird-sounds on 10/10/2017

[8] "Infinite Drum Machine". Accessed through https://experiments.withgoogle.com/ai/drum-machine on 10/10/2017

[9] "Comparative Audio Analysis with Wavenet, MFCCs, UMAP, T-SNE and PCA" Medium Post by Leon Fedden. Published on 15/11/2017. Accessed through https://medium.com/@LeonFedden/comparative-audio-analysis-with-wavenet-mfccs-umap-t-sne-and-pca-cb8237bfce2f on 25/11/2017

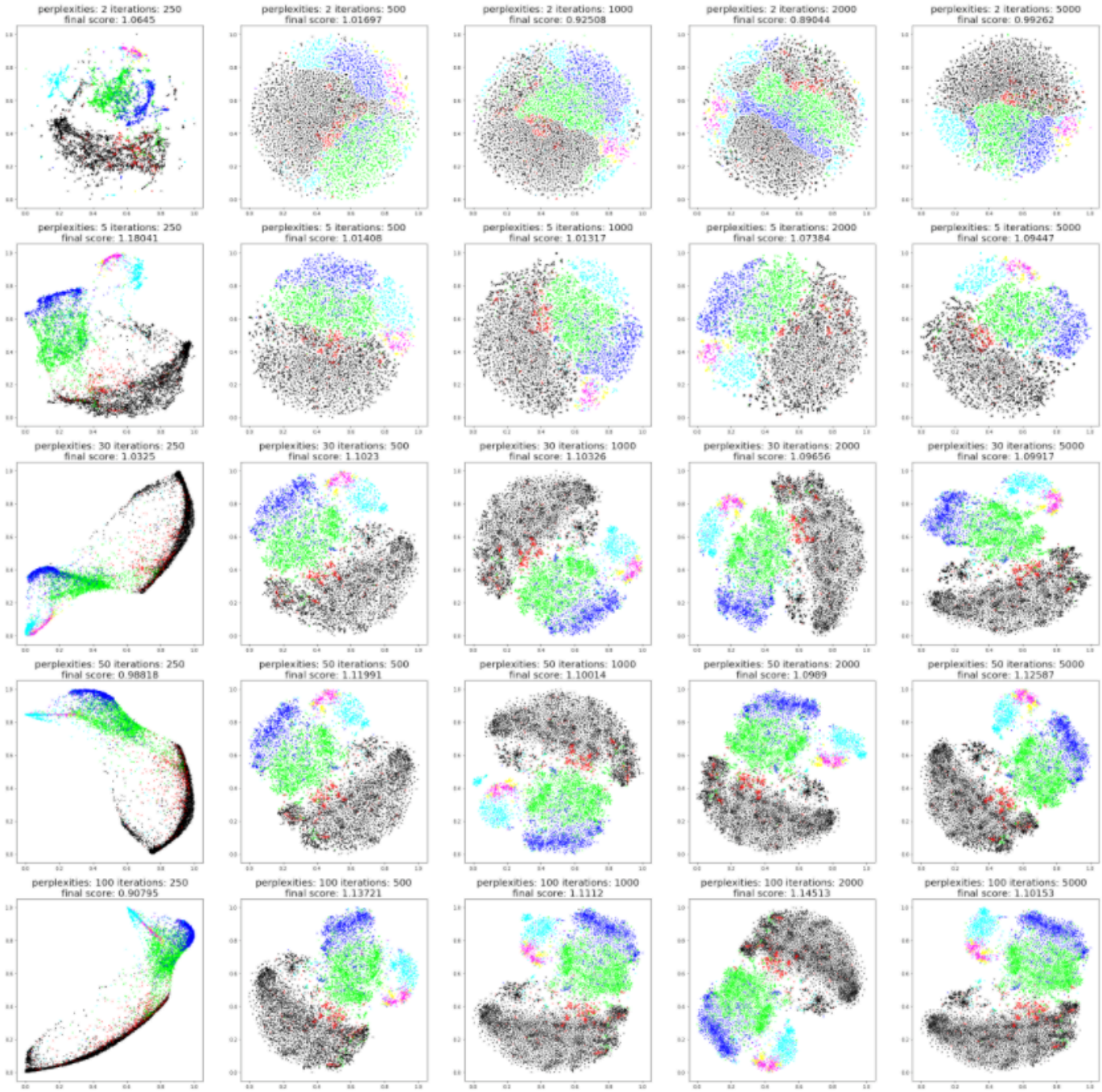
[10] "Uniform Manifold Approximation and Projection UMAP". GitHub Repository accessed through https://github.com/lmcinnes/umap on 1/12/2017. Paper for this technique is unpublished as of 4/12/2017

[11] Oord, Aaron van den, et al. "Wavenet: A generative model for raw audio." *arXiv preprint arXiv:1609.03499* (2016).

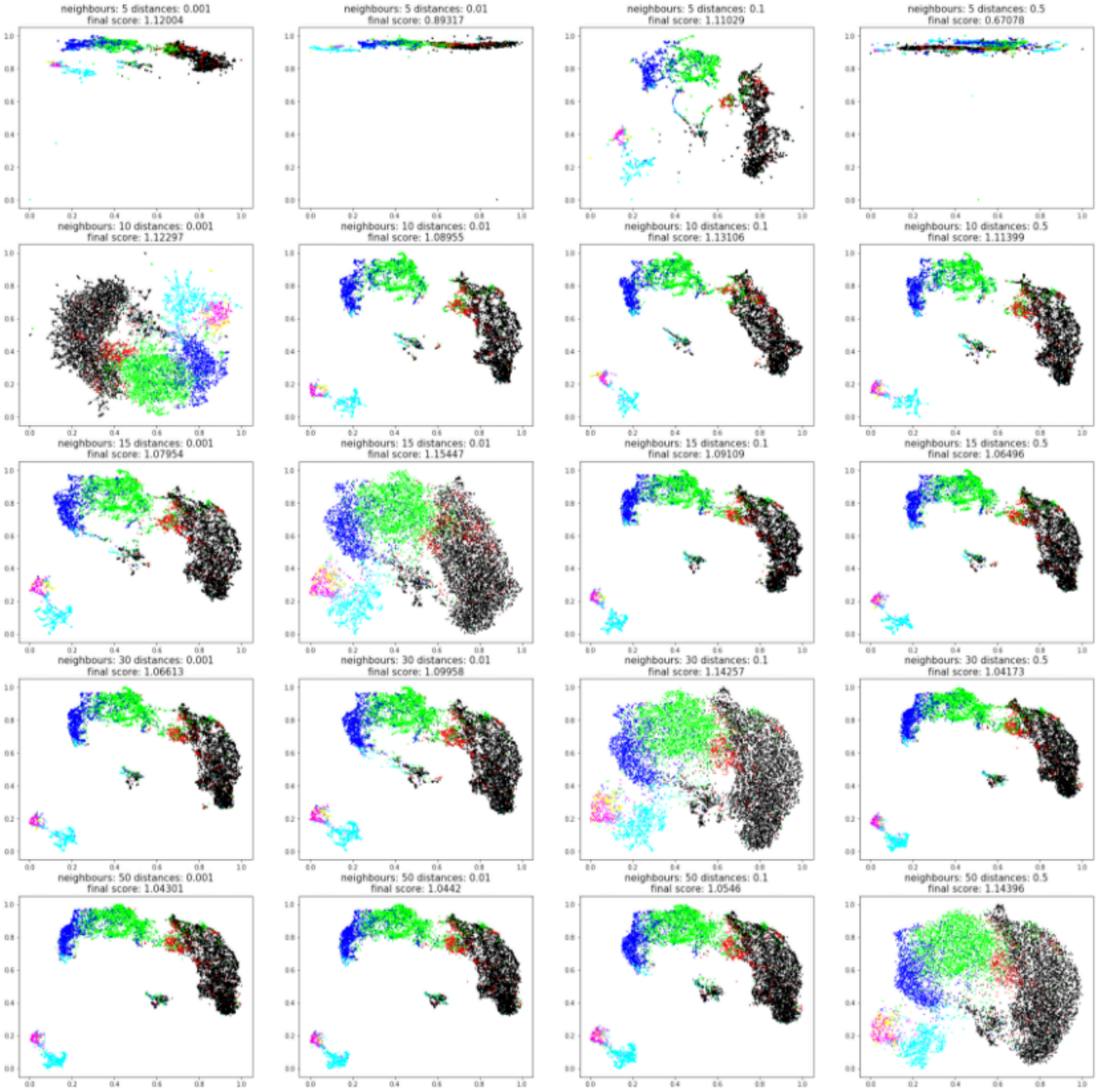
[12] "sklearn.metrics.silhouette_score" documentation in sklearn library. Accessed through http://scikit-learn.org/stable/modules/generated/sklearn.metrics.silhouette_score.html on 10/11/2017

[13] Polsby, Daniel D., and Robert D. Popper. "The third criterion: Compactness as a procedural safeguard against partisan gerrymandering." *Yale Law & Policy Review* 9.2 (1991): 301-353.

**Appendix A:** Grid search over TSNE for STFT features



**Appendix B:** Grid search over UMAP for MIR features (note the failure cases of UMAP in the top row)



**Appendix C:** Poor performance of UMAP on WaveNet features.