Noise Clustering

THE PROBLEM:

- Voice interfaces become more common for day-to-day communication. Users tend to use these interfaces on the go in very noisy environments.

- There is no software-level audio noise cancellation technique that was proven to work in real-time applications.

- Common intersections between DSP tasks and machine learning algorithms go through deep learning and require long and costly learning time.

The future belongs to algorithms that just know.

GOALS :

- To find a way to reduce noise from speech (voice) recordings
- To cluster an audio signal into two groups: ‘voice’ and ‘noise’
  (to find a model, not to predict)
- To apply machine learning techniques and algorithms for signal processing tasks
- To find a method that could be applied in real-time applications
  (‘production-ready’)

POTENTIAL APPLICATIONS:

- Fast noise reduction on mobile voice messages

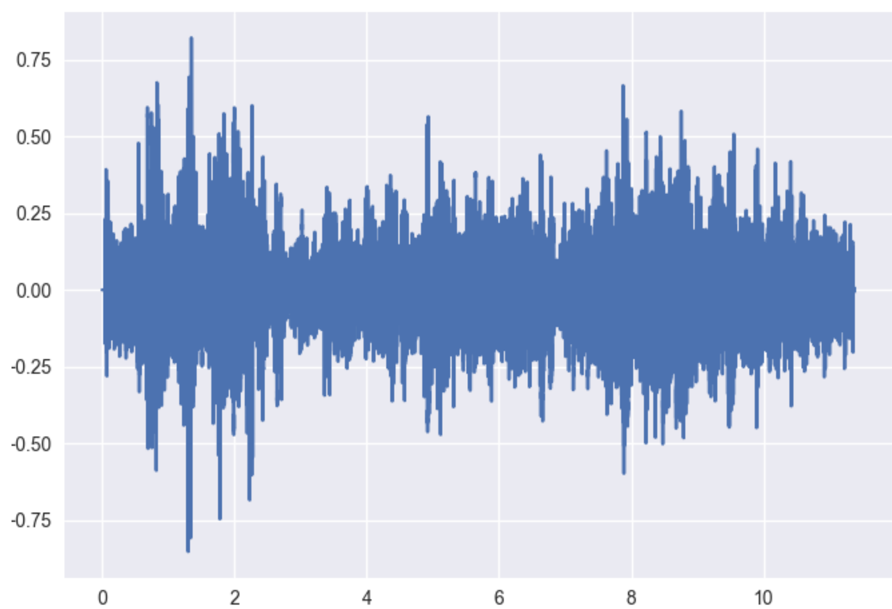
- Better speech-to-text capabilities, that wouldn’t require deep learning

- Audio signal manipulations (voice filters, fun)

Methods

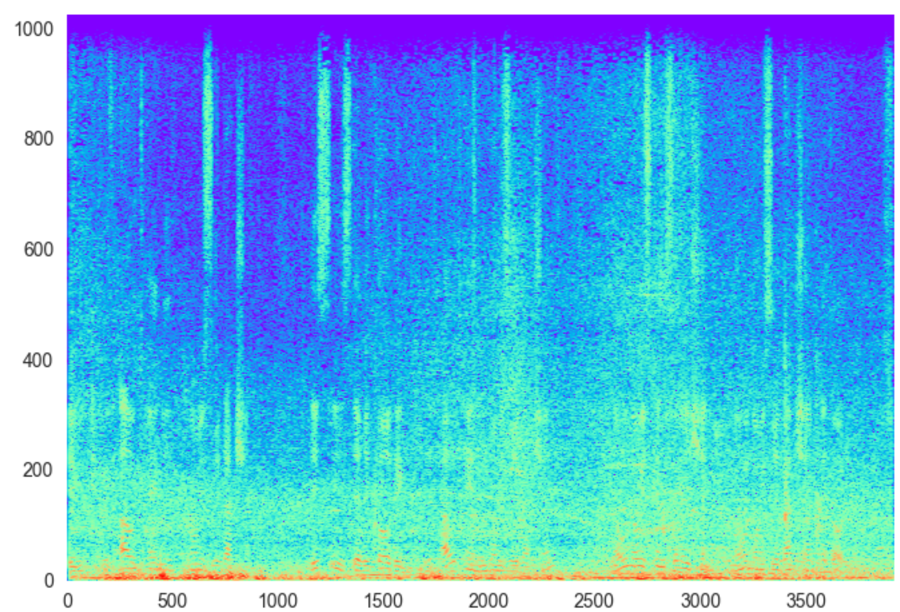
DATASET: AUDIO SIGNAL AS A DATASET

Audio time series




```
array([  0.00000000e+00,   0.00000000e+00,
0.00000000e+00, …, -9.15527344e-05,  -6.10351562e-05,
-9.15527344e-05], dtype=float32)
```

Spectrogram




```
array([[  2.03640684e-05 -0.00000000e+00j,
          5.99053465e-02 -0.00000000e+00j,
          4.25433785e-01 -0.00000000e+00j, ...,
          3.46554875e-01 -0.00000000e+00j,
          1.12801301e+00 -0.00000000e+00j,
         -2.69750923e-01 -0.00000000e+00j],
        ...,
        [ -1.78232608e-06 -0.00000000e+00j,
         -7.45655780e-05 -0.00000000e+00j,
         -4.86985336e-05 -0.00000000e+00j, ...,
          1.32114466e-04 -0.00000000e+00j,
         -9.93174908e-05 -0.00000000e+00j,
          5.87694813e-04 -0.00000000e+00j]],
dtype=complex64)
```

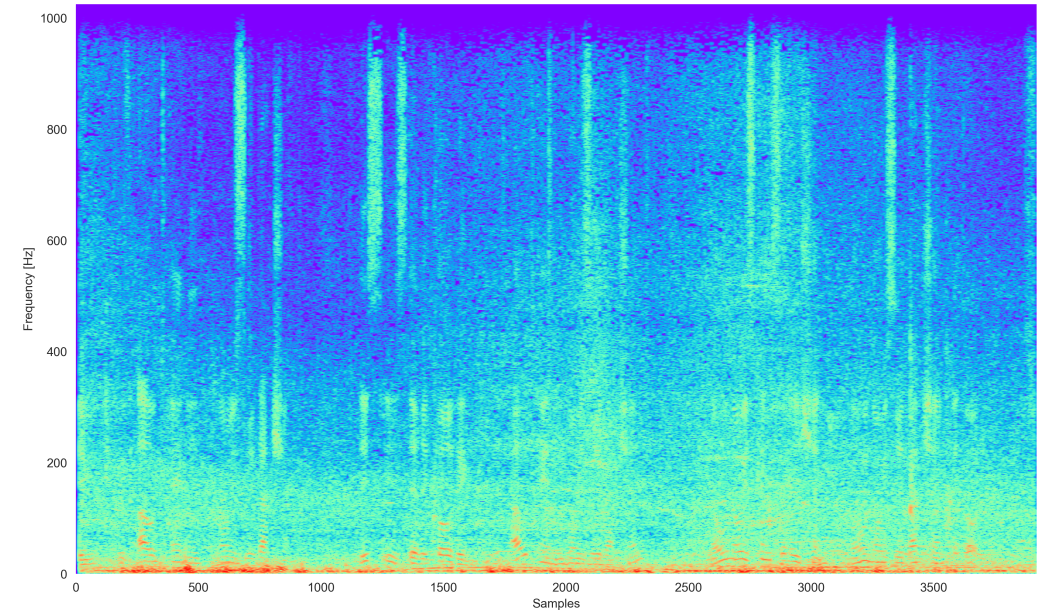
3D table

3.000000000000000000e+00	0.000000000000000000e+00	0.000000000000000000e+00
4.000000000000000000e+00	0.000000000000000000e+00	1.000000000000000000e+00
5.000000000000000000e+00	0.000000000000000000e+00	-1.000000000000000000e+00
6.000000000000000000e+00	0.000000000000000000e+00	-2.000000000000000000e+00
7.000000000000000000e+00	0.000000000000000000e+00	0.000000000000000000e+00
8.000000000000000000e+00	0.000000000000000000e+00	0.000000000000000000e+00
9.000000000000000000e+00	0.000000000000000000e+00	0.000000000000000000e+00
1.000000000000000000e+01	0.000000000000000000e+00	0.000000000000000000e+00
1.100000000000000000e+01	0.000000000000000000e+00	0.000000000000000000e+00
1.200000000000000000e+01	0.000000000000000000e+00	0.000000000000000000e+00
1.300000000000000000e+01	0.000000000000000000e+00	0.000000000000000000e+00
1.400000000000000000e+01	0.000000000000000000e+00	0.000000000000000000e+00
1.500000000000000000e+01	0.000000000000000000e+00	0.000000000000000000e+00
1.600000000000000000e+01	0.000000000000000000e+00	0.000000000000000000e+00

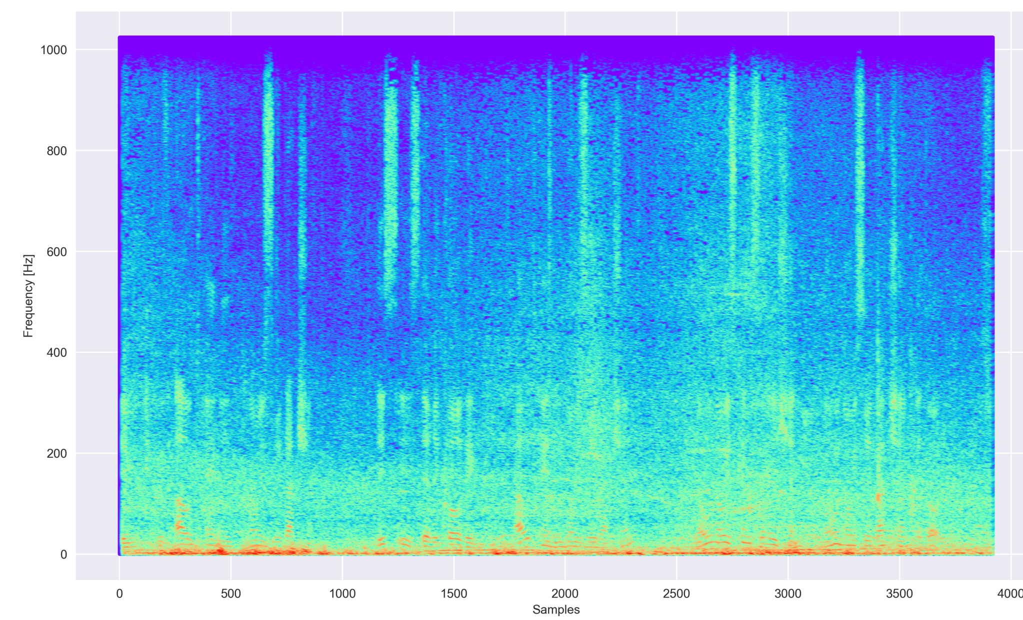
```
array([[   0,    0,    0],
       [   1,    0,    0],
       [   2,    0,    0],
       ...,
       [ 487, 1024,    0],
       [ 488, 1024,    0],
       [ 489, 1024,    0]])
```

USING 3D TABLES FOR CLUSTERING AND VISUALIZATION

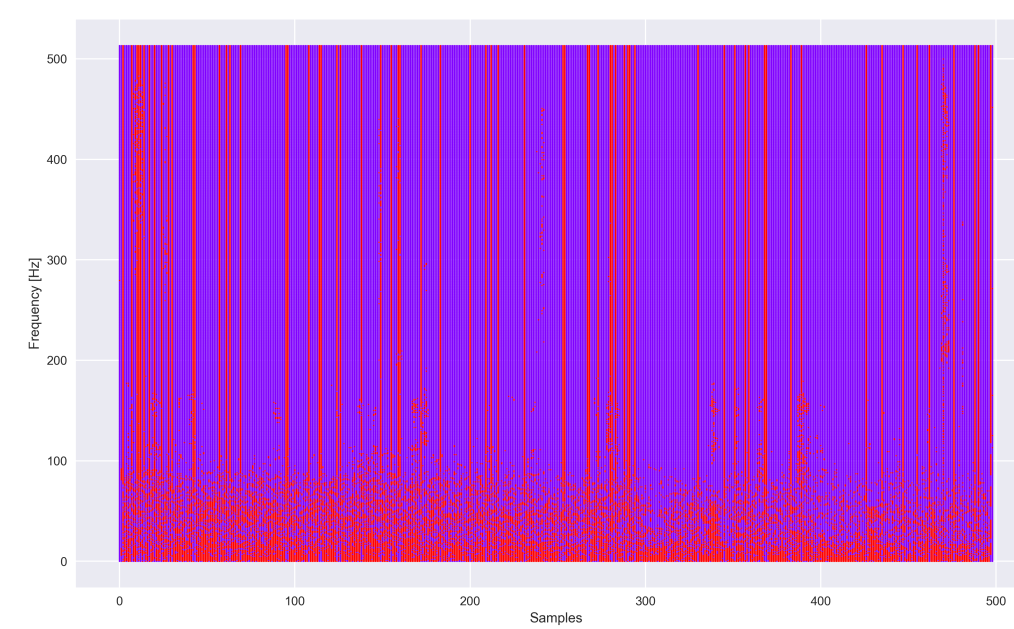
`plt.pcolormesh(spectrogram)`



`plt.scatter(X[:,0], X[:,1], c=X[:,2])`



`plt.scatter(X[:,0], X[:,1], c=spectral_prediction)`



ALGORITHMS:

- Spectral Clustering
    - ‘rbf’ VS. ‘nearest_neighbors’ to create the affinity matrix
    - ‘discretize’ VS. ‘kmeans' to assign the labels
- ICA (Independent Component Analysis)

PROCESS:

1. Load audio file
   => Get time series (array)

2. Run Short-time Fourier transform
   => Get spectrogram of amplitudes (matrix, bins * frames)

3. [optional] Change the structure of the data to improve clustering results
   => Get a new matrix with row per sample

4. Cluster the data using a clustering algorithm
   => Get a matrix with cluster label per sample

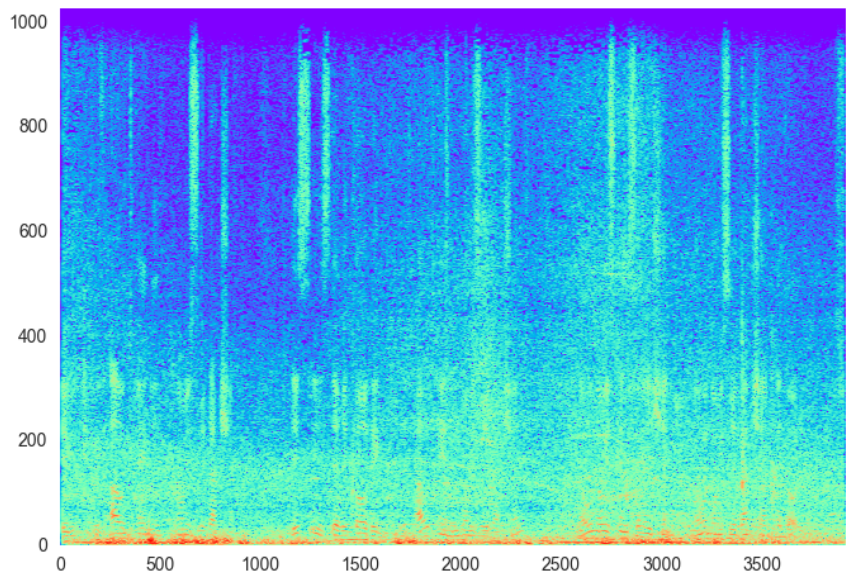
5. Remove (or reduce) the samples that were clustered as noise
   => Get noise reduced spectrogram (matrix)

6. Run Inverse short-time Fourier transform
   => Get time series (array)

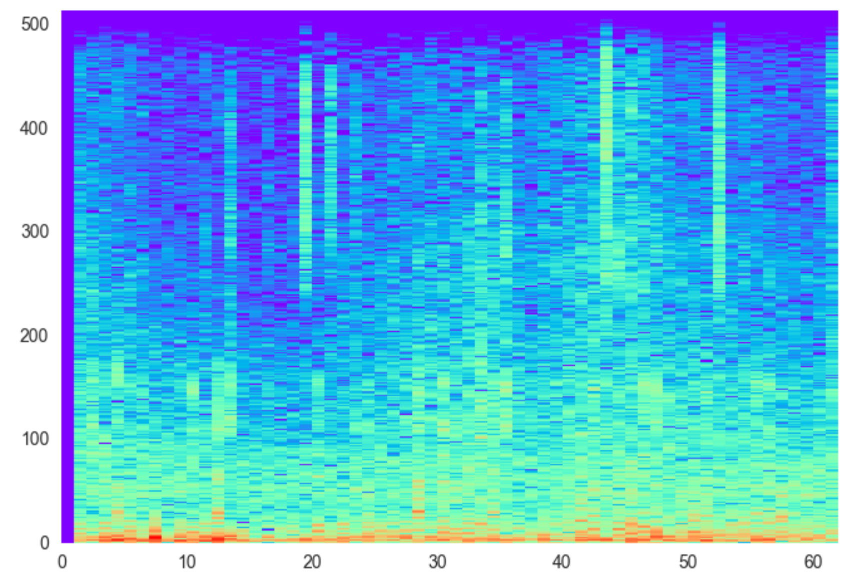
7. Write a file using the new time series array
   => Output .wav file

REDUCING COMPUTATION TIME

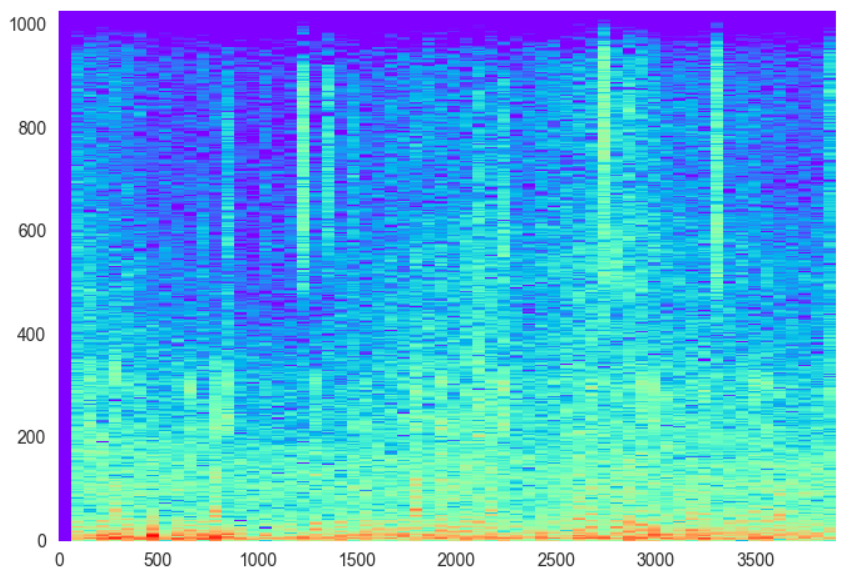
High-res > Low-res > High-res



2049 x 1960 =
4,016,040 samples



683 x 70 =
47,810 samples



2049 x 1960 =
4,016,040 samples

OPEN-SOURCE PYTHON3 PACKAGES:

- **Scikit-learn**
  - Spectral Clustering: http://scikit-learn.org/stable/modules/generated/sklearn.cluster.SpectralClustering.html
  - FastICA: http://scikit-learn.org/stable/modules/generated/sklearn.decomposition.FastICA.html
- **LibROSA** (Brian McFee, PhD @ NYU Steinhardt) http://librosa.github.io/librosa/index.html
- Graphical representation
  - **Matplotlib** http://matplotlib.org/
  - **Seaborn** https://seaborn.pydata.org
- **Pandas** http://pandas.pydata.org/
- blind_source_separation.py GitHub Gist by **abinashpanda** https://gist.github.com/abinashpanda/11113098

Results

https://dodiku.github.io/audio_noise_clustering/results/

THE ORIGINAL RECORDING

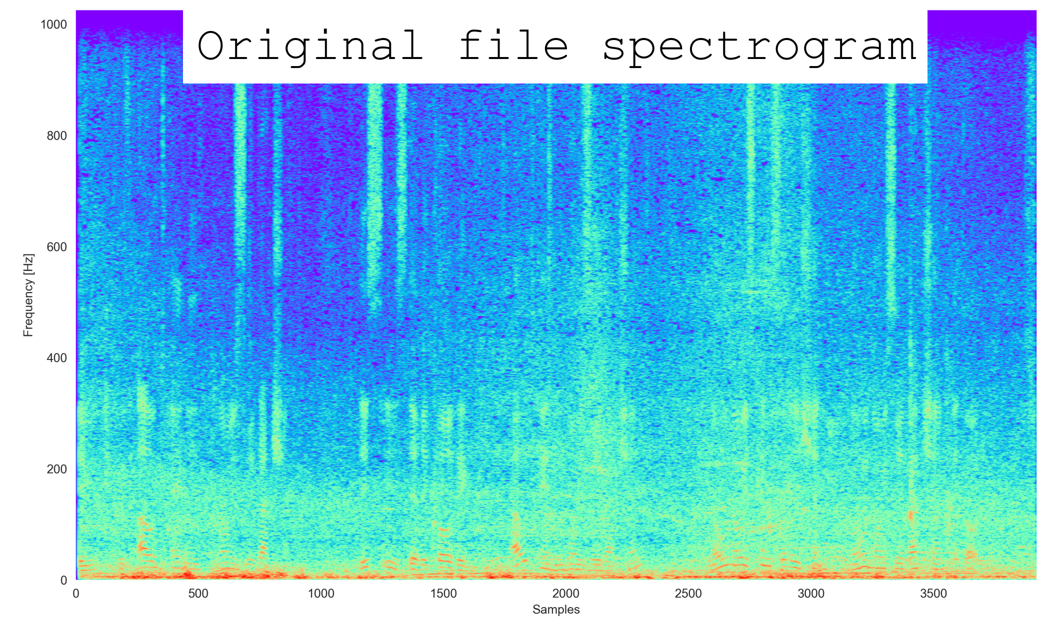
SPECTRAL CLUSTERING 01

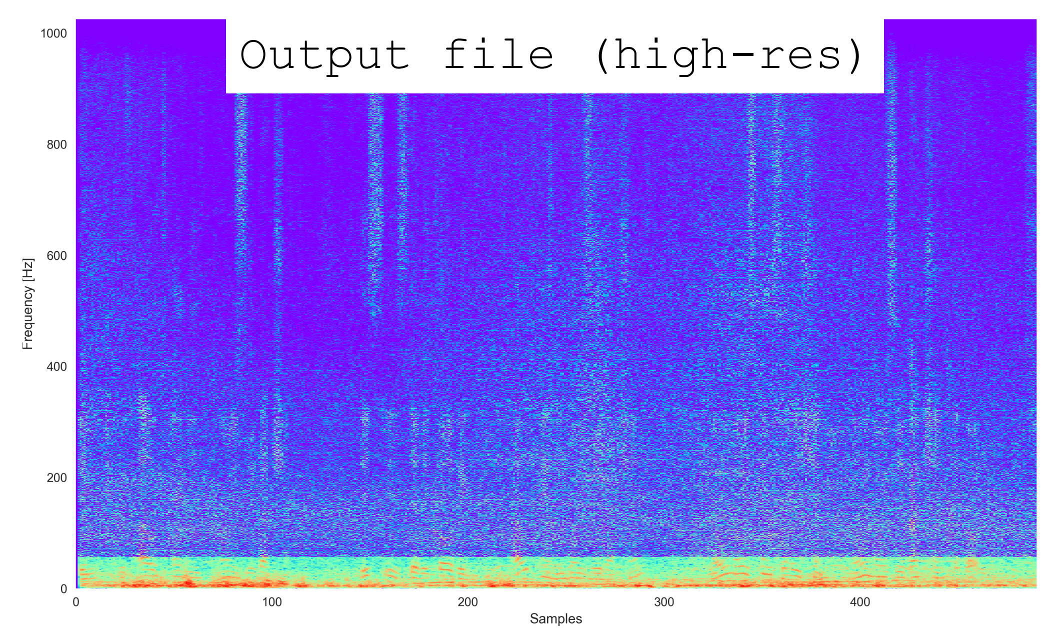
- Full spectrogram (matrix) as dataset

- Using ‘nearest_neighbors’ to create the affinity matrix (adjacency matrix)

  Using ‘arpack’ as the eigen solver

- Runtime = 4.4s





SPECTRAL CLUSTERING 02

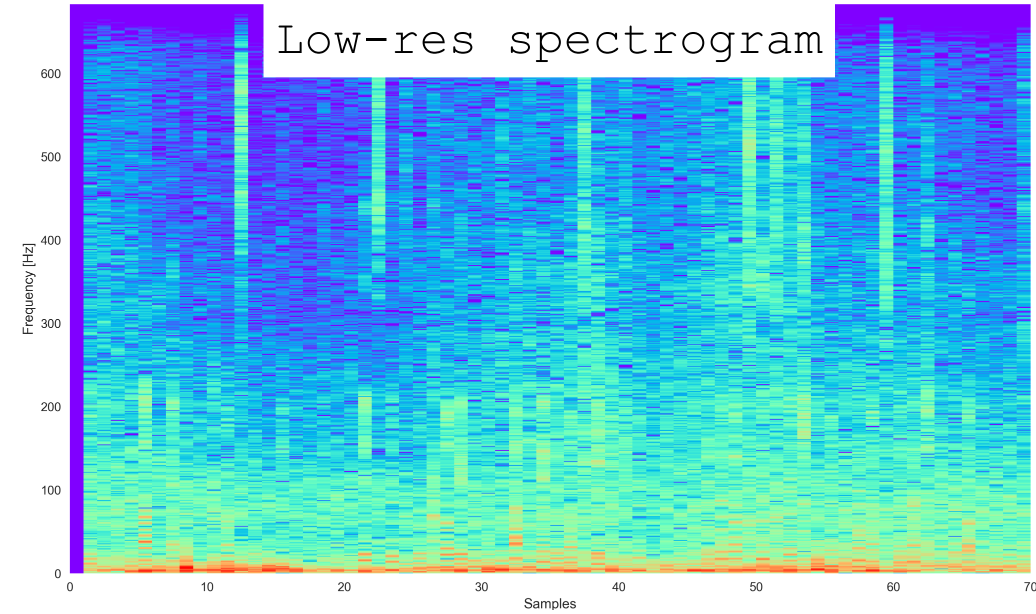
- Full spectrogram (matrix) as dataset

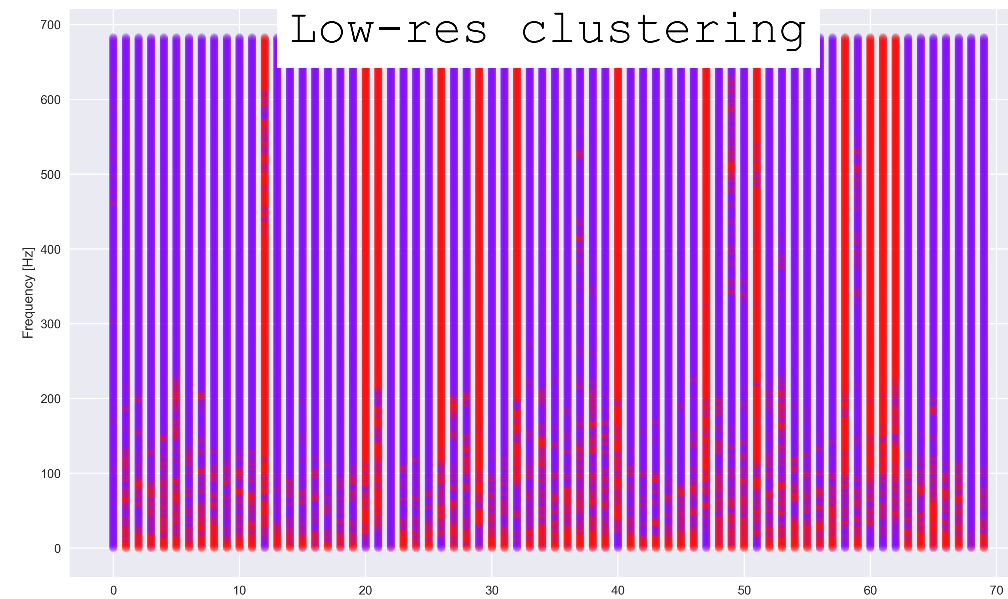
- Column-by-column clustering

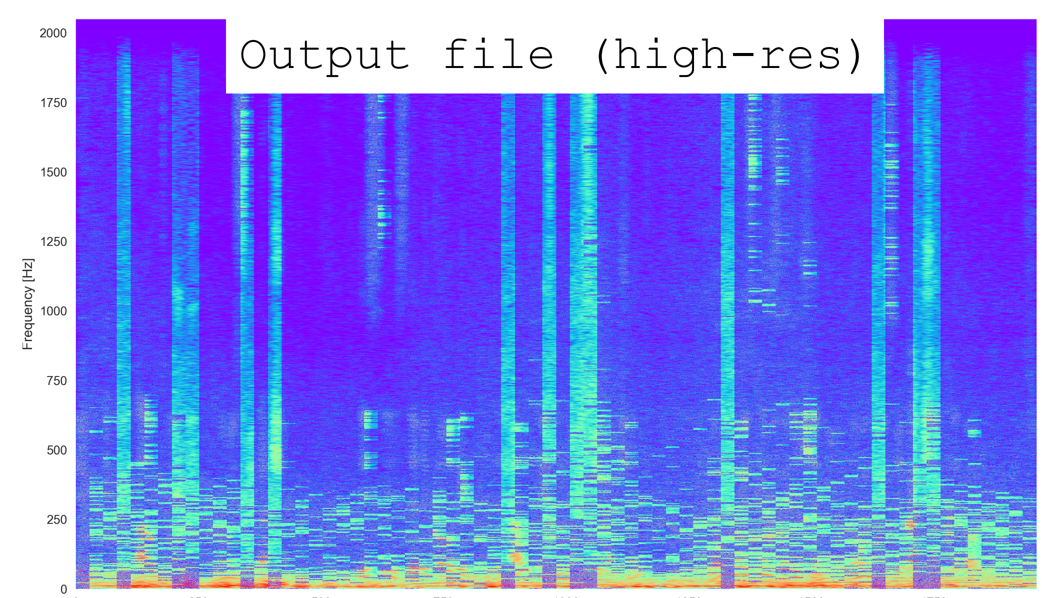
- Using ‘rbf’ to create the affinity matrix

- Reducing res > clustering > applying on high res

- Runtime = 24.2s - 26.9s
  (in full res = ~1:30h)







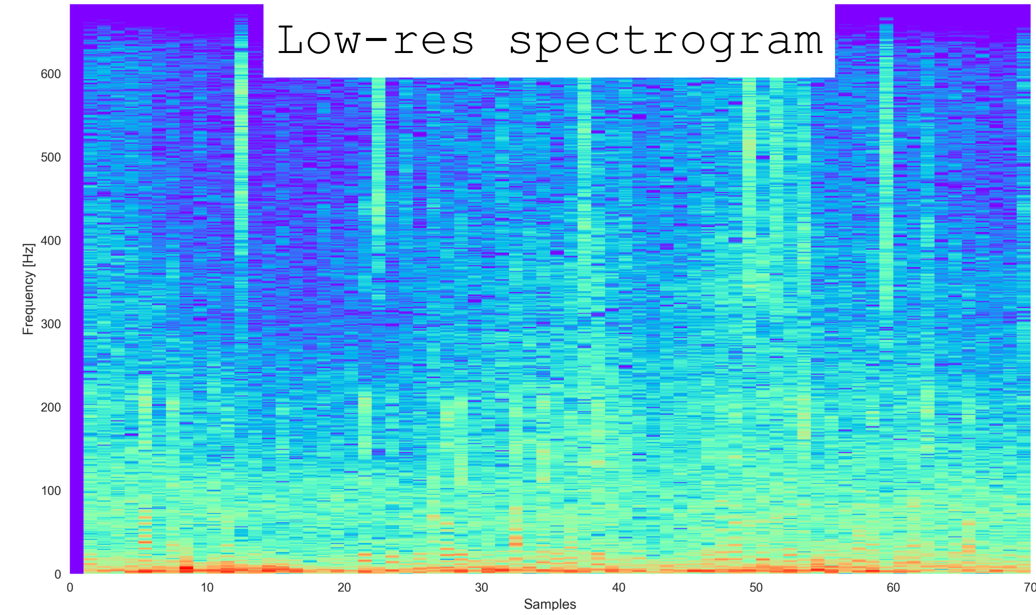
SPECTRAL CLUSTERING 03

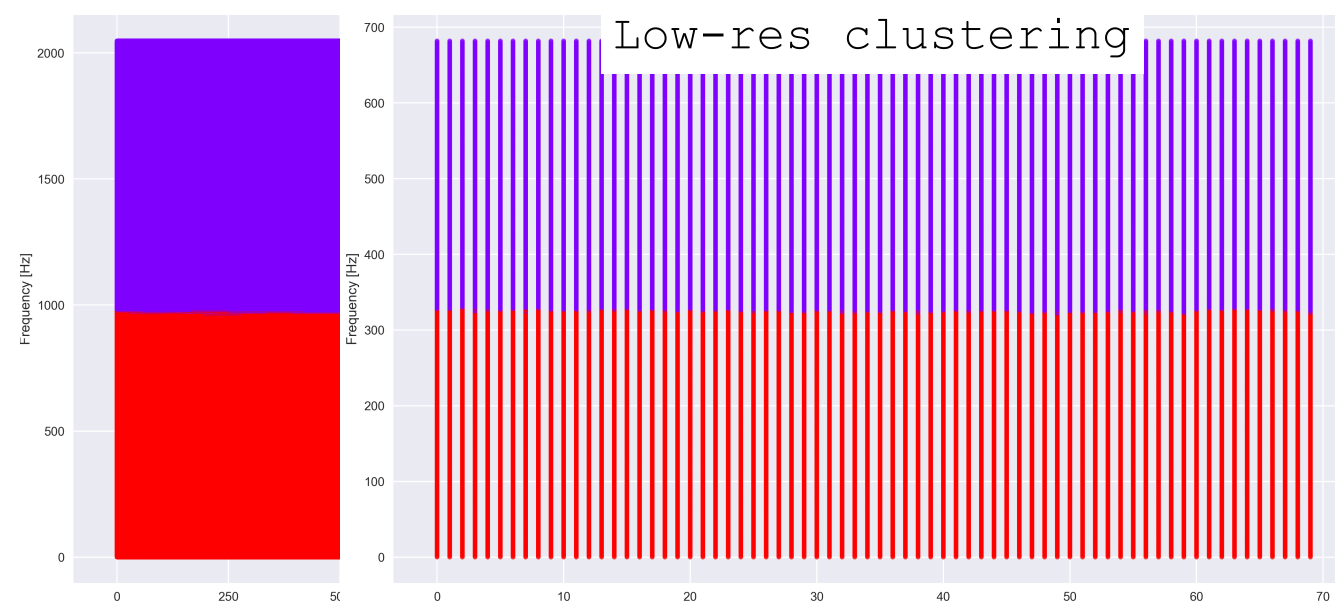
- Full 3D table as dataset

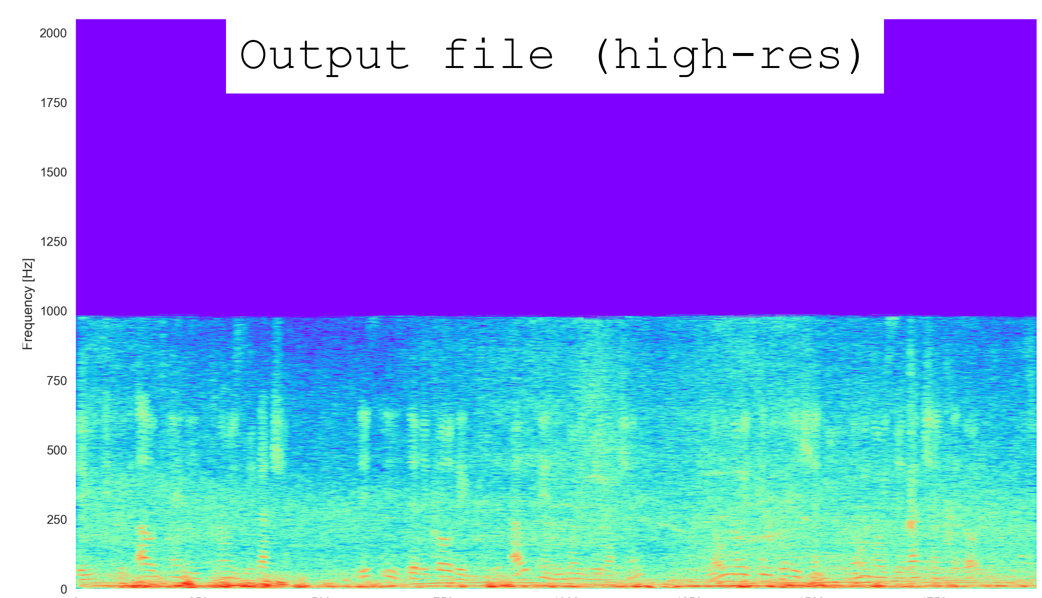
- All methods showed similar results

- Reducing res > clustering > applying on high res

- Runtime = ~4:10m (in full res = ∞)

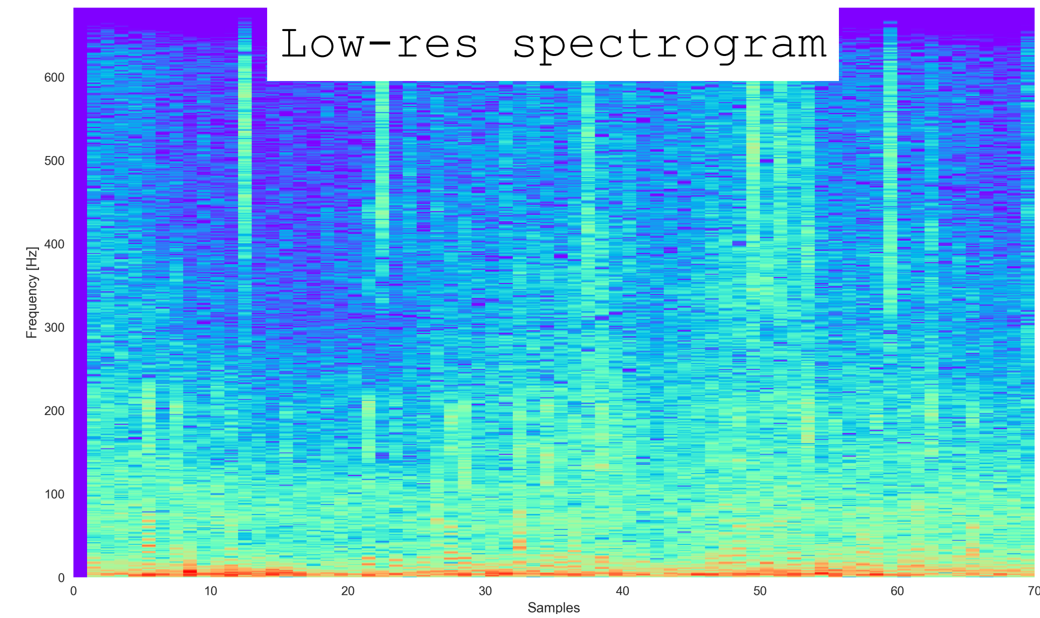


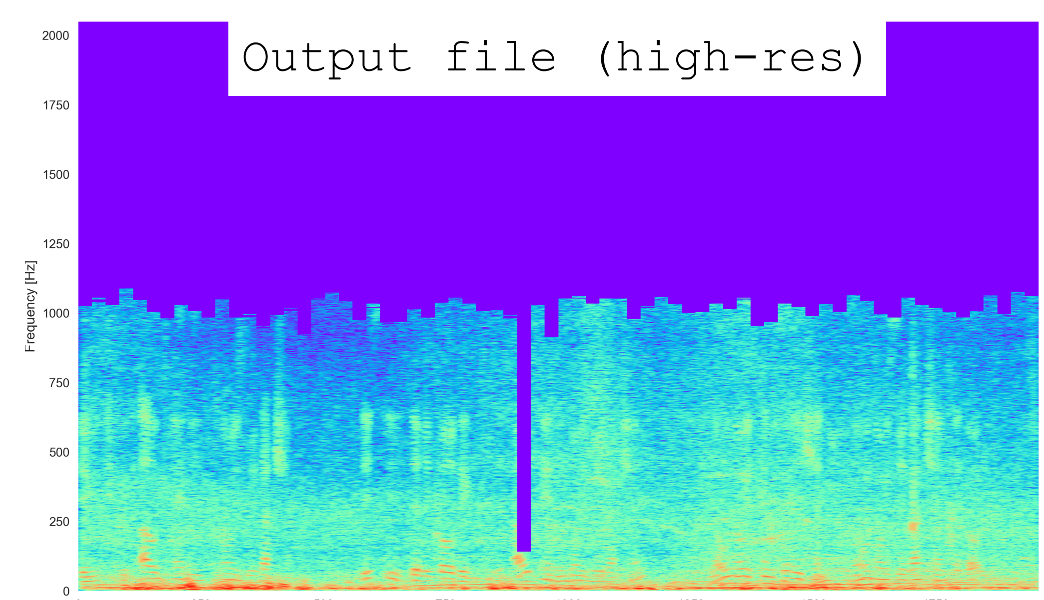




SPECTRAL CLUSTERING 04

- Full 3D table as dataset
- Column-by-column clustering
- All methods showed similar results
- Reducing res > clustering > applying on high res
- Runtime = ~34.4s
  (in full res = ~2.5h)





ICA: INDEPENDENT COMPONENT ANALYSIS

- Convolving 2 spectral clustering results.

- Generating two audio files:
  one with noise
  one with (supposedly) clearer speech

- Runtime = 0.2s-0.8s

Conclusions

CONCLUSIONS:

- The complex nature of audio signals makes it very hard (maybe impossible?) to cluster away noise.

- The tested clustering technique could not produce better results than existing production techniques.

- Computation time Computation time and the nature of the data makes the research hard to do on a laptop machine 💻.

- DSP is great! The impact of machine learning on audio applications (besides speech-to-text) has yet to come. I’ll keep on searching for it.

FURTHER RESEARCH:

- Implementing a solution using other clustering techniques, such as kmeans and hierarchical clustering.

- Expanding the data by adding a column that describes the distance between a sample (a bin) and the centroid of the recording.

- Generating a solid ICA pipeline (results as an input, noise as an input)

Thanks 🙏