Zebra Finch Song Classification

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Can you tell the difference?

Background

Working with the Laboratory of Neural Circuit Formation, here at BU.

They are researching how information is stored in the brain. More specifically, the lab studies neural firing patterns of zebra finches when they sing.

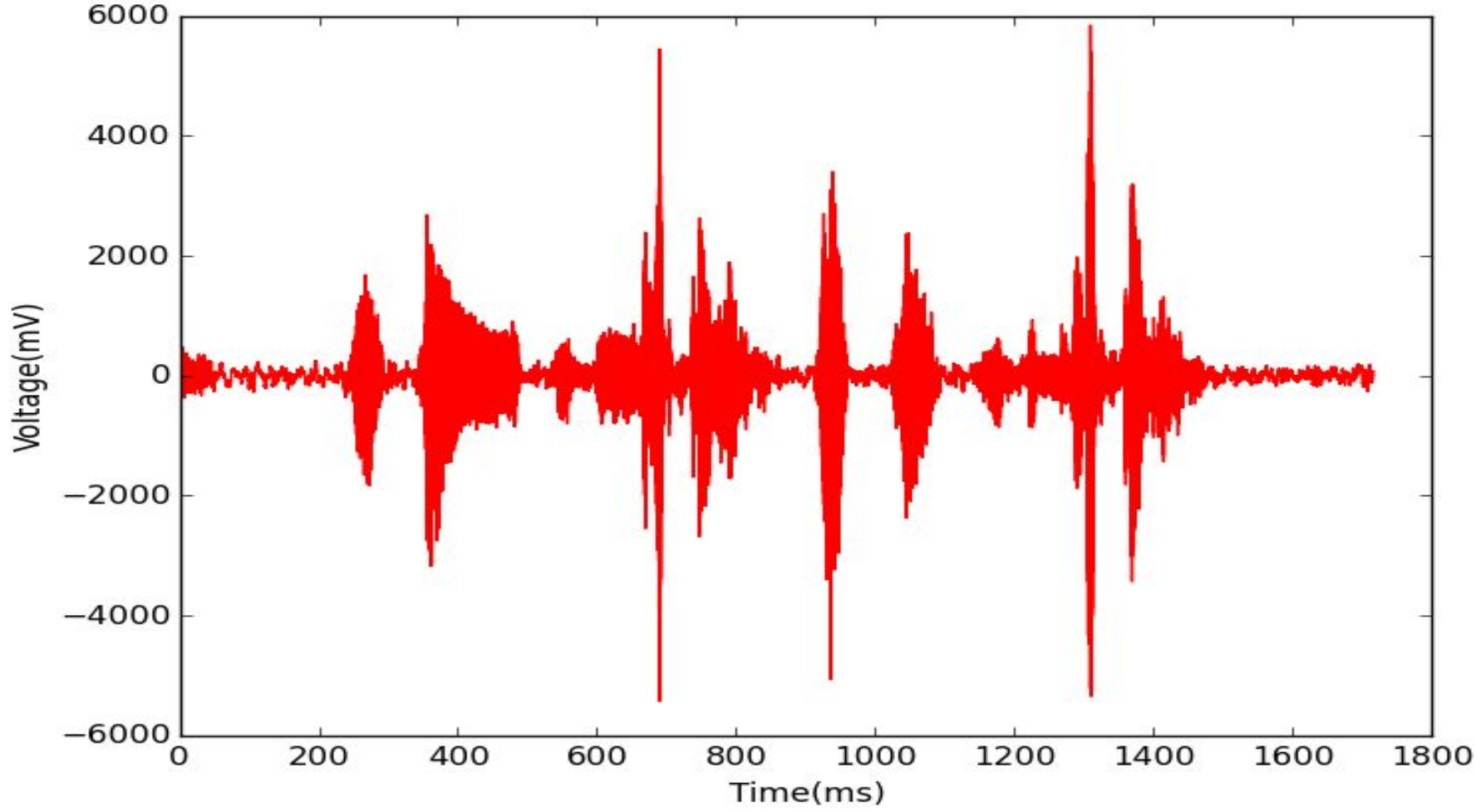
In order to record images of this neural activity at the right time, they need to know when a zebra finch is singing.

Data

We were provided with data representing 146 songs, from two different birds

Things to remember:

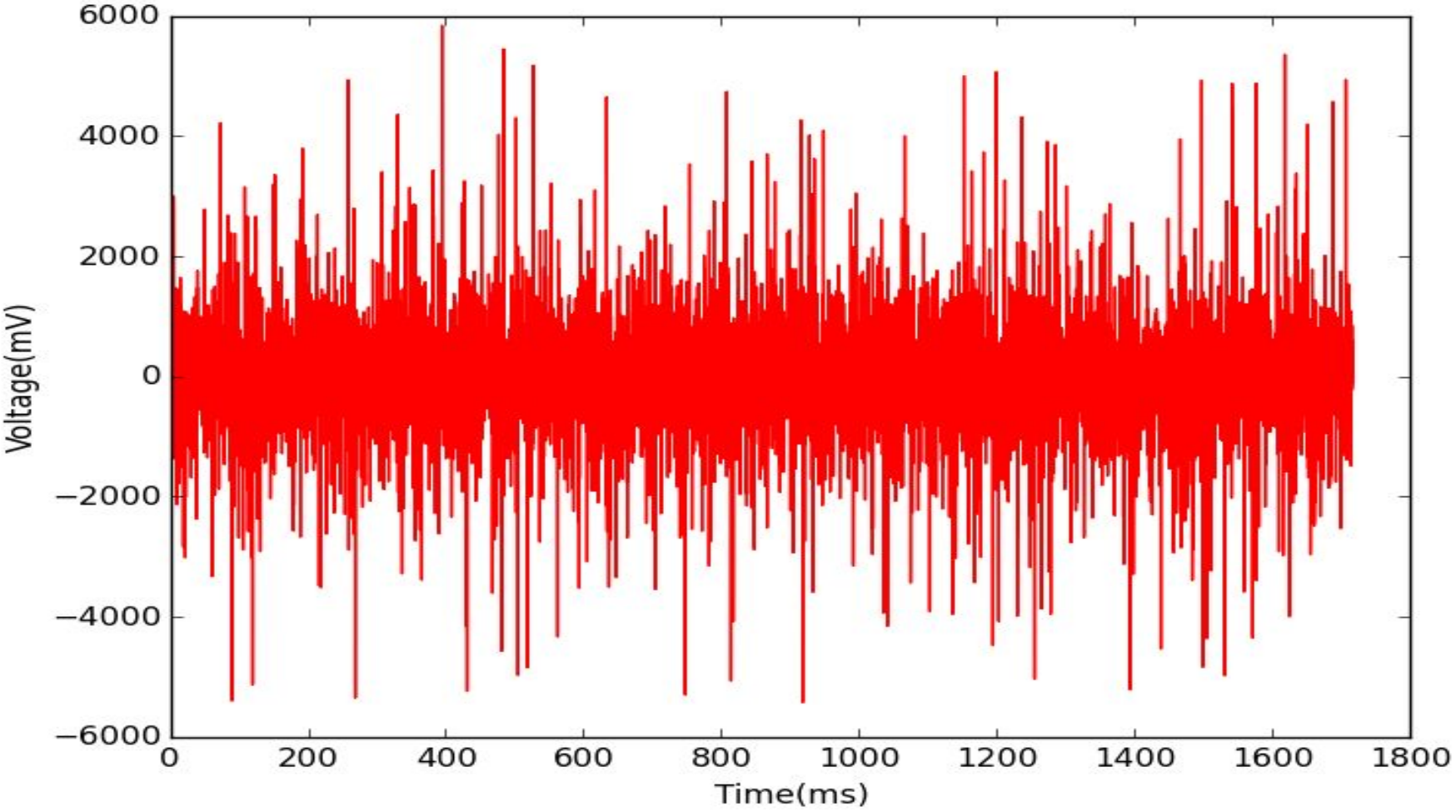
- Each bird can only sing one song
- Songs from the same bird can vary in voltage signals and duration


6000
4000
2000
0
−2000
−4000
−6000
Voltage(mV)
0
200
400
600
800
1000
1200
1400
1600
1800
Time(ms)

Noise Generation

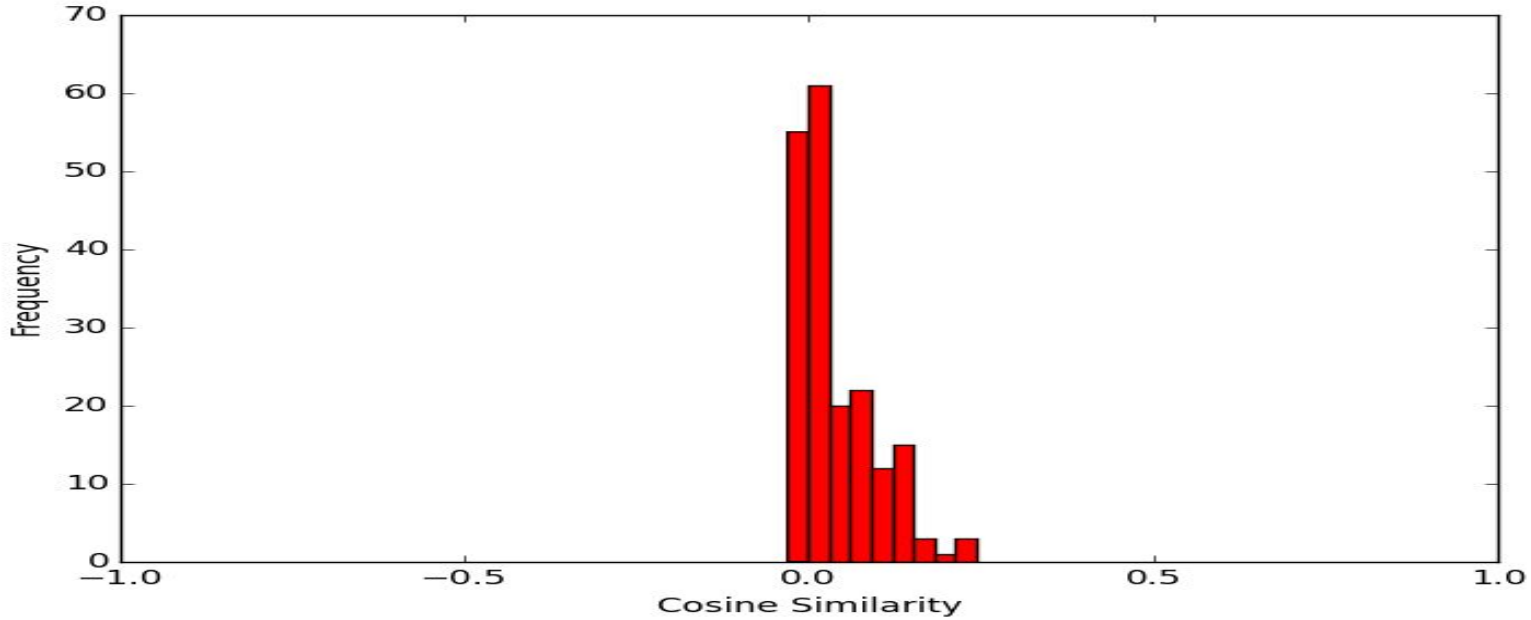
In order to start classifying the songs, we needed to create other sounds as a baseline to test against our song data.

To do this, we generated random permutations of the songs from our data.


6000
4000
2000
0
−2000
−4000
−6000
Voltage(mV)
0
200
400
600
800
1000
1200
1400
1600
1800
Time(ms)

Initial Tests

Averaged the voltage across songs and compared that average to individual songs and generated noise using their cosine similarity.

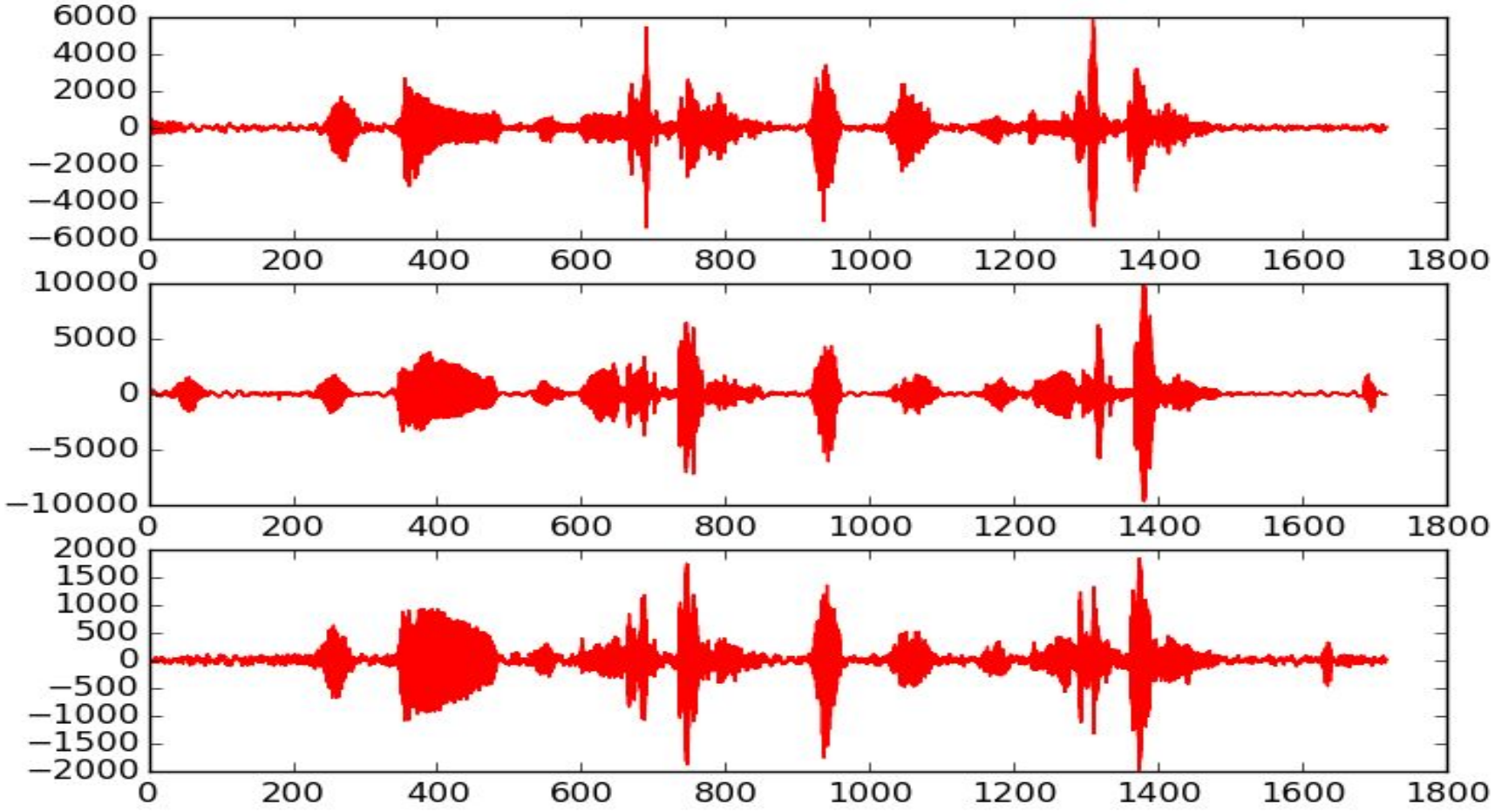


Unclear Results

We were hoping for a clear distinction between our generated noise and or song data but as one can see, there was not much difference.

Issues:

- Millisecond differences in the recordings
- Same sample peaks varied in voltage


6000
4000
2000
0
−2000
−4000
−6000
0
200
400
600
800
1000
1200
1400
1600
1800
10000
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2000
1500
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500
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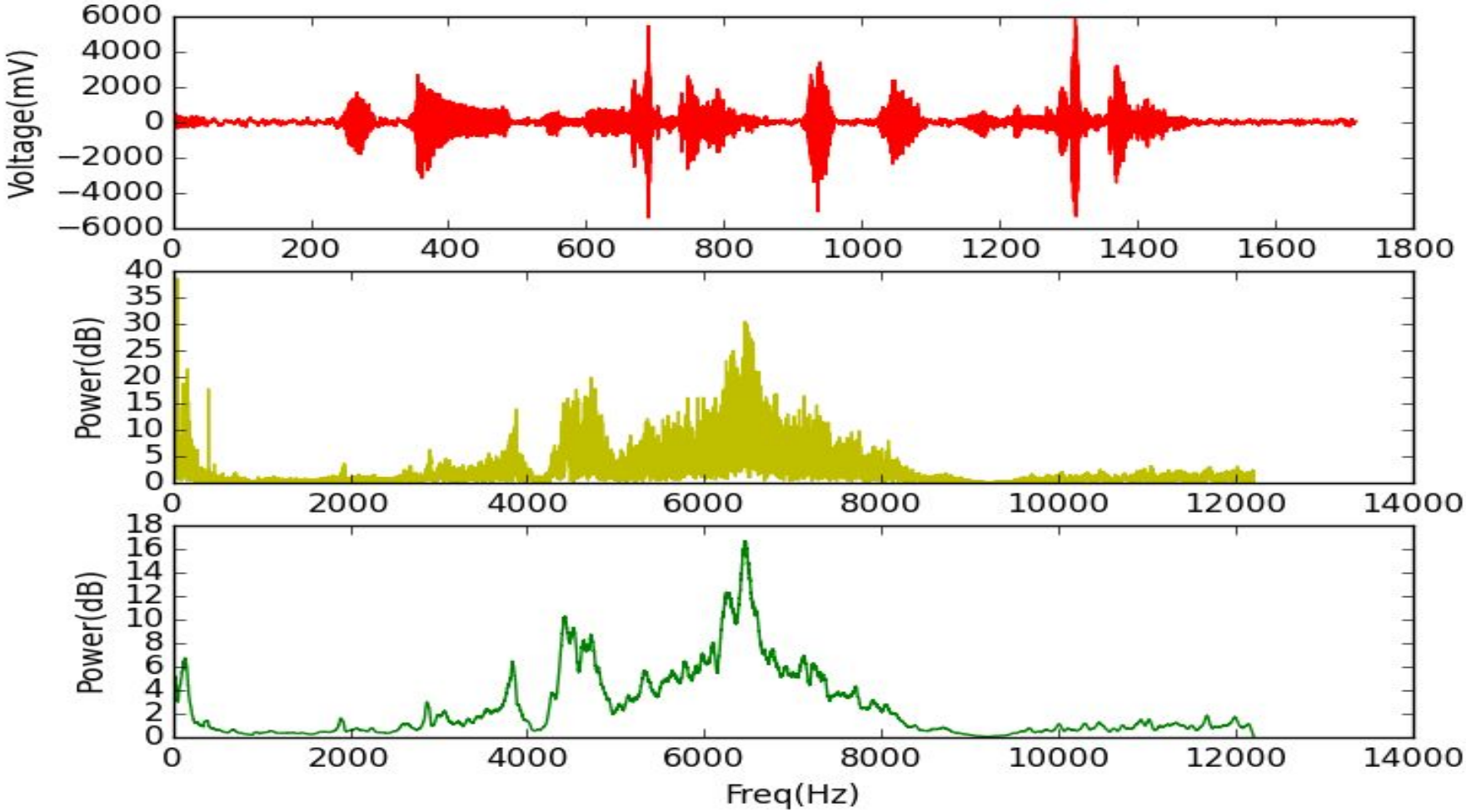
−500
−1000
−1500
−2000
0
200
400
600
800
1000
1200
1400
1600
1800

Data Processing

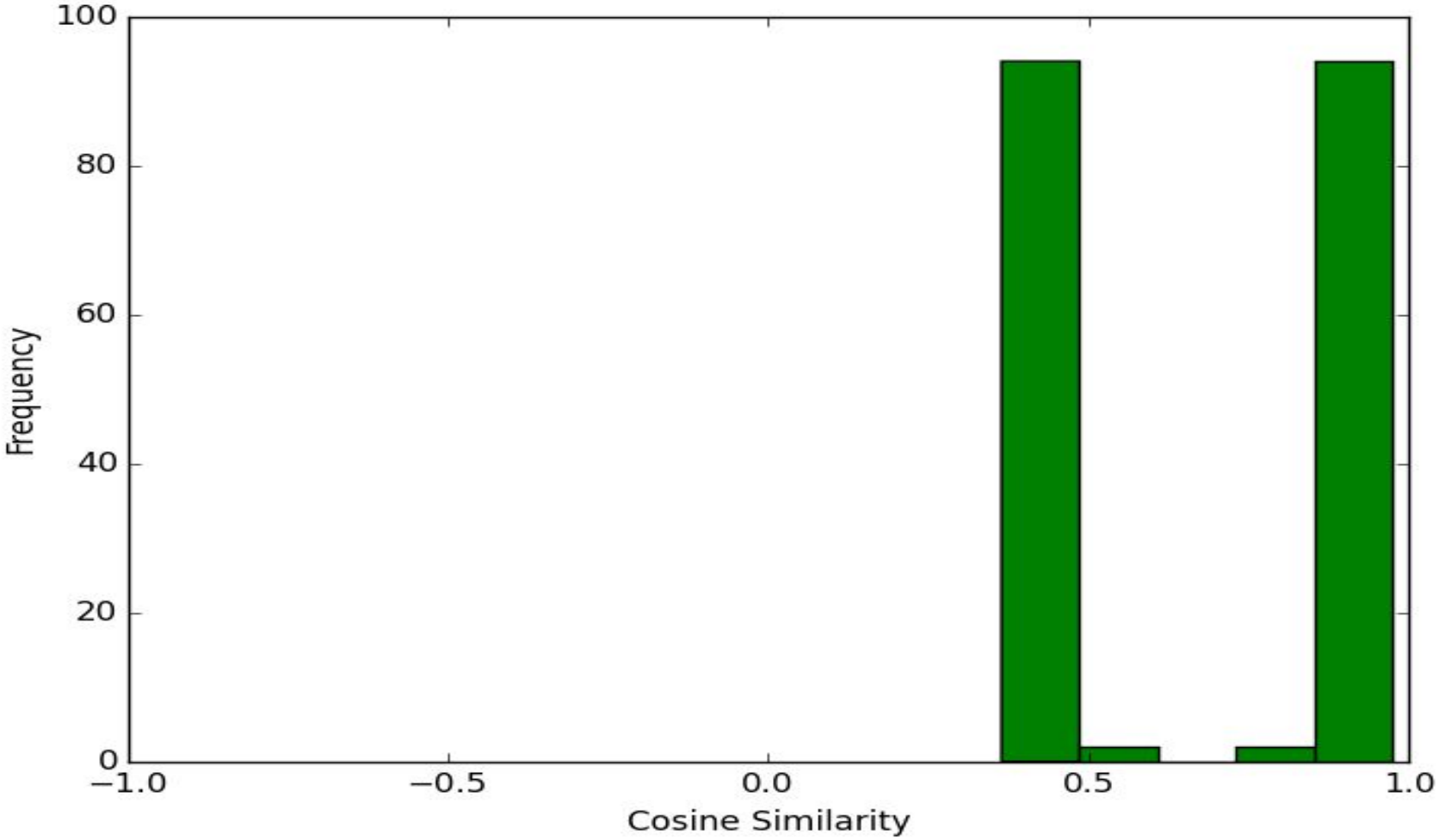
To remedy our timing and voltage issues, we needed to clean our data. We performed a Fourier Transform to all our songs to get the power and frequency over time and then we took the running mean over each song to ‘smooth’ the data.


Voltage(mV)
6000
4000
2000
0
−2000
−4000
−6000
0
200
400
600
800
1000
1200
1400
1600
1800
Power(dB)
40
35
30
25
20
15
10
5
0
0
2000
4000
6000
8000
10000
12000
14000
Power(dB)
18
16
14
12
10
8
6
4
2
0
0
2000
4000
6000
8000
10000
12000
14000
Freq(Hz)

Secondary Tests

After transforming our data, we were hoping to see:

- Cosine similarity score increase for or song data.
- A clear distinction between our song data and our generated noise.


100
80
60
40
20
0
Frequency
−1.0
−0.5
0.0
0.5
1.0
Cosine Similarity

Better Results

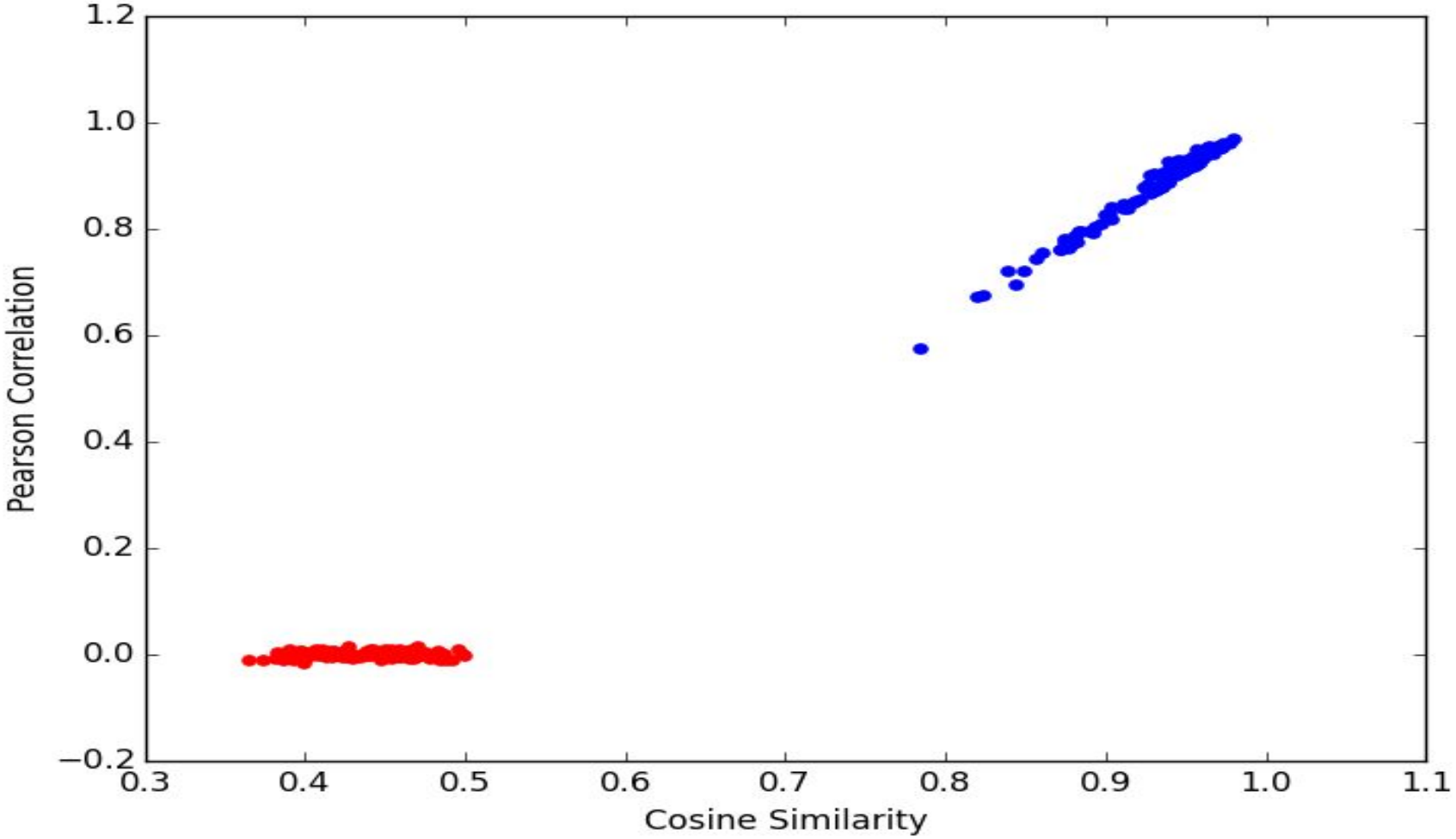
From the histogram, we can see that there are two distinct groups where our training data fell into, our generated noise and our song data.

We also see that our cosine similarity scores increased across the board, even for the noise intervals which we generated.

Clustering the Data

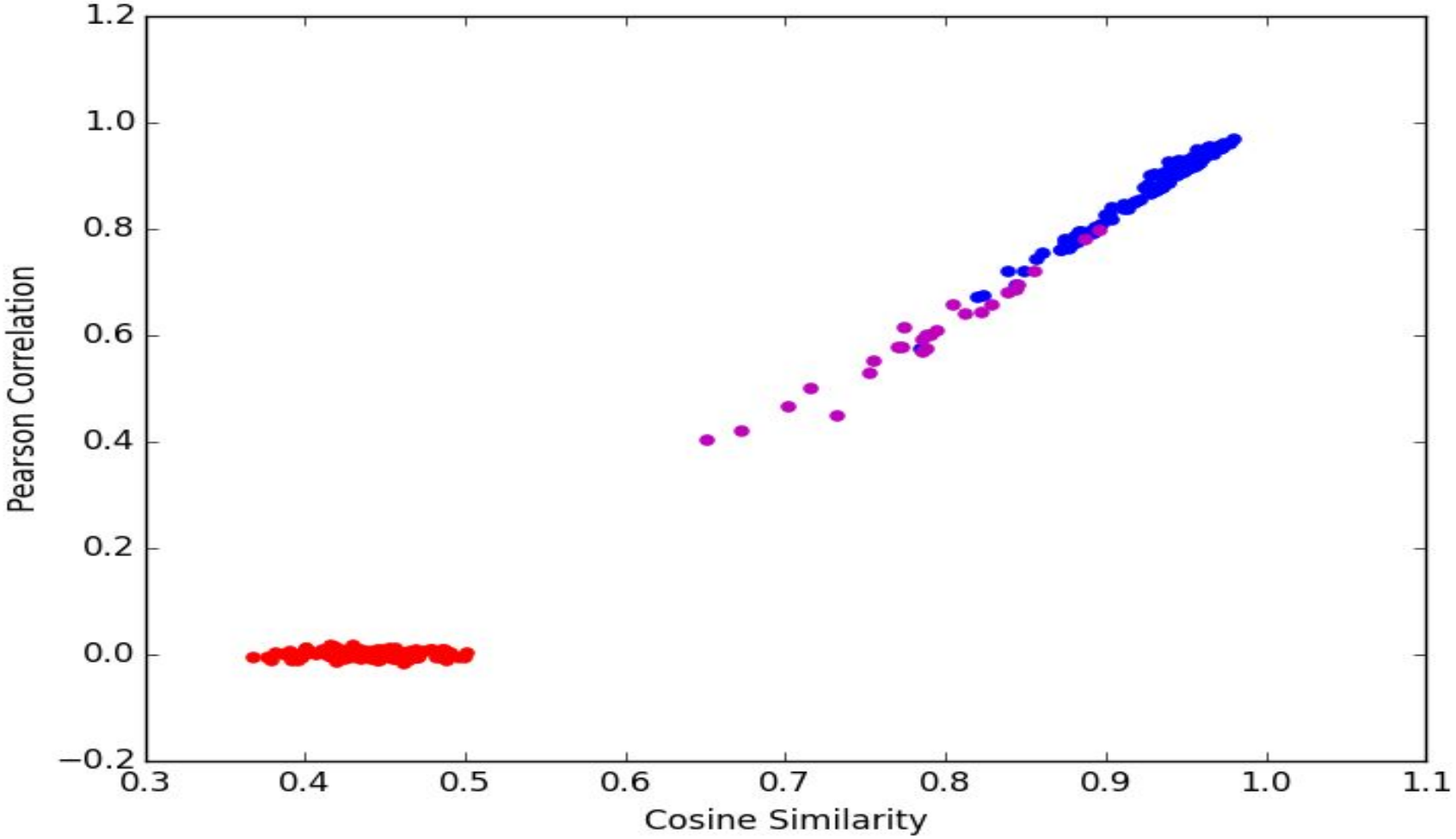
Since there was a small distinction between the cosine similarity scores of the noise and song data, we decided to compare the data using their Pearson Correlation Coefficients as well.

By doing this, we hoped to separate these data heaps further away from one another


1.2
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
Pearson Correlation
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
1.1
Cosine Similarity

We have our Benchmark!

We can make two distinct clusters out of our noise and songs, but now we need to move on to the more challenging problem of differentiating between the songs of zebra finches.


1.2
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
Pearson Correlation
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
1.1
Cosine Similarity

Distinguishing between birds is hard!

We need to make sure that these clusters are distinct, matching each cluster of data points to a particular bird.

We plan on using SVM and K-Means to isolate the grouped clusters