

# Chirp Checker

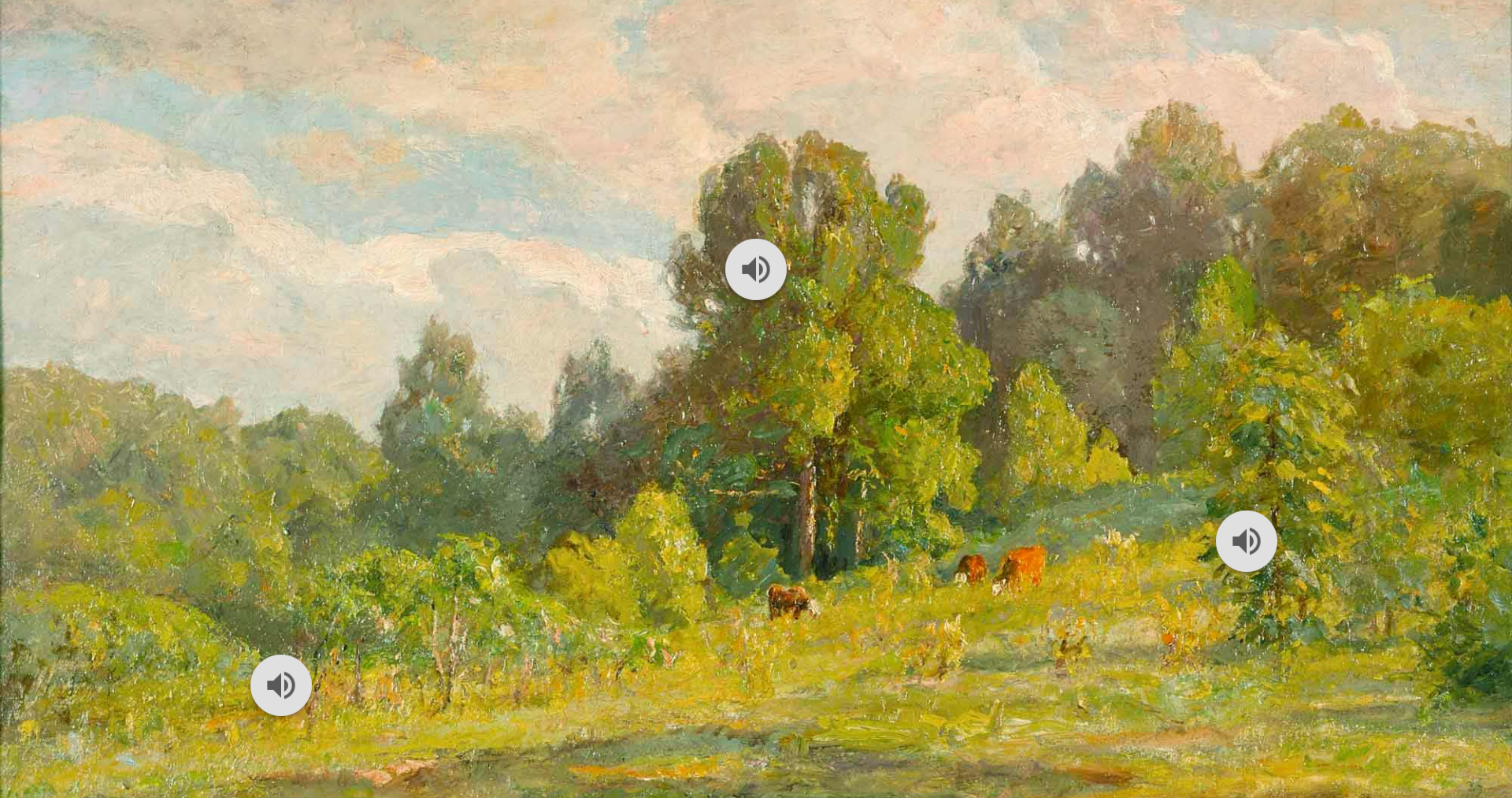
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Calvin Yost-Wolff, Yang Yang



**THE ERDŐS INSTITUTE**

Data Science Bootcamp | Summer 2024

Photo: [songsofinsects.com](https://www.sonsofinsects.com)



Painting: T.C. Steele | Sounds: [InsectSingers.com](https://www.insectsingers.com) & [OrthSoc.org](https://www.orthsoc.org)

## CRITTER NAMES



Crickets



Katydids



Cicadas



## CRITTER NAMES



**Crickets**

## FAMILY / SUBFAMILY

Eneopterinae, Gryllinae,  
Gryllotalpidae, Hapithinae,  
Mogoplistinae, Nemobiinae,  
Oecanthinae, Trigonidiinae



**Katydids**

Conocephalinae, Listroscolidinae,  
Phaneropterinae, Phalangopsidae,  
Pseudophyllinae, Tettigoniinae

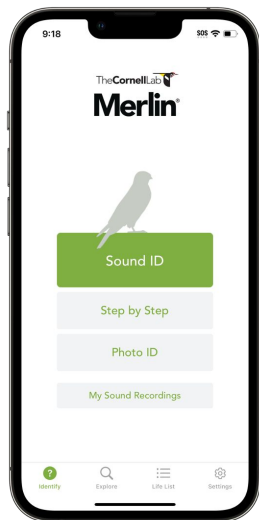


**Cicadas**

**Cicadidae**

# Models for classifying insect sounds could be useful for

**Apps**



**Passive Acoustic  
Monitoring**



*Samuel R.P.-J. Ross*

# **Objective:**

build models that can  
coarsely classify insect sounds

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(a) three broad categories

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build models that can  
coarsely classify insect sounds

(a) three broad categories

(b) families and subfamilies



**13,462** files

From the Macaulay Library of Natural Sounds

The **Cornell** Lab  of Ornithology

**Macaulay Library**

**5,899** files

after filtering out human speech

**3,949**

Crickets

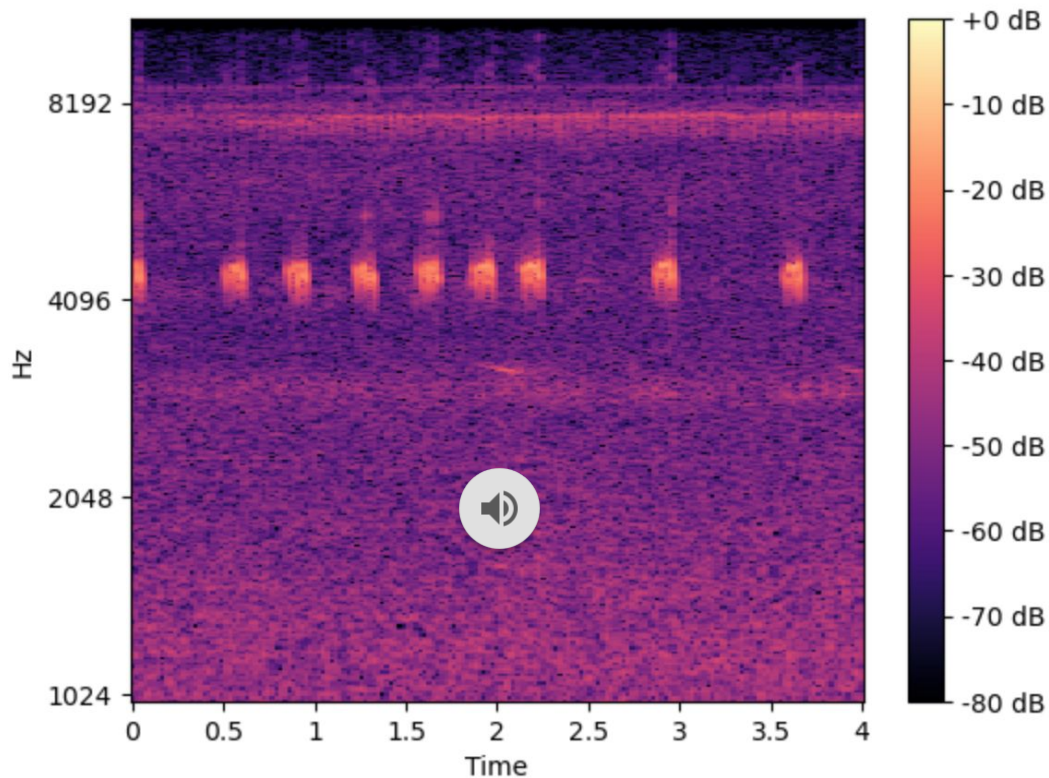
**1,895**

Katydids

**55**

Cicadas

# Data Visualization: Spectrogram

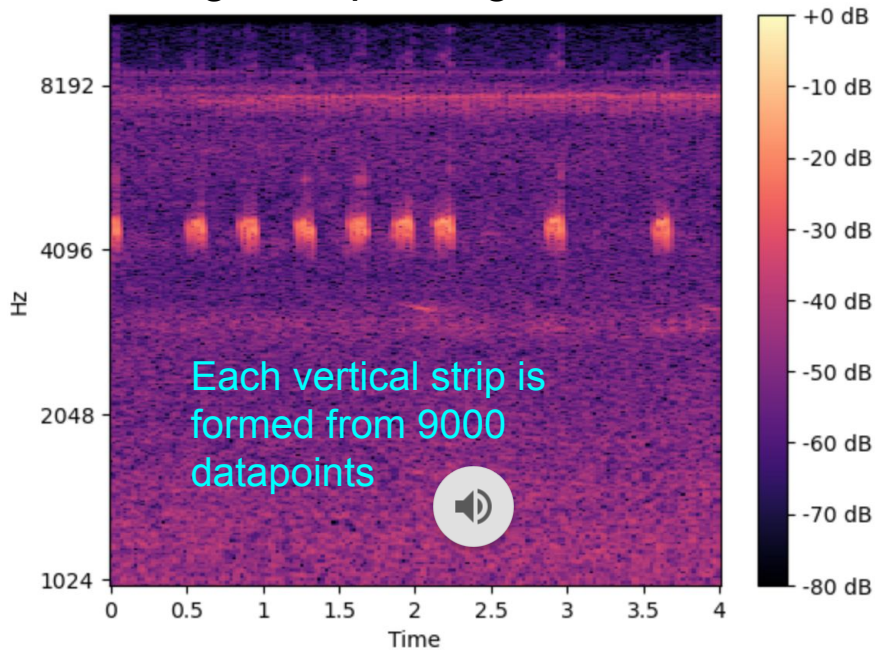


By using the fast fourier transform built in to librosa applied to small time intervals, we get a form a heat map describing which frequencies we are hearing.

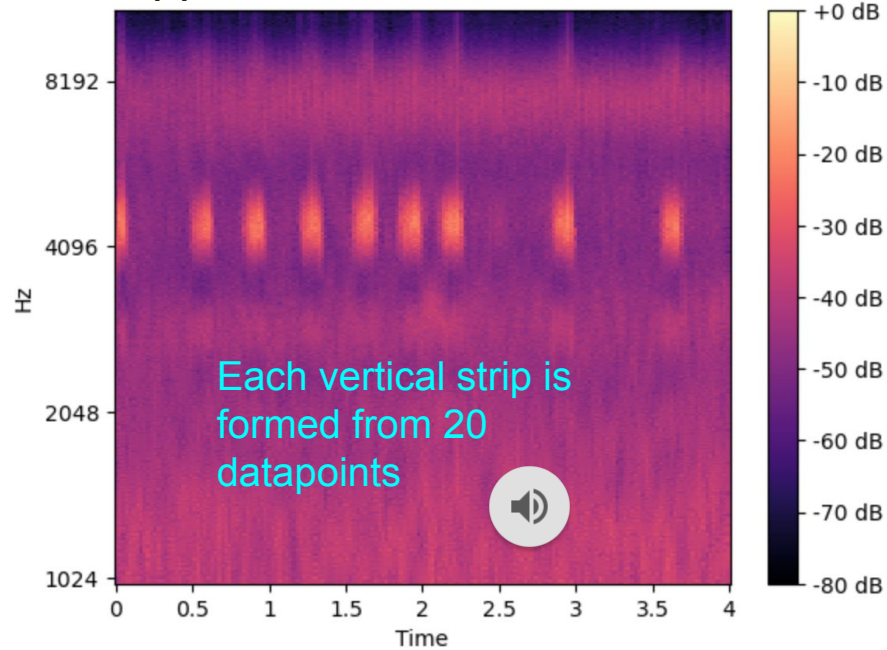
# Data Compression: MFCCs

To compress our frequency data, we use Mel-Frequency cepstral coefficients (MFCCs), which represents smoothing each vertical strip in our spectrogram.

## Original Spectrogram

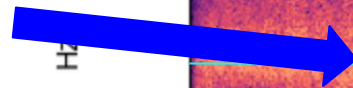


## Approximation with 20 MFCCs

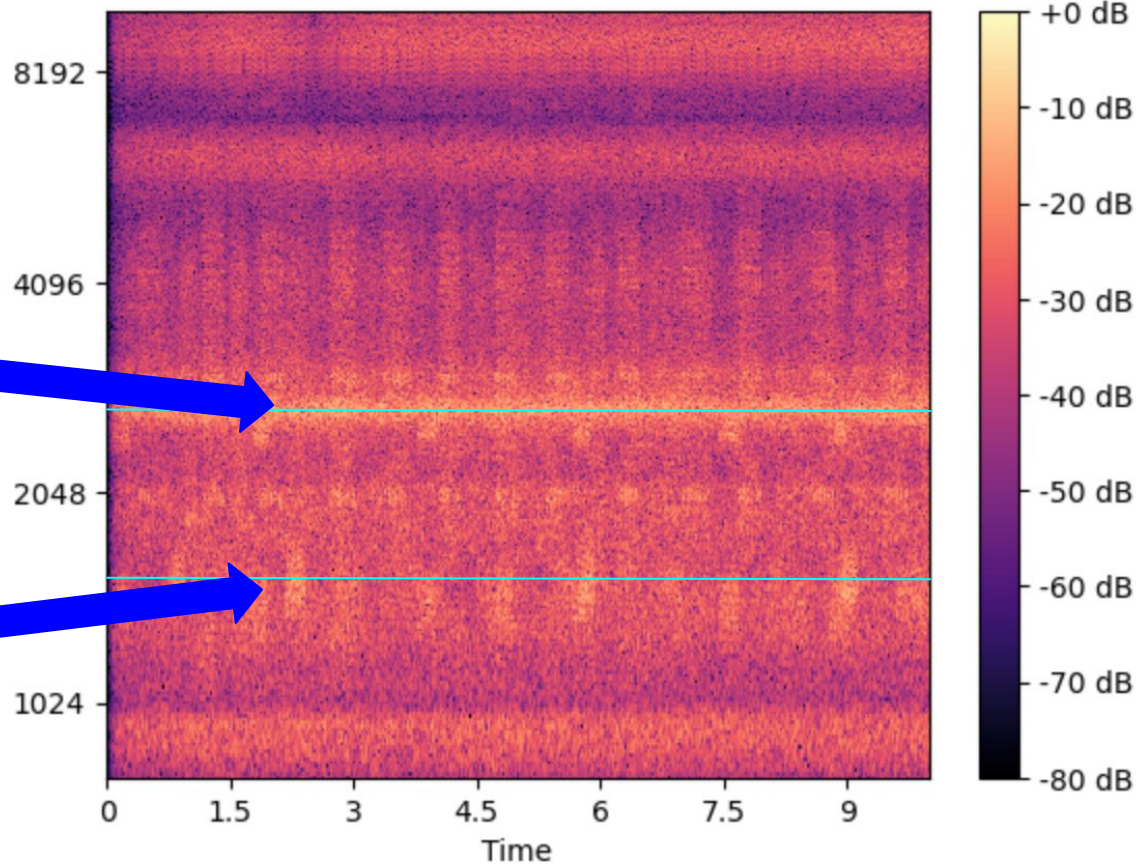
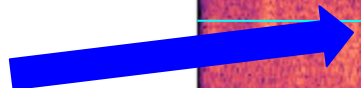


What is the main frequency the insect is chirping at?

Loudest Frequency



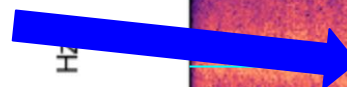
Frequency with the most variance



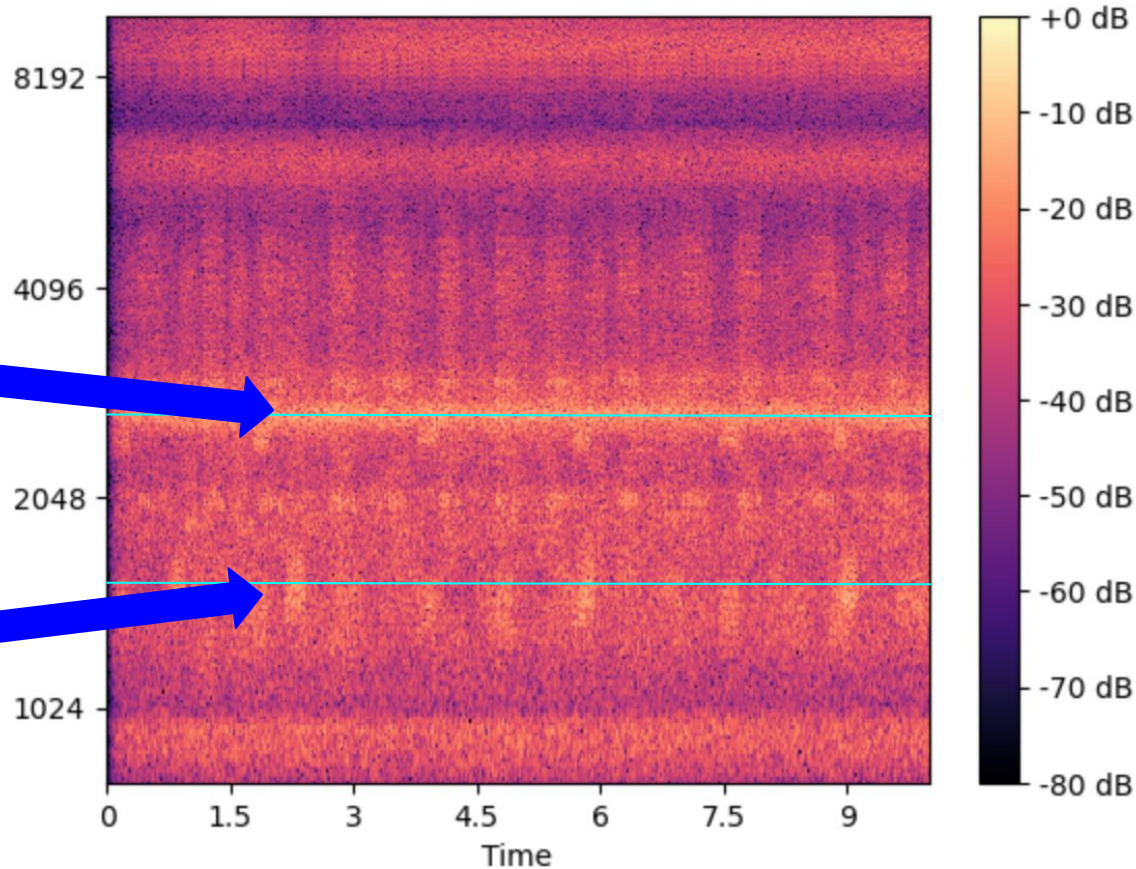
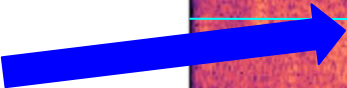


Two methods to try and extract the predominant frequency: The loudest frequency or the one with the most variance.

Loudest Frequency



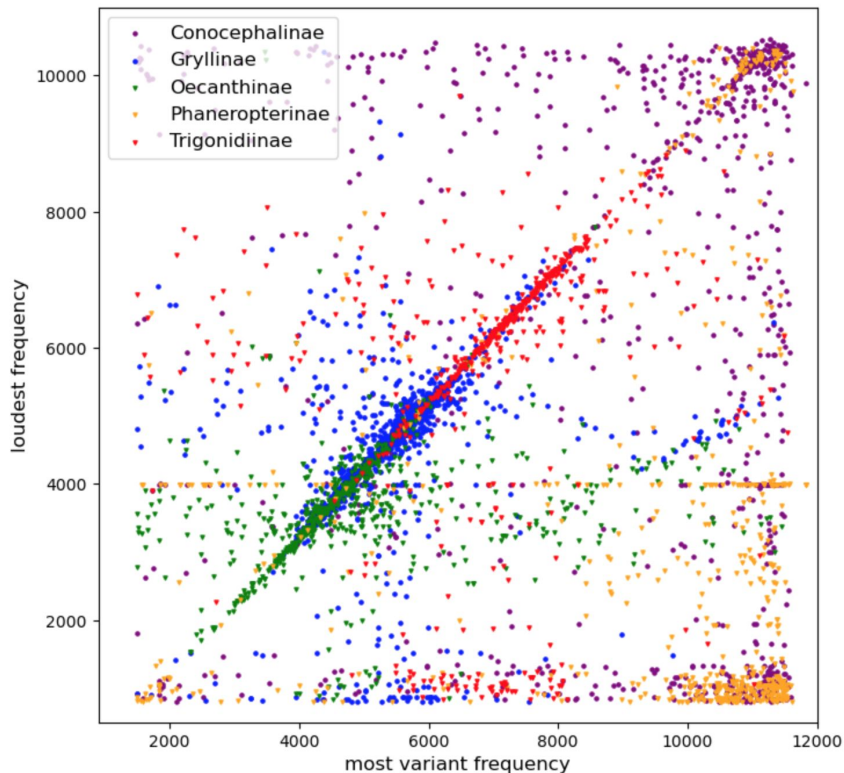
Frequency with the most variance





# These two data points are good predictors!

5 most common fam/subfams



An rbf Support Vector Classifier (SVC) with just these two data points gets the fam/subfam correct with 50% accuracy.

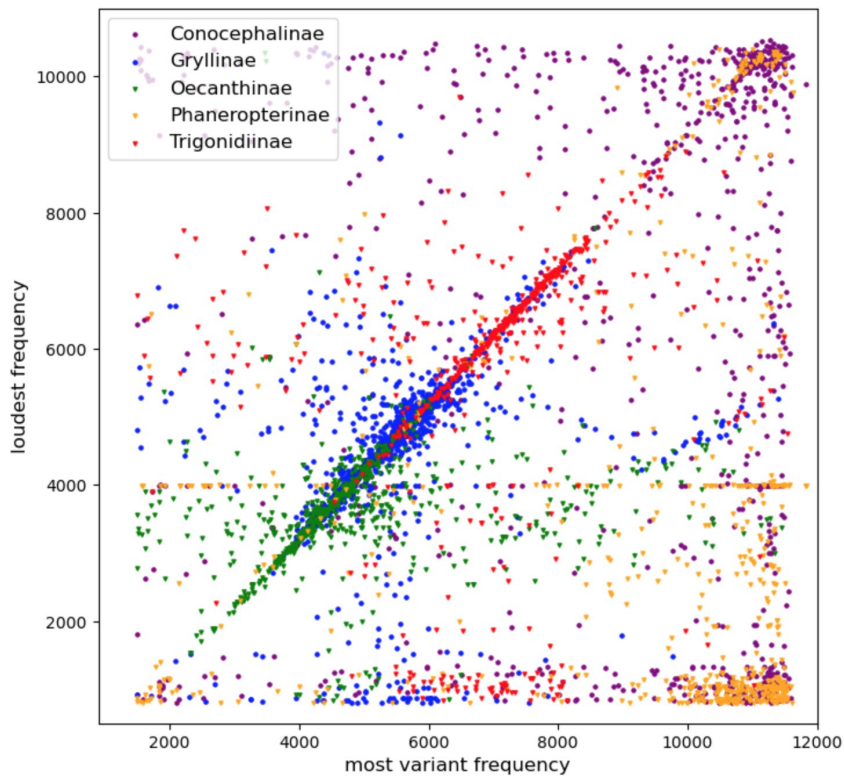
[Baseline guess the most common fam/subfam does 24%].

When mapping our fam/subfam back to its appropriate critter name we get 86.5%!

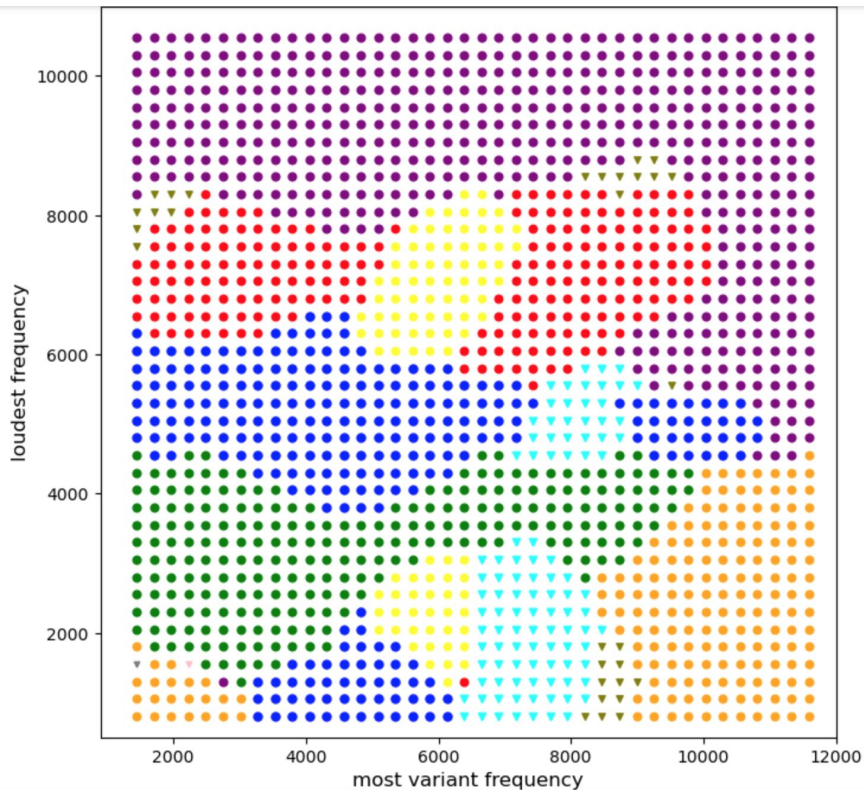
[Baseline guess the most common critter does 57%]

# These two data points are good predictors!

5 most common fam/subfams



Decision boundaries for SVC model



# Whole recording features

-loudest and most variant frequency

-each (of 40) MFCCs mean and variance

-each (of 40) MFCCs mean and variance during the loudest half-second

-range of variant frequencies

-number of chirps per minute

**k-Nearest Neighbors,  
SVC, linear regression**

# Time dependent features

-spectrogram (a 257x862 matrix)

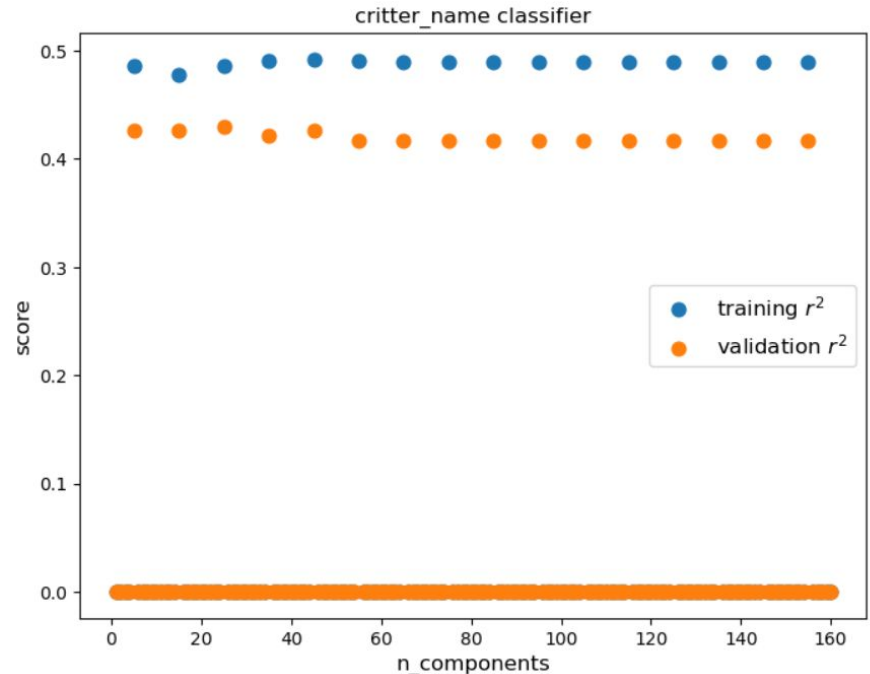
-MFCC/LFCC compression of spectrogram (a 40x216 matrix)

-MFCC compression from loudest half second (a 40x22 matrix)

**Convolutional  
Neural Net**

# Linear regression does not work

- Horizontal: **number of features** to be used in linear regression (obtained by PCA)
- Vertical:  **$r^2$  value** of the linear regression classifier
- **The  $r^2$  value never exceeds 0.5** (close to 1.0 is desirable)



# k-Nearest Neighbors

Classifying 15 families/subfamilies:

- 62% accuracy vs. 24% baseline
  - k=5

Classifying critter name:

- 87% accuracy vs. 67% baseline
  - k=5, trained on family/subfamily
- 89% accuracy vs. 67% baseline
  - k=4, trained on critter name

Using **all whole recording features** gave the greatest accuracy

	Predicted cicada	Predicted cricket	Predicted katydid
Actual cicada	1	4	6
Actual cricket	5	684	100
Actual katydid	2	37	341

	Predicted cicada	Predicted cricket	Predicted katydid
Actual cicada	0	6	5
Actual cricket	0	737	52
Actual katydid	0	74	306

# RBF Support Vector Classifier

Classifying 15 families/subfamilies:

- 67% accuracy vs. 24% baseline
  - C=1.5

Classifying critter name:

- 91% accuracy vs. 67% baseline
  - C=1.5, trained on family/subfamily
- 91% accuracy vs. 67% baseline
  - C=1.4, trained on critter name

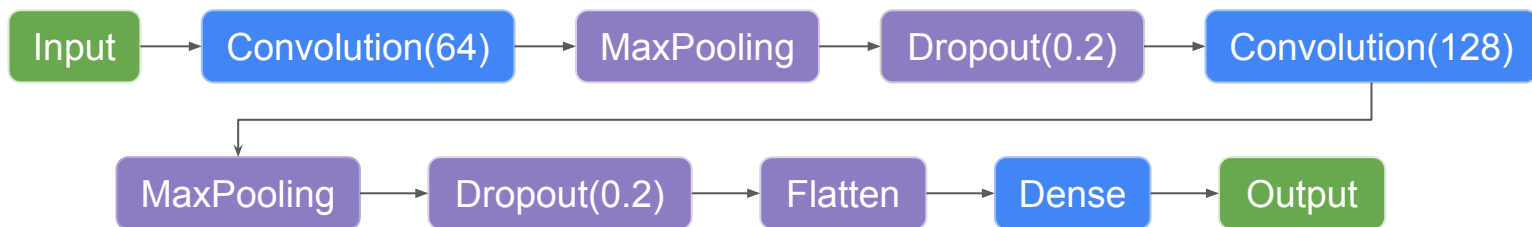
Using **all whole recording features** gave the greatest accuracy

	Predicted cicada	Predicted cricket	Predicted katydid
Actual cicada	0	9	2
Actual cricket	0	742	47
Actual katydid	0	48	332

	Predicted cicada	Predicted cricket	Predicted katydid
Actual cicada	0	9	2
Actual cricket	0	760	29
Actual katydid	0	61	319



# Convolutional Neural Network



- Feature performance:

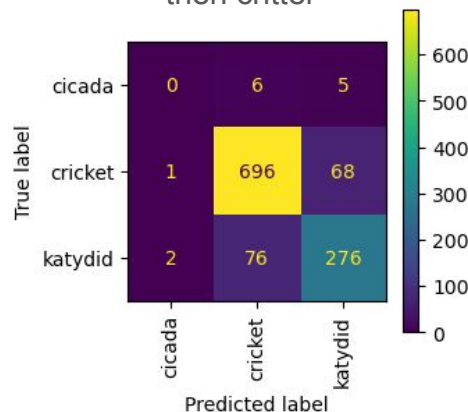
MFCC(5s)  $\approx$  MFCC(0.5s) > MFCC  
mean/var  $\approx$  Spectrogram > LFCC

- Classifying family/subfamily accuracy: 57%\* (86% after converting to critter name)
- Classifying critter name accuracy: 90%\*

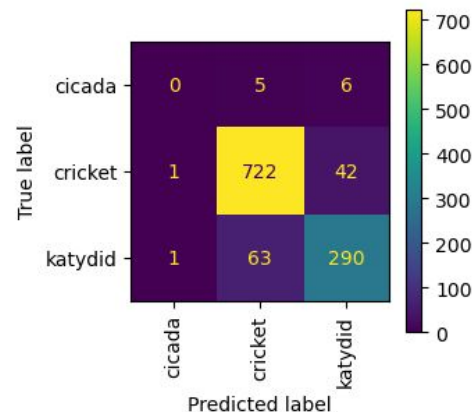
\*Accuracy of guessing the largest family/subfamily: 25%; guessing the largest critter name: 68%\*\*

\*\*Dataset used for CNN is a subset of the dataset used in other models

Classify into fam/subfam then critter



Classify into critter name



# Key Takeaways

## **Model Performance:**

KNN, RBF Support Vector Classifier, and CNN significantly improves classification accuracy compared to baseline.

KNN and RBF Support Vector Classifier perform relatively well compared to linear regression.

# Future work

## **Expand Dataset:**

- Collect additional cicada samples

- Increase the number of samples across all insect groups

## **Quality Comparison:**

- Compare model performance with clean, high-quality samples

- Assess the impact of background noise on classification accuracy

# Future work

## **Noise Reduction:**

Develop and integrate noise reduction techniques

Analyze the effectiveness of various noise filtering methods

## **Real-Time Classification:**

Implement real-time sound classification capabilities

Test model performance in live, field conditions

# Future work

## **Broaden Insect Categories:**

Include additional insect groups beyond crickets, katydids, and cicadas

Examine and classify different families within these insect groups for more detailed analysis

## **User Interface:**

Develop a user-friendly interface for model deployment

Create visualization tools for classification results