Audio Processing With Deep Learning

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Problem Statement

Cornell Birdcall Identification

Objective: Challenge in this project is to identify which birds are calling in long recordings, given training data generated in meaningfully different contexts.

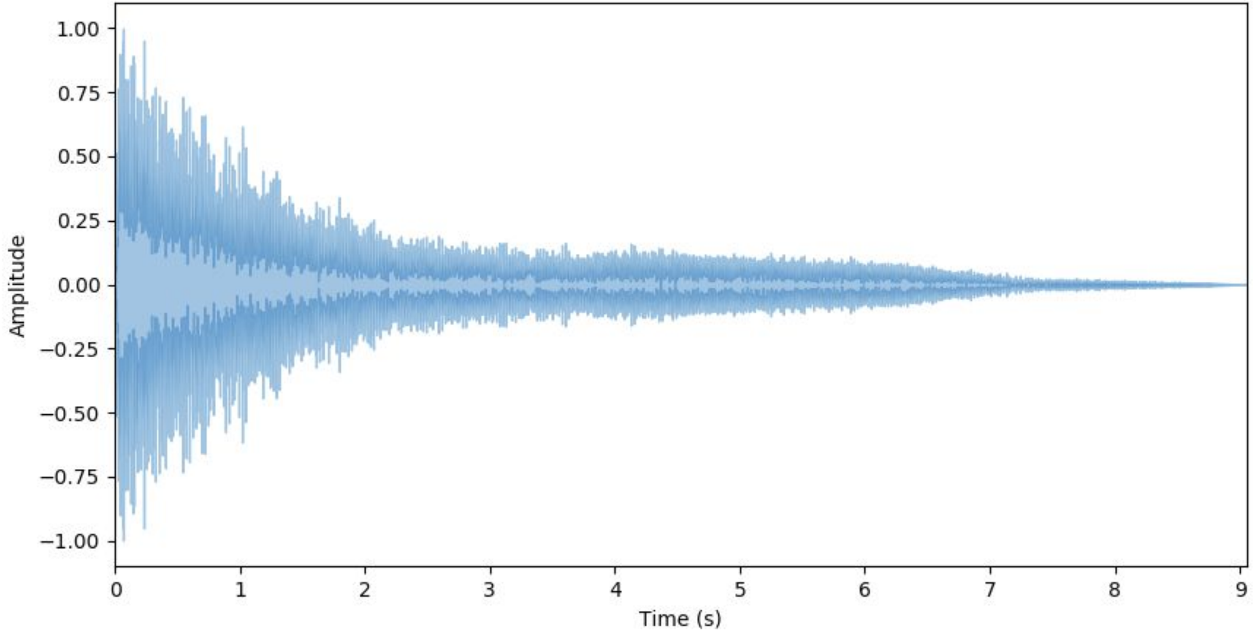
Problem Link: https://www.kaggle.com/c/birdsong-recognition/data

Code Link: https://github.com/abhinav8292/Deep_learning

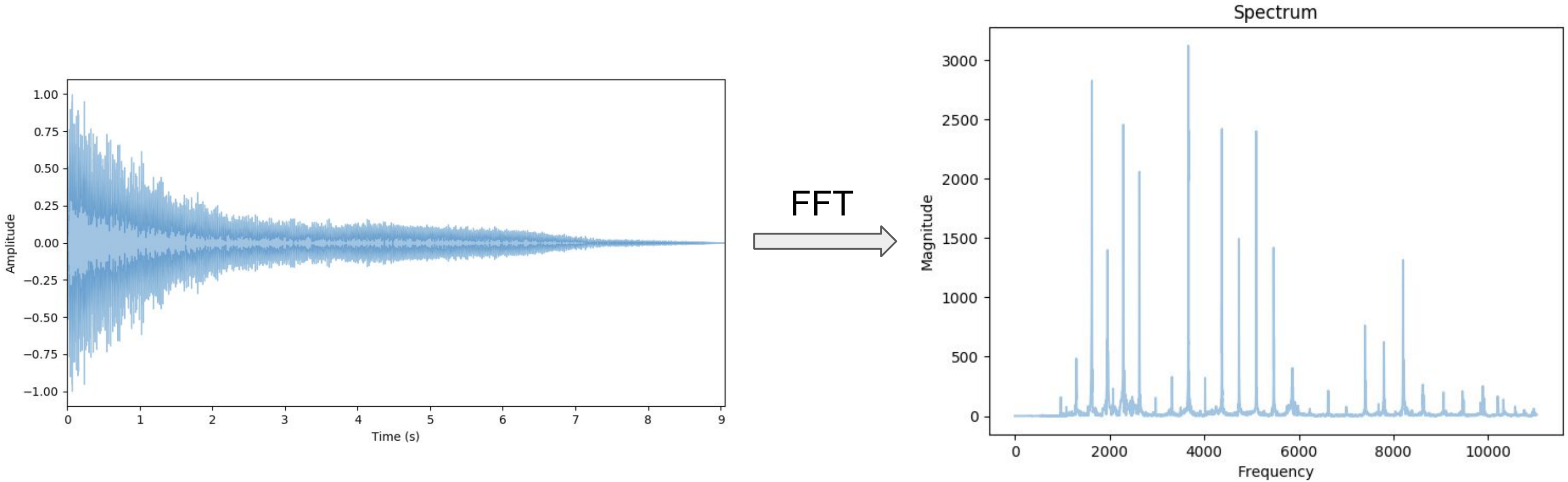
Techstack: Python, Librosa, Numpy, Tensorflow, Matplotlib, Jupyter, VsCode

Understanding audio data for deep learning

A real-world sound wave (piano key)



Fourier transform

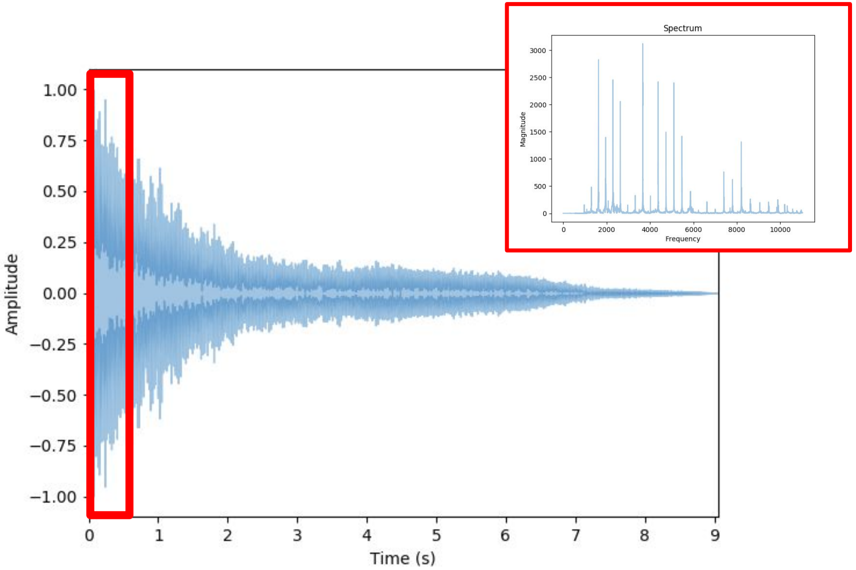


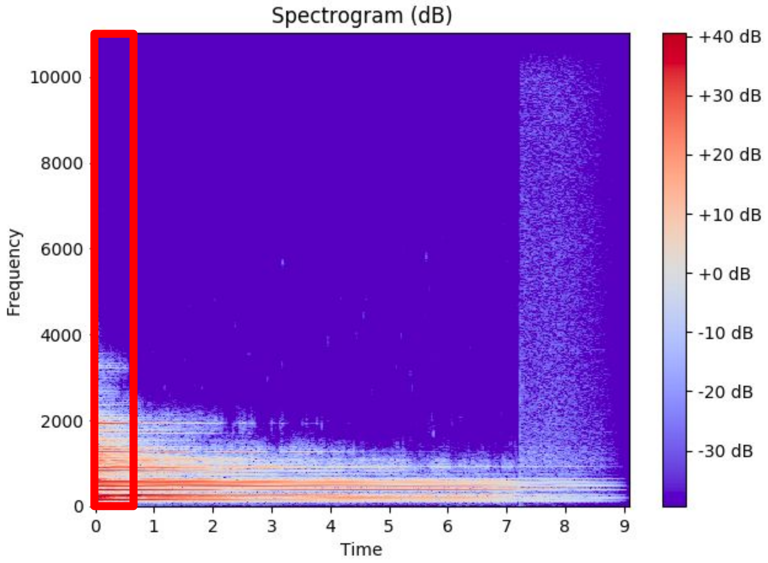
- From *time domain* to *frequency domain*
- No time information

Short Time Fourier Transform (STFT)

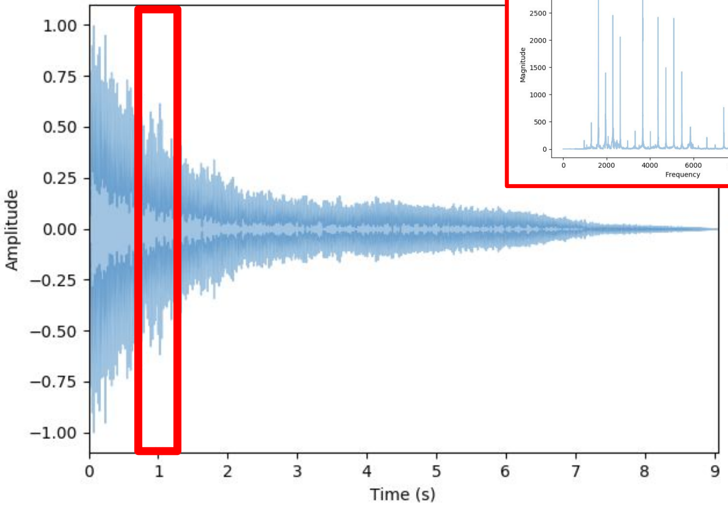
- Computes several FFT at different intervals
- Preserves time information
- Fixed frame size (e.g., 2048 samples)
- Gives a *spectrogram* (time + frequency + magnitude)

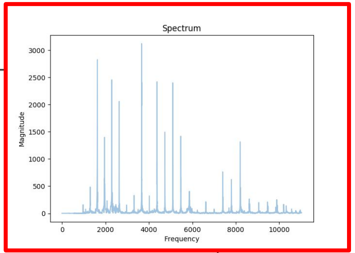
Short Time Fourier Transform (STFT)

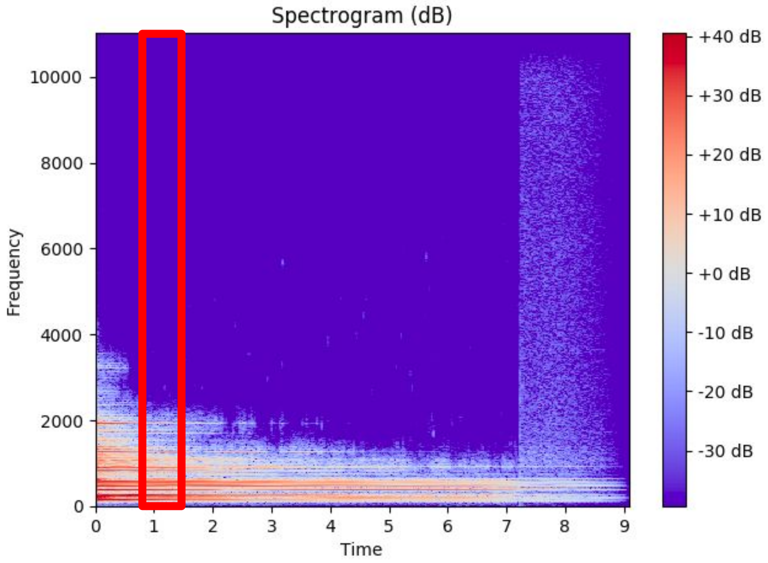




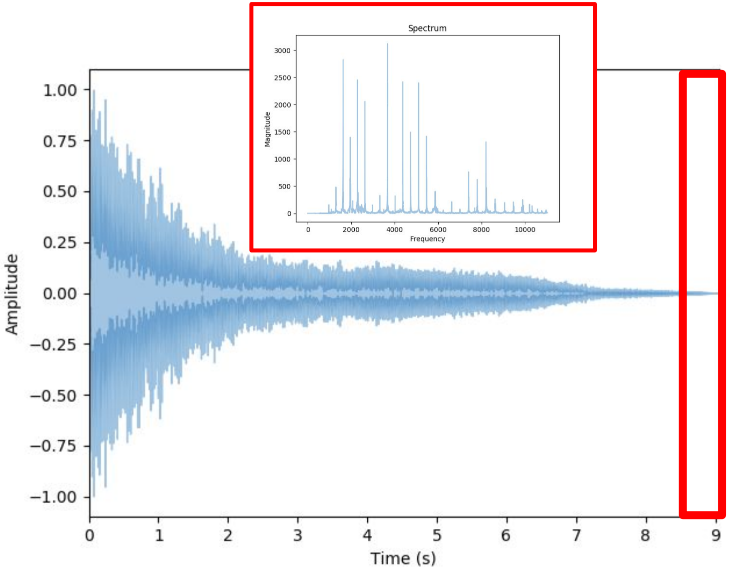
Short Time Fourier Transform (STFT)

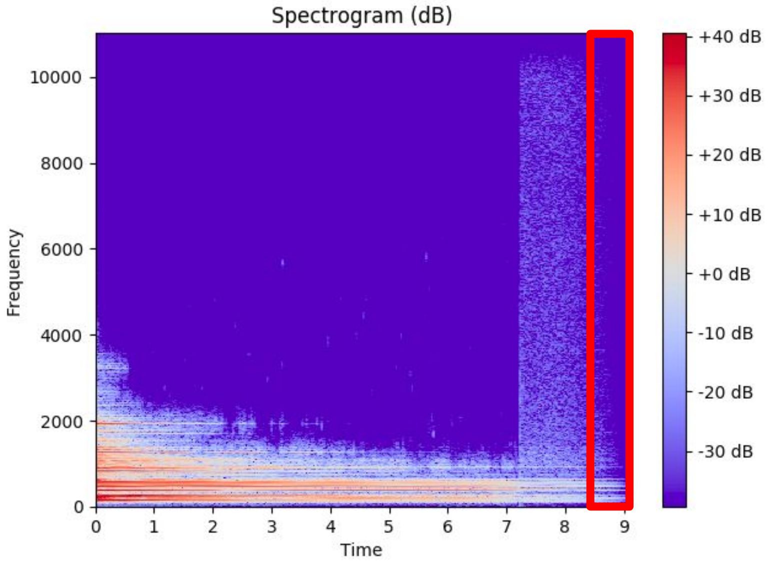




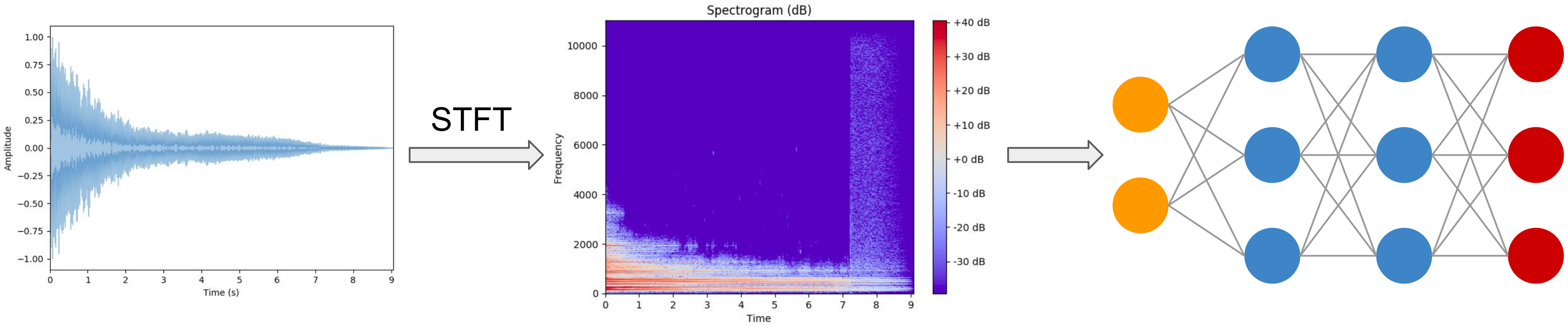


Short Time Fourier Transform (STFT)





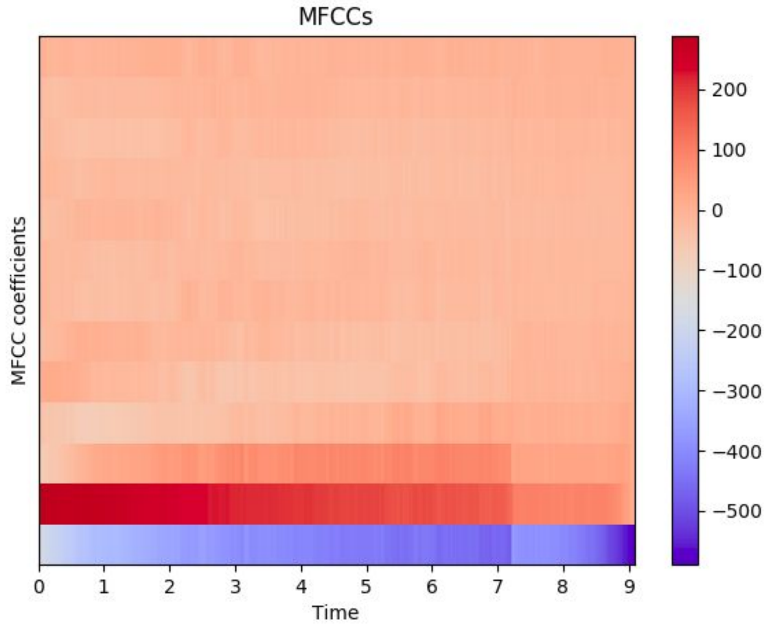
DL pre-proprocessing pipeline for audio data



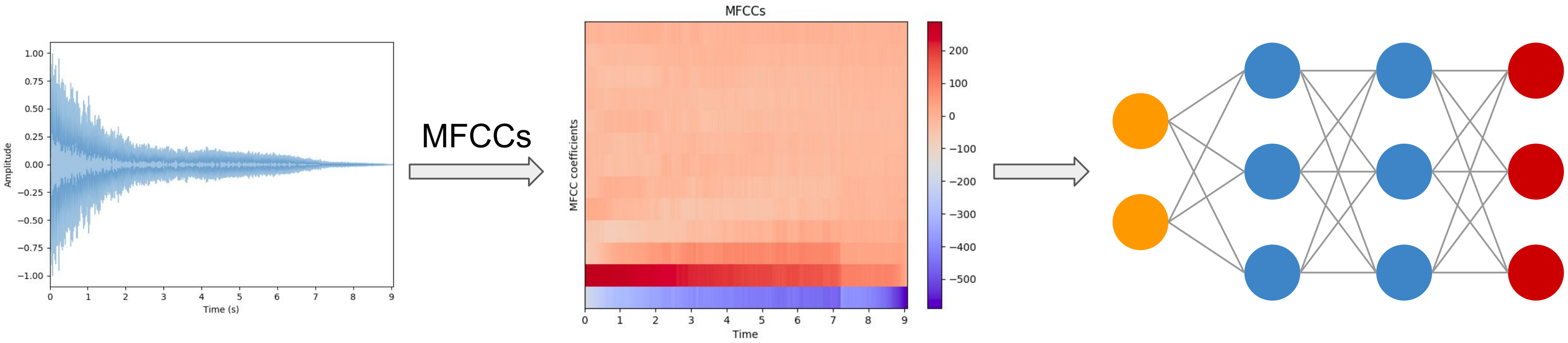
Mel Frequency Cepstral Coefficients (MFCCs)

- Capture timbral/textural aspects of sound
- Frequency domain feature
- Approximate human auditory system
- 13 to 40 coefficients
- Calculated at each frame

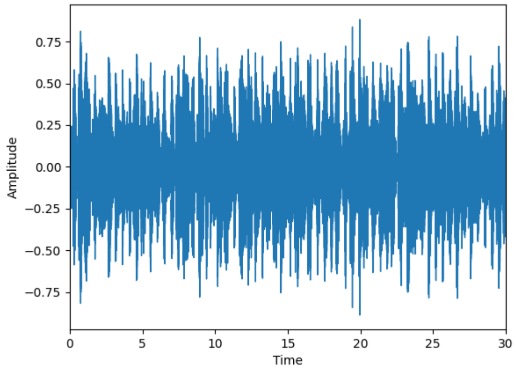
Mel Frequency Cepstral Coefficients (MFCCs)



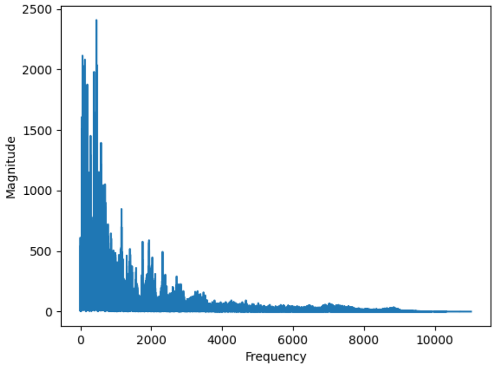
DL pre-proprocessing pipeline for audio data



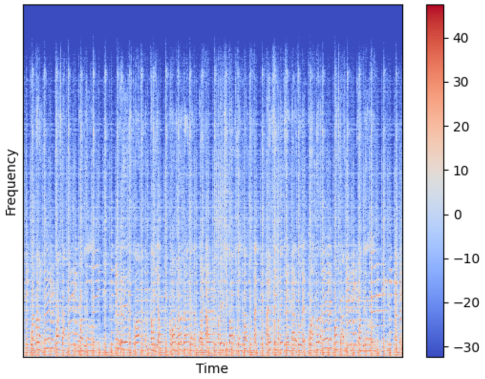
Birdsong Audio Features



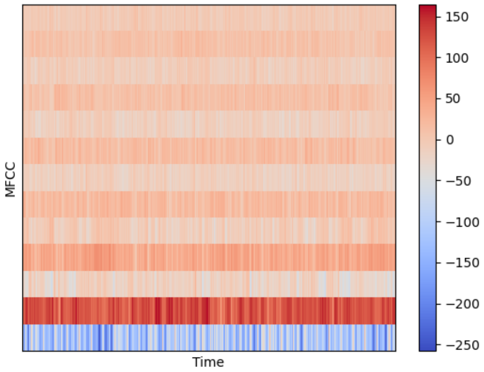
Audio Waveform



FFT

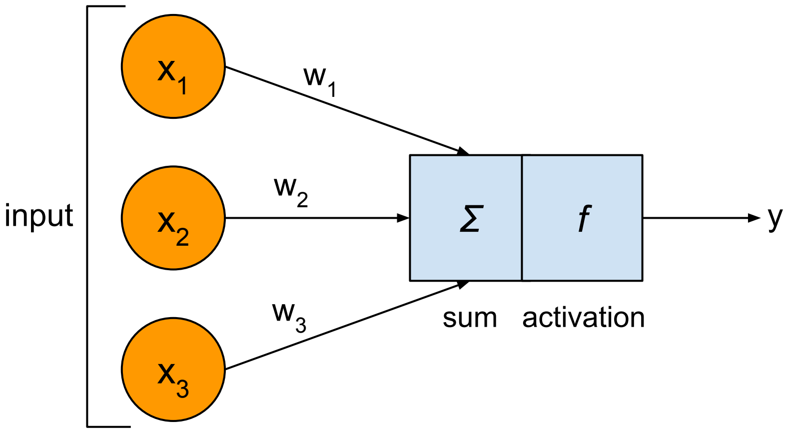


Spectrogram



MFCC

The artificial neuron



$$h = \sum_i x_i w_i = x_1 w_1 + x_2 w_2 + x_3 w_3$$

$$y = f(h) = f(x_1 w_1 + x_2 w_2 + x_3 w_3)$$

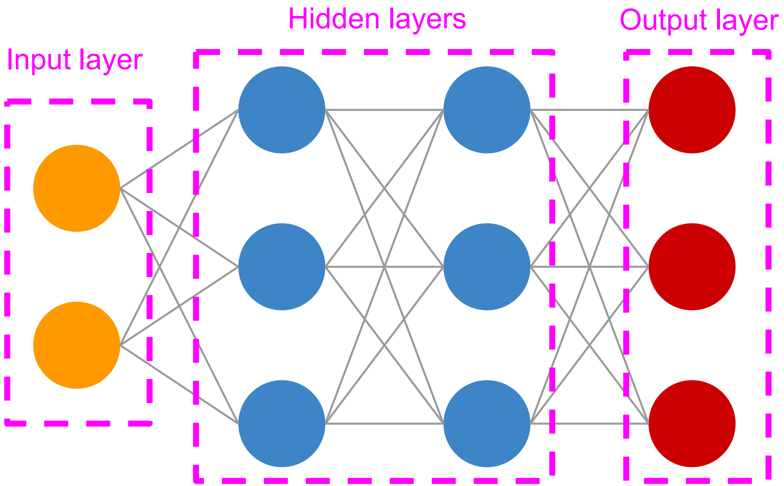
$$y = \frac{1}{1 + e^{-(x_1 w_1 + x_2 w_2 + x_3 w_3)}}$$

Why is a neural network needed?

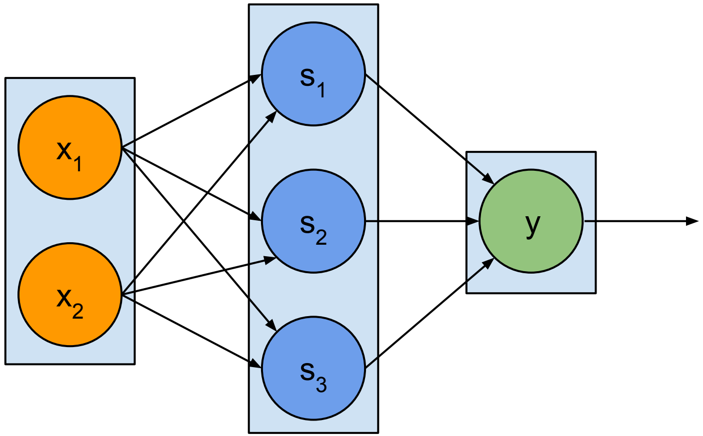
- A single neuron works for linear problems
- Real-world problems are complex
- ANNs can reproduce highly non-linear functions

The components of an artificial neural network (ANN)

- Neurons
- Input, hidden, output layers
- Weighted connections
- Activation function



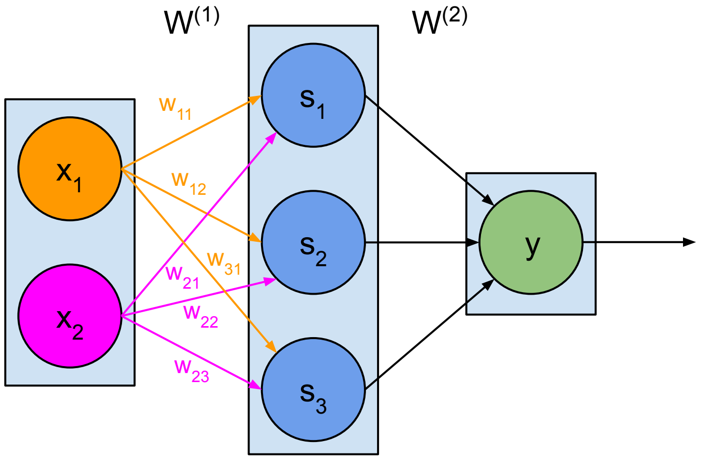
The multilayer perceptron (MLP)



Computation in MLP

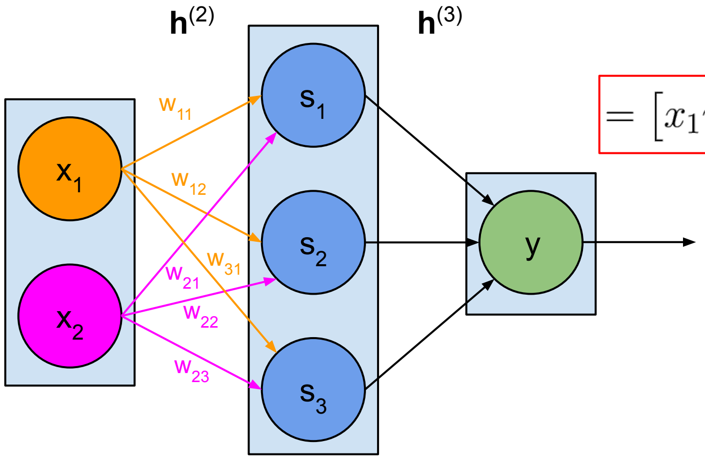
- Weights
- Net inputs (sum of weighted inputs)
- Activations (output of neurons to next layer)

Weights



$$W^{(1)} = \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \end{bmatrix}$$

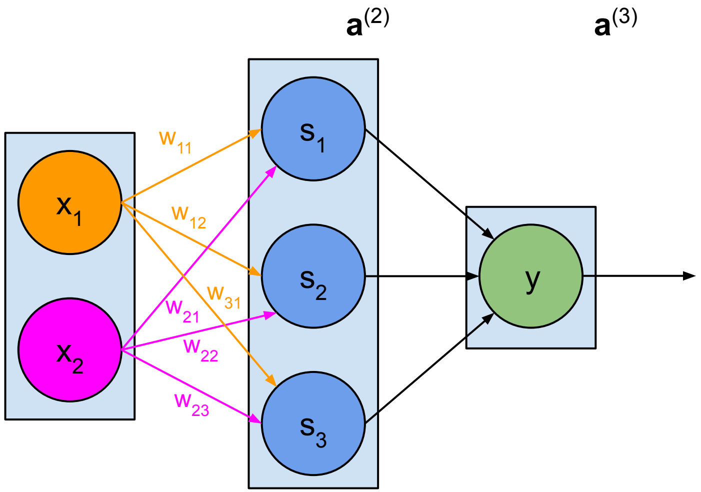
Net input



$$\mathbf{h}^{(2)} = \mathbf{x}W^{(1)} = \begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \end{bmatrix}$$

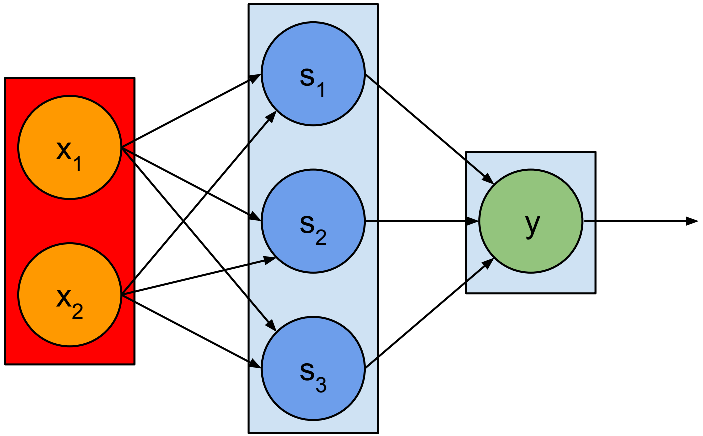
$$\boxed{= \begin{bmatrix} x_1 w_{11} + x_2 w_{21} & x_1 w_{12} + x_2 w_{22} & x_1 w_{13} + x_2 w_{23} \end{bmatrix} = \begin{bmatrix} h_1 & h_2 & h_3 \end{bmatrix}}$$

Activation



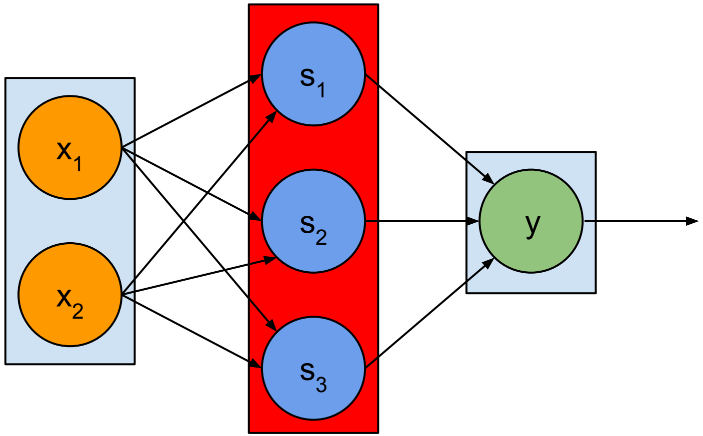
$$\mathbf{a}^{(2)} = f(\mathbf{h}^{(2)})$$

Computation in MLP (1st layer)



$\mathbf{x}$

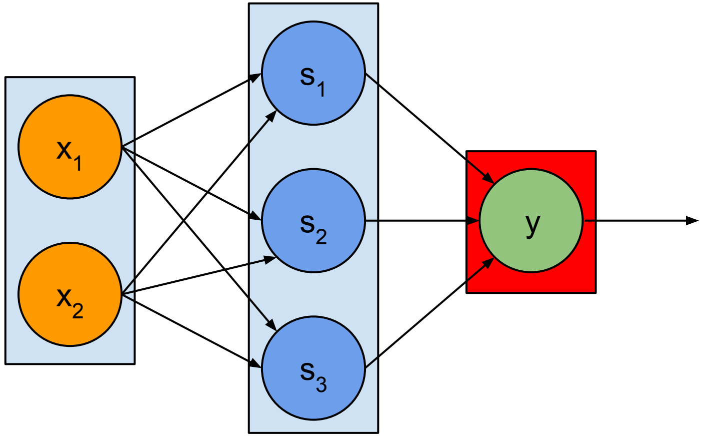
Computation in MLP (2nd layer)



$$\mathbf{h}^{(2)} = \mathbf{x}W^{(1)}$$

$$\mathbf{a}^{(2)} = f(\mathbf{h}^{(2)})$$

Computation in MLP (3d layer)



$$\mathbf{h}^{(3)} = \mathbf{a}^{(\mathbf{2})} W^{(2)}$$

$$y = f(\mathbf{h}^{(3)})$$

Results using MLP

Train Accuracy: 32.27%
Test Accuracy: 29.24%

```
Epoch 30/50
219/219 [==============================] - 5s 21ms/step - loss: 3.0097 - accuracy: 0.2564 - val_loss: 3.0020 - val_accuracy: 0.2423
Epoch 31/50
219/219 [==============================] - 5s 21ms/step - loss: 2.9821 - accuracy: 0.2604 - val_loss: 2.9528 - val_accuracy: 0.2543
Epoch 32/50
219/219 [==============================] - 5s 21ms/step - loss: 2.9545 - accuracy: 0.2665 - val_loss: 2.9373 - val_accuracy: 0.2500
Epoch 33/50
219/219 [==============================] - 5s 21ms/step - loss: 2.9208 - accuracy: 0.2691 - val_loss: 2.8952 - val_accuracy: 0.2607
Epoch 34/50
219/219 [==============================] - 5s 21ms/step - loss: 2.8836 - accuracy: 0.2741 - val_loss: 2.8738 - val_accuracy: 0.2664
Epoch 35/50
219/219 [==============================] - 5s 22ms/step - loss: 2.8497 - accuracy: 0.2835 - val_loss: 2.8267 - val_accuracy: 0.2710
Epoch 36/50
219/219 [==============================] - 5s 21ms/step - loss: 2.8143 - accuracy: 0.2810 - val_loss: 2.8008 - val_accuracy: 0.2680
Epoch 37/50
219/219 [==============================] - 5s 21ms/step - loss: 2.7743 - accuracy: 0.2847 - val_loss: 2.7811 - val_accuracy: 0.2657
Epoch 38/50
219/219 [==============================] - 5s 21ms/step - loss: 2.7386 - accuracy: 0.2910 - val_loss: 2.7171 - val_accuracy: 0.2787
Epoch 39/50
219/219 [==============================] - 5s 21ms/step - loss: 2.7143 - accuracy: 0.2927 - val_loss: 2.6848 - val_accuracy: 0.2810
Epoch 40/50
219/219 [==============================] - 5s 22ms/step - loss: 2.6727 - accuracy: 0.2931 - val_loss: 2.6710 - val_accuracy: 0.2804
Epoch 41/50
219/219 [==============================] - 5s 22ms/step - loss: 2.6408 - accuracy: 0.2990 - val_loss: 2.6394 - val_accuracy: 0.2804
Epoch 42/50
219/219 [==============================] - 5s 21ms/step - loss: 2.6056 - accuracy: 0.3063 - val_loss: 2.6051 - val_accuracy: 0.2891
Epoch 43/50
219/219 [==============================] - 5s 21ms/step - loss: 2.5809 - accuracy: 0.3034 - val_loss: 2.5807 - val_accuracy: 0.2881
Epoch 44/50
219/219 [==============================] - 5s 21ms/step - loss: 2.5459 - accuracy: 0.3059 - val_loss: 2.5477 - val_accuracy: 0.2951
Epoch 45/50
219/219 [==============================] - 5s 22ms/step - loss: 2.5165 - accuracy: 0.3107 - val_loss: 2.5258 - val_accuracy: 0.2887
Epoch 46/50
219/219 [==============================] - 5s 22ms/step - loss: 2.4941 - accuracy: 0.3136 - val_loss: 2.4958 - val_accuracy: 0.2931
Epoch 47/50
219/219 [==============================] - 5s 21ms/step - loss: 2.4538 - accuracy: 0.3139 - val_loss: 2.4737 - val_accuracy: 0.2921
Epoch 48/50
219/219 [==============================] - 5s 22ms/step - loss: 2.4252 - accuracy: 0.3200 - val_loss: 2.4484 - val_accuracy: 0.2967
Epoch 49/50
219/219 [==============================] - 5s 21ms/step - loss: 2.4004 - accuracy: 0.3159 - val_loss: 2.4226 - val_accuracy: 0.2994
Epoch 50/50
219/219 [==============================] - 5s 22ms/step - loss: 2.3664 - accuracy: 0.3227 - val_loss: 2.4033 - val_accuracy: 0.2924
```

CNNs

- Mainly used for processing images
- Perform better than multilayer perceptron
- Less parameters than dense layers

Intuition

- Image data is structured
  - Edges, shapes
  - Translation invariance
  - Scale invariance
- CNN emulates human vision system
- Components of a CNN learn to extract different features

CNN components

- Convolution
- Pooling

Convolution

- *Kernel* = grid of weights
- Kernel is “applied” to the image
- Traditionally used in image processing

1	2	-1
0	1	2
-2	1	0

Convolution

5	2	3	1	2	4
2	4	1	0	3	1
5	1	0	2	8	3
0	2	1	5	2	4
2	7	0	0	2	1
1	3	2	8	7	0

Convolution: Zero padding

Image

0	0	0	0	0	0	0	0
0	5	2	3	1	2	4	0
0	2	4	1	0	3	1	0
0	5	1	0	2	8	3	0
0	0	2	1	5	2	4	0
0	2	7	0	0	2	1	0
0	1	3	2	8	7	0	0
0	0	0	0	0	0	0	0

Kernel

1	0	0
2	1	0
1	0	-1

Output

-1					
	18	10	-3	5	
	12	?	?	?	
	?	?	?	?	
	?	?	?	?	

Convolution

Image

0	0	0	0	0	0	0	0
0	5	2	3	1	2	4	0
0	2	4	1	0	3	1	0
0	5	1	0	2	8	3	0
0	0	2	1	5	2	4	0
0	2	7	0	0	2	1	0
0	1	3	2	8	7	0	0
0	0	0	0	0	0	0	0

Kernel

1	0	0
2	1	0
1	0	-1

Output

-1	?	?	?	?	?
?	18	10	-3	5	?
?	12	?	?	?	?
?	?	?	?	?	?
?	?	?	?	?	?
?	?	?	?	?	?

Kernels

- Feature detectors
- Kernels are learned

Oblique line detector

1	0	0
0	1	0
0	0	1

Vertical line detector

0	1	0
0	1	0
0	1	0

Architectural decisions for convolution

- Grid size
- Stride
- Depth
- Number of kernels

Grid size

- # of pixels for height/width
- Odd numbers

3 by 3

1	2	9
1	6	5
2	2	3

Grid size

- # of pixels for height/width
- Odd numbers

5 by 5

1	2	9	8	7
1	6	5	0	0
2	2	3	1	0
1	1	-3	0	-1
1	-2	2	2	3

Stride

- Step size used for sliding kernel on image
- Indicated in pixels

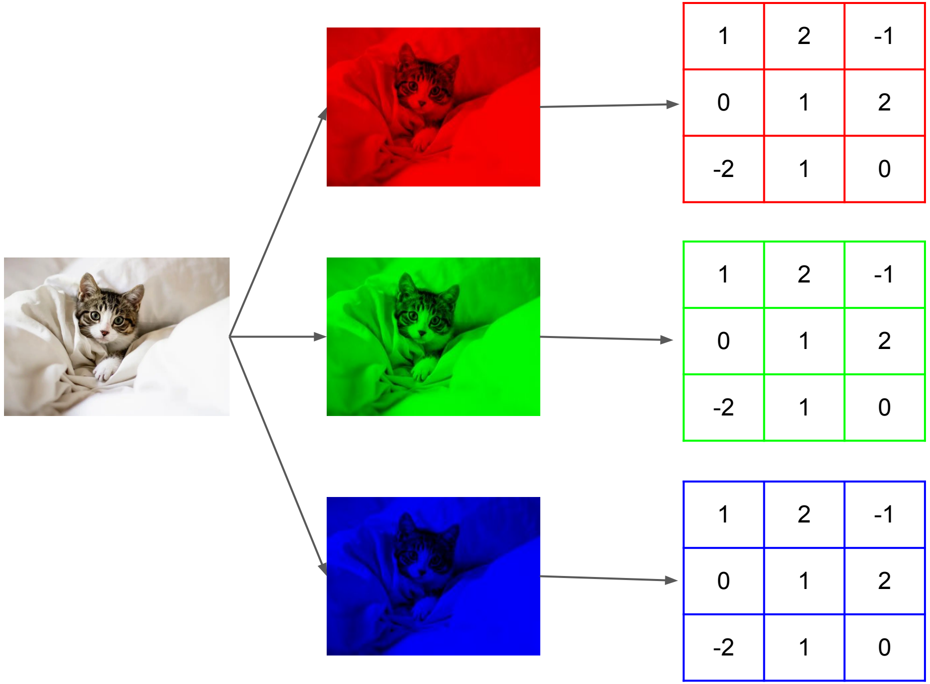
5	2	3	1	2	4
2	4	1	0	3	1
5	1	0	2	8	3
0	2	1	5	2	4
2	7	0	0	2	1
1	3	2	8	7	0

Stride

- Step size used for sliding kernel on image
- Indicated in pixels

5	2	3	1	2	4
2	4	1	0	3	1
5	1	0	2	8	3
0	2	1	5	2	4
2	7	0	0	2	1
1	3	2	8	7	0

Depth



Kernel = 3 x 3 x 3

weights = 27

of kernels

- A conv layer has multiple kernels
- Each kernel outputs a single 2D array
- Output from a layer has as many 2d arrays as # kernels

Pooling

- Downsample the image
- Overlaying grid on image
- Max/average pooling
- No parameters

Pooling settings

- Grid size
- Stride
- Type (e.g., max, average)

Max pooling (2x2, stride 2)

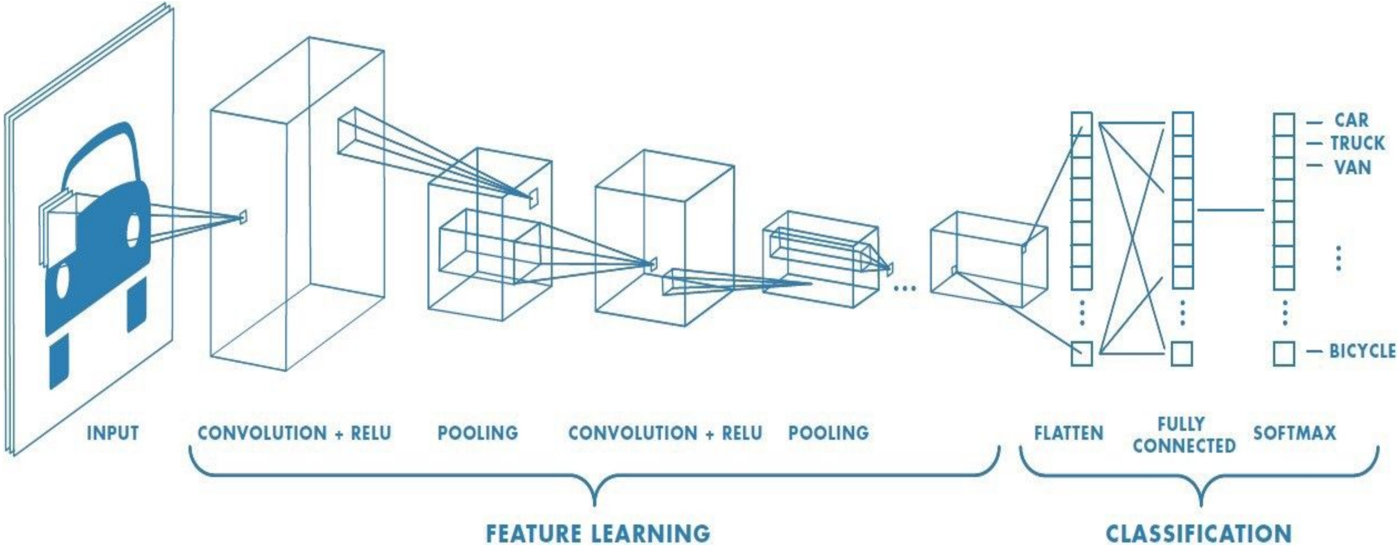
Input

-1	2	0	2
3	18	10	-3
2	12	5	2
1	3	7	4

Output

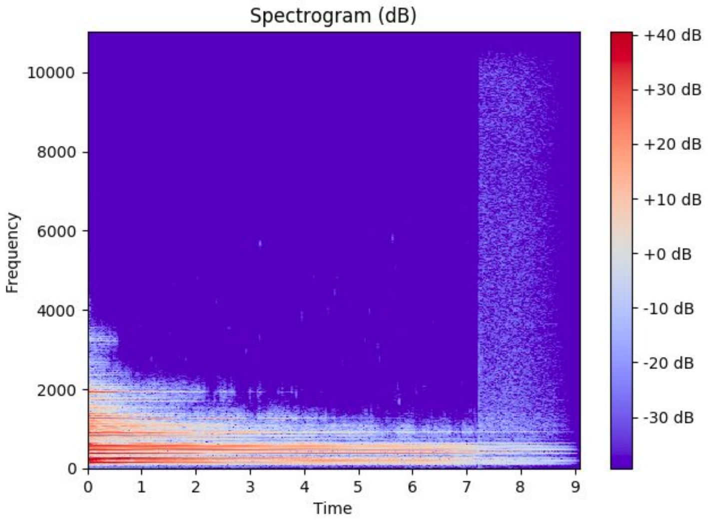
10	18
12	7

CNN architecture



How does convolution/pooling apply to audio?

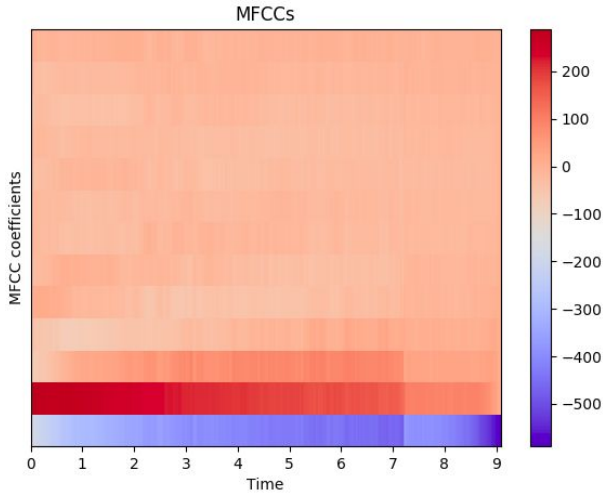
- Spectrogram/MFCC = image
- Time, frequency = x, y
- Amplitude = pixel value



Preparing MFCCs for a CNN

- 13 MFCCs
- Hop length = 512 samples
- # samples in audio file = 51200

Data shape = 100 x 13 x 1



Results Using CNN

Train Accuracy: 74.29%
Test Accuracy: 71.21%%

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL

```
Epoch 10/30
188/188 [==============================] - 6s 35ms/step - loss: 1.2037 - accuracy: 0.5635 - val_loss: 1.1246 - val_accuracy: 0.6021
Epoch 11/30
188/188 [==============================] - 6s 34ms/step - loss: 1.1689 - accuracy: 0.5790 - val_loss: 1.0918 - val_accuracy: 0.6075
Epoch 12/30
188/188 [==============================] - 6s 34ms/step - loss: 1.1256 - accuracy: 0.5981 - val_loss: 1.0733 - val_accuracy: 0.6222
Epoch 13/30
188/188 [==============================] - 6s 33ms/step - loss: 1.1000 - accuracy: 0.6006 - val_loss: 1.0493 - val_accuracy: 0.6235
Epoch 14/30
188/188 [==============================] - 6s 34ms/step - loss: 1.0530 - accuracy: 0.6216 - val_loss: 1.0325 - val_accuracy: 0.6375
Epoch 15/30
188/188 [==============================] - 6s 34ms/step - loss: 1.0505 - accuracy: 0.6266 - val_loss: 1.0265 - val_accuracy: 0.6328
Epoch 16/30
188/188 [==============================] - 6s 34ms/step - loss: 1.0009 - accuracy: 0.6385 - val_loss: 1.0051 - val_accuracy: 0.6449
Epoch 17/30
188/188 [==============================] - 6s 34ms/step - loss: 0.9702 - accuracy: 0.6515 - val_loss: 0.9883 - val_accuracy: 0.6529
Epoch 18/30
188/188 [==============================] - 7s 37ms/step - loss: 0.9548 - accuracy: 0.6688 - val_loss: 0.9621 - val_accuracy: 0.6582
Epoch 19/30
188/188 [==============================] - 6s 33ms/step - loss: 0.9304 - accuracy: 0.6738 - val_loss: 0.9608 - val_accuracy: 0.6602
Epoch 20/30
188/188 [==============================] - 6s 34ms/step - loss: 0.9057 - accuracy: 0.6757 - val_loss: 0.9404 - val_accuracy: 0.6702
Epoch 21/30
188/188 [==============================] - 6s 33ms/step - loss: 0.8945 - accuracy: 0.6874 - val_loss: 0.9596 - val_accuracy: 0.6595
Epoch 22/30
188/188 [==============================] - 6s 33ms/step - loss: 0.8668 - accuracy: 0.6954 - val_loss: 0.9220 - val_accuracy: 0.6689
Epoch 23/30
188/188 [==============================] - 6s 34ms/step - loss: 0.8635 - accuracy: 0.6980 - val_loss: 0.8998 - val_accuracy: 0.6816
Epoch 24/30
188/188 [==============================] - 6s 34ms/step - loss: 0.8404 - accuracy: 0.6990 - val_loss: 0.9145 - val_accuracy: 0.6789
Epoch 25/30
188/188 [==============================] - 6s 34ms/step - loss: 0.8233 - accuracy: 0.7096 - val_loss: 0.9015 - val_accuracy: 0.6876
Epoch 26/30
188/188 [==============================] - 6s 33ms/step - loss: 0.7988 - accuracy: 0.7134 - val_loss: 0.8712 - val_accuracy: 0.6943
Epoch 27/30
188/188 [==============================] - 6s 33ms/step - loss: 0.7670 - accuracy: 0.7276 - val_loss: 0.8711 - val_accuracy: 0.6949
Epoch 28/30
188/188 [==============================] - 6s 33ms/step - loss: 0.7701 - accuracy: 0.7311 - val_loss: 0.8691 - val_accuracy: 0.6943
Epoch 29/30
188/188 [==============================] - 6s 33ms/step - loss: 0.7580 - accuracy: 0.7328 - val_loss: 0.8772 - val_accuracy: 0.6876
Epoch 30/30
188/188 [==============================] - 6s 33ms/step - loss: 0.7398 - accuracy: 0.7429 - val_loss: 0.8612 - val_accuracy: 0.6916
79/79 - 1s - loss: 0.8288 - accuracy: 0.7121
Accuracy on test set is: 0.7120544910430908
Expected index: 4, Predicted index, [4]
```

Observation

Got 29.24% using MLP
Got 71.21% using CNN
CNN gave around 42% more accuracy than MLP

Refrences

Problem link: https://www.kaggle.com/c/birdsong-recognition/overview

Learn Data Science: https://www.youtube.com/watch?v=YJFnBPhTi0Y&t=2825s

Analytics Vidya: https://www.analyticsvidhya.com/blog/2021/05/convolutional-neural-networks-cnn/

viso.ai: https://viso.ai/deep-learning/deep-neural-network-three-popular-types/