

#### **AGENDA**

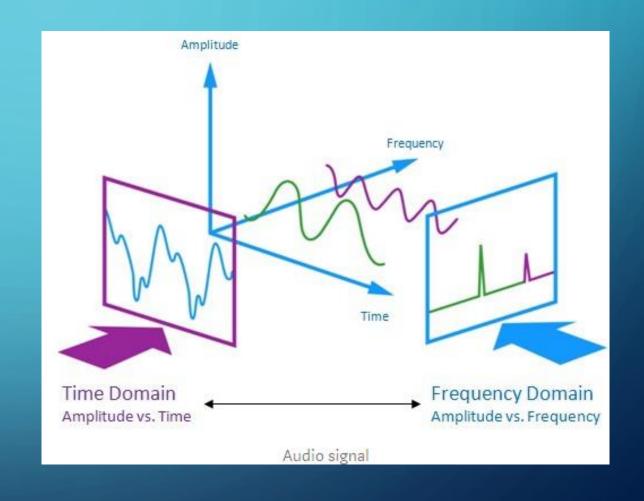
- Problem Statement
- Context Audio Signal
- Feature extraction from Speech
- Model pipeline
- Results (Speaker Recognition / Spoken Digit Recognition)
- Conclusion
- Industry Trends

#### PROBLEM STATEMENT

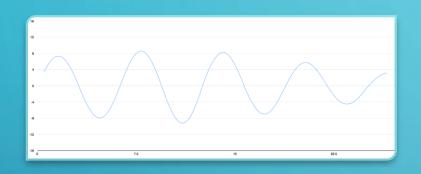
- Business Problem:
  - Biometric authentication using the speech dataset Speaker Recognition (usage : Service Centers)
  - Inference of the digits as said by users on phone Spoken Digit Recognition (usage : Navigate Menu or input digit datasets)

### CONTEXT – AUDIO SIGNAL

- Audio signal is a three-dimensional signal in which three axes represent time, amplitude and frequency.
- Problems:
  - "Ooonnnnneeeee" vs "One!"
  - Align audio files of various length to a fixed piece
  - Convert audio wave into set of numbers record the height of wave at equallyspaced points.



### AUDIO WAVE SAMPLING — CONVERTING WAVE TO NUMBERS



- Reading thousands of times a second and recording number representing the height of sound wave at that time
- Speech recognition can be done at a sampling rate of 16Khz (16000 times per second

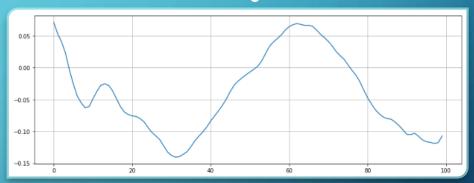
-1274, -1252, -1160, -986, -792, -692, -614, -429, -286, -134, -57, -41, -169, -456, -450, -541, -761, -1067, -1231, -1047, -952, -645, -489, -448 -397, -212, 193, 114, -17, -110, 128, 261, 198, 390, 461, 772, 948, 1451, 1974, 2624, 3793, 4968, 5939, 6057, 6581, 7302, 7640, 7223, 6119, 5461, 4820, 4353, 3611, 2740, 2004, 1349, 1178, 1085, 901, 301, -262, -499, -488, -707, -1406, -1997, -2377, -2494, -2605, -2675, -2627, -2500, -2148, -648, -970, -364, 13, 260, 494, 788, 1011, 938, 717, 507, 323, 324, 325, 350, 103, -113, 64, 176, 93, -249, -461, -606, -909, -1159, -1307, -1544]

Here is an example of sample for "Hello"

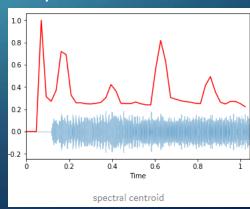
#### FEATURE ENGINEERING

- Energy / RMSE: The of a signal corresponds to the total magnitude of the signal and roughly corresponds to how loud the signal is. The energy in a signal is defined by  $\sum n|x(n)|2$ . The root mean square of this formula is called RMSE
- Zero Crossing Rate: Rate of sign changes along a signal (ie the rate at which the signal changes from positive to negative or back.
- Spectral Centroid: It indicates where the "center of mass" for a sound is located and is calculated as weighted mean of the frequencies present in the sound.

#### **Zero Crossing Rate**

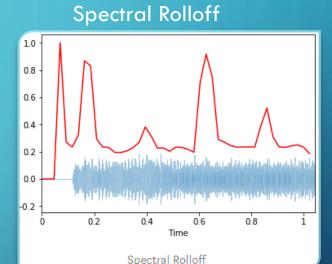


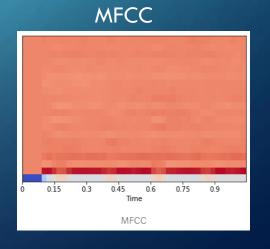
Spectral centroid



#### FEATURE ENGINEERING

- **Spectral Roll off**: It's the frequency below which a specified percentage of the total spectral energy, e.g. 85%, lies.
- **Chroma**: It's a typically 12-element feature vector indicating how much energy of each pitch class is present in the signal
- Spectral Bandwidth: It's the p'th-order spectral bandwidth.
- MFCC (Mel-Frequency Cepstral Coefficients): These are small set of features (usually about 10–20) which concisely describe the overall shape of a spectral envelope.
  - PS: It uses Fourier transform, to break apart the complex sound wave into the simple sound waves and then add up to get a sum of energy contained in each one.





# MODEL PIPELINE – SPEAKER RECOGNITION / SPOKEN DIGIT RECOGNITION

Extract sound features

Preprocess and transform the dataset

Apply the Neural Network (Keras)

Tensorflow backend

Prediction

Calculate accuracy matrix

#### DATA PREPROCESSING STEPS

- Step 1: Sound features extraction using librosa
- Step 2: Reading through the files in training set and appending to train matrix
- Step 3: Data Classification and labelling
- Step 4: Data Scaling of the feature set
- Step 5: Divide the dataset into training, validation and test set

#### NEURAL NETWORK EXPLAINED

Denselayer(256, relu)

Dropout(0.5)

Denselayer(128, relu)

Dropout(0.5)

Denselayer(64m relu)

Dropout(0.5)

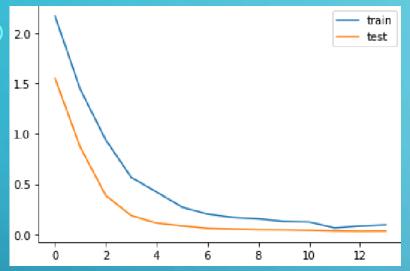
Denselayer(10,softmax)

#### TEST DATA EXPLAINED

• Experiment 1: Got the speech dataset for 3 users (Jackson, Theo, Nicholas) for digits 0-9 repeated 49 different (training) and use the last one set as the test sample.

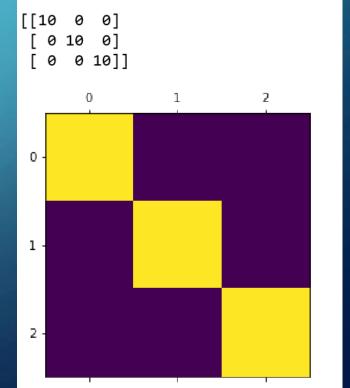
• Experiment 2: Got the speech dataset for 3 additional users (Ankur, Rodolfo, Caroline) for digits 0-9 (training) and use the another speech set as the test sample.

## MODEL RESULTS : SPEAKER RECOGNITION EXP - 1

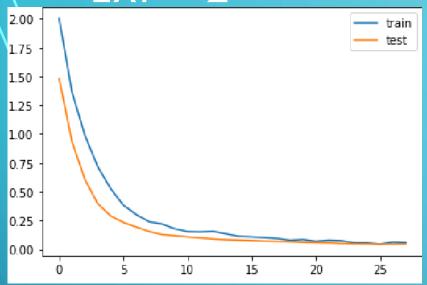


- Train Data Set 1 :: (Jackson, Theo, Nicholas) 48 samples of each digit
- Test Data 1: (Jackson, Theo, Nicholas) 49<sup>th</sup>
   recording
   Classification Report for Test Data
- Accuracy: 100% (predict speaker)

Classification Report					
	precision	recall	f1-score	support	
0	1.00	1.00	1.00	10	
1	1.00	1.00	1.00	10	
2	1.00	1.00	1.00	10	
			4 00		
accuracy			1.00	30	
macro avg	1.00	1.00	1.00	30	
weighted avg	1.00	1.00	1.00	30	

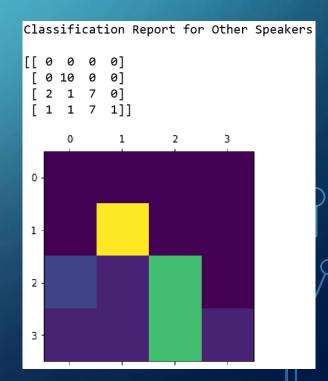


## MODEL RESULTS: SPEAKER RECOGNITION EXP - 2

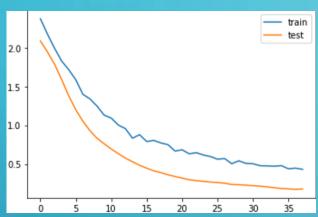


- Train Data Set 2 : : (Jackson, Theo, Nicholas) 48
   samples of each digit + (Ankur, Rodolfo, Caroline)
   1 sample for each digit
- Test Data 2: (Ankur, Rodolfo, Caroline) one recording
- Accuracy: 60% (Predict speaker)

Classification	n Report			
	precision	recall	f1-score	support
0	0.00	0.00	0.00	0
3	0.83	1.00	0.91	10
4	0.50	0.70	0.58	10
5	1.00	0.10	0.18	10
accuracy			0.60	30
macro avg	0.58	0.45	0.42	30
weighted avg	0.78	0.60	0.56	30

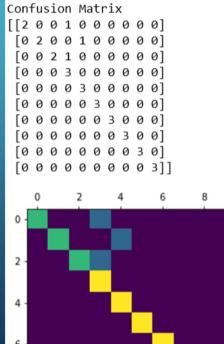


### MODEL RESULTS: SPOKEN DIGIT RECOGNITION EXP - 1



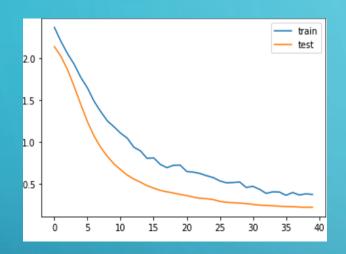
- Train Data Set 1 :: (Jackson, Theo, Nicholas) 48 samples of each digit
- Test Data 1: (Jackson, Theo, Nicholas) 49<sup>th</sup> recording
- Accuracy: 90% (predict digit from audio)

Classificatio	n Report				
	precision	recall	f1-score	support	
0	1.00	0.67	0.80	3	
1	1.00	0.67	0.80	3	
2	1.00	0.67	0.80	3	
3	0.60	1.00	0.75	3	
4	0.75	1.00	0.86	3	
5	1.00	1.00	1.00	3	
6	1.00	1.00	1.00	3	
7	1.00	1.00	1.00	3	
8	1.00	1.00	1.00	3	
9	1.00	1.00	1.00	3	
accuracy			0.90	30	
macro avg	0.93	0.90	0.90	30	
weighted avg	0.94	0.90	0.90	30	



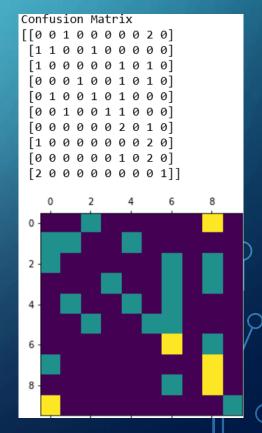
### MODEL RESULTS: SPOKEN DIGIT RECOGNITION

**EXP - 2** 



- Train Data Set 2:: (Jackson, Theo, Nicholas) 48
   samples of each digit + (Ankur, Rodolfo, Caroline)
   1 sample for each digit
- Test Data 2: (Ankur, Rodolfo, Caroline) one recording
- Accuracy: 30% (predict digit from audio)

Classification Report				
	precision	recall	f1-score	support
0	0.00	0.00	0.00	3
1	0.50	0.33	0.40	3
2	0.00	0.00	0.00	3
3	1.00	0.33	0.50	3
4	0.50	0.33	0.40	3
5	1.00	0.33	0.50	3
6	0.29	0.67	0.40	3
7	0.00	0.00	0.00	3
8	0.22	0.67	0.33	3
9	1.00	0.33	0.50	3
accuracy			0.30	30
macro avg	0.45	0.30	0.30	30
weighted avg	0.45	0.30	0.30	30



#### CONCLUSION



Neural networks can help predict both spoken digits and speaker to a great extent with an accuracy of more than 90%



Lots of training dataset is required in order to get a good working model.



The models fails to give good accuracy results for new speakers.

Possible Reasons:

More noise signals

Ethnicity and origin of country can change the features of

audio.

### INDUSTRY TRENDS



#### Good

Alexa / Siri / Google : Able to understand majority of our voice commands

Multifactor authentication includes some speech analysis to confirm user identity.



#### Bad

Privacy concerns around speech datasets and requirements to store a lot of datasets in order to predict correctly.

Increase in Voice Deepfakes attacks:

https://www.forbes.com/sites/jesse damiani/2019/09/03/a-voicedeepfake-was-used-to-scam-a-ceoout-of-243000/#1e4979a52241

#### PROJECT DETAILS

- Github location:
  - https://github.com/ravasconcelos/spoken-digits-recognition
- Youtube video: <a href="https://www.youtube.com/watch?v="https://www.youtube.com/watch

