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Hardware Architectures for Embedded and Edge AI

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Exercise session 5 – Keyword spotting training

What's keyword spotting?

- Keyword spotting is one of the most successful examples of TinyML
 - Low-power, continuous, on-device
 - Started with english, expanded to many more languages (on-going process)
- General ASR (Automatic Speech Recognition) still requires larger, power-hungry models
 - But it can run on mobile devices (offline dictation on smartphones)

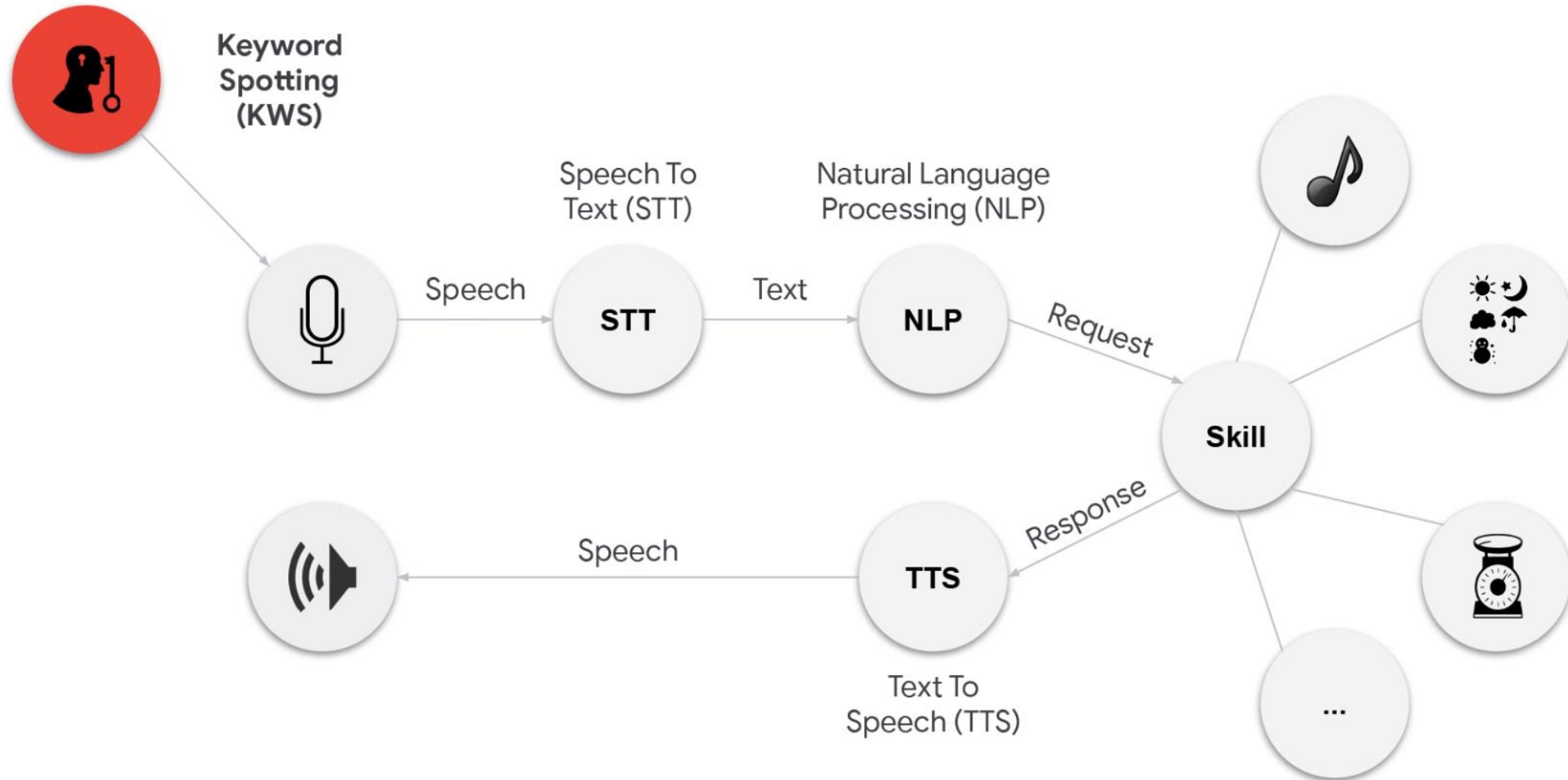


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The application



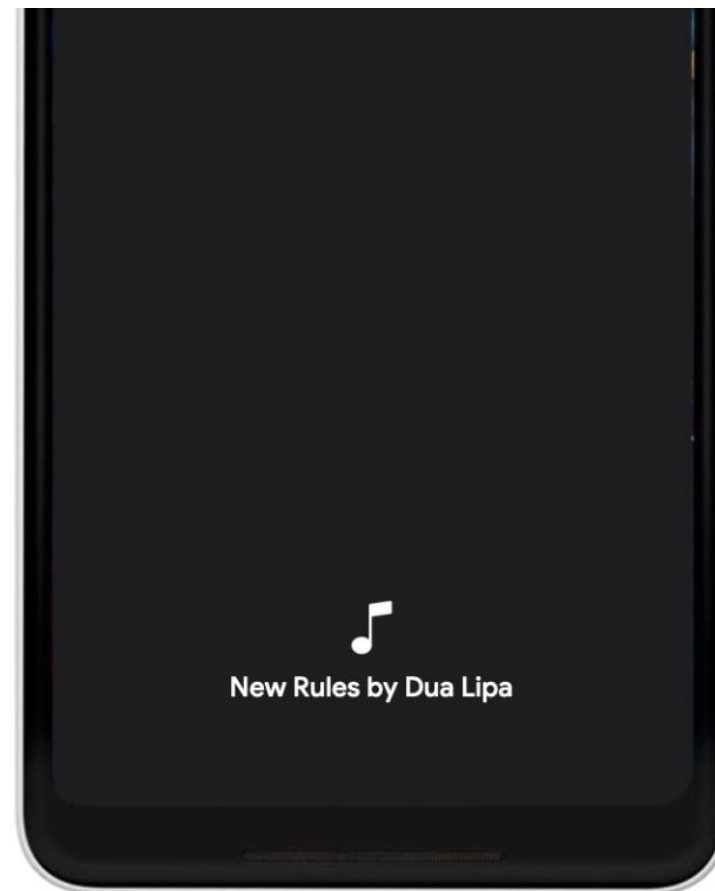
Cascade infrastructure!



Interesting application with audio?

What else can TinyML do with audio data?

Now Playing
by Google



Challenges in wake-word detection



Latency & Bandwidth



Accuracy & Personalization



Security & Privacy



Battery & Memory

Challenges in wake-word detection



Latency & Bandwidth



Accuracy & Personalization



Security & Privacy



Battery & Memory

Latency

Provide results
quickly, respond
in **real-time** to
the user

Challenges in wake-word detection



Latency & Bandwidth



Accuracy & Personalization



Security & Privacy



Battery & Memory

Bandwidth

Minimize data sent over the network (slow and expensive)

Challenges in wake-word detection



Latency & Bandwidth



Accuracy & Personalization



Security & Privacy



Battery & Memory

Accuracy

Listen
continuously,
but only trigger
at the right time

Challenges in wake-word detection



Latency & Bandwidth



Accuracy & Personalization



Security & Privacy



Battery & Memory

Personalization

Trigger for the user and **not** for background noise

Challenges in wake-word detection



Latency & Bandwidth



Accuracy & Personalization



Security & Privacy



Battery & Memory

Security

Safeguarding the data that is being sent to the cloud
(from a malevolous actor)

Challenges in wake-word detection



Latency & Bandwidth



Accuracy & Personalization



Security & Privacy



Battery & Memory

Privacy

Safeguarding the data that is being sent to the cloud (from anyone)

Challenges in wake-word detection



Latency & Bandwidth



Accuracy & Personalization



Security & Privacy



Battery & Memory

Battery

Limited energy,
operate on
coin-cell type
batteries

Challenges in wake-word detection



Latency & Bandwidth



Accuracy & Personalization



Security & Privacy

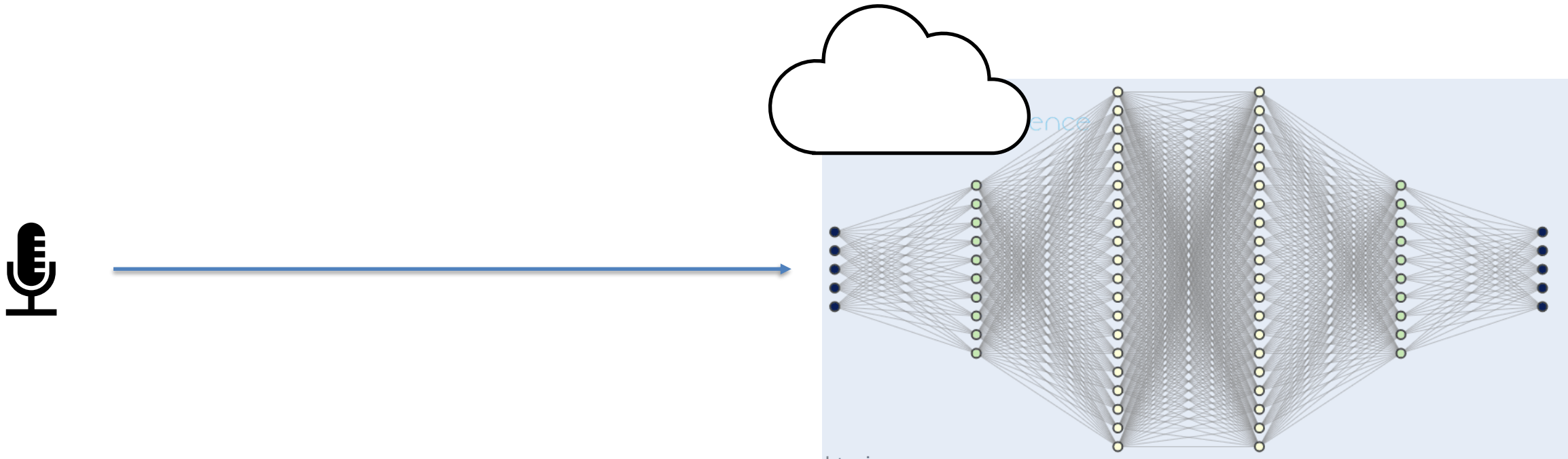


Battery & Memory

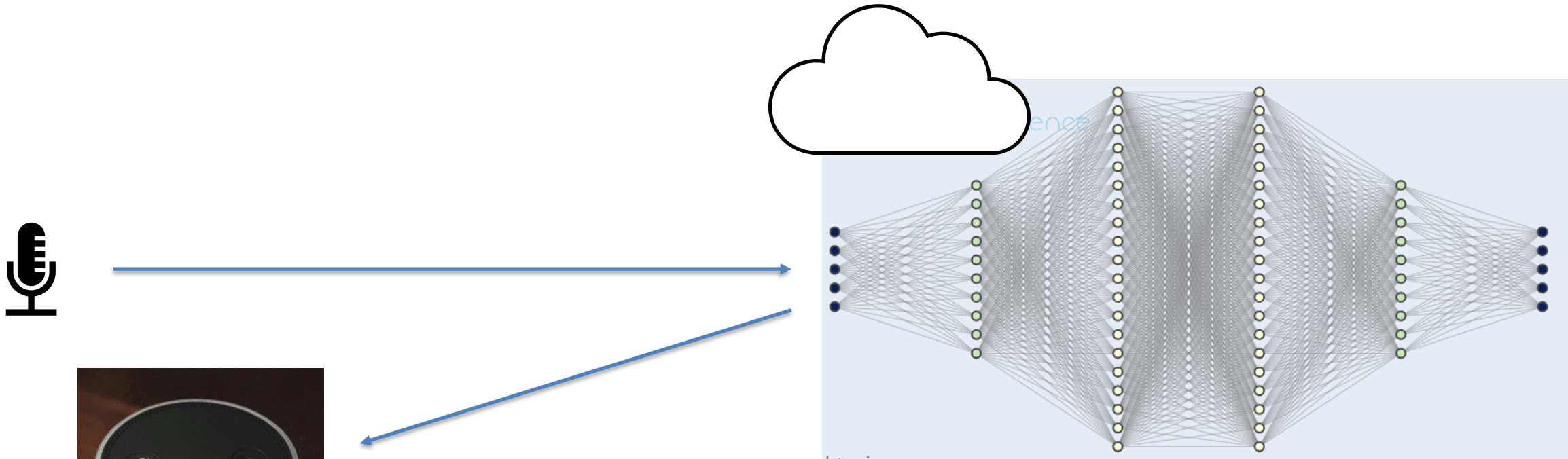
Memory

Run on resource
constrained
devices

Why do we need keyword spotting?



Why do we need keyword spotting?



Play response

Need #1: Latency

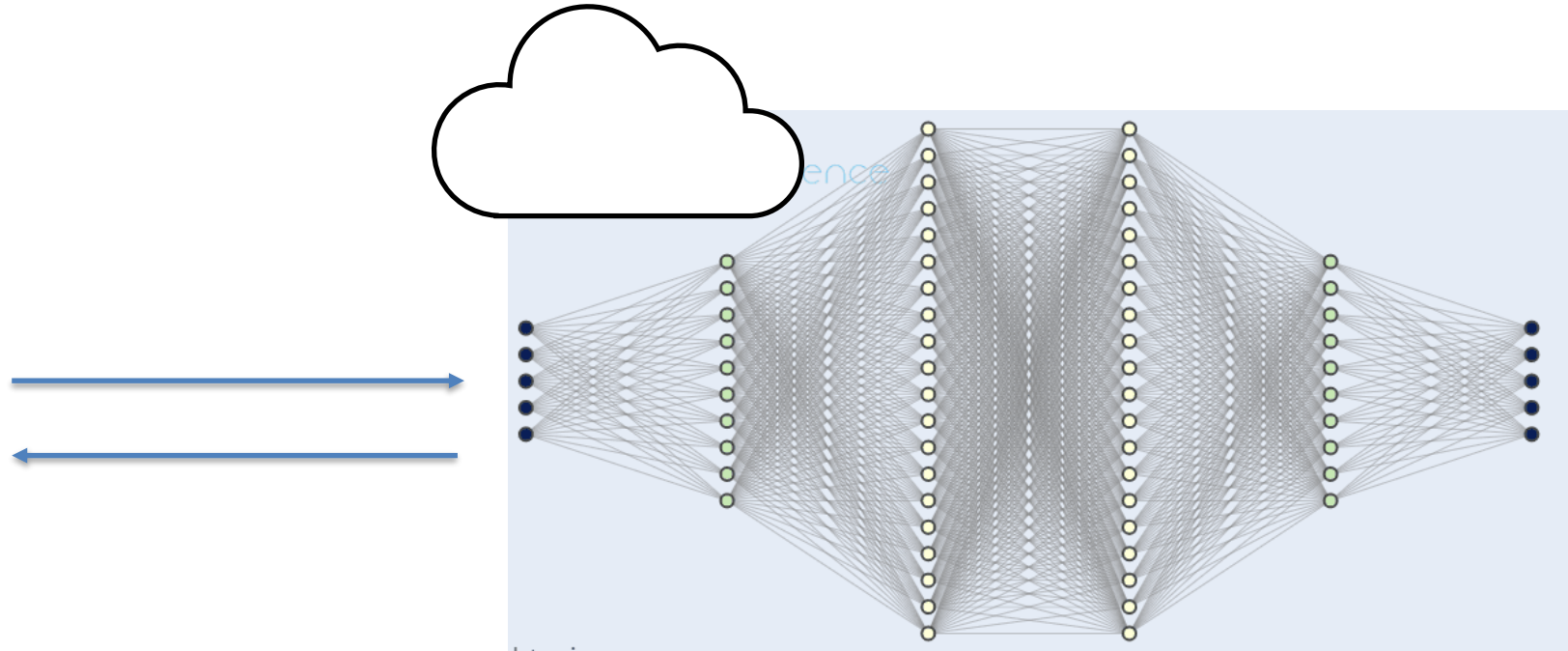
Why do we need keyword spotting?



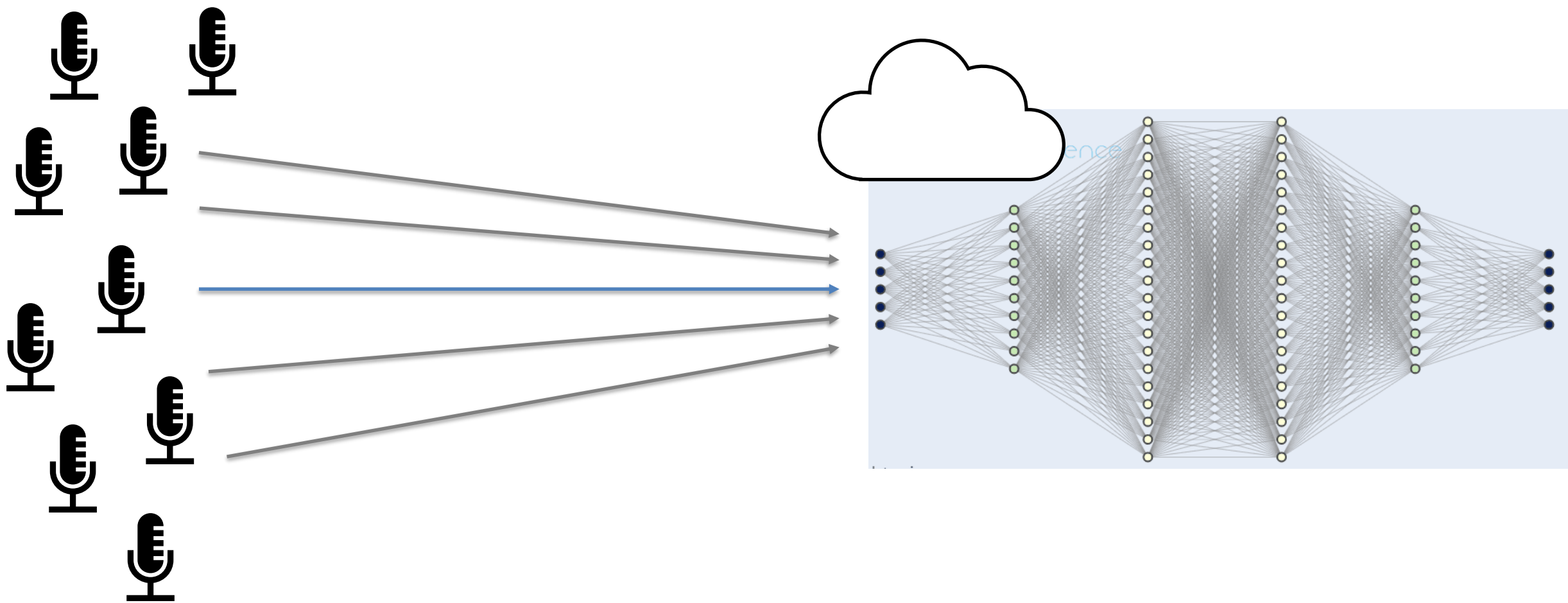
1 – KS detection:
visual feedback



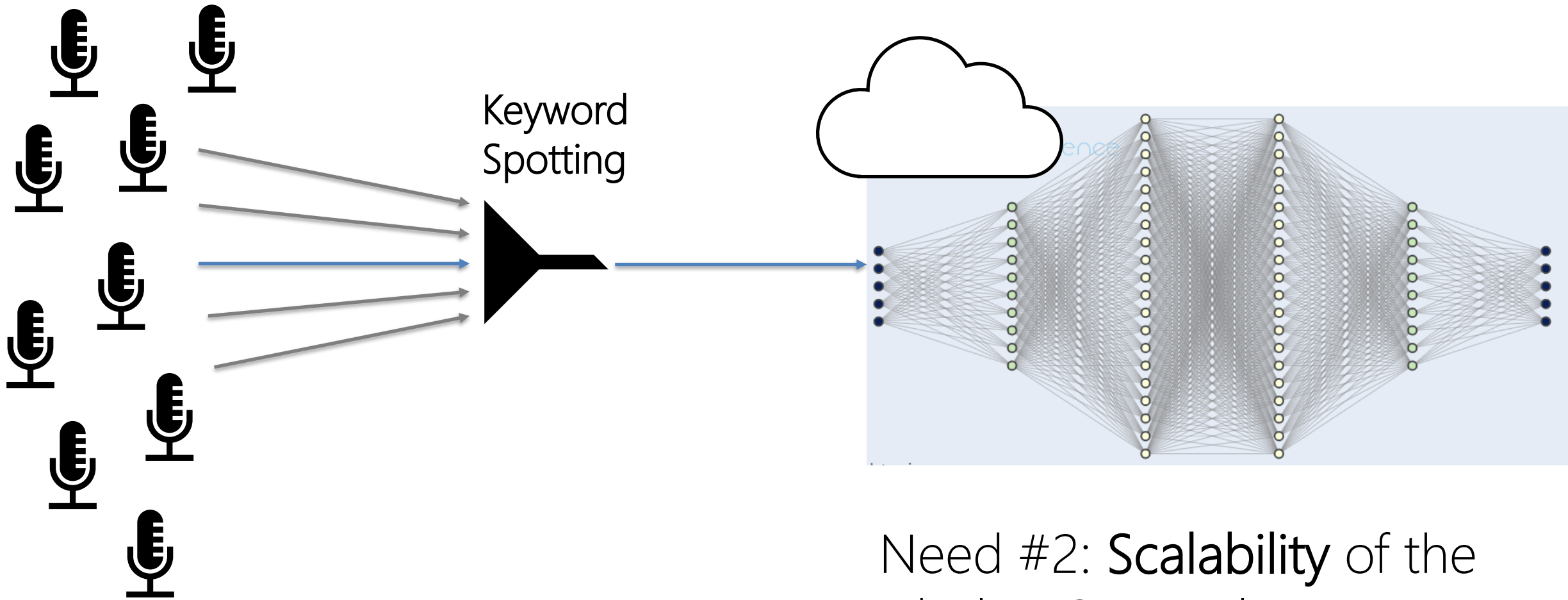
2- Play
response



Why do we need keyword spotting?



Why do we need keyword spotting?

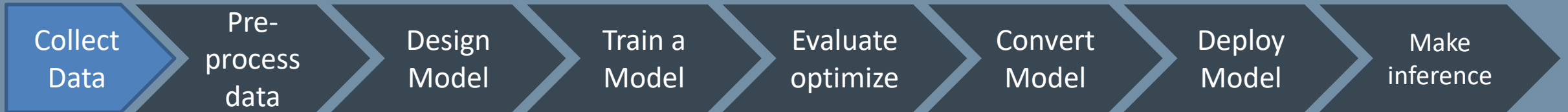


Need #2: **Scalability** of the whole ASR pipeline



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The input data



Data collection with edge impulse


 Data collection

Label: silence

Length: 10s.

Category: Training

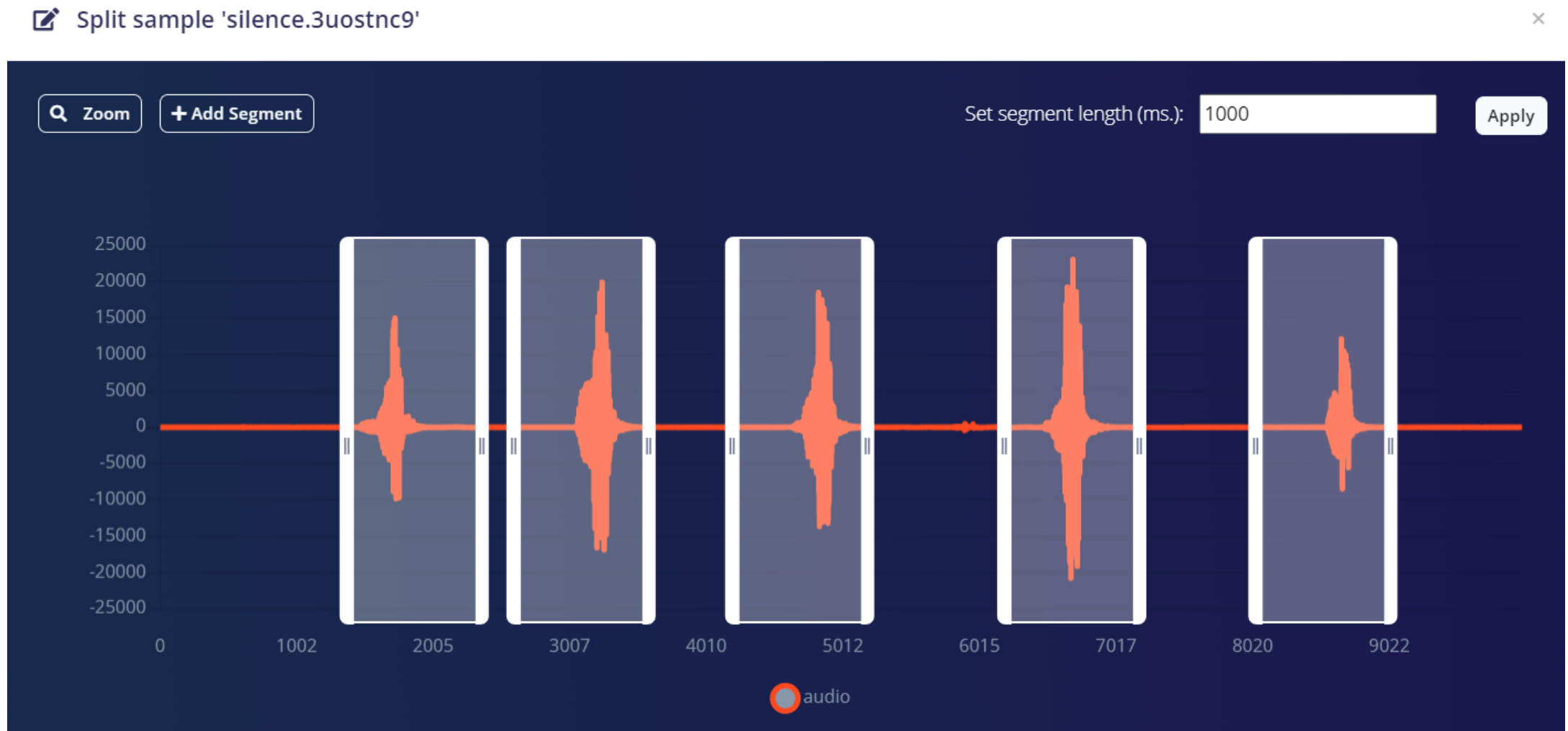


 Start recording

Audio captured with current settings: 10s



Data collection with edge impulse



Keyword spotting dataset

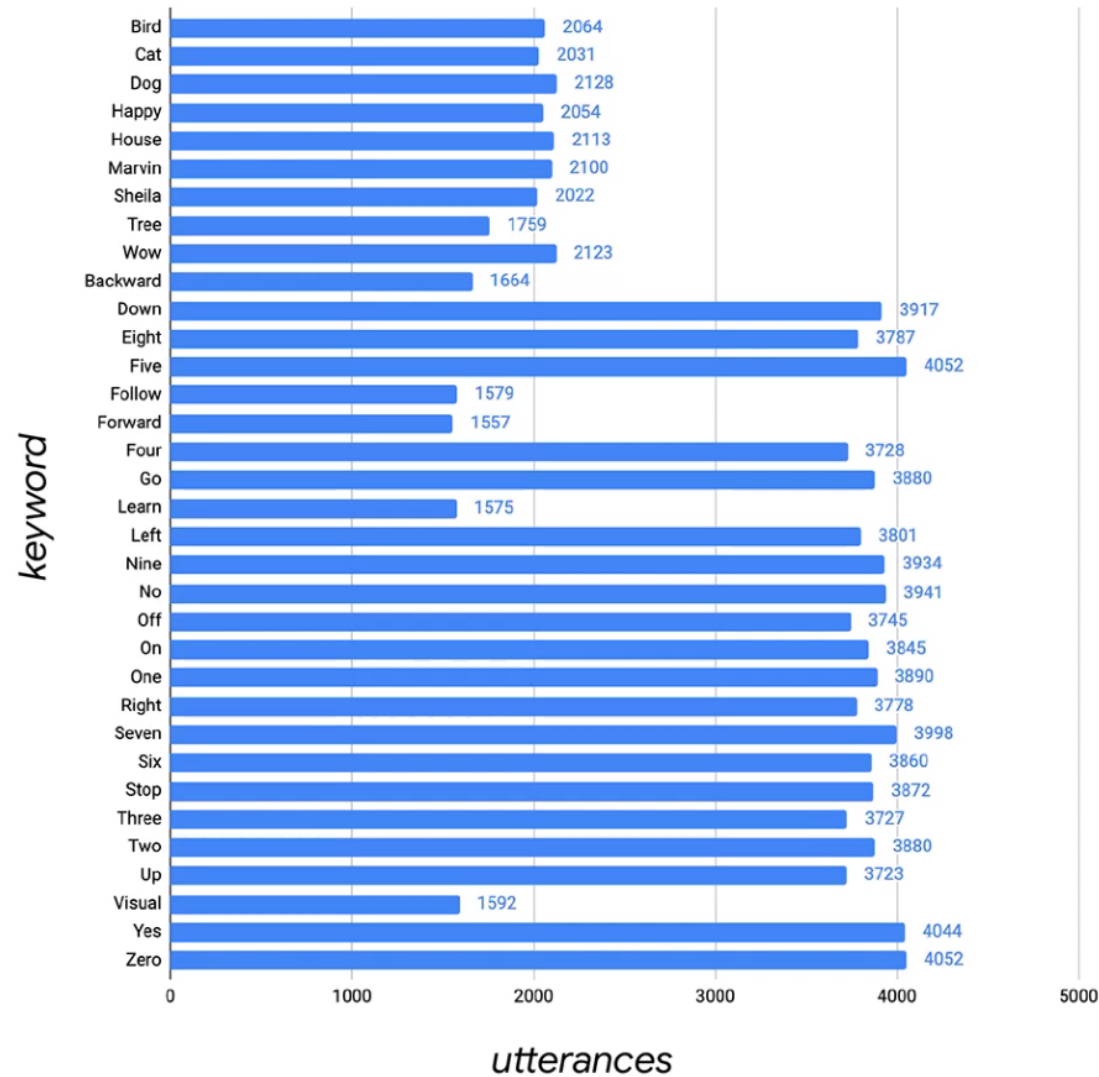
Speech Commands: A Dataset for Limited-Vocabulary Speech Recognition

Pete Warden
Google Brain
Mountain View, California
`petewarden@google.com`

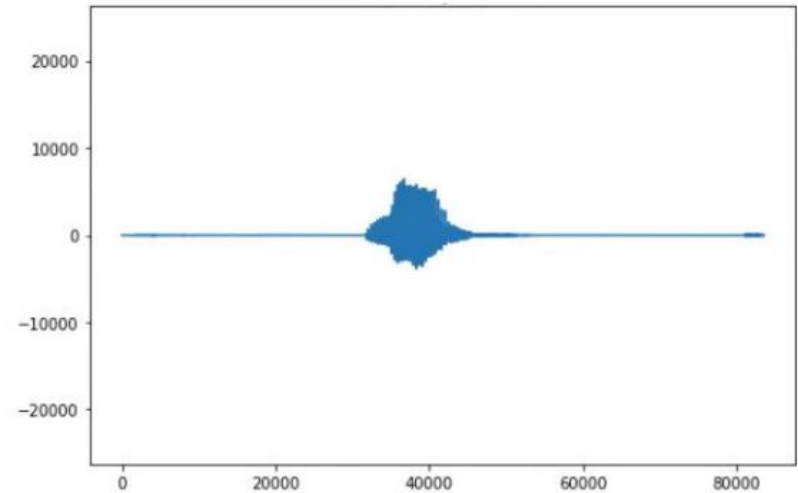
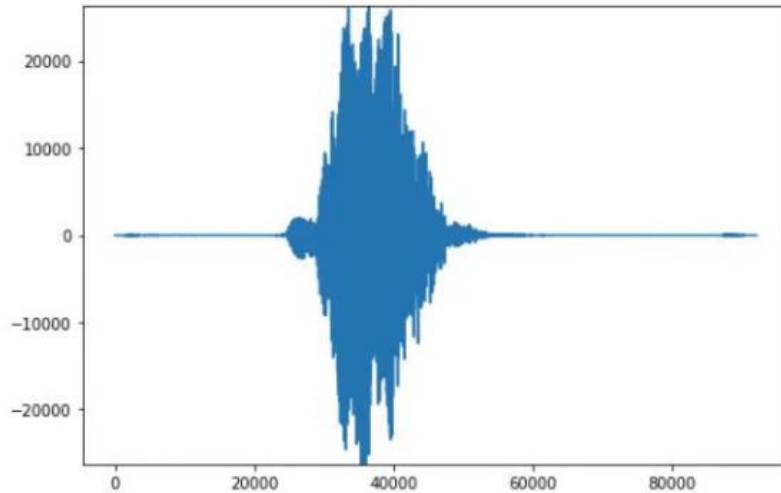
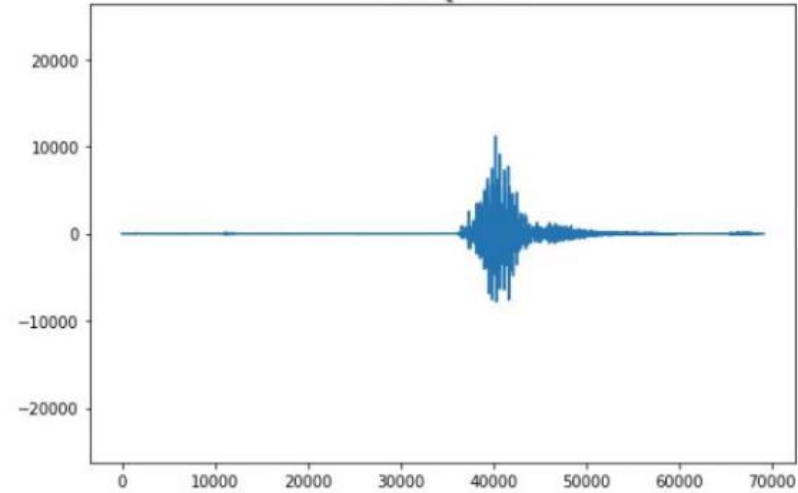
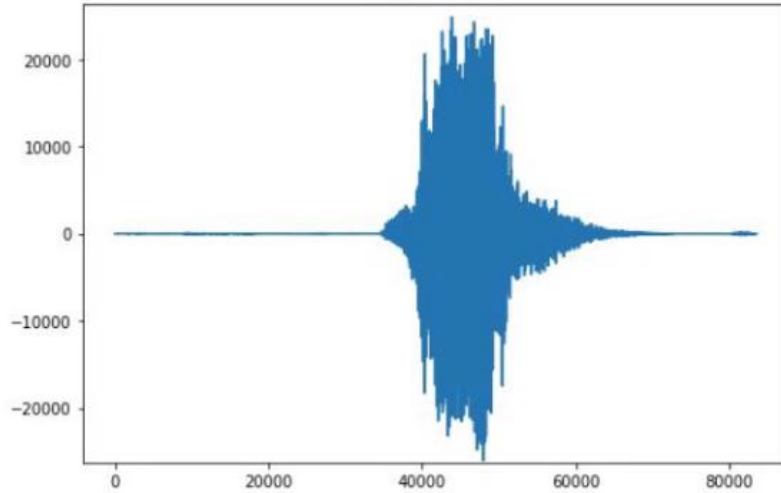
April 2018

- Recorded as individual words not phrases
- 1000-4000 examples for each word
- >2,500 people collecting words

Keywords on the dataset



Raw data may be confusing...



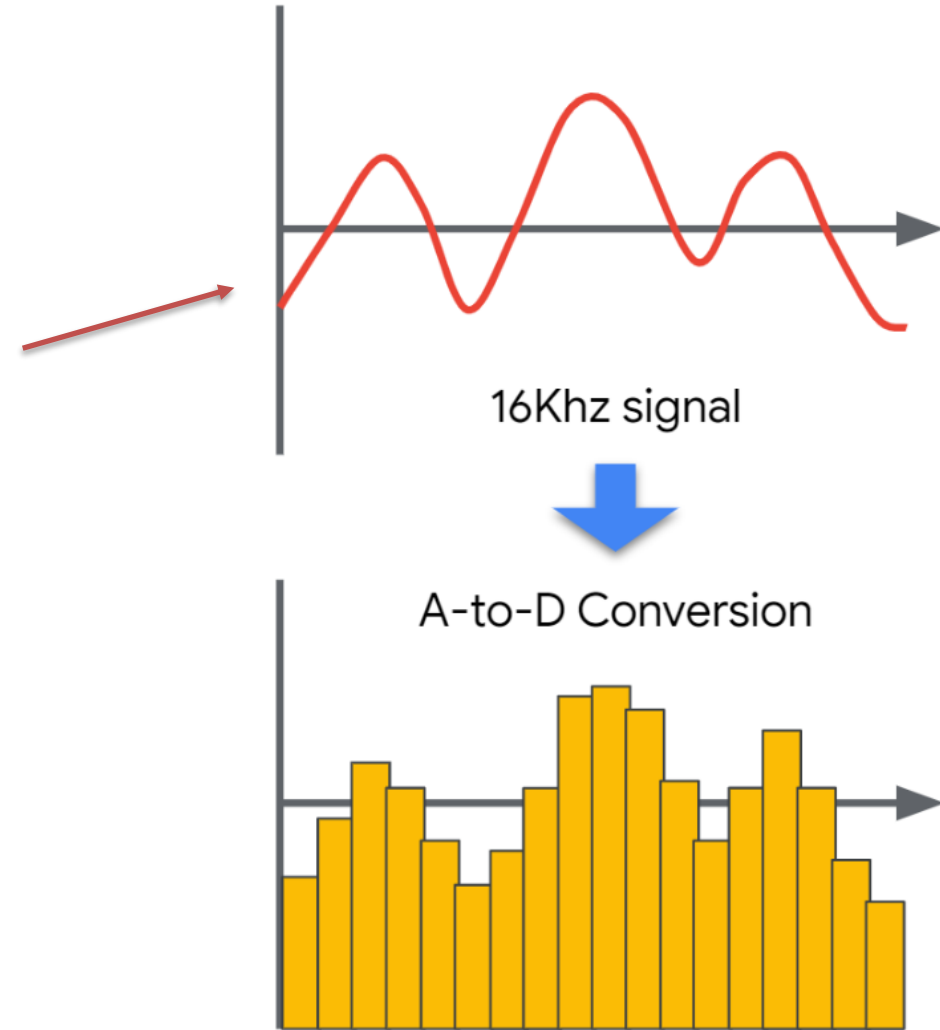
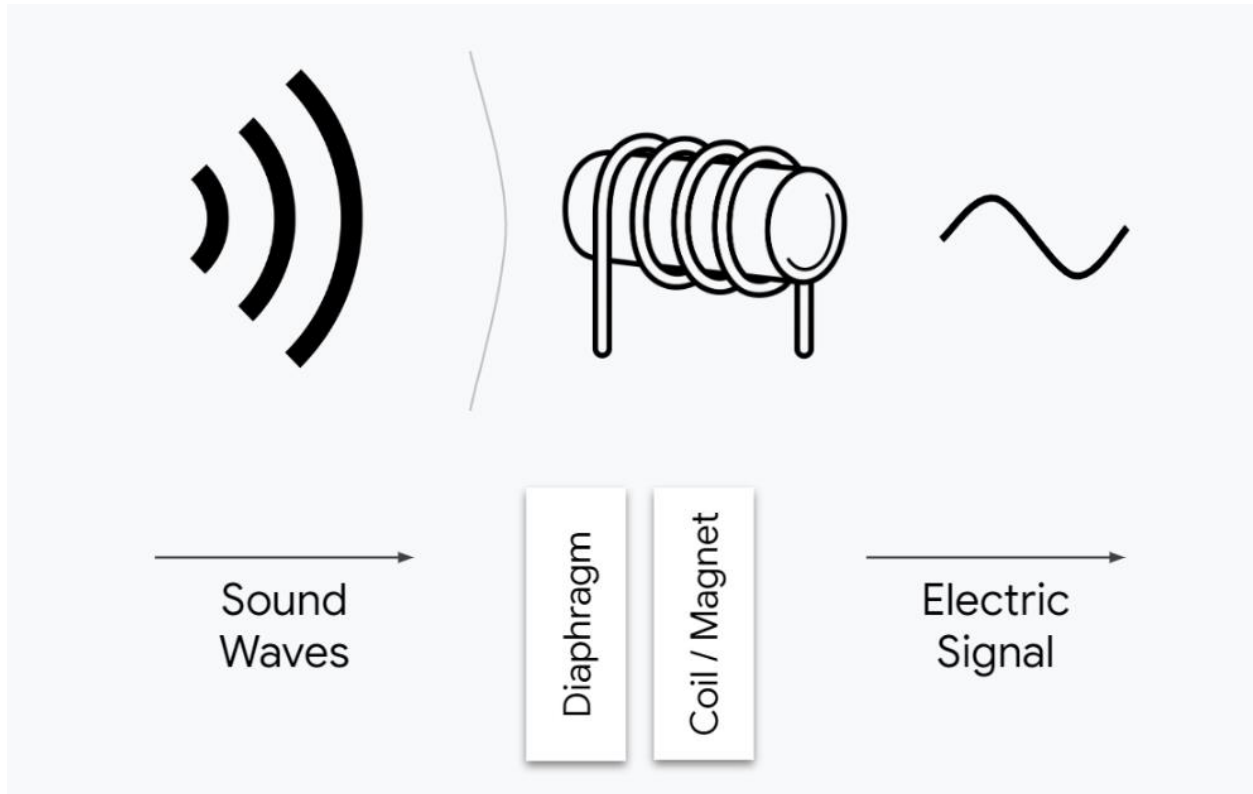


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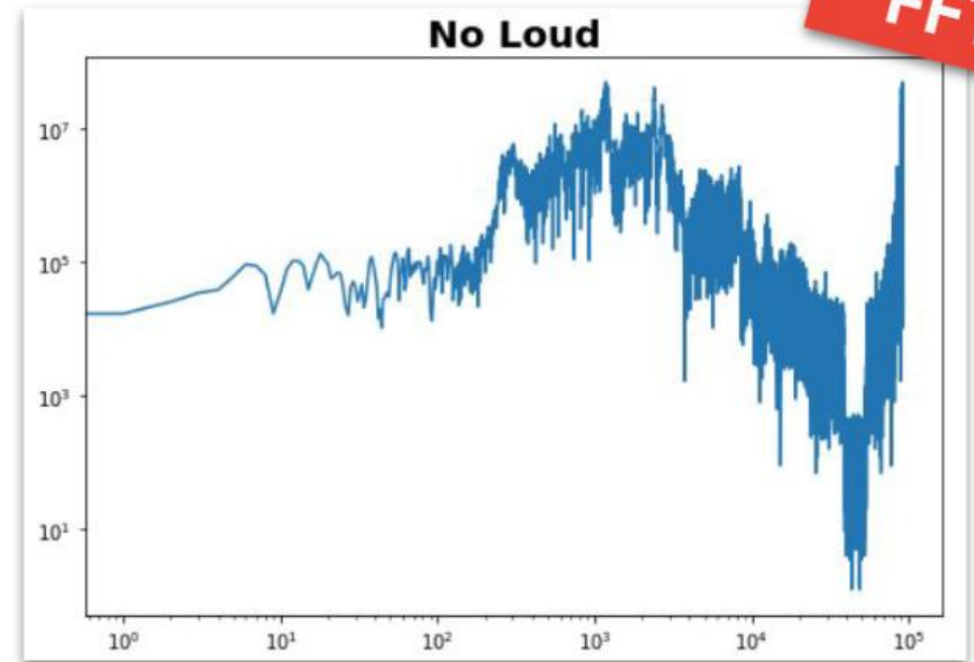
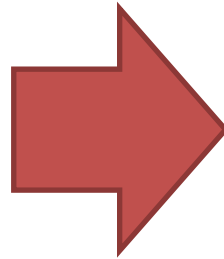
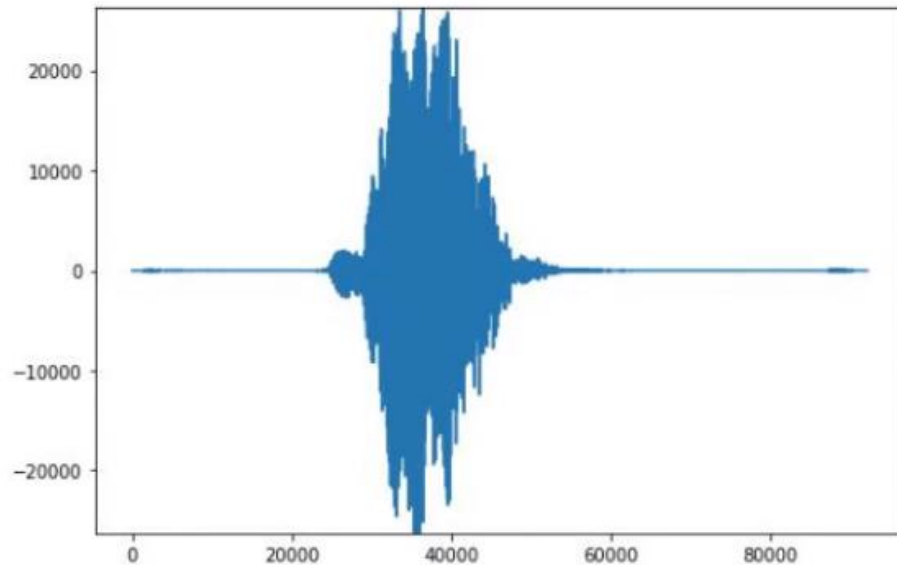
Pre-processing



Sensor data

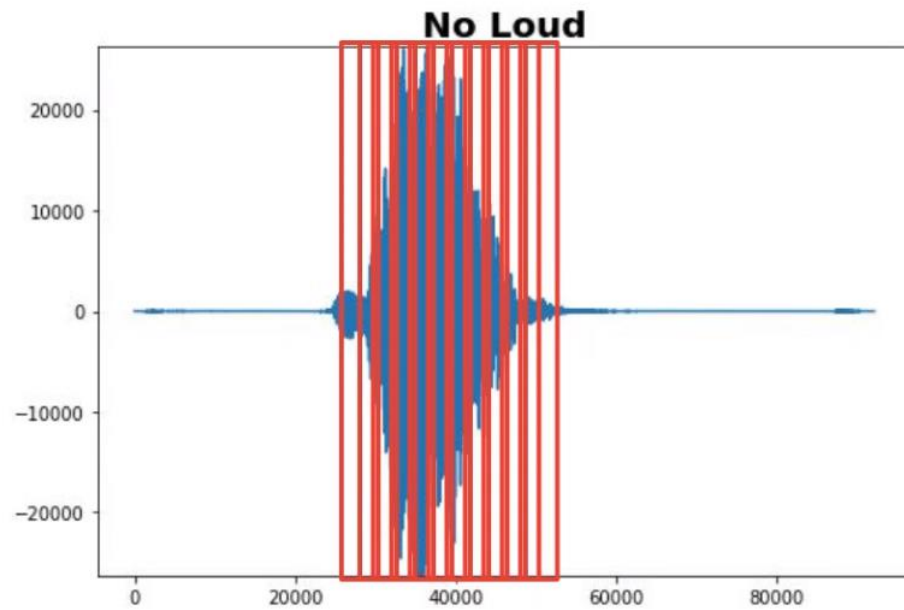


Shifting from Time Domain to Frequency Domain

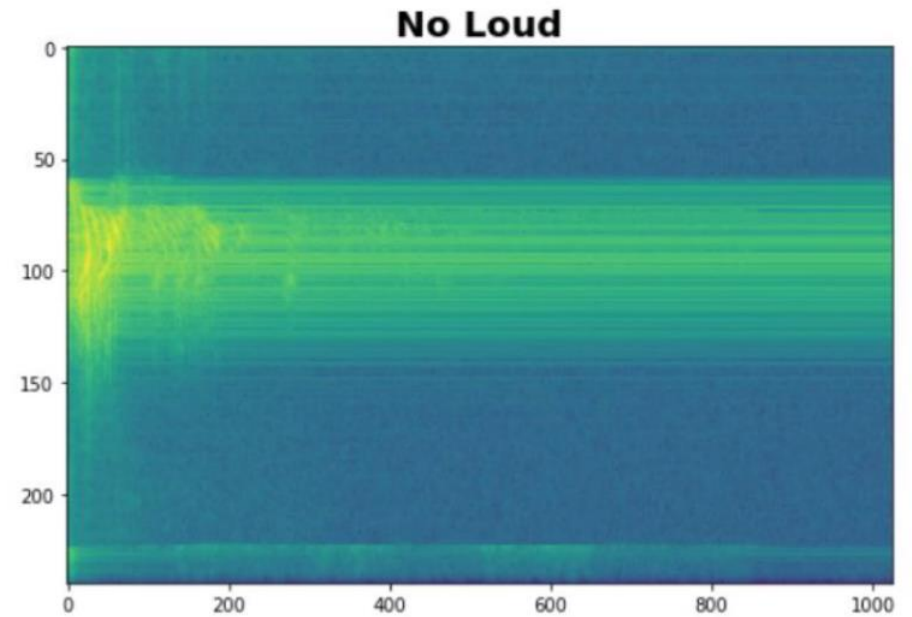


FFT

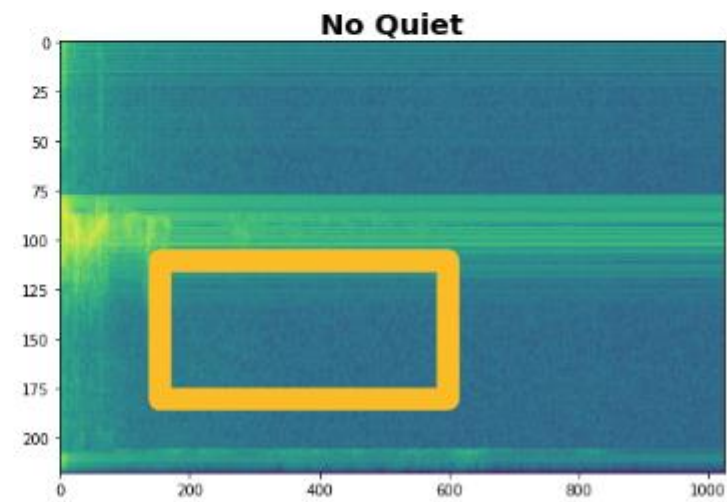
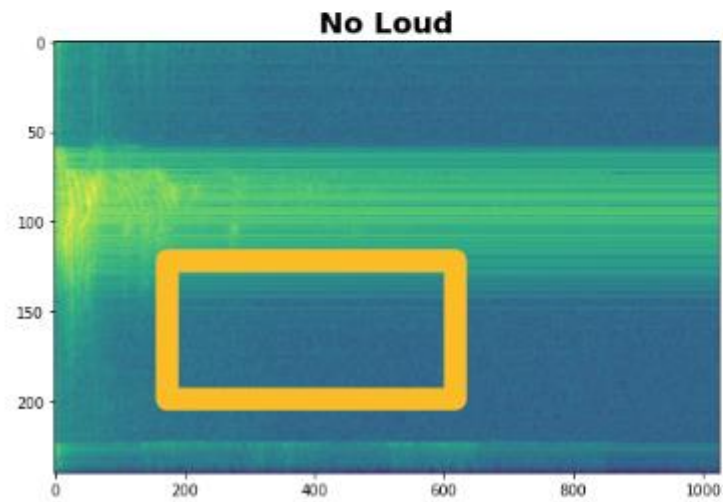
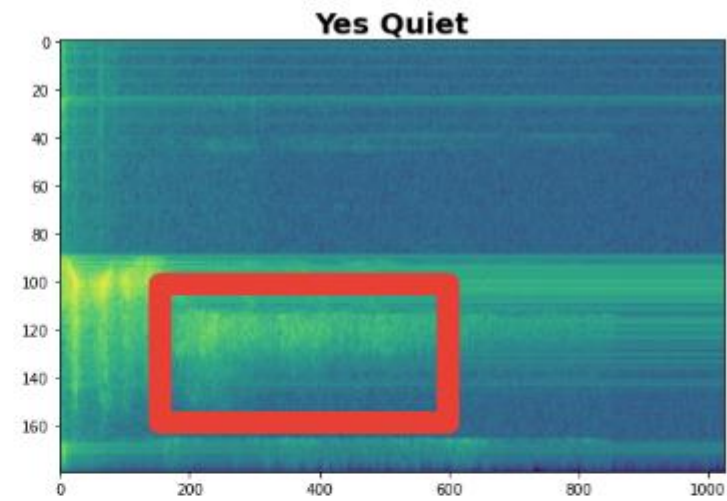
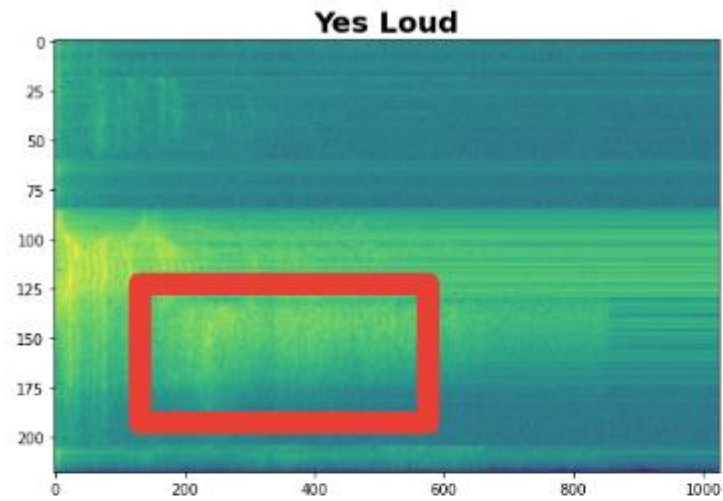
Extracting spectrograms!



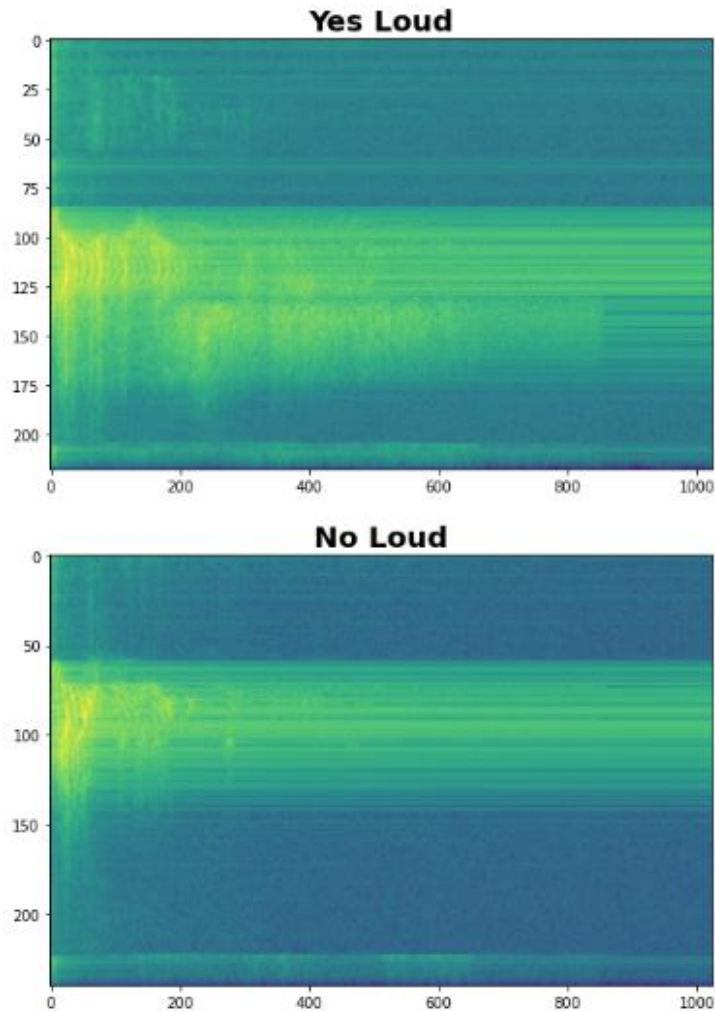
FFT!



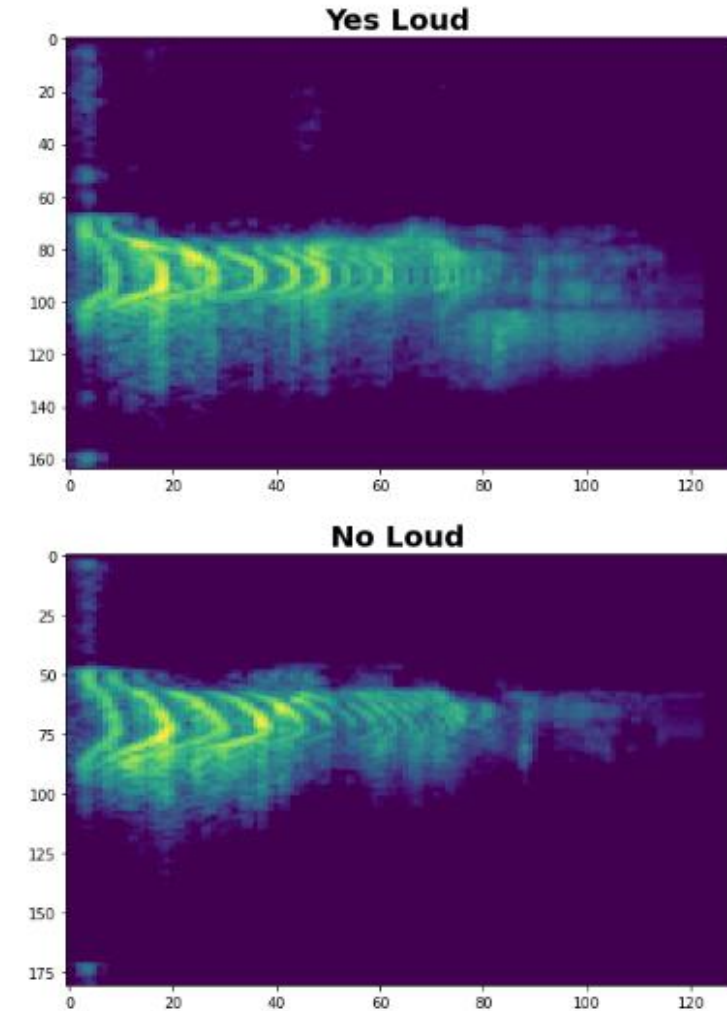
Better!



Preprocessing is essential

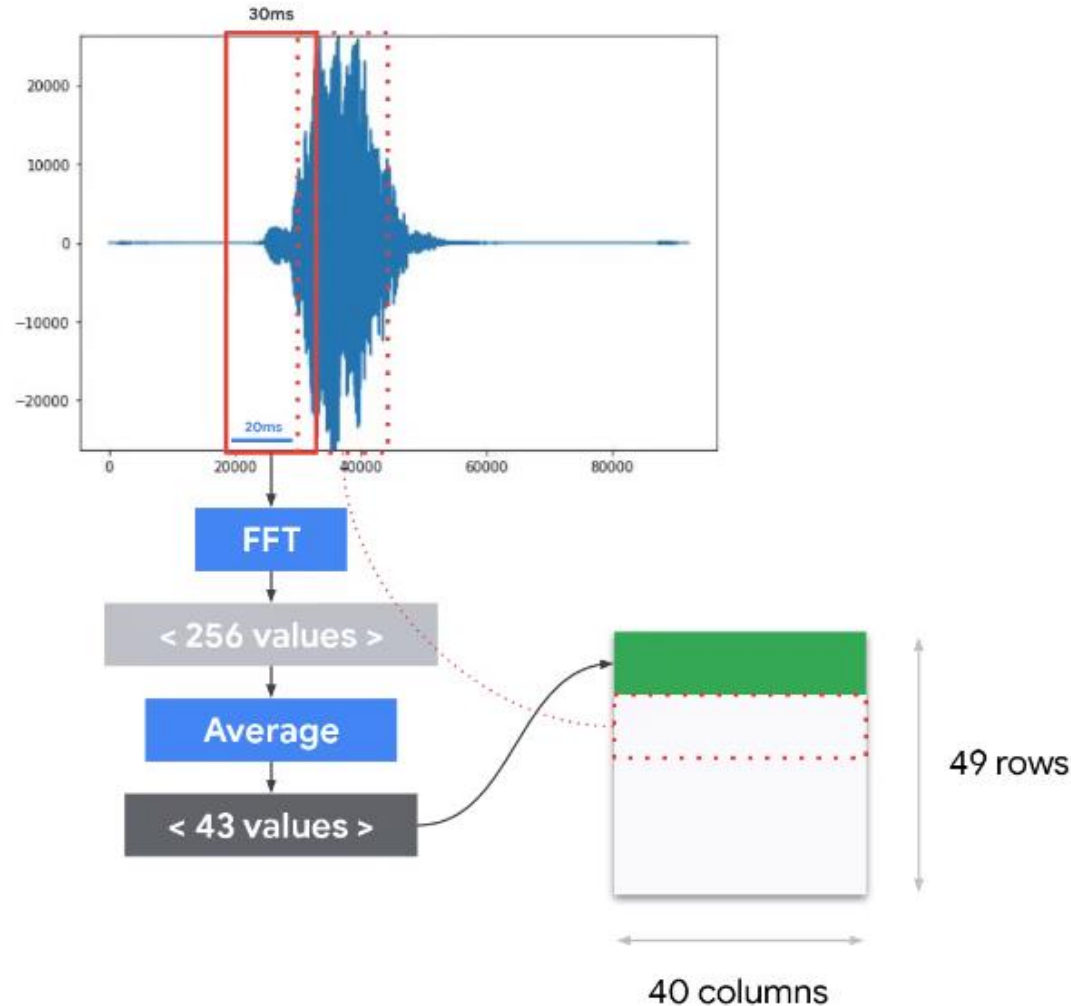


FFT preprocessing



Mel filters preprocessing

Pre-processing can help with dimensionality reduction

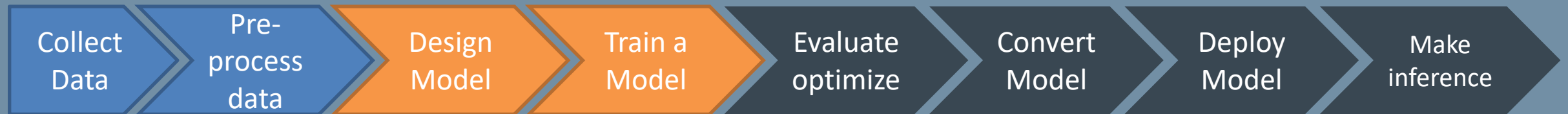


For 1 second inputs,
collected at 16KHz, we go
from 16000 values to
 $40 \times 49 = 1960$ values

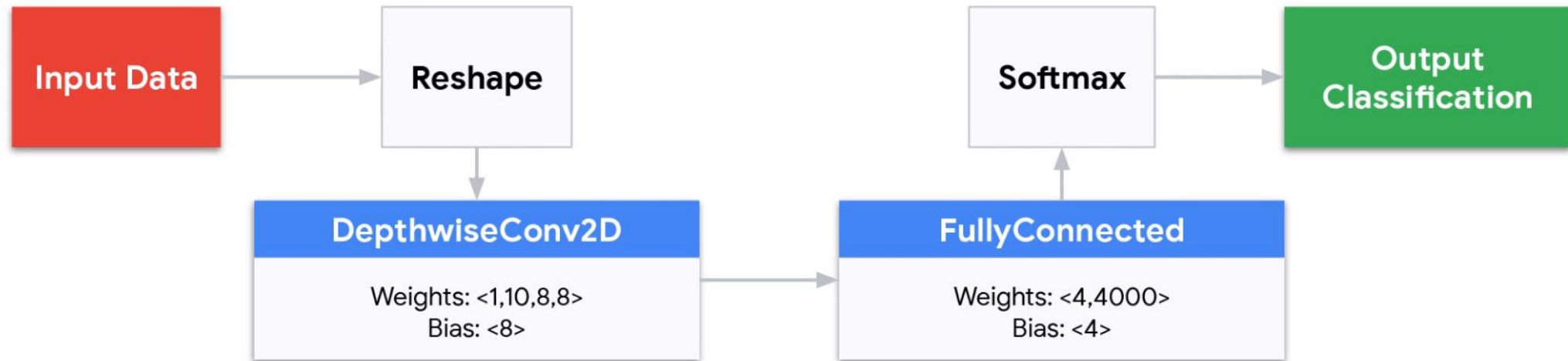


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Designing and training a model

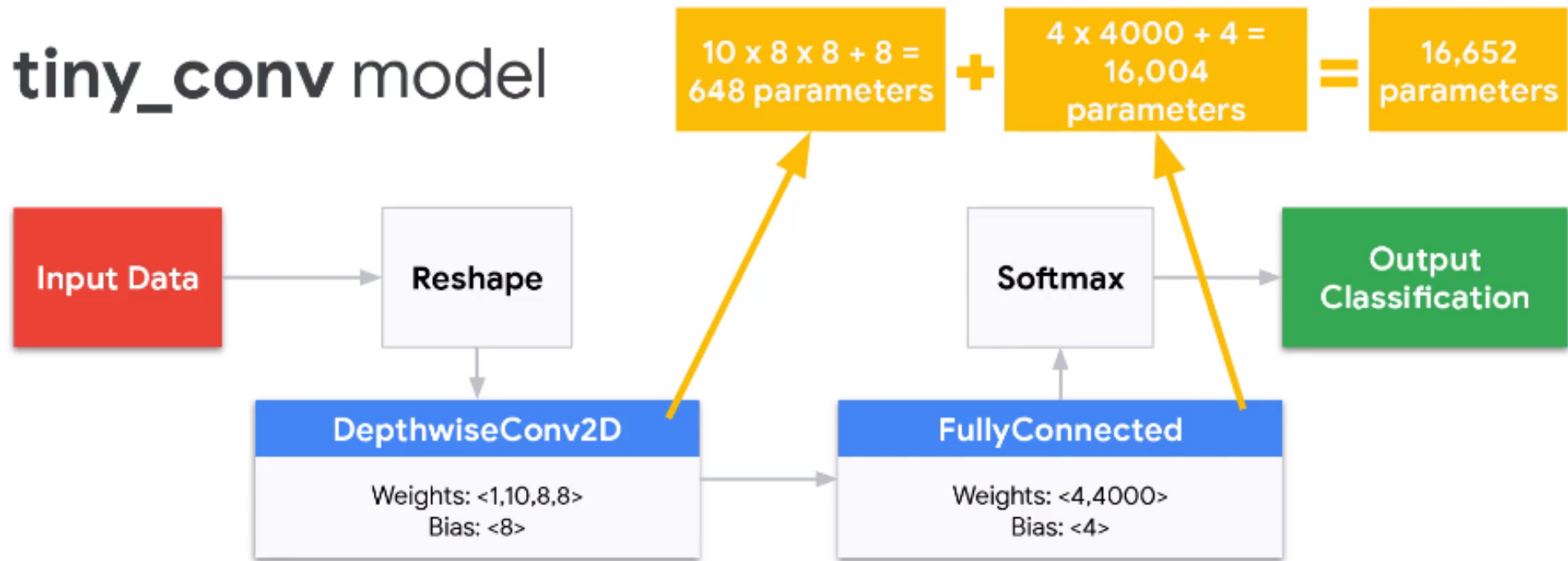


Tiny_conv model



In terms of weights?

tiny_conv model



For floats that's <70Kb
Quantized that's <17Kb

Let's try a pre-trained network for recognizing «yes» from «no» from «other»

COLAB:

<https://colab.research.google.com/drive/1YH6vXIDzzCRZOT-sLx50TNAE-LhVkcOK?usp=sharing>

Train your own!

COLAB:

Feature extraction:

<https://colab.research.google.com/drive/10pxaPTL0QAhlU4L7U2DAqzCwuiKAe8nC?usp=sharing>

Training:

<https://colab.research.google.com/drive/1j3mGVMuoQRT-TWRgmyqxb-AeVVIMcwbL?usp=sharing>

Additional data and code:

https://drive.google.com/drive/folders/1_L3HJjCn536UmYnzBdzY7d2-_N9LMyXQ?usp=sharing



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Evaluating a model



Metrics during training

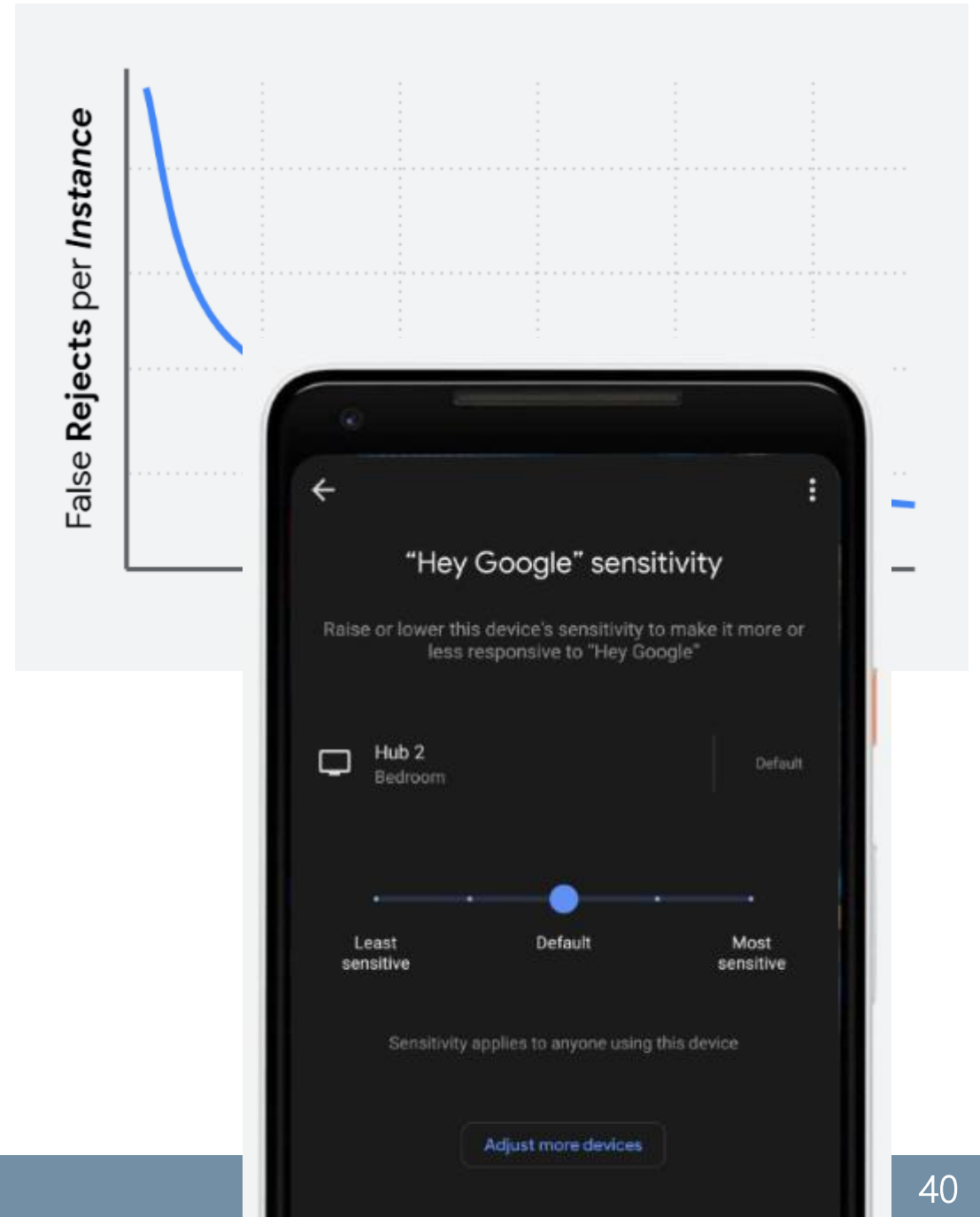
- Since during training we control the composition of the datasets, accuracy is a good metric during this phase of the algorithm.
- In general, it's good to plot the confusion matrix to control also false positive and false negative rates.
- Accuracy, precision recall and F1 score can be taken in consideration

	Actual Class: 1	Actual Class: 0
Predicted Class: 1	tp	fp
Predicted Class: 0	fn	tn

$$Acc = \frac{tp + tn}{N} \quad Pre = \frac{tp}{tp + fp} \quad \text{Recall: } Rec = \frac{tp}{tp + fn} \quad F1 = \frac{2 \cdot Pre \cdot Rec}{Pre + Rec}$$

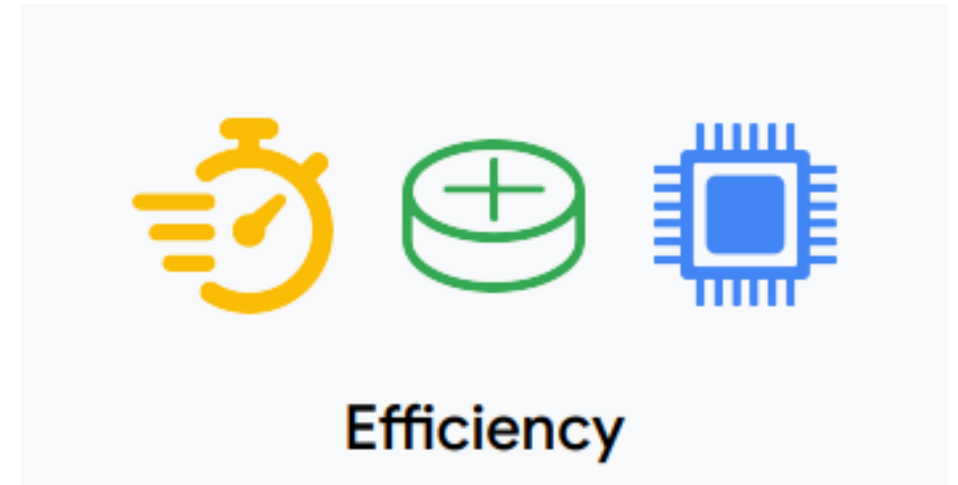
Metrics during use

- With many algorithms, it's possible to trade off false positive for false negatives.
- With multiple models, we can draw a receiver-operator curve (ROC) and select an operating point.



Other metrics: efficiency

- Latency:
 - Model must be fast enough to keep up with the speech input
 - The model must run fast enough to be responsive to the end user
 - But it must run efficiently on a small processor TinyML
- Memory Usage:
 - Need to be resource aware
 - Less compute
 - Less memory
 - Use quantization





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Appendix

Credits and reference

- "TinyML: Machine Learning with TensorFlow Lite on Arduino and Ultra-Low-Power Microcontrollers", Daniel Situnayake, Pete Warden, O'Reilly Media, Inc.
- Online course:
 - <https://www.edx.org/professional-certificate/harvardx-tiny-machine-learning>
- A lot more material on TinyML:
 - <http://tinyml.seas.harvard.edu/>
- Special thanks to Gioele Mombelli for letting me use the code he developed for his master thesis
- Colab to better understand pre-processing and spectrograms generations:
 - <https://colab.research.google.com/github/tinyMLx/colabs/blob/master/3-5-10-SpectrogramsMFCCs.ipynb>