



2019 Intelligent Sensing Summer school
CIS - Queen Mary University of London

The challenges and benefits of sound sensing

Dr Sacha Krstulović

Director of Research – Audio Analytic

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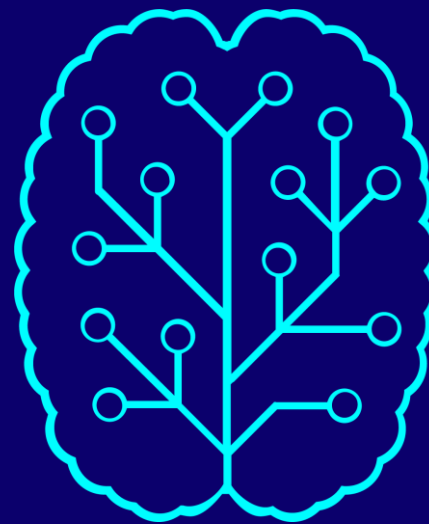
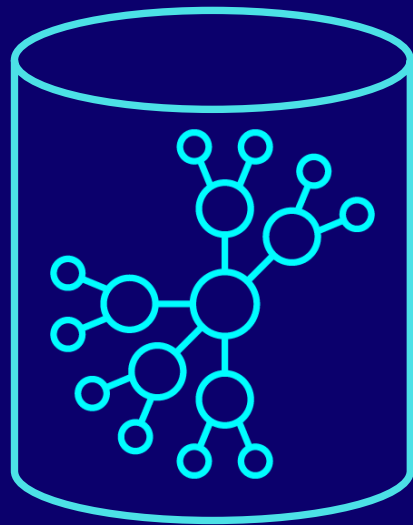
“Like a Shazam for
real-world sounds”

Bloomberg

as featured in

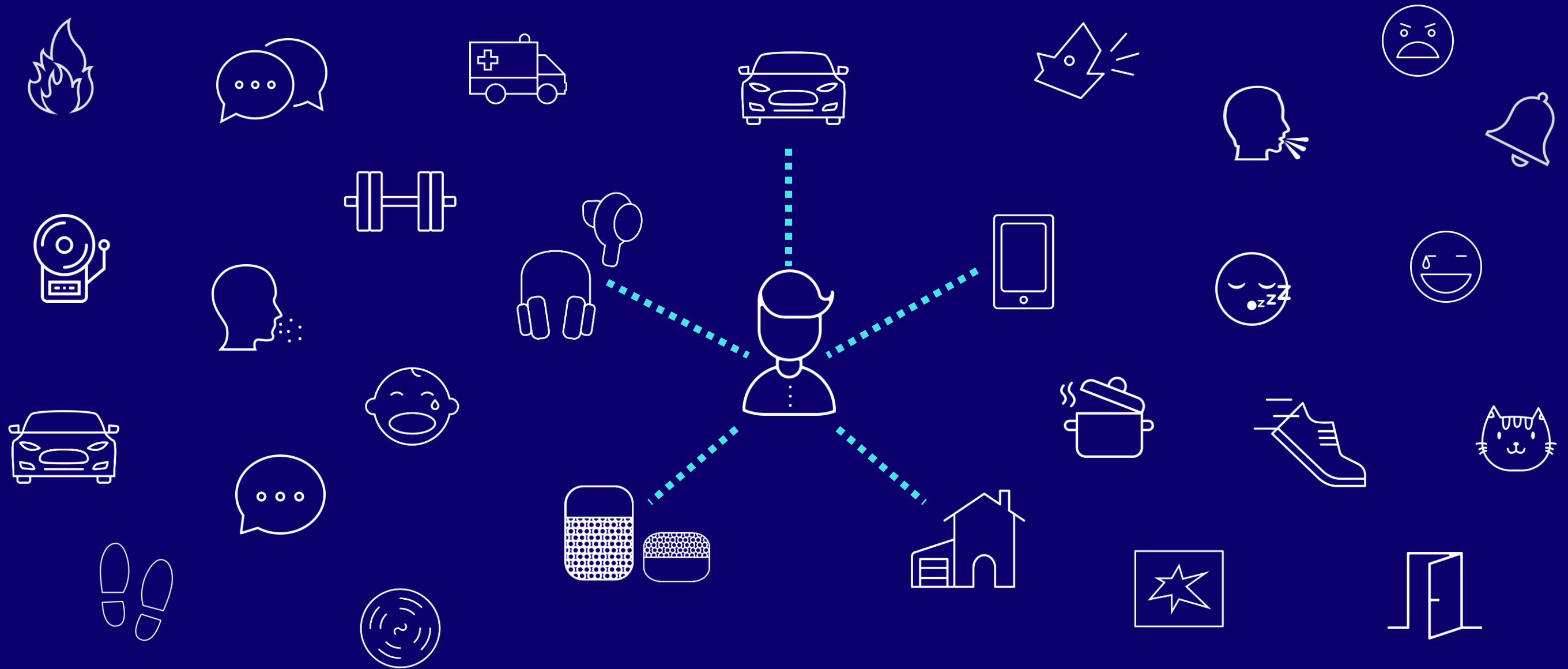


**Audio Analytic's software and technology
give machines the broader sense of hearing.**



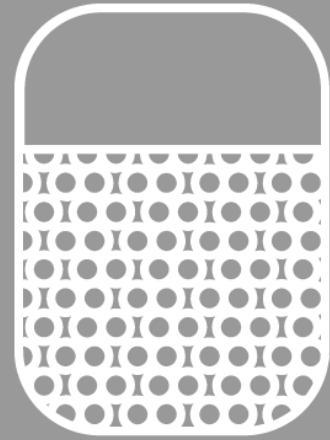
The benefits

Evolving from 'connected devices' to 'intelligent experiences'





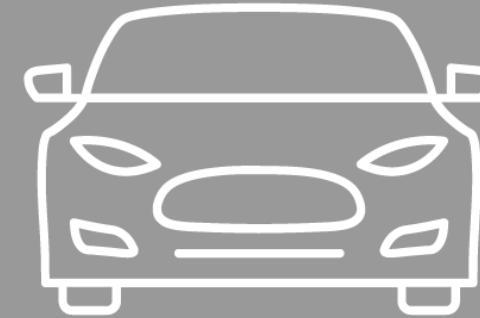
230m smart home devices in 2021*



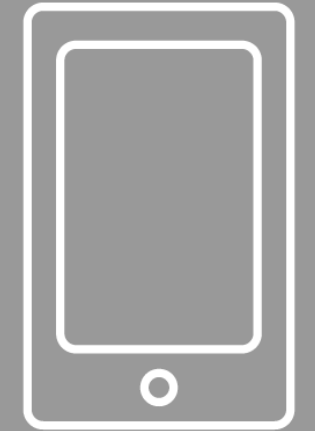
206m smart speakers in 2021*



82m hearables in 2021^



92m connected cars in 2021*



1.7bn smartphones in 2021*

“Sound recognition is a key strategic technology that should be made available in all connected devices.”

Francisco Jeronimo, IDC

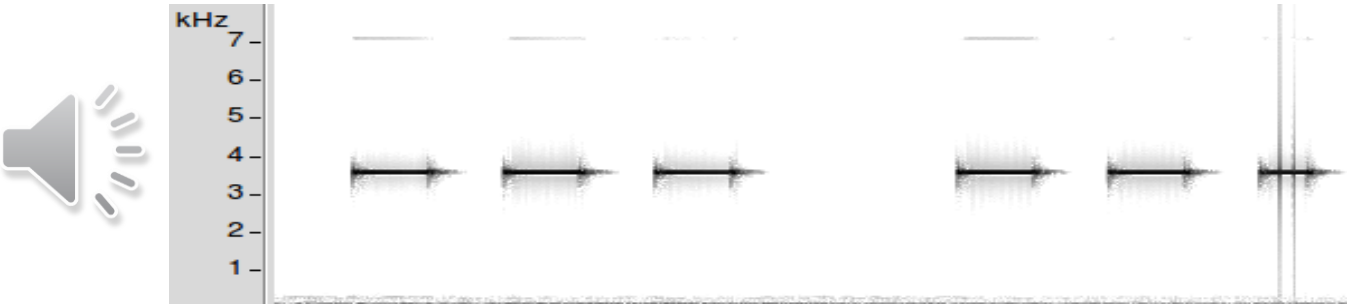
The challenges

The core challenge: acoustic variability

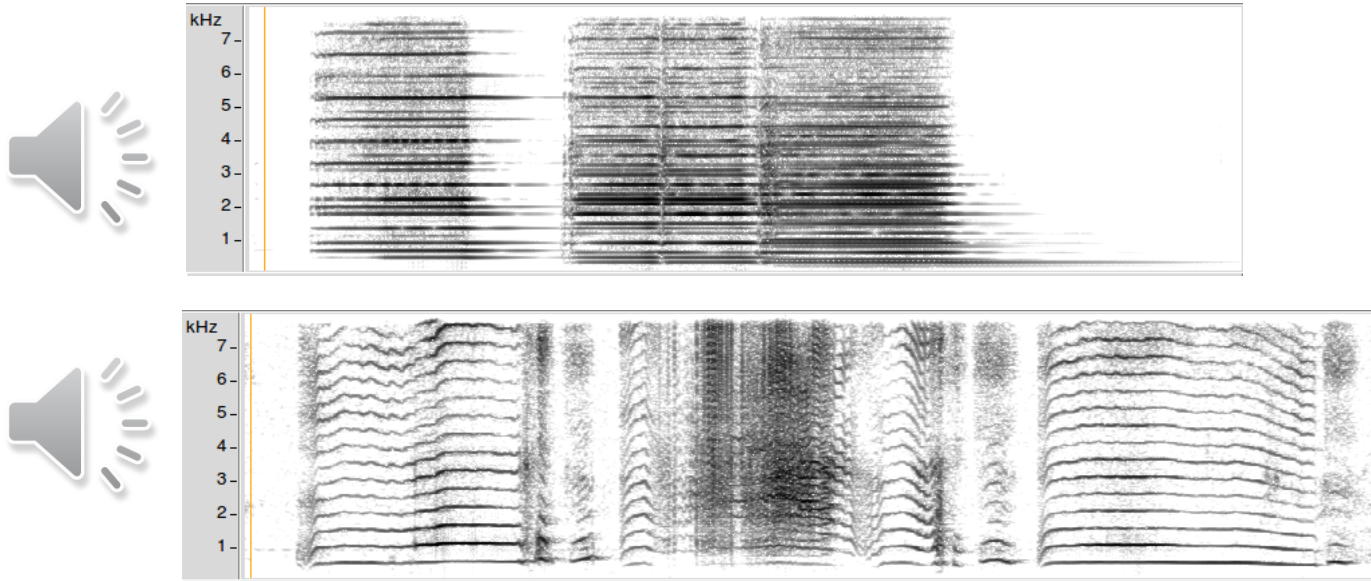


Variety of production processes = variety of acoustic features.

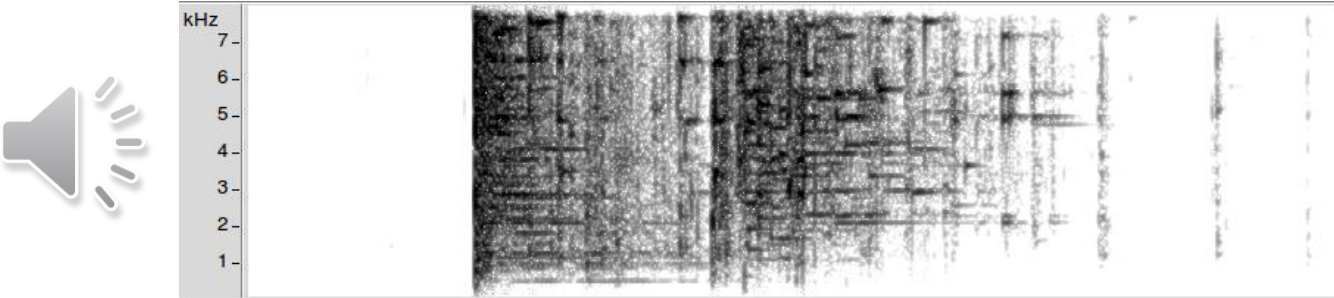
Beeps



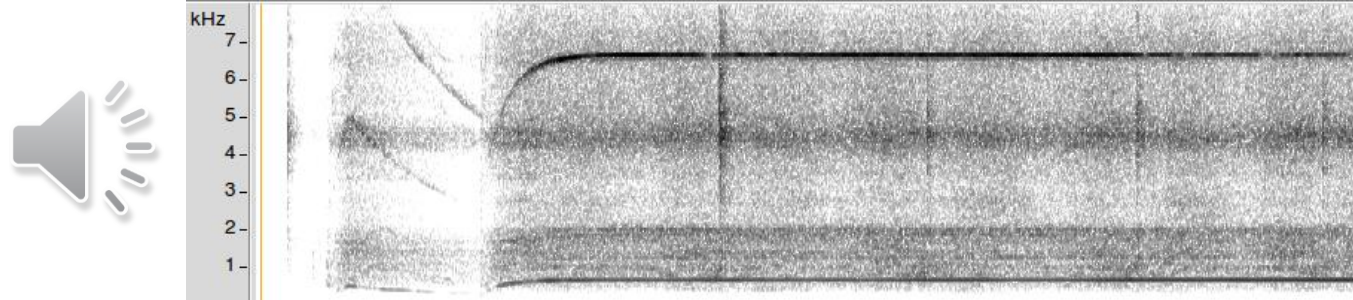
Harmonic Sounds



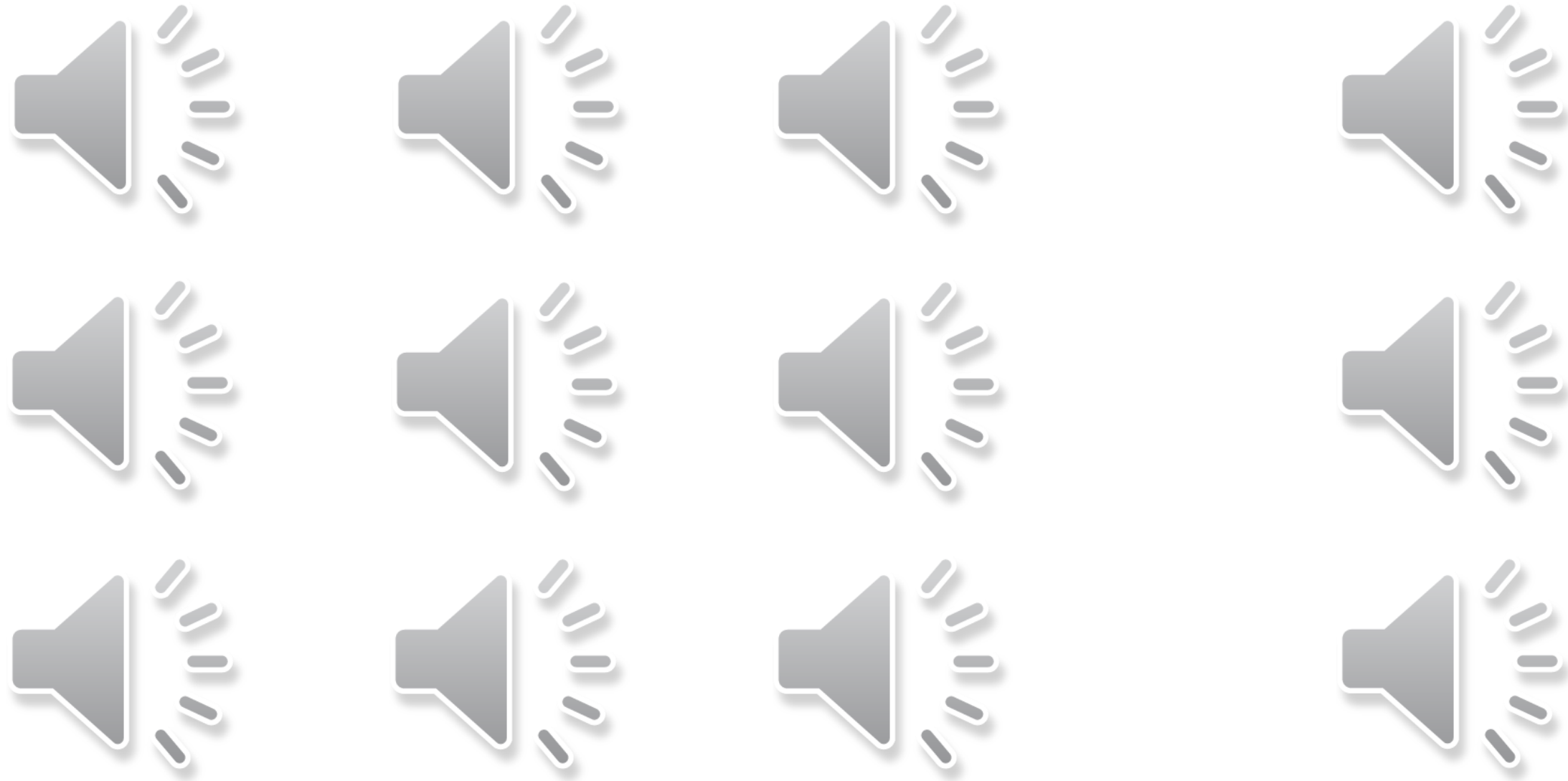
Crash/Bangs



Shaped noise

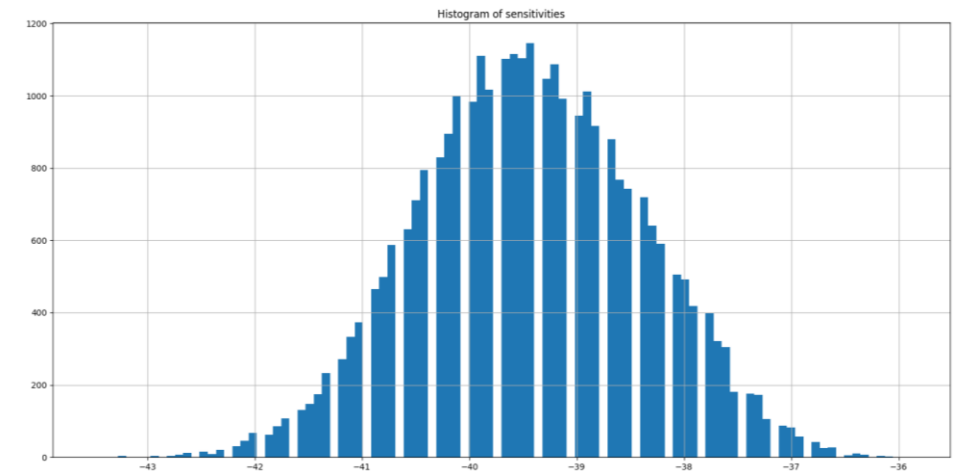
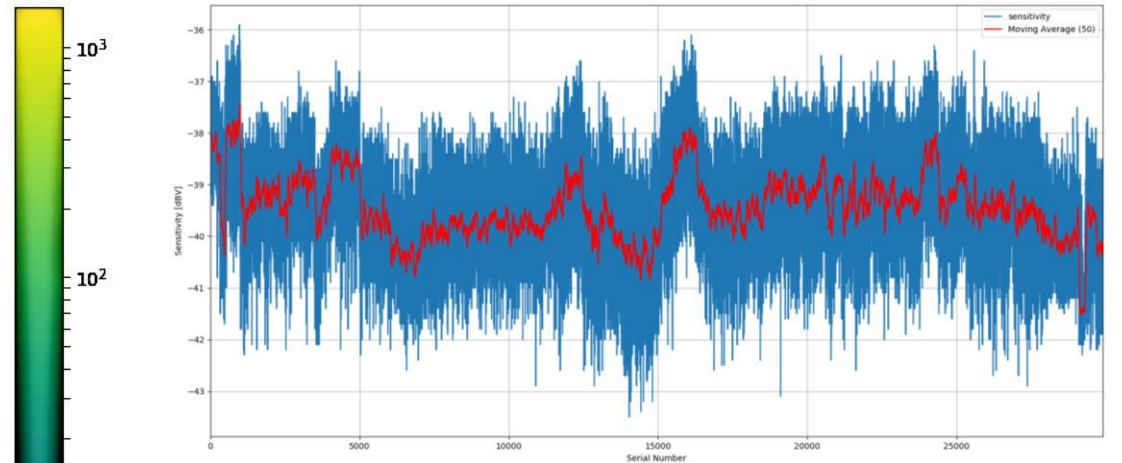
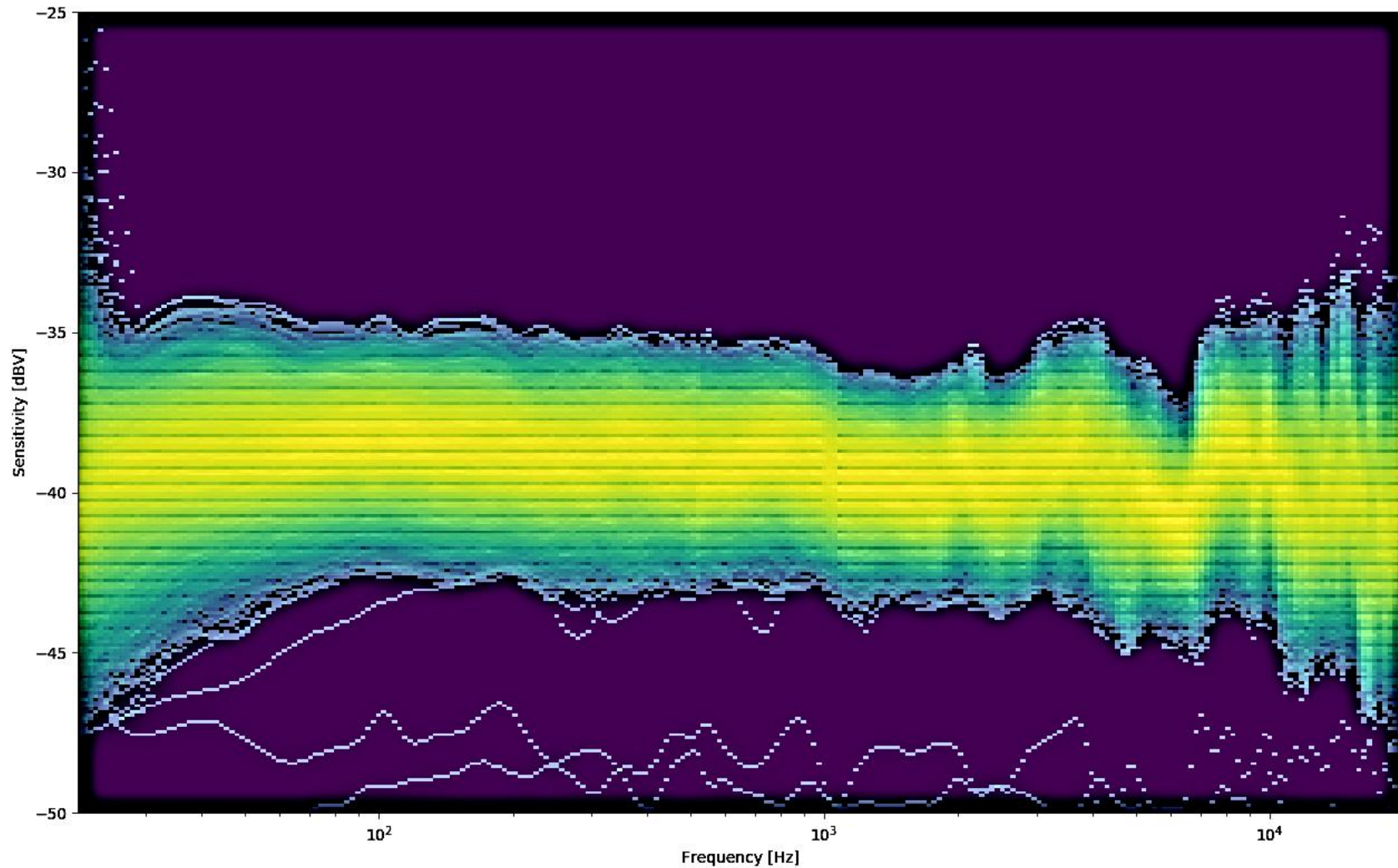


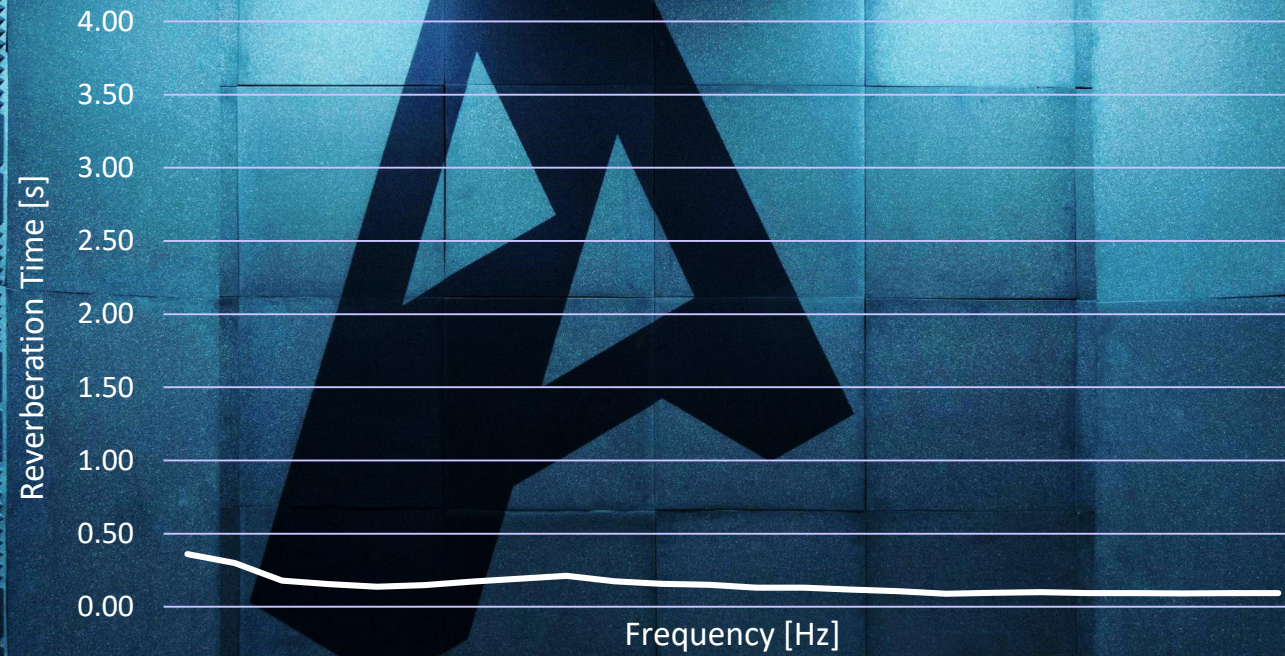
Effects of channel and room variety



Microphone variability

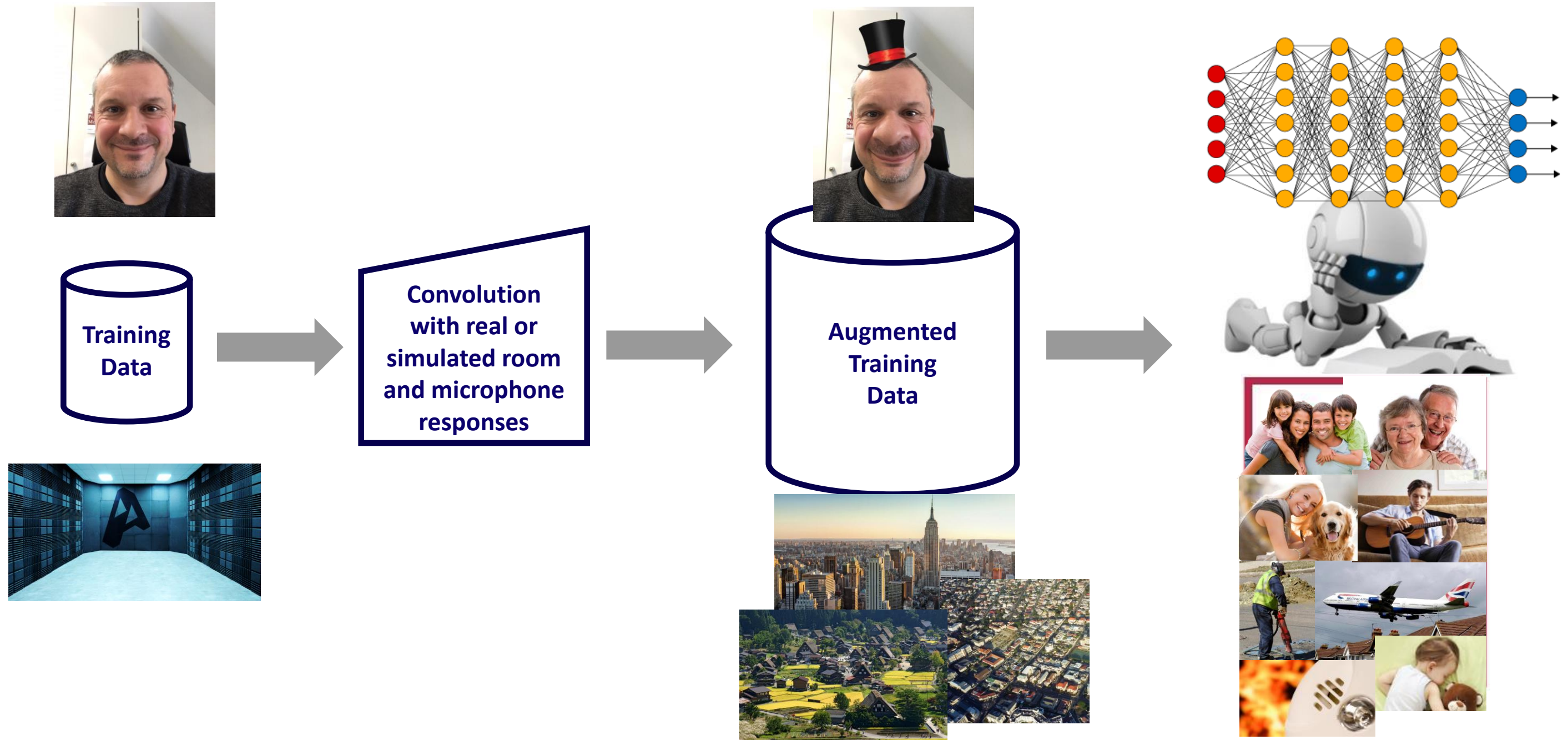
Analysis of 29,900 microphone response curves from the same manufacturer and model:





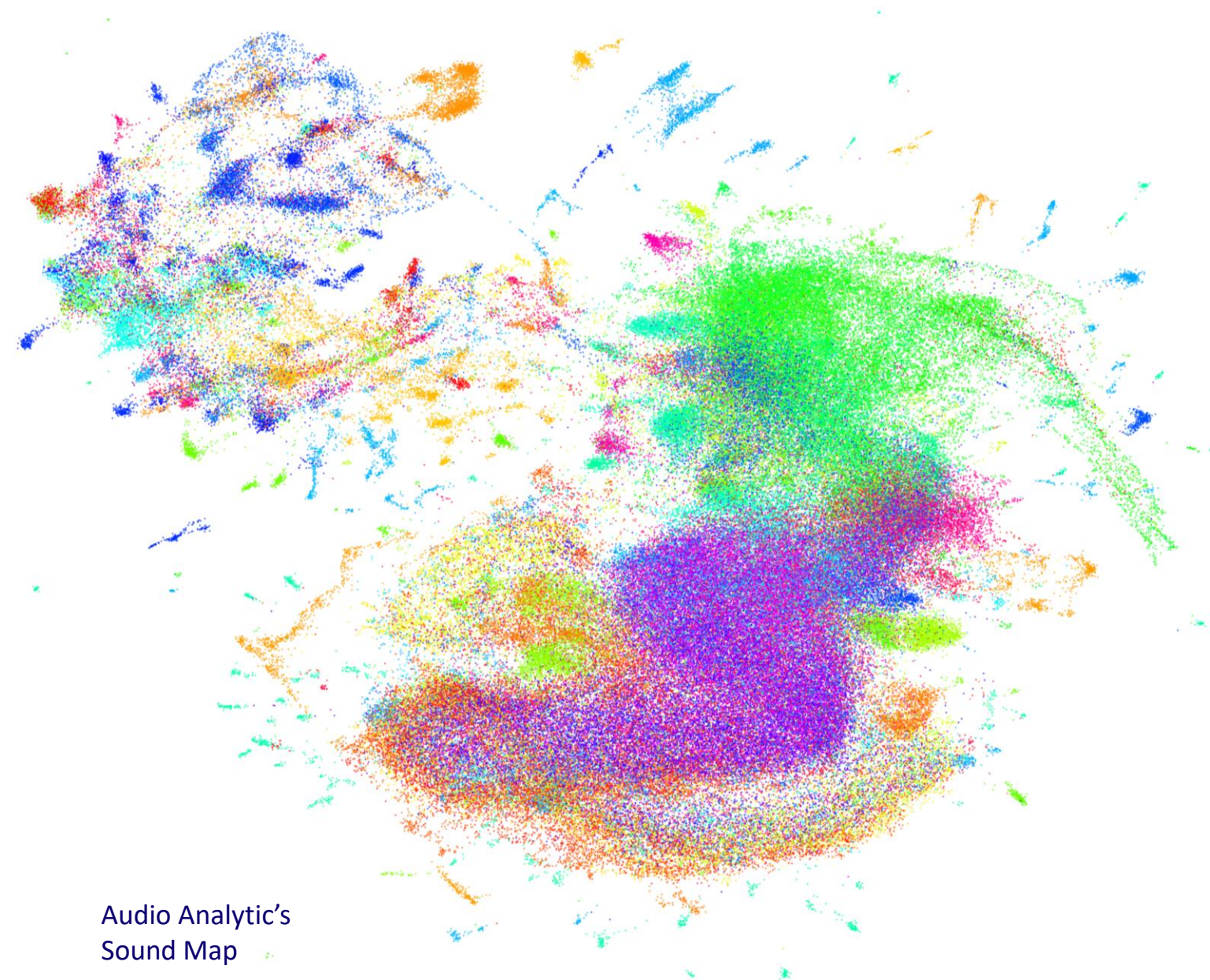
**We designed and built a semi-anechoic sound lab.
(Reverberation time < 0.15s)**

Data augmentation with realistic conditions



Not quite zero data anymore...

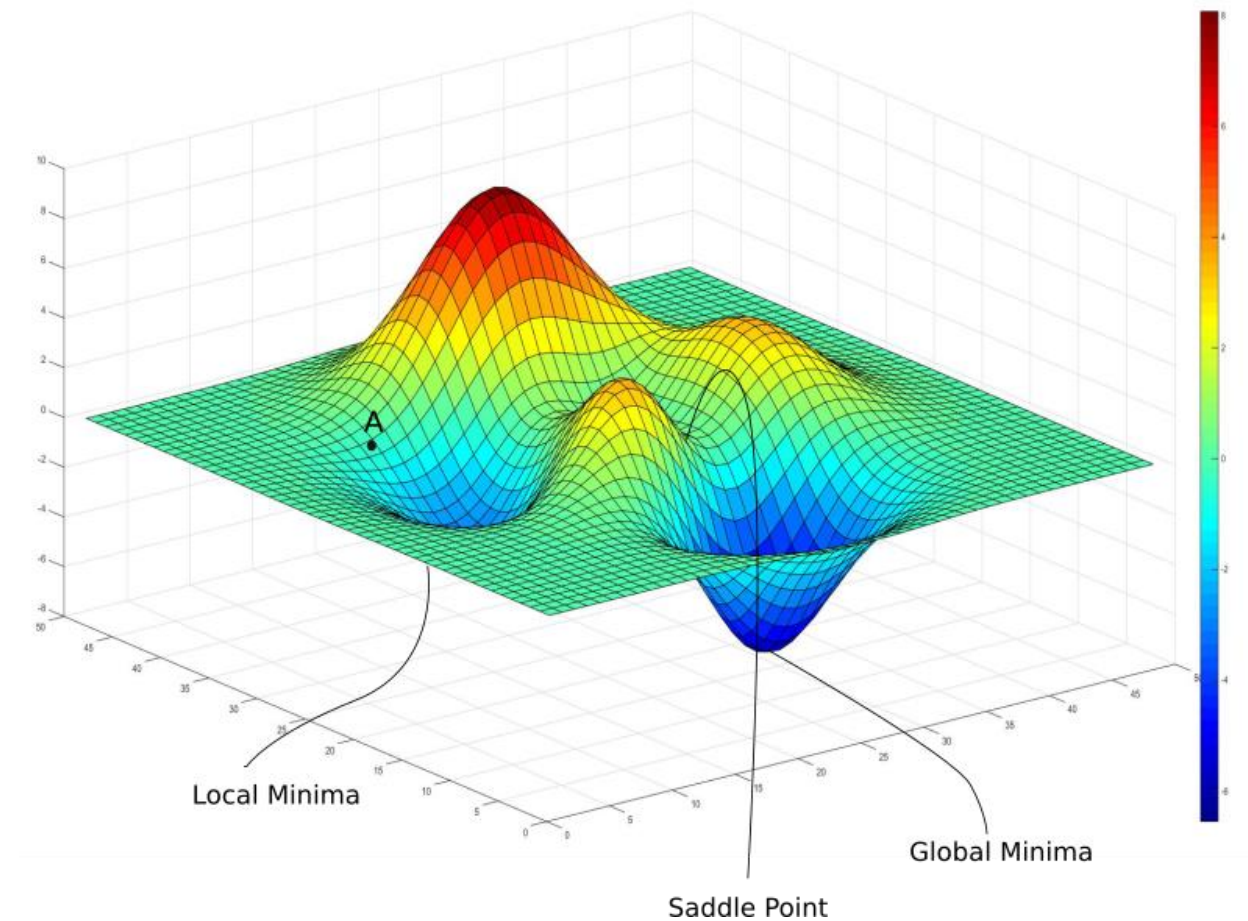
- AA's Alexandria™ database contains 13,508,727 labelled sound events across ~600 label types.



Audio Analytic's
Sound Map

What is the best sound recognition model?

- Think of it as an optimisation problem:
 - Given a realistic data set
 - And a meaningful metric for sound classification
 - And a search space of DNN architecturesthen find the best performing architecture
- Meaningful metric:
 - Is cross-entropy on audio frames meaningful?
 - True positives are discrete, but what about false positives in continuous audio?
 - Prior probabilities: empty home or busy home? What is the system really exposed to?
- Model search space: Software 2.0 approach where guided search yields AuditoryNet™



Differentiable programming / Software 2.0



*“Deep Learning est mort. Vive Differentiable Programming!
People are now building a new kind of software by assembling networks of parameterized functional blocks and by training them from examples using some form of gradient-based optimization. It’s really very much like a regular program, except it’s parameterized, automatically differentiated, and trainable/optimizable.”*

- Yann LeCun, Director of Facebook AI Research

The “classical stack” of Software 1.0 is what we’re all familiar with — it is written in languages such as Python, C++, etc. [...] By writing each line of code, the programmer identifies a specific point in program space with some desirable behavior.

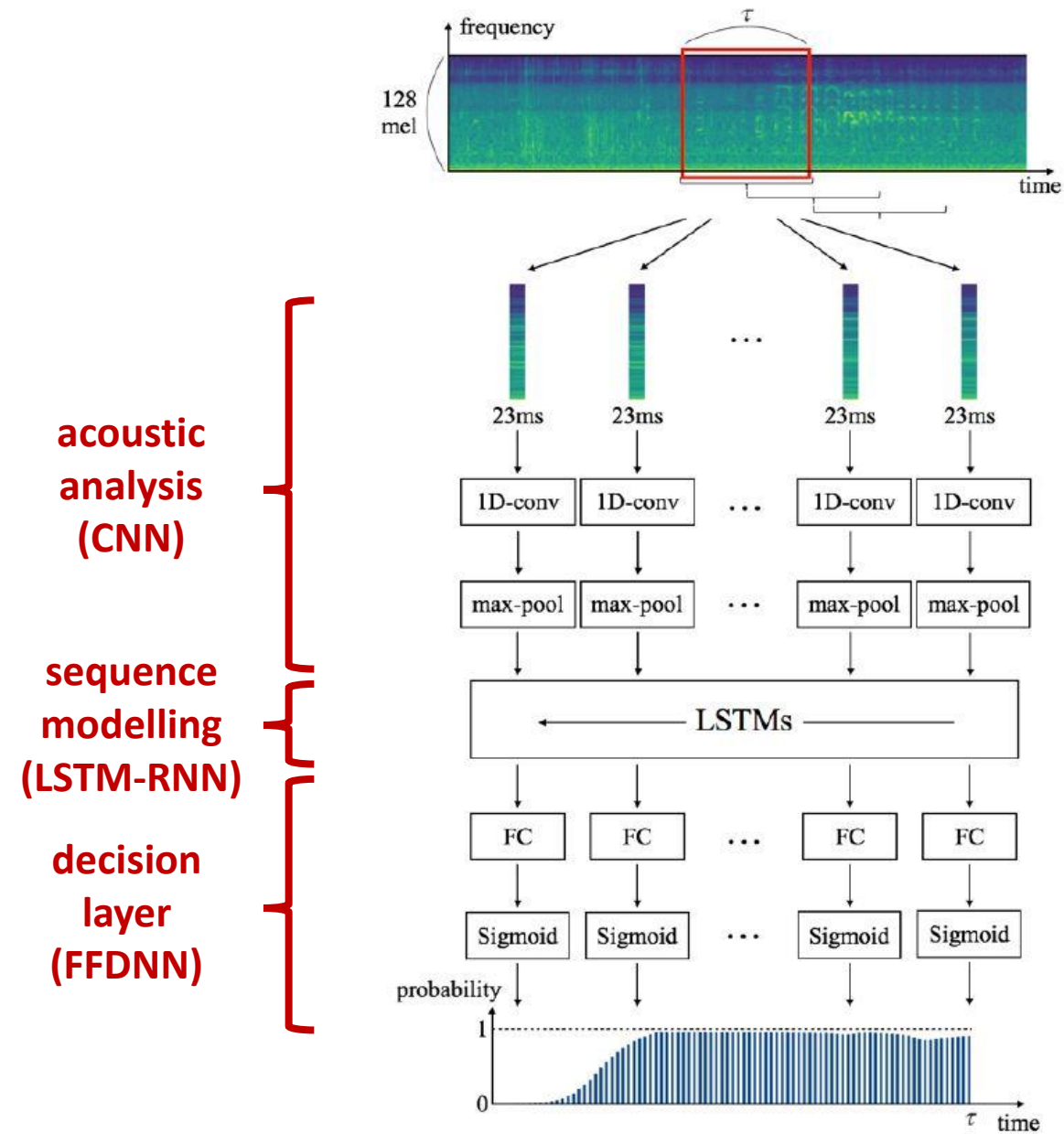
In contrast, Software 2.0 [...] approach is to specify some goal on the behavior of a desirable program (e.g., “satisfy a dataset of input output pairs of examples”, or “win a game of Go”), write a rough skeleton of the code (e.g. a neural net architecture) that identifies a subset of program space to search, and use the computational resources at our disposal to search this space for a program that works [...] the search process can be made efficient with backpropagation and stochastic gradient descent.

- Andrej Karpathy, Senior Director of AI at Tesla

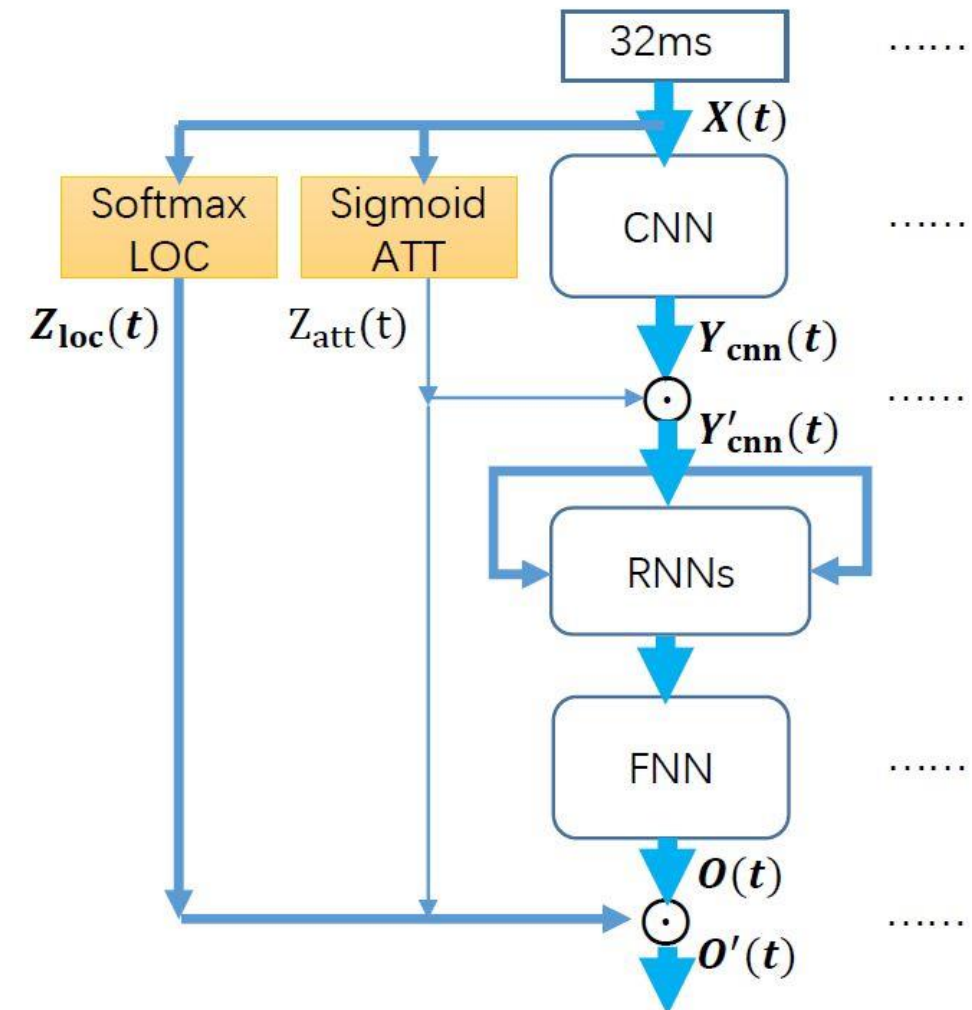
<https://vimeo.com/274274744>



Software 2.0 search space: e.g. recent DCASE challenges



H. Lim, J. Park and Y. Han, DCASE 2017 T2



“Attention and Localization Based on a Deep Convolutional Recurrent Model for Weakly Supervised Audio Tagging”
 Y. Xu, Q. Kong, Q. Huang, W. Wang and M. D. Plumbley
 Interspeech 2017 - DCASE 2016 Task4

System evaluation matters

- Open evaluations can be useful
 - Supply reference data, foster development and exchange of novel ideas
 - Sound scenes and events recognition: DCASE
- Open evaluations can also bias the problem significantly
 - Is the database realistic or whatever was affordable?
 - Solving the problem or winning the competitive eval?
 - Are comparative eval metrics relevant to user experience?
- Evaluation in real conditions is hard and costly, but necessary for industrial success
 - Real time operation on a consumer chip?
 - Required audio and computation hardware?
 - Were significant variability effects neglected?
- Is your system really doing what you think it is doing?
 - Clever Hans was a horse who could do mathematics...



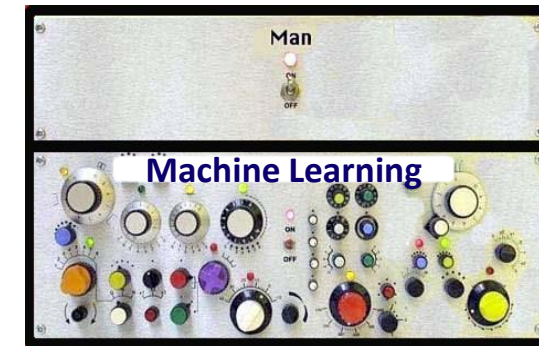
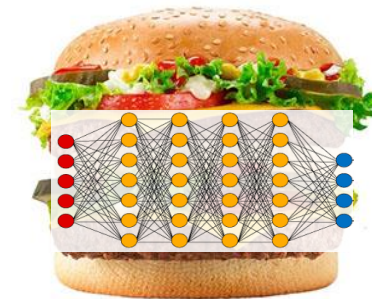
Privacy

- Privacy concerns can be traced back to WWII
 - Privacy laws largely rely on definitions of *sensitive* and *identifiable* information
 - Consent matters
- Public perception matters and impacts commercial success.
 - Limited faith in how data is being protected and processed in the cloud
 - Limited faith in T&Cs
- People would like AI devices to be more like humans: all the knowledge is locked into the head
 - Running onboard the device matters
 - Avoid data leaving the device
- New technical solutions are emerging
 - E.g., federated learning



Take aways

- Data is a parameter: must capture full real-world variability
 - Part of industrial expertise is about judging coverage, relevance and variability in order to build high performance data sets
- DNNs are a given, but what is the best model?
 - It's an optimisation problem: Software 2.0, expert-guided search into the model space given realistic data
- Meaningful metrics are crucial
 - Comparative metrics may not be relevant to user experience
 - The system is a horse until proven otherwise
- AI is expected to remain as private as the brain



Many thanks!



We are hiring!

<http://www.audioanalytic.com/careers>

UK headquarters

2 Quayside
Cambridge
CB5 8AB, UK

Sound Labs

Unit 11b, Nuffield Road
Cambridge
CB4 1TF, UK

US office

44 Montgomery Street
San Francisco
CA 94104, USA

info@audioanalytic.com
audioanalytic.com