AI Anarchies

Introduction to Adversarial Acoustics

Introduction

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Workshop Structure

PART 1	Lecture
PART 2	Practical: Colab Notebooks
PART 3	Group Discussion

Workshop Structure

https://tinyurl.com/aianarchies

Methods

The effort is not simply to import well-known methods - be they from humanities, social science or computing. Rather, the focus is on how methods may change, however slightly or wholesale, owing to the technical specificities of new media.

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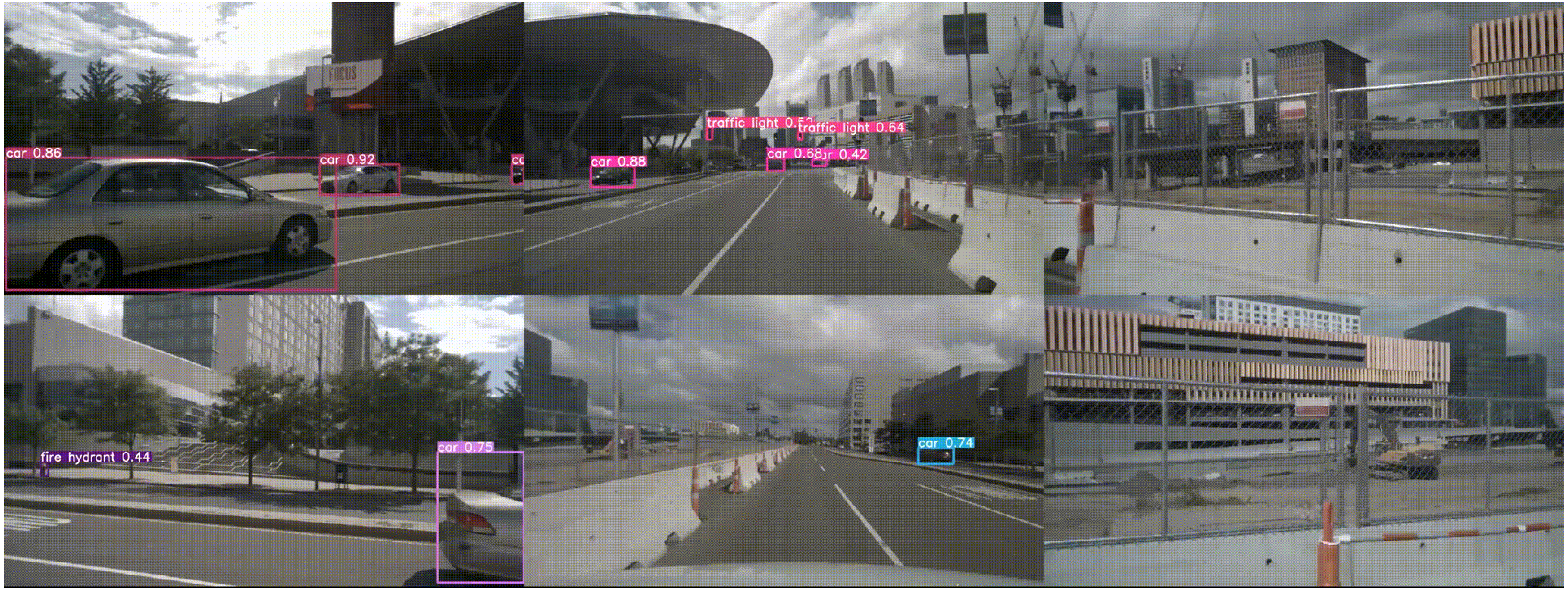
Digital Methods Initiative Wiki

Practice



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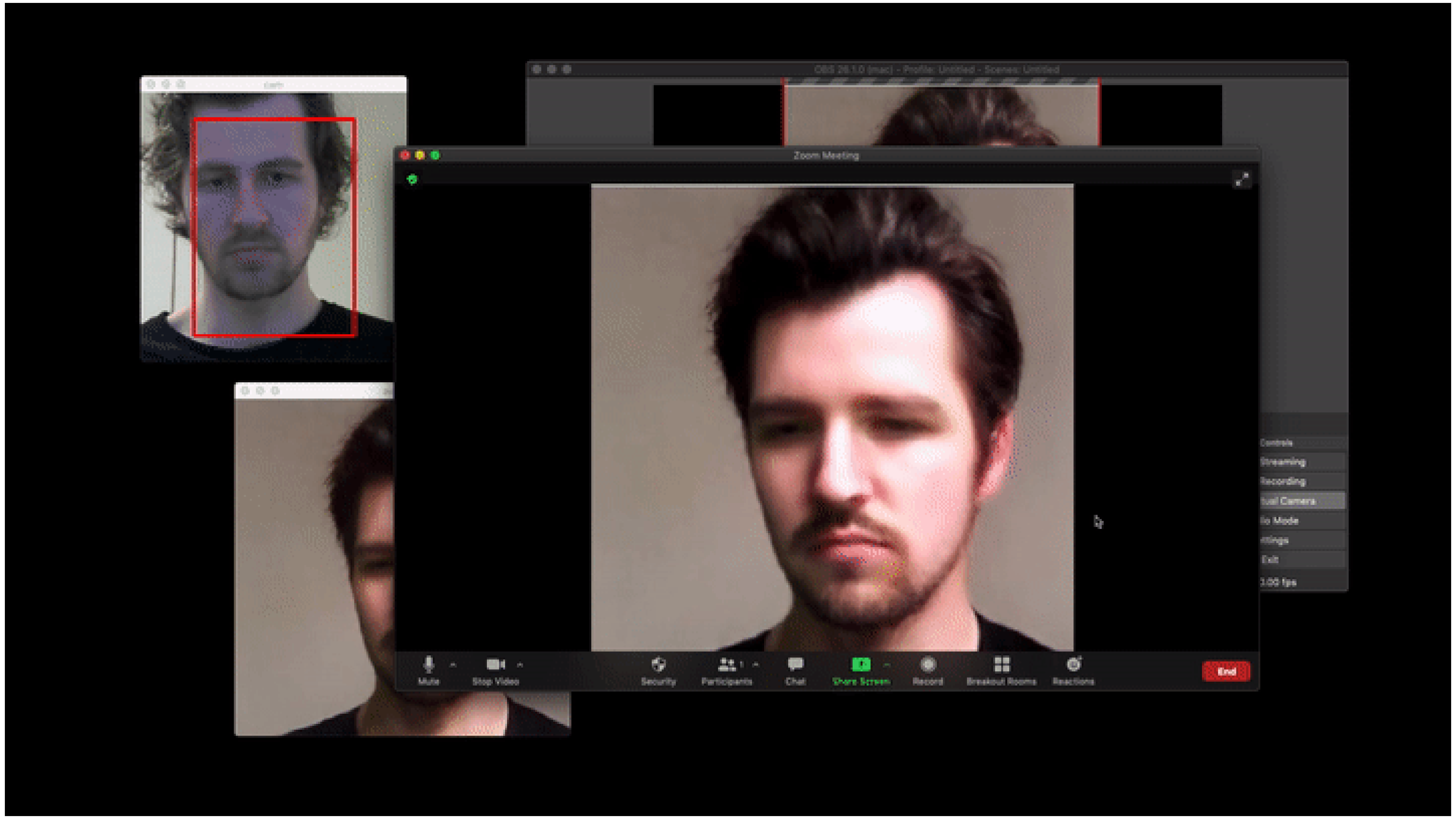
Excerpt from Future False Positive (2019)
Martin Disley

Practice



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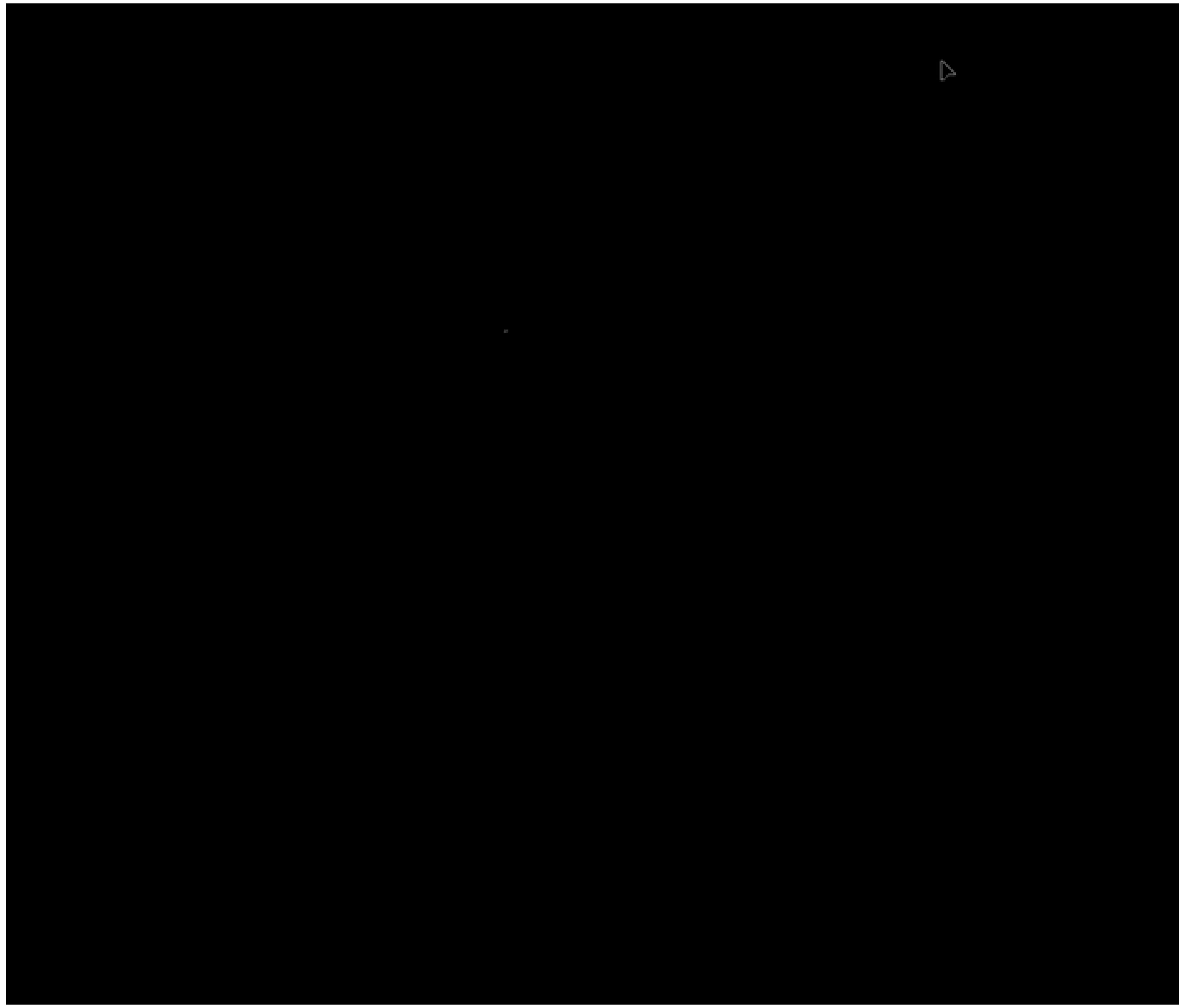
Excerpt from How They Met Themselves (2021)
Martin Disley

Practice



Excerpt from Layers of Abstraction: A Pixel at the Heart of Identity (2018)
Murad Khan

Practice

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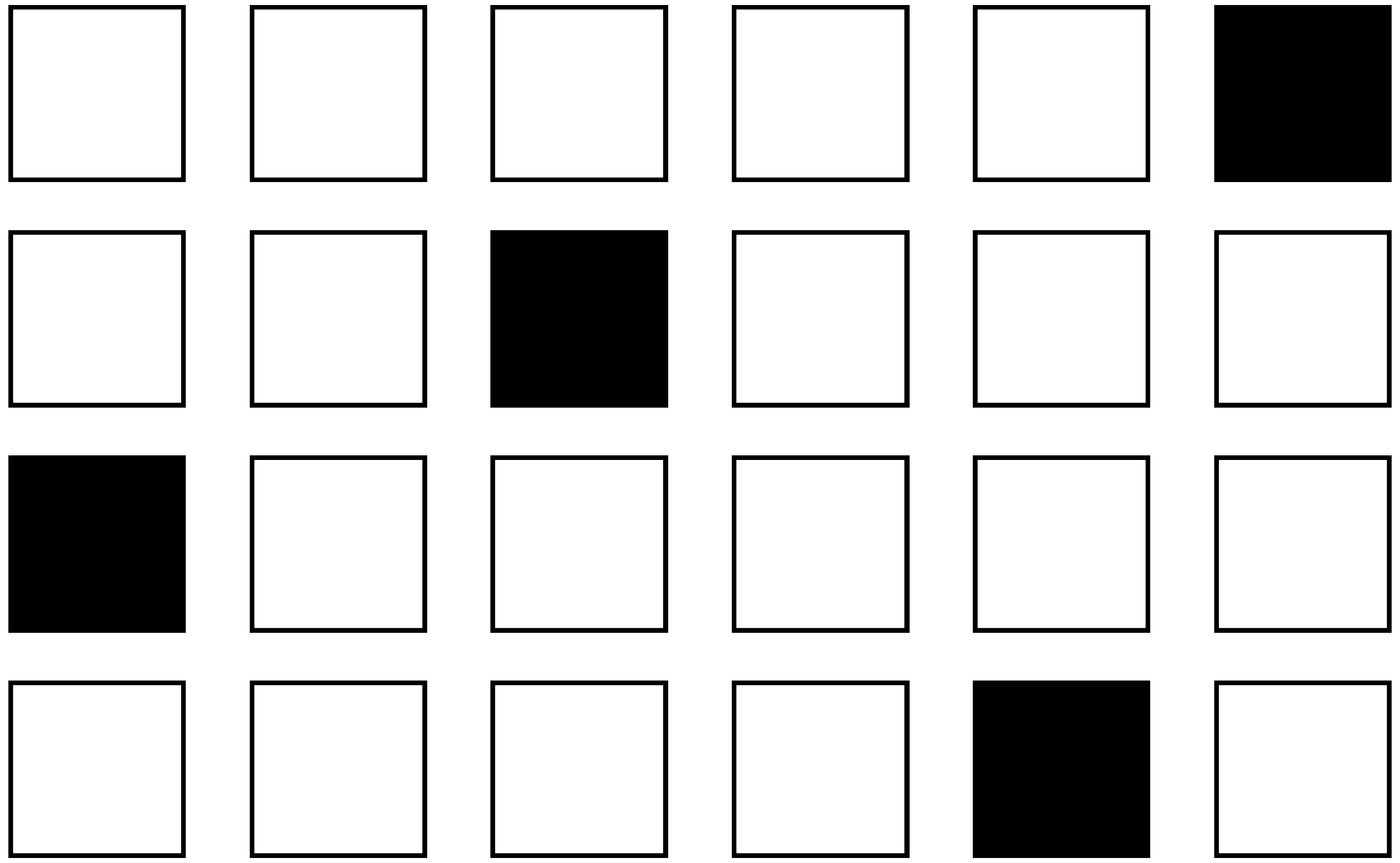
Excerpt from Speech2Face research (2022)
Unit Test

Adversarial Machine Learning

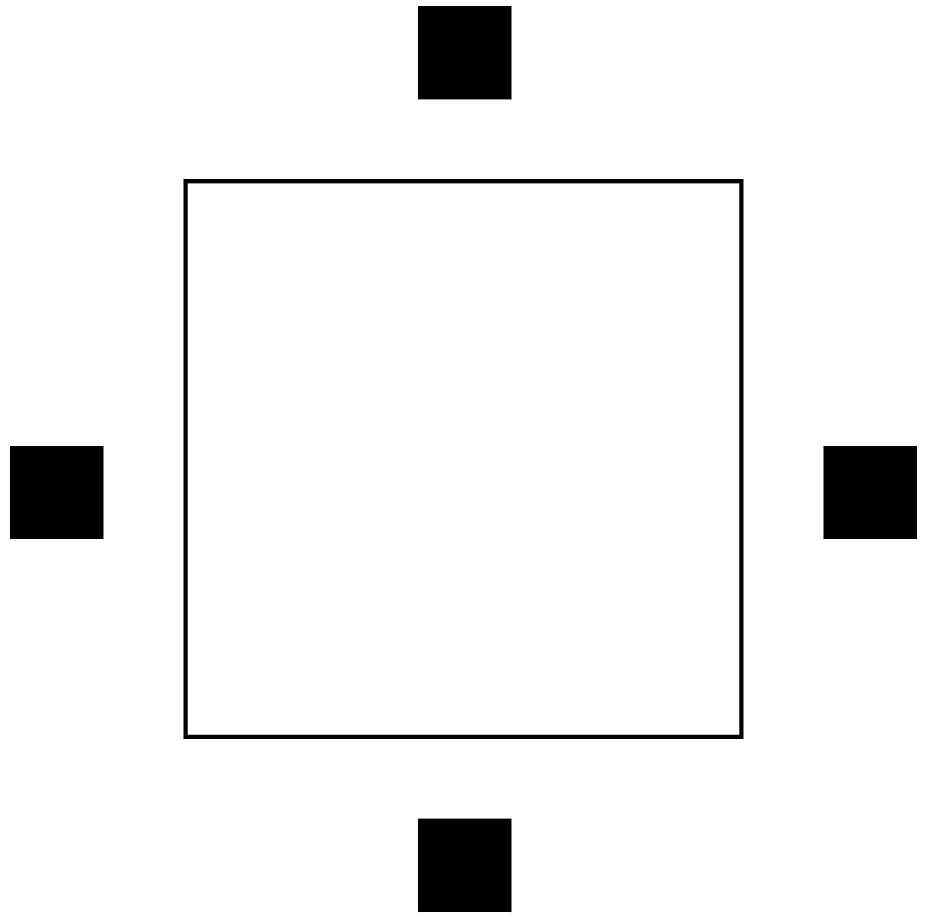
Adversarial machine learning is a field of research concerned with the study of vulnerabilities in machine learning systems, developing a set of techniques and toolkits to both test the robustness of a model and to improve accuracy.

Types of Attack

01 **Causative** attacks occur at training time, focused on the data used to train a model.

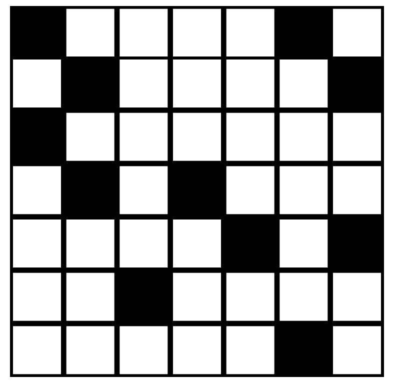


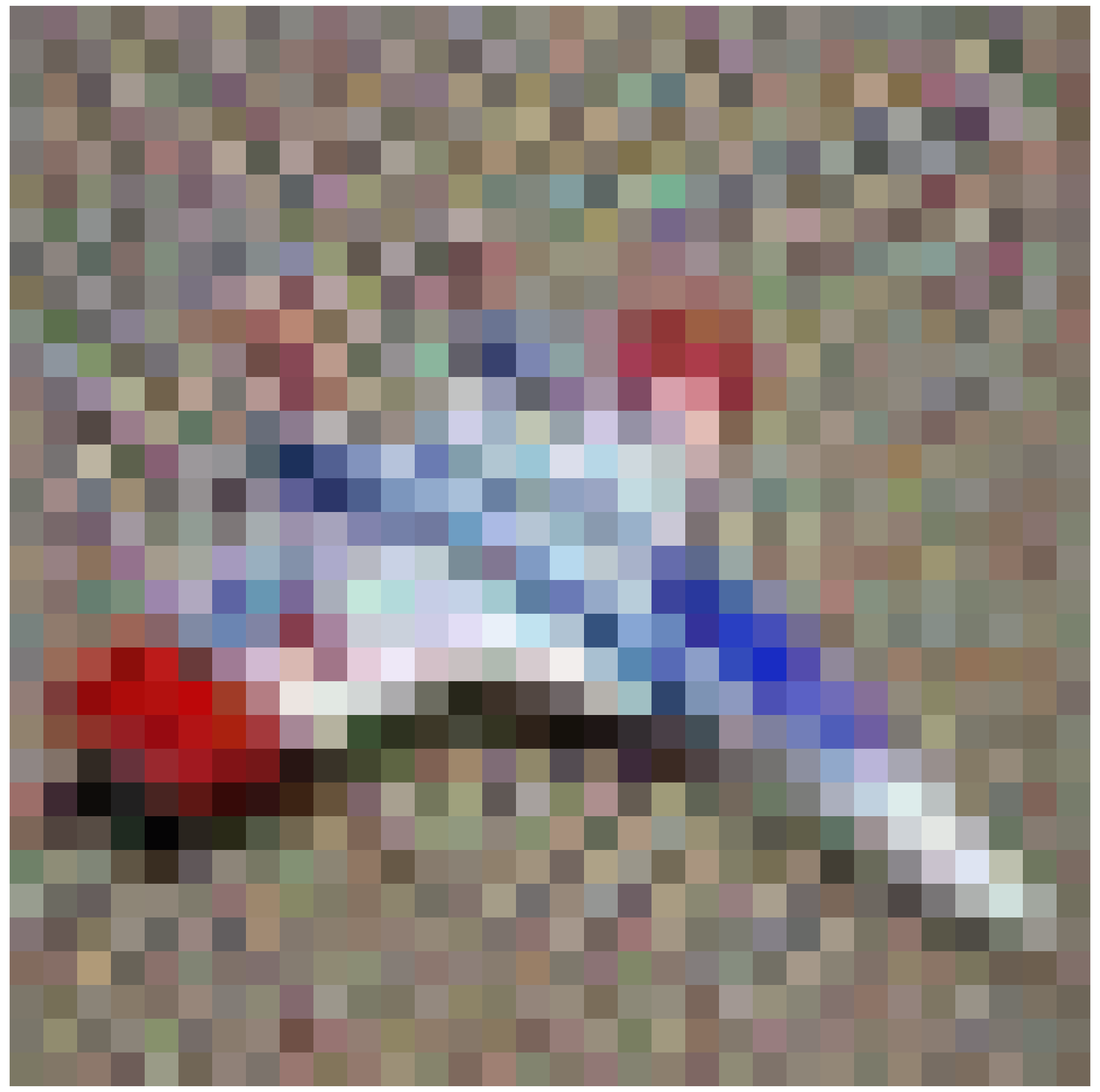
02 **Exploratory** attacks occur at testing time, probing the model via its inferential capacity.



Adversarial Examples

Original Image
Prediction: Plane





Adversarial Image
Prediction: Bird

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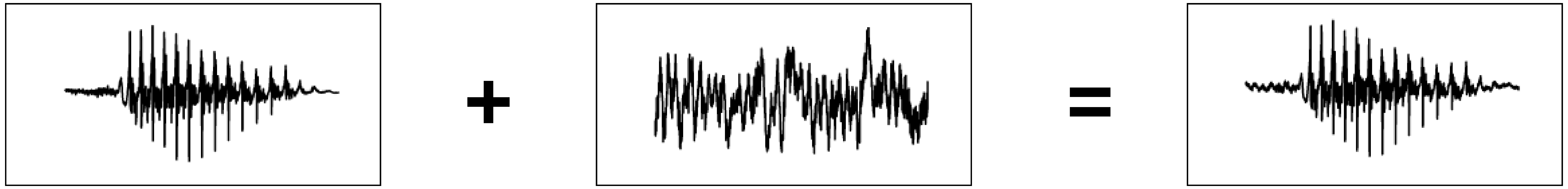
Method: Carlini and Wagner algorithm

Model: CIFAR-10

Adversarial Examples



"it was the best of times, it was the worst of times" → "it is a truth universally acknowledged that a single"

—

Method: Carlini and Wagner algorithm

Model: Deep Speech (Mozilla Implementation)

Experiments

The development of techniques for facial recognition models has reinvigorated the relationship between interior and exterior common to the pseudo-sciences of physiognomy and phrenology, in which the exterior body speaks for, or reveals, a necessary and hidden interior character - an essential and stable subject.

An acoustic approach to this question offers us a chance to explore a different conceptual frame when thinking about the problems of machine learning models.

Crip Technoscience

Disability technoscience reinforces the sense that disabled people are not already making, hacking, and tinkering with existing material arrangements. Disability is cast as an object of innovation discourse, rather than as a driver of technological change

—

Hamraie, A. and Fritsch, K., 2019. Crip technoscience manifesto. Catalyst: Feminism, Theory, Technoscience, 5(1), pp.10

Questions

01 How can we think about adapting the tools of machine learning to develop a more experimental vocal practice?

02 How do we negotiate the boundaries that are enforced in the development and application of sociotechnical systems?

03 How do we point beyond their limits?

Measurable

Acoustic properties of speech typically made amenable to scientific analysis.

Symbolic

The dynamics of listening and interpretation.

Source Filter

Pink Trombone

https://dood.al/pinktrombone/

Measuring Difference

The introduction of the spectrograph focused attention away from the voice as unique aspects of the individual, and towards a standardised framework for speech sounds.

Measuring Difference

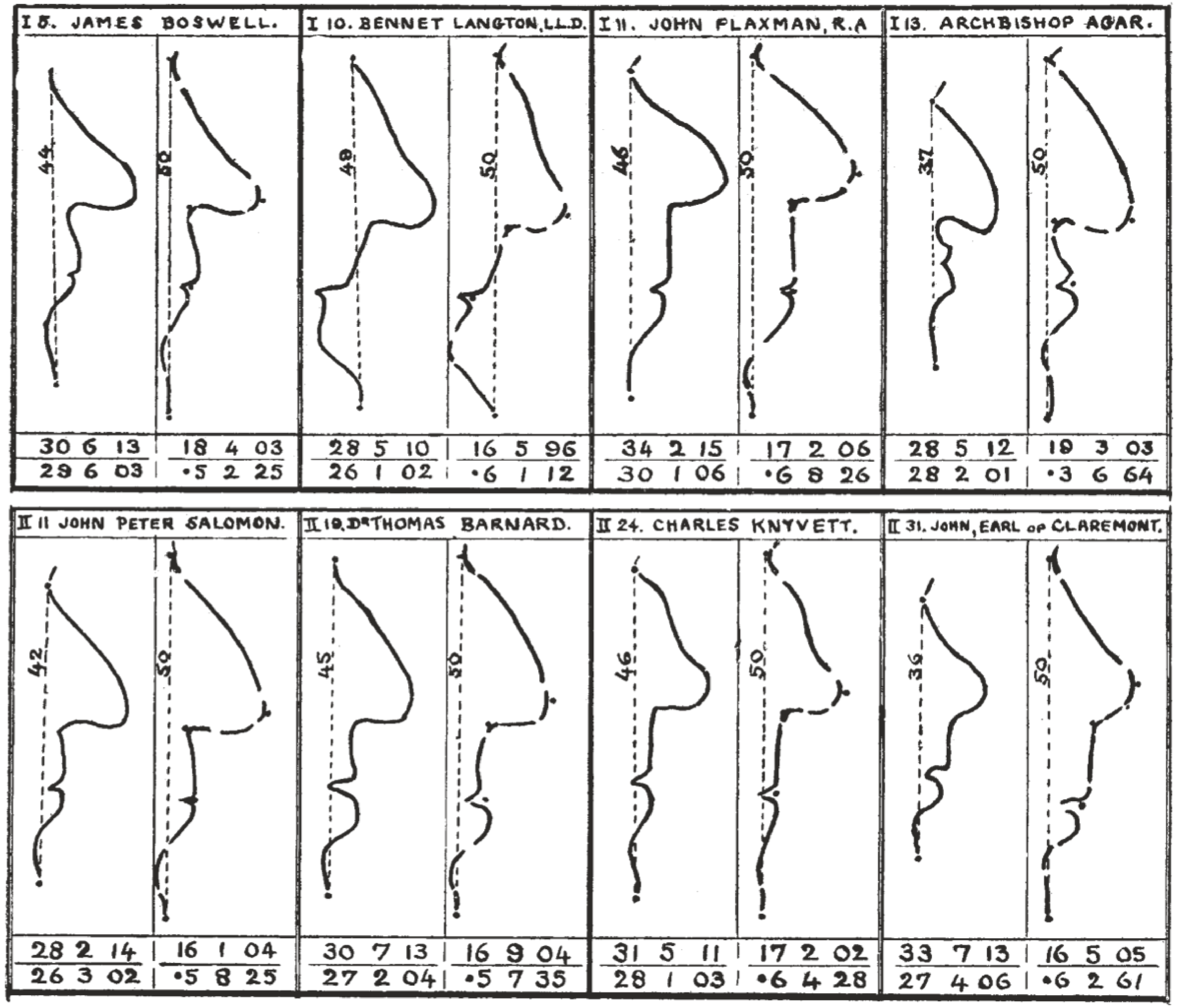


FIG. 5.

Explanation of the first formula, namely, that of James Boswell; the others are to be read on the same principle. N_x, 30; N_y, 13. U_x, 28; U_y, 03. L_x, 18; L_y, 03. The small letters are, *n*, 6; *u*, 6; *lp*, 4. *b*, 5; *g*, 2; *ll*, 2; *k*, 5.

Measuring Difference

What we see emerge in an acoustic model of the voice is the extrapolation of acoustic features, mediated by digital representation (a ‘numeralised’ profile), which is then taken back out to the contingencies of the body in order to *reveal* something about the speaker, about the subject that stands static behind the signal.

Sonicity is where time and technology meet

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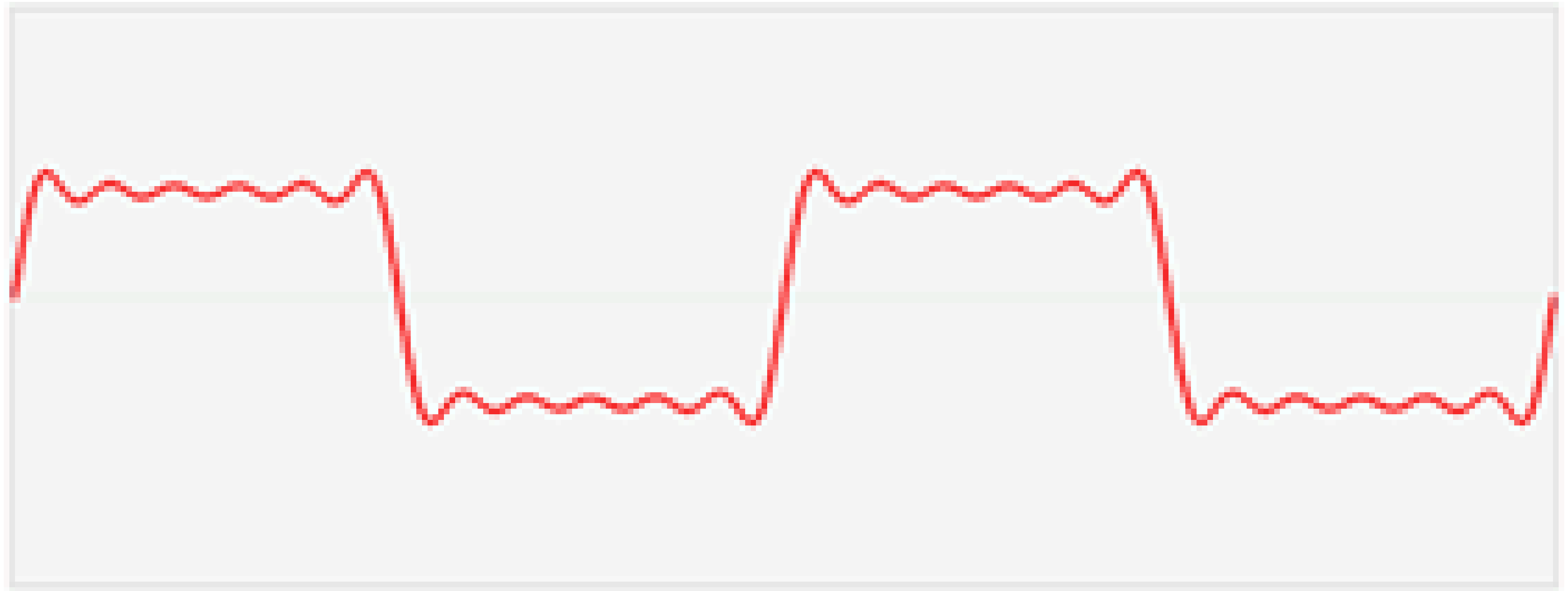
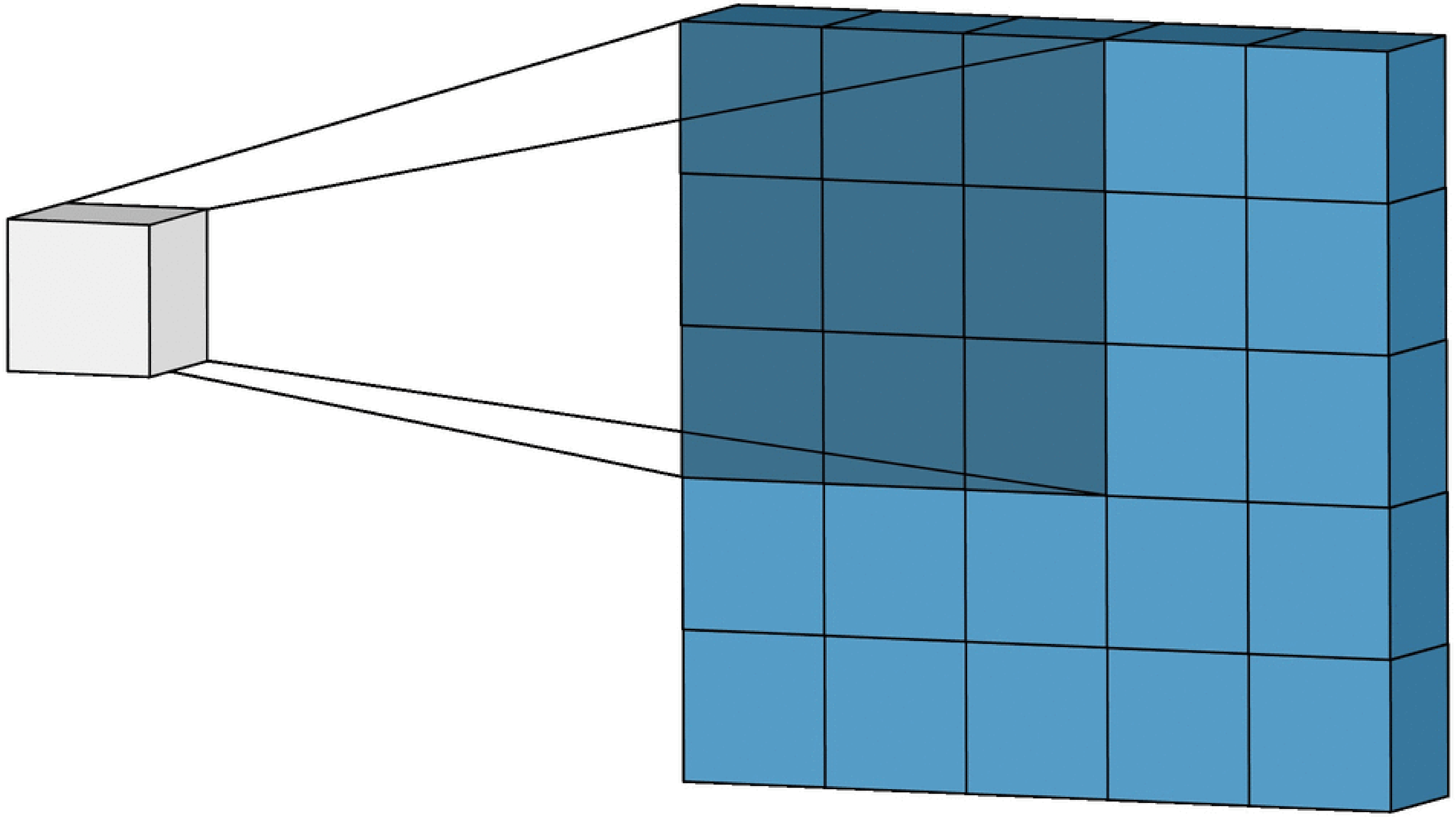
Ernst, W., 2016. Sonic time machines: Explicit sound, sirenic voices, and implicit sonicity. Amsterdam University Press, 21.

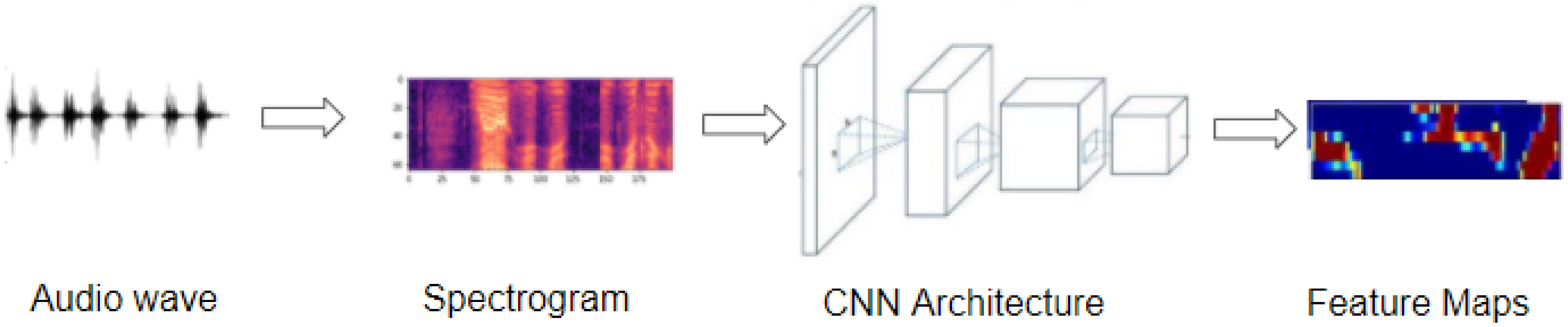
Fourier Transform



Convolutional Neural Networks



Convolutional Neural Networks



An Unstable Image

I call my vocal condition experimental: every day, every encounter is an experiment where my voice, once a constant in my self-conception, is now a variable.

Sterne, J., 2019. Ballad of the dork-o-phone: Towards a crip vocal technoscience. Journal of Interdisciplinary Voice Studies, 4(2), pp.179-189.

An Unstable Image

> …one of the core questions for a political phenomenology of vocal impairment: what happens to a subject when something that was stable becomes a variable, and that something is one of the mechanisms through which others infer the subject's subjectivity?

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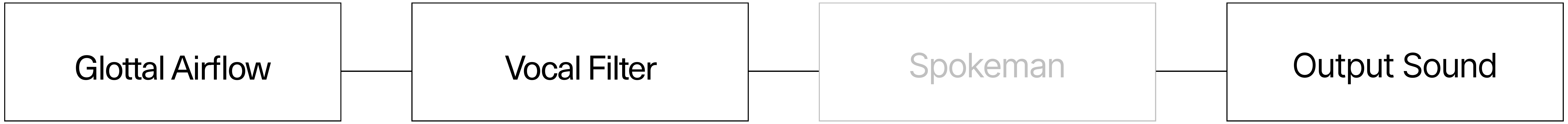
Sterne, J., 2019. Ballad of the dork-o-phone: Towards a crip vocal technoscience. Journal of Interdisciplinary Voice Studies, 4(2), 181

An Unstable Image

Jonathan Sterne's Spokeman Personal Voice Amplifier (AKA the 'dork-o-phone)

An Unstable Image



Measuring Difference

Whilst vocal forensics often accounts for epigenetic reconfiguration of the voice, it fails to resolve this ontogenetic condition of Sterne's voice - now developing in unison with the technical environment in noisy and non-linear fashion.

Questions?

Practical

01

Notebook 1: Encoding

Walk through the process of encoding and analysing your voice.

02

Notebook 2: Embedding

Create embeddings of your voice in a latent space and explore how difference is understood by the model.

03

Notebook 3: Decoding

Intervene in the encoded representation and decode this back to the audio domain.