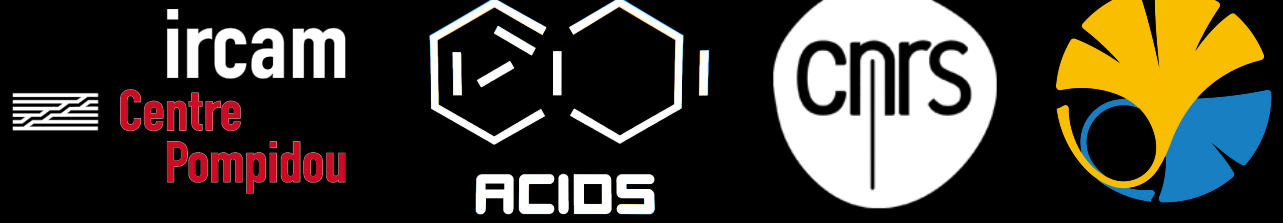


Creative Machine Learning

General introduction

Pr. Philippe Esling
esling@ircam.fr

General introduction

Artificial *intelligence* ?

- Requires to first understand what intelligence is !
- Must have something to do with *thinking*
- But in a broader sense, might also be about *perception* and *action*

Why bothering at all ?

- In terms of philosophy, we would talk about problems involving these
- However, we *try to understand the mechanisms of our thinking itself*
- *We seek models* targeted at thinking, perception and actions

Our overarching goal

Construct *mathematical models reproducing human behaviors*

Hopefully helping us in understanding our own thinking process

Artificial *intelligence ?*

Hard to define intelligence and thinking

Creation ex-nihilo does not exist
(*Laplace*)

> « *Man can only desire what he has already perceived* »
> **William Blake**

Try to invent a new animal right now

Intelligence: *the capacity to assemble two ideas that seemed heterogeneous*

We exist (morphologically) since ~200 kYears, and around ~50 kYears

> « *Take two concepts and create a third one without impairing the two first* »
> **Noam Chomsky**

So thinking is finding similarity, discriminating and seeing common patterns

NB: Frames of Mind: the Theory of multiple intelligence – **Howard Gardner**
(logico-mathematic, spatial, inter-personal, corporal, linguistic, intra-personnal, musical, ecologist, existential)

To have a model, we will need a *representation* that exposes *constraints* on thinking

Brief history of AI

Engineer view « *Building smarter programs* »

Scientific secret goal « *Build a computational account of intelligence* »

1842 - *Lady Ada Lovelace*

First-ever computer programmer

(decades before computers even existed)

The analytical engine has no pretentions to originate anything, it can do whatever we know how to order it to perform

1950 - *Alan Turing*

Inventor of *Bombe* and Turing test

(code-breaking machine that turned the war)

1955 - *Marvin Minski*

Coins the term *artificial intelligence*

"Steps towards artificial intelligence"

1960s - *Early dawn age*

1966 - ELIZA Chatbot

First-ever chatbot (*Rogerian psychotherapy)*

Beginning of Natural Language Processing (NLP)

https://www.masswerk.at/elizabot/

1967 - Symbolic integration

Program written by Joel Moses at MIT

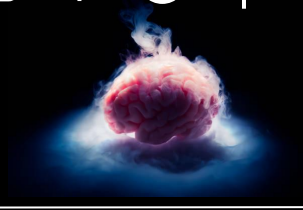
Scores better than 98% of the students

1966 - Shakey

First *electronic person* at Stanford

(general mobile robot with reasoning)

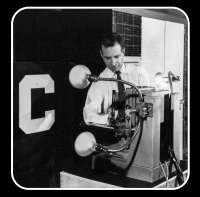
1970 - 1980 1st AI Winter



Brief history of AI

1943 - Neuron

First model by McCulloch & Pitts (purely theoretical)



1957 - Perceptron

Actual **learning machine** built by Frank Rosenblatt
Learns character recognition analogically

Lesson #2

1986 - Backpropagation

First to learn neural networks efficiently (*G. Hinton*)

Lesson #3

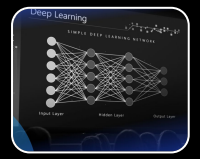
1989 - *Convolutional NN*

Mimicking the vision system in cats (*Y. LeCun*)

Lesson #4

2012 - *Deep learning*

Layerwise training to have deeper architectures
Swoop all state-of-art in classification competitions



Lesson #6

2015 - *Generative model*

First wave of interest in generating data
Led to current model craze (VAEs, GANs, Diffusion)

1970 - 1980 1st AI Winter

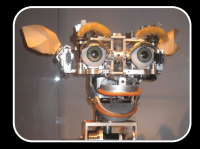
1980s - *Expert systems*

Emulates decisions of human experts
Rising use in healthcare (and still today)

1985 - 1995 2nd AI Winter

1997 - *Deep blue*

First defeat of human chess champion
Based on alpha-beta min-max algorithm



2000s - Robotic explosion

1998 - Kismet	First emotional robot
1999 - Aibo	Robotic dog
2002 - Roomba	Robotic vacuum
2011 - Siri	Personal assistant

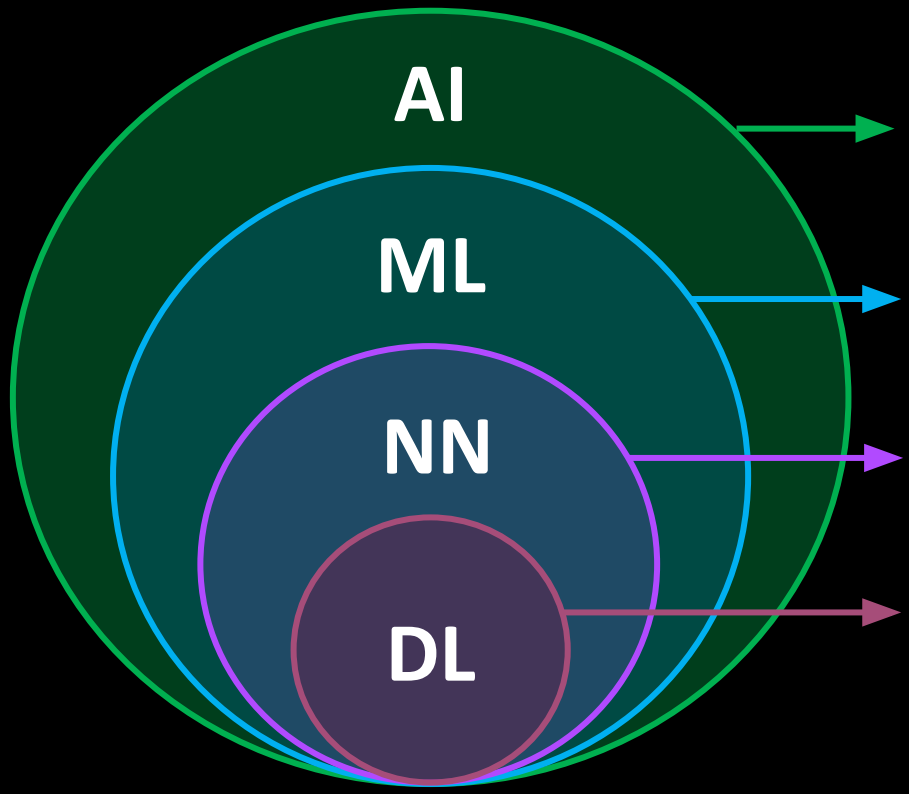
2012 onwards Deep learning era

Families of Artificial Intelligence

Solving confusion around machine ***intelligence***

There is wide controversies about AI (*weak vs. strong, feasible vs. fake*)
Avoiding any debate, we will only discuss here *machine learning*.

- Can we automatically learn parameters of an approximation
- The most active field recently, and also very wide topics inside it



Artificial Intelligence (AI)
Any technique allowing machines to solve human tasks

Machine Learning (ML)
Learning inference models from examples

Neural Networks (NN)
Brain-inspired ML models

Deep Learning (DL)
Building (deep) hierarchies of NN representations

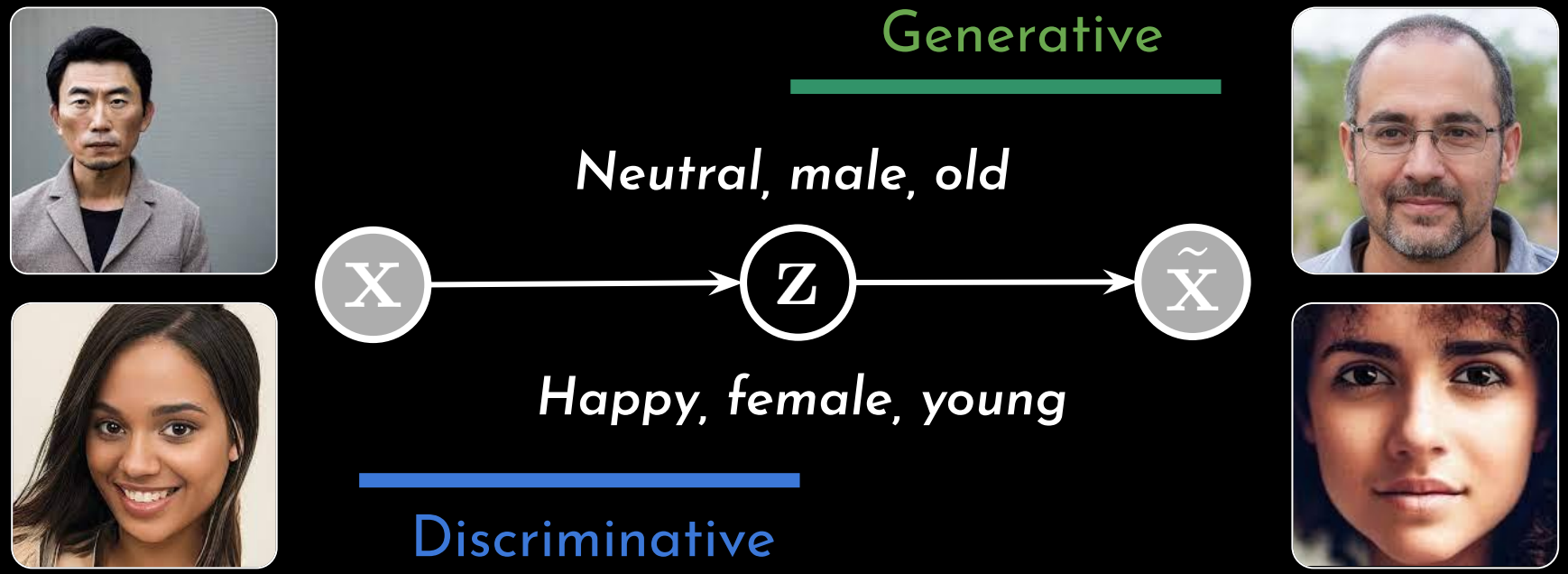
Why creative ?

3 major types of learning

- **Supervised learning** is inferring a function from labeled training data
- **Unsupervised learning** is trying to find hidden structure in unlabeled data
- **Reinforcement learning** is acting to maximize a notion of cumulative reward

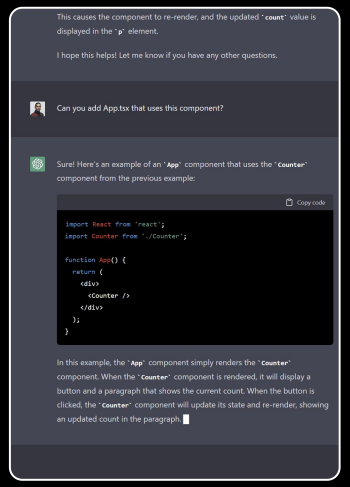
Self-supervised learning is using the data itself directly to define tasks to solve

Discriminative or generative ?



Two sides of the same coin

Major players in the generative field



ChatGPT

AI language model (OpenAI) based on Transformers (GPT)
Trained on vast corpus of text to generate chat answers
Impressive question answering and reasoning abilities

Lesson #5 = Transformers

Midjourney - StableDiffusion




Image-generation AI by Stability based on GANs and diffusion
Trained to generate HQ images based on prompts
Impressive capabilities used in art, entertainment, and fashion

Lesson #9 = Generative Adversarial Networks (GANs)

Lesson #10 = Diffusion models

What about musical data ?

Creep by Radiohead
... but by The Beatles

Jukebox

Generative model by OpenAI creates original music with lyrics and singing.
Combination of VQ-VAE and Transformer for raw audio at 44.1 kHz.
Can generate music in various styles, and even mimic specific artists

MusicLM

Generative model by Google to perform text-to-music
Based on AudioLM and CLIP for generative audio at 44.1 kHz.
Allows to directly prompt what music you want and generates waveform

A fusion of reggaeton and electronic dance music, with a spacey, otherworldly sound. Induces the experience of being lost in space [...]

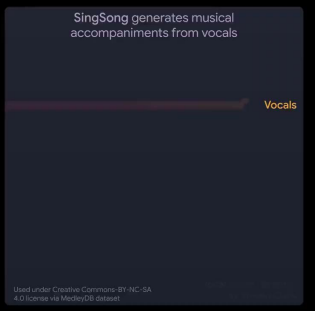
Voice cloning

Text-to-speech allows to clone any voice
Cyberduck app

Thank you Barack !

Reverse Karaoke

Generate music to accompany vocals
SingSong project



Course program

Goal of this course

- Ability to construct (math) and develop (code) your own *generative models*
- True and deep understanding of the mathematical theory behind those models
- Constant flow between theory, implementation and creative application

Detailed program

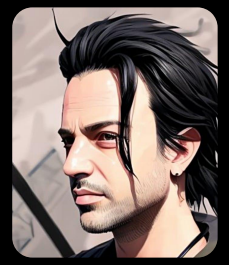
Discriminative

1. Introduction
2. Machine learning
3. Neural networks
4. Advanced networks
5. Deep learning
6. Probabilities and Bayesian inference

Generative

7. Latent models, EM and GMM
8. Approximate inference
9. Variational Auto-Encoders (VAEs) and flows
10. Adversarial learning (GANs)
11. Diffusion models

Why should you even listen to me



Professor Philippe Esling - esling@ircam.fr

Sorbonne université (Paris)
Teaching machine learning for 10 years

The University of Tokyo
Invited professor in ML

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ircam ACIDS

ACIDS - Artificial Creative Intelligence and Data Science
Lead of research group (in A/S team) on generative models for music

Japanese-French Laboratory for Informatics
Invited researcher for leading the Creative AI axis

Google Research (Brain)
Invited researcher at the Magenta team

Presentation of my research in the second half of this course

---

Guest lecturers

Taketo Akama
Industrial research
Sony CSL Tokyo
Generative models

Pr. Tatsuya Harada
Academic research
University of Tokyo
Computer vision, robotics

Course information

Basic administrative information

Type : 2-credits graduate school course
Period : April - July 2023
Span : 14 classes of 105 minutes
Date : Every thursday at 2:55 - 4:40 pm (JST)
Onsite : *Room 214, 2nd Floor, Sci. 7 Building*

Online course
https://u-tokyo-ac-jp.zoom.us/j/81363691008?pwd=cmxiRURMdm9udXBKbTNjQkZvblNFQT09

Github page

github.com/esling/creative_ml

Professor

Philippe Esling - esling@ircam.fr

Pre-requisites

Notions required but not covered in this course

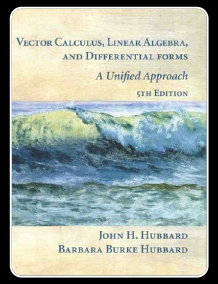
Resources to help you out if you feel behind on these topics

Calculus

Limits and infinitesimals
Differential calculus
Integral calculus

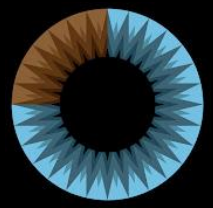
Linear algebra

Vector spaces
Matrix calculus
Geometry and analysis



Hubbard J. & Hubbard B.B
Vector Calculus, Linear Algebra, and Differential Forms: A Unified Approach (5th edition)

- Linear algebra slides
- Probability revision slides
- Statistics course notes
- Sampling pages
- Matrix Cookbook



3 Blue 1 Brown

Essence of linear algebra
Essence of calculus

Programming

Python basics
Functional notions
Object-oriented prog.

Data analysis

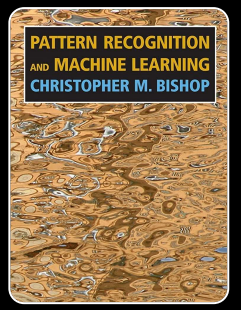
Data visualization
Basic filtering, processing

codewars

codecademy

Machine learning bible

Christopher M. Bishop
Pattern recognition and machine learning



Course teaser

Overarching construction

#1 - Interactive animations

Course heavily based on **interactive learning** principles
Merging **theory and application** as much as possible

#2 - Jupyter notebooks

#3 - Interactive panels

- Interactive coding environment with exercises
- Used during the class with dynamic panels
- Will also serve to fill in evaluated exercises
- Submission system impending

Fully online

Slides
slides.google.com

Colab
colab.google.com

GitHub **fork** (+ star)
Jupyterlab environment

Best solution

Course and exercises are always evolving

Help each others out and work as groups
Post issues on GitHub and Discord

Join discord
https://discord.gg/gpF82wnh

Understanding philosophy

General principle

We will be exploring all concepts by

1. Deriving the mathematical bases ourselves
2. Implementing low-level aspects directly as well
3. Moving up to higher-level (simpler) implementation

Essential principle for a profound understanding of concepts

ML Libraries

Concept mirrored in our choice of libraries

1. **Numpy** forces us to do mathematical derivation
2. **JAX** adds automatic differentiation over Numpy
3. **Pytorch** allows to define networks in seconds

Numpy

JAX

PyTorch

Other helpful libraries

Librosa

Scipy

Seaborn

Bokeh

Scikit

Panel

Matplot

Manim

Evaluation methodology

One major evaluation and project

Continuous evaluation

Course based on interactive Jupyter **notebooks to fill and submit**

- Each notebook contains a set of exercises
- We will start exercises together but you have to finish at home
- Automatic submission system will be set in place
- Rolling deadlines of 3 sessions (~3 weeks) to submit your work

Project-based evaluation

Supplementary evaluation will be based on a large-scale project

- Several projects will be proposed
- Groups of **4 to 8 students** per project
- Projects are coded in **Python** (cf. Coding style section underneath)
- All projects should be **accompanied with a small report** in english
- The **report should be of 8 pages** following scientific papers style
- Reports are written in LaTeX with famous conferences (*ICLR*, *NeurIPS*) format style

Setup and course follow-up

Following the course

All lessons will follow the same structure
Mixture of animated slides and notebooks
You can follow the online or offline version

	Slides	Notebooks
Online	Slides online	Notebook collab
Offline	Slides download	Notebook download

The course is updated prior to each lesson

Course not available yet Slides none

Installing the course github.com/esling/creative_ml

You need a GitHub account

1. **Star the repo** to get updates on new courses and corrections
2. **Fork the repo** to have your own copy (for exercises)
3. **Clone the repo** to your local machine

Setup your environment

1. **Install jupyter lab** (see instructions in Setup section)
2. **Install all required libraries** (see the requirements.txt file)
3. **Test your setup** by using the 00_setup.ipynb notebook

[Setup time]

5 minutes + 5 minutes break

Github page

github.com/esling/creative_ml

Installation guide

creative_ml#setup

Machine learning

Problem statement

We witness a phenomenon
Through a set of observations

$$(x_1, y_1)\ (x_2, y_2)\ \cdots\ (x_n, y_n)$$

We know there exists a relation between $\mathcal{X}$ and $\mathcal{Y}$

But we do not know its nature

$$f : \mathcal{X} \to \mathcal{Y}$$

Machine learning constructs approximations

$$f_\theta : \mathcal{X} \to \mathcal{Y}$$

such that

$$y_i \approx \bar{y}_i = f_\theta(x_i)$$

Regression and classification

The two most classical machine learning problems

Machine learning

Formal problem statement

We aim to model the relationship between $\mathcal{X}$ and $\mathcal{Y}$

$$f : \mathcal{X} \to \mathcal{Y}$$

We collect a **dataset** that is representative of that relation

$$\mathcal{D} = \{(\mathbf{x}_1, \mathbf{y}_1) \cdots (\mathbf{x}_n, \mathbf{y}_n)\}$$

We will construct a **parametric approximation** $f_\theta \in \mathcal{F}_\Theta$

$$f_\theta : \mathcal{X} \to \mathcal{Y} \quad \bar{\mathbf{y}} = f_\theta(\mathbf{x})$$

We want to find the best f_θ^* so that $\bar{\mathbf{y}} \approx \mathbf{y}$

So we need to find the best parameters $\theta^* \in \Theta$

Need to compute the errors (**loss**) of our model

$$\mathcal{L}(\bar{\mathbf{y}}, \mathbf{y} \mid f_\theta, \theta)$$

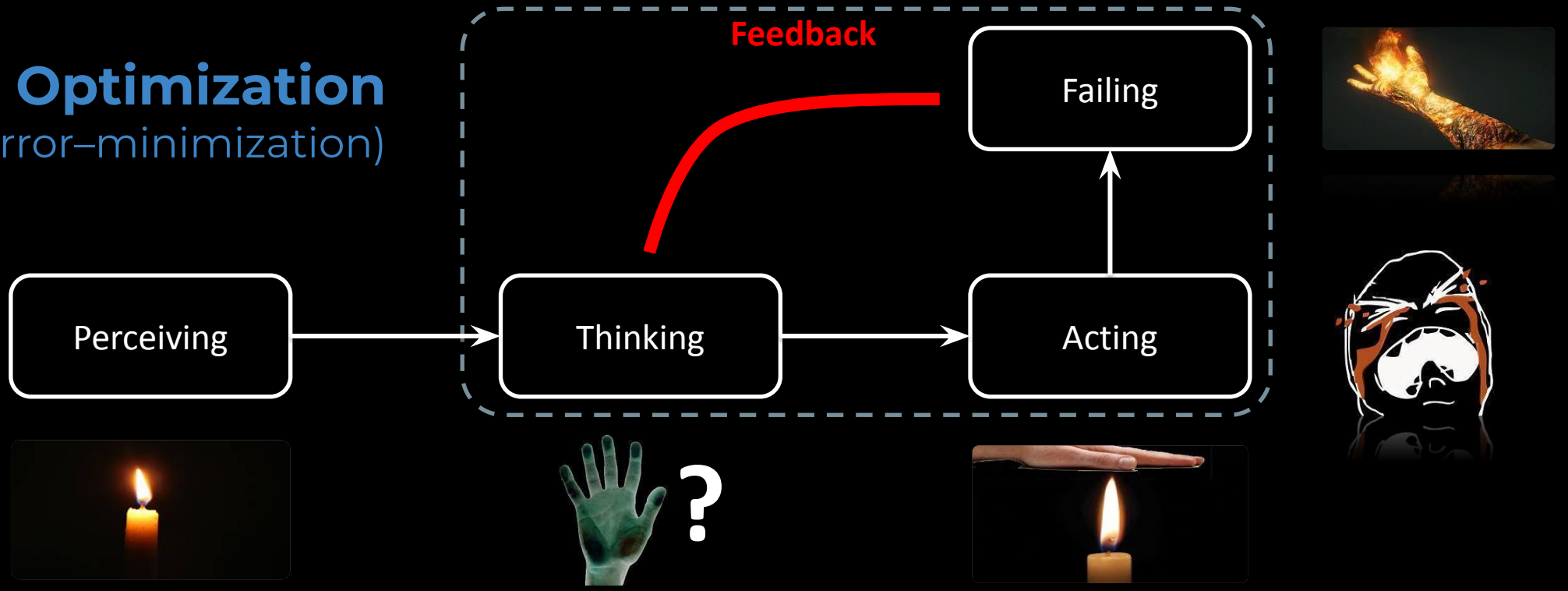
And minimize (**optimize**) this amount of errors

$$\theta^* = \underset{\theta}{\operatorname{argmin}}\ \mathcal{L}(\bar{\mathbf{y}}, \mathbf{y} \mid f_\theta, \theta)$$

Learning as error minimization

Why it makes sense in real-life

Optimization
(error–minimization)



- **Goal-directed learning** = acquiring, modifying or reinforcing knowledge
- Most problems can be summarized by a **trial-error process**
- Is a nickname for **optimization** (through **error minimization**)
  - So what can we do with ML ? Some examples from our team (ACIDS)

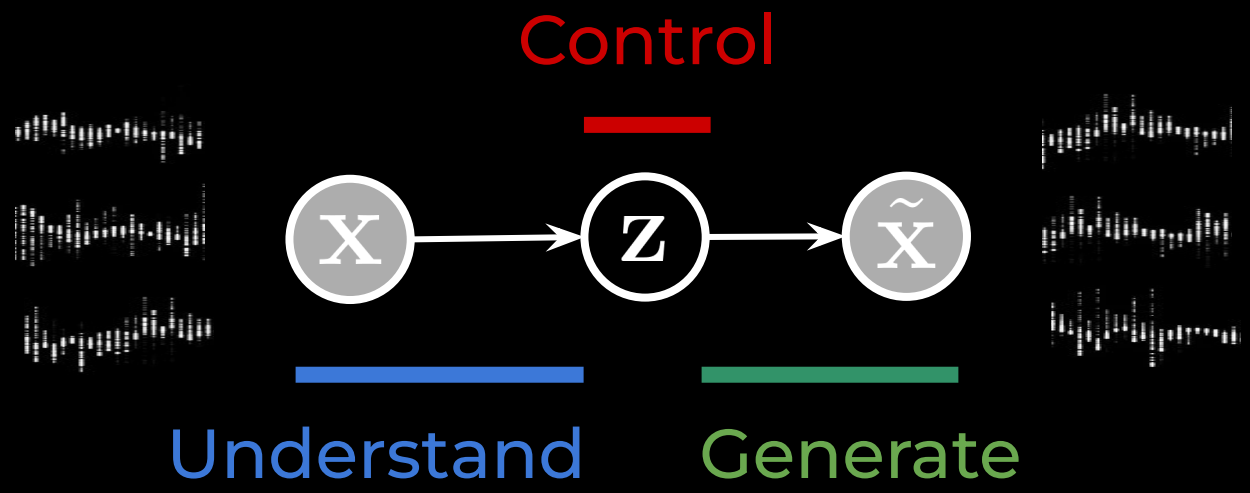
ACIDS Project

Artificial Creative Intelligence and Data Science

Research group at IRCAM, Sorbonne, Paris - Analysis / Synthesis team

Academic machine learning research since 2012

Theoretical and applied research in generative models for musical creation



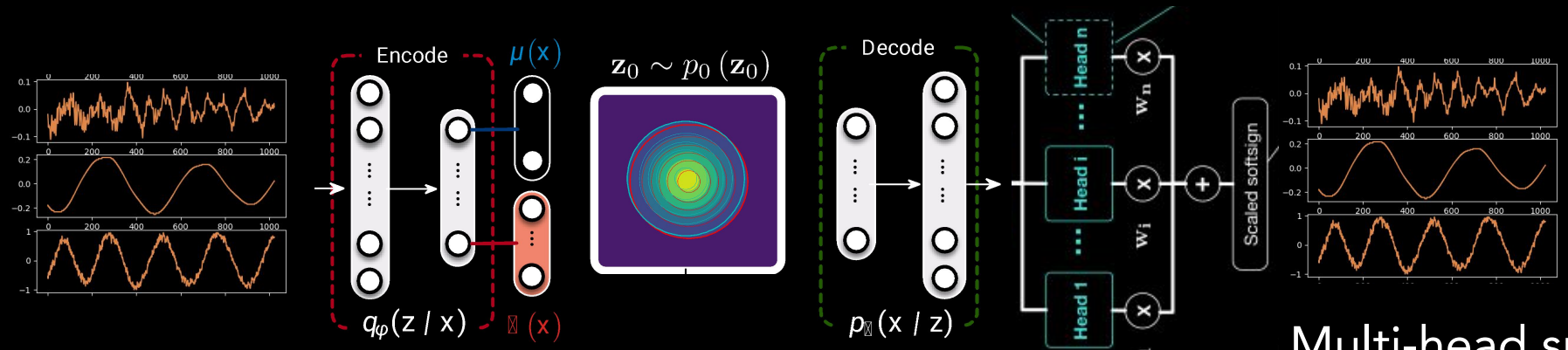
- Neural drum machine
- Timbre transfer applications
- High-level controls
- [**RAVE**] - Real-time synthesis
- [**FlowSynth**] - Synthesizer control
- [**Neurorack**] - Neural synthesizer

Pushing the limits of musical creativity through the use of machine learning

Creating the next generation of musical instruments

Applications - Drums generation

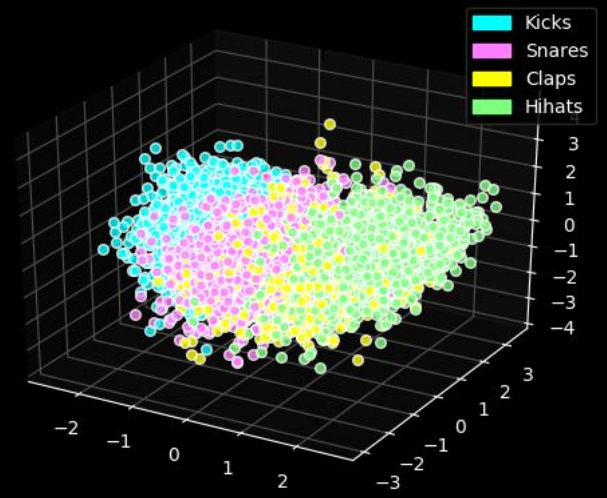
Drums are mostly noisy, require end-to-end training with waveforms



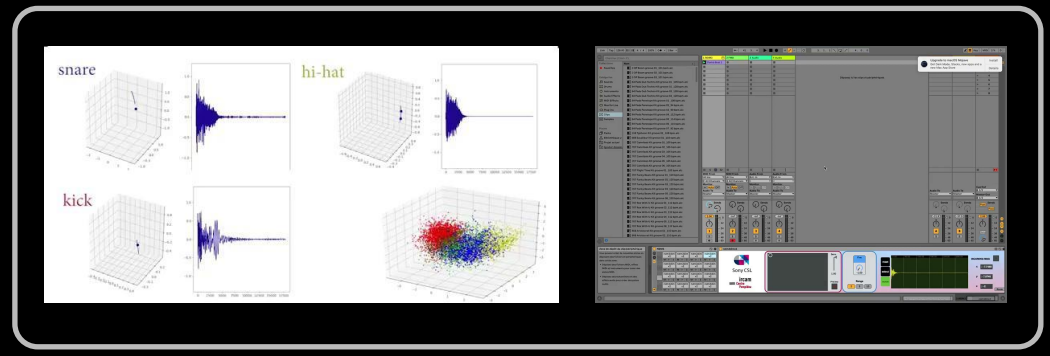
Multi-head spectrum inversion

Heads unsupervisedly split into bands

Work with Axel CRS and Cyran Aouameur



Real-time version demonstration



Ableton plugin and web-based interface

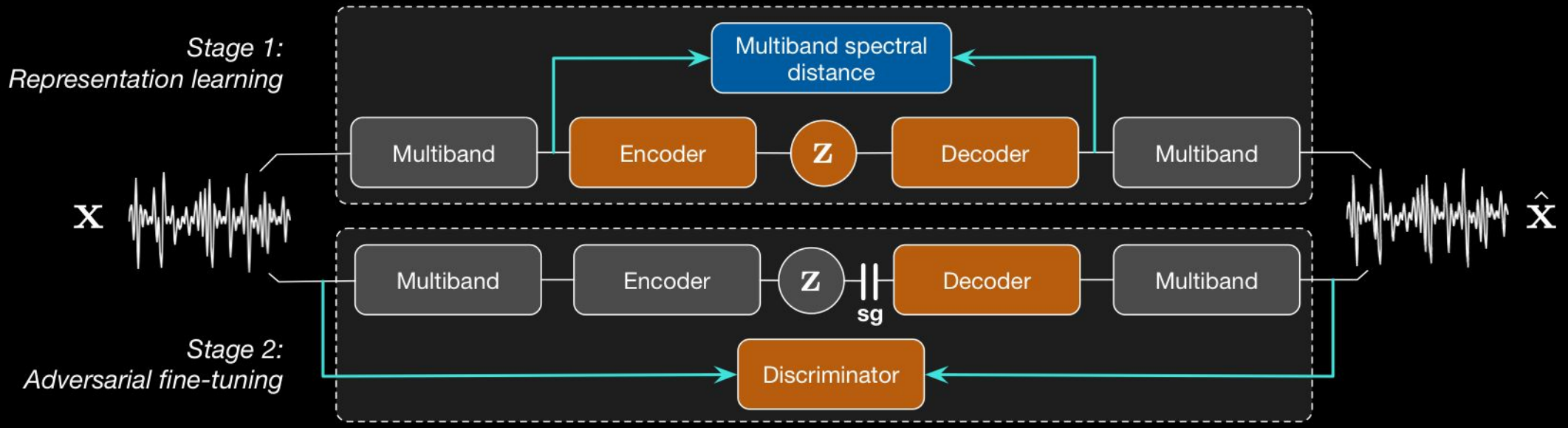
Aouameur, C. Esling, P. and Hadjeres G. Neural drum machine: An interactive system for real-time synthesis of drum sounds. arXiv:1907.02637, 2019.

RAVE - Realtime audio waveform VAE

Recently, we vastly improved VAE generation

Full paper submitted to ICLR 2022

Work with Antoine Caillon



High-quality (48kHz) synthesis with **25x realtime on a laptop CPU**

Perform *timbre tranfer* without any specific training

Allows *polyphonic unconditional generation* of signals

Caillon, A. Esling, P. RAVE: A variational auto-encoder for fast and high-quality neural audio synthesis. arXiv:2111.05011, 2021.

RAVE - Multiple outputs / interactions

Realtime demo

Jetson embedding

RAVE is available as multiple types of open source possibilities

https://github.com/acids-ircam/RAVE

PureData / MaxMSP https://github.com/acids-ircam/nn_tilde

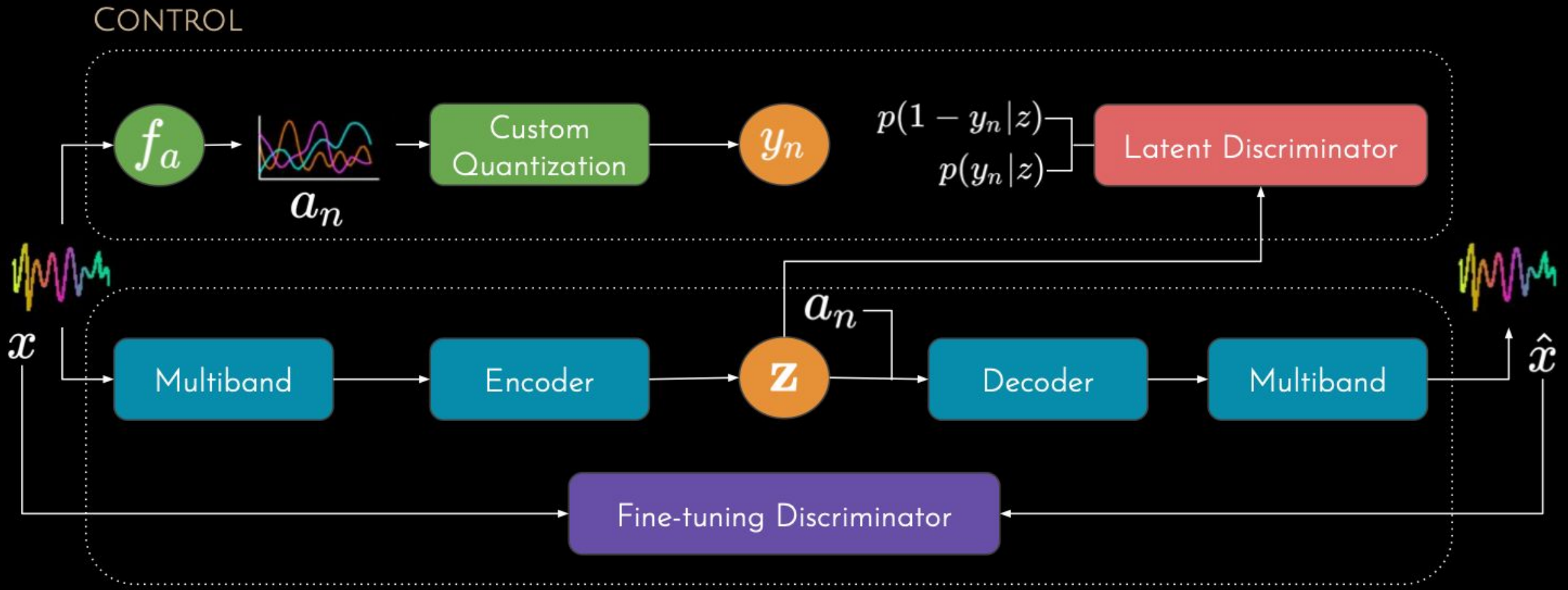
VST (multi-platform) https://github.com/acids-ircam/rave_vst

Caillon, A. Esling, P. RAVE: A variational auto-encoder for fast and high-quality neural audio synthesis. arXiv:2111.05011, 2021.

Descriptor-based synthesis

Further improve the real-time generative model with high-level control

Work with Ninon Devis, Nils Demerlé, Sarah Nabi and David Genova



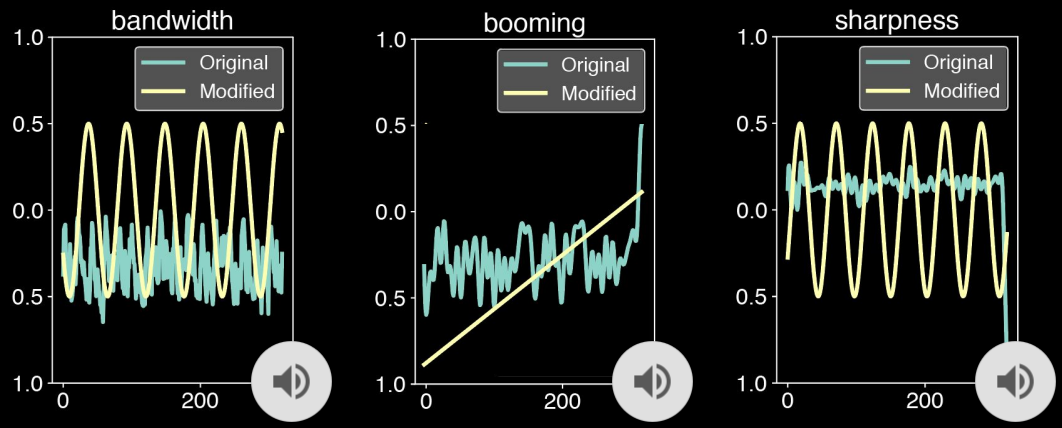
Devis, N. Demerle, N. Nabi, S. Genova, D. and Esling, P. Continuous descriptor-based control for deep audio synthesis. ICASSP 2023

Descriptor-based synthesis

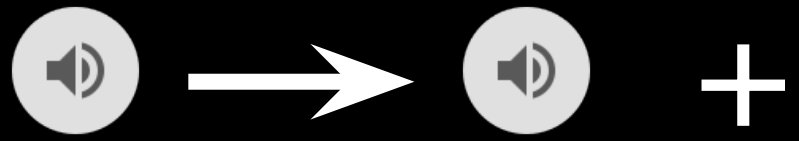
Descriptor-based synthesis (attribute transfer)

Model generation

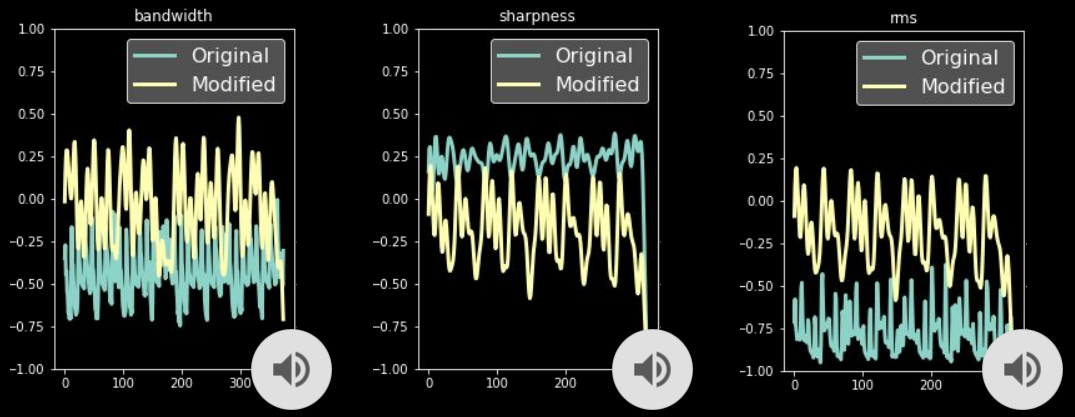
(Derbouka)



Combining timbre and attribute transfer



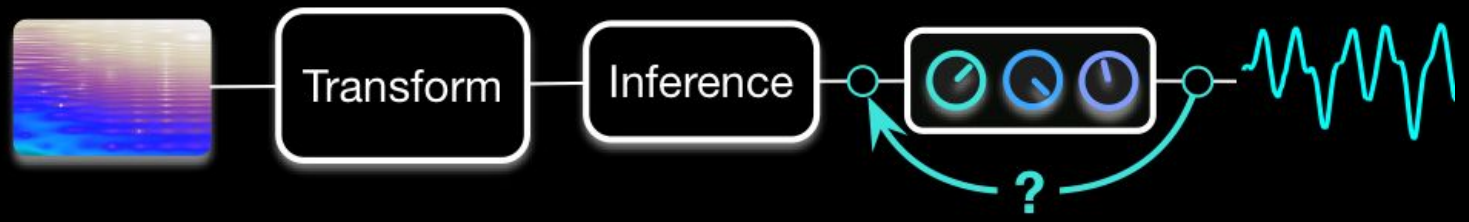
(Derbouka) (Japanese)



Devis, N. Demerle, N. Nabi, S. Genova, D. and Esling, P. Continuous descriptor-based control for deep audio synthesis. ICASSP 2023

Universal synthesizer control with FlowSynth

Compared to previous approaches (limited to parameters inference)



Our proposal = Universal synthesizer control with flows

Organize the auditory space of a synthesizer audio possibilities

Infer **invertible mapping** between these spaces

Control organization of dimensions with semantic attributes

Organize the parameters space

Parameter space

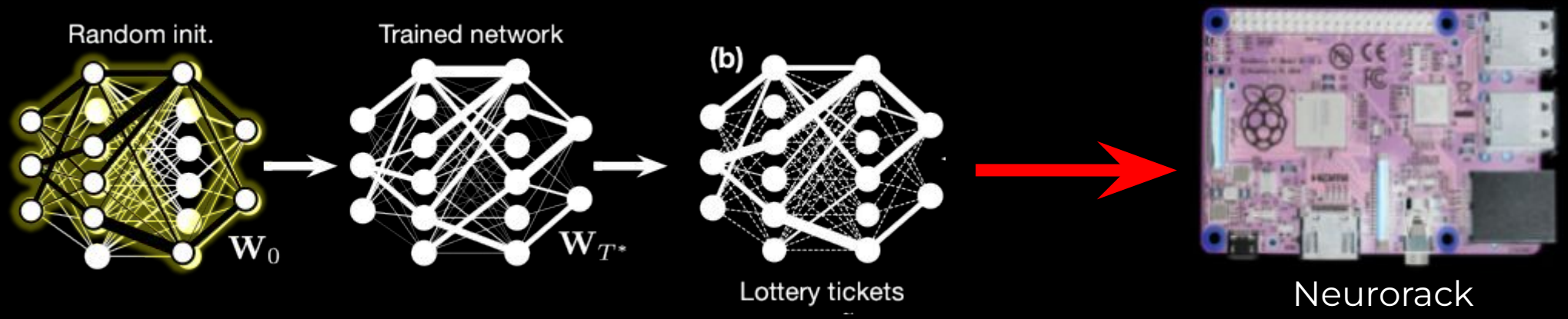
FlowSynth - Demo video

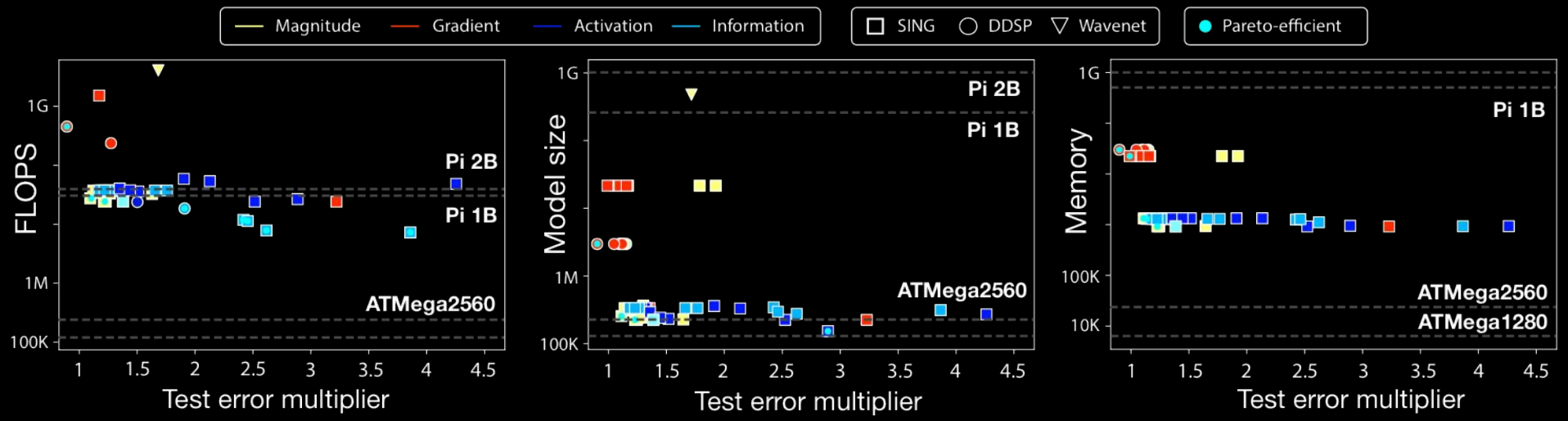
https://github.com/acids-ircam/flow_synthesizer

https://www.youtube.com/watch?v=UufQwUitBIw

Lottery ticket hypothesis

Reducing deep models onto embedded chips



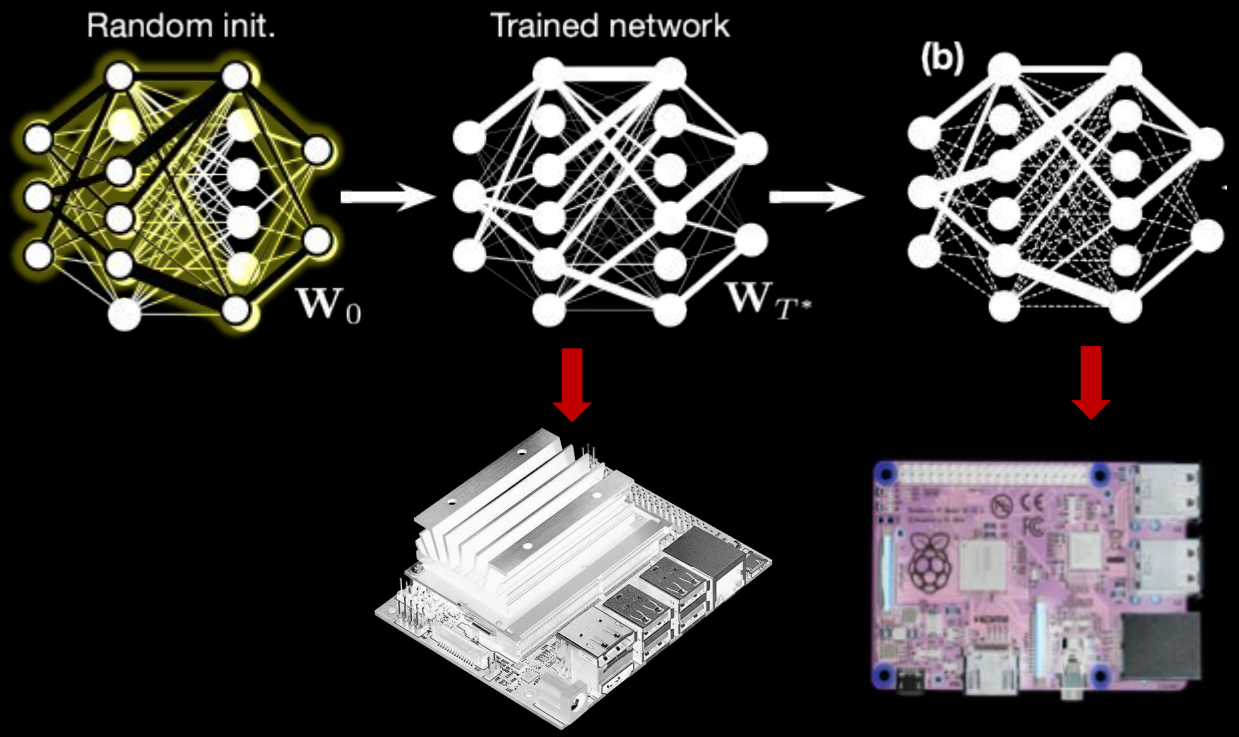


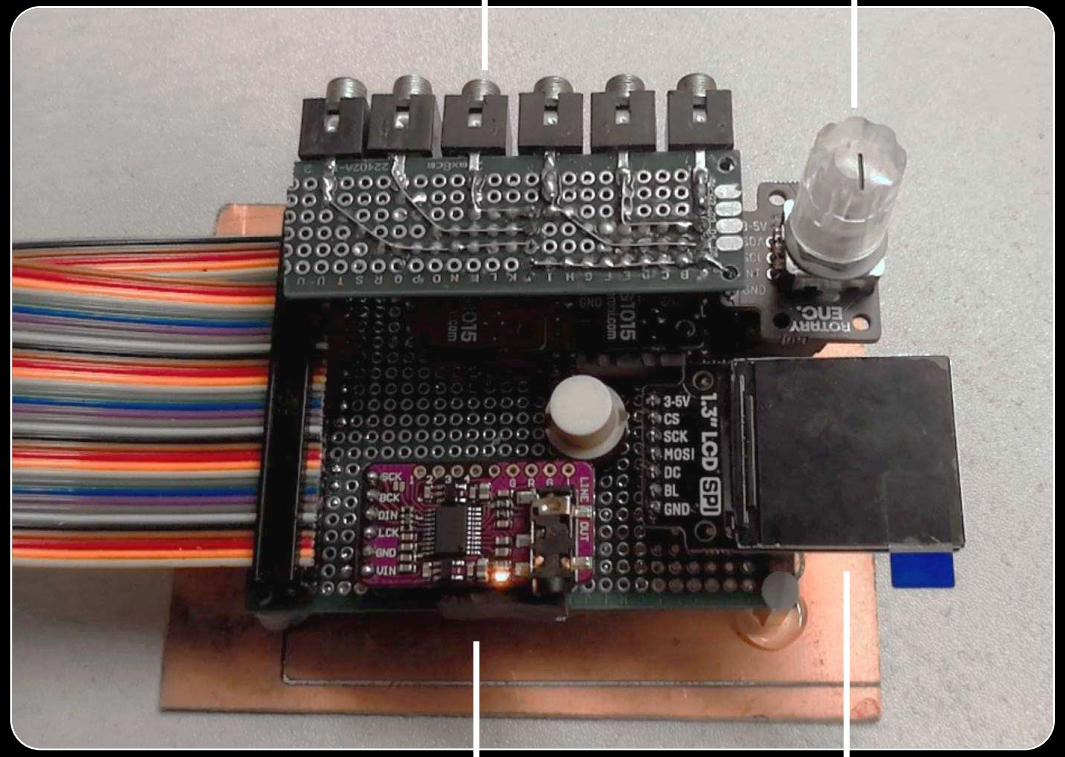
Esling, et al. *Diet deep generative audio models with structured lottery*. Proceedings of International Conference on Digital Audio Effects (DAFx), 2020

Neurorack first prototype

Deep models in embedded constrained platforms

Neurorack // Work with **Ninon Devis** and **Martin Vert**

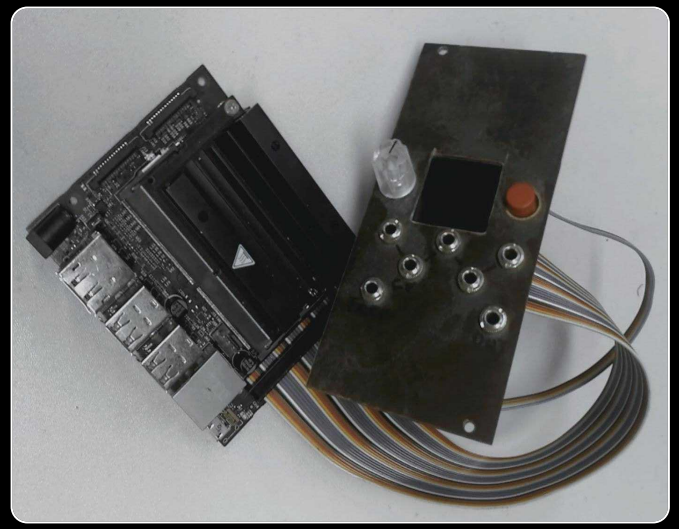




First-ever Neurorack prototype built ourselves with simple components

Devis, N. and Esling, P. *Neurorack: deep audio learning in hardware synthesizers*. EPFL PhD Converence (Lausanne), 2021

Final neurorack prototype interface

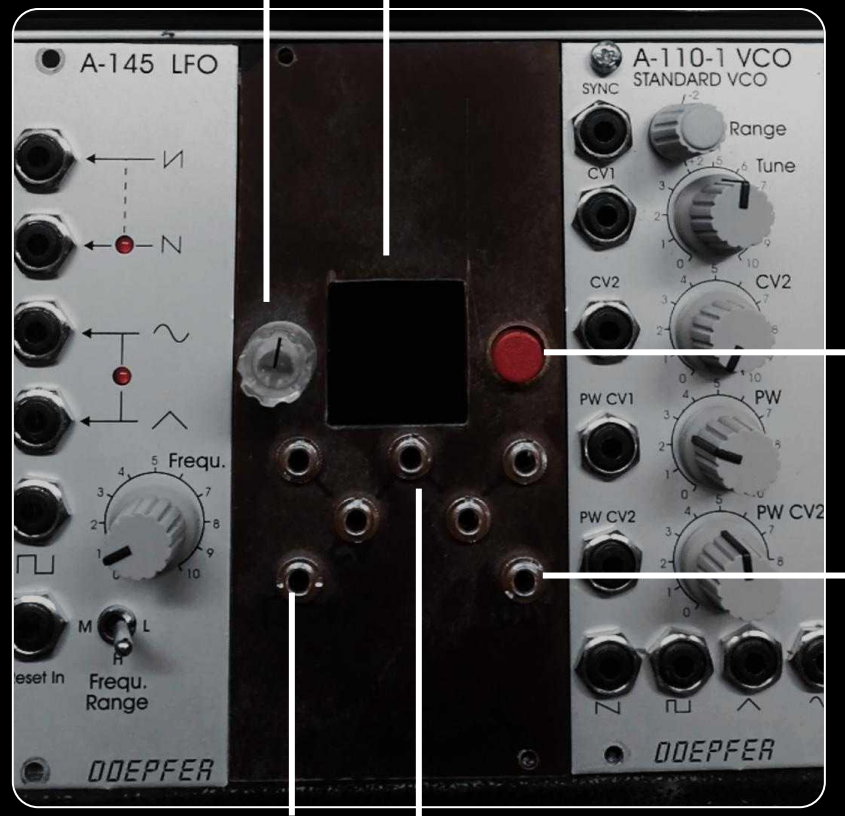


Navigate the menu

Rotary

Display interactive menu

Screen



Button

Select and click

Audio out

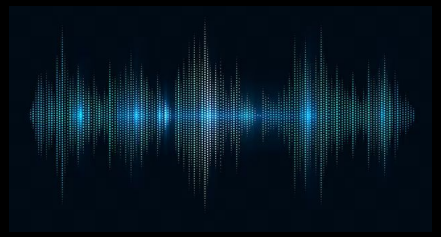
Control Voltage

Vary sound features

Gate

Trigger generation or interpolation

Other applications (*discriminative*)



Genre: *Acid techno*
Tempo: *140 BPM*
Key: *B#*
Lyrics: *Avin' it*

Music Information Retrieval (MIR)

Music Genre Classification

Automatically classifying music genres from audio samples.

Nam, J et a. (2018). Deep learning for audio-based music classification and tagging. IEEE signal processing magazine, 36(1), 41-51
https://e-tarjome.com/storage/panel/fileuploads/2019-07-04/1562228921_E11422-e-tarjome.pdf

Beat and Tempo Detection

Analyzing music to detect beat patterns and tempo using deep learning.

Schreiber, H., & Müller, M. (2018). "A Single-Step Approach to Musical Tempo Estimation Using a Convolutional Neural Network." ISMIR.
https://www.tagtraum.com/download/2018_schreiber_tempo_cnn.pdf

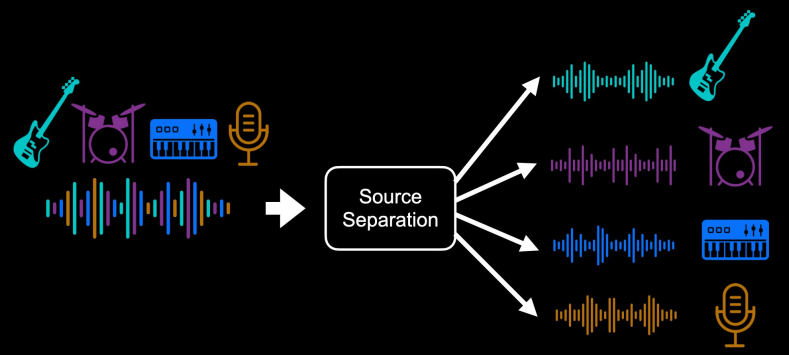
Automatic Music Tagging

Assigning genre, mood, or other descriptive tags to songs using deep learning.

Choi, K., Fazekas, G., Sandler, M., & Cho, K. (2016). "Convolutional Recurrent Neural Networks for Music Classification."arXiv:1609.04243.
https://arxiv.org/abs/1609.04243

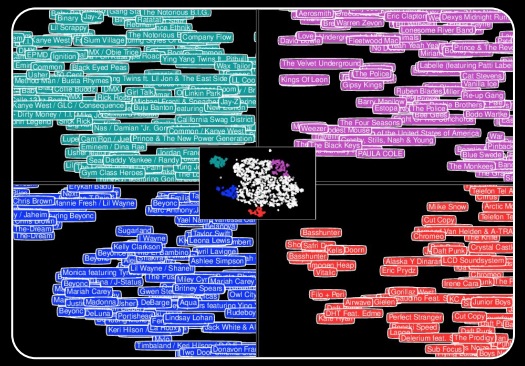
Source Separation

Separating individual instruments or voices from a mixed audio signal.
Usual problem of frequency coverage and bandwidth
Recent models provide stunning results



Jansonn A. et al. (2017). "Singing Voice Separation with Deep U-Net Convolutional Networks." ISMIR.

Other applications (*discriminative*)



Music Recommendation

Using deep learning to create personalized music recommendations

Analyze users' preference and listening history.

Well-known *cold start* problem

Aaron van den Oord et al. *"Deep Content-based Music Recommendation"* (2013)
https://proceedings.neurips.cc/paper/2013/file/b3ba8f1bee1238a2f37603d90b58898d-Paper.pdf

Query-by-Humming

Fingerprinting for efficient music retrieval in large databases.

Mapping the query and songs to a common reduced space

Provides efficient query-by-humming system

Chris liberator

Mostafa, N. et al (2017). A Note Based Query By Humming System Using Convolutional Neural Network. In Interspeech
https://www.isca-speech.org/archive_v0/Interspeech_2017/pdfs/1590.PDF

Audio-to-Score Conversion

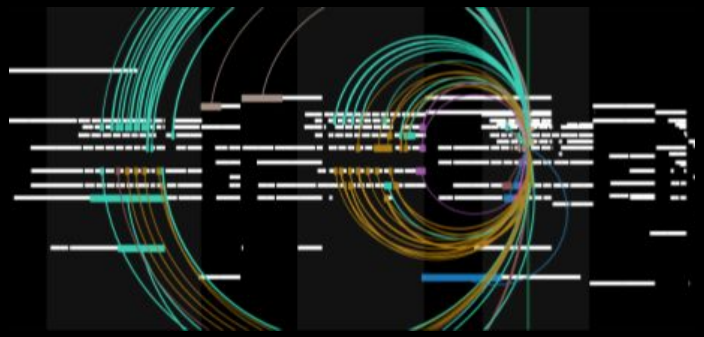
Transcribing audio recordings into sheet music using deep models.

Non-unicity of the solution and polyphonic problem

Almost solved for piano but still hard for orchestra

Hawthorne et al. (2018). "Onsets and Frames: Dual-Objective Piano Transcription." ISMIR 2018.
https://arxiv.org/abs/1710.11153

Other applications (*generative*)



Symbolic music generation

Generating symbolic music with advanced models

Handle long-range dependencies for coherent musical structures.

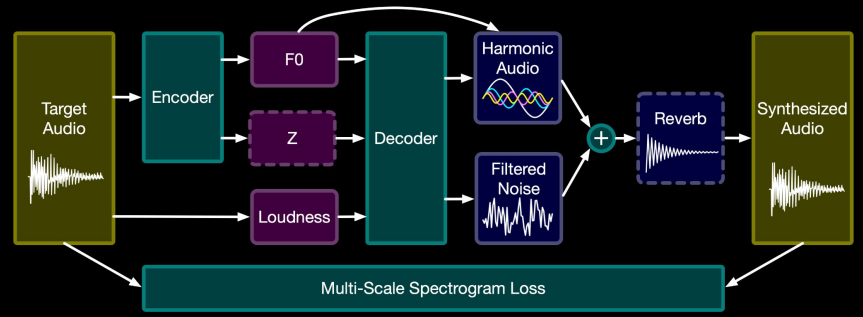
Huang, C. Z. A., & Du, S. (2020). "Pop Music Transformer: Generating Music with Rhythm and Harmony." arXiv:2002.00212.
https://arxiv.org/abs/2002.00212

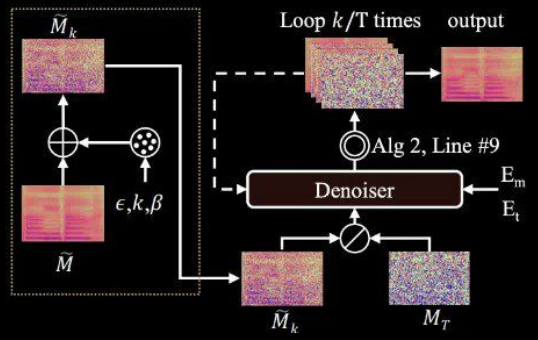
Neural Music Synthesis

Generating novel synthesized instruments and soundscapes

Current trends increasingly mixes traditional DSP elements

Engel, J. et al. (2020). "DDSP: Differentiable Digital Signal Processing." ICLR. 2020
https://openreview.net/forum?id=B1x1ma4tDr





Text-to-singing

Singing voice generation based on input text

Also needs to handle prosody and emotional response

Liu, J. et al. (2022). Diffsinger: Singing voice synthesis via shallow diffusion mechanism. In AAAI 2022.
https://ojs.aaai.org/index.php/AAAI/article/view/21350/21099

Algorithmic DJing

Analyze structure to create seamless transitions between songs

Enables automated DJing and playlist creation.

Huang, J. et al. Modeling the compatibility of stem tracks to generate music mashups. In AAAI 2021
https://ojs.aaai.org/index.php/AAAI/article/view/16092/15899