Music Machine Learning

1 – Machine Learning

Master ATIAM - Informatique

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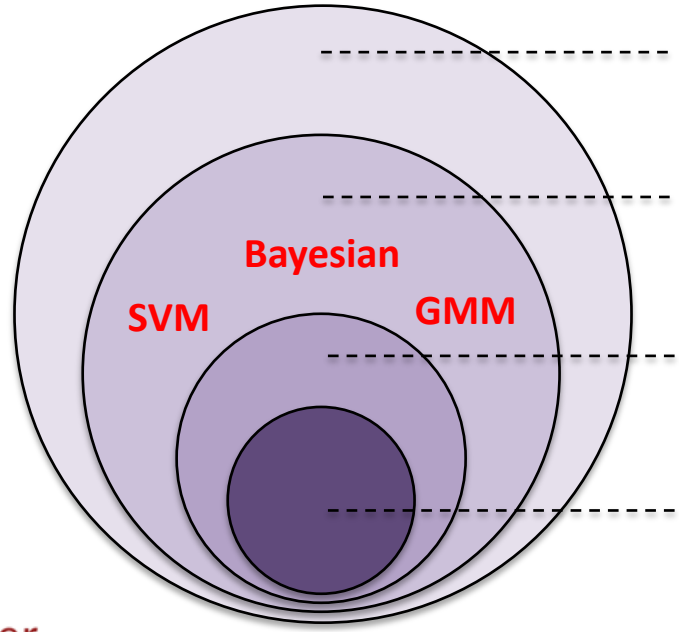
Going machine learning

As we have discussed earlier …

- Artificial intelligence was set to simulate intelligence
- But this is mostly through symbolic and rule-based approaches
- 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

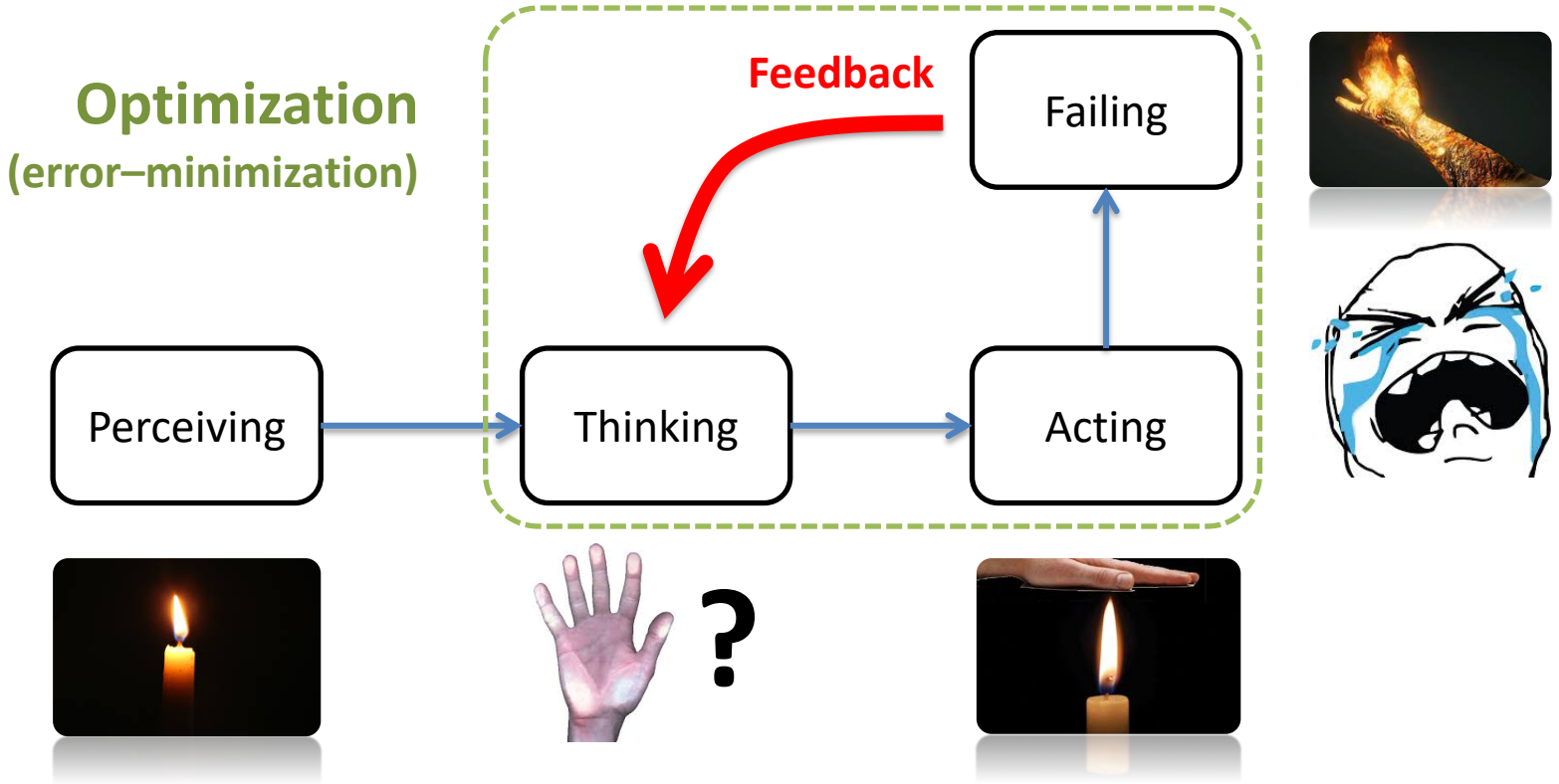
Neural Networks (NN)

Brain-inspired ML models

Deep Learning (DL)

Building (deep) hierarchies of NN representations

Learning ?



- **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 us (ACIDS)

Example (ACIDS-Sony) : drums

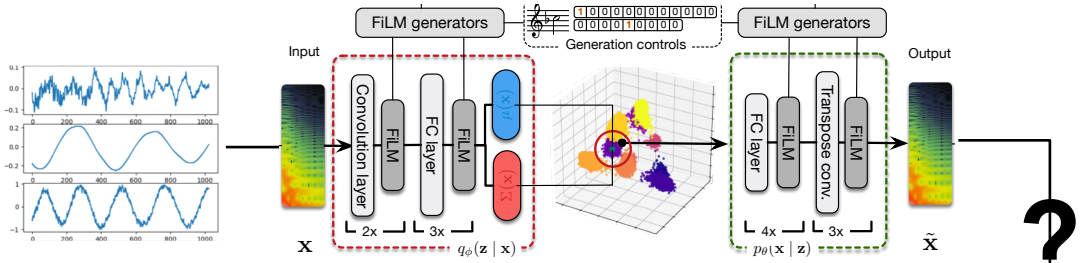
C. Aouameur G. Hadjeres

Variational learning for drums waveform

Drums are **mostly noisy**, therefore less adapted to spectrum

Can we perform end-to-end training with waveforms ?

Problems of *WaveNet complexity* and *posterior collapse*



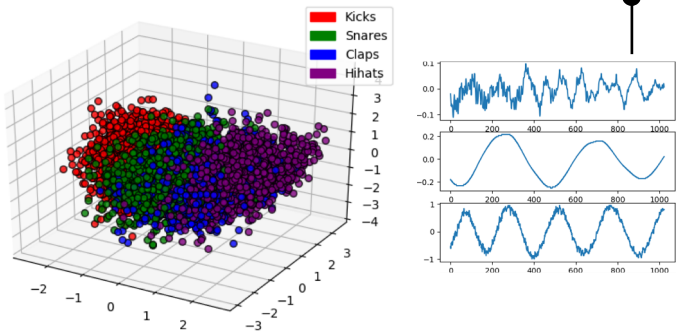
Control space

User-friendly map

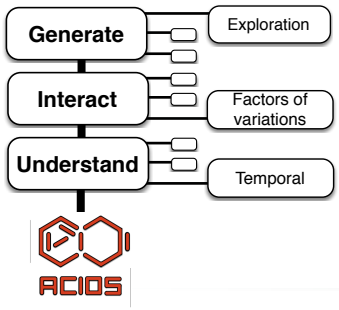
Allows **exploration**

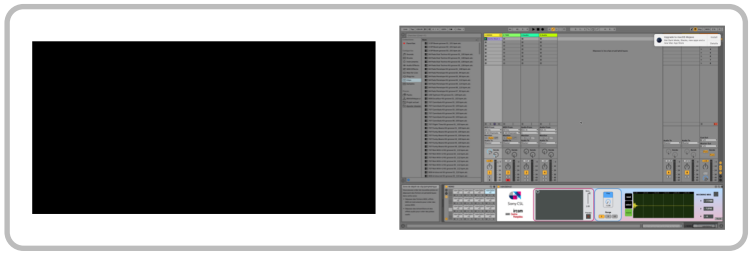
Generates waveform

Real-time inference



Ableton plugin and web-based interface



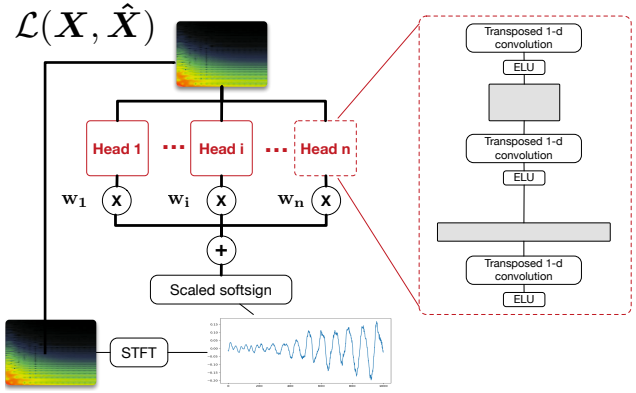


Multi-head spectrum inversion

Fits the natural properties of audio signal

Allows a feed-forward spectrum inversion

Heads unsupervisedly split into bands



Spectral convergence losses

$$\| |\mathrm{STFT}(s)| - |\mathrm{STFT}(\hat{s})| \|_F / \| |\mathrm{STFT}(s)| \|_F,$$

$$\| \log(|\mathrm{STFT}(s)| + \epsilon) - \log(|\mathrm{STFT}(\hat{s})| + \epsilon) \|_1,$$

Instantaneous phase loss

$$\left\| \frac{\partial}{\partial t} \phi(\mathrm{STFT}(s)) - \frac{\partial}{\partial t} \phi(\mathrm{STFT}(\hat{s})) \right\|_1,$$

Arık, S. Ö., Jun, H., & Diamos, G. (2019). Fast spectrogram inversion using multi-head convolutional neural networks. *IEEE Signal Processing Letters*, *26*(1), 94-98.

Real-time version demonstration

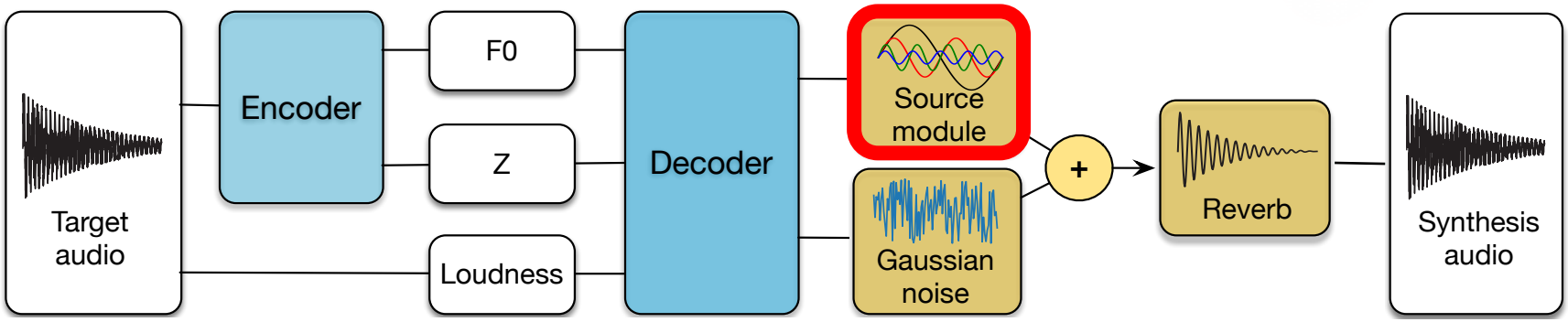
See you at the workshop ☺

Example (ACIDS) : DDSP

A. Caillon

Engel, J. Hantrakul, L. Gu, C. and Roberts, A. – Differentiable Digital Signal Processing ICLR 2020

Take traditional signal processing



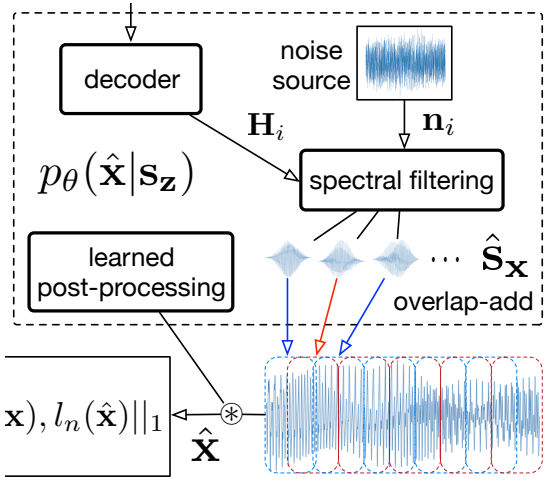
We can train a control model over it

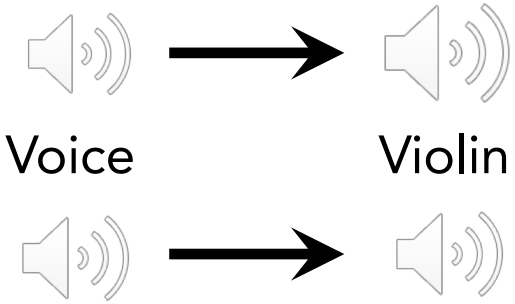
And make it differentiable

Original model too restrictive

Transfer results (vanilla)

We implement a granular substractive



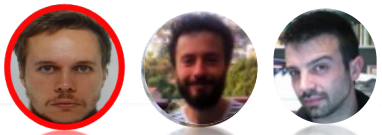


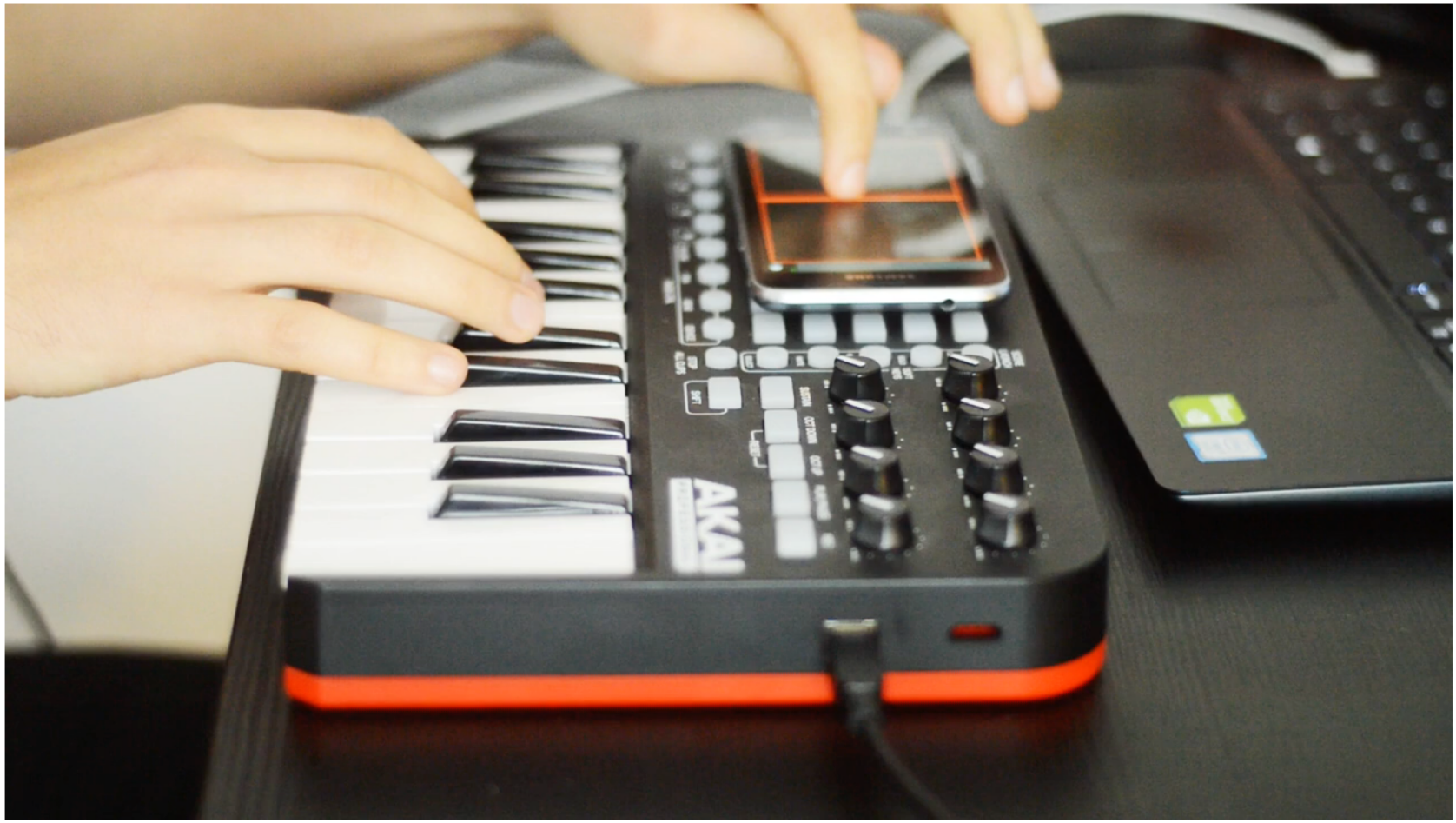
Get Screechy

Get Lucky - voice transfer to screech and drills dataset

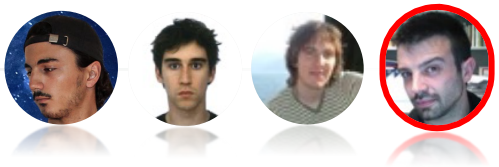
Demo video

A. Caillon



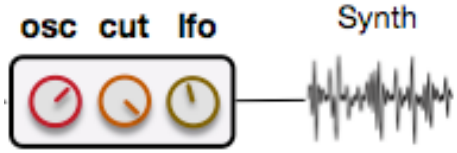


Universal audio synthesis control



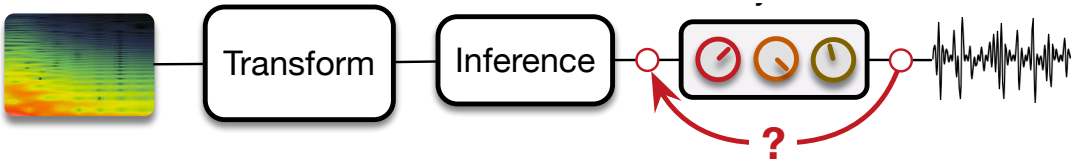
Audio synthesizer are complex generation functions

Impact of parameters is non-linear and complex
Needs expert knowledge and hard work
Does not correlate to perception



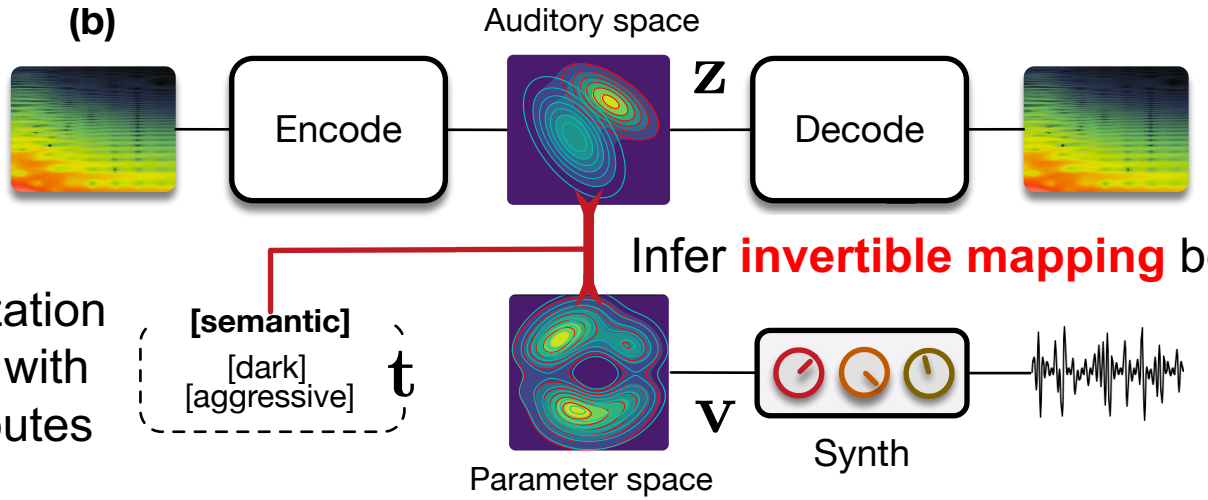
Parameters inference models

Feed-forward inference
But non-differentiable synth
Also just input a waveform



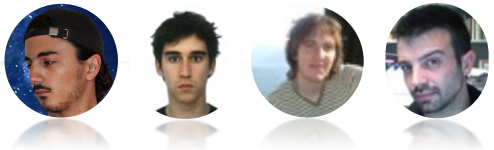
Our proposal = Universal synthesizer control with disentangling flows

Organize the auditory space of possibilities



Organize the parameters space

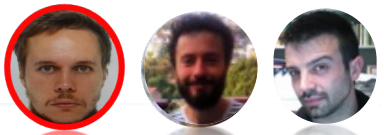
Demo video



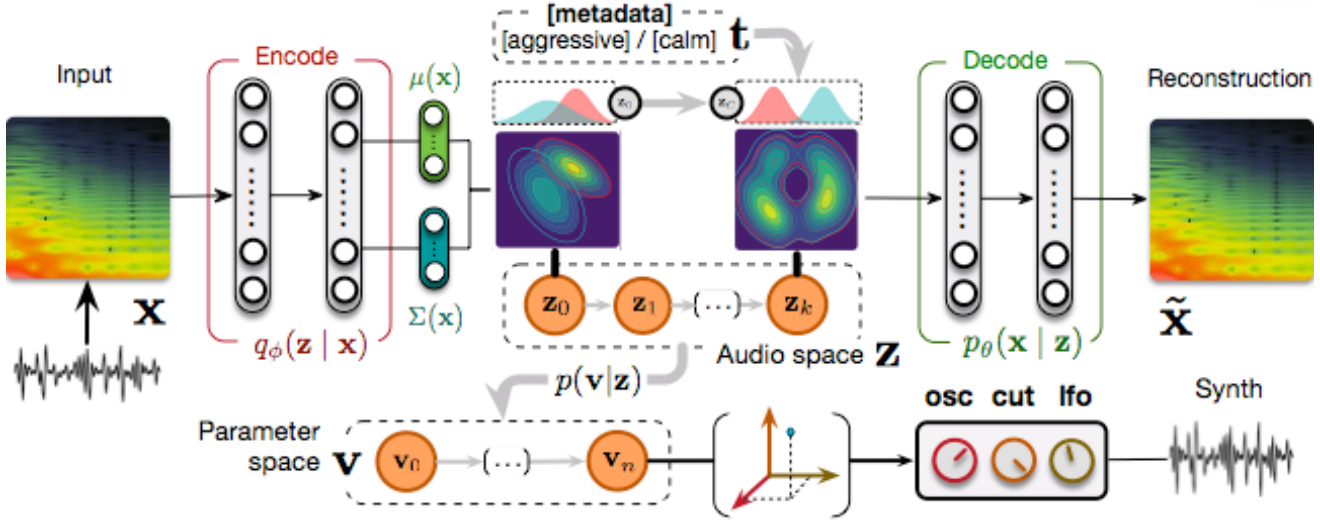
https://www.youtube.com/watch?v=UufQwUitBIw

Multiple flux synthesis (WavAE)

A. Caillon



Complete formalization

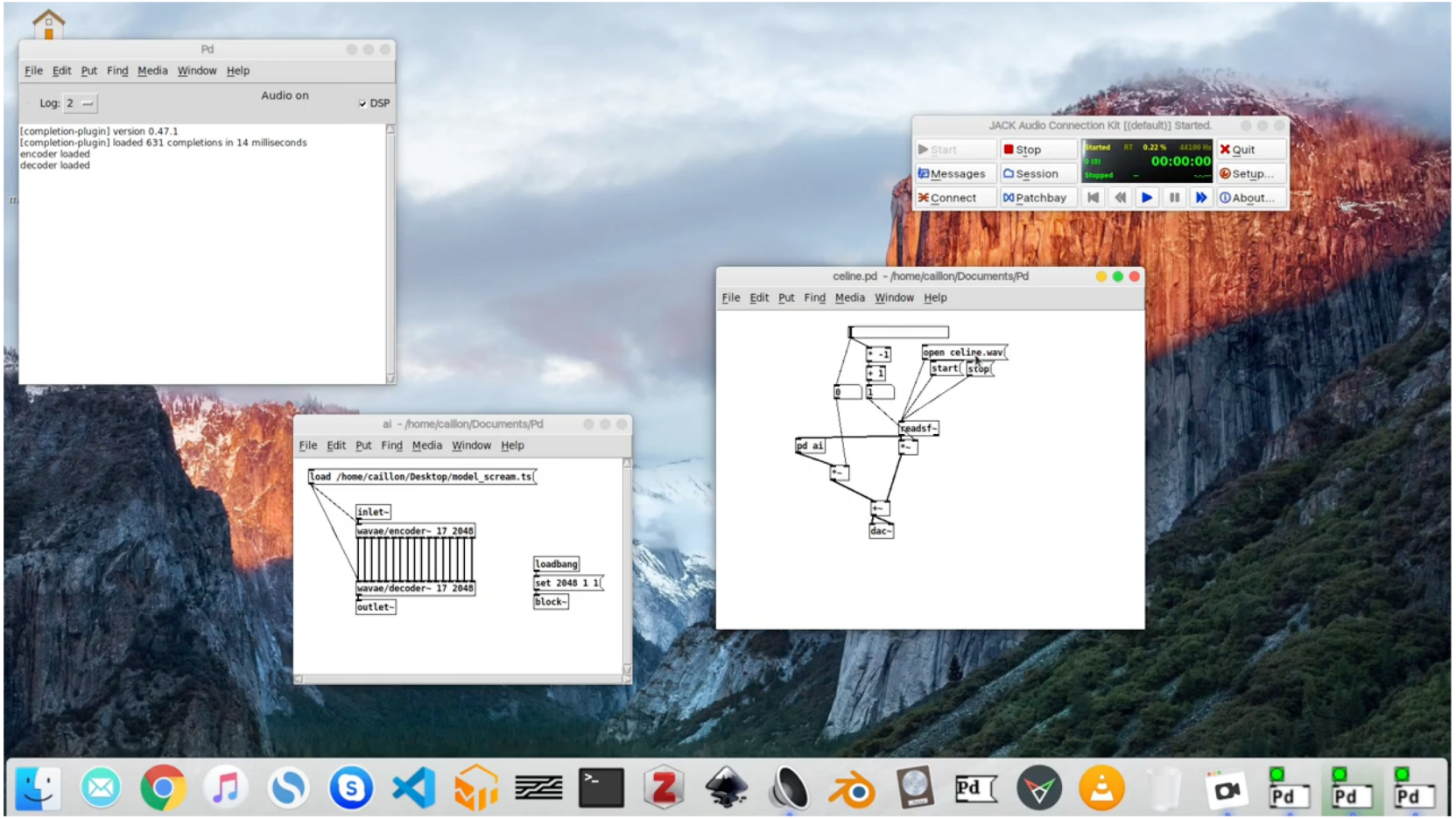


Similar to the flow synth overall approach

- Using different learning flux
- Allowing for multiple tasks and datasets
- In the future, simultaneous multiple waveform generation

Demo video

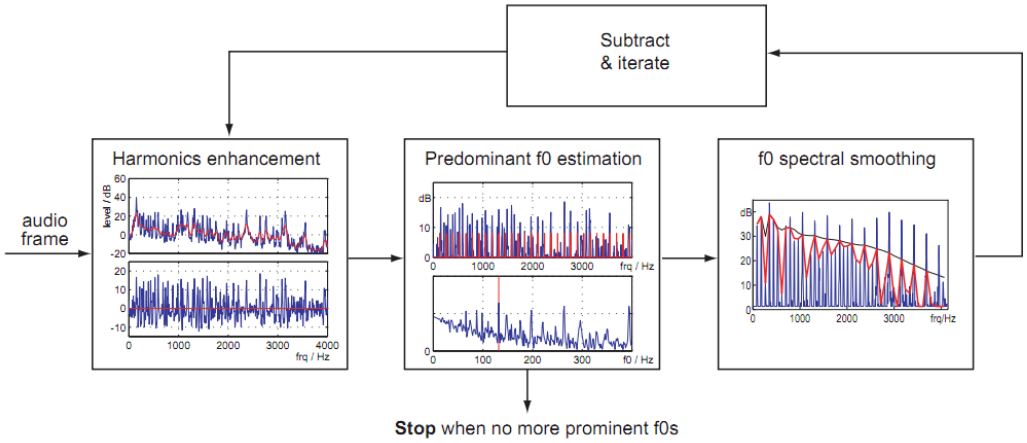
A. Caillon

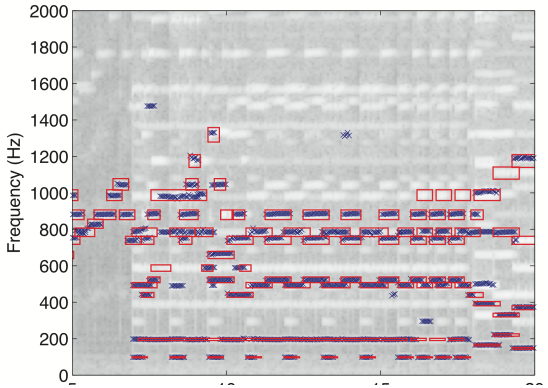


Why learning ?

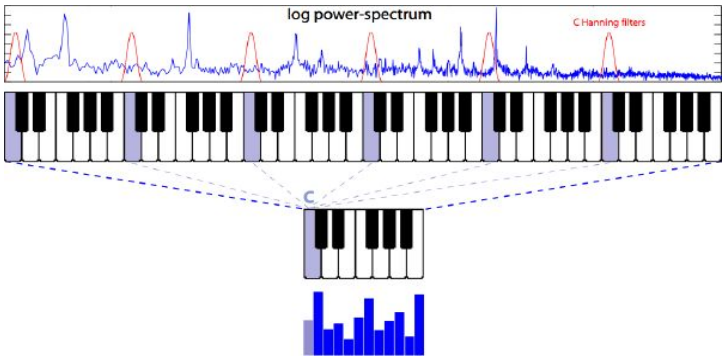
Applications of **pattern classification**

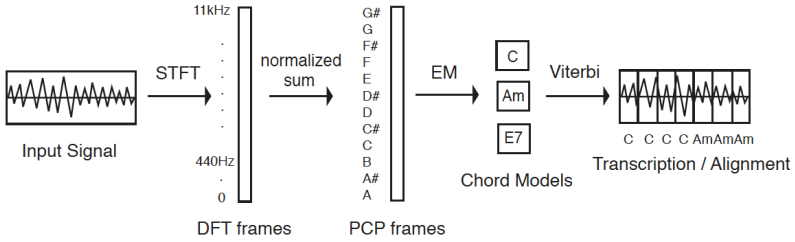
Multi-F0 estimation (figures from *Yeh, 2010*)





Chords estimation (figures from *Padapopoulos, 2007*)

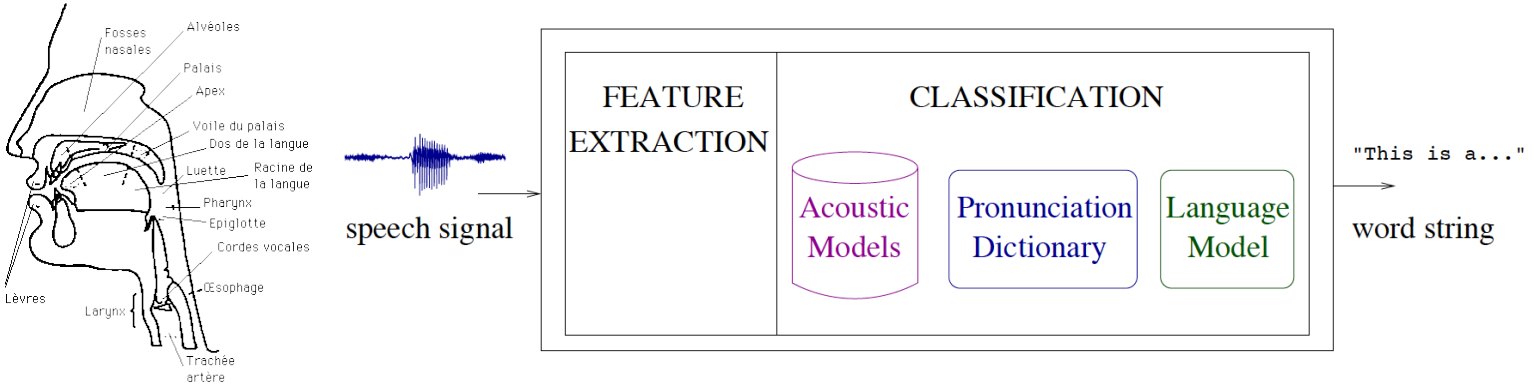




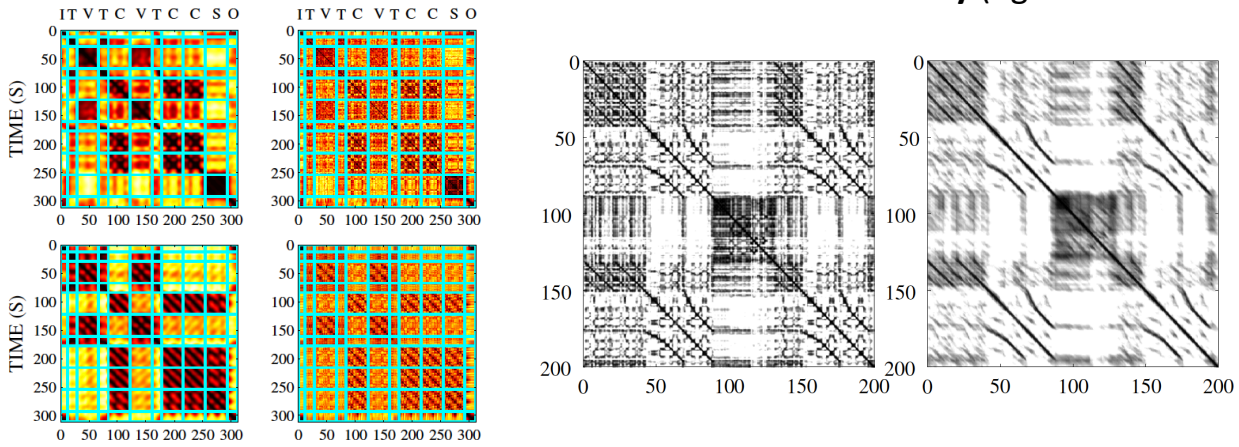
Why learning ?

Applications of **pattern classification**

Speech recognition (figures from *HTK Documentation*)

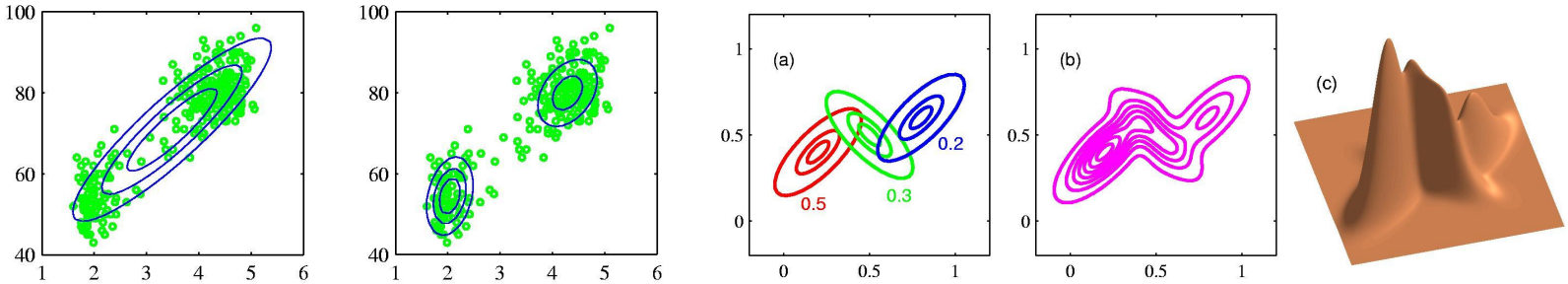


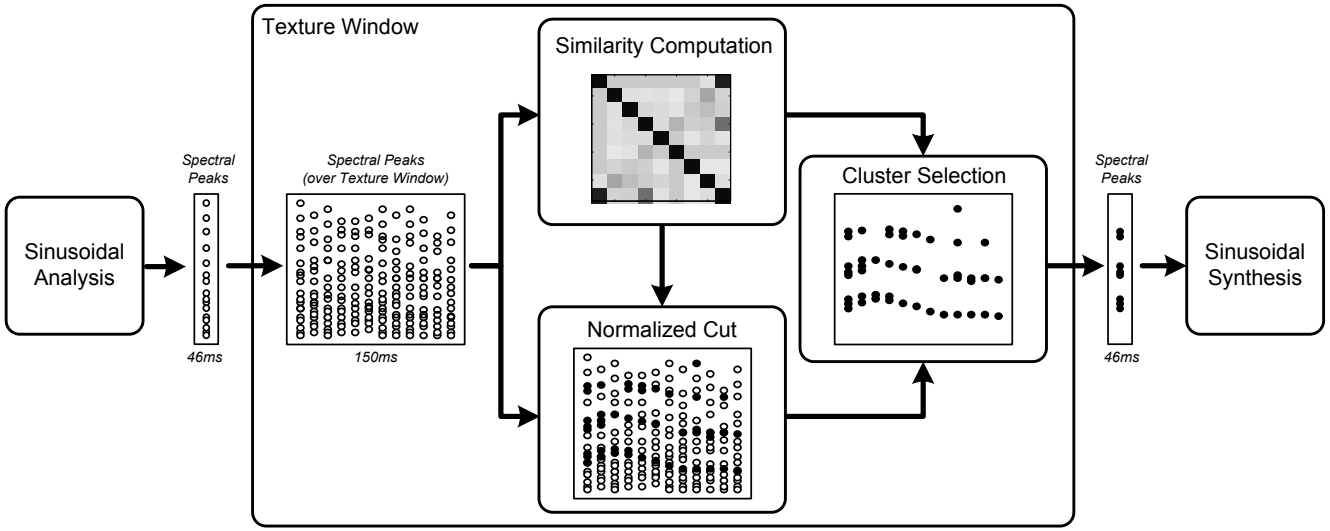
Structure discovery (figures from *Paulus, 2010*)



Why learning ?

Typical learning problem: **clustering**



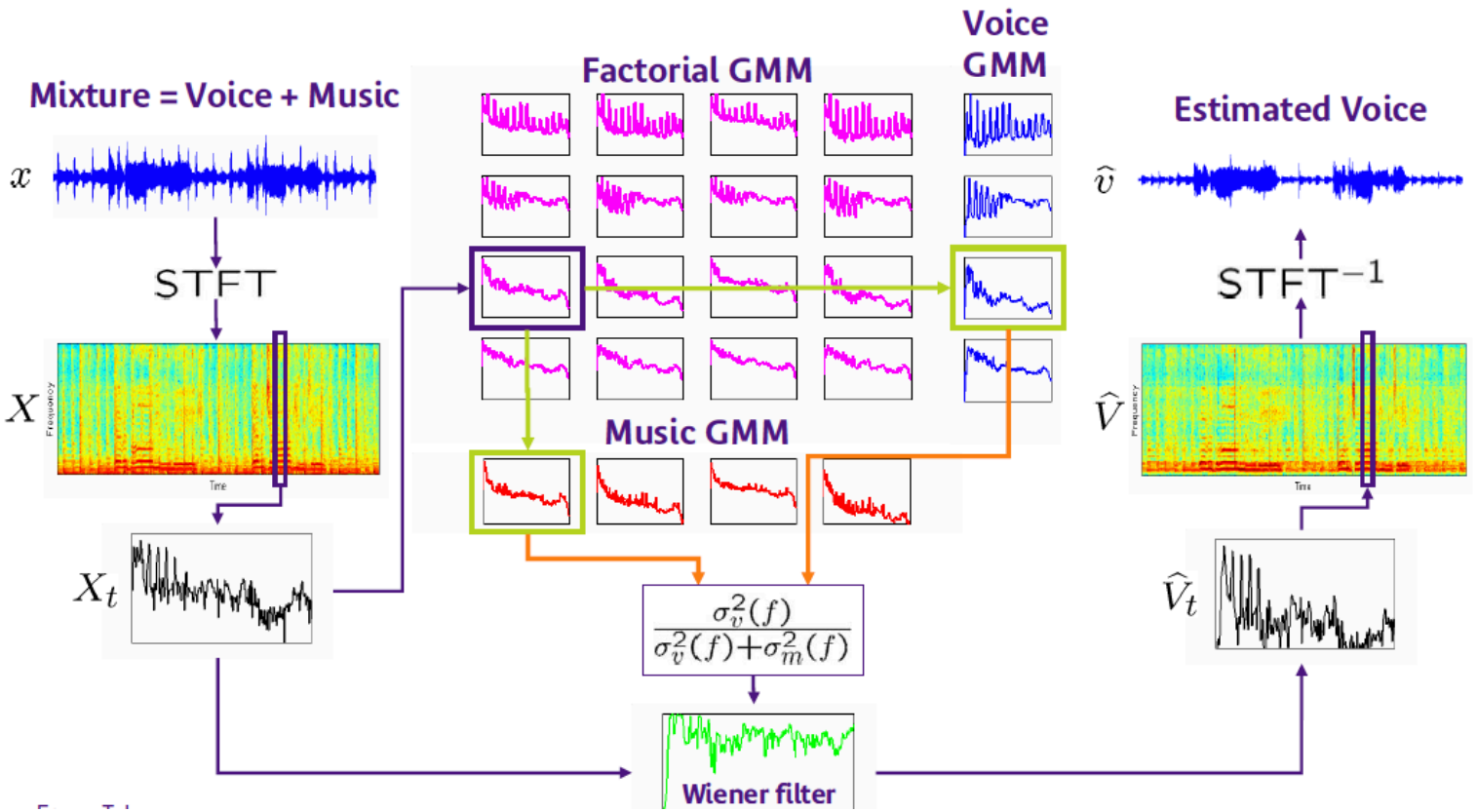


Computational Audio Scene Analysis (CASA) – *Figures from Barker, 2011*

Why learning ?

Applications of **clustering**

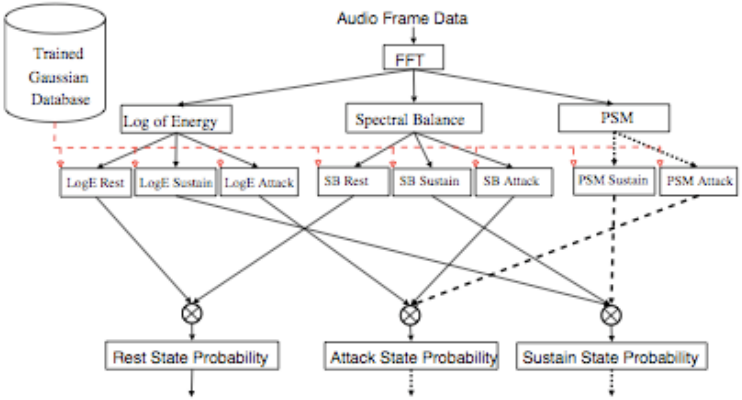
GMM-Based Sound Source Separation – *Figures from Ozerov, 2005*

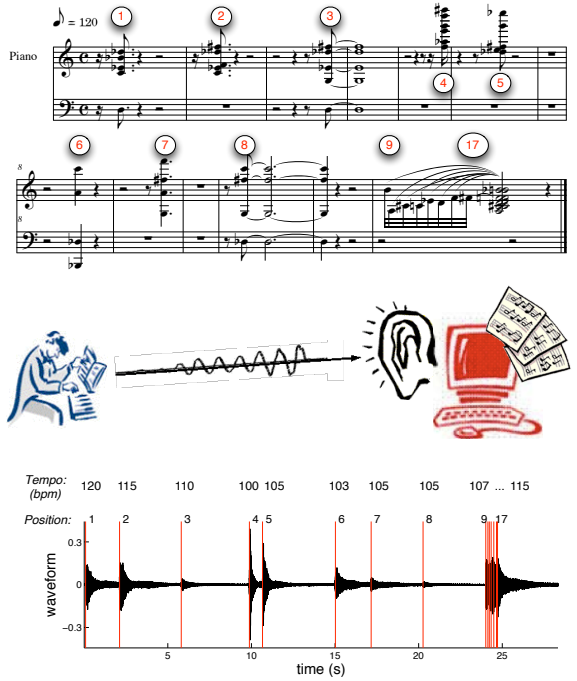


Why learning ?

Sequential learning (temporal models)

- The score following problem:
  - Need *observation models* at the front-end.
  - From audio frames to low-level state probs:

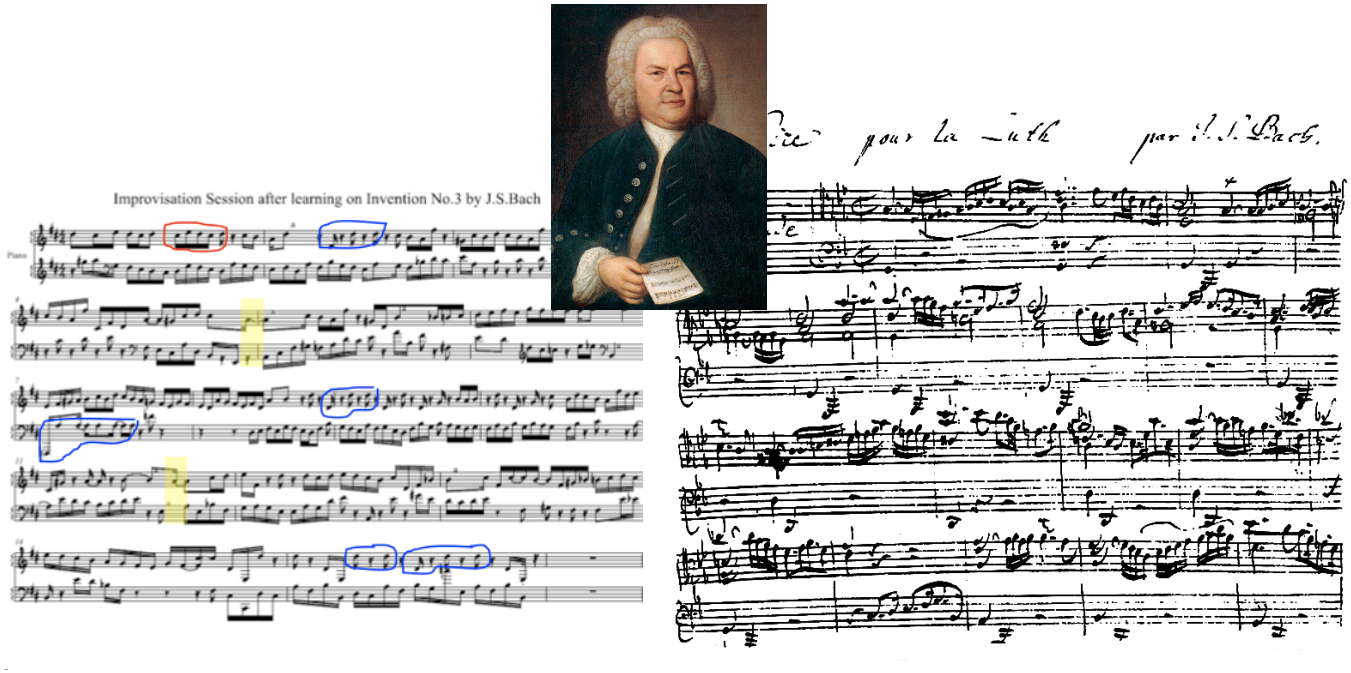


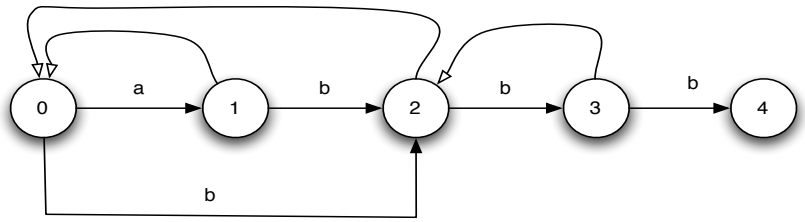


Figures from Cont, 2011

Why learning ?

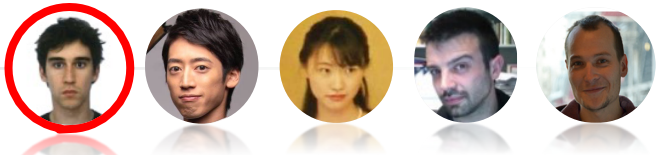
Sequential learning (temporal models)





Computational orchestration

L. Crestel

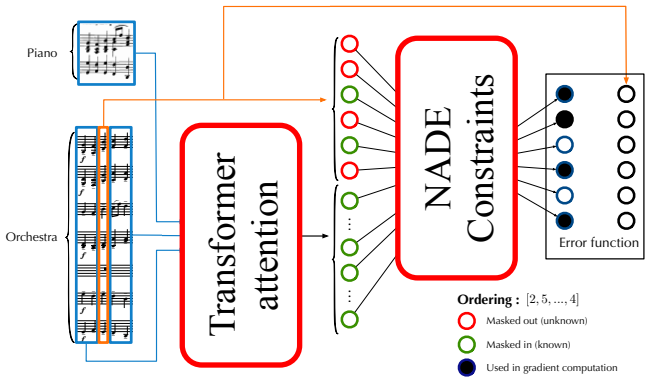


Computer-assisted projective orchestration

Asking somewhat **the inverse question …**

Can we play the whole orchestra **simply by playing a piano** ?

Targeting signal solely through symbolic information



Multivariate predictive learning

Piano **time series constraining a multivariate series**

Mixing temporal, recurrent and feed-forward embeddings

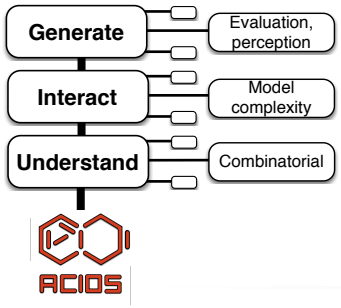
Constrained generation with Neural Distribution Estimator (NADE)

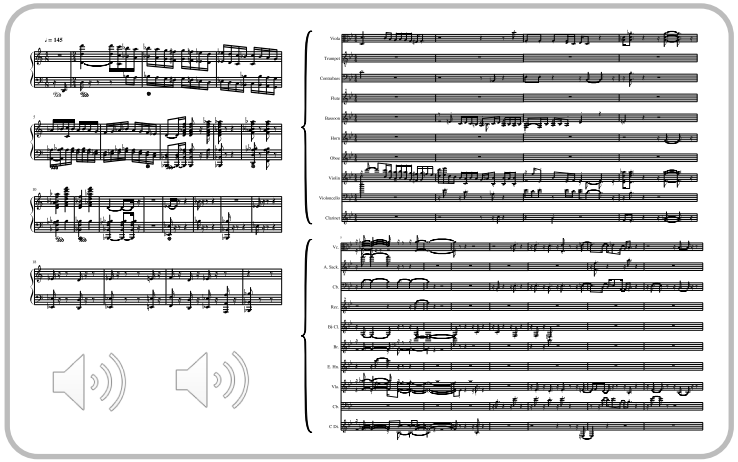
First ever dataset on the problem (**LOP** - https://qsdfo.github.io/LOP)

Hand-checked, corrected and entirely open data (~200 score pairs)

Results

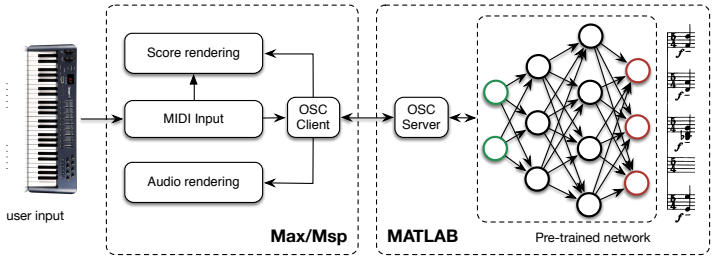
Liszt piano piece
Symphony No. 3, S.464/3





Real-time version demonstration

1st system to play orchestra on a keyboard
See you at the workshop ☺



Learning

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

What will we see along these courses?

1. **Nearest neighbors**
2. **Neural Networks – Single and multilayers [+ advanced networks]**
3. **Support Vector Machines and Kernels**
4. **Probabilities and distributions**
5. **Probabilistic (Bayesian) inference**
6. **Latent models and Expectation-Maximization (EM)**
7. **Gaussian Mixture Models (GMM)**
8. **Approximate inference (sampling, MCMC and variational)**
9. **Deep learning**
10. **Variational auto-encoder and normalizing flows**
11. **Adversarial learning**
12. **Audio applications (project)**

Learning

Using machine learning to model music ?

- **Supervised learning** is inferring a function from labeled training data
- **Unsupervised learning** is trying to find hidden structure in unlabeled data

We can define any problem as $\hat{\mathbf{y}} = f_\theta(\mathbf{x})$

So we first need to define what **function** could *approximate* this process

$$f_\theta \in \mathcal{F} \qquad \theta \in \Theta$$

Then we need to **evaluate the « quality »** of this approximation

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

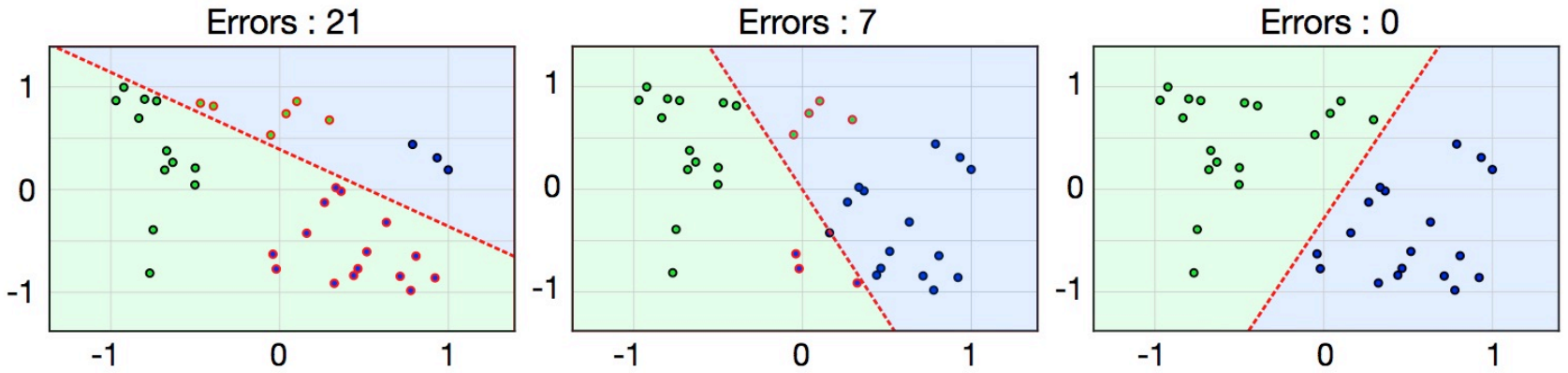
Answer of the model ***The « real » answer (groundtruth)***

Expected risk $\mathcal{R}(f_\theta) = \mathbb{E}_{p(\mathbf{x},\mathbf{y})}\left[\mathcal{L}(f_\theta(\mathbf{x}), \mathbf{y})\right]$

The quality of our model **over the whole world of possibilities** ?

Learning ?

- But how to learn the parameters $\theta \in \Theta$ of our function $f_\theta \in \mathcal{F}$?
- Learning is possible through weight *optimization.*



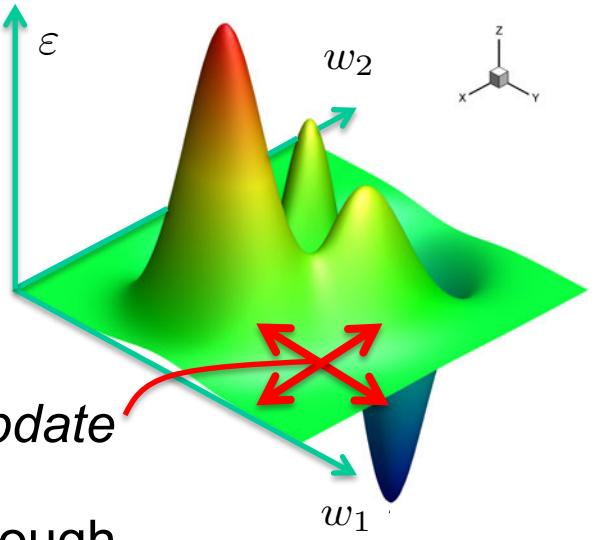
Example function : $f_\theta(\mathbf{x}) = \mathbf{W}\mathbf{x} + \mathbf{b}$ $\theta = \{\mathbf{W}, \mathbf{b}\}$

- This is done through a **training phase**
- We have a set of input vectors $\mathbf{X} = \{x_1, ..., x_n\}$
- For which we know the desired output $\mathbf{D} = \{d_1, ..., d_n\}$
- Therefore we can compute the error $\varepsilon = \sum_i (d_i - x_i)^2$

- So training amounts to adjust $\theta \in \Theta$ so that $y_i \sim d_i$
- Entering the beautiful world of *gradient descent*

Gradient descent

- Gradient descent is path following
- Need to find the lowest error point
- This amounts to error minimization
- Look around different directions
- Compute the difference in error

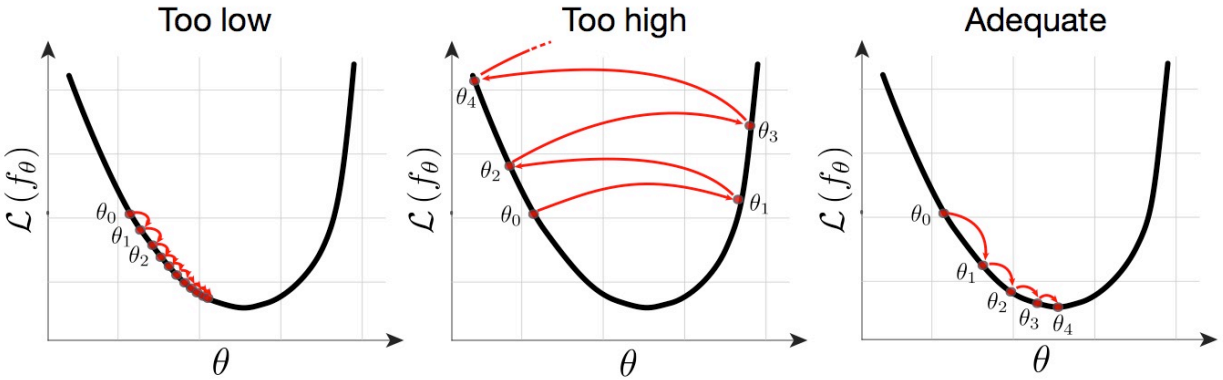


$$\Delta\bar{w} = r\left(\frac{\delta\mathcal{P}}{\delta w_1}, \frac{\delta\mathcal{P}}{\delta w_2}\right)$$ « Go down hills » and *update*

So we will iteratively update the parameters through

$$\theta_{n+1} = \theta_n - \eta\Delta_\theta\mathcal{L}(\theta_n)$$

with $\Delta_\theta\mathcal{L}(\theta_n)$ the gradient of the loss function, and η the *learning rate*

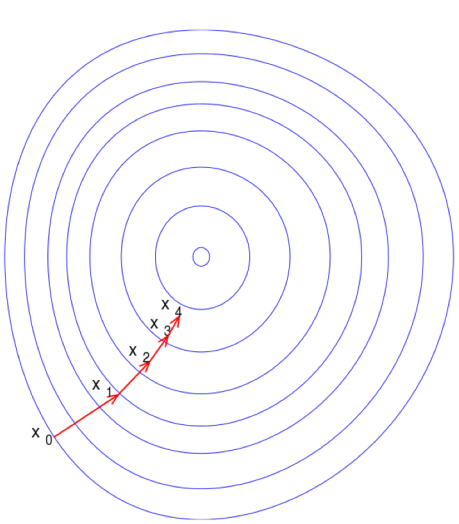


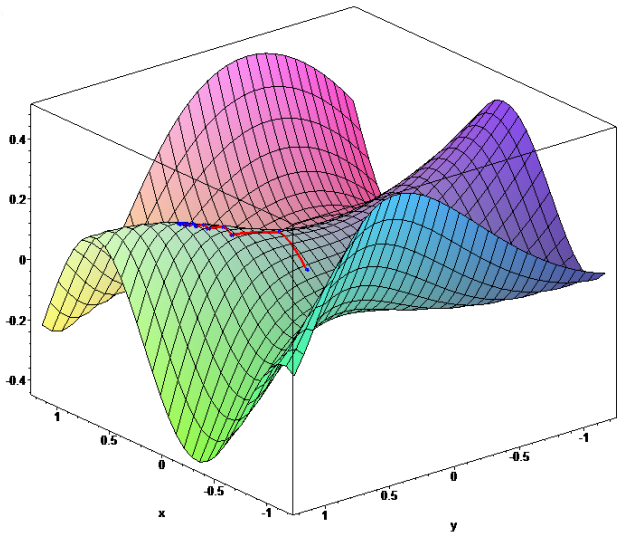
Effect of the learning rate η

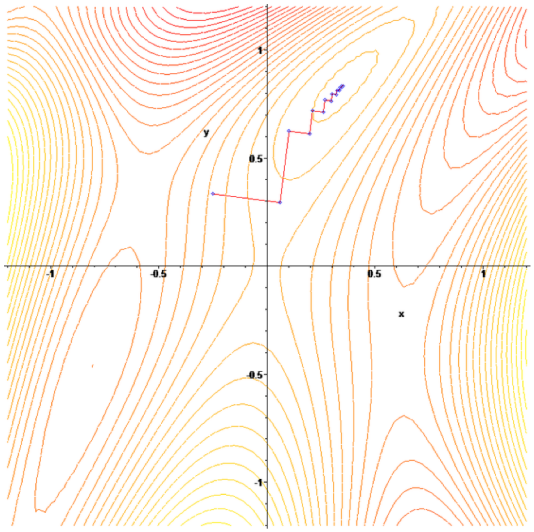
Search (optimization)

A wide part of the optimization field is centered on search

- (Note that **not all ML approaches use gradient descent**)
- Depth-first (lexical order) - Breadth-first
- Heuristic – genetic algorithms







- Unfortunately, we will not spend too much time on *optimization* aspects
- But still explain everything that you need ☺

Generic machine learning

- Natural processes relate some objects
- We observe relationships between $\mathcal{X}$ and $\mathcal{Y}$

Natural process (task)

Machine learning tries to approximate this as

$$\hat{\mathbf{y}} = f_\theta(\mathbf{x})$$

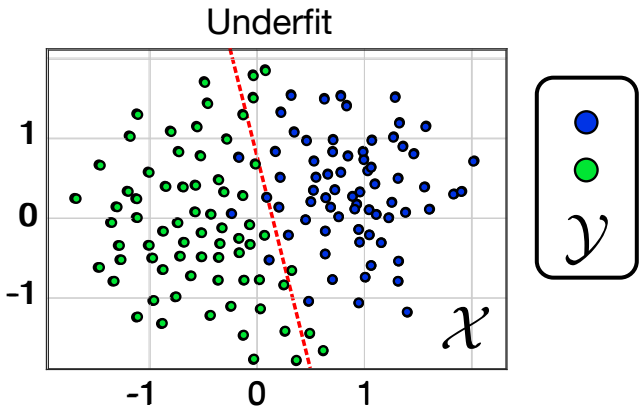
So we need to define what **function** $f_\theta \in \mathcal{F}$

This function depends on some parameters $\theta \in \Theta$

By evaluating the « quality » of this function $\mathcal{L}(\hat{\mathbf{y}}, \mathbf{y} \mid \theta, f_\theta)$

We can optimize parameters $\theta \in \Theta$ to obtain the best approximation f_{θ^*}

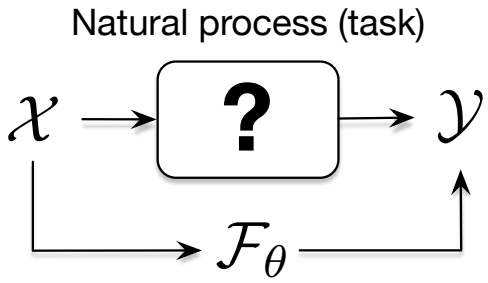
So everything boils down to our choice of $\mathcal{F}_\theta$



« Too simple »

Choice of approximation families

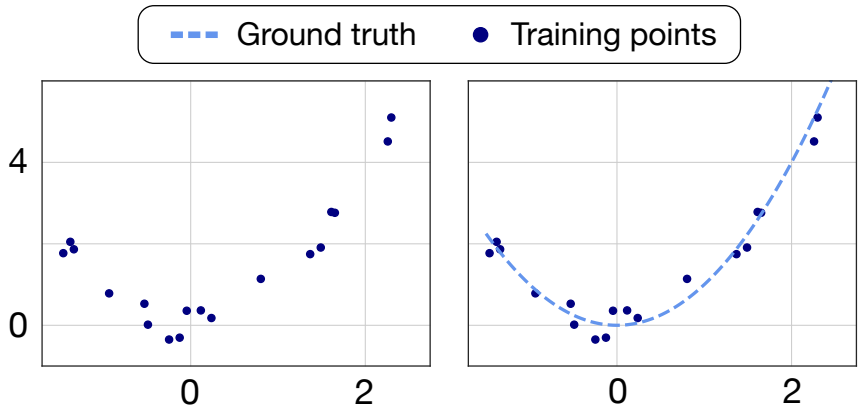
- Quality depends heavily on the *family* $\mathcal{F}_\theta$
- Notion of *model capacity* (~ complexity)
- There are some inclusions



Approximation families

Constant $\mathcal{F}_0$

$\mathcal{F}_0(x) = \theta_0$



Choice of approximation families

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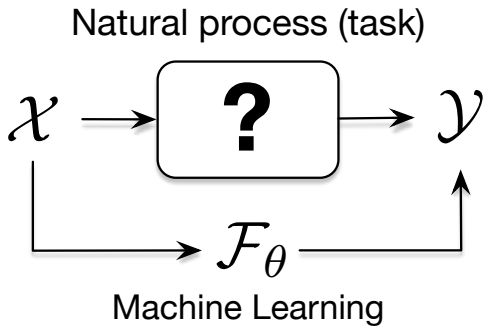
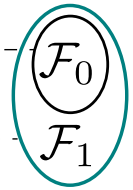
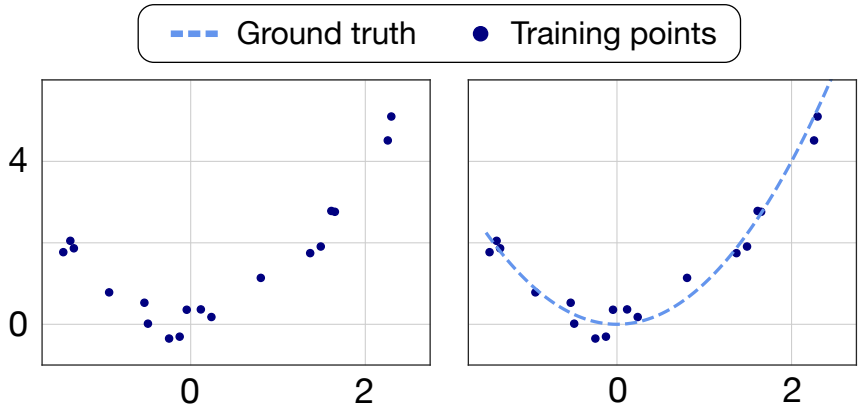


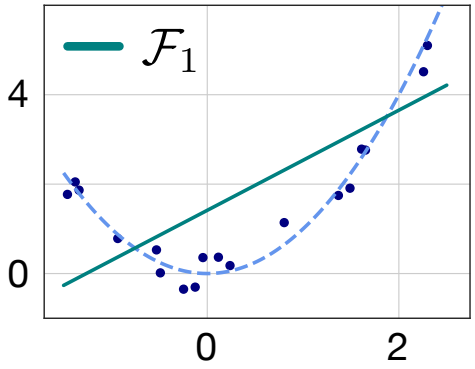
Approximation families

Constant
$\mathcal{F}_0(x) = \theta_0$

Linear
$\mathcal{F}_1(x) = \theta_1 x + \theta_0$

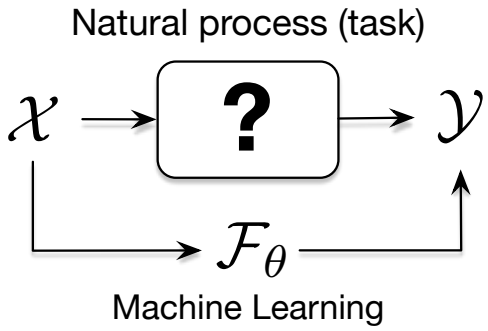






Choice of approximation families

- Quality depends heavily on the *family* $\mathcal{F}_\theta$
- Notion of *model capacity* (~ complexity)
- There are some inclusions

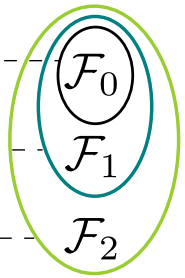


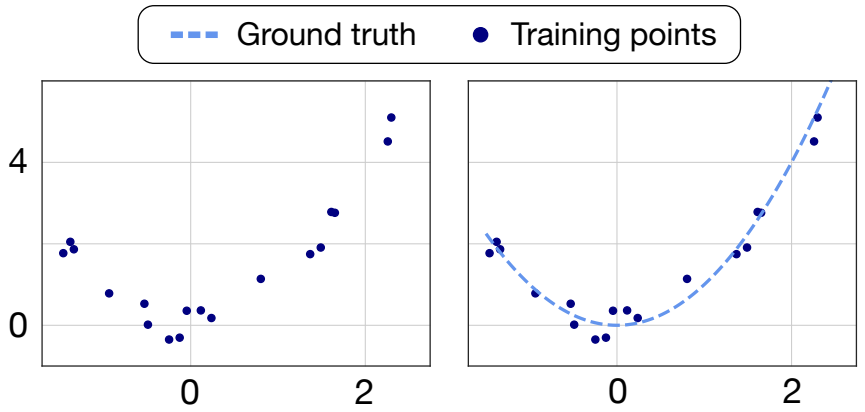
Approximation families

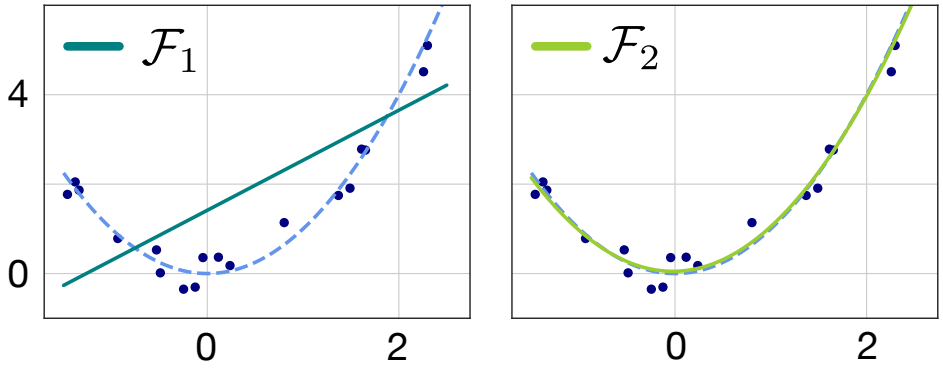
Constant
$\mathcal{F}_0(x) = \theta_0$

Linear
$\mathcal{F}_1(x) = \theta_1 x + \theta_0$

Square
$\mathcal{F}_2(x) = \theta_2 x^2 + \theta_1 x + \theta_0$

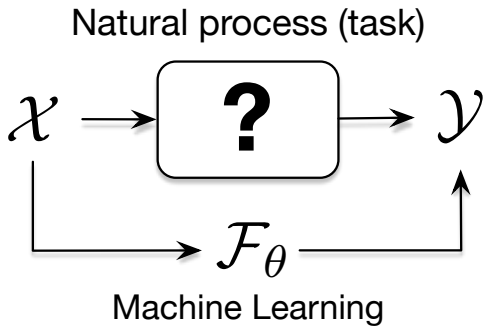






Choice of approximation families

- Quality depends heavily on the *family* $\mathcal{F}_\theta$
- Notion of *model capacity* (~ complexity)
- There are some inclusions



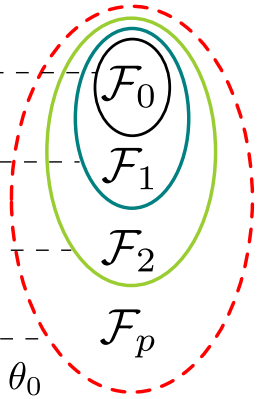
Approximation families

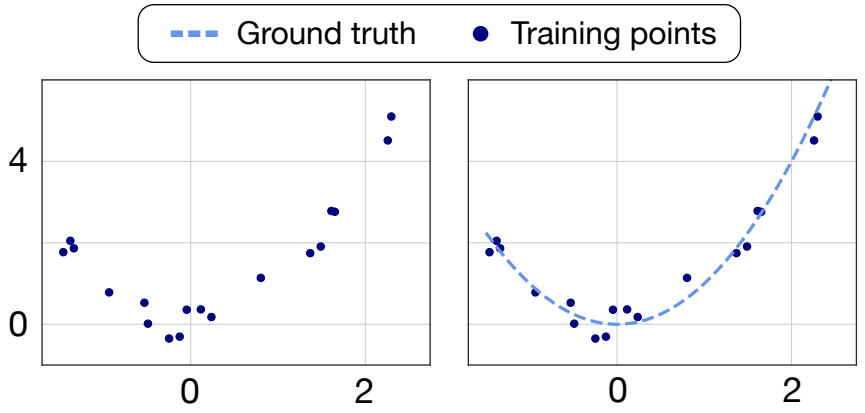
Constant
$\mathcal{F}_0(x) = \theta_0$

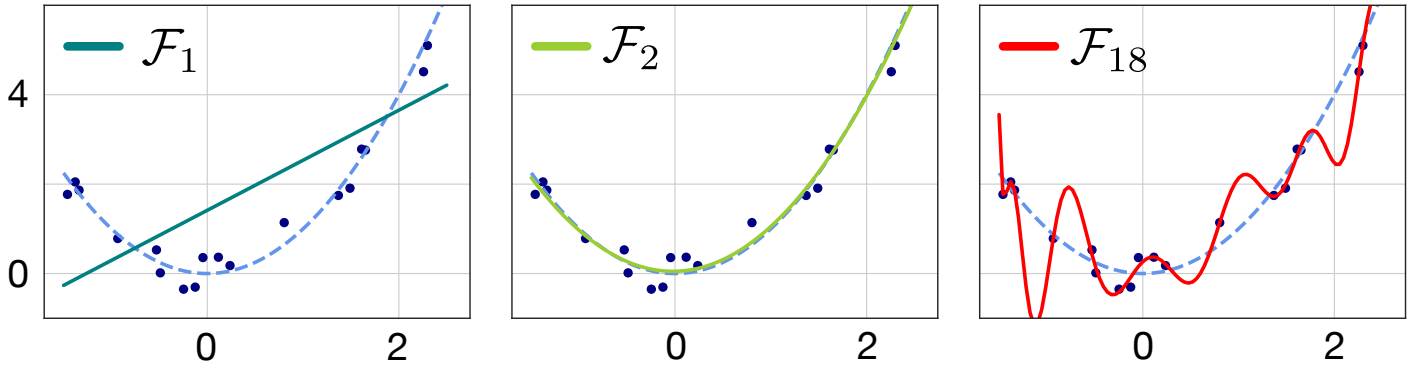
Linear
$\mathcal{F}_1(x) = \theta_1 x + \theta_0$

Square
$\mathcal{F}_2(x) = \theta_2 x^2 + \theta_1 x + \theta_0$

Polynomial
$\mathcal{F}_p(x) = \theta_p x^p + \cdots + \theta_1 x + \theta_0$

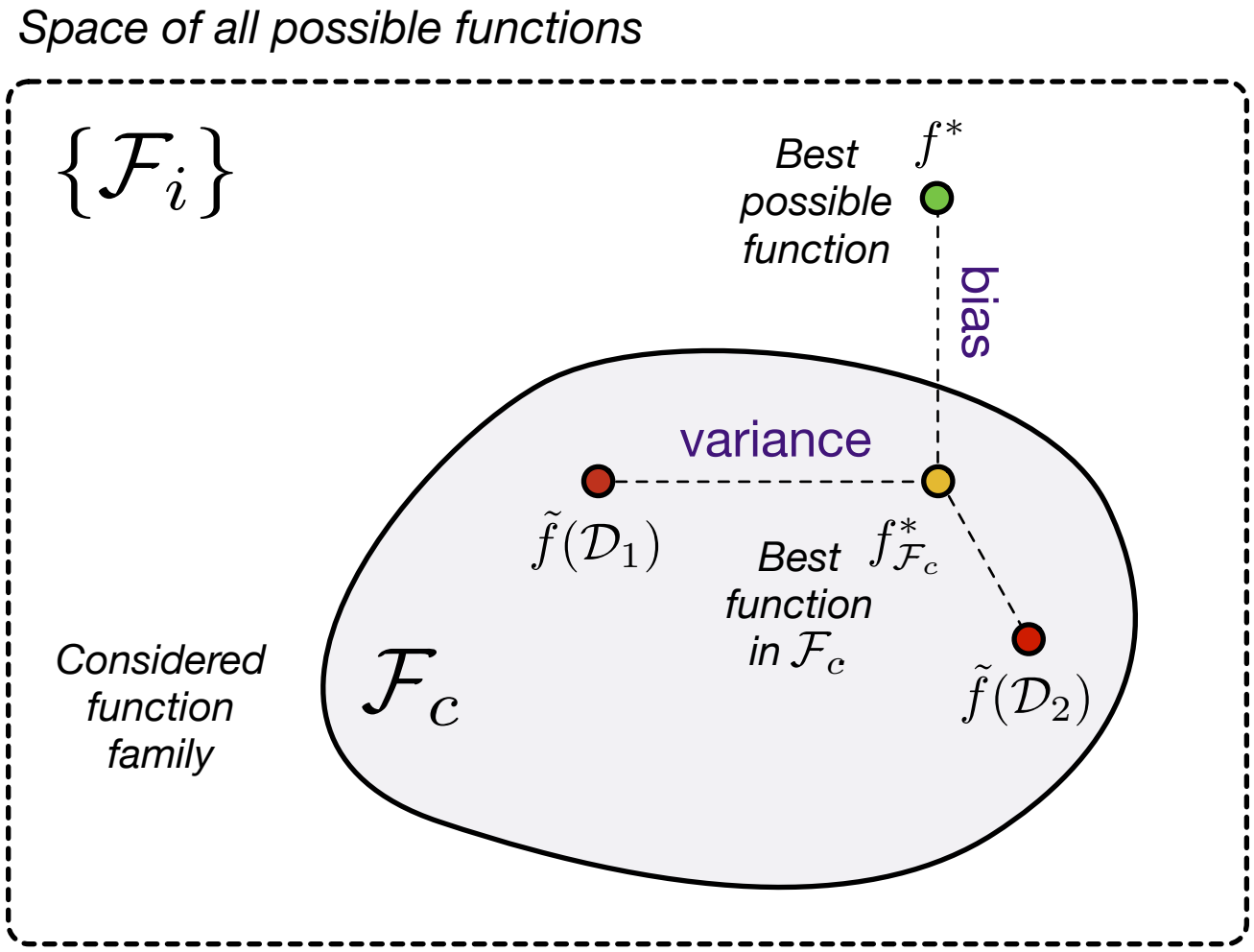






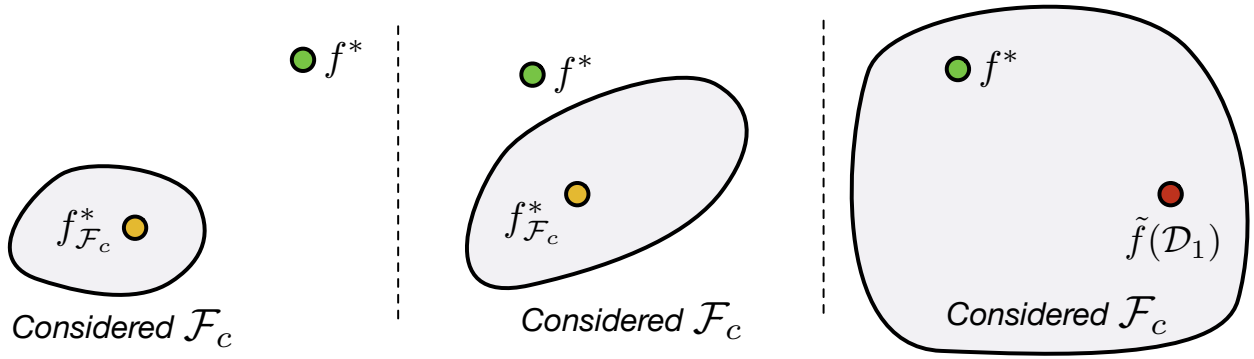
Bias and variance

This problem lies between the *bias* and *variance* of our approximation



Bias and variance - details

So how can we adequately choose the family ?



Low variance
High bias

Good trade-off

High variance
Low bias

Problem in the **variance** aspect is the *discrepancy* lying between

Expected risk
(what we want)

$$\mathcal{R}(f_\theta) = \mathbb{E}_{p(\mathbf{x},\mathbf{y})}\left[\mathcal{L}\left(f_\theta(\mathbf{x}), \mathbf{y}\right)\right]$$

Empirical risk
(what we have)

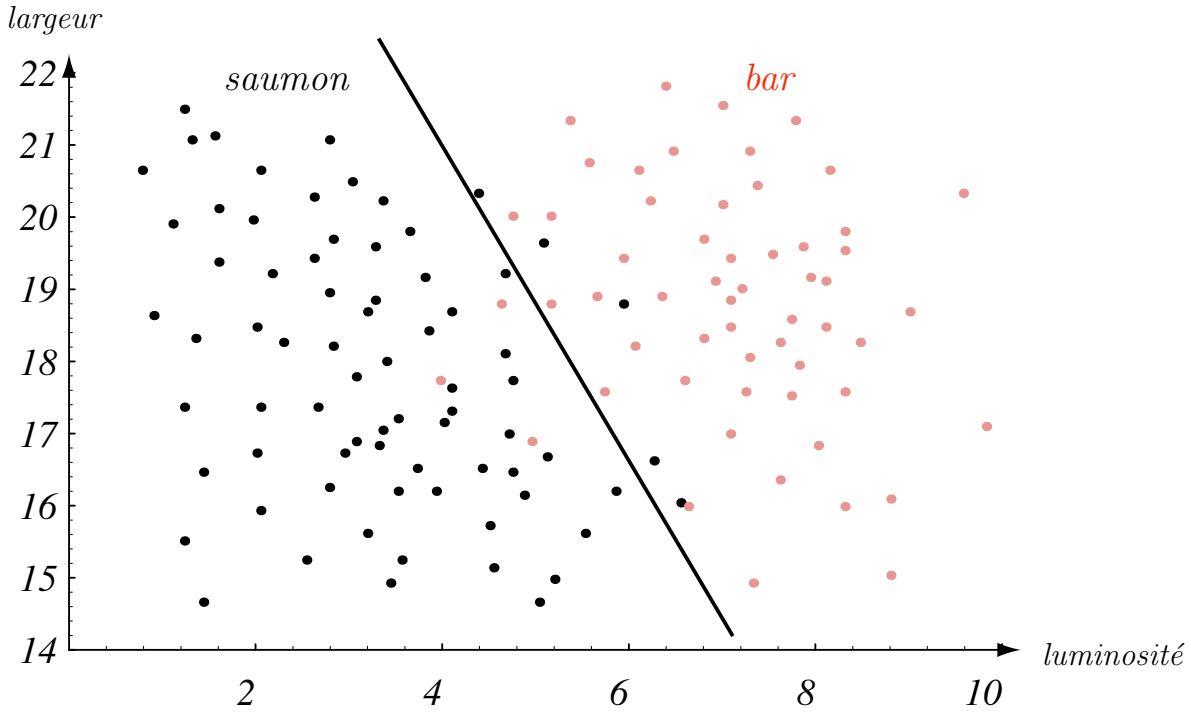
$$\hat{\mathcal{R}}(f_\theta, \mathcal{D}) = \frac{1}{|\mathcal{D}|} \sum_{(\mathbf{x},\mathbf{y})\in\mathcal{D}} \mathcal{L}\left(f_\theta(\mathbf{x}), \mathbf{y}\right)$$

Defining Machine Learning

Ex: 2D classification

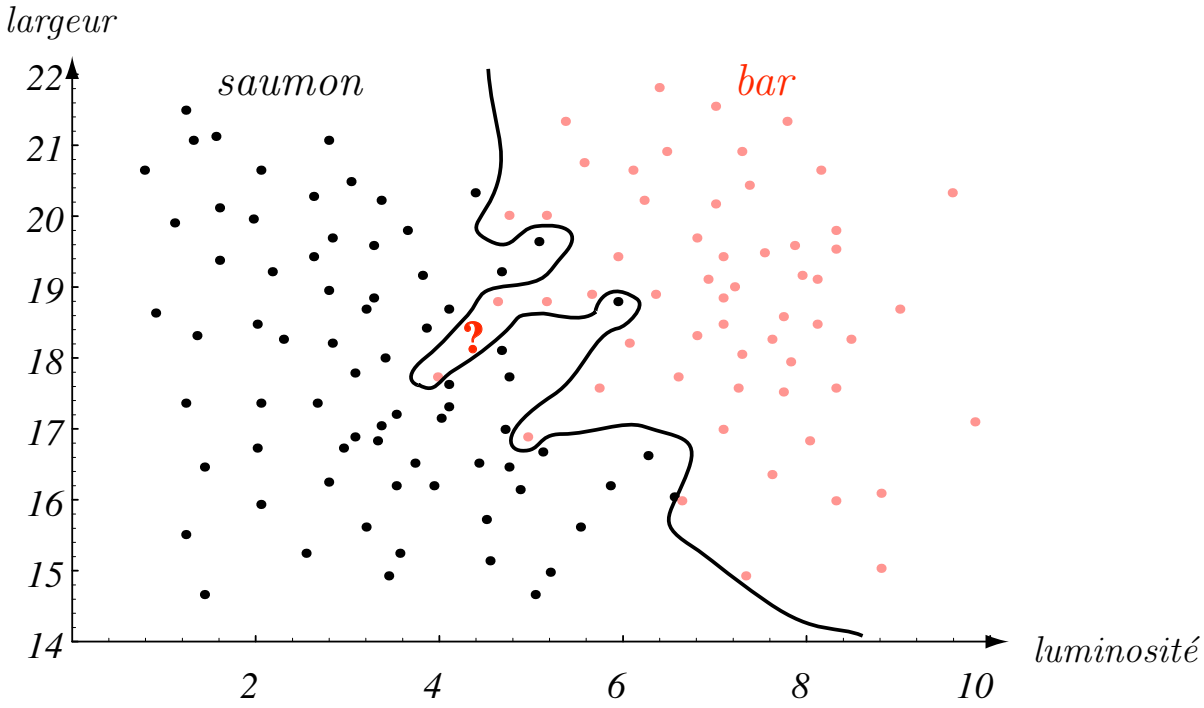
Linear classifier

- Function family too poor (too inflexible)
- = **Capacity too low** for this problem (relative to number of examples)
- => Under-fitting



Defining Machine Learning

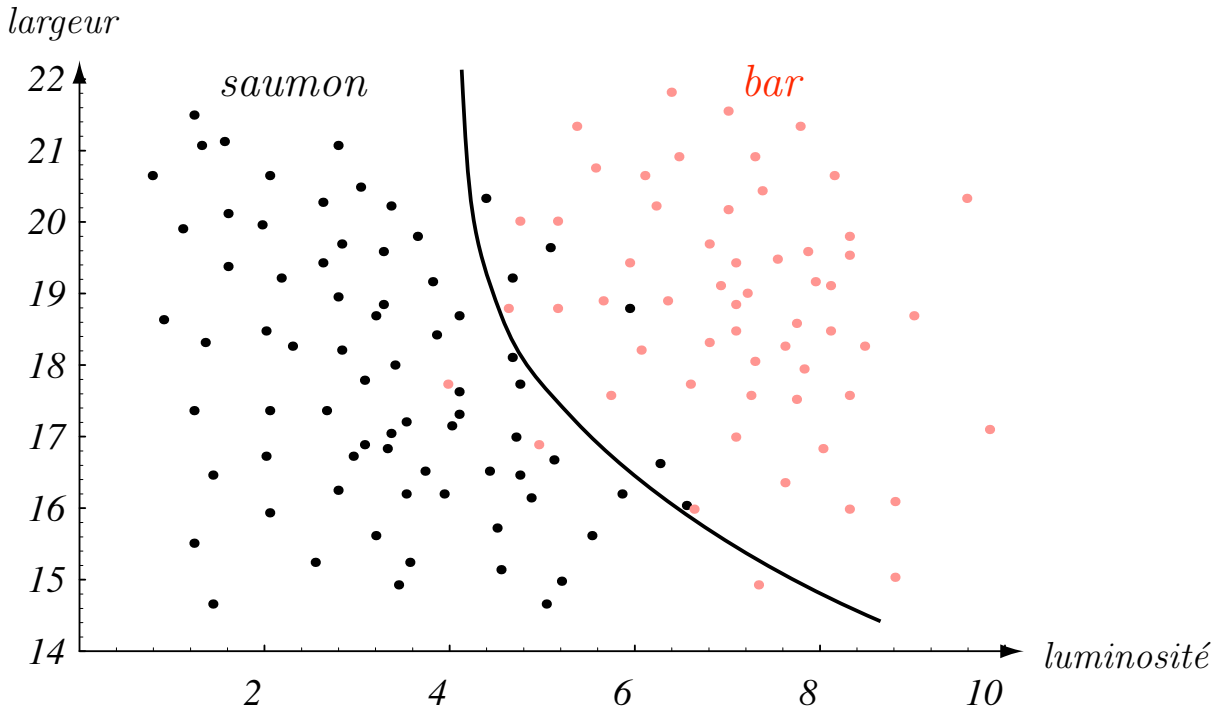
- Function family too rich
  (too flexible)
- = **Capacity too high** for this problem
  (relative to the number of examples)
- => Over-fitting



Nombre d'erreurs d'entrainement: 0

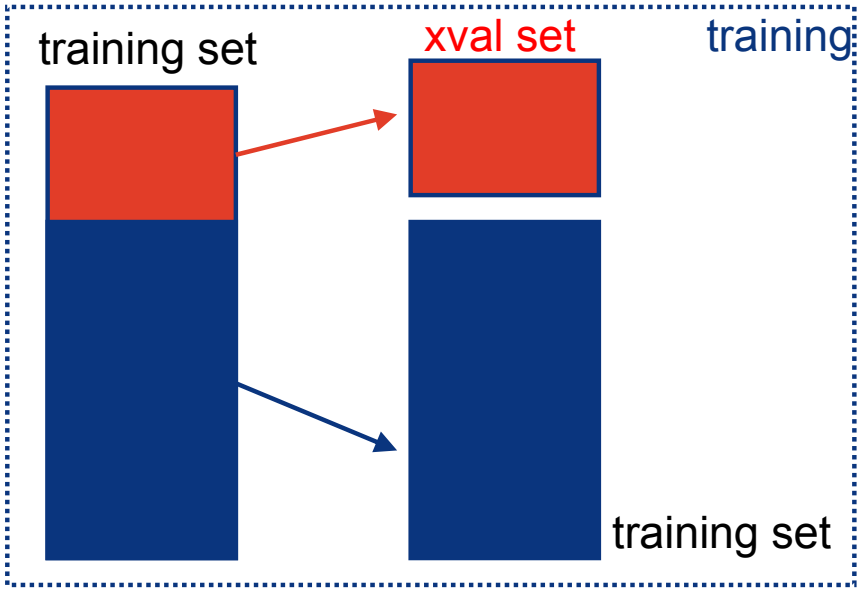
Defining Machine Learning

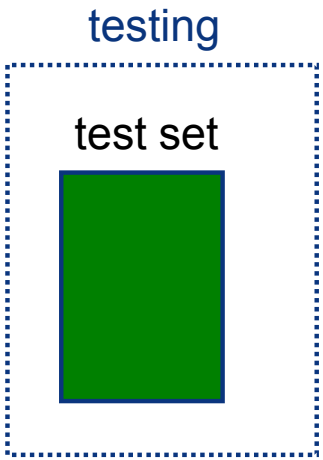
- **Optimal capacity** for this problem
  (par rapport à la quantité de données)
- => Best generalization
  (on future test points)



Cross-validation

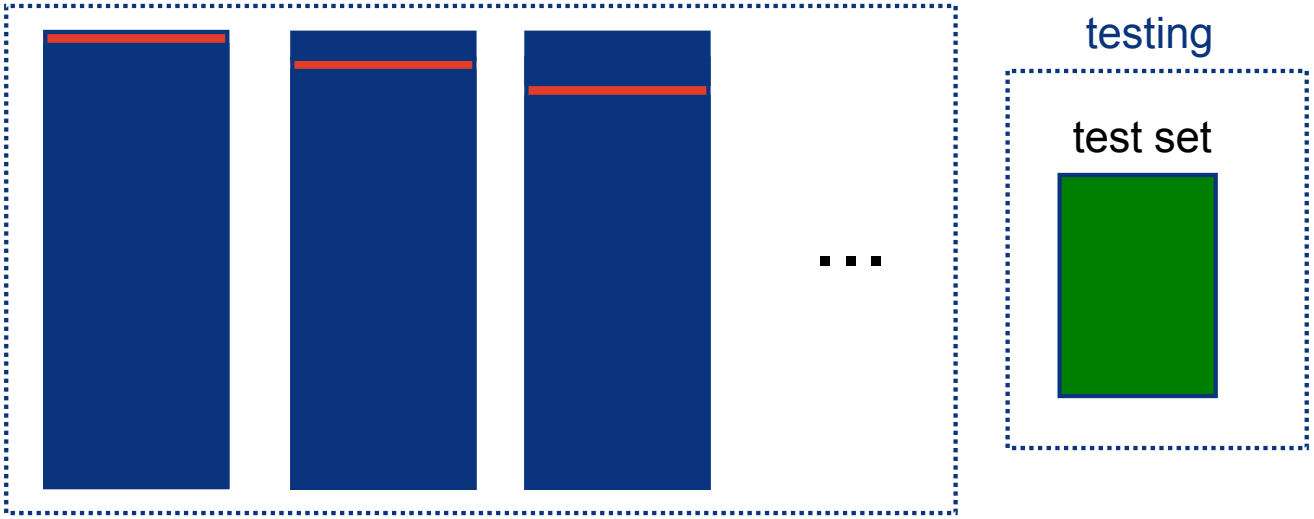
- basic idea:
  - leave some data out of your training set (cross validation set)
  - train with different parameters
  - evaluate performance on cross validation set
  - pick best parameter configuration





Cross-validation

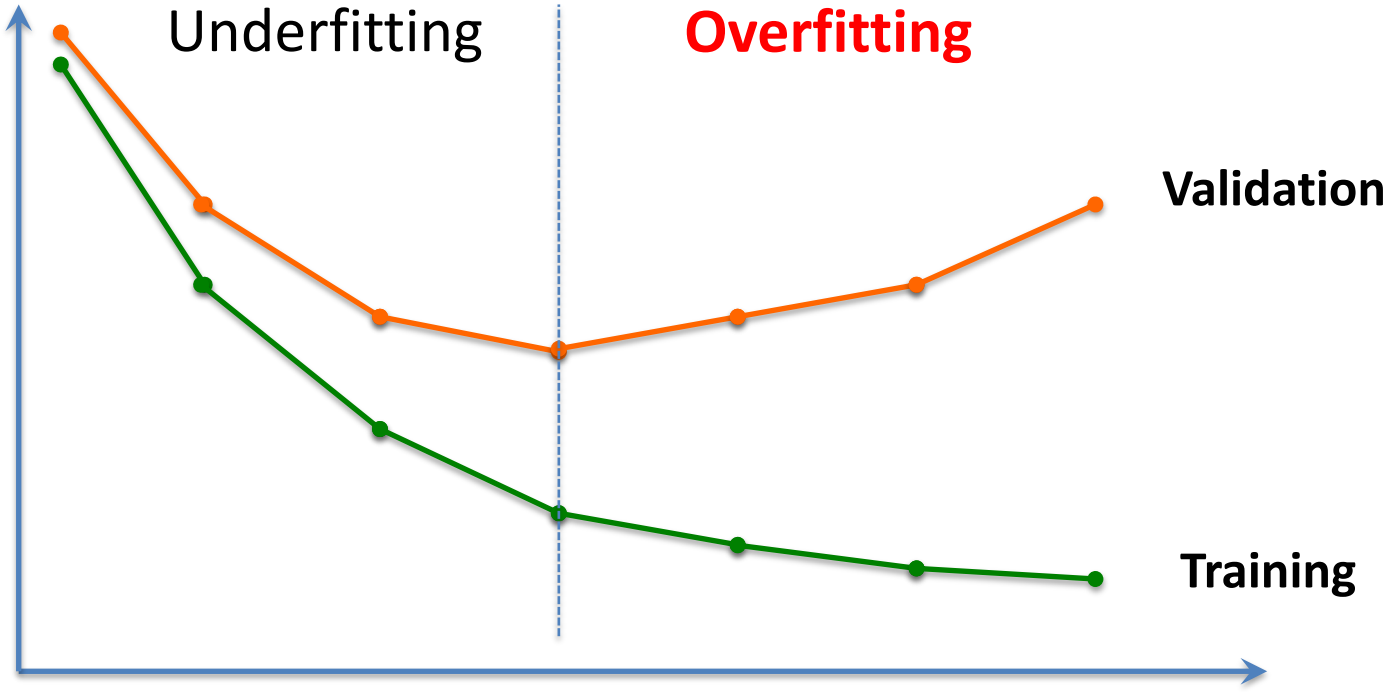
- many variations
- leave-one-out CV:
  - compute n estimators of $P_X(x)$ by leaving one X_i out at a time
  - for each $P_X(x)$ evaluate $P_X(X_i)$ on the point that was left out
  - pick $P_X(x)$ that maximizes this likelihood



Knowing when to stop

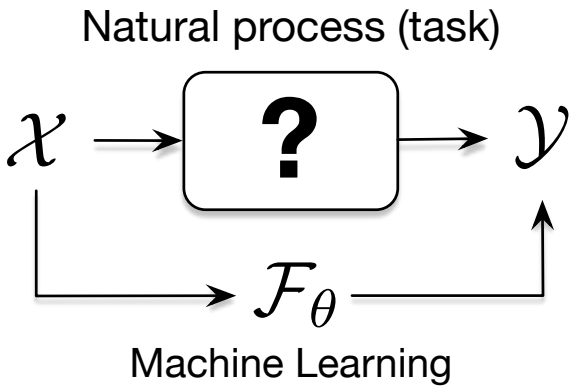
Early stopping

Stop the learning when the error increases on the validation set
(Approximates the generalization power)



Understanding the input space

- Up to now we have talked on an abstract level
- We observe relationships between $\mathcal{X}$ and $\mathcal{Y}$



So what is the *nature* of the input space $\mathcal{X}$?

This is defined by the set of *observations*

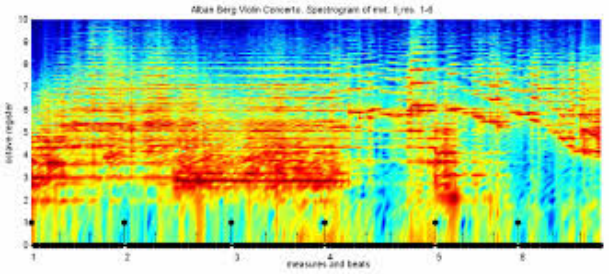
$$\mathbf{X} = \{x_1, \ldots, x_n\}$$

The major problem is the *dimensionality of* these observations

In the case of waveform audio data, this problem is **huge**

5 seconds of 44.1k audio

220,500 dimensions

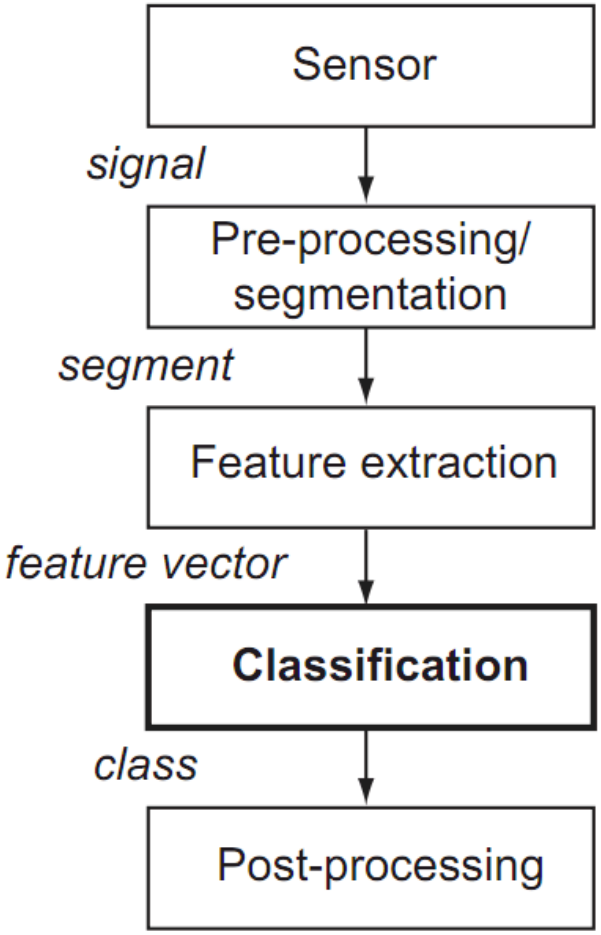


- *Pitch*
- *Loudness*
- *Centroid*

Seminal approach of

feature-based learning

Feature-based learning



- In order to define a « sane » problem
- We first process the observations
- And extract some relevant features
  - Highly problem-dependent

$\mathcal{X}$ = Set of high-level features

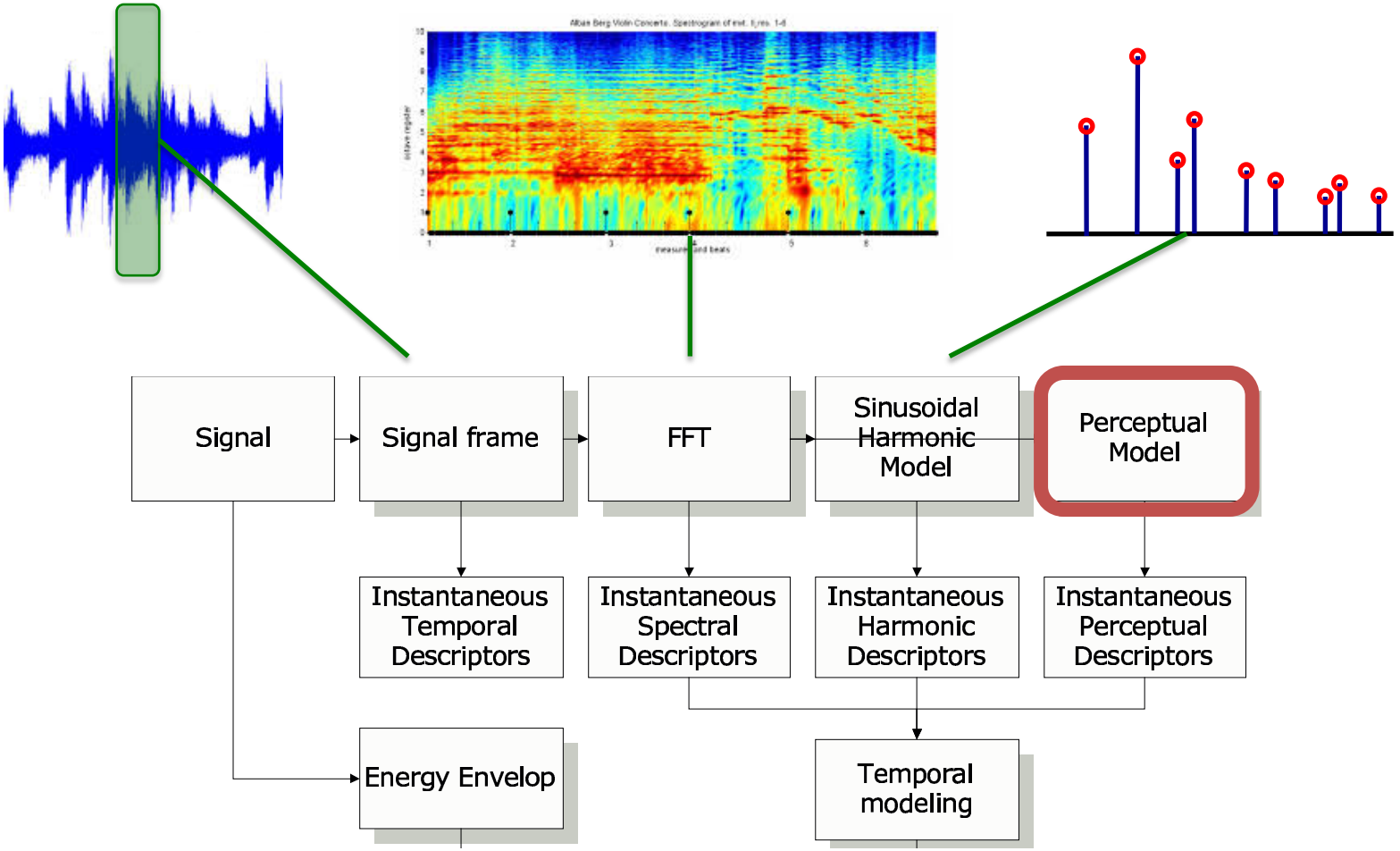
$\mathcal{Y}$ = Still our classes

- But on which features ?
- Highly depends on the task at hand !
- Years of research on audio features

Retrieving musical information (MIR)

1. **Harmonic analysis**
    1. Pitch tracking, melody estimation
    2. Multiple F0 estimation, chord estimation
2. **Rhythmic analysis**
    1. Onset detection
    2. Tempo estimation, beat tracking
3. **Content-based analysis**
    1. Instrument recognition
    2. Structure analysis
    3. Classification (genre recognition, tags, mood, …)
    4. Music similarity and cover detection
    5. Query by content (query by humming)

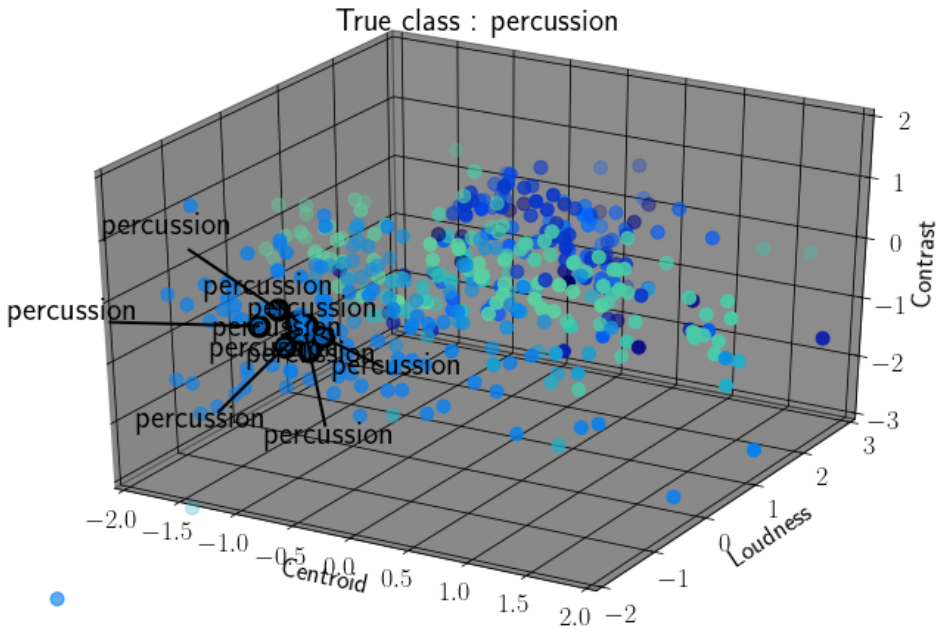
Audio features



So what can we do with these features ?

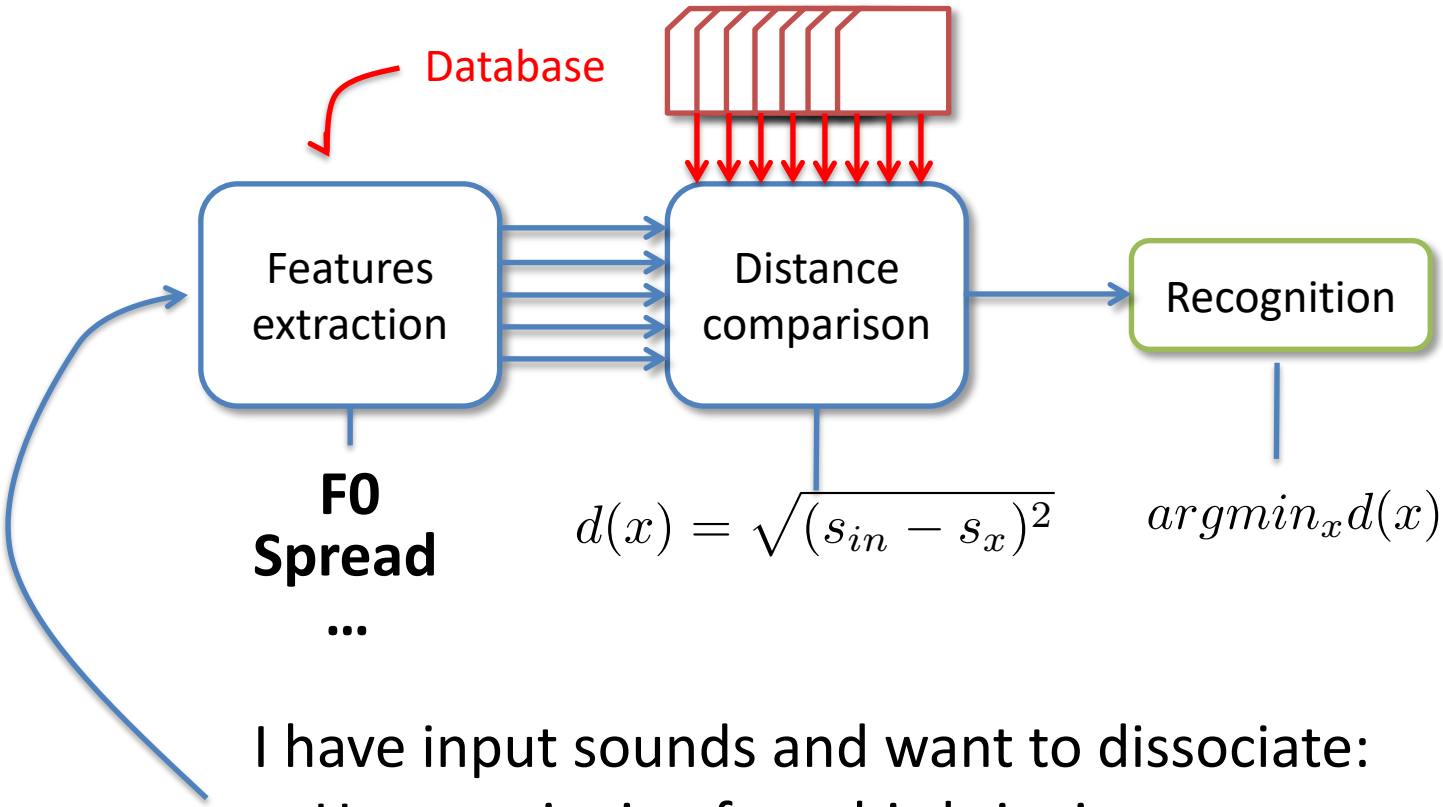
Feature-based learning ?

If we look at a typical feature space (here audio)



- *Similar examples are usually grouped*
- Naïve way of adressing our classification = *look at neighbors*

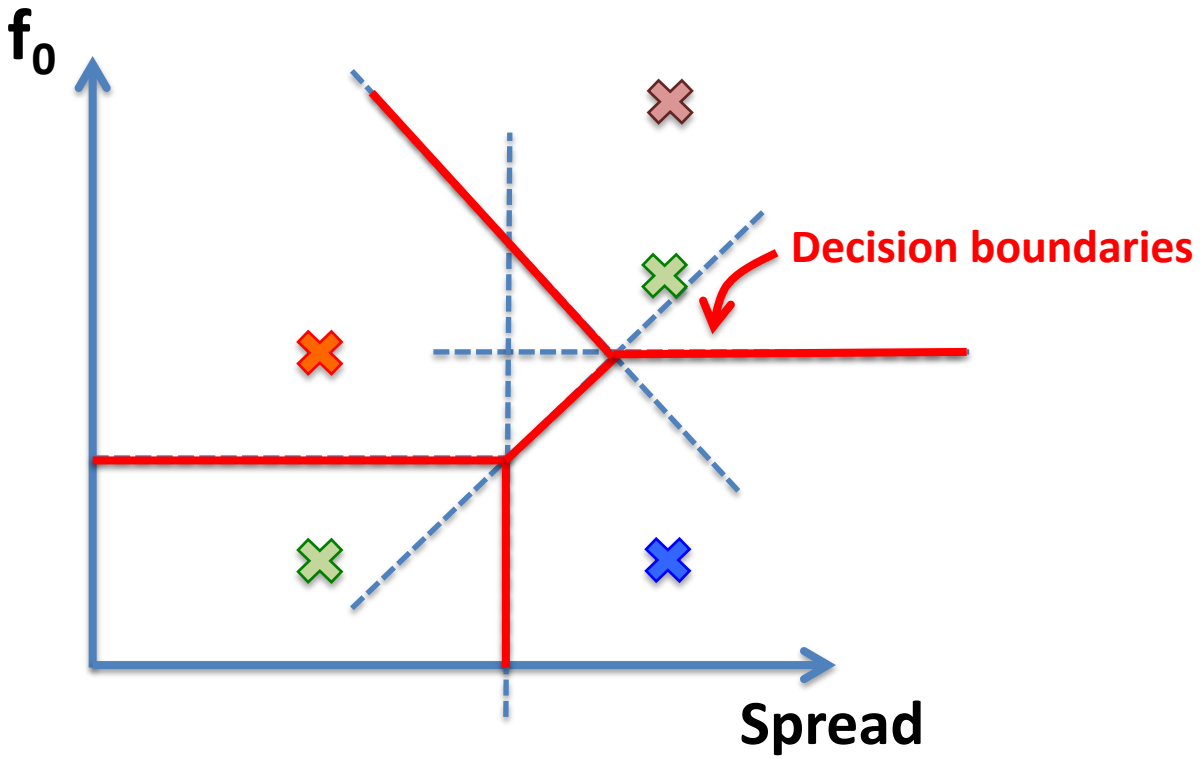
Nearest-Neighbor



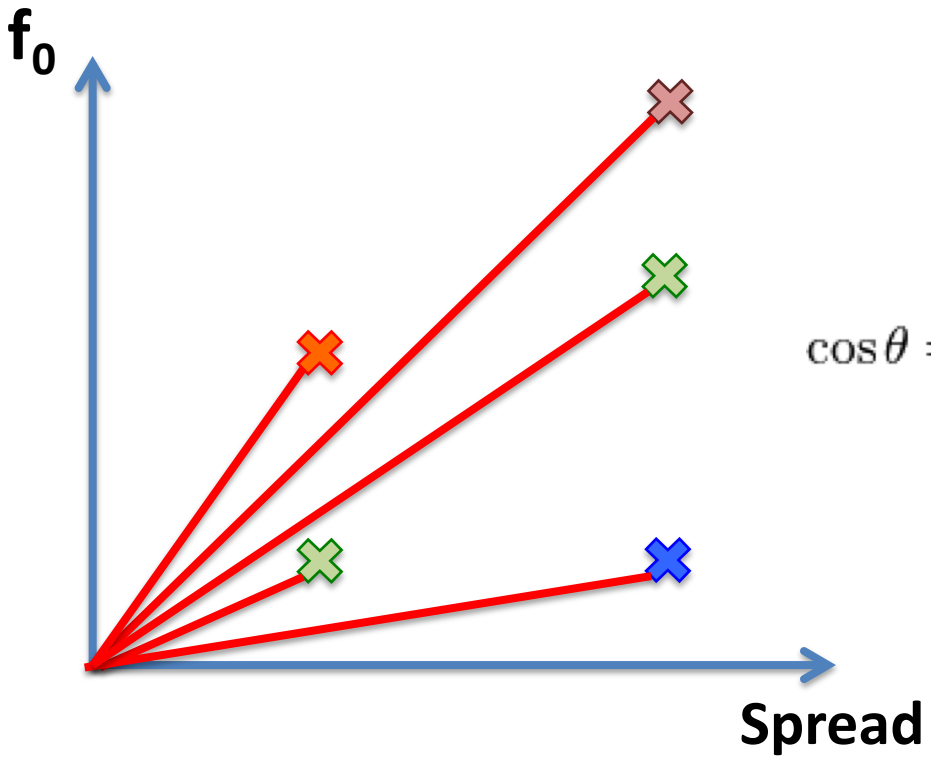
I have input sounds and want to dissociate:

- Human singing from bird singing

Nearest-Neighbor

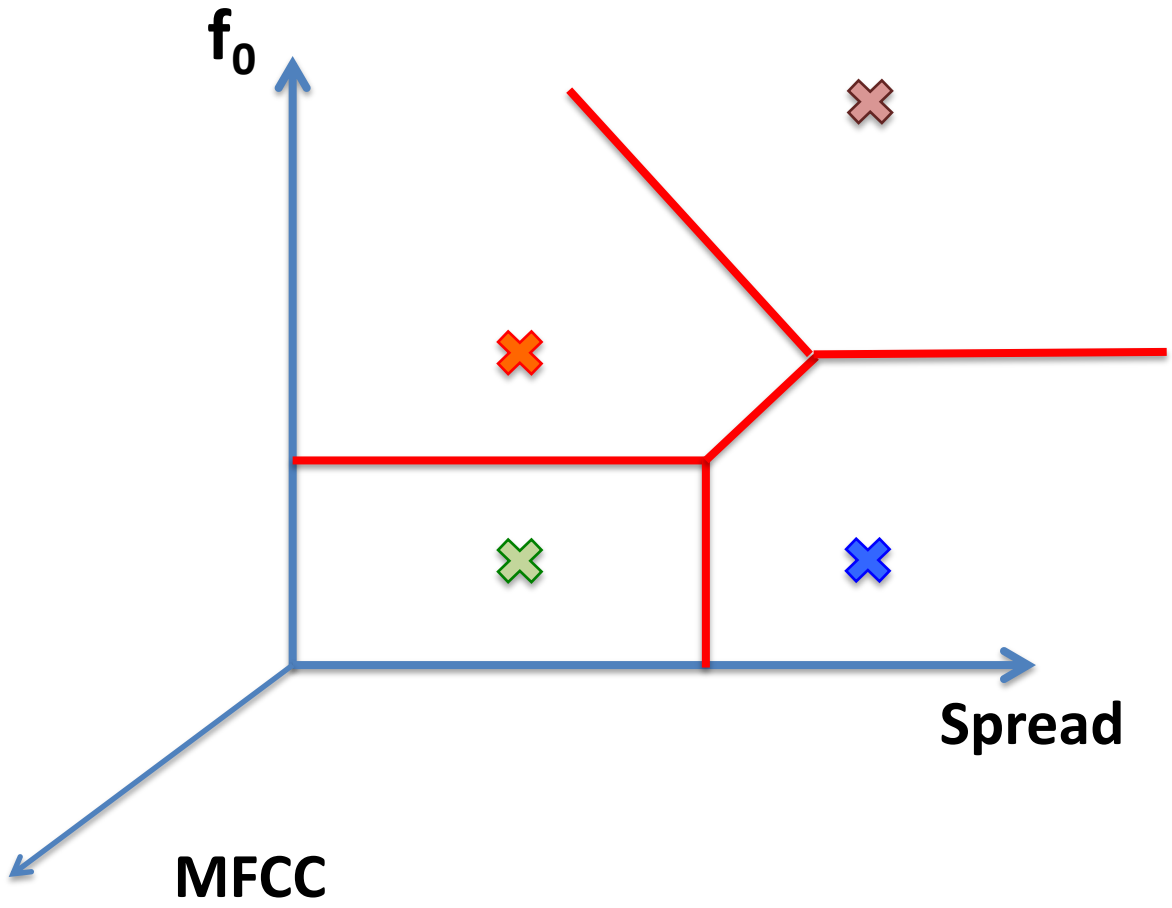


Nearest-Neighbor



$$\cos\theta = \frac{A \cdot B}{\|A\| \cdot \|B\|}$$

Nearest-Neighbor



Nearest-Neighbor

Typical turnarounds of Nearest-Neighbor

⇒ Improve your features (make them problem-specific)

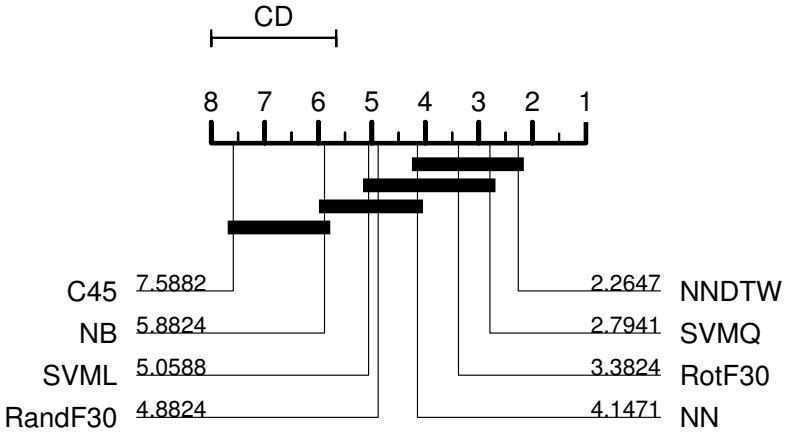
⇒ Add dimensions (without overspecifying the problem)

⇒ Rely on non-standard metrics (cosine, Bregman, …)

⇒ Go from 1-NN to k-NN (eventually with variable k)

- Nearest-Neighbor might seem like a quite dull approach
- However recent researches show that features are more important than classifier
- A dull classifier works perfectly if features are great

Cf. the ant's path and Occam's razor



Results from [Bagnall et. al 2012] on the **17** datasets from the UCR time series archive

1-NN with DTW is statistically superior to other classification methods (even though not *critical* with SVMQ and RotF30)