Théophile Mohr Durdez

CEO, Volta Medical

Intelligence artificielle et Cardiologie: des algorithmes à l'application médicale

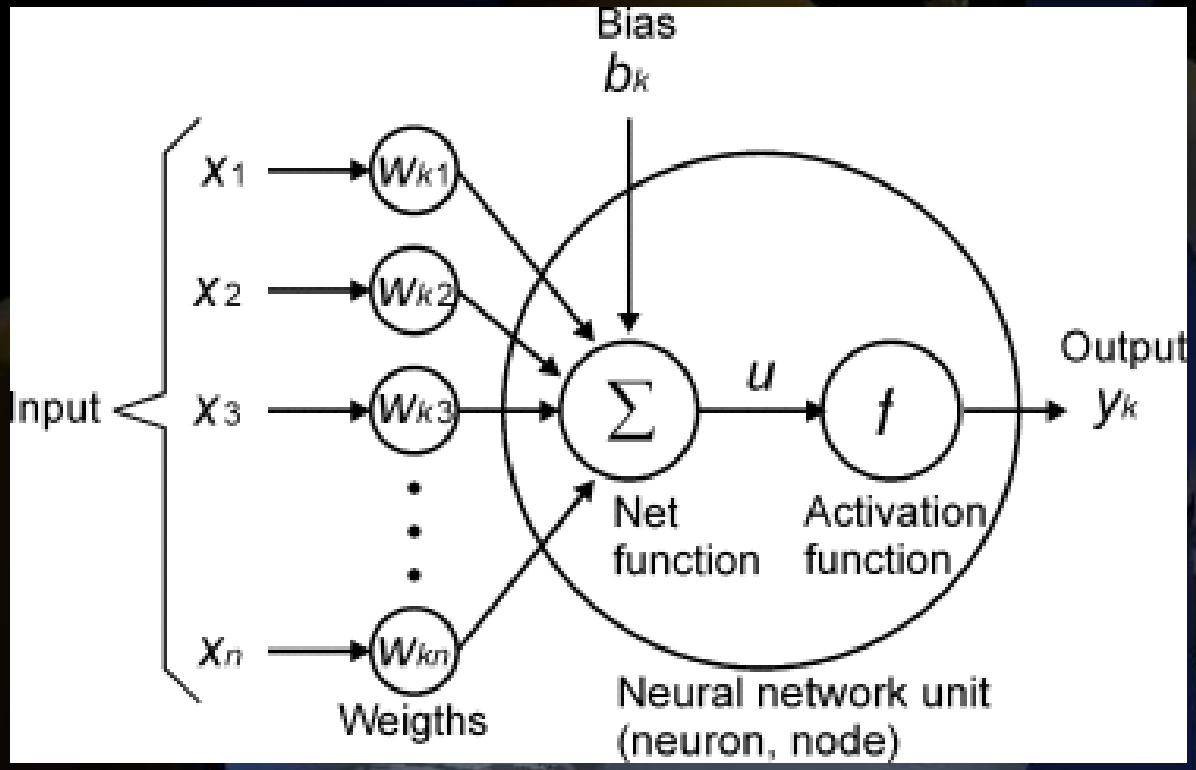
JAT – Nice 2020

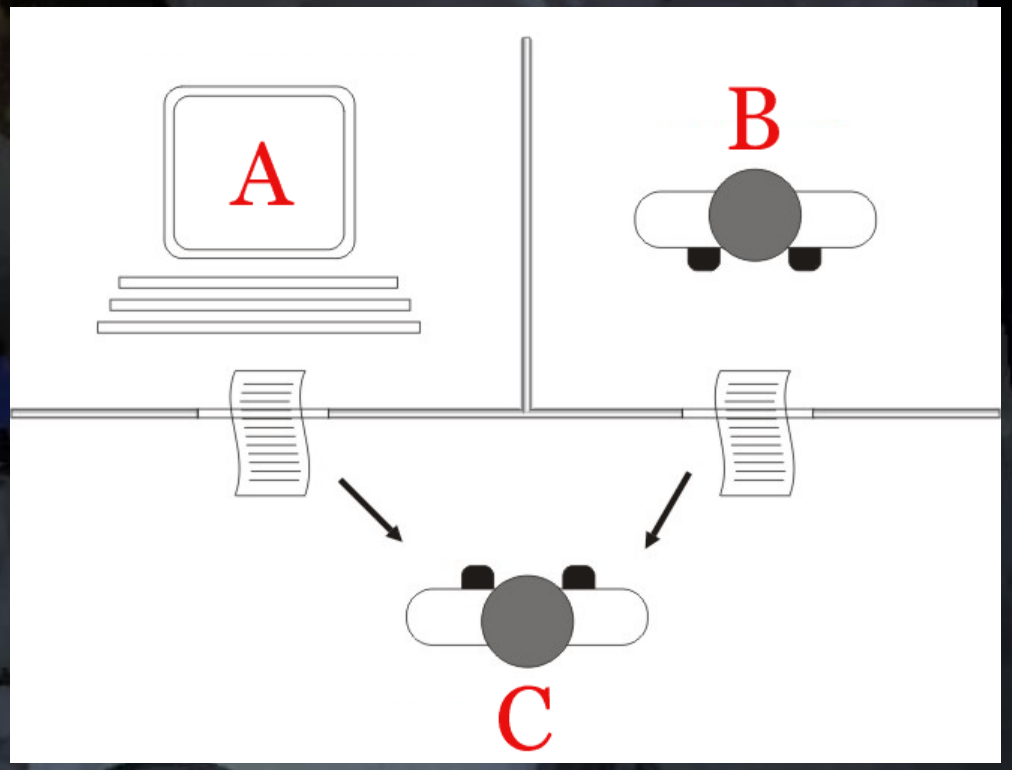
12/SEP/2020

L’avènement de l’Intelligence Artificielle?

Une vieille histoire

Premier article sur le potentiel des réseaux de neurones artificiels





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Go

2016

Alphago gagne face à **Lee Sedol**

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Poker

2017

Libratus gagne face à champions du monde

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Qu’est-ce que l’IA?


1. Apprentissage
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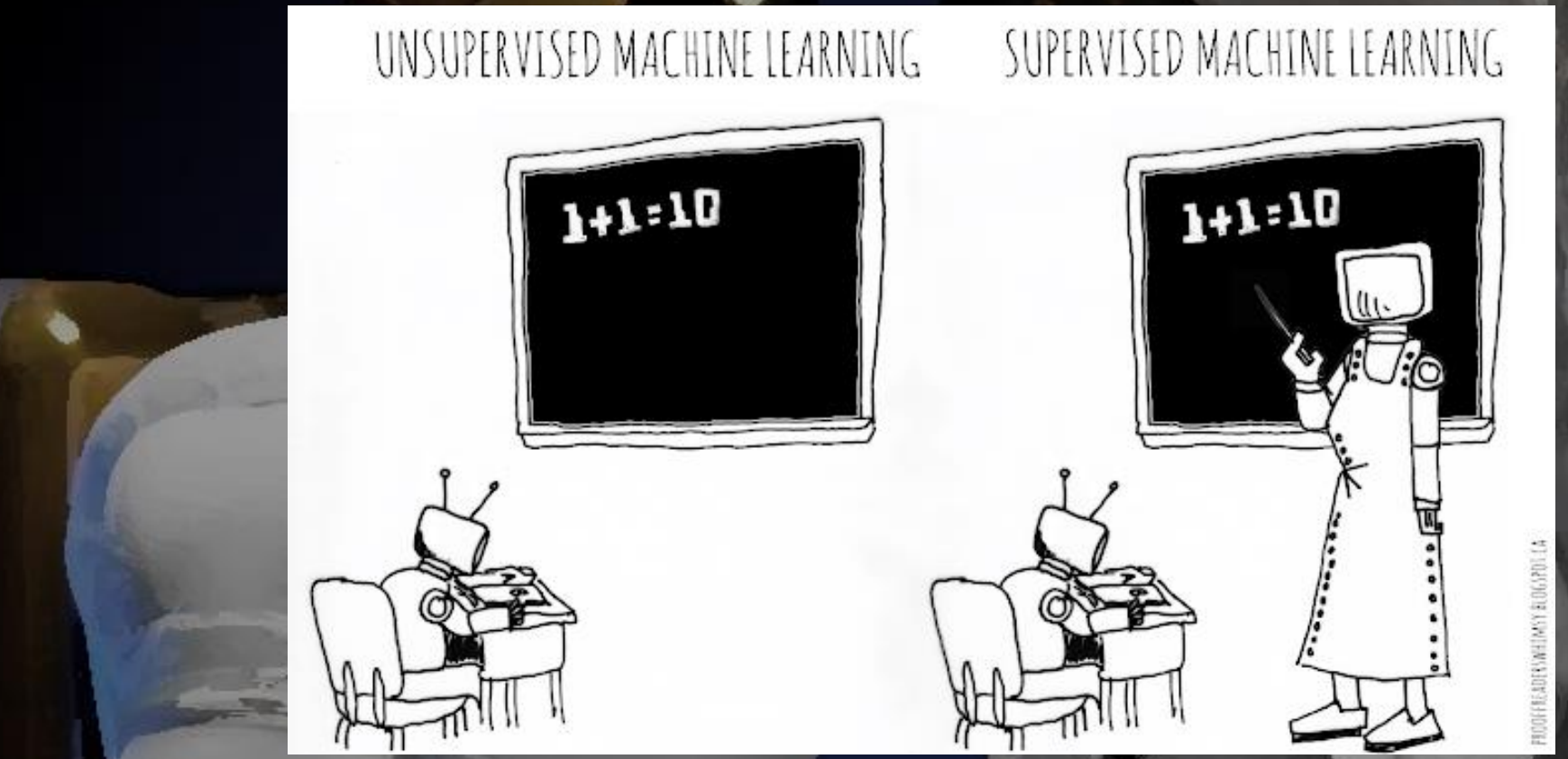
1. Deux types d’apprentissage



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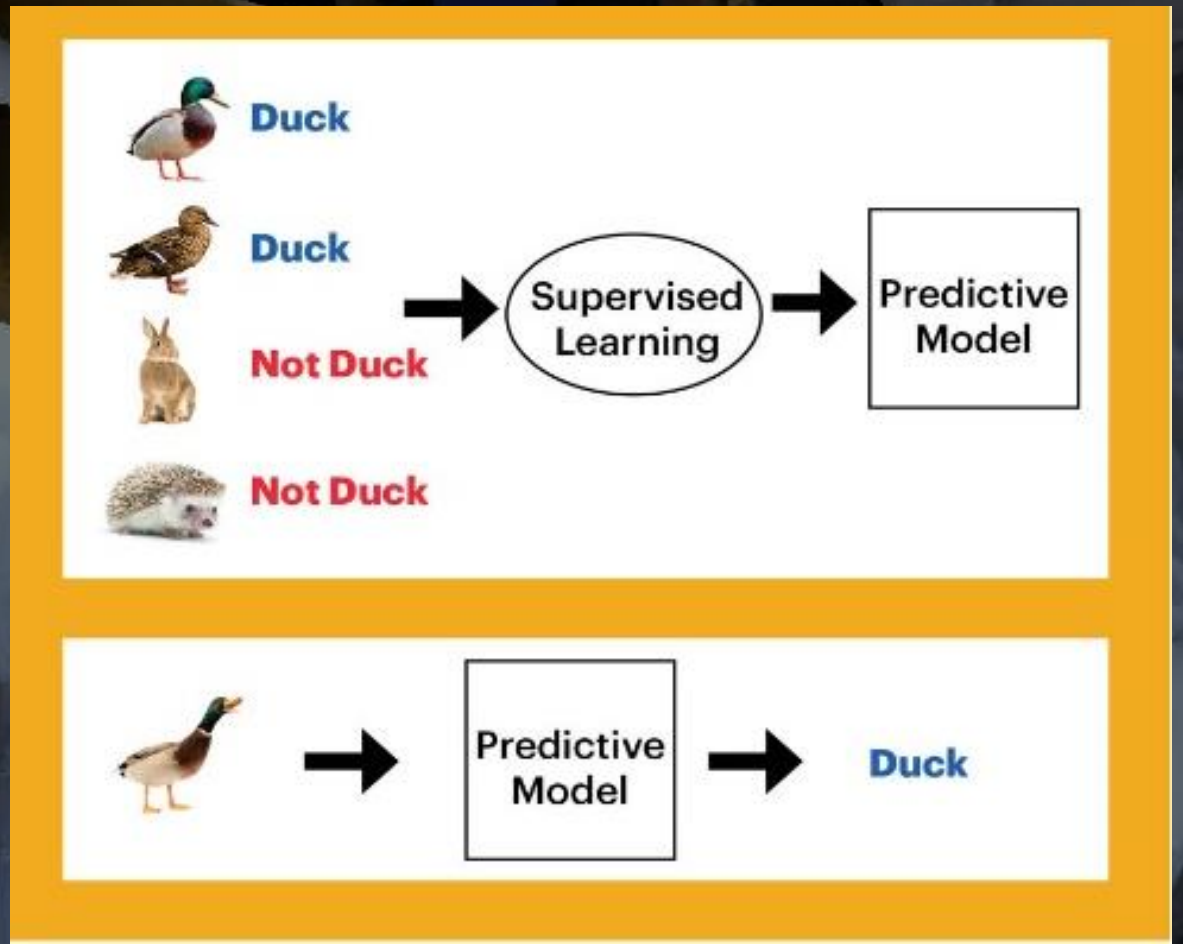
A. Apprentissage Supervisé

Utilisation d'information humaine pour "aider" lors de l'apprentissage



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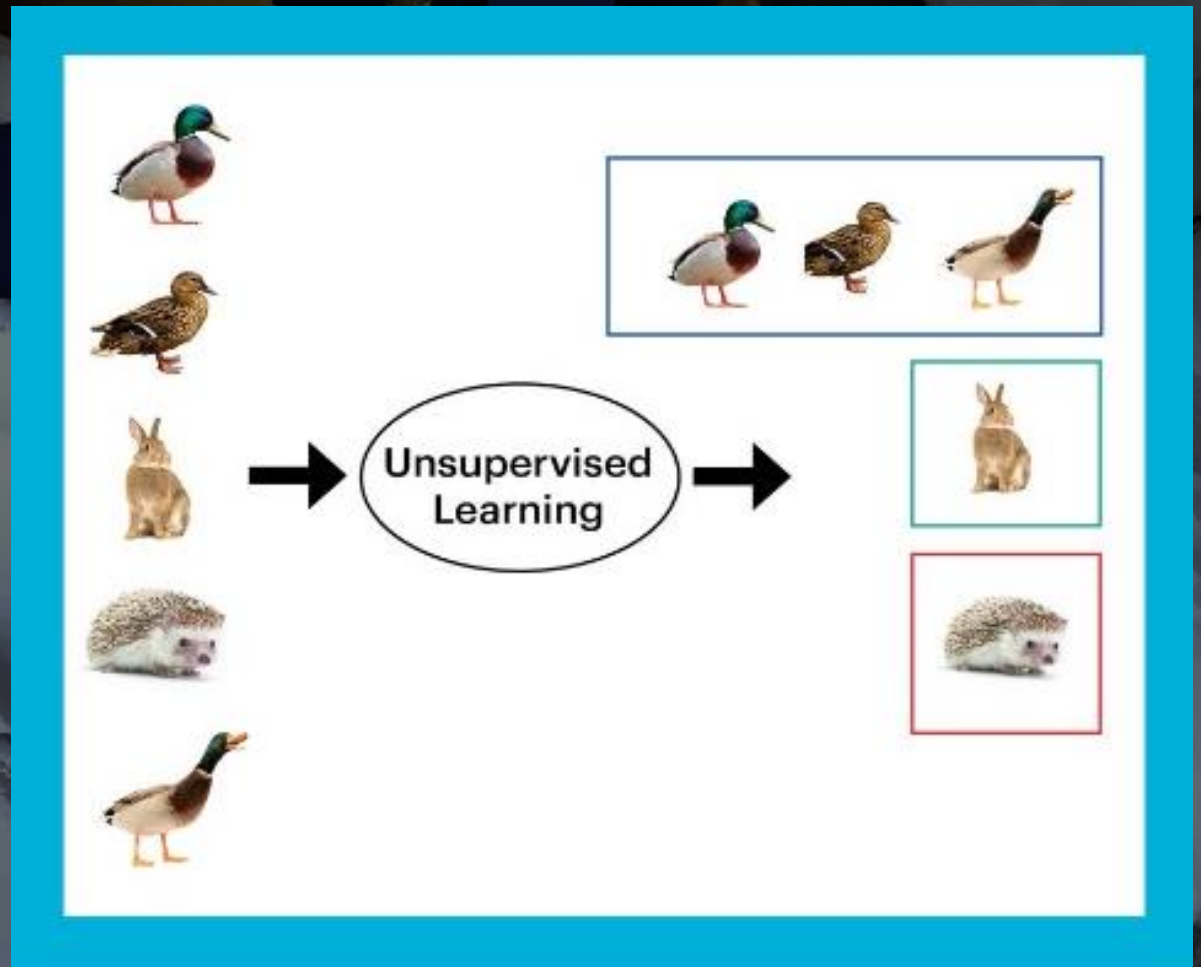
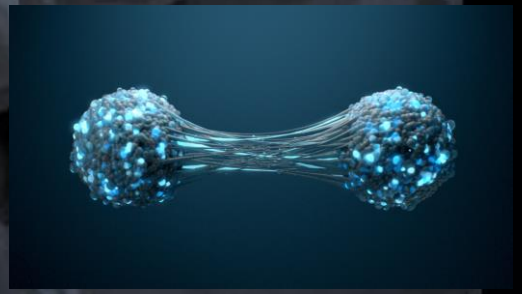
B. Apprentissage Non-supervisé

Aucune information humaine pour “aider” lors de l’apprentissage

NETFLIX





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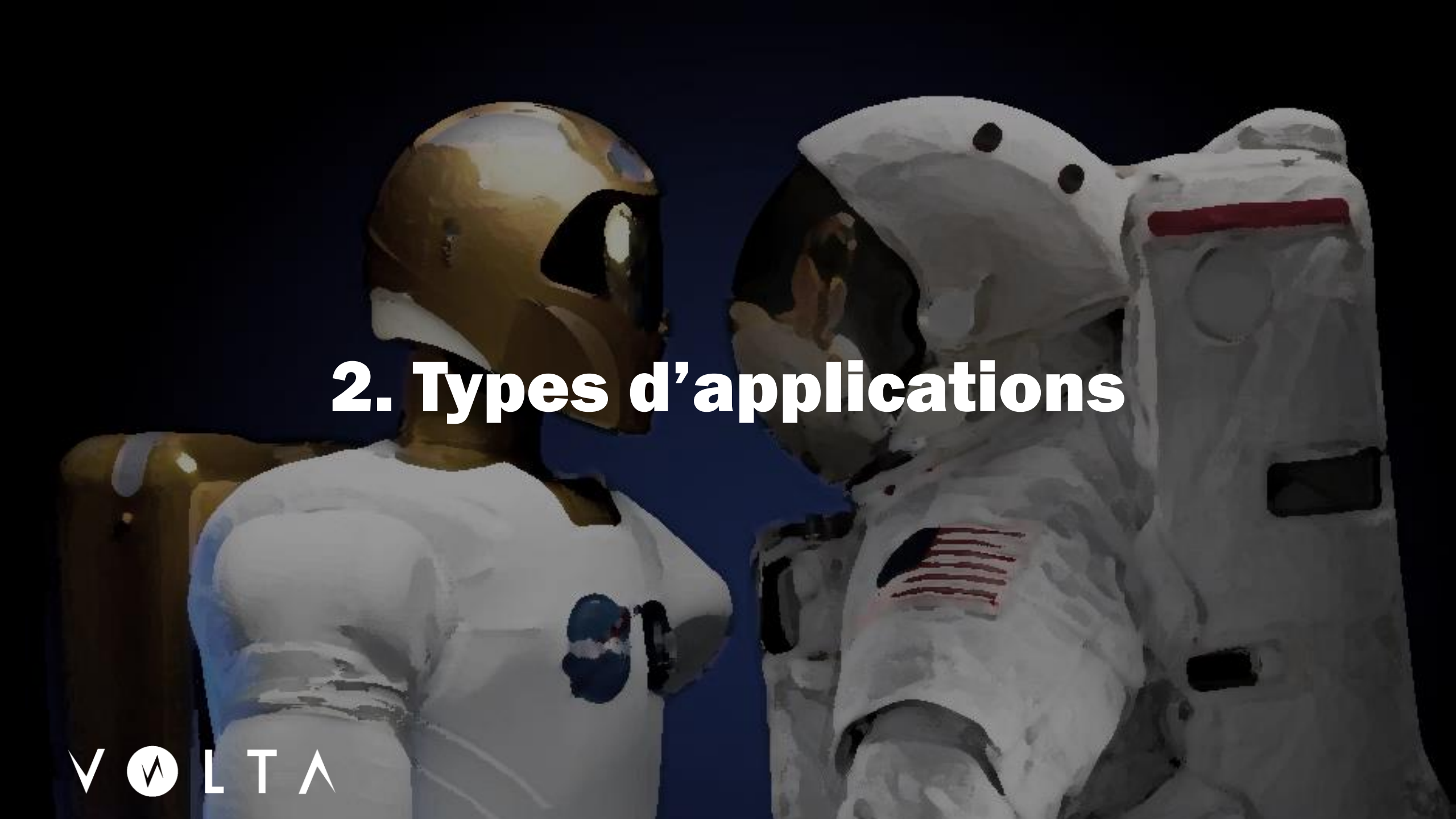

2. Types d’applications

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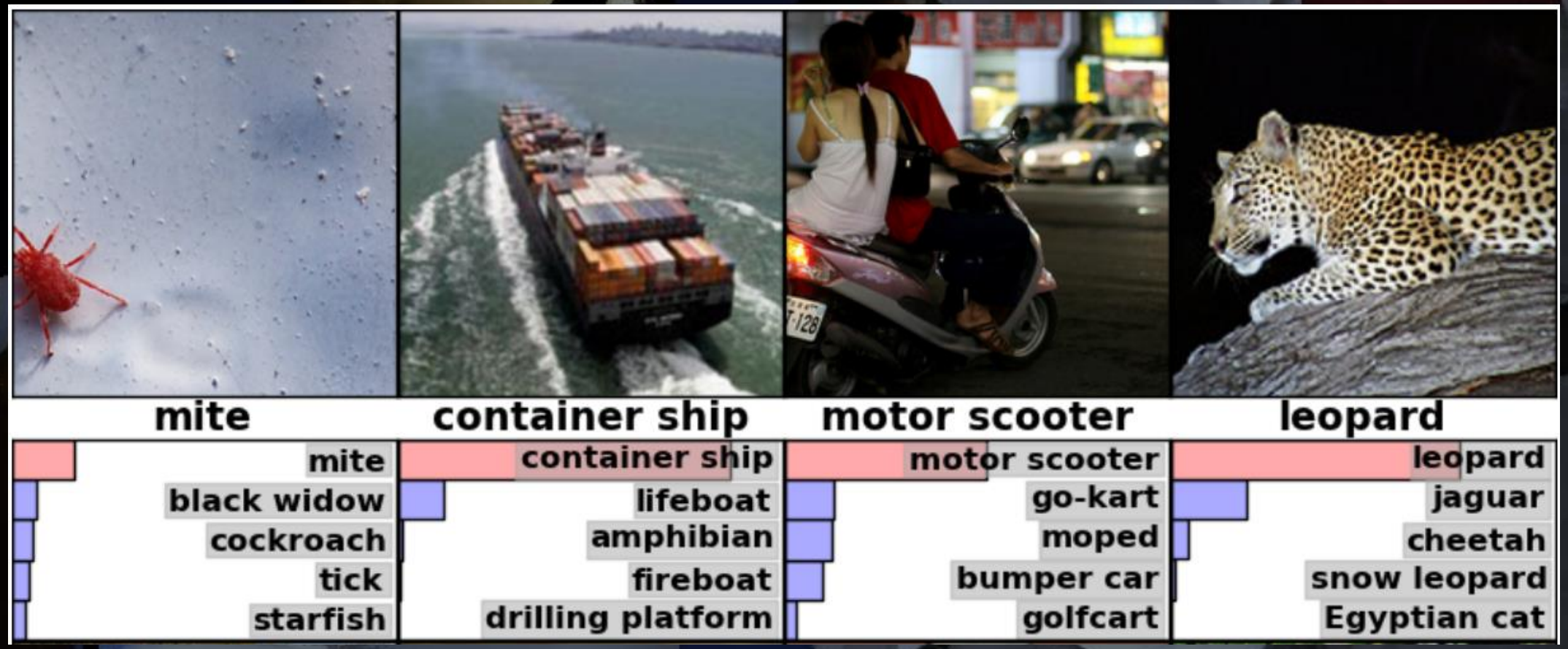
A. Classification

Identifying to which category an object belongs to.



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Dermatology: Diagnostic Images

nature
International journal of science

Dermatologist-level classification of skin cancer with deep neural networks

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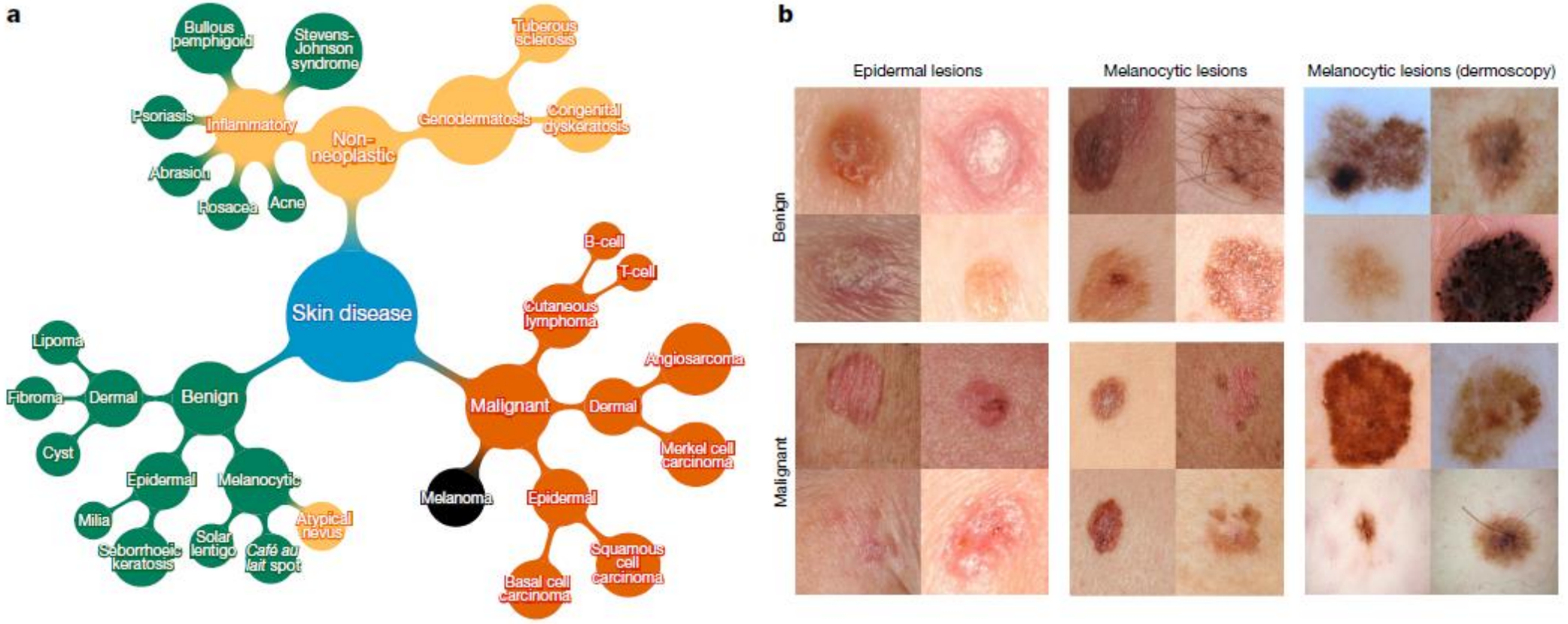
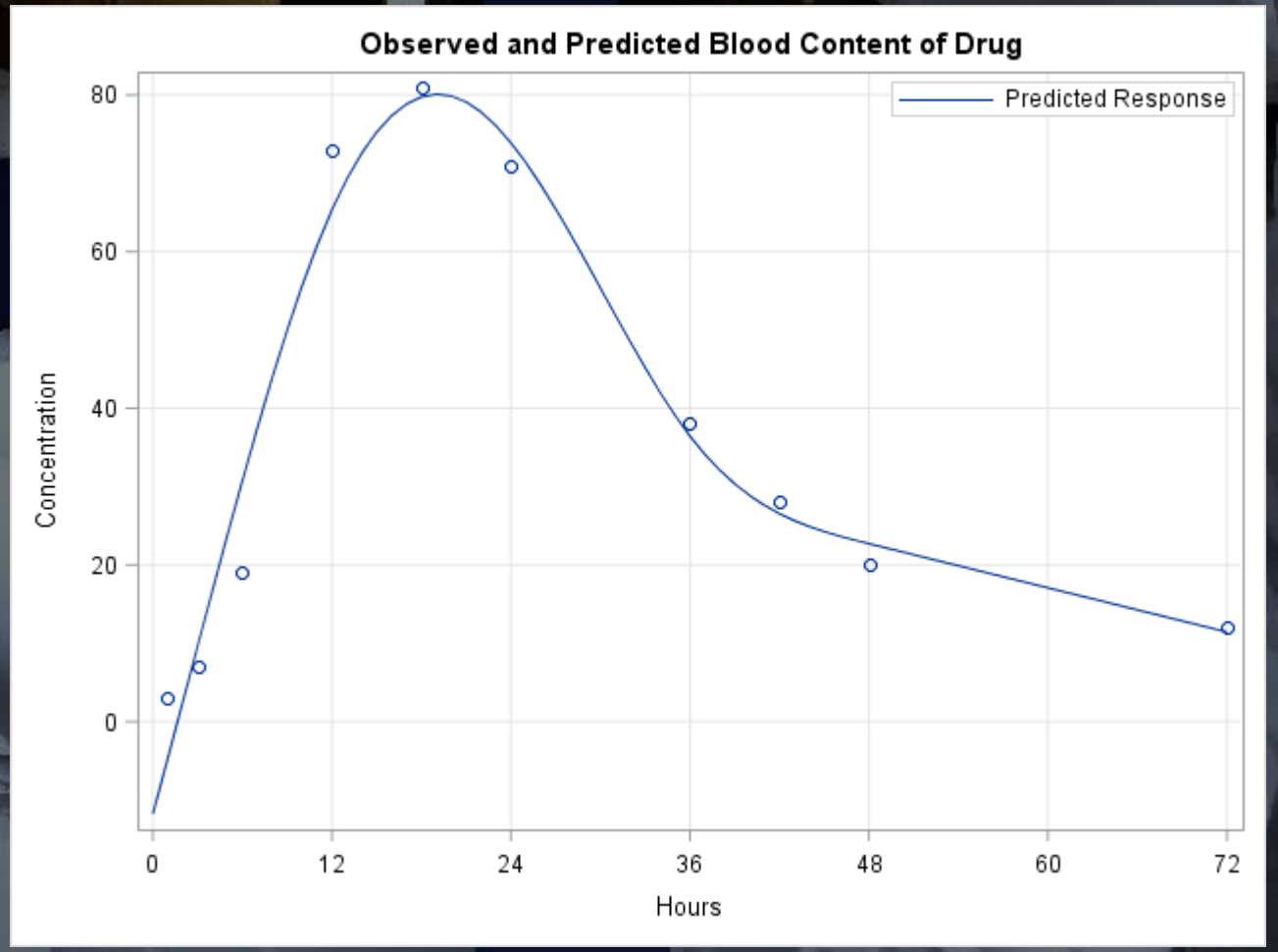


B. Regression

Predicting a continuous-valued attribute associated with an object.



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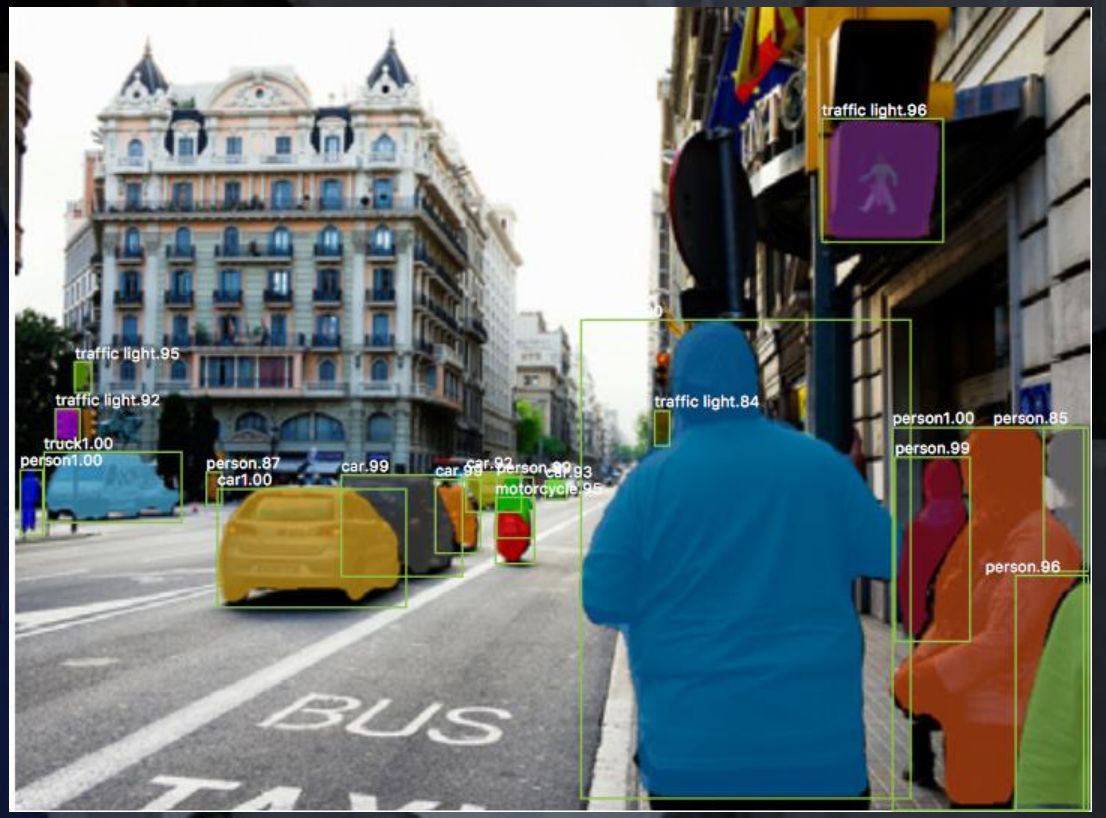
C. Segmentation

Predicting where an object is located in another object.



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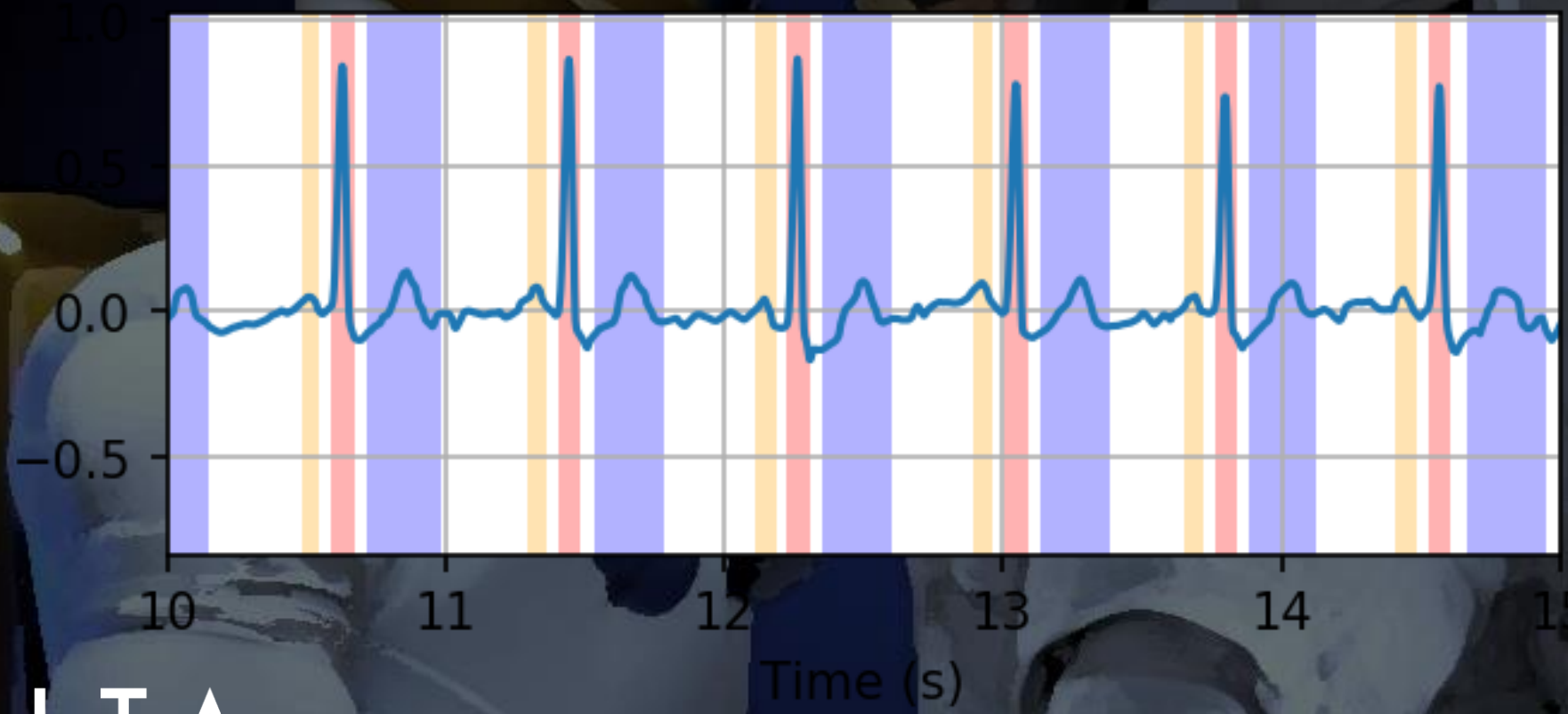

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C. Segmentation

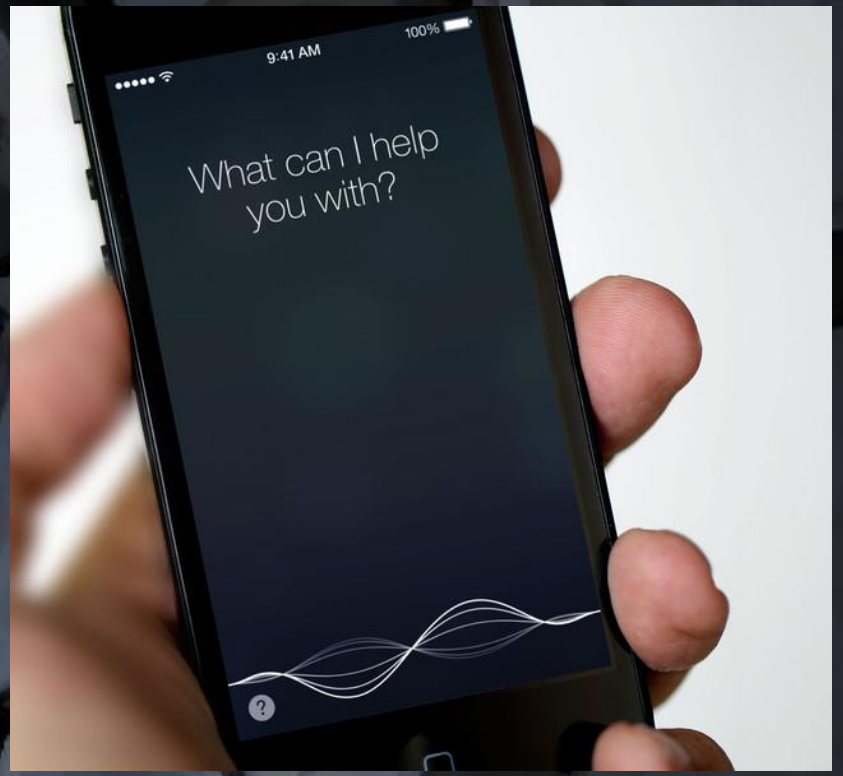
D. Natural Language Processing

Understanding Human Language

Segmentation / Classification

Translation

Speech Recognition



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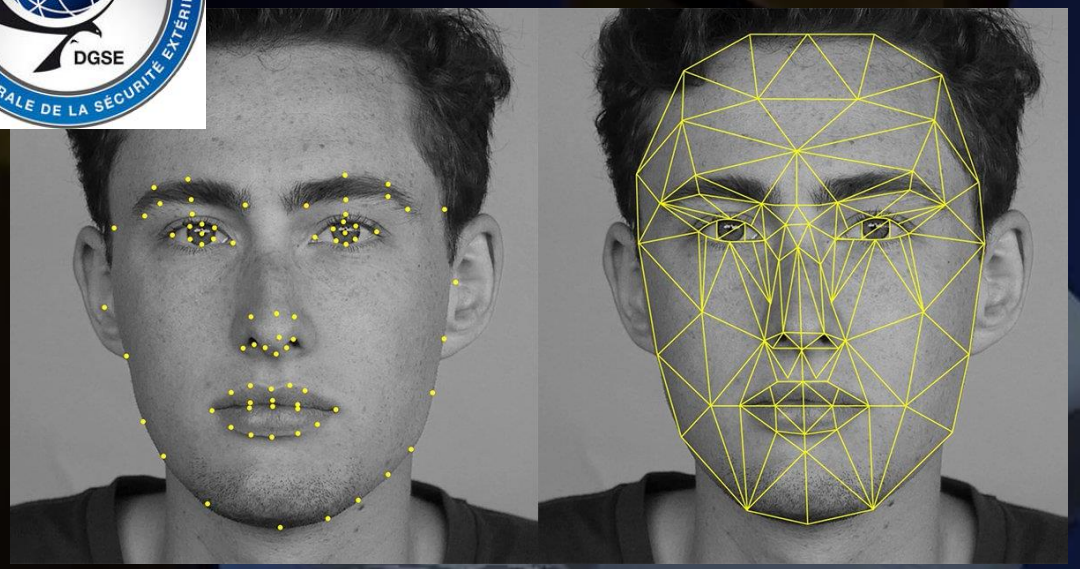
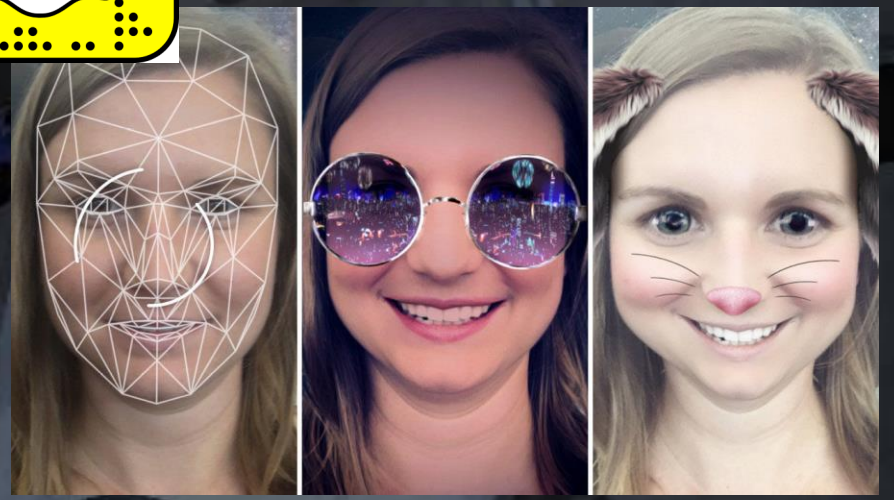
E. Face Recognition

Understanding Human Language

Segmentation / Classification





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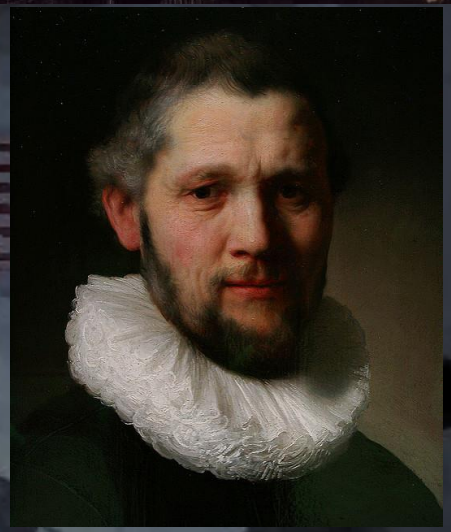
F. Content Generation

Creating « plausible » content with an algorithm



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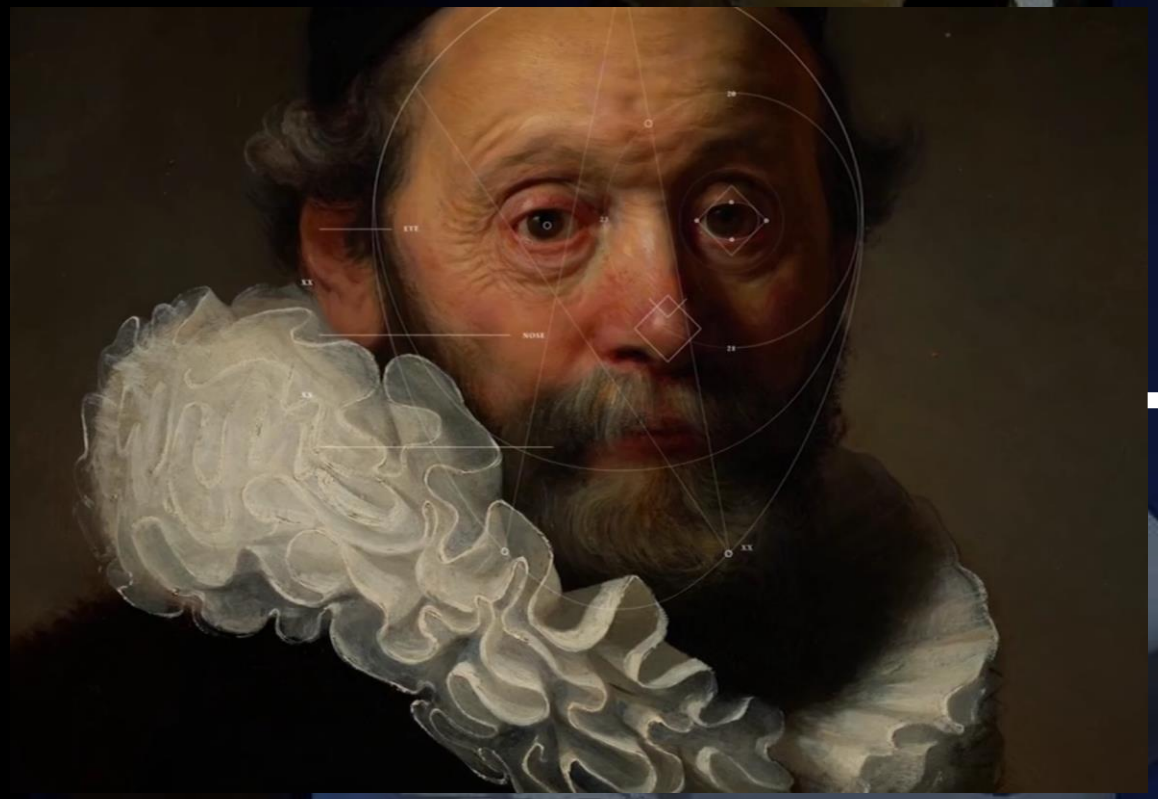

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Méthodes

Deux Approches:

- **Feature Engineering**

- **Apprentissage profond**

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Apprentissage machine

Sick

Apprentissage machine

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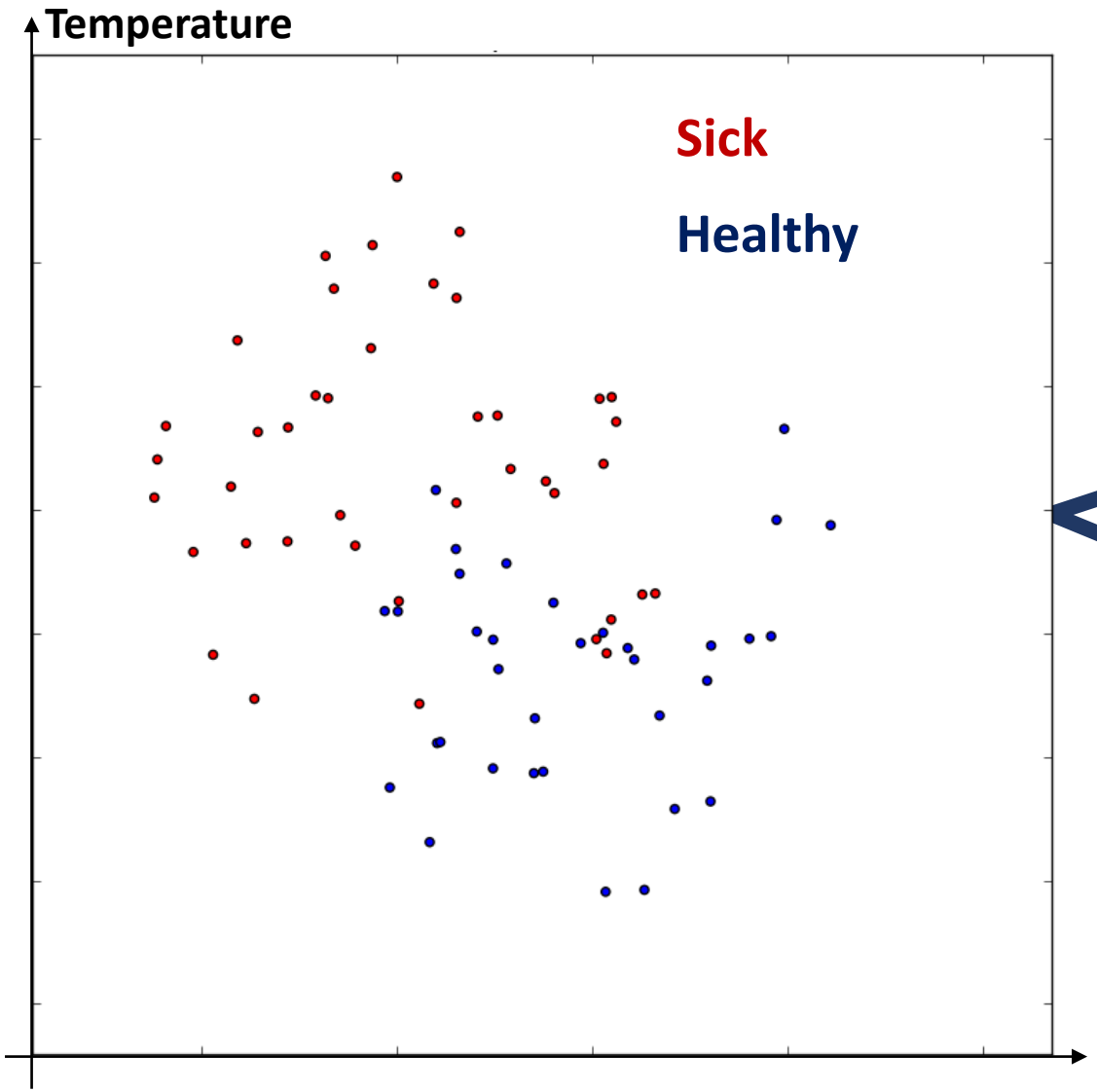
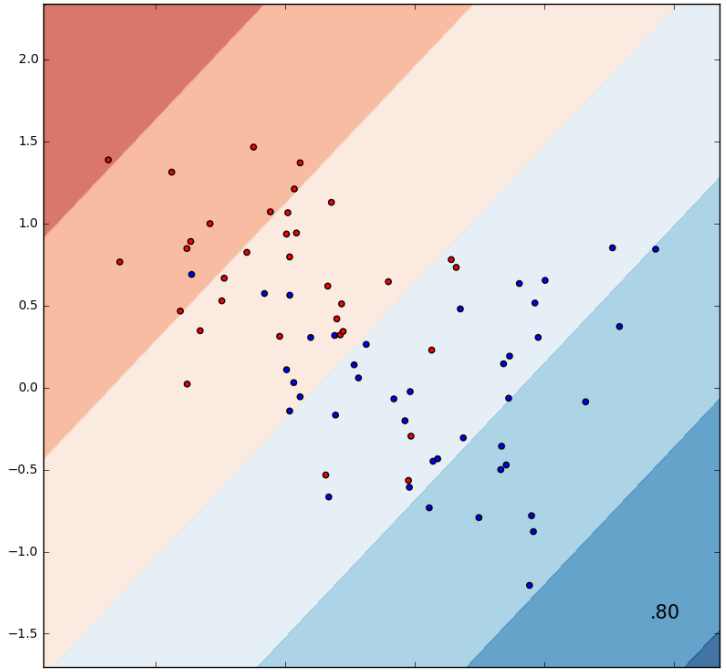
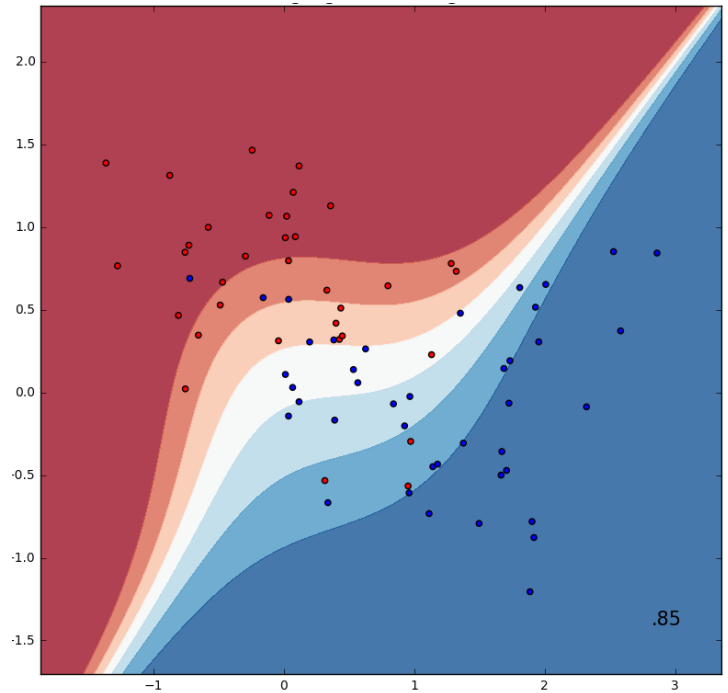
Machine learning



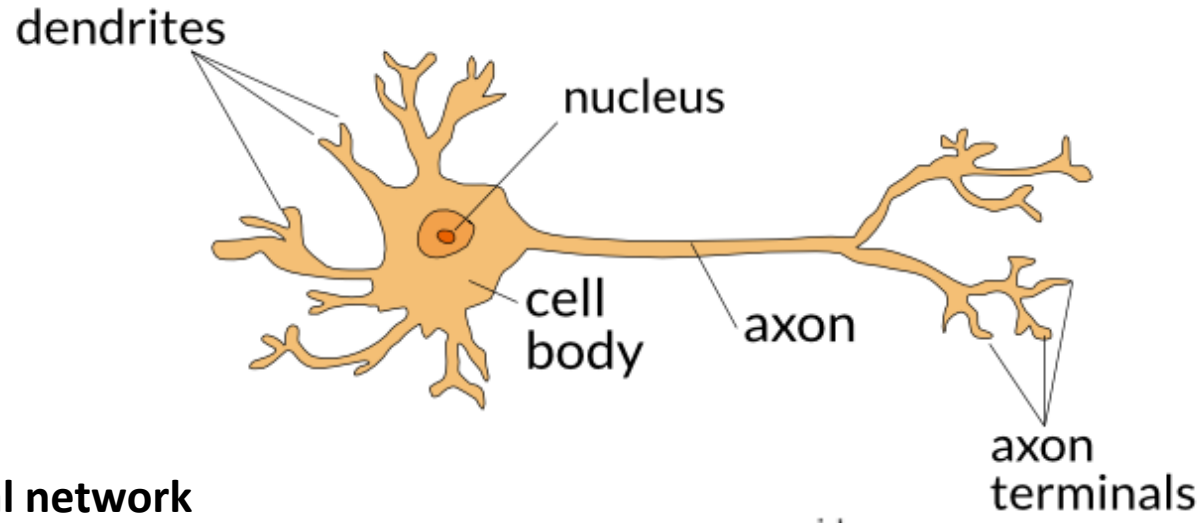
Conventional Algorithm

ML Algorithm



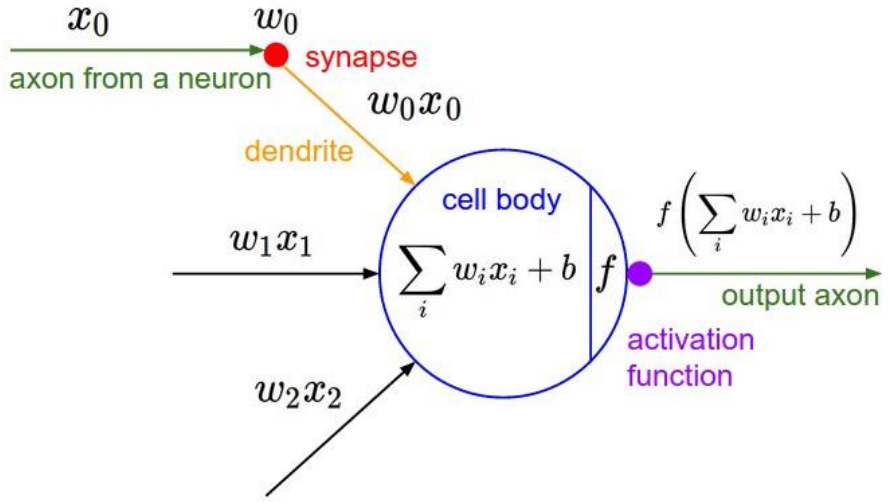


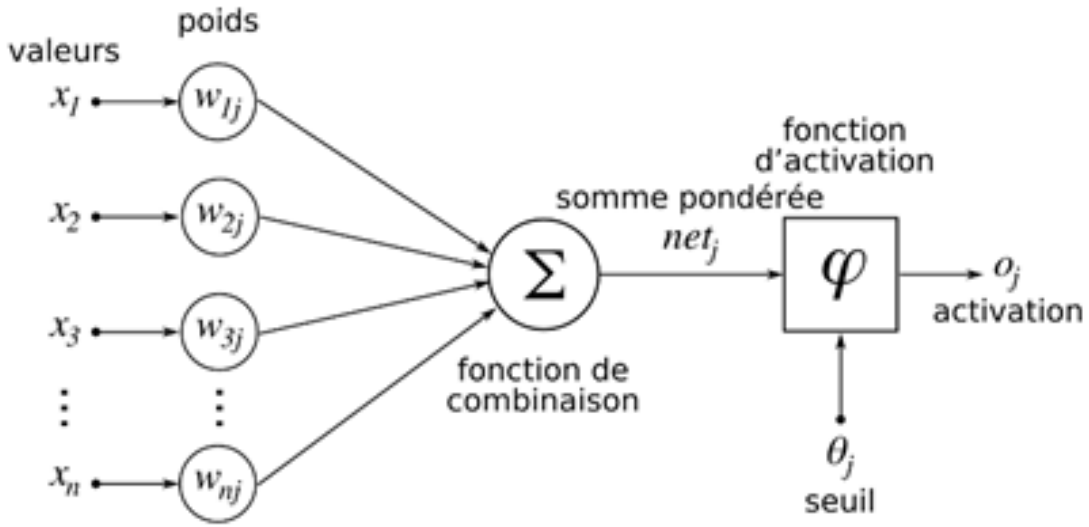
Apprentissage profond



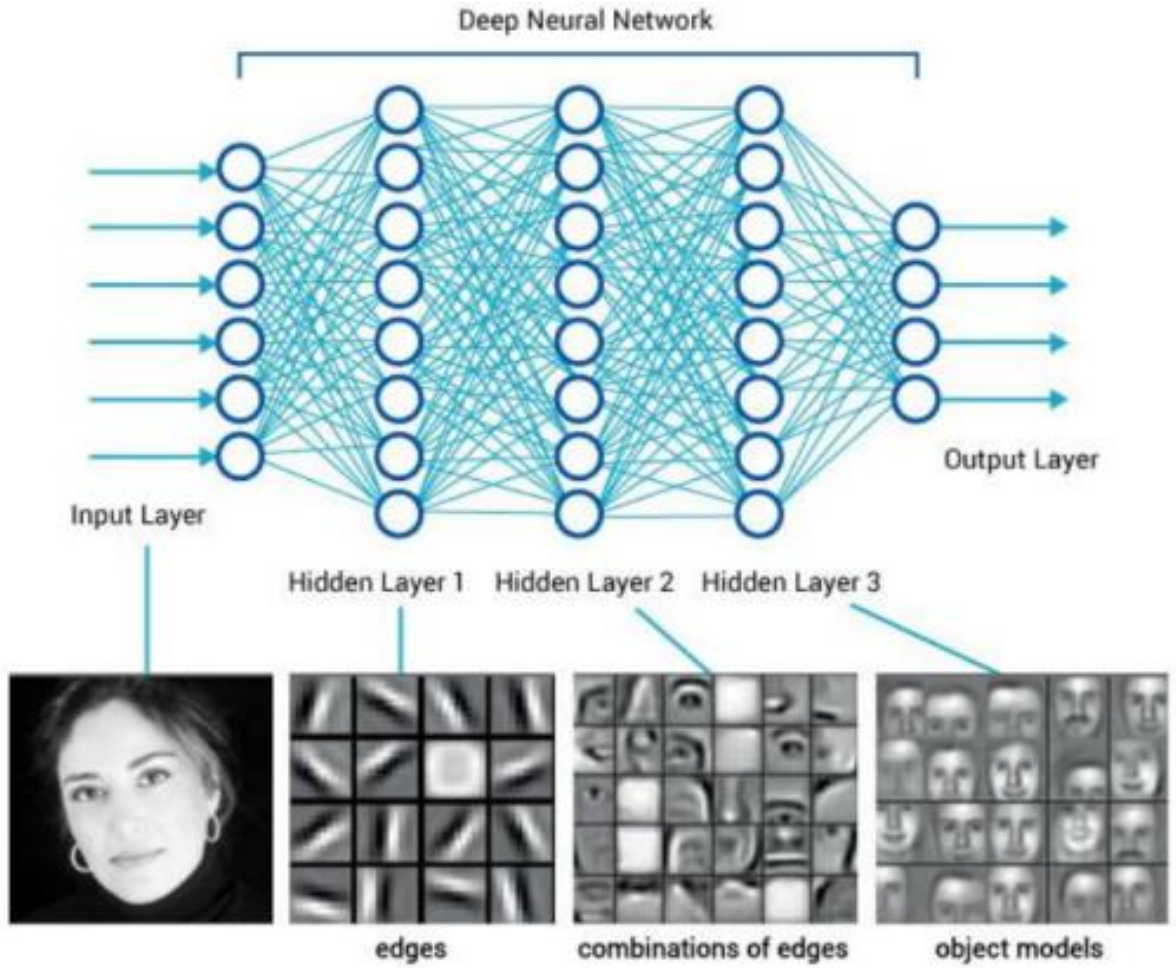
Perceptron

Elementary unit of artificial neural network





Apprentissage profond



Apprentissage profond
Convolution

$1_{\times 1}$	$1_{\times 0}$	$1_{\times 1}$	0	0
$0_{\times 0}$	$1_{\times 1}$	$1_{\times 0}$	1	0
$0_{\times 1}$	$0_{\times 0}$	$1_{\times 1}$	1	1
0	0	1	1	0
0	1	1	0	0

Image

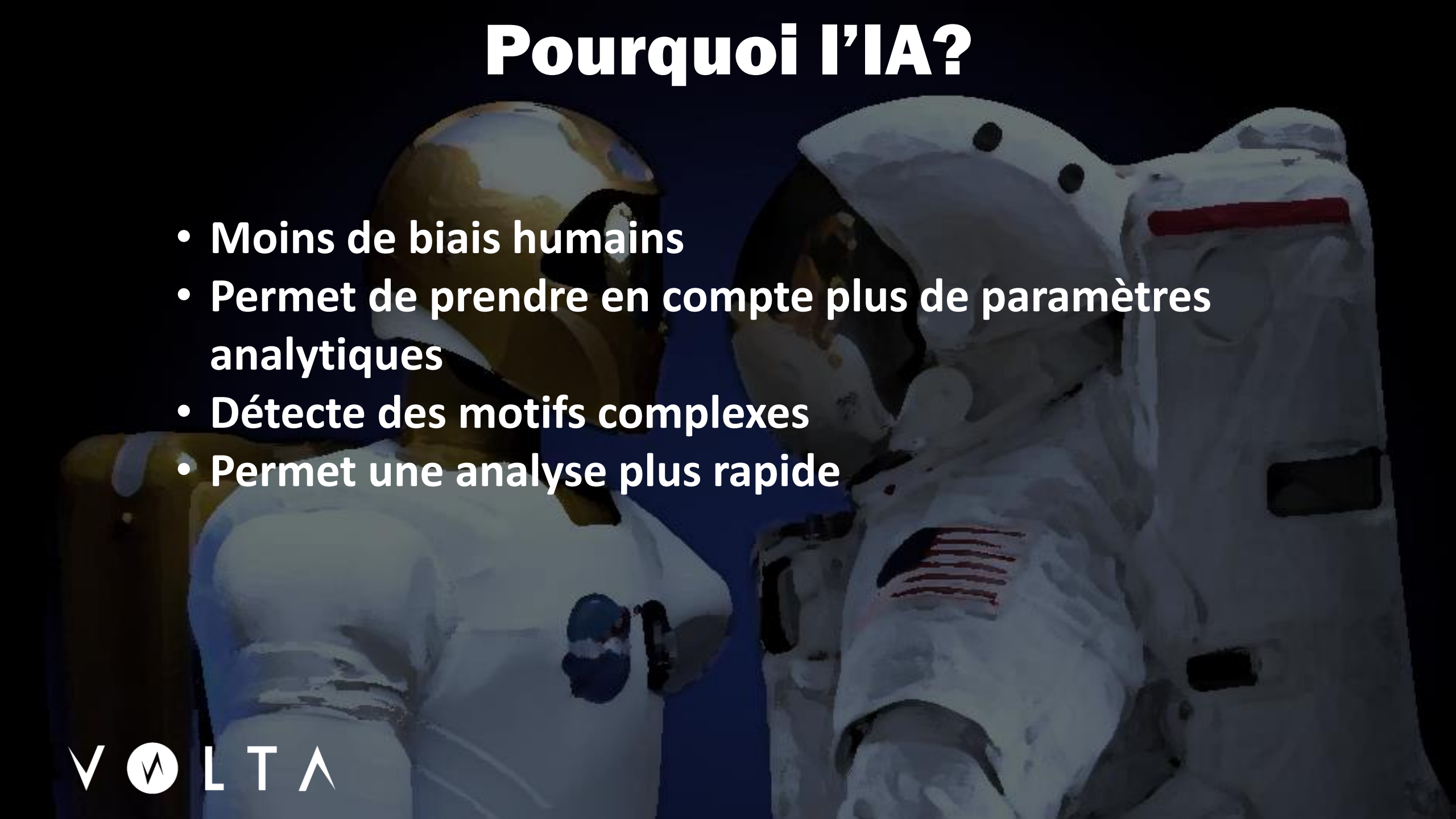
4		

Convolved Feature

$*$

1	0	-1
2	0	-2
1	0	-1

Pourquoi l'IA?



- Moins de biais humains
- Permet de prendre en compte plus de paramètres analytiques
- Détecte des motifs complexes
- Permet une analyse plus rapide

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Est-ce Magique?
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NON !
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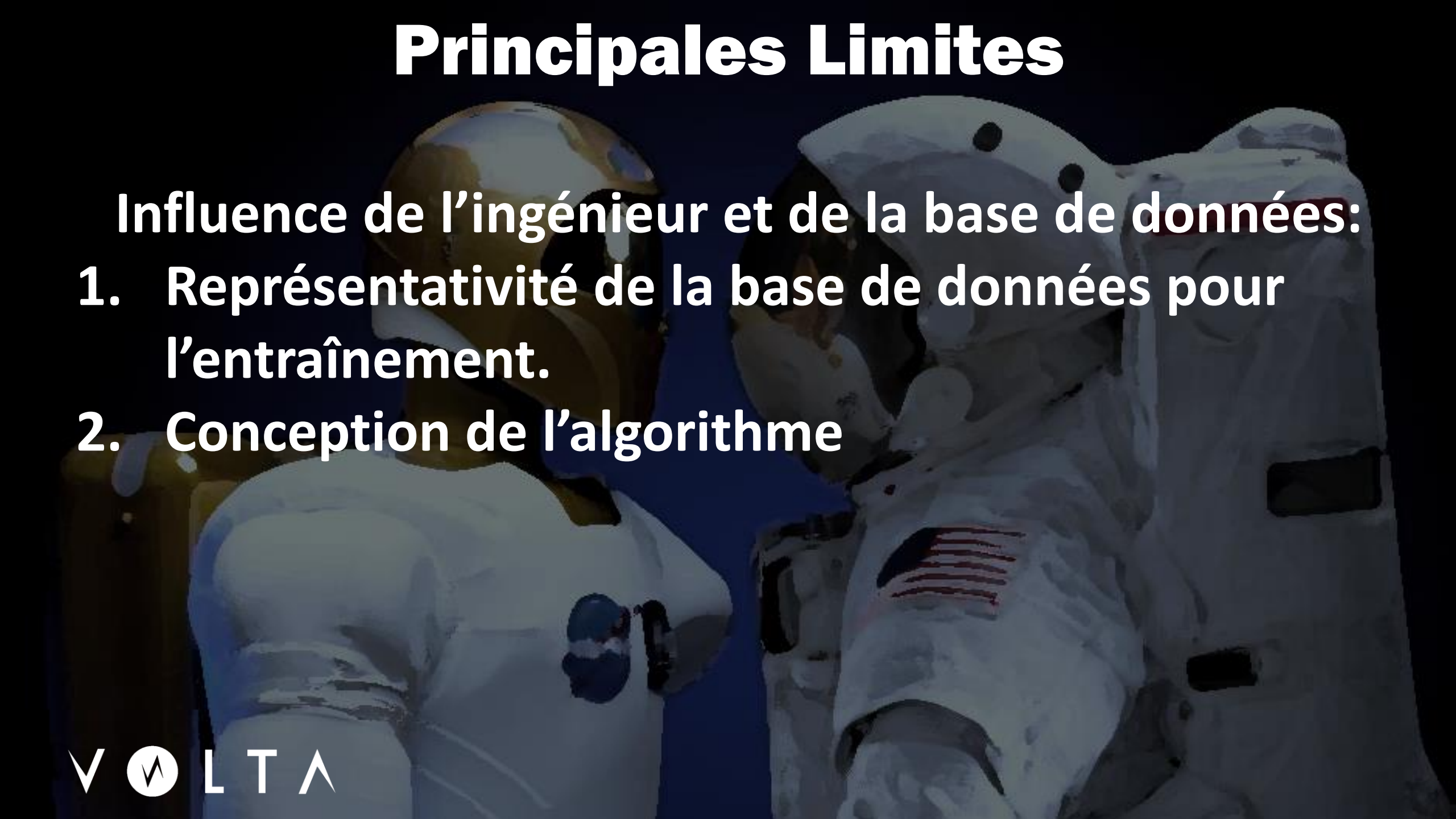
Principales Limites



Influence de l’ingénieur et de la base de données:

1. Représentativité de la base de données pour l’entraînement.
2. Conception de l’algorithme

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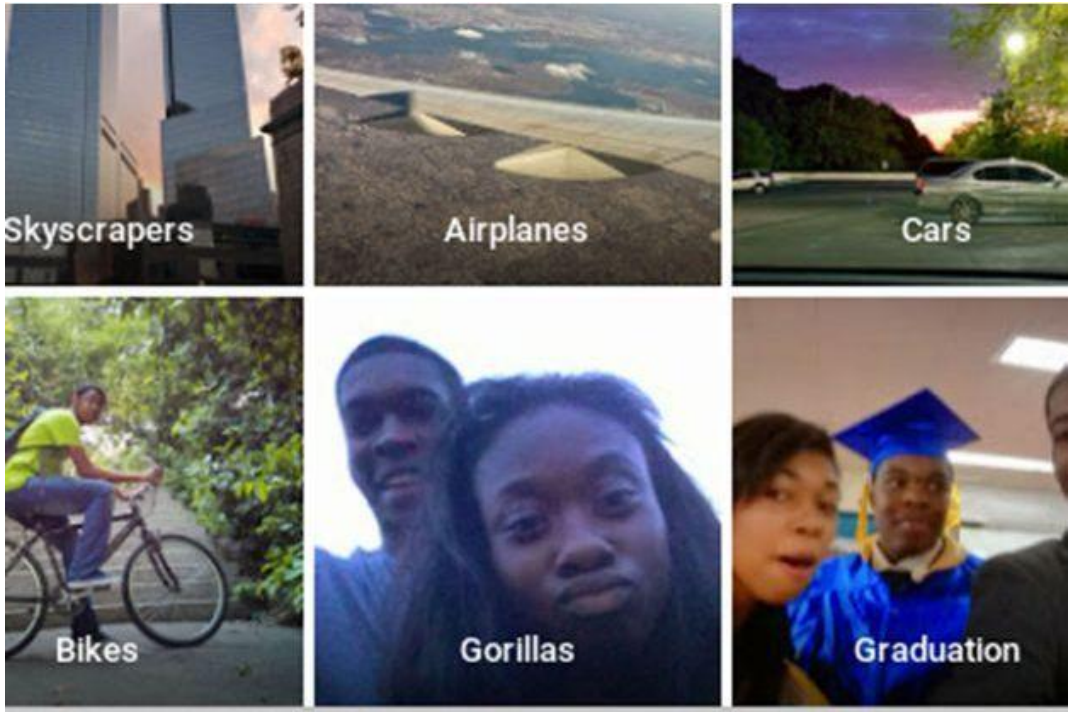
Principales limites

- Biais présents dans la base de donnée d'entraînement
- Phénomène de renforcement des biais
- Attention à la représentativité des données



November 2018

Machine Learning and Health Care Disparities in Dermatology

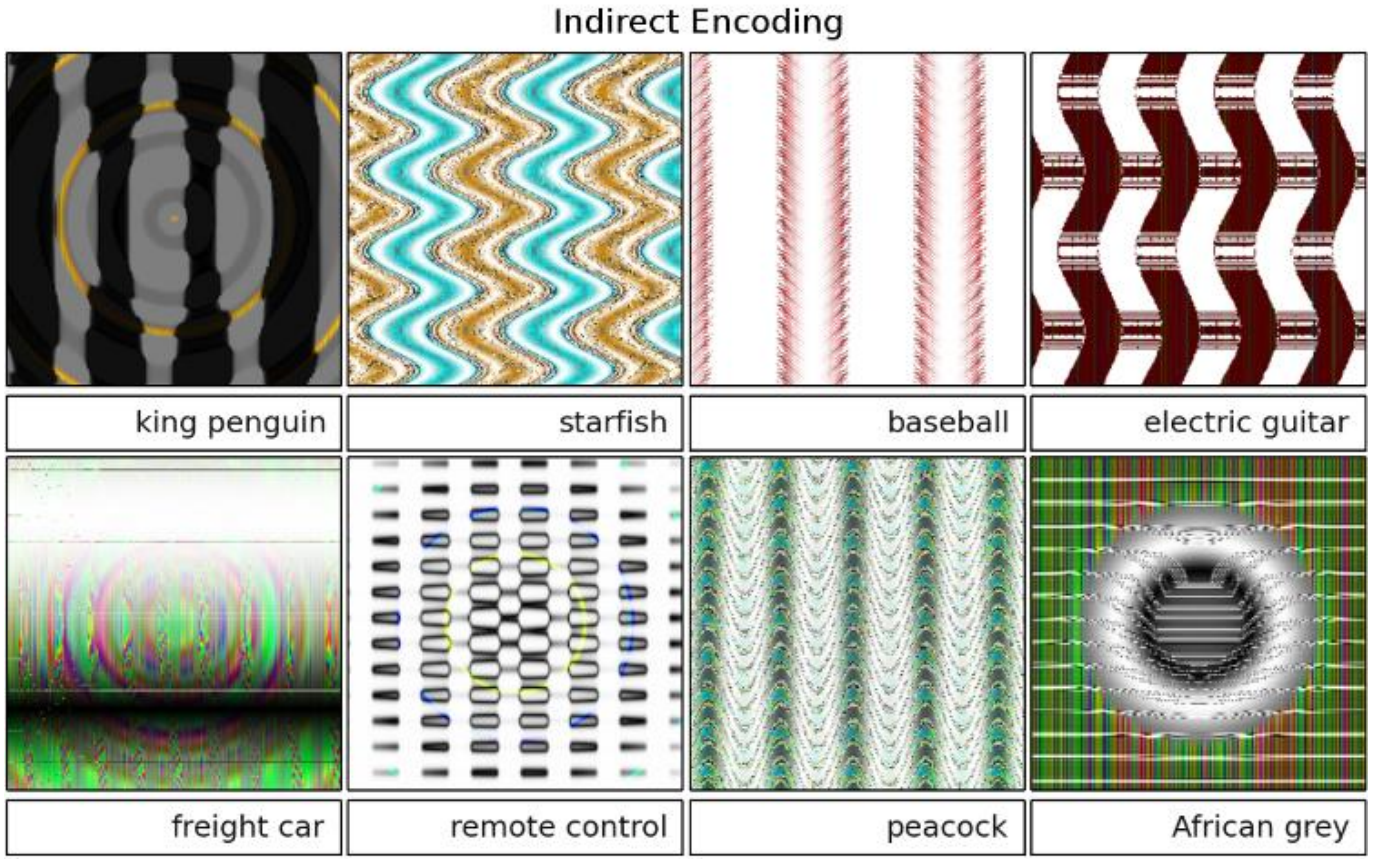
Adewole S. Adamson, MD, MPP[1,2]; Avery Smith, MS[3]

Principales limites

- Phénomène « black box »
- Possibilité de corrompre un algorithme

-> Influence de l'ingénieur / data scientist

- En médecine utiliser autant que possible des critères de performances cliniques et non pas historiques (cf jeu de Go)



Principales limites

- Question de la responsabilité (ex. véhicule autonome)
- Question de la propriété et de la maîtrise des technologies: agrandissement des fossés sociaux (Laurent Alexandre)
- Question éthiques


Applications médicales
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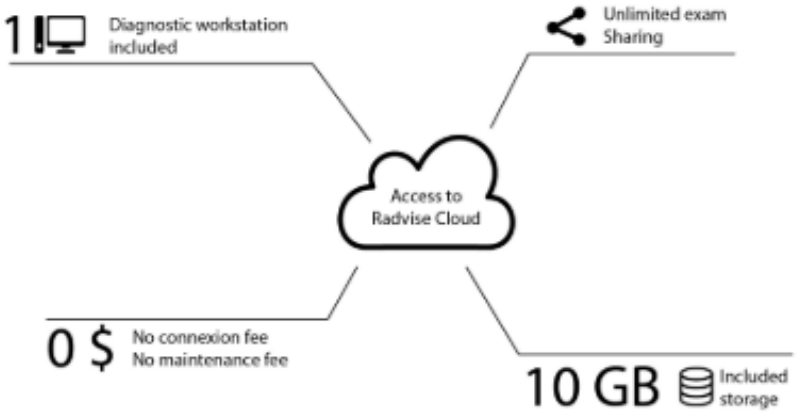
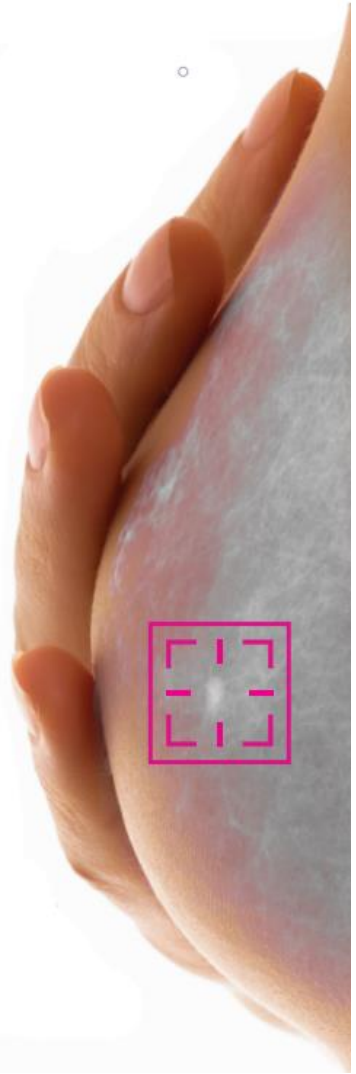
Oncology: Therapixel

Inria
inventeurs du monde numérique





Dermatology: Diagnostic Images

nature
International journal of science

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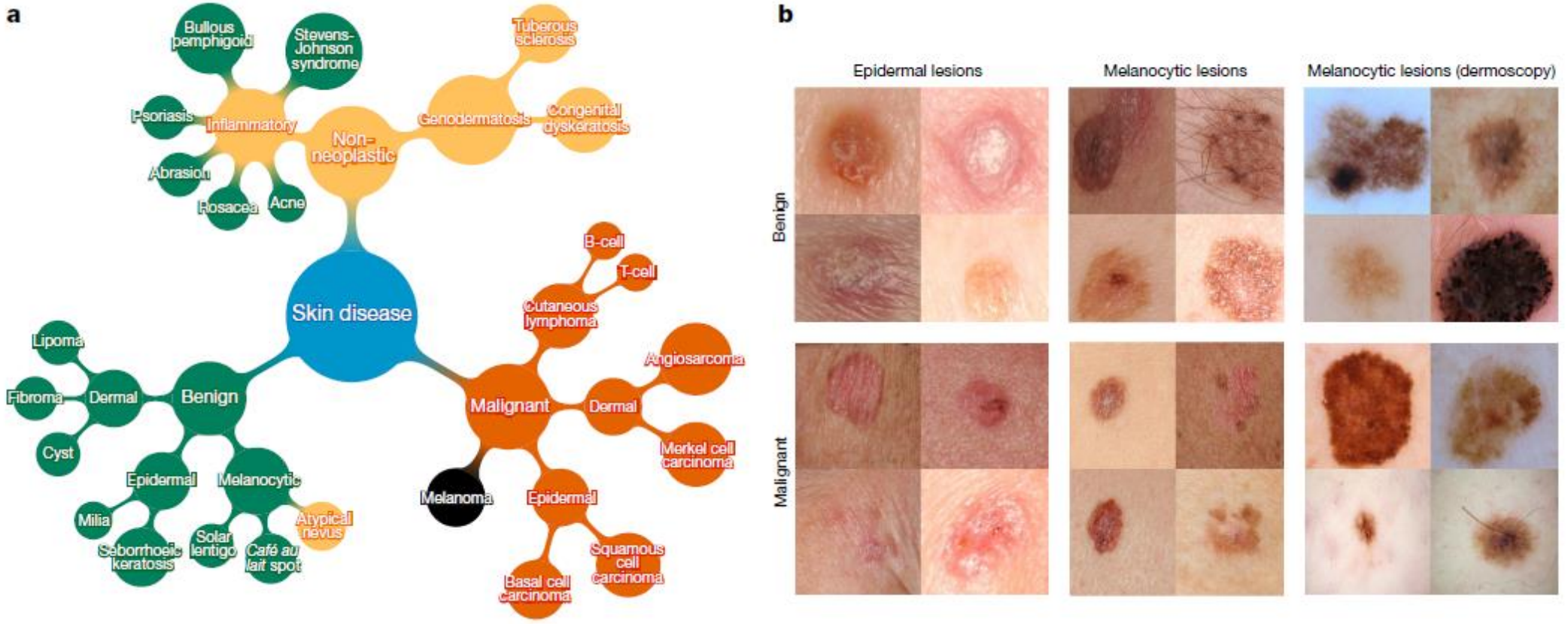

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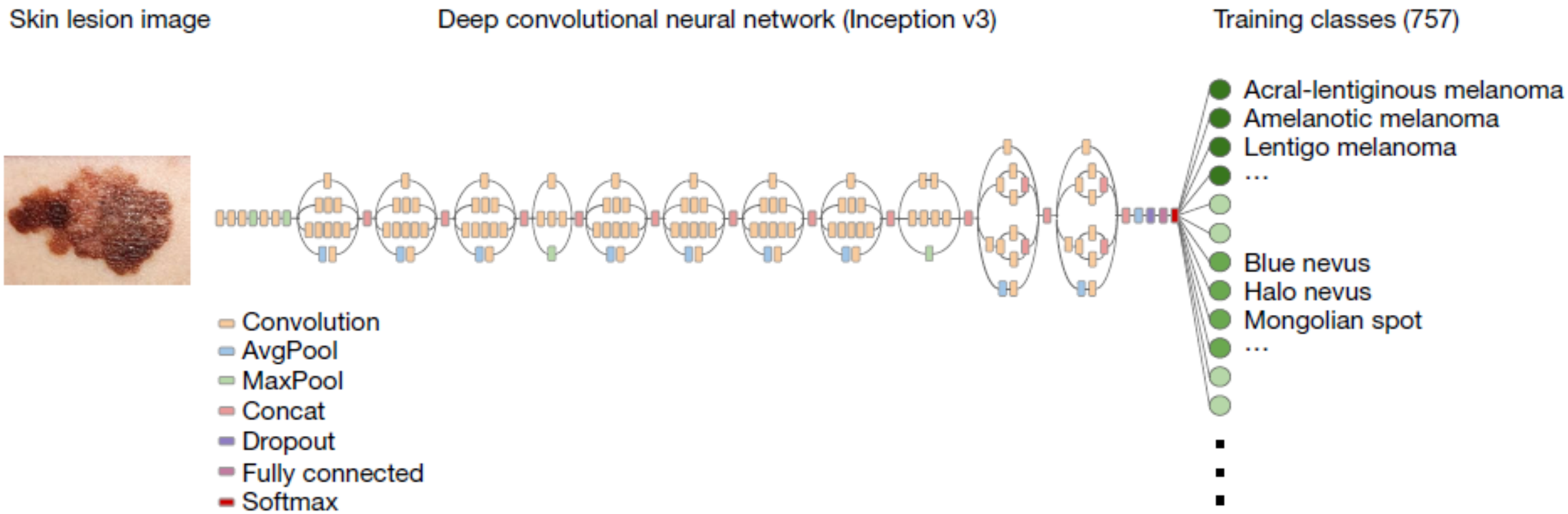

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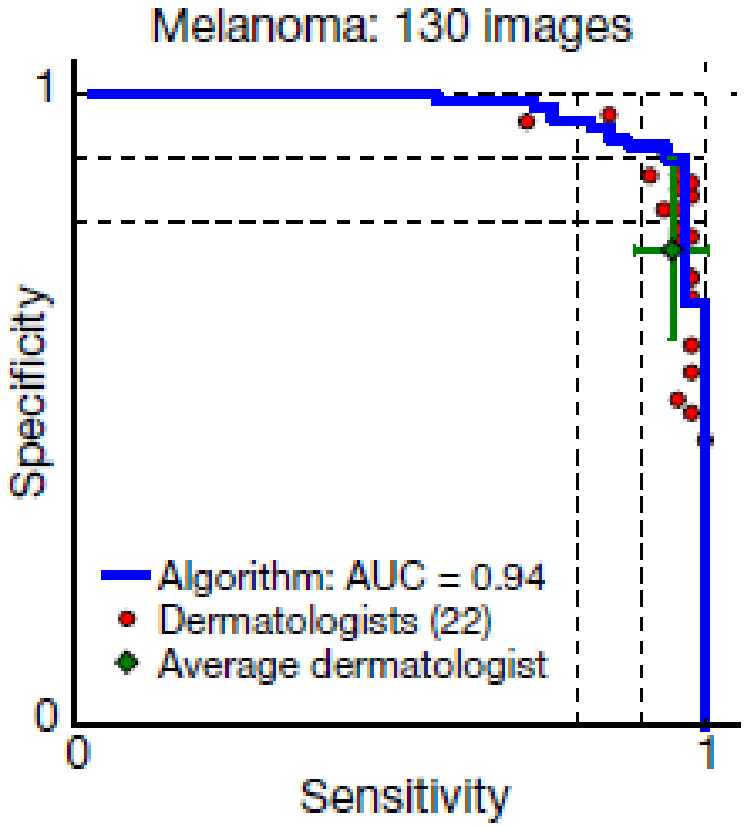
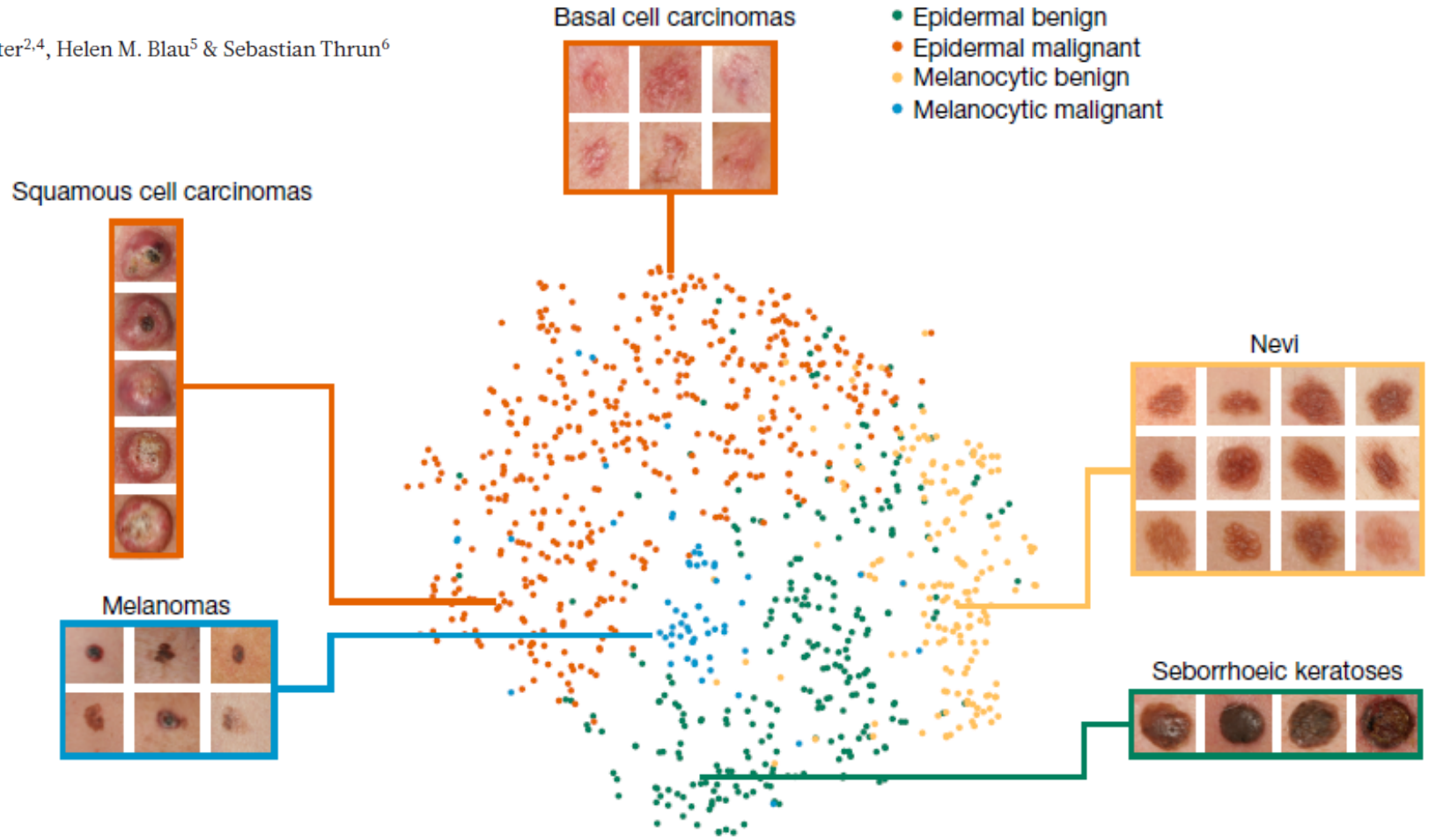


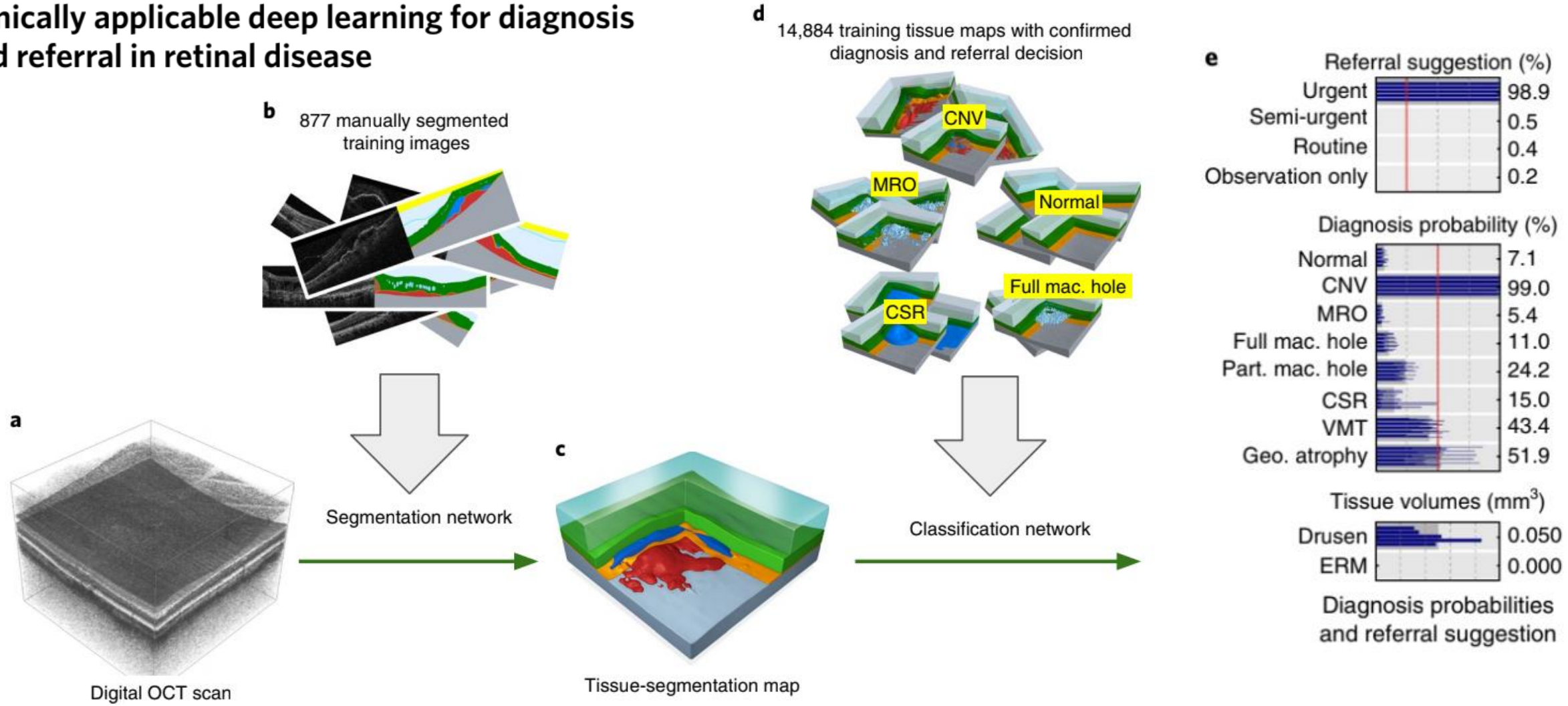


Ophtalmology: 3D OCT Diagnostic Scans

nature medicine
ARTICLES
https://doi.org/10.1038/s41591-018-0107-6

Jeffrey De Fauw, Joseph R. Ledsam, [...] Olaf Ronneberger

Clinically applicable deep learning for diagnosis and referral in retinal disease



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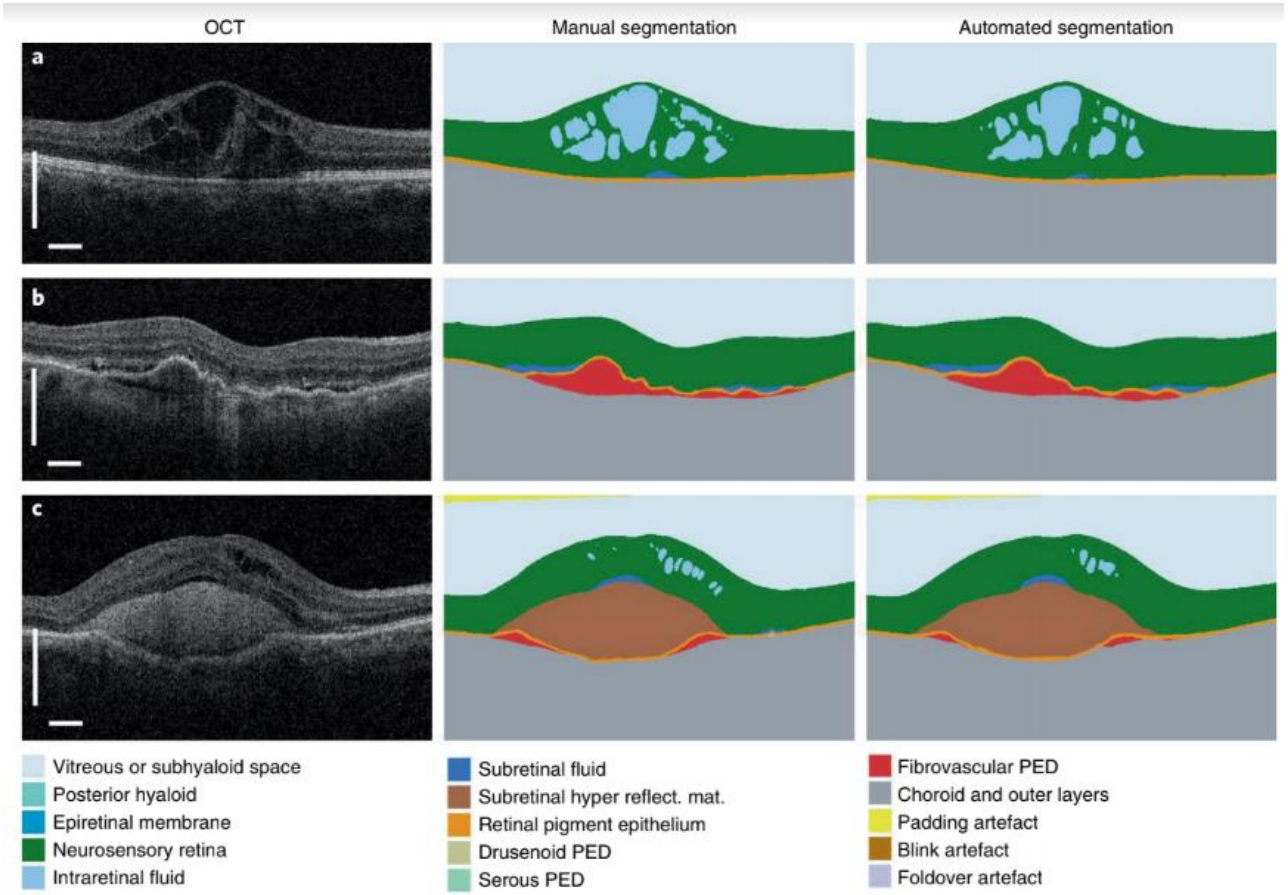
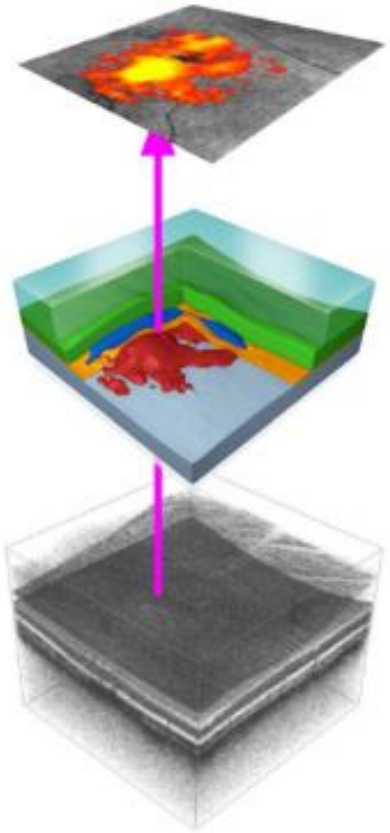
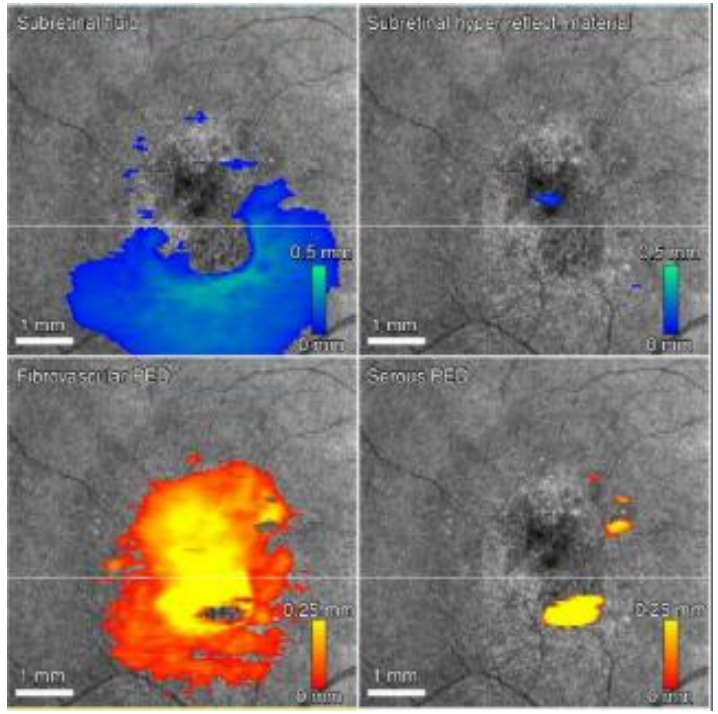


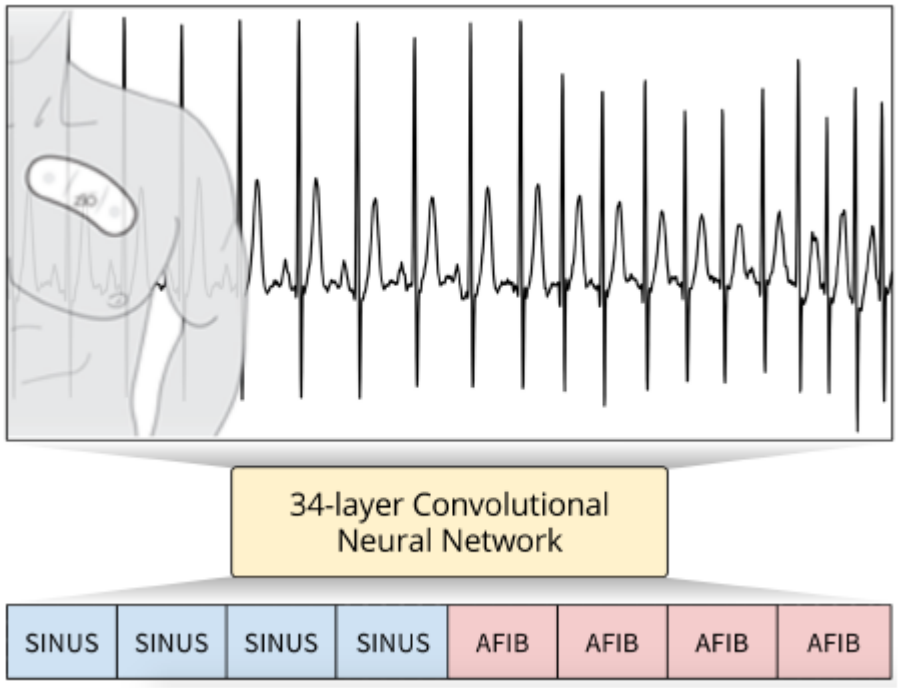


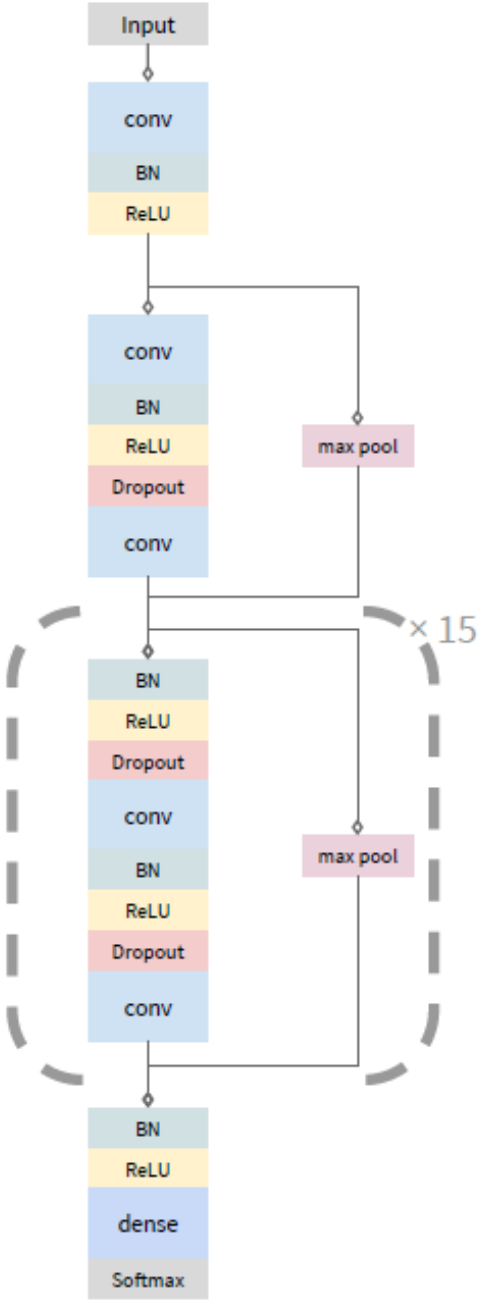


Cardiology: ECG Analysis

Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks

Pranav Rajpurkar*
Awni Y. Hannun*
Masoumeh Haghpanahi
Codie Bourn
Andrew Y. Ng





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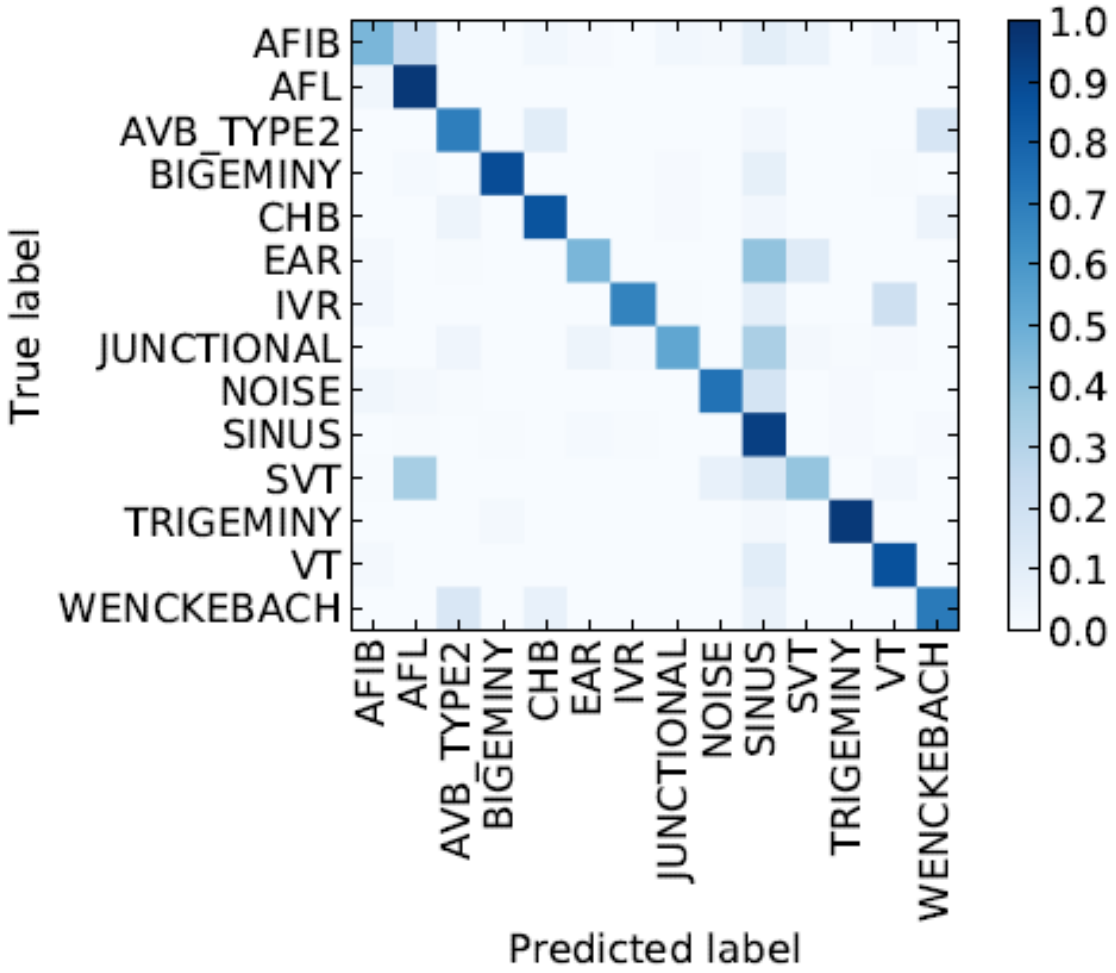


Cardiologs

The first ECG analysis solution powered by Artificial Intelligence.

Yann Fleureau
CEO

Et le médecin dans tout ça?

- Une importance renforcée
- Propositions de *OpenHealth Company*: La nécessité d'un rapprochement entre concepteurs de technologies et médecins.

-> Prendre l'initiative des projets entrepreneuriaux ou académiques de demain

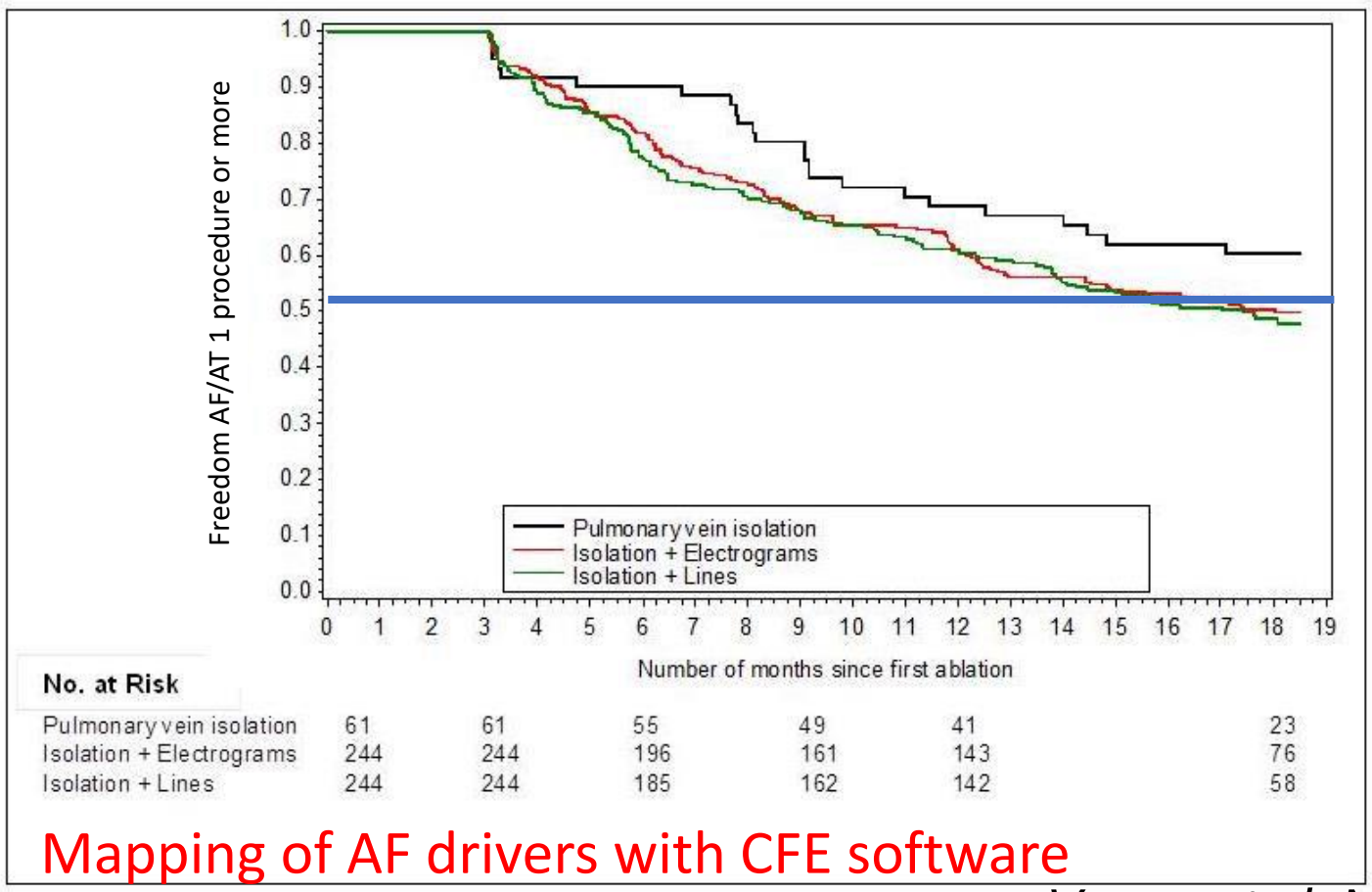
OpenHealth COMPANY

Qu’en est-il de l’électrophysiologie cardiaque?

PVI for persistent & LS-persistent AF:

~ 50% Freedom from AF/AT after multiple procedures with or without AA drugs

Averaged results (589 patients , no statistical difference between techniques):



~ 50 %

Mapping of AF drivers with CFE software

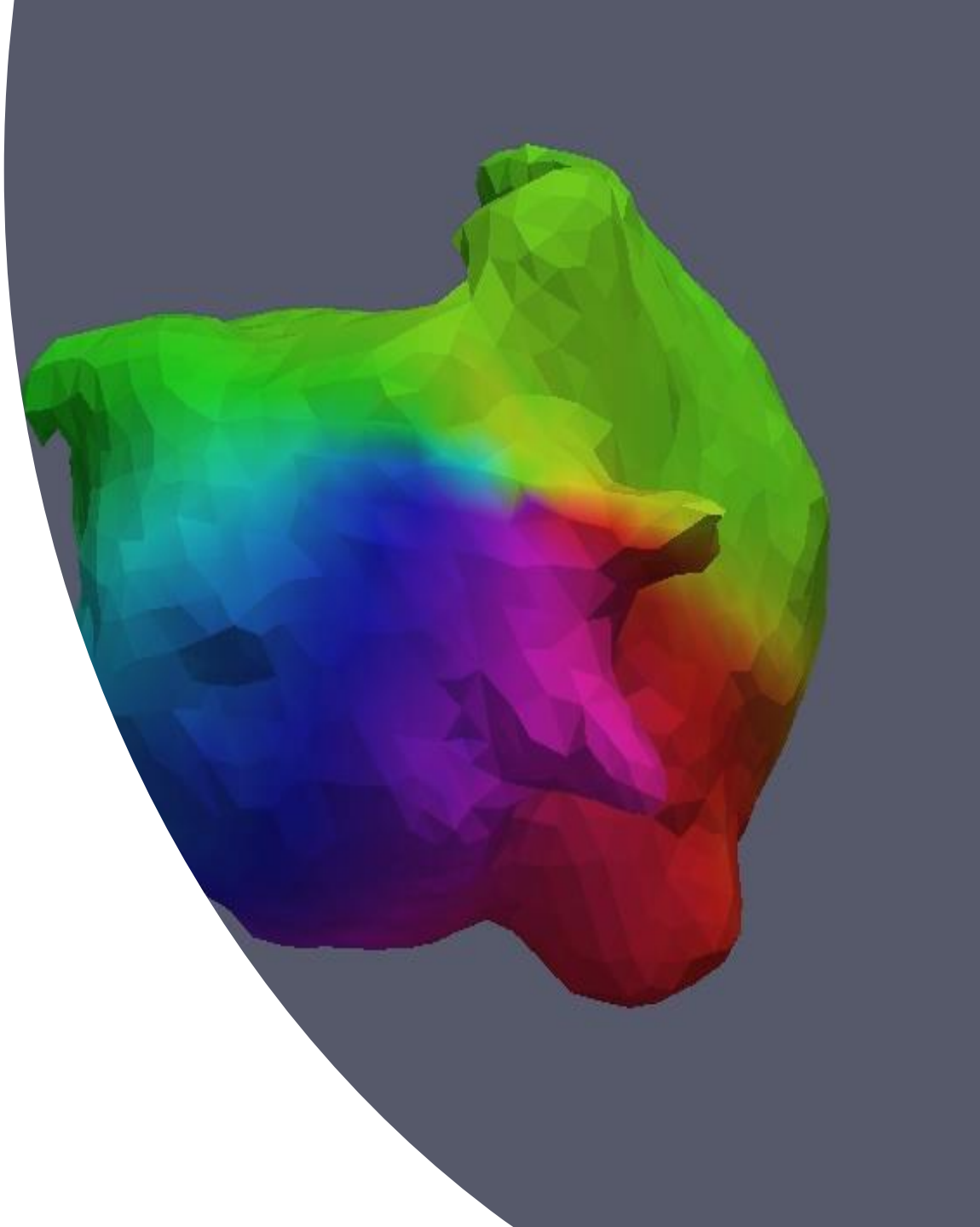
Verma et al. NEJM 2015

Comment mieux faire?

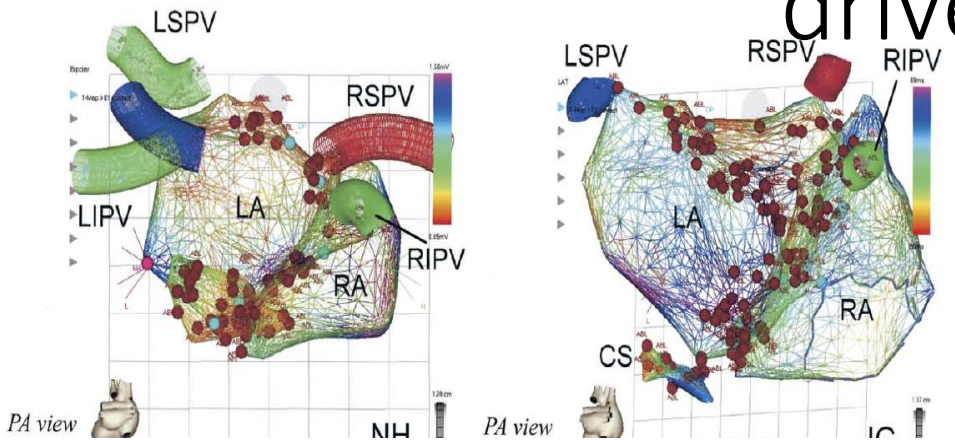
- Visualisation des drivers avec un software sophistiqué
- Analyse visuelle des électrogrammes intracardiaques

Approches panoramiques

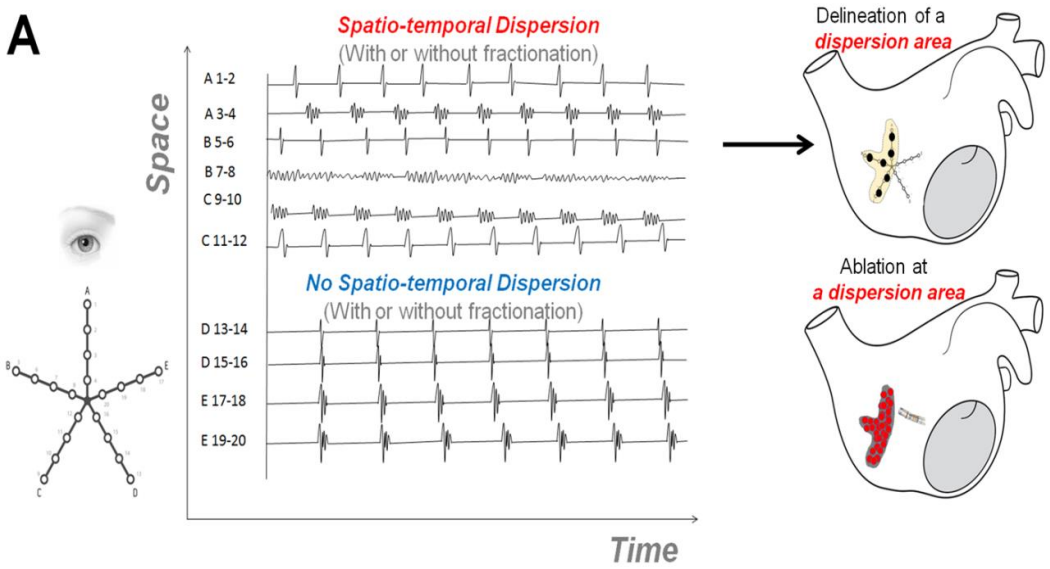
- Reposent sur **des modèles de propagation des ondes**: Ces modèles sont-ils proches de la réalité?
- Tentent de reproduire la propagation des ondes dans **une géométrie hétérogène et complexe**
- Produisent des **cartes complexes difficiles à analyser**
- Difficultés à **localiser précisement les drivers**



Visual approaches for the detection of AF drivers



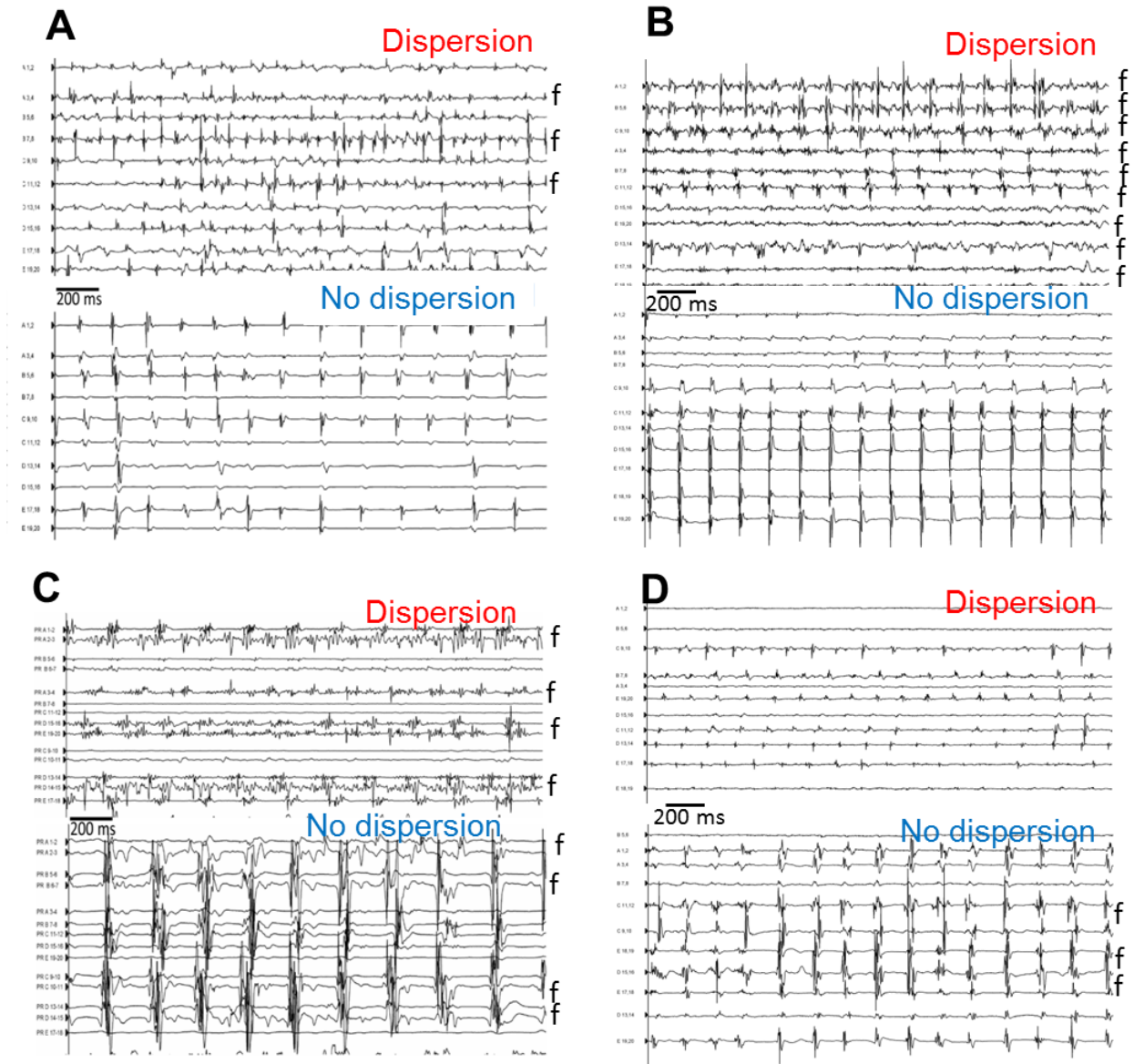
Electrogram-based ablation
Complex Fractionated Atrial Electrograms
Nademanee et al. , JACC 2004



Spatio-Temporal Dispersion of Electrograms: Non-simultaneous activation at multiple neighboring electrode locations (with or without fractionation)
Seitz et al., JACC 2017

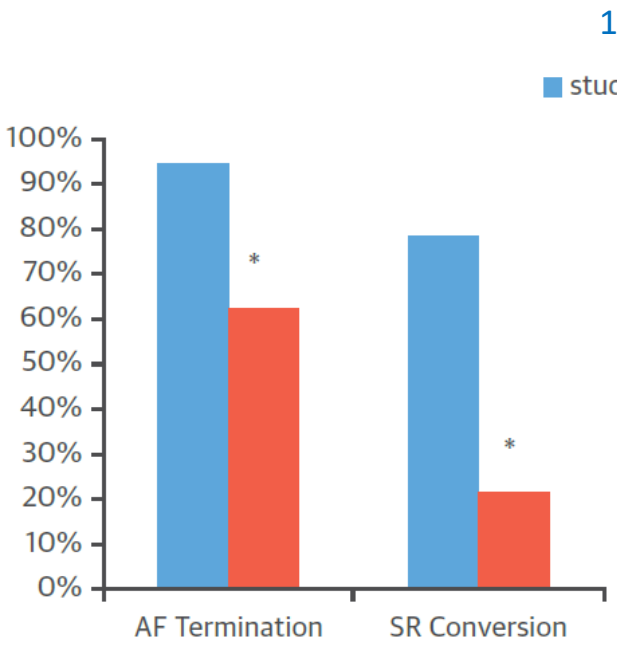
Two close definitions of AF driver's footprints with good clinical outcomes but limited reproducibility

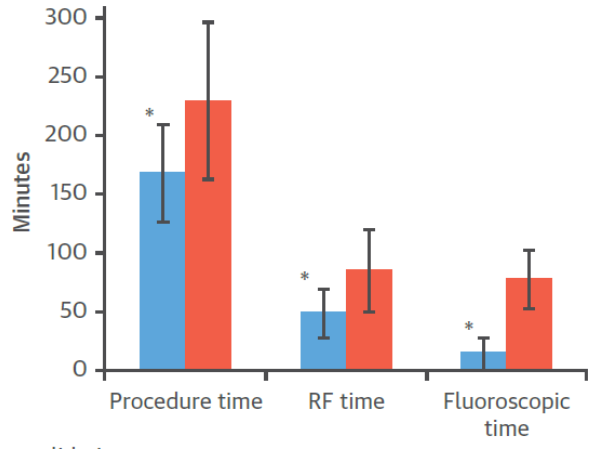
Spatio-Temporal Dispersion of Electrograms: Examples

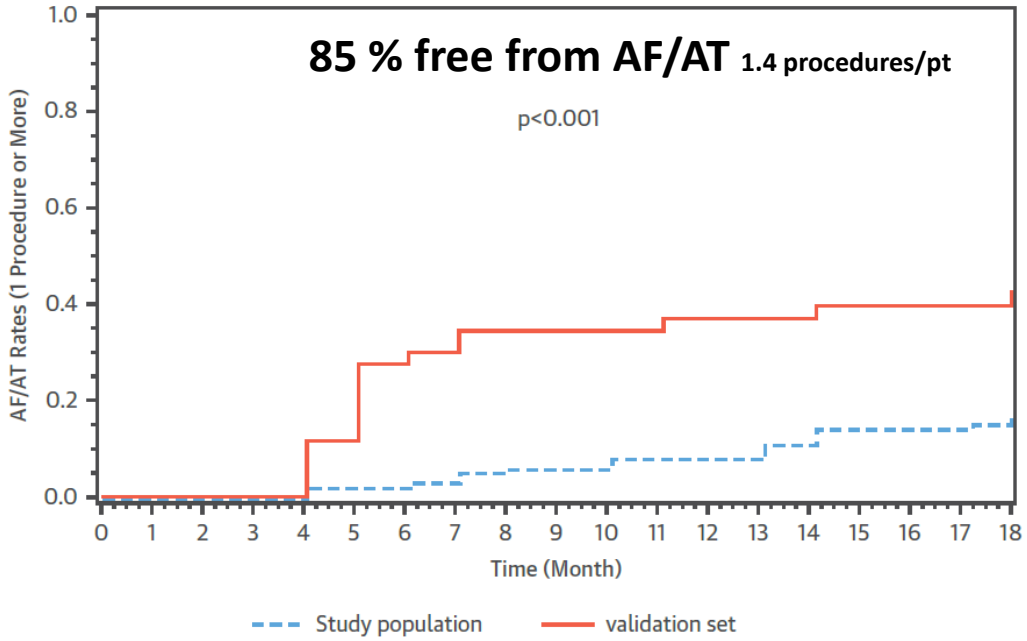


Different patterns of drivers electrograms illustrating the comlexity of the visual analysis

Drivers ablation Vs classical approach: Better efficacy with shorter ablation



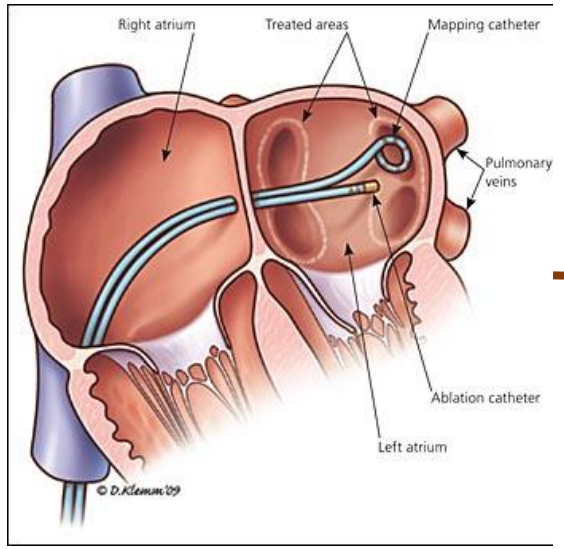




But the detection of drivers was based on EGM visual analysis…

Seitz J, Bars C, Theodore G, Kalifa J et al.
J Am Coll Cardiol. 24;69(3):303-321. 2017 Jan

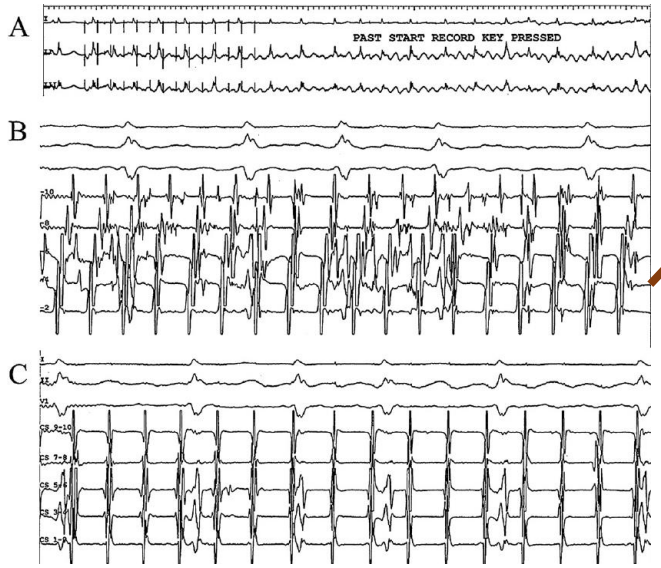
Les opérateurs sont limités



Manipulation

Family
Patients
Staff

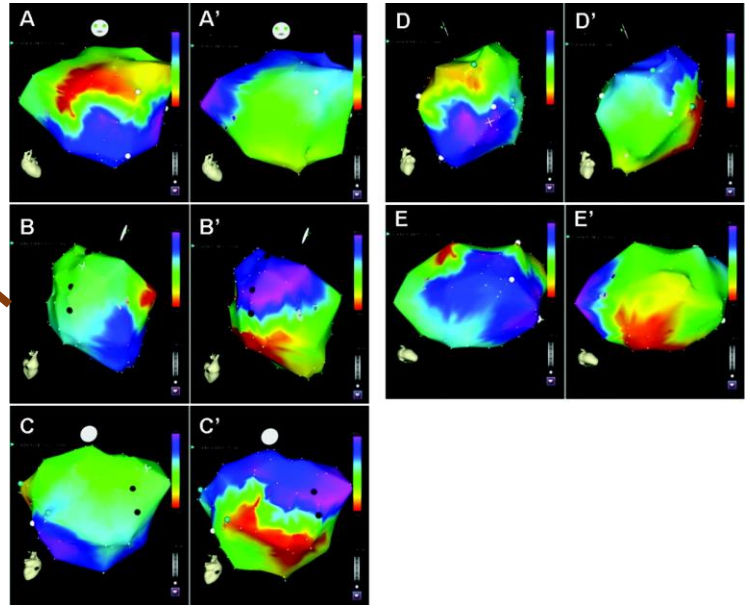
Signal
Analysis



Stress

Fatigue

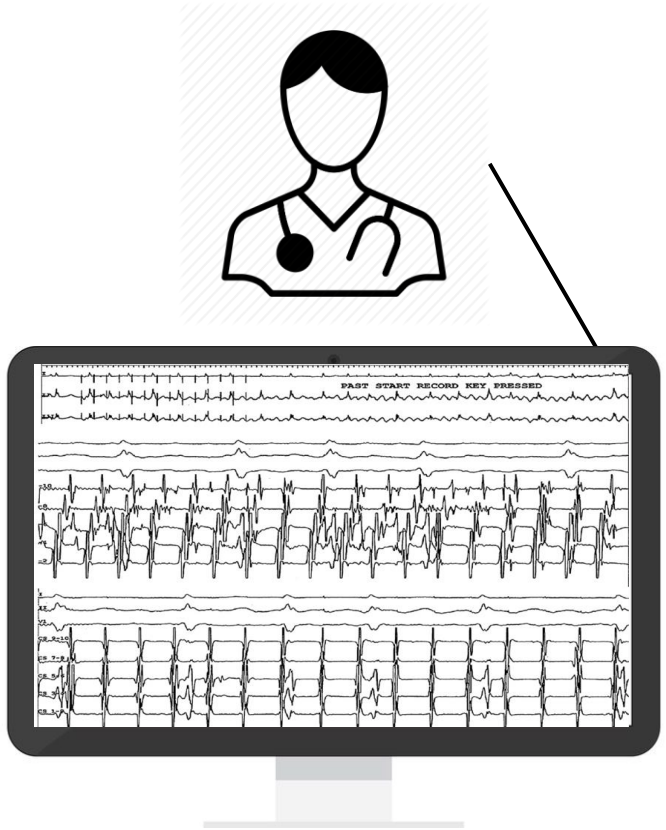
Mapping

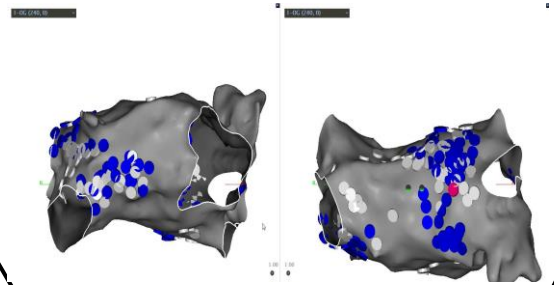


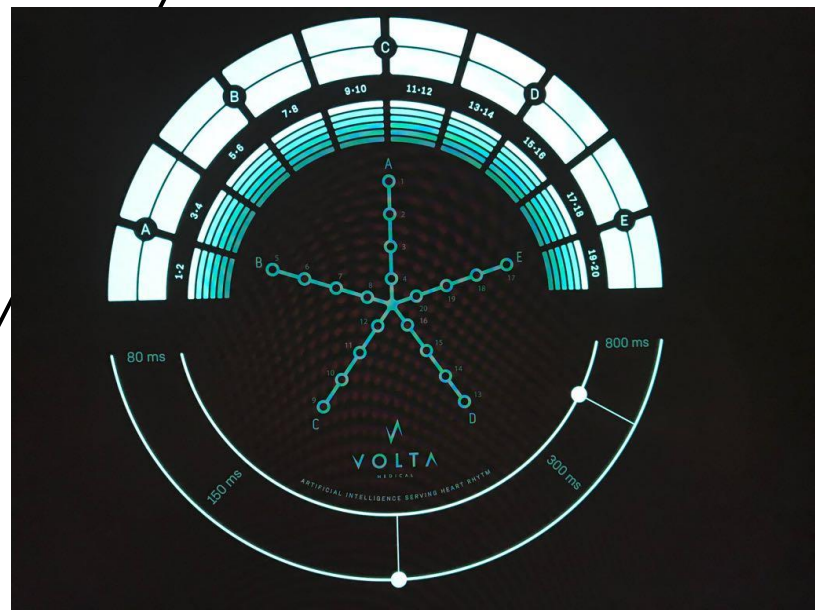
VX1

VOLTA

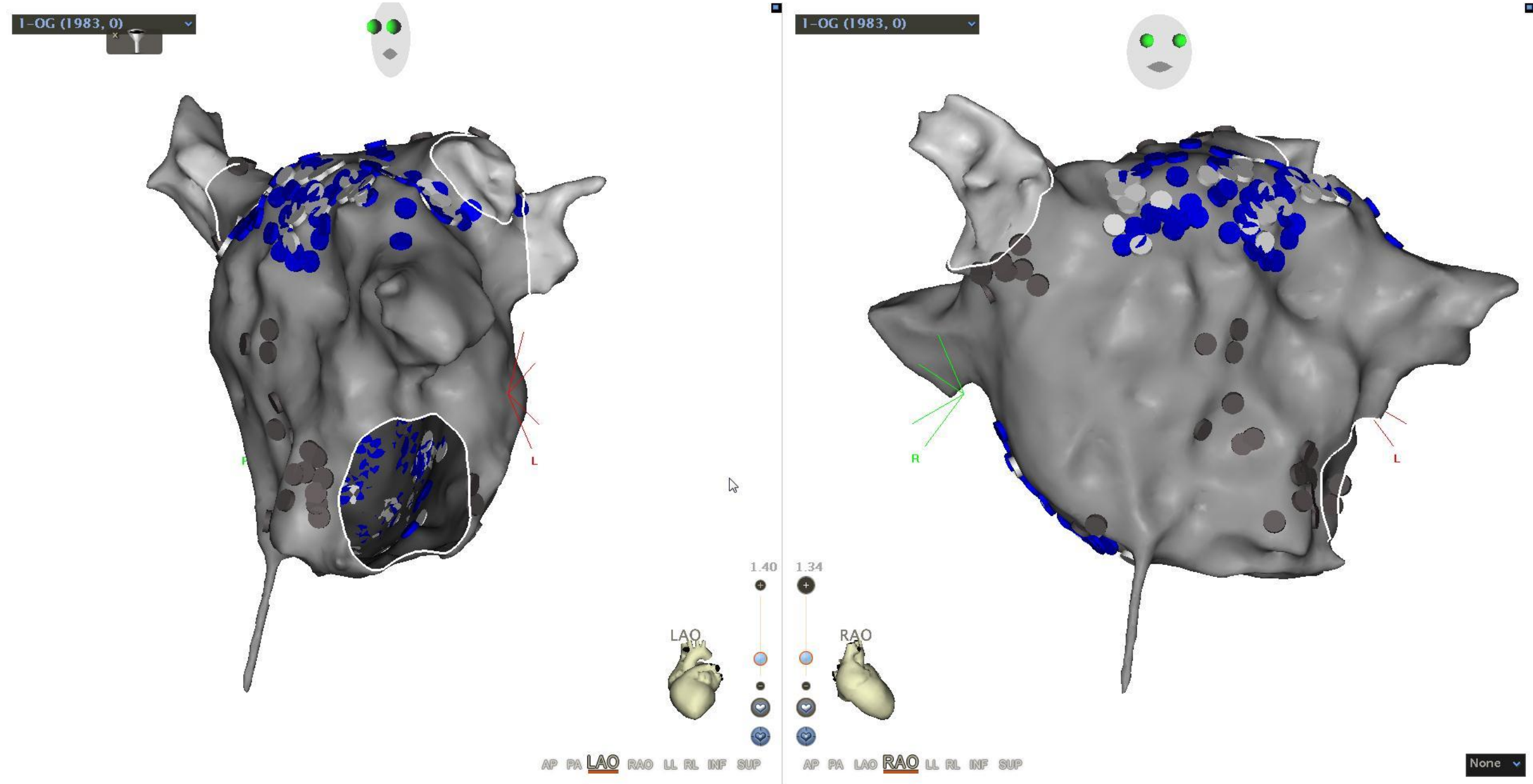
Double Blind Tests

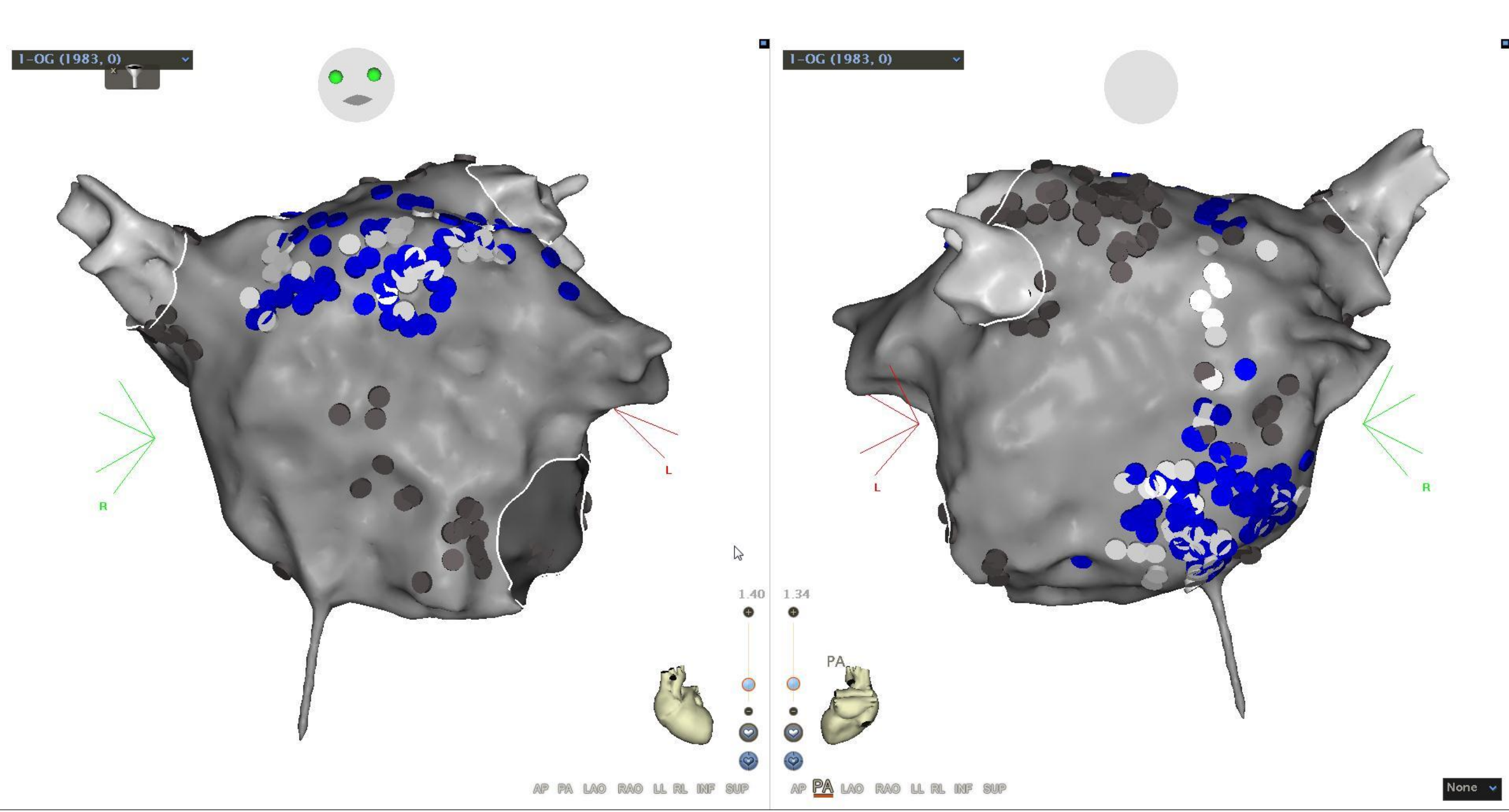


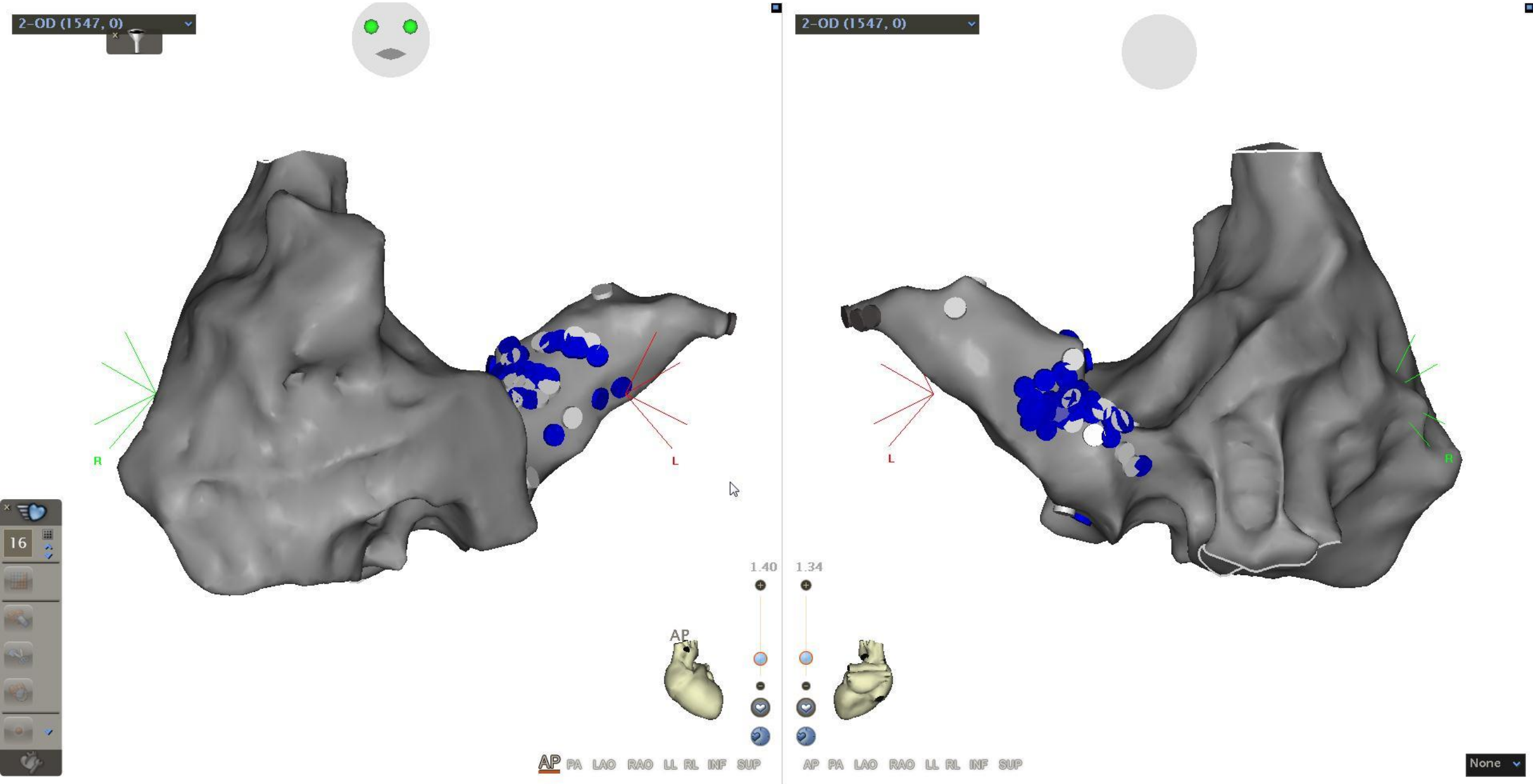


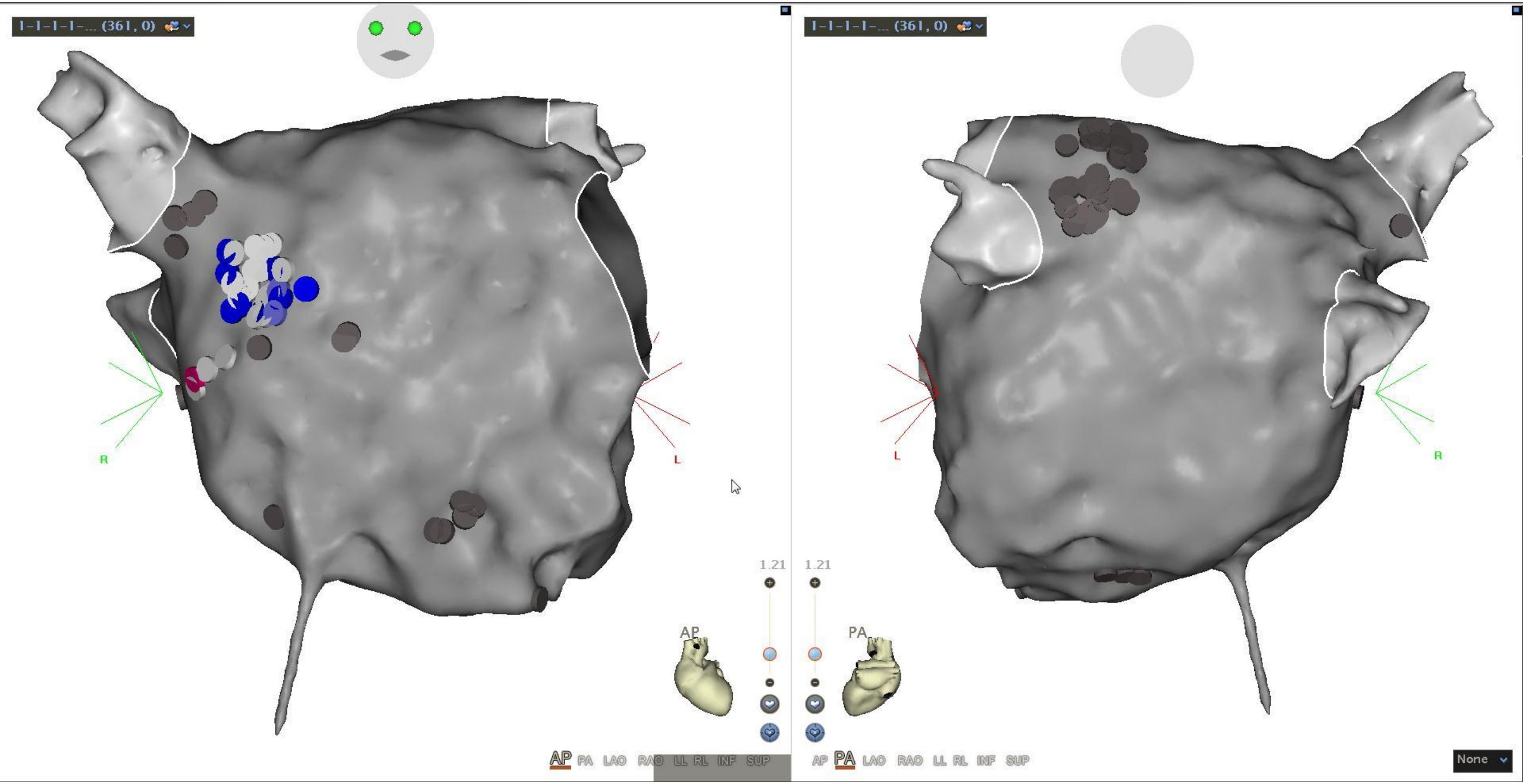


VOLTA


1-OG (1983, 0)
1-OG (1983, 0)
R
L
R
L
1.40
1.34
LAO
RAO
AP PA LAO RAO LL RL INF SUP
AP PA LAO RAO LL RL INF SUP
None


1-OG (1983, 0)
R
L
1.40
AP PA LAO RAO LL RL INF SUP
1-OG (1983, 0)
L
R
1.34
PA
AP PA LAO RAO LL RL INF SUP
None

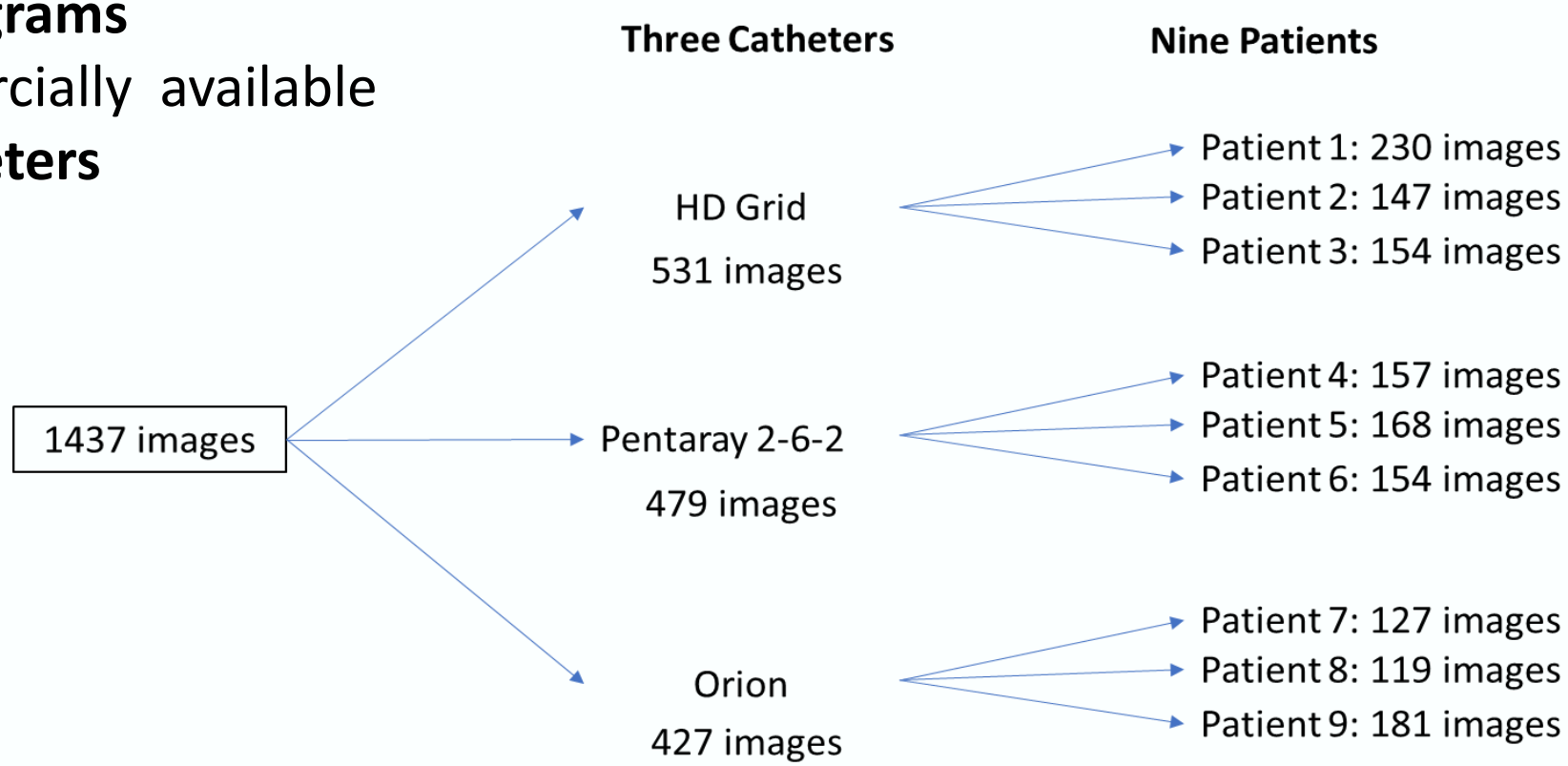

2-OD (1547, 0)
2-OD (1547, 0)
R
L
L
R
1.40
1.34
AP
AP PA LAO RAO LL RL INF SUP
AP PA LAO RAO LL RL INF SUP
None


1-1-1-1-... (361, 0)
R
L
1.21
AP
AP PA LAO RAO LL RL INF SUP
1-1-1-1-... (361, 0)
L
R
1.21
PA
AP PA LAO RAO LL RL INF SUP
None

The « Reader » Study

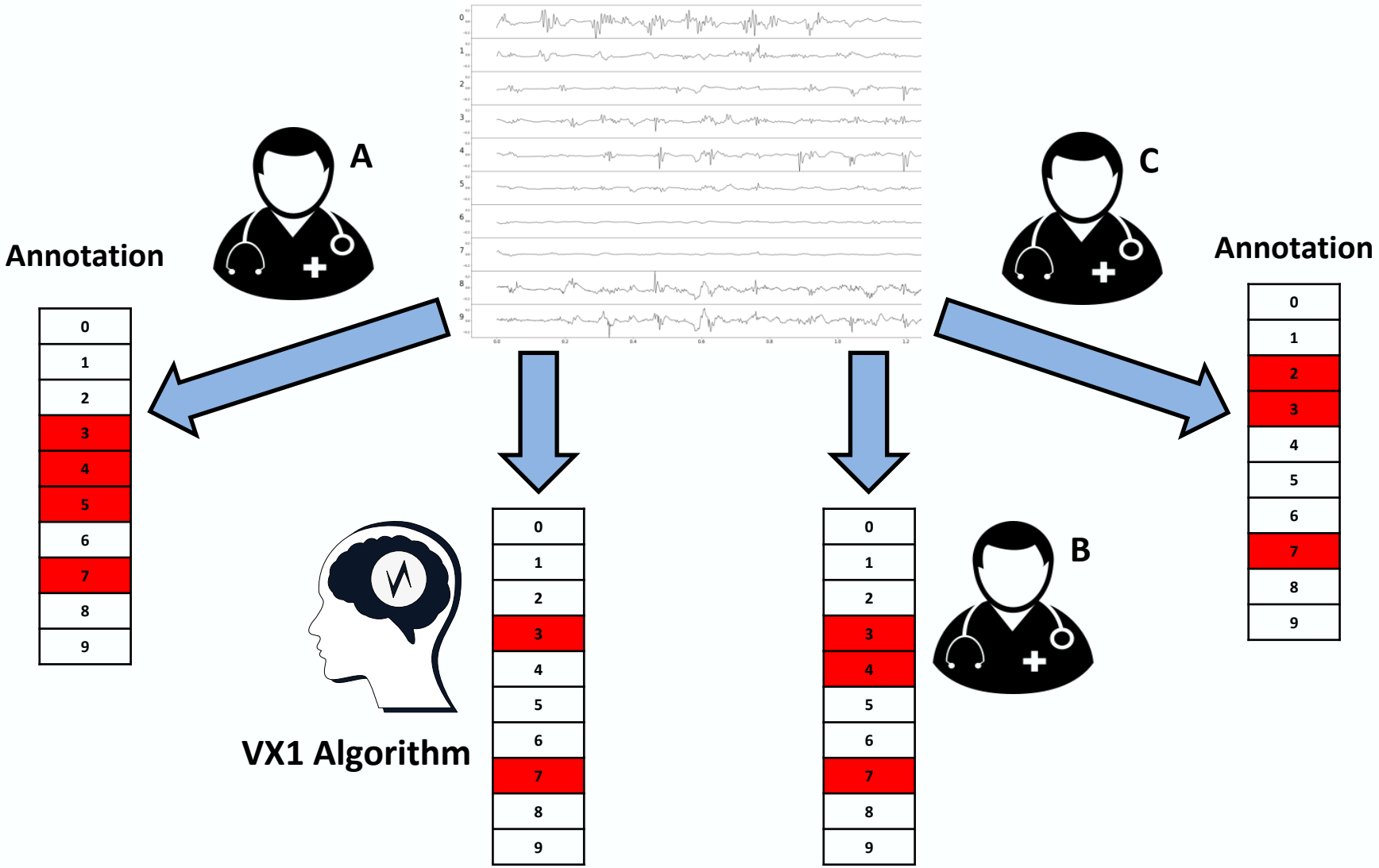
Dataset

- **14370 electrograms**
- **Three** commercially available **mapping catheters**
- **9 patients**



The « Reader » Study

Methods



The « Reader » Study

Methods

- Electrograms adjudicated as **non-dispersed** by each of the three readers are considered “**non-dispersed**”;

- Electrograms adjudicated as dispersed by **one reader only** are considered “**little dispersed**”;

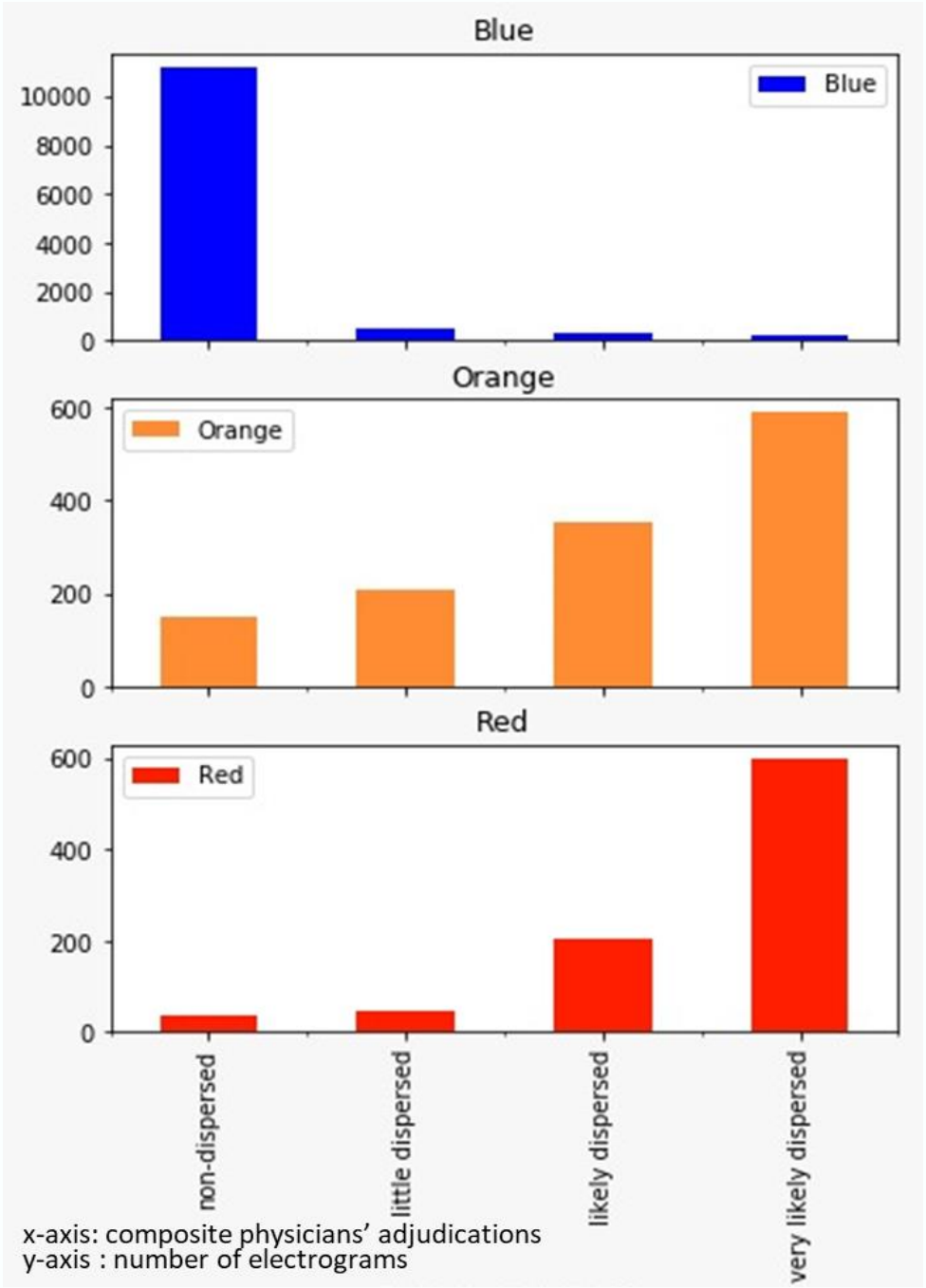
- Electrograms adjudicated as dispersed by **two readers** are considered “**likely dispersed**”;

- Electrograms adjudicated as dispersed by **each of the three readers** are considered “**very likely dispersed**”.

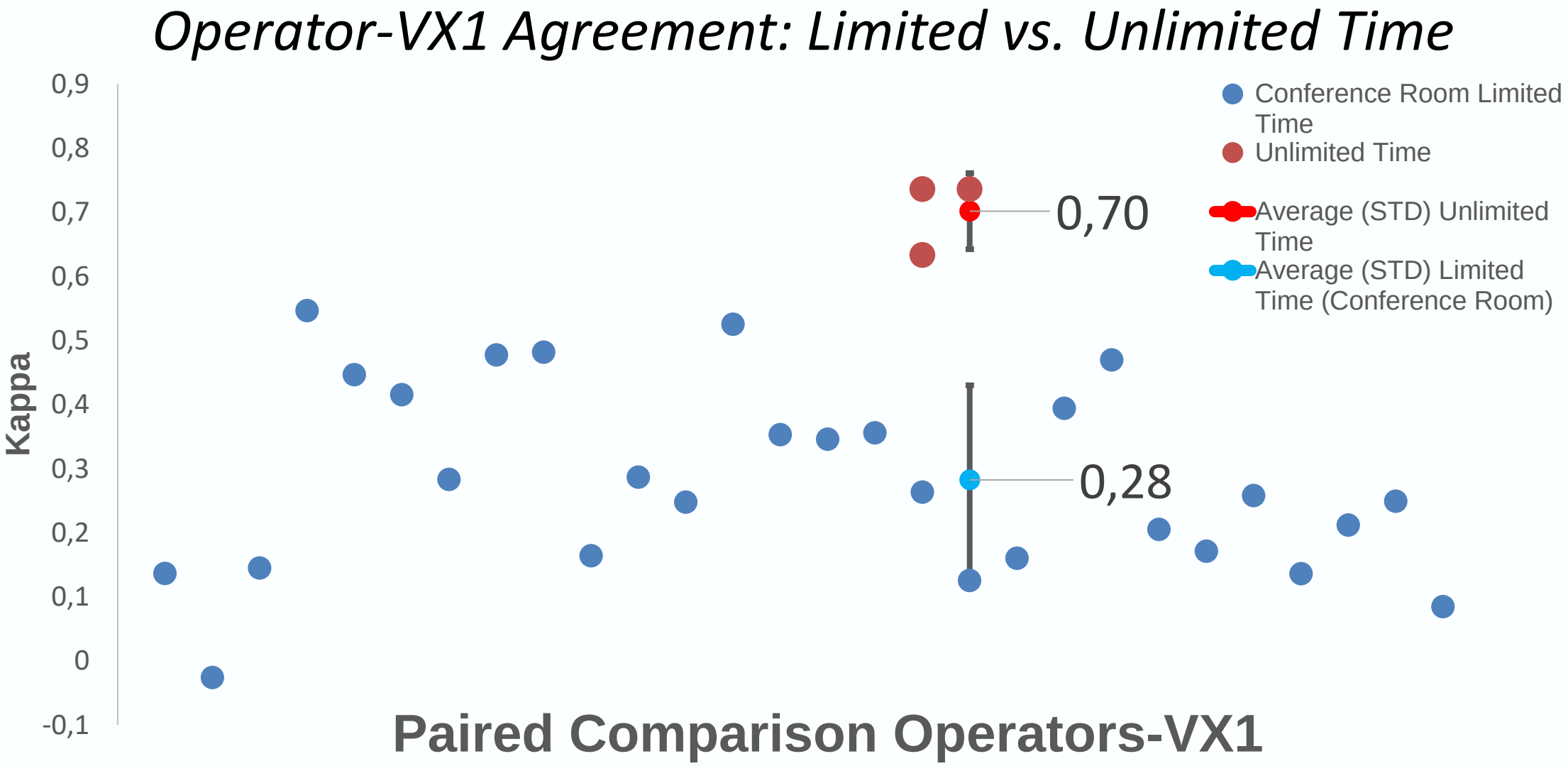
The « Reader » Study

Three histograms of electrograms:

- those annotated by **VX1** as **blue (normal zone)**,
- those annotated by **VX1** as **orange (region of interest)**
- those annotated by **VX1** as **red (region of special interest)**.



The « Reader » Study



The « Reader » Study

Conclusions

(i) VX1 adjudications highly correlate with the likelihood of electrograms to be classified as dispersed by a group of trained operators with unlimited time.

(ii) Agreement levels are much higher when operators are given unlimited analysis time.

(iii) VX1 cannot be distinguished from a trained operator with unlimited analysis time but works in a real-time configuration.

➡ VX1 is able to mimic a specific clinical expertise at its best.

Comment le logiciel est-il intégré au bloc opératoire?

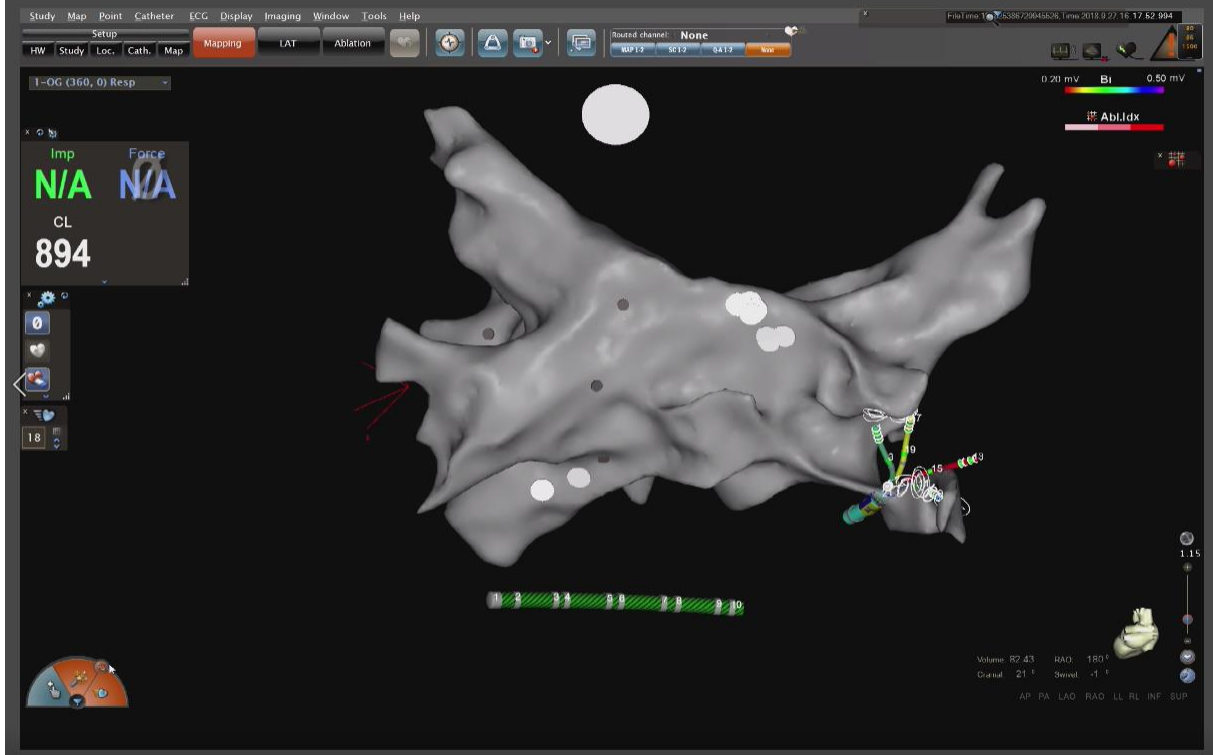
AF module of Volta software

Needs multipolar endocardial AF signals

Our workstation

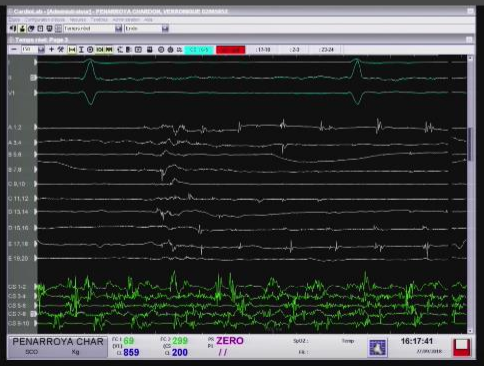
Films et TV

Atrial 3D reconstruction



Electrograms analysis

Electrograms recording



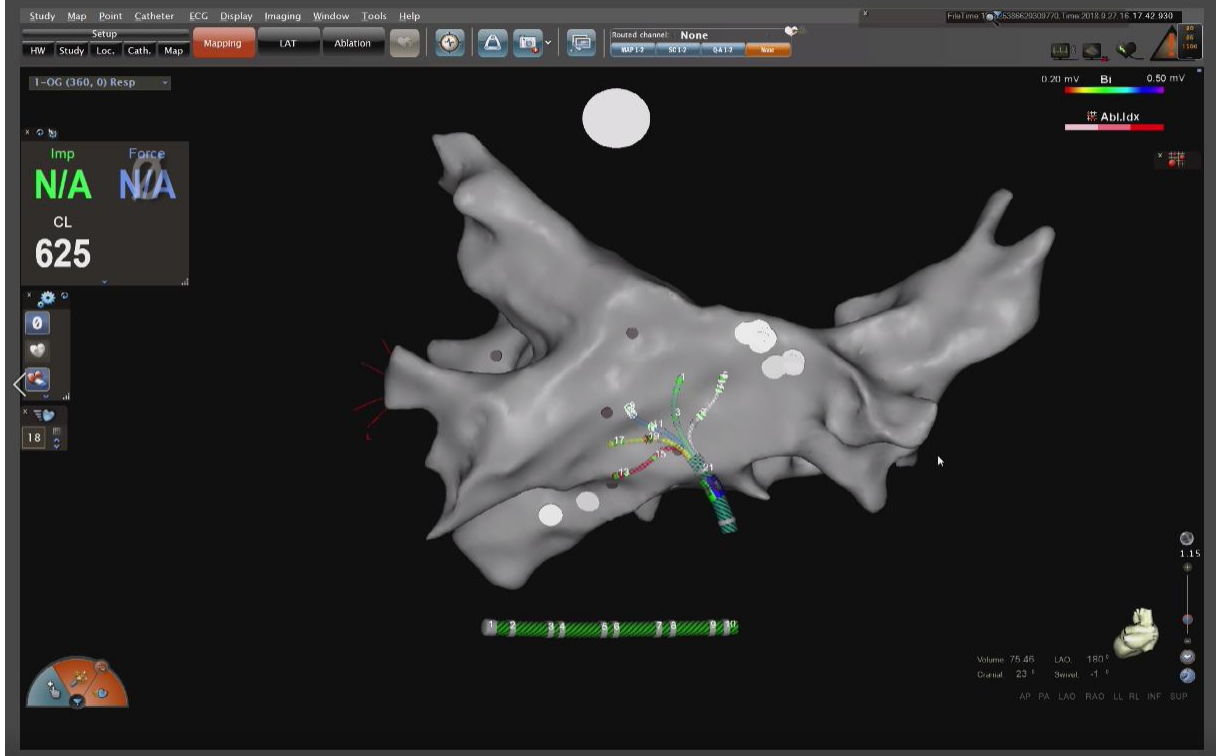
00:12:18

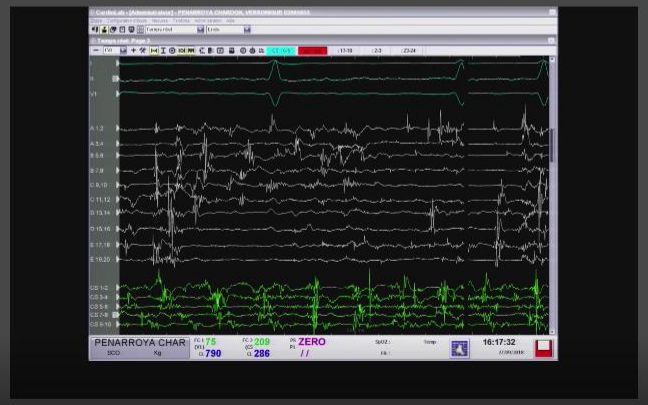
01:28:04

Films et TV

MAPPING

COLD REGION

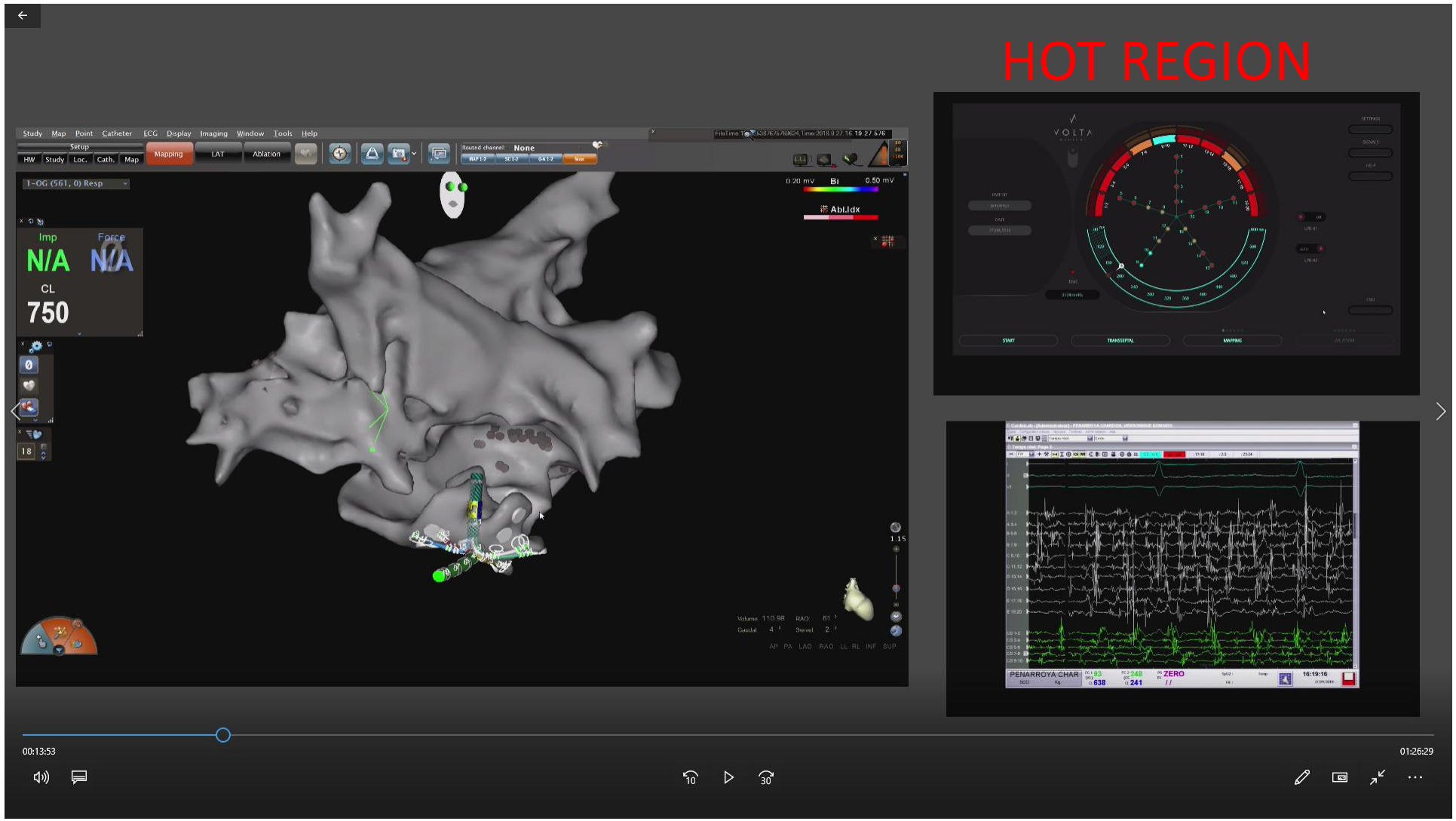




00:12:08

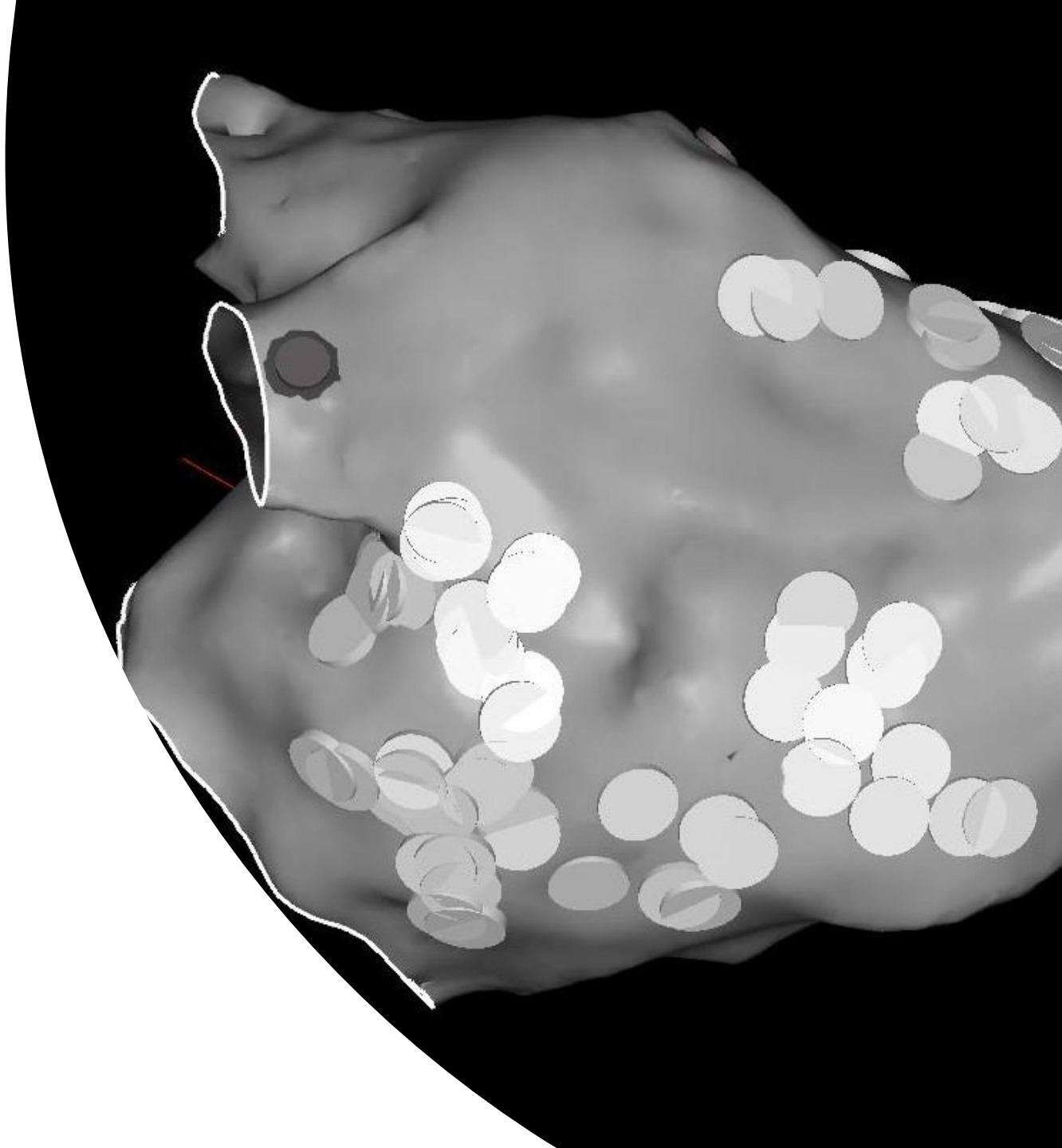
01:28:14

HOT REGION


Study Map Point Catheter ECG Display Imaging Window Tools Help
Setup
HW Study Loc. Cath. Map
Mapping
LAT
Ablation
Routed channel: None
1-OG (561, 0) Resp
Imp
Force
N/A
N/A
CL
750
0.20 mV
Bi
0.50 mV
Abl.Idx
18
1.15
Volume 110.98
RAO 61
Caudal 4
Swivel 2
AP PA LAO RAO LL RL INF SUP
VOLTA
START
TRANSSEPTAL
MAPPING
PENARROYA CHAR
ZERO
16:19:16
00:13:53
01:26:29
10
30

AI-guided Regional HD Approach

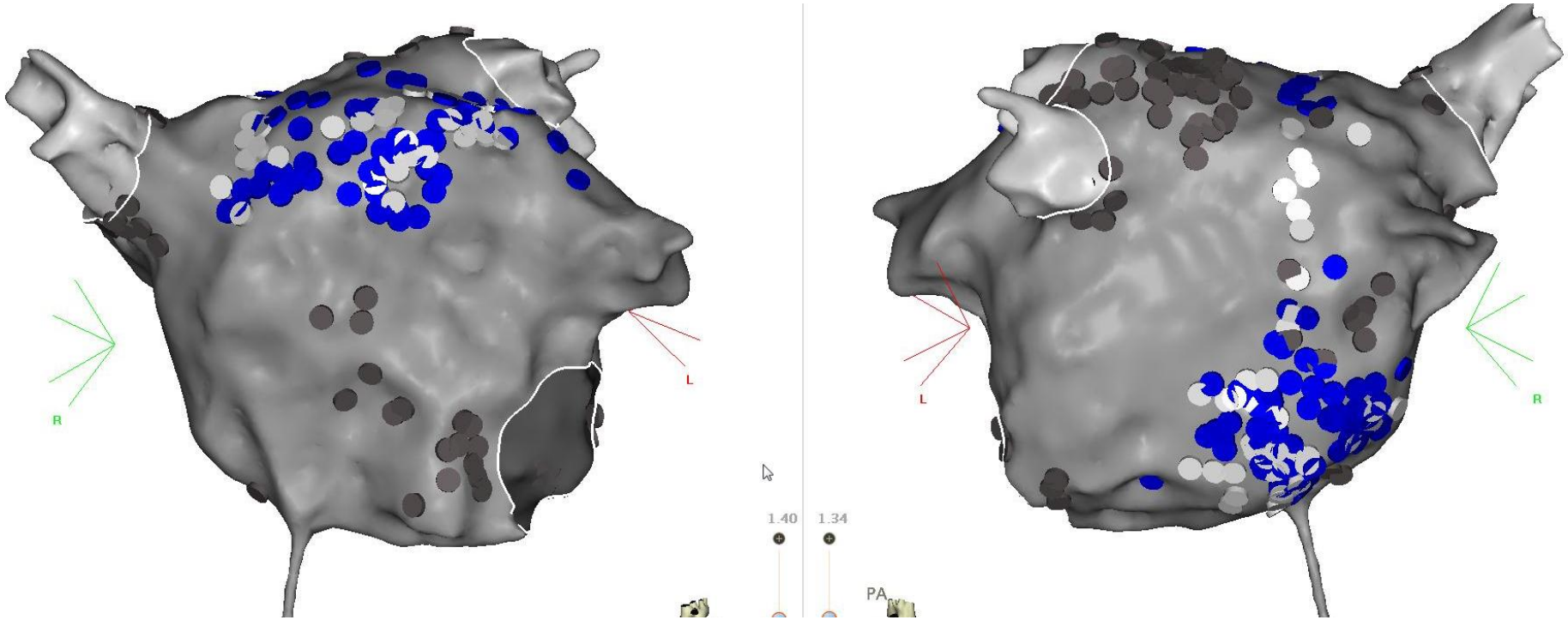
- High density maps
- Patient-tailored
- Easy to use
- Precisely locating AF drivers
- Guided mapping
- Data-driven performance



VOLTA

Improvements & Limitations

- Learn from failures
- Ablate less
- Predict the zones
- Ablation support



Towards an AI-based guidance

Data-driven tools may revolutionize interventional electrophysiology

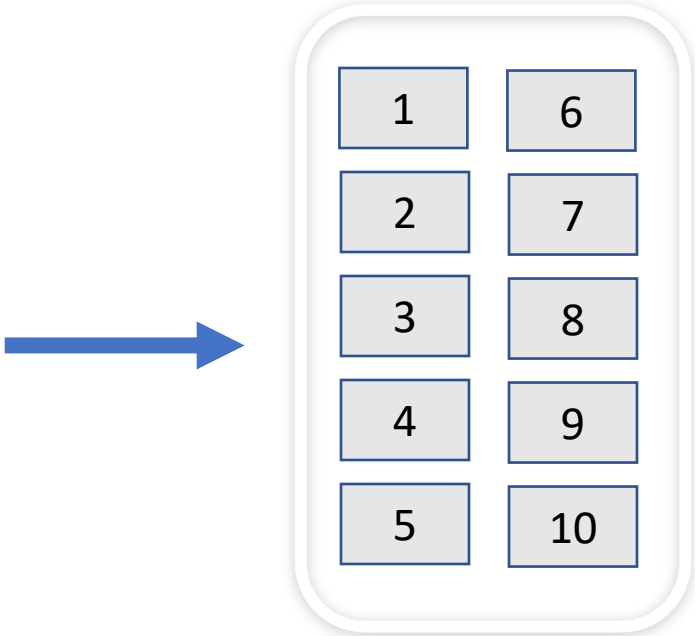

Thank you

VOLTA

MEDICAL

ARTIFICIAL INTELLIGENCE SERVING HEART RHYTHM

EGMs Quizz
28 cardiac electrophysiologists

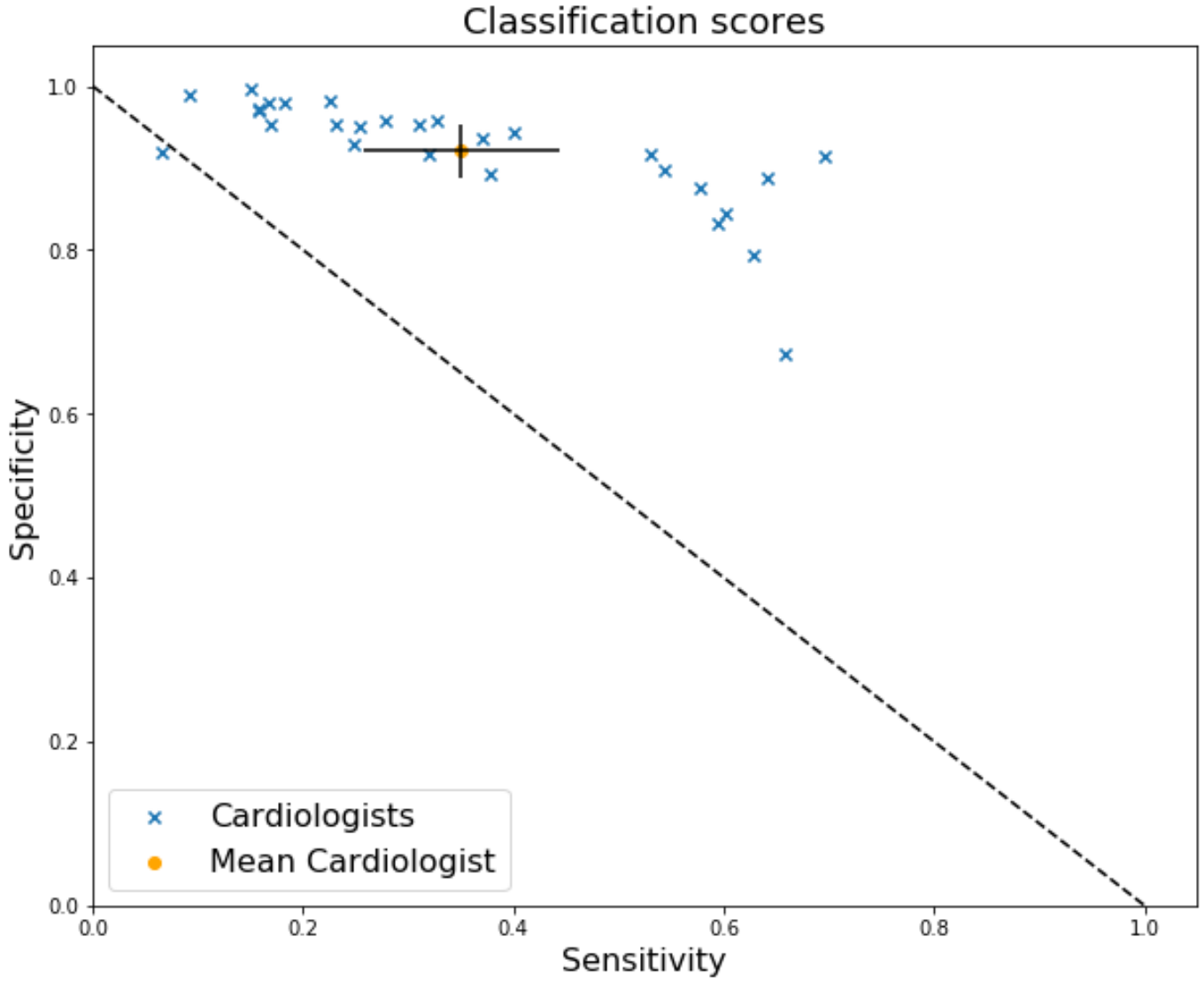


17 sec.
to answer

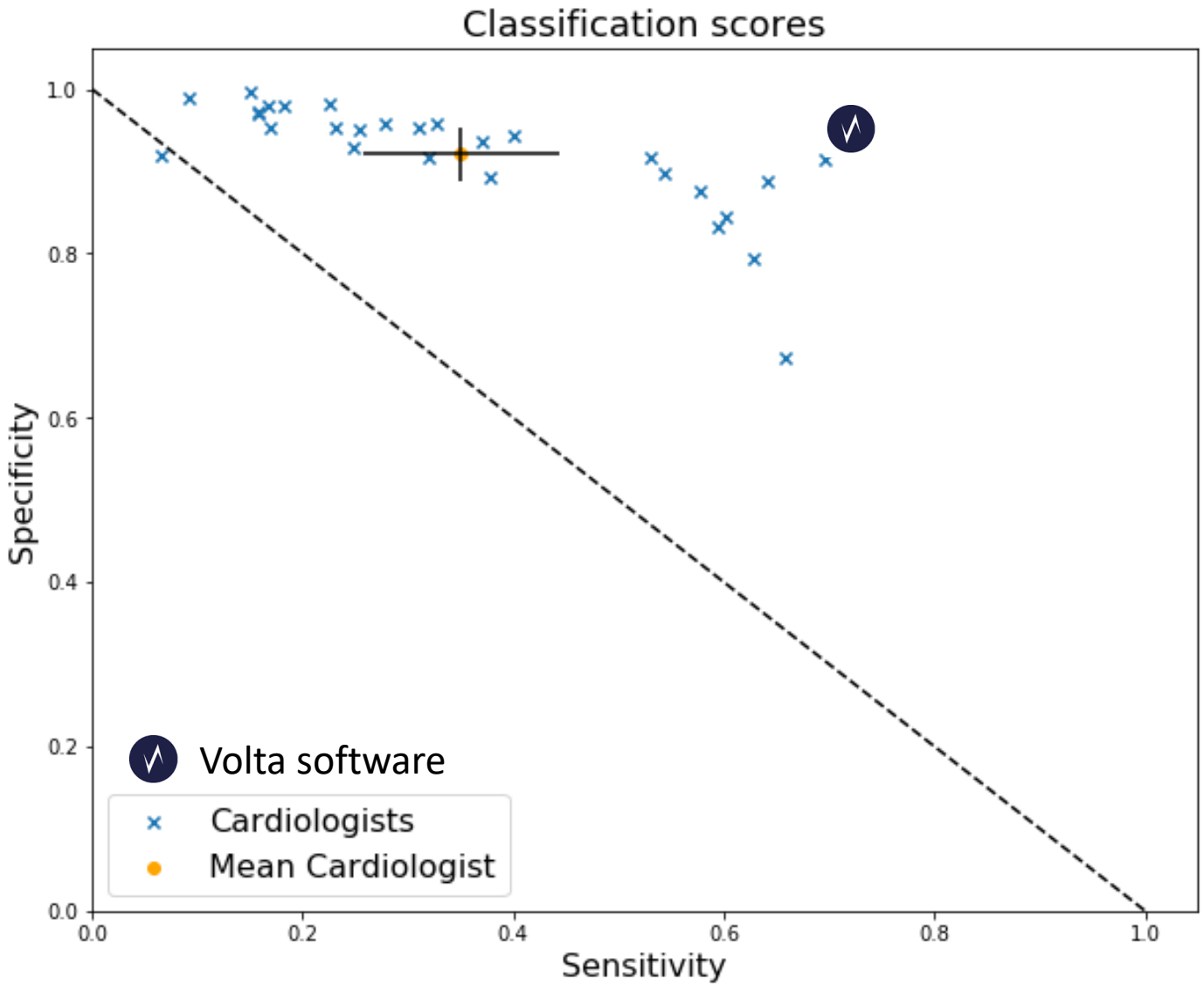
102 still-images=1020 EGMs
60 % from AF termination sites (“hot” signals)

At which of those electrogram locations would you ablate?

Cardiologists



EPs vs Volta Software



Volta software outperforms a panel of 28 EPs experts in EGM-based AF ablation

AIFib outperforms Humans

Our pre-clinical and clinical studies met all endpoints with outstanding results [1]

- **Monocentric clinical trial**:

- **Double-blind maps** during atrial fibrillation

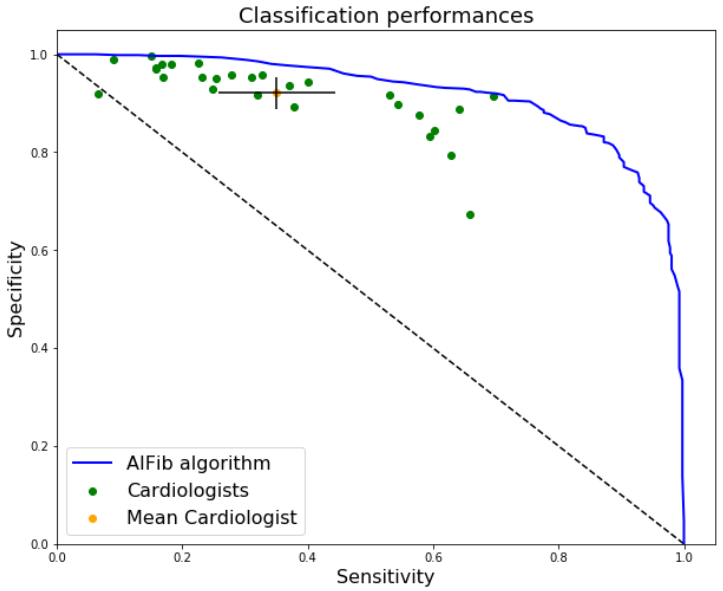
✓ **Less aggressive**: Ablated regions were significantly smaller (23.4±12.6 vs. 30.0±7.6 cm², p=0.046)

- **Ablation guidance in 76 patients** in Marseille

✓ **92%** of acute atrial fibrillation **termination**

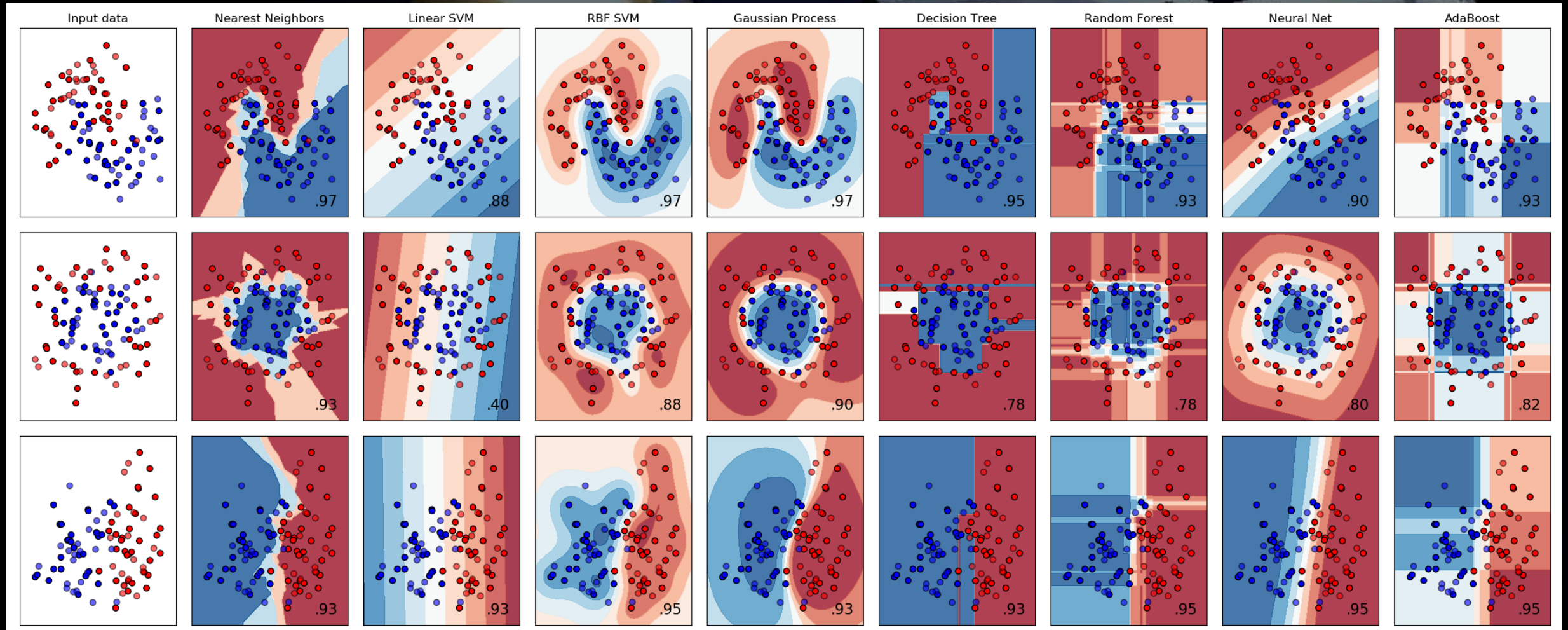
- **Comparative test** with a panel of **experienced electrophysiologists**

✓ **AIFib outperforms all 28 cardiac electrophysiologists** (1020 signals)



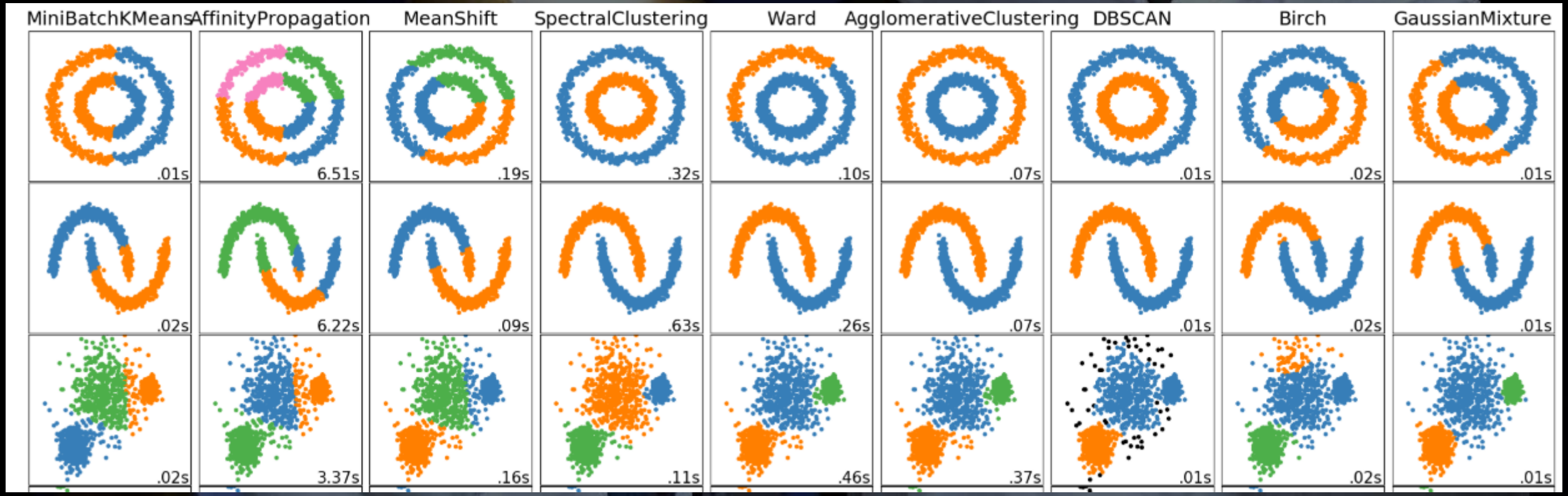
1. *Submitted to the Heart Rhythm Society Late Breaking Clinical Trials Session*

Principales Limites



VOLTA

Principales Limites



VOLTA

Echec

1997

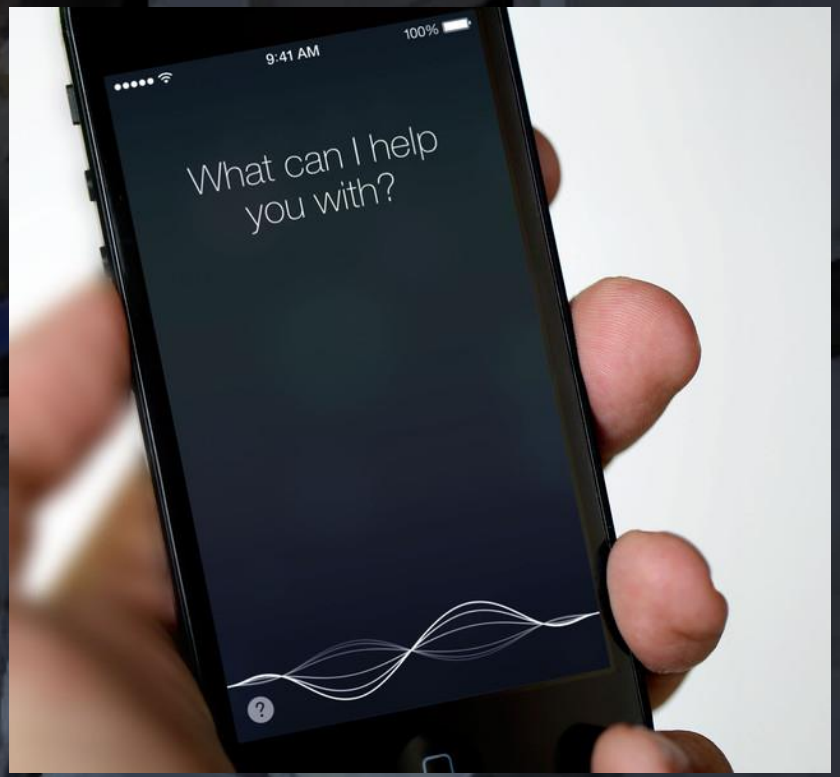
DeepBlue gagne face à Garry Kasparov

VOLTA

Natural Language Processing

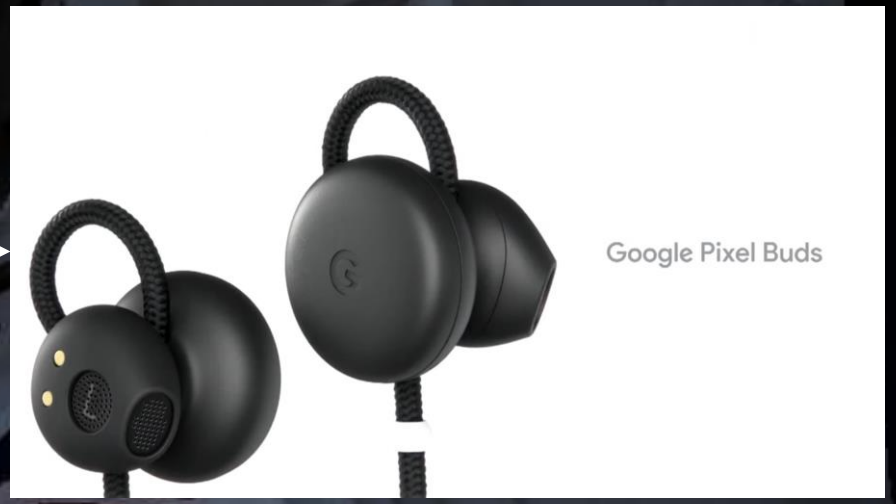
Translation

Speech Recognition



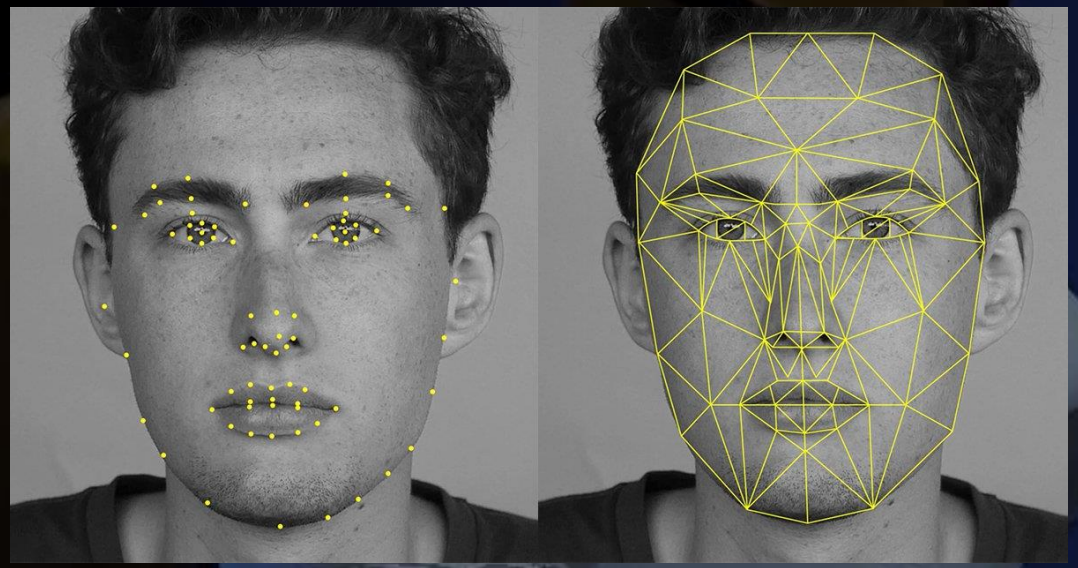
VOLTA

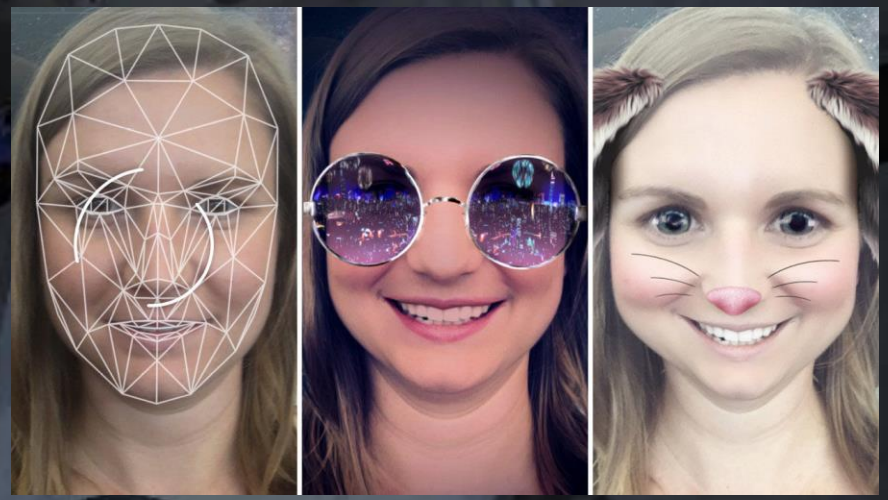
Natural Language Processing



VOLTA

Face Recognition





VOLTA

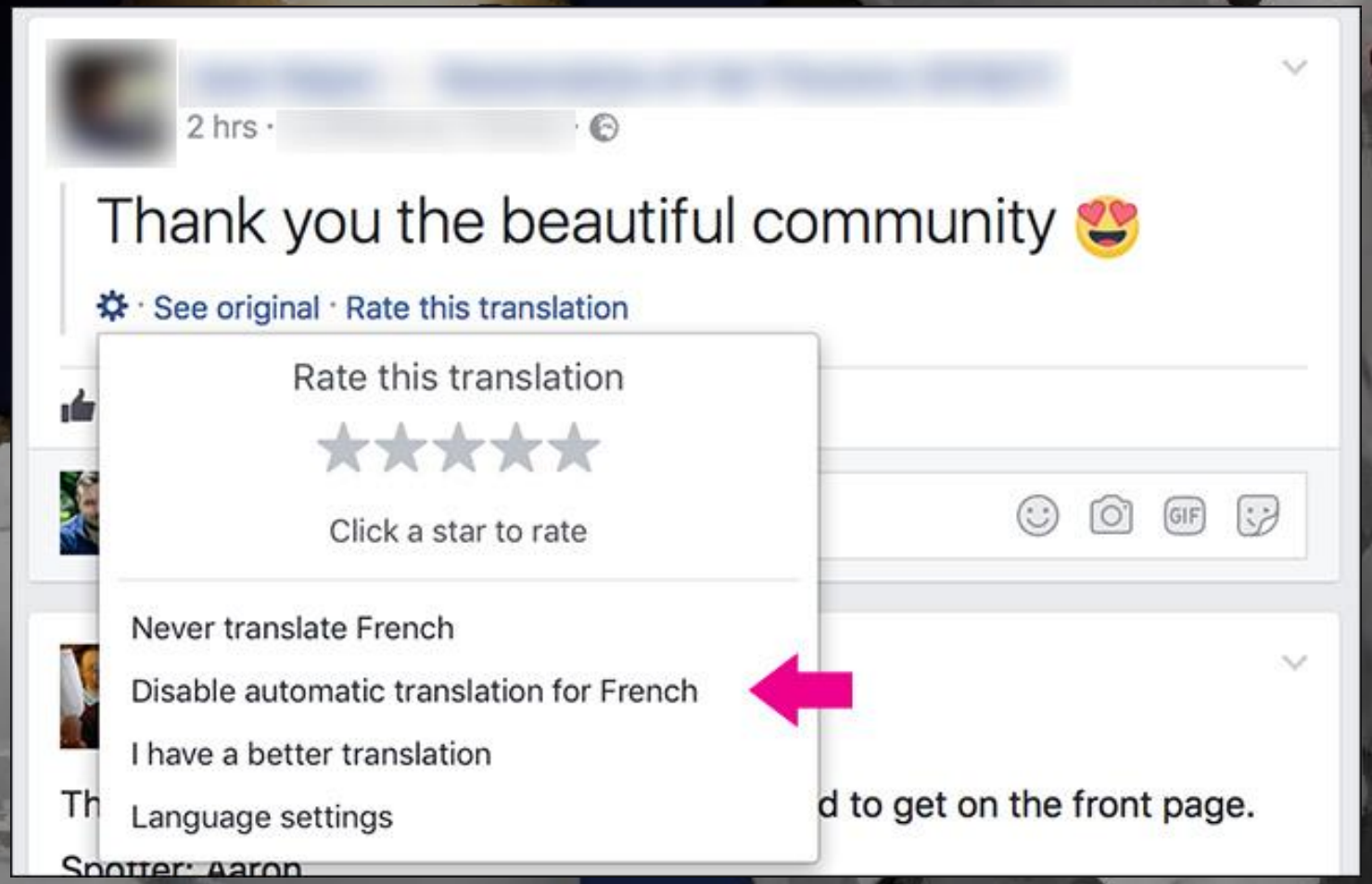

How to get a labelled DataBase?
VOLTA


Either you pay...
VOLTA


Let users do the job for you !
VOLTA

Let users do the job for you !

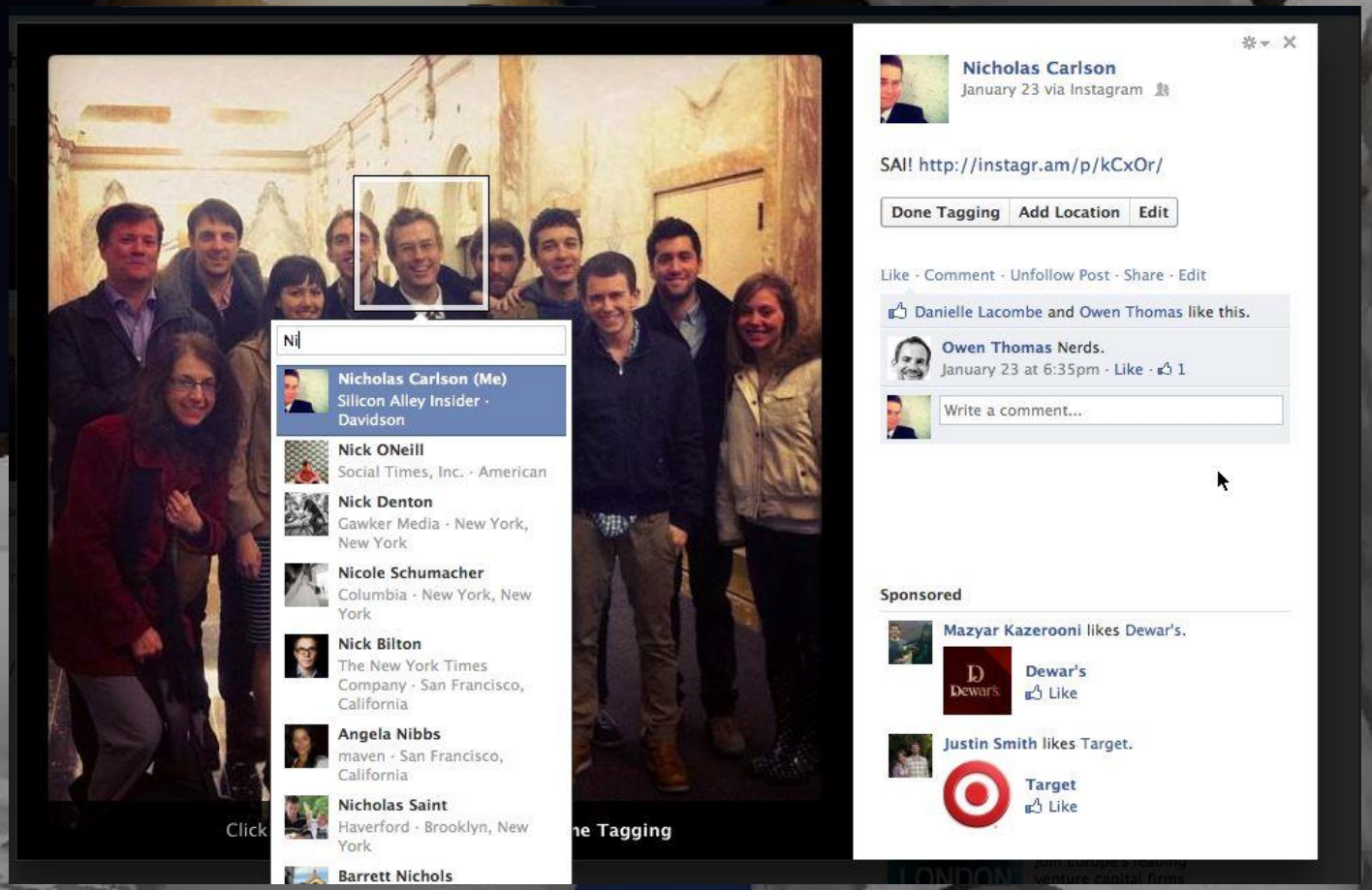
Facebook translation



VOLTA

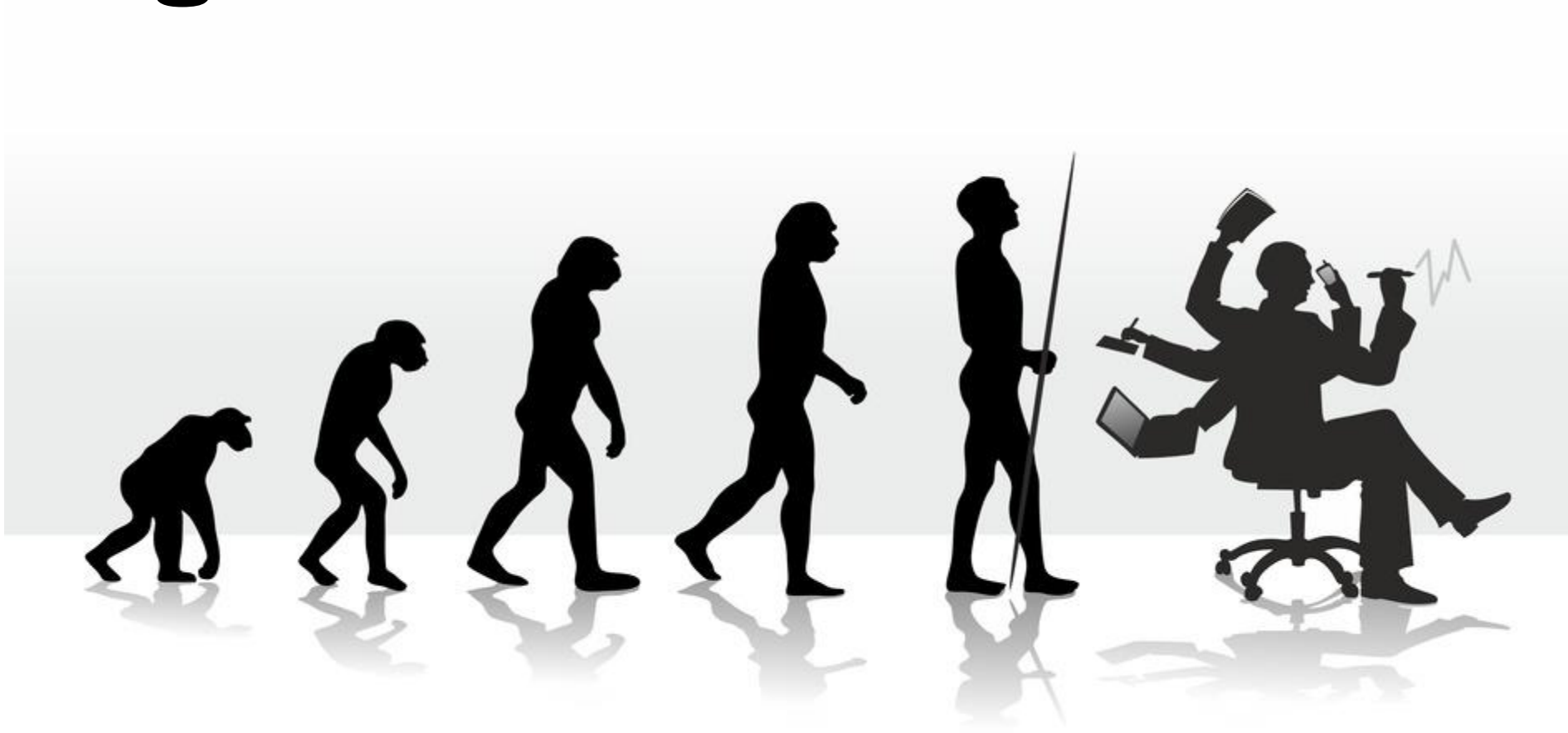
Let users do the job for you !

Face Recognition Facebook



VOLTA

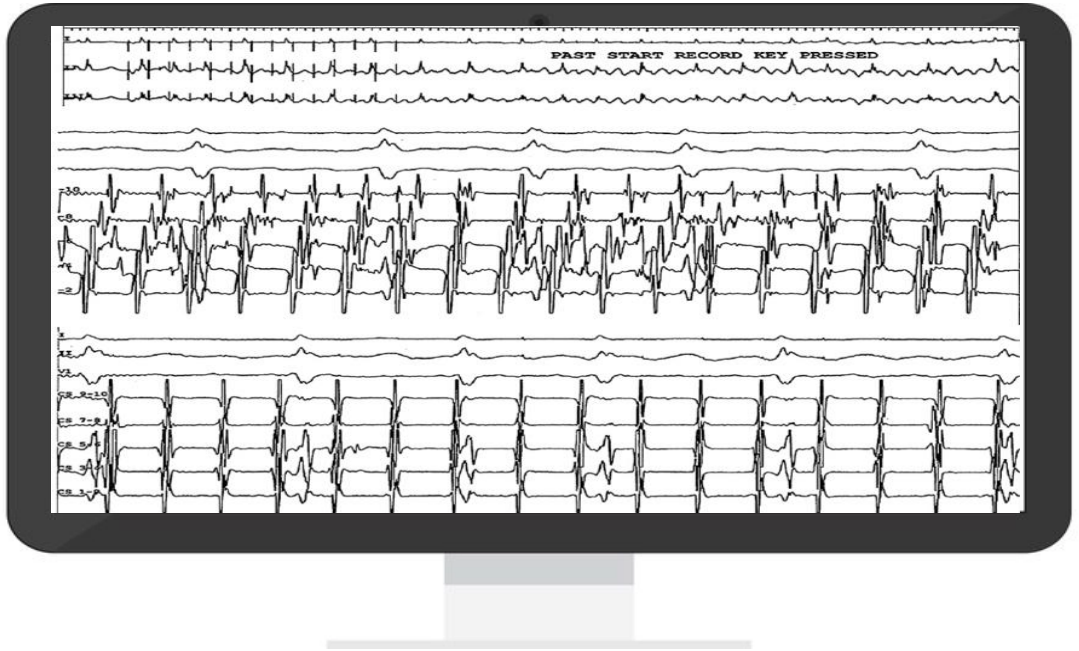
Un grand besoin d’automatisation



VOLTA

Currently available local electrograms analytical tools

- **Voltage Maps**
- **CFAE Maps** (CARTO, SJM versions)
- **Dominant Frequency Maps**



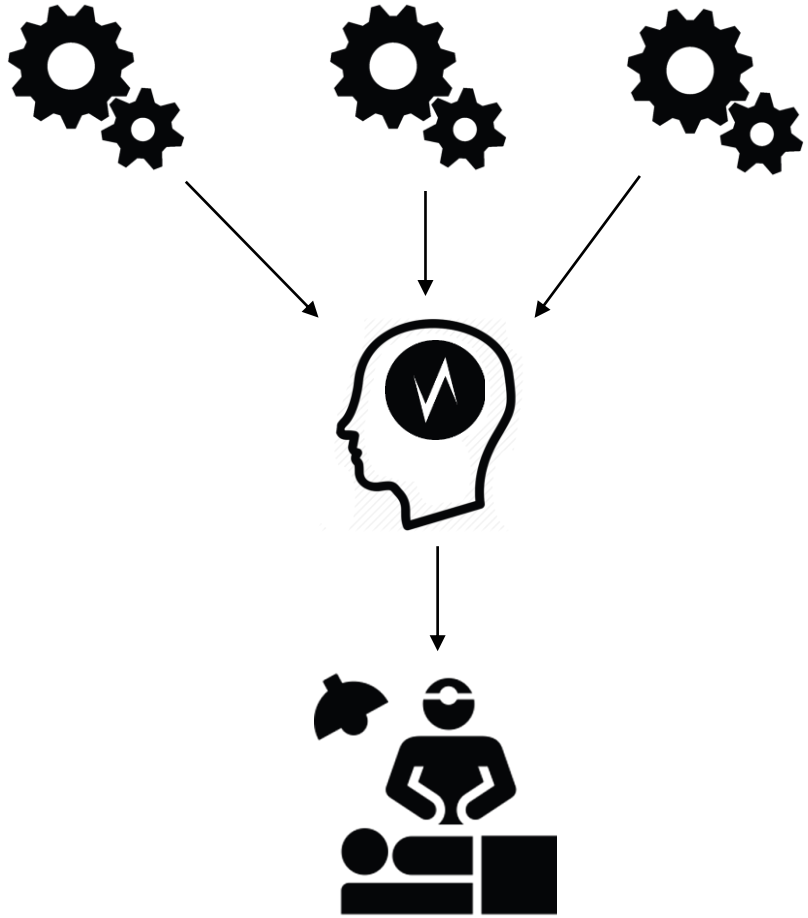
VOLTA

Several attempts with conventional methods

- Too **many analytical parameters**: frequency, voltage, fractionation, sequential activation
- Each patient is unique: **too many types of electrograms**
- During ablation **EGM morphology can change** (with AF cycle length increase)
- Unable to **associate the prediction with a probability**

VOLTA

AIFib



VOLTA