CHALLENGES in SMART PATIENT MONITORING:

from Raw Data to Decision Support

Prof. Sabine Van Huffel

sabine.vanhuffel@kuleuven.be

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Contents Overview

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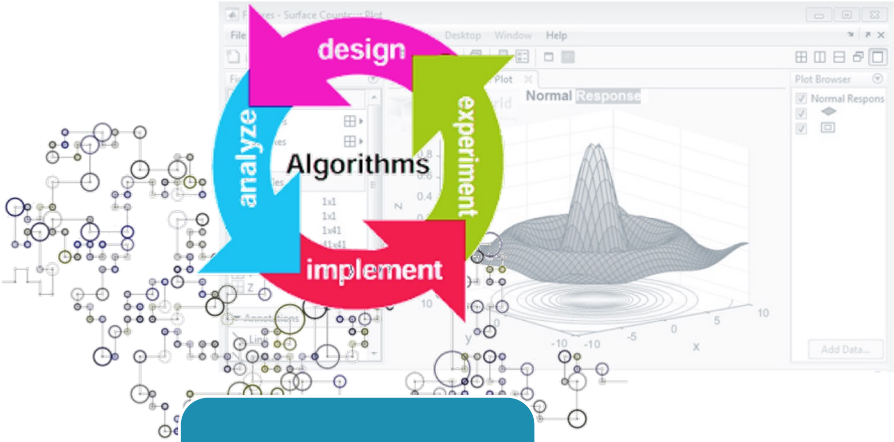
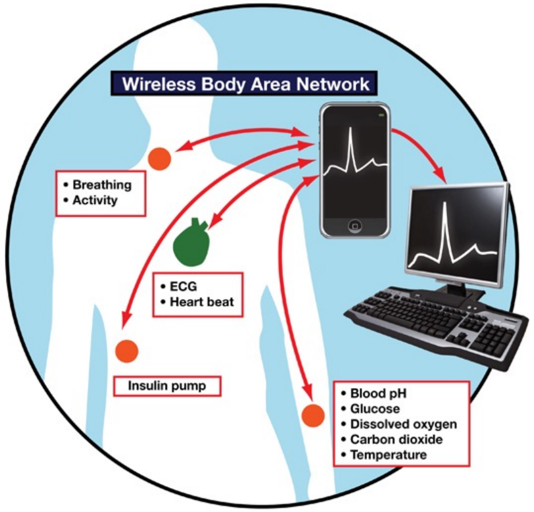


Sensors
(Carriers)

Algorithms
(Technology)

Pathologies
(Applications)

Smart Patient Monitoring



Brain monitoring for neurological diseases

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Vital signs monitoring: sleep, stress, cardio risk stratification

Oncology: cancer diagnosis and prognosis

Chronic disease management & telemonitoring application

Hospital of the FUTURE

Move healthcare away from hospitals to HOME environment

- **UNOBTRUSIVE**
- **MULTIMODAL**
- **LONG-TERM**

Challenges:

- **ARTEFACTS**
- **BIG DATA**
- **AUTOMATED**


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Health forecast

What can we expect from the hospital of the future?

Over the next 30 years, innovations like telemedicine and virtual reality will vastly improve the healthcare experience for patients and providers

Paid for by

OPTUM

Imagine a surgeon is perched in front of a telecommunications console in New York City while his patient lies on an operating table 3,870 miles away at a hospital in Strasbourg, France. From the console, the physician remotely guides the movement of a three-armed surgical robot named Zeus to remove the 68-year-old patient's diseased gallbladder. The operation takes less than an hour, and the patient recovers as expected, returning home two days later.

Sounds like something out of science fiction, doesn't it? It's not.

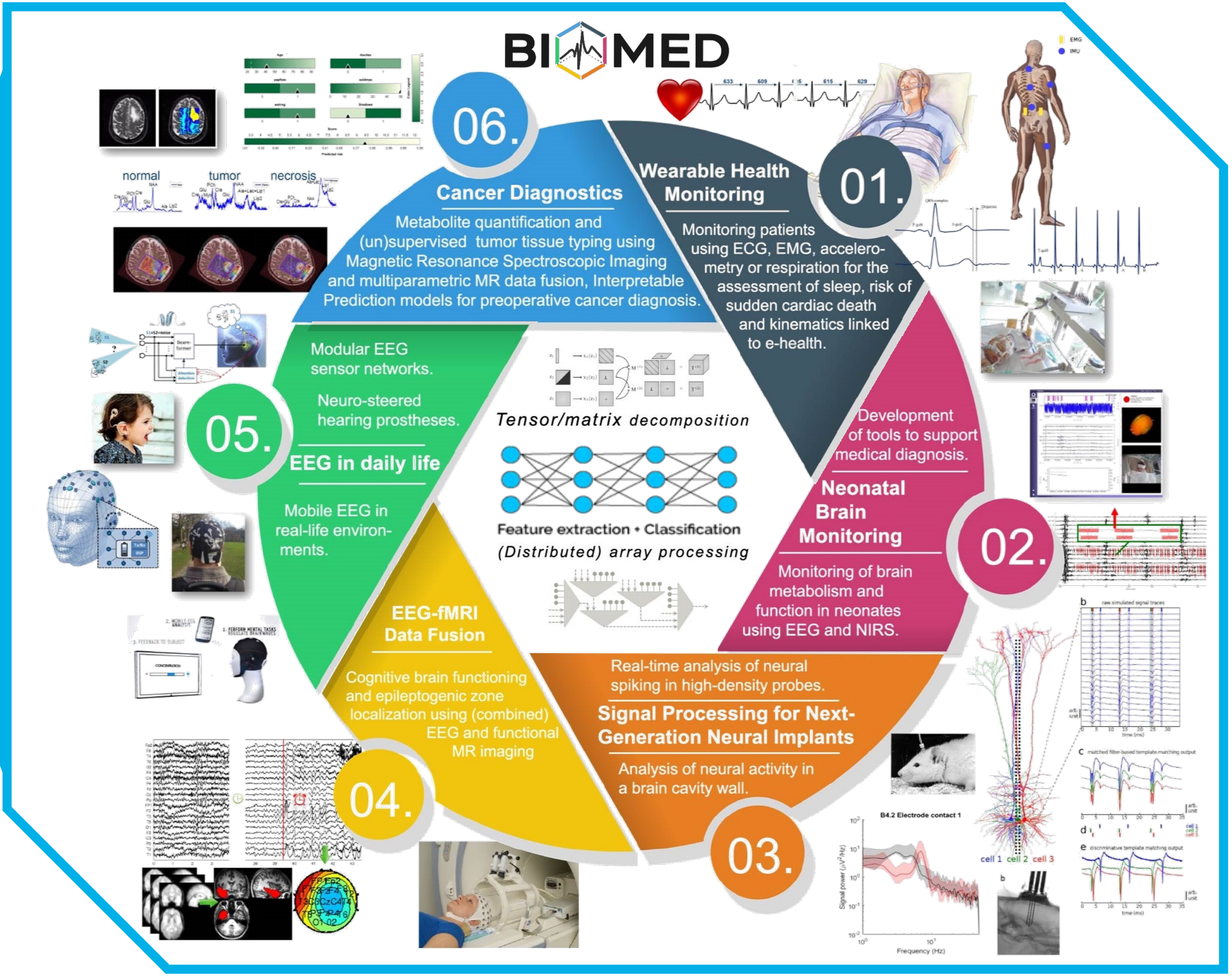
The transatlantic procedure actually happened in 2001. Known as Operation Lindbergh, named after American aviator Charles Lindbergh, the breakthrough event

The Guardian, 6.11.2016

Knack,21.10.2015

Research in close collaboration with

UZ LEUVEN



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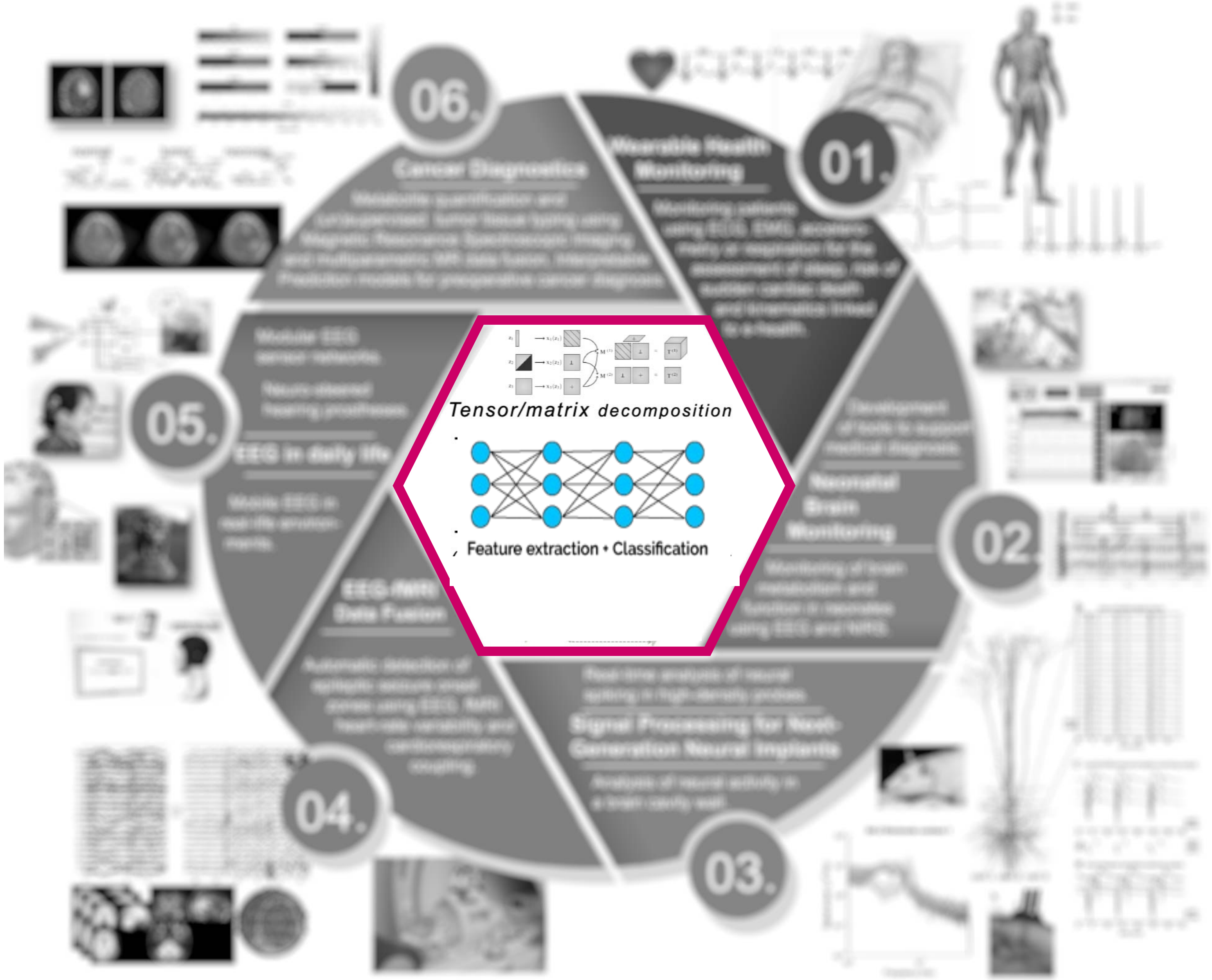

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KEYTOOL : Blind source separation

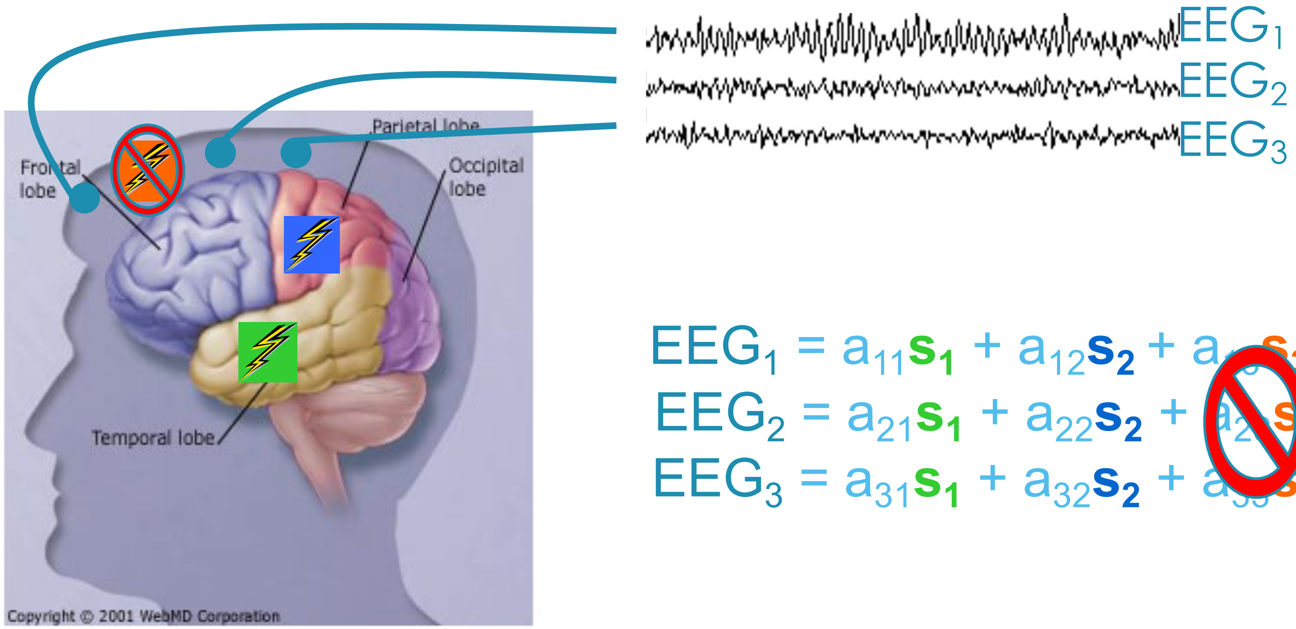
Signal analysis difficult because of artefacts → **REMOVE**

Matrix based Blind Source Separation (BSS)

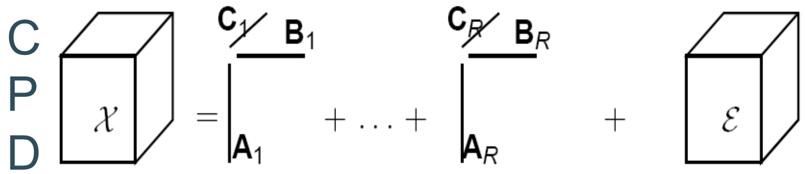
- ***Non-unique*** →*Constraints are needed (orthogonal, independency)*

TENSOR based BSS: unique under mild conditions

ADD extra problem-specific constraints (nonnegative, sparse)

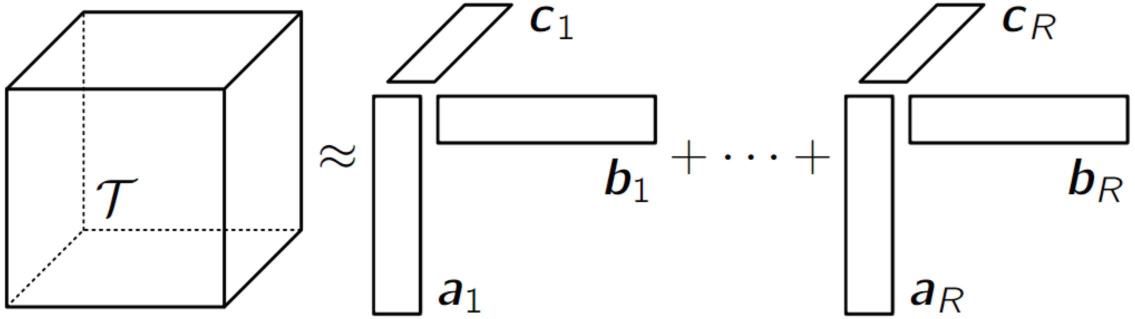


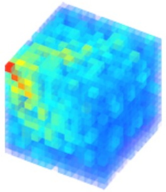
$EEG_1 = a_{11}\mathbf{s_1} + a_{12}\mathbf{s_2} + \cancel{a_{13}\mathbf{s_3}}$
$EEG_2 = a_{21}\mathbf{s_1} + a_{22}\mathbf{s_2} + \cancel{a_{23}\mathbf{s_3}}$
$EEG_3 = a_{31}\mathbf{s_1} + a_{32}\mathbf{s_2} + \cancel{a_{33}\mathbf{s_3}}$



EEG = A ? S^T ?

Canonical Polyadic Decomposition - CPD



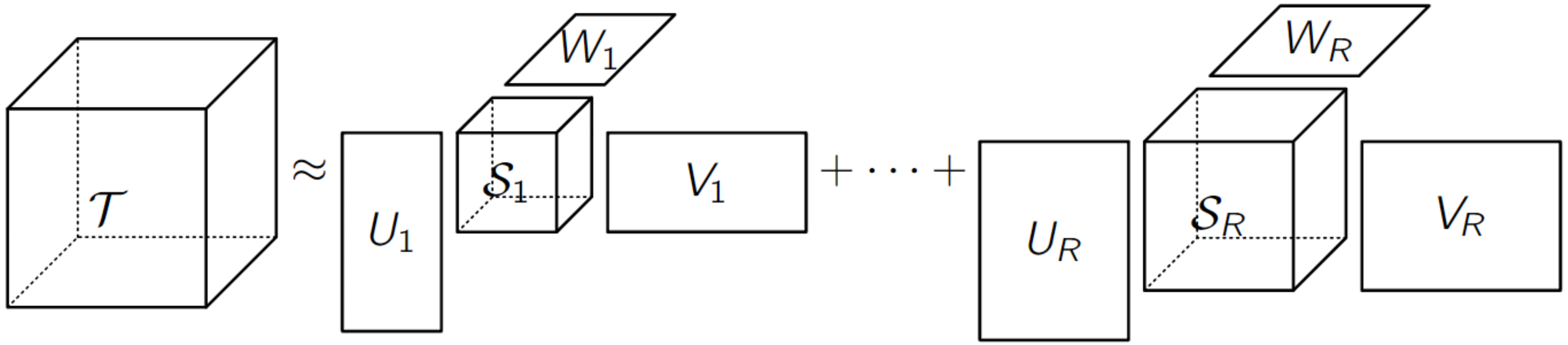


Tensorlab

A MATLAB package for tensor computations.

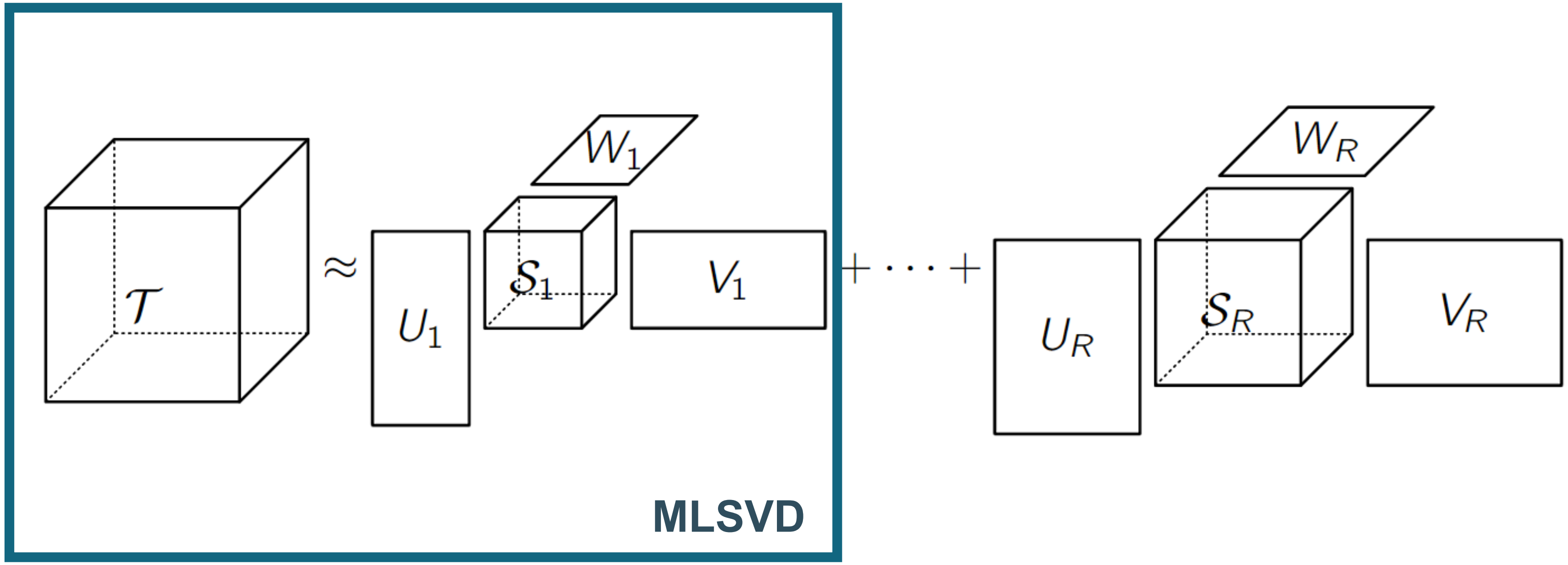
www.tensorlab.net

From CPD to Block Tensor Decomposition



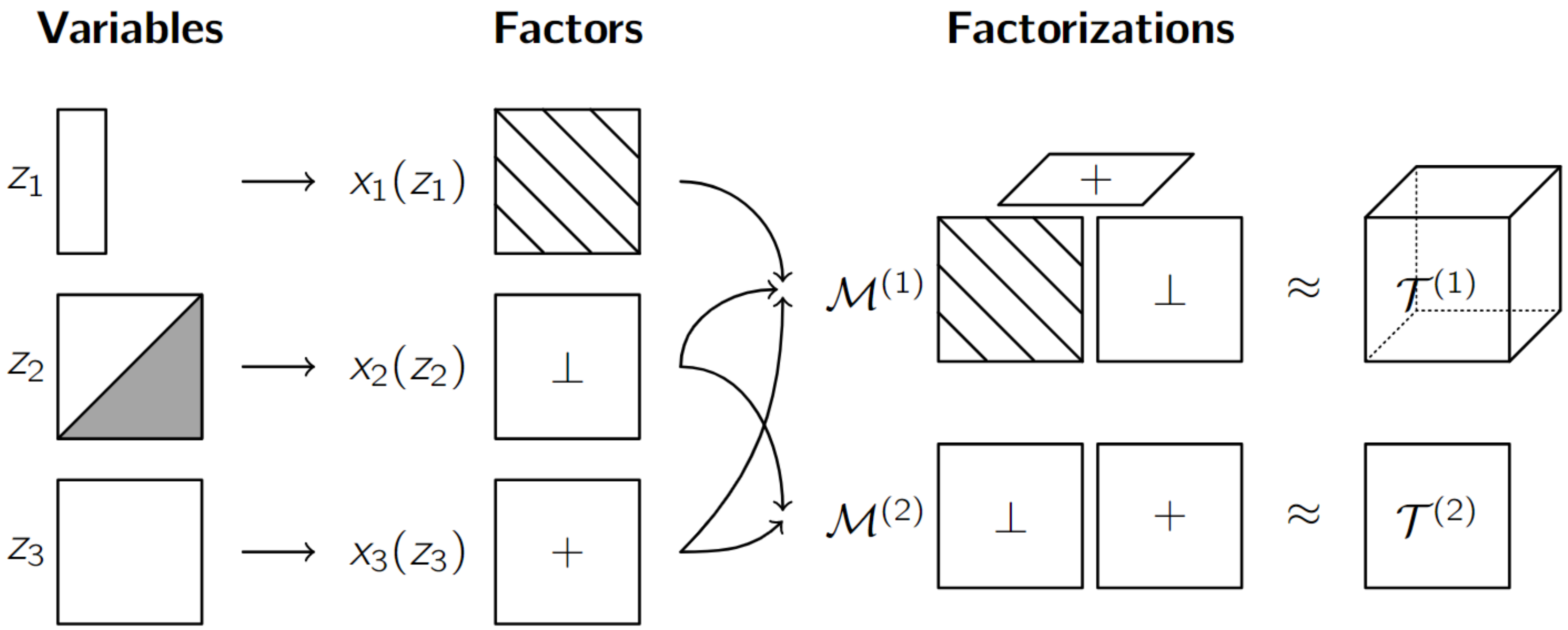
De Lathauwer et al., SIMAX, 2008; Sorber et al., SIOPT, 2013

From CPD to MLSVD and Block Tensor Decomposition



De Lathauwer et al., SIMAX, 2008; Sorber et al., SIOPT, 2013

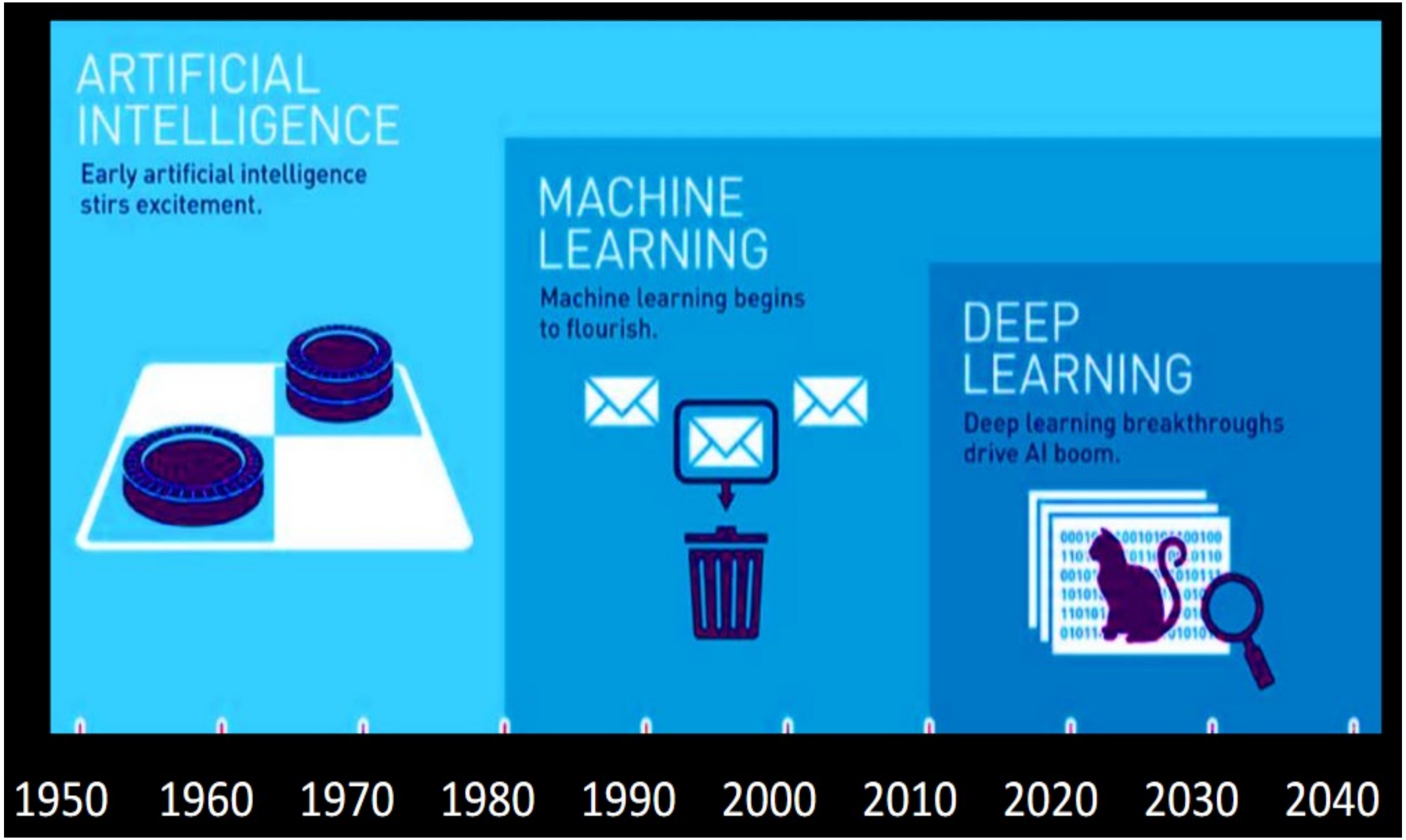
Structured Data Fusion



$$\underset{z}{\text{minimize}} \quad \sum_{d=1}^{D} \frac{\omega_d}{2} \left\| \mathcal{M}^{(d)}(\mathcal{X}(z)) - \mathcal{T}^{(d)} \right\|_{\mathcal{W}^{(d)}}^2,$$

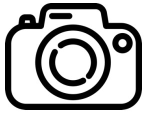
Sorber L, Van Barel M, De Lathauwer L, IEEE J. of Selected Topics in Signal Proc., 2015

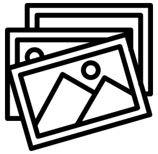
Evolution of AI: from machine learning to deep learning

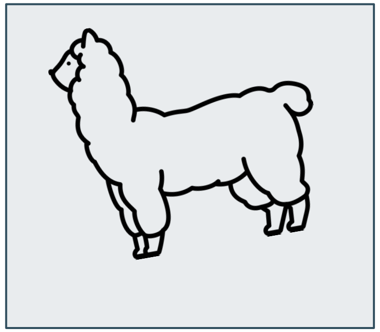


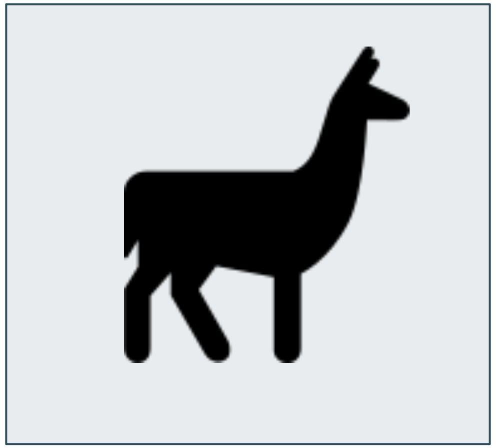
https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

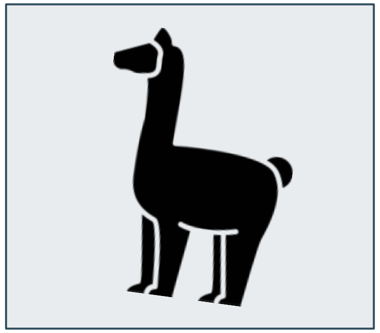
Introduction to Machine Learning

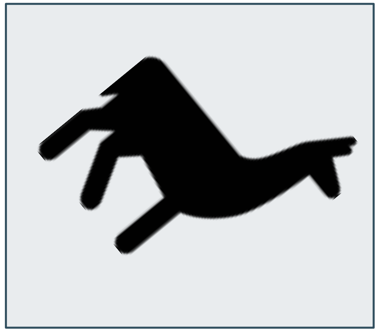


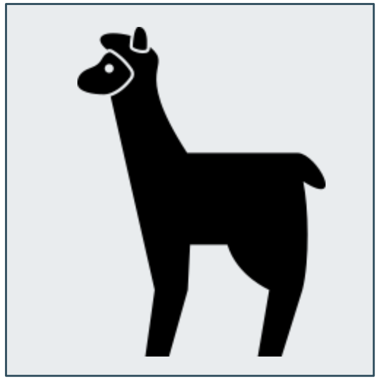


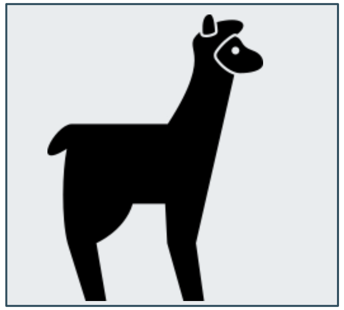


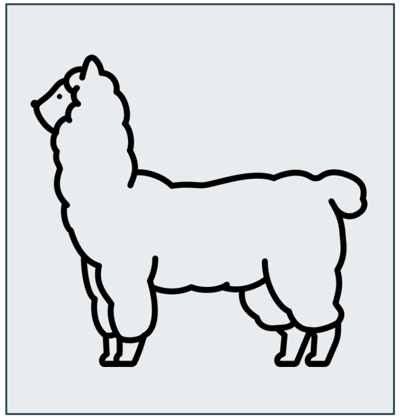


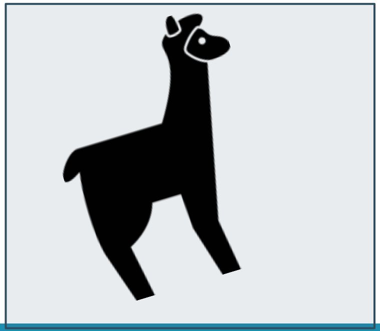


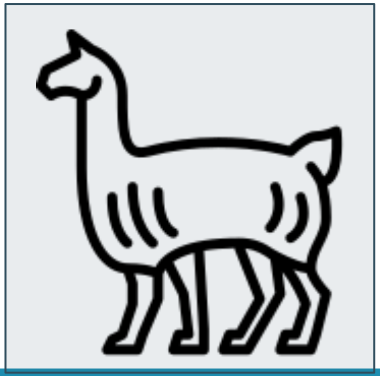






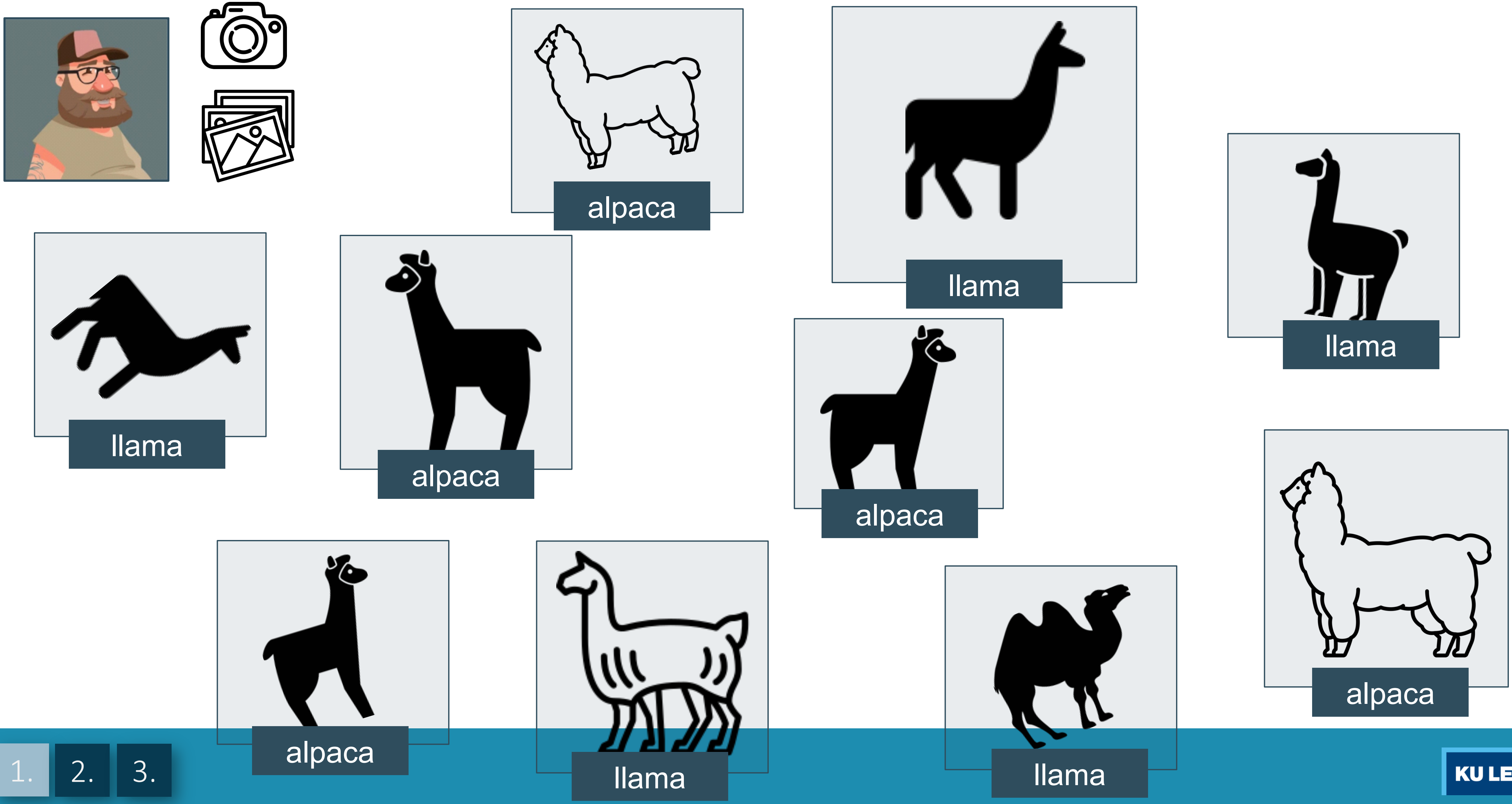






In collaboration with Johan Suykens & group

Machine Learning



alpaca

llama

Feature	Angle Ears [degrees]	Relative Shoulder Height [%]	Relative Tail Length [%]
Average Value			
Average Value			

alpaca

llama

Feature	Angle Ears [degrees]	Relative Shoulder Height [%]	Relative Tail Length [%]
Average Value	90		
Average Value	45		

alpaca

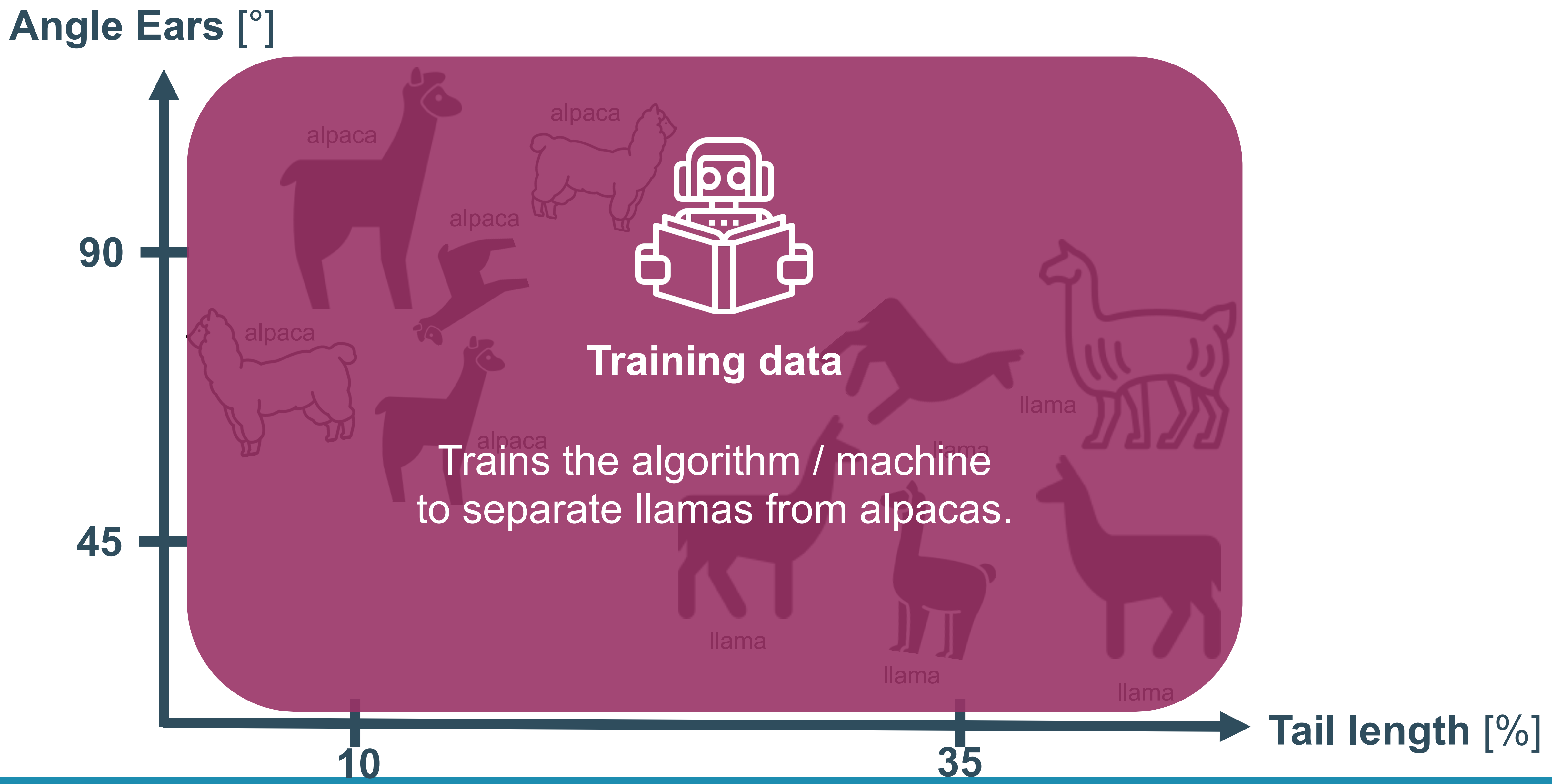
llama

Feature	Angle Ears [degrees]	Relative Shoulder Height [%]	Relative Tail Length [%]
Average Value	90	80	10
Average Value	45	73	35

alpaca

llama

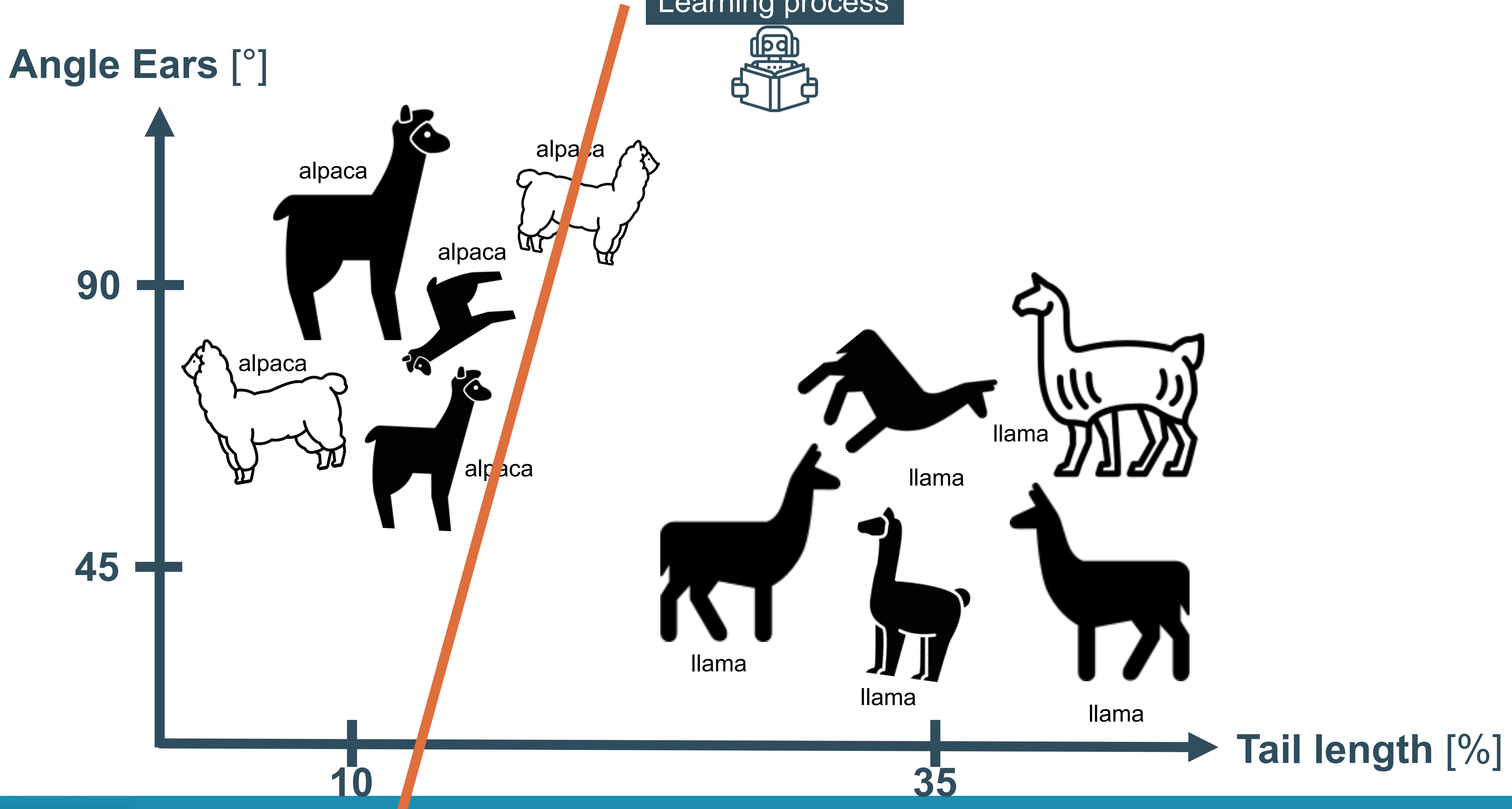
Feature	Angle Ears [degrees]	Relative Shoulder Height [%]	Relative Tail Length [%]
Average Value	90	80	10
Average Value	45	73	35

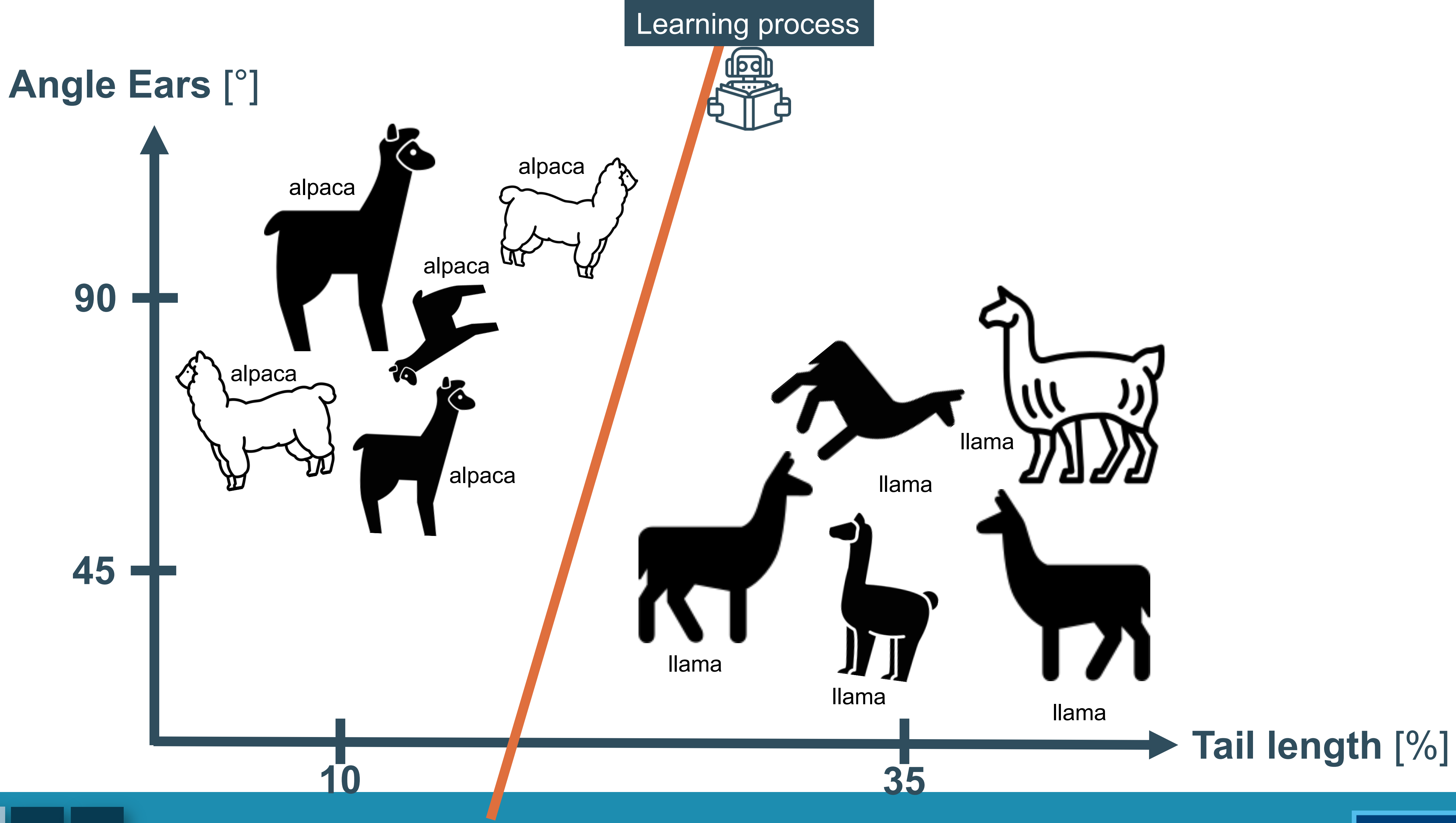


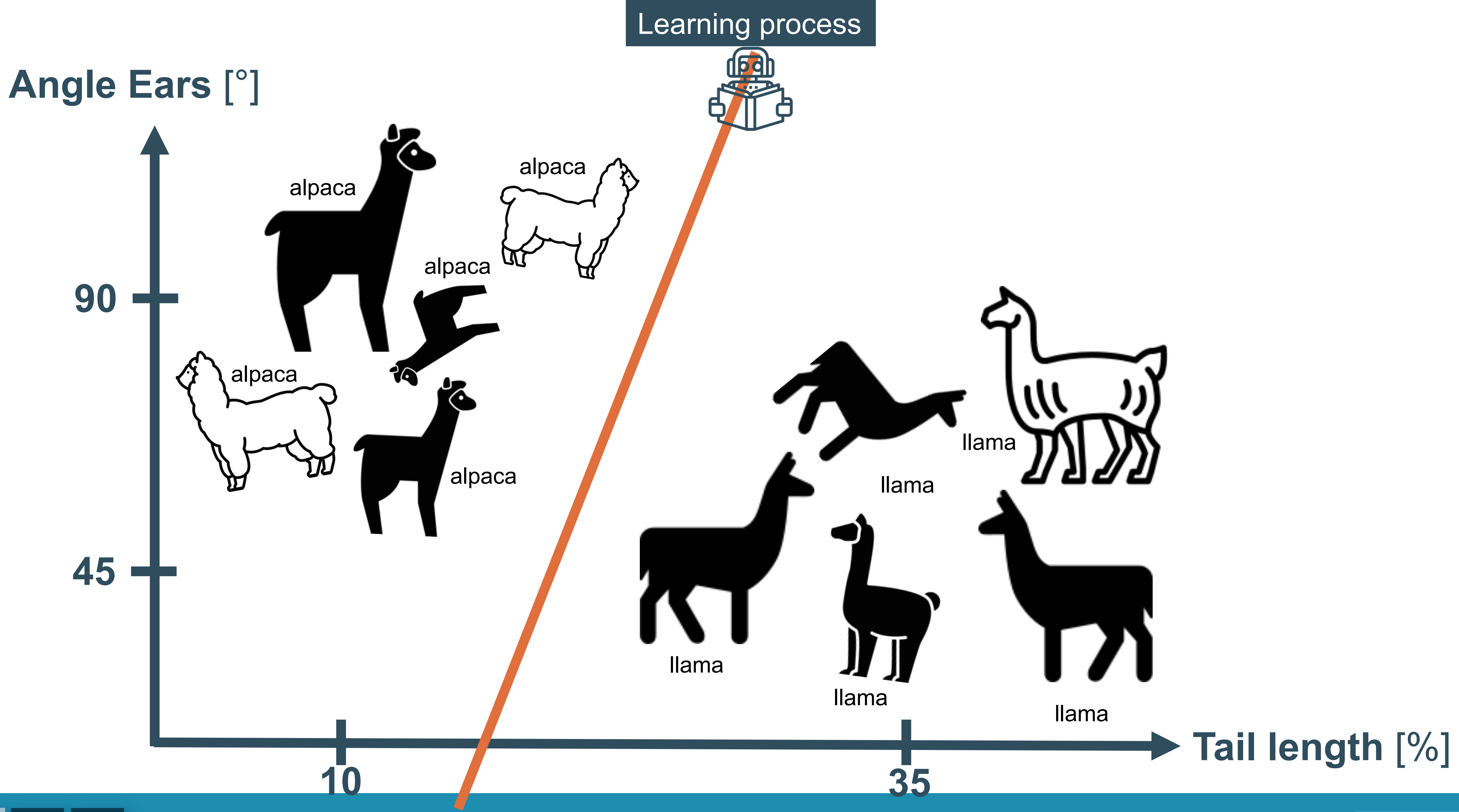
Training data

Trains the algorithm / machine
to separate llamas from alpacas.

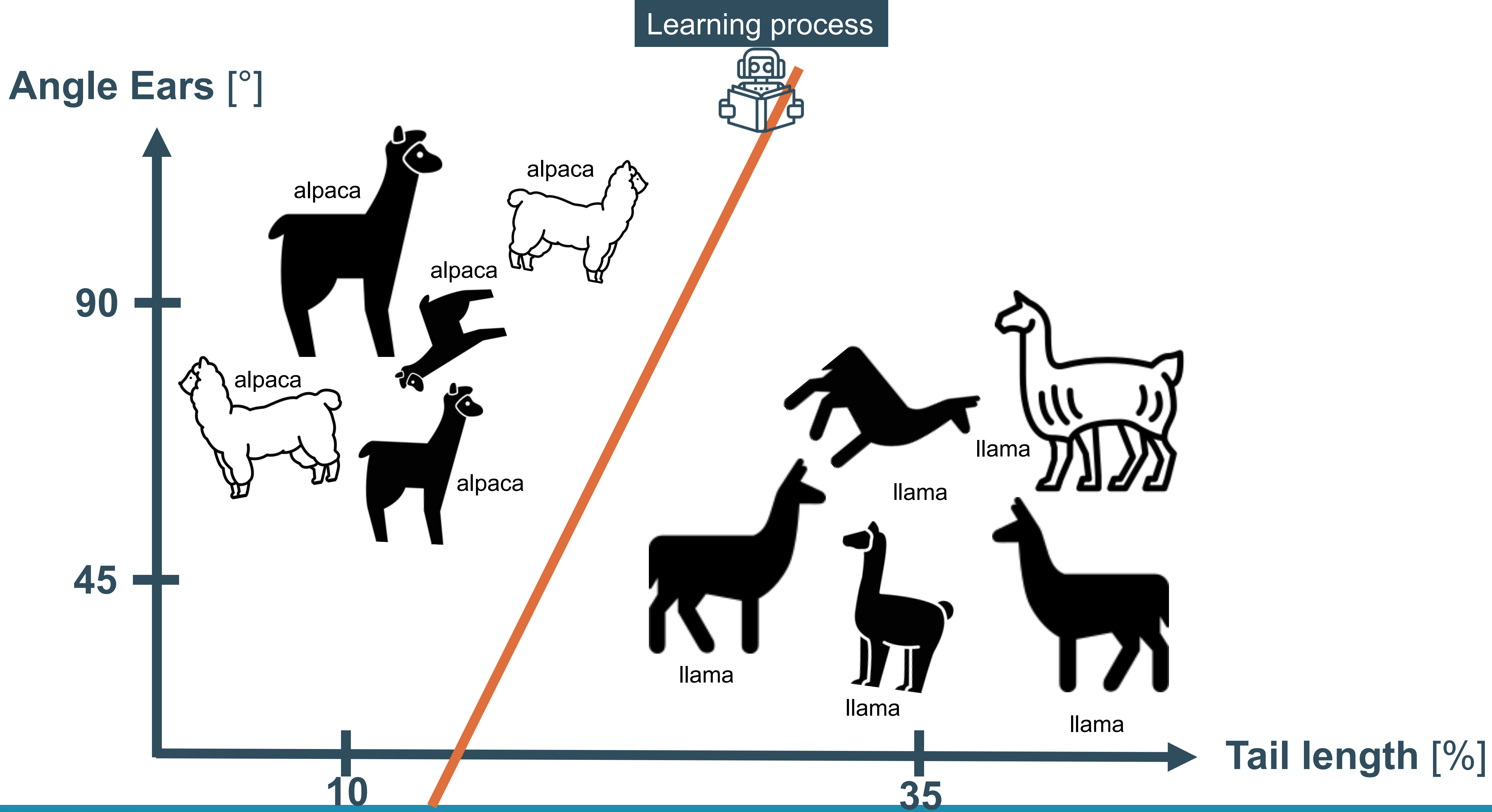
Learning process

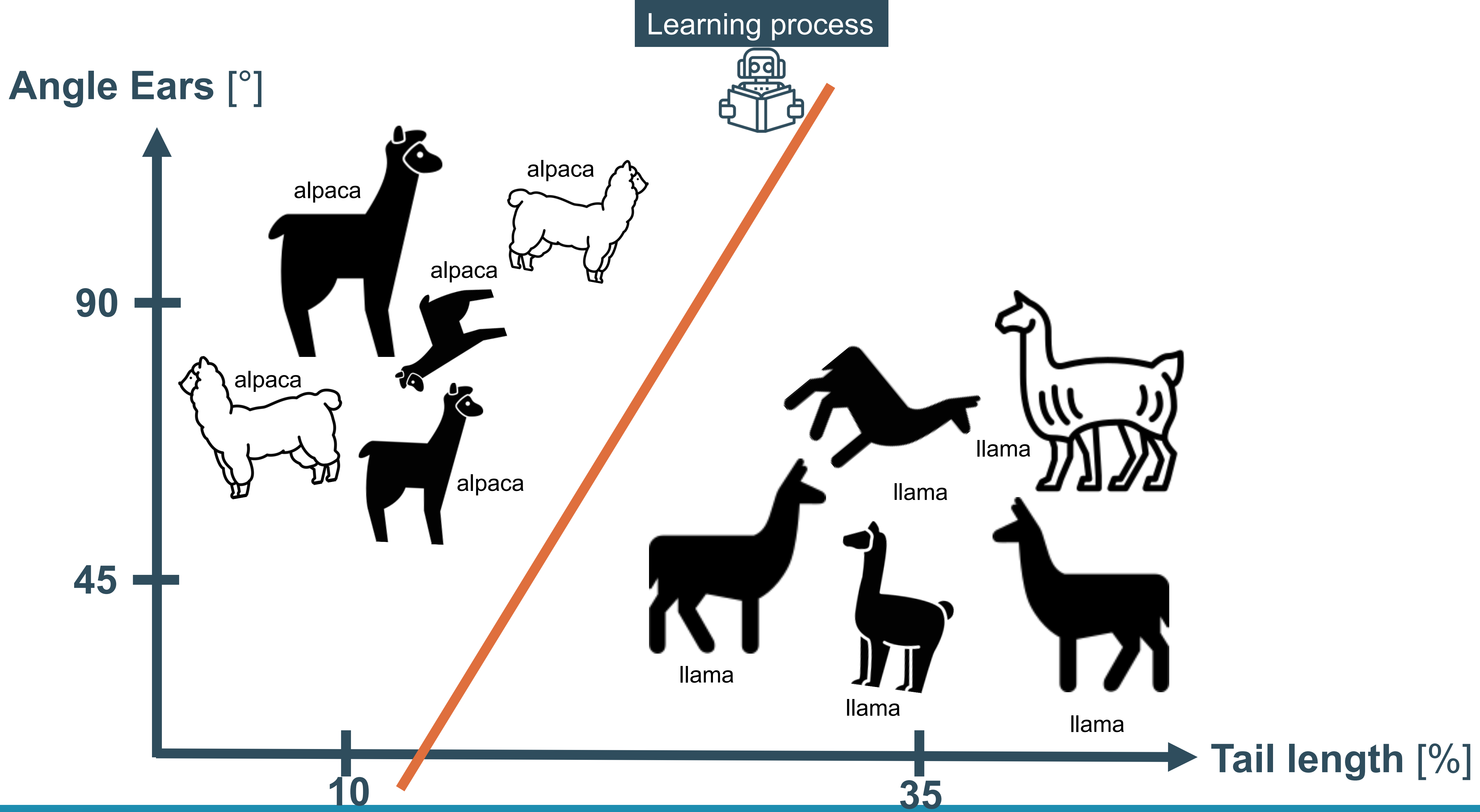


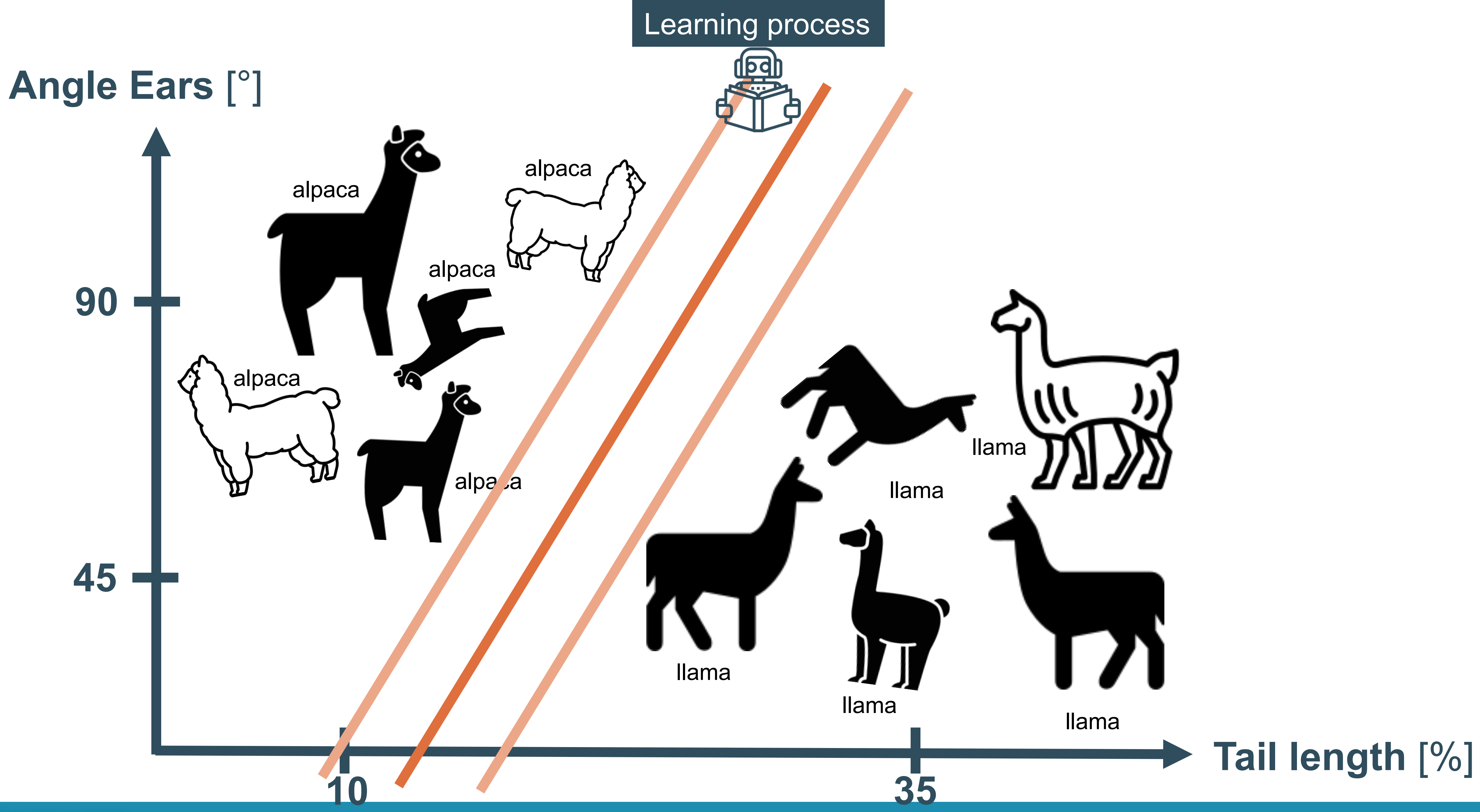

Learning process
Angle Ears [°]
90
45
alpaca
alpaca
alpaca
alpaca
alpaca
llama
llama
llama
llama
llama
Tail length [%]
10
35



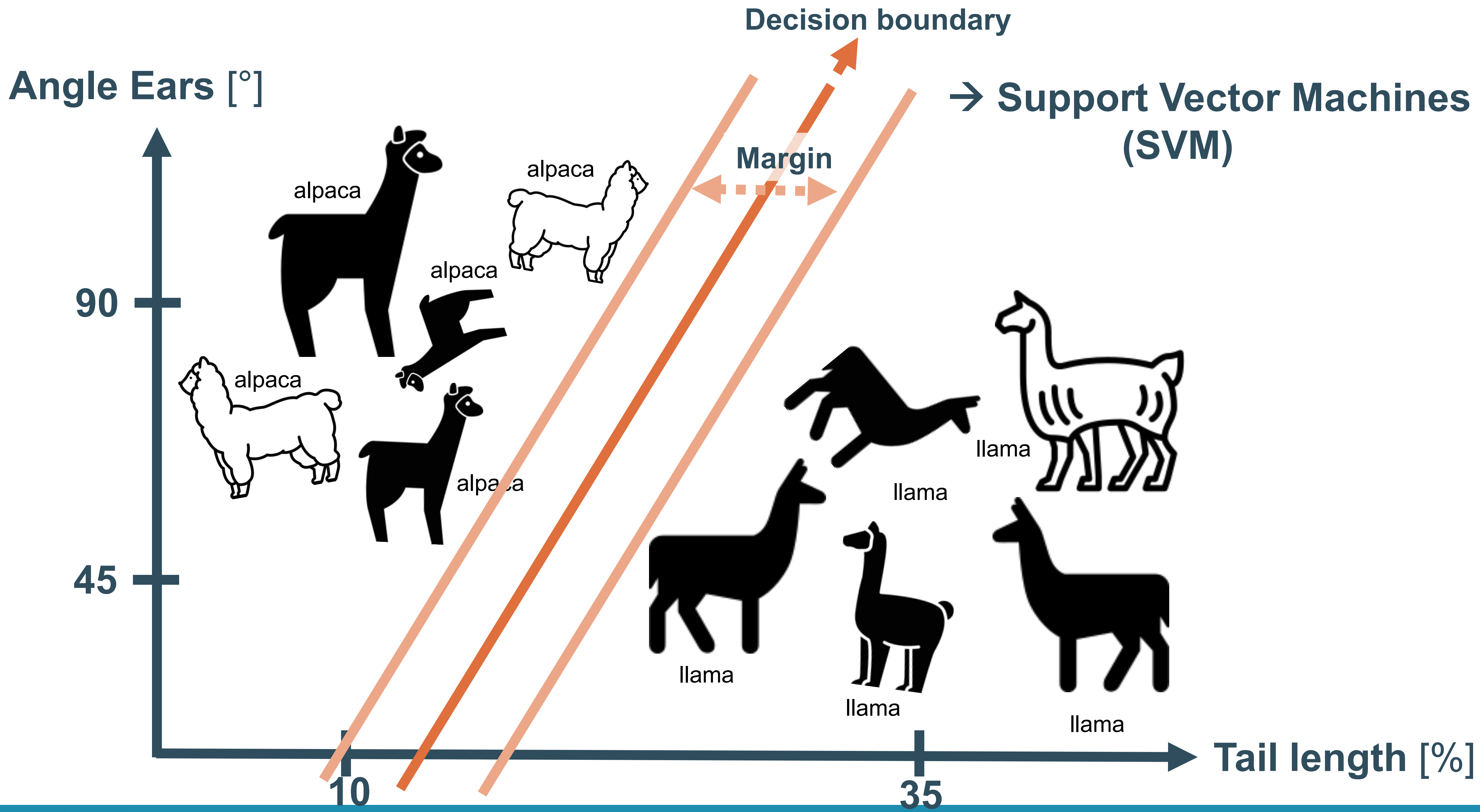
Learning process
Angle Ears [°]
90
45
alpaca
alpaca
alpaca
alpaca
alpaca
llama
llama
llama
llama
llama
10
35
Tail length [%]

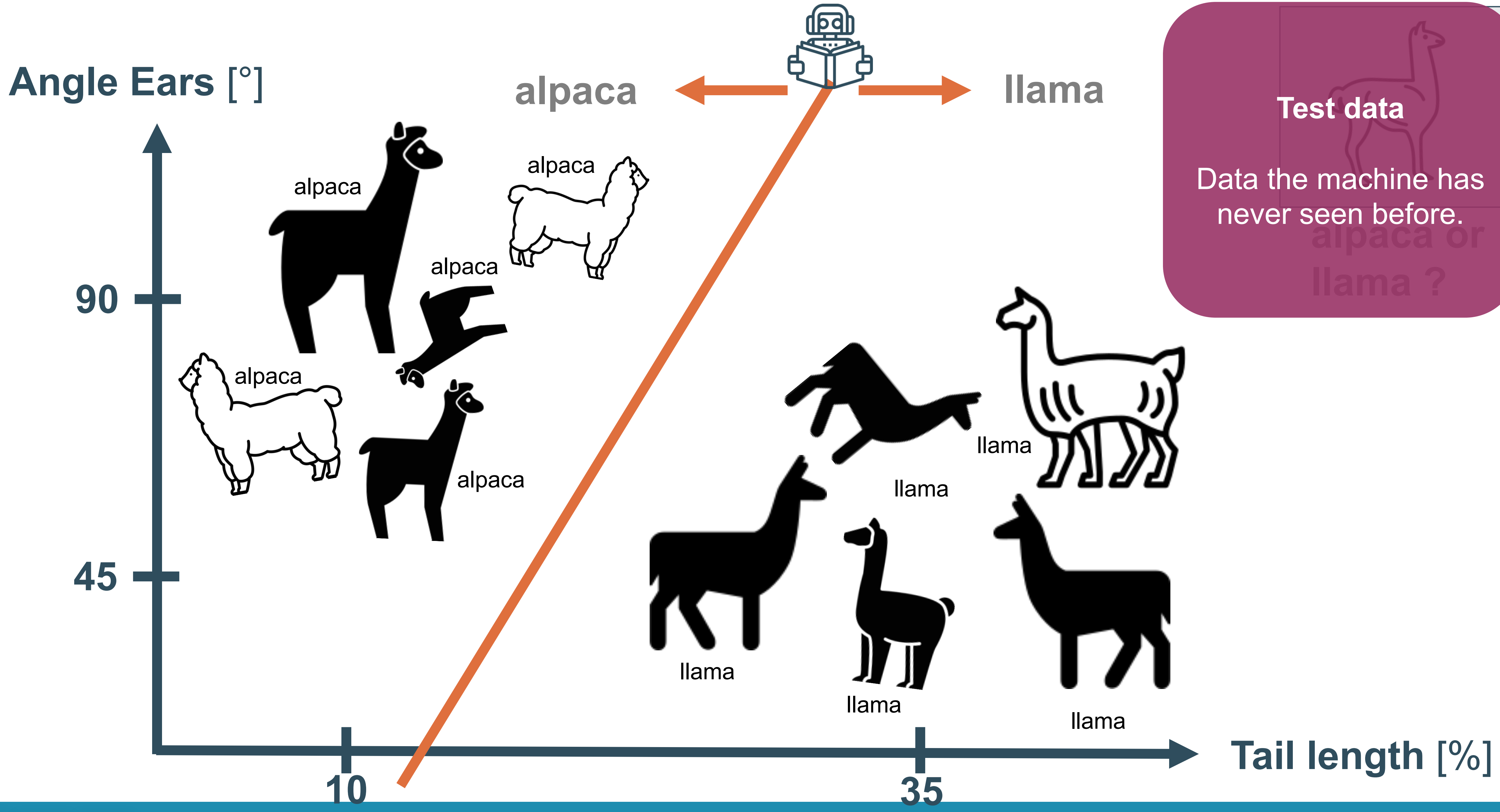

Learning process
Angle Ears [°]
90
45
alpaca
alpaca
alpaca
alpaca
alpaca
llama
llama
llama
llama
llama
10
35
Tail length [%]


Learning process
Angle Ears [°]
90
45
alpaca
alpaca
alpaca
alpaca
alpaca
llama
llama
llama
llama
llama
Tail length [%]
10
35


Learning process
Angle Ears [°]
90
45
alpaca
alpaca
alpaca
alpaca
alpaca
llama
llama
llama
llama
llama
10
35
Tail length [%]

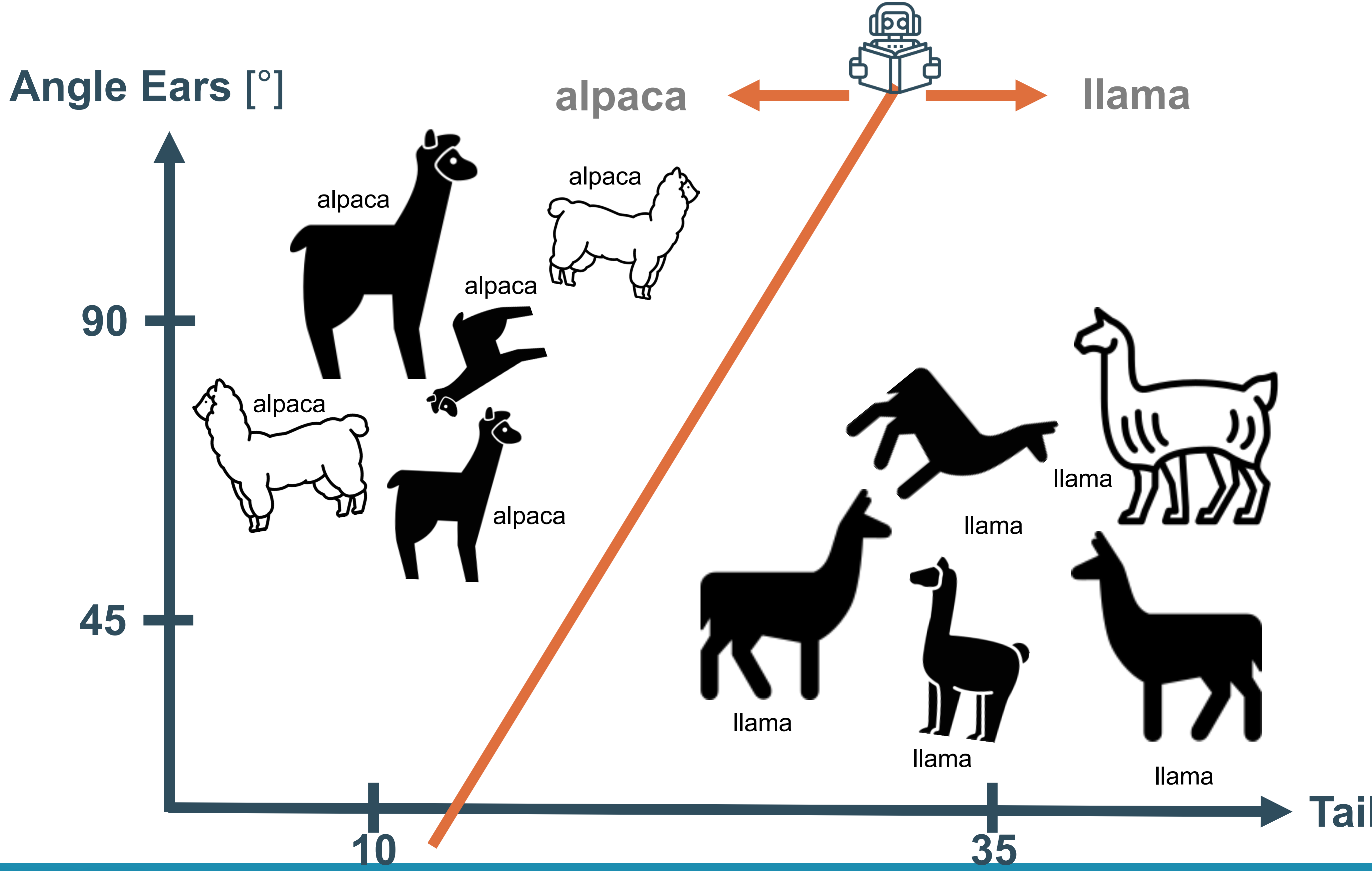
→ Support Vector Machines (SVM)

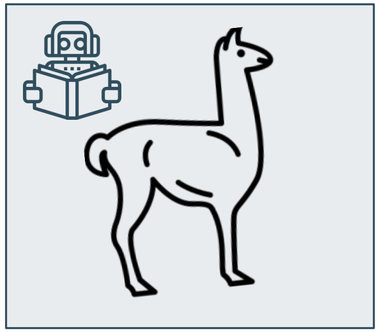




Test data

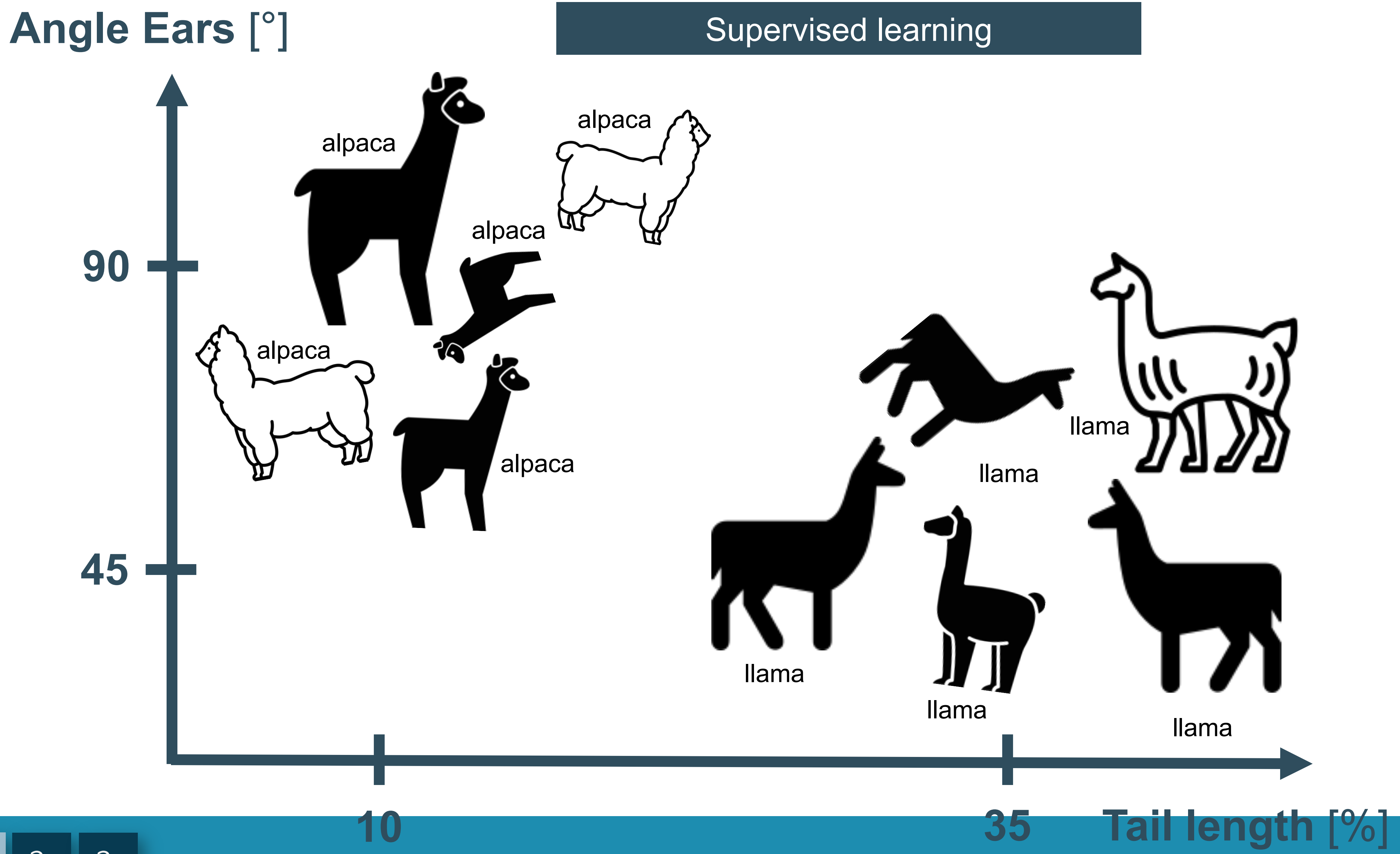
Data the machine has never seen before.



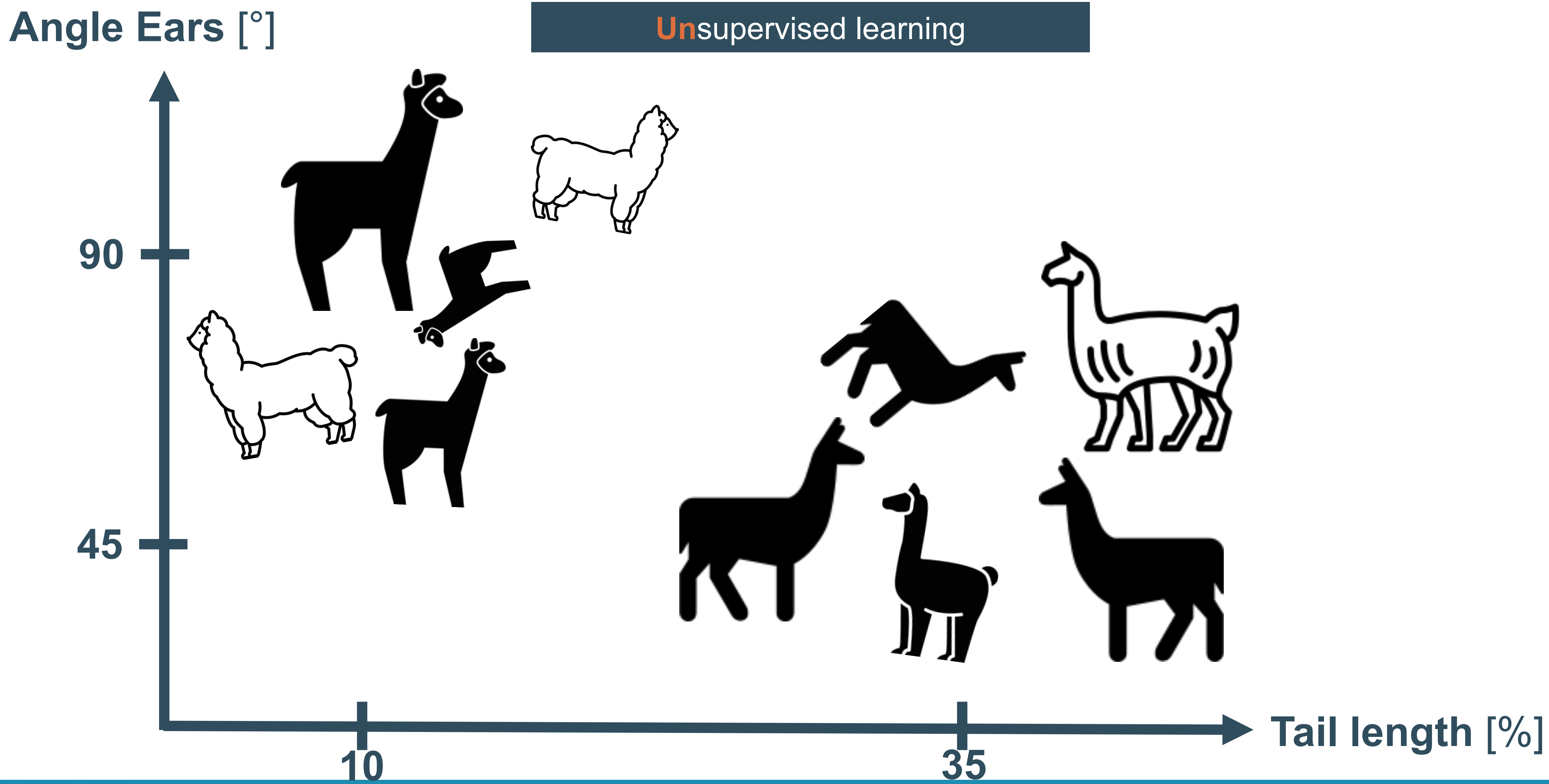


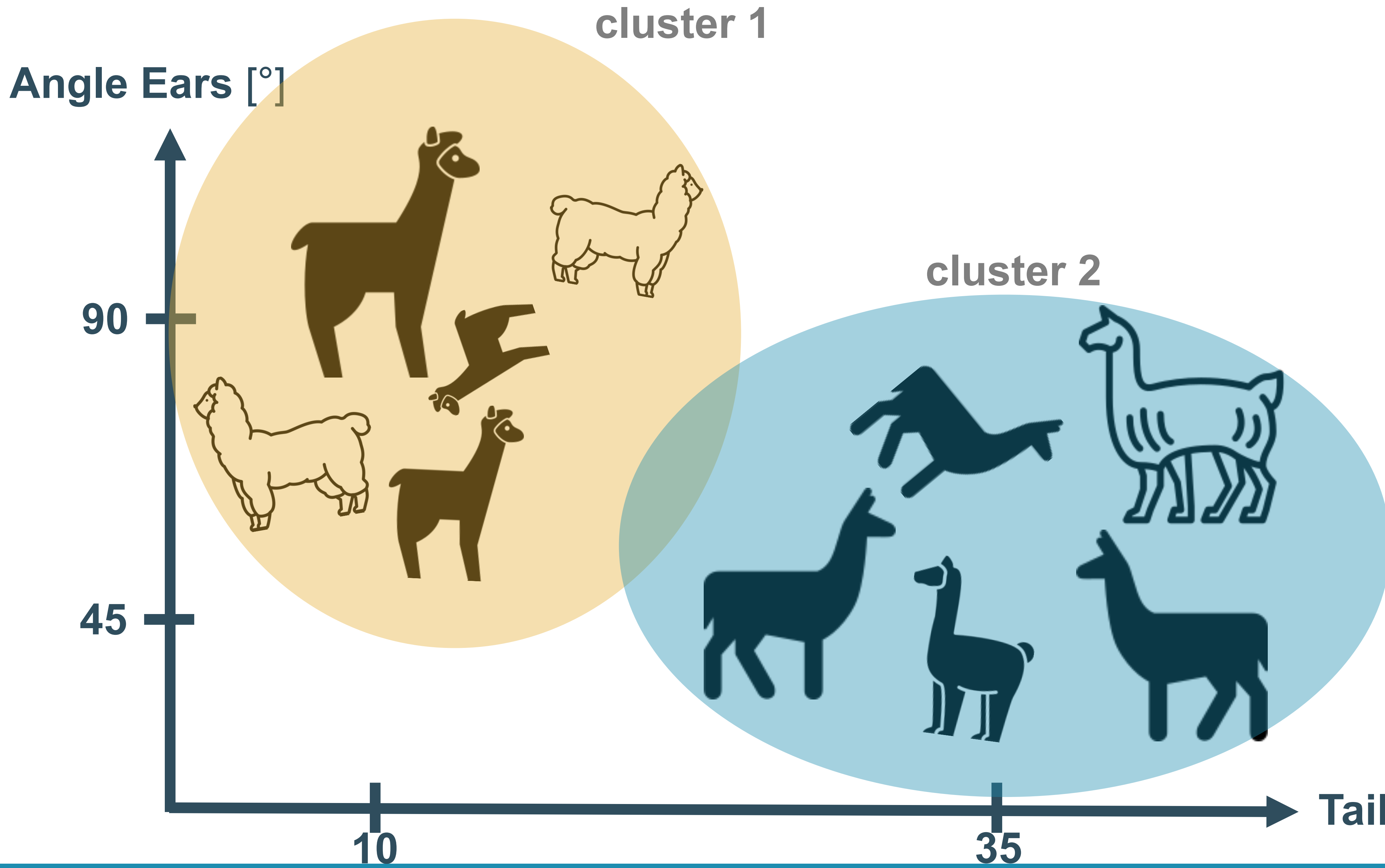
alpaca or llama ?

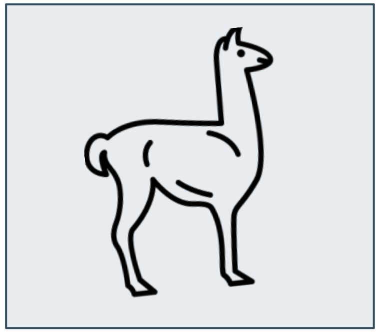
Supervised learning



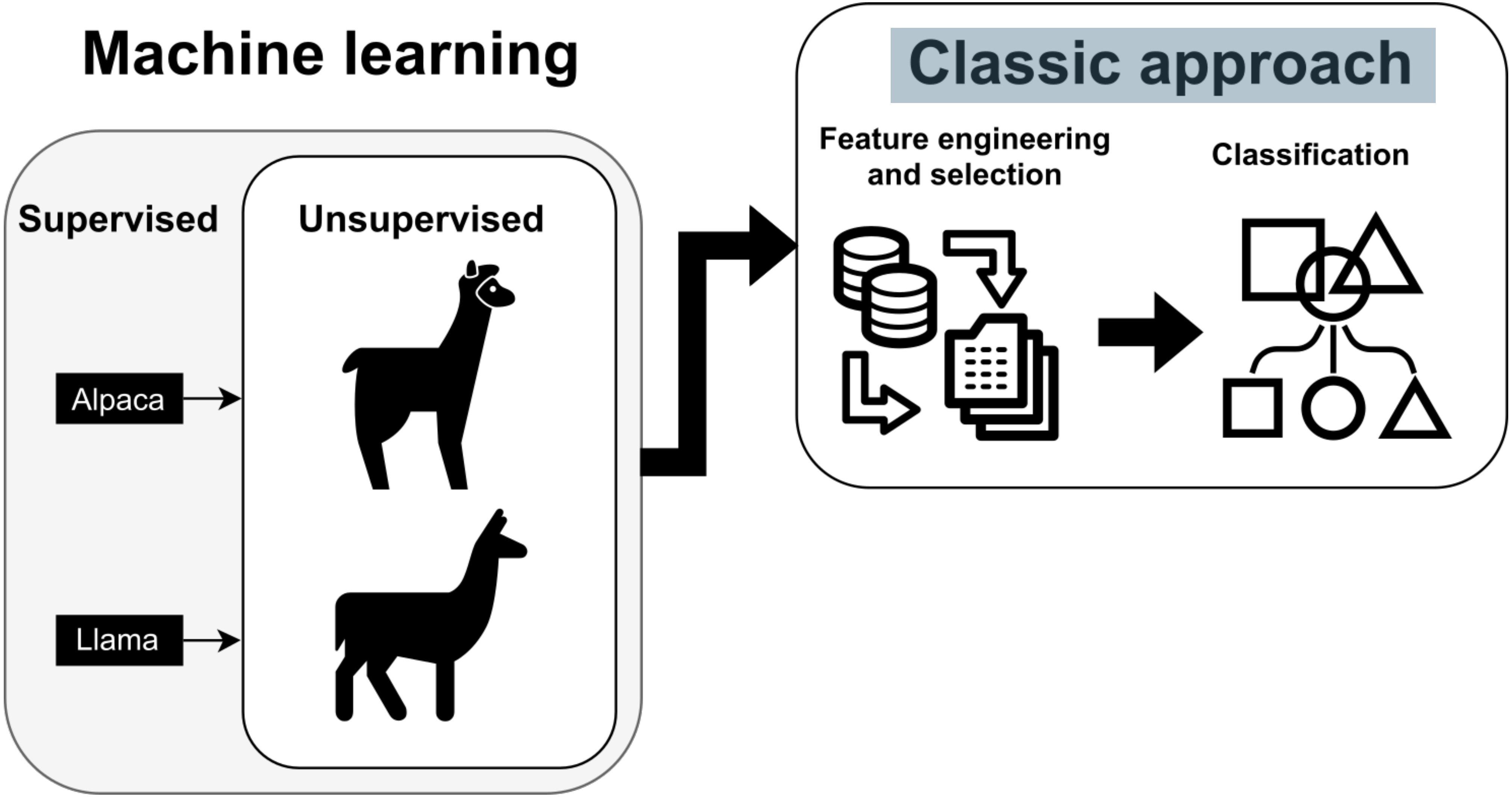
Unsupervised learning



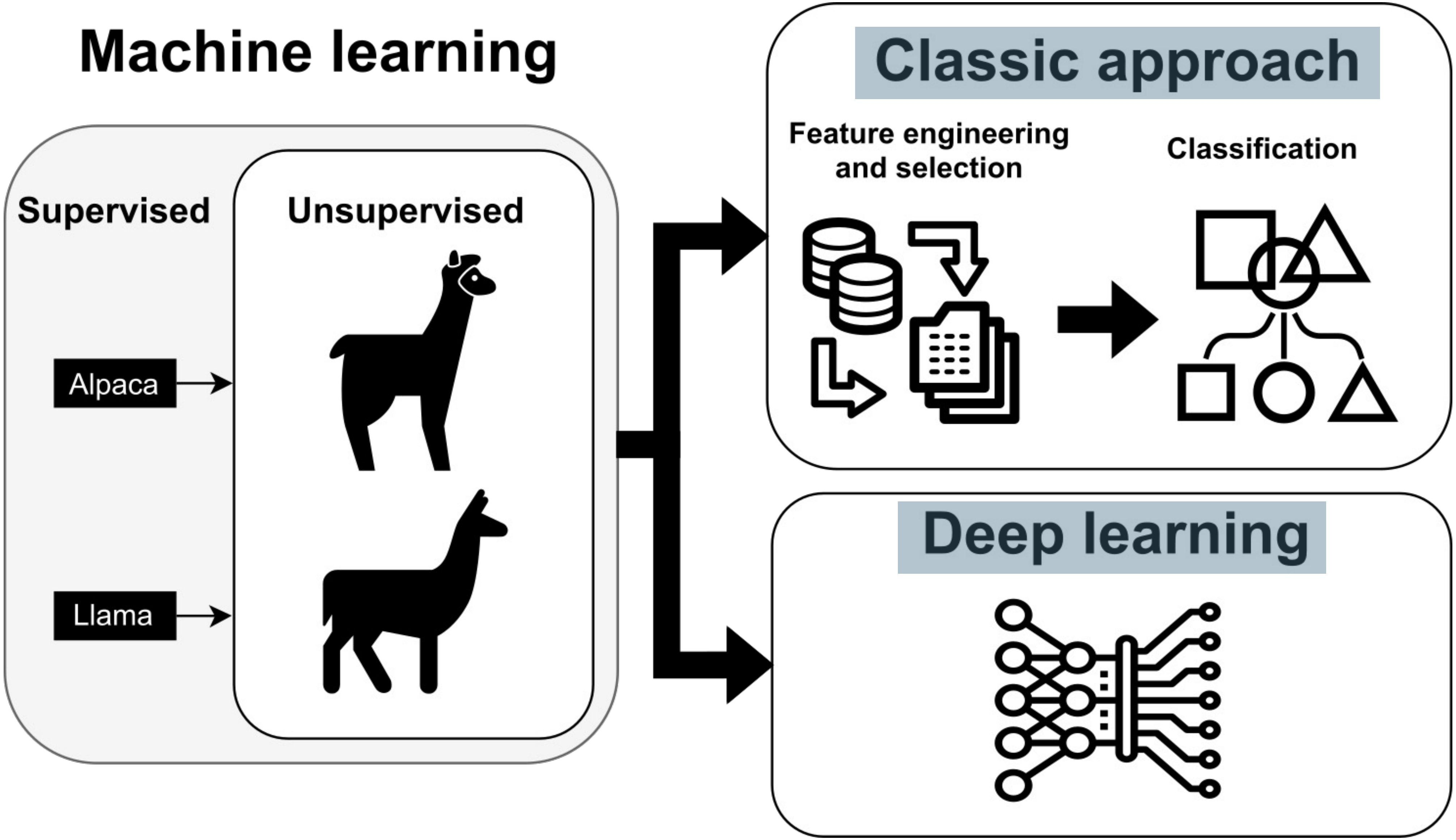




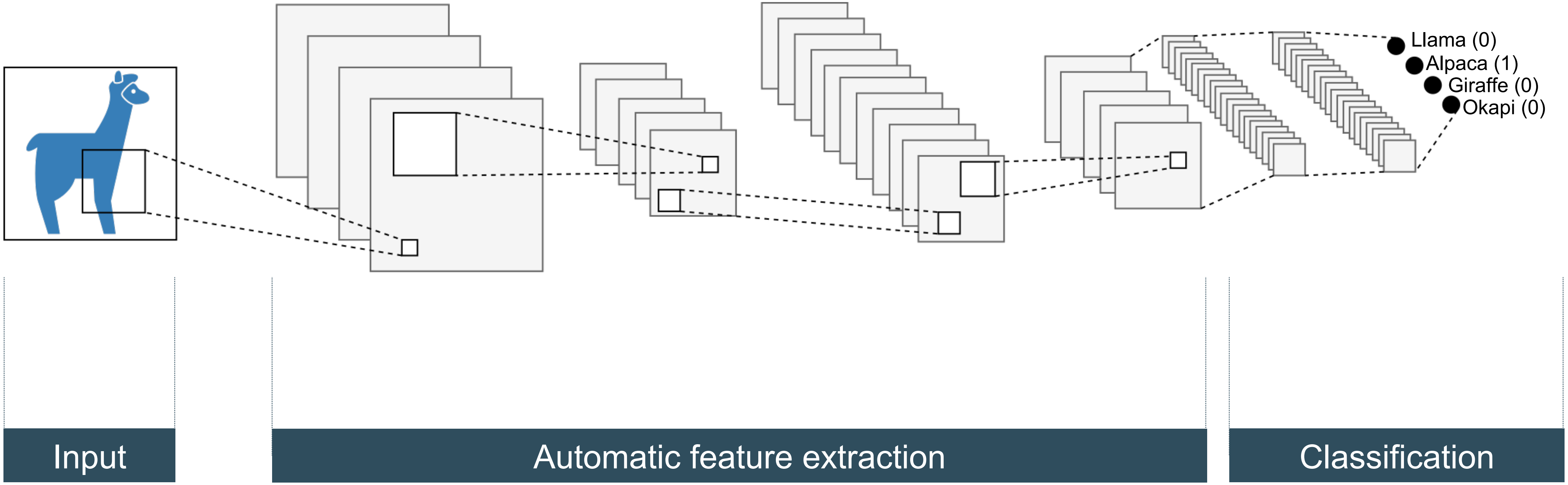
cluster 1 or cluster 2 ?


Machine learning
Supervised
Unsupervised
Alpaca
Llama
Classic approach
Feature engineering and selection
Classification

Machine learning



Deep Learning using convolutional neural networks (CNN)



Contents Overview

| Cancer Diagnostics

UZ Leuven departments

Imaging & Pathology

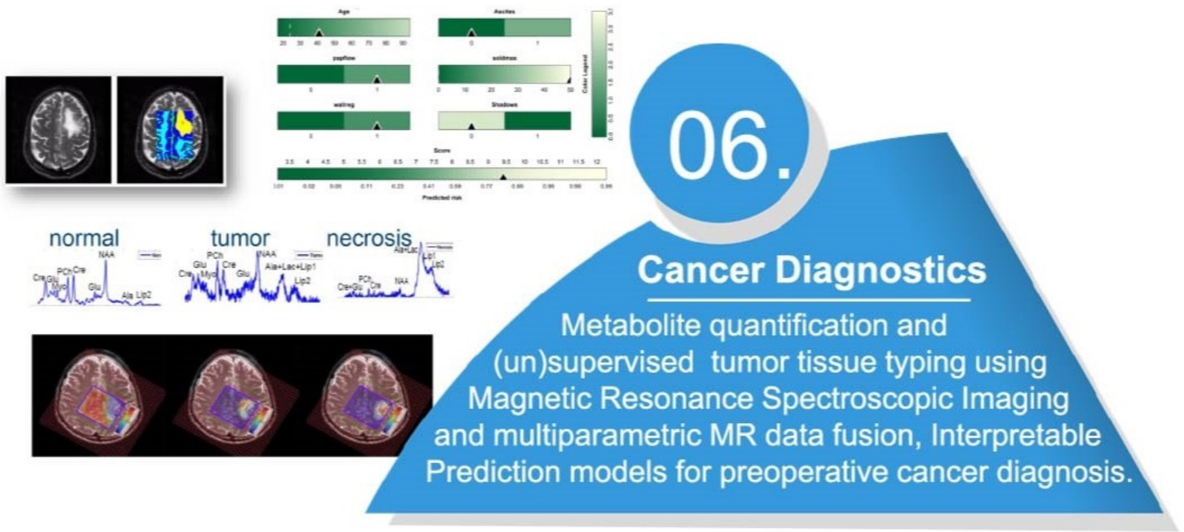
Radiology

Neurosurgery

Development and Regeneration

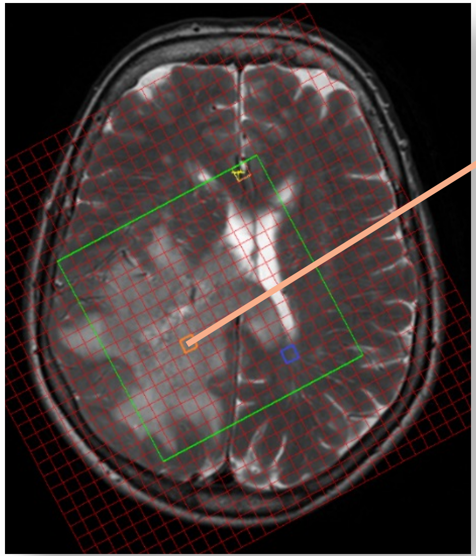
UZ Gent department

Radiology

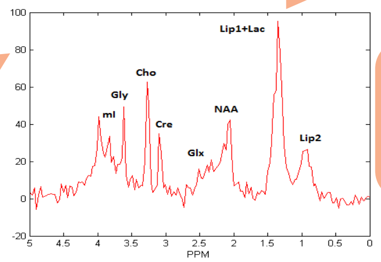


EXAMPLE

Unsupervised tissue type differentiation: Blind Source Separation for MRSI data



MRSI

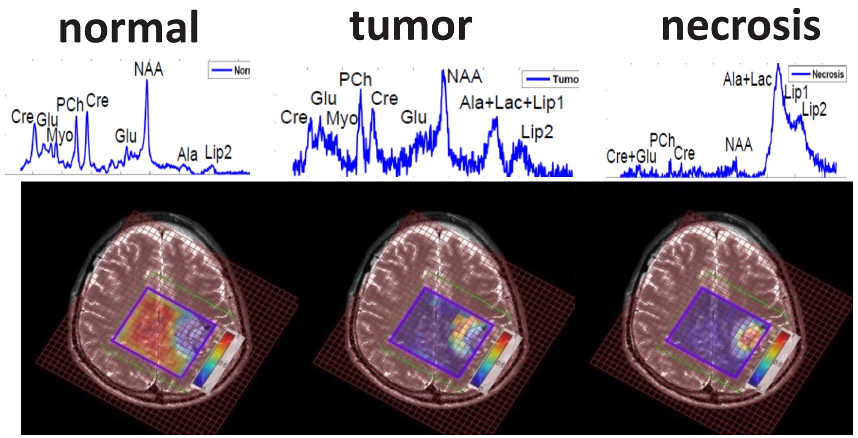


X = matrix of spectra, $X \approx W H$

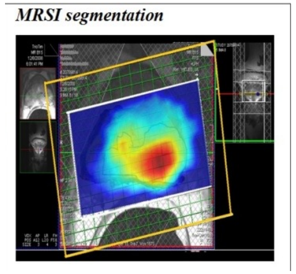
$$\min \| X - W H \| \quad \text{such that } W \geq 0, H \geq 0$$

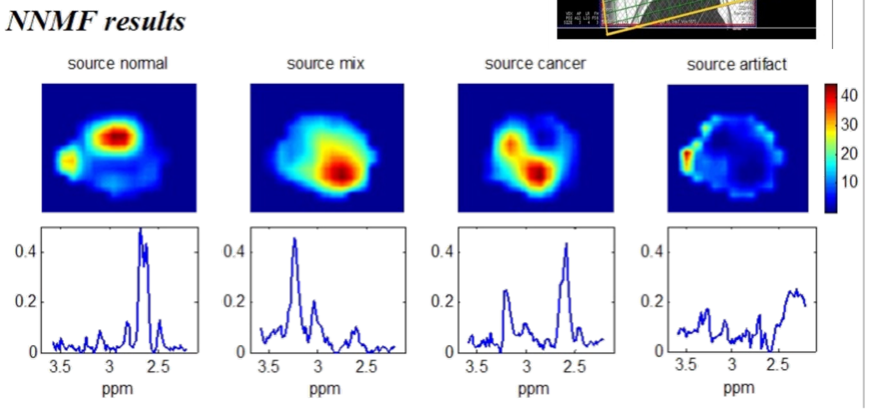
non-negative matrix/tensor factorization

Brain tumor tissue typing



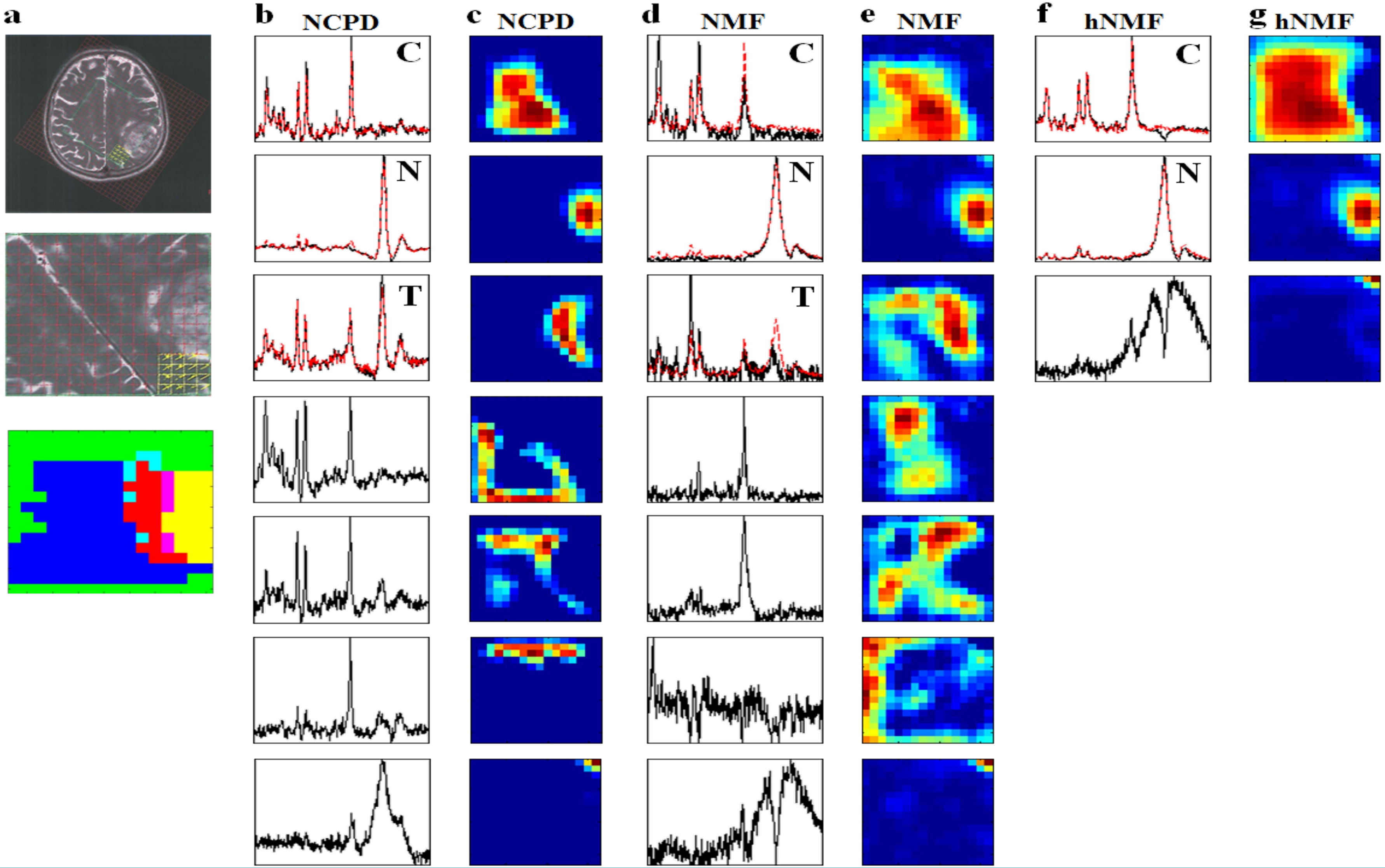
Prostate segmentation





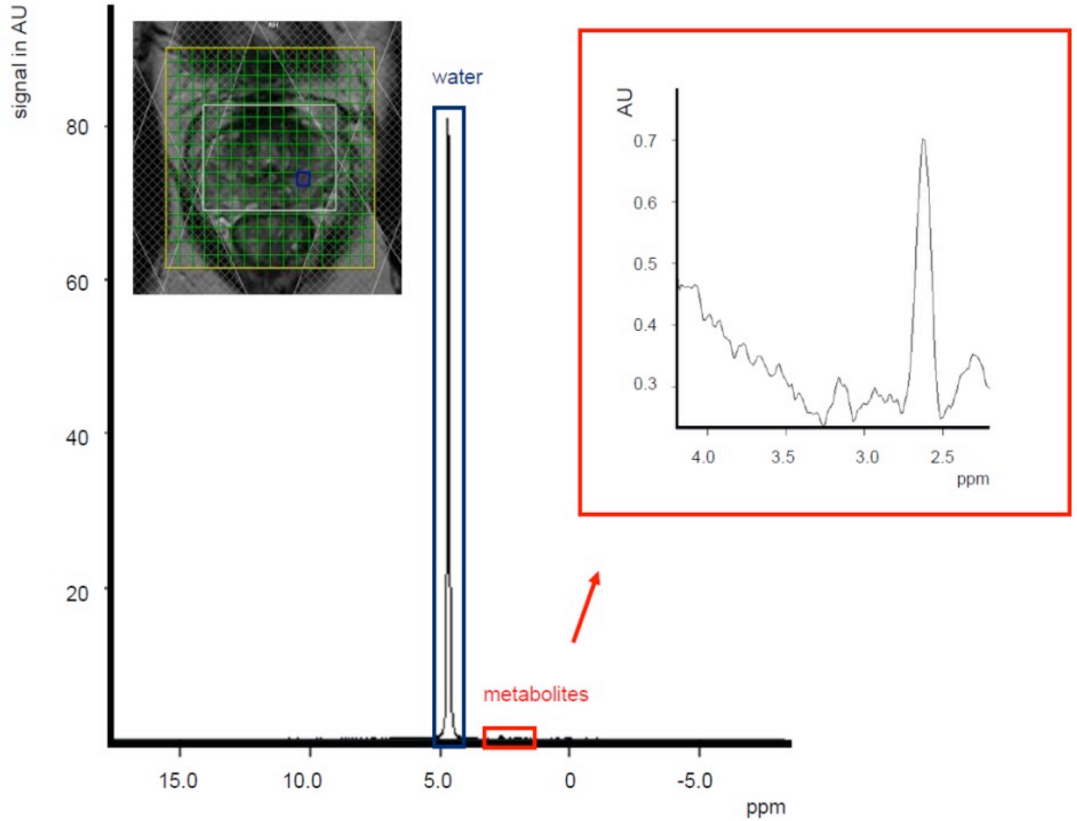
Sauwen N., Acou M., Bharath H.N., Sima D., Veraart J., Maes F., Himmelreich U., Achten E., Van Huffel S., The successive projection algorithm as an initialization method for brain tumor segmentation using nonnegative matrix factorization, *PLOS ONE*, vol. 12, Aug. 2017, pp. 1-17

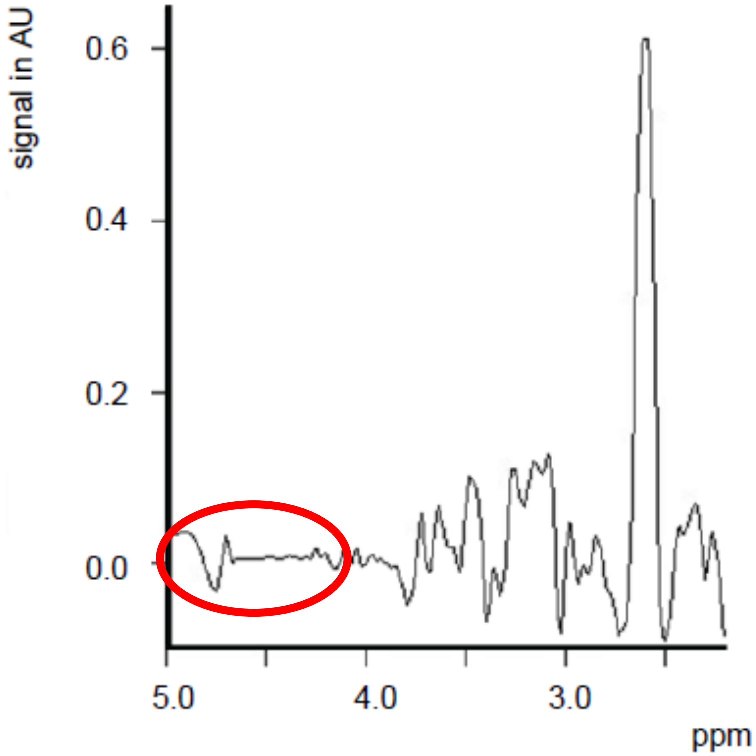
Brain tumor recognition using Non-negative CPD



Bharath H.N., Sima D.M., Sauwen N., Himmelreich U., De Lathauwer L., Van Huffel S., Non-Negative Canonical Polyadic Decomposition for Tissue Type Differentiation in Gliomas, *IEEE Journal of Biomedical and Health Informatics*, vol. 21, no. 4, Jul. 2017, pp. 1124-1132

Tensor based water suppression in MRSI





Frequency domain Model

$$S(f) = \sum_{r=1}^{R} \frac{a_r e^{j\phi_r}/2\pi}{d_r + j2\pi(f - f_r)} + \eta(f)$$

$$S = WH^T$$

Time domain Model

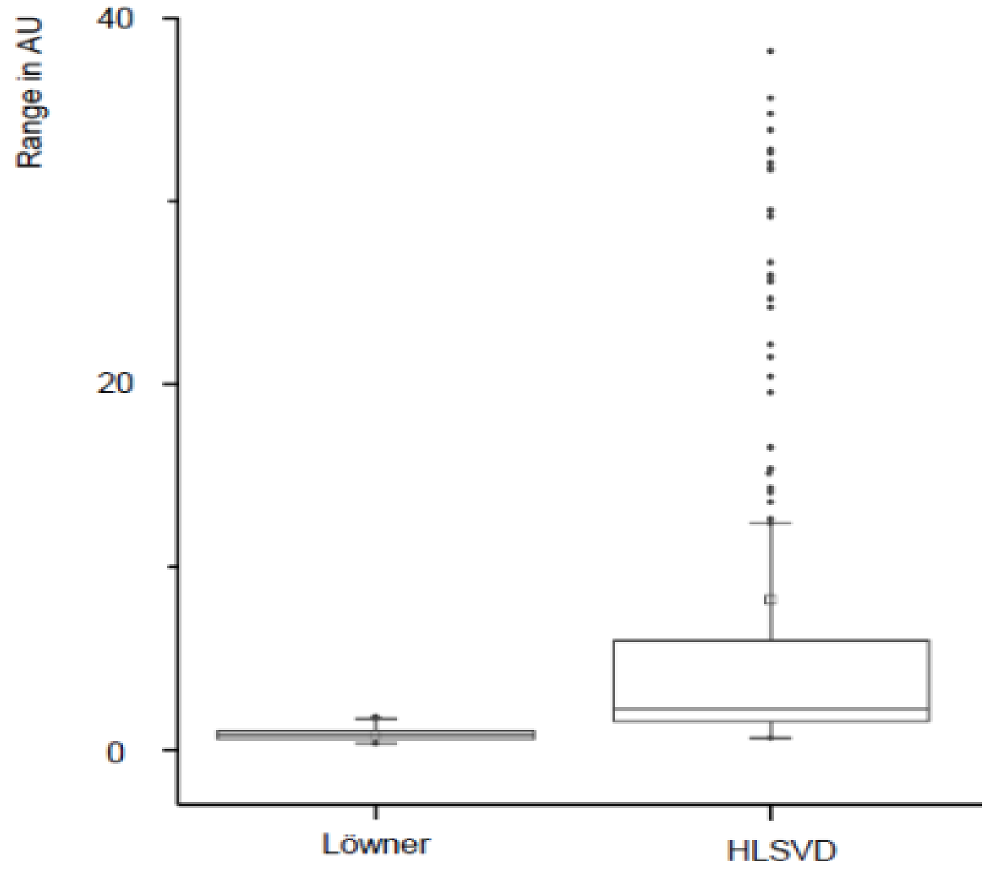
$$S(t) = \sum_{r=1}^{R} a_r e^{j\phi_r} e^{(-d_r + j2\pi f_r)t} + \eta(t)$$

Löwner Tensor → **ALL voxels** (2D or 3D)

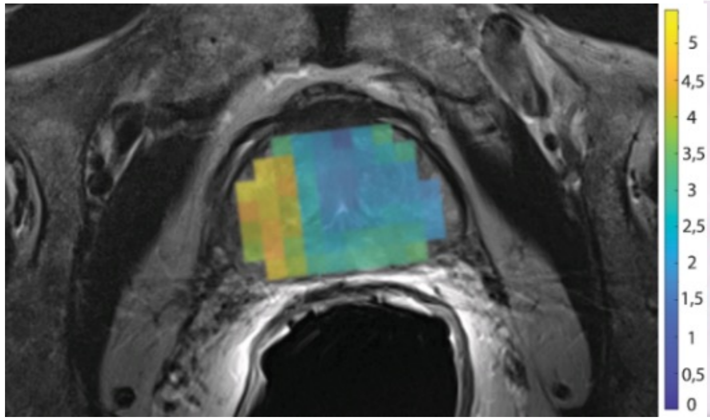
HSVD matrix based suppression → **voxel per voxel**

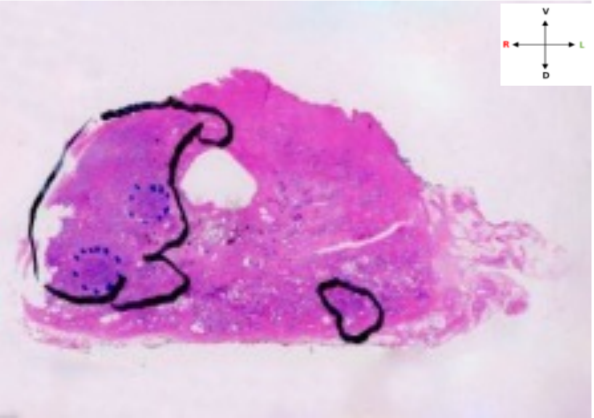
Tensor based water suppression in MRSI

Box-plot displays differences in variance in suppressed region of 306 in-vivo MRSI signals:
Tensor based BSS uses info from ALL voxels while HLSVD does it voxelwise



Metabolite maps of a patient with prostate cancer: The two tumors in peripheral prostate zone have relatively high Cho levels

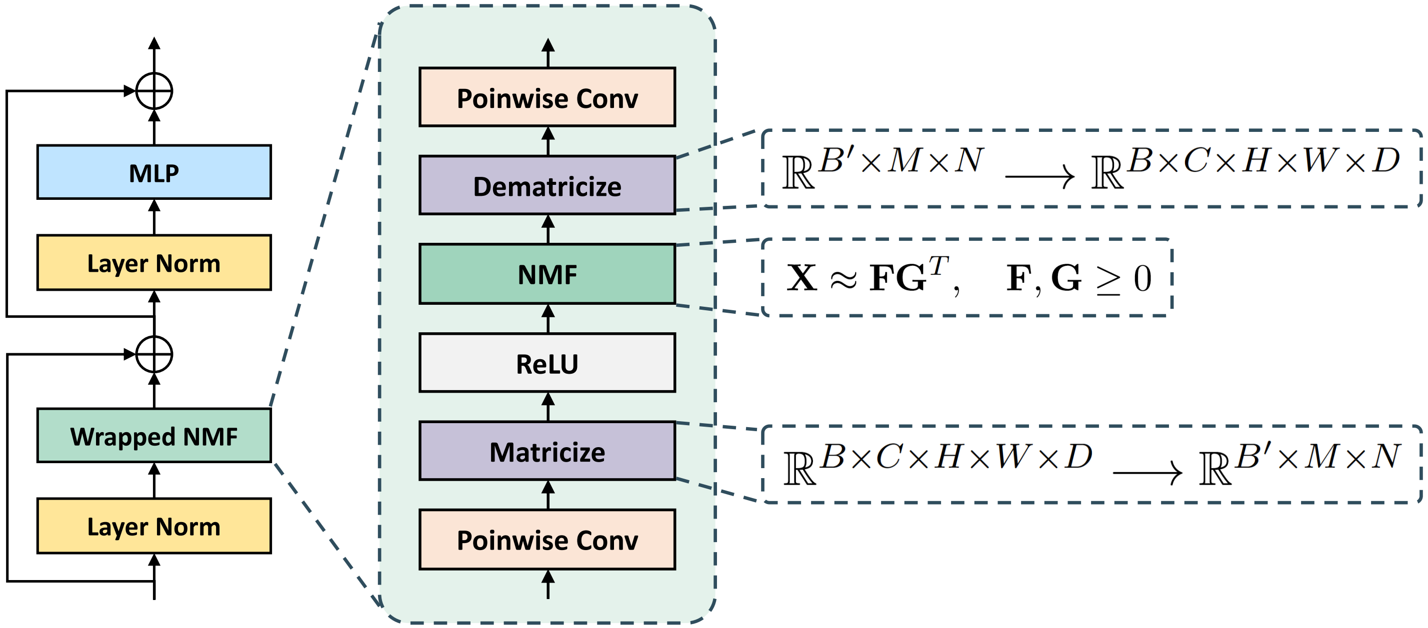




A. Stamatelatou et al, Post-acquisition water-signal removal in 3D water-unsuppressed 1H-MR Spectroscopic Imaging of the prostate, submitted to MRM, 2022.

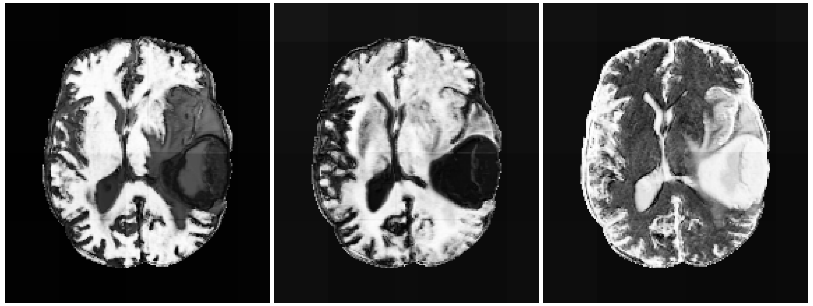
Factorizer: Interpretable Approach to Brain Tumor Segmentation

Factorizer Block

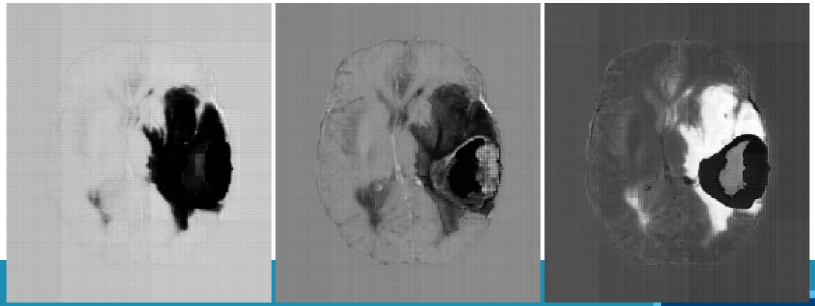


Interpretability

Ground Truth

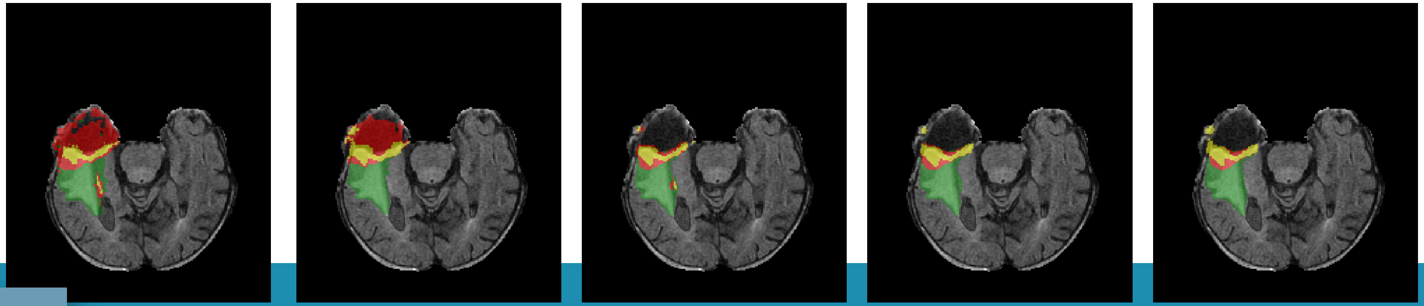


Shallowest NMF Layer Components



Deepest NMF Layer Components

Qualitative Results



Ground Truth | Factorizer | Transformer | Res-U-Net | U-Net

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P. Ashtari et al, Factorizer: A Scalable Interpretable Approach to Context Modeling for Medical Image Segmentation, submitted to Medical Image Analysis 2022

European Research Council
Established by the European Commission

Neonatal Brain Monitoring

UZ Leuven departments:

Neonatology

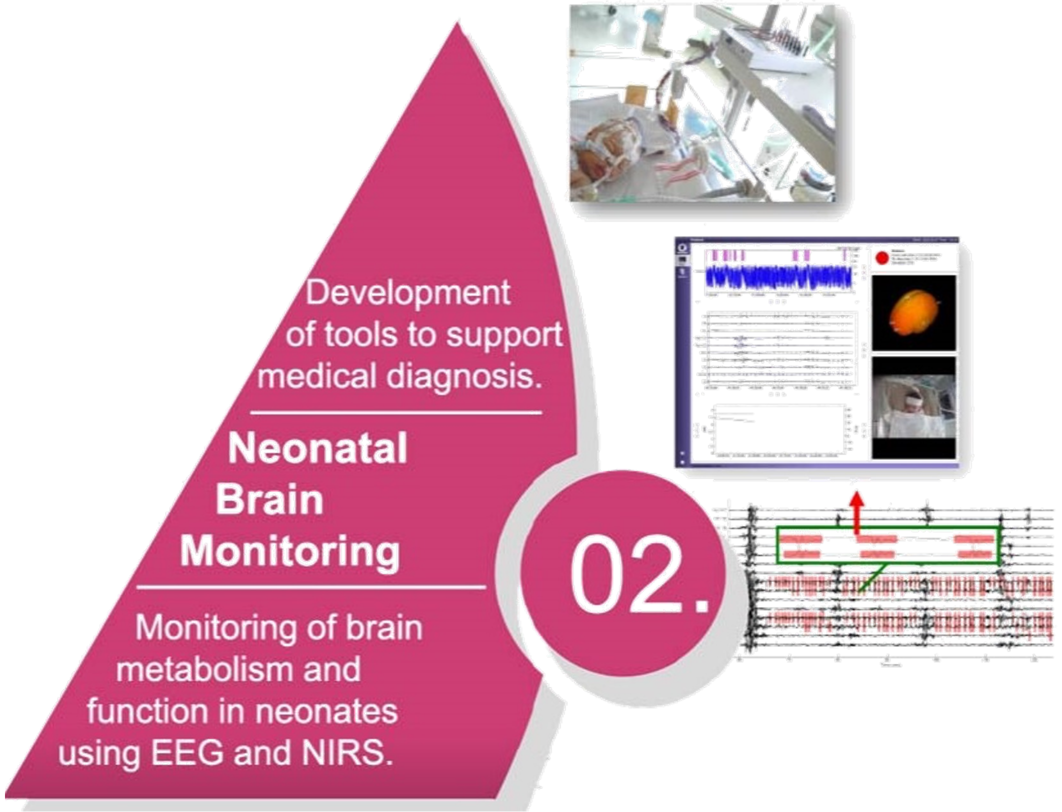
Pediatric neurology

Eindhoven University of Technology

Maxima Medical Centre

Oxford University:

Dept. of Engineering Science



EXAMPLE

Monitoring in the NICU

Development of a Neonatal EEG Monitor for Automated Brain Analysis

Neonatal brain monitoring: why?

Newborn baby is admitted at the the
Neonatal Intensive Care Unit

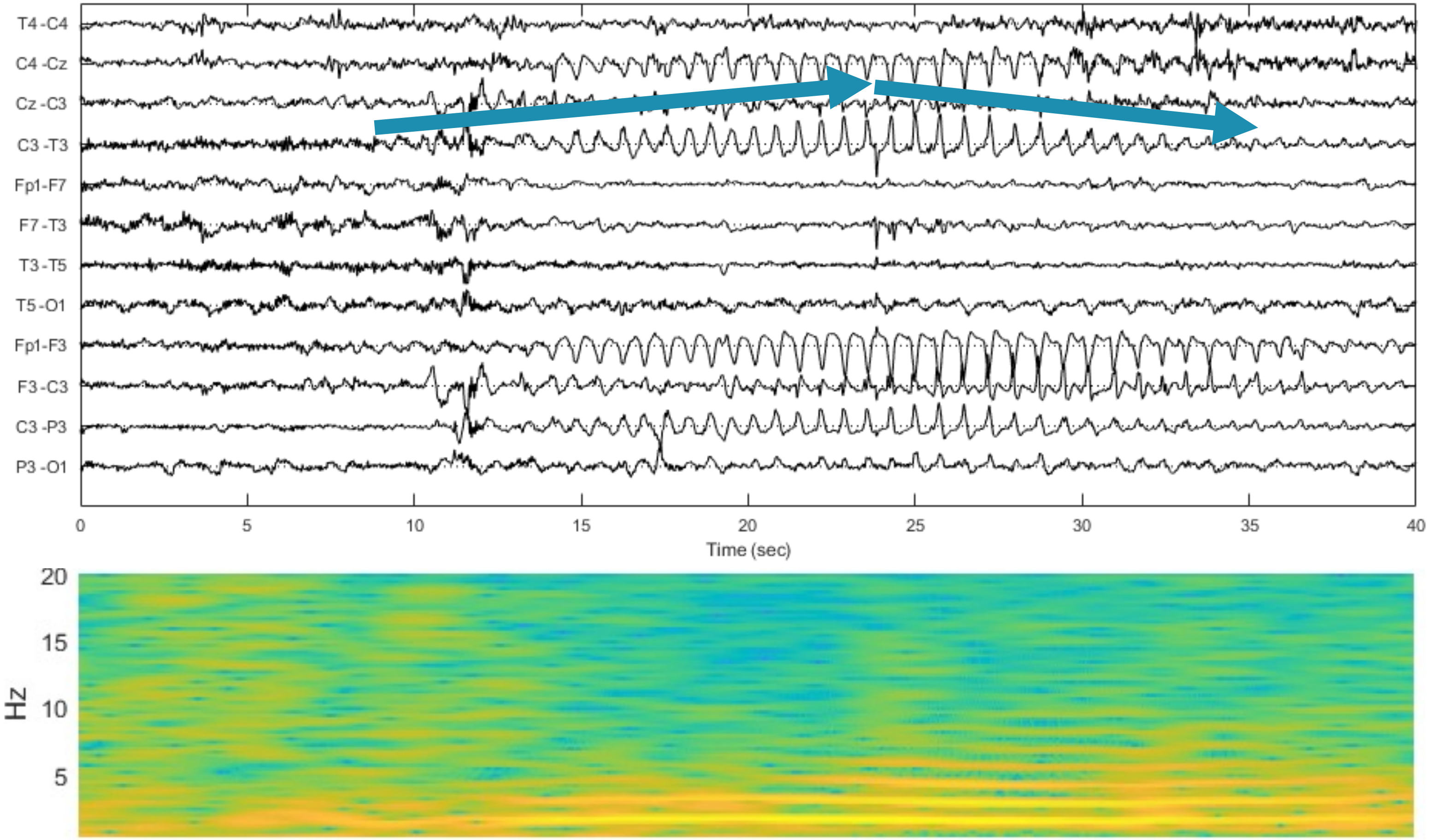
- Prematurity (24-32w): 1/8 births in USA
- Hypoxic insult: 1-6/1000 births in USA

Shortage of oxygen supply to brain (or risk):

- Brain monitoring Starts promptly !
  - Electro-EncephaloGraphy (EEG)
  - Cerebral Functional Monitoring (CFM)
  - Near-InfraRed Spectroscopy (NIRS)
- Why brain monitoring?
  - No neurological experts present 24/7
  - No MRI scans for small babies
- Limited time window for interventions
  - Therapeutic hypothermia has to start within 6 hours after birth

Neonatal Seizures

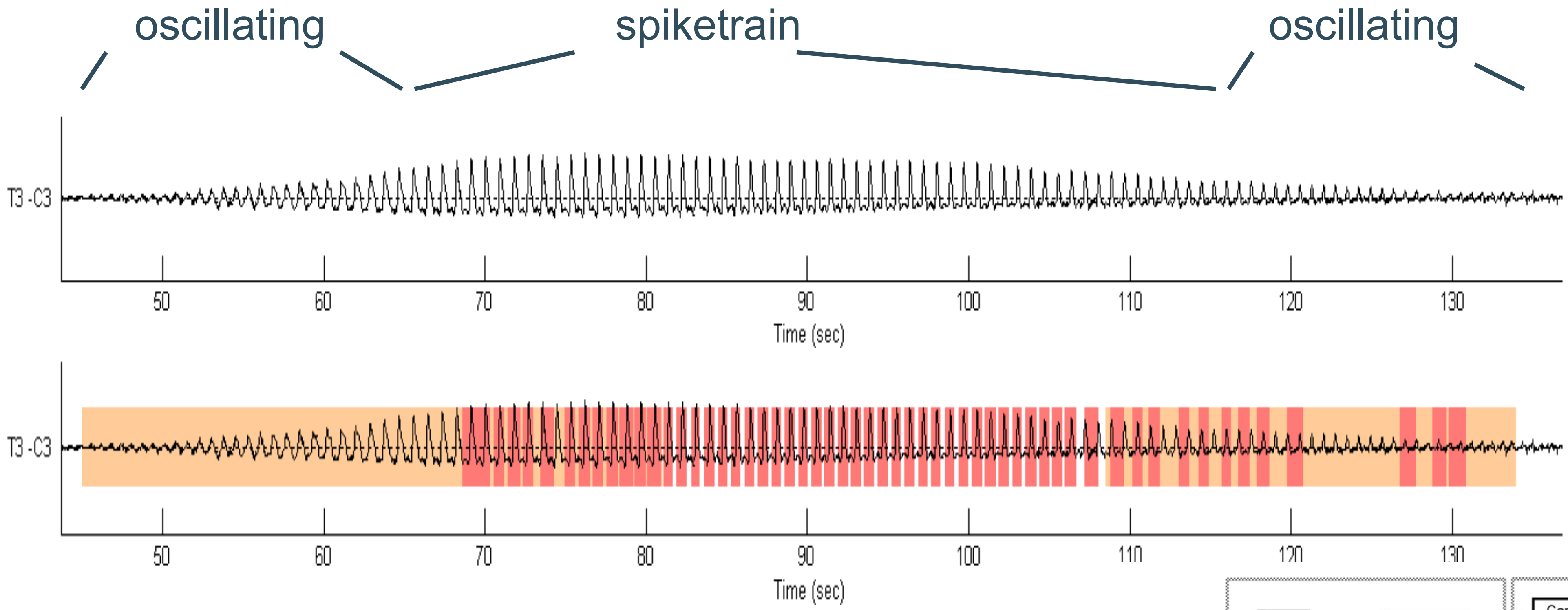
Abnormal, excessive, and synchronous neuronal activity in the brain



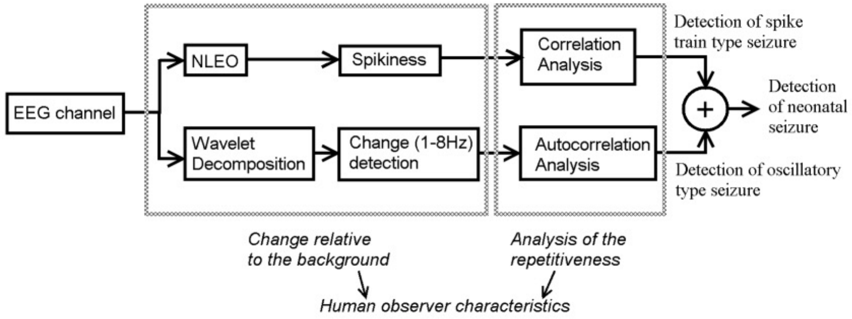
CHALLENGES: How to automate seizure detection?
→ Scoring
→ Low interrater agreement

Ansari AH et al., NeoGuard: a public, online learning platform for neonatal seizures. arXiv preprint arXiv:1905.12382. 2019 May 29.

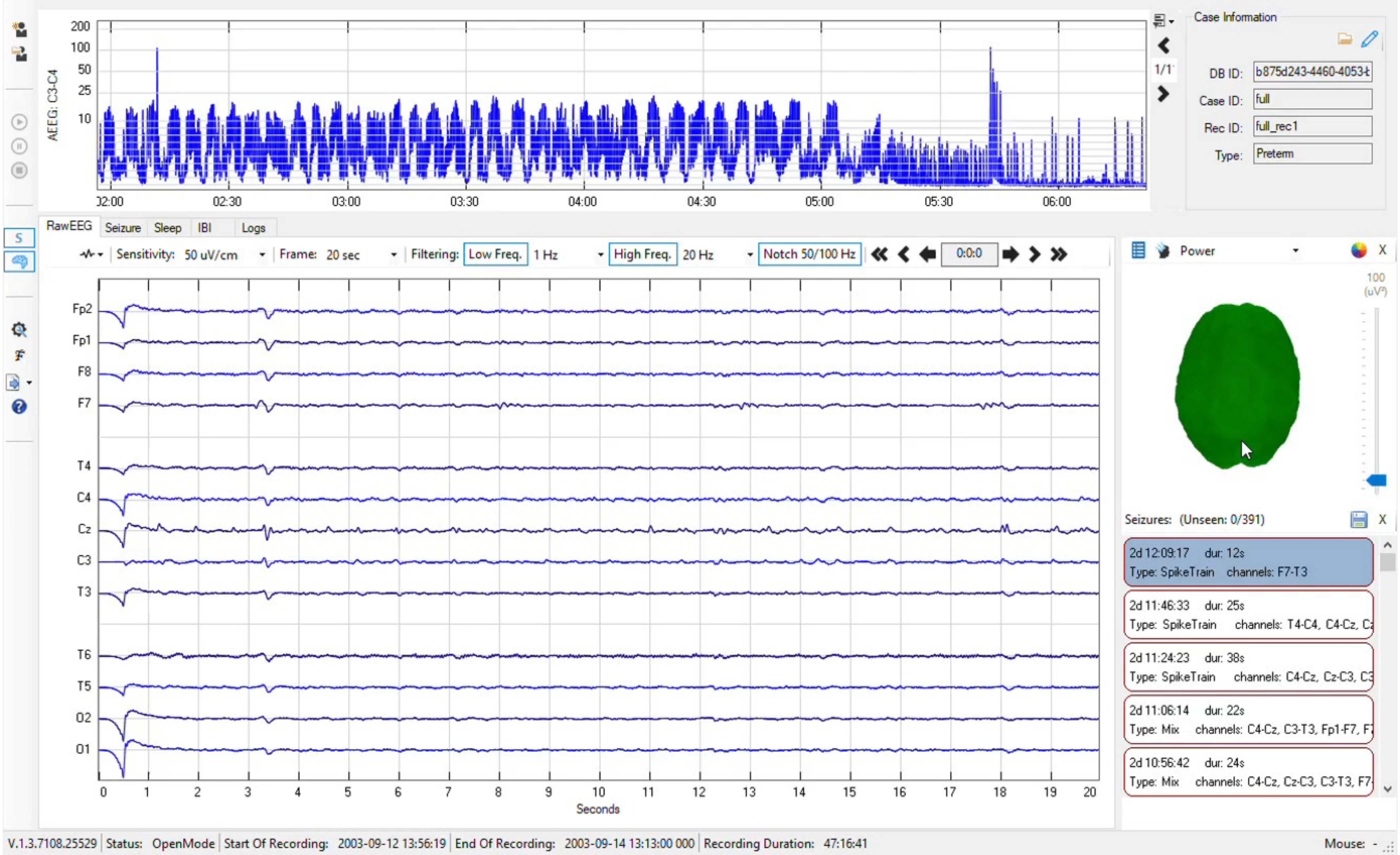
Seizure Detection: *heuristic approach*



Mimicking the neurologist: **heuristic**, feature based →



W. Deburchgraeve, PhD thesis, 2011; P.J. Cherian 2011; W. Deburchgraeve et al, Clin. Neurophys. 2008
Alternatives using classification: See pubs of Temko, G. Boylan, etc.



NeoGuard

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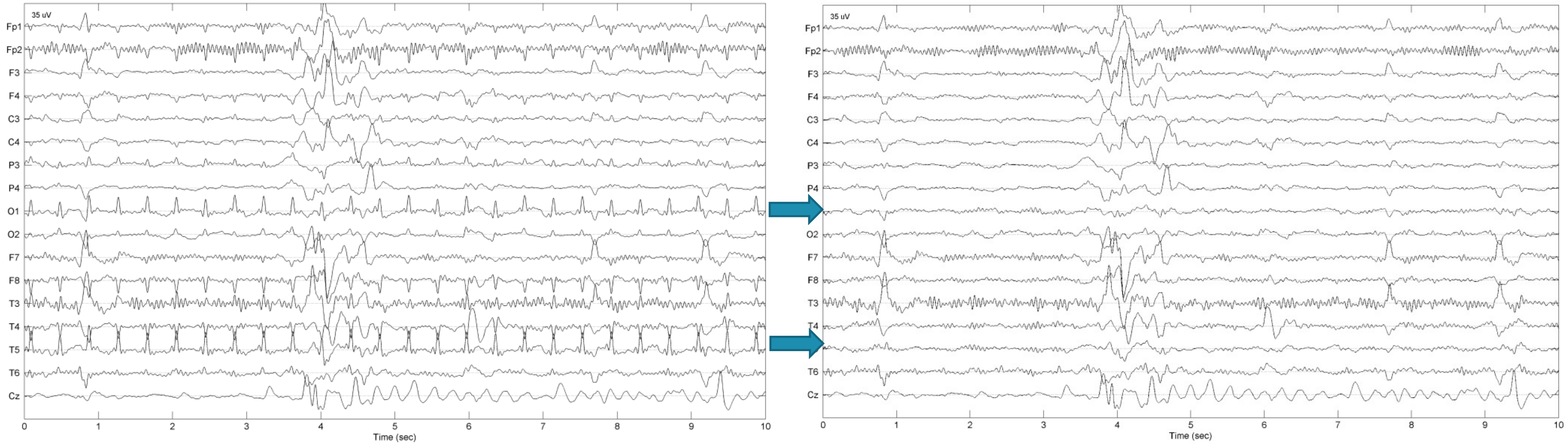
Improve Seizure Detection: *via Artefact removal*

Artefacts: ECG, respiration, blood vessel pulsation most important ones
→ lead to false positive seizure detections

→ detect & remove using **various Blind Source Separation (BSS)** methods

Note: other artefacts (eye, tremor, nonbiological, …) to be removed

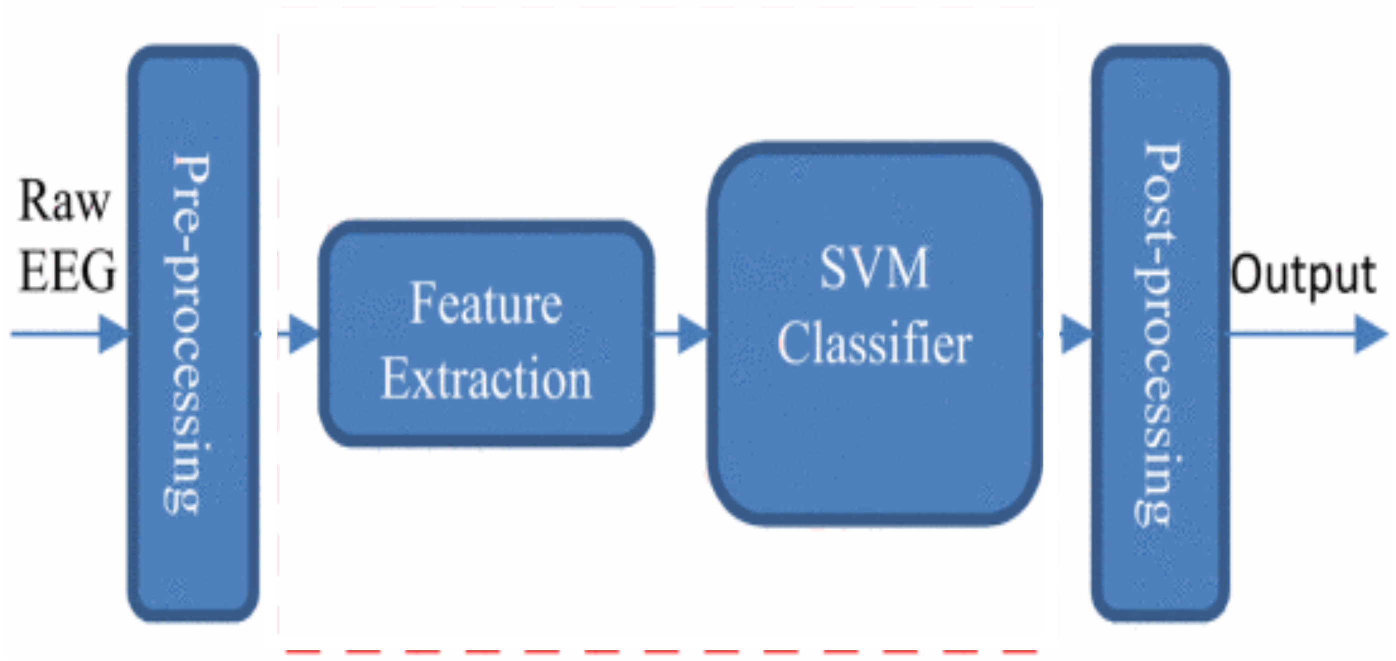
ECG spike artefact — Cleaned EEG



1. 2. 3.

De Vos M., Deburchgraeve W., Cherian P.J., Matic V., Swarte R.M., Visser G.H., Govaert P., Van Huffel S., ``Automated artifact removal as preprocessing refines neonatal seizure detection'', *Clinical Neurophysiology*, Dec. 2011, pp. 2345-2354.

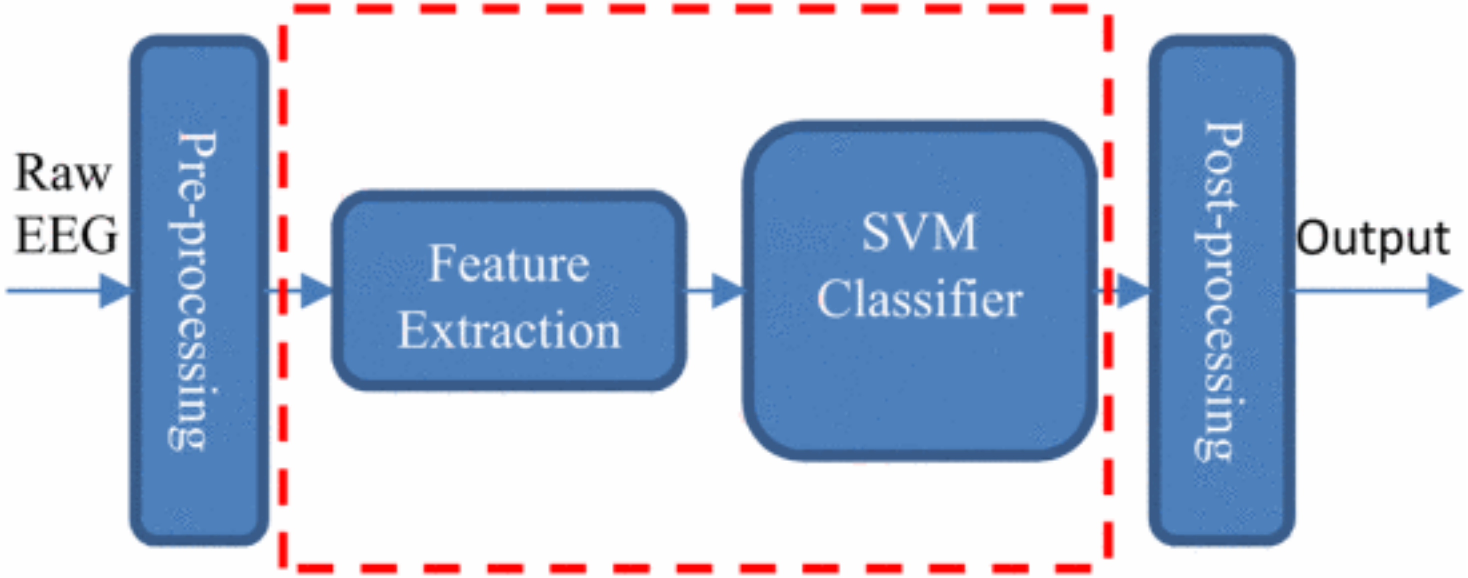
Seizure Detection: *Features-SVM*



Extracted Features	
Frequency Domain	Total power (0-12Hz) Peak frequency of Spectrum Spectral edge frequency (80%, 90%, 95%) Power in 2HZ wide sub-bands Normalized power in sub-bands Wavelet energy
Time Domain	Curve length Number of maxima and minima Root mean squared amplitude Hjorth parameters Zero crossings (raw epoch, Δ, ΔΔ) Autoregressive modelling error (order 1-9) Skewness Kurtosis Nonlinear energy Variance (Δ, ΔΔ)
Information Theory	Shannon entropy Singular value decomposition entropy Fisher information Spectral entropy

Temko, A., et al. "EEG-based neonatal seizure detection with support vector machines." *Clinical Neurophysiology* 122.3 (**2011**): 464-473.

Seizure Detection: *Deep learning*

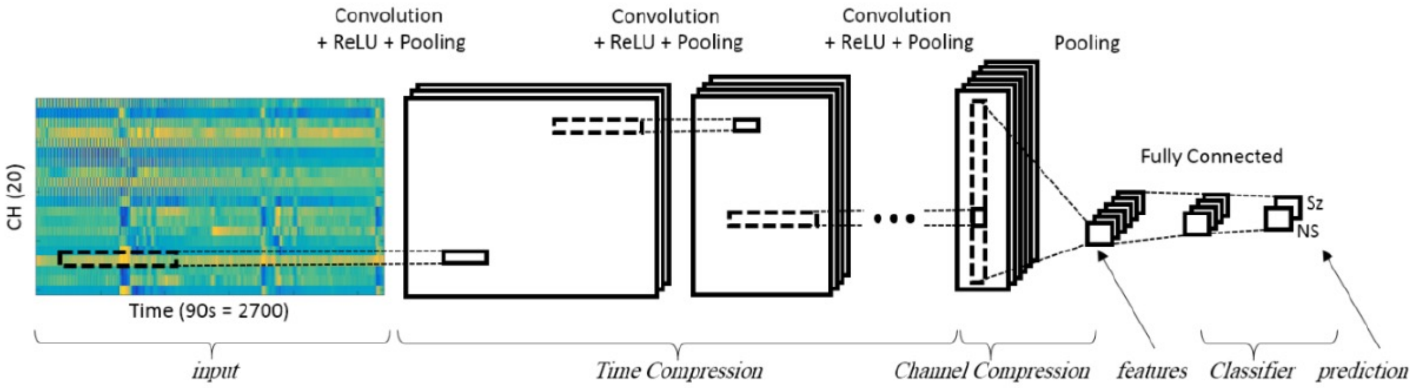


Layer Type	Shape	Output Shape	Parameters
Input	256	256x1	0
1D Convolution	32 filters 4x1 kernel Stride 1	32x253x1	160
1DConvolution	32 filters 4x1 kernel Stride 1	32x250x1	4128
1DConvolution	32 filters 4x1 kernel Stride 1	32x247x1	4128
Batch Norm.		32x247x1	64
Average Pooling	Pool 8 Stride 2	32x120x1	0
1DConvolution	32 filters 4x1 kernel Stride 1	32x117x1	4128
1DConvolution	32 filters 4x1 kernel Stride 1	32x114x1	4128
Average Pooling	Pool 4 Stride 2	32x56x1	0
1DConvolution	2 filters 4x1 kernel Stride 1	2x53x1	258
GAP		2x1	0
Softmax		2	0

O'Shea, Alison, et al. "Neonatal seizure detection using convolutional neural networks.“ *2017 IEEE 27th International Workshop on Machine Learning for Signal Processing (MLSP)*. IEEE, **2017**.

Improve Convolutional Neural Networks architecture

		Layer Info	Output Size		
		Input:	(20,	2700,	1)
Feature Extraction	1	Conv (1, 5) × 5	(20,	2696,	5)
	2	MPool (1, 3), s: 2	(20,	1347,	5)
	3	ReLU	(20,	1347,	5)
	4	Conv (1, 5) × 8	(20,	1343,	8)
	5	MPool (1, 3), s: 2	(20,	671,	8)
	6	ReLU	(20,	671,	8)
	7	Conv (1, 5) × 10	(20,	667,	10)
	8	MPool (1, 3), s: 2	(20,	333,	10)
	9	ReLU	(20,	333,	10)
	10	Conv (1, 5) × 15	(20,	329,	15)
	11	MPool (1, 3), s: 2	(20,	164,	15)
	12	ReLU	(20,	164,	15)
	13	Conv (1, 20) × 20	(20,	145,	20)
	14	MPool (1, 10), s: 5	(20,	28,	20)
	15	ReLU	(20,	28,	20)
	16	MPool (1, 5), s: 3	(20,	8,	20)
	17	APool (1, 8), s: 1	(20,	1,	20)
	18	MPool (20, 1), s: 1	(1,	1,	20)
Classifier	19	Conv (1, 1) × 5	(1,	1,	5)
	20	Sigmoid	(1,	1,	5)
	21	Conv (1, 1) × 2	(1,	1,	2)
	22	Sigmoid	(1,	1,	2)
	23	Loss	(1,	1,	1)
Total Number of Parameters:			7600		



Using 39000 recordings of 48 Neonates (EMC Rotterdam)

X

Ansari A.H., Cherian P. J., Caicedo A., Naulaers G., De Vos M., Van Huffel S., ``Neonatal Seizure Detection Using Deep Convolutional Neural Networks'', *International Journal of Neural Systems*, vol. 28, no. 0, Apr. 2018, pp. 1850011-1 - 1850011-20.

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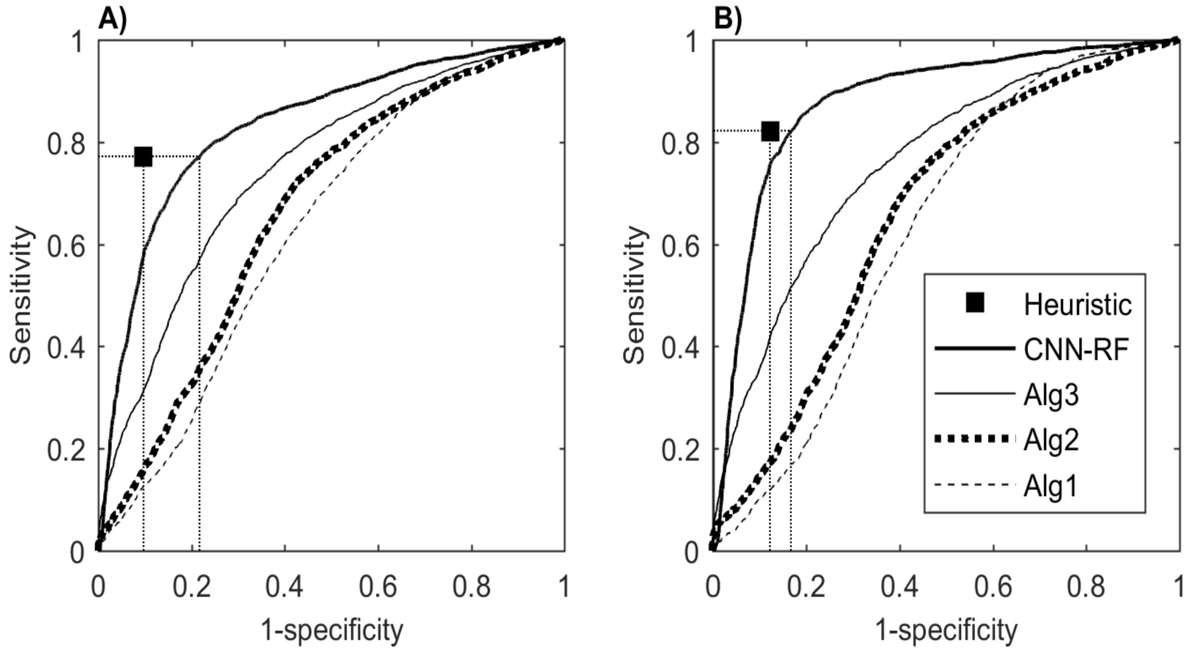
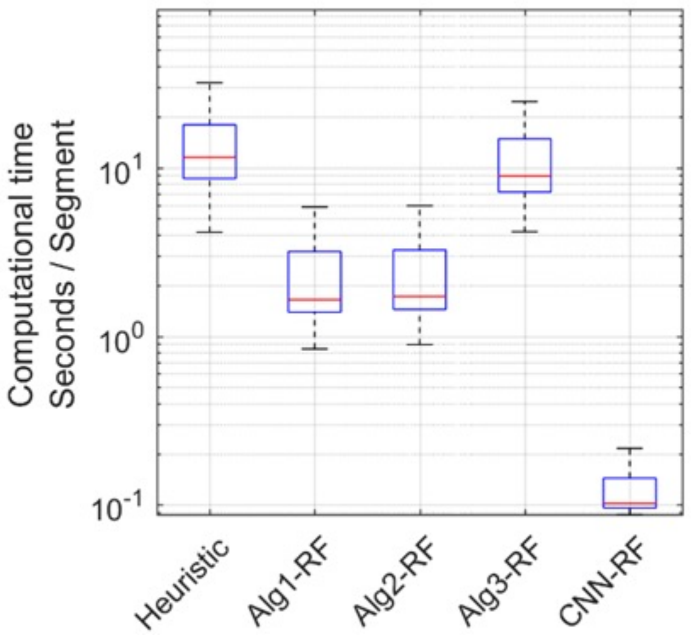
Seizure Detection: *Performance*

Results of the tested seizure detector: Heuristic, CNN, feature-based Alg 1-3.
A) all recordings, B) after excluding some recordings with unique pattern



Recall Speed of the tested seizure detectors:
Heuristic, CNN, feature-based Alg 1-3.



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EEG-fMRI data fusion

UZ Leuven Departments:

Radiology

Neurology

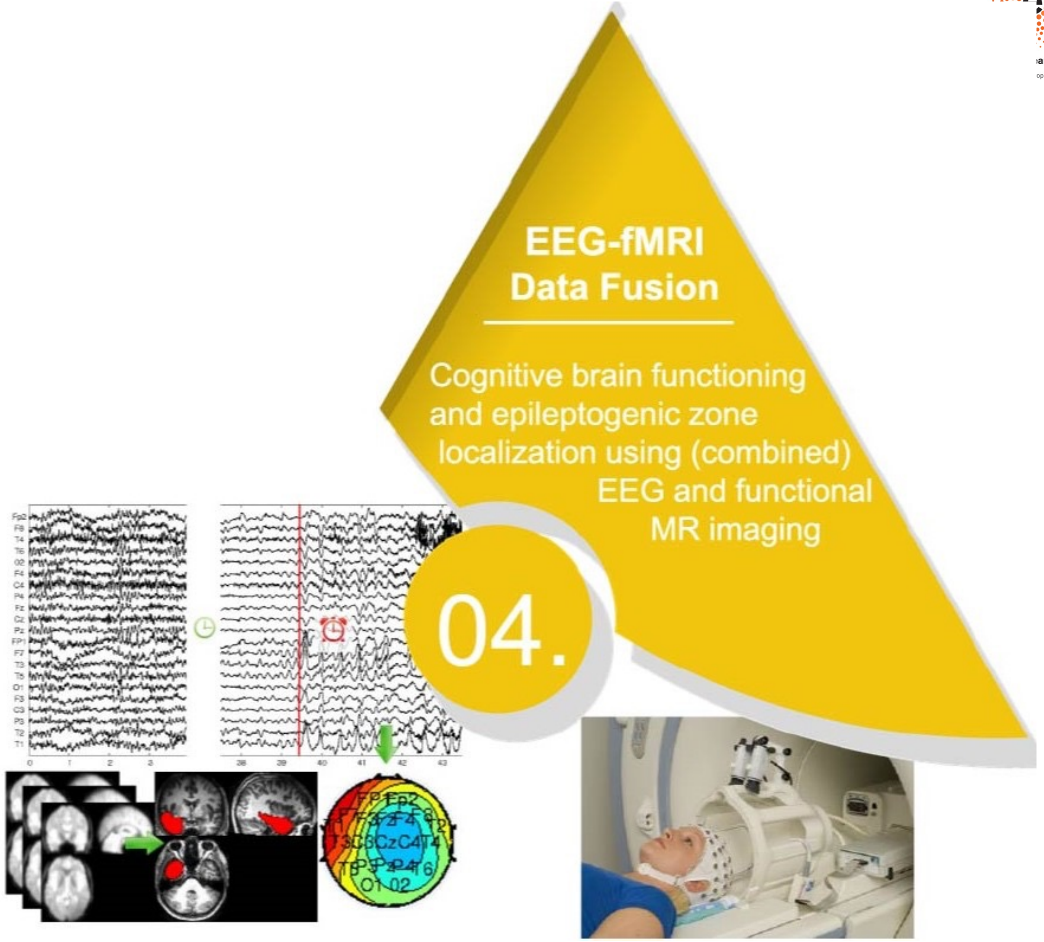
KU Leuven:

Dept. of Psychology

Dept. of Kinesiology and Rehabilitation Sciences

Oxford University:

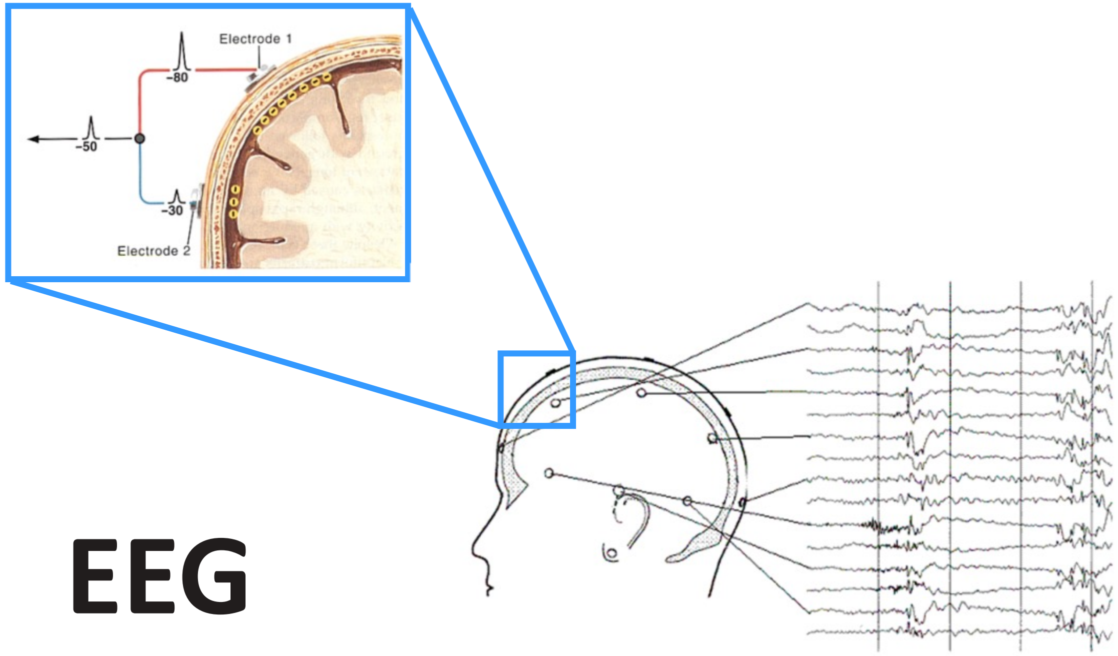
Dept. of Engineering Science



EXAMPLE

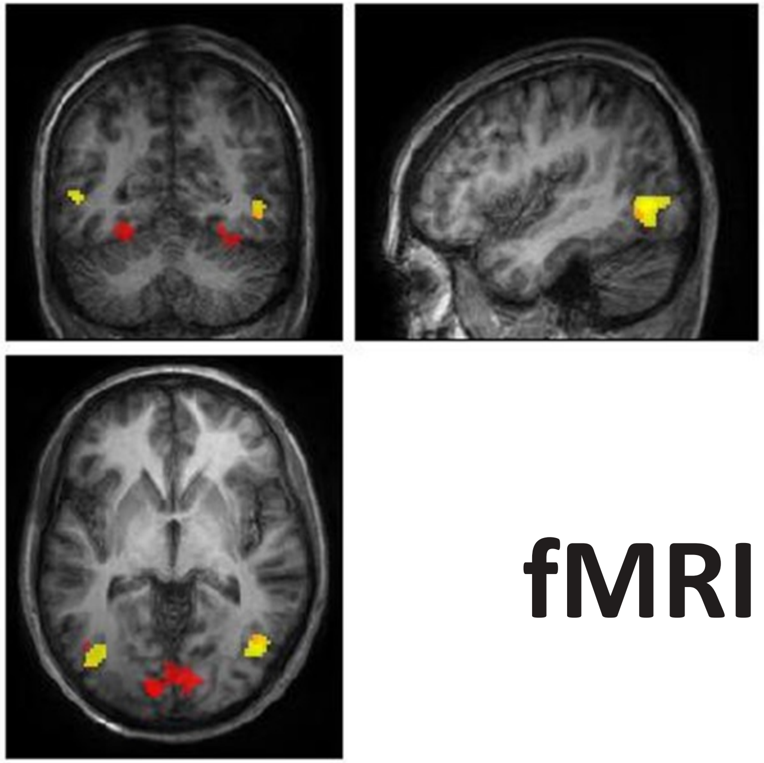
Combined EEG-fMRI analysis

EEG measures electrical potentials on the scalp



EEG

fMRI localizes active brain regions



fMRI

Combining EEG and fMRI:

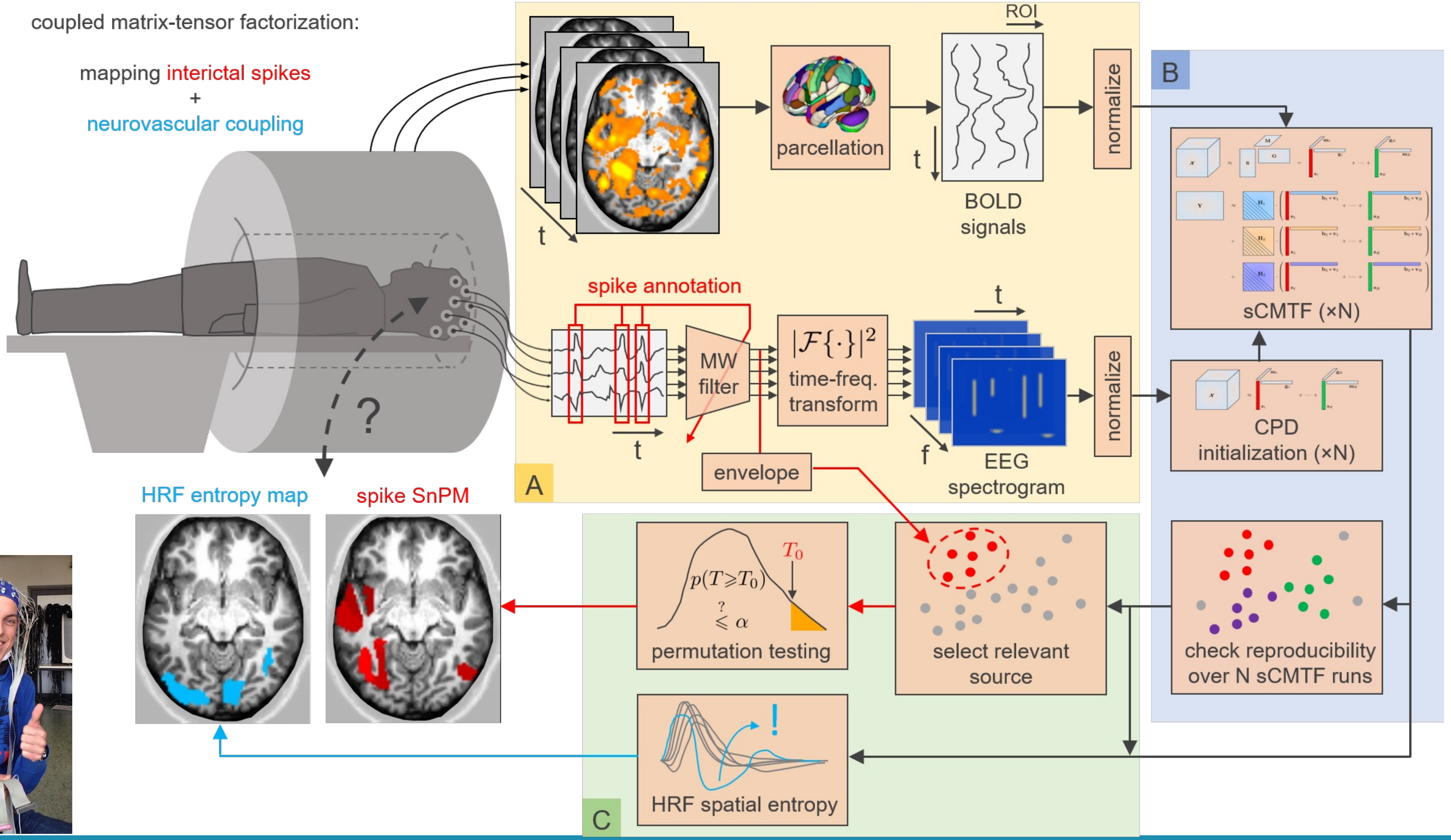
***EEG** good **temporal resolution** (~ ms)*

***fMRI** good **spatial resolution** (~ mm)*

Coupled MTF revealing neurovascular coupling localizes seizure onset

coupled matrix-tensor factorization:

mapping interictal spikes
+
neurovascular coupling



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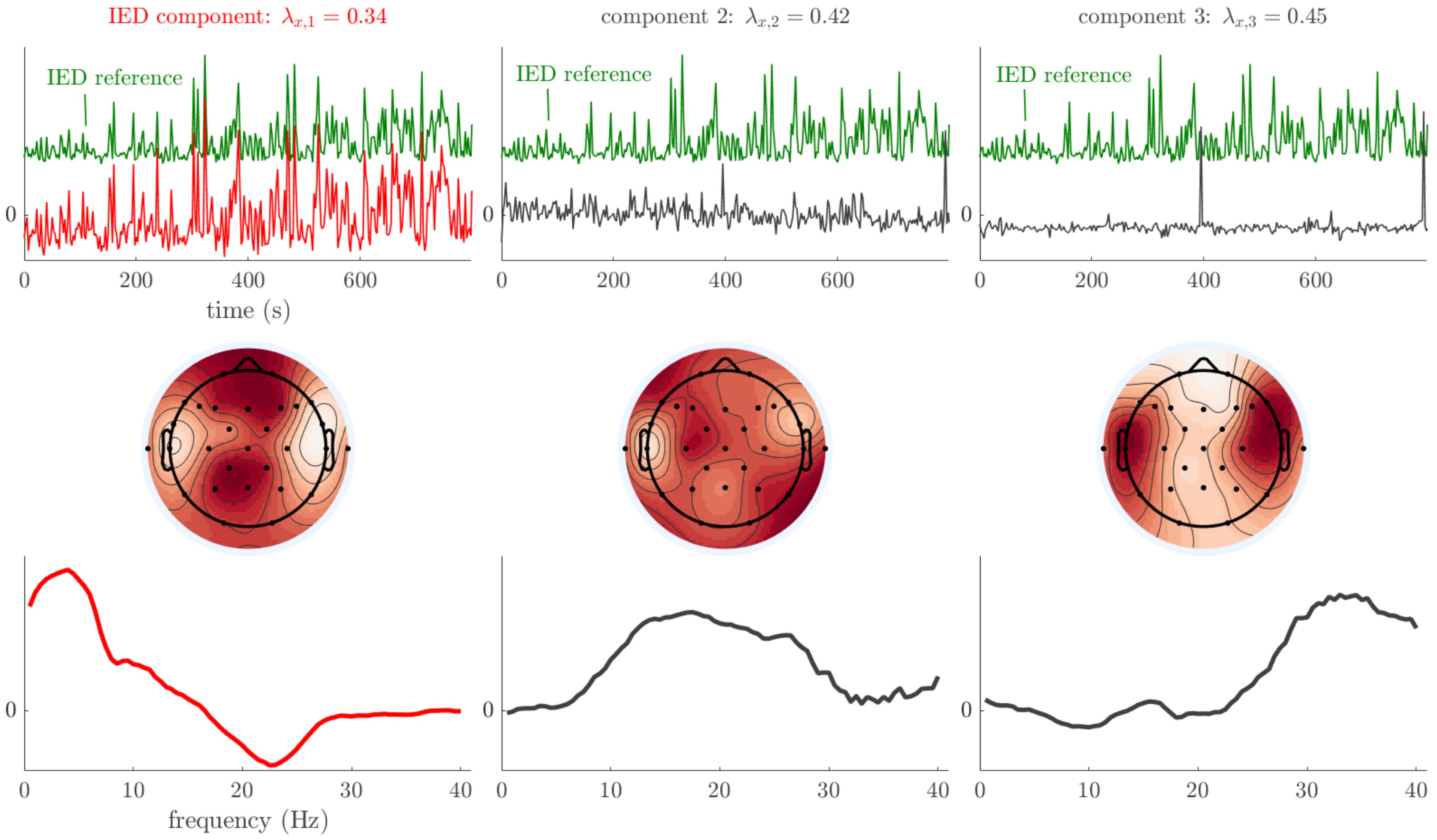
Low-rank models disentangle the EEG

temporal

spatial

spectral



European Research Council
Established by the European Commission

Wearable
Health Monitoring

UZ Leuven departments:

Cardiology

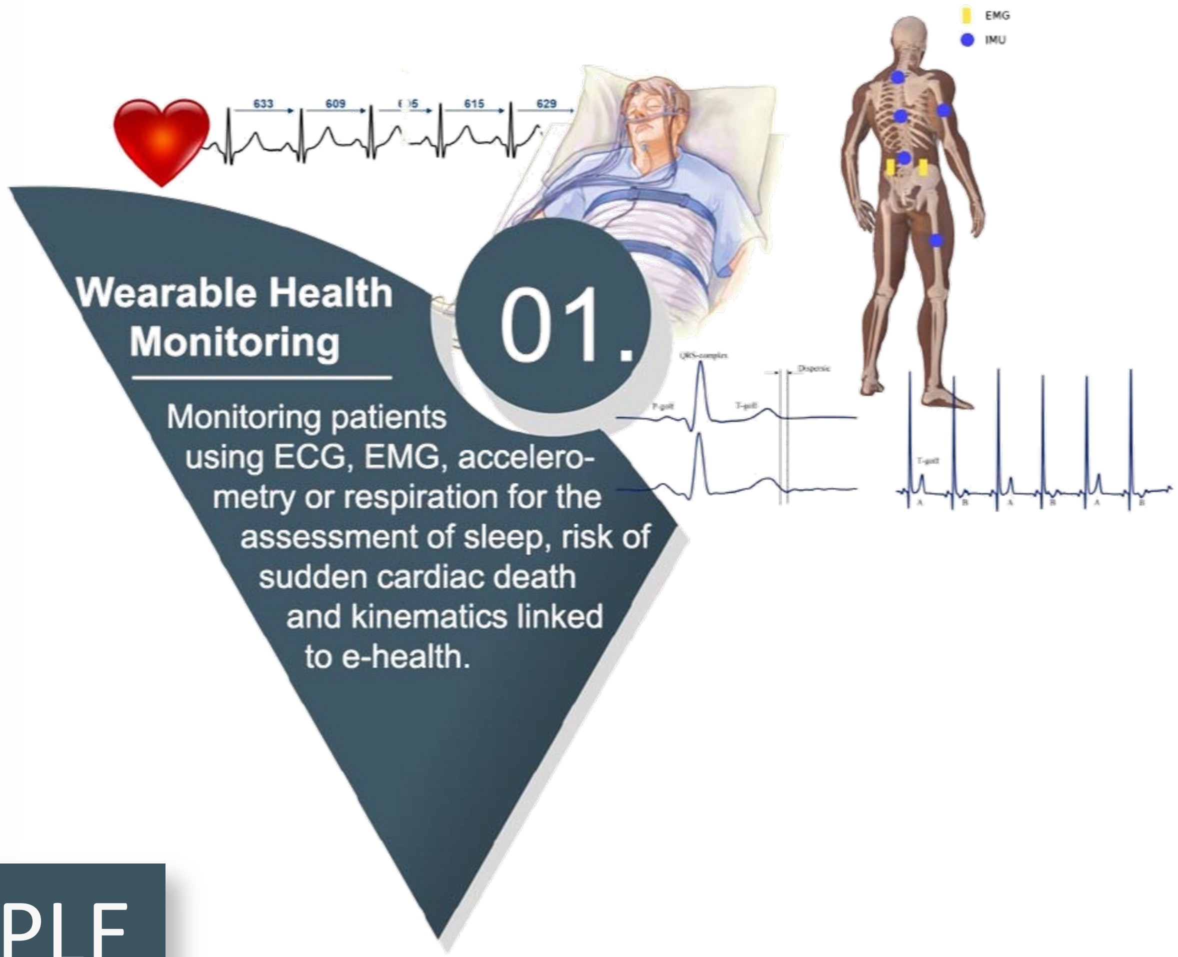
Neurology

Pneumology

Rheumatology

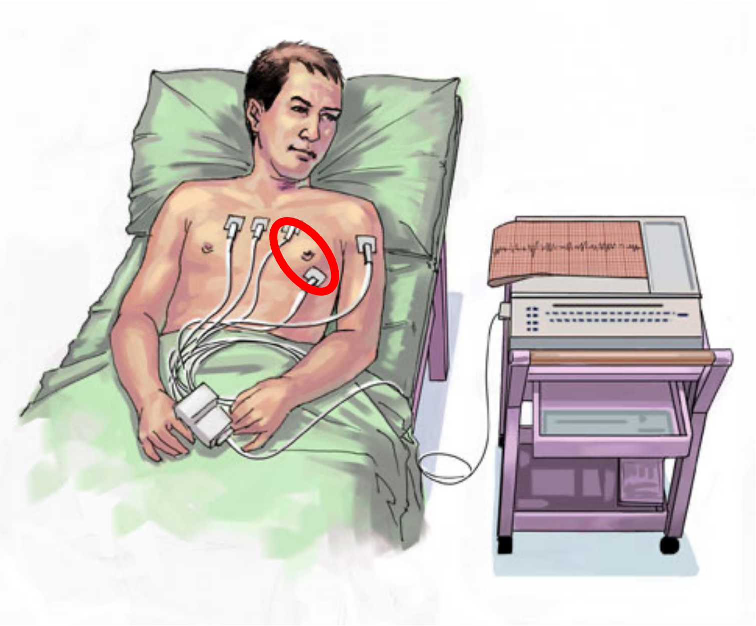
Pulderbos Revalidation Center

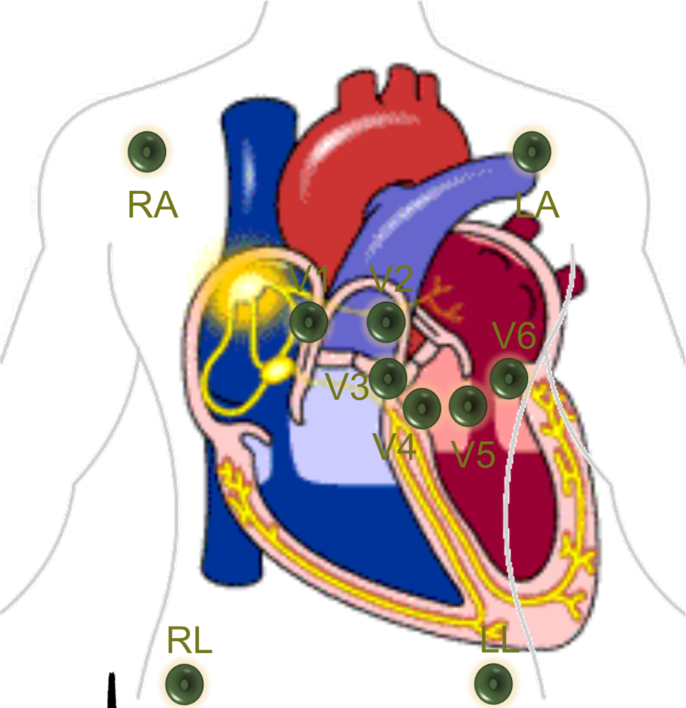
EXAMPLE

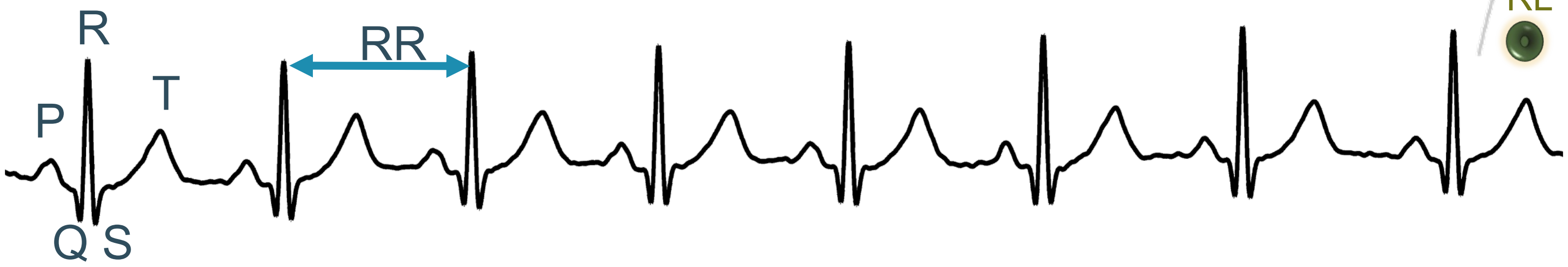


Introduction:THE ECG

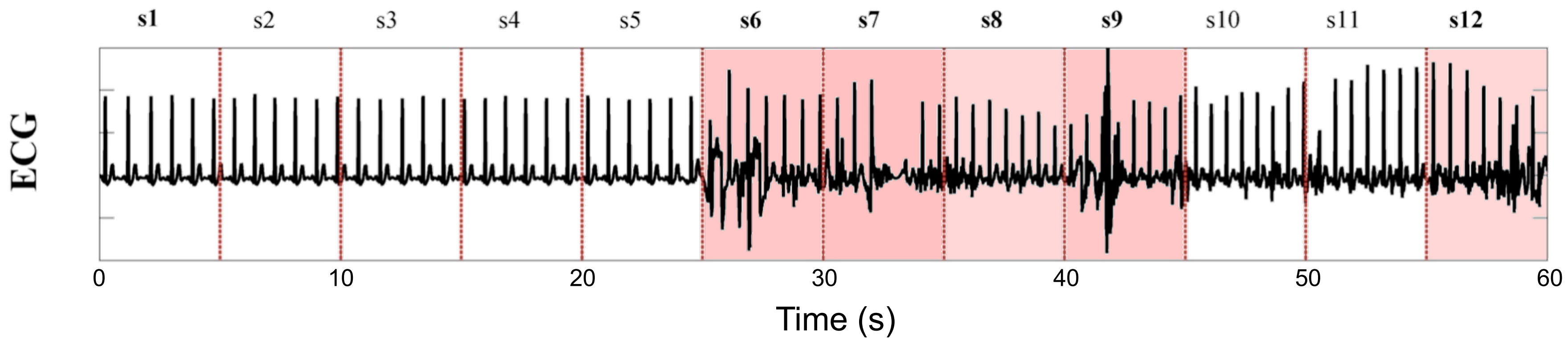
Electrocardiogram (ECG)

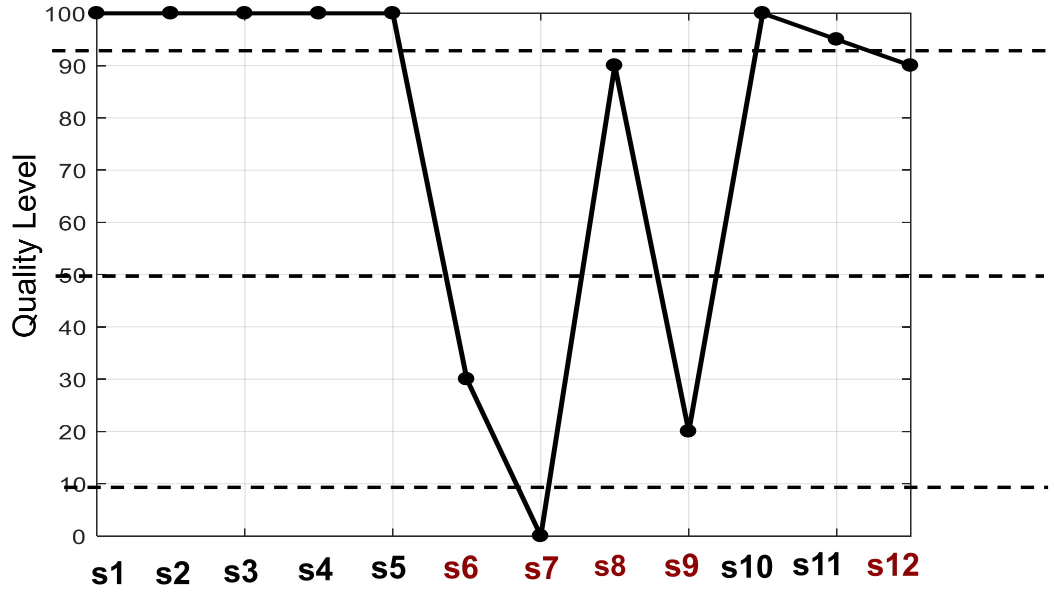






ECG quality indication using supervised ML





Creation of an annotated ECG dataset

3 different recording systems

Continuous ECG Quality Index

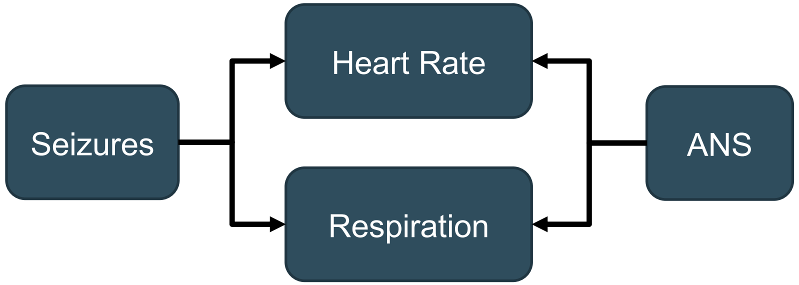
Accuracy of about 99% in the detection of noisy segments

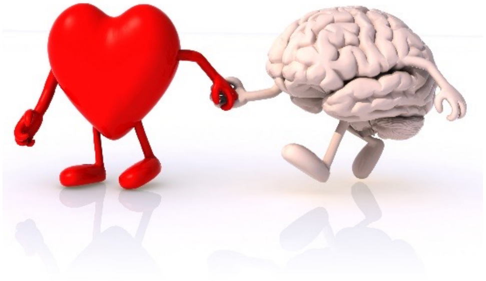
Easy to implement
LOW
Computational load

Moeyersons J., Smets E., Morales J., Amalia Villa, De Raedt W., Testelmans D., Buyse B., Van Hoof C., Willems R., Van Huffel S., Varon C., Artefact detection and quality assessment of ambulatory ECG signals, *Computer methods and programs in biomedicine*, vol. 182, Dec. 2019, pp. 105-113.

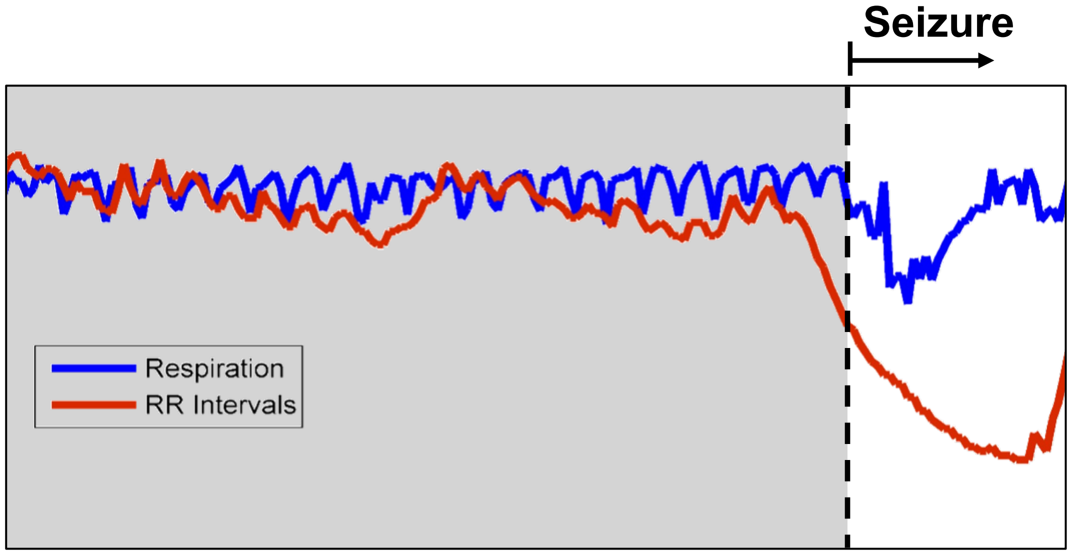
Epileptic seizure detectors based on ECG

Seizures and the autonomic nervous system (ANS)





Goal: Detect cardiac and respiratory changes caused by seizures

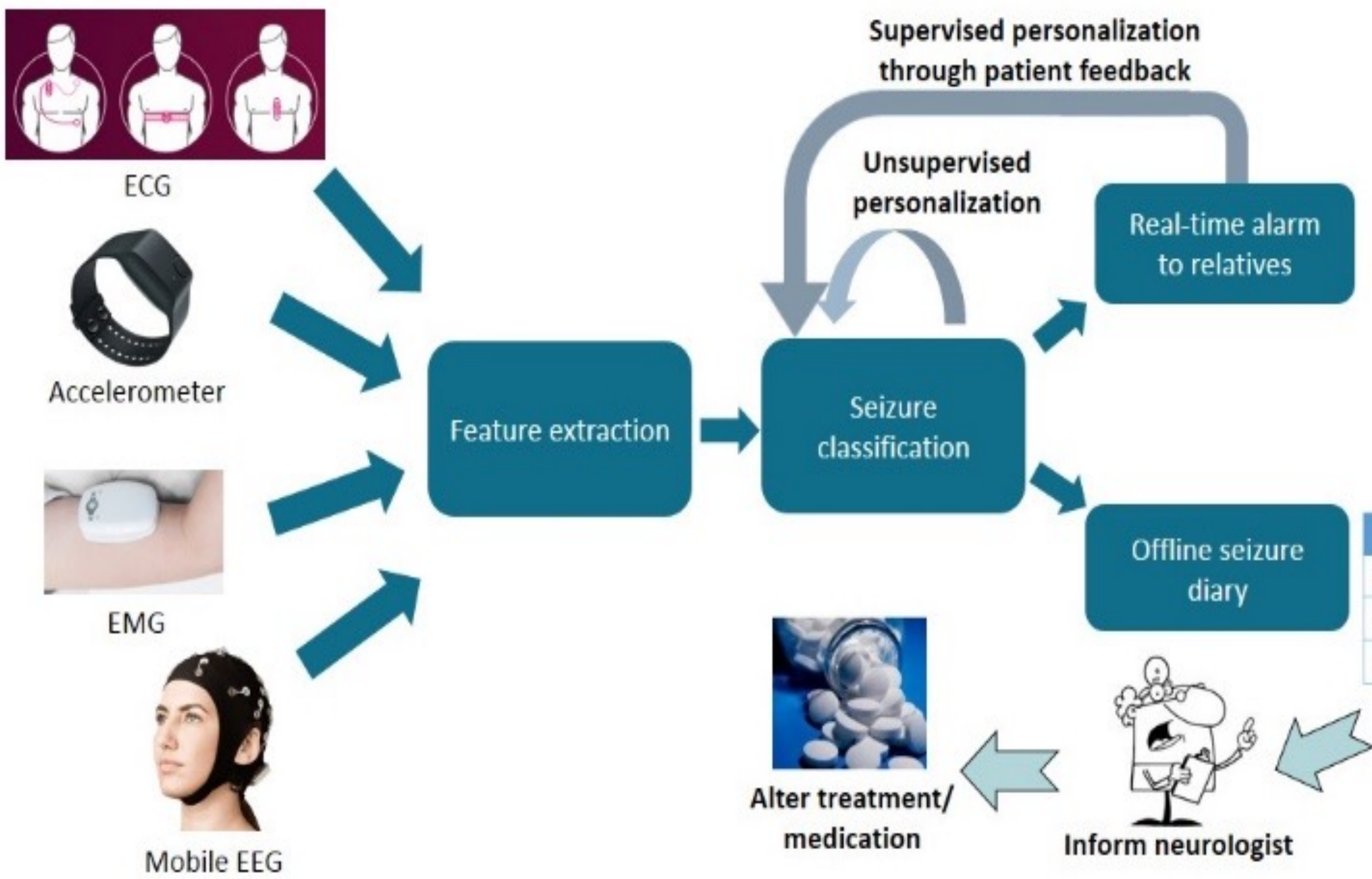


Seizures

- ✓ Pre-ictal changes
- ✓ Autonomic symptoms
- ✓ Motor activity
- ✓ Stress response
- ✓ Apnea episodes
- ✓ Reduced HRV
- ✓ Tachycardia or bradycardia

Varon C., Caicedo A., Testelmans D., Buyse B., Van Huffel S., A novel algorithm for the automatic detection of sleep apnea from single-lead ECG, *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 9, Sep. 2015, pp. 2269-2278.
De Cooman T., Varon C., Hunyadi B., Van Paesschen W., Lagae L., Van Huffel S., `Online Automated Seizure Detection In Temporal Lobe Epilepsy Patients Using Single-Lead ECG, *International Journal Of Neural Systems*, vol. 27, No. 7, Mar. 2017, pp. 1750022

Automated real-time seizure detection @ home



	Data	Time	Description
1	22/01/18	22:37:16	CLONIC seizure
2	24/01/18	23:13:36	TONIC seizure
3	...		

SeizeIT prototype

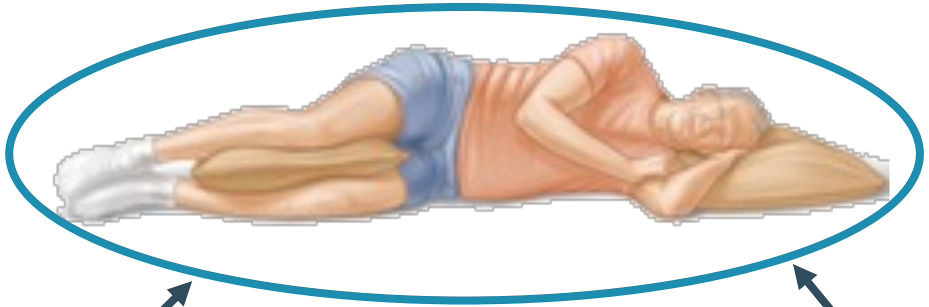
De Cooman T., *Epileptic Seizure Detection in a Home Environment*, PhD thesis, Faculty of Engineering, KU Leuven, Belgium, Dec. 2018

Sleep Monitoring @ home

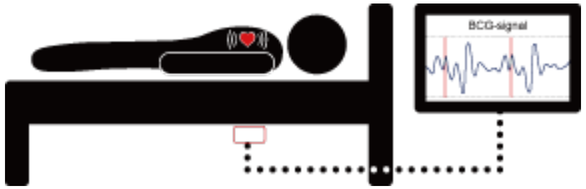
PPG

SpO$_2$

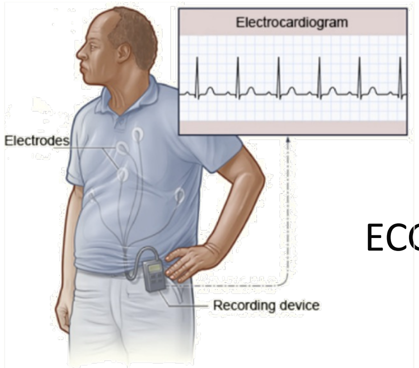
Classical in-hospital polysomnography



Unobtrusive (home) monitoring



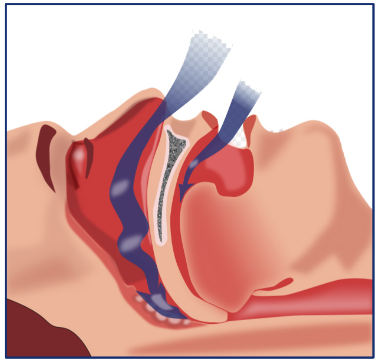
Ballistocardiography



ECG

Sleep staging

Obstructive Sleep Apnea (OSA) detection and phenotyping

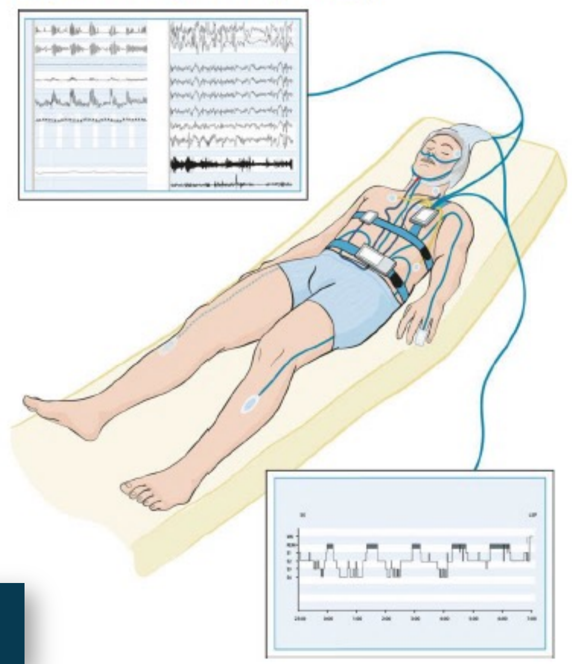


Huysmans D., *Advances in unobtrusive monitoring of sleep apnea using machine learning*, PhD thesis, Faculty of Engineering, KU Leuven (Leuven, Belgium), Oct. 2021, 216 p

Current situation

- Prevalence 6-33 % and increasing
- Clinical diagnosis
  - ☺ Highly accurate
  - ☹ Expertise required
  - ☹ Extensive equipment
  - ☹ Uncomfortable
  - ☹ Single night

➔ **Patients remain undiagnosed**



Goal

- Comfortable “unobtrusive” sensors
- Multiple nights

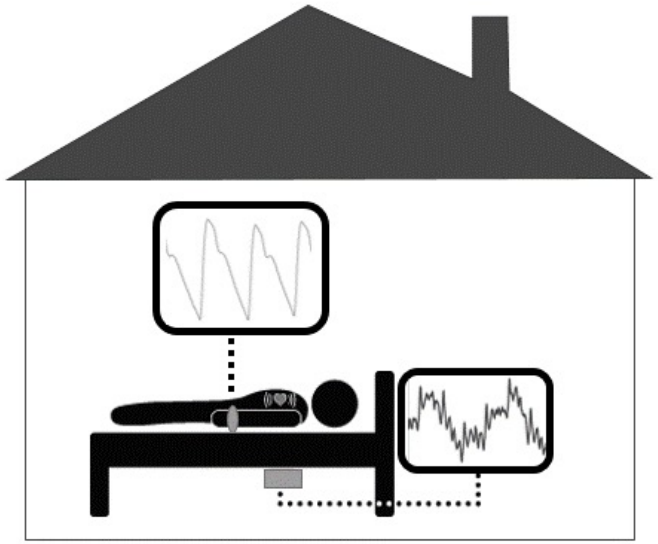
☺ **Captures normal sleeping pattern**

☺ **Allows large scale monitoring**

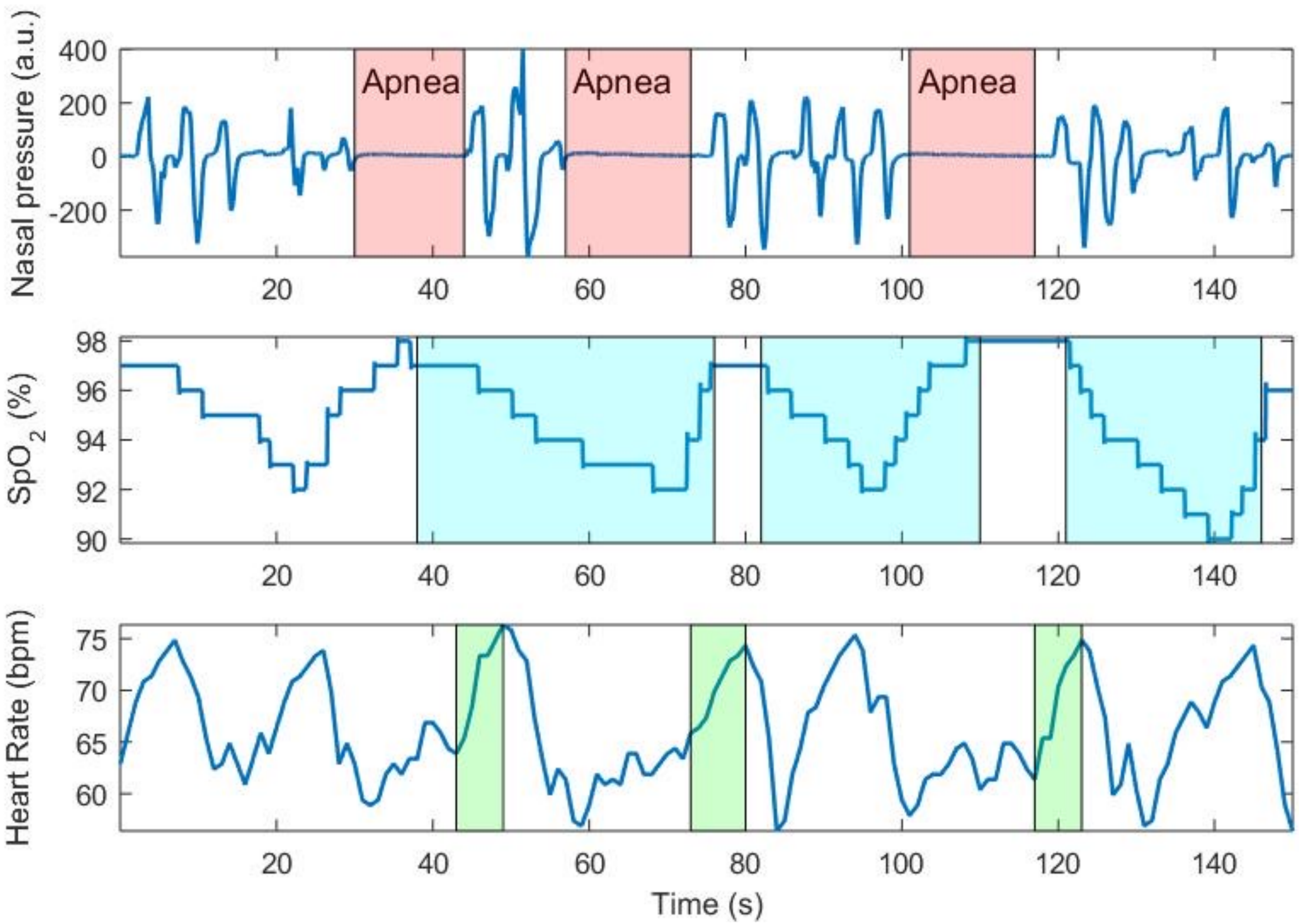
Unobtrusive sensors

☹ **Lower quality**

☹ **Timing issues with other sensors**



Sleep Apnea Detection



Cessation of breathing

Oxygen desaturation

Autonomic arousal

Apnea Hypopnea Index (AHI)

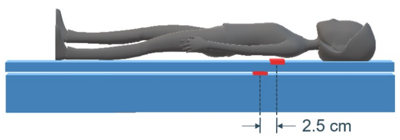
Apnea breathing stop
Hypopnea breathing reduction

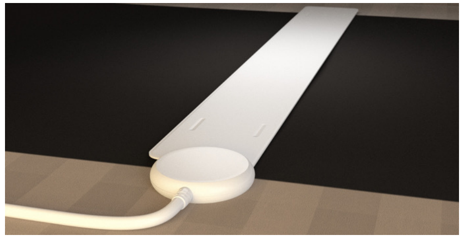
Severity of sleep apnea ~ **AHI** = $\frac{\text{\# (Hypo)Apneas}}{\text{Hours of sleep}}$

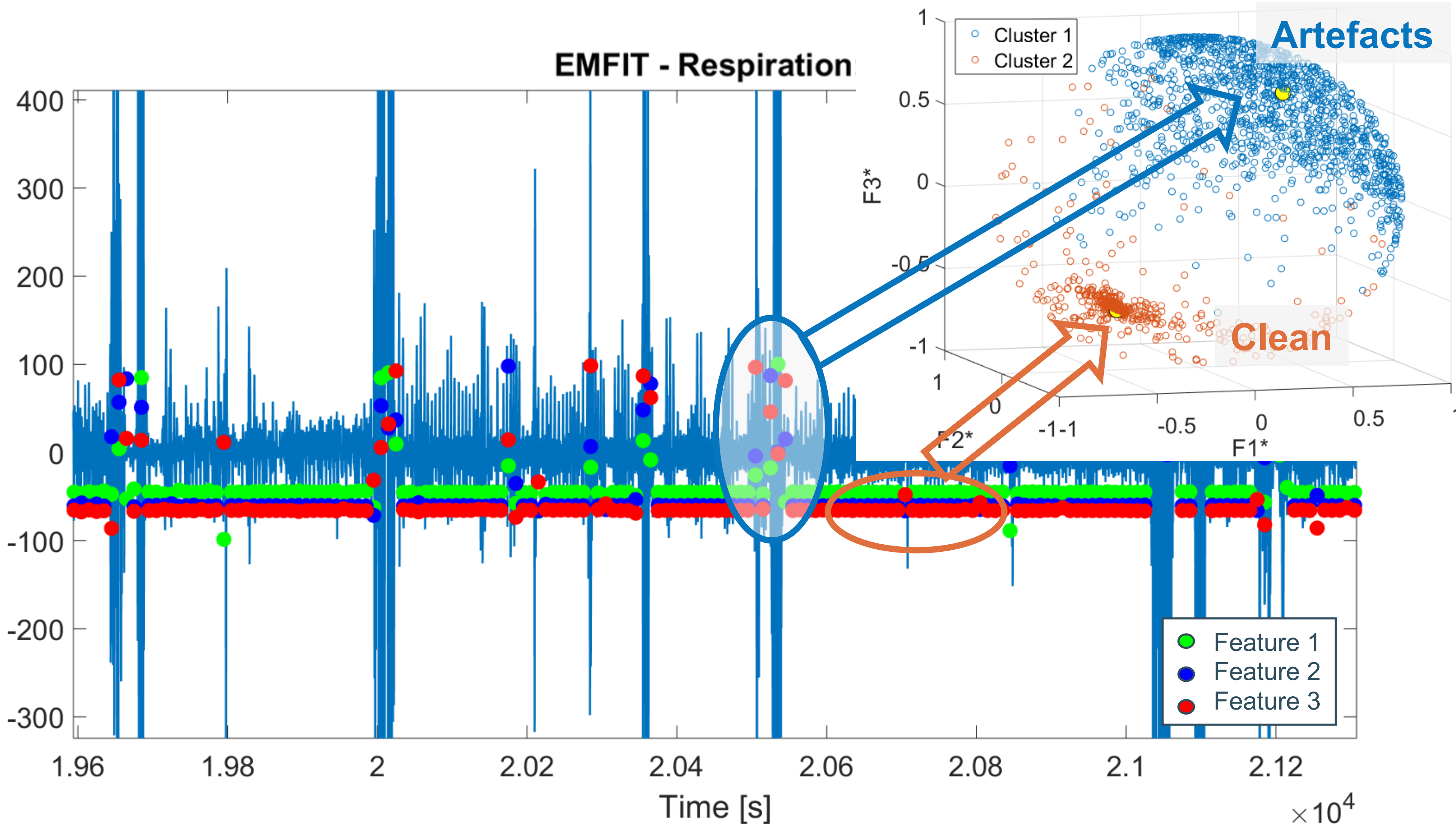
No apnea	AHI < 5	**No sleep apnea**
Mild apnea	5 ≤ AHI < 15 + symptoms	
Moderate apnea	15 ≤ AHI < 30	**Sleep apnea**
Severe apnea	AHI ≥ 30	

Automated artefact detection in the novel Emfit sensor

Emfit







Contribution

- ✓ Artefacts detected automatically in a novel sensor w/o labeling

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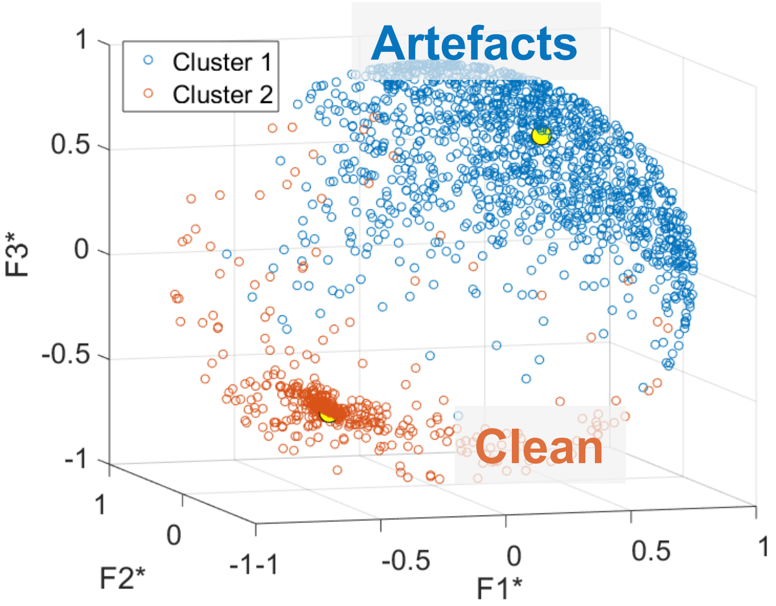
Identification of patients with OSA based on Emfit



Hypothesis

Emfit data of OSA patients contains more artefacts

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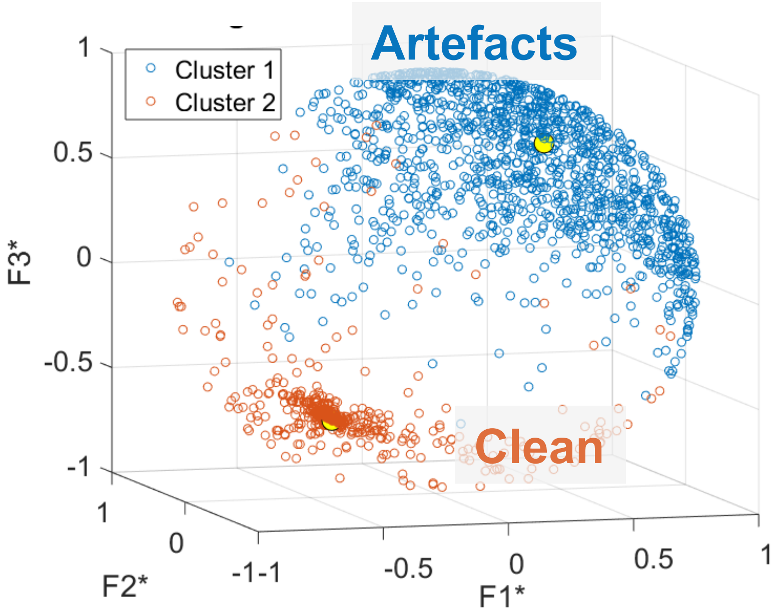
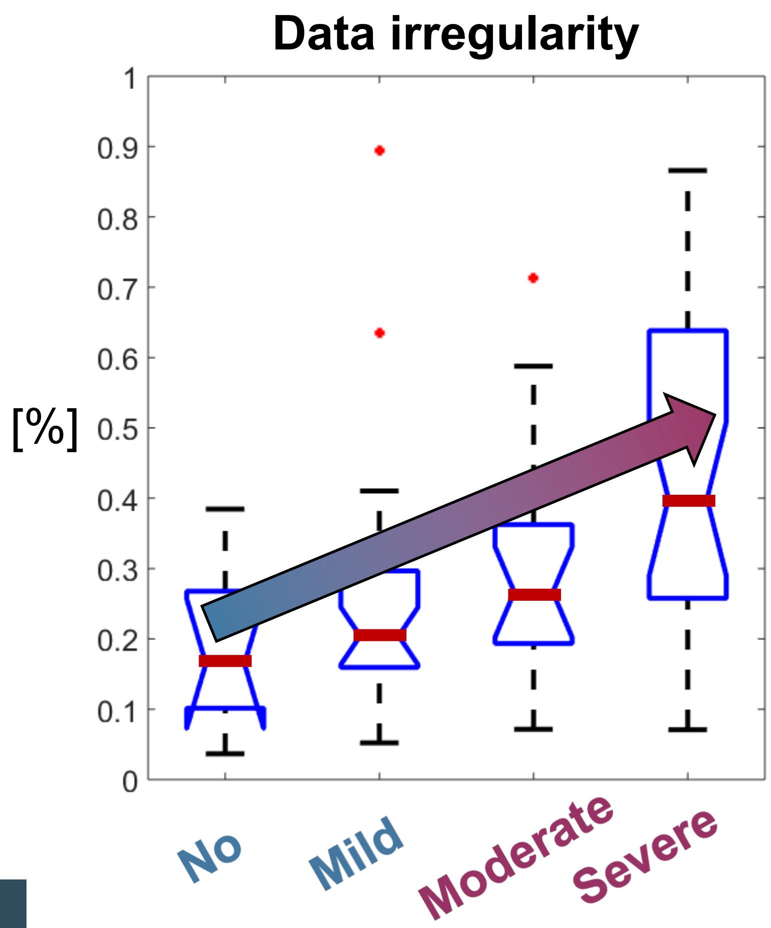
Identification of patients with OSA based on Emfit



Hypothesis

Emfit data of OSA patients contains more artefacts

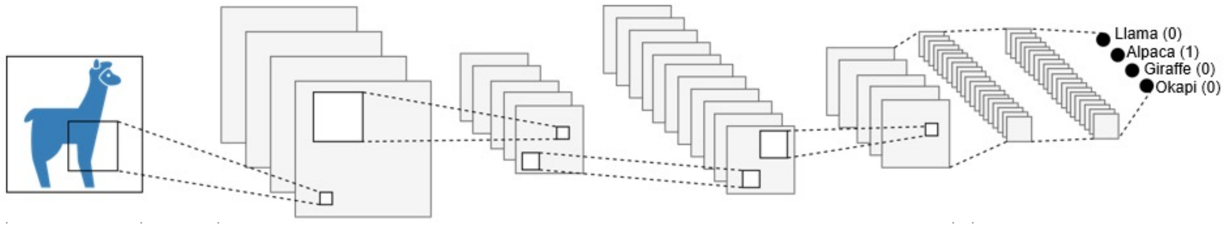


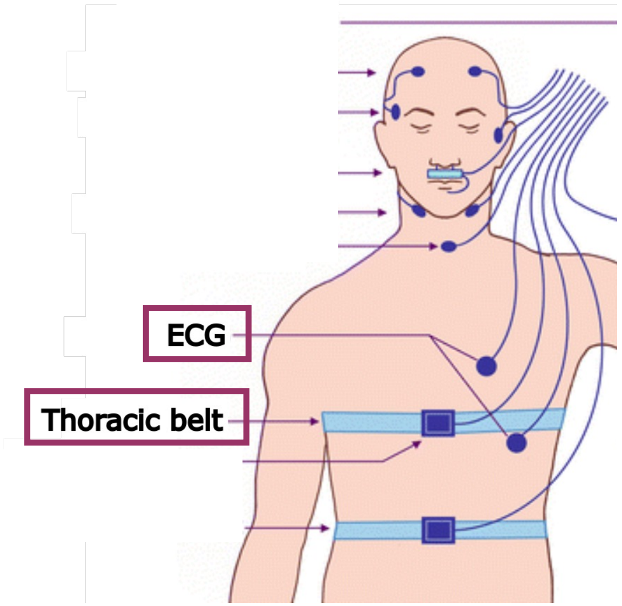
Contribution

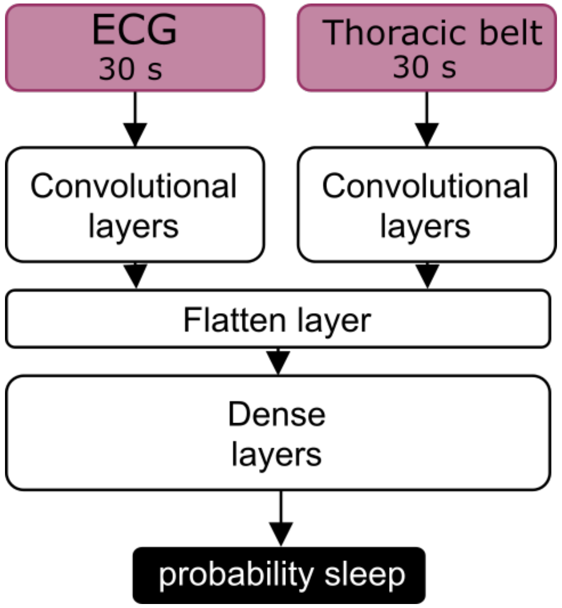
- ✓ Data irregularity as a marker for OSA
- ✓ Detection of OSA patients

Huysmans D., Borzée P., Testelmans D., Buyse B., Willemen T., Van Huffel S., Varon C., ``Evaluation of a commercial ballistocardiography sensor for sleep apnea screening and sleep monitoring.'', ***Sensors***, Special Issue Wearable and Nearable Biosensors and Systems for Healthcare, vol. 19, no. 9, May 2019

Detection of sleep in OSA patients based on ECG and thoracic belt







Contribution

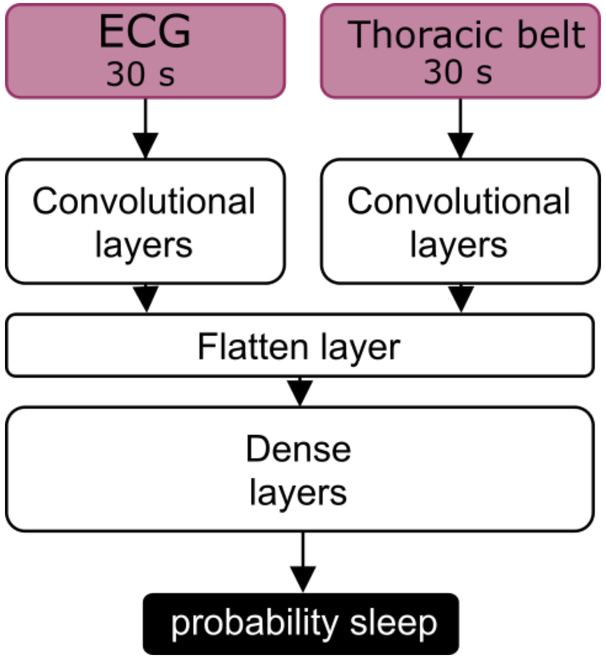
- ✓ Sleep time estimation comparable to literature
- ✓ Short independent windows account for data loss and artefacts ←→ literature: long range features

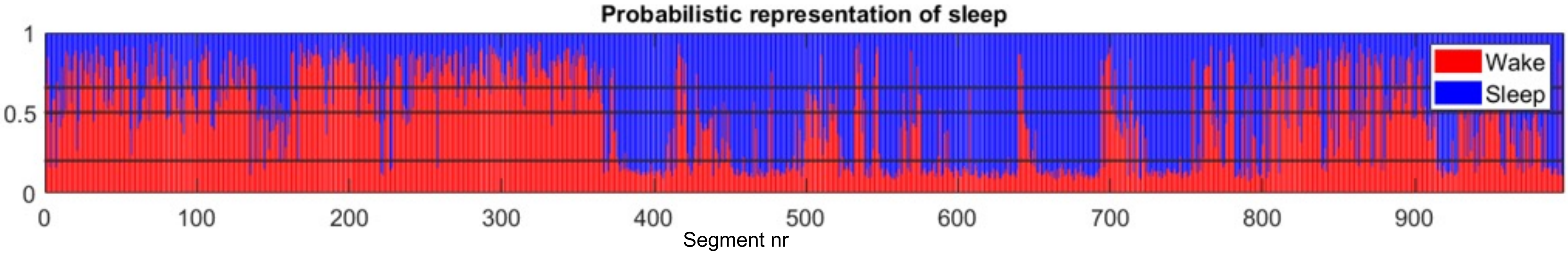
Huysmans D., Borzée P., Buyse B., Testelmans D., Van Huffel S., Varon C., ``Sleep Diagnostics for Home Monitoring of Sleep Apnea Patients'', ***Frontiers in Digital Health***, section Health Informatics, vol. 3, Jun. 2021, pp. 1-13.

Identification of OSA patients based on ECG and thoracic belt

Hypothesis

- More uncertainty predictions in OSA patients
- More awakenings predicted in OSA patients





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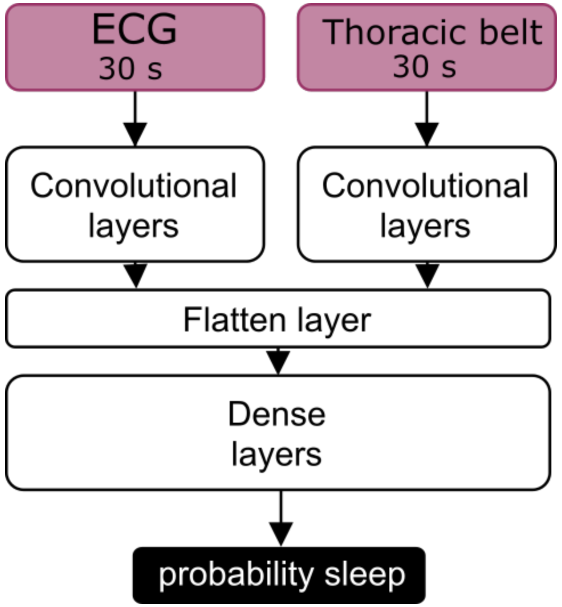
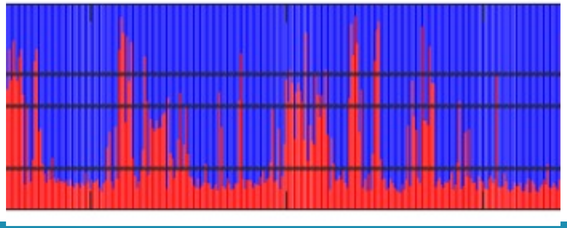
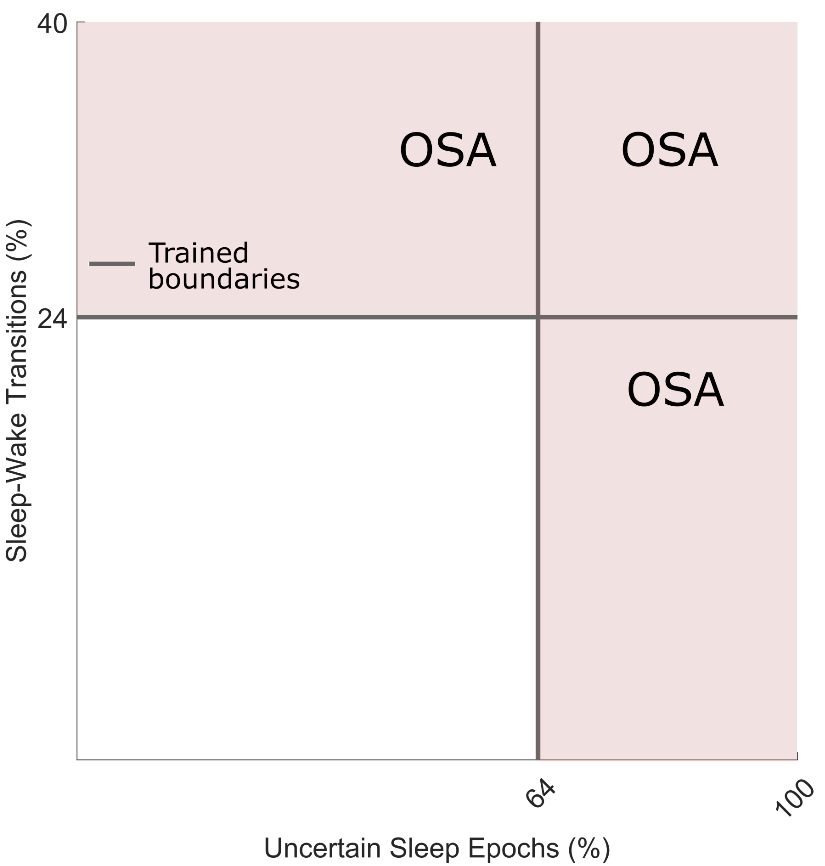


Probabilistic representation of sleep





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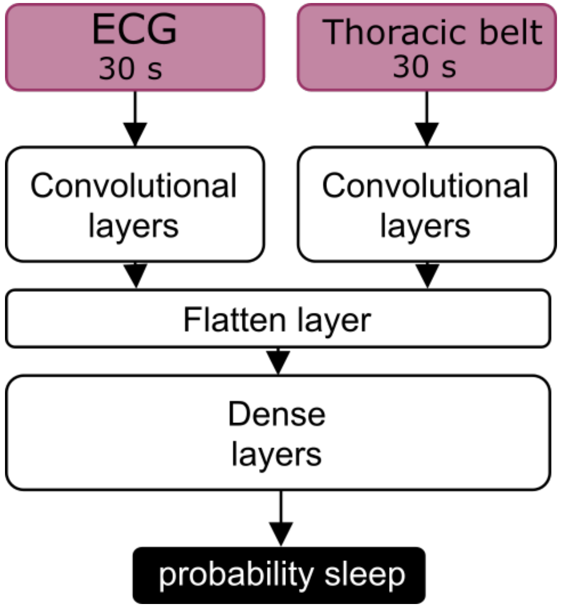

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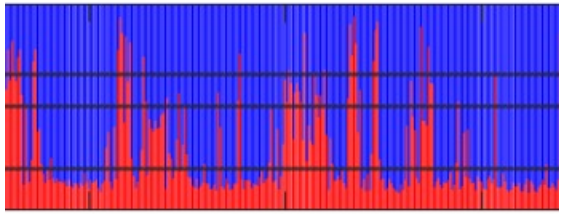
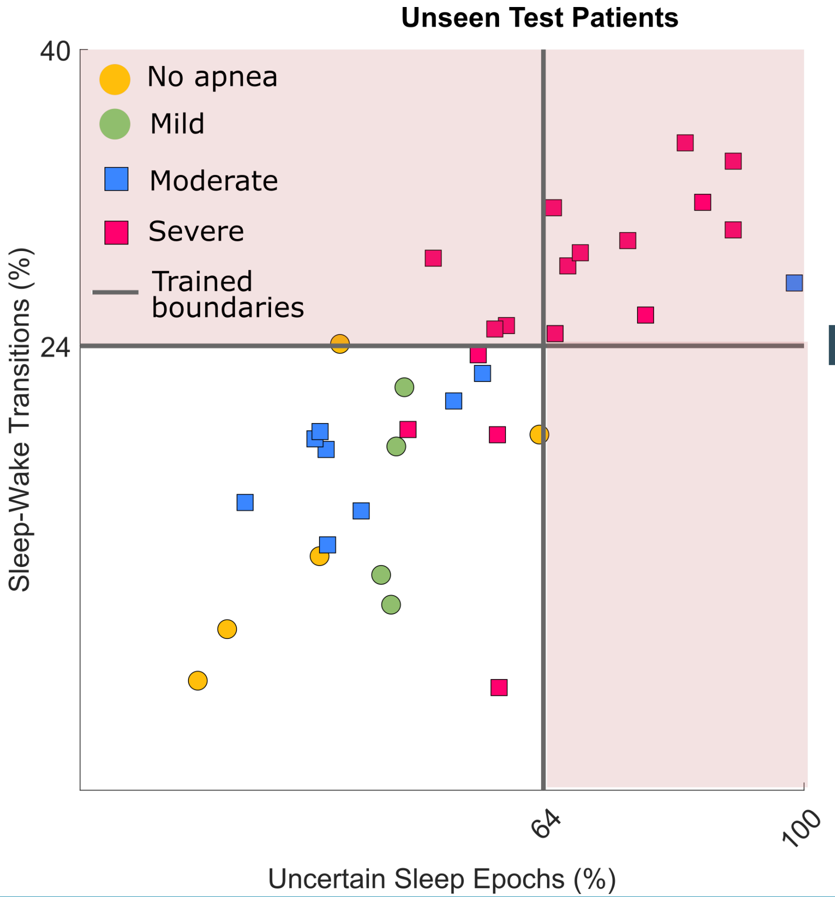


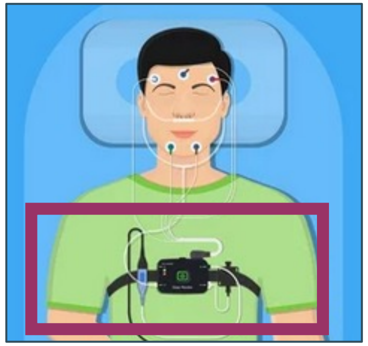


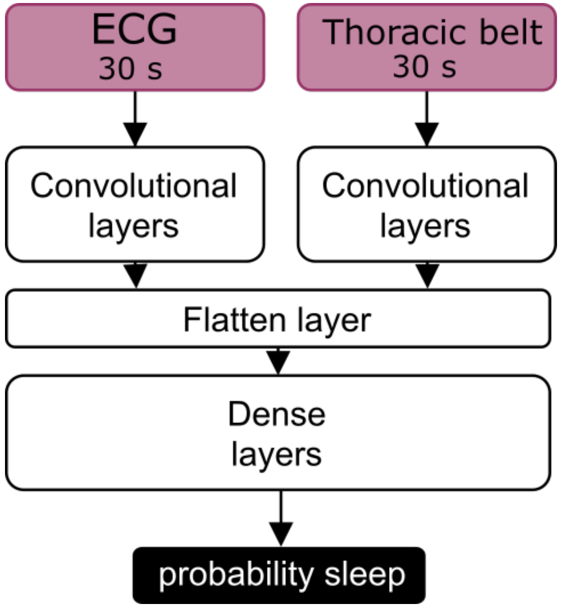
Contribution

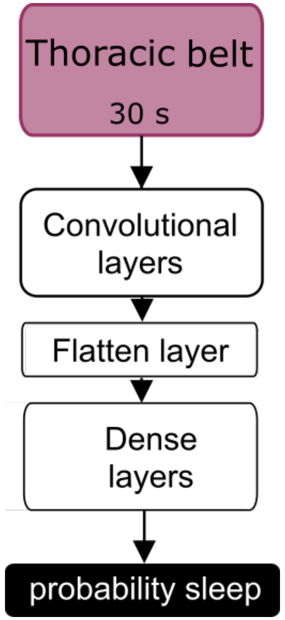
- ✓ Transformation of uncertainty into useful information
- ✓ Interpretable graph
- ✓ Detection of severe OSA patients
  ➔ Refined methods for mild patients

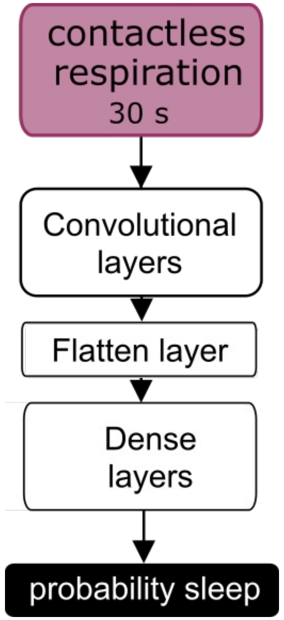
Huysmans D., Borzée P., Buyse B., Testelmans D., Van Huffel S., Varon C., ``Sleep Diagnostics for Home Monitoring of Sleep Apnea Patients'', ***Frontiers in Digital Health***, section Health Informatics, vol. 3, Jun. 2021, pp. 1-13.

Detection of sleep in OSA patients based on contactless ECG & respiration







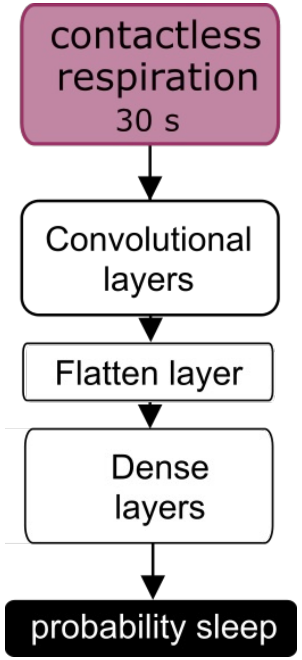


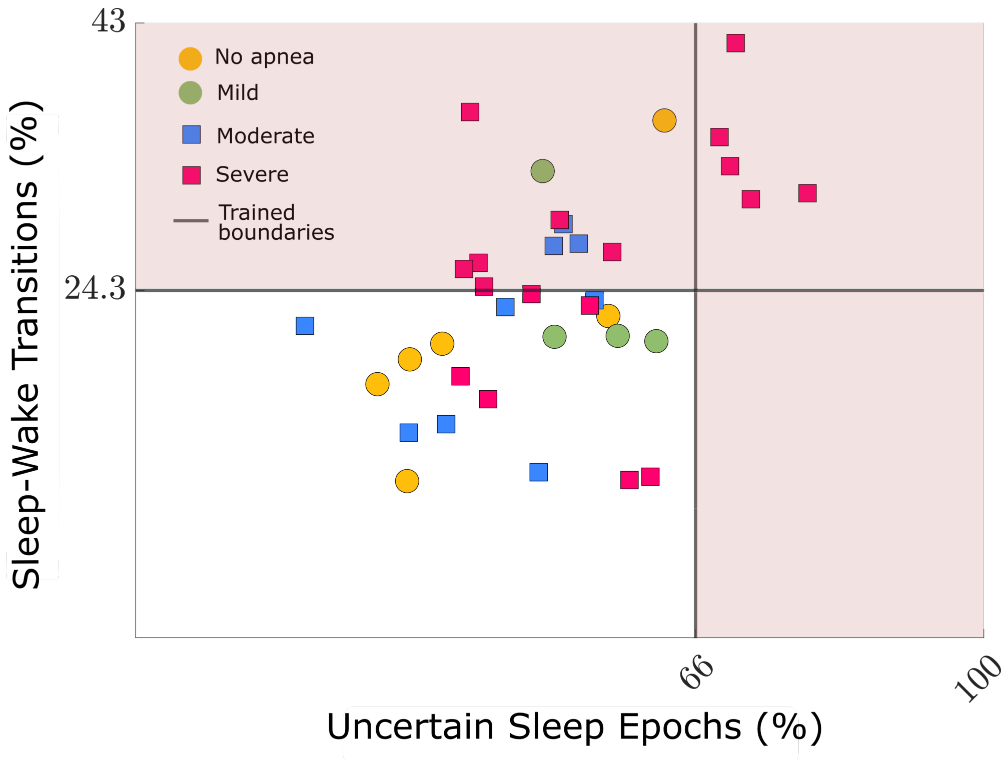
Contribution

✓ Sleep time based on contactless respiration

Huysmans D., Castro I., Borzée P., Patel A., Torfs T., Buyse B., Testelmans T., Van Huffel S., Varon C., ``Capacitively-coupled ECG and respiration for sleep-wake prediction and risk detection in sleep apnea patients'', ***Sensors***, vol. 21, no. 19, Sep 2021, 6409

Identification of patients with OSA based on contactless ECG and contactless respiration





Contribution

✓ Detection of severe OSA patients using only contactless respiration

➔ Prioritization for treatment

Contents Overview

Smart Patient Monitoring: *Future Challenges*

How to bridge the gap to clinical practice?

- **Hardware**: equipment, sensors, …
  → *wearable, unobtrusive, contactless, invisible*
- **Software**: long-term monitoring, (multiple) modalities
  → *low-quality data, 24/7 days reliability, big data*
- **Validation studies**: long-term followup, GDPR regulations
  → *patient data labeling uncertain & labor-intensive*
- **Training**: learning platform, (online) courses, interdisciplinar
  → *new Ba/Ma programmes in Medicine and BME*
- **Tech transfer to market in medical technology tough job !**
  → *models, many stakeholders*
  ethical and legal Non-trivial business issues, hyper-regulated →CE/FDA approval
  small niche market: societal value > economical value

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| Eindhoven University of Technology

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