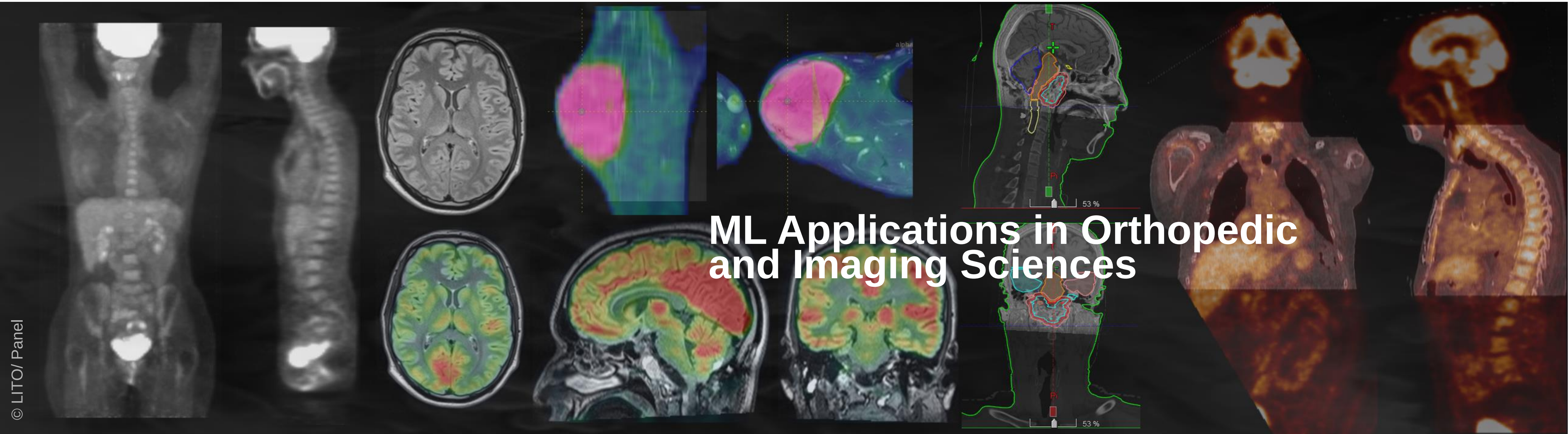
LITO

institut Curie

Inserm
La science pour la santé
From science to health

ML Applications in Orthopedic and Imaging Sciences



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EOS

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EOSapps

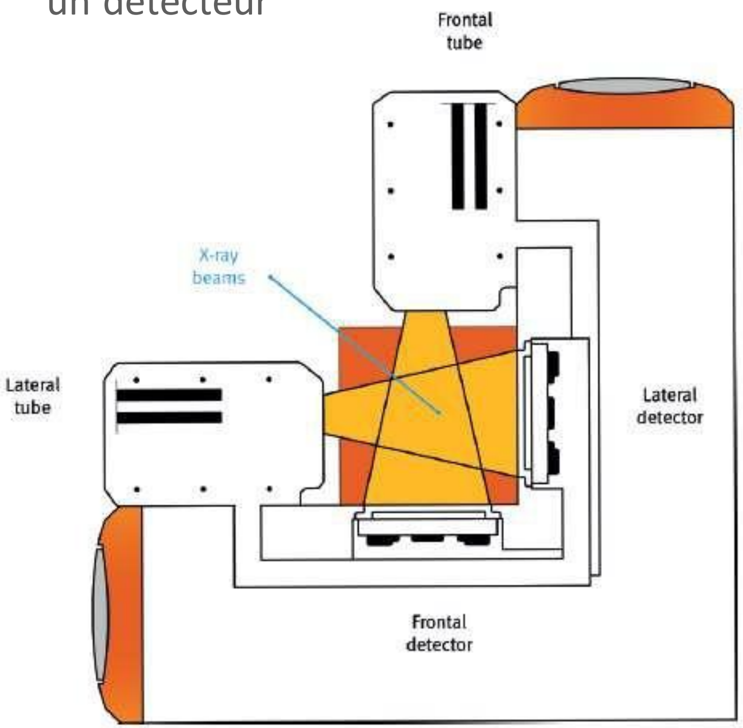
Chirurgie

EOSlink™

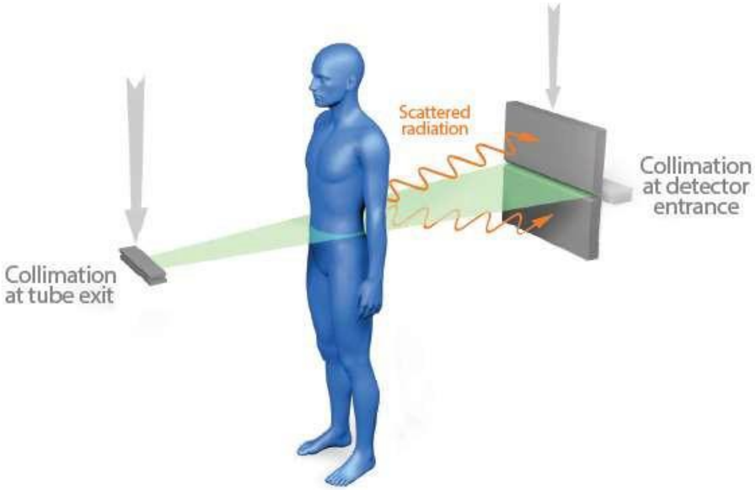
La technologie EOS

Système d'imagerie biplan utilisant une technologie de balayage vertical

- Imagerie biplan
  - Système composé de 2 bras verticaux perpendiculaires
  - Chaque bras contient un tube à rayons X et un détecteur

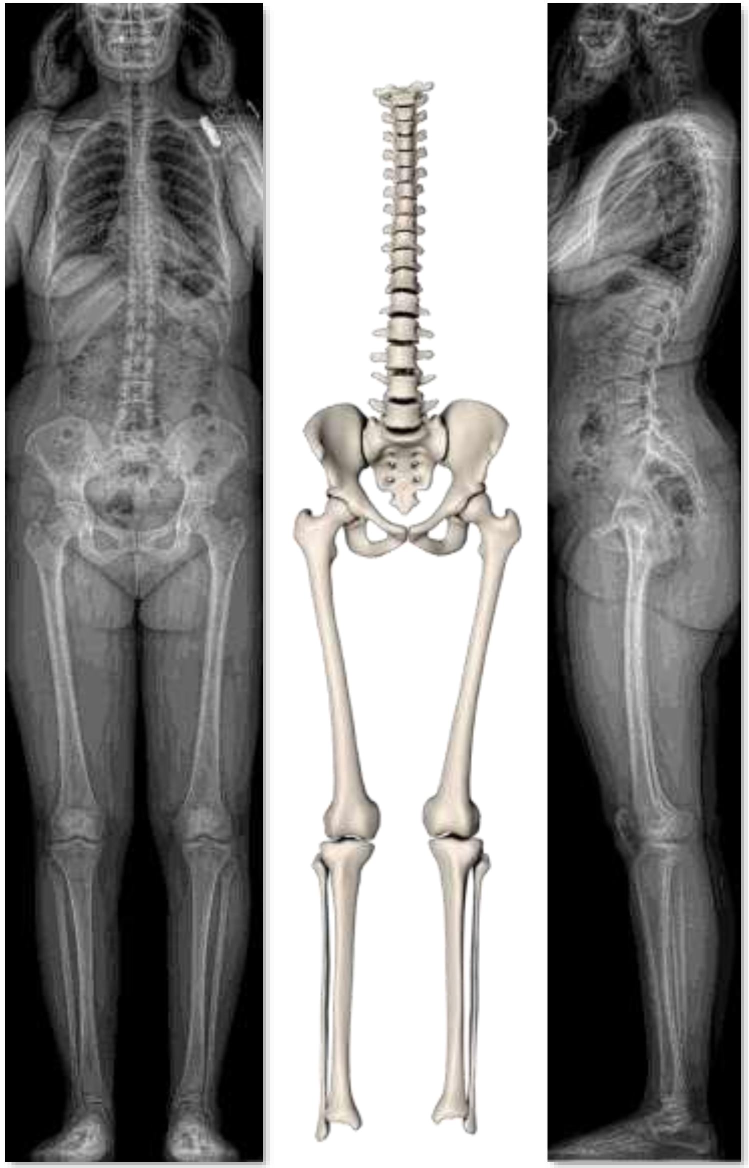


- Balayage vertical
  - Un faisceau de rayons X en éventail correspondant à la hauteur du détecteur linéaire
  - Images de face et de profil acquises simultanément grâce au déplacement vertical des faisceaux de rayons X en éventail et des détecteurs



Images 2D/3D du corps entier en position fonctionnelle

- Acquisition simultanée d’images de face et de profil
- Images du corps entier ou localisées
- Modélisation 3D : calcul automatique des paramètres cliniques



Exposition réduite aux rayonnements

Une dose optimisée pour des images homogènes

Flex Dose ™

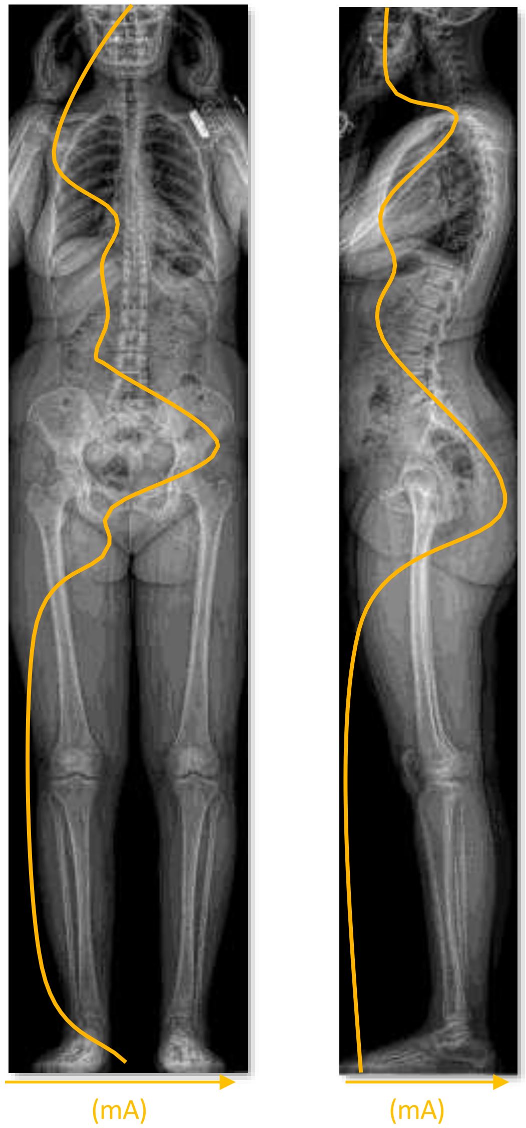
Premier système de radiologie général
avec modulation mA

- La technologie innovante Flex Dose s'appuie sur la morphologie du patient pour moduler la dose tout au long de l'examen, de manière à assurer une exposition optimale du patient aux rayonnements.
  - Distribution intelligente de la dose
  - Qualité d'image uniforme sur l'ensemble du corps

Jusqu'à 80 % de réduction de dose

Comparé à la même acquisition sans Flex Dose
chez des patients dont l'IMC est inférieur à 25*

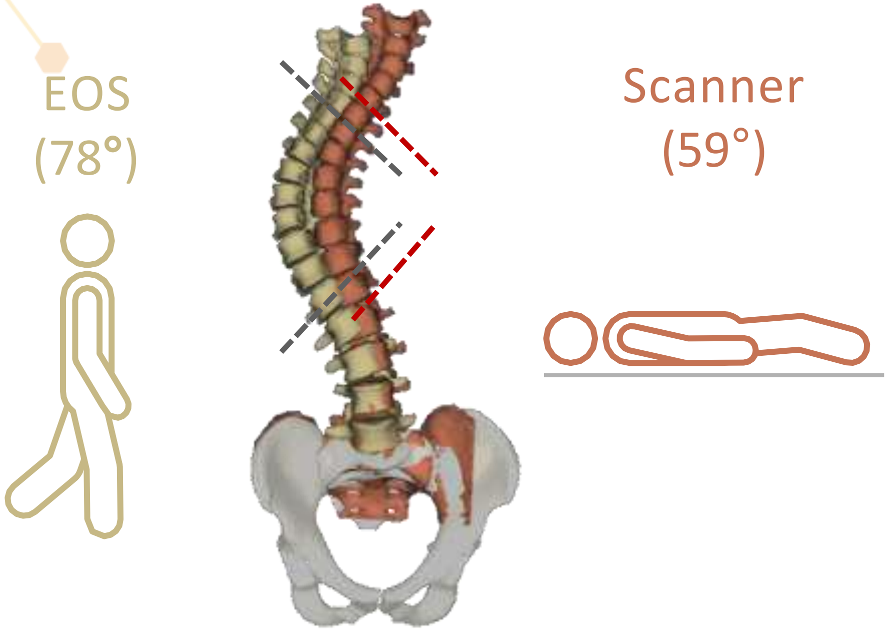
*Données internes



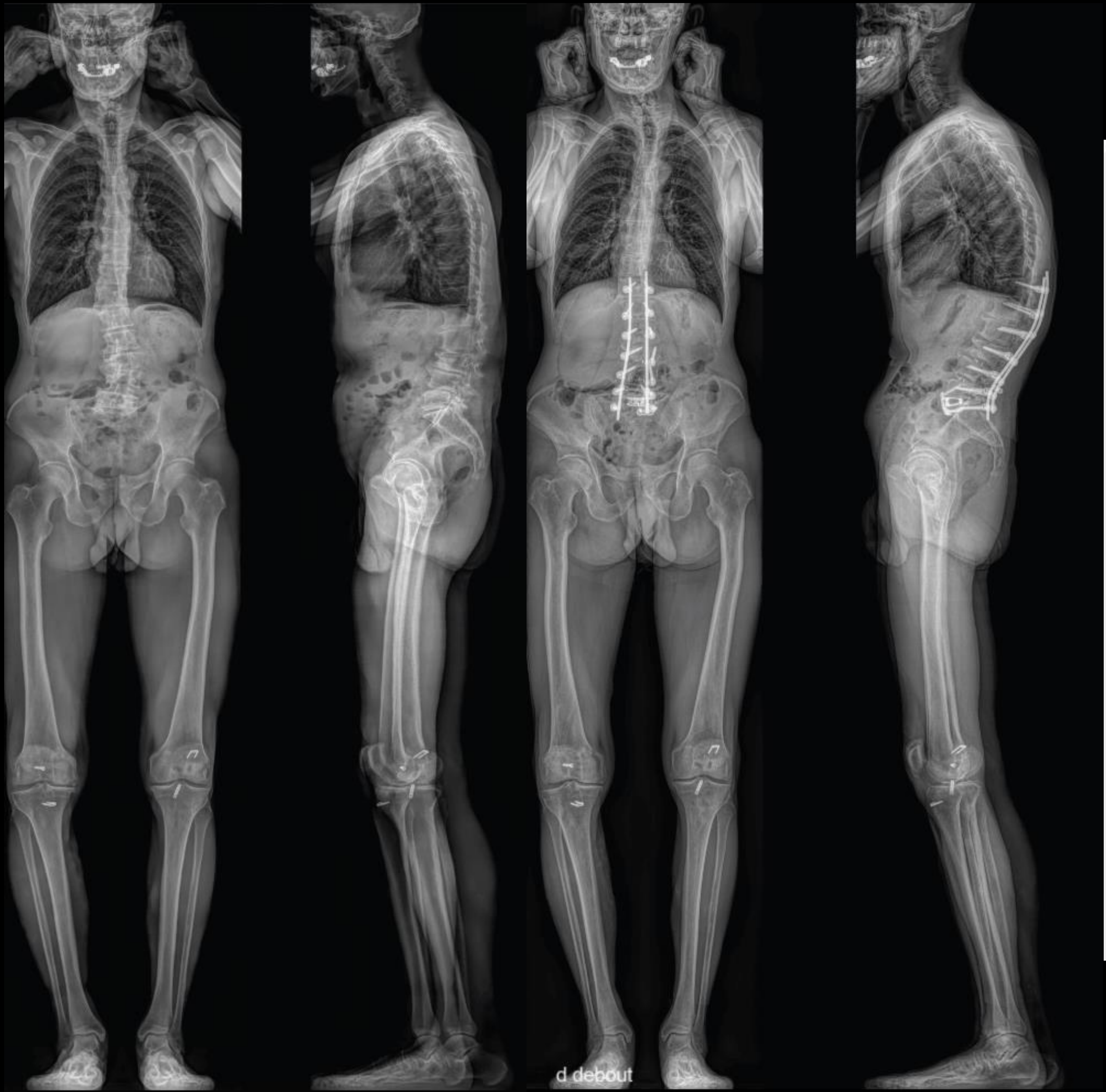
32

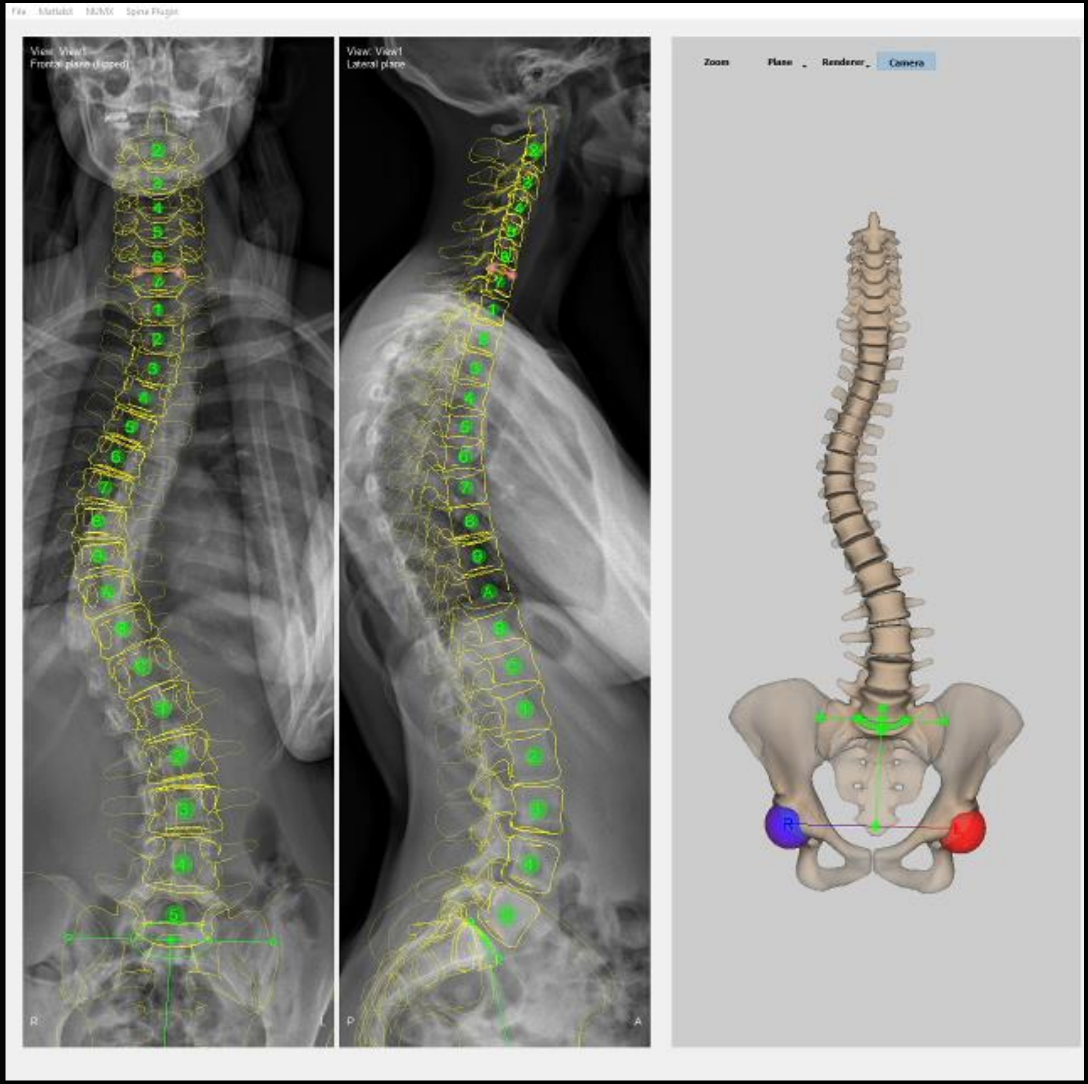
Images 2D/3D du corps entier en position fonctionnelle

- Acquisition simultanée d’images de face et de profil
- Images du corps entier ou localisées
- Modélisation 3D : calcul automatique des paramètres cliniques
- Imagerie en position fonctionnelle (assis-debout)



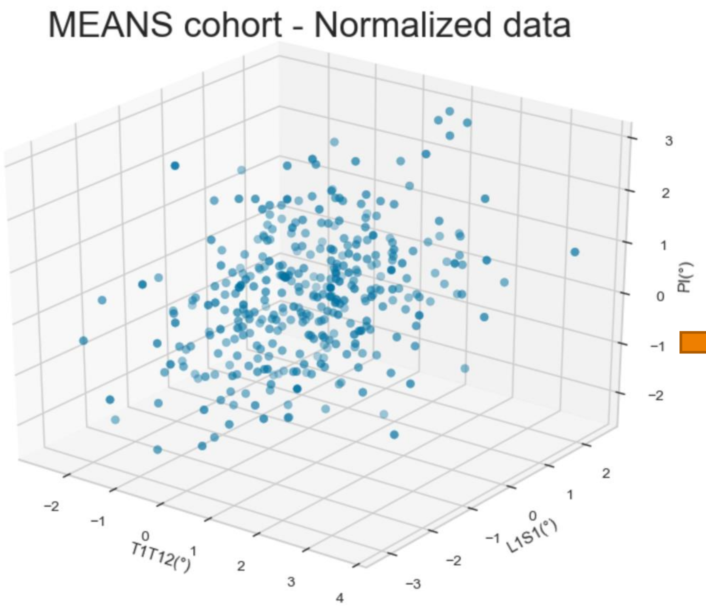
Impact de l’imagerie en position fonctionnelle
sur les paramètres cliniques

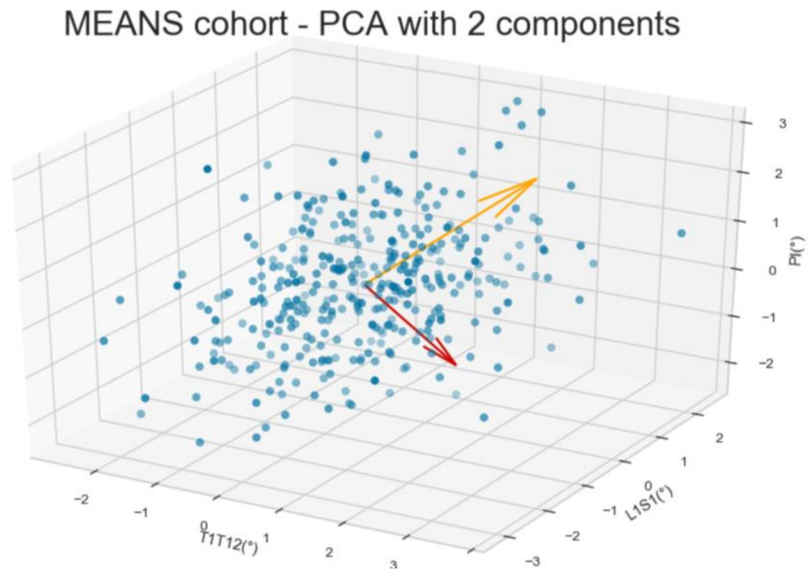

d debout


View: View1
Frontal plane (flipped)
View: View1
Lateral plane
Zoom
Plane
Renderer
Camera
R
L
P
A

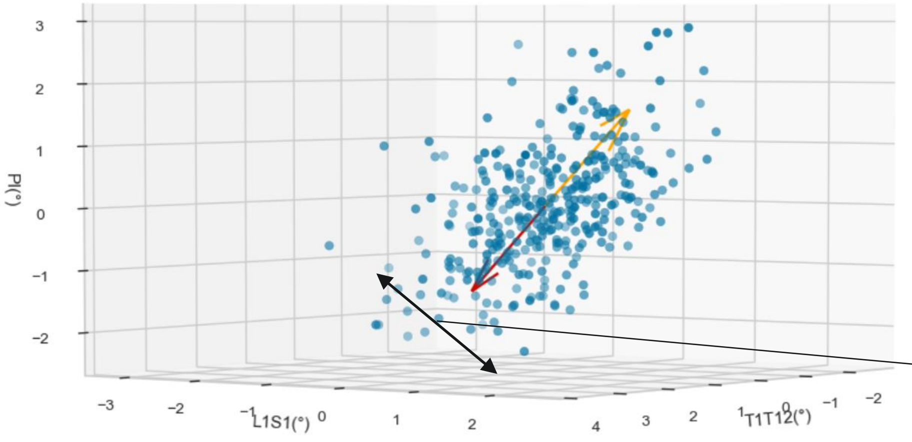
Dimension reduction - From 3D to 2D

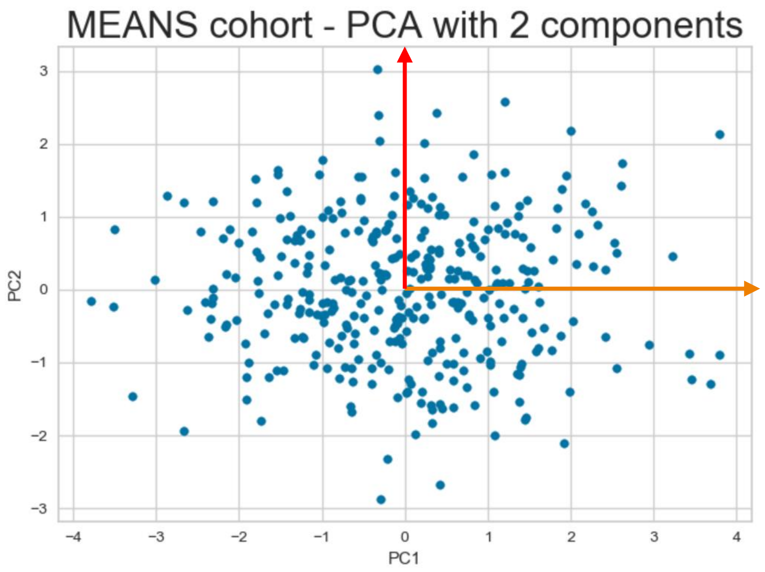
PCA





PC1 (describes 58% of total variability)
PC2 (describes 31% of total variability)



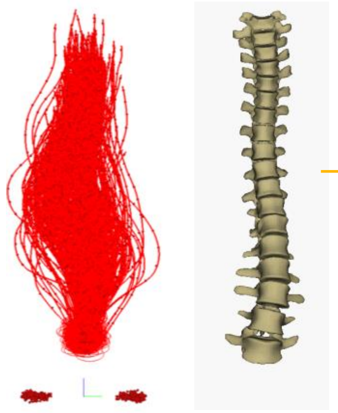


Data projected into the plan defined by PC1 and PC2.
- 89% of total variability explained

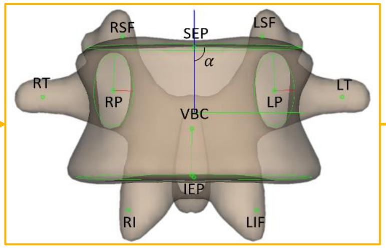
11% of total variability « lost » (black arrow)

Spine modeling

> Training using PCA

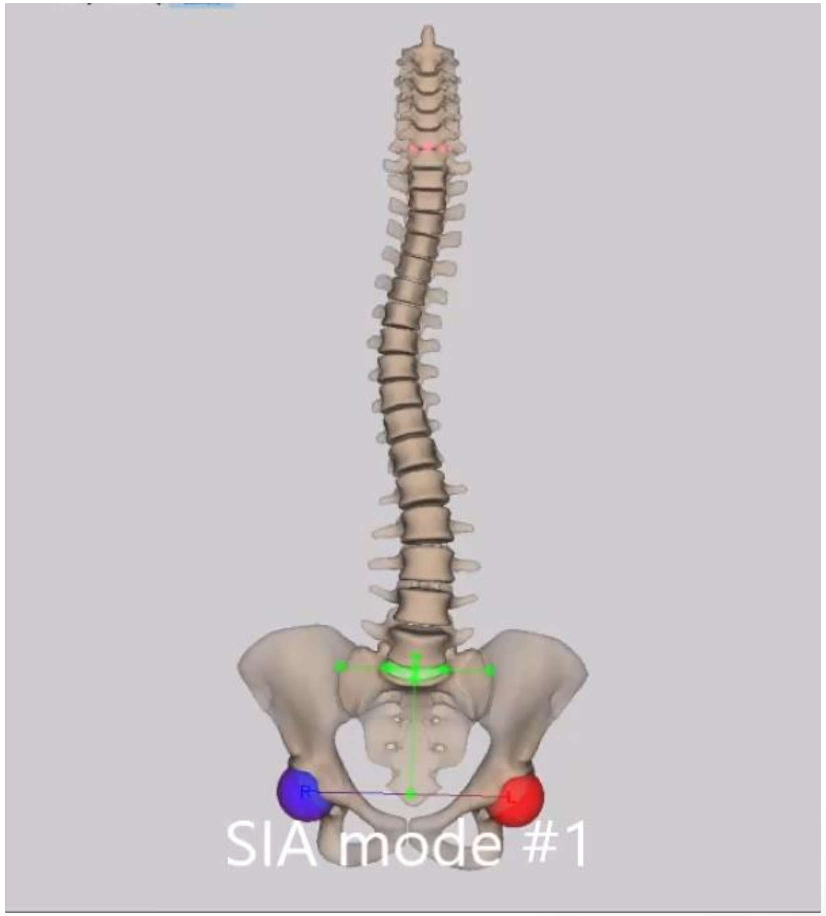


450 AIS patients
(3D reconstructions)



Parametrization

Deformation modes computed (PCA)



Modes of variations

$$|\, m \,| << |\, x \,|$$

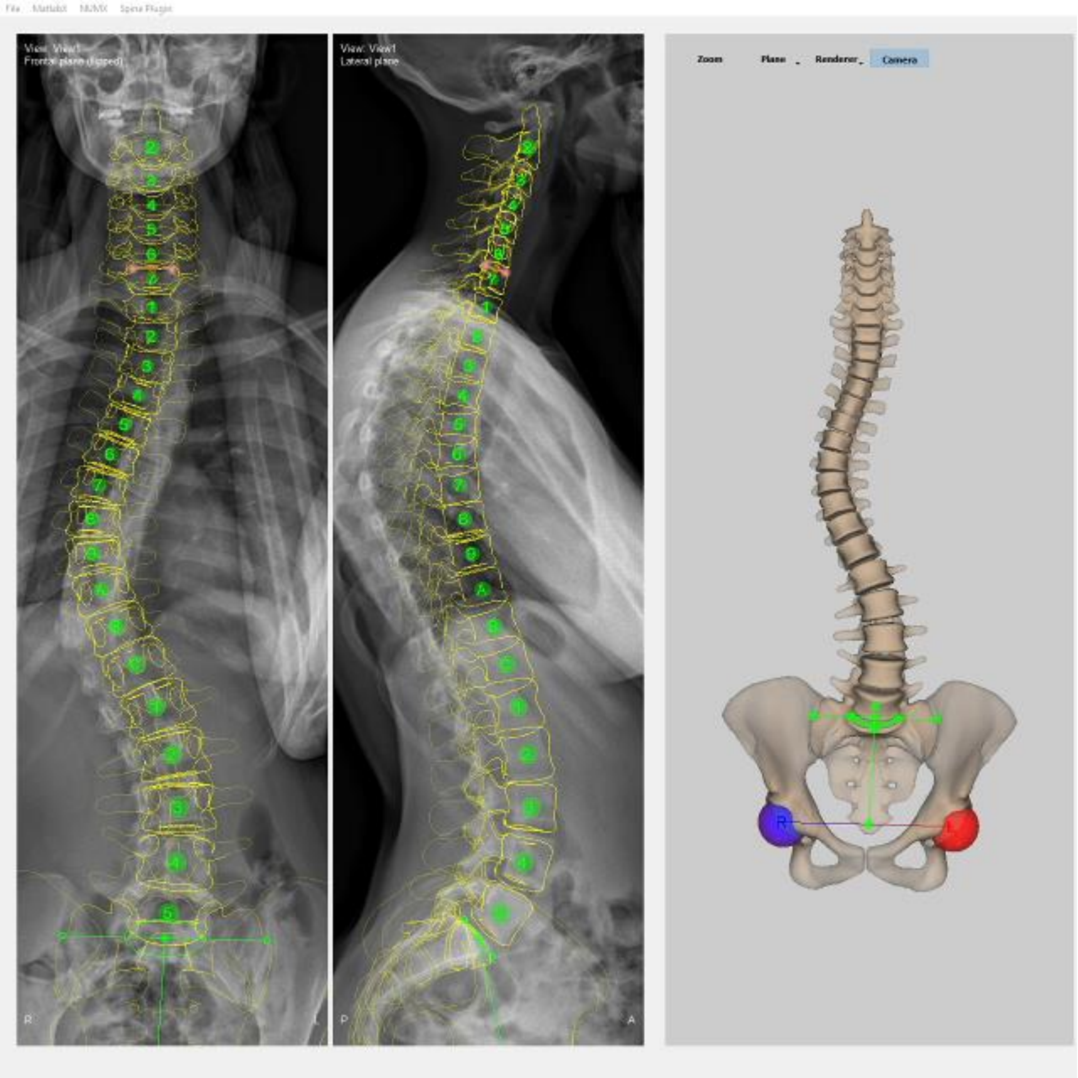
$$\underbrace{x}_{\text{Shape instance}} = \bar{x} + \underbrace{Bm}_{\text{Deformation}}$$

Deformation modes vector (shape descriptors in the reduced latent space)

$-\mathbf{3}\sqrt{\lambda_i} < m_i < \mathbf{3}\sqrt{\lambda_i}$ (with λ_i the eigenvalue corresponding to the ith eigenvector)

Spine modeling

> Inference from sparse data (model fit)



For data set $X \in \mathcal{R}^{n\,X\,d}$ and coordinate i:

$$\hat{m} = \underset{m}{\operatorname{argmin}} \sum_{i=1}^{d} w_i\big(x_{o,i} - \underbrace{(\bar{x} + Bm)_i}_{\text{Reconstructed landmarks}}\big)^2 + \underbrace{\frac{\beta}{2}\sum_{k=1}^{|m|} m_k^2}_{\text{L2 Regularization}}$$

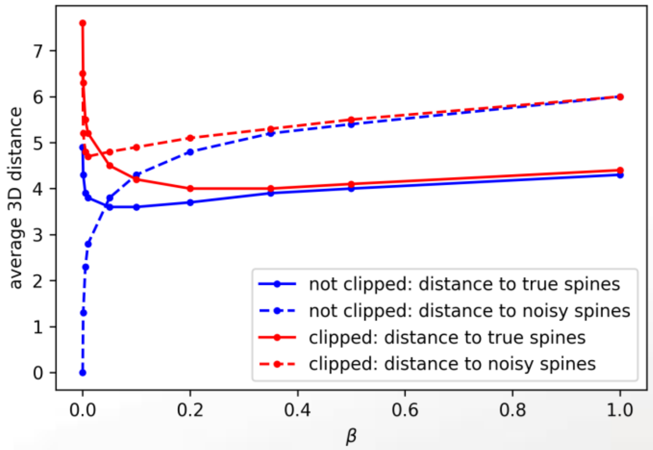
Target observed landmarks

B being the latent representation vectors and m the latent representation

β : regularization weight

Least squares solution (weights $w_i = 1$):

$$\hat{m} = (B_o^T B_o + \beta^2 I)^{-1} B_o^T (x_o - \bar{x}_o)$$



Trade off between model fitting and reconstruction error

(Ansart et al. 2022)

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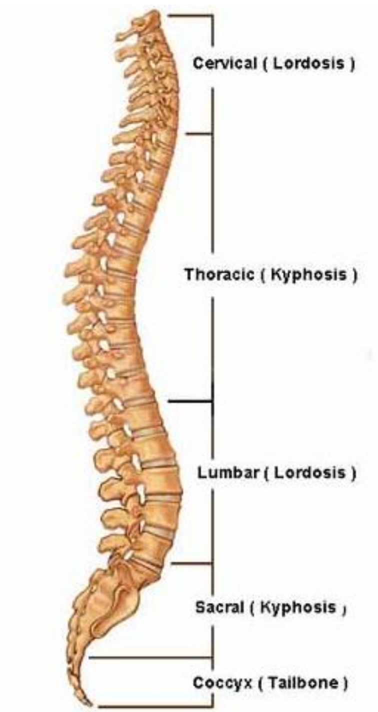
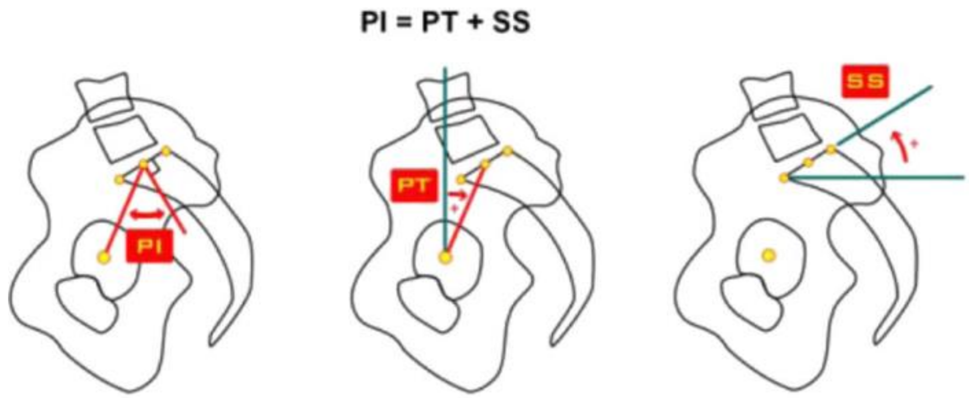
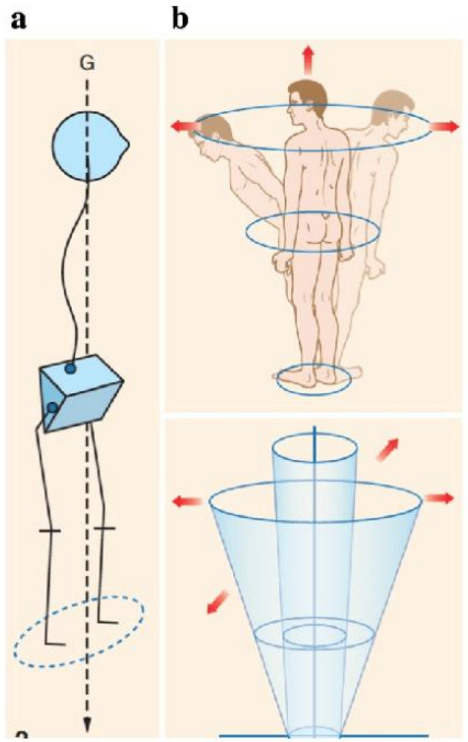
Spinal anatomy and sagittal balance





Pelvic parameters: PT pelvic tilt, SS sacral slope, PI pelvic incidence



> 24 vertebrae (7 cervical – 12 thoracic – 5 lumbar)
> Spongious intervertebral discs
> Kyphotic and lordotic normal curves to keep balance

> Pelvic incidence: fixed anatomical parameter
> When PT ↑, SS ↓
> Pelvic geometry → high impact on spinal shape

> Cone of economy: position that minimizes efforts while maintaining a horizontal gaze

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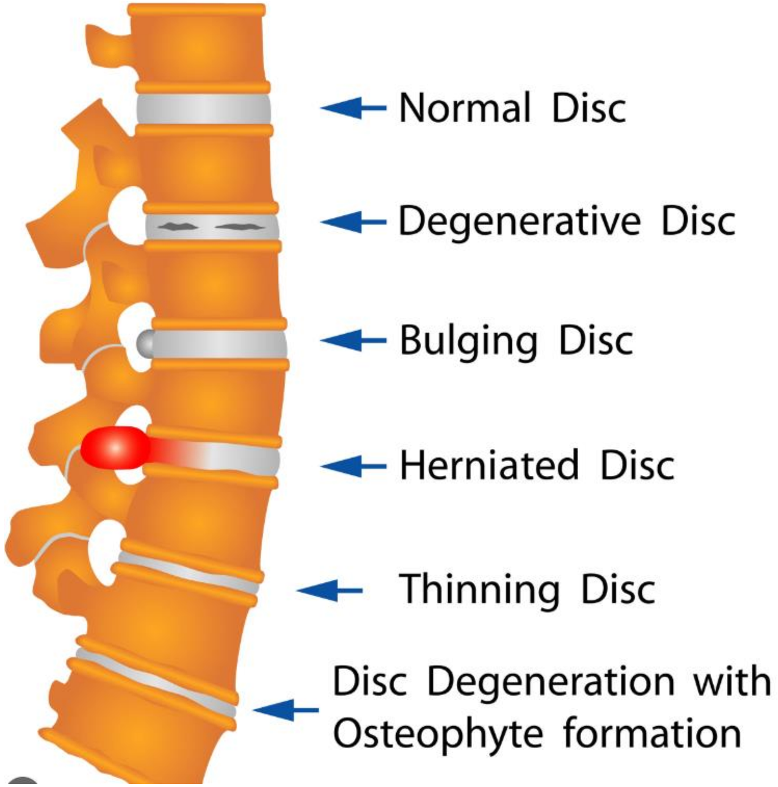
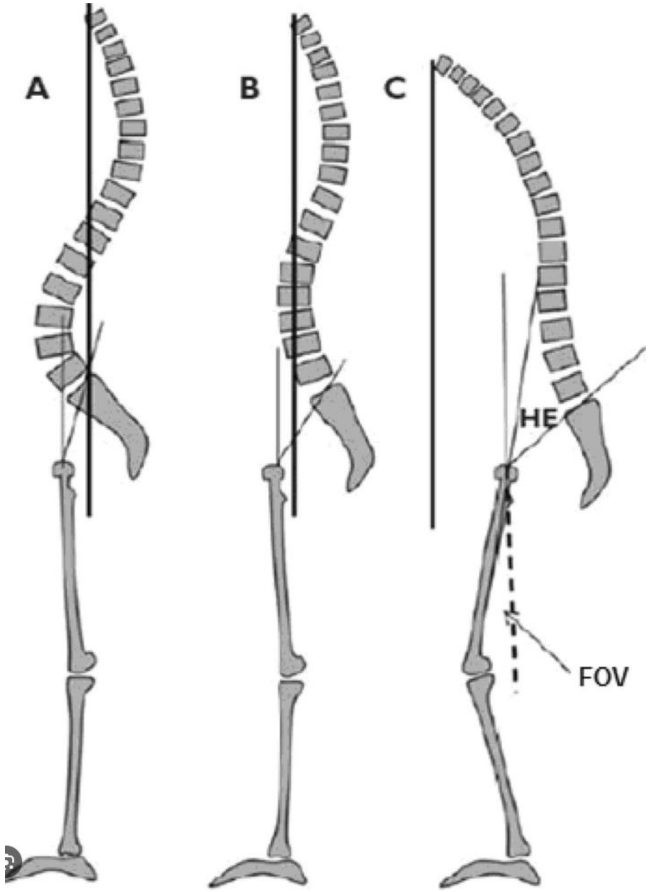
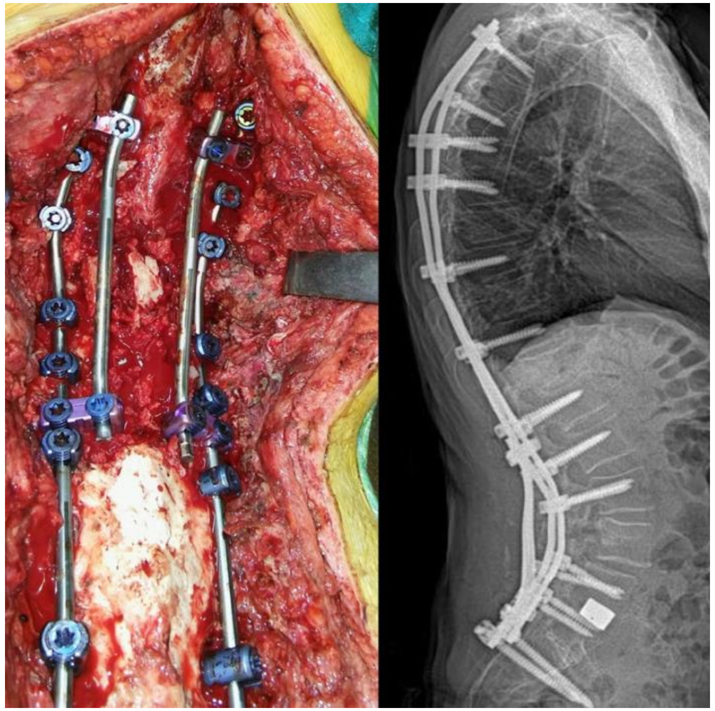
Spinal anatomy and sagittal balance







- With age: degenerative process
- Loss of disc height → Compensatory mechanisms chain
- Lumbar lordosis loss + thoracic kyphosis increasing
- To avoid leaning forward and keep & horizontal gaze → pelvic retroversion, cervical lordosis extension and knee flexion

UNTIL UNBALANCE

need for surgery !

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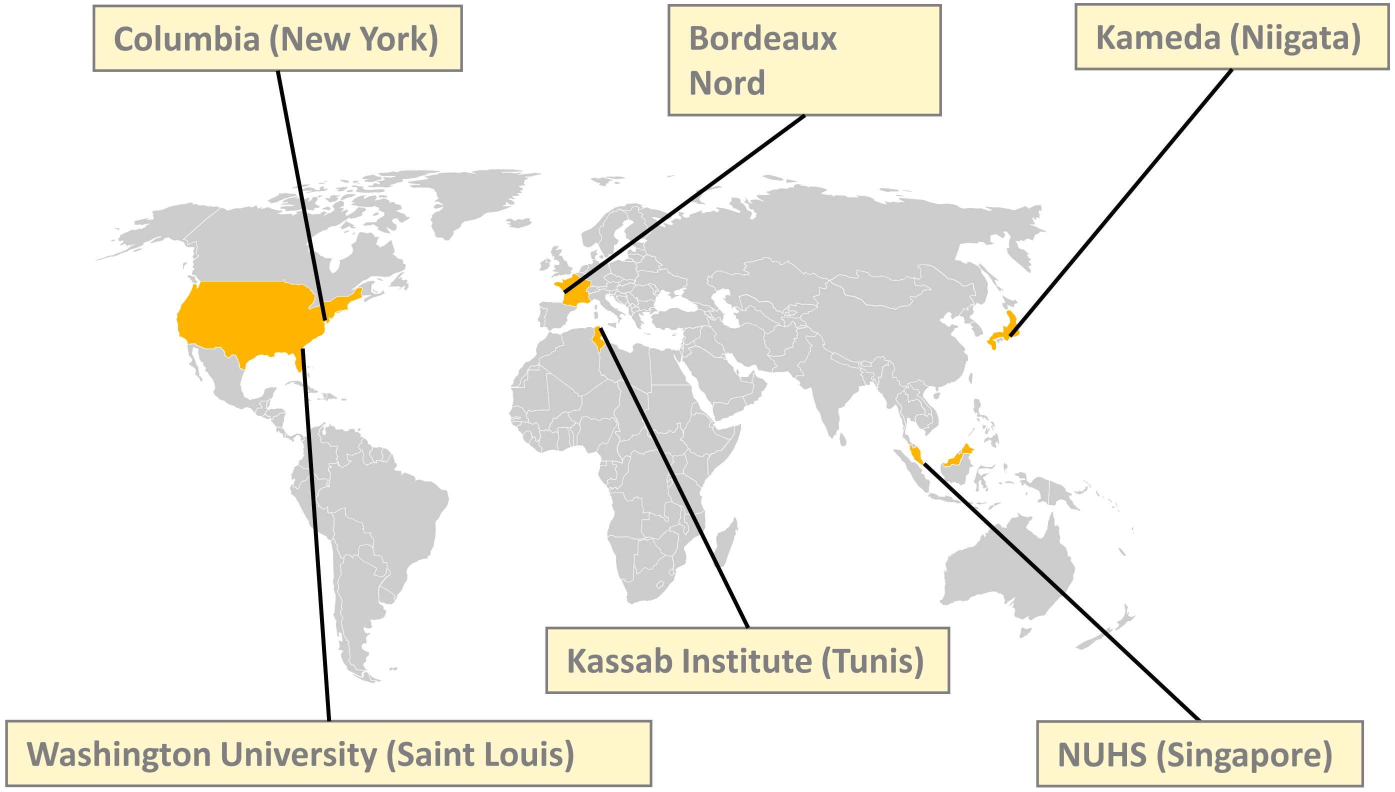
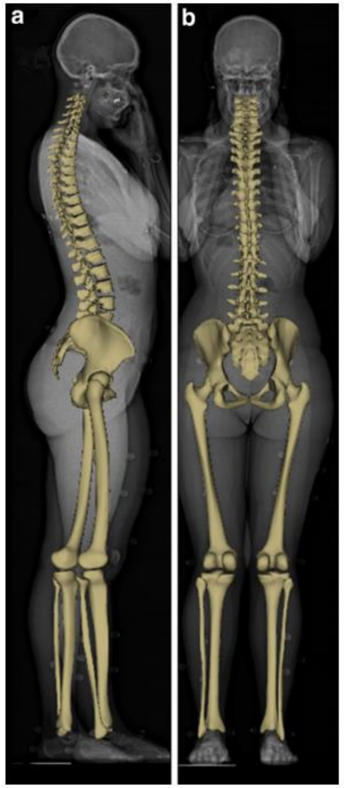
MEANS GROUP – Define Normative alignment

10 Top KOLS in adult spine

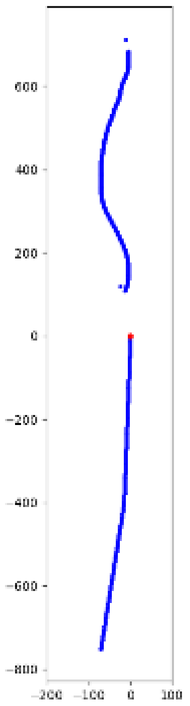
- 6 sites / 5 different countries (NAM, APAC, EMEA)
- 488 EOS 3D reconstructions with new sterEOS 2 full-body parameters
- +10 manuscripts / + 20 posters presentations

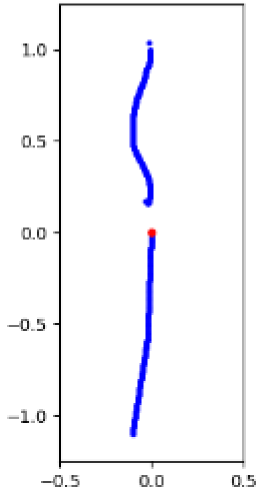


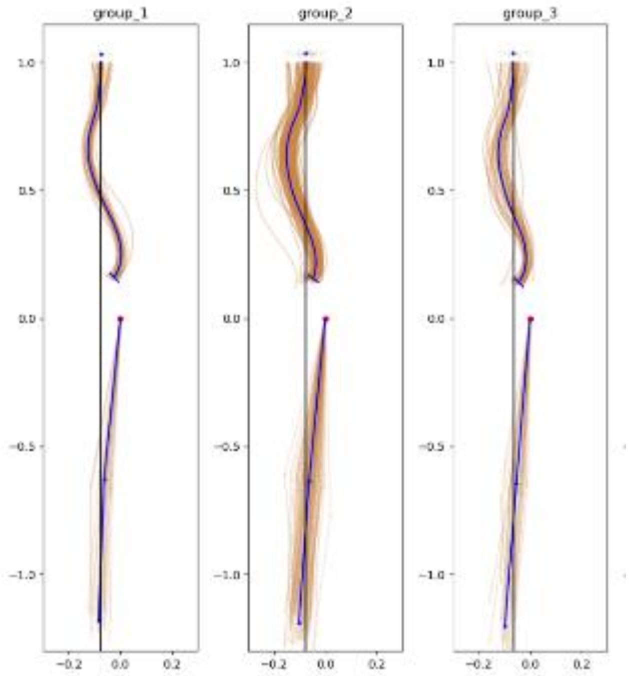


- What is a "NORMAL" alignment ?
  - Cluster analysis to try identifying patterns and potential evolution with age
  - Defining personalized sagittal shape "targets" for surgery based on pelvic morphology

Method







Coordinates of vertebrae centers + sacral slopes + hip axis + knees centers + vertebrae orientation in sagittal patient plane

Uniform scaling to set HA to 0 and OD to 1

Dimension reduction

Machine learning tools to enhance data density

Unsupervised data clustering

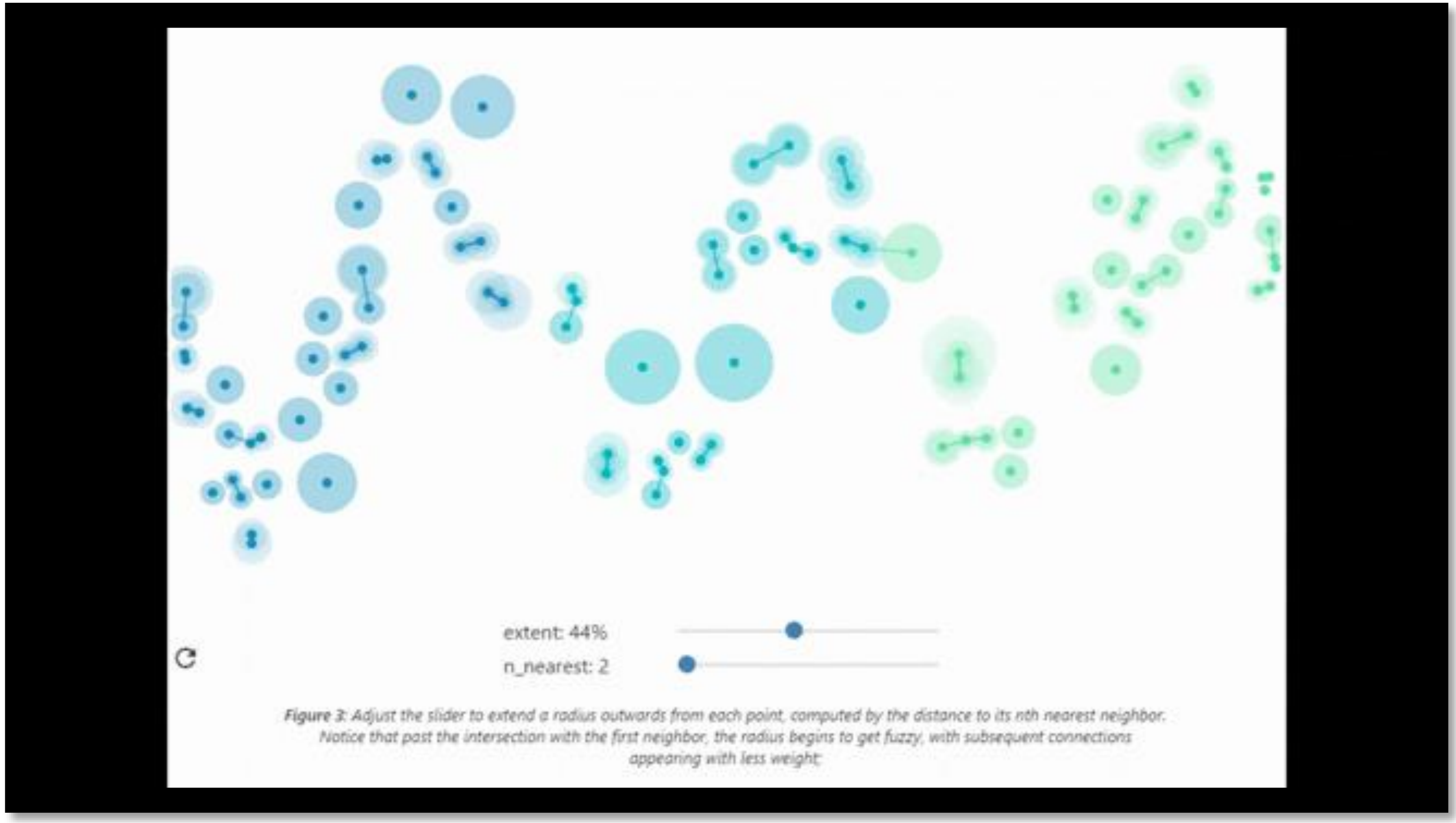
From 3D models to clustered sagittal shapes…

EOS imaging

UMAP

Machine learning tool based on topological structure of the data

- Takes as input the number of k neighbors to consider
- Creates links with the points embedded in the circle created associated to a weight
- Projects the data into lower number of dimension while keeping the same structure for data linked

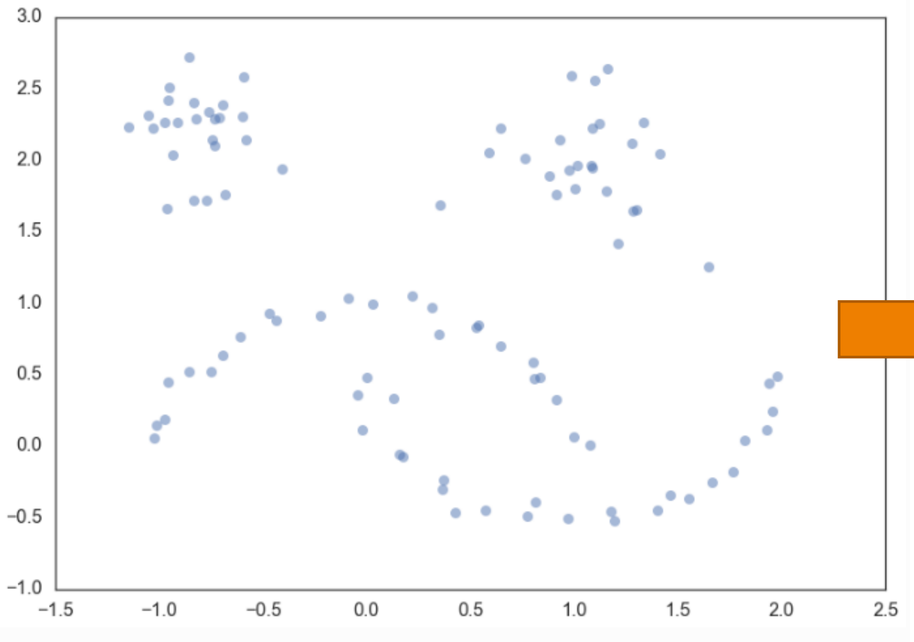


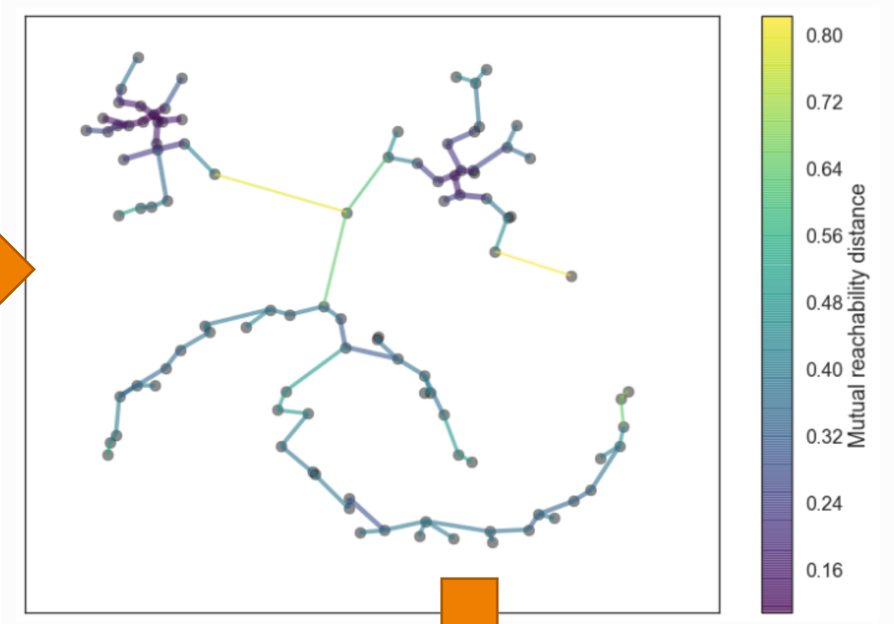
UMAP allows to “enhance” data density by gluing similar data points

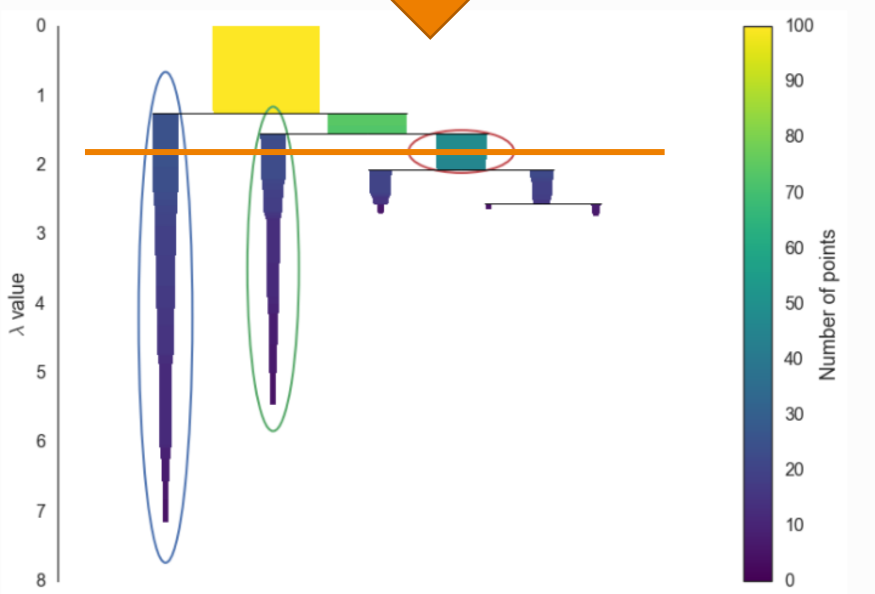
Hierarchical Density based clustering algorithm

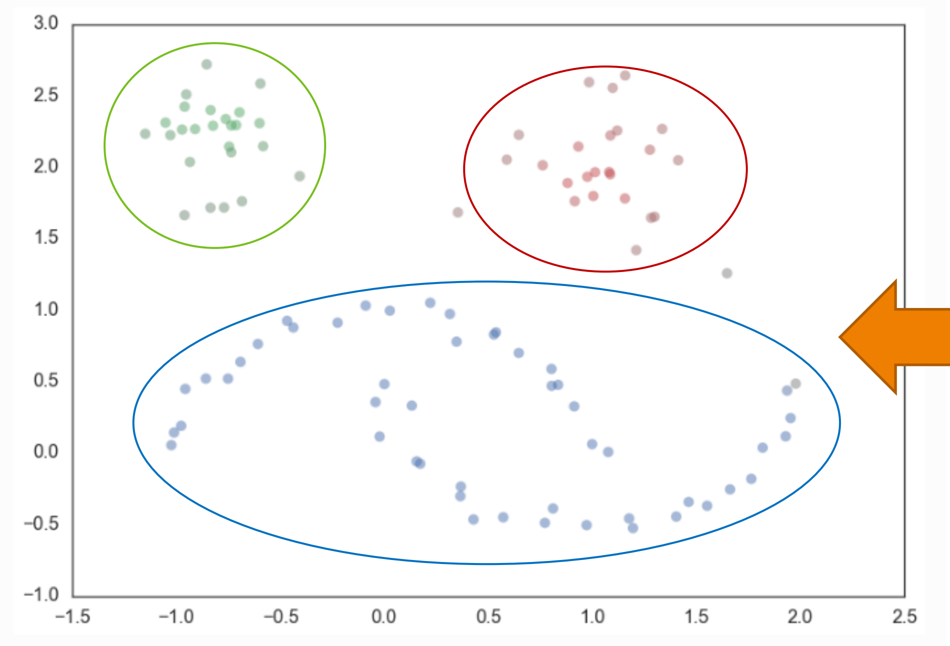
HDBSCAN

- > **Builds a simplified hierarchical tree based on mutual reachability distance = density**
- > **λ value = cutoff value that divide the tree into clusters**
- > **Finds the λ value that maximize the conservation of the clusters**
- > **Allows outliers detection and nonconvex clusters detection**





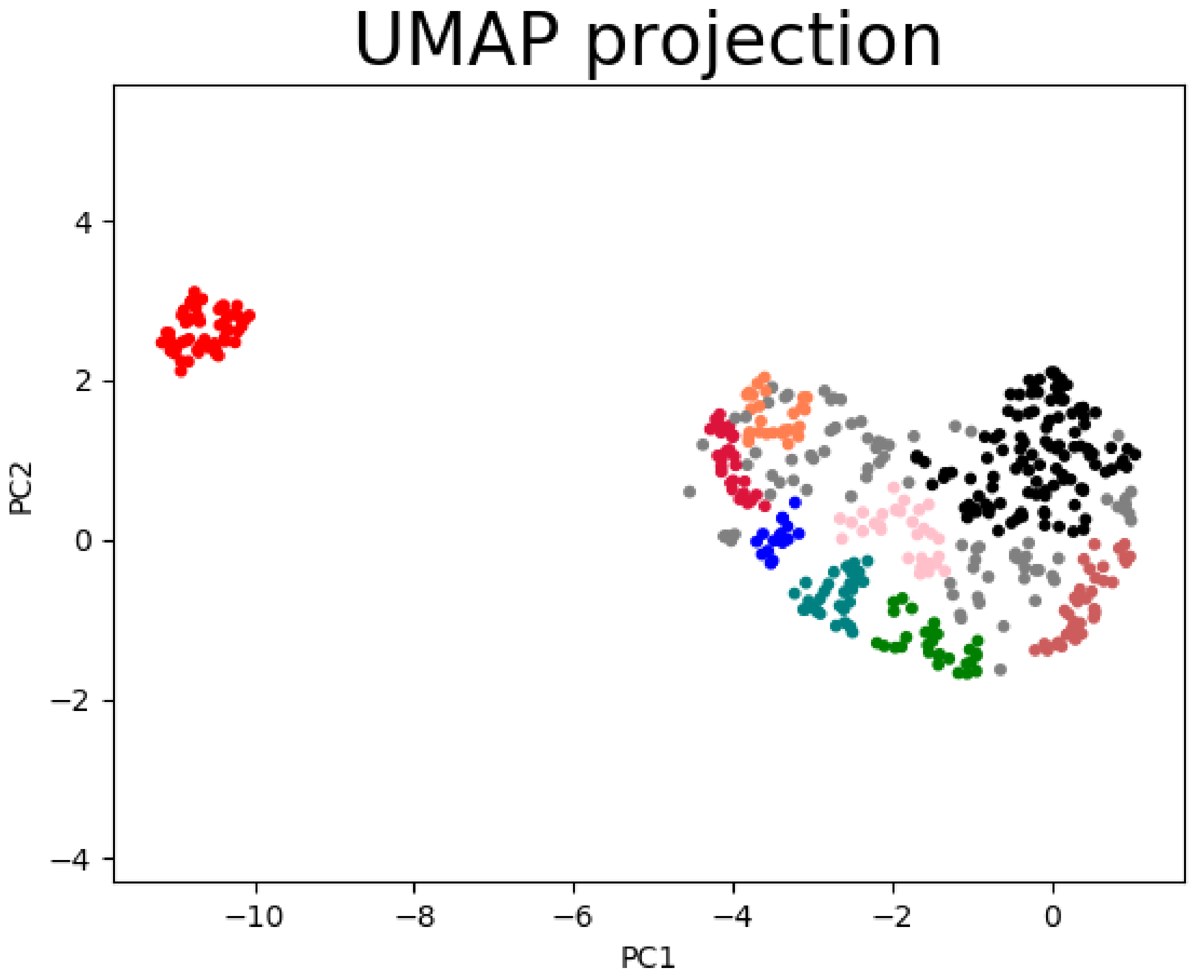


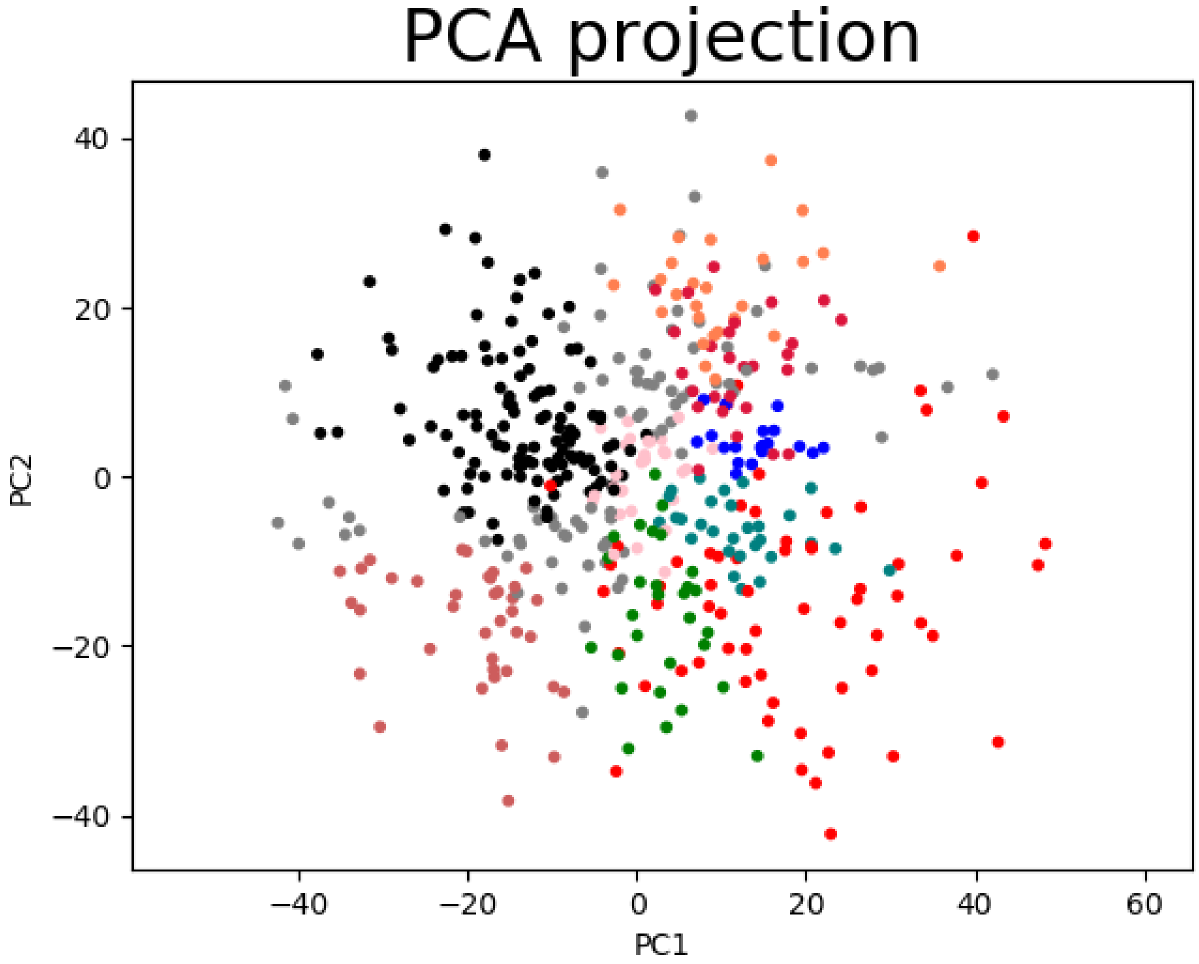


imaging

Example data clustered in 2D using UMAP + HDBSCAN and displayed using PCA and UMAP

PCA vs UMAP





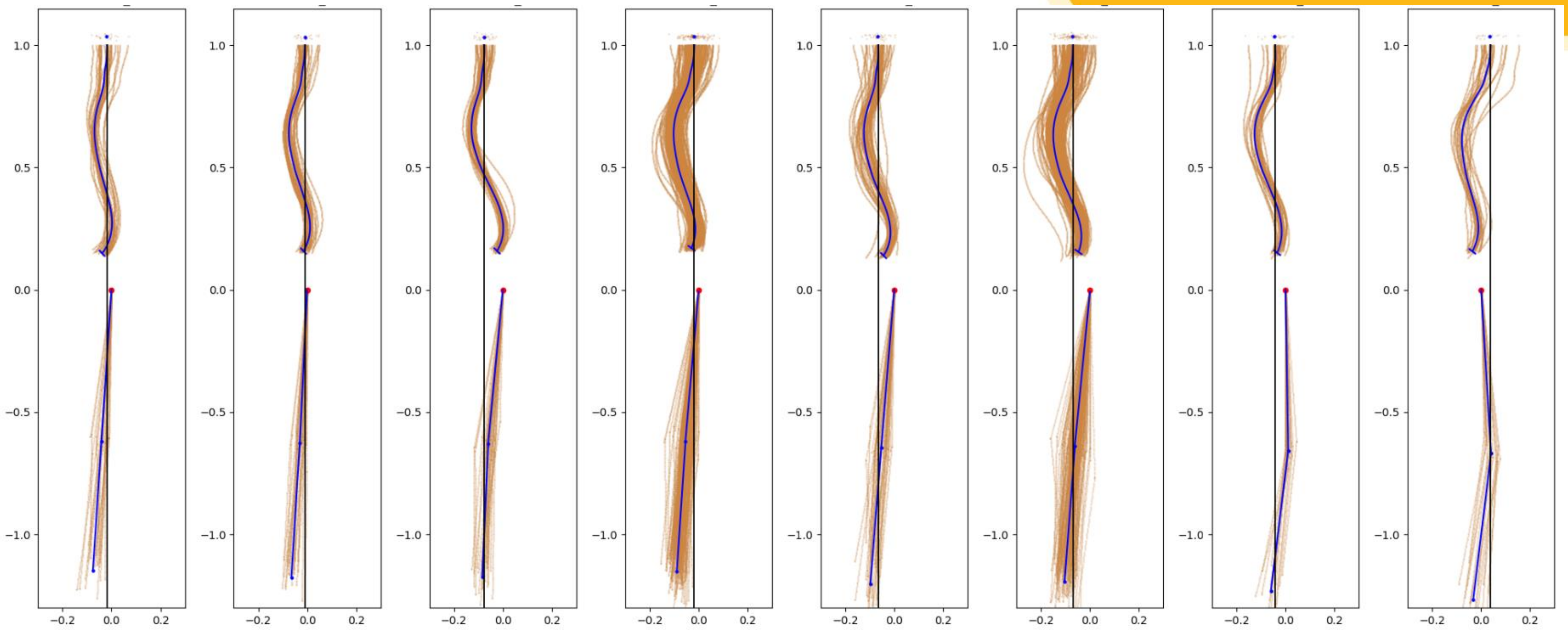
> **UMAP helps defining clear clusters, even in 2D**

EOS imaging

Results

In increasing order of median age

8 clusters



N1 = 22 N2 = 28 N3 = 33 N4 = 104 N5 = 37 N6 = 99 N7 = 23 N8 = 19

Sagittal shapes (expressed in patient plane) superposed within each cluster
Mean sagittal shape within each cluster
Mean OD plumb line
Hip axis (set at the origin)

N = 456

N outliers = 91

Compensatory mechanisms with age

In literature:

> Increase of PT

> Loss of lordosis

> Increase of cervical and O-C2 CL to maintain horizontal gaze

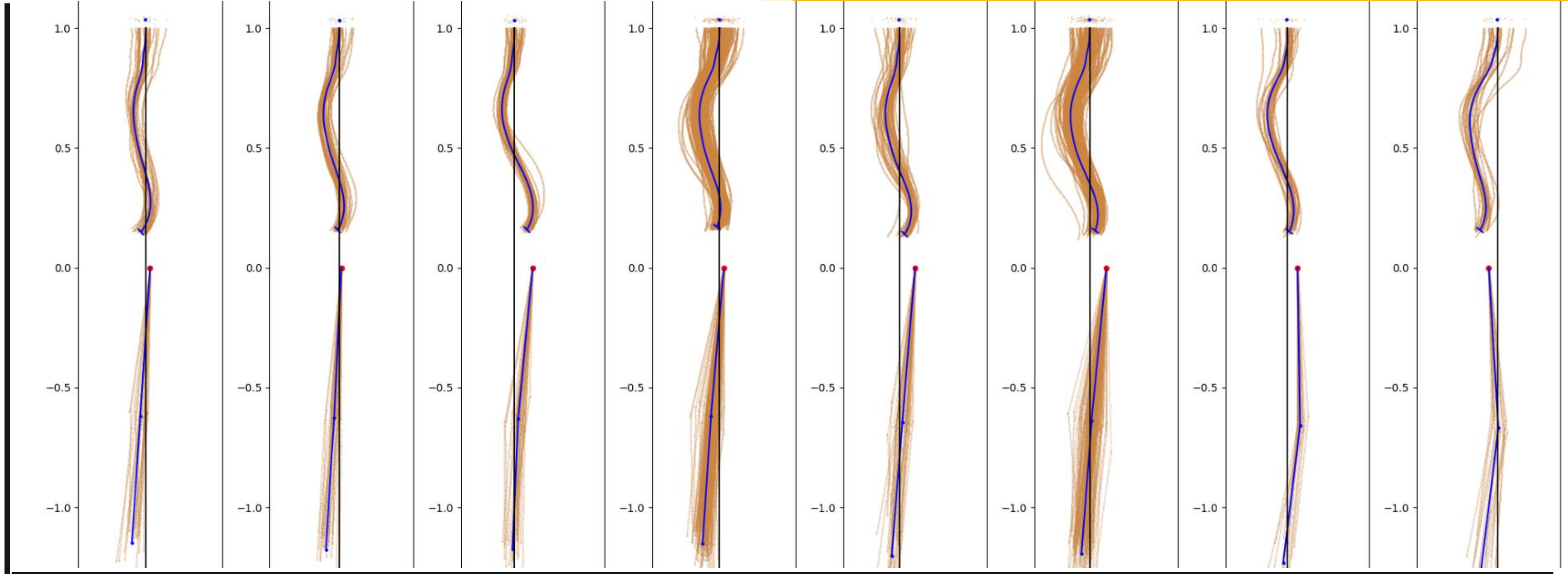
> Knee flexion

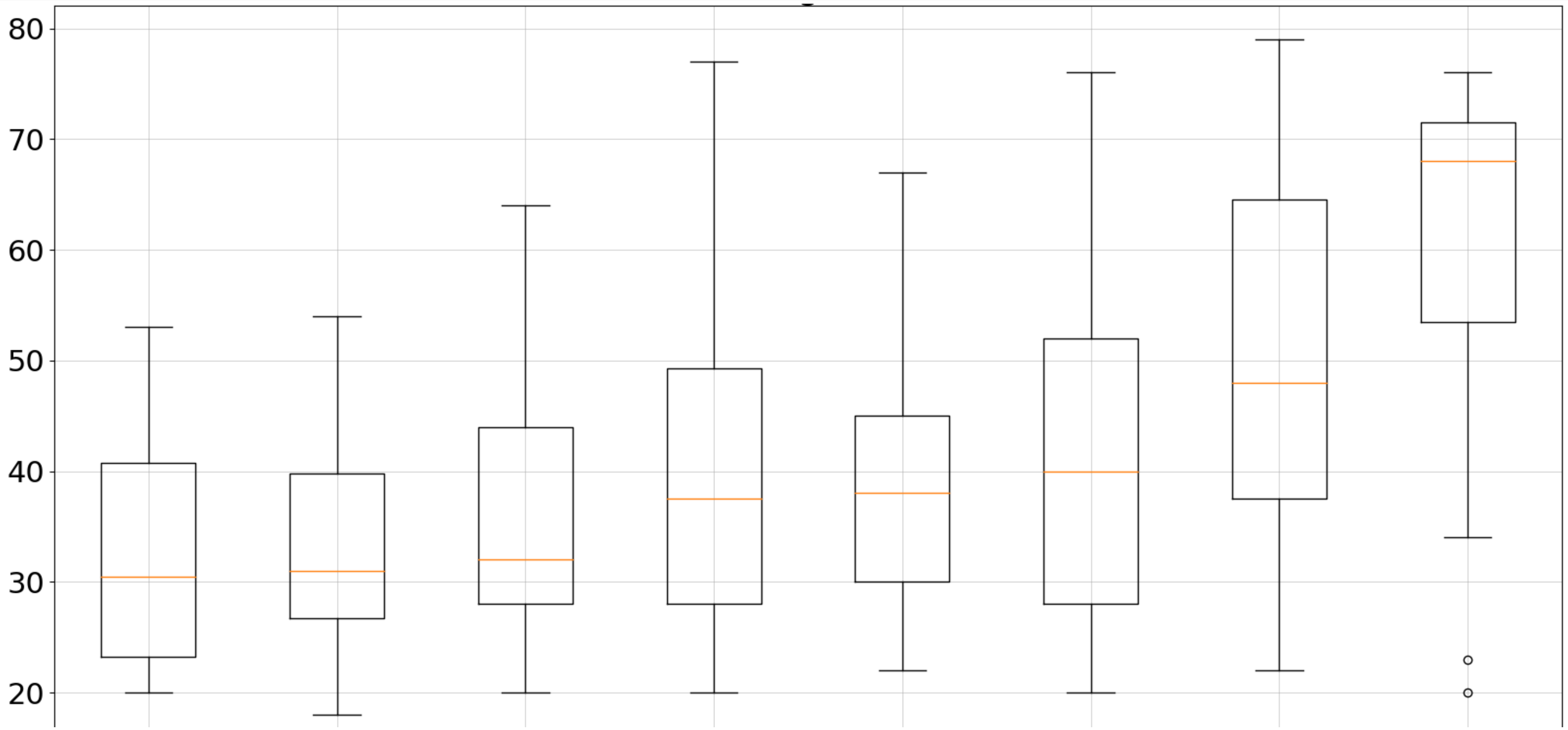
From MEANS abstracts:

> Increase of TK

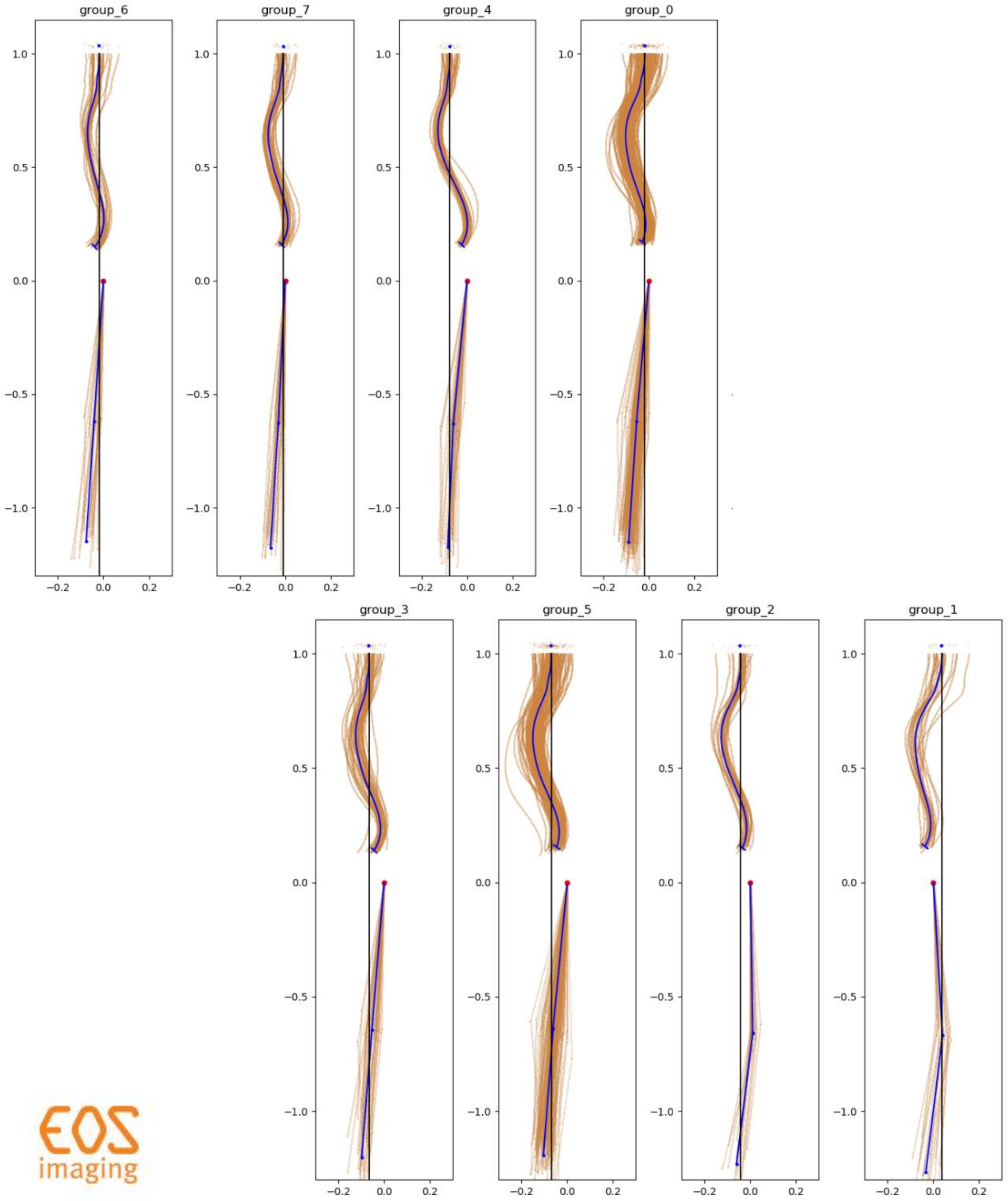
> Head maintained over the knees more than the HA

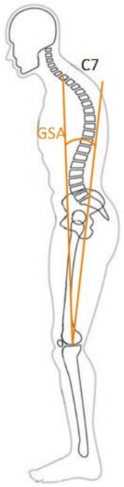
Age

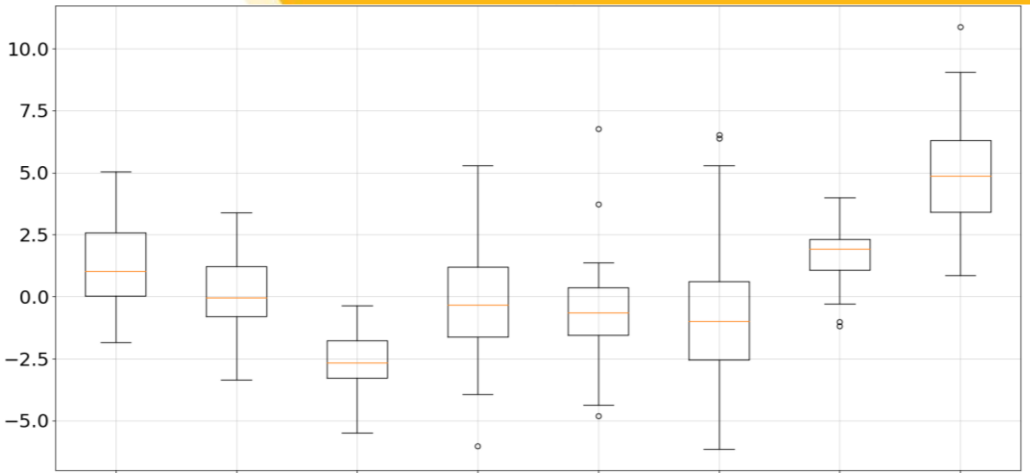


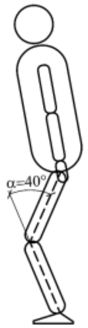


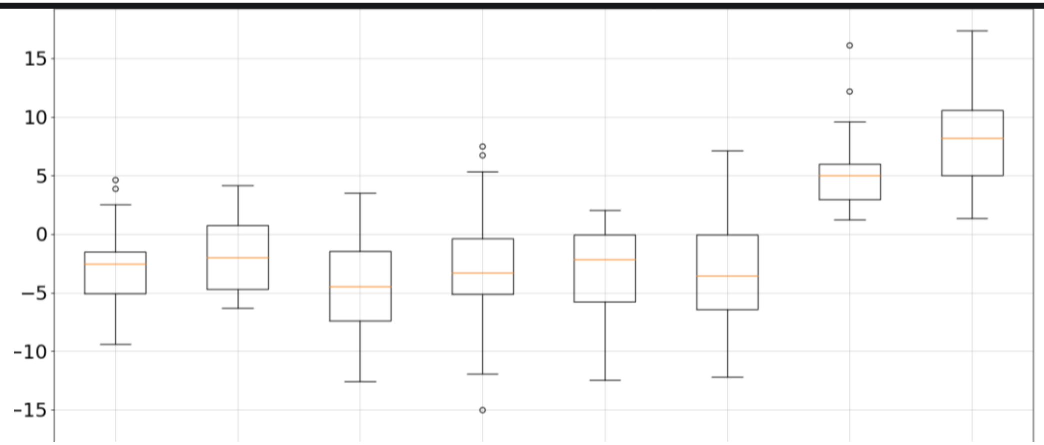
Clinical parameters – compensatory mechanisms

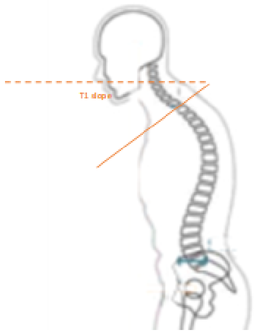


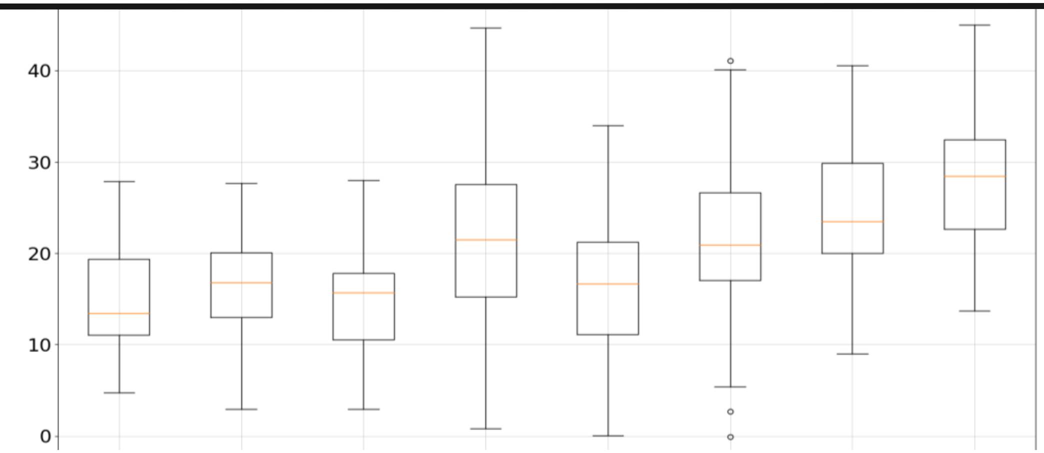




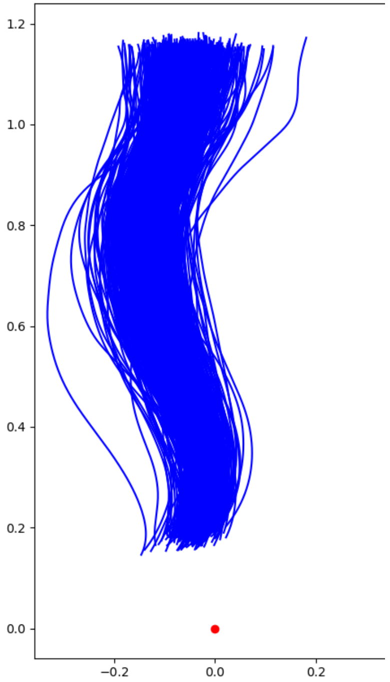




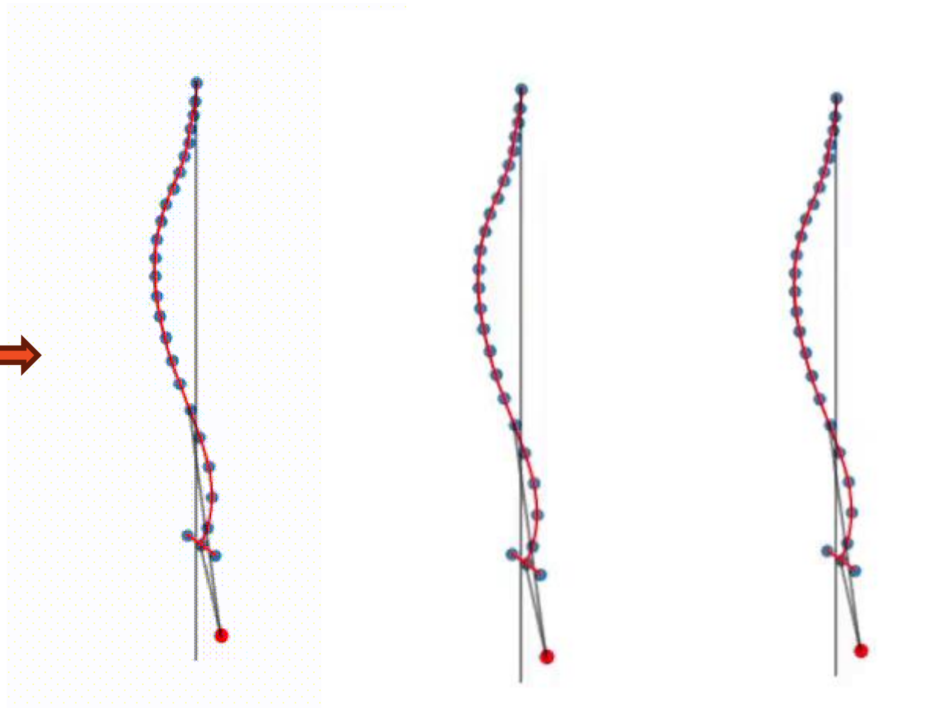




Sagittal « targets » for spine surgery based on pelvic morphology



All shapes superimposed for model creation

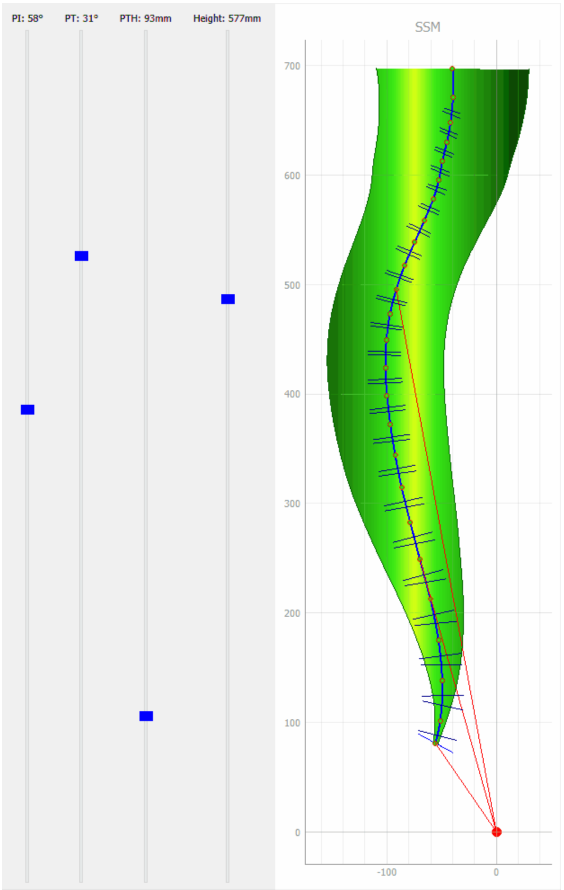


3 first principal modes of variation

$$\underbrace{x}_{\text{Shape instance}} = \bar{x} + \underbrace{Bm}_{\text{Deformation}}$$

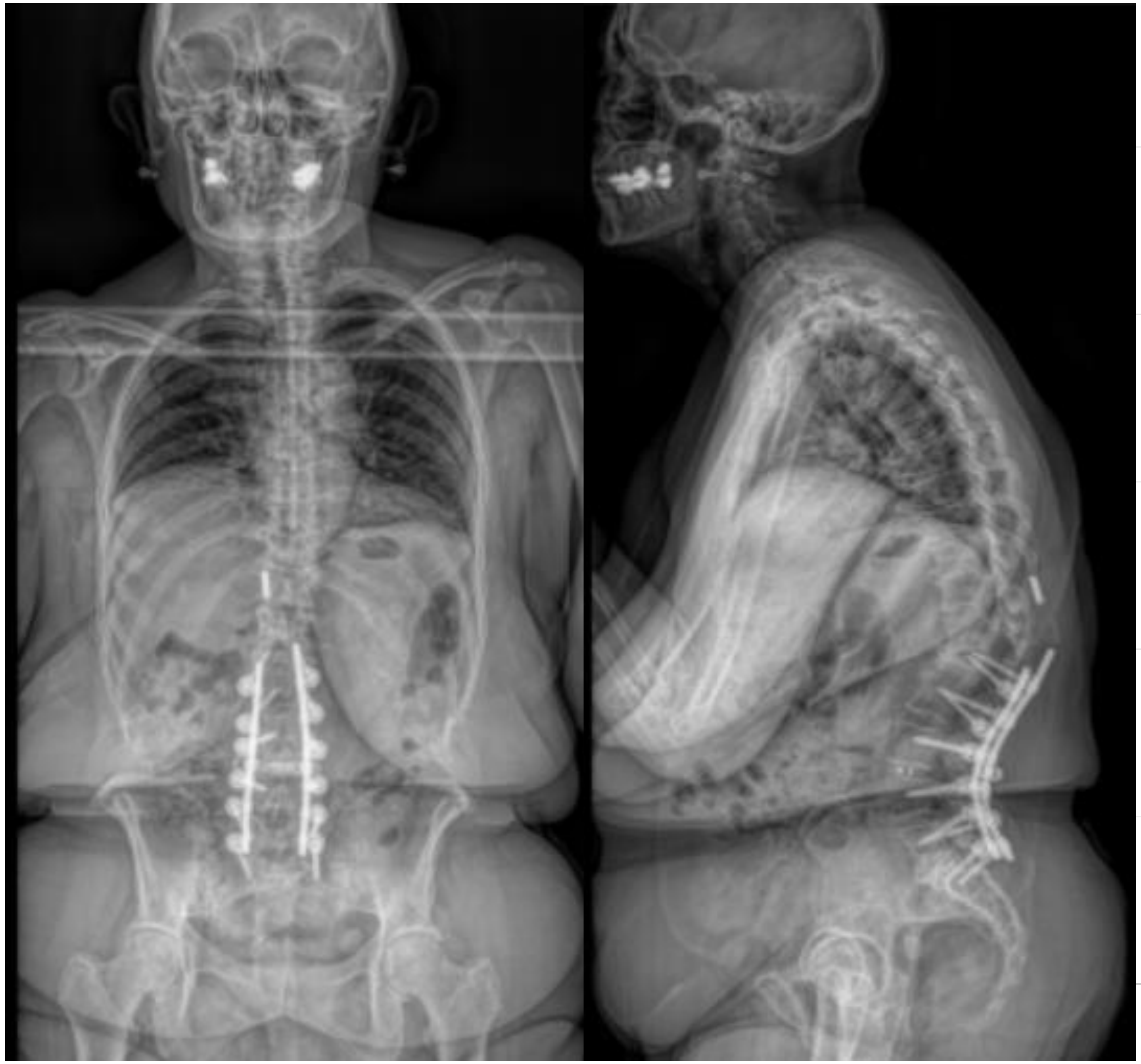
Deformation modes vector (shape descriptors in the reduced latent space)

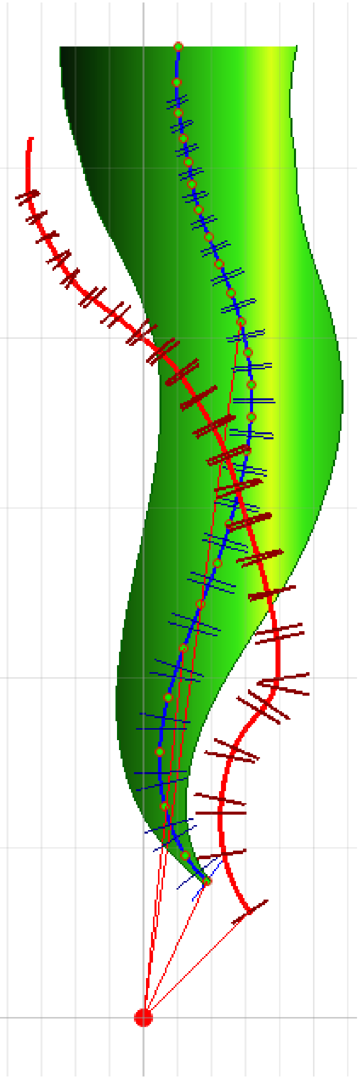
$-3\sqrt{\lambda_i} < m_i < 3\sqrt{\lambda_i}$ (with λ_i the eigenvalue corresponding to the ith eigenvector)



SSM inferences computation based on pelvic constraints + error corridor

Sagittal « targets » for spine surgery based on pelvic morphology





Proximal Junctional Kyphosis (PJK) – Construct too short ?

PhD

Thèse supervisée par Irène Buvat & Frédérique Frouin:

- Programme AI.DReaM (GE Healthcare): consortium sites cliniques/centres de recherche/PME/start-ups – accélérer développement IA en imagerie médicale
- **Développement de méthodes pour l'évaluation & prédiction de la robustesse d'algorithmes d'IA en imagerie médicale**

Thématiques : Imagerie médicale (IRM, TEP), apprentissage machine, Python, méthodes génériques, robustesse/fiabilité

How to predict model performance given new data instance(s) ?

1- A- Features extraction from raw images (+ segmentation if available) :

- Classic radiomic feature extraction
- Deep radiomic: autoencoder (pre trained ?, embedding of evaluated model if available ?)

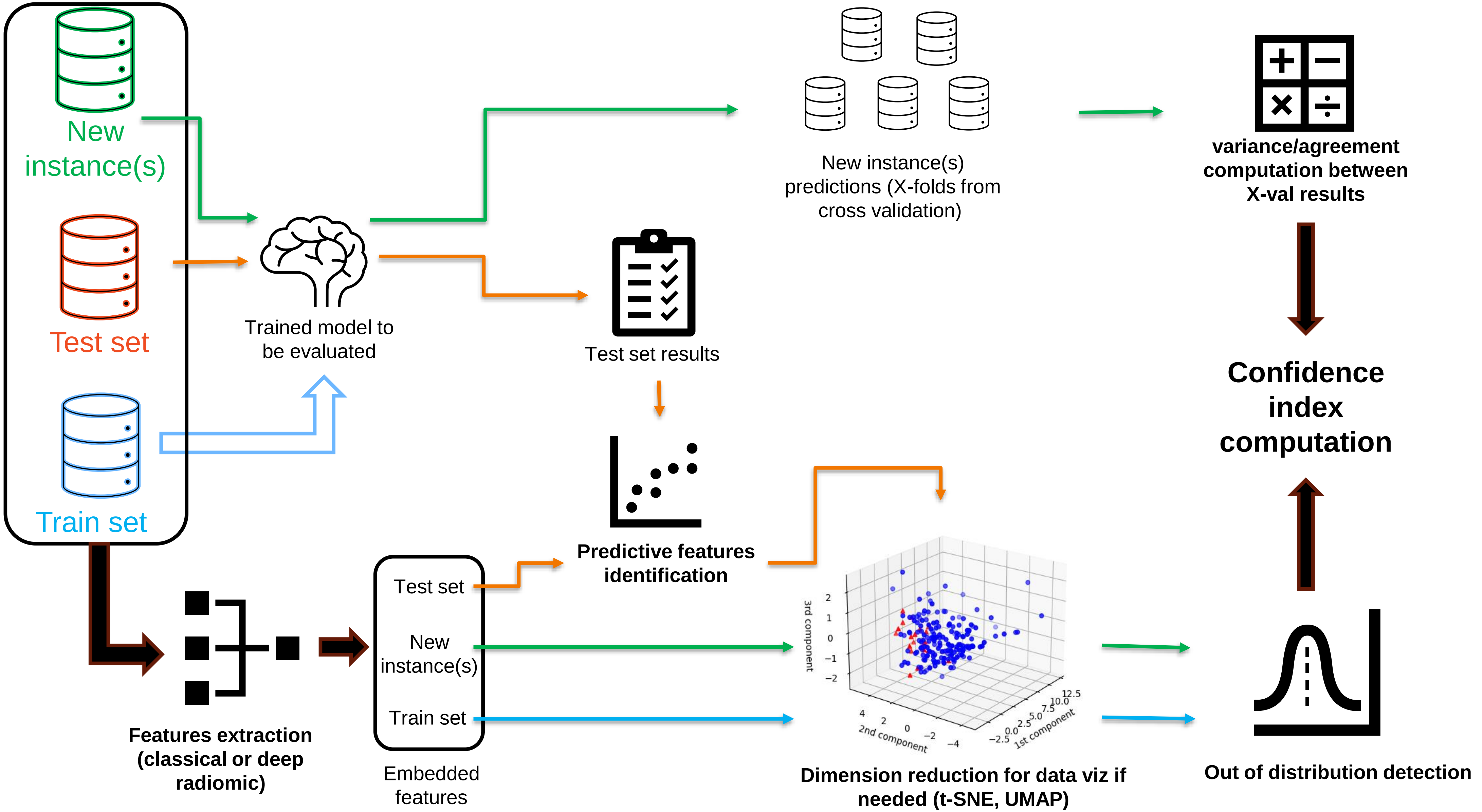
B- Evaluation of features having an impact on prediction using test set results

C- Calculation of the probability that the new instance belongs to same distribution as that of the train set using identified key features

2- Using predictions from the models corresponding to the different folds in a CV scheme to compute agreement between predictions

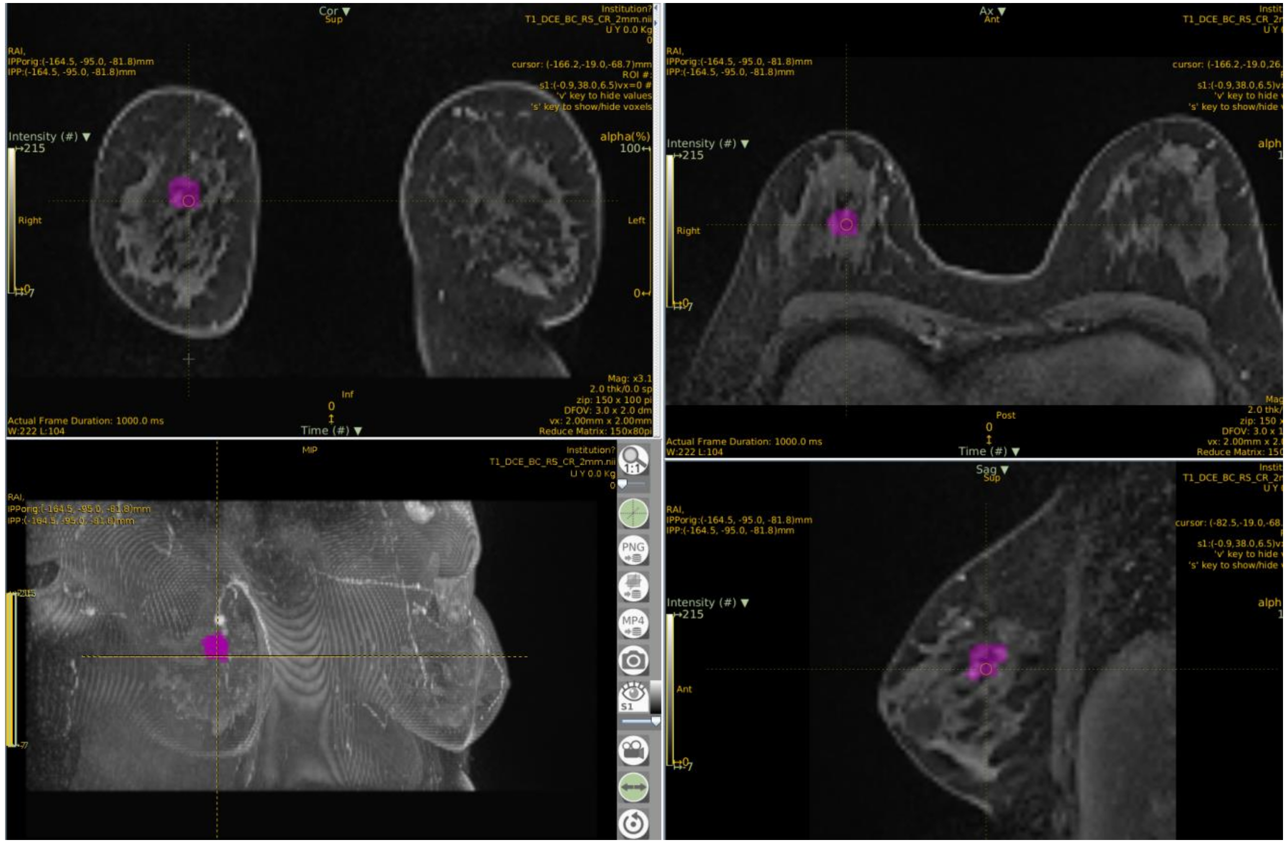
3- Using 1-C & 2 results to compute a confidence index in the new instance model prediction

How to predict model performance given new data instance(s) ?



Neotex dataset

Breast tumor MRI sequences (baseline scans and post NAC scans)



T1-MRI + Manually segmented GT - LifeX

1- CNN training using GT manual segmentation
2- 5-folds cross validation using different sequences
3- Model trained and tested on various set of data (baseline / baseline + post NAC, …)

Shape features analysis

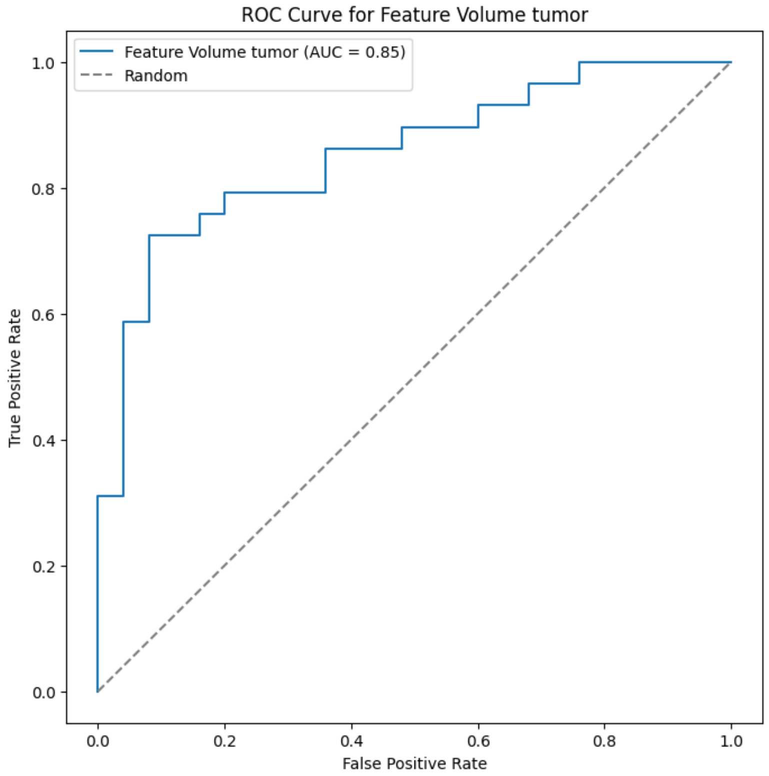
Is tumors shape enough to predict a segmentation score ?

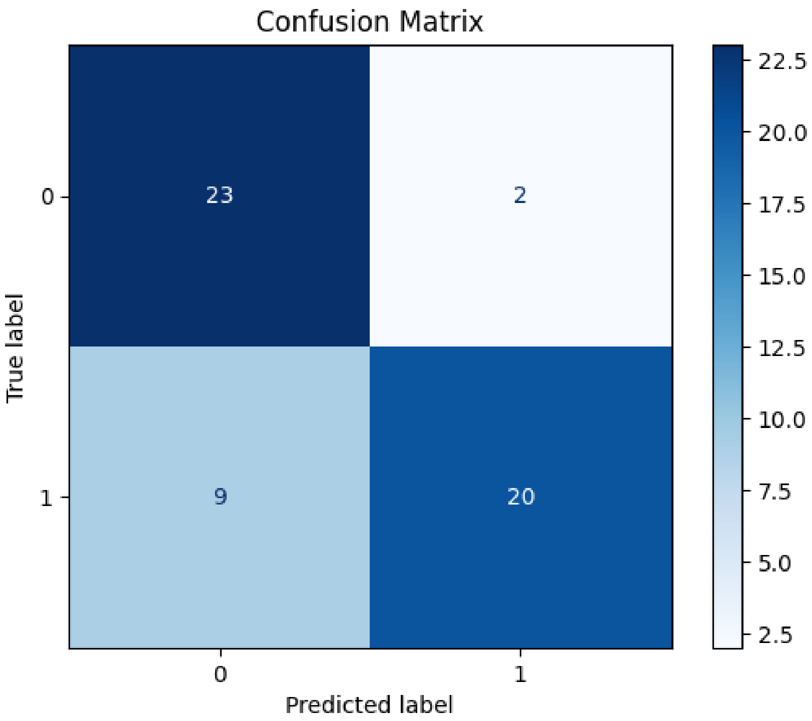
Radiomics features score computation using pyradiomics:

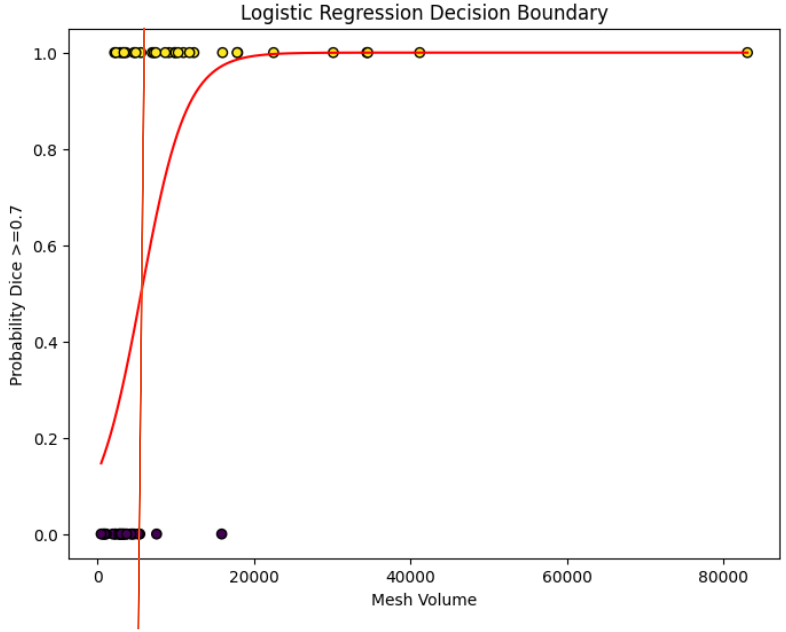
- 14 features, high correlations.
- Features kept for 1st evaluation:
  - Mesh volume
  - Elongation
  - Sphericity
  - Surface volume ratio

Predictive power of shape features

Logistic reg for CNN dice >= 0.7 pred using only shape features: Mesh volume (baseline test cases + post NAC test cases)





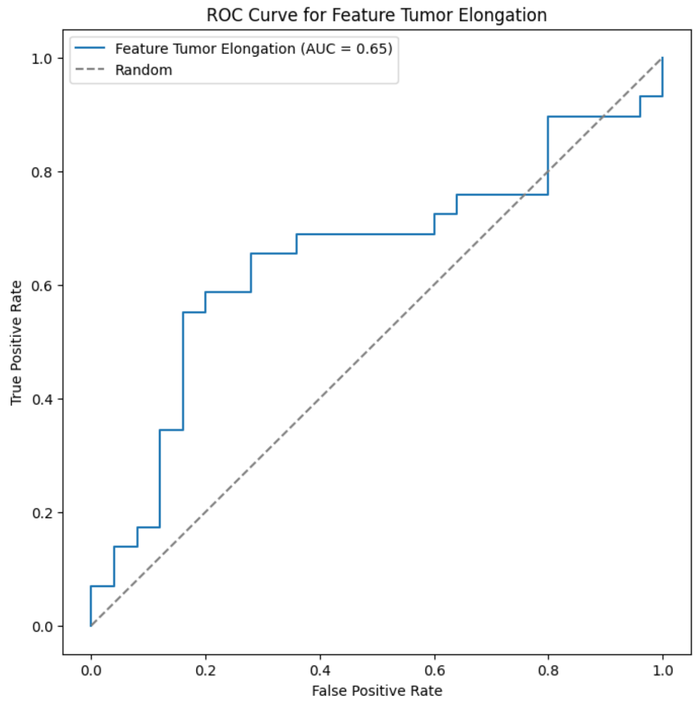


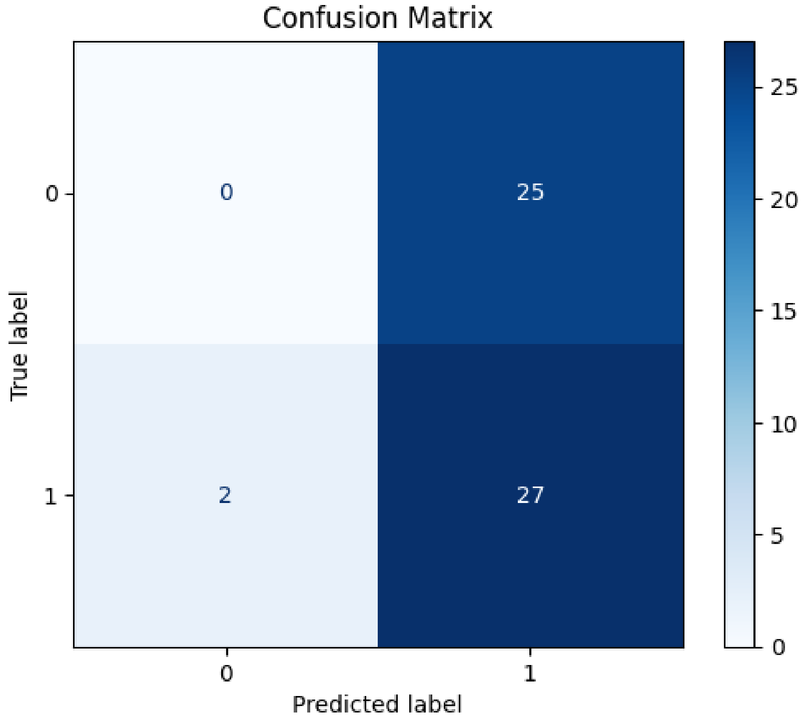
Accuracy= 0.79

AUC = 0.85

Predictive power of shape features

Logistic reg for CNN dice >= 0.7 pred using only shape features: Elongation (baseline test cases + post NAC test cases)





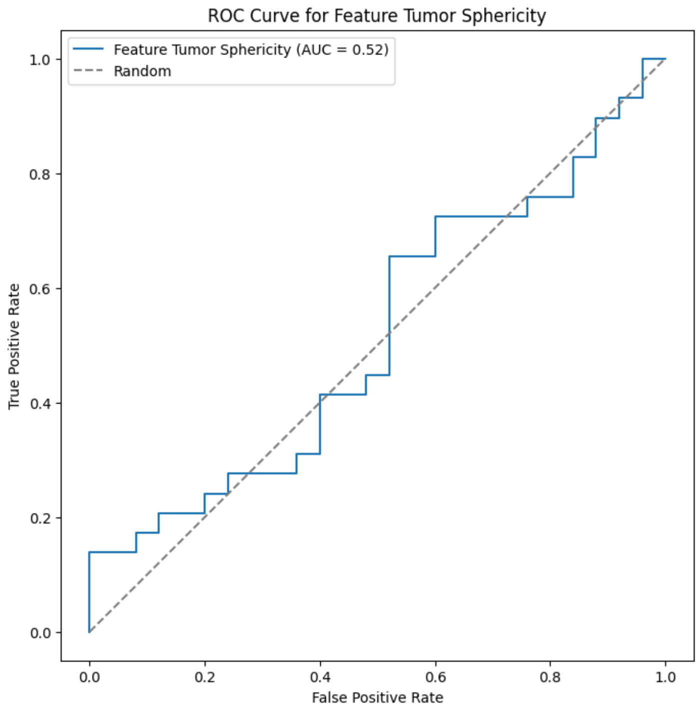
Accuracy= 0.5

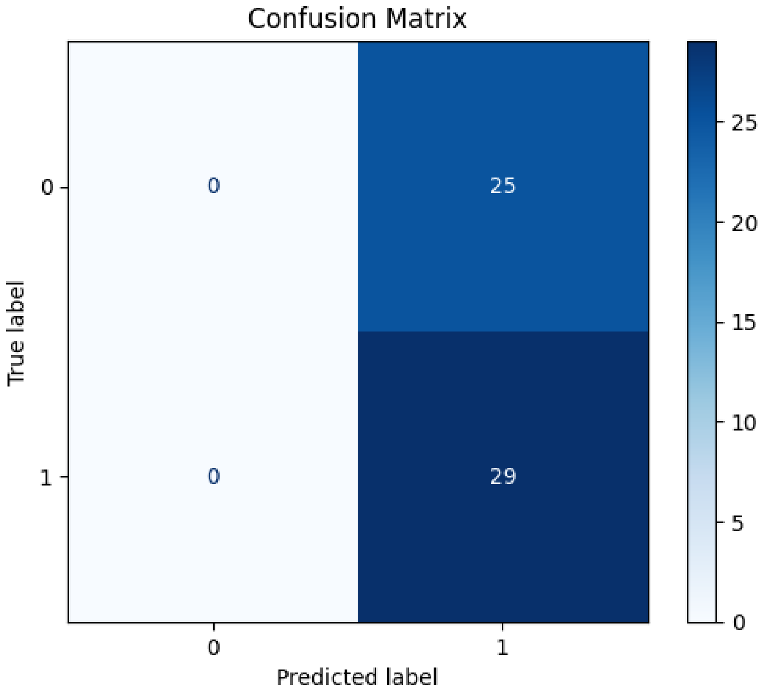
AUC = 0.65

--> no better than random classification

Predictive power of shape features

Logistic reg for CNN dice >= 0.7 pred using only shape features: Sphericity (baseline test cases + post NAC test cases)





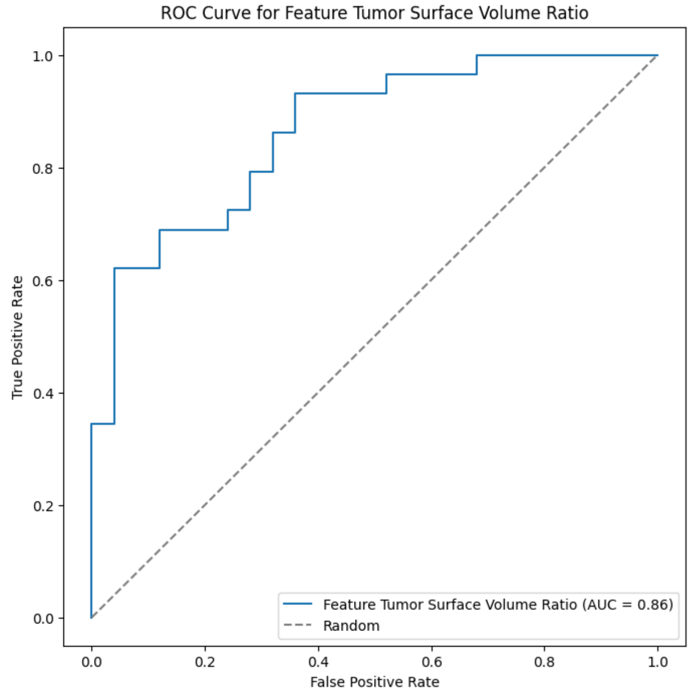
Accuracy= 0.54

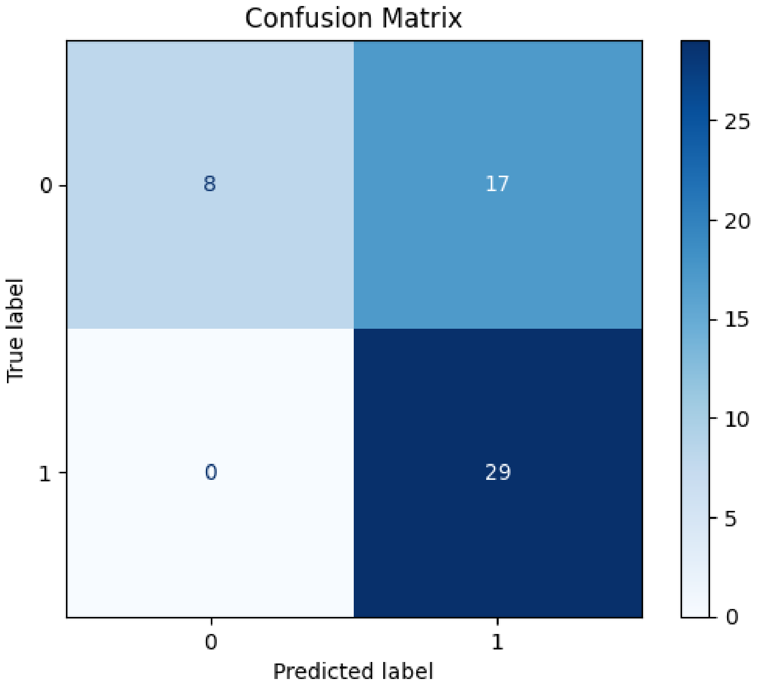
AUC = 0.52

--> no better than random classification

Predictive power of shape features

Logistic reg for CNN dice >= 0.7 pred using only shape features: Surface Volume ratio (baseline test cases + post NAC test cases)





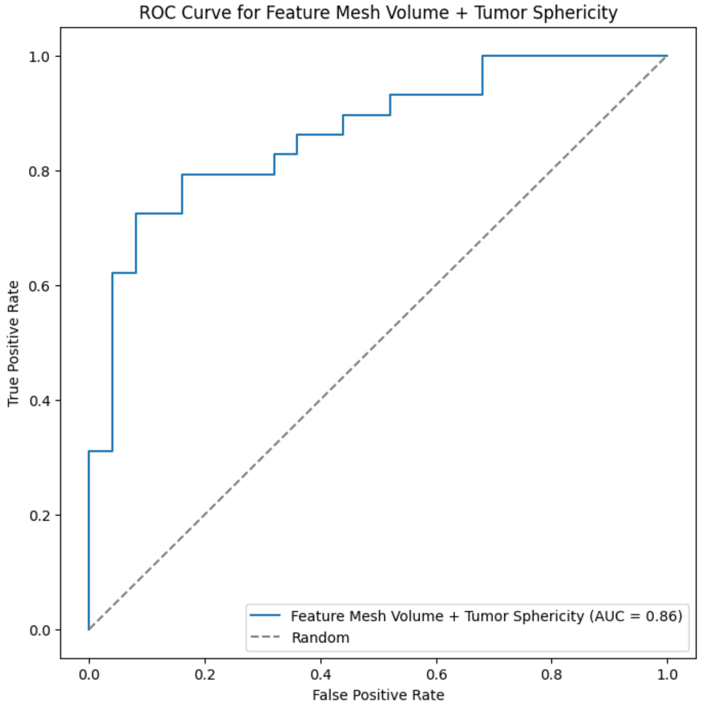
Accuracy= 0.69

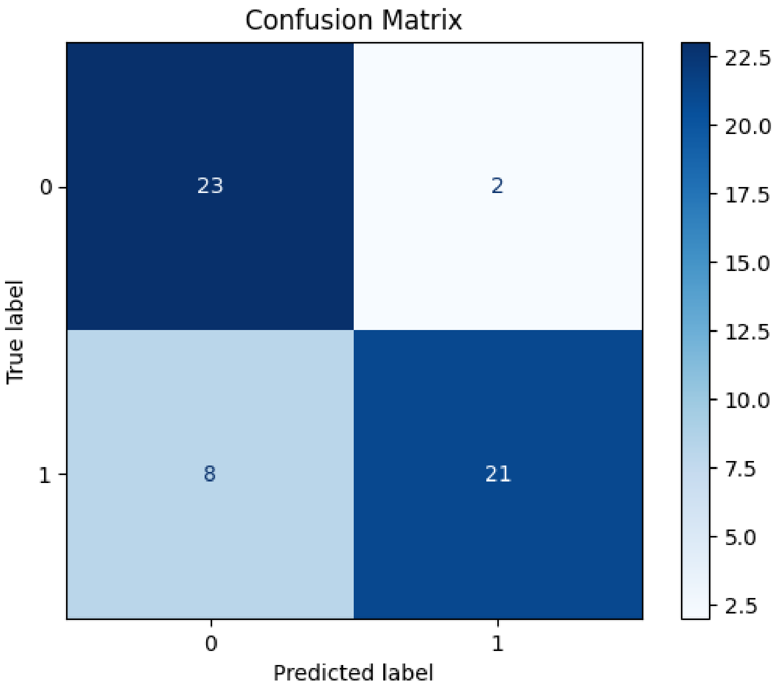
AUC = 0.86

Specificity = 0.6

Predictive power of shape features

Logistic reg for CNN dice >= 0.7 pred using only shape features: Volume + Surface volume ratio





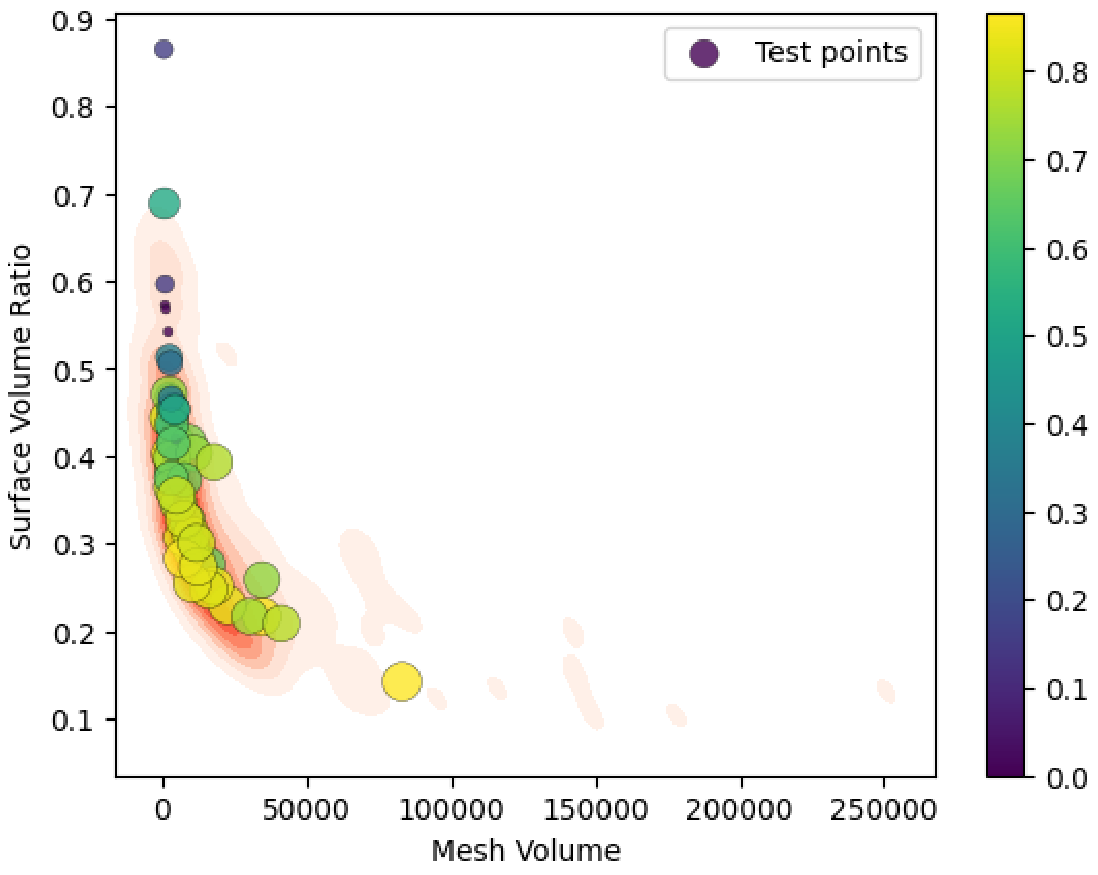
Accuracy= 0.81

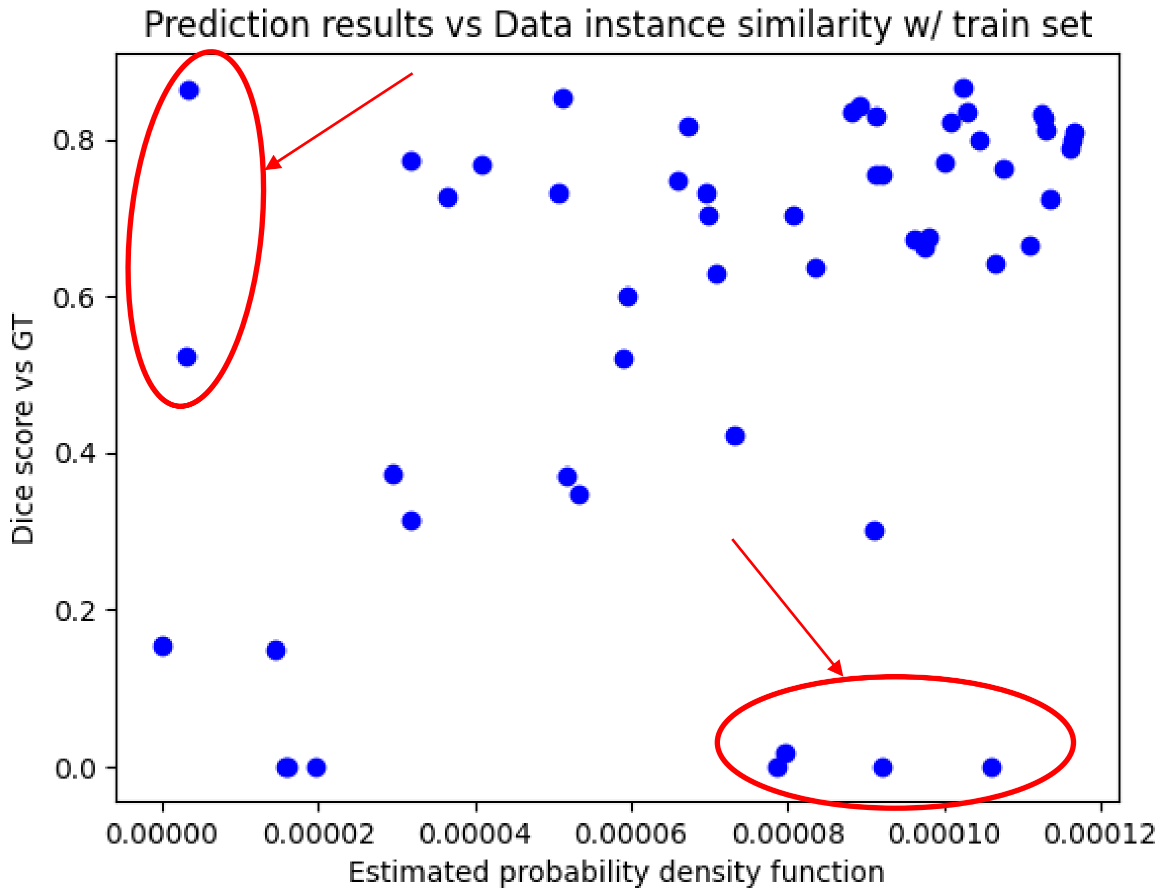
AUC = 0.86 Specificity=0.92

--> more complex shapes + small tumors = worst performances

LITO

Predictive power of shape features





- Need to add image radiomic features