Classifying nasal pathologies with Computational Fluid Dynamics and Machine Learning

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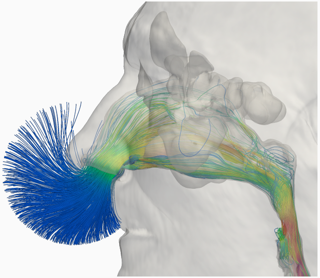
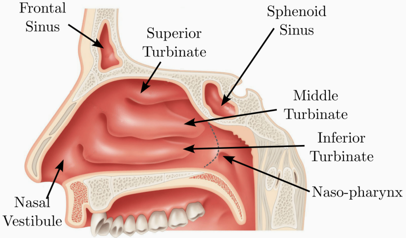
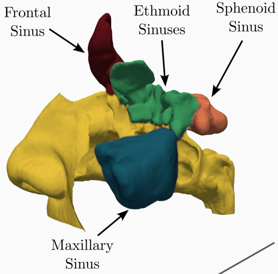
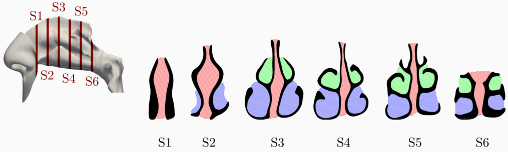
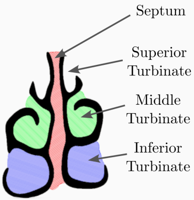


The human nose: anatomy and functions









Function of the nose:

- Thermal exchange
- Humidification
- Filtering
- Olfaction and taste

Why studying it?

- Large incidence: 1/3 of adult world population [1]
- Huge societal cost ($22b for cronic rhinosinusits alone in USA)[2]
- Large failure rate of surgical corrections[3](up tp 50%!)

[1]Canonica, *et al.* A survey of the burden of allergic rhinitis in Europe. *Allergy*. 2007

[2]Smith, *et al.* Cost of adult chronic rhinosinusitis: A systematic review. *The Laryngoscope*. 2015

[3]Illum Septoplasty and compensatory inferior turbinate hypertrophy: long-term results after randomized turbinoplasty. *Eur. Arch. Otorhinolaryngol.* 1997

What's a surgeon from an engineer's perspective

- Given a patient to two different surgeons, they can have different ideas on how to proceed, even **whether** to perform a surgery
- Surgeons are mainly driven by intuition and experience

Looking at the doctor's workflow

The typical doctor wants to know whether and where to operate

- **Sino-Nasal Outcome Tests: subjective**

Need to blow the nose	0	1	2	3	4	5
Sneezing	0	1	2	3	4	5
Dizziness	0	1	2	3	4	5
Ear pain	0	1	2	3	4	5
Facial pain	0	1	2	3	4	5
Difficulty falling asleep	0	1	2	3	4	5
Waking up at night	0	1	2	3	4	5
TOTAL SCORE						

Looking at the doctor's workflow

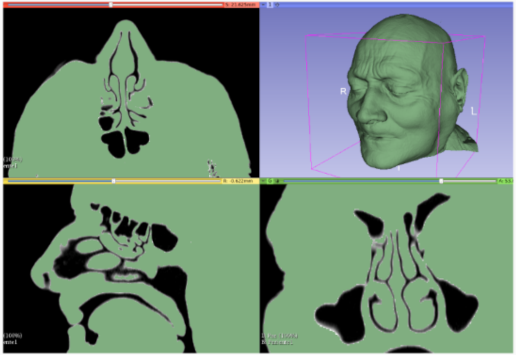
The typical doctor wants to know whether and where to operate

- Sino-Nasal Outcome Tests: subjective
- **Rhinomanometry,** $R = \frac{\Delta p_{l,r}}{Q_{l,r}}$**: too macroscopic**

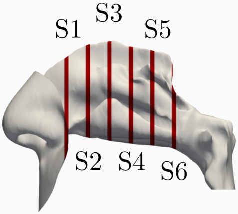
Looking at the doctor's workflow

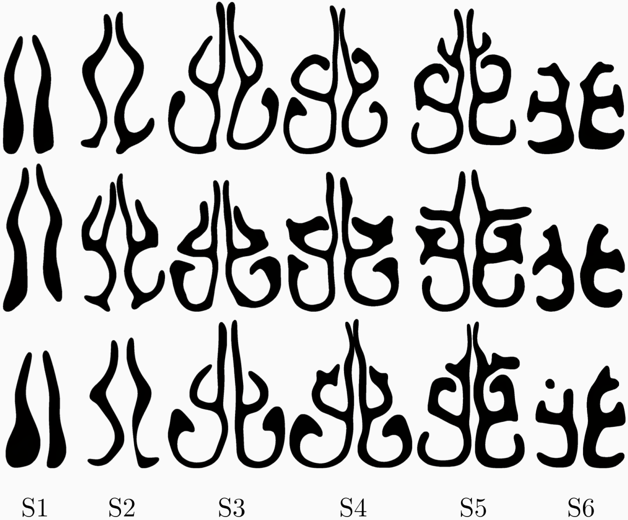
The typical doctor wants to know whether and where to operate

- Sino-Nasal Outcome Tests: subjective
- Rhinomanometry, $R = \frac{\Delta p_{l,r}}{Q_{l,r}}$: too macroscopic
- **CT-Scan: full spatial information**

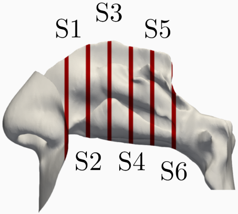


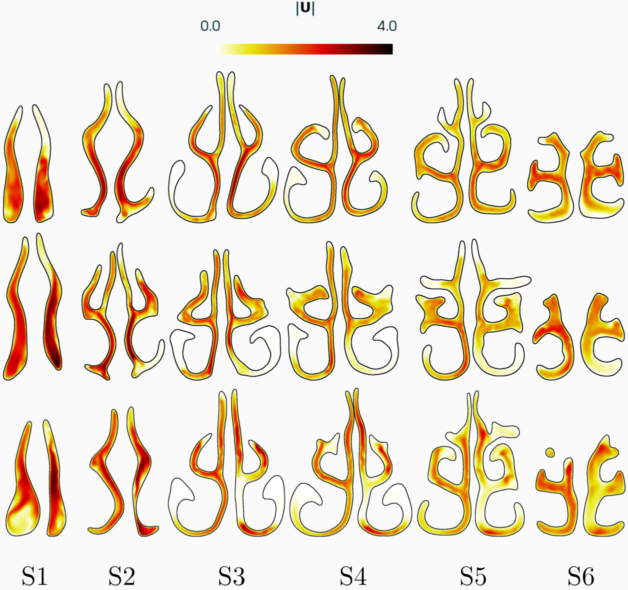
Is a CT-scan the best we can do?





Let's try to perform a fluid simulation!





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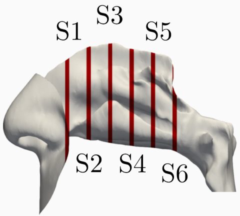
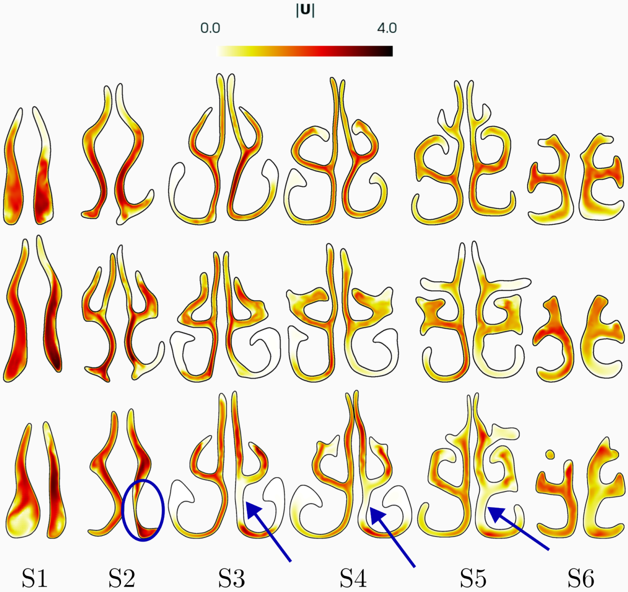
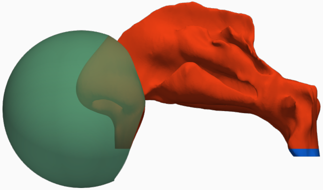
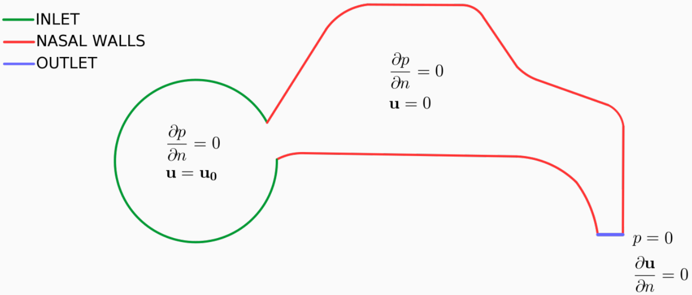




The CFD setup

- Meshes of around 13 Millions cells without sinuses
- LES simulations, WALE turbulence model
- Constant flow rate 266.66 ml/s
- 0.6 s simulated (excluding transient)





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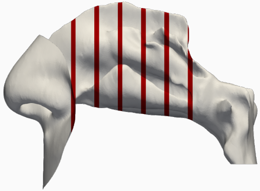

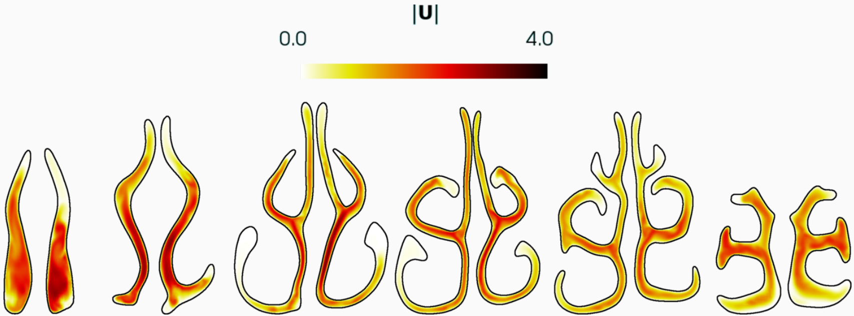

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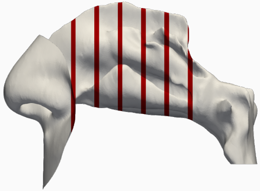

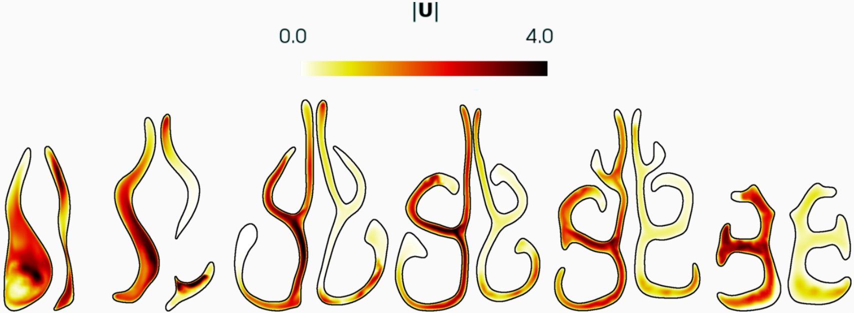

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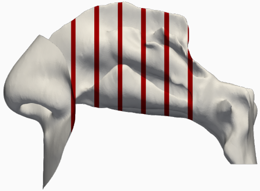
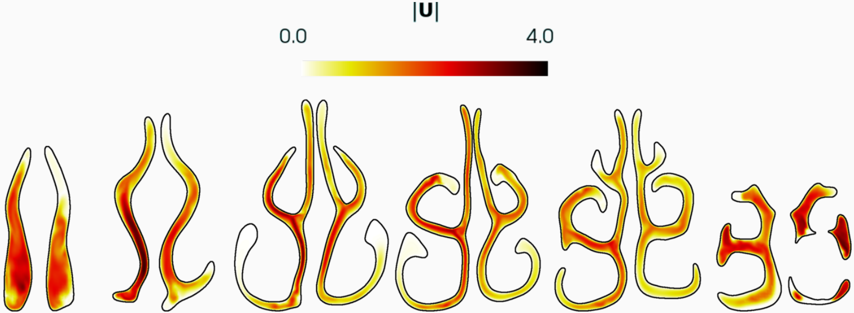
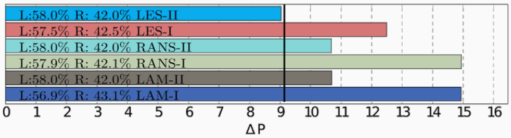
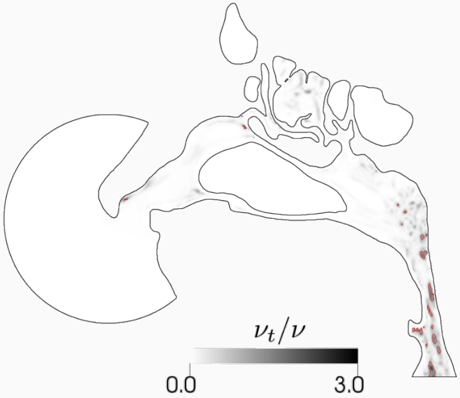




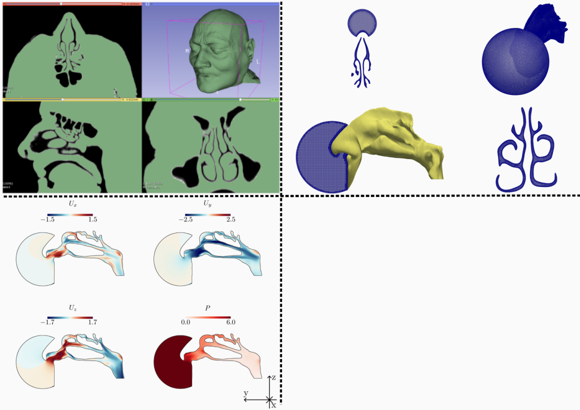
CFD can be tricky





So is CFD the solution?

- Accuracy and cost proportional to domain discretization
- Flow simulation returns detailed information (order of GB)
- Highlights functional properties of the system...



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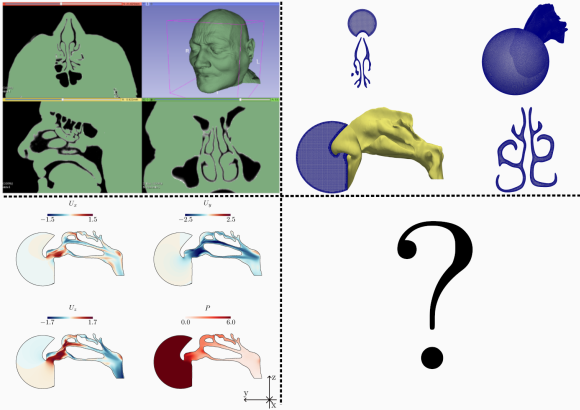

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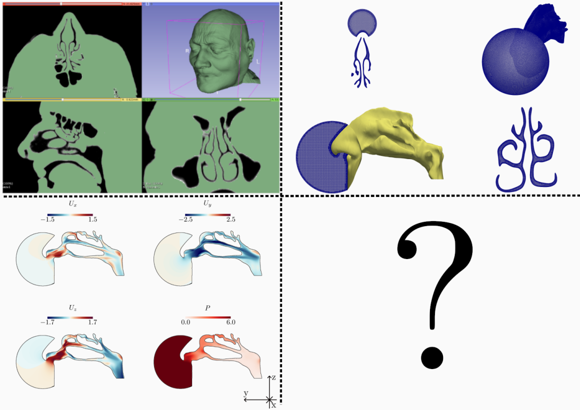
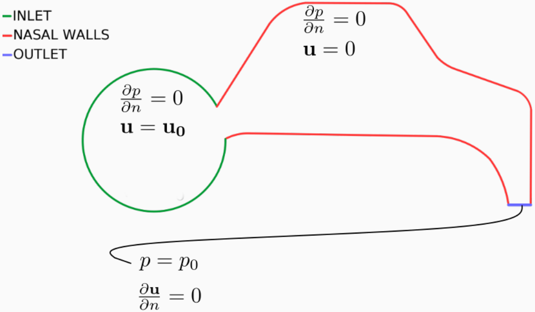


Two approaches possible: adjoint optimization or data-driven

First approach: adjoint method

- Suggests which surgery to perform
- Easy to read for the surgeons
- Requires a **cost function** f (flow rate imbalance, dissipation)
- Two flow simulations: direct $(\mathbf{u}, p)$ and adjoint $(\mathbf{v}, q)$
- Not all surgeries are possible

Dissipated power: $\boxed{f = \int_\Gamma \left(p + \frac{1}{2}u^2\right) \mathbf{u} \cdot \mathbf{n} \, d\Gamma}$



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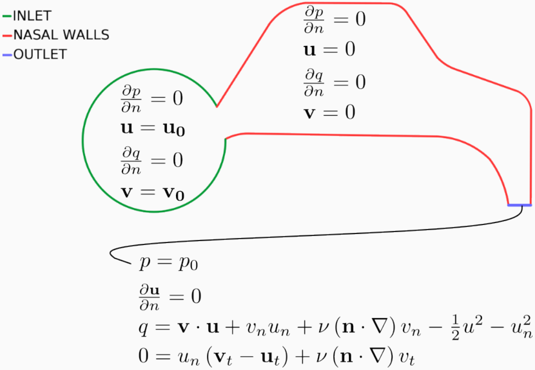

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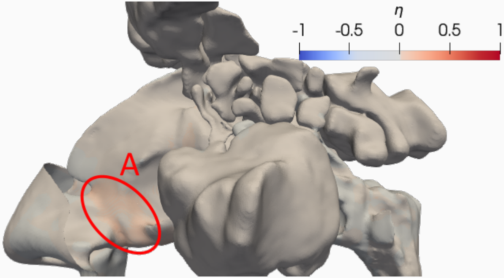


Second approach: data-driven

- Clear input X: the CFD solution
- Clear output Y: diagnosis

$$f : X \to Y$$

We need a dataset!

...But a good one

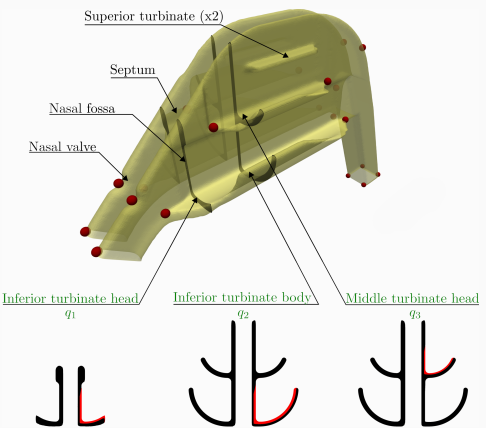
1. Avoid ambiguity of labels
2. Balanced classes

...But a good one

1. Avoid ambiguity of labels $\rightarrow$ convert a patient into clear label
2. Balanced classes $\rightarrow$ many patients with the exact **same** pathology

First approach: isn't geometry enough?

Objective: predict the parameters q_1, q_2, q_3 using both geometrical and flow features



Problem: How to compare features on different domains?

Mapping domains - Functional maps

- Computational geometry tool
- Generalization of Fourier basis on surfaces
- Basis: eigenfunction (ϕ) of the Laplace-Beltrami operator
- Compare *real valued function* on surfaces

$$T_F \approx \phi_{\mathcal{N}} \;\; A \;\; \phi_{\mathcal{M}}^{+}$$

Ovsjanikov M., et al. Functional maps: a flexible representation of maps between shapes. ACM Transactions on Graphics 2012

Computing the functional map A

Given a pair of shapes $\mathcal{M}, \mathcal{N}$:

- We associate to them the positive semi-definite Laplacian matrices $L_{\mathcal{M}}$ and $L_{\mathcal{N}}$. So that $L_{\mathcal{M}} = D_{\mathcal{M}}^{-1} W_{\mathcal{M}}$, where $D_{\mathcal{M}}^{-1}$ is the diagonal matrix of lumped area elements and $W_{\mathcal{M}}$ is the cotangent weight matrix
- Compute a basis consisting of the first $k_{\mathcal{M}}$ eigenfunctions of the Laplacian matrix: $\phi_{\mathcal{M}}^{k_{\mathcal{M}}}$
- Given a point-to-point map T_F, its matrix representation is Π, such that $\Pi(i,j) = 1$ if $T_F(i) = j$ and zero otherwise
- The corresponding functional map is: $A = \phi_{\mathcal{M}}^{+} \Pi \phi_{\mathcal{N}}$

Zoom-out: better method for shape correspondence

Starting from a *small* map A_0, the objective is to extend it to a new map A_1 of size $(k_{\mathcal{M}}+1) \times (k_{\mathcal{N}}+1)$:

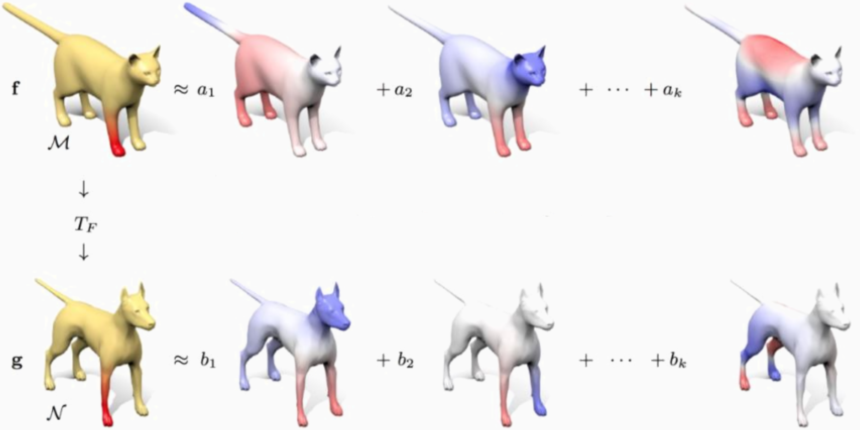
1. Compute a point-to-point map T_F, and encode it as a matrix Π
2. Set $A_1 = (\phi_{\mathcal{M}}^{k_{\mathcal{M}}})^T D_{\mathcal{M}} \Pi \phi_{\mathcal{N}}^{k_{\mathcal{N}}}$

$T_f(p) = argmin_q ||A(\phi_{\mathcal{N}}(q))^T - (\phi_{\mathcal{M}}(p))^T||_2, \forall p \in \mathcal{M}$

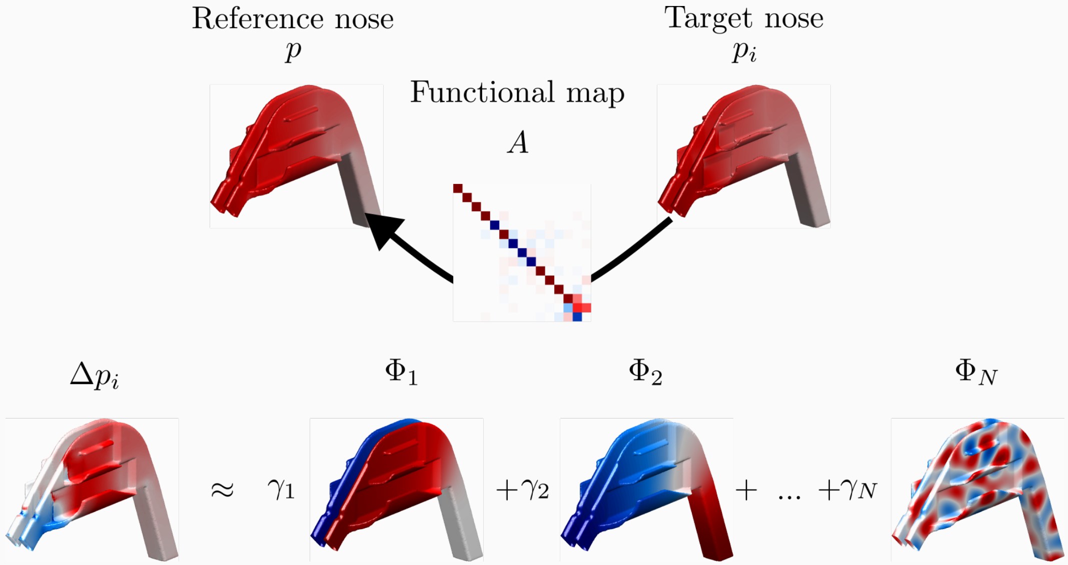
Where $\phi_{\mathcal{M}}(p)$ denotes the p^{th} row of the matrix of eigenvectors $\phi_{\mathcal{M}}$

The Laplace-Beltrami operator

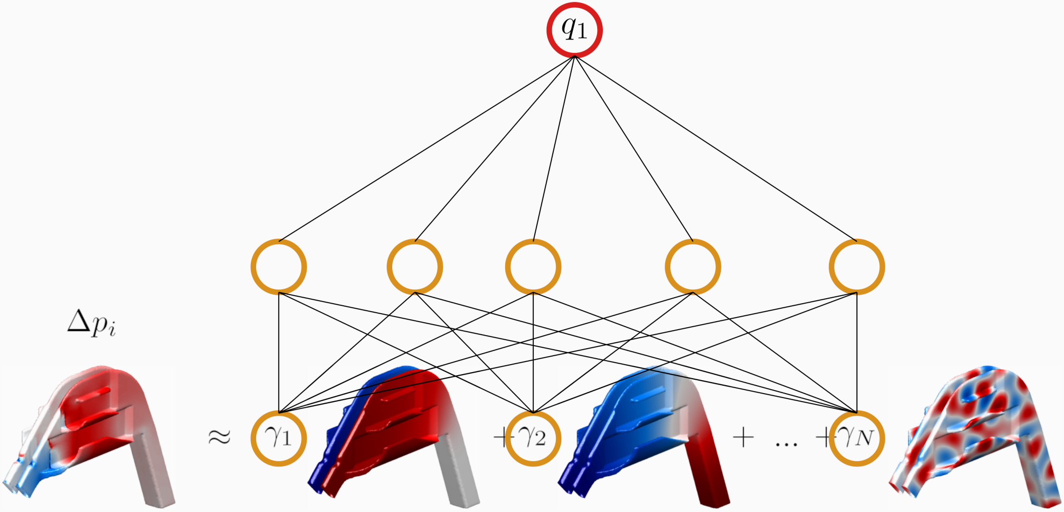
The ordered eigenvalues provide a natural scale.



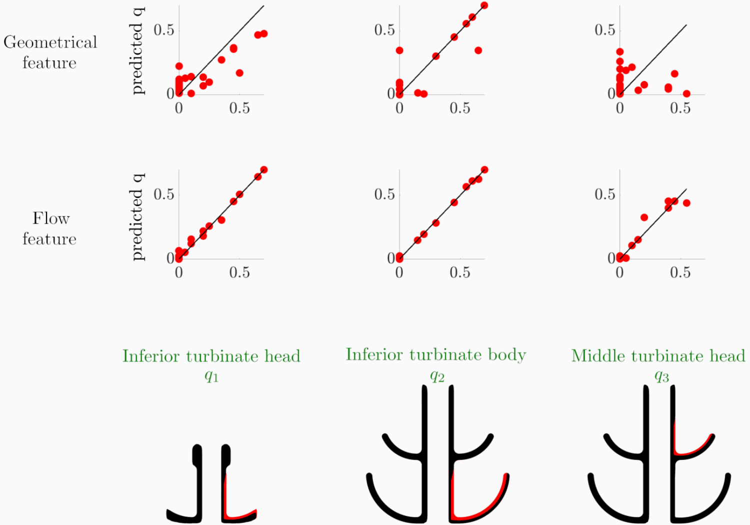
Comparing flow features on different domains



Estimation of the pathological parameters



First approach: results

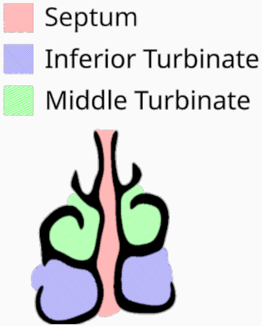


Real case with clear labels: The deformation tree

- Nose
  - Healthy
  - Pathological
    - Hypertrophy
      - Inferior
        - Tail
        - Body
        - Head
      - Middle
        - Tail
        - Body
        - Head
    - Septal Deviation
      - Posterior
        - Inferior
        - Middle
        - Superior
      - Anterior
        - Inferior
        - Middle
        - Superior

E1

E2



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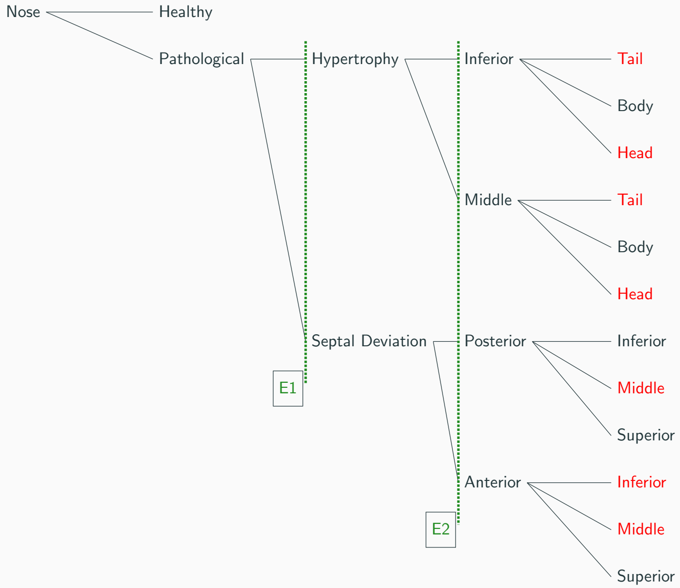
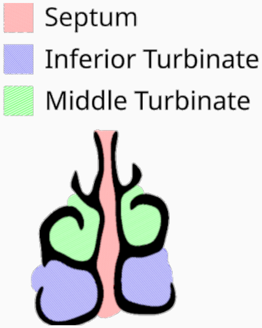
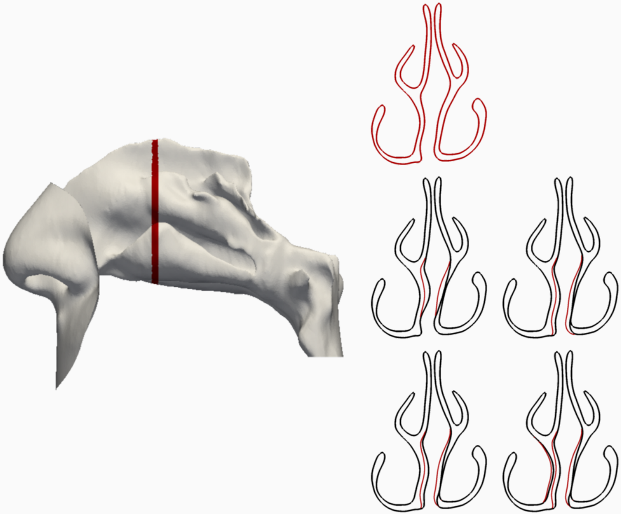




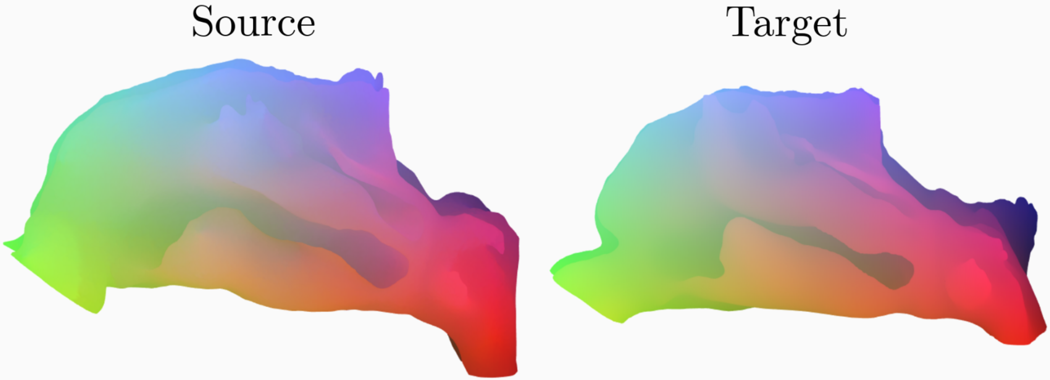
- Few patients with these pathologies
- Perform inverse surgeries on healthy patients

The cost of $(\textit{virtual surgery})^{-1}$

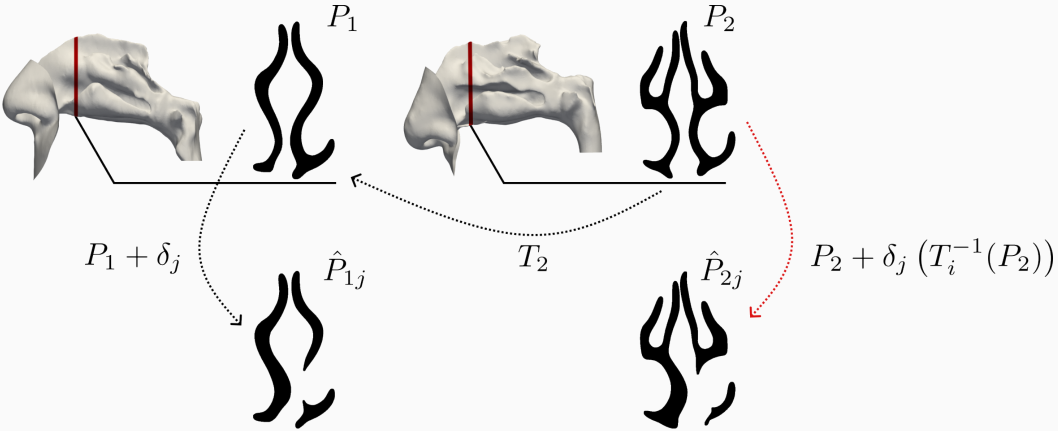


The operation is extremely time consuming: ~ 10 hours

Automatic and consistent process - Functional maps



Automatic and consistent process - Workflow



At the end of the process 277 Geometries

The classification problem

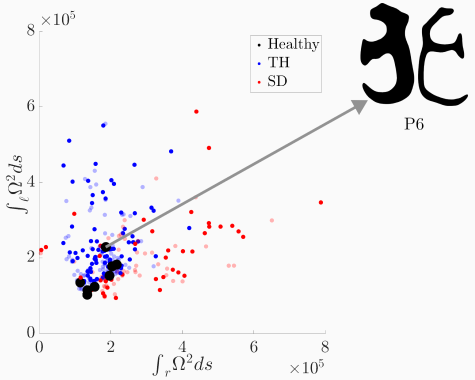
The task:
Classify 28 pathologies from 277 LES into 2 classes.

Challenges:

- Each flow simulation carries around 2 GB of information
- Need for feature engineering!

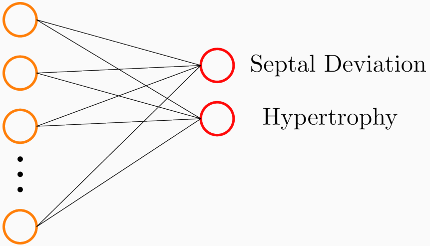
Feature engineering example: Streamlines' statistics

- Compute the integral of flow quantities along the streamlines
- Extract statistic out of the integrated quantities

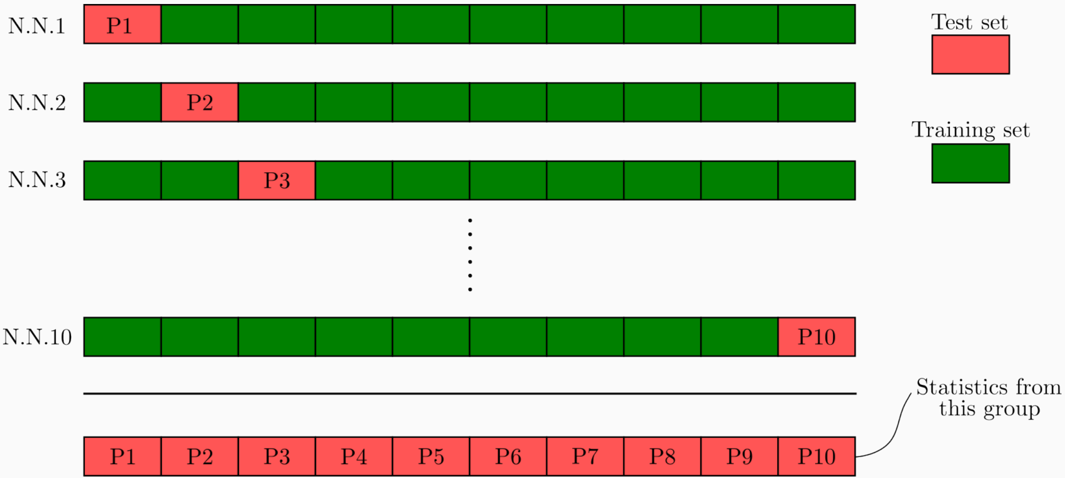


The classifier

- Input layer 12 nodes
- Hidden layer: 30, 20, 10
- Loss function: Cross-entropy
- Backpropagation: Levenberg-Marquardt
- Output layer: 2 node (binary), 4 nodes (multiclass)



How to test the dataset



Binary classification results: E1

	k-fold accuracy	LOO accuracy
$\lvert U \rvert$	0.97	0.85
Ω^2	0.95	0.74
$\lvert \nabla P \rvert$	0.96	0.76
$P_{in} - P$	0.91	0.76
$P_1 - P$	0.91	0.76
$P - P_{out}$	0.89	0.68
$P - P_6$	0.92	0.74
ν_t	0.87	0.67
R	0.85	0.64

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Multiclass classification results: E2

Observations with ambiguous labels are pruned: the dataset shrinks to 154 observations

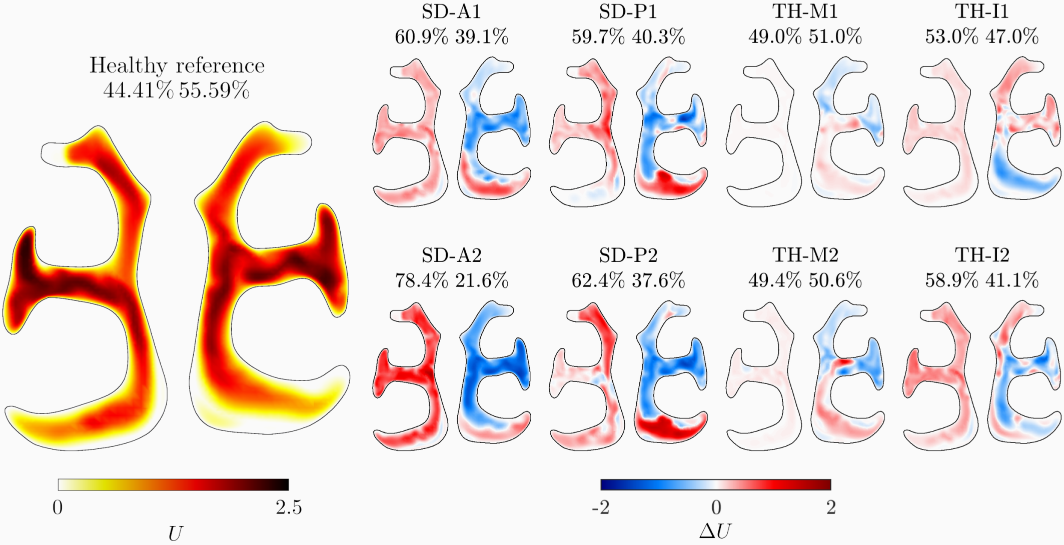
Results with the best feature $|U|$:

Class	accuracy
Anterior septal deviation	0.91
Posterior septal deviation	0.90
Middle turbinate hypertrophy	0.67
Inferior turbinate hypertrophy	0.71

Final remarks

- Successful use of CFD data as input of ML to obtain a medical label
- 2GB of information converted into a handful of significant numbers
- Geometry parameterization is a crucial step
- Need for clinical testing
- The developed workflow is flexible: works on a airfoil dataset
- (Very) interdisciplinary project

First results using explainability methods



How to measure the mapping error?

Given:

$$f : \mathcal{M} \to \mathcal{N} \text{ and } f_{True} : \mathcal{M} \to \mathcal{N}$$

Geodesic error defined as:

$$Err(f, f_{True}) = \sum_{p \in M} d_{\mathcal{N}}\Big(f(p), f(p_{True})\Big)$$

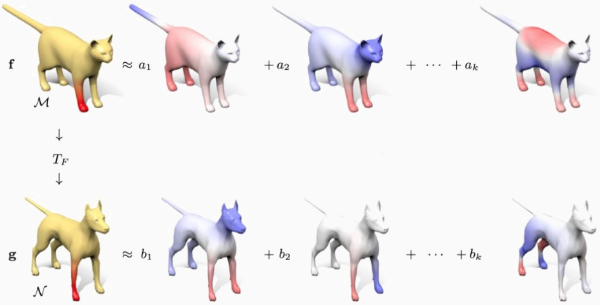
Where $d_{\mathcal{N}}\Big(f(p), f(p_{True})\Big)$ is normalized by $\sqrt{Area_{\mathcal{N}}}$

The Laplace-Beltrami operator

Eigenfunctions of Laplace-Beltrami operator:

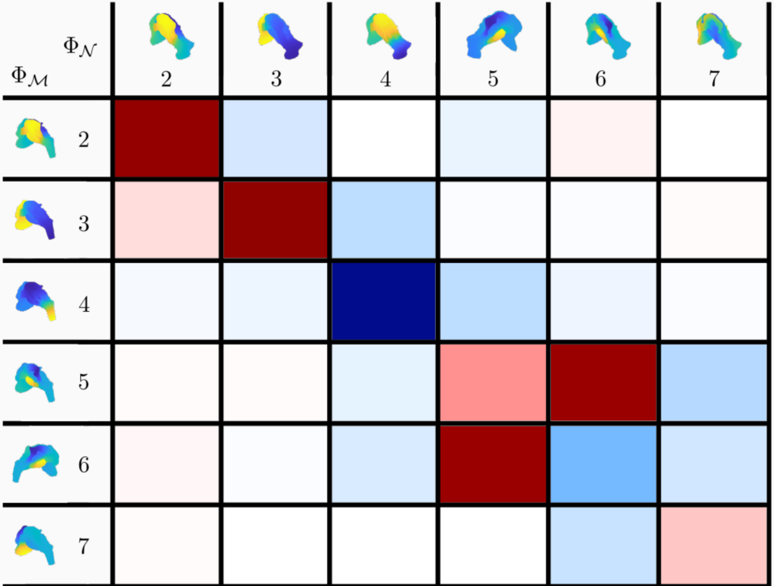
$$\Delta\phi_i = \lambda_i\phi_i \qquad \Delta(f) = -div\Delta(f)$$

The ordered eigenvalues provide a natural scale.



Iterations with ENT surgeons

Laplace-Beltrami on the nose



Functional map - The pipeline

Given a pair of shapes $\mathcal{M}, \mathcal{N}$:

- Compute the first ~ 100 eigenfunctions of Laplace-Beltrami operator: $\phi_{\mathcal{M}}$ and $\phi_{\mathcal{N}}$
- Compute descriptor functions (e.g. landmarks, Wave kernel signature) on $\mathcal{M}$ and $\mathcal{N}$. Express them as columns X, Y
- Solve $A_{opt} = argmin_A ||CX - Y||^2 + ||A\Delta_{\mathcal{M}} - \Delta_{\mathcal{N}} A||^2$. With $\Delta_{\mathcal{M}}$ and $\Delta_{\mathcal{N}}$ diagonal matrices of eigenvalues of LB operator.
- Convert the functional map A_{opt} to a point-to-point map Π