

# Repairing Inconsistent Curve Networks on Non-parallel Cross-sections

Z. Y. Huang<sup>1</sup>, M. Holloway<sup>1</sup>, N. Carr<sup>2</sup>, T. Ju<sup>1</sup>

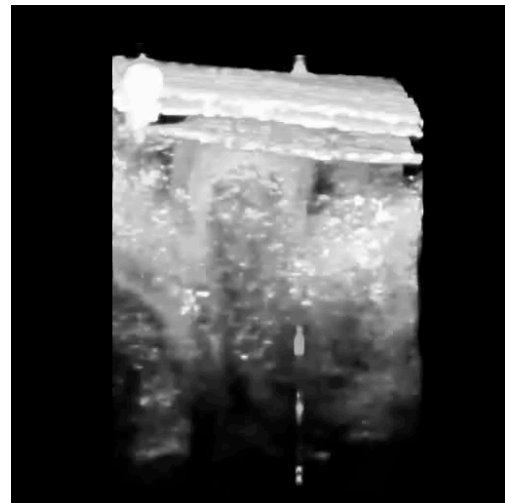
<sup>1</sup> Washington University in St. Louis, USA

<sup>2</sup> Adobe Inc., USA



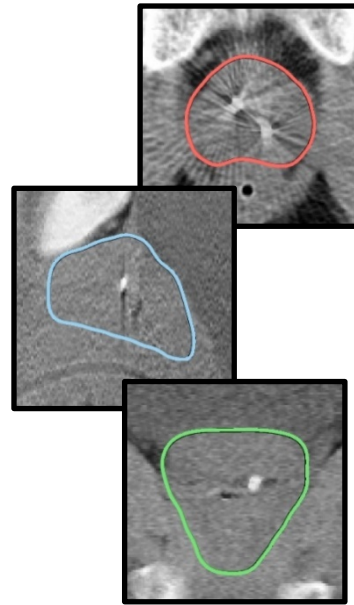
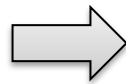
# Motivation: Image segmentation

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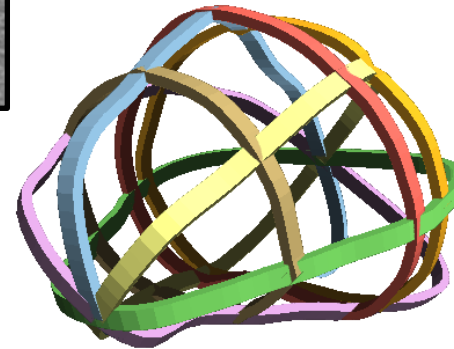


3D Image Volume

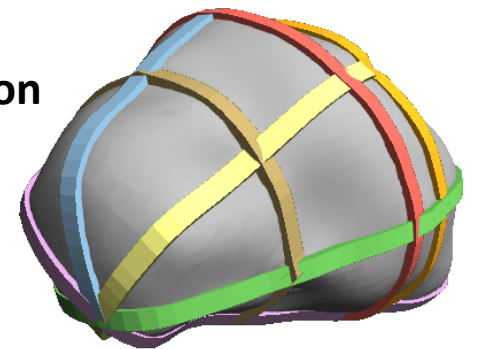
Interaction



Contours on cross-sections



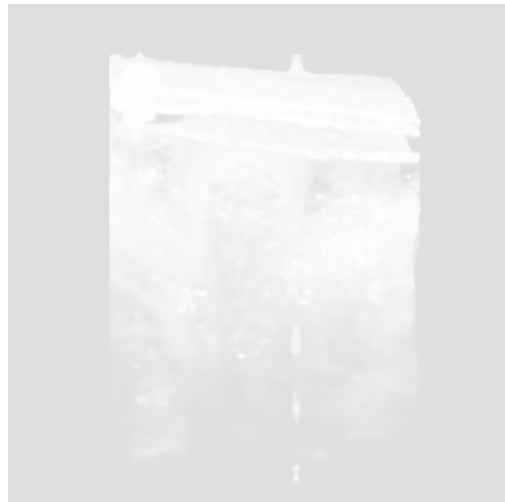
Reconstruction



Segmented shape

# Motivation: Image segmentation

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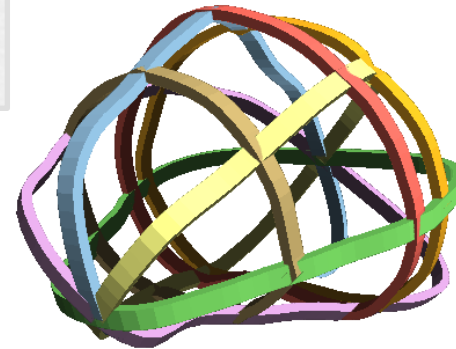


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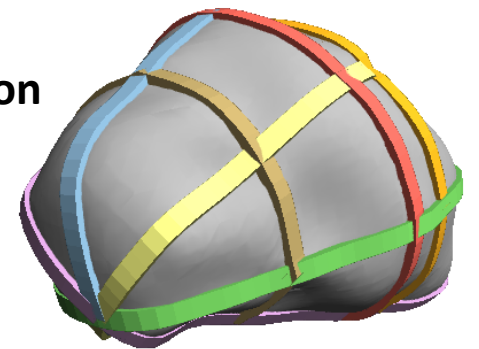
Interaction



Contours on cross-sections



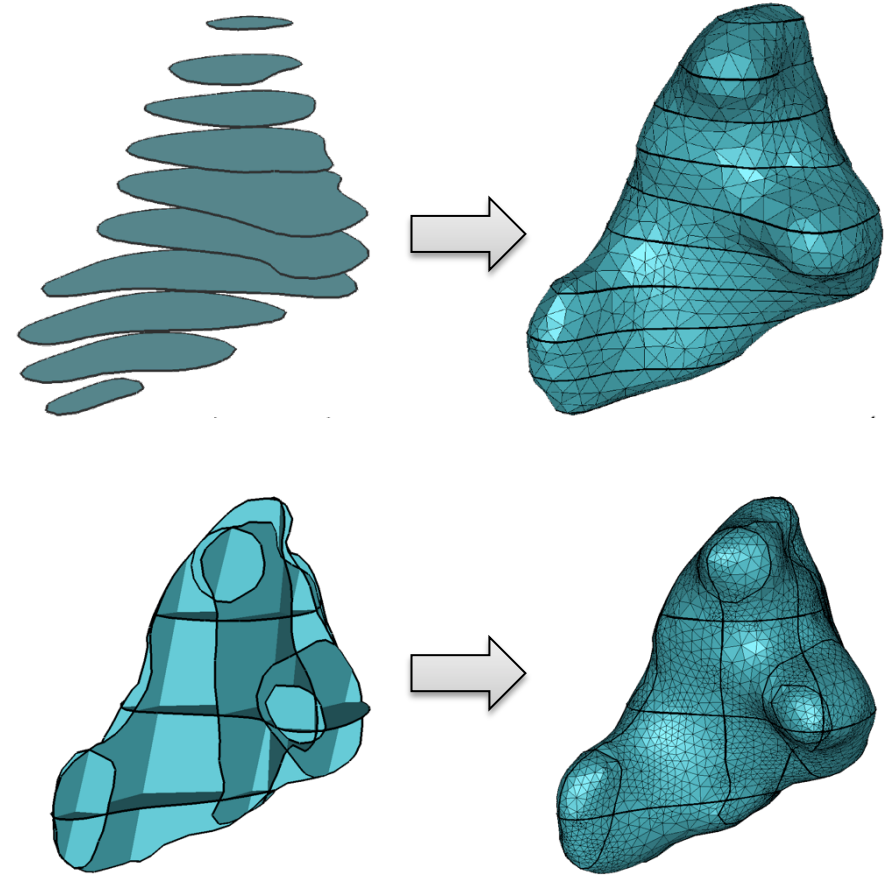
Reconstruction



Segmented shape

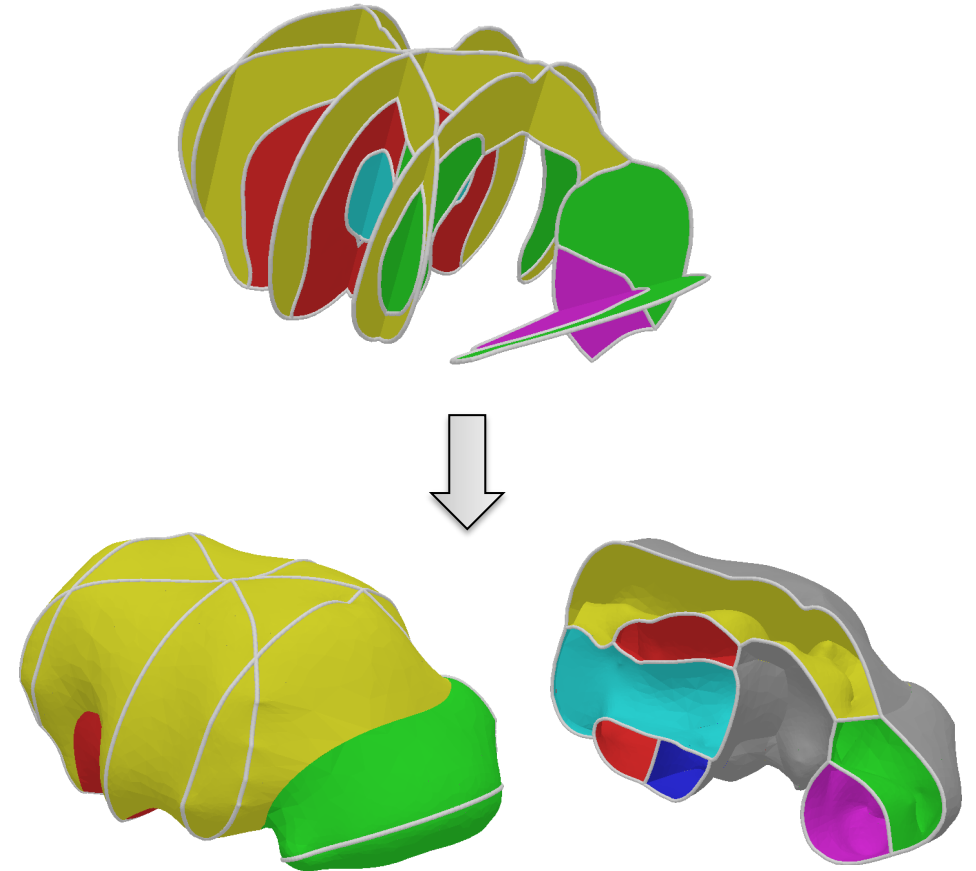
# Background: Reconstruction from cross-sections

- A well-studied problem dated back to 70s
- **Parallel** planes
  - Natural choice for 3D images, but may require many cross-sections to describe shape
- **Non-parallel** planes
  - Well-chosen planes can describe shape with fewer **cross-sections** [Boissonnat 07, Liu 08, Barequet 09, Bermano 11, Heckel 11, Zou 15, Holloway 16, Huang 17]



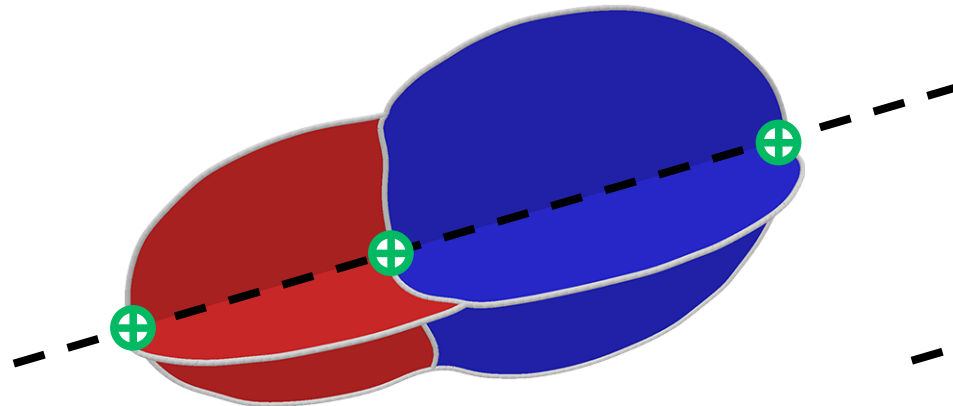
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  - Well-chosen planes can describe shape with fewer cross-sections [Boissonnat 07, Liu 08, Barequet 09, Bermano 11, Heckel 11, Zou 15, Holloway 16, Huang 17]
  - Extension to model multi-labelled domains from multi-labelled cross-sections

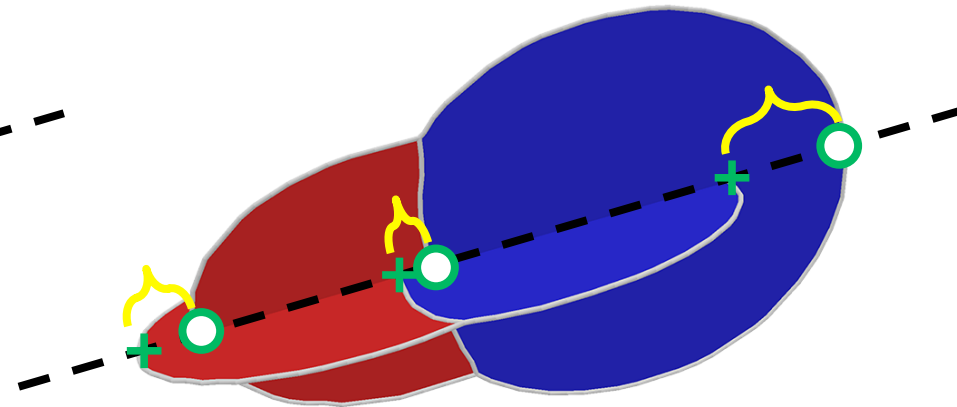


# Background: Consistency

- Methods handling **non-parallel** cross-sections require **consistent** input
  - Intersecting cross-sections share the same labelling along the intersection line



Consistent

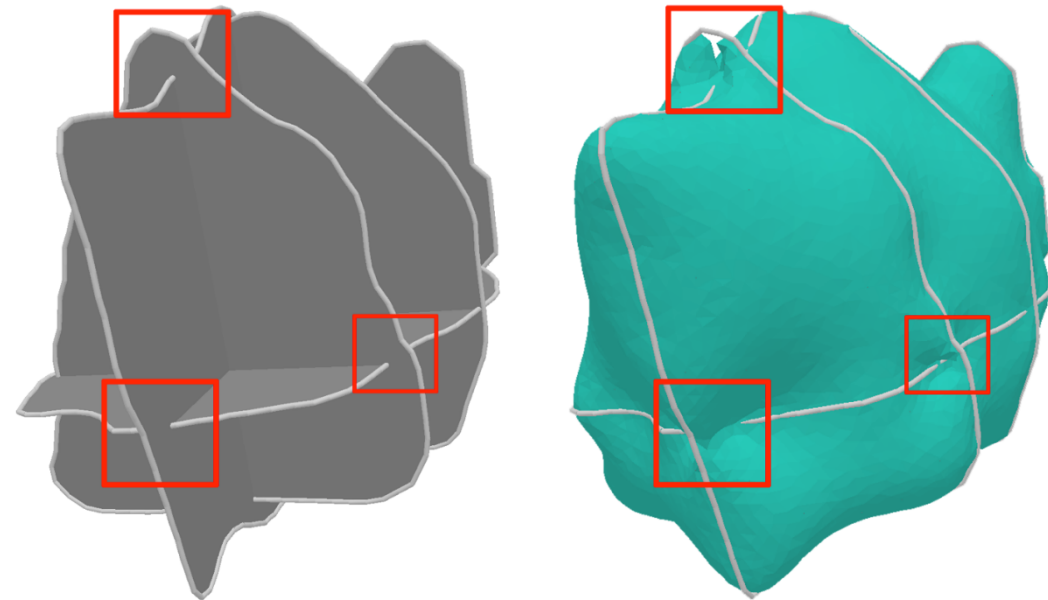


Inconsistent

# Background: Consistency

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- All interpolating methods fail on inconsistent cross-sections
- Approximating methods work, but create surface artifacts

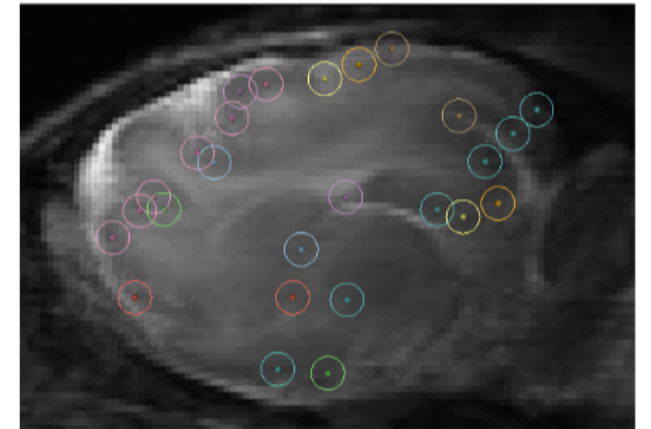
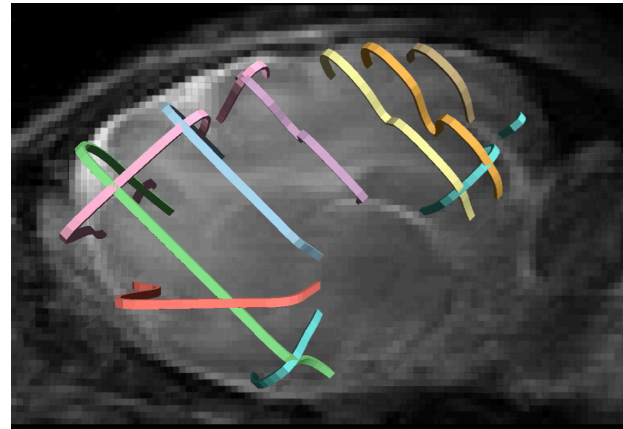


[Bermano 11]

# Background: where does inconsistency come from?

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- Cross-sections are often created independently from each other
- We can ask the users/software to be more careful. But...
  - Adds labor and distraction
  - Requires changes to existing software
  - Cannot process existing data

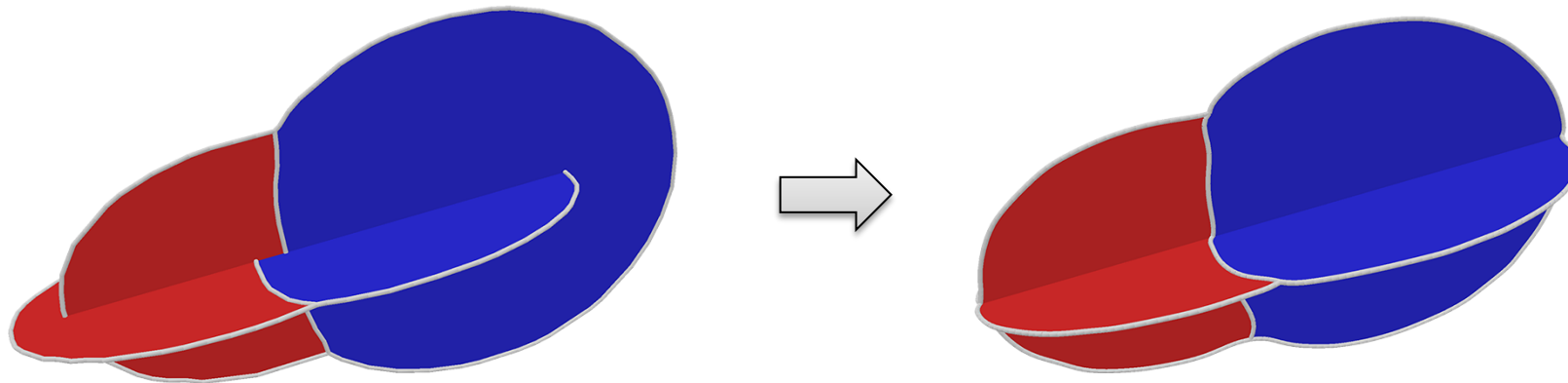




# Objective

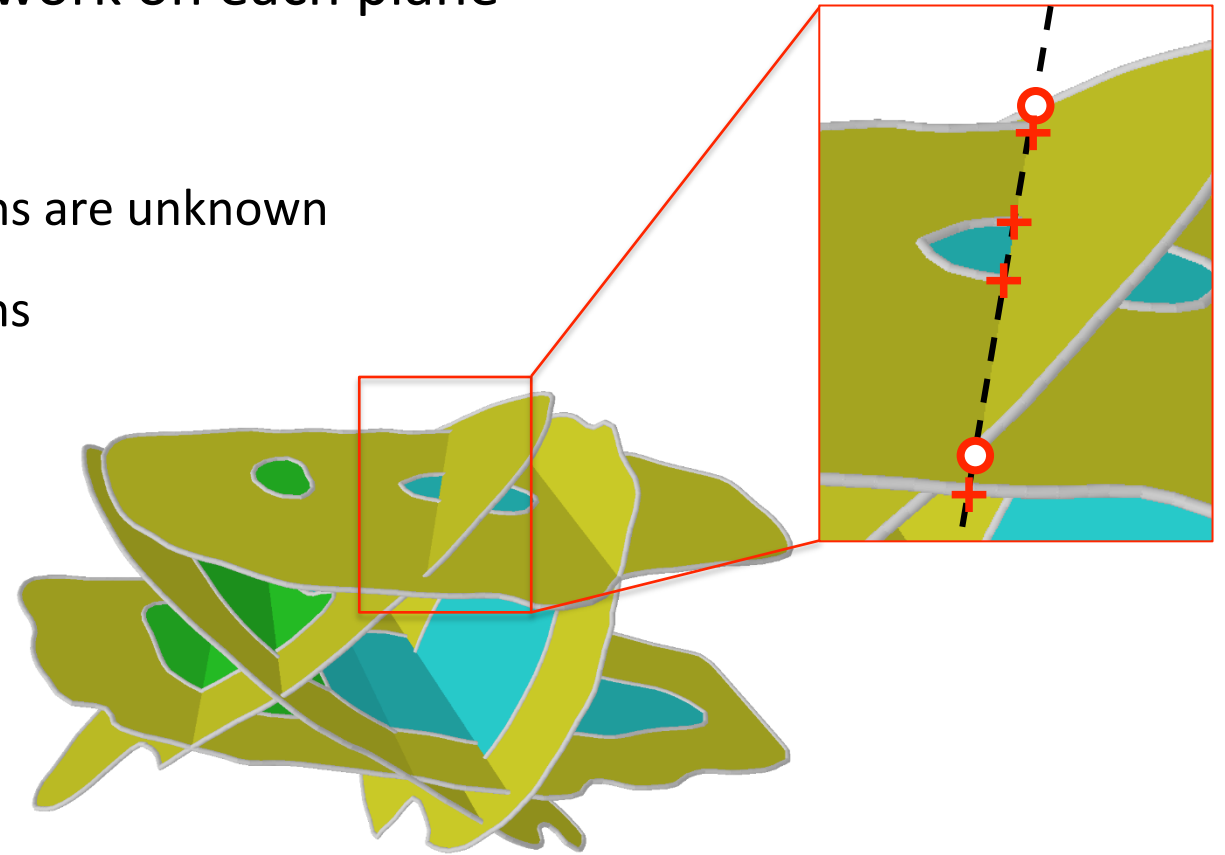
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- Given a set of (possibly inconsistent) multi-labelled non-parallel cross-sections
- Modify curves on each cross-section to restore consistency



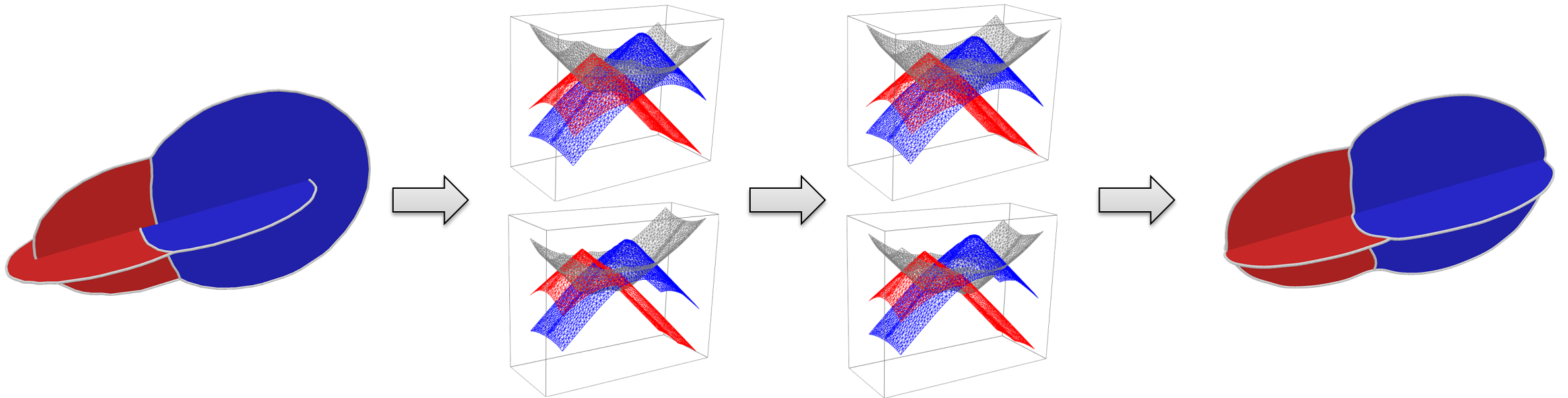
# Explicit approach

- Geometric deformation of the curve network on each plane
- Difficult to enforce consistency
  - Both the number and location of intersections are unknown
  - Deformation may introduce new intersections
- Cannot change curve network topology
  - May result in large deformations



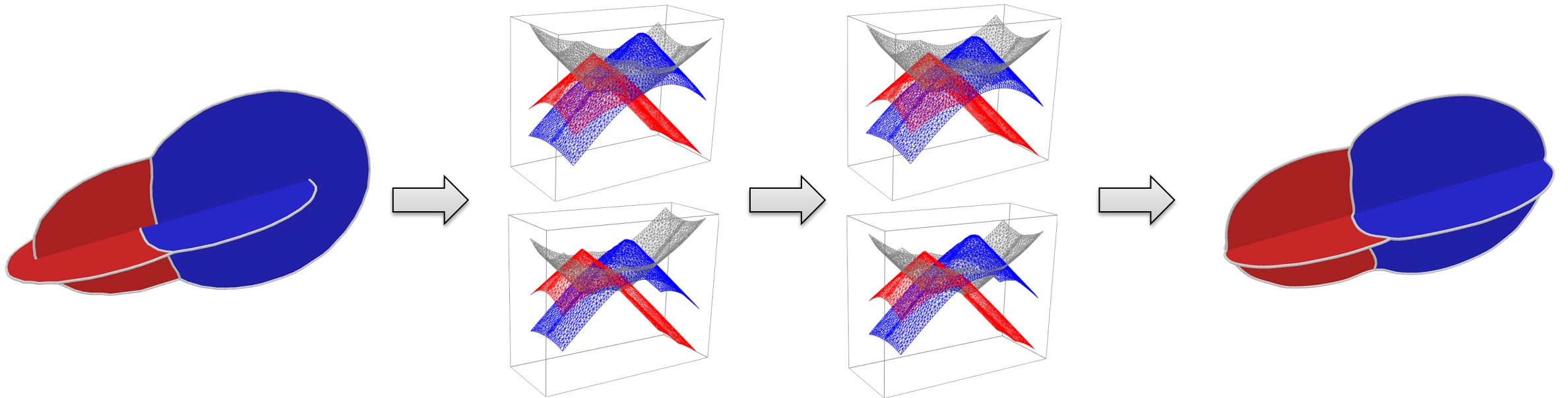
# Implicit approach

- Represent the curve network on each cross-section by an implicit function
- Modify the implicit functions
- Reconstruct the curve networks from the modified functions



# Implicit approach

- Easy to enforce consistency
  - As **inequality constraints** on the implicit functions
- Flexible in topological changes



# Implicit representation

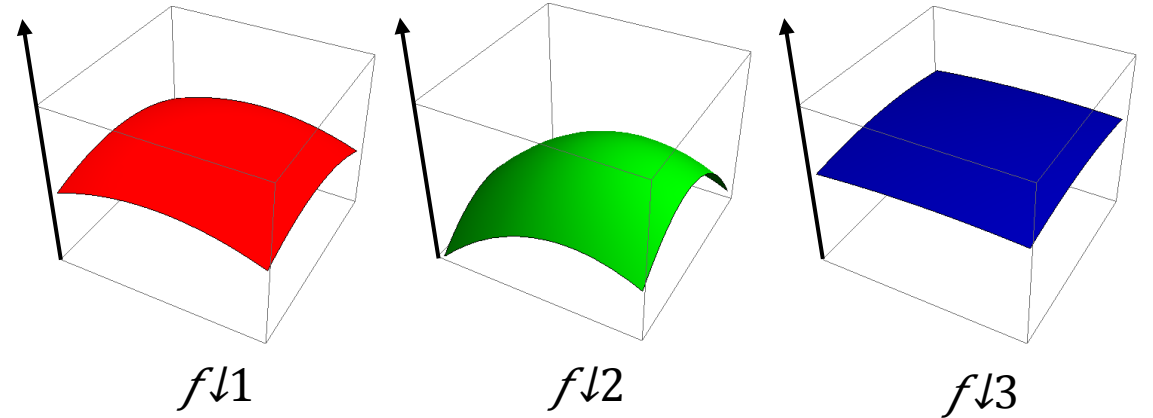
- Representing a  $n$ -labelled plane:

[Losasso 06, Feng 10, Yuan 12, Huang 17]

- Define  $n$  scalar functions  $f_{\downarrow 1}(x), \dots, f_{\downarrow n}(x)$
- Label as index of the function that achieves maximum value:

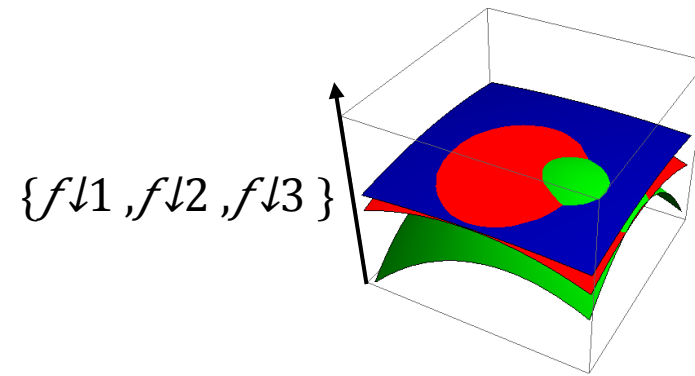
$$\text{Label}(x) = \underset{i}{\operatorname{argmax}} \ f_{\downarrow i}(x)$$

- Labelled regions are bounded by a non-manifold curve network

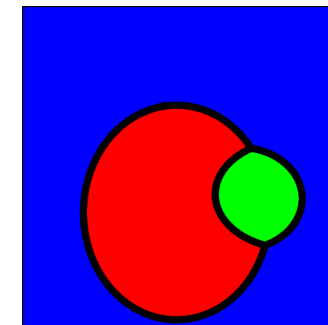


# Implicit representation

- Representing a  $n$ -labelled plane: [Losasso 06, Feng 10, Yuan 12, Huang 17]
  - Define  $n$  scalar functions  $f_1(x), \dots, f_n(x)$
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$$\text{Label}(x) = \arg\max_i f_i(x)$$
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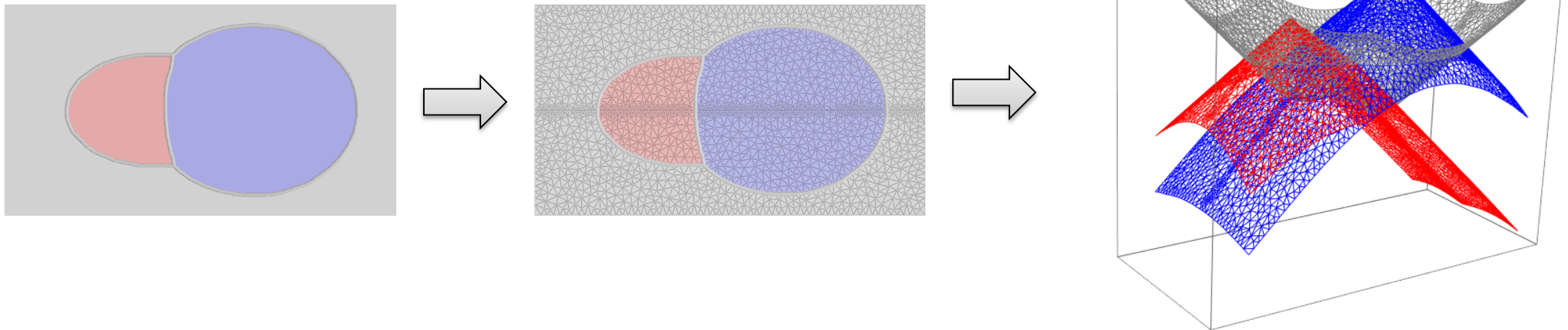


*Label*



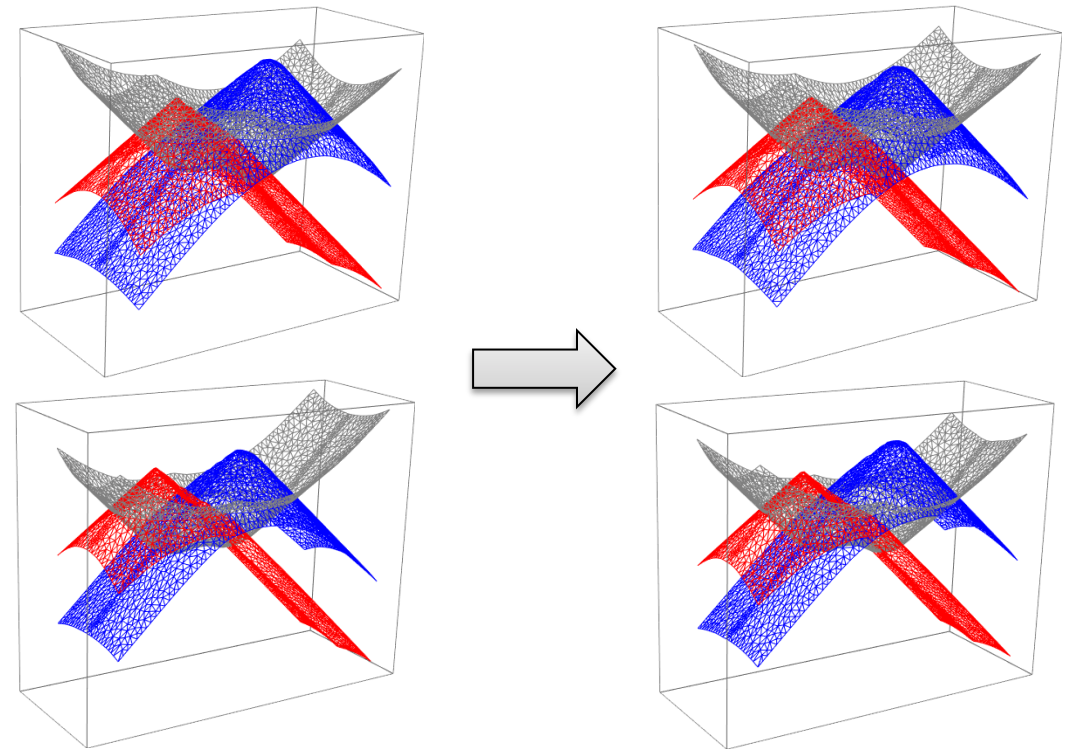
# Implicit representation

- Define initial scalar functions as signed distance functions
  - Triangulate each cross-section
  - Compute  $f_{i \uparrow P}(v)$  for label  $i$  at vertex  $v$  on plane  $P$  as signed distance to boundaries of label  $i$



# Problem formulation

- Given implicit functions on each cross-section
- Modify the functions so that:
  - Labelling is consistent on intersection lines
  - Distortion to curve networks is minimized



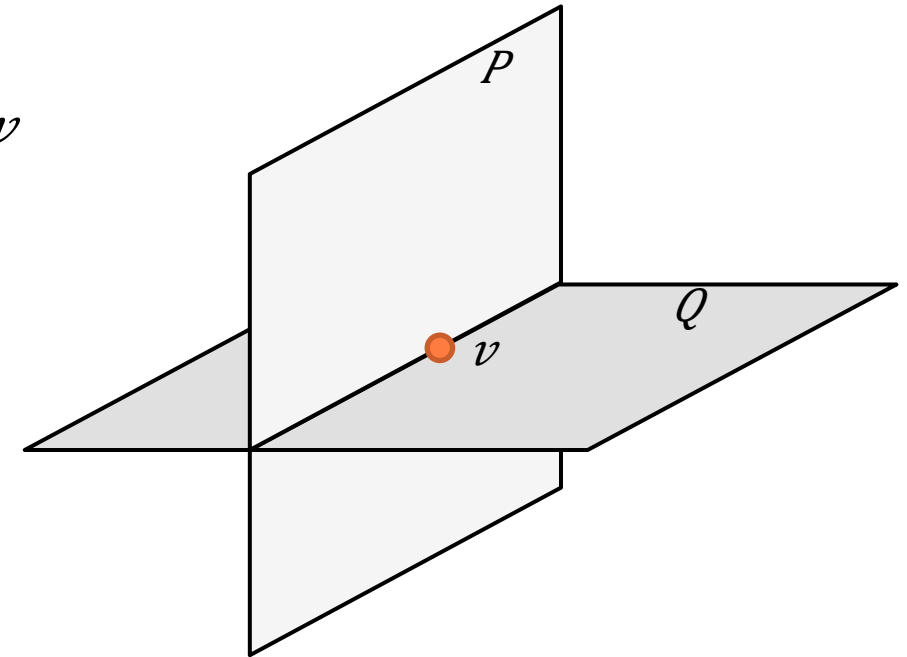


# Consistency constraints

- Consider vertex  $v$  on the intersection line between cross-sections  $P, Q$ 
  - $f \downarrow 1, \dots, n \uparrow P(v), f \downarrow 1, \dots, n \uparrow Q(v)$ : scalar values on plane  $P, Q$
- Suppose the final label at  $v$  is known,  $l(v)$ 
  - Then function value of  $l(v)$  is greater than any other label at  $v$

$$f \downarrow l(v) \uparrow P(v) \geq f \downarrow i \uparrow P(v) + \varepsilon, f \downarrow l(v) \uparrow Q(v) \geq f \downarrow i \uparrow Q(v) + \varepsilon, \\ \forall i \neq l(v)$$

- Since we don't know  $l(v)$ , we leave it as a variable.



# Deformation energy

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- Deviation from input curve networks
  - How far have the curves moved? (zero order)
  - How much have the curve tangents changed? (1<sup>st</sup> order)

$$E(f) = \lambda \sum_{P, v, i} \|f \downarrow i \uparrow P(v) - f \downarrow i \uparrow P(v)\|^2 \quad \text{(zero order)}$$

$$+ \sum_{P, v, i, j} \|G(f \downarrow i \uparrow P - f \downarrow j \uparrow P)(v) - G(f \downarrow i \uparrow P - f \downarrow j \uparrow P)(v)\|^2 \quad \text{(1<sup>st</sup> order)}$$

$f$ : input function;  $L$ : discrete gradient

# Mixed-Integer Programming (MIP)

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- Continuous variables:  $f \downarrow i \uparrow P(v)$  // *Implicit function values at all vertices*
- Integer variables:  $l(v)$  // *Labels at vertices on intersection lines*
- Minimize:  $E(f)$  // *Quadratic deformation energy*
- Subject to:  $f \downarrow l(v) \uparrow P(v) \geq f \downarrow i \uparrow P(v) + \varepsilon$  // *Consistency constraints*

# Optimization

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- MIPs are computationally expensive to solve
- We propose an efficient solution strategy by iteratively solving **Quadratic Programming** problems


# Quadratic Programming (QP)

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- For a given set of labels  $l(v)$  at each vertex  $v$  on intersection lines:
  - Continuous variables:  $f \downarrow i \uparrow P(v)$  // *Implicit function values at all vertices*
  - Minimize:  $E(f)$  // *Quadratic deformation energy*
  - Subject to:  $f \downarrow l(v) \uparrow P(v) \geq f \downarrow i \uparrow P(v) + \varepsilon$  // *Consistency constraints*

# Optimization strategy

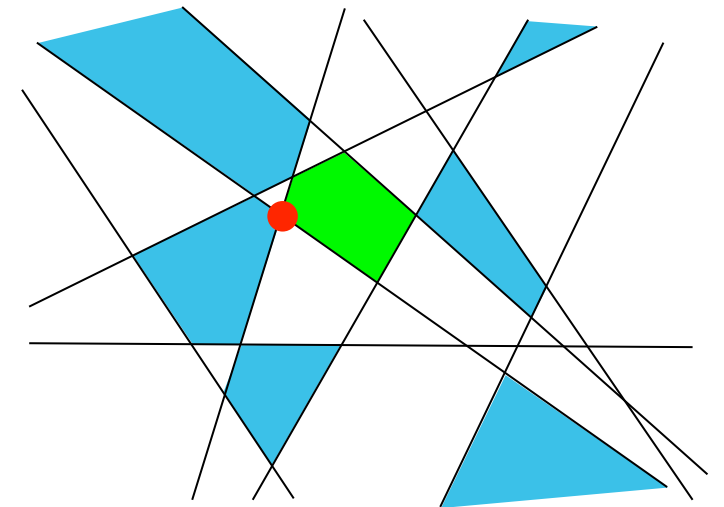
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- Start with an initial set of labels on the intersection lines
  - By averaging values from multiple planes
- Solve QP
- Update labels and repeat 
  - Until energy no longer decreases

# Updating labels

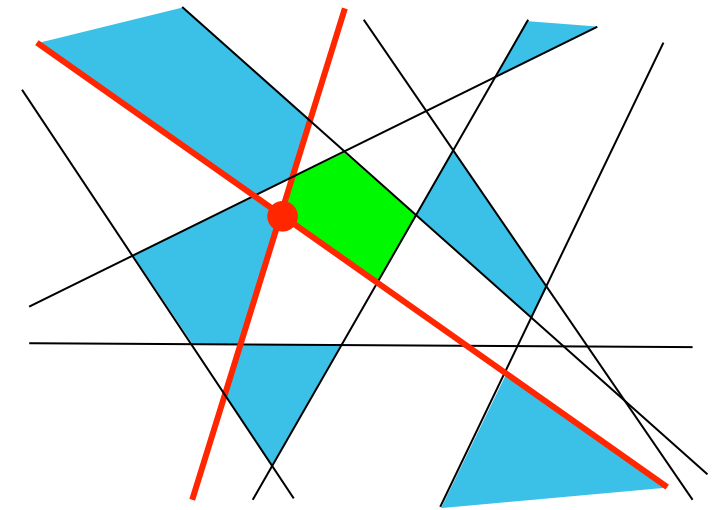
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- A set of labels defines a set of inequality constraints
  - A convex cell in the solution space
- Minimizer of QP lies on the boundary of the cell
  - Otherwise, the input is already consistent



# Updating labels

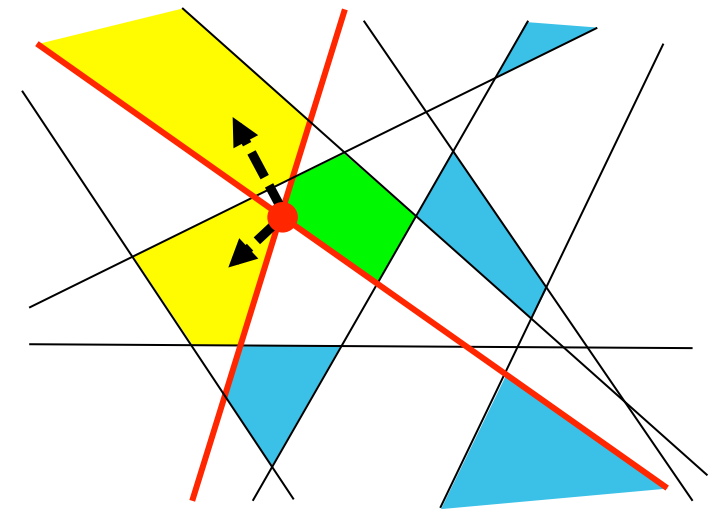
- A set of labels defines a set of inequality constraints
  - A convex cell in the solution space
- Minimizer of QP lies on the boundary of the cell
  - Otherwise, the input is already consistent
  - Each hyperplane containing the minimizer corresponds to a pair of labels  $l(v), i$  with similar values at some vertex  $v$
  - Setting  $l(v)=i$  potentially lowers the energy





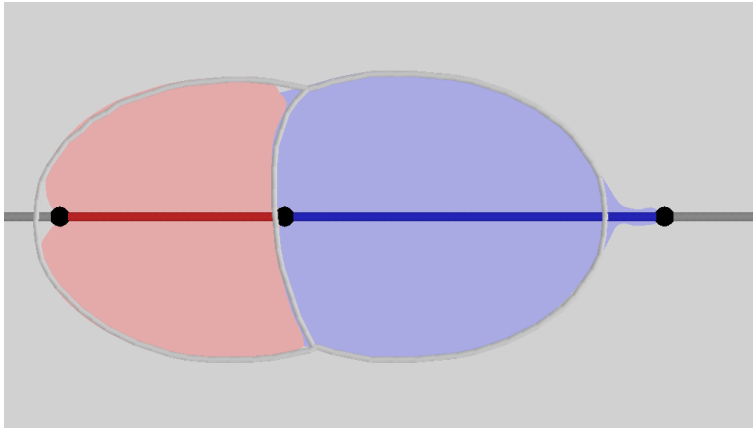
# Updating labels

- Sort all hyperplanes by magnitude of energy gradient across the hyperplane
- Visit each hyperplane, flip label, and compute QP of the new label set
- Take the next label set as the first hyperplane with positive reduction in energy

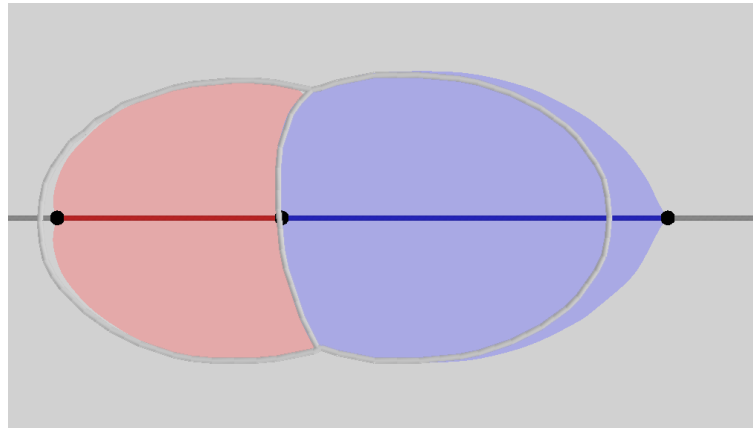


# Experiments: Parameter selection

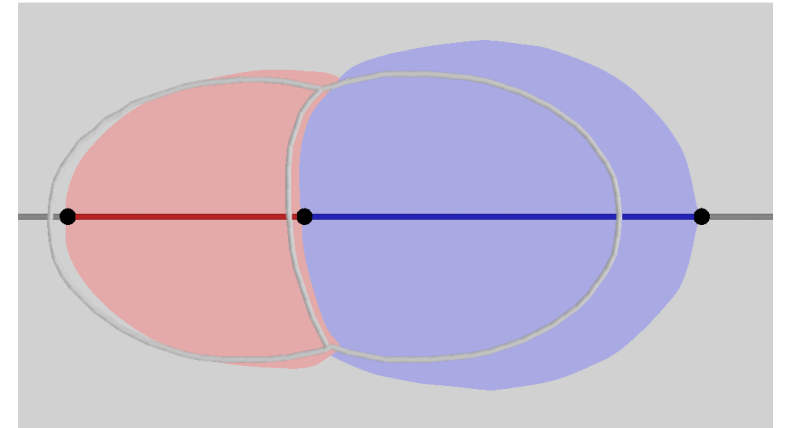
- Choosing  $\lambda$ : trade-off proximity with shape preservation
  - Energy =  $\lambda$  \* 0-order difference + 1<sup>st</sup>-order difference



$\lambda=100$



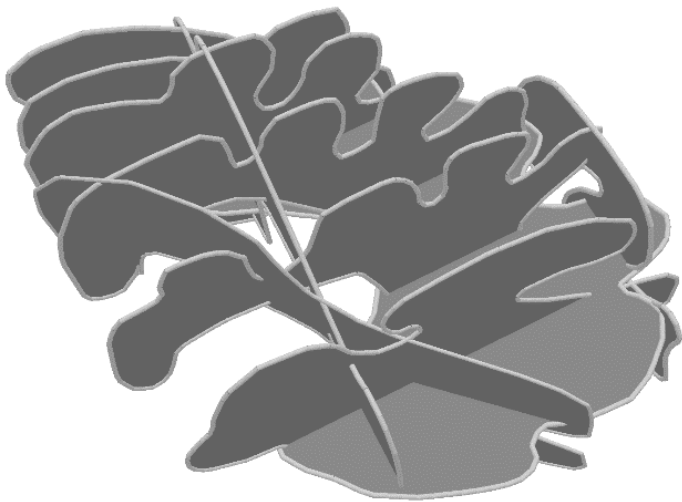
$\lambda=1$



$\lambda=0.01$

# Experiments: Performance

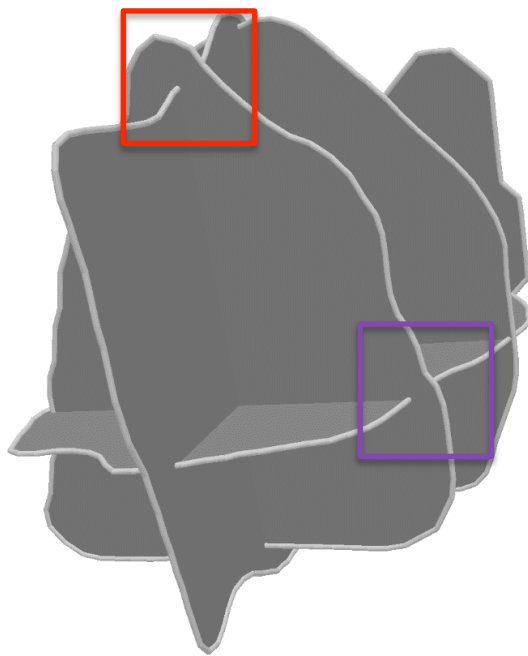
- Comparing with off-the-shelf MIP solver (Gurobi)
  - 2-labels input: increasing number of cross-section planes
  - Our method produces similar energy but using significantly less time



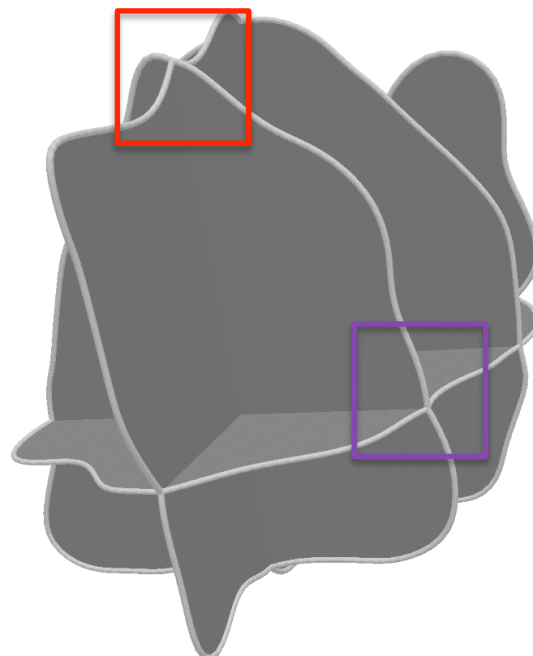
# planes	Our energy	Gurobi energy	Our Time (s)	Gurobi Time (s)
2	16.65	16.65	0.845	1.05
3	24.95	24.95	1.253	11.28
4	25.02	25.03	3.024	33.16
5	29.55	29.55	33.218	619.91

# Experiments: More examples

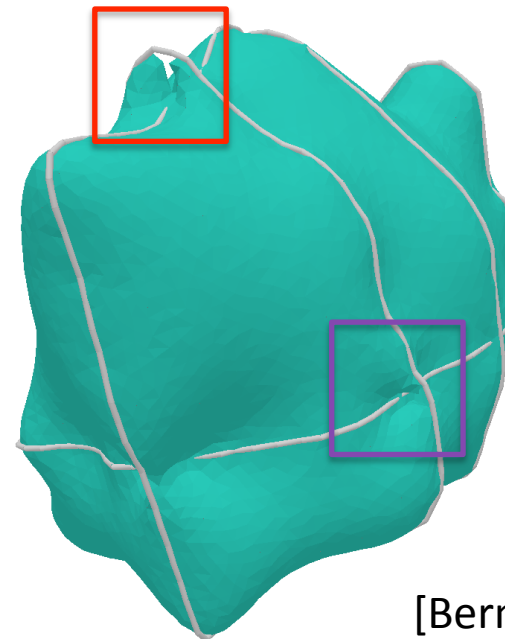
- Atrium (2 labels, 5 planes, time: 1 sec)



Input

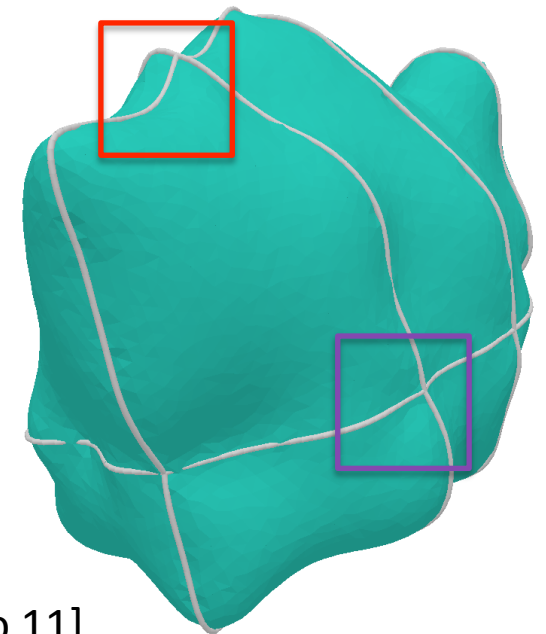


Consistent output



Surface from input

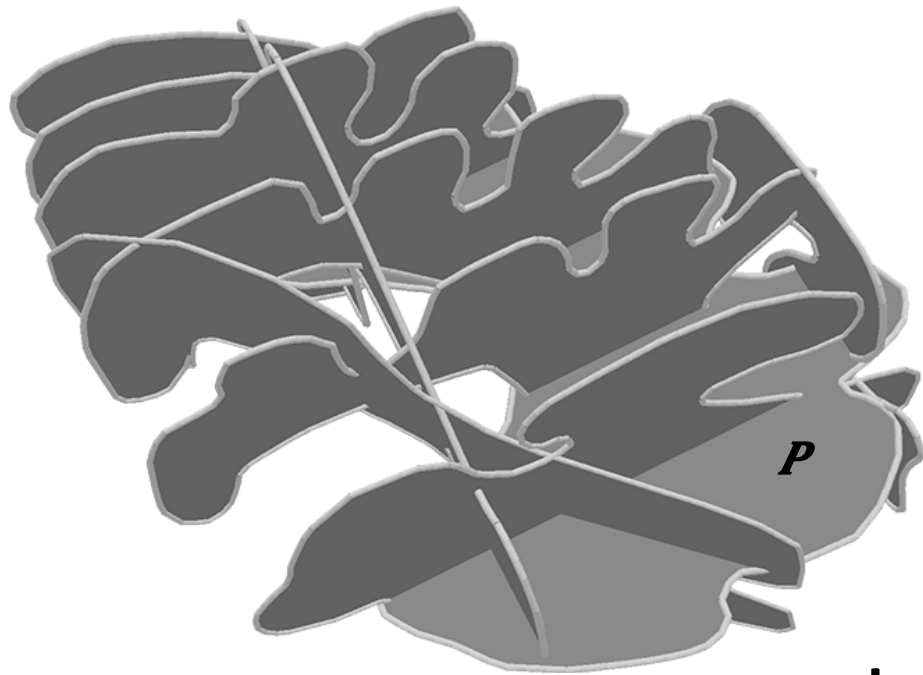
[Bermano 11]



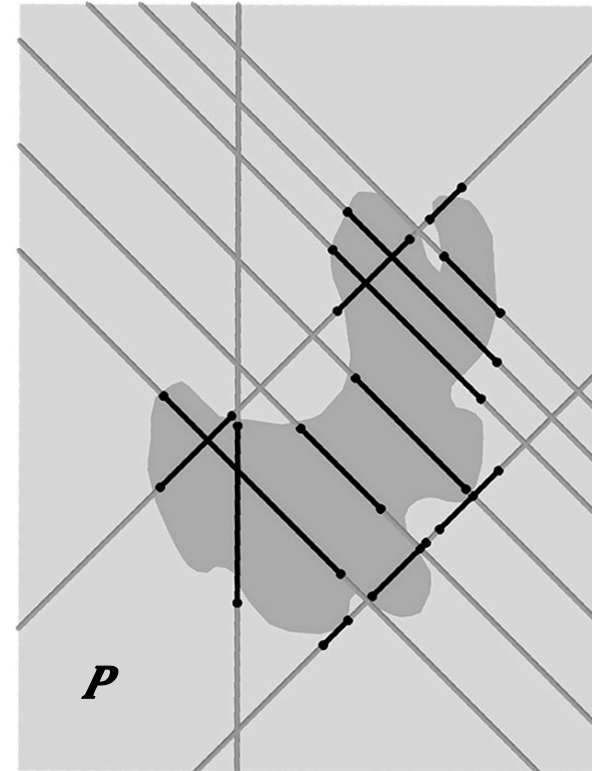
Surface from output

# Experiments: More examples

- Ferret brain (2 labels, 10 planes, time: 66 sec)

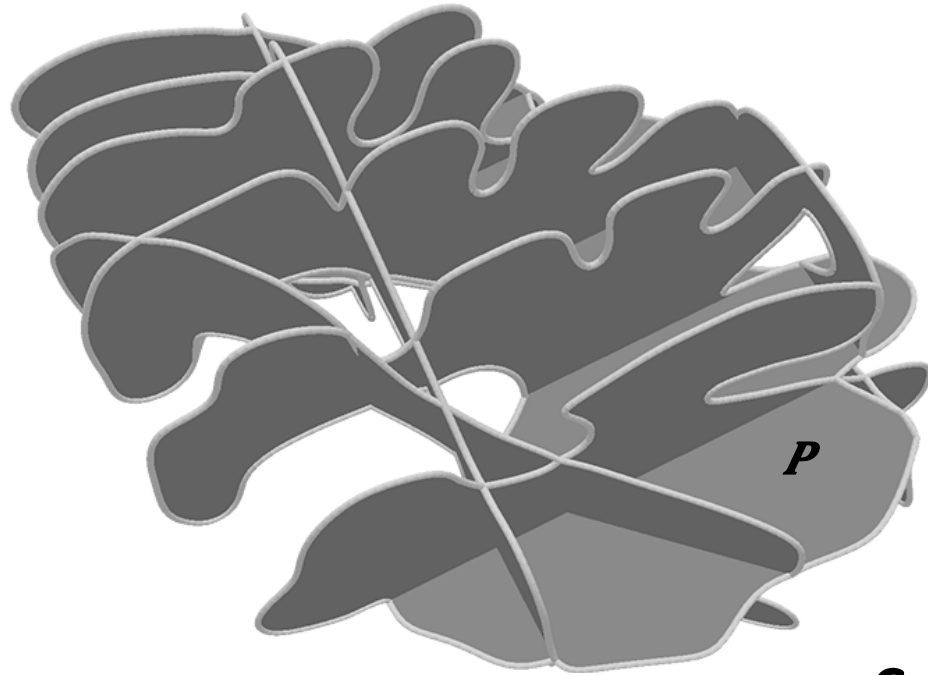


Inconsistent

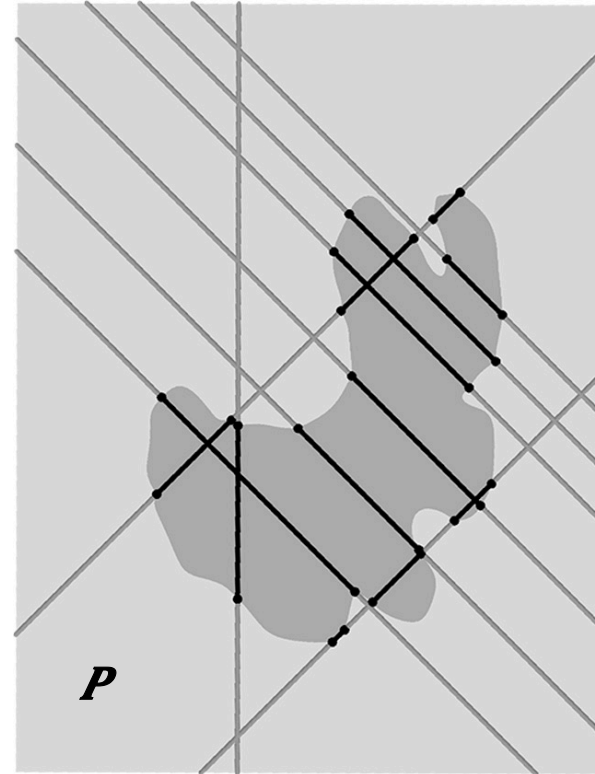


# Experiments: More examples

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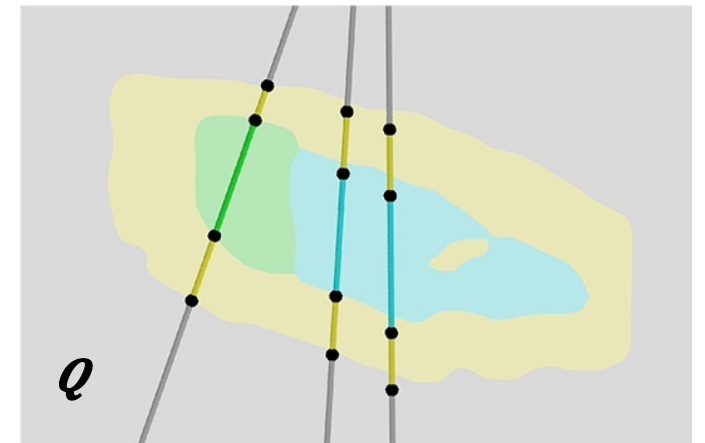
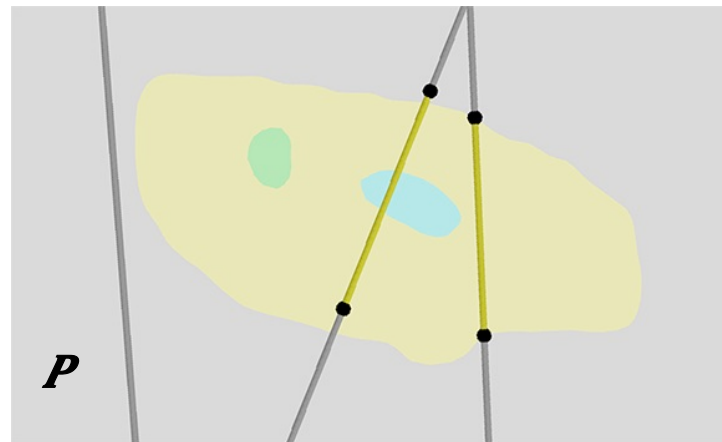
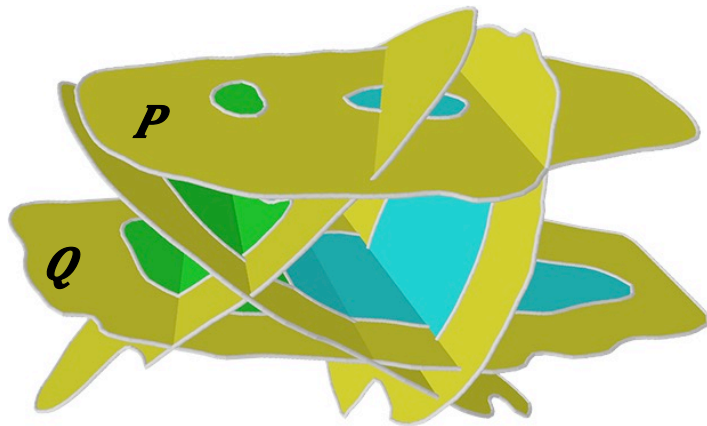


Consistent



# Experiments: More examples

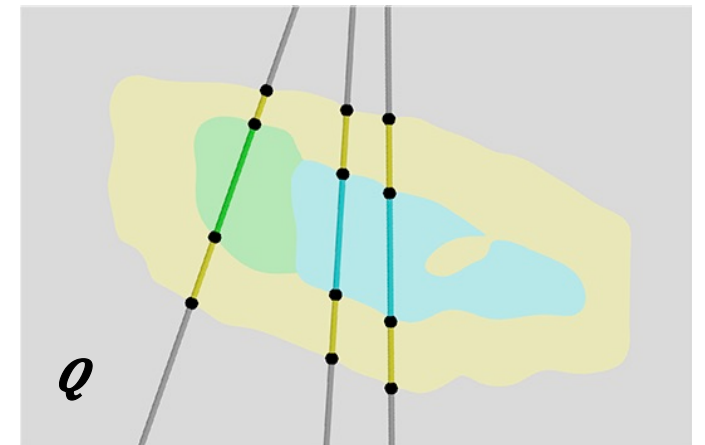
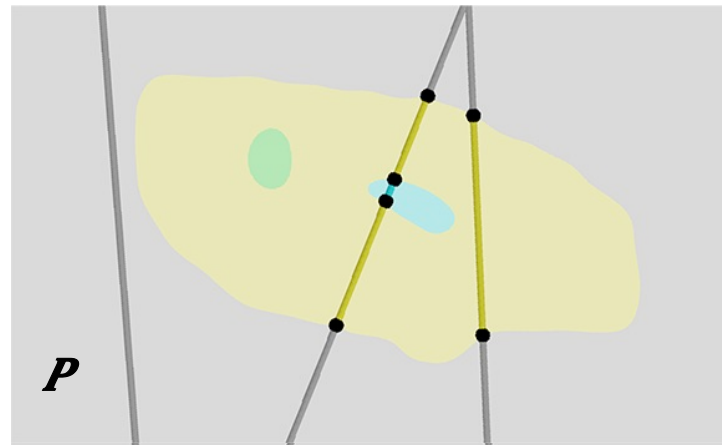
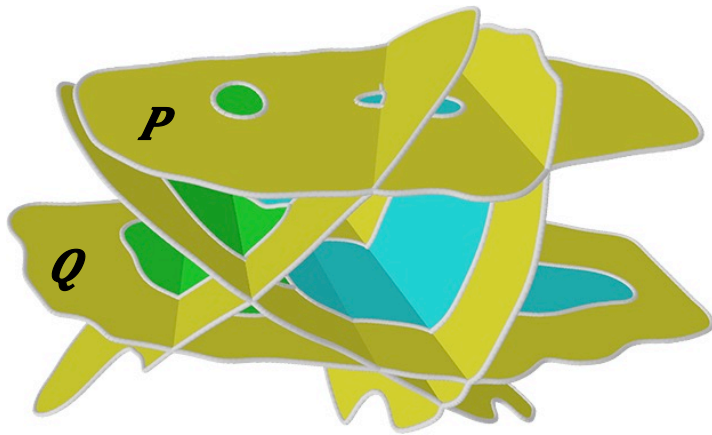
- Livers (5 planes, 4 labels , total time: 25s)



Inconsistent

# Experiments: More examples

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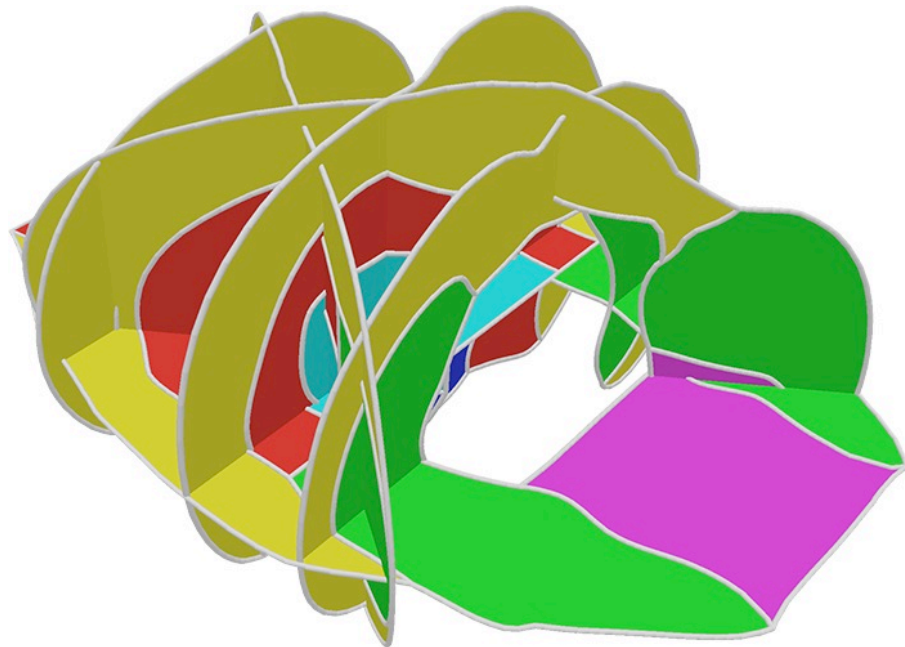
Consistent



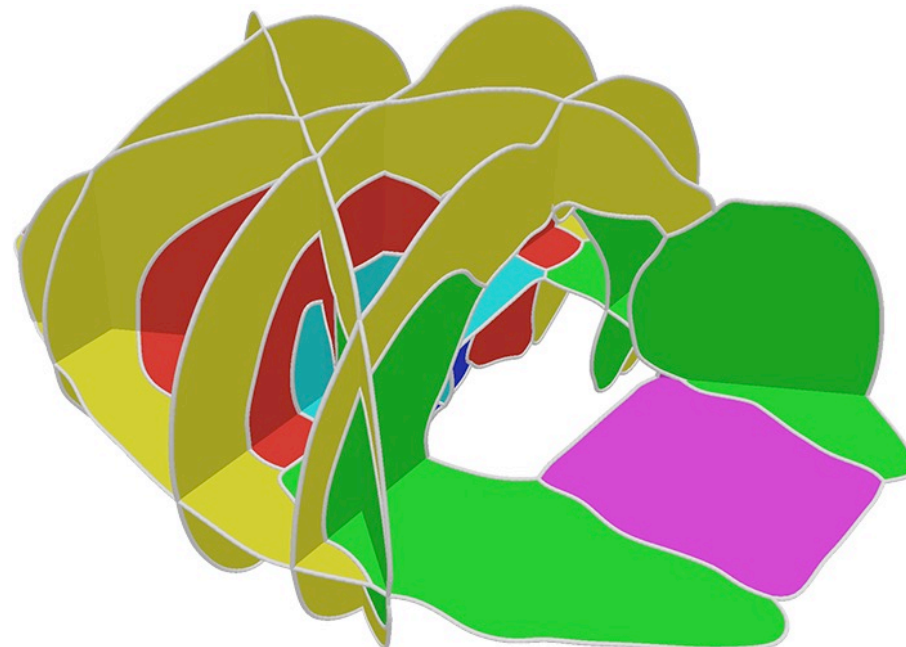
# Experiments: More examples

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- Mouse brain (6 planes, 7 labels, total time: 421s)



**Inconsistent**



**Consistent**

# Conclusion

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- An algorithm for restoring consistency to non-parallel cross-sections
  - Formulating and solving an MIP on implicit functions
  - Allowing existing surface reconstruction methods to work on imperfect cross-section inputs
- Limitations and future work
  - Improving deformation energy to better preserve smooth/sharp features
  - Integration into interactive volume segmentation (real-time feedback to users)