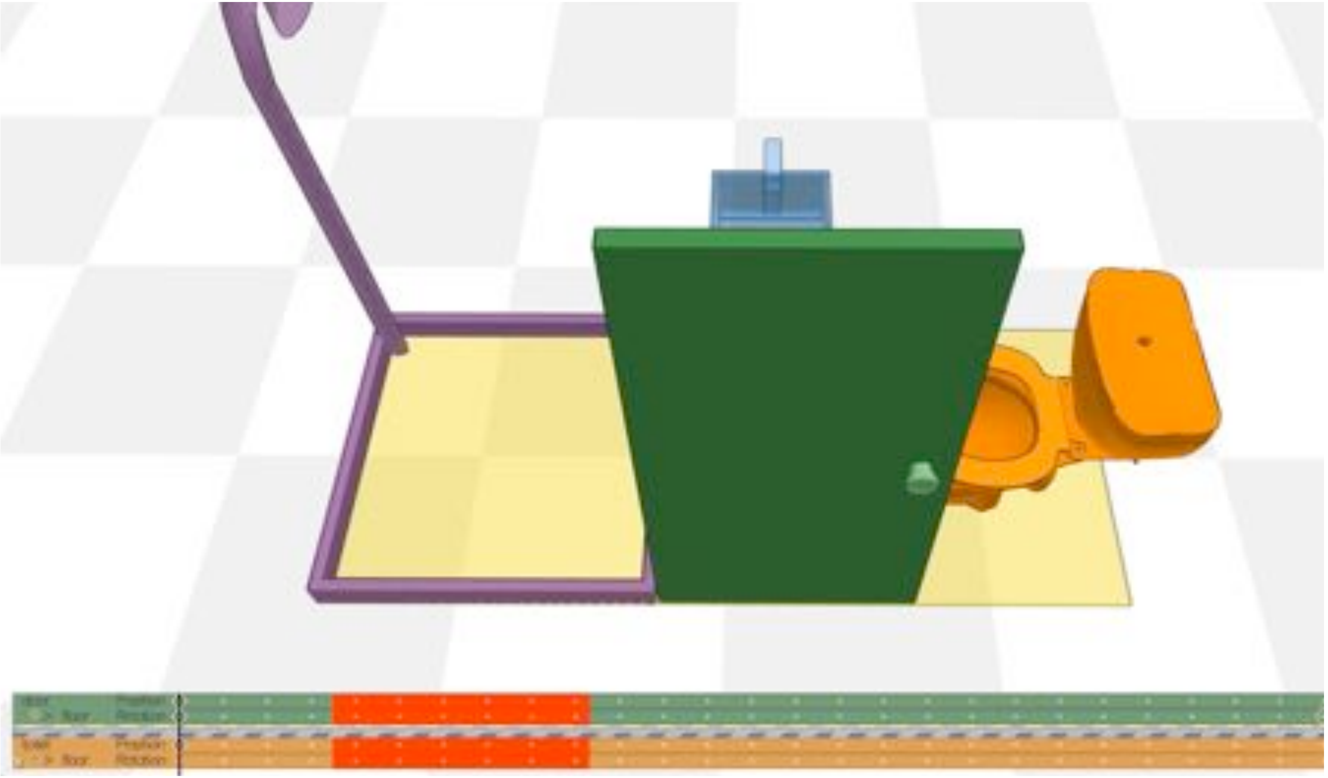
Generalized Matryoshka
Computational Design of Nesting Objects

Alec Jacobson
University of Toronto

Previous work enables computational design of *reconfigurables*



[Garg et al. 2016]

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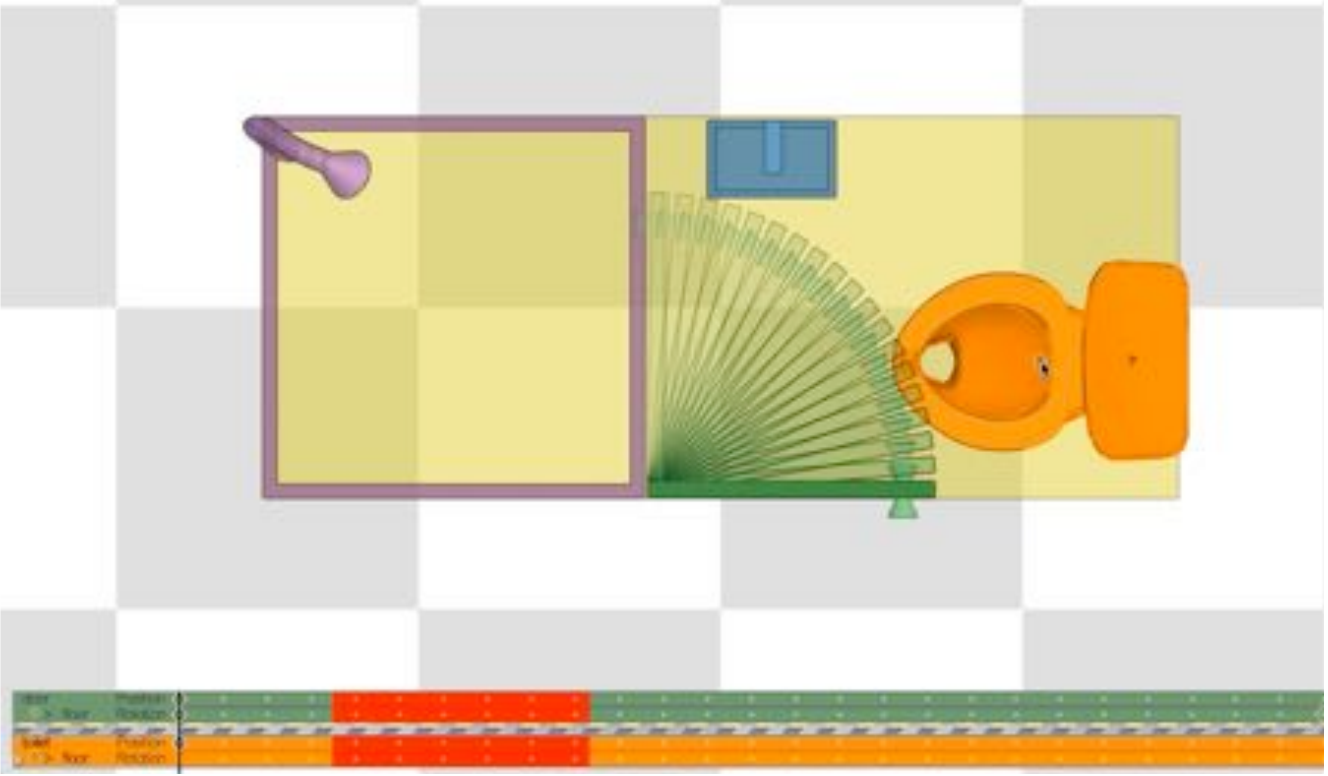

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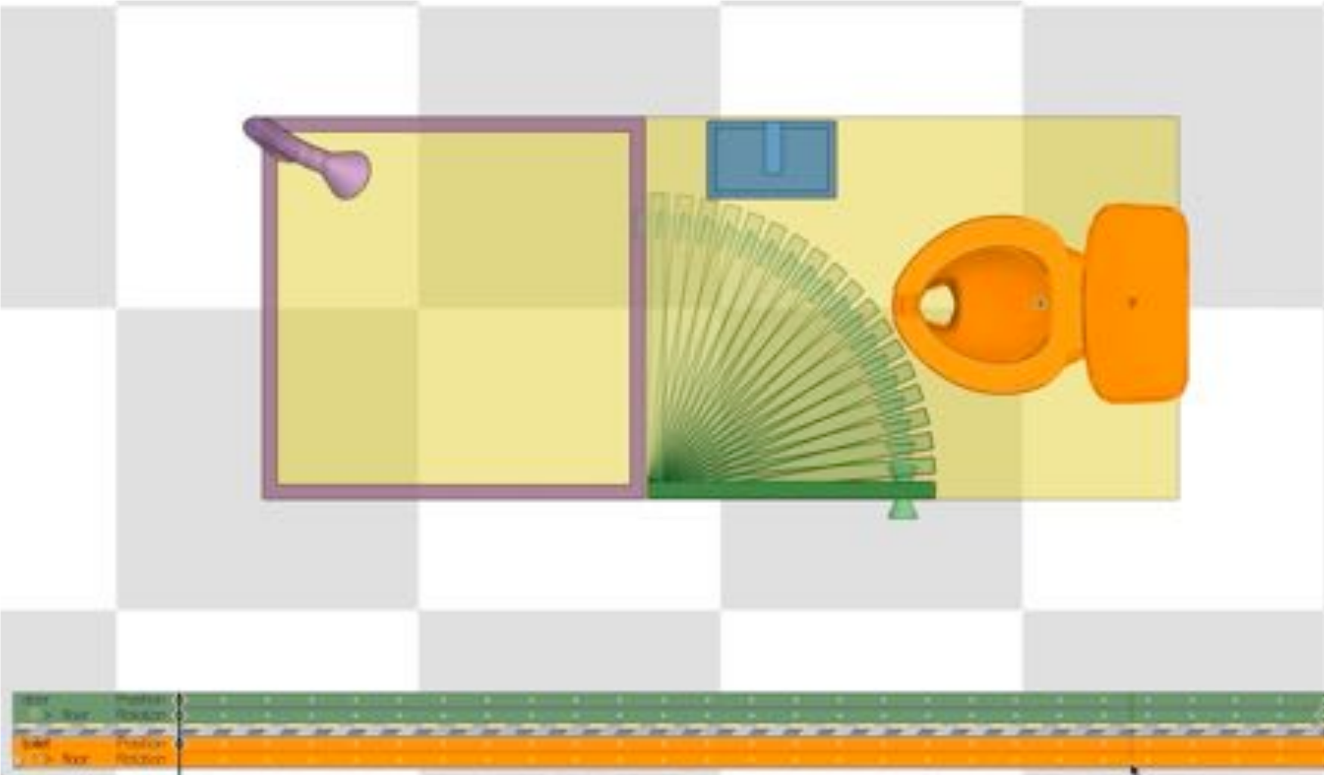

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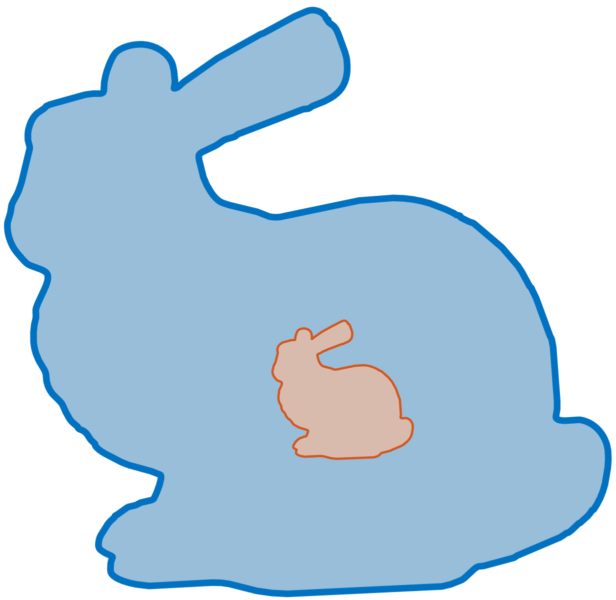

loose enclosure

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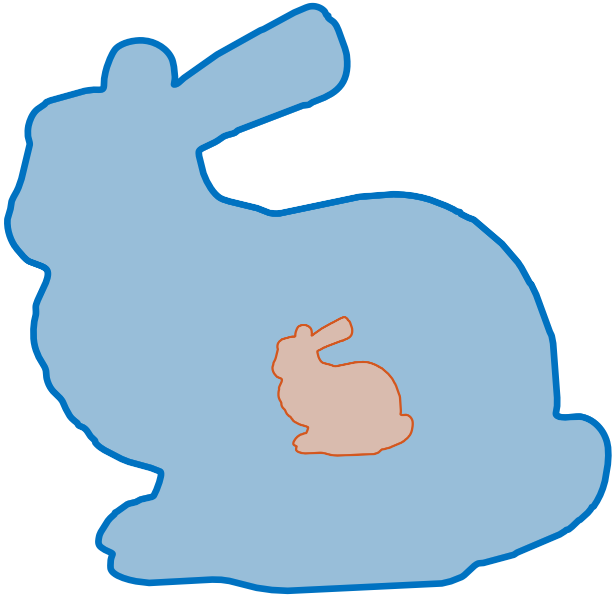


enclosure

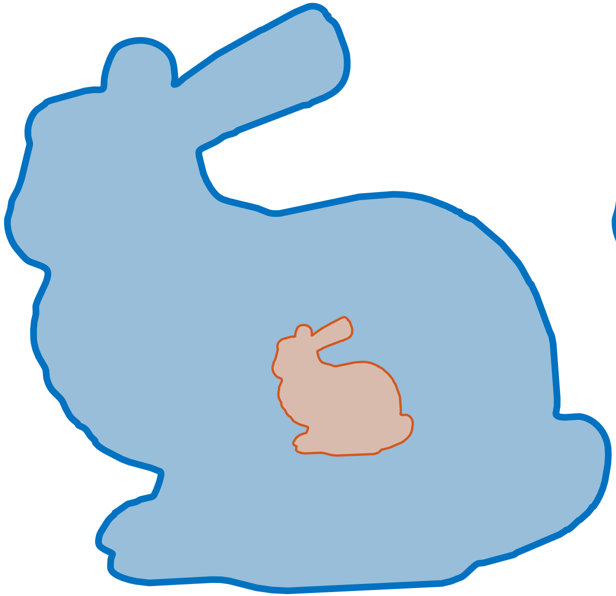
Nested Cages *ACM SIGGRAPH Asia 2015*

Leonardo Sacht[1] Etienne Vouga[2] Alec Jacobson[3]

[1]Universidade Federal de Santa Catarina [2]University of Texas at Austin [3]Columbia University

Given an input shape (yellow on bottom right), our method constructs nested cages: each subsequent mesh is coarser than the last and fully encloses it without intersections. A slice through all layers (left), shows a tightly encaged Bunny.

Nesting also requires *removal*



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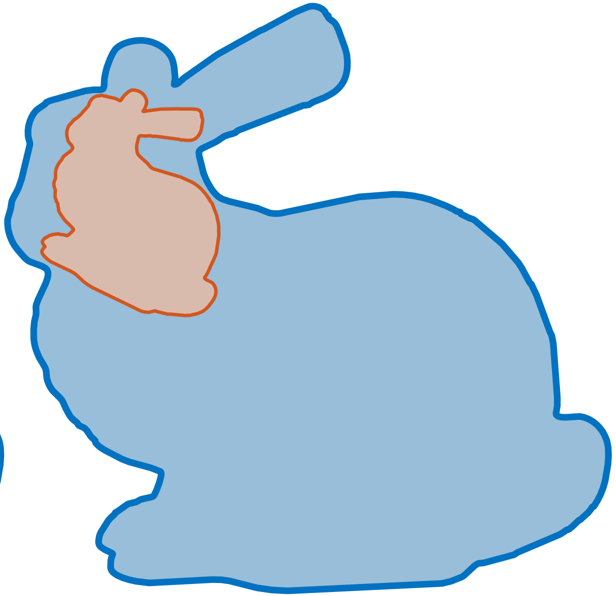

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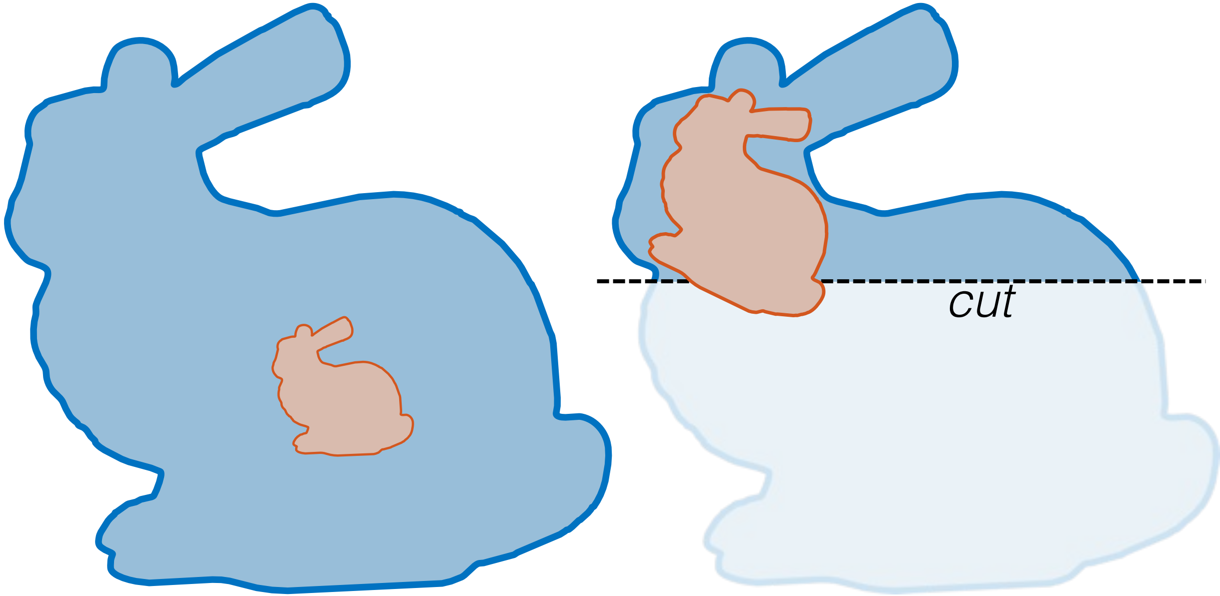

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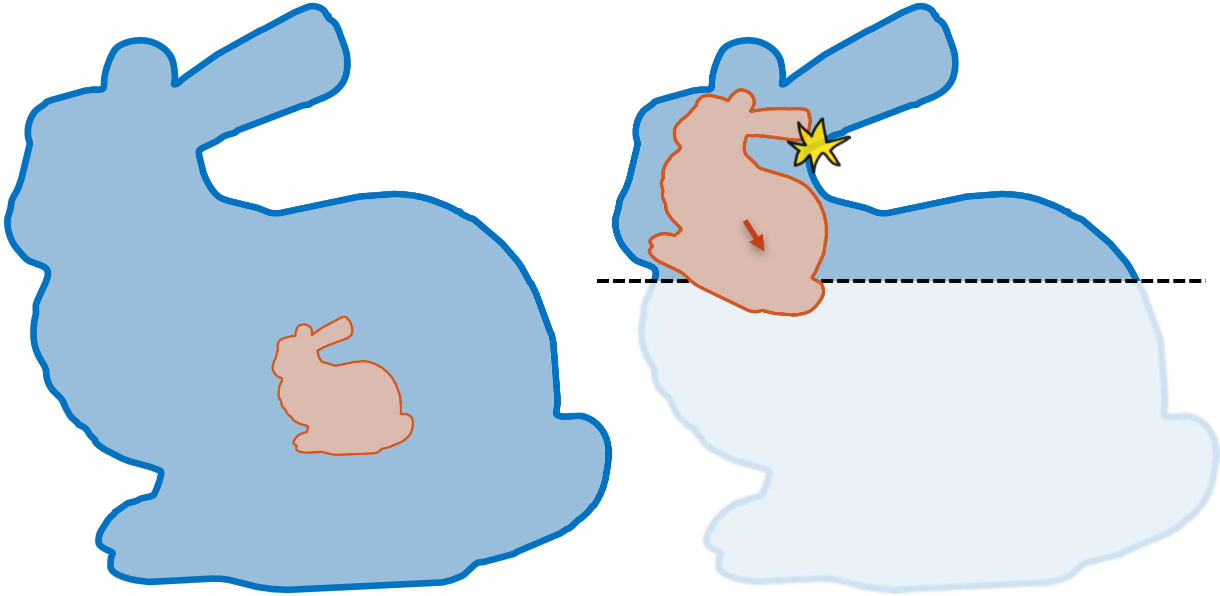

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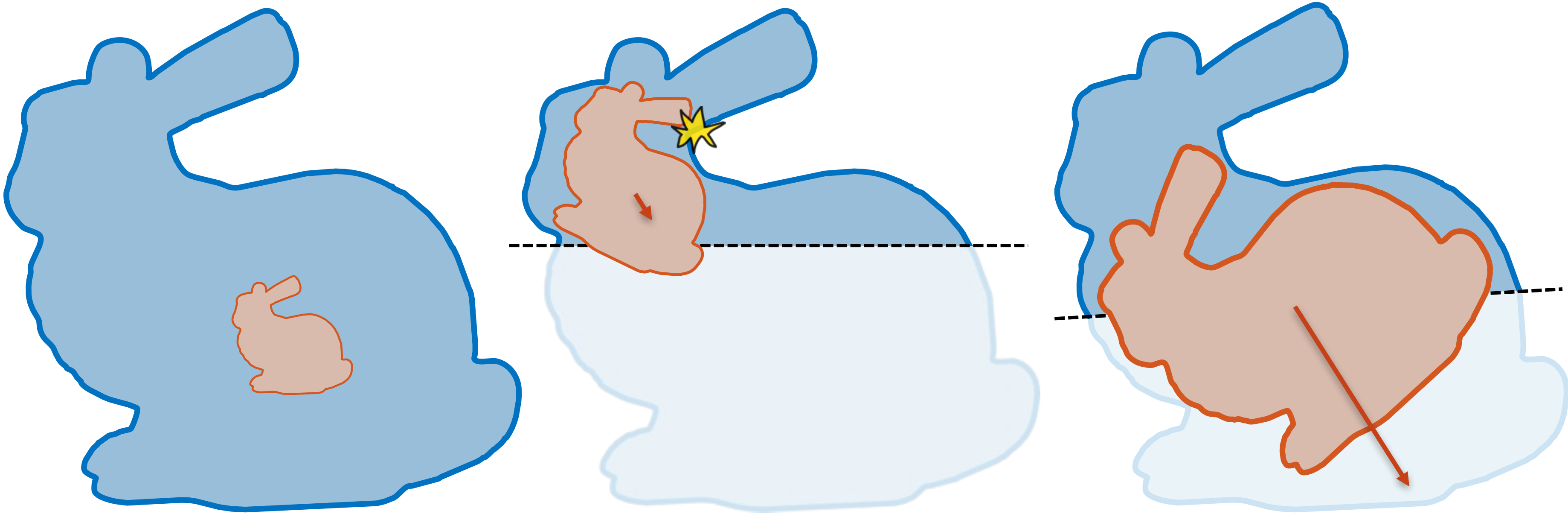

loose enclosure | enclosed, but not removable | enclosed and removable

We present highly parallelizable methods to…

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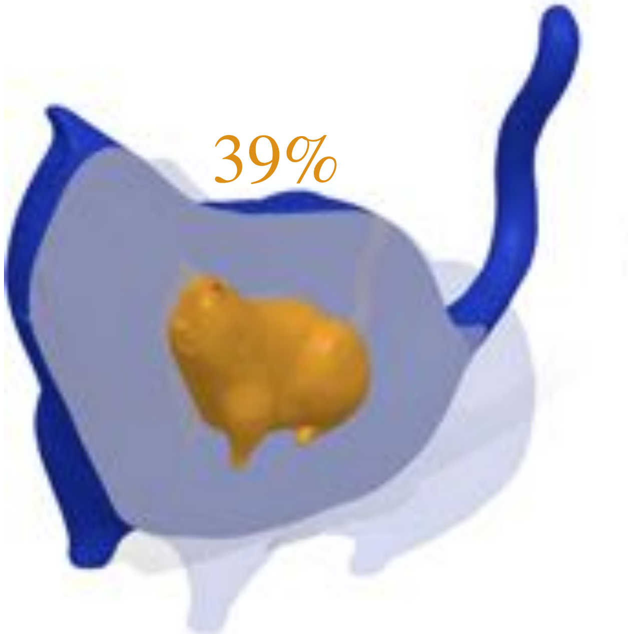
- determine feasibility of nesting,
- find maximum scale, and
- optimize nesting scale
  over some or all parameters

Our optimization utilizes rigid motion for tighter nesting



fixed position+rotation

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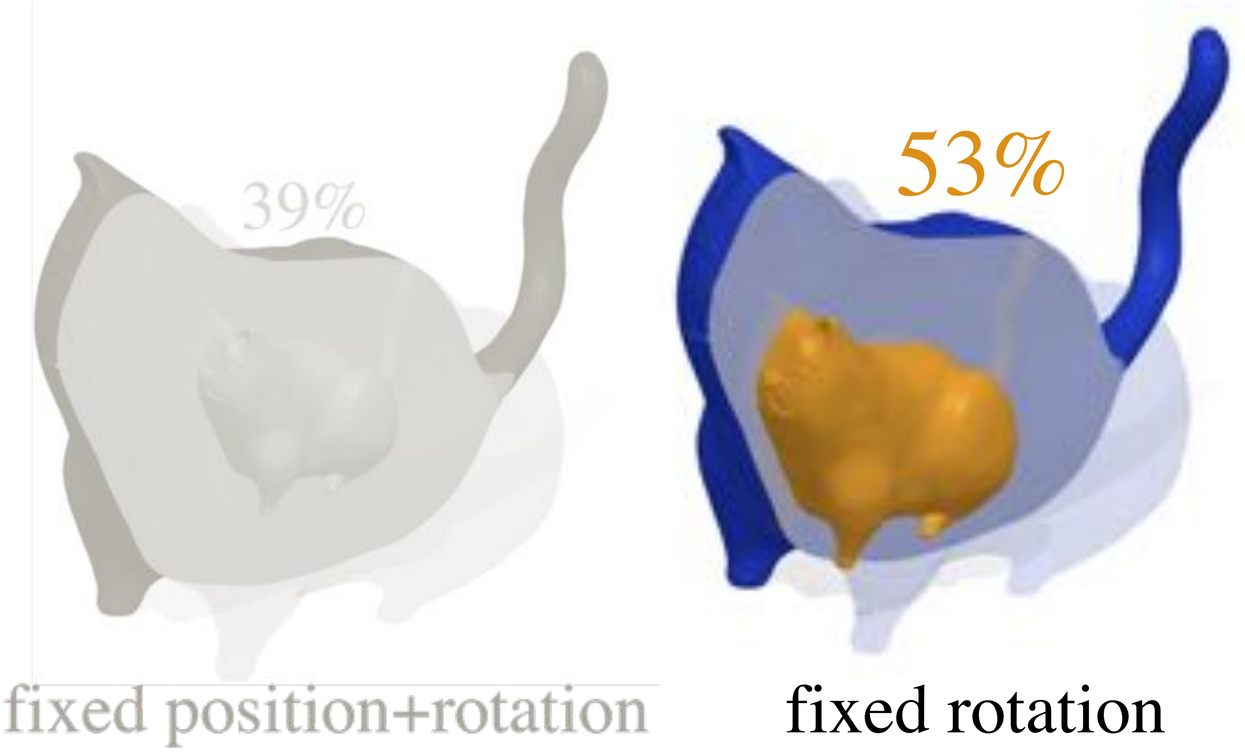

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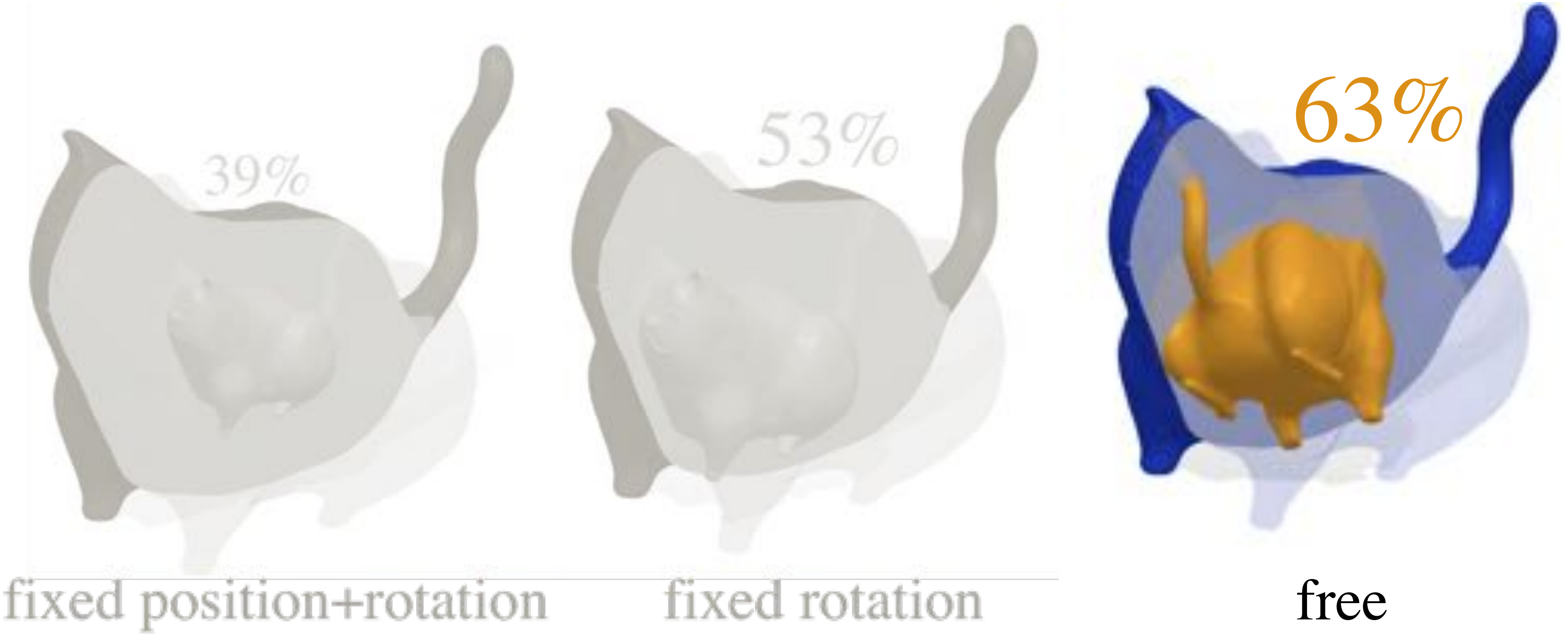
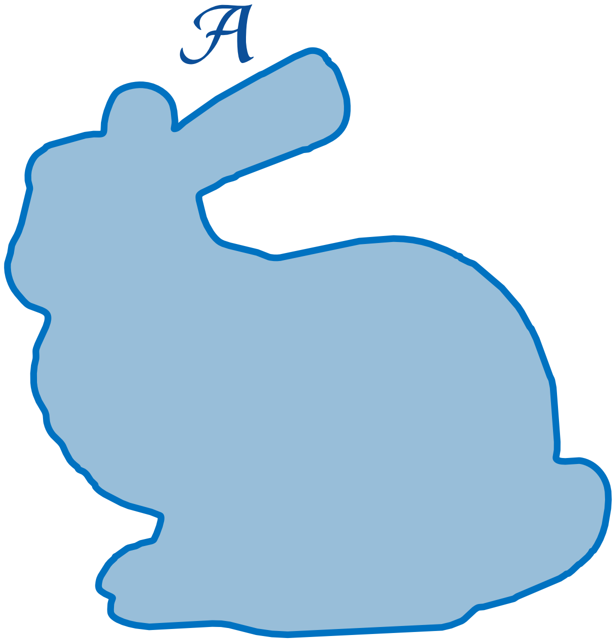


We define *valid self-nesting*

Given:

1. shape $\mathcal{A}$,



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Given:

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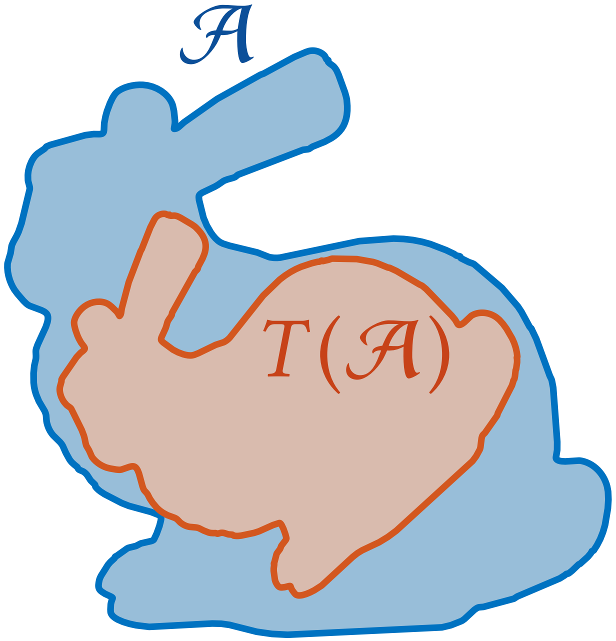

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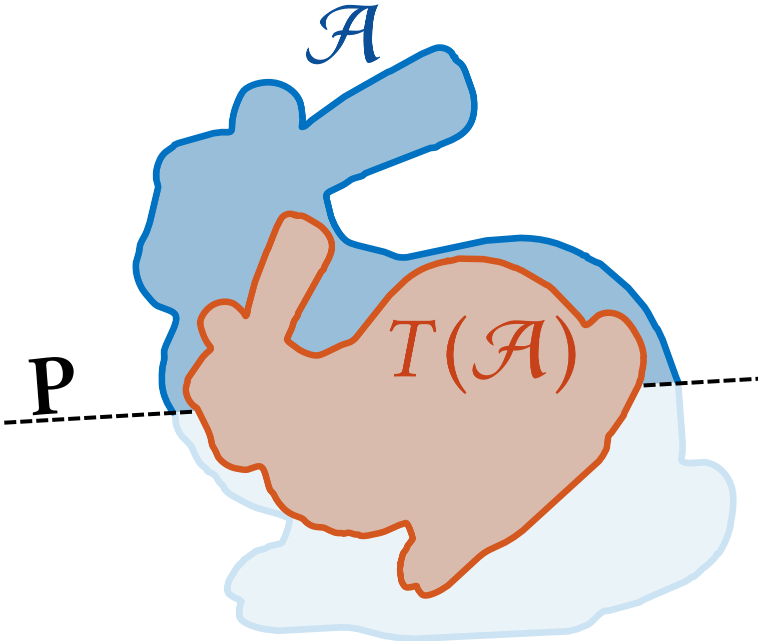

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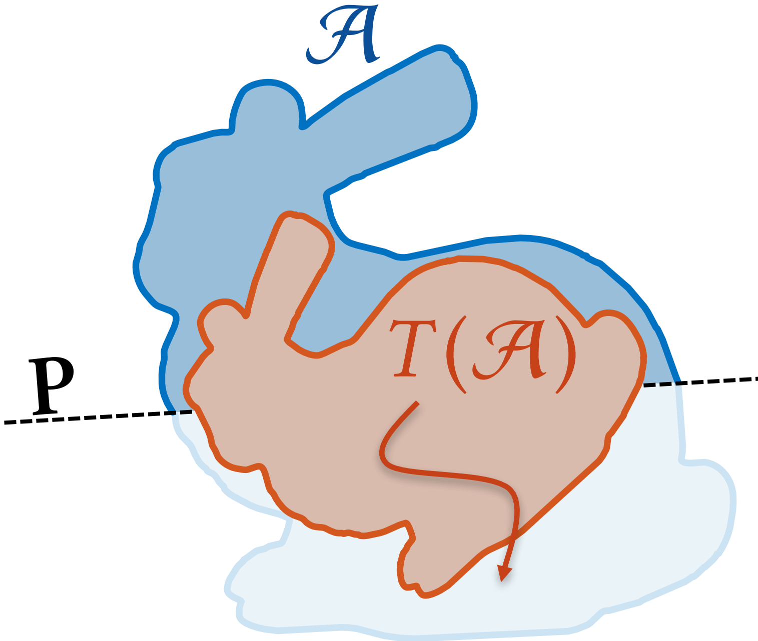

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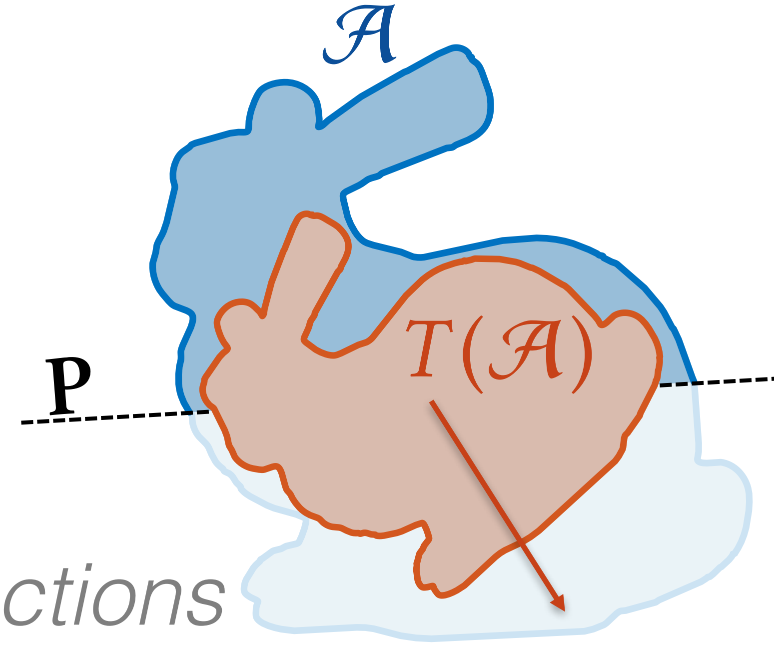

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1. $T(\mathcal{A}) \subset \mathcal{A}$, and
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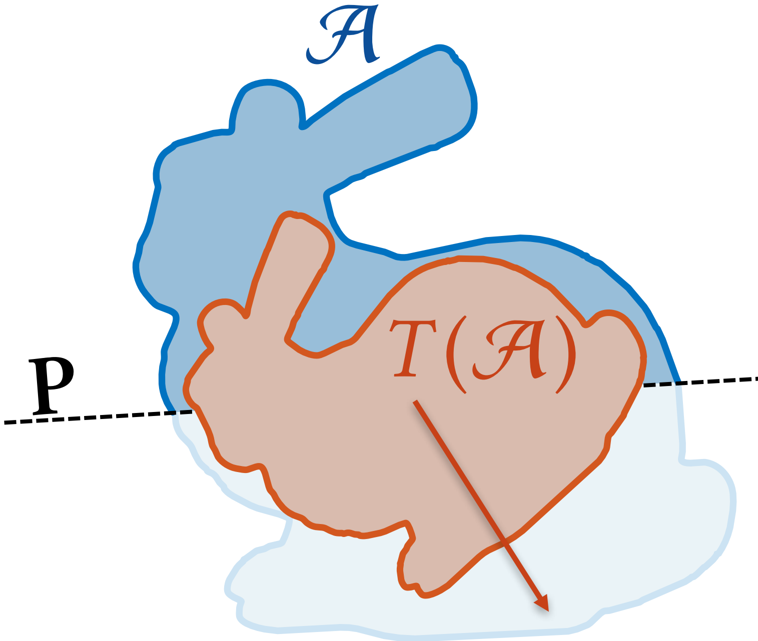

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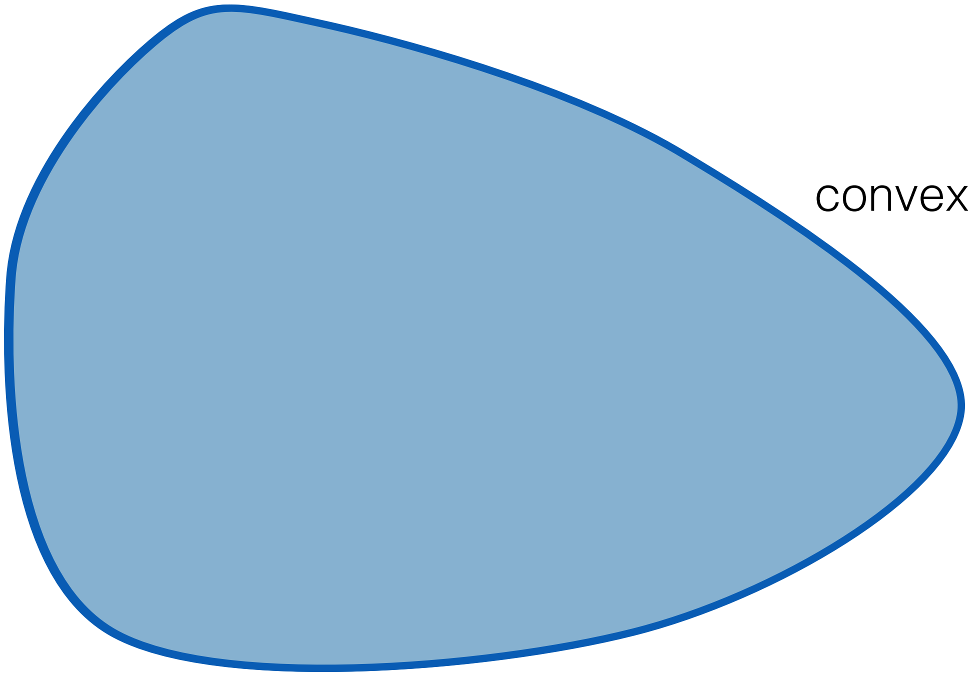
Definition depends on choice of cut plane and removal directions.

Some configurations admit *perfect self-nesting*



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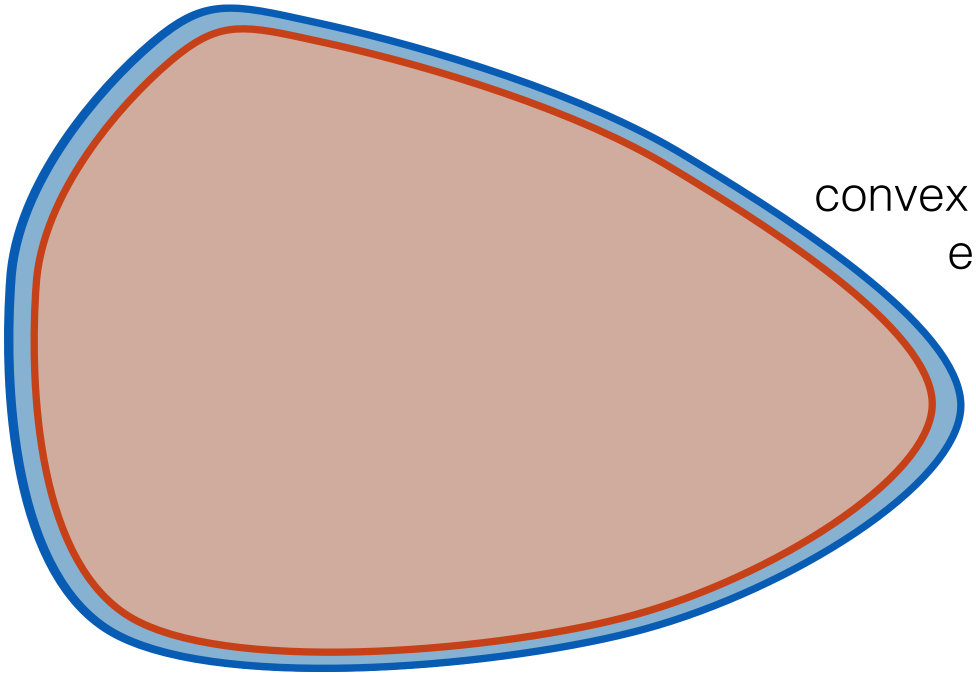

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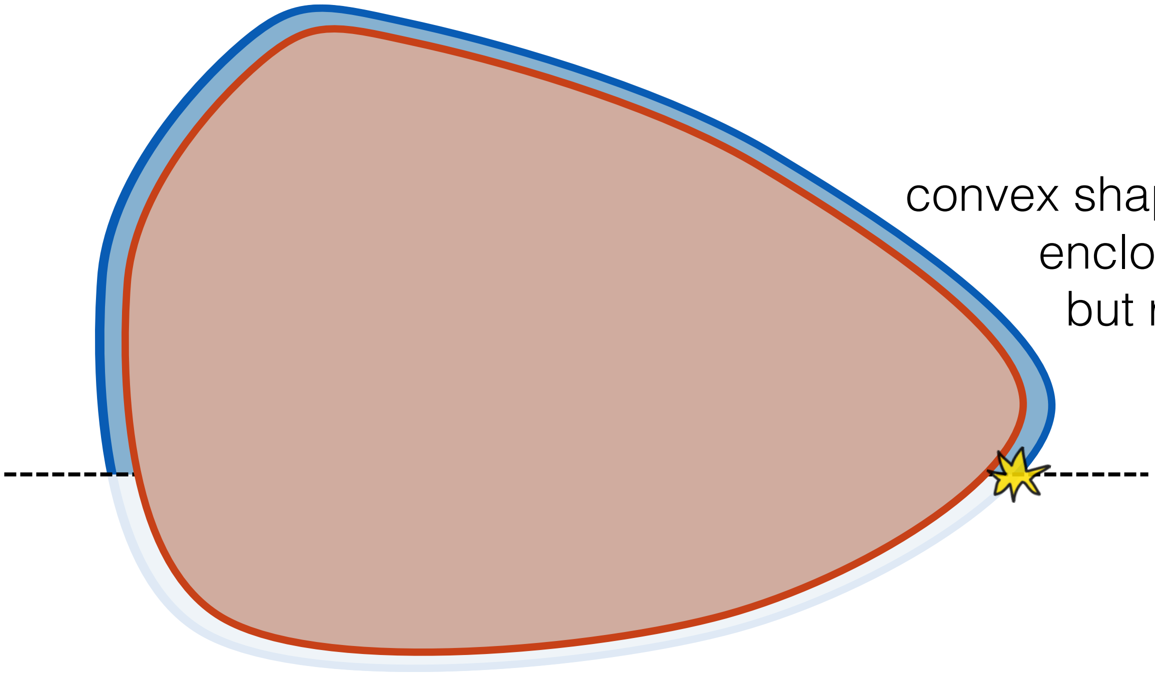
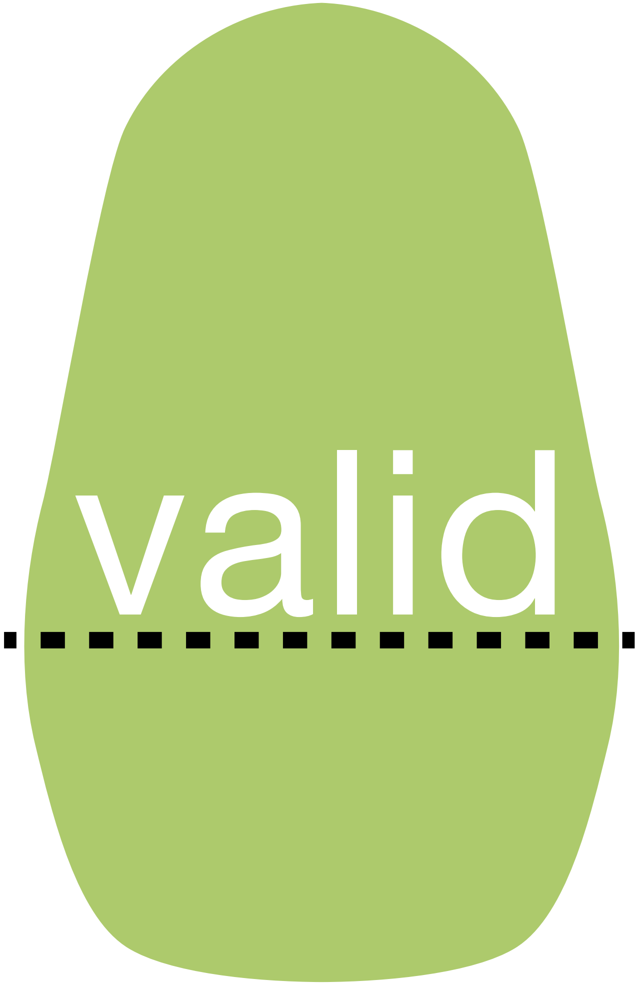


convex shapes?

enclosure is easy ….

but removal depends on cut plane!

[Zvyozdochkin & Malyutin 1890]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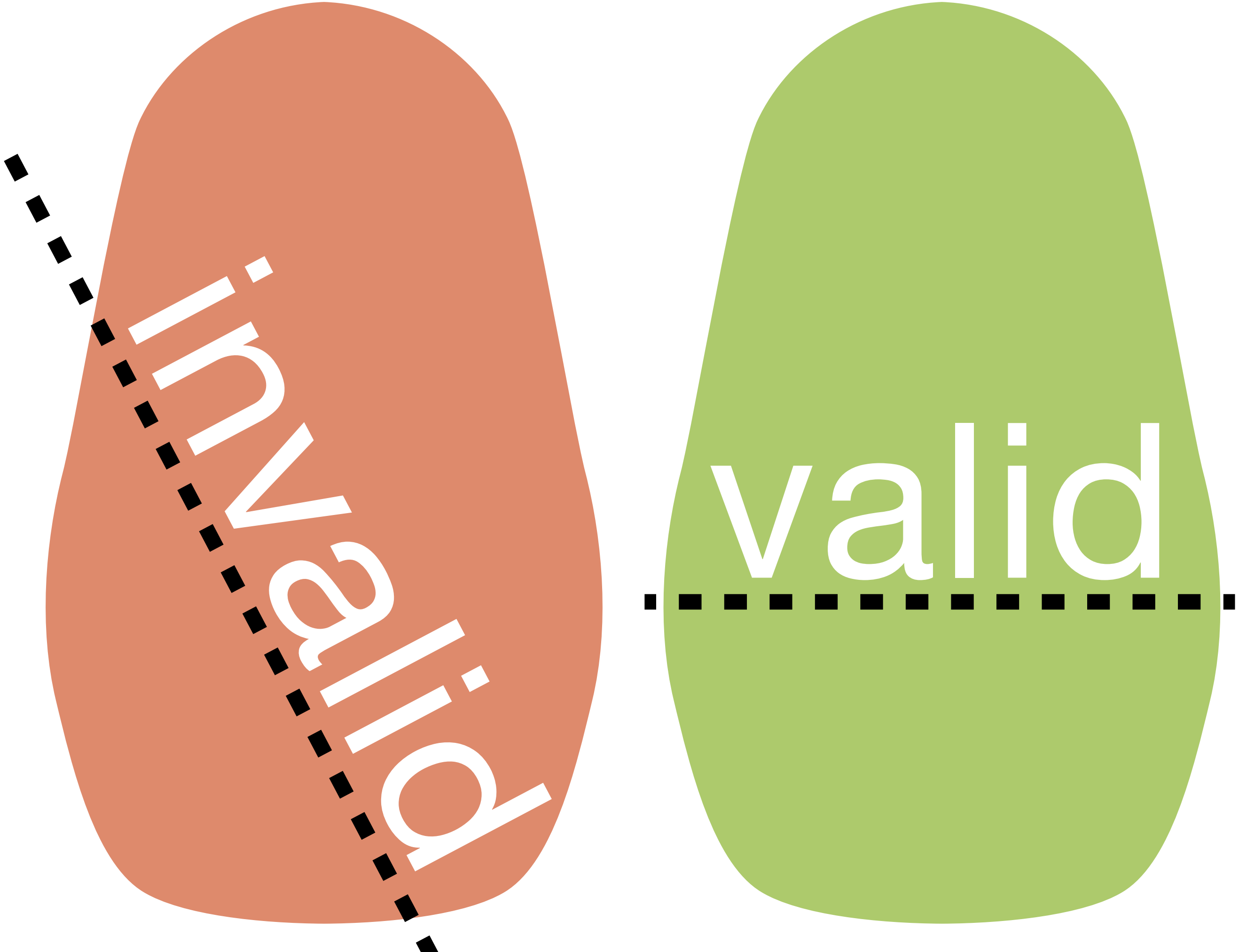
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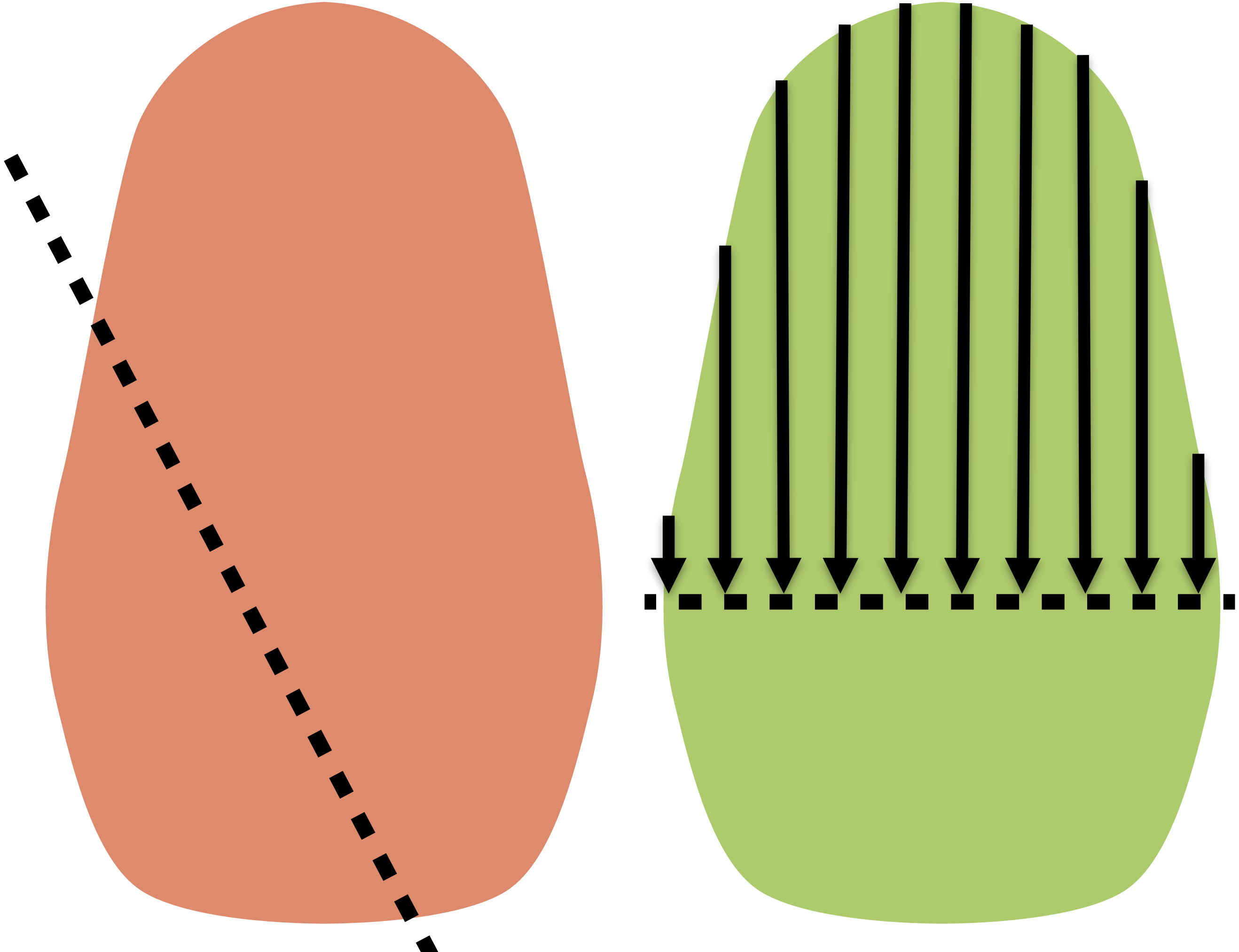

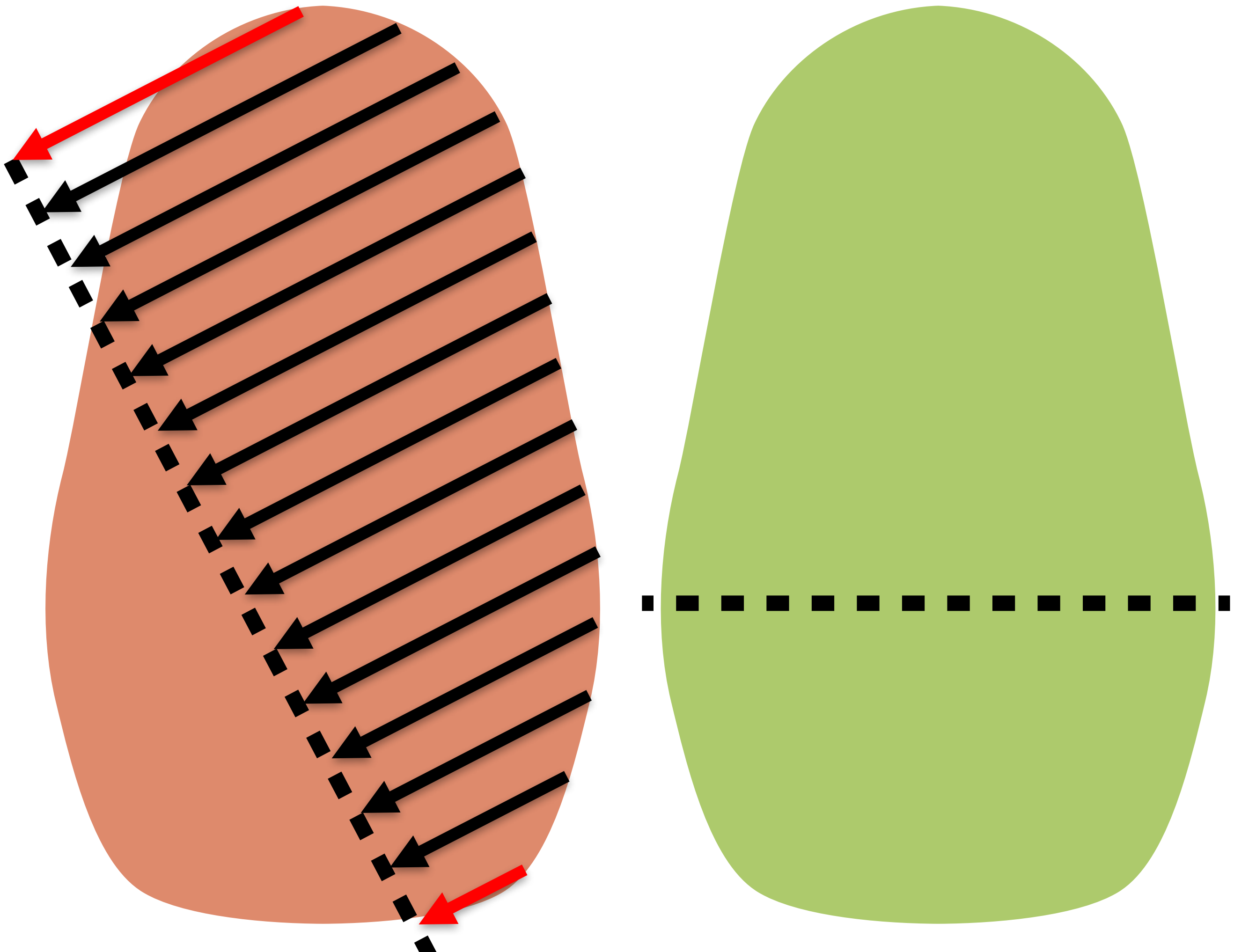

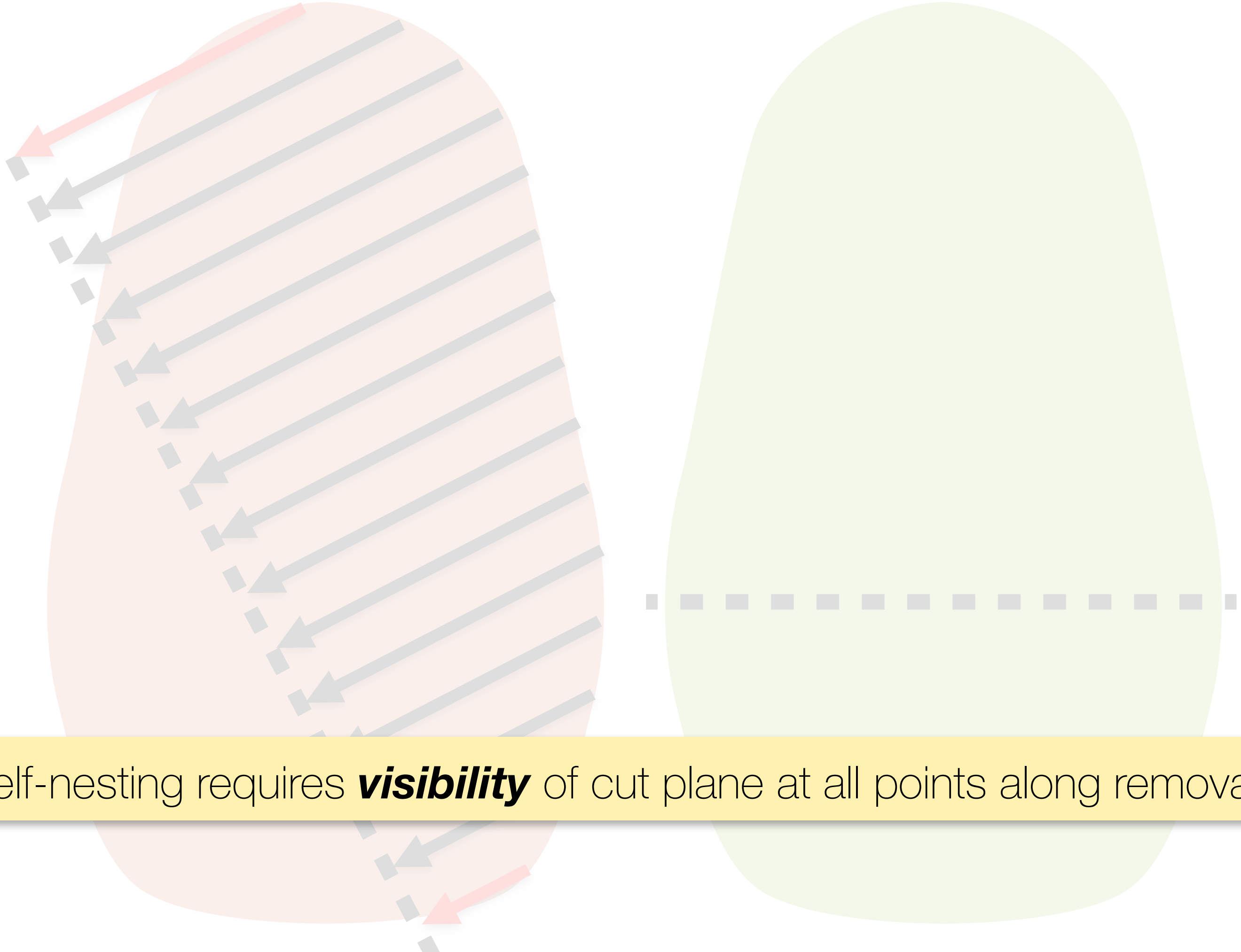

Perfect self-nesting requires ***visibility*** of cut plane at all points along removal directions

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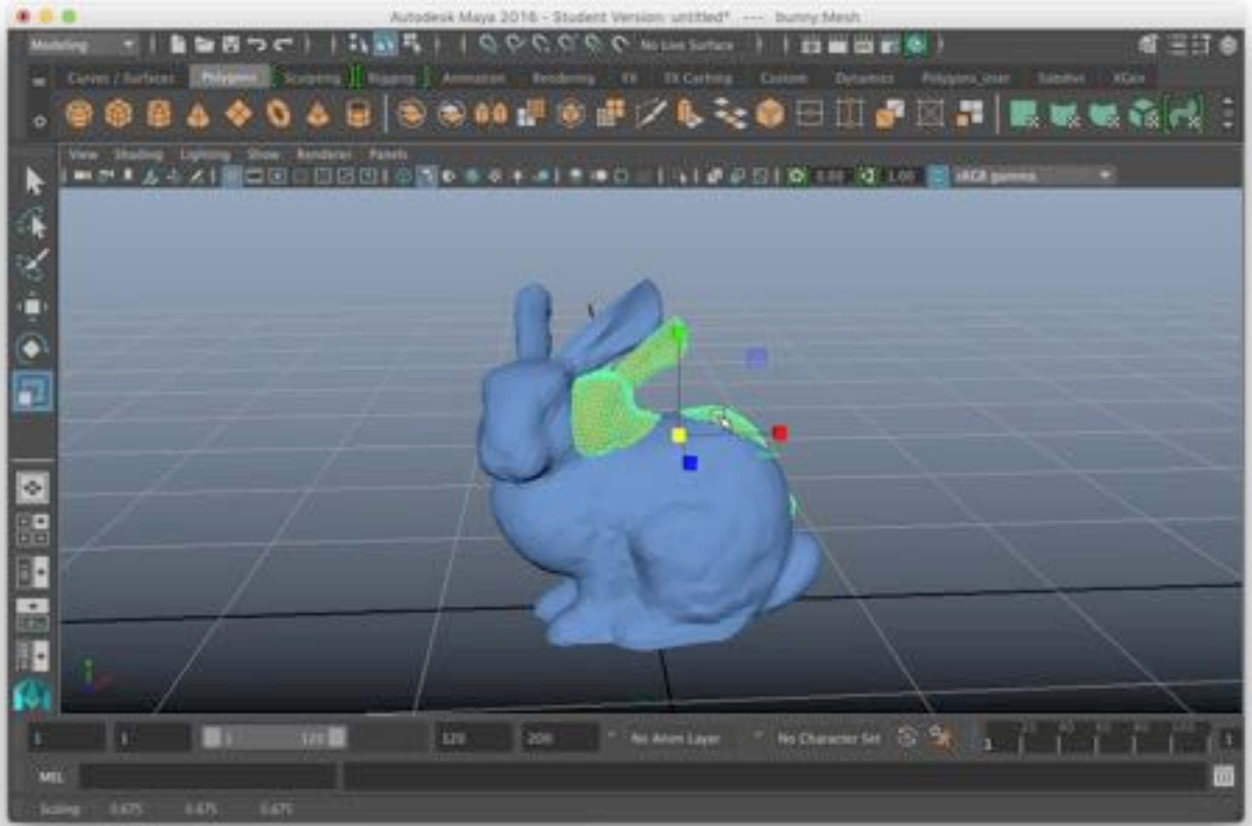

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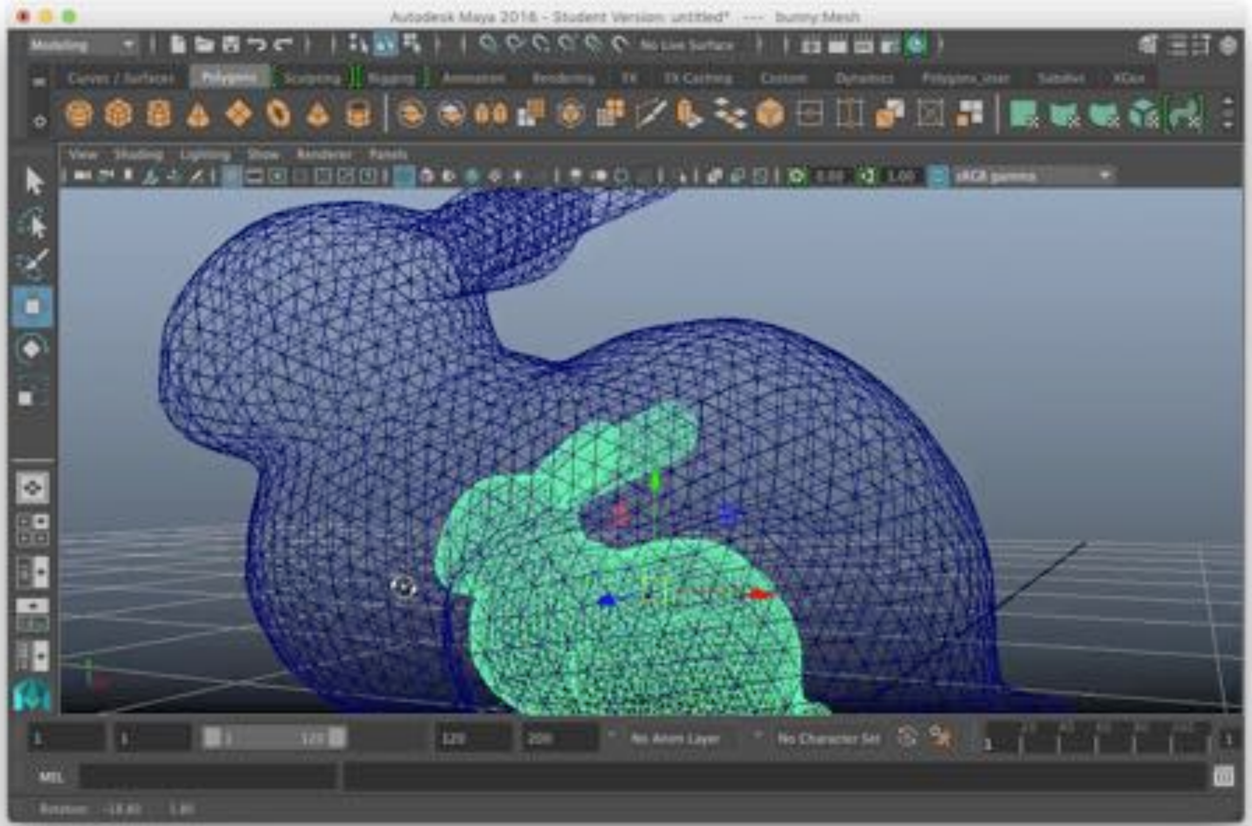

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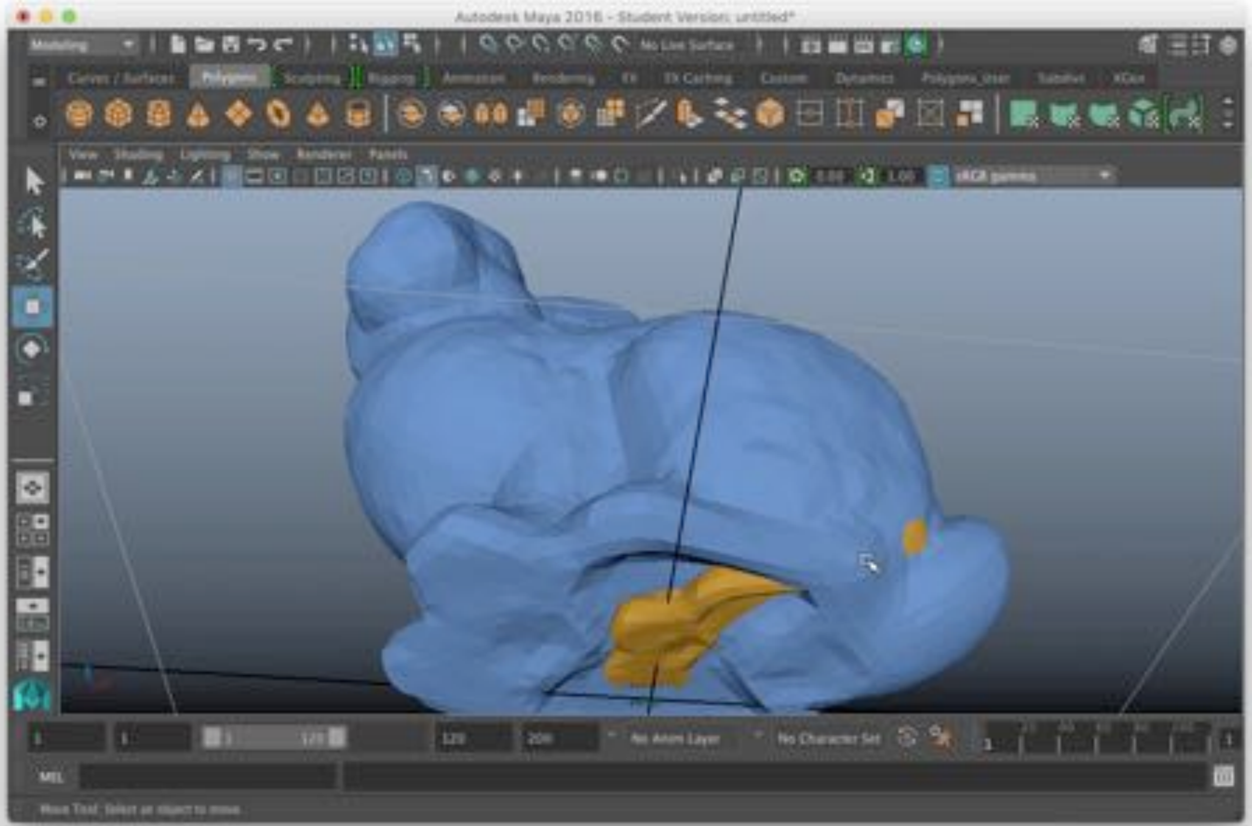

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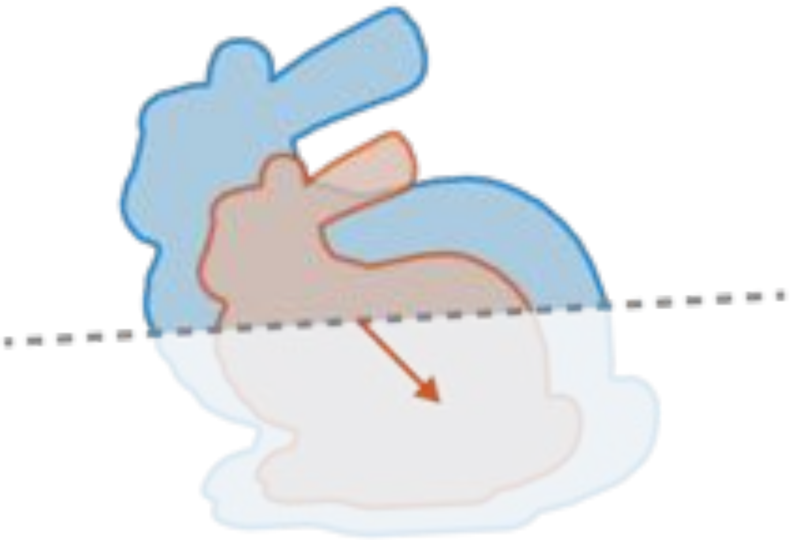
Step 1: we determine feasibility in real-time by exploiting orthographic rendering



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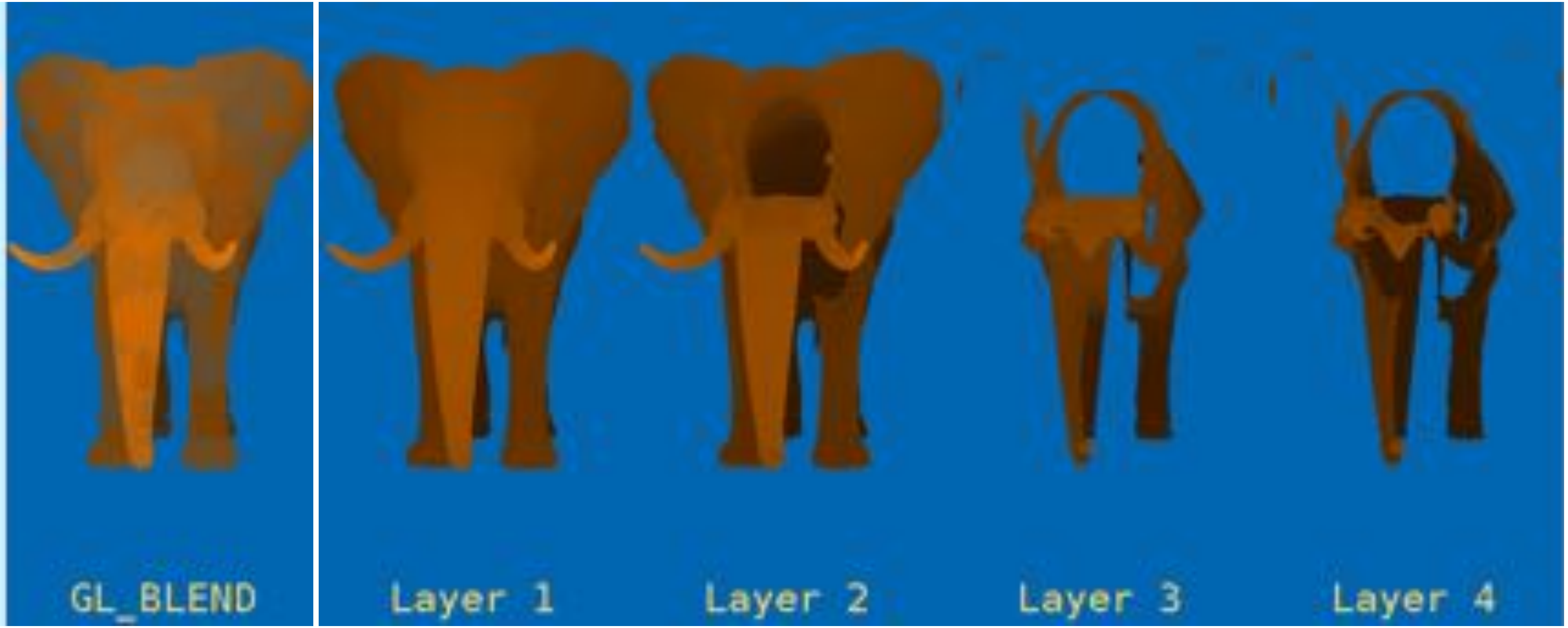

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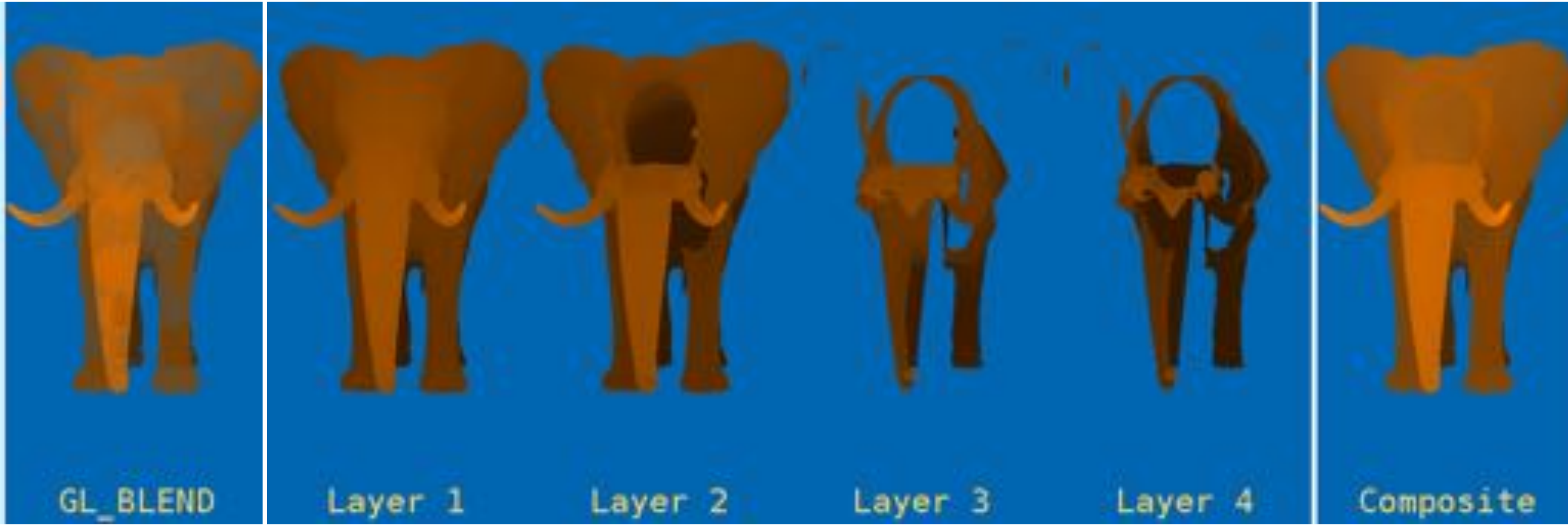

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a.k.a. K-Buffer, Layered Depth Images

transparency	[Everitt 2001, Bavoil et al. 2007]
shape diameter	[Baldacci et al. 2016]
image-based rendering	[Shade et al. 1998]
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collision detection	[Myszkowski et al.1995, Knott & Pai 2003, Heidelberger et al. 2004]
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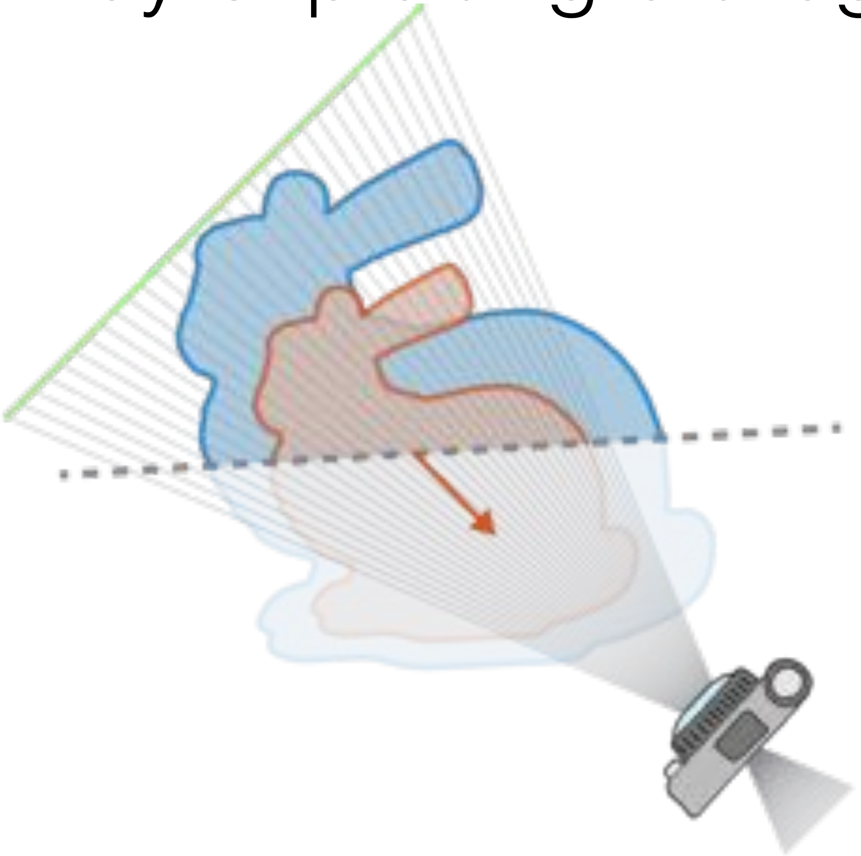

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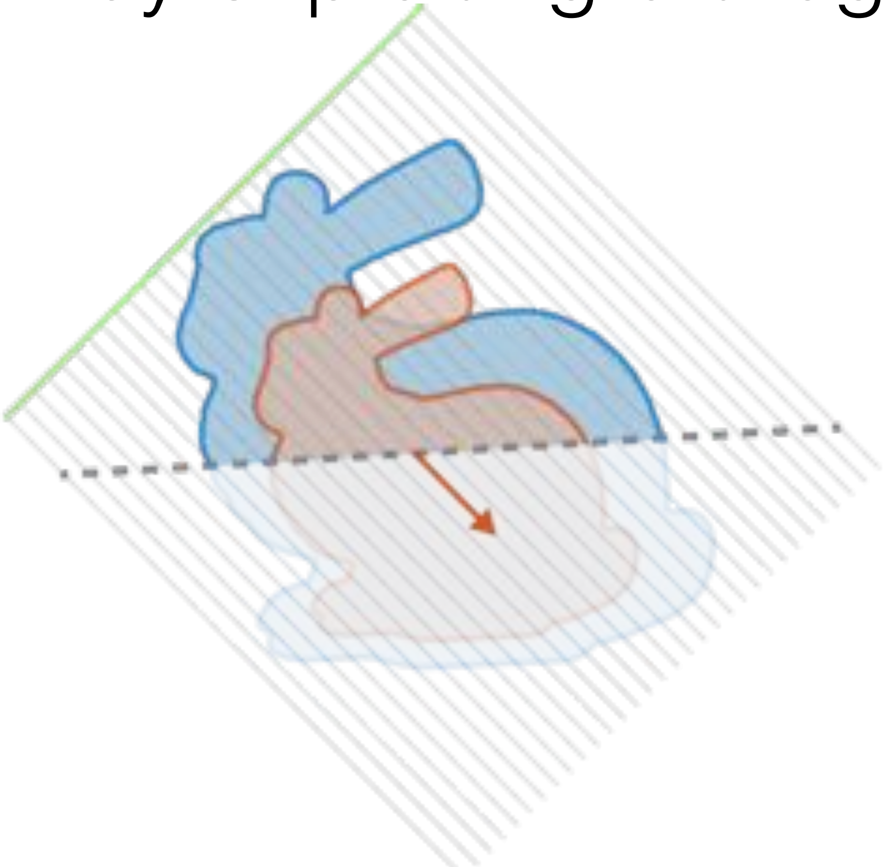

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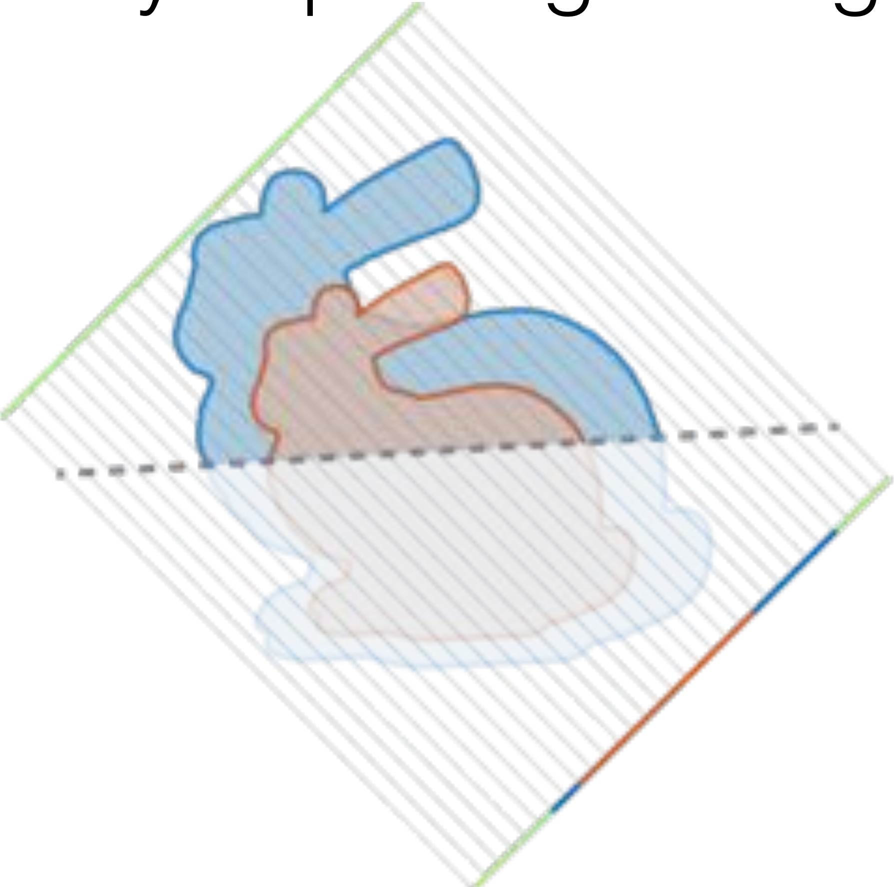

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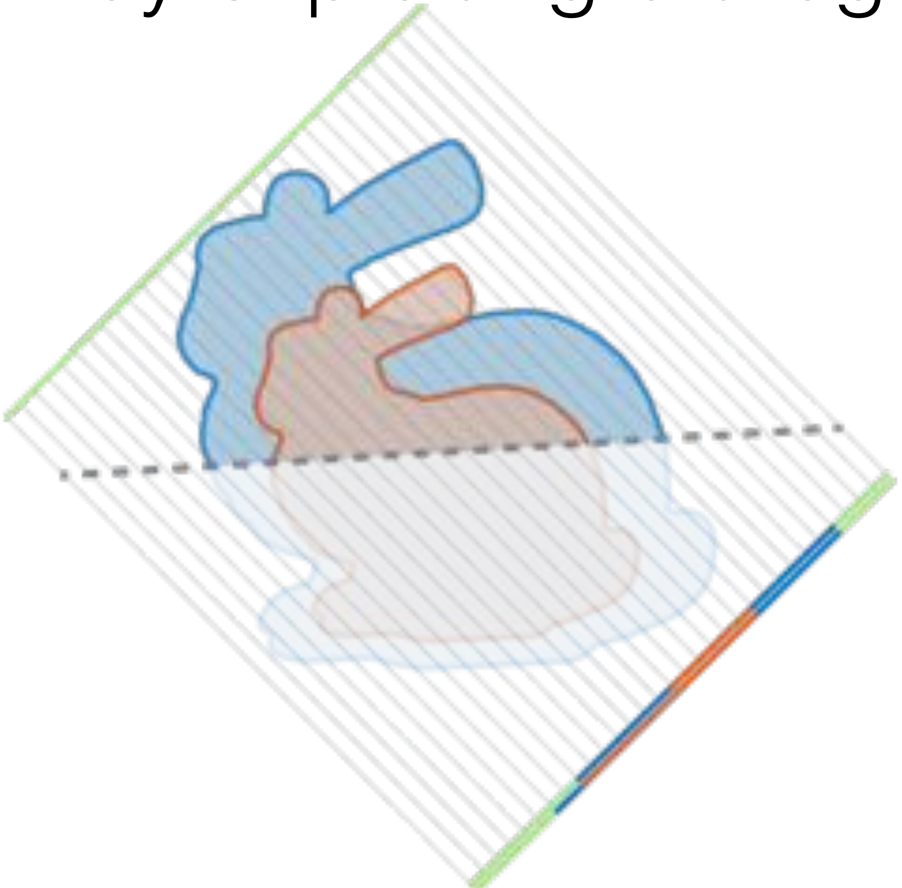

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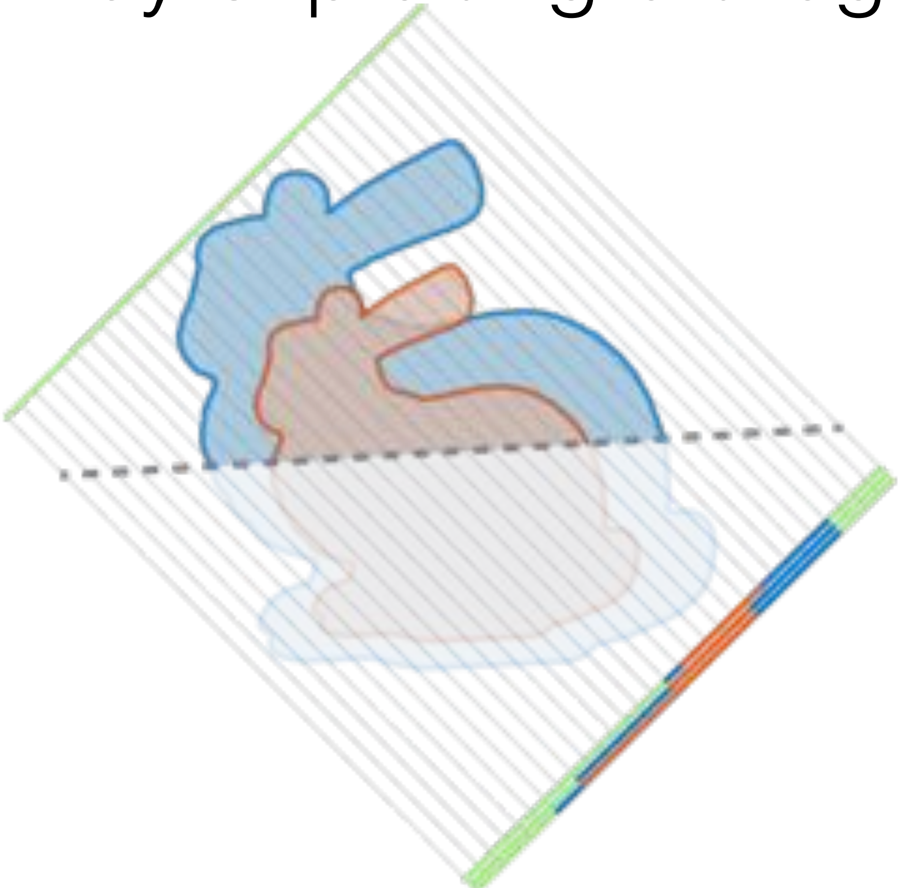

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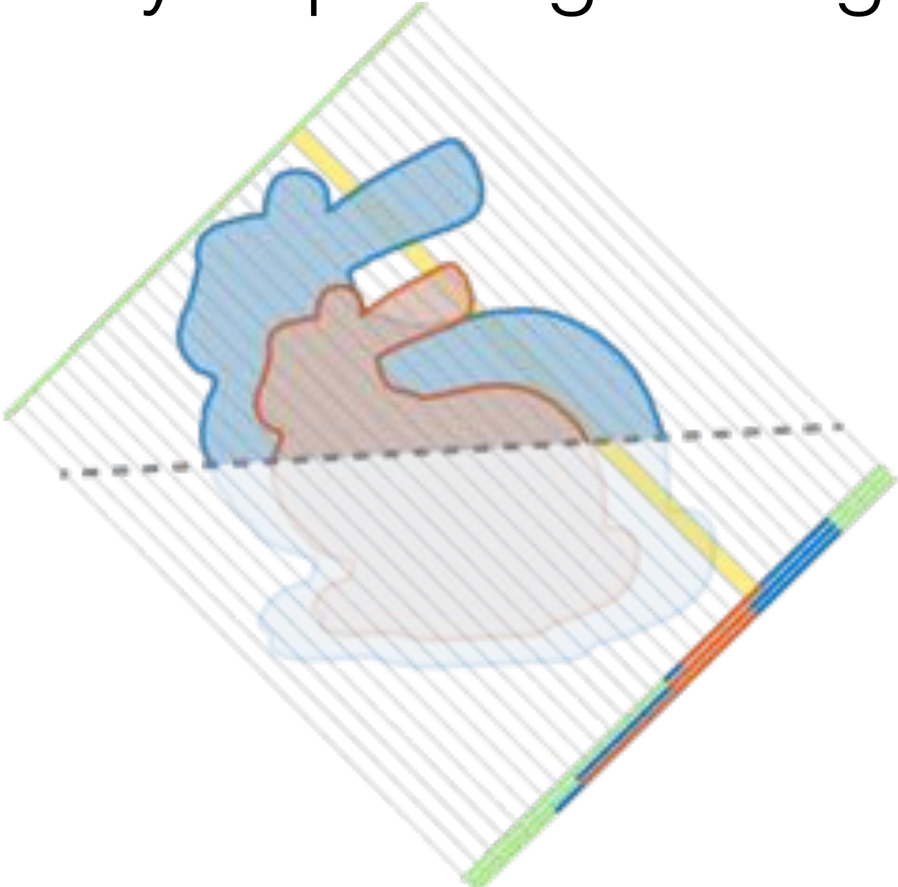

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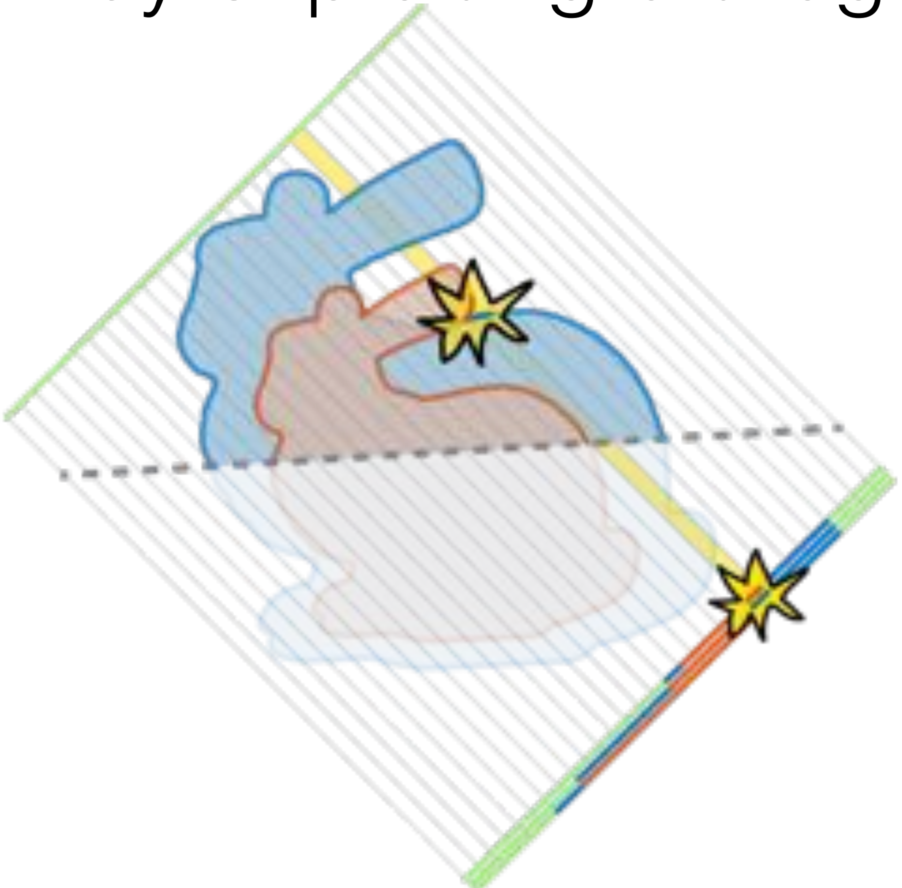

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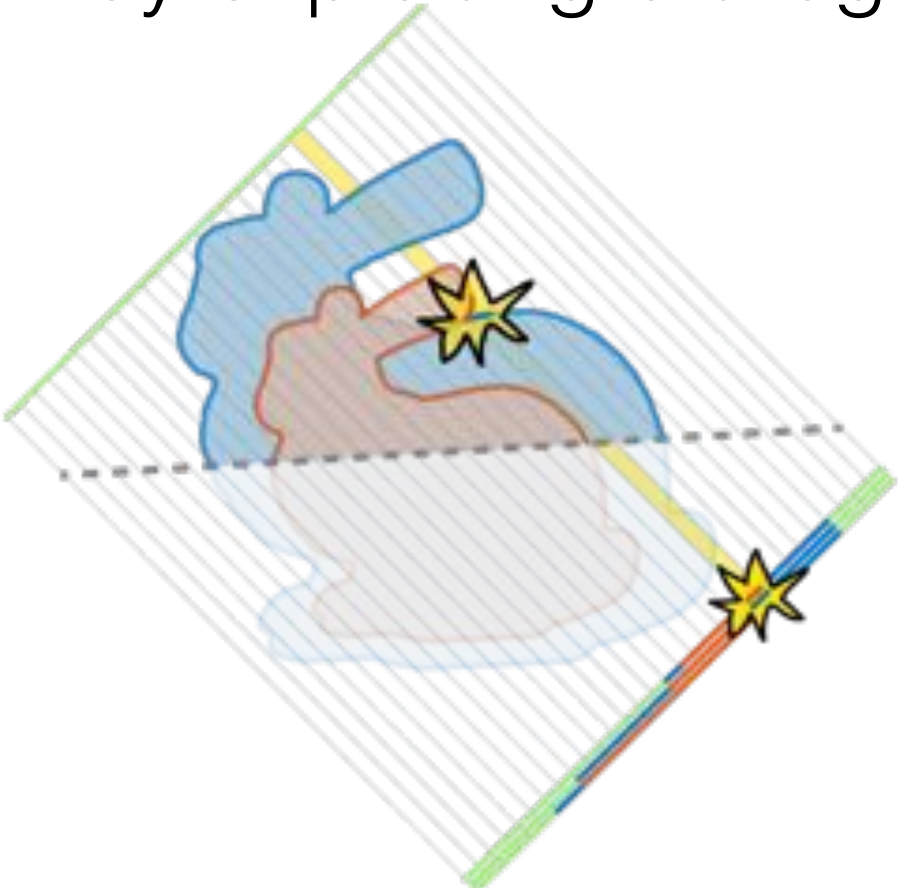

Bad “codes”:

- **blue** before **orange**
- **orange** before **green**
- **orange** before front-facing **blue**

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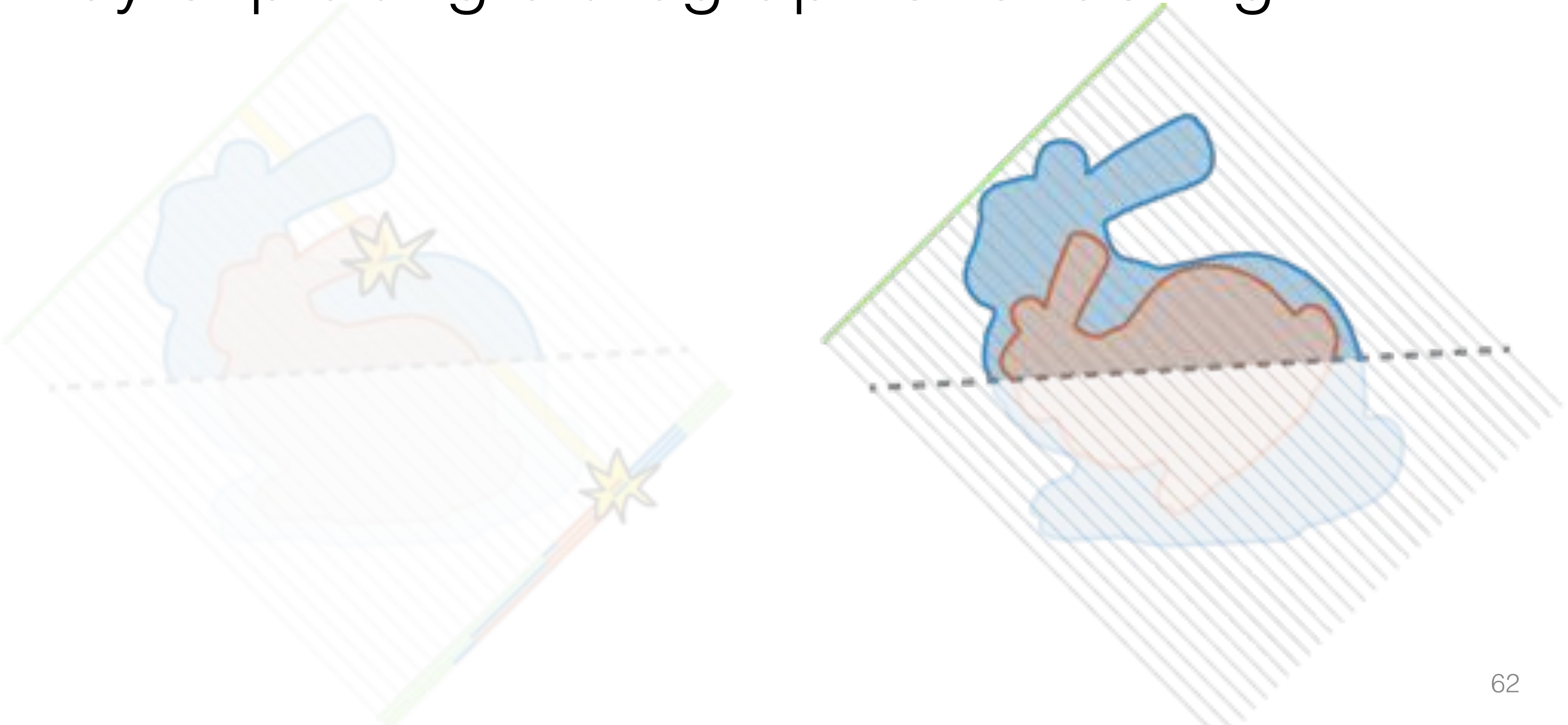

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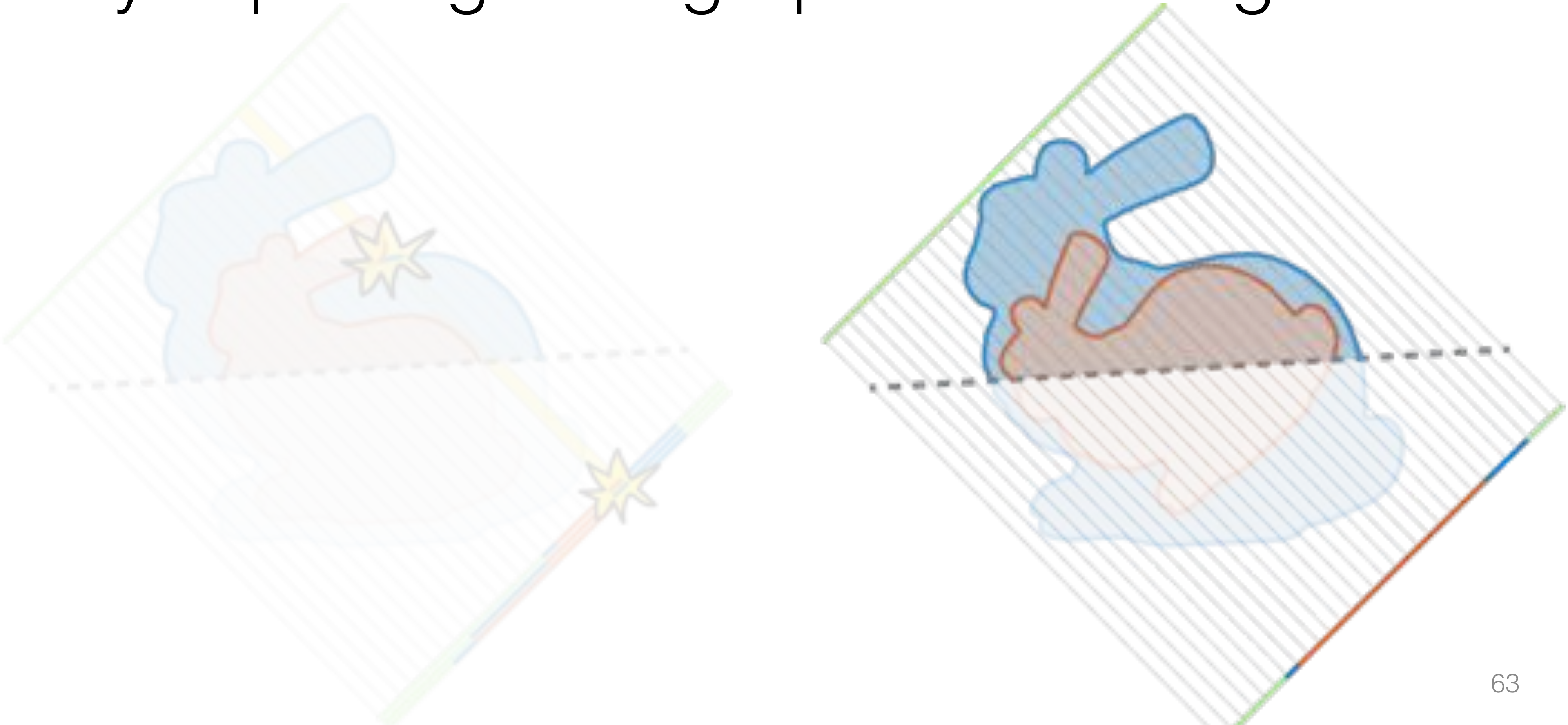

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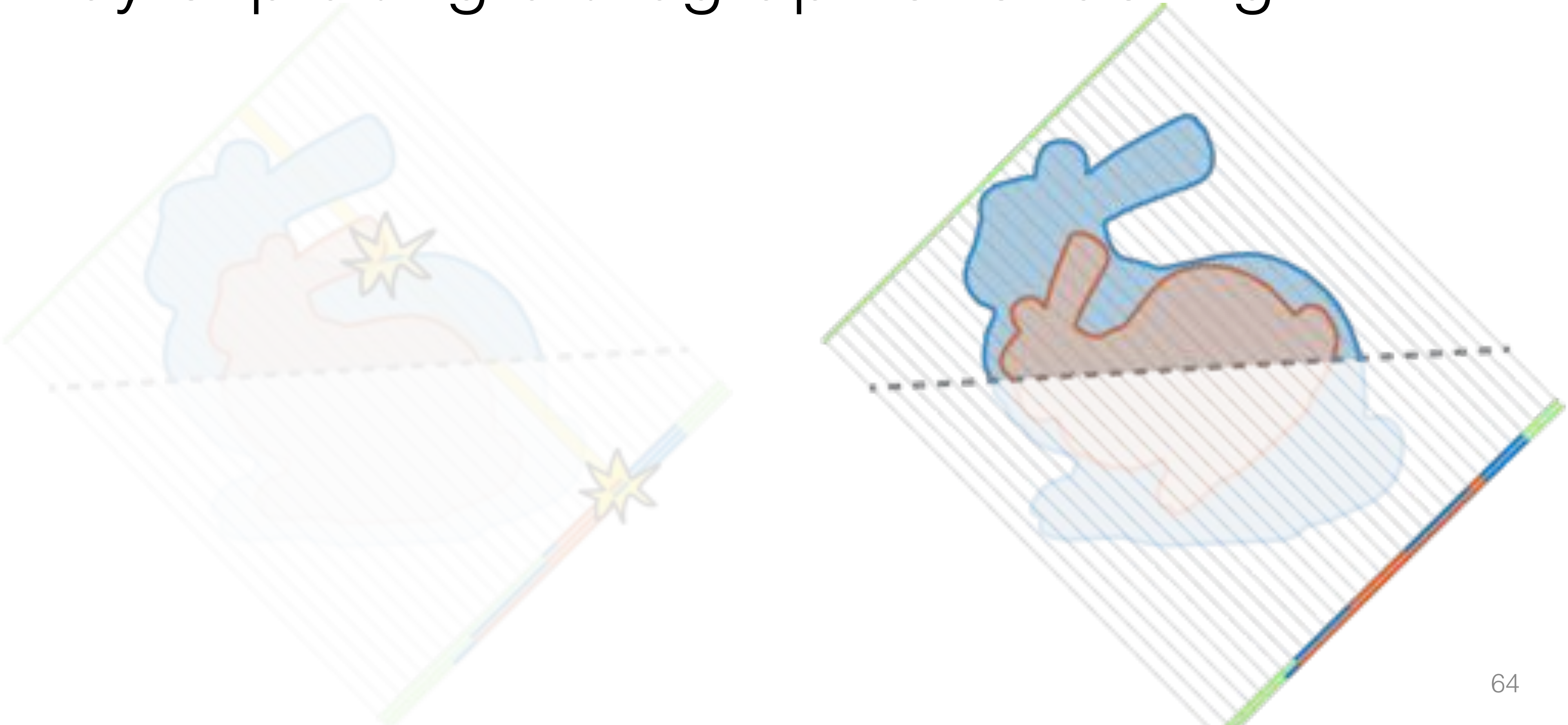

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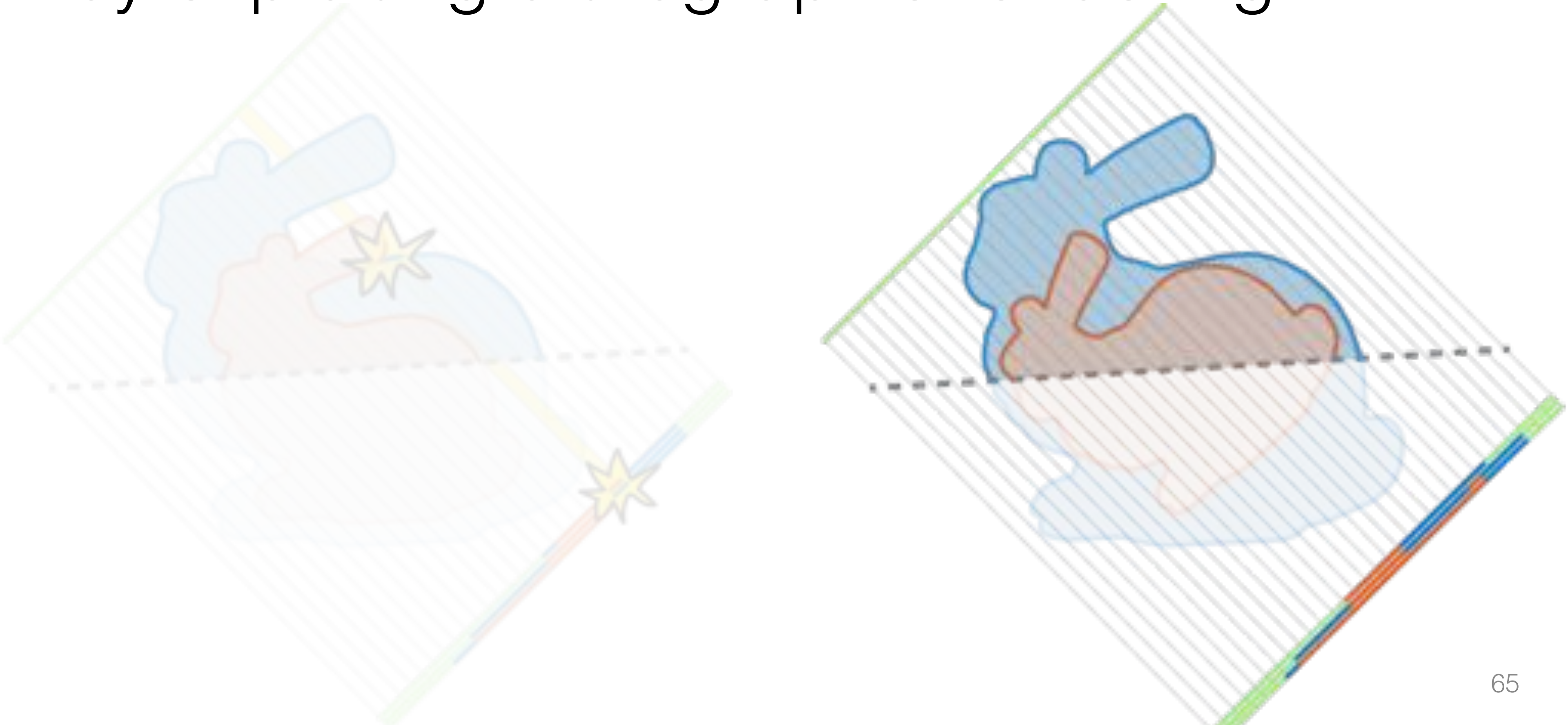

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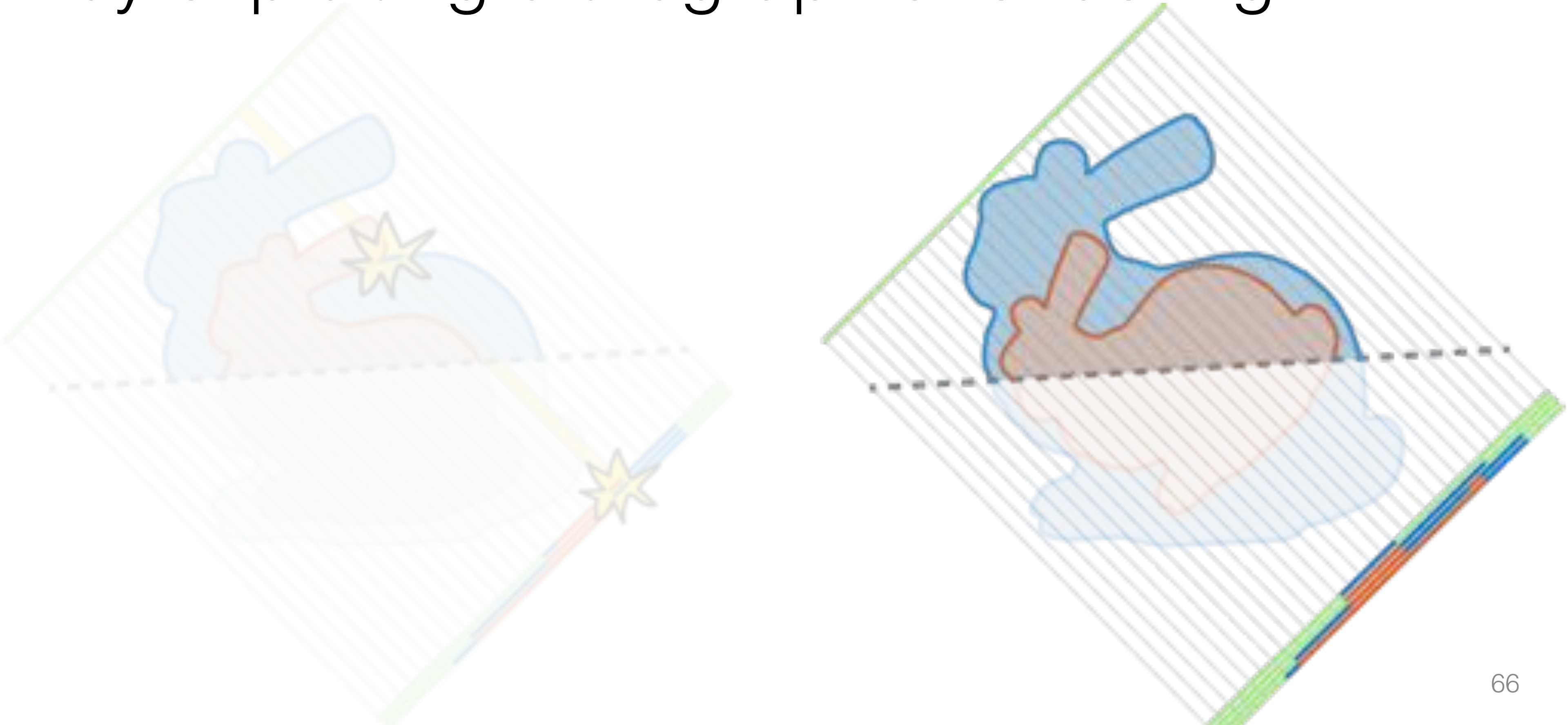

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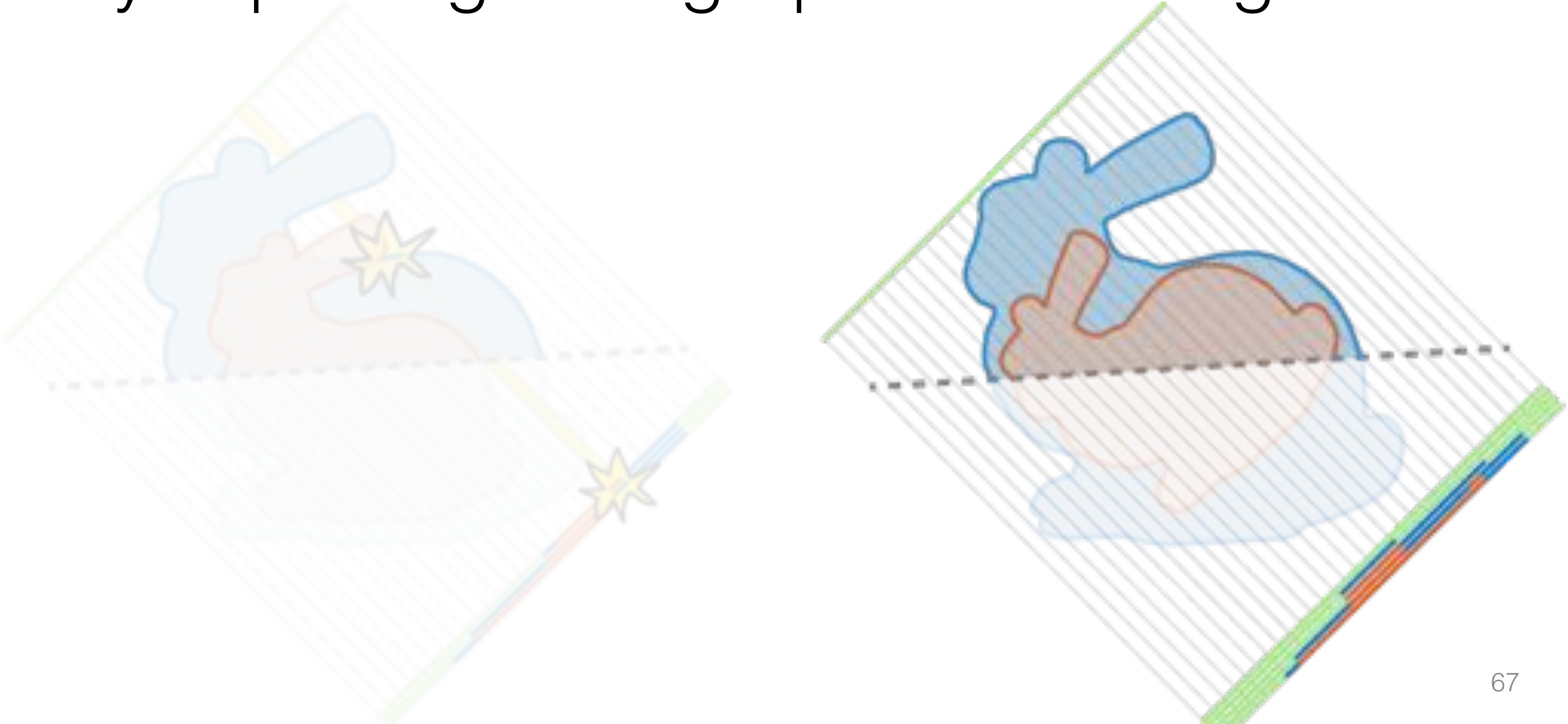

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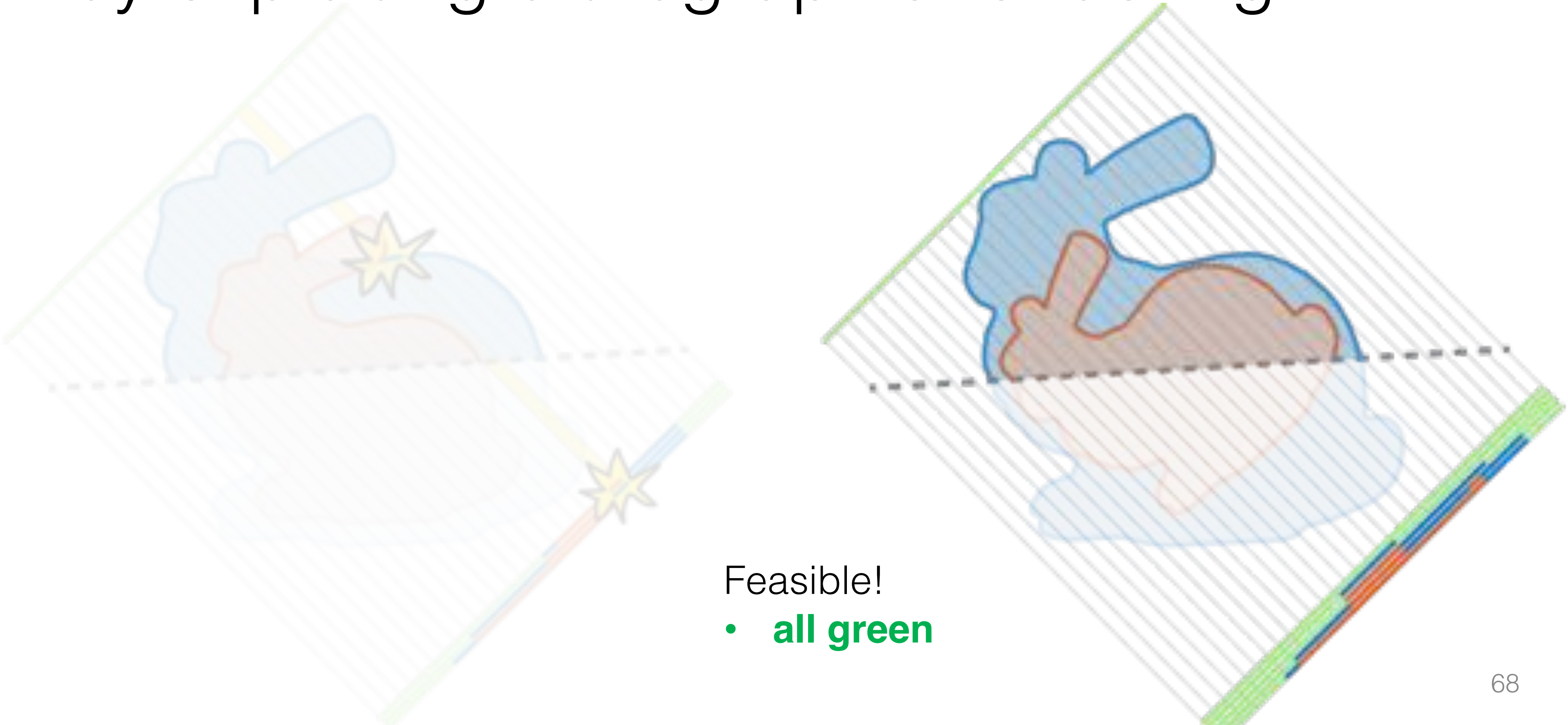

Feasible!

- **all green**

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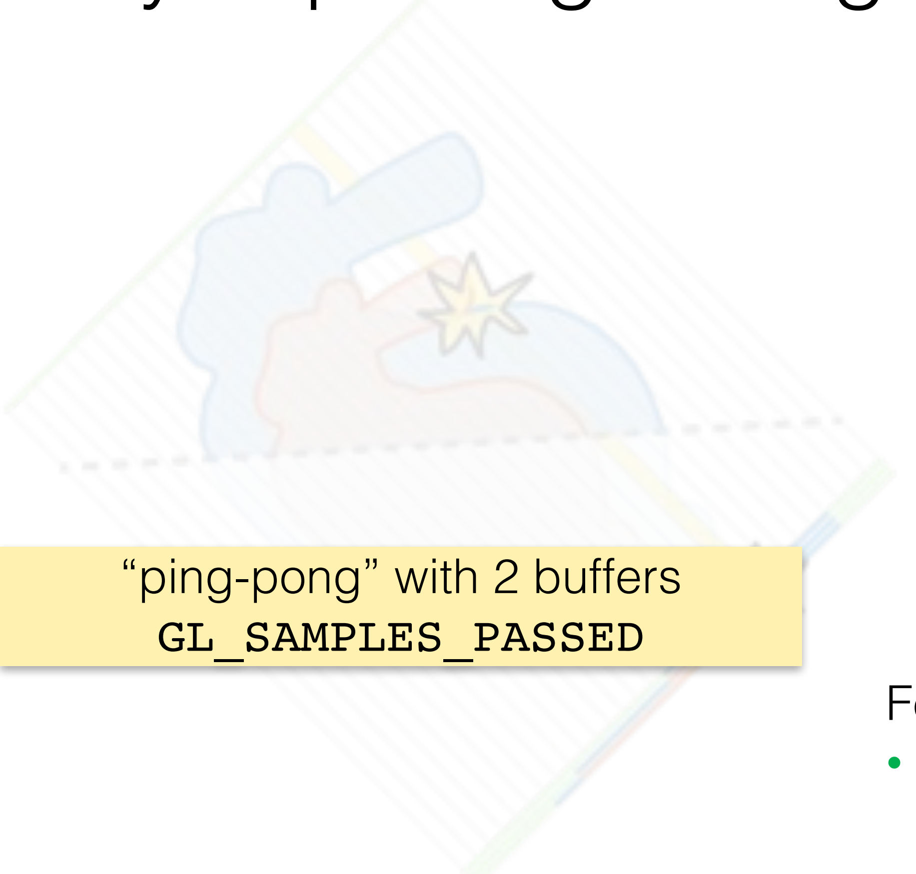
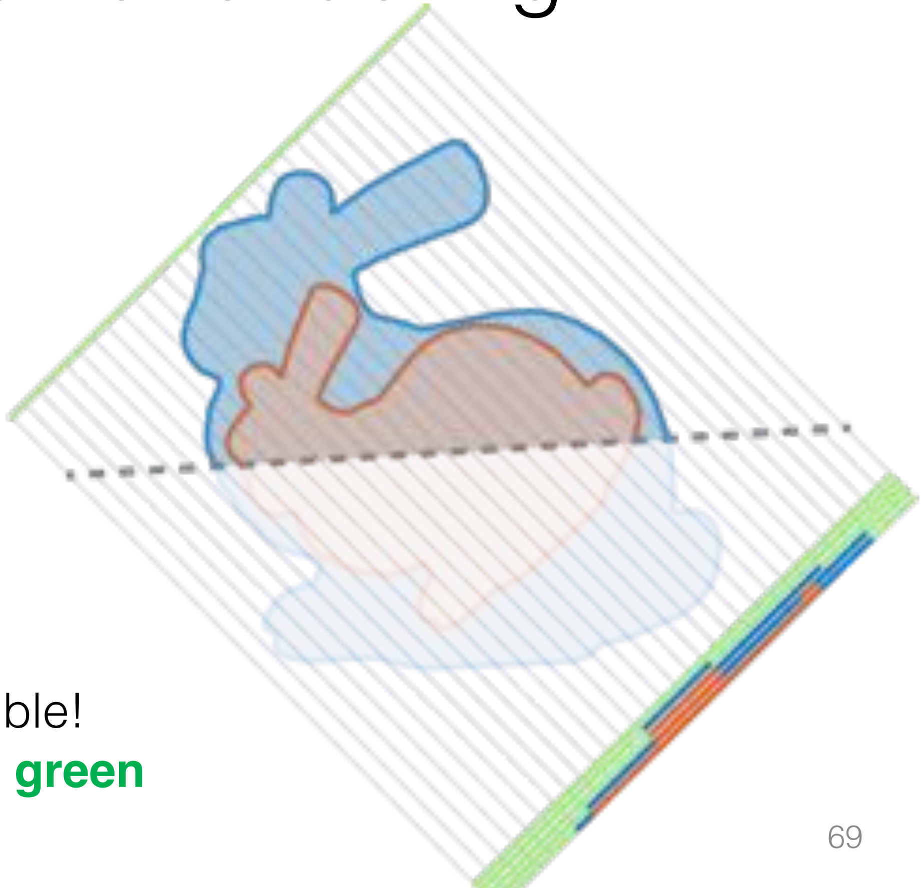


“ping-pong” with 2 buffers

`GL_SAMPLES_PASSED`



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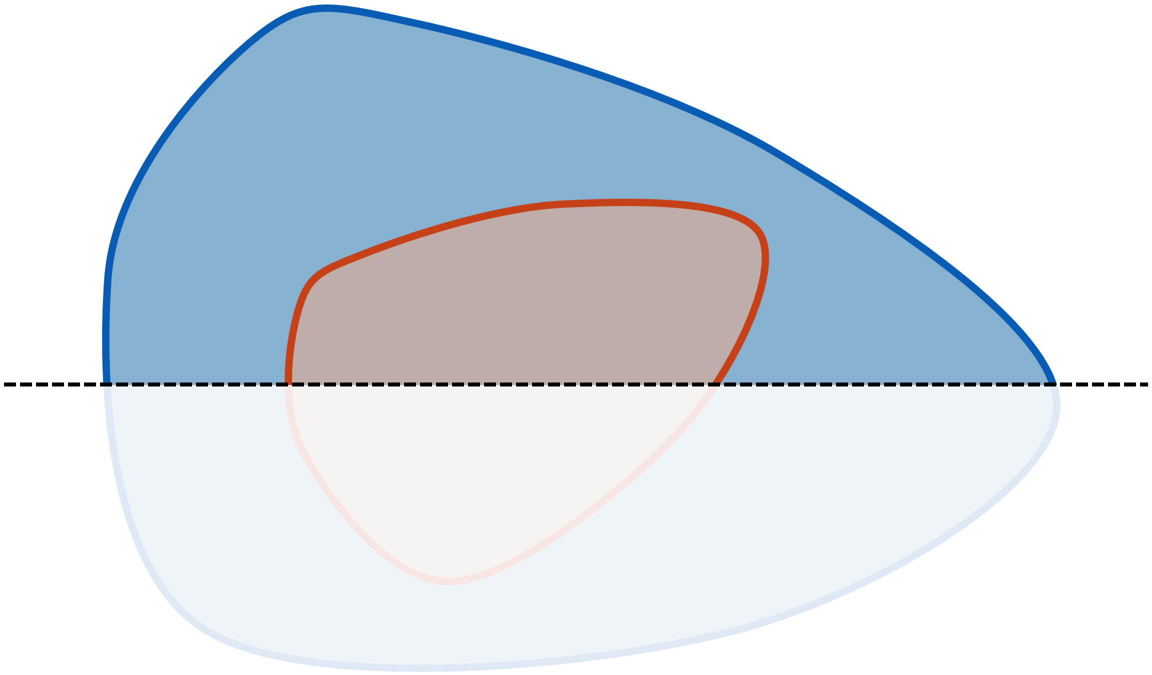
Step 2: binary search to maximize scale



Assume *momentarily* that shape is convex

Fix cut plane, center of mass, rotation

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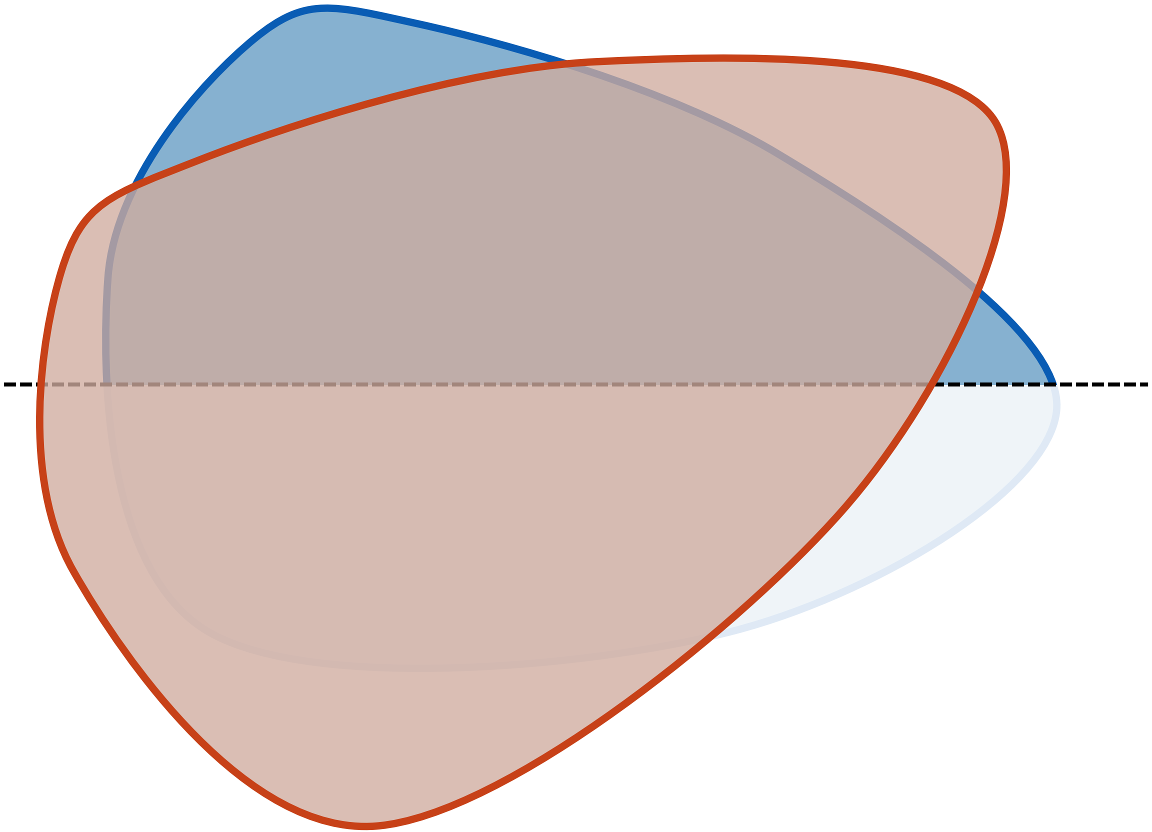

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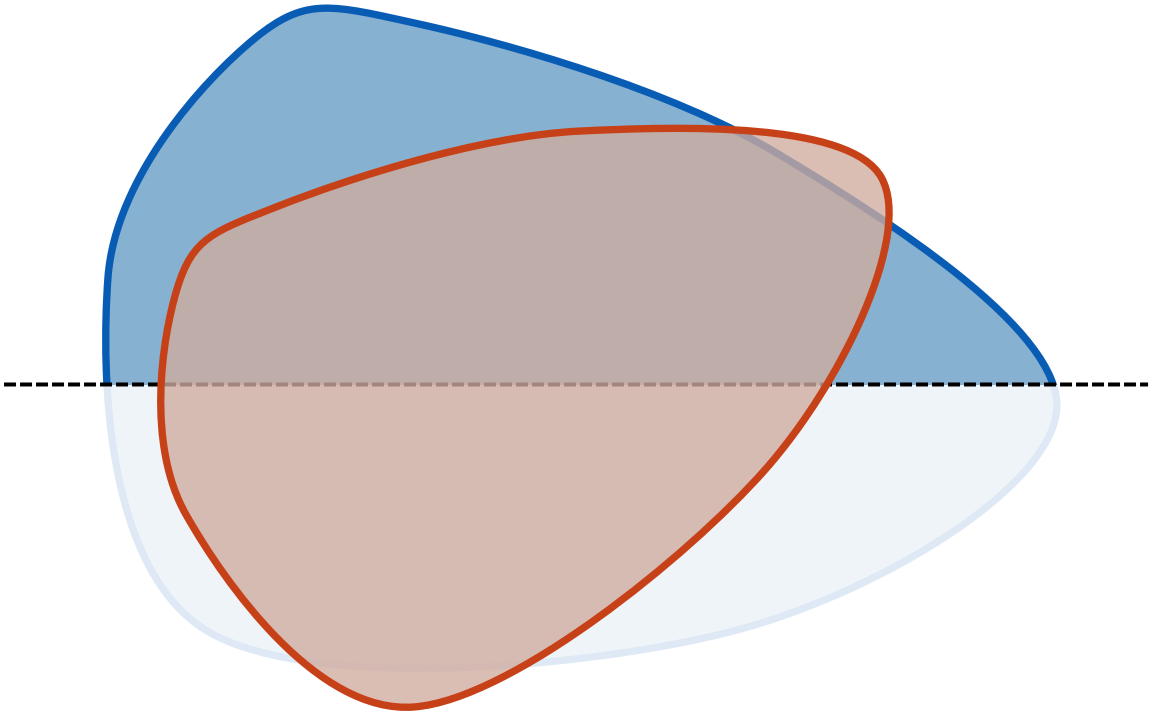

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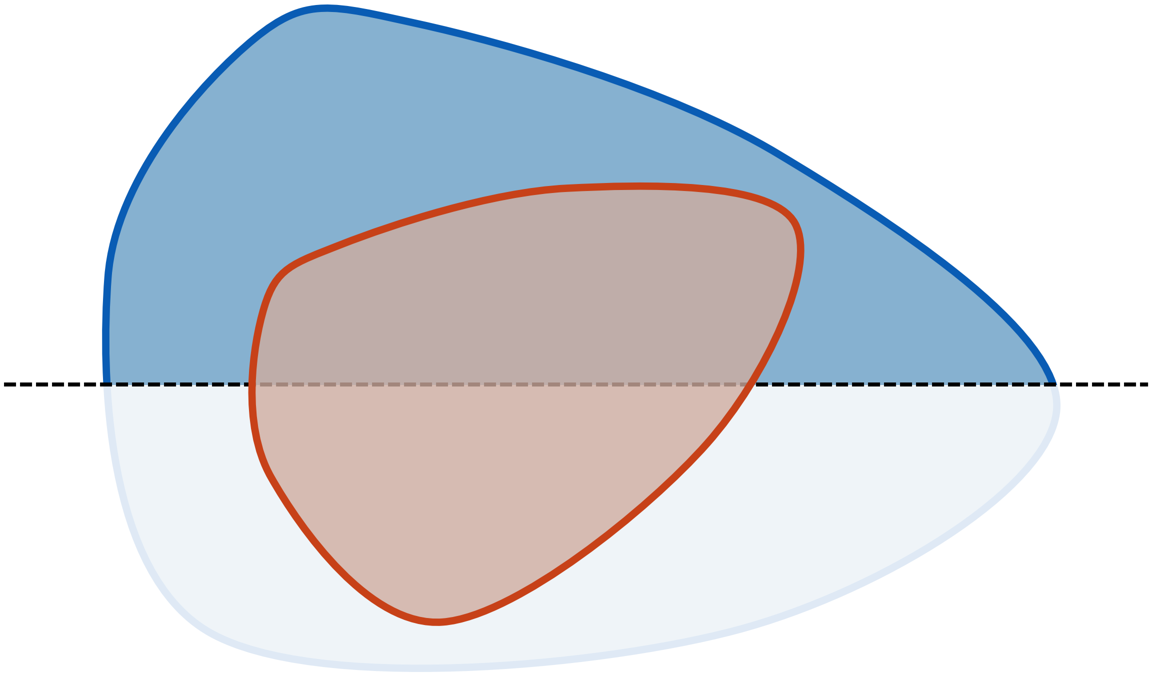

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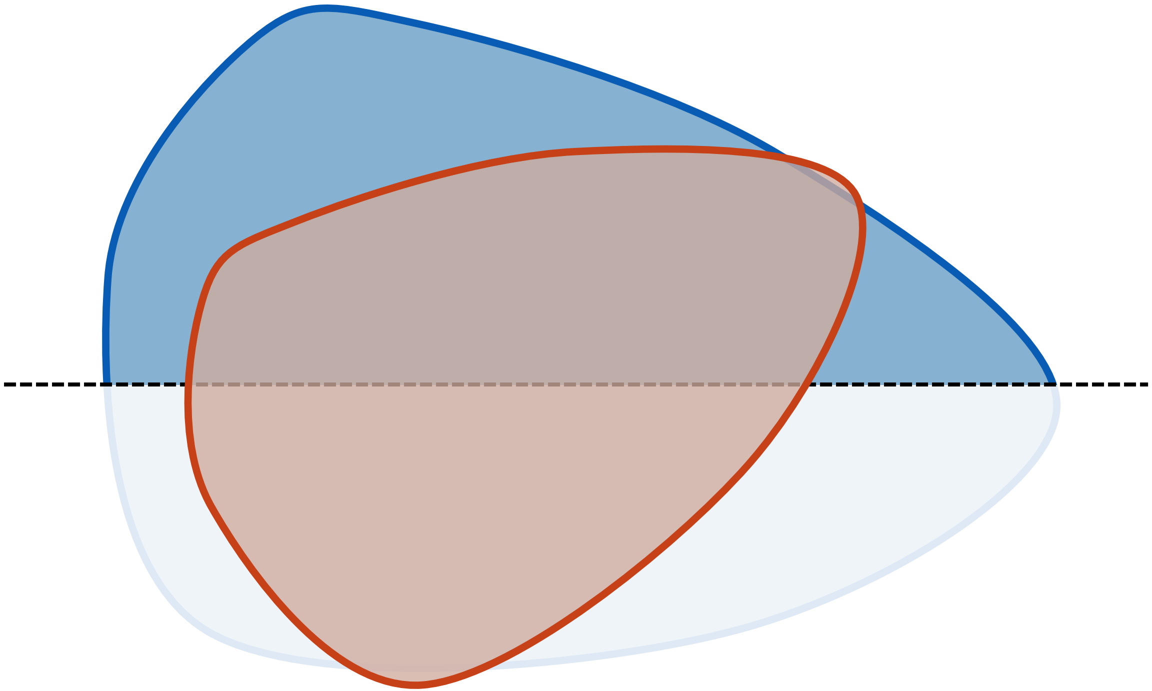

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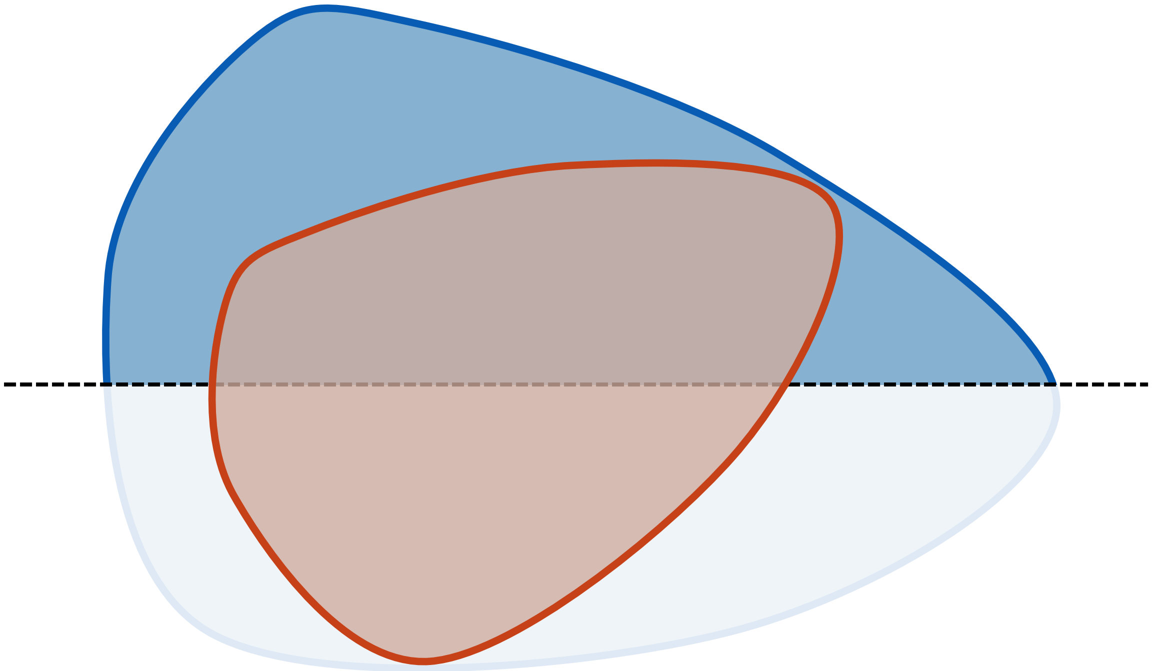

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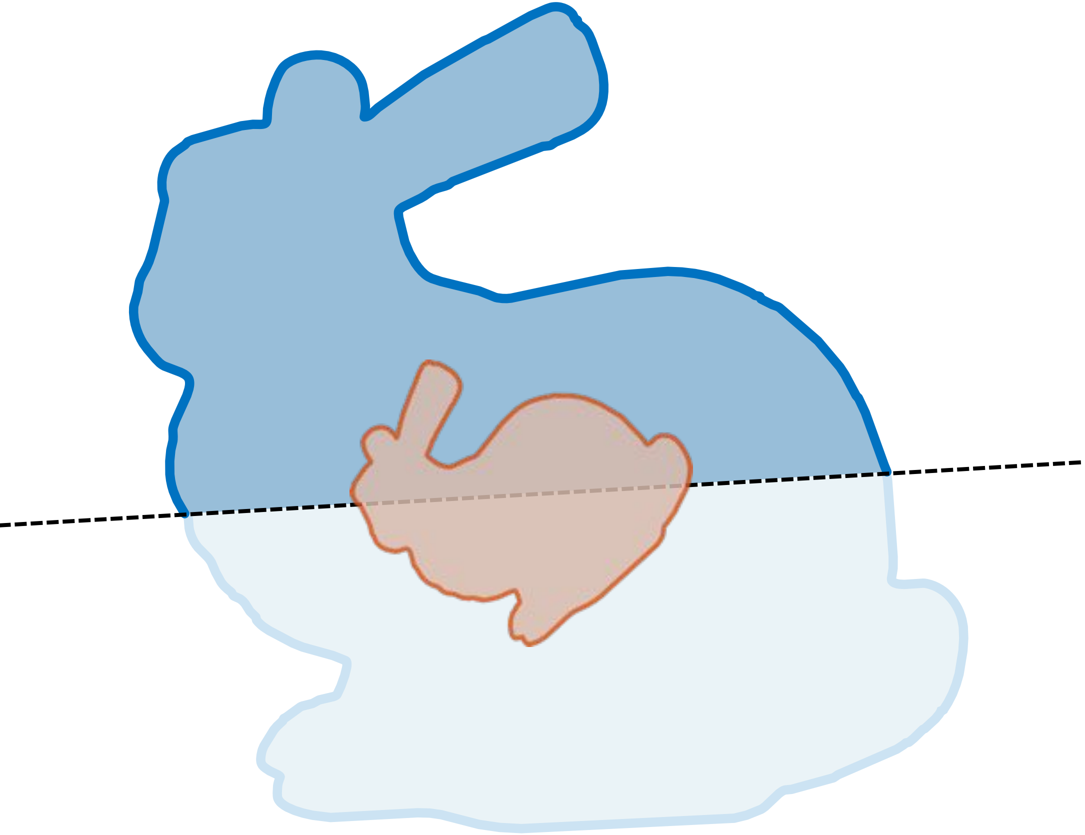

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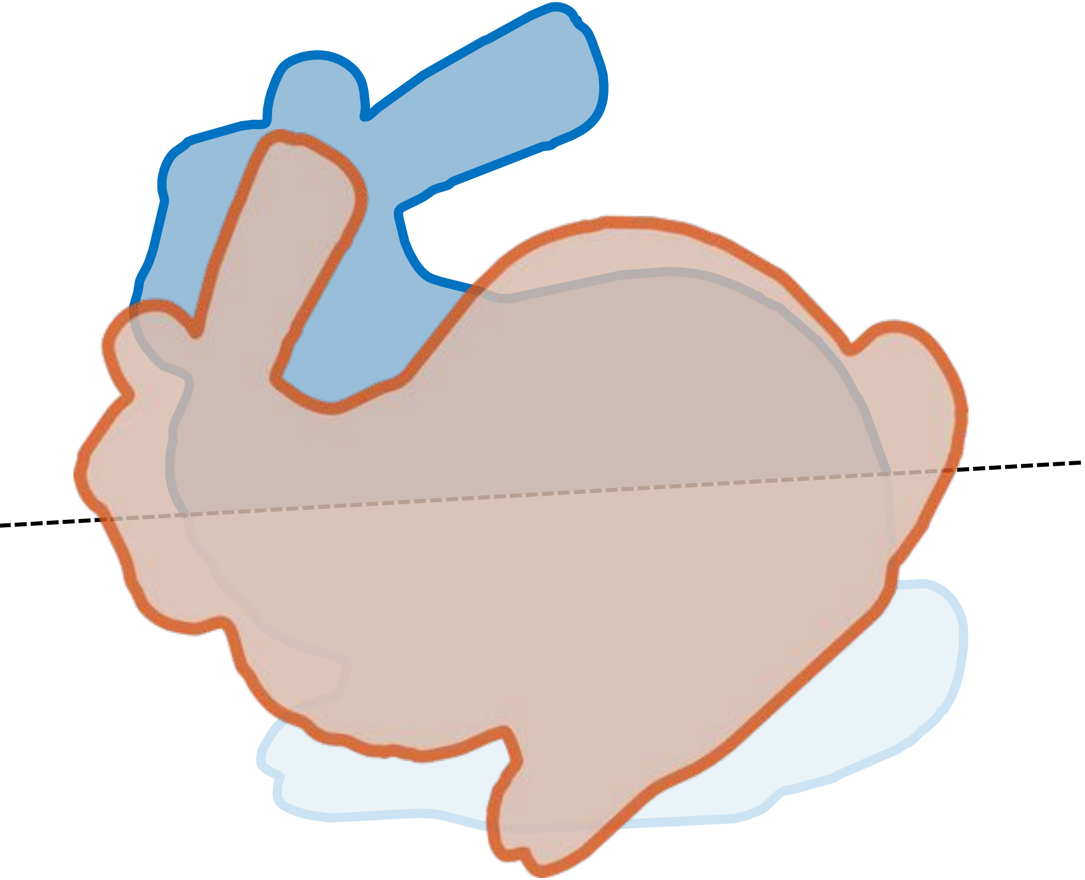

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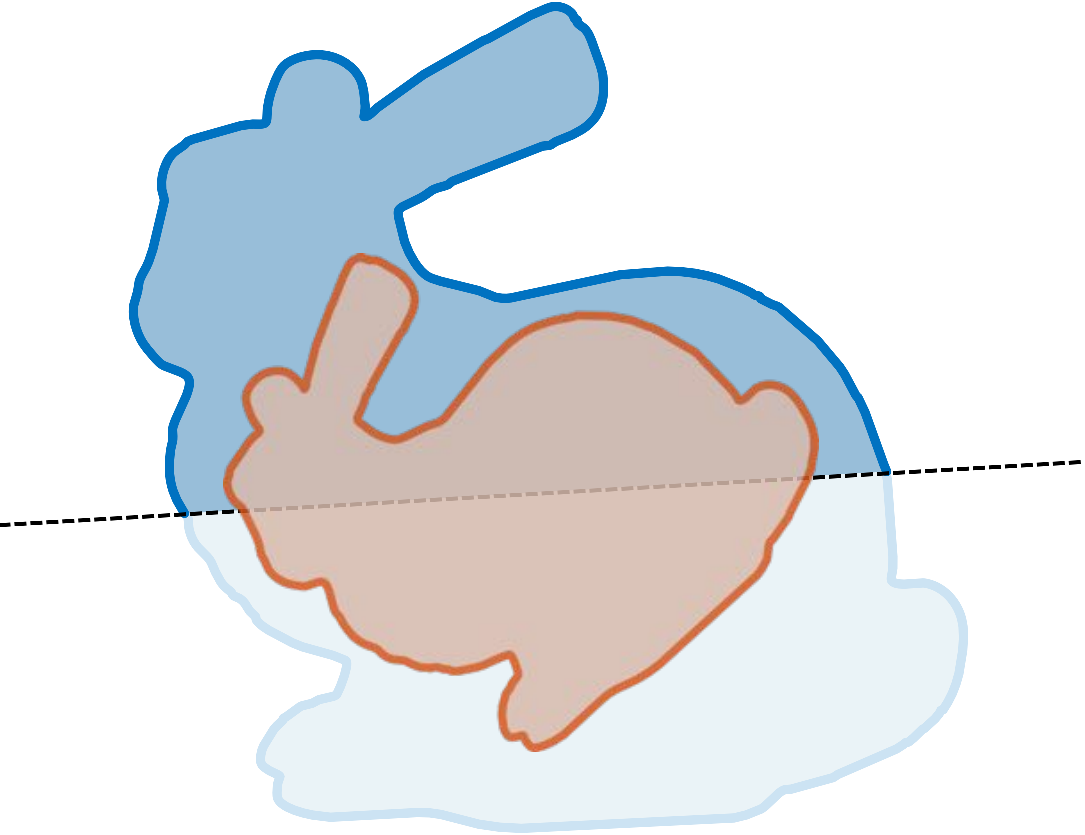
Step 2: binary search to maximize scale



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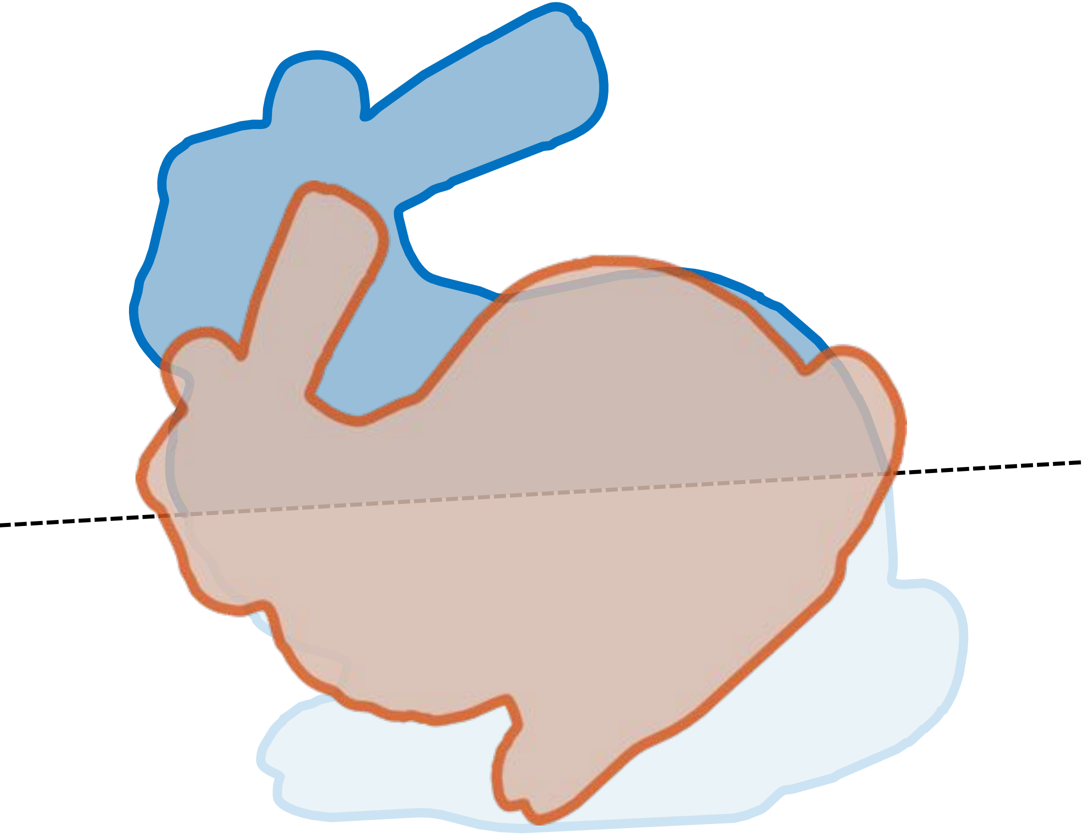

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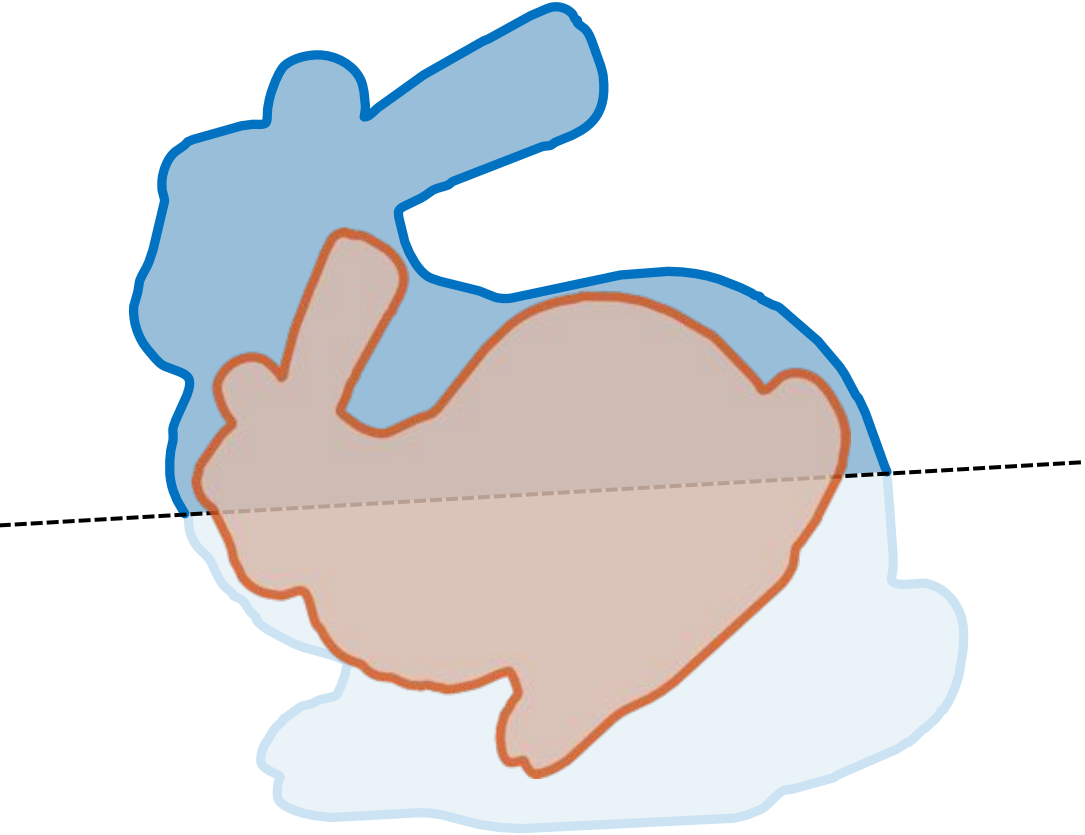

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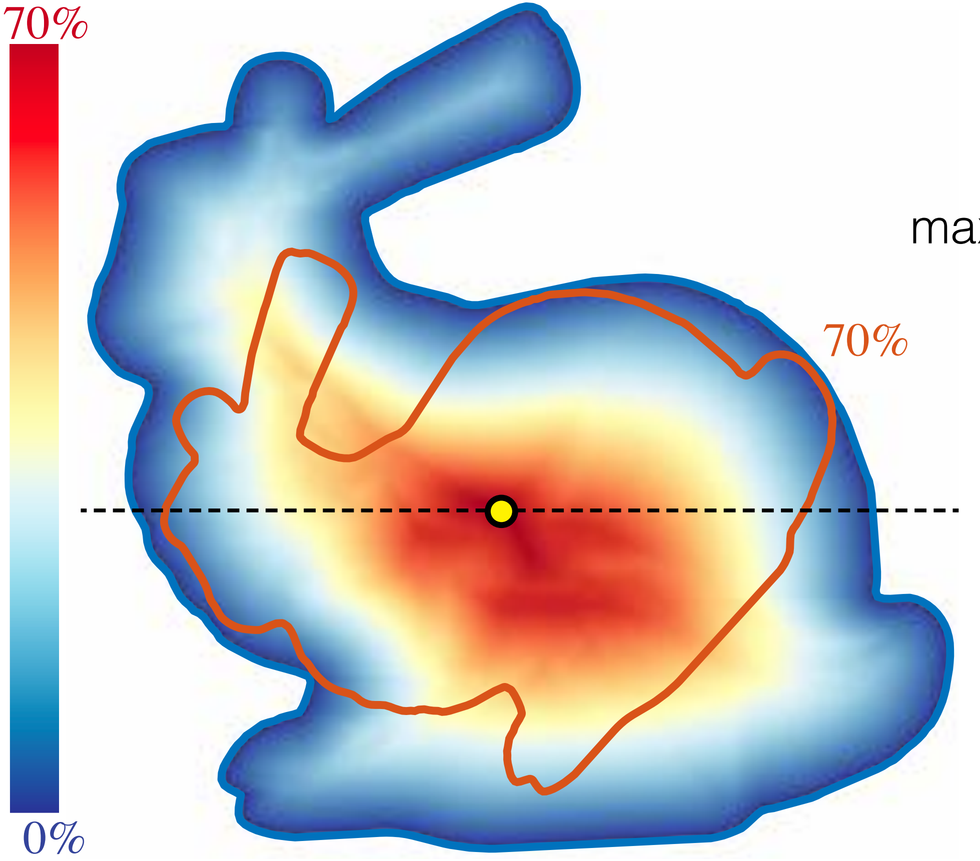
Step 3: optimize over all parameters



maximize *scale* subject to *nesting constraint*

↓

non-convex energy landscape

Step 3: optimize over all parameters *via particle swarm optimization*

k parameter vector as point in *n*D $\mathbf{x}_i \in \mathbb{R}^n$

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k parameter vector as point in *n*D $\mathbf{x}_i \in \mathbb{R}^n$

update each iteration according to "velocity"

$$\mathbf{x}_i \leftarrow \mathbf{x}_i + \mathbf{v}_i,$$

Step 3: optimize over all parameters *via particle swarm optimization*

k parameter vector as point in *n*D $\mathbf{x}_i \in \mathbb{R}^n$

pull velocity toward ***personal best*** *and* ***global best*** *of swarm*

$$\mathbf{v}_i \leftarrow \omega \mathbf{v}_i + \phi_p r_p (\mathbf{x}_i^p - \mathbf{x}_i) + \phi_g r_g (\mathbf{x}^g - \mathbf{x}_i),$$

$$\mathbf{x}_i \leftarrow \mathbf{x}_i + \mathbf{v}_i,$$

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random perturbations

Naive P-Swarm would treat scale as just another parameter (coordinate)…

$$\begin{aligned} \underset{s,\mathbf{R},\mathbf{c},\mathbf{P},\mathbf{a}^+,\mathbf{a}^-}{\text{maximize}} \quad & s \\ \text{such that} \quad & \mathbf{T}(\mathcal{B}) \text{ nests in } \mathcal{A} \text{ w.r.t. } \mathbf{P}, \mathbf{a}^+, \mathbf{a}^- \end{aligned}$$

… instead optimize over all others,

$$\underset{\mathbf{R},\mathbf{c},\mathbf{P},\mathbf{a}^+,\mathbf{a}^-}{\text{maximize}} \quad f(\mathbf{R}, \mathbf{c}, \mathbf{P}, \mathbf{a}^+, \mathbf{a}^-)$$

all other parameters

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$$\underset{\mathbf{R},\mathbf{c},\mathbf{P},\mathbf{a}^+,\mathbf{a}^-}{\text{maximize}} \quad f(\mathbf{R},\mathbf{c},\mathbf{P},\mathbf{a}^+,\mathbf{a}^-)$$

where

$$f(\mathbf{R},\mathbf{c},\mathbf{P},\mathbf{a}^+,\mathbf{a}^-) = \underset{s}{\text{maximize}} \quad s$$

$$\text{such that} \quad \mathbf{T}(\mathcal{B}) \text{ nests in } \mathcal{A} \text{ w.r.t. } \mathbf{P},\mathbf{a}^+,\mathbf{a}^-$$

… instead optimize over all others, and *search* for max scale

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$$f \approx \underset{s}{\text{search}}(\mathbf{R}, \mathbf{c}, \mathbf{P}, \mathbf{a}^+, \mathbf{a}^-)$$

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where

$$f \approx \underset{s}{\text{search}}(\mathbf{R}, \mathbf{c}, \mathbf{P}, \mathbf{a}^+, \mathbf{a}^-)$$

abort search early if
upper bound < *best*

Our optimization enables fully automatic Matryoshka generation…

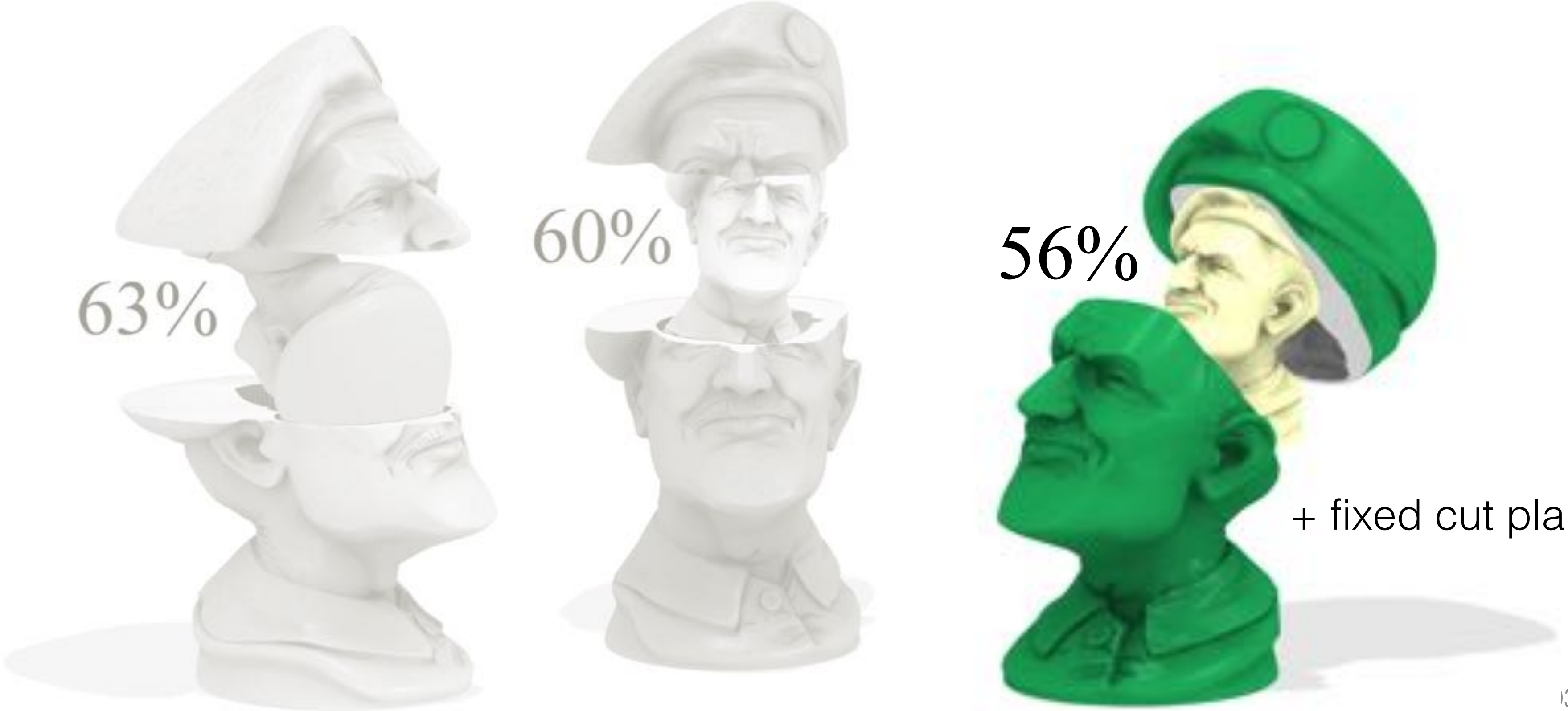
63%

fully optimized

… or partially constrained interactive design

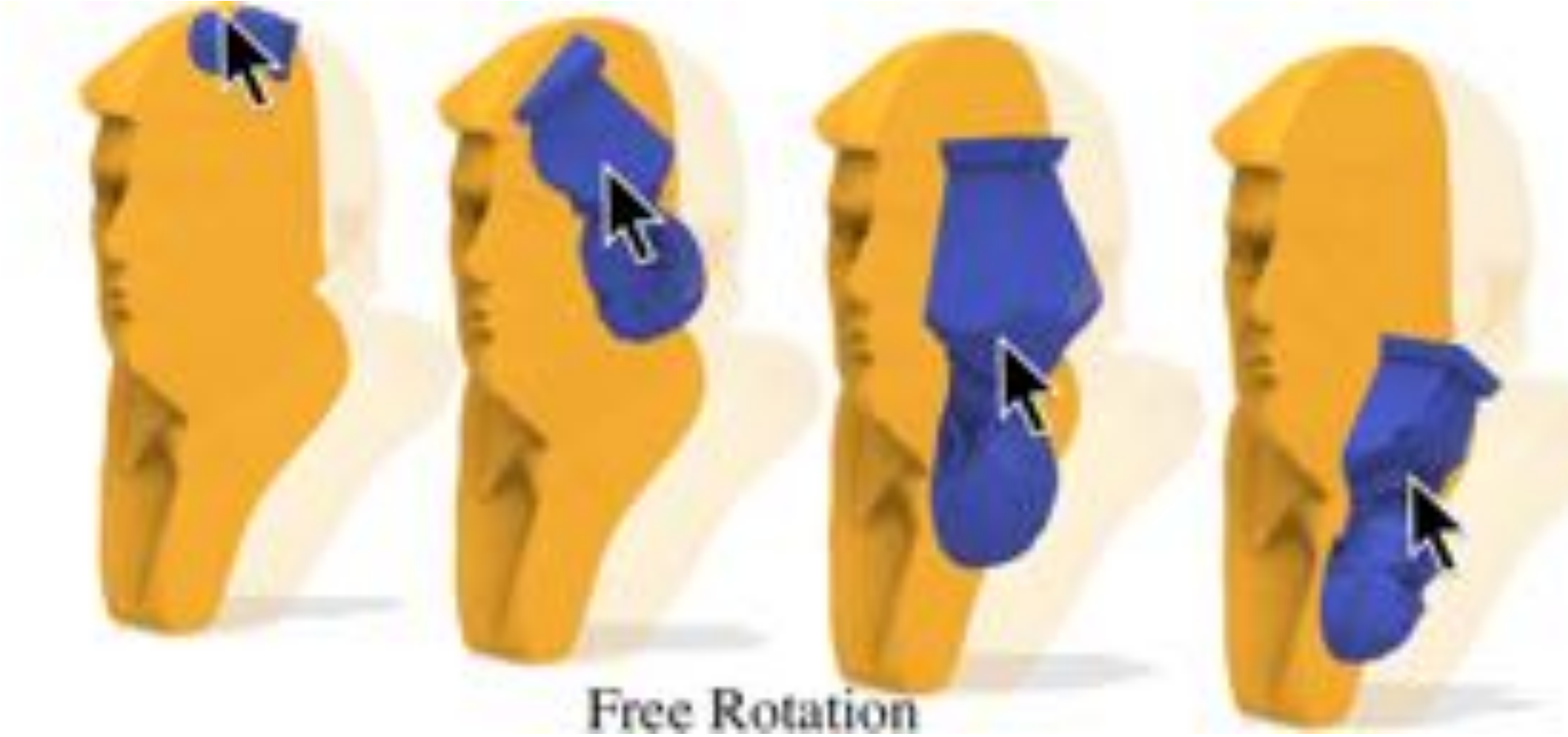
fixed upright orientation

… or partially constrained interactive design



+ fixed cut plane

Tool performs fast enough for interaction



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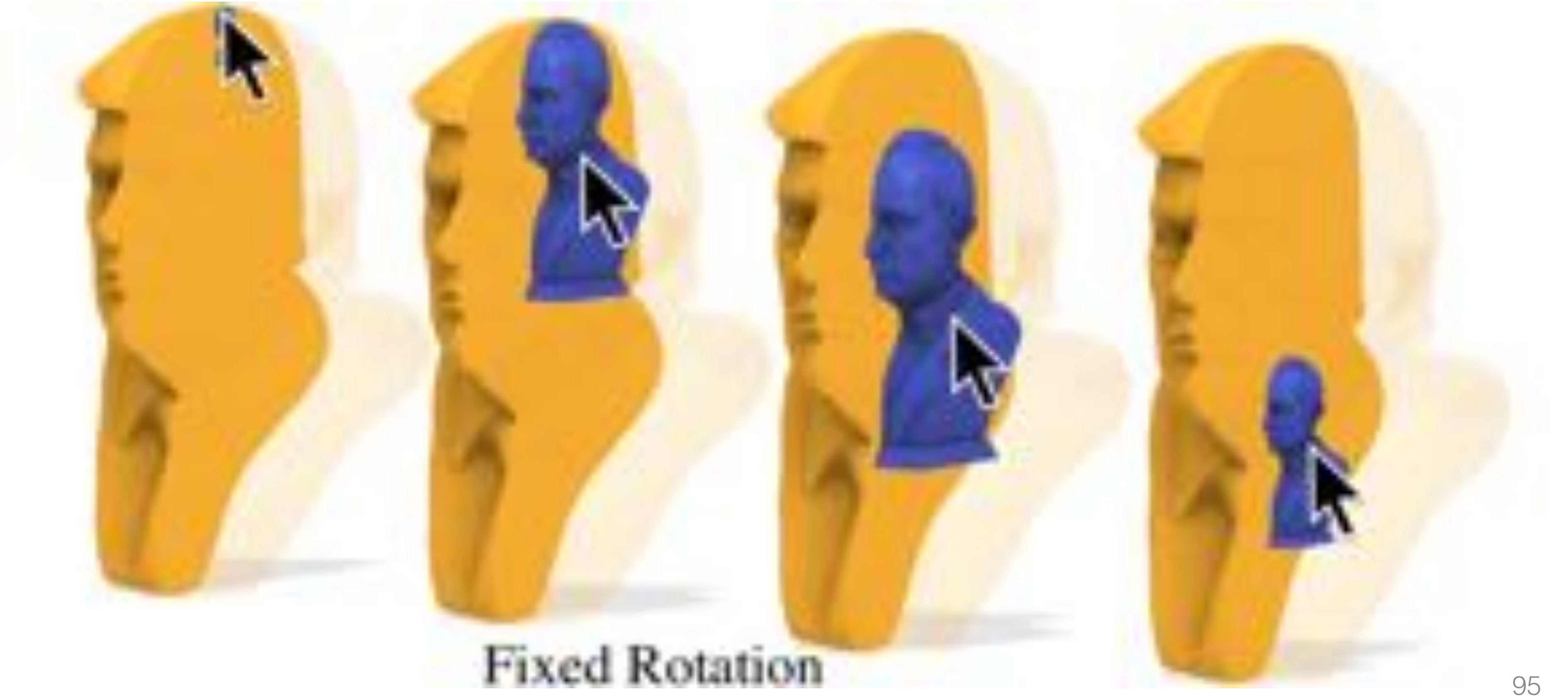

We validate our results via 3D printing

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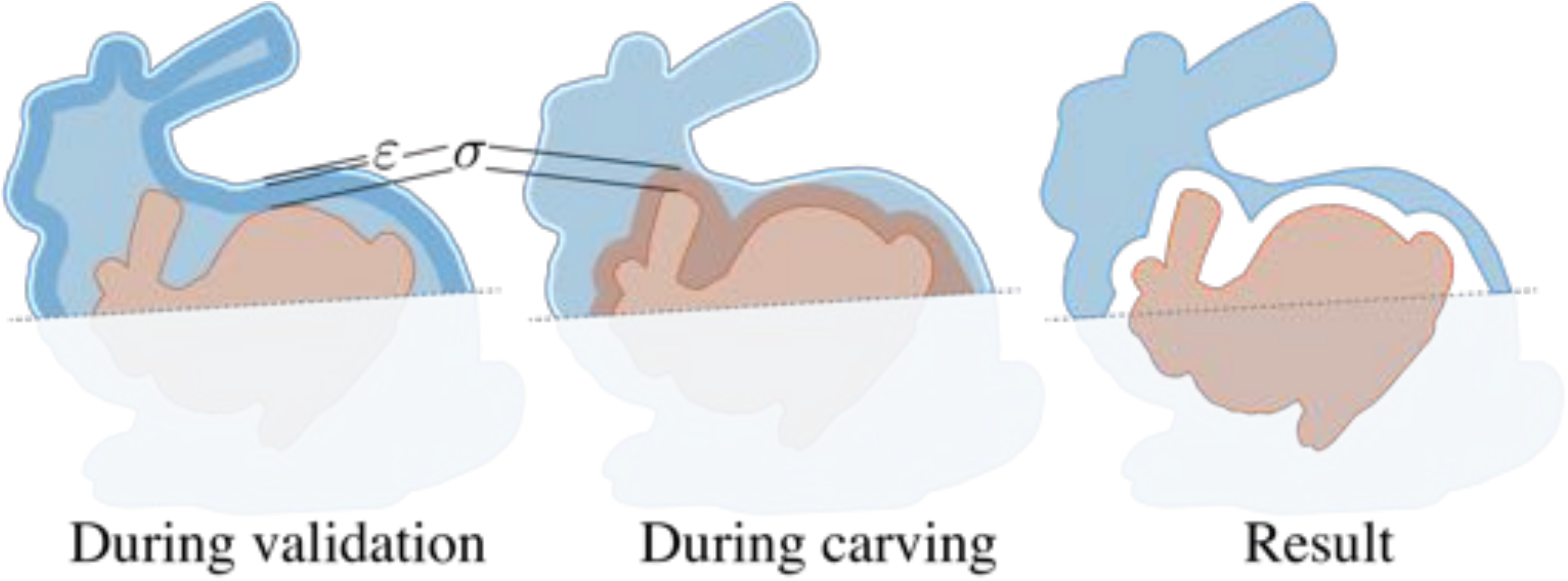
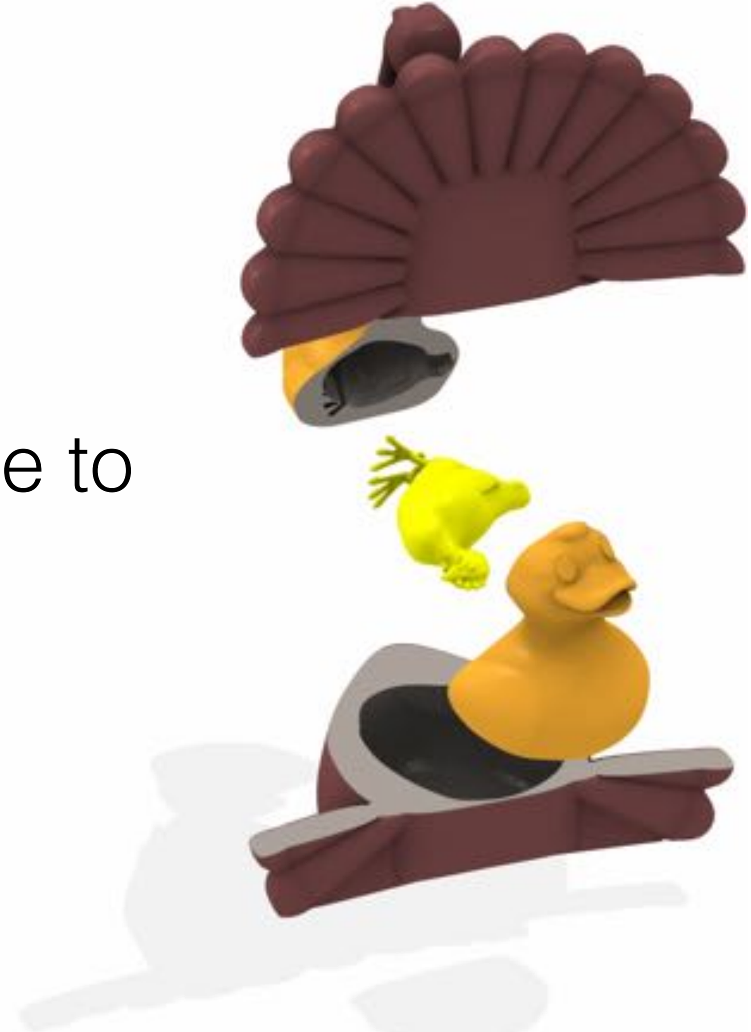
We accommodate printer tolerances by nesting *within* an offset surface



Our tools trivially generalize to nesting disparate shapes



Limitations & Future Work

- no global optimum guarantee

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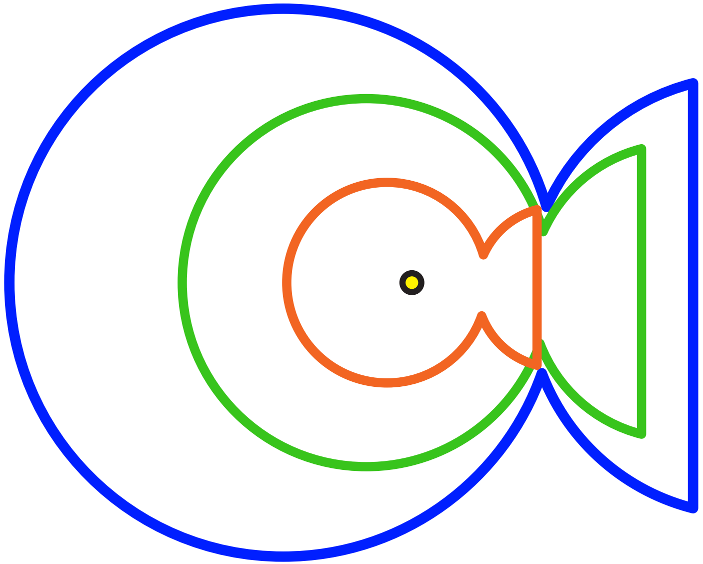

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Prevost et al.

Limitations & Future Work

- no global optimum guarantee
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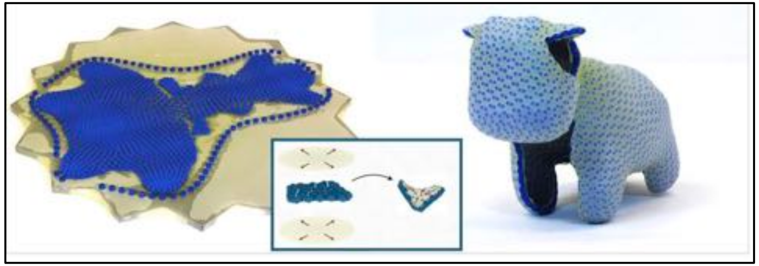
- thin shapes don't *rigidly* nest well
- deformable nesting?
  1. deform during design
  2. nest soft physical objects



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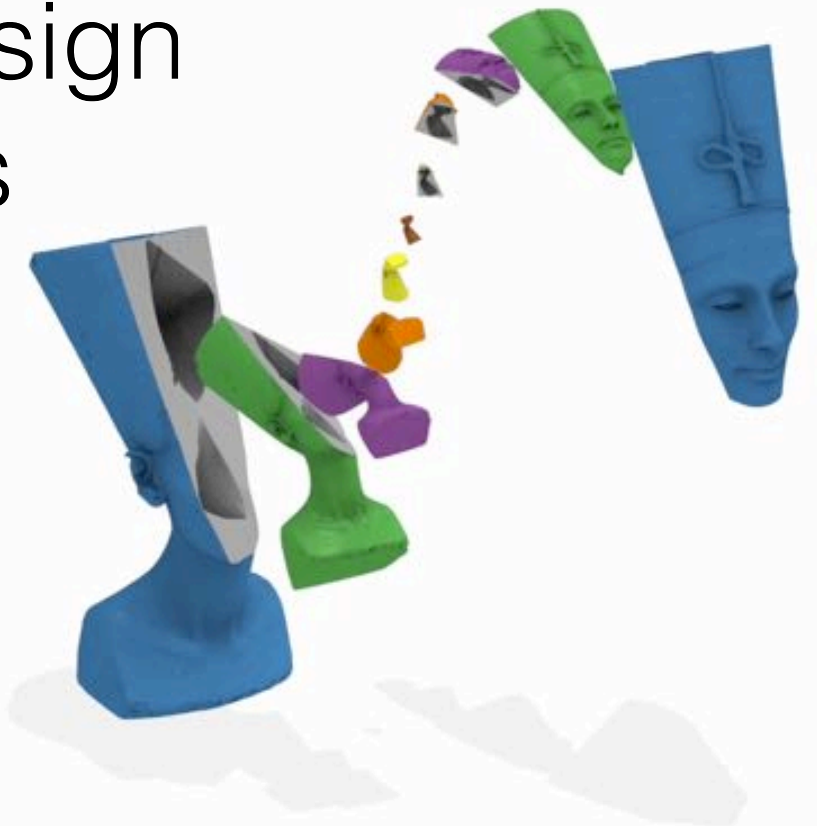
Generalized Matryoshka

Computational Design of Nesting Objects



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