UC San Diego

Machine Learning meets Geometry

L18: Mesh Processing

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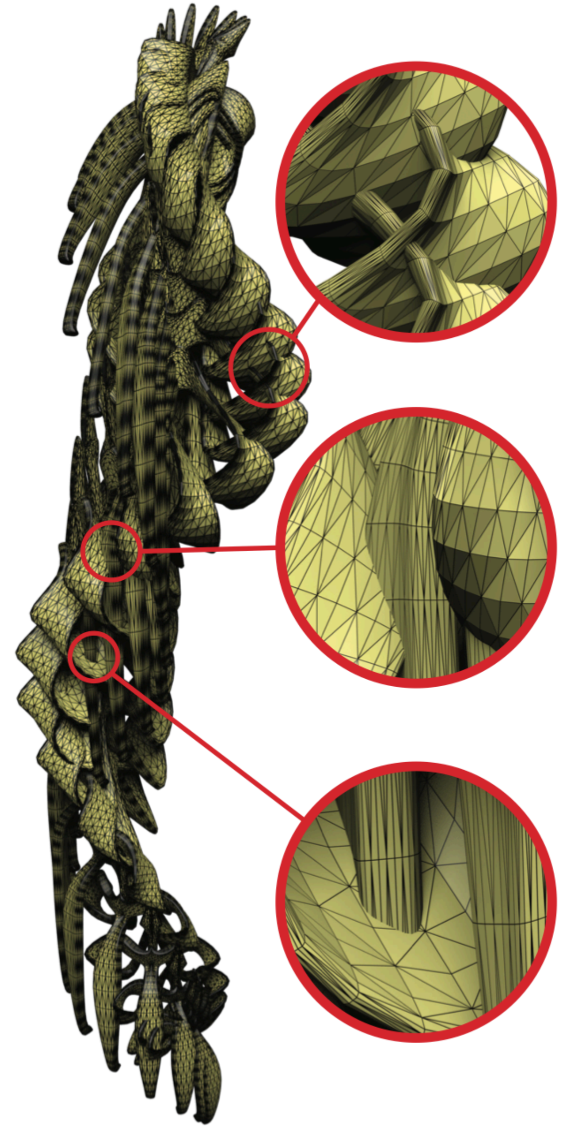
Ack: Minghua Liu helped to prepare slides

A Peek into Various Mesh Processing Algorithms

Watertight Manifold Surface Generation

- Many downstream tasks require the input mesh to be a watertight manifold.

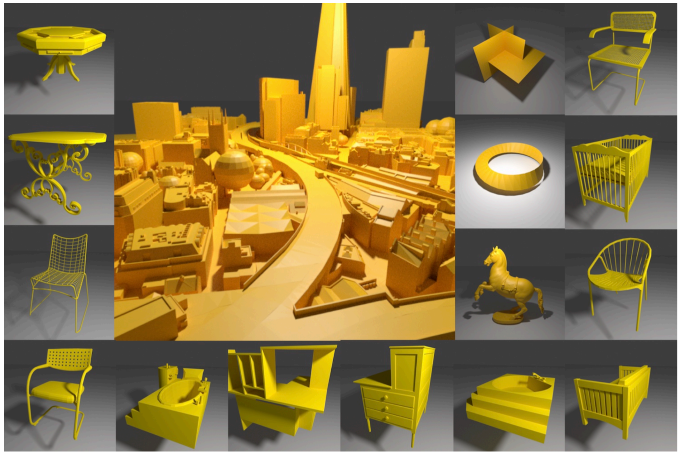
- However, meshes designed by artists or reconstructed by some algorithms are often non-manifold:
  - open boundaries
  - self-intersections
  - incorrect connectivity
  - ambiguous face orientation
  - double surfaces



Hu et al., "**Tetrahedral meshing in the wild.**", *Siggraph 2018*

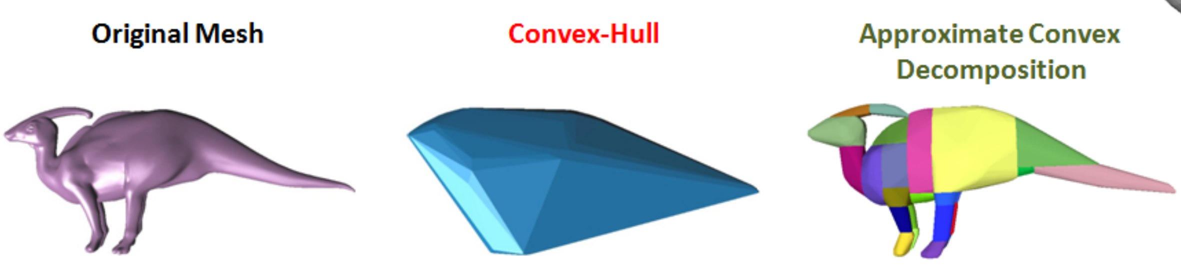
Watertight Manifold Surface Generation

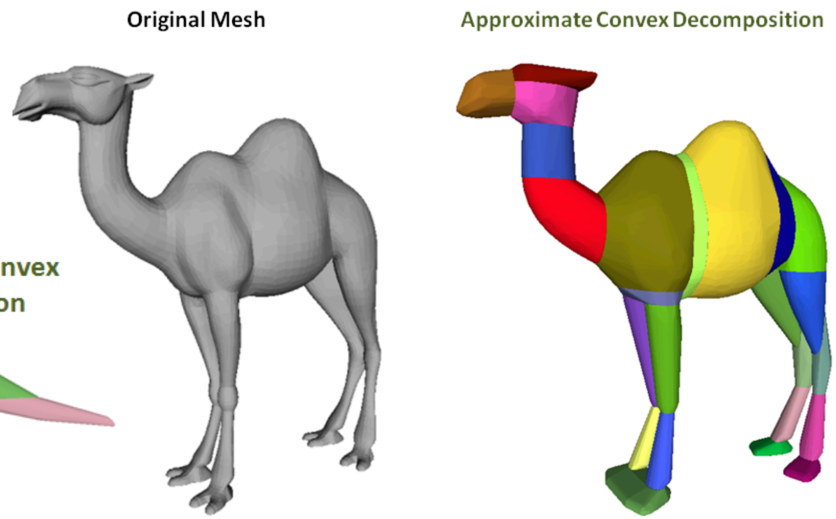
- Huang J, Su H, Guibas L. “**Robust watertight manifold surface generation method for shapenet models.**”
  - Small artifacts, all surface have volume
- Huang J, Zhou Y, Guibas L. “**ManifoldPlus: A Robust and Scalable Watertight Manifold Surface Generation Method for Triangle Soups.**”
  - Less artifacts, may contain zero-volume structures
- Basic steps:
  - Voxelize the surface
  - Extracts exterior faces between occupied voxels and empty voxels
  - Projection-based optimization



Convex Decomposition

- In some applications (e.g., collision detection), convex shapes is an input requirement.
- Directly using convex-hull provides poor approximation for concave surfaces.
- Exact convex decomposition is NP-hard and may produce a high number of primitives.





https://github.com/kmammou/v-hacd

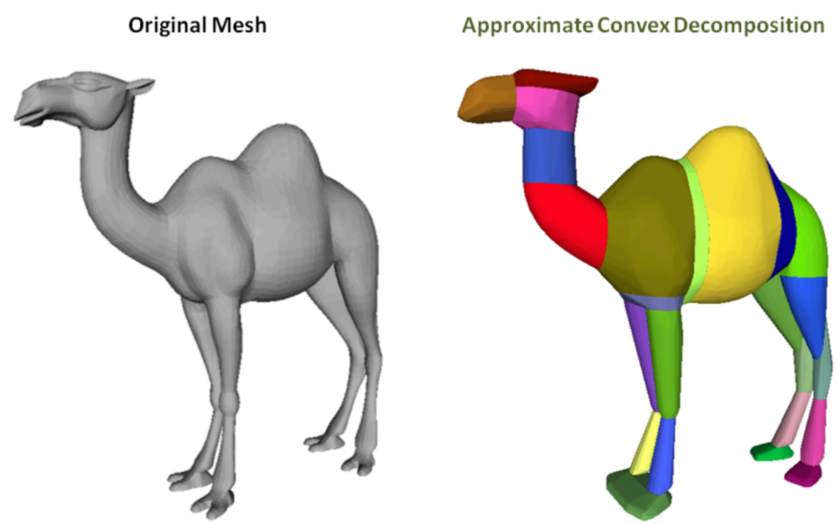
Approximate Convex Decomposition

- Goal: partition the mesh into a minimal number of clusters while ensuring that each cluster has a concavity metric lower than a pre-defined threshold

V-HACD

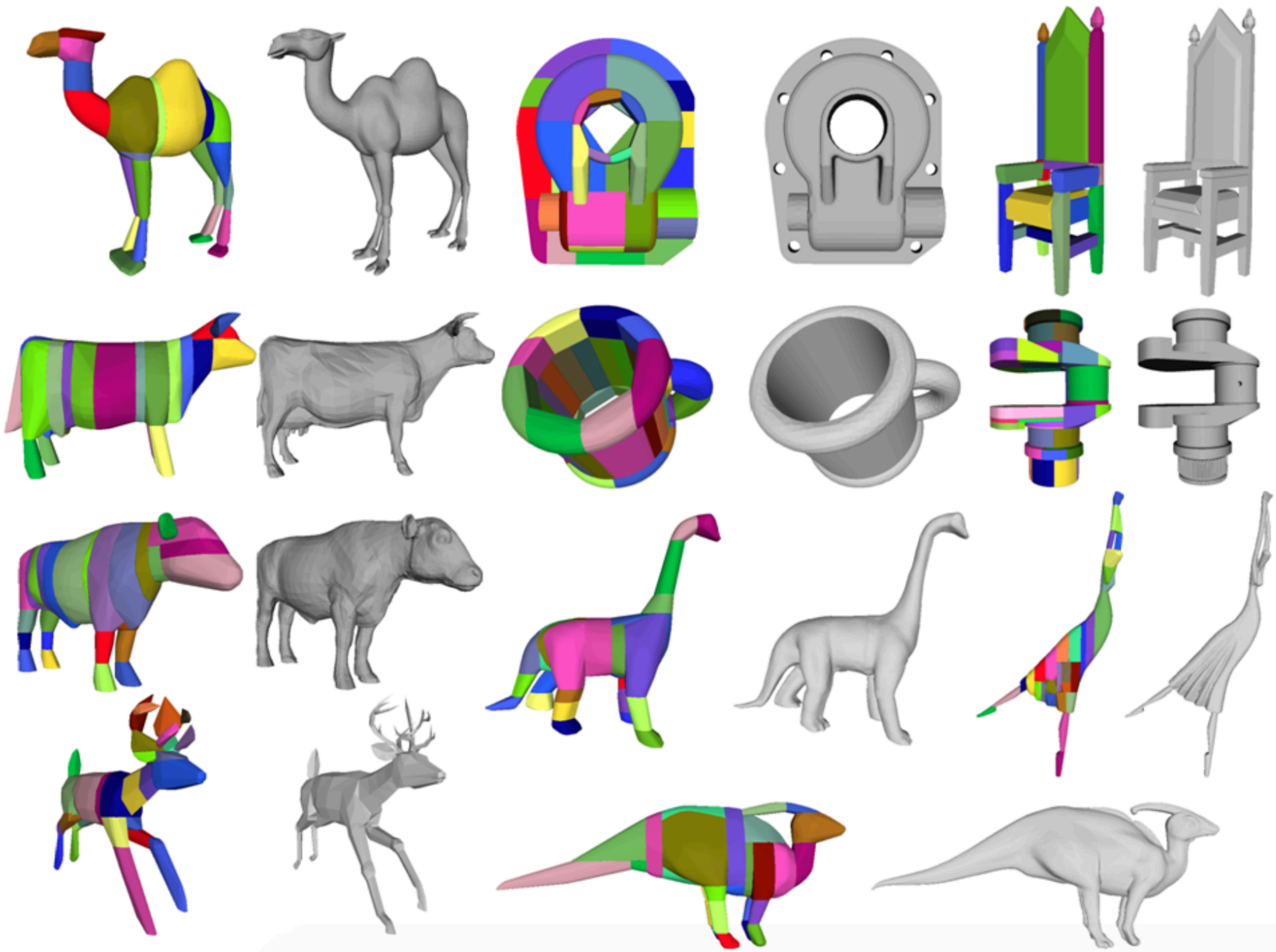
- First voxelize the shape
- Then use a heuristic algorithm (e.g., cut by axis-aligned plane) to segment the shape into parts
- The segmentation optimizes a volume-based concavity measure:

$$\frac{V(ConvexHull(Sub_1)) + V(ConvexHull(Sub_2)) - V(original)}{V(original)}$$



https://github.com/kmammou/v-hacd

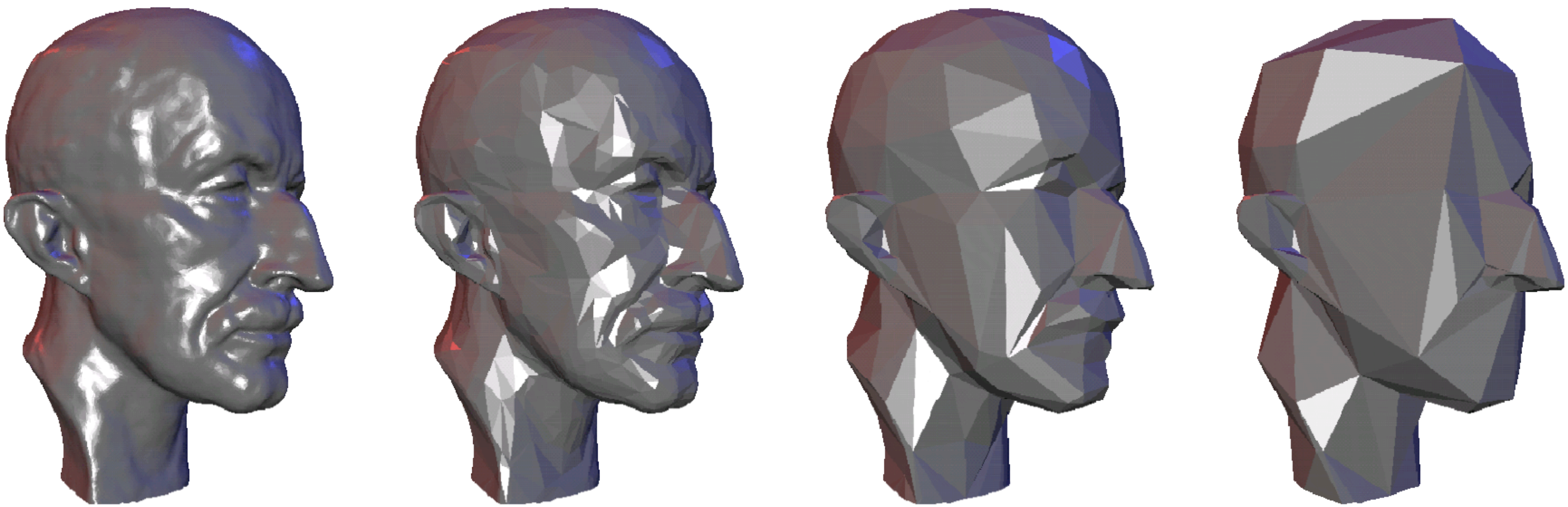
V-HACD Results



https://github.com/kmammou/v-hacd

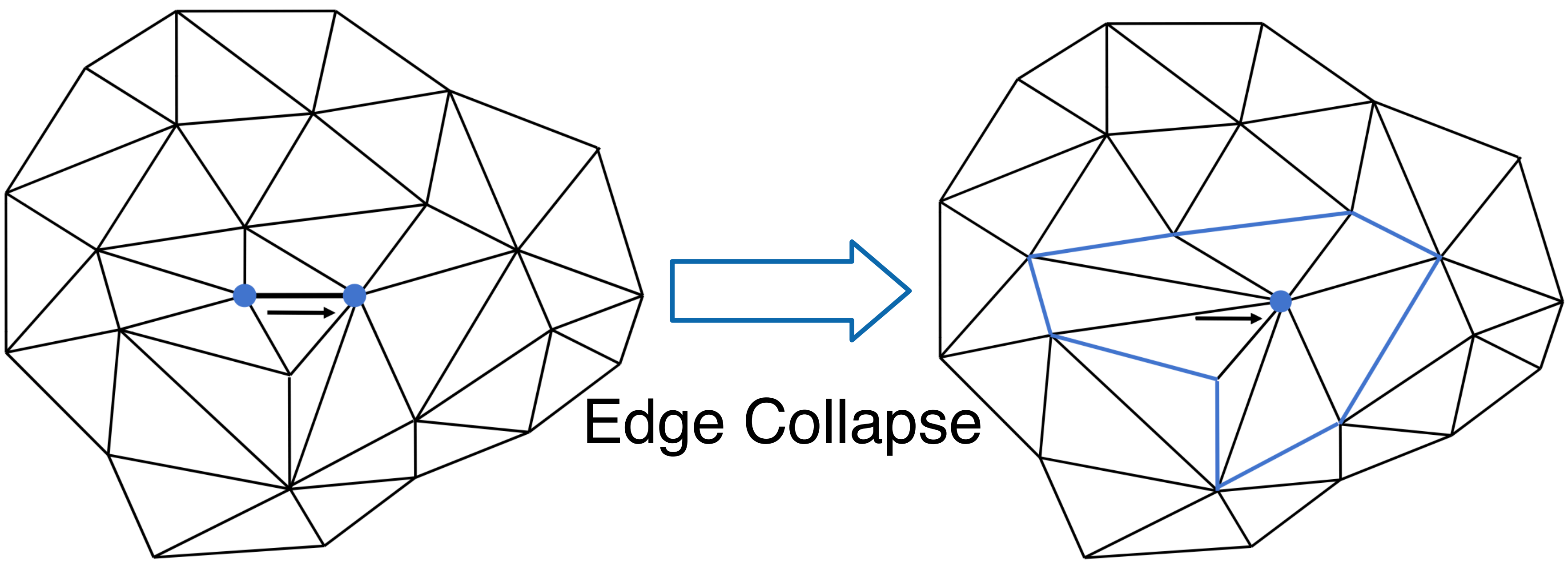
Mesh Simplification (Downsampling)

- Represent a mesh with fewer vertices



http://graphics.stanford.edu/courses/cs468-10-fall/LectureSlides/08_Simplification.pdf

Basic Procedure



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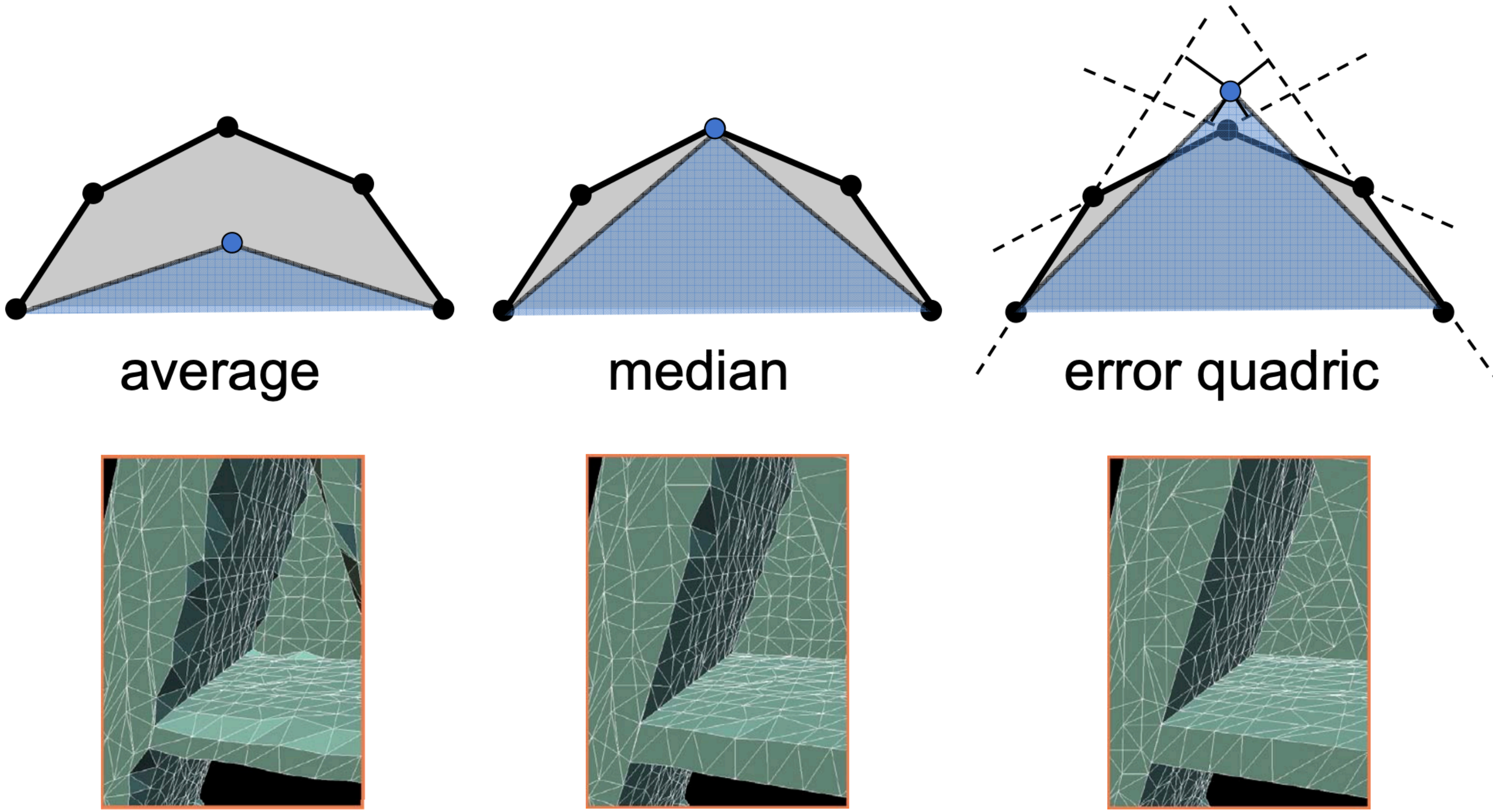
Adjustment of New Node Position



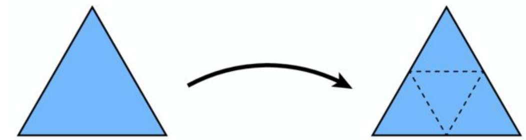
$$\min_p \sum_i \operatorname{dist}(q_i, p)^2$$

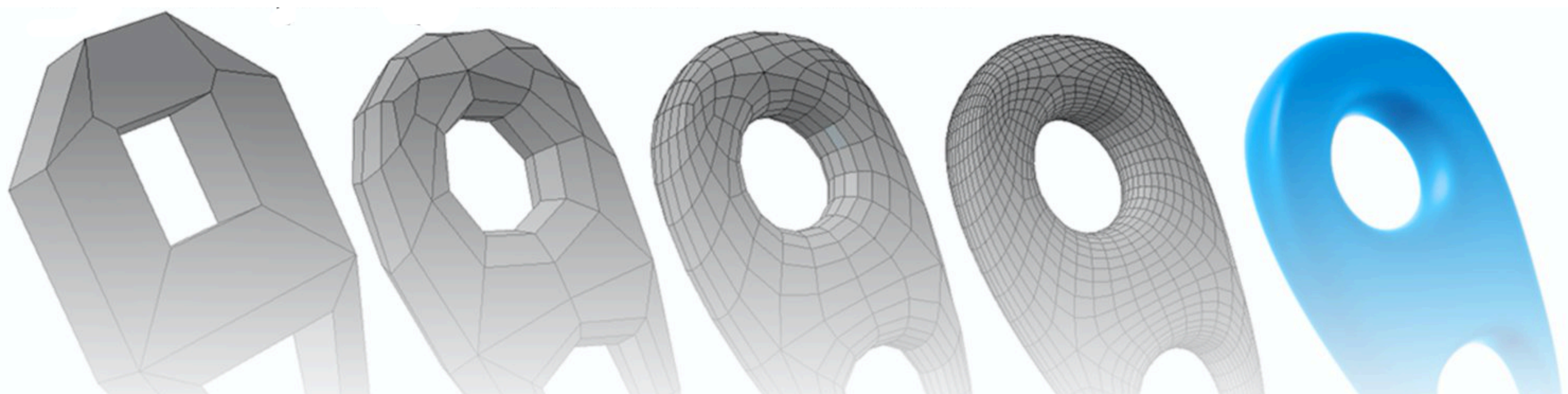
q_i: planes in the cell

http://graphics.stanford.edu/courses/cs468-10-fall/LectureSlides/08_Simplification.pdf

Mesh Upsampling via Subdivision

- Coarse mesh: memory efficient
- Fine-grained mesh: smooth, details
- Subdivision: coarse mesh -> fine-grained mesh
- Recursive upsampling:
  - Divide mesh element (one triangle becomes three)
  - Calculate new positions of the mesh vertices

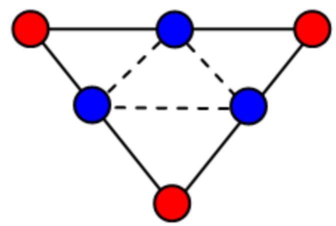




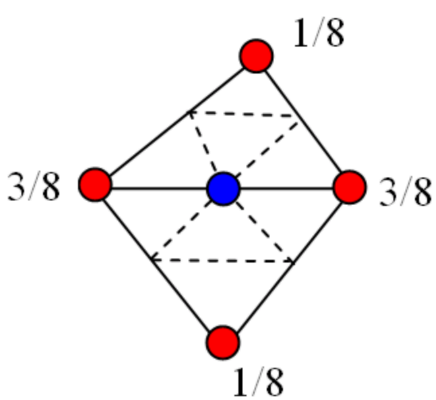
http://cs248.stanford.edu/winter21/lecture/geometryprocessing/slide_37

Loop Subdivision

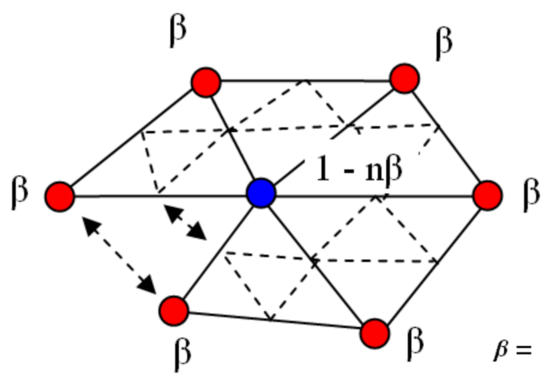
- Divide mesh element (one triangle becomes four)



- Calculate new positions of the mesh vertices (linear combinations of original positions)

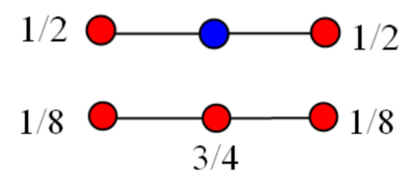


new vertices



$$\beta = \begin{cases} \frac{3}{8n} & n > 3 \\ \frac{3}{16} & n = 3 \end{cases}$$

original vertices

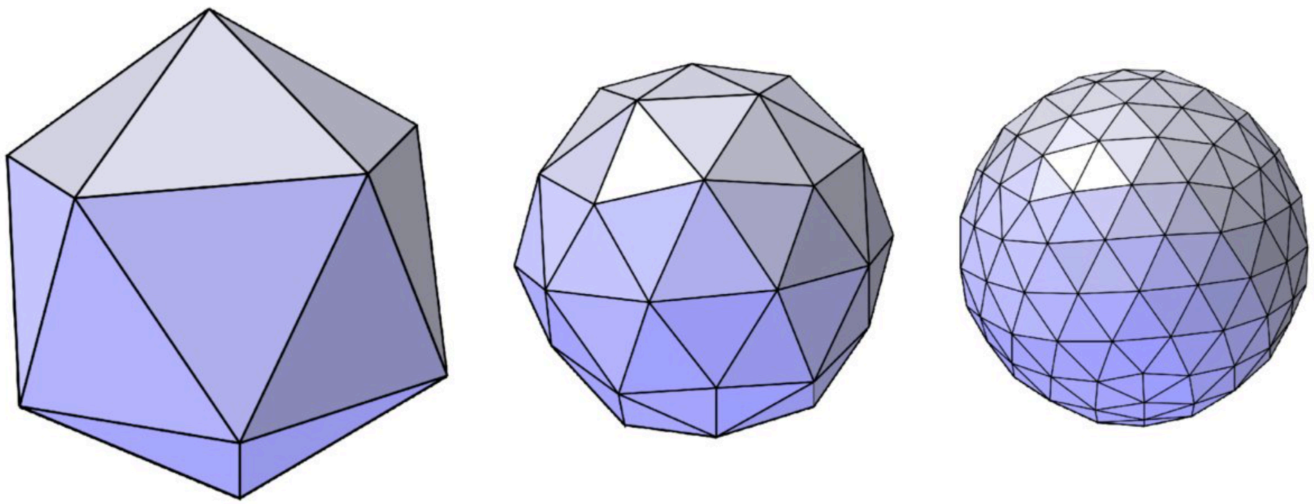


boundary cases

https://graphics.stanford.edu/~mdfisher/subdivision.html

Loop Subdivision

- Common subdivision rule
- “C2” smoothness of its limit shape
- Approximating, not interpolating



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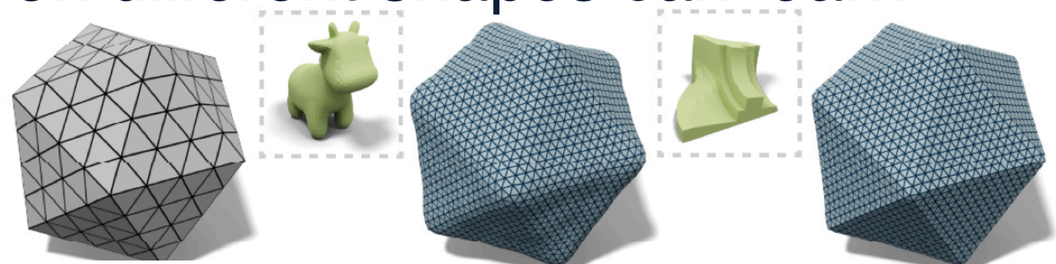
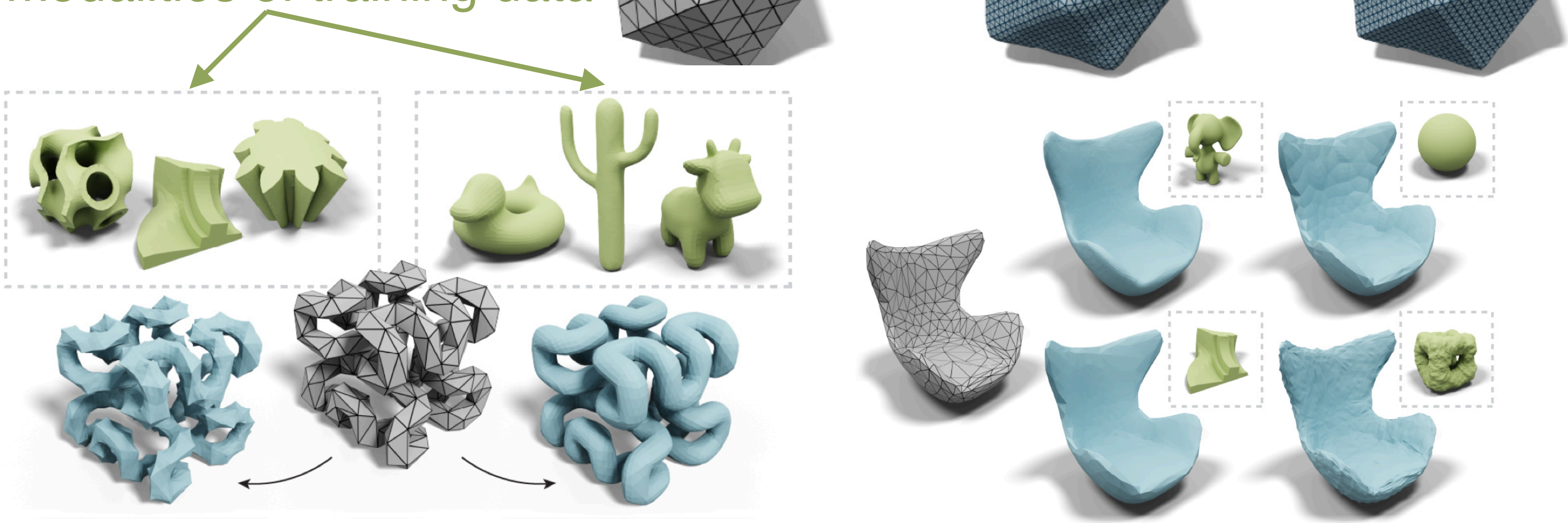
Neural Subdivision

- Using network to predict vertex positions conditioned on the local geometry enables us to learn complex non-linear subdivision scheme (more than smoothing).
- Data-driven: training on different shapes can learn different styles



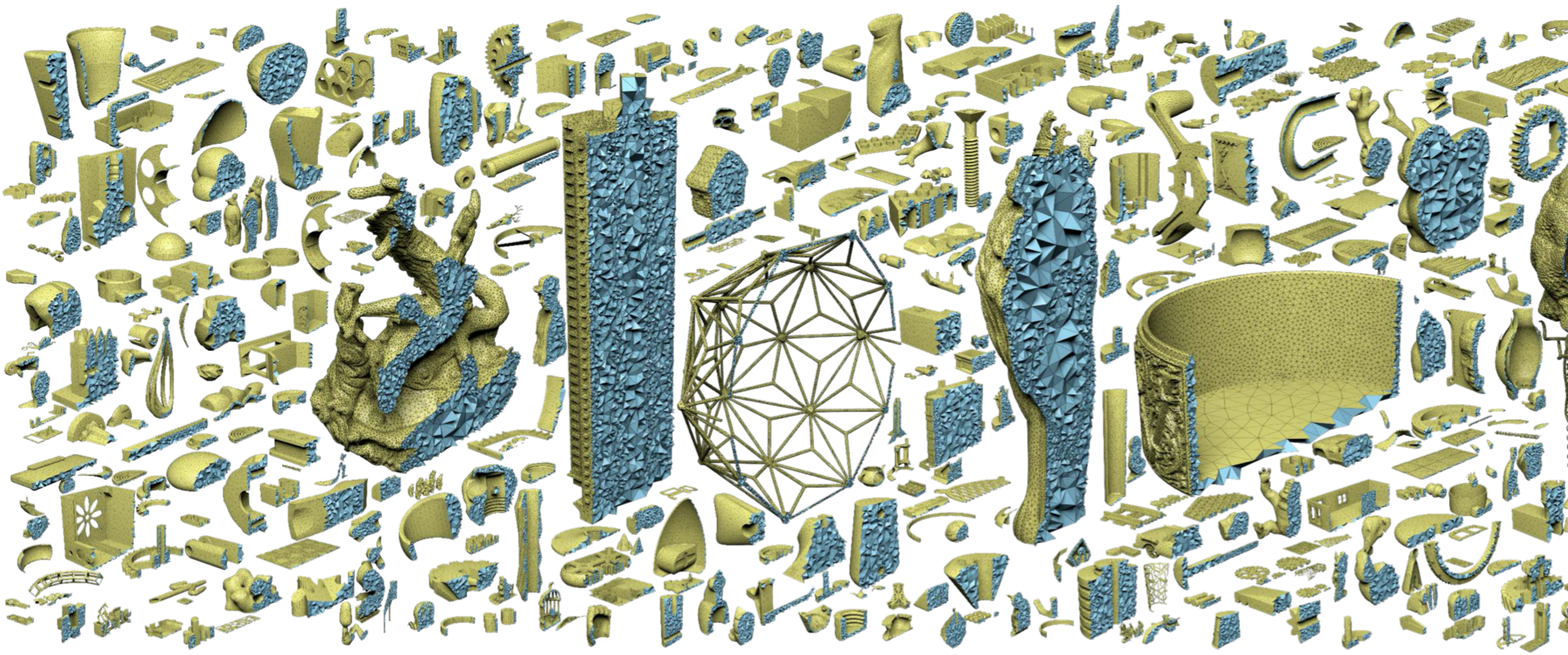
Two modalities of training data



Liu et al., "**Neural subdivision.**", *Siggraph 2020*

Tetrahedral Meshing

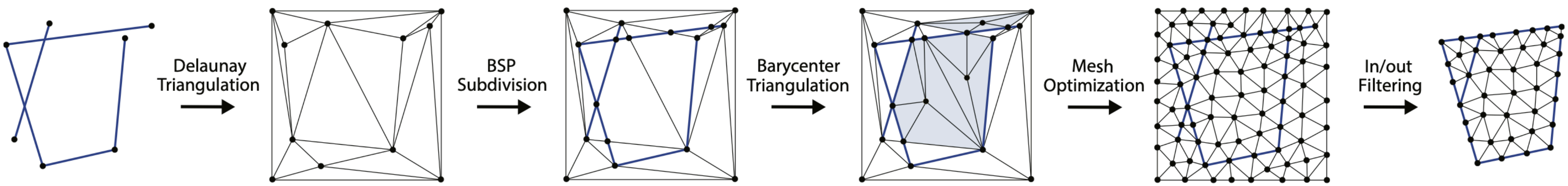
- Triangle mesh -> tetrahedral mesh
- Surface (triangle) -> Volume (tetrahedron)
- Finite element method



Hu et al., “**Tetrahedral meshing in the wild.**”, *Siggraph 2018*

Tetrahedral Meshing

- Hu Y, Zhou Q, Gao X, Jacobson A, Zorin D, Panozzo D. "**Tetrahedral meshing in the wild**". Siggraph 2018
- Hu Y, Schneider T, Wang B, Zorin D, Panozzo D. "**Fast tetrahedral meshing in the wild.**" Siggraph 2020



2D pipeline

Hu et al., "**Tetrahedral meshing in the wild.**", *Siggraph 2018*

Intro to CSE291-D for Spring, 2021

Machine Learning for Robotics

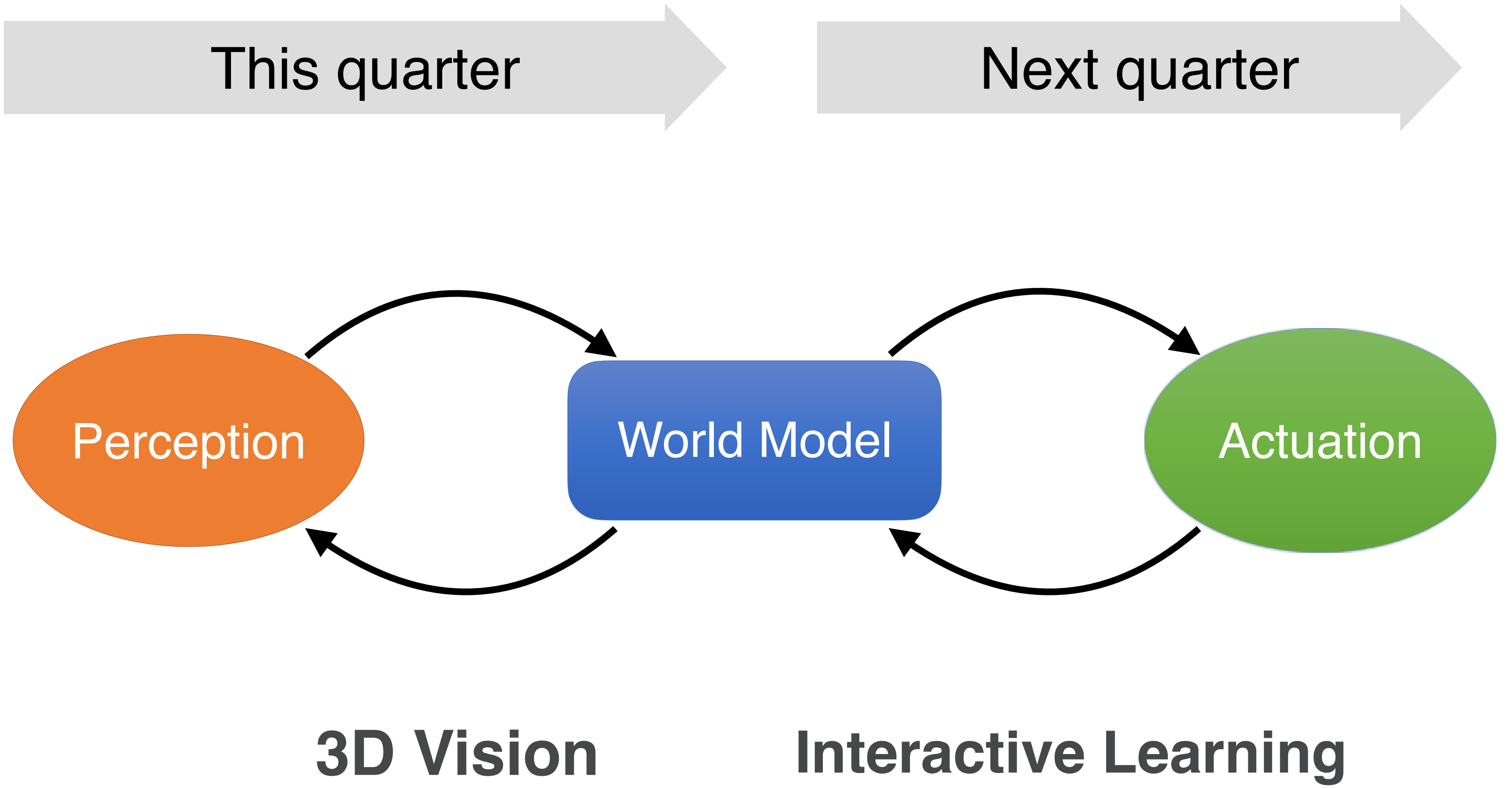
Why Are We Interested In Robotics?

Passive AI

- We know how to fit data well (by “deep learning”)
  - e.g., computer vision, natural language processing

Why Are We Interested In Robotics?

- We aspire that autonomous agents can perform tasks and “grow” through interaction experiences
  - Need the ability to **interact**


This quarter
Next quarter
Perception
World Model
Actuation
3D Vision
Interactive Learning

Syllabus

- Part I: Geometry and Physics of Robots
  - Robot Body
  - Robot Motion
  - Robot-Object Interaction
  - Physical Simulation
  - Classical Robotics Pipeline
- Part II: Reinforcement Learning
  - RL Concepts
  - RL as an Optimization Problem
  - Long-horizon RL
  - Generalizable RL

Thank you for the efforts of the the quarter!