Shape Segmentation

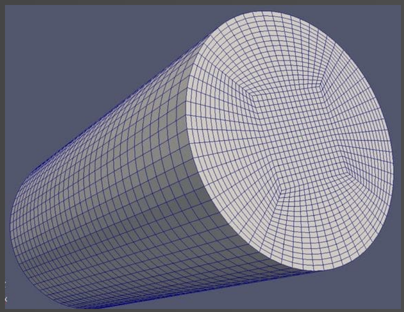
Model- vs. Data-Driven | Structures

Richard (Hao) Zhang

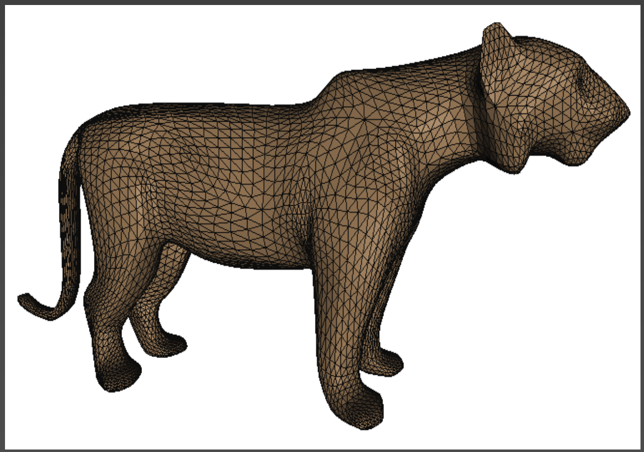
CMPT 464/764: Geometric Modeling in Computer Graphics

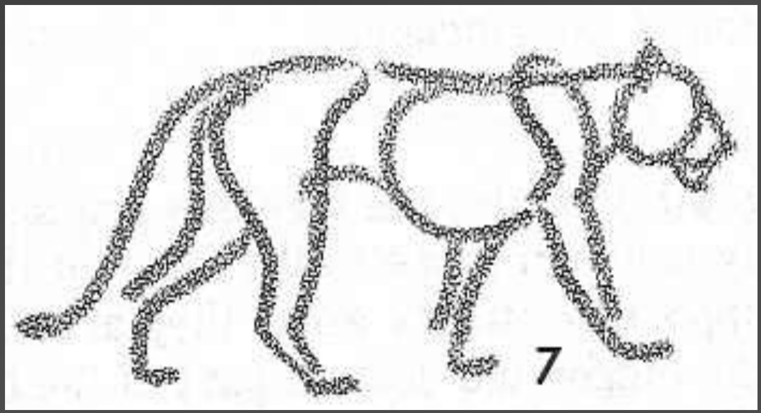
Lecture 10

Shape perception through abstraction



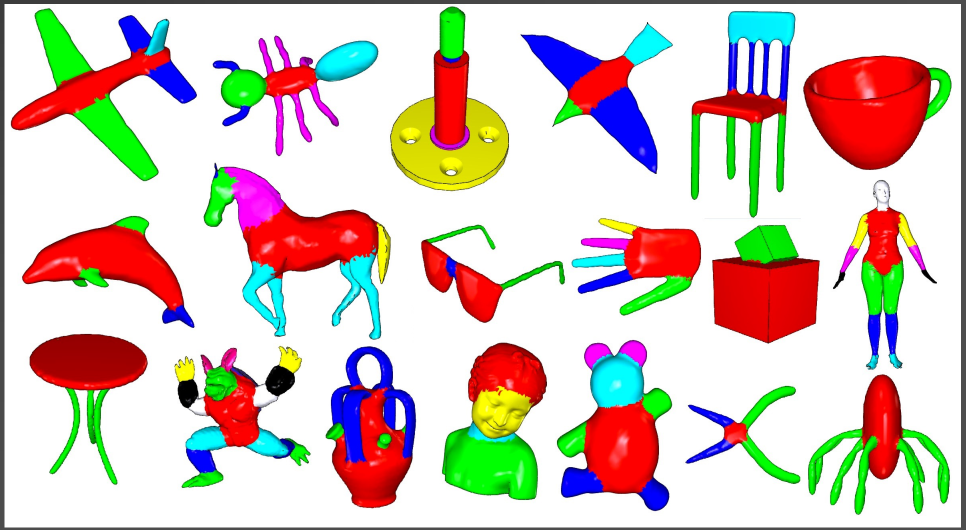
- Mesh objects may contain much redundancy
  - Do I need >10K triangles to represent a cylinder?
- Humans can often perceive a shape by just an **abstraction**
  - E.g., a few **sketches** or a **high-level structural understanding**



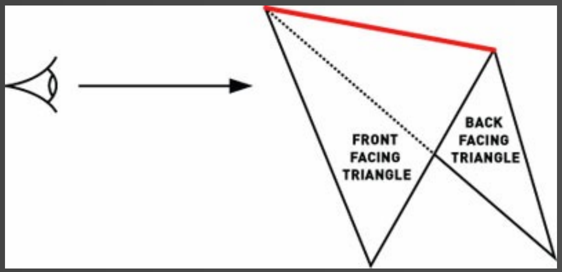


Feature analysis & segmentation

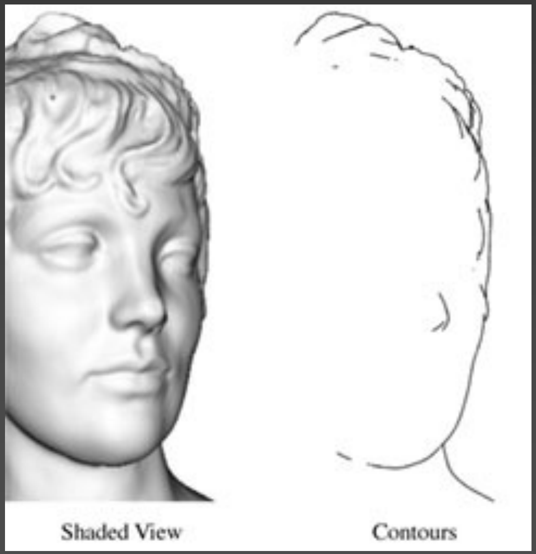
- How to capture the **essence (a high-level abstraction)** of a shape?
- The essence of a shape can be captured either by
  - **Feature curves** – crease lines, silhouette, etc. – **feature extraction**
  - Or its **constituent parts** – humans perceive shape by decomposing it into meaningful parts [Hoffman & Richards 84] – **mesh segmentation**



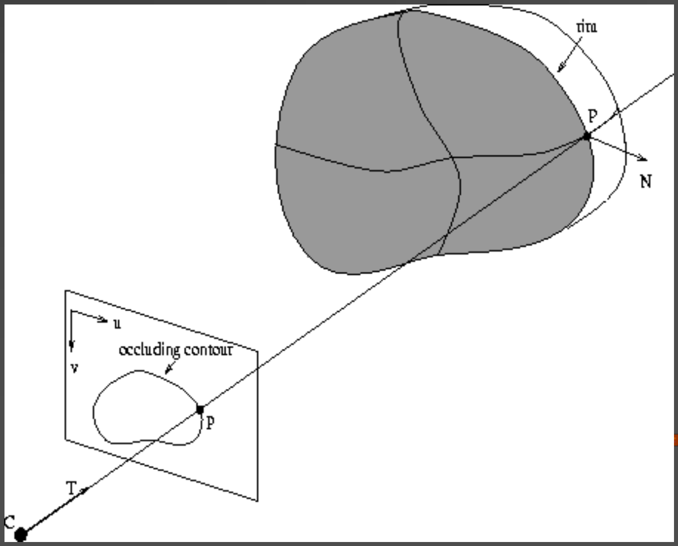
Various feature lines



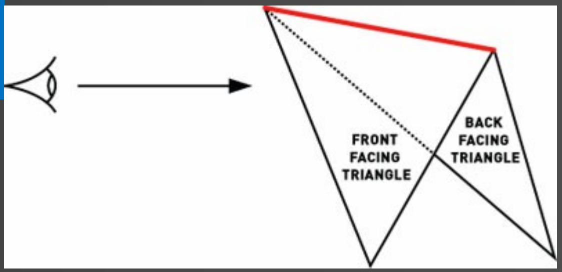
- Silhouettes/outlines/contours: **view-dependent**
- **Edges**; crest lines; ridges and valleys: view-independent
- What are **visually more "important" or "apparent"**?



Visible points whose normals are perpendicular to the view vectors



Various feature lines (aside)



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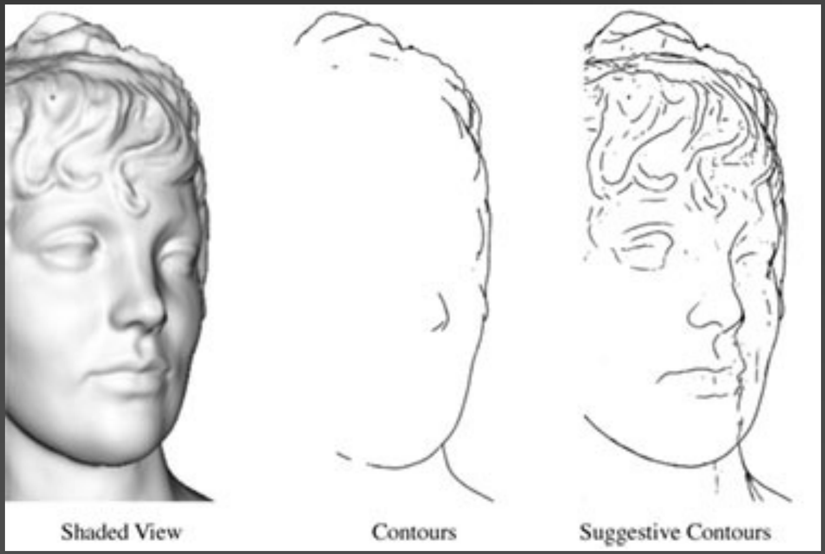
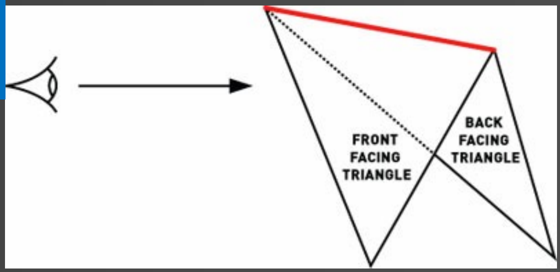


https://gfx.cs.princeton.edu/pubs/DeCarlo_2003_SCF/DeCarlo2003.pdf

Various feature lines (aside)



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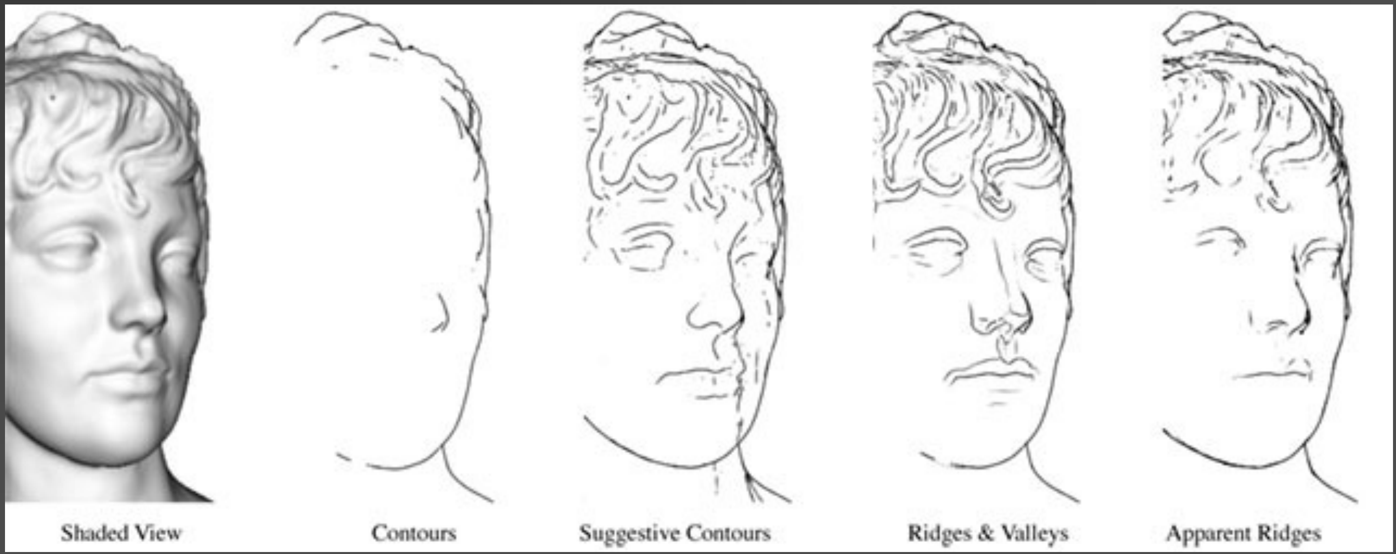


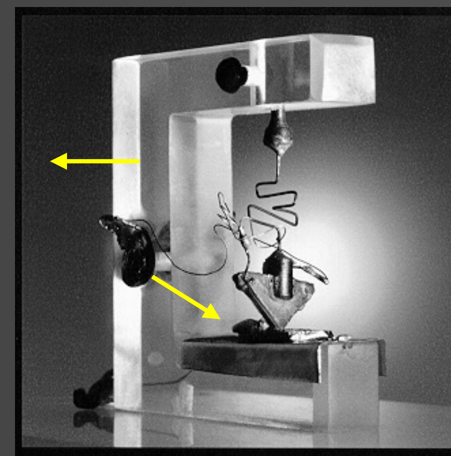
https://people.csail.mit.edu/tjudd/apparentridges.html

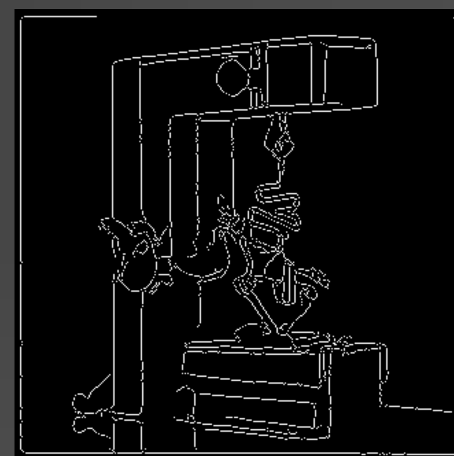
Technical definition of edges

- Geometric features are mostly of two types:
  - Point features, e.g., spikes, corner, extremities
  - Line-type features, e.g., edges, ridge, valley, or crest lines – most common
- How to define line-type features?
  - From image processing, edges are composed of pixels where the magnitude of the gradient of the image intensities has a local maximum in the direction of the gradient

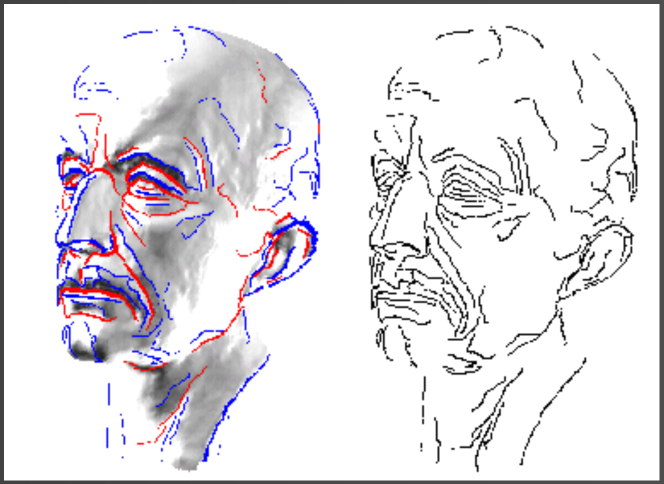
$$\nabla i(x,y) = [\partial_x i(x,y), \partial_y i(x,y)]$$

where gradient captures direction of fastest ascent

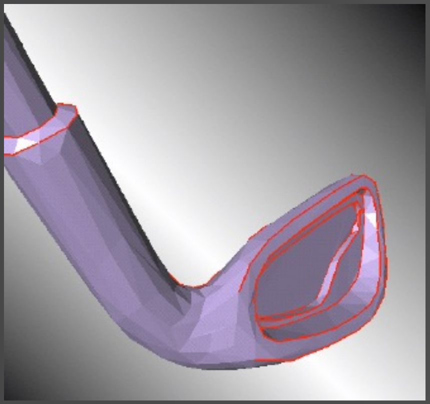




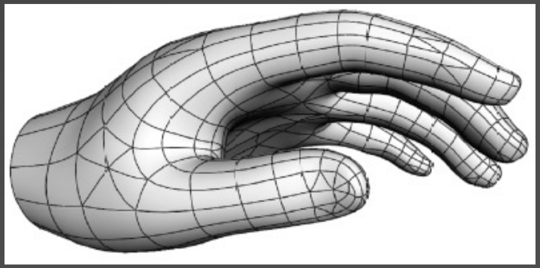
Edges on 3D surface



- Intensity changes ⇔ variation of normals
- Variation of normals ⇔ curvatures
- Positive curvature ⇒ ridge (blue); negative ⇒ valley
- Feature edge: loci of points attaining local extrema principal curvatures along lines of curvature
  - Lines of curvature depict direction of principle curvatures

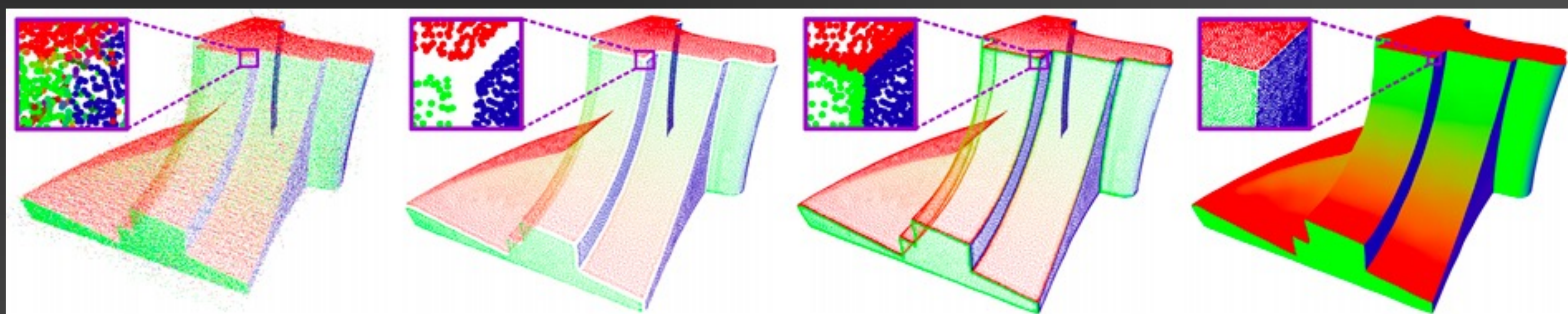


- Edges as **part boundaries for segmentation**



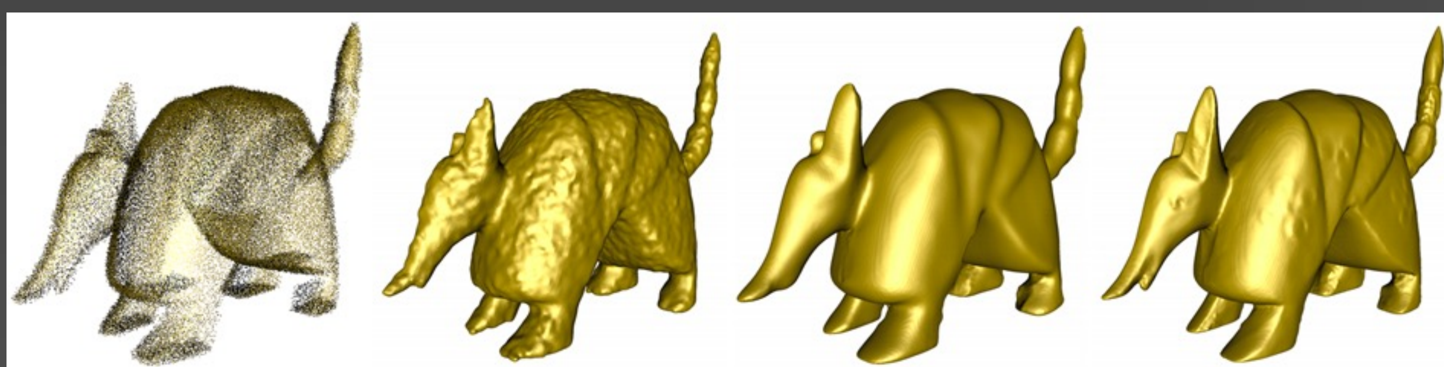
Edge detection in point clouds

- Not just "detection" since edge points may not have been sampled
- **Edge-Aware Resampling (EAR)**, e.g., upsampling on/near edges



(a) Noisy input. (b) Resampling away from edges. (c) Edge-aware upsampling. (d) Upsampling for rendering.

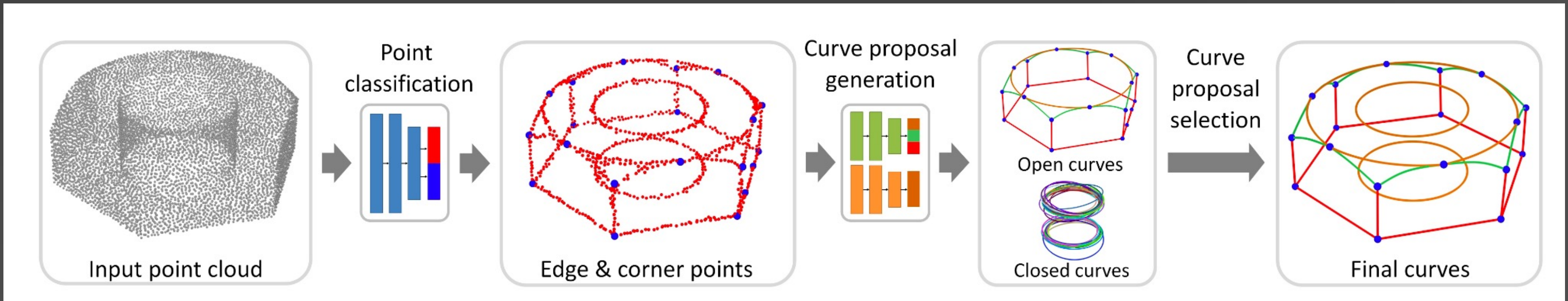
- Would facilitate surface reconstruction with shape features



(a) Raw scan. (b) Poisson over PCA normals. (c) Poisson over MLS. (d) Poisson over EAR.

What is an edge: model- vs. data-driven

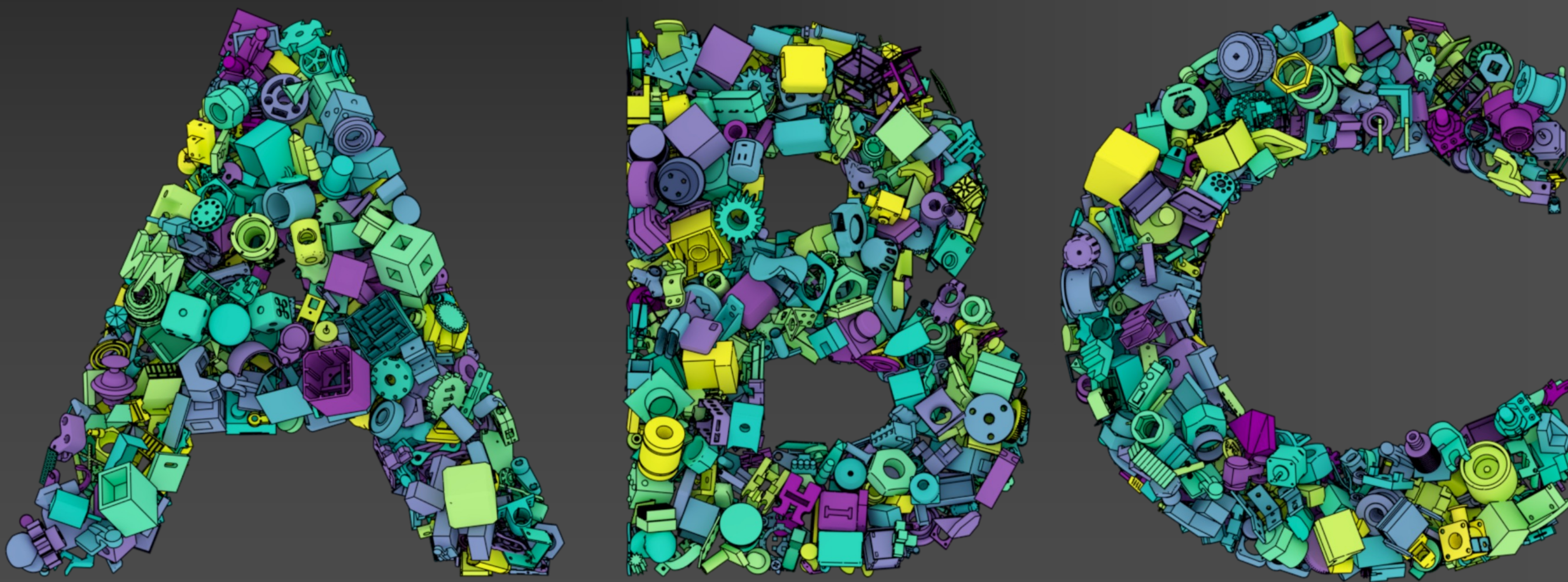
- Model-based edge definition may not work robustly on real data
  - “Soft” edges and non-uniform data, especially over point clouds
  - Local extrema may lead to too many edge points, e.g., thick edges
  - Noise, sparsity, and missing data
- It is possible to **“learn” edge extraction** for point clouds



[Wang et al. NeurIPS 2020]

Dataset: A Big CAD dataset

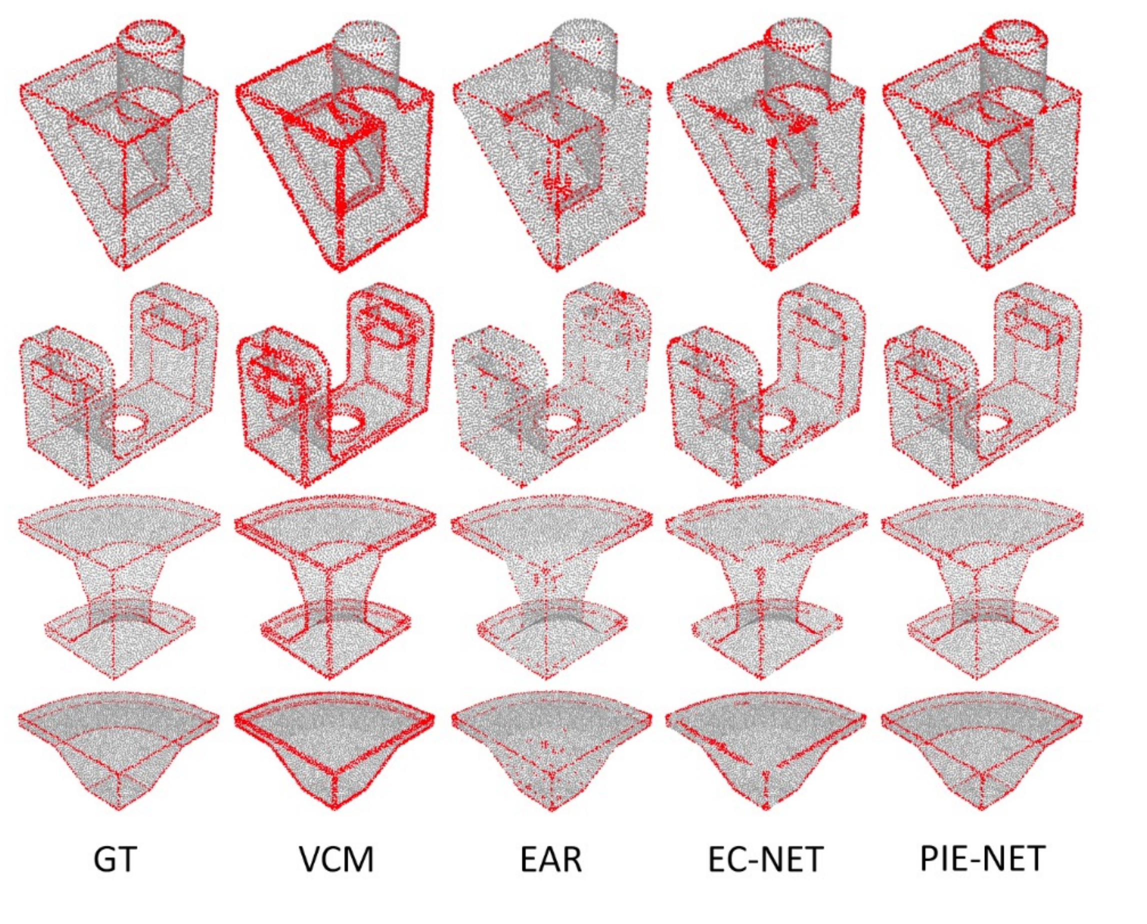
- 1 millions CAD models in various formats and parametric edges!



Comparisons

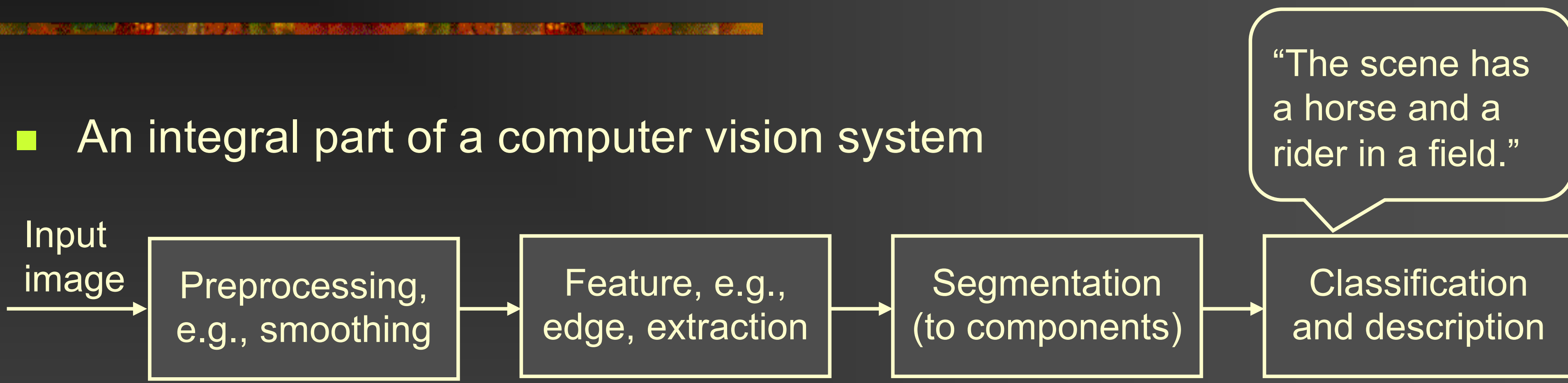
	VCM			EAR			EC-NET	**PIE**
	τ=0.12	τ=0.17	τ=0.22	τ=0.03	τ=0.035	τ=0.04		
ECD ↓	0.0321	0.0430	0.0569	0.0679	0.0696	0.0864	0.0360	**0.0088**
IOU ↑	0.2841	0.2854	0.2855	0.3404	0.3250	0.2844	0.3561	**0.6223**
Precision ↑	0.3063	0.3244	0.3456	0.5560	0.4149	0.6523	0.4872	**0.6918**
Recall ↑	0.8385	0.7644	0.6937	0.4820	0.5910	0.3578	0.5736	**0.8584**

Fig. 9. **State-of-the-art comparisons** – Qualitative (top) and quantitative (bottom) comparisons of PIE compared to VCM [Merigot et al. 2011], EAR [Huang et al. 2013a], and EC [Yu et al. 2018a].



Segmentation

- An integral part of a computer vision system



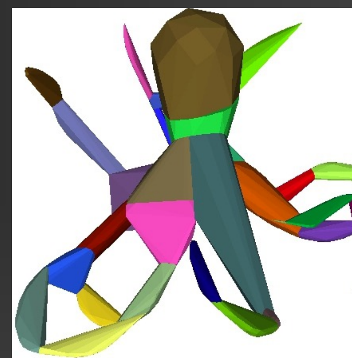
- Plays a critical role in 3D object recognition

  "… for the task of visual recognition, the visual system **decomposes shapes into parts**, …"

  — [Hoffman & Richards] in *Cognition*, 1984

What is a part: geometry vs. semantics

- Geometric criteria
  - Convexity
  - Cylindrical
  - Pyramidal, etc.

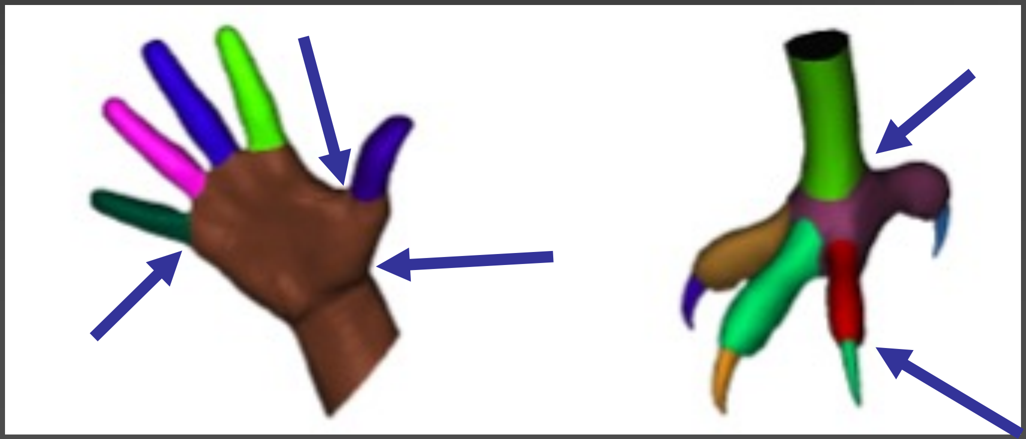


- **Semantics** (related to meaning): a **meaningful** part
  - Appeals to human intuition or knowledge
  - Often no general math formulation — **knowledge-driven**
  - Semantics may lead to geometric criteria: e.g., minima rule

Segmentation by minima rule

- Partition a shape into meaningful components
- Minimal rule from study of visual perception

Minima rule: cut boundary at negative minima of curvature, i.e., over concavity (a local criterion)



Use of the minima rule

5 parts

16 parts

More meaningful …

"An understanding of semantics"

Symmetry

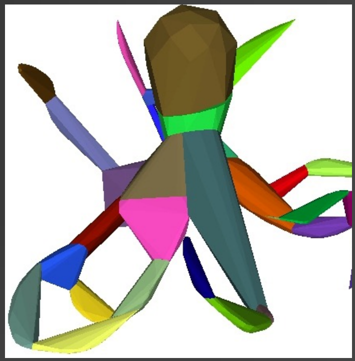
5 parts

5 parts

A non-local criterion: a segment is self-symmetric!
Yet, symmetry is still a geometric criterion!

What is a part: model- vs. data-driven

- Model-driven: model “hand-crafted” from knowledge/exp
  - Convexity
  - Minima rule
  - Pyramidal: application-driven
  - Symmetry



- Data-driven: **learn from data**, e.g., human segmentation
  - Supervised vs. un-supervised vs. semi-supervised learning
  - Recent developments in deep-learning-based methods

From parts (segmentation) to structure

"We propose that, for the task of **object recognition**, the visual system **decomposes shapes into parts**, that it does so using a rule defining part boundaries rather than part shapes (**minimal rule**), … , and that **parts with their descriptions and spatial relations** provide a first index into a memory of shapes.

From "Parts of Recognition" by Hoffman and Richards, *Cognition*, 1984

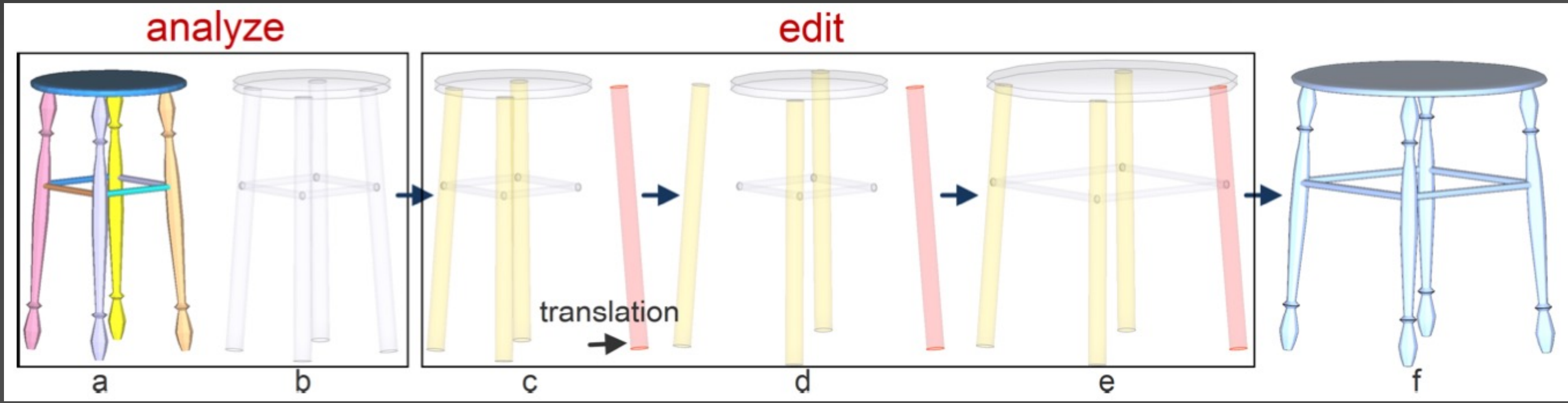
From parts (segmentation) to structures

- **Structure = part structure** = part composition and **relations** between the constituent parts of a shape
- Part composition = how a shape is segmented
- Part relations:
  - Symmetry or repetitions
  - Proximity
  - Angle between parts
  - Relative positioning, e.g., co-planarity

Structure-aware editing

- Cuboids and generalized cylinders enclose parts
- Analyze shape to detect symmetry, proximity, angle, …
- Edits preserve structural relations among controllers, mainly symmetry and proximity

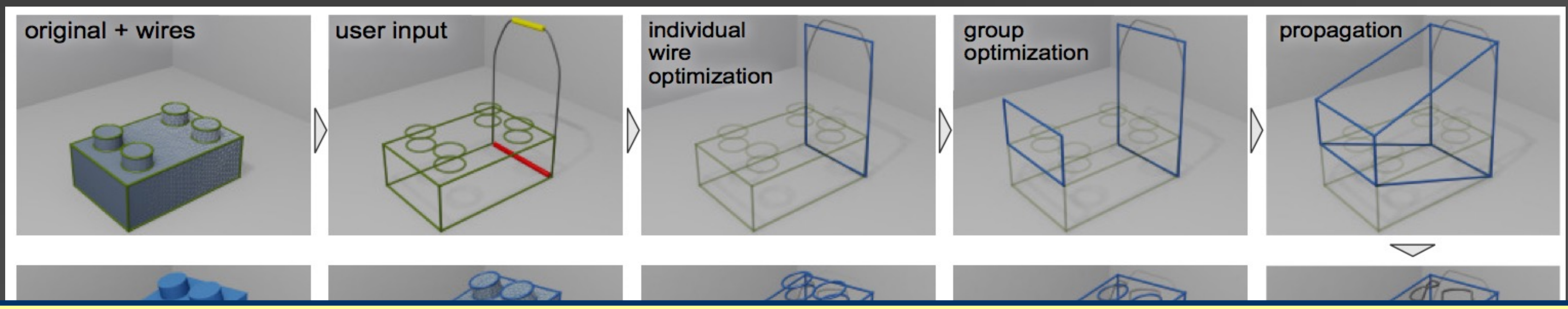
[Zheng et al. 2010]



Structure-aware editing: iWires

- Wires as control/editing handles [Singh & Fiume 1999]
- Analyze shape first, to detect symmetry, co-planarity
- Edits preserve structural relations among wires

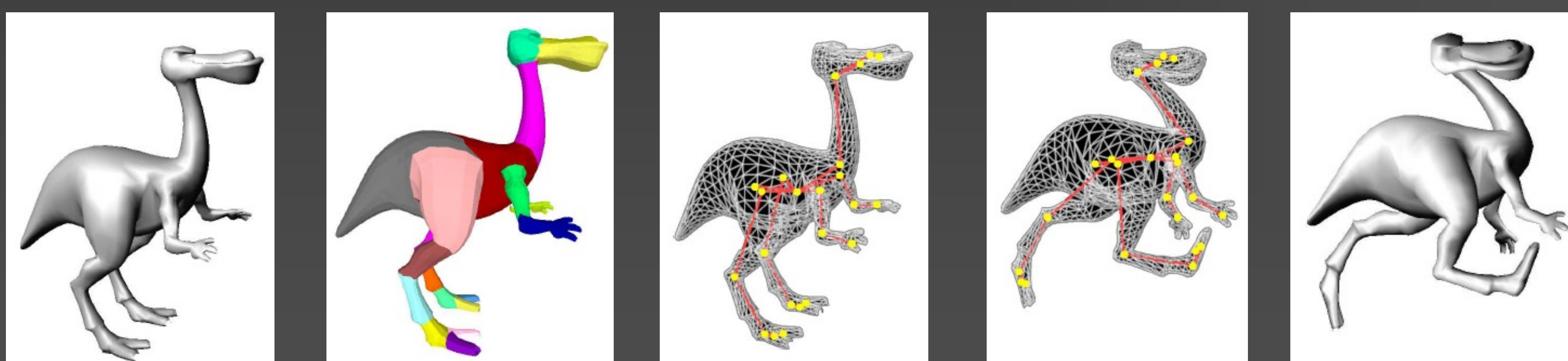
https://www.youtube.com/watch?v=se1fz2RRdKY [Gal et al. 2009]



Survey: Structure-Aware Shape Processing
http://www.cs.sfu.ca/~haoz/pubs/mitra_star13.pdf

Many applications for segmentation

- Define a shape descriptor for recognition, classification, retrieval, …
- **Structure-aware shape processing**; structure = part composition
- First step towards higher-level understanding, e.g., **functionality**
- Extraction of **skeletal representation** for animation [Katz & Tal 03]



Patch-type segmentation

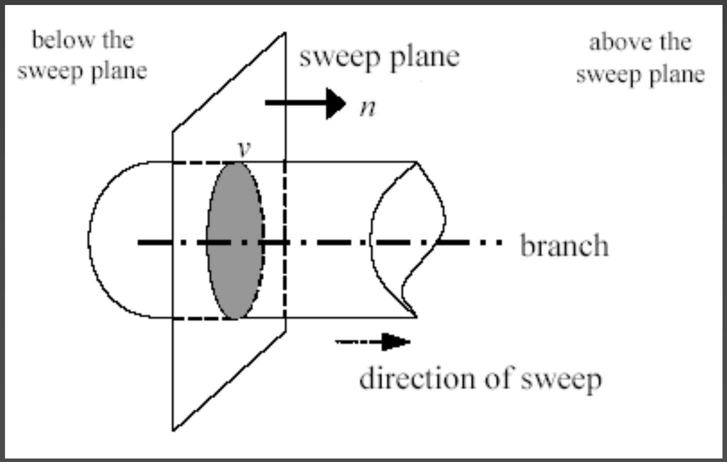
- Partition a mesh into disk-like patches obeying certain geometric properties, e.g., planarity, size, or convexity
- Applications:
  - Texture mapping
  - Mesh decimation,
  - Mesh compression,
  - Remeshing,
  - Fast collision detection
  - etc.

Our focus: part-type segmentation

- Partition shape into meaningful parts
- Applications
  - Object recognition
  - Morphing
  - Skeletal animation
  - Shape correspondence
- Main challenges
  - No universal or mathematical definition for a “part”
  - Autonomy of algorithms

Classification of approaches (aside)

- Skeleton-based [Li et al. 01]
  - Plane sweep with respect to a **curve skeleton** of input shape
  - Keep track of the planar 2D **cut profiles** along the skeleton
  - A part = swept volume between **"critical points"** of profile function



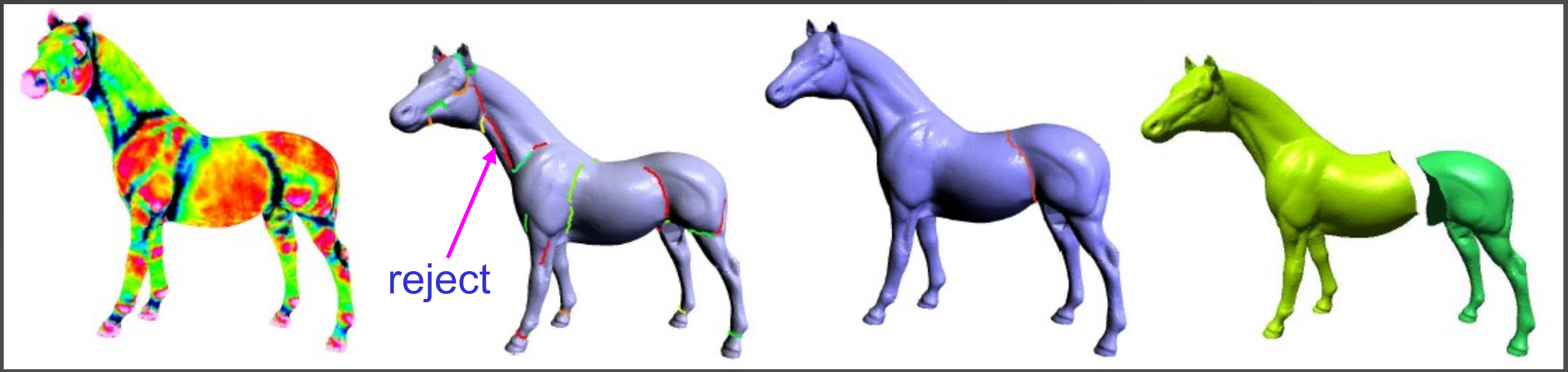
Classification of approaches

- Surface-based: most common
  - Boundary-based : cut shape into parts
    - – feature (edge) extraction followed by cut formation
  - Region growing, e.g., watershed
  - Clustering: k-means, fuzzy clustering, spectral clustering
- Volume-based: similar but work with voxels

Within each class, skeleton-, surface-, or volume-based, there can be model- or data-driven approaches

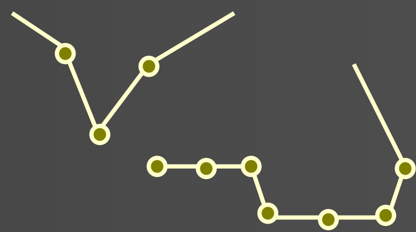
Boundary-based & model-driven

- **Mesh scissoring**, basic steps:
  1. Feature edge extraction from a dense mesh
  2. Feature selection — rely on user intervention for feature rejection
  3. Contour completion to form closed cuts
  4. Post processing of contours to better adapt to real features



[Lee et al. 04]

Region-growing: watershed (aside)

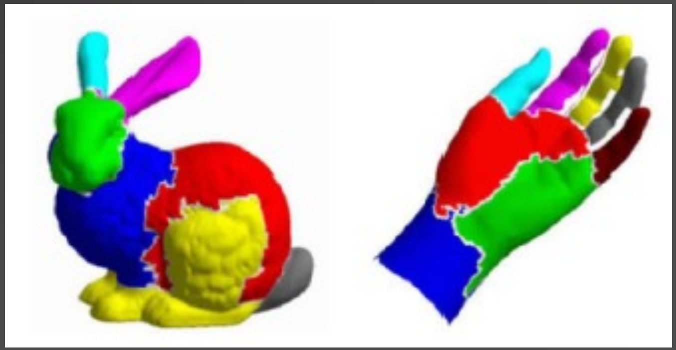


Think about **water flowing down to bottom of basins**

1. Assign a weight, e.g., curvature, to each vertex
2. Threshold weights to identify **local minima or minima plateau**
3. Flow each unlinked vertex *v* : link *v* to neighbor with **smallest weight**
4. Continue until reaching a local minima or minima plateau
5. All vertices that can flow to such a minima or minima plateau belong to the same segment
6. Flow is **from cut boundary (dividing water basins) to region centers**

Watershed: pros and cons (aside)

- Pro: no need to specify how many segments — fairly automated
- Pro: pretty fast algorithms, e.g., using fast marching
- Con: prone to **over-segmentation**, so need to post merging
- Con: boundaries may not be smooth



Clustering-based approaches

- ***k*-means clustering** in spatial domain [Shlafman et al. 02]
- **Fuzzy** *k*-means clustering [Katz & Tal 03]
- *k*-means clustering in the **spectral domain** [Liu & Zhang 04]

- Other clustering methods are possible; there are many alternatives!

Clustering problem

- Given a set of data points, group them into clusters of similar points
- An extremely important problem in machine learning and Big Data
  - Pattern classification, e.g., grouping of geometric shapes, protein structures, faces, gestures, customers, etc.
  - Vector quantization for compact representations
- Also a challenging problem: what is a cluster?

> "… Classification, in its widest sense, is necessary for the development of language which consists of words which help us recognize and discuss the different types of events, objects, and people we encounter."
>
> — Everitt, Landau, and Leese, *Cluster Analysis*, 4th edition, 2001

Important issues

- Measurement of proximity/affinity/similarity between data is KEY!
  - How to mix binary data, category data, with numerical data
  - Continuous data with variables of **different types and scales**
  - Missing data values
- How to determine number of clusters?
  - Try many of them and see what gets the best result
- How to evaluate quality of clustering results
  - Various measures: Fisher's criterion, silhouette coefficients, etc.

$$\gamma(A,B) = \frac{(\mu_A - \mu_B)^2}{\sigma_A^2 + \sigma_B^2}$$

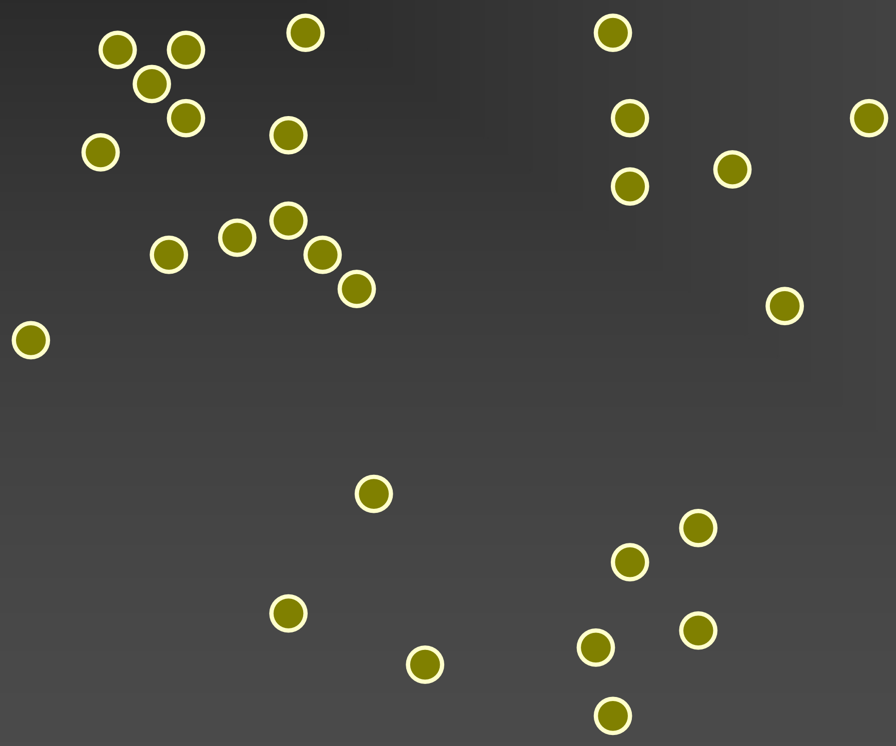
K-means clustering

- Perhaps the most well-known, also known as Lloyd or Lloyd-Max algorithm
- Given a set of data points, compute *K* clusters S_j that **minimize the total squared distances from the points to their respective cluster centers** μ_j

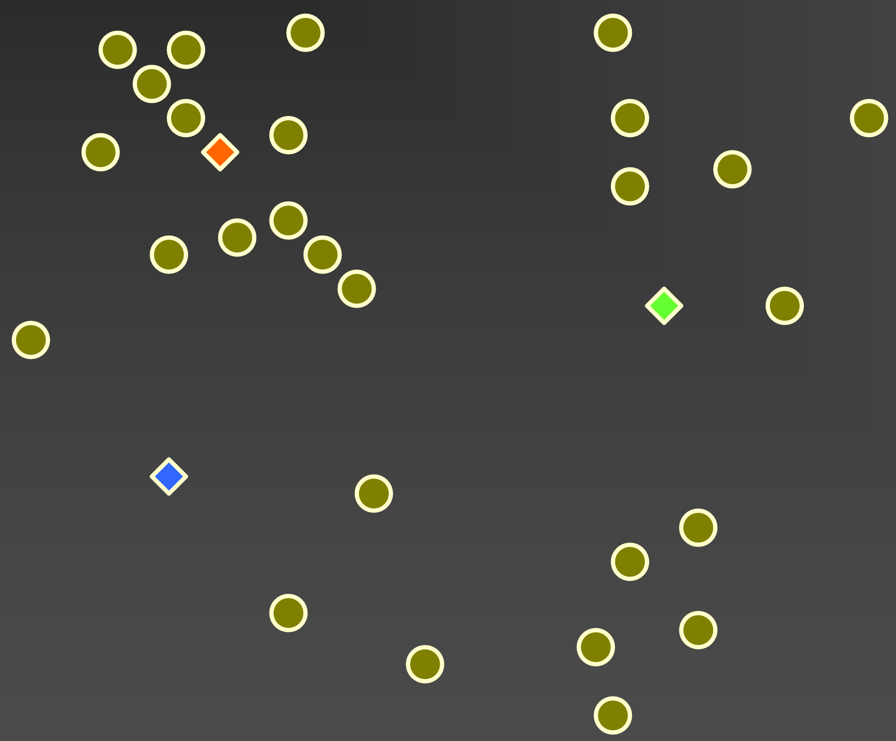
$$\text{minimize} \quad J = \sum_{j=1}^{K} \sum_{x \in S_j} \left\| x - \mu_j \right\|^2$$

- An **unsupervised learning** technique and NP-hard
- *Algorithm:* iteratively assigns data to its closest cluster center and then re-compute the cluster centers, starting with random centers (vs. *k*-medoids)
- Bad start can lead to (numerous) bad **local minima**

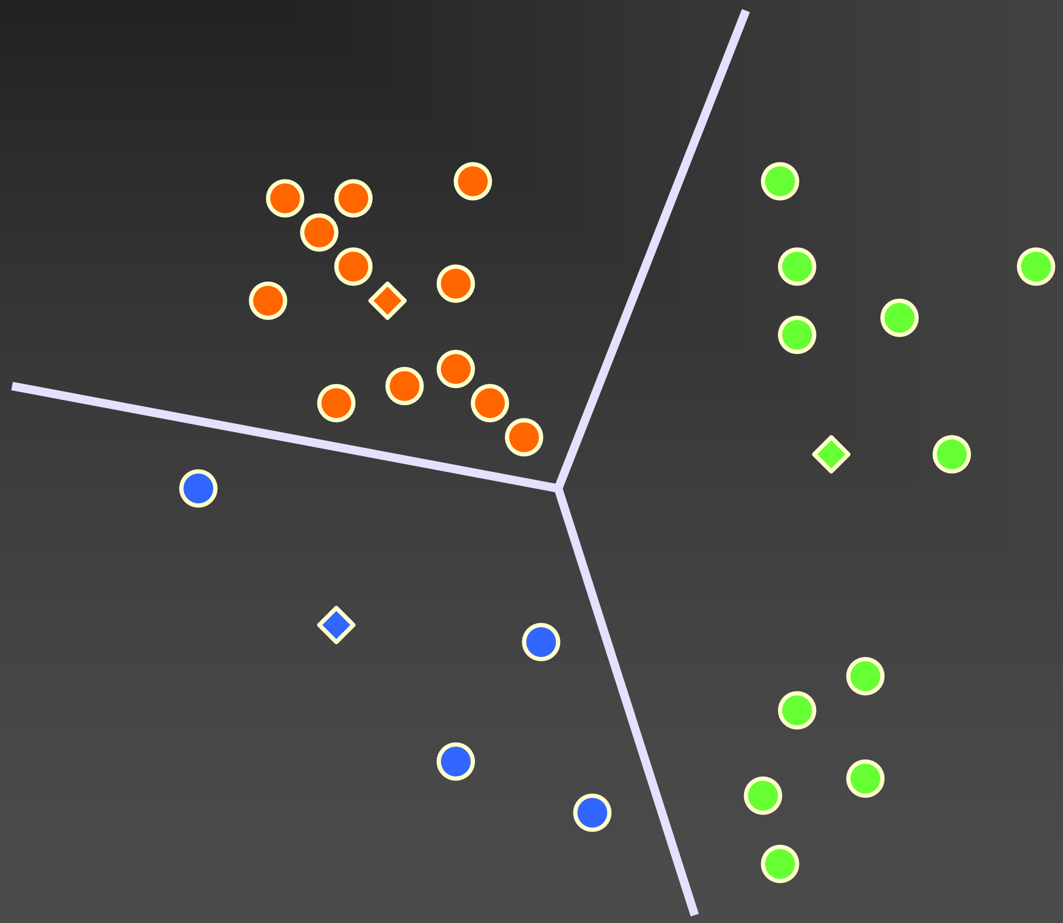
k-means illustrated: *k* = 3



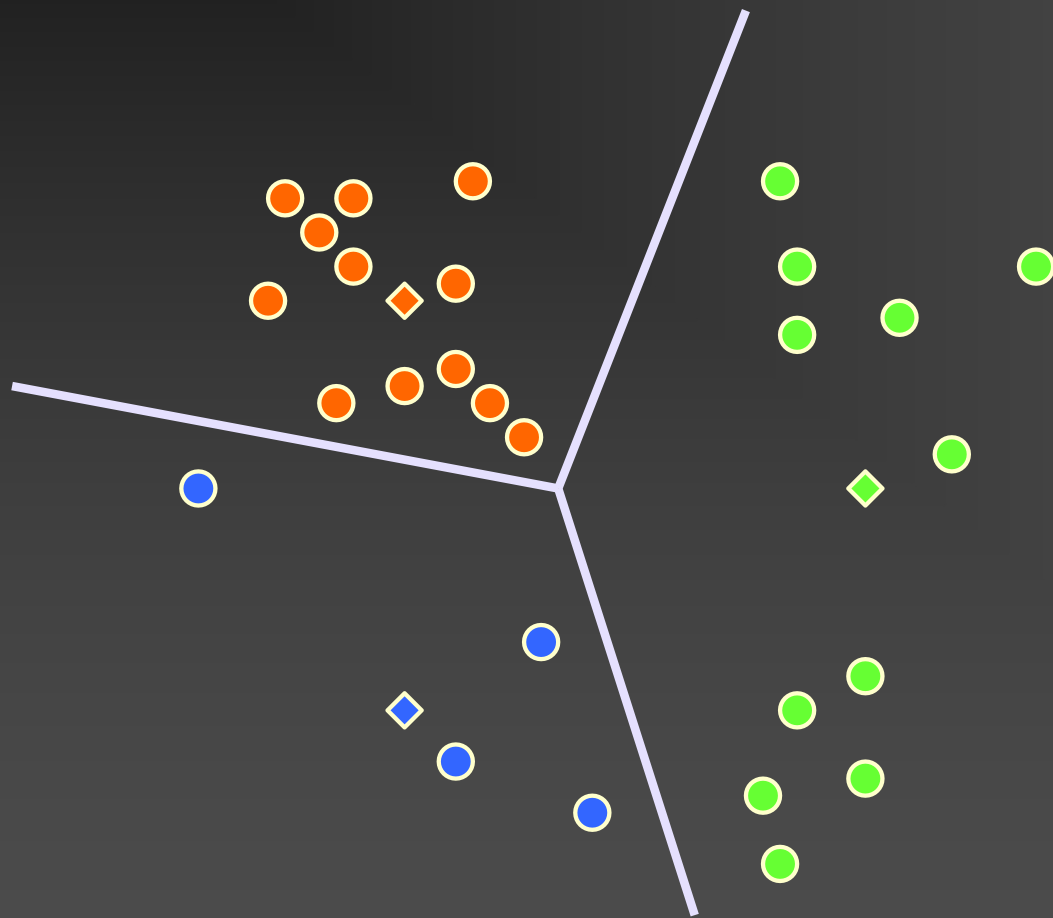
Random cluster centers/centroids



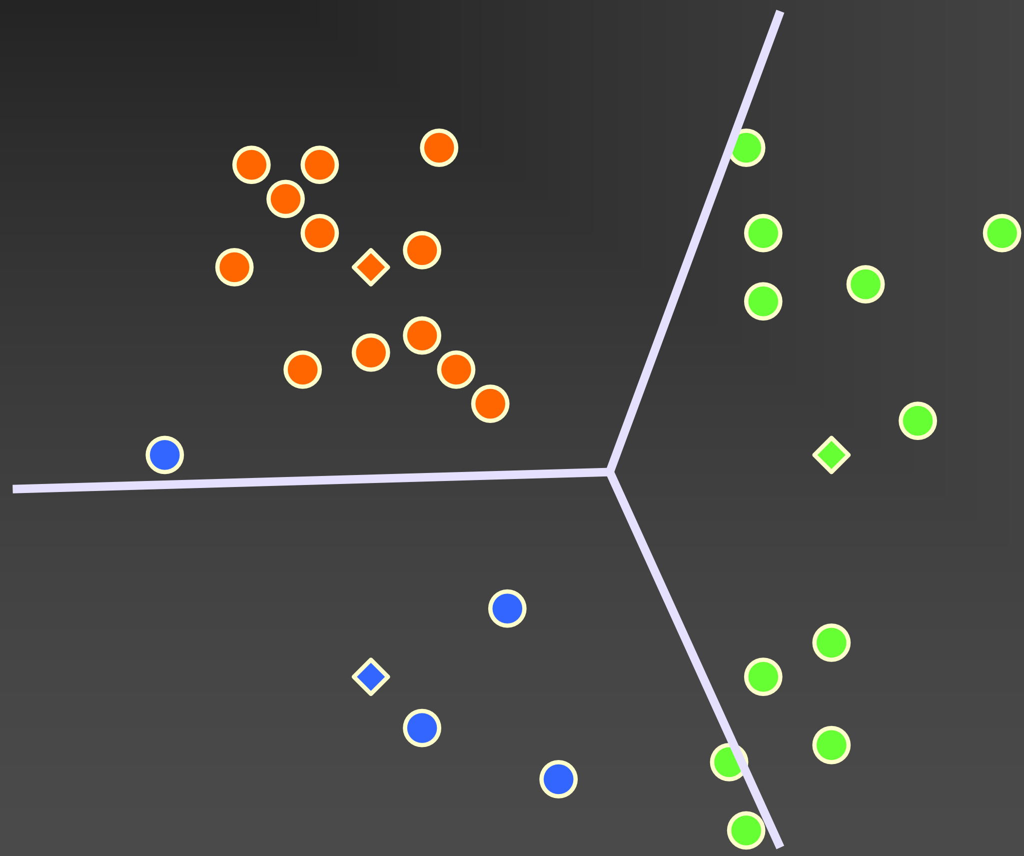
Assign points to cluster centers (Voronoi)



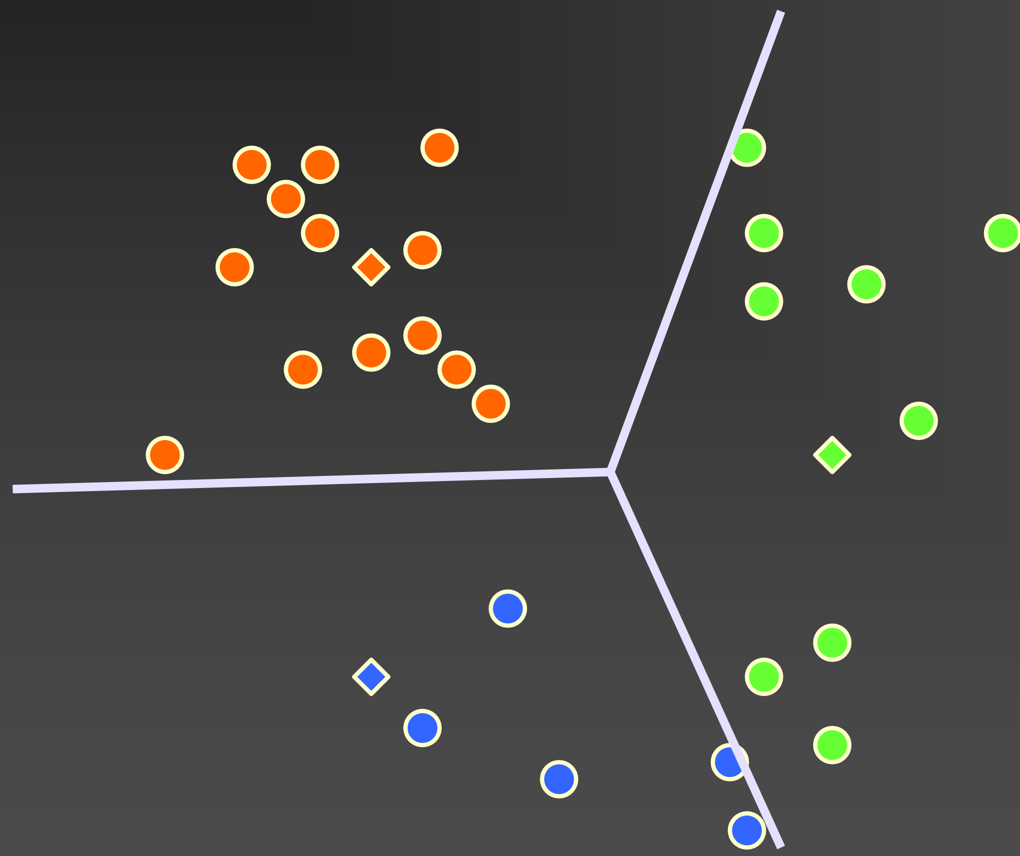
Re-compute cluster centroids



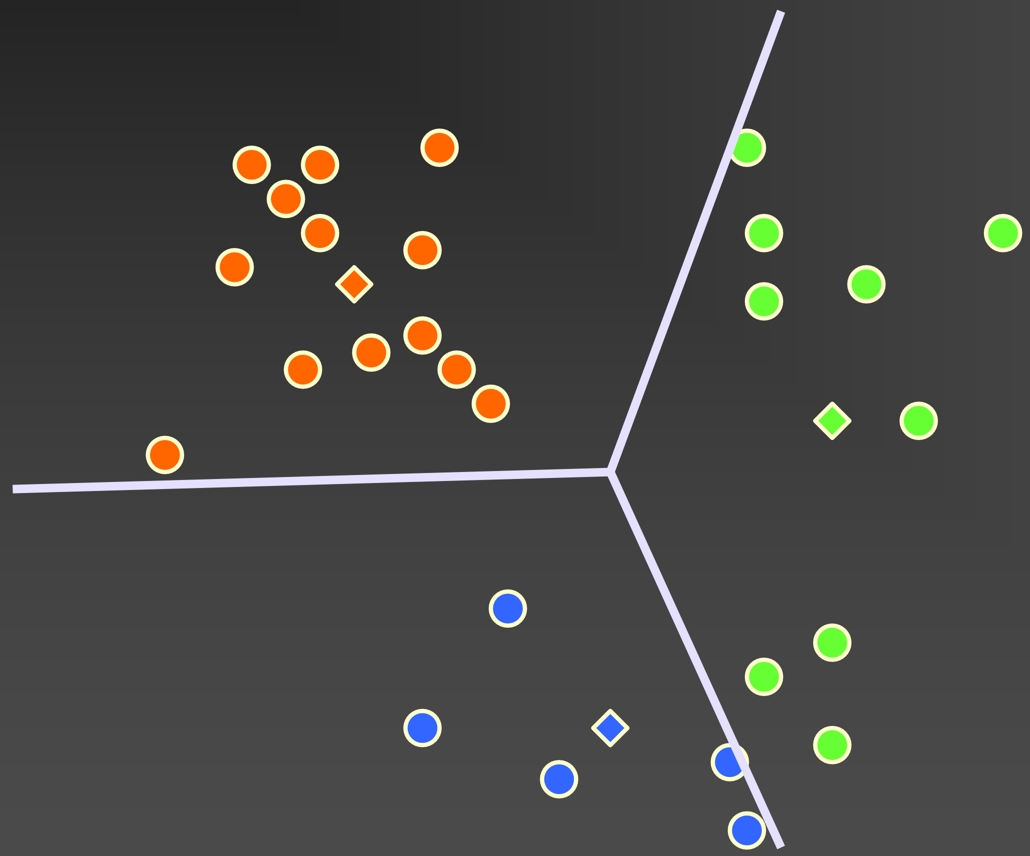
Re-computer Voronoi diagrams



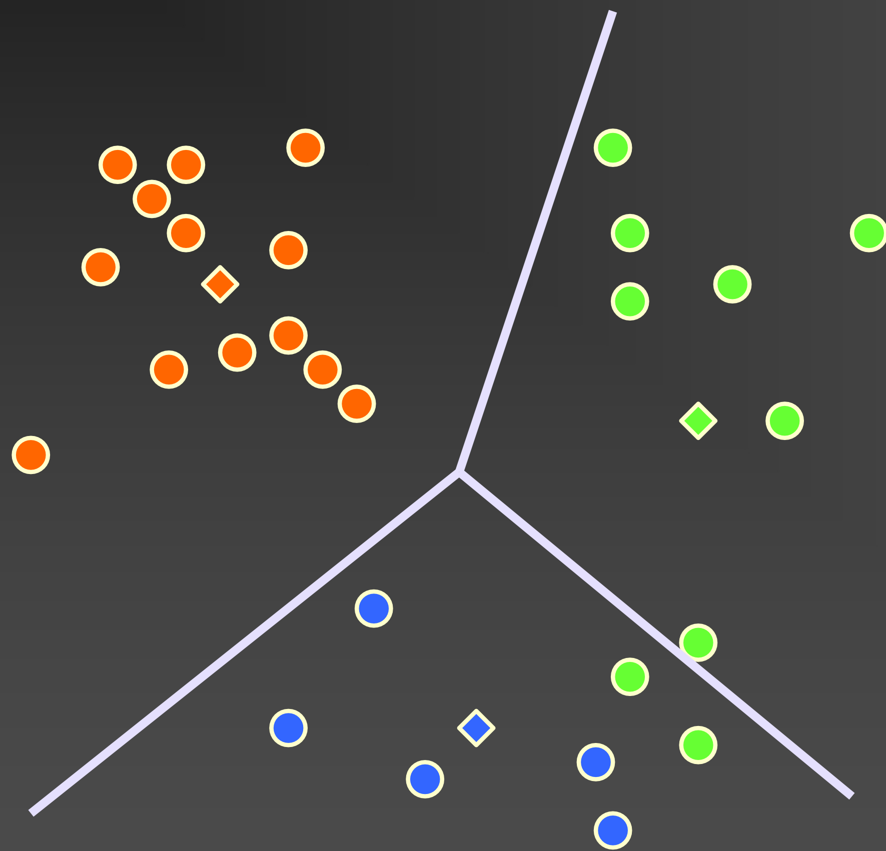
Re-assign points to cluster centers



Iterate



Iterate



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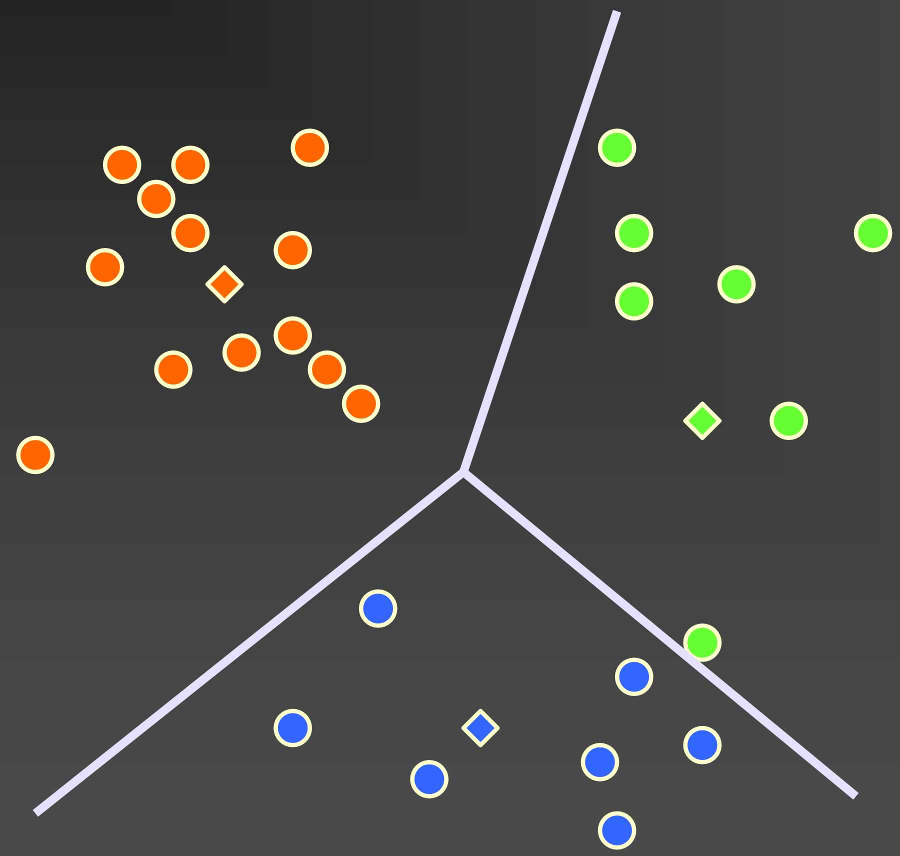

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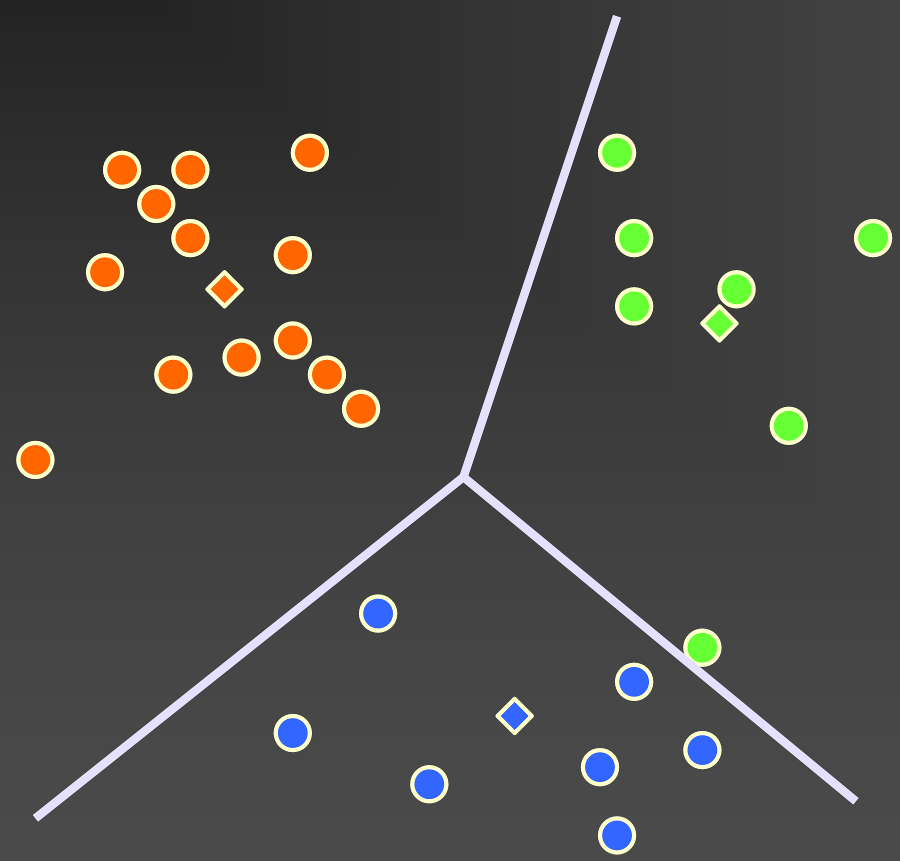
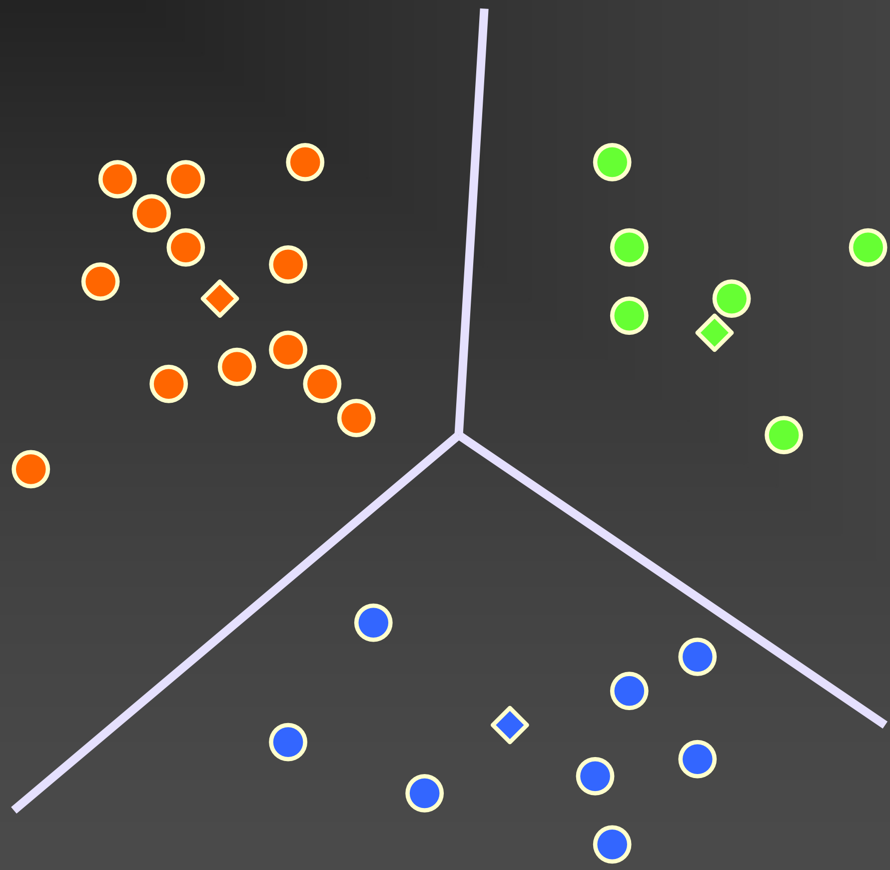
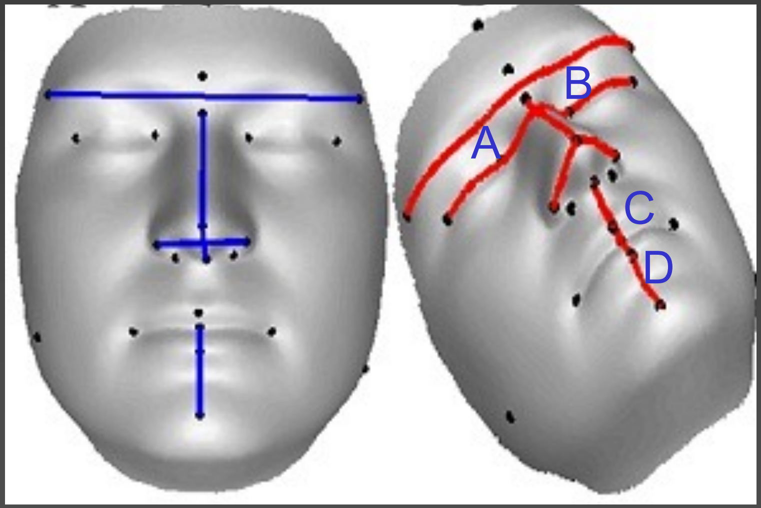


Converging



k-means for mesh segmentation

- Compute pair-wise distances between mesh faces — $\Theta(n^2 \log n)$
- Distances have both **geodesic** and **angle** components
  - Place more emphasis on concave angle distances due to **minima rule**
  - So faces separated by **concave regions** are less likely to be clustered



d(A, B) < d(C, D)

k-means for mesh segmentation

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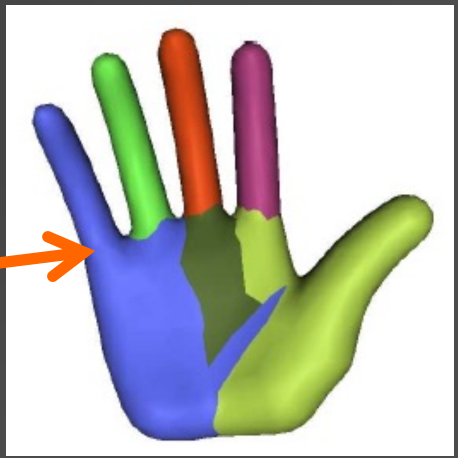
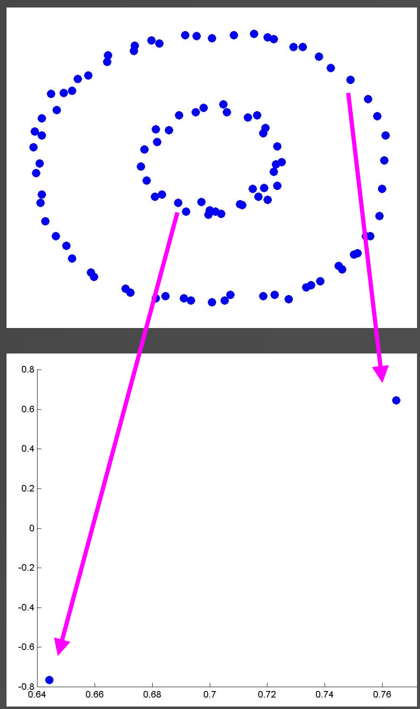
- Distances have both **geodesic** and **angle** components
  - Place more emphasis on concave angle distances due to **minima rule**
  - So faces separated by **concave regions** are less likely to be clustered
- All *k*-means approaches face:
  - Local minima
  - How to choose *k* – not easy
  - **Chaining over featureless regions**
  - Jaggie boundaries – no boundary optimization



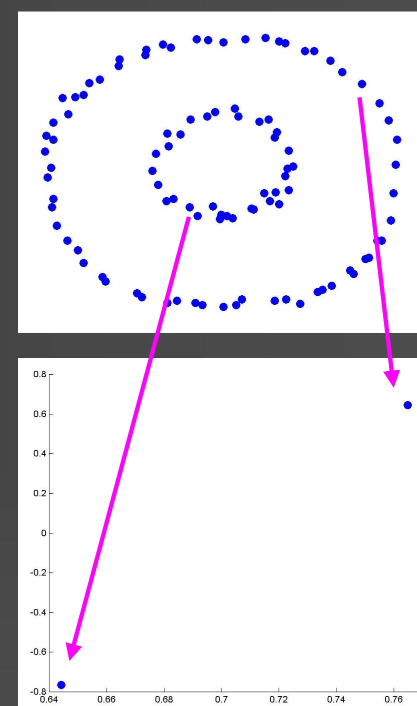
Improvements over classical *k*-means

- Fuzzy *k*-means [Katz & Tal 03]
  - Identify fuzzy region containing faces whose membership is uncertain
  - **Explicit graph min-cut** over fuzzy region
  - Iterative and expensive — $\Theta(n^2 \log n)$
- Spectral *k*-means [Liu & Zhang 04]
  - Clustering is **more pronounced in spectral domain**
  - No need for graph min-cut
  - Improved boundary
  - Transform mesh elements vis **spectral embedding**

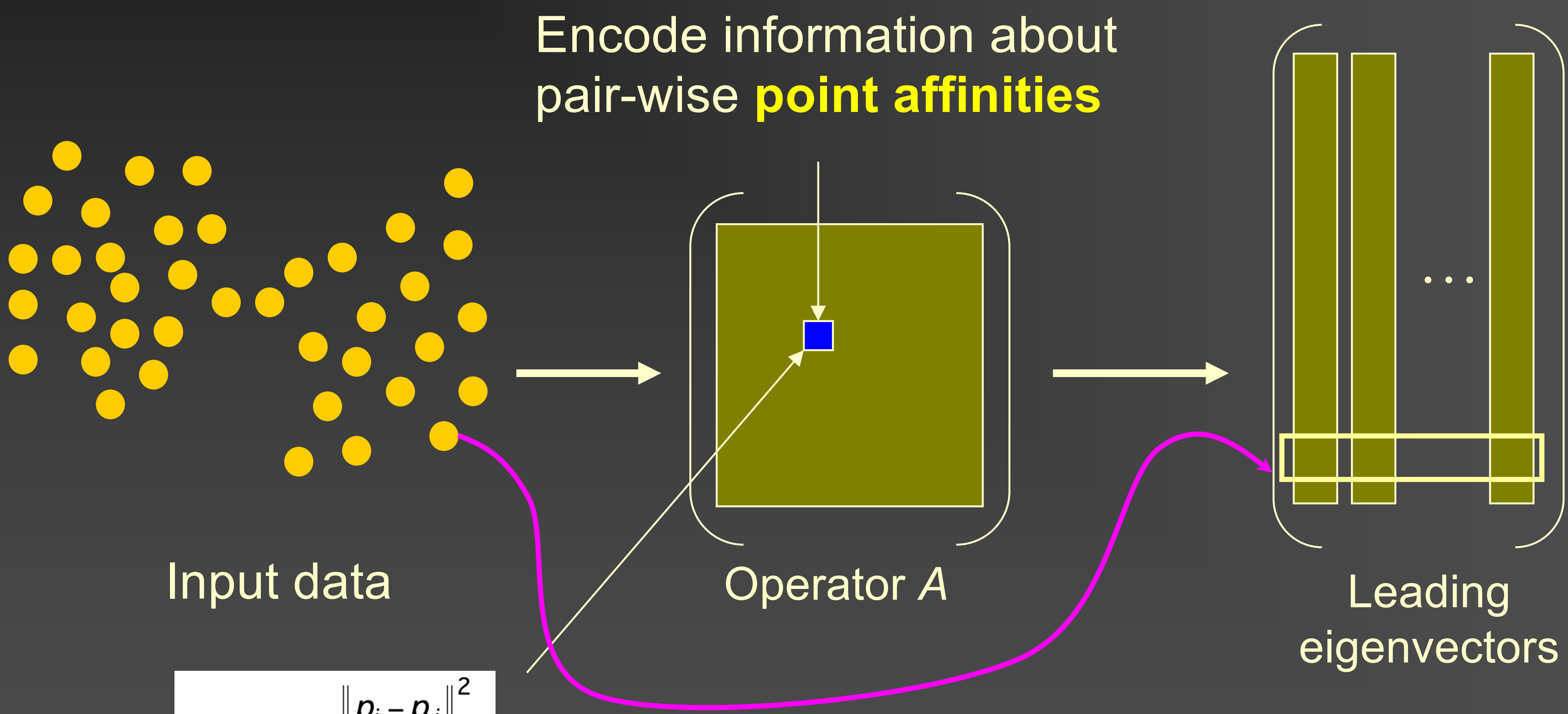


Spectral embedding (aside)

- Use eigen-decomposition of graph adjacency (or Laplacian) matrix
- Generalize adjacencies to encode **pair-wise distances or affinities**
  - Affinities encode pair relations between mesh elements
- Spectral *k*-d embedding from *k* leading eigenvectors
- Use of Laplacian matrix $L = D - A$ is also possible
- Example:
  - ***k*-means clustering in the spectral domain**
  - Distance is Euclidean and using a Gaussian



Spectral clustering (aside)



$$A_{ij} = e^{-\frac{\|p_i - p_j\|^2}{2\sigma^2}}$$

Spectral clustering (aside)

eigenvectors

In spectral domain

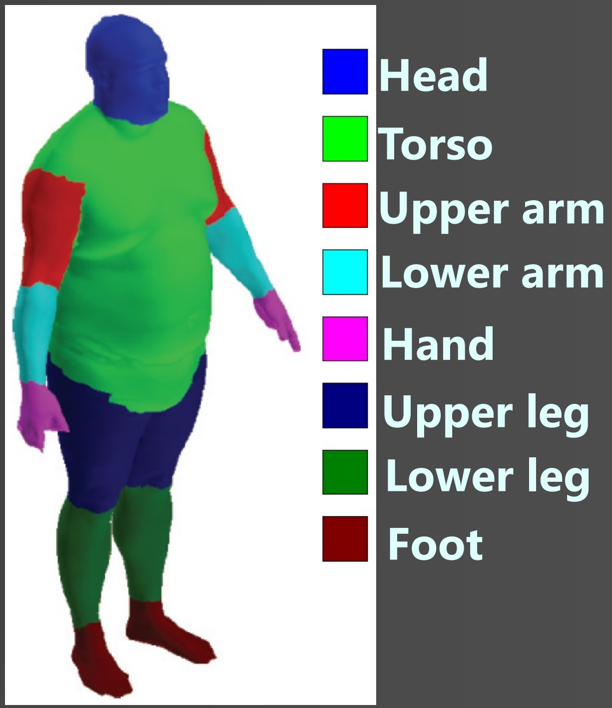
Perform any clustering

Key app in computer graphics: shape segmentation, also in surface reconstruction, etc.

A lot of coverage from Machine Learning literature

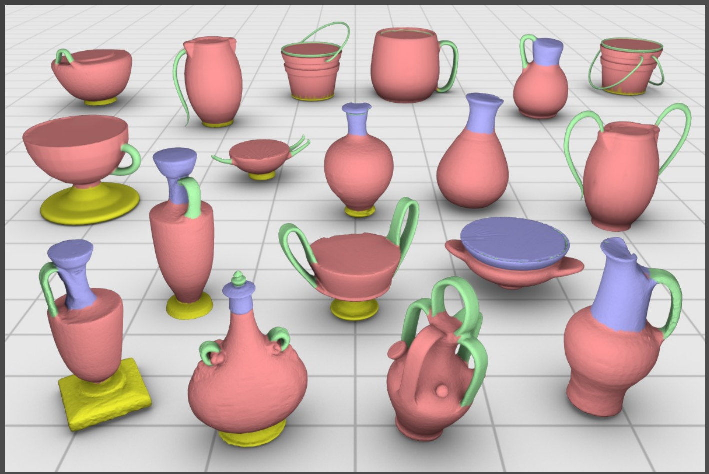
Data-driven mesh segmentation

- Supervised learning [Kalogerakis et al. 09]
  - Turn segmentation into a **labeling** problem
  - Learn from **human labeling of meshes**
  - 380 human labeled meshes over 19 categories

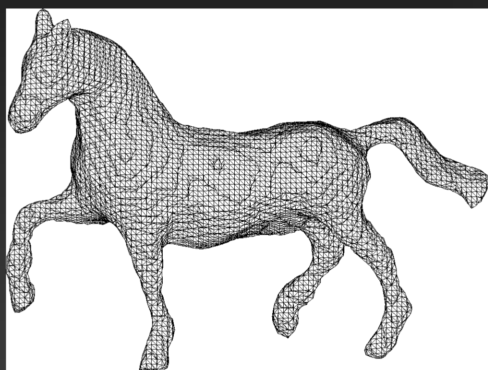


Data-driven mesh segmentation

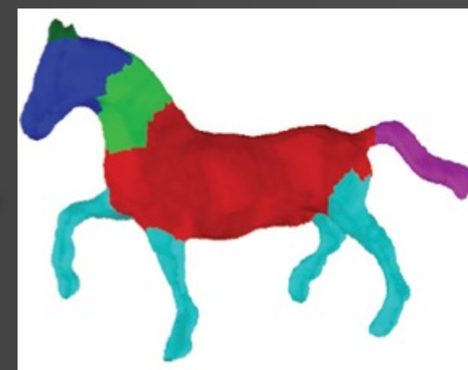
- Supervised learning [Kalogerakis et al. 09]
  - Turn segmentation into a **labeling** problem
  - Learn from **human labeling of meshes**
  - 380 human labeled meshes over 19 categories
- Unsupervised learning [Sidi et al. 11]
  - **Co-analysis: analyzing a set** together
  - Weak knowledge utilized
  - Resulting in a **co-segmentation** over set
- Semi-supervised learning [Wang et al. 12]



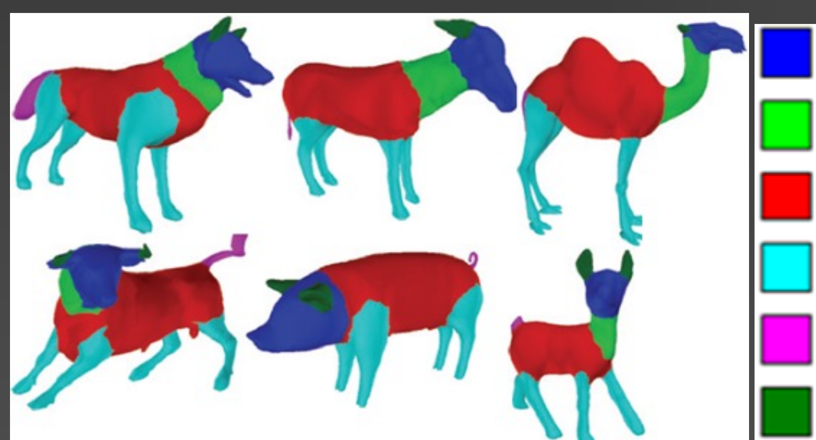
Learning mesh segmentation (2009)



Input Mesh



Labeled Mesh

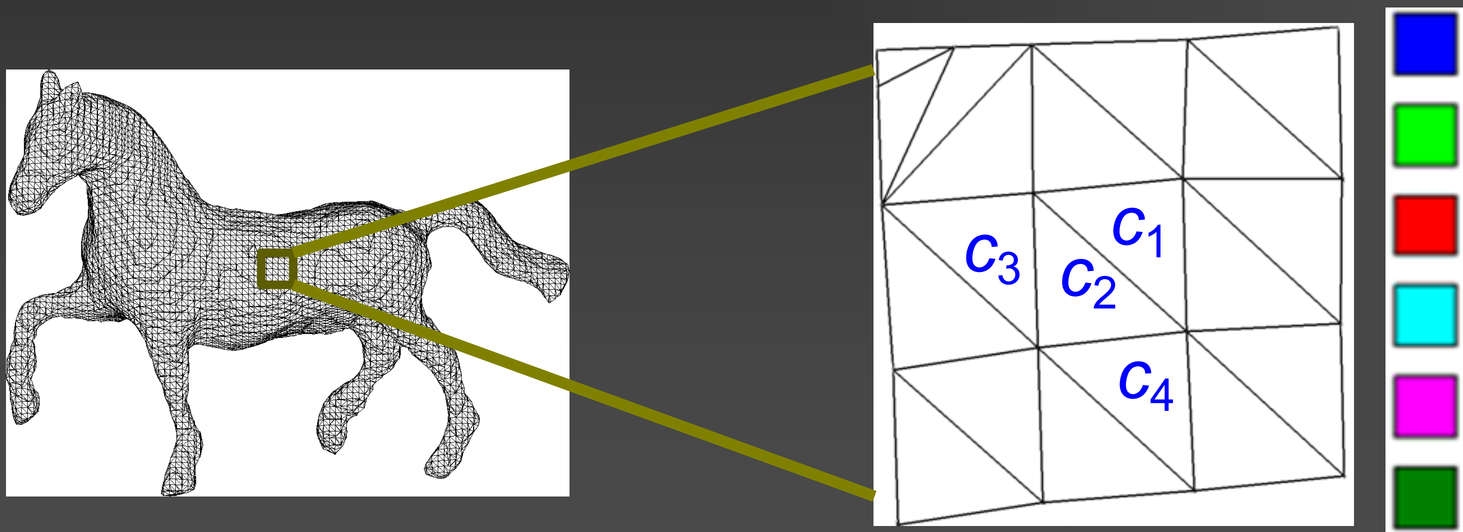


Head
Neck
Torso
Leg
Tail
Ear

Training Meshes

Labeling problem

- Each face is encoded with a **(unary) feature** vector (curvature, etc.)
- **Edge feature** encodes label compatibility, geodesic/angle distance
- Face labeling solved by a **classifier** based on training data



$c_1, c_2, c_3 \in C$

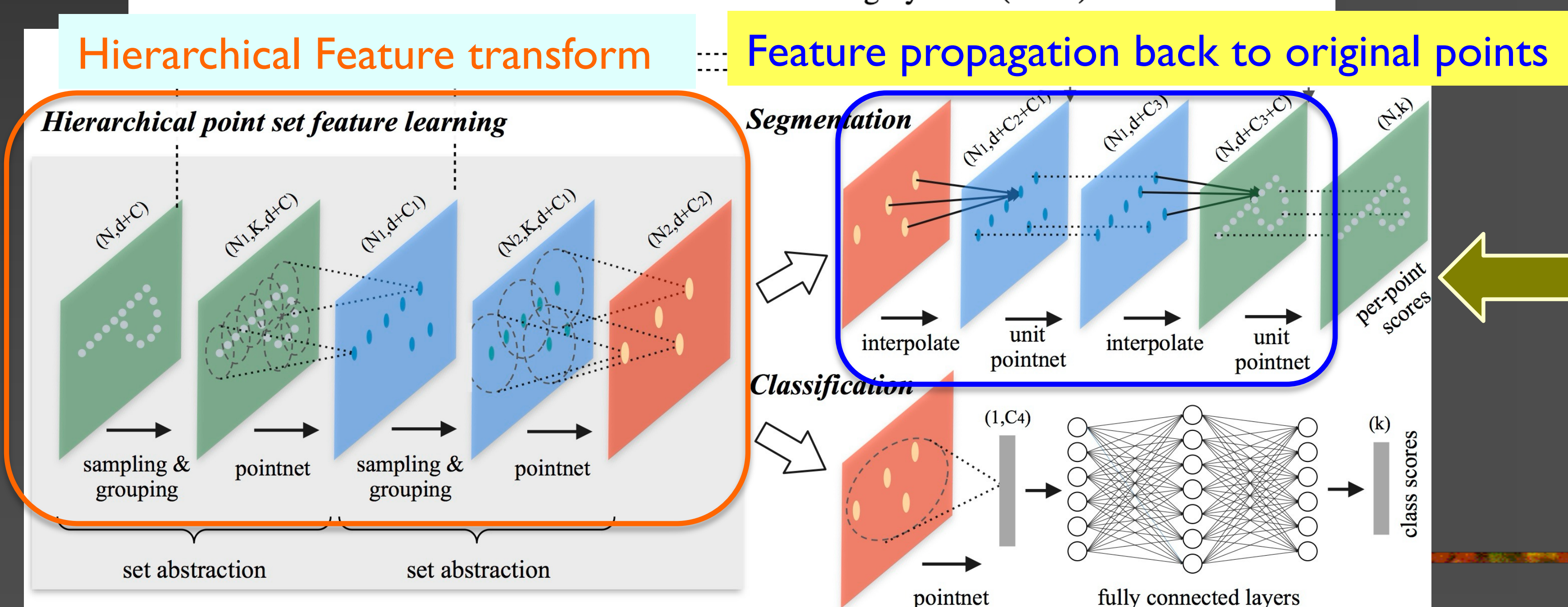
$C = \{$ head, neck, torso, leg, tail, ear $\}$

Modern-day segmentation using NNs

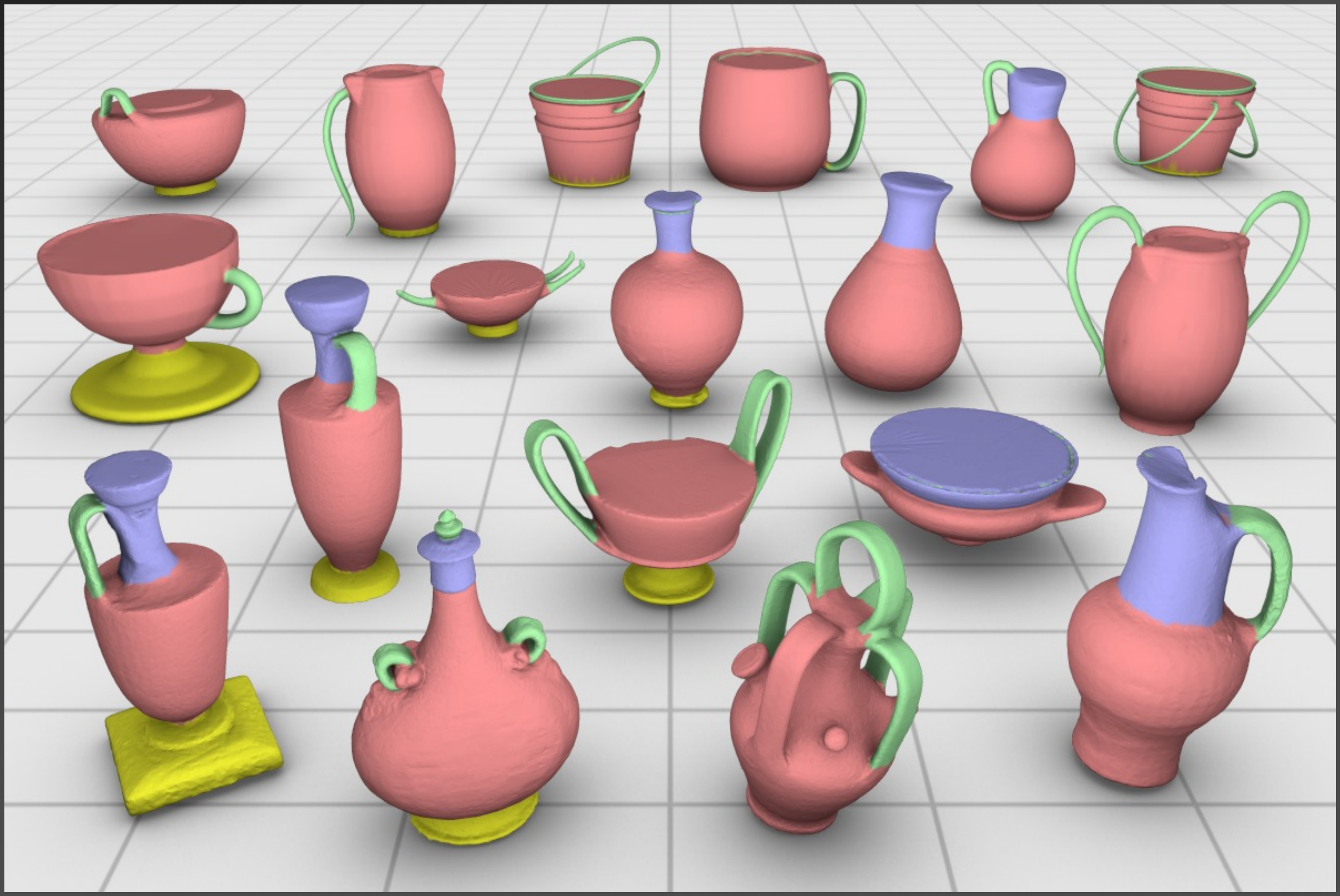
PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space

Charles R. Qi   Li Yi   Hao Su   Leonidas J. Guibas
Stanford University

Conference on Neural Information Processing Systems (NIPS) 2017



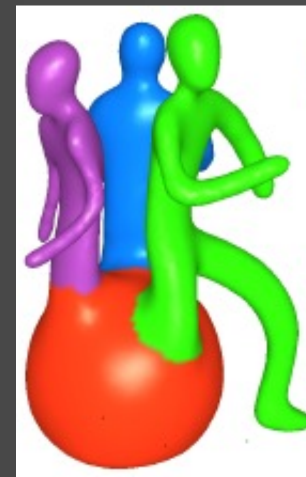
Unsupervised co-segmentation (aside)

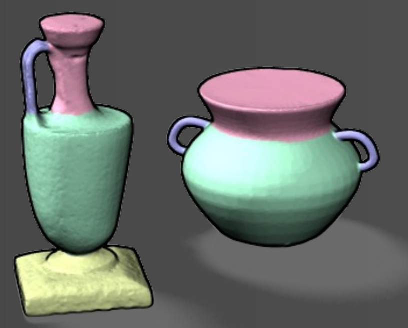


[Sidi et al. 11]

From one, two, to a set (aside)

- Classical segmentation: one shape
- Correspondence: a pair of shapes





[Sidi et al. 11]

From one, two, to a set (aside)

- Classical segmentation: one shape
- Correspondence: a pair of shapes
- **Can we gain by having a set?**
  - A set should contain more information
  - Training set is useful, but expensive to obtain
  - Final result is a **segmentation over the entire set: co-segmentation**

[Sidi et al. 11]

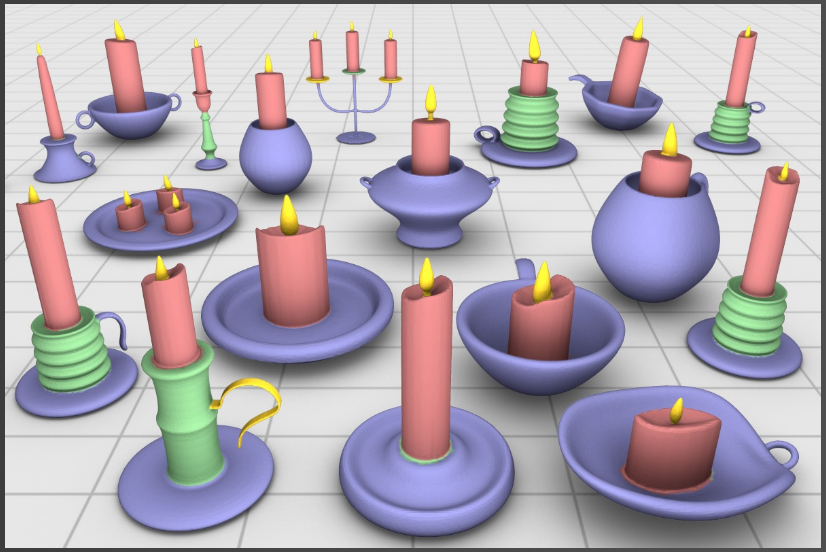
Unsupervised (weakly) learning (aside)

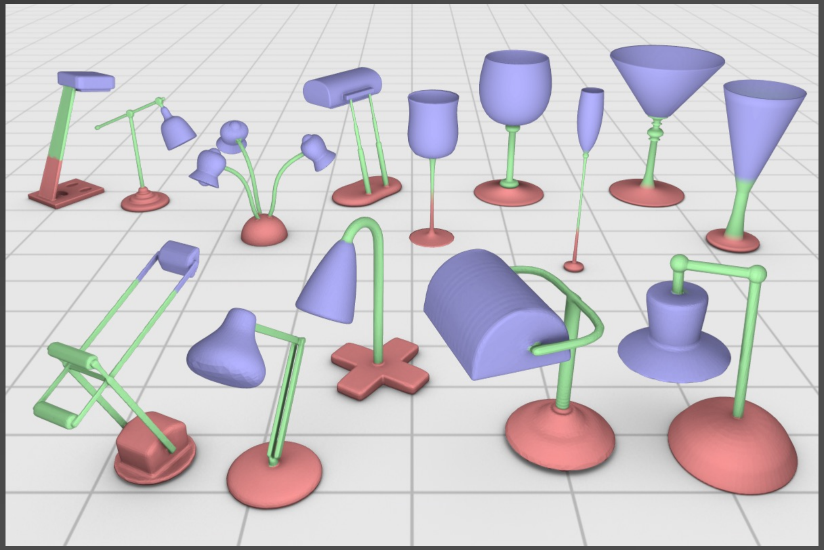
- No training data to define prior knowledge
- Everything is learned from the input set
- Weak knowledge: **input set belongs to the same family,** e.g., all cars, chairs, or vases, ...
- Key criterion is the **consistency** of the segmentation over whole set

[Sidi et al. 11]

Power of a set (aside)

- Two dissimilar parts maybe clustered via **"third parties" in the set**
- The set provides necessary **linkage**





[Sidi et al. 11]

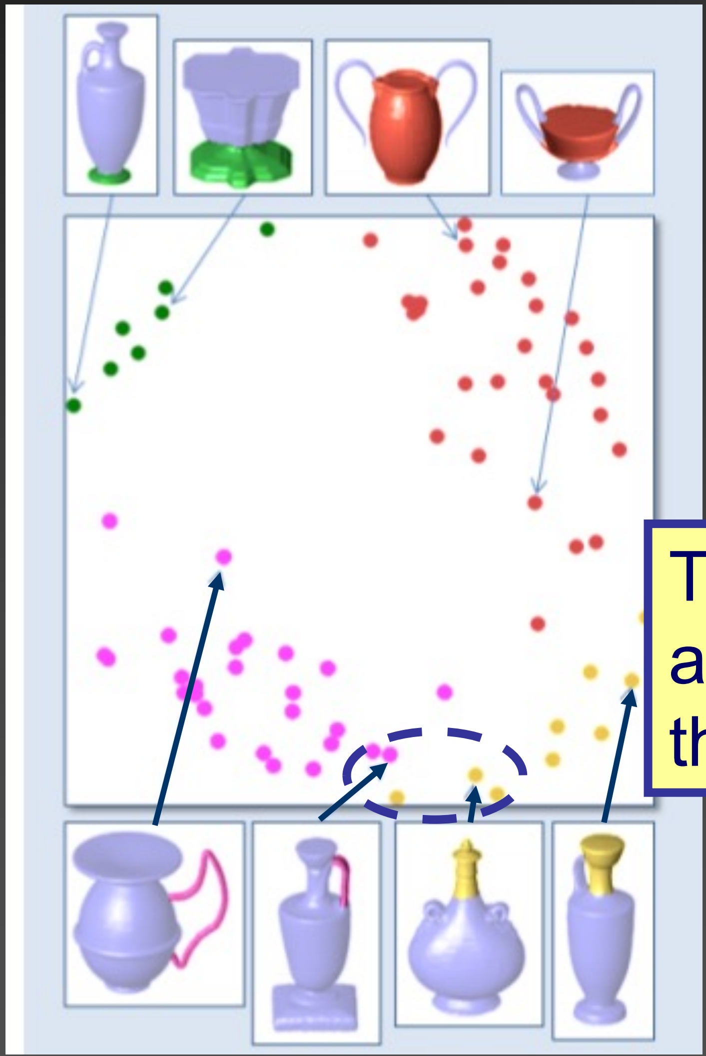
How it works … (aside)

- Start by identifying **candidate shape segments** in each shape
- Candidates segments obtained by any reasonable existing algorithm
  - Key is to obtain a consistent segmentation across the set!
- Map each candidate segment into a feature space
- Perform clustering analysis …

[Sidi et al. 11]

How it works … (aside)

Feature space



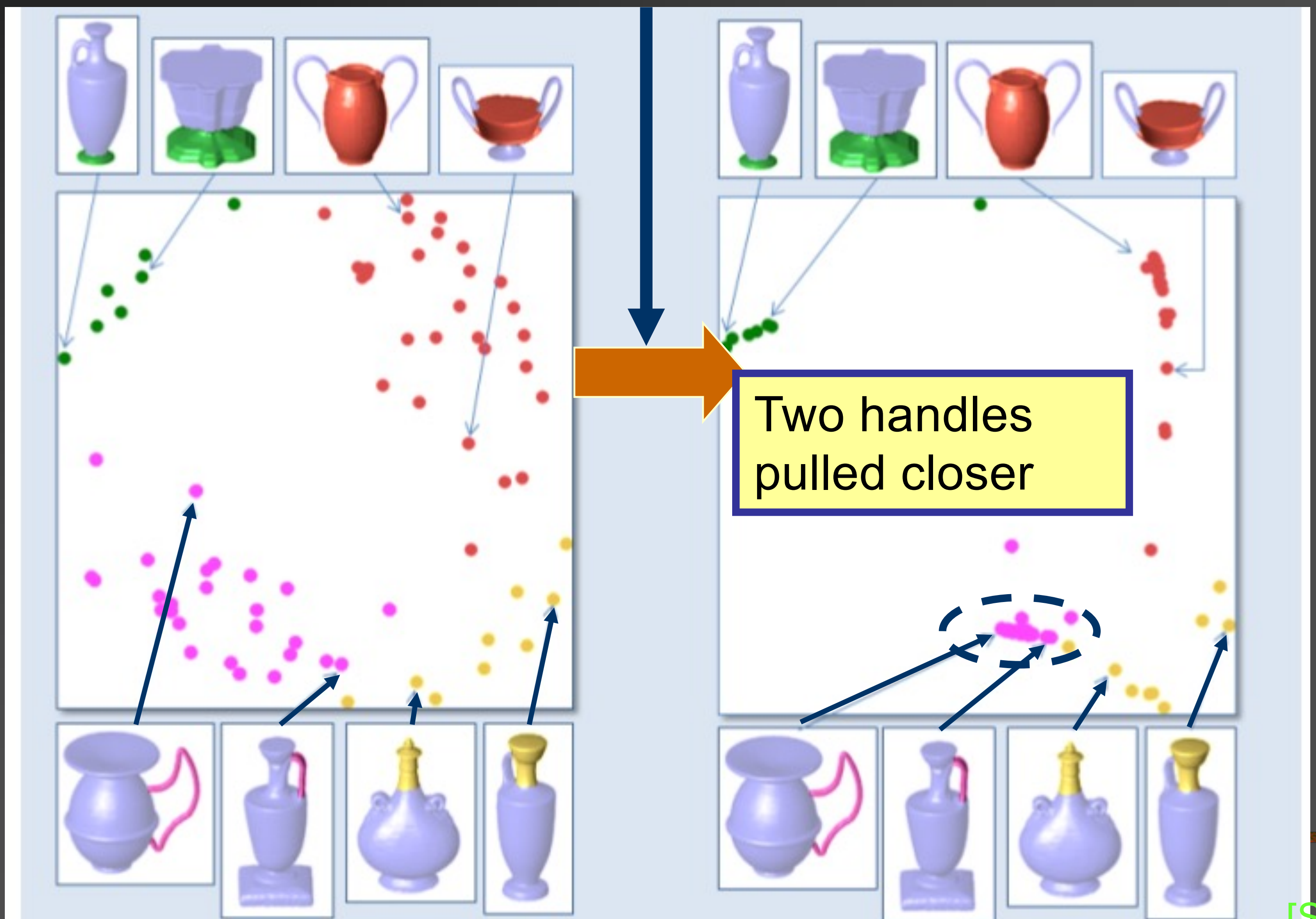
Candidate shape segments mapped to some feature space

Two different kinds of segments are closer to each other than to their respective matches

[Sidi et al. 11]

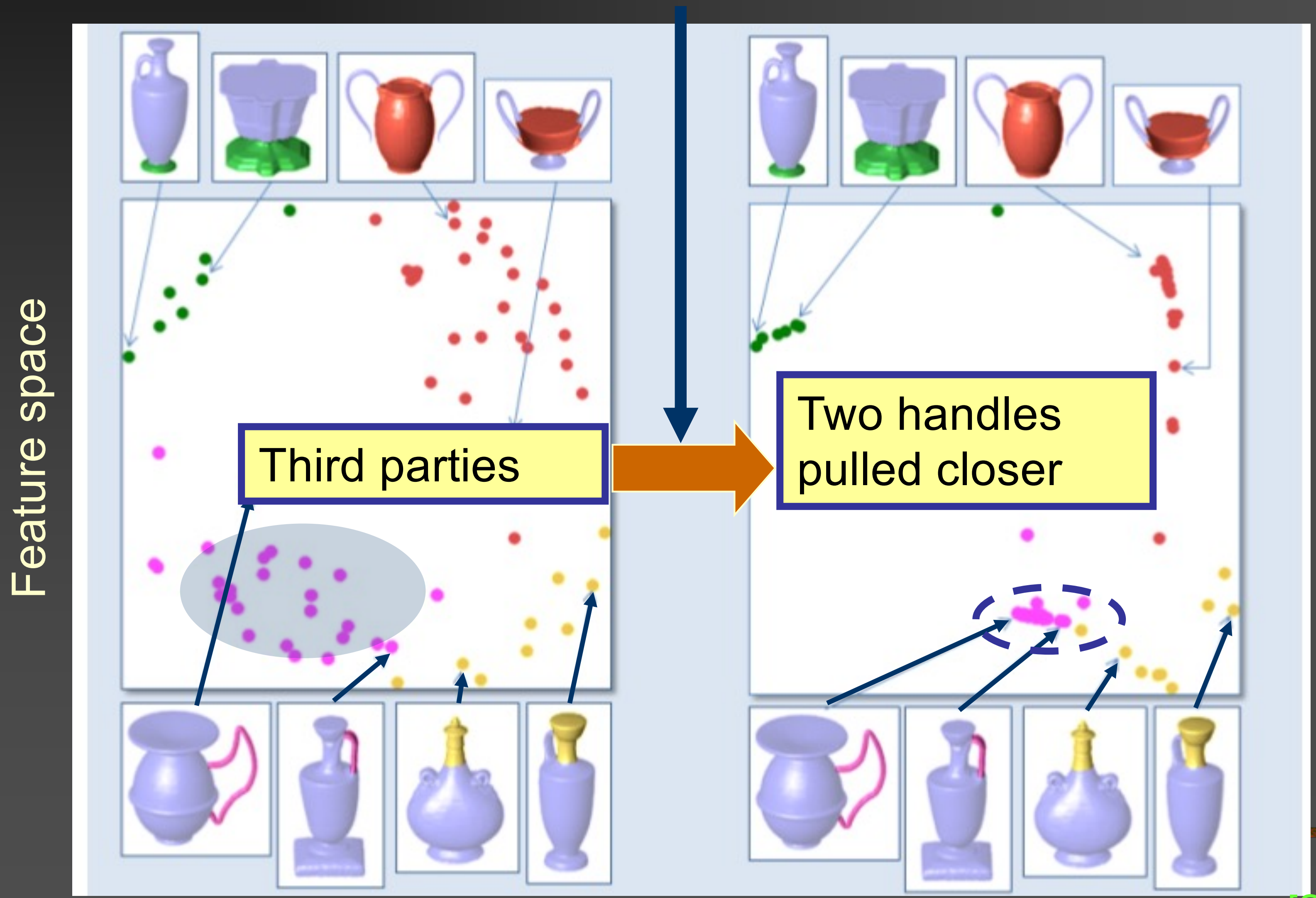
After a "spectral transform" (aside)

Feature space



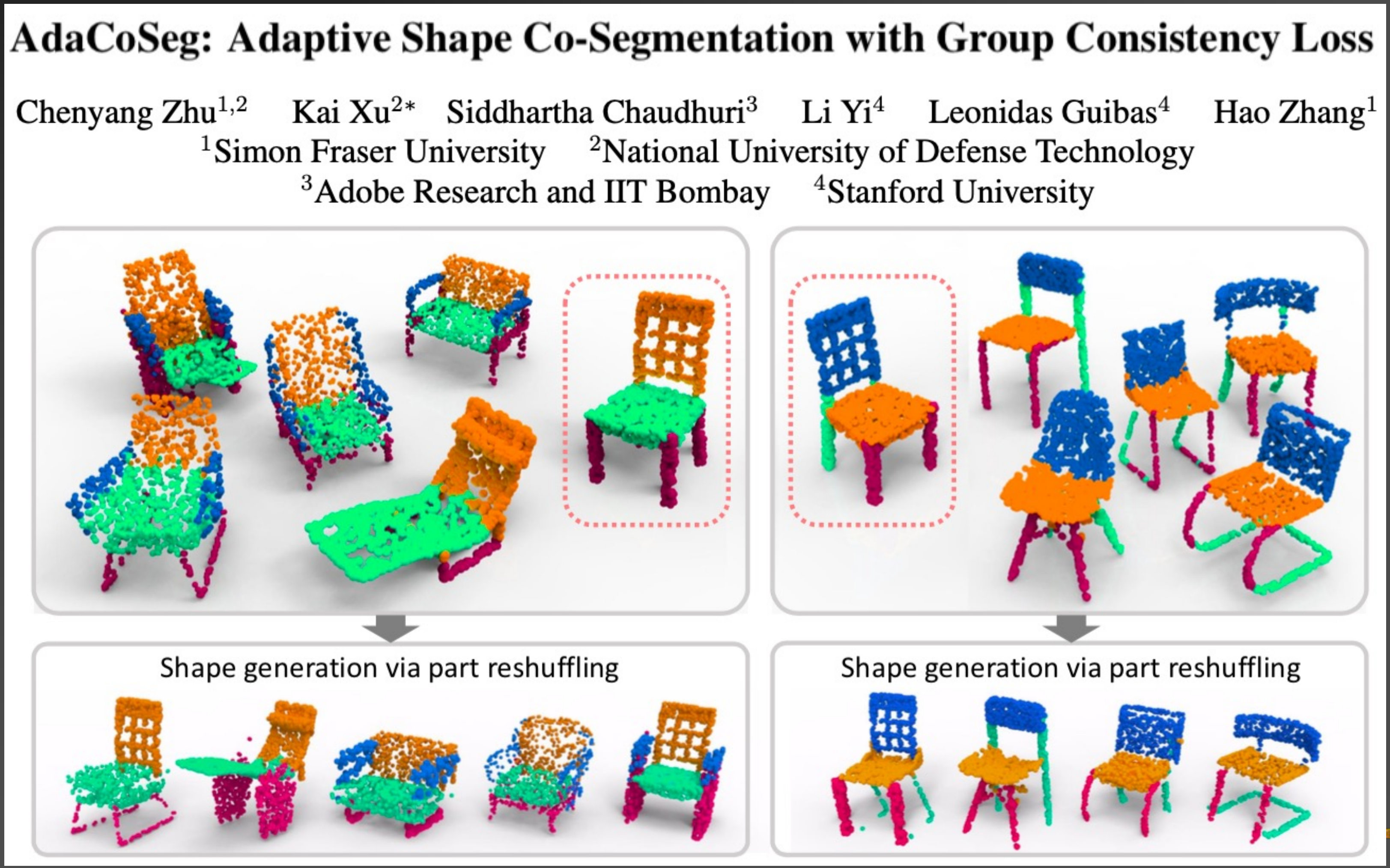
[Sidi et al. 11]

Connection made by “3rd parties” (aside)



[Sidi et al. 11]

Deep learning co-segmentation (aside)



[Zhu et al. 22]

Semi-supervised: active learning

- **Human-in-the-loop** machine learning
- Key is to **minimize human-labeling** efforts: a trade-off

Active Co-Analysis of a Set of Shapes

Yunhai Wang[*] Shmulik Asafi[†] Oliver van Kaick[‡] Hao Zhang[‡] Daniel Cohen-Or[†] Baoquan Chen[*]
[*]Shenzhen VisuCA Key Lab/SIAT [†]Tel-Aviv University [‡]Simon Fraser University

[Wang et al. 12]

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Initial segmentation: supervised or unsupervised

[Wang et al. 12]

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Human labeling: cannot links plus must links

[Wang et al. 12]

Semi-supervised: active learning

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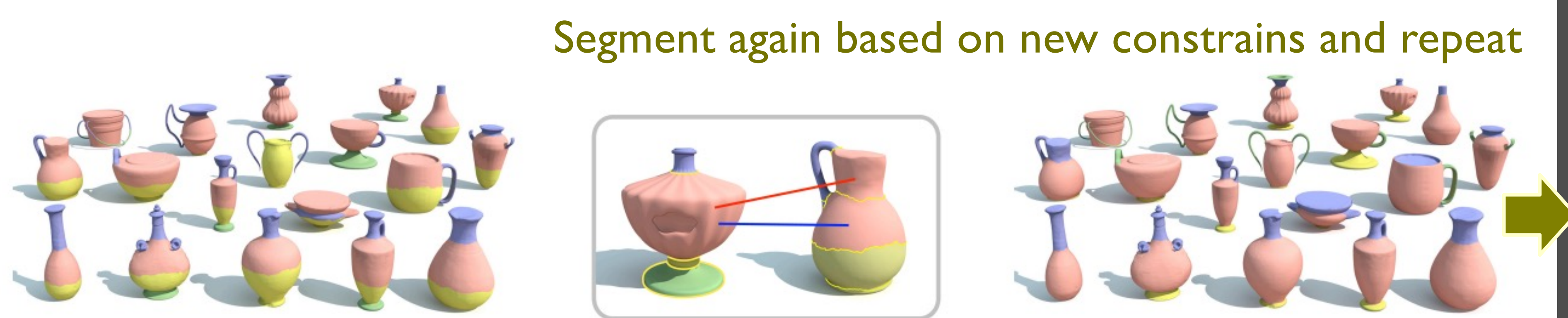
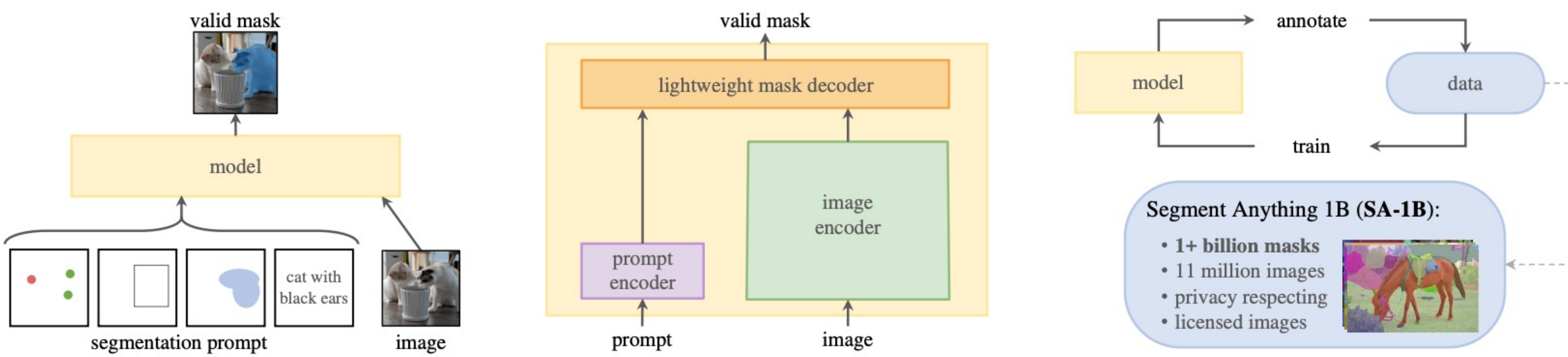


[Wang et al. 12]

Zero-shot with LFMs (aside)

Segment Anything

Alexander Kirillov[1,2,4] Eric Mintun[2] Nikhila Ravi[1,2] Hanzi Mao[2] Chloe Rolland[3] Laura Gustafson[3]
Tete Xiao[3] Spencer Whitehead Alexander C. Berg Wan-Yen Lo Piotr Dollár[4] Ross Girshick[4]
[1]project lead [2]joint first author [3]equal contribution [4]directional lead
Meta AI Research, FAIR



(a) **Task**: promptable segmentation (b) **Model**: Segment Anything Model (**SAM**) (c) **Data**: data engine (top) & dataset (bottom)

[Kirillov et al. 23]