GENERATIONS / VANCOUVER 12-16 AUGUST
SIGGRAPH2018

Photography &
Recording Encouraged

PERCEPTION-DRIVEN SEMI-STRUCTURED BOUNDARY VECTORIZATION

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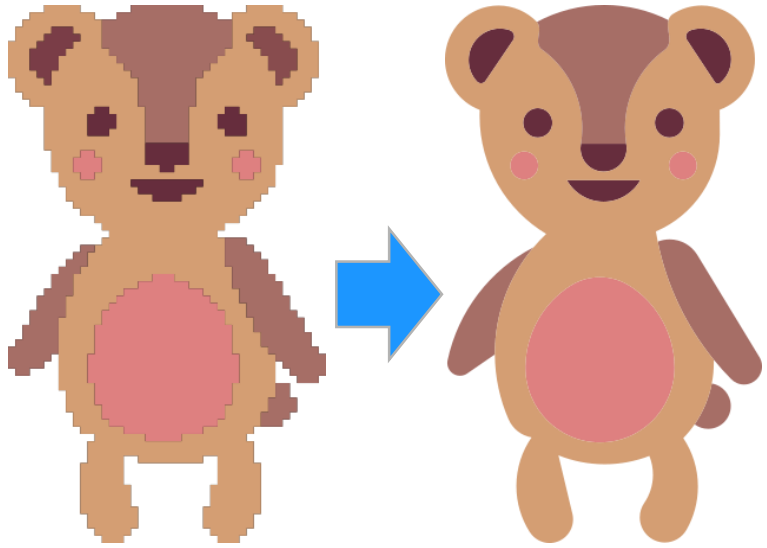
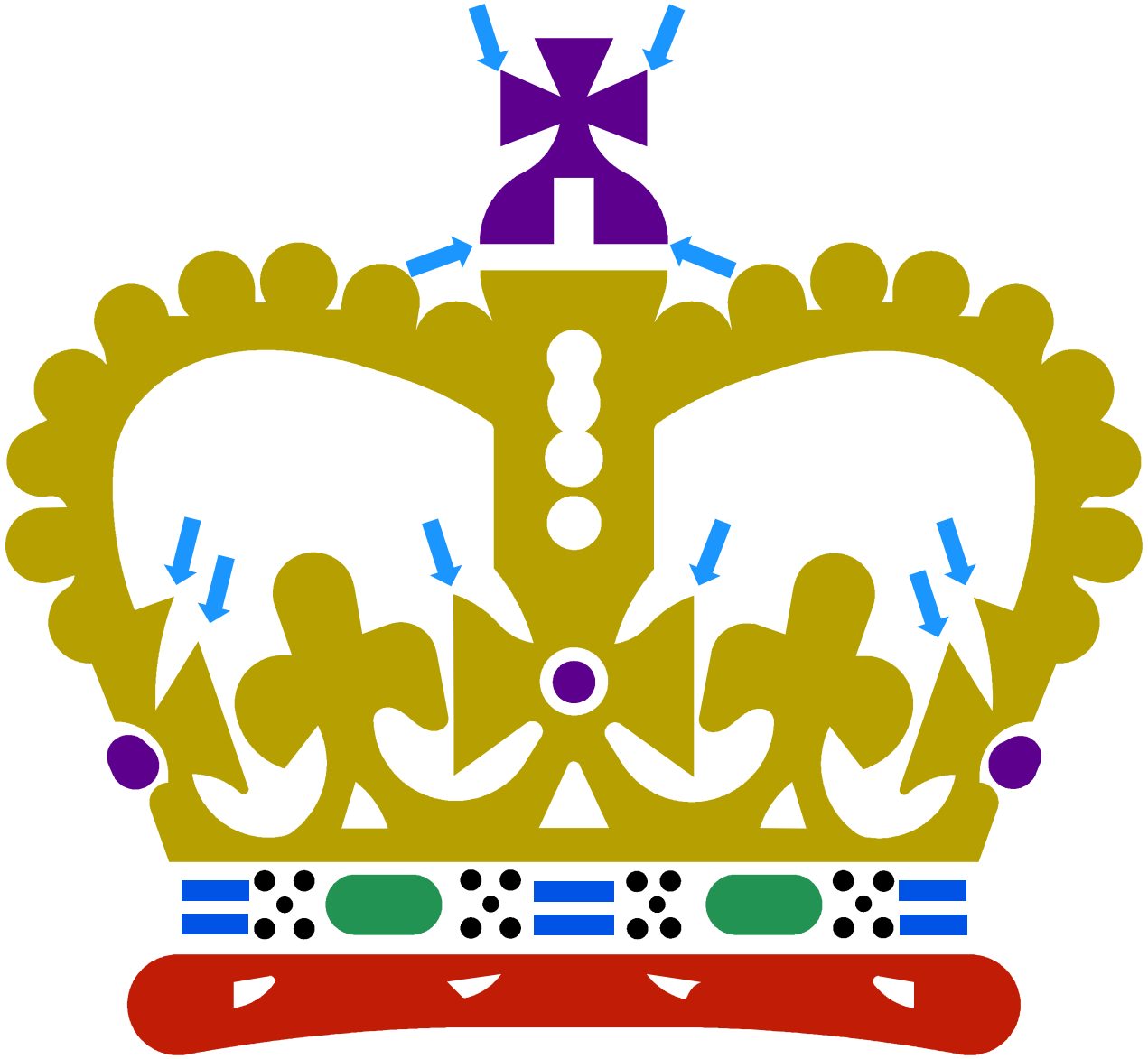
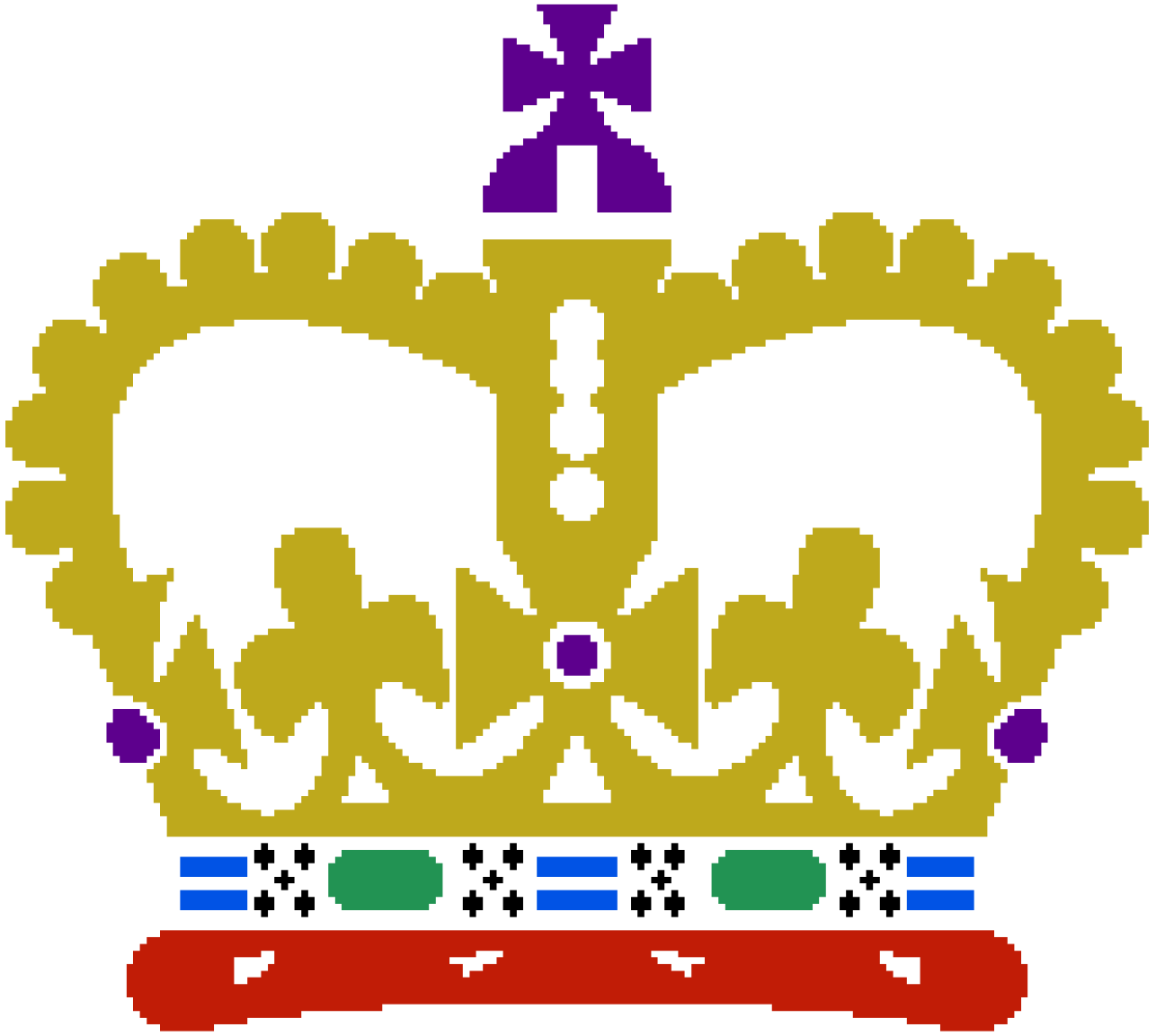


Semi-Structured Images



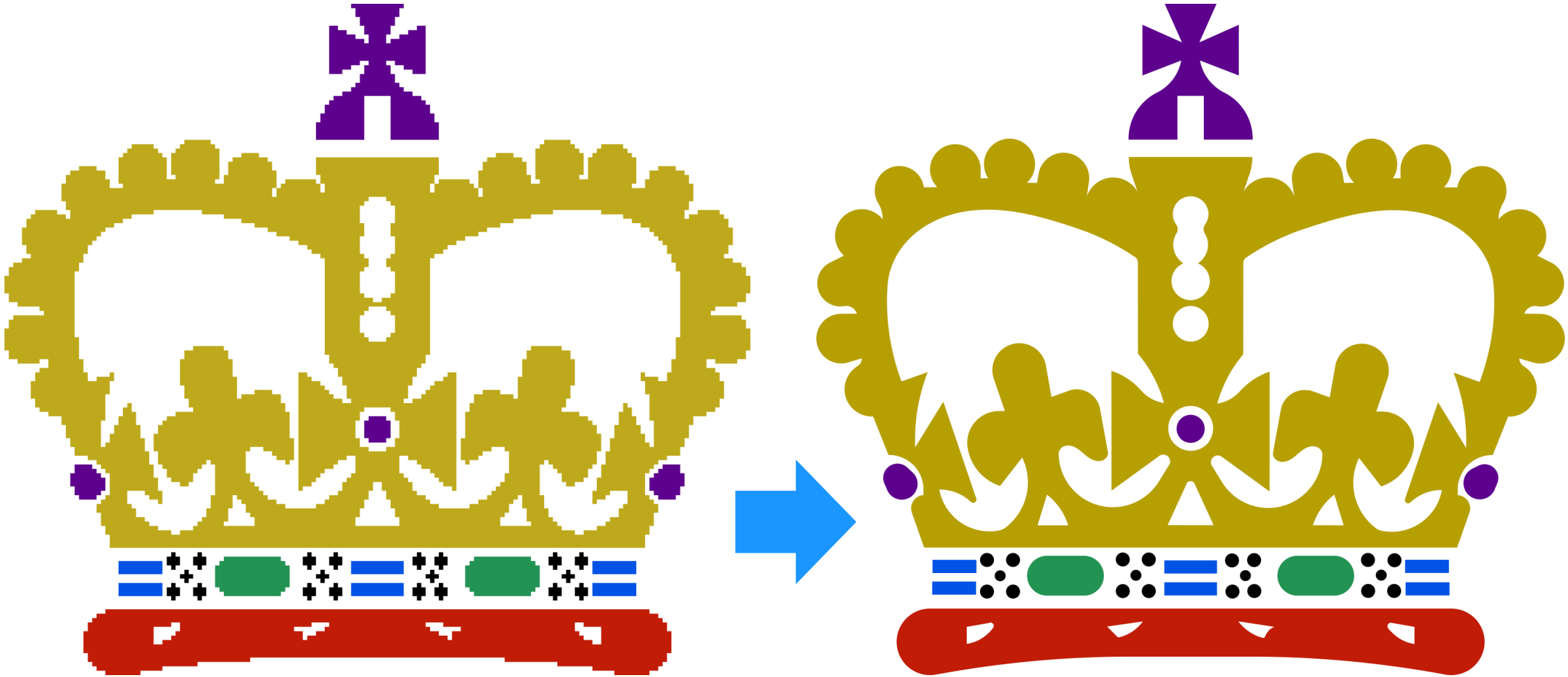
- Artists often create images with
  - Distinctly colored regions
  - Piecewise continuous boundaries
  - Visually pronounced corners
- Natural candidates for vector representation

Semi-Structured *Raster* Images



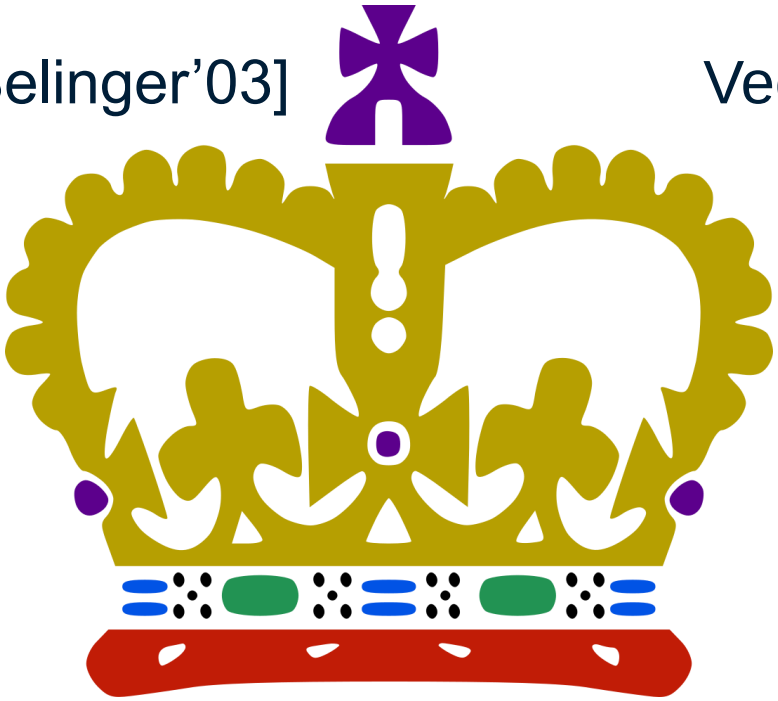
- But … often stored as **low-resolution** raster
  - Large portions of raster databases (9M images in Adobe Stock)

Unambiguous Mental Vector Representation



Vectorization Methods vs. Semi-Structured Images

[Selinger'03]

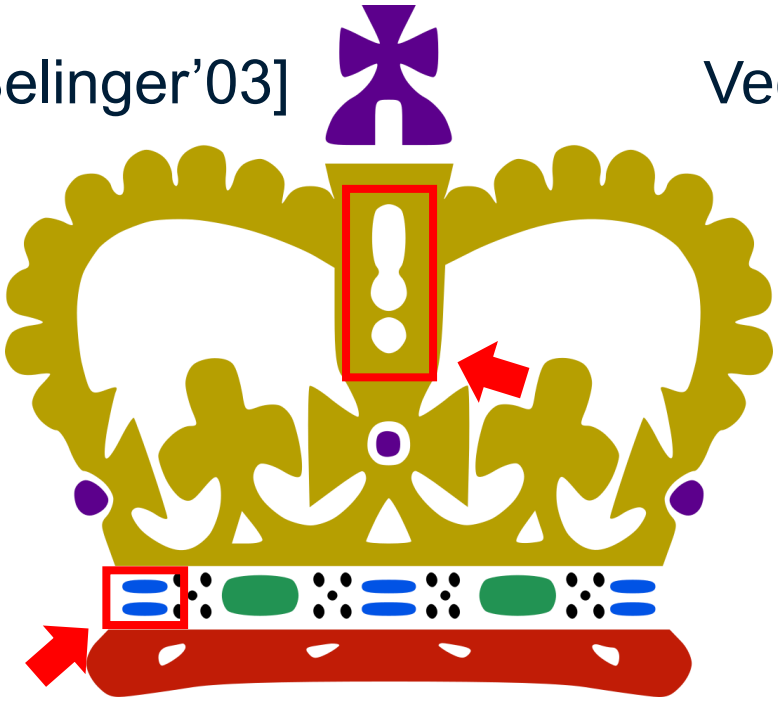


Vector Magic

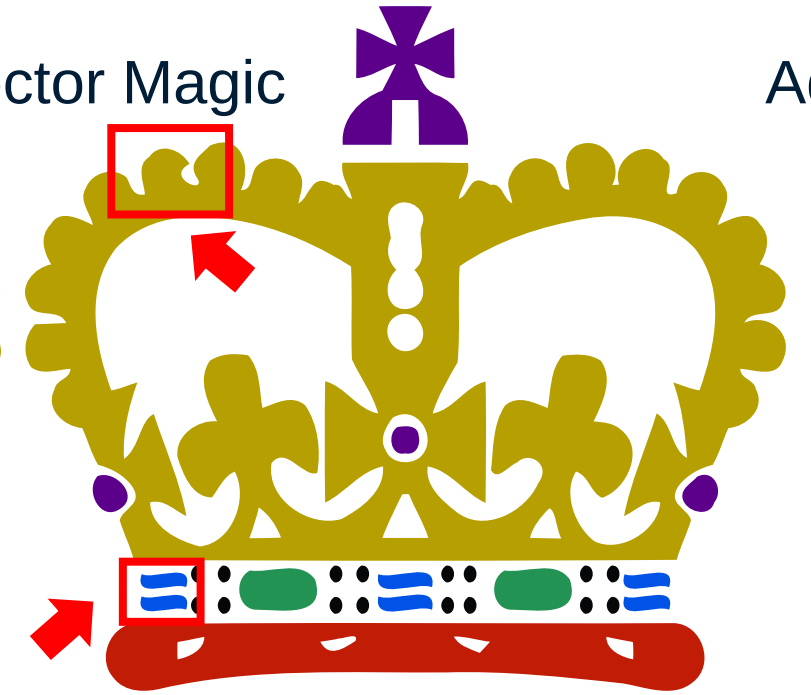
Adobe Trace

Vectorization Methods vs. Semi-Structured Images

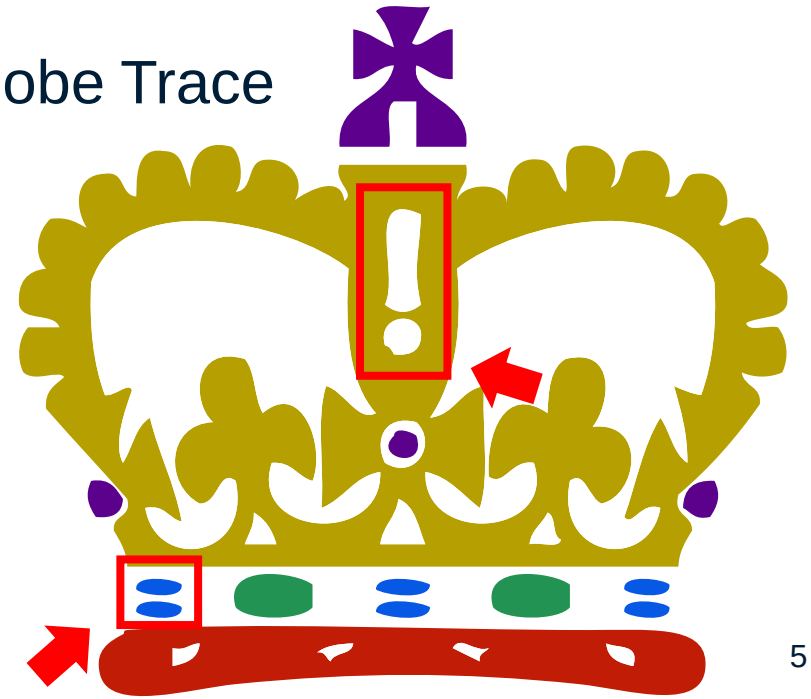
[Selinger'03]



Vector Magic



Adobe Trace



Objective

- Goal: algorithmic ***perceptually consistent*** vectorization of semi-structured images
  - Outputs align with human expectations

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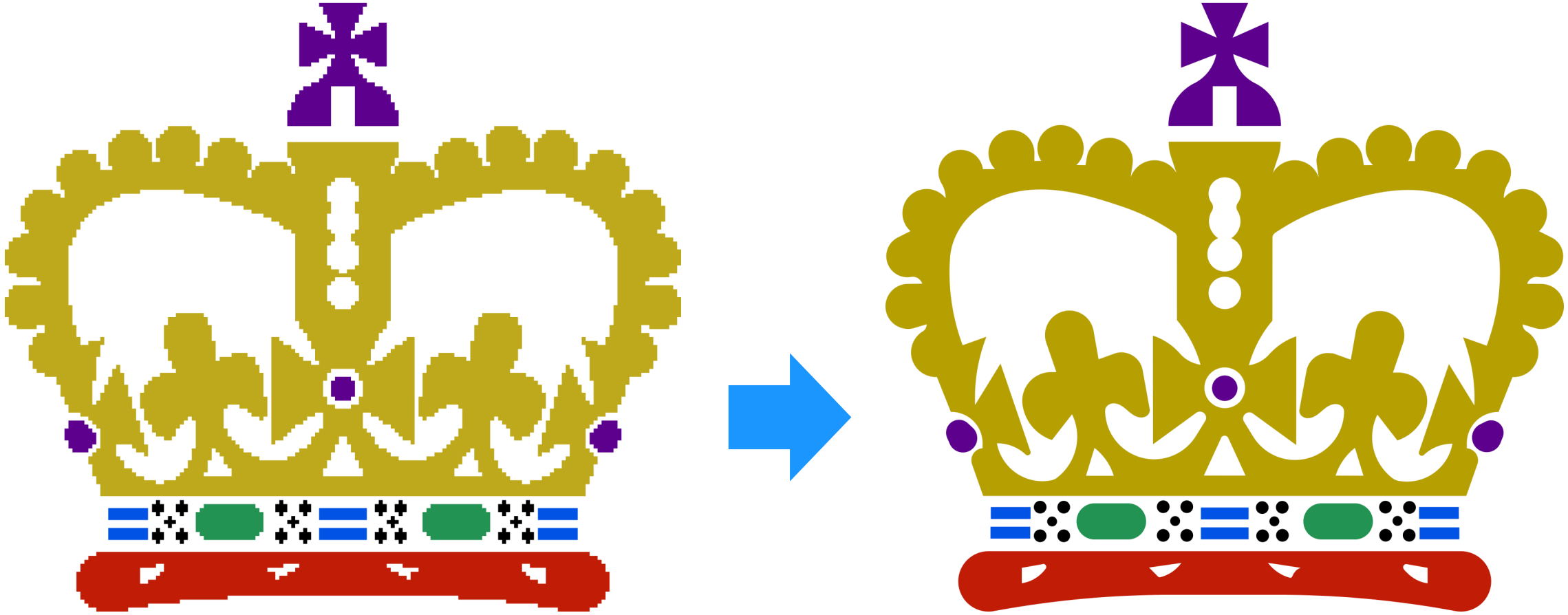
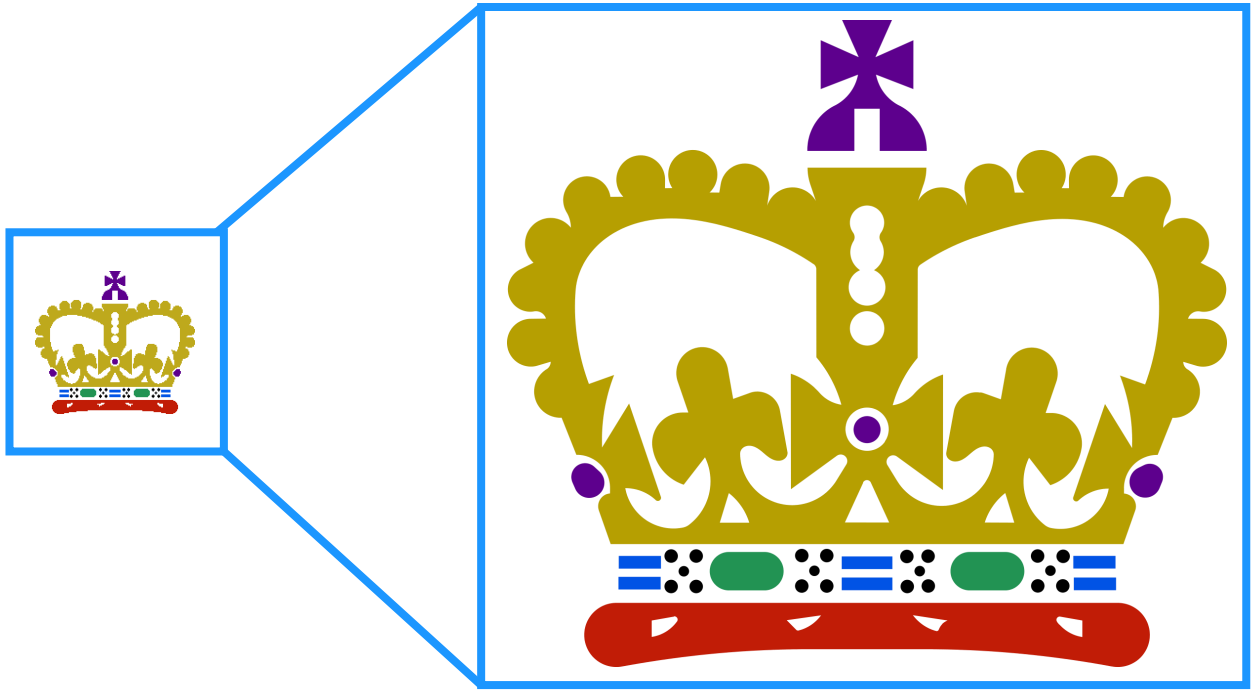
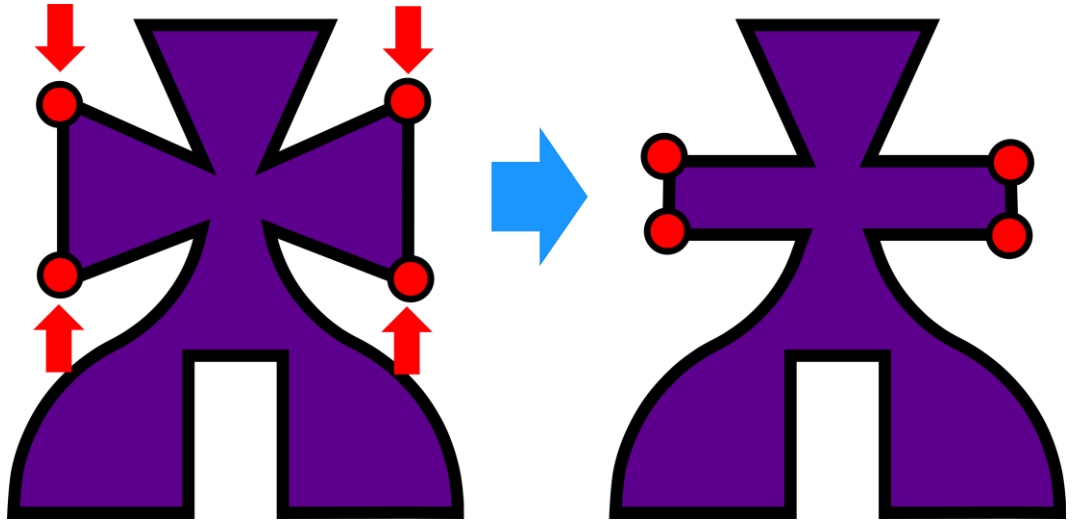


Objective

- Goal: algorithmic ***perceptually consistent*** vectorization of semi-structured images
  - Outputs align with human expectations
- Enables many applications

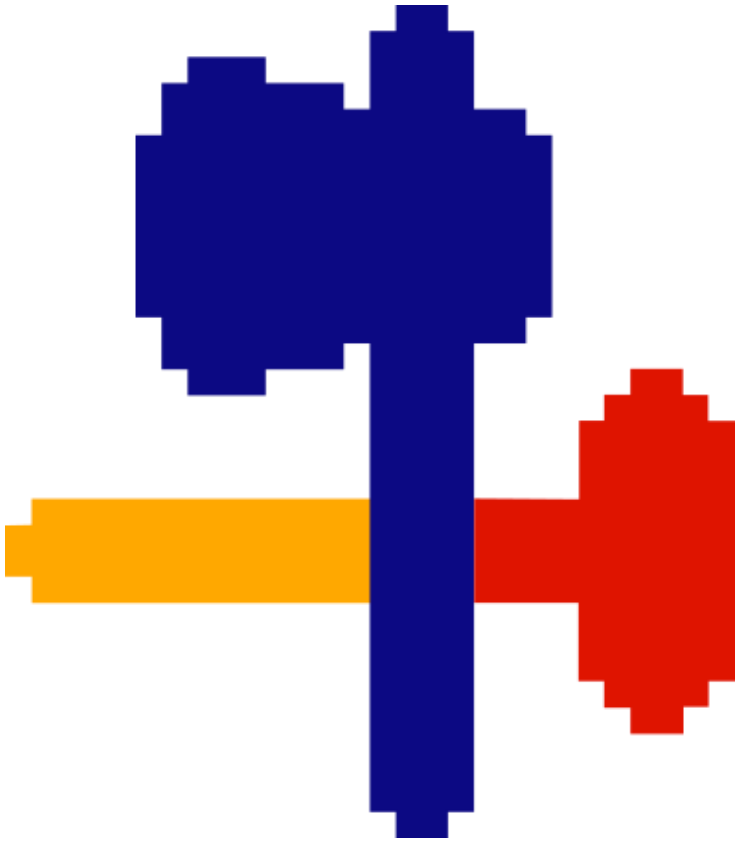


Artifact Free Resizing



Geometric Editing

Core Challenge: Raster Boundary Vectorization



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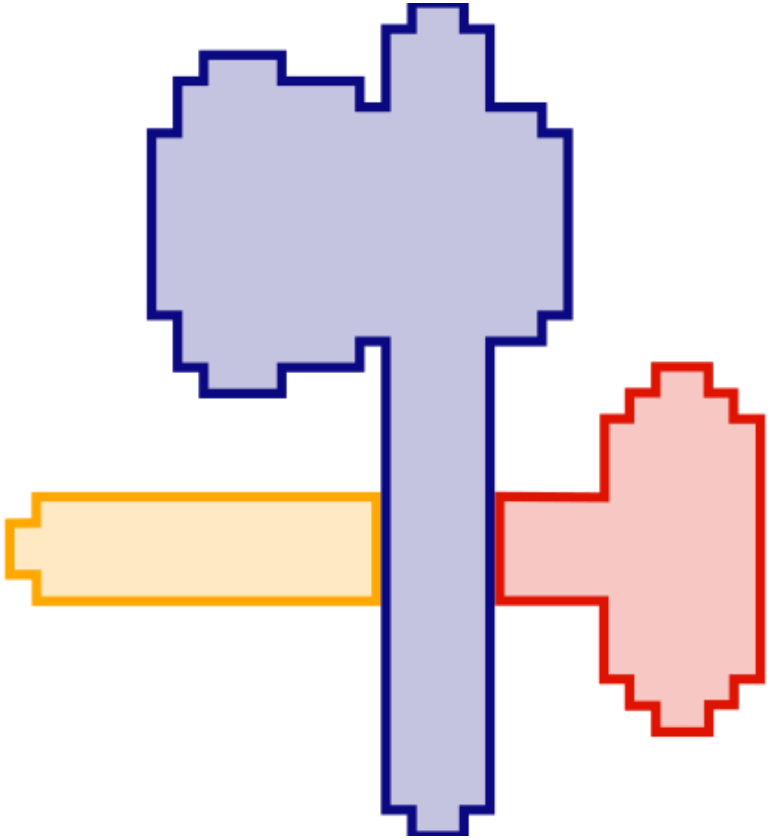
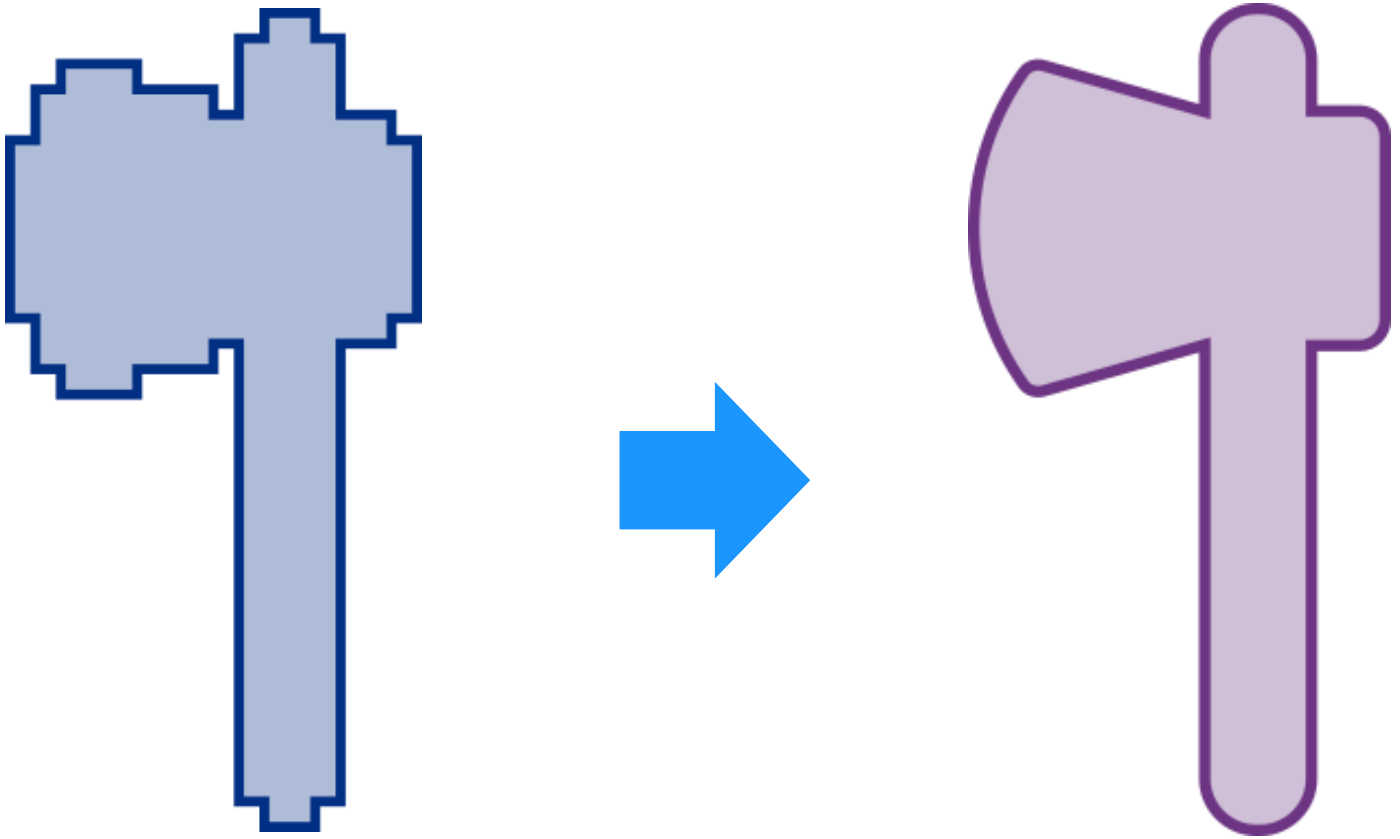


Core Challenge: Raster Boundary Vectorization

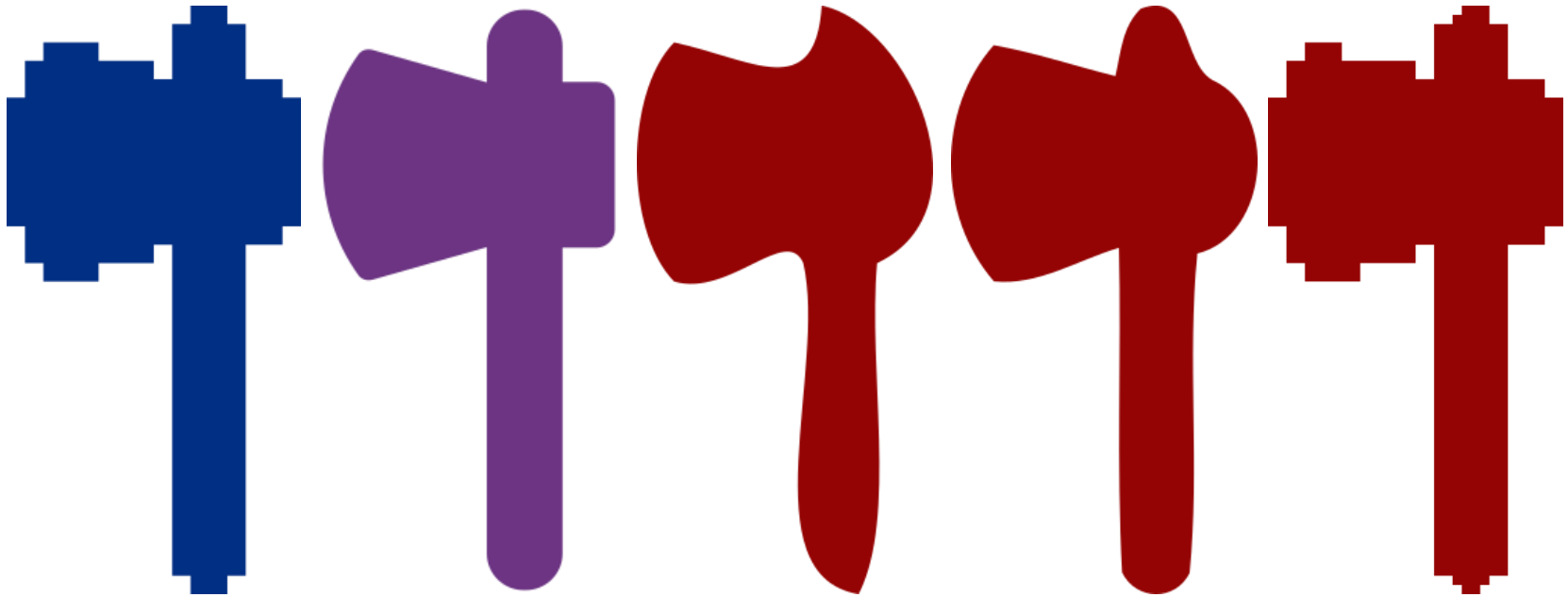


Input

Manual Vectorization

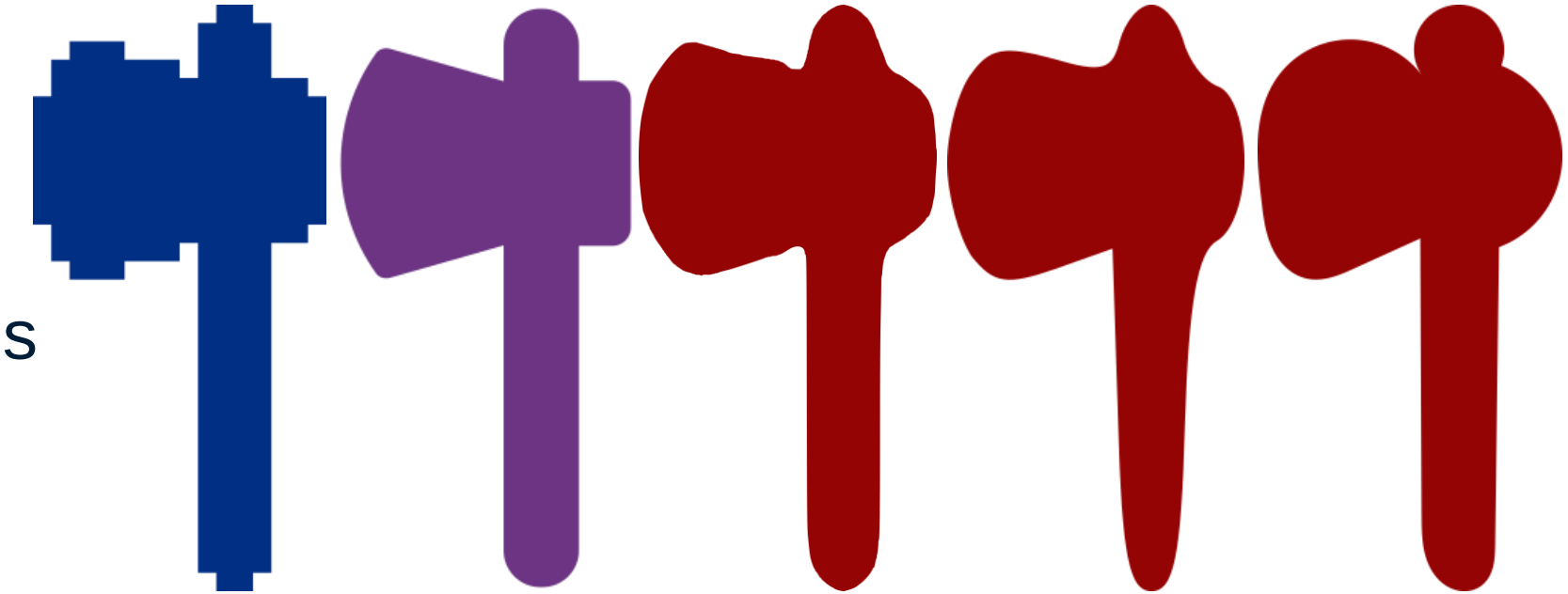
Previous Vectorization & Upscaling Methods: Natural Images

- Vectorization [Vector Magic; Adobe Trace; Favreau‘17; ...]
- Upscaling [Dahl‘17; Wang‘15; ...]
- Focus on segmentation
- Target irregular boundaries & higher resolutions
- *Fail on semi-structured data*



Previous Vectorization & Upscaling Methods: Artist Imagery

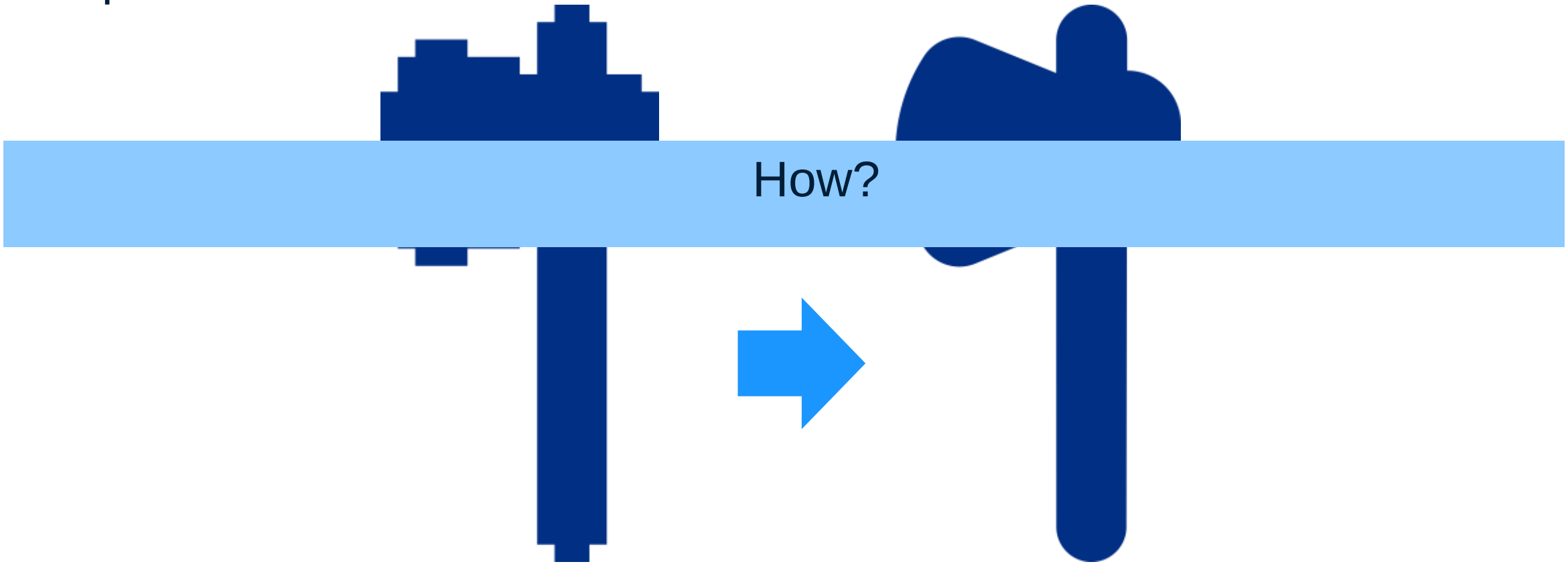
- Vectorizing cartoons [Zhang'09; Sykora'05; ...]
  & pixel-art [Kopf ‘11; ...]
  - Assume C^2 continuity – fit boundaries with globally smooth curves
- Open-source tools
  [Weber'04; Selinger'03]
  - Heuristics based
- Curve fitting to polylines
  [McCrae'11; Baran‘10]
  - Focus on artist strokes



Input Manual [Kopf'11] [Selinger'03] [Baran’10]

Goal: Vectorization Method That Works!

- Need to do better!
- Vectorization of semi-structured images aligned with human expectations



Solution Candidate: Machine Learning?

- Learn from pairs of raster and vector images

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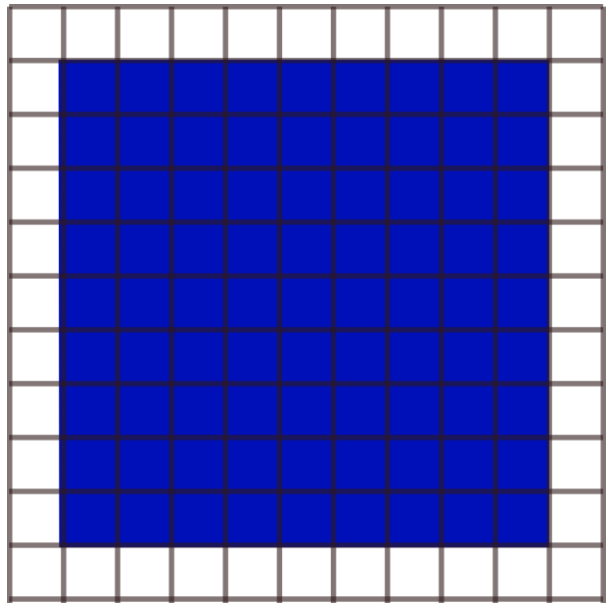
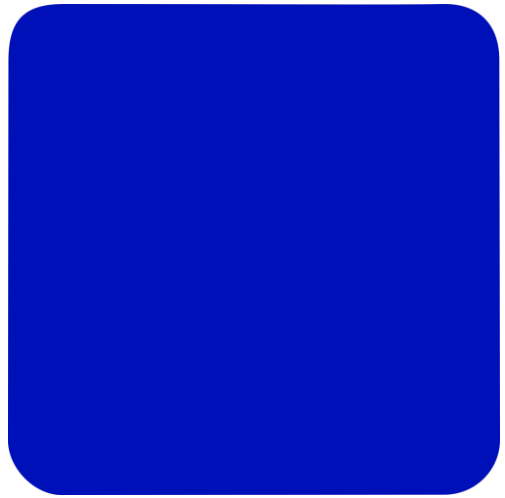
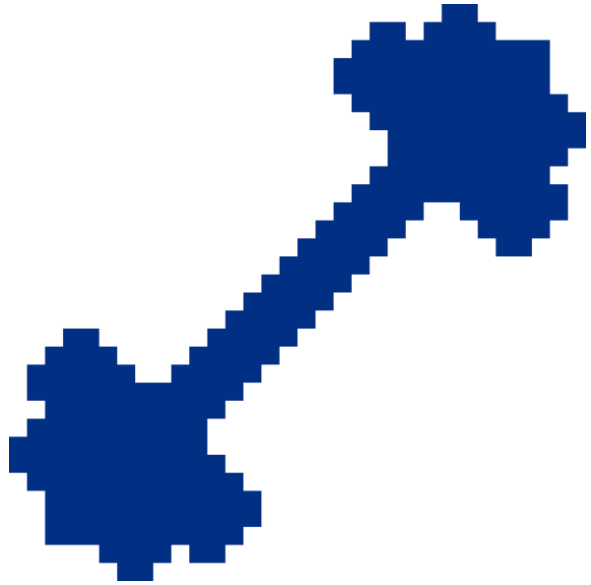
- Learn from pairs of raster and vector images
- Which pairs?
  - Rasterize vector inputs & seek to recover input from raster output
    - Many to one
    - Not what humans expect



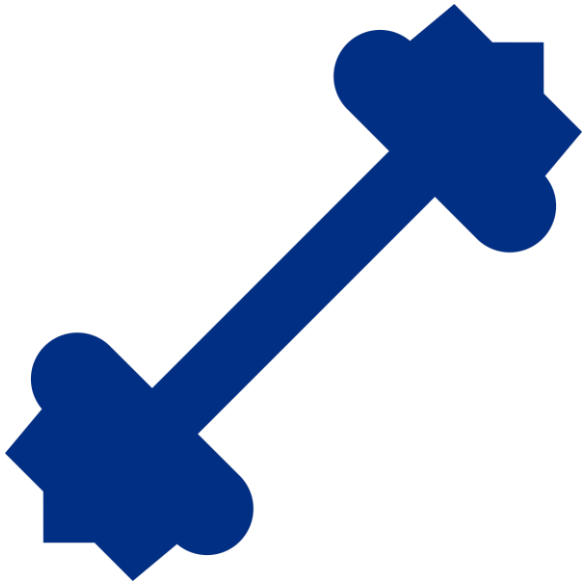


Solution Candidate: Machine Learning?

- Learn from pairs of raster and vector images
- Which pairs?
  - Rasterize vector inputs & seek to recover input from raster output
    - Many to one
    - Not what humans expect
  - Alternative: learn from manual vectorizations
    - Expensive to create



Raster Image



Artist vectorization (30-45 min)

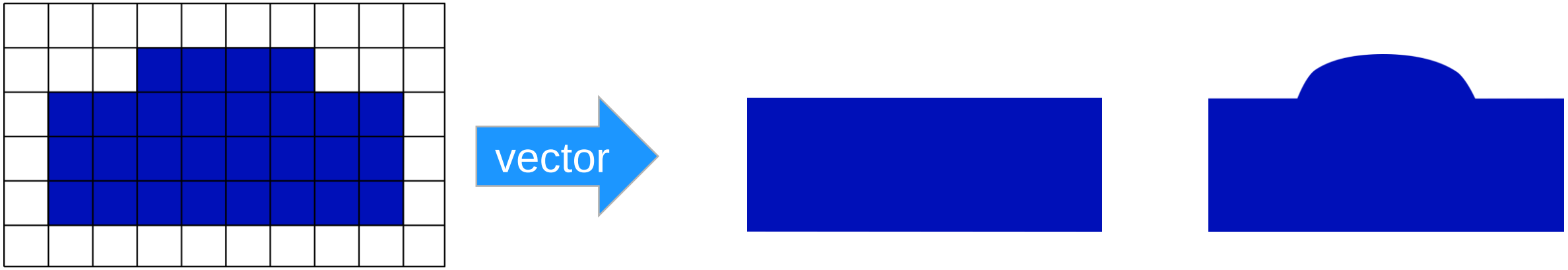
Solution Candidate: Perception Based Method?

- Used successfully for related problems
  [Bessmeltsev ‘16; Xu ‘14; …]

- Which perceptual cues to use?

Perceptual Principles: Accuracy

- Raster(vector output) ≈ input raster



Perceptual Principles: Accuracy

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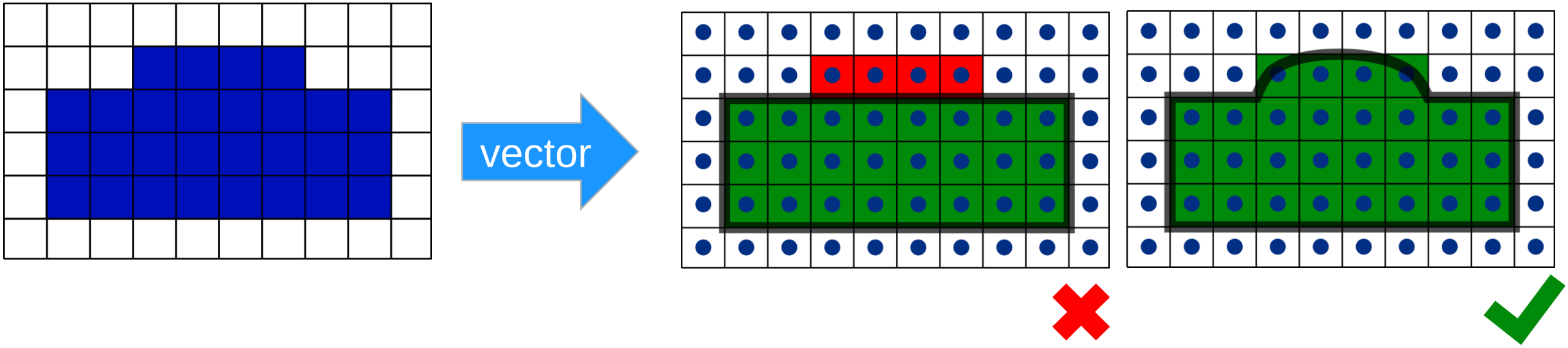
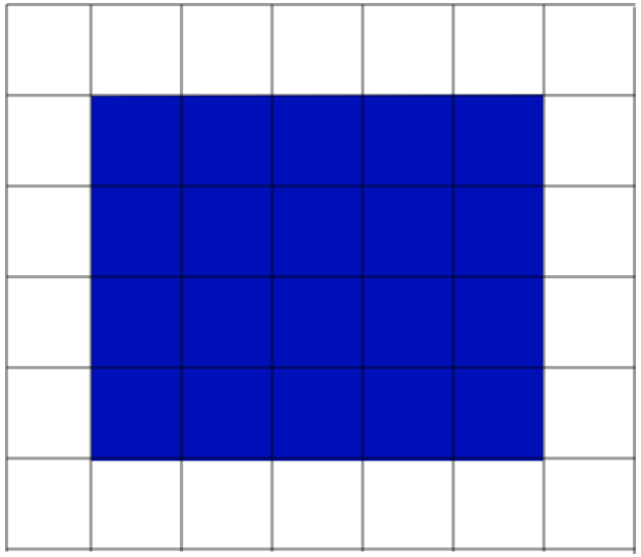
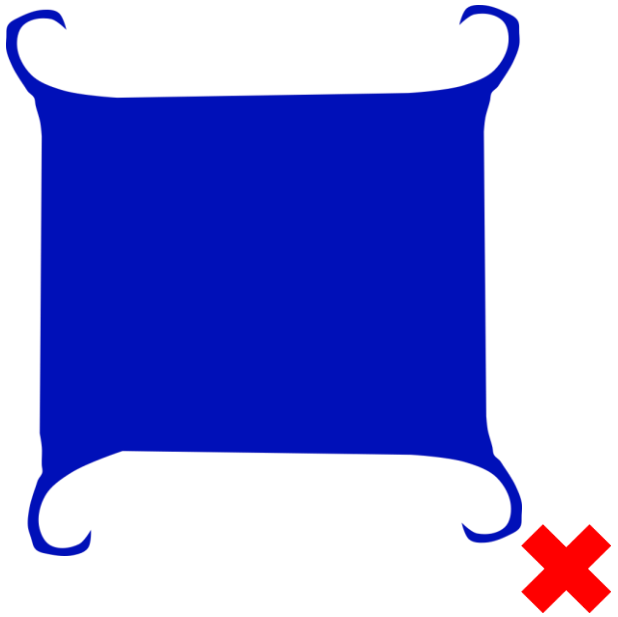
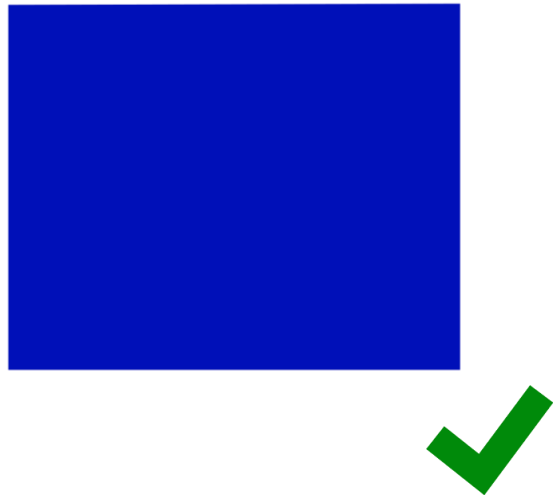


Perceptual Principles: Accuracy

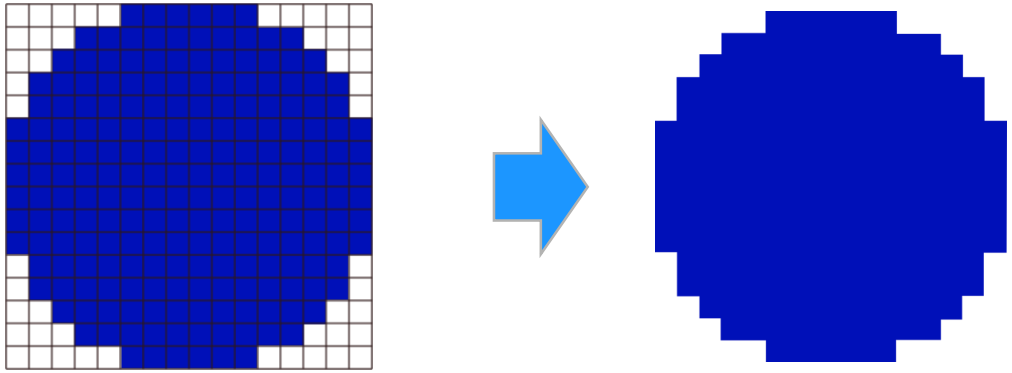
- No detail hallucination [WYSIWIG principle]







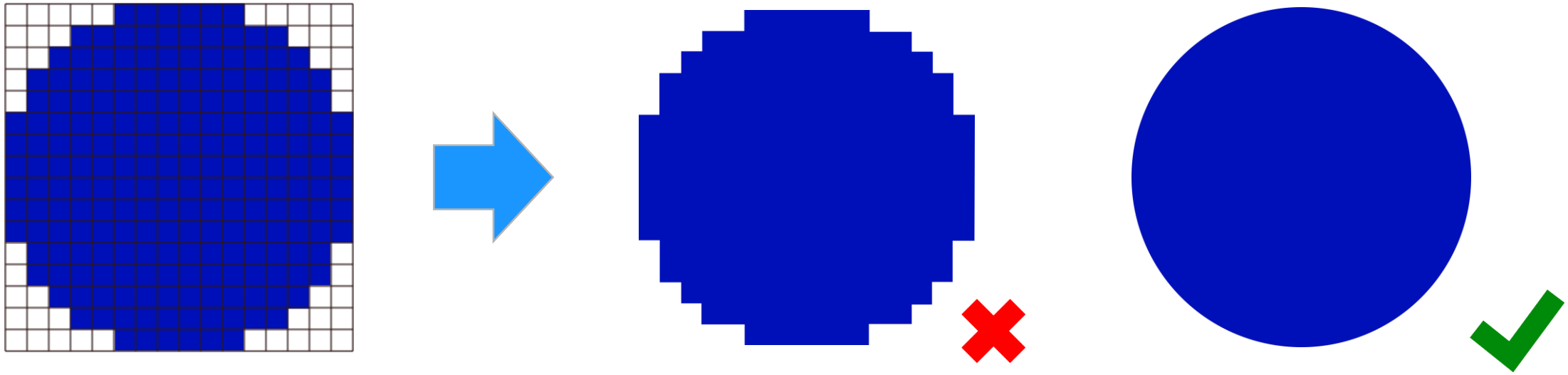
- Accuracy alone: vectorized boundary = raster boundary



Perceptual Principles: Continuity

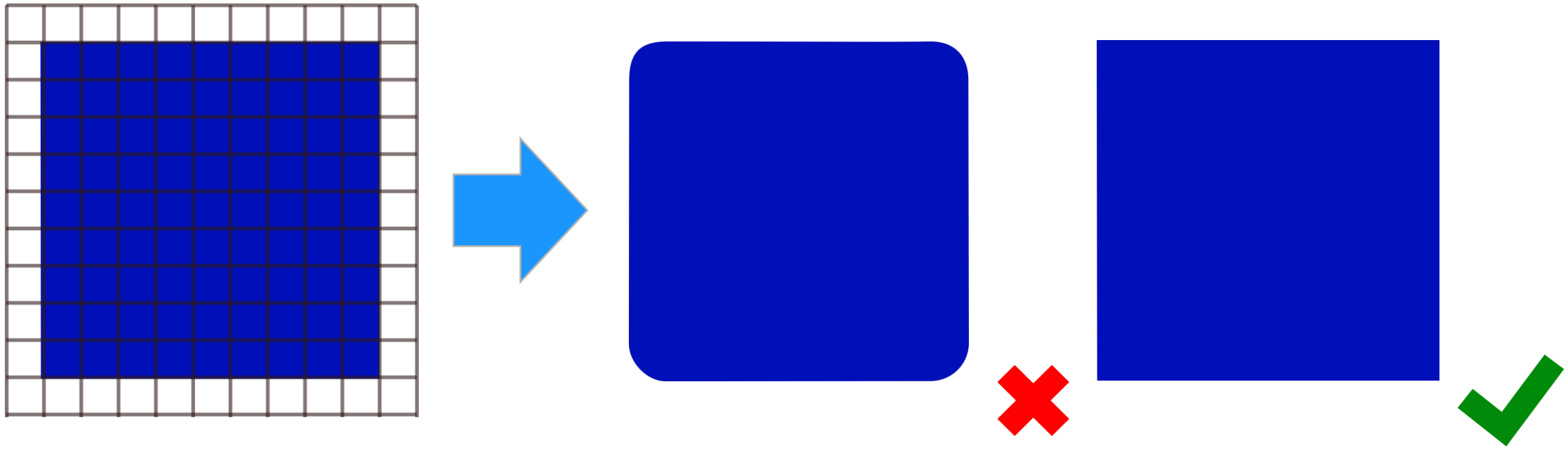
- Continuity : Humans group stimuli into continuous patterns [Koffka 1955; Wagemans ‘12]

- In our context: expect few corners



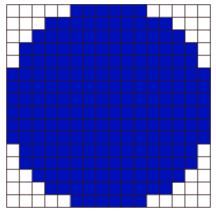
Perceptual Principles: Simplicity

- Simplicity: preference for simpler geometric interpretations [Koffka 1955; Wagemans ‘12]

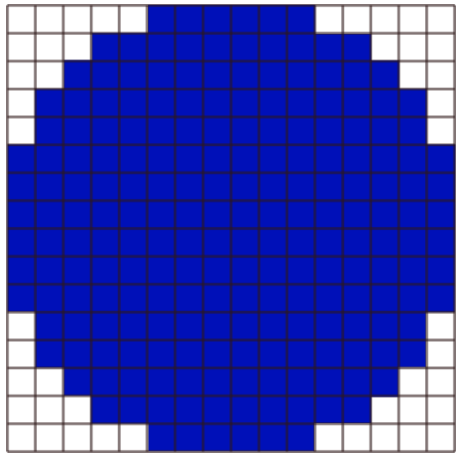


Challenge: Conflicting Principles

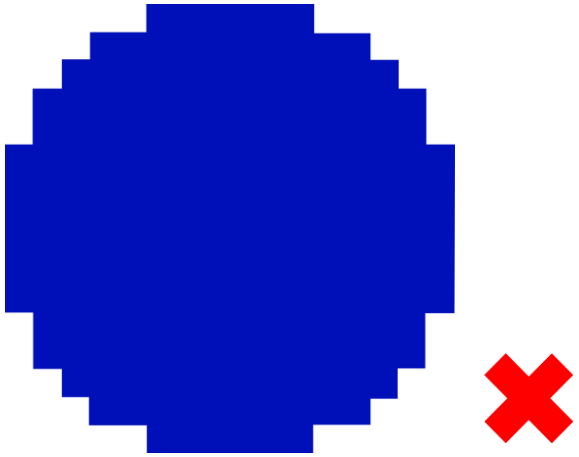
raster image



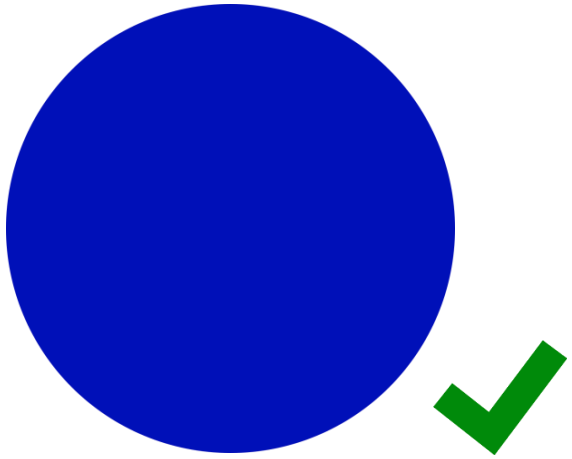
magnified

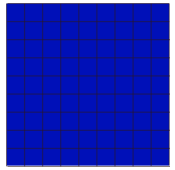


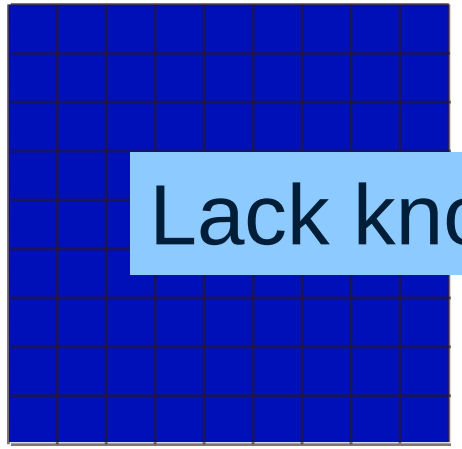
simple & accurate

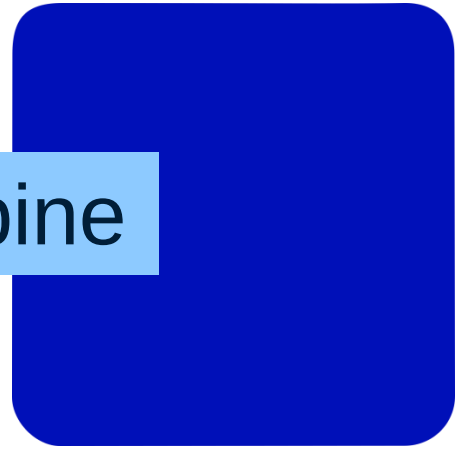


continuous







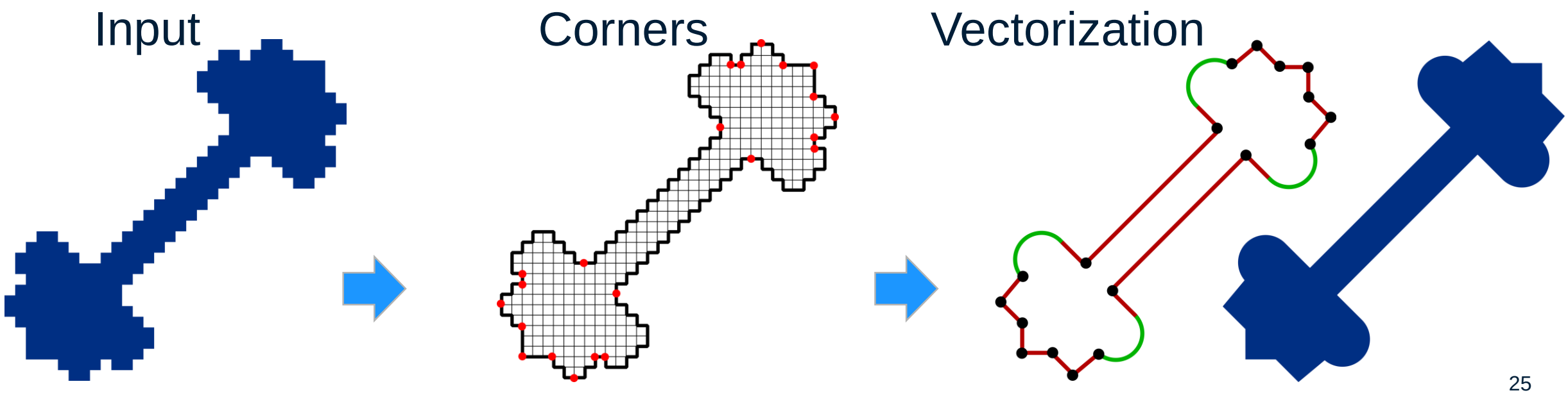


Lack knowledge on how to combine

How to Solve Our Problem?

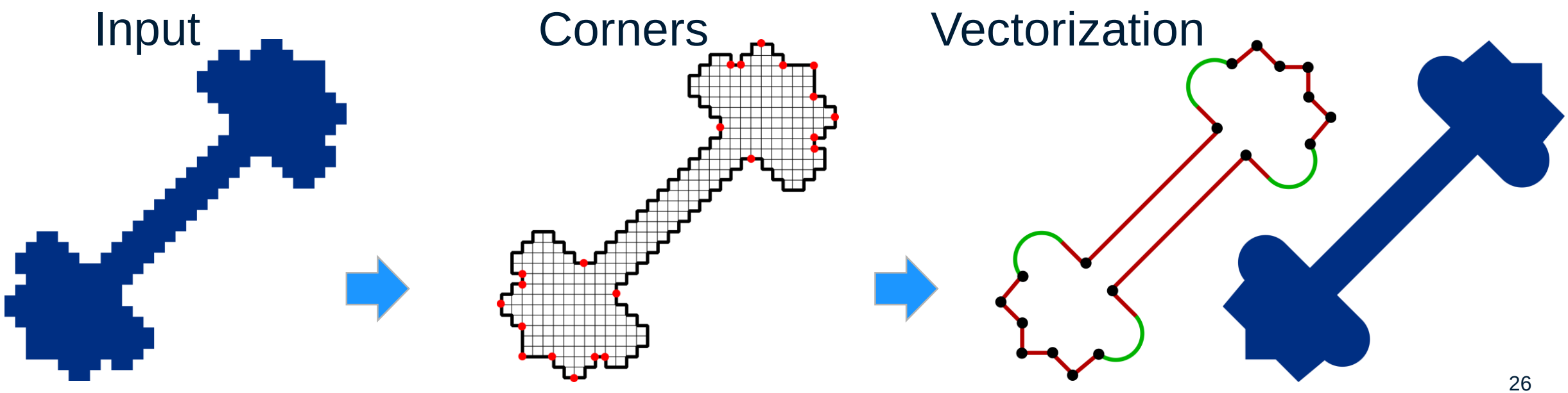
- Divide the problem into two parts:

  1. Detect corner locations
  2. Vectorize each polyline segment adherent to perceptual principles



How to Find the Corners?

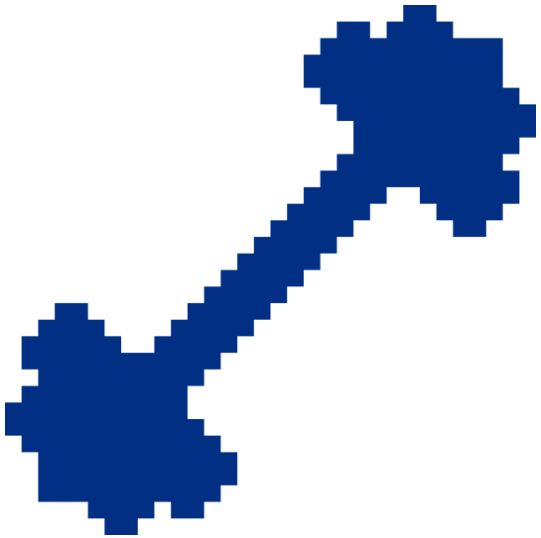
- Use Machine Learning
  - Corner annotation is cheap
  - Can get accurate results



How to Find the Corners?

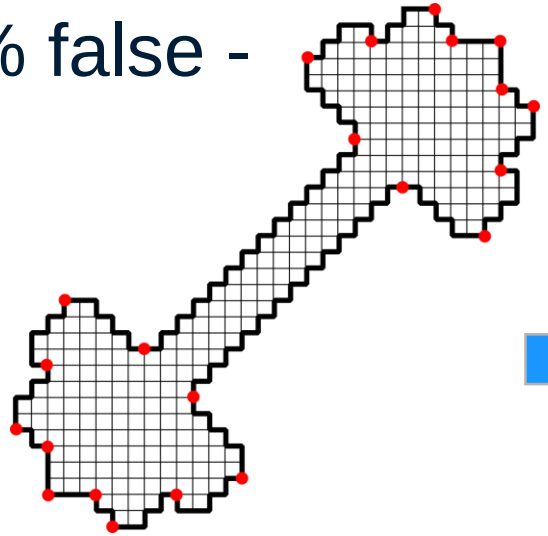
- Use Machine Learning
  - Corner annotation is cheap
  - Can get accurate results
- Challenge: vectorized output is very sensitive to the corner locations

Input

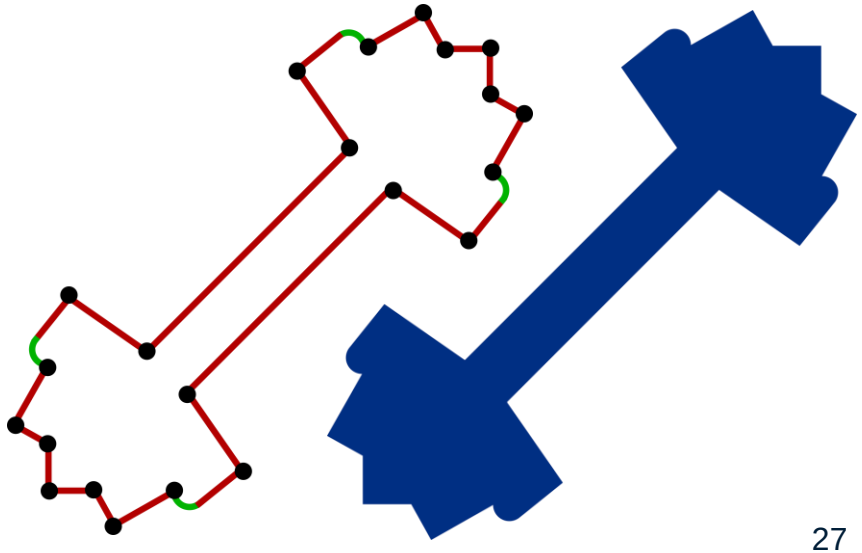


+

Corners with
~10% false +
~10% false -

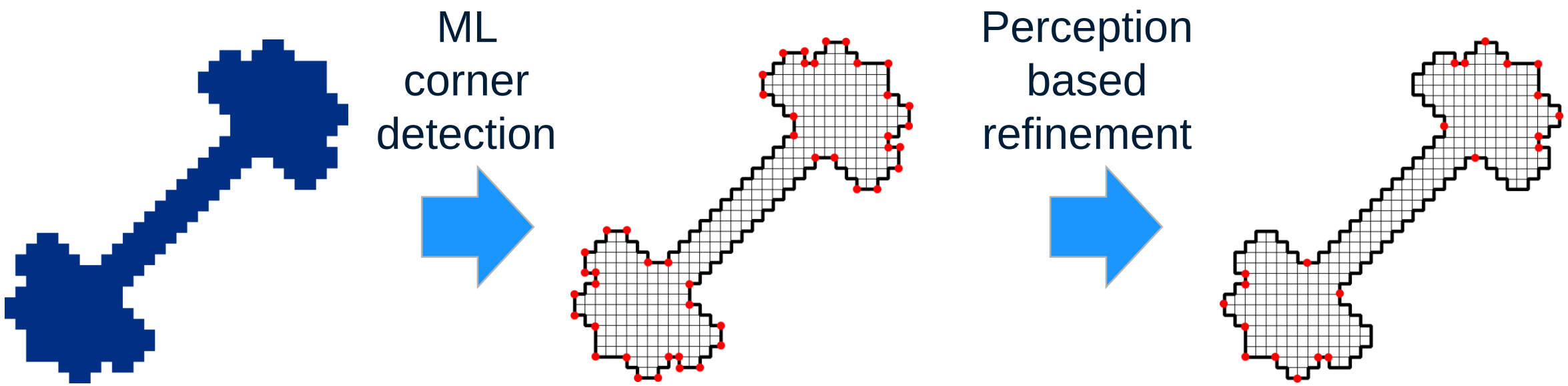


Vectorization



How to Find the Corners?

- Solution:
  - Use ***ML*** to find a set of *likely* corners
  - Use ***perception based refinement*** to find the *final* set of corners

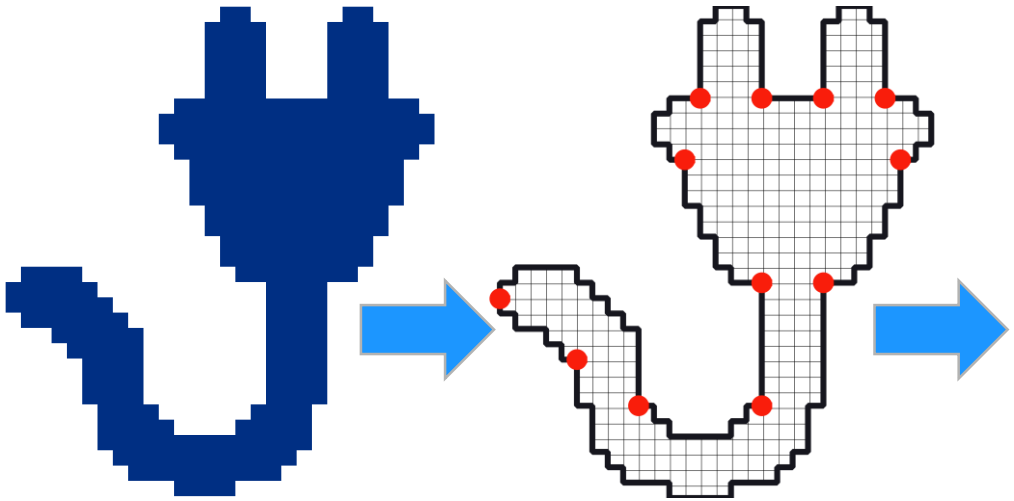


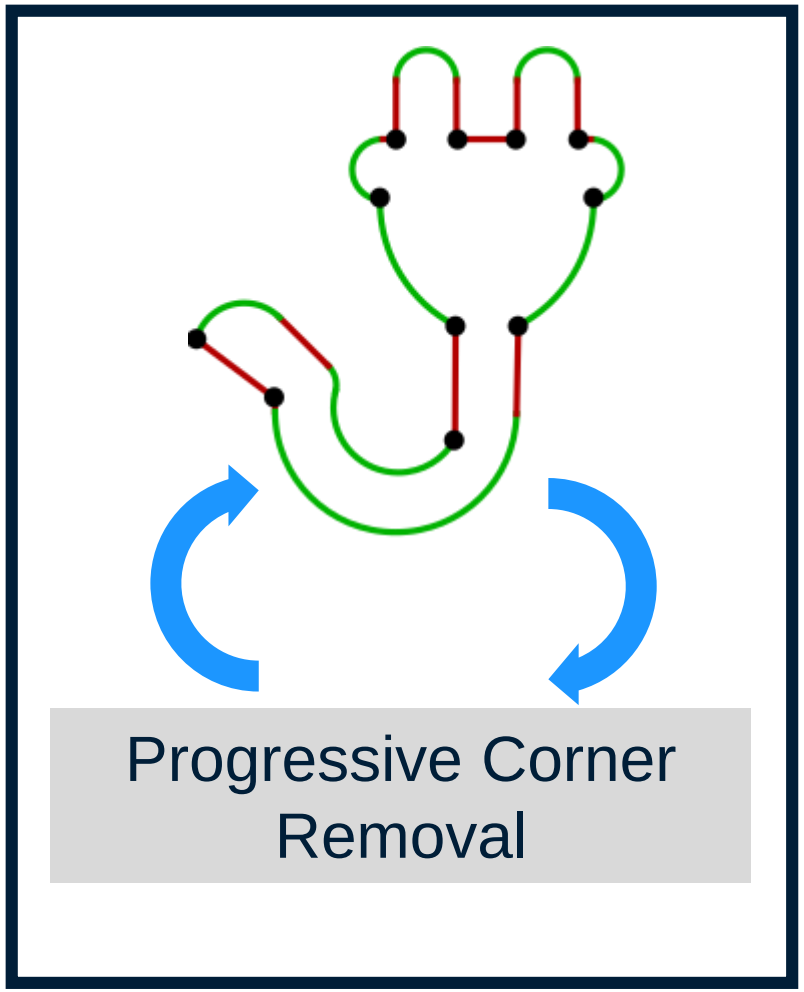
Method Overview

Input

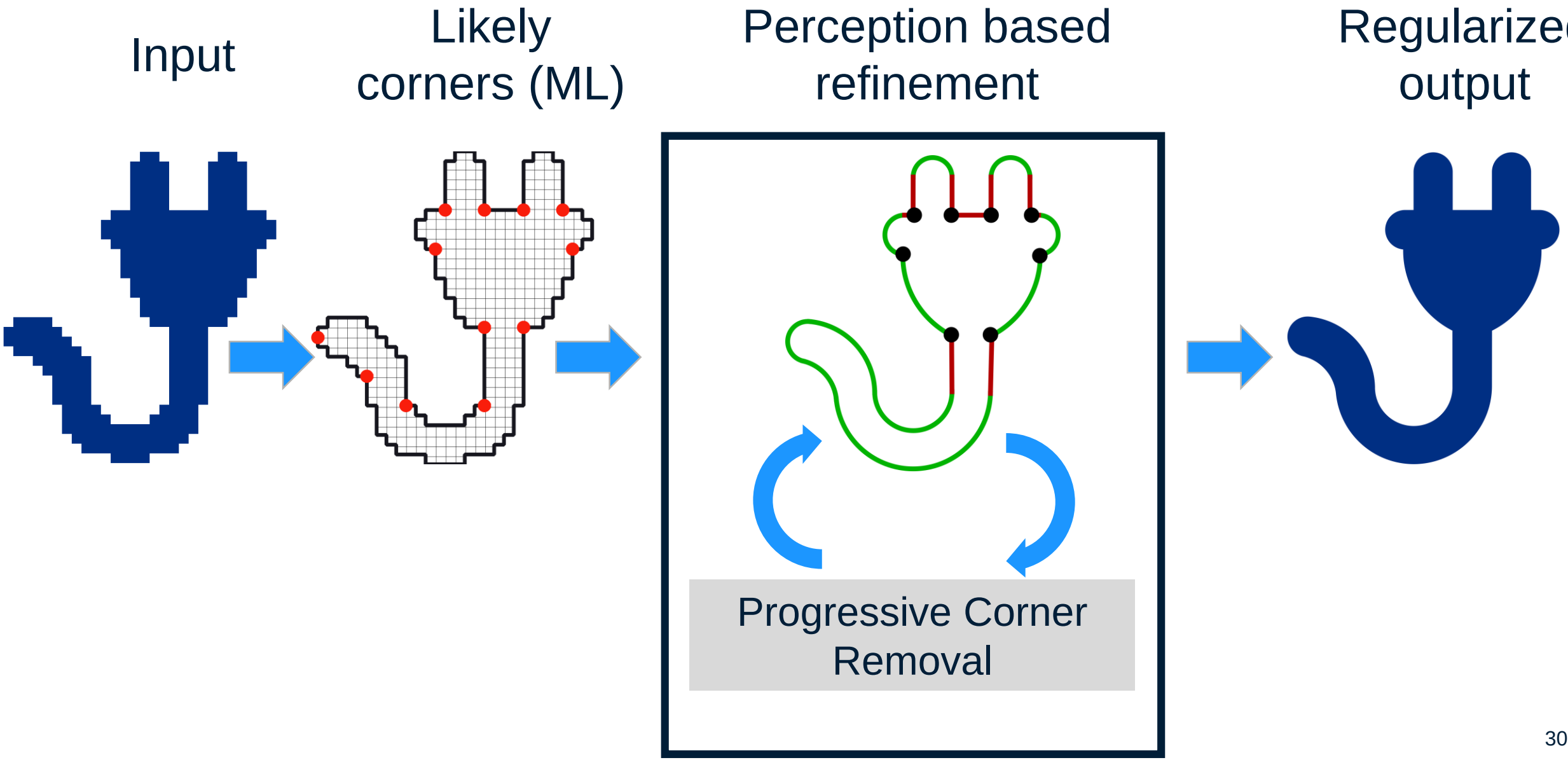
Likely corners (ML)

Perception based refinement



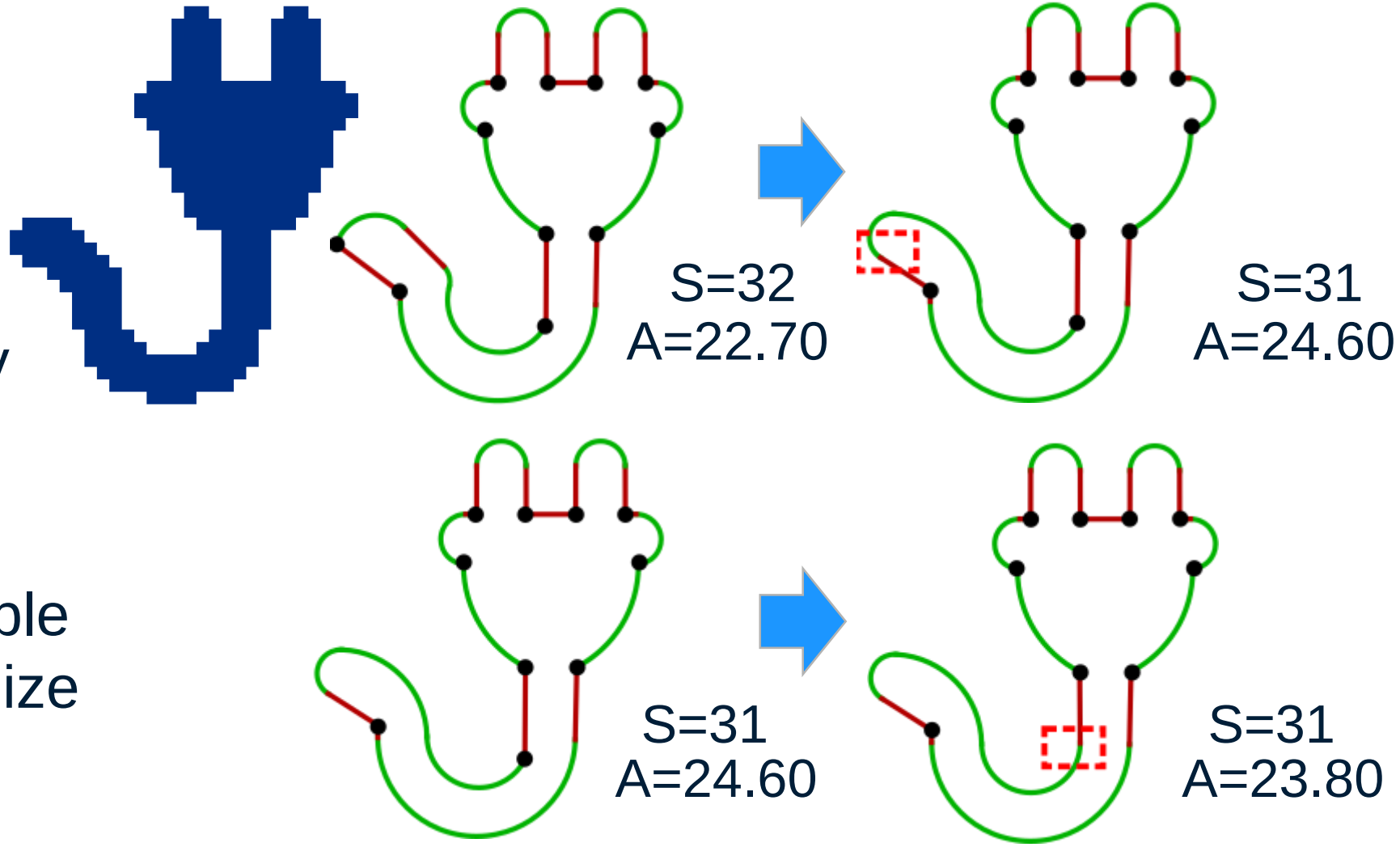


Method Overview

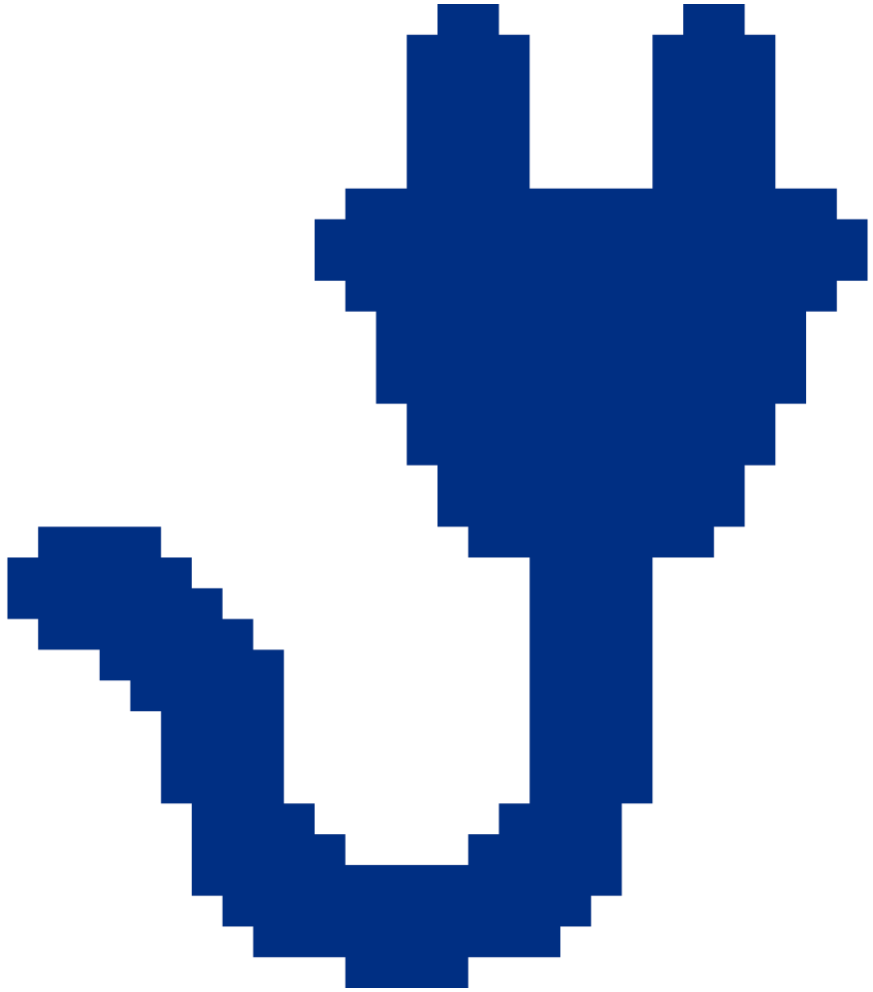


Perception Based Refinement

- Continuity implied by corner sparsity
- Optimize simplicity
- Given equally simple alternatives, optimize accuracy



Example



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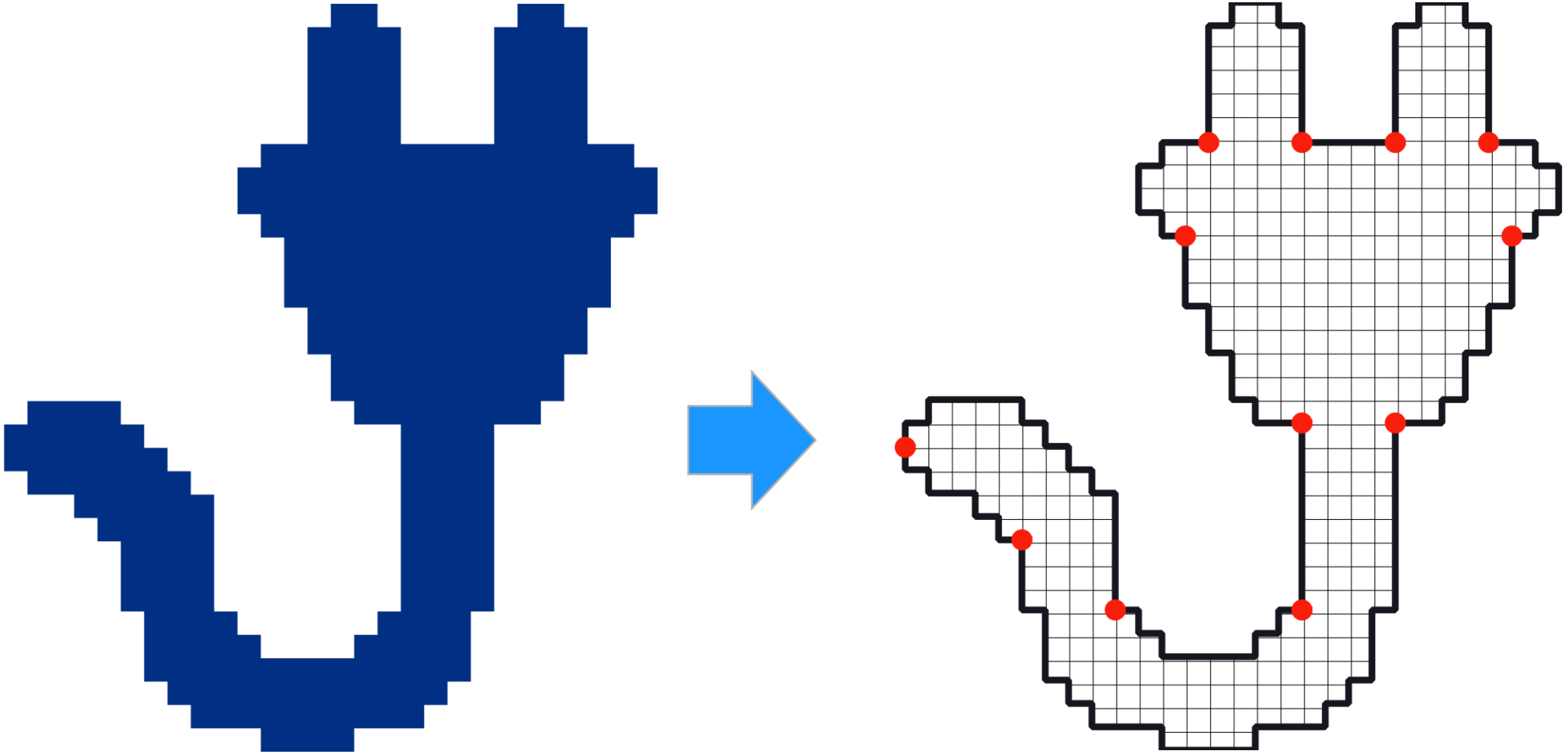
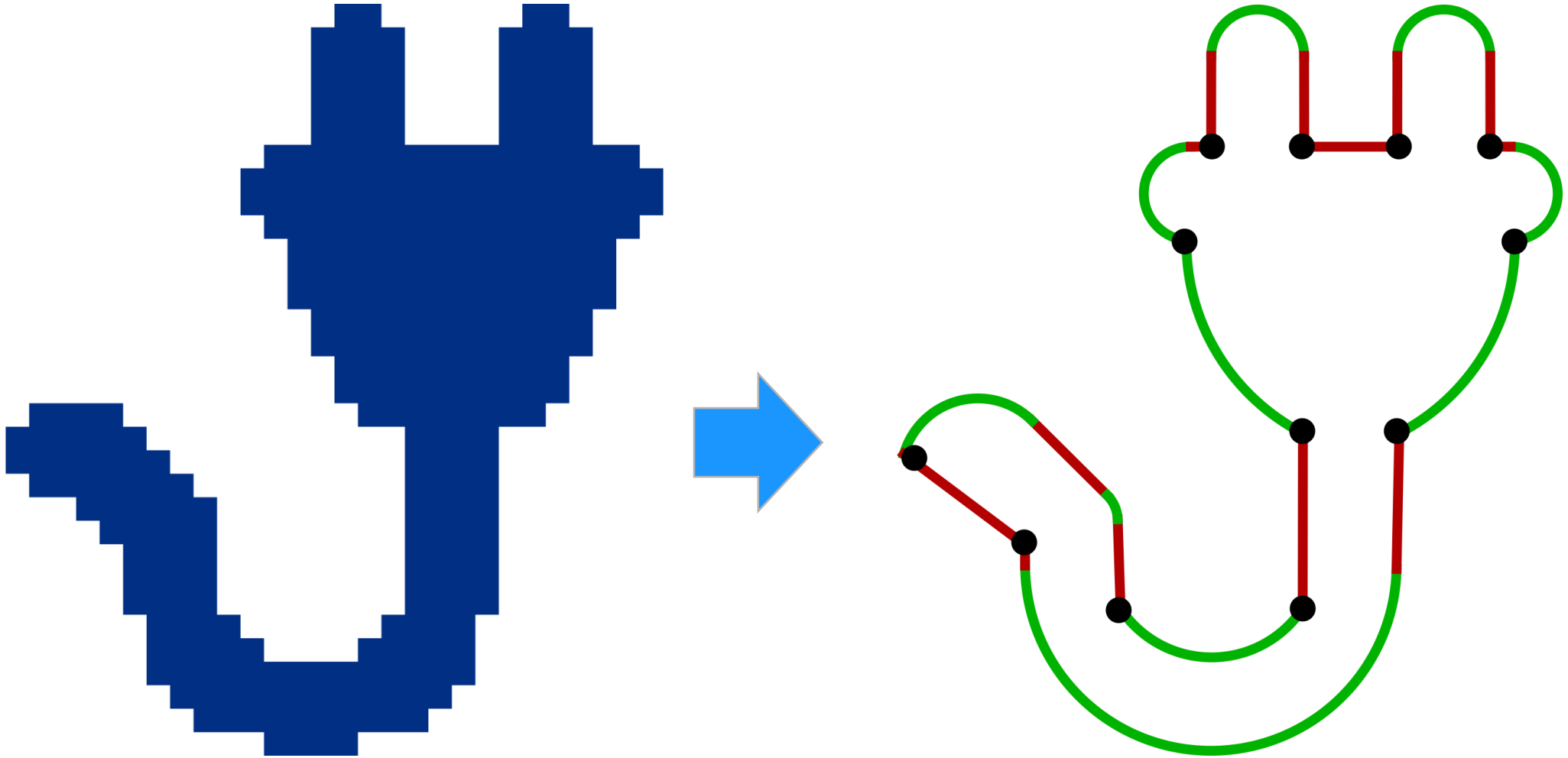
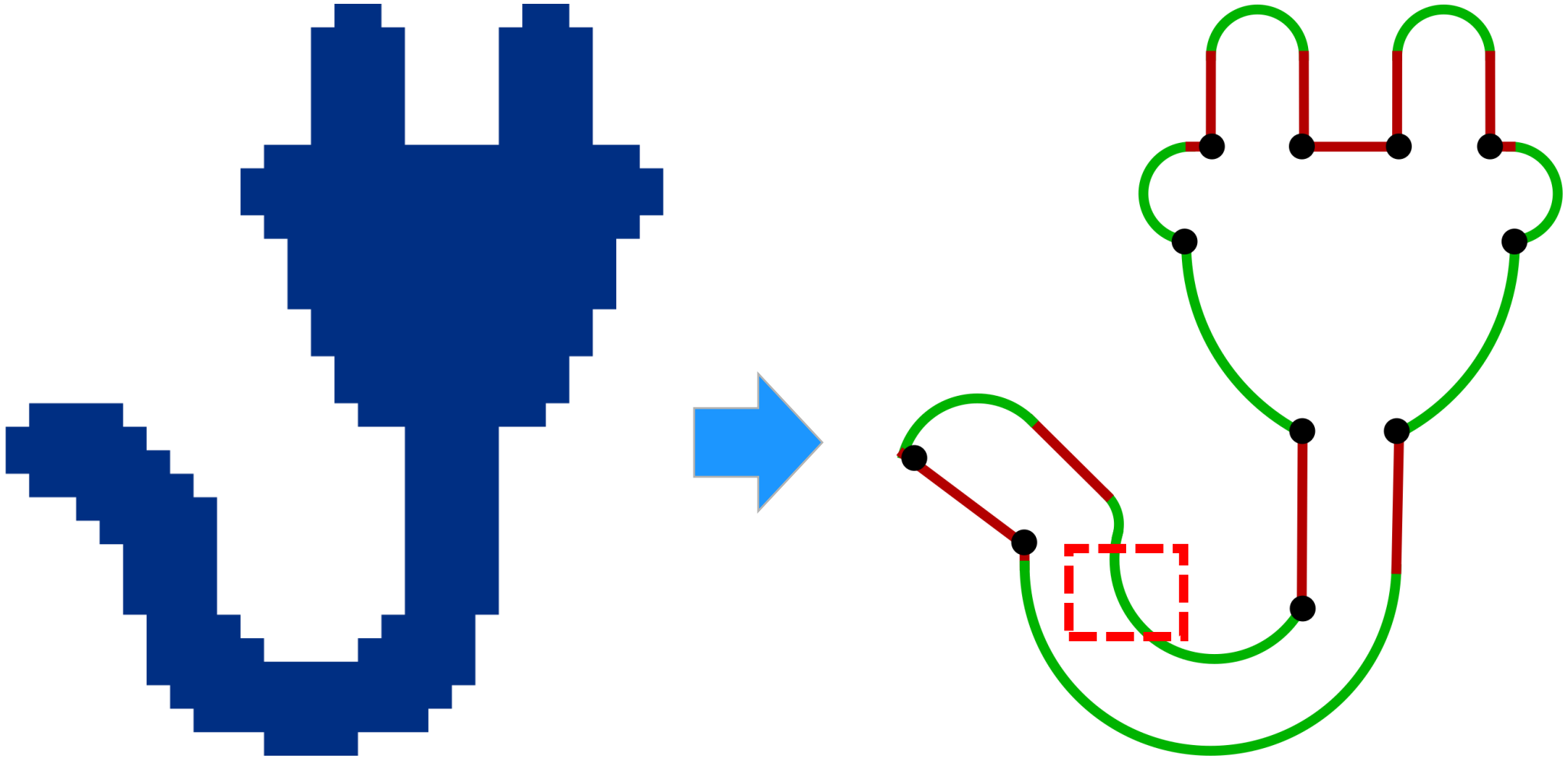


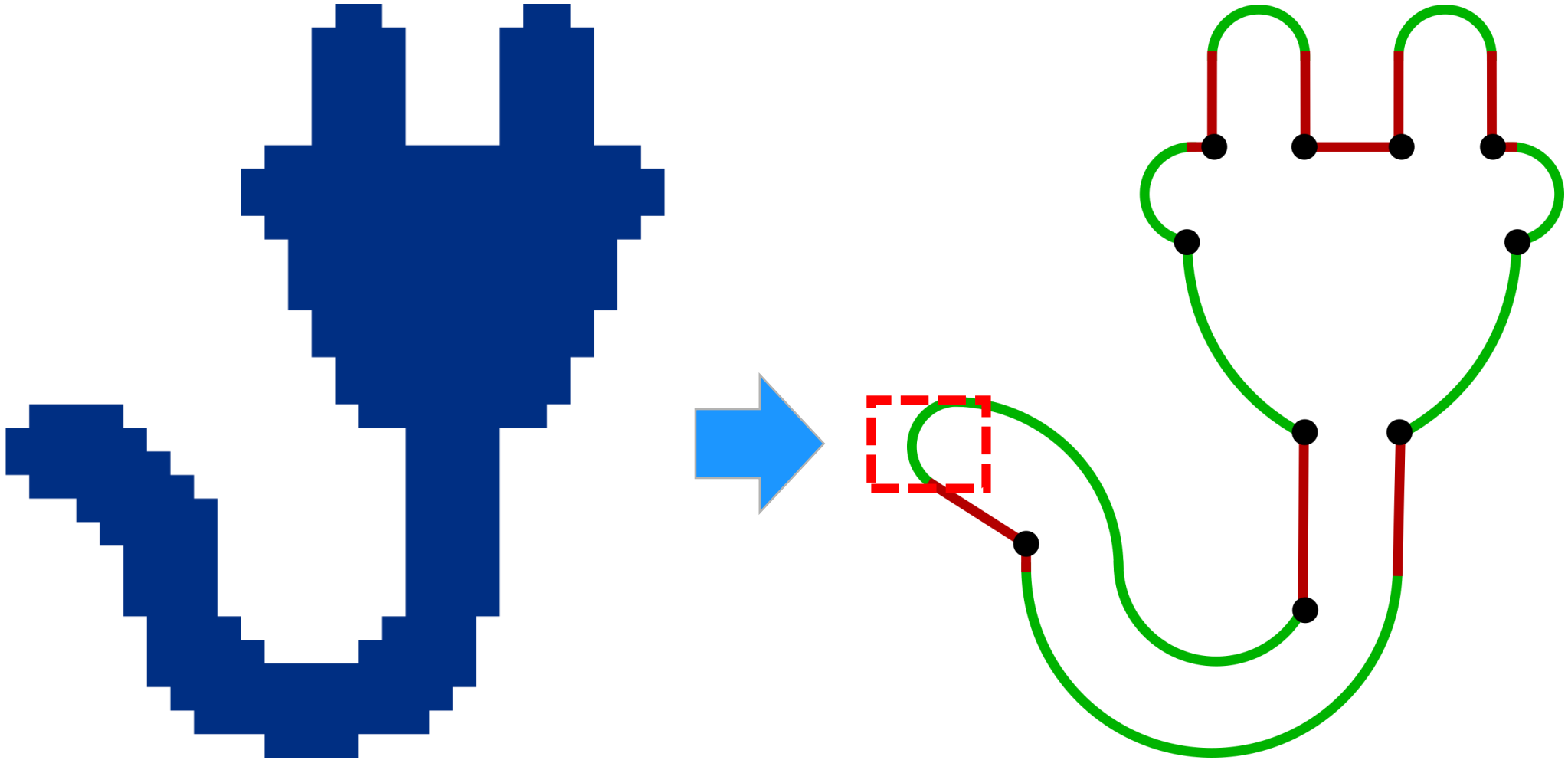
Example



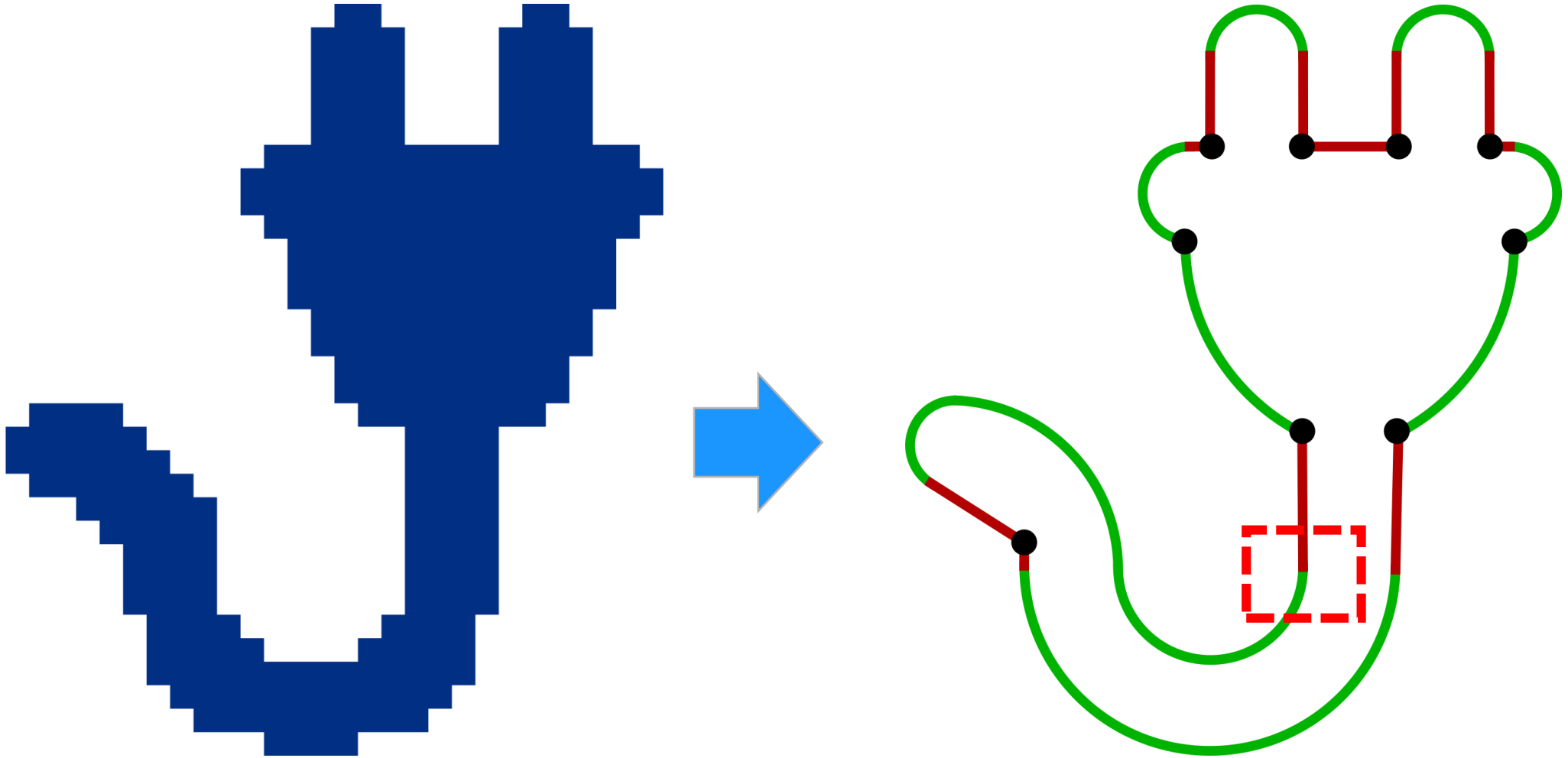
Example



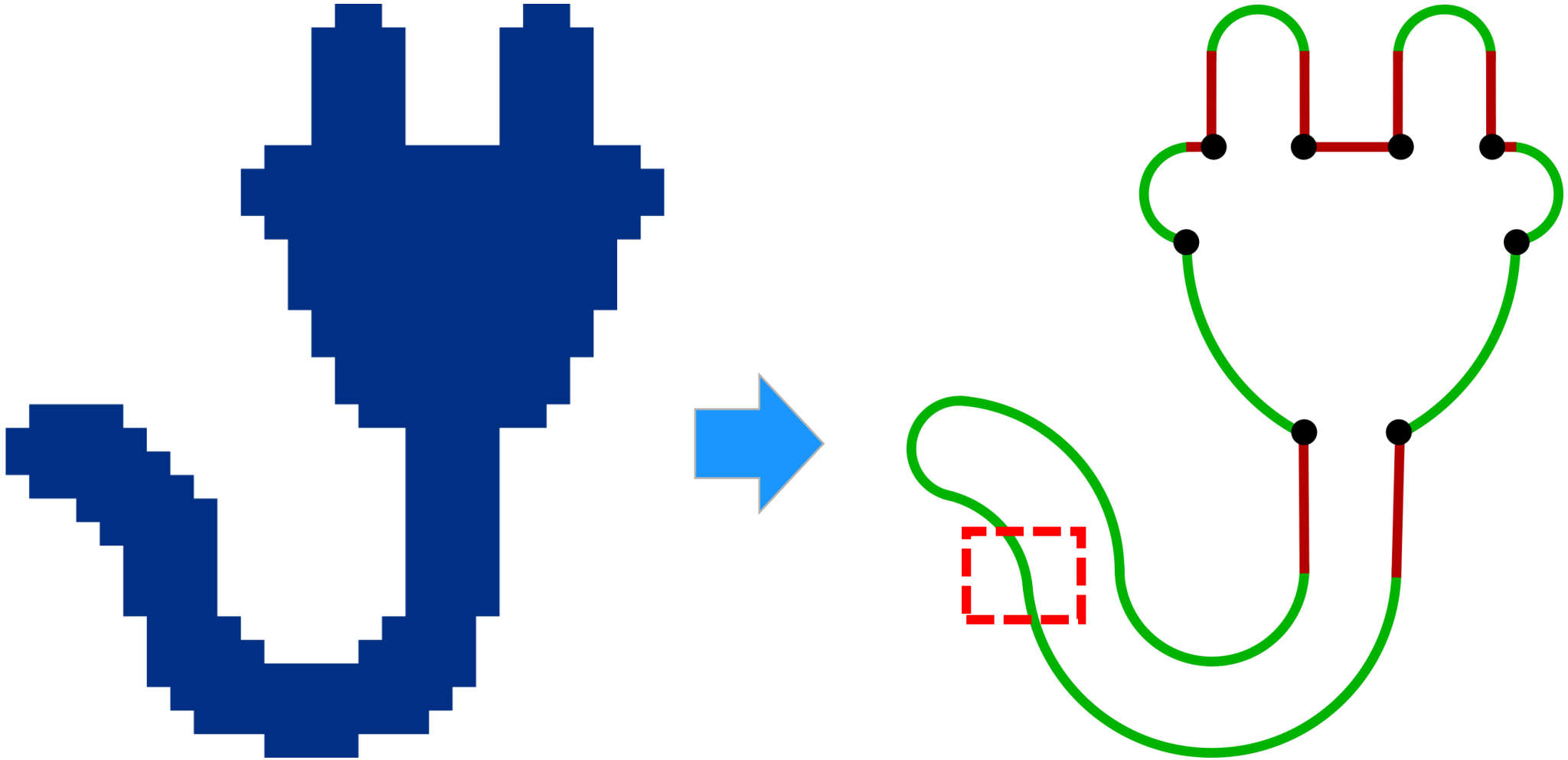
Example



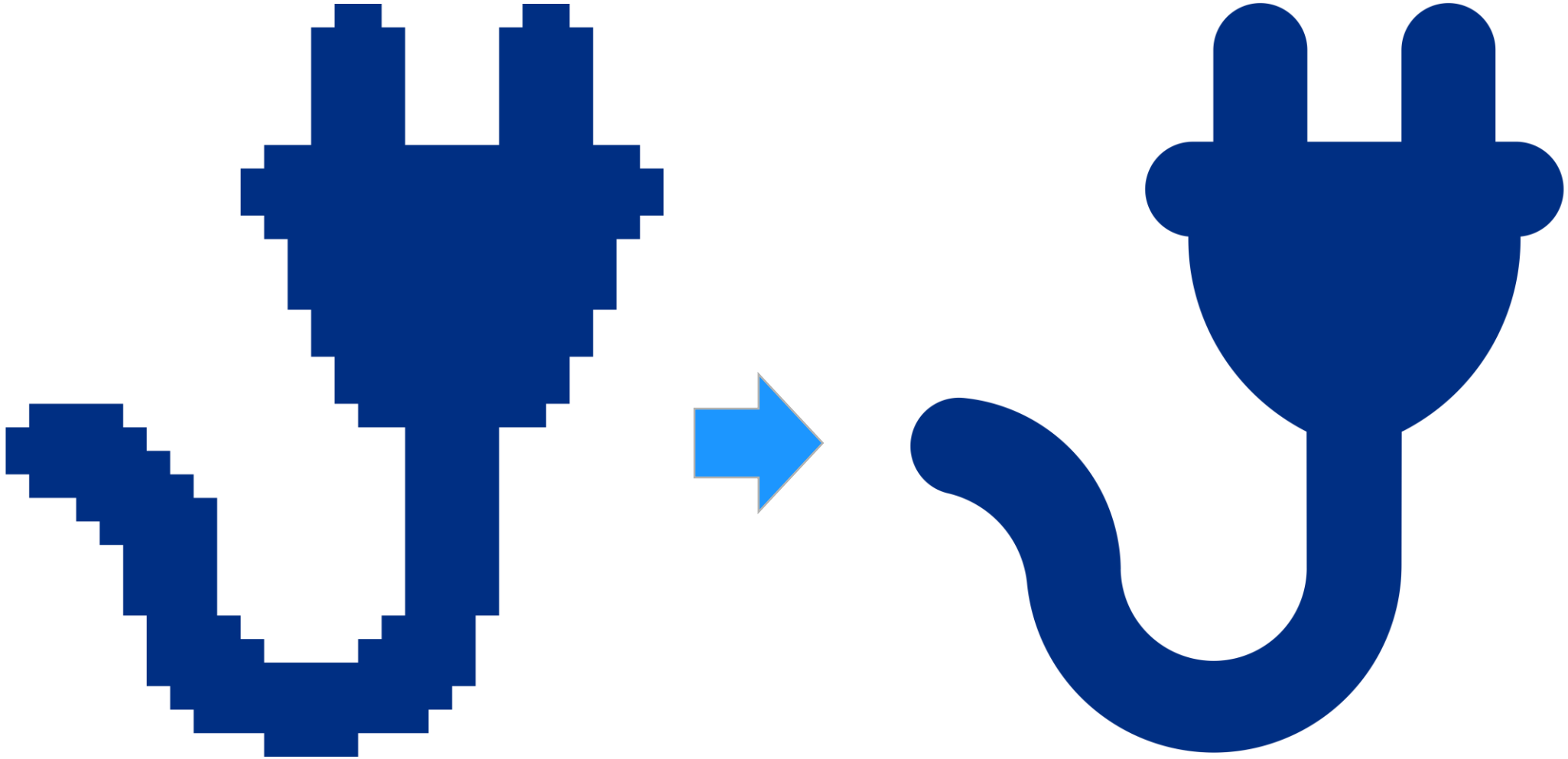
Example



Example

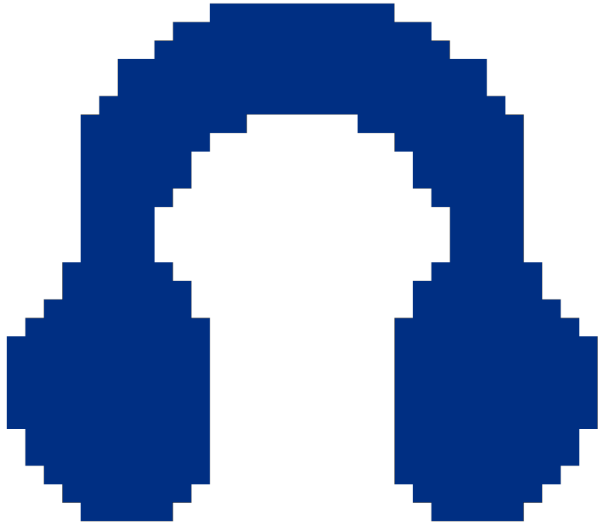


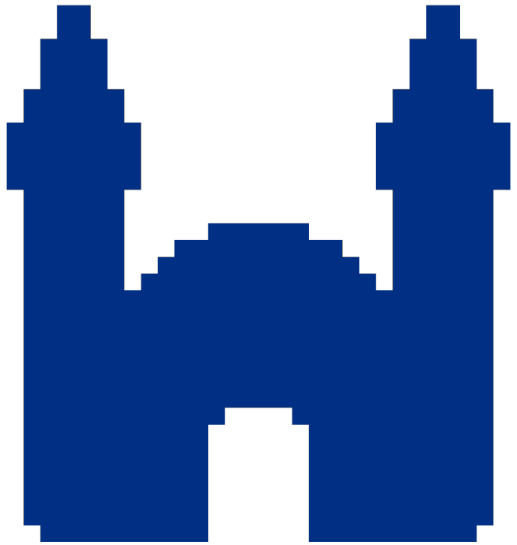
Example



Results & Validation

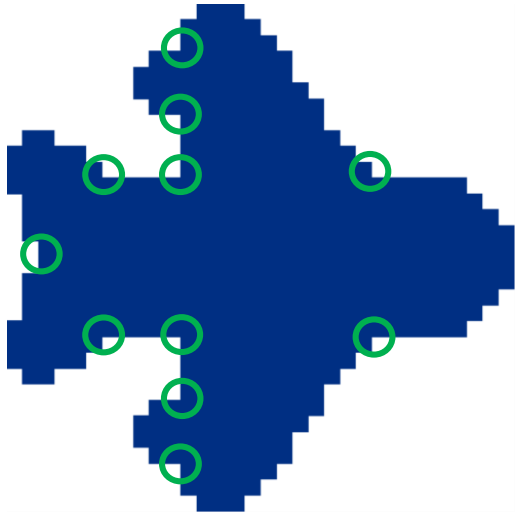
Low Resolution Raster Vectorizations - Binary



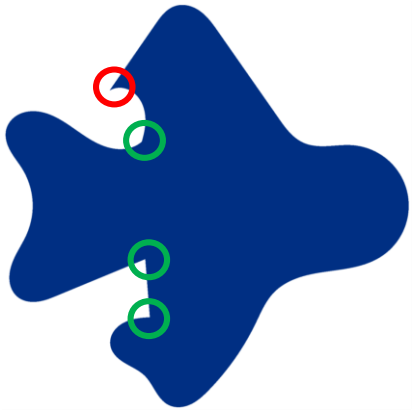


Low Resolution Raster Vectorizations - Color

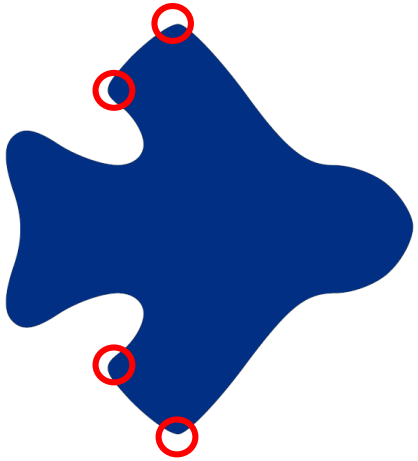
Comparison to Alternative Methods



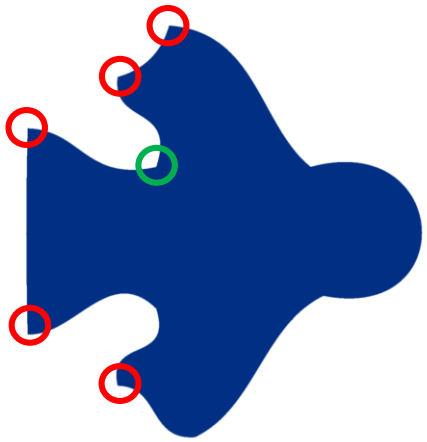
Misplaced discontinuities lead to incorrect reconstructions



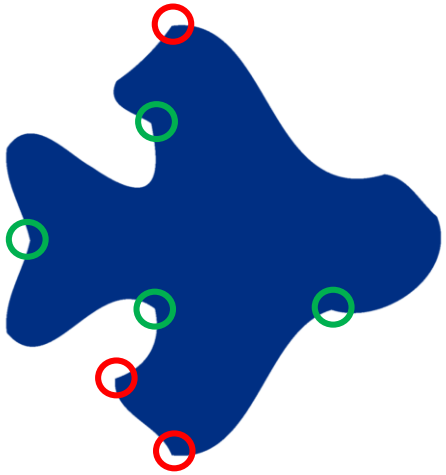
[Baran'10]



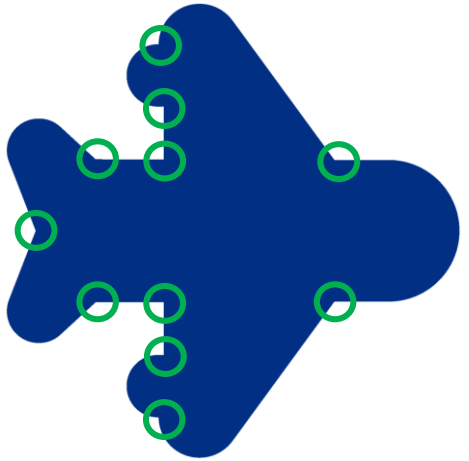
[Selinger'03]



Adobe Trace

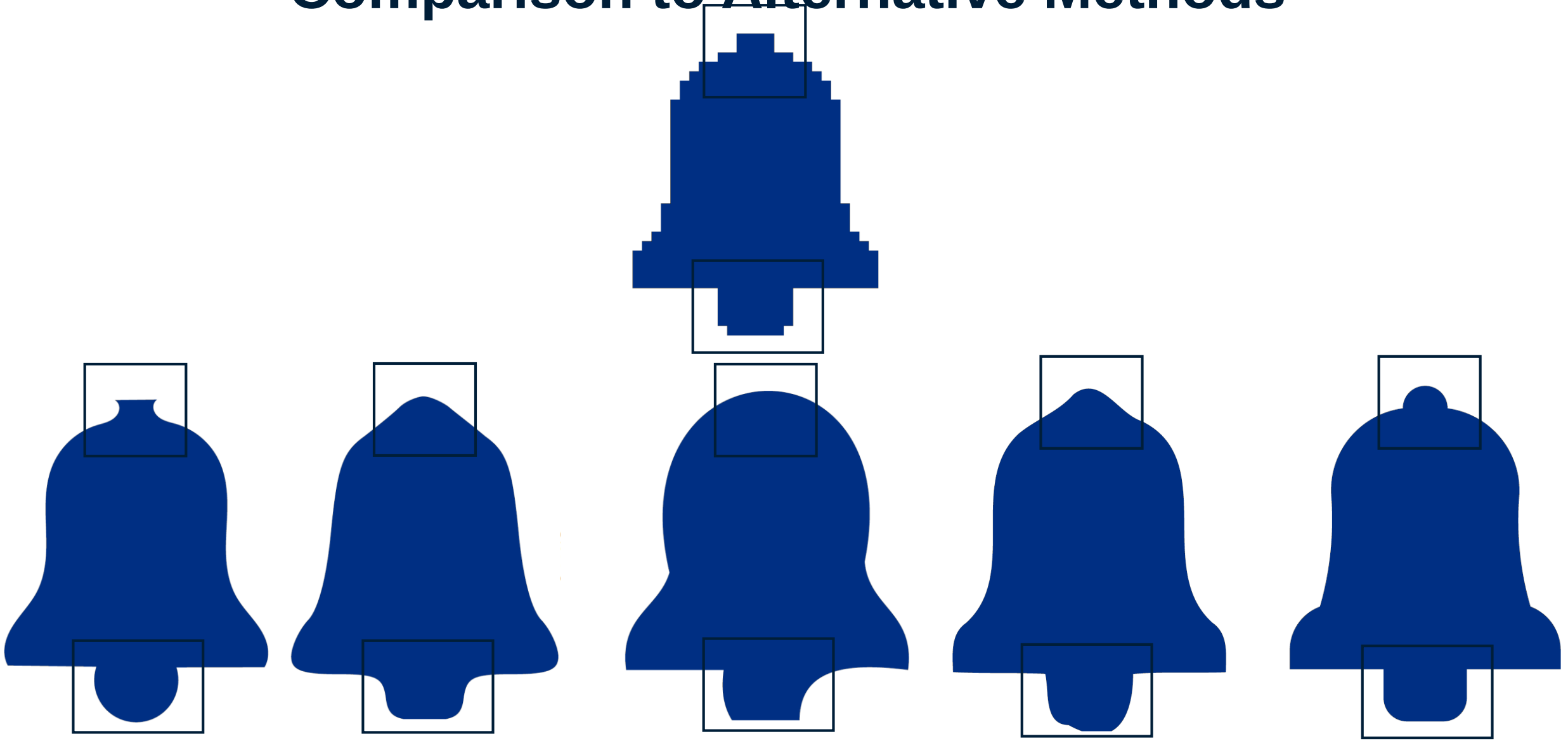


Vector Magic



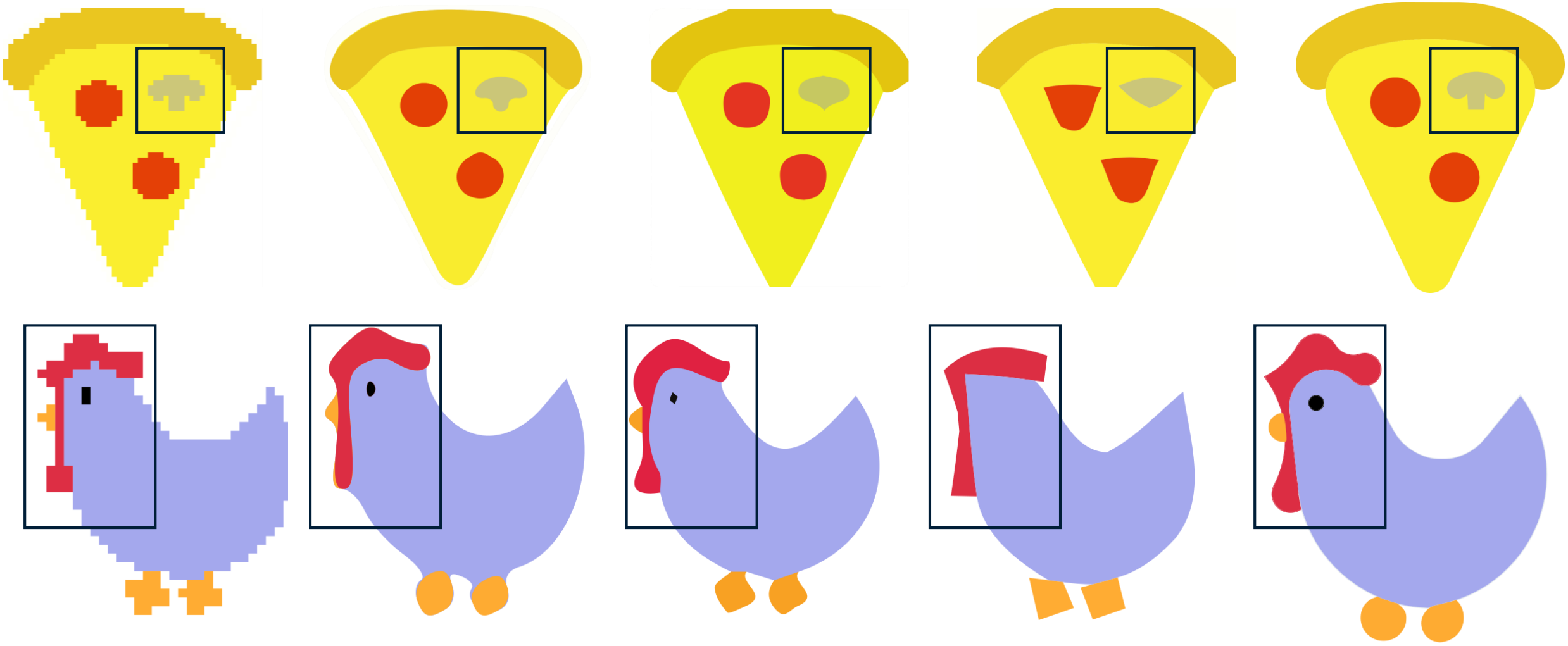
Ours

Comparison to Alternative Methods



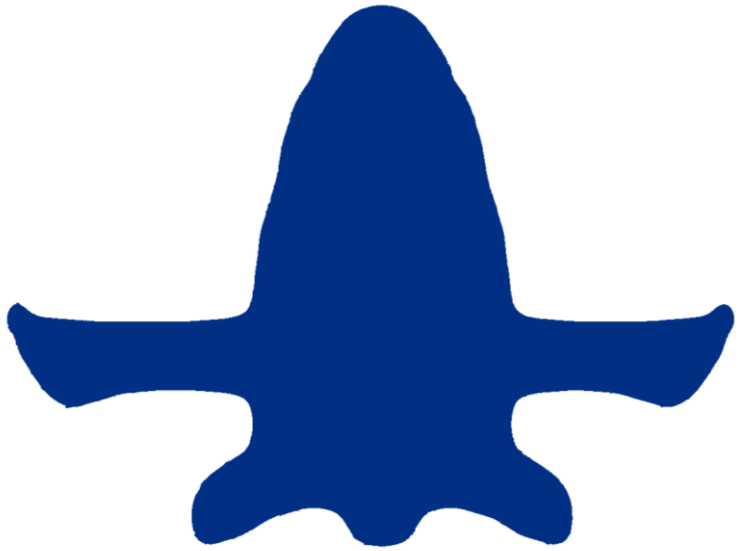
[Baran'10] [Selinger'03] Adobe Trace Vector Magic **Ours**

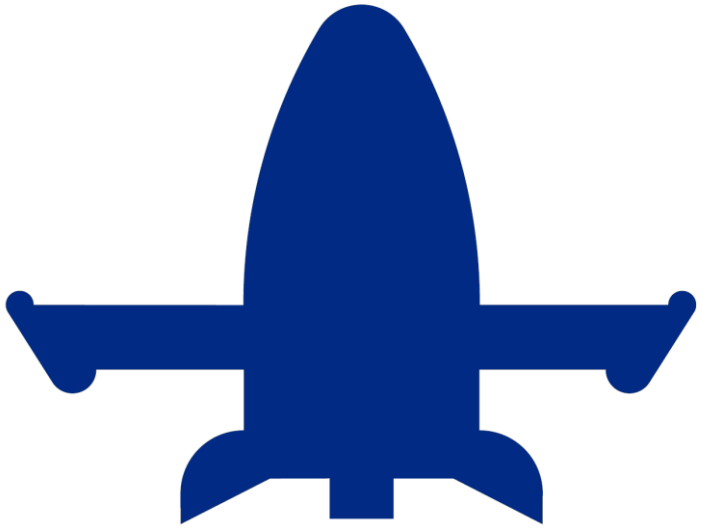
Comparison to Alternative Methods

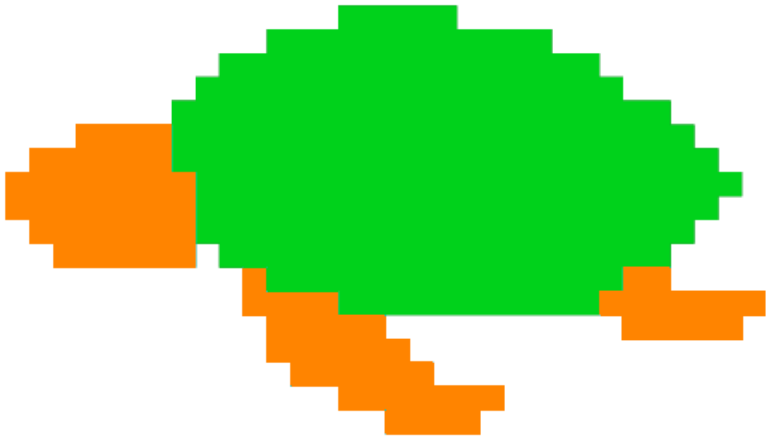


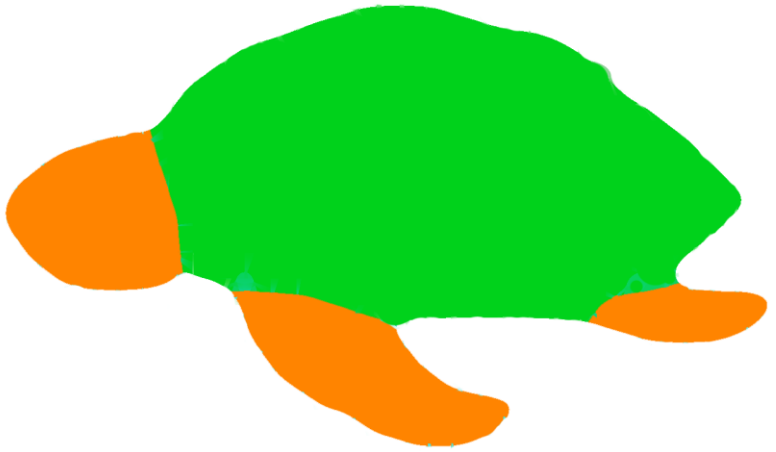
Input [Selinger'03] Adobe Trace Vector Magic **Ours**

Comparison to Pixel Art

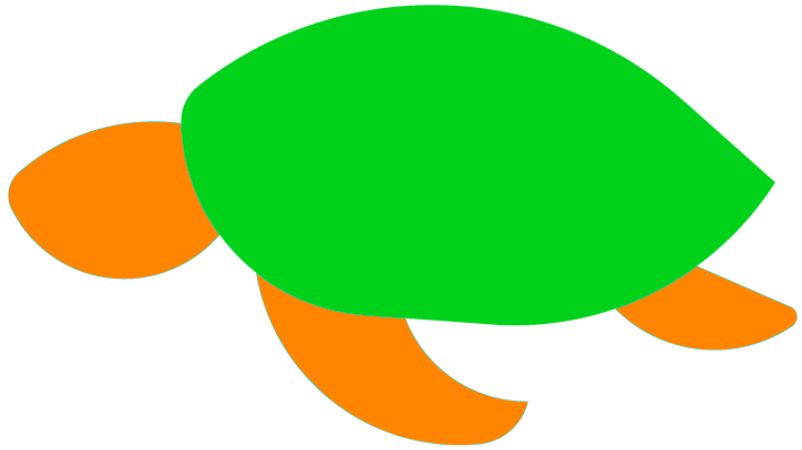








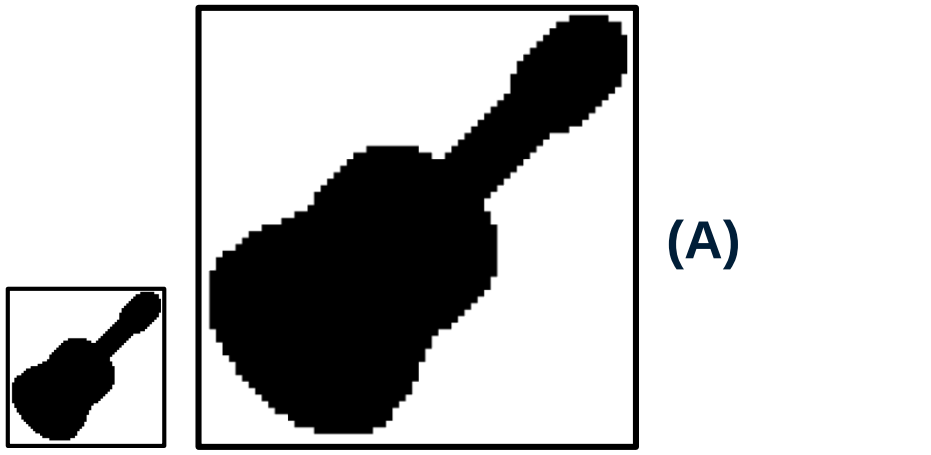
[Kopf'11]

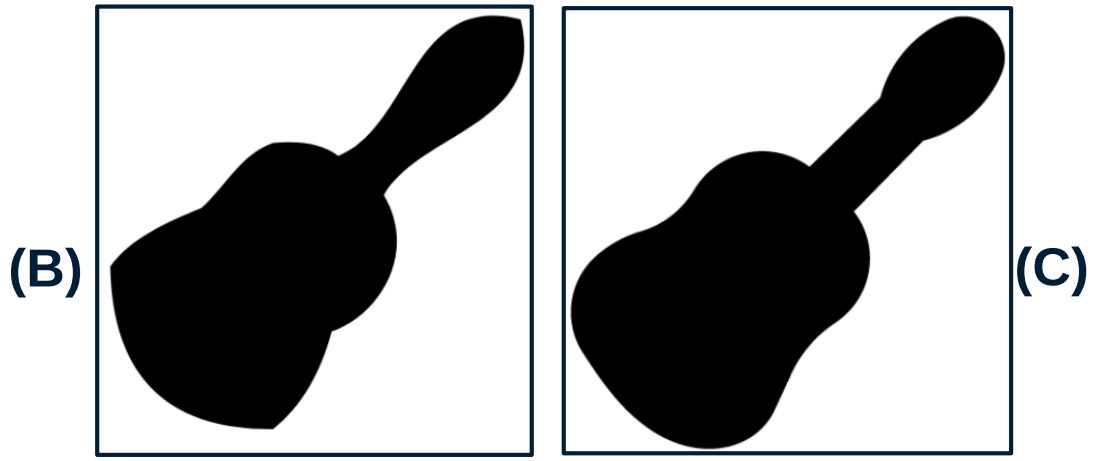


Ours

Quantitative Comparative Evaluation

*Which of the two images on the bottom **(B)** or **(C)** better represents image **(A)**? If both are equally good then select 'Both', and if neither represents **(A)**) then select 'Neither'.*





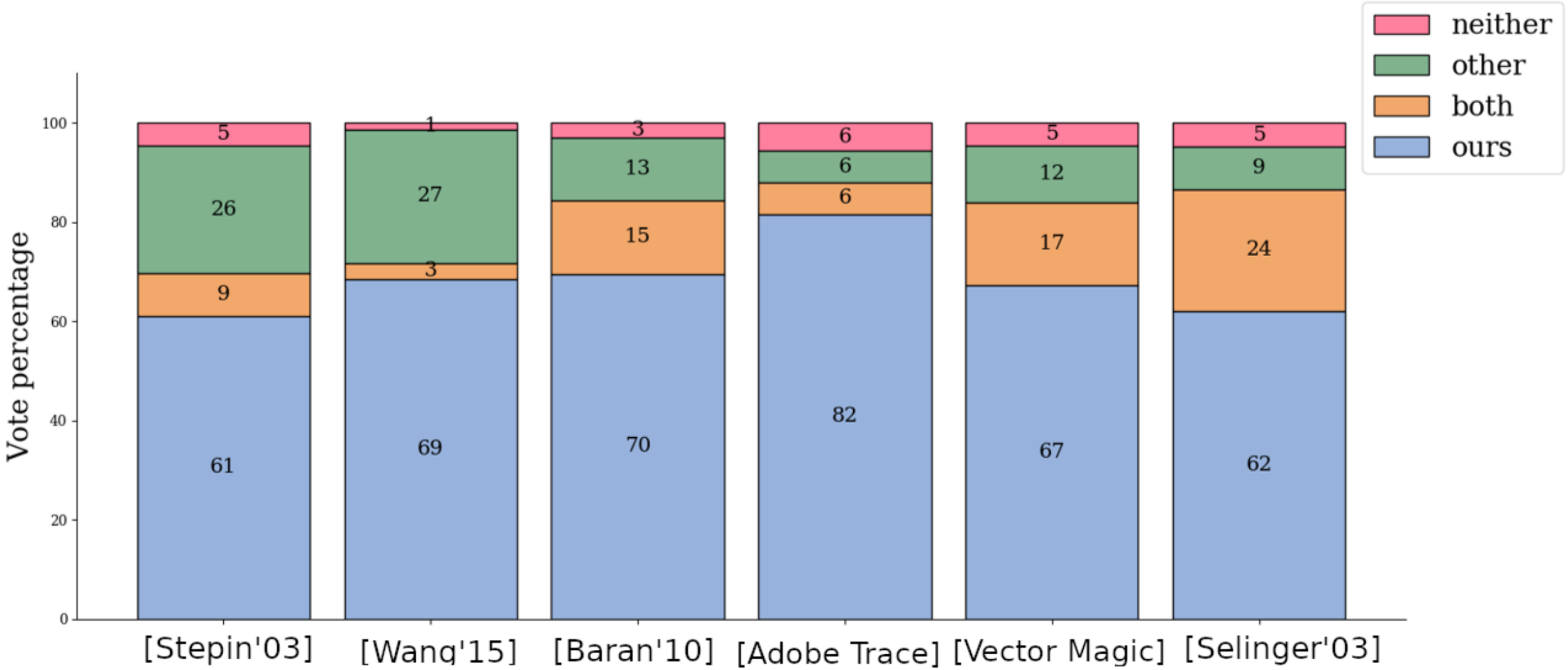
Amazon Mechanical Turk Platform

32px, 64px, 128px resolutions

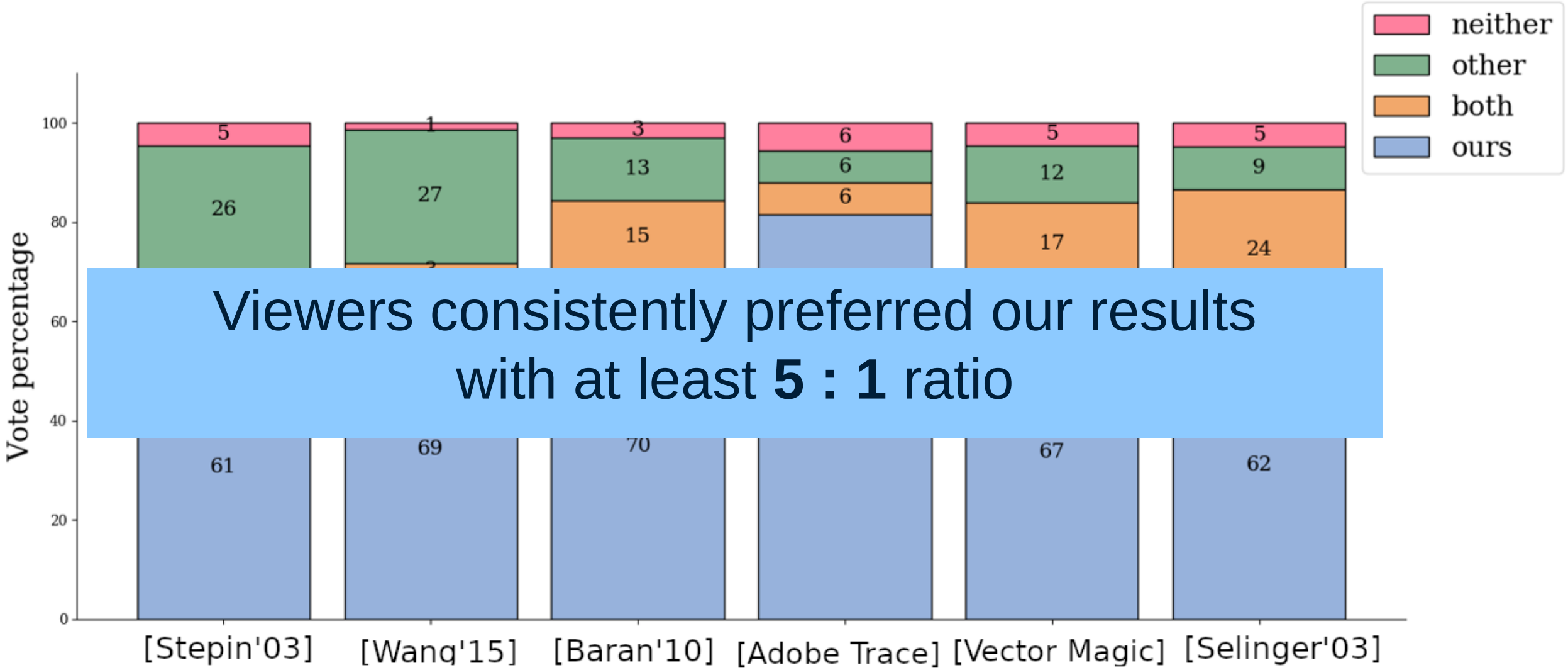
Adobe Trace
Vector Magic
Baran'10
Serling'03
Wang'15
Stepin'15

2520 questions asked to 126 participants

Quantitative Evaluation

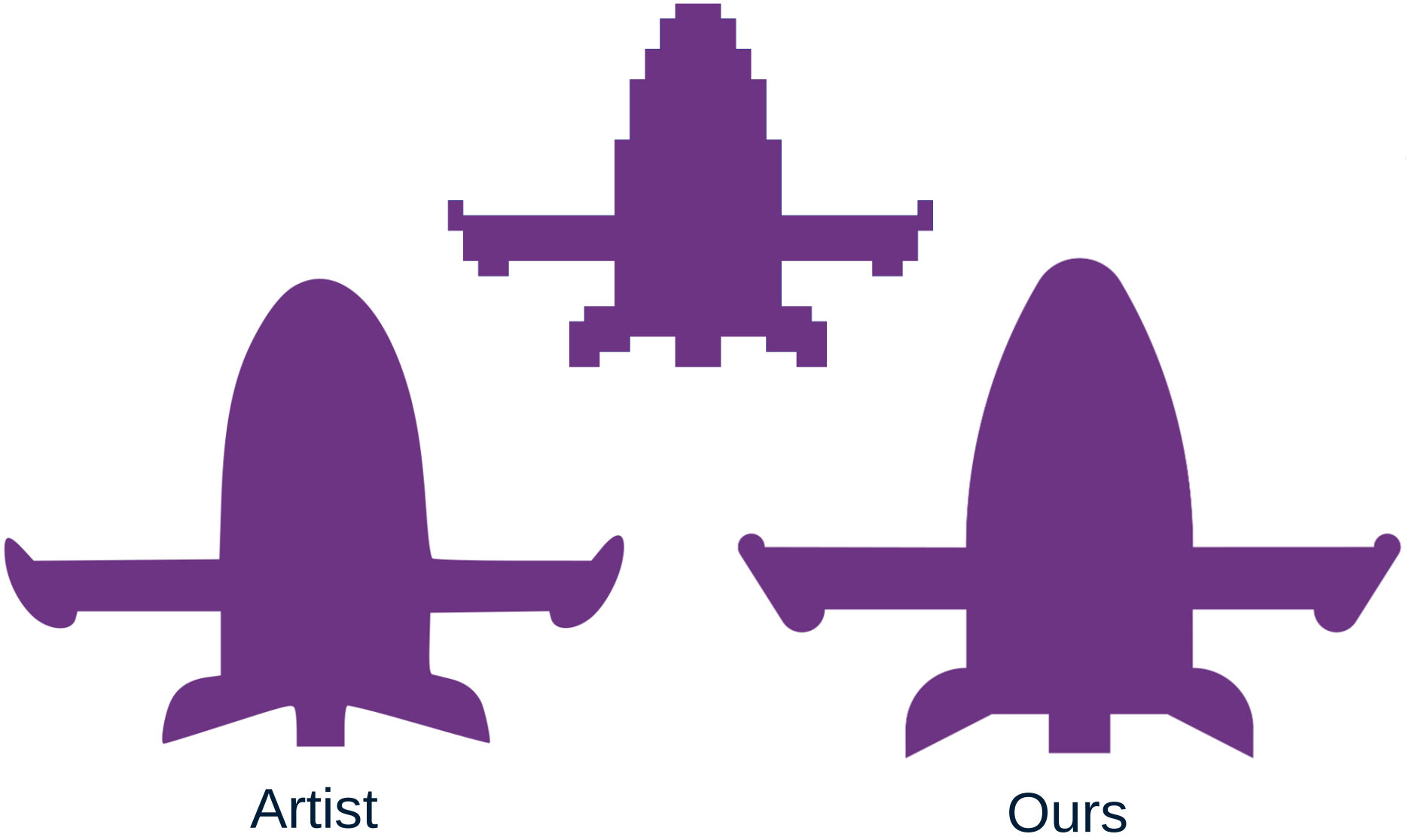


Quantitative Evaluation



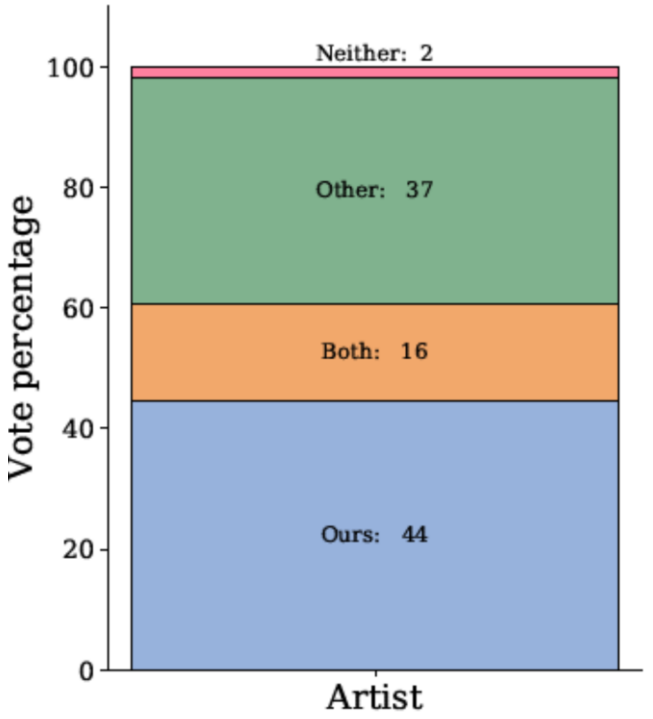
Viewers consistently preferred our results with at least **5 : 1** ratio

Qualitative Evaluation

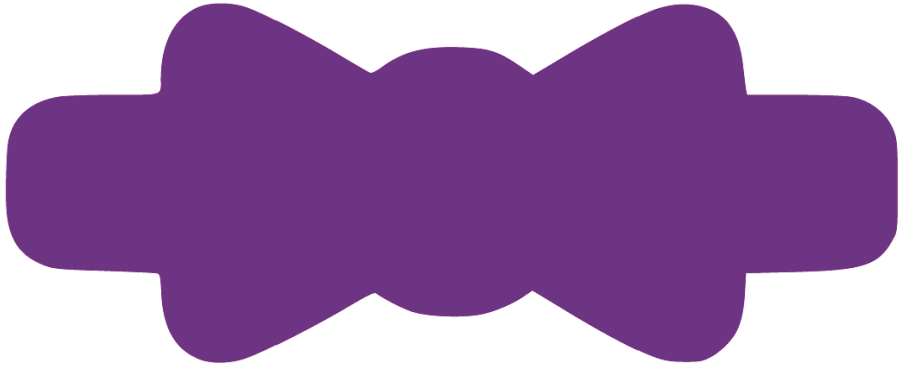


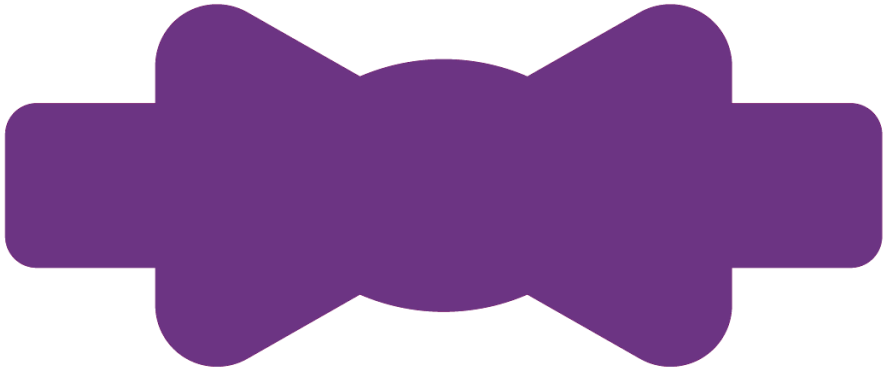
Artist

Ours



Qualitative Evaluation





Artist

30 – 45 min

Ours

2min

Evaluation of Corner Detection

- Considered methods:
  - Random Forests [Breiman'01]
  - Perceptron Neural Network [Yi'16]

Resolution	Precision/Recall/F1	
	Neural Network	Random Forest
32	0.793/0.847/0.819	0.835/0.910/0.871
64	0.944/0.770/0.848	0.907/0.850/0.877
128	0.939/0.837/0.885	0.923/0.880/0.901

Leave-one-out cross-validation metrics

Evaluation of Corner Detection

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  - **Random Forests** [Breiman'01]
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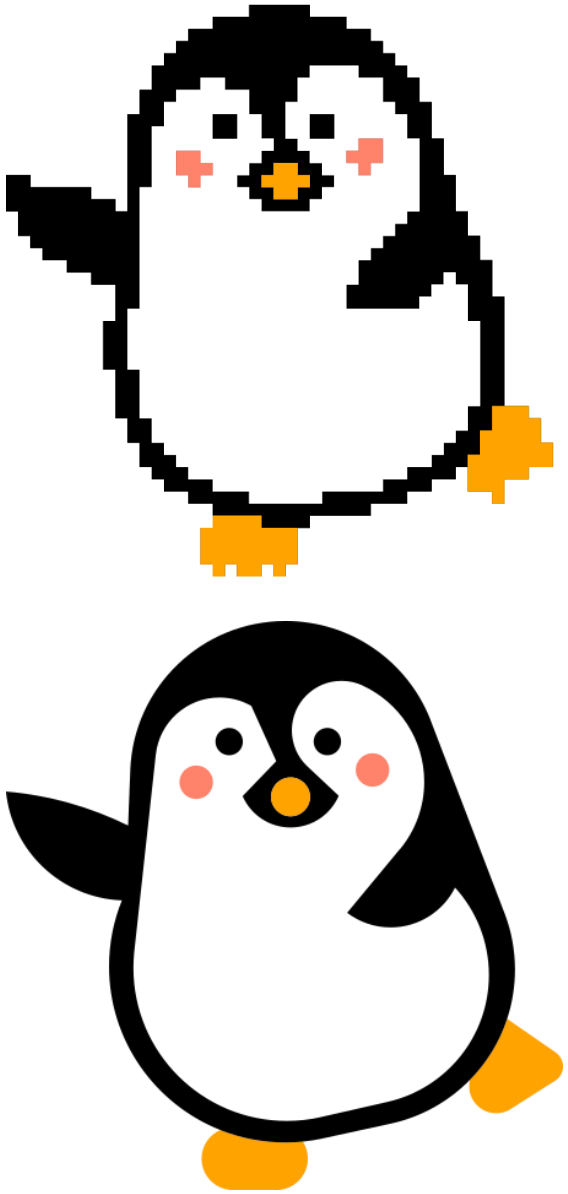
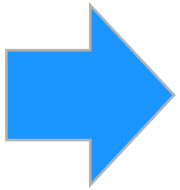
128	0.939/0.837/0.885	0.923/0.880/**0.901**

Leave-one-out cross-validation metrics

Conclusion

- Semi-structured ***raster*** images are ubiquitous
- Prior methods fail to vectorize this data in a manner consistent with human expectations
- Contribution: Algorithmic vectorization of such images consistent with viewer expectations
  - Core idea: Principled combination of machine learning and perception-driven processing
  - Validated via extensive user study



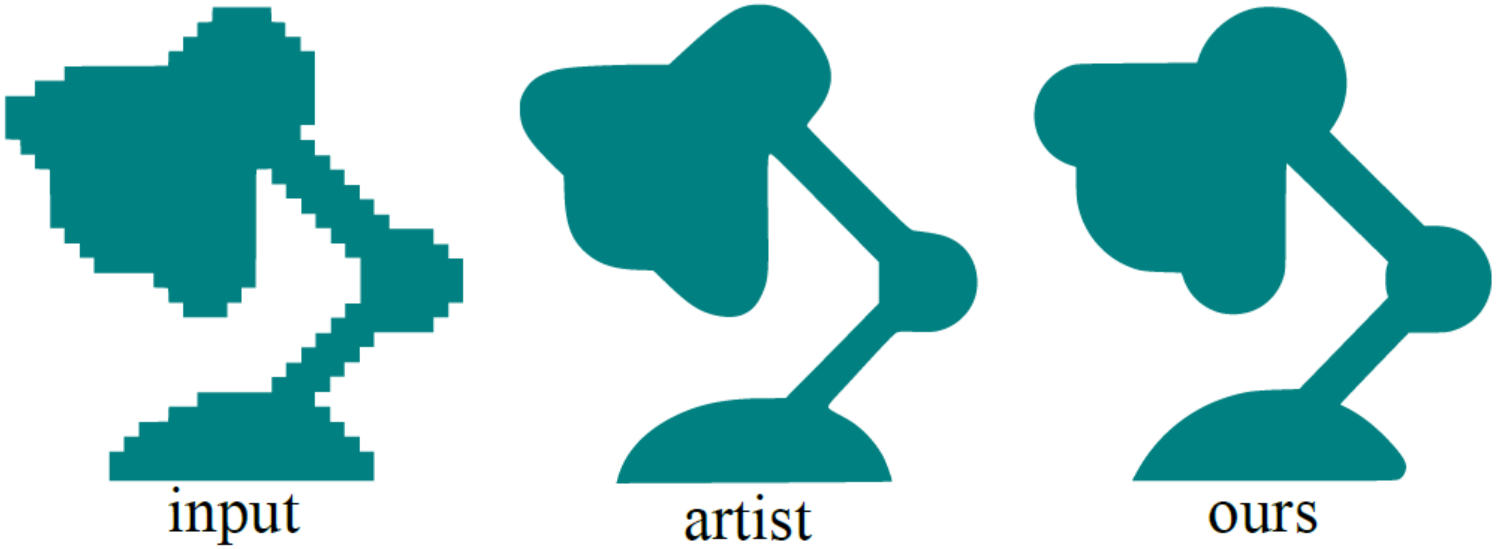


Thank You.

Extra Slides

User Study Failure Cases

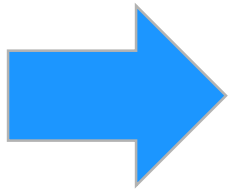
hqx: 75%
ours: 7%
both: 3%
neither: 15%

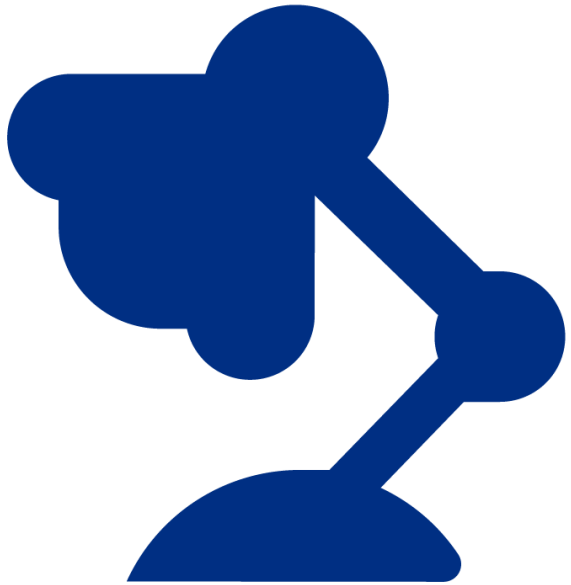


artist: 75%
ours: 7%
both: 11%
neither: 7%

Effects of Anti-Aliasing

Clean Input





Antialiased Input

After Thresholding