# Crowd-Guided Ensembles

# How Can We Choreograph Crowd Workers for Video Segmentation?

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# Motivations

Movie post-production

(CC) Blender Foundation | Tears of Steel, see mango.blender.org

Video understanding

Playing for Data [Richter 2016]

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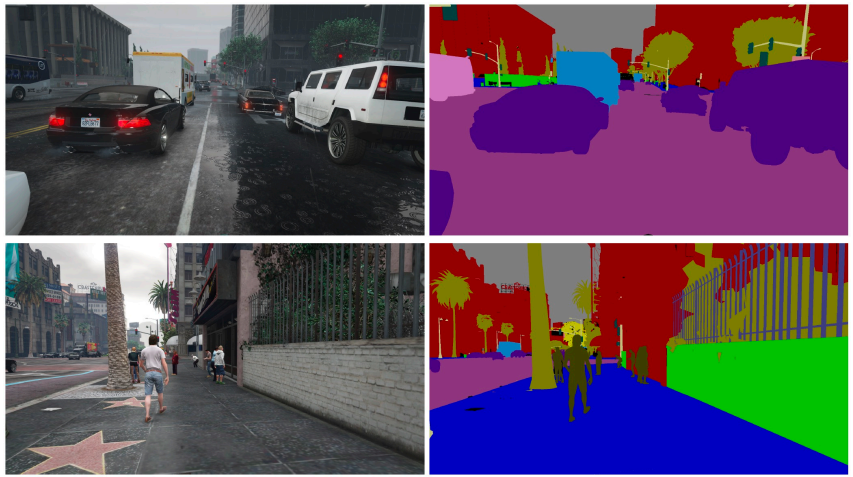
Video understanding

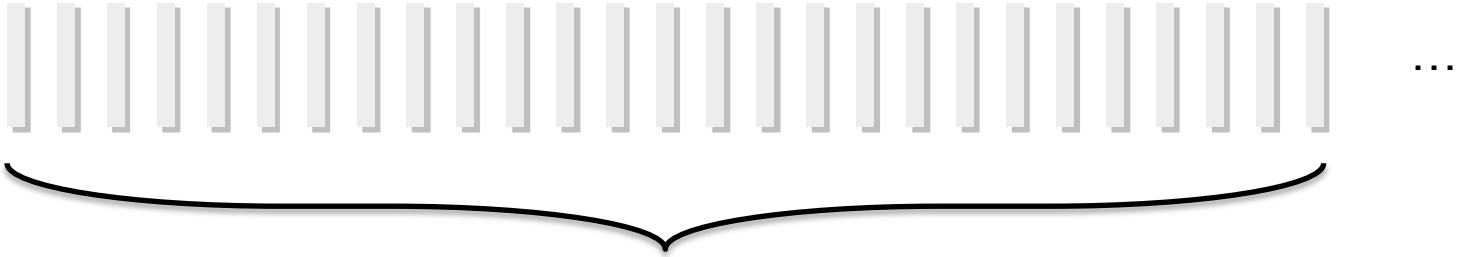


Playing for Data [Richter 2016]

Brief introduction to

# ROTOSCOPING

# Rotoscoping

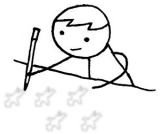


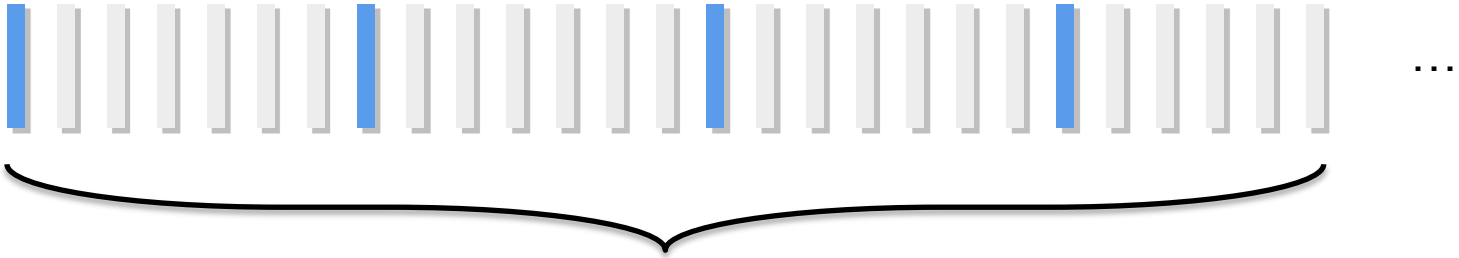
…

Frames of video sequence

Artist

# Rotoscoping

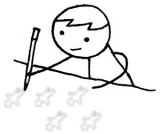


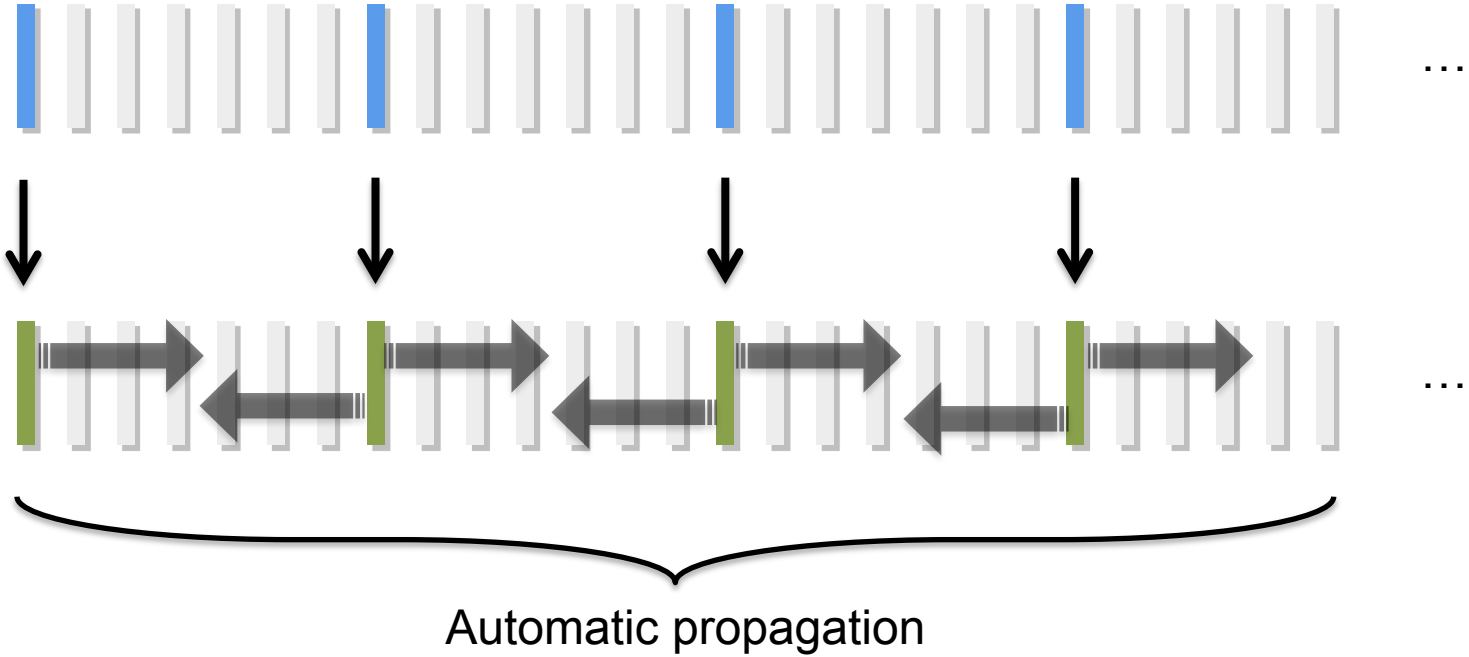



Keyframe: direct segmentation & manipulation

Remaining frame

# Rotoscoping





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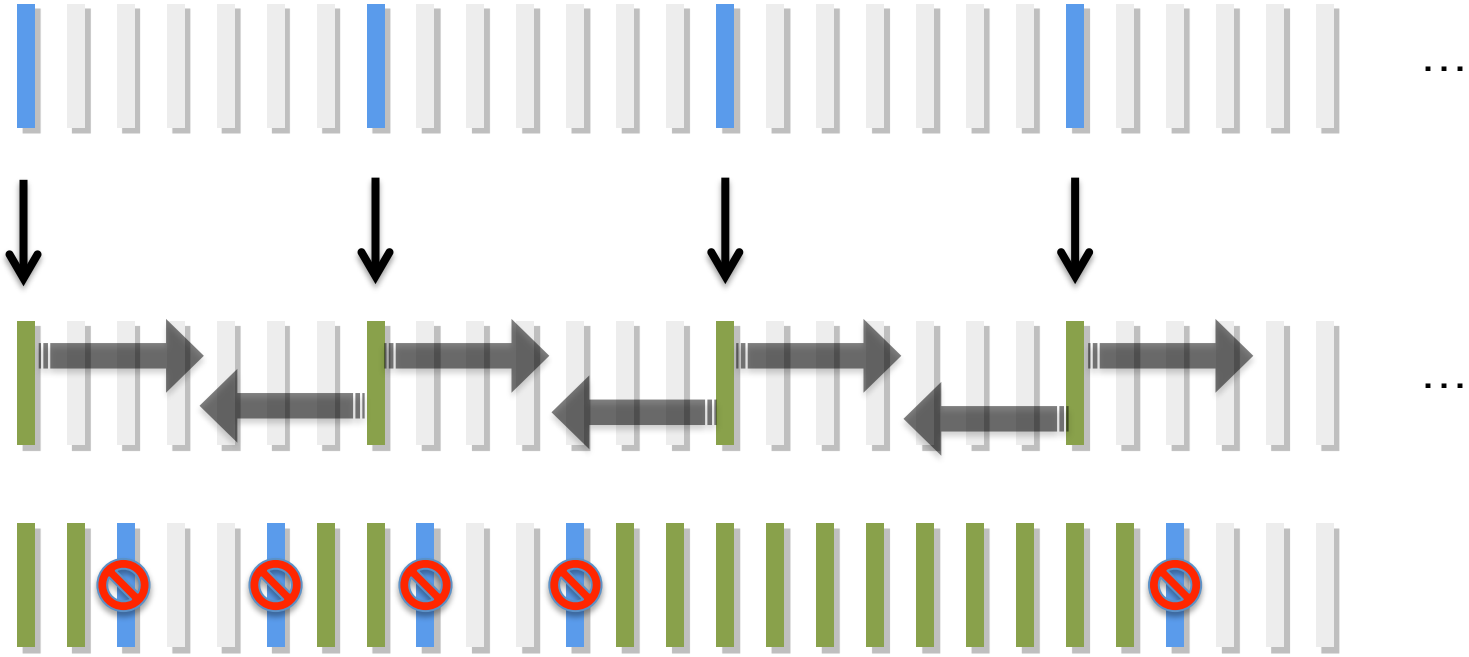

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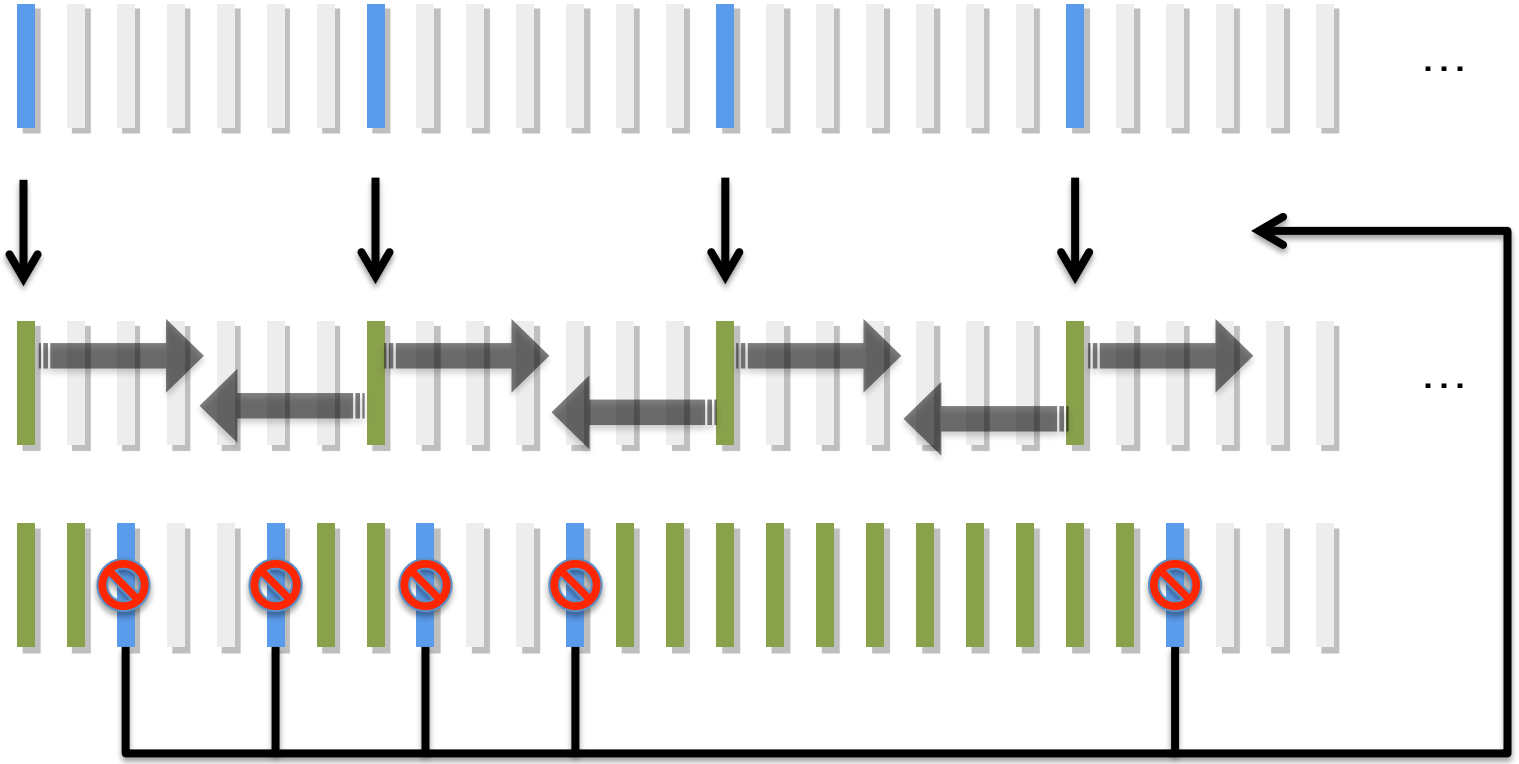
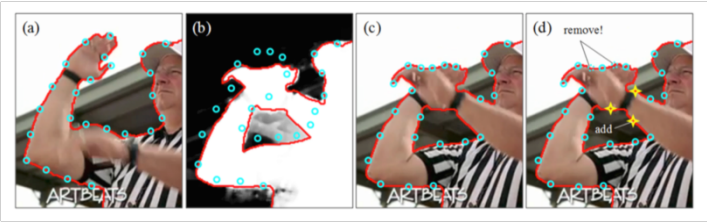



Roto++ [Li 2016]
Professional Roto-Artist
Replay at x5

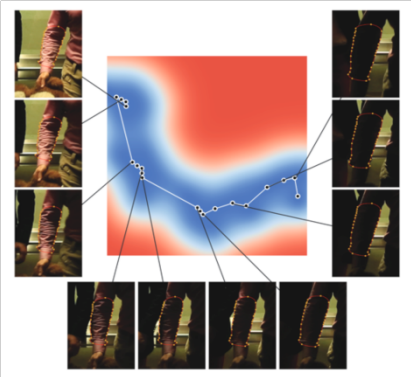
# RELATED WORK

# Related Work: Interactive Segmentation



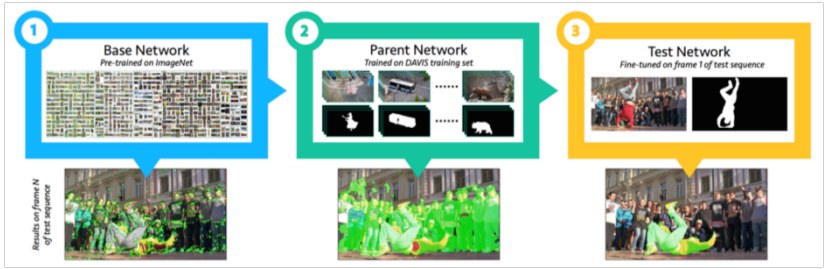

Video SnapCut: Robust Video Object Cutout Using Localized Classifiers [Bai 2009]


JumpCut: Non-Successive Mask Transfer and Interpolation for Video Cutout [Fan 2015]



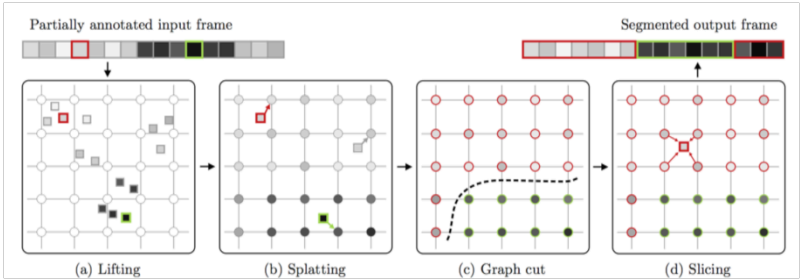
Roto++: Accelerating Professional Rotoscoping using Shape Manifolds [Li 2016]

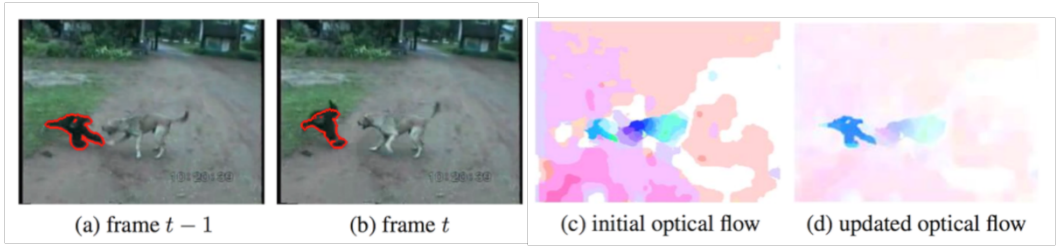
# Related Work: Computer Vision




One-Shot Video Object Segmentation [Caelles 2017]

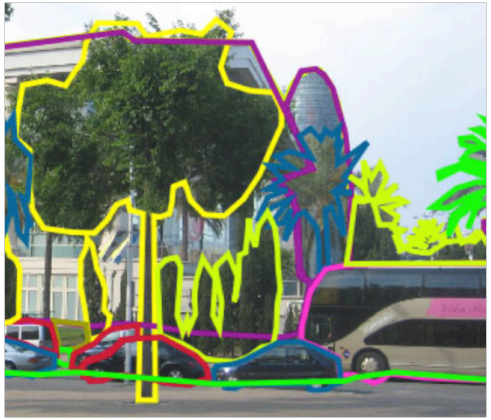
Bilateral Space Video Segmentation [Märki 2016]



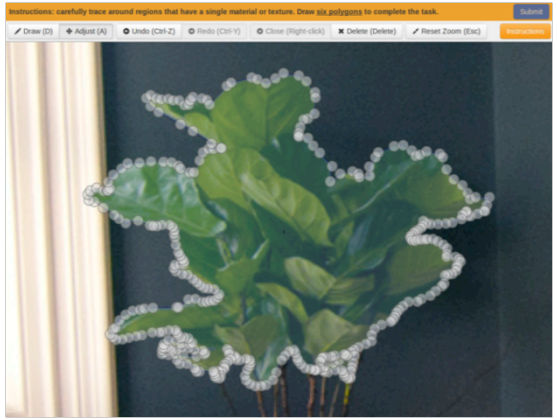

Video Segmentation via Object Flow [Tsai 2016]

# Related Work: Crowdsourcing



LabelMe [Russell 2007]

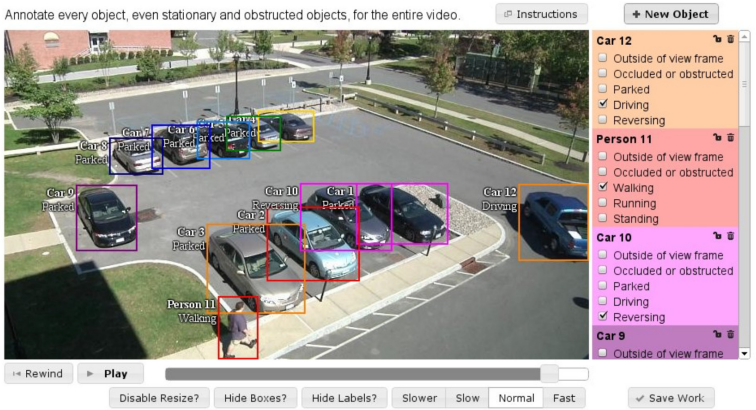
COCO [Lin 2014]




Open Surfaces [Bell 2013]

# Related Work: Video Annotation

LabelMe video: Vuilding a Video Database with Human Annotations [Yuen 2009]



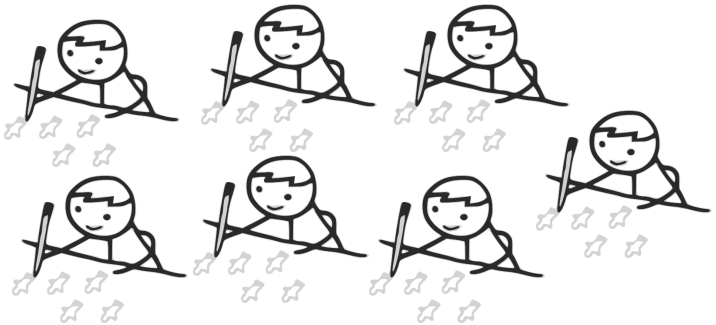

Efficiently Scaling Up Crowdsourced Video Annotation [Vondrick 2012]

Crowdsourcing

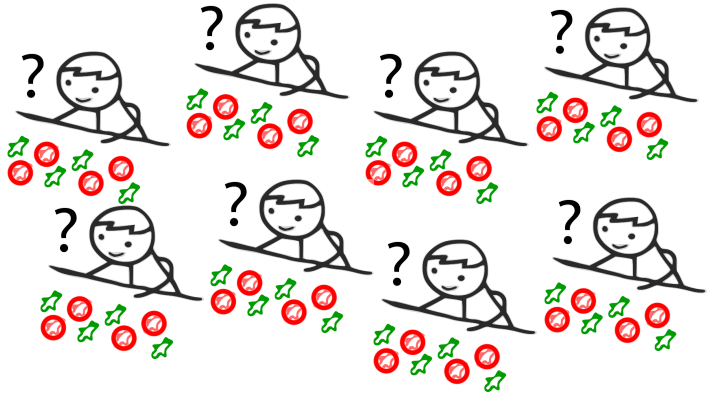
Higher-Quality Segmentation

# OVERVIEW

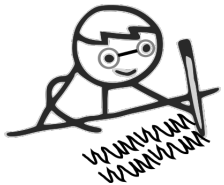
## Segmentation



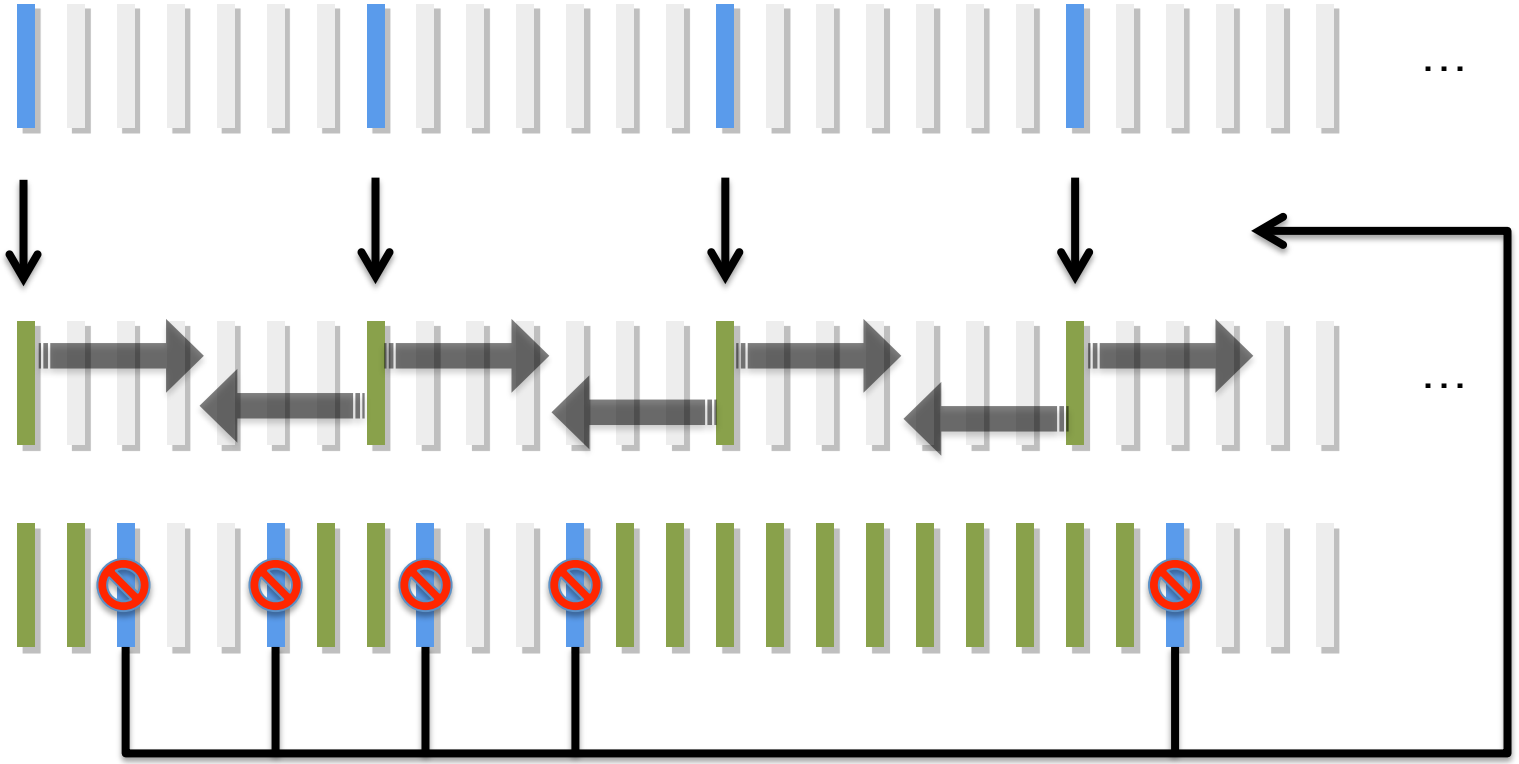
## Propagation




## Requester



# Rotoscoping



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Requester

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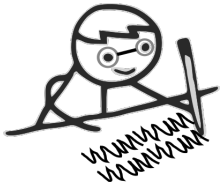

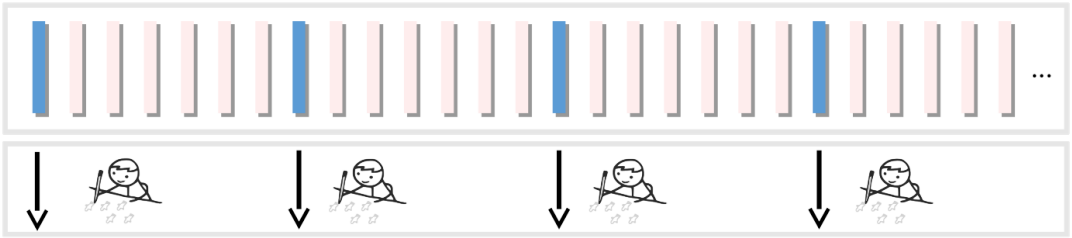

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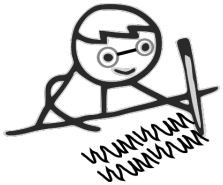

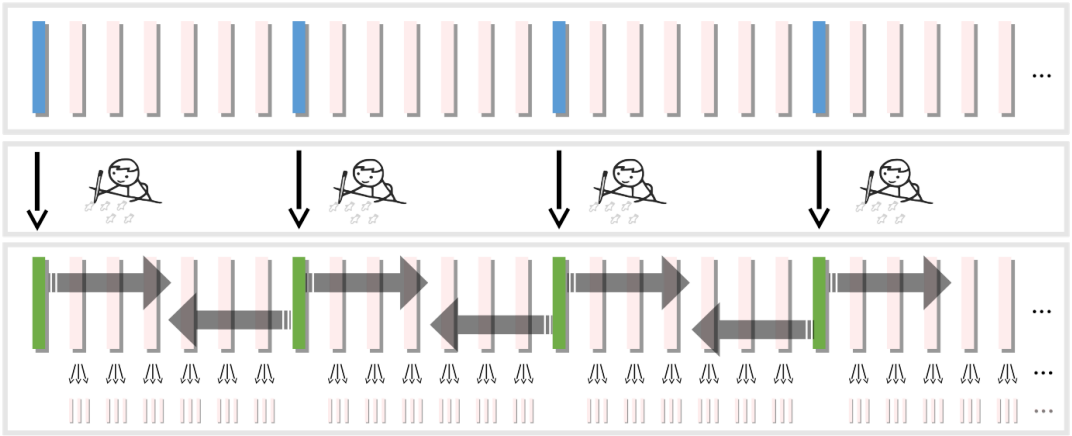

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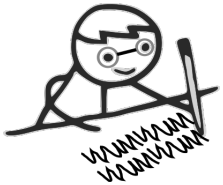
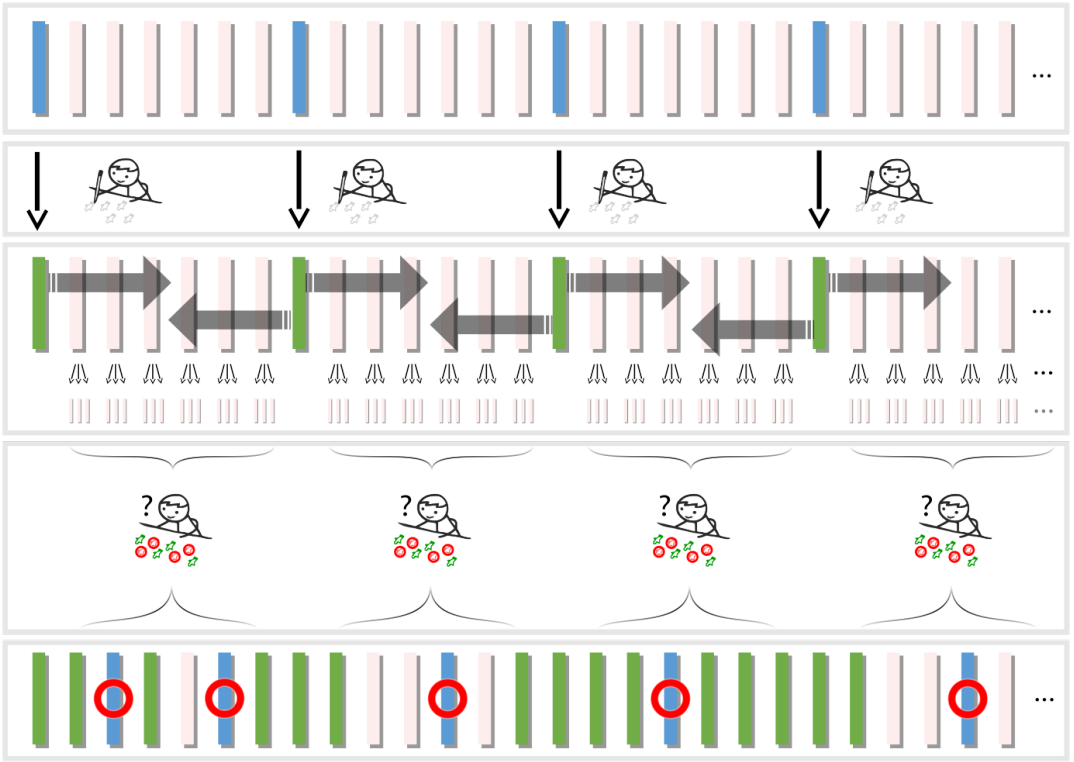
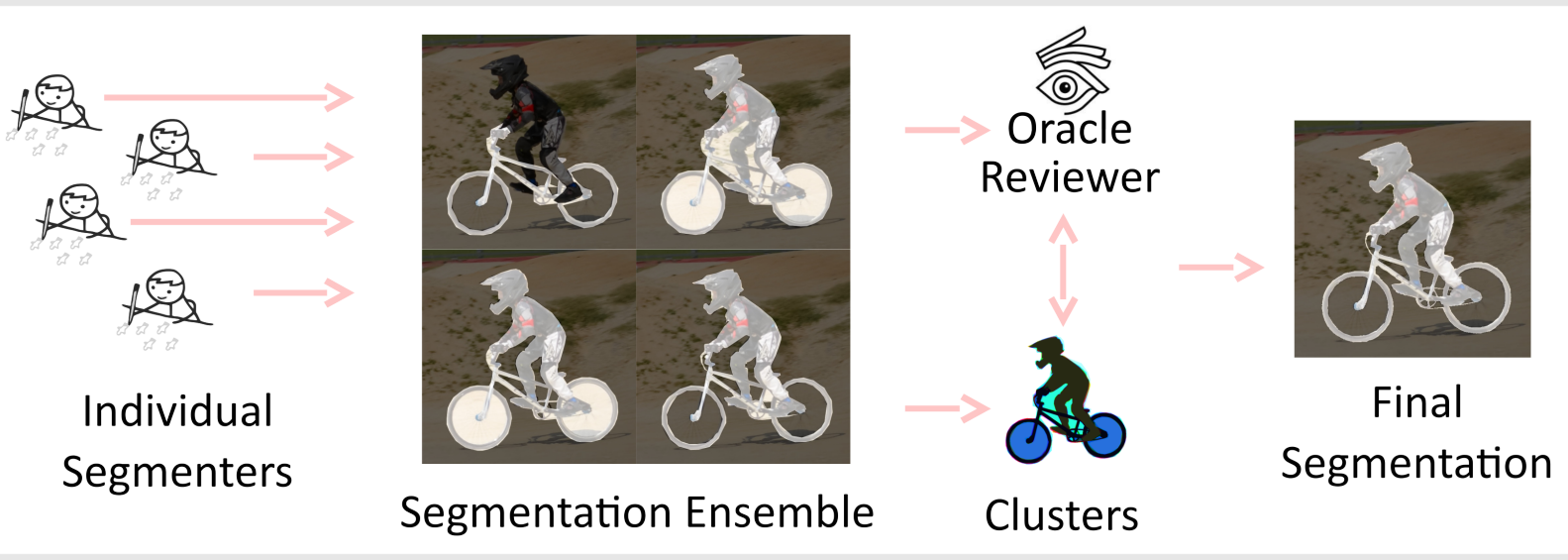




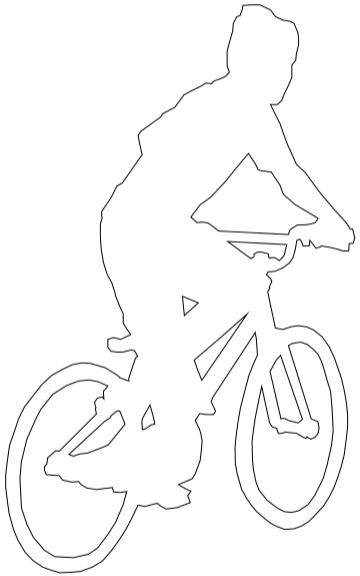
# SEGMENTATION ENSEMBLE

# Overview


Individual
Segmenters
Segmentation Ensemble
Oracle
Reviewer
Clusters
Final
Segmentation

# Need for Replication

# Need for Replication



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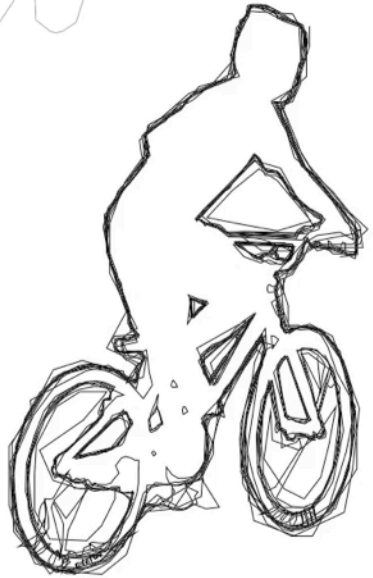


# Need for Replication

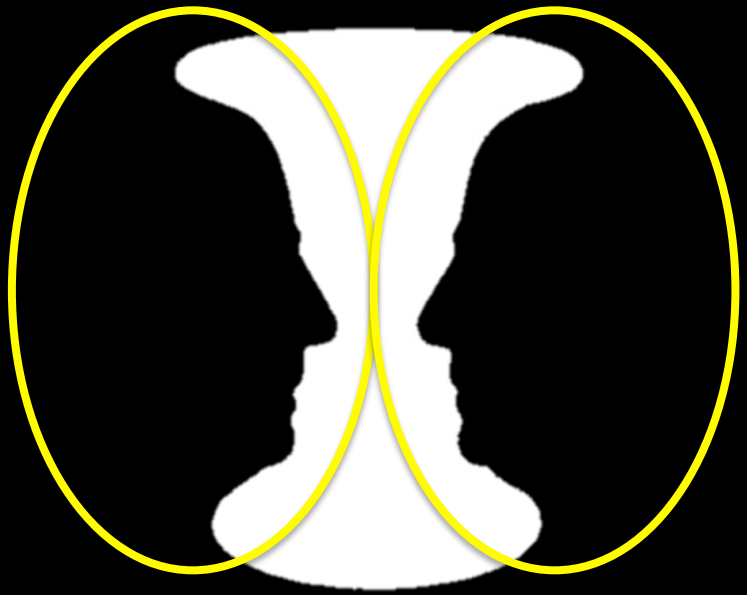
# Segmentation Ensemble

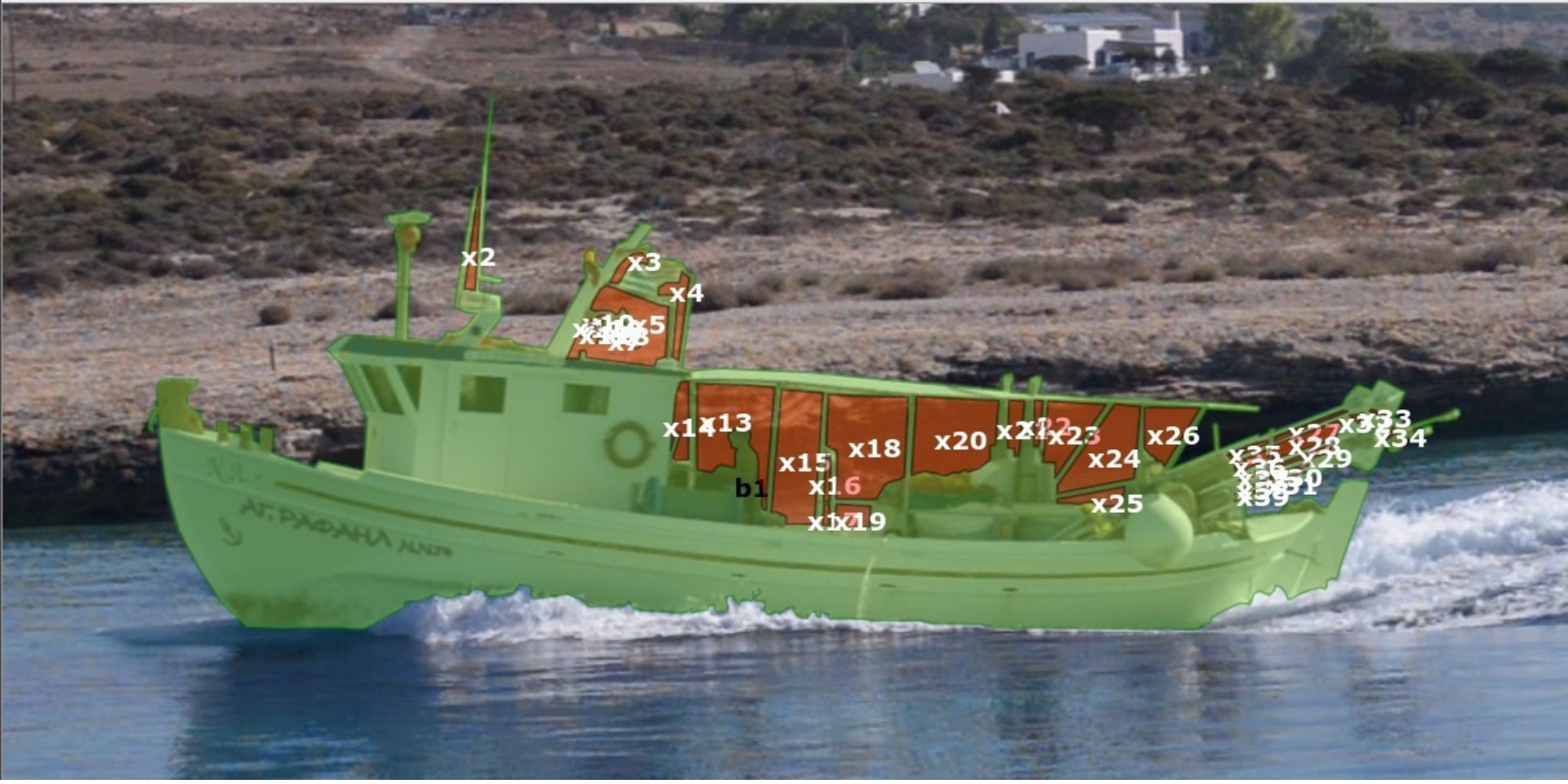
- Negative polygons
- Clustered merging
- Reviewer weighting
  (serving two purposes)

# Negative Space

# Negative Space

# Negative Space

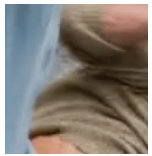


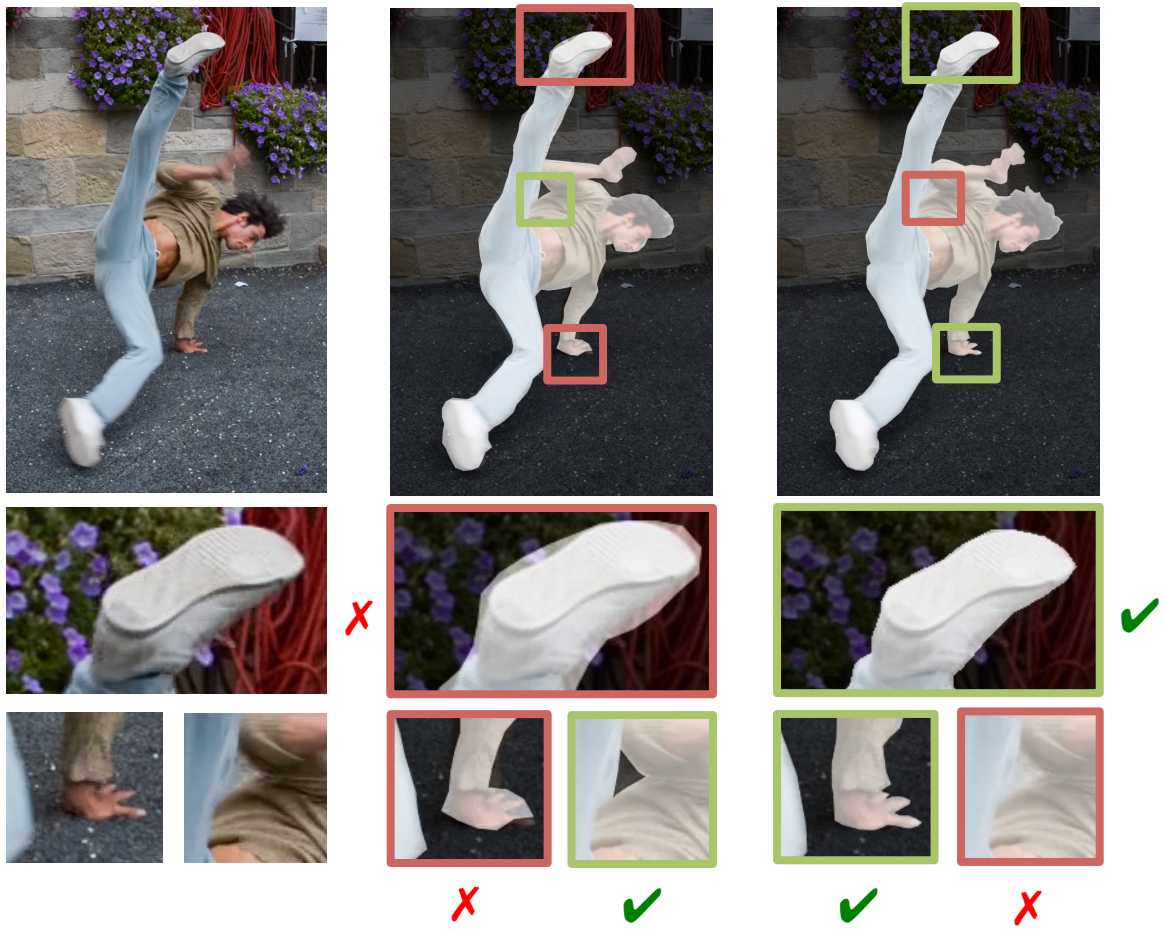

x2
x3
x4
x5
x13
x14
x15
x16
x18
x19
x20
x23
x24
x25
x26
x29
x33
x34
b1

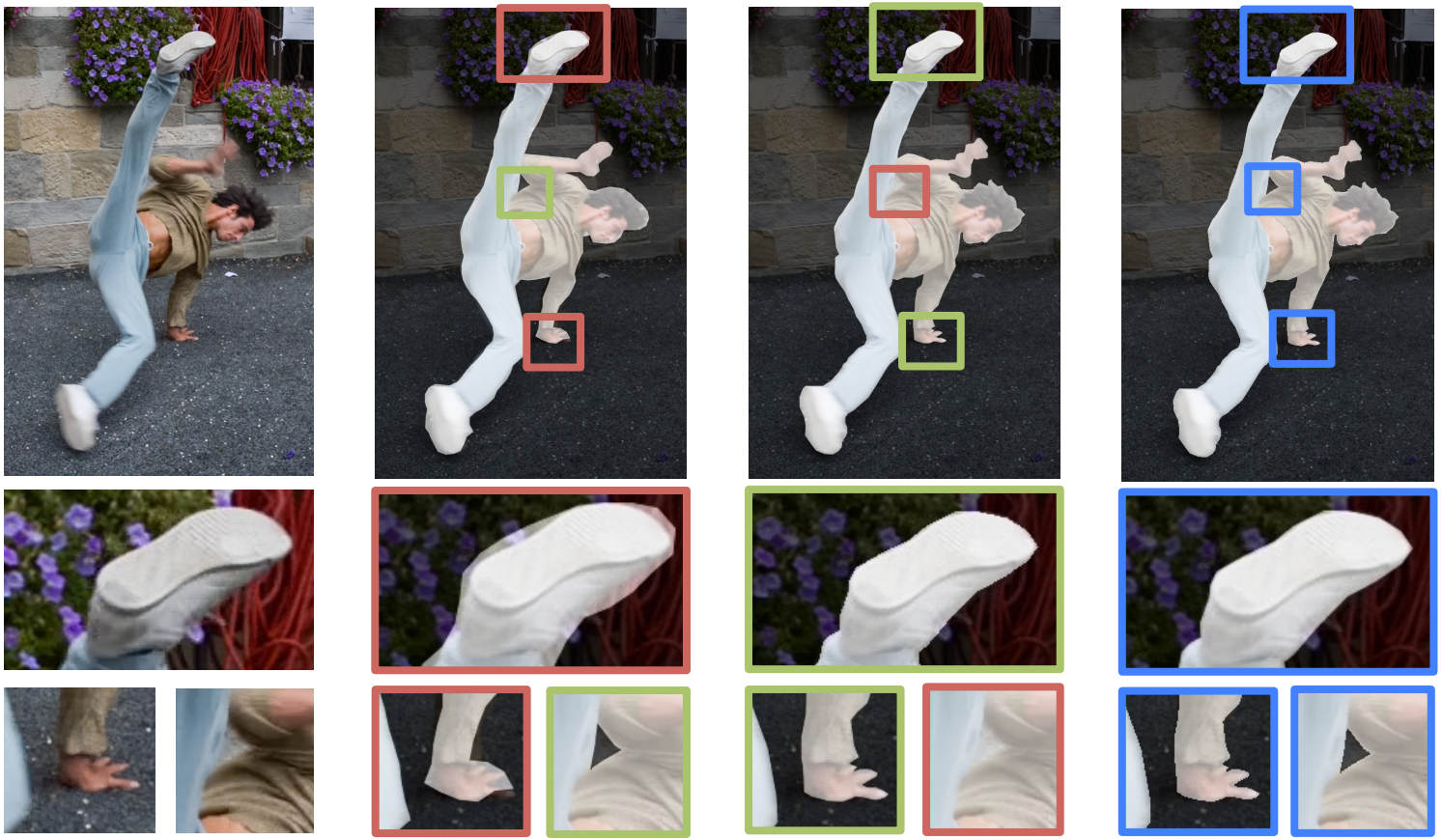

ΑΓ. ΡΑΦΑΗΛ

# Merging Segmentations

- **Clustering** by overlap + type of polygon
- **Weighted** combination







# Weights as bonuses

Total task reward:

$$R_i = ?$$

# Weights as bonuses

Total task reward:

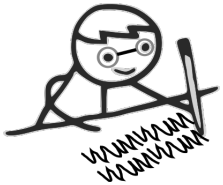
$$R_i = r + \beta_i$$

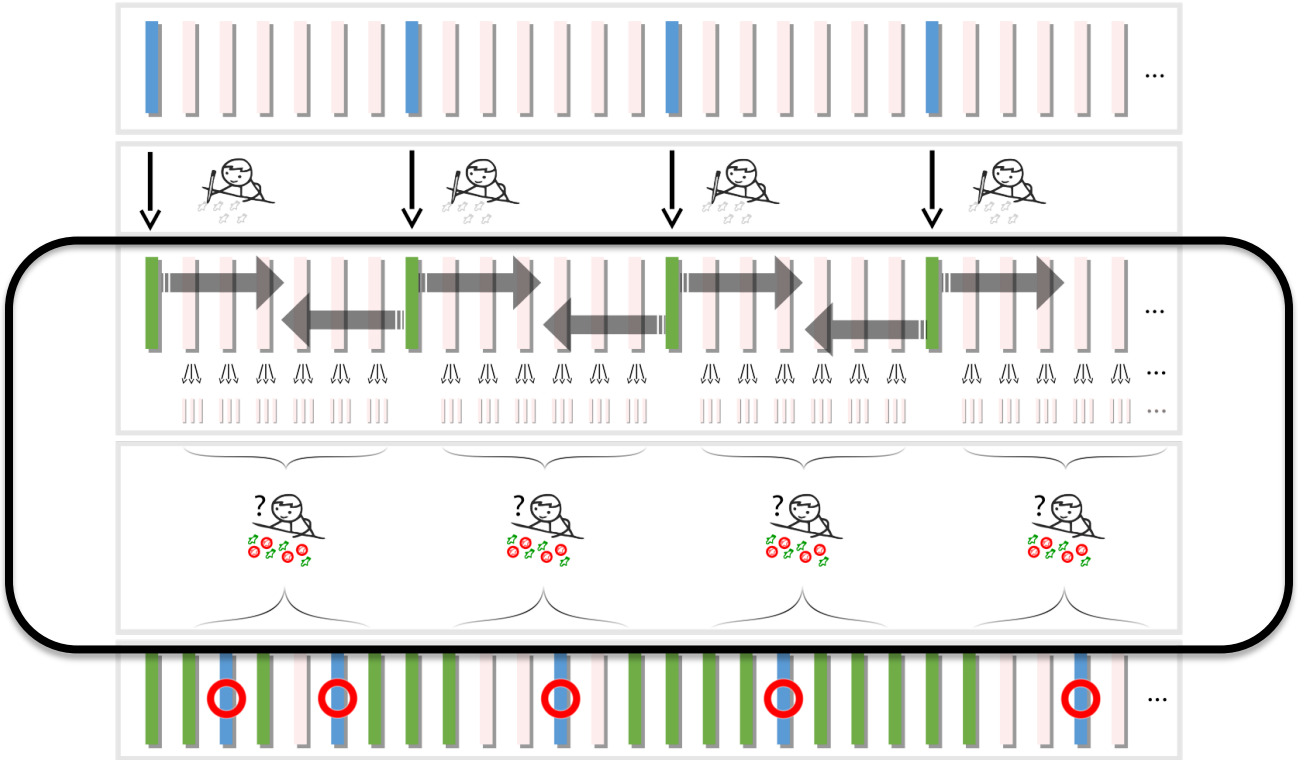
Weights and bonuses:

$$w_i = 1 + \beta_i$$

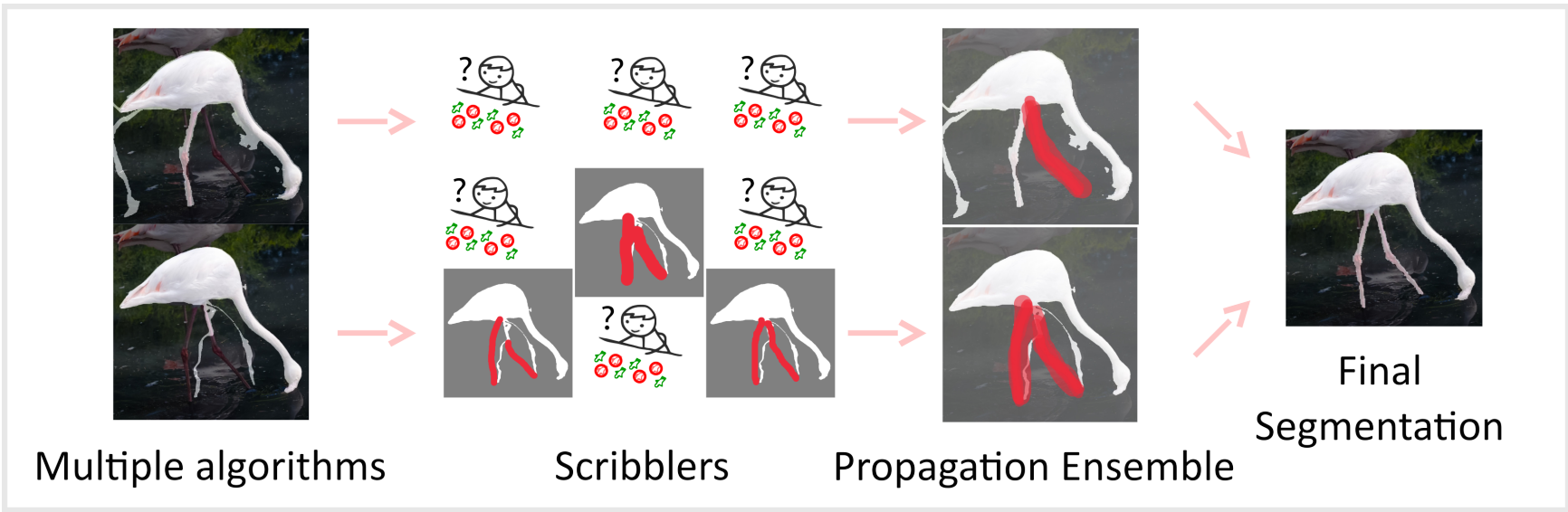
# PROPAGATION ENSEMBLE

# Rotoscoping





# Overview


Multiple algorithms
Scribblers
Propagation Ensemble
Final Segmentation

# Scribble Task


Click on the images below to see the frame with more or less of the mask.

Click on the circles below to change the marker size.



< play > undo

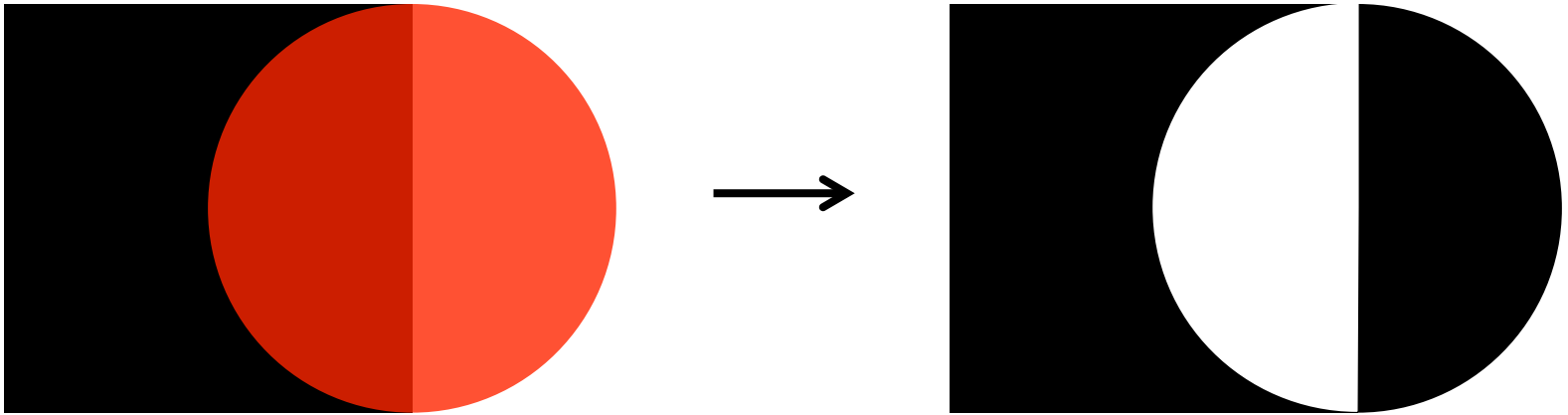
# Different Brush Scenarios

1. Corrective Fixing
   (inverting brushes)

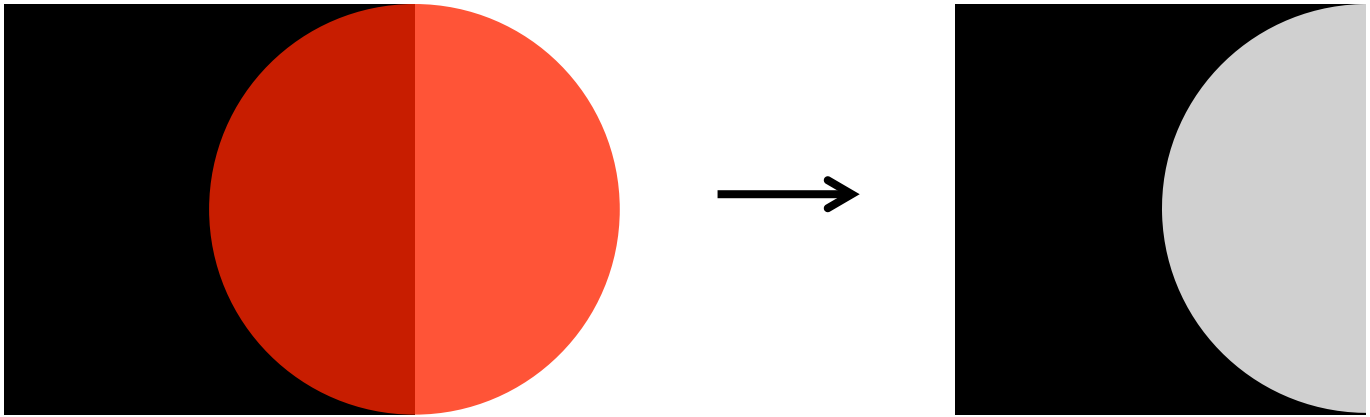
2. Penalty-based Weighting
   (weighting brushes)

3. Segmentation Refinement
   (2 brushes)

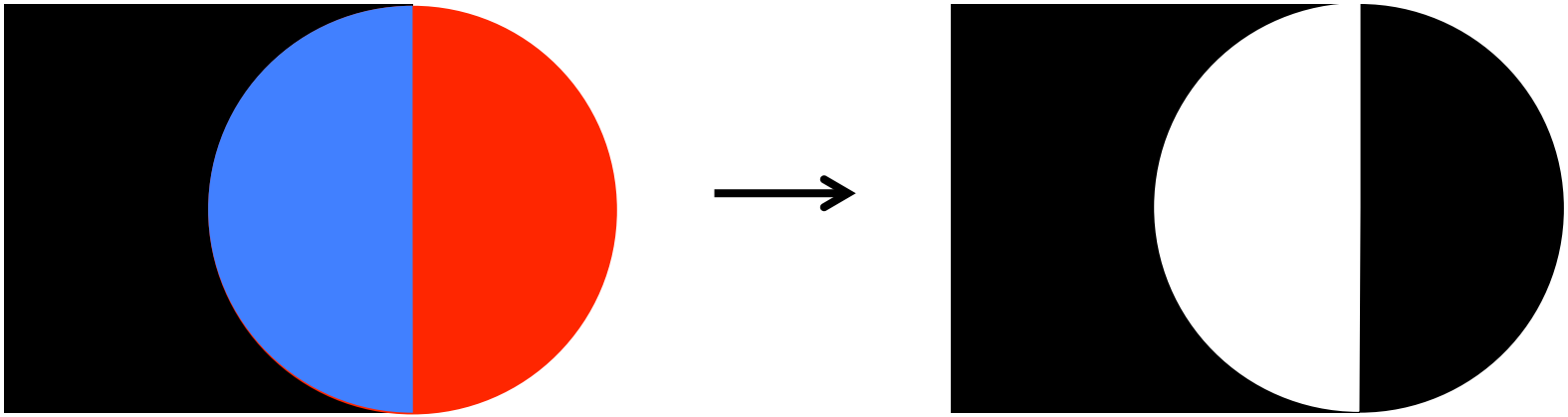
# Corrective Fixing



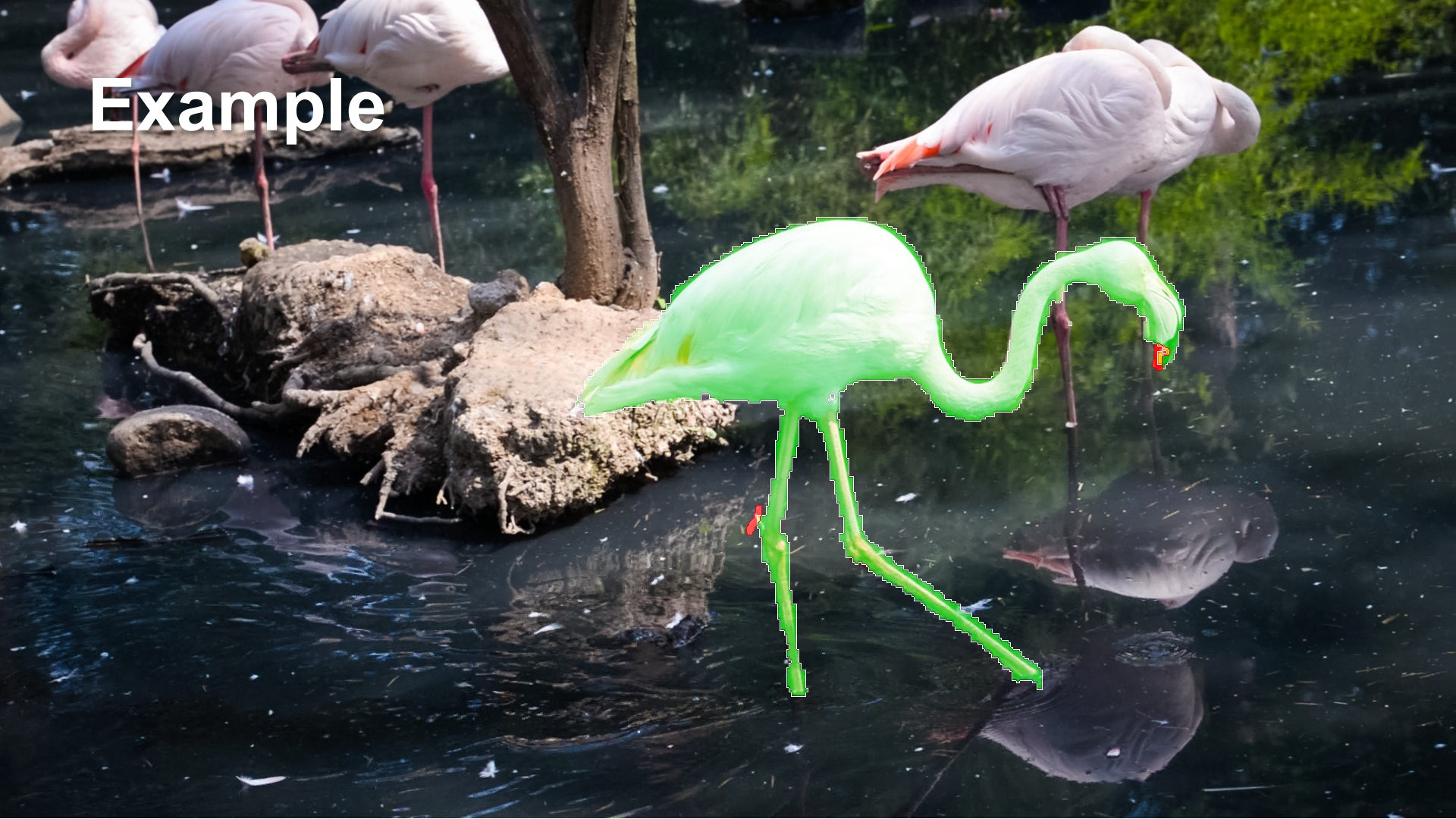
# Penalty-based Weighting



# Segmentation Refinement




Example


Example


Example

# Example

# Example

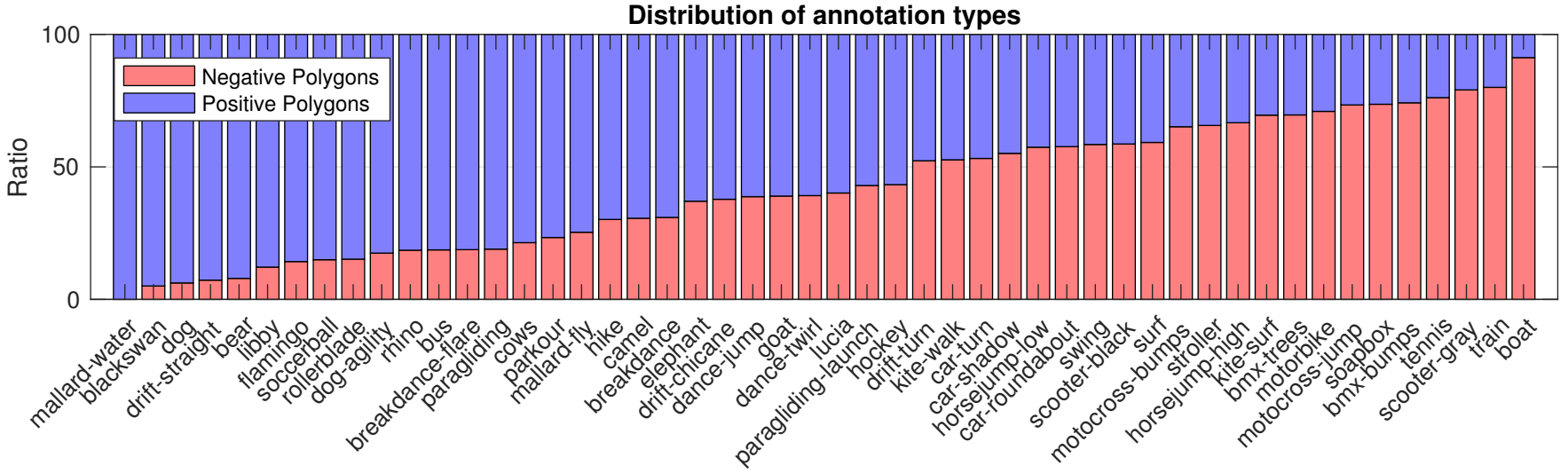
# Example

# EVALUATION


DAVIS Dataset

# Segmentation Ensemble

- Do workers use our negative polygons?
  - ✔ Yes. Extensively.



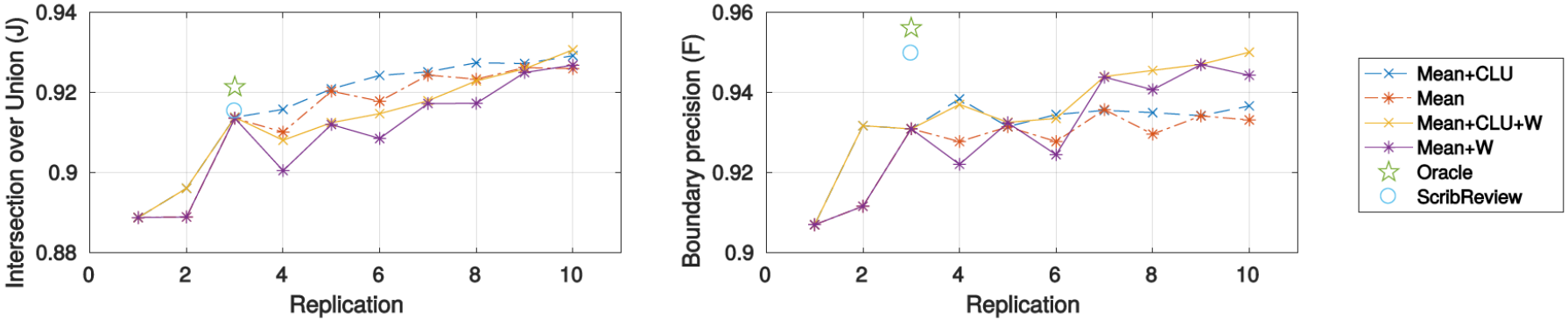
# Segmentation Ensemble

- Does our strategy produce higher quality?
  ✔ Yes. Notably for the boundaries.

| Metrics | Oracle | Automatic | | | |
|---|---|---|---|---|---|
| | **Clu/Mean** | Best | Clu/Mean | SDF | Worst |
| $J \uparrow$ | **0.917** | **0.914** | 0.903 | 0.875 | 0.842 |
| $F \uparrow$ | **0.952** | **0.939** | 0.928 | 0.880 | 0.879 |
| $T \downarrow$ | 0.380 | 0.372 | 0.359 | **0.350** | 0.483 |

# Segmentation Ensemble

- How does replication impact the quality?
  - ✔ Positively!



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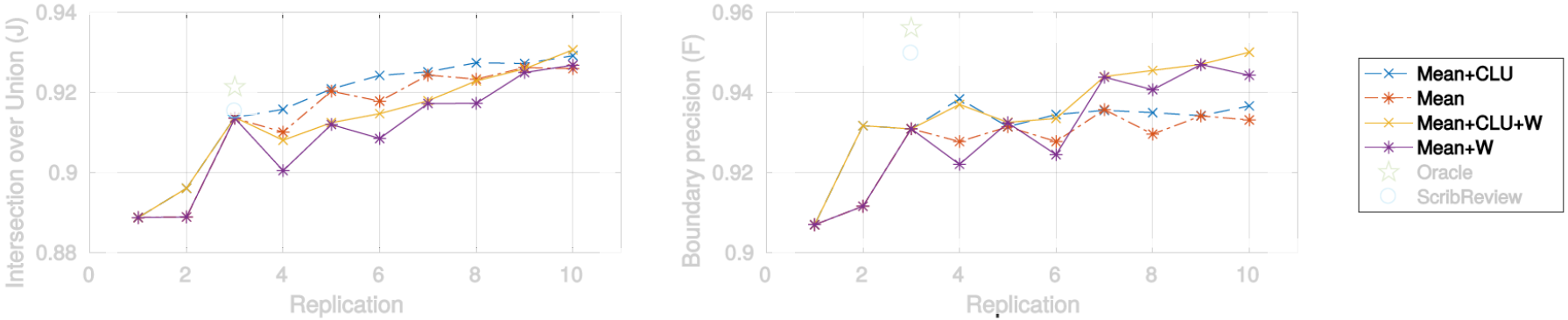

# Segmentation Ensemble

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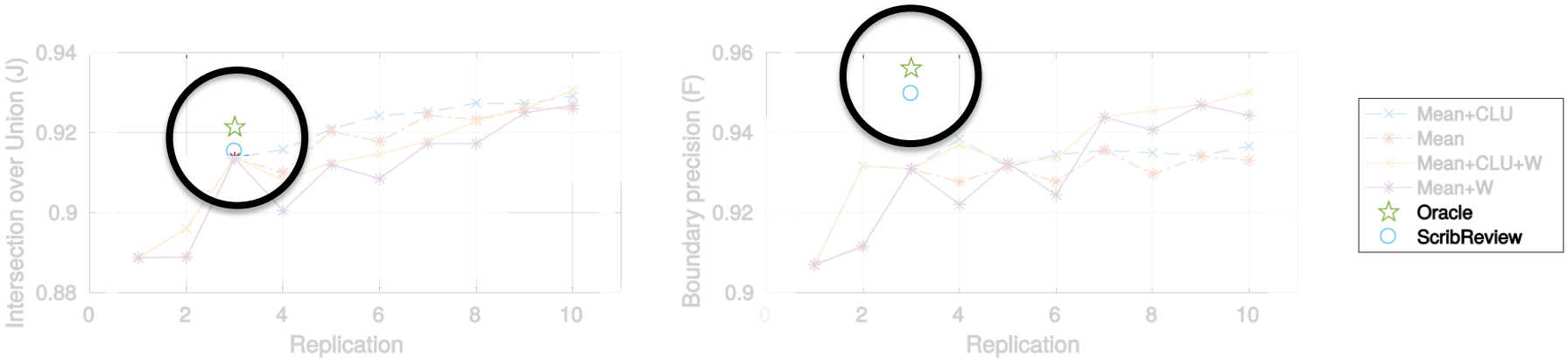
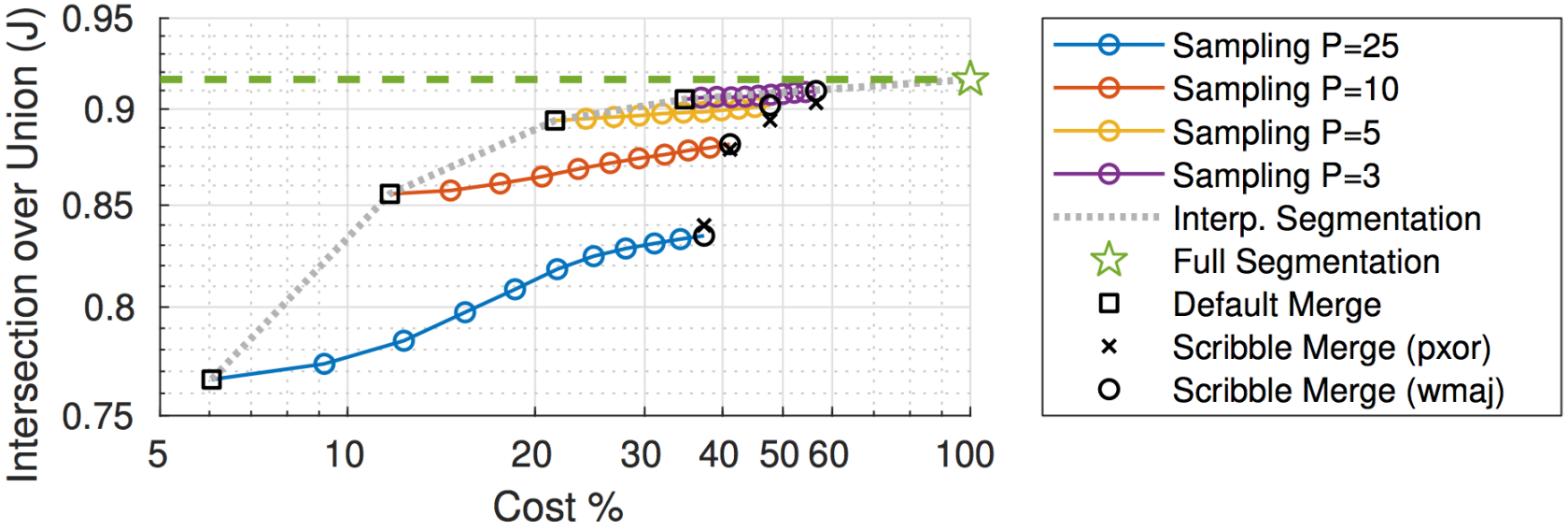


# Propagation Ensemble

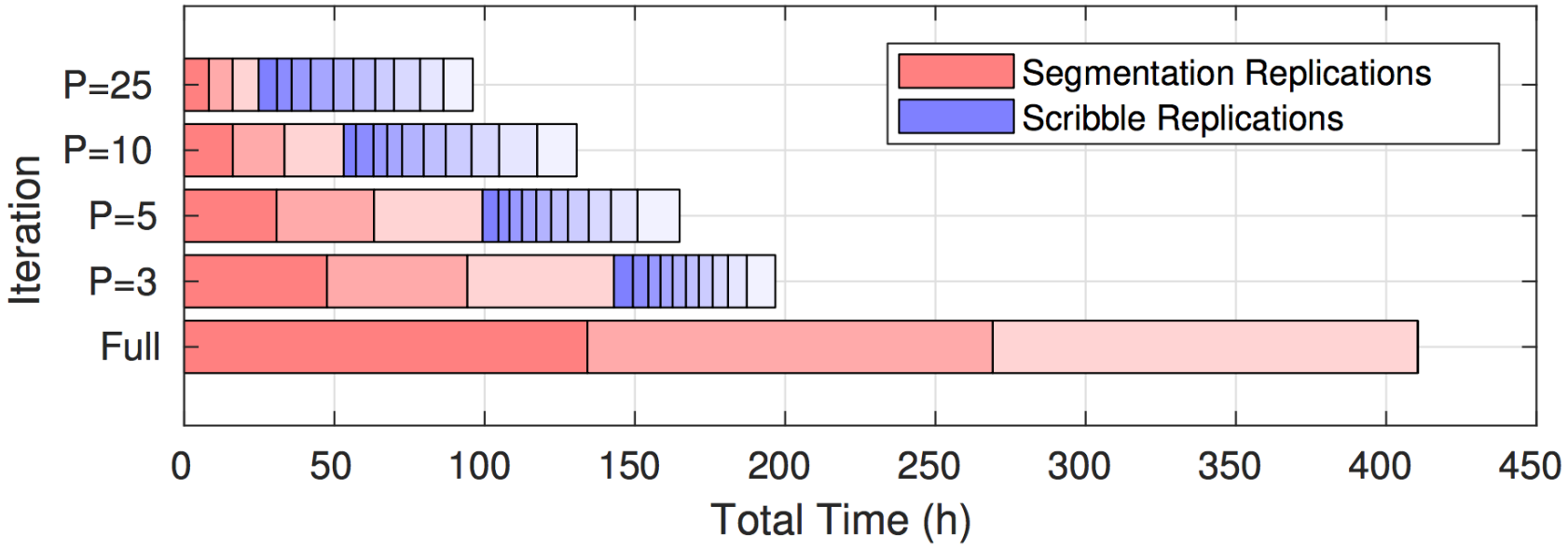
- Do the scribble improve quality?
  - ✔ Yes, consistently.

- Are they efficient?
  - ✗ Not for coarse samplings.
  - ~ Maybe for fine samplings.

# Propagation Ensemble



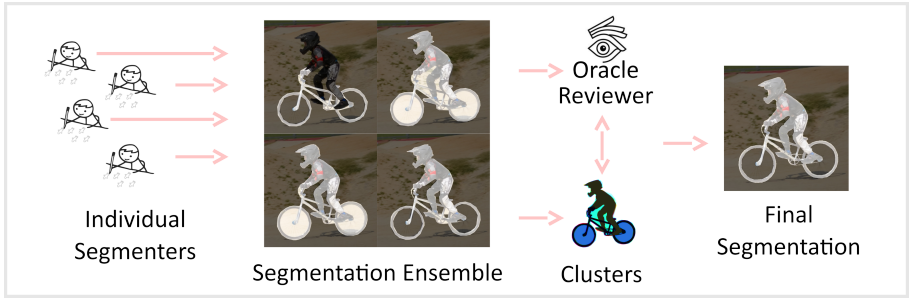
# Propagation Ensemble

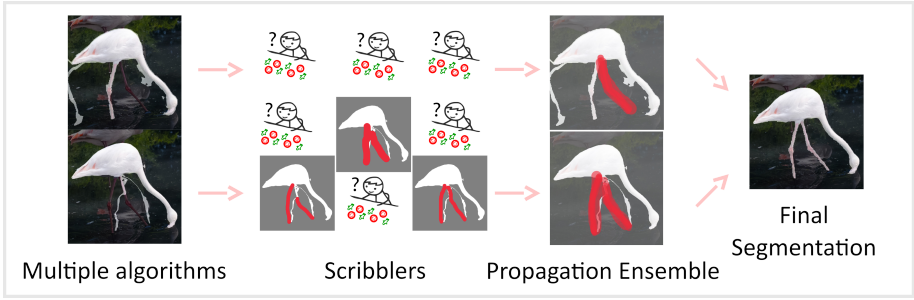


# Propagation Ensemble

- Which scribble scenario is most effective?
  As penalty weighting.

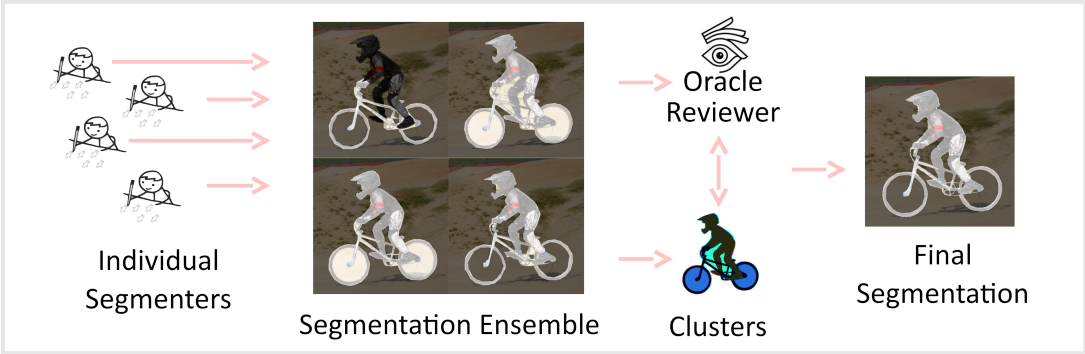
- Corrective fixing:
  - Unstable (see paper).
  - Single candidates cannot be improved.

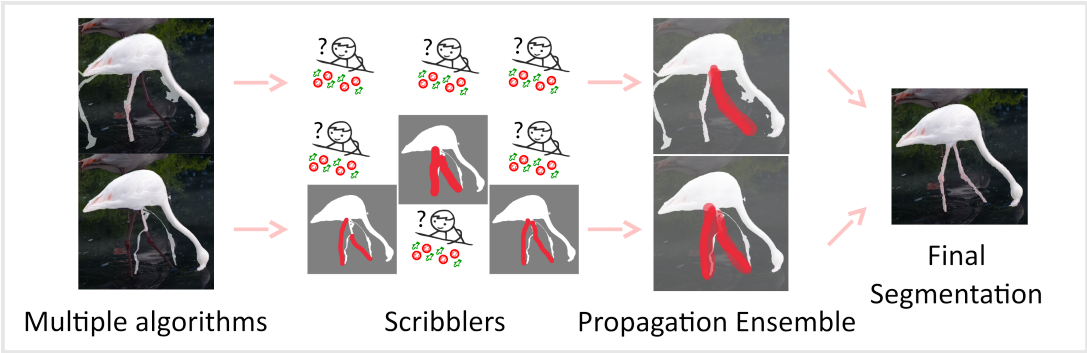



# Crowd workers can create (much) higher quality segmentation!

Tools and data will be made available online:
http://crowdensembles.csail.mit.edu




Tools and data will be made available online:

http://crowdensembles.csail.mit.edu

# Are the metrics meaningful?

| Method | Metric | | | |
|---|---|---|---|---|
| | $J$ | $F$ | $T$ | $W$ |
| LDOF | 0.760 | 0.749 | 0.250 | **0.204** |
| DF+SVM | 0.764 | 0.782 | **0.250** | 0.192 |
| DF+SVM+Att | **0.822** | **0.823** | 0.317 | 0.198 |

**Table 7. Comparisons between the scores $W$ evaluated by crowd workers and the $J$, $F$, and $T$ metrics, as in Table 1. All values are averages over all sequences of the DAVIS dataset. The score $W$ is defined as the average number of positive evaluations for a frame segmentation.**