



INTERNATIONAL COURSE

Optics, Forces & Development

SANTIAGO / CHILE

$$\left(\partial_\theta^2 + \cot \theta \partial_\theta - \frac{1}{\sin^2 \theta} + \frac{1}{2} - \frac{R^2}{l^2} \right) \frac{v_\theta}{R} = -\frac{\partial_\theta C_\theta(\theta)}{4\eta_0^2}$$

MARCH⁵⁻¹⁴
2024



CELL MORPHODYNAMICS
LATIN AMERICA



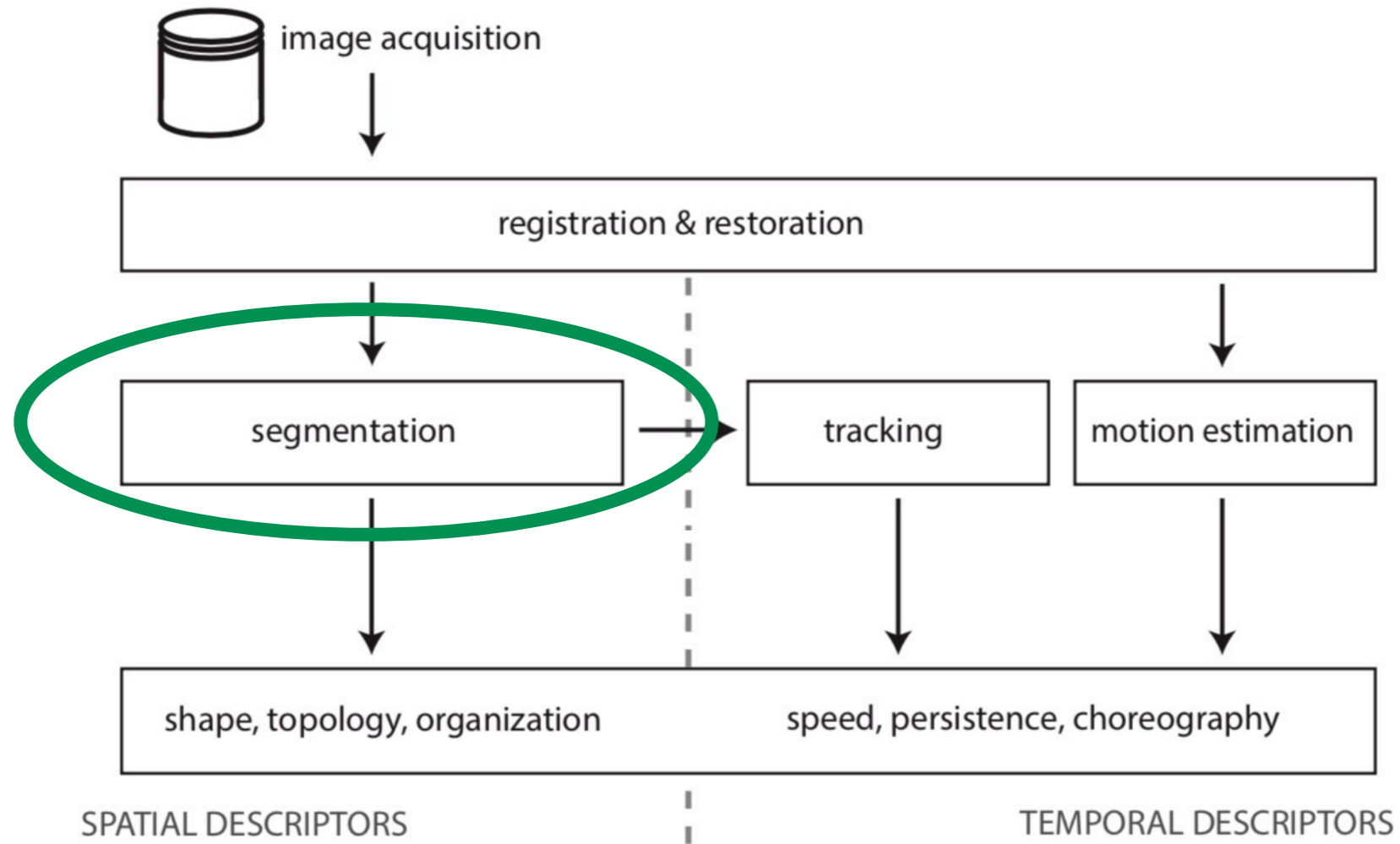
United Nations
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UNU-BIOLAC



Principles of Image Processing & Quantification: automatic segmentation


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IMAGE SEGMENTATION: SUMMARY



Computational Methods for Analysis of Dynamic Events In Cell Migration.

Castañeda V, Cerda M, Santibañez F, Jara J, Pulgar E, Palma K, Lemus CG, Concha M, Härtel S
Current Molecular Medicine, 14(2), 291-307.

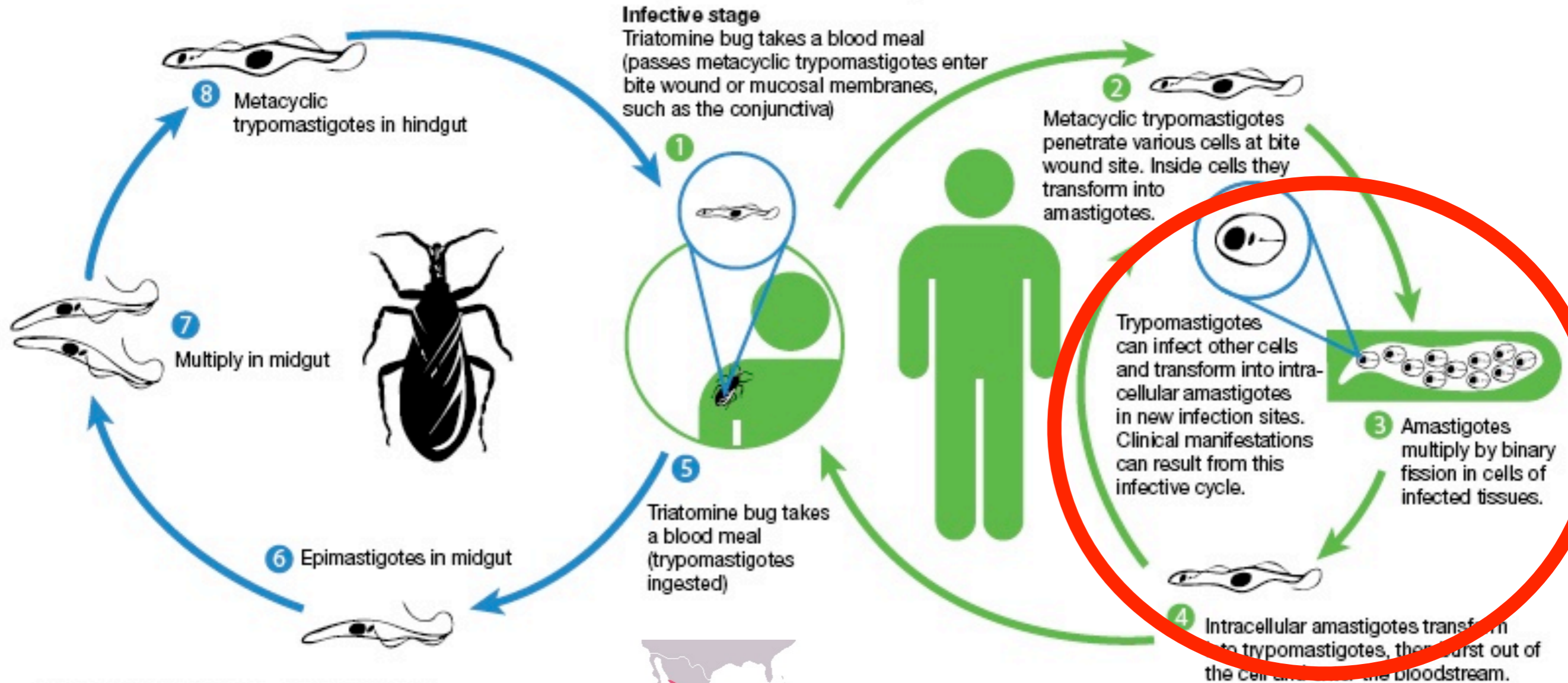
Show Abstract 

OUTLINE

- ▶ Segmentation (clustering)
- ▶ Segmentation (random forest)

- ▶ <http://fiji.sc/>

Infection cycles of Chagas disease



Source: www.dpd-cdc.gov/dpdx

A



IMAGE PROCESSING: PARASITES

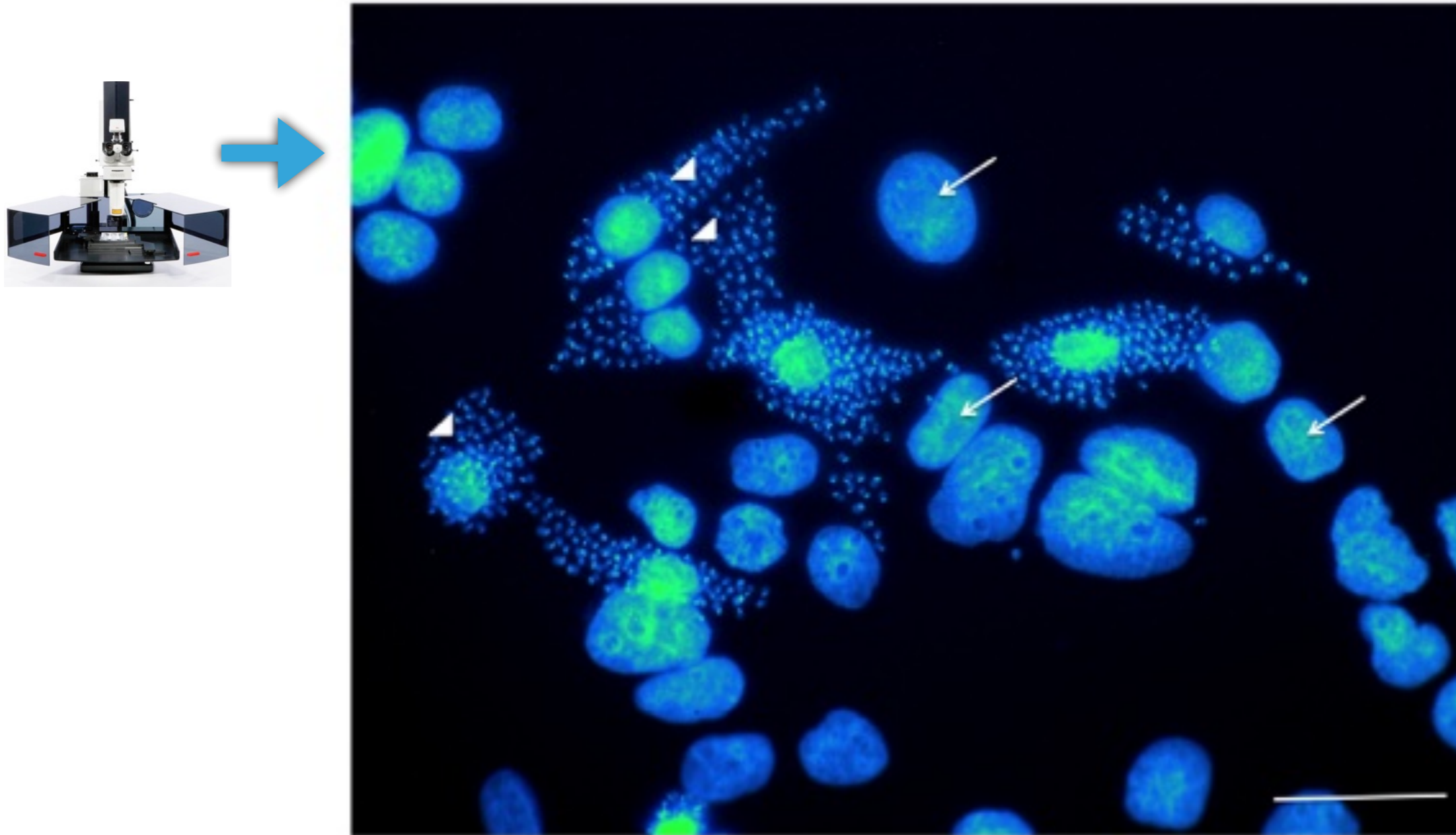
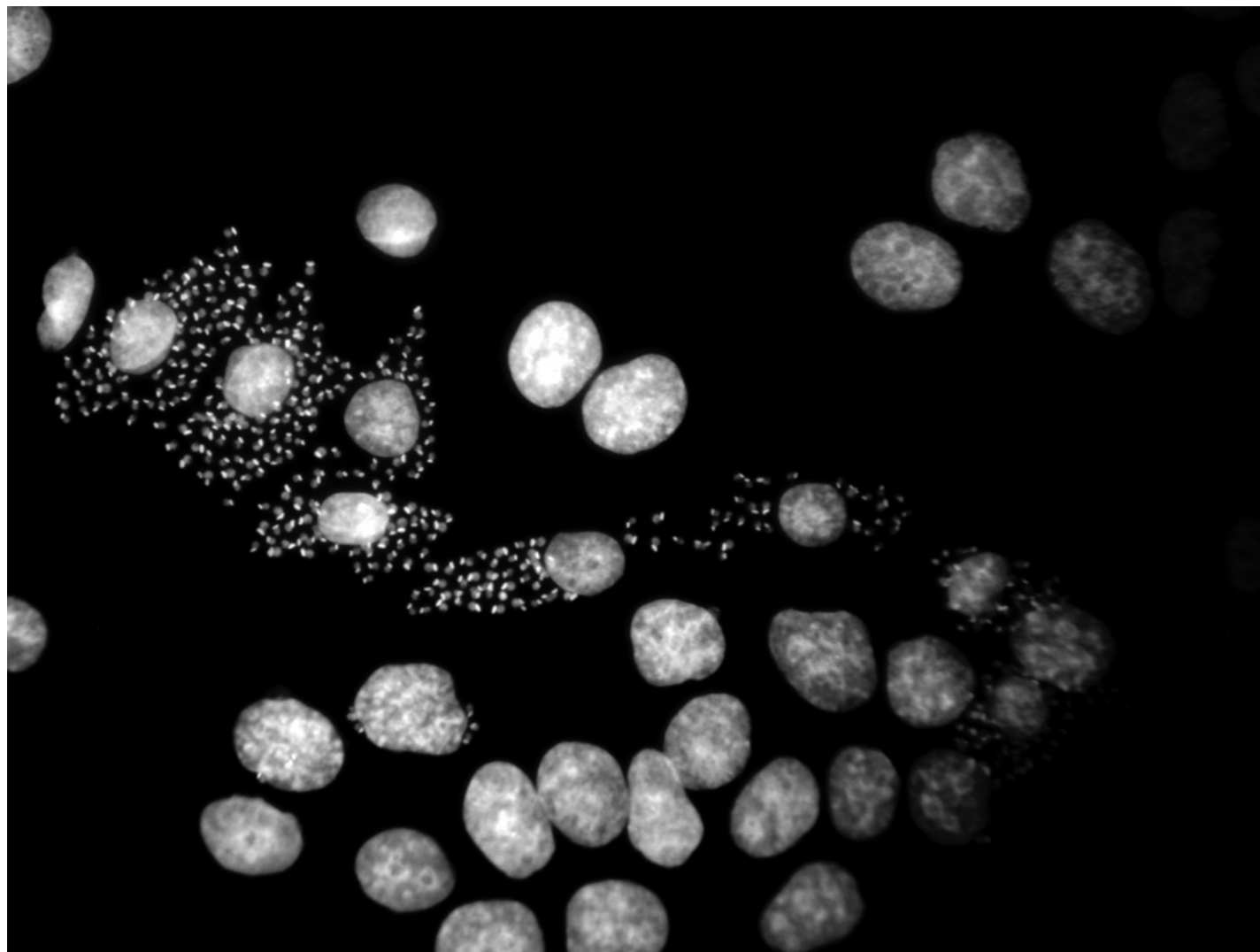


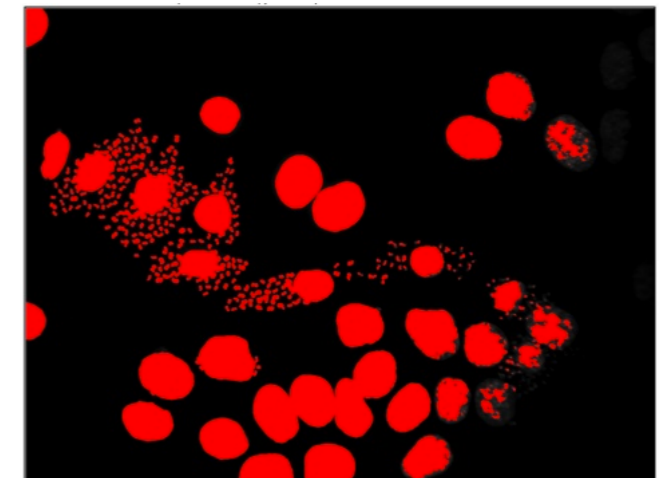
Fig. 1. Infection of BeWo cells with *T. cruzi* amastigotes. BeWo cells were challenged with *T. cruzi* Ypsilon strain trypomastigotes at a parasite:cell ratio of 1:1 for 24 h and were processed for DAPI staining after 48 h. The arrows show BeWo cell nuclei, and the arrowheads show intracellular amastigotes. Scale bar: 10 μm.

► Pregnancy?

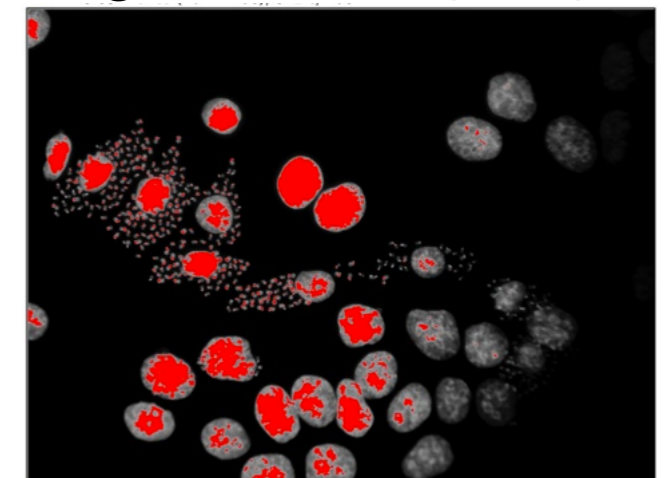
- ▶ The simplest segmentation... a manual global threshold



raw image

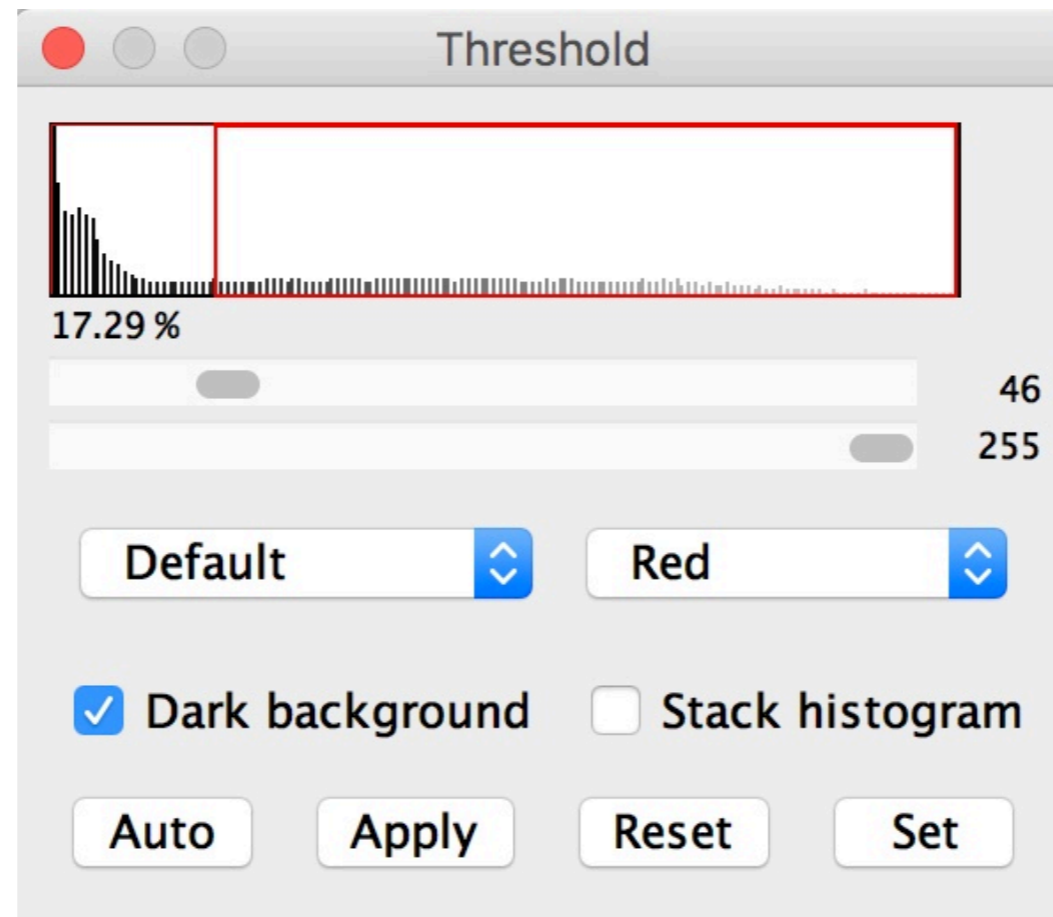


segmentation (>46)

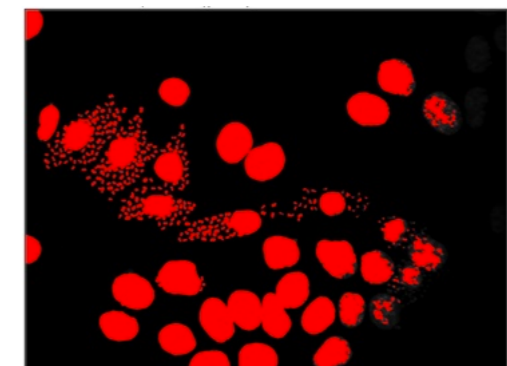
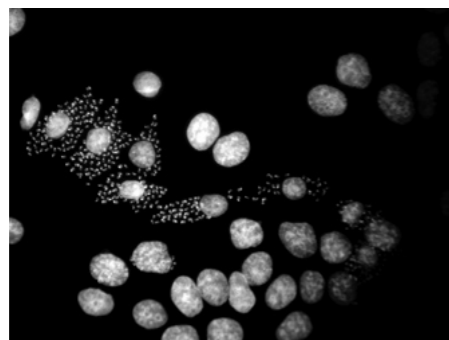


segmentation (>158)

- ▶ How to define the threshold ? ...



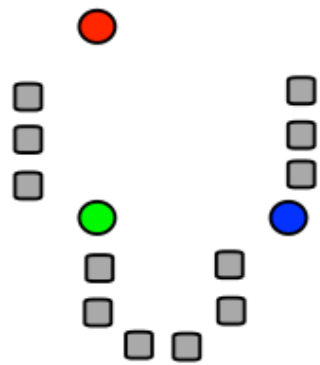
FIJI interface



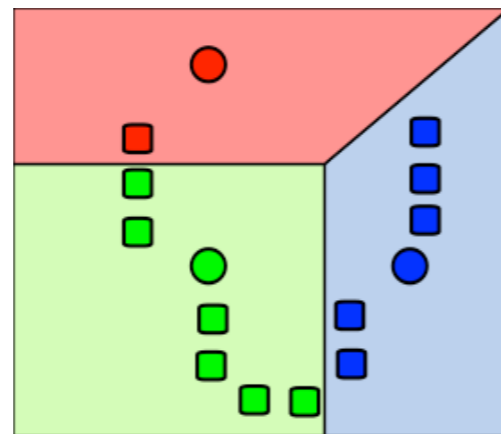
- ▶ We have free parameters (!)
- ▶ BUT, we know there are two groups of pixels: cells, and background.
- ▶ A kind of (statistical) learning problem!
 - ▶ **clustering**
 - ▶ **classification**

IMAGE SEGMENTATION: UNSUPERVISED APPROACH

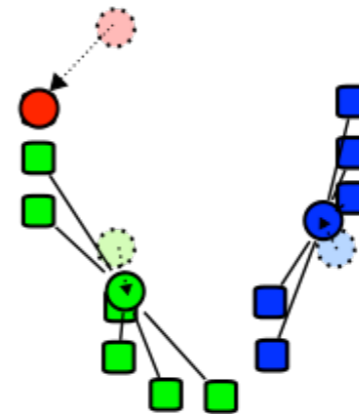
- ▶ We can model threshold selection as how to discover the best k groups or clusters at a pixel level.
- ▶ K-means clustering ($k=3$):



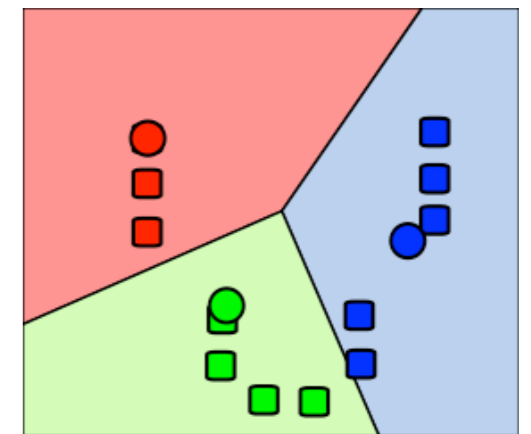
Random centroids



clusters assignation + voronoi diagram



centroids re-computation



cluster assignation + voronoi diagram



IMAGE SEGMENTATION: UNSUPERVISED APPROACH

- ▶ K-means for our image...
- ▶ Using the histogram:

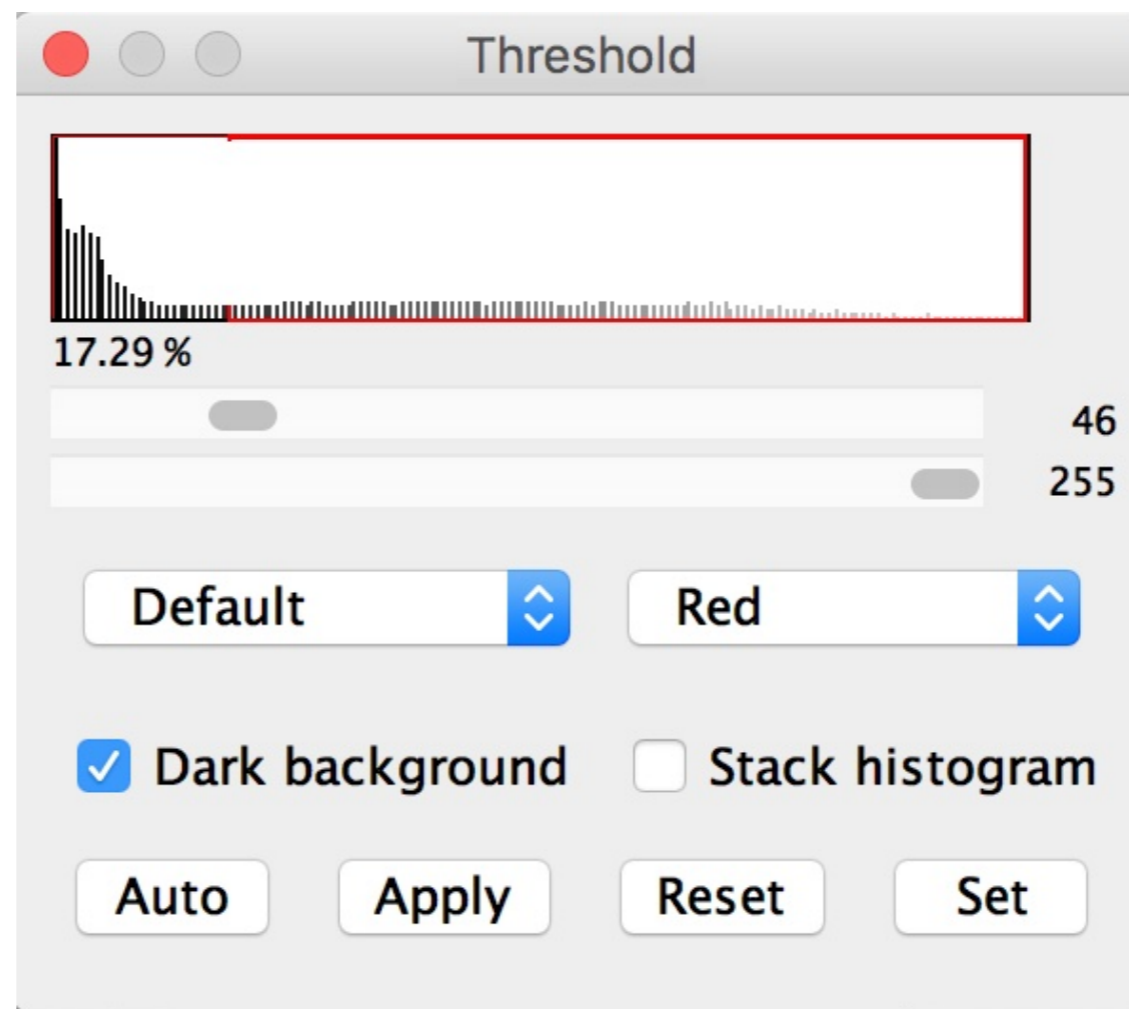
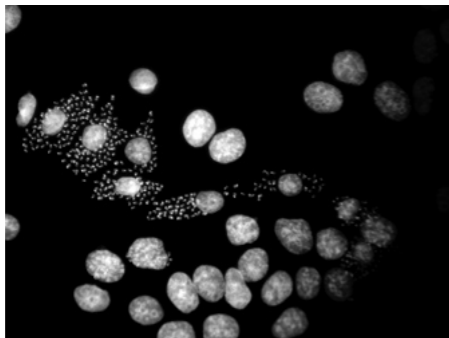
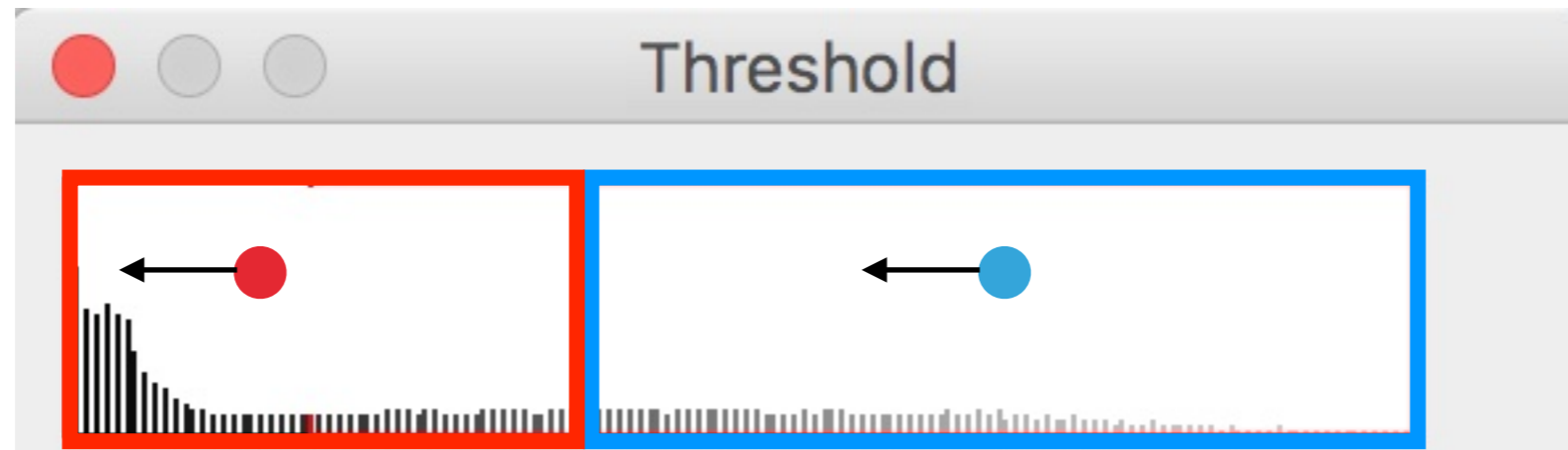


IMAGE SEGMENTATION: UNSUPERVISED APPROACH



- ▶ 1.- Start by guessing 2 centroids.
- ▶ 2.- Associate each intensity to 1 centroid.
- ▶ 3.- Recompute centroids
- ▶ 4.- **Repeat step 2.**

IMAGE SEGMENTATION: SUPERVISED APPROACH

- If we know input and **expected output**: supervised learning.
- Features: voxel intensity, color, shape, size.
- Learning = **how** to identify classes using features.

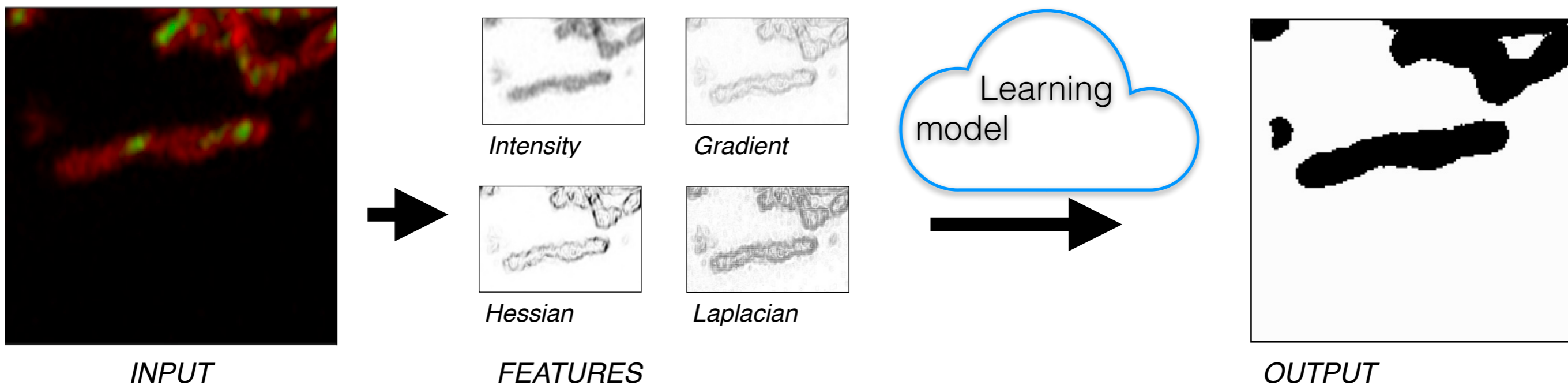
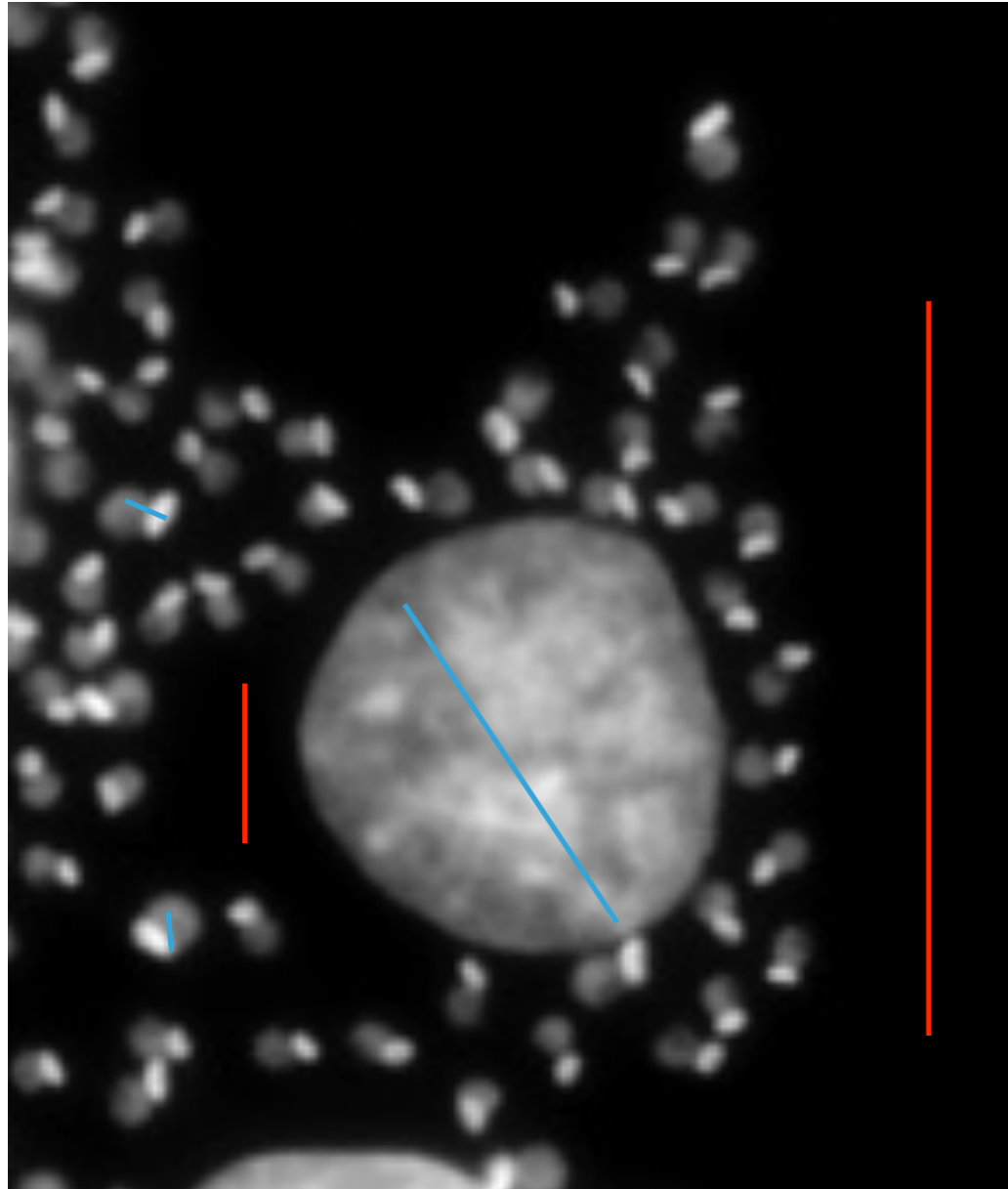
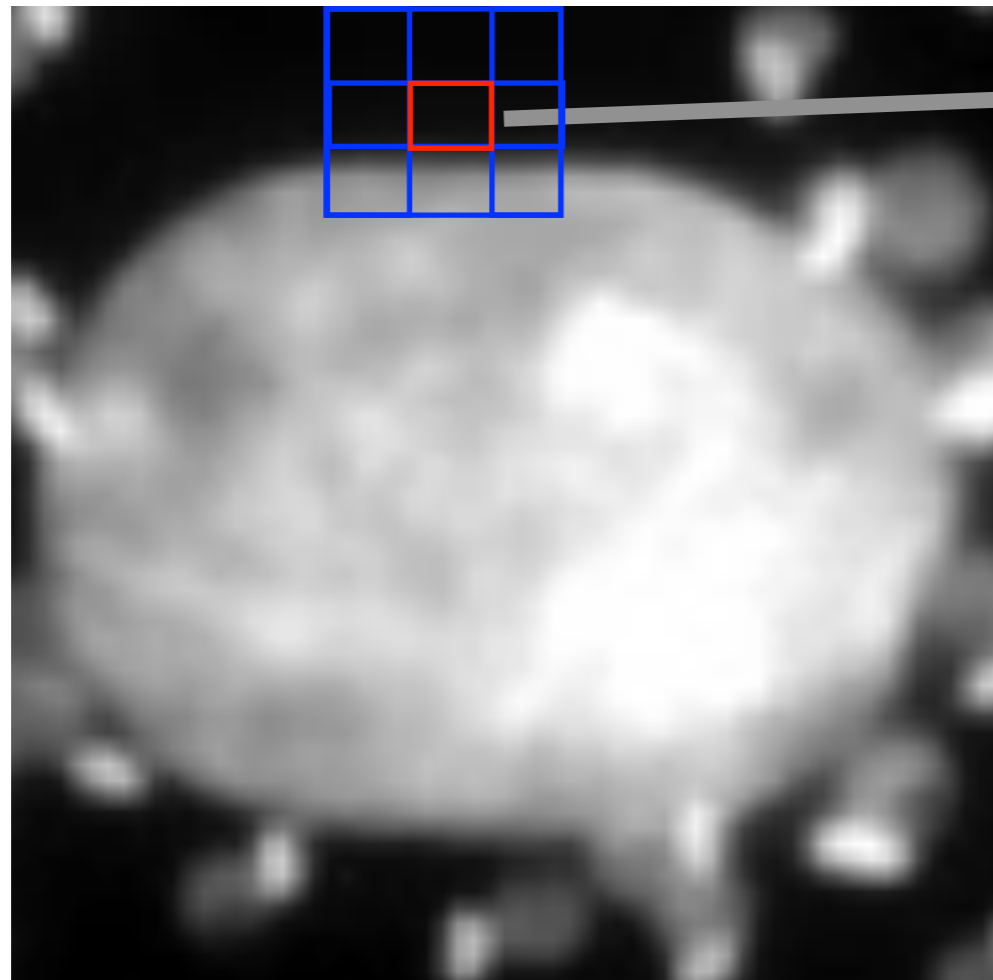


IMAGE SEGMENTATION: SUPERVISED APPROACH



- ▶ We may not have examples of segmentation, BUT we can quickly build examples.
- ▶ Class A (**background**)
- ▶ Class B (**objects**)

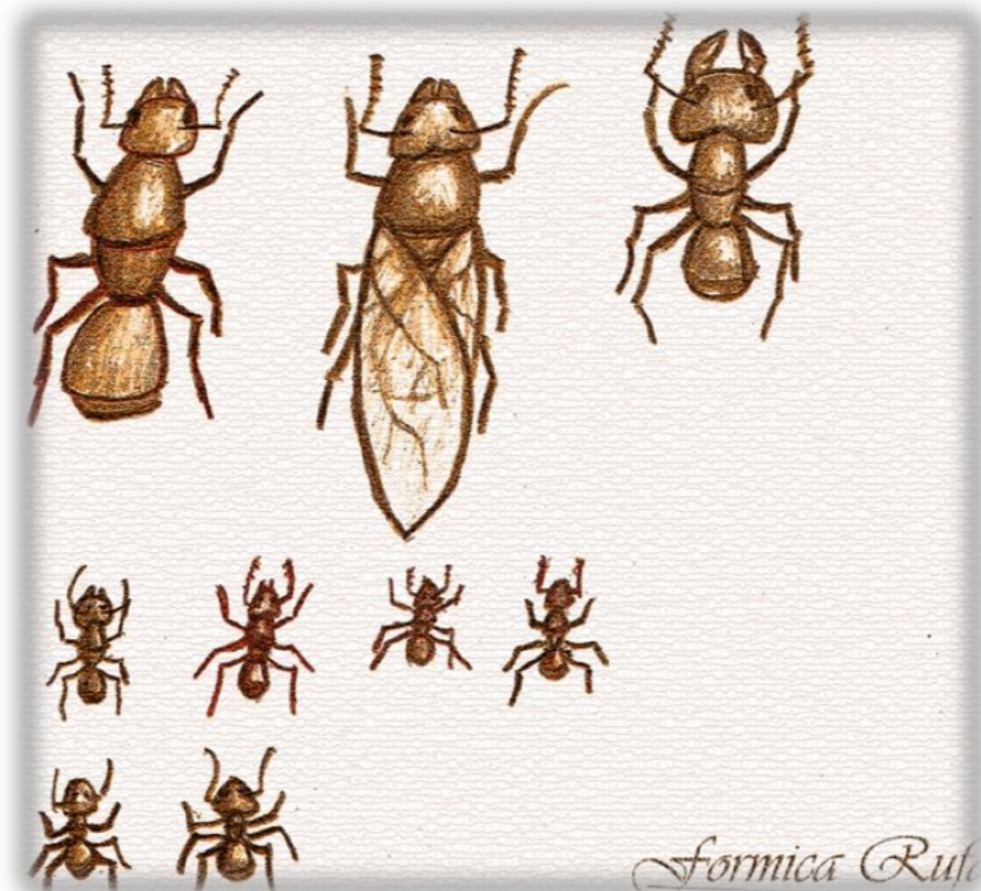
- ▶ We can understand pixels in higher dimensions.



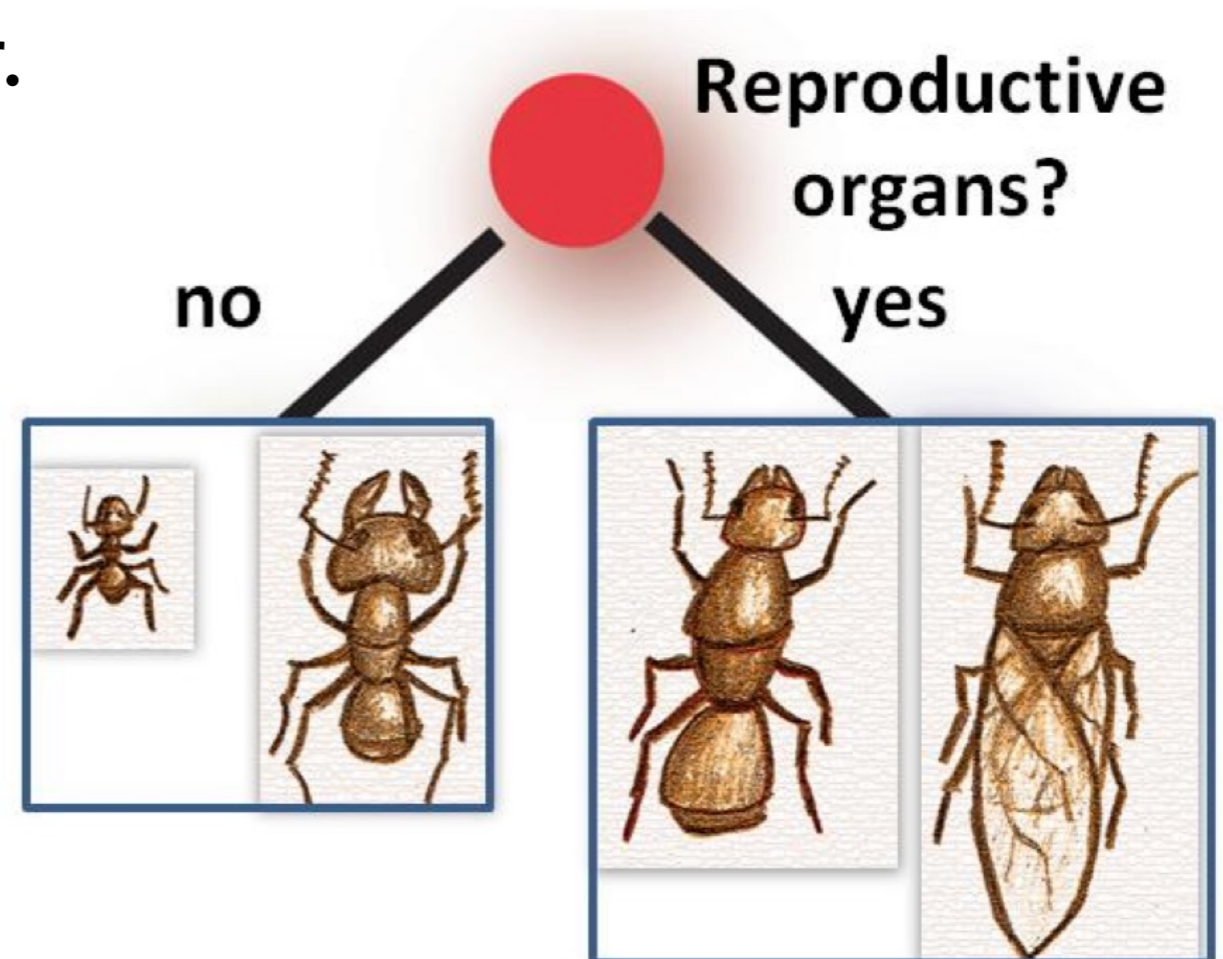
- ▶ Intensity (0)
- ▶ Variance 3×3
- ▶ Mean 3×3
- ▶ Sobel 3×3
- ▶ ...

- ▶ How to build rules to **identify cells and parasites?**

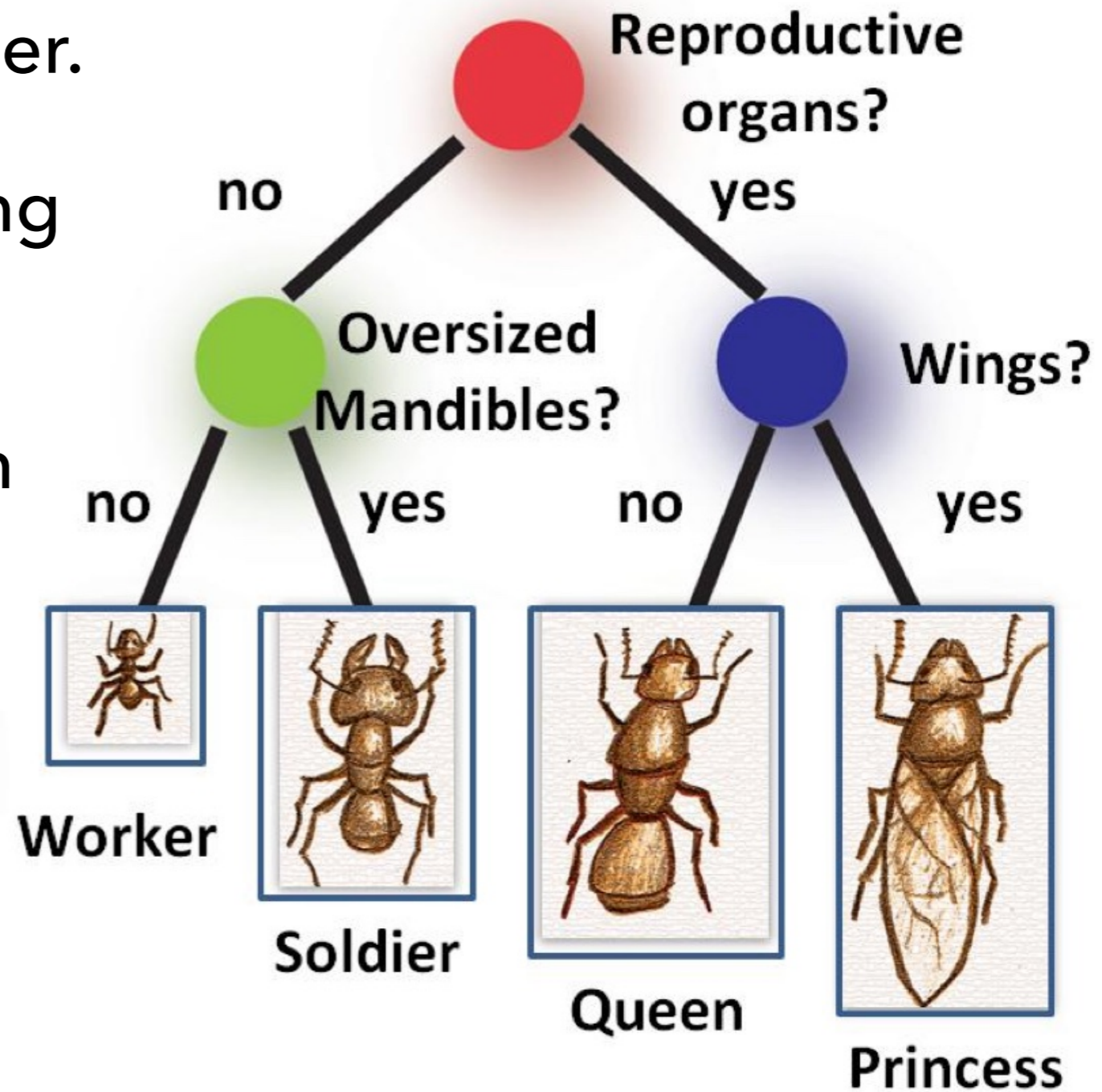
- ▶ To classify pixels we can use many methods (SVM, Neural networks), even in high dimensions. For instance decision trees.
- ▶ We can think pixels information as “ants” that we want to classify.



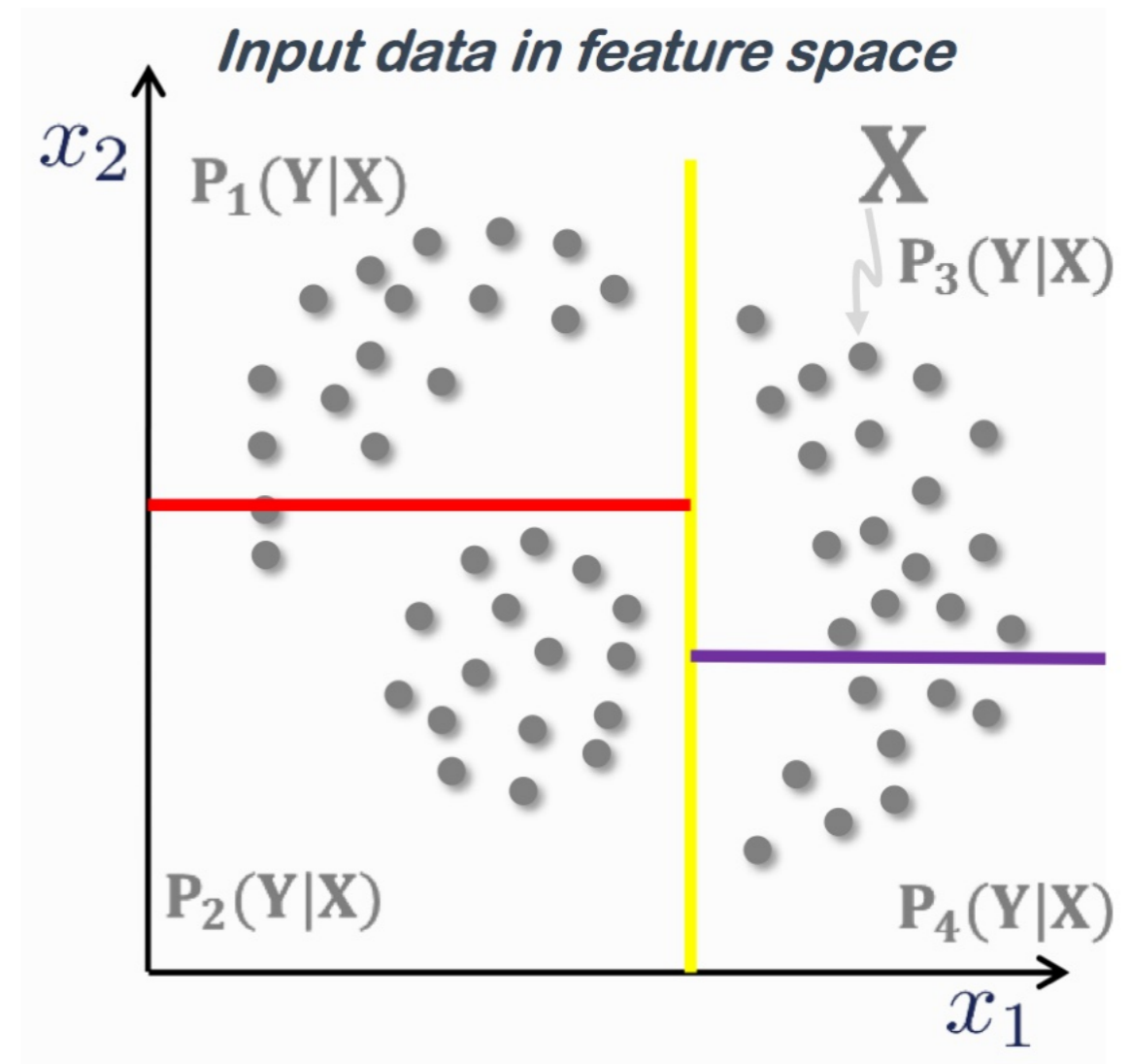
- ▶ Main idea: divide & conquer.
 - ▶ (1) Divide examples using simple rules.
 - ▶ (2) Conquer: repeat with subgroups



- ▶ Main idea: divide & conquer.
 - ▶ (1) Divide examples using simple rules.
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- ▶ **Objective:** From observations (X), identify the probability of class (Y), or $P(Y|X)$.
 - ▶ (1) Partition: each rule divide feature space.
 - ▶ (2) Model: Compute $P(Y|X)$ per partition.
- ▶ The tree estimates $P(Y|X)$ by parts (partitions).



- ▶ We still need to know:
 - ▶ How to build the tree?
 - ▶ How to measure how good the tree is?

IMAGE SEGMENTATION: HOW TO BUILD TREES?

Node training

$$\theta^* = \arg \max_{\theta \in \mathcal{T}} I$$

Information gain

$$I = H(\mathcal{S}) - \sum_{i \in \{1,2\}} \frac{|\mathcal{S}^i|}{|\mathcal{S}|} H(\mathcal{S}^i)$$

Shannon's entropy

$$H(\mathcal{S}) = - \sum_{c \in \mathcal{C}} p(c) \log(p(c))$$

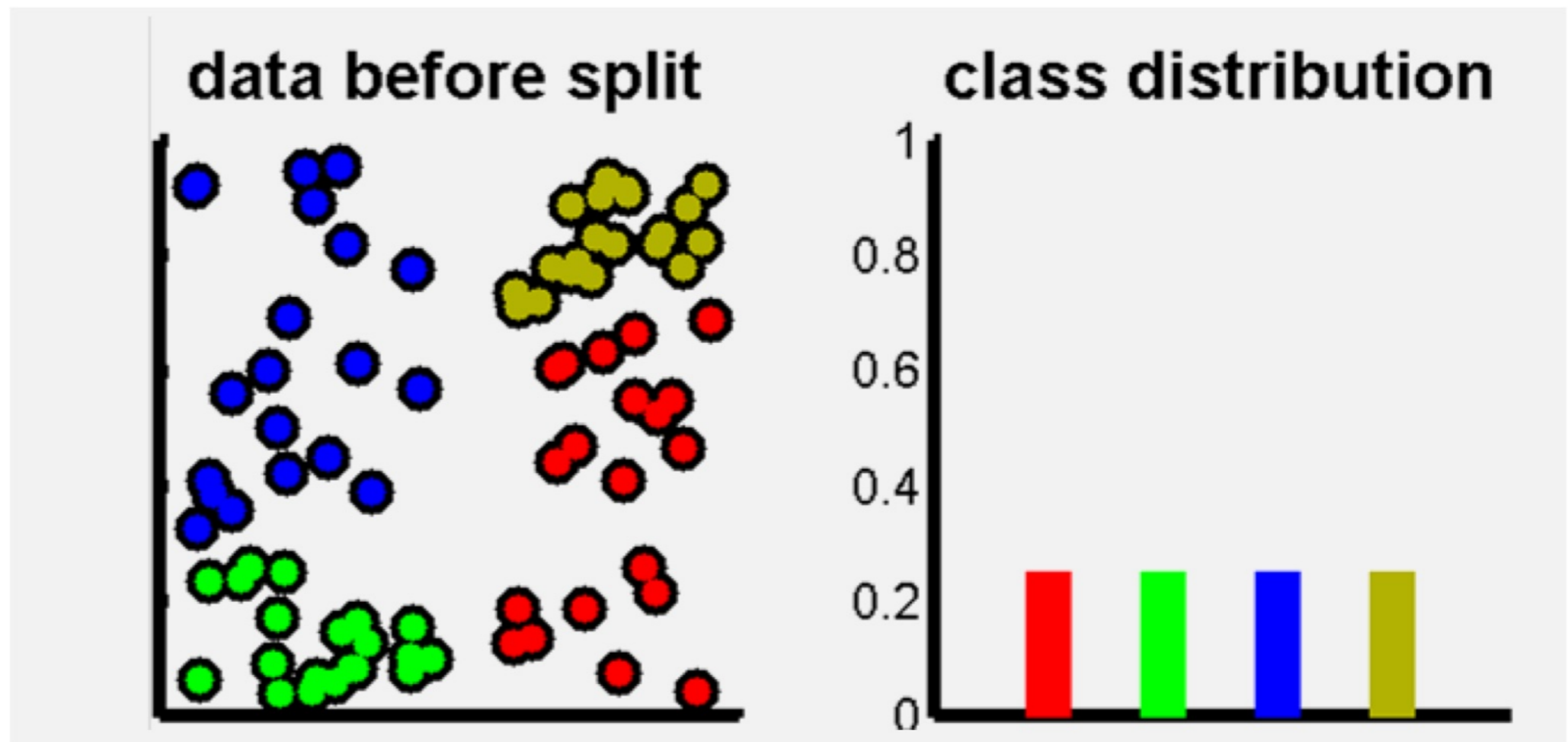
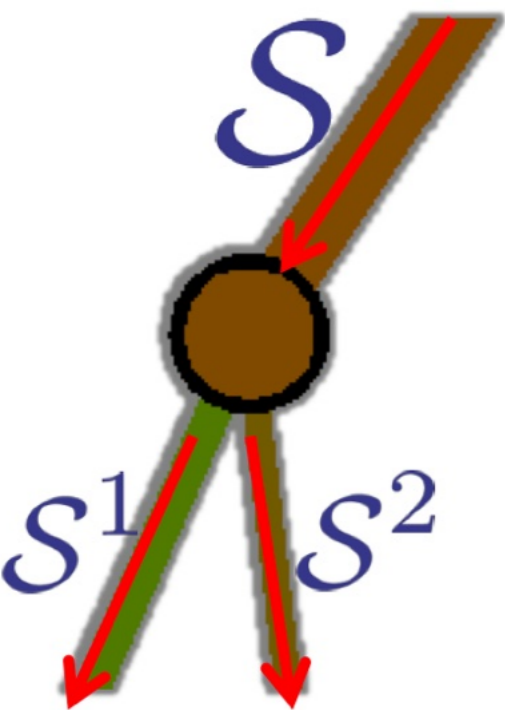


IMAGE SEGMENTATION: HOW TO BUILD TREES?

- ▶ We will compare two rules: **horizontal** or vertical partition.

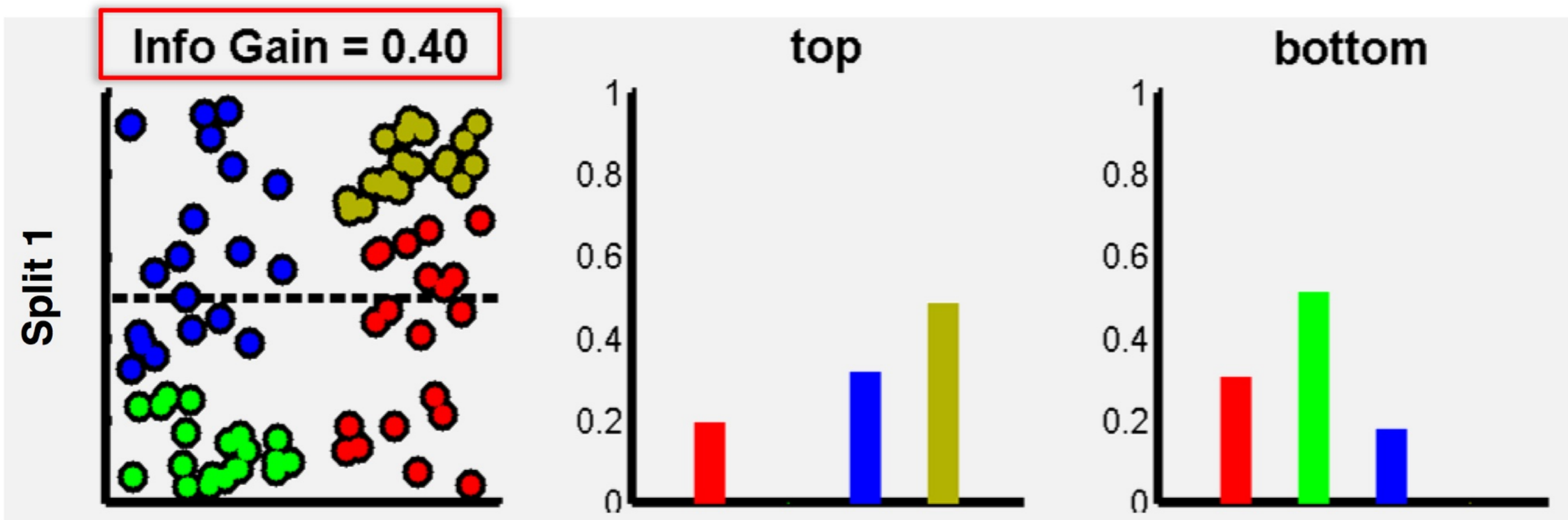


IMAGE SEGMENTATION: HOW TO BUILD TREES?

- ▶ We will compare two rules: horizontal or **vertical** partition.



IMAGE SEGMENTATION: HOW TO BUILD TREES?

► Horizontal or vertical?

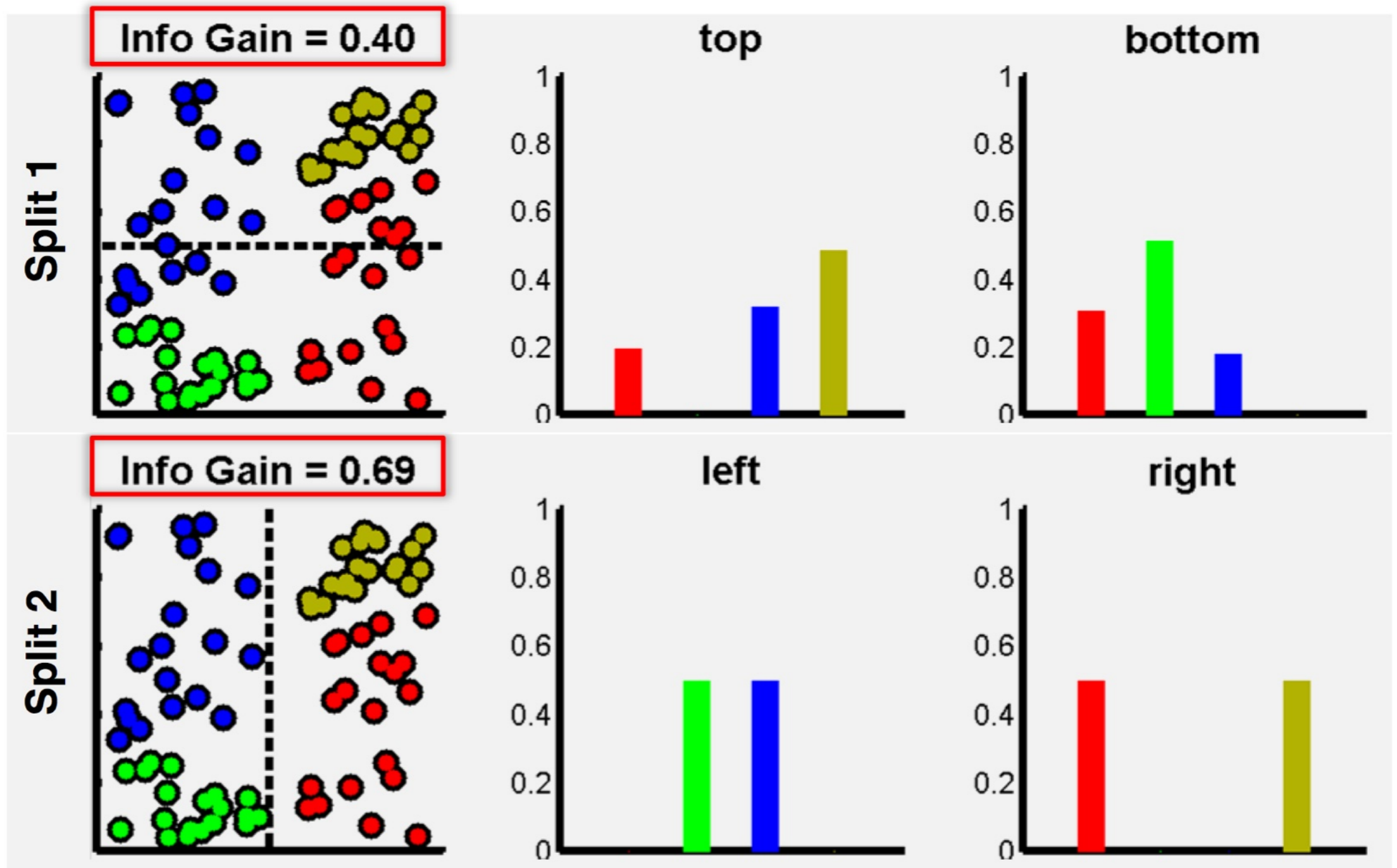
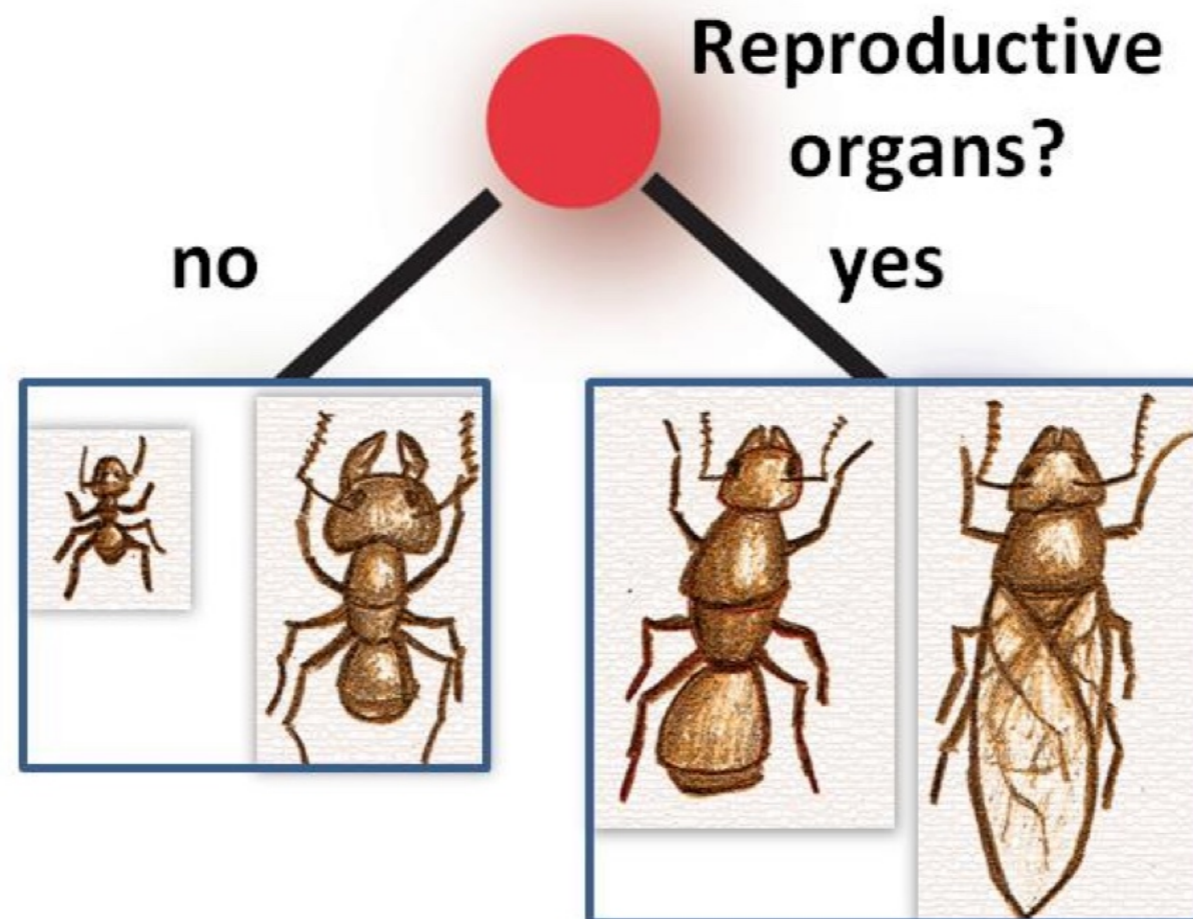
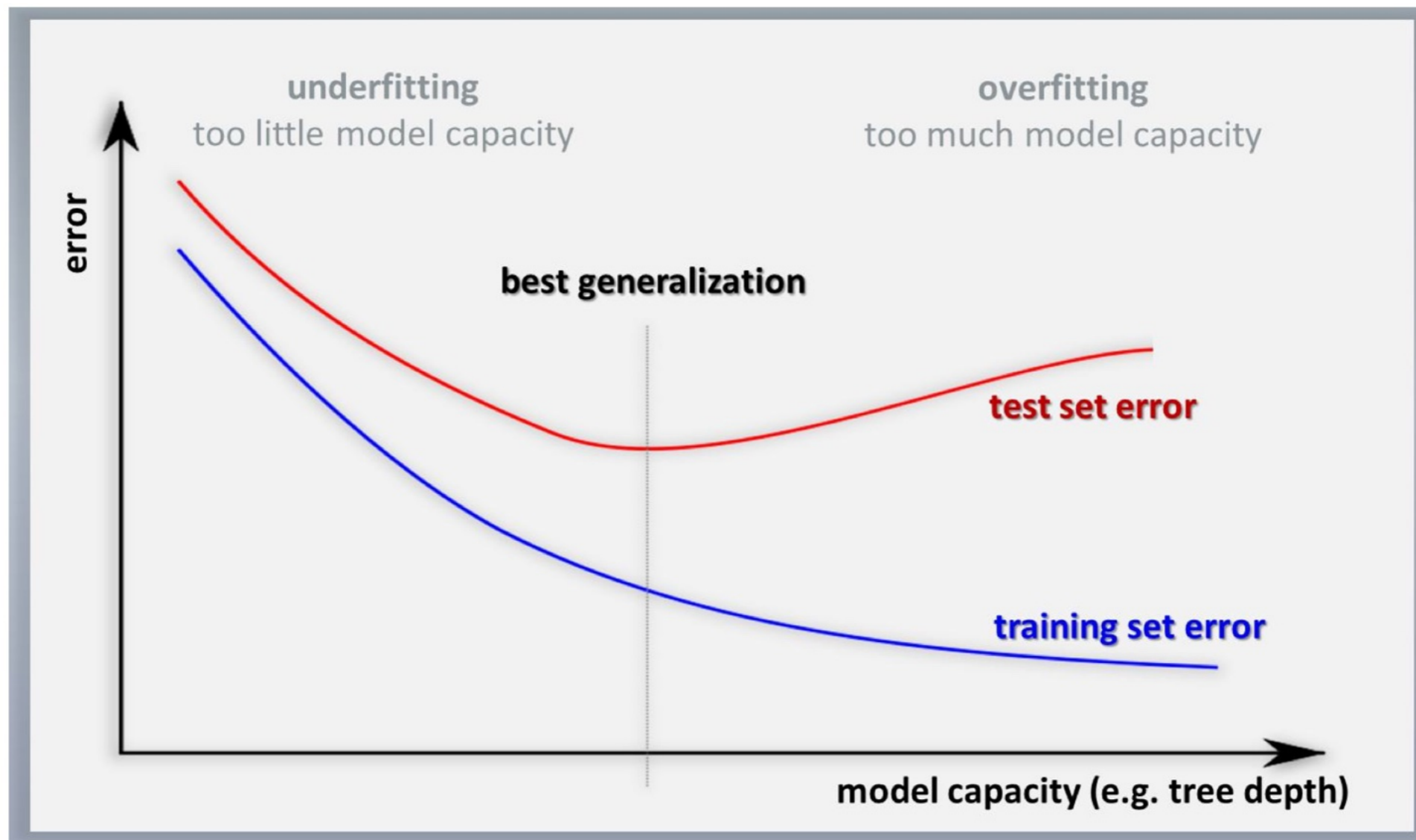


IMAGE SEGMENTATION: HOW GOOD THE TREE IS?

- ▶ But maybe, “Reproductive organs” was a too good or too bad question to start with or we did too many questions (overfitting)



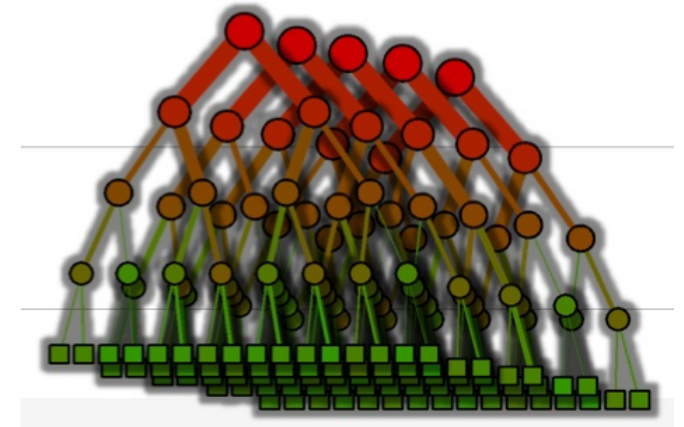
- ▶ A single **decision tree** is sensitive to overfitting.



- ▶ **Idea:** to replace the tree by a forest.
- ▶ In a forest each tree is slightly different.
- ▶ The uncorrelated tree set improves generalization properties.



- ▶ Main parameters:
 - ▶ Trees depth
 - ▶ Number of trees
 - ▶ Select input features



- ▶ **DEMO: Use weka to train for k-mean threshold a random forest to segment nuclei + parasites [FIJI plugin]**