From Hierarchies of Regions to Image Understanding

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Acknowledgment

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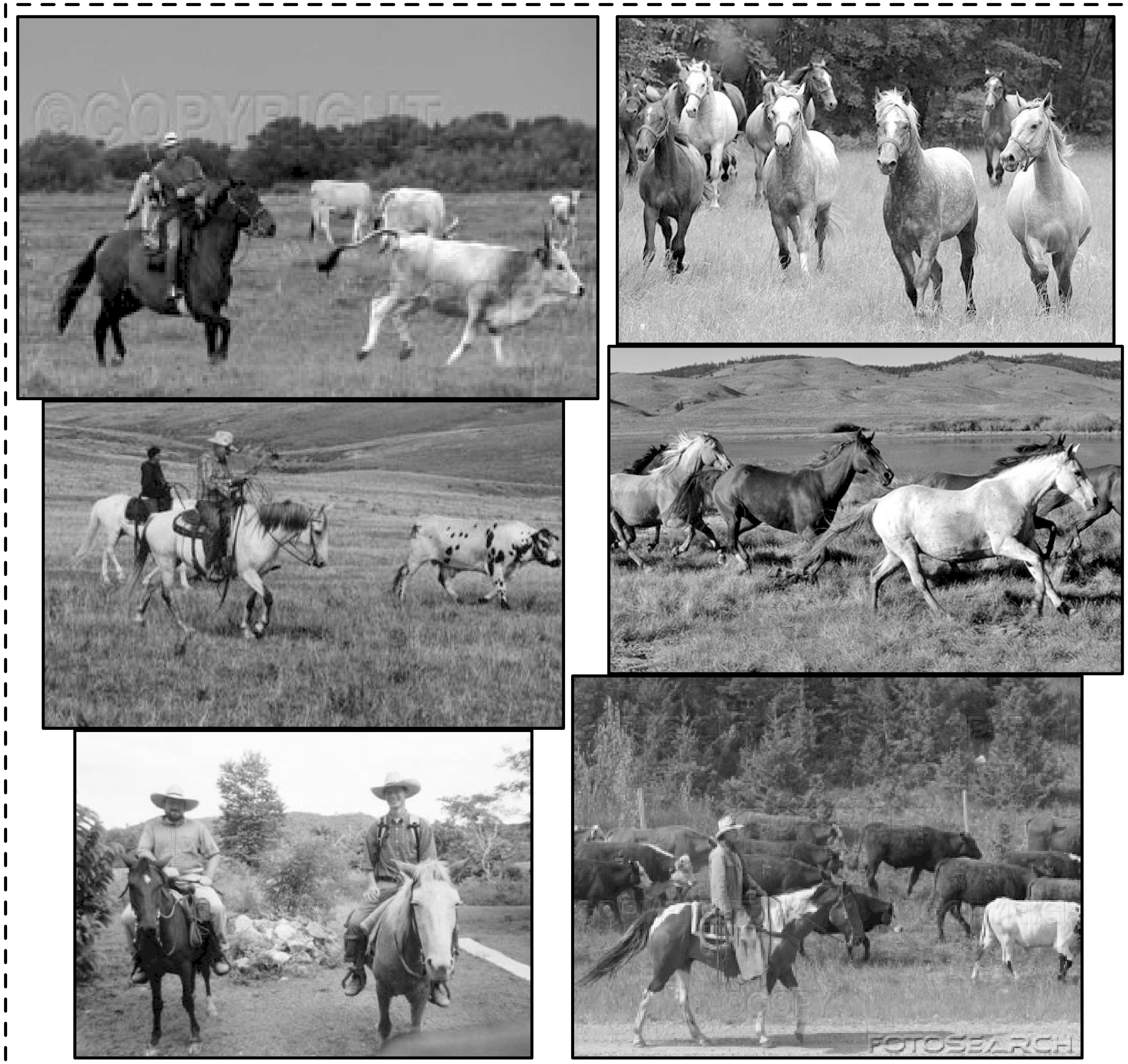
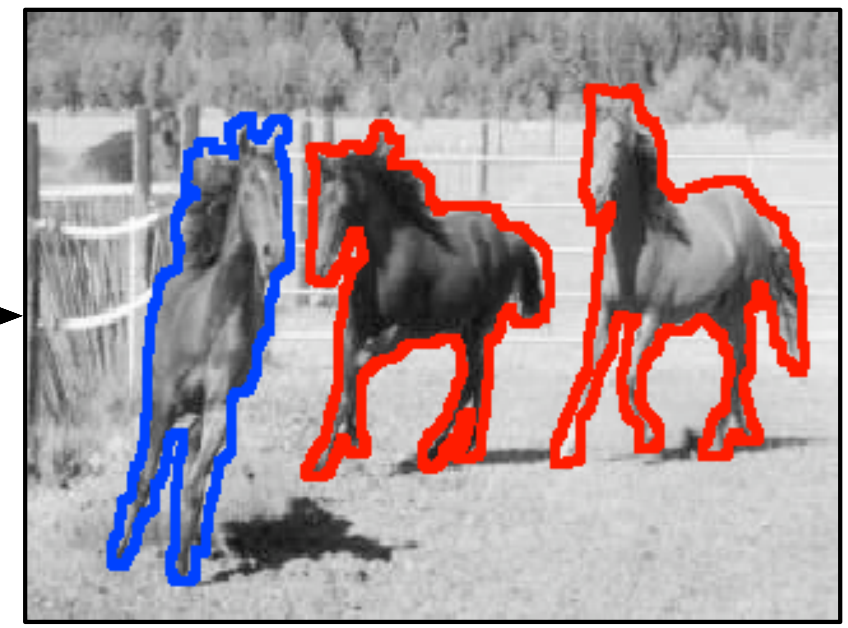
Goals: Object Recognition

input image set



discover and learn all objects present

new image



detect
segment
explain
***all* occurrences**
of the learned objects

Goal: Video Painterly Rendering

video sequence enhanced with multiple painting styles
-- one per each object

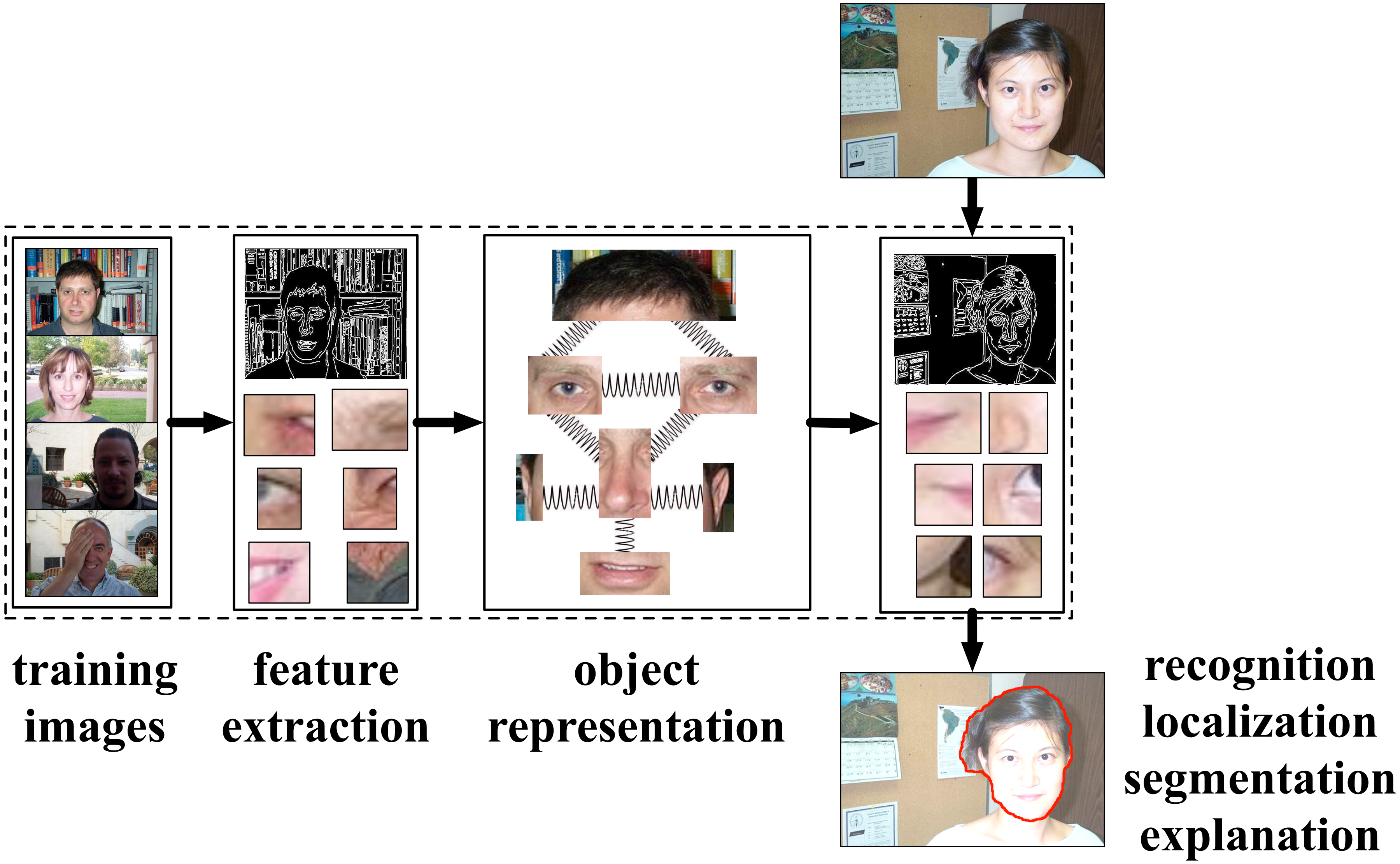
flower petals = van Gogh
stamens = expressionism
background = pointilism

Goals: Texel-based Texture Segmentation

Many applications require unsupervised partitioning of the image into textured and non-textured subimages

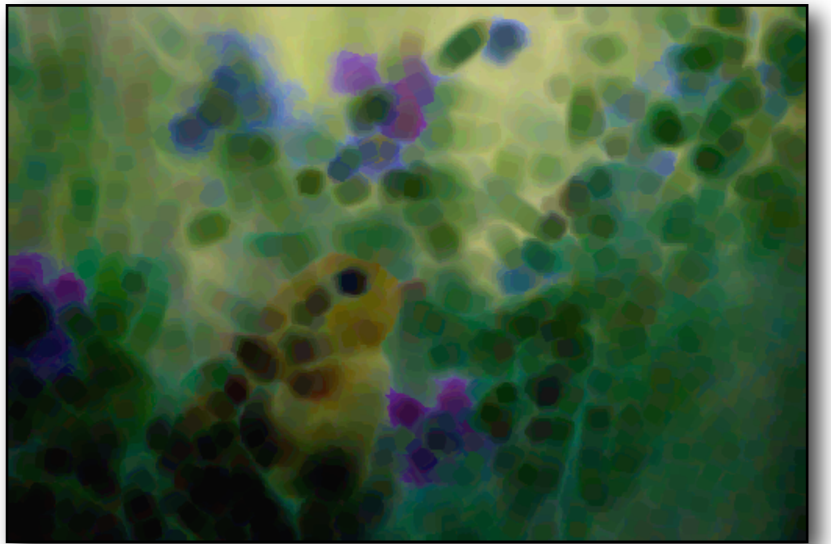
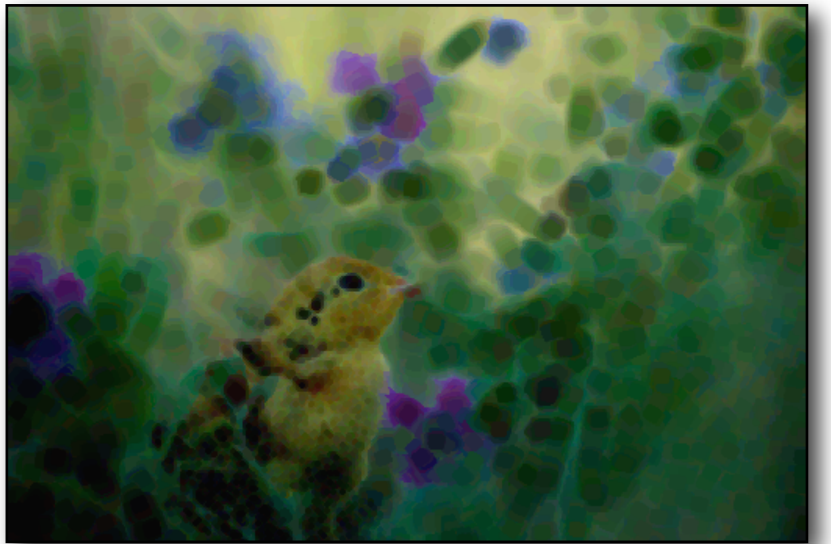
Prior Work: Object Recognition

PRIOR WORK	OUR EXTENSIONS
high degree of supervision	relaxing supervision requirements
predominance of keypoint features	using richer features: regions
ignoring the spatial info	accounting for multiscale spatial info
limited goals	unified framework for many goals



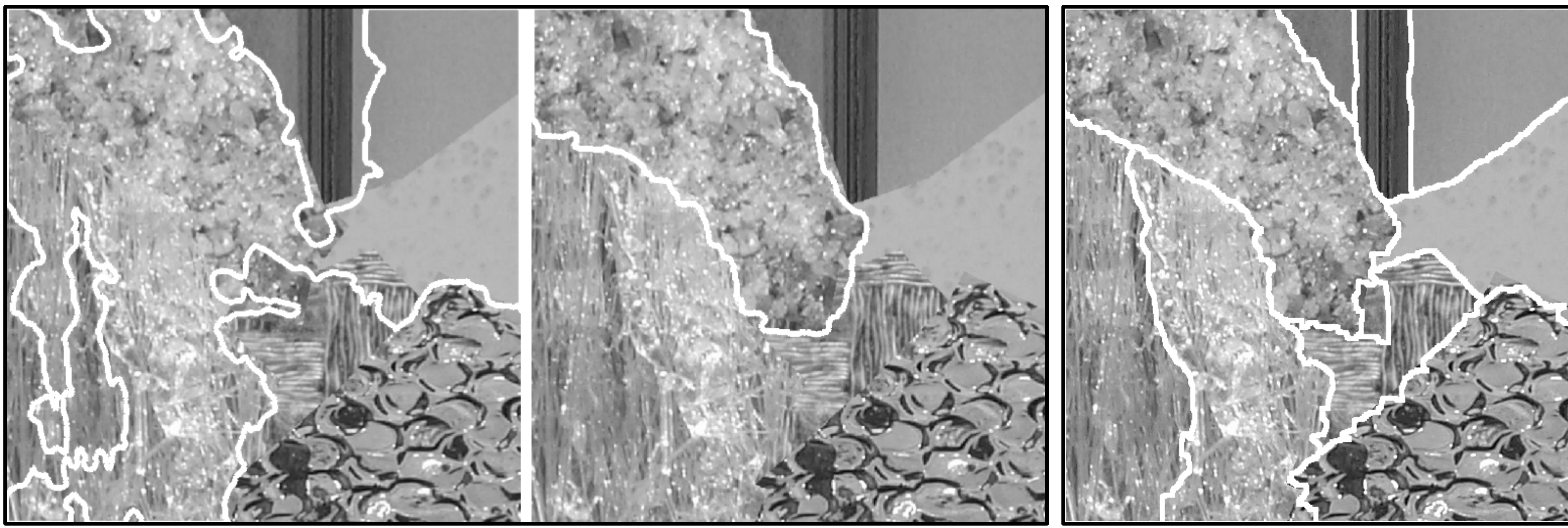
Prior Work: Painterly Rendering

PRIOR WORK	OUR EXTENSIONS
Uses only a single style	Object-based multiple styles
Unrealistic, poor artistic expression	Rich artistic expression

Prior Work: Texture Segmentation

PRIOR WORK	OUR EXTENSIONS
Uses a pre-specified bank of filters	Extraction of texels
Assumptions: smoothness, scale	Relaxing the assumptions



meanshift active contours our results

WHAT IS AN OBJECT?

Properties of Objects

3D objects in the scene $\longrightarrow$ 2D objects in the image

cohesive	occupy regions
form characteristic spatial configurations with other objects	context
have parts	subregions
parts have characteristic spatial layout	spatial layout of subregions

Rationale for Learning – Like a Small Child

input images

It is likely to be meaningful:

- **If some parts repeat in the set of images**
- **If some configurations of the learned parts repeat in the set**

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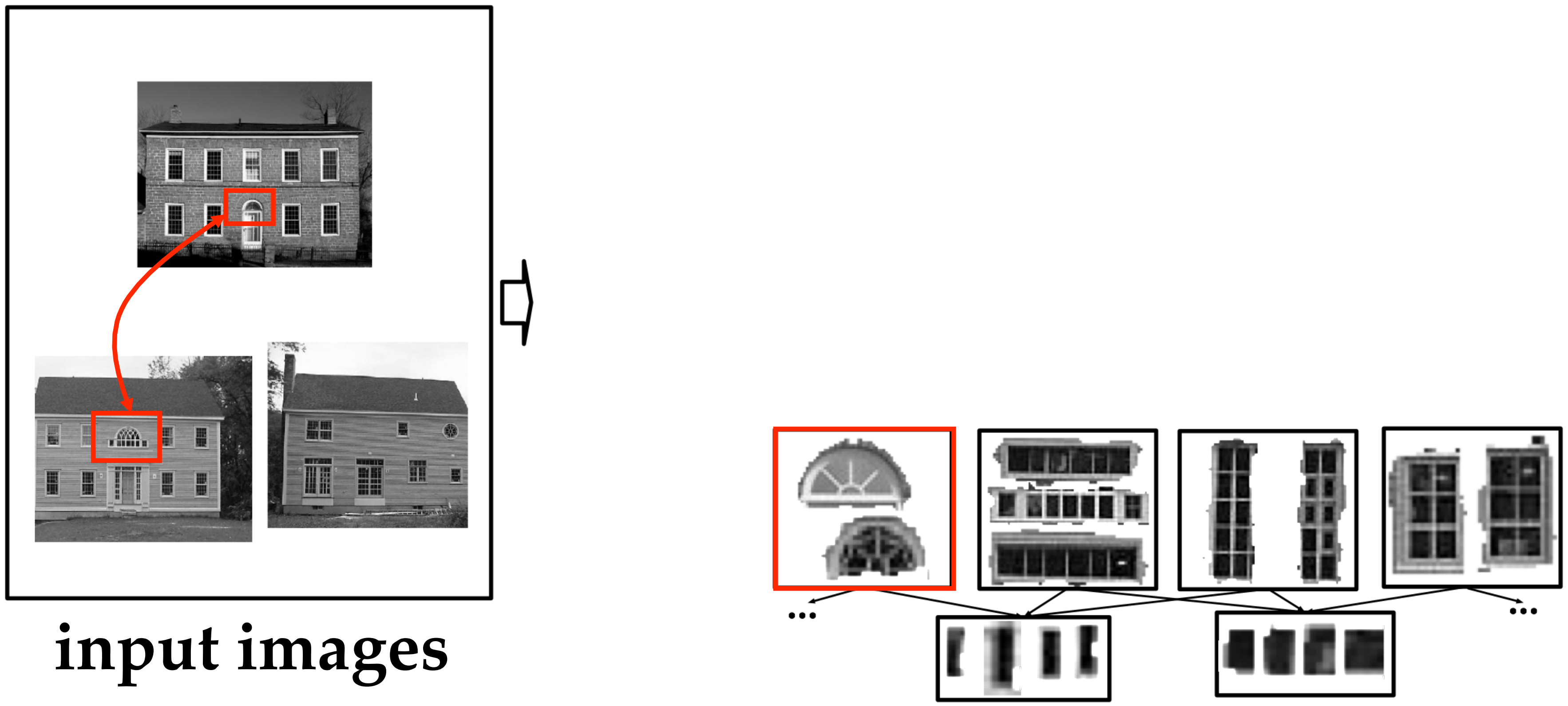

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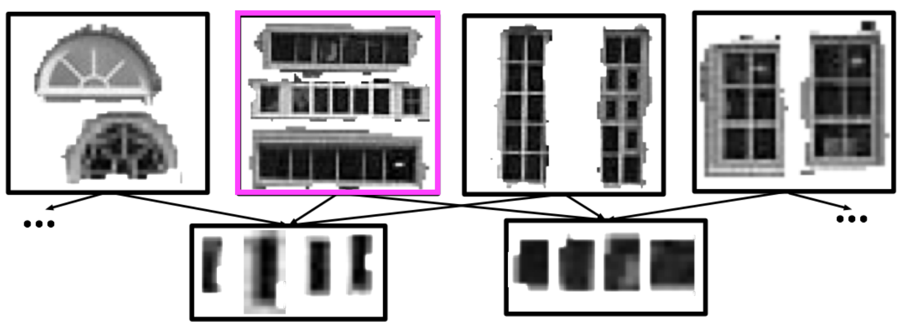

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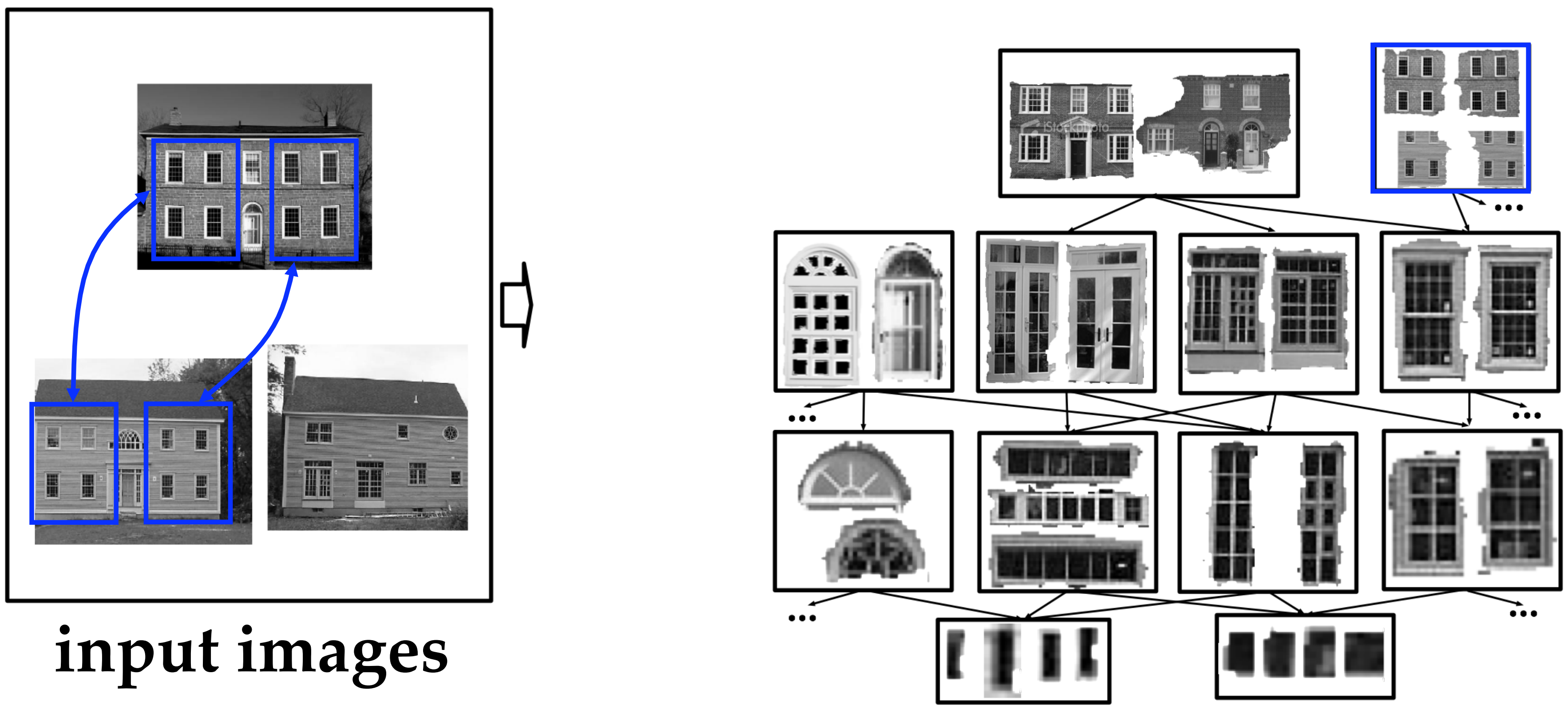

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Category = Set of Recurring Similar 2D Objects

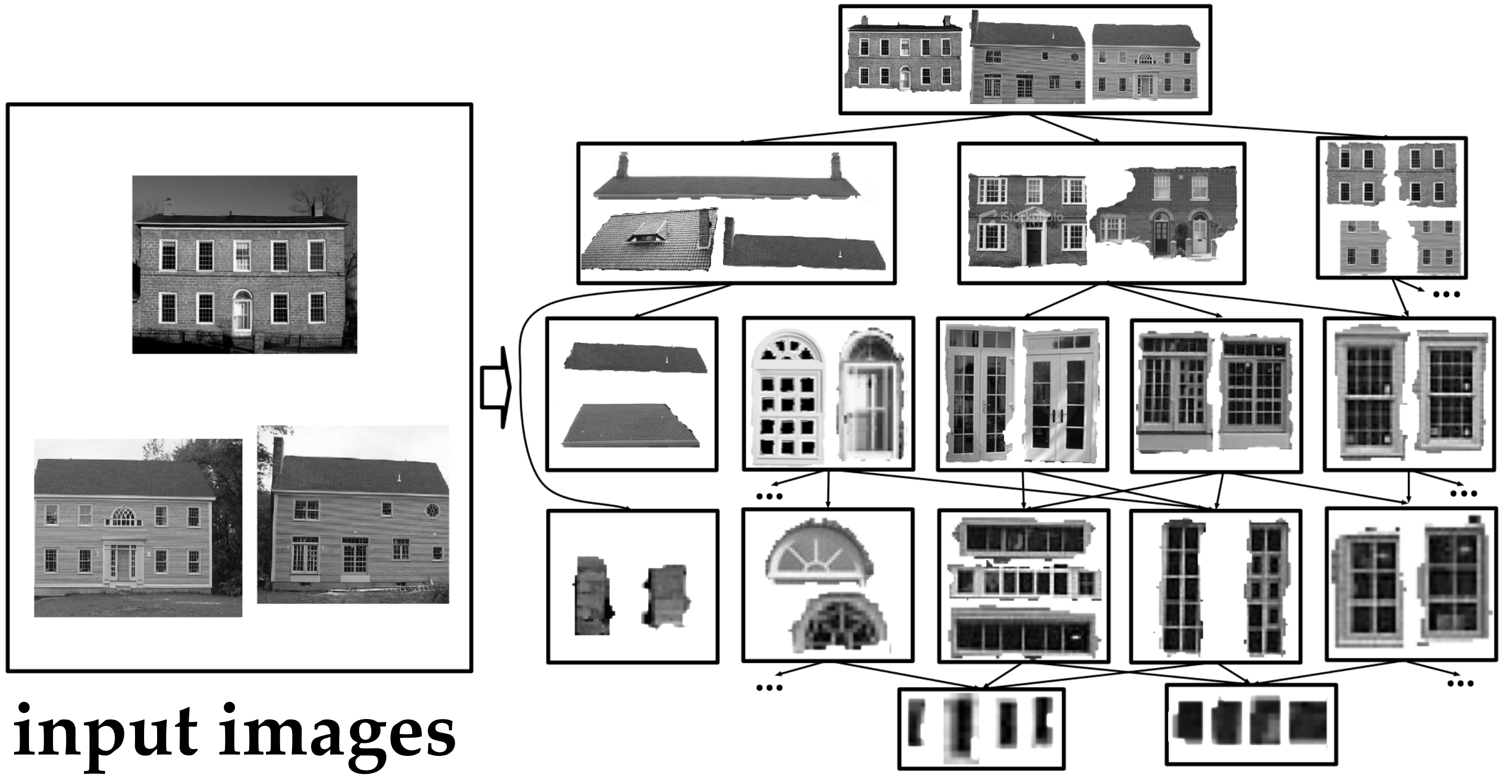
(1) Photometric (e.g., color)

(2) Geometric (e.g., area, shape)

(3) Structural:

spatial layout of subcategories

containment of subcategories



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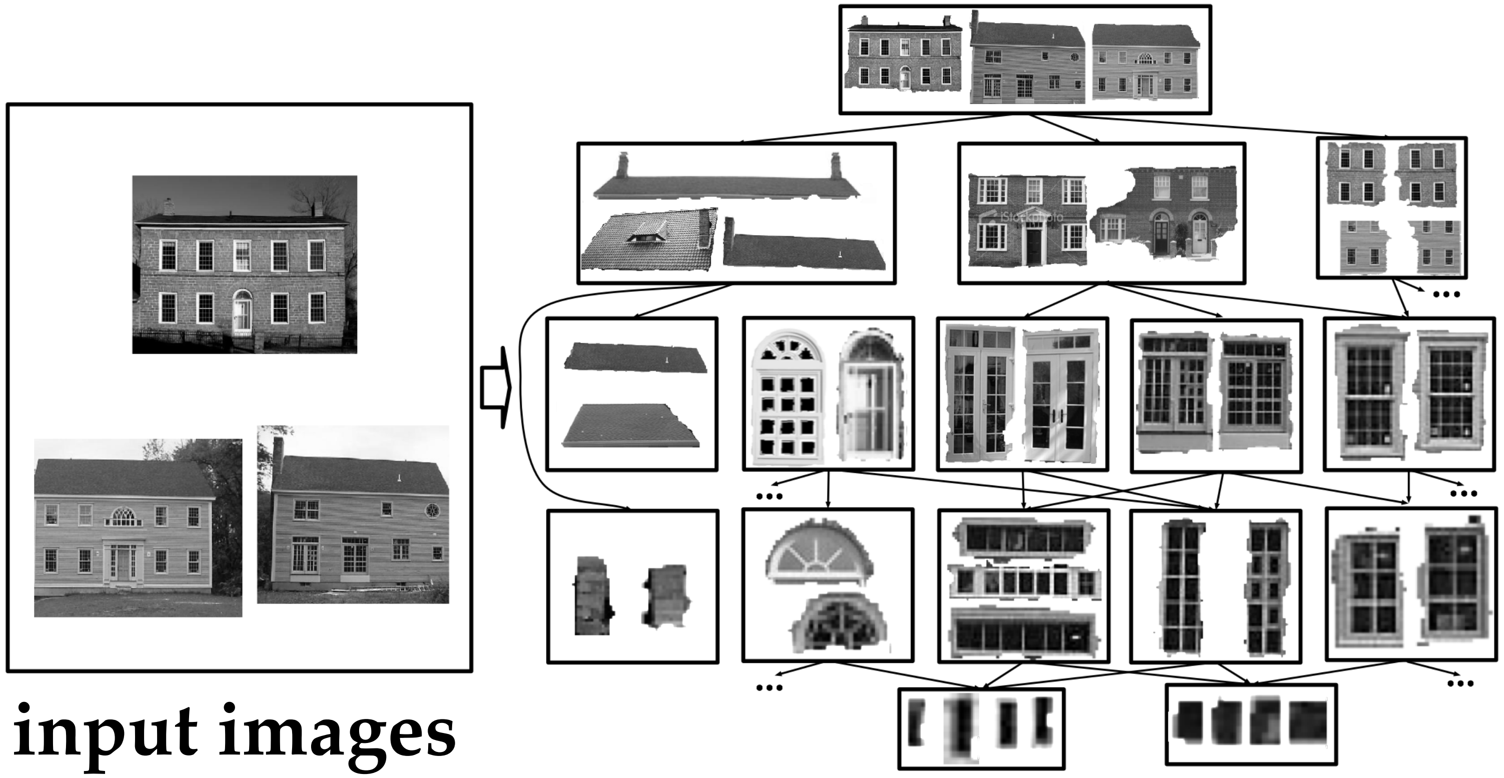
recursive definition



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Problem Statement

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  - **Under illumination and scale changes**
  - **Amidst background clutter**
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  - **Under illumination and scale changes**
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  - **Under partial occlusion**
- **Learn their generative, statistical models**
- **Use the models for**
  - **Object recognition**
  - **Object-based painterly rendering and synthesis**
  - **Texel-based texture segmentation**

Rest of the Talk

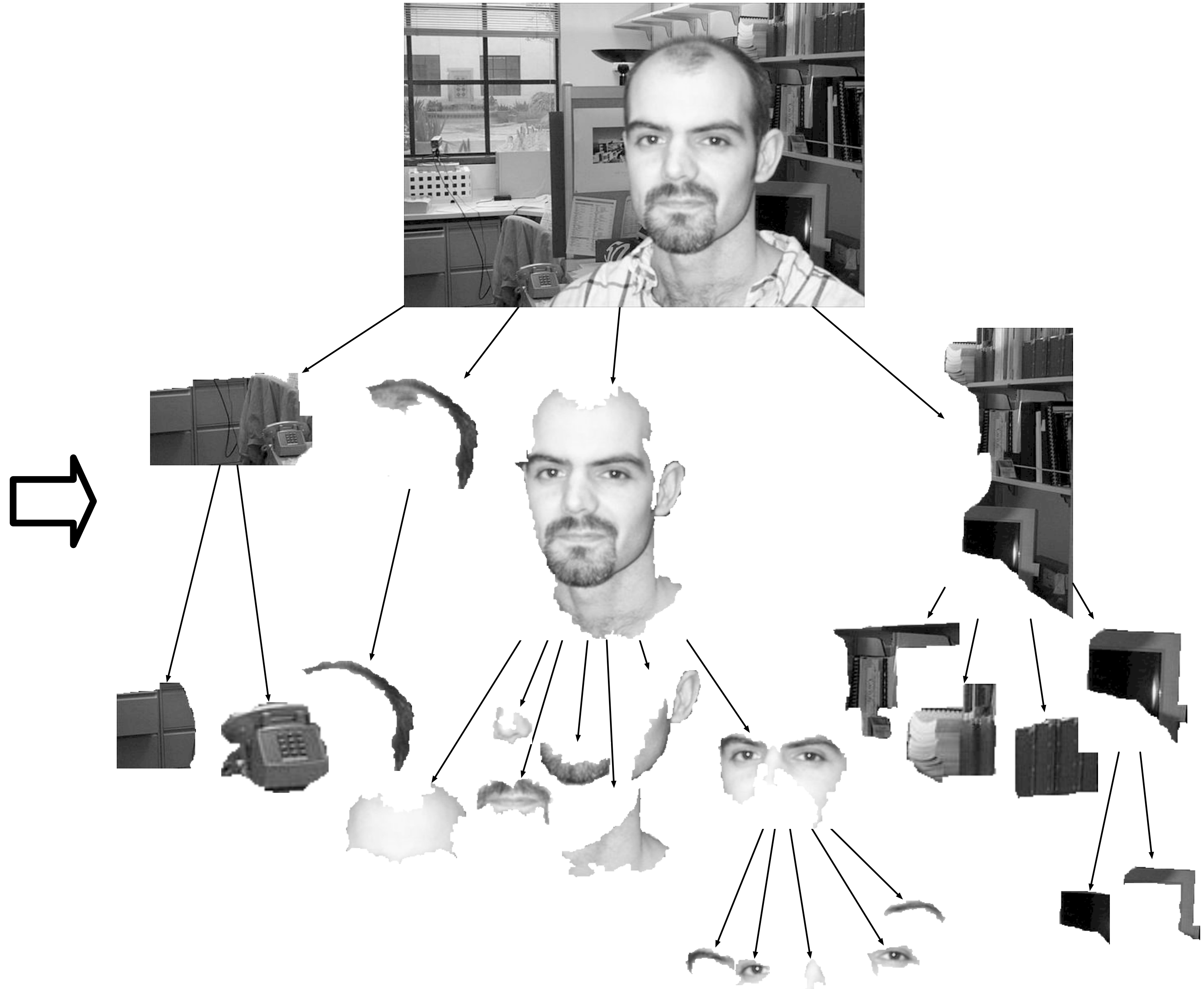
1. **Image representation = Hierarchy of regions**

2. **Region matching**

3. **Applications and results**

Image = Tree ⇒ Object = Subtree

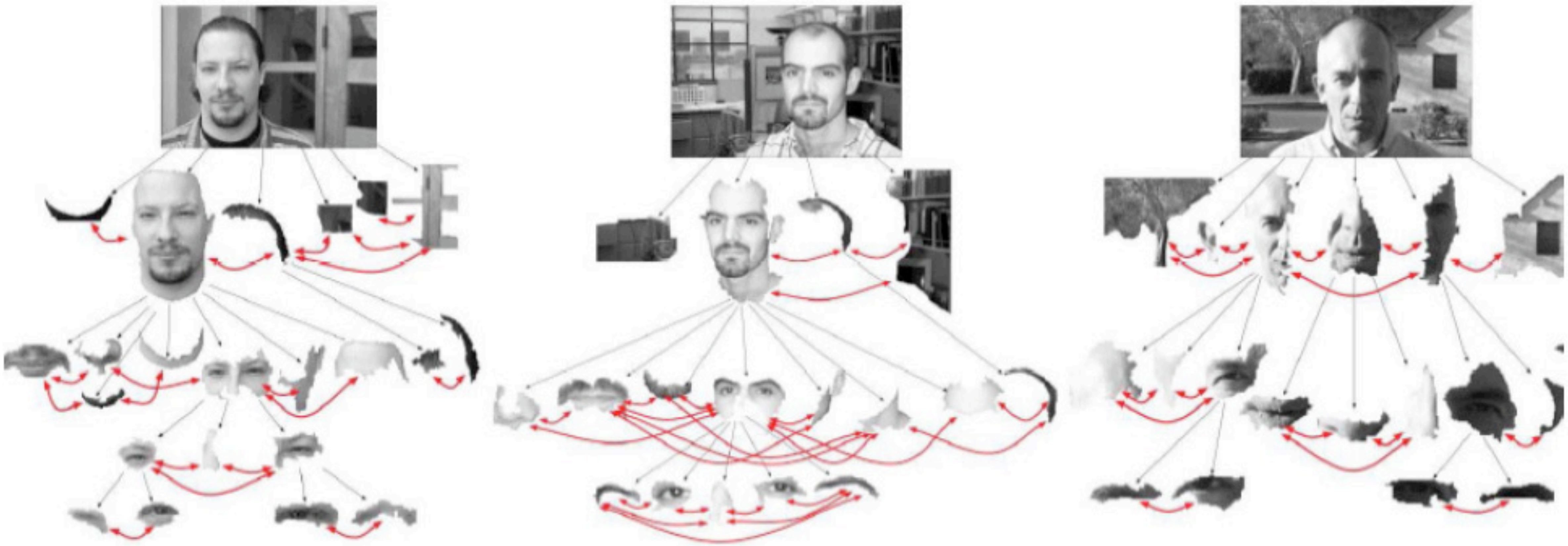
multiscale segmentation



segmentation tree

Ahuja PAMI96, Tobb & Ahuja TIP97, Arora&Ahuja ICPR06

Connected Segmentation Trees



Lateral links = Region neighbor relations

Hierarchical links = Region embedding

Ahuja&Todorovic CVPR08

Region Properties Associated with Each Node

- **Gray-level contrast with surround**
- **Boundary shape**
- **Displacement of centroids**
- **Orientation**

$\vdots$

Properties relative wrt parent $\Rightarrow$ Scale and in-plane rotation invariance

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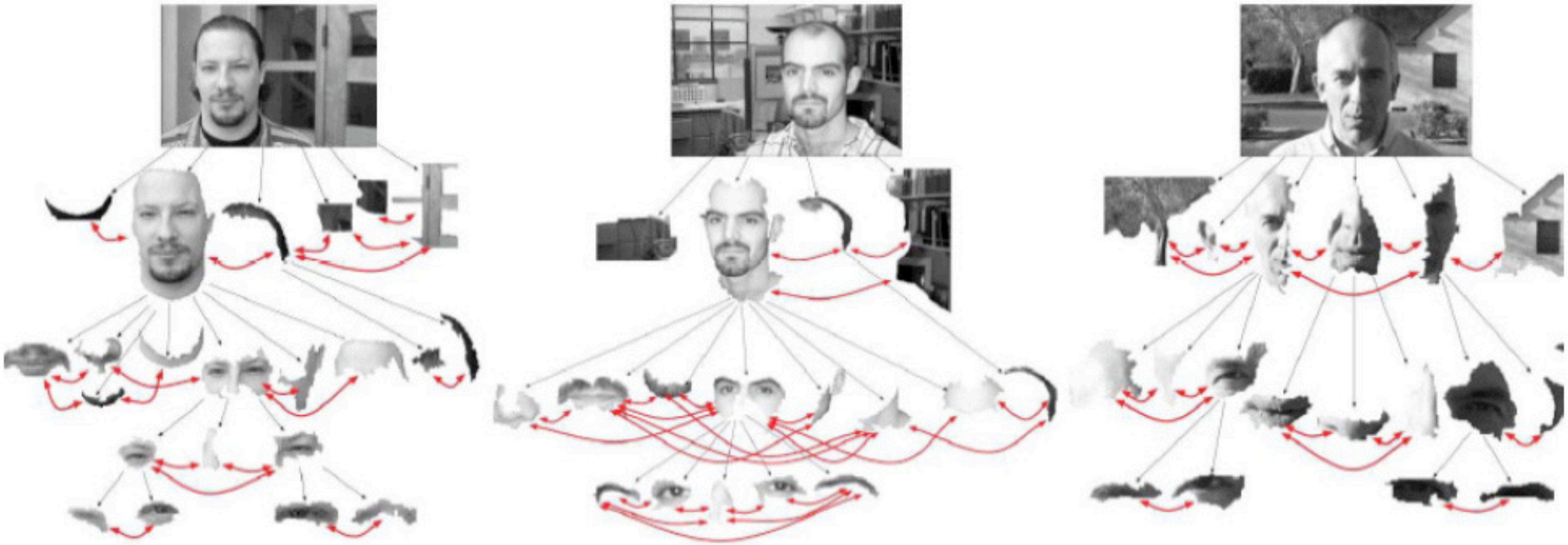
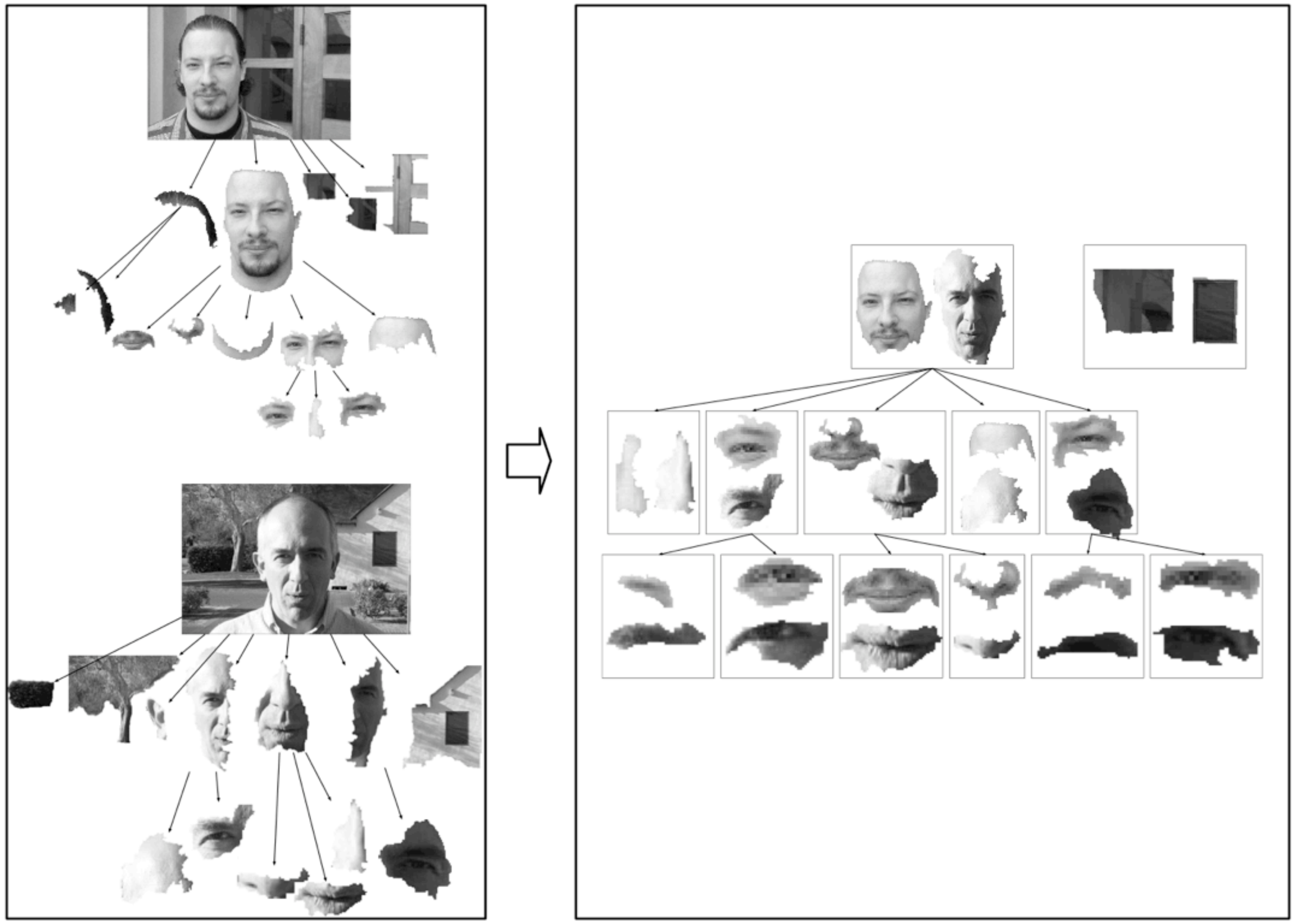
How to Discover Repeating Image Parts?



Object category is present = Many similar subgraphs

Discovering objects = Graph matching

Graph Matching = Subgraph Isomorphism



Match two regions

- **If their immediate properties are similar**
- **AND the same holds for their subregions**
- **AND the same holds for their neighbors**

Graph Matching: Formulation

Given two graphs: $G = (V, E)$ **and** $G' = (V', E')$

Find the mapping $f = \{(v, v')\} \subset V \times V'$

which minimizes their cost of matching:

$$COST_{GG'} = \min_f \left[\sum_{(v,v') \in f} \psi_{vv'} + \sum_{(v,v',u,u') \in f \times f} \phi_{vv'uu'} \right]$$

unary potential
function of region properties

pairwise potential
function of spatial relationships

Graph Matching: Formulation

Linearization by introducing an indicator vector

$$\boldsymbol{X} = [0\ 0\ 1\ 0\ 0\ 1\ \ldots\ 0\ 1\ 0]^T$$

matched pair (v, v') **unmatched pair** (u, u')

$$\Downarrow$$

Discrete problem

$$\min_{\boldsymbol{X}} \left[\boldsymbol{\Psi}^T \boldsymbol{X} + \boldsymbol{X}^T \boldsymbol{\Phi} \boldsymbol{X} \right]$$

$$\textbf{s.t.} \quad x_{vv'} \in \{0, 1\}$$

Graph Matching: Formulation

Relaxation of the discrete problem

$$\min_{\boldsymbol{X}} \left[\boldsymbol{\Psi}^T \boldsymbol{X} + \boldsymbol{X}^T \boldsymbol{\Phi} \boldsymbol{X}\right]$$

$$\textbf{s.t.} \quad \forall \boldsymbol{x}_{vv'} \geq \mathbf{0}, \quad \sum_{v} \boldsymbol{x}_{vv'} = \mathbf{1}, \quad \sum_{v'} \boldsymbol{x}_{vv'} = \mathbf{1}$$

Todorovic&Ahuja IJCV08, PAMI08, CVPR06-08, ICCV07, ICPR06-08

Rest of the Talk

1. Image representation = Hierarchy of regions

2. Region matching

3. **Applications and results**

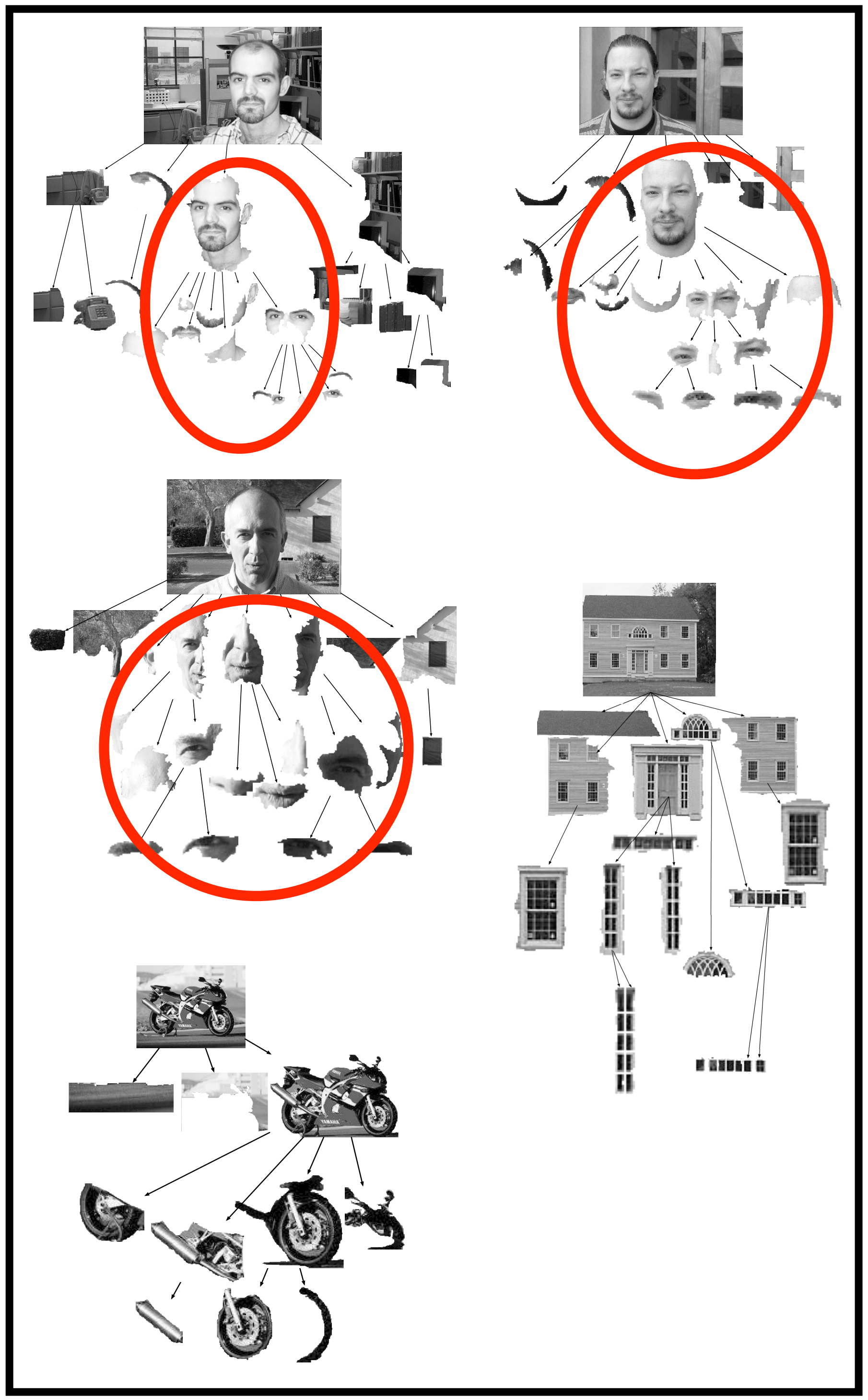
   a. **Object recognition**

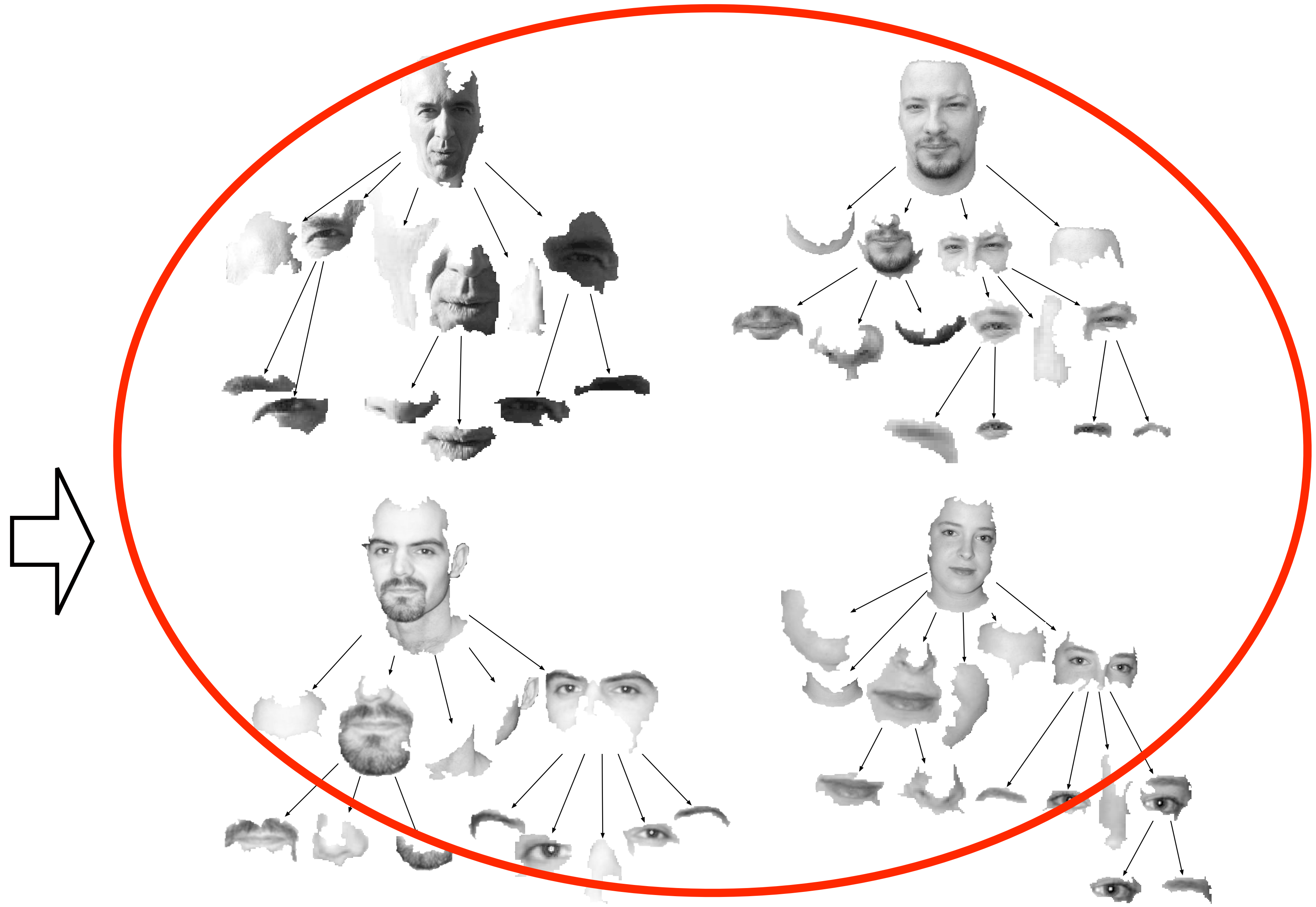
   b. Painterly rendering

   c. Texture segmentation

Discovering Objects = Matching + Clustering

training images





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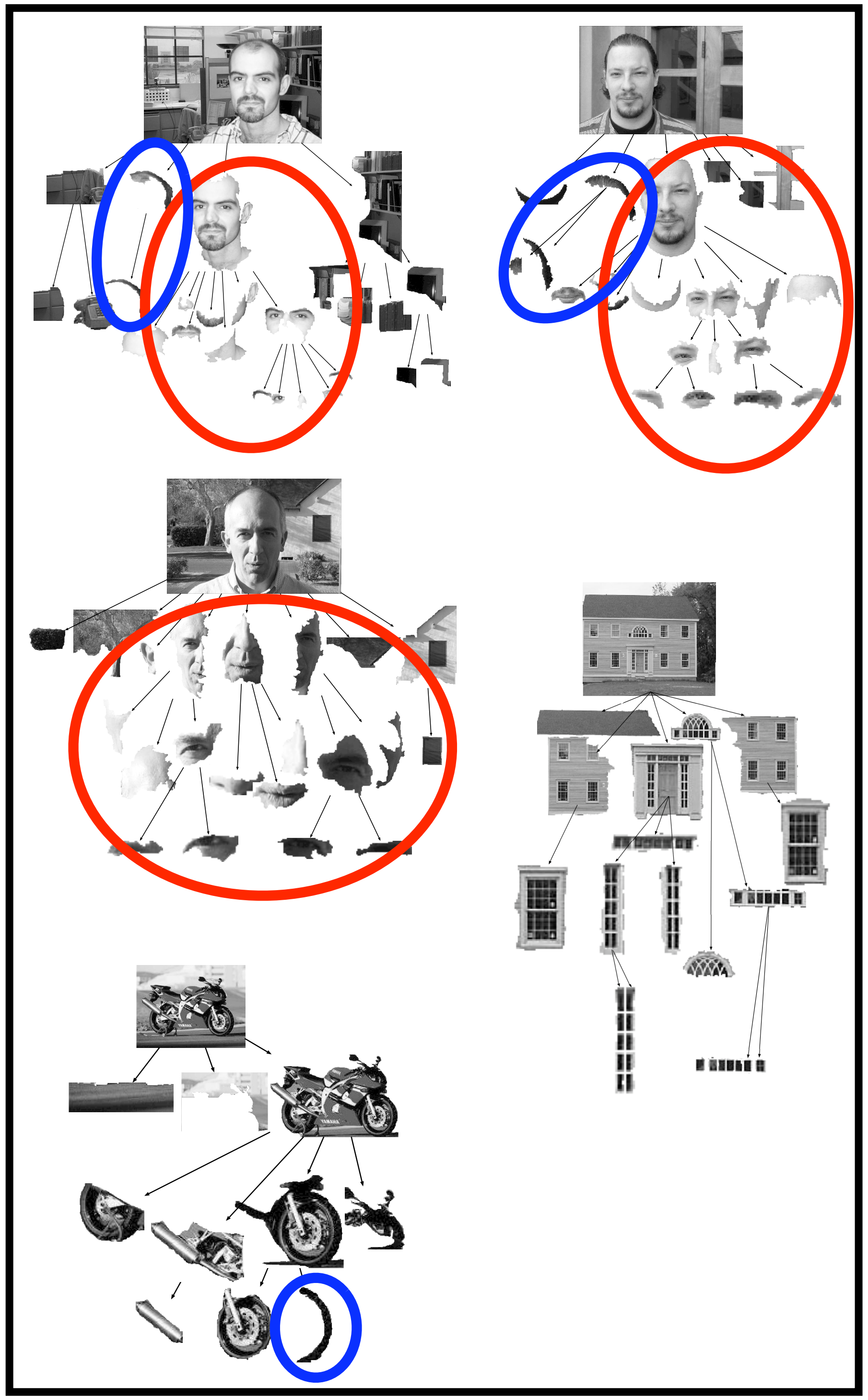
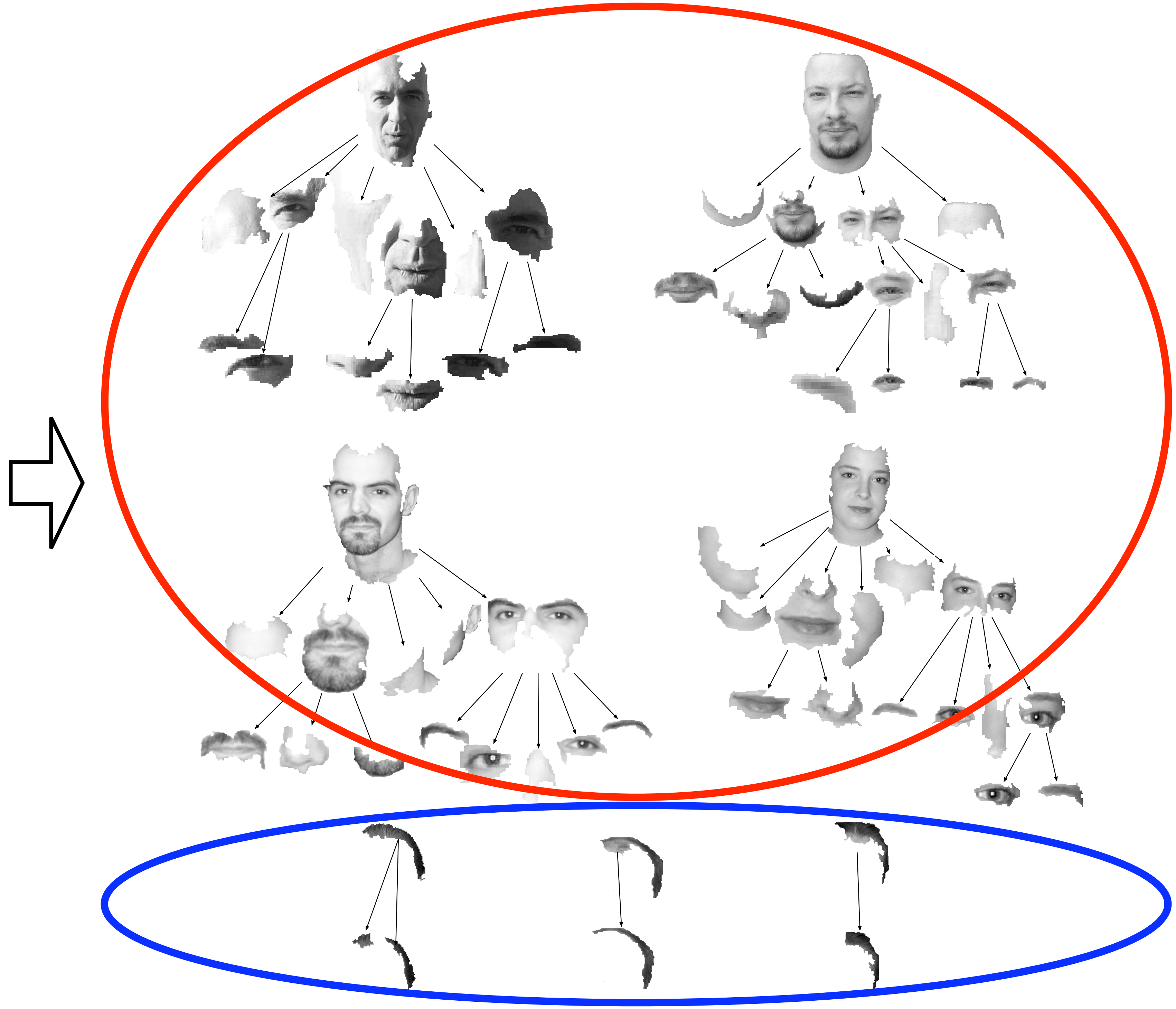
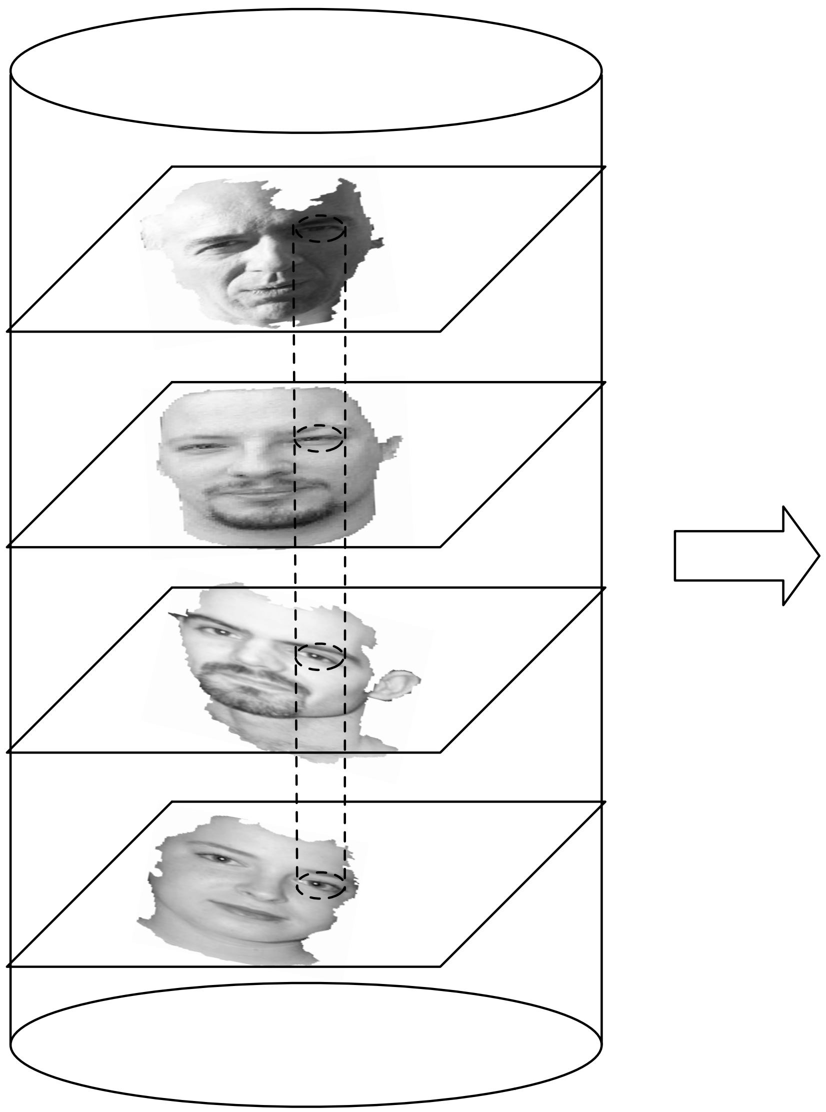


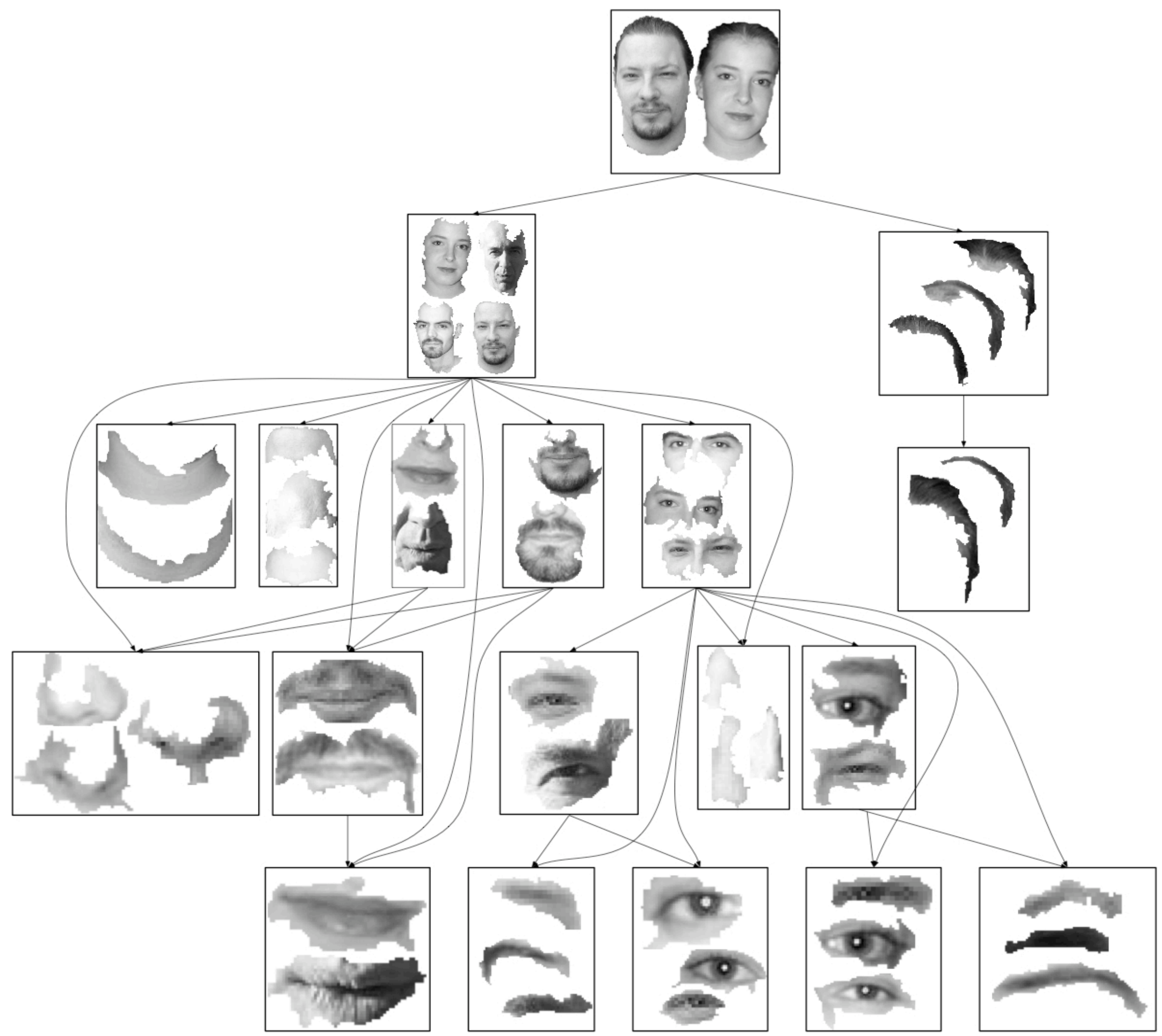


Each cluster = Distinct Object

Learning a Model of Each Cluster = Structural EM



matched subgraphs

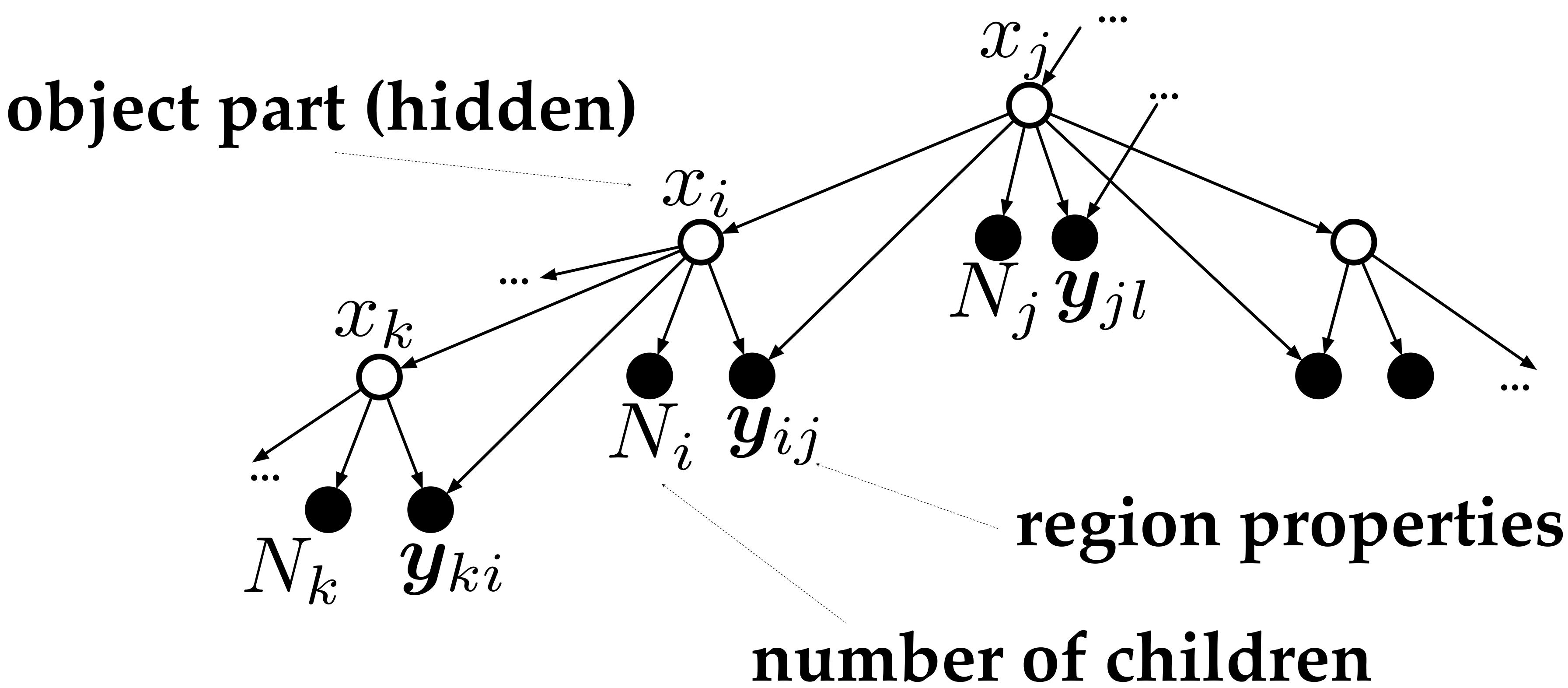


hierarchical object model

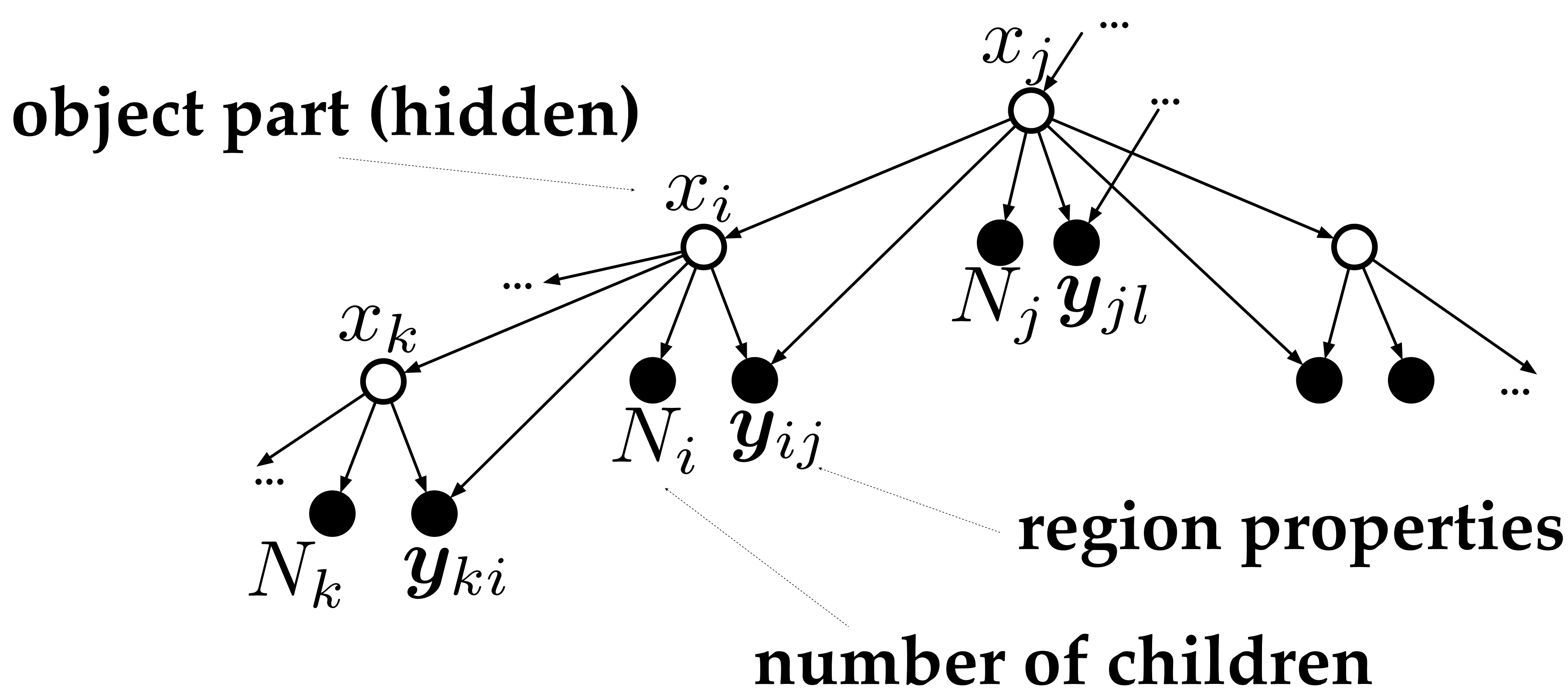
model structure ?

model parameters ?

Category Model = Bayesian Net



Category Model = Bayesian Net



$$P(X, Y, N|\mathcal{T}, \Omega) = \prod_{j \in \mathcal{T}} P(N_j|x_j) \prod_{i=1}^{N_j} P(x_i|x_j) P(y_{ij}|x_i x_j)$$

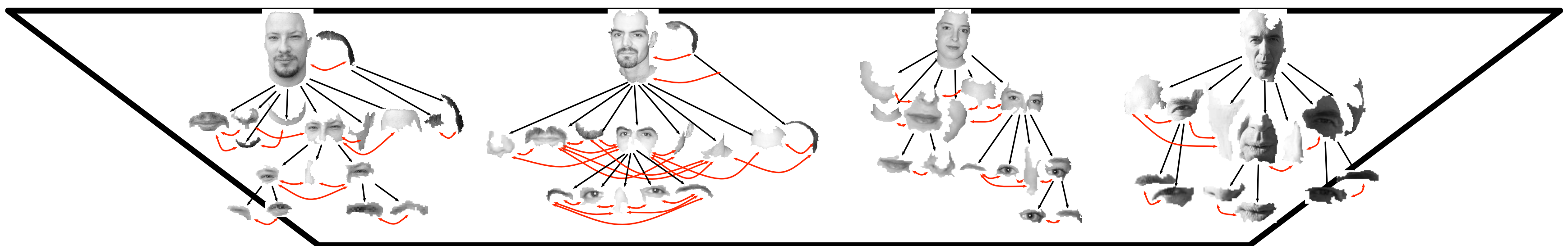
structure + parameters

Markovian chain

Exponential

Gaussian

Learning a Model = Structural EM



Given $\mathcal{T}$

Belief propagation $\Rightarrow \Omega$

Given Ω

Graph matching $\Rightarrow \mathcal{T}$

Category model

$\mathcal{T}$ Ω

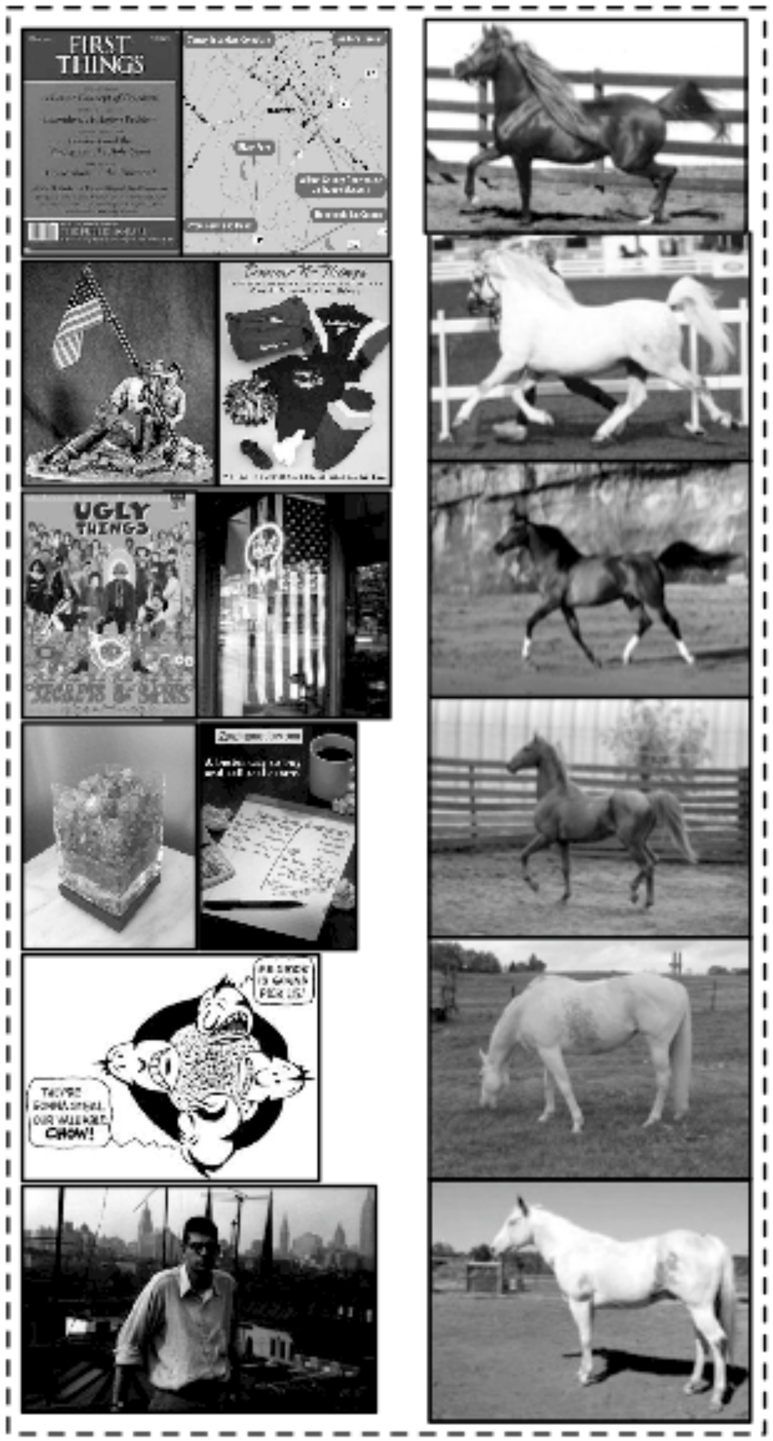
$\mathcal{T}$ **model structure**

Ω **model parameters**

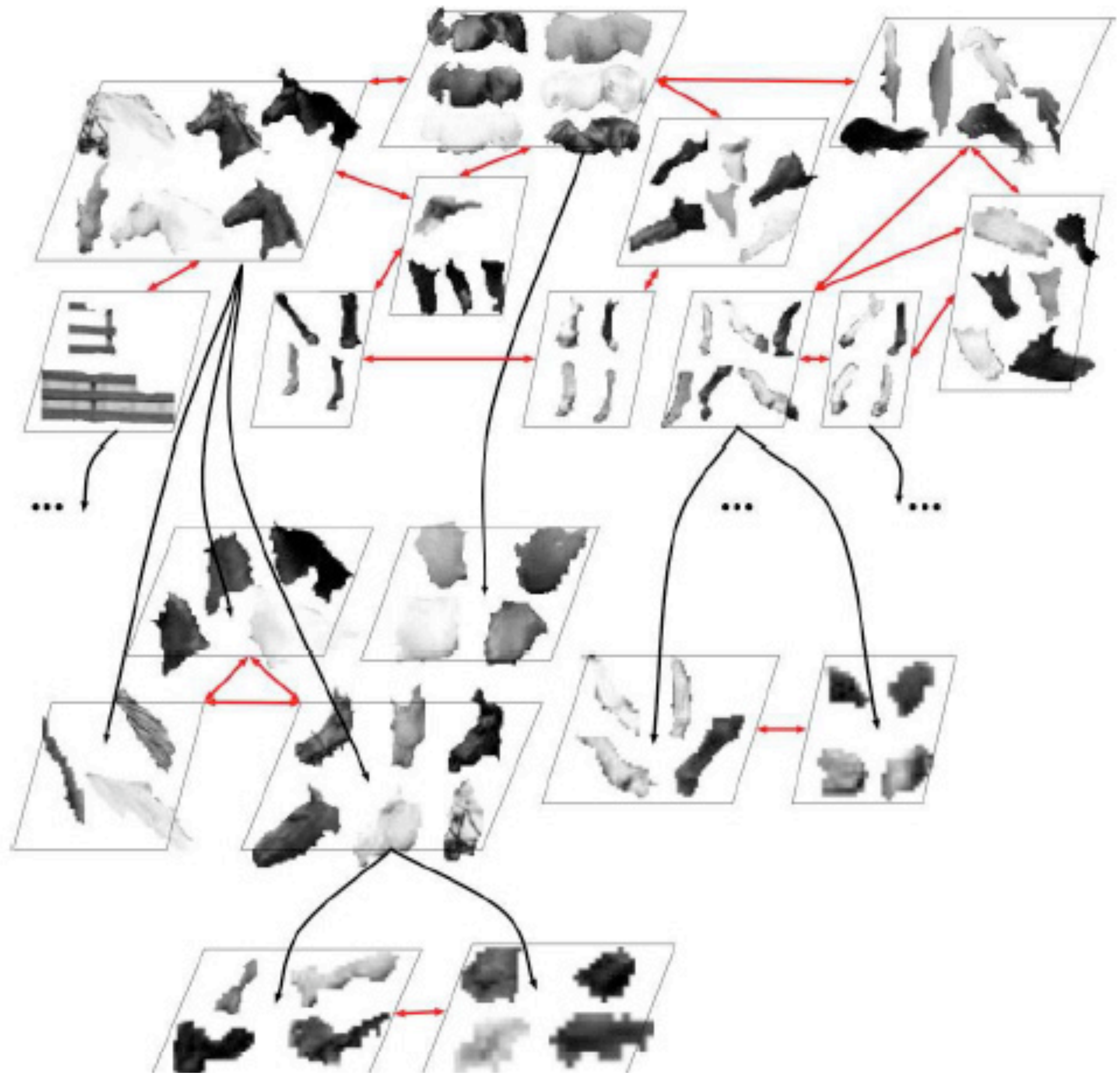
Todorovic&Ahuja ICCV07

Results: Weizmann Horses

training images

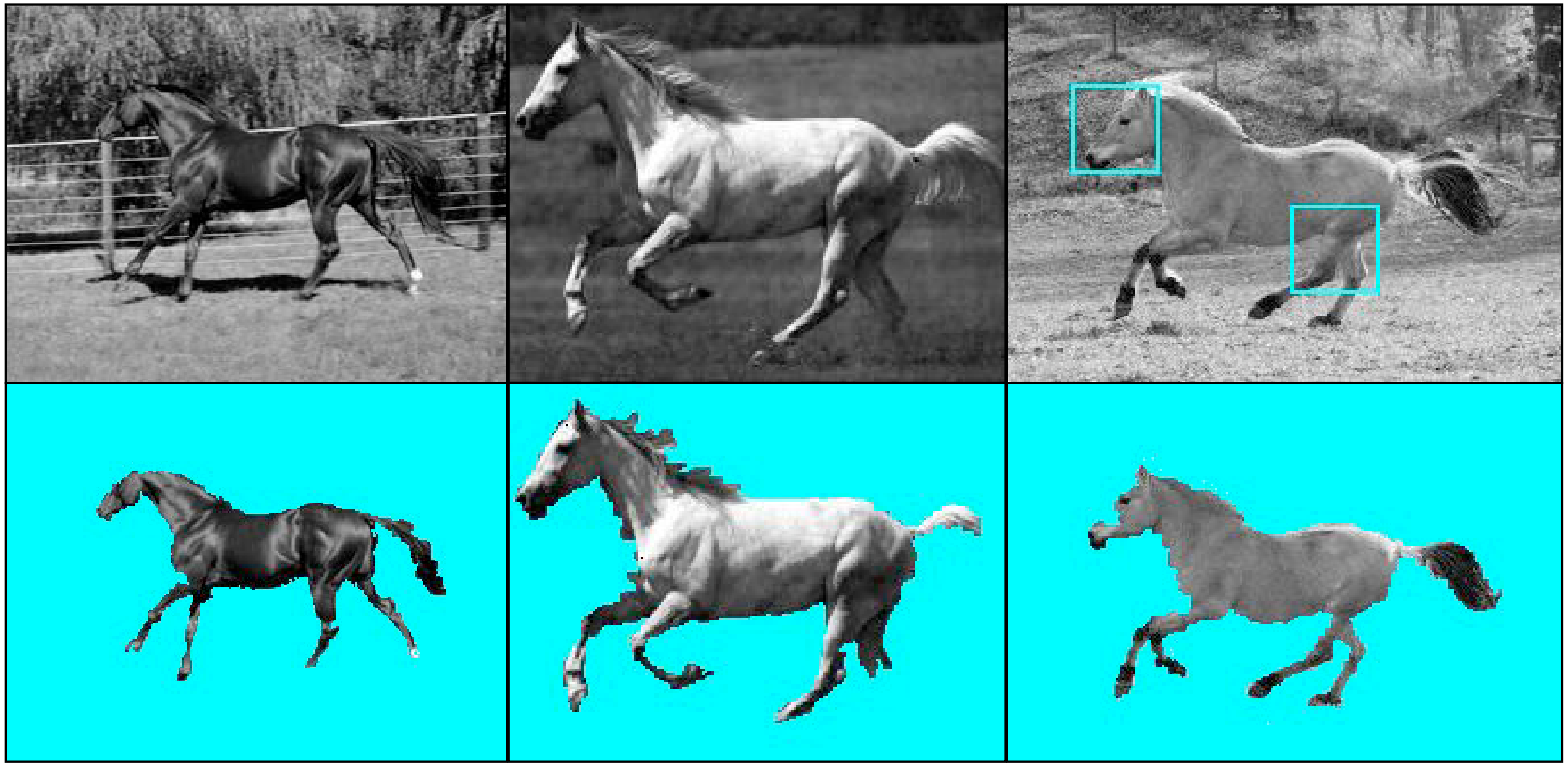


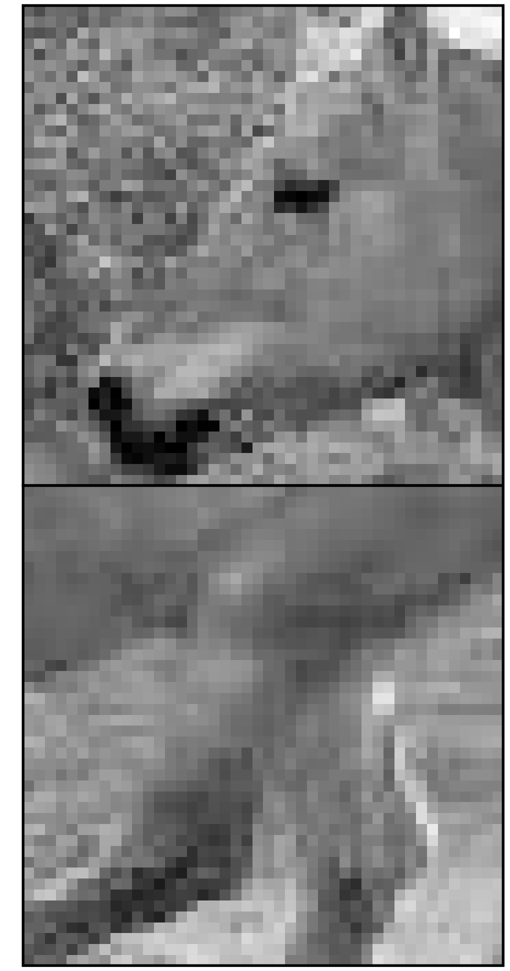
category model



Todorovic&Ahuja PAMI08

Results: Weizmann Horses





- Object segmentation is good on contours that are:
  - Jagged
  - Blurred
  - Form complex patterns
- Low-contrast regions merge with background

Todorovic&Ahuja PAMI09

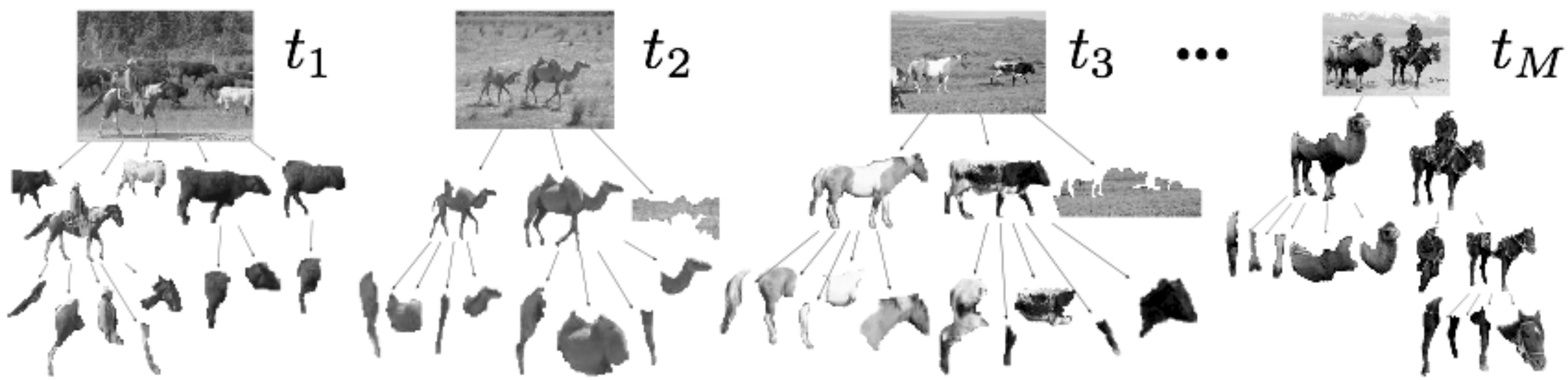
UIUC Hoofed Animals Dataset

http://vision.ai.uiuc.edu/~sintod/HoofedAnimalsDataset.html

training images

Multi-Object Recognition

1. TREE MATCHING



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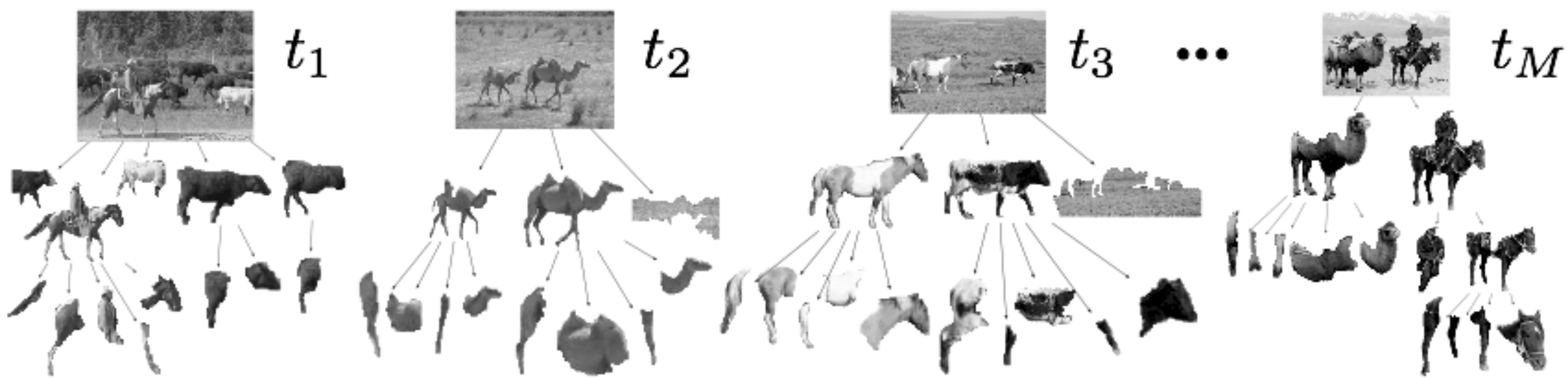

2. CLUSTERING

Multi-Object Recognition

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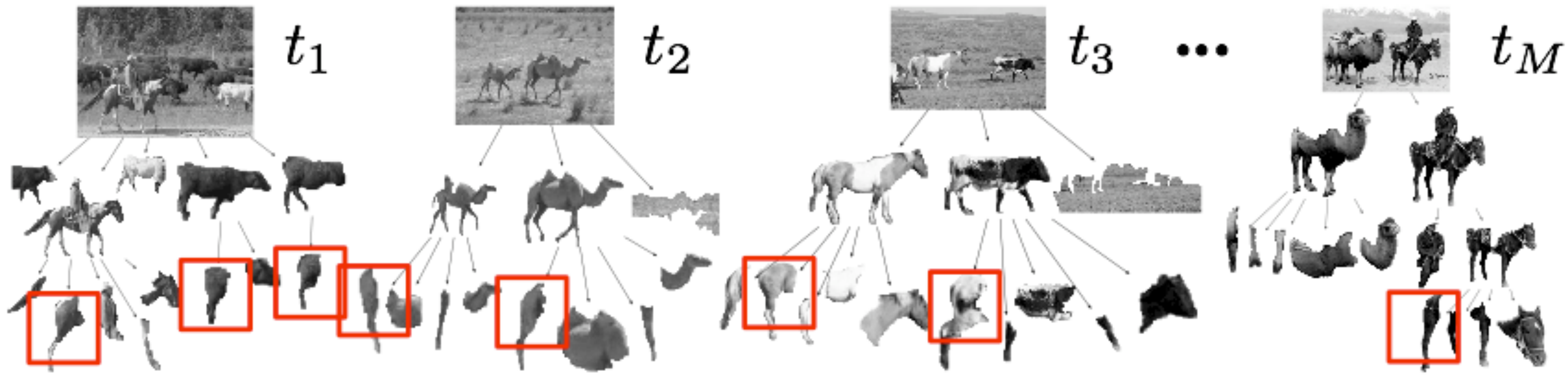

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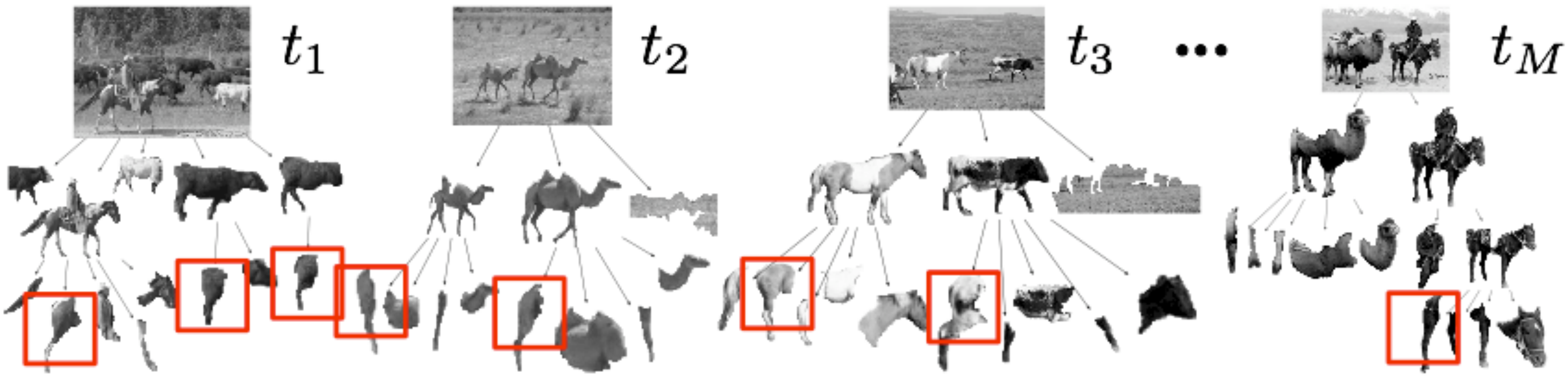

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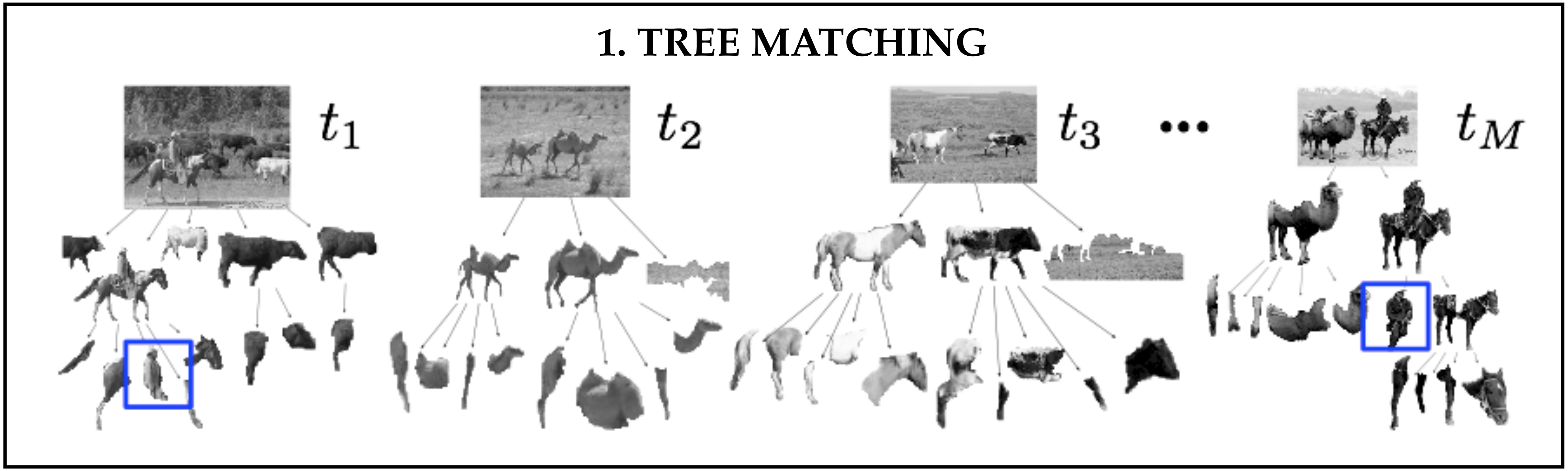

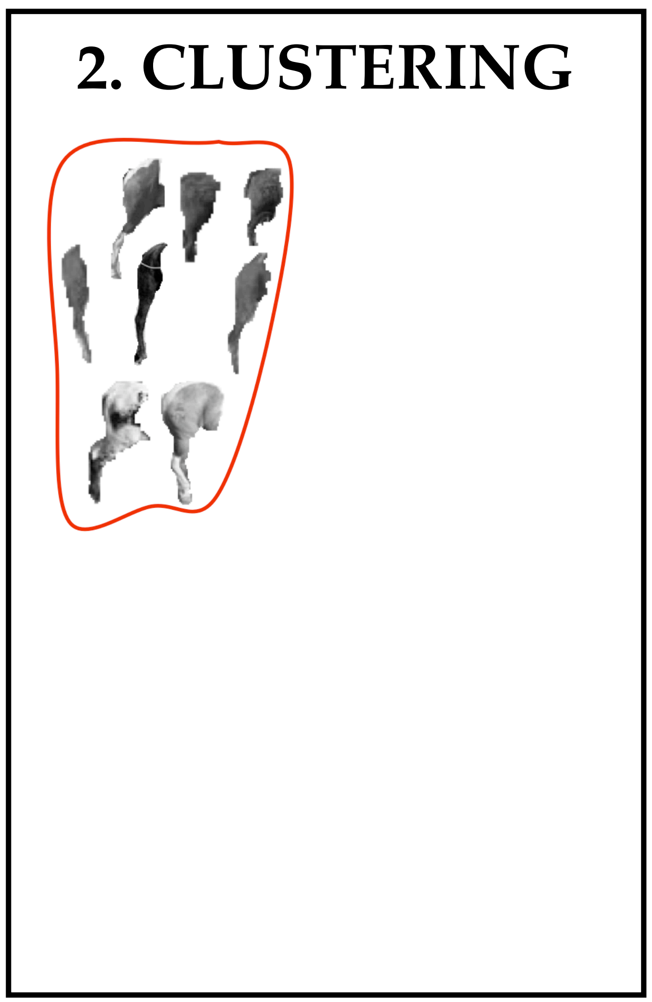

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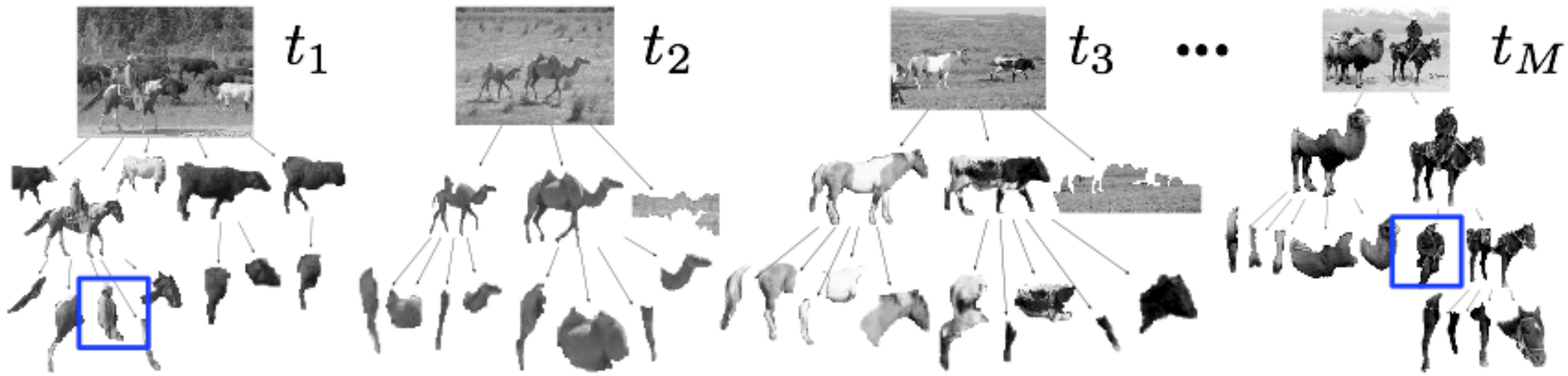

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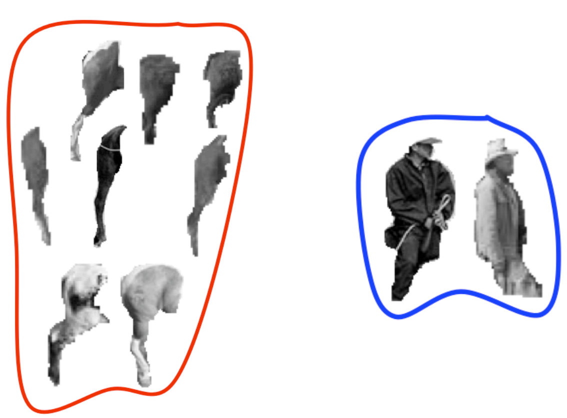

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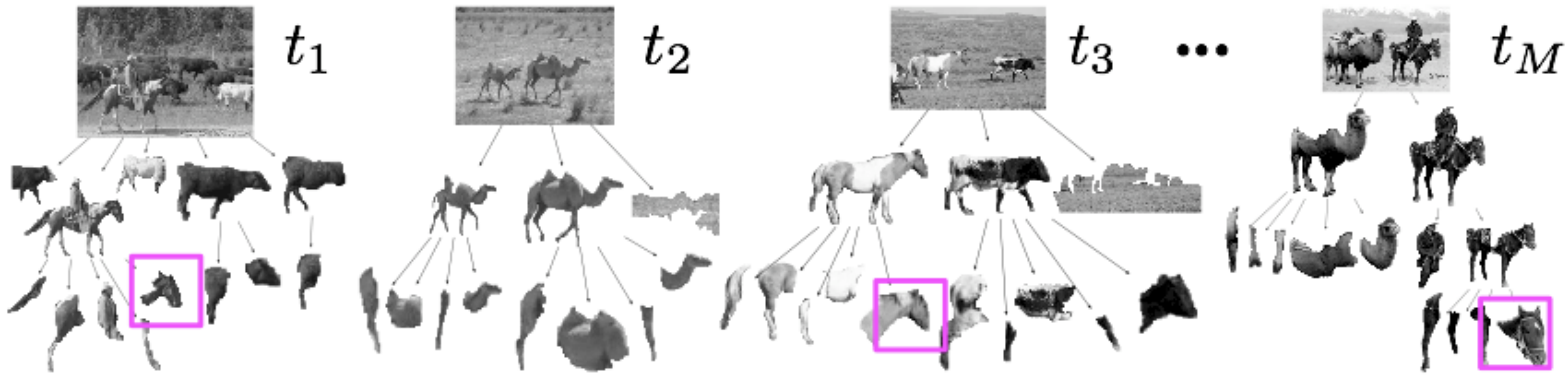

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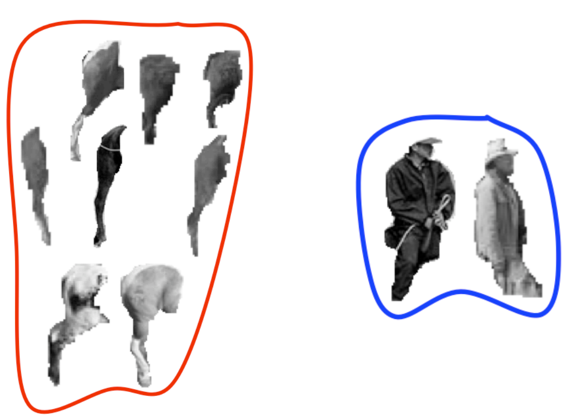

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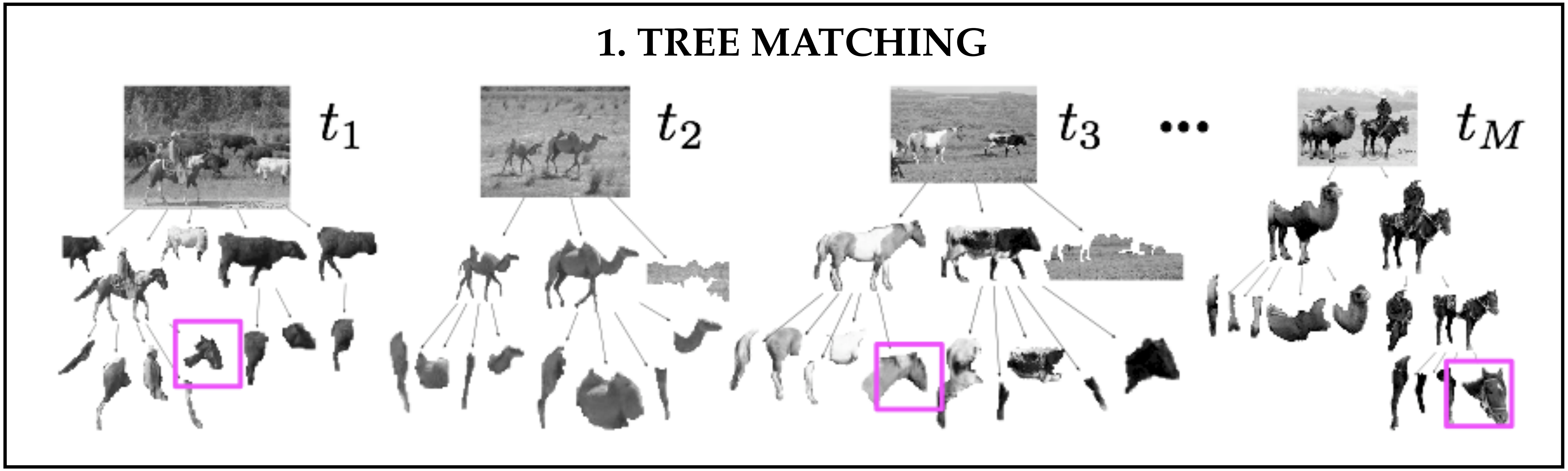

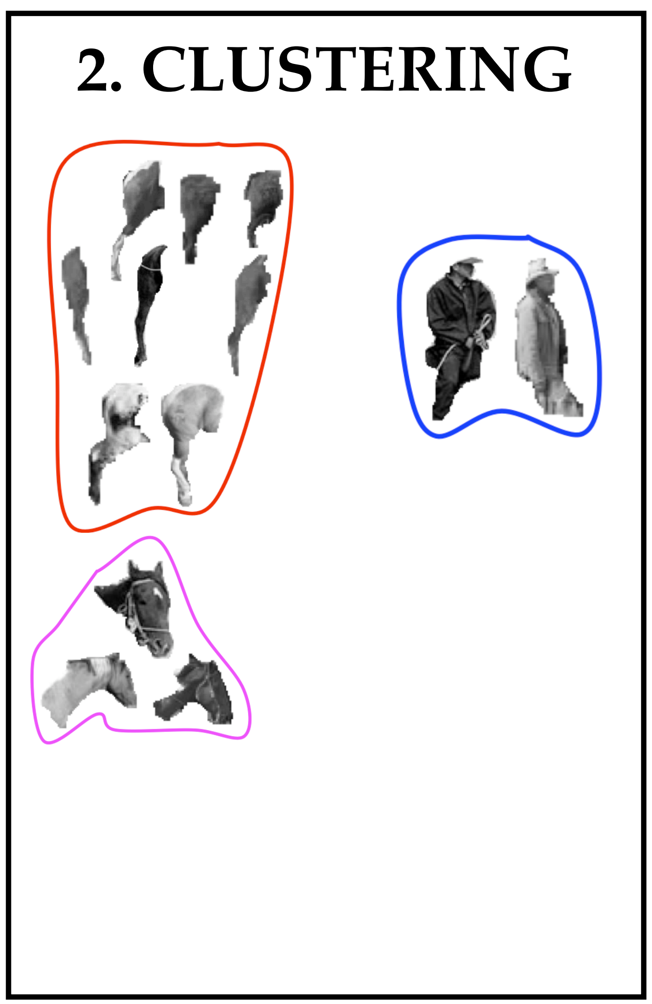

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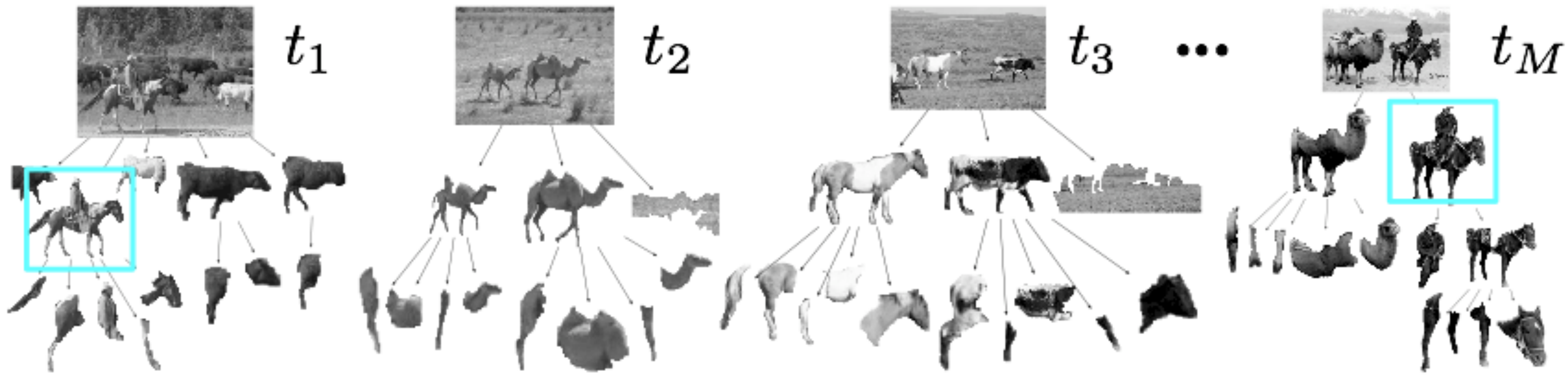

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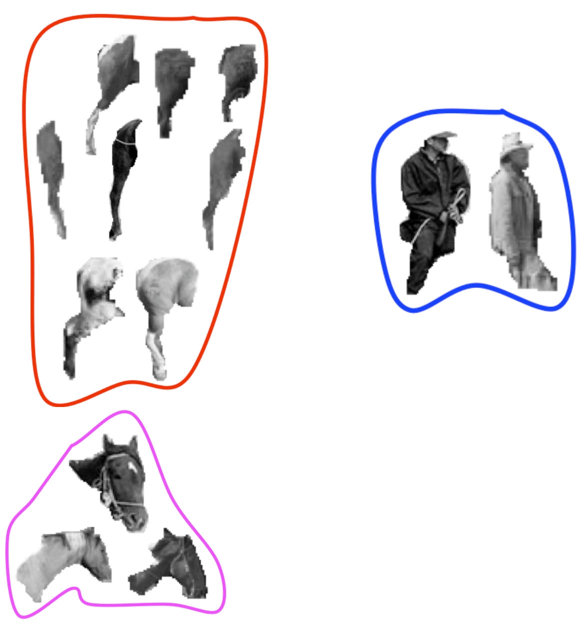

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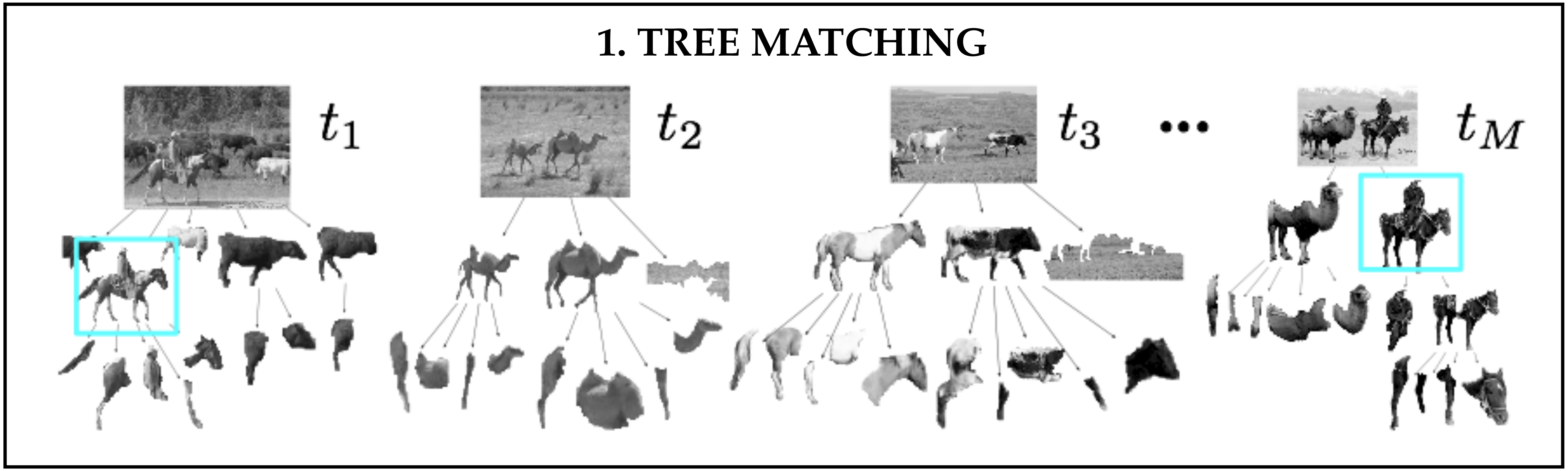

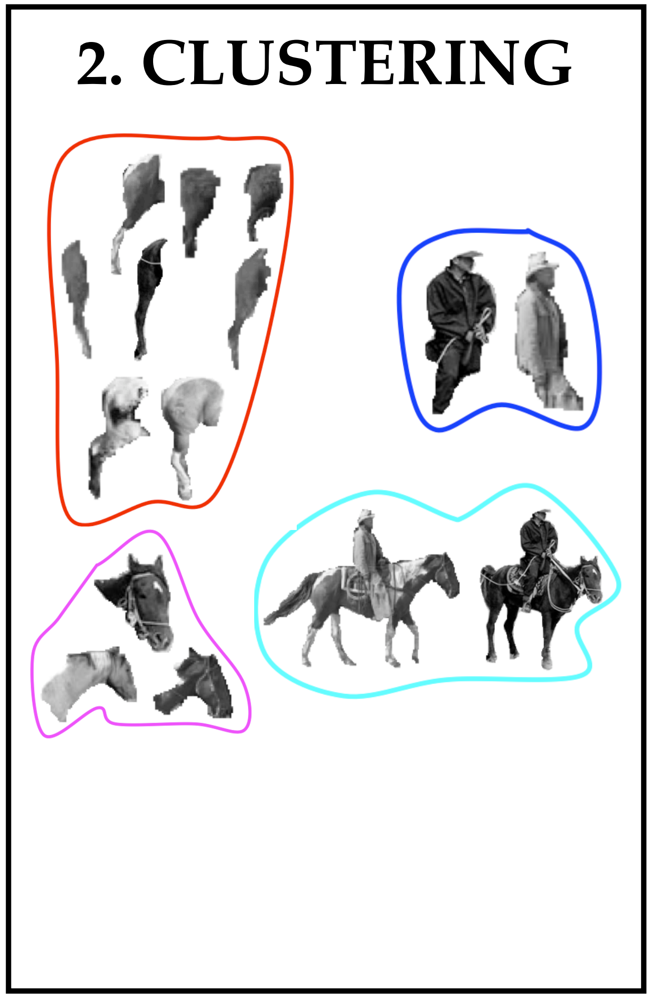

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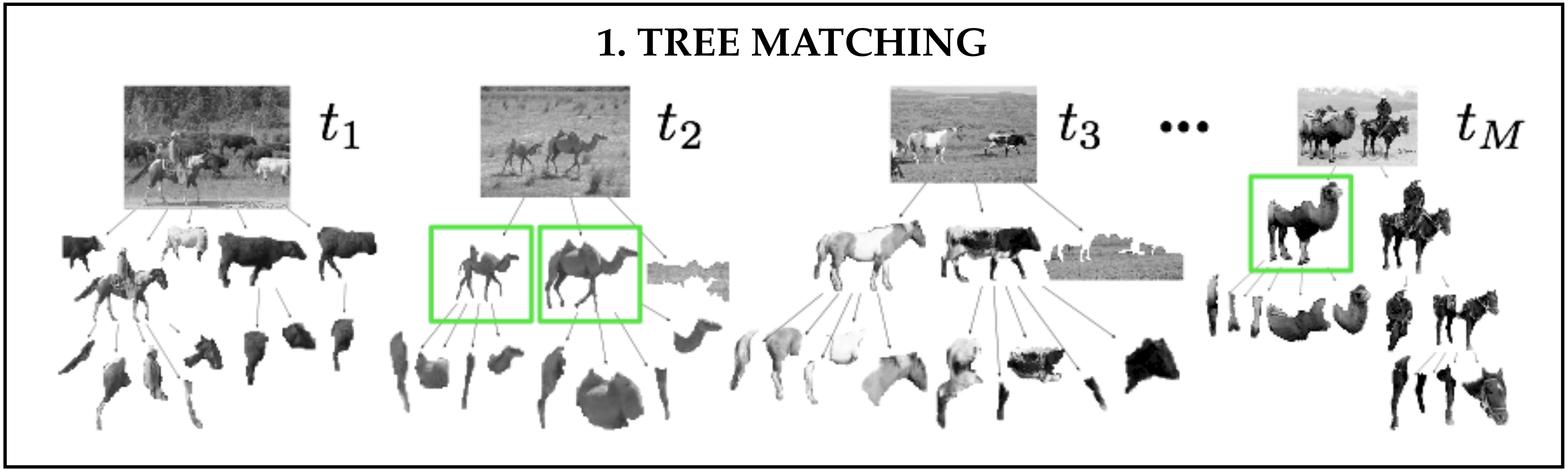

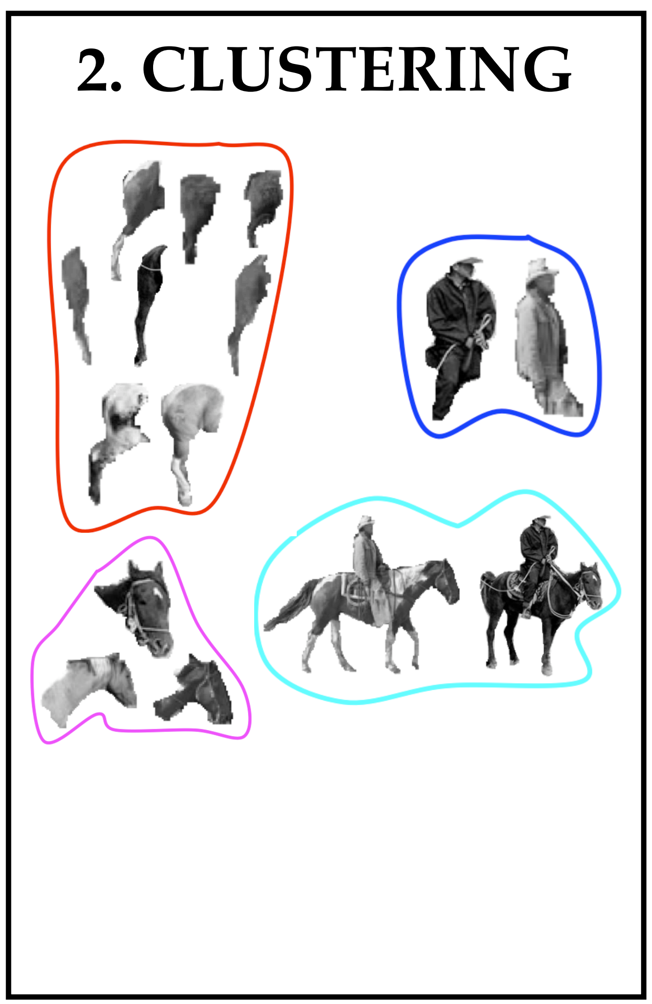

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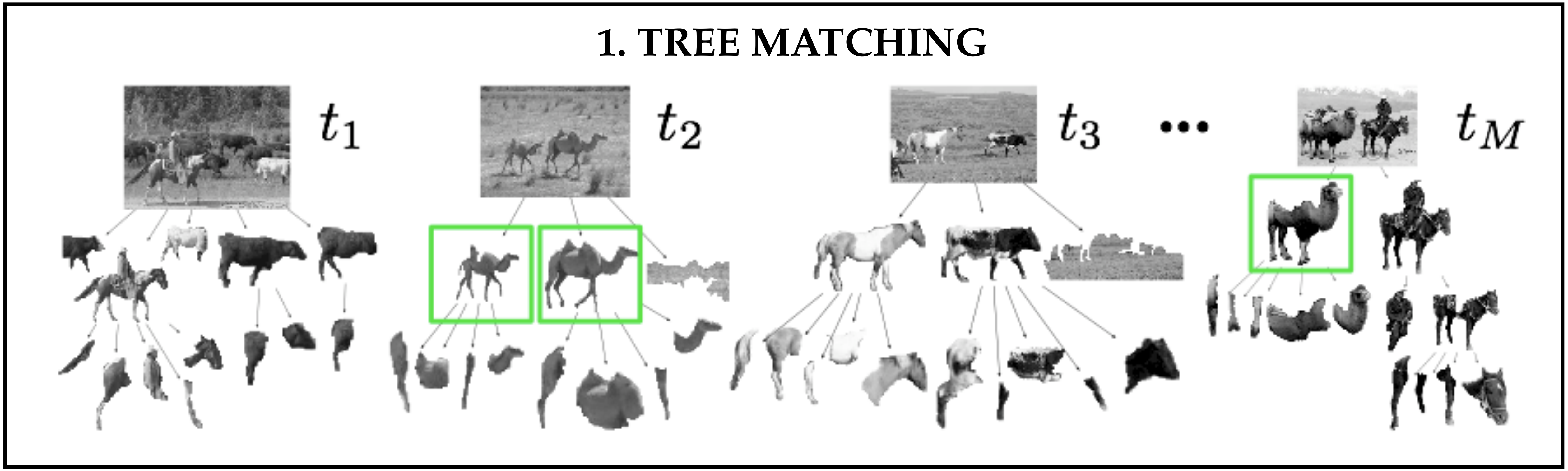
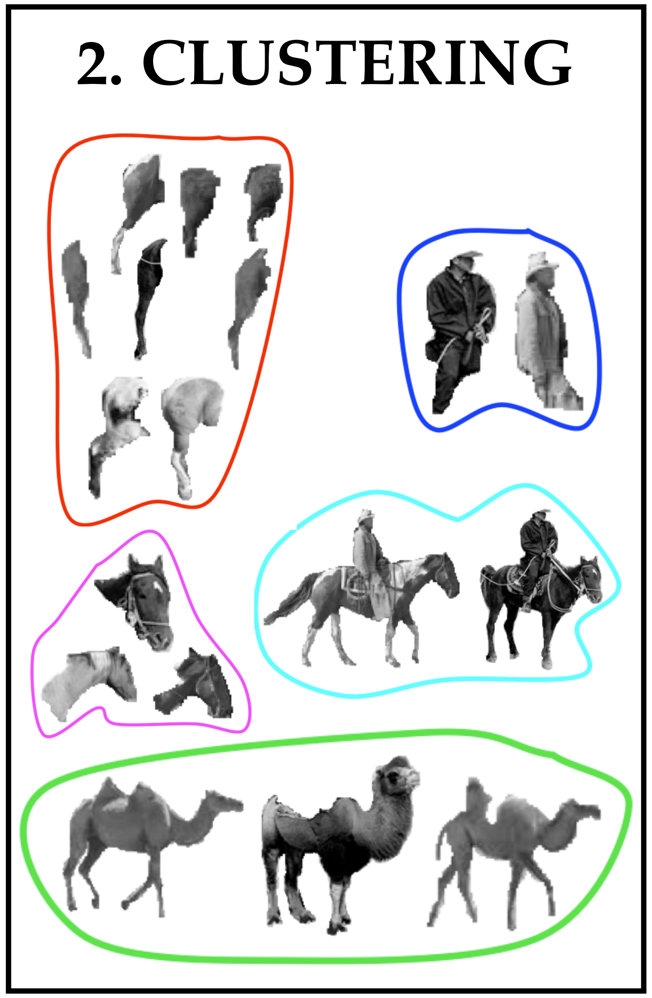
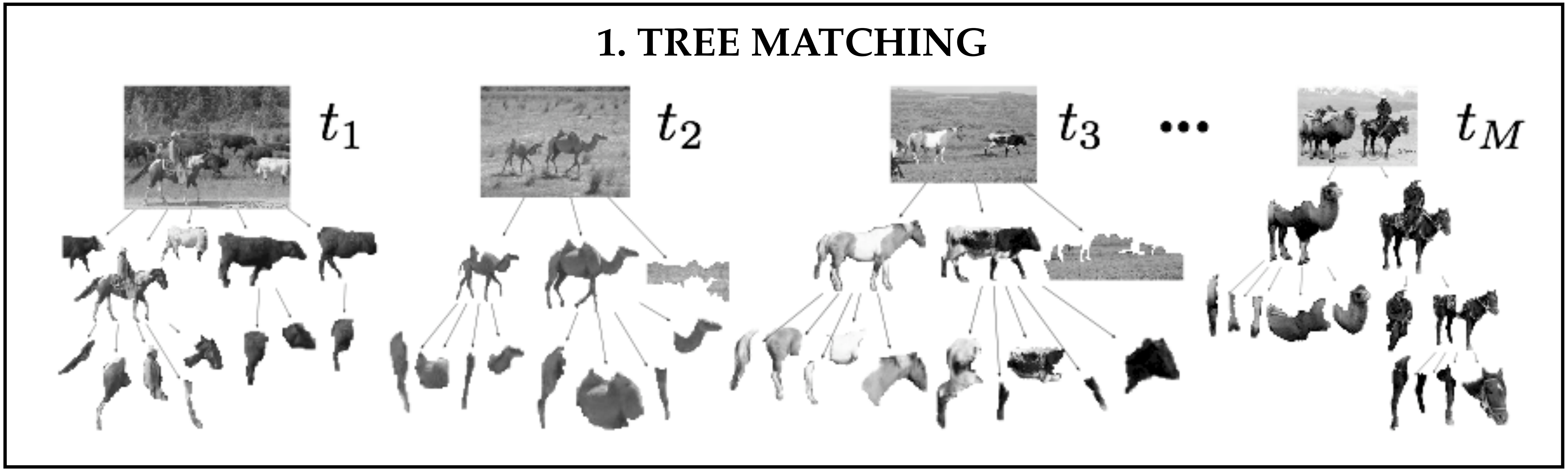
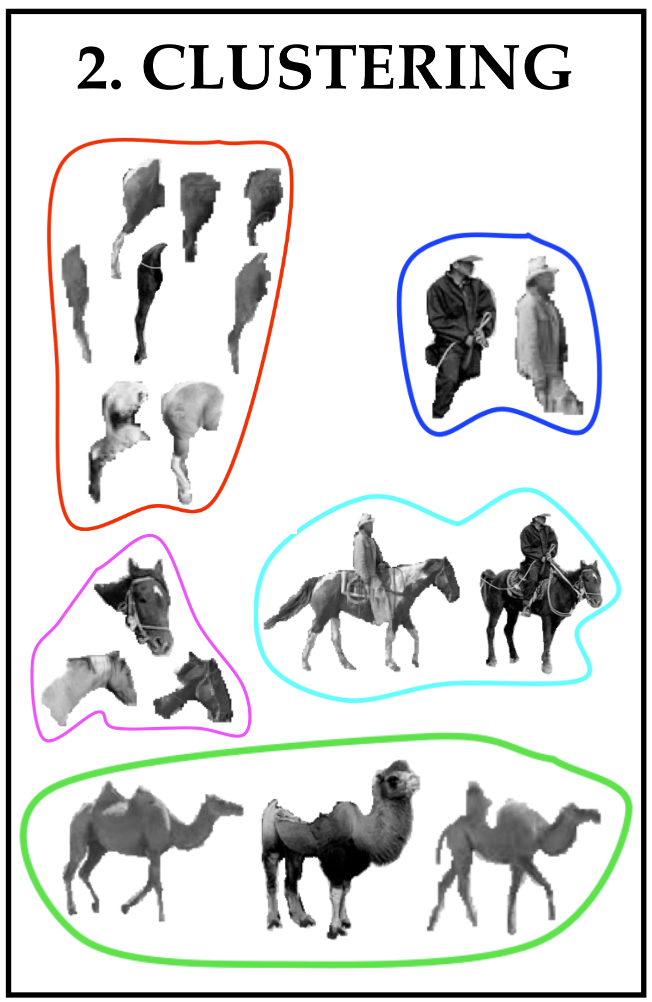




Overview of Multi-Category Recognition





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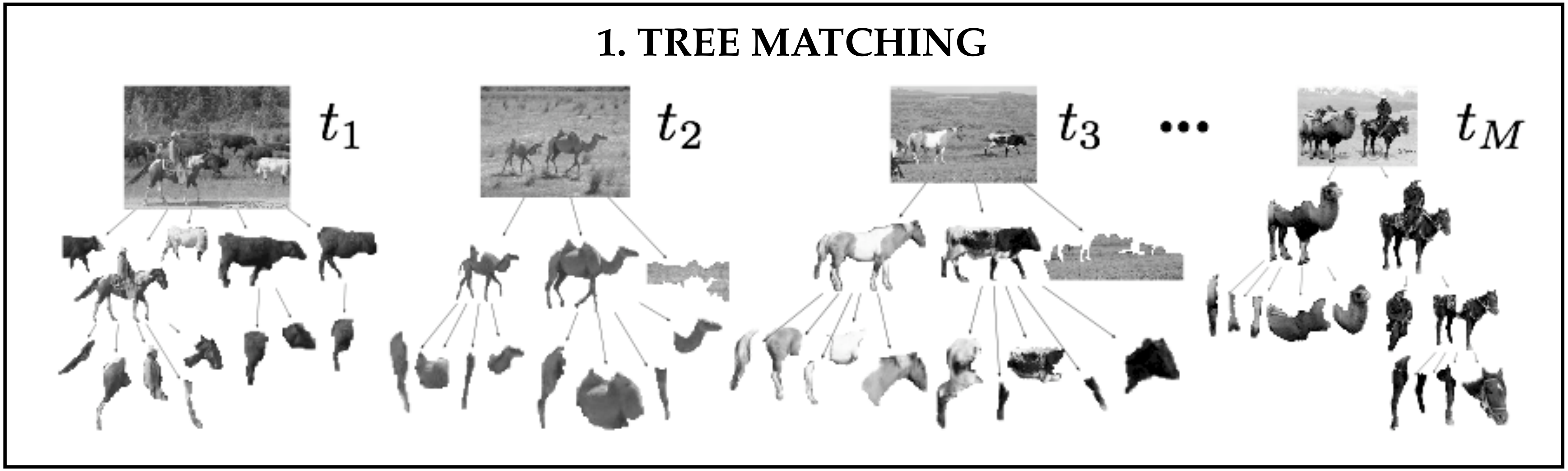
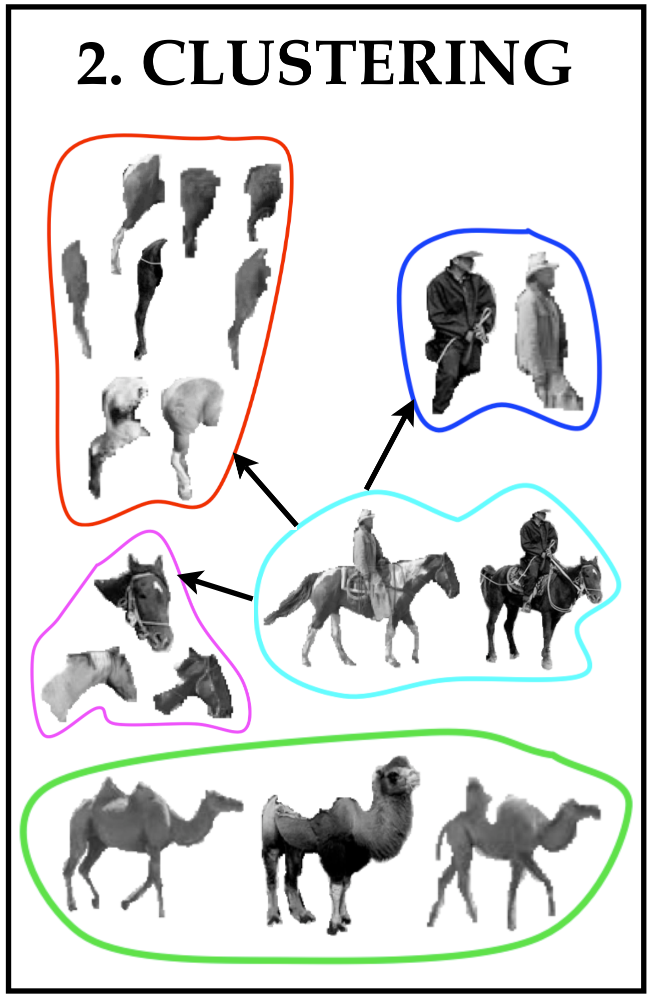
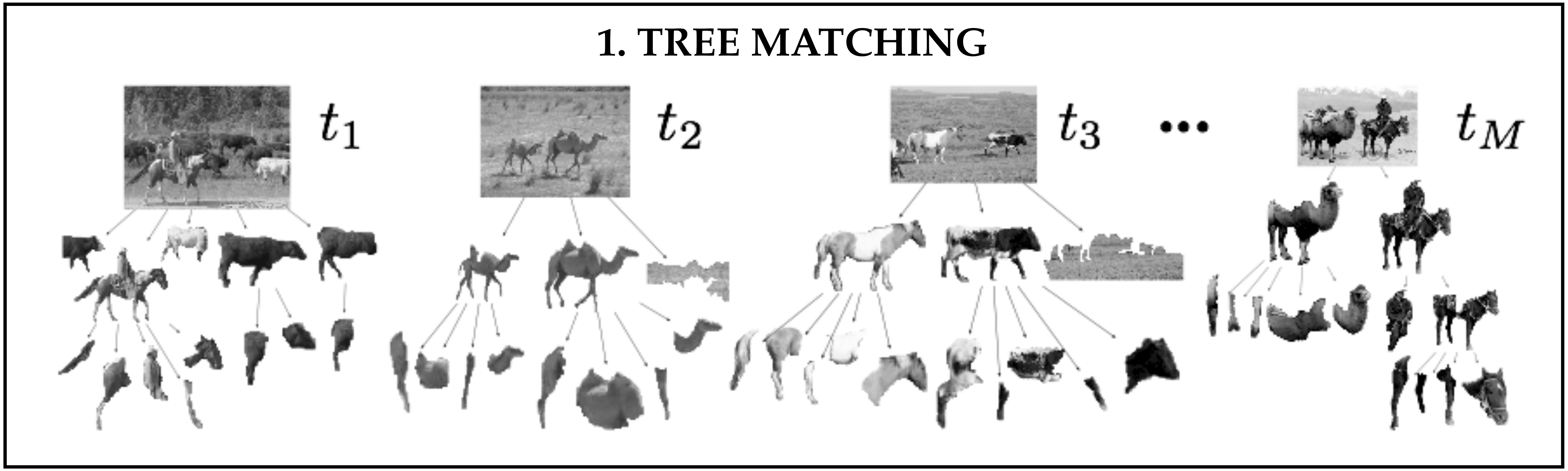
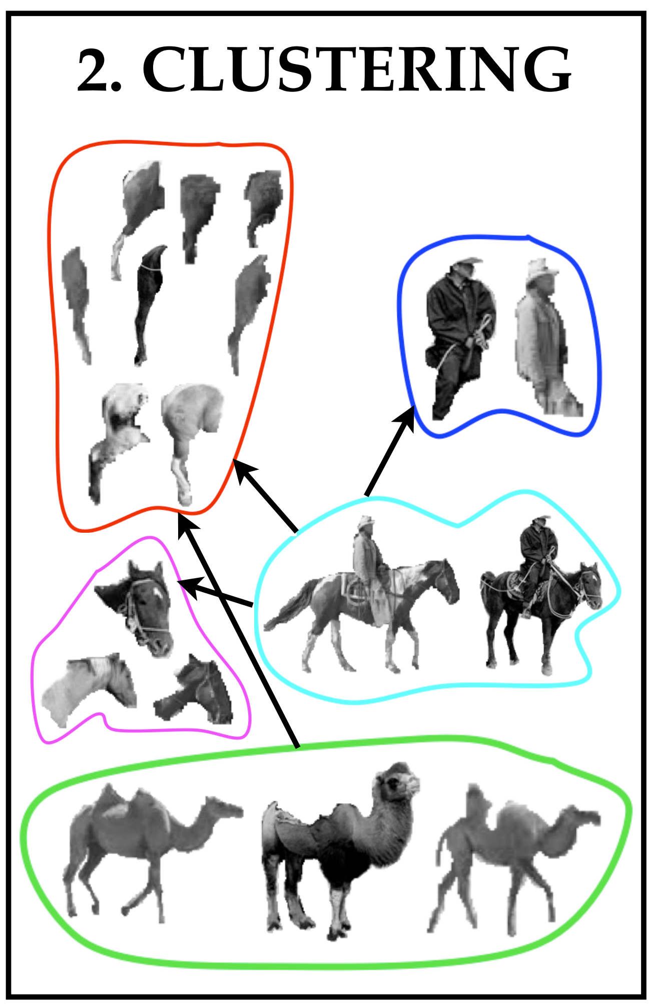




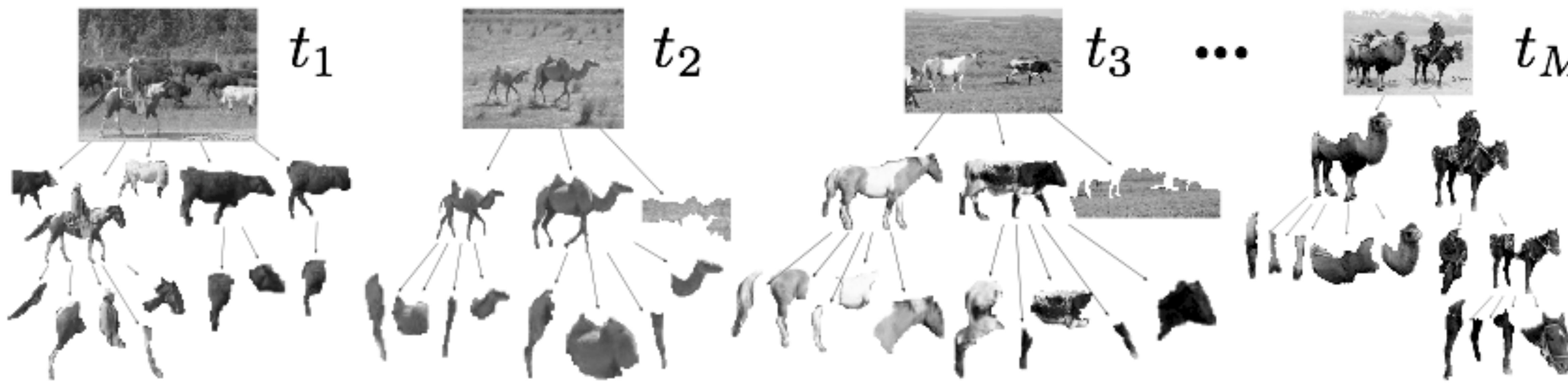
Overview of Multi-Category Recognition



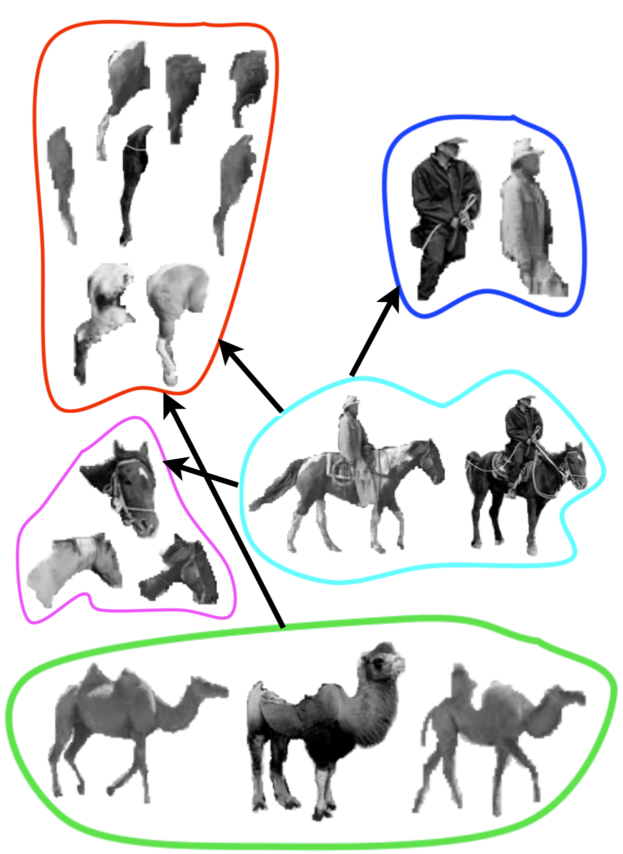


Overview of Multi-Category Recognition

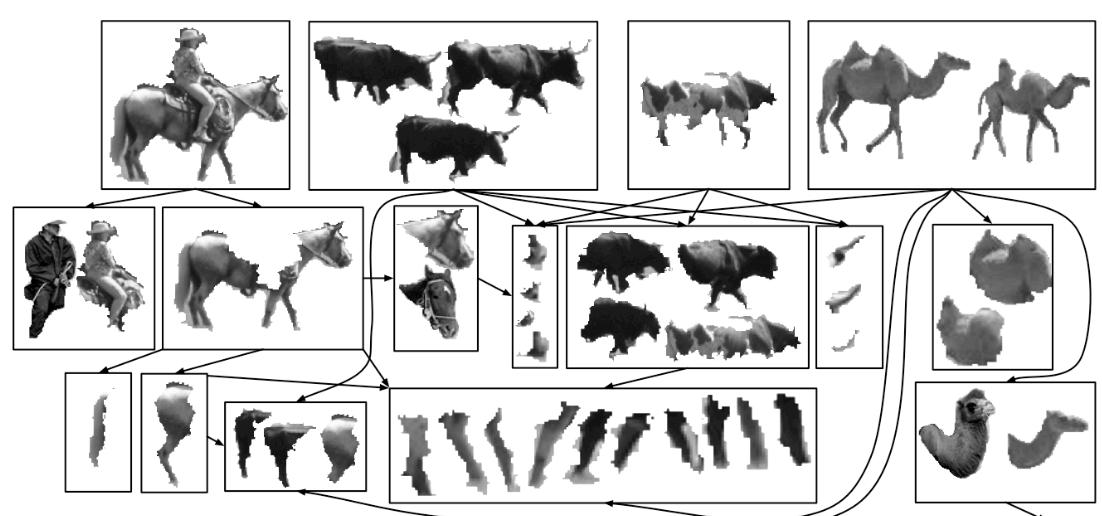
1. TREE MATCHING



2. CLUSTERING



3. TAXONOMY OF ALL DISCOVERED CATEGORIES WITH DIFFERENT COMPLEXITIES



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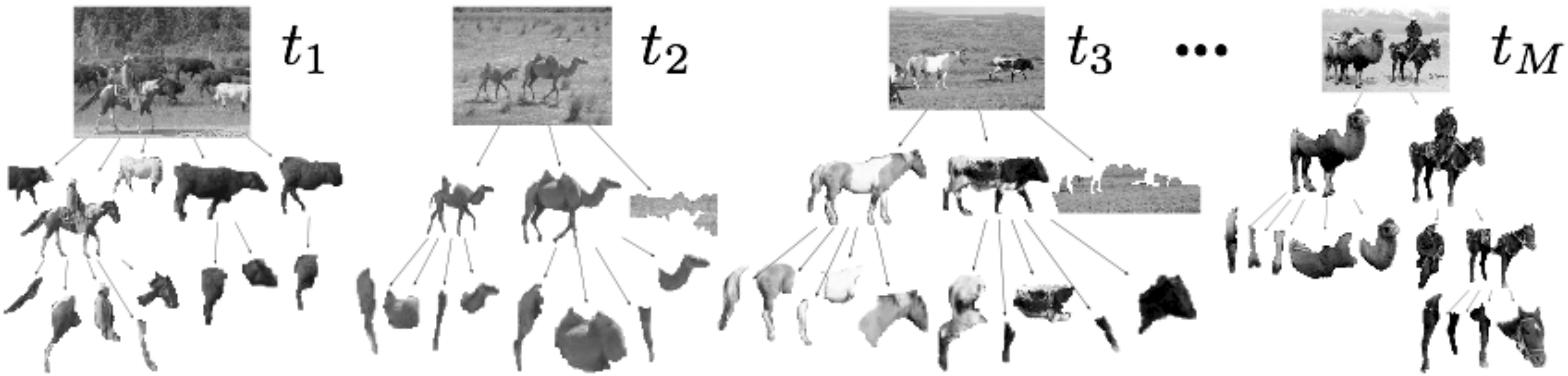

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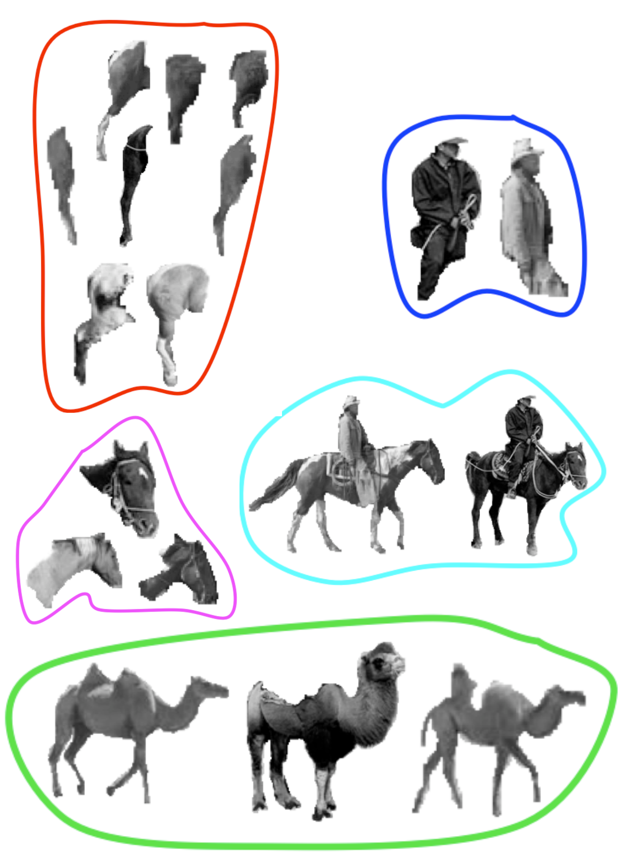

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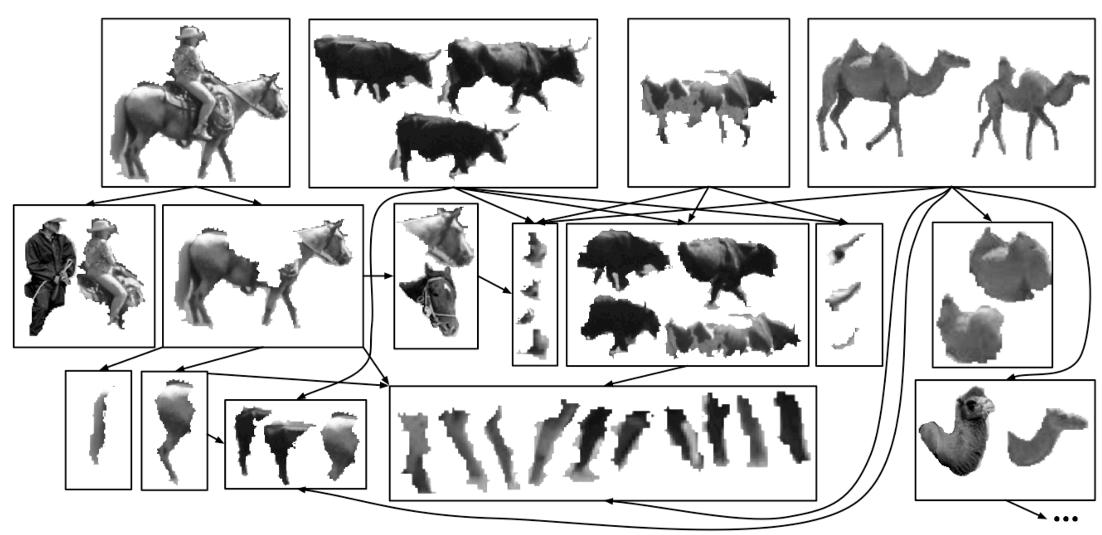
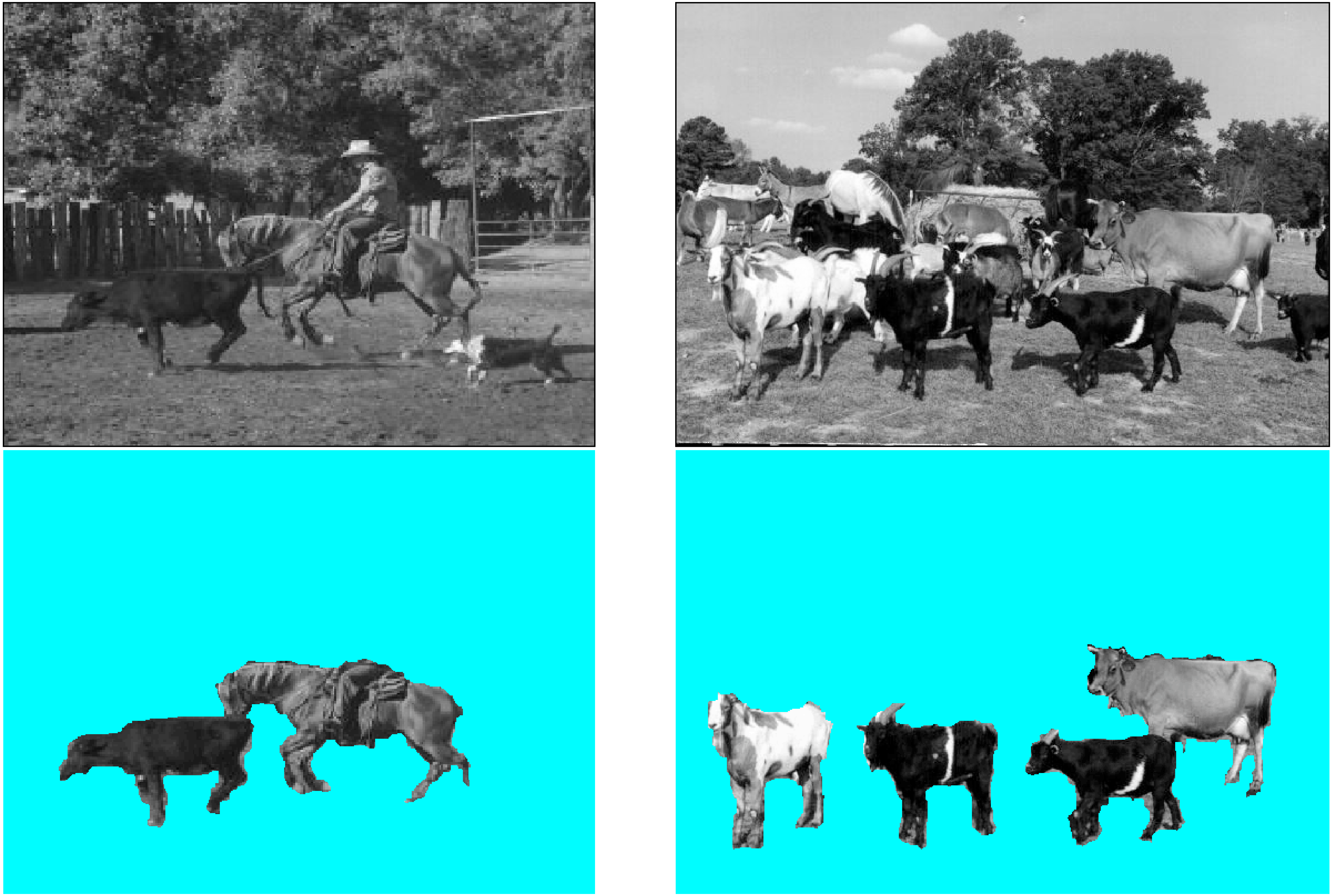
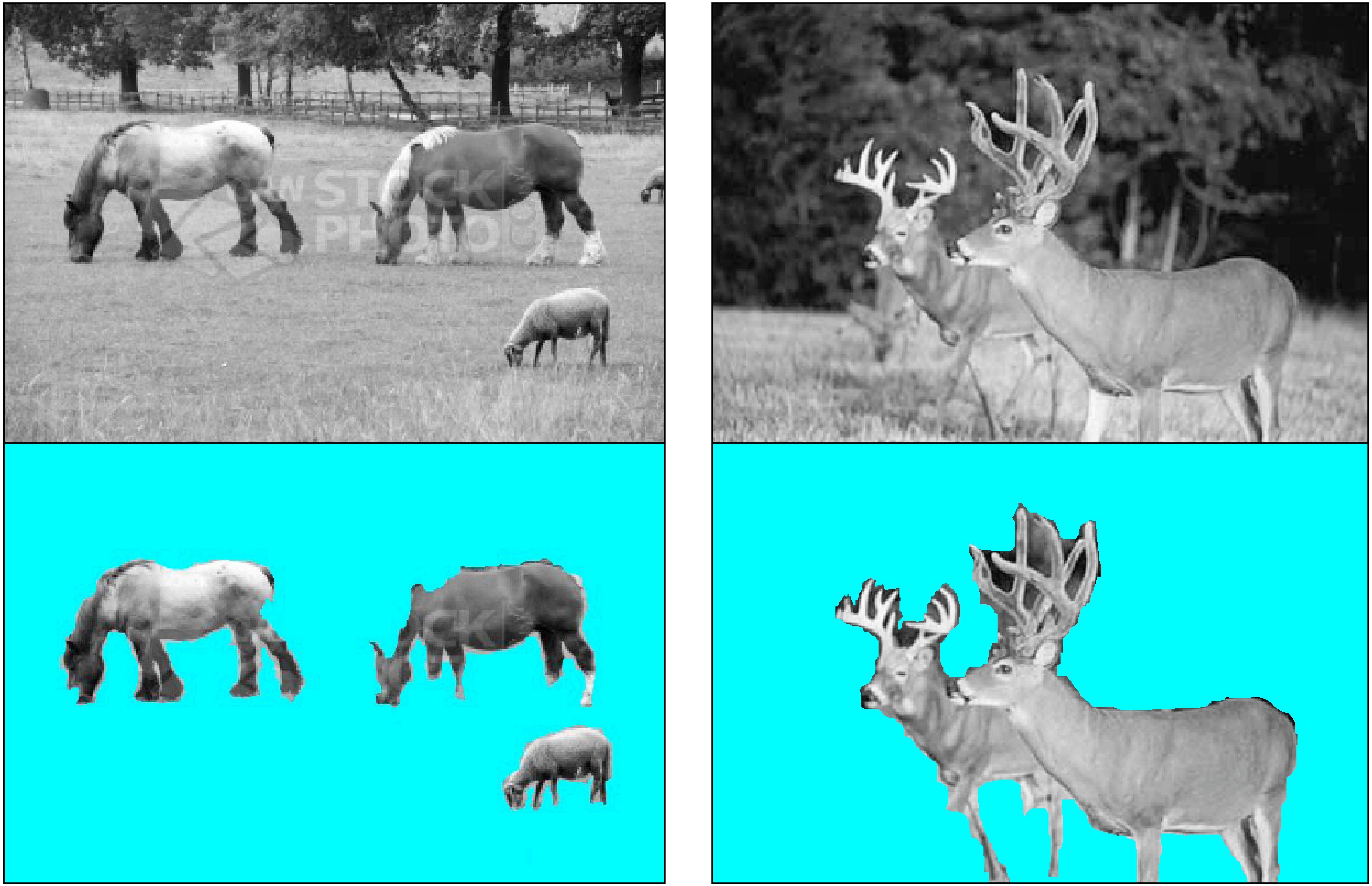


4. RECOGNIZE SEGMENT EXPLAIN

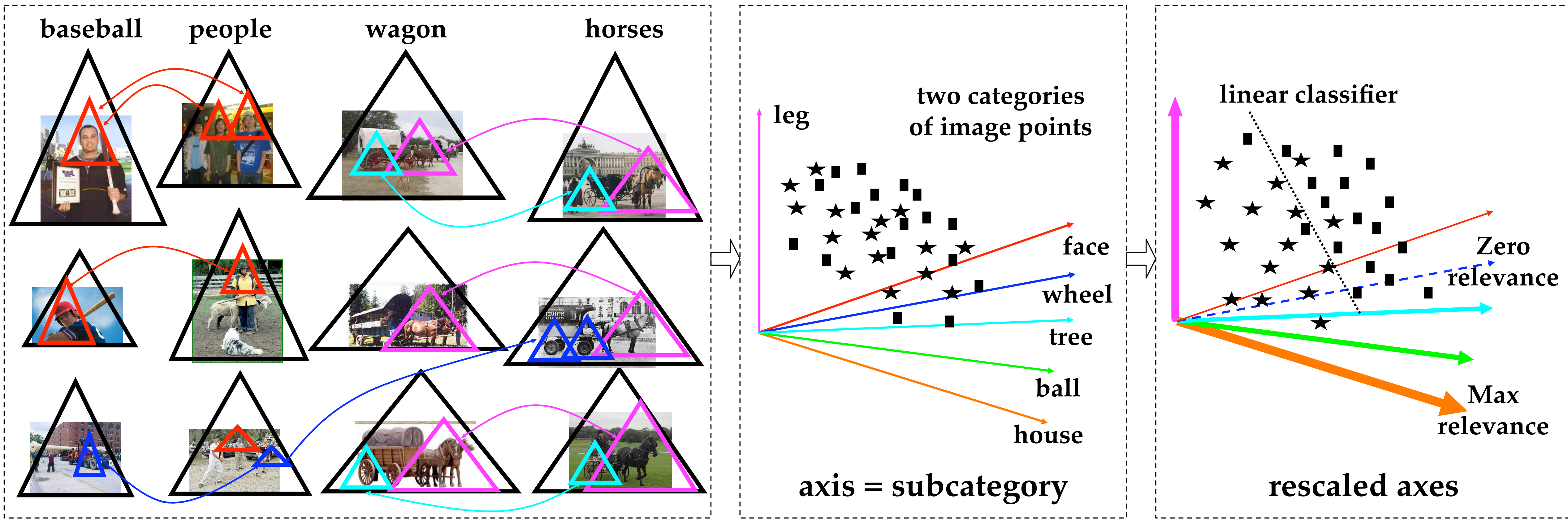
Simultaneous Recognition and Segmentation



Simultaneous Recognition and Segmentation



Discriminative Learning of Object Parts

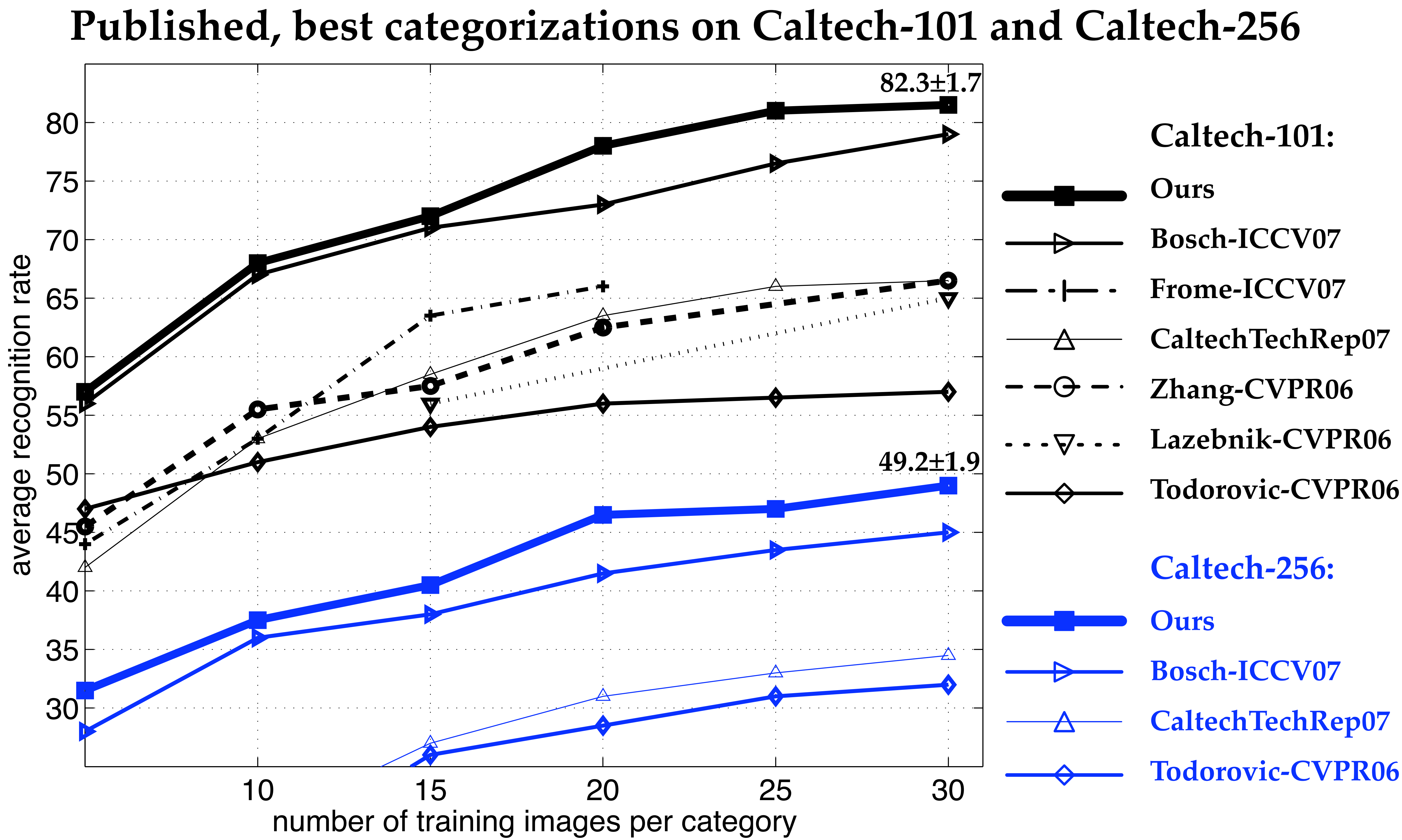


discovery of subcategories in segmentation trees

trees = points in the feature space of subcategories

Todorovic&Ahuja CVPR08

CVPR 2008: Results on Caltech-256



Rest of the Talk

1. **Image representation = Hierarchy of regions**

2. **Region matching under unstable segmentations**

3. **Applications and results**

    a. **Object recognition**

    b. **Painterly rendering**

    c. **Texture segmentation**

Multi-style Painterly Rendering

Collaboration with Prof. Eugene Zhang at Oregon State University

Results: Video Object Segmentation

Brendel&Todorovic ICCV09

Results: Multi-style Painterly Rendering

Collaboration with Prof. Eugene Zhang at Oregon State University

Rest of the Talk

1. Image representation = Hierarchy of regions

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3. **Applications and results**

    a. Object recognition

    b. Video object segmentation

    c. Painterly rendering

    d. **Texture segmentation**

What is image texture?

...Repeated occurrence of image texture elements (or texels)...

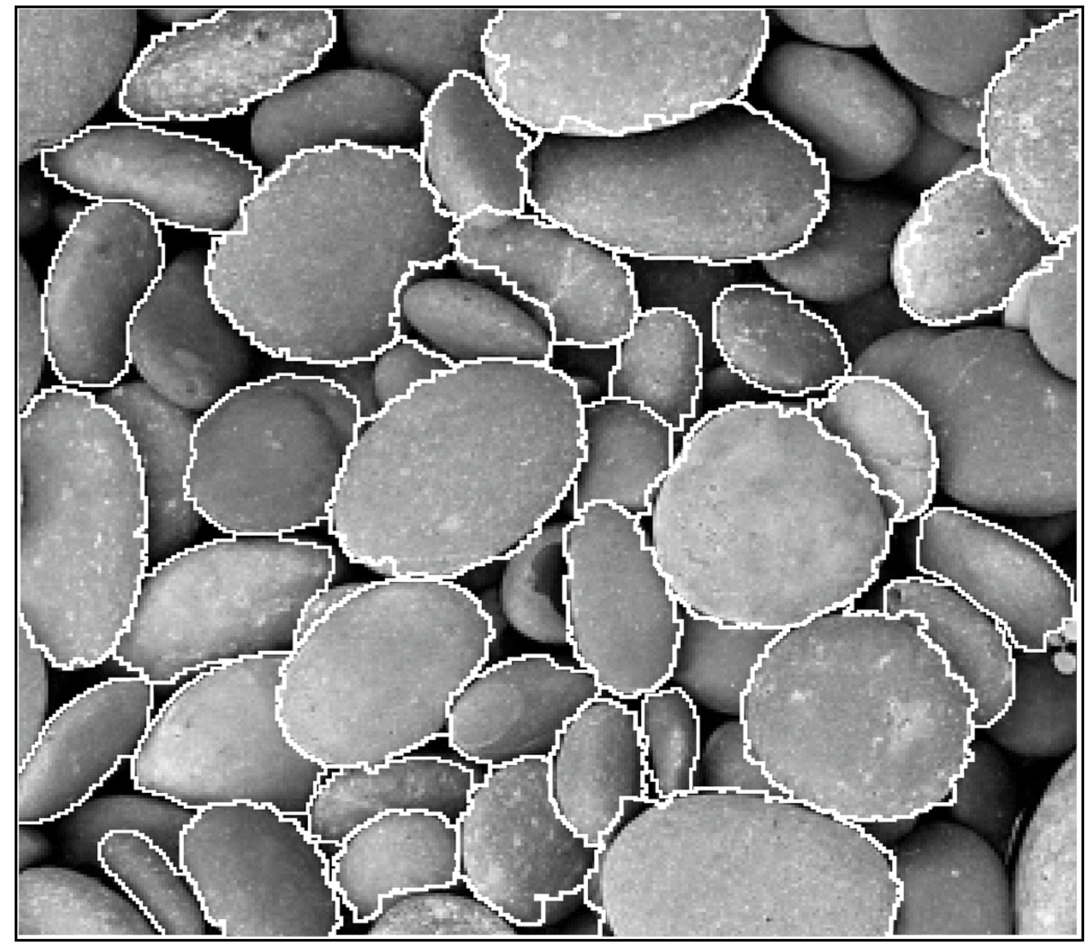
[Beck ‘82]

Texture = Spatial Repetition of Texels

- Image texels = Images of physical texture elements
- Texels are not identical, only statistically similar
- Texel placement is not regular


Results: UIUC Texture Dataset

original image

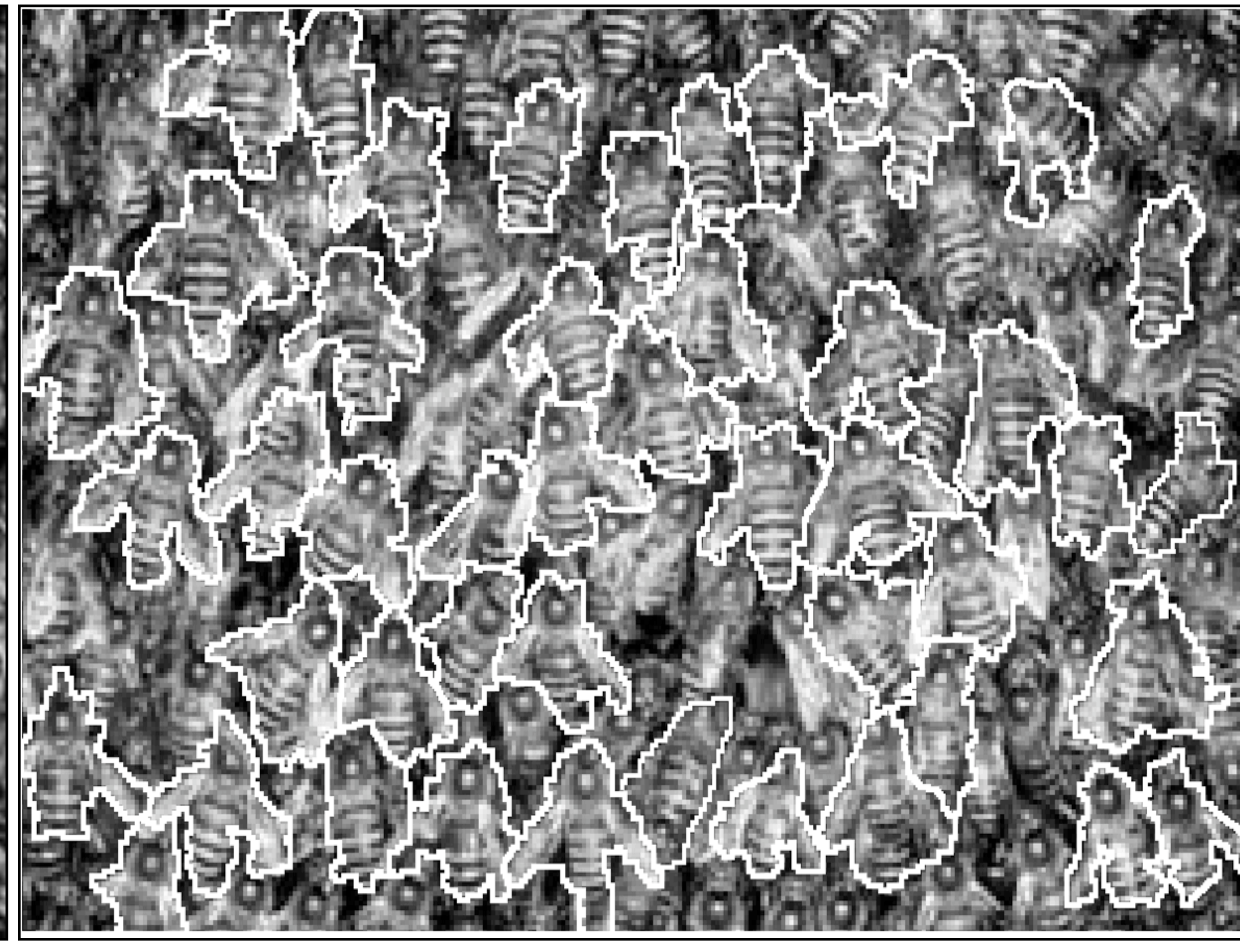


extracted texels

Ahuja&Todorovic ICCV07

Results: UIUC Texture Dataset

original image



texel segmentation

Ahuja&Todorovic ICCV07

Results: Texture Segmentation

Todorovic&Ahuja ICCV09

Results: Texture Segmentation

original image

texel-based
Todorovic&Ahuja ICCV09

filter-based
Galun et al ICCV03

Summary

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- **Hierarchical region-based image representation**

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- **Robust matching of regions**

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Summary

- Hierarchical region-based image representation
- Robust matching of regions
- Operative definition of an object category
- Hierarchical taxonomy of shared categories
- The framework allows:
  - Simultaneous recognition and segmentation
  - Semantic basis of recognition
  - Space-time coherent video object segmentation
  - Texel-based texture analysis

Thank you!