Cuts with Constraints

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Segmentation given partial grouping

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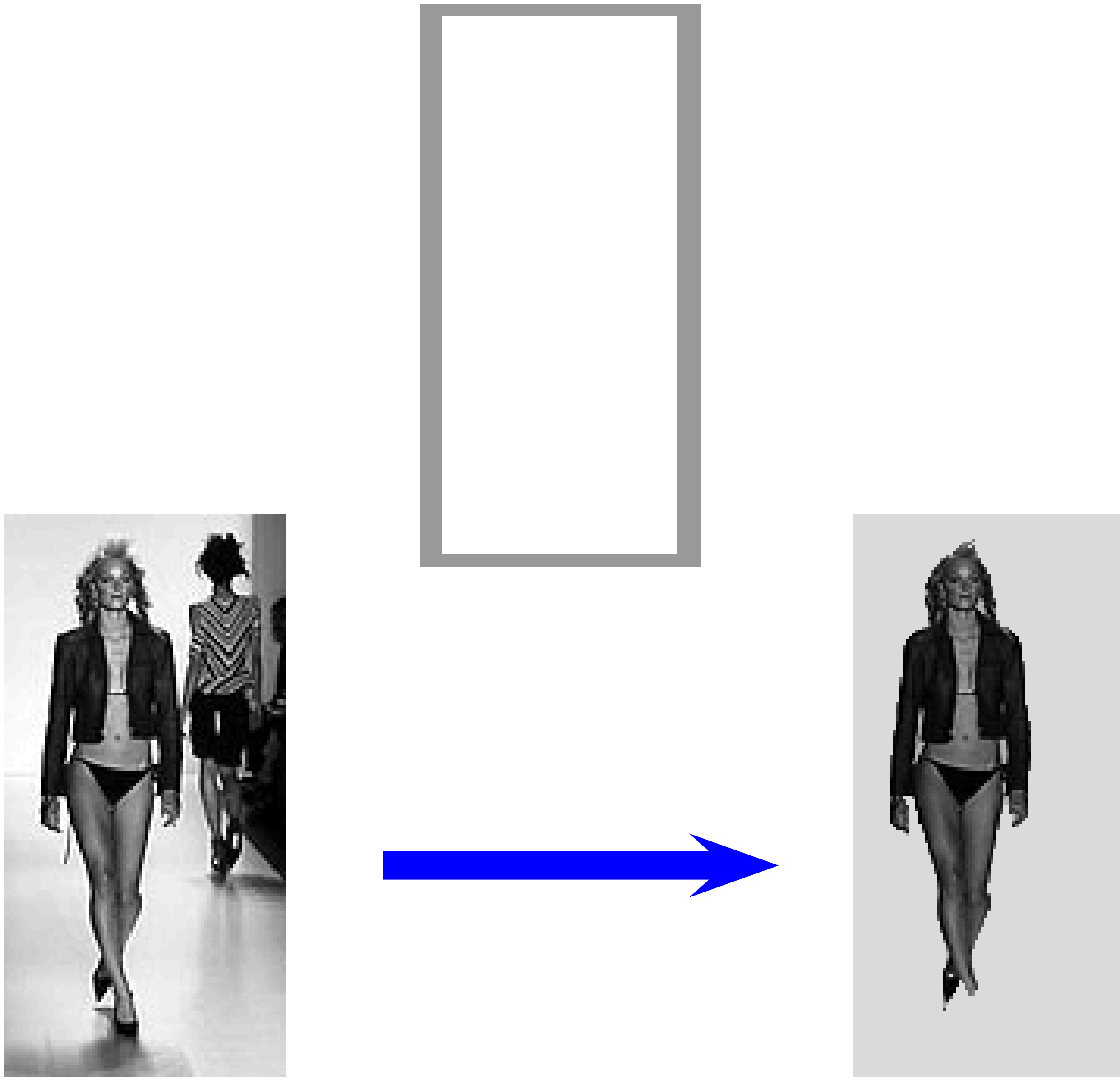

Segmentation with object knowledge

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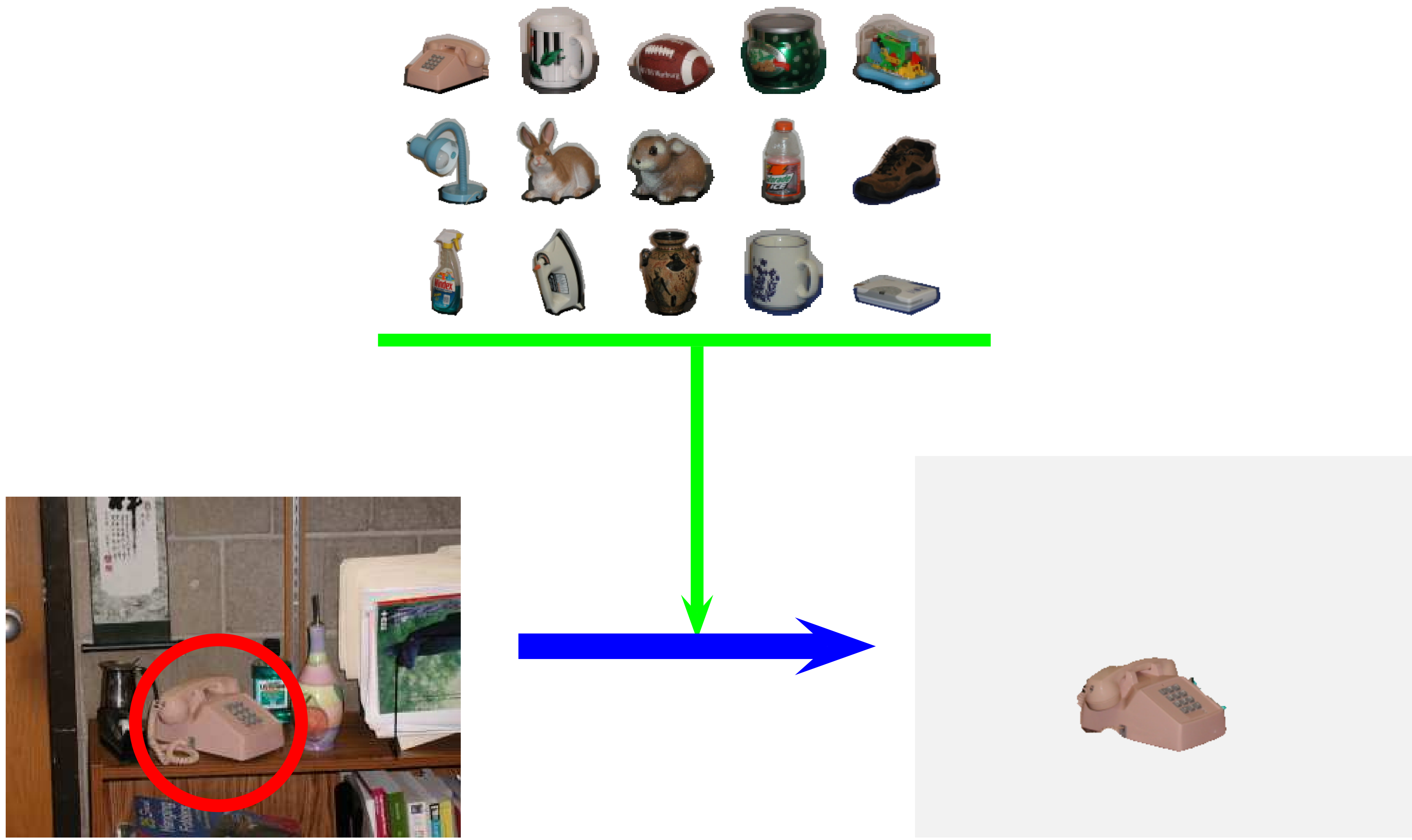


Papers

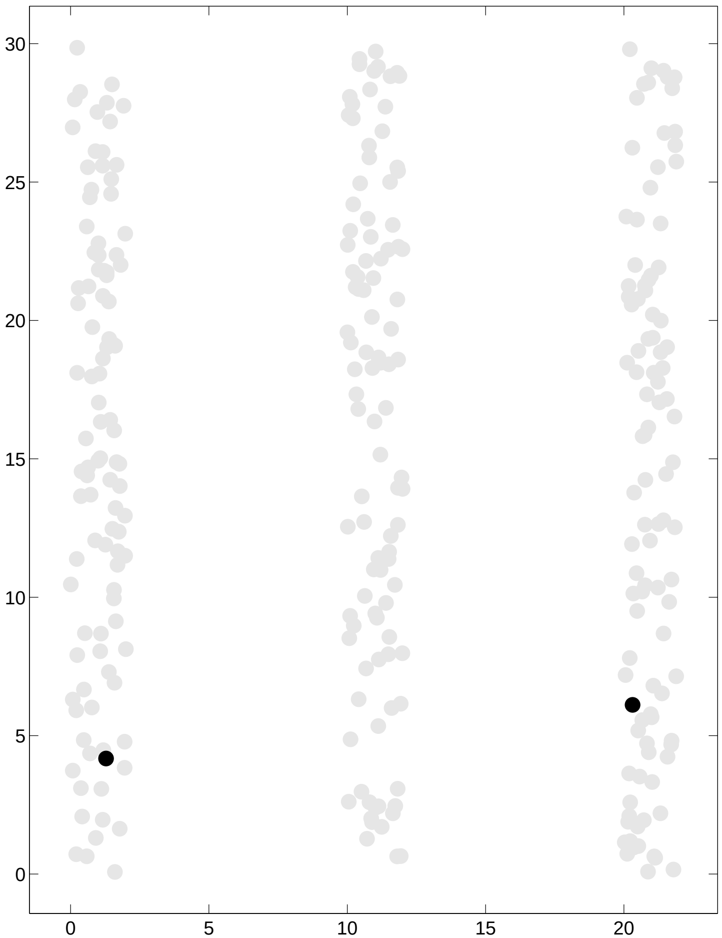
1. Grouping with bias,
   Stella X. Yu and Jianbo Shi, NIPS 2001.

2. Concurrent object recognition and segmentation by graph partitioning,
   Stella X. Yu, Ralph Gross and Jianbo Shi, NIPS 2002.

3. Object-specific figure-ground segregation,
   Stella X. Yu and Jianbo Shi, submitted to CVPR 2003.

4. Other issues: www.cs.cmu.edu/˜xingyu/research.html

Basic problem: grouping with constraints



$$\max \quad \epsilon(f|D)$$
$$\text{s.t.} \quad f(i) = f(j)$$

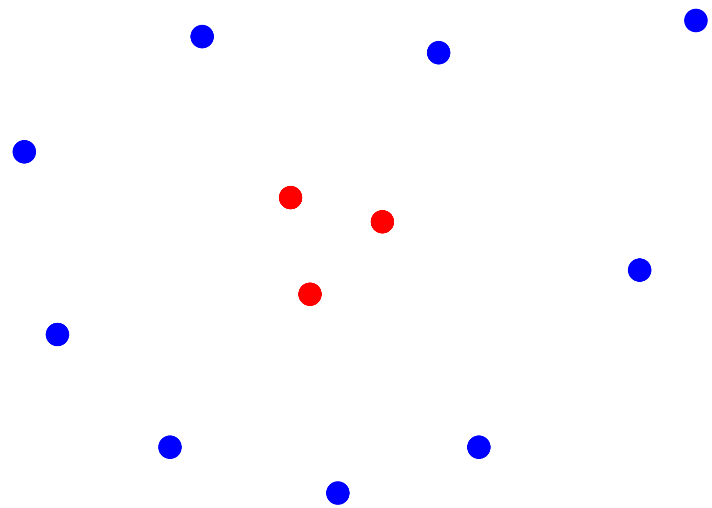
ϵ: goodness of grouping

f: label distribution

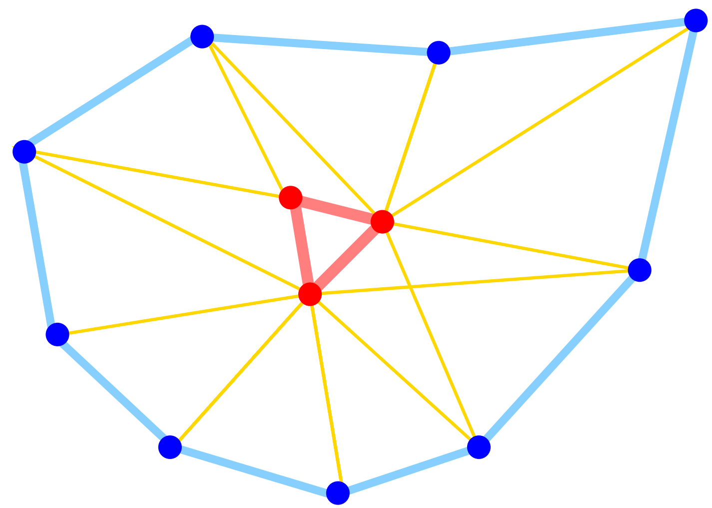
D: observation, e.g. data location

i, j: data index

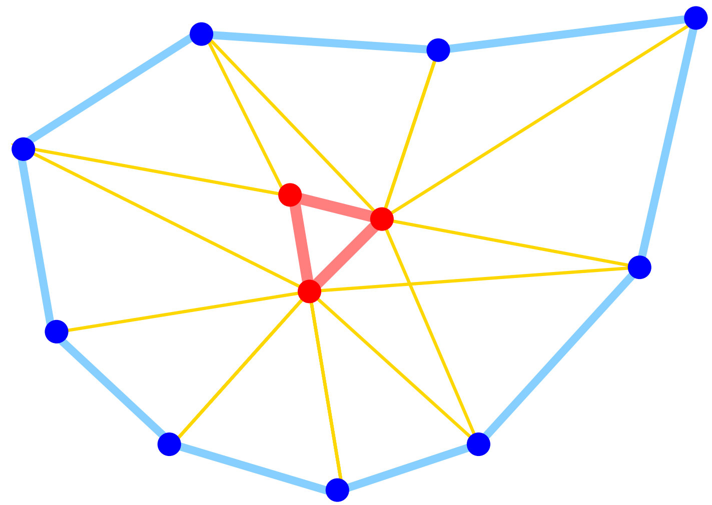
Review on normalized cuts



Review on normalized cuts



Review on normalized cuts



$$\epsilon(f|D) = \sum \frac{\text{within-group weights}}{\text{group degree}}$$

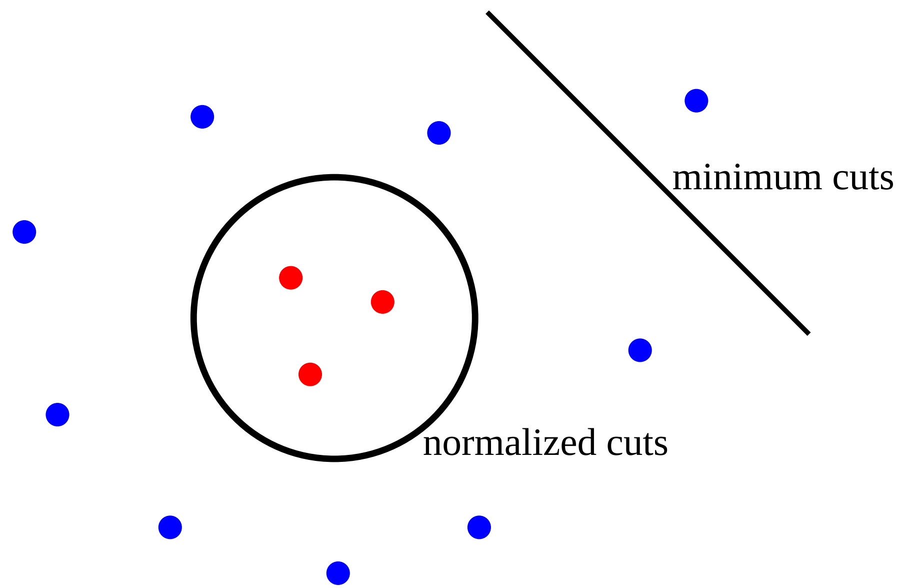
$$= \frac{red}{red + yellow} + \frac{blue}{blue + yellow}$$

Properties of normalized cuts

1. Duality

   max within-group weight ratio $\leftrightarrow$
   min between-group weight ratio

2. Normalization for global structure



Computing constrained normalized cuts

Optimization problem:

$$\begin{array}{ll} \text{maximize} & \epsilon(z;W) = \frac{z^T W z}{z^T D z} \\ \text{subject to} & U^T z = 0. \end{array}$$

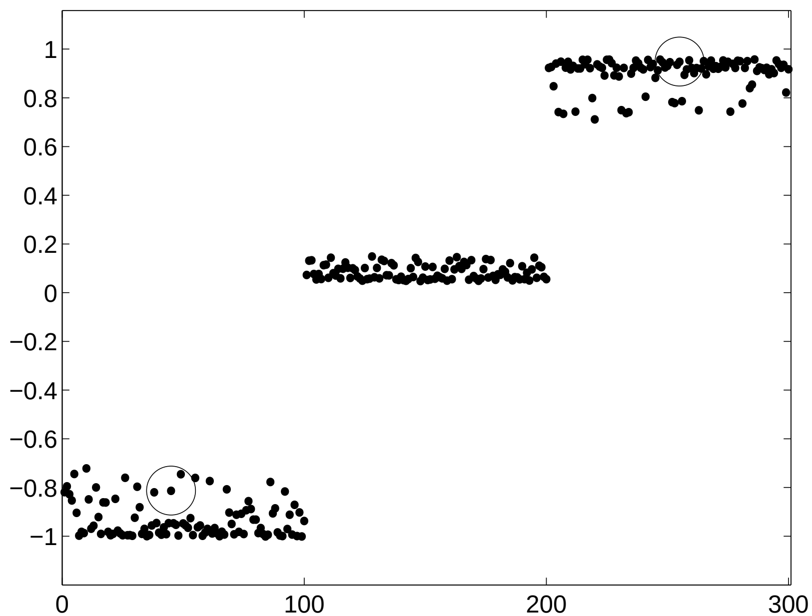
Solution: eigenvector with the largest nontrivial eigenvalue:

$$\begin{aligned} QPz^* &= \lambda z^*, \\ P &= D^{-1}W, \end{aligned}$$

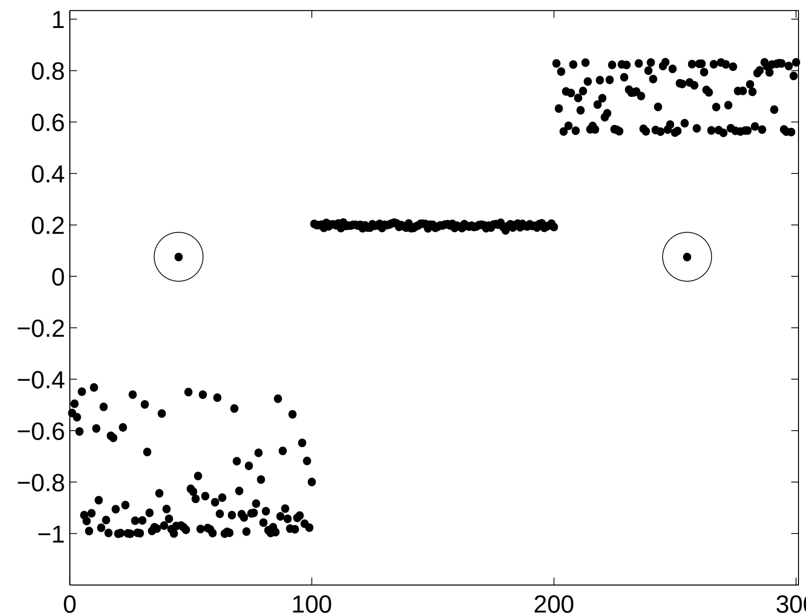
where Q is a projector to the feasible solution space:

$$Q = I - D^{-1}U(U^T D^{-1} U)^{-1} U^T.$$

Results given partial grouping constraints



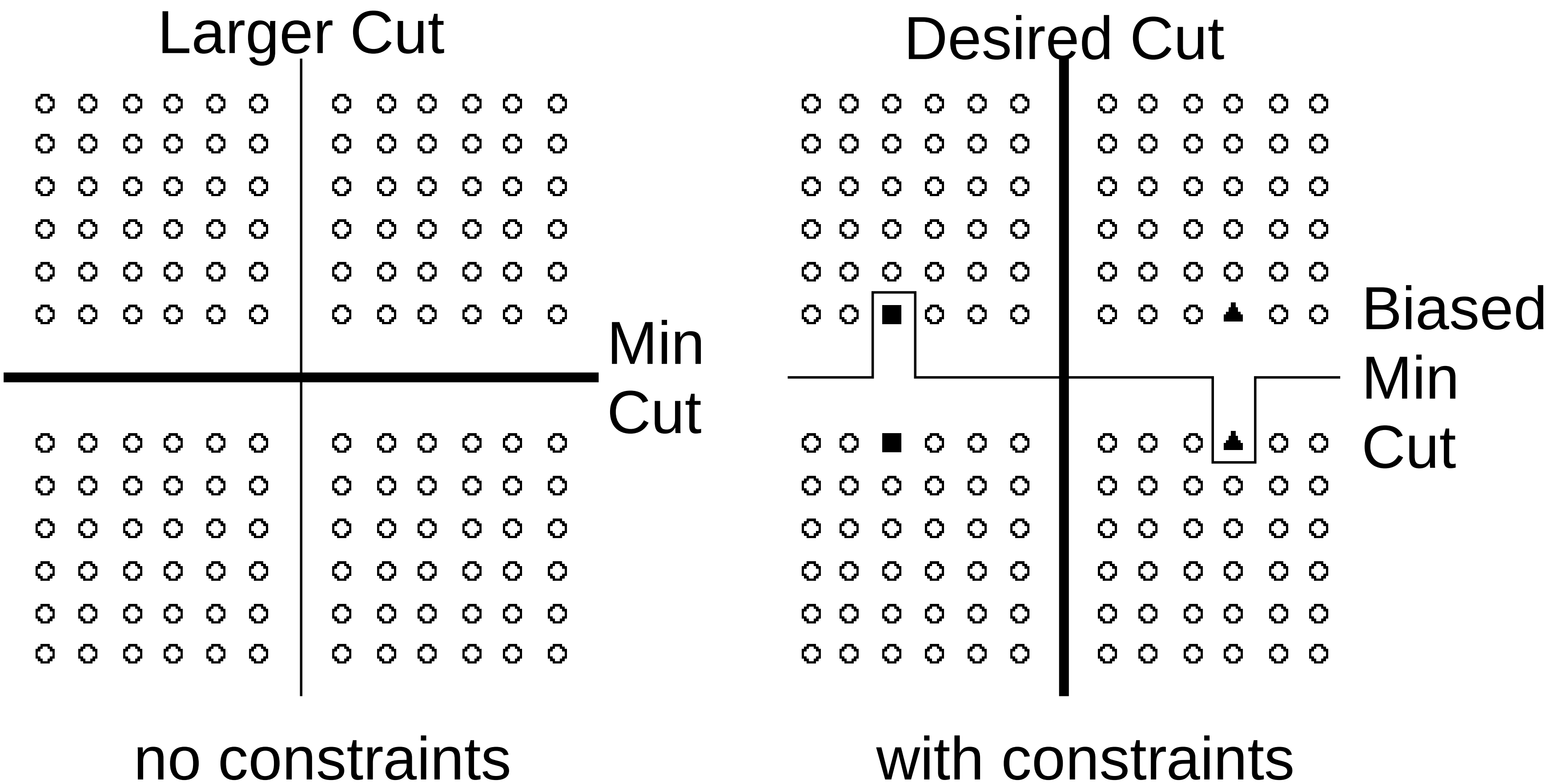
natural clustering



constrained clustering

Not desirable when partial grouping cues are sparse!

Why simple constraints are not sufficient



Solution: condition a grouping

$$\begin{aligned} \text{max} \quad & \epsilon(f|D) \\ \text{s.t.} \quad & S \circ f(i) = S \circ f(j) \end{aligned}$$

S: local smoothing kernel

$S \circ f$: average label distribution

Solution: condition a grouping

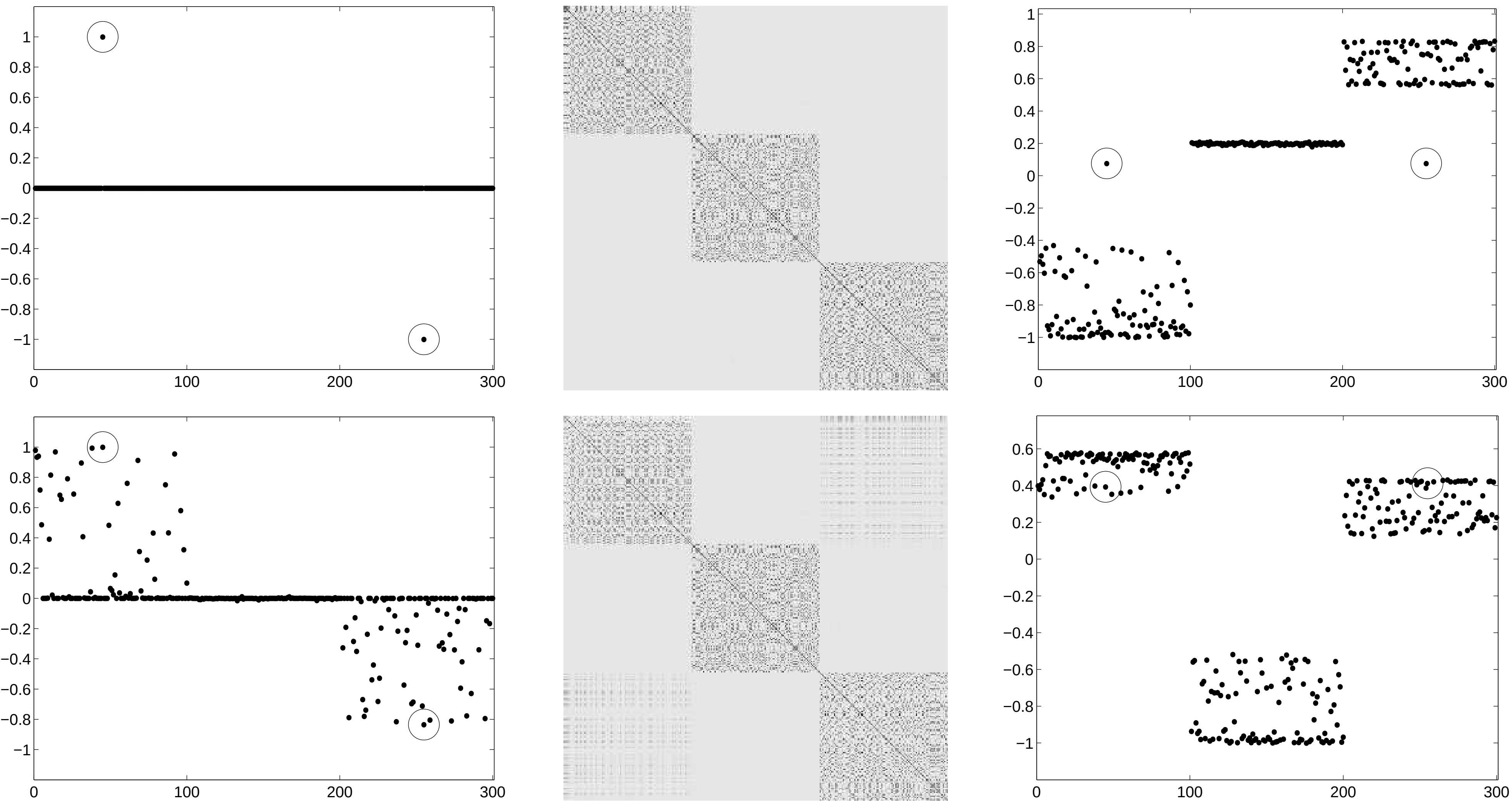
max $\epsilon(f \mid D)$
s.t. $S \circ f(i) = S \circ f(j)$

S: local smoothing kernel
$S \circ f$: average label distribution

max $\epsilon(z; W) = \frac{z^T W z}{z^T D z}$
s.t. $(P^T U)^T z = 0$

P: transition matrix
$\sum_k P(i,k) z(k) = \sum_k P(j,k) z(k)$

Results given smoothed constraints



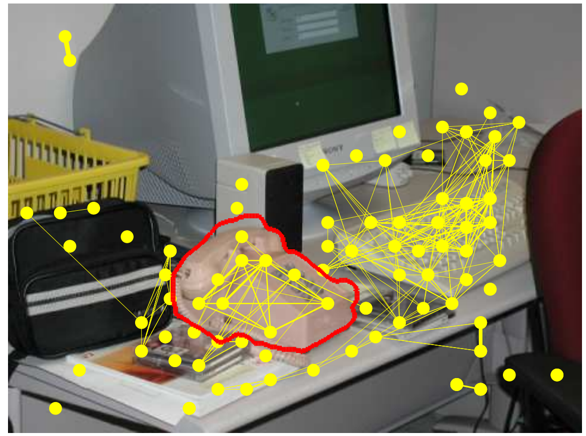
constraints | QP | eigenvector

173×109 No constraints: 30s Smoothed constraints: 24s

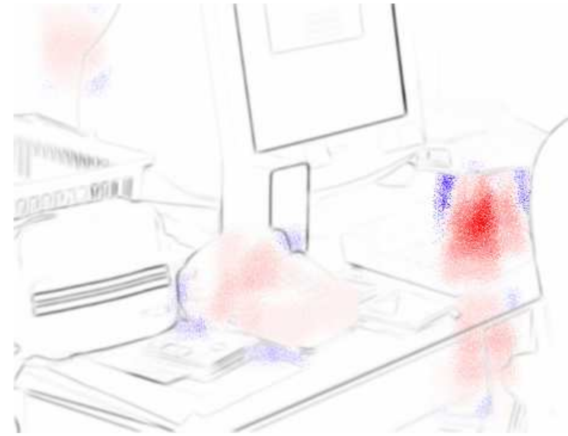
Segment an object without knowing what it is

Approach to object segmentation

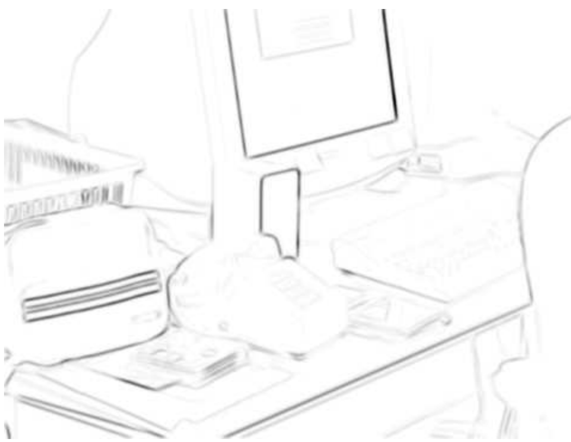
Patches



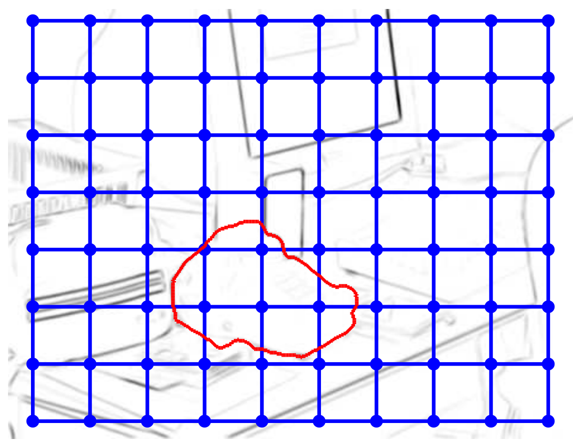
Patch grouping



Correspondence



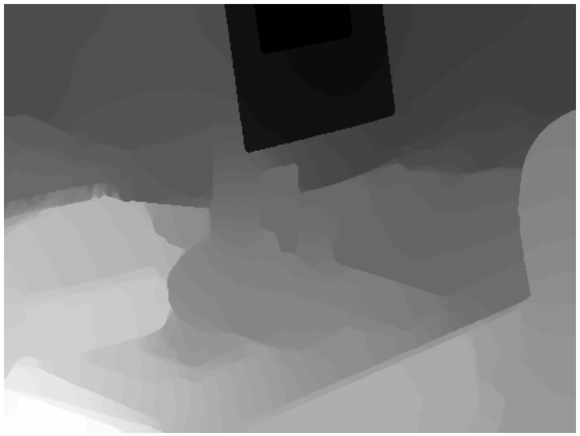
Edges

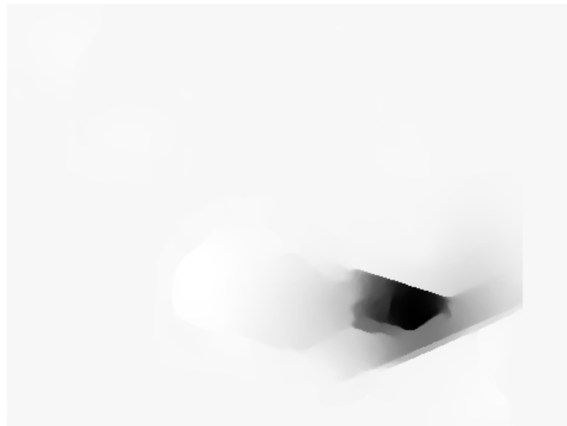


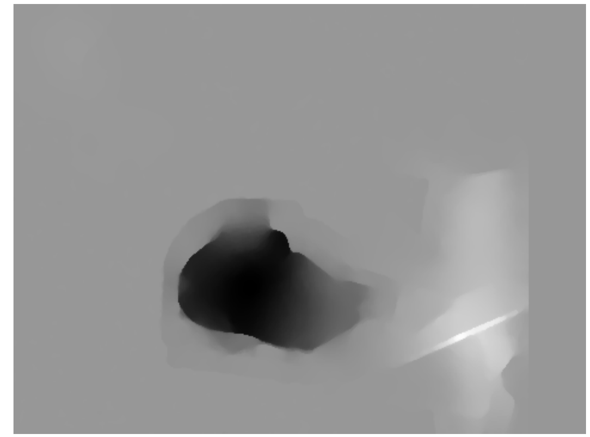
Pixel grouping

Figure-ground

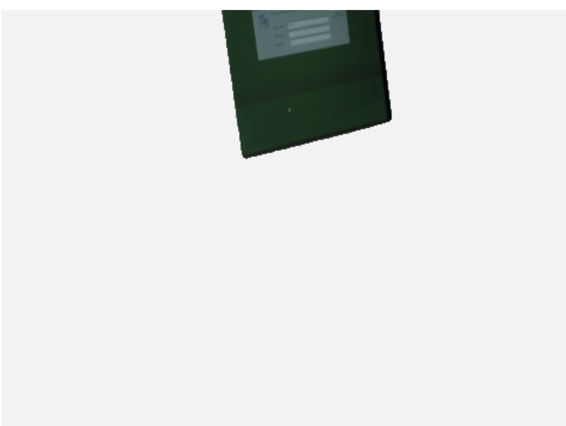
How object knowledge helps







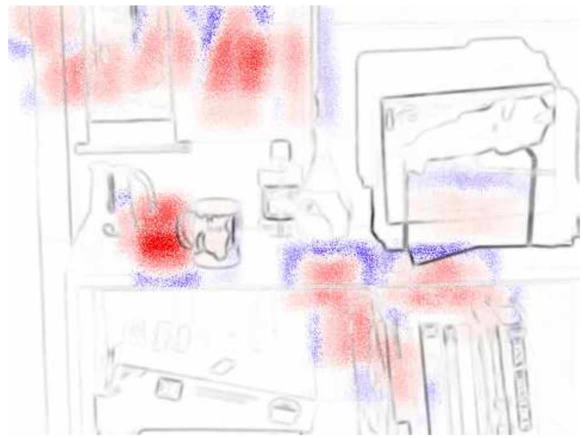
Pixel only	Pixel w/ ROI	Pixel-patch
541s	150s	206s



Pixel only | Pixel w/ ROI | Pixel-patch

How low-level image features help

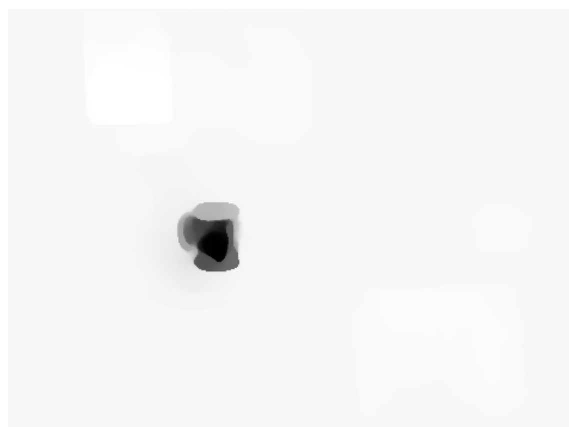
patches



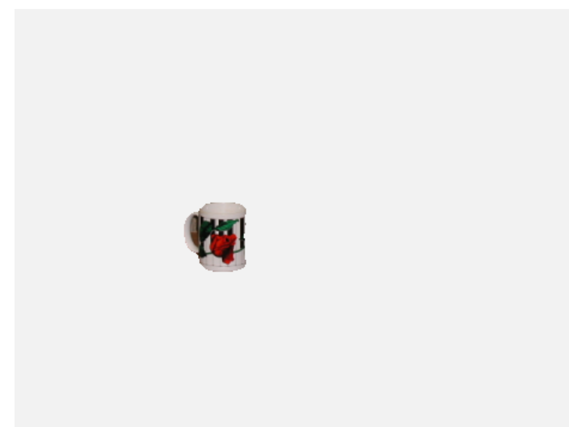
correspondence

image

edges



eigenvector



segmentation