Image segmentation for photography

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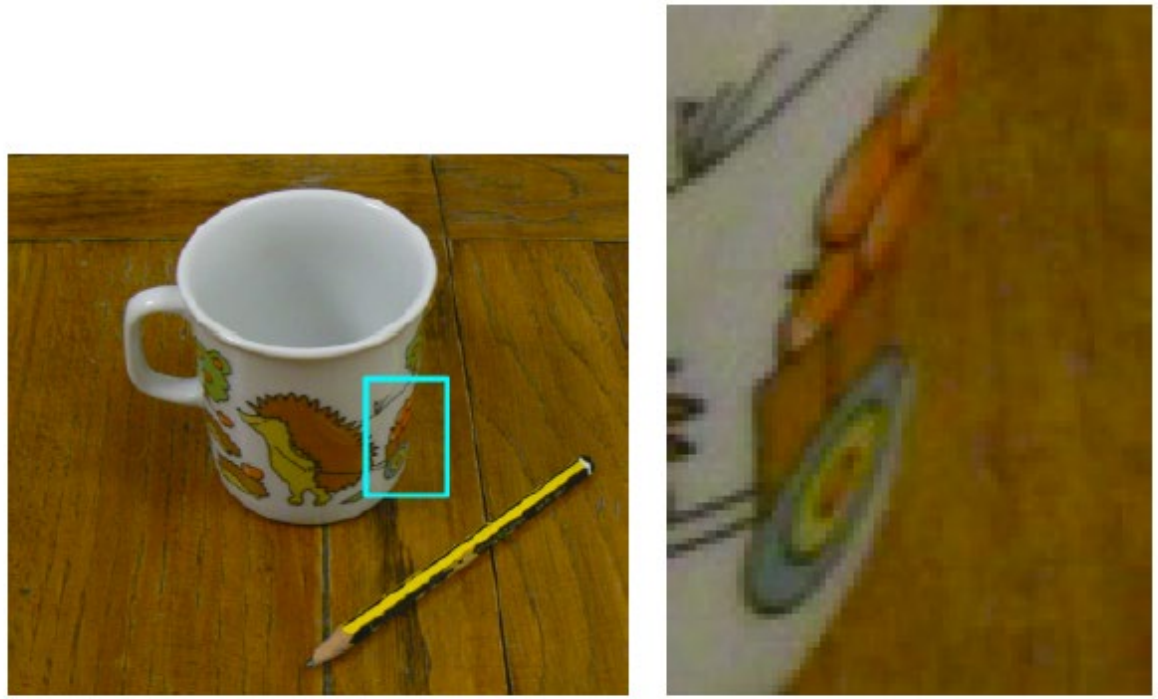
What is segmentation? Motivating picture

Image, courtesy Ondřej Drbohlav

What is image segmentation?

- Segmentation is a collection of methods that interpret spatially close parts of the image as objects.
- Regions (i.e., compact sets) represent spatial closeness naturally and thus are important building steps towards segmentation. Objects in a 2D image very often correspond to distinguishable regions.
- The object is everything what is of interest in the image (from the particular application point of view). The rest of the image is background.
- The approach is similar to that used in pattern recognition, i.e., division of the image into set of equivalence classes.

Segmentation can be difficult, example

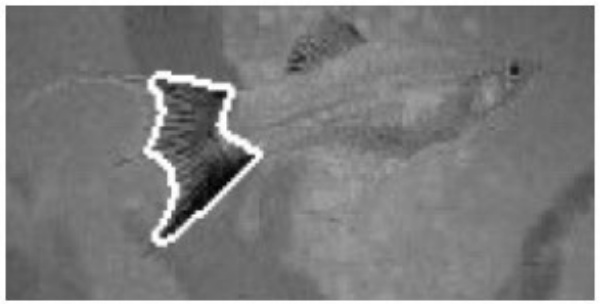


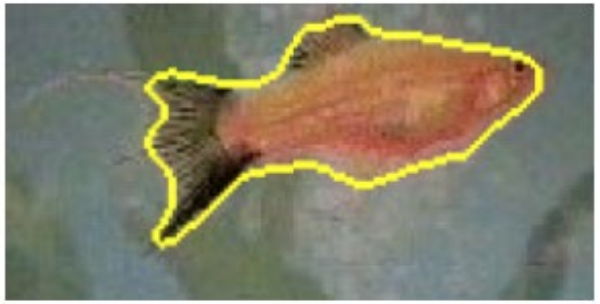
Image, courtesy Ondřej Drbohlav

- Finding a border between the cup and background in the indicated region is problematic because it does not differ from a local view.
- Only knowledge of the cup semantics can solve the puzzle.

Image segmentation, a bit of magic

- There is often no single answer on how to segment. Ad hoc methods prevail.
- There is no encompassing broad theory of segmentation. However, several recent theoretically grounded approaches have formulated segmentation as an optimization task.
- The particular case of foreground vs. background segmentation.
- Segmentation usually makes sense in a scope of a particular application.





Courtesy, images: Thomas Brox, TU Dresden, 2008

Complete vs. partial segmentation

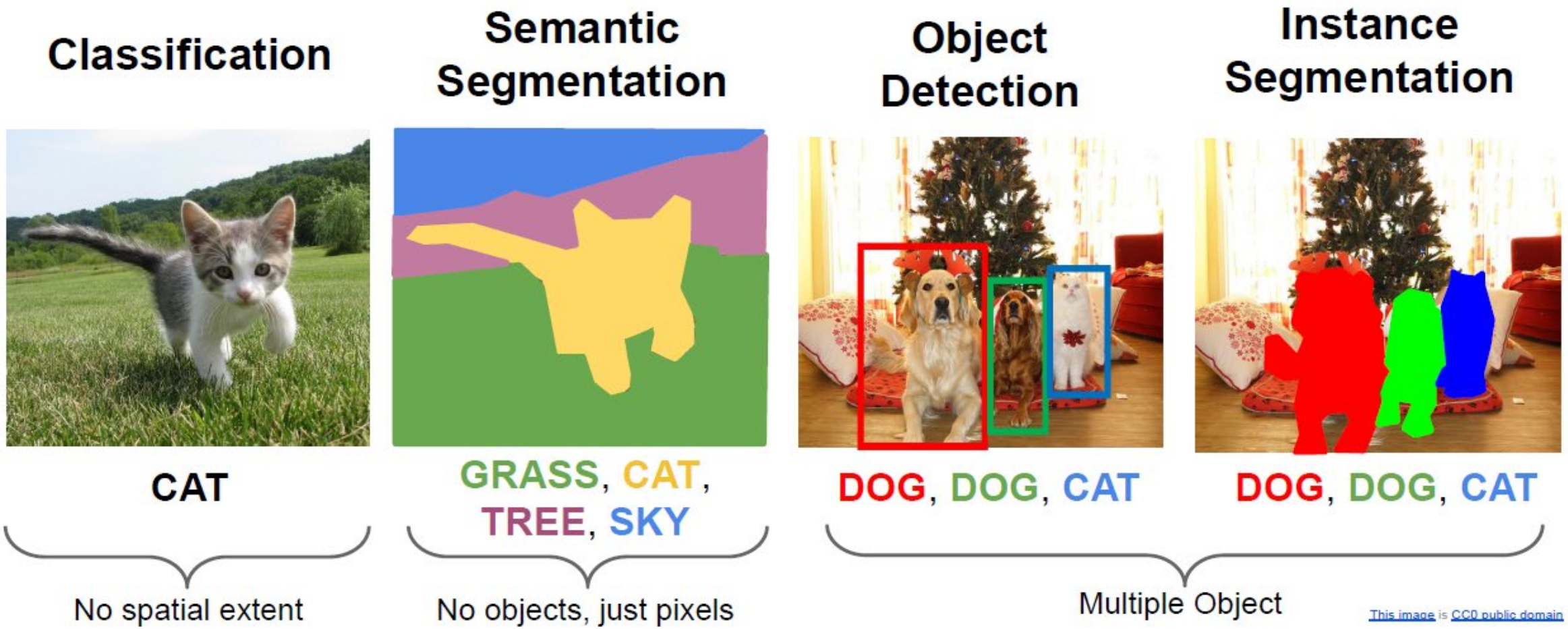
Complete segmentation -- divides an image into non-overlapping regions that match to the real world objects.

Complete segmentation divides an image R into the finite number S of regions $R_1, \ldots, R_S$

$$R = \bigcup_{i=1}^{S} R_i \,, \qquad R_i \cap R_j = \emptyset \,, \qquad i \neq j \,.$$

Partial segmentation -- it is possible to find only parts with semantic meaning in the image (e.g., regions, collection of edgels) which will lead to interpretation in later analysis.

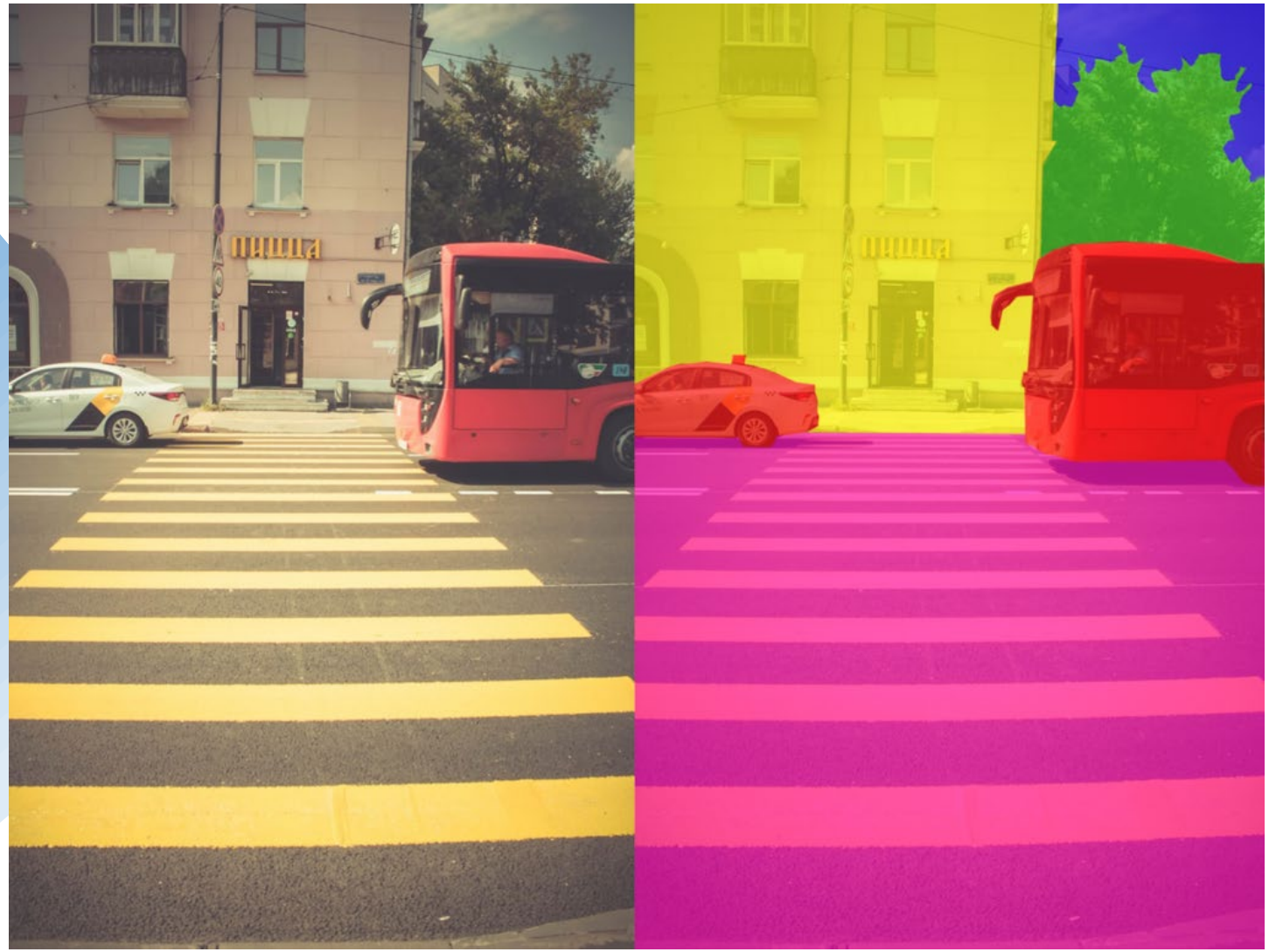
Computer vision tasks



Types of segmentations

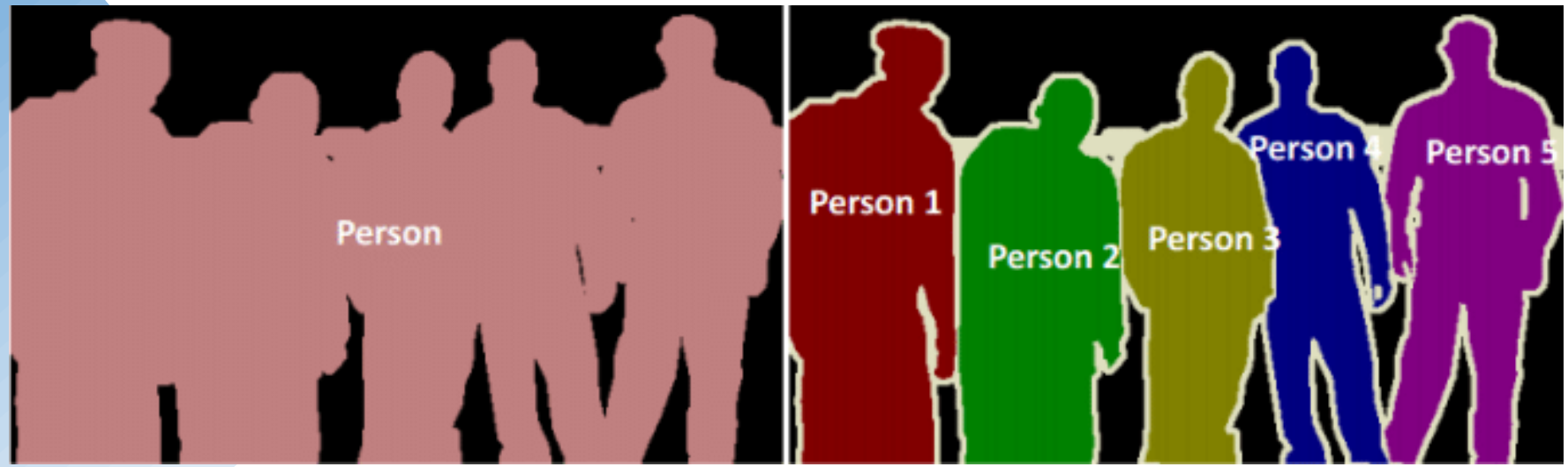
- Semantic segmentation – labeling pixels by semantic classes.
- Instance Segmentation – Instance segmentation involves classifying pixels based on the instances of an object (as opposed to object classes). Instance segmentation algorithms do not know which class each region belongs to—instead, they separate similar or overlapping regions based on the boundaries of objects.
- Panoptic segmentation – a combination of semantic and instance segmentation. It predicts the identity of each object, segregating every instance of each object in the image.

Semantic segmentation example



Source: Wikimedia Commons

Instance segmentation example



Source: ResearchGate

Panoptic segmentation example

Source: Kharshit Kumar

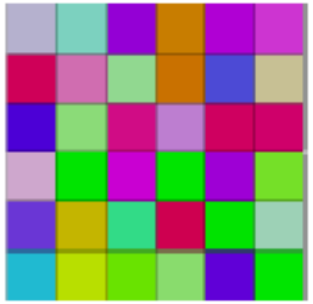
Approaches to image segmentation

1. Similarity approach
   This approach is based on detecting similarity between image pixels to form a segment based on a threshold. ML algorithms like clustering are based on this approach to segment an image.
2. Discontinuity approach
   This approach relies on the discontinuity of the image‘s pixel intensity values. Line, Point, and Edge Detection techniques use this approach to obtain intermediate segmentation results, which can be later processed to get the final segmented image.

List of image segmentation techniques

- Threshold-based segmentation
- Edge-based segmentation
- Region-based segmentation
- Clustering-based segmentation
- Optimization-based segmentation exploring Markov fields model (e.g., graph-cut, grab-cut)
- Watershed-based segmentation
- Deep learning-based segmentation

An image represented as a graph

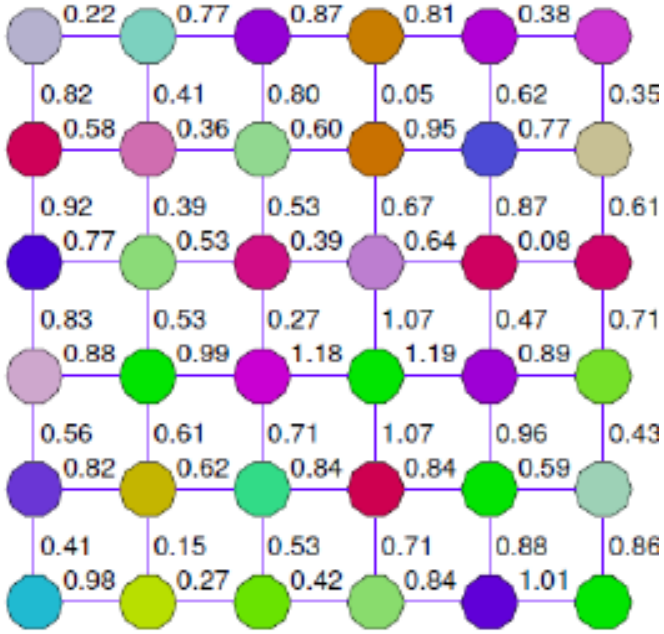


image

nodes

nodes and edges

- Nodes correspond to pixels.
- Edges connect neighboring pixels. 4-neighbors are considered in the example.
- Edges weights express the similarity between the neighboring pixels (binary relation).

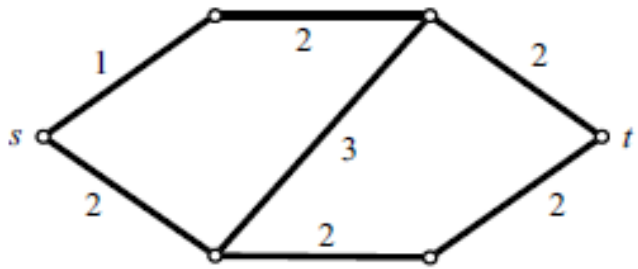


graph with weighted edges

Undirected/directed graph

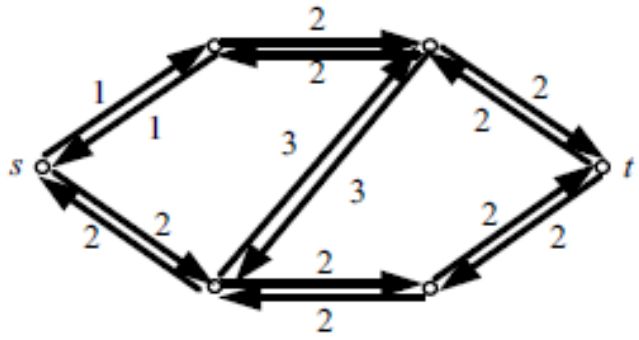
Undirected graph

- $G = (V, E)$ is composed of vertices V and undirected edges E representing a relation between two vertices.
- If a weight w_e is assigned to all edges then the graph becomes undirected weighted graph.



Directed graph

- $G = (V, E)$ is composed of vertices V and directed edges E representing an ordered relation between two vertices.
- Oriented edge $e = (u, v)$ has the tail u and the head v (denoted by the arrow). The edge e is different from $e' = (v, u)$ in general.



Graph based image segmentation

- Bottom-up segmentation

Original Image

Incorrect Segmentation

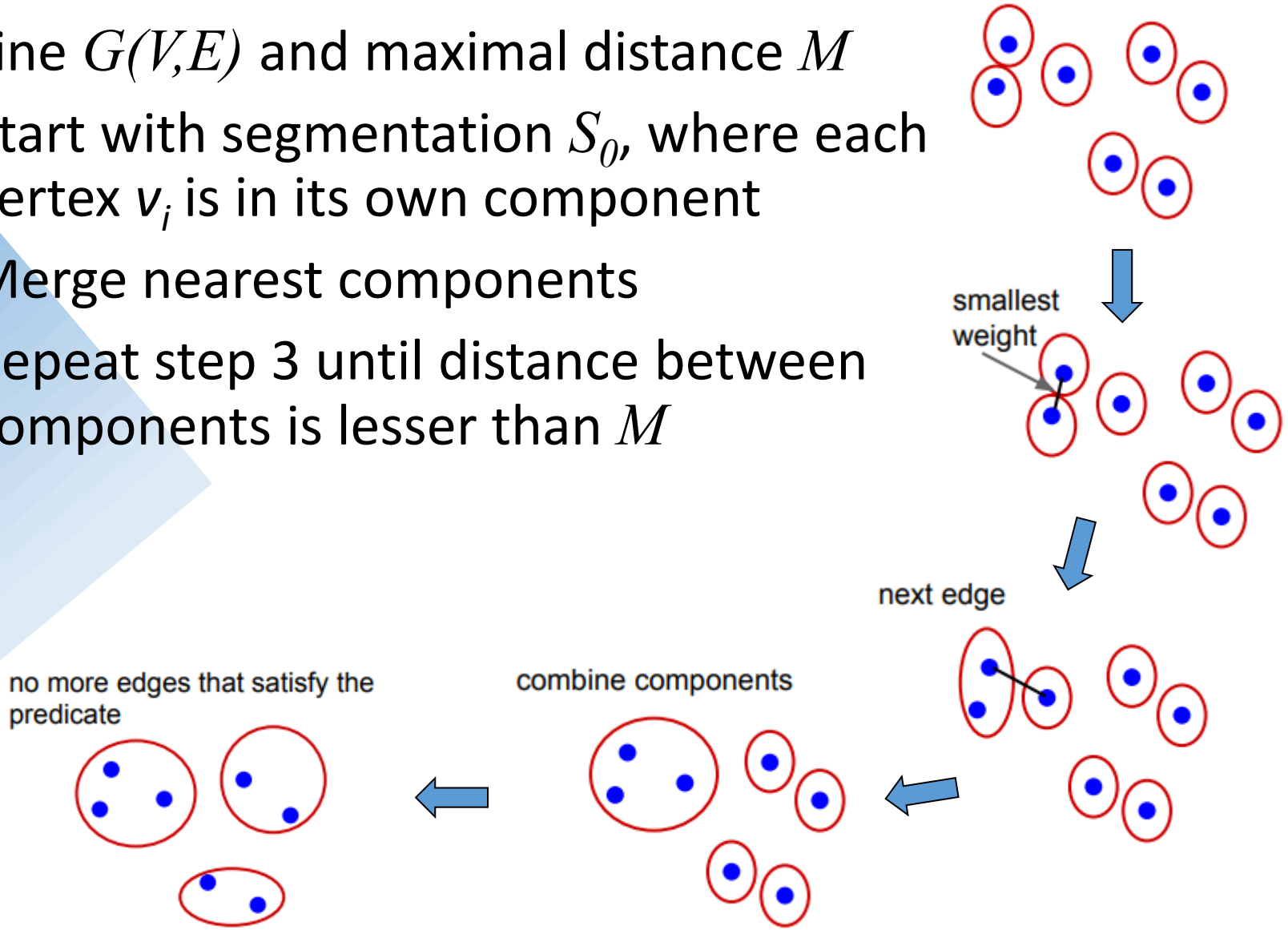
Correct Segmentation

- Based on Kruskal's minimum-spanning-tree algorithm

Graph based image segmentation

Define $G(V,E)$ and maximal distance M

1. Start with segmentation S_0, where each vertex v_i is in its own component
2. Merge nearest components
3. Repeat step 3 until distance between components is lesser than M



Grid graph based

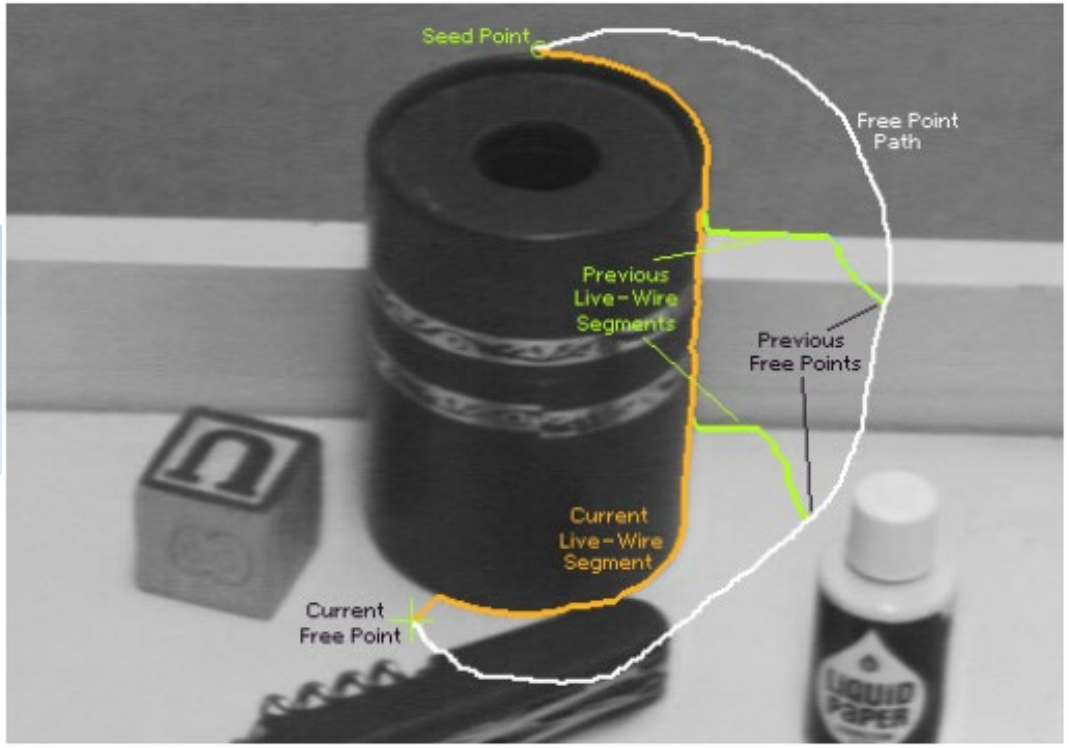
- Every pixel is connected to its four neighboring pixels
- The difference in intensities determines weights. For color images - the algorithm runs three times using R values, then using G values and finally B values. Two pixels in the same component are the same only if they appear in the same component in all three color channels.
- Features
  - Preserves small components, doesn’t have problem with small changes in gradient

Nearest-neighbor image segmentation

- Project every pixel into feature space defined by (x,y,r,g,b)
- Weight between pixels is determined using Euclidian distance
- Edges are chosen for only the top 10 nearest neighbors in the feature space
- Features
  - Non-spatially connected regions of the image can be placed in the same component. (see flowers or tower and lights)

Using the shortest path algorithm

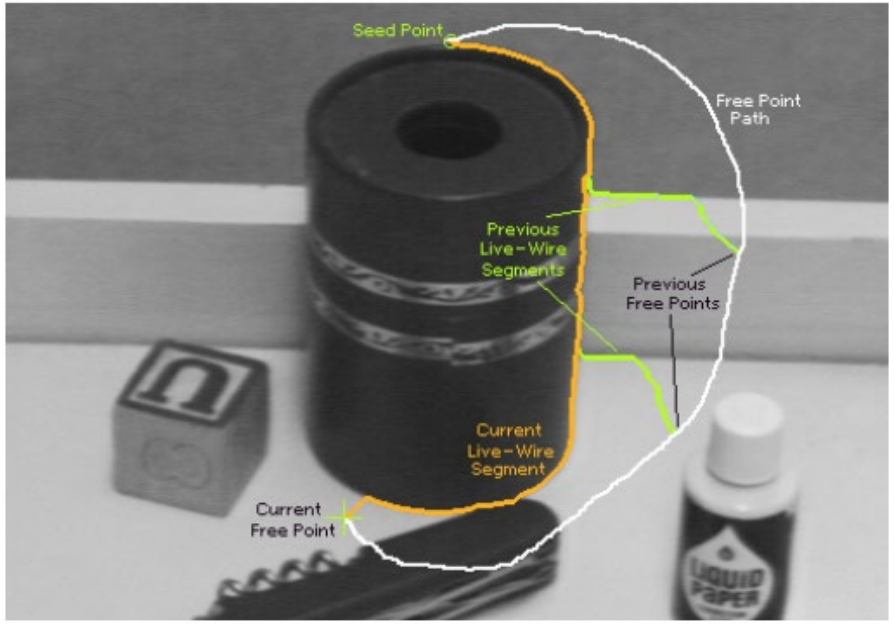
- Dijkstra's shortest path algorithm
- Used for intelligent scissors, aka live-Wire



Mortenson and Barrett (SIGGRAPH 1995)

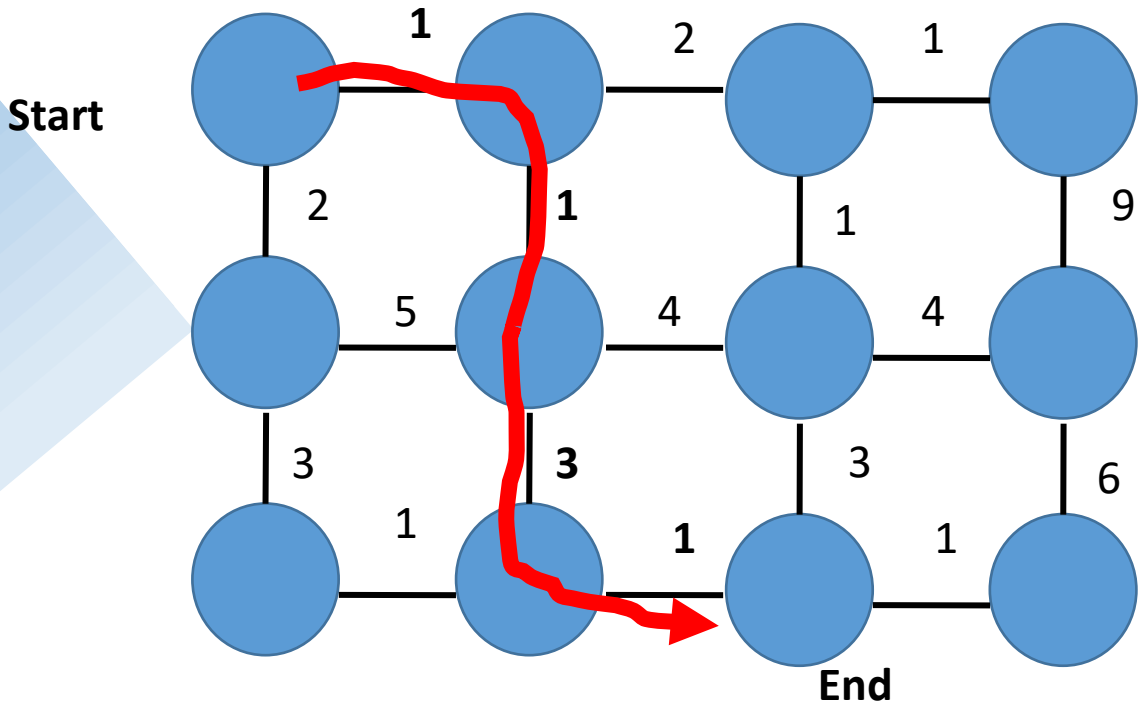
Intelligent scissors

- Formulation: find good boundary between seed points
- Challenges
  - Minimize interaction time
  - Define what makes a good boundary
  - Efficiently find it



Intelligent scissors

A good image boundary has a short path through the graph.



Mortenson and Barrett (SIGGRAPH 1995)

Dijkstra's shortest path algorithm

Initialize, given seed *s*:

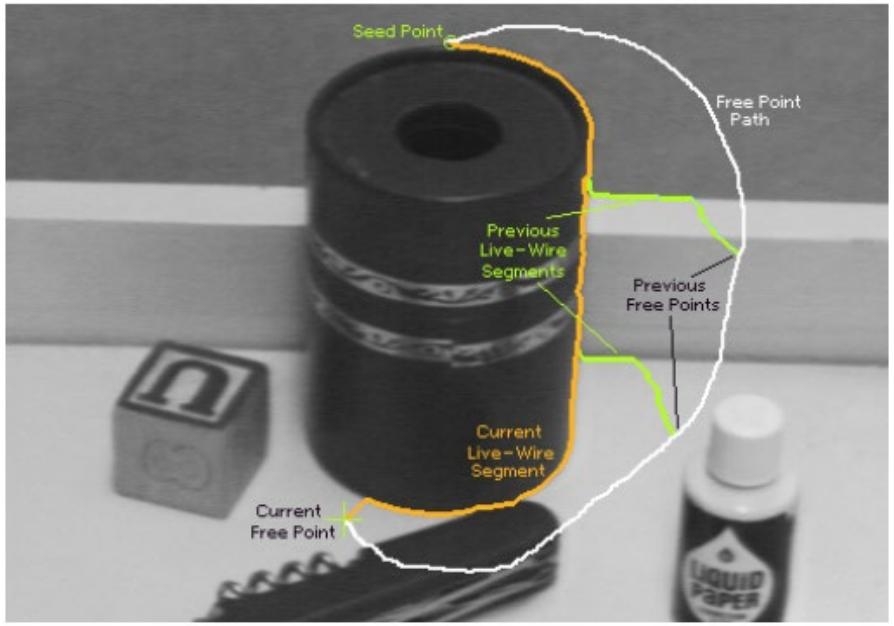
- Compute $cost_2(q, r)$ % cost for boundary from pixel *q* to neighboring pixel *r*
- cost(*s*) = 0 % total cost from seed to this point
- **A** = {*s*} % set to be expanded
- **E** = { } % set of expanded pixels
- **P**(q) % pointer to pixel that leads to *q*

Loop while **A** is not empty

1. *q* = pixel in **A** with lowest cost
2. Add q to **E**
3. for each pixel *r* in neighborhood of *q* that is not in **E**
   a) cost_tmp = cost(*q*) + $cost_2(q,r)$
   b) if (*r* is not in **A**) OR (cost_tmp < cost(*r*))
      i. cost(*r*) = cost_tmp
      ii. **P**(*r*) = *q*
      iii. Add *r* to **A**

Intelligent scissors: method (1)

1. Define boundary cost between neighboring pixels
2. User specifies a starting point (seed)
3. Compute lowest cost from seed to each other pixel
4. Get path from seed to cursor, choose new seed, repeat



Intelligent scissors: method (2)

Define boundary cost between neighboring pixels

a) Lower if edgel is present (e.g., with edge(im, ‘canny’))
b) Lower if gradient magnitude is strong
c) Lower if gradient direction matches the boundary

Gradients, edgels, and path cost

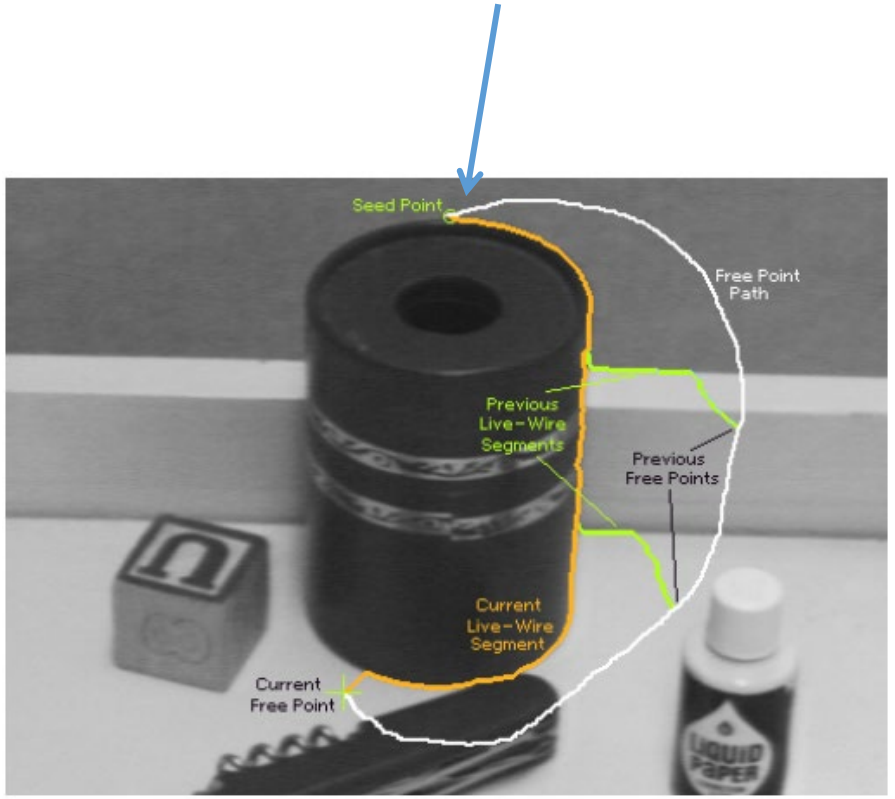
Gradient magnitude

Edgel image

Path cost

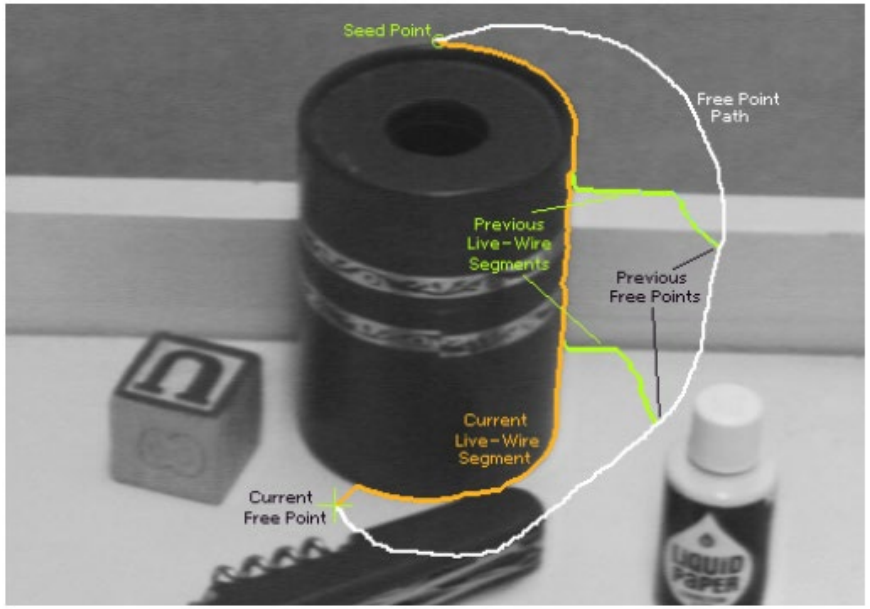
Intelligent scissors: method (3)

1. Define boundary cost between neighboring pixels
2. User specifies a starting point (seed)
   - Snapping



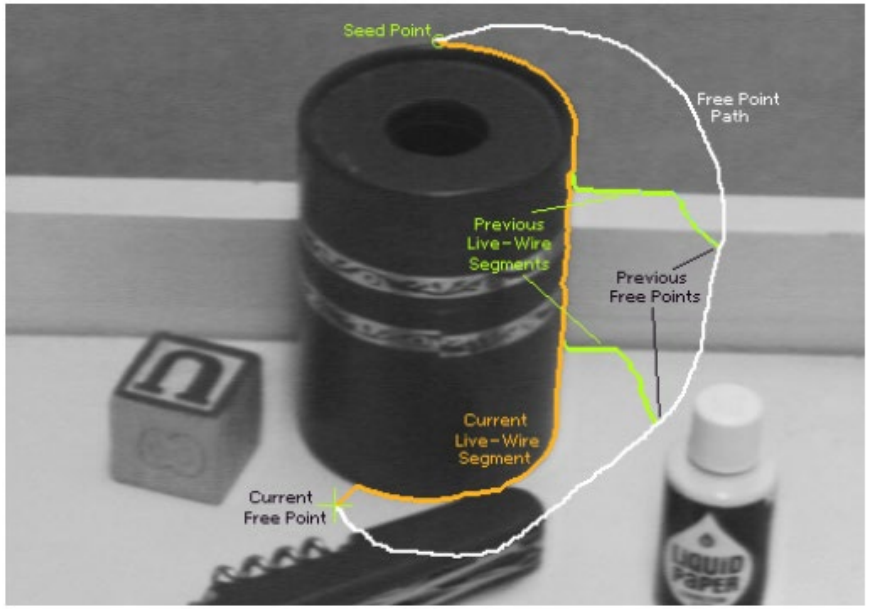
Intelligent scissors: method (4)

1. Define boundary cost between neighboring pixels
2. User specifies a starting point (seed)
3. Compute lowest cost from seed to each other pixel
   - Dijkstra's shortest path algorithm



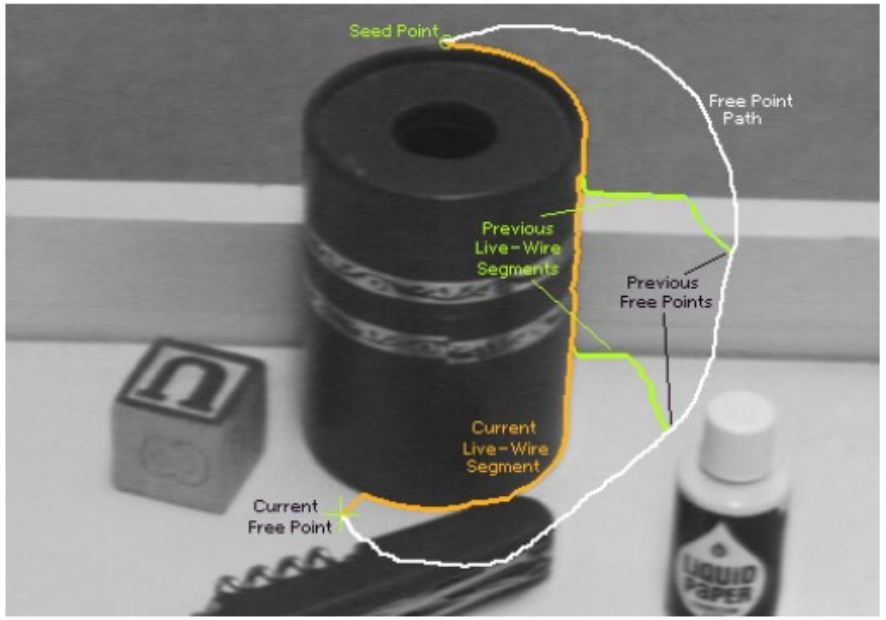
Intelligent scissors: method (5)

1. Define boundary cost between neighboring pixels
2. User specifies a starting point (seed)
3. Compute lowest cost from seed to each other pixel
4. Get new seed, get path between seeds, repeat



Intelligent scissors: improving interaction

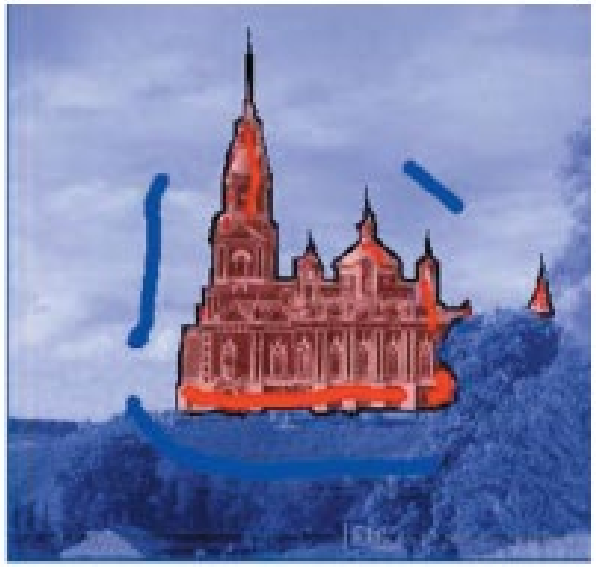
1. Snap when placing first seed
2. Automatically adjust to boundary as user drags
3. Freeze stable boundary points to make new seeds



Using the minimal graph cuts in image segmentation

- Main aim is to segment the object from background
  - User defines „seeds“ for object and background

(a) A woman from a village



(b) A church in Mozhaisk (near Moscow)

Flow network, flow

- A flow network is a directed graph with nonnegative edge weights (called also capacities).
- A flow is a real-valued (often integer) function, which satisfies the following three properties:

1. Capacity c constraint

   For all $u, v \in V$, $f(u, v) \leq c(u, v)$.

2. Skew symmetry

   For all $u, v \in V$, $f(u, v) = -f(v, u)$.

3. Flow conservation

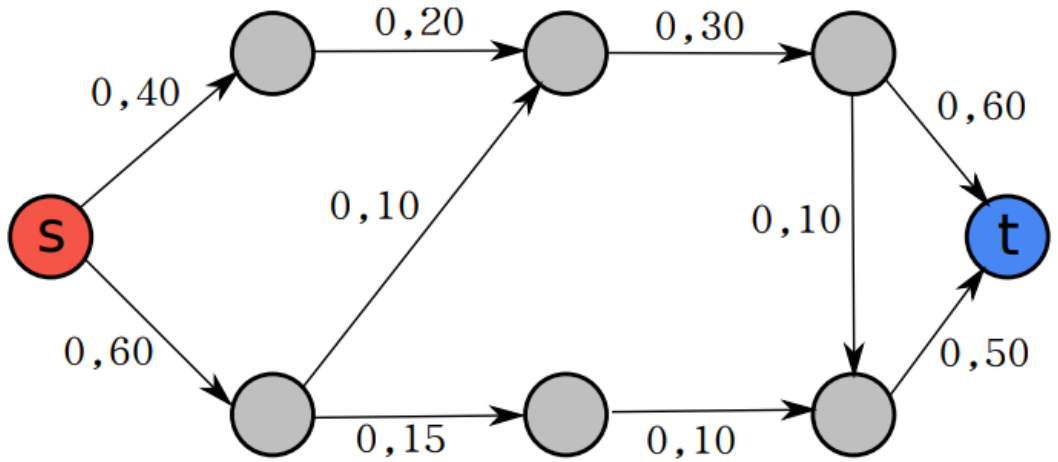
   For all $u \in (V \setminus \{s, t\})$, $\sum_{v \in V} f(u, v) = 0$.

A cut of a graph

- A cut is a set of edges $C \subset E$ such that two vertices (called terminals) became separated on the induced graph $G' = (V, E \setminus C)$.
- Denoting a source terminal as s and a sink terminal as t, a cut (S, T) of $G = (V, E)$ is a partition of V into S and $T = V \setminus S$, such that $s \in S$ and $t \in T$.

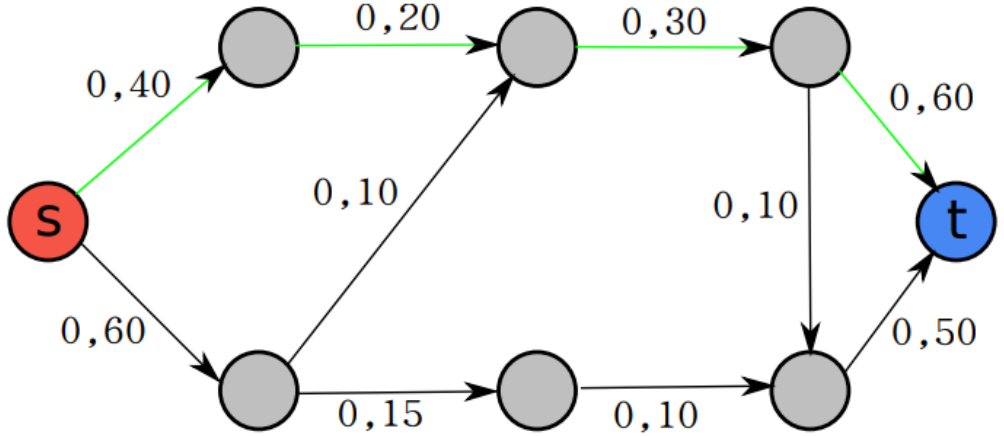
Max flow (1)

- Directed graph with one source & one sink node
- Directed edge = pipe
- Edge label = capacity
- What is the max flow from source to sink?



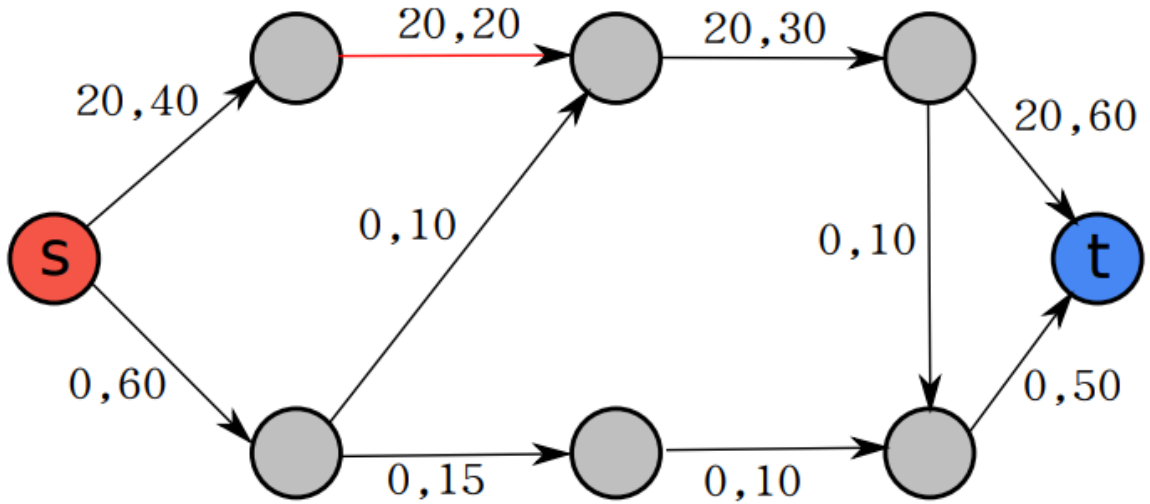
Max flow (2)

- Graph with one source & one sink node
- Edge = pipe
- Edge label = capacity
- What is the max flow from source to sink?
- 1st step: find any path with free capacity
  - Path can go in the opposite way if there is any flow. The value of the flow is then substracted.



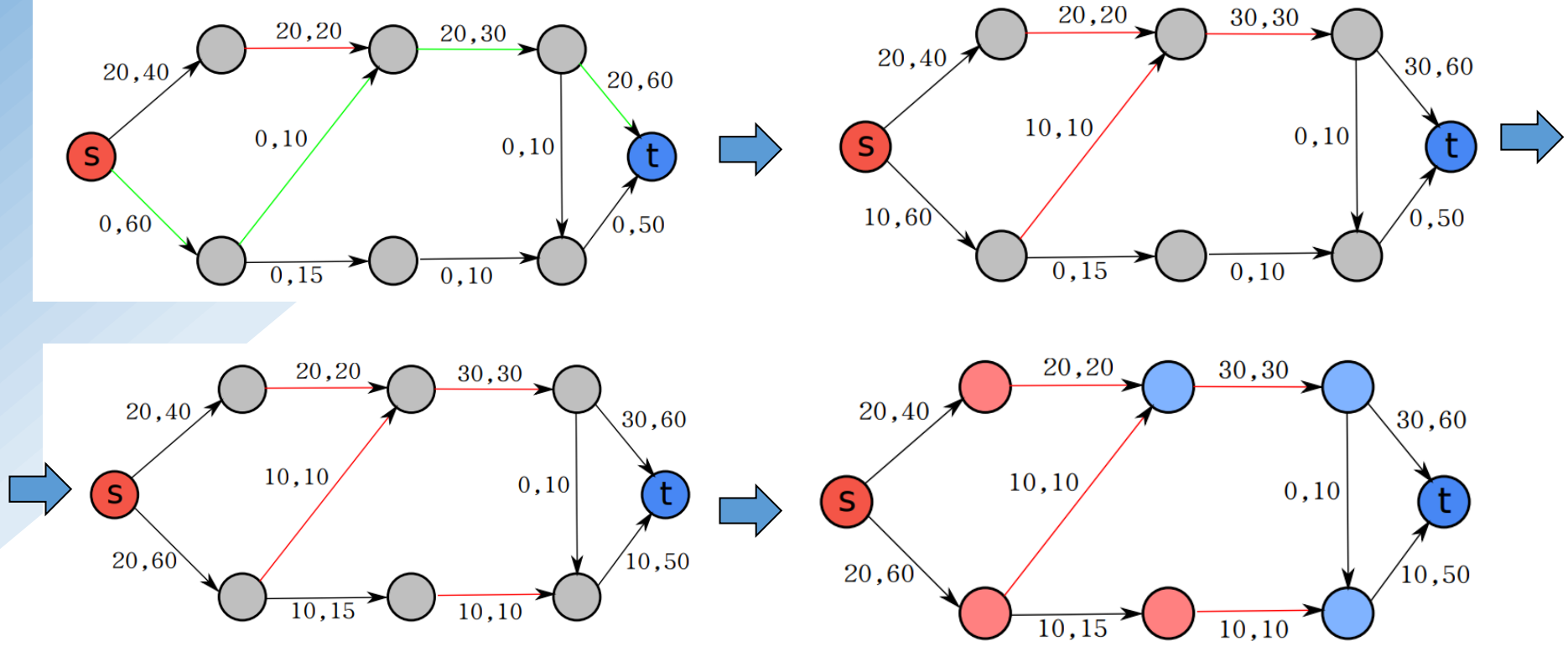
Max flow (3)

- 2nd step: Fill the path with the maximal capacity



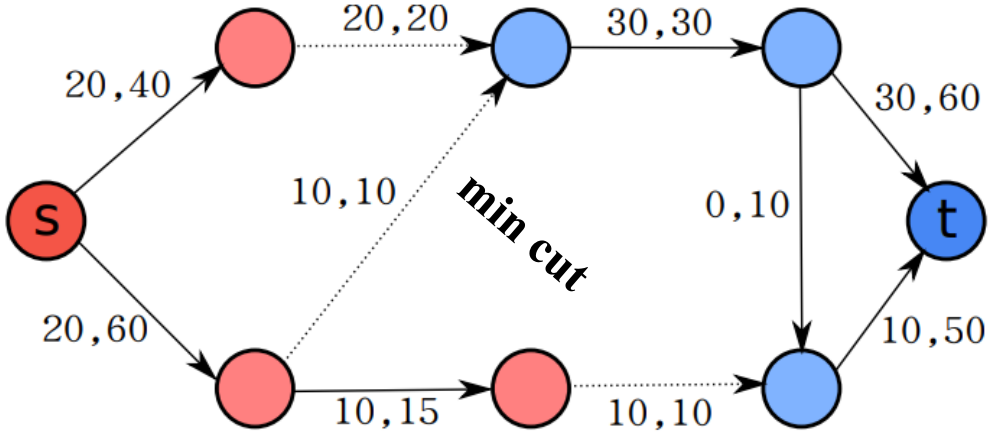
Max flow (4)

- 3rd step: return to step 1 until there is no free path



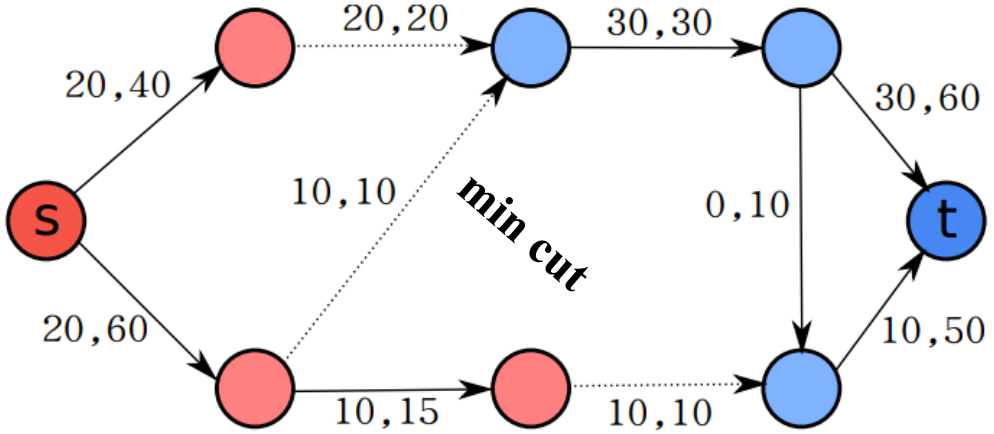
Max flow (5)

- What is the max flow from the source s to sink t ?
- Look at a residual graph
  - min cut is at the boundary between two connected components

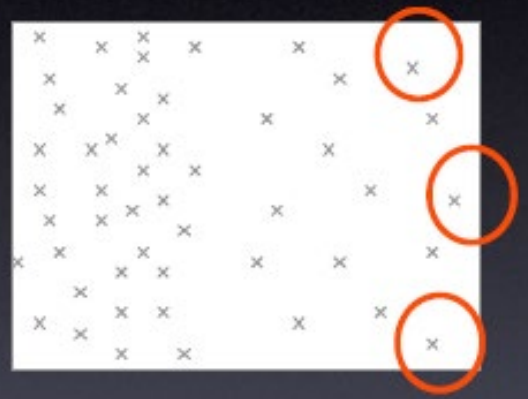


Equivalence of min cut and max flow

- The three following statements are equivalent
  - The maximum flow is f
  - The minimum cut has weight f
  - The residual graph for flow f contains no directed path from source to sink



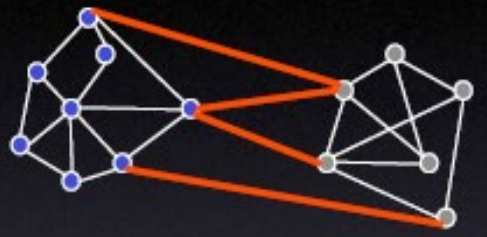
Problem with min cuts



Min. cuts favors isolated clusters

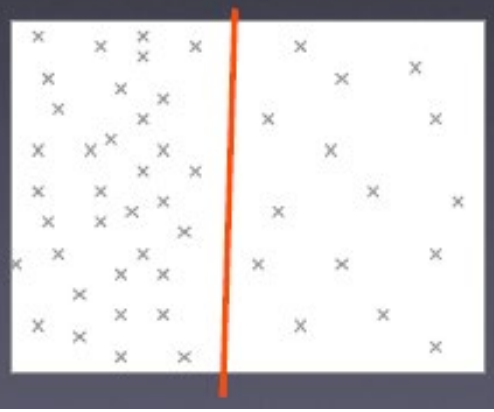
Normalize cuts in a graph

- (edge) Ncut = balanced cut

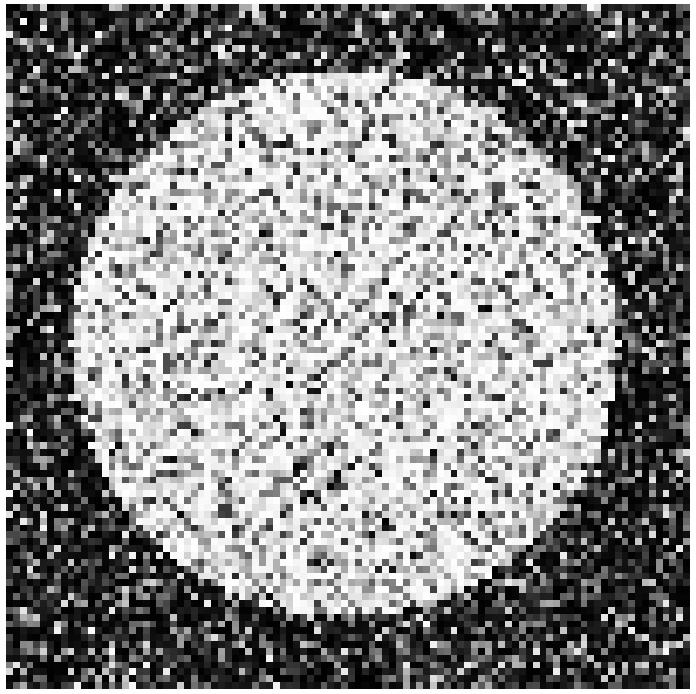


$$Ncut(A,B) = cut(A,B)(\frac{1}{vol(A)} + \frac{1}{vol(B)})$$

NP-Hard!



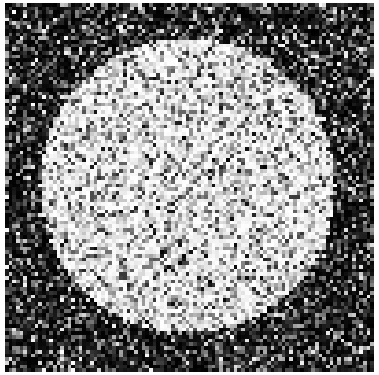
Pixel-based statistical model



$P(foreground \mid image)$

has limitations because of existing relations to other pixels.

Solution: encode dependences between pixels



$P(foreground \mid image)$

Normalizing constant called “partition function”

$$P(\mathbf{y};\theta,data) = \frac{1}{Z}\prod_{i=1..N} p_1(y_i;\theta,data) \prod_{i,j\in edges} p_2(y_i,y_j;\theta,data)$$

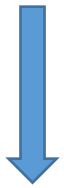
Labels to be predicted

Individual predictions

Pairwise predictions

Writing likelihood as an energy

$$P(\mathbf{y};\theta,data) = \frac{1}{Z}\prod_{i=1..N} p_1(y_i;\theta,data)\prod_{i,j\in edges} p_2(y_i,y_j;\theta,data)$$



$-\log(.)$

$$Energy(\mathbf{y};\theta,data) = \sum_i \psi_1(y_i;\theta,data) + \sum_{i,j\in edges} \psi_2(y_i,y_j;\theta,data)$$

Cost of assignment y_i

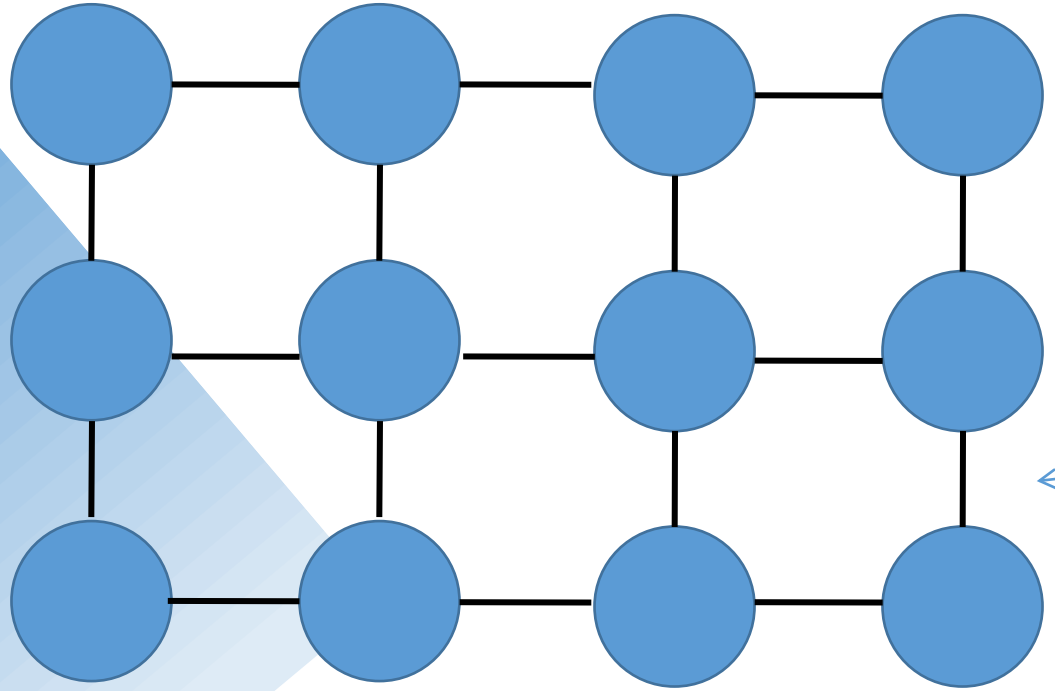
Cost of pairwise assignment y_i, y_j

Notes on energy-based formulation

$$Energy(\mathbf{y};\theta,data) = \sum_i \psi_1(y_i;\theta,data) + \sum_{i,j\in edges} \psi_2(y_i,y_j;\theta,data)$$

- Primarily used when one only cares about the most likely solution (not the confidences).
- Can think of it as a general cost function.
- Can have larger “cliques” than 2. The clique is the set of variables that go into a potential function.

Markov Random Fields



Node y_i: pixel label

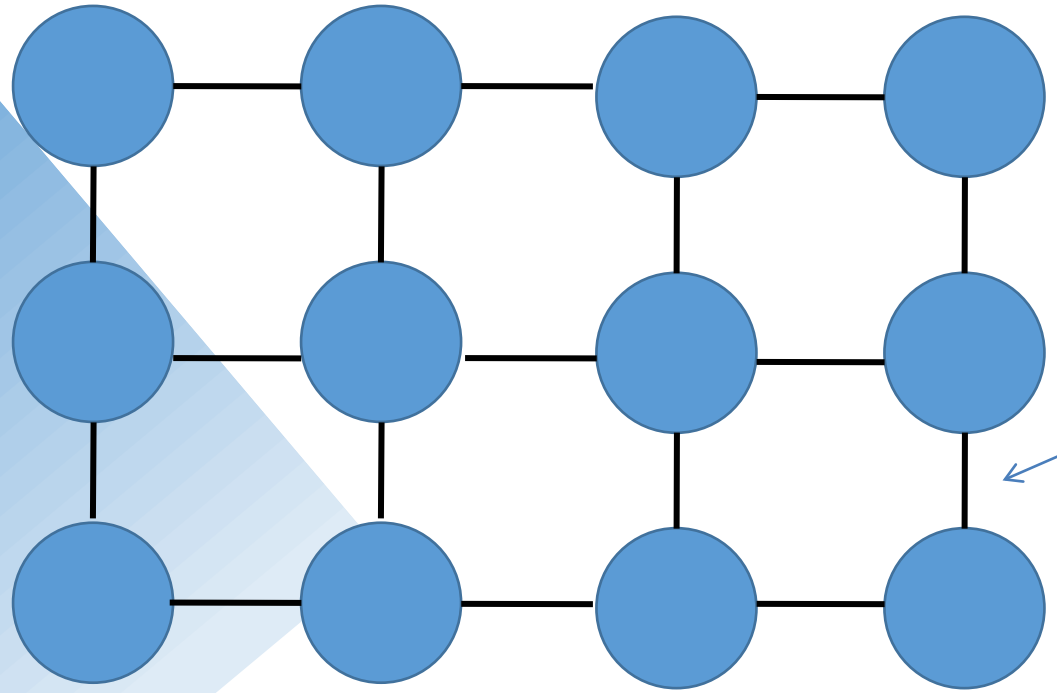
Edge: constrained pairs

Cost to assign a label to each pixel

Cost to assign a pair of labels to connected pixels

$$Energy(\mathbf{y};\theta,data) = \sum_i \psi_1(y_i;\theta,data) + \sum_{i,j\in edges} \psi_2(y_i,y_j;\theta,data)$$

Label smoothing grid example



Unary potential

0: $-\log P(y_i = 0 \mid data)$

1: $-\log P(y_i = 1 \mid data)$

Pairwise Potential

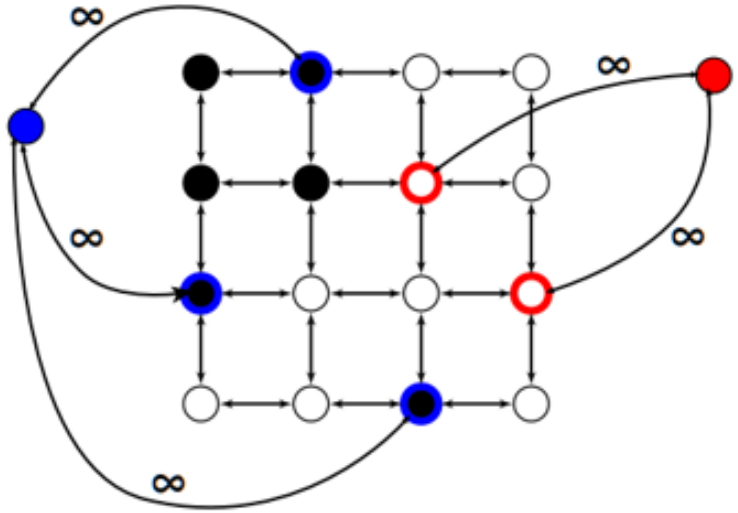
	0	1
0	0	K
1	K	0

$K>0$

$$Energy(\mathbf{y};\theta,data) = \sum_i \psi_1(y_i;\theta,data) + \sum_{i,j\in edges} \psi_2(y_i,y_j;\theta,data)$$

Creating the graph from image

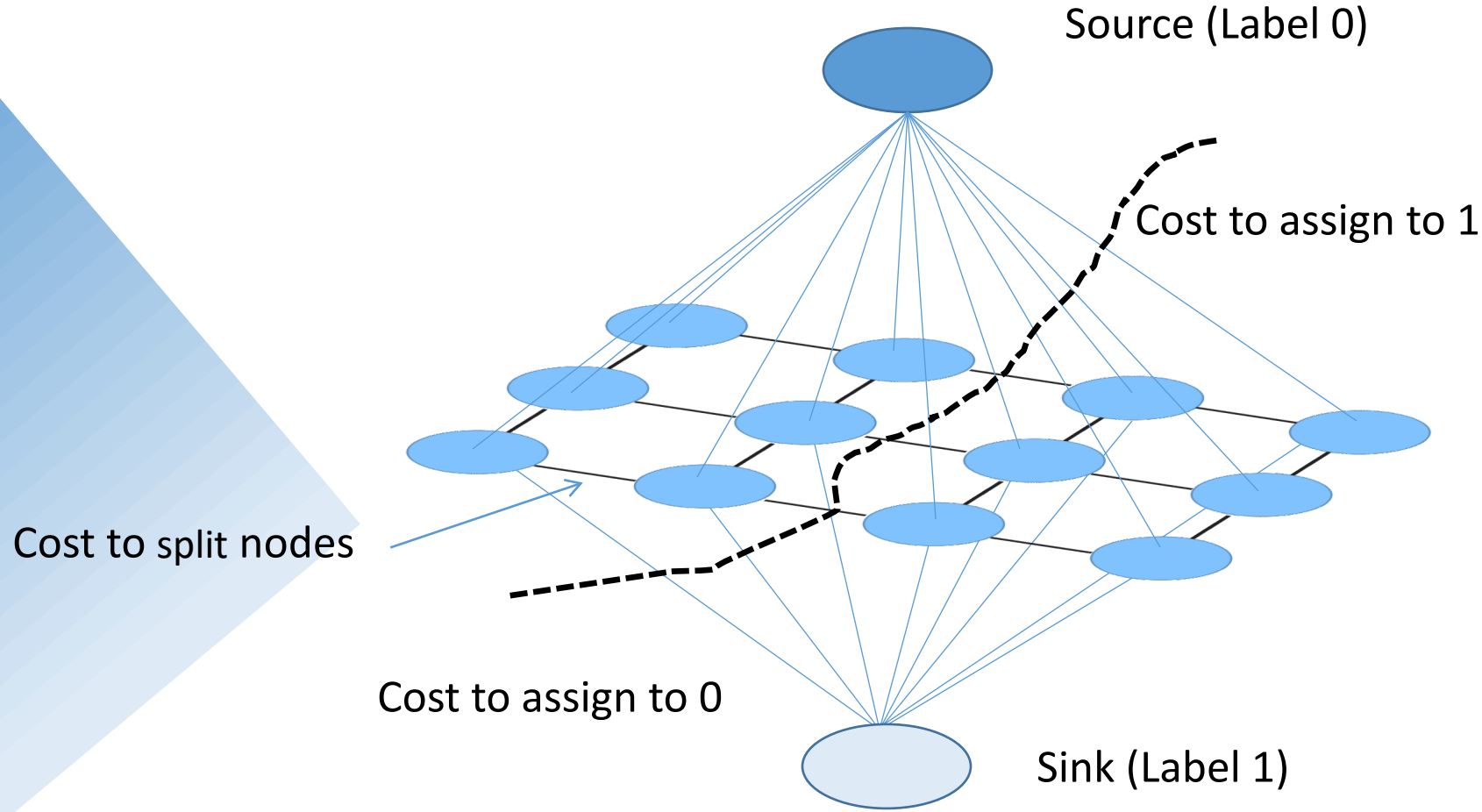
- Each pixel has a corresponding vertex
- Additionally, a source (“object”) and a sink (“background”)
- Each pixel vertex has an edge to its neighbors (e.g. 4 adjacent neighbors in 2D), an edge to the source, an edge to the sink
- Pixels connected with seeds have an infinite capacity



Edge weights between pixels

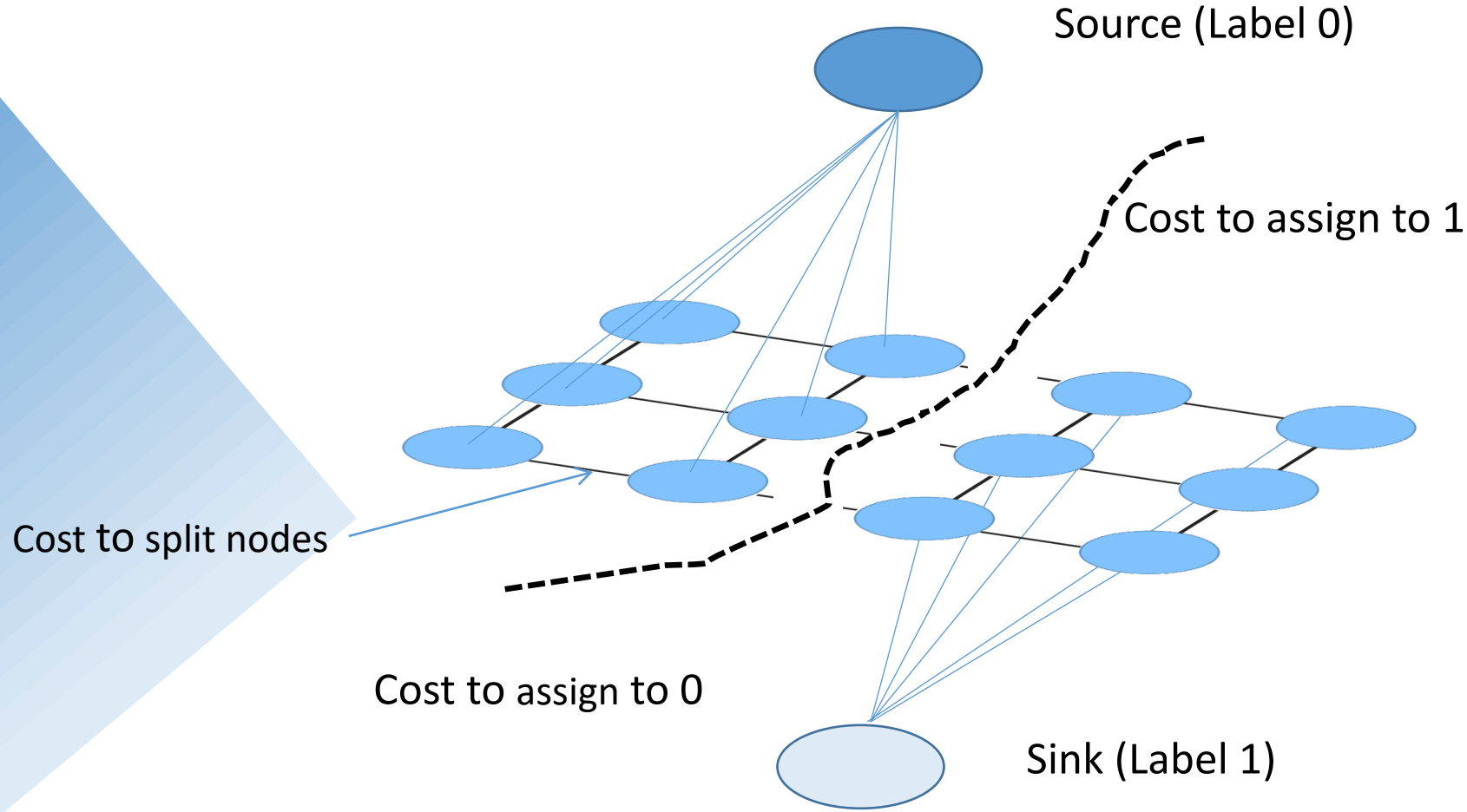
- Weight of edges between pixel vertices are determined by the function expressing dependence between two pixels
- Low score when boundary is likely to pass between the vertices
- High score when vertices are probably part of the same element
- E.g. the difference in pixel intensities, the image gradient

Solving MRFs with graph cuts



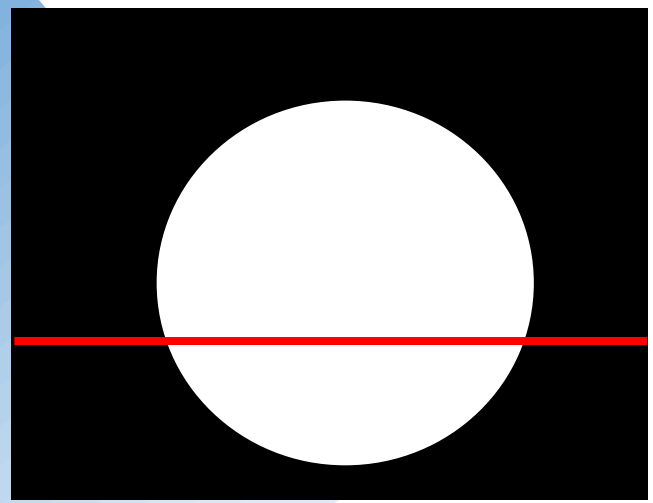
$$Energy(\mathbf{y};\theta,data) = \sum_i \psi_1(y_i;\theta,data) + \sum_{i,j\in edges} \psi_2(y_i,y_j;\theta,data)$$

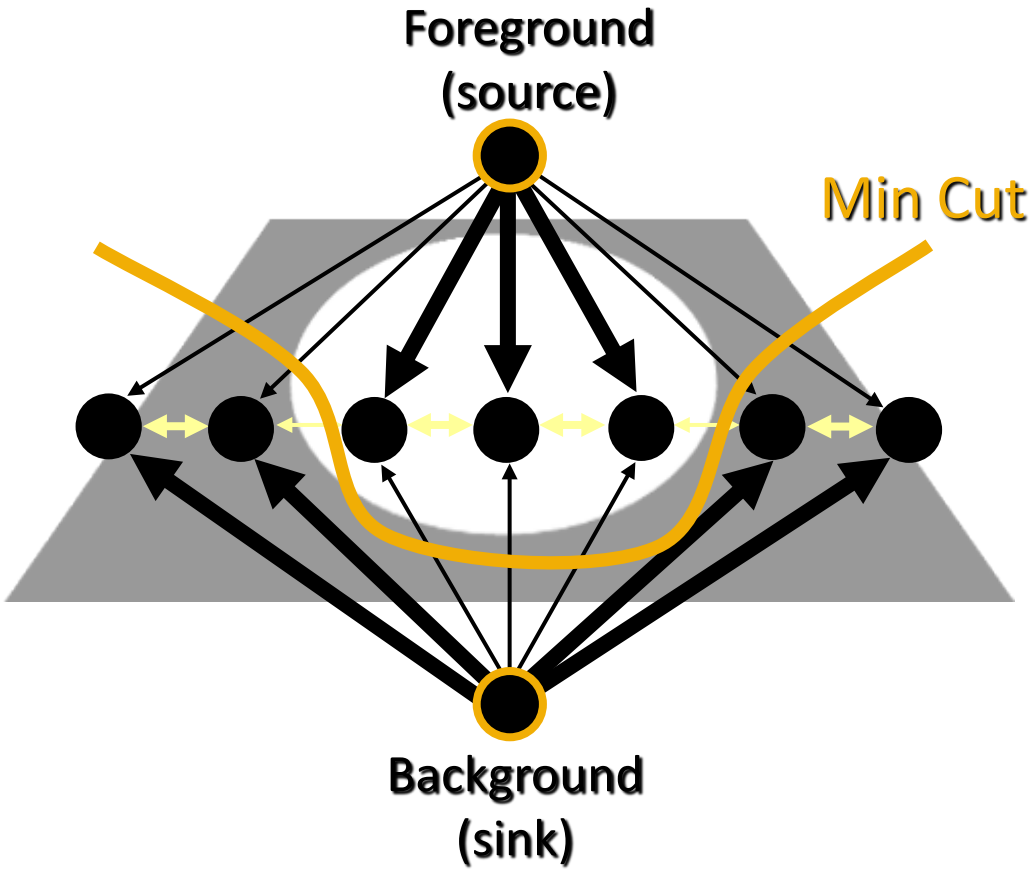
Solving MRFs with graph cuts



$$Energy(\mathbf{y};\theta,data) = \sum_i \psi_1(y_i;\theta,data) + \sum_{i,j\in edges} \psi_2(y_i,y_j;\theta,data)$$

Graph cut, Boykov & Jolly 2001

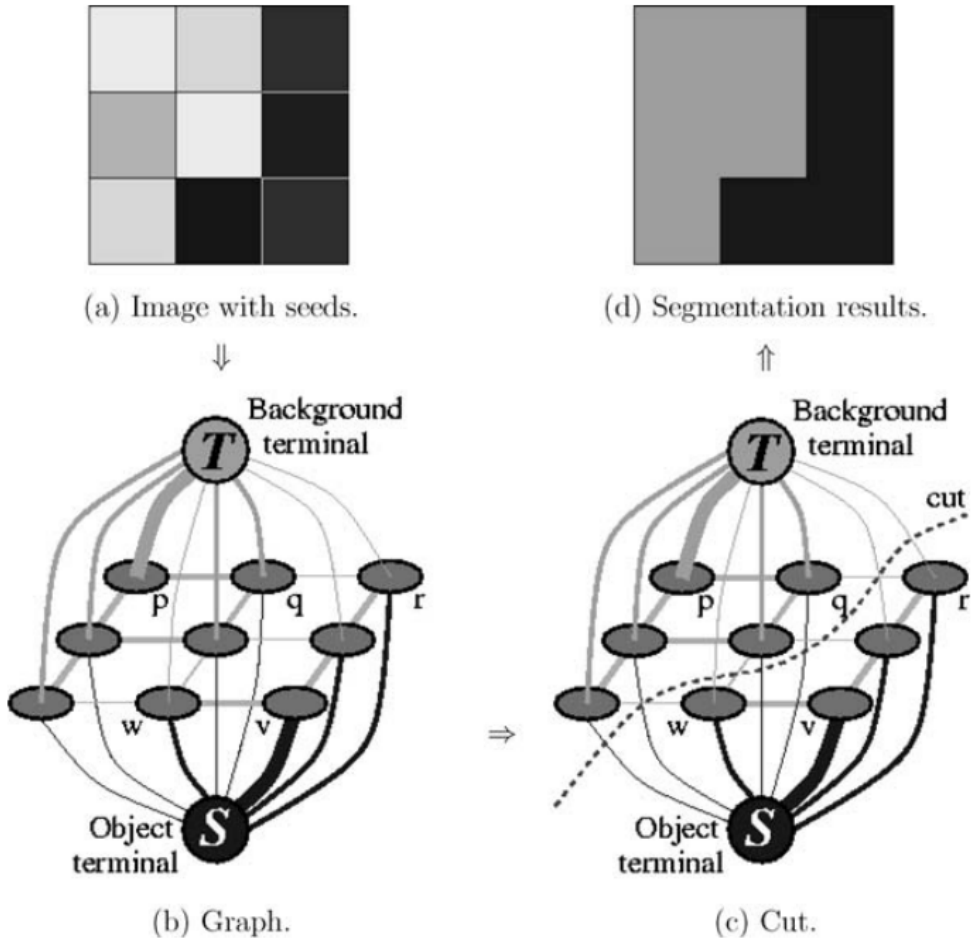




Cut: Separating source and sink; Energy: collection of edges

Min Cut: Global minimal energy in polynomial time

Minimal graph cuts and image labeling



Minimum graph cut segmentation of a 3x3 image. [Boykov and V. Kolmogorov]

Normalized cut

- A minimum cut penalizes large segments
- This can be fixed by normalizing the cut by component size
- The *normalized cut* cost is:

$$\frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)}$$

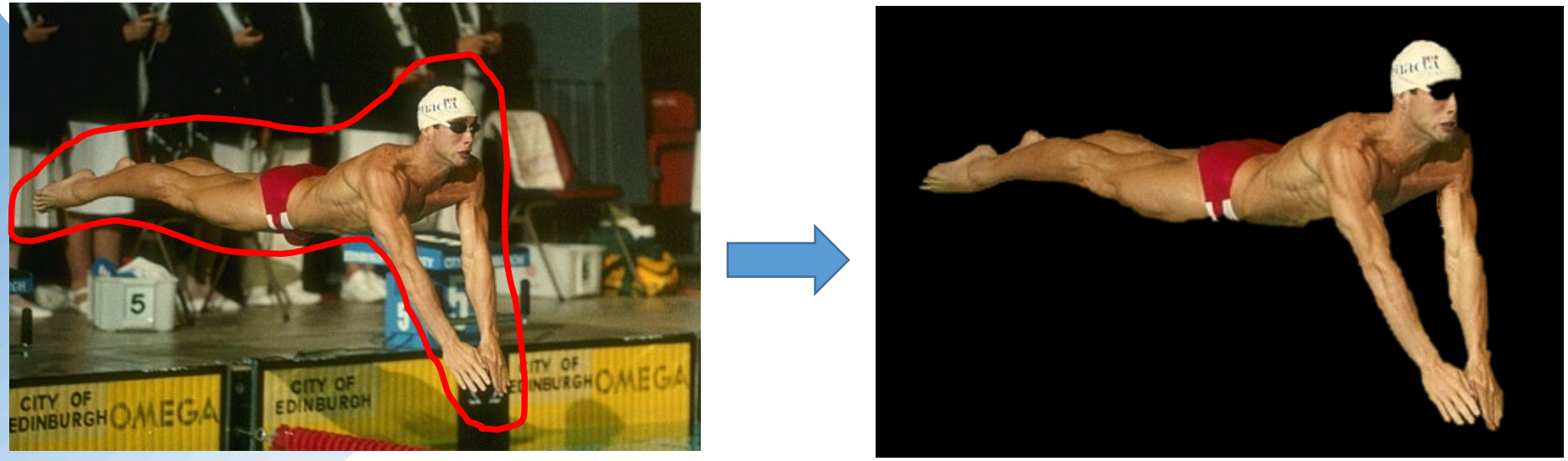
assoc(*A*, *V*) = sum of weights of all edges in V that touch A

- The exact solution is NP-hard but an approximation can be computed by solving a *generalized eigenvalue* problem

J. Shi and J. Malik. Normalized cuts and image segmentation. PAMI 2000

GrabCut segmentation

Carsten Rother et al. 2004



User provides rough indication of foreground region.

Goal: Automatically provide a pixel-level segmentation.

- Less user input, rectangle only.
- Handles color

GrabCut segmentation

1. Define graph
   - usually 4-connected or 8-connected
     - Divide diagonal potentials by sqrt(2)
2. Define unary potentials
   - Color histogram or mixture of Gaussians for background and foreground

$$unary\_potential(x) = -\log\left(\frac{P(c(x);\theta_{foreground})}{P(c(x);\theta_{background})}\right)$$

3. Define pairwise potentials

$$edge\_potential(x,y) = k_1 + k_2 \exp\left\{\frac{-\|c(x)-c(y)\|^2}{2\sigma^2}\right\}$$

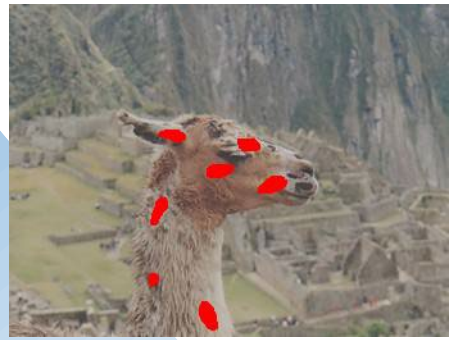
4. Apply graph cuts
5. Return to 2, using current labels to compute foreground, background models

GrabCuts and graph cuts

User Input

Result

Magic Wand
(198?)

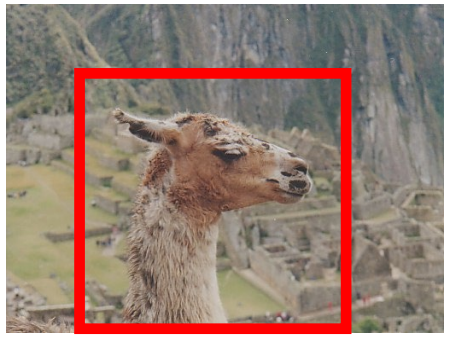


Regions

Intelligent Scissors
Mortensen and Barrett (1995)

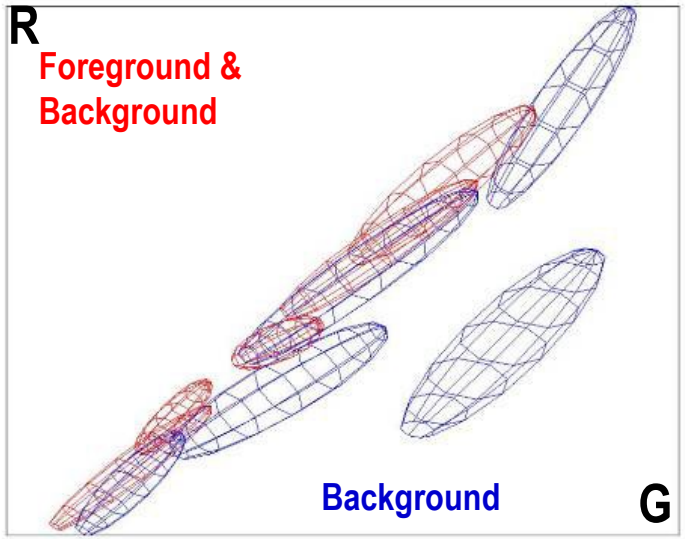
Boundary

GrabCut



Source: C. Rother

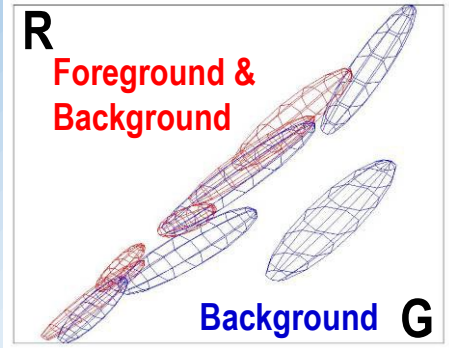
Color model (1)



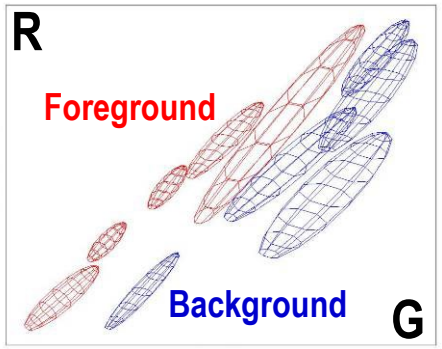
Gaussian Mixture Model (typically 5-8 components)

Source: K. Rother

Color model (2)



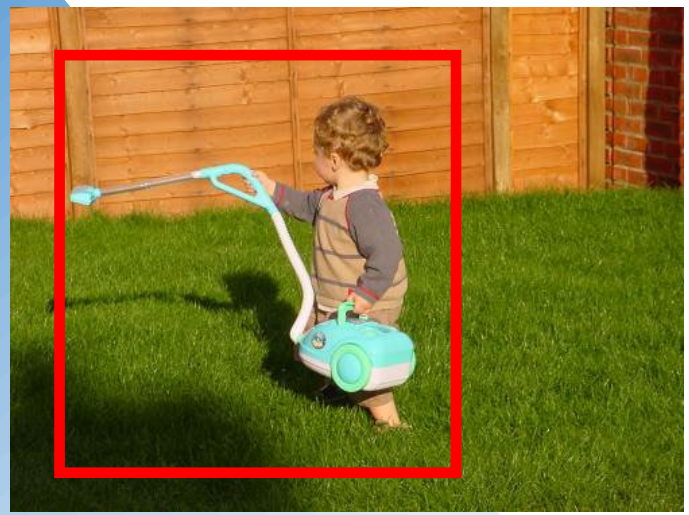
Iterated
graph cut



Gaussian Mixture Model (typically 5-8 components)

Source: K. Rother

What is easy or hard about these cases for graphcut-based segmentation?



Easier examples

More difficult examples

Camouflage & Low Contrast

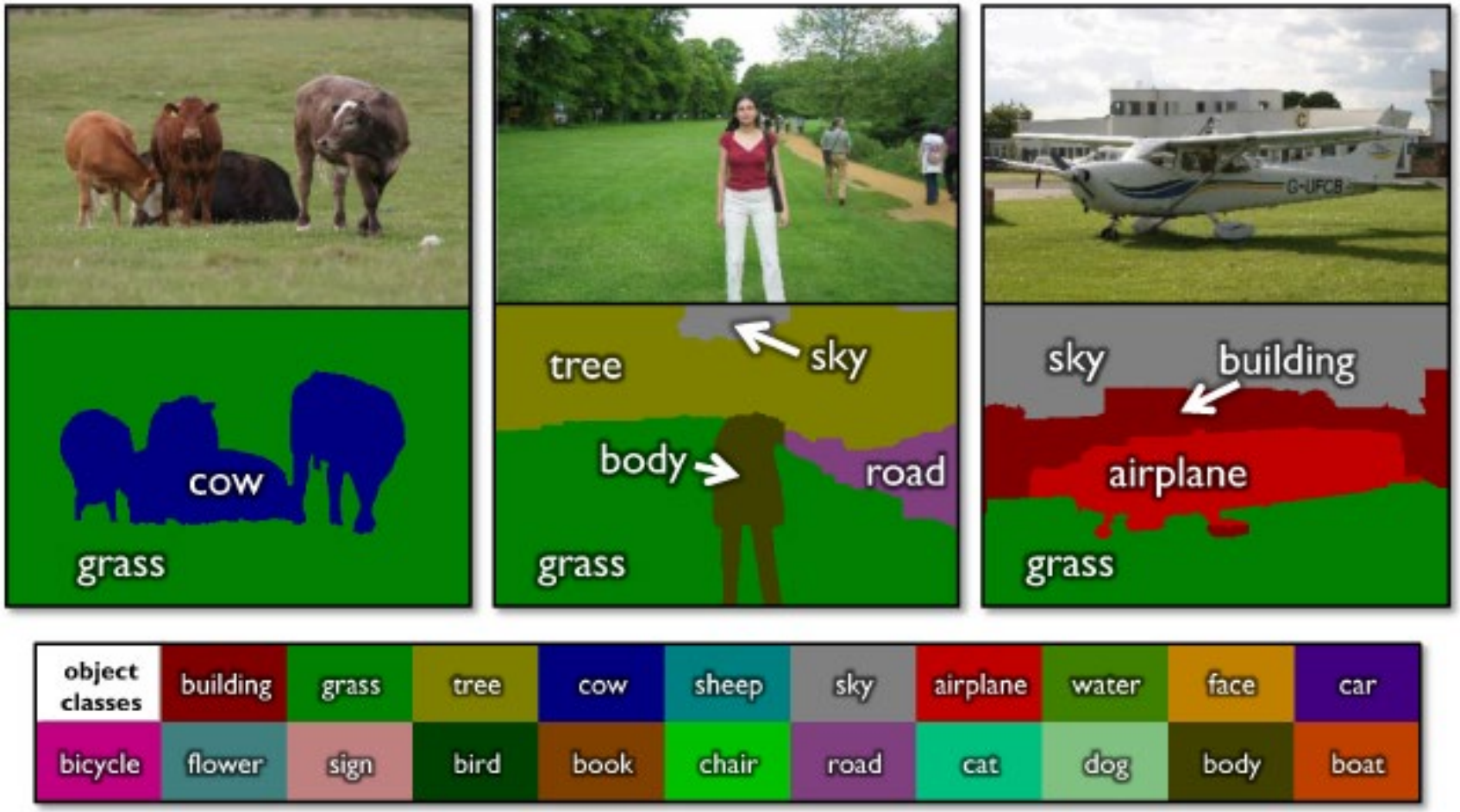
Fine structure

Harder Case

Initial Rectangle

Initial Result

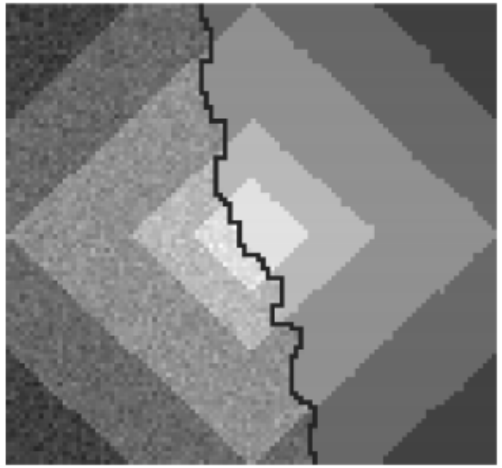
Using graph cuts for recognition



TextonBoost (Shotton et al. 2009 IJCV)

Other applications of minimal graph cuts

- Image restoration



- Stereo disparity