

Interactive Graph Cuts

for Optimal Boundary & Region Segmentation of Objects in N-D Images

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Outline

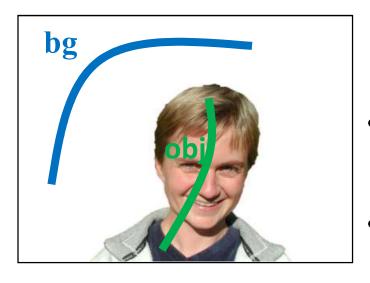
- Introduction
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 - Graph Construction
 - Cost Function Definition
 - Cost Minimization





Motivation

• The problems from automatic segmentation can be alleviated via user guidance



interactive segmentation

- identify the parts of the object
 (obj) and background (bg)
- compute a segmentation that adheres to the user setting



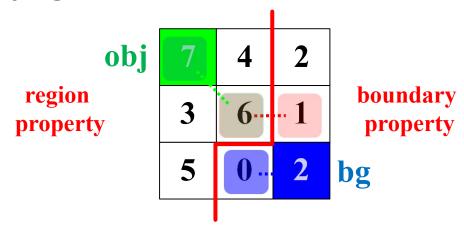


- Problem Description
 - Given: an image and two sets of **obj/bg** points provided by the user
 - Goal: find a segmentation (an assignment of points)
 - well separate the object points from background ones
 - adhere to user's constraints

obj	7	4	2	assign a label (obj/bg)	(7)	4	2	
	3	6	1	to every point	3	6	1	
	5	0	2	bg	5	0	(2)	
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- Central Idea
 - enforce both **boundary** and **region** properties
 - boundary property: pixels with significant intensity differences from their neighbors are boundaries
 - region property: pixels with similar intensities to
 obj/bg are inclined to be labeled as obj/bg







- Central Idea
 - formulate segmentation as an **optimization** problem
 - define a cost function E(.) based on two properties of the segmentation c.

$$E(c) = \Re(c) + \Re(c)$$

a segmentation rigiportance boundary cost function cost function

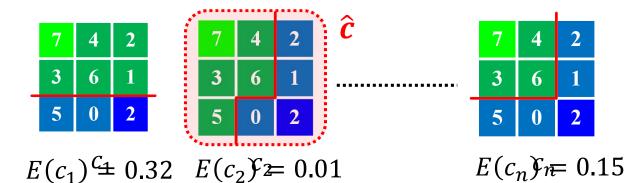
7	4	2	7	4	2		7	4	2
3	6	1	3	6	1		3	6	1
5	0	2	5	0	2	_	5	0	2
	c_1			c_2				c_n	





- Central Idea
 - formulate segmentation as an **optimization** problem
 - minimize E(.) to find an optimal segmentation \hat{c}

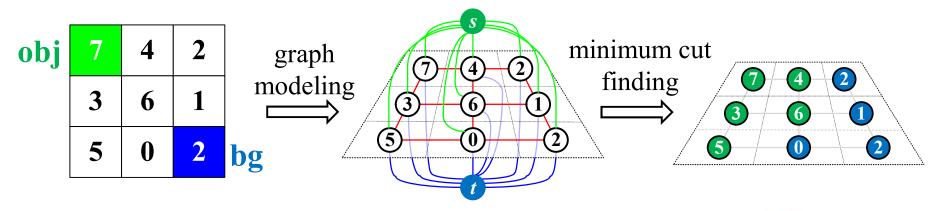
$$\hat{\boldsymbol{c}} = \operatorname{argmin}_{c} E(\boldsymbol{c})$$







- Central Idea
 - solve the problem via the **graph-cut** algorithm
 - model the optimization problem as a graph
 - determine the \hat{c} through minimum cut algorithm







- Graph Construction
 - use an undirected graph **G** = (**V**, **E**, **W**) to describe an image
 - $\mathbf{V} = \{ \boldsymbol{v} \}$: a set of vertices
 - $\mathbf{E} = \{e\}$: a set of edges $e = (v_i, v_j)$ defined under a neighborbooh system.
 - $\mathbf{W} = \{\mathbf{w}\}$: a set of weights assigned to the edges \mathbf{E}



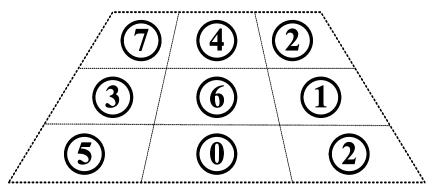


- Graph Construction: V (vertices) definition
 - $oldsymbol{\cdot}$ model each pixel as a pixel vertex $oldsymbol{v}$
 - add two terminal vertices source (s) and sink (t)

$$\mathbf{V} = \{\boldsymbol{v}\} \cup \{\boldsymbol{s}, \boldsymbol{t}\}$$



7	4	2
3	6	1
5	0	2



sink (background)





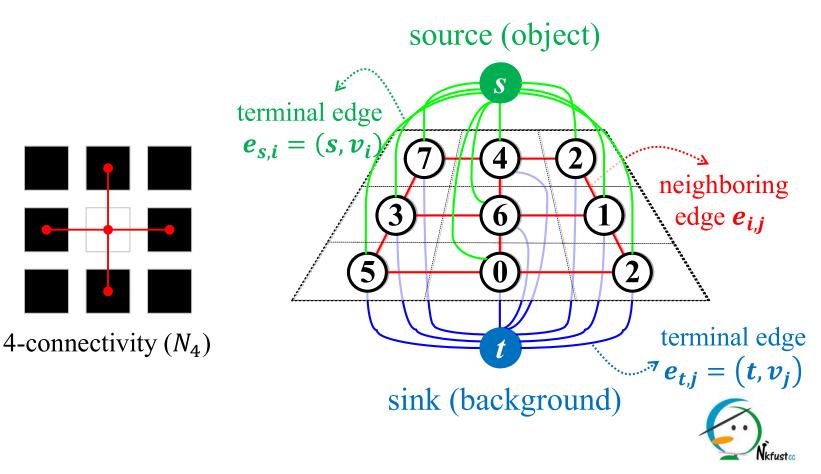
- Graph Construction: E (edges) definition
 - model spatial relation between v_i and v_j by a neighboring edge $e_{i,j} = (v_i, v_j)$
 - add two <u>terminal edges</u> $e_{s,i} = (s, v_i)$ and $e_{t,i} = (t, v_i)$ for every pixel vertex v_i

$$\mathbf{E} = \{\boldsymbol{e}_{i,j}\} \cup \{\boldsymbol{e}_{s,i}\} \cup \{\boldsymbol{e}_{t,j}\}$$



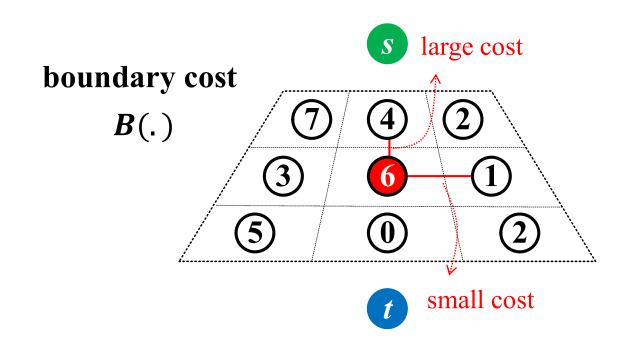


• Graph Construction: **E** (edges) definition





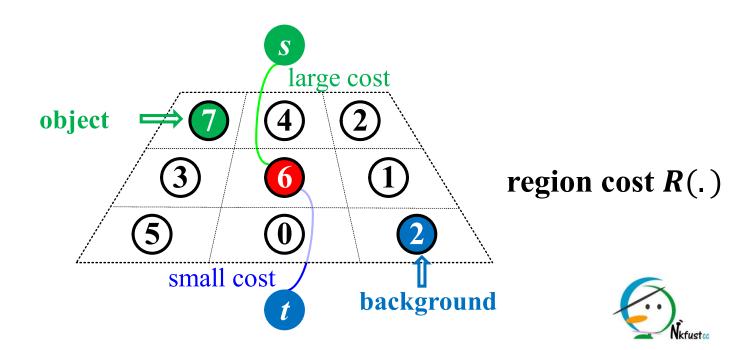
- Graph Construction: W (weights) definition
 - a weight assigned to an edge $e_{ij} = (v_i, v_j)$ is the penalty (cost) when $l(v_i) \neq l(v_i)$







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 - a weight assigned to an edge $e_{ij} = (v_i, v_j)$ is the penalty (cost) when $l(v_i) \neq l(v_i)$





- Cost Function Definition: $e_{i,j} = (v_i, v_j)$
 - $w(e_{i,i})$ is modeled using <u>ad-hoc</u> function

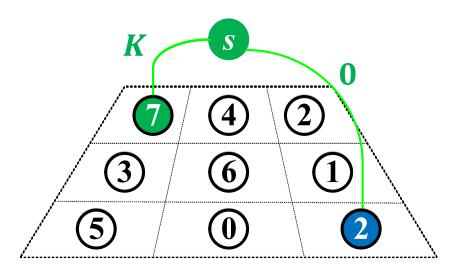
$$w(e_{i,j}) = exp\left(-\frac{(v_i)^2}{2 \times \sigma^2}\right)$$
 pixel intensity camera noise (2.0)

$$\begin{array}{c|c}
\hline
7 & 4 & 2 \\
\hline
3 & 6 & 1 \\
\hline
\hline
5 & 0 & 2
\end{array}
\qquad \exp\left(-\frac{(6-4)^2}{2\times 2^2}\right) = \exp(-0.5) = 0.60$$

$$\exp\left(-\frac{(6-1)^2}{2\times 2^2}\right) = \exp(-3.125) = 0.04$$



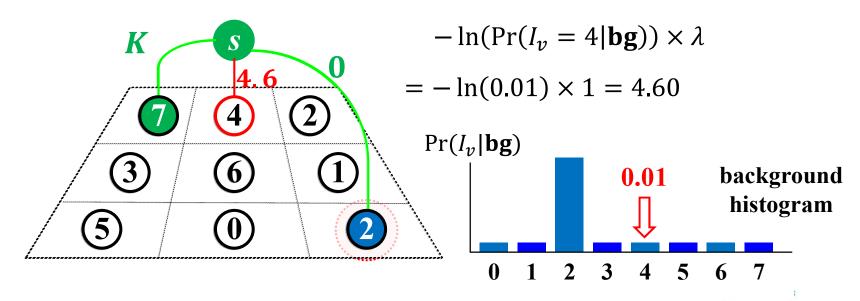
- Cost Function Definition: $e_{s,i} = (s, v_i)$
 - $w(e_{s,i})$ is the **penalty** (cost) when $l(v_i) \neq \underline{obj}$
 - v_i is obj vertex: $w(e_{s,i}) = K$ (large weight)
 - v_i is **bg** vertex: $w(e_{s,i}) = 0$





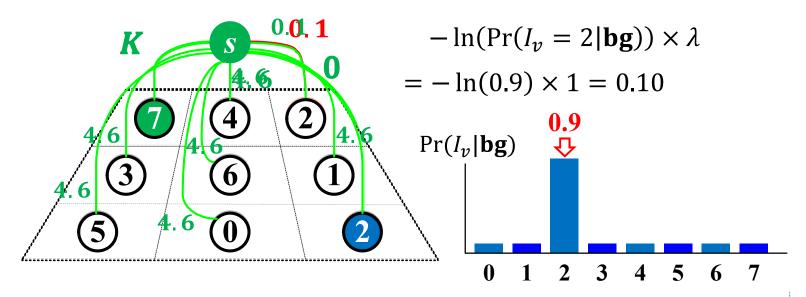


- Cost Function Definition: $e_{s,i} = (s, v_i)$
 - $w(e_{s,i})$ is the **penalty** (cost) when $l(v_i) \neq \underline{obj}$
 - v_i is UNK vertex: <u>negative log-likelihood</u> of intensity distribution of <u>background region</u>



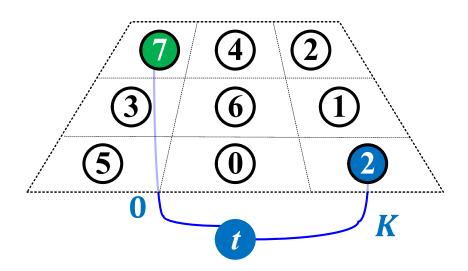


- Cost Function Definition: $e_{s,i} = (s, v_i)$
 - $w(e_{s,i})$ is the **penalty** (cost) when $l(v_i) \neq \underline{obj}$
 - *v* is **UNK** vertex: <u>negative log-likelihood</u> of intensity distribution of **background region**





- Cost Function Definition: $e_{t,i} = (t, v_i)$
 - $w(e_{t,i})$ is the penalty (cost) when $l(v_i) \neq \underline{bg}$
 - v_i is obj vertex: $w(e_{t,i}) = 0$
 - v_i is **bg** vertex: $w(e_{t,i}) = K$ (large weight)



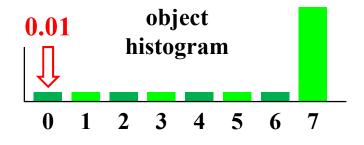


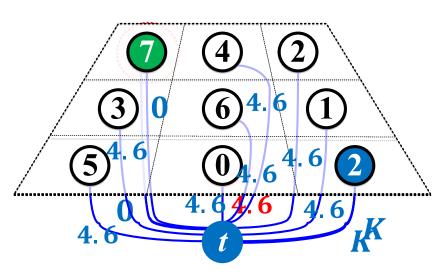


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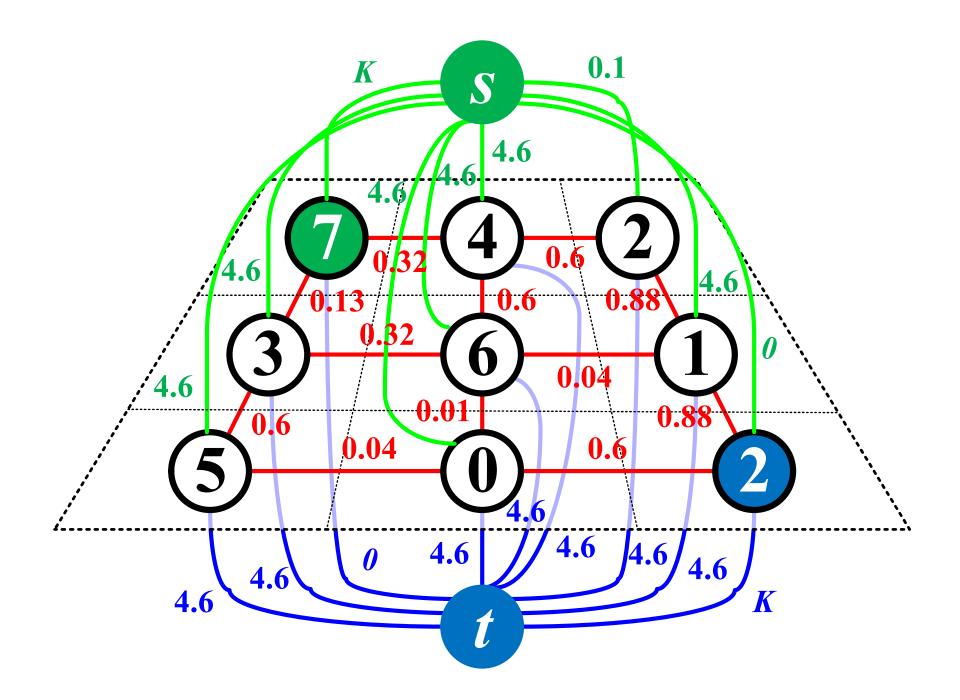
$$-\ln(\Pr(I_v = 0|\mathbf{obj})) \times \lambda$$

$$= -\ln(0.01) \times 1 = 4.6$$











- Cost Minimization
 - A segmentation is a partition (cut) c = (S, T) of vertices into two disjoint sets S and T
 - $S \cup T = V$ and $S \cap T = \emptyset$
 - $s \in S$ and $t \in T$
 - The cost of a partition (cut) c is the sum of the weights of edges between S and T

$$E(c) = \sum_{e=(v_i \in S, v_j \in T)} w(e)$$





- Cost Minimization
 - The optimal segmentation \hat{c} is the cut with the minimum cost (minimum cut).

$$\hat{\boldsymbol{c}} = \operatorname{argmin}_{c} E(\boldsymbol{c})$$

The minimum cut can be found via well-known maximum flow algorithm

Y. Boykov and V. Kolmogorov, "An Experimental Comparison of Min-Cut/Max-Flow Algorithms for Energy Minimization in Vision," *EMMCVPR*, 2001



