CS4670: Computer Vision

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Lecture 34: Segmentation

From Sandlot Science

Announcements

- In-class exam this Friday, December 3
- Review session in class on Wednesday

- Final projects:
  - **Slides due:** Sunday, December 12, 7:59pm
  - **Final presentation:** Monday, December 13, 9-11:30am
  - **Webpage / code:** Tuesday, December 14, 11:59pm

The ultimate camera

Infinite resolution

Infinite zoom control

Desired object(s) are in focus

No noise

No motion blur

Infinite dynamic range (can see dark and bright things)

...

Creating the ultimate camera

The “analog” camera has changed very little in >100 yrs

- we’re unlikely to get there following this path

More promising is to combine “analog” optics with computational techniques

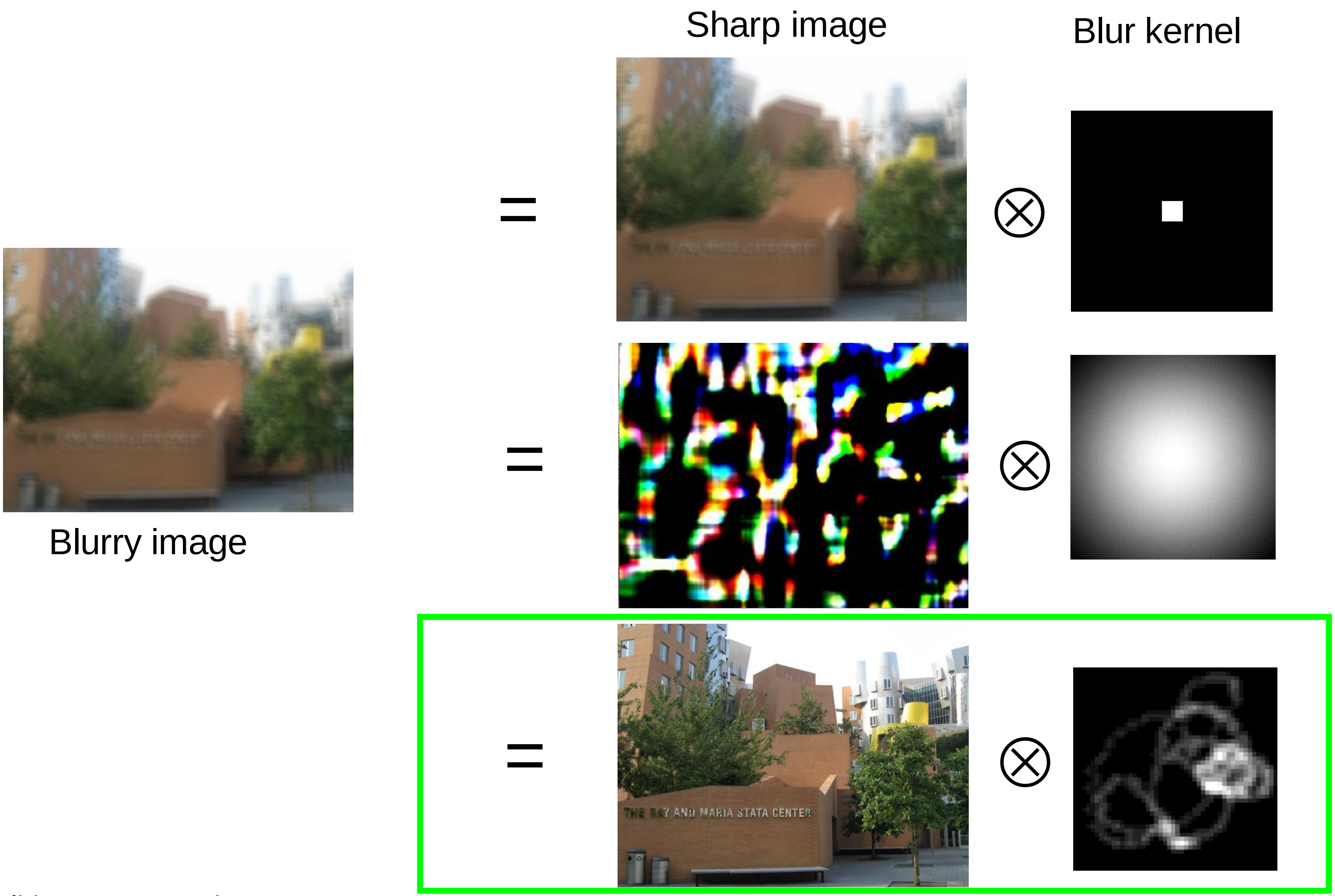
- “Computational cameras” or “Computational photography”

This lecture will survey techniques for producing higher quality images by combining optics and computation

Common themes:

- take multiple photos
- modify the camera

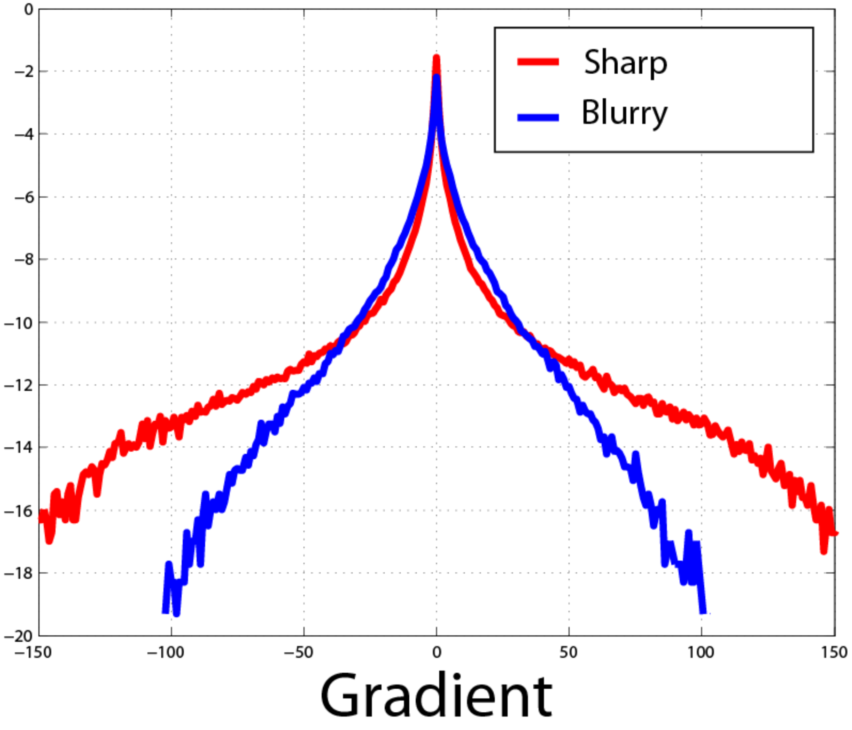
Motion Blur



Slide courtesy Rob Fergus

Blurry images have different statistics

Histogram of image gradients



Three sources of information

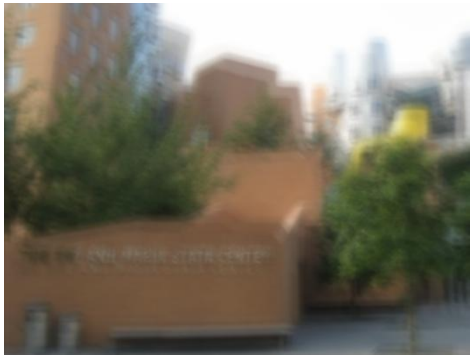
1. Reconstruction constraint:

Estimated sharp image

$\otimes$

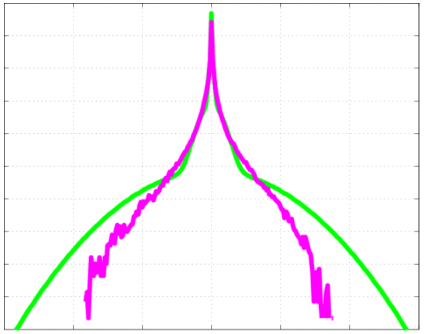
Estimated blur kernel

=



Input blurry image

2. Image prior:



Distribution of gradients

3. Blur prior:

Positive & Sparse

Results [Fergus, *et al*, 2006]

Original

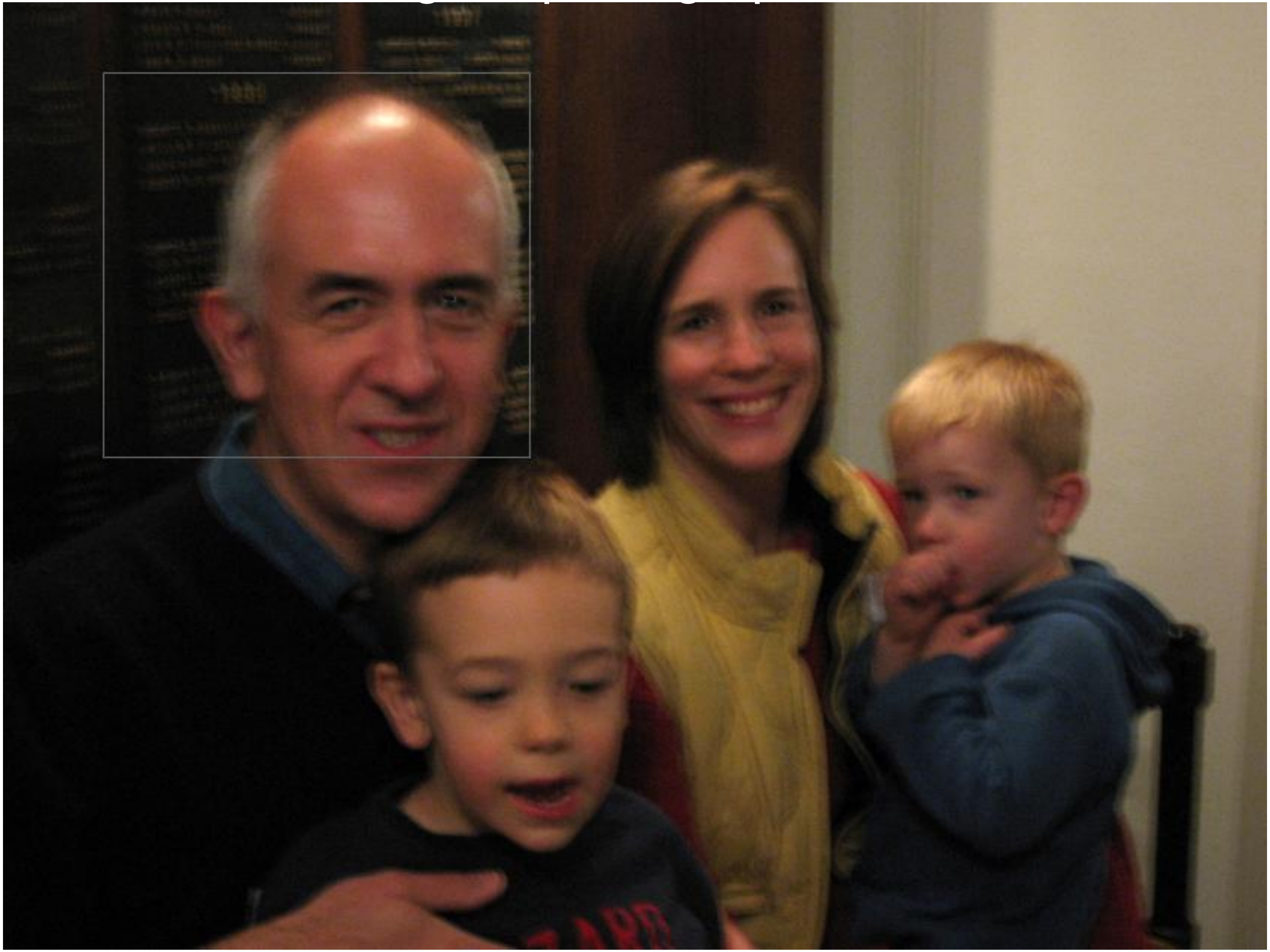
Algorithm of Fergus

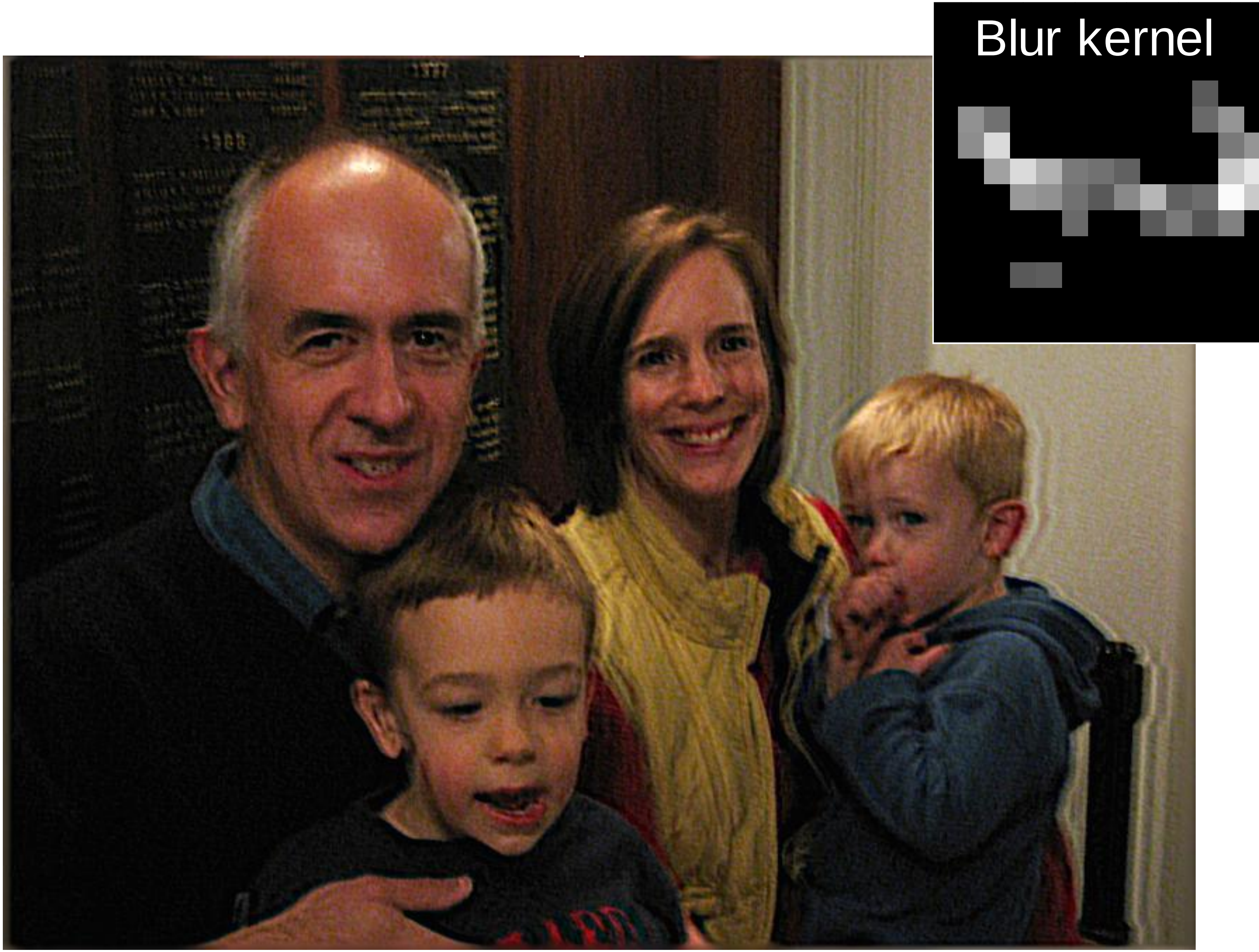
Close-up

Original

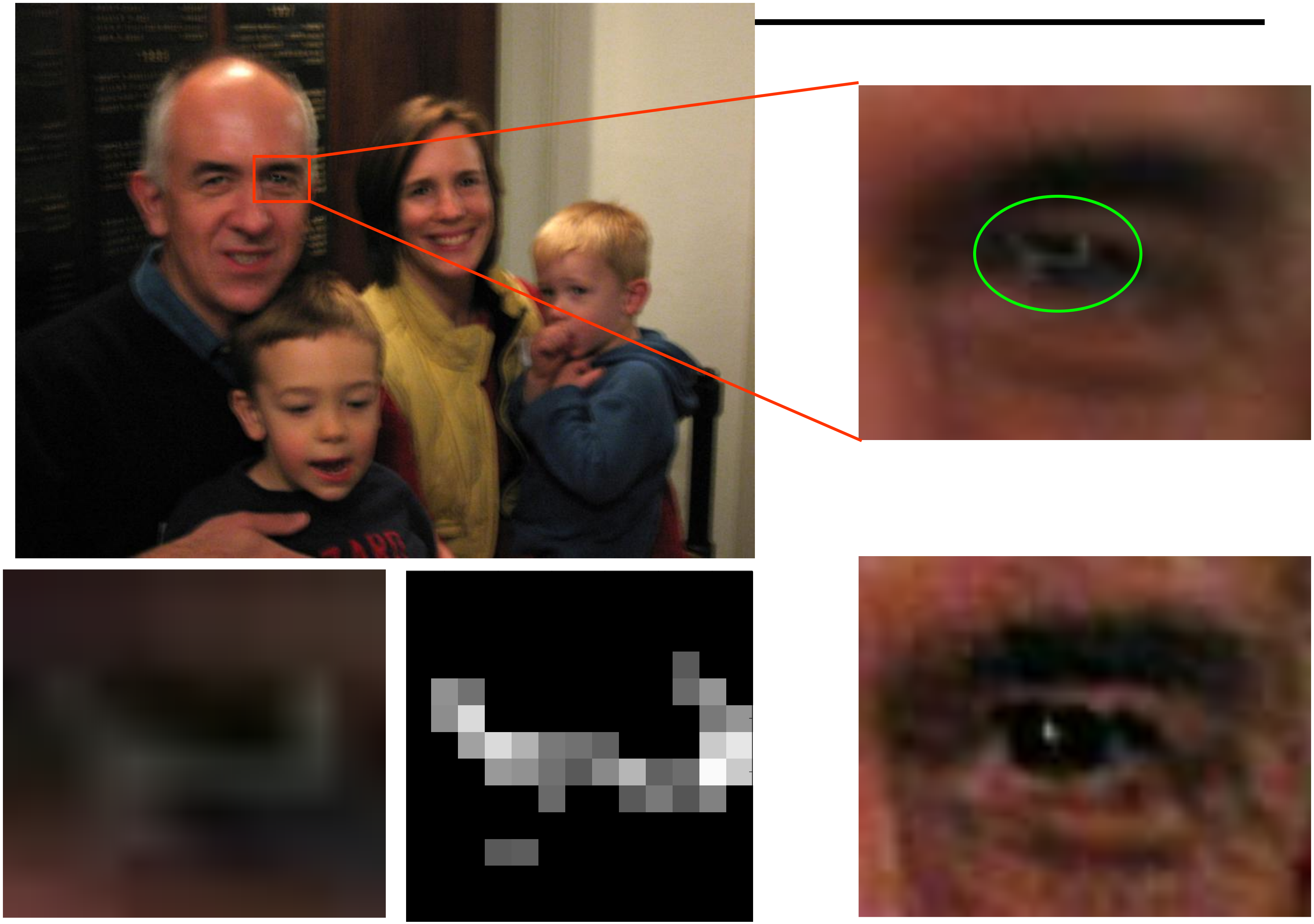
Naïve Sharpening

Algorithm of Fergus





Blur kernel



All-in-focus

If you only want to produce an all-focus image, there are simpler alternatives

E.g.,

- Wavefront coding [Dowsky 1995]
- Coded aperture [Levin SIGGRAPH 2007], [Raskar SIGGRAPH 2007]
  - can also produce change in focus (ala Ng’s light field camera)

Build your own coded aperture

Levin et al., SIGGRAPH 2007

Voila!

Levin et al., SIGGRAPH 2007

Input

All-focused (deconvolved)

Close-up

Original image

All-focus image

Questions?

Stereo as a minimization problem

$$E(d) = E_d(d) + \lambda E_s(d)$$

- The 2D problem has many local minima
  - Gradient descent doesn't work well
  - Simulated annealing works a little better
- And a large search space
  - *n* x *m* image w/ *k* disparities has k^{nm} possible solutions
  - Finding the global minimum is NP-hard

- Good approximations exist…

Related problem: binary segmentation

- Suppose we want to segment an image into foreground and background

Related problem: binary segmentation

- Suppose we want to segment an image into foreground and background

User sketches out a few strokes on foreground and background…

How do we classify the rest of the pixels?

Binary segmentation as energy minimization

- Define a labeling *L* as an assignment of each pixel with a 0-1 label (background or foreground)

- Problem statement: find the labeling *L* that minimizes

$$E(L) = \underbrace{E_d(L)}_{\text{match cost}} + \lambda \underbrace{E_s(L)}_{\text{smoothness cost}}$$

("how similar is each labeled pixel to the foreground / background?")

$$E(L) = E_d(L) + \lambda E_s(L)$$

$\tilde{L}(x,y)$

$$E_d(L) = \sum_{(x,y)} C(x,y,L(x,y))$$

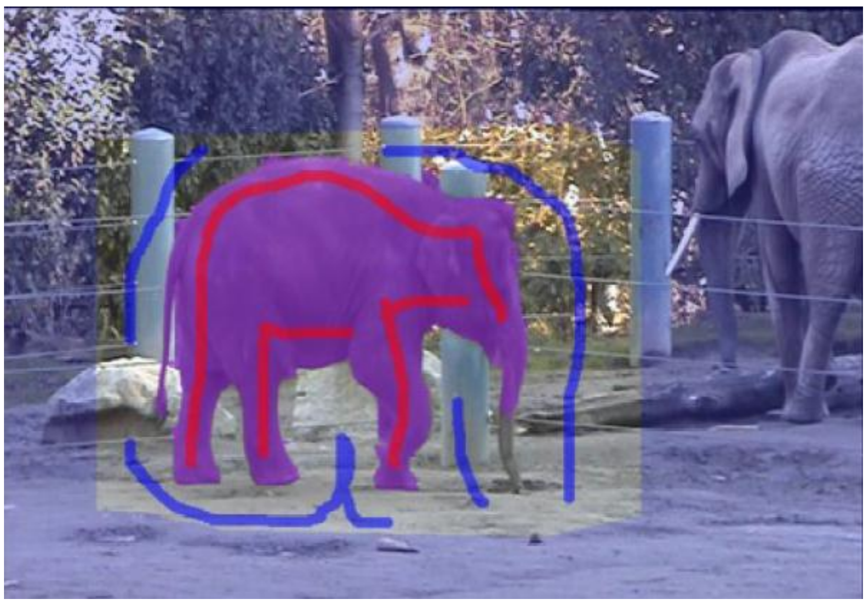
$$C(x,y,L(x,y)) = \begin{cases} \infty & \text{if } L(x,y) \neq \tilde{L}(x,y) \\ C'(x,y,L(x,y)) & \text{otherwise} \end{cases}$$

$C'(x,y,0)$: "distance" from pixel to background pixels

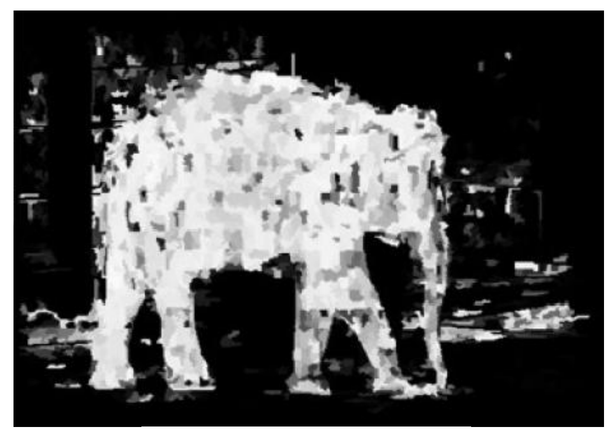
$C'(x,y,1)$: "distance" from pixel to foreground pixels

usually computed by creating a color model from user-labeled pixels

$$E(L) = E_d(L) + \lambda E_s(L)$$



$C'(x, y, 0)$



$C'(x, y, 1)$

$$E(L) = E_d(L) + \lambda E_s(L)$$

- Neighboring pixels should generally have the same labels
  - Unless the pixels have very different intensities

w_{pq} = 10.0

w_{pq} = 0.1

$$E_s(L) = \sum_{\text{neighbors } (p,q)} w_{pq} |L(p) - L(q)|$$

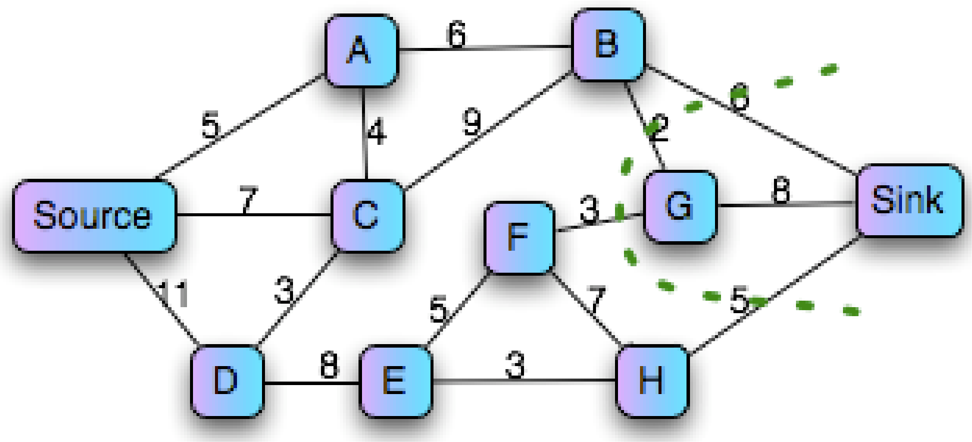
w_{pq} : similarity in intensity of *p* and *q*

Binary segmentation as energy minimization

$$E(L) = E_d(L) + \lambda E_s(L)$$

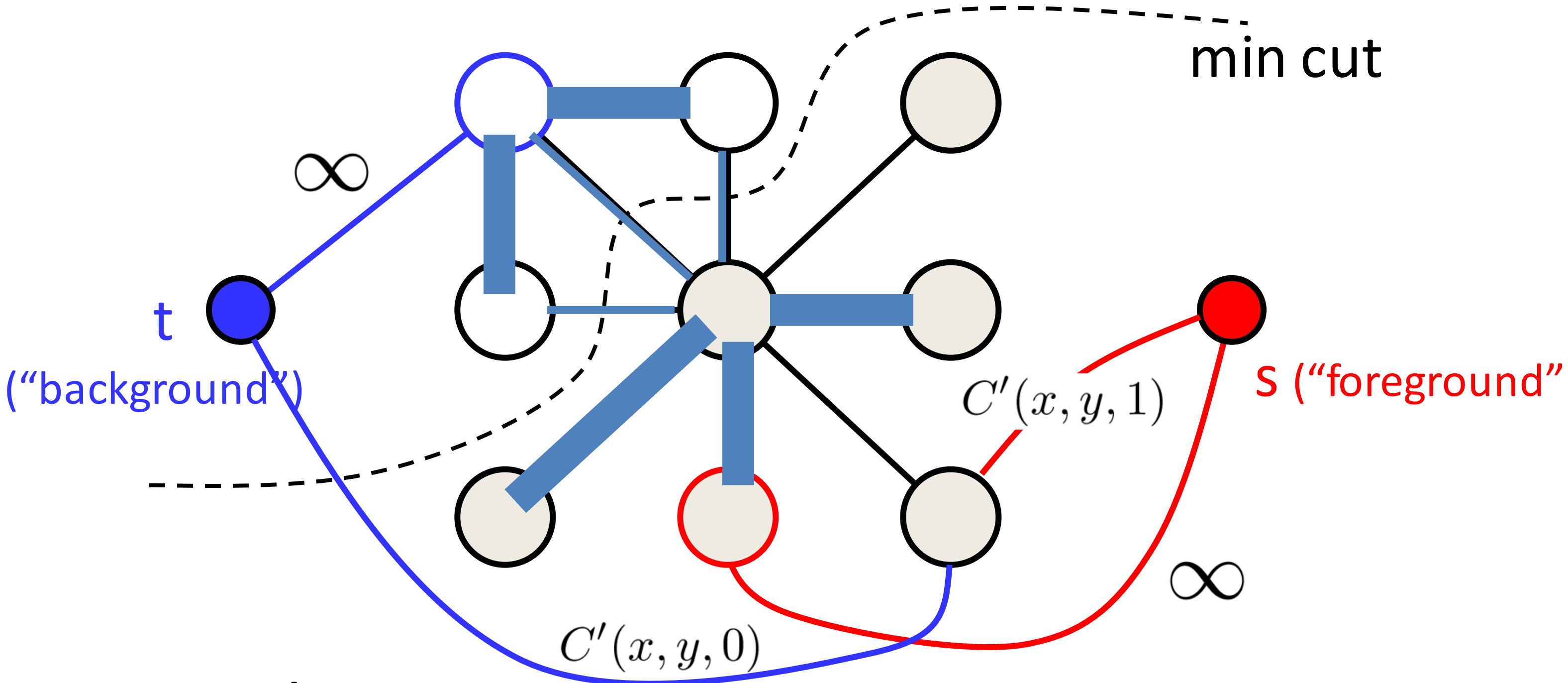
- For this problem, we can easily find the global minimum!
- Use max flow / min cut algorithm

Graph min cut problem



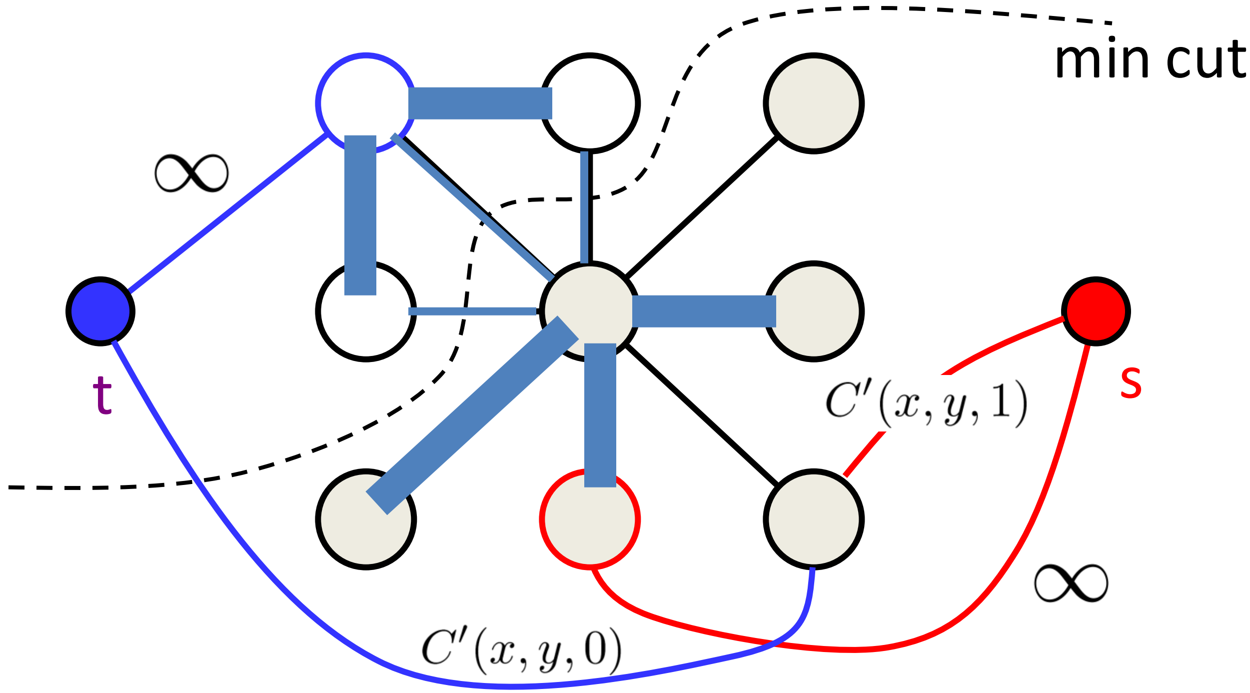
- Given a weighted graph *G* with source and sink nodes (*s* and *t*), partition the nodes into two sets, *S* and *T* such that the sum of edge weights spanning the partition is minimized
  - and $s \in S$ and $t \in T$

Segmentation by min cut



- Graph
  - node for each pixel, link between adjacent pixels
  - specify a few pixels as foreground and background
    - create an infinite cost link from each bg pixel to the *t* node
    - create an infinite cost link from each fg pixel to the *s* node
    - create finite cost links from *s* and *t* to each other node
  - compute min cut that separates s from t
    - The min-cut max-flow theorem [Ford and Fulkerson 1956]

Segmentation by min cut



- The partitions *S* and *T* formed by the min cut give the optimal foreground and background segmentation
- I.e., the resulting labels minimize

$$E(d) = E_d(d) + \lambda E_s(d)$$

GrabCut

Grabcut [Rother et al., SIGGRAPH 2004]

Is user-input required?

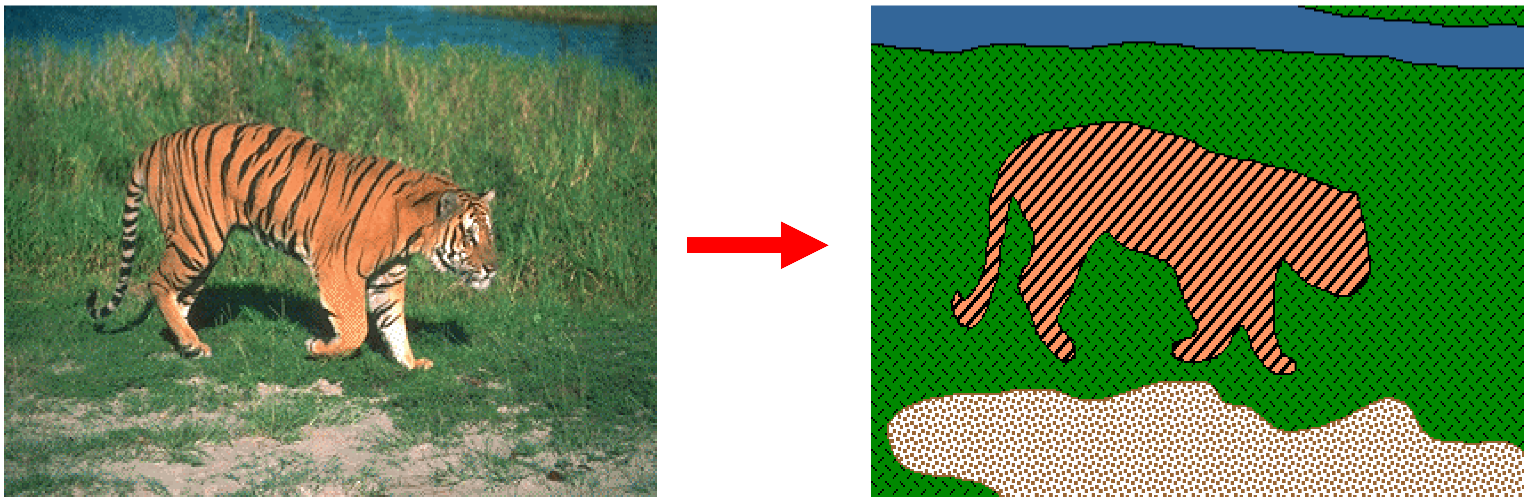
Our visual system is proof that automatic methods are possible

- classical image segmentation methods are automatic

Argument for user-directed methods?

- only user knows desired scale/object of interest

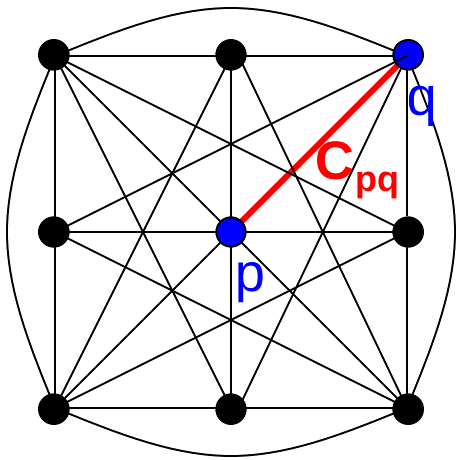
From images to objects

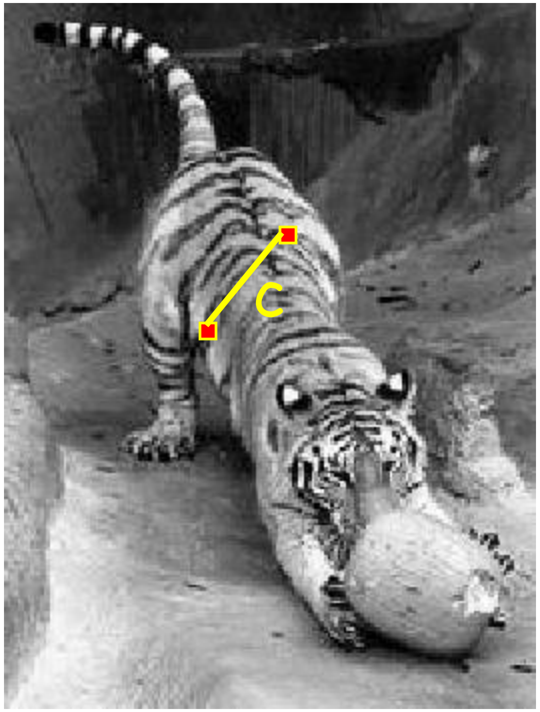


What defines an object?

- Subjective problem, but has been well-studied
- Gestalt Laws seek to formalize this
  - proximity, similarity, continuation, closure, common fate
  - see notes by Steve Joordens, U. Toronto

Automatic graph cut [Shi & Malik]

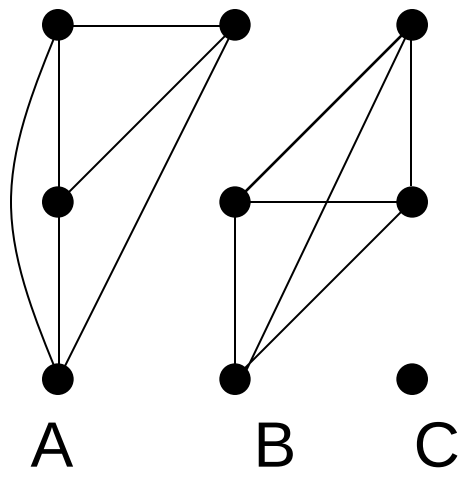




Fully-connected graph

- node for every pixel
- link between *every* pair of pixels, **p**,**q**
- cost $\mathbf{c_{pq}}$ for each link
  - $\mathbf{c_{pq}}$ measures *similarity*
    - » similarity is *inversely proportional* to difference in color and position

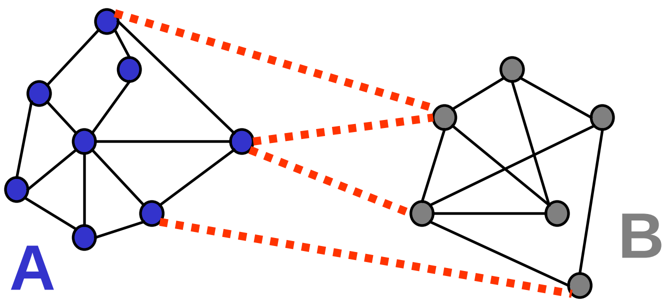
Segmentation by Graph Cuts



Break Graph into Segments

- Delete links that cross between segments
- Easiest to break links that have low cost (similarity)
  - similar pixels should be in the same segments
  - dissimilar pixels should be in different segments

Cuts in a graph



Link Cut

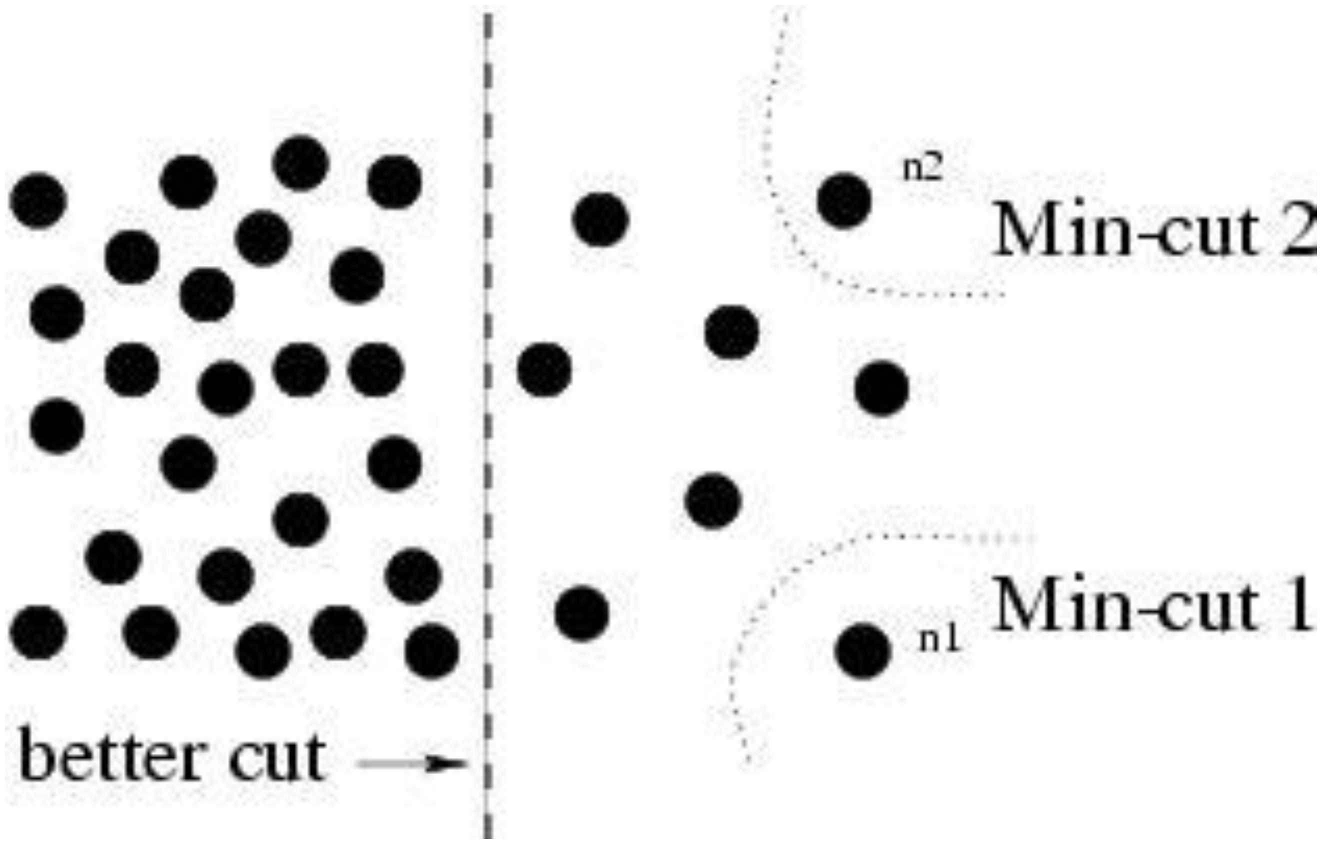
- set of links whose removal makes a graph disconnected
- cost of a cut:

$$cut(A,B) = \sum_{p \in A, q \in B} c_{p,q}$$

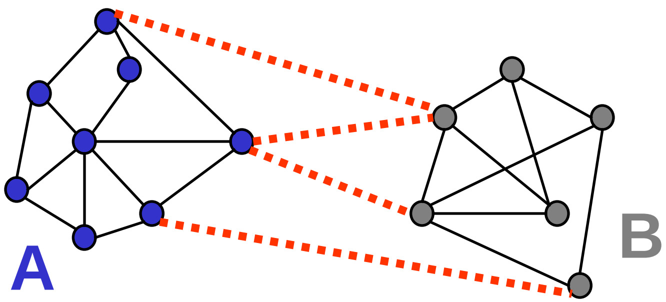
Find minimum cut

- gives you a segmentation

But min cut is not always the best cut...



Cuts in a graph



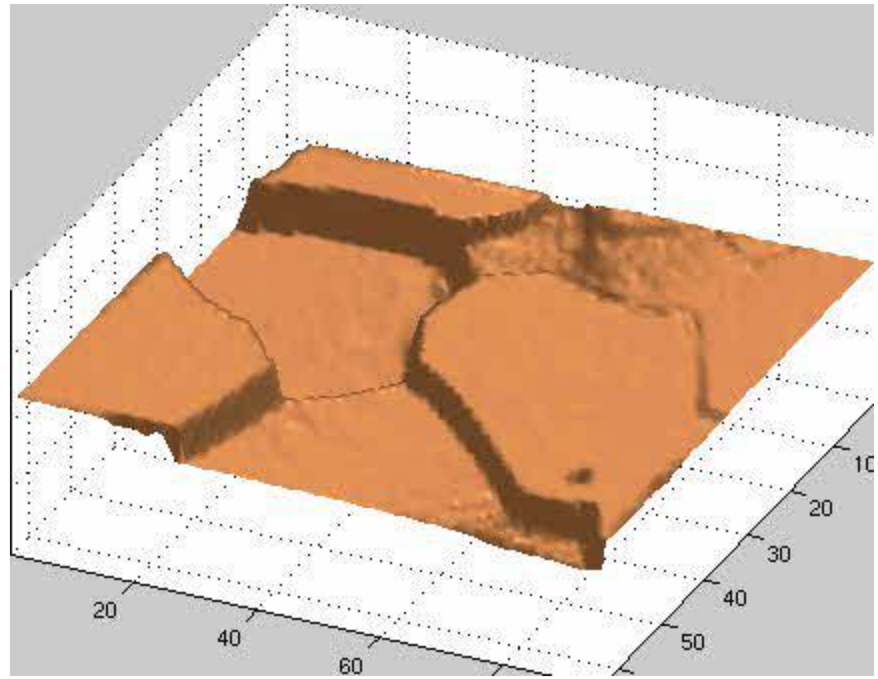
Normalized Cut

- a cut penalizes large segments
- fix by normalizing for size of segments

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

- volume(A) = sum of costs of all edges that touch A

Interpretation as a Dynamical System



Treat the links as springs and shake the system

- elasticity proportional to cost
- vibration "modes" correspond to segments
  - can compute these by solving an eigenvector problem
  - http://www.cis.upenn.edu/~jshi/papers/pami_ncut.pdf

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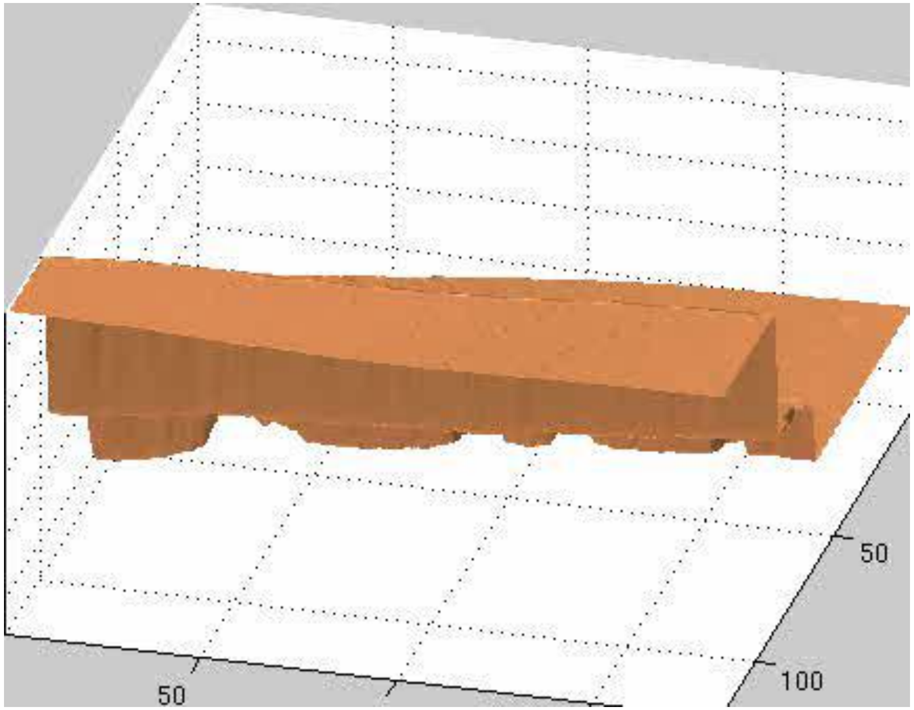

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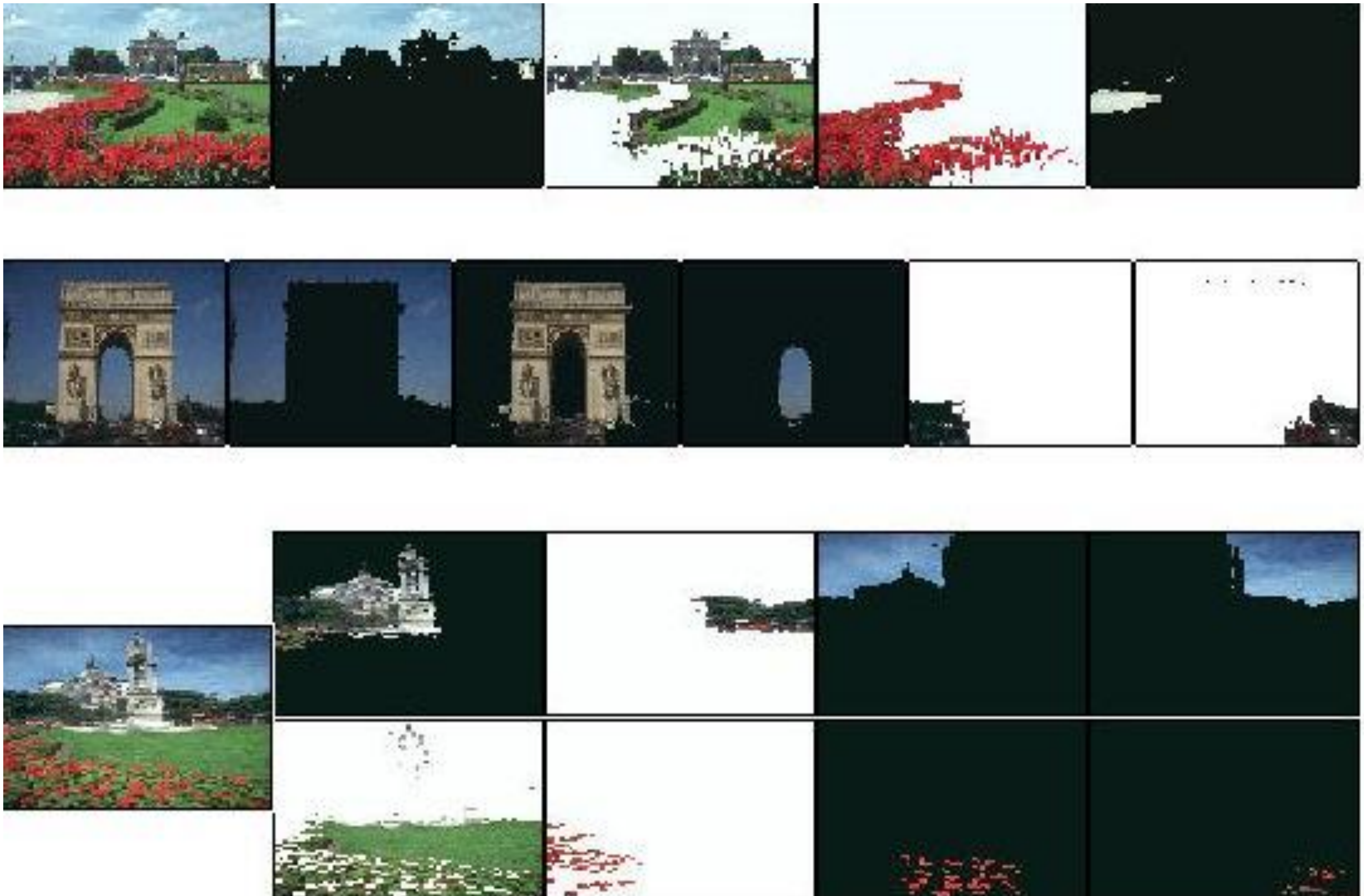
Color Image Segmentation



Extension to Soft Segmentation

- Each pixel is convex combination of segments. [Levin et al. 2006]
  - compute mattes by solving eigenvector problem

Questions?