

Lecture : Segmentation

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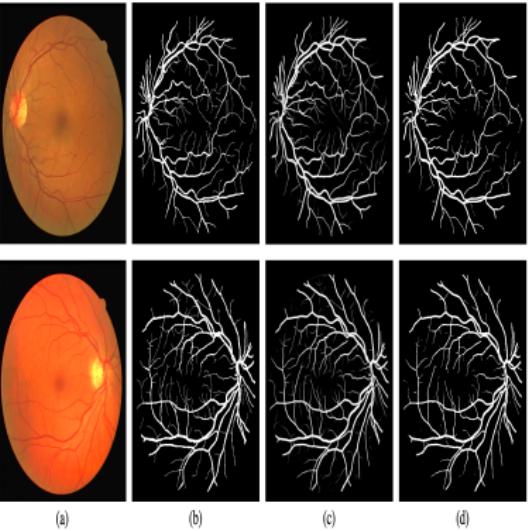
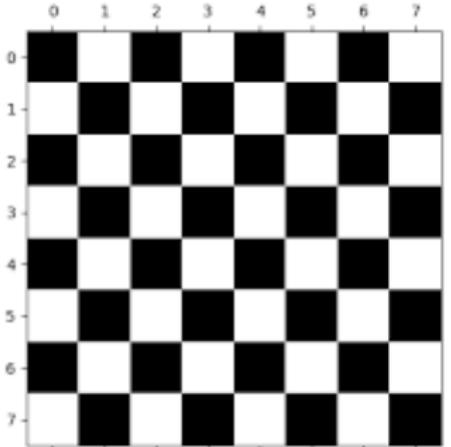


- 1 What is segmentation
- 2 A simple algorithm to detect characters in number plate
- 3 Network Flow
 - Ford-Fulkerson algorithm to find Max Flow
 - Max-Flow Min-Cut Theorem
 - Image Reconstruction using Max-Flow
 - Image Segmentation using Min-Cut
- 4 Mean shift segmentation algorithm
- 5 Segmentation using K-Means Clustering

Definition of segmentation

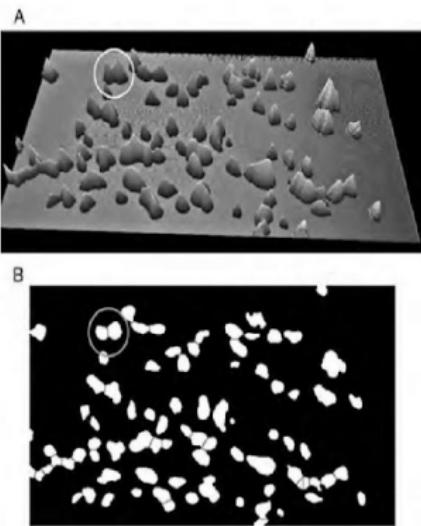
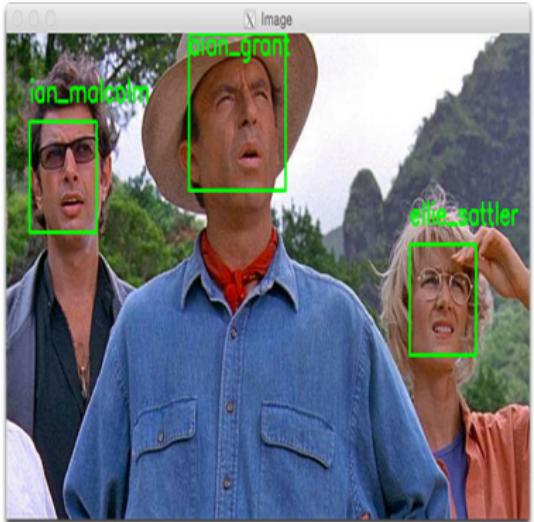
- ▶ Let I be the image, R be the set of pixel locations in I
- ▶ The segmentation of image I is the partition of R into (R_1, R_2, \dots, R_k) with the following conditions
 - $R = \bigcup_{i=1}^k R_i$
 - $R_i \cap R_j = \emptyset$ for all $i \neq j$
 - For each i , R_i is connected
 - For each i , $Q(R_i)$ is true, where Q is some predicate on similarity
 - For each i, j , If $Q(R_i) = \text{True}$, and $Q(R_j)$ is true, and also R_i and R_j are adjacent, then $Q(R_i \cup R_j)$ is false

Examples of segmentation



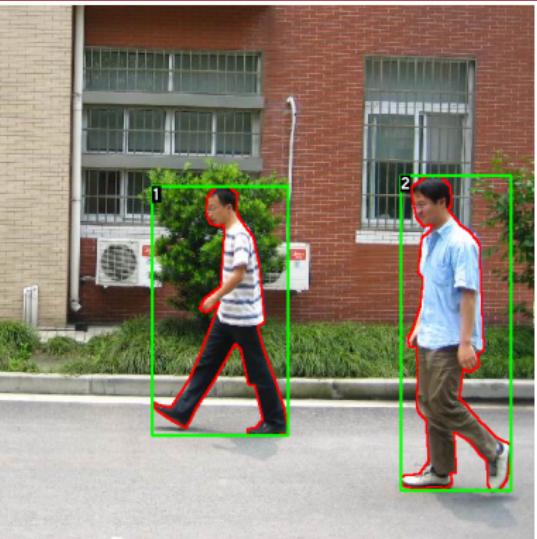
- ▶ In Chessboard image, each square(black/white) is a segment
- ▶ For the retina, white pixels constitute a region, black pixels constitute another region

Examples of segmentation (cont.)



- ▶ Face detection is a segmentation problem
- ▶ Face recognition is a classification problem

Examples of segmentation (cont.)



The semantics of segments are problem dependent

- ▶ In the same input image, whole face can be a single segment or each part may be a single segment
- ▶ In the same input image, whole person may a single segment or face alone may be a single segment

Algorithm to segment the characters in the number plate

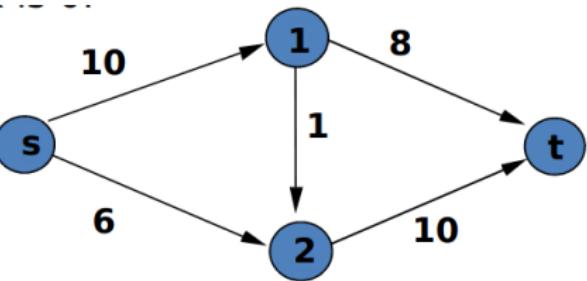
- ▶ Convert RGB to gray scale image
- ▶ Binarize the gray scale image using thresholding
- ▶ Find connected component(CC), and declare each CC as a segment



Definition of flow network:

Flow network is a directed weighted graph $G=(V,E,c)$ such that

- ▶ Weight(capacity) $c(u, v) \geq 0$.
- ▶ Two distinguished vertices exist in G namely :
 - Source (denoted by s) : In-degree of this vertex is 0.
 - Sink (denoted by t) : Out-degree of this vertex is 0.



Network Flow (cont.)

Definition of flow

Flow in a network is an integer-valued function f defined on the edges of G satisfying:

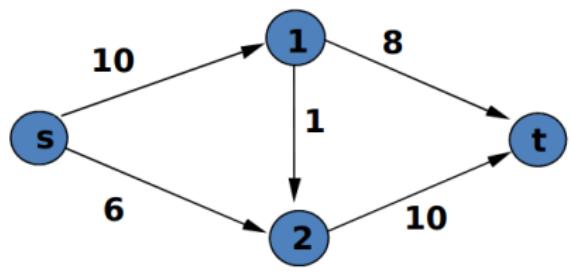
- ▶ $0 \leq f(u, v)$, for every edge (u, v) in E .
- ▶ Capacity constraint: $\forall u, v \in V, f(u, v) \leq c(u, v)$
- ▶ Skew symmetry: $\forall u, v \in V, f(u, v) = -f(v, u)$
- ▶ Flow conservation: For each vertex v other than s and t ,
 $\text{inflow}(v) = \text{outflow}(v)$

Skew symmetry condition implies that $f(u, u) = 0$

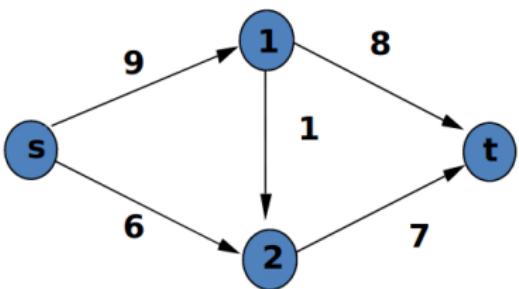
Network Flow (cont.)



Flow Network:



Flow:





Definition of Max Flow

- ▶ The value of a flow is given by :

$$|f| = \sum_{v \in V} f(s, v) = \sum_{v \in V} f(v, t)$$

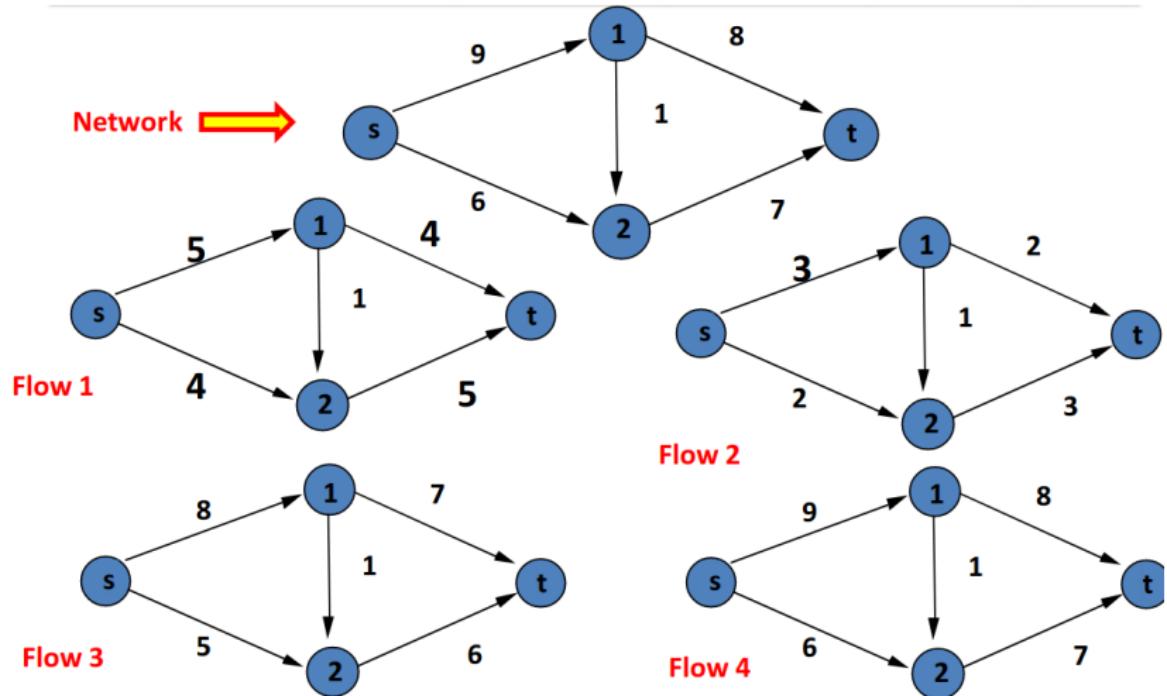
- ▶ Definition of max flow:

- Given a graph $G=(V, E)$ with capacities on edges, find flow f , such that $|f|$ is maximum.

Network Flow (cont.)



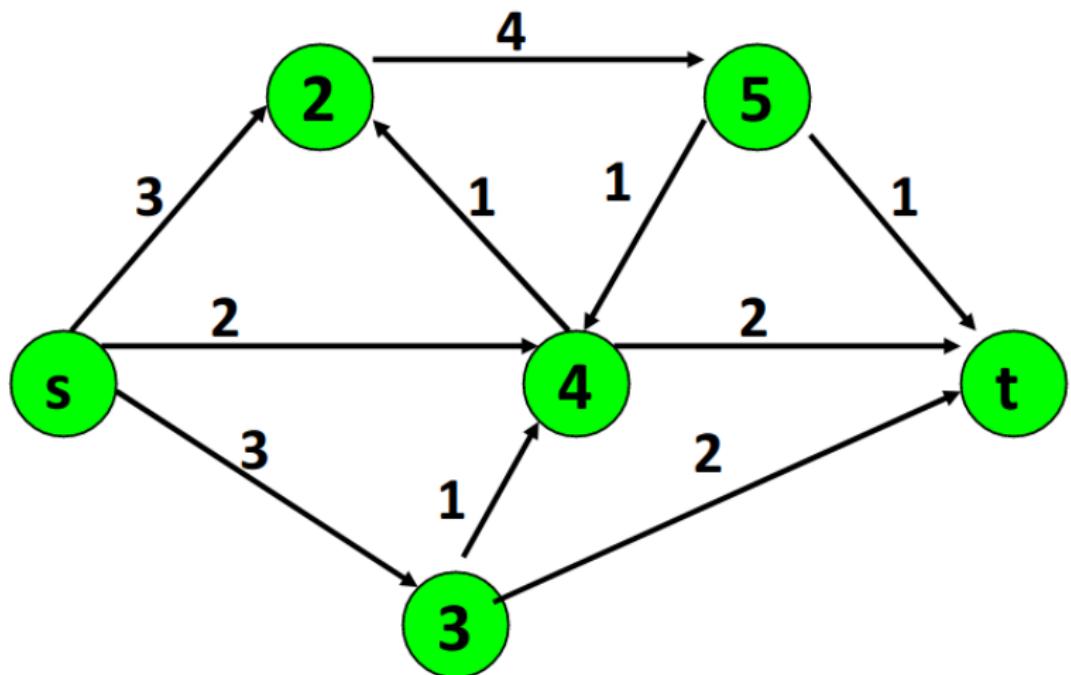
Example of a Max Flow



Ford-Fulkerson algorithm to find Max Flow



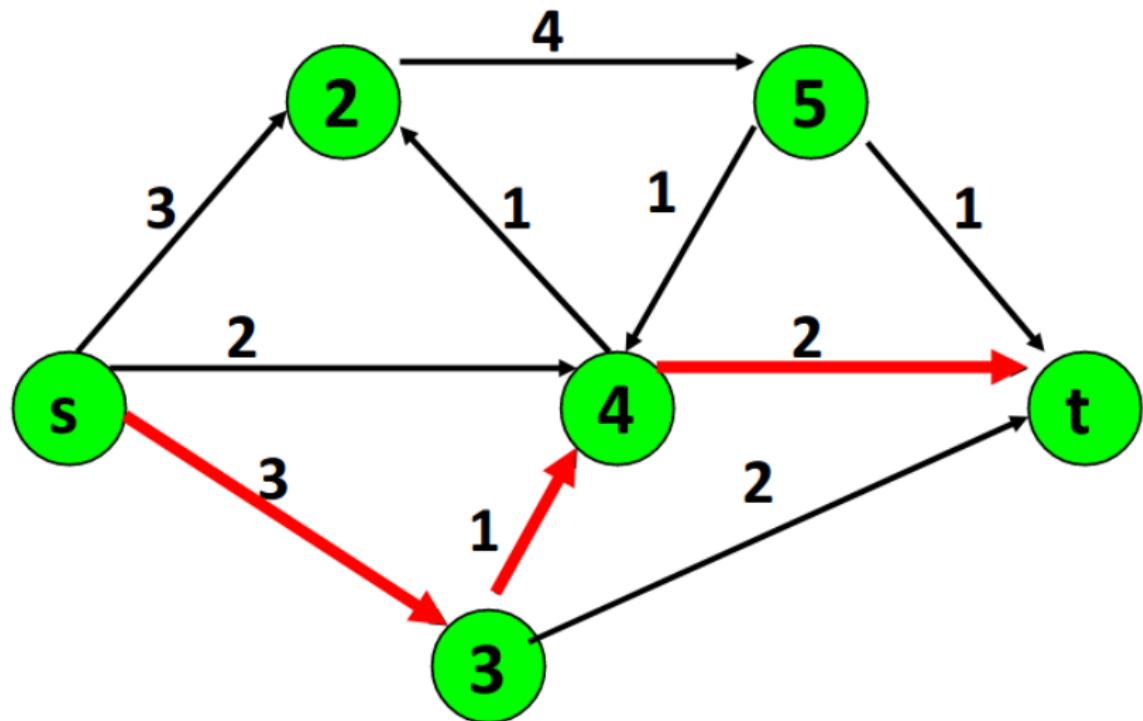
Flow network



Ford-Fulkerson algorithm to find Max Flow (cont.)



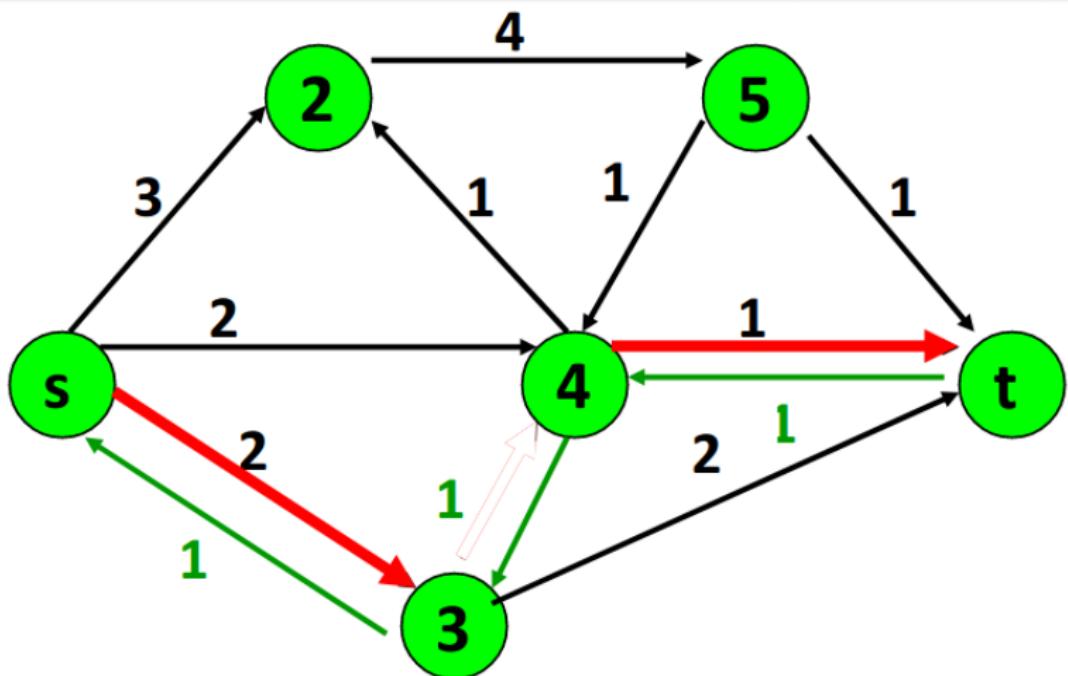
Find any s-t path in $G(x)$



Ford-Fulkerson algorithm to find Max Flow (cont.)



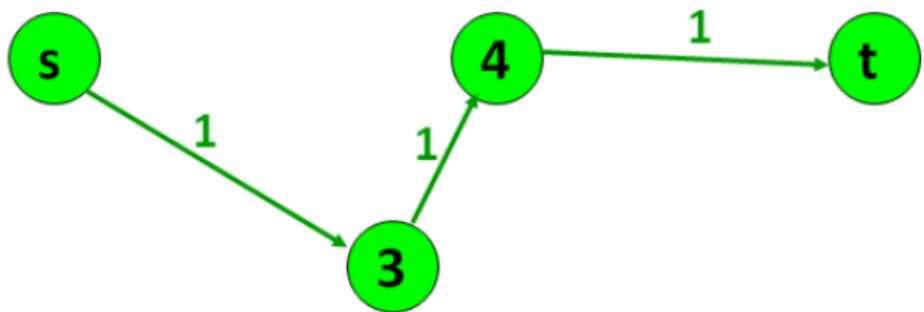
Residual graph:



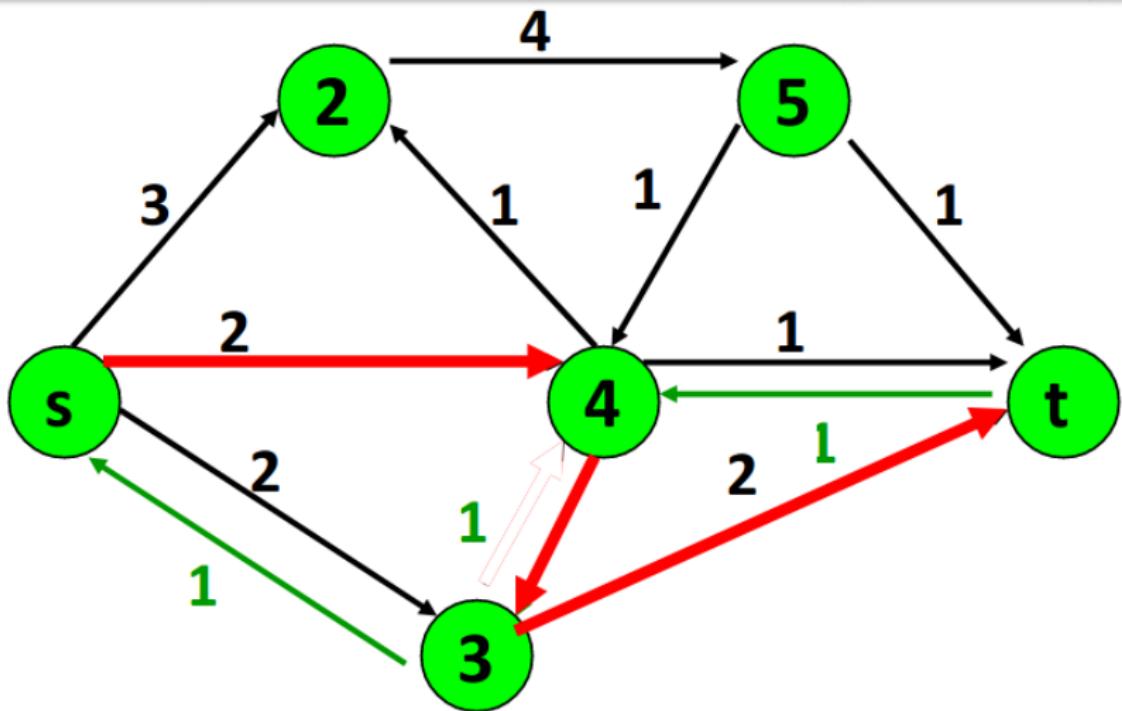
Ford-Fulkerson algorithm to find Max Flow (cont.)



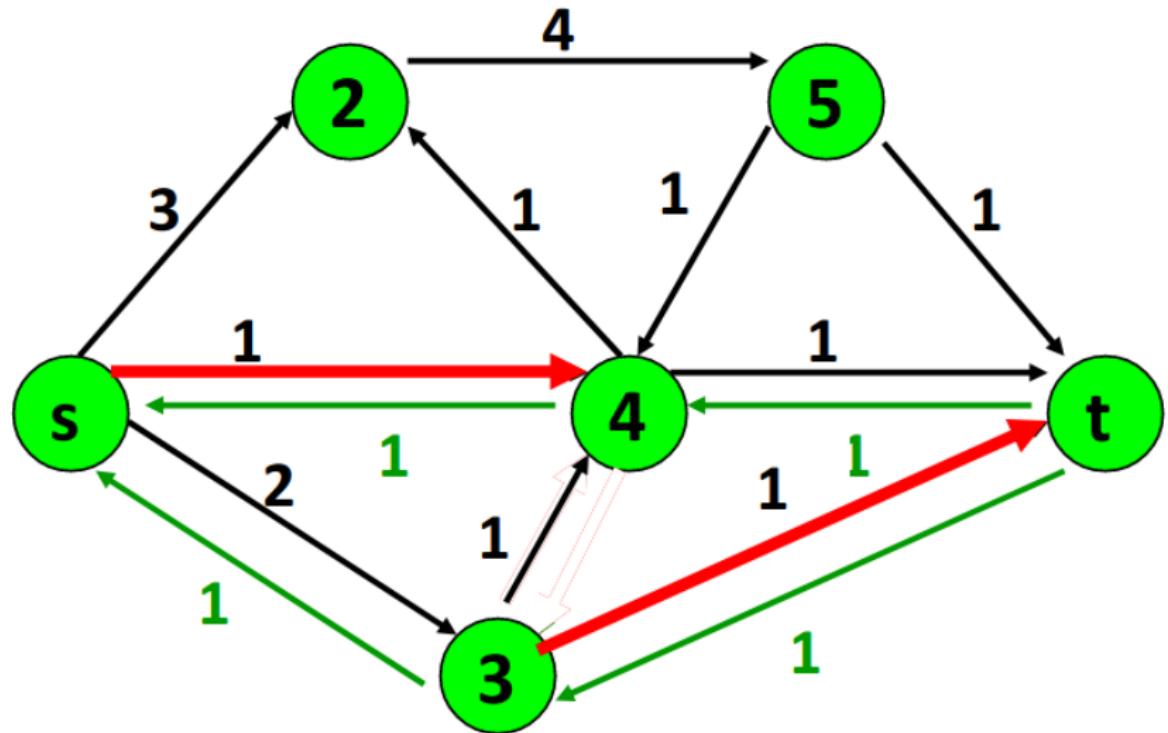
Flow:



Ford-Fulkerson algorithm to find Max Flow (cont.)



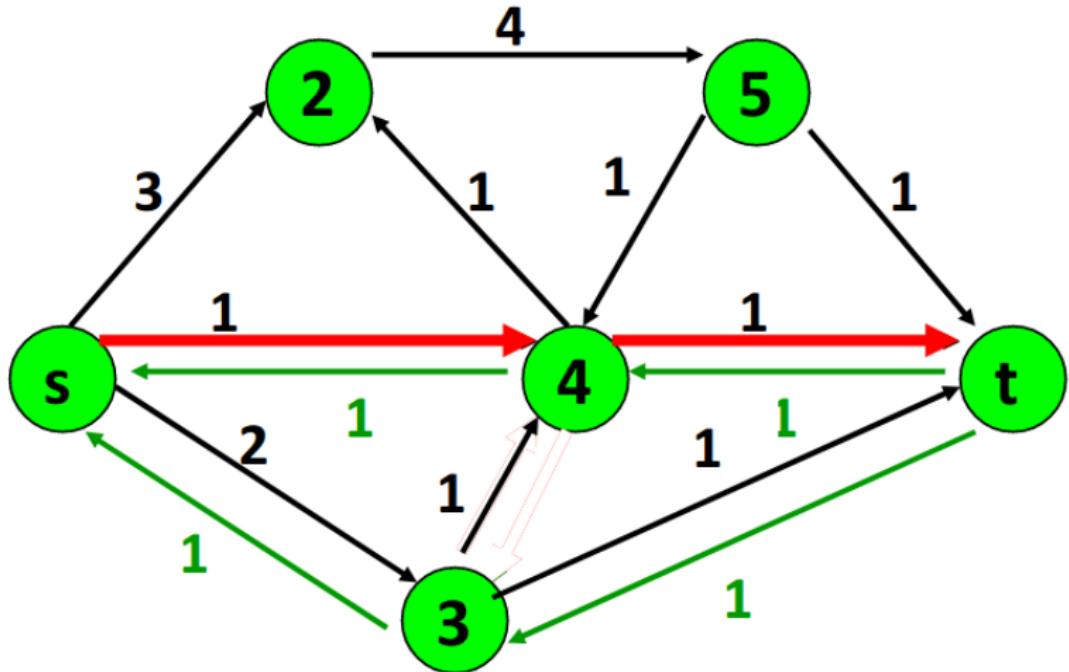
Ford-Fulkerson algorithm to find Max Flow (cont.)



Ford-Fulkerson algorithm to find Max Flow (cont.)



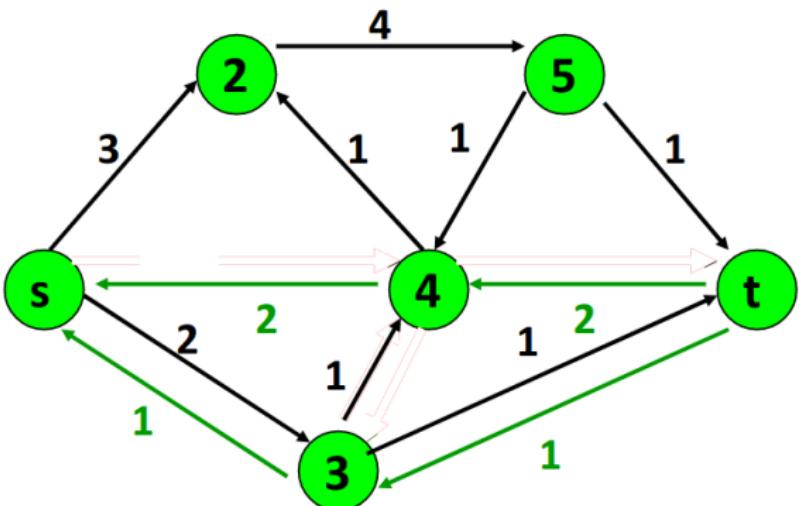
Find any s-t path



Ford-Fulkerson algorithm to find Max Flow (cont.)



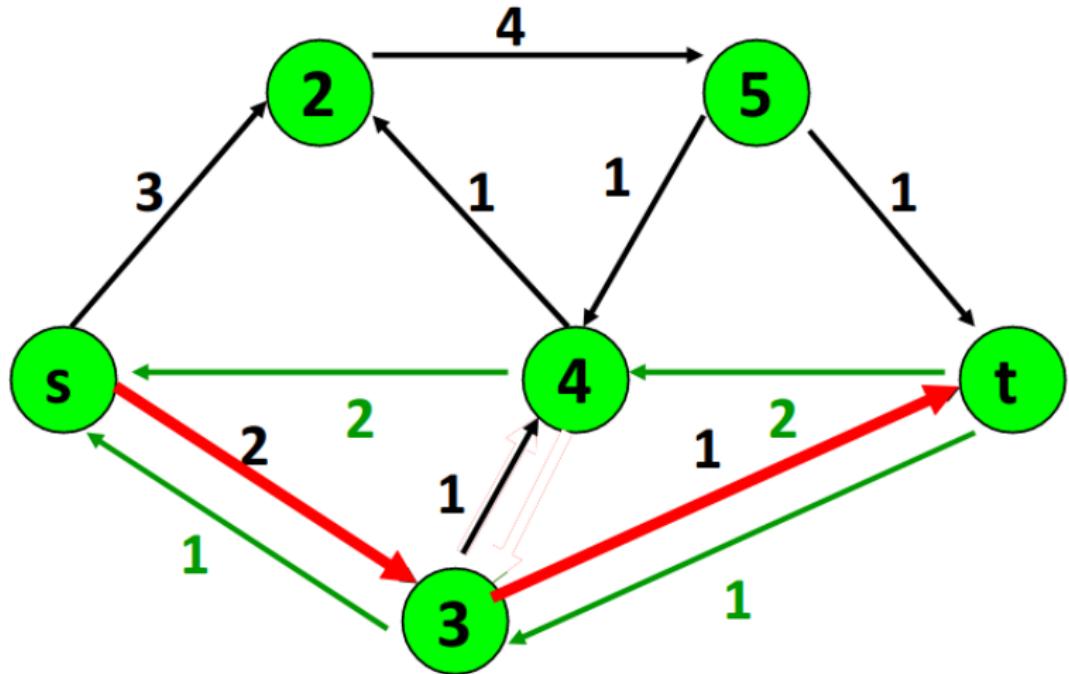
- ▶ Determine the capacity Δ of the path
- ▶ Send Δ units of flow in the path
- ▶ Update residual capacities



Ford-Fulkerson algorithm to find Max Flow (cont.)



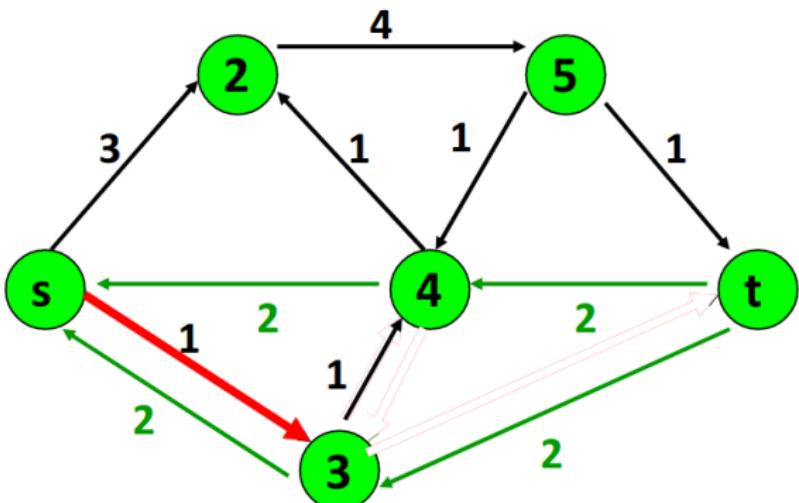
Find any s-t path



Ford-Fulkerson algorithm to find Max Flow (cont.)



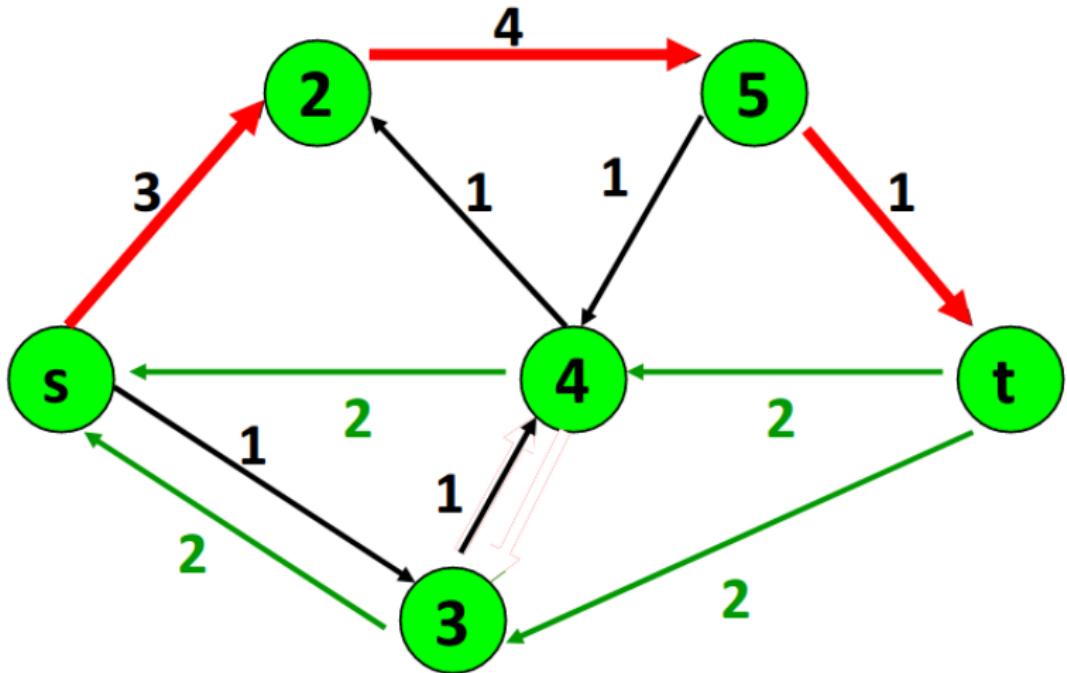
- ▶ Determine the capacity Δ of the path
- ▶ Send Δ units of flow in the path
- ▶ Update residual capacities



Ford-Fulkerson algorithm to find Max Flow (cont.)



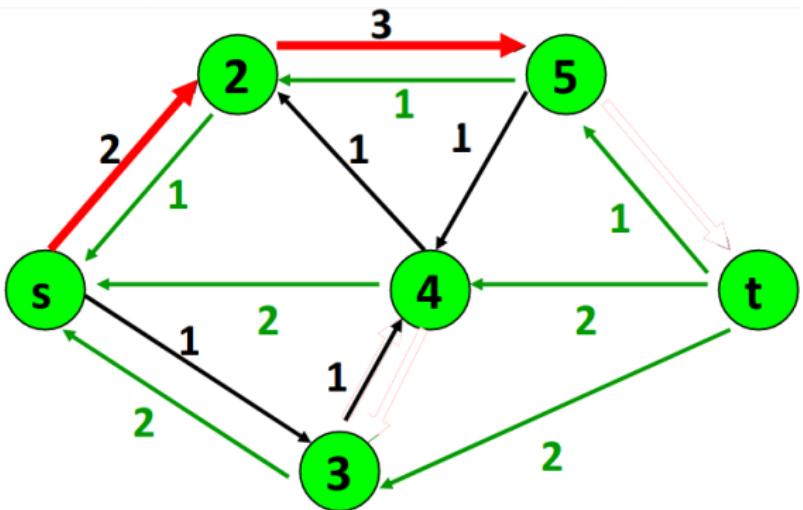
Find any s-t path



Ford-Fulkerson algorithm to find Max Flow (cont.)



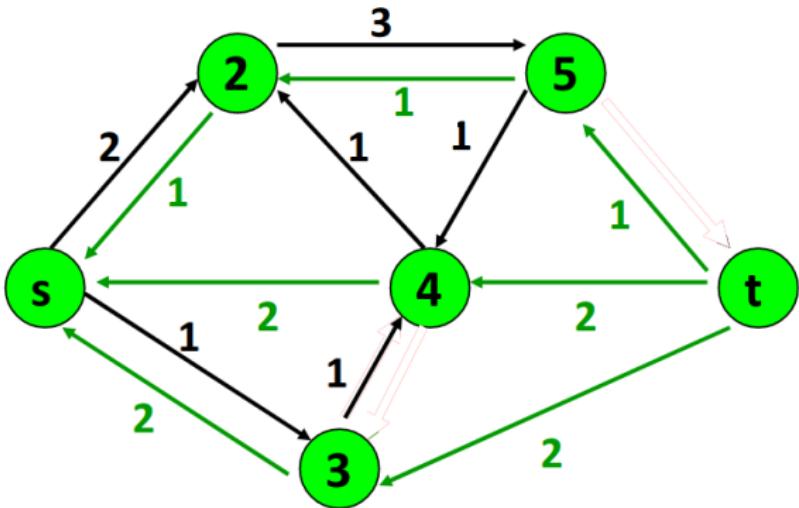
- ▶ Determine the capacity Δ of the path
- ▶ Send Δ units of flow in the path
- ▶ Update residual capacities



Ford-Fulkerson algorithm to find Max Flow (cont.)



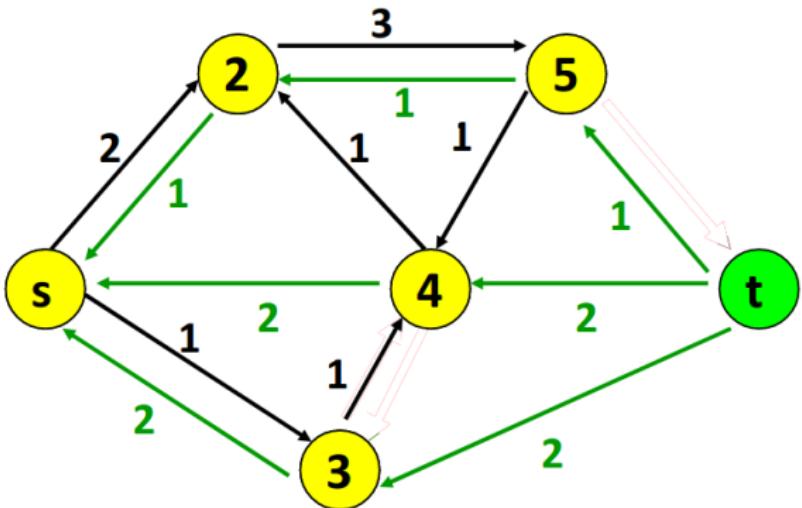
- There is no s-t path in the residual network.



Ford-Fulkerson algorithm to find Max Flow (cont.)



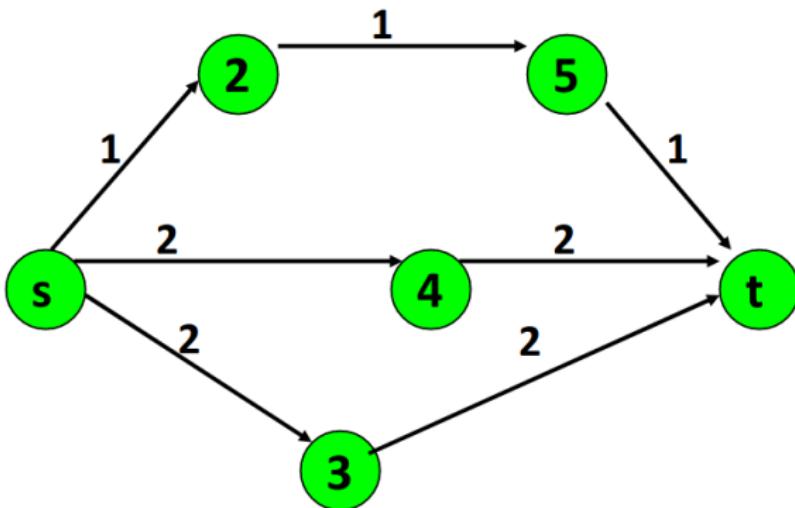
- ▶ These are the nodes that are reachable from node s .



Ford-Fulkerson algorithm to find Max Flow (cont.)



- Here is the optimal flow



Steps of Ford Fulkerson Algorithm



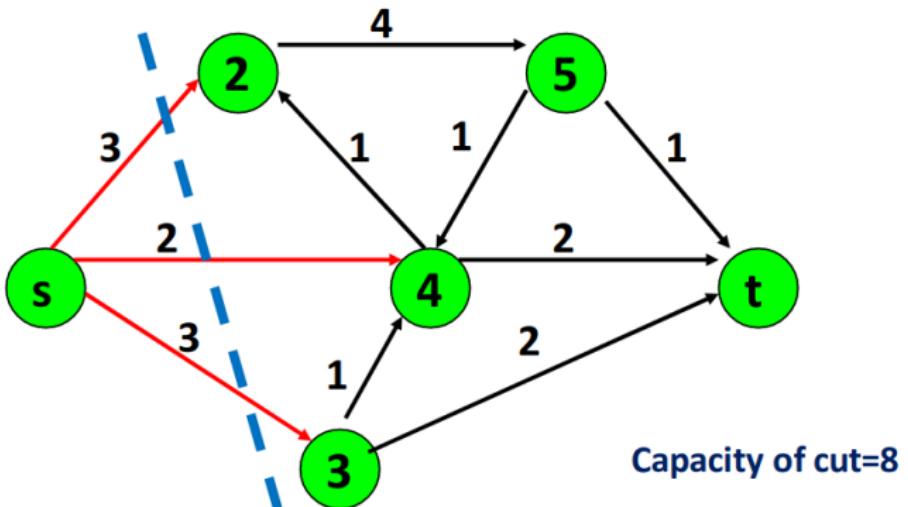
Input $G = (V, E, C)$, s, t

Assume $G = (V, V \times V, C)$, where $C(u,v)=0$ if (u, v) is not in E

- ▶ Find s-t path in G
- ▶ Mind min weight in the s-t path, say a
- ▶ Save the flow with the s-t path with weight a
- ▶ Find residual graph $G' = (V, V, C')$ where
 - $C'(u, v) = C(u, v) - a$ when (u, v) is in the path
 - $C'(v, u) = C(v, u) + a$ when (u, v) is in the path
 - $C'(u, v) = C(u, v)$ when (u, v) is not in the path
- ▶ $G = G'$
- ▶ Repeat the above five steps until there is no s-t path
- ▶ output the accumulated flow

Definition of s-t Cut

- ▶ Set of edges is said to be a cut if they are removed from the graph, graph should be disconnected into two components, one with source and the other one with sink.



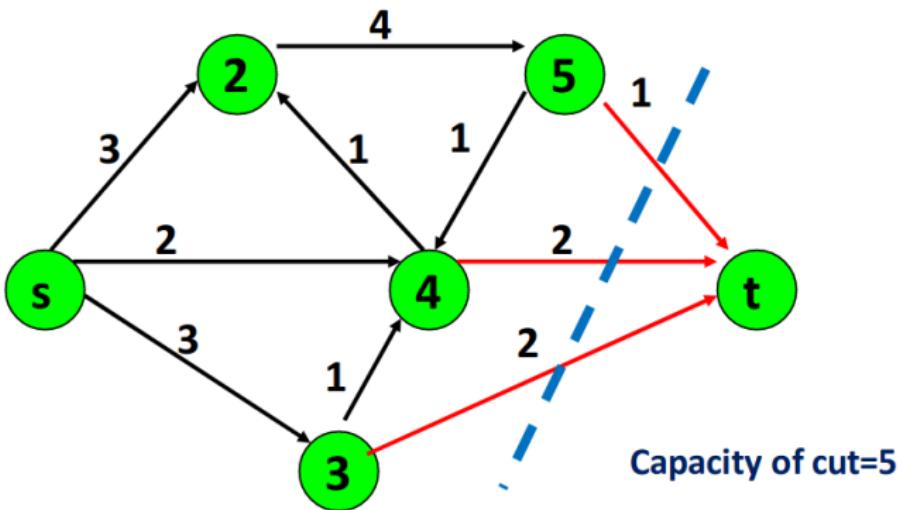
Max-Flow and Min-cut Theorem

Max-Flow Min-Cut Theorem (cont.)



- ▶ The maximum flow value is the same as the minimum cut value

Max-Flow Min-Cut Theorem (cont.)



Max-Flow Min-Cut Theorem (cont.)

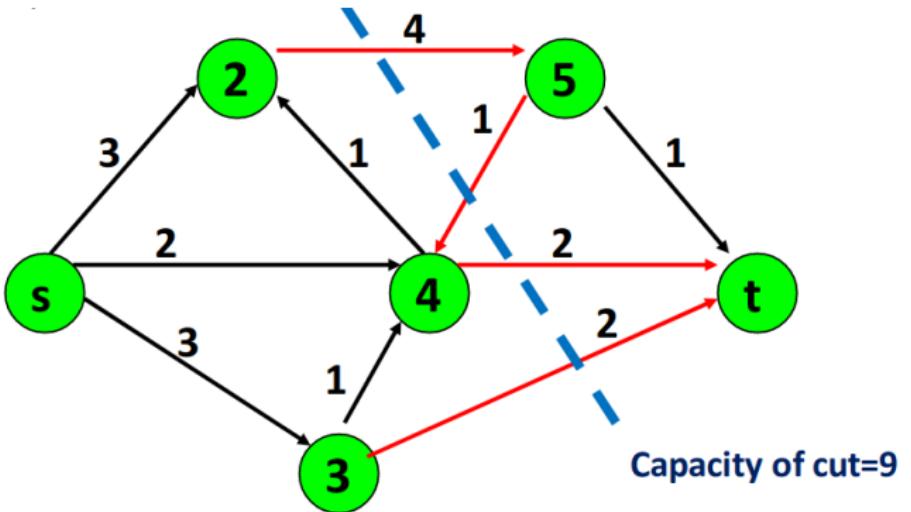
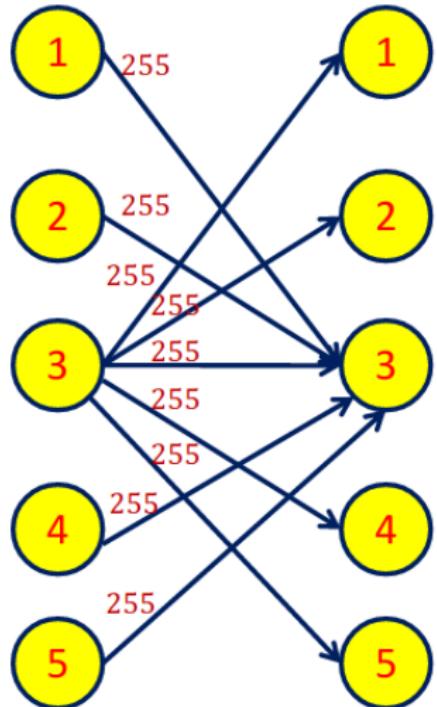
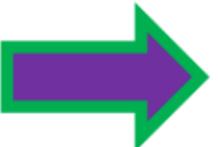


Image Reconstruction using Max-Flow



Image Reconstruction using Max-Flow (cont.)

	1	2	3	4	5
1	0	0	255	0	0
2	0	0	255	0	0
3	255	255	255	255	255
4	0	0	255	0	0
5	0	0	255	0	0



Image

Graph representation

Image Segmentation using Min-Cut



Image Segmentation



Image Segmentation using Min-Cut (cont.)



Image Segmentation

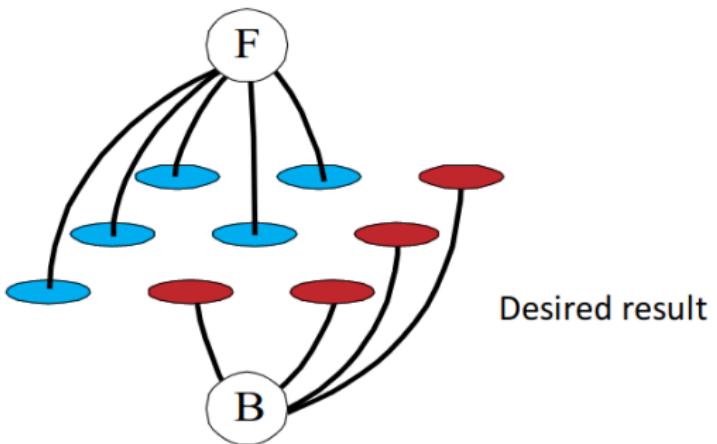


Image Segmentation using Min-Cut (cont.)



- ▶ Each pixel = node
- ▶ Add two nodes F & B
- ▶ Labeling: link each pixel to either F or B

F	F	B
F	F	B
F	B	B



► Construct graph with data term

- Put one edge between each pixel and F
- Put one edge between each pixel and B
- Weight of edge between i and F: $w_{iF} = -\lambda \log(P_B(i))$
- Weight of edge between i and B: $w_{iB} = -\lambda \log(P_F(i))$

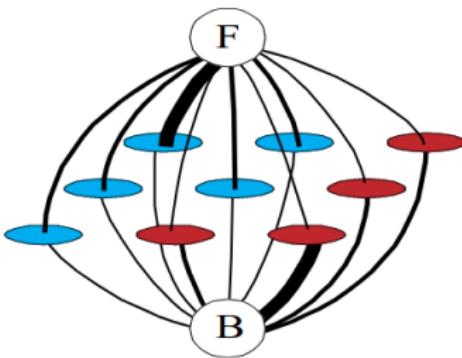
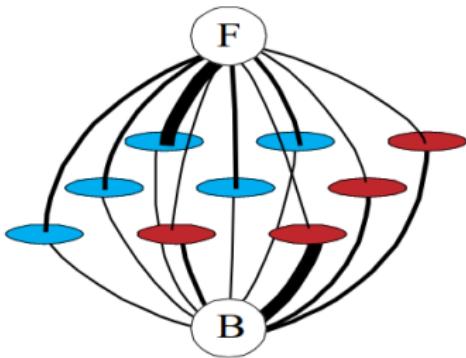


Image Segmentation using Min-Cut (cont.)



► Add Smoothness term to the Graph

- Add an edge between each neighbor pair (i,j)
- Weight of edge between i and j: $w_{ij} = \exp(-(I_i - I_j)^2 / 2\sigma^2)$



► Min-Cut

- Cut: Remove edges to disconnect F from B
- Min Cut: Cut with sum of its edge weights is minimum

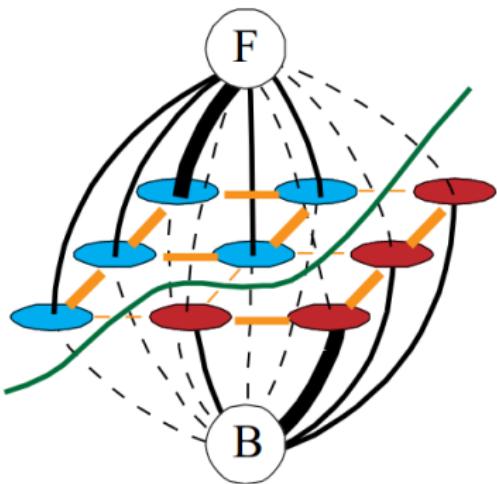
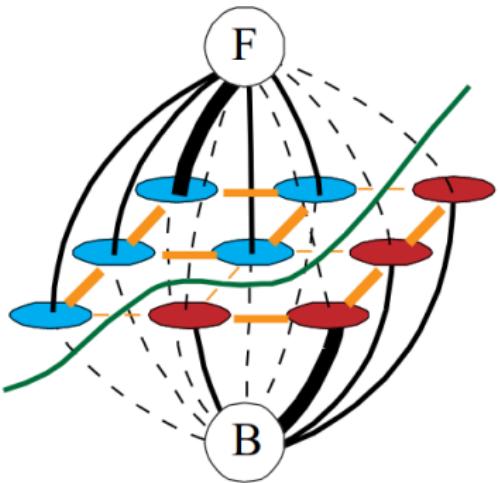


Image Segmentation using Min-Cut (cont.)



- ▶ In order to be a cut:
 - For each pixel, either the F or G edge has to be cut
- ▶ In order to be minimal
 - Only one edge to F or B per pixel can be cut



- ▶ Which edges are to be removed?
 - Edges with least cost

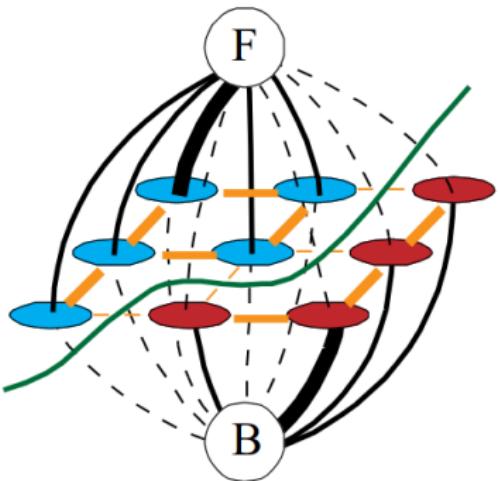


Image Segmentation using Min-Cut (cont.)



- ▶ Since $w_{iF} = -\lambda \log(P_B(i))$, larger value of $P_B(i)$ will lead to smaller value of w_{iF}
 - Hence edge (i,F) will be removed, and edge (i,B) will stay
 - i.e. Edge (i,B) will stay after cut if prob of i to be background is high

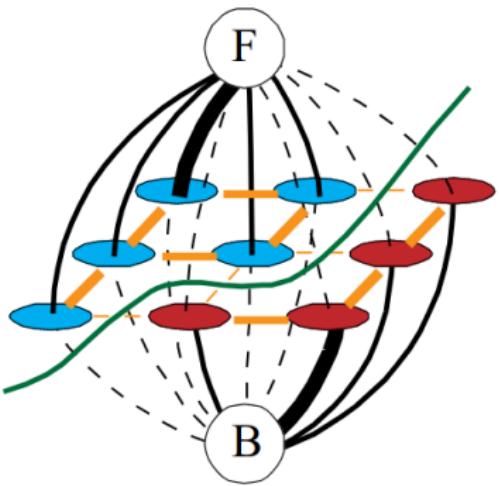


Image Segmentation using Min-Cut (cont.)



- ▶ Since $w_{iB} = -\lambda \log(P_F(i))$, larger value of $P_F(i)$ will lead to smaller value of w_{iB}
 - Hence edge (i, B) will be removed, and edge (i, F) will stay
 - i.e. Edge (i, F) will stay after cut if prob of i to be background is high

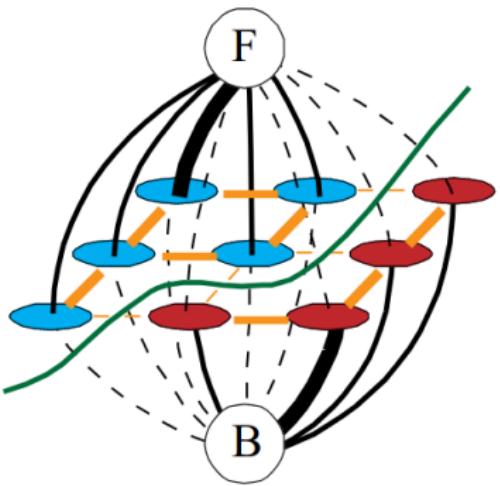


Image Segmentation using Min-Cut (cont.)



- ▶ Since for neighboring pixels (i,j) , $w_{ij} = \exp(-(I_i - I_j)^2/2\sigma^2)$, similar i and j , w_{ij} is very high
- ▶ Hence edge between similar pixels will stay after graph cut.
- ▶ This provides smoothness

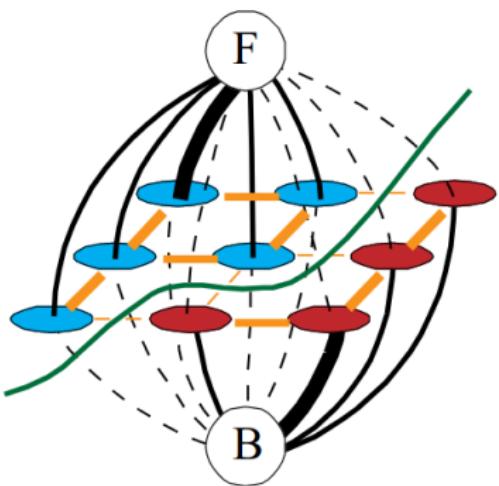


Image Segmentation using Min-Cut (cont.)

► How to find min-cut

- Apply max-flow algorithm
- The output of max-flow algorithm will result in min-cut (max-flow min-cut theorem)

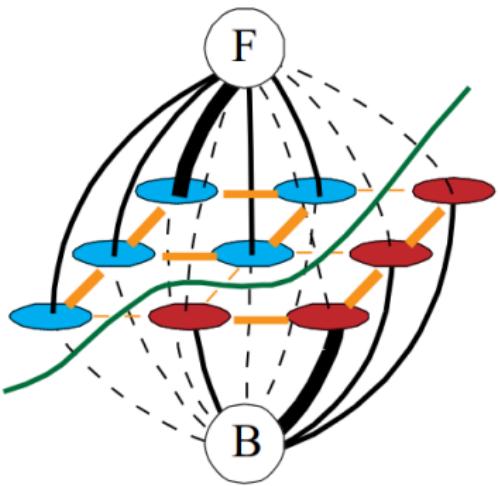
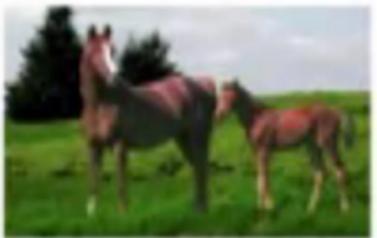


Image Segmentation using Min-Cut (cont.)

- ▶ How to find $P_B(i)$ and $P_F(i)$ for pixel i ?
 - User will give some seed of the background and foreground
 - From seed points of background compute $P_B(i)$
 - From seed points of foreground compute $P_F(i)$



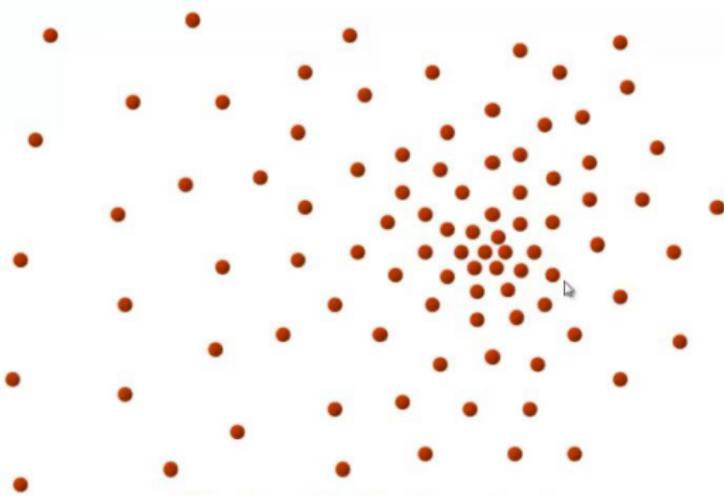


- ▶ Ford-Fulkerson algorithm to find max-flow is discussed
- ▶ Relationship between image and graph is discussed
- ▶ Graph-cut was computed using Ford-Fulkerson
- ▶ Couple of applications for graph-cut were illustrated
- ▶ As computation of graph-cut algorithm is polynomial, the applications discussed require only polynomial time.

Mean shift segmentation algorithm



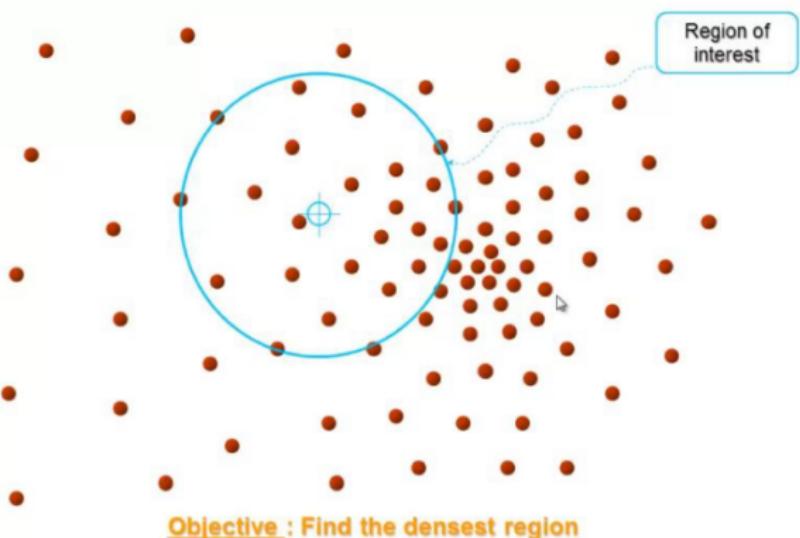
Mean Shift: Given a distribution of points, and also a point x , mean shift is a procedure for finding the centroid of local densest region for x .



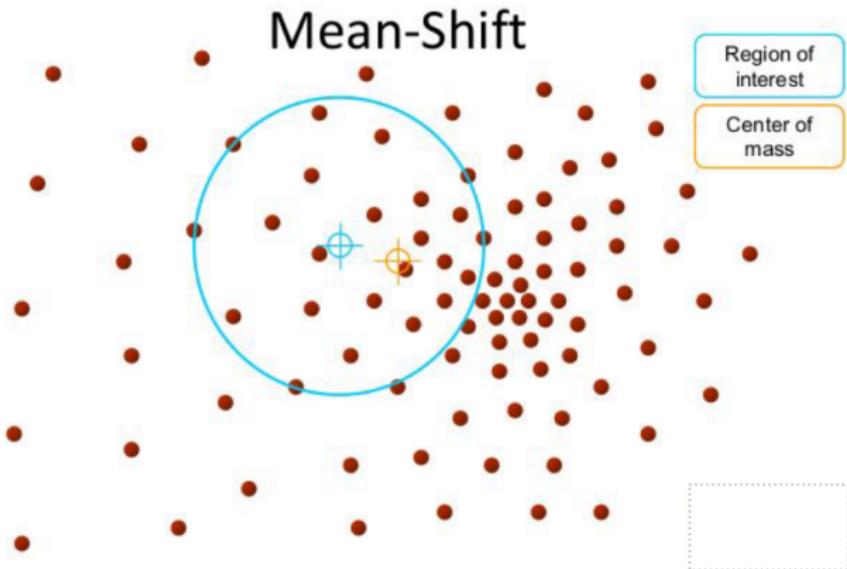
Objective : Find the densest region

How to find centroid of local densest region for given x

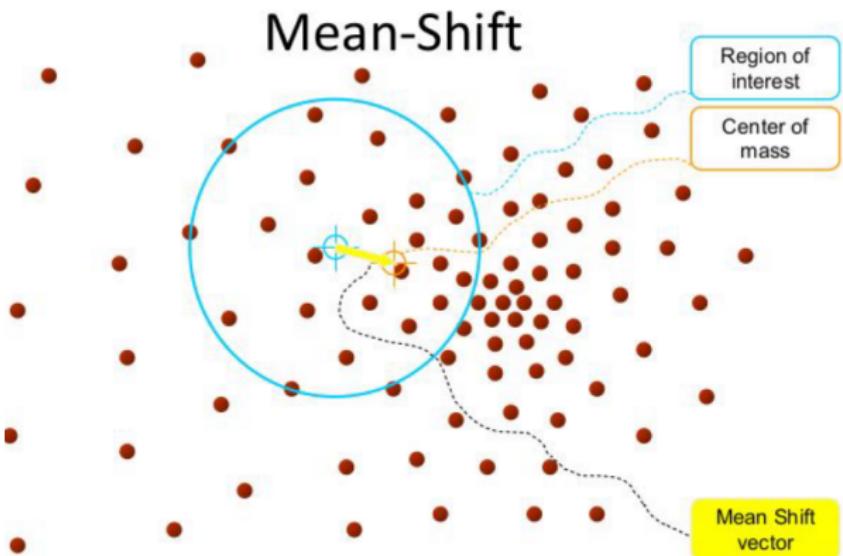
Step 1: Find the centroid of points centered at x with radius r , say such centroid as c



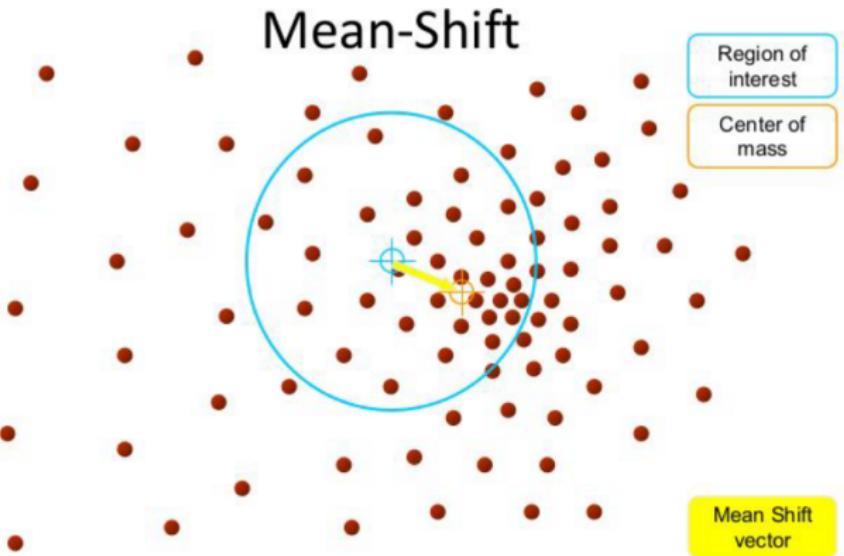
Step 2: Find the centroid of points centered at c with radius r , say such centroid as c'



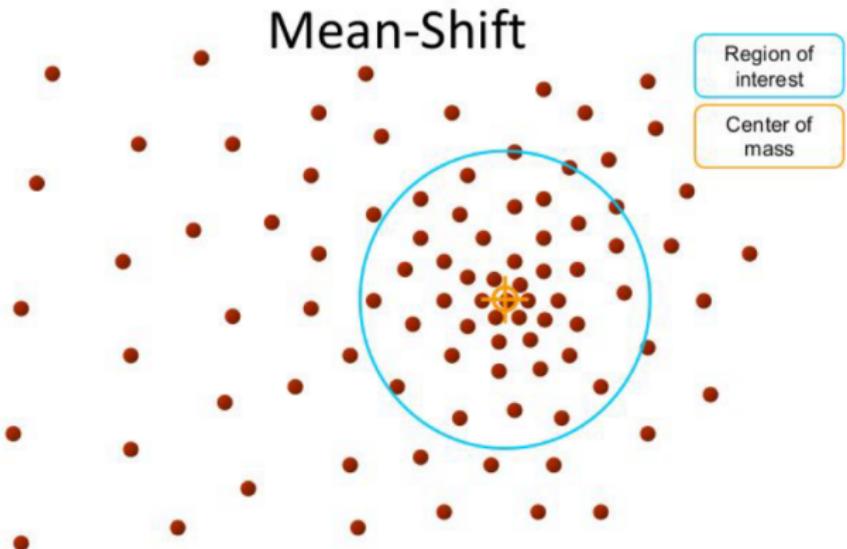
Step 3: $c = c'$, and goto step 2 when $|c - c'| > T$



Mean shift segmentation algorithm (cont.)



Mean shift segmentation algorithm (cont.)





Mean shift procedure for labelling point x

Input: Set of points, and x

1. Find the centroid of points centered at x with radius r , say such centroid as c
2. Find the centroid of points centered at c with radius r , say such centroid as c'
3. $c = c'$, and goto step 2 when $|c - c'| > T$
4. Assign a label l to the centroid c'
5. Assign the label l to x also



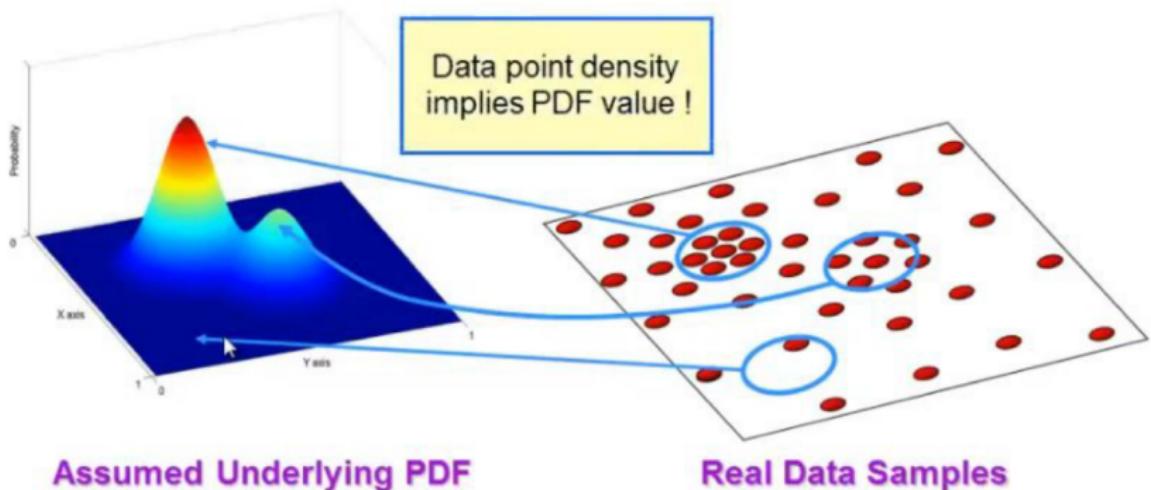
How to label pixel

- ▶ All the pixels with feature vector x will be labelled with the label of x

Mean Shift Image Segmentation

- ▶ For each point x , find the label using mean shift procedure
- ▶ All the pixels with feature vector x will be labelled with the label of x

Mean shift segmentation algorithm (cont.)





Mean Shift Vector Computation

- ▶ Gaussian Kernel

$$K(x; h) = \frac{2\pi^{-d}}{h^d} \exp\left(-\frac{1}{2} \frac{\|x\|^2}{h}\right)$$

- ▶ let

$$f(x) = C \sum_{i=1}^N K\left(\left\|\frac{x-x_i}{h}\right\|^2\right)$$

Mean shift segmentation algorithm (cont.)



- We want to find a maximum in f i.e gradient = 0

$$\nabla f(y) = 0$$

$$C \sum_i \nabla K\left(\left\|\frac{x_i - y}{h}\right\|^2\right) = 0$$

$$C \frac{2}{h} \sum_i [x_i - y] [K'\left(\left\|\frac{x_i - y}{h}\right\|^2\right)] = 0$$

$$C \frac{2}{h} \left[\frac{\sum_i x_i K'\left(\left\|\frac{x_i - y}{h}\right\|^2\right)}{\sum_i k'\left(\left\|\frac{x_i - y}{h}\right\|^2\right)} - y \right] * \left[\sum_i k'\left(\left\|\frac{x_i - y}{h}\right\|^2\right) \right] = 0$$

Mean shift segmentation algorithm (cont.)

Since $K'(\|\frac{x_i - y}{h}\|^2)$ is non zero,

$$[\frac{\sum_i x_i K'(\|\frac{x_i - y}{h}\|^2)}{\sum_i K'(\|\frac{x_i - y}{h}\|^2)} - y] = 0$$

$$y = \frac{\sum_i x_i K'(\|\frac{x_i - y}{h}\|^2)}{\sum_i K'(\|\frac{x_i - y}{h}\|^2)}$$

$$y^{(j+1)} = \frac{\sum_i x_i K'(\|\frac{x_i - y^j}{h}\|^2)}{\sum_i K'(\|\frac{x_i - y^j}{h}\|^2)}$$

here $[\frac{\sum_i x_i K'(\|\frac{x_i - y}{h}\|^2)}{\sum_i K'(\|\frac{x_i - y}{h}\|^2)} - y]$ is the mean shift vector

How to find mean shift with optimal weights?



Mean shift segmentation algorithm (cont.)



Examples

```
In[1]:= MeanShiftFilter[, 3, .1, MaxIterations -> 100]
```

```
>ut[1]=
```



Mean shift segmentation algorithm (cont.)



Examples



Original Satellite Imagery



Mean Shift Clustered Imagery

Examples



Segmentation using K-Means Clustering

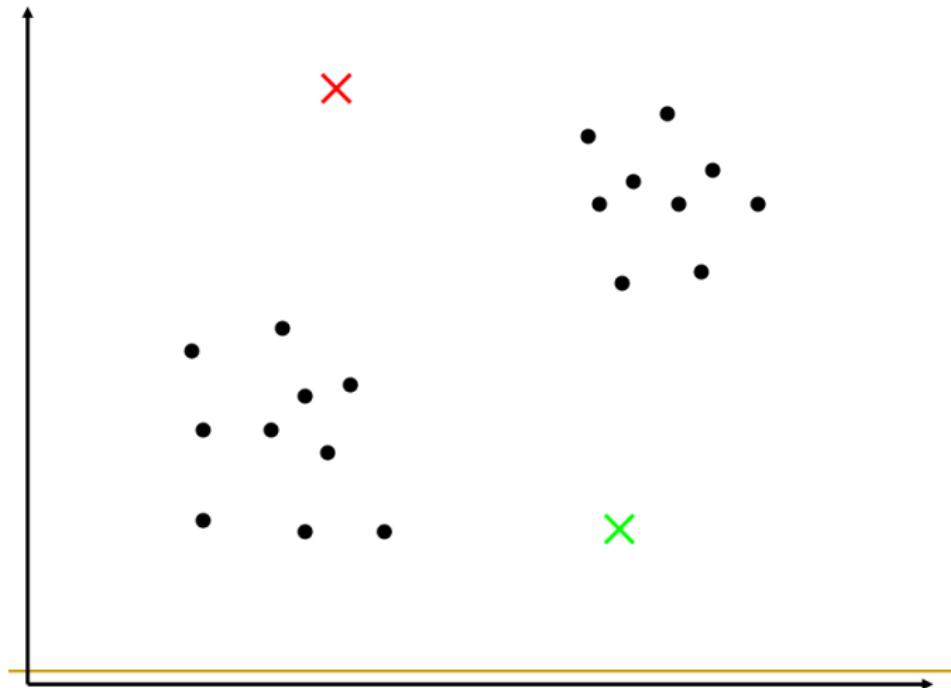


1. Partition the data points into K clusters randomly. Find the centroids of each cluster.
2. For each data point:
 - 2.1 Calculate the distance from the data point to each cluster.
 - 2.2 Assign the data point to the closest cluster.
3. Recompute the centroid of each cluster.
4. Repeat steps 2 and 3 until there is no further change in the assignment of data points (or in the centroids).

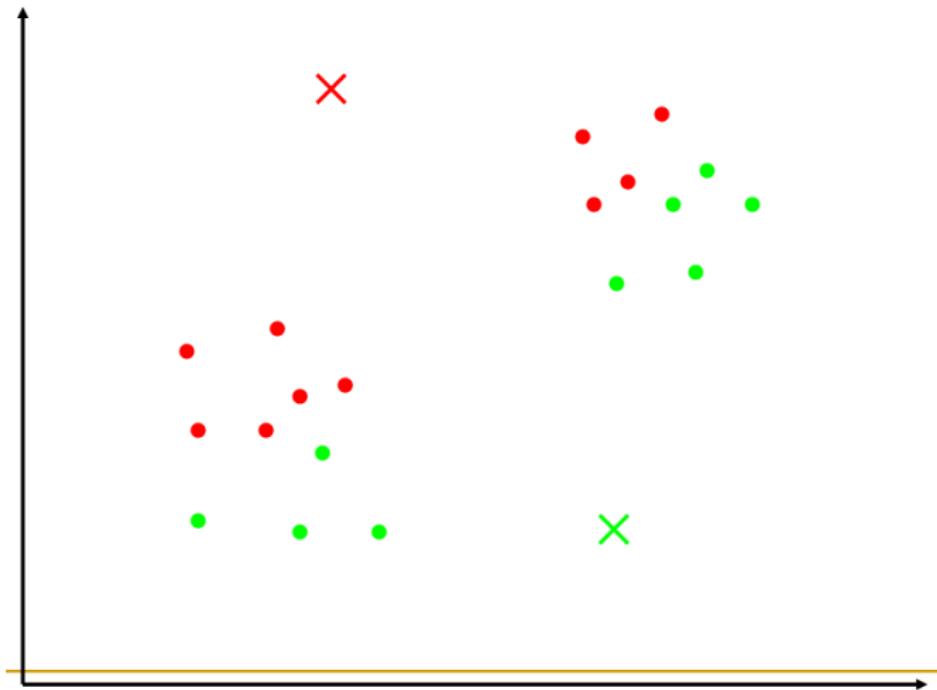
Segmentation using K-Means Clustering (cont.)



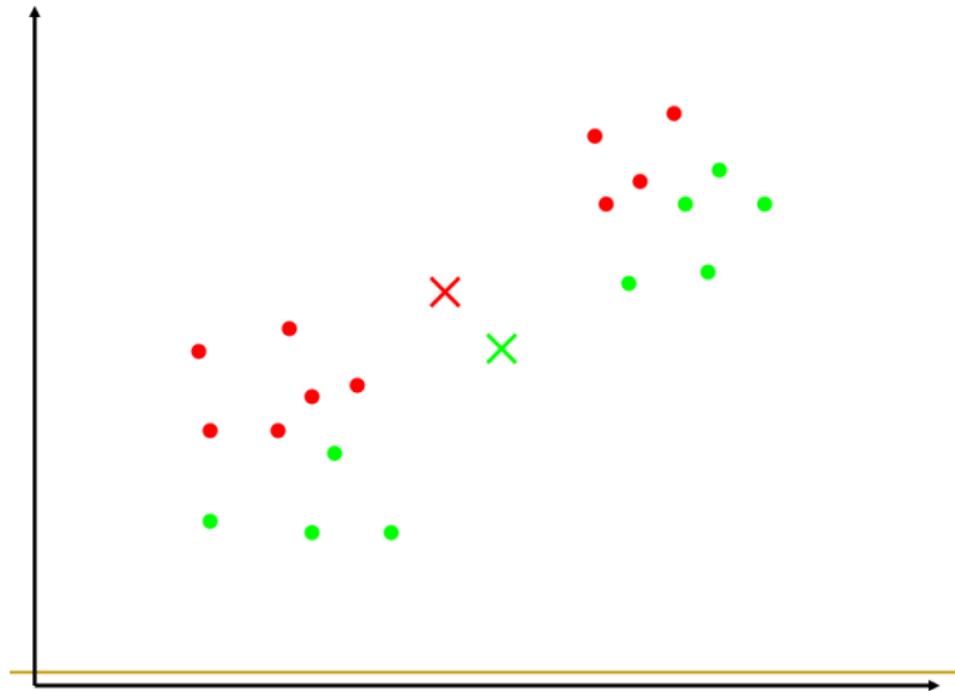
Segmentation using K-Means Clustering (cont.)



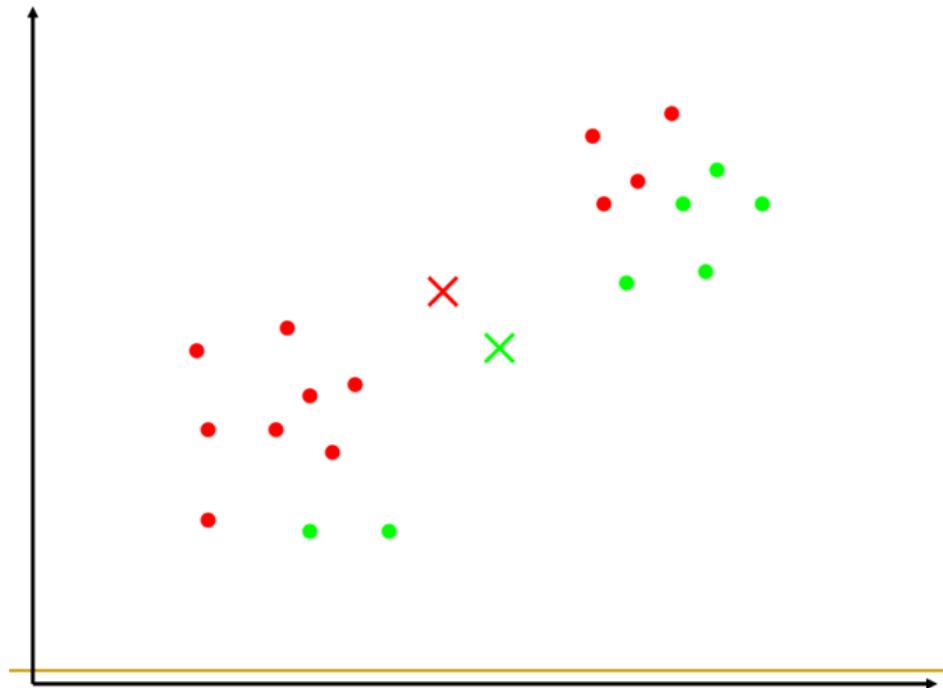
Segmentation using K-Means Clustering (cont.)



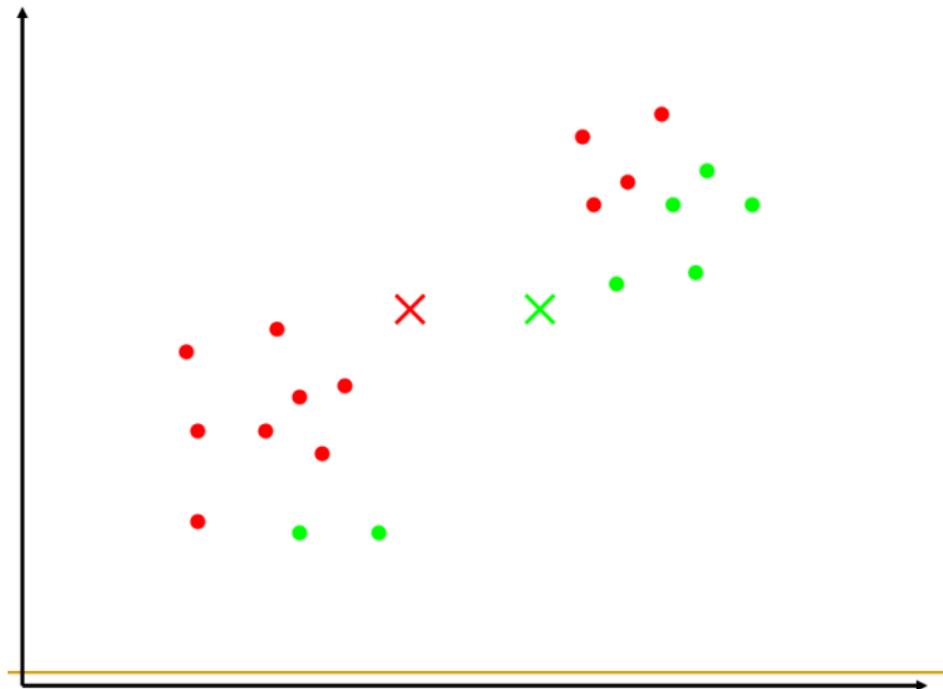
Segmentation using K-Means Clustering (cont.)



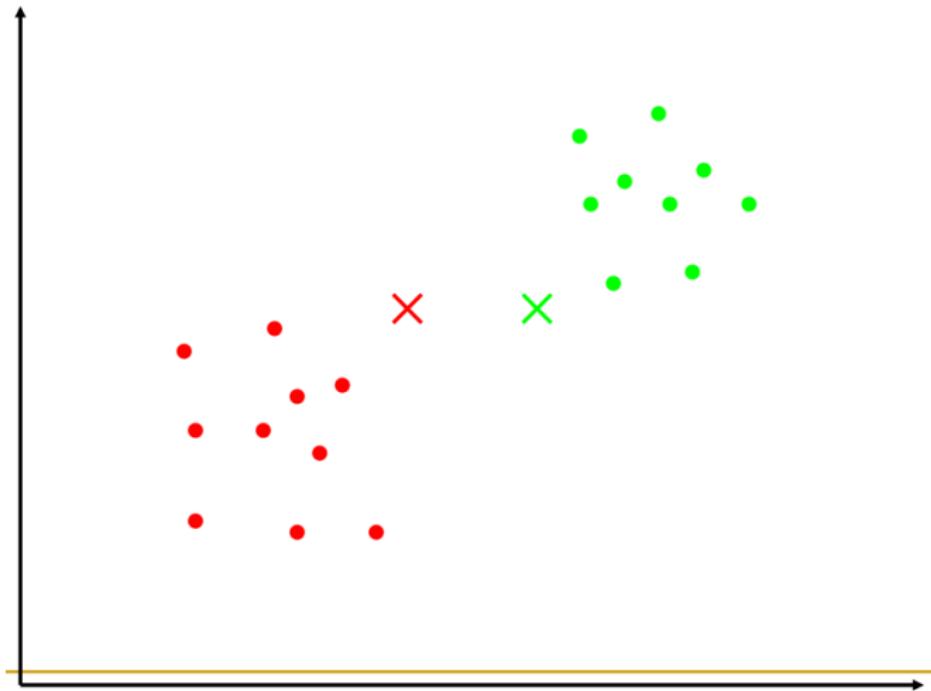
Segmentation using K-Means Clustering (cont.)



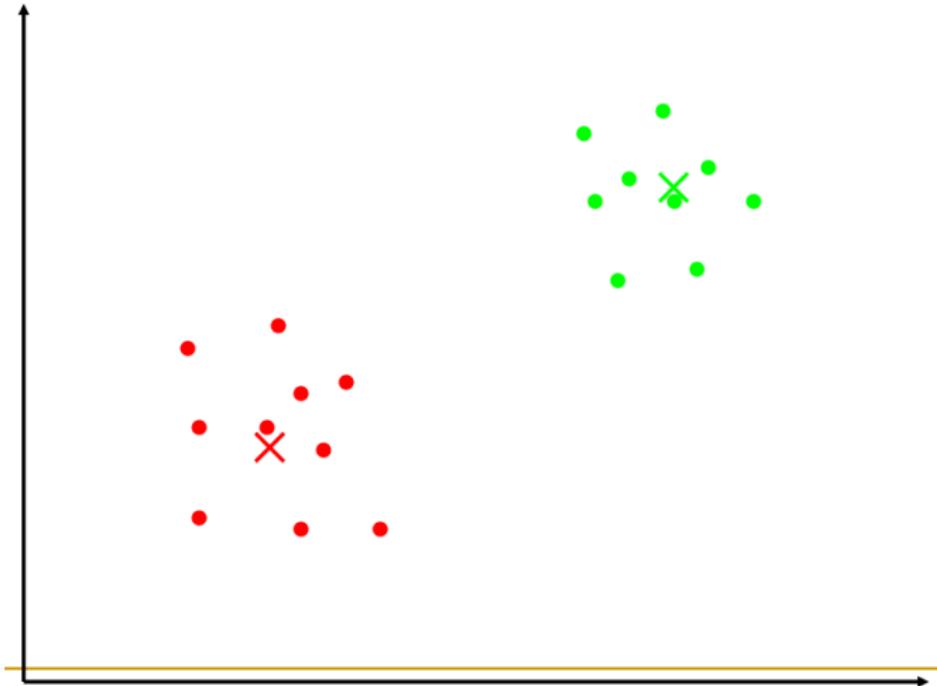
Segmentation using K-Means Clustering (cont.)



Segmentation using K-Means Clustering (cont.)



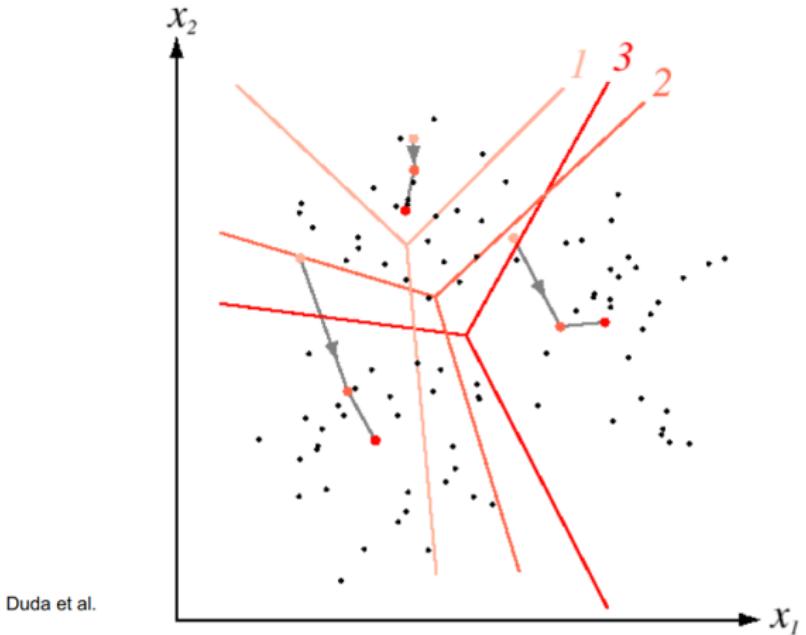
Segmentation using K-Means Clustering (cont.)



Segmentation using K-Means Clustering (cont.)



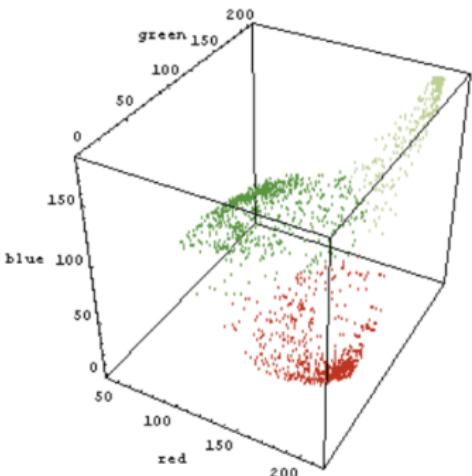
► Example



Segmentation using K-Means Clustering (cont.)



- ▶ RGB vector



- ▶ K-means clustering minimizes

$$\sum_{i \in \text{clusters}} \left\{ \sum_{j \in \text{elements of } i^{\text{th}} \text{ cluster}} \|x_j - \mu_i\|^2 \right\}$$

Segmentation using K-Means Clustering (cont.)



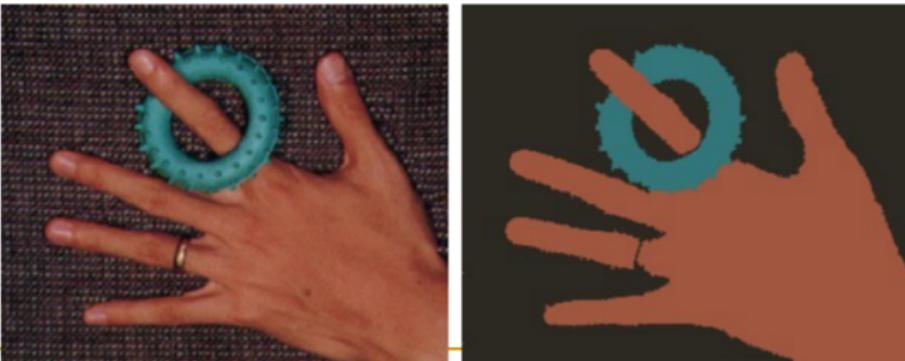
Examples



Segmentation using K-Means Clustering (cont.)



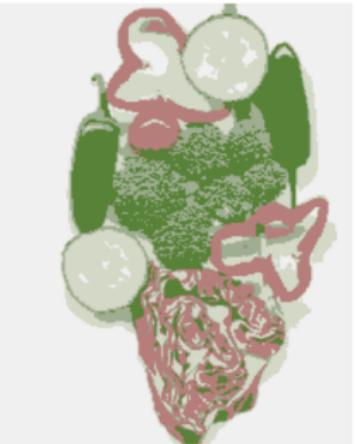
D. Comaniciu and P.
Meer, *Robust Analysis
of Feature Spaces:
Color Image
Segmentation*, 1997.



Segmentation using K-Means Clustering (cont.)



Original



K=5



K=11



K-Means Clustering: Axis Scaling

- ▶ Features of different types may have different scales.
 - For example, pixel coordinates on a 100×100 image vs. RGB color values in the range $[0,1]$.
- ▶ Problem: Features with larger scales dominate clustering.
- ▶ Solution: Scale the features.