Region Segmentation

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Artificial Inteligence
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Laboratory

I N D E X

What is image segmentation?

Type of region segmentation

Approaches

Clustering

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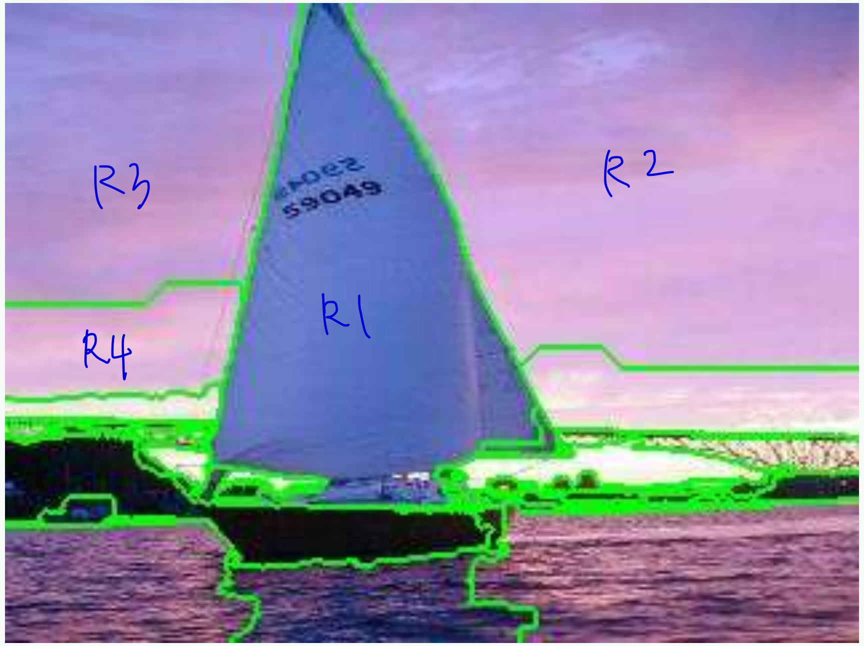
Image Segmentation : 이미지를 분할.

- Image segmentation is the operation of partitioning an image into a collection of connected sets of pixels (regions)

속성을 고려.

feature -

similar property를 갖는 pixel 끼리 연결해서 region으로 묶음.



Region-based Segmentation

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- **Goal:** find coherent (homogeneous) regions in the image

- Coherent regions contain pixel which share some ***similar property***

- ***Advantages:*** Better for noisy images
- ***Disadvantages: Oversegmented (too many regions),*** → similar property를 빡빡하게 설정하면.
  Undersegmented (too few regions) → 〃 느슨하게 설정하면.

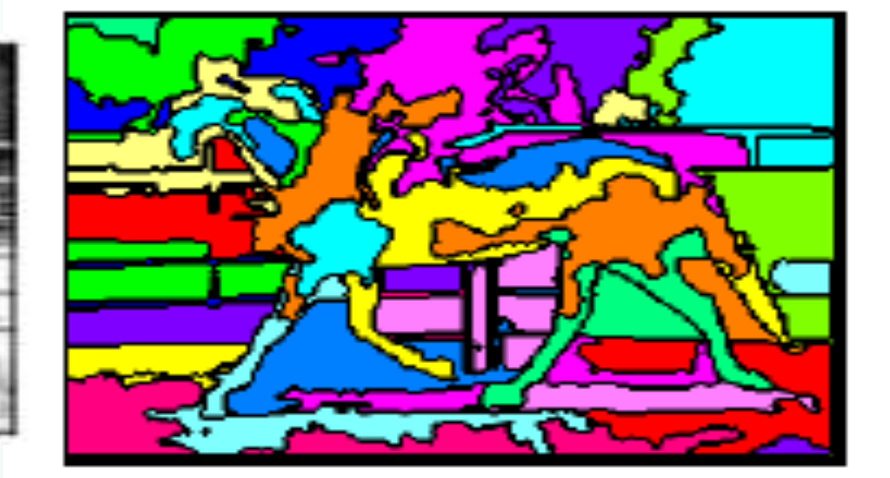
⇒ similar를 잘 조정해야함.

- ***Can't find objects that span multiple disconnected regions***

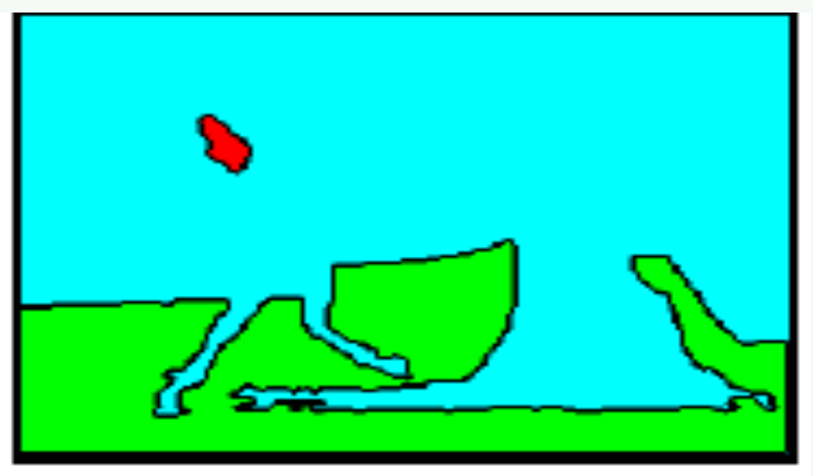
☆ 늘 경계 고려하면 Over를 고침.

Types of Segmentation

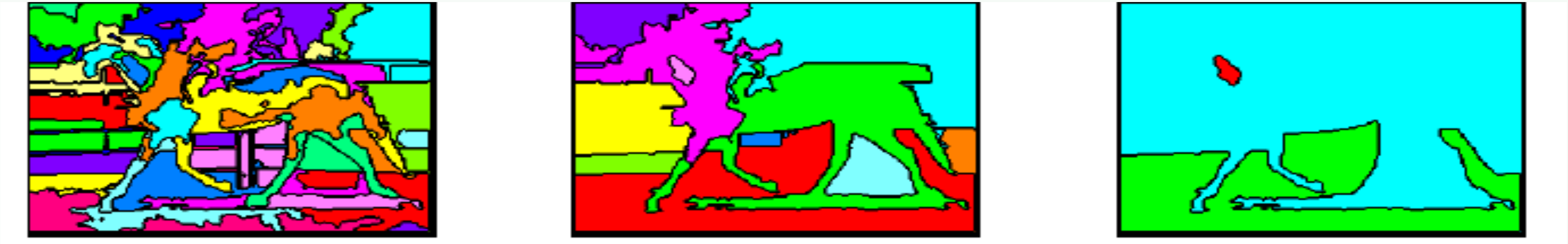
Input



Oversegmentation



Undersegmentation



Multiple Segmentations

Region-based Segmentation:Criteria

A segmentation is a partition of an image I into a set of regions S satisfying:

1. $\cup\, Si = S$ Partition covers the whole image.
2. $Si \cap Sj = \phi,\ i \neq j$ No regions intersect. → 하나의 영역이 2개의 영역에 속하면 X.
3. $\forall\, Si,\ P(Si) = \text{true}$ → Si 에 대한 Property가 similar 해야 한다.
4. $P(Si \cup Sj) = \text{false},\ i \neq j$, Si adjacent Sj → 다른 영역의 Property는 similar하지 않아야한다.

Define and implement the **similarity** predicate.

17:30.

Method of Region Segmentation

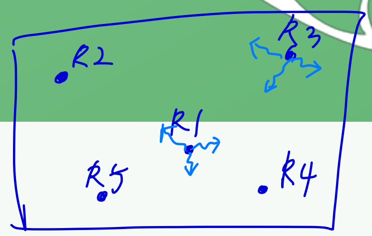
- **Region growing**
- **Split and merge**
- ☆ **Clustering**
  - 요즘 많이 씀

Region Growing

대부분 over segmentation을 하고 Region Growing을 함

핵심 : 처음의 영역 시작점이 될 pixel을 잘 고르는거

=seed pixel



- It start with one pixel of a potential region → 처음 시작은 한 픽셀을 한 영역이라 라고 가정하고 시작.

- Try to grow it by adding adjacent pixels till the pixels being compared are too dissimilar

핵심

- The first pixel selected can be
  - The first unlabeled pixel in the image (region 번호 부여 이전이라)
  - A set of seed pixels can be chosen from the image.

- Usually a statistical test is used to decide which pixels can be added to a region

Split and Merge

- Split into four disjoint coordinates any region R_i for which $Q(R_i)$=false

  ⇒ 비슷하지 않다는 조건 하에 4개 영역으로 나눔

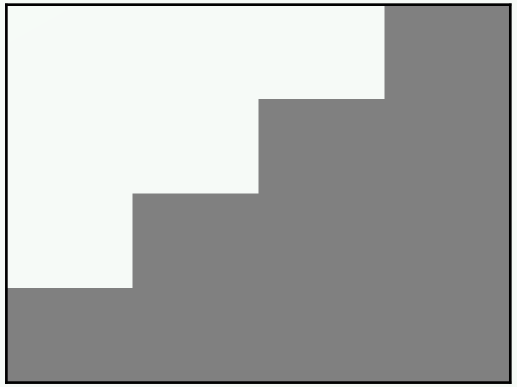
- When no further splitting is possible, merge **adjacent** region for which $Q(R_i \cup R_j)$= true

  비슷하다면,

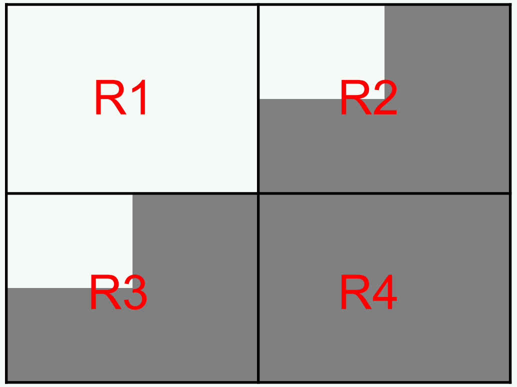
  ⇒ 가능한만큼 split 하다가, split을 더 이상 못하면 merge.
  가능한만큼 merge 하다가, 더 이상 못하면 stop

- Stop when no further merging is possible

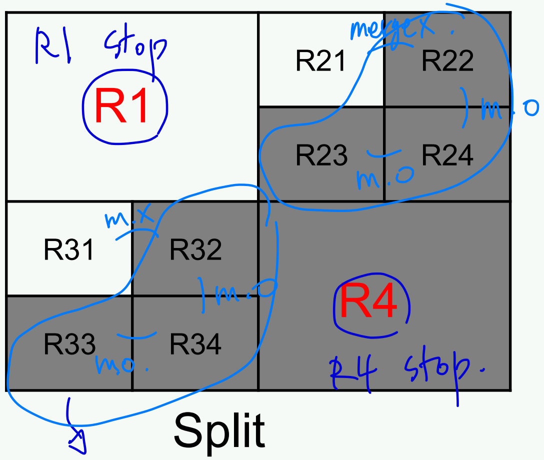
Exercise



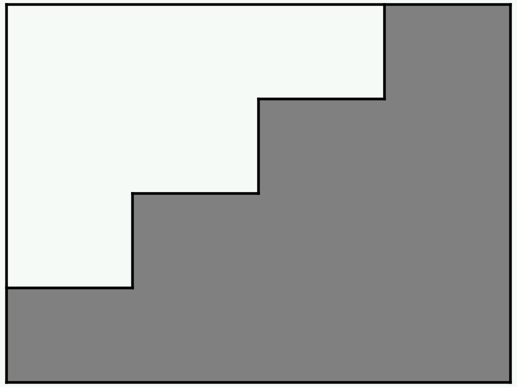
Input image



Split



Split



Merge

R1, R4는 속성이 다 같으니까 split stop.

Clustering

☆ 많이 사용

비교 앞의 두 방식은 Image의 spatial information을 기반으로 split, merge 하는 방식.

Clustering은 spatial Info를 아예 무시.
pixel들이 가지는 property (feature)만 이용함.
그래서 spatial Info를 적용하는 후처리 필요.

- Task of grouping a set of objects

이런 정보 이용.

- Objects in the same group (called a **cluster**) are more similar (in some sense or another) to each other

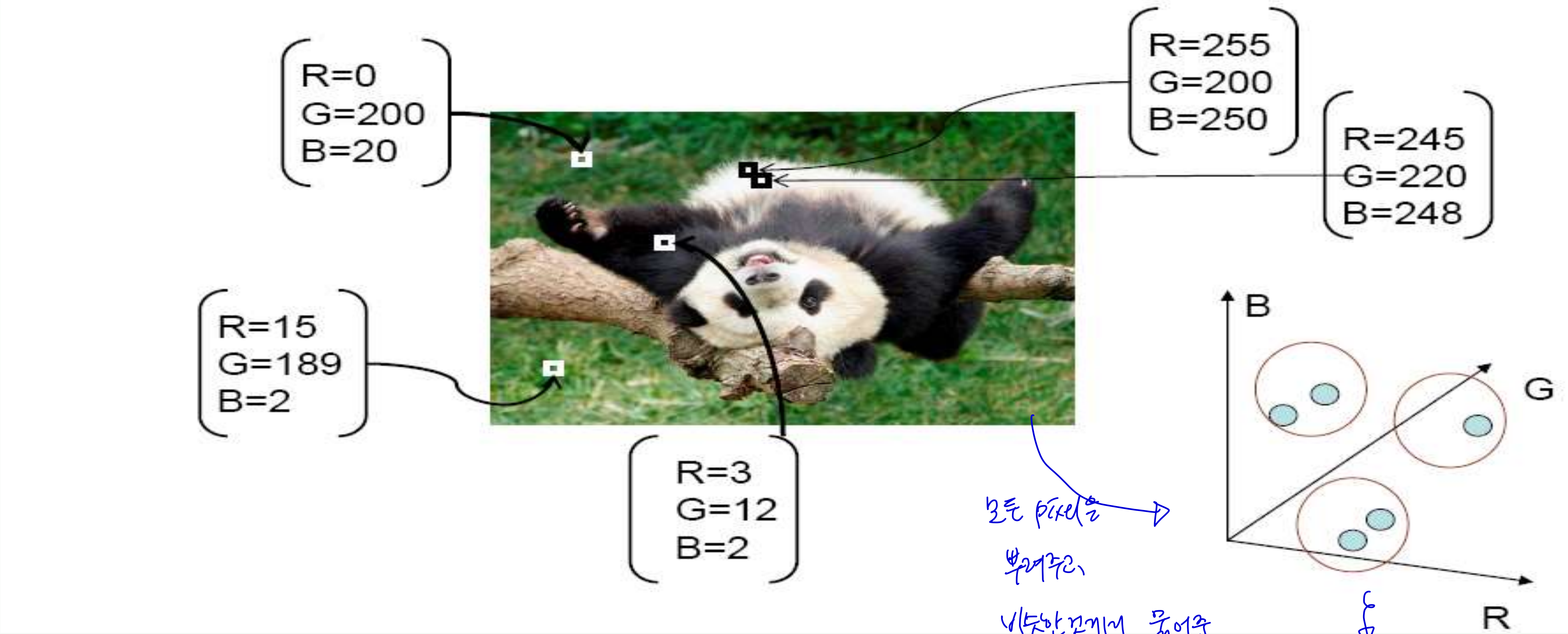
- Object of one cluster is different from an object of the another cluster

- Connectivity model, centroid model, distribution model, density model, graph based model, hard clustering, soft-clustering, …

Clustering: feature space

에서 동작함.

→ 그림 각각의 pixel을 feature space로 뿌려야함 : plot.



모든 pixel을 뿌려주고,
비슷한 것끼리 묶어줌.

한 cluster라도 그 안의 pixel의 색은 다 다르기에, 대표색으로 cluster로 정의 해줌

Centroid Model

Clustering의 가장 simple 한 모델.

→ 센터를 이용해서 중심좌표를 가지고 판단함.

- Computational time is short
- User have to decide the number of clusters before starting classifying data
- The concept of **centroid**
- One of the famous method: **K-means** Method

Clustering

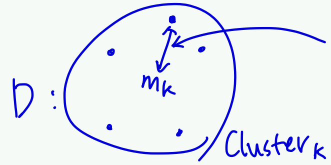
- There are K clusters C1,…, CK with means m1,…, mK.

cluster center

- The least-squares error is defined as

같은 cluster 내에서는 feature가 유사해야 하고,
다른 〃
달라야하는 걸 비교하는 기준

$$D = \sum_{k=1}^{K} \sum_{x_i \in C_k} \| x_i - m_k \|^2 .$$



이 차이의 모든 합

- Out of all possible partitions into K clusters, choose the one that minimizes D.

K-means Clustering

Alg)

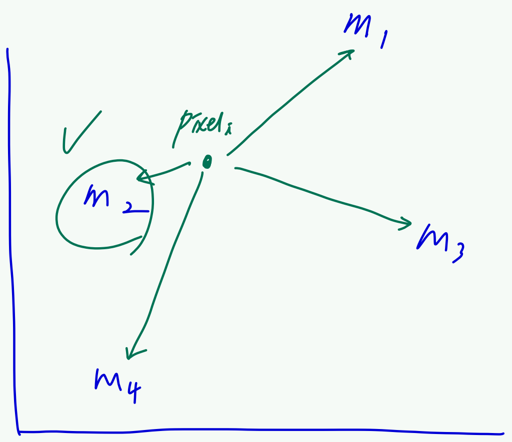
color space의 dimension으로 결정

Form K-means clusters from a set of n-dimensional vectors

1. Set ic (iteration count) to 1
2. Choose randomly a set of K means $m_1(1), \ldots, m_K(1)$.
3. For each vector x_i compute $D(x_i, m_k(ic))$, $k=1,\ldots K$ and assign x_i to the cluster C_j with nearest mean.
4. Increment ic by 1, update the means to get $m_1(ic),\ldots,m_K(ic)$.

↳ 모든 pixel 소속을 정하면, 모든 mean을 업데이트 함.

5. Repeat steps 3 and 4 until $C_k(ic) = C_k(ic+1)$ for all k.



pixel$_i$ 가 mean과 거리가 가장 짧은 cluster로 assign.

47:20

Partitional Clustering

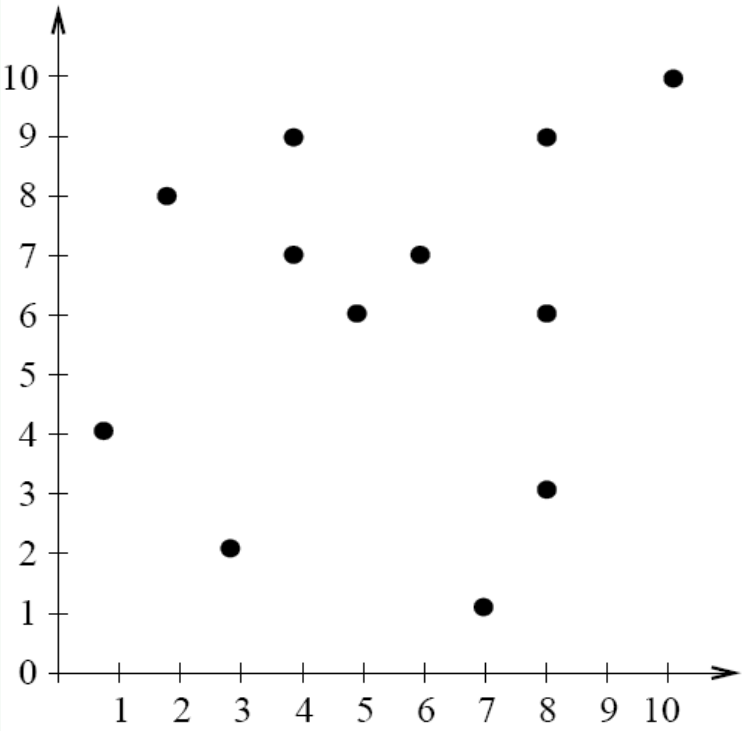
Clustering = K means Clu- = Partitional Clu-

과제 ①

Apply the K-means algorithm on the following input: 12개

(4,7), (6,7), (8,6), (8,9), (4,9), (10,10), (1,4), (8,3), (7,1), (3,2), (2,8), (5,6)

Select an initial clusters (k = 3)



interaction count

random 3개 선택

$$R_1^{(1)} = \boxed{1 \quad 6}$$

$$R_2^{(1)} = \boxed{9 \quad 7}$$

$$R_3^{(1)} = \boxed{4 \quad 3}$$

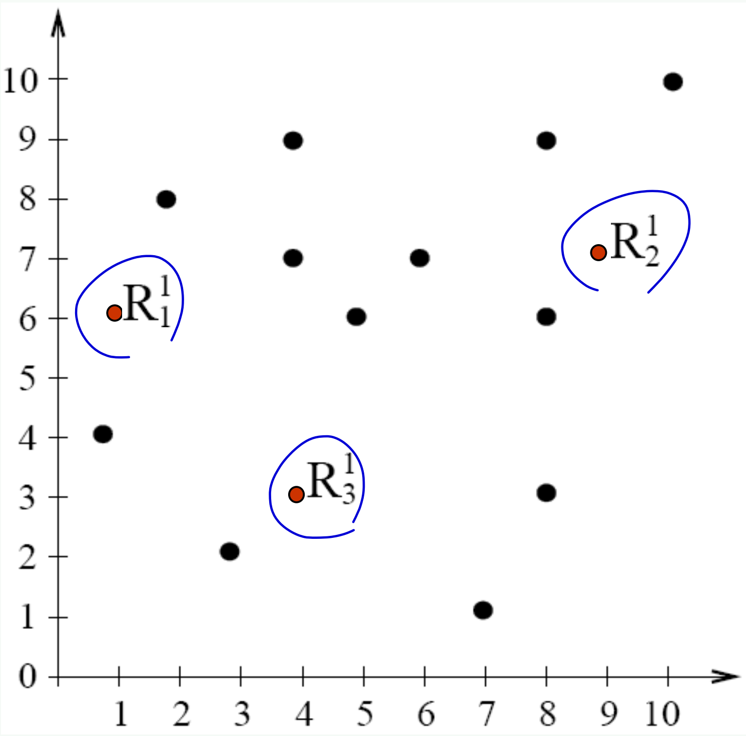
Partitional Clustering

과제②

Apply the K-means algorithm on the following input:

(4,7), (6,7), (8,6), (8,9), (4,9), (10,10), (1,4), (8,3), (7,1), (3,2), (2,8), (5,6)

Plot these clusters (k = 3)



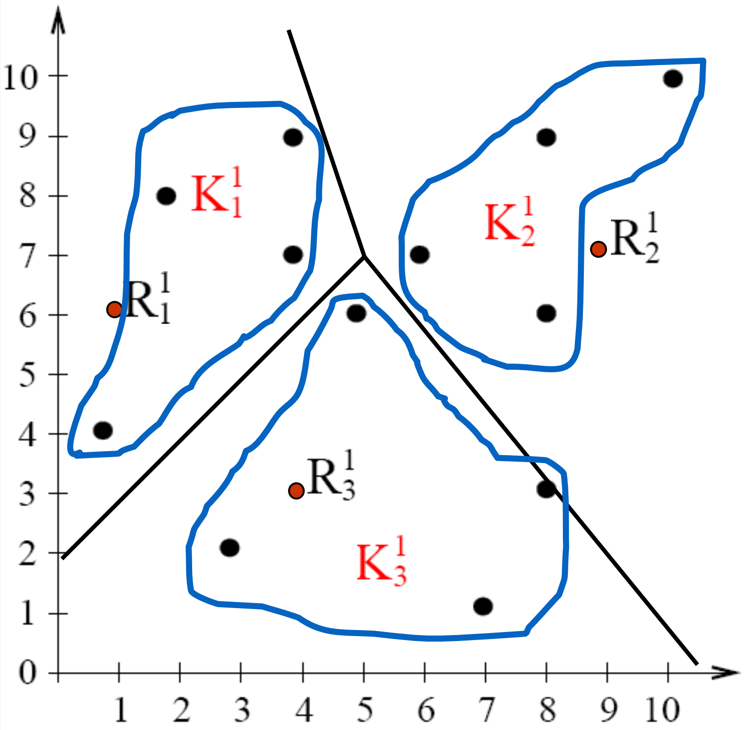
$R_1^1 =$	1	6
$R_2^1 =$	9	7
$R_3^1 =$	4	3

Partitional Clustering

Apply the K-means algorithm on the following input:

(4,7), (6,7), (8,6), (8,9), (4,9), (10,10), (1,4), (8,3), (7,1), (3,2), (2,8), (5,6)

Group vectors around the cluster entries and build clusters



$R_1^1 = \boxed{1 \quad 6}$

$R_2^1 = \boxed{9 \quad 7}$

$R_3^1 = \boxed{4 \quad 3}$

$K_1^1 =$	4 7	4 9	1 4	2 8
$K_2^1 =$	6 7	8 6	8 9	10 10
$K_3^1 =$	8 3	7 1	3 2	5 6

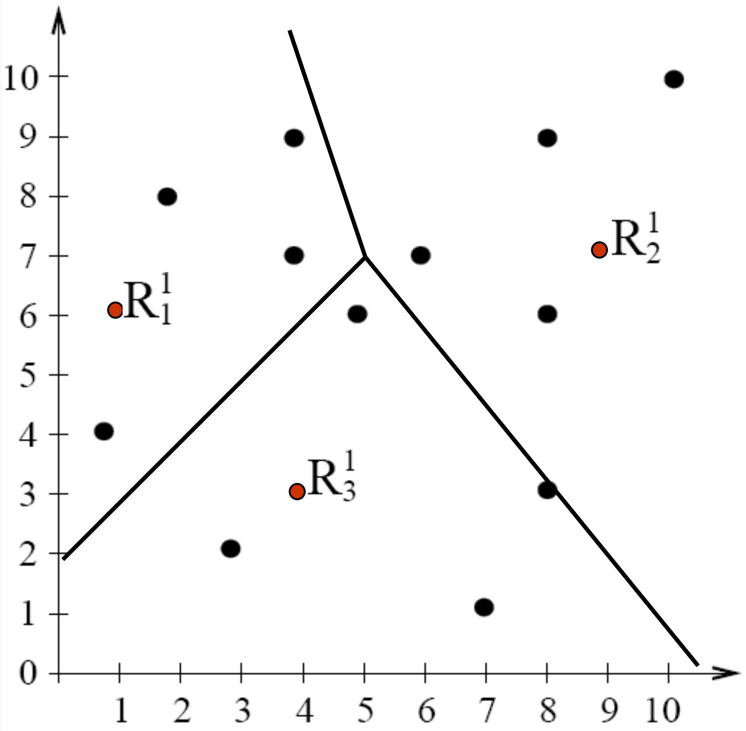
Partitional Clustering

과제!

Apply the K-means algorithm on the following input:

(4,7), (6,7), (8,6), (8,9), (4,9), (10,10), (1,4), (8,3), (7,1), (3,2), (2,8), (5,6)

Calculate centroids for each cluster and
Use these centroids as the new cluster



$R_1^1 = \boxed{1 \quad 6}$

$R_2^1 = \boxed{9 \quad 7}$

$R_3^1 = \boxed{4 \quad 3}$

변경.

						Centroids
$K_1^1 =$	4 7	4 9	1 4	2 8	=	2.75 7
$K_2^1 =$	6 7	8 6	8 9	10 10	=	8 8
$K_3^1 =$	8 3	7 1	3 2	5 6	=	5.75 3

Distortion = 8.67

Partitional Clustering

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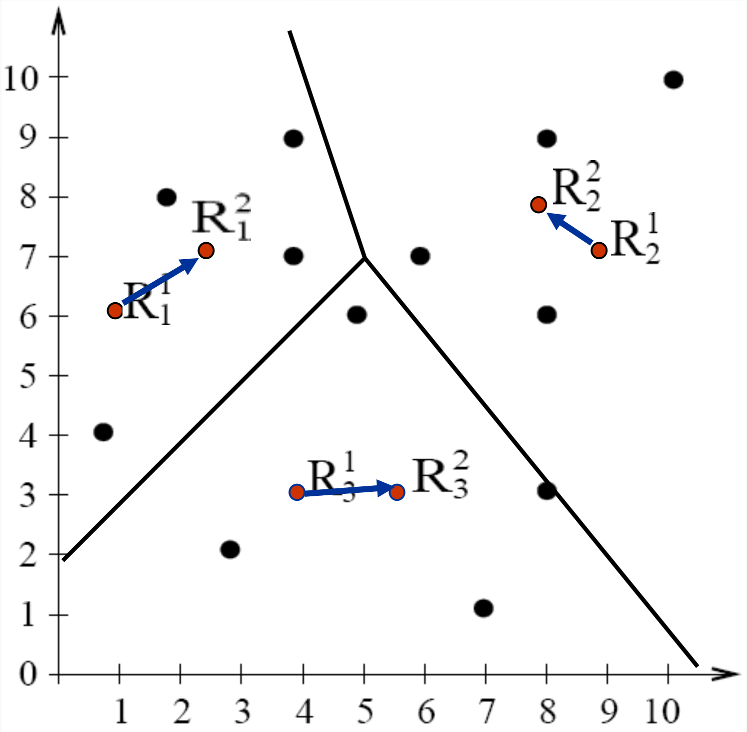
Apply the K-means algorithm on the following input:

(4,7), (6,7), (8,6), (8,9), (4,9), (10,10), (1,4), (8,3), (7,1), (3,2), (2,8), (5,6)

Update the Plot and clustering



$R_1^2 = \boxed{2.75 \quad 7}$

$R_2^2 = \boxed{8 \quad 8}$

$R_3^2 = \boxed{5.75 \quad 3}$

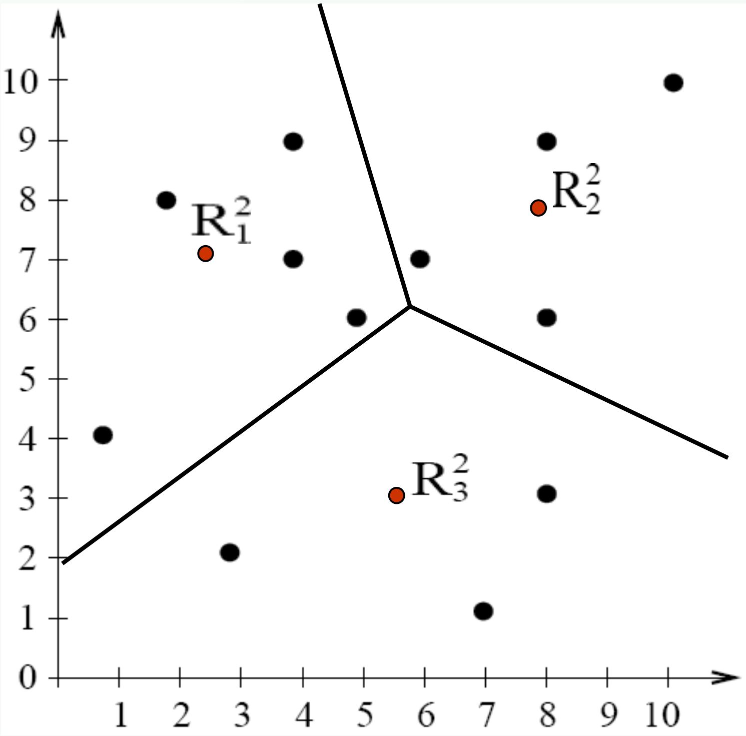
Partitional Clustering

6

Apply the K-means algorithm on the following input:

(4,7), (6,7), (8,6), (8,9), (4,9), (10,10), (1,4), (8,3), (7,1), (3,2), (2,8), (5,6)

Update the Plot and clustering



$R_1^2 = \boxed{2.75 \quad 7}$

$R_2^2 = \boxed{8 \quad 8}$

$R_3^2 = \boxed{5.75 \quad 3}$

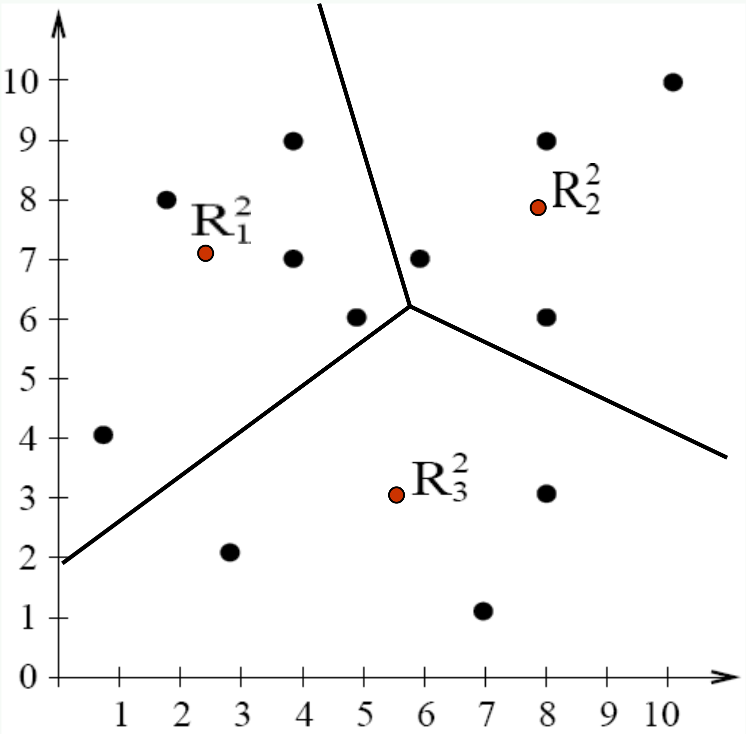
Partitional Clustering

1

Apply the K-means algorithm on the following input:

(4,7), (6,7), (8,6), (8,9), (4,9), (10,10), (1,4), (8,3), (7,1), (3,2), (2,8), (5,6)

Update the Plot and clustering



$R_1^2 = \boxed{2.75 \quad 7}$

$R_2^2 = \boxed{8 \quad 8}$

$R_3^2 = \boxed{5.75 \quad 3}$

$K_1^2 = \boxed{4 \quad 7}\ \boxed{4 \quad 9}\ \boxed{1 \quad 4}\ \boxed{2 \quad 8}\ \boxed{5 \quad 6}$

$K_2^2 = \boxed{6 \quad 7}\ \boxed{8 \quad 6}\ \boxed{8 \quad 9}\ \boxed{10\ 10}$

$K_3^2 = \boxed{8 \quad 3}\ \boxed{7 \quad 1}\ \boxed{3 \quad 2}$

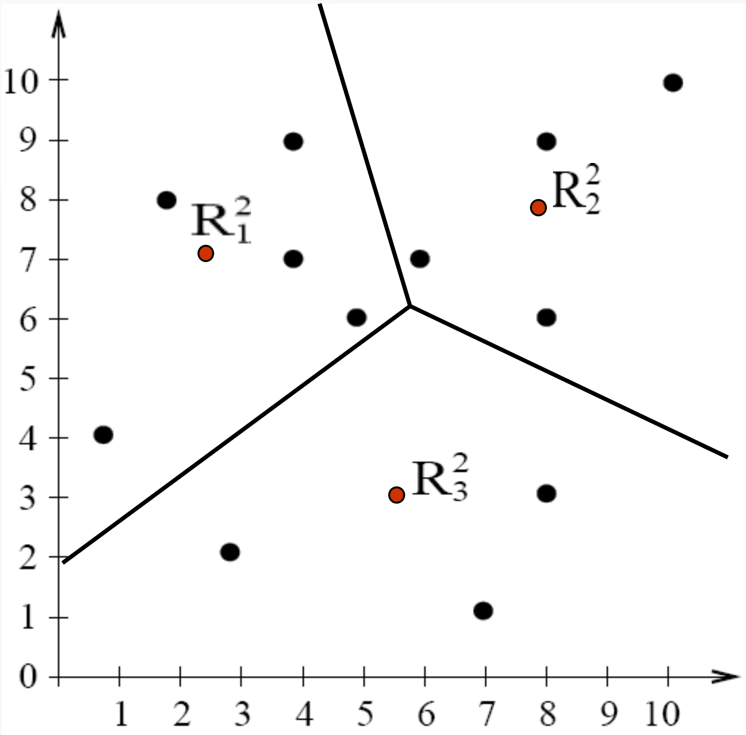
Distortion = 5.34

Partitional Clustering

Apply the K-means algorithm on the following input:

(4,7), (6,7), (8,6), (8,9), (4,9), (10,10), (1,4), (8,3), (7,1), (3,2), (2,8), (5,6)

Calculate the new centroids and use as cluster



$R_1^3 = \boxed{3.2\ 6.8}$

$R_2^3 = \boxed{8\quad 8}$

$R_3^3 = \boxed{6\quad 2}$

$K_1^2 = \boxed{4\ \ 7}\ \boxed{4\ \ 9}\ \boxed{1\ \ 4}\ \boxed{2\ \ 8}\ \boxed{5\ \ 6}$

$K_2^2 = \boxed{6\ \ 7}\ \boxed{8\ \ 6}\ \boxed{8\ \ 9}\ \boxed{10\ 10}$

$K_3^2 = \boxed{8\ \ 3}\ \boxed{7\ \ 1}\ \boxed{3\ \ 2}$

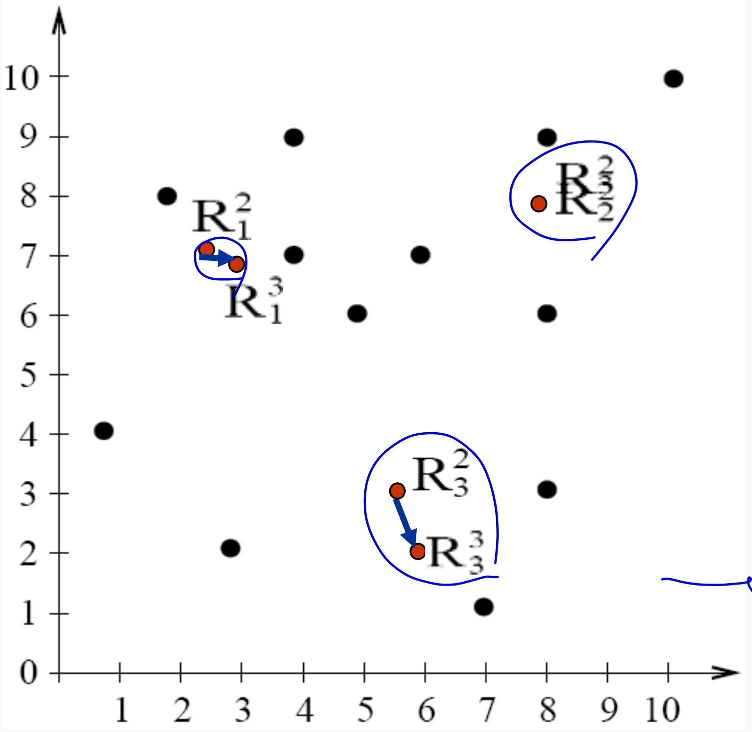
Partitional Clustering

9

Apply the K-means algorithm on the following input:

(4,7), (6,7), (8,6), (8,9), (4,9), (10,10), (1,4), (8,3), (7,1), (3,2), (2,8), (5,6)

Update the Plot



$R_1^3 = \boxed{3.2\ 6.8}$

$R_2^3 = \boxed{8\ \ 8}$

$R_3^3 = \boxed{6\ \ 2}$

$K_1^2 =$	4 7	4 9	1 4	2 8	5 6
$K_2^2 =$	6 7	8 6	8 9	10 10	
$K_3^2 =$	8 3	7 1	3 2		

처음에 비해 움직이는 폭이 좁음
== 수렴되고 있다~

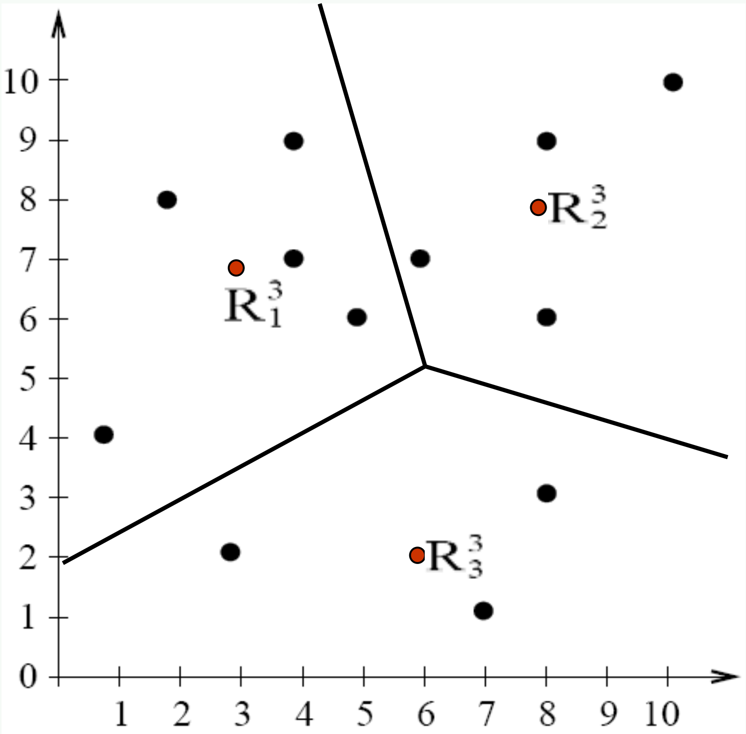
Partitional Clustering

10

Apply the K-means algorithm on the following input:

(4,7), (6,7), (8,6), (8,9), (4,9), (10,10), (1,4), (8,3), (7,1), (3,2), (2,8), (5,6)

Update the Plot



$R_1^3 = \boxed{3.2\ 6.8}$

$R_2^3 = \boxed{8 \quad 8}$

$R_3^3 = \boxed{6 \quad 2}$

$K_1^2 =$	4 7	4 9	1 4	2 8	5 6
$K_2^2 =$	6 7	8 6	8 9	10 10	
$K_3^2 =$	8 3	7 1	3 2		

Partitional Clustering

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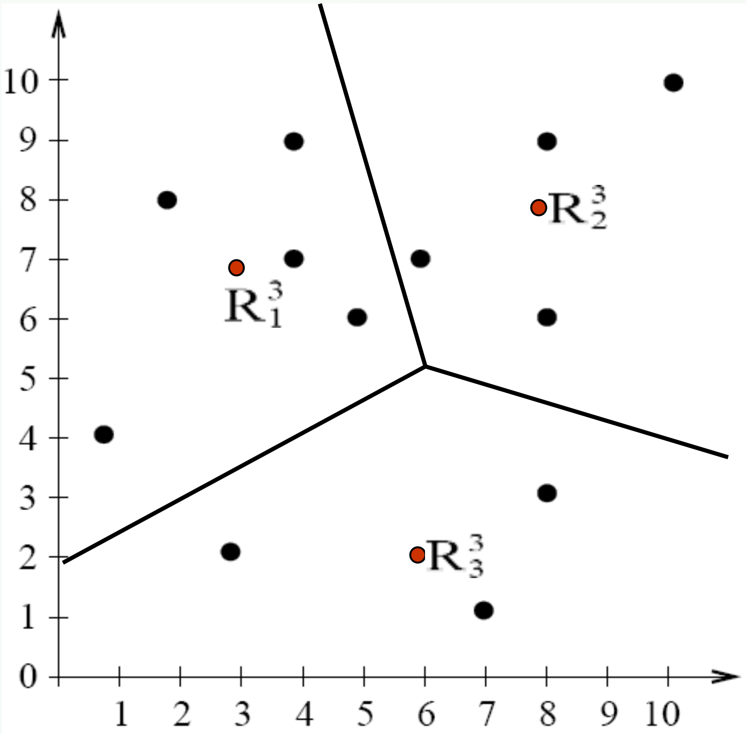
Apply the K-means algorithm on the following input:

(4,7), (6,7), (8,6), (8,9), (4,9), (10,10), (1,4), (8,3), (7,1), (3,2), (2,8), (5,6)

Clusters remain the same (and so do the centroins), so we finish



$$R_1^3 = \boxed{3.2\ \ 6.8}$$
$$R_2^3 = \boxed{8\ \ \ 8}$$
$$R_3^3 = \boxed{6\ \ \ 2}$$

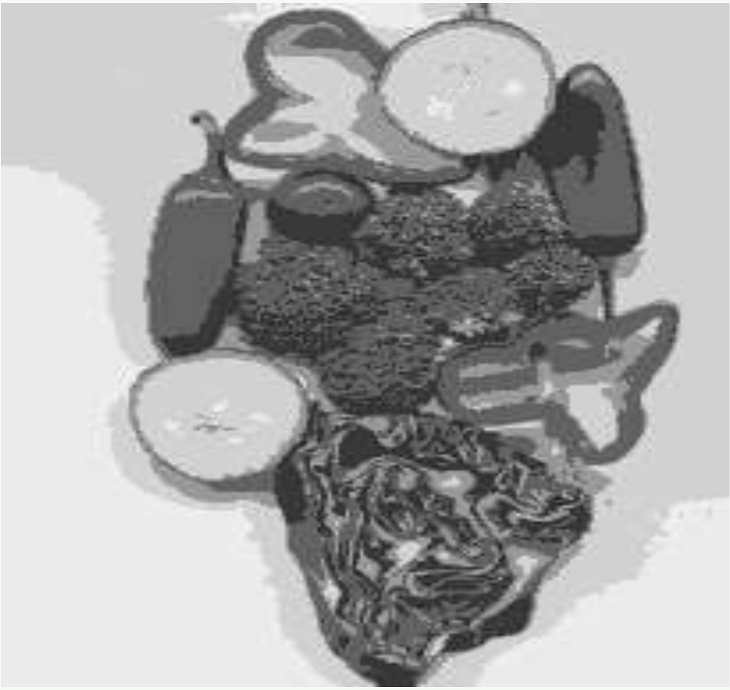
$$K_1^2 = \boxed{4\ \ 7}\ \boxed{4\ \ 9}\ \boxed{1\ \ 4}\ \boxed{2\ \ 8}\ \boxed{5\ \ 6}$$
$$K_2^2 = \boxed{6\ \ 7}\ \boxed{8\ \ 6}\ \boxed{8\ \ 9}\ \boxed{10\ 10}$$
$$K_3^2 = \boxed{8\ \ 3}\ \boxed{7\ \ 1}\ \boxed{3\ \ 2}$$

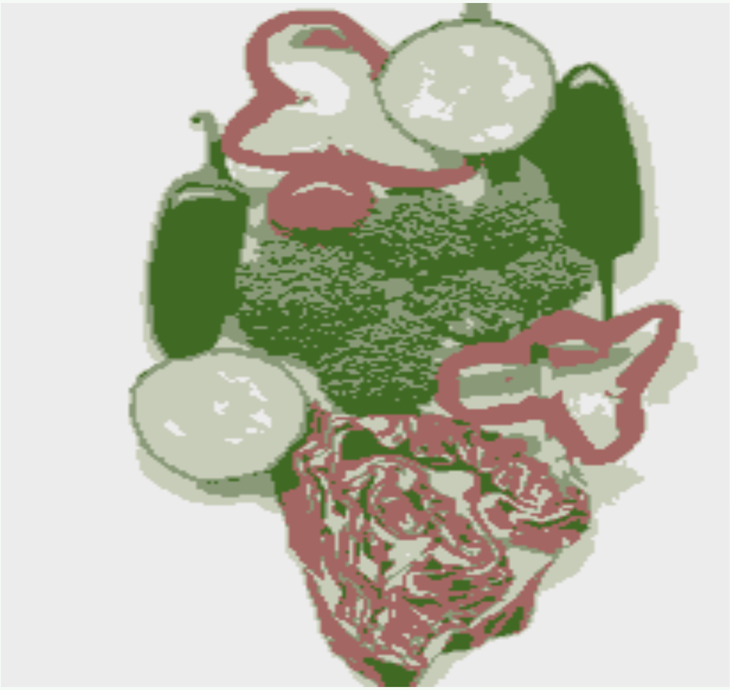
$$\text{Distortion} = 4.97$$

Exercise

더 좋다

(origin) Image | Clusters on intensity | ≪ Clusters on color





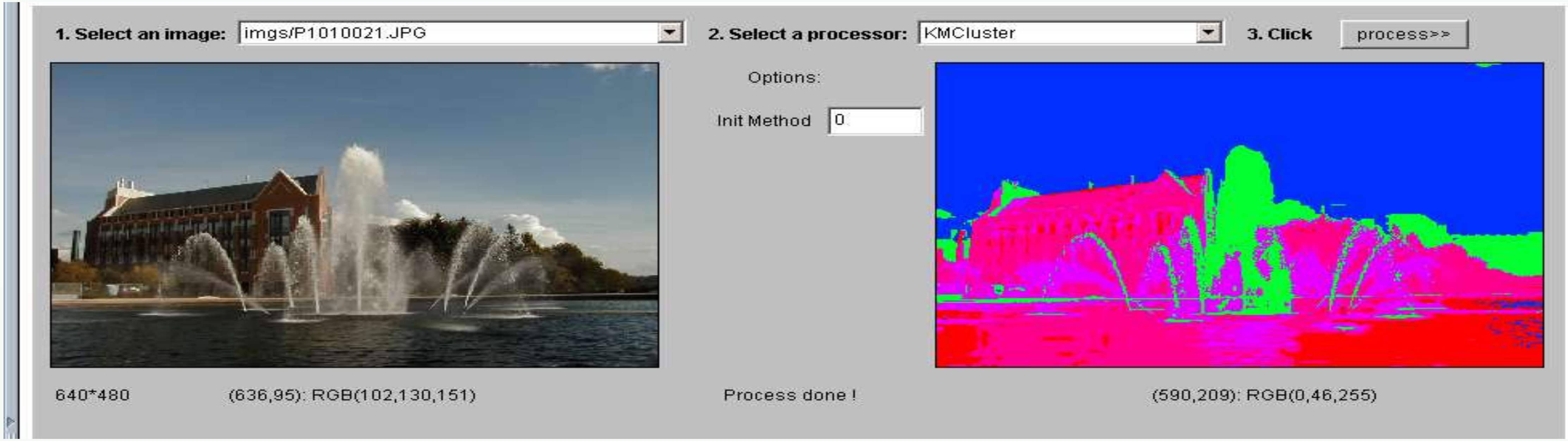
CCL

Slides by D.A. Forsyth

K-Means Example 1

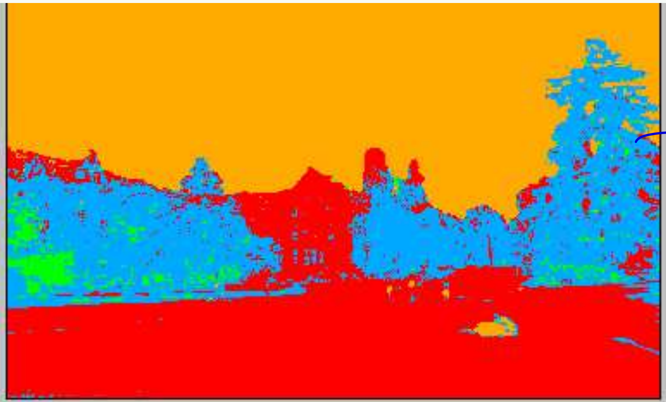
- Quick help: select an Image and a Processor, click the Process button.
- Option:

K-Means Example 2



K-Means Example 3

Init Method 0



처리전 Smoothing을 하면 좋음.

640*480 (607,118): RGB(20,22,1) Process done ! (228,26): RGB(255,170,0)

- Quick help: **select an Image and a Processor, click the Process button.**
- Option:
  - Init Method: 0-Random, 1-Linear, 2-CUBE, 3-Statistics, 4-Possibility
- Processors:
  - *KMCluster*. Interative K-Means Cluster

[comments to yi@cs.washington.edu]
Last Modified: January 1, 1970 GMT

K-Means Segmentation

재미로.

~~Agglomerative clustering~~ → 함 공부해보기.

과제를 할 때 이해까지 할 필요 X.