

23 - Segmentasi Citra (Bagian 2)

IF4073 Interpretasi dan Pengolahan Citra

Oleh: Rinaldi Munir

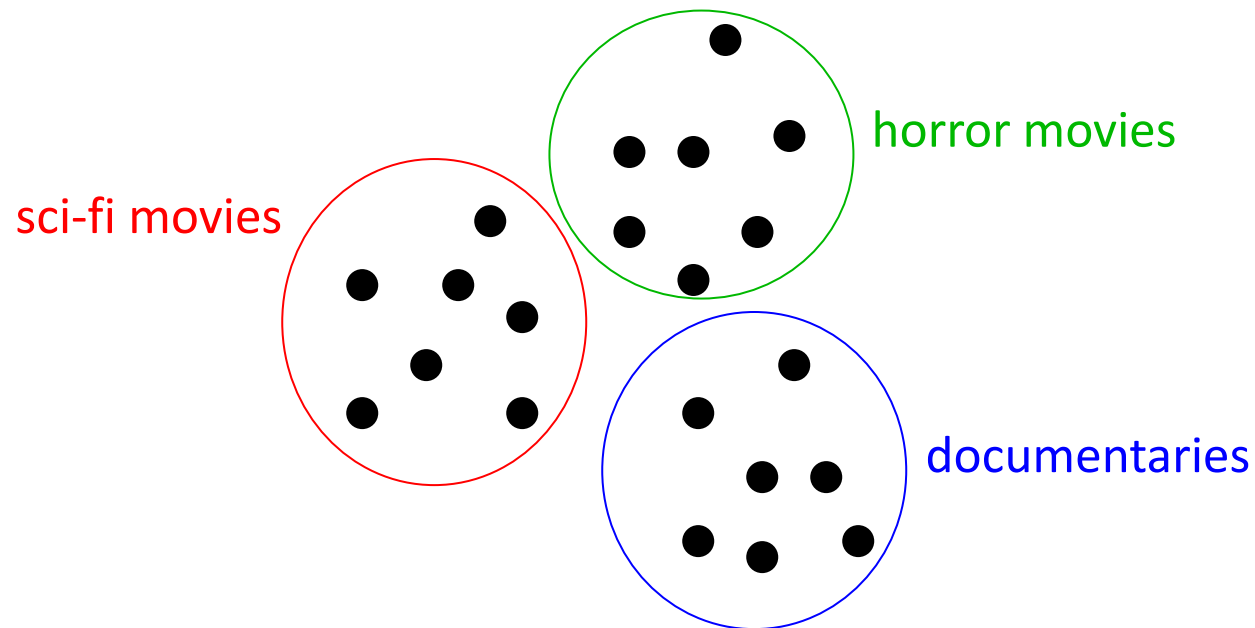


Program Studi Teknik Informatika
Sekolah Teknik Elektro dan Informatika
Institut Teknologi Bandung
2021

4. Clustering

Prinsip *clustering* secara umum

- Misalkan terdapat N buah titik data (terokan, vektor fitur, dll), $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$
- Kelompokkan (*cluster*) titik-titik yang mirip dalam kelompok yang sama



Bagaimana kaitan *clustering* pada segmentasi citra?

- Nyatakan citra sebagai vektor fitur $\mathbf{x}_1, \dots, \mathbf{x}_n$
 - Sebagai contoh, setiap *pixel* dapat dinyatakan sebagai vektor:
 - Intensitas \rightarrow menghasilkan vektor dimensi satu
 - Warna \rightarrow menghasilkan vektor berdimensi tiga (R, G, B)
 - Warna + koordinat, \rightarrow menghasilkan vektor berdimensi lima
- Kelompokkan vektor-vektor fitur ke dalam k kluster

citra input

9 4 2	7 3 1	8 6 8
8 2 4	5 8 5	3 7 2
9 4 5	2 9 3	1 4 4

**Vektor fitur untuk clustering
berdasarkan warna**

[9 4 2]	[7 3 1]	[8 6 8]
[8 2 4]	[5 8 5]	[3 7 2]
[9 4 5]	[2 9 3]	[1 4 4]

RGB (or YUV) space clustering

citra input

9 4 2	7 3 1	8 6 8
8 2 4	5 8 5	3 7 2
9 4 5	2 9 3	1 4 4

Vektor fitur untuk clustering
berdasarkan warna dan
koordinat pixel

[9 4 2 0 0] [7 3 1 0 1] [8 6 8 0 2]
 [8 2 4 1 0] [5 8 5 1 1] [3 7 2 1 2]
 [9 4 5 2 0] [2 9 3 2 1] [1 4 4 2 2]

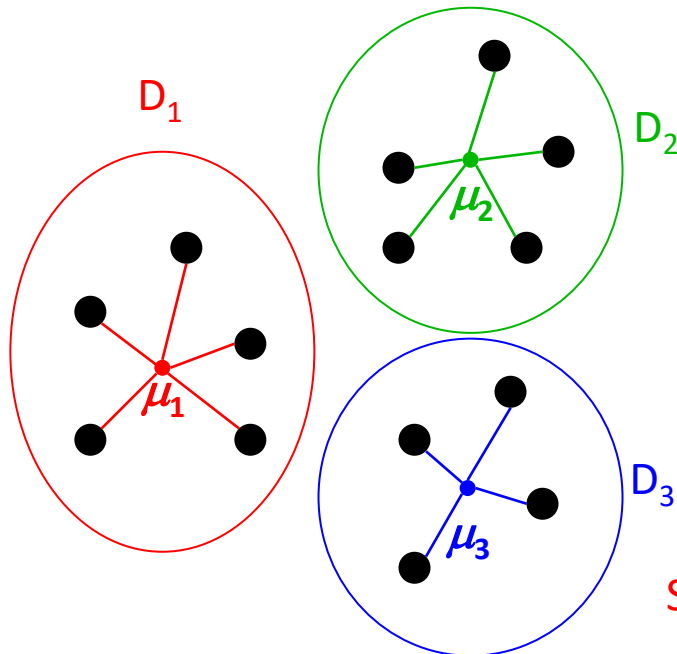
RGBXY (or YUVXY) space clustering

K-Means Clustering

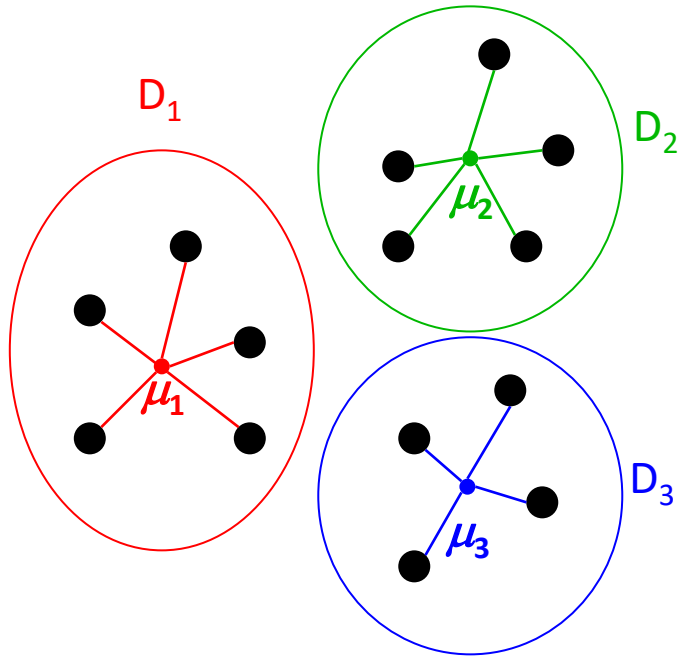
- *K-means clustering* merupakan algoritma *clustering* yang paling populer
- Asumsikan jumlah cluster adalah k
- Mengoptimalkan (secara hampiran) fungsi objektif berikut untuk variabel D_i dan μ_i

$$E_k = SSE = \sum_{i=1}^k \sum_{x \in D_i} \|x - \mu_i\|^2$$

sum of squared errors dari kluster dengan pusat μ_i

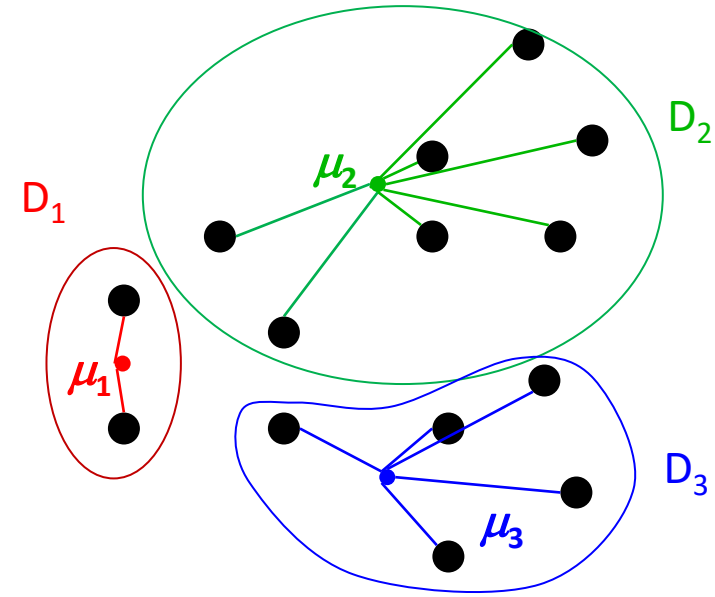


$$SSE = \text{red star} + \text{green star} + \text{blue star}$$



$$SSE = \text{red star} + \text{green star} + \text{blue star}$$

Good (tight) clustering
smaller value of SSE

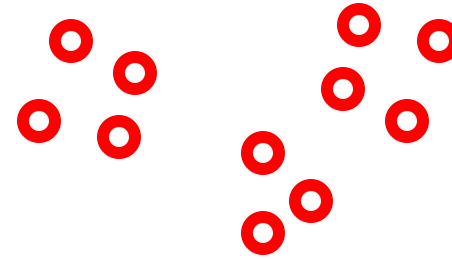


$$SEE = \text{red star} + \text{green star} + \text{blue star}$$

Bad (loose) clustering
larger value of SSE

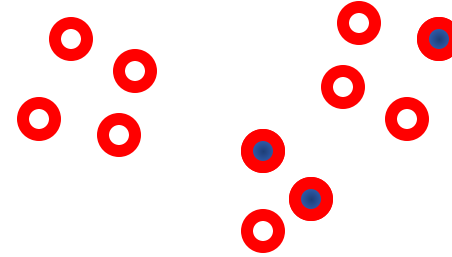
Algoritma K-means Clustering

- Initialization step
 1. pick k cluster centers randomly



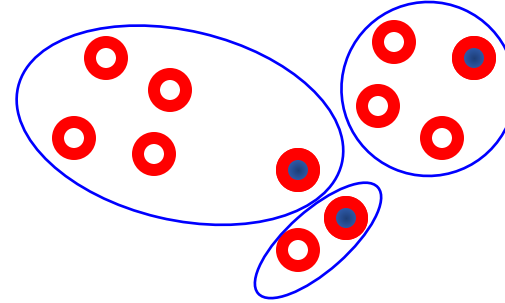
Algoritma K-means Clustering

- Initialization step
 1. pick k cluster centers randomly



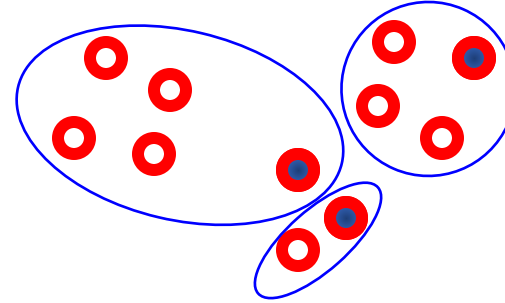
Algoritma K-means Clustering

- Initialization step
 1. pick k cluster centers randomly
 2. assign each sample to closest center



Algoritma K-means Clustering

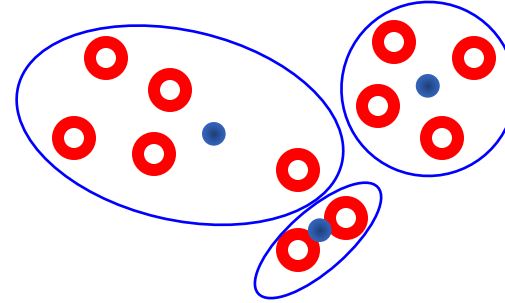
- Initialization step
 1. pick k cluster centers randomly
 2. assign each sample to closest center



Algoritma K-means Clustering

- Initialization step

1. pick k cluster centers randomly
2. assign each sample to closest center

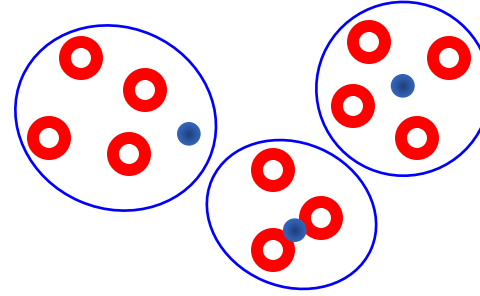


- Iteration steps

1. compute means in each cluster $\mu_i = \frac{1}{|D_i|} \sum_{x \in D_i} x$

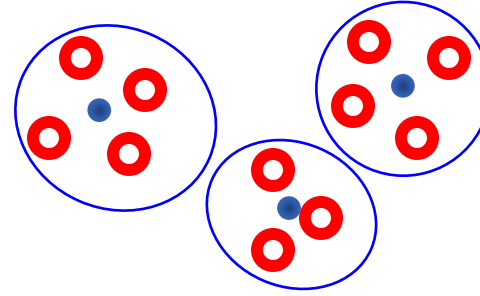
Algoritma K-means Clustering

- Initialization step
 1. pick k cluster centers randomly
 2. assign each sample to closest center
- Iteration steps
 1. compute means in each cluster $\mu_i = \frac{1}{|D_i|} \sum_{x \in D_i} x$
 2. re-assign each sample to the closest mean



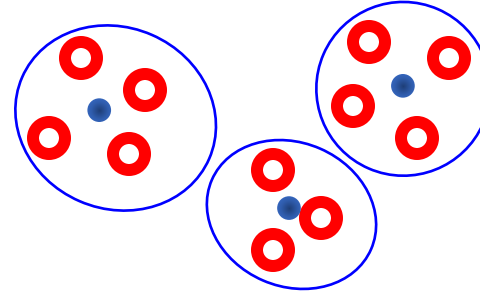
Algoritma K-means Clustering

- Initialization step
 1. pick k cluster centers randomly
 2. assign each sample to closest center
- Iteration steps
 1. compute means in each cluster $\mu_i = \frac{1}{|D_i|} \sum_{x \in D_i} x$
 2. re-assign each sample to the closest mean
- Iterate until clusters stop changing



Algoritma K-means Clustering

- Initialization step
 - pick k cluster centers randomly
 - assign each sample to closest center



- Iteration steps
 - compute means in each cluster $\mu_i = \frac{1}{|D_i|} \sum_{x \in D_i} x$
 - re-assign each sample to the closest mean
- Iterate until clusters stop changing

- This procedure decreases the value of the objective function

$$E_k(D, \mu) = \sum_{i=1}^k \sum_{x \in D_i} \|x - \mu_i\|^2$$

↖ ↗

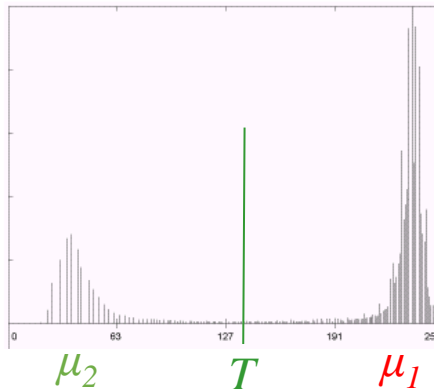
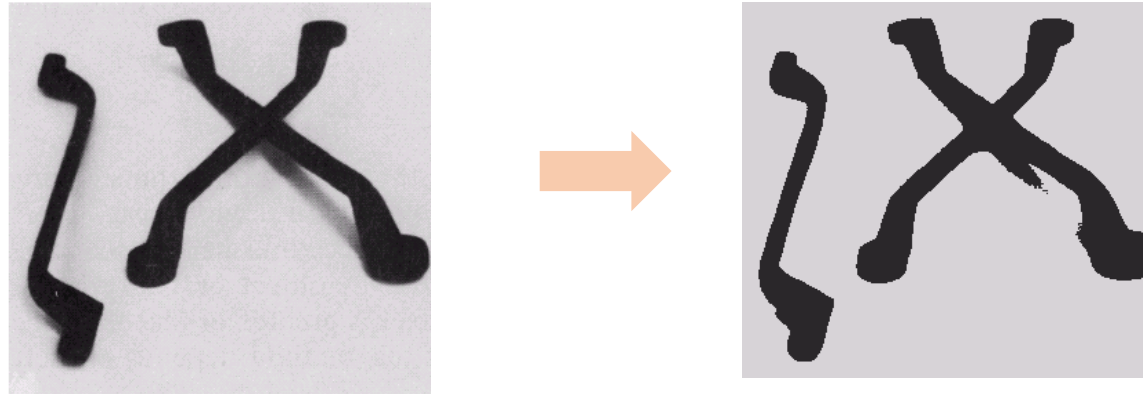
optimization variables

$$D = (D_1, \dots, D_k)$$

$$\mu = (\mu_1, \dots, \mu_k)$$

block-coordinate descent: step 1 optimizes μ , step 2 optimizes D

Contoh hasil *K-means clustering*



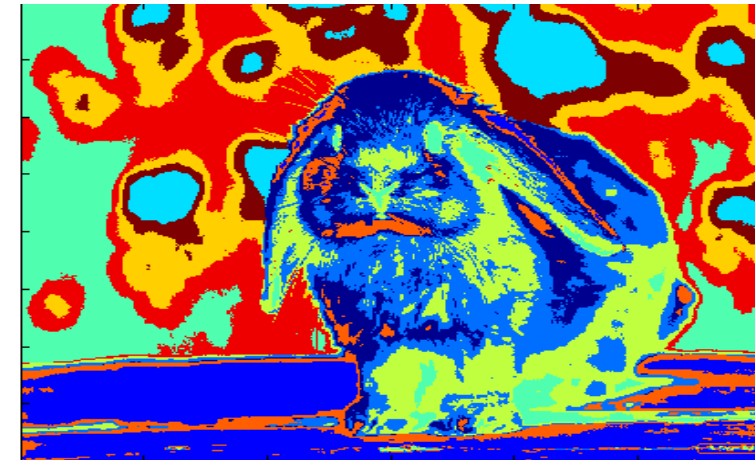
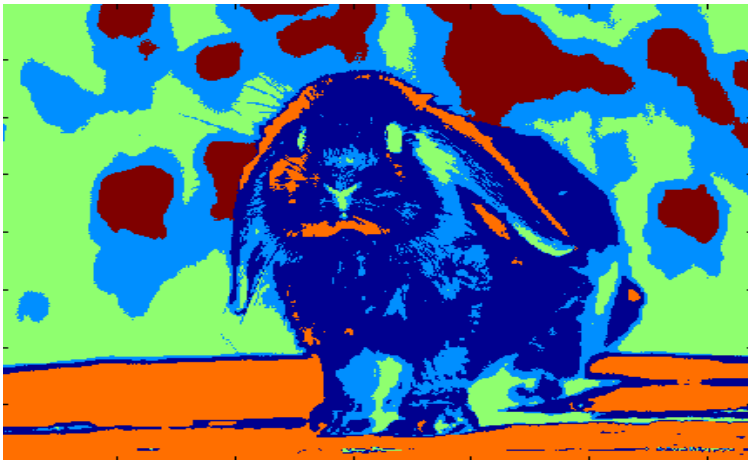
K-means menghasilkan
Pengelompokan yang kompak

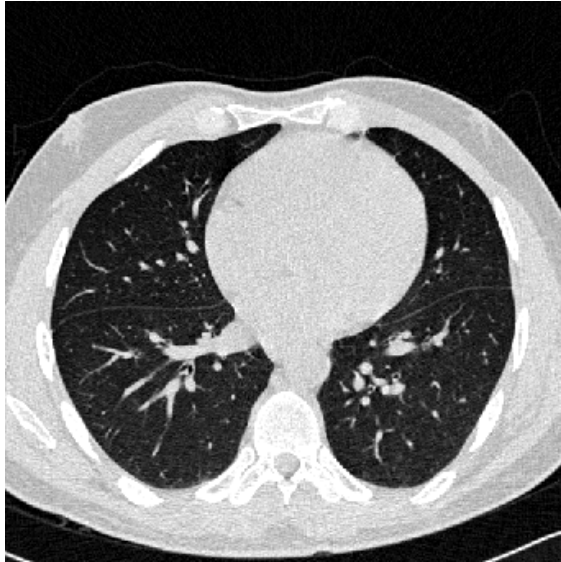
Pada kasus ini, K-means ($K=2$) secara otomatis menemukan nilai ambang yang bagus antara 2 cluster



$k = 3$

(random colors are used to better show segments/clusters)





An image(I)



**Three cluster
image (J)on gray
values of I**

1. Select an image:

2. Select a processor:

3. Click



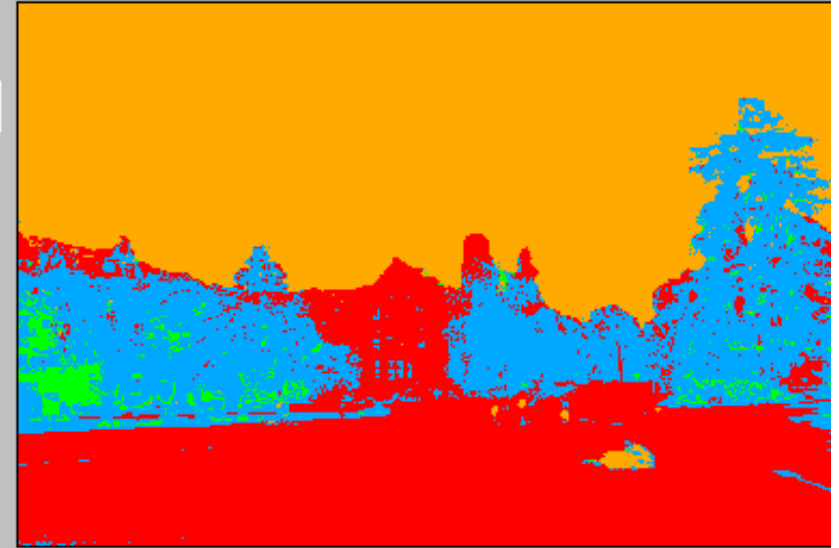
640*480

(607,118): RGB(20,22,1)

Options:

Init Method

Process done !



(228,26): RGB(255,170,0)

1. Select an image:



640*480

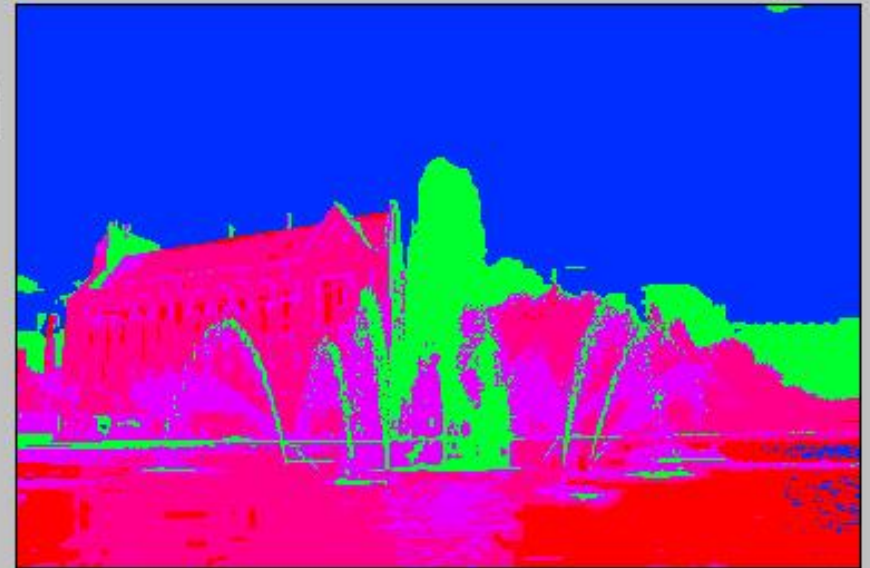
(636,95): RGB(102,130,151)

2. Select a processor:

3. Click

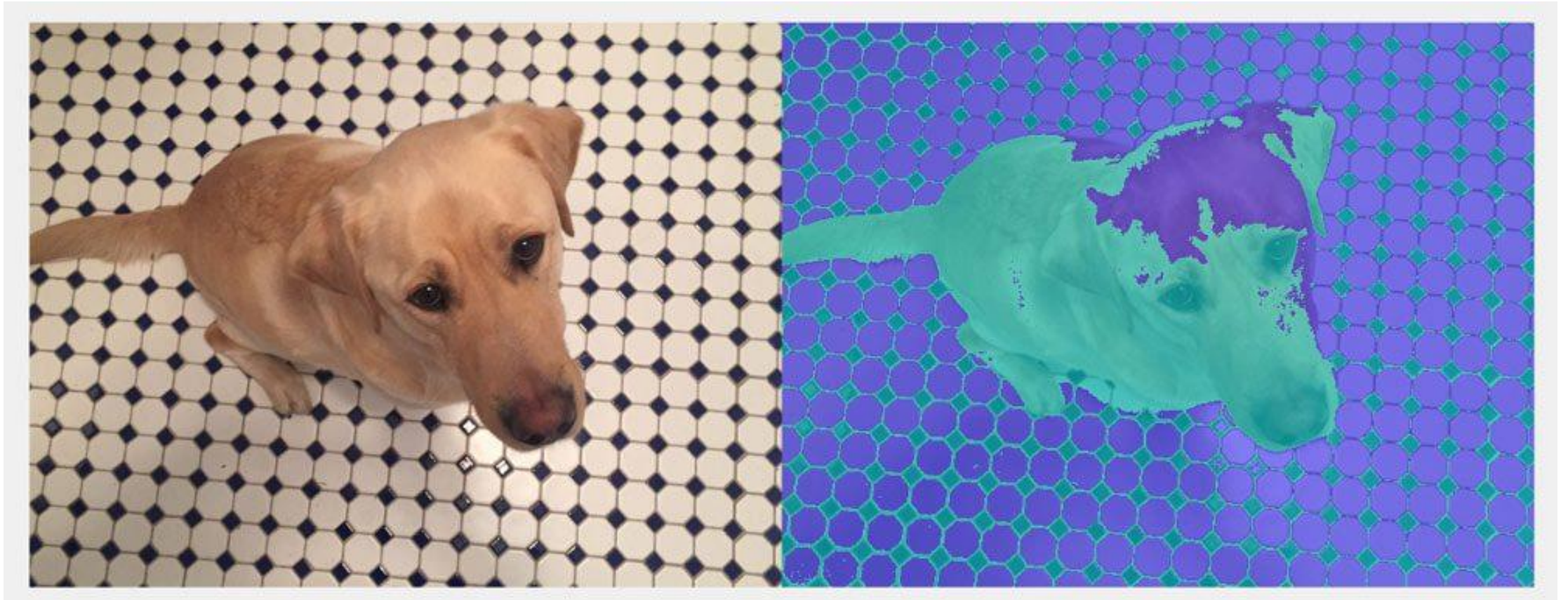
Options:

Init Method



(590,209): RGB(0,46,255)

Process done !



Sumber: <https://www.mathworks.com/discovery/image-segmentation.html>

Contoh hasil *K-means clustering* (berdasarkan warna)



0 100 200 300 400



0 100 200 300 400



0 100 200 300 400 500



0 100 200 300 400 500

Contoh hasil *K-means clustering* (berdasarkan warna + koordinat)

color quantization



RGB features

superpixels



RGBXY features

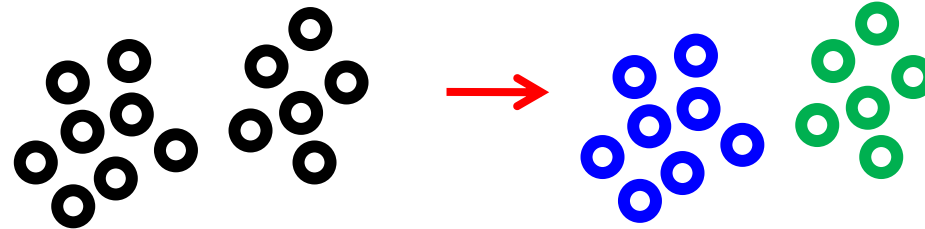
Voronoi cells



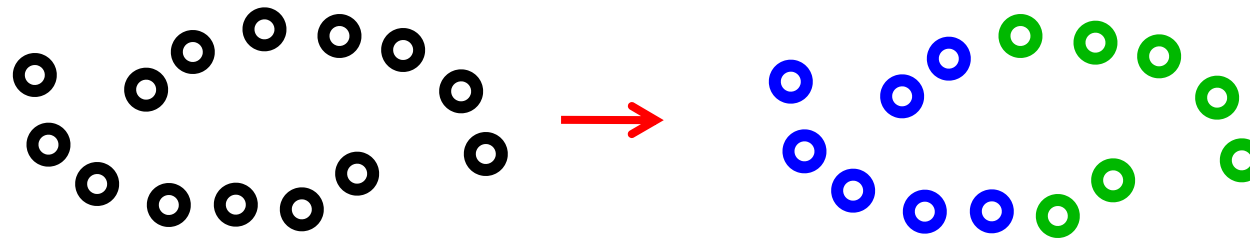
XY features only

Sifat-sifat K-means

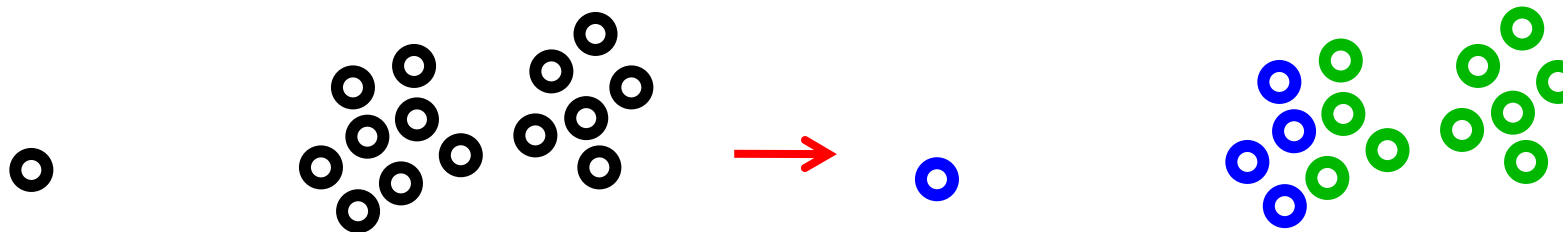
- Works best when clusters are spherical (blob like)



- Fails for elongated clusters
 - SSE is not an appropriate objective function in this case



- Sensitive to outliers



maximum likelihood (ML) fitting
of parameters μ_i (means) of Gaussian distributions

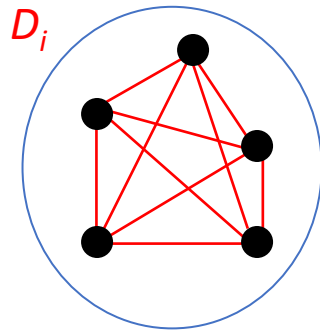
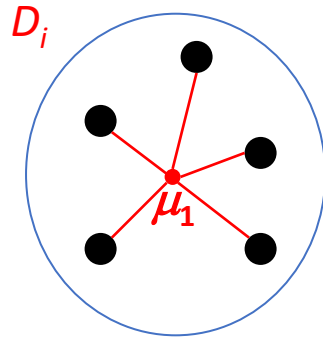
$$E_k = \sum_{i=1}^k \sum_{x \in D_i} \|x - \mu_i\|^2$$



equivalent (easy to check)

$$E_k \sim - \sum_{i=1}^k \sum_{x \in D_i} \log P(x | \mu_i) + \text{const}$$

Gaussian distribution $P(x | \mu_i) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{\|x - \mu_i\|^2}{2\sigma^2}\right)$



$$E_k = \sum_{i=1}^k \sum_{x \in D_i} \|x - \mu_i\|^2$$

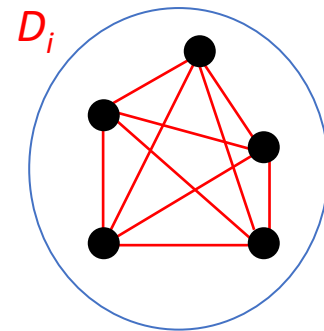
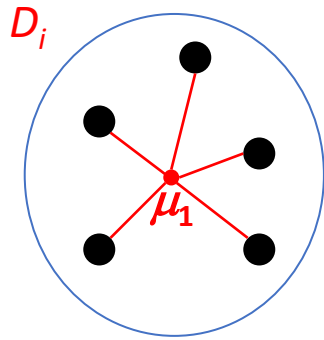
just plug-in
expression
 $\mu_i = \frac{1}{|D_i|} \sum_{y \in D_i} y$



equivalent (easy to check)

$$E_k = \sum_{i=1}^k \sum_{x, y \in D_i} \frac{\|x - y\|^2}{2 \cdot |D_i|}$$

sample variance: $\text{var}(D_i) = \frac{1}{|D_i|} \sum_{x \in D_i} \|x - \mu_i\|^2 = \frac{1}{2|D_i|^2} \sum_{x, y \in D_i} \|x - y\|^2$



both formulas can be written as

$$E_k = \sum_{i=1}^k |D_i| \cdot \text{var}(D_i)$$

sample variance: $\text{var}(D_i) = \frac{1}{|D_i|} \sum_{x \in D_i} \|x - \mu_i\|^2 = \frac{1}{2|D_i|^2} \sum_{x, y \in D_i} \|x - y\|^2$

Rangkuman K-means

- Advantages
 - Principled (objective function) approach to clustering
 - Simple to implement (the approximate iterative optimization)
 - Fast
- Disadvantages
 - Only a local minimum is found (sensitive to initialization)
 - May fail for non-blob like clusters ← K-means fits Gaussian models
 - Sensitive to outliers ← Quadratic errors are such
 - Sensitive to choice of k ← Can add sparsity term and make k an additional variable

$$E = \sum_{i=1}^k \sum_{x \in D_i} \|x - \mu_i\|^2 + \gamma \cdot |k|$$

*Akaike Information Criterion (AIC) or
Bayesian Information Criterion (BIC)*

Program Matlab untuk image segmentation dengan K-means

- Fungsi **imsegkmeans** hanya tersedia untuk Matlab R2022a

```
I = imread('camera.bmp');  
imshow(I)  
title('Original Image');  
[L,Centers] = imsegkmeans(I,3); % Segmentasi citra menjadi tiga  
label dengan K-means clustering  
B = labeloverlay(I,L);  
imshow(B)  
title('Labeled Image')
```

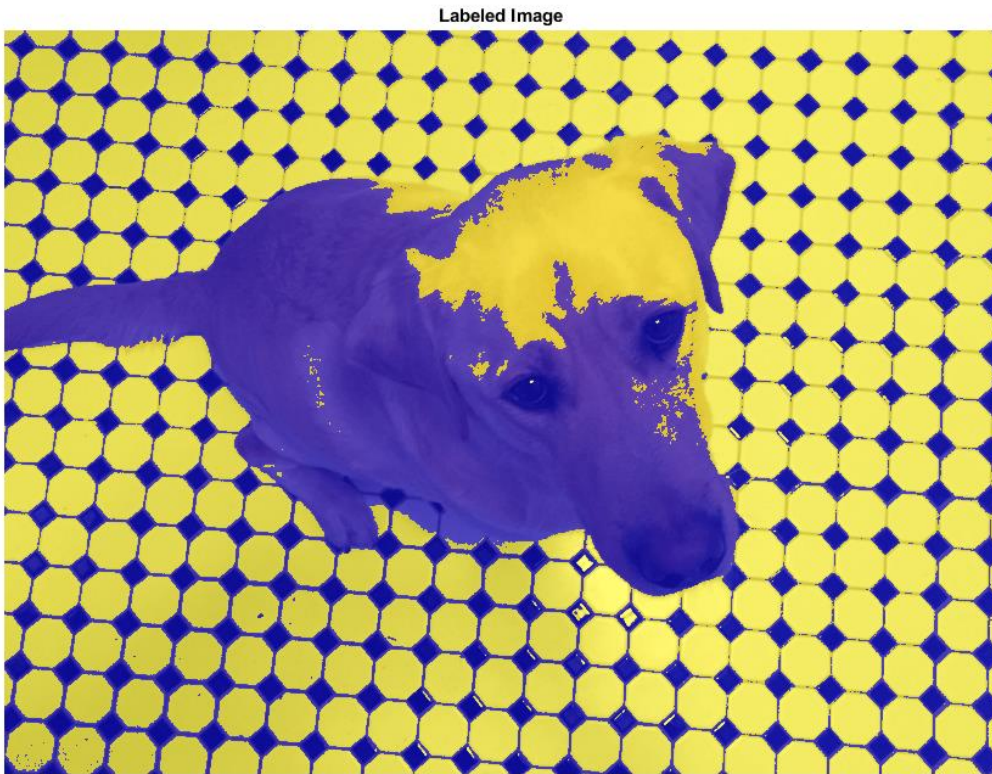
Original Image



Labeled Image



```
RGB = imread("kobi.png");  
RGB = imresize(RGB,0.5);  
imshow(RGB)  
L = imsegkmeans(RGB,2);  
B = labeloverlay(RGB,L);  
imshow(B)  
title("Labeled Image")
```



Segmentasi Citra dengan Deep Learning

- Disebut juga *semantic segmentation*
- Tiap *pixel* di dalam citra diasosiasikan dengan sebuah label kelas

