Seeing the Big Picture

Segmenting Images to Create Data

15.071x – The Analytics Edge

Image Segmentation

- Divide up digital images to salient regions/clusters corresponding to individual surfaces, objects, or natural parts of objects

- Clusters should be uniform and homogenous with respect to certain characteristics (color, intensity, texture)

- Goal: Useful and analyzable image representation

Wide Applications

- Medical Imaging
  - Locate tissue classes, organs, pathologies and tumors
  - Measure tissue/tumor volume
- Object Detection
  - Detect facial features in photos
  - Detect pedestrians in footages of surveillance videos
- Recognition tasks
  - Fingerprint/Iris recognition

Various Methods

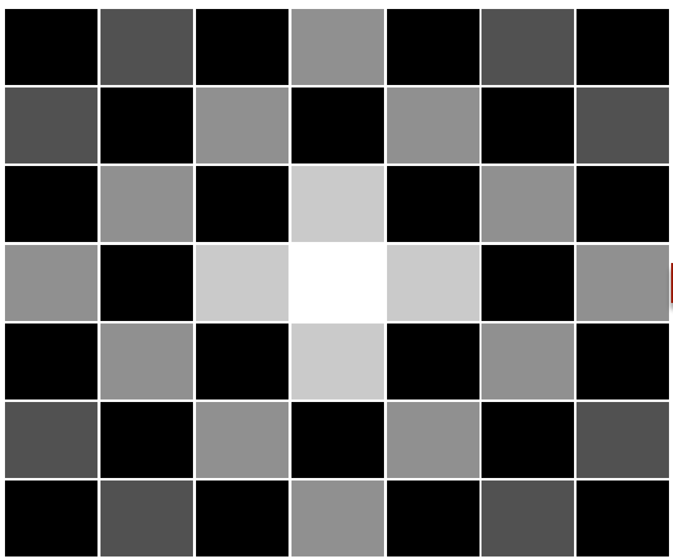
- Clustering methods
  - Partition image to clusters based on differences in pixel colors, intensity or texture
- Edge detection
  - Based on the detection of discontinuity, such as an abrupt change in the gray level in gray-scale images
- Region-growing methods
  - Divides image into regions, then sequentially merges sufficiently similar regions

In this Recitation…

- Review hierarchical and *k*-means clustering in R
- Restrict ourselves to gray-scale images
  - Simple example of a flower image (flower.csv)
  - Medical imaging application with examples of transverse MRI images of the brain (healthy.csv and tumor.csv)
- Compare the use, pros and cons of all analytics methods we have seen so far

Grayscale Images

- Image is represented as a matrix of pixel intensity values ranging from 0 (black) to 1 (white)
- For 8 bits/pixel (bpp), 256 color levels



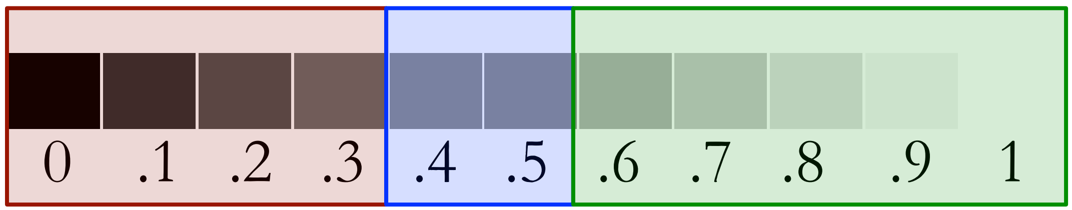
7 pixels

7 pixels

0	.2	0	.5	0	.2	0
.2	0	.5	0	.5	0	.2
0	.5	0	.7	0	.5	0
.5	0	.7	1	.7	0	.5
0	.5	0	.7	0	.5	0
.2	0	.5	0	.5	0	.2
0	.2	0	.5	0	.2	0

Grayscale Image Segmentation

- Cluster pixels according to their intensity values



0	.2	0	.5	0	.2	0
.2	0	.5	0	.5	0	.2
0	.5	0	.7	0	.5	0
.5	0	.7	1	.7	0	.5
0	.5	0	.7	0	.5	0
.2	0	.5	0	.5	0	.2
0	.2	0	.5	0	.2	0

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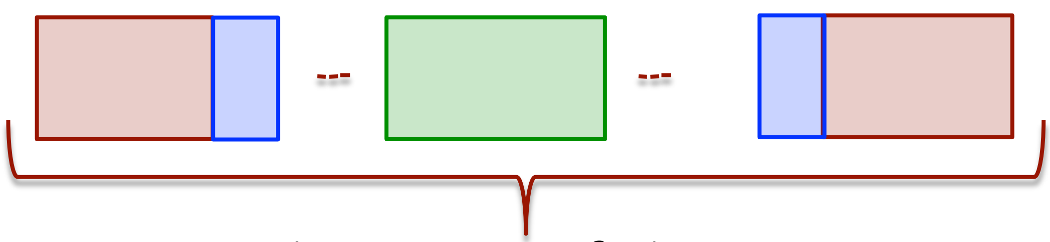
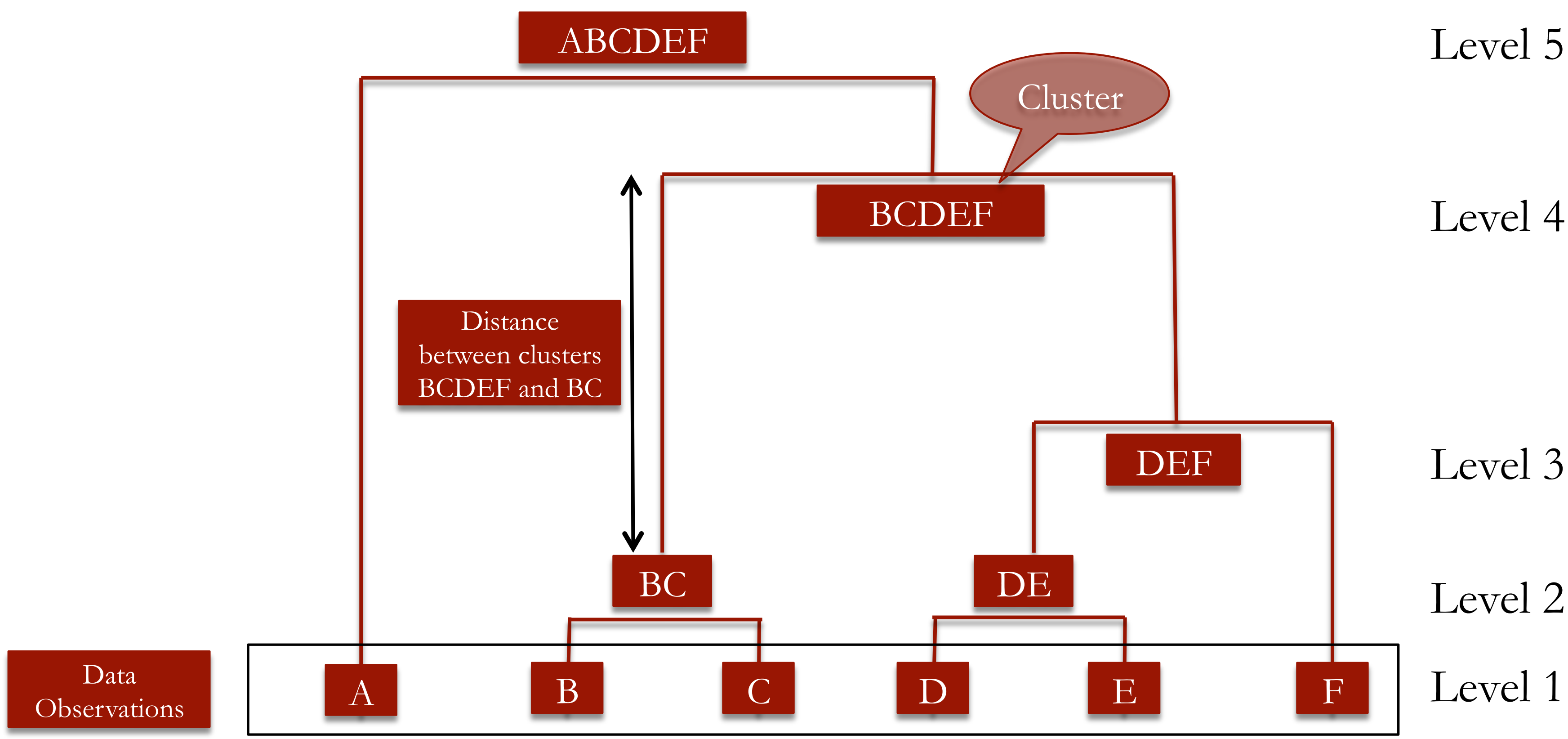


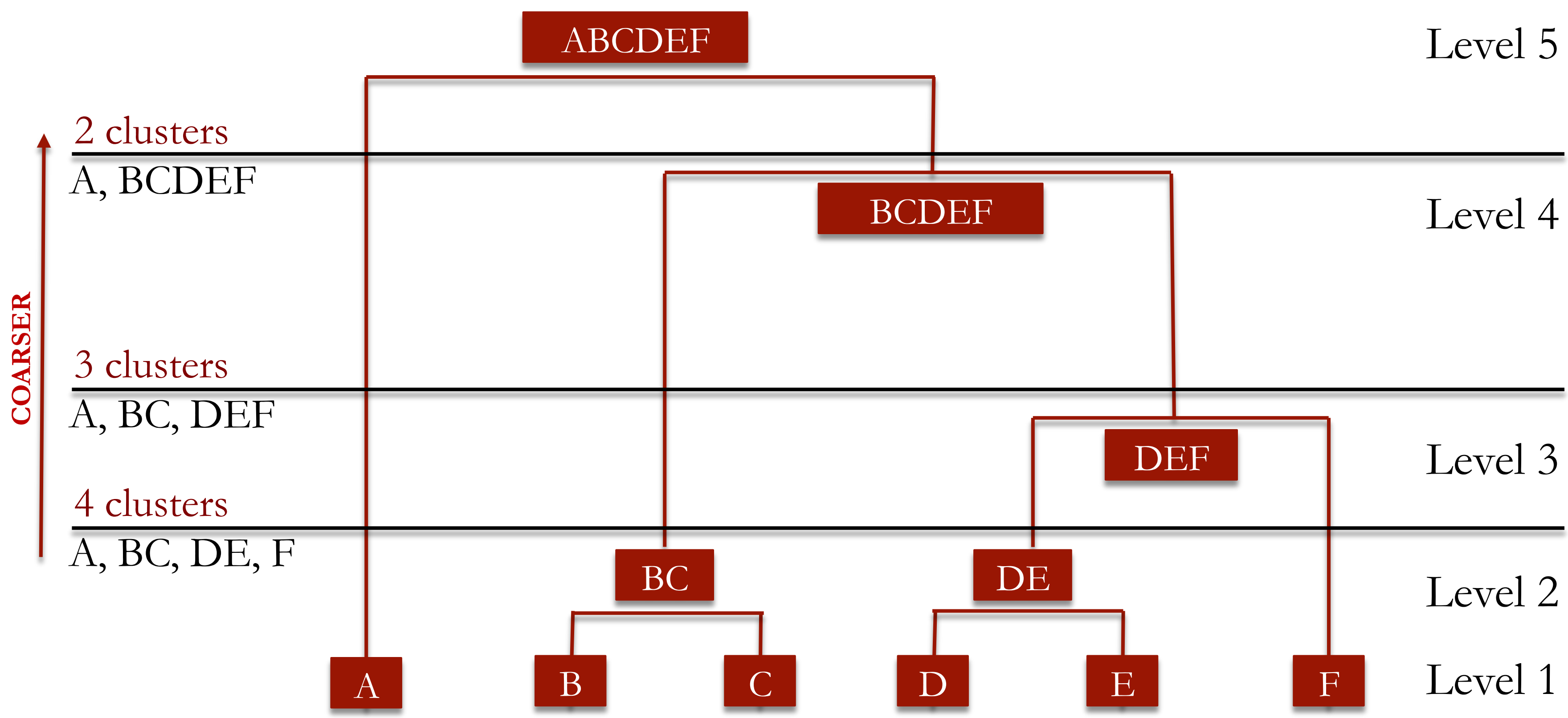
Intensity Vector of size n = 7x7

Pairwise distances n(n-1)/2

Dendrogram Example



Dendrogram Example



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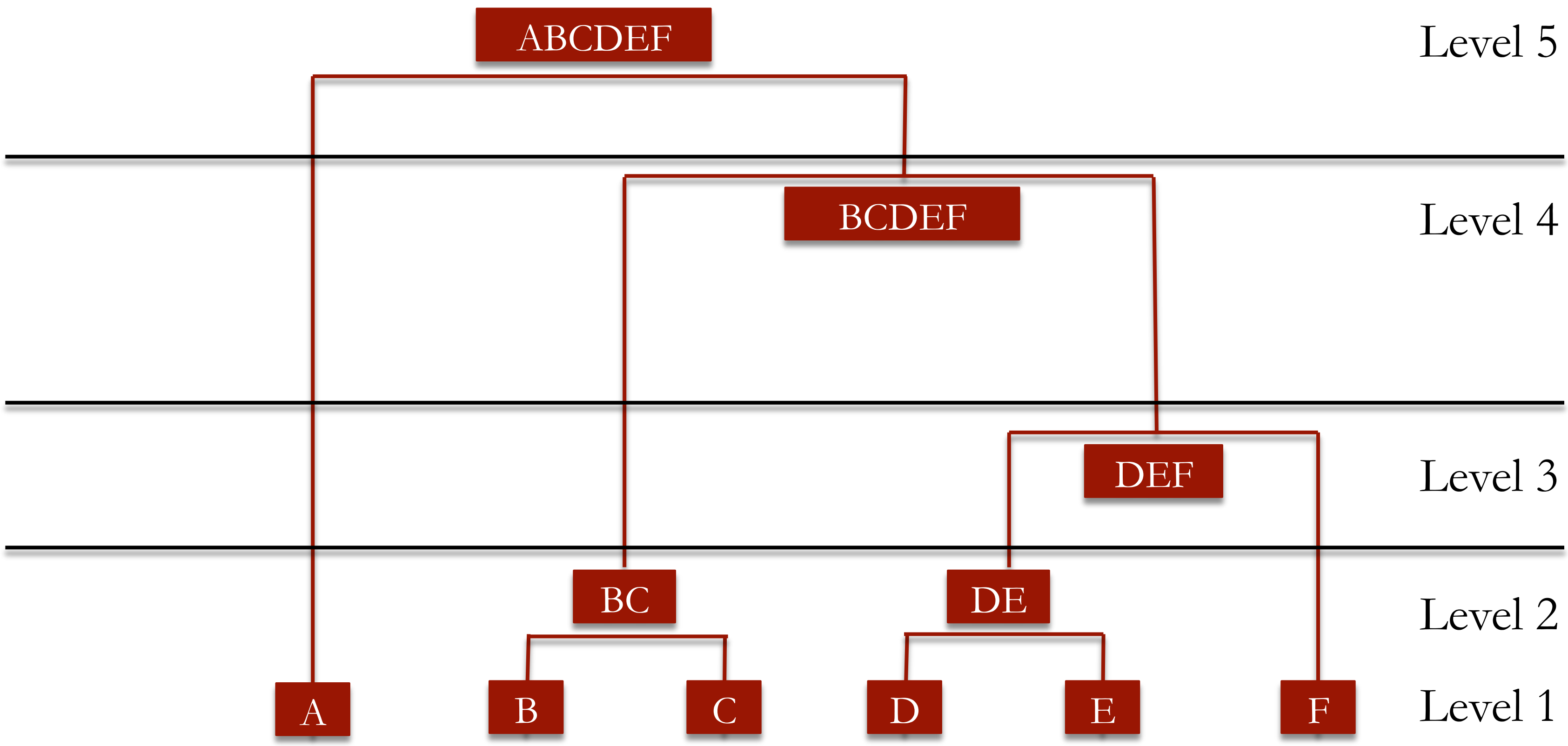
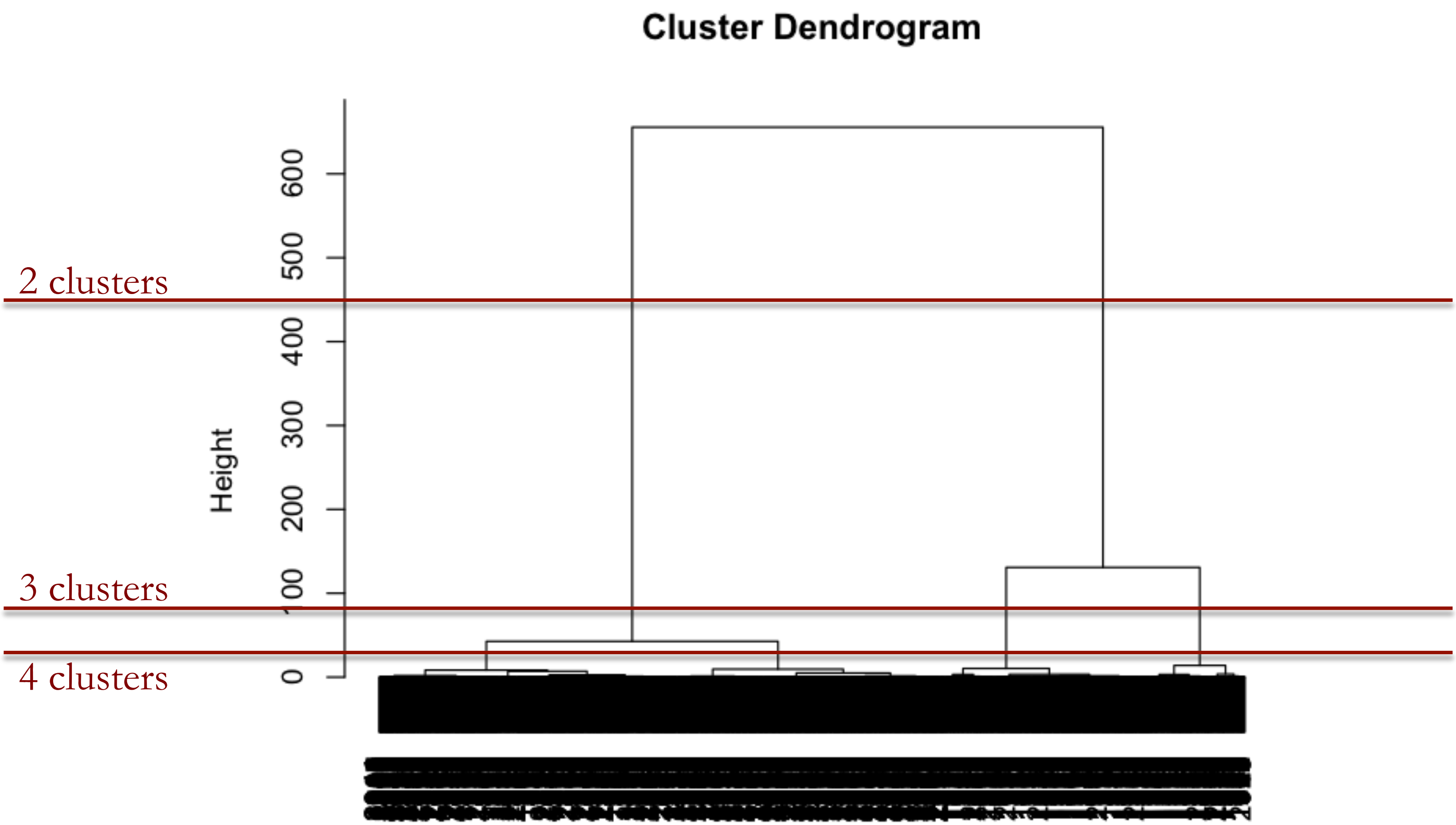


Flower Dendrogram



k-Means Clustering

- The k-means clustering aims at partitioning the data into k clusters in which each data point belongs to the cluster whose mean is the nearest

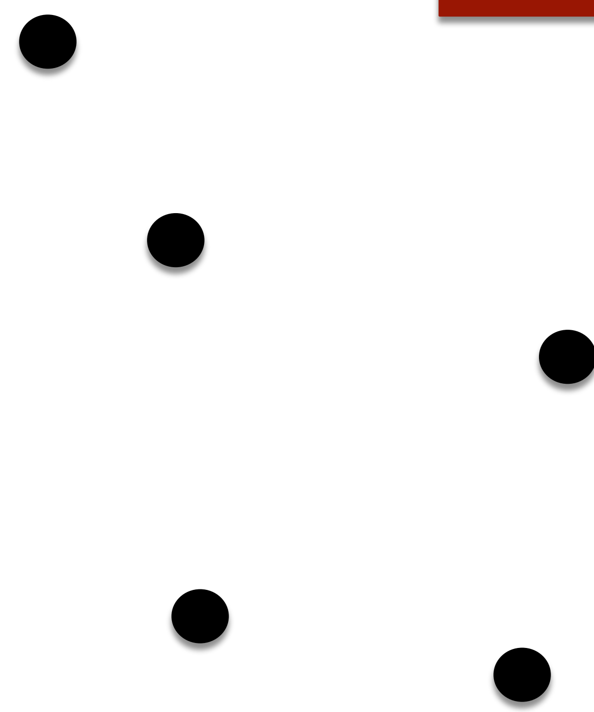
k-Means Clustering Algorithm
1. Specify desired number of clusters k
2. Randomly assign each data point to a cluster
3. Compute cluster centroids
4. Re-assign each point to the closest cluster centroid
5. Re-compute cluster centroids
6. Repeat 4 and 5 until no improvement is made

k-Means Clustering

k-Means Clustering Algorithm

1. Specify desired number of clusters k

$k = 2$



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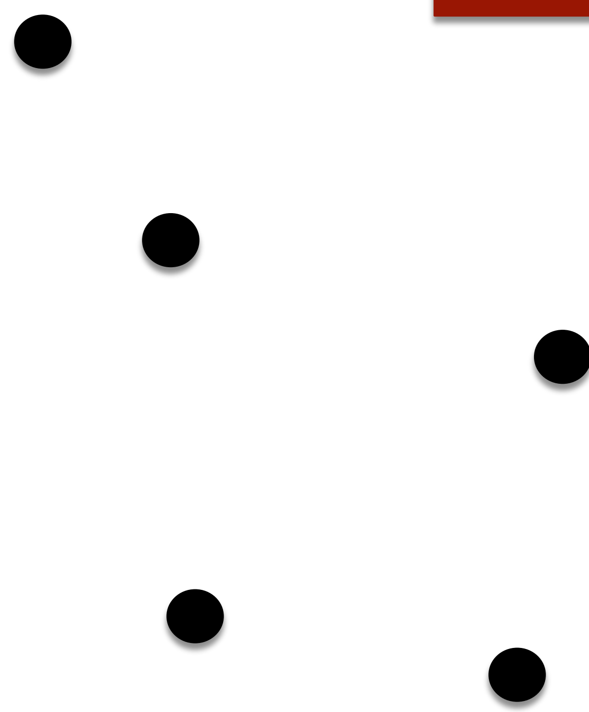

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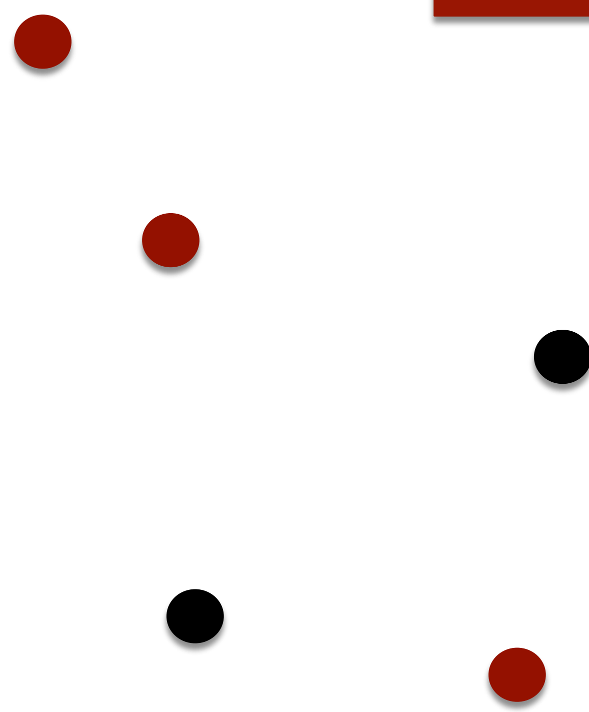

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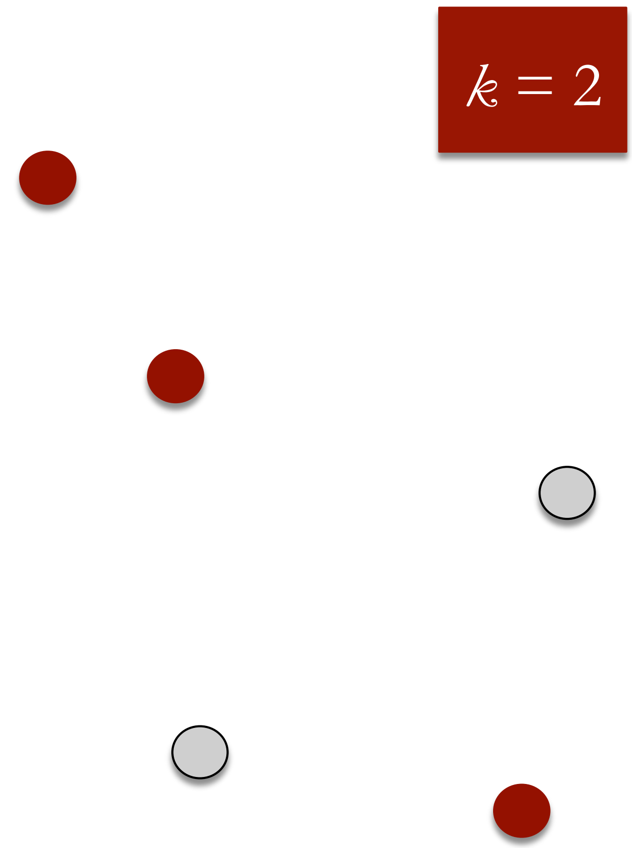

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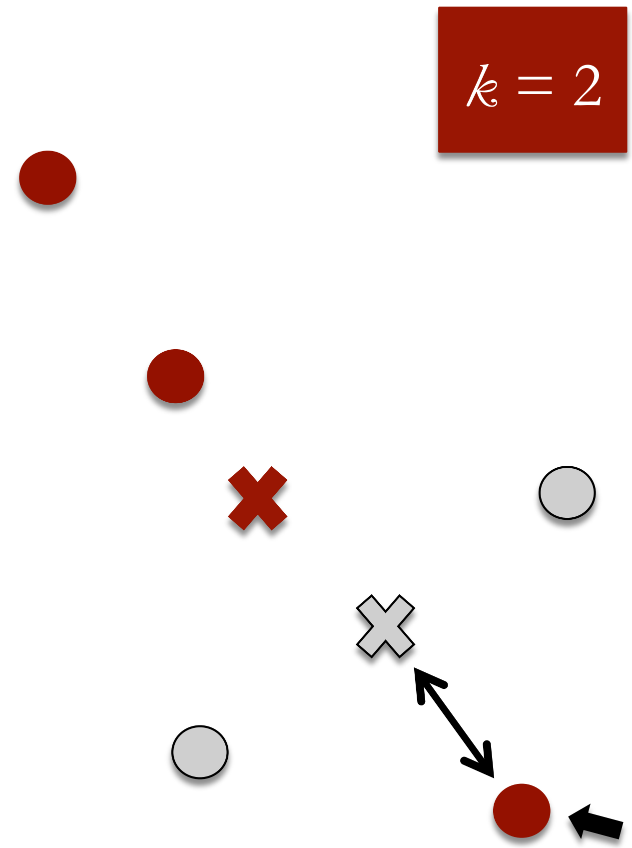

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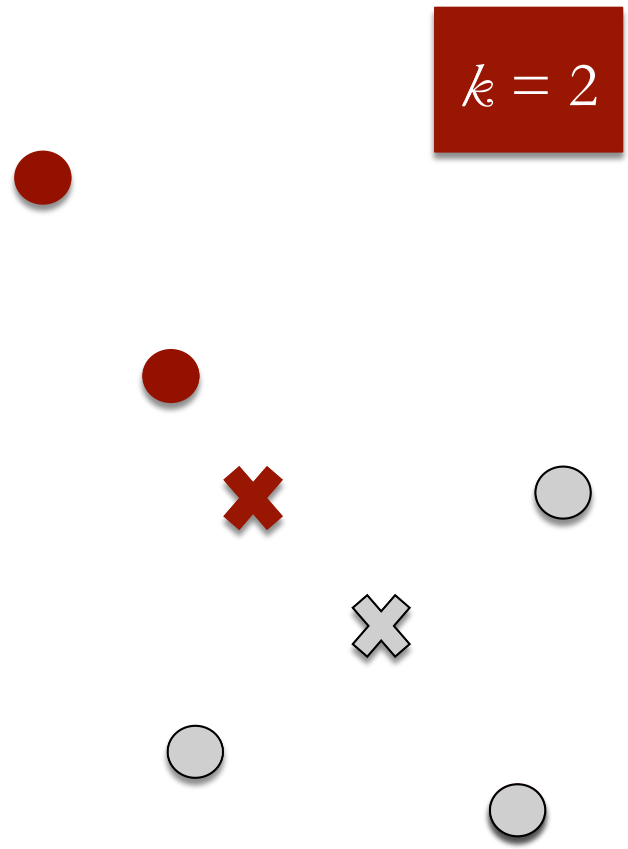

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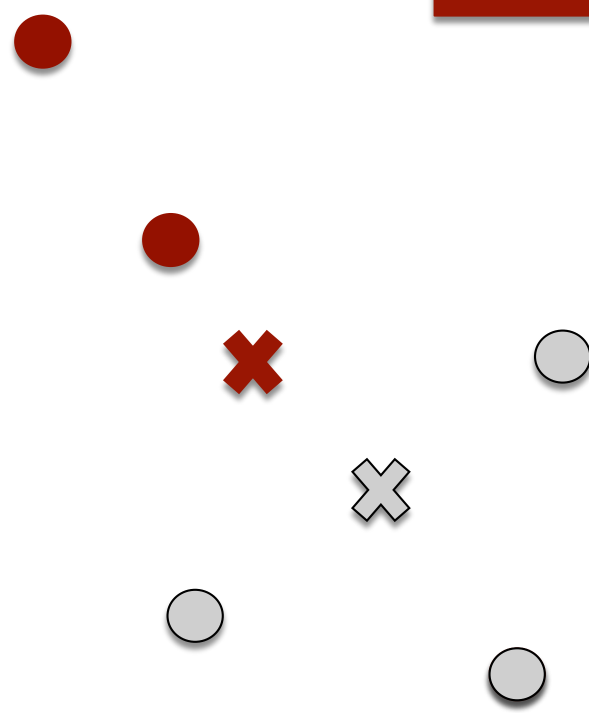

First Taste of a Fascinating Field

- MRI image segmentation is subject of ongoing research

- *k*-means is a good starting point, but not enough
  - Advanced clustering techniques such as the modified fuzzy k-means (MFCM) clustering technique
  - Packages in R specialized for medical image analysis

    http://cran.r-project.org/web/views/MedicalImaging.html

3D Reconstruction

MRI image removed due to copyright restrictions.

- 3D reconstruction from 2D cross sectional MRI images
- Important in the medical field for diagnosis, surgical planning and biological research

Comparison of Methods

	Used For	Pros	Cons
Linear Regression	Predicting a continuous outcome (salary, price, number of votes, etc.)	• Simple, well recognized • Works on small and large datasets	• Assumes a linear relationship $Y = a\ \underbrace{\log(X)}+b$
Logistic Regression	Predicting a categorical outcome (Yes/No, Sell/Buy, Accept/Reject, etc.)	• Computes probabilities that can be used to assess confidence of the prediction	• Assumes a linear relationship

Comparison of Methods

	Used For	Pros	Cons
CART	Predicting a categorical outcome (quality rating 1--5, Buy/Sell/Hold) or a continuous outcome (salary, price, etc.)	• Can handle datasets without a linear relationship • Easy to explain and interpret	• May not work well with small datasets
Random Forests	Same as CART	• Can improve accuracy over CART	• Many parameters to adjust • Not as easy to explain as CART

Comparison of Methods

	Used For	Pros	Cons
Hierarchical Clustering	• Finding similar groups • Clustering into smaller groups and applying predictive methods on groups	• No need to select number of clusters a priori • Visualize with a dendrogram	• Hard to use with large datasets
***k*-means Clustering**	Same as Hierarchical Clustering	• Works with any dataset size	• Need to select number of clusters before algorithm