Clustering Analysis and K-Means

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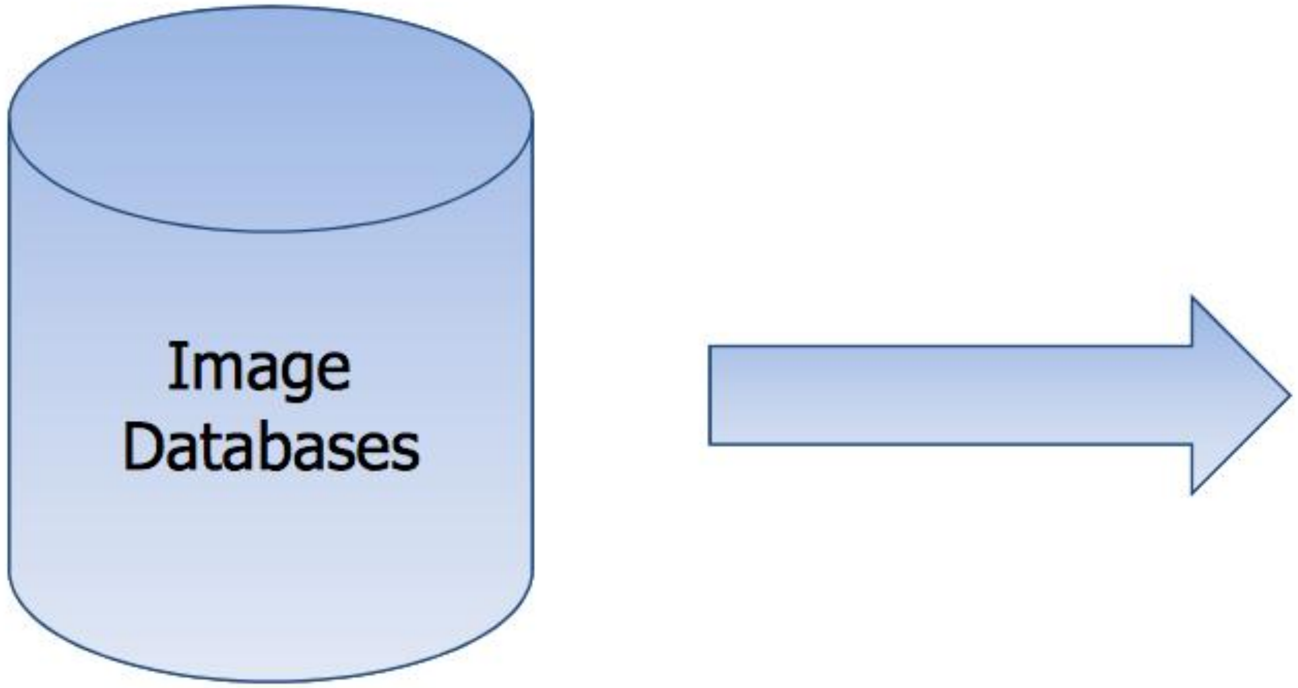
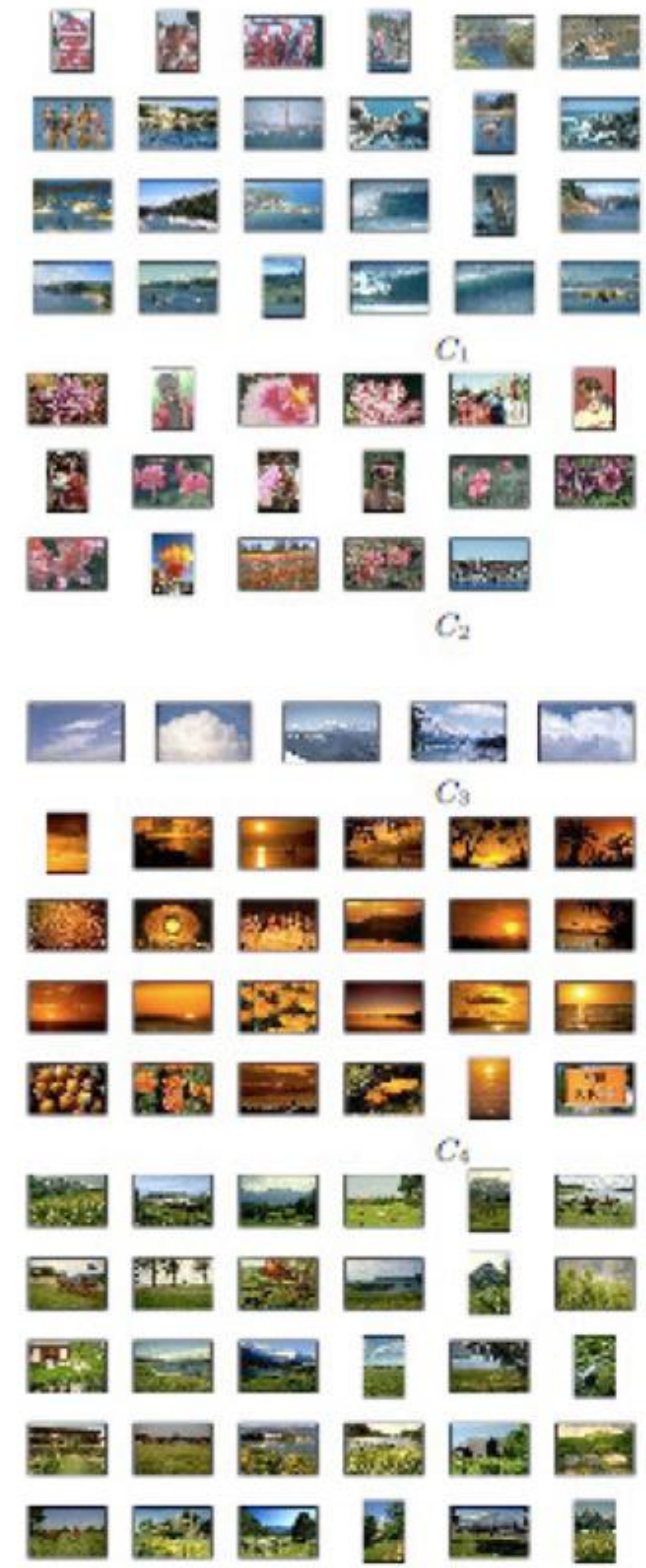
Some of the slides are inspired based on slides from Chao Zhang, and Le Song.

Outline

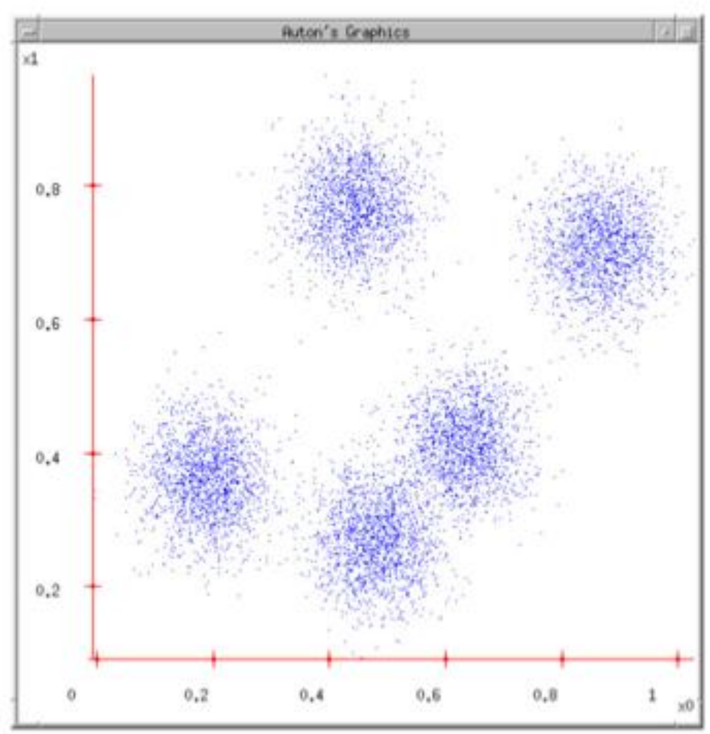
- Clustering ⬅
- Distance Function
- K-Means Algorithm
- Analysis of K-Means

Clustering Images





Goal of clustering:
Divide object into groups, and objects within a group are more similar than those outside the group

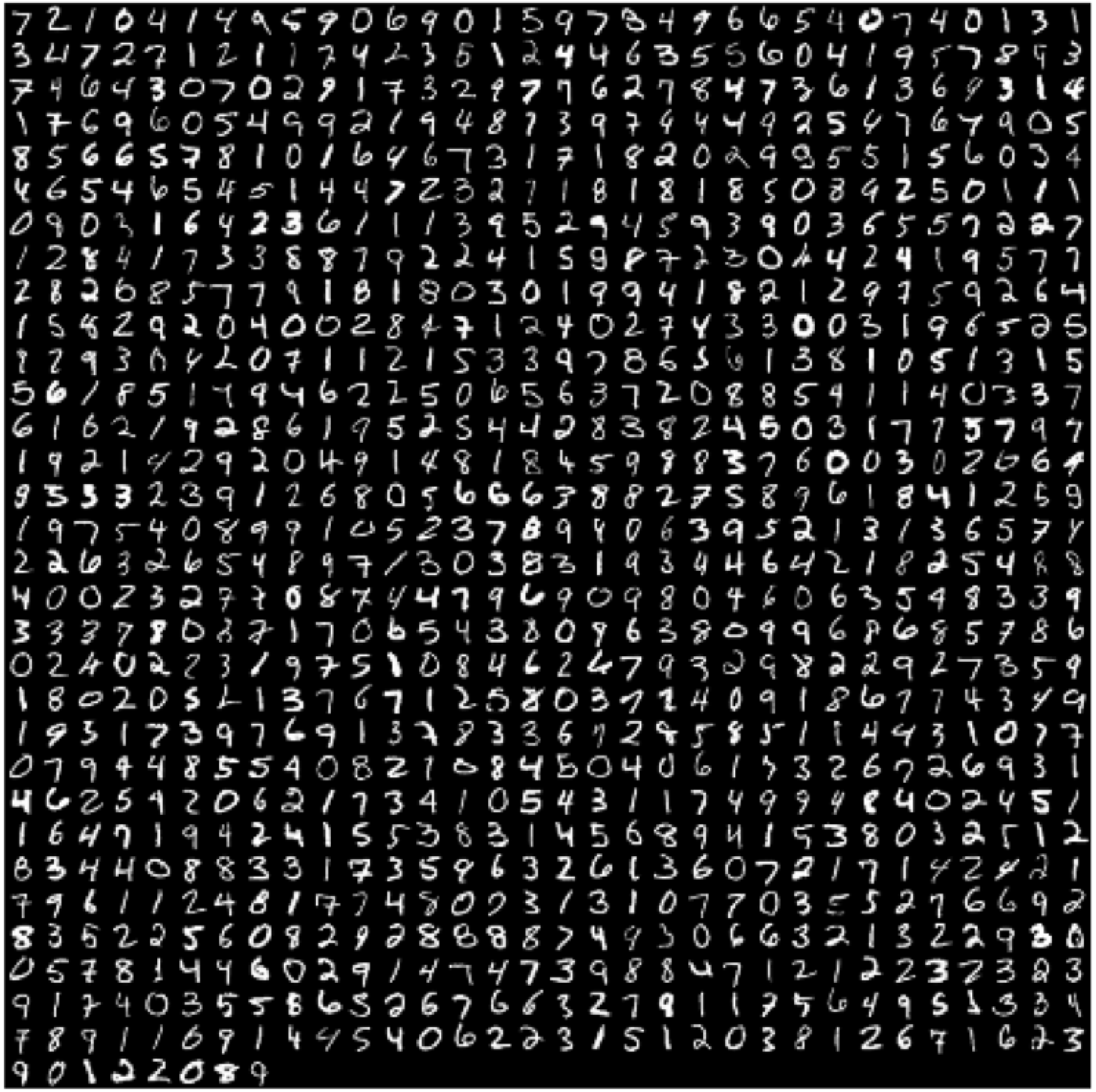


Clustering Other Objects

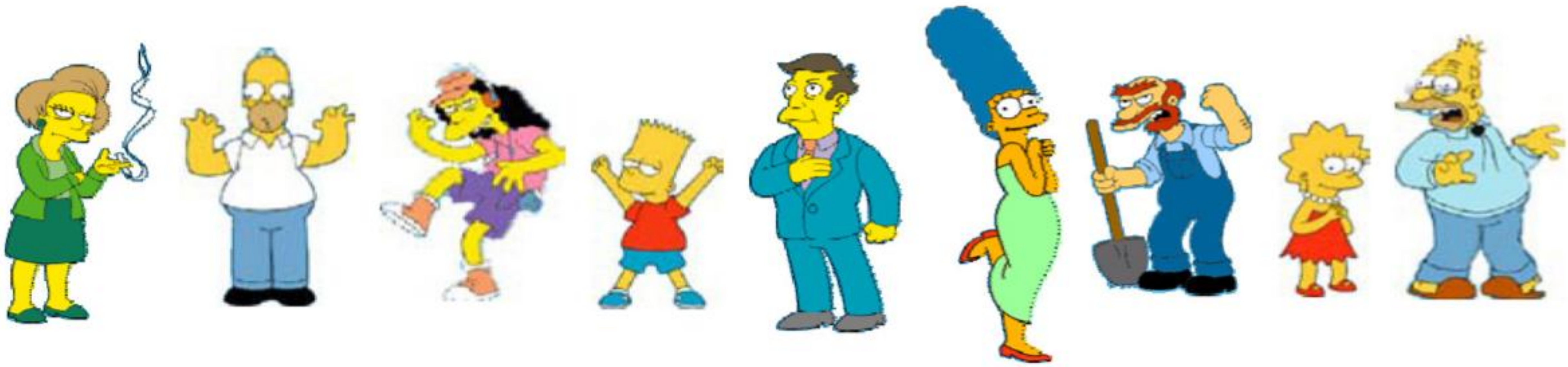
Piotr — Belarusian
Pyotr — Azerbaijani
Petros — Greek
Pietro — Italian
Pedro — Portuguese
Pierre — French
Piero — Italian
Peter — Dutch
Peder — Danish
Peka — Couldn't find it – Finish?
Peadar — Irish

Linguistic Similarity

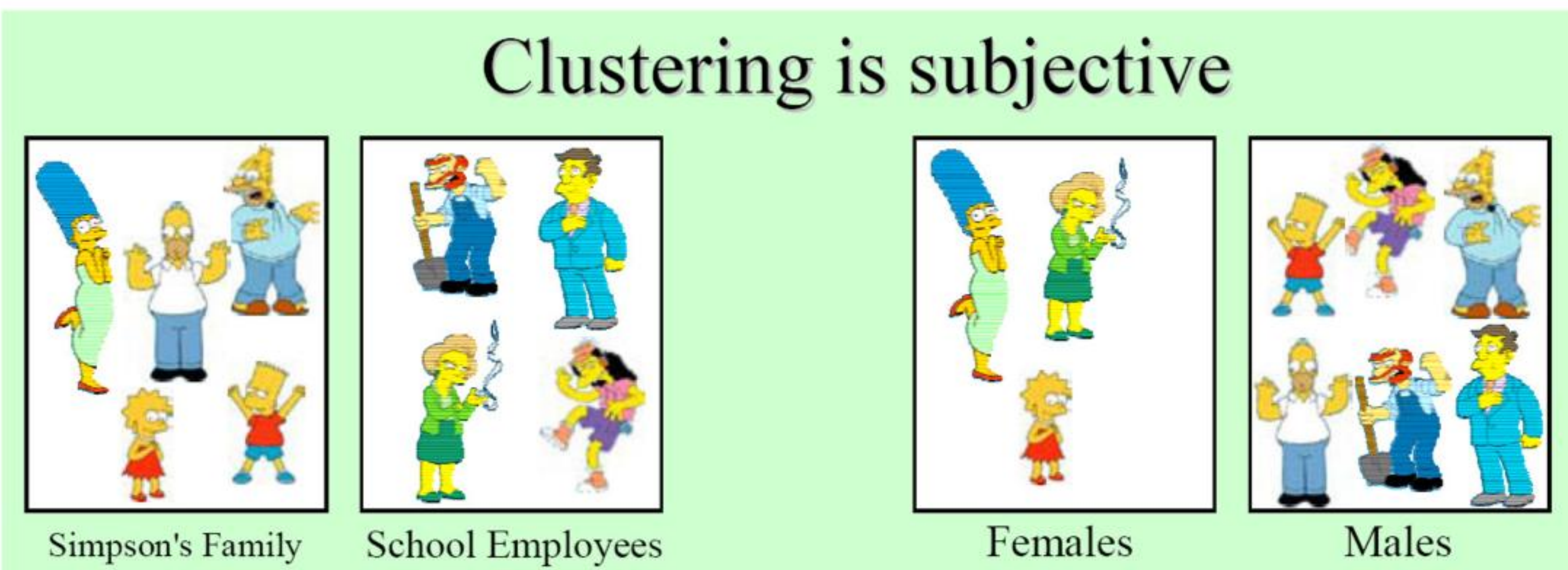
Clustering Hand Digits



Clustering is Subjective



What is consider similar/dissimilar?



Are they similar or not?

So What is Clustering in General?

- You pick your similarity/dissimilarity function
- The algorithm figures out the grouping of objects based on the chosen similarity/dissimilarity function
  - Points within a cluster is similar
  - Points across clusters are not so similar
- Issues for clustering
  - How to represent objects? (Vector space? Normalization?)
  - What is a similarity/dissimilarity function for your data?
  - What are the algorithm steps?

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Properties of Similarity Function

- Desired properties of dissimilarity function
  - Symmetry: $d(x, y) = d(y, x)$
    - *Otherwise you could claim "Alex looks like Bob, but Bob looks nothing like Alex"*
  - Positive separability: $d(x, y) = 0$, if and only if $x = y$
    - *Otherwise there are objects that are different, but you cannot tell apart*
  - Triangular inequality: $d(x, y) \leq d(x, z) + d(z, y)$
    - *Otherwise you could claim "Alex is very like Bob, and Alex is very like Carl, but Bob is very unlike Carl"*

Distance Functions for Vectors

- Suppose two data points, both in R^d
  - $x = (x_1, x_2, \dots, x_d)$
  - $y = (y_1, y_2, \dots, y_d)$

- Euclidean distance: $d(x, y) = \sqrt{\sum_{i=1}^{d} (x_i - y_i)^2}$

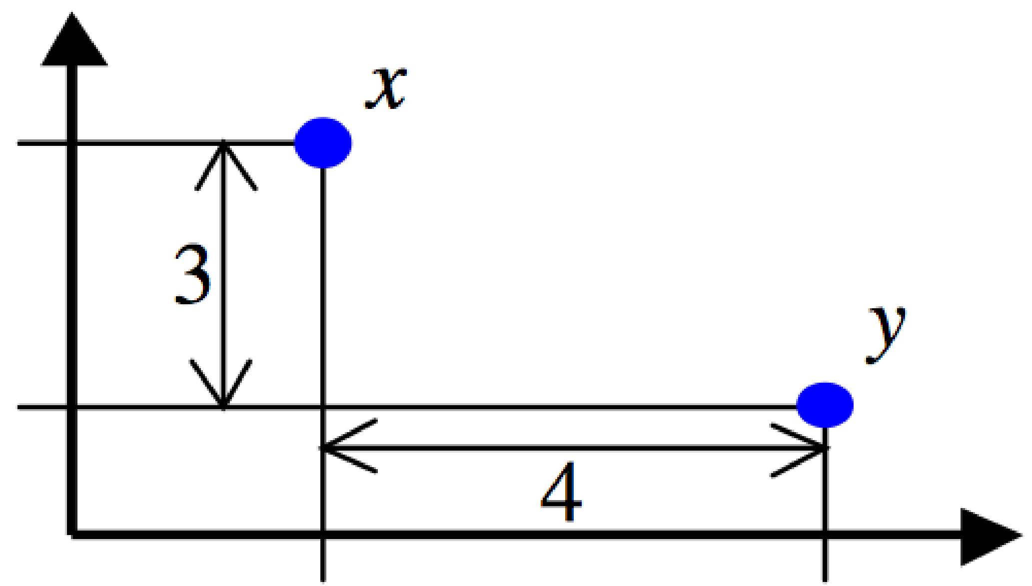
- Minkowski distance: $d(x, y) = \sqrt[p]{\sum_{i=1}^{d} (x_i - y_i)^p}$

  - Euclidean distance: $p = 2$

  - Manhattan distance: $p = 1, d(x, y) = \sum_{i=1}^{d} |x_i - y_i|$

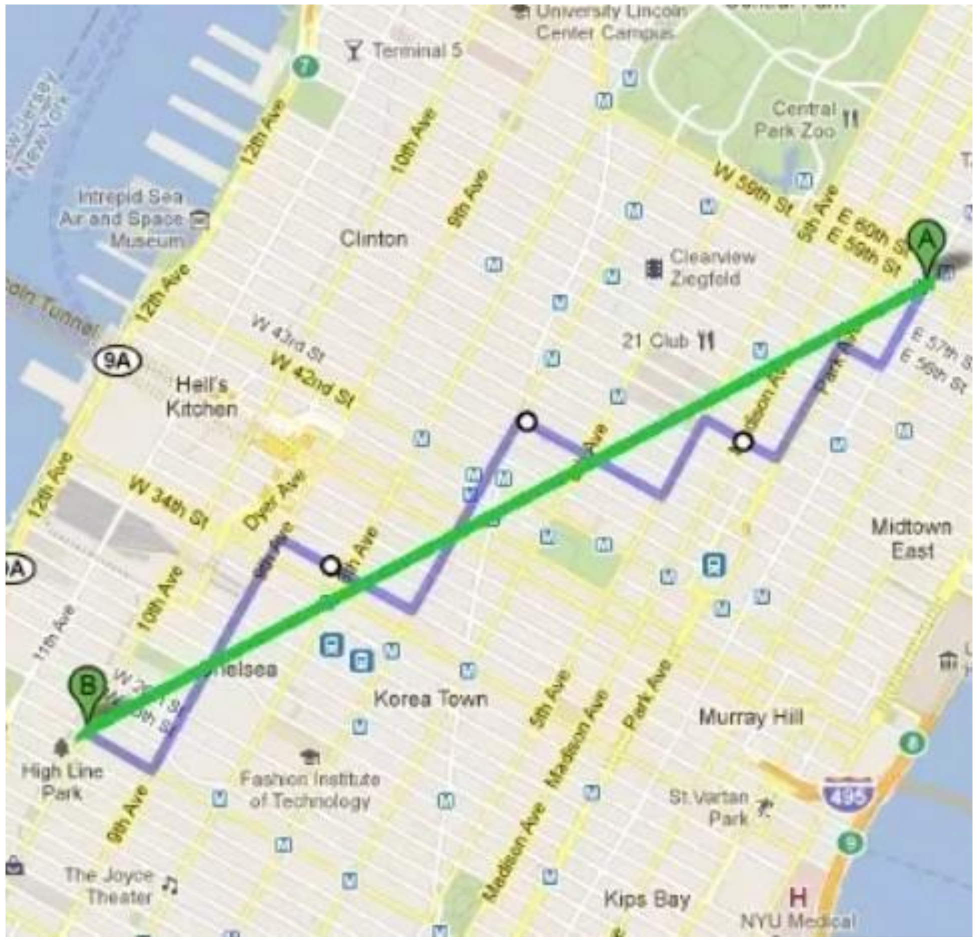
  - "inf"-distance: $p = \infty, d(x, y) = \max_{i=1}^{d} |x_i - y_i|$

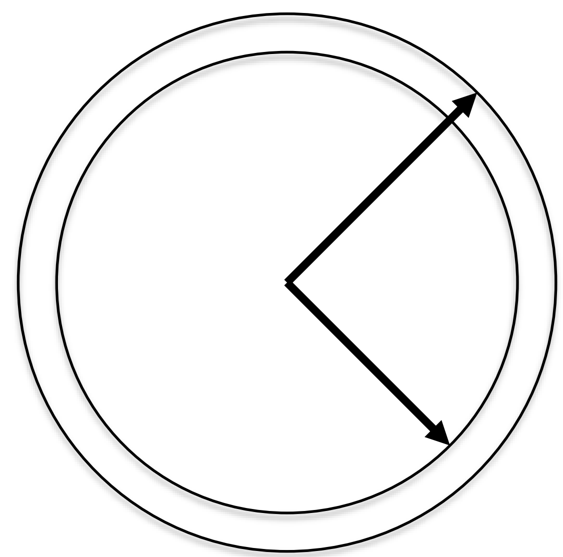
Example



- Euclidean distance: $\sqrt{4^2 + 3^2} = 5$
- Manhattan distance: $4 + 3 = 7$
- "inf"-distance: $max\{4,3\} = 4$

Some problems with Euclidean distance





[Curse of dimensionality]

Hamming Distance

- Manhattan distance is also called *Hamming distance* when all features are binary
  - Count the number of difference between two binary vectors
  - Example, $x, y \in \{0,1\}^{17}$

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
x	0	1	1	0	0	1	0	0	1	0	0	1	1	1	0	0	1
y	0	1	1	1	0	0	0	0	1	1	1	1	1	1	0	1	1

$$d(x, y) = 5$$

Edit Distance

- Transform one of the objects into the other, and measure how much effort it takes

```
x   I N T E * N T I O N
    | | | | | | | | | |
y   * E X E C U T I O N
    d s s   i s
```

d: deletion (cost 5)
s: substitution (cost 1)
i: insertion (cost 2)

$$d(x, y) = 5 \times 1 + 3 \times 1 + 1 \times 2 = 10$$

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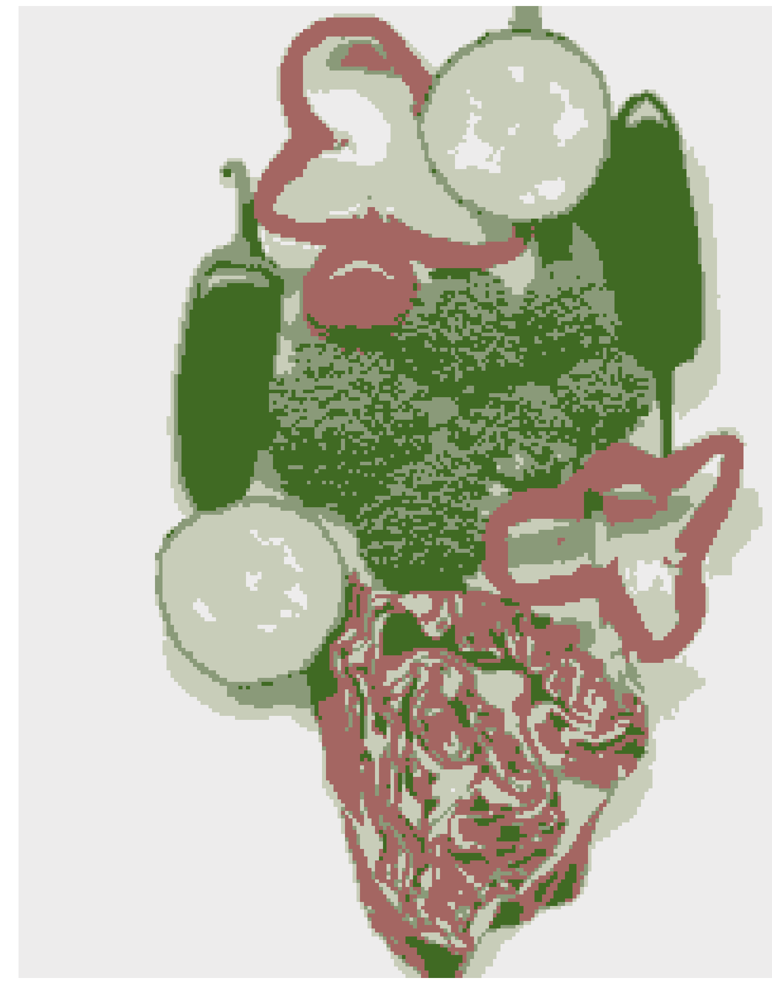
Results of K-Means Clustering:

Image

Clusters on intensity



Clusters on color

K-means clustering using intensity alone and color alone

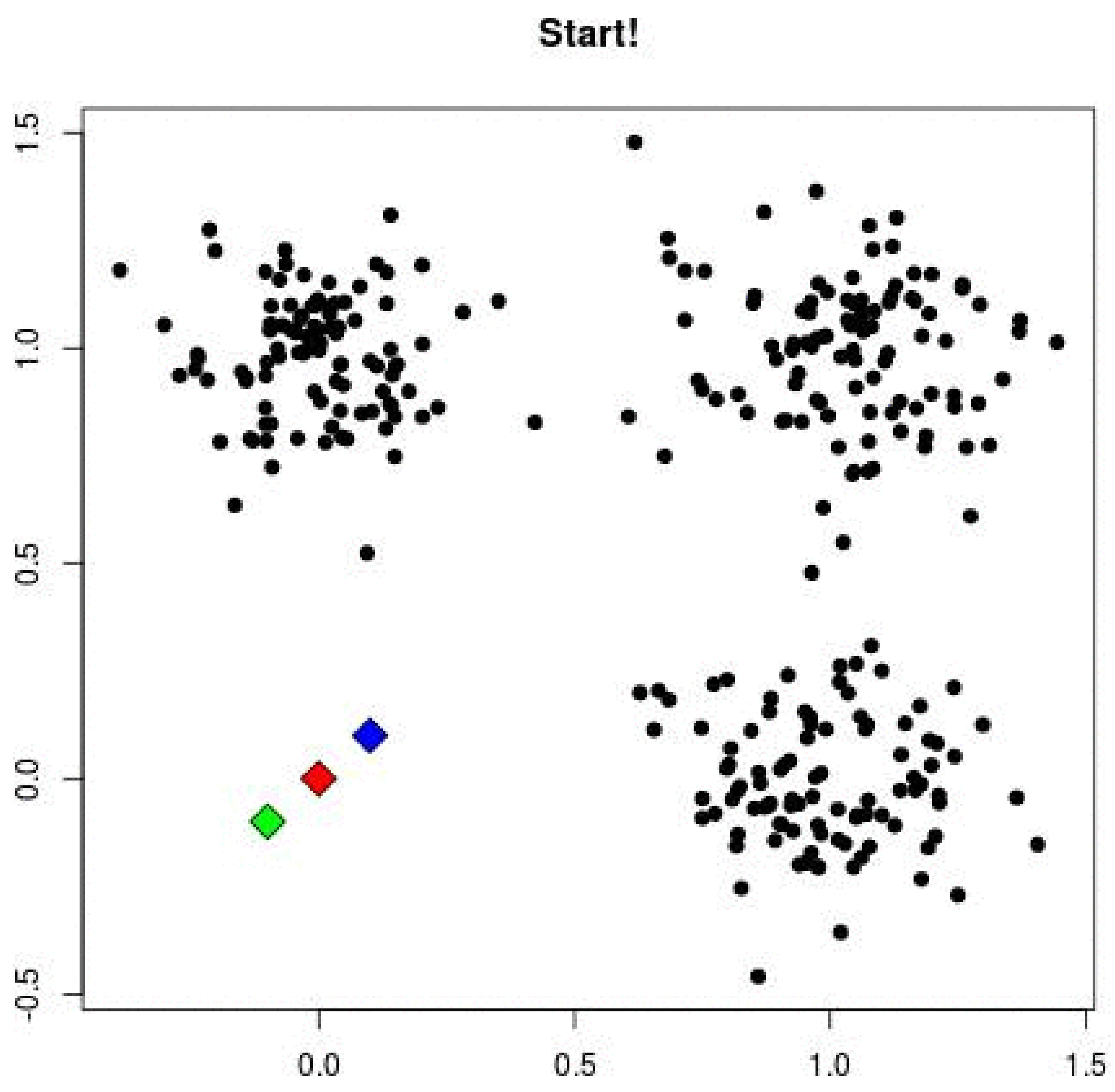
Image

Clusters on color

K-means using color alone, 11 segments (clusters)

* Pictures from Mean Shift: A Robust Approach toward Feature Space Analysis, by D. Comaniciu and P. Meer http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

K-Means Algorithm



Visualizing K-Means Clustering

K-Means Algorithm

- Initialize k cluster centers, $\{c_1, c_2, \ldots, c_k\}$, randomly
- Do
  - Decide the cluster memberships of each data point, x_i by assigning it to the nearest cluster center (cluster assignment)

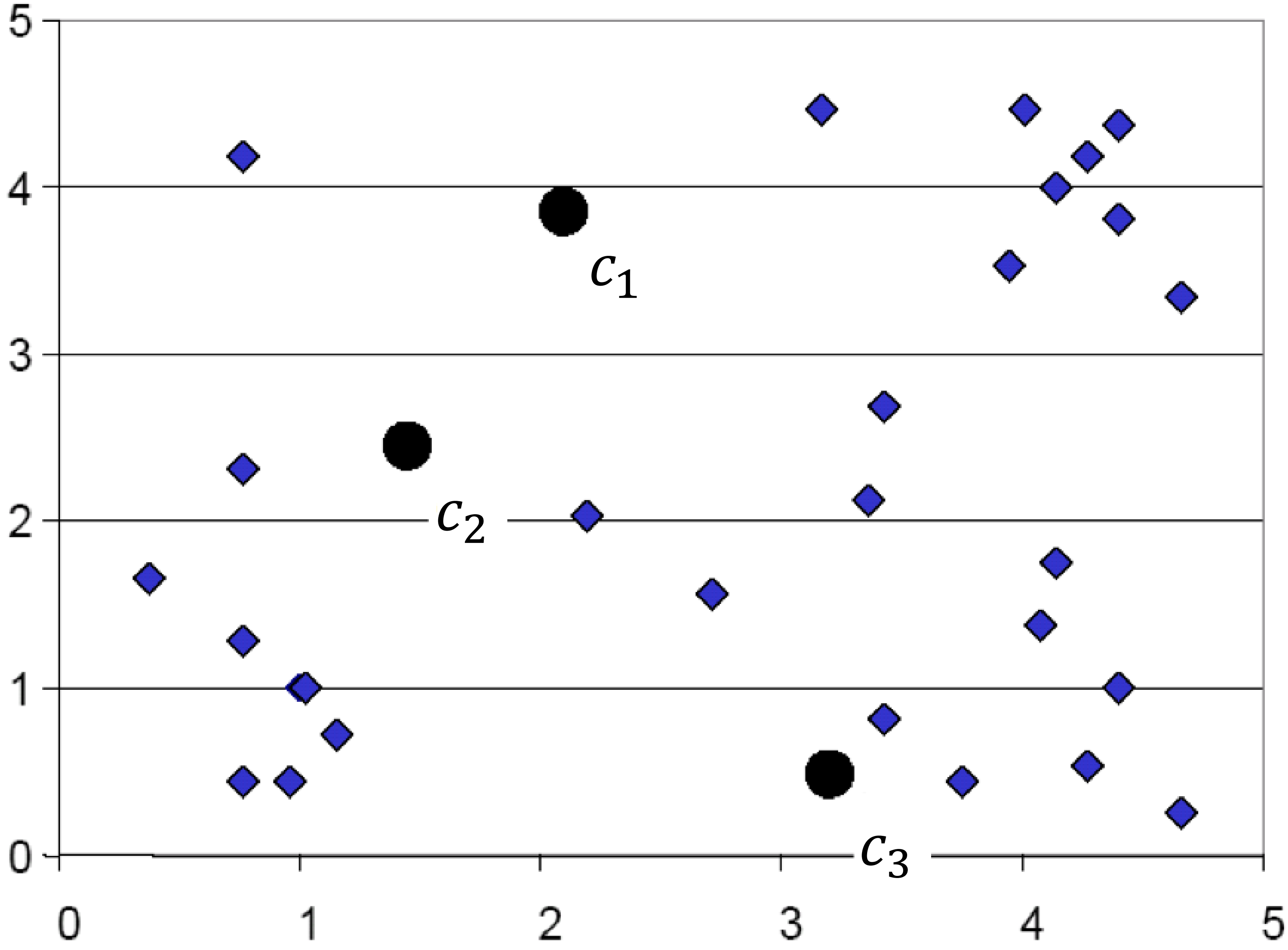
    $$\pi(i) = argmin_{j=1,\ldots,k} \quad \left\|x_i - c_j\right\|^2$$

  - Adjust the cluster centers (center adjustment)

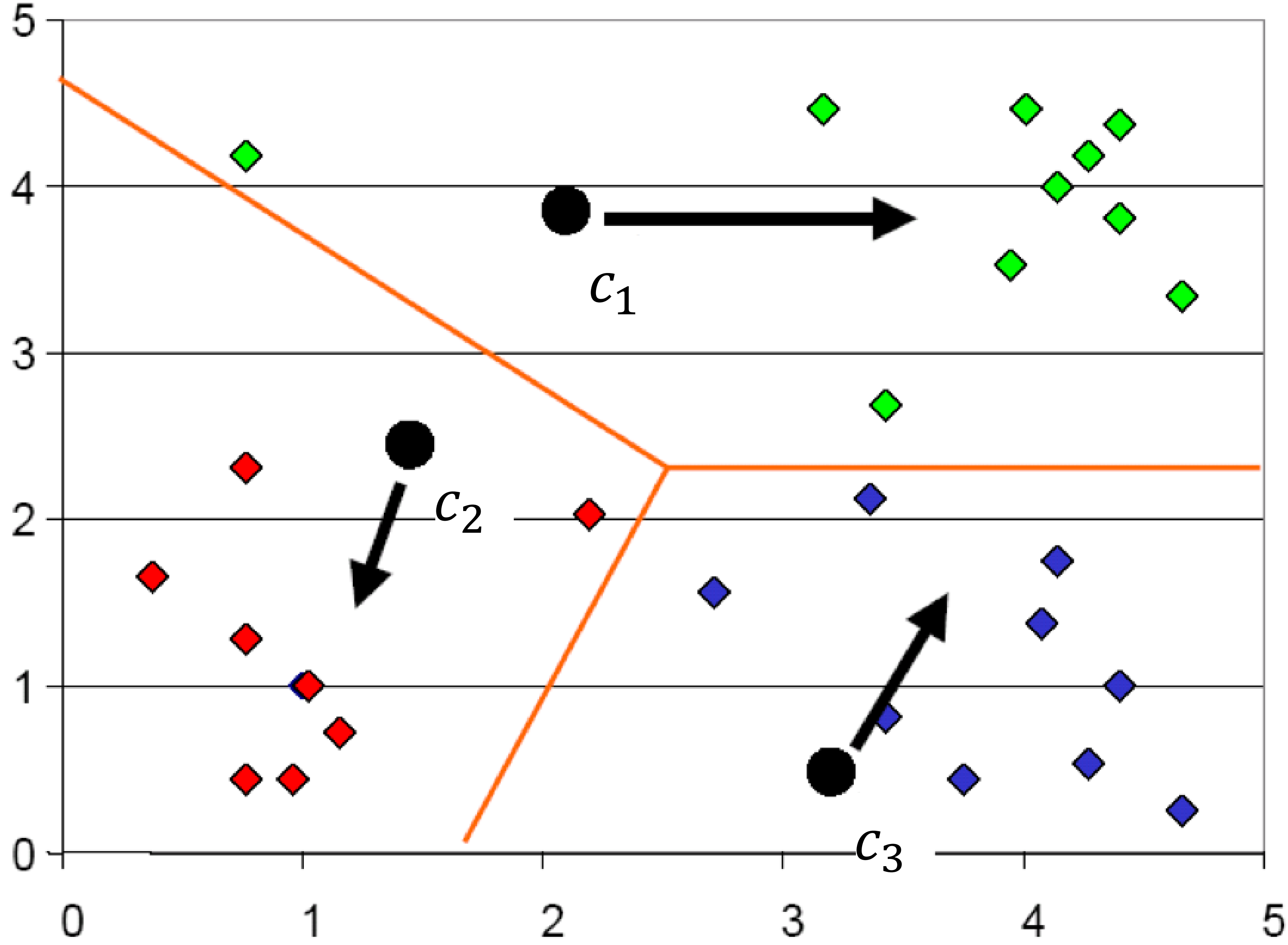
    $$c_j = \frac{1}{|\{i: \pi(i) = j\}|} \sum_{i:\pi(i)} x_i$$

- While any cluster center has been changed

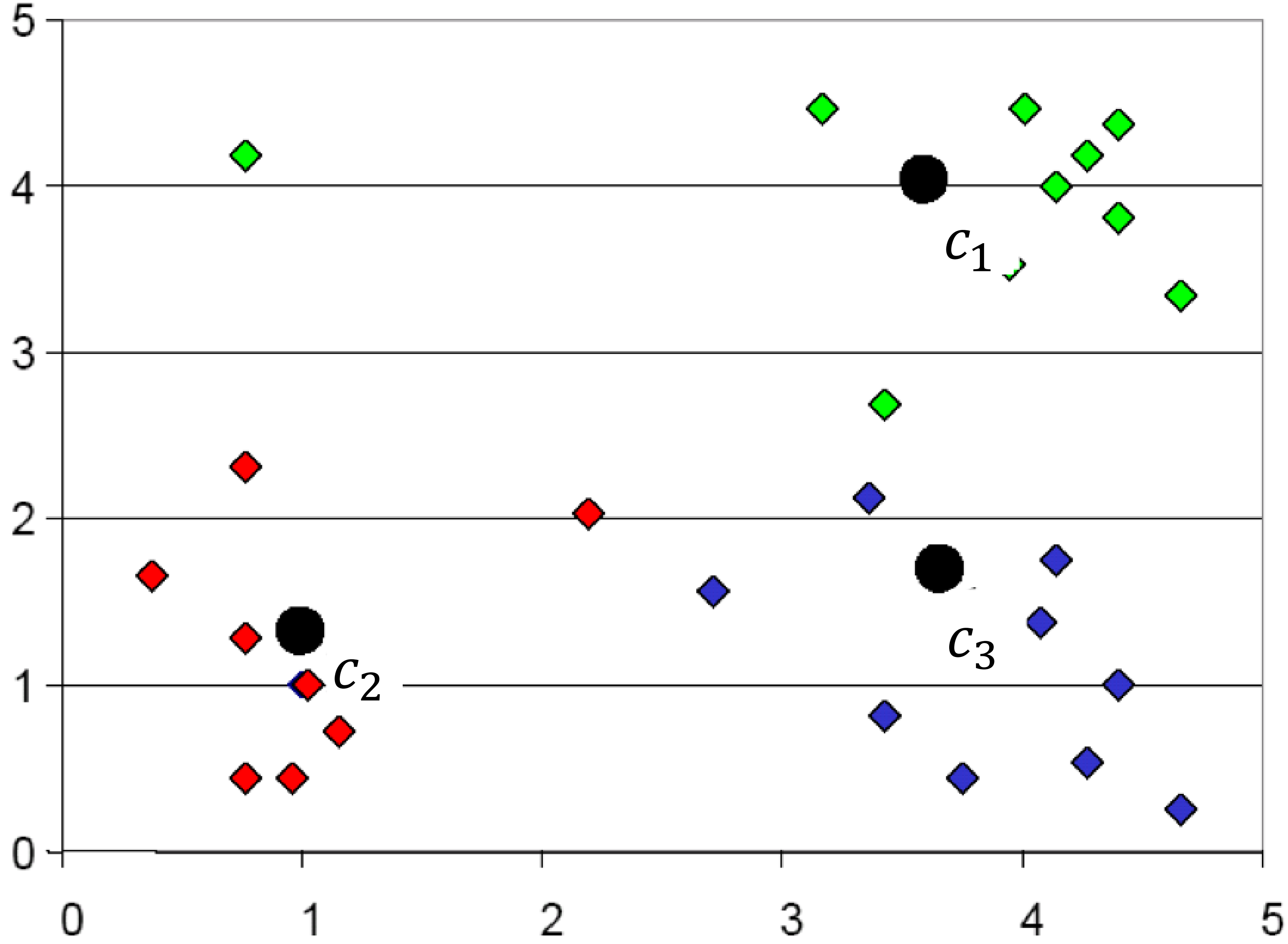
K-Means: Step 1



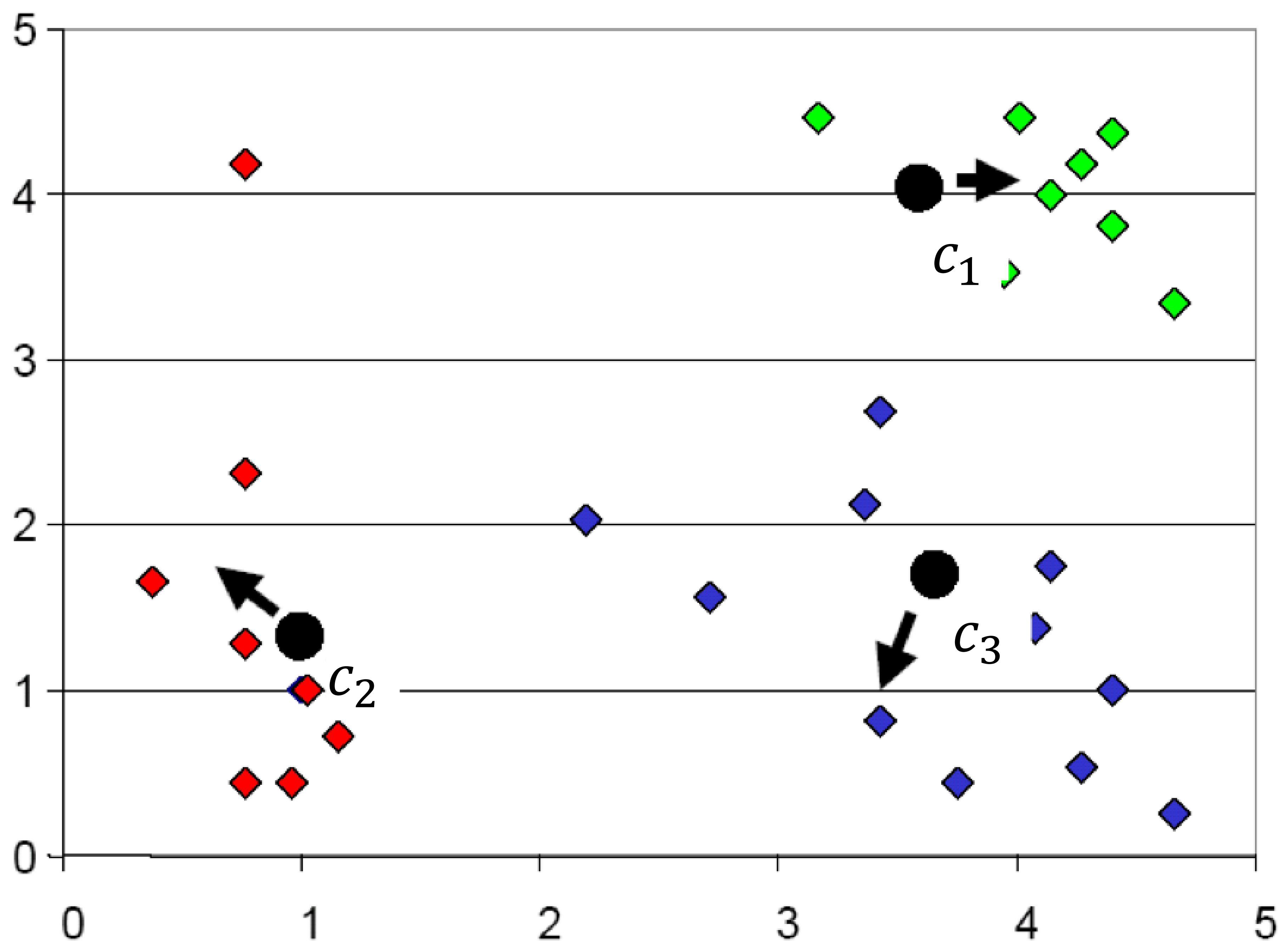
K-Means: Step 2



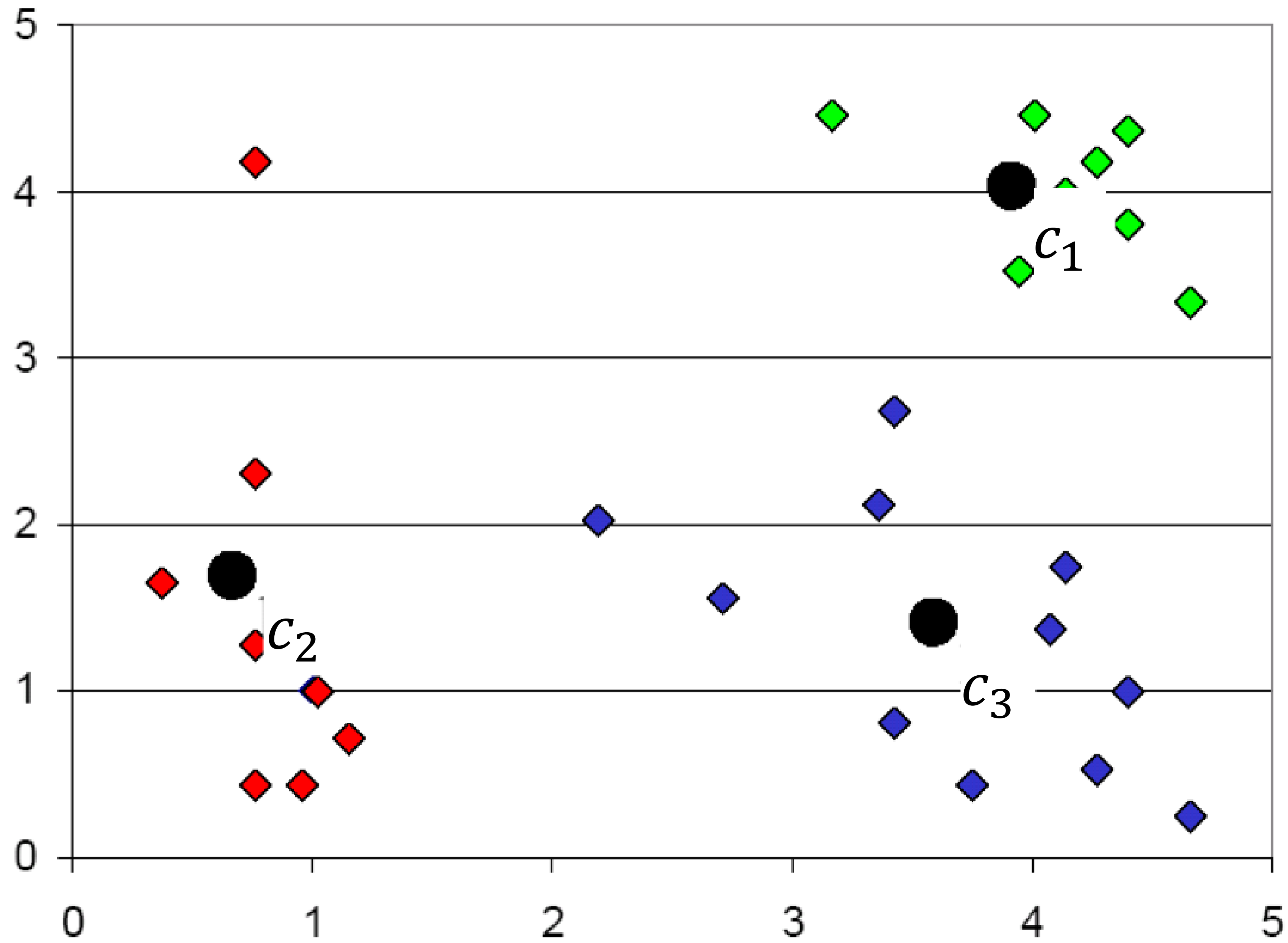
K-Means: Step 3



K-Means: Step 4



K-Means: Step 5



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Questions

- Will different initialization lead to different results?
  - Yes
  - No
  - Sometimes

- Will the algorithm always stop after some iteration?
  - Yes
  - No (we have to set a maximum number of iterations)
  - Sometimes

Formal Statement of the Clustering Problem

- Given n data points, $\{x_1, x_2, \ldots, x_n\}$ $x \in R^d$
- Find k cluster centers, $\{c_1, c_2, \ldots, c_k\}$ $c \in R^d$
- And assign each datapoint i to one cluster, $\pi(i) \in \{1, \ldots, k\}$
- Such that the averaged square distances from each datapoint to its respective cluster center is small

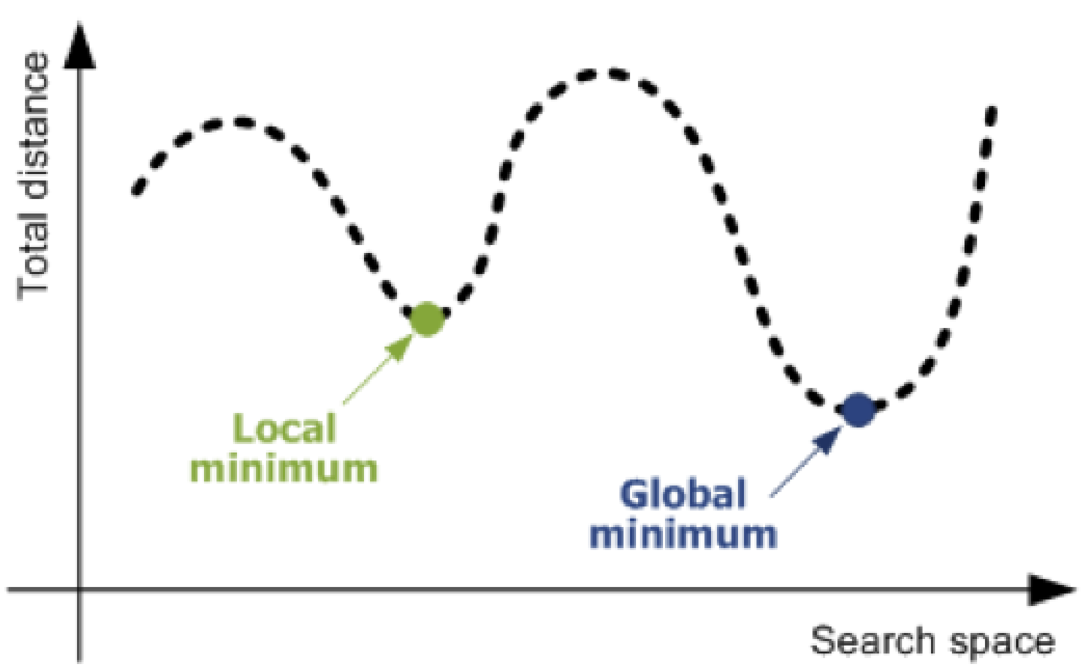
$$\min_{c,\pi} \sum_{i=1}^{n} \left\| x_i - c_{\pi(i)} \right\|^2$$

Clustering is NP-Hard

- Find k cluster centers, $\{c_1, c_2, \ldots, c_k\}$ $c \in R^d$, and assign each data point i to one cluster, $\pi(i) \in \{1, \ldots, k\}$, to minimize

$$\min_{c,\pi} \sum_{i=1}^{n} \left\| x_i - c_{\pi(i)} \right\|^2$$

- A search problem over the space of discrete assignments
  - For all n data point together, there are k^n possibility
  - The cluster assignment determines cluster centers, and vice versa



- For all n data point together, there are k^n possibility

X = {A,B,C}

n=3 (data points)

k=2 clusters of two members

Cluster 1 Cluster 2

Convergence of K-Means

- Will kmeans objective oscillate?

$$\min_{c,\pi} \sum_{i=1}^{n} \left\| x_i - c_{\pi(i)} \right\|^2$$

- The minimum value of the objective is finite
- Each iteration of kmeans algorithm decrease the objective
  - Cluster assignment step decreases objective
    - $\pi(i) = argmin_{j=1,\ldots,k} \ \left\| x_i - c_{\pi(j)} \right\|^2$ for each data point i
  - Center adjustment step decreases objective
    - $c_i = \frac{1}{|\{i:\pi(i)=j\}|} \sum_{i:\pi(i)=j} x_i = argmin_c \sum_{i:\pi(i)=j} \left\| x_i - c_{\pi(j)} \right\|^2$

Time Complexity

- Assume computing distance between two instances is O(d) where d is the dimensionality of the vectors.

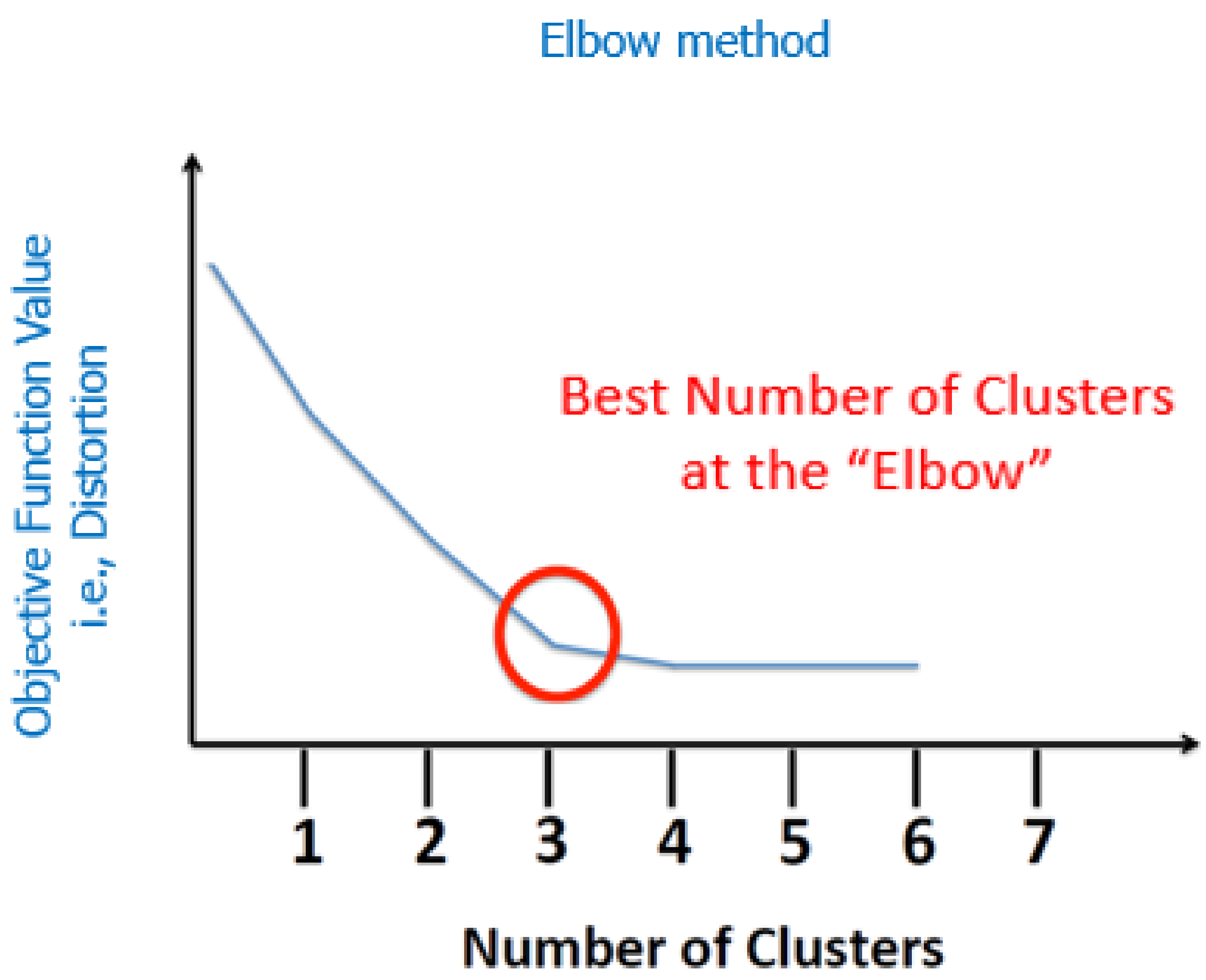
- Reassigning clusters for all datapoints:
  - O(kn) distance computations (when there is one feature)
  - O(knd) (when there is d features)

- Computing centroids: Each instance vector gets added once to some centroid (Finding centroid for each feature): O(nd).

- Assume these two steps are each done once for I iterations: O(Iknd).

Slide credit: Ray Mooney.

How to Choose K?



Distortion score: computing the sum of squared distances from each point to its assigned center

Image credit: Dileka Madushan.