

Clustering: K-Means, Nearest Neighbors

Foundation of Data Analysis

01/30/2020

Clustering Example



Original image

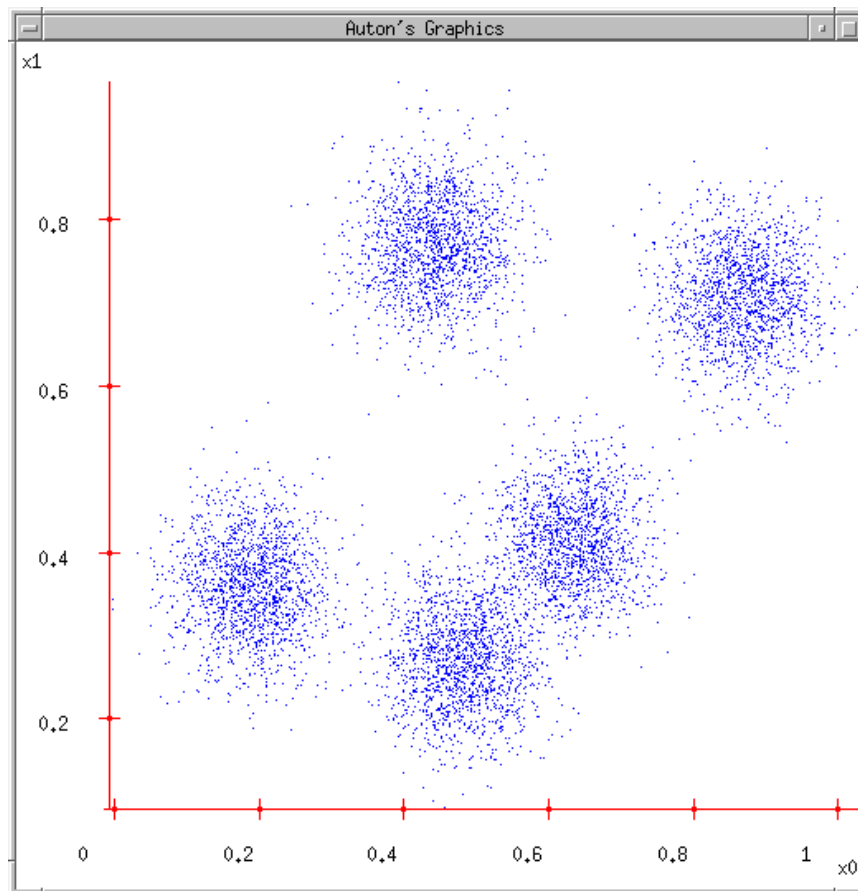


Segmented image

Divide data into different groups

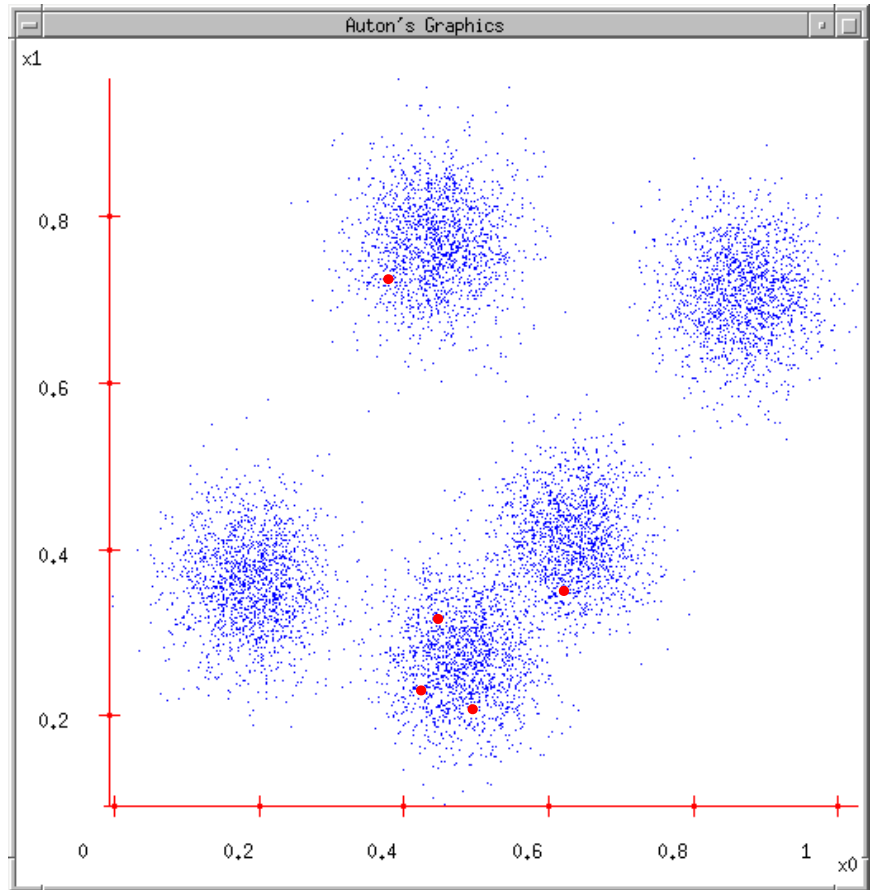
Clustering: K-means

1. Ask user how many clusters they'd like (e.g. $k=5$)



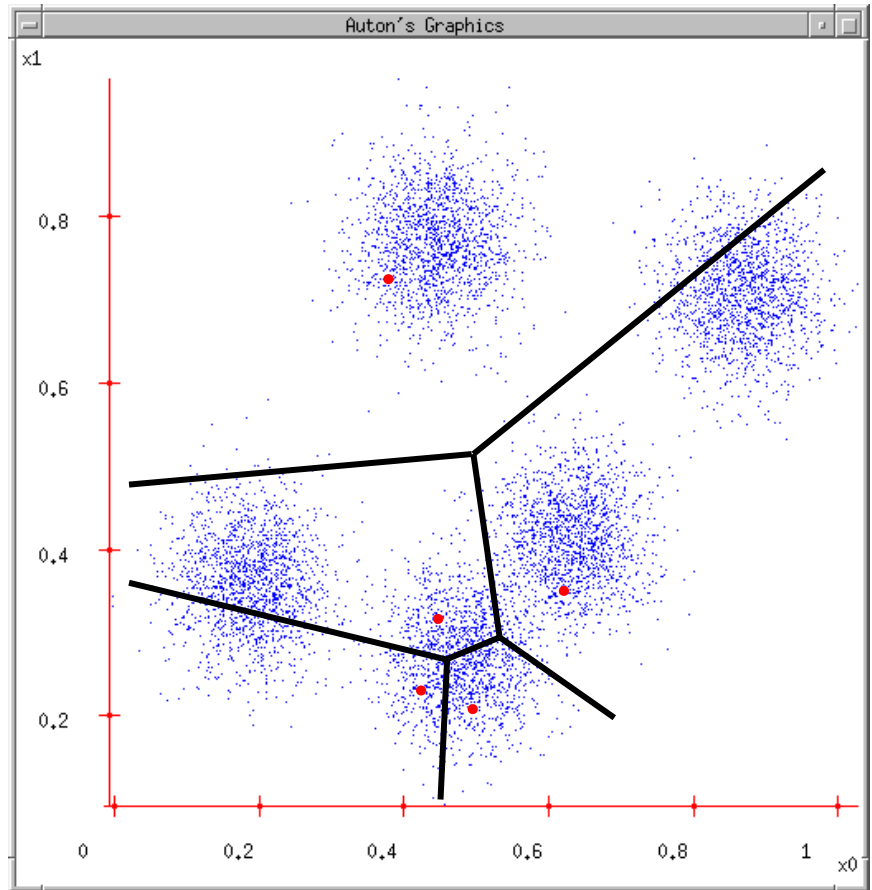
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2. Randomly guess k cluster Center locations



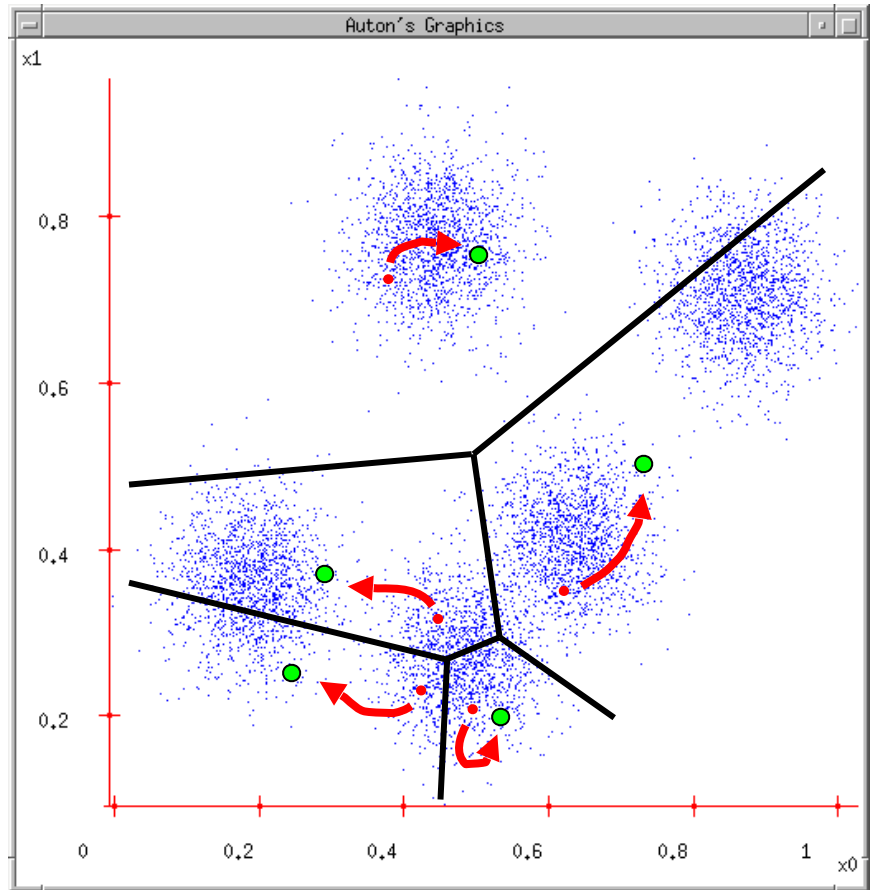
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3. Each datapoint finds out which Center it's closest to.



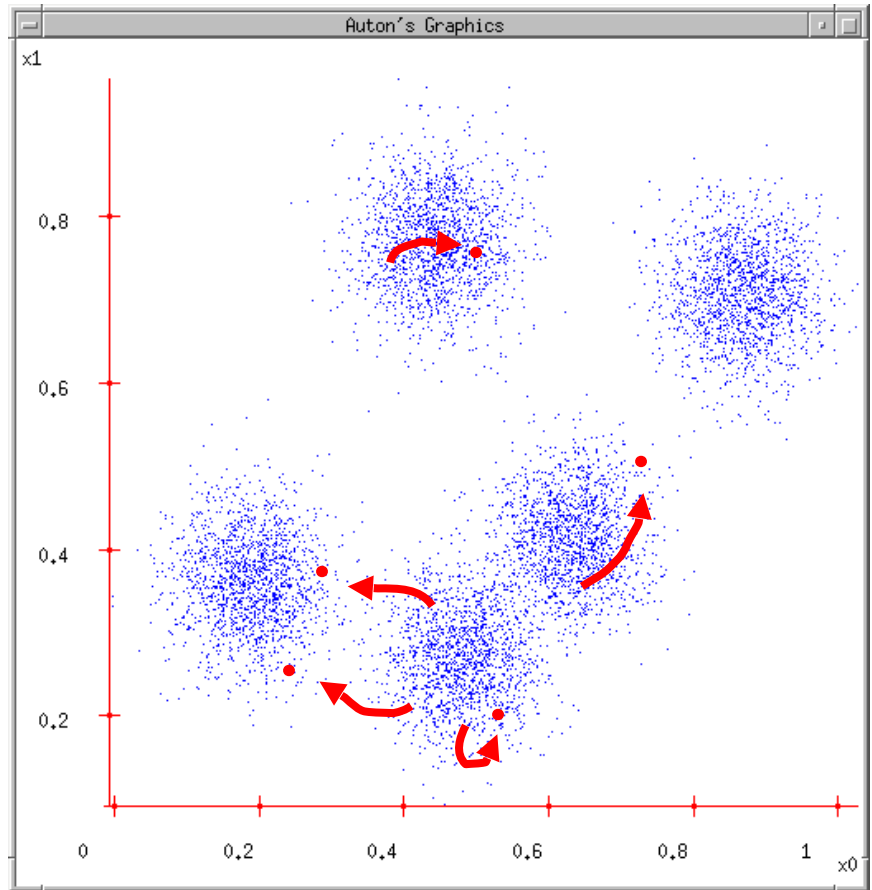
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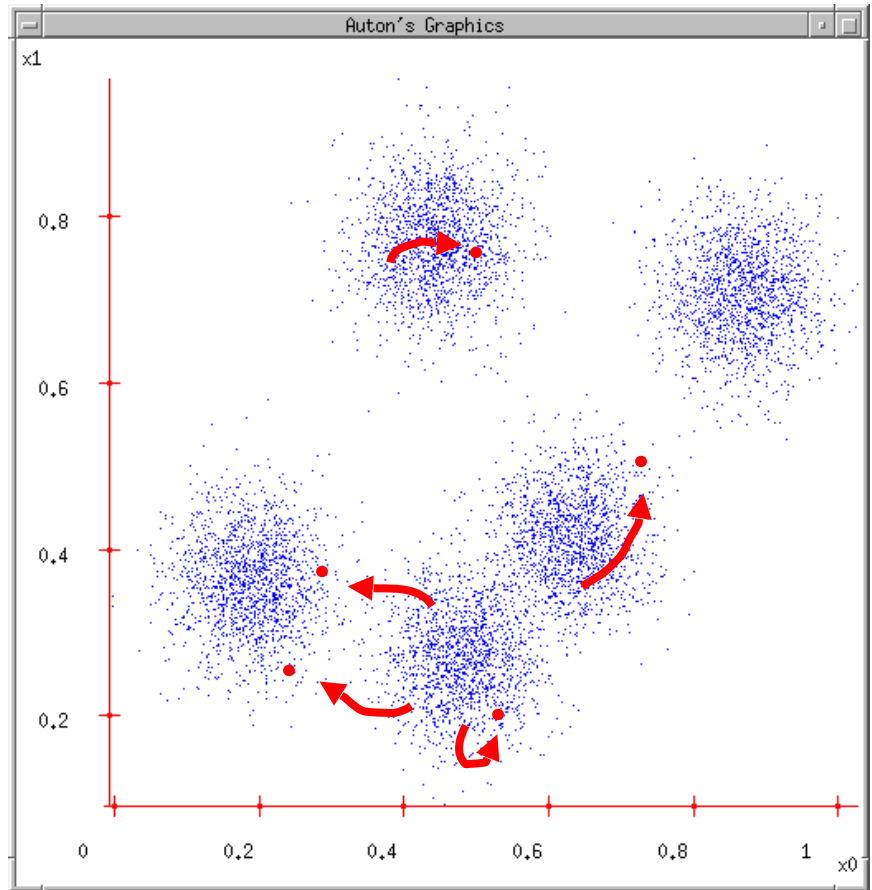
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6. ...Repeat steps 3-5 until terminated!



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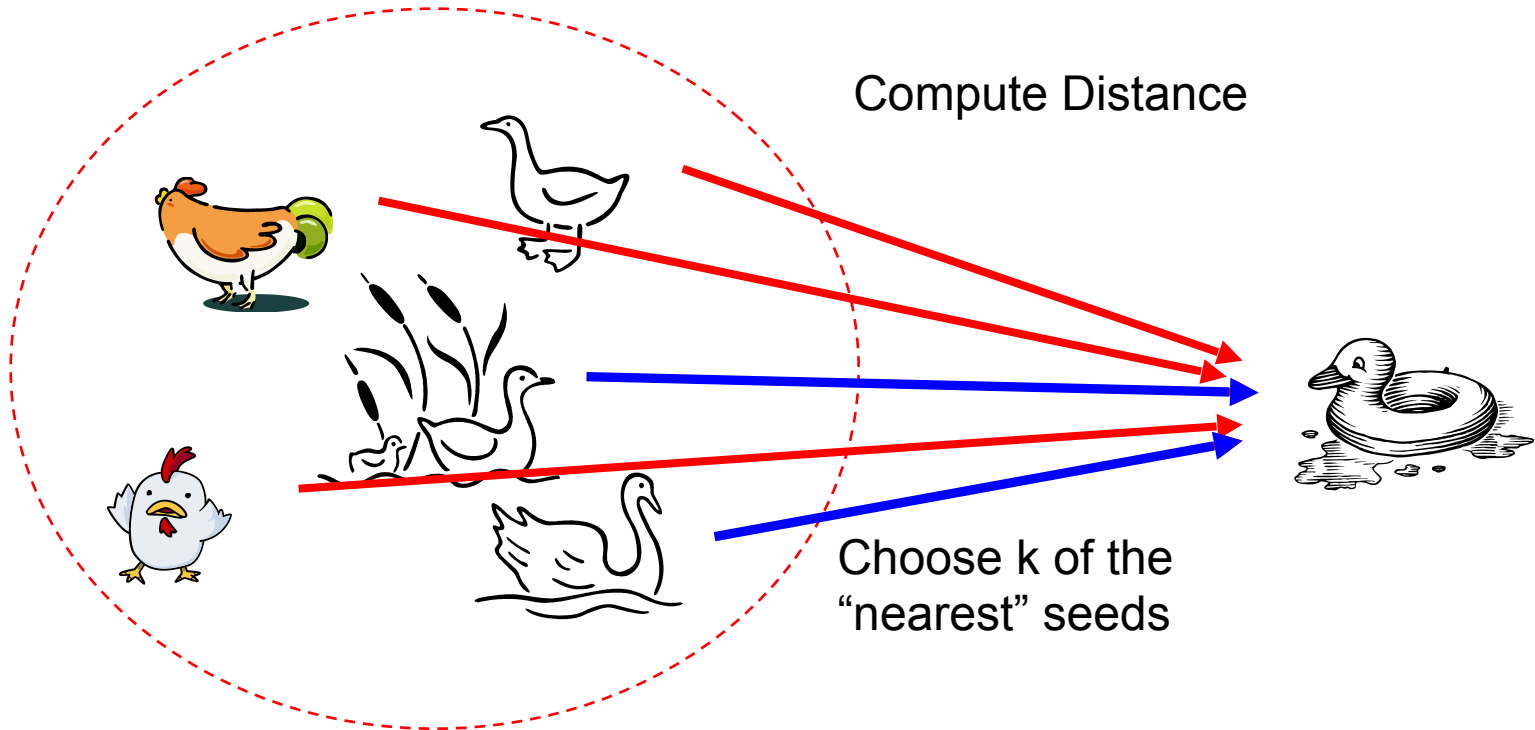
Disadvantages of K-means

- Does not work efficiently with complex structured data (mostly non-linear)
- Hard assignment for labels might lead to misgrouping
- Random guess for initialization might be a hassle

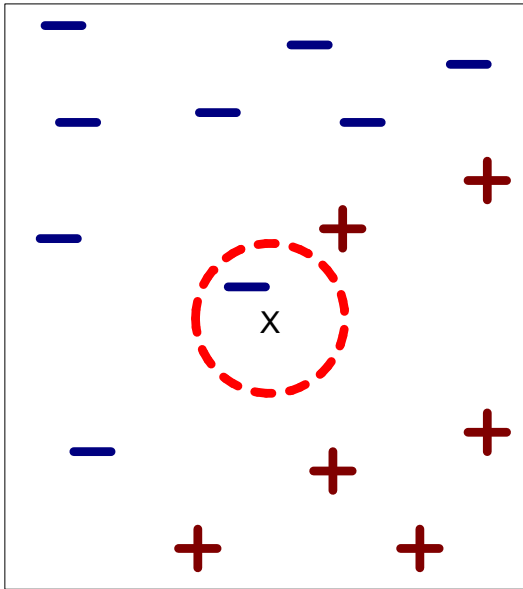
- Nearest Neighbors: (Un)supervised Learning (non-parametric model)

Nearest Neighbors: Unsupervised Learning

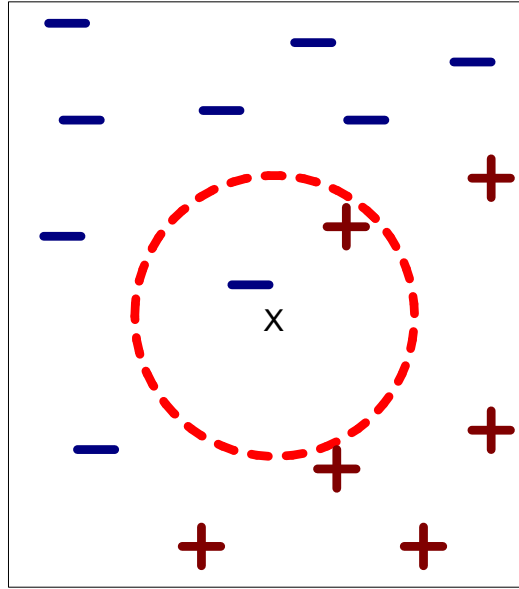
- Basic idea:
 - If it walks like a duck, quacks like a duck, then it's probably a duck



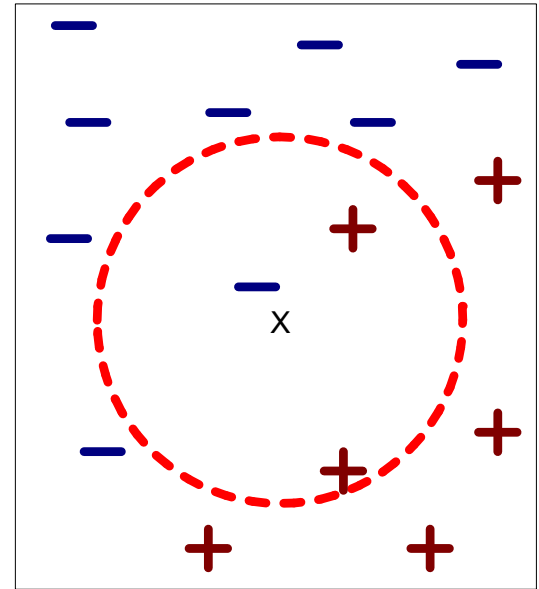
Nearest Neighbors



(a) 1-nearest neighbor



(b) 2-nearest neighbor

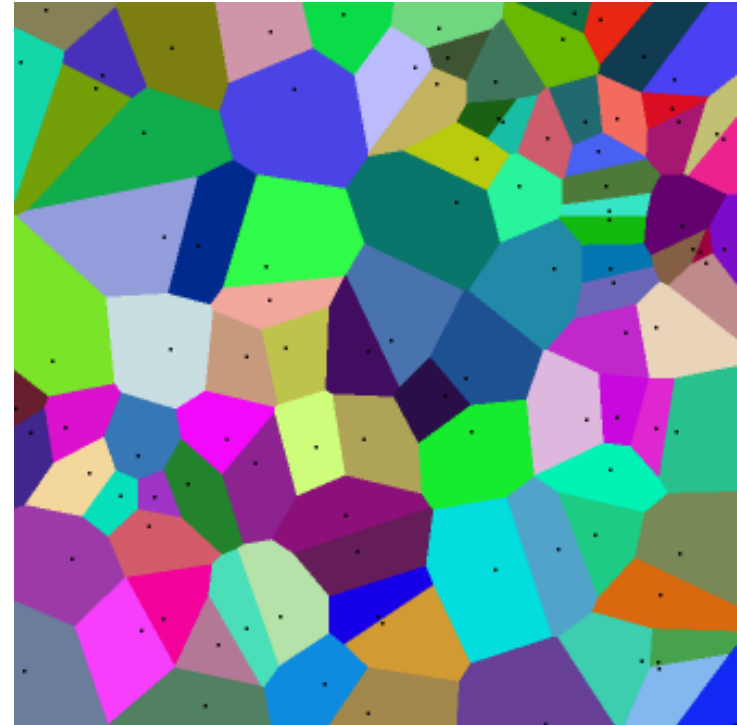
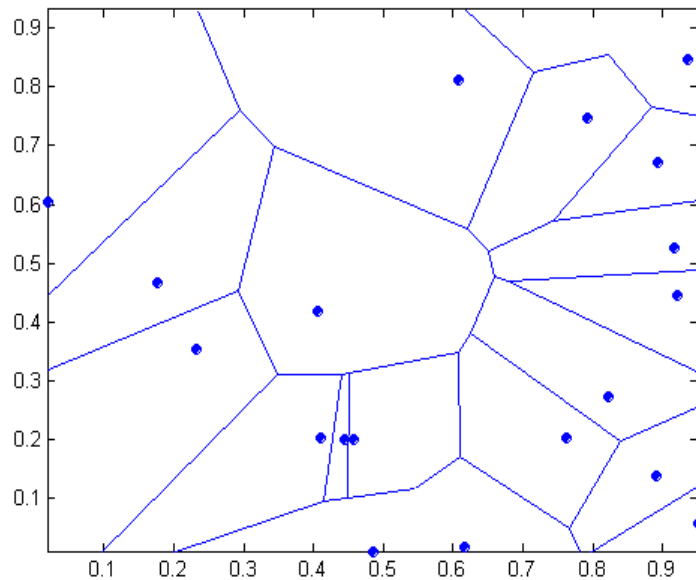


(c) 3-nearest neighbor

K-nearest neighbors of **seed x**: data points that have the k smallest distance to x.

Nearest Neighbor

Voronoi Diagram

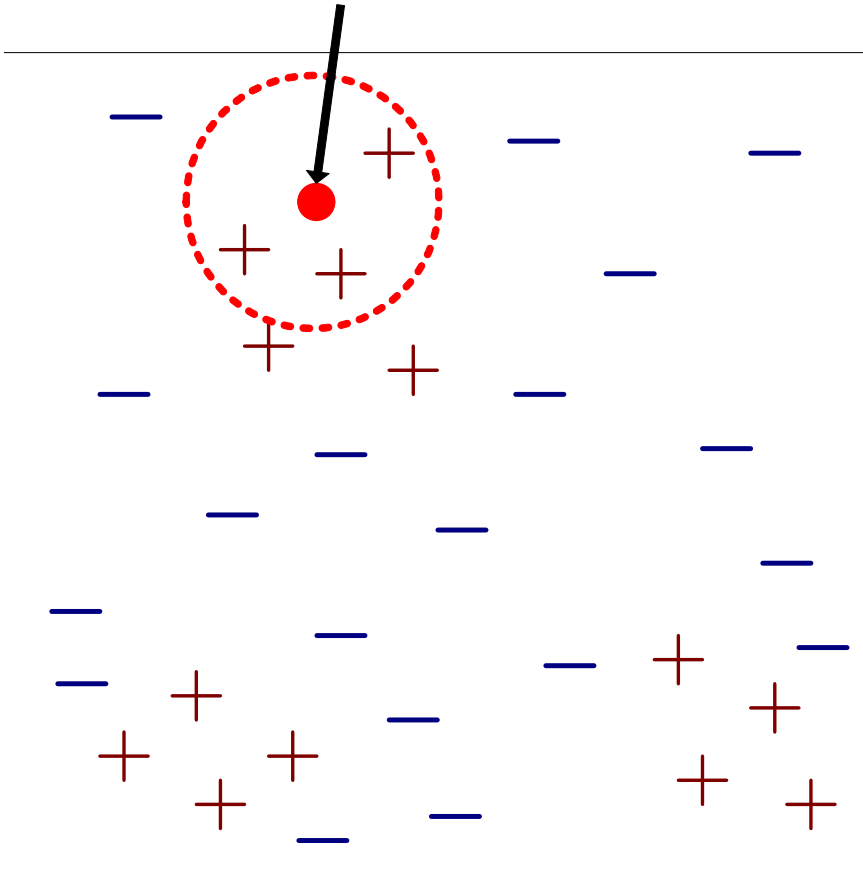


- Partitions space into regions
- boundary: points at the same distance from two different training examples

- K-Nearest Neighbor (KNN) classification - supervised learning

KNN Classifiers

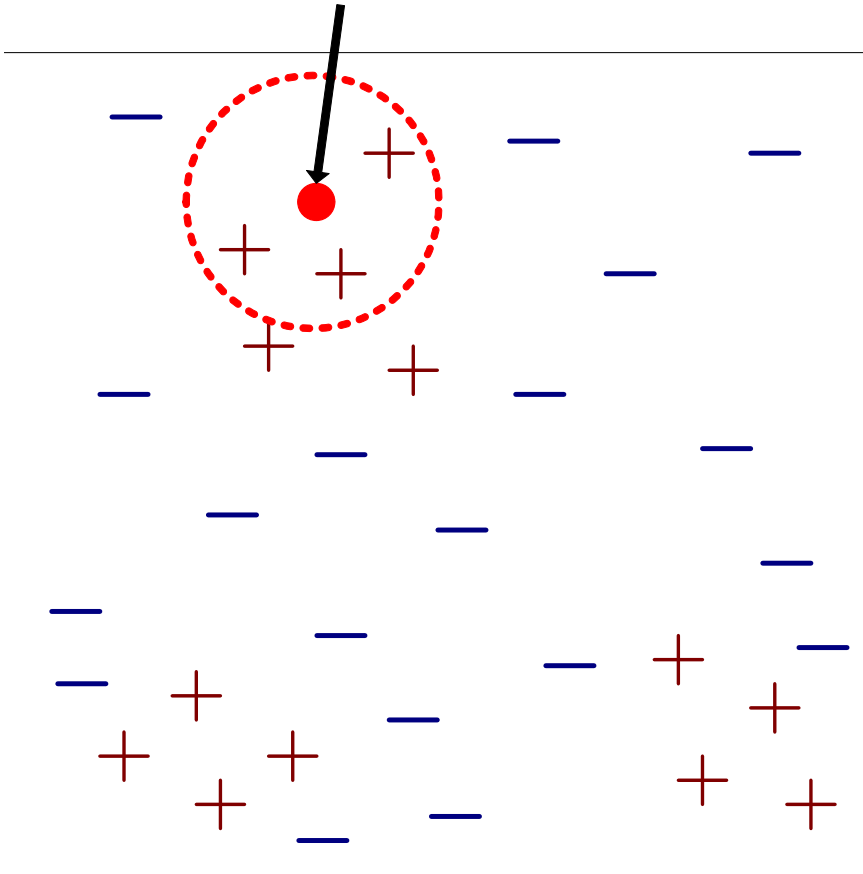
Unknown seed



- Requires three things
 - The set of stored records
 - Distance metric
 - The value of k , the number of nearest neighbors to retrieve

KNN Classifiers

Unknown seed



- Requires three things
 - The set of stored records
 - Distance metric
 - The value of k , the number of nearest neighbors to retrieve
- To classify an unknown seed:
 - Compute distance to other training seeds
 - Identify k nearest neighbors
 - Use class labels of nearest neighbors to determine the class label of unknown seed (e.g., by taking majority vote)

Nearest Neighbor Classification

- Compute distance between two points:

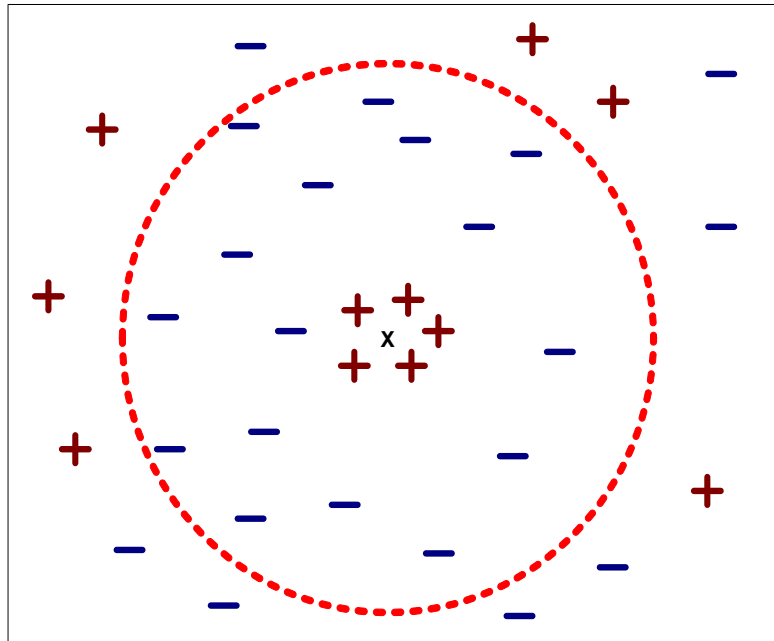
- Euclidean distance (L2 norm)

$$d(p, q) = \sqrt{\sum_i (p_i - q_i)^2}$$

- Determine the class from nearest neighbor list
 - take the majority vote of class labels among the k-nearest neighbors
 - Weight the vote according to distance
 - weight factor, $w = 1/d^2$

Nearest Neighbor Classification...

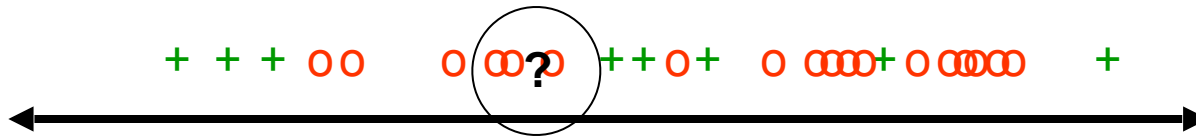
- Choosing the value of k :
 - If k is too small, sensitive to noise points
 - If k is too large, neighborhood may include points from other classes



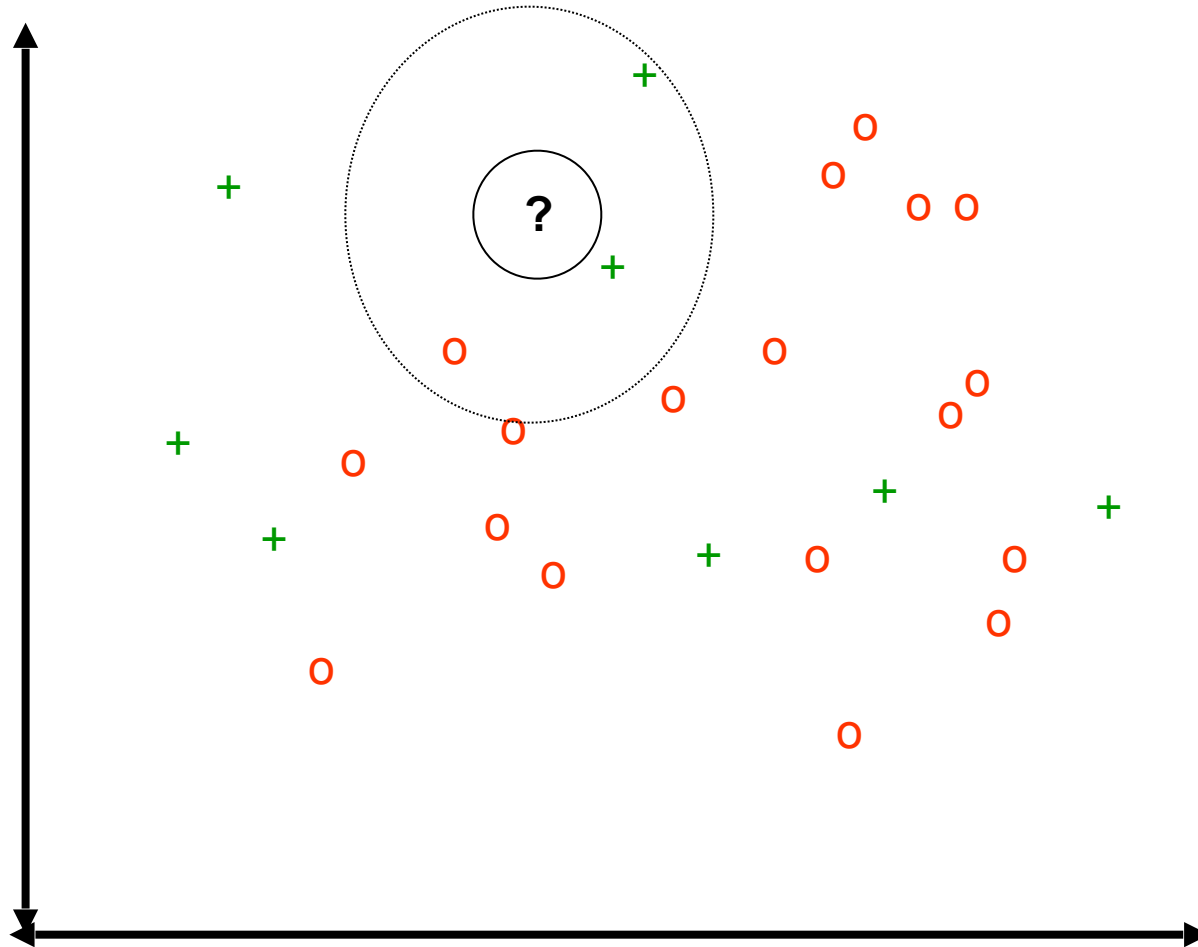
Issues of Nearest Neighbor Classification

- Scaling issues
 - Attributes may have to be scaled to prevent distance measures from being dominated by one of the attributes
 - Example:
 - height of a person may vary from 1.5m to 1.8m
 - weight of a person may vary from 90lb to 300lb
 - income of a person may vary from \$10K to \$1M

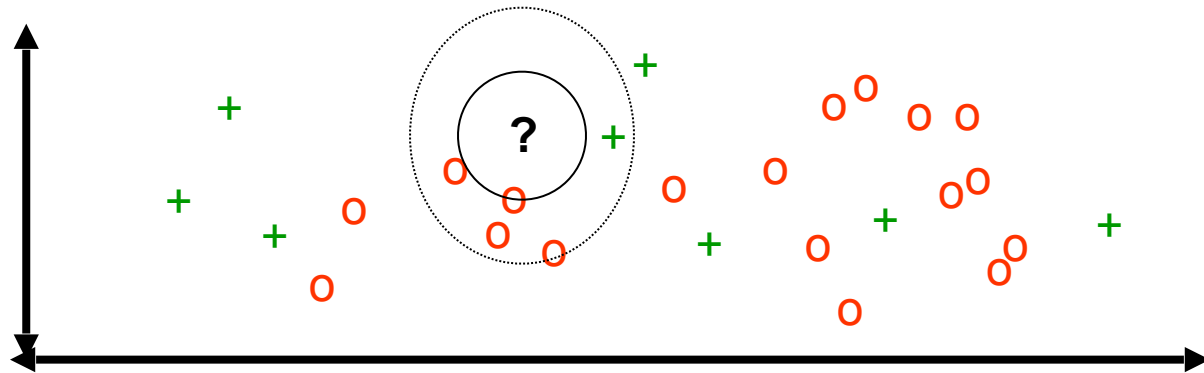
K-NN and Irrelevant Features



K-NN and Irrelevant Features



K-NN and Irrelevant Features



Issues of Nearest Neighbor Classification

- Problem with Euclidean measure:
 - High dimensional data
 - **curse of dimensionality**
 - Can produce counter-intuitive results

1	1	1	1	1	1	1	1	1	1	1	0
---	---	---	---	---	---	---	---	---	---	---	---

0	1	1	1	1	1	1	1	1	1	1	1
---	---	---	---	---	---	---	---	---	---	---	---

$d = 1.4142$

VS

1	0	0	0	0	0	0	0	0	0	0	0
---	---	---	---	---	---	---	---	---	---	---	---

0	0	0	0	0	0	0	0	0	0	0	1
---	---	---	---	---	---	---	---	---	---	---	---

$d = 1.4142$

Solution: Normalize the vectors to unit length.

K-NN Algorithm

- Training:
 - Save the training examples
- At prediction:
 - Find the k training examples $(x_1, y_1), \dots, (x_k, y_k)$ that are closest to the test example x
 - Predict the most frequent class among those y_i 's.

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- Improvements:
 - Weighting examples from the neighborhood
 - Measuring “closeness”
 - Finding “close” examples in a large training set quickly

Tricks with Fast k-NN

K-means using r-NN

1. Pick k points $c_1=x_1, \dots, c_k=x_k$ as centers
2. For each x_i , find $D_i = \text{Neighborhood}(x_i)$
3. For each x_i , let $c_i = \text{mean}(D_i)$
4. Go to step 2....