

Classification: Alternative Techniques

Lecture Notes for Chapter 4

Instance-Based Learning

Introduction to Data Mining , 2nd Edition

by

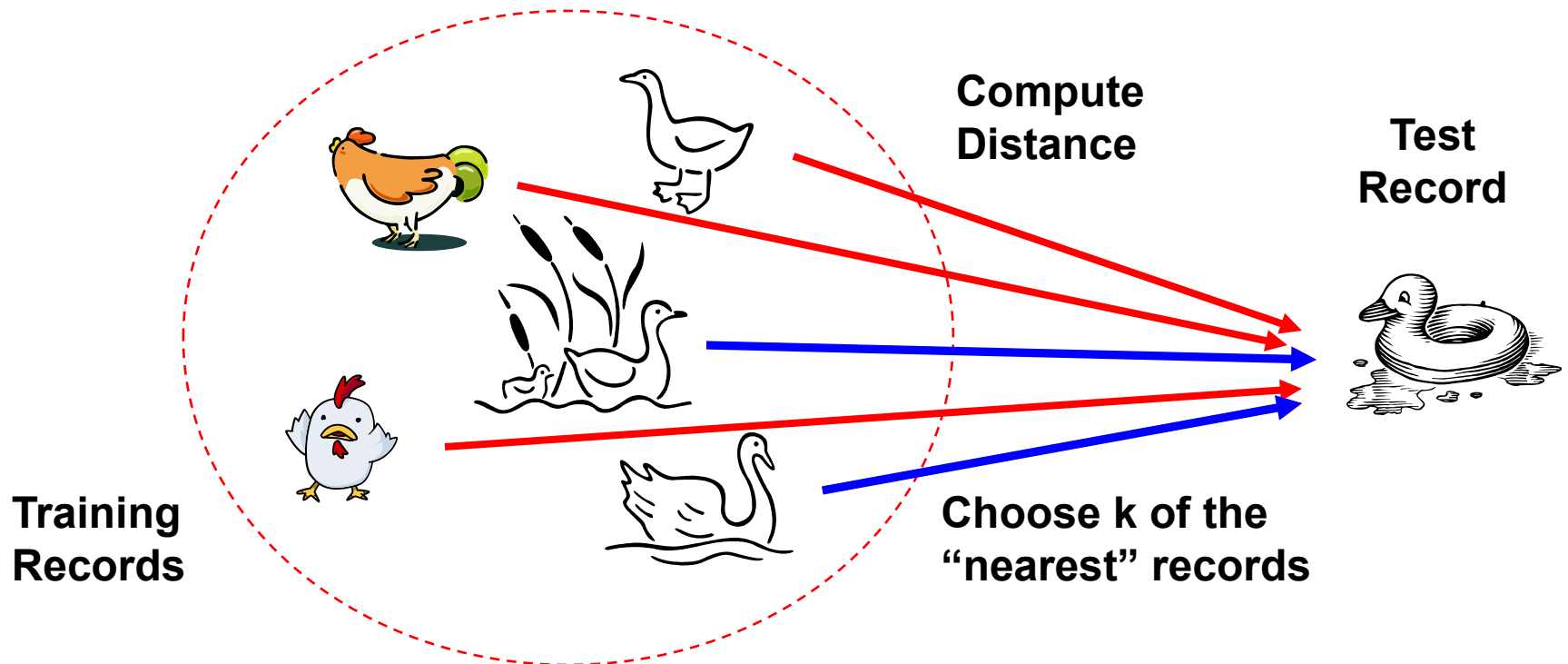
Tan, Steinbach, Karpatne, Kumar

Instance Based Classifiers

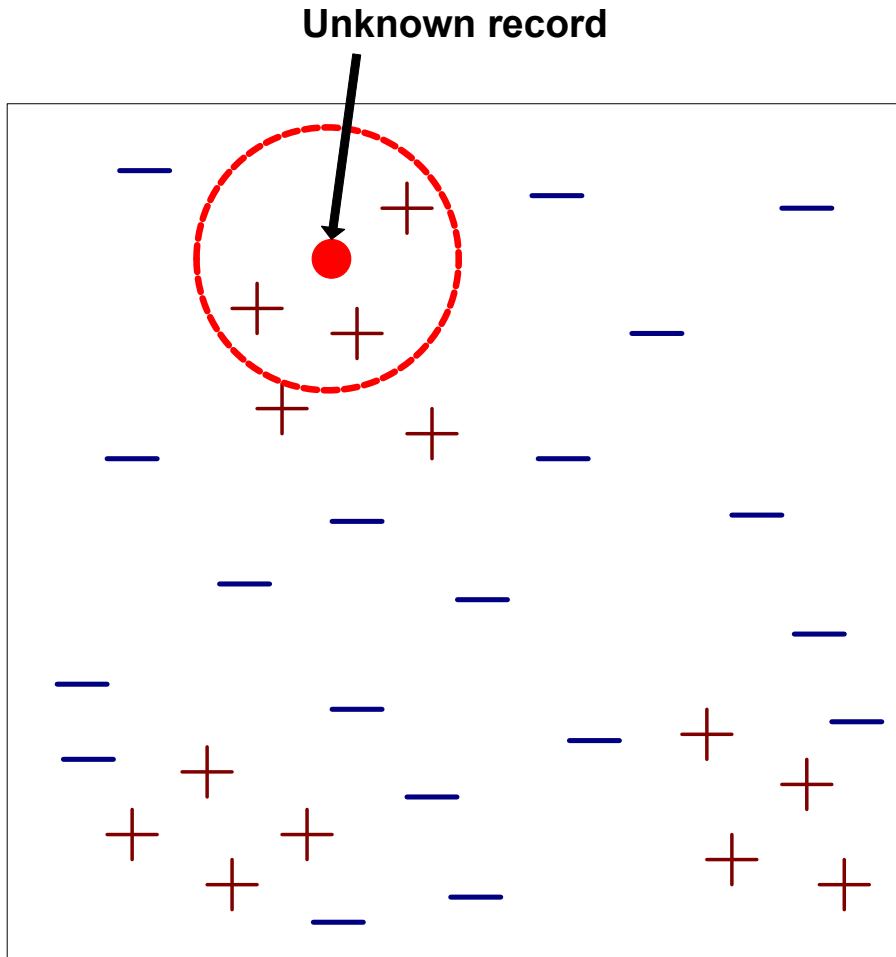
- Examples:
 - Rote-learner
 - ◆ Memorizes entire training data and performs classification only if attributes of record match one of the training examples exactly
 - Nearest neighbor
 - ◆ Uses k “closest” points (nearest neighbors) for performing classification

Nearest Neighbor Classifiers

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

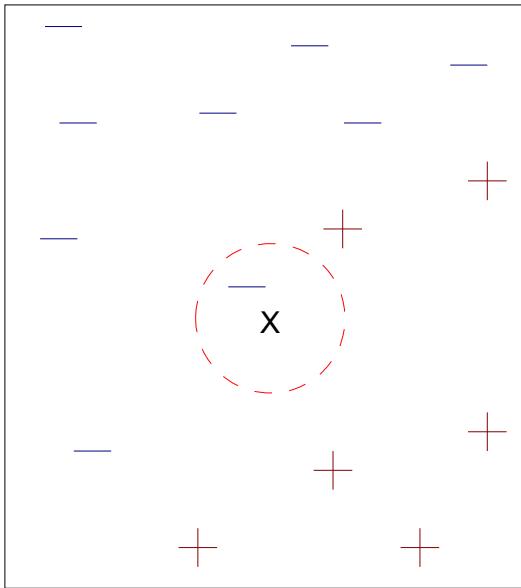


Nearest-Neighbor Classifiers

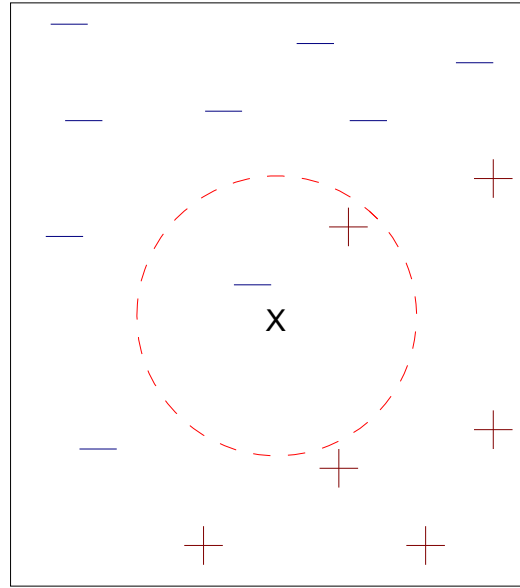


- Requires three things
 - The set of labeled records
 - Distance Metric to compute distance between records
 - The value of k , the number of nearest neighbors to retrieve
- To classify an unknown record:
 - Compute distance to other training records
 - Identify k nearest neighbors
 - Use class labels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

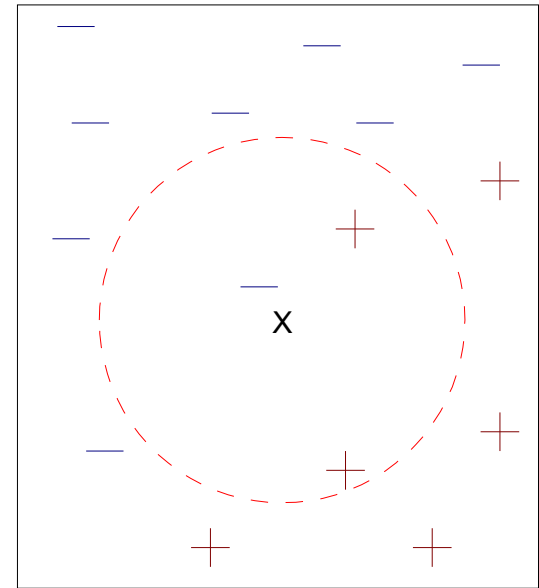
Definition of Nearest Neighbor



(a) 1-nearest neighbor



(b) 2-nearest neighbor

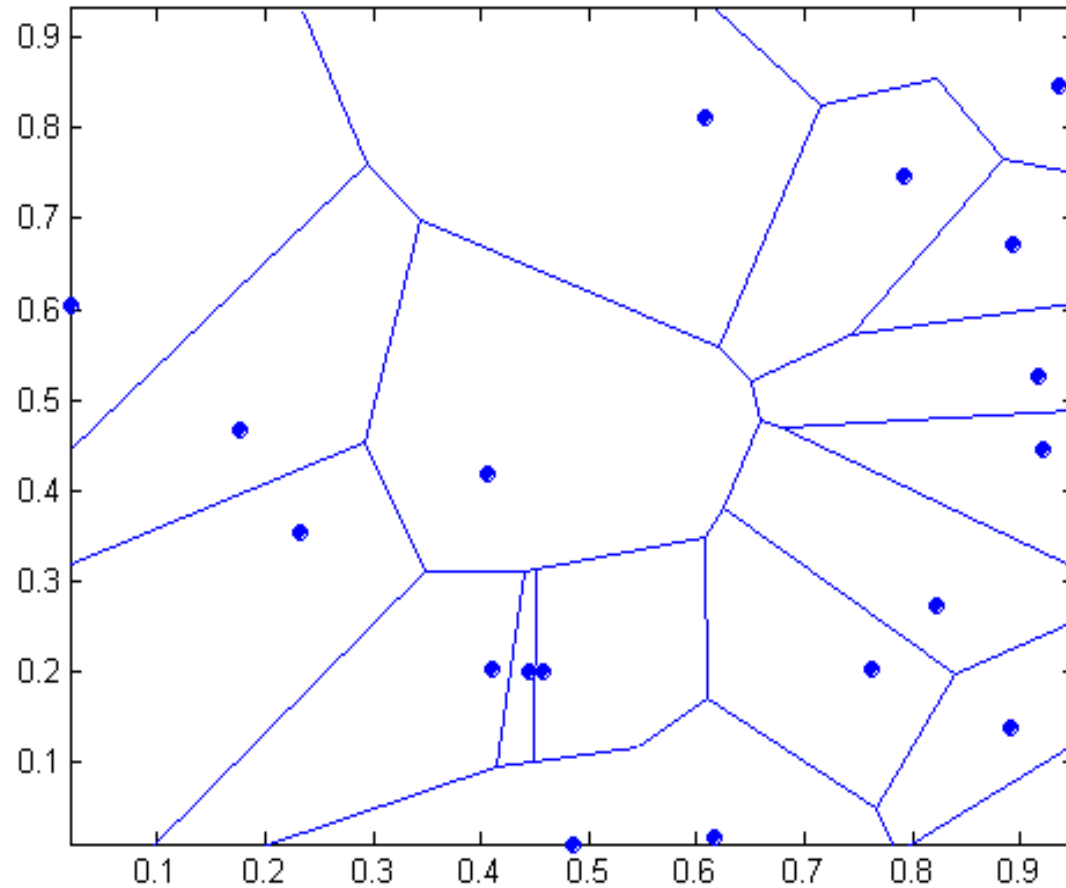


(c) 3-nearest neighbor

K-nearest neighbors of a record x are data points that have the k smallest distances to x

1 nearest-neighbor

Voronoi Diagram



Nearest Neighbor Classification

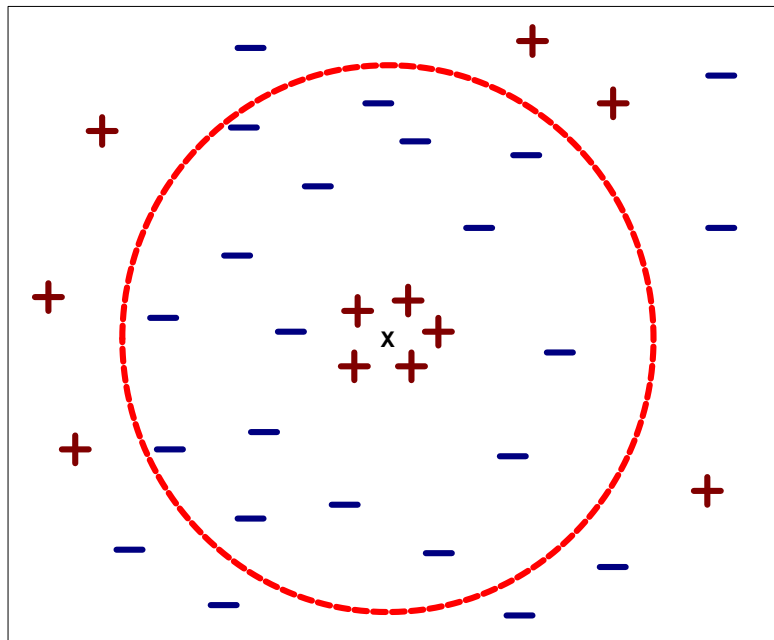
- Compute distance between two points:
 - Euclidean distance

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

- Determine the class from nearest neighbor list
 - Take the majority vote of class labels among the k-nearest neighbors
 - Weigh 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



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

Nearest Neighbor Classification...

- Selection of the right similarity measure is critical:

1 1 1 1 1 1 1 1 1 1 1 0	VS	0 0 0 0 0 0 0 0 0 0 0 1
0 1 1 1 1 1 1 1 1 1 1 1		1 0 0 0 0 0 0 0 0 0 0 0

Euclidean distance = 1.4142 for both pairs

Nearest neighbor Classification...

- k-NN classifiers are lazy learners since they do not build models explicitly
- Classifying unknown records are relatively expensive
- Can produce arbitrarily shaped decision boundaries
- Easy to handle variable interactions since the decisions are based on local information
- Selection of right proximity measure is essential
- Superfluous or redundant attributes can create problems
- Missing attributes are hard to handle

Improving KNN Efficiency

- Avoid having to compute distance to all objects in the training set
 - Multi-dimensional access methods (k-d trees)
 - Fast approximate similarity search
 - Locality Sensitive Hashing (LSH)
- Condensing
 - Determine a smaller set of objects that give the same performance
- Editing
 - Remove objects to improve efficiency

KNN and Proximity Graphs

- Proximity graphs
 - a graph in which two vertices are connected by an edge if and only if the vertices satisfy particular geometric requirements
 - nearest neighbor graphs,
 - minimum spanning trees
 - Delaunay triangulations
 - relative neighborhood graphs
 - Gabriel graphs
- See recent papers by Toussaint
 - G. T. Toussaint. Proximity graphs for nearest neighbor decision rules: recent progress. In Interface-2002, 34th Symposium on Computing and Statistics, ontreal, Canada, April 17–20 2002.
 - G. T. Toussaint. Open problems in geometric methods for instance based learning. In Discrete and Computational Geometry, volume 2866 of Lecture Notes in Computer Science, pages 273–283, December 6-9, 2003.
 - G. T. Toussaint. Geometric proximity graphs for improving nearest neighbor methods in instance-based learning and data mining. Int. J. Comput. Geometry Appl., 15(2):101–150, 2005.