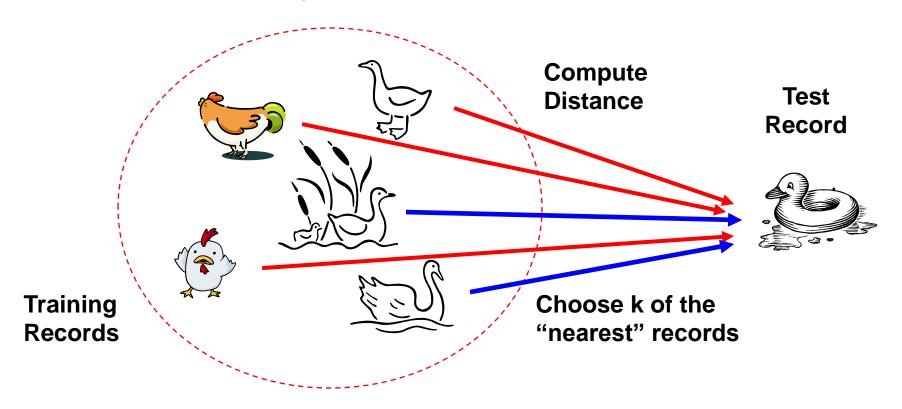
Data Mining

Instance-Based Learning

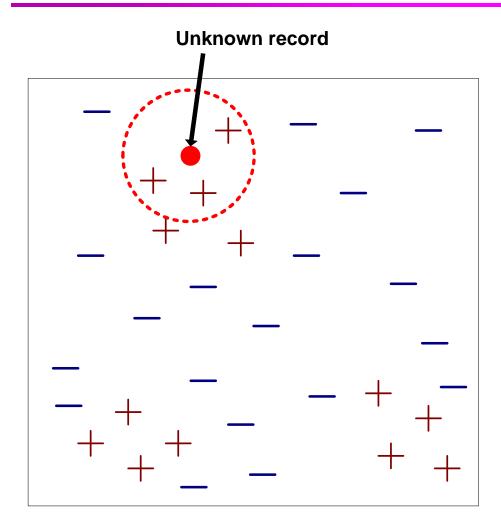
Nearest Neighbor Classifiers

Basic idea:

 If it walks like a duck, quacks like a duck, then it's probably a duck



Nearest-Neighbor Classifiers



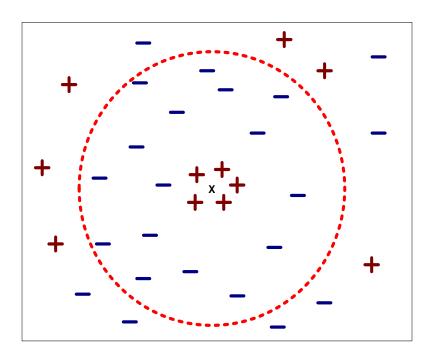
- Requires three things
 - The set of labeled records
 - Distance metric to compute distance between records
 - The value of k, the number of nearest neighbors to retrieve
- To classify an unknown record:
 - Compute distance to other training records
 - Identify k nearest neighbors
 - Use class labels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

- Compute proximity between two points:
 - Example: Euclidean distance

$$d(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{i} (\mathbf{x}_{i} - \mathbf{y}_{i})^{2}}$$

- 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, $w = 1/d^2$

- 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



Choice of proximity measure matters

 For documents, cosine is better than correlation or Euclidean

11111111110

VS

 $0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1$

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100000000000

Euclidean distance = 1.4142 for both pairs

Data preprocessing is often required

 Attributes may have to be scaled to prevent distance measures from being dominated by one of the attributes

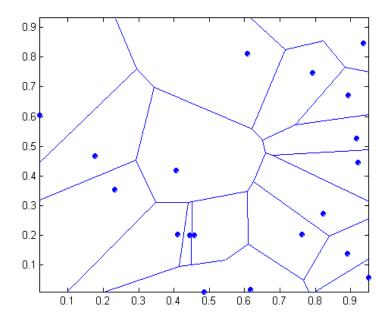
◆Example:

- 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
- Time series are often standardized to have 0 means a standard deviation of 1

Nearest-neighbor classifiers

- Nearest neighbor classifiers are local classifiers
- They can produce decision boundaries of arbitrary shapes.

1-nn decision boundary is a Voronoi Diagram



- How to handle missing values in training and test sets?
 - Proximity computations normally require the presence of all attributes
 - Some approaches use the subset of attributes present in two instances
 - This may not produce good results since it effectively uses different proximity measures for each pair of instances
 - Thus, proximities are not comparable

Handling irrelevant and redundant attributes

- Irrelevant attributes add noise to the proximity measure
- Redundant attributes bias the proximity measure towards certain attributes
- Can use variable selection or dimensionality reduction to address irrelevant and redundant attributes

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