Statistical Learning and Data Mining
CS 363D/ SSC 358

Lecture: Nearest Neighbor Classifiers

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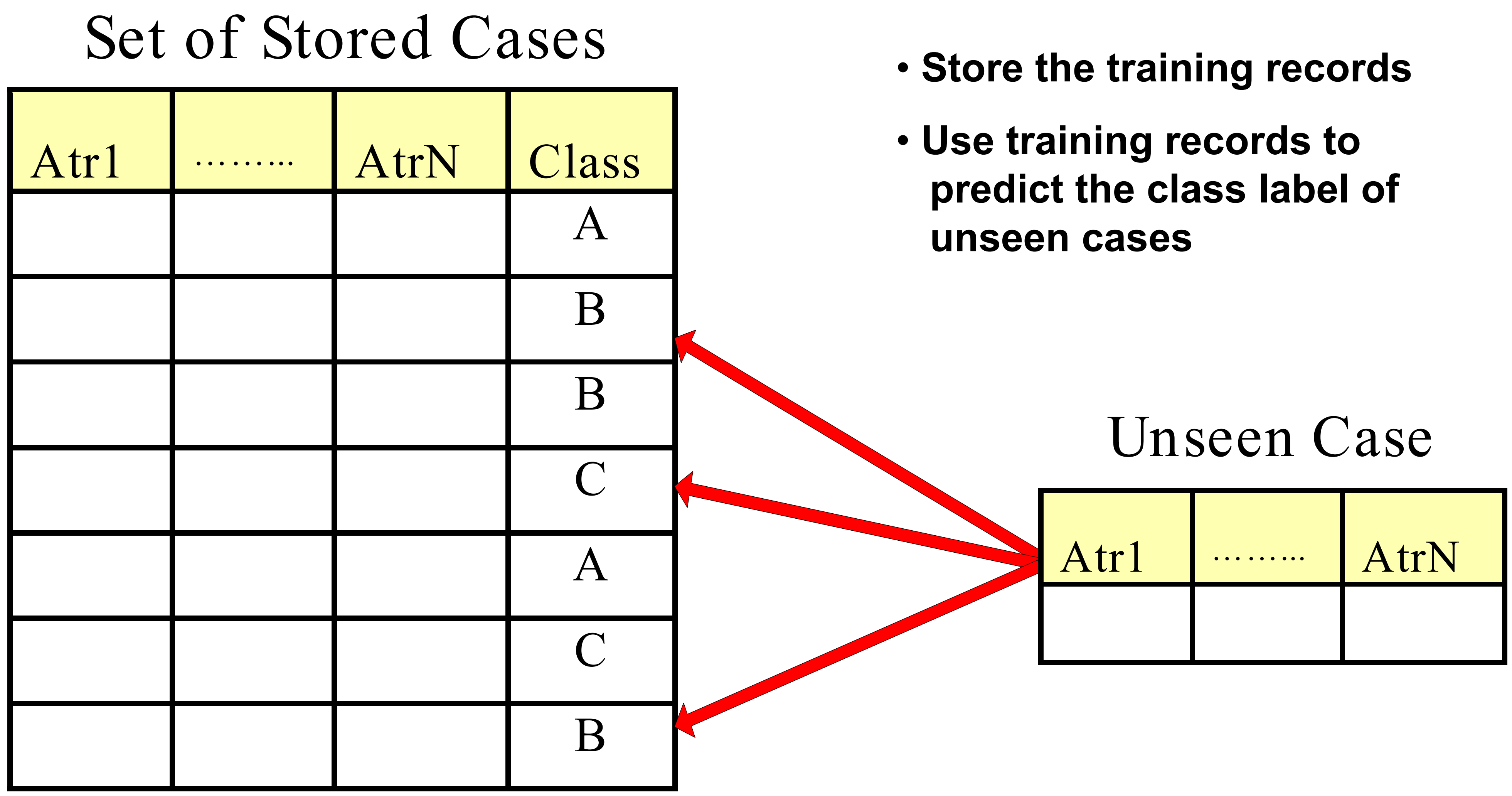
Adapted From: Pang-Ning Tan, Steinbach, Kumar

Instance-Based Classifiers



- Store the training records
- Use training records to predict the class label of unseen cases

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

Instance-Based Classifiers

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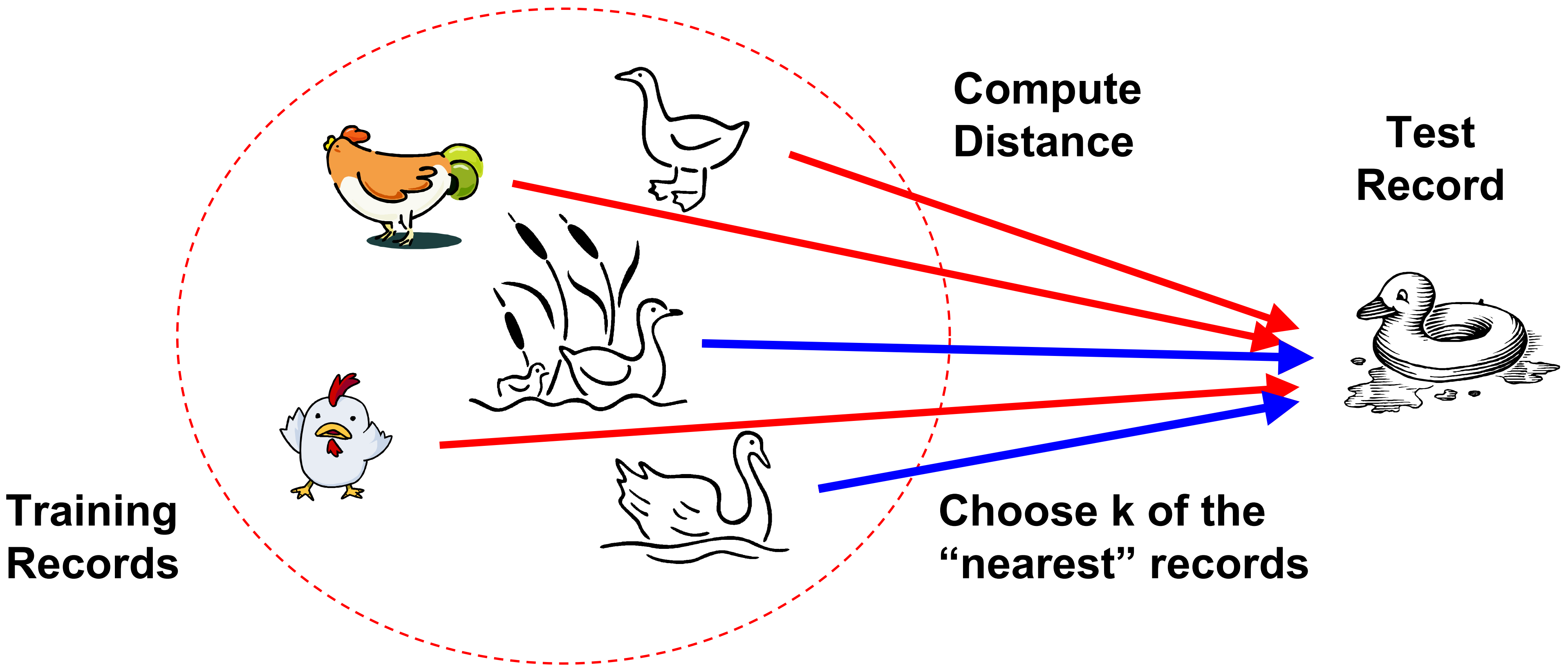
  - Rote-learner
    - Memorizes entire training data and performs classification only if attributes of record match one of the training examples exactly
  - Nearest neighbor
    - Uses k “closest” points (nearest neighbors) for performing classification

Nearest-Neighbor Classifiers

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



Nearest-Neighbor Classifiers

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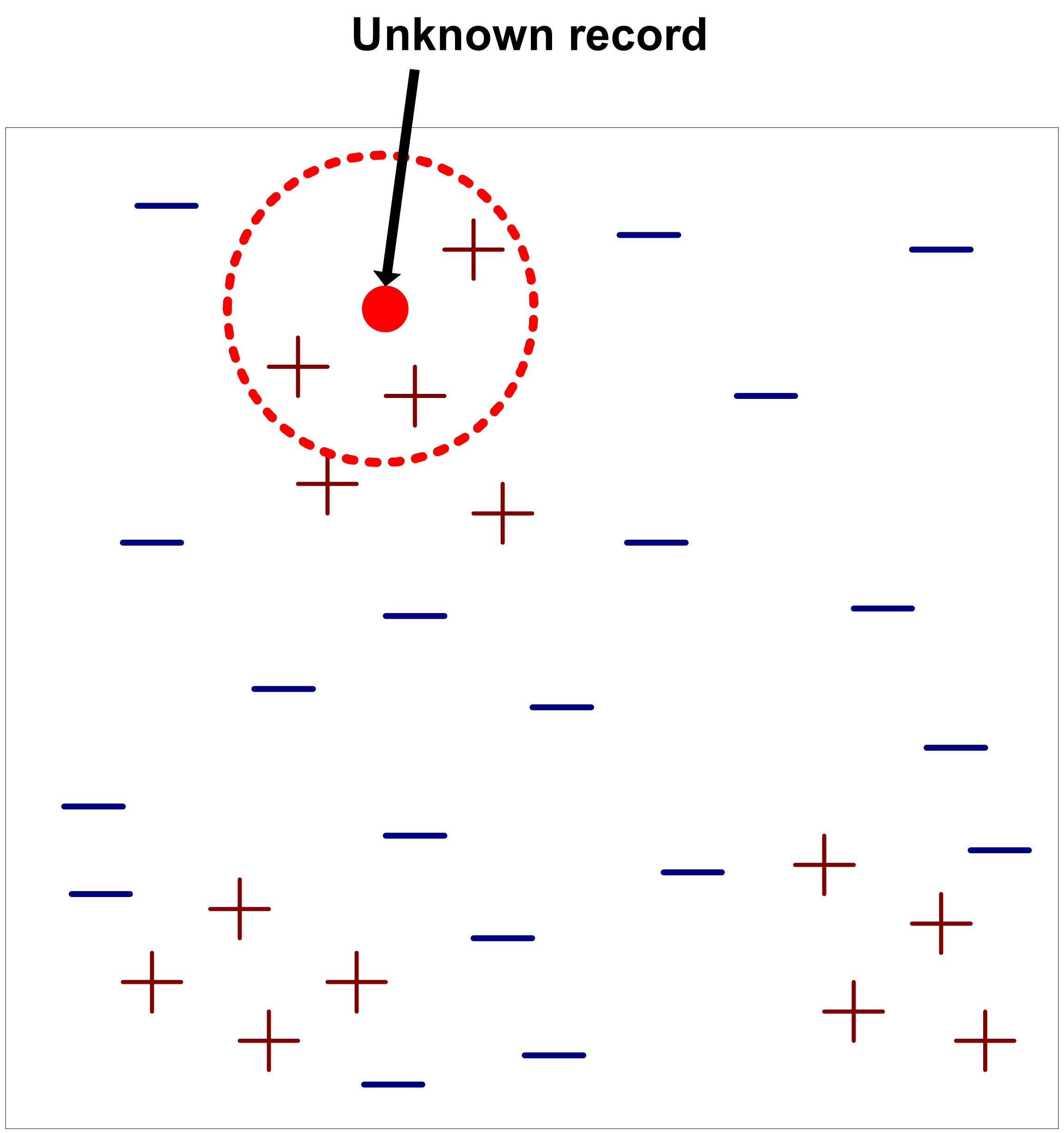
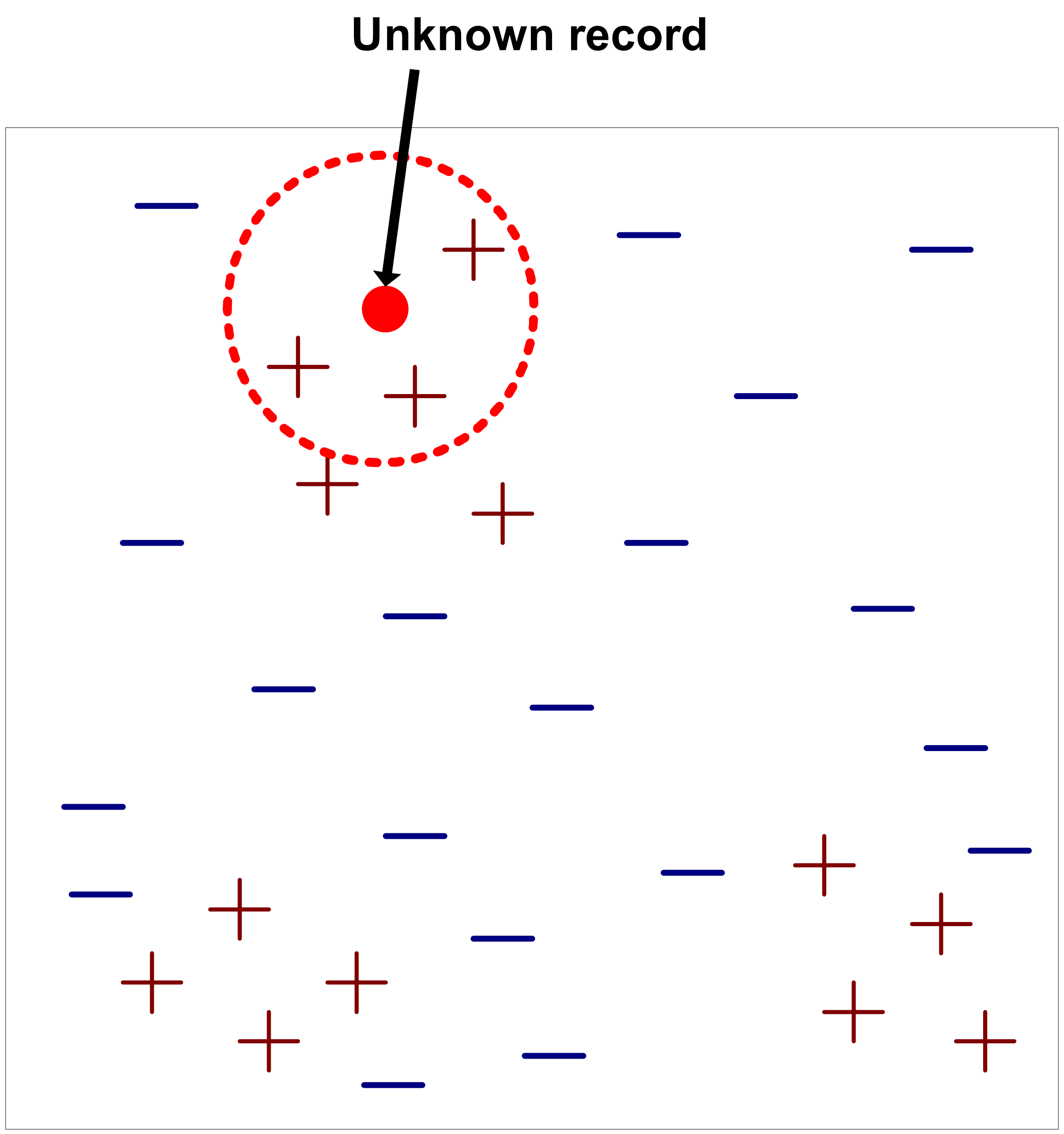
Nearest-Neighbor Classifiers



- Requires three things
  - The set of stored records
  - Distance Metric to compute distance between records
  - The value of *k*, the number of nearest neighbors to retrieve

Nearest-Neighbor Classifiers



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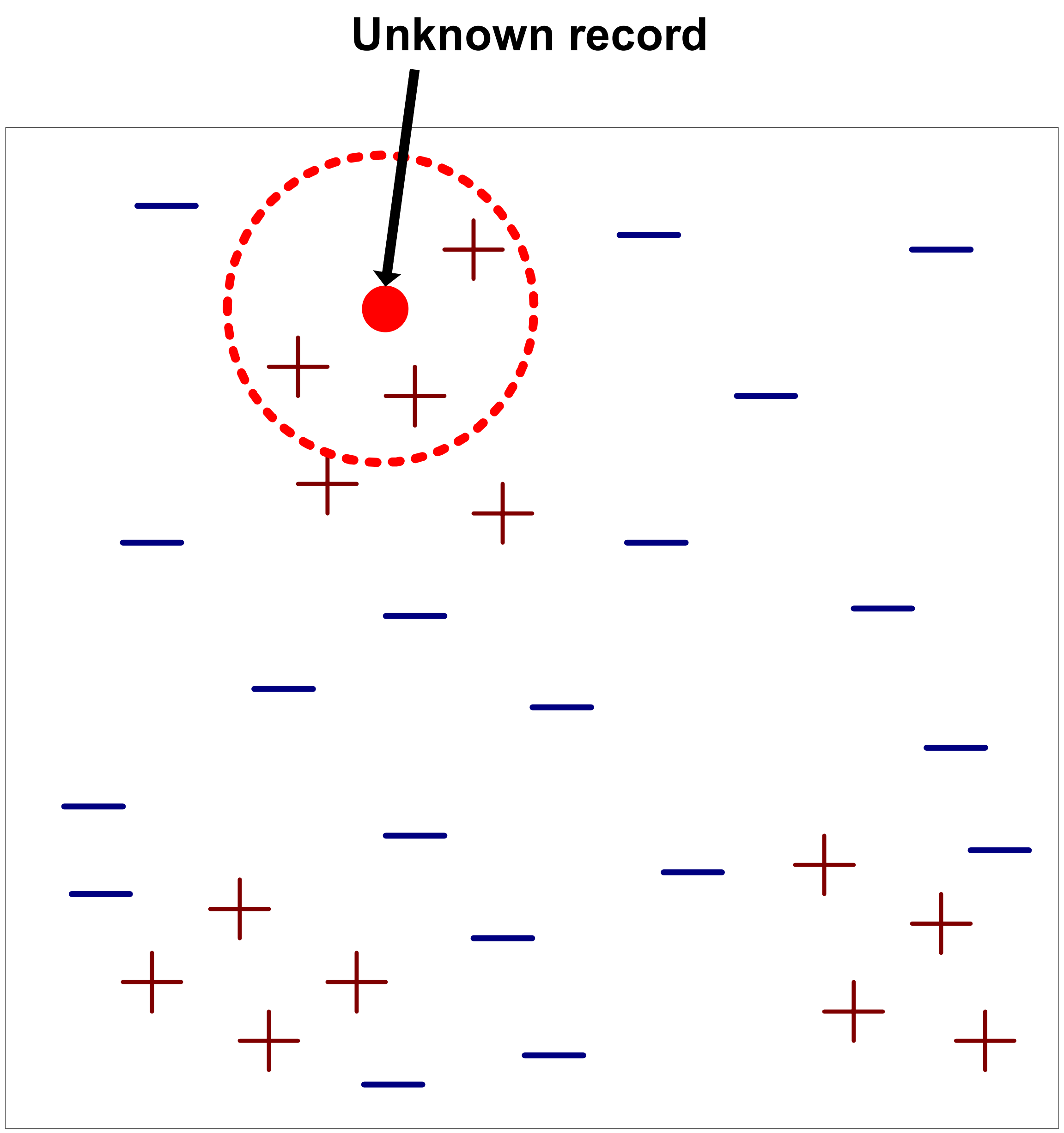
Nearest-Neighbor Classifiers



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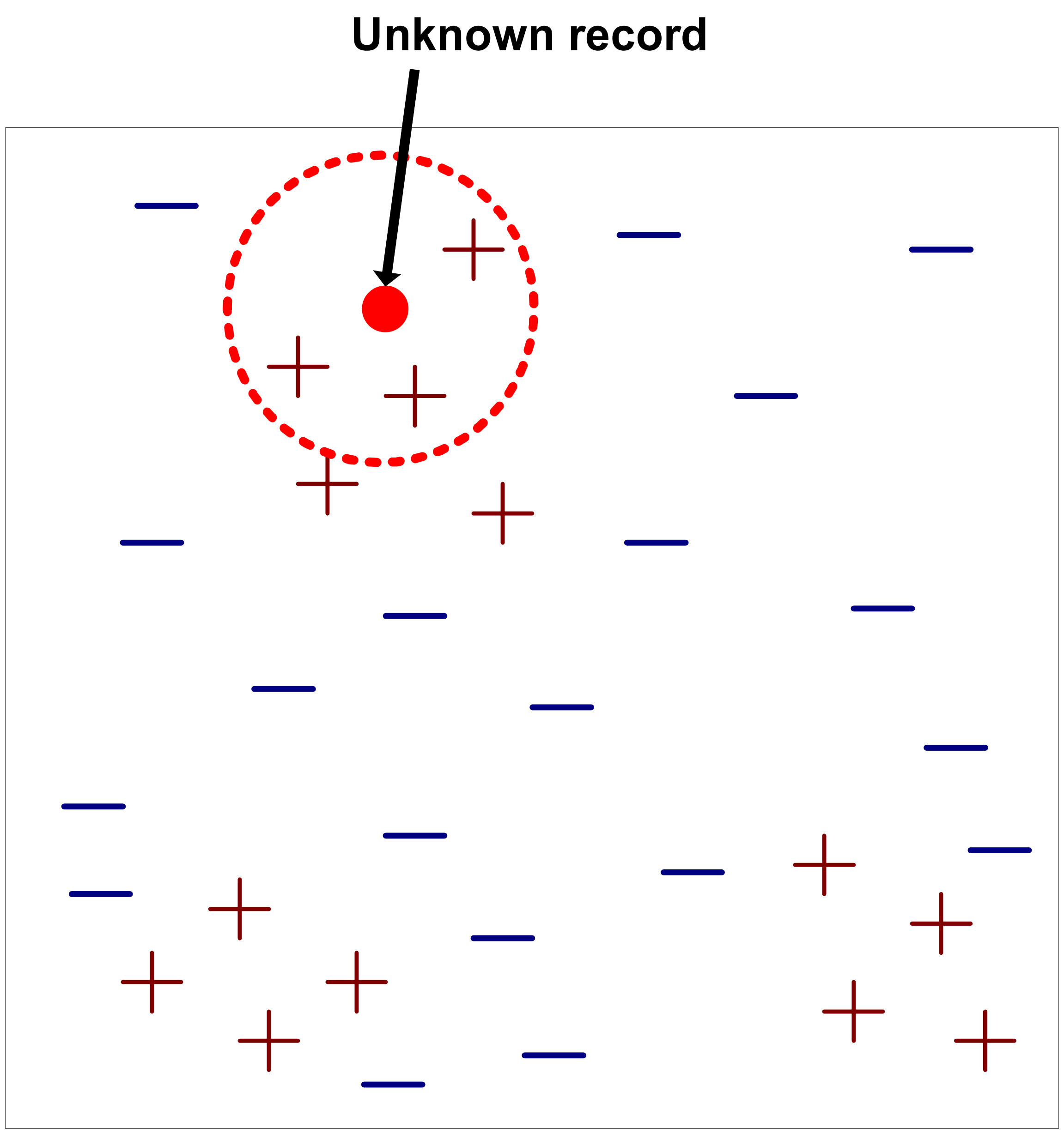

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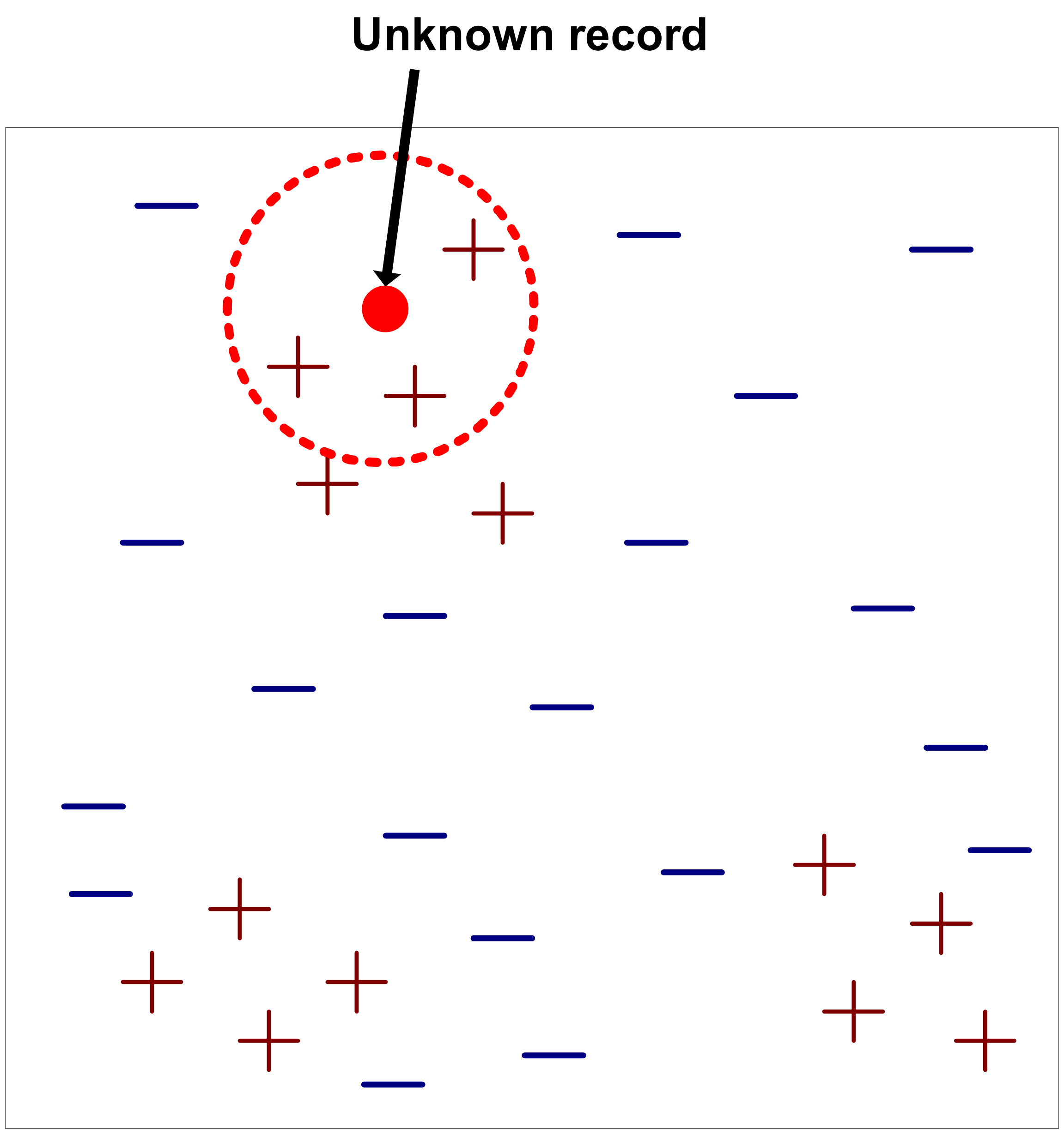

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- To classify an unknown record:
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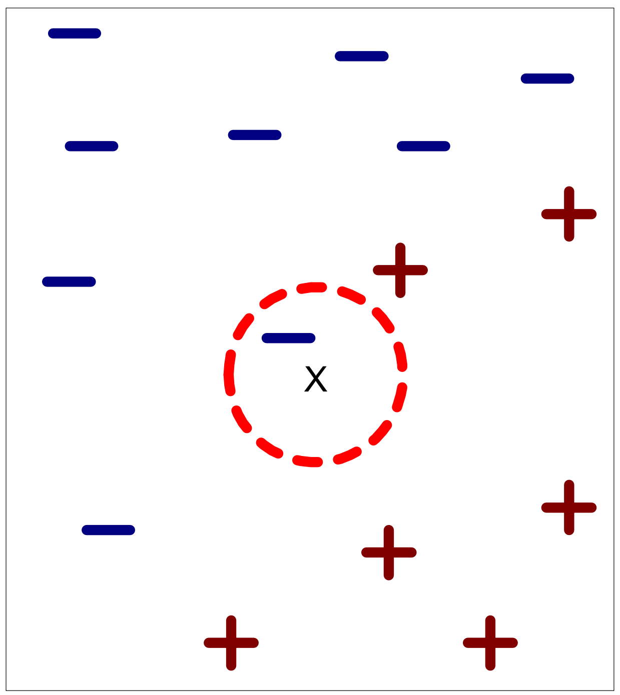
  - Identify *k* nearest neighbors
  - Use class labels of nearest neighbors to determine the class label of unknown record (e.g., by taking majority vote)

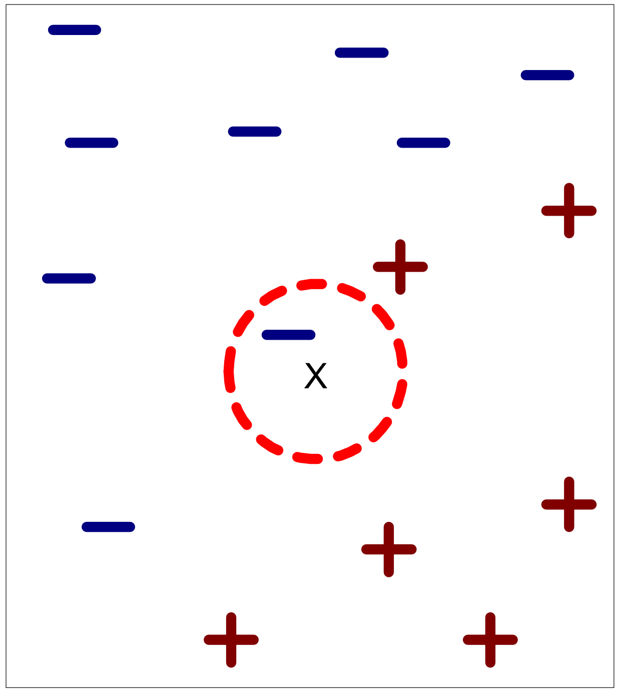
Definition of Nearest Neighbor



(a) 1-nearest neighbor

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

Definition of Nearest Neighbor



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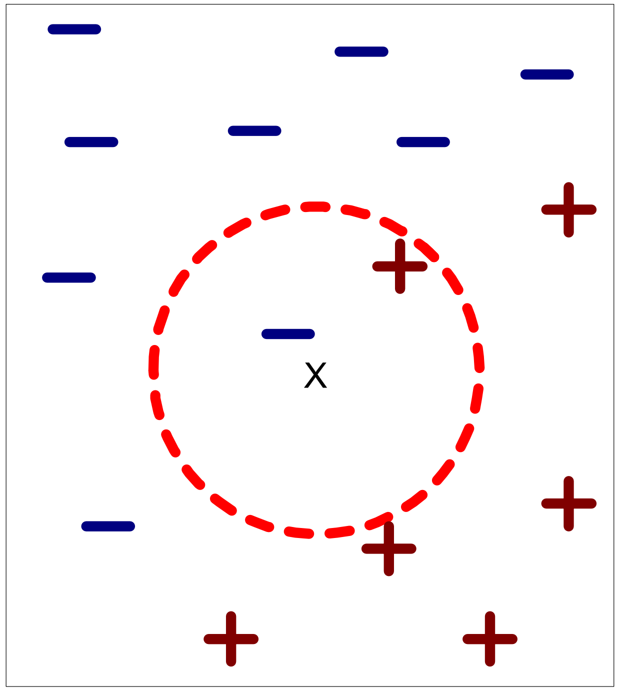
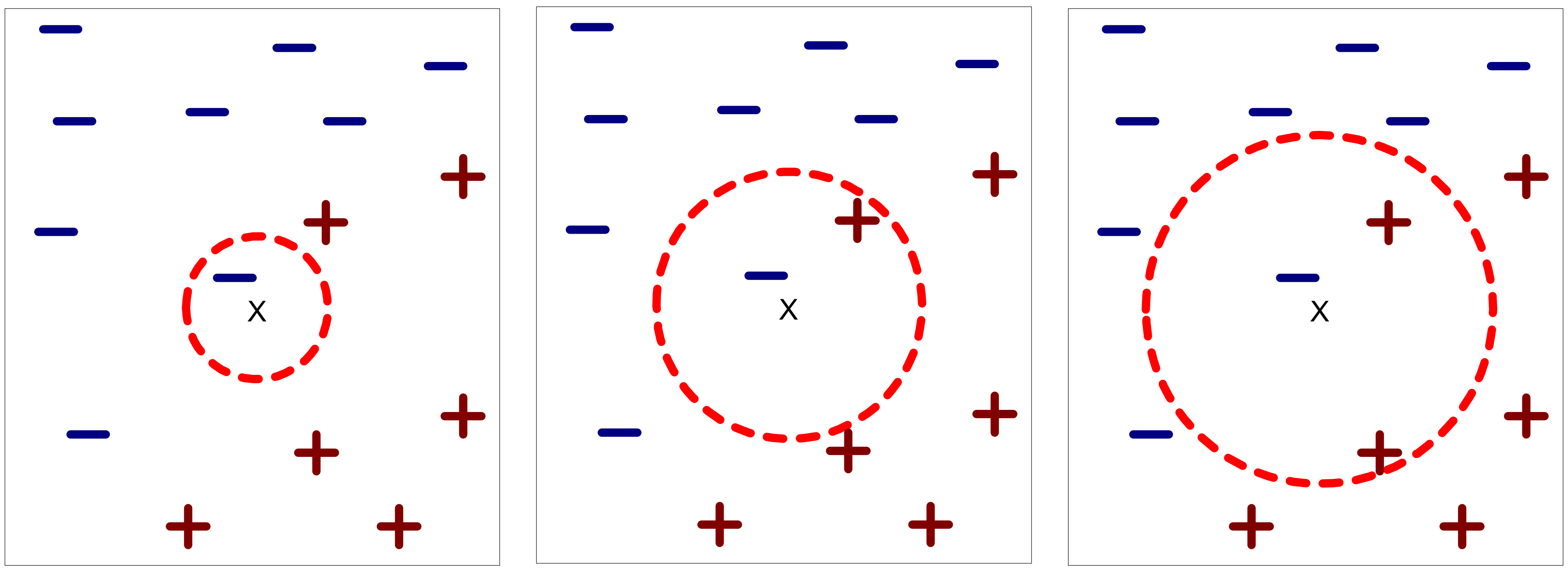


(b) 2-nearest neighbor

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

Definition of Nearest Neighbor

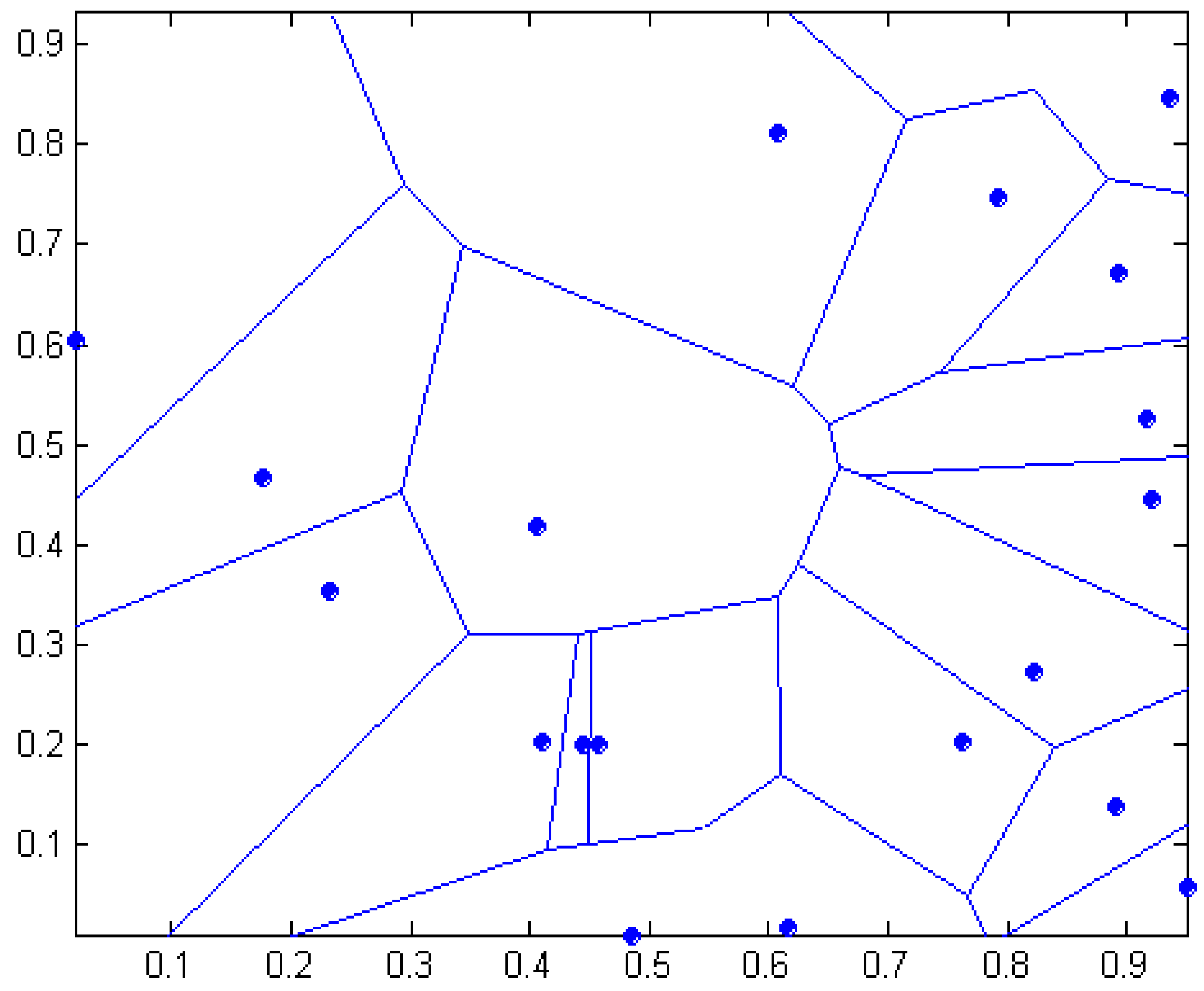


(a) 1-nearest neighbor (b) 2-nearest neighbor (c) 3-nearest neighbor

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

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  - 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

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  - If k is too small,

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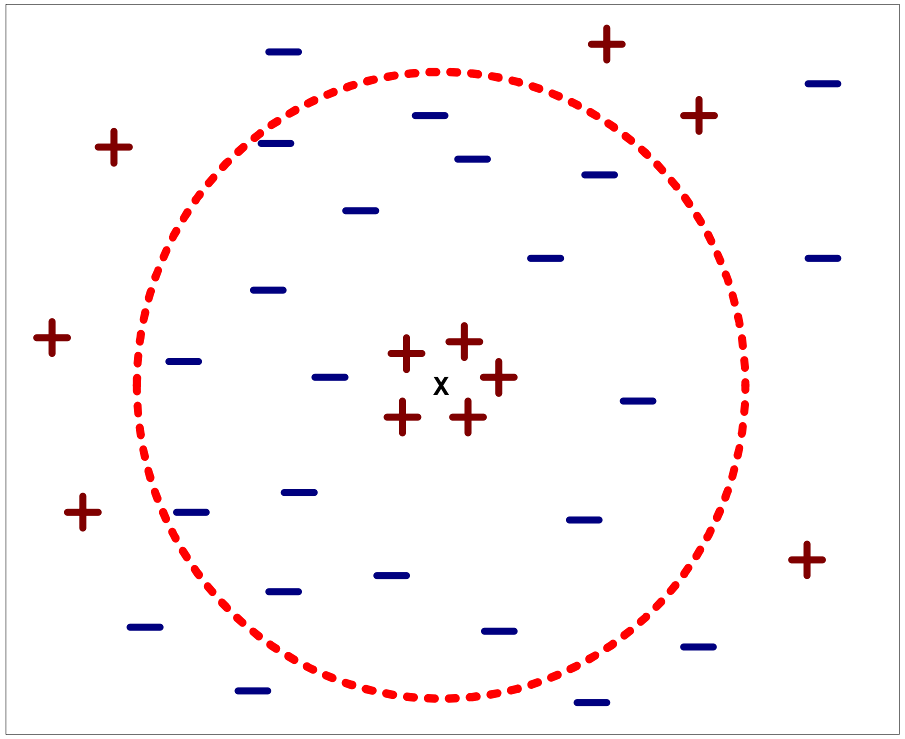
  - If k is too large,

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

- Problem with Euclidean measure:
  - High dimensional data
    - curse of dimensionality

Nearest Neighbor Classification

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  - Can produce counter-intuitive results

1 1 1 1 1 1 1 1 1 1 1 0		1 0 0 0 0 0 0 0 0 0 0 0
0 1 1 1 1 1 1 1 1 1 1 1	vs	0 0 0 0 0 0 0 0 0 0 0 1
d = 1.4142		**d = 1.4142**

Nearest Neighbor Classification

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	vs		
0 1 1 1 1 1 1 1 1 1 1 1		**0 0 0 0 0 0 0 0 0 0 0 1**	
d = 1.4142		**d = 1.4142**	

- Solution: Normalize the vectors to unit length

Nearest Neighbor Classification

- k-NN classifiers are lazy learners
  – It does not build models explicitly
  – Unlike eager learners such as decision tree induction and rule-based systems
  – Classifying unknown records are relatively expensive

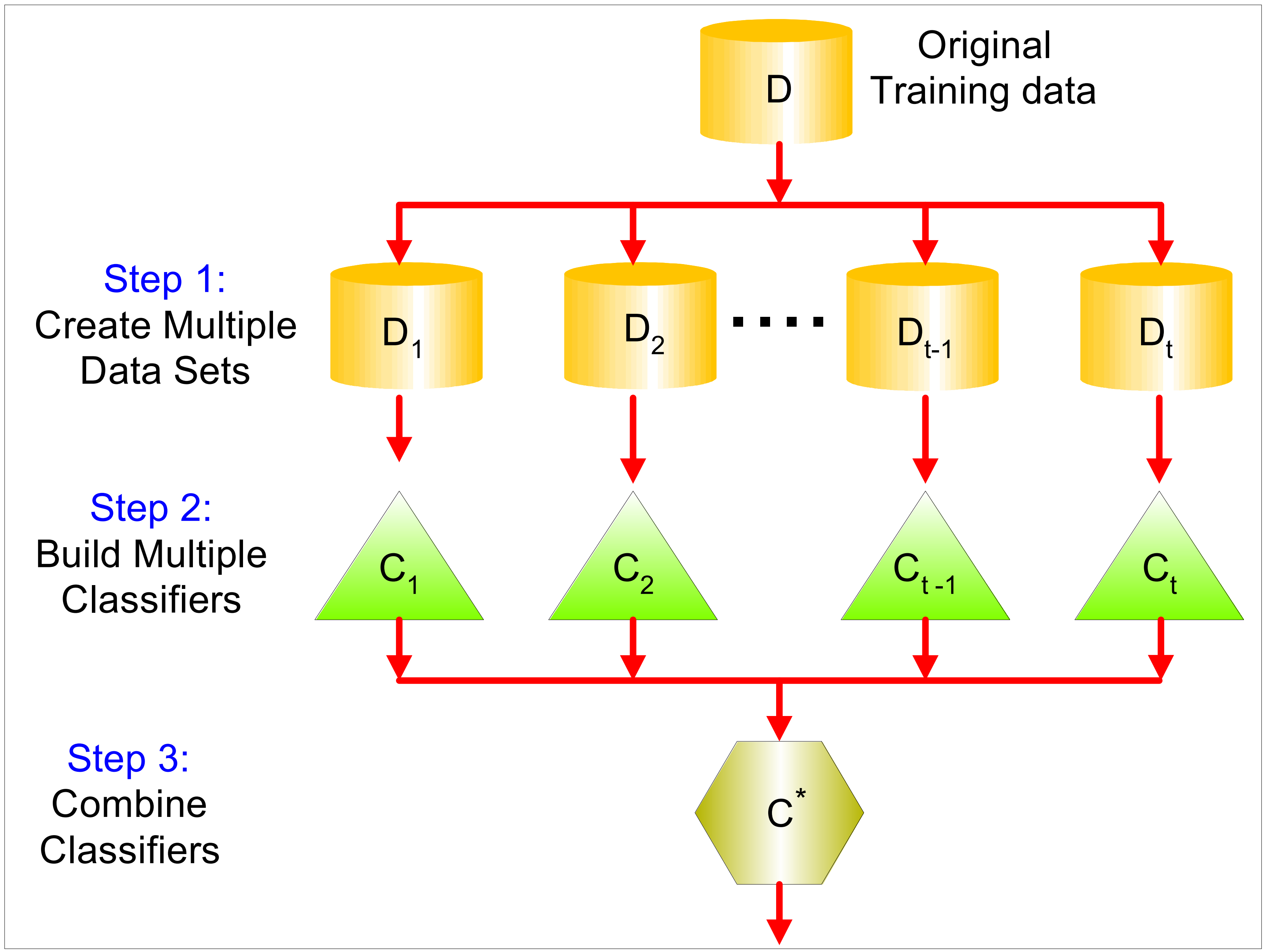
Ensemble Methods

Ensemble Methods

- Construct a set of classifiers from the training data

- Predict class label of previously unseen records by aggregating predictions made by multiple classifiers

General Idea



Why does it work?

- Suppose there are 25 base classifiers
  - Each classifier has error rate, $\varepsilon = 0.35$
  - Assume classifiers are independent
  - Probability that the ensemble classifier makes a wrong prediction:

$$\sum_{i=13}^{25} \binom{25}{i} \varepsilon^i (1-\varepsilon)^{25-i} = 0.06$$

Many Approaches to Step 1 (Creating Multiple Datasets)

- Copy the dataset multiple times
- Partitioning the dataset
- Bagging
- Boosting

Bagging

- Sampling with replacement

Original Data	1	2	3	4	5	6	7	8	9	10
Bagging (Round 1)	7	8	10	8	2	5	10	10	5	9
Bagging (Round 2)	1	4	9	1	2	3	2	7	3	2
Bagging (Round 3)	1	8	5	10	5	5	9	6	3	7

- Build classifier on each bootstrap sample