



Lecture 5: alternative classification techniques

Outline

- Rule-based method
- Nearest Neighbor
- Support Vector Machine
- Neural network
- Naïve Bayes Classifier
- Boosting

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Rule-Based Classifier

- Classify records by using a collection of “if...then...” rules
- Rule: $(Condition) \rightarrow y$
 - where
 - ◆ *Condition* is a conjunctions of attributes
 - ◆ *y* is the class label
 - *Left-hand side*: condition
 - *Right-hand side*: consequent
- Examples of classification rules:
 - ◆ $(\text{Blood Type}=\text{Warm}) \wedge (\text{Lay Eggs}=\text{Yes}) \rightarrow \text{Birds}$
 - ◆ $(\text{Taxable Income} < 50\text{K}) \wedge (\text{Refund}=\text{Yes}) \rightarrow \text{Evade}=\text{No}$

Rule-based Classifier (Example)

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
human	warm	yes	no	no	mammals
python	cold	no	no	no	reptiles
salmon	cold	no	no	yes	fishes
whale	warm	yes	no	yes	mammals
frog	cold	no	no	sometimes	amphibians
komodo	cold	no	no	no	reptiles
bat	warm	yes	yes	no	mammals
pigeon	warm	no	yes	no	birds
cat	warm	yes	no	no	mammals
leopard shark	cold	yes	no	yes	fishes
turtle	cold	no	no	sometimes	reptiles
penguin	warm	no	no	sometimes	birds
porcupine	warm	yes	no	no	mammals
eel	cold	no	no	yes	fishes
salamander	cold	no	no	sometimes	amphibians
gila monster	cold	no	no	no	reptiles
platypus	warm	no	no	no	mammals
owl	warm	no	yes	no	birds
dolphin	warm	yes	no	yes	mammals
eagle	warm	no	yes	no	birds

R1: (Give Birth = no) \wedge (Can Fly = yes) \rightarrow Birds

R2: (Give Birth = no) \wedge (Live in Water = yes) \rightarrow Fishes

R3: (Give Birth = yes) \wedge (Blood Type = warm) \rightarrow Mammals

R4: (Give Birth = no) \wedge (Can Fly = no) \rightarrow Reptiles

R5: (Live in Water = sometimes) \rightarrow Amphibians

Application of Rule-Based Classifier

- A rule r **covers** an instance x if the attributes of the instance satisfy the condition of the rule

R1: (Give Birth = no) \wedge (Can Fly = yes) \rightarrow Birds

R2: (Give Birth = no) \wedge (Live in Water = yes) \rightarrow Fishes

R3: (Give Birth = yes) \wedge (Blood Type = warm) \rightarrow Mammals

R4: (Give Birth = no) \wedge (Can Fly = no) \rightarrow Reptiles

R5: (Live in Water = sometimes) \rightarrow Amphibians

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
hawk	warm	no	yes	no	?
grizzly bear	warm	yes	no	no	?

The rule R1 covers a hawk \Rightarrow Bird

The rule R3 covers the grizzly bear \Rightarrow Mammal

Rule Coverage and Accuracy

- Coverage of a rule:
 - Fraction of records that satisfy the antecedent of a rule
- Accuracy of a rule:
 - Fraction of records that satisfy both the antecedent and consequent of a rule

Tid	Refund	Marital Status	Taxable Income	Class
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

(Status=Single) → No

Coverage = 40%, Accuracy = 50%

How does Rule-based Classifier Work?

R1: (Give Birth = no) \wedge (Can Fly = yes) \rightarrow Birds

R2: (Give Birth = no) \wedge (Live in Water = yes) \rightarrow Fishes

R3: (Give Birth = yes) \wedge (Blood Type = warm) \rightarrow Mammals

R4: (Give Birth = no) \wedge (Can Fly = no) \rightarrow Reptiles

R5: (Live in Water = sometimes) \rightarrow Amphibians

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
lemur	warm	yes	no	no	?
turtle	cold	no	no	sometimes	?
dogfish shark	cold	yes	no	yes	?

A lemur triggers rule R3, so it is classified as a mammal

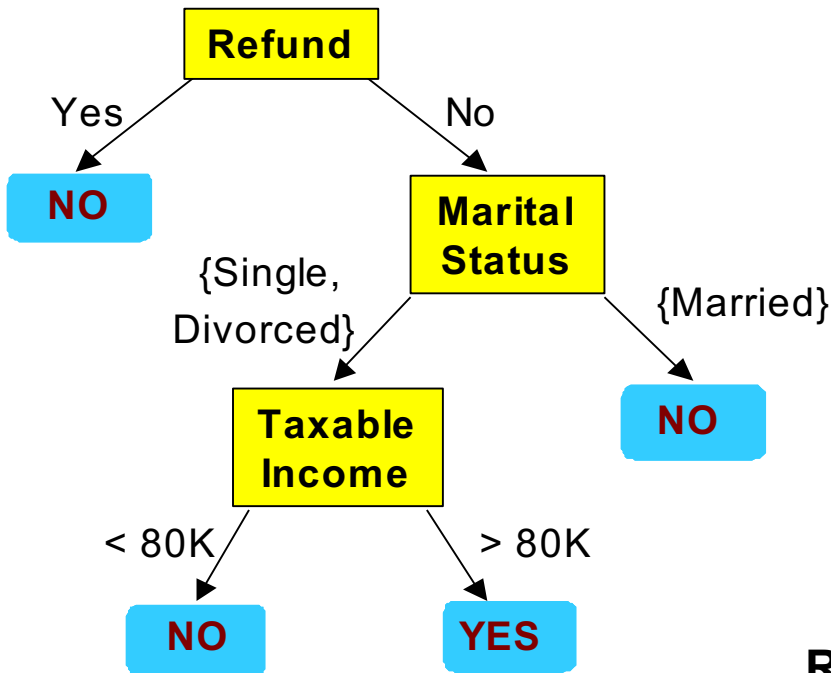
A turtle triggers both R4 and R5

A dogfish shark triggers none of the rules

Characteristics of Rule-Based Classifier

- Mutually exclusive rules
 - Classifier contains mutually exclusive rules if the rules are independent of each other
 - Every record is covered by at most one rule
- Exhaustive rules
 - Classifier has exhaustive coverage if it accounts for every possible combination of attribute values
 - Each record is covered by at least one rule

From Decision Trees To Rules



Classification Rules

(Refund=Yes) ==> No

(Refund=No, Marital Status={Single, Divorced}, Taxable Income<80K) ==> No

(Refund=No, Marital Status={Single, Divorced}, Taxable Income>80K) ==> Yes

(Refund=No, Marital Status={Married}) ==> No

Rules are mutually exclusive and exhaustive

Rule set contains as much information as the tree

Ordered Rule Set

- Rules are rank ordered according to their priority
 - An ordered rule set is known as a decision list
- When a test record is presented to the classifier
 - It is assigned to the class label of the highest ranked rule it has triggered
 - If none of the rules fired, it is assigned to the default class

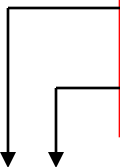
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R3: (Give Birth = yes) \wedge (Blood Type = warm) \rightarrow Mammals

R4: (Give Birth = no) \wedge (Can Fly = no) \rightarrow Reptiles

R5: (Live in Water = sometimes) \rightarrow Amphibians



Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
turtle	cold	no	no	sometimes	?

Rule Ordering Schemes

- Rule-based ordering

- Individual rules are ranked based on their quality

- Class-based ordering

- Rules that belong to the same class appear together

Rule-based Ordering

(Refund=Yes) ==> No

(Refund=No, Marital Status={Single,Divorced},
Taxable Income<80K) ==> No

(Refund=No, Marital Status={Single,Divorced},
Taxable Income>80K) ==> Yes

(Refund=No, Marital Status={Married}) ==> No

Class-based Ordering

(Refund=Yes) ==> No

(Refund=No, Marital Status={Single,Divorced},
Taxable Income<80K) ==> No

(Refund=No, Marital Status={Married}) ==> No

(Refund=No, Marital Status={Single,Divorced},
Taxable Income>80K) ==> Yes

Building Classification Rules

- Direct Method:

- ◆ Extract rules directly from data
- ◆ e.g.: RIPPER, CN2, Holte's 1R

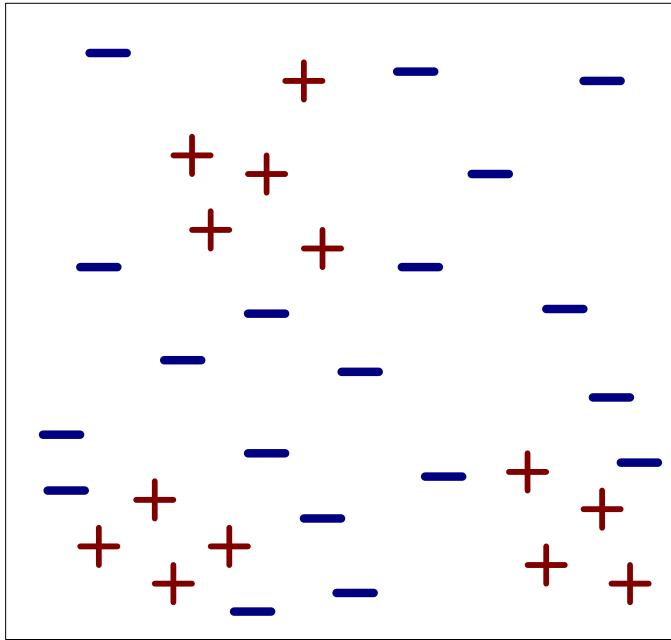
- Indirect Method:

- ◆ Extract rules from other classification models (e.g. decision trees, neural networks, etc).
- ◆ e.g: C4.5rules

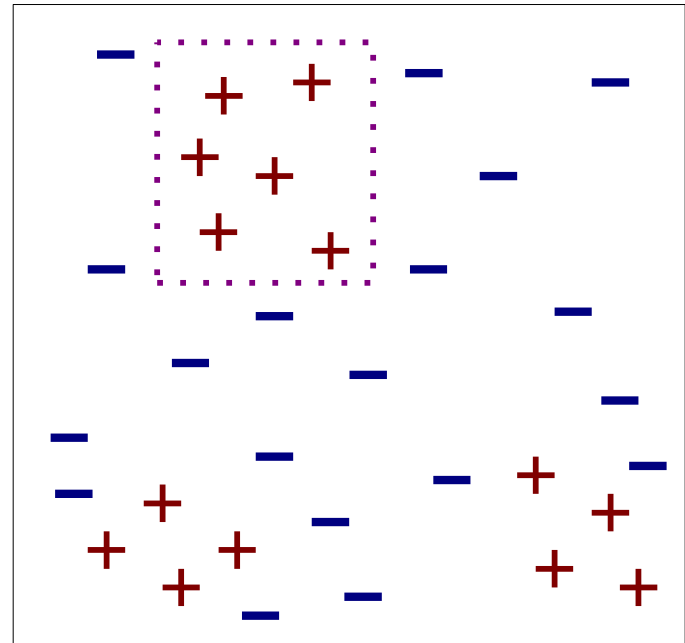
Direct Method: Sequential Covering

1. Start from an empty rule
2. Grow a rule using the Learn-One-Rule function
3. Remove training records covered by the rule
4. Repeat Step (2) and (3) until stopping criterion is met

Example of Sequential Covering

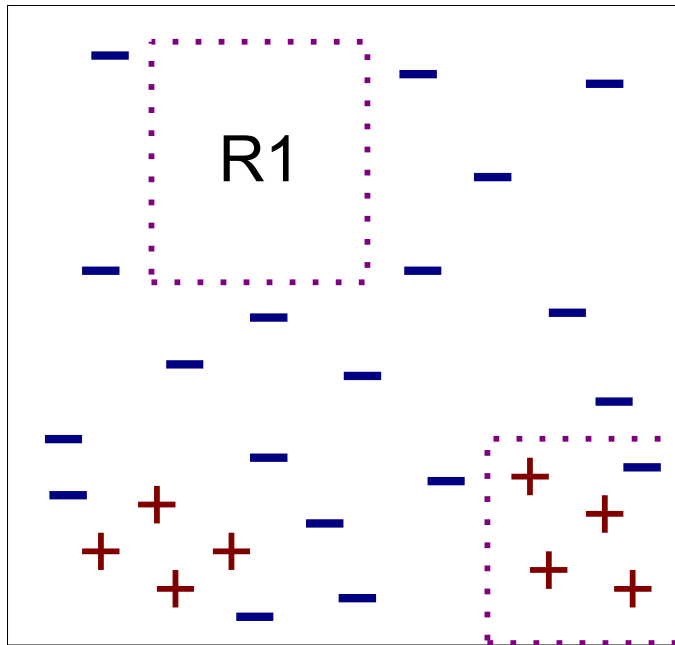


(i) Original Data

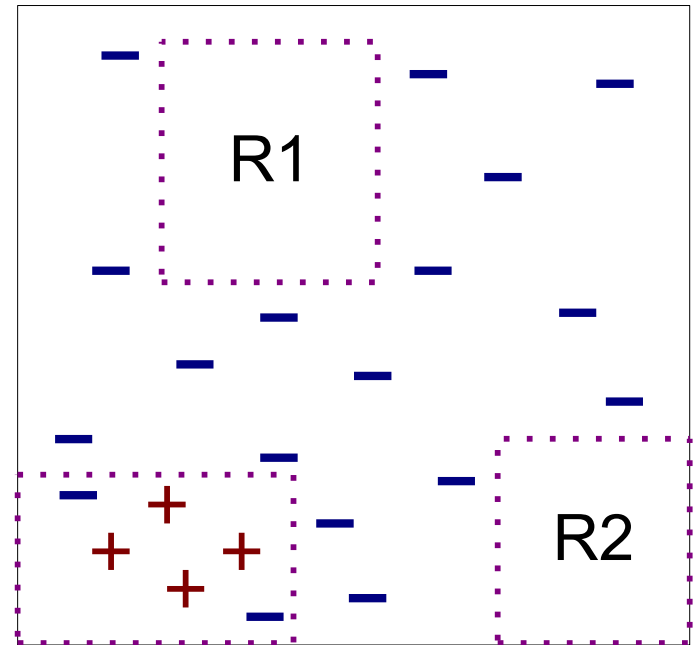


(ii) Step 1

Example of Sequential Covering...



(iii) Step 2



(iv) Step 3

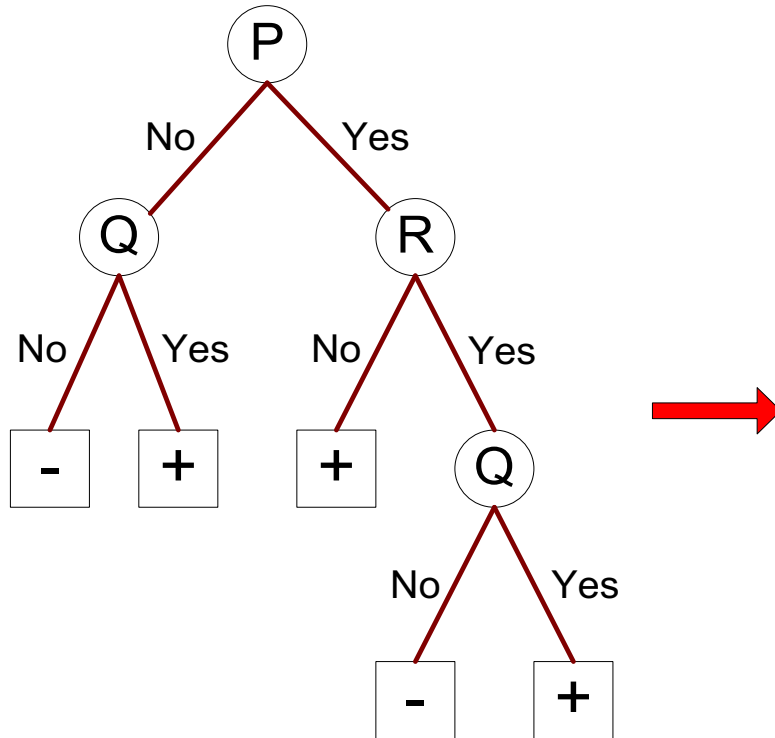
Aspects of Sequential Covering

- Rule Growing
- Instance Elimination
- Rule Evaluation
- Stopping Criterion
- Rule Pruning

Summary of Direct Method

- Grow a single rule
- Remove Instances from rule
- Prune the rule (if necessary)
- Add rule to Current Rule Set
- Repeat

Indirect Methods



Rule Set

- r1: (P=No,Q=No) ==> -
- r2: (P=No,Q=Yes) ==> +
- r3: (P=Yes,R=No) ==> +
- r4: (P=Yes,R=Yes,Q=No) ==> -
- r5: (P=Yes,R=Yes,Q=Yes) ==> +

Indirect Method: C4.5rules

- Extract rules from an unpruned decision tree
- For each rule, $r: A \rightarrow y$,
 - consider an alternative rule $r': A' \rightarrow y$ where A' is obtained by removing one of the conjuncts in A
 - Compare the pessimistic error rate for r against all r 's
 - Prune if one of the r 's has lower pessimistic error rate
 - Repeat until we can no longer improve generalization error

Advantages of Rule-Based Classifiers

- As highly expressive as decision trees
- Easy to interpret
- Easy to generate
- Can classify new instances rapidly
- Performance comparable to decision trees

Outline

- Rule-based method
- **Nearest Neighbor**
- Support Vector Machine
- Neural network
- Naïve Bayes Classifier
- Boosting

Instance-Based Classifiers

Set of Stored Cases

Atr1	AtrN	Class
			A
			B
			B
			C
			A
			C
			B

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

Unseen Case

Atr1	AtrN

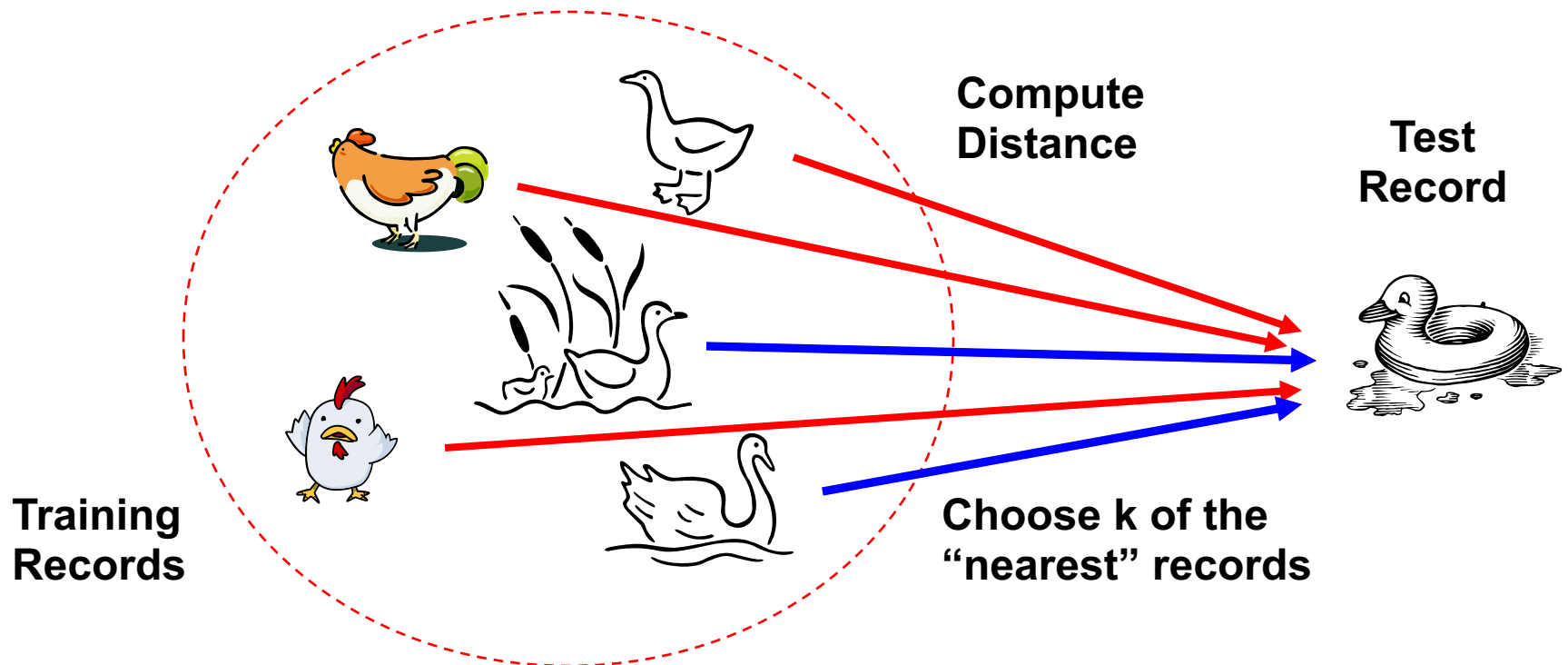
Instance Based Classifiers

- 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

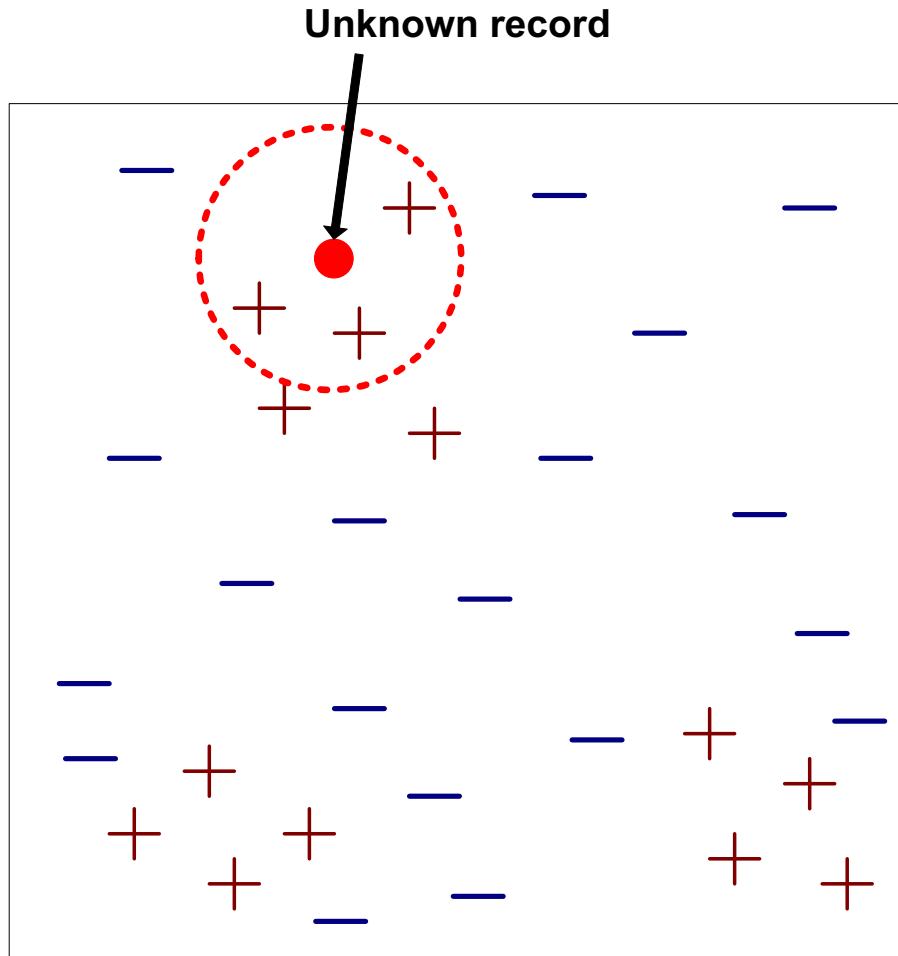
Nearest Neighbor Classifiers

- Basic idea:

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

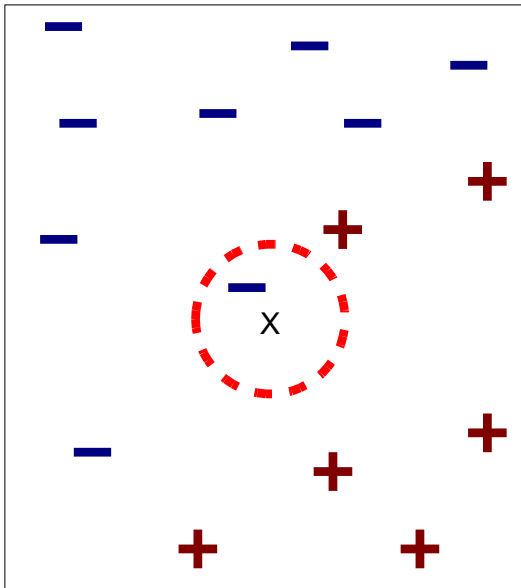


Nearest-Neighbor Classifiers

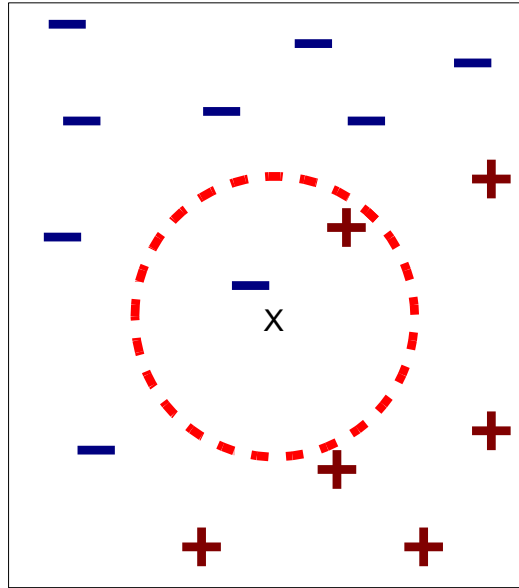


- Requires three things
 - The set of stored records
 - Distance Metric to compute distance between records
 - The value of k , the number of nearest neighbors to retrieve
- To classify an unknown record:
 - Compute distance to other training records
 - Identify k nearest neighbors
 - Use class labels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

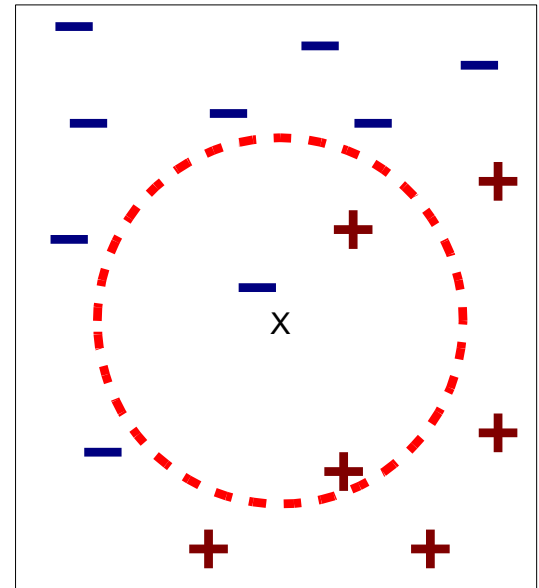
Definition of Nearest Neighbor



(a) 1-nearest neighbor



(b) 2-nearest neighbor

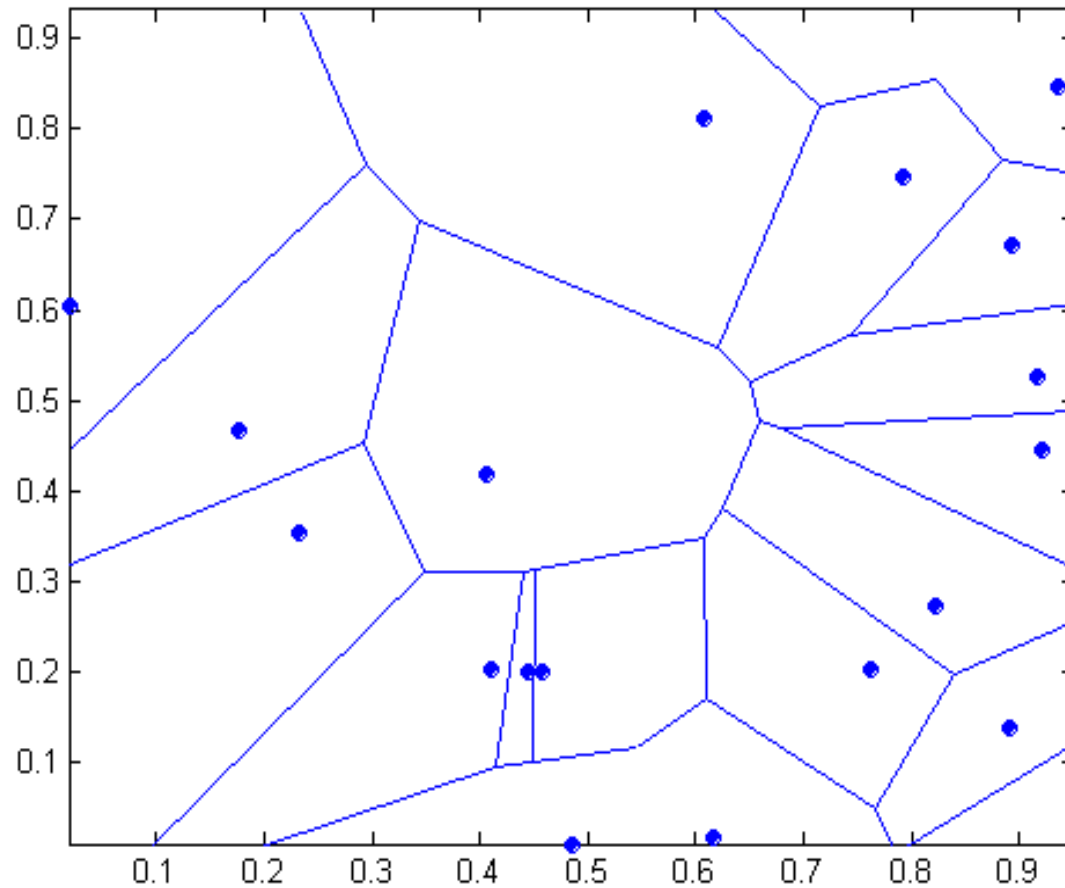


(c) 3-nearest neighbor

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

nearest-neighbor

Voronoi Diagram



Nearest Neighbor Classification

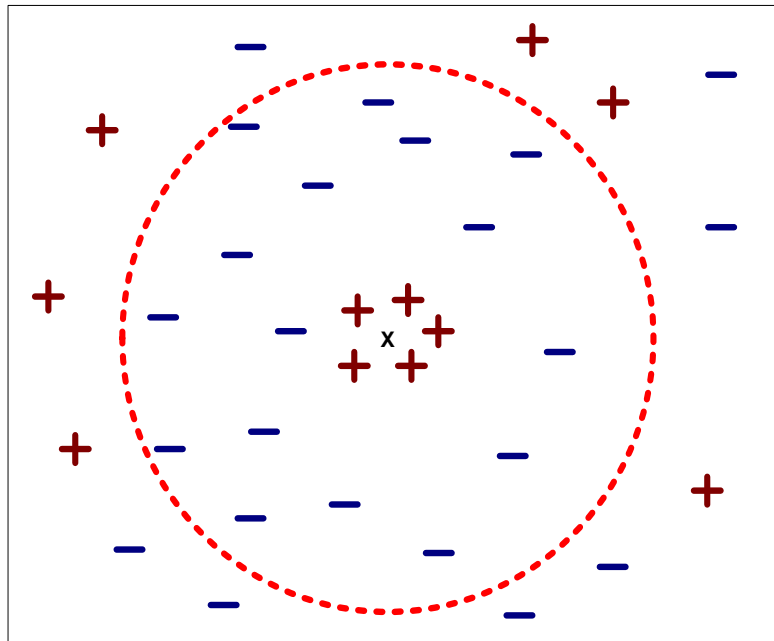
- Compute distance between two points:
 - Euclidean distance

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

- 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...

- 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

Example: PEBLS

- PEBLS: Parallel Exemplar-Based Learning System (Cost & Salzberg)
 - Works with both continuous and nominal features
 - ◆ For nominal features, distance between two nominal values is computed using modified value difference metric (MVDM)
 - Each record is assigned a weight factor
 - Number of nearest neighbor, $k = 1$

Example: PEBLS

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Distance between nominal attribute values:

$d(\text{Single}, \text{Married})$

$$= |2/4 - 0/4| + |2/4 - 4/4| = 1$$

$d(\text{Single}, \text{Divorced})$

$$= |2/4 - 1/2| + |2/4 - 1/2| = 0$$

$d(\text{Married}, \text{Divorced})$

$$= |0/4 - 1/2| + |4/4 - 1/2| = 1$$

$d(\text{Refund}=\text{Yes}, \text{Refund}=\text{No})$

$$= |0/3 - 3/7| + |3/3 - 4/7| = 6/7$$

Class	Marital Status		
	Single	Married	Divorced
Yes	2	0	1
No	2	4	1

Class	Refund	
	Yes	No
Yes	0	3
No	3	4

$$d(V_1, V_2) = \sum_i \left| \frac{n_{1i}}{n_1} - \frac{n_{2i}}{n_2} \right|$$

Example: PEBLS

<i>Tid</i>	Refund	Marital Status	Taxable Income	Cheat
X	Yes	Single	125K	No
Y	No	Married	100K	No

Distance between record X and record Y:

$$\Delta(X, Y) = w_X w_Y \sum_{i=1}^d d(X_i, Y_i)^2$$

where: $w_X = \frac{\text{Number of times X is used for prediction}}{\text{Number of times X predicts correctly}}$

$w_X \cong 1$ if X makes accurate prediction most of the time

$w_X > 1$ if X is not reliable for making predictions

Conclusion

- Rule-based method
- Nearest Neighbor
- Support Vector Machine
- Neural network
- Naïve Bayes Classifier
- Boosting