# Data Mining

## 3.5 Lazy Learners (Instance-Based Learners)

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# Outline

- Introduction
- k-Nearest-Neighbor Classifiers
- References

# Introduction

# Introduction

- **Lazy vs. eager learning**
  - **Eager learning**
    - e.g. decision tree induction, Bayesian classification, rule-based classification
    - Given a set of training set, constructs a classification model before receiving new (e.g., test) data to classify
  - **Lazy learning**
    - e.g., k-nearest-neighbor classifiers, case-based reasoning classifiers
    - Simply stores training data (or only minor processing) and waits until it is given a new instance
- Lazy: less time in training but more time in predicting

# Introduction

- Lazy learners store training examples and delay the processing ("lazy evaluation") until a new instance must be classified
- Accuracy
  - Lazy method effectively uses a richer hypothesis space since it uses many local linear functions to form its implicit global approximation to the target function
  - Eager: must commit to a single hypothesis that covers the entire instance space

# Example Problem: Face Recognition

- We have a database of (say) 1 million face images
- We are given a new image and want to find the most similar images in the database
- Represent faces by (relatively) invariant values, e.g., ratio of nose width to eye width
- Each image represented by a large number of numerical features
- Problem: given the features of a new face, find those in the DB that are close in at least ¾ (say) of the features

# Introduction

- Typical approaches
  - *k*-nearest neighbor approach
    - Instances represented as points in a Euclidean space.
  - Case-based reasoning
    - Uses symbolic representations and knowledge-based inference

# k-Nearest-Neighbor Classifiers

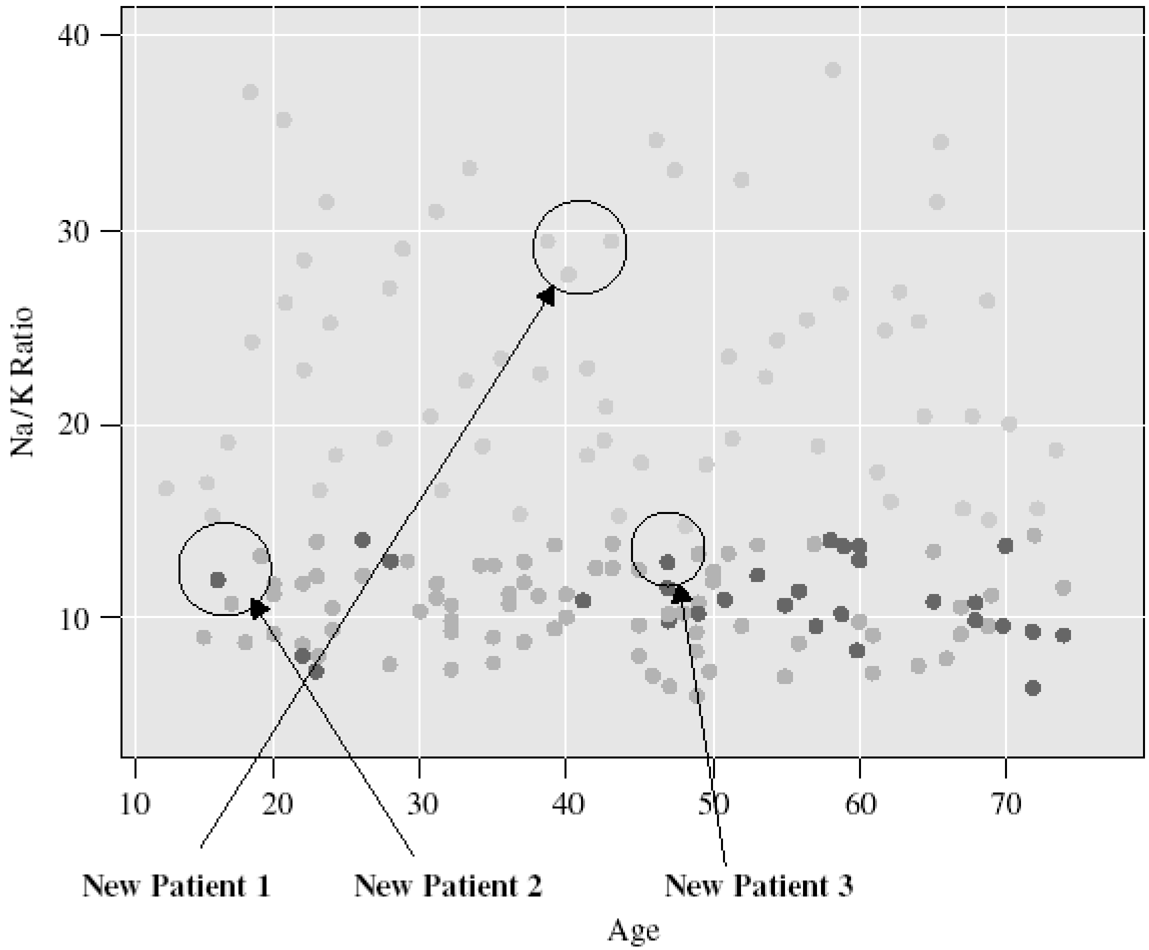
# k-Nearest-Neighbor Classifiers

- All instances correspond to points in the n-dimentional space
- The training tuples are described by *n* attributes.
- *Each* tuple represents a point in an *n-dimensional* space.
- A **k-nearest-neighbor classifier** searches the pattern space for the k training tuples that are closest to the unknown tuple.

# k-Nearest-Neighbor Classifiers

- Example:
  - We are interested in classifying the type of drug a patient should be prescribed
  - Based on the age of the patient and the patient's sodium/potassium ratio (Na/K)
  - Dataset includes 200 patients

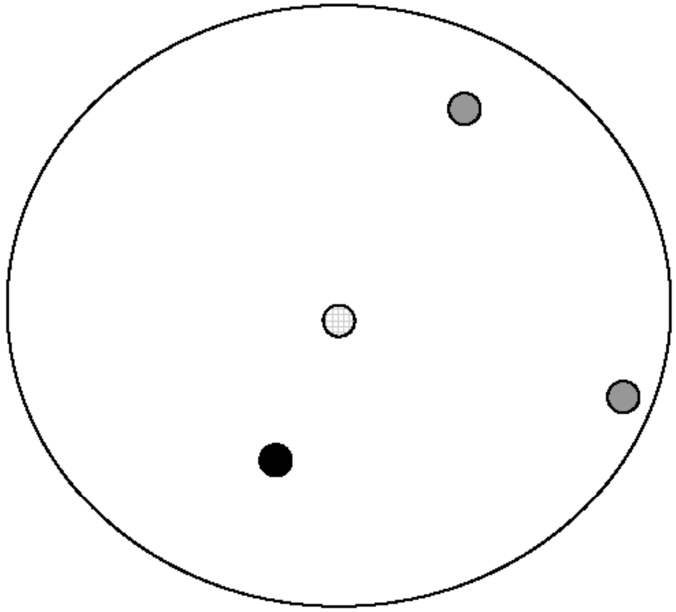
# Scatter plot




On the scatter plot; light gray points indicate drug Y; medium gray points indicate drug A or X; dark gray points indicate drug B or C

# Close-up of neighbors to new patient 2

- $k$=1 => drugs B and C (dark gray)
- k=2 => ?
- K=3 => drugs A and X (medium gray)



- Main questions:
  - How many neighbors should we consider? That is, what is $k$?
  - How do we measure distance?
  - Should all points be weighted equally, or should some points have more influence than others?

# k-Nearest-Neighbor Classifiers

- The nearest neighbor are defined in terms of Euclidean distance, dist($\mathbf{X_1}$, $\mathbf{X_2}$)
- The Euclidean distance between two points or tuples, say, X1 = ($x_{11}$, $x_{12}$, … , $x_{1n}$) and $X_2$ = ($x_{21}$, $x_{22}$, ... , $x_{2n}$), is:

$$dist(X_1, X_2) = \sqrt{\sum_{i=1}^{n} (x_{1i} - x_{2i})^2}$$

  – Nominal attributes: distance either 0 or 1

# k-Nearest-Neighbor Classifiers

- Typically, we normalize the values of each attribute in advanced.
- This helps prevent attributes with initially large ranges (such as *income*) from outweighing attributes with initially smaller ranges (such as binary attributes).
- Min-max normalization:

$$v' = \frac{v - min_A}{max_A - min_A}$$

  – all attribute values lie between 0 and 1

# k-Nearest-Neighbor Classifiers

- Common policy for missing values: assumed to be maximally distant (given normalized attributes)
- Other popular metric: Manhattan (city-block) metric
  - Taking absolute differences value without squaring them

# k-Nearest-Neighbor Classifiers

- For k-nearest-neighbor classification, the unknown tuple is assigned the most common class among its *k* nearest neighbors.
- When *k = 1,* the unknown tuple is assigned the class of the training tuple that is closest to it in pattern space.
- Nearest-neighbor classifiers can also be used for prediction, that is, to return a real-valued prediction for a given unknown tuple.
  – In this case, the classifier returns the average value of the real-valued labels associated with the *k nearest neighbors of the unknown* tuple.

# Categorical Attributes

- A simple method is to compare the corresponding value of the attribute in tuple X1 with that in tuple X2.
- If the two are identical (e.g., tuples X1 and X2 both have the color *blue*), then the difference between the two is taken as 0, otherwise 1.
- Other methods may incorporate more sophisticated schemes for differential grading (e.g., where a difference score is assigned, say, for blue and white than for blue and black).

# Missing Values

- In general, if the value of a given attribute *A is missing in* tuple X1 and/or in tuple X2, we assume the maximum possible difference.
- For categorical attributes, we take the difference value to be 1 if either one or both of the corresponding values of *A* are missing.
- If *A* is numeric and missing from both tuples X1 and X2, then the difference is also taken to be 1.
  - If only one value is missing and the other (which we'll call *v') is* present and normalized, then we can take the difference to be either |1 - v'| or |0 – v'| , whichever is greater.

# Determining a good value for k

- k can be determined experimentally.
- Starting with *k = 1,* we use a test set to estimate the error rate of the classifier.
- This process can be repeated each time by incrementing *k* to allow for one more neighbor.
- The *k* value that gives the minimum error rate may be selected*.*
- In general, the larger the number of training tuples is, the larger the value of *k* will be

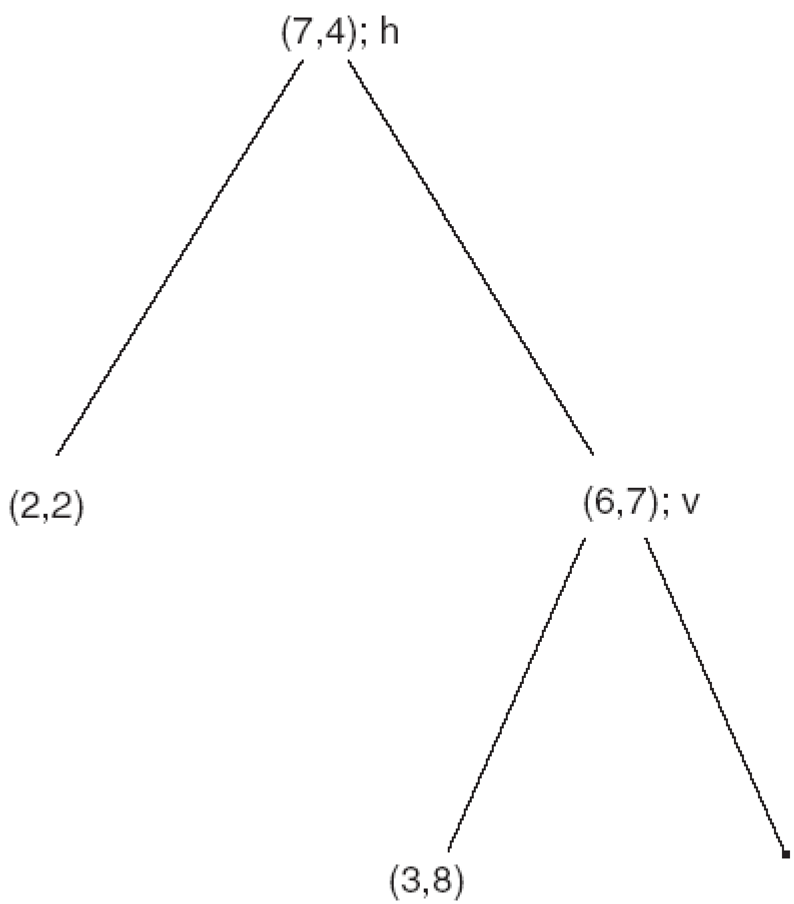
# Finding nearest neighbors efficiently

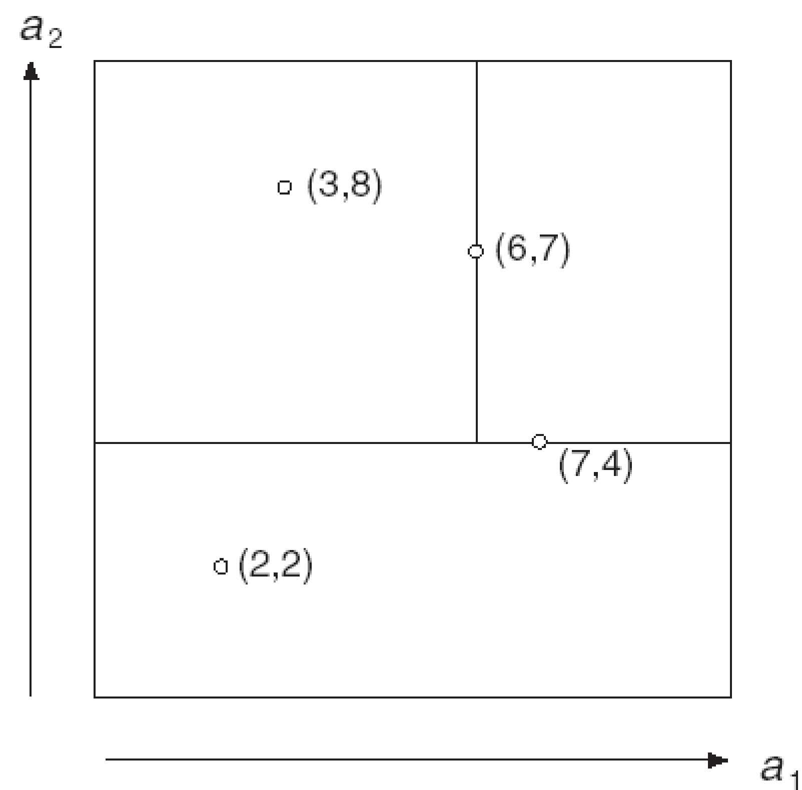
- Simplest way of finding nearest neighbor: linear scan of the data
  - Classification takes time proportional to the product of the number of instances in training and test sets
- Nearest-neighbor search can be done more efficiently using appropriate data structures
- There two methods that represent training data in a tree structure:
  - *kD-trees (k-dimensional trees)*
  - *Ball trees*

# *k*D-trees

- kD-tree is a binary tree that divides the input space with a hyperplane and then splits each partition again, recursively.
- The data structure is called a *kD-tree* because it stores a set of points in *k-dimensional* space, *k* being the number of attributes.

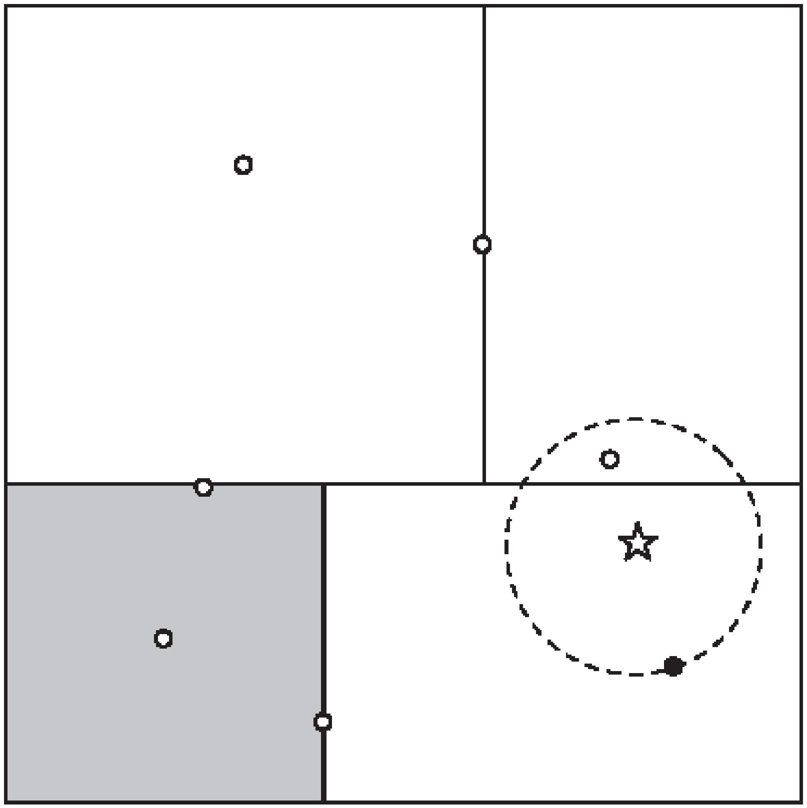
# *k*D-tree example



# Using kD-trees: example

- The target, which is not one of the instances in the tree, is marked by a star.
- The leaf node of the region containing the target is colored black.
- To determine whether one closer exists, first check whether it is possible for a closer neighbor to lie within the node's sibling.
- Then back up to the parent node and check *its sibling*



# More on *k*D-trees

- Complexity depends on depth of tree
- Amount of backtracking required depends on quality of tree
- How to build a good tree? Need to find good split point and split direction
  - Split direction: direction with greatest variance
  - Split point: median value or value closest to mean along that direction
- Can apply this recursively

# Building trees incrementally

- Big advantage of instance-based learning: classifier can be updated incrementally
  - Just add new training instance!
- We can do the same with *k*D-trees
- Heuristic strategy:
  - Find leaf node containing new instance
  - Place instance into leaf if leaf is empty
  - Otherwise, split leaf
- Tree should be rebuilt occasionally

# References

# References


- J. Han, M. Kamber, **Data Mining: Concepts and Techniques**, Elsevier Inc. (2006). (Chapter 6)

- I. H. Witten and E. Frank, **Data Mining: Practical Machine Learning Tools and Techniques**, 2nd Edition, Elsevier Inc., 2005. (Chapter 6)

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