Data Analysis

ECE 356
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Learning Outcomes

- Decision Support Systems
- Data Warehousing
- Data Mining
- Classification
- Association Rules
- Clustering

- Textbook sections (6th ed.): Chapter 20

Decision-Support Systems

- **Decision-support systems** are used to make business decisions, often based on data collected by on-line transaction-processing systems.
- Examples of business decisions:
  - Question answering:
    - What items to stock?
    - What insurance premium to change?
    - To whom to send advertisements?
  - Knowledge acquisition
    - Given this data, what insights (that I don’t currently know) is it telling me?
- Examples of data used for making decisions
  - Retail sales transaction details
  - Customer profiles (income, age, gender, *etc.*)

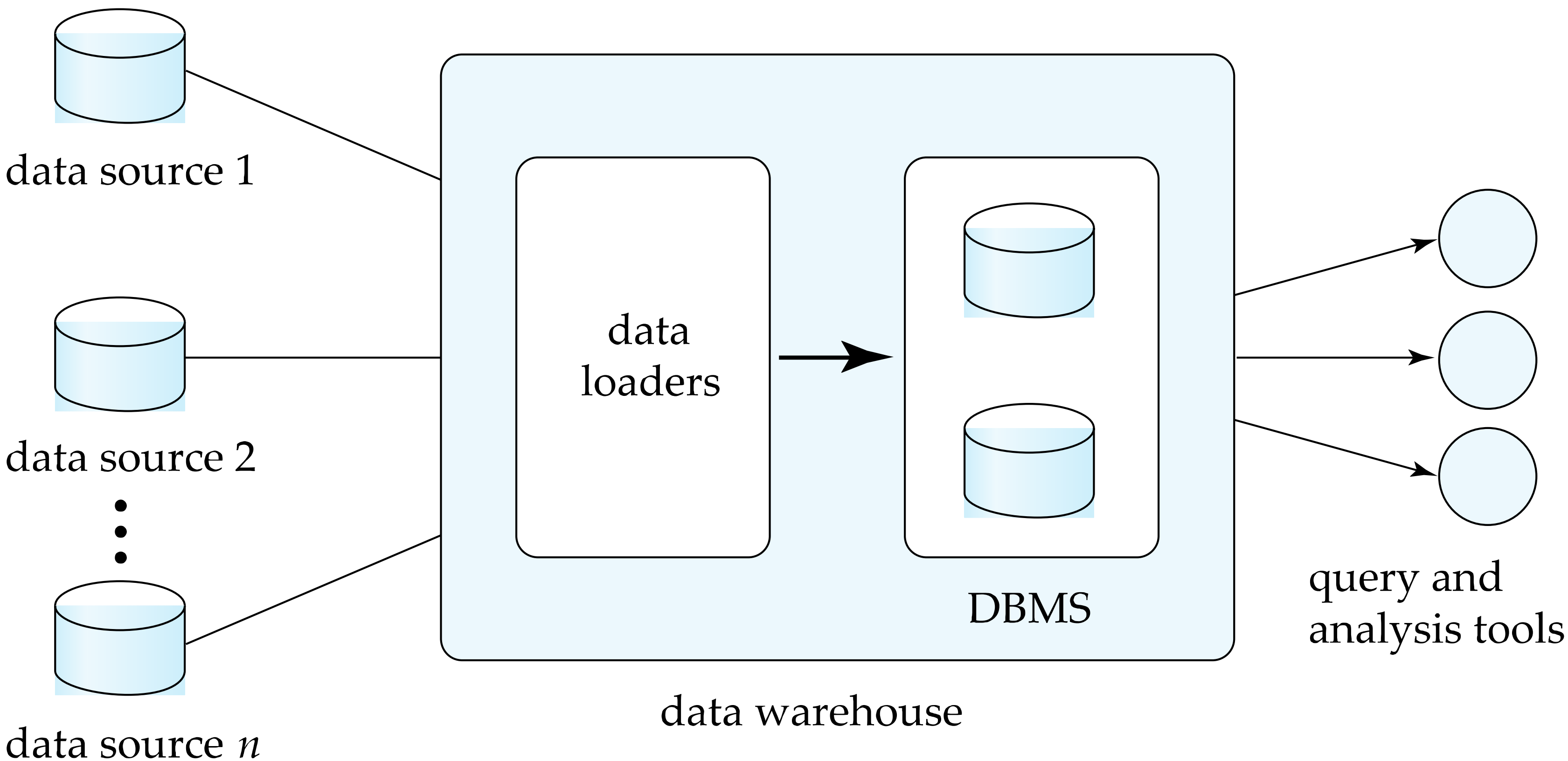
Decision-Support Systems: Overview

- **Data analysis** tasks are simplified by specialized tools and SQL extensions
  - Example tasks
    - For each product category and each region, what were the total sales in the last quarter and how do they compare with the same quarter last year
    - As above, for each product category and each customer category
- **Statistical analysis** packages (*e.g.*, : S++; R, Weka) can be interfaced with databases
  - Statistical analysis is a large field, but not covered here
- **Data mining** seeks to discover knowledge automatically in the form of statistical rules and patterns from large databases.
- A **data warehouse** archives information gathered from multiple sources, and stores it under a unified schema, at a single site.
  - Important for large businesses that generate data from multiple divisions, possibly at multiple sites
  - Data may also be purchased externally
    - *e.g.*, Google maps

Data Warehousing

- Data sources often store only current data, not historical data
- Corporate decision making requires a unified view of all organizational data, including historical data
- A **data warehouse** is a repository (archive) of information gathered from multiple sources, stored under a unified schema, at a single site
  - Greatly simplifies querying, permits study of historical trends
  - Shifts decision-support query load away from transaction processing systems

Data Warehousing



Design Issues

- *When and how to gather data*
  - **Source-driven architecture**: data sources transmit new information to warehouse, either continuously or periodically (*e.g*., at night)
  - **Destination-driven architecture**: warehouse periodically requests new information from data sources
  - Keeping warehouse exactly synchronized with data sources (*e.g*., using two-phase commit) is too expensive
    - Usually OK to have slightly out-of-date data at warehouse
    - Data/updates are periodically downloaded form online transaction processing (OLTP) systems.
- *What schema to use*
  - Schema integration

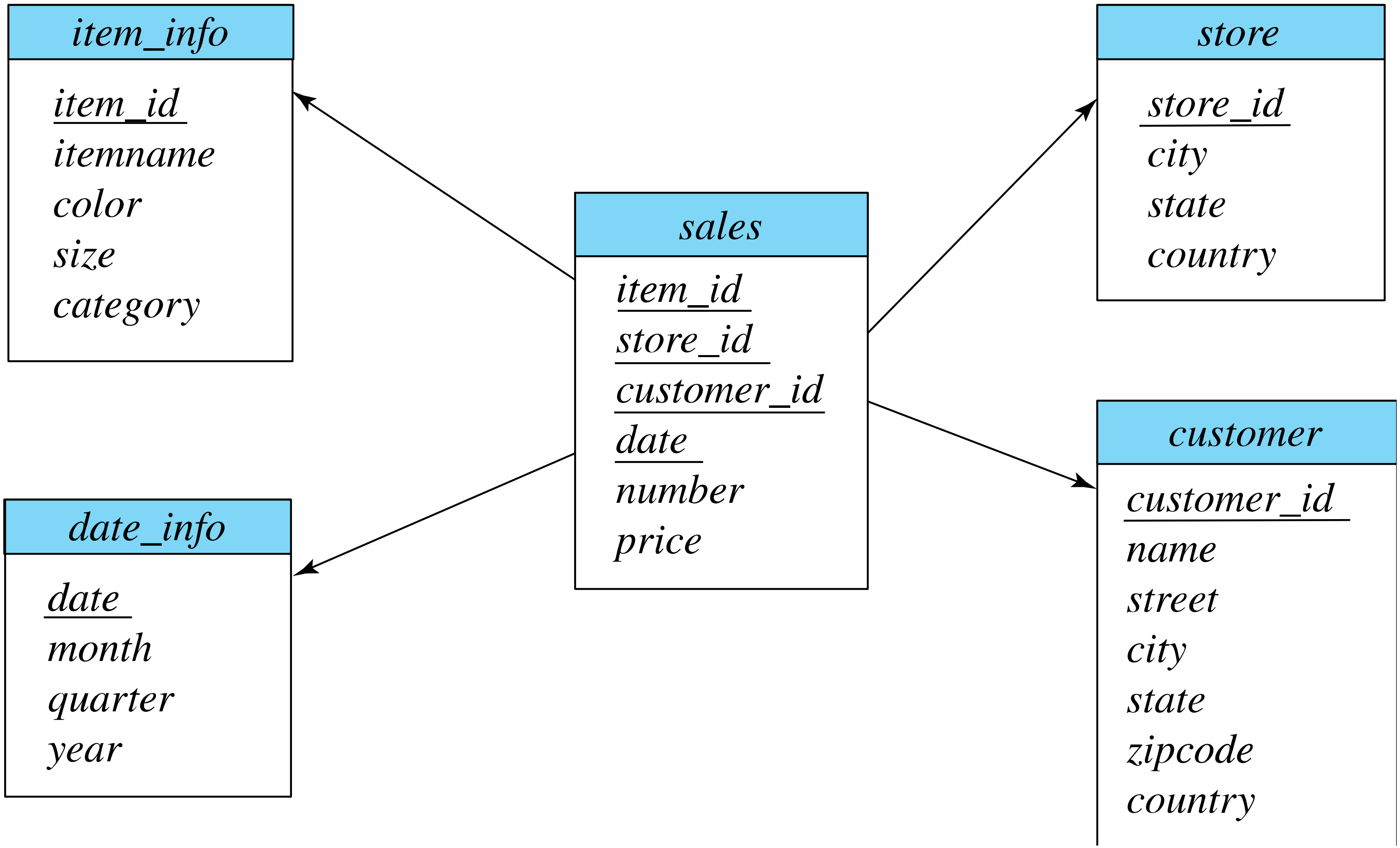
More Warehouse Design Issues

- *Data cleansing*
  - *E.g.*, correct mistakes in addresses (misspellings, zip code errors)
  - If sampling, ensure sample consistency
  - **Merge** address lists from different sources and **purge** duplicates
- *How to propagate updates*
  - Warehouse schema may be a (materialized) view of schema from data sources
- *What data to summarize*
  - Raw data may be too large to store on-line
    - Not anymore
      - Walmart: ~5 billion purchases per year in US
      - Shouldn't be a problem these days
  - Aggregate values (totals/subtotals) often suffice
  - Queries on raw data can often be transformed by query optimizer to use aggregate values

Warehouse Schemas

- Dimension values are usually encoded using small integers and mapped to full values via dimension tables
- Resultant schema is called a **star schema**
  - More complicated schema structures
    - **Snowflake schema**: multiple levels of dimension tables
    - **Constellation**: multiple fact tables

Data Warehouse Schema



Data Mining

- Data mining is the process of semi-automatically analyzing large databases to find useful patterns
- **Prediction** based on past history
  - Predict if a credit-card applicant poses a good credit risk, based on some attributes (income, job type, age, ...) and past history
  - Predict if a pattern of credit-card usage is likely to be fraudulent
- Some examples of prediction mechanisms:
  - **Classification**
    - Given a new item whose class is unknown, predict to which class it belongs
  - **Regression** formulæ
    - Given a set of mappings for an unknown function, predict the function result for a new parameter value

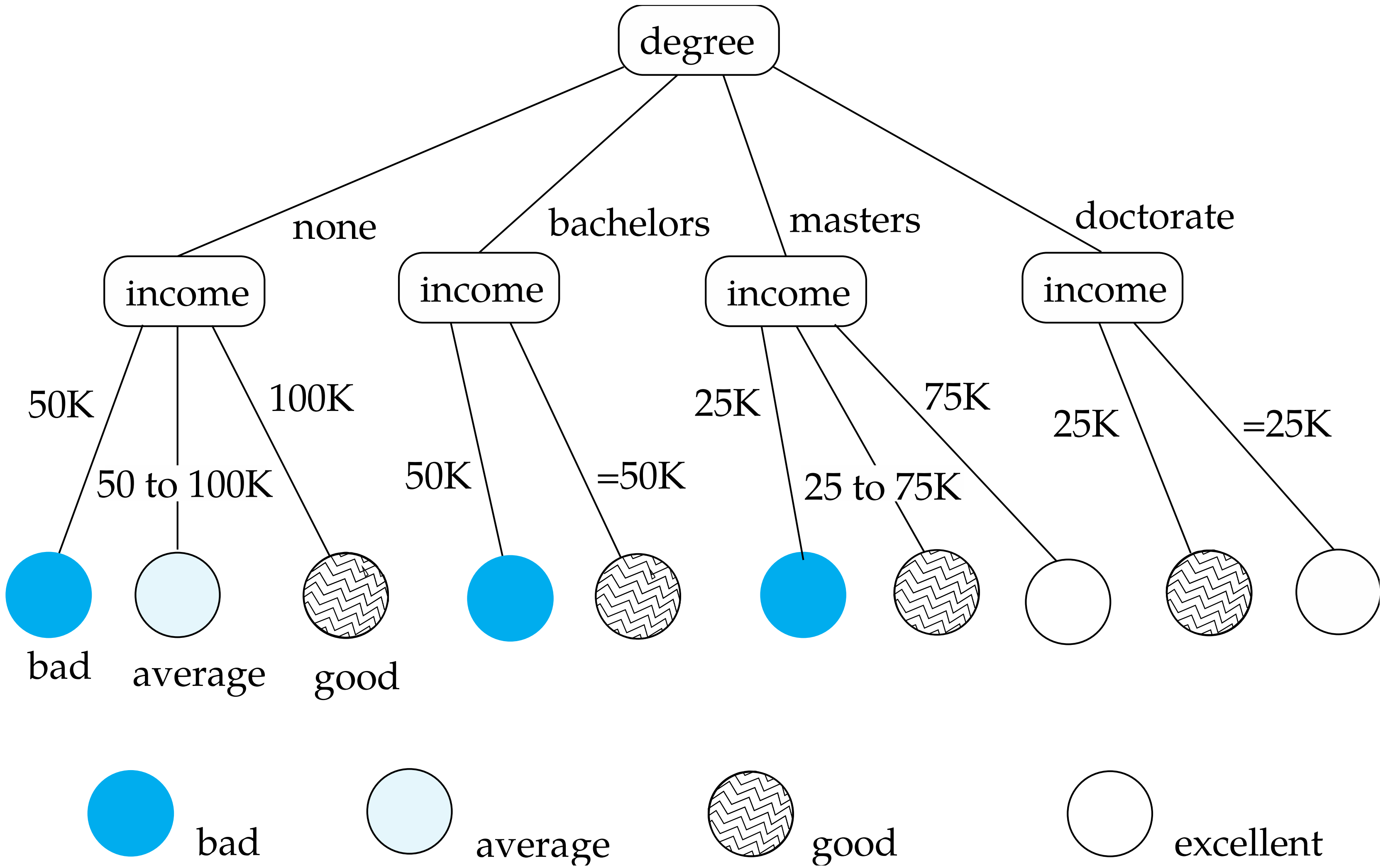
Data Mining (Cont.)

- **Descriptive Patterns**
  - **Associations**
    - Find books that are often bought by "similar" customers. If a new such customer buys one such book, suggest the others too.
  - Associations may be used as a first step in detecting **causation**
    - *E.g.*, association between exposure to chemical X and cancer
  - **Clusters**
    - *E.g.*, typhoid cases were clustered in an area surrounding a contaminated well
    - Detection of clusters remains important in detecting epidemics

Classification Rules

- Classification rules help assign new objects to classes.
  - *E.g.*, given a new automobile insurance applicant, should he or she be classified as low risk, medium risk or high risk?
- Classification rules for above example could use a variety of data, such as educational level, salary, age, *etc.*
  - $\forall$person P, P.degree = masters **and** P.income > 75,000
    $\rightarrow$ P.credit = excellent
  - $\forall$person P, P.degree = bachelors **and**
    (P.income > 25,000 and P.income < 75,000)
    $\rightarrow$ P.credit = good
- Rules are not necessarily exact: there may be some misclassifications
- Classification rules can be shown compactly as a decision tree.

Decision Tree



Construction of Decision Trees

- **Training set**: a data sample in which the classification is already known.
- **Greedy** top down generation of decision trees.
  - Each internal node of the tree partitions the data into groups based on a **partitioning attribute**, and a **partitioning condition** for the node
  - **Leaf** node:
    - all (or sufficient) of the items at the node belong to the same class, **or**
    - all attributes have been considered, and no further partitioning is possible.

Best Splits

- Pick best attributes and conditions on which to partition
- The impurity of a set S of training instances can be measured quantitatively in several ways.
  - Notation: number of classes = k, number of instances = $|S|$, fraction of instances in class $i = p_i$.
- The **Gini** measure of impurity is defined as:

$$\text{Impurity}(S) = \text{Gini}(S) = 1 - \sum_{i=1}^{k} p_i^2$$

  - When all instances are in a single class, the Gini value is 0
  - It reaches its maximum (of $1 - \frac{1}{k}$) if each class has the same number of instances.

Best Splits (2)

- Another measure of impurity is the **entropy** measure, which is defined as:

$$\text{Impurity}(S) = \text{Entropy}(S) = -\sum_{i=1}^{k} p_i \log_2 p_i$$

- A third measure of purity is **Classification Error** which is:

$$\text{Impurity}(S) = \text{Classification Error}(S) = 1 - \max(p_i)$$

Best Splits (3)

- When a set S is split into multiple sets S_i, i=1, 2, …, r, we can measure the impurity of the resultant set of sets as:

$$\text{Impurity}(S_1, S_2, S_3, \ldots, S_r) = \sum_{i=1}^{r} \frac{|S_i|}{|S|} \text{Impurity}(S_i)$$

- The information gain due to particular split of S into S_i, i = 1, 2, …., r:

InformationGain $(S, \{S_1, S_2, \ldots, S_r\}) = \text{Impurity}(S) - \text{Impurity}(S_1, S_2, \ldots S_r)$

Best Splits (4)

- Measure of "cost" of a split:

$$\text{InformationContent}(S, S, \{S_1, S_2, \ldots, S_r\}) = -\sum_{i=1}^{r} \frac{|S_i|}{|S|} \log_2 \frac{|S_i|}{|S|}$$

- **Information-gain ratio:**

$$\text{InformationGainRatio} = \frac{\text{InformationGain}(S, S, \{S_1, S_2, \ldots, S_r\})}{\text{InformationContent}(S, S, \{S_1, S_2, \ldots, S_r\})}$$

- The best split is the one that gives the maximum information-gain ratio

Finding Best Splits

- Categorical attributes (with no meaningful order):
  - Multi-way split, one child for each value
  - Binary split: try all possible breakup of values into two sets, and pick the best
- Continuous-valued attributes (can be sorted in a meaningful order)
  - Binary split:
    - Sort values, try each as a split point
      - *E.g.*, if values are 1, 10, 15, 25,
        - split at ≤ 1, ≤ 10, ≤ 15
        - Pick the value that gives best split
  - Multi-way split:
    - A series of binary splits on the same attribute has roughly equivalent effect

Decision-Tree Construction Algorithm

- **Procedure** *GrowTree* (S)
  Partition (S);

  Procedure Partition (S)
  if (*impurity* (S) $< \delta_p$ or $|S| < \delta_s$) **then**
      return;
  for each attribute A
      evaluate splits on attribute A;
  Use best split found (across all attributes) to partition
      S into $S_1, S_2, \ldots, S_r$,
  for $i = 1, 2, \ldots, r$
      Partition (S_i);

δ

Other Types of Classifiers

- Neural net classifiers are studied in artificial intelligence and are not covered here
- Bayesian classifiers use **Bayes theorem**, which says

$$p\,(c_j \mid d\,) = \frac{p\,(d \mid c_j)\; p\,(c_j)}{p\,(\,d\,)}$$

where

$p\,(c_j \mid d\,)$ = probability of instance d being in class c_j,

$p\,(d \mid c_j)$ = probability of generating instance d given class c_j,

$p\,(c_j\,)$ = probability of occurrence of class c_j, and

$p\,(d\,)$ = probability of instance d occurring

Naïve Bayesian Classifiers

- Bayesian classifiers require
  - computation of $p\ (d \mid c_j)$
  - precomputation of $p\ (c_j)$
  - $p\ (d)$ can be ignored since it is the same for all classes
- To simplify the task, **naïve Bayesian classifiers** assume attributes have independent distributions, and thereby estimate

$$p\ (d \mid c_j) = p\ (d_1 \mid c_j) * p\ (d_2 \mid c_j) * \ldots * (p\ (d_n \mid c_j)$$

  - Each of the $p\ (d_i \mid c_j)$ can be estimated from a histogram on d_i values for each class c_j
    - the histogram is computed from the training instances
  - Histograms on multiple attributes are more expensive to compute and store

Regression

- Regression deals with the prediction of a value, rather than a class.
  - Given values for a set of variables, X_1, X_2, …, X_n, we wish to predict the value of a variable Y.
- One way is to infer coefficients a_0, a_1, a_1, …, a_n such that

  $$Y = a_0 + a_1 * X_1 + a_2 * X_2 + \ldots + a_n * X_n$$

- Finding such a linear polynomial is called **linear regression**.
  - In general, the process of finding a curve that fits the data is also called **curve fitting**.
- The fit may only be approximate
  - because of noise in the data, or
  - because the relationship is not exactly a polynomial
- Regression aims to find coefficients that give the best possible fit.

Association Rules

- Retail shops are often interested in associations between different items that people buy.
  - Someone who buys bread is quite likely also to buy milk
  - A person who bought the book *Database System Concepts* is quite likely also to buy the book *Operating System Concepts*.
- Associations information can be used in several ways.
  - *E.g.*, when a customer buys a particular book, an online shop may suggest associated books.
- **Association rules**:

  bread → *milk*   *DB-Concepts, OS-Concepts* → Networks

  - Left-hand side: **antecedent**,   right-hand side: **consequent**
  - An association rule must have an associated **population**; the population consists of a set of **instances**
    - *E.g.*, each transaction (sale) at a shop is an instance, and the set of all transactions is the population

Association Rules (Cont.)

- Rules have an associated support, as well as an associated confidence.
- **Support** is a measure of what fraction of the population satisfies both the antecedent and the consequent of the rule.
  - *E.g.*, suppose only 0.001 percent of all purchases include milk and screwdrivers. The support for the rule is *milk* → *screwdrivers* is low.
- **Confidence** is a measure of how often the consequent is true when the antecedent is true.
  - *E.g.*, the rule *bread* → *milk* has a confidence of 80 percent if 80 percent of the purchases that include bread also include milk.

Finding Association Rules

- We are generally only interested in association rules with reasonably high support (*e.g.*, support of 2% or greater)
- Naïve algorithm
  1. Consider all possible sets of relevant items.
  2. For each set find its support (*i.e.*, count how many transactions purchase all items in the set).
     - **Large itemsets**: sets with sufficiently high support
  3. Use large itemsets to generate association rules.
     1. From itemset A generate the rule $A - \{b\} \rightarrow b$ for each $b \in A$.
        - Support of rule = support (A).
        - Confidence of rule = support (A) / support ($A - \{b\}$)

Finding Support

- Determine support of itemsets via a single pass on set of transactions
  - Large itemsets: sets with a high count at the end of the pass
- If memory not enough to hold all counts for all itemsets use multiple passes, considering only some itemsets in each pass.
- Optimization: Once an itemset is eliminated because its count (support) is too small none of its supersets needs to be considered.
- The ***a priori*** technique to find large itemsets:
  - Pass 1: count support of all sets with just 1 item. Eliminate those items with low support
  - Pass *i*: **candidates**: every set of *i* items such that all its *i-1* item subsets are large
    - Count support of all candidates
    - Stop if there are no candidates

Other Types of Associations

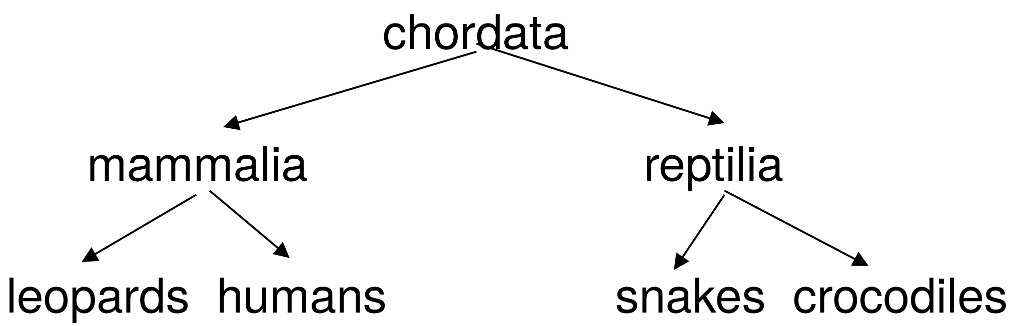
- Basic association rules have several limitations
- Deviations from the expected probability are often more interesting
  - *E.g.*, if many people purchase bread, and many people purchase cereal, quite a few would be expected to purchase both
  - We are interested in **positive** as well as **negative correlations** between sets of items
    - Positive correlation: co-occurrence is higher than predicted
    - Negative correlation: co-occurrence is lower than predicted
- Sequence associations / correlations
  - *E.g.*, whenever bonds go up, stock prices go down in 2 days
- Deviations from temporal patterns
  - *E.g.*, deviation from a steady growth
  - *E.g.*, sales of winter wear go down in summer
    - Not surprising, part of a known pattern.
    - Look for deviation from value predicted using past patterns

Clustering

- Clustering: Intuitively, finding clusters of points in the given data such that similar points lie in the same cluster
- Can be formalized using distance metrics in several ways
  - Group points into *k* sets (for a given *k*) such that the average distance of points from the centroid of their assigned group is minimized
    - Centroid: point defined by taking average of coordinates in each dimension.
  - Another metric: minimize average distance between every pair of points in a cluster
- Has been studied extensively in statistics, but on small data sets
  - Data mining systems aim at clustering techniques that can handle very large data sets
  - *E.g.*, the Birch clustering algorithm (slide 32)

Hierarchical Clustering

- Example from biological classification
  - (the word classification here does not mean a prediction mechanism)



- Other examples: Internet directory systems (*e.g.*, Yahoo, more on this later)
- **Agglomerative clustering algorithms**
  - Build small clusters, then cluster small clusters into bigger clusters, and so on
- **Divisive clustering algorithms**
  - Start with all items in a single cluster, repeatedly refine (break) clusters into smaller ones

Clustering Algorithms

- Clustering algorithms have been designed to handle very large datasets
- *E.g.*, the **Birch algorithm**
  - Main idea: use an in-memory R-tree to store points that are being clustered
  - Insert points one at a time into the R-tree, merging a new point with an existing cluster if is less than some δ distance away
  - If there are more leaf nodes than fit in memory, merge existing clusters that are close to each other
  - At the end of first pass we get a large number of clusters at the leaves of the R-tree
    - Merge clusters to reduce the number of clusters

Collaborative Filtering

- Goal: predict what movies/books/… a person may be interested in, on the basis of
  - Past preferences of the person
  - Other people with similar past preferences
  - The preferences of such people for a new movie/book/…
- One approach based on repeated clustering
  - Cluster people on the basis of preferences for movies
  - Then cluster movies on the basis of being liked by the same clusters of people
  - Again cluster people based on their preferences for (the newly created clusters of) movies
  - Repeat above till equilibrium
- Above problem is an instance of **collaborative filtering**, where users collaborate in the task of filtering information to find information of interest

Other Types of Mining

- **Text mining**: application of data mining to textual documents
  - cluster Web pages to find related pages
  - cluster pages a user has visited to organize their visit history
  - classify Web pages automatically into a Web directory
- **Data visualization** systems help users examine large volumes of data and detect patterns visually
  - Can visually encode large amounts of information on a single screen
  - Humans are very good a detecting visual patterns