Chapter 18: Data Analysis and Mining

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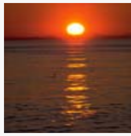
- Decision Support Systems
- Data Analysis and OLAP
- Data Warehousing
- Data Mining

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:
  - What items to stock?
  - What insurance premium to change?
  - To whom to send advertisements?
- 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++) 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

Data Analysis and OLAP

- **Online Analytical Processing (OLAP)**
  - Interactive analysis of data, allowing data to be summarized and viewed in different ways in an online fashion (with negligible delay)
- Data that can be modeled as dimension attributes and measure attributes are called **multidimensional data**.
  - **Measure attributes**
    - measure some value
    - can be aggregated upon
    - e.g. the attribute *number* of the *sales* relation
  - **Dimension attributes**
    - define the dimensions on which measure attributes (or aggregates thereof) are viewed
    - e.g. the attributes *item_name, color,* and *size* of the *sales* relation

Cross Tabulation of *sales* by *item-name* and *color*

size: **all**

item-name \ *color*	dark	pastel	white	Total
skirt	8	35	10	53
dress	20	10	5	35
shirt	14	7	28	49
pant	20	2	5	27
Total	62	54	48	164

- The table above is an example of a **cross-tabulation** (**cross-tab**), also referred to as a **pivot-table**.
  - Values for one of the dimension attributes form the row headers
  - Values for another dimension attribute form the column headers
  - Other dimension attributes are listed on top
  - Values in individual cells are (aggregates of) the values of the dimension attributes that specify the cell.

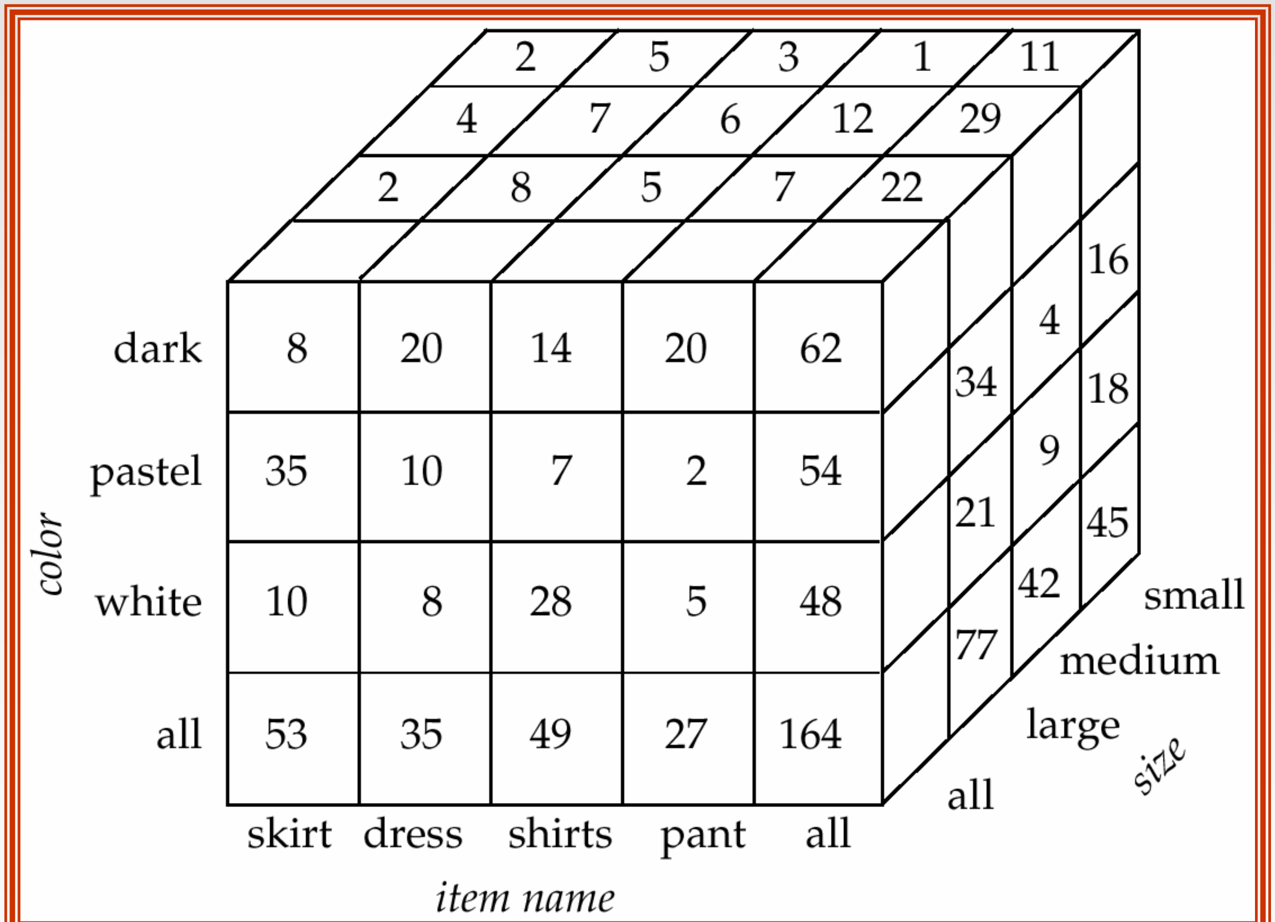
Relational Representation of Cross-tabs

- Cross-tabs can be represented as relations
  - We use the value **all** is used to represent aggregates
  - The SQL:1999 standard actually uses null values in place of **all** despite confusion with regular null values

item-name	*color*	*number*
skirt	dark	8
skirt	pastel	35
skirt	white	10
skirt	**all**	53
dress	dark	20
dress	pastel	10
dress	white	5
dress	**all**	35
shirt	dark	14
shirt	pastel	7
shirt	white	28
shirt	**all**	49
pant	dark	20
pant	pastel	2
pant	white	5
pant	**all**	27
all	dark	62
all	pastel	54
all	white	48
all	**all**	164

Data Cube

- A **data cube** is a multidimensional generalization of a cross-tab
- Can have *n* dimensions; we show 3 below
- Cross-tabs can be used as views on a data cube

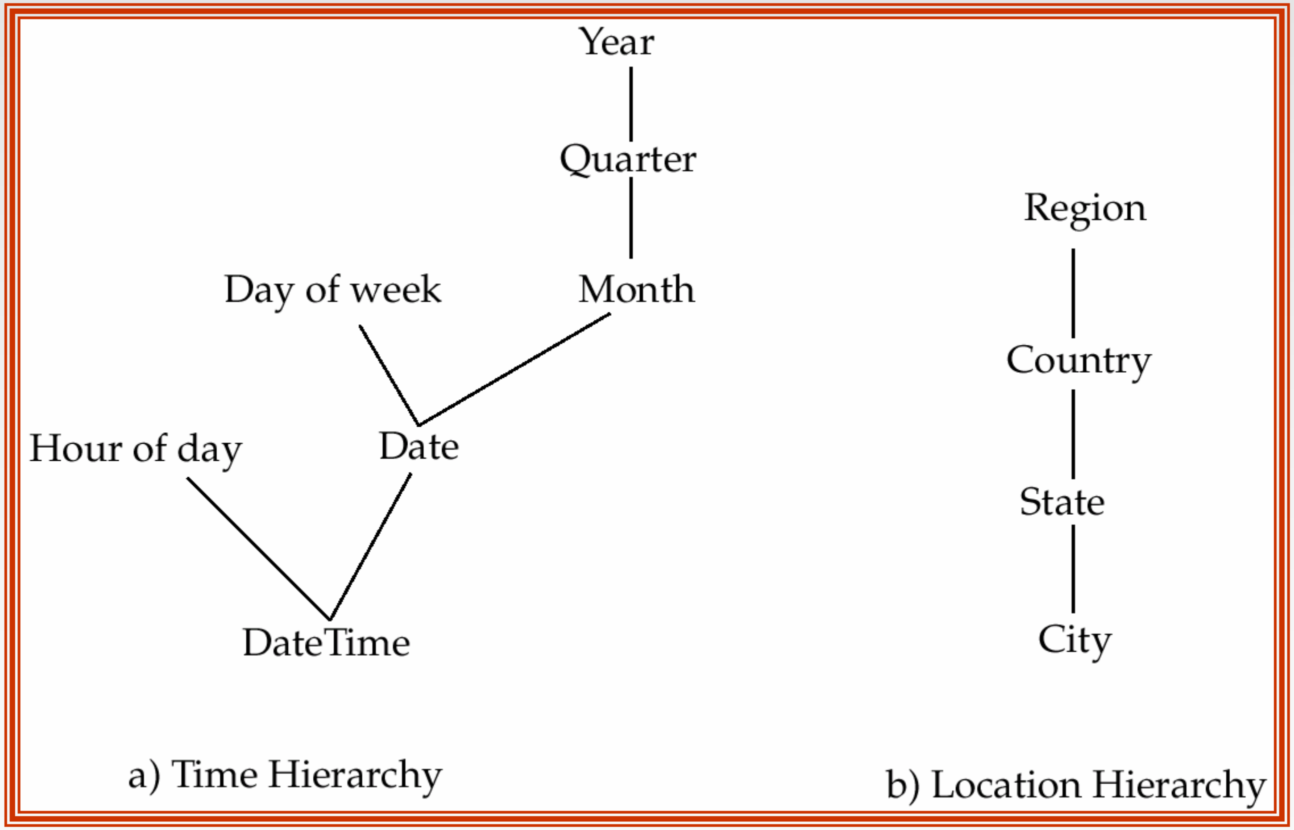


Online Analytical Processing

- **Pivoting**: changing the dimensions used in a cross-tab is called
- **Slicing:** creating a cross-tab for fixed values only
  - Sometimes called **dicing**, particularly when values for multiple dimensions are fixed.
- **Rollup:** moving from finer-granularity data to a coarser granularity
- **Drill down:** The opposite operation - that of moving from coarser-granularity data to finer-granularity data

Hierarchies on Dimensions

- **Hierarchy** on dimension attributes: lets dimensions to be viewed at different levels of detail
  - E.g. the dimension DateTime can be used to aggregate by hour of day, date, day of week, month, quarter or year



Cross Tabulation With Hierarchy

- Cross-tabs can be easily extended to deal with hierarchies
  - Can drill down or roll up on a hierarchy

category	*item-name*	dark	pastel	white	total	
womenswear	skirt	8	8	10	53	
	dress	20	20	5	35	
	subtotal	28	28	15		88
menswear	pants	14	14	28	49	
	shirt	20	20	5	27	
	subtotal	34	34	33		76
total		62	62	48		164

OLAP Implementation

- The earliest OLAP systems used multidimensional arrays in memory to store data cubes, and are referred to as **multidimensional OLAP (MOLAP)** systems.
- OLAP implementations using only relational database features are called **relational OLAP (ROLAP)** systems
- Hybrid systems, which store some summaries in memory and store the base data and other summaries in a relational database, are called **hybrid OLAP (HOLAP)** systems.

OLAP Implementation (Cont.)

- Early OLAP systems precomputed *all* possible aggregates in order to provide online response
  - Space and time requirements for doing so can be very high
    - 2^n combinations of **group by**
  - It suffices to precompute some aggregates, and compute others on demand from one of the precomputed aggregates
    - Can compute aggregate on (*item-name, color*) from an aggregate on (*item-name, color, size*)
      - For all but a few "non-decomposable" aggregates such as *median*
      - is cheaper than computing it from scratch
- Several optimizations available for computing multiple aggregates
  - Can compute aggregate on (*item-name, color*) from an aggregate on (*item-name, color, size*)
  - Can compute aggregates on (*item-name, color, size*), (*item-name, color*) and (*item-name*) using a single sorting of the base data

Extended Aggregation in SQL:1999

- The **cube** operation computes union of **group by**'s on every subset of the specified attributes
- E.g. consider the query

  select *item-name, color, size,* **sum**(*number*)
  from *sales*
  group by cube(*item-name, color, size*)

  This computes the union of eight different groupings of the *sales* relation:

  { (*item-name, color, size*), (*item-name, color*),
  (*item-name, size*), (*color, size*),
  (*item-name*), (*color*),
  (*size*), ( ) }

  where ( ) denotes an empty **group by** list.
- For each grouping, the result contains the null value for attributes not present in the grouping.

Extended Aggregation (Cont.)

- Relational representation of cross-tab that we saw earlier, but with *null* in place of **all**, can be computed by

  select *item-name*, *color*, **sum**(*number*)
  from *sales*
  group by cube(*item-name, color*)

- The function **grouping()** can be applied on an attribute
  - Returns 1 if the value is a null value representing all, and returns 0 in all other cases.

select *item-name, color, size*, **sum**(*number*),
  grouping(*item-name*) **as** *item-name-flag*,
  grouping(*color*) **as** *color-flag*,
  grouping(*size*) **as** *size-flag*,
from *sales*
group by cube(*item-name, color, size*)

- Can use the function **decode()** in the **select** clause to replace such nulls by a value such as **all**
  - E.g. replace *item-name* in first query by

    decode(**grouping**(item-*name*), 1, ‘all’, *item-name*)

Extended Aggregation (Cont.)

- The **rollup** construct generates union on every prefix of specified list of attributes
- E.g.

  select *item-name*, *color*, *size*, **sum**(*number*)
  from *sales*
  group by rollup(*item-name, color, size*)

  Generates union of four groupings:

  { (*item-name, color, size*), (*item-name, color*), (*item-name*), ( ) }
- Rollup can be used to generate aggregates at multiple levels of a hierarchy.
- E.g., suppose table *itemcategory*(*item-name, category*) gives the category of each item. Then

  select *category, item-name*, **sum**(*number*)
  from *sales, itemcategory*
  where *sales.item-name = itemcategory.item-name*
  group by rollup(*category, item-name*)

  would give a hierarchical summary by *item-name* and by *category.*

Extended Aggregation (Cont.)

- Multiple rollups and cubes can be used in a single group by clause
  - Each generates set of group by lists, cross product of sets gives overall set of group by lists
- E.g.,

  select *item-name, color, size*, **sum**(*number*)
  from *sales*
  group by rollup(*item-name*), **rollup**(*color, size*)

  generates the groupings

  {item-name, ()} X {(color, size), (color), ()}

  = { (*item-name, color, size*), (*item-name, color*), (*item-name*), (*color, size*), (*color*), ( ) }

Ranking

- Ranking is done in conjunction with an order by specification.
- Given a relation student-marks(student-id, marks) find the rank of each student.

  select *student-id*, **rank**( ) **over** (**order by** *marks* **desc) as** *s-rank*
  from *student-marks*

- An extra **order by** clause is needed to get them in sorted order

  select *student-id*, **rank** ( ) **over** (**order by** *marks* **desc**) **as** *s-rank*
  from *student-marks*
  order by *s-rank*

- Ranking may leave gaps: e.g. if 2 students have the same top mark, both have rank 1, and the next rank is 3
  - **dense_rank** does not leave gaps, so next dense rank would be 2

Ranking (Cont.)

- Ranking can be done within partition of the data.
- "Find the rank of students within each section."

```
select student-id, section,
        rank ( ) over (partition by section order by marks desc)
          as sec-rank
from student-marks, student-section
where student-marks.student-id = student-section.student-id
order by section, sec-rank
```

- Multiple **rank** clauses can occur in a single **select** clause
- Ranking is done *after* applying **group by** clause/aggregation

Ranking (Cont.)

- Other ranking functions:
  - **percent_rank** (within partition, if partitioning is done)
  - **cume_dist** (cumulative distribution)
    - fraction of tuples with preceding values
  - **row_number** (non-deterministic in presence of duplicates)
- SQL:1999 permits the user to specify **nulls first** or **nulls last**

select *student-id*,
        rank ( ) **over** (**order by** *marks* **desc nulls last**) **as** *s-rank*
from *student-marks*

Ranking (Cont.)

- For a given constant *n*, the ranking the function *ntile*(*n*) takes the tuples in each partition in the specified order, and divides them into *n* buckets with equal numbers of tuples.
- E.g.:

select *threetile*, **sum**(*salary*)
from (
    select *salary*, **ntile**(3) **over** (**order by** *salary*) **as** *threetile*
    from *employee*) **as** *s*
group by *threetile*

Windowing

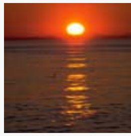
- Used to smooth out random variations.
- E.g.: moving average: "Given sales values for each date, calculate for each date the average of the sales on that day, the previous day, and the next day"
- **Window specification** in SQL:
  - Given relation *sales(date, value)*

    select *date*, ***sum***(*value*) **over**
        (**order by** *date* **between rows** 1 **preceding and** 1 **following**)
    from *sales*
- Examples of other window specifications:
  - **between rows unbounded preceding and current**
  - **rows unbounded preceding**
  - **range between** 10 **preceding and current row**
    - All rows with values between current row value –10 to current value
  - **range interval** 10 **day preceding**
    - Not including current row

Windowing (Cont.)

- Can do windowing within partitions
- E.g. Given a relation *transaction* (*account-number, date-time, value*), where value is positive for a deposit and negative for a withdrawal
  - "Find total balance of each account after each transaction on the account"

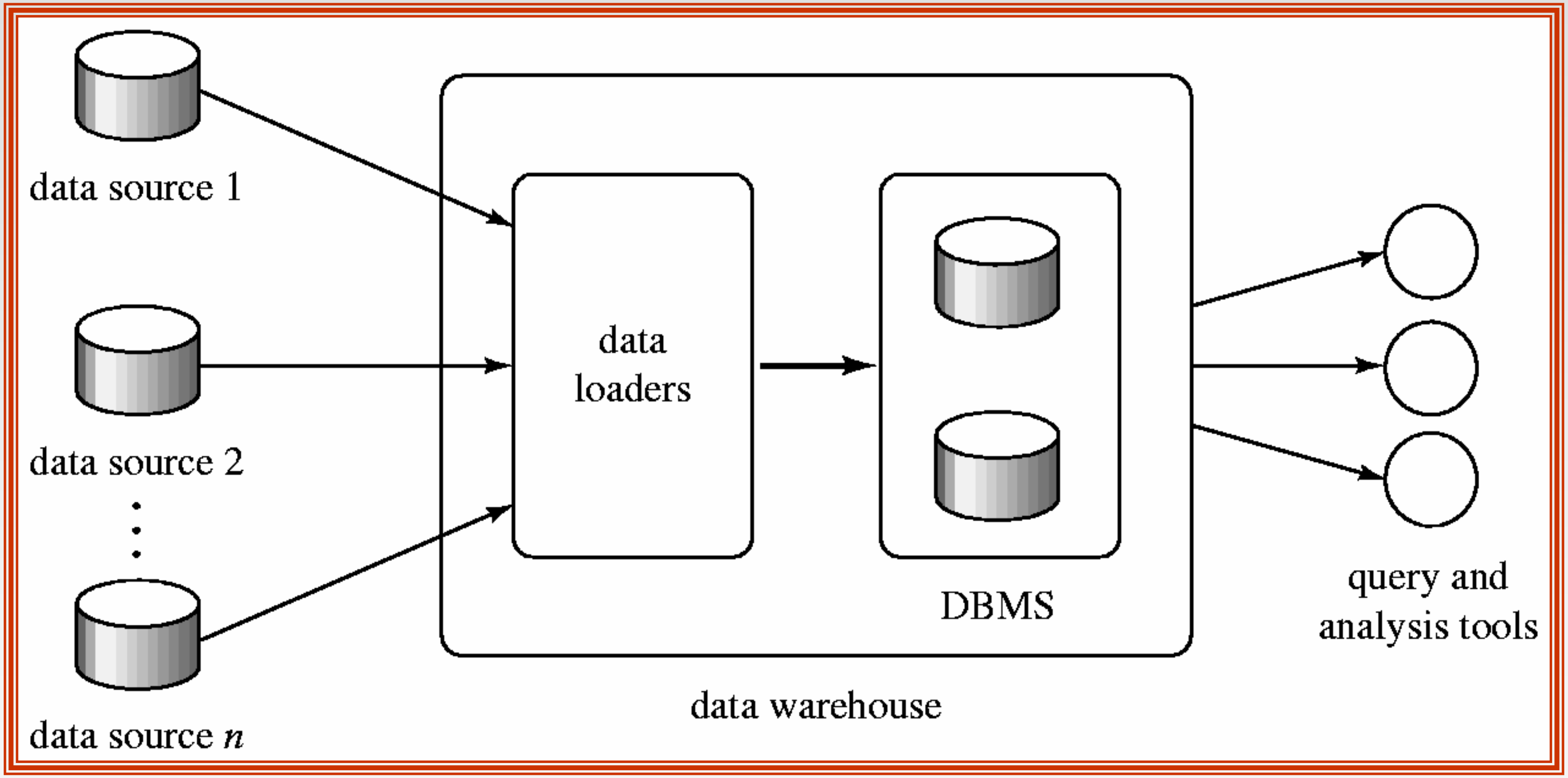
    select *account-number, date-time*,
        sum (*value*) **over**
                (**partition by** *account-number*
                order by *date-time*
                rows unbounded preceding)
       as *balance*
    from *transaction*
    order by *account-number, date-time*



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

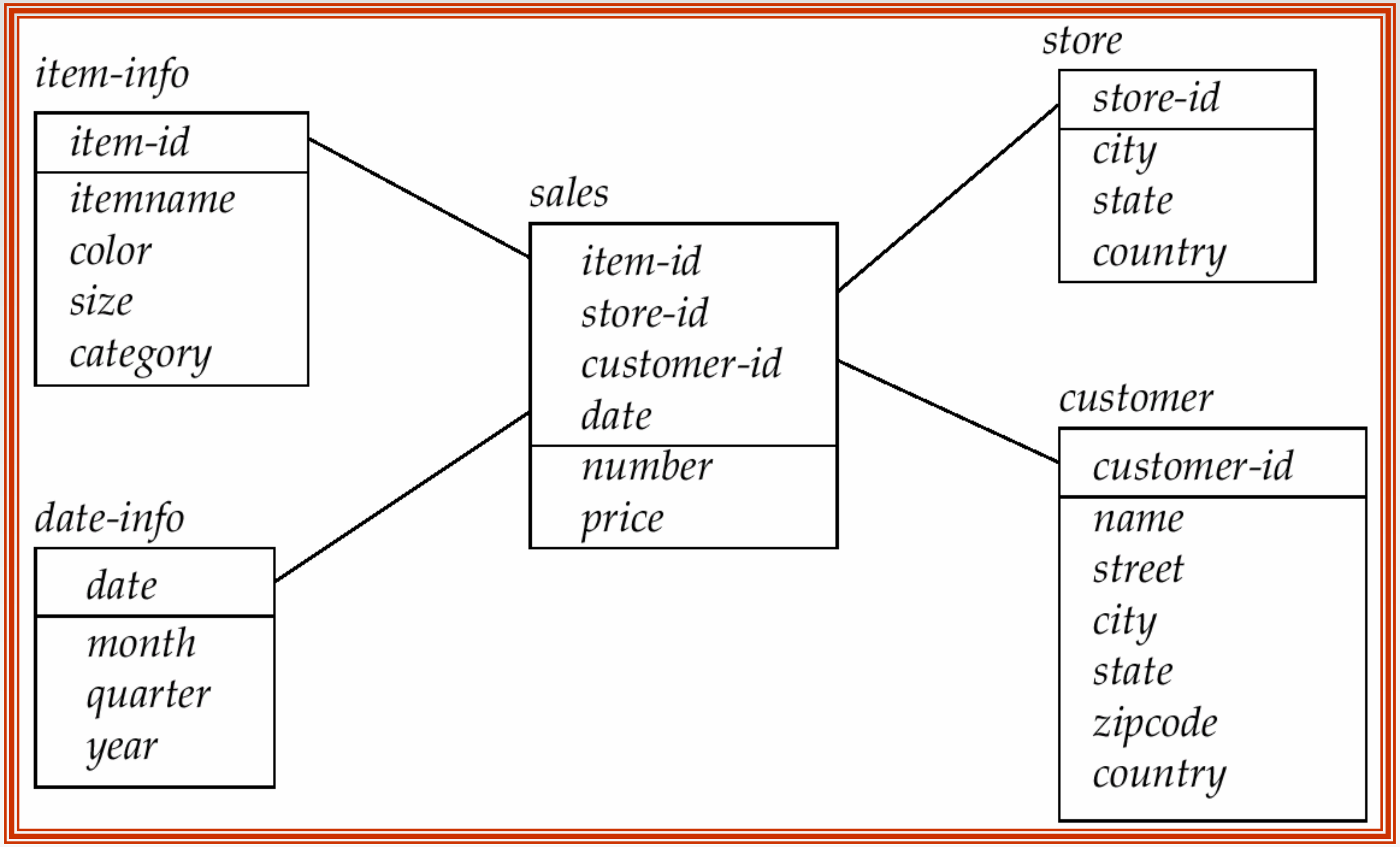
More Warehouse Design Issues

- *Data cleansing*
  - E.g. correct mistakes in addresses (misspellings, zip code errors)
  - 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
  - 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 phone calling 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** formulae
    - 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

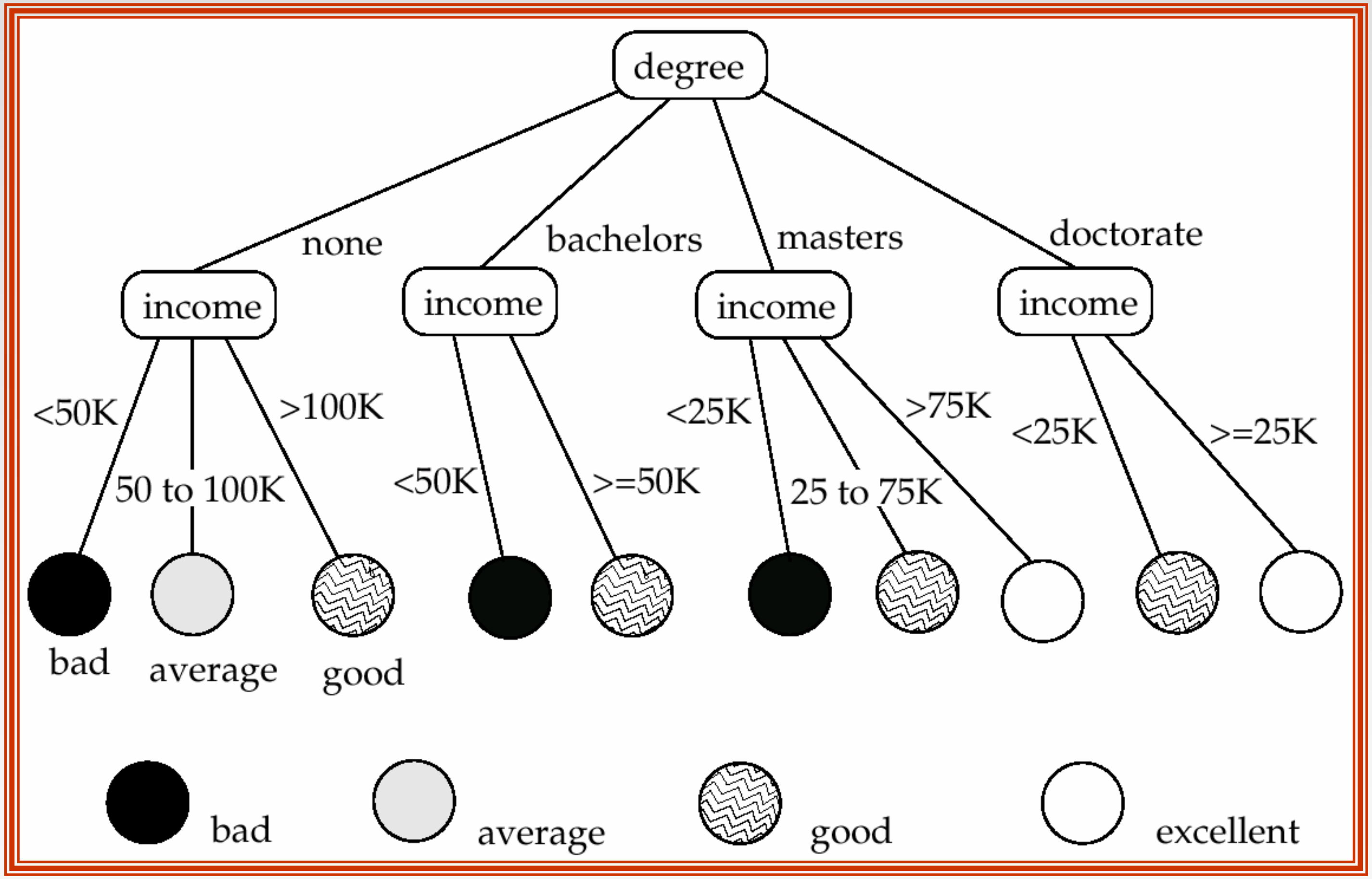
- Classification rules help assign new objects to classes.
  - E.g., given a new automobile insurance applicant, should he or she be classified as low risk, medium risk or high risk?
- Classification rules for above example could use a variety of data, such as educational level, salary, age, etc.
  - $\forall$ person P, P.degree = masters **and** P.income > 75,000

    $\Rightarrow$ P.credit = excellent
  - $\forall$ person P, P.degree = bachelors **and**

    (P.income $\geq$ 25,000 and P.income $\leq$ 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 most) 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 purity 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 purity is defined as

[

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

  - When all instances are in a single class, the Gini value is 0
  - It reaches its maximum (of 1 –1 /k) if each class the same number of instances.

Best Splits (Cont.)

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

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

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

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

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

  Information-gain $(S, \{S_1, S_2, \ldots., S_r) = \text{purity}(S) - \text{purity}(S_1, S_2, \ldots S_r)$

Best Splits (Cont.)

- Measure of "cost" of a split:

  Information-content (S, {S_1, S_2, ….., S_r})) $= -\sum_{i=1}^{r} \frac{|S_i|}{|S|} \log_2 \frac{|S_i|}{|S|}$

- **Information-gain ratio** = $\dfrac{\text{Information-gain } (S, \{S_1, S_2, \ldots\ldots, S_r\})}{\text{Information-content } (S, \{S_1, S_2, \ldots.., S_r\})}$

- 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 (*purity* (*S*) > δ_p or |*S*| < δ_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, ….., *r*
    Partition (S_i);

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

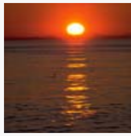
$p\,(d\,)$ = probability of instance d occuring

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* $\Rightarrow$ *screwdrivers* is low.
- **Confidence** is a measure of how often the consequent is true when the antecedent is true.
  - E.g. the rule *bread* $\Rightarrow$ *milk* has a confidence of 80 percent if 80 percent of the purchases that include bread also include milk.

Finding Association Rules

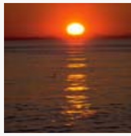
- We are generally only interested in association rules with reasonably high support (e.g. support of 2% or greater)
- Naïve algorithm
  1. Consider all possible sets of relevant items.
  2. For each set find its support (i.e. count how many transactions purchase all items in the set).
     - **Large 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 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

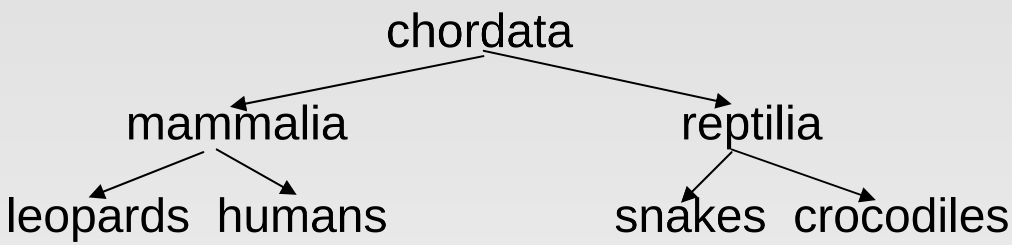


Clustering

- 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 (more shortly)

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