Chapter 22: Advanced Querying and Information Retrieval

- Decision-Support Systems
  - Data Analysis
    - OLAP
    - Extended aggregation features in SQL
      - Windowing and ranking
  - Data Mining
  - Data Warehousing
- Information-Retrieval Systems
  - Including Web search

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?
  - Who to send advertisements to?
- Examples of data used for making decisions
  - Retail sales transaction details
  - Customer profiles (income, age, sex, 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 will not study it 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 which generate data from multiple divisions, possibly at multiple sites
  - Data may also be purchased externally

Data Analysis and OLAP

- Aggregate functions summarize large volumes of data
- **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**.
  - Given a relation used for data analysis, we can identify some of its attributes as **measure attributes**, since they measure some value, and can be aggregated upon. For instance, the attribute *number* of the *sales* relation is a measure attribute, since it measures the number of units sold.
  - Some of the other attributes of the relation are identified as **dimension attributes**, since they define the dimensions on which measure attributes, and summaries of measure attributes, are viewed.

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

size: **all**

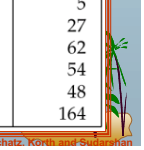
item-name \ *color*	dark	pastel	white	Total
skirt	8	35	10	53
dress	20	10	5	35
shirt	14	7	28	49
pant	20	2	5	27
Total	62	54	48	164

- The table above is an example of a **cross-tabulation** (**cross-tab**), also referred to as a **pivot-table**.
- A cross-tab is a table where
  - 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 Crosstabs

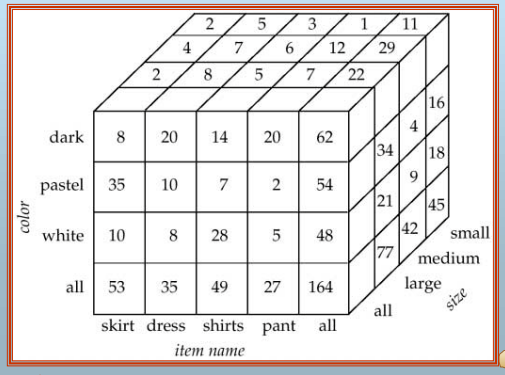
- Crosstabs can be represented as relations
  - The value **all** is used to represent aggregates
  - The SQL:1999 standard actually uses null values in place of **all**
    - More on this later….

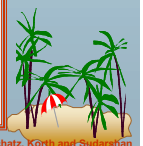
item-name	*color*	*number*
skirt	dark	8
skirt	pastel	35
skirt	white	10
skirt	**all**	53
dress	dark	20
dress	pastel	10
dress	white	5
dress	**all**	35
shirt	dark	14
shirt	pastel	7
shirt	white	28
shirt	**all**	49
pant	dark	20
pant	pastel	2
pant	white	5
pant	**all**	27
all	dark	62
all	pastel	54
all	white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



Three-Dimensional Data Cube

- A **data cube** is a multidimensional generalization of a crosstab
  - Cannot view a three-dimensional object in its entirety
    - but crosstabs can be used as views on a data cube



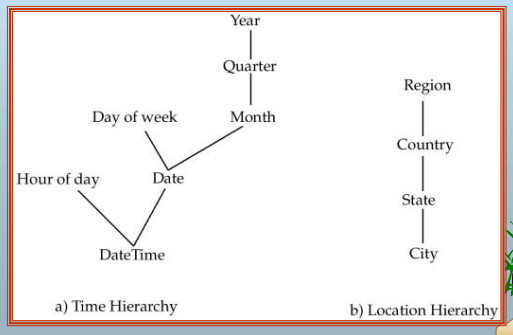


Online Analytical Processing

- The operation of changing the dimensions used in a cross-tab is called **pivoting**
- Suppose an analyst wishes to see a cross-tab on *item-name* and *color* for a fixed value of *size*, for example, large, instead of the sum across all sizes.
  - Such an operation is referred to as **slicing**.
    - The operation is sometimes called **dicing**, particularly when values for multiple dimensions are fixed.
- The operation of moving from finer-granularity data to a coarser granularity is called a **rollup**.
- The opposite operation - that of moving from coarser-granularity data to finer-granularity data – is called a **drill down**.

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

- Crosstabs 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

- SQL-92 aggregation quite limited
  - Many useful aggregates are either very hard or impossible to specify
    - Data cube
    - Complex aggregates (median, variance)
    - binary aggregates (correlation, regression curves)
    - ranking queries ("assign each student a rank based on the total marks"
- SQL:1999 OLAP extensions provide a variety of aggregation functions to address above limitations
  - Supported by several databases, including Oracle and IBM DB2

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 crosstab 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*), *()*}

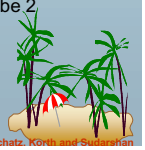
  = { (*item-name, color, size*), (*item-name, color*), (*item-name*), (*color, size*), (*color*), ( ) }

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
- Exercises:
  - Find students with top n ranks
    - Many systems provide special (non-standard) syntax for "top-n" queries
  - Rank students by sum of their marks in different courses
    - given relation *student-course-marks(student-id, course, marks)*

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.)

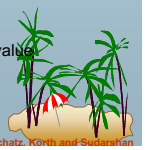
- For a given constant n, the ranking the function ntile(n) takes the tuples in each partition in the specified order, and divides them into n buckets with qual numbers of tuples. For instance, we an sort employees by salary, and use ntile(3) to find which range (bottom third, middle third, or top third) each employee is in, and compute the total salary earned by employees in each range:

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

Windowing

- E.g.: "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"
- Such *moving average* queries are used to smooth out random variations.
- In contrast to group by, the same tuple can exist in multiple windows
- **Window specification** in SQL:
  - Ordering of tuples, size of window for each tuple, aggregate function
  - E.g. 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 Mining

Data Mining

- Broadly speaking, data mining is the process of semi-automatically analyzing large databases to find useful patterns
- Like knowledge discovery in artificial intelligence data mining discovers statistical rules and patterns
- Differs from machine learning in that it deals with large volumes of data stored primarily on disk.
- Some types of knowledge discovered from a database can be represented by a set of rules.
  - e.g.,: "Young women with annual incomes greater than $50,000 are most likely to buy sports cars"
- Other types of knowledge represented by equations, or by prediction functions
- Some manual intervention is usually required
  - Pre-processing of data, choice of which type of pattern to find, postprocessing to find novel patterns

Applications of Data Mining

- **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 customer is likely to switch brand loyalty
  - Predict if a customer is likely to respond to "junk mail"
  - Predict if a pattern of phone calling card usage is likely to be fraudulent
- Some examples of prediction mechanisms:
  - **Classification**
    - Given a training set consisting of items belonging to different classes, and a new item whose class is unknown, predict which class it belongs to
  - **Regression** formulae
    - given a set of parameter-value to function-result mappings for an unknown function, predict the function-result for a new parameter-value

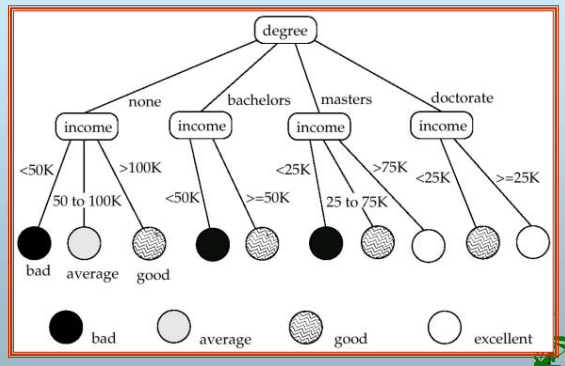
Applications of Data Mining (Cont.)

- **Descriptive Patterns**
  - **Associations**
    - Find books that are often bought by the same customers. If a new customer buys one such book, suggest that he buys the others too.
    - Other similar applications: camera accessories, clothes, etc.
  - Associations may also be used as a first step in detecting **causation**
    - E.g. association between exposure to chemical X and cancer, or new medicine and cardiac problems
  - **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 a set of 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 knowledge, such as educational level of applicant, salary of applicant, age of applicant, 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 compactly shown as a decision tree.

Decision Tree



Construction of Decision Trees

- **Training set**: a data sample in which the grouping for each tuple is already known.
- Consider credit risk example: Suppose *degree* is chosen to partition the data at the root.
  - Since degree has a small number of possible values, one child is created for each value.
- At each child node of the root, further classification is done if required. Here, partitions are defined by *income*.
  - Since income is a continuous attribute, some number of intervals are chosen, and one child created for each interval.
- Different classification algorithms use different ways of choosing which attribute to partition on at each node, and what the intervals, if any, are.
- In general
  - Different branches of the tree could grow to different levels.
  - Different nodes at the same level may use different partitioning attributes.

Construction of Decision Trees (Cont.)

- **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
    - More on choosing partioning attribute/condition shortly
    - Algorithm is greedy: the choice is made once and not revisited as more of the tree is constructed
  - The data at a node is not partitioned further if either
    - 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.

    Such a node is a leaf node.
  - Otherwise the data at the node is partitioned further by picking an attribute for partitioning data at the node.

Best Splits

- Idea: evaluate different attributes and partitioning conditions and pick the one that best improves the "purity" of the training set examples
  - The initial training set has a mixture of instances from different classes and is thus relatively impure
  - E.g. if degree exactly predicts credit risk, partitioning on degree would result in each child having instances of only one class
    - I.e., the child nodes would be *pure*
- 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

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

  - When all instances are in a single class, the Gini value is 0, while 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

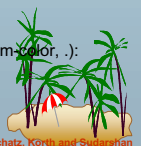
  Information-gain $(S, \{S_1, S_2, \ldots, S_r\})$ =
  purity(S) – purity $(S_1, S_2, \ldots S_r)$

Best Splits (Cont.)

- Measure of "cost" of a split:
  Information-content(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** = Information-gain $(S, \{S_1, S_2, \ldots, S_r\})$ / Information-content $(S, \{S_1, S_2, \ldots, S_r\})$
- The best split for an attribute is the one that gives the maximum information gain ratio
- **Continuous valued attributes**
  - Can be ordered in a fashion meaningful to classification
  - e.g. integer and real values
- **Categorical attributes**
  - Cannot be meaningfully ordered (e.g. country, school/university, item-color, .):



Finding Best Splits

- Categorical attributes:
  - Multi-way split, one child for each value
    - may have too many children in some cases
  - Binary split: try all possible breakup of values into two sets, and pick the best
- Continuous valued attribute
  - Binary split:
    - Sort values in the instances, 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: more complicated, see bibliographic notes
    - A series of binary splits on the same attribute has roughly equivalent effect

Decision-Tree Construction Algorithm

Procedure *Grow.Tree(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);

Decision Tree Constr'n Algo's. (Cont.)

- Variety of algorithms have been developed to
  - Reduce CPU cost and/or
  - Reduce IO cost when handling datasets larger than memory
  - Improve accuracy of classification
- Decision tree may be **overfitted**, i.e., overly tuned to given training set
  - Pruning of decision tree may be done on branches that have too few training instances
    - When a subtree is pruned, an internal node becomes a leaf
      - and its class is set to the majority class of the instances that map to the node
  - Pruning can be done by using a part of the training set to build tree, and a second part to test the tree
    - prune subtrees that increase misclassification on second part

Other Types of Classifiers

- Further types of classifiers
  - Neural net classifiers
  - Bayesian classifiers
- Neural net classifiers use the training data to train artificial neural nets
  - Widely studied in AI, won't cover here
- Bayesian classifiers use **Bayes theorem**, which says

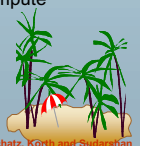
$$p(c_j \mid d) = \frac{p(d \mid c_j)\, p(c_j)}{p(d)}$$

  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

  $p(d|c_j) = p(d_1|c_j) * p(d_2|c_j) * \ldots * (p(d_n|c_j)$
  - Each of the $p(d_i|c_j)$ 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, $X_1, X_2, \ldots, X_n$, we wish to predict the value of a variable Y.
- One way is to infer coefficients $a_0, a_1, a_1, \ldots, a_n$ 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

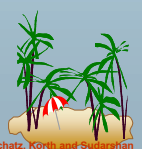
- Retail shops are often interested in associations between different items that people buy.
  - Someone who buys bread is quite likely also to buy milk
  - A person who bought the book *Database System Concepts* is quite likely also to buy the book *Operating System Concepts*.
- Associations information 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.)

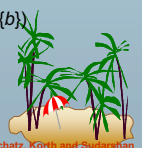
- Rules have an associated support, as well as an associated confidence.
- **Support** is a measure of what fraction of the population satisfies both the antecedent and the consequent of the rule.
  - E.g. suppose only 0.001 percent of all purchases include milk and screwdrivers. The support for the rule is *milk* ⇒ *screwdrivers* is low.
  - We usually want rules with a reasonably high support
    - Rules with low support are usually not very useful
- **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.
  - Usually want rules with reasonably large confidence.
    - A rule with a low confidence is not meaningful.

Note that the confidence of *bread* ⇒ *milk* may be very different from the confidence of *milk* ⇒ *bread*, although both have the same supports.



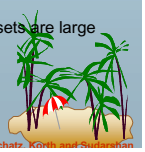
Finding Association Rules

- 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*} ⇒ *b* for each *b* ∈ *A*.
        - Support of rule = support (*A*).
        - Confidence of rule = support (*A*) / support (*A* - {*b*})



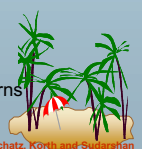
Finding Support

- Few itemsets: determine support of all itemsets via a single pass on set of transactions
  - A count is maintained for each itemset, initially set to 0.
  - When a transaction is fetched, the count is incremented for each set of items that is contained in the transaction.
  - Large itemsets: sets with a high count at the end of the pass
- Many itemsets: 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 (prob1 * prob2)
  - 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

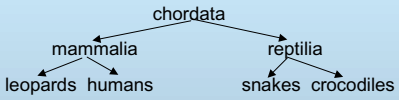


Clustering

- 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
- E.g. 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

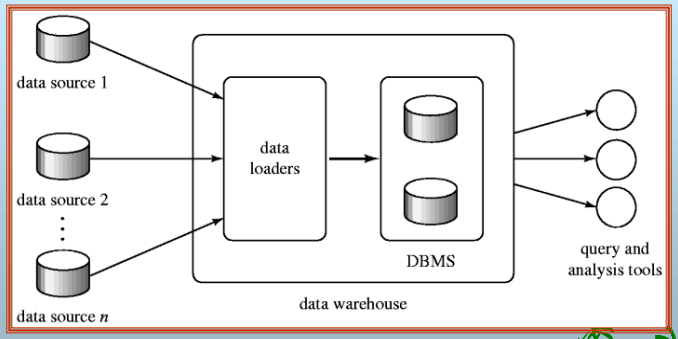
- **Text mining**: application of data mining to textual documents
  - E.g. cluster Web pages to find related pages
  - E.g. cluster pages a user has visited to organize their visit history
  - E.g. classify Web pages automatically into a Web directory
- **Data visualization** systems help users examine large volumes of data and detect patterns visually
  - E.g. maps, charts, and color-coding
    - E.g. locations with problems shown in red on a map
  - Can visually encode large amounts of information on a single screen
  - Humans are very good a detecting visual patterns

Data Warehousing

Data Warehousing

- Large organizations have complex internal organizations, and have data stored at different locations, on different operational (transaction processing) systems, under different schemas
- 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



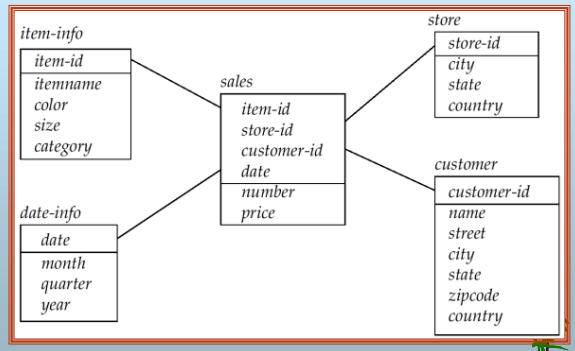
Components of Data Warehouse

- *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

Components of Data Warehouse (Cont.)

- *Data cleansing*
  - E.g. correct mistakes in addresses
    - E.g. misspellings, zip code errors
  - Merge address lists from different sources and purge duplicates
    - Keep only one address record per household ("householding")
- *How to propagate updates*
  - Warehouse schema may be a (materialized) view of schema from data sources
  - Efficient techniques for update of materialized views
- *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

Data Warehouse Schemas



Warehouse Schemas

- Typically warehouse data is multidimensional, with very large **fact tables**
  - Examples of dimensions: item-id, date/time of sale, store where sale was made, customer identifier
  - Examples of measures: number of items sold, price of items
- 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

Information Retrieval

Information Retrieval Systems

- **Information retrieval** (**IR**) systems use a simpler data model than database systems
  - Information organized as a collection of documents
  - Documents are unstructured, no schema
- Information retrieval locates relevant documents, on the basis of user input such as keywords or example documents
  - e.g., find documents containing the words "database systems"
- Can be used even on textual descriptions provided with non-textual data such as images
- IR on Web documents has become extremely important
  - E.g. google, altavista, …

Information Retrieval Systems (Cont.)

- Differences from database systems
  - IR systems don't deal with transactional updates (including concurrency control and recovery)
  - Database systems deal with structured data, with schemas that define the data organization
  - IR systems deal with some querying issues not generally addressed by database systems
    - Approximate searching by keywords
    - Ranking of retrieved answers by estimated degree of relevance

Keyword Search

- In **full text** retrieval, all the words in each document are considered to be keywords.
  - We use the word **term** to refer to the words in a document
- Information-retrieval systems typically allow query expressions formed using keywords and the logical connectives *and, or,* and *not*
  - *And*s are implicit, even if not explicitly specified
- Ranking of documents on the basis of estimated relevance to a query is critical
  - Relevance ranking is based on factors such as
    - Term frequency
      - Frequency of occurrence of query keyword in document
    - Inverse document frequency
      - How many documents the query keyword occurs in
        - » Fewer ➔ give more importance to keyword
    - Hyperlinks to documents
      - More links to a document ➔ document is more important

Relevance Ranking Using Terms

- **TF-IDF** (Term frequency/Inverse Document frequency) ranking:
  - Let $n(d)$ = number of terms in the document d
  - $n(d, t)$ = number of occurrences of term t in the document d.
  - Then relevance of a document d to a term t

$$r(d, t) = log\left(1 + \frac{n(d, t)}{n(d)}\right)$$

    - The log factor is to avoid excessive weightage to frequent terms
  - And relevance of document to query Q

$$r(d, Q) = \sum_{t \in Q} \frac{r(d, t)}{n(t)}$$

Relevance Ranking Using Terms (Cont.)

- Most systems add to the above model
  - Words that occur in title, author list, section headings, etc. are given greater importance
  - Words whose first occurrence is late in the document are given lower importance
  - Very common words such as "a", "an", "the", "it" etc are eliminated
    - Called **stop words**
  - **Proximity**: if keywords in query occur close together in the document, the document has higher importance than if they occur far apart
- Documents are returned in decreasing order of relevance score
  - Usually only top few documents are returned, not all

Relevance Using Hyperlinks

- When using keyword queries on the Web, the number of documents is enormous (many billions)
  - Number of documents relevant to a query can be enormous if only term frequencies are taken into account
- Using term frequencies makes "spamming" easy
  - E.g. a travel agent can add many occurrences of the words "travel agent" to his page to make its rank very high
- Most of the time people are looking for pages from popular sites
- Idea: use popularity of Web site (e.g. how many people visit it) to rank site pages that match given keywords
- Problem: hard to find actual popularity of site
  - Solution: next slide

Relevance Using Hyperlinks (Cont.)

- Solution: use number of hyperlinks to a site as a measure of the popularity or prestige of the site
  - Count only one hyperlink from each site (why?)
  - Popularity measure is for site, not for individual page
    - Most hyperlinks are to root of site
    - Site-popularity computation is cheaper than page popularity computation
- Refinements
  - When computing prestige based on links to a site, give more weightage to links from sites that themselves have higher prestige
    - Definition is circular
    - Set up and solve system of simultaneous linear equations
  - Above idea is basis of the Google PageRank ranking mechanism

Relevance Using Hyperlinks (Cont.)

- Connections to social networking theories that ranked prestige of people
  - E.g. the president of the US has a high prestige since many people know him
  - Someone known by multiple prestigious people has high prestige
- Hub and authority based ranking
  - A **hub** is a page that stores links to many pages (on a topic)
  - An **authority** is a page that contains actual information on a topic
  - Each page gets a **hub prestige** based on prestige of authorities that it points to
  - Each page gets an **authority prestige** based on prestige of hubs that point to it
  - Again, prestige definitions are cyclic, and can be got by solving linear equations
  - Use authority prestige when ranking answers to a query

Similarity Based Retrieval

- Similarity based retrieval - retrieve documents similar to a given document
  - Similarity may be defined on the basis of common words
    - E.g. find k terms in A with highest $r(d, t)$ and use these terms to find relevance of other documents; each of the terms carries a weight of $r(d,t)$
- Similarity can be used to refine answer set to keyword query
  - User selects a few relevant documents from those retrieved by keyword query, and system finds other documents similar to these

Synonyms and Homonyms

- Synonyms
  - E.g. document: "motorcycle repair", query: "motorcycle maintenance"
    - need to realize that "maintenance" and "repair" are synonyms
  - System can extend query as "motorcycle and (repair or maintenance)"
- Homonyms
  - E.g. "object" has different meanings as noun/verb
  - Can disambiguate meanings (to some extent) from the context
- Extending queries automatically using synonyms can be problematic
  - Need to understand intended meaning in order to infer synonyms
    - Or verify synonyms with user
  - Synonyms may have other meanings as well

Indexing of Documents

- An inverted index maps each keyword K_i to a set of documents S_i that contain the keyword
  - Documents identified by identifiers
- Inverted index may record
  - Keyword locations within document to allow proximity based ranking
  - Counts of number of occurrences of keyword to compute TF
- **and** operation: Finds documents that contain all of $K_1, K_2, ..., K_n$.
  - Intersection $S_1 \cap S_2 \cap ..... \cap S_n$
- **or** operation: documents that contain at least one of $K_1, K_2, ..., K_n$
  - union, $S_1 \cap S_2 \cap ..... \cap S_n$,.
- Each S_i is kept sorted to allow efficient intersection/union by merging
  - "**not**" can also be efficiently implemented by merging of sorted lists

Measuring Retrieval Effectiveness

- IR systems save space by using index structures that support only approximate retrieval. May result in:
  - **false negative (false drop)** - some relevant documents may not be retrieved.
  - **false positive** - some irrelevant documents may be retrieved.
  - For many applications a good index should not permit any false drops, but may permit a few false positives.
- Relevant performance metrics:
  - **Precision** - what percentage of the retrieved documents are relevant to the query.
  - **Recall** - what percentage of the documents relevant to the query were retrieved.

Measuring Retrieval Effectiveness (Cont.)

- Ranking order can also result in false positives/false negatives
  - Recall vs. precision tradeoff:
    - Can increase recall by retrieving many documents (down to a low level of relevance ranking), but many irrelevant documents would be fetched, reducing precision
  - Measures of retrieval effectiveness:
    - Recall as a function of number of documents fetched, or
    - Precision as a function of recall
      - Equivalently, as a function of number of documents fetched
    - E.g. "precision of 75% at recall of 50%, and 60% at a recall of 75%"
      - In general: draw a graph of precision vs recall.
- Problem: which documents are actually relevant, and which are not
  - Usual solution: human judges
  - Create a corpus of documents and queries, with humans deciding which documents are relevant to which queries
    - TREC (Text REtrieval Conference) Benchmark

Web Crawling

- **Web crawlers** are programs that locate and gather information on the Web
  - Recursively follow hyperlinks present in known documents, to find other documents
    - Starting from a *seed* set of documents
  - Fetched documents
    - Handed over to an indexing system
    - Can be discarded after indexing, or store as a *cached* copy
- Crawling the entire Web would take a very large amount of time
  - Search engines typically cover only a part of the Web, not all of it
  - Take months to perform a single crawl

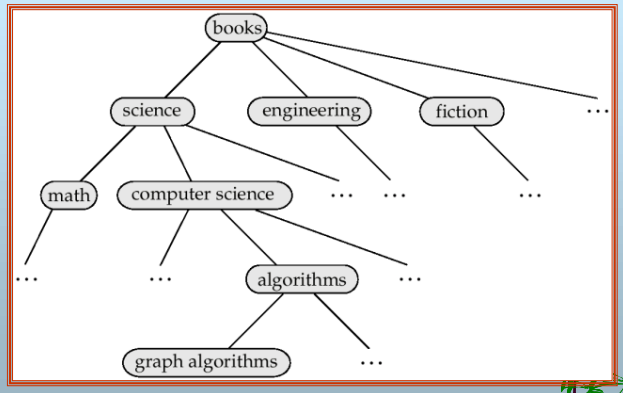
Web Crawling (Cont.)

- Crawling is done by multiple processes on multiple machines, running in parallel
  - Set of links to be crawled stored in a database
  - New links found in crawled pages added to this set, to be crawled later
- Indexing process also runs on multiple machines
  - Creates a new copy of index instead of modifying old index
  - Old index is used to answer queries
  - After a crawl is "completed" new index becomes "old" index
- Multiple machines used to answer queries
  - Indices may be kept in memory
  - Queries may be routed to different machines for load balancing

Browsing

- Storing related documents together in a library facilitates browsing
  - users can see not only requested document but also related ones.
- Browsing is facilitated by classification system that organizes logically related documents together.
- Organization is hierarchical: **classification hierarchy**

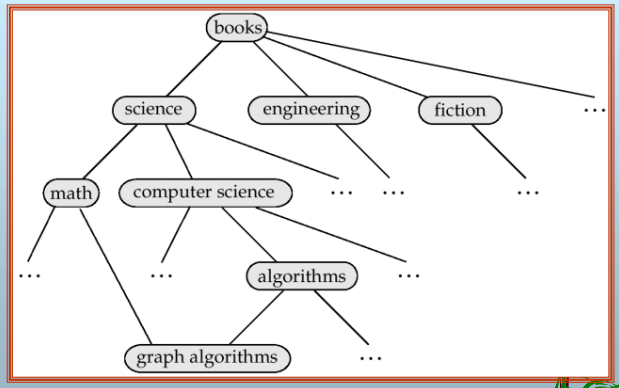
A Classification Hierarchy For A Library System



Classification DAG

- Documents can reside in multiple places in a hierarchy in an information retrieval system, since physical location is not important.
- Classification hierarchy is thus Directed Acyclic Graph (DAG)

A Classification DAG For A Library Information Retrieval System



Web Directories

- A **Web directory** is just a classification directory on Web pages
  - E.g. Yahoo! Directory, Open Directory project
  - Issues:
    - What should the directory hierarchy be?
    - Given a document, which nodes of the directory are categories relevant to the document
  - Often done manually
    - Classification of documents into a hierarchy may be done based on term similarity