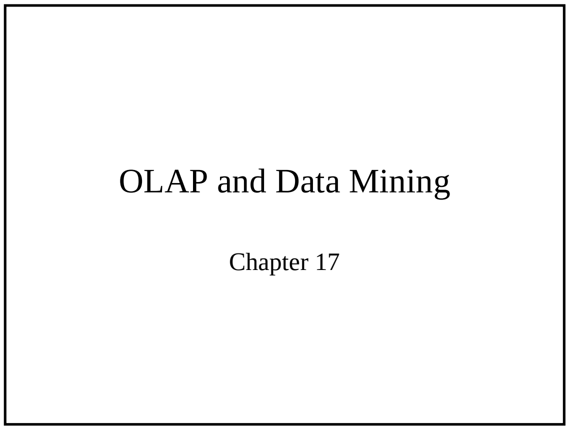
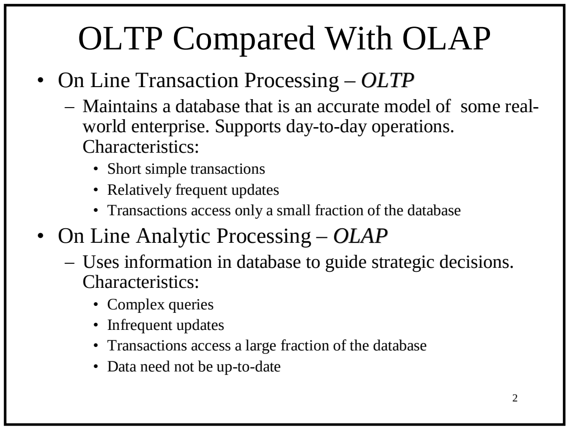


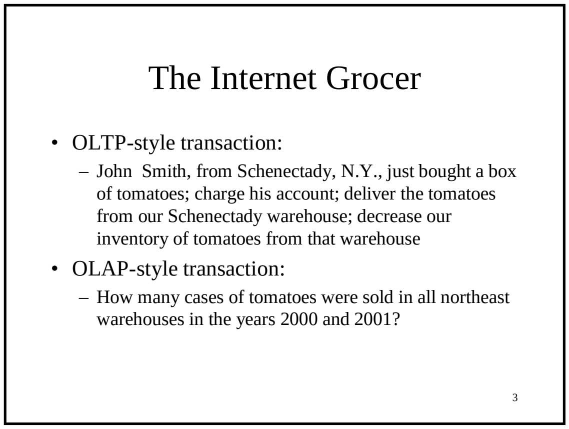
OLAP and Data Mining

Chapter 17



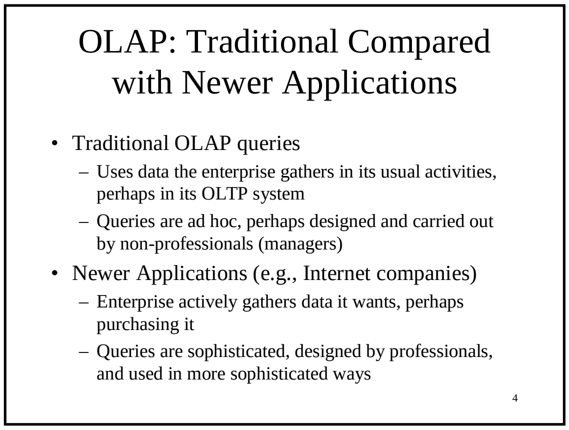
OLTP Compared With OLAP

- On Line Transaction Processing – *OLTP*
  - Maintains a database that is an accurate model of some real-world enterprise. Supports day-to-day operations. Characteristics:
    - Short simple transactions
    - Relatively frequent updates
    - Transactions access only a small fraction of the database
- On Line Analytic Processing – *OLAP*
  - Uses information in database to guide strategic decisions. Characteristics:
    - Complex queries
    - Infrequent updates
    - Transactions access a large fraction of the database
    - Data need not be up-to-date



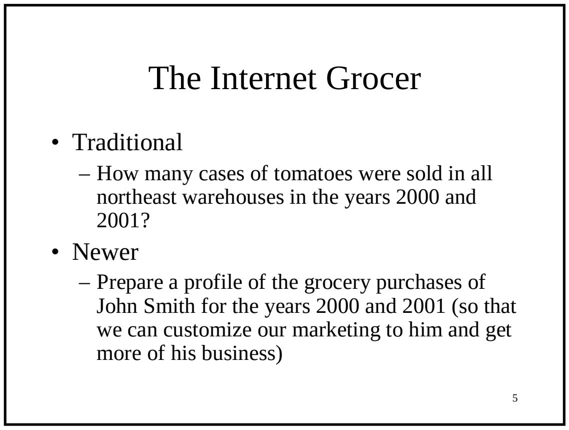
The Internet Grocer

- OLTP-style transaction:
  - John Smith, from Schenectady, N.Y., just bought a box of tomatoes; charge his account; deliver the tomatoes from our Schenectady warehouse; decrease our inventory of tomatoes from that warehouse
- OLAP-style transaction:
  - How many cases of tomatoes were sold in all northeast warehouses in the years 2000 and 2001?



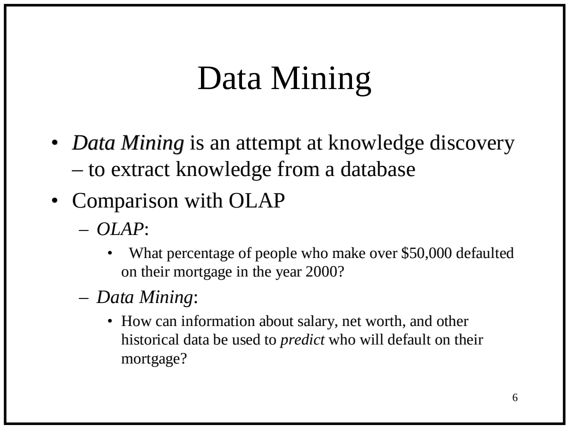
OLAP: Traditional Compared with Newer Applications

- Traditional OLAP queries
  - Uses data the enterprise gathers in its usual activities, perhaps in its OLTP system
  - Queries are ad hoc, perhaps designed and carried out by non-professionals (managers)
- Newer Applications (e.g., Internet companies)
  - Enterprise actively gathers data it wants, perhaps purchasing it
  - Queries are sophisticated, designed by professionals, and used in more sophisticated ways



The Internet Grocer

- Traditional
  - How many cases of tomatoes were sold in all northeast warehouses in the years 2000 and 2001?
- Newer
  - Prepare a profile of the grocery purchases of John Smith for the years 2000 and 2001 (so that we can customize our marketing to him and get more of his business)



Data Mining

- *Data Mining* is an attempt at knowledge discovery – to extract knowledge from a database
- Comparison with OLAP
  - *OLAP*:
    - What percentage of people who make over $50,000 defaulted on their mortgage in the year 2000?
  - *Data Mining*:
    - How can information about salary, net worth, and other historical data be used to *predict* who will default on their mortgage?

Data Warehouses

- OLAP and data mining databases are frequently stored on special servers called ***data warehouses***:
  - Can accommodate the huge amount of data generated by OLTP systems
  - Allow OLAP queries and data mining to be run off-line so as not to impact the performance of OLTP

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OLAP, Data Mining, and Analysis

- The “A” in OLAP stands for “Analytical”
- Many OLAP and Data Mining applications involve sophisticated analysis methods from the fields of mathematics, statistical analysis, and artificial intelligence
- Our main interest is in the database aspects of these fields, not the sophisticated analysis techniques

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Fact Tables

- Many OLAP applications are based on a ***fact table***
- For example, a supermarket application might be based on a table

  Sales (*Market_Id*, *Product_Id*, *Time_Id*, *Sales_Amt*)
- The table can be viewed as *multidimensional*
  - *Market_Id*, *Product_Id*, *Time_Id* are the dimensions that represent specific supermarkets, products, and time intervals
  - *Sales_Amt* is a function of the other three

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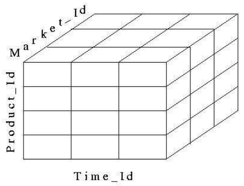
A Data Cube

- Fact tables can be viewed as an N-dimensional *data cube* (3-dimensional in our example)
  - The entries in the cube are the values for *Sales_Amts*



Dimension Tables

- The dimensions of the fact table are further described with ***dimension tables***
- Fact table:

  Sales (*Market_id*, *Product_Id*, *Time_Id*, *Sales_Amt*)
- Dimension Tables:

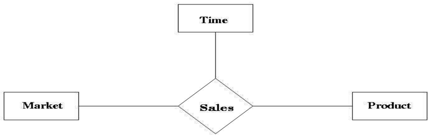
  Market (*Market_Id*, *City*, *State*, *Region*)

  Product (*Product_Id*, *Name*, *Category*, *Price*)

  Time (*Time_Id*, *Week*, *Month*, *Quarter*)

Star Schema

- The fact and dimension relations can be displayed in an E-R diagram, which looks like a star and is called a ***star schema***



Aggregation

- Many OLAP queries involve ***aggregation*** of the data in the fact table
- For example, to find the total sales (over time) of each product in each market, we might use

```
SELECT      S.Market_Id, S.Product_Id, SUM (S.Sales_Amt)
FROM        Sales  S
GROUP BY  S.Market_Id, S.Product_Id
```

- The aggregation is over the entire time dimension and thus produces a two-dimensional view of the data

Aggregation over Time

- The output of the previous query

Market_Id

Product_Id

SUM(*Sales_Amt*)	M1	M2	M3	M4
P1	3003	1503	…	
P2	6003	2402	…	
P3	4503	3	…	
P4	7503	7000	…	
P5	…	…	…	

Drilling Down and Rolling Up

- Some dimension tables form an ***aggregation hierarchy***

  Market_Id → *City* → *State* → *Region*
- Executing a series of queries that moves down a hierarchy (*e.g.*, from aggregation over regions to that over states) is called ***drilling down***
  - Requires the use of the fact table or information more specific than the requested aggregation (*e.g.*, cities)
- Executing a series of queries that moves up the hierarchy (e.g., from states to regions) is called ***rolling up***
  - Note: In a rollup, coarser aggregations can be computed using prior queries for finer aggregations

Drilling Down

- Drilling down on market: from *Region* to *State*

  Sales (*Market_Id, Product_Id, Time_Id, Sales_Amt*)

  Market (*Market_Id, City, State, Region*)

```
1.  SELECT     S.Product_Id, M.Region, SUM (S.Sales_Amt)
    FROM       Sales S,  Market M
    WHERE      M.Market_Id = S.Market_Id
    GROUP BY  S.Product_Id,  M.Region

2.  SELECT     S.Product_Id, M.State, SUM (S.Sales_Amt)
    FROM       Sales S,  Market M
    WHERE      M.Market_Id = S.Market_Id
    GROUP BY  S.Product_Id,  M.State,
```

Rolling Up

- Rolling up on market, from *State* to *Region*
  - If we have already created a table, State_Sales, using

```
1.  SELECT     S.Product_Id,  M.State, SUM (S.Sales_Amt)
    FROM       Sales S,   Market M
    WHERE      M.Market_Id = S.Market_Id
    GROUP BY  S.Product_Id,  M.State
```

then we can roll up from there to:

```
2.  SELECT     T.Product_Id,  M.Region, SUM (T.Sales_Amt)
    FROM       State_Sales  T,  Market  M
    WHERE      M.State = T.State
    GROUP BY T.Product_Id,  M.Region
```

Pivoting

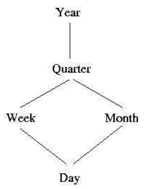
- When we view the data as a multi-dimensional cube and group on a subset of the axes, we are said to be performing a *pivot* on those axes
  - Pivoting on dimensions $D_1,\ldots,D_k$ in a data cube $D_1,\ldots,D_k,D_{k+1},\ldots,D_n$ means that we use GROUP BY $A_1,\ldots,A_k$ and aggregate over $A_{k+1},\ldots A_n$, where A_i is an attribute of the dimension D_i
  - *Example*: Pivoting on Product and Time corresponds to grouping on *Product_id* and *Quarter* and aggregating *Sales_Amt* over *Market_id:*

```
SELECT     S.Product_Id,  T.Quarter,  SUM (S.Sales_Amt)
FROM       Sales S,  Time T
WHERE      T.Time_Id = S.Time_Id
GROUP BY  S.Product_Id,  T.Quarter
```

Pivot

Time Hierarchy as a Lattice

- Not all aggregation hierarchies are linear
  - The time hierarchy is a lattice
    - Weeks are not contained in months
    - We can roll up days into weeks or months, but we can only roll up weeks into quarters



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Slicing-and-Dicing

- When we use WHERE to specify a particular value for an axis (or several axes), we are performing a ***slice***
  - Slicing the data cube in the Time dimension (choosing sales only in week 12) then pivoting to *Product_id* (aggregating over *Market_id*)

```
SELECT    S.Product_Id,  SUM (Sales_Amt)
FROM      Sales S, Time T
WHERE     T.Time_Id = S.Time_Id  AND  T.Week = ‘Wk-12’
GROUP BY    S. Product_Id
```

Slice

Pivot

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Slicing-and-Dicing

- Typically slicing and dicing involves several queries to find the “right slice.”

  For instance, change the slice and the axes:
  - Slicing on Time and Market dimensions then pivoting to *Product_id* and *Week* (in the time dimension)

```
SELECT      S.Product_Id,  T.Quarter,  SUM (Sales_Amt)
FROM        Sales S,  Time T
WHERE       T.Time_Id = S.Time_Id
                 AND  T.Quarter =  4
                 AND  S.Market_id = 12345
GROUP BY  S.Product_Id,  T.Week
```

Slice

Pivot

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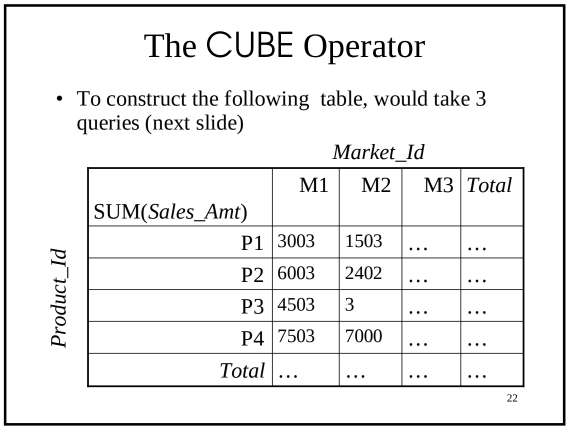


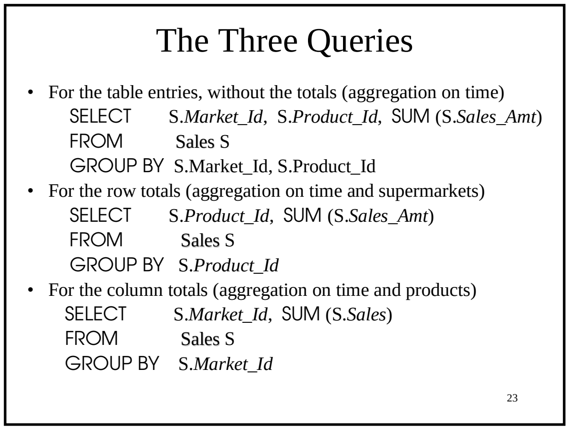
The CUBE Operator

- To construct the following table, would take 3 queries (next slide)

Market_Id

Product_Id

SUM(*Sales_Amt*)	M1	M2	M3	*Total*
P1	3003	1503	…	…
P2	6003	2402	…	…
P3	4503	3	…	…
P4	7503	7000	…	…
Total	…	…	…	…



The Three Queries

- For the table entries, without the totals (aggregation on time)

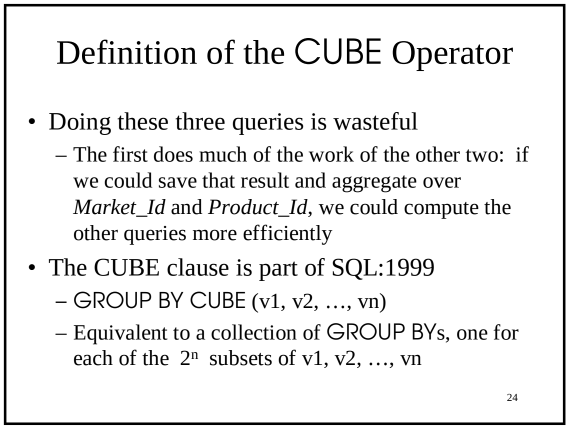
```
SELECT     S.Market_Id,  S.Product_Id,  SUM (S.Sales_Amt)
FROM        Sales S
GROUP BY  S.Market_Id, S.Product_Id
```

- For the row totals (aggregation on time and supermarkets)

```
SELECT     S.Product_Id,  SUM (S.Sales_Amt)
FROM        Sales S
GROUP BY  S.Product_Id
```

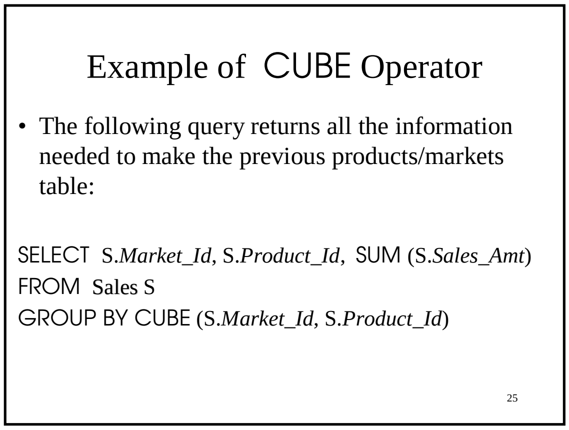
- For the column totals (aggregation on time and products)

```
SELECT     S.Market_Id,  SUM (S.Sales)
FROM        Sales S
GROUP BY  S.Market_Id
```



Definition of the CUBE Operator

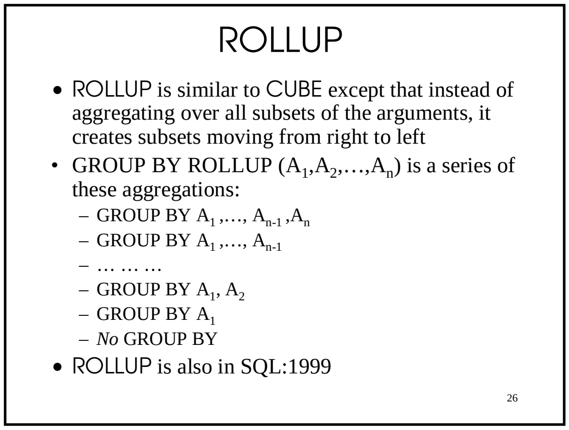
- Doing these three queries is wasteful
  - The first does much of the work of the other two: if we could save that result and aggregate over *Market_Id* and *Product_Id*, we could compute the other queries more efficiently
- The CUBE clause is part of SQL:1999
  - GROUP BY CUBE (v1, v2, …, vn)
  - Equivalent to a collection of GROUP BYs, one for each of the 2^n subsets of v1, v2, …, vn



Example of CUBE Operator

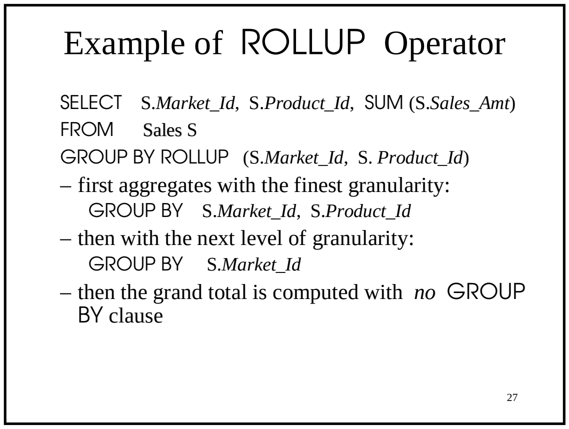
- The following query returns all the information needed to make the previous products/markets table:

```
SELECT  S.Market_Id, S.Product_Id,  SUM (S.Sales_Amt)
FROM  Sales S
GROUP BY CUBE (S.Market_Id, S.Product_Id)
```



ROLLUP

- ROLLUP is similar to CUBE except that instead of aggregating over all subsets of the arguments, it creates subsets moving from right to left
- GROUP BY ROLLUP (A_1,A_2,…,A_n) is a series of these aggregations:
  - GROUP BY A_1 ,…, A_{n-1} ,A_n
  - GROUP BY A_1 ,…, A_{n-1}
  - … … …
  - GROUP BY A_1, A_2
  - GROUP BY A_1
  - *No* GROUP BY
- ROLLUP is also in SQL:1999



Example of ROLLUP Operator

```
SELECT    S.Market_Id,  S.Product_Id,  SUM (S.Sales_Amt)
FROM      Sales S
GROUP BY ROLLUP   (S.Market_Id,  S. Product_Id)
```

– first aggregates with the finest granularity:
GROUP BY   S.*Market_Id*, S.*Product_Id*

– then with the next level of granularity:
GROUP BY   S.*Market_Id*

– then the grand total is computed with *no* GROUP BY clause

ROLLUP vs. CUBE

- The same query with CUBE:
  - first aggregates with the finest granularity:

    GROUP BY S.*Market_Id*, S.*Product_Id*
  - then with the next level of granularity:

    GROUP BY S.*Market_Id*

    and

    GROUP BY S.*Product_Id*
  - then the grand total with *no* GROUP BY

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Materialized Views

The CUBE operator is often used to precompute aggregations on all dimensions of a fact table and then save them as a *materialized views* to speed up future queries

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ROLAP and MOLAP

- Relational OLAP: ROLAP
  - OLAP data is stored in a relational database as previously described. Data cube is a conceptual view – way to *think about* a fact table
- Multidimensional OLAP: MOLAP
  - Vendor provides an OLAP server that *implements* a fact table as a data cube using a special multi-dimensional (non-relational) data structure

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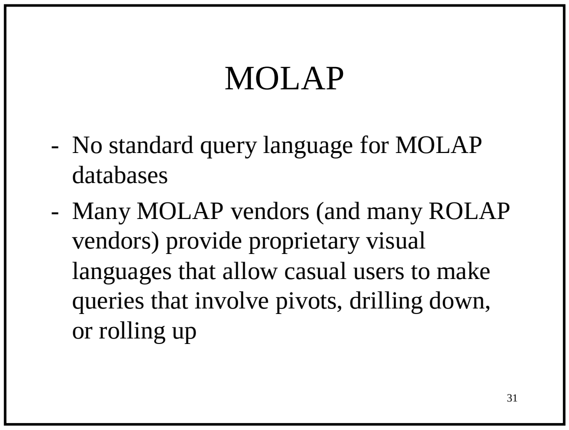

MOLAP

- No standard query language for MOLAP databases
- Many MOLAP vendors (and many ROLAP vendors) provide proprietary visual languages that allow casual users to make queries that involve pivots, drilling down, or rolling up

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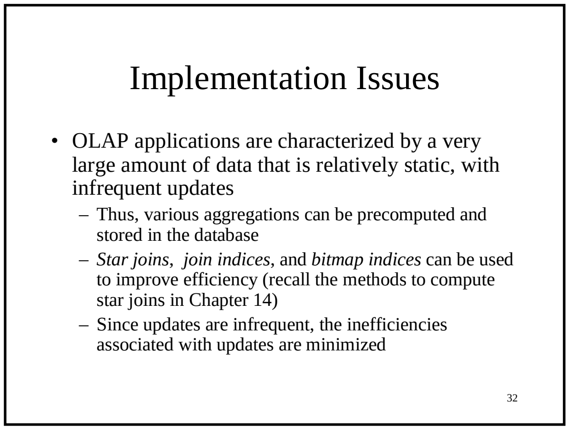

Implementation Issues

- OLAP applications are characterized by a very large amount of data that is relatively static, with infrequent updates
  - Thus, various aggregations can be precomputed and stored in the database
  - *Star joins*, *join indices*, and *bitmap indices* can be used to improve efficiency (recall the methods to compute star joins in Chapter 14)
  - Since updates are infrequent, the inefficiencies associated with updates are minimized

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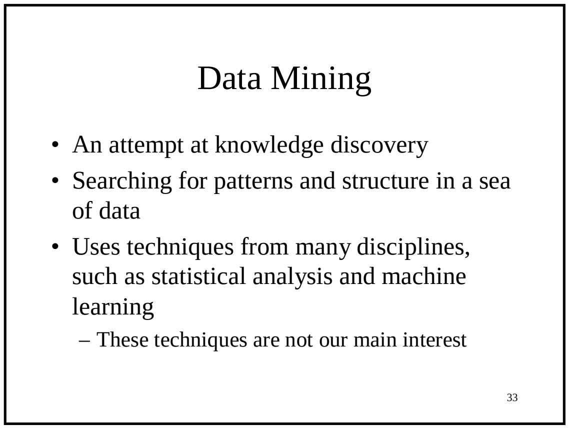

Data Mining

- An attempt at knowledge discovery
- Searching for patterns and structure in a sea of data
- Uses techniques from many disciplines, such as statistical analysis and machine learning
  - These techniques are not our main interest

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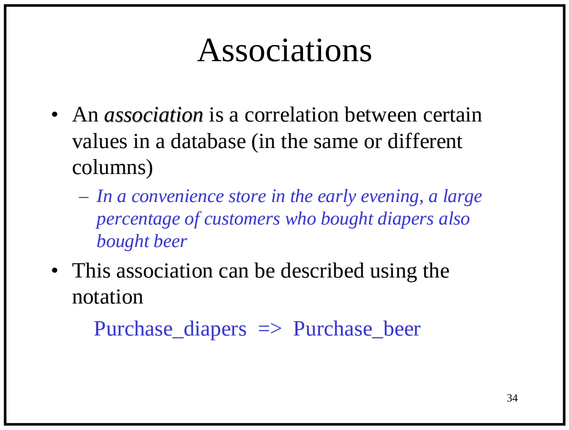
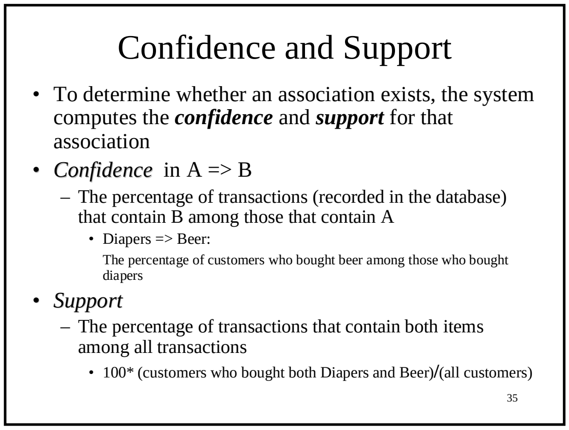


Associations

- An *association* is a correlation between certain values in a database (in the same or different columns)
  - *In a convenience store in the early evening, a large percentage of customers who bought diapers also bought beer*
- This association can be described using the notation

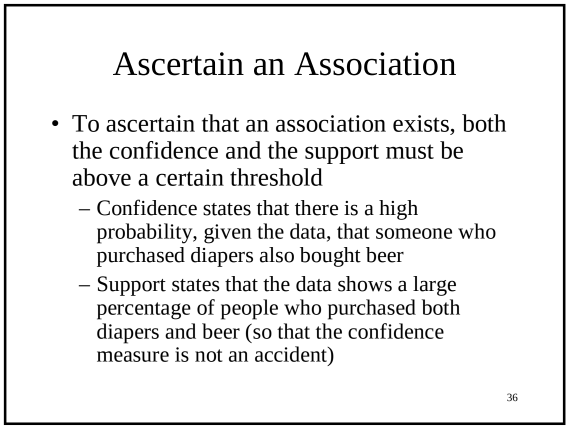
Purchase_diapers => Purchase_beer



Confidence and Support

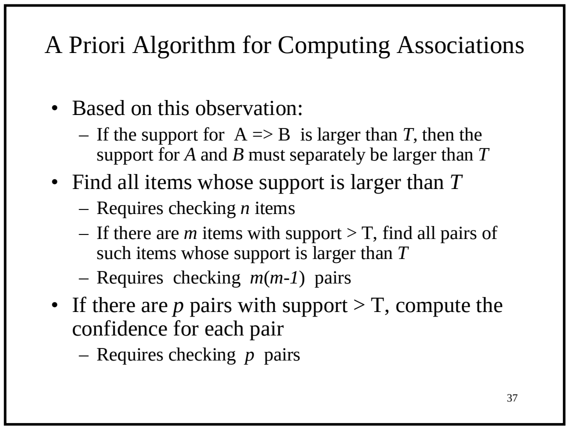
- To determine whether an association exists, the system computes the ***confidence*** and ***support*** for that association
- *Confidence* in A => B
  - The percentage of transactions (recorded in the database) that contain B among those that contain A
    - Diapers => Beer:

      The percentage of customers who bought beer among those who bought diapers
- *Support*
  - The percentage of transactions that contain both items among all transactions
    - 100* (customers who bought both Diapers and Beer)/(all customers)



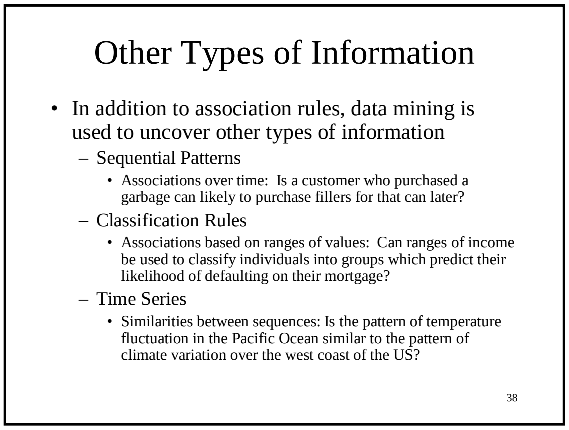
Ascertain an Association

- To ascertain that an association exists, both the confidence and the support must be above a certain threshold
  - Confidence states that there is a high probability, given the data, that someone who purchased diapers also bought beer
  - Support states that the data shows a large percentage of people who purchased both diapers and beer (so that the confidence measure is not an accident)



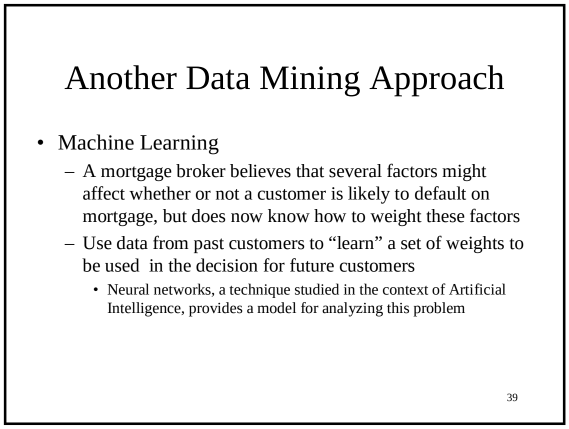
A Priori Algorithm for Computing Associations

- Based on this observation:
  - – If the support for A => B is larger than *T*, then the support for *A* and *B* must separately be larger than *T*
- Find all items whose support is larger than *T*
  - – Requires checking *n* items
  - – If there are *m* items with support > T, find all pairs of such items whose support is larger than *T*
  - – Requires checking *m*(*m-1*) pairs
- If there are *p* pairs with support > T, compute the confidence for each pair
  - – Requires checking *p* pairs



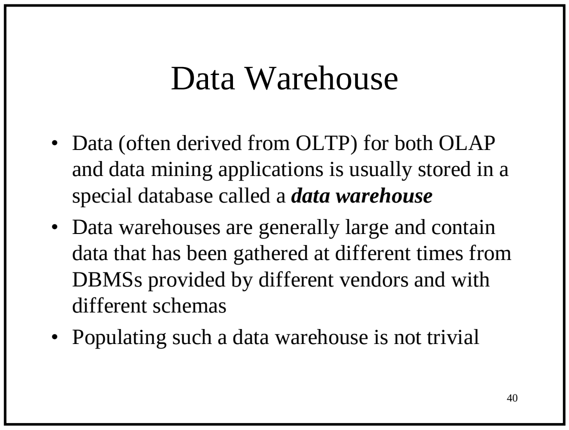
Other Types of Information

- In addition to association rules, data mining is used to uncover other types of information
  - – Sequential Patterns
    - Associations over time: Is a customer who purchased a garbage can likely to purchase fillers for that can later?
  - – Classification Rules
    - Associations based on ranges of values: Can ranges of income be used to classify individuals into groups which predict their likelihood of defaulting on their mortgage?
  - – Time Series
    - Similarities between sequences: Is the pattern of temperature fluctuation in the Pacific Ocean similar to the pattern of climate variation over the west coast of the US?



Another Data Mining Approach

- Machine Learning
  - – A mortgage broker believes that several factors might affect whether or not a customer is likely to default on mortgage, but does now know how to weight these factors
  - – Use data from past customers to “learn” a set of weights to be used in the decision for future customers
    - Neural networks, a technique studied in the context of Artificial Intelligence, provides a model for analyzing this problem



Data Warehouse

- Data (often derived from OLTP) for both OLAP and data mining applications is usually stored in a special database called a ***data warehouse***
- Data warehouses are generally large and contain data that has been gathered at different times from DBMSs provided by different vendors and with different schemas
- Populating such a data warehouse is not trivial

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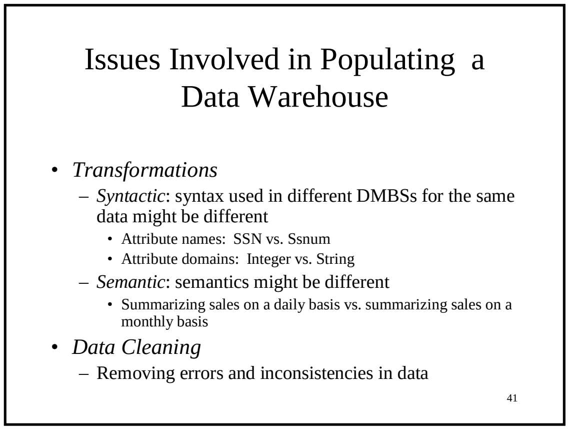

Issues Involved in Populating a Data Warehouse

- *Transformations*
  - *Syntactic*: syntax used in different DMBSs for the same data might be different
    - Attribute names: SSN vs. Ssnum
    - Attribute domains: Integer vs. String
  - *Semantic*: semantics might be different
    - Summarizing sales on a daily basis vs. summarizing sales on a monthly basis
- *Data Cleaning*
  - Removing errors and inconsistencies in data

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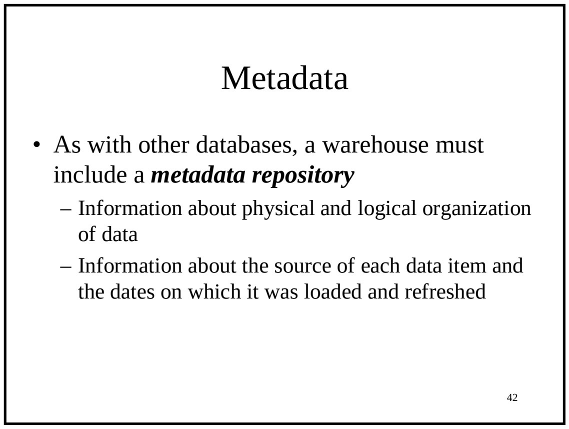

Metadata

- As with other databases, a warehouse must include a ***metadata repository***
  - Information about physical and logical organization of data
  - Information about the source of each data item and the dates on which it was loaded and refreshed

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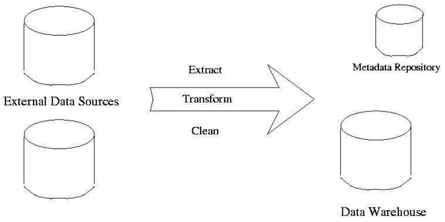
Incremental Updates

- The large volume of data in a data warehouse makes loading and updating a significant task
- For efficiency, updating is usually incremental
  - Different parts are updated at different times
- Incremental updates might result in the database being in an inconsistent state
  - Usually not important because queries involve only statistical summaries of data, which are not greatly affected by such inconsistencies

Loading Data into A Data Warehouse



External Data Sources

Extract

Transform

Clean

Metadata Repository

Data Warehouse