On-Line Application Processing

Warehousing

Data Cubes

Data Mining

Overview

- Traditional database systems are tuned to many, small, simple queries.
- Some new applications use fewer, more time-consuming, *analytic* queries.
- New architectures have been developed to handle analytic queries efficiently.

The Data Warehouse

- The most common form of data integration.
  - Copy sources into a single DB (*warehouse*) and try to keep it up-to-date.
  - Usual method: periodic reconstruction of the warehouse, perhaps overnight.
  - Frequently essential for analytic queries.

OLTP

- Most database operations involve *On-Line Transaction Processing* (OTLP).
  - Short, simple, frequent queries and/or modifications, each involving a small number of tuples.
  - Examples: Answering queries from a Web interface, sales at cash registers, selling airline tickets.

OLAP

- *On-Line Application Processing* (OLAP, or "analytic") queries are, typically:
  - Few, but complex queries --- may run for hours.
  - Queries do not depend on having an absolutely up-to-date database.

OLAP Examples

1. Amazon analyzes purchases by its customers to come up with an individual screen with products of likely interest to the customer.
2. Analysts at Wal-Mart look for items with increasing sales in some region.
    - Use empty trucks to move merchandise between stores.

Common Architecture

- Databases at store branches handle OLTP.
- Local store databases copied to a central warehouse overnight.
- Analysts use the warehouse for OLAP.

Star Schemas

- A *star schema* is a common organization for data at a warehouse. It consists of:
  1. *Fact table* : a very large accumulation of facts such as sales.
     - Often "insert-only."
  2. *Dimension tables* : smaller, generally static information about the entities involved in the facts.

Example: Star Schema

- Suppose we want to record in a warehouse information about every beer sale: the bar, the brand of beer, the drinker who bought the beer, the day, the time, and the price charged.
- The fact table is a relation:

Sales(bar, beer, drinker, day, time, price)

Example -- Continued

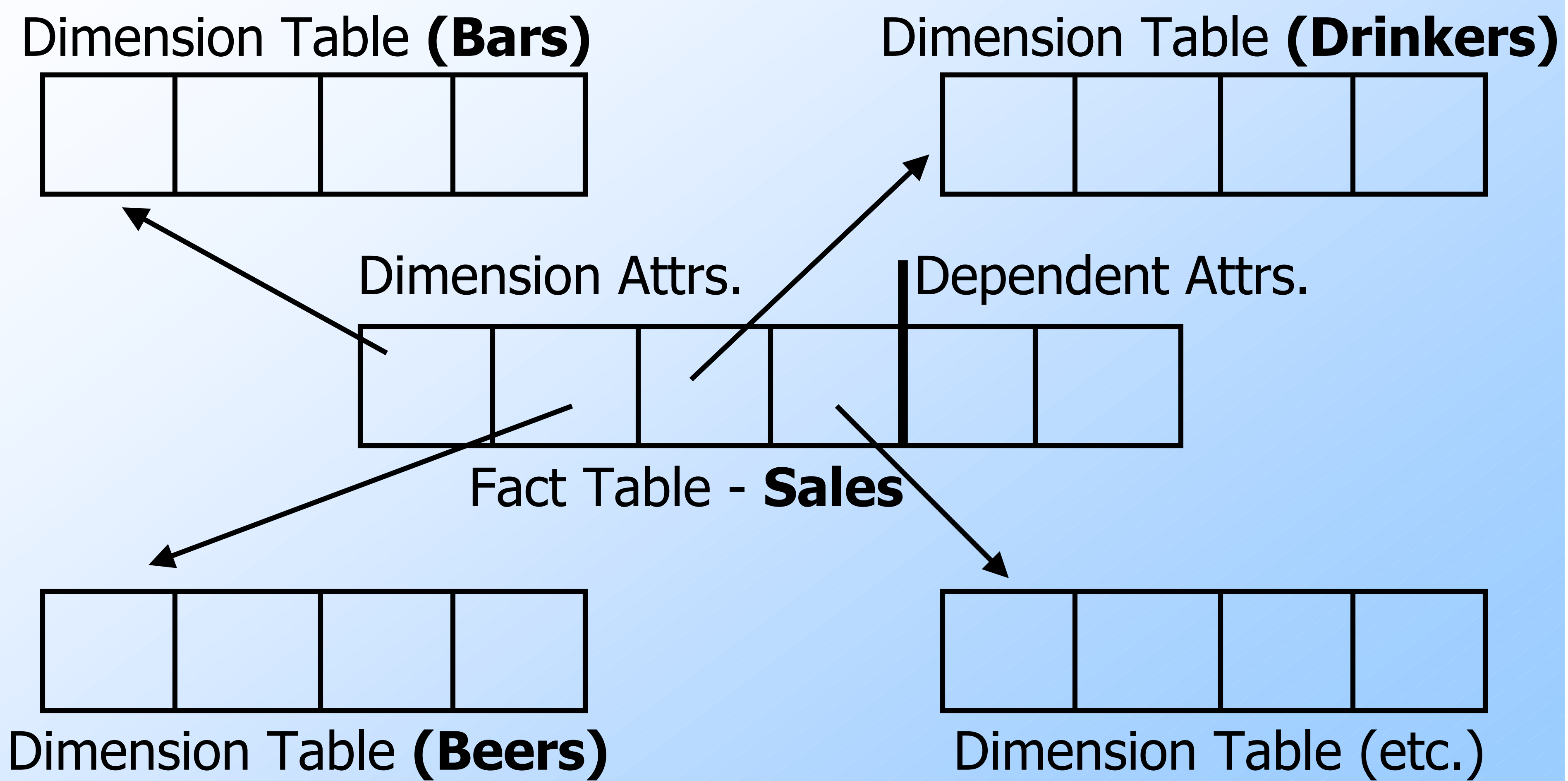
- The dimension tables include information about the bar, beer, and drinker "dimensions":

  Bars(bar, addr, license)

  Beers(beer, manf)

  Drinkers(drinker, addr, phone)

Visualization – Star Schema



Dimensions and Dependent Attributes

- Two classes of fact-table attributes:
  1. *Dimension attributes* : the key of a dimension table.
  2. *Dependent attributes* : a value determined by the dimension attributes of the tuple.

Example: Dependent Attribute

- price is the dependent attribute of our example Sales relation.
- It is determined by the combination of dimension attributes: bar, beer, drinker, and the time (combination of day and time-of-day attributes).

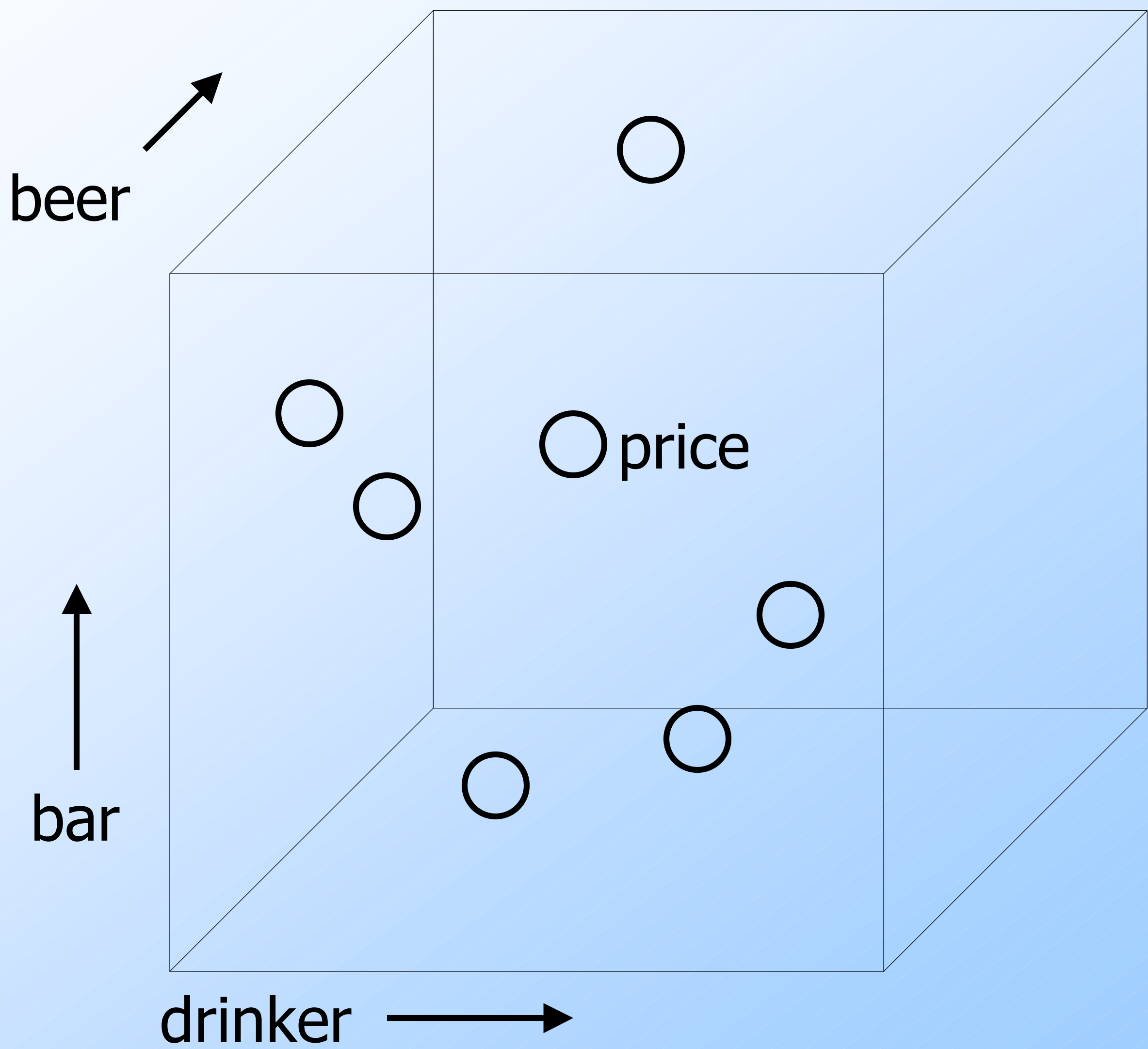
Approaches to Building Warehouses

1. *ROLAP* = "relational OLAP": Tune a relational DBMS to support star schemas.
2. *MOLAP* = "multidimensional OLAP": Use a specialized DBMS with a model such as the "data cube."

MOLAP and Data Cubes

- Keys of dimension tables are the dimensions of a hypercube.
  - Example: for the Sales data, the four dimensions are bar, beer, drinker, and time.
- Dependent attributes (e.g., price) appear at the points of the cube.

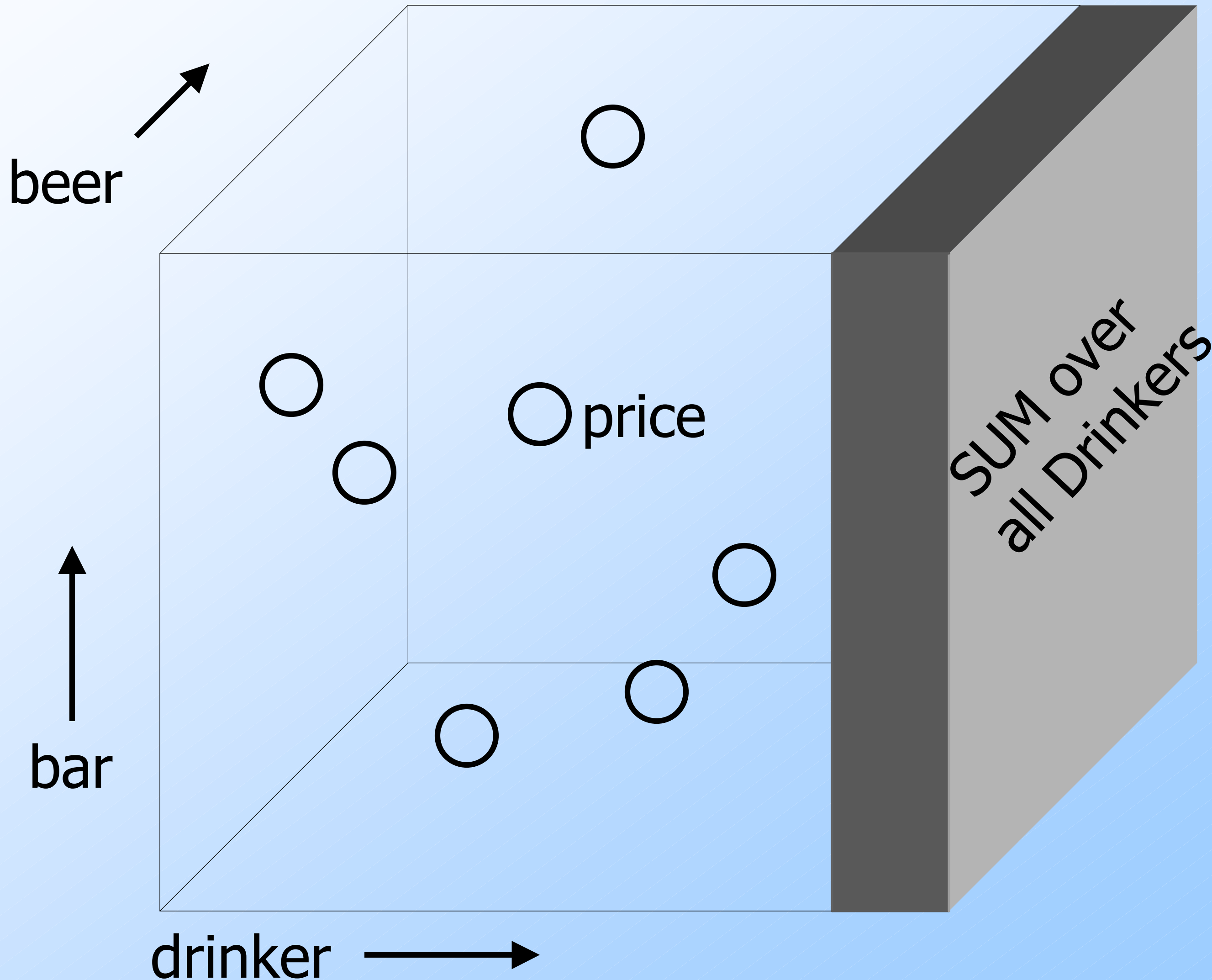
Visualization -- Data Cubes



Marginals

- The data cube also includes aggregation (typically SUM) along the margins of the cube.
- The *marginals* include aggregations over one dimension, two dimensions,...

Visualization --- Data Cube w/Aggregation



Example: Marginals

- Our 4-dimensional Sales cube includes the sum of price over each bar, each beer, each drinker, and each time unit (perhaps days).
- It would also have the sum of price over all bar-beer pairs, all bar-drinker-day triples,…

Structure of the Cube

- Think of each dimension as having an additional value *.
- A point with one or more *'s in its coordinates aggregates over the dimensions with the *'s.
- Example: Sales("Joe's Bar", "Bud", *, *) holds the sum, over all drinkers and all time, of the Bud consumed at Joe's.

Drill-Down

- *Drill-down* = "de-aggregate" = break an aggregate into its constituents.
- Example: having determined that Joe's Bar sells very few Anheuser-Busch beers, break down his sales by particular A.-B. beer.

Roll-Up

- *Roll-up* = aggregate along one or more dimensions.
- Example: given a table of how much Bud each drinker consumes at each bar, roll it up into a table giving total amount of Bud consumed by each drinker.

Example: Roll Up and Drill Down

$ of Anheuser-Busch by drinker/bar

	Jim	Bob	Mary
Joe's Bar	45	33	30
Nut-House	50	36	42
Blue Chalk	38	31	40

Roll up by Bar

$ of A-B / drinker

Jim	Bob	Mary
133	100	112

Drill down by Beer

$ of A-B Beers / drinker

	Jim	Bob	Mary
Bud	40	29	40
M'lob	45	31	37
Bud Light	48	40	35

Data Mining

- *Data mining* is a popular term for queries that summarize big data sets in useful ways.
- Examples:
  1. Clustering all Web pages by topic.
  2. Finding characteristics of fraudulent credit-card use.

Course Plug

- Winter 2007-8: Anand Rajaraman and Jeff Ullman are offering CS345A *Data Mining*.
  - MW 4:15-5:30, Herrin, T185.

Market-Basket Data

- An important form of mining from relational data involves *market baskets* = sets of "items" that are purchased together as a customer leaves a store.
- Summary of basket data is *frequent itemsets* = sets of items that often appear together in baskets.

Example: Market Baskets

- If people often buy hamburger and ketchup together, the store can:
  1. Put hamburger and ketchup near each other and put potato chips between.
  2. Run a sale on hamburger and raise the price of ketchup.

Finding Frequent Pairs

- The simplest case is when we only want to find "frequent pairs" of items.
- Assume data is in a relation Baskets(basket, item).
- The *support threshold* s is the minimum number of baskets in which a pair appears before we are interested.

Frequent Pairs in SQL

```
SELECT b1.item, b2.item
FROM Baskets b1, Baskets b2
WHERE b1.basket = b2.basket
  AND b1.item < b2.item
GROUP BY b1.item, b2.item
HAVING COUNT(*) >= s;
```

Look for two Basket tuples with the same basket and different items. First item must precede second, so we don't count the same pair twice.

Create a group for each pair of items that appears in at least one basket.

Throw away pairs of items that do not appear at least *s* times.

A-Priori Trick – (1)

- Straightforward implementation involves a join of a huge Baskets relation with itself.
- The *a-priori algorithm* speeds the query by recognizing that a pair of items $\{i, j\}$ cannot have support s unless both $\{i\}$ and $\{j\}$ do.

A-Priori Trick – (2)

- Use a materialized view to hold only information about frequent items.

```
INSERT INTO Baskets1(basket, item)
SELECT * FROM Baskets
WHERE item IN (
  SELECT item FROM Baskets
  GROUP BY item
  HAVING COUNT(*) >= s
);
```

Items that appear in at least *s* baskets.

A-Priori Algorithm

1. Materialize the view Baskets1.
2. Run the obvious query, but on Baskets1 instead of Baskets.

- Computing Baskets1 is cheap, since it doesn't involve a join.
- Baskets1 *probably* has many fewer tuples than Baskets.
  - Running time shrinks with the *square* of the number of tuples involved in the join.

Example: A-Priori

- Suppose:
  1. A supermarket sells 10,000 items.
  2. The average basket has 10 items.
  3. The support threshold is 1% of the baskets.
- At most 1/10 of the items can be frequent.
- *Probably*, the minority of items in one basket are frequent -> factor 4 speedup.