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* (OLTP).

- 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 data 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.
   - e.g., information about products.

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":

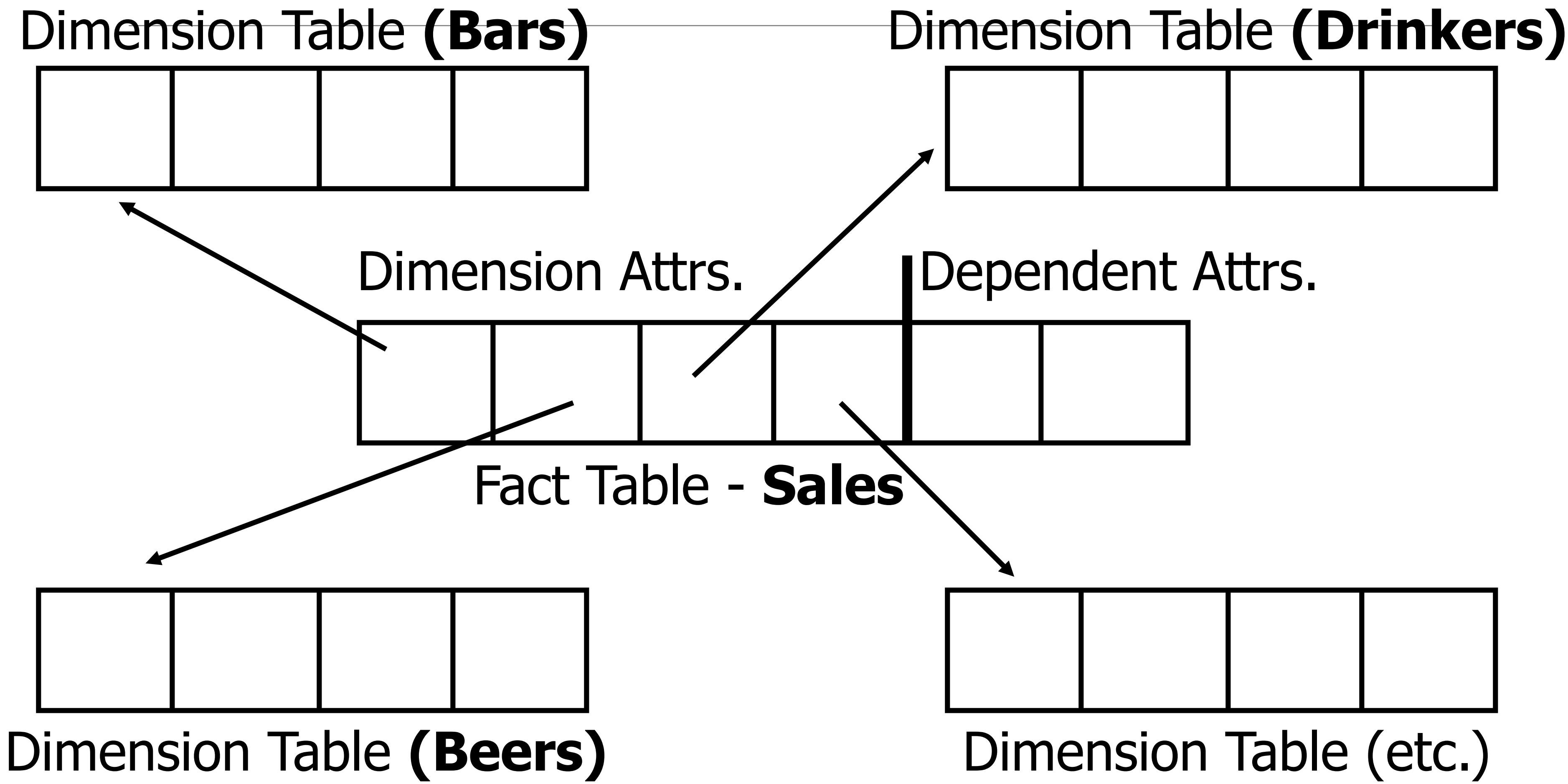
Bars(bar, addr, license)

Beers(beer, manf)

Drinkers(drinker, addr, phone)

...

Visualization – Star Schema



Dimensions and Dependent Attributes

Two classes of fact-table attributes:

1. *Dimension attributes* : the foreign 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."

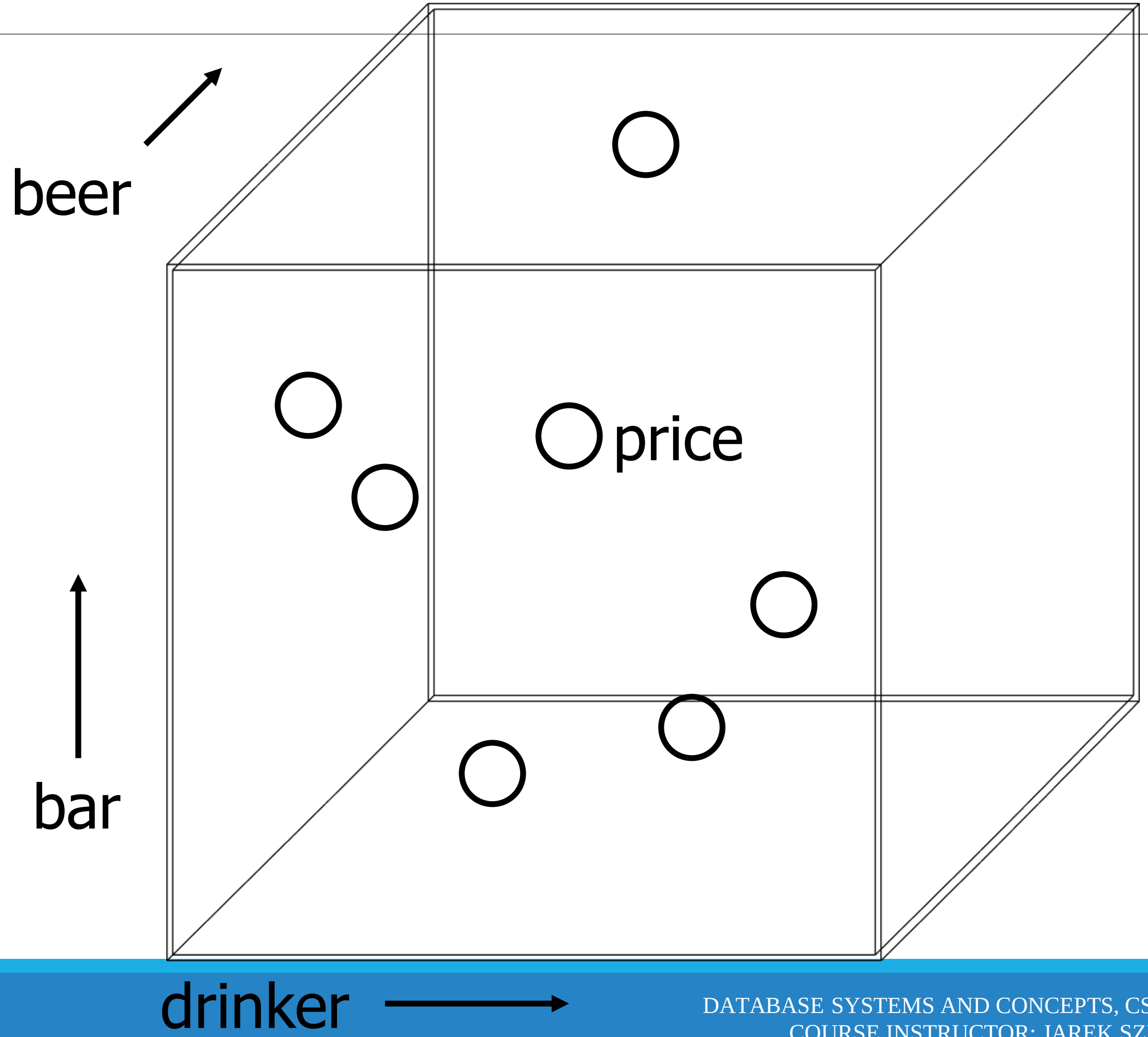
MOLAP and Data Cubes

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

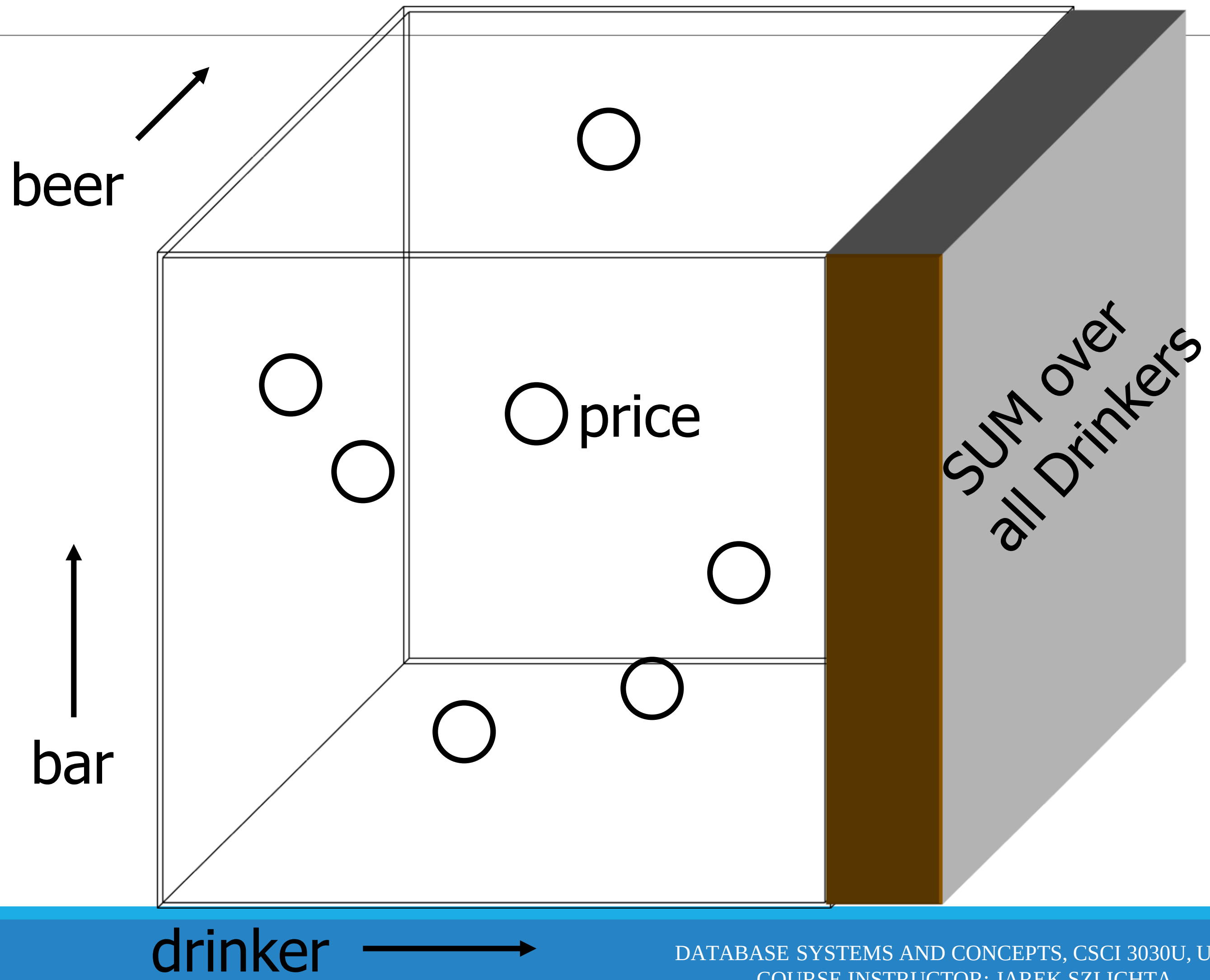


Marginals

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 (at all bars).

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.

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.

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.

Factor 4 speedup.

Course Plug

Big Data Analytics – Winter 2018

Actions

Read chapters: Information Integration (21.1, 21.2) and Data Mining (22.1, 22.2).