Data Warehousing and Decision Support

CS634
Class 22, Apr 25, 2016

Slides based on "Database Management Systems" 3rd ed, Ramakrishnan and Gehrke, Chapter 25

Introduction

- Increasingly, organizations are analyzing current and historical data to identify useful patterns and support business strategies.
- Emphasis is on complex, interactive, exploratory analysis of very large datasets created by integrating data from across all parts of an enterprise; data is fairly static.
  - Contrast such **Data Warehousing** and **On-Line Analytic Processing (OLAP)** with traditional **On-line Transaction Processing (OLTP):** mostly long queries, instead of the short update Xacts of OLTP.
  - These are both using "structured data" that can be fairly easily loaded into a database

Structured vs. Unstructured Data

- So far, we have been working with structured data
- Structured data:
  - Entities with attributes, each fitting a SQL data type
  - Relationships
  - Each row of data is precious
  - Loads into relational tables, long-term storage
  - Can be huge
- Unstructured data, realm of "big data"
  - Often doesn't fit into E/R model, too sloppy
  - Each piece of data is not precious—it's statistical
  - Sometimes just processed and thrown away
  - No permanent specialized repository, maybe saved in files
  - Can be really huge

Bigness of Data

Big data warehouses, all on Teradata systems

See http://gigaom.com/2013/03/27/why-apple-ebay-and-walmart-have-some-of-the-biggest-data-warehouses-youve-ever-seen

- Biggest DW: Walmart, passed 1TB in 1992, 2.8 PB (petabytes) = 2800 TB in 2008, 30 PB in 2014, growing…
- eBay: 9 PB DW in 2013, also has 40 PB of big data
- Apple: multiple-PB DW

- Big data:
  - Usually over 50TB, can't fit on one machine
  - Is judged by "velocity" as well as size
  - Google: processed 24 **PB** of **data** per day in 2009, invented Map-Reduce, published 2004

Teradata

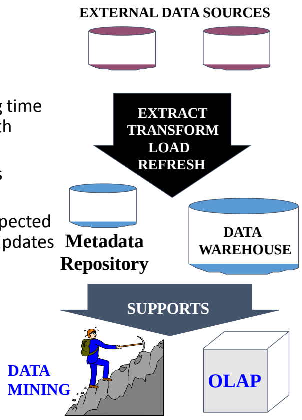
- Teradata provides a relational database with ANSI compliant SQL, targeted to data warehouses
- Proprietary, expensive ($millions)
- Uses a shared-nothing architecture on many independent nodes
- Partitioning by rows or (more recently) columns
- Scales up well: add node, add network bandwidth for it

Three Complementary Trends

- Data Warehousing: Consolidate data from many sources in one large repository (relational database).
  - Loading, periodic synchronization of replicas.
  - Semantic integration, Data cleaning of data on way in
  - Both simple and complex SQL queries and views.
- OLAP:
  - Complex SQL queries (in effect, but not composed by users).
  - Queries based on spreadsheet-style operations and "multidimensional" view of data.
  - Interactive and "online" queries.
- Data Mining: Exploratory search for interesting trends and anomalies.

Data Warehousing

- Integrated data spanning long time periods, often augmented with summary information.
- Several gigabytes to terabytes common, now petabytes too.
- Interactive response times expected for complex queries; ad-hoc updates uncommon.
- Read-mostly data



Warehousing Issues

- Semantic Integration: When getting data from multiple sources, must eliminate mismatches, e.g., different currencies, schemas.
- Heterogeneous Sources: Must access data from a variety of source formats and repositories.
  - Replication capabilities can be exploited here.
- Load, Refresh, Purge: Must load data, periodically refresh it, and purge too-old data.
- Metadata Management: Must keep track of source (lineage) loading time, and other information for all data in the warehouse.

OLAP: Multidimensional data model

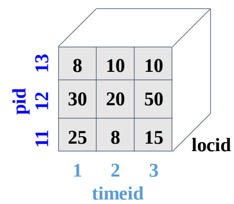
- Example: sales data
- Dimensions: Product, Location, Time
- A measure is a numeric value like sales we want to understand in terms of the dimensions
- Example measure: dollar sales value "sales"
- Example data point (one row of fact/cube table):
  - Sales = 25 for pid=1, timeid=1, locid=1 is the sum of sales for that day, in that location, for that product
  - Pid=1: details in Product table
  - Locid = 1: details in Location table
- Note aggregation here: sum of sales is most detailed data

Multidimensional Data Model

SalesCube(pid, timeid, locid, sales)

- Collection of numeric measures, which depend on a set of dimensions.
  - E.g., measure **sales**, dimensions **Product** (key: pid), **Location** (locid), and **Time** (timeid).
  - Full table, pg. 851

Slice locid=1 is shown:



pid	timeid	locid	sales
11	1	1	25
11	2	1	8
11	3	1	15
12	1	1	30
12	2	1	20
12	3	1	50
13	1	1	8
13	2	1	10
13	3	1	10
11	1	2	35

. . .

Granularity of Data

- Example of last slide uses time at granularity of days
- Individual transactions (sales at cashier) have been added together to make one row in this table
- Note: "measures" can always be aggregated
- Current hardware can handle more data
- Typical data warehouses hold the original transaction data
- So such a fact table has more columns, for example
- dateid, timeofday, prodid, storeid, txnid, clerkid, sales, …

Data Warehouse vs. Data for OLAP

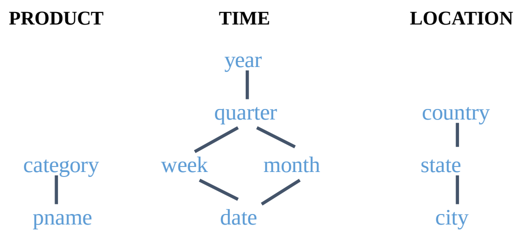
- Current DW fact table is huge, with individual transactions, large number of dimensions
- Can only use a subset of this for OLAP, because of explosion of cells
- Take DW fact table, roll up to days (say), drop less important columns, get much smaller data for OLAP
- Load data into OLAP, another tool.
- Table on pg. 851 is a cube table, not a DW fact table
- Can think of OLAP as a cache of most important aggregates of DW tables

MOLAP vs ROLAP vs HOLAP

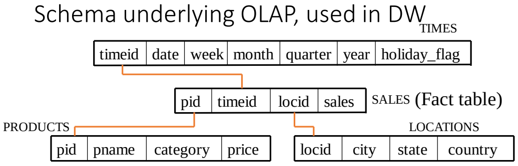
- Multidimensional data can be stored physically in a (disk-resident, persistent) array; called MOLAP systems. Alternatively, can store as a relation; called ROLAP systems;
- hybrid of these = HOLAP, current systems
- The main relation, which relates dimensions to a measure, is called the fact table. Each dimension can have additional attributes and an associated dimension table.
  - E.g., **Products(pid, pname, category,price)**
  - Fact tables are *much* larger than dimensional tables.

Dimension Hierarchies: OLAP, DW

- For each dimension, the set of values can be organized in a hierarchy:



Schema underlying OLAP, used in DW



- Fact/cube table in BCNF; dimension tables not normalized.
  - Dimension tables are small; updates/inserts/deletes are rare. So, anomalies less important than good query performance.
- This kind of schema is very common in DW and OLAP, and is called a star schema; computing the join of all these relations is called a star join.
- Note: in OLAP, this is not what the user sees, it's hidden underneath
- In DW, this is the basic setup, but usually with more dimensions
- Here only one measure, sales, but can have several

OLAP (and DW) Queries

- Influenced by SQL and by spreadsheets.
- A common operation is to aggregate a measure over one or more dimensions.
  - Find total sales.
  - Find total sales for each city, or for each state.
  - Find top five products ranked by total sales.
- Roll-up: Aggregating at different levels of a dimension hierarchy.
  - E.g., Given total sales by city, we can roll-up to get sales by state.

OLAP Queries: MDX (**Multidimensional Expressions**)

- Originally a Microsoft SQL Server project, but now supported widely in the OLAP industry: Oracle, SAS, SAP, Teradata on server side, as well as Microsoft. Allows client programs to specify OLAP datasets.
- Example from Wikipedia

```
SELECT
   { [Measures].[Store Sales] } ON COLUMNS,
   { [Date].[2002], [Date].[2003] } ON ROWS
FROM Sales
WHERE ( [Store].[USA].[CA] )
```

- The SELECT clause sets the query axes as the Store Sales member of the Measures dimension, and the 2002 and 2003 members of the Date dimension.
- The FROM clause indicates that the data source is the Sales cube.
- The WHERE clause defines the "slicer axis" as the California member of the Store dimension.

OLAP Queries

- Drill-down: The inverse of roll-up: go from sum to details that were added up before
  - E.g., Given total sales by state, can drill-down to get total sales by county.
  - Drill down again, see total sales by city
  - E.g., Can also drill-down on different dimension to get total sales by product for each state.

OLAP Queries: cross-tabs

With relational DBs, we are used to tables with column names across the top, rows of data.

With OLAP, a spreadsheet-like representation is common,

Called a cross-tabulation:

- One dimension horizontally
- Another vertically

	WI	CA	Total
1995	63	81	144
1996	38	107	145
1997	75	35	110
Total	176	223	339

OLAP Queries: Pivoting

- Example cross-tabulation:

	WI	CA	Total
1995	63	81	144
1996	38	107	145
1997	75	35	110
Total	176	223	339

- Pivoting: switching dimensions on axes, or choosing what dimensions to show on axes
- Switching dimensions means pivoting around a point in the upper-left-hand corner
  - End up with "1995 1996 1997 Total" across top,
  - "WI CA Total" down the side

Oracle 11 supports cross-tabs display

```
select * from (
   select times_purchased, state_code
   from customers t
) pivot (
  count(state_code)
  for state_code in ('NY','CT','NJ','FL','MO')
) order by times_purchased
```

Here is the output:

```
TIMES_PURCHASED 'NY'  'CT'  'NJ'   'FL'    'MO'
--------------- ---------- ---------- ---------- ---------- --
       0      16601  90     0      0      0
       1      33048  165    0      0      0
       2      33151  179    0      0      0
       3      32978  173    0      0      0
       4      33109  173    0      1      0
... and so on ...
  (We have Oracle 10, unfortunately)
```

SQL Queries for cross-tab entries

	WI	CA	Total
1995	63	81	144
1996	38	107	145
1997	75	35	110
Total	176	223	339

The cross-tabulation values can be computed using a collection of SQL queries:

```
SELECT SUM(S.sales)
FROM    Sales S, Times T, Locations L
WHERE  S.timeid=T.timeid AND S.timeid=L.timeid
GROUP BY T.year, L.state
```

```
SELECT SUM(S.sales)
FROM    Sales S, Times T
WHERE  S.timeid=T.timeid
GROUP BY T.year
```

```
SELECT SUM(S.sales)
FROM    Sales S, Location L
WHERE  S.timeid=L.timeid
GROUP BY L.state
```

The CUBE Operator

- Generalizing the previous example, if there are k dimensions, we have 2^k possible SQL GROUP BY queries that can be generated through pivoting on a subset of dimensions.
- CUBE Query, pg. 857

```
SELECT T.year, L.state, SUM(S.sales)
FROM    Sales S, Times T, Locations L
WHERE S.timeid = T.timeid and S.locid = L.locid
GROUP BY CUBE (T.year, L.state)
```

- Equivalent to rolling up Sales on all eight subsets of the set {pid, locid, timeid}; each roll-up corresponds to an SQL query of the form:

```
SELECT SUM(S.sales)
FROM    Sales S
GROUP BY grouping-list
```

Oracle 10 supports CUBE queries

```
select t.year, s.store_state, sum(dollar_sales)
from salesfact f, times t, store s
where f.time_key = t.time_key and s.store_key = f.store_key
group by cube(t.year, s.store_state);
```

```
YEAR     STORE_STATE          SUM(DOLLAR_SALES)
--------   -------------------- ----------------
                                 781403.59
           AZ                     35684
           CA                     77420.82
           CO                     38335.26  (some rows deleted)
            TX                     40886.54
           WA                     39540.16
  1994                            396355.76
  1994      AZ                   17903.04
  1994      CA                   38966.54
  1994      CO                   17870.33
  1994      DC                   20901.18   … from dbs2 output
```

DW data → OLAP

- The CUBE query can do the roll-ups on DW data needed for OLAP

Excel is the champ at OLAP queries

- Next time will do Excel pivot table demo
- Based on video by Minder Chen of UCI (Cal state U/Channel Islands)
- https://www.youtube.com/watch?v=eGhjklYyv6Y
- Setup:
- His MS Access database with star schema for sales
- Create view of fact joined with desired dimension data (a star join)
- Point Excel at this big view, ask it to create pivot table
- Pivot table: drill down, roll up, pivot, …

Excel can use Oracle data too

- The database from Chen's demo is now in dbs2's Oracle
- We could point Excel to an Oracle view of joined tables.
- How does that work?
- Use ODBC (Open Database Connectivity), older than JDBC, but roughly same idea
  - Provides client API for accessing multiple databases
  - Each database provides a ODBC driver
  - Unfortunately, it's not easy to set up ODBC on a Windows system even though Microsoft invented it
  - Another way: MDX driver to allow Excel to use live Oracle OLAP data
  - http://download.oracle.com/otndocs/products/warehouse/olap/videos/excel_olap_demo/Excel_Demo_for_Web.html

Star queries

- Oracle definition: a query that joins a large (fact) table to a number of small (dimension) tables, with provided WHERE predicates on the dimension tables to reduce the result set to a very small percentage of the fact table
- The select list still has sum(sales), etc., as desired.

```
SELECT store.sales_district,
 time.fiscal_period, SUM(sales.dollar_sales)
 FROM sales, store, time
WHERE sales.store_key = store.store_key AND
 sales.time_key = time.time_key AND
 store.sales_district IN ('San Francisco',
 'Los Angeles') AND time.fiscal_period IN ('3Q95',
 '4Q95', '1Q96')
GROUP BY
 store.sales_district,time.fiscal_period;
```

Star queries

- Oracle: A better way to write the query would be:

(i.e., give the QP a hint on how to do it)

```
SELECT … FROM sales
 WHERE store_key IN
  ( SELECT store_key FROM store
      WHERE sales_district IN ('WEST', 'SOUTHWEST'))
  AND time_key IN
    ( SELECT time_key FROM time
       WHERE quarter IN ('3Q96', '4Q96', '1Q97'))
  AND product_key IN
    ( SELECT product_key FROM product
       WHERE department = 'GROCERY')
  GROUP BY …;
```

- Oracle will rewrite the query this way if you add the STAR_TRANSFORMATION hint to your SQL, or the DBA has set STAR_TRANSFORMATION_ENABLED

Excel can do Star queries

- Recall GROUP BY queries for individual crosstab entries
- A Star query is of this form, plus WHERE clause predicates on dimension tables such as
  - store.sales_district IN ('WEST', 'SOUTHWEST')
  - time.quarter IN ('3Q96', '4Q96', '1Q97')
- Excel allows "filters" on data that correspond to these predicates of the WHERE clause

Indexes related to data warehousing

- New indexing techniques: Bitmap indexes, Join indexes, array representations, compression, precomputation of aggregations, etc.
- E.g., Bitmap index:

Bit-vector: **1 bit for each possible value.**
Many queries can be answered using bit-vector ops!

sex	custid	name	sex	rating	rating
10	112	Joe	M	3	00100
10	115	Ram	M	5	00001
01	119	Sue	F	5	00001
10	112	Woo	M	4	00010

F M

Bitmap Indexes

- A bitmap index uses one bit vector (BV) for each distinct keyval
- The number of bits = #rows
- Example of last slide, 4 rows, 2 columns with bitmap indexes
  - Sex = 'M': BV = 1101
  - Sex = 'F': BV = 0010

  $\}$ Bitmap index for sex column
  - Rating = 3, BV = 1000
  - Rating = 4, BV = 0001
  - Rating = 5, BV = 0110

  $\}$ Bitmap index for rating column
- Underlying idea: it's not hard to convert between a table's row numbers and the row RIDs
- RIDs have file#, page#, row# within page, where file# is fixed for one heap table, and page# ranges from 0 up to some limit.
- For the kind of read-mostly data that bitmap indexes are used, the pages are full, so the RIDs (page#, row# in a certain file) look like (0,0), (0,1), (0,2), (1,0), (1,1), … easily converted to row indexes 0, 1, 2, 3, 4, 5, … and back again

Bitmap Indexes

- Implementation: B+-tree of key values, bitmap for each key
- Size = #values*#rows/8 if not compressed
- Bitmaps can be compressed, done by Oracle and others
- Main restriction: slow row insert/delete, so NG for OLTP
  - But great for data warehouses:
  - Data warehouses are updated only periodically, traditionally
- Low cardinality (#values in column) a clear fit
  - Example: rating, with 10 values
- But in fact, cardinality can be fairly high with compression
- Oracle example: bitmap index on unique column!

Bitmap Indexes

- Oracle: create bitmap index sexx on custs(sex);
- Bitmap indexes can be used with AND and OR predicates
- Example

  Select name from sailors s

  where s.rating = 10 and sex = 'M' or sex = 'F'

  BV1 BV2 BV3

  ResultBV = BV1 & BV2 | BV3
- Each bit on in ResultBV shows a row that satisfies the predicate
- Loop through on-bits, finding rows and output name

Oracle Bitmap index plan

- EXPLAIN PLAN FOR SELECT * FROM t WHERE c1 = 2 AND c2 <> 6 OR c3 BETWEEN 10 AND 20;
-
- EXPLAIN PLAN FOR
- SELECT * FROM t WHERE c1 = 2 AND c2 <> 6 OR c3 BETWEEN 10 AND 20;
- SELECT STATEMENT
- TABLE ACCESS T BY INDEX ROWID
- BITMAP CONVERSION TO ROWID -- get ROWIDs for each on-bit
- BITMAP OR --top level OR
- BITMAP MINUS --to remove null values of c2
- BITMAP MINUS -- to calc c1 = 2 AND c2 <> 6
- BITMAP INDEX C1_IND SINGLE VALUE --c1= 2 BV
- BITMAP INDEX C2_IND SINGLE VALUE --c2 = 6 BV
- BITMAP INDEX C2_IND SINGLE VALUE --c2 = null BV (no not null on col)
- BITMAP MERGE --merge BV's over C3 range
- BITMAP INDEX C3_IND RANGE SCAN

Bitmaps for star schemas, to be continued

- The dimension tables are not large, maybe 100 rows
- Thus the FK columns in the fact table have only 100 values
- Bitmap indexes can pinpoint rows once determined.
- Bitmaps can be AND'd and OR'd
- Example: `time.fiscal_period IN ('3Q95', '4Q95')` matches say 180 days in time table, so 180 FK values in fact's time_key column
- OR together the 180 bitmaps, get a bitmap locating all fact rows that satisfy this predicate