Data Warehousing and Data Mining

CompSci 316

Introduction to Database Systems

Announcements (Tue. Dec. 3)

- Final next Wednesday 9am-12pm, in this room
  - Open-book, open-notes
  - No communication devices
  - Solution to sample final will be posted on Thursday
  - Will cover all materials through Thursday
    - But more focus will be on parts that you already "exercised"
- Sign up for the final project demo!
  - You can still sign up for the in-class demo on Thursday
  - "Regular" demo slot sign-up deadline is this Friday 5pm
- Homework #4 sample solution will be posted by this Thursday

Announcements (Thu. Dec. 5)

- See previous slide for info on the final exam, project demo, and Homework #4 sample solution
- Online course evaluation in ACES
  - Deadline this Sunday 11:59pm

Data integration

- Data resides in many distributed, heterogeneous OLTP (On-Line Transaction Processing) sources
  - Sales, inventory, customer, …
  - NC branch, NY branch, CA branch, …
- Need to support OLAP (On-Line Analytical Processing) over an integrated view of the data
- Possible approaches to integration
  - Eager: integrate in advance and store the integrated data at a central repository called the data warehouse
  - Lazy: integrate on demand; process queries over distributed sources—mediated or federated systems

OLTP versus OLAP

OLTP	OLAP
Mostly updates	Mostly reads
Short, simple transactions	Long, complex queries
Clerical users	Analysts, decision makers
Goal: transaction throughput	Goal: fast queries

Implications on database design and optimization?

OLAP databases do not care much about redundancy

- "Denormalize" tables
- Many, many indexes
- Precomputed query results

Eager versus lazy integration

Eager (warehousing)	Lazy
In advance: before queries	On demand: at query time
Copy data from sources	Leave data at sources
☞ Answer could be stale	☞ Answer is more up-to-date
☞ Need to maintain consistency	☞ No need to maintain consistency
☞ Query processing is local to the warehouse ▪ Faster ▪ Can operate when sources are unavailable	☞ Sources participate in query processing ▪ Slower ▪ Interferes with local processing

Maintaining a data warehouse

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- The "ETL" process
  - Extraction: extract relevant data and/or changes from sources
  - Transformation: transform data to match the warehouse schema
  - Loading: integrate data/changes into the warehouse
- Approaches
  - Recomputation
    - Easy to implement; just take periodic dumps of the sources, say, every night
    - What if there is no "night," e.g., a global organization?
    - What if recomputation takes more than a day?
  - Incremental maintenance
    - Compute and apply only incremental changes
    - Fast if changes are small
    - Not easy to do for complicated transformations
    - Need to detect incremental changes at the sources

"Star" schema of a data warehouse

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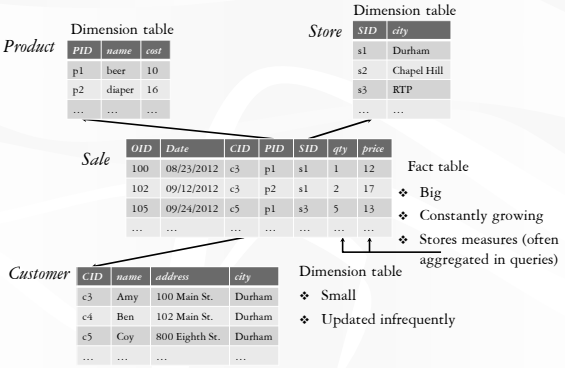

Data cube

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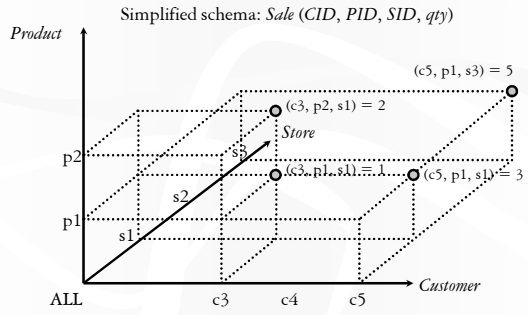
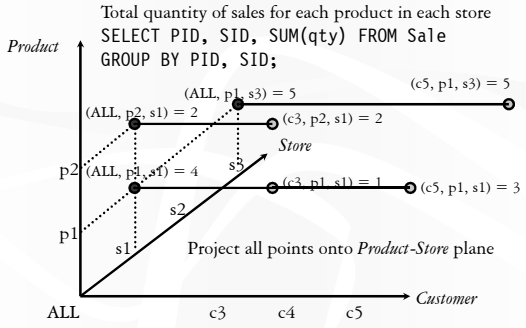


Completing the cube—plane

10



Completing the cube—axis

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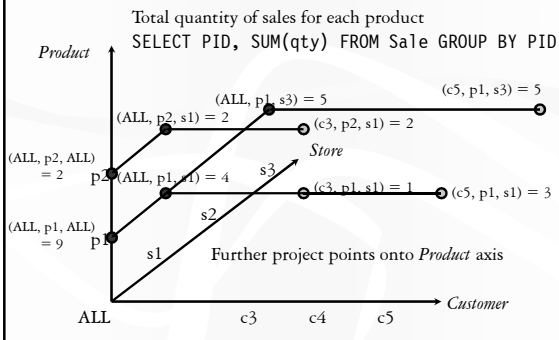

Completing the cube—origin

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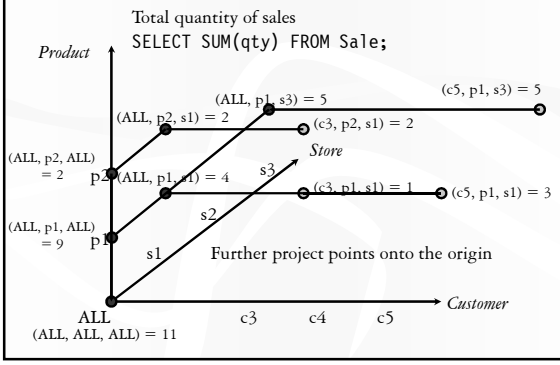

CUBE operator

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- *Sale* (*CID*, *PID*, *SID*, *qty*)
- Proposed SQL extension:
  ```
  SELECT SUM(qty) FROM Sale
  GROUP BY CUBE CID, PID, SID;
  ```
- Output contains:
  - Normal groups produced by GROUP BY
    - (c1, p1, s1, sum), (c1, p2, s3, sum), etc.
  - Groups with one or more ALL's
    - (ALL, p1, s1, sum), (c2, ALL, ALL, sum), (ALL, ALL, ALL, sum), etc.
- Can you write a CUBE query using only GROUP BY's?

Gray et al., "Data Cube: A Relational Aggregation Operator Generalizing Group-By, Cross-Tab, and Sub-Total." *ICDE* 1996

Aggregation lattice

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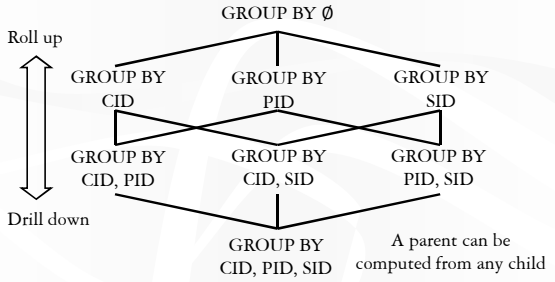

Materialized views

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- Computing GROUP BY and CUBE aggregates is expensive
- OLAP queries perform these operations over and over again

☞ Idea: precompute and store the aggregates as materialized views
- Maintained automatically as base data changes
- No. 1 user-requested feature in PostgreSQL!

Selecting views to materialize

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- Factors in deciding what to materialize
  - What is its storage cost?
  - What is its update cost?
  - Which queries can benefit from it?
  - How much can a query benefit from it?
- Example
  - GROUP BY ∅ is small, but not useful to most queries
  - GROUP BY CID, PID, SID is useful to any query, but too large to be beneficial

Harinarayan et al., "Implementing Data Cubes Efficiently." *SIGMOD* 1996

Other OLAP extensions

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- Besides extended grouping capabilities (e.g., CUBE), window operations have also been added to SQL
- A "window" specifies an ordered list of rows related to the "current row"
- A window function computes a value from this list and the "current row"
  - Standard aggregates: COUNT, SUM, AVG, MIN, MAX
  - New functions: RANK, PERCENT_RANK, LAG, LEAD, …

RANK window function example

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sid	pid	cid	qty
Durham	beer	Alice	10
Durham	beer	Bob	2
Durham	chips	Bob	3
Durham	diaper	Alice	5
Raleigh	beer	Alice	2
Raleigh	diaper	Bob	100

⇩ GROUP BY

sid	pid	cid	qty
Durham	beer	Alice	10
		Bob	2
Durham	chips	Bob	3
Durham	diaper	Alice	5
Raleigh	beer	Alice	2
Raleigh	diaper	Bob	100

```
SELECT SID, PID, SUM(qty),
       RANK() OVER w
FROM Sale GROUP BY SID, PID
WINDOW w AS
(PARTITION BY SID
 ORDER BY SUM(qty) DESC);
```

Apply WINDOW after processing FROM, WHERE, GROUP BY, HAVING

- PARTITION defines the related set and ORDER BY orders it

E.g., for the following "row," the related list is:

Durham	beer	Alice	10
		Bob	2

Durham	beer	Alice	10
		Bob	2
Durham	diaper	Alice	5
Durham	chips	Bob	3

RANK window function example (cont'd)

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sid	pid	cid	qty
Durham	beer	Alice	10
		Bob	2
Durham	chips	Bob	3
Durham	diaper	Alice	5
Raleigh	beer	Alice	2
Raleigh	diaper	Bob	100

```
SELECT SID, PID, SUM(qty),
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FROM Sale GROUP BY SID, PID
WINDOW w AS
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E.g., for the following "row," the related list is:

Durham	beer	Alice	10
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Durham	beer	Alice	10
		Bob	2
Durham	diaper	Alice	5
Durham	chips	Bob	3

Then, for each "row" and its related list, evaluate SELECT and return:

sid	pid	sum	rank
Durham	beer	12	1
Durham	diaper	5	2
Durham	chips	3	3
Raleigh	diaper	100	1
Raleigh	beer	2	2

Multiple windows

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sid	pid	cid	qty
Durham	beer	Alice	10
		Bob	2
Durham	chips	Bob	3
Durham	diaper	Alice	5
Raleigh	beer	Alice	2
Raleigh	diaper	Bob	100

```
SELECT SID, PID, SUM(qty),
  RANK() OVER w,
  RANK() OVER w1 AS rank1
FROM Sale GROUP BY SID, PID
WINDOW w AS
  (PARTITION BY SID
   ORDER BY SUM(qty) DESC),
w1 AS
  (ORDER BY SUM(qty) DESC)
ORDER BY SID, rank;
```

No PARTITION means all "rows" are related to the current one

So rank1 is the "global" rank:

sid	pid	sum	rank	rank1
Durham	beer	12	1	2
Durham	diaper	5	2	3
Durham	chips	3	3	4
Raleigh	diaper	100	1	1
Raleigh	beer	2	2	5

Data mining

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- Data → knowledge
- DBMS meets AI and statistics
- Clustering, prediction (classification and regression), association analysis, outlier analysis, evolution analysis, etc.
  - Usually complex statistical "queries" that are difficult to answer → often specialized algorithms outside DBMS
- We will focus on frequent itemset mining

Mining frequent itemsets

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- Given: a large database of transactions, each containing a set of items
  - Example: market baskets
- Find all frequent itemsets
  - A set of items X is frequent if no less than $s_{min}\%$ of all transactions contain X
  - Examples: {diaper, beer}, {scanner, color printer}

TID	*items*
T001	diaper, milk, candy
T002	milk, egg
T003	milk, beer
T004	diaper, milk, egg
T005	diaper, beer
T006	milk, beer
T007	diaper, beer
T008	diaper, milk, beer, candy
T009	diaper, milk, beer
…	…

First try

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- A naïve algorithm
  - Keep a running count for each possible itemset
  - For each transaction T, and for each itemset X, if T contains X then increment the count for X
  - Return itemsets with large enough counts
- Problem: The number of itemsets is huge!
  - 2^n, where n is the number of items
- Think: How do we prune the search space?

The Apriori property

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- All subsets of a frequent itemset must also be frequent
  - Because any transaction that contains X must also contains subsets of X

☞ If we have already verified that X is infrequent, there is no need to count X's supersets because they must be infrequent too

The Apriori algorithm

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Multiple passes over the transactions

- Pass k finds all frequent k-itemsets (i.e., itemsets of size k)
- Use the set of frequent k-itemsets found in pass k to construct candidate $(k+1)$-itemsets to be counted in pass $(k+1)$
  - A $(k+1)$-itemset is a candidate only if all its subsets of size k are frequent

Example: pass 1

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TID	items
T001	A, B, E
T002	B, D
T003	B, C
T004	A, B, D
T005	A, C
T006	B, C
T007	A, C
T008	A, B, C, E
T009	A, B, C
T010	F

Transactions

$s_{min}\% = 20\%$

itemset	count
{A}	6
{B}	7
{C}	6
{D}	2
{E}	2

Frequent 1-itemsets

(Itemset {F} is infrequent)

Example: pass 2

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Generate candidates → Scan and count → Check min. support

TID	items
T001	A, B, E
T002	B, D
T003	B, C
T004	A, B, D
T005	A, C
T006	B, C
T007	A, C
T008	A, B, C, E
T009	A, B, C
T010	F

Transactions

$s_{min}\% = 20\%$

itemset	count
{A}	6
{B}	7
{C}	6
{D}	2
{E}	2

Frequent 1-itemsets

itemset	count
{A,B}	4
{A,C}	4
{A,D}	1
{A,E}	2
{B,C}	4
{B,D}	2
{B,E}	2
{C,D}	0
{C,E}	1
{D,E}	0

Candidate 2-itemsets

itemset	count
{A,B}	4
{A,C}	4
{A,E}	2
{B,C}	4
{B,D}	2
{B,E}	2

Frequent 2-itemsets

Example: pass 3

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Generate candidates → Scan and count → Check min. support

TID	items
T001	A, B, E
T002	B, D
T003	B, C
T004	A, B, D
T005	A, C
T006	B, C
T007	A, C
T008	A, B, C, E
T009	A, B, C
T010	F

Transactions

$s_{min}\% = 20\%$

itemset	count
{A,B}	4
{A,C}	4
{A,E}	2
{B,C}	4
{B,D}	2
{B,E}	2

Frequent 2-itemsets

itemset	count
{A,B,C}	2
{A,B,E}	2

Candidate 3-itemsets

itemset	count
{A,B,C}	2
{A,B,E}	2

Frequent 3-itemsets

Example: pass 4

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Generate candidates

TID	items
T001	A, B, E
T002	B, D
T003	B, C
T004	A, B, D
T005	A, C
T006	B, C
T007	A, C
T008	A, B, C, E
T009	A, B, C
T010	F

Transactions

$s_{min}\% = 20\%$

itemset	count
{A,B,C}	2
{A,B,E}	2

Frequent 3-itemsets

Candidate 4-itemsets

No more itemsets to count!

Example: final answer

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itemset	count
{A}	6
{B}	7
{C}	6
{D}	2
{E}	2

Frequent 1-itemsets

itemset	count
{A,B}	4
{A,C}	4
{A,E}	2
{B,C}	4
{B,D}	2
{B,E}	2

Frequent 2-itemsets

itemset	count
{A,B,C}	2
{A,B,E}	2

Frequent 3-itemsets

Summary

- Data warehousing
  - Eagerly integrate data from operational sources and store a redundant copy to support OLAP
  - OLAP vs. OLTP: different workload → different degree of redundancy
  - SQL extensions: grouping and windowing
- Data mining
  - Only covered frequent itemset counting
  - Skipped many other techniques (clustering, classification, regression, etc.)
  - One key difference from statistics and machine learning: massive datasets and I/O-efficient algorithms