Data Warehousing and Data Mining

Introduction to Databases

CompSci 316 Fall 2017

DUKE
COMPUTER SCIENCE

Announcements (Tue., Dec. 5)

- Homework #4 due today
  - Sample solution to be posted by this weekend
- Project demos to start Thursday
  - Check your email for schedule
  - Submit report/code before demo
- Final exam Sat. Dec. 16 2-5pm
  - **This room**
  - Open-book, open-notes
  - Comprehensive, but with strong emphasis on the second half of the course
  - Sample final + solution posted on Sakai

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

- Mostly updates
- Short, simple transactions
- Clerical users
- Goal: transaction throughput

OLAP

- Mostly reads
- Long, complex queries
- Analysts, decision makers
- 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)

- In advance: before queries
- Copy data from sources

☞Answer could be stale

☞Need to maintain consistency

☞Query processing is local to the warehouse
  - Faster
  - Can operate when sources are unavailable

Lazy

- On demand: at query time
- Leave data at sources

☞Answer is more up-to-date

☞No need to maintain consistency

☞Sources participate in query processing
  - Slower
  - Interferes with local processing
  - Still has consistency issues

Maintaining a data warehouse

- The "ETL" process
  - Extract relevant data and/or changes from sources
  - Transform data to match the warehouse schema
  - Load/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

Dimension table

Product

PID	name	cost
p1	beer	10
p2	diaper	16
…	…	…

Dimension table

Store

SID	city
s1	Durham
s2	Chapel Hill
s3	RTP
…	…

Sale

OID	Date	CID	PID	SID	qty	price
100	08/23/2017	c3	p1	s1	1	12
102	09/12/2017	c3	p2	s1	2	17
105	09/24/2017	c5	p1	s3	5	13
…	…	…	…	…	…	…

Fact table

- Big
- Constantly growing
- Stores measures (often aggregated in queries)

Customer

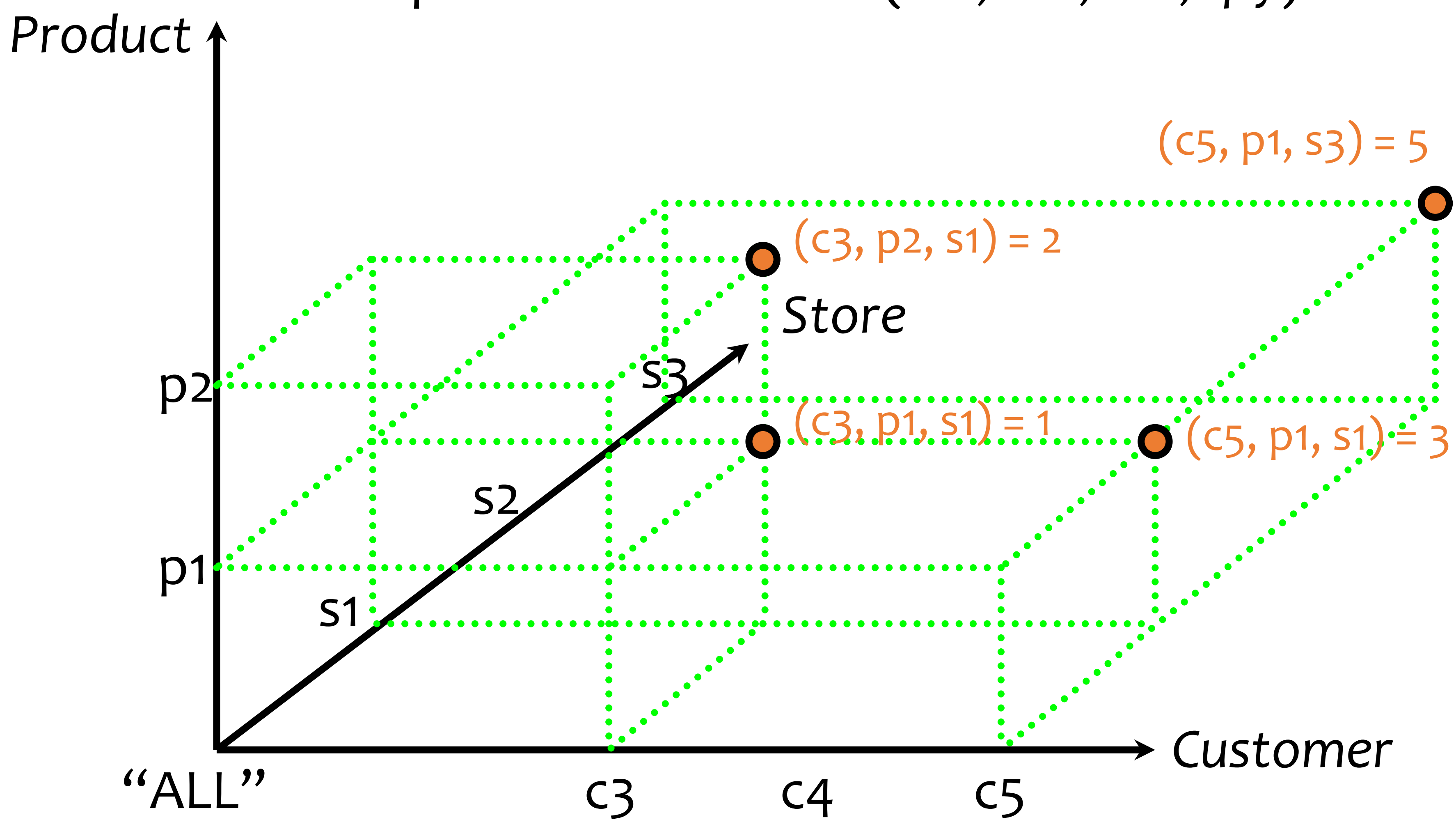
CID	name	address	city
c3	Amy	100 Main St.	Durham
c4	Ben	102 Main St.	Durham
c5	Coy	800 Eighth St.	Durham
…	…	…	…

Dimension table

- Small
- Updated infrequently

Data cube

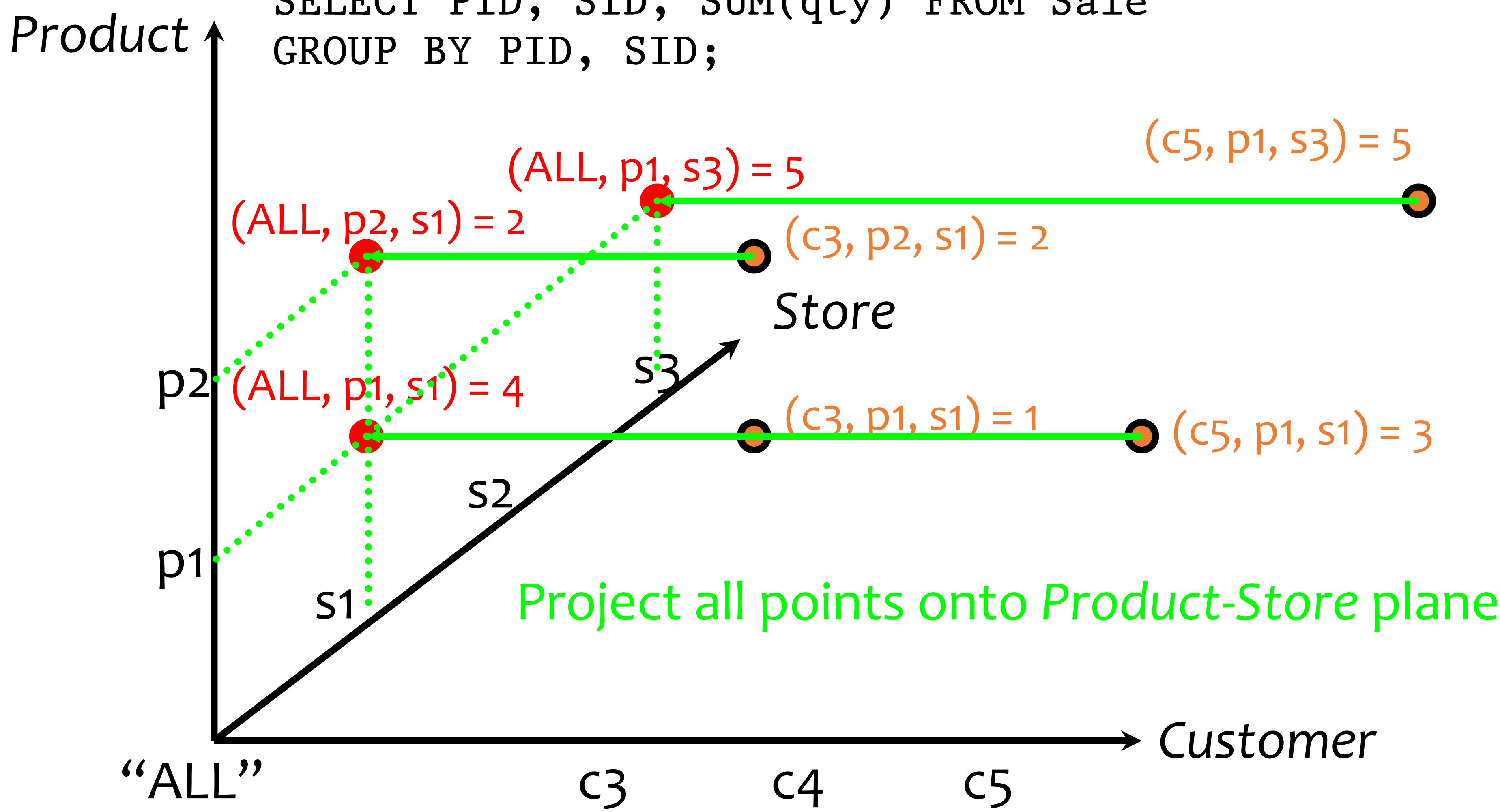
Simplified schema: *Sale* (*CID*, *PID*, *SID*, *qty*)



Completing the cube—plane

Total quantity of sales for each product in each store

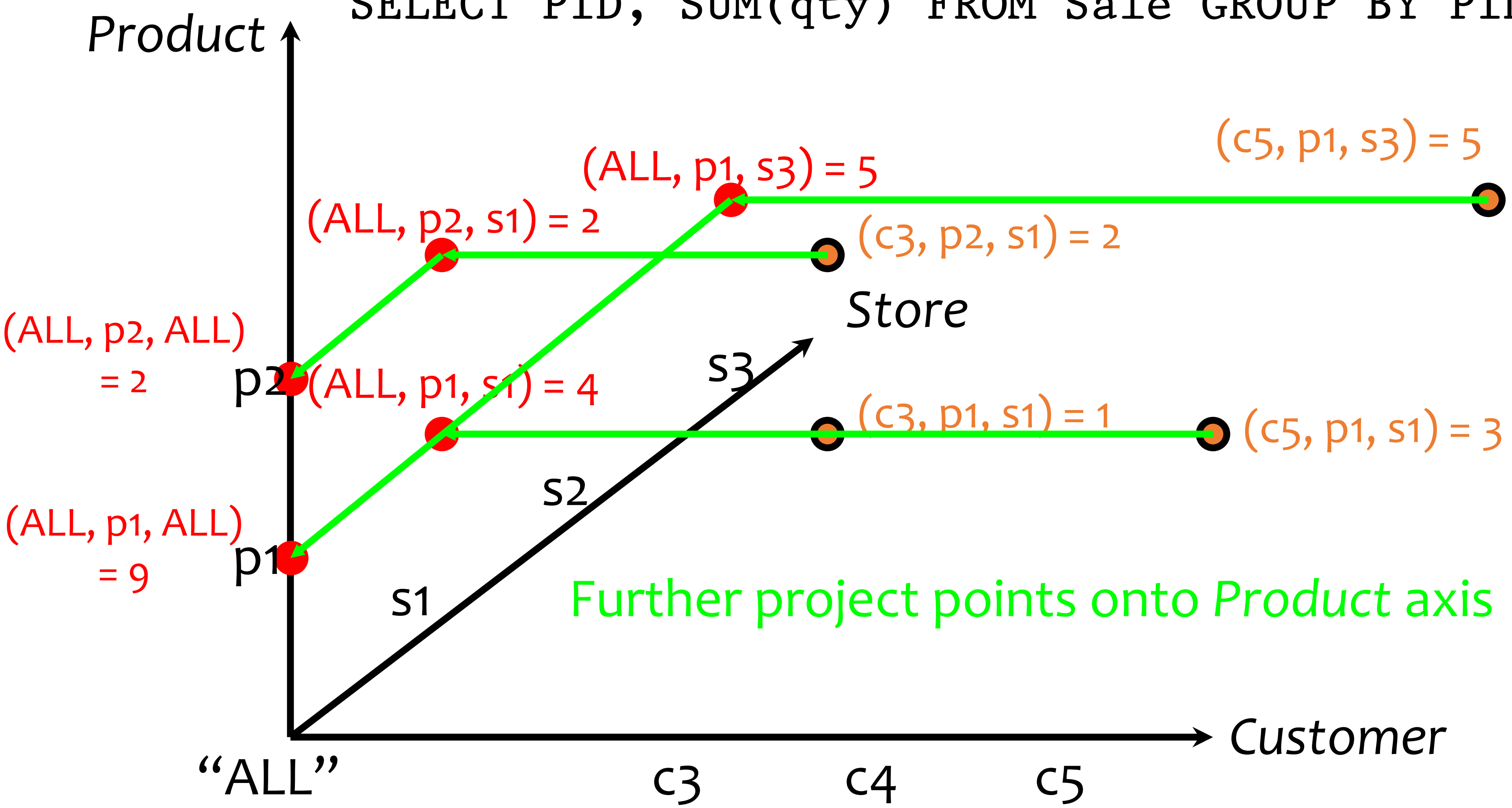
```
SELECT PID, SID, SUM(qty) FROM Sale
GROUP BY PID, SID;
```



Completing the cube—axis

Total quantity of sales for each product

```
SELECT PID, SUM(qty) FROM Sale GROUP BY PID;
```

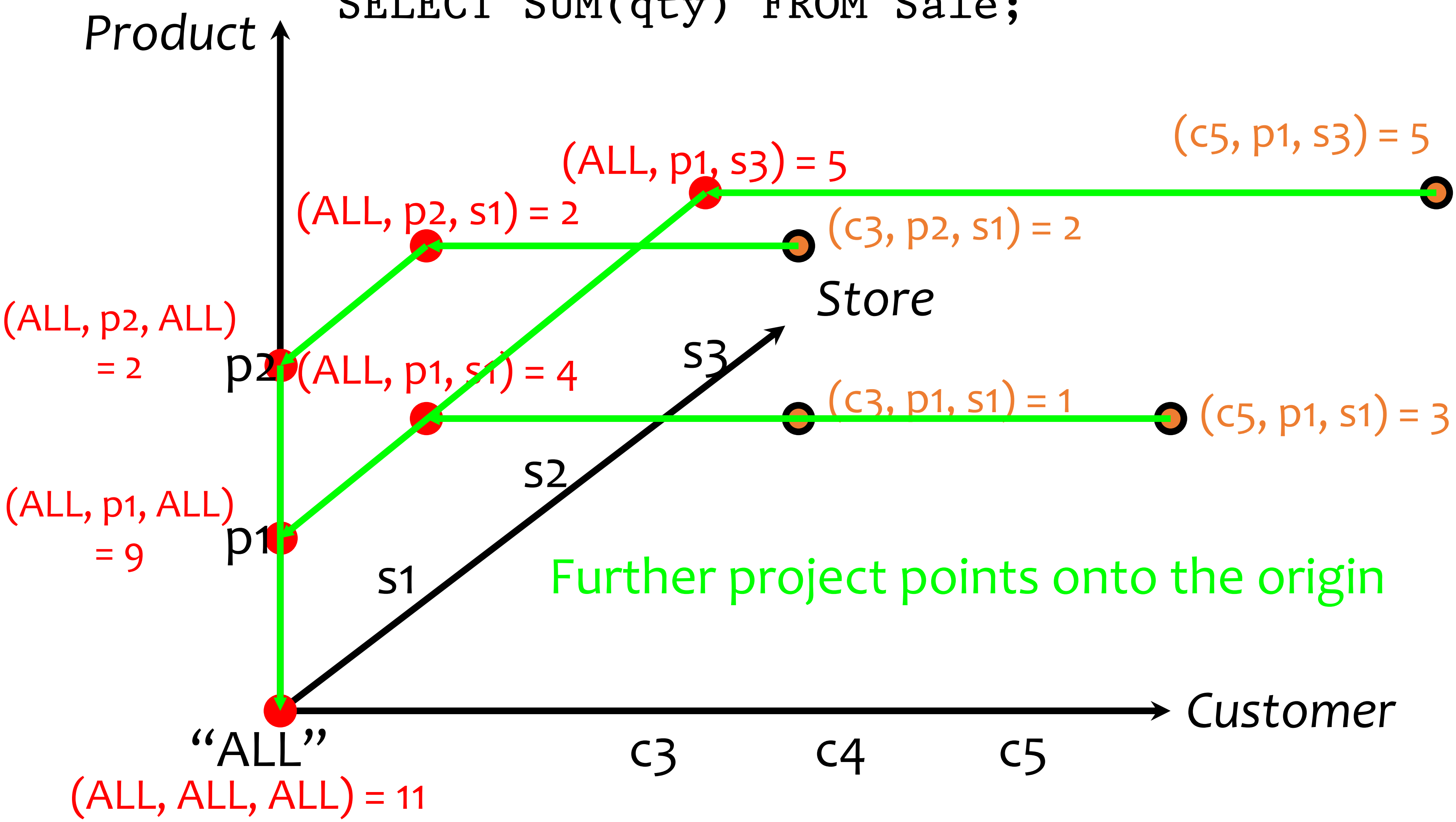


Further project points onto *Product* axis

Completing the cube—origin

Total quantity of sales

```
SELECT SUM(qty) FROM Sale;
```

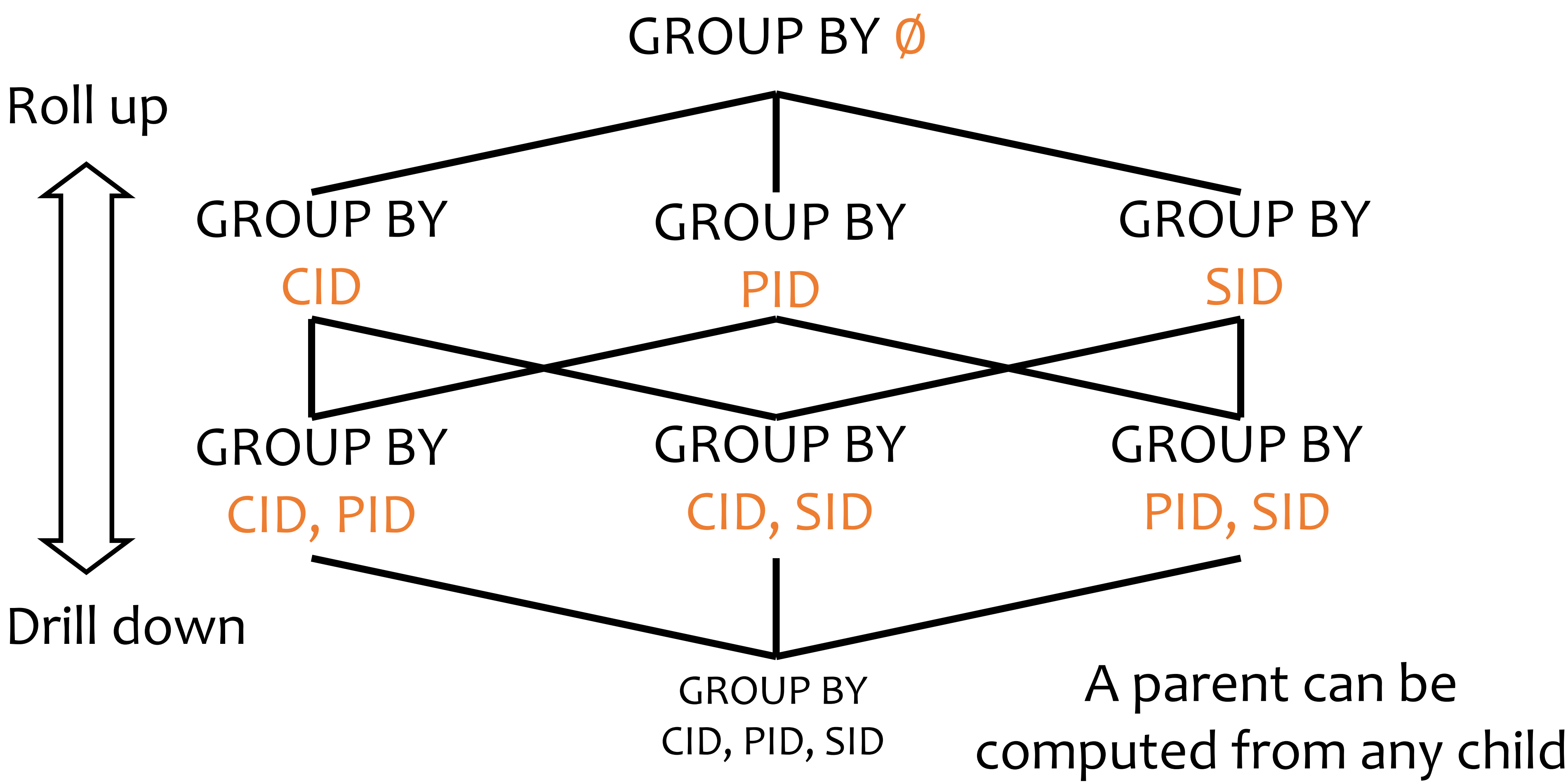


`CUBE` operator

- *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



Materialized views

- 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

- 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

Other OLAP extensions

- 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

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

```
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);
```

GROUP BY

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

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,"

Durham	beer	Alice Bob	10 2

the related list is:

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

RANK example (cont'd)

sid	pid	cid	qty
Durham	beer	Alice Bob	10 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);
```

E.g., for the following "row,"

Durham	beer	Alice Bob	10 2

the related list is:

Durham	beer	Alice Bob	10 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

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

Summary

- 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

- 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, as a sample problem in data mining

Mining frequent itemsets

- 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

- 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

- 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

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

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

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

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

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

Generate candidates

Scan and count

Check min. support

Candidate 3-itemsets

Frequent 3-itemsets

Example: pass 4

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

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

Generate candidates

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

Frequent 3-itemsets

itemset	*count*

Candidate 4-itemsets

No more itemsets to count!

Example: final answer

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

- Only covered frequent itemset counting
- Skipped many other techniques (clustering, classification, regression, etc.)
- Compared with statistics and machine learning: more focus on massive datasets and I/O-efficient algorithms