OLAP/Data Warehouses

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What is a Database?

From Wikipedia:

- A database is a <u>structured</u> collection of records or <u>data</u>. A <u>computer</u> database relies upon <u>software</u> to organize the storage of data. The software models the database structure in what are known as <u>database models</u>. The model in most common use today is the <u>relational model</u>. Other models such as the <u>hierarchical model</u> and the <u>network model</u> use a more explicit representation of relationships ...
- Database management systems (DBMS) are the software used to organize and maintain the database. These are categorized according to the <u>database model</u> that they support. The model tends to determine the query languages that are available to access the database. A great deal of the internal engineering of a DBMS, however, is independent of the data model, and is concerned with managing factors such as performance, concurrency, integrity, and recovery from <u>hardware failures</u>. ...

Note

 Term "database" often used interchangeably for both the data and the system that manages it

Basic Database Usage (1): Querying

Relations

Statements (select columns and rows)

Results



Basic Database Usage (2): Updates

- Banking transaction: transfer 100 euro from account A to account B
 - What can go wrong?

Account	Balance	
А	275	-100
В	64	+100

Issue 1: Partial results

 System failure prior to adding funds to account B (but after deleting them from A)

Account	Balance	
А	175	-100 🗹
В	64	+100 SYSTEM FAILURE

Issue 2: No isolation

 For an observer that monitors all funds money seem to temporality disappear (and reappear again)

Account	Balance		
А	175	-100	total funds are
			reduced by 100
В	64	+100	

Issue 3: lost update

- Two concurrent transactions on account A
 - T1: remove 100
 - T2: remove 50

	Account	Balance	
T2 <mark>Read balance (275)</mark> Subtract 50 Write balance 225	A	275	T1 Read balance (275) Subtract 100 Write balance 175
	В	64	

Programming abstraction: Transactions

• Implement real-world transactions



- DBMSs guarantee ACID properties
 - Atomicity
 - Consistency
 - Isolation
 - Durability

Atomicity (A.C.I.D.)

- The "all or nothing" property.
 - Programmer needn't worry about partial states persisting.
 - Two possible outcomes: transaction commits or rollbacks (aborts)



- Examples:
 - T1: Delete person from consultants table, insert person into employees table
 - T2: Transfer funds from account A to account B

Consistency (A.C.I.D)

- The database should start out "consistent" (legal state), and at the end of transaction remain "consistent".
- The definition of "consistent" is up to the database administrator to define to the system
 - integrity constraints
 - other notions of consistency must be handled by the application.

Integrity or correctness of data

 Would like data to be "accurate" or "correct" at all times

FMP.	Name	Age
	John	52
	Jim	24
	Martha	1

CREATE TABLE EMP (Name varchar(255) NOT NULL, Age int, CHECK (Age>=18));

Integrity/consistency constraints

- Predicates data must satisfy
- Examples:
 - age >= 18 and age < 65</p>
 - x is key of relation R
 - $-x \rightarrow y$ holds in R
 - Domain(x) = {Red, Blue, Green}
 - no employee should make more than twice the average salary

Isolation (A.C.I.D)

- Each transaction must appear to be executed as if no other transaction is executing at the same time.
- Transfer funds from A to B (T1).
- Another teller makes a query on A and B (T2).
- T2 could see funds on A or B but not in both!
 - Result may be independent of the time transactions were submitted

Durability (A.C.I.D.)

- Once committed, the transactions effects should not disappear.
 - Of course, they may be overwritten by subsequent committed transactions.

Implementation

- A, C, and D are mostly guaranteed by recovery (usually implemented via logging).
- I is mostly guaranteed by concurrency control (usually implemented via locking).
- Of course, life is not so simple. For example, recovery typically requires concurrency control and depends on certain behavior by the buffer manager...

Operational DBs: OLTP systems

- OLTP= On-Line Transaction Processing
 - order update: pull up order# XXX and update status flag to "completed"

update Orders set status="Completed" where orderID="XXX"



Reconstruction of logical records

Employees		Projects	j	Assignment	ts	
<u>EmplD</u>	Ename	<u>ProjID</u>	Pname	<u>EmplD</u>	<u>ProjID</u>	<u>Hours</u>
101	John Smith	2	Web_TV	101	3	16
102	Nick Long	3	Web_portal	102	2	24
103	Susan Goal	4	Billing	102	3	8
104	John English			104	4	32
105	Alice Web			105	4	24
106	Patricia Kane			106	4	24

• List projects & hours assigned to employee Nick Long

Select Pname,Hours From Employees E, Projects P, Assignments A Where E.Ename = "Nick Long" And E.EmpID=A.EmpID And A.ProjID=P.ProjID

Physical Plan (step a): IndexSeek

Employees		Projects	5	Assignment	ts	
<u>EmplD</u>	Ename	<u>ProjID</u>	Pname	<u>EmplD</u>	<u>ProjID</u>	<u>Hours</u>
101	John Smith	2	Web_TV	101	3	16
102	Nick Long	3	Web_portal	102	2	24
103	Susan Goal	4	Billing	102	3	8
104	John English			104	4	32
105	Alice Web			105	4	24
106	Patricia Kane			106	4	24

 $\sigma_{E.name="Nick Long"}$ (Employees) Nick Long \rightarrow <102,Nick Long Index on Employees.Ename

Physical Plan (step b): INLJ(Employees,Assignments)

Employees		Projects		Assignment	ts	
<u>EmplD</u>	Ename	<u>ProjID</u>	Pname	<u>EmplD</u>	<u>ProjID</u>	<u>Hours</u>
101	John Smith	2	Web_TV	101	3	16
102	Nick Long	3	Web_portal	102	2	24
103	Susan Goal	4	Billing	102	3	8
104	John English			104	4	32
105	Alice Web			105	4	24
106	Patricia Kane			106	4	24



Physical Plan (step c): INLJ(Assignments,Projects)

Employees		Projects	5	Assignment	S	
<u>EmplD</u>	Ename	<u>ProjID</u>	Pname	<u>EmplD</u>	<u>ProjID</u>	<u>Hours</u>
101	John Smith	2	Web_TV	101	3	16
102	Nick Long	3	Web_portal	102	2	24
103	Susan Goal	4	Billing	102	3	8
104	John English			104	4	32
105	Alice Web			105	4	24
106	Patricia Kane			106	4	24



Assignments >>>> Projects

On-Line Transaction Processing

- Examples
 - order update: pull up order# XXX and update status flag to "completed"
 - banking: transfer 100 euros from account #A to account #B
- Transactions:
 - Implement structured, repetitive clerical data processing tasks
 - Require detailed, up-to-date data
 - Are (most of the times) short-lived
 - read and/or update a few records
- Integrity of the database is critical
 - DBMS should manage hundreds or thousands of concurrent transactions
- Systems supporting this kind of activity are called *transactional* systems
 - Most traditional database management systems

Transactional Systems

- Transactional systems are optimized primarily for the here and now
- Can support many simultaneous users

 concurrent read/write access
- Transactional systems don't necessarily record all previous data states

- E.g. customer updates its address (moves to new town)

Lots of data gets thrown away or archived
 — Old orders are deleted/archived to reduce size



Analytical queries on a production system?

- CEO wants to report total sales per store in Athens, for stores with at least 500 sales
- 3 tables: Sales(custid, productid, storeid, amt)

Stores(storeid, manager,addressid)

Addresses(addressid,number,street,city)





Addresses(addressid,number,street,city)

What happens if new sales take place while this query executes?

Sad realization

- Analytical queries on an operational database often take for ever
 - Schema favors small atomic actions
 - Excessive normalization results in costly joins
 - Need to scan LOTS of records
 - Indexes are not very useful when queries are not selective
 - Interference with daily transactions
 - Overhead of OLTP engine (logging, locking)

My employees & their projects

<u>EmplD</u>	Ename	<u>ProjID</u>	Pname	City	<u>Hours</u>
101	John Smith	3	Web_portal	Thessaloniki	16
102	Nick Long	2	Web_TV	Athens	24
103	Susan Goal	3	Web_portal	Thessaloniki	8
104	John English	4	Billing	Athens	32
105	Alice Web	4	Billing	Athens	24
106	Patricia Kane	4	Billing	Athens	24

- Schema is bad for OLTP (1NF)
 - Update anomalies, repetition of values
- But is all we need for reporting our employees and their projects!

OLAP: ONLINE ANALYTICAL PROCESSING

OLAP

- OLAP = online analytical processing
- OLAP is the process of creating and summarizing historical, multidimensional data
 - To help organizations understand their data better
 - Provide a basis for informed decisions (Decision Support Systems, Business Intelligence)
 - Allow users to manipulate and explore data easily and intuitively

Data Analytics Stack

OLAP

- Well defined computations over data categorized by multiple dimensions of interest
 - Enables users to easily and selectively extract and query data in order to analyse it from different points of view

Data Mining

- Seek to find relationships and patterns in data
 - Frequent itemset
 - Association rules
 - Clustering

Machine Learning

- Build models for prediction, classification etc.
 - Image classification
 - Speech processing
 - Sentiment analysis
 - NLP

OLAP Examples

OLAP

- Well defined computations over data categorized by multiple dimensions of interest
 - Enables users to easily and selectively extract and query data in order to analyse it from different points of view

- A. Group sales data across different dimensions:
 Product, Customer, Location (point of sale) and
 Time
 - Dimensions identify what, who, where & when
- B. Compute interesting stats on selected measures

Examples:

- 1. "Average January sales (€) for all stores in Attika"
- "Number of shoes over 100€ sold to female customers between ages 18 and 25"
- "Top-10 product-categories whose sales (%) increased the most over the past year"

Can you identify the dimensions in these queries???

1st query in more details

OLAP

- Well defined computations over data categorized by multiple dimensions of interest
 - Enables users to easily and selectively extract and query data in order to analyse it from different points of view



2nd dimension denotes where

A common aggregate function: AVG() over the available measure (sales)

Other examples: Max(), Min(), Count(), StDev(), Median()

OLAP vs. OLTP

	OLTP	OLAP
User	Clerk, IT professional	Knowledge worker
Function	Day to day operations	Decision support
DB design	Application-oriented	Subject-oriented
	(E-R based)	(Star, snowflake)
Data	Current, Isolated	Historical, Consolidated
View	Detailed, Flat relational	Summarized, Multidimensional
Usage	Structured, Repetitive	Ad hoc
Unit of work	Short, simple transaction	Complex query
Access	Read/write	Read mostly
Operations	Index/hash on prim. key	Lots of scans
# Records accessed	Tens	Millions
# Users	Thousands	Hundreds
Db size	100 MB - GB	100 GB - TB
Metric	Trans. throughput	Query throughput, response

DATA WAREHOUSES

The Data Warehouse

- In order to support OLAP, data is collected from multiple data sources, cleansed and organized in data warehouses
- The data warehouse is a huge repository of enterprise data that will be used for decision making
- After data is loaded in the data warehouse, OLAP cubes are often pre-summarized across dimensions of interest to drastically improve query time

Data Warehouse definition

- A decision support database that is maintained separately from the organization's operational databases.
- A data warehouse is a
 - subject-oriented,
 - integrated,
 - time-varying,
 - non-volatile

collection of data that is used primarily in organizational decision making.

-- W.H. Inmon, Building the Data Warehouse, 1992.
Subject-Oriented

- Organized around major subjects, such as customer, product, sales
- Focusing on the modeling and analysis of data for decision makers, not on daily operations or transaction processing
- Provide a simple and concise view around particular subject issues by excluding data that are not useful in the decision support process

Integrated

 Constructed by integrating multiple, heterogeneous data sources

- relational databases, files, external sources

- Data cleaning and data integration techniques are applied
 - Ensure consistency in naming conventions, keys, attribute measures, etc. among different data sources
 - E.g., Hotel price: currency, tax, breakfast covered, etc.
 - When data is moved to the warehouse, it is transformed

Time-Variant

- The time horizon for the data warehouse is significantly longer than that of operational systems
 - Operational database: current data, old values overwritten, deleted or archived
 - Data warehouse: provides data from a historical perspective (e.g., past 5-10 years) for trend analysis

Non-volatile

- A **physically separate** store of data transformed from the operational environment
- Operational update of data does not occur in the data warehouse environment
 - Does not require transaction processing, recovery, and concurrency control mechanisms
 - Requires only **two operations** in data accessing:
 - loading of data and access to data

Data Warehouse Architecture



Implementation

- Warehouse database server
 - Almost always a relational DBMS.
- OLAP Servers (for computing OLAP Cubes)
 - *Relational OLAP (ROLAP):* extended relational DBMS that maps operations on multidimensional data to standard relational operations.
 - Multidimensional OLAP (MOLAP): special purpose server that directly implements multidimensional data and operations.
- Clients
 - Query and reporting tools.
 - Analysis tools.
 - Data mining tools.

Data Marts

- Smaller warehouses
- Span part of organization

-e.g., marketing (customers, products, sales)

- Do not require enterprise-wide consensus
 - But may lead to long term integration problems

Basic Query Pattern

- Analyst projects data into a selected subset of dimensions and computes interesting statistics
- In SQL this is expressed by grouping records using the selected attributes and computing aggregate functions (e.g. sum(), average(), count(), max()) over each group
 - "Group by followed by aggregation"
 - Additional filtering may be used to restrict the scope of the query

Example

- "Compute the total revenue (=sum) the minimum and maximum price for each combination of customer and store"
 - Sales Data:

Time	Customer	Store	Product	Price	
T1	C1	S2	P1	\$90	
T2	C2	S1	P2	\$70	
Т3	C1	S1	P2	\$45	
T4	C3	S 1	P1	\$40	
T5	C1	S2	P2	\$25	
T6	C1	S2	P2	\$50	
Τ7	C2	S1	P4	\$45	
Т8	C3	S1	P1	\$10	

facts

available dimensions

measure

In SQL: Group By + Aggregation

Select Customer, Store, SUM(Price) as Revenue, MIN(Price) as MinPrice, MAX(Price) as MaxPrice

From Sales Group by Customer, Store

C1

S2

1. Identify groups:

C1,S1 C2,S1 C3,S1 C1,S2

2. Perform aggregation

Time	Customer	Store	Product	Price	
T1	C1	S2	P1	\$90	
T2	C2	S 1	P2	\$70	
T3	C1	S 1	P2	\$45	
T4	C3	S 1	P1	\$40	
T5	C1	S2	P2	\$25	
T6	C1	S2	P2	\$50	
T7	C2	S 1	P4	<i>\$45</i>	
Т8	C3	S 1	P1	\$10	
Customer	Store	Revenue	Min Price	e Max Pric	
C2	S 1	\$115	\$45	\$70	
C1	S1	\$45	\$45	\$45	
C3	S1	\$50	\$10	\$40	

\$165

\$25

\$90

Relational Algebra (logical plan)

VStore, Customer, SUM(Price)->Revenue, MIN(Price)->MinPrice, MAX(Price)->MaxPrice

Sales

Map data and aggregates into a highdimensional space

accumulated here

• Example: compute total *sales* volume per *productID* and *storeID*

Total		ProductID				
Sales		1	2	3	4	
StoreID	1	\$454	-	-	\$925	
	2	\$468	\$800	-	_	
	3	\$296	-	\$240	_	
	4	\$652	-	\$540	\$745	



aggregation

Multidimensional Data Model

- Database is a set of **facts** (points) in a multidimensional space
 - E.g. a sale/an order/a contract
- A fact has
 - A set of **dimensions** with respect to which data is analyzed
 - e.g., store, product, date associated with a sale
 - A set of measures
 - quantity that is analyzed, e.g., sale amount, quantity
- Dimensions form a sparsely populated coordinate system
 - Not all combinations exist as facts. E.g. a customer does not visit all stores worldwide
- Each dimension has a set of **attributes**
 - e.g., owner, city and state of store
 - Often attributes are used to encode a hierarchy

Product Hierarchy



Κωδικοί για όλα τα τυριά τύπου «φέτα»

More on Attribute Hierarchies

- Values of a dimension may be related
 Hierarchies are most common
- Dependency graph may be:
 - Hierarchy (tree): e.g.,
 - city \rightarrow state \rightarrow country
 - Lattice:

date \rightarrow month \rightarrow year

date \rightarrow week (of a year) \rightarrow year



Another example

- VIN: Vehicle Identification Number (unique key)
- Model: e.g. Fiesta
- Type: e.g. Compact Car
- Manufacturer: e.g.
 Ford



Using hierarchies

 While projecting the data into a set of dimensions, we may select an appropriate hierarchy level for each dimension

"Compute total sales per productID"

Vs

– "Compute total sales per product-category"

 In the second query, sales of different productIDs that all belong to the same category e.g. "Milk" will be accumulated together in the same "coordinate" (value) of the category dimension

Multidimensional View of selected hierarchy levels per dimension

 Aggregate sales volume as a function of product (category), time (day-of-week), geography (city)

All NY's sales of milk on a Sunday are aggregated in this cell

. . . .



Roll-up Operation

- Dimension reduction:
 - e.g., total sales by city by product
 - e.g., total sales by city



- e.g., sales by city

•

- ightarrow total sales by state
- ightarrow total sales by country
- e.g., total sales by city and year
 - ightarrow total sales by **state** and by **year**
 - \rightarrow total sales by **country**

		Product			
		1	2	3	4
	NY	\$454	-	-	\$925
ty	SF	\$468	\$485	- -	\$315
Ci	LA	\$296	-	\$340	-
	SE	\$652	_	\$640	\$645



Roll-up

Drill-Down

- Drill-down: Inverse operation of roll-up
 - Provides the data set that was aggregated
 - e.g., show "base" data for total sales figure of the state of CA

Other Operations

- Selection (*slice & dice*) defines a subcube
 - Project the cube on fewer dimensions by specifying coordinates of remaining dimensions
 - e.g., sales to customer XXX
- Ranking
 - top 3% of cities by average sales



Fact data: Sales sum in \$

Warehouse Database Schema

- Relational design should reflect multidimensional view
- Typical schemas:
 - Star Schema
 - Snowflake Schema
 - Fact Constellation Schema
- Data tables (relations) are of two types: fact tables and dimension tables

The Star Schema (Example 1)



Fact Table

- A table in the data warehouse that contains facts consisting of
 - Numerical performance measures

SALES

- Foreign keys that tie the fact data to the dimension tables
- Each row records measurements describing a fact
 - Where? When? Who? How much? How many?
- Provides the most detailed view of the data an analyst has access to in the data warehouse
 - this denotes the grain of the design

<u>time_key</u>	product_key	location_key	units	amount
T1	P44	L4	1	12
T2	P157	L4	3	180
T2	P6	L1	14	2560
Т3	P25	L3	1	2
Т3	P157	L1	1	60
)		
	γ			γ

Foreign keys to dimension tables measures



encodes product \rightarrow category hierarchy

- Dimension Tables contain
 - a key column linked to a foreign key in the fact table
 - textual descriptors such as name of products, addresses etc
 - attributes that encode dependences within the dimension (e.g. hierarchies)
- Dimension tables may be wide
- Dimension tables are usually shallow (e.g. few thousand rows)

Advantages of Star Schema

- A single fact table where to look for facts to analyze
- One table for each dimension

 dimensions are clearly depicted in the schema
- Easy to comprehend (and write queries)
- Loading of data
 - dimension tables are relatively static
 - data is loaded (append mostly) into fact table(s)
 - new indexing opportunities

Querying the Star Schema

"Find total sales per product-category in our stores in Europe"



Querying the Star Schema

"Find total sales per product-category in our stores in Europe"

SELECT PRODUCT.category, SUM(SALES.amount) FROM SALES, PRODUCT,LOCATION WHERE SALES.product_key = PRODUCT.product_key AND SALES.location_key = LOCATION.location_key AND LOCATION.region="Europe" GROUP BY PRODUCT.category

Join fact table SALES with dimension tables PRODUCT, LOCATION to fetch required attributes (category & region in this example)

Star Schema Query Processing



Another Example



Fact constellation

- Multiple fact tables that share common dimension tables
 - Example: Delivery and
 Sales fact tables share
 dimension tables Time &
 Product



Snowflake Schema: represents dimensional hierarchy by normalization



Multidimensional Modeling Stages (adapted from https://www.kimballgroup.com/)



Gather Business Requirements and Data Realities

- Study the underlying business processes
 - Understand their objectives based on key performance indicators (KPIs), compelling business issues, decision-making processes, and supporting analytic need
- Identify available data sources (internal and external)
 - Assess their quality and completeness

Grain

- Establishes exactly what a single fact table row represents
 - Different grains must not be mixed in the same fact table
- Atomic grain refers to the lowest level at which data is captured by a given business process
 - Safer to start with the atomic grain in order to cope with unpredictable query workload

Identify the dimensions

 Dimensions provide the "who, what, where, when, why, and how" context surrounding a business process event.

 Dimension tables contain descriptive attributes used by BI applications for filtering and grouping the facts.
Identify the facts

- A single fact table row has a one-to-one relationship to a measurement event as described by the fact table's grain.
- *Facts* contain measurements that result from a business process event.
- Within a fact table, only facts consistent with the declared grain are allowed.

Indexing Techniques

- Exploiting indexes to reduce scanning of data is of crucial importance
- ROLAP
 - Bitmap Indexes
 - Join Indexes
- MOLAP
 - Array representation

Base Table

Region Index

Cust	Region	Rating
C1	N	Н
C2	S	Μ
C3	W	L
C4	W	Н
C5	S	L
C6	W	L
C7	Ν	Н

RowID	Ν	S	Е	W
1	1	0	0	0
2	0	1	0	0
3	0	0	0	1
4	0	0	0	1
5	0	1	0	0
6	0	0	0	1
7	1	0	0	0

Base Table

Region Index

Cust	Region	Rating
C1	N	Н
C2	S	Μ
C3	W	L
C4	W	Н
C5	S	L
C6	W	L
C7	Ν	Н

RowID	N	S	E	W
1	1	0	0	0
2	0	1	0	0
3	0	0	0	1
4	0	0	0	1
5	0	1	0	0
6	0	0	0	1
7	1	0	0	0

Bitmap encodes position of customer records in the base table (rows 1,7) that reside in the North Region

Base Table

Region Index

Rating Index

Cust	Region	Rating
C1	Ν	Н
C2	S	Μ
C3	W	L
C4	W	Н
C5	S	L
C6	W	L
C7	Ν	Н

RowID	Ν	S	E	W
1	1	0	0	0
2	0	1	0	0
3	0	0	0	1
4	0	0	0	1
5	0	1	0	0
6	0	0	0	1
7	1	0	0	0

RowID	Η	Μ	L
1	1	0	0
2	0	1	0
3	0	0	1
4	1	0	0
5	0	0	1
6	0	0	1
7	1	0	0

Base Table Region Rating Cust C1 Ν Н C2 S Μ C3 W L C4 W Η C5 S L C6 W I C7 Н Ν



Rating Index



Customers wher

0011010 AND 0010110=0010010 (rows 3,6)

Base Table

Region Index

Cust	Region	Rating	
C1	Ν	Н	
C2	S	М	
C3	W	L	
C4	W	Н	
C5	S	L	
C6	W	L	
C7	Ν	н	

RowID	Ν	S	E	W
1	1	0	0	0
2	0	1	0	0
3	0	0	0	1
4	0	0	0	1
5	0	1	0	0
6	0	0	0	1
7	1	0	0	0

How many customers in W region?

Bitmap Index

- An alternative representation of RID-list
- Comparison, join and aggregation operations are reduced to *bit arithmetic*
- Especially advantageous for low-cardinality domains
 - Significant reduction in space and I/O (30:1)
 - Have been adapted for higher cardinality domains
 - Compression (e.g., run-length encoding) exploited
- Products: Model 204, Redbrick, IQ (Sybase), Oracle, etc

Join Index

- Traditional index maps the value in a column to a list of rows with that value
- Join index maintains relationships between attribute value of a dimension and the matching rows in the fact table
- Join index may span multiple dimensions (composite join index)

Example: Join Indexes

• "Combine" SALE, PRODUCT relations

	V								
sale	prodld	storeld	date	amt		product	id	name	pric
	p1	c1	1	12	\rightarrow .	-	p1	bolt	10
	p2	c1	1	11			p2	nut	5
	p1	c3	1	50					
	p2	c2	1	8					
	p1	c1	2	44					
	p1	c2	2	4					

joinTb	prodld	name	price	storeld	date	amt
	p1	bolt	10	c1	1	12
	p2	nut	5	c1	1	11
	p1	bolt	10	c3	1	50
	p2	nut	5	c2	1	8
	p1	bolt	10	c1	2	44
	p1	bolt	10	c2	2	4

Join Indexes

join index

produc	t id	name	price	jln	dex			
	p1	bolt	10	r1,r3	,r5,r6			
	p2	nut	5	r2	2,r4	<u> </u>	— — -ı	
						_	!	
sale	rld	prodld	store	eld o	date	amt		
	r1	p1	c1		1	12	← +	
	r2	p2	c1		1	11	←	
	r3	p1	c3		1	50	←	
	r4	p2	c2		1	8	← — ¦	
	r5	p1	c1		2	44	←	
	r6	p1	c2		2	4	←	

Example: Compute total sales in AFRICA



Join-Index in the Star Schema

- Join index relates the values of the <u>dimensions</u> of a star schema to <u>rows</u> in the fact table.
 - a join index on *region* maintains for each distinct
 region a list of ROW-IDs of
 the tuples recording the sales
 in the region
- Join indices can be implemented as bitmapindexes (next slides)



Join Index on Location.Region implemented as bitmap index

Fact Table Sales

time_key	product_key	location_key	units	amount
T1	P44	L4	1	12
Т2	P157	L4	3	180
Т2	P6	L1	14	2560
Т3	P25	L3	1	2
Т3	P157	L1	1	60

Bitmaps for Location.Region

Africa	Asia	Europe	America
0	0	0	1
0	0	0	1
1	0	0	0
0	0	1	0
1	0	0	0

Assuming L1 refers to a store location in Africa, L2 to a store location in Asia etc This information is stored in the dimension table Location

In SQL

- Join index implemented as bitmap index: CREATE BITMAP INDEX loc_sales_bit ON sales(location.region) FROM sales, location WHERE sales.loc_location_key = location.location_key;
- The following query uses the index to avoid computing the join
 SELECT SUM(sales.amount)
 FROM sales,location
 WHERE sales.location_key=location.location_key
 AND location.region="AFRICA"

THE DATA CUBE

Aggregation (on a single group via filtering)

- Sum up amounts for day 1
- In SQL: SELECT sum(amt) FROM SALE WHERE day = 1

Assume following fact table:

sale	prodld	storeld	day	amt
	p1	s1	1	12
	p2	s1	1	11
	p1	s3	1	50
	p2	s2	1	8
	p1	s1	2	44
	p1	s2	2	4



Group by & Aggregation

• Sum up amounts by day

SELECT day, sum(amt) FROM SALE GROUP BY day

sale	prodld	storeld	day	amt
	p1	s1	1	12
	p2	s1	1	11
	p1	s3	1	50
	p2	s2	1	8
	p1	s1	2	44
	p1	s2	2	4



Common operations

- Sum up amounts by day, product
- In SQL: SELECT prodid,day,sum(amt) FROM SALE GROUP BY prodId, day

sale	prodld	storeld	day	amt					
	p1	c1	1	12		sale	prodid	day	amt
	p2	c1	1	11	•		p1	1	62
	p1	c3	1	50			n2	1	10
	p2	c2	1	8			μ <u>2</u>	ו ר	19
	p1	c1	2	44			рт	2	48
	p1	c2	2	4					





Recall: Star Schema Example 1



Compute volume of sales per product_key and store

							Store	Product_key	sum(amount)
							1	1	454
C	alaa		P	roduct_	_key		1	4	925
3	ales	1	2	3	4		2	1	468
	1	151			025		2	2	800
	1	434	-	_	923		3	1	296
ore	2	468	800	-	-		3	3	240
Sto	3	296	-	240	-		4	1	652
	1	650		540	715		4	3	540
	4	032	_	540	743		4	4	745

SQL: SELECT LOCATION.store, SALES.product_key, SUM (amount) FROM SALES, LOCATION WHERE SALES.location_key=LOCATION.location_key GROUP BY SALES.product_key, LOCATION.store



C	alaa		Р	roduct_	_key		
S	ales	1	2	3	4	ALL	
	1	454	-	-	925	1370	Aggregate sales
	2	468	800		-	1268	group by (store,product_key
tore	3	296		240	_	536	
	4	652	-	540	745	1937	
	ALL	1870	800	780	1670	5120	

C	alaa		Р	roduct_	_key			
3	ales	1	2	3	4	ALL		
	1	454	-	-	925	1379	>	Aggregate sales
0	2 468	800	-	_	1268		group by (store)	
Store	3	296	-	240	_	536		
	4	652	-	540	745	1937		
	ALL	1870	800	780	1670	5120		

Cross-Tabulation (products/store)

Salas		Product_key							
3	ales	1	2	3	4	ALL			
	1	454	-	-	925	1379			
tore	2	468	800	-	-	1268			
	3	296	-	240	-	536			
	4	652	-	540	745	1937			
	ALL	1870	800	780	1670	5120			

Aggregate sales group by (product_key)

Sales			Р				
		1	2	3	4	ALL	
	1	454	-	-	925	1379	
	2	468	800	-	_	1268	
Store	3	296	-	240	_	536	
	4	652	-	540	745	1937	
	ALL	1870	800	780	1670	5120	What is this?

Cross-Tabulation (products/store)



4 Group-bys here:

(store, product key)

Multiple Simultaneous Aggregates: Optimizations?

Cross-Tabulation (products/store)

Salas		Product_key							
3	ales	1 2		3	4	ALL			
	1	454	Ι	-	925	1379			
0	2	468	800	I	I	1268			
Store	3	296	-	240	-	536			
	4	652	-	540	745	1937			
	ALL	1870	800	780	1670	5120			

<u>4 Group-bys here:</u> (store,product_key) (store) (product_key) ()



The Data Cube Operator (Gray et al)

• All previous aggregates in a single query:

SELECT LOCATION.store, SALES.product_key, SUM (amount) FROM SALES, LOCATION WHERE SALES.location_key=LOCATION.location_key GROUP BY SALES.product_key, LOCATION.store WITH CUBE

<u>Challenge</u>: Optimize Cube Computation

Relational View of Data Cube

Sales		Product							
		1	2	3	4	ALL			
	1	454	-	-	925	1379			
	2	468	800	-	-	1268			
Store	3	296	1	240	-	536			
ST.	4	652	-	540	745	1937			
	ALL	1870	800	780	1670	5120			

SELECT LOCATION.store, SALES.product_key, SUM (amount) FROM SALES, LOCATION

WHERE SALES.location_key=LOCATION.location_key

GROUP BY SALES.product_key, LOCATION.store WITH CUBE

Store	Product_key	sum(amount)
1	1	454
1	4	925
2	1	468
2	2	800
3	1	296
3	3	240
4	1	652
4	3	540
_4	4	745
1	ALL	1379
2	ALL	1268
3	ALL	536
_4	ALL	1937
ALL	1	1870
ALL	2	800
ALL	3	780
ALL	4	1670
ALL	ALL	5120

Quiz

- SALES(customer, sales_person, store, product, amt)
- Assume the SUM() aggregate function
- What is the meaning of the following data cube records?

(ALL,'JOHN',ALL,ALL,5000)

('NICK',ALL,ALL,'BEER',250)

(ALL,ALL,ALL,'MILK',70000)

(ALL,ALL,ALL,ALL,250000)

Group by (Product, Quarter, Region)

SUM() aggregate function



Group by (Product, Quarter, Region)



Group by (Product, Quarter, Region) Total sales of DVDs in the 1st Qtr in America



Data Cube: Multidimensional View



How are aggregates computed?

- 1. Bring all records with same values in the groupping attributes together
- 2. Aggregate their measures

- (1) is done via Hashing / Sorting
- (2) depends on the type of function used
 - Simple calculations for max, sum, count etc
 - Harder for median
Example: Sum sales/prodId ?

Raw data (fact table)

sale	prodld	storeld	date	amt
	p1	s1	1	12
	p2	s1	1	11
	p1	s3	1	50
	p2	s2	1	8
	p1	s1	2	44
	p1	s2	2	4

Step 1: Sort tuples by prodId Raw data (fact table)

sale	prodld	storeld	date	amt
	p1	s1	1	12
	p2	s1	1	11
	p1	s3	1	50
	p2	s2	1	8
	p1	s1	2	44
	p1	s2	2	4

	sale	prodld	storeld	date	amt
Sort(prodId)		p1	s1	1	12
		р1	s1	2	44
	-	p1	s2	2	4
		p1	s3	1	50
		p2	s1	1	11
		p2	s2	1	8

Step 2: Aggregate records (sum amt)

Sorted Raw data

sale	prodld	storeld	date	amt	
	p1	s1	1	12	
	p1	s1	2	44	Sales for prodid=1
	p1	s2	2	4	
	p1	s3	1	50	
	p2	s1	1	11	
	p2	s2	1	8	



More on aggregate

- Assumed SUM() function
- How much space needed?
- How about AVG()?
- How about MEDIAN()?

S	sale	prodld	storeld	date	amt
		p1	s1	1	12
		p1	s1	2	44
		p1	s2	2	4
		p1	s3	1	50
		p2	s1	1	11
		p2	s2	1	8

Aggregate Computation

• Certain functions

(SUM,MIN,MAX,COUNT,AVERAGE, etc) require small (bounded) space for storing their state and may be computed on the fly, while executing the merging phase of the 2-phase sort algorithm.

• Cost = 3 * B(R), assuming $M^2 \ge B(R) > M$



Example: 2 records/bucket

INSERT: h(a) = 1 h(b) = 2 h(c) = 1 h(d) = 0



h(e) = 1

How does this work for aggregates?

Hash on prodId

prodid	storeld	date	amt
p1	s1	1	12
p1	s3	1	50
p1	s1	2	44
p1	s2	2	4
<mark>р3</mark>	s5	1	7
p7	s2	2	1

Possibly keep records sorted within bucket

h(*prodId*) = *prodId* mod 2

prodld	storeld	date	amt
p2	s1	1	11
p2	s2	1	8

Two buckets

Not the best hash function

Naïve Data Cube Computation

• Fact table:

sale	prodld	storeld	amt
	p1	s1	12
	p2	s1	11
	p1	s3	50
	p2	s2	8
	p1	s1	44
	p1	s2	4

- Compute: SUM(amt) GROUP BY prodId, storeId WITH CUBE
 - 4 group bys contained in this Data Cube:

prodld	storeld	sum(amt)
p1	s1	56
p1	s2	4
p1	s3	50
p2	s1	11
p2	s2	8

prodld	amt	storeld	amt	amt
p1	110	s1	67	129
p2	19	s2	12	
		s3	50	

Full Data Cube (from previous example)

prodId	storeId	sum(amt)
p1	s1	56
p1	s2	4
p1	s3	50
p2	s1	11
p2	s2	8
p1	ALL	110
p2	ALL	19
ALL	s1	67
ALL	s2	12
ALL	s3	50
ALL	ALL	129

How much does it cost to compute?

- Assume B(SALES)=1 Million Blocks, larger than main memory
- Our (brute force) strategy: compute each group by indepedently
 - Compute GROUP BY prodId, storeId
 - Compute GROUP BY prodId
 - Compute GROUP BY storeId
 - Compute GROUP BY none (=total amt)

First Group By: prodld, storeld

• In SQL

SELECT prodId,storeId,sum(amt) FROM SALES GROUP BY prodId,storeId

• Use sorting: 3*B(SALES) = 3M I/O

Second Group By: prodld

• In SQL

SELECT prodId,sum(amt) FROM SALES GROUP BY prodId

• Use sorting: 3*B(SALES) = 3M I/O (same)

Third Group By: storeld

• In SQL

SELECT storeld, sum(amt) FROM SALES GROUP BY storeld

• Use sorting: 3*B(SALES) = 3M I/O (same)

Group By (none) = sum(amt)

• SQL:

SELECT sum(amt) FROM SALES

• Cost ?

Recap

- Group By prodId, storeId : 3M I/Os
- Group By prodId : 3M I/Os
- Group By storeId : 3M I/Os
- Group By none : 1M I/Os
 - Compute aggregate function over all records, no sorting necessary
- Total Cost for the Data Cube: 10M I/Os
 Is this a lot?

Practice Problem

- Rotation speed 7200rpm
- 128 sectors/track
- 4096 bytes/sector
- 4 sectors/block (16KB page size)
- Sequential I/O: ignore SEEKTIME, gaps, etc

Sustained disk speed

- 1 full rotation
 - takes 60/7200=8.33ms
 - retrieves 1 track = 128 sectors = 32 pages (blocks)
- 10 Million blocks in
 8.33/1000 * 10M/32 = 43.5 minutes

• Can we do better?

Share sort orders

If sorted on (prodId, storeId)

prodld	storeld	date	amt
p1	s1	1	12
p1	s1	2	44
p1	s2	2	4
p1	s3	1	50
p2	s1	1	11
p2	s2	1	8

Then, also sorted on (prodId)

prodld	storeld	date	amt
p1	s1	1	12
p1	s1	2	44
p1	s2	2	4
p1	s3	1	50
p2	s1	1	11
p2	s2	1	8

Thus, no need to sort SALES twice!

Two group-bys with a single sort on (prodId, storeId)

Output of 2-phase sort algorithm Maintain 2 variables output (one row at a time) SUM2 SUM1 prodld storeld date amt 12 12 12 p1 s1 1 2 s1 44 56 56 **p1** + 2 4 4 60 p1,s1,56 s2 **p1** s3 1 50 50 110 p1,s2,4 p1 1 p2 s1 11 11 11 p1,s3,50 p1,110 1 8 8 19 p2 s2 p2,s1,11 p2,s2,8 p2,19 EOT (End-Of-Table)

- SUM1 is used for group-by(prodId,storeId), SUM2 for group-by(prodId)

-Each time we see a new (prodId,storeId) combination we report the previous pair and SUM1 value and initialize SUM1 to the new amt

- Similar logic for SUM2
- Report last combination at EOT

Share sort orders for multiple group bys

- Sort SALES on prodld, storeld
 - At the merging phase compute both group by prodId and prodId,storeId
 - Also compute group by none
- Then compute group by storeld by sorting SALES on storeld
- Cost = 3B(SALES) + 3B(SALES) = 6M I/Os
 - Compared to 10M I/Os
 - 40% savings

prodld	storeld	date	amt
p1	s1	1	12
p1	s1	2	44
p1	s2	2	4
p1	s3	1	50
p2	s1	1	11
p2	s2	1	8

Can we do better?

- Sort SALES on prodld, storeld
 - At the merging phase compute both group by (prodId,storeId)) and group by (prodId)
 - Also compute group by none at the same time
- Compute group by (storeld) by sorting the result of group by (prodld,storeld) on storeld
 - Notice that by construction
 B(gb(prodId,storeId)) ≤ B(SALES)
 - Each tuple in gb(prodId,storeId) is produced by one or more tuples in SALES

gb(prodId,storeId)

prodld	storeld	sum(amt)
p1	s1	56
p1	s2	4
p1	s3	50
p2	s1	11
p2	s2	8



3D Data Cube Lattice

 Model dependencies among the aggregates (independently of the method of computation, e.g. by sorting or otherwise)



can be computed from *grouby* (product,store,quarter) by summing-up all quarterly sales

gb(product,store) is equivalent
to gb(store,product)

Discussed optimization (sharing sort orders) on the 3D Data Cube

- Sort SALES on product, store, quarter (also get gb product, store, gb product and gb none)
- Sort SALES on product, quarter
- Sort SALES on store, quarter (also get gb store)



Compute from "smallest parent" vs "sharing sort orders"

- Consider computation of gb product, quarter
- Previously: Sort SALES on product, quarter
- Alternative: read and sort previously computed gb product,store,quarter
 - This gb will be smaller than SALES
 - It may even fit in memory (one-pass sort)
 - This gb is *partially* sorted (common prefix)



ESTIMATING THE DATA CUBE SIZE

How many group bys in the Data Cube?

• N-dimensional data, no hierarchies



2D Data Cube lattice

2-dimensional data (product, store)
 2² =4 group bys



Let's add a simple hierarchy

- Assume that products are organized into categories
- When we group the sales (facts) we have the option to use this knowledge
 - Aggregate sales per category
 - Aggregate sales per category and store
 - But it does not make sense to aggregate sales per product and category (WHY?)

Compare these two results

product	category	sum(amt)	product	sum(amt)
p1	cat1	110	p1	110
p2	cat1	19	p2	19
p3	cat3	240	р3	240
p4	cat2	255	p4	255
p5	cat1	75	p5	75

Notice that there is no difference in the computed aggregates, since prodId \rightarrow category

2D Data Cube lattice with simple hierarchy



2D Data Cube lattice with 2 separate hierarchies on the product dimension



Notice lack of gb on (product, store, brand, category)

#of group bys when there is a single hierarchy per dimension

- N dimensions
- Dimension d_i has a hierachy of length L_i
- Location: store→city→country

L_{Location} =3

– If no hierarchy, then $L_i = 1$

- Number of group bys = $(1+L_1)(1+L_2)...(1+L_N)$ - No need to memorize formulas! Seek to
 - understand their derivation instead (next slide)

How is the formula derived

- Consider Location dimension with hierarchy
 - store→city→country (i.e. L_{Location} =3)
- In a group by (aggregate) query I may
 - Not consider location at all (e.g. total sales per product)
 - Another way to think about this is that +1 stands for ALL
 - Consider location information at the store-level
 - (e.g. total sales per customer, store)
 - Consider location information at the city-level
 - (e.g. total sales per product, city)
 - Consider location information at the country-level
 - (e.g. total sales per sales_person, country)
- There are (1+3) choices regarding that dimension independently on what other dimensions I select in a gb
 - Thus, $(1+L_1) (1+L_2)... (1+L_N)$ possible combinations of dimensions in a query

Example

- 8 dimensions (typical)
- 3-level hierarchy/dimension
- Number of group bys = 4^8 =65536 group bys!
- BUT, how many tuples in the cube?
 - Depends on data distribution
 - Worst case is uniform

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Upper bound on the size of each group by

- Assume relation R (fact table) has T(R) tuples
- Each dimension has cardinality t_i
- Size of group by (d₁, d₂,... d_k) is upper bounded by both
 - $-t_1^* t_2^* .. t_k$
 - T(R) (since records in the group by are produced by combination of attribute values that appear in existing facts)
Example gb(customer,product)

- Assume I have 1000 customers and 50 products
- Assume uniform distribution (customers buy products with same probability)
 - There can be 1000 x 50 combinations of pairs (customer, product) in the fact table (sales)
 - Thus, 50000 records in gb(customer, product) (at most)
- Each record in this gb is derived from a real sale
 - There can not be an aggregated record if there are not base records in the fact table to support it
- Thus, there can not be more records in the gb than the number of actual sales in the fact table

Example

- Consider R(product, store, quarter, amt) with 1M records
- 10,000 products, 30 stores, 4 quarters
 - Let G(x,y) denote the maximum number of records in group by x,y
 - G(product,store,quarter)=min(1M,10000*30*4)=1,000,000
 - G(product,store)=min(1M,10000*30)=300,000
 - G(product,quarter)=min(1M,10000*4)=40,000
 - G(store,quarter)=min(1M,30*4)=120
 - G(product)=min(1M,10000)=10,000
 - G(store)=min(1M,30)=30
 - G(quarter)=min(1M,4)=4
 - G(none)=1
 - Maximum cube size = 1,350,155 records

Quick and Dirty Upper Bound

MAX-SIZE<=10001*31*5 = 1550155

 $(1+t_1)^*(1+t_2)^*(1+t_3)$

(compare with 1350155)

This upper bound ignores size of fact table WHY ??

Data Cube: Multidimensional View



Extended Cube with Hierarchies

- Products are organized in 50 categories
- Additional group bys in extended cube
 - +G(category, store, quarter) = min(1M, 50*30*4) = 6,000
 - +G(category,store)=min(1M,50*30)=1,500
 - +G(category,quarter)=min(1M,50*4)=200
 - +G(category)=min(1M,50)=50
 - Maximum ext-cube size = 1,357,905 records

Correlated Attributes

- In practice there is some correlation between different dimensions
- Example 1: each store sells up to 1,000 products (specialized stores)
- Example 2: some products are not sold through-out the year

- Ice cream, watermelon, snow-chains

Solve Example-1

- R(product,store,customer) with 1M records
- 1,000 products, 20 stores, 100 customers
- Each customer buys from one store (closest)
 FD: customer → store

G(store,customer)=min(1M,1*100)=100

G(product,store,customer)=min(1M,1000*1*100) =100,000

More realistic example

- 100,000 parts
- 20,000 customers
- 2,000 suppliers
- 5 years (=365 *5 days)
- 100 stores
- 1,000 sales persons
- Max-cube size = 738,855,253,876,896,582,426 (tuples)

Catch With Data Cube

- toooooo many aggregates
- So Data Cube is large!

-And takes time to compute...

What to Materialize?

- Data Cube extremely large for many applications
- Store in warehouse results useful for common queries
- Example:
 - -Total sales per product, store
 - -Max sales per product
 - -Avg sales per store, day

Materialization Factors

- Type/frequency of queries
- Query response time
- Storage cost
- Update cost

MATERIALIZED VIEWS

Preliminaries

- We will consider solutions that selectively materialize some of the groups by in the Data Cube
- We will be referring to the group bys as "views"
- When a group by is materialized we will call it "materialized view"

Views in OLTP databases

- Views are **derived** tables
 - Instance of view is generated on demand by executing the view query:
 - create view V as
 - select ename, age, address, telno
 - from employee
 - where employee.dept = "Sales"
- Views have many uses
 - Shortcuts for complex queries
 - Logical-physical independence
 - Hide details from the end-user
 - Integration systems

Employee(ename, age, dept, address, telno, salary)

Materialized Views (OLAP)

- Sometimes, we may want to compute and store the content of the view in the database
 - Such Views are called materialized
 - Queries on the materialized view instance will be much faster
 - Materialized views are now supported by some vendors
 - Otherwise we will be storing their data in regular tables
- This is our extended architecture:

Data Warehouse=

detailed records (star schema) + aggregates (materialized views)

Used to speed up certain queries of interest

Materialized views in OLAP

- Contain derived data
 - Can be computed from the star schema
- Populated while updating the data warehouse
 - Usually they contain results of complex aggregate queries
- Several interesting problems:
 - How to select which views to materialize?
 - How to compute/refresh these views?
 - How to store these views in the relational schema?
 - How to use these views at query time?

View selection problem

- Set up as an optimization problem
 - $-V_{DC}$ = set of all group bys (=views) in the Data Cube
 - Give a constraint
 - Usually space bound B, e.g. materialize up to 100GB from the CUBE
 - What else?
 - Give an objective
 - Minimize cost of answering set of (frequent/interesting) queries Q
- View selection problem (with space constraint):

```
\begin{array}{l} \underset{V \subseteq V_{DC}}{\text{minimize}} & Cost(Q) \\ \text{such that Size}(V) \leq B \end{array}
```

• Problem is NP-hard

View Selection Problem: Heuristic

• Use some notion of *benefit* per view based on the dependencies depicted in the Data Cube lattice



group by(product,store)

product	store	sum(amt)
р1	s1	56
р1	s2	4
p1	s3	50
p2	s1	11
p2	s2	8

Queries related to these group bys can be computed from a materialized view on group by (product,store), independently of the method of computation (sort, hash, etc)

A simple greedy algorithm

- Utilize a benefit criterion
 - Assume V is the views we have chosen so far
 - Let v be a candidate view not in V
 - Benefit(v) = cost of answering queries using V cost of answering queries using V U {v}
 - Measures the reduction in query answering cost if this view is materialized
 - Benefit(v) ≥ 0
- Greedy algorithm
 - At each step, pick the view that has the maximum benefit
 - Re-compute benefits of remaining views
 - Update B=B-sizeof(v)
 - Remove views that do not fit in new B
 - Stop if no more space available or no view fits in the remaining space

Simple Example

- Star schema with three dimensions
 Product (p), Store location (s), Quarter (q)
- Assume the following queries Q = {(p,s),(s,q), (p,q), (p),(s)}
 - Notation: (s,q) is a query on group by (store,quarter)

(s,q): SELECT store, quarter, sum(amt) FROM SALES GROUP BY store, quarter

Query computation cost

• For ease of presentation, let us assume that each query can be computed from the fact table SALES with the same cost 100 I/O

> (s,q): SELECT store, quarter, sum(amt) FROM SALES GROUP BY store, quarter

> > Cost = 100 I/O

Data Cube sizes

 Assume each group by in the Data Cube requires the depicted number of blocks, when stored as a materialized view



Assumption (for this simple example)

 A group by query is computable from an ancestor materialized view V with Cost=size(V)



Computation for (s,q) from Sales:

(s,q): SELECT store, quarter, sum(amt) FROM SALES GROUP BY store, quarter Cost = 100 I/O

Alternative computation for (s,q):

SELECT store, quarter, sum(amt) FROM V_{product,store,quarter} GROUP BY store, quarter Cost = 80 I/O

View Selection Problem

• Minimize the cost of answering the depicted queries when available space B=100



Initial Benefits (no view is materialized yet)

Group By (Materialized	Benefit for
View)	$Q = \{(p,s),(s,q), (p,q), (p),(s)\}$
p,s,q	(100-80)+(100-80)+(100-
	80+(100-80)+(100-80)=100
p,q	2*(100-25)=150
s,q	2*(100-13)=174
p,s	3*(100-60)=120
p	100-4=96
S	100-3=97
q	0
None	0

Step-1

- Materialize view V_{s,q}
- Update space budget B = 100-13 = 87
- Recompute benefits (next slide)

Updated Benefits

Space=87 V={(s,q)}

Group By (Materialized	Benefit for		
View)	Q={(p,s),(s,q), (p,q), (p),(s)}		
p,s,q	3 *(100-80)=60		
p,q	(100-25)+(100-25)=150		
s,q	MATERIALIZED		
p,s	2*(100-60)+0=80 (careful)		
р	100-4=96		
S	13-3=10 (careful)		
q	0		
None	0		

Step-2

- Materialize view V_{p,q}
- Update space budget B = 87-25 = 62
- Update benefits (next slide)

Updated Benefits

Space=62 V={(s,q),(p,q)}

Group By (Materialized	Benefit for		
View)	$Q = \{(p,s),(s,q), (p,q), (p),(s)\}$		
p,s,q	Not-enough-space-left		
p,q	MATERIALIZED		
s,q	MATERIALIZED		
p,s	(100-60)=40 (careful)		
р	25-4 =21 (careful)		
S	13-3=10 (careful)		
q	0		
None	0		

Step-3

- Materialize view V_{p,s}
- Update space budget B = 62-60 = 2
- Update benefits

Updated Benefits

Space=2 V={(s,q),(p,q),(p,s)}

Group By (Materialized	Benefit for		
View)	Q={(p,s),(s,q), (p,q), (p),(s)}		
p,s,q	Not-enough-space-left		
p,q	MATERIALIZED		
s,q	MATERIALIZED		
p,s	MATERIALIZED		
p	Not-enough-space-left		
S	Not-enough-space-left		
q	0		
None	0		

Greedy algorithm selection

- Final choice V={(s,q),(p,q),(p,s)}
 - Utilize 25+13+69=98 blocks out of 100 available



Query costs for this selection

- Q = {(p,s),(s,q),
 (p,q), (p),(s)}
 - Cost(p,s) = 60
 - Cost(s,q) = 13
 - Cost(p,q) = 25
 - Cost(p) = 25
 - Cost(s) = ?



Benefit of using Materialized Views Q = {(p,s),(s,q), (p,q), (p),(s)}

Using the suggested Materialized Views

Cost(p,s) = 60 Cost(s,q) = 13 Cost(p,q) = 25 Cost(p) = 25Cost(s) = 13 Querying the Fact Table Cost(p,s) = 100Cost(s,q) = 100Cost(p,q) = 100Cost(p) = 100Cost(s) = 100

Total Query Cost = 136

Total QueryCost = 500

The View Update problem

Materialized View: Vsc

Table Deltas:

(new records to be appended in the fact table)

Store	Customer	Price		Store	Customer	Product	Price
			New sale:	S 1	C2	P2	\$55
S 1	C2	\$700					
S1	C3	\$240		S1	C2	Р3	\$15
S 2	C1	\$190					
S2	C3	\$450		S 1	C1	P1	\$50
How to	update this v	'IEW ?		S2	C1	P3	\$20

Choice 1: Re-compute from fact table

- First update fact table (append new facts)
- Then re-execute SQL query to obtain view

In SQL:

//load new records insert into Fact select * from Delta //drop and recreate View drop Vsc; create table Vsc(store,customer,price); //recompute View from scratch insert into Vsc select store,customer,sum(price) from Fact group by store,customer;
Choice-2: Incremental Updates

- Adding delta tuples means
 - Step 1: Update sum() from combinations already in the view
 - Step 2: Insert sum() with new coordinates for rest

Store	Customer	Price
S 1	C2	\$700
S 1	C3	\$240
S 2	C1	\$190
S 2	C3	\$450

Store	Customer	Product	Price
S1	C2	P2	\$55
S1	C2	Р3	\$15
S1	C1	P1	\$50
S2	C1	Р3	\$20

Step 1: Increment existing combinations

update Vsc

set Vsc.m=Vsc.m+(select sum(price) from Delta
 where Vsc.store=Delta.store and
 Vsc.customer=Delta.customer)
 where (Vsc.store,Vsc.customer)
 in
 (select store,customer from Delta);

Step 2: Add new combinations

insert into Vsc

select store,customer,sum(price)
from Delta where (store,customer) not in
 (select store,customer from Vsc)
group by store,customer;

Choice-2: Alternative

 Idea: add delta records to the view, create a new table to hold updated records, then rename

insert into Vsc

select store, customer, sum (price) from Delta

group by store, customer;

create table Vnew(store,customer,price);

insert into Vnew

select store,customer,sum(price) from Vsc

group by store, customer

drop table Vsc;

rename table Vnew to Vsc;

Simple Example

After insertion of deltas

Final View

Store	Customer	Price	
S 1	C2	\$700	<
S1	C3	\$240	
S 2	C1	\$190	•
S2	C3	\$450	
S 1	C1	\$50	
S 1	C2	\$70	
S2	C1	\$20	

Store	Customer	Price
S1	C1	\$50
S 1	C2	\$770
S 1	C3	\$240
S 2	C1	\$210
S2	C3	\$450

Multiple View Update

Assume V2 descendant of V1 in the Data Cube Lattice (e.g. V1 can be used to compute V2)





Scenario 1: Re-compute views after finishing updating the Fact table





Scenario 3: Incrementally update V1 from delta then recompute V2 from V1



Scenario 4: Incrementally update both V1 and V2 from delta



Consider

• More scenarios?

• Now consider the case of 100 views

PHYSICAL REPRESENTATION OF MATERIALIZED VIEWS IN THE STAR SCHEMA

Want to create View: SUM(Quantity), SUM(TotalPrice) per Category, CityName



SQL Επερώτηση

Select Category,CityName,SUM(TotalPrice) as Sum_TotalPrice,SUM(Quantity) as Sum_Quantity From Fact,Product Where Fact.ProdNo=Product.ProdNo Group by Category,CityName

Create New Fact Table (= this view)



Using Materialized Views through Selection

- A query can use a view through a selection if
 - Each selection condition C on each dimension d in the query logically implies a condition C' on dimension d in the view
- Example: A view has sum(sales) by product and by year for products introduced after 1991
 - OK to use for sum(sales) by product for products introduced after 1992
 - CANNOT use for sum(sales) for products introduced after 1989

Using Materialized Views through Group By (Roll Up)

- The view V may be applicable via roll-up if for every grouping attribute g of the query Q:
 - Q has Group By a1,..,g, an
 - V has Group By a1,..,h, an
 - Attribute *g* is higher than *h* in the attribute hierarchy
 - Aggregation functions are distributive (sum, count, max, etc)
- Example: Compute "sum(sales) by category" from the view "sum(sales) by product"

Using Views

- Need cost-based optimization to decide which view(s) to use for answering a query
 - Consider a query on (category, state) and three materialized aggregate views on
 - 1. (product, state)
 - 2. (category, city)
 - 3. (category, country)
 - (product, state) and (category, city) are candidate materialized views to answer the query

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Σημείωση

 Τα παρακάτω slides είναι εκτός ύλης για το μάθημα του Σχεδιασμού Βάσεων Δεδομένων

Data Cube Storage and Indexing

- Several approaches within the relational world
 Cubetrees, QC-trees, Dwarf, CURE
- Main idea: exploit inherent redundancy of multidimensional aggregates

The Dwarf (sigmod 2002)

- Data-Driven DAG
 - Factors out inter-view redundancies
 - 100% accurate (no approximation)
 - All views are included
 - Indexes for free
 - Partial materialization possible
- Look at the Data Cube Records
 - Common Prefixes
 - high in dense areas
 - Common Suffixes
 - extremely high in sparse areas

Redundancy in the Cube (1)

Common Prefixes

S2,C1,P1,90 S2,C1,P2,50 S2,C1,ALL,140

Mostly in dense areas:

- customer C1 buys a lot of products at store S2
- all these records have the same prefix: S2,C1

Store	Customer	tomer Product	
S 1	C2	C2 P2	
S1	C3	P1	\$40
S2	C1	P1	\$90
S2	C1	P2	\$50

Redundancy in the Cube (2)

Common Suffices

S2,C1,P1,90 S2,ALL,P1,90 ALL,C1,P1,90

Mostly in sparse areas C1 only visits S2 and is the only customer that buys P1,P2

Store	Customer	Product	Price
S 1	C2	P2	\$70
S 1	C3	P1	\$40
S2	C1	P1	\$90
S2	C1	P2	\$50

Dwarf Example



Store	Customer	Product	Price
S 1	C2	P2	\$70
S 1	C3	P1	\$40
S2	C1	P1	\$90
S2	C1	P2	\$50

Dwarf Example



Store	Customer	Product	Price
S 1	C2	P2	\$70
S 1	C3	P1	\$40
S2	C1	P1	\$90
S2	C1	P2	\$50

Group-by Product:

Store	Customer	Product	Sum(Price)
ALL	ALL	P1	\$130
ALL	ALL	P2	\$120

Dwarf Example



Store	Customer	Product	Price
S 1	C2	P2	\$70
S 1	C3	P1	\$40
S2	C1	P1	\$90
S2	C1	P2	\$50

Group-by Store:

Store	Customer	Product	Sum(Price)
S1	ALL	ALL	\$110
S2	ALL	ALL	\$140