CompSci 516
Database Systems

Lecture 22
Data Warehousing
and
Data Cube

Instructor: Sudeepa Roy

Reading Material

- [RG]
  - Chapter 25

- Gray-Chaudhuri-Bosworth-Layman-Reichart-Venkatrao-Pellow-Pirahesh, ICDE 1996 "*Data Cube: A Relational Aggregation Operator Generalizing Group-By, Cross-Tab, and Sub-Totals*"

- Harinarayan-Rajaraman-Ullman, SIGMOD 1996 "*Implementing data cubes efficiently*"

Acknowledgement:
- The following slides have been created adapting the instructor material of the [RG] book provided by the authors Dr. Ramakrishnan and Dr. Gehrke.
- Some slides have been prepared by Prof. Shivnath Babu

Data Warehousing

Warehousing

- Growing industry: $8 billion way back in 1998
- Data warehouse vendor like Teradata
    - big "Petabyte scale"customers
    - Apple, Walmart (2008-2.5PB), eBay (2013-primary DW 9.2 PB, other big data 40PB, single table with 1 trillion rows), Verizon, AT&T, Bank of America
    - supports data into and out of Hadoop
- Lots of buzzwords, hype
    - – slice & dice, rollup, MOLAP, pivot, ...

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

Ack: Slide by Prof. Shivnath Babu

Motivating Examples

- Forecasting
- Comparing performance of units
- Monitoring, detecting fraud
- Visualization

Introduction

- Organizations analyze current and historical data
  - to identify useful patterns
  - to 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
- Relevant once again for the recent "Big Data analysis"
  - to figure out what we can reuse, what we cannot

Three Complementary Trends

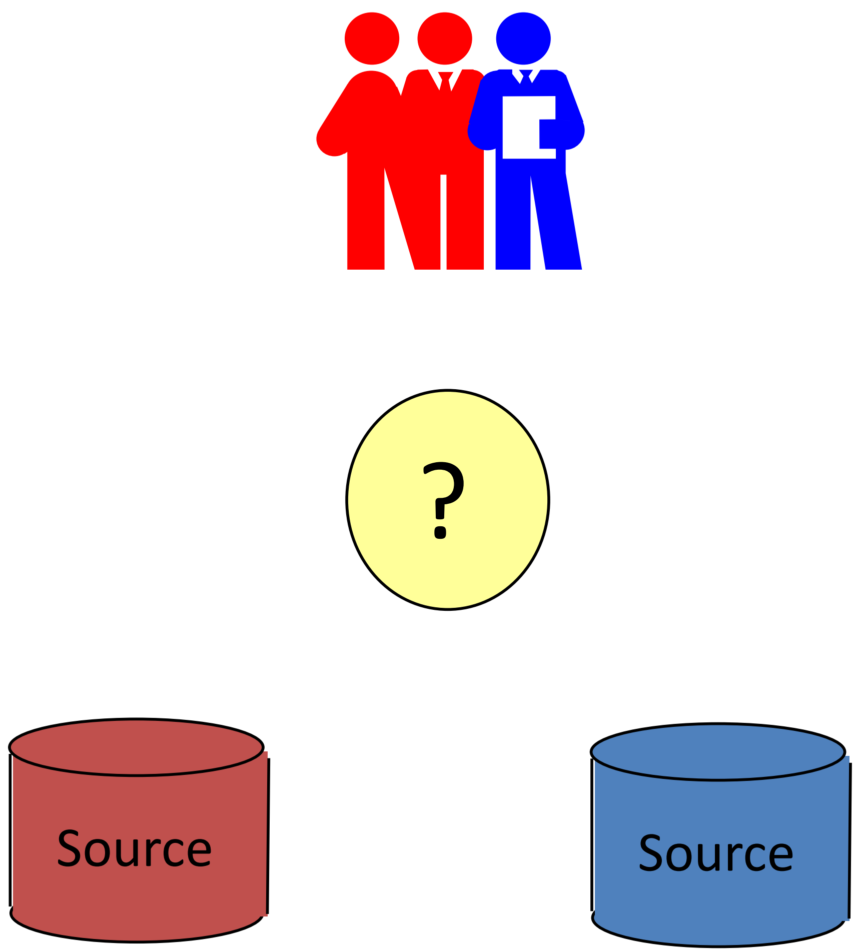
- Data Warehousing (DW):
  - Consolidate data from many sources in one large repository
  - Loading, periodic synchronization of replicas
  - Semantic integration
- OLAP:
  - Complex SQL queries and views.
  - Queries based on spreadsheet-style operations and "multidimensional" view of data.
  - Interactive and "online" queries.
- Data Mining:
  - Exploratory search for interesting trends and anomalies
  - Next lecture!

Data Warehousing

- A collection of decision support technologies
- To enable people in industry/organizations to make better decisions
  - Supports OLAP (On-Line Analytical Processing)
- Applications in
  - Manufacturing
  - Retail
  - Finance
  - Transportation
  - Healthcare
  - …
- Typically maintained separately from "Operational Databases"
  - Operational Databases support OLTP (On-Line Transaction Processing)

Why a Warehouse?

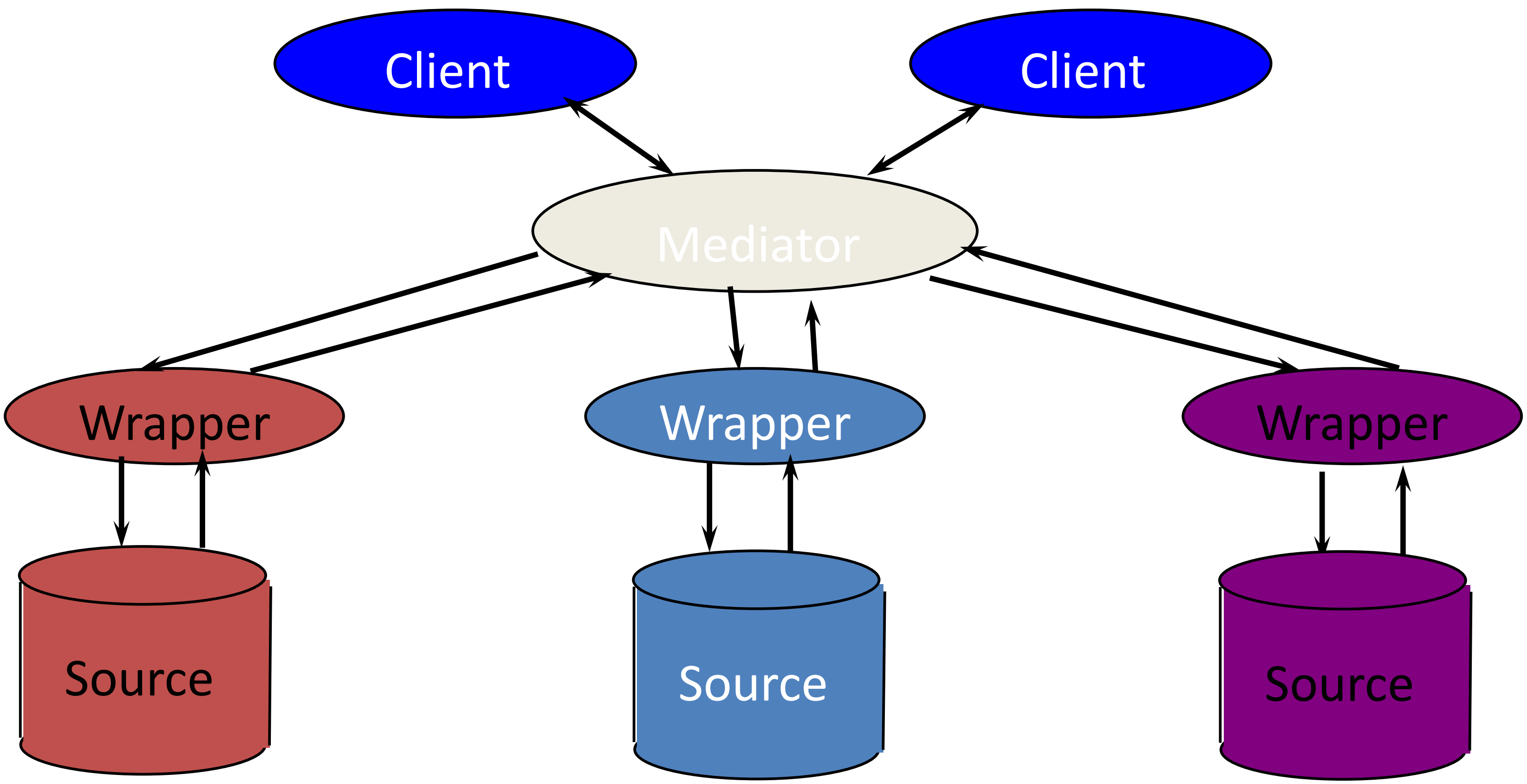
- Two Approaches:
  – Query-Driven (Lazy)
  – Warehouse (Eager)



Advantages of Warehousing

- High query performance
- Queries not visible outside warehouse
- Local processing at sources unaffected
- Can operate when sources unavailable
- Can query data not stored in a DBMS
- Extra information at warehouse
  - Modify, summarize (store aggregates)
  - Add historical information

Query-Driven Approach



Advantages of Query-Driven

- No need to copy data
  - less storage
  - no need to purchase data
- More up-to-date data
- Query needs can be unknown
- Only query interface needed at sources
- May be less draining on sources

OLTP	Data Warehousing/OLAP
Mostly updates	Mostly reads
Applications: Order entry, sales update, banking transactions	Applications: Decision support in industry/organization
Detailed, up-to-date data	Summarized, historical data (from multiple operational db, grows over time)
Structured, repetitive, short tasks	Query intensive, ad hoc, complex queries
Each transaction reads/updates only a few tuples (tens of)	Each query can accesses many records, and perform many joins, scans, aggregates
MB-GB data	GB-TB data
Typically clerical users	Decision makers, analysts as users
Important: Consistency, recoverability, Maximizing tr. throughput	Important: Query throughput Response times

Data Marts

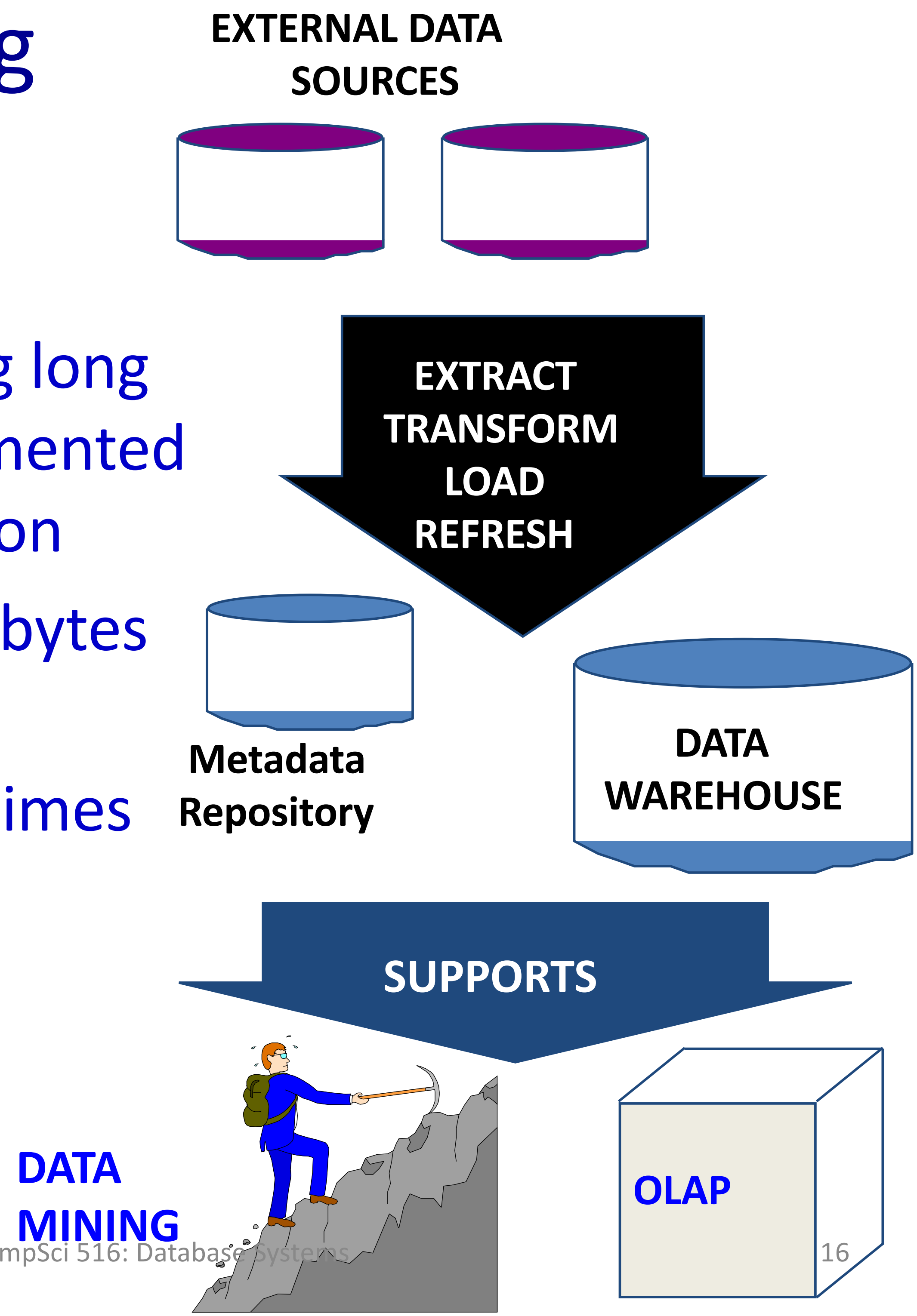
- smaller datawarehouse
- subsets of data on selected subjects
- e.g. Marketing data mart can include customer, product, sales
- Department-focused, no enterprise-wide consensus needed
- But may lead to complex integration problems in the long run

ROLAP and MOLAP

- Relational OLAP (ROLAP)
  - On top of standard relational DBMS
  - Data is stored in relational DBMS
  - Supports extensions to SQL to access multi-dimensional data
- Multidimensional OLAP (MOLAP)
  - Directly stores multidimensional data in special data structures (e.g. arrays)

Data Warehousing to Mining

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



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, loading time, and other information for all data in the warehouse

DW Architecture

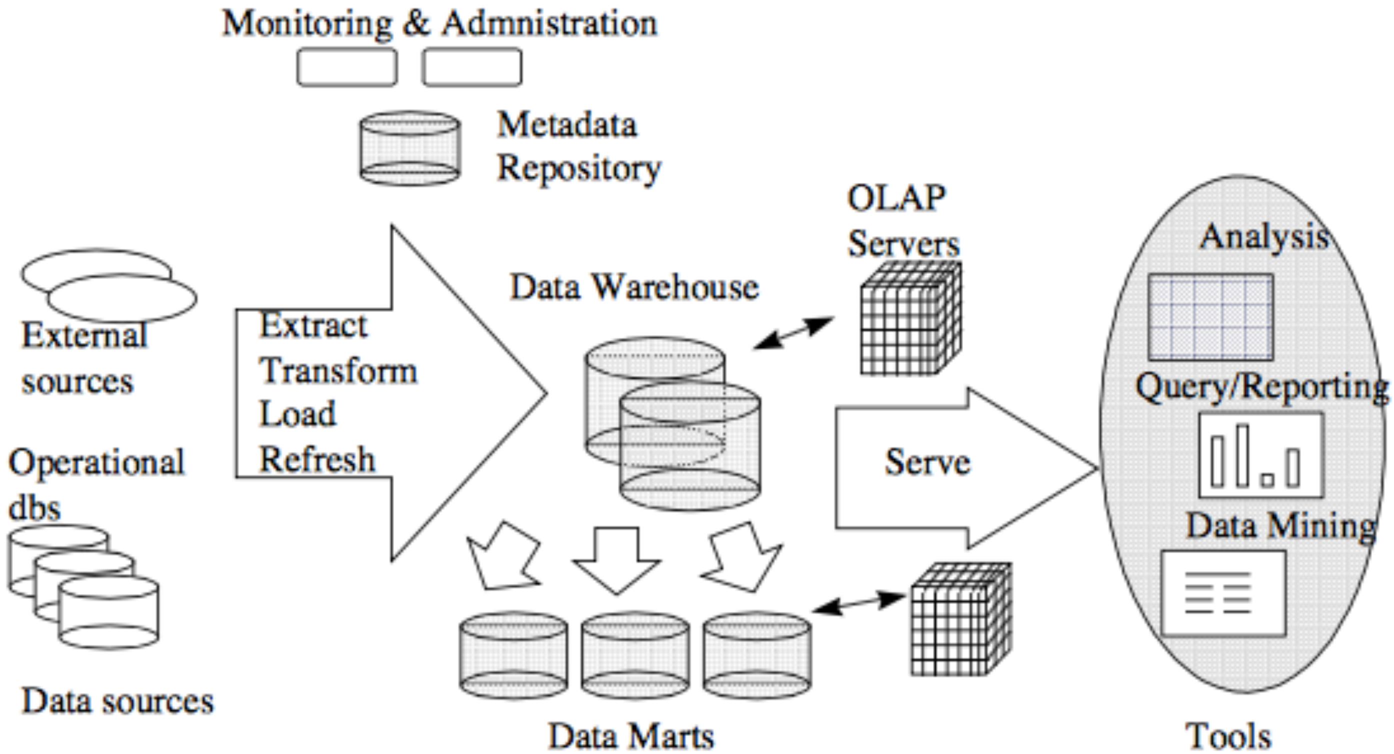


Figure 1. Data Warehousing Architecture

- Extract data from multiple operational DB and external sources
- Clean/integrate/transform/store
- Refresh periodically
  – update base and derived data
  – admin decides when and how

- Main DW and several data marts (possibly)
- Managed by one or more servers and front end tools
- Additional meta data and monitoring/admin tools

ROLAP: Star Schema

- To reflect multi-dimensional views of data
- Single fact table
- Single table for every dimension
- Each tuple in the fact table consists of
  - pointers (foreign key) to each of the dimensions (multi-dimensional coordinates)
  - numeric value for those coordinates
- Each dimension table contains attributes of that dimension

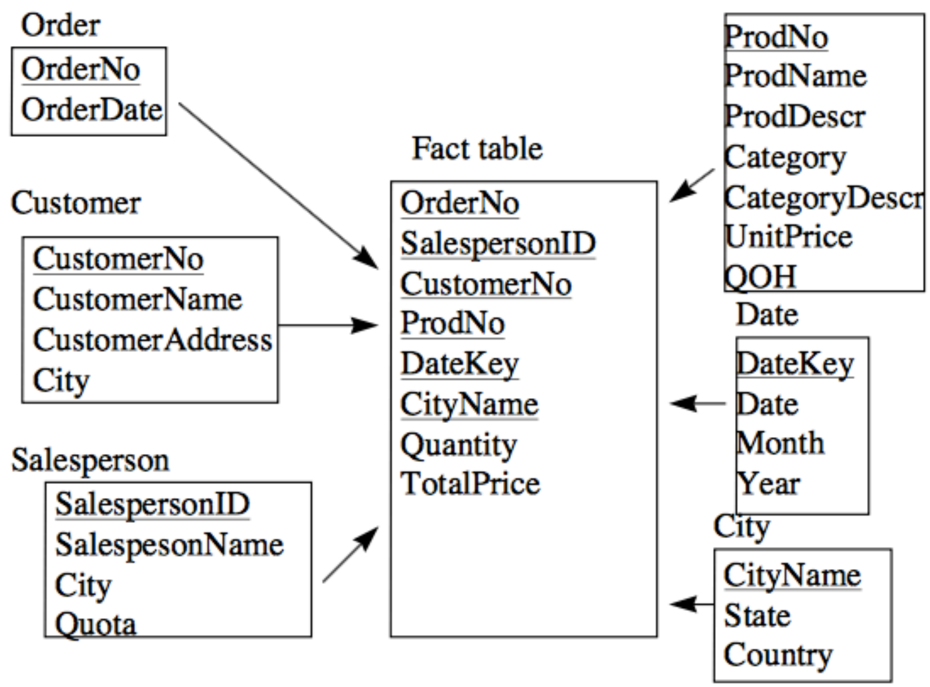


Figure 3. A Star Schema.

No support for attribute hierarchies

Dimension Hierarchies

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

ROLAP: Snowflake Schema

- Refines star-schema
- Dimensional hierarchy is explicitly represented
- (+) Dimension tables easier to maintain
  - suppose the “category description is being changed
- (-) Need additional joins
- Fact Constellations
  - Multiple fact tables share some dimensional tables
  - e.g. Projected and Actual Expenses may share many dimensions

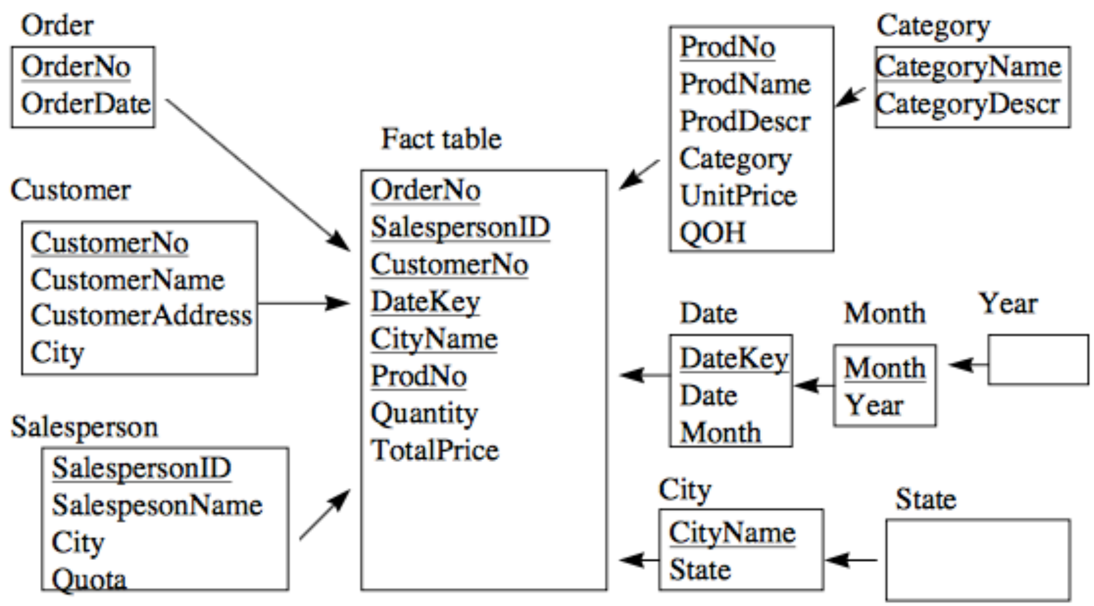


Figure 4. A Snowflake Schema.

Sales (Model, Year, Color, Units)

Motivation: OLAP Queries

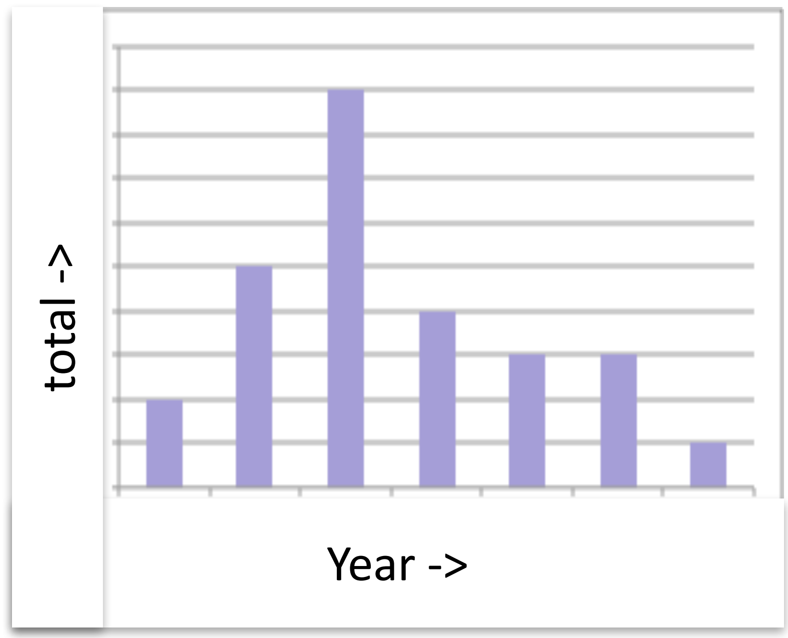
- Data analysts are interested in exploring trends and anomalies
  - Possibly by visualization (Excel) - 2D or 3D plots
  - “Dimensionality Reduction” by summarizing data and computing aggregates
  - Influenced by SQL and by spreadsheets.
  - A common operation is to aggregate a measure over one or more dimensions.
- Find total unit sales for each
  1. Model
  2. Model, broken into years
  3. Year, broken into colors
  4. Year
  5. Model, broken into color, ….

OLAP
and
Data Cube

Histograms

A tabulated frequency of computed values

```
SELECT Year, COUNT(Units) as total
FROM Sales
GROUP BY Year
ORDER BY Year
```



May require a nested SELECT to compute

Sales (Model, Year, Color, Units)

Roll-Ups

- Analysis reports start at a coarse level, go to finer levels
- Order of attribute matters
- Not relational data (empty cells no keys)

Roll-ups

Drill-downs

GROUP BY

Model	Year	Color	Model, Year, Color	Model, Year	Model
Chevy	1994	Black	50		
Chevy	1994	White	40		
				90	
Chevy	1995	Black	115		
Chevy	1995	White	85		
				200	
					290

Sales (Model, Year, Color, Units)

Roll-Ups

- Another representation (Chris Date'96)
- Relational, but
  - long attribute names
  - hard to express in SQL and repetition

GROUP BY

Model	Year	Color	Model, Year, Color	Model, Year	Model
Chevy	1994	Black	50	90	290
Chevy	1994	White	40	90	290
Chevy	1995	Black	85	200	290
Chevy	1995	Black	115	200	290

Sales (Model, Year, Color, Units)

‘ALL’ Construct

Easier to visualize roll-up if allow ALL to fill in the super-aggregates

```
SELECT Model, Year, Color, SUM(Units)
     FROM Sales
     WHERE Model = 'Chevy'
         GROUP BY Model, Year, Color
UNION
SELECT Model, Year, 'ALL', SUM(Units)
     FROM Sales
     WHERE Model = 'Chevy'
     GROUP BY Model, Year
UNION
…
UNION
SELECT 'ALL', 'ALL', 'ALL', SUM(Units)
     FROM Sales
     WHERE Model = 'Chevy';
```

Model	Year	Color	Units
Chevy	1994	Black	50
Chevy	1994	White	40
Chevy	1994	‘ALL’	90
Chevy	1995	Black	85
Chevy	1995	White	115
Chevy	1995	‘ALL’	200
Chevy	‘ALL’	‘ALL’	290

Sales (Model, Year, Color, Units)

Traditional Roll-Up

Model	Year	Color	Model, Year, Color	Model, Year	Model
Chevy	1994	Black	50		
Chevy	1994	White	40		
				90	
Chevy	1995	Black	115		
Chevy	1995	White	85		
				200	
					290

'ALL' Roll-Up

Model	Year	Color	Units
Chevy	1994	Black	50
Chevy	1994	White	40
Chevy	1994	'ALL'	90
Chevy	1995	Black	85
Chevy	1995	White	115
Chevy	1995	'ALL'	200
Chevy	'ALL'	'ALL'	290

- Roll-ups are asymmetric

Sales (Model, Year, Color, Units)

Cross Tabulation

- If we made the roll-up symmetric, we would get a cross-tabulation
- Generalizes to higher dimensions

```
SELECT Model, 'ALL', Color, SUM(Units)
     FROM Sales
     WHERE Model = 'Chevy'
     GROUP BY Model, Color
```

Chevy	**1994**	**1995**	**Total (ALL)**
Black	50	85	135
White	40	115	155
Total (ALL)	90	200	290

Is the problem solved with Cross-Tab and GROUP-BYs with 'ALL'?

- Requires a lot of GROUP BYs (64 for 6-dimension)
- Too complex to optimize (64 scans, 64 sort/hash, slow)

Sales (Model, Year, Color, Units)

Naïve Approach

Run a number of queries

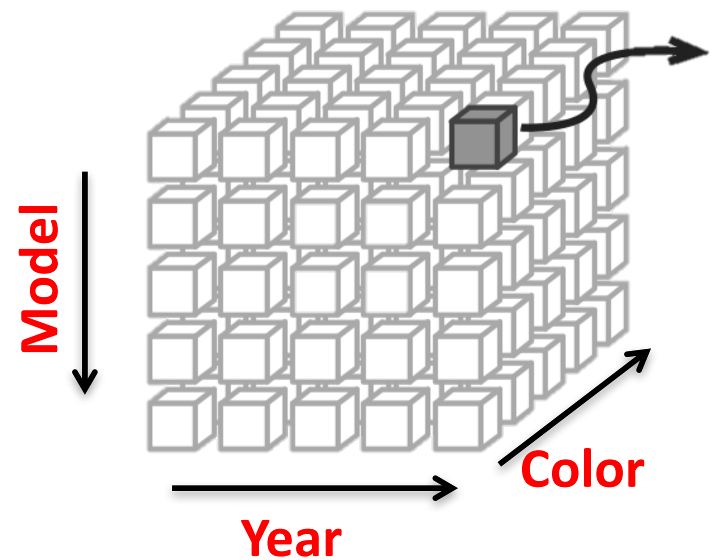
```
SELECT sum(units)
FROM Sales

SELECT Color, sum(units)
FROM Sales
GROUP BY Color

SELECT Year, sum(units)
FROM Sales
GROUP BY Year

SELECT Model, Year, sum(units)
FROM Sales
GROUP BY Model, Year
….
```

Total Unit sales



- Data cube generalizes Histogram, Roll-Ups, Cross-Tabs
- More complex to do these with GROUP-BY

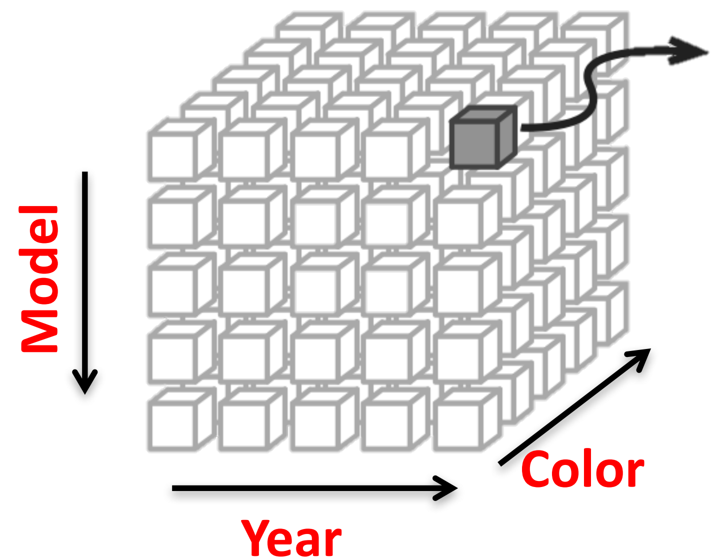
- How many sub-queries?
- How many sub-queries for 8 attributes?

Sales (Model, Year, Color, Units)

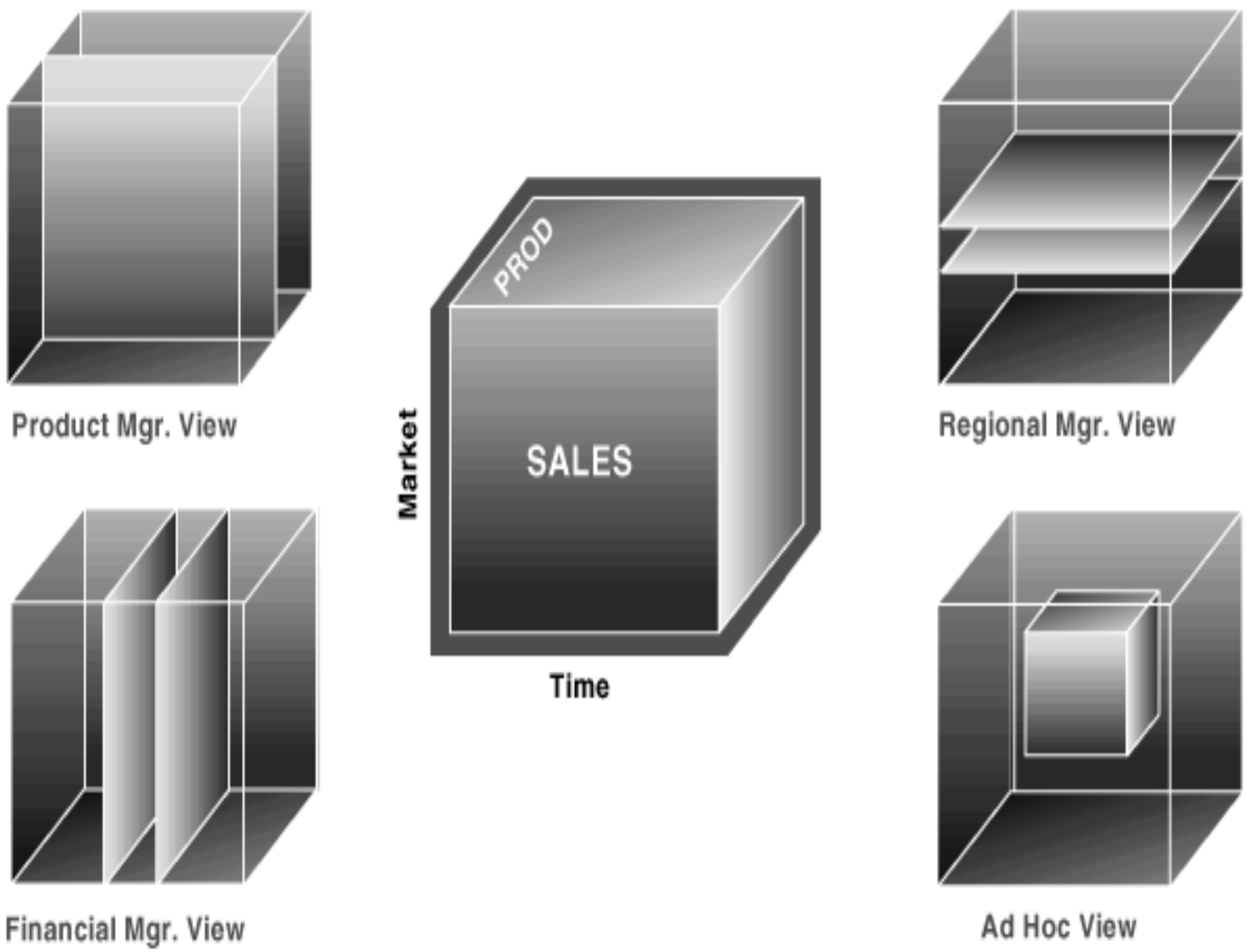
Data Cube: Intuition

```
SELECT 'ALL', 'ALL', 'ALL', sum(units)
FROM Sales
UNION
SELECT 'ALL', 'ALL', Color, sum(units)
FROM Sales
GROUP BY Color
UNION
SELECT 'ALL', Year, 'ALL', sum(units)
FROM Sales
GROUP BY Year
UNION
SELECT Model, Year, 'ALL', sum(units)
FROM Sales
GROUP BY Model, Year
UNION
….
```

Total Unit sales



Data Cube



Ack: from slides by Laurel Orr and Jeremy Hyrkas, UW

Data Cube

- Computes the aggregate on all possible combinations of group by columns.

- If there are N attributes, there are 2^N-1 super-aggregates.

- If the cardinality of the N attributes are C_1,..., C_N, then there are a total of $(C_1+1)...(C_N+1)$ values in the cube.

- ROLL-UP is similar but just looks at N aggregates

Sales (Model, Year, Color, Units)

Data Cube Syntax

- SQL Server

```
SELECT Model, Year, Color, sum(units)
FROM Sales
GROUP BY Model, Year, Color
WITH CUBE
```

Types of Aggregates

- Distributive: input can be partitioned into disjoint sets and aggregated separately
  - COUNT, SUM, MIN
- Algebraic: can be composed of distributive aggregates
  - AVG
- Holistic: aggregate must be computed over the entire input set
  - MEDIAN

- Efficient computation of the CUBE operator depends on the type of aggregate
  - Distributive and Algebraic aggregates motivate optimizations

Implementing Data Cube

Basic Ideas

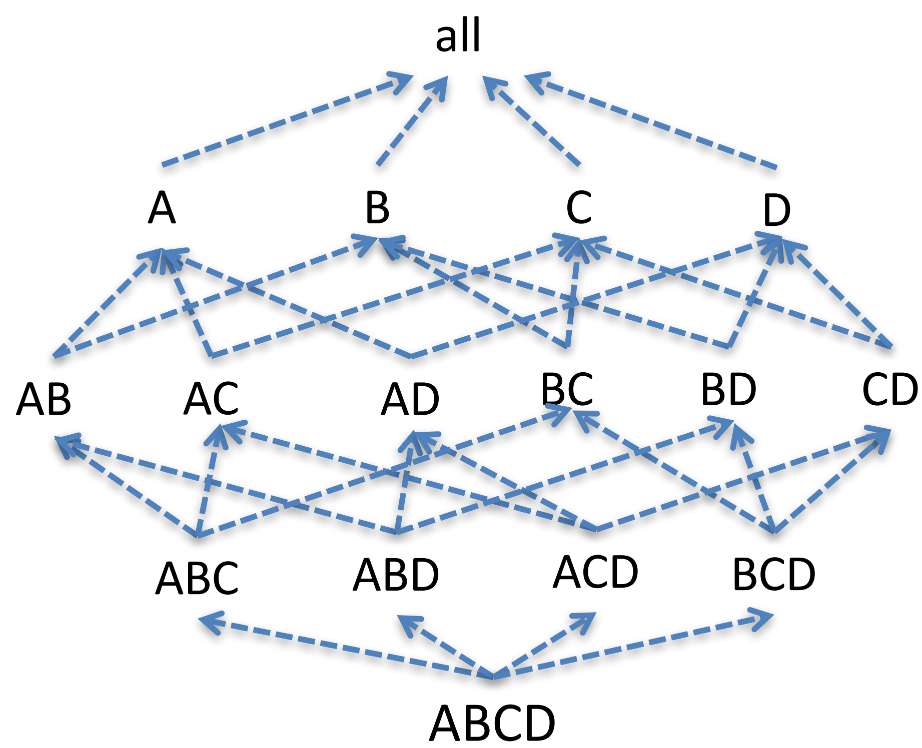
- Need to compute all group-by-s:
  - ABCD, ABC, ABD, BCD, AB, AC, AD, BC, BD, CD, A, B, C, D
- Compute GROUP-BYs from previously computed GROUP-BYs
  - e.g. first ABCD
  - then ABC or ACD
  - then AB or AC …
- Which order ABCD is sorted, matters for subsequent computations
  - if (ABCD) is the sorted order, ABC is cheap, ACD or BCD is expensive

Notations

- ABCD
  - group-by on attributes A, B, C, D
  - no guarantee on the order of tuples
- (ABCD)
  - sorted according to A -> B -> C -> D
- ABCD and (ABCD) and (BCDA)
  - all contain the same results
  - but in different sorted order

Optimization 1: Smallest Parent

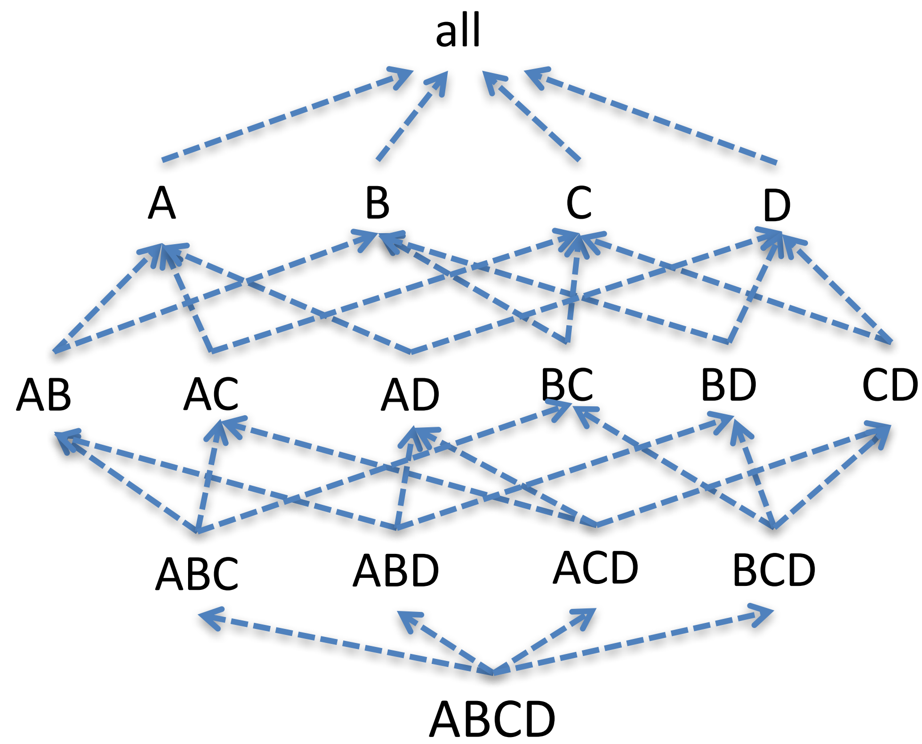
- Compute GROUP-BY from the smallest (size) previously computed GROUP-BY as a parent
  - AB can be computed from ABC, ABD, or ABCD
  - ABC or ABD better than ABCD
  - Even ABC or ABD may have different sizes, try to choose the smaller parent



LATTICE STRUCTURE of data cube

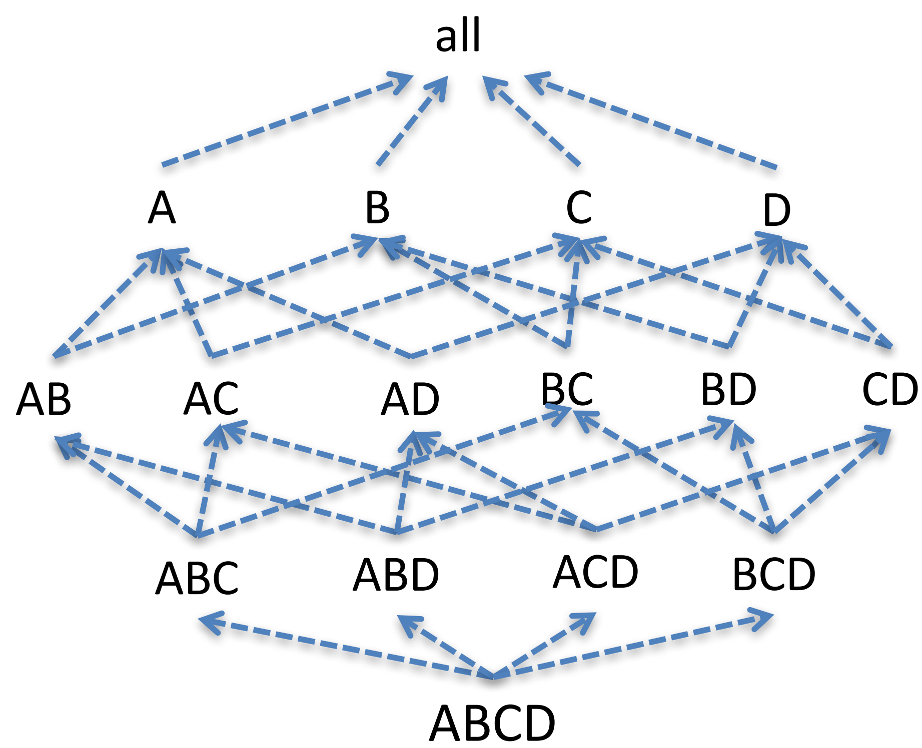
Optimization 2: Cache Results

- Cache result of one GROUP-BY in memory to reduce disk I/O
  - Compute AB from ABC while ABC is still in memory



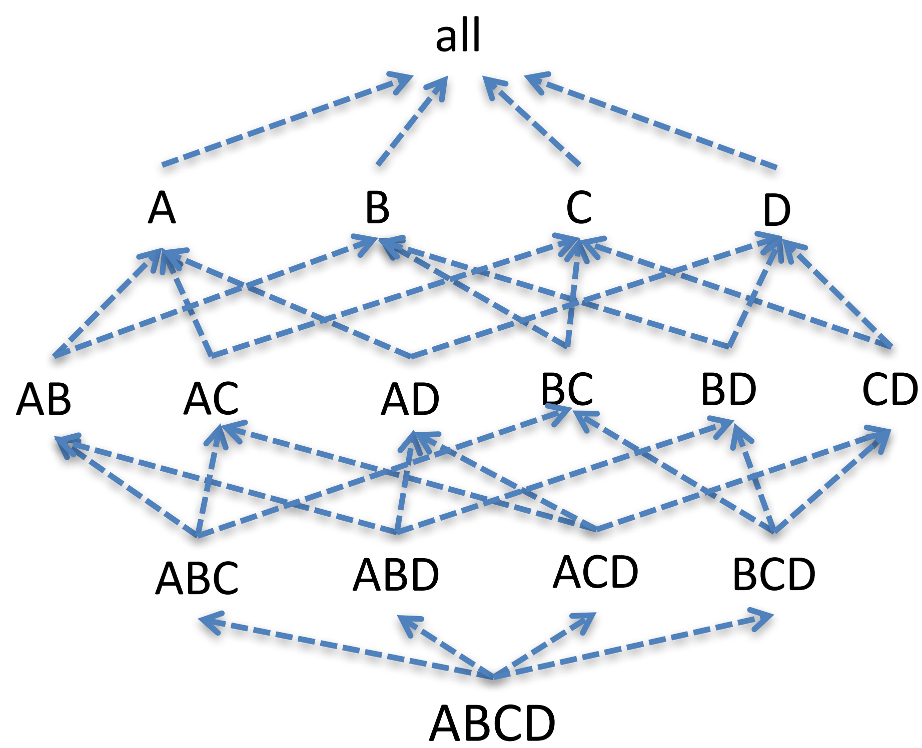
Optimization 3: Amortize Disk Scans

- Amortize disk reads for multiple GROUP-BYs
  - Suppose the result for ABCD is stored on disk
  - Compute all of ABC, ABD, ACD, BCD simultaneously in one scan of ABCD



Optimization 4, 5 (next)

- 4. Share-sort
  - for sort-based algorithms
  - pipe-sort algorithm
  - covered in class
- 5. Shared-partition
  - for hash-based algorithms
  - pipe-hash algorithm
    - Uses hash tables to compute smaller GROUP-Bys
    - If the hash tables for AB and AC fit in memory, compute both in one scan of ABC
    - Otherwise can partition on A, and can compute HTs of AB and AC in different partitions
  - not covered (see paper)

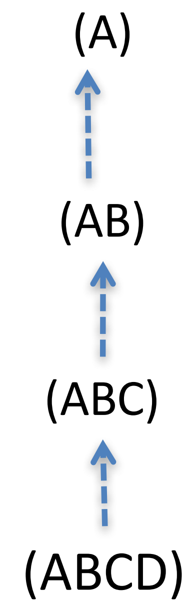


PipeSort: Idea

- Combines two optimizations: “shared-sorts” and “smallest-parent”
- Also includes “cache-results” and “amortized-scans”

PipeSort: Share-sort optimization

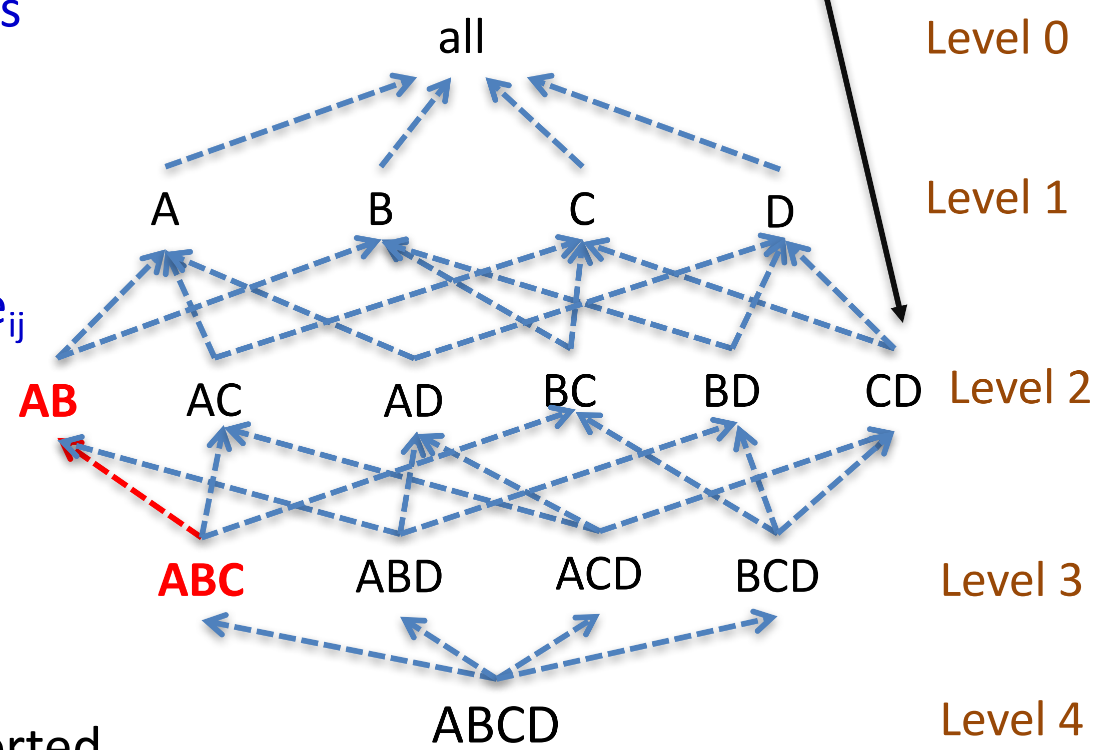
- Data sorted in one order
- Compute all GROUP-BYs prefixed in that order
- Compute one tuple of ABCD, propagate upward in the pipeline by a single scan
- Example:
  - GROUP-BY over attributes ABCD
  - Sort raw data by (ABCD)
  - Compute (ABCD) -> (ABC) -> (AB) -> (A) in pipelined fashion
  - No additional sort needed
- BUT, may have a conflict with “smallest-parent” optimization
  - (ABD) -> (AB) could be a better choice
  - Figure out the best parent choice by running a weighted-matching algorithm layer by layer



Search Lattice

- No parenthesis: order of tuples can be arbitrary

- Directed edge => one attribute less and possible computation
- Level k contains k attributes
  - all = 0 attribute
- Two possible costs for each edge e_{ij} = i ---> j
- $A(e_{ij})$: i is sorted for j
  - (BCA) -> (BC)
- $S(e_{ij})$: i is NOT sorted for j
  - e.g. ABC -> (BCA) -> (BC) or hash



Sorted

A	B	C	sum
a1	b1	c1	5
a1	b1	c2	10
a1	b2	c3	8
a2	b2	c1	2
a2	b2	c3	11

Not Sorted

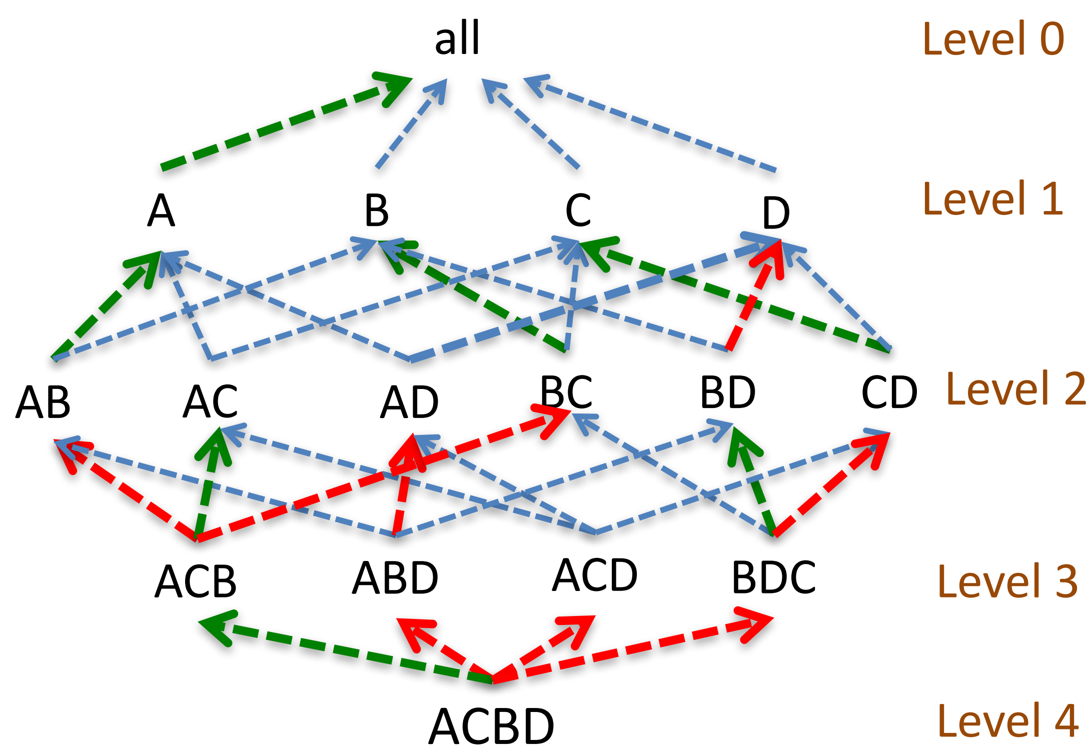
A	B	C	sum
a2	b2	c3	11
a1	b1	c2	10
a2	b2	c1	2
a1	b1	c1	5
a1	b2	c3	8

A	B	sum
a1	b1	15
a1	b2	8
a2	b2	13

Sorted (A)
Not-Sorted (S)

PipeSort Output

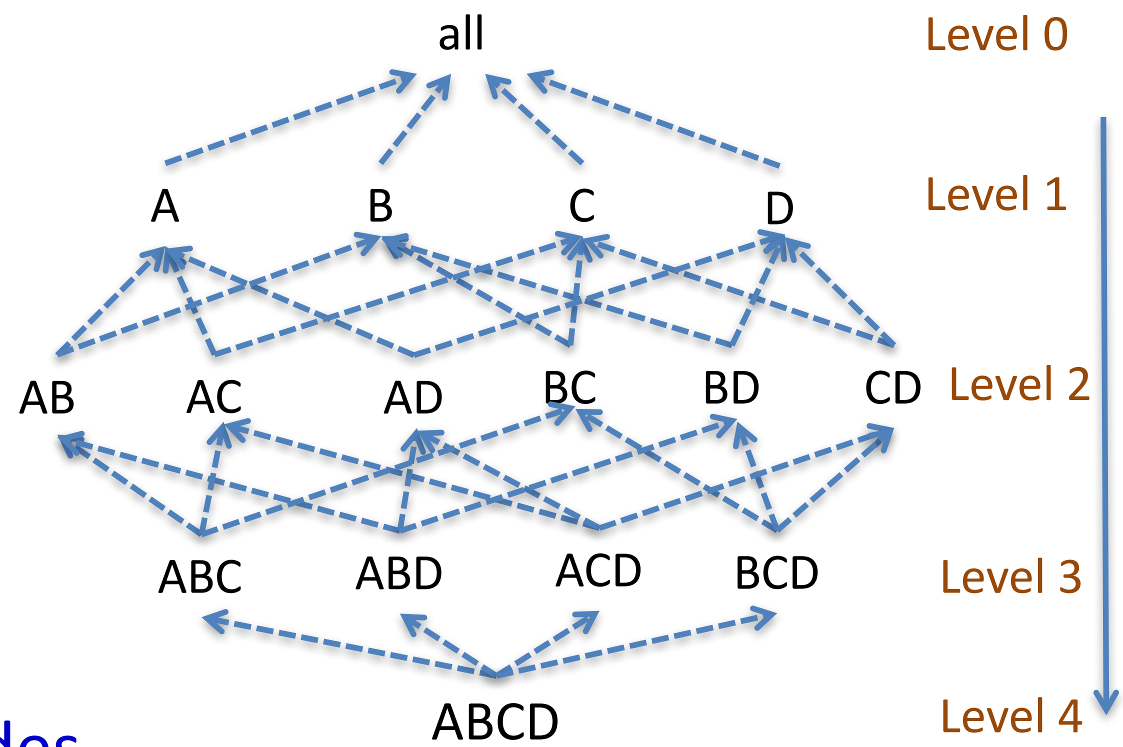
- Outputs a subgraph O
  - each node has a single parent
  - each node has a sorted order of attributes
- if parent's sorted order is a prefix, cost = **$A(e_{ij})$**, else **$S(e_{ij})$**
  - Mark by A or S
  - At most one **A-out-edge**
  - Note: for some nodes, there may be no **green A-out-edge**



Goal: Find O with min total cost

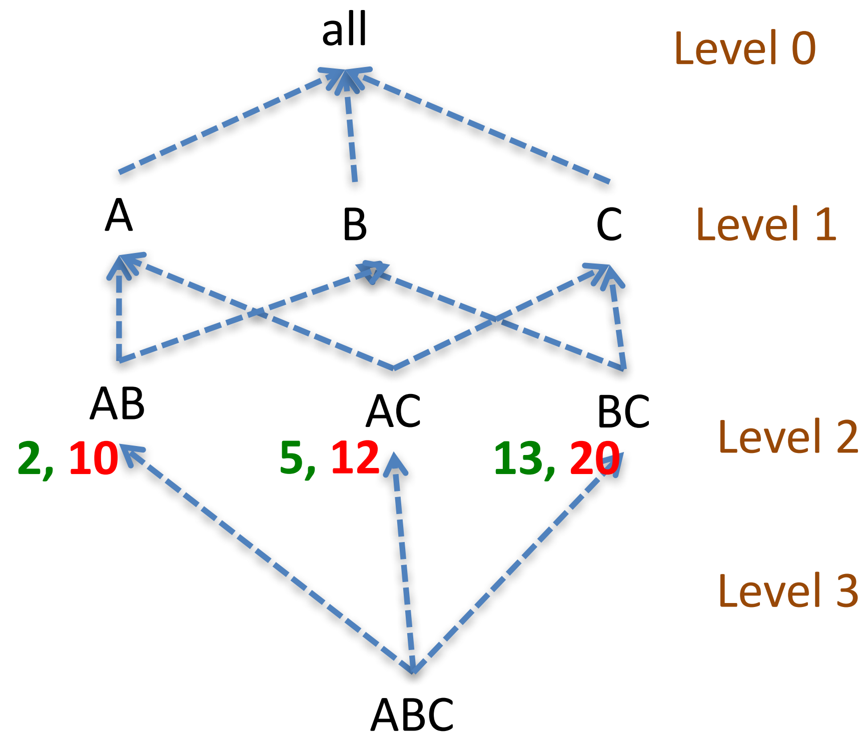
Outline: PipeSort Algorithm (1)

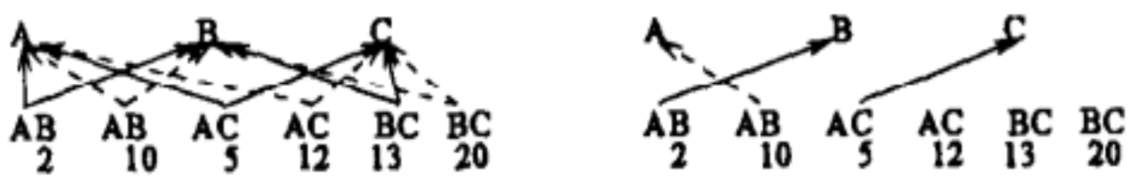
- Go from level 0 to N-1
  - here N = 4
- For each level k, find the best way to construct it from level k+1
- uses "min-cost weighted bipartite matching"
- creates k new copies of nodes at level k+1
- edges from original copy
  - cost **A(e_{ij})**
- edges from new copies
  - cost **S(e_{ij})**



Outline: PipeSort Algorithm (2)

- Illustration with a smaller example
- Level k = 1 from level k+1 = 2
  - one new copy (dotted edges)
  - one existing copy (solid edge)
- Assumption for simplicity
  - same cost for all outgoing edges
  - $A(e_{ij}) = A(e_{ij'})$ for all j, j'
  - $S(e_{ij}) = S(e_{i'j})$ for all i, i'

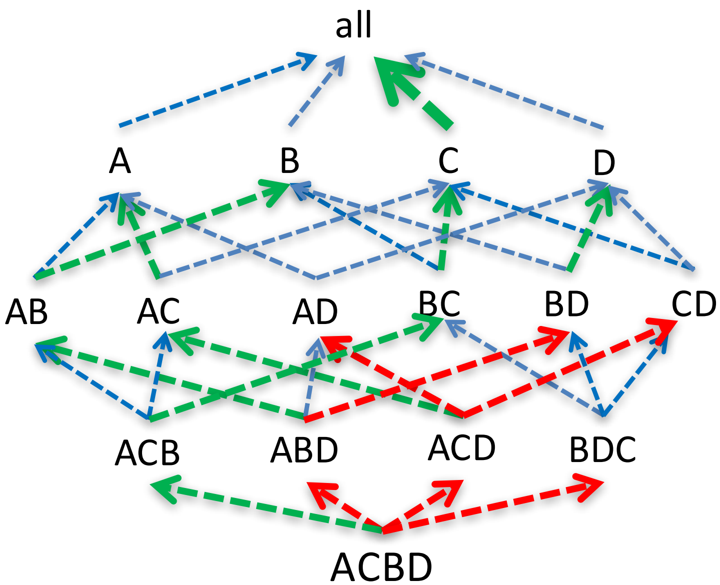




(a) Transformed search lattice

(b) Minimum cost matching

Outline: PipeSort Algorithm (3)

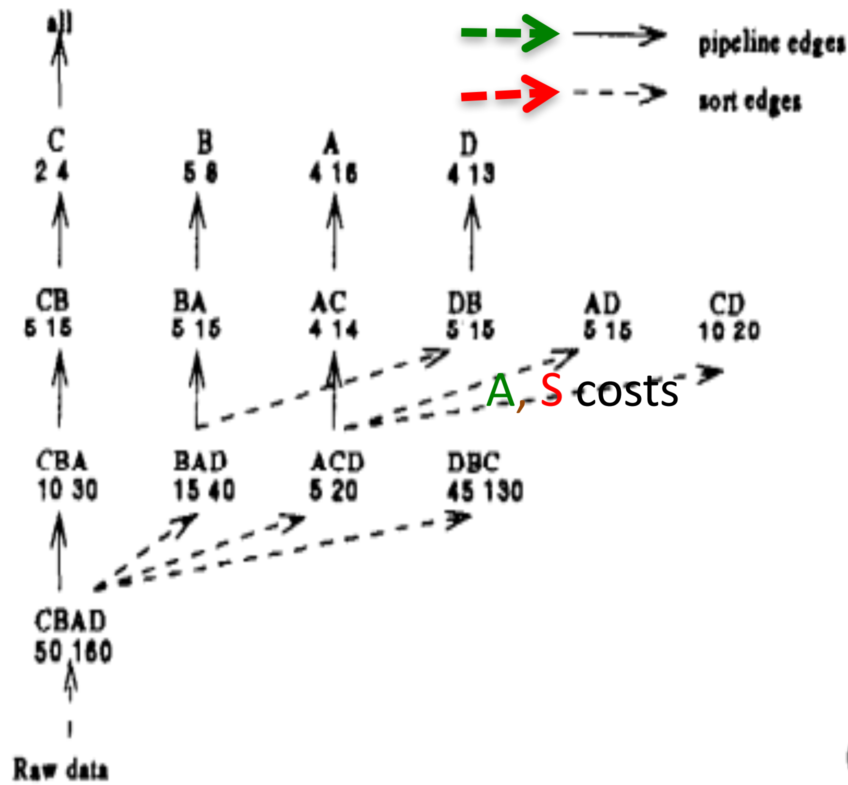


After computing the plan, execute all pipelines

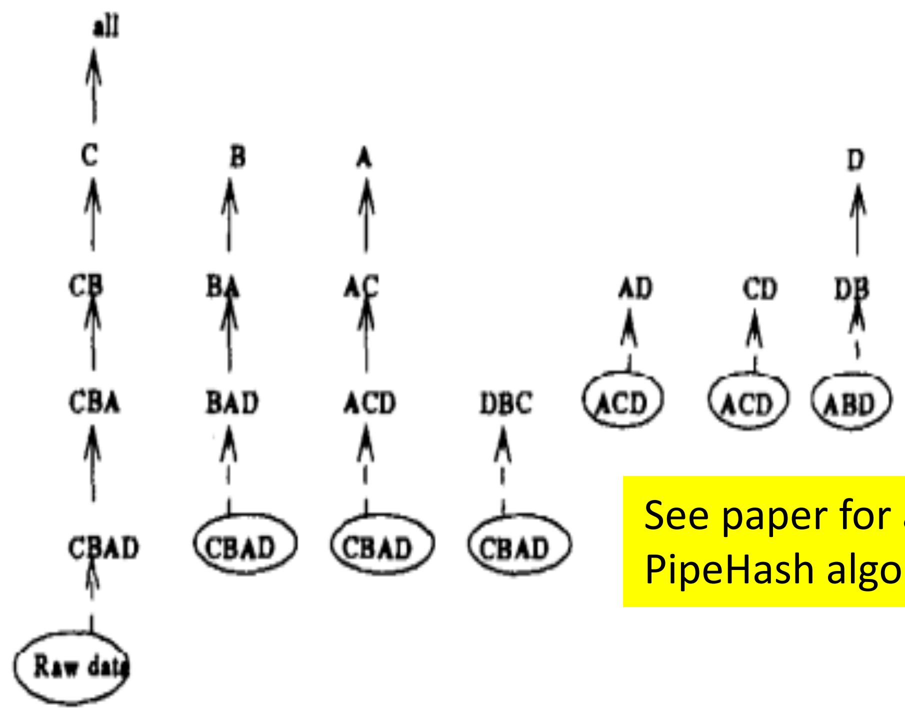
1. First pipeline is executed by one scan of the data

2. Sort (CBAD) -> (BADC),
compute the second pipeline

3. .....



(a) The minimum cost sort plan



(b) The pipelines that are executed

See paper for another PipeHash algorithm