Data Mining:
Concepts and Techniques

— Chapter 4 —

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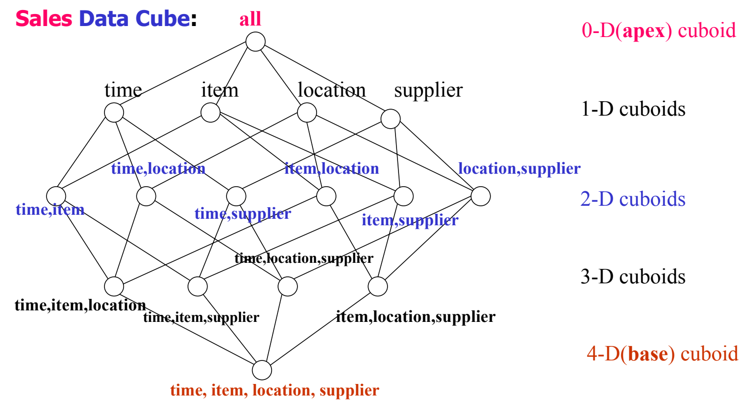
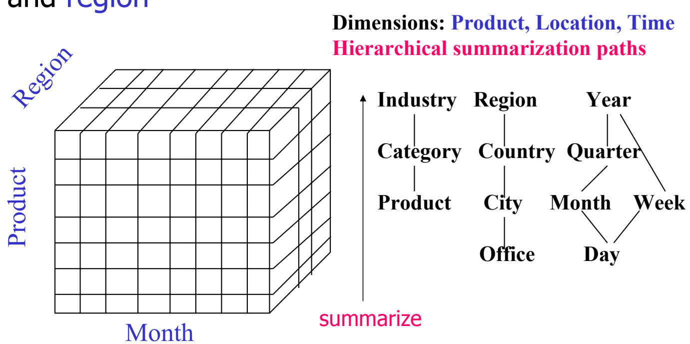
A Short Recap on Data Cubes
Data Cube: A Lattice of Cuboids

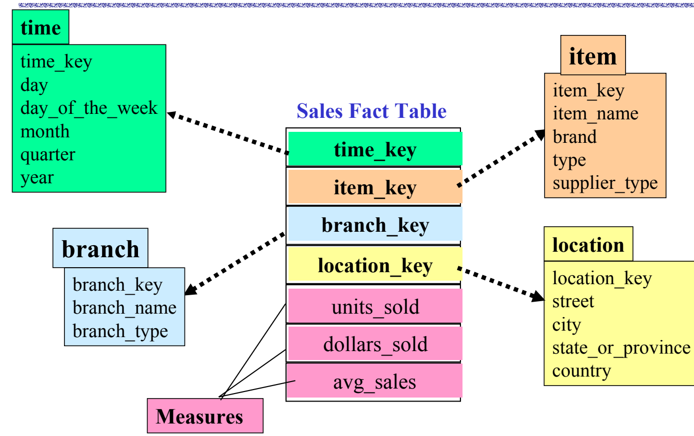


Multidimensional Data

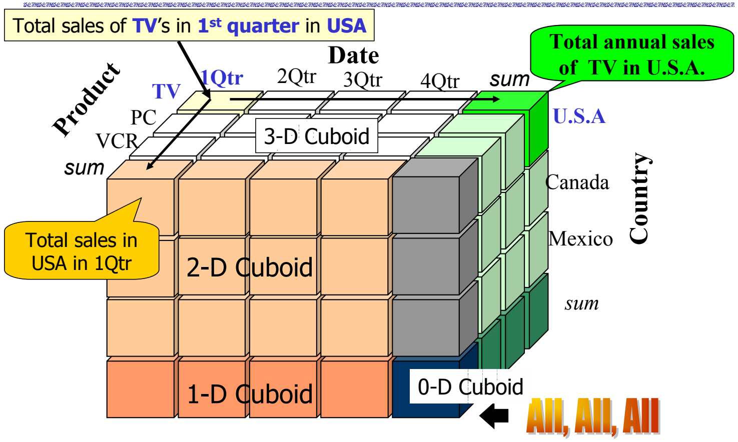
- Sales volume as a function of product, month, and region

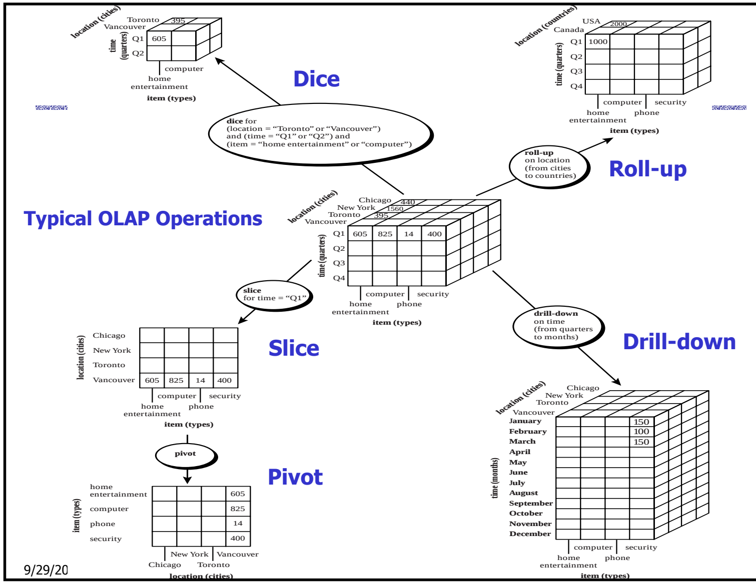


Example of Star Schema

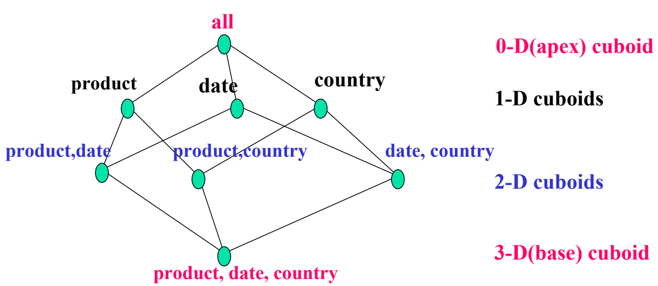


A Sample Data Cube

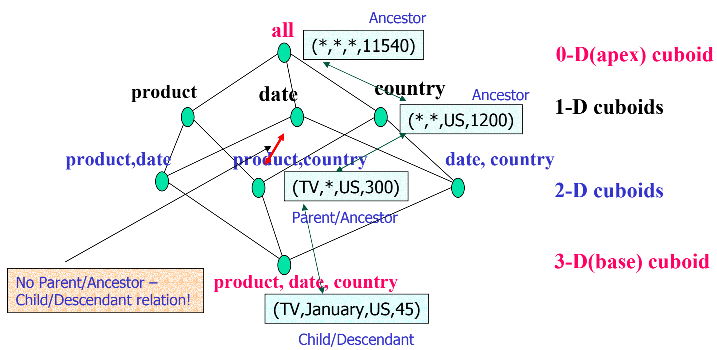




Cuboids Corresponding to the Cube



Data Cubes: Ancestor – Descendent relation



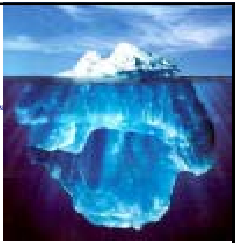
Chapter 4: Data Cube Computation and Data Generalization

- Efficient Computation of Data Cubes
- Exploration and Discovery in Multidimensional Databases
- Attribute-Oriented Induction ― An Alternative Data Generalization Method

Efficient Computation of Data Cubes

- Preliminary cube computation tricks (Agarwal et al.'96)
- Computing full/iceberg cubes: 3 methodologies
  - Top-Down: Multi-Way array aggregation (Zhao, Deshpande & Naughton, SIGMOD'97)
  - Bottom-Up:
    - Bottom-up computation: BUC (Beyer & Ramarkrishnan, SIGMOD'99)
    - H-cubing technique (Han, Pei, Dong & Wang: SIGMOD'01)
  - Integrating Top-Down and Bottom-Up:
    - Star-cubing algorithm (Xin, Han, Li & Wah: VLDB'03)
- High-dimensional OLAP: A Minimal Cubing Approach (Li, et al. VLDB'04)
- Computing alternative kinds of cubes:
  - Partial cube, closed cube, approximate cube, etc.

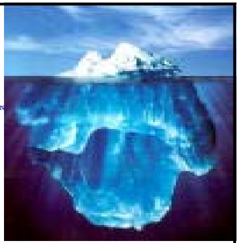
Iceberg Cube



- Computing only the cuboid cells whose count or other aggregates satisfying the condition like

  HAVING COUNT(*) >= *minsup*
- Motivation
  - Only a small portion of cube cells may be "above the water" in a sparse cube
  - Only calculate "interesting" cells—data above certain threshold
  - Avoid explosive growth of the cube
    - Suppose 100 dimensions, only 1 base cell. How many aggregate cells if count >= 1? What about count >= 2?

Iceberg Cube



- Computing only the cuboid cells whose count or other aggregates satisfying the condition like

  HAVING COUNT(*) >= *minsup*

```
compute cube sales_iceberg as
select month, city, customer_group, count(*)
from salesinfo
cube by month, city, customer_group
having count(*) >= minsup
```

Closed Cubes

- Database of 100 dimensions has 2 base cells:

$\{(a_1,a_2,a_3 \ldots, a_{100})$: 10, $(a_1,a_2,b_3, \ldots, b_{100})$: 10$\}$

⇒ 2^{101}-6 not so interesting aggregate cells:

$\{(a_1,a_2,a_3 \ldots, *)$: 10, $(a_1,a_{2.*},a_4 \ldots, a_{100})$: 10, …, $(a_1,a_2,a_{3,*} \ldots, *)$: 10$\}$

The only 3 interesting aggregate cells would be:

$\{(a_1,a_2,a_3 \ldots, a_{100})$: 10, $\{(a_1,a_2,b_3 \ldots, b_{100})$: 10, $(a_1,a_2,*, \ldots, *)$: 20$\}$

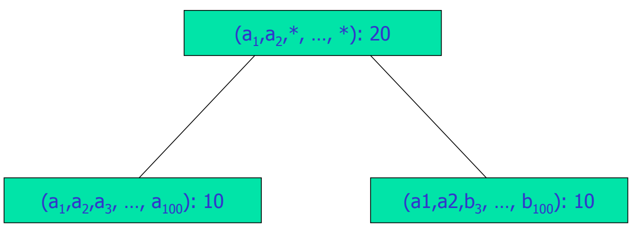
Closed Cubes

- A cell c, is a closed cell, if there exists no cell d such that d is a specialization (descendant) of cell c *(i.e., replacing a * in c with a non-* value),* and d has the same measure value as c (i.e., d will have strictly smaller measure value than c).
- A closed cube is a data cube consisting of only closed cells.

For example the previous three form a lattice of closed cells for a closed cube.

Closed Cubes

- Closed cube lattice:

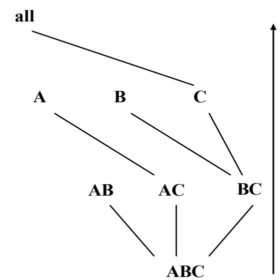


Preliminary Tricks (Agarwal et al. VLDB'96)

- Sorting, hashing, and grouping operations are applied to the dimension attributes in order to reorder and cluster related tuples
- Aggregates may be computed from previously computed aggregates, rather than from the base fact table
  - **Smallest-child:** computing a cuboid from the smallest, previously computed cuboid
  - **Cache-results:** caching results of a cuboid from which other cuboids are computed to reduce disk I/Os
  - **Amortize-scans:** computing as many as possible cuboids at the same time to amortize disk reads
  - **Share-sorts:** sharing sorting costs cross multiple cuboids when a sort-based method is used
  - **Share-partitions:** sharing the partitioning cost across multiple cuboids when hash-based algorithms are used

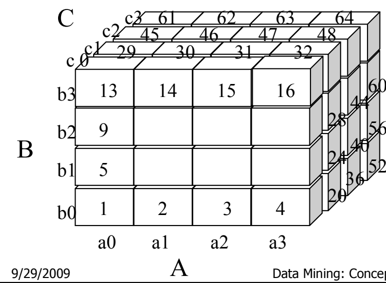
Multi-Way Array Aggregation

- Array-based "bottom-up" algorithm
- Using multi-dimensional chunks
- No direct tuple comparisons
- Simultaneous aggregation on multiple dimensions
- Intermediate aggregate values are re-used for computing ancestor cuboids
- Cannot do *Apriori* pruning: No iceberg optimization



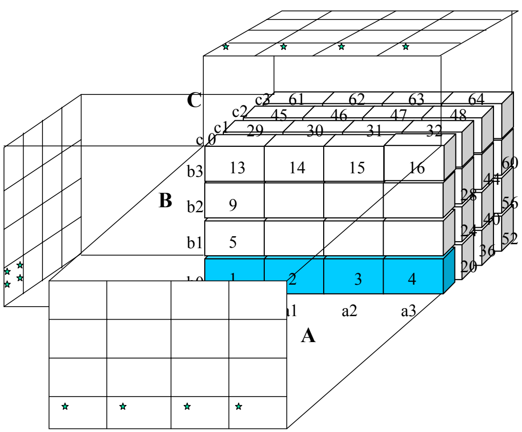
Multi-way Array Aggregation for Cube Computation (MOLAP)

- Partition arrays into chunks (a small subcube which fits in memory).
- Compressed sparse array addressing: (chunk_id, offset)
- Compute aggregates in "multiway" by visiting cube cells in the order which minimizes the # of times to visit each cell, and reduces memory access and storage cost.

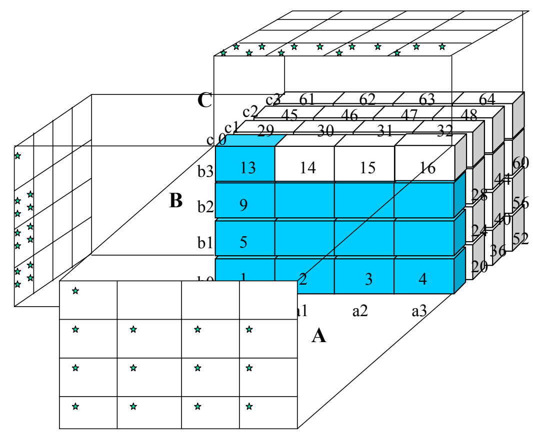


What is the best traversing order to do multi-way aggregation?

Multi-way Array Aggregation for Cube Computation



Multi-way Array Aggregation for Cube Computation

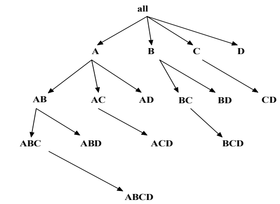


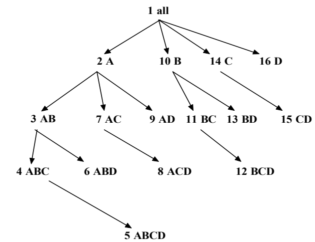
Multi-Way Array Aggregation for Cube Computation (Cont.)

- Method: the planes should be sorted and computed according to their size in ascending order
  - Idea: keep the smallest plane in the main memory, fetch and compute only one chunk at a time for the largest plane
- Limitation of the method: computing well only for a small number of dimensions
  - If there are a large number of dimensions, "top-down" computation and iceberg cube computation methods can be explored

Bottom-Up Computation (BUC)

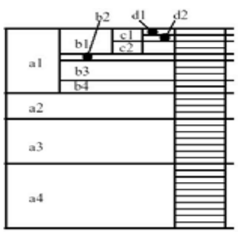
- BUC (Beyer & Ramakrishnan, SIGMOD'99)
- Bottom-up cube computation
  (Note: top-down in our view!)
- Divides dimensions into partitions and facilitates iceberg pruning
  - If a partition does not satisfy *min_sup*, its descendants can be pruned
  - If *minsup* = 1 $\Rightarrow$ compute full CUBE!
- No simultaneous aggregation





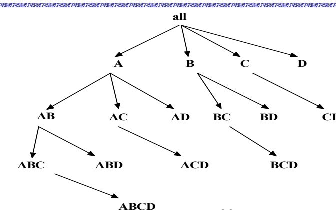
BUC: Partitioning

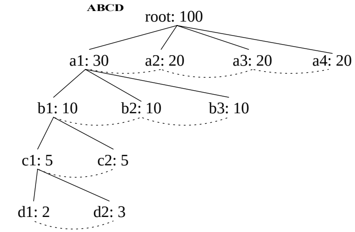
- Usually, entire data set can't fit in main memory
- Sort *distinct* values, partition into blocks that fit
- Continue processing
- Optimizations
  - Partitioning
    - External Sorting, Hashing, Counting Sort
  - Ordering dimensions to encourage pruning
    - Cardinality, Skew, Correlation
  - Collapsing duplicates
    - Can't do holistic aggregates anymore!



H-Cubing: Using H-Tree Structure

- Bottom-up computation
- Exploring an H-tree structure
- If the current computation of an H-tree cannot pass min_sup, do not proceed further (pruning)
- No simultaneous aggregation



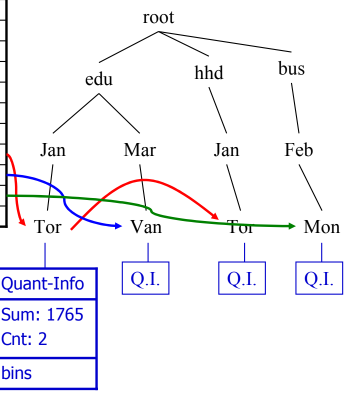


H-tree: A Prefix Hyper-tree

Header table

Attr. Val.	Quant-Info	Side-link
Edu	Sum:2285 ...	
Hhd	...	
Bus	...	
...	...	
Jan	...	
Feb	...	
...	...	
Tor	**...**	
Van	**...**	
Mon	**...**	
...	...	

Month	City	Cust_grp	Prod	Cost	Price
Jan	Tor	Edu	Printer	500	485
Jan	Tor	Hhd	TV	800	1200
Jan	Tor	Edu	Camera	1160	1280
Feb	Mon	Bus	Laptop	1500	2500
Mar	Van	Edu	HD	540	520
...	...	...	...	...	...



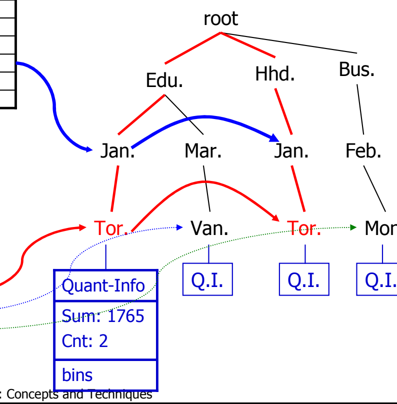
H-Cubing: Computing Cells Involving Dimension City

Header Table H_{Tor}

Attr. Val.	Q.I.	Side-link
Edu	...	
Hhd	...	
Bus	...	
...	...	
Jan	**...**	
Feb	...	
...	...	

From (*, *, Tor) to (*, Jan, Tor)

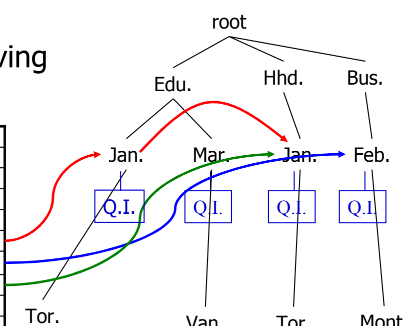
Attr. Val.	Quant-Info	Side-link
Edu	Sum:2285 ...	
Hhd	...	
Bus	...	
...	...	
Jan	...	
Feb	...	
...	...	
Tor	**...**	
Van	...	
Mon	...	
...	...	



Computing Cells Involving Month But No City

1. Roll up quant-info
2. Compute cells involving month but no city

Attr. Val.	Quant-Info	Side-link
Edu.	Sum:2285 ...	
Hhd.	...	
Bus.	...	
...	...	
Jan.	**...**	
Feb.	**...**	
Mar.	**...**	
...	...	
Tor.	...	
Van.	...	
Mont.	...	
...	...	

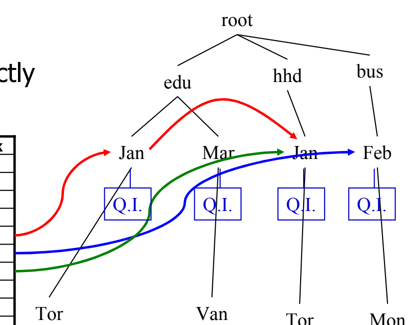


Top-k OK mark: if Q.I. in a child passes top-k avg threshold, so does its parents. No binning is needed!

Computing Cells Involving Only Cust_grp

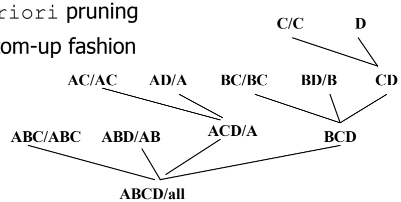
Check header table directly

Attr. Val.	Quant-Info	Side-link
Edu	**Sum:2285 ...**	
Hhd	**...**	
Bus	**...**	
...	...	
Jan	...	
Feb	...	
Mar	...	
...	...	
Tor	...	
Van	...	
Mon	...	
...	...	



Star-Cubing: An Integrating Method

- Integrate the top-down and bottom-up methods
- ***Explore shared dimensions***
  - E.g., dimension `A` is the shared dimension of `ACD` and `AD`
  - `ABD/AB` means cuboid `ABD` has shared dimensions `AB`
- Allows for shared computations
  - e.g., cuboid `AB` is computed simultaneously as `ABD`
- Aggregate in a top-down manner but with the bottom-up sub-layer underneath which will allow `Apriori` pruning
- Shared dimensions grow in bottom-up fashion

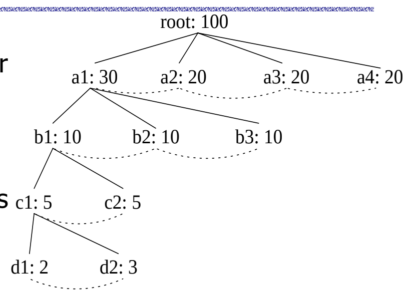


Iceberg Pruning in Shared Dimensions

- Anti-monotonic property of shared dimensions
  - If the measure is *anti-monotonic*, and if the aggregate value on a shared dimension does not satisfy the *iceberg condition*, then all the cells extended from this shared dimension cannot satisfy the condition either
- Intuition: if we can compute the shared dimensions before the actual cuboid, we can use them to do `Apriori` pruning
- Problem: how to prune while still aggregate simultaneously on multiple dimensions?

Cell Trees

- Use a tree structure similar to H-tree to represent cuboids
- Collapses common prefixes to save memory
- Keep count at node
- Traverse the tree to retrieve a particular tuple



Star Attributes and Star Nodes

- Intuition: If a single-dimensional aggregate on an attribute value *p* does not satisfy the iceberg condition, it is useless to distinguish them during the iceberg computation
  - E.g., b_2, b_3, b_4, c_1, c_2, c_4, d_1, d_2, d_3
- Solution: Replace such attributes by a *. Such attributes are *star attributes*, and the corresponding nodes in the cell tree are *star nodes*

A	B	C	D	Count
a1	b1	c1	d1	1
a1	b1	c4	d3	1
a1	b2	c2	d2	1
a2	b3	c3	d4	1
a2	b4	c3	d4	1

Example: Star Reduction

- Suppose minsup = 2
- Perform one-dimensional aggregation. Replace attribute values whose count < 2 with *. And collapse all *'s together
- Resulting table has all such attributes replaced with the star-attribute
- With regards to the iceberg computation, this new table is a *loseless compression* of the original table

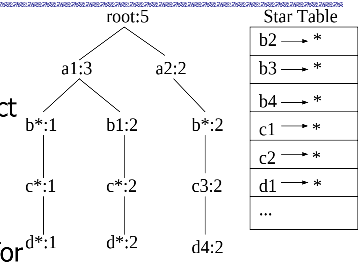
A	B	C	D	Count
a1	b1	*	*	1
a1	b1	*	*	1
a1	*	*	*	1
a2	*	c3	d4	1
a2	*	c3	d4	1

↓

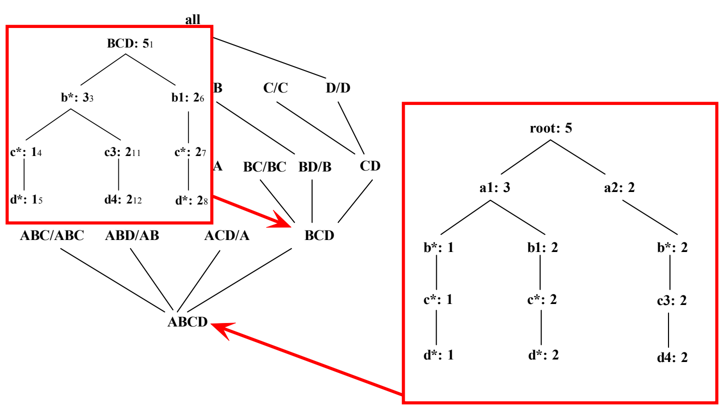
A	B	C	D	Count
a1	b1	*	*	2
a1	*	*	*	1
a2	*	c3	d4	2

Star Tree

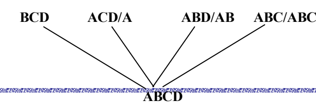
- Given the new compressed table, it is possible to construct the corresponding cell tree—called star tree
- Keep a star table at the side for easy lookup of star attributes
- The star tree is a *loseless compression* of the original cell tree

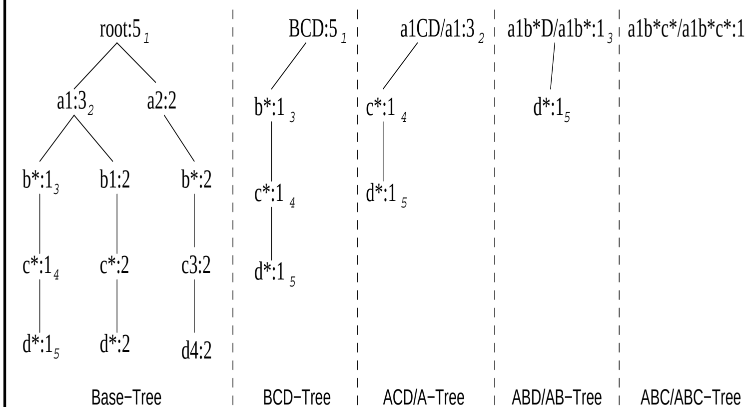


Star-Cubing Algorithm—DFS on Lattice Tree

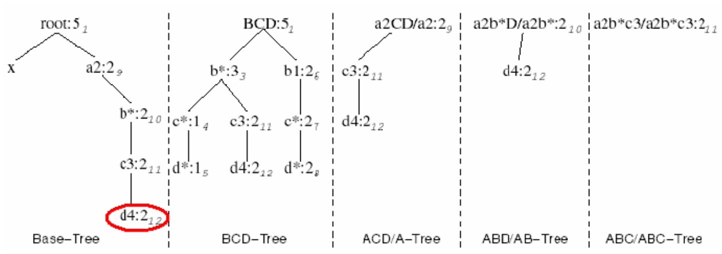


Multi-Way Aggregation





Star-Cubing Algorithm—DFS on Star-Tree



Multi-Way Star-Tree Aggregation

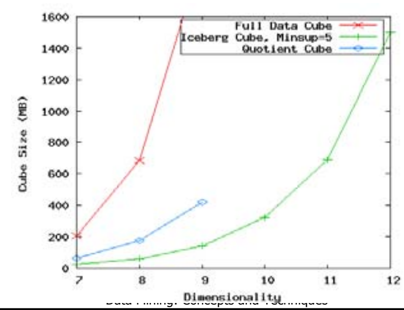
- Start depth-first search at the root of the base star tree
- At each new node in the DFS, create corresponding star tree that are descendents of the current tree according to the integrated traversal ordering
  - E.g., in the base tree, when DFS reaches `a1`, the ACD/A tree is created
  - When DFS reaches `b*`, the ABD/AD tree is created
- The counts in the base tree are carried over to the new trees

Multi-Way Aggregation (2)

- When DFS reaches a leaf node (e.g., `d*`), start backtracking
- On every backtracking branch, the count in the corresponding trees are output, the tree is destroyed, and the node in the base tree is destroyed
- Example
  - When traversing from `d*` back to `c*`, the `a1b*c*/a1b*c*` tree is output and destroyed
  - When traversing from `c*` back to `b*`, the `a1b*D/a1b*` tree is output and destroyed
  - When at `b*`, jump to `b1` and repeat similar process

The Curse of Dimensionality

- None of the previous cubing method can handle high dimensionality!
- A database of 600k tuples. Each dimension has cardinality of 100 and *zipf* of 2.



Motivation of High-D OLAP

- Challenge to current cubing methods:
  - The "curse of dimensionality" problem
  - Iceberg cube and compressed cubes: only delay the inevitable explosion
  - Full materialization: still significant overhead in accessing results on disk
- High-D OLAP is needed in applications
  - Science and engineering analysis
  - Bio-data analysis: thousands of genes
  - Statistical surveys: hundreds of variables

Fast High-D OLAP with Minimal Cubing

- Observation: OLAP occurs only on a small subset of dimensions at a time
- Semi-Online Computational Model
  1. Partition the set of dimensions into **shell fragments**
  2. Compute data cubes for each shell fragment while retaining **inverted indices** or **value-list indices**
  3. Given the pre-computed **fragment cubes**, dynamically compute cube cells of the high-dimensional data cube *online*

Properties of Proposed Method

- Partitions the data vertically
- Reduces high-dimensional cube into a set of lower dimensional cubes
- Online re-construction of original high-dimensional space
- Lossless reduction
- Offers tradeoffs between the amount of pre-processing and the speed of online computation

Example Computation

- Let the cube aggregation function be `count`

tid	**A**	**B**	**C**	**D**	**E**
1	a1	b1	c1	d1	e1
2	a1	b2	c1	d2	e1
3	a1	b2	c1	d1	e2
4	a2	b1	c1	d1	e2
5	a2	b1	c1	d1	e3

- Divide the 5 dimensions into 2 shell fragments:
  - (`A, B, C`) and (`D, E`)

1-D Inverted Indices

- Build traditional inverted index or RID list

Attribute Value	TID List	List Size
a1	1 2 3	3
a2	4 5	2
b1	1 4 5	3
b2	2 3	2
c1	1 2 3 4 5	5
d1	1 3 4 5	4
d2	2	1
e1	1 2	2
e2	3 4	2
e3	5	1

Shell Fragment Cubes

- Generalize the 1-D inverted indices to multi-dimensional ones in the data cube sense

Cell	Intersection	TID List	List Size
a1 b1	1 2 3 $\cap$ 1 4 5	1	1
a1 b2	1 2 3 $\cap$ 2 3	2 3	2
a2 b1	4 5 $\cap$ 1 4 5	4 5	2
a2 b2	4 5 $\cap$ 2 3	$\otimes$	0

Shell Fragment Cubes (2)

- Compute all cuboids for data cubes `ABC` and `DE` while retaining the inverted indices
- For example, shell fragment cube `ABC` contains 7 cuboids:
  - `A, B, C`
  - `AB, AC, BC`
  - `ABC`
- This completes the offline computation stage

Shell Fragment Cubes (3)

- Given a database of T tuples, D dimensions, and F shell fragment size, the fragment cubes' space requirement is:

$$O\left(T\left\lceil \frac{D}{F} \right\rceil (2^F - 1)\right)$$

- For F < 5, the growth is sub-linear.

Shell Fragment Cubes (4)

- Shell fragments do not have to be disjoint
- Fragment groupings can be arbitrary to allow for maximum online performance
  - Known common combinations (e.g.,<city, state>) should be grouped together.
- Shell fragment sizes can be adjusted for optimal balance between offline and online computation

ID_Measure Table

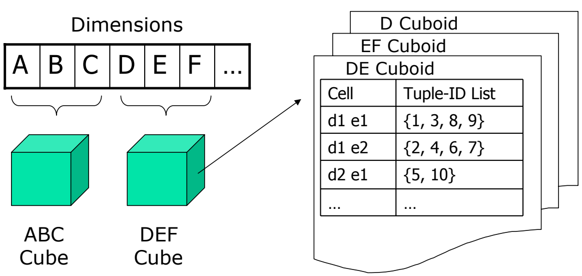
- If measures other than `count` are present, store in *ID_measure* table separate from the shell fragments

tid	count	sum
1	5	70
2	3	10
3	8	20
4	5	40
5	2	30

The Frag-Shells Algorithm

1. Partition set of dimension (A_1,…,A_n) into a set of *k* fragments (P_1,…,P_k).
2. Scan base table once and do the following
3. insert <tid, measure> into ID_measure table.
4. for each attribute value a_i of each dimension A_i
5. build inverted index entry <a_i, tidlist>
6. For each fragment partition P_i
7. build local fragment cube S_i by intersecting tid-lists in bottom-up fashion.

Frag-Shells (2)



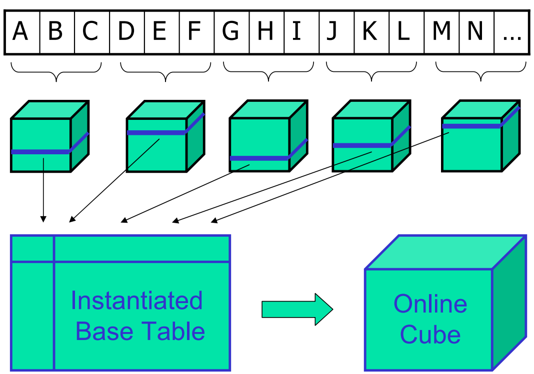
Online Query Computation

- A query has the general form $\langle a_1, a_2, \ldots, a_n : M \rangle$
- Each a_i has 3 possible values
  1. Instantiated value
  2. Aggregate * function
  3. Inquire ? function
- For example, $\langle 3 \quad ? \quad ? \quad * \quad 1 : count \rangle$ returns a 2-D data cube.

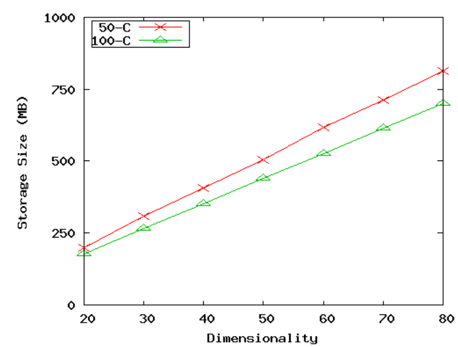
Online Query Computation (2)

- Given the fragment cubes, process a query as follows
  1. Divide the query into fragment, same as the shell
  2. Fetch the corresponding TID list for each fragment from the fragment cube
  3. Intersect the TID lists from each fragment to construct **instantiated base table**
  4. Compute the data cube using the base table with any cubing algorithm

Online Query Computation (3)

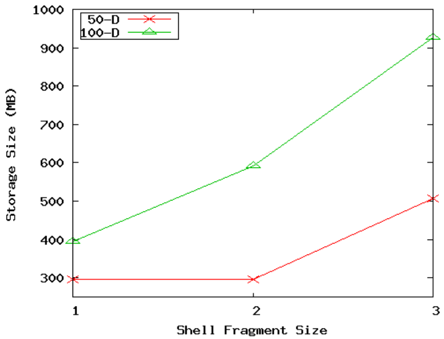


Experiment: Size vs. Dimensionality (50 and 100 cardinality)



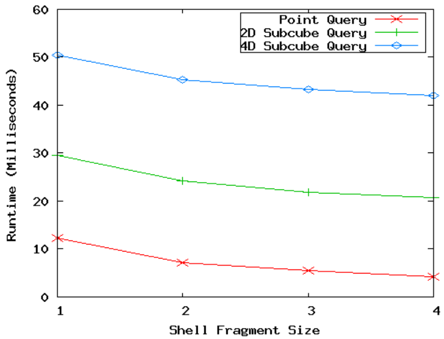
- (50-C): 10^6 tuples, 0 skew, 50 cardinality, fragment size 3.
- (100-C): 10^6 tuples, 2 skew, 100 cardinality, fragment size 2.

Experiment: Size vs. Shell-Fragment Size



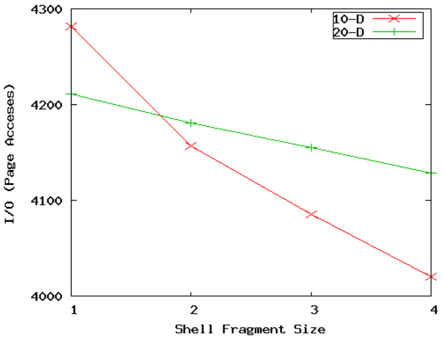
- (50-D): 10^6 tuples, 50 dimensions, 0 skew, 50 cardinality.
- (100-D): 10^6 tuples, 100 dimensions, 2 skew, 25 cardinality.

Experiment: Run-time vs. Shell-Fragment Size



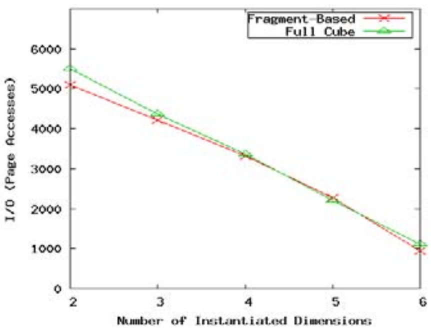
- 10^6 tuples, 20 dimensions, 10 cardinality, skew 1, fragment size 3, 3 instantiated dimensions.

Experiment: I/O vs. Shell-Fragment Size



- (10-D): 10^6 tuples, 10 dimensions, 10 cardinalty, 0 skew, 4 inst., 4 query.
- (20-D): 10^6 tuples, 20 dimensions, 10 cardinalty, 1 skew, 3 inst., 4 query.

Experiment: I/O vs. # of Instantiated Dimensions



- 10^6 tuples, 10 dimensions, 10 cardinalty, 0 skew, fragment size 1, 7 total relevant dimensions.

Experiments on Real World Data

- UCI Forest CoverType data set
  - 54 dimensions, 581K tuples
  - Shell fragments of size 2 took 33 seconds and 325MB to compute
  - 3-D subquery with 1 instantiate D: 85ms~1.4 sec.
- Longitudinal Study of Vocational Rehab. Data
  - 24 dimensions, 8818 tuples
  - Shell fragments of size 3 took 0.9 seconds and 60MB to compute
  - 5-D query with 0 instantiated D: 227ms~2.6 sec.

Comparisons to Related Work

- [Harinarayan96] computes low-dimensional cuboids by further aggregation of high-dimensional cuboids. Opposite of our method's direction.
- Inverted indexing structures [Witten99] focus on single dimensional data or multi-dimensional data with no aggregation.
- Tree-stripping [Berchtold00] uses similar vertical partitioning of database but no aggregation.

Further Implementation Considerations

- Incremental Update:
  - Append more TIDs to inverted list
  - Add <tid: measure> to ID_measure table
- Incremental adding new dimensions
  - Form new inverted list and add new fragments
- Bitmap indexing
  - May further improve space usage and speed
- Inverted index compression
  - Store as d-gaps
  - Explore more IR compression methods

Chapter 4: Data Cube Computation and Data Generalization

- Efficient Computation of Data Cubes
- Exploration and Discovery in Multidimensional Databases
- Attribute-Oriented Induction — An Alternative Data Generalization Method

Computing Cubes with Non-Antimonotonic Iceberg Conditions

- Most cubing algorithms cannot compute cubes with non-antimonotonic iceberg conditions efficiently
- Example

```
CREATE CUBE Sales_Iceberg AS
SELECT month, city, cust_grp,
  AVG(price), COUNT(*)
FROM Sales_Infor
CUBEBY month, city, cust_grp
HAVING AVG(price) >= 800 AND
  COUNT(*) >= 50
```

- Needs to study how to push constraint into the cubing process

Non-Anti-Monotonic Iceberg Condition

- Anti-monotonic: if a process fails a condition, continue processing will still fail
- The cubing query with avg is non-anti-monotonic!
  - (Mar, *, *, 600, 1800) fails the HAVING clause
  - (Mar, *, Bus, 1300, 360) passes the clause

Month	City	Cust_grp	Prod	Cost	Price
Jan	Tor	Edu	Printer	500	485
Jan	Tor	Hld	TV	800	1200
Jan	Tor	Edu	Camera	1160	1280
Feb	Mon	Bus	Laptop	1500	2500
Mar	Van	Edu	HD	540	520
…	…	…	…	…	…

```
CREATE CUBE Sales_Iceberg AS
SELECT month, city, cust_grp,
    AVG(price), COUNT(*)
FROM Sales_Infor
CUBEBY month, city, cust_grp
HAVING AVG(price) >= 800 AND
    COUNT(*) >= 50
```


From Average to Top-k Average

- Let (*, Van, *) cover 1,000 records
  - Avg(price) is the average price of those 1000 sales
  - Avg^{50}(price) is the average price of the top-50 sales (top-50 according to the sales price
- Top-k average is anti-monotonic
  - The top 50 sales in Van. is with avg(price) <= 800 → the top 50 deals in Van. during Feb. must be with avg(price) <= 800

Month	City	Cust_grp	Prod	Cost	Price
…	…	…	…	…	…

Binning for Top-k Average

- Computing top-k avg is costly with large k
- Binning idea
  - Avg^{50}(c) >= 800
  - Large value collapsing: use a sum and a count to summarize records with measure >= 800
    - If count>=800, no need to check "small" records
  - Small value binning: a group of bins
    - One bin covers a range, e.g., 600~800, 400~600, etc.
    - Register a sum and a count for each bin

Computing Approximate top-k average

Suppose for (*, Van, *), we have

Range	Sum	Count
Over 800	28000	20
600~800	10600	15
400~600	15200	30
…	…	…

Top 50

Approximate avg^{50}()=
(28000+10600+600*15)/50=952

The cell may pass the HAVING clause

Month	City	Cust_grp	Prod	Cost	Price
…	…	…	…	…	…

Computing Iceberg Cubes with Other Complex Measures

- Computing other complex measures
  - Key point: find a function which is weaker but ensures certain anti-monotonicity
- Examples
  - Avg() ≤ v: avg$_k$(c) ≤ v (bottom-k avg)
  - Avg() ≥ v only (no count): max(price) ≥ v
  - Sum(profit) (profit can be negative):
    - p_sum(c) ≥ v if p_count(c) ≥ k; or otherwise, sum^k(c) ≥ v
  - Others: conjunctions of multiple conditions

Weakened Conditions Facilitate Pushing

- Accumulate quant-info for cells to compute average iceberg cubes efficiently
  - Three pieces: sum, count, top-k bins
  - Use top-k bins to estimate/prune descendants
  - Use sum and count to consolidate current cell

weakest → strongest

Approximate avg^{50}()	real avg^{50}()	avg()
Anti-monotonic, can be computed efficiently	**Anti-monotonic, but computationally costly**	**Not anti-monotonic**

Compressed Cubes: Condensed or Closed Cubes

- W. Wang, H. Lu, J. Feng, J. X. Yu, Condensed Cube: An Effective Approach to Reducing Data Cube Size, ICDE'02.
- Iceberg cube cannot solve all the problems
  - Suppose 100 dimensions, only 1 base cell with count = 10. How many aggregate (non-base) cells if count >= 10?
- Condensed cube
  - Only need to store one cell (a_1, a_2, …, a_{100}, 10), which represents all the corresponding aggregate cells
  - Adv.
    - Fully precomputed cube without compression
  - Efficient computation of the minimal condensed cube
- Closed cube
  - Dong Xin, Jiawei Han, Zheng Shao, and Hongyan Liu, "C-Cubing: Efficient Computation of Closed Cubes by Aggregation-Based Checking", ICDE'06.

Chapter 4: Data Cube Computation and Data Generalization

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Discovery-Driven Exploration of Data Cubes

- Hypothesis-driven
  - exploration by user, huge search space
- Discovery-driven (Sarawagi, et al.'98)
  - Effective navigation of large OLAP data cubes
  - pre-compute measures indicating exceptions, guide user in the data analysis, at all levels of aggregation
  - Exception: significantly different from the value anticipated, based on a statistical model
  - Visual cues such as background color are used to reflect the degree of exception of each cell

Kinds of Exceptions and their Computation

- Parameters
  - SelfExp: surprise of cell relative to other cells at same level of aggregation
  - InExp: surprise beneath the cell
  - PathExp: surprise beneath cell for each drill-down path
- Computation of exception indicator (modeling fitting and computing SelfExp, InExp, and PathExp values) can be overlapped with cube construction
- Exception themselves can be stored, indexed and retrieved like precomputed aggregates

Examples: Discovery-Driven Data Cubes

item	all
region	all

Sum of sales	month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Total		1%	-1%	0%	1%	3%	-1	-9%	-1%	2%	-4%	3%

Avg sales	month											
item	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Sony b/w printer		9%	-8%	2%	-5%	14%	-4%	0%	41%	-13%	-15%	-11%
Sony color printer		0%	0%	3%	2%	4%	-10%	-13%	0%	4%	-6%	4%
HP b/w printer		-2%	1%	2%	3%	8%	0%	-12%	-9%	3%	-3%	6%
HP color printer		0%	0%	-2%	1%	0%	-1%	-7%	-2%	1%	-5%	1%
IBM home computer		1%	-2%	-1%	-1%	3%	3%	-10%	4%	1%	-4%	-1%
IBM laptop computer		0%	0%	-1%	3%	4%	2%	-10%	-2%	0%	-9%	3%
Toshiba home computer		-2%	-5%	1%	1%	-1%	1%	5%	-3%	-5%	-1%	-1%
Toshiba laptop computer		1%	0%	3%	0%	-2%	-2%	-5%	3%	2%	-1%	0%
Logitech mouse		3%	-2%	-1%	0%	4%	6%	-11%	2%	1%	-4%	0%
Ergo-way mouse		0%	0%	2%	3%	1%	-2%	-2%	-5%	0%	-5%	8%

item	IBM home computer

Avg sales	month											
region	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
North		-1%	-3%	-1%	0%	3%	4%	-7%	1%	0%	-3%	-3%
South		-1%	1%	-9%	6%	-1%	-39%	9%	-34%	4%	1%	7%
East		-1%	-2%	2%	-3%	1%	18%	-2%	11%	-3%	-2%	-1%
West		4%	0%	-1%	-3%	5%	1%	-18%	8%	5%	-8%	1%

Complex Aggregation at Multiple Granularities: Multi-Feature Cubes

- Multi-feature cubes (Ross, et al. 1998): Compute complex queries involving multiple dependent aggregates at multiple granularities
- Ex. Grouping by all subsets of {item, region, month}, find the maximum price in 1997 for each group, and the total sales among all maximum price tuples

```
select item, region, month, max(price), sum(R.sales)
from purchases
where year = 1997
cube by item, region, month: R
such that R.price = max(price)
```

- Continuing the last example, among the max price tuples, find the min and max shelf live, and find the fraction of the total sales due to tuple that have min shelf life within the set of all max price tuples

Cube-Gradient (Cubegrade)

- Analysis of changes of sophisticated measures in multi-dimensional spaces
  - Query: changes of average house price in Vancouver in '00 comparing against '99
  - Answer: Apts in West went down 20%, houses in Metrotown went up 10%
- Cubegrade problem by Imielinski et al.
  - Changes in dimensions → changes in measures
  - Drill-down, roll-up, and mutation

From Cubegrade to Multi-dimensional Constrained Gradients in Data Cubes

- Significantly more expressive than association rules
  - Capture trends in user-specified measures
- Serious challenges
  - Many trivial cells in a cube → "significance constraint" to prune trivial cells
  - Numerate pairs of cells → "probe constraint" to select a subset of cells to examine
  - Only interesting changes wanted→ "gradient constraint" to capture significant changes

MD Constrained Gradient Mining

- Significance constraint C_{sig}: (cnt≥100)
- Probe constraint $C_{prb:}$ (city="Van", cust_grp="busi", prod_grp="*")
- Gradient constraint $C_{grad}(c_g, c_p)$: $(avg\_price(c_g)/avg\_price(c_p) \geq 1.3)$

Probe cell: satisfied C_{prb}

(c4, c2) satisfies C_{grad}!

Base cell

Aggregated cell

Siblings

Ancestor

Dimensions					Measures	
cid	Yr	City	Cst_grp	Prd_grp	Cnt	Avg_price
c1	00	Van	Busi	PC	300	2100
c2	*	Van	Busi	PC	2800	1800
c3	*	Tor	Busi	PC	7900	2350
c4	*	*	busi	PC	58600	2250

Efficient Computing Cube-gradients

- Compute probe cells using C_{sig} and C_{prb}
  - The set of probe cells P is often very small
- Use probe P and constraints to find gradients
  - Pushing selection deeply
  - Set-oriented processing for probe cells
  - Iceberg growing from low to high dimensionalities
  - Dynamic pruning probe cells during growth
  - Incorporating efficient iceberg cubing method

Chapter 4: Data Cube Computation and Data Generalization

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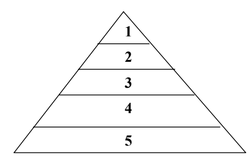
What is Concept Description?

- Descriptive vs. predictive data mining
  - Descriptive mining: describes concepts or task-relevant data sets in concise, summarative, informative, discriminative forms
  - Predictive mining: Based on data and analysis, constructs models for the database, and predicts the trend and properties of unknown data
- Concept description:
  - Characterization: provides a concise and succinct summarization of the given collection of data
  - Comparison: provides descriptions comparing two or more collections of data

Data Generalization and Summarization-based Characterization

- Data generalization
  - A process which abstracts a large set of task-relevant data in a database from a low conceptual levels to higher ones.



Conceptual levels

  - Approaches:
    - Data cube approach(OLAP approach)
    - Attribute-oriented induction approach

Concept Description vs. OLAP

- Similarity:
  - Data generalization
  - Presentation of data summarization at multiple levels of abstraction.
  - Interactive drilling, pivoting, slicing and dicing.
- Differences:
  - Can handle complex data types of the attributes and their aggregations
  - Automated desired level allocation.
  - Dimension relevance analysis and ranking when there are many relevant dimensions.
  - Sophisticated typing on dimensions and measures.
  - Analytical characterization: data dispersion analysis

Attribute-Oriented Induction

- Proposed in 1989 (KDD '89 workshop)
- Not confined to categorical data nor particular measures
- How it is done?
  - Collect the task-relevant data (*initial relation*) using a relational database query
  - Perform generalization by <u>attribute removal</u> or <u>attribute generalization</u>
  - Apply aggregation by merging identical, generalized tuples and accumulating their respective counts
  - Interactive presentation with users

Basic Principles of Attribute-Oriented Induction

- <u>Data focusing</u>: task-relevant data, including dimensions, and the result is the *initial relation*
- <u>Attribute-removal</u>: remove attribute *A* if there is a large set of distinct values for *A* but (1) there is no generalization operator on *A*, or (2) *A*'s higher level concepts are expressed in terms of other attributes
- <u>Attribute-generalization</u>: If there is a large set of distinct values for *A*, and there exists a set of generalization operators on *A*, then select an operator and generalize *A*
- <u>Attribute-threshold control</u>: typical 2-8, specified/default
- <u>Generalized relation threshold control</u>: control the final relation/rule size

Attribute-Oriented Induction: Basic Algorithm

- <u>InitialRel</u>: Query processing of task-relevant data, deriving the *initial relation*.
- <u>PreGen:</u> Based on the analysis of the number of distinct values in each attribute, determine generalization plan for each attribute: removal? or how high to generalize?
- <u>PrimeGen</u>: Based on the PreGen plan, perform generalization to the right level to derive a "prime generalized relation", accumulating the counts.
- <u>Presentation</u>: User interaction: (1) adjust levels by drilling, (2) pivoting, (3) mapping into rules, cross tabs, visualization presentations.

Example

- DMQL: Describe general characteristics of graduate students in the Big-University database

```
use Big_University_DB
mine characteristics as "Science_Students"
in relevance to name, gender, major, birth_place,
  birth_date, residence, phone#, gpa
from student
where  status in "graduate"
```

- Corresponding SQL statement:

```
Select name, gender, major, birth_place, birth_date,
  residence, phone#, gpa
from student
where  status in {"Msc", "MBA", "PhD" }
```


Class Characterization: An Example

Initial Relation

Name	Gender	Major	Birth-Place	Birth_date	Residence	Phone #	GPA
Jim Woodman	M	CS	Vancouver,BC, Canada	8-12-76	3511 Main St., Richmond	687-4598	3.67
Scott Lachance	M	CS	Montreal, Que, Canada	28-7-75	345 1st Ave., Richmond	253-9106	3.70
Laura Lee	F	Physics	Seattle, WA, USA	25-8-70	125 Austin Ave., Burnaby	420-5232	3.83
…	…	…	…	…	…	…	…
Removed	Retained	Sci,Eng, Bus	Country	Age range	City	Removed	Excl, VG,..

Prime Generalized Relation

Gender	Major	Birth_region	Age_range	Residence	GPA	Count
M	Science	Canada	20-25	Richmond	Very-good	16
F	Science	Foreign	25-30	Burnaby	Excellent	22
…	…	…	…	…	…	…

Gender \ Birth_Region	Canada	Foreign	Total
M	16	14	30
F	10	22	32
Total	26	36	62

Presentation of Generalized Results

- Generalized relation:
  - Relations where some or all attributes are generalized, with counts or other aggregation values accumulated.
- Cross tabulation:
  - Mapping results into cross tabulation form (similar to contingency tables).
  - Visualization techniques:
  - Pie charts, bar charts, curves, cubes, and other visual forms.
- Quantitative characteristic rules:
  - Mapping generalized result into characteristic rules with quantitative information associated with it, e.g.,

$$grad(x) \wedge male(x) \Rightarrow$$
$$birth\_region(x) = "Canada"[t:53\%] \vee birth\_region(x) = "foreign"[t:47\%].$$

Mining Class Comparisons

- Comparison: Comparing two or more classes
- Method:
  - Partition the set of relevant data into the target class and the contrasting class(es)
  - Generalize both classes to the same high level concepts
  - Compare tuples with the same high level descriptions
  - Present for every tuple its description and two measures
    - support - distribution within single class
    - comparison - distribution between classes
  - Highlight the tuples with strong discriminant features
- Relevance Analysis:
  - Find attributes (features) which best distinguish different classes

Quantitative Discriminant Rules

- Cj = target class
- q_a = a generalized tuple covers some tuples of class
  - but can also cover some tuples of contrasting class
- d-weight
  - range: [0, 1]

$$d-weight = \frac{count(q_a \in C_j)}{\sum_{i=1}^{m} count(q_a \in C_i)}$$

- quantitative discriminant rule form

$$\forall X,\ target\_class(X) \Leftarrow condition(X) \quad [d : d\_weight]$$

Example: Quantitative Discriminant Rule

Status	Birth_country	Age_range	Gpa	Count
Graduate	Canada	25-30	Good	90
Undergraduate	Canada	25-30	Good	210

Count distribution between graduate and undergraduate students for a generalized tuple

- Quantitative discriminant rule

$$\forall X,\ graduate\_student(X) \Leftarrow$$
$$birth\_country(X) = \text{"Canada"} \wedge age\_range(X) = \text{"25-30"} \wedge gpa(X) = \text{"good"} \quad [d : 30\%]$$

  - where 90/(90 + 210) = 30%

Class Description

- Quantitative characteristic rule

$$\forall X,\ target\_class(X) \Rightarrow condition(X) \quad [t : t\_weight]$$

  - necessary
- Quantitative discriminant rule

$$\forall X,\ target\_class(X) \Leftarrow condition(X) \quad [d : d\_weight]$$

  - sufficient
- Quantitative description rule

$$\forall X,\ target\_class(X) \Leftrightarrow$$
$$condition_1(X)\,[t : w_1, d : w'_1] \vee \ldots \vee condition_n(X)\,[t : w_n, d : w'_n]$$

  - necessary and sufficient

Example: Quantitative Description Rule

Location/item		**TV**			**Computer**			**Both_items**	
	Count	*t-wt*	*d-wt*	*Count*	*t-wt*	*d-wt*	*Count*	*t-wt*	*d-wt*
Europe	80	25%	40%	240	75%	30%	320	100%	32%
N_Am	120	17.65%	60%	560	82.35%	70%	680	100%	68%
Both_ regions	200	20%	100%	800	80%	100%	1000	100%	100%

Crosstab showing associated t-weight, d-weight values and total number (in thousands) of TVs and computers sold at AllElectronics in 1998

- Quantitative description rule for target class *Europe*

$$\forall X, Europe(X) \Leftrightarrow$$
$$(item(X) = \text{"TV"})\,[t : 25\%, d : 40\%] \vee (item(X) = \text{"computer"})\,[t : 75\%, d : 30\%]$$

Summary

- Efficient algorithms for computing data cubes
  - Multiway array aggregation
  - BUC
  - H-cubing
  - Star-cubing
  - High-D OLAP by minimal cubing
- Further development of data cube technology
  - Discovery-drive cube
  - Multi-feature cubes
  - Cube-gradient analysis
- Anther generalization approach: Attribute-Oriented Induction

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SQL Group By statement

SQL GROUP BY Example

We have the following "Orders" table:

O_Id	OrderDate	OrderPrice	Customer
1	2008/11/12	1000	Hansen
2	2008/10/23	1600	Nilsen
3	2008/09/02	700	Hansen
4	2008/09/03	300	Hansen
5	2008/08/30	2000	Jensen
6	2008/10/04	100	Nilsen

Now we want to find the total sum (total order) of each customer.

We will have to use the GROUP BY statement to group the customers.

We use the following SQL statement:

```
SELECT Customer,SUM(OrderPrice) FROM Orders
GROUP BY Customer
```

The result-set will look like this:

Customer	SUM(OrderPrice)
Hansen	2000
Nilsen	1700
Jensen	2000

From: http://www.w3schools.com/sql/sql_groupby.asp