Architecture and Implementation of Database Systems (Winter 2015/16)

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Part XI

Online Analytical Processing (OLAP)

Motivation

Scenario: A bookstore chain collects sales data:

Sales			
Book	City	Month	Units Sold
Arlington Road Atlas	Arlington	January	134
Arlington Road Atlas	Arlington	February	327
⋮	⋮	⋮	⋮
Arlington Road Atlas	Springfield	December	193
Gone With the Wind	Arlington	January	9
⋮	⋮	⋮	⋮
Tropical Food	Springfield	December	374

Motivation

Goal: Spread sheet-style analyses ($\rightsquigarrow$ "Pivot Table")

	January	February	$\cdots$	Grand Total
Arlington	198	449	$\cdots$	1022
Boston	226	212	$\cdots$	707
Miami	152	130	$\cdots$	467
Springfield	304	498	$\cdots$	1303
Grand Total	880	1289	$\cdots$	3499

Challenge: Large data volumes

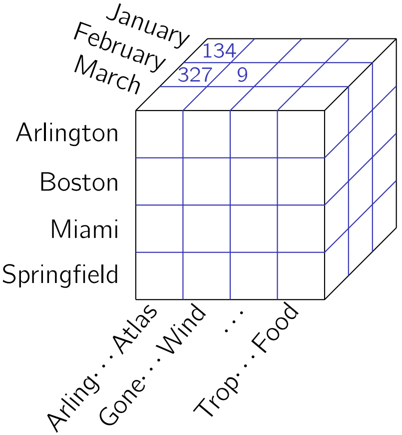
→ How do we **model** such data (*e.g.*, in a relational system)?

→ How can we **implement** pivot tables efficiently?

→ What about *k*-**dimensional data**?

Data Cubes

Idea: Model data as a multi-dimensional **cube**



Data cube:

- **Facts** are stored as **cells** of the cube.
- Facts have **measures** associated with them (here: sales counts).
- Cells may be empty.

Real-world:

- 4–12 dimensions
- **Project** to 2 or 3 for analysis/viewing

Relational Representation: Star Schema

Star Schema:

- One **dimension table** per dimension
- **Fact table** entries reference dimension table entries.

Cities		
CityID	City	State
⋮	⋮	⋮

Sales			
BookID	CityID	DayID	Sold
⋮	⋮	⋮	⋮

Books		
BookID	Title	Genre
⋮	⋮	⋮

Time			
DayID	Day	Month	Year
⋮	⋮	⋮	⋮

Star Schema

Fact Table:

- One row per multidimensional fact.
- This table will hold the lion's share of the entire database.

Dimension Tables:

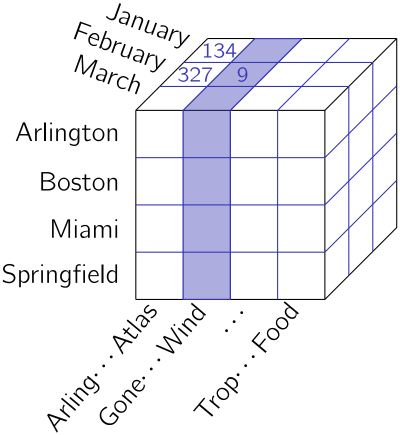
- **Key:** Artificial key (usually an integer number)
- Typically: One column per level if dimension is **hierarchical**
  $\rightarrow$ **Redundancy**

OLAP is ran on data **extracted** from transactional system.

- Load data in **batches**; most of it goes into **fact table**.
- Fact table ends up approximately **ordered by date**.

"Slicing and Dicing"

Typical queries: **aggregate** over **sub-ranges** of the full cube.




```
SELECT SUM(Sold)
  FROM Sales AS s, Books AS b
 WHERE s.BookID = b.BookID
   AND b.Title = "Gone..."
```

Roll-Up, Drill-Down, Pivot Tables

Analysts will want to look at aggregates from many different angles.

Roll-Up / Drill-Down:

- $\rightarrow$ For hierarchical dimensions, move up or down the hierarchy
- $\rightarrow$ See more or less details, "zoom" in or out

Pivot Tables:

- $\rightarrow$ Visualize roll-up/drill-down ($\leadsto$ dedicated OLAP tools)

	January	February	···	Grand Total
Arlington	198	449	···	1022
Boston	226	212	···	707
Fiction	*121*	*98*	···	*346*
Cooking	*105*	*114*	···	*361*
Miami	152	130	···	467
Springfield	304	498	···	1303
Grand Total	880	1289	···	3499

SQL OLAP Extensions

A number of **SQL extensions** ease these tasks.

E.g., multi-dimensional grouping (⇝ Pivot Table):

```
SELECT c.City, t.Month, SUM(s.Sold)
  FROM Sales AS s, Cities AS c, Time AS t
 WHERE s.DayID = t.DayID AND s.CityID = c.CityID
 GROUP BY CUBE(City, Month)
```

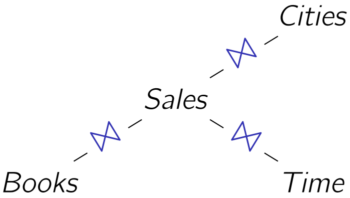
→ Likewise: `GROUP BY ROLLUP(·)`

E.g., ranking, partitioning

```
SELECT c.City, t.Day,
       RANK() OVER (PARTITION BY City ORDER BY Sold)
  FROM Sales AS s, Cities AS c, Time AS t, Books AS b
 WHERE s.DayID = t.DayID AND s.CityID = c.CityID
   AND s.BookID = b.BookID AND b.Title = "Gone..."
```

Star Join

The common query pattern is the **star join**.



✎ **How will a standard RDBMS execute such a query?**

Indexes and Star Queries

Strategy 1: Index on **value columns of dimension tables**

1. For each **dimension table** D_i:
   a. Use index to find **matching dimension table rows** $d_{i,j}$.
   b. **Fetch** those $d_{i,j}$ to obtain **key columns** of D_i.
   c. Collect a list of **fact table rids** that reference those dimension keys.

      ✎ **How?**

2. **Intersect** lists of fact table *rid*s.
3. **Fetch** remaining fact table rows, group, and aggregate.

Strategy 2: Index on **primary key of dimension tables**

1. **Scan fact table**
2. For each fact table row f:
   a. **Fetch** corresponding dimension table row d.
   b. Check slice and dice conditions on d;
      skip to next fact table row if predicate not met.
   c. Repeat 2.a for each dimension table.
3. Group and aggregate all remaining fact table rows.

✎ **Problems and advantages of Strategy 1?**

+ Fetch only **relevant** fact table rows (good for selective queries).
− Index → fetch → index → intersect → fetch is cumbersome. ⋆
− **List intersection** is expensive.
  1. Again, lists may be large, intersection small.
  2. Lists are generally **not sorted**.

Index-Only Queries

Problem $\star$ can be reduced with a trick:

- Create an index that contains value **and** key column of the dimension table.
  - → No **fetch** needed to obtain dimension key.
- Such indexes allow for **index-only querying** (↗ slide 174).
  - → Acess only index, but not data pages of a table.

E.g.,

```
CREATE INDEX QuarterIndex
    ON DateDimension ( Quarter , DateKey )
```

→ Will only use *Quarter* as a **search criterion** (but not *DateKey*).

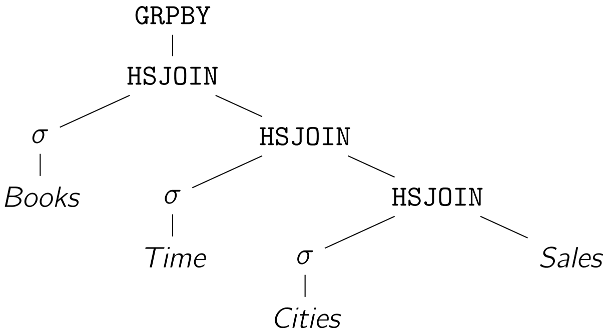
✎ **Problems and advantages of Strategy 2?**

+ For small dimension tables, all indexes might fit into memory.
  - → On the other hand, indexes might not be worth it; can simply build a hash table on the fly.
- − Fact table is **large** → **many** index accesses.
- − **Individually**, each dimension predicate may have low selectivity.

  E.g., four dimensions, each restricted with 10 % selectivity:
  - → Overall selectivity as low as 0.01 %.
  - → But as many as 10 %/1 %/... of fact table tuples pass individual dimension filters (and fact table is huge).

  Together, dimension predicates may still be highly selective.
- Cost is independent of predicate selecitivites.

Implementing Star Join Using Hash Joins



- (Hopefully) dimension subsets are small enough
  → Hash table(s) fit into memory.
- Here, hash joins effectively act like a **filter**.

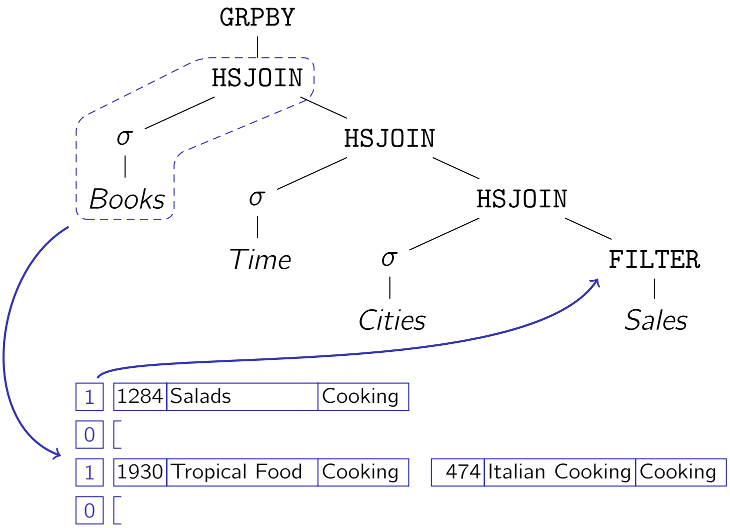
Implementing Star Join Using Hash Joins

Problems:

- Which of the filter predicates is most restrictive? — Tough optimizer task!
- A lot of processing time is invested in tuples that are eventually discarded.

- This strategy will have real trouble as soon as not **all** hash tables fit into memory.

Hash-Based Filters



→ Use compact bit vector to **pre-filter** data.

Hash-Based Filters

- Size of bit vector is independent of dimension tuple size.
  - → And bit vector is **much smaller** than dimension tuples.
- Filtering may lead to **false positives**, however.
  - → Must still do hash join in the end.
- Key benefit: **Discard tuples early**.

Nice side effect:

- In practice, will do pre-filtering according to all dimensions involved.
  - → Can **re-arrange** filters according to actual(!) selectivity.

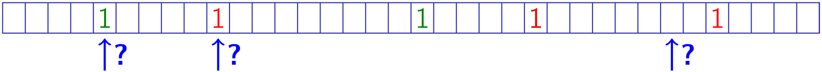
Bloom Filters

Bloom filters can improve filter efficiency.

Idea:

- Create (empty) bit field B with m bits.
- Choose k independent hash functions.
- For every dim. tuple, set k bits in B, according to hashed key values.

⟨1284, Salads, Cooking⟩
⟨1930, Tropical Food, Cooking⟩



⟨1735, Gone With the Wind, Fiction⟩

- To probe a fact tuple, check k bit positions
  - $\rightarrow$ Discard tuple if any of these bits is 0.

Bloom Filters

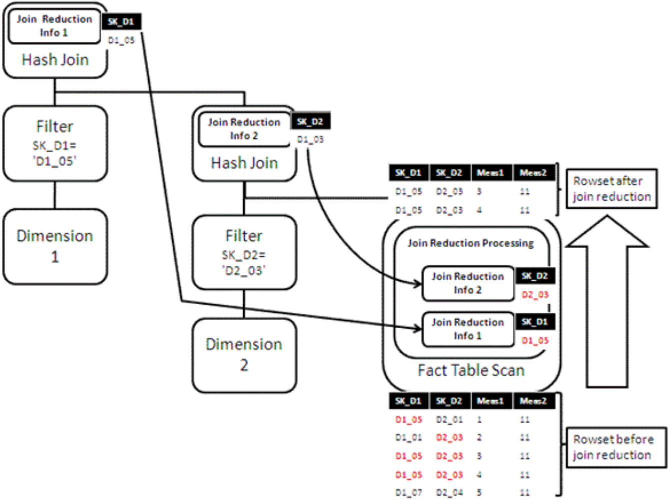
Parameters:

- Number of bits in B: m
  - $\rightarrow$ Typically measured in "bits per stored entry"
- Number of hash functions: k
  - $\rightarrow$ Optimal: about 0.7 times number of bits per entry.
  - $\rightarrow$ Too many hash functions may lead to high CPU load!

Example:

- 10 bits per stored entry lead to a filter accuracy of about 1 %.

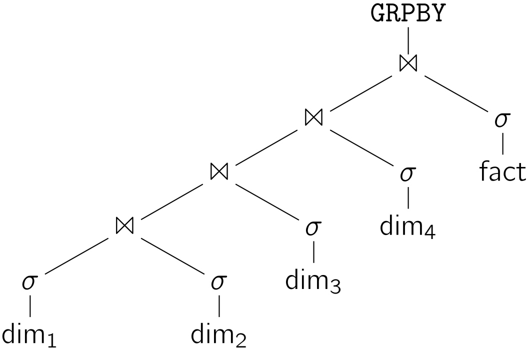
Microsoft SQL Server uses hash-based pre-filtering since version 2008.



Hub Star Join

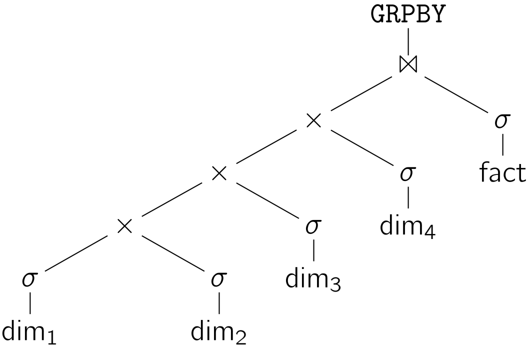
✎ **What do you think about this query plan?**

⇝ Join dimension tables first, then fact table as last relation.



Hub Star Join

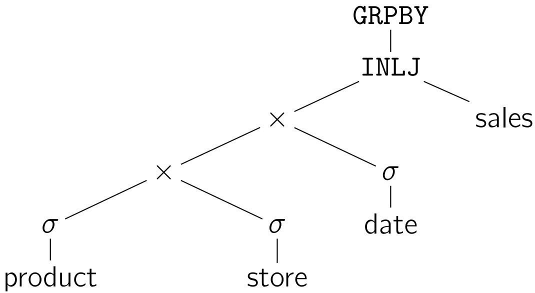
Joins between dimension tables are effectively **Cartesian products**.



→ Clearly won't work if (filtered) dimension tables are large.

Hub Star Join

Idea:



- Cartesian product approximates the set of foreign key values relevant in the fact table.
- Join Cartesian product with fact table using **index nested loops join** (multi-column index on foreign keys).

Hub Star Join

Advantages:

+ Fetch only **relevant** fact table rows.
+ No **intersection** needed.
+ No **sorting** or **duplicate removal** needed.

Down Sides:

– Cartesian product **overestimates** foreign key combinations in the fact table.
  - → Many key combinations won't exist in the fact table.
  - → Many unnecessary index probes.

Overall:

- Hub Join works well if **Cartesian product is small**.

Zigzag Join

cartesian product of dimension keys		
prodkey	classkey	perkey
1	1	1
1	1	3
1	1	5
1	1	6
1	1	7
1	2	1
1	2	3
1	2	5
1	2	6
1	2	7
1	3	1
1	3	3
1	3	5
1	3	6
1	3	7
2	1	1
2	1	3
2	1	5
....	....	....
....	....	....
....	....	....

unproductive probes which are skipped

unproductive probes which are skipped

multi-column index on aroma_sales		
prodkey	classkey	perkey
1	1	1
1	1	2
1	2	2
1	3	2
2	1	1
2	1	2
....	....	....
....	....	....
....	....	....
....	....	....
....	....	....

probes

match

Join Indices

To reduce join cost, we could **pre-compute** (partial) join results.

$\leadsto$ Database terminology: "materialize"

$\leadsto$ More generally: "materialized views"

Pre-computed join results are also called **join indices**.

Example: $\mathit{Cities} \bowtie \mathit{Sales}$

RID lists

- **Type 1:** $\mathit{join\ key} \rightarrow \langle \{\mathit{rid}_{\mathit{Cities}}\}, \{\mathit{rid}_{\mathit{Sales}}\} \rangle$
  (Record ids from *Cities* and *Sales* that contain given join key value.)
- **Type 2:** $\mathit{rid}_{\mathit{Cities}} \rightarrow \{\mathit{rid}_{\mathit{Sales}}\}$
  (Record ids from *Sales* that match given record in *Cities*.)
- **Type 3:** $\mathit{dim\ value} \rightarrow \{\mathit{rid}_{\mathit{Sales}}\}$
  (Record ids from *Sales* that join with *Cities* tuples that have given dimension value.)

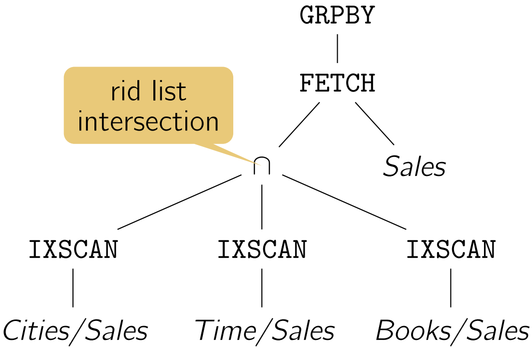
(Conventional B^+-trees are often $\mathit{value} \rightarrow \{\mathit{rid}\}$ mappings; cf. slide 79.)

Example: *Cities* ⋈ *Sales* Join Index

Cities			
rid	CtyID	City	State
c_1	6371	Arlington	VA
c_2	6590	Boston	MA
c_3	7882	Miami	FL
c_4	7372	Springfield	MA
⋮	⋮	⋮	⋮

Sales				
rid	BkID	CtyID	DayID	Sold
s_1	372	6371	95638	17
s_2	372	6590	95638	39
s_3	1930	6371	95638	21
s_4	2204	6371	95638	29
s_5	2204	6590	95638	13
s_6	1930	7372	95638	9
s_7	372	7882	65748	53
⋮	⋮	⋮	⋮	⋮

Star Join with Join Indices



1. For each of the dimensions, find matching *Sales* rids.
2. Intersect rid lists to determine relevant *Sales*.

Star Join with Join Indices

The strategy makes **rid list intersection** a critical operation.

→ Rid lists may be **sorted**.

→ Efficient implementation is (still) active research topic.

Down side:

- Rid list sorted only for (per-dimension) point lookups.

Challenge:

- Efficient **rid list implementation**.

Idea: Create **bit vector** for each possible column value.

Example: Relation that holds information about students:

Students		
LegiNo	Name	Program
1234	John Smith	Bachelor
2345	Marc Johnson	Master
3456	Rob Mercer	Bachelor
4567	Dave Miller	PhD
5678	Chuck Myers	Master

Program Index			
BSc	MSc	PhD	Dipl
1	0	0	0
0	1	0	0
1	0	0	0
0	0	1	0
0	1	0	0

bit vector

Query Processing with Bitmap Indexes

Benefit of bitmap indexes:

- Boolean query operations (**and**, **or**, etc.) can be performed directly on bit vectors.

```
SELECT ···
  FROM Cities
 WHERE State = 'MA'
   AND (City = 'Boston' OR City = 'Springfield')
```

$$\downarrow$$

$$B_{\text{MA}} \wedge \left(B_{\text{Boston}} \vee B_{\text{Springfield}}\right)$$

- Bit operations are well-supported by modern computing hardware (↗ SIMD).

Equality vs. Range Encoding

Alternative encoding for **ordered domains**:

Students		
LegiNo	Name	Semester
1234	John Smith	3
2345	Marc Johnson	2
3456	Rob Mercer	4
4567	Dave Miller	1

Semester Index				
1	2	3	4	5
1	1	1	0	0
1	1	0	0	0
1	1	1	1	0
1	0	0	0	0

(set $B_{c_i}[k] = 1$ for all c_i smaller or equal than the attribute value $a[k]$).

✎ **Why would this be useful?**

Range predicates can be evaluated more efficiently:

$$c_i > a[k] \geq c_j \;\leftrightarrow\; (\neg B_{c_i}[k]) \wedge B_{c_j}[k] \;\; .$$

(but equality predicates become more expensive).

Data Warehousing Example

Index: D4.brand -> {RID}

RID	D4.id	D4.product	D4.brand	D4.group
0	1	Latitude E6400	Dell	Computers
1	2	Lenovo T61	Lenovo	Computers
2	3	SGH-i600	Samsung	Handheld
3	4	Axim X5	Dell	Handheld
4	5	i900 OMNIA	Samsung	Mobile
5	6	XPERIA X1	Sony	Mobile

Index: D4.group -> {RID}

Bitmap Index: D4.brand

B_{Dell}	B_{Len}	B_{Sam}	B_{Sony}
1	0	0	0
0	1	0	0
0	0	1	0
1	0	0	0
0	0	1	0
0	0	0	1

Bitmap Index: D4.group

B_{Com}	B_{Hand}	B_{Mob}
1	0	0
1	0	0
0	1	0
0	1	0
0	0	1
0	0	1

Query Processing: Example

Sales in group 'Computers' for brands 'Dell', 'Lenovo'?

```
SELECT SUM(F.price)
  FROM D4
 WHERE group = 'Computer'
   AND (brand = 'Dell'
        OR brand = 'Lenovo')
```

→ Calculate bit-wise operation

$$B_{Com} \wedge (B_{Dell} \vee B_{Len})$$

to find matching records.

B_{Dell}	B_{Len}	B_{Sam}	B_{Sony}
1	**0**	0	0
0	**1**	0	0
0	**0**	1	0
1	**0**	0	0
0	**0**	1	0
0	**0**	0	1

Bitmap Index: D4.brand

B_{Com}	B_{Hand}	B_{Mob}
1	0	0
1	0	0
0	1	0
0	1	0
0	0	1
0	0	1

Bitmap Index: D4.group

Bitmap Indices for Star Joins

Bitmap indices are useful to implement **join indices**.

Here: Type 2 index for *Cities* ⋈ *Sales*

Cities			
rid	CtyID	City	State
c_1	6371	Arlington	VA
c_2	6590	Boston	MA
c_3	7882	Miami	FL
c_4	7372	Springfield	MA
⋮	⋮	⋮	⋮

Sales					Idx		
rid	BkID	CtyID	DayID	Sold	c_1	c_2	···
s_1	372	6371	95638	17	1	0	···
s_2	372	6590	95638	39	0	1	···
s_3	1930	6371	95638	21	1	0	···
s_4	2204	6371	95638	29	1	0	···
s_5	2204	6590	95638	13	0	1	···
s_6	1930	7372	95638	9	0	0	···
s_7	372	7882	65748	53	0	0	···
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋱

→ One bit vector per RID in *Cities*.

→ Length of bit vector ≡ length of fact table (*Sales*).

Bitmap Indices for Star Joins

Similarly: Type 3 index $State \rightarrow \{Sales.rid\}$

Cities			
rid	CtyID	City	State
c_1	6371	Arlington	VA
c_2	6590	Boston	MA
c_3	7882	Miami	FL
c_4	7372	Springfield	MA
⋮	⋮	⋮	⋮

Sales				
rid	BkID	CtyID	DayID	Sold
s_1	372	6371	95638	17
s_2	372	6590	95638	39
s_3	1930	6371	95638	21
s_4	2204	6371	95638	29
s_5	2204	6590	95638	13
s_6	1930	7372	95638	9
s_7	372	7882	65748	53
⋮	⋮	⋮	⋮	⋮

Idx			
VA	MA	FL	⋯
1	0	0	⋯
0	1	0	⋯
1	0	0	⋯
1	0	0	⋯
0	1	0	⋯
0	1	0	⋯
0	0	1	⋯
⋮	⋮	⋱	

→ One bit vector per *State* value in *Cities*.

→ Length of bit vector ≡ length of fact table (*Sales*).

Space Consumption

For a column with n **distinct values**, n bit vectors are required to build a bitmap index.

For a table wit N rows, this leads to a **space consumption** of

$$N \cdot n \text{ bits}$$

for the full bitmap index.

This suggests the use of bitmap indexes for **low-cardinality attributes**.

$\rightarrow$ *e.g.*, product categories, sales regions, etc.

For comparison: A 4-byte integer column needs $N \cdot 32$ bits.

$\rightarrow$ For $n \lesssim 32$, a bitmap index is more compact.

Reducing Space Consumption

For larger n, space consumption can be reduced by

1. **alternative bit vector representations** or
2. **compression**.

Both may be a **space/performance trade-off**.

Decomposed Bitmap Indexes:

- Express all attribute values v as a **linear combination**

$$v = v_0 + \underbrace{c_1}\, v_1 + \underbrace{c_1 c_2}\, v_2 + \cdots + \underbrace{c_1 \cdots c_k}\, v_k \quad (c_1, \ldots, c_k \text{ constants}).$$

- Create a **separate bitmap index** for each variable v_i.

Decomposed Bitmap Indexes

Example: Index column with domain $[0, \ldots, 999]$.

- Regular bitmap index would require 1000 bit vectors.
- Decomposition ($c_1 = c_2 = 10$):

$$v = 1v_1 + 10v_2 + 100v_3 \quad .$$

- Need to create **3 bitmap indexes** now, each for **10 different values**
  $\rightarrow$ 30 bit vectors now instead of 1000.
- However, need to **read 3 bit vectors** now (and **and** them) to answer **point query**.

Decomposed Bitmap Indexes

- **Query:**
  `a=576=5*100+7*10+6*1`
- **RIDs:**
  $B_{v3,5} \wedge B_{v2,7} \wedge B_{v1,6} =$ [0010…0]

=> RID 3, ...

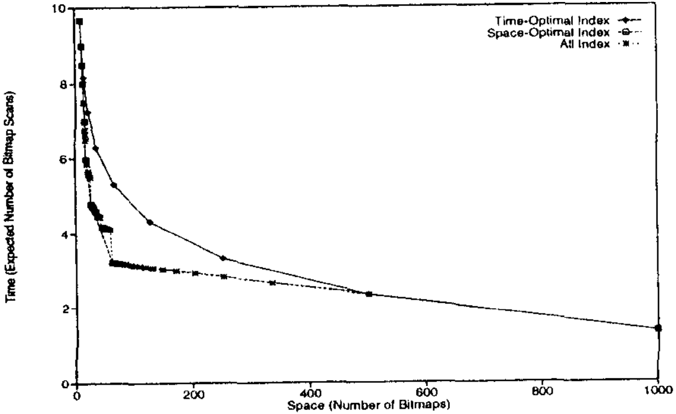
RID	a
0	998
1	999
2	576
3	578
1000	976

$B_{v1.0}$	$B_{v1.1}$	$B_{v1.2}$	$B_{v1.3}$	$B_{v1.4}$	$B_{v1.5}$	$B_{v1.6}$	$B_{v1.7}$	$B_{v1.8}$	$B_{v1.9}$
0	0	0	0	0	0	**0**	0	1	0
0	0	0	0	0	0	**0**	0	0	1
0	0	0	0	0	0	**1**	0	0	0
0	0	0	0	0	0	**0**	0	1	0
0	0	0	0	0	0	**1**	0	0	0

$B_{v2.0}$	$B_{v2.1}$	$B_{v2.2}$	$B_{v2.3}$	$B_{v2.4}$	$B_{v2.5}$	$B_{v2.6}$	$B_{v2.7}$	$B_{v2.8}$	$B_{v2.9}$
0	0	0	0	0	0	0	**0**	0	1
0	0	0	0	0	0	0	**0**	0	1
0	0	0	0	0	0	0	**1**	0	0
0	0	0	0	0	0	0	**1**	0	0
0	0	0	0	0	0	0	**1**	0	0

$B_{v3.0}$	$B_{v3.1}$	$B_{v3.2}$	$B_{v3.3}$	$B_{v3.4}$	$B_{v3.5}$	$B_{v3.6}$	$B_{v3.7}$	$B_{v3.8}$	$B_{v3.9}$
0	0	0	0	0	**0**	0	0	0	1
0	0	0	0	0	**0**	0	0	0	1
0	0	0	0	0	**1**	0	0	0	0
0	0	0	0	0	**1**	0	0	0	0
0	0	0	0	0	**0**	0	0	0	1

Setting c_i parameters allows to trade space and performance:



source: Chee-Yong Chan and Yannis Ioannidis. Bitmap Index Design and Evaluation. *SIGMOD 1998*.

Compression

Orthogonal to bitmap decomposition: Use **compression**.

- *E.g.*, straightforward equality encoding for a column with cardinality n: $1/n$ of all entries will be 0.

✎ **Which compression algorithm would you choose?**

Compression

Problem: Complexity of (de)compression $\leftrightarrow$ simplicity of bit operations.

- Extraction and manipulation of **individual bits** during (de)compression can be expensive.
- Likely, this would off-set any efficiency gained from logical operations on **large CPU words**.

Thus:

- Use (rather simple) **run-length encoding**,
- but respect **system word size** in compression scheme.

↗ Wu, Otoo, and Shoshani. Optimizing Bitmap Indices with Efficient Compression. *TODS*, vol. 31(1). March 2006.

Word-Aligned Hybrid (WAH) Compression

Compress into a sequence of 32-bit words:

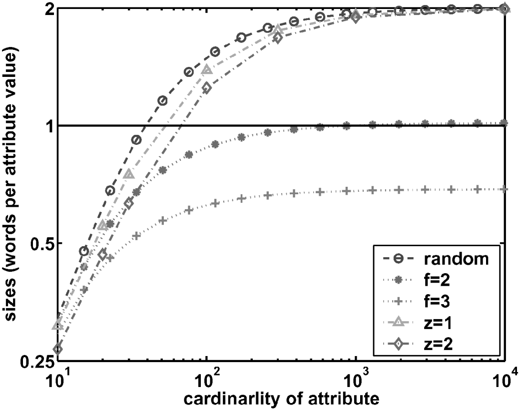
Bit tells whether this is a **fill word** or a **literal word**.

- **Fill word ($= 1$):**
  - Bit tells whether to fill with 1s or 0s.
  - Remaining 30 bits indicate the number of fill bits.
    - → This is the number of **31-bit blocks** with only 1s or 0s.
    - → *e.g.*, $= 3$: represents 93 1s/0s.
- **Literal word ($= 0$):**
  - Copy 31 bits directly into the result.

WAH: Effectiveness of Compression

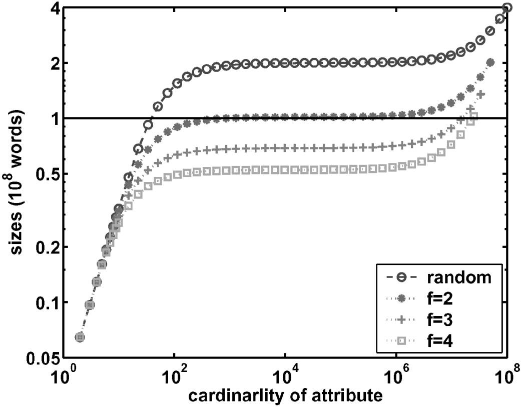
WAH is good to counter the space explosion for **high-cardinality attributes**.

- At most 2 words per '1' bit in the data set
  - $\rightsquigarrow$ At most $\approx 2 \cdot N$ words for a table with N rows, even for large n (assuming a bitmap that uses equality encoding).



Source: Wu et al. TODS 31(1), 2006.

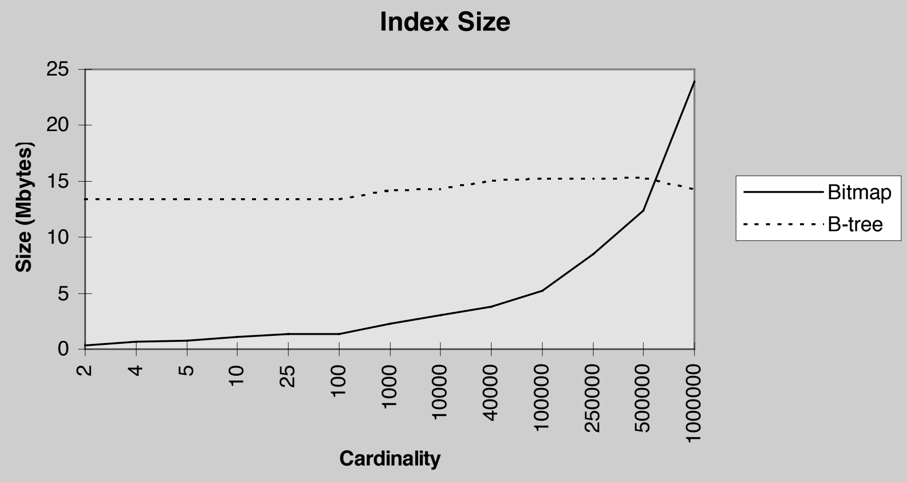
WAH: Effectiveness of Compression



(b) $n = 10^8$

- If (almost) all values are distinct, additional **bookkeeping** may need some more space ($\rightsquigarrow 4 \cdot 10^8$ bits for cardinality 10^8).

Bitmap Indexes in Oracle 8



Encoding $\leftrightarrow$ Bitmap Sparseness/Attribute Cardinality

The most space-efficient bitmap representation depends on the **number of distinct values** (*i.e.*, the **sparseness** of the bitmap).

- **low attribute cardinality** (dense bitmap)
  - $\rightarrow$ can use **un-compressed bitmap**
    WAH compression won't help much (but also won't hurt much)
- **medium attribute cardinality**
  - $\rightarrow$ use (WAH-)**compressed bitmap**
- **high attribute cardinality** (many distinct values; sparse bitmap)
  - $\rightarrow$ Encode "bitmap" as **list of bit positions**

In addition, compressed bitmaps may be a good choice for data with **clustered content** (this is true for many real-world data).

Bitmaps ↔ Row IDs?

✎ **Bitvectors encode a list of integer positions. But we need RIDs. What gives?**

RID Lists

Conversely, bitmaps may be a good way to encode **lists of rows**.

$\rightarrow$ Represent **RID lists** in B-tree leaves as (compressed) bit vectors.

In practice:

- Divide table into **segments** ($\approx$ 32,000 tuples/segment).
- Separate bitmap for each segment.
- Per segment can decide on WAH $\leftrightarrow$ RID list.

$\rightarrow$ *E.g.*, Oracle's bitmap indexes are essentially that (though exact encoding is proprietary).

Benefits:

- May be able to **skip** over entire segments.
- Keep **update** cost reasonable.