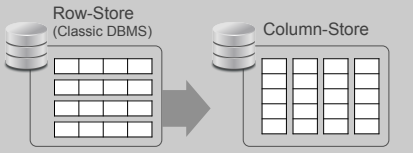
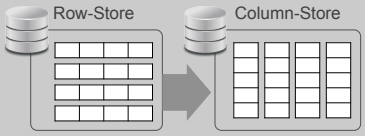
Column-Store: An Overview



Store one tuple at-a-time

Store one column at-a-time

Row-Store vs Column-Store



Tuple Insertion:	⊕ Fast	⊖ Requires multiple seeks
Queries:	⊖ May access more data than needed	⊕ Read only relevant data
		Perfect for analytics!

Column-Store Optimizations

Operating on columns enables and/or is combined with the following optimizations:

- Compression
  Compress values per column
- Late Tuple Materialization
  Construct tuples as late as possible
- Block Iteration
  Pass blocks of values between operators
- Invisible Join

Column-Store Optimizations

Compression

Compress column data

Column-Store Optimizations > Compression

Why Compression

Advantages of compression in general:

- Lower storage space requirements
  Minor
- Better I/O performance
  Read fewer data (from disk, SSD, or RAM), gain from cache locality
- Better query processing performance
  Typically when operating directly on compressed data

Column-Store Optimizations > Compression

Why Column Store

Compress column data:

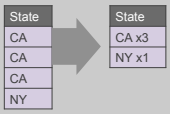
- One column at a time
  Data in a column more similar than data across columns

Name	Phone	City	State
Fred Flintstone	858-123-4567	San Diego	CA
Barney Rubble	619-000-0000	San Diego	CA
Maggie Simpson	415-999-2222	San Francisco	CA
James Bond	212-007-0000	New York	NY

Column-Store Optimizations > Compression

Compression Example

- Run-length encoding
  Replace list of identical values by pair (value, count)

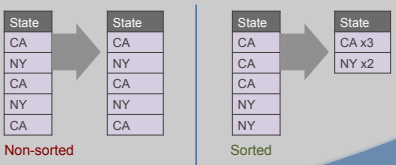


Column-Store Optimizations > Compression

Compression Example

- Run-length encoding
  Replace list of identical values by run pair (value, count)

⊕ Good for sorted columns



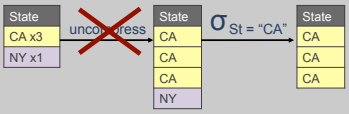
Column-Store Optimizations > Compression

Compression Example

- Run-length encoding
  Replace list of identical values by pair (value, count)

⊕ Enables query processing on compressed data directly

e.g., Select persons in CA



Column-Store Optimizations > Compression

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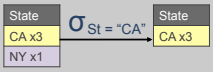


Column-Store Optimizations > Compression

Other Compression Algos

- Dictionary Encoding
  Replace frequent patterns with smaller fixed length codes:
  eg, instead of string values "Dasgupta" → 0, "Freund" → 1, "Papakonstantinou" → 2

  Commonly used in row-stores also, since it enables fixed length fields, therefore random access.
- Bit-Vector Encoding
  Create for each possible value a bit vector with 1s in the positions containing the value: Useful for small domains.

  (Covered in the indexing section.)
- Heavyweight, Variable-Length Compression Schemes
  e.g., Huffman: Excellent compression ratio but (1) no random access (2) possibly poor decompression CPU performance

  Currently not used – they are good for selected workloads

Column-Store Optimizations

Late Tuple Materialization

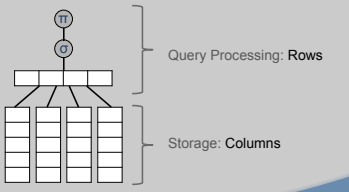
Create tuples as late in the query plan as possible

Column-Store Optimizations > Late Tuple Mat.

Early Tuple Materialization

Naïve method of query evaluation in a column store:

- Read relevant columns & create tuples
- Run query at a tuple-level as usual



Column-Store Optimizations > Late Tuple Mat.

Early Tuple Materialization

e.g., SELECT Name FROM Person WHERE City="SD" AND State="CA"

Π_{Name}

$\sigma_{City = "SD" \wedge State="CA"}$

Create tuples

Name	Phone	City	State
Flintstone	858	SD	CA
Barney	619	SD	CA
Simpson	415	SF	CA
Bond	212	NY	NY

Column-Store Optimizations > Late Tuple Mat.

Early Tuple Materialization

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Column-Store Optimizations > Late Tuple Mat.

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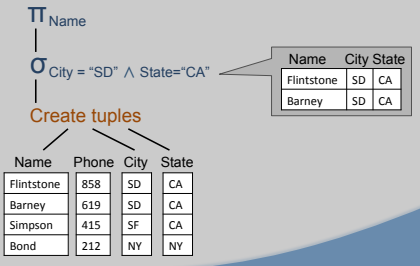

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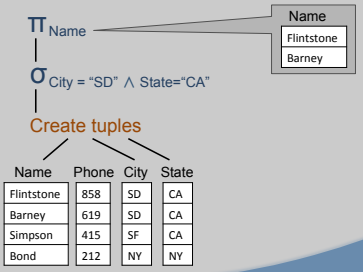

Name
Flintstone
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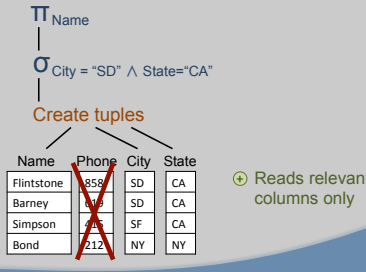

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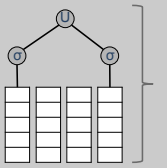
⊕ Reads relevant columns only

Column-Store Optimizations > Late Tuple Mat.

Late Tuple Materialization

- Create tuples as late in the plan as possible



Storage & Query Processing: **Columns**

Column-Store Optimizations > Late Tuple Mat.

Late Tuple Materialization

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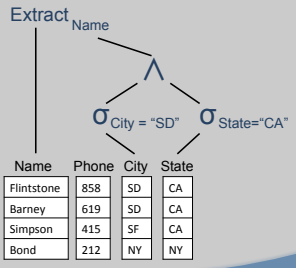

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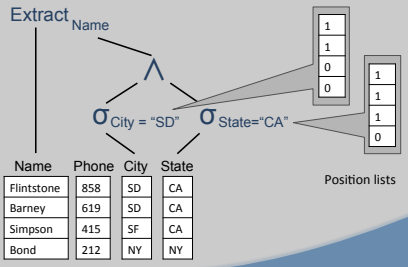

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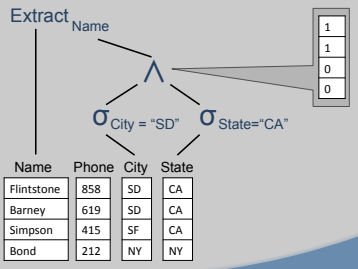

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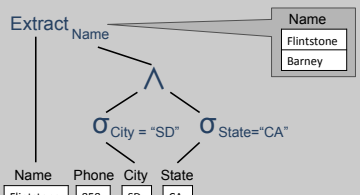

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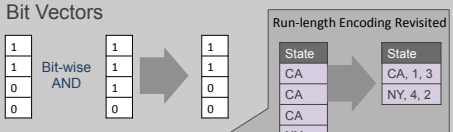
Column-Store Optimizations > Late Tuple Mat.

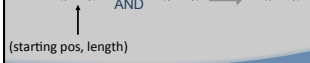
Representing Position Lists

Position lists can be represented as:

- Bit Vectors



- Ranges of positions



Column-Store Optimizations > Late Tuple Mat.

Late Materialization Benefits

- Avoid materializing certain tuples
  since they may be filtered out before being materialized
  (Reminds of pushing selections down.)
- Avoid data decompression
  which has to be done when a tuple is materialized
- Leverage improved cache locality
  which exists when operating on a single column
- Leverage optimizations for fixed-width attributes
  which would not be possible if operating on the tuple level, since a tuple with at least one variable-width attribute becomes variable-width

Column-Store Optimizations

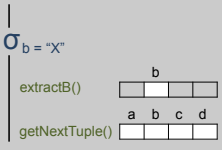
Block Iteration

Pass blocks of values between operators

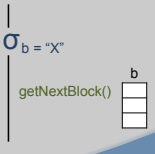
Column-Store Optimizations

Block Iteration

- Row Store
  - Pass single tuples between operators
  - Extract attribute value through function calls



- Column Store
  - Pass blocks of values between operators
  - No need for attribute extraction



Column-Store Optimizations

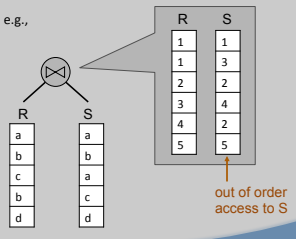
Invisible Join

Join Optimization for Star Schemas

Column Store Optimizations > Invisible Join

Joins & Late Tuple Mat.

- Late Tuple Materialization requires out of order access when we join tables



Column Store Optimizations

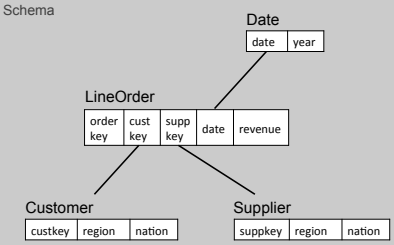
Invisible Join

- Optimization for joins on Star Schemas
  - Make sure that the fact table is accessed in order
  - Reduce the amount of data that are accessed out of order from the dimension tables
  - Reminiscent of bitmap intersection technique

Column Store Optimizations

Invisible Join Example

Schema



Example taken from VLDB 09 Tutorial by Harizopoulos, Abadi, Boncz

Column Store Optimizations

Invisible Join Example

Query

```
SELECT c_nation, s_nation, d_year, sum(lo_revenue) as revenue
FROM customer, lineorder, supplier, date
WHERE   lo_custkey = c_custkey AND
        lo_suppkey = s_suppkey AND
        lo_orderdate = d_datekey AND
        c_region = 'ASIA' AND
        s_region = 'ASIA' AND
        d_year >= 1992 AND d_year <= 1997
GROUP BY c_nation, s_nation, d_year
ORDER BY d_year asc, revenue desc;
```

Column Store Optimizations

Invisible Join Example

Data

Lineorder

order key	cust key	supp key	date	revenue
1	3	1	010197	43256
2	3	2	010197	33333
3	4	3	010297	12121
4	1	1	010297	23233
5	4	2	010297	45456
6	1	2	010397	43251
7	3	2	010397	34235

Supplier

suppkey	region	nation
1	Asia	Russia
2	Europe	Spain
3	Asia	Japan

Customer

custkey	region	nation
1	Asia	China
2	Asia	India
3	Asia	India
4	Europe	France

Date

date	year
010197	1997
010297	1997
010397	1997

Column Store Optimizations

Invisible Join Example

Step 1: Apply selections on dimension tables

Supplier

suppkey	region	nation
1	Asia	Russia
2	Europe	Spain
3	Asia	Japan

$\sigma_{region = \text{“Asia”}}$ → Hashtable {1, 3}

Customer

custkey	region	nation
1	Asia	China
2	Asia	India
3	Asia	India
4	Europe	France

$\sigma_{region = \text{“Asia”}}$ → Hashtable {1, 2, 3}

Date

date	year
010197	1997
010297	1997
010397	1997

$\sigma_{year\ in\ [1992, 1997]}$ → Hashtable {*}

Column Store Optimizations

Invisible Join Example

Step 2: Find fact table tuples satisfying all selections on dimension tables

supp key		cust key		date	
1	1	3	1	010197	1
2	0	3	1	010197	1
3	1	4	0	010297	1
1	1	1	1	010297	1
2	0	4	0	010297	1
2	0	1	1	010397	1
2	0	3	1	010397	1
+ Hashtable {1, 3}		+ Hashtable {1, 2, 3}		+ Hashtable {010197, 010297, 010397}	

Column Store Optimizations

Invisible Join Example

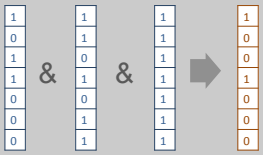
Step 2: Find fact table tuples satisfying *all* selections on dimension tables

1	1	1
0	1	1
1	0	1
1	1	1
0	0	1
0	1	1
0	1	1

Column Store Optimizations

Invisible Join Example

Step 2: Find fact table tuples satisfying *all* selections on dimension tables



Column Store Optimizations

Invisible Join Example

Step 3: Extract data from dimension tables

Lineorder

supp key
1
2
3
1
2
2
2

+

1
0
0
1
0
0
0

1
1

+ Supplier

suppkey	region	nation
1	Asia	Russia
2	Europe	Spain
3	Asia	Japan

Russia
Russia

Column Store Optimizations

Invisible Join Example

Step 3: Extract data from dimension tables

Lineorder

cust key
3
3
4
1
4
1
3

+

1
0
0
1
0
0
0

3
1

+ Customer

custkey	region	nation
1	Asia	China
2	Asia	India
3	Asia	India
4	Europe	France

India
China

Column Store Optimizations

Invisible Join Example

Step 3: Extract data from dimension tables

Lineorder

Columm-Store Optimizations

Optimizations Summary

- Compression
- Late Tuple Materialization
- Block Iteration
- Invisible Join

Column-Store Optimizations

Comparing Optimizations

What is the speedup of each column-store optimization?

- Compression — 2x(avg)/10x(sorted)
- Late Tuple Materialization — 3x
- Block Iteration — 1.05-1.5x
- Invisible Join — 1.5-1.75x

From "Column-Stores vs. Row-Stores: How Different Are They Really"

Column-Store vs Row-Store

- How better is a column-store than a row-store?
  Heated debate: (Exaggerated) claims of performance up to 16,200x
- Can we simulate it in a row-store and get the performance benefits or does the row-store have to be internally modified?
  Another heated debate: Many papers on the topic
- Can we create a hybrid that will accommodate both transactional and analytics workloads?

Column-Store Simulation

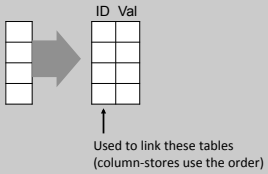
A column-store can be simulated in a row-store through:

- Vertical Partitioning
  Create one table per column
- Index-only Plans
  Create one index per column & use only indexes
- Materialized Views
  Create views of interest for given workload
- C-Table

Column-Store Simulation

Vertical Partitioning

- Create one table per column



Column-Store Simulation

Vertical Partitioning

e.g.,

Name	Phone	City	State
Flintstone	858	SD	CA
Barney	619	SD	CA
Simpson	415	SF	CA
Bond	212	NY	NY

ID	Name
1	Flintstone
2	Barney
3	Simpson
4	Bond

ID	Phone
1	858
2	619
3	415
4	212

ID	City
1	SD
2	SD
3	SF
4	NY

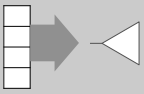
ID	State
1	CA
2	CA
3	CA
4	NY

- ⊖ Overhead from storing tuple-ID
- ⊖ Excessive joins

Column-Store Simulation

Index-only Plans

- Create one index per column & use only indexes
  Data are kept as rows but are never accessed



Column-Store Simulation

Index-only Plans

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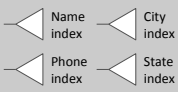
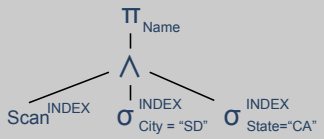


Column-Store Simulation

Index-only Plans

e.g., SELECT Name FROM Person WHERE City="SD" AND State="CA"



Column-Store Simulation

Index-only Plans

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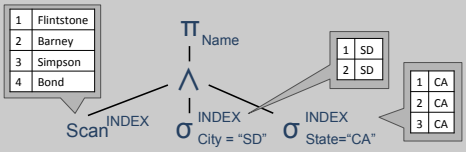

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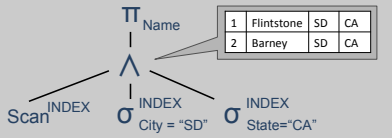

Column-Store Simulation

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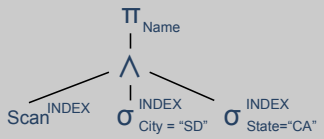


⊕ Avoids table access

⊖ Have to scan index for attributes wo predicate

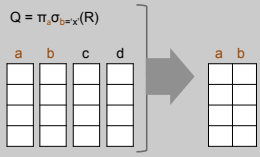
Create indexes with composite keys!

Column-Store Simulation

Materialized Views

- Create optimal view(s) for each query

  For each relation involved in the query, create a view including only columns needed to answer the query



Column-Store Simulation

Materialized Views

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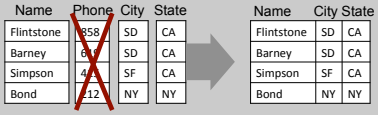


Name	Phone	City	State
Flintstone	1358	SD	CA
Barney	6[illegible]	SD	CA
Simpson	4[illegible]	SF	CA
Bond	212	NY	NY

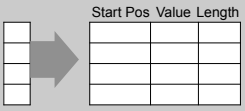
Name	City	State
Flintstone	SD	CA
Barney	SD	CA
Simpson	SF	CA
Bond	NY	NY

⊖ Requires workload knowledge

Column-Store Simulation

C-Table

- Extend vertical partitioning with run-length encoding
- Rewrite queries to operate on the compressed data



Column-Store Simulation

C-Table

e.g.,

State
CA
CA
CA
NY

Start Pos	State	Length
1	CA	3
4	NY	1

⊕ Pretty close to performance of native column-store

Back to our question:

Column-Store vs Row-Store

- Column-Stores have a definite advantage on analytic workflows…
- …but Row-Stores can be improved by taking lessons from them

Implementations

Open Source

C-Store

Commercial