Column-Oriented Databases

Exploiting Vertical Fragmentation to the Extreme

Column-Oriented Databases

- Meant to accelerate read-only workloads
  - Use, to the extreme, of vertical partitioning
  - Do not allow variable record sizes and apply efficient compression techniques
  - Specific query processing techniques assuming the items above
    - In-memory query processing
- Recall the limitations yielded by vertical partitioning when reconstructing the original tuples
  - As such, these DBs are meant for **read-only databases**
  - Extremely inefficient in front of write-intensive database workloads

Column-Oriented Databases: Types

- Column-oriented DBs are inherently aligned with decisional systems
  - A <u>must</u> for Data Warehousing! ~ Terabytes
  - A <u>must</u> for read-only Big Data Systems ~ Petabytes
- Two main types:
  - Relational Column-Oriented DBs (aka NewSQL)
    - First system: C-Store
    - Industrial examples: MonetDB, HP Vertica, SAP Hana, Oracle in-memory column store, MariaDB ColumnStore, PostgreSQL Zedstore… in general, ANY relational database provides, in one way or another, a columnar engine
  - Column-Oriented NOSQL databases
    - Apache Druid (first OLAP-like NOSQL engine) - first non-relational column-oriented DB
    - Hadoop Ecosystem
      - Apache Parquet and Apache Arrow file-formats for HDFS
      - Apache Kudu
    - Google BigQuery (former Dremel)
    - Amazon Redshift (former DynamoDB)
    - Snowflake

  In general, most Cloud Providers provide a column-oriented PaaS

*NOTE: Many classify Apache HBase as a column-oriented DB. **IT IS NOT**. HBase applies a hybrid partitioning strategy with horizontal partiotining as its primary partitioning strategy. Therefore, it cannot apply to its whole the optimizations for query processing*

Column-Oriented Databases: Features

- Column-Oriented Specific Features:
  - Data model
    - Pure Vertical Partitioning
    - Tuples are identified by their position (no PK needed to be replicated in each fragment)
      - Multiple sorting of data (if needed, different in each replica)
    - Remove variable size records and work with fix-sized records (dictionaries or bitmaps needed)
    - Column-specific compression techniques
  - Specific query processing
    - Late materialization: apply as many processing operators to the vertical fragments before joining them
    - Block iteration: exploit the fix-sized records to process data per blocks
    - *Vectorized query processing:* when late materialization and block iteration are combined
    - Specific join algorithms (e.g., invisible join) exploiting the previous items

Activity: Column-Oriented Specific Features

- *Objective: Understand the column-oriented specificities that tuned row-oriented databases cannot meet*
- *Tasks:*
  1. *(15') In group of two, each of you must read one of these specific features. Namely:*
     I. *Compression*
     II. *Late materialization and block iteration*
  2. *(5') Think tank*

Data Model: Vertical Partitioning

- Most column-oriented DBs create a fragment per column

Table T

A	B	C
Bravo	Lleida	A
Bravo	BCN	A
null	Girona	A
null	Lleida	E
null	Vic	C
Charlie	Salt	E
Charlie	BCN	E
Charlie	BCN	A

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Table T (partitioned)

A	B	C
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Charlie	BCN	E
Charlie	BCN	A

- Relevantly, some DBs allow to define groups of columns

Data Model: Compression

- Each column is not store as a regular file, but as a compressed file
- In these DBs, the compression main objective is not reducing data space but reducing I/Os
  - Yet, data in columnar format is more compressible than data stored in rows
    - High data value locality (less value entropy)
    - Benefits from sorting
- Two main trends
  - Heavy weight compression algorithms (e.g., Lempel-Ziv)
    - In general, not that useful but it might be if there is a (huge) gap between memory bandwidth and CPU performance
  - Lightweight compression (e.g., Run-Length Encoding) may allow the query optimizer work directly on compressed data
    - Improves performance by reducing CPU cost
    - Decompression is needed in front of bitwise AND / OR

Data Model: Lightweight Compression

- Mainly based on dictionaries <u>or bitmaps</u>
- Example of Run-length Encoding (with dictionary)

Bravo
Bravo
null
null
null
Charlie
Charlie
Charlie

Column A

Data Model: Lightweight Compression

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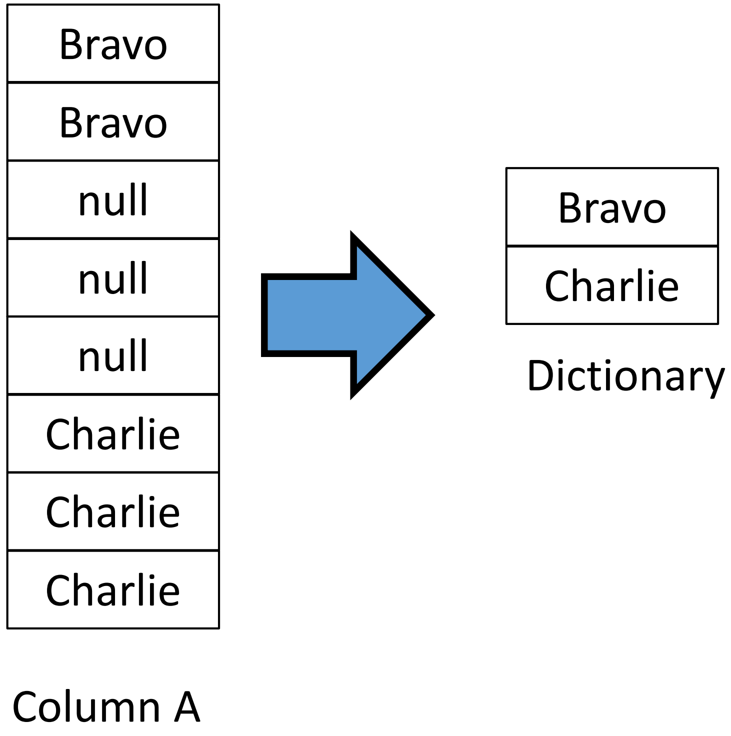

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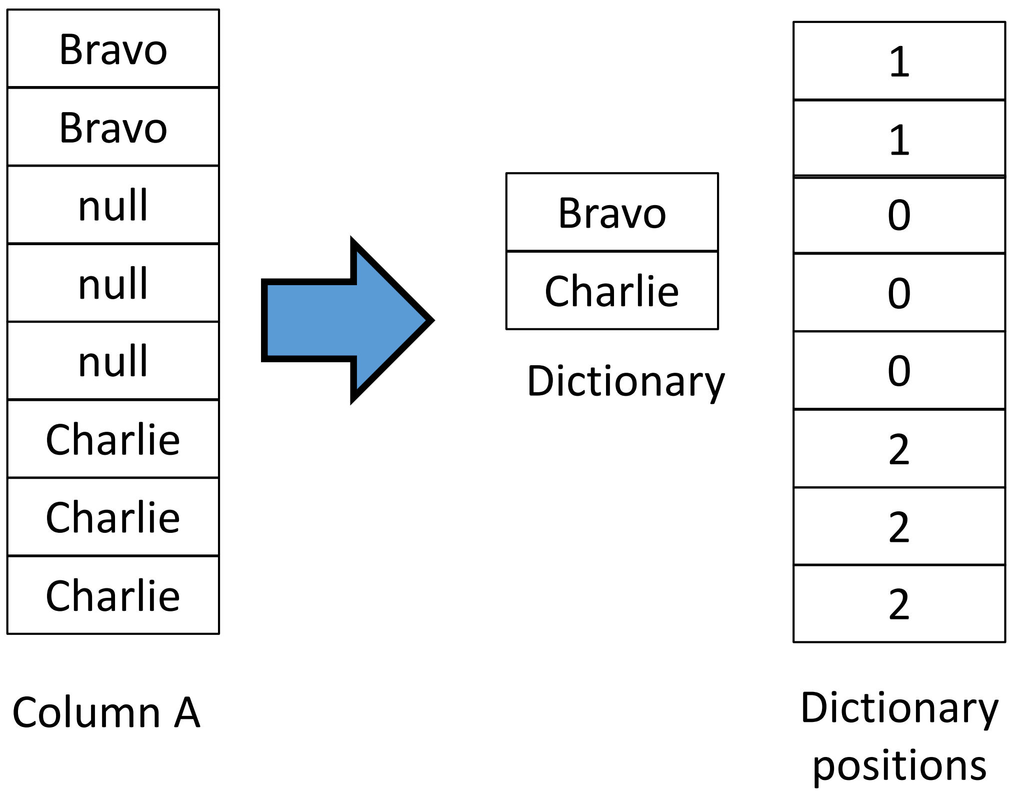

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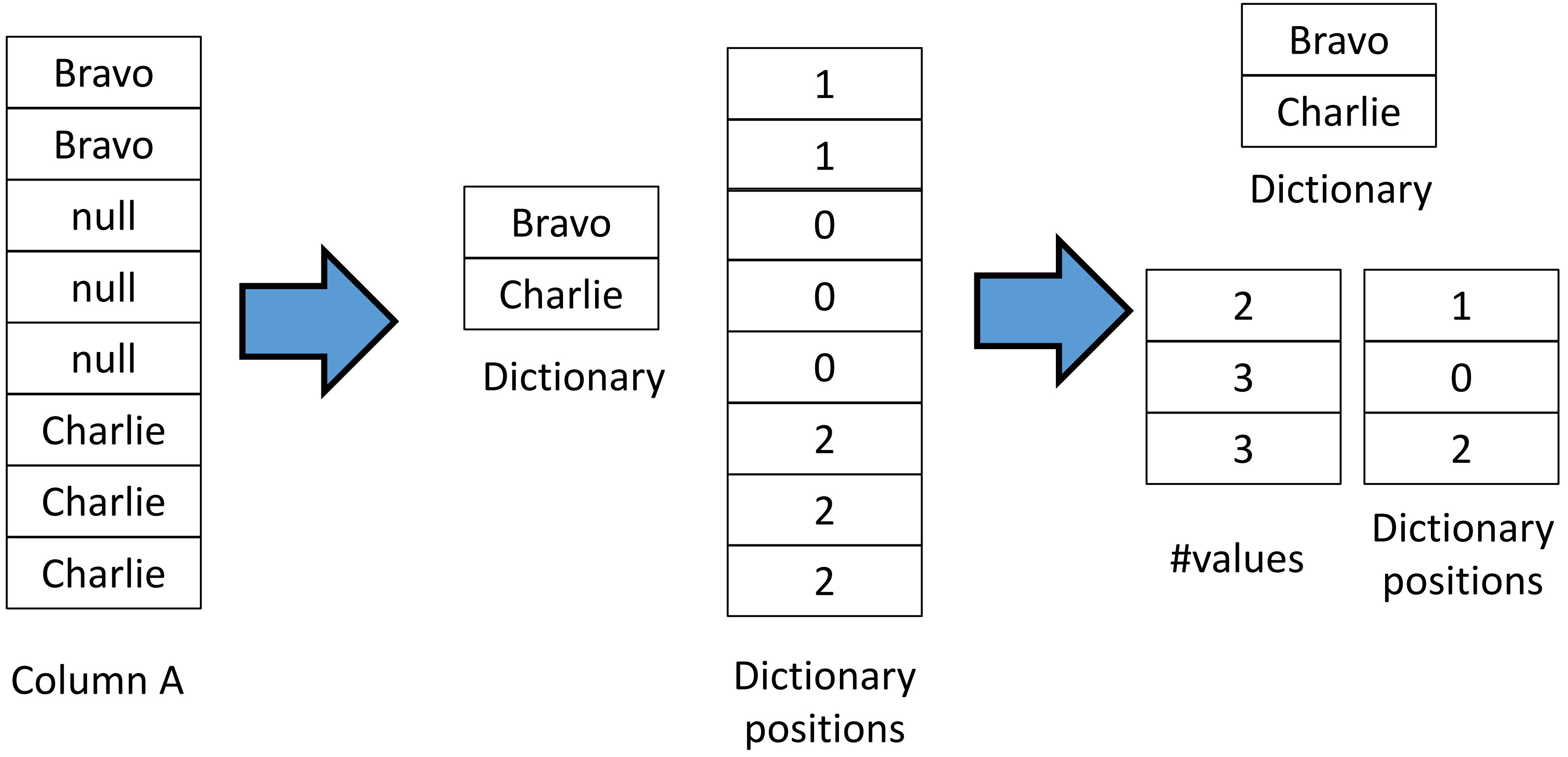

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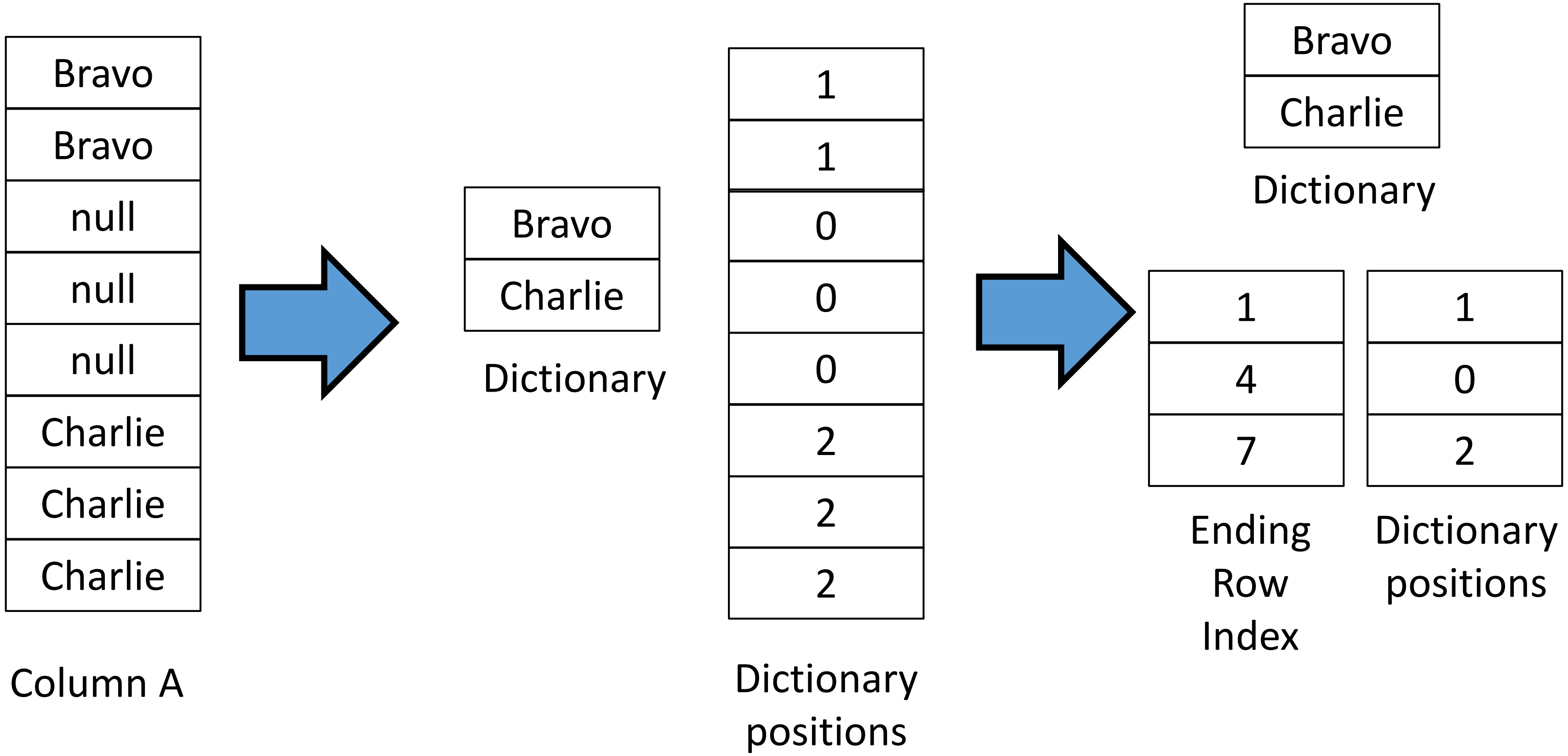

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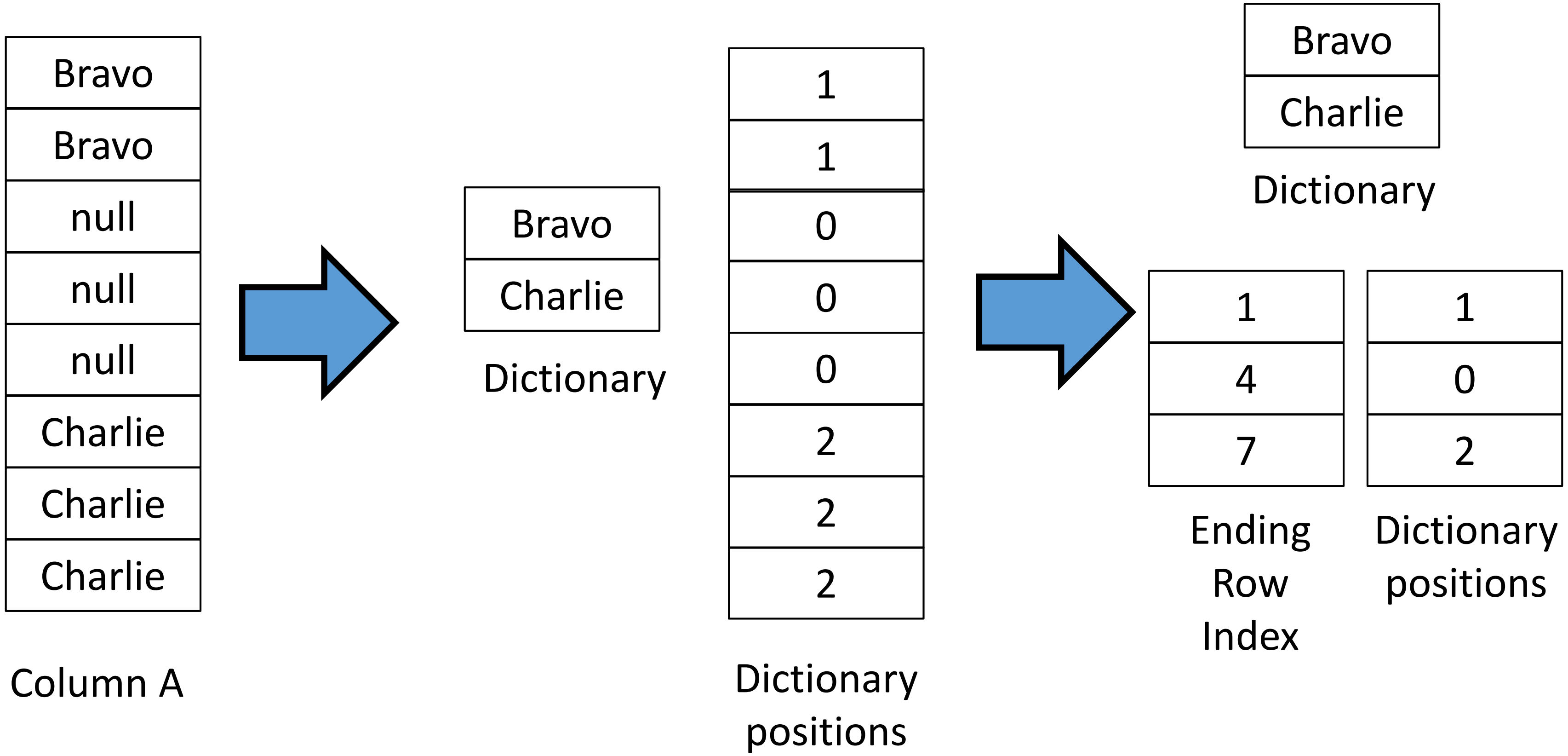

Realise that the ERI and Dictionary positions are always fixed-size

Data Model: Reconstructing Records

- From each table, 3*N vectors are generated (N=#attributes)
- To reconstruct the original tuple, the original vertical fragmentation strategy we study used the PK (to be included in each fragment)
- **Alternatively**, in column-oriented DBs each record has the same position in all the columns (vectors) created from that table
  - Thus, column-oriented DBs **do not join fragments** to reconstruct the record
- Relevantly, a certain order might benefit a column and harm another
  - If necessary, in the presence of replicas, each replica might use a different order (<u>*the order must be the same for all fragments of a table in a given replica*</u>)

Activity: Data Model (I)

- *Objective: Understand Run-Length Encoding*
- *Tasks:*
  1. *(15') Apply the Run-Length Encoding for the table in the next slide (dictionary-based + Ending-Row Index)*

  For this exercise, do not play with the order of the rows. Use the one given. At the end, identify those columns where a different order might have generated a more compact representation

  1. *(5') Think tank*

Activity: Data Model (I)

BookID	Date	Price	#ItemsBought
1	1/01/2012	19,99	1
99	1/01/2012	9,99	1
301	2/01/2012	19,99	1
44	2/01/2012	9,99	1
56	2/01/2012	9,99	1
1	2/01/2012	19,99	1
77	3/01/2012	9,99	2
8	3/01/2012	19,99	1
78	3/01/2012	9,99	1
10	3/01/2012	19,99	1

Data Model: Create Vertical Partitioning

- Creating a fragment per column, in general, is suboptimal. Thus, most advanced DBs allow the user to define partitions (each, potentially, as a set of columns)
- In these cases, finding the optimal vertical partitioning is a problem that must take into account the query workload
  - Identify correlations in the query workload and group those columns with high *affinity* (i.e., frequently queried together)
  - For m non-key attributes the search space is B(m), i.e., the *mth* Bell number, which counts the possible partitions of a set of m elements
  - For large numbers, $B(m) \approx m^m$

- Two main approaches to compute the optimal partitioning
  - Grouping
    - Attribute affinity matrix
    - Clustering algorithms
    - …
  - Splitting

- [RECAP] Partitioning must guarantee
  - Completeness
  - Disjointness
  - Reconstruction

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- [RECAP] Partitioning must guarantee
  - Completeness
  - ~~Disjointness~~ ((for the sake of performance, some DBMS might sacrifice it)
  - Reconstruction

Example

Schema:

Compres(llibreId^FK, date, preu, numUnitats)
Llibre(llibreId, autor, any, editorial, ISBN)

Queries:

```
SELECT llibreId, SUM(numUnitats) FROM compres c, llibre l
WHERE c.llibreId = l.llibreId AND editorial = 'RBA'
GROUP BY llibreId

SELECT editorial, AVG(preu) FROM compres c, llibres l
WHERE c.llibreId = l.llibreId
GROUP BY editorial

SELECT AVG(numUnitats) FROM compres c
WHERE date BETWEEN '01/01/xxxx' AND '31/12/XXXX'
GROUP BY llibreID

SELECT autor, any, COUNT(*) FROM llibre l
GROUP BY autor, any
```

Attribute Affinity Matrix

- Algorithm:
  1. For each relation, generate the **attribute usage matrix**

$$\begin{array}{ccccc} & llibreId & date & preu & numUnitats \\ Q1 & 1 & 0 & 0 & 1 \\ Q2 & 1 & 0 & 1 & 0 \\ Q3 & 1 & 1 & 0 & 1 \\ Q4 & 0 & 0 & 0 & 0 \end{array}$$

Now, create the attribute usage matrix for *Llibre*

Attribute Affinity Matrix

- Algorithm:
  2. For each relation, generate the **attribute affinity matrix**
     - Consider Q1 frequency is 50%, Q2 10%, Q3 30%, Q4 10%
     - For a pair of attributes A_i, A_j, compute its affinity by adding up all the frequencies in which they appear together

	$llibreId$	$date$	$preu$	$numUnitats$
$Q1$	1	0	0	1
$Q2$	1	0	1	0
$Q3$	1	1	0	1
$Q4$	0	0	0	0

Step 1 Output: Query-Attribute Usage Matrix

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$Q4$	0	0	0	0

Step 1 Output: Query-Attribute Usage Matrix

	$llibreId$	$date$	$preu$	$numUnitats$
$llibreId$	90	30	10	80
$date$	30	30	0	30
$preu$	10	0	10	0
$numUnitats$	80	30	0	80

Step 2 Output: Query-Attribute Affinity Matrix

Now, create the attribute affinity matrix for *Llibre*

Attribute Affinity Matrix

- Algorithm:
  3. For each matrix, reorganize the attribute orders to form clusters where the attributes in each cluster show high affinity to one another

	$llibreId$	$numUnitats$	$preu$	$date$
$llibreId$	90	80	10	30
$numUnitats$	80	80	0	30
$preu$	10	0	10	0
$date$	30	30	0	30

Now, do the same for *Llibres*

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Now, do the same for *Llibres*

Attribute Affinity Matrix

- Output:
  - P1: LlibreID, numUnitats
  - P2: Preu
  - P3: Date
- Assess the result: compute the **effective read ratio**
  - For each query, for each partition it must read, compute the following ratio:

$$\#Atr(Q_j, P_i) / \#Atr(P_i)$$

Where $\#Atr(Q_j, P_i)$ means the number of attributes Q_j must read from P_i and $\#Atr(P_i)$ is the total number of attributes in P_i

- Example: $RR(Q_1, P_1): 2/2 = 1$

Data Processing: Late Materialization

- *Tuple reconstruction* can be done at the beginning or at the end of the query

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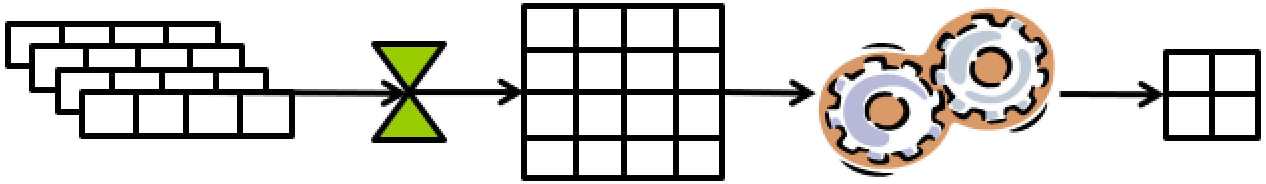
Beginning:



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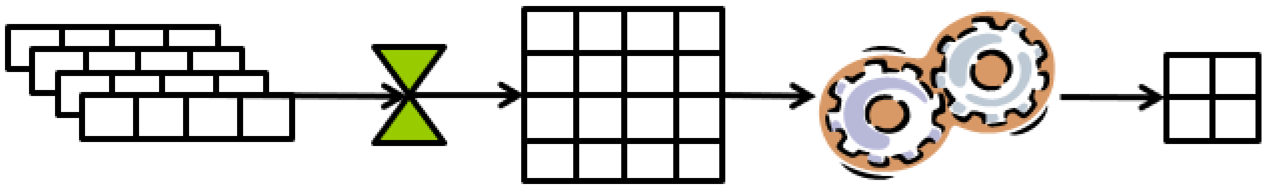
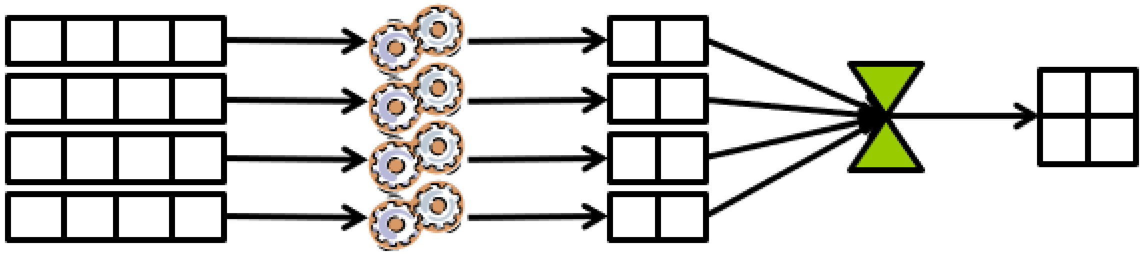
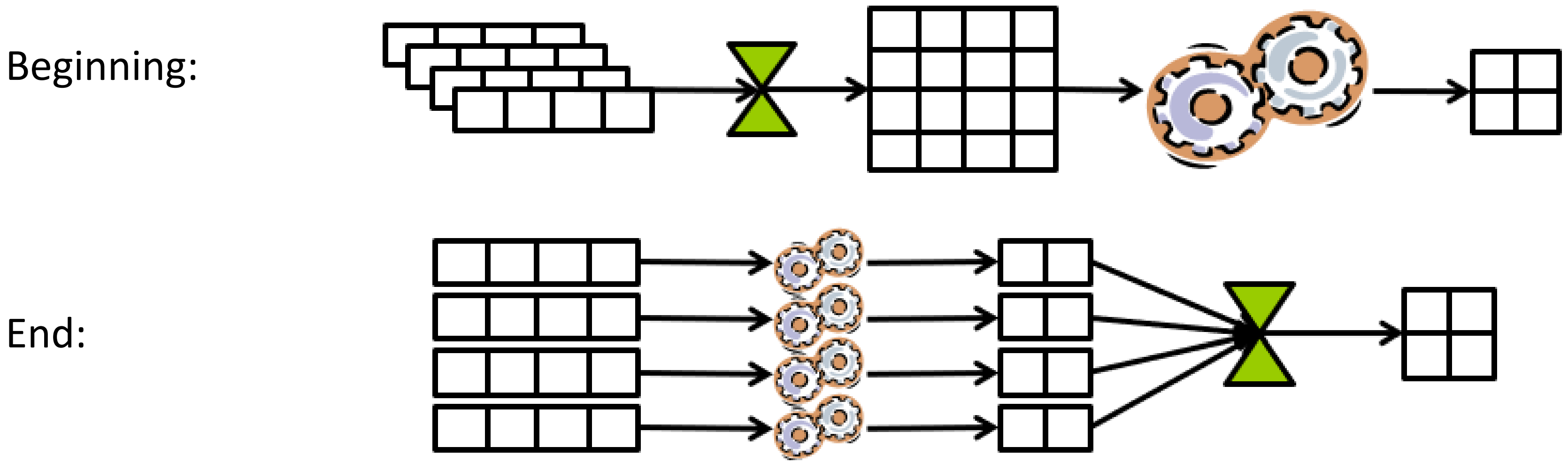


End:



Data Processing: Late Materialization

- *Tuple reconstruction* can be done at the beginning or at the end of the query



- Advantages of reconstructing the tuple at the end:
  - Some tuples do not need to be constructed (because of selections and projections)
  - Some columns remain compressed more time
  - Cache performance is improved (kept at column level)
  - Helps block iteration for values of fixed length columns

Data Processing: Block Iteration

- Blocks of values of the same column are passed to the next operation in a single function call
- Values inside the block can be:
  - Iterated as in an array (fixed-width)
  - Remain compressed together
    - Not necessarily using multiples of 8 bits
    - Counting or even identifying the tuples for which the predicate is true
  - Exploits parallelism / pipelining

Ending Row Index	Dictionary positions
1	1
4	0
7	2

Summary

- Advantages of column-oriented databases
  - Bring into memory only relevant data
  - Provide fewer and simpler internal functions
  - Easier to recognize all execution strategies
  - Simpler tuning required by users
- Pioneers: Daniel Abadi & Michael Stonebraker (M.I.T.)
  - C-Store (blueprint)
  - MonetDB (academic edition, open-source)
    - http://www.monetdb.org/Home
  - Vertica (commercial version, bought by HP)
    - http://www.vertica.com/