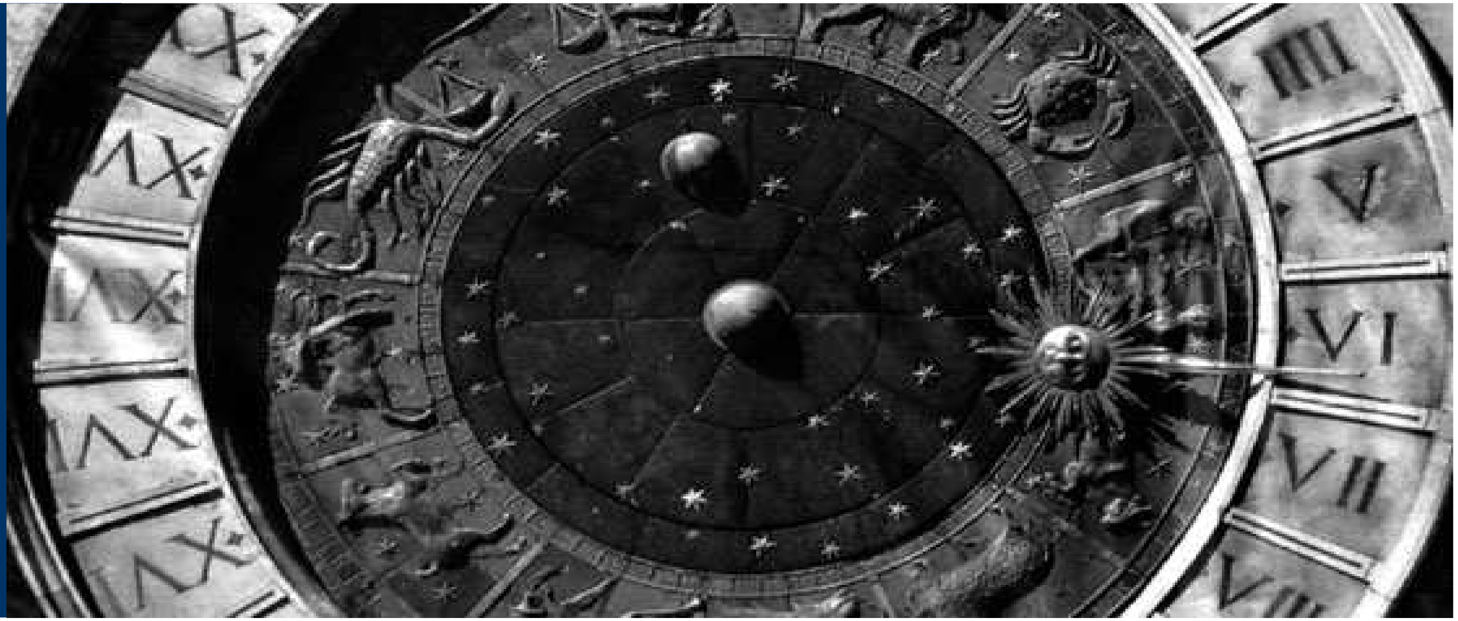

Data Mining with the SAP Netweaver BI Accelerator

Thomas Legler t.legler@sap.com
Wolfgang Lehner lehner@inf.tu-dresden.de
Andrew Ross a.ross@sap.com

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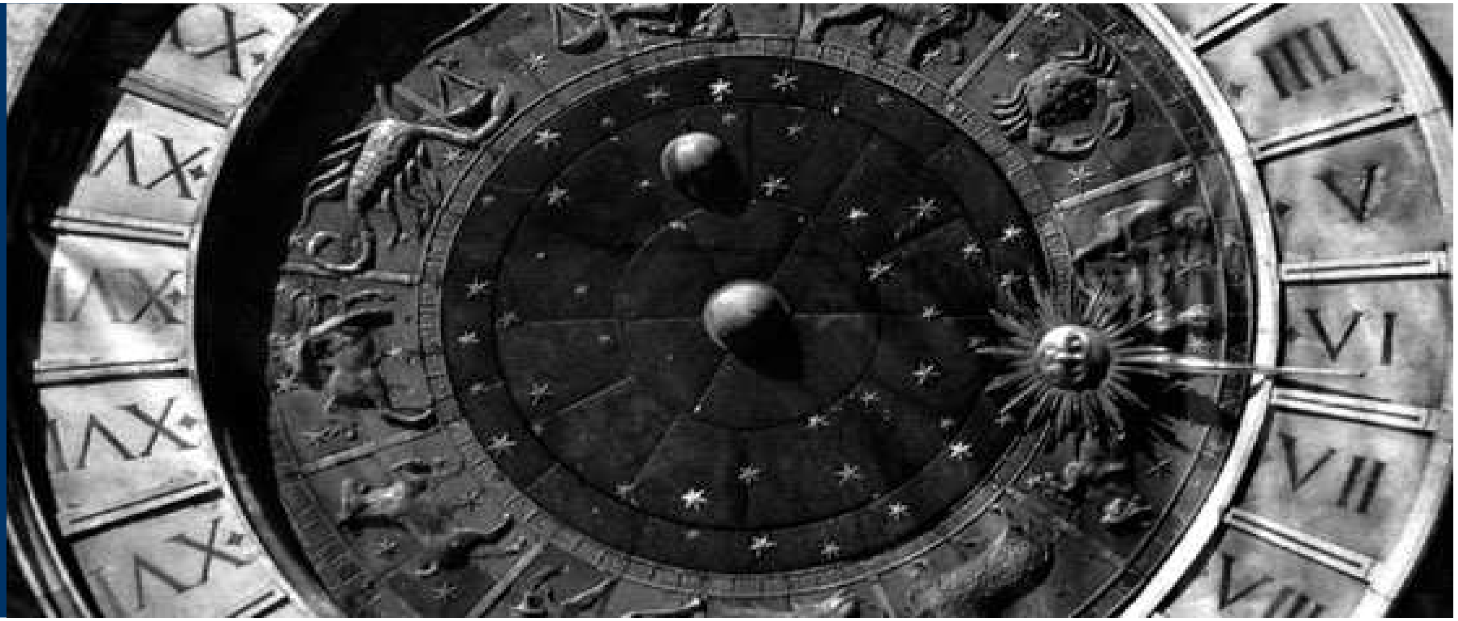
TECHNISCHE UNIVERSITÄT DRESDEN

THE BEST-RUN BUSINESSES RUN SAP™



SAP Netweaver BI Accelerator
- Architecture
- Index Structures

BIA Association Rule Mining
- Distributed Mining
- Frequent Pattern Mining

Summary

Introduction

The Problem for a BI system

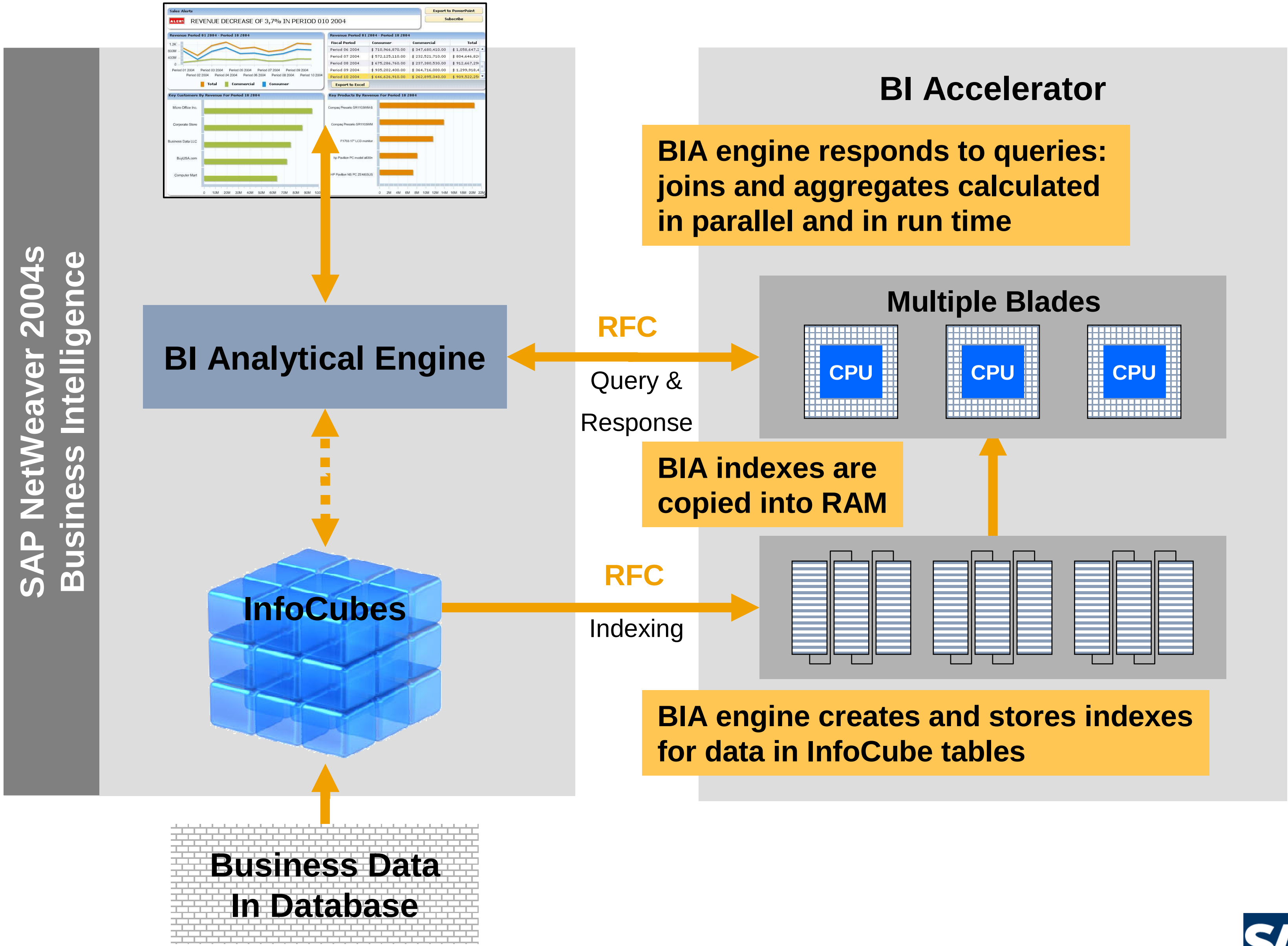
- Report queries can be very slow (some minutes, up to hours)
- Hard to predict how long a query execution may take

Current Solution

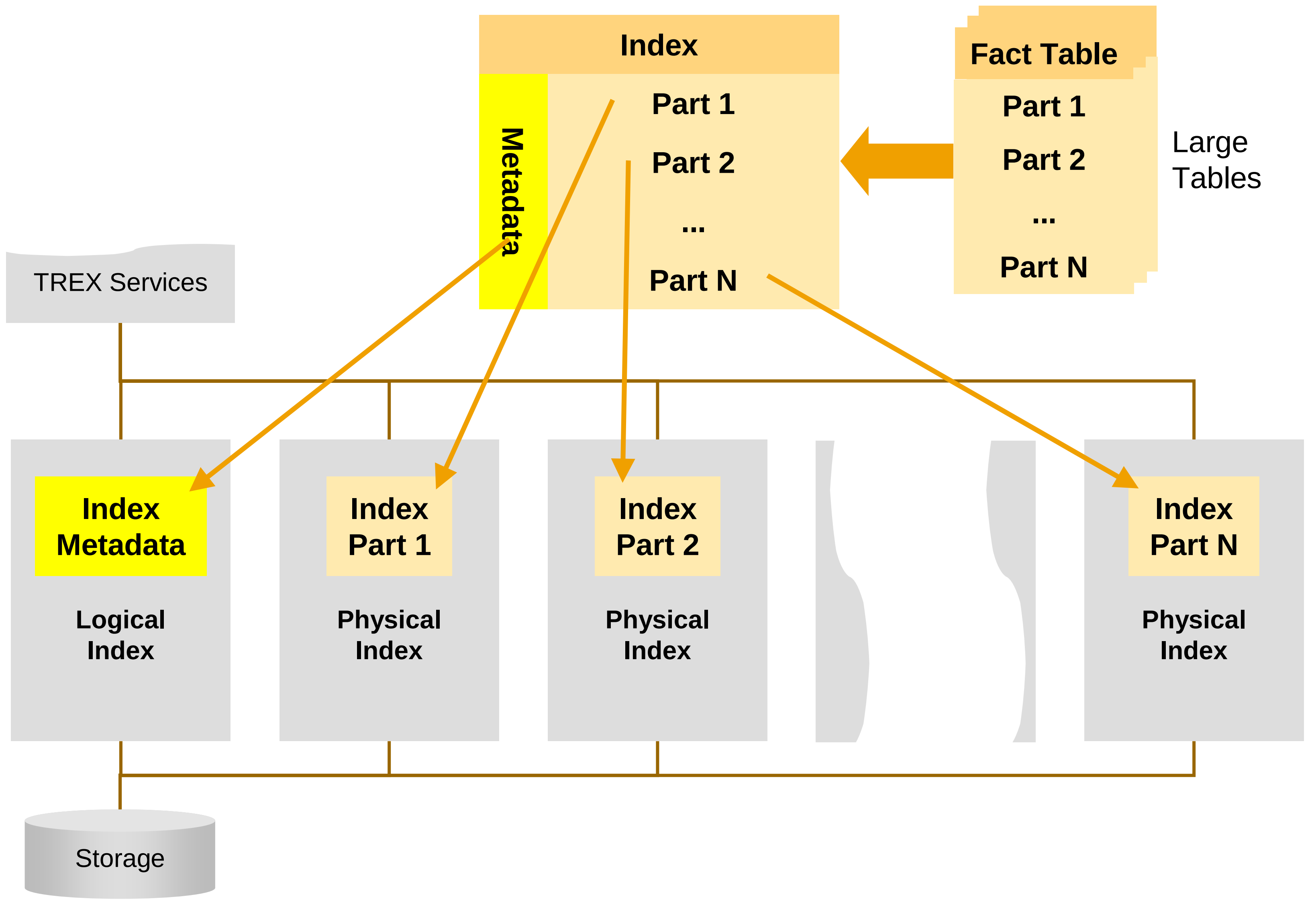
- Build materialized views (SAP: aggregates) for top X queries
  - ➔ Top X queries fast
  - ➔ Other queries slow
- You never cover every possible query
- You increase aggregate maintenance effort
  (for data loads, master data changes, …)
- You increase consulting/know-how required at customer site
- You increase space consumption on database

Aggregates: Flexibility ←→ Performance

BI Accelerator Architecture



BI Accelerator Horizontal Partitioning



Physical Index Structure

- **Column-based approach**
  - **Only needed attributes in memory**
  - **Fast attribute scan and aggregation**
- **Compressed**
  - **Integer-coded**
  - **Several compression methods for AttributeTable and Dictionaries**
  - **Compression factor ~1:20**
- **Read optimized structures**
  - **Additional small and write optimized index**
  - **Queries use both indices and merge results**
  - **Periodical merge of delta and main index**

Single valued attribute data structure

Attribute Table

DocId	ValueId
1	24
2	3
3	7
4	17

Dictionary

ValueId	Value
1	IBM
2	Microsoft
…	
17	SAP

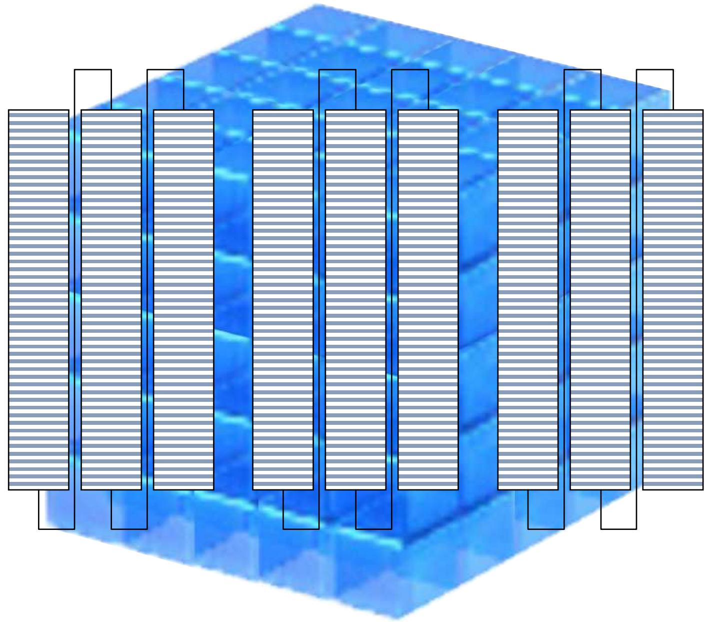
Index

ValueId	DocIdList
1	…
2	2, 5
…	
17	4

Logical Index Structures

The BIA Index

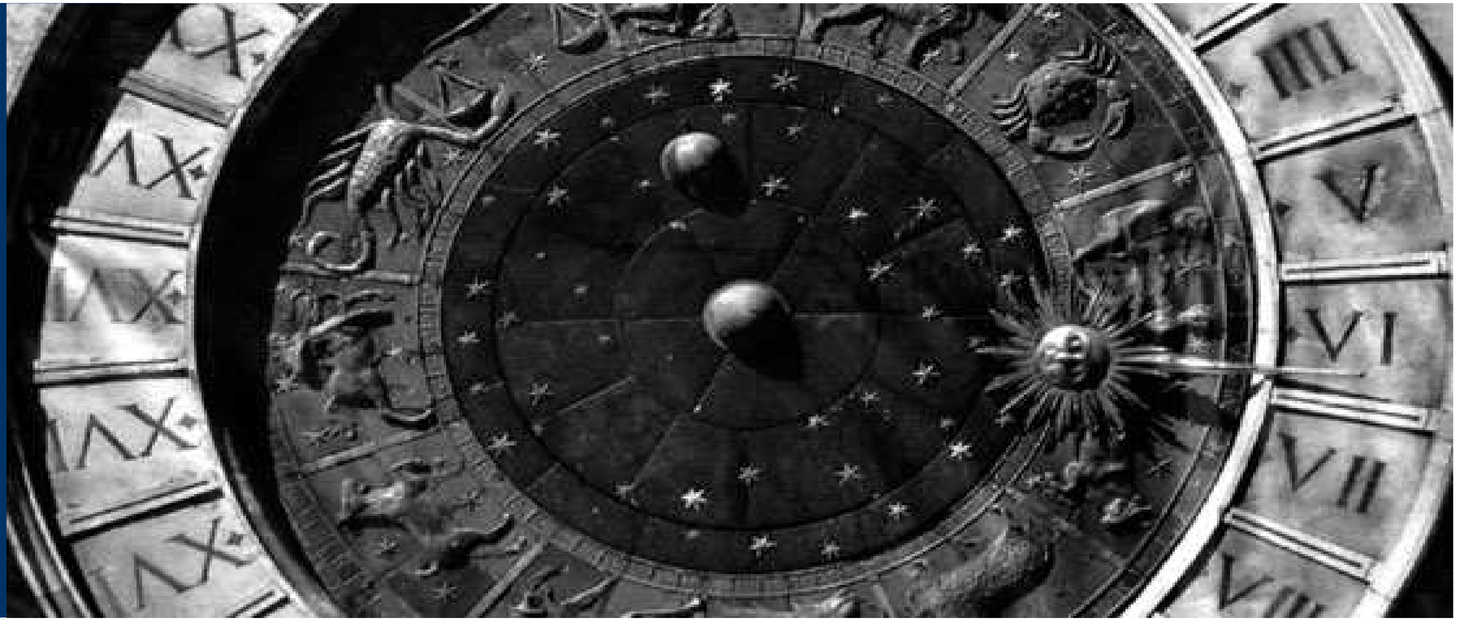
- Store meta data of BI InfoCube
- Contains lists of
  - Index names
  - Join conditions
  - Join paths
  - View attributes
  - Semantic relations
  - Key figures



- Represent an interface for an InfoCube
- Executes multi-dimensional queries

The BI accelerator

- Joins indexes in parallel wherever possible
- Aggregates index entries in parallel and on the fly



SAP Netweaver BI Accelerator
- Architecture
- Index Structures

BIA Association Rule Mining
- **Distributed Mining**
- **Frequent Pattern Mining**

Summary

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THE BEST-RUN BUSINESSES RUN SAP™

The Goal

Data Mining as a First-Class Citizen, but reporting has top priority

- Data distribution and partitioning optimized for reporting
- Use available structures to minimize additional resource consumption

Algorithms must fit to the architecture

- Partitioning
- Shared-nothing architecture

We have:

- Big Tables with a lot of attributes

We search for rules like:

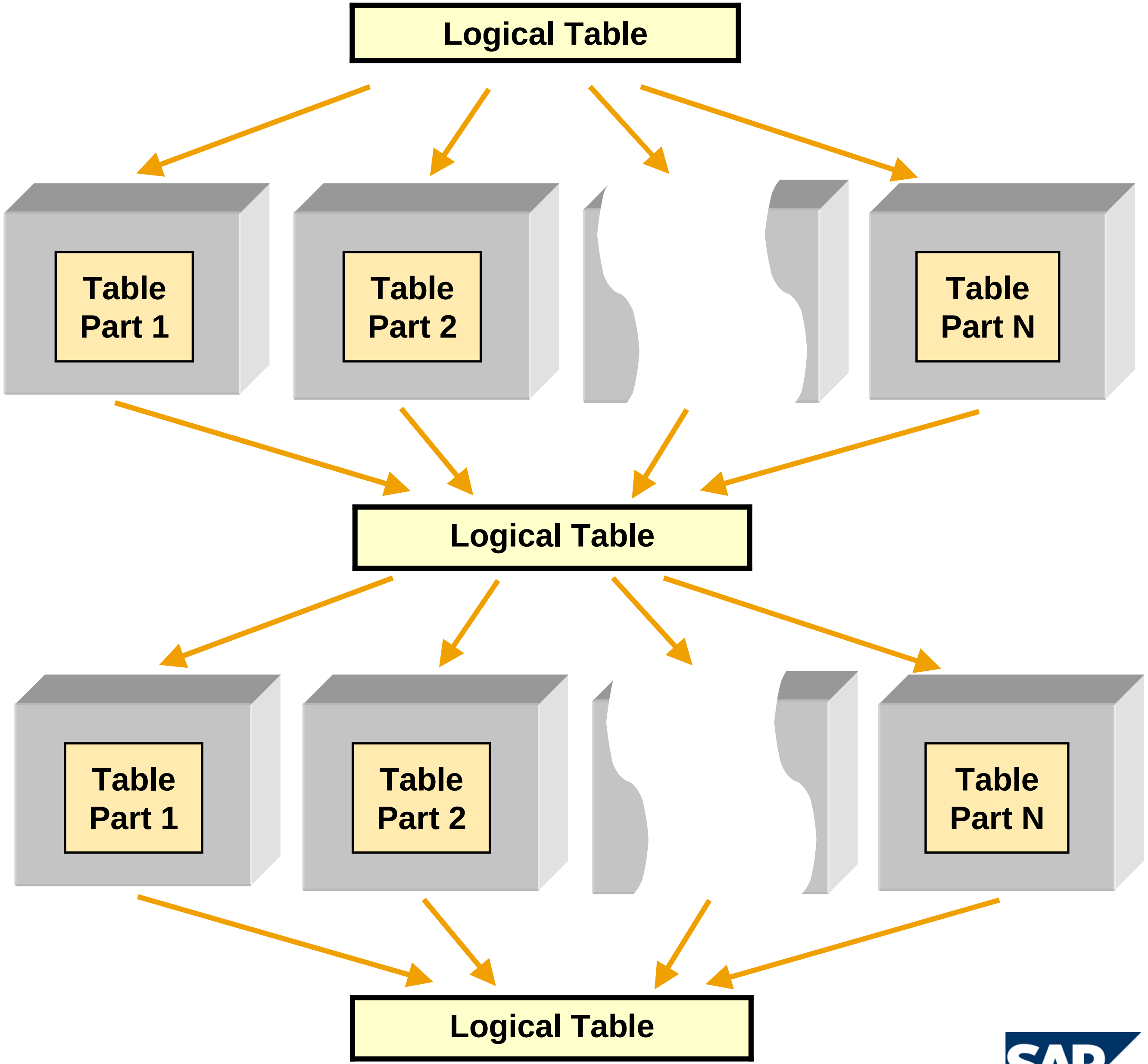
- If a customer is German and buys a black BMW, (s)he often requests manual transmission

We need two steps:

1. Filter frequent item sets to reduce the data to probably interesting rows
2. Discover (hopefully interesting) rules using these frequent item sets

Distributed Association Rule Mining (PARTITION)

1. Request
2. Local mining with relative support
3. Merge results
4. Scan for missing item sets
5. Final merge



Distributed Association Rule Mining (PARTITION)

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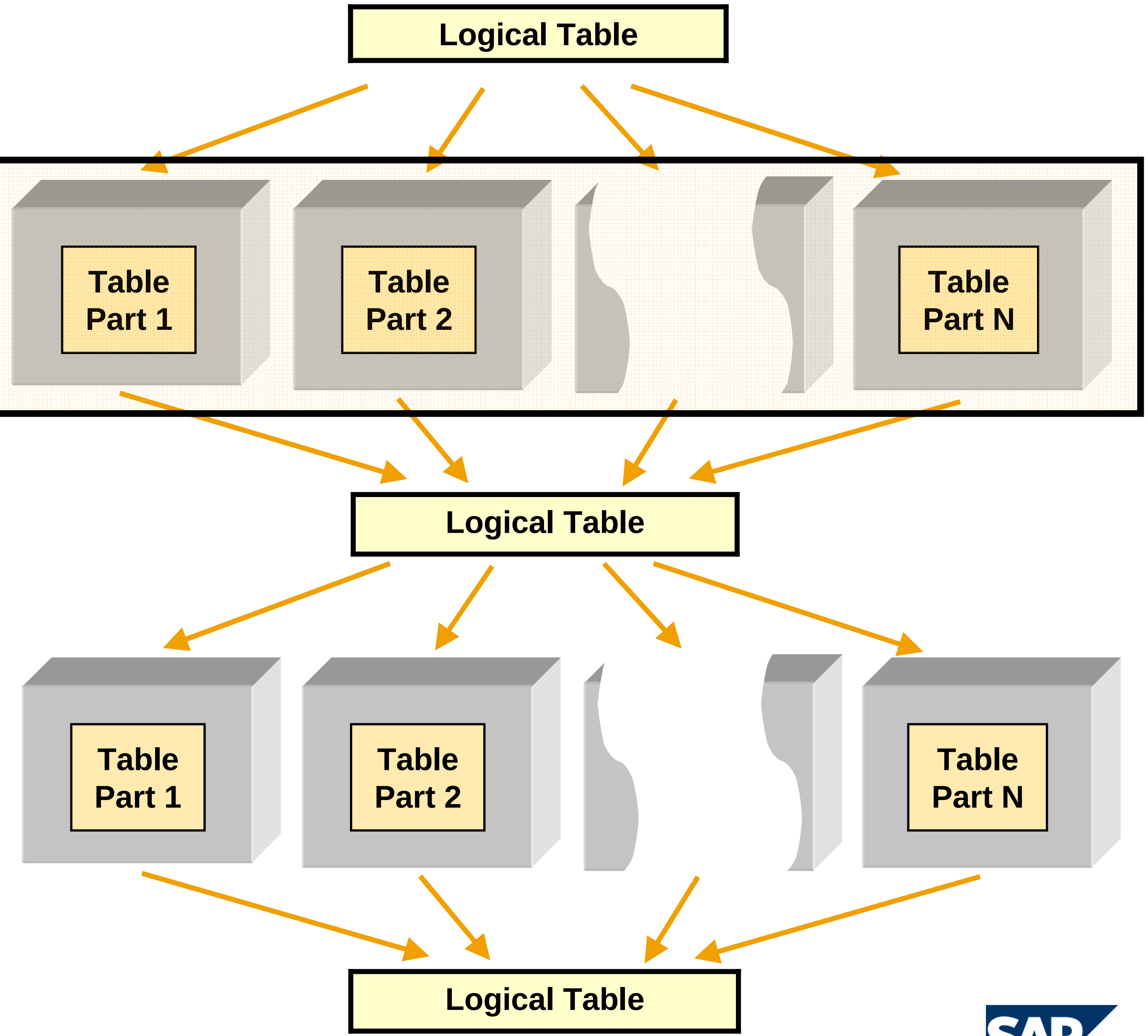

Standard Algorithms for Frequent Pattern Mining

Apriori by Agrawal et al.

- Generate (n+1)-item set candidates out of frequent n-item sets
- Count support for candidates

  ➔ Candidate generation prevents slow database scans

  But the table scans are fast for the BI accelerator

FP-Growth by Han et al.

- Build frequent pattern tree and mine the tree

  ➔ Needs a lot of additional memory to replicate the data

Eclat by Zaki et al.

- Build Transaction-ID list for each value
- Mine depth-first

  ➔ List comparisons needs transformation of the data to TID lists

Modified Approach

Like BUC iceberg cubing by Beyer et al. 1999 (similiar to Eclat)

- Find frequent 1-item sets
- Get their row-numbers
- Check each value of next attribute for these row-numbers
- If combinations are still frequent, check next attribute
- …

Our algorithm

- Is depth-first
- Does not need expensive list comparisons or transformations
- Needs a lot of short scans, but
  - We are in memory
  - We have direct access via row-numbers
  - Data is transformed to integers

  So scanning the data and counting the support for all is cheaper than list comparisons and checks to find candidates
- Has very low additional memory consumption

Example – Frequent Item Sets

Support = 2

country	car	color	trans.
GER	BMW	Red	MT
FRA	VW	Red	MT
PL	Audi	Black	AT
GER	VW	Red	AT
FRA	VW	Silver	MT
GER	BMW	Red	MT
GER	BWM	Silver	AT
FRA	VW	Black	AT
GER	BMW	Red	MT

- Country: (GER: 5, FRA: 3)
- Car: (BMW: 4, VW: 4)
- Color: (Red: 5, Black: 2, Silver: 2)
- Trans: (MT: 5, AT: 4)

↓

- GER, BMW: 4, FRA, VW: 3
- GER, Red: 4
- GER, MT: 3 GER, AT: 2 FRA, MT: 2
- BMW, Red: 3 VW, Red: 2
- BMW, MT: 3 VW, MT: 2 VW, AT: 2
- Red, MT: 4 Black, AT: 2

↓

…

↓

- GER, BMW, RED, MT: 3

Example – Frequent Item Sets

Support = 2

country	car	color	trans.
GER	BMW	Red	MT
FRA	VW	Red	MT
PL	Audi	Black	AT
GER	VW	Red	AT
FRA	VW	Silver	MT
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- GER, BMW: 4, FRA, VW: 3
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↓

...

↓

- GER, BMW, RED, MT: 3

Example – Frequent Item Sets

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GER	BWM	Silver	AT
FRA	VW	Black	AT
GER	BMW	Red	MT

- Country: (GER: 5, FRA: 3)
- Car: (BMW: 4, VW: 4)
- Color: (Red: 5, Black: 2, Silver: 2)
- Trans: (MT: 5, AT: 4)

↓

- GER, BMW: 4, FRA, VW: 3
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- BMW, MT: 3   VW, MT: 2   VW, AT: 2
- Red, MT: 4   Black, AT: 2

↓

...

↓

- GER, BMW, RED: 3

Example – Frequent Item Sets

Support = 2

country	car	color	trans.
GER	BMW	Red	MT
FRA	VW	Red	MT
PL	Audi	Black	AT
GER	VW	Red	AT
FRA	VW	Silver	MT
GER	BMW	Red	MT
GER	BWM	Silver	AT
FRA	VW	Black	AT
GER	BMW	Red	MT

- Country: (GER: 5, FRA: 3)
- Car: (BMW: 4, VW: 4)
- Color: (Red: 5, Black: 2, Silver: 2)
- Trans: (MT: 5, AT: 4)

↓

- GER, BMW: 4, FRA, VW: 3
- GER, Red: 4
- GER, MT: 3 GER, AT: 2 FRA, MT: 2
- BMW, Red: 3 VW, Red: 2
- BMW, MT: 3 VW, MT: 2 VW, AT: 2
- Red, MT: 4 Black, AT: 2

↓

...

↓

- GER, BMW, RED, MT: 3

Distributed Association Rule Mining (PARTITION)

1. Request
2. Local mining with relative support
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4. Scan for missing item sets
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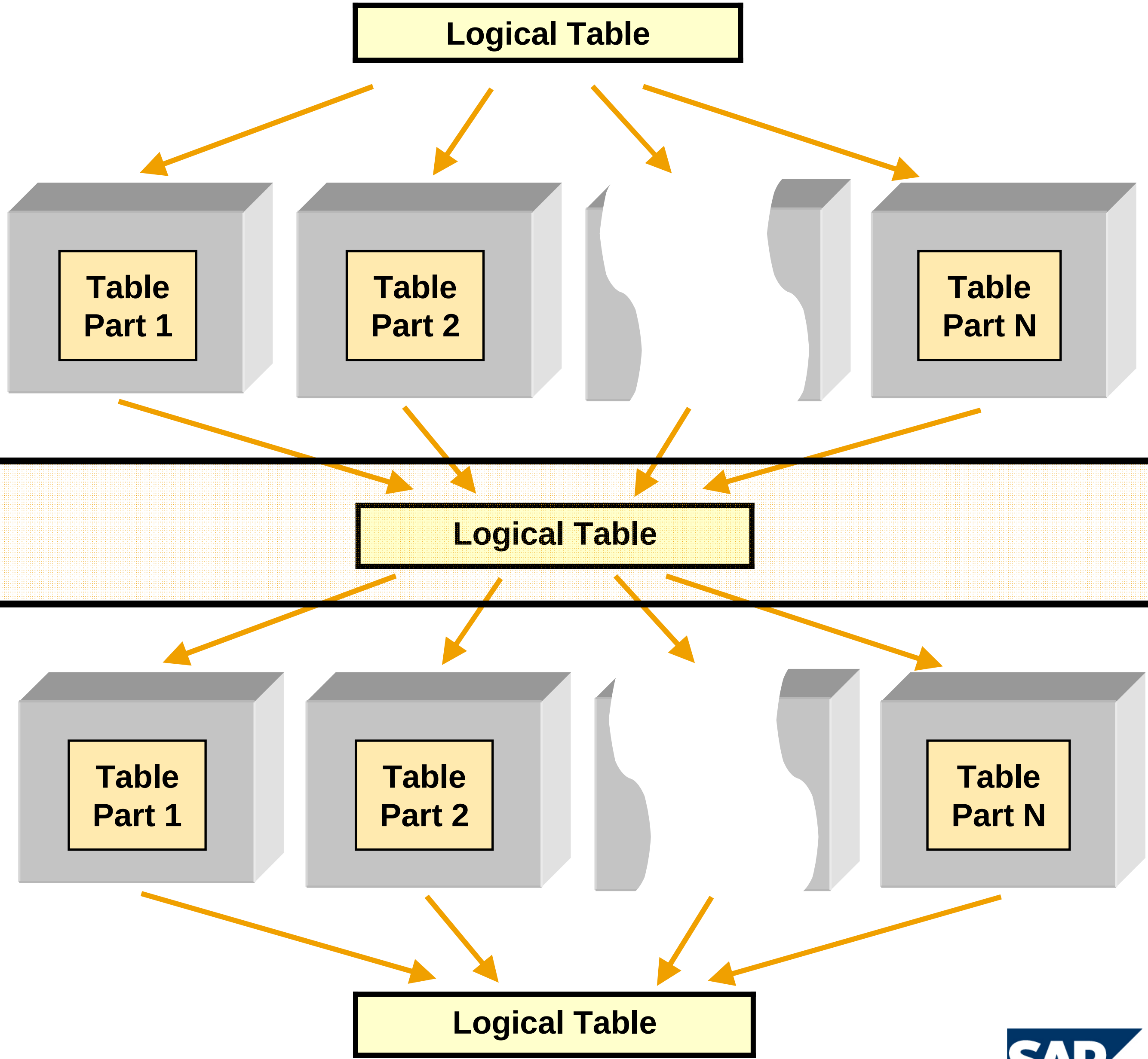


Example – Distributed Association Rule Mining

country	car	color	trans.
GER	BMW	Red	MT
FRA	VW	Red	MT
PL	Audi	Black	AT
USA	Ford	Blue	MT
GER	VW	Red	AT

country	car	color	trans.
FRA	VW	Silver	MT
GER	BMW	Red	MT
GER	BWM	Silver	AT
FRA	VW	Silver	AT
GER	BMW	Red	MT

global support = 4 → local support = 4/2 = 2

•GER: 2, VW: 2, Red:3, MT: 3, AT:2

•GER: 3, FRA: 2, VW: 2, BMW: 3, Red:2, Silver: 3, MT: 3, AT:2

GER: 2 + 3 = 5 → OK!!

BMW: ?? + 3 = ?? → maybe OK

FRA: ?? + 2 = ??? → not OK (?? < 2)

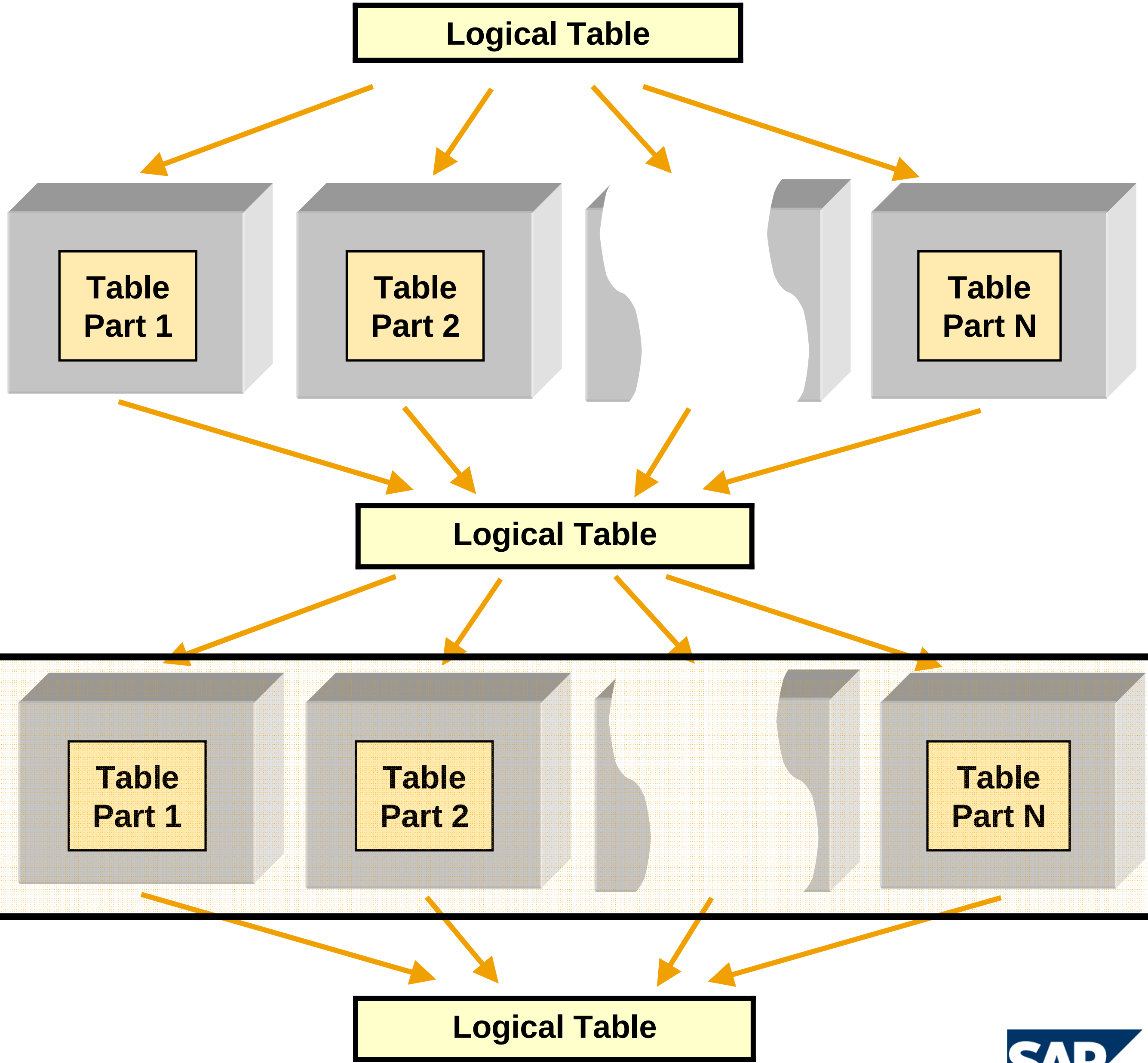
...

BMW: 1 + 3 =4 → OK!!

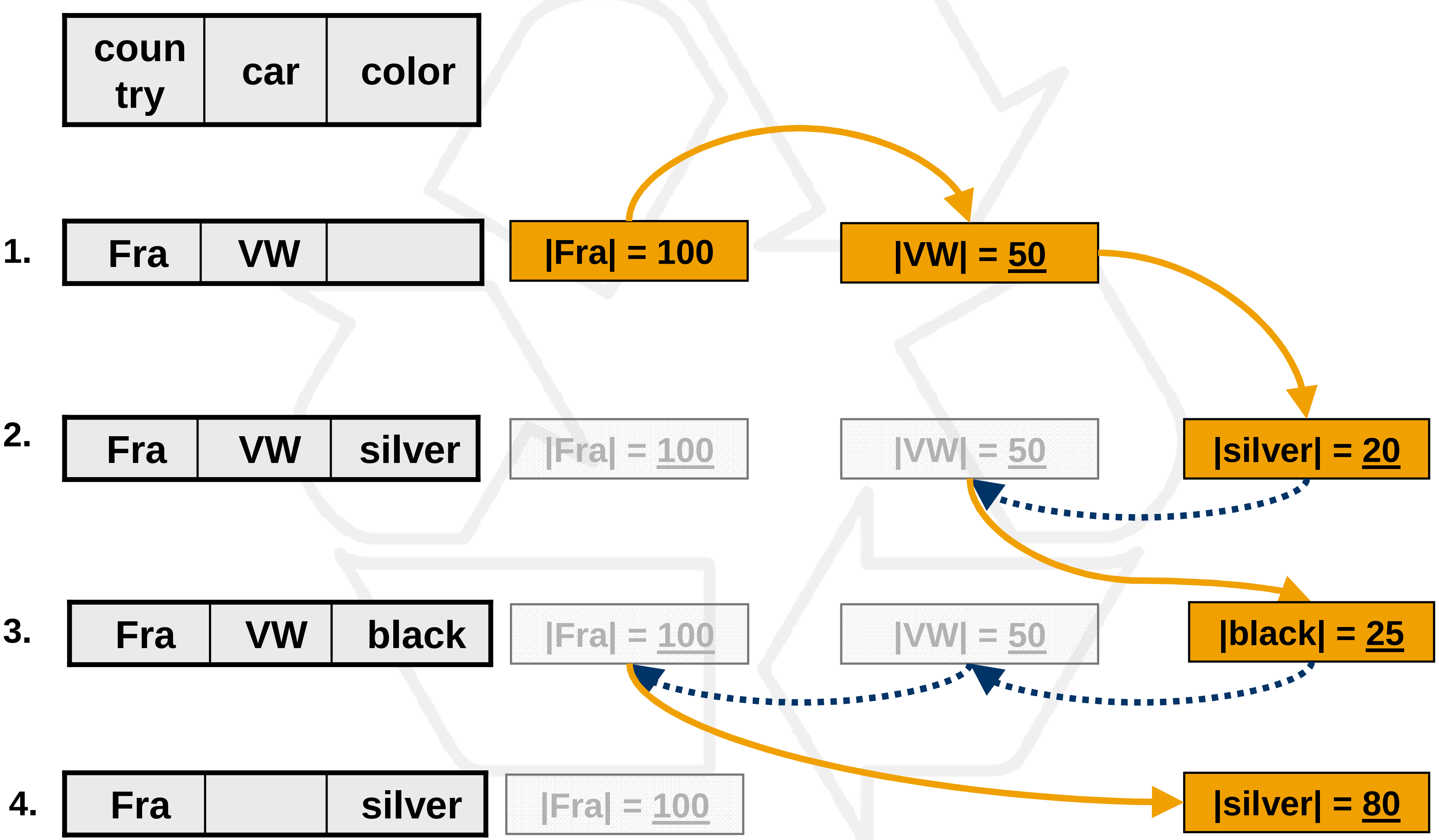
...

Distributed Association Rule Mining (PARTITION)

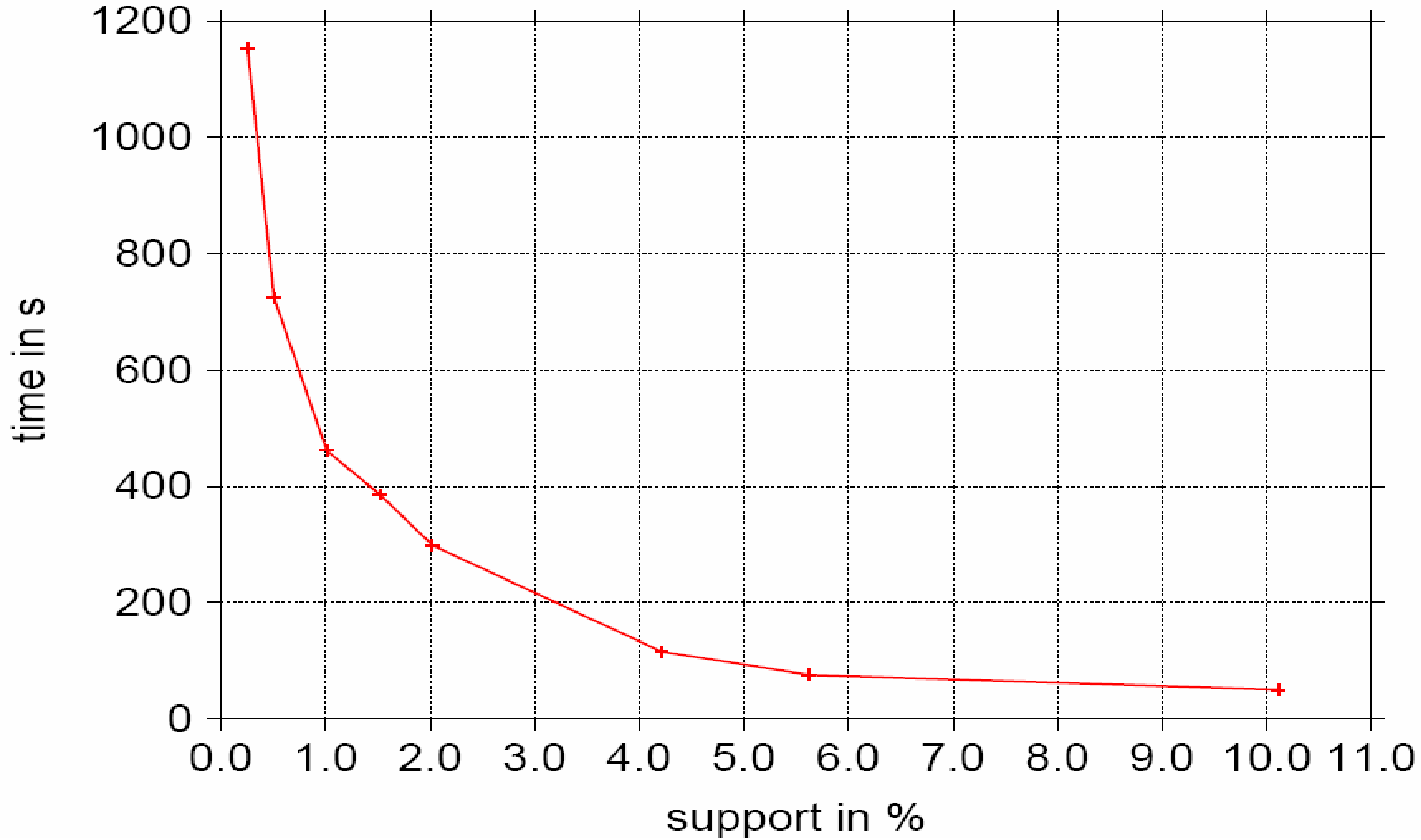
1. Request
2. Local mining with relative support
3. Merge results
4. Scan for missing item sets
5. Final merge



Scan for missing item sets

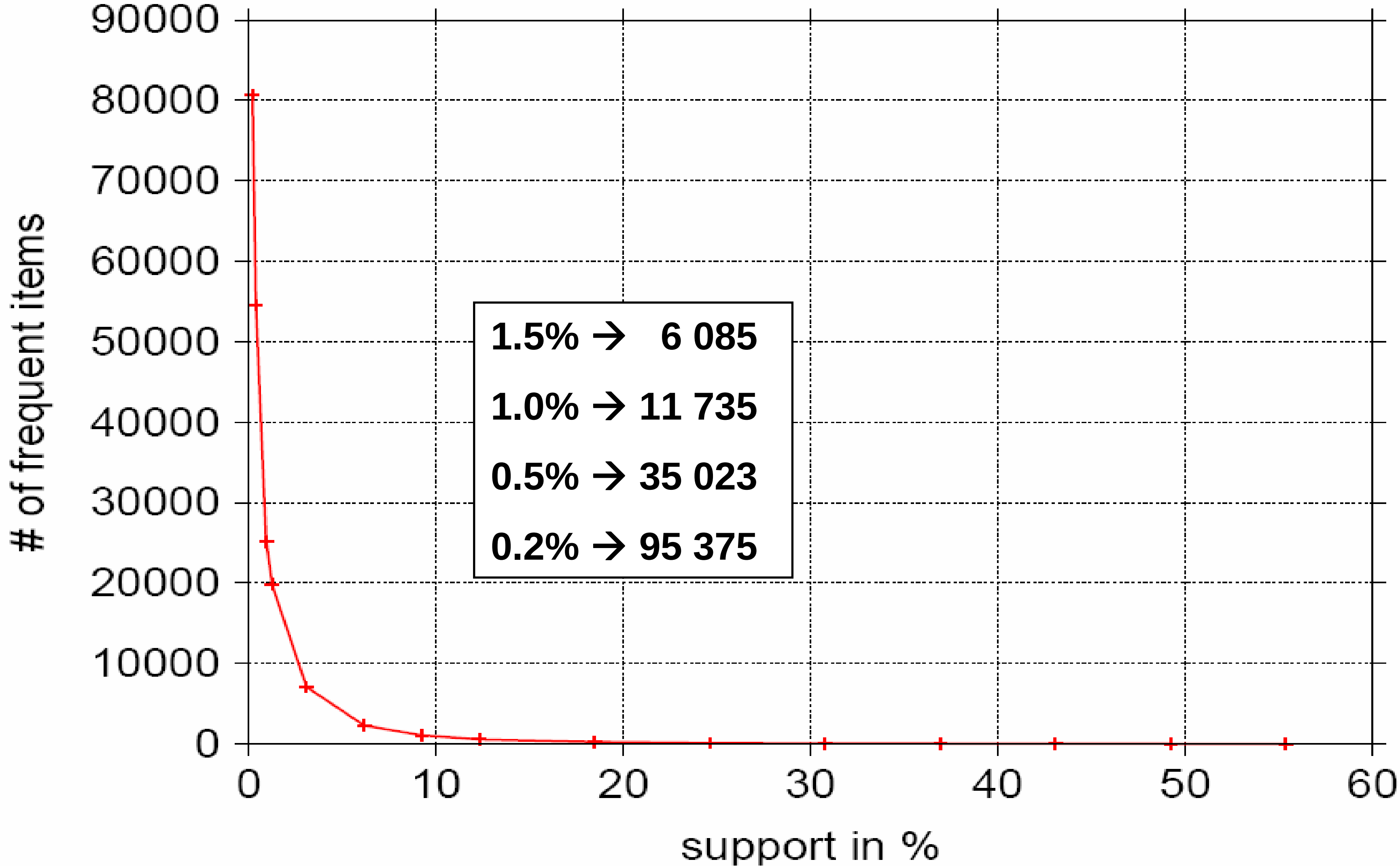


Performance - Runtime



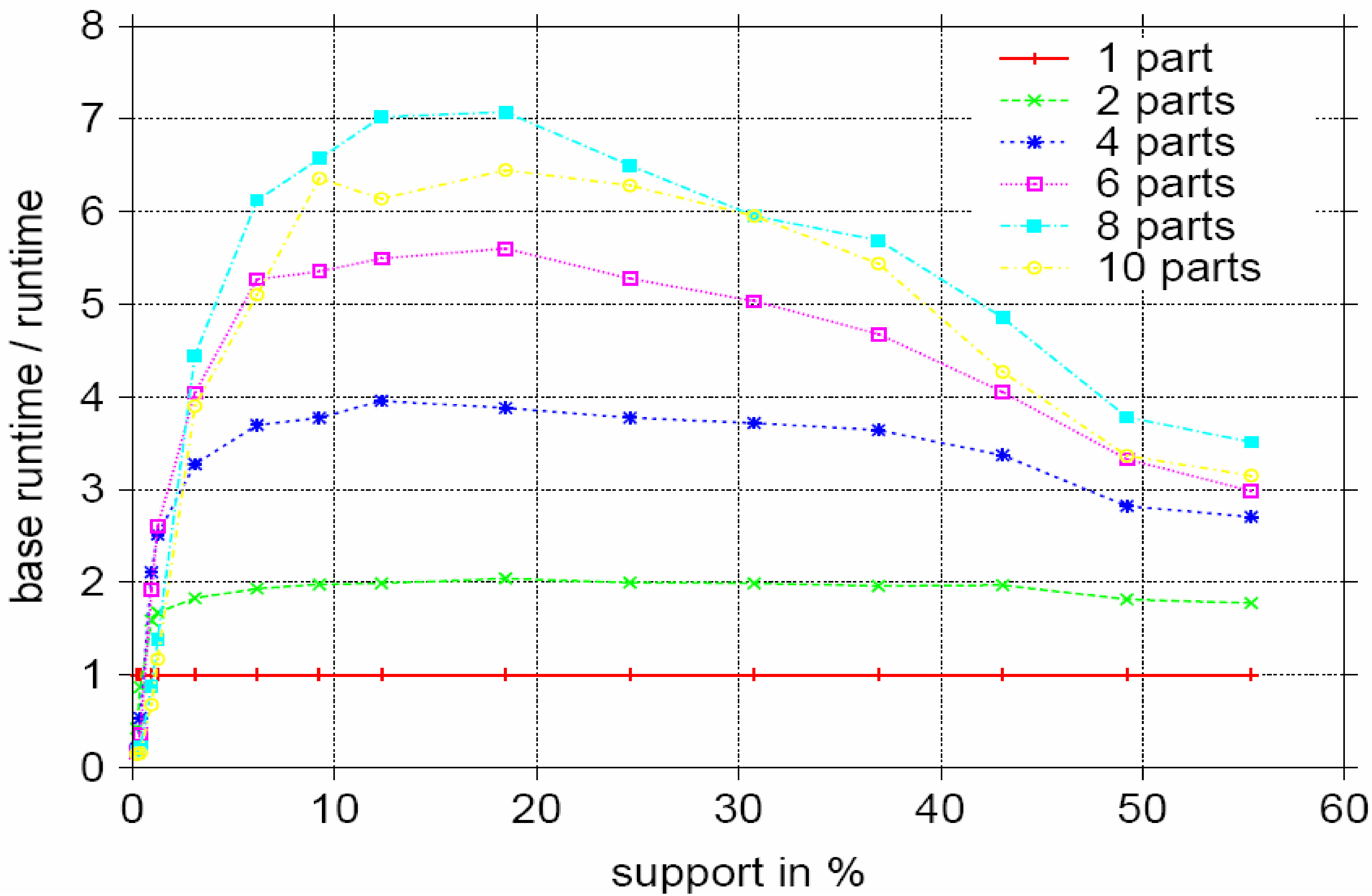
For index with 180 million rows distributed on 10 blades (32 bit)

Performance - Complexity

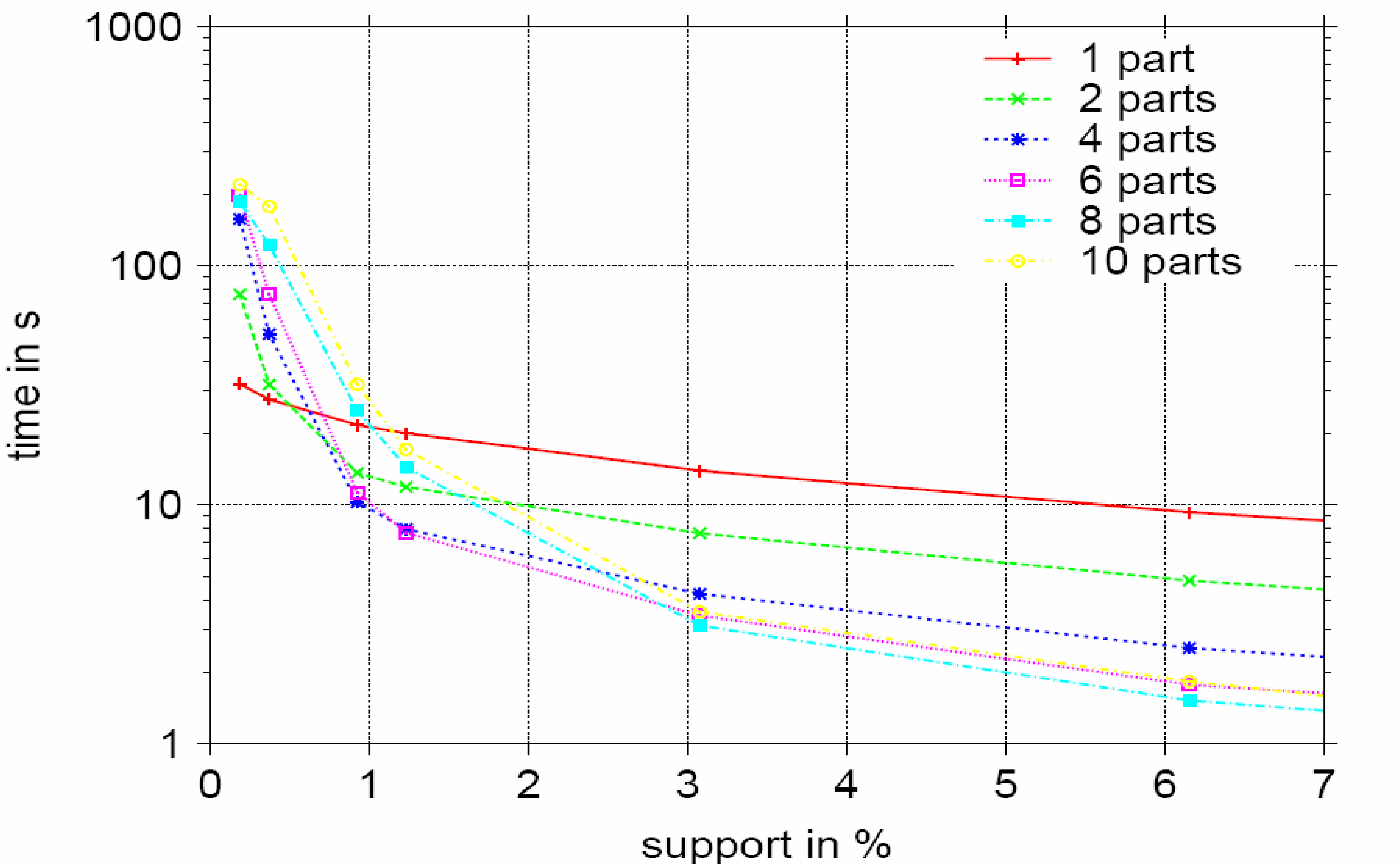


8 million row version of mushroom data set

Performance - Scaling



The Negative Effect of Distribution



Summary

The SAP BI accelerator

- Distributed, compressed, and column-based in-memory data structures
- One new “virtual aggregate” replaces all previous relational aggregates
- Reduced aggregate maintenance effort
- Stable, appreciable, and fast query response time

BIA Association Rule Mining

- Mine standard-SAP BI scenarios
- No additional replication of data for mining
- PARTITION to handle distribution
- BUC for frequent pattern mining

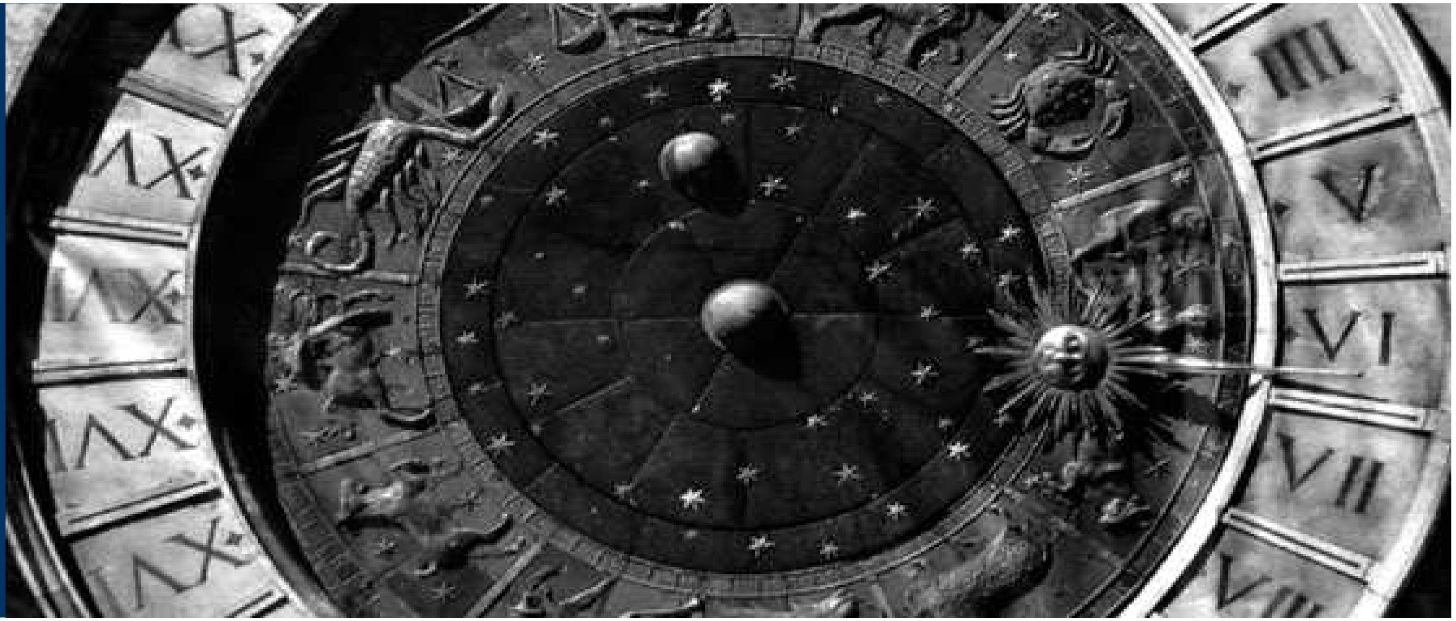
Thank You!

Q&A

Thomas Legler (t.legler@sap.com)

For more information about
SAP BI accelerator please contact

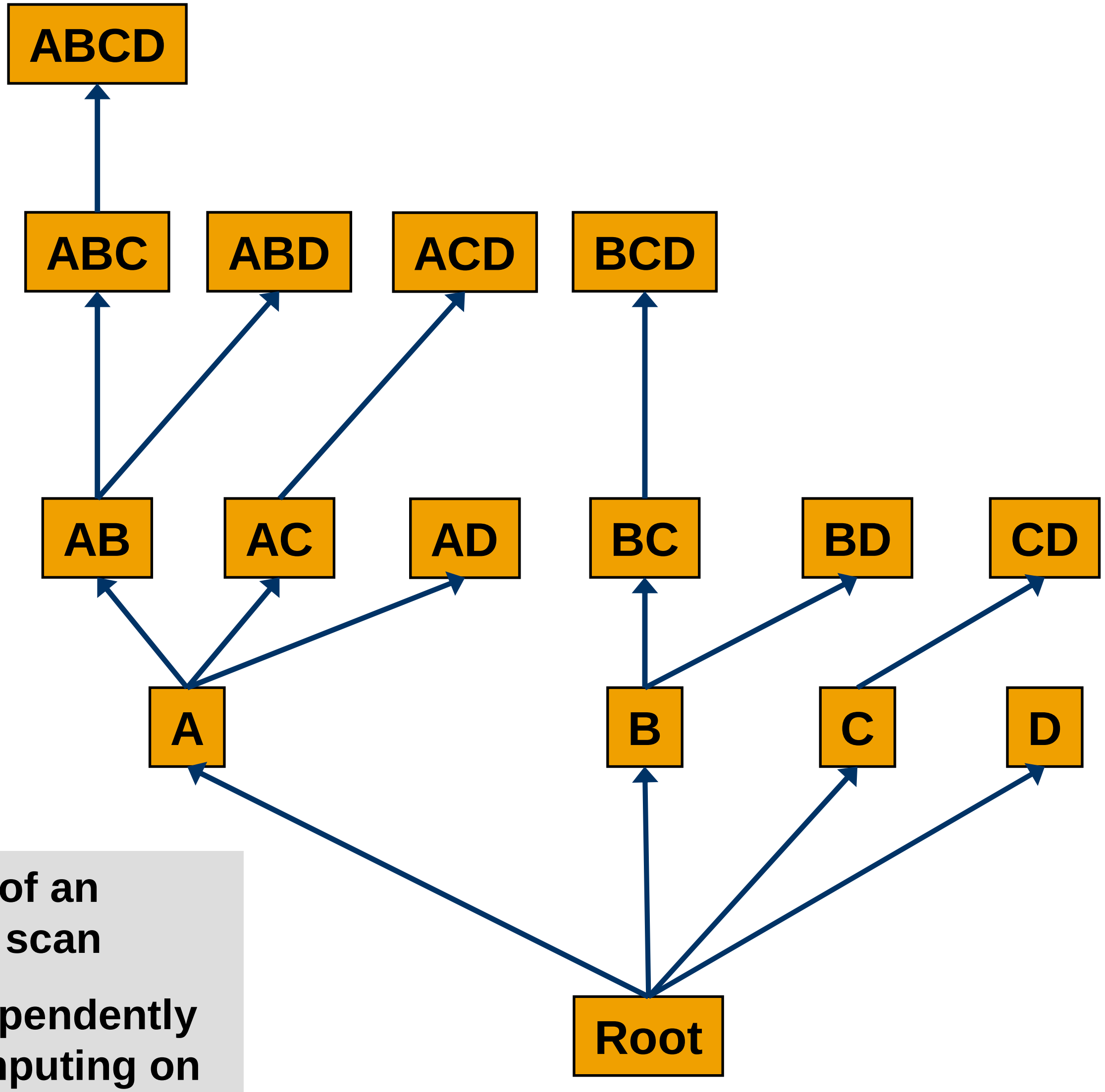
Andrew Ross (a.ross@sap.com)



Backups

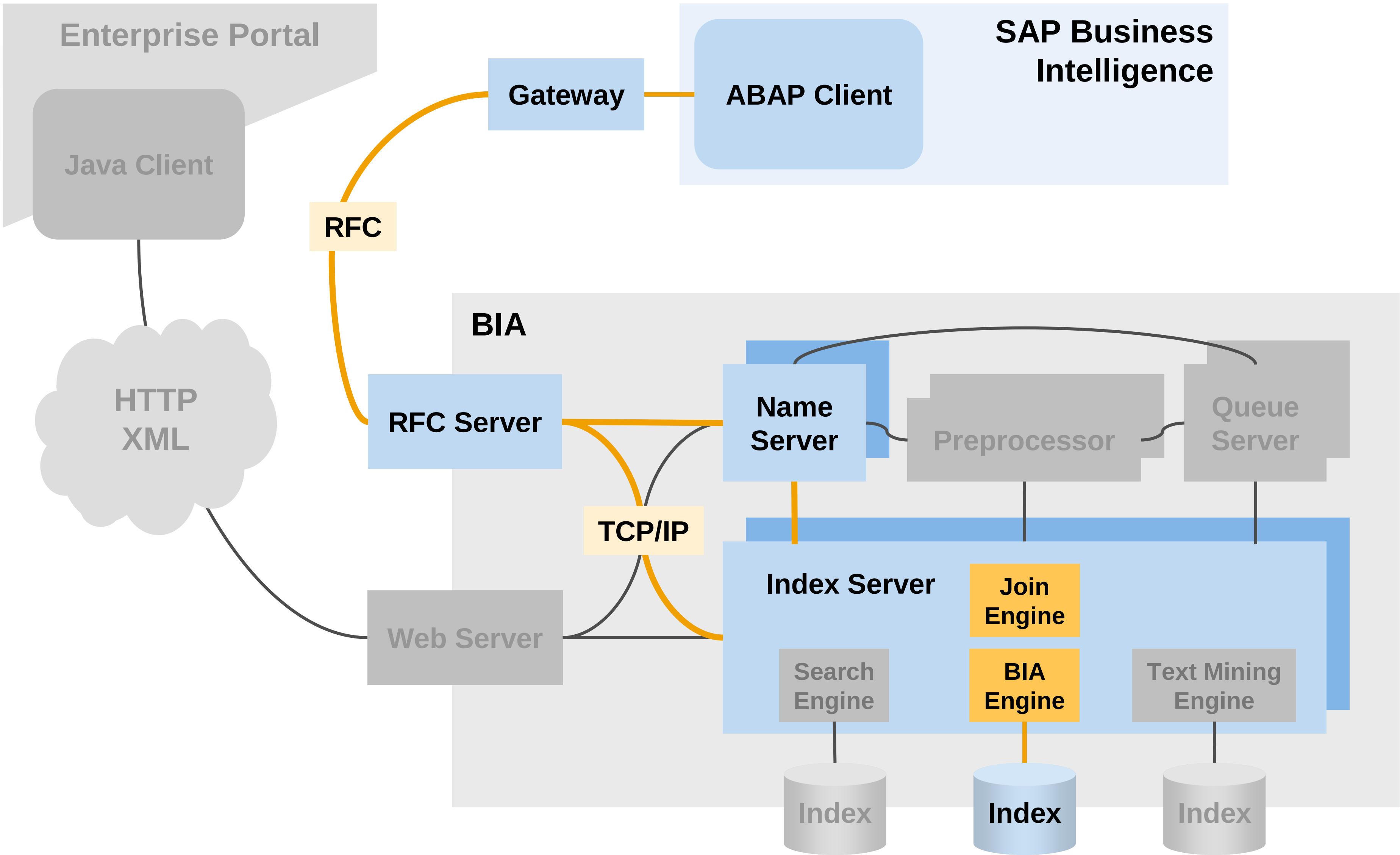
Example - Association Rule Mining

1. Count values on A, B, C, and D
2. Check AB based on rows of A: if AB is still frequent, check ABC and ABCD
3. If all ABs are checked, test AC
4. Continue until all combinations are tested



- Count support for all values of an attribute combination in one scan
- Branches can be mined independently of each other ➔ Parallel computing on multiple or multicore processors

BI Accelerator Engine



BI Accelerator Engine Details

For each query, the engine

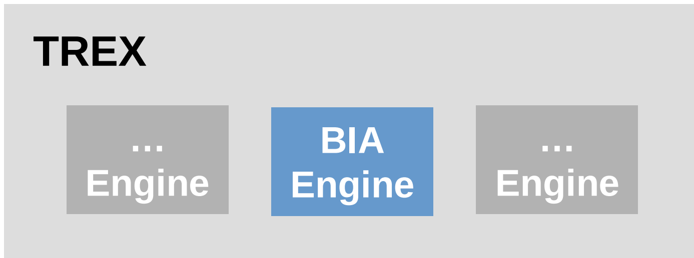
- Executes table joins as specified in the BIA index
- Processes boolean expressions
- Restricts rows for aggregation
- Aggregates data in parallel

Very fast aggregation algorithm

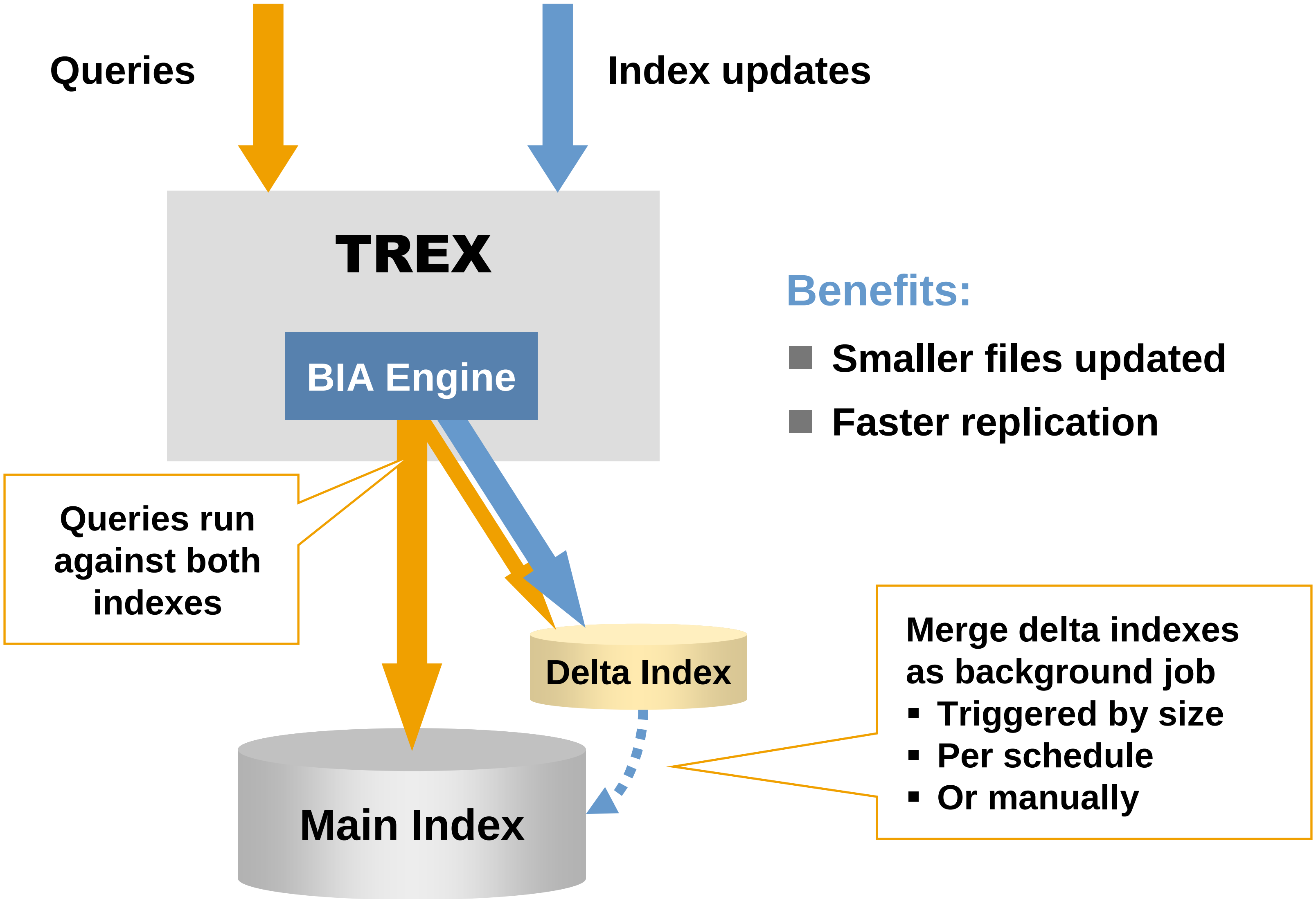
- Exploits integer coding for max speed and min I/O
- Runs on latest blade servers and grid landscapes
- Optimizes usage of memory and cache resources
- Is optimized for BI

Dynamically loaded index

- Enables indexing of huge volumes of structured data
- Keeps only required columns in memory, others stay on disk



BI Accelerator Fast Index Update

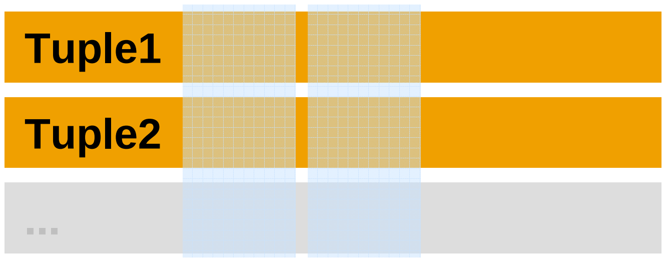


Benefits:

- Smaller files updated
- Faster replication

BI Accelerator Vertical Decomposition

Classical DB
stores tables by row



To find all instances of an attribute value:

- Go to the first row
- Check the attribute value
- Repeat for each row in the table

BI accelerator
stores tables by column

To find all instances of an attribute value:

- Go to the attribute column
- Read its row values

Related data for aggregation is compact → use Caches

BI Accelerator Smart Compression

BI accelerator storage for a single valued attribute

- **Dictionaries**

  Lists of all used values

  Values stored in compressed form

- **Attribute tables**

  Minimal number of bits used to represent values

- **Indexes**

  Represented compactly using highly optimized compression coding

Single valued attribute data structure

Attribute Table

DocId	ValueId
1	24
2	3
3	7
4	17
5	3

Dictionary

ValueId	Value
1	IBM
2	Microsoft
…	
17	SAP
…	

Index

ValueId	DocIdList
1	…
2	…
3	2, 5
4	…
…	
17	4

Example: Front Coded Blocks

Dictionary

ValueId	Value
1	IBM
2	Microsoft
…	
20	SAP
21	SAP_Press
22	SAP_SI

Blocks with x values

ValueId	Value
1	IBM
2	Microsoft
…	

ValueId	Value
20	SAP
21	SAP_Press
22	SAP_SI

ValueId	Value
20	SAP
21	[3] + “ _Press”
22	[4] + “SI”

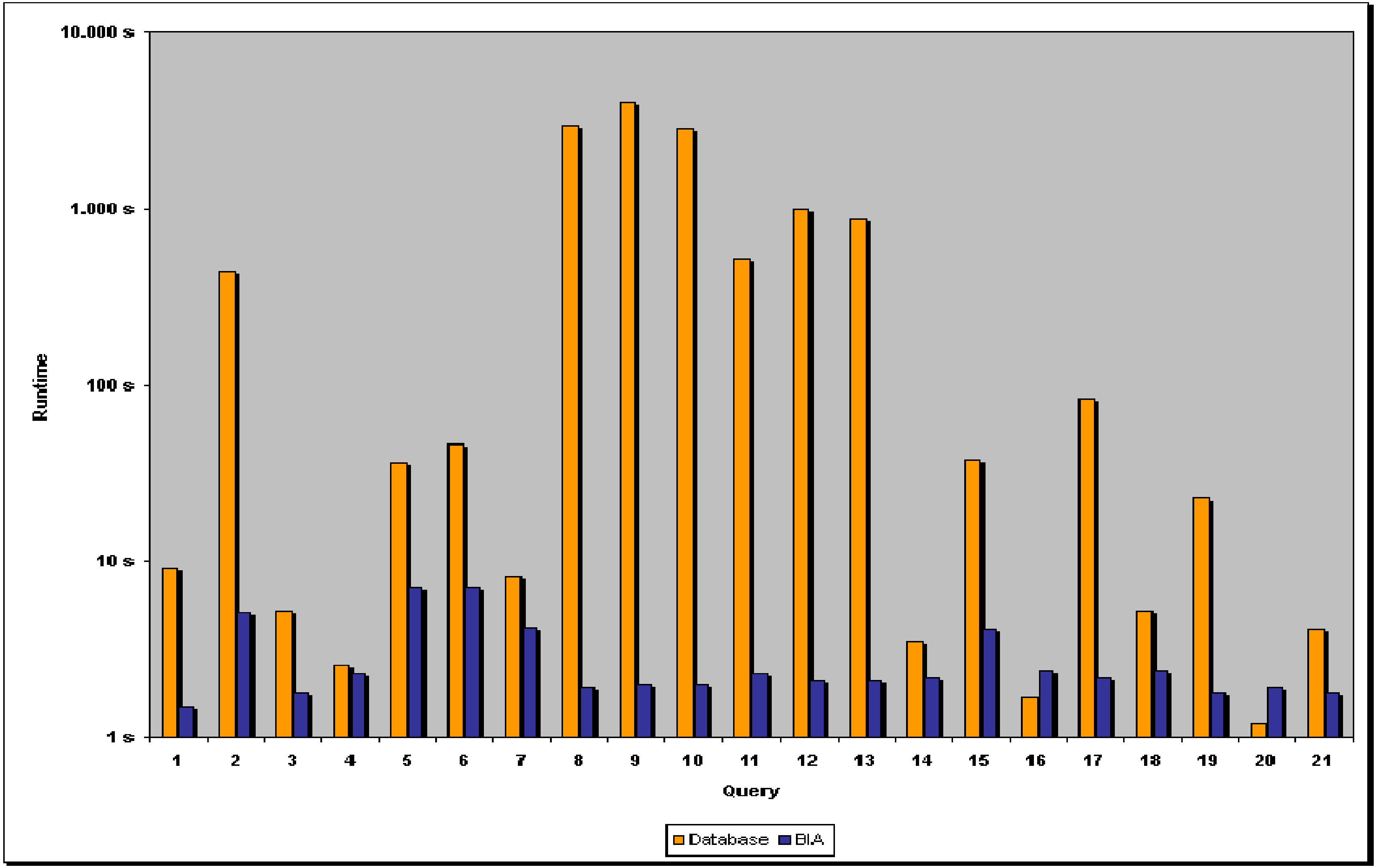
Sorted by value → **Good chance that similar values are in one block** → **Good Compression**

Find ValueId (or not) ← **Search in decompressed block** ← decompress ← **Find block** ← SEARCH

The Queries

1. Shortage/Overage Keep
2. Sales, Delivery, Billing Cubes over 2 years
3. Customer Net Sales
4. Handling Charge Analysis over 2 cubes
5. Return Value by Reason code
6. Handling Fee by National Grp, ChainId, Customer
7. Solution Management Optimization with a partner

Query Execution Times



Customer Scenario

Queries over multiple InfoCubes

- 9 InfoCubes with approx. 850 million rows in fact tables
- 22 aggregates
- Storage on Oracle 9.2.0.4.0
- InfoCubes approx. 130 GB + aggregates 6 GB = 136 GB

Storage on BI accelerator

- Overall: 30.4 GB
- Database used as backup for rebuilding indexes

BI accelerator	Versus	Database
64-bit SUSE Linux SLES 9		SunOS 5.9
6 * Dual Xeon 3.6 GHz		Sun V440 4 CPUs
6 * 8 GB RAM		16 GB RAM

Query Execution Times (Top 7 Queries)

Query	Info Cubes	Aggr	RDBMS (sec)	BI accelerator (sec)	Improvement (factor)	Rows after filtering	Rows after aggregn.
Query 1	6		9.1	1.5	6	2 540	10
Query 2	8	*	435.3	5.2	84	13 434 508	1 322
Query 3	3	*	5.3	1.8	3	283 020	126
Query 4	4	*	2.6	2.3	1	96 712	5 771
Query 5	4		36.3	3.4	11	590 784	27 798
Query 6	4		46.1	3.2	15	590 784	27 798
Query 7	5		8.2	4.2	2	59 870	15 803
Total			542.9	21.5	25		

Query Execution Times

Query	Info Cubes	Aggr	RDBMS (sec)	BI accelerator (sec)	Improvement (factor)	Rows after filtering	Rows after aggregn.
Query 8	1		2924.9	1.9	1538	67 318 176	281
Query 9	1		4015.3	2.0	2008	67 318 176	149
Query 10	2		516.4	2.3	224	33 801 513	32
Query 11	2		865.7	2.1	411	33 801 513	32
Query 12	4		37.5	4.1	9	88 435 773	6 280
Query 13	3	*	1.2	1.9	0	348 957	262
Query 14	3	*	5.3	2.4	2	348 957	209
Total			8 366.0	16.7	501		

SAP NetWeaver BI Accelerator

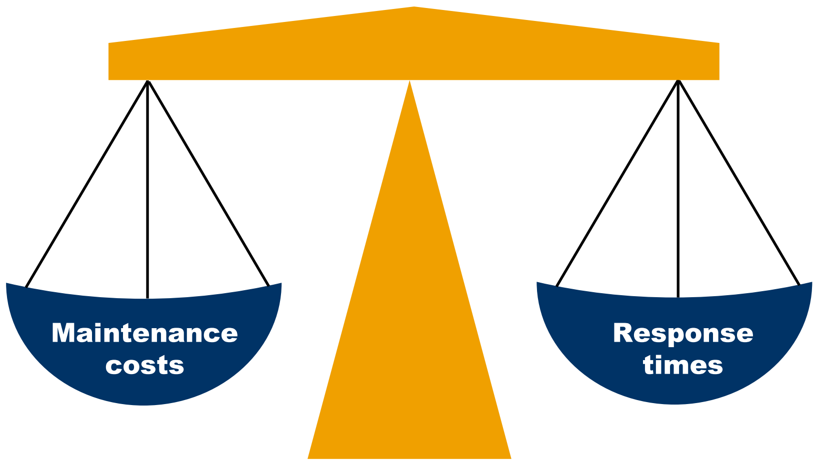
Aggregates: Flexibility ←→ Performance

- You never cover every possible query
- You increase aggregate maintenance effort
  (for data loads, master data changes, …)
- You increase consulting/know-how required at customer site
- You increase space consumption on database

The SAP solution:

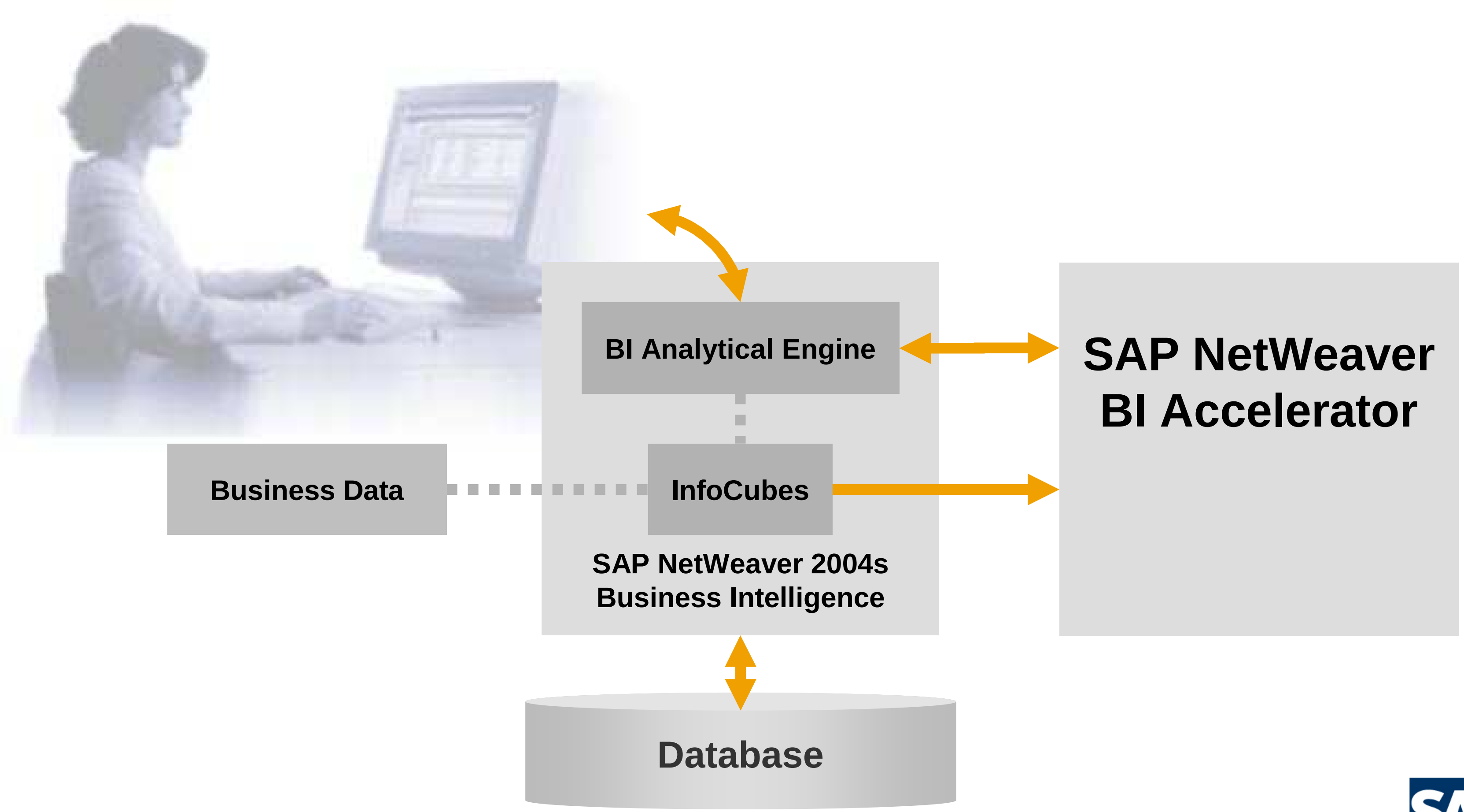
The BI accelerator

- An aggregation engine based on search engine technology



A new accelerator functionality for SAP NW BI

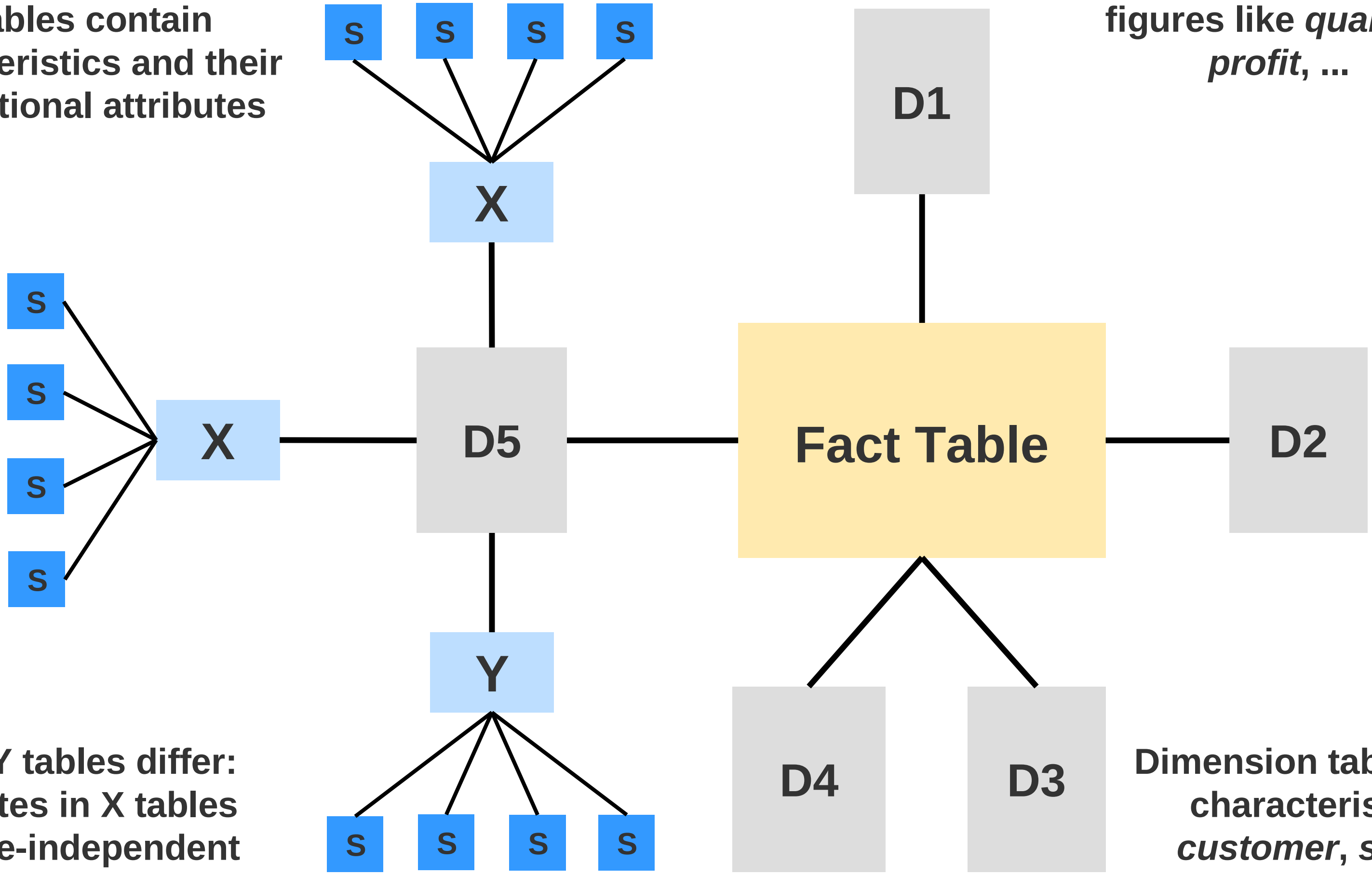
- A new approach to boost BI query performance
- Performance speedup factor typically between 10 and 100



Star Schema for BI InfoCube

S tables contain
key values (strings)
X tables contain
characteristics and their
navigational attributes

Fact table contains all
characteristics and key
figures like *quantity*,
profit, ...



X and Y tables differ:
Attributes in X tables
are time-independent
Attributes in Y tables
are time-dependent

Dimension tables contain
characteristics like
customer, *sold to*, ...

Two Nice Theorems

Any subset of a frequent item set is frequent too

Example

- If you sold 4 BMWs in Germany ➔ You sold at least 4 BMWs worldwide and you sold at least 4 cars in Germany

➔ You can build big frequent item sets out of smaller subsets

If an item set is globally frequent on partitioned data, the item set is frequent on at least one partition (relative to size of partition)

Example

- Overall 6 balls in 2 boxes ➔ At least one box with $\geq 6/2 = 3$ balls

➔ You never miss a frequent item set on distributed landscapes

The Problem: A Customer Scenario

Bob Boss, the CEO of WallMart Germany, wants to view the profit figures for all stores in South Germany for 2004 on a quarterly basis and to compare these numbers with the profits in Germany and Europe

How was the WallMart year 2004 in South Germany and how does it compare with Europe and all of Germany?

The challenge for BI is to calculate this aggregate table

Profit 2004	Q1	Q2	Q3	Q4
South Germany	???	???	???	???
Germany	???	???	???	???
Europe	???	???	???	???

The Goal

Data Mining as a First-Class Citizen, but reporting has top priority

- Data distribution and partitioning optimized for reporting
- Minimize additional resource consumption for mining

Use already loaded data and structures

Algorithms must fit the architecture

- Processing in memory
- Partitioning
- Shared-nothing architecture