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Dresden Database Research Group

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Dirk Habich

Scalable Data Management (SDM)

Modern Database System Architecture

Previous focus

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1 Foundations
- Relational Data and SQL
- Traditional Database Architecture
- Transactions

2 Parallelism
- Data-oriented Architecture
- Coarse- and Fine-grained parallelism
- Data Fragmentation

3 Transactions
- Data Replication
- Distributed Transactions
- CAP-Theorem

4 Additional
- Map/Reduce and Hadoop
- Spark and its Ecosystem
- Database in the cloud

New focus – Modern Database Systems

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1 Foundations

- Relational Data and SQL
- Traditional Database Architecture
- Transactions

2 Parallelism

- Data-oriented Architecture
- Coarse- and Fine-grained parallelism
- Data Fragmentation

3 Transactions

- Data Replication
- Distributed Transactions
- CAP-Theorem

4 Additional

- Map/Reduce and Hadoop
- Spark and its Ecosystem
- Database in the cloud

Importance of Complex Data Analyses

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Industry 4.0

Electronic Patient Records

Business Intelligence

Trends to Face

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Application trends

Complex analytical queries

Example: Star Schema Benchmark (SSB) Query 3.1

```
SELECT c_nation, s_nation, d_year, SUM(lo_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;
```

Hardware trends

Main Memory

Increasingly large capacities

Access only a few columns

In-Memory Column-Store

Store all data in main memory

Recap: Traditional Row-based Storage

Physical Data Storage

- Properties: The unit of a tuple with all attributes is preserved

Pro (+) / Cons (-)

\+ Easy to add/modify a tuple

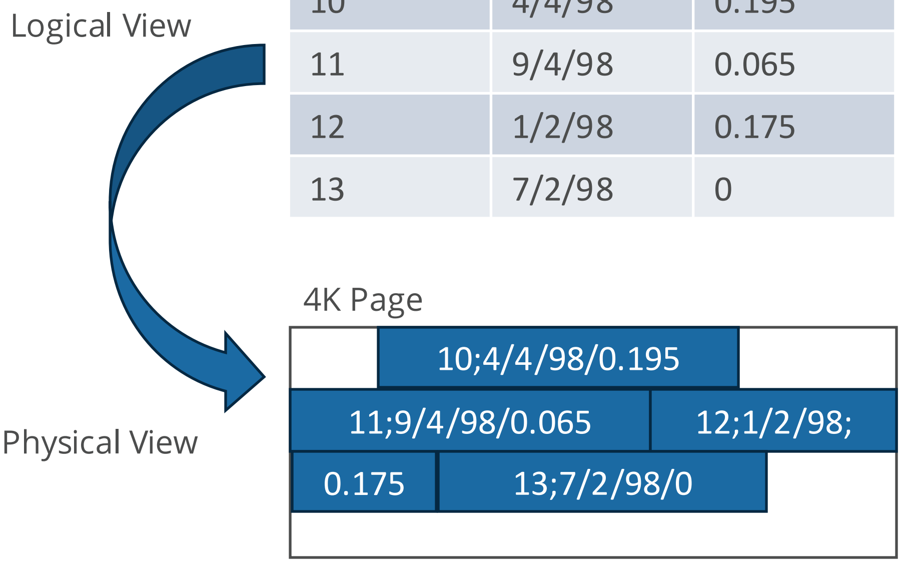
\- Even if only a few attributes are needded, all attributes have to be read
→ unnecessary I/O-cost

\- Compression is hard since consecutive values are from different domains (e.g., name, age, street addr, zip code, etc).

Illustration

Table A

ID	Day	Discount
10	4/4/98	0.195
11	9/4/98	0.065
12	1/2/98	0.175
13	7/2/98	0



Modern Column-based Storage

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Physical Data Storage

- Storage model based on vertical fragmentation
- Instead of storing all attributes of each relational tuple in one record, each column is stored in a separate table called BAT
- BAT = Binary Association Tuple
  - The left column is called head and is required to reconstruct the relational tuples
  - The right column is called tail and is holding the actual attribute

Illustration

Table A

ID	Day	Discount
10	4/4/98	0.195
11	9/4/98	0.065
12	1/2/98	0.175
13	7/2/98	0

Vertical Fragmentation

OID	ID
100	10
101	11
102	12
103	13

OID	Day
100	4/4/98
101	9/4/98
102	1/2/98
103	7/2/98

OID	ID
100	0.195
101	0.065
102	0.175
103	0

Modern Column-based Storage/2

Physical Data Storage

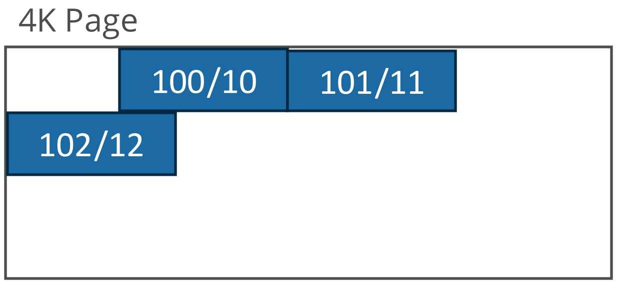
- Every relational table is internally represented as a collection of BATS
- For a table of k attributes, there exists k BATs and each BAT stores the attribute as (OID, value) pairs
- System generated OID values identifies the relational tuple that the attribute value belongs to, i.e., all attribute values of a single tuple are assigned the same OID.
- BATs are stored in regular 4K-pages → each BAT considers as single table with two attributes

Illustration

OID	ID
100	10
101	11
102	12
103	13

OID	Day
100	4/4/98
101	9/4/98
102	1/2/98
103	7/2/98

OID	ID
100	0.195
101	0.065
102	0.175
103	0



Modern Column-based Storage/3

Pro / Cons

+ Only need to read in relevant data, more efficient scan operators

- tuple writes require multiple accesses

- Reading all columns of a single row requires expensive row-reconstruction (1:1 join)

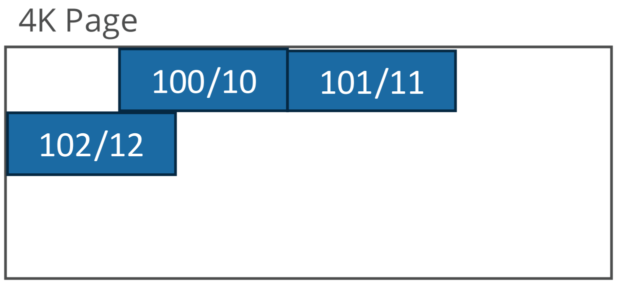
- High storage overhead due to additional OID attribute

Illustration

OID	ID
100	10
101	11
102	12
103	13

OID	Day
100	4/4/98
101	9/4/98
102	1/2/98
103	7/2/98

OID	ID
100	0.195
101	0.065
102	0.175
103	0



Columnar Storage Optimization

Storage Optimization

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(1) Elimination of OIDs

- Implicit instead of explicit OIDs
- The order of the tuples is now crucial

Advantages

- Each attribute is now a simple array without any additional information
- Each array has a unique data type
- OID could be on-the-fly generated based on the position within the array

(2) Compression

- Compression easily possible for each single array

OID	ID
100	10
101	11
102	12
103	13

OID	Day
100	4/4/98
101	9/4/98
102	1/2/98
103	7/2/98

OID	ID
100	0.195
101	0.065
102	0.175
103	0

ID
10
11
12
13

Day
4/4/98
9/4/98
1/2/98
7/2/98

ID
0.195
0.065
0.175
0

Compression Overview

Storing Relational Data Column-wise

- Each column as a sequence of values

	Integers	Fixed Point	Strings
ID	**Number of Items**	**Total Order Prize**	**Shipping Mode**
1	5	173 665.47	“Mail”
2	10	46 929.18	“Air”
3	3	193 846.25	“Rail”

✓ **Only need to read in relevant data attributes during query processing**

– Tuple writes require multiple accesses

Reducing Memory Footprint

- All logical data is mapped to integer data on the physical level

All Integers (64-Bit)

ID	Number of Items	Total Order Prize	Shipping Mode
1	5	17 366 547	10
2	10	4 692 918	20
3	3	19 384 625	30

DICT

768-Bit

Lightweight Integer Compression

ID	Number of Items	Total Order Prize	Shipping Mode
01	010	11 000 001 0 110 001 0 01 011 101	01010
10	111	01 000 111 1 001 100 1 10 110 010	10100
11	000	11 100 000 0 010 110 1 01 111 011	11110

102-Bit

Preprocessing Technique: DICT

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Dictionary Coding – DICT

- replaces each (string-)value by its unique key in a dictionary
- achieve small integer values

City
Berlin
Berlin
Berlin
Ilmenau
Ilmenau
Ilmenau
Magdeburg
Rostock
Rostock

City-Code
1
1
1
2
2
2
3
4
4

Dictionary

City	City-Code
Berlin	1
Ilmenau	2
Magdeburg	3
Rostock	4

Preprocessing Technique: FOR

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Frame-of-Reference – FOR

- represents each value as the difference to a certain given reference value (FOR)
- Achieve smaller integer values

Preis
45
54
48
55
51
53
40
50
49

FOR = 40 →

Preis (FOR)
5
14
8
15
11
13
0
10
9

Reference values (FOR) has to be stored to be able to decompress data

Preprocessing Technique: DELTA

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DELTA Coding – DELTA

- represents each value as the difference to its predecessor value
- achieve smaller integer values
- Sorting helpful for optimized compression ratio

Preis
10
15
20
21
23
25
30

DELTA
10
5
5
1
2
2
5

Compression Technique: RLE

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Run Length Encoding – RLE

- tackles uninterrupted sequences of occurrences of the same value, so called runs
- each run is represented by its value and length

City
Berlin
Berlin
Berlin
Ilmenau
Ilmenau
Ilmenau
Magdeburg
Rostock
Rostock

Run Value	Run Length
Berlin	3
Ilmenau	3
Magdeburg	1
Rostock	2

Compression Technique: NS

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Null Suppression – NS

- addresses the physical level of bits or bytes to reduce the number of bits per value

DICT

City
Berlin
Berlin
Berlin
Ilmenau
Ilmenau
Ilmenau
Magdeburg
Rostock
Rostock

→

City-Code
1
1
1
2
2
2
3
4
4

3 Bits per value

NS →

Column Code
001
001
001
010
010
010
011
100
100

Null Suppression Algorithms

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Bit-Aligned

- compress an integer value with a minimal number of bits

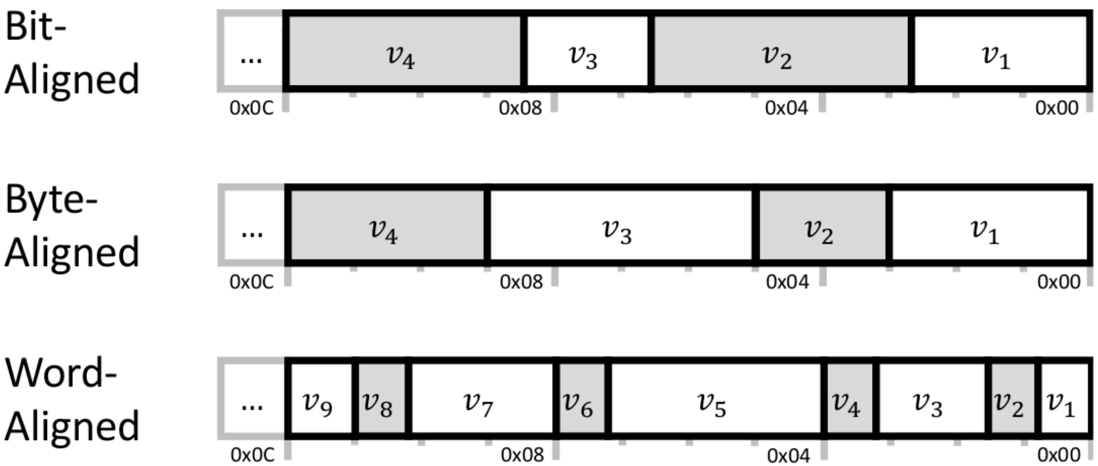
Byte-Aligned

- Compress an integer value with a minimal number of bytes

Word-Aligned

- Encode as many integer values as possible into 32-bit or 64-bit words

Alignment Examples

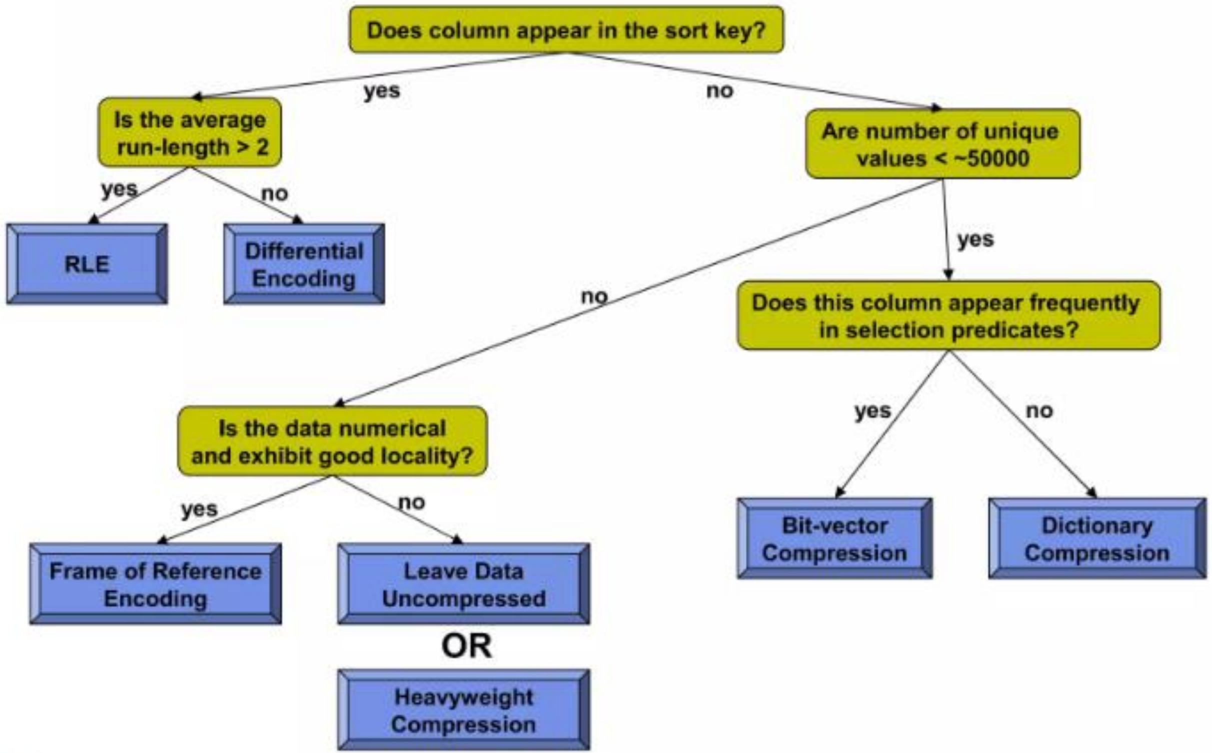


Compression Techniques Summary

RLE	DELTA	FOR	DICT	NS
Run Length Encoding Replace run by value & length	**Delta Coding** Replace data elem. by difference to predecessor	**Frame-of-Reference** Replace data elem. by difference to reference value	**Dictionary Coding** Replace data elem. by key in dictionary	**Null Suppression** Eliminate leading zero-bits
Repetitions	Sorting	Value range	# distinct values	Small integers

Logical	Level	Physical
natural numbers	data	bits and bytes
preprocessing	*role*	*actual compression*

What Compression Scheme To Use?



Storage Summary

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Most Important Properties

- Every column is encoded as a sequence of integer values
- Every column is stored in a contiguous memory area
- Heavily use of integer compression
  - to fit more data in main memory
  - To increase effective bandwidth

Impact on Query Processing

- Only relevant columns have to be accessed
- Query processing is mostly done on integer sequences

Processing Model

Processing Model

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A processing model

- Defines how the system execute a query plan and moves data from one operator to the next

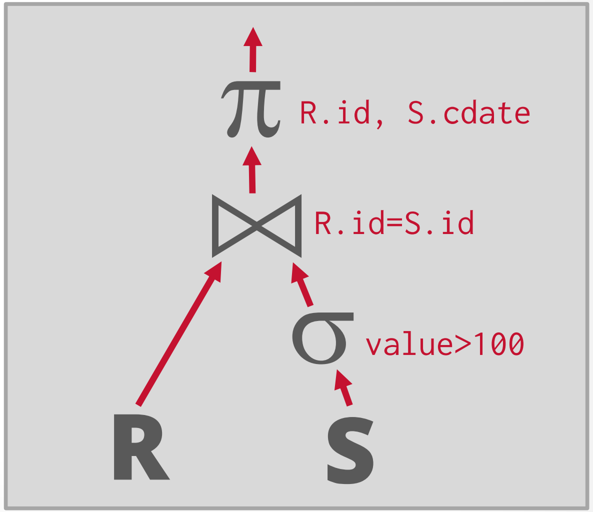
Each processing model

- Is comprised of two types of execution paths
  → Control Flow: How the system invokes an operator
  → Data Flow: How an operator send its result

The output

- of an operator can be either whole tuples (row-storage) or subset of columns (columnar storage)

```
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Evolution of Processing Models

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Iterator Model → Materialization Model → Batch Model

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Iterator Model

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Each query plan operator implements a Next() function.

- On each invocation, the operator returns either a single tuple or a EOF marker if there are no more tuples.
- The operator implements a loop that calls next on is children to retrieve their tuples and then process them.

Each operator implementation

- also has Open() and Close() functions.
- Analogous to constructors/destructors, but for operators.

Also called Volcano or Pipeline Model

Iterator Model - Example

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Control Flow →
Data Flow →

```sql
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```

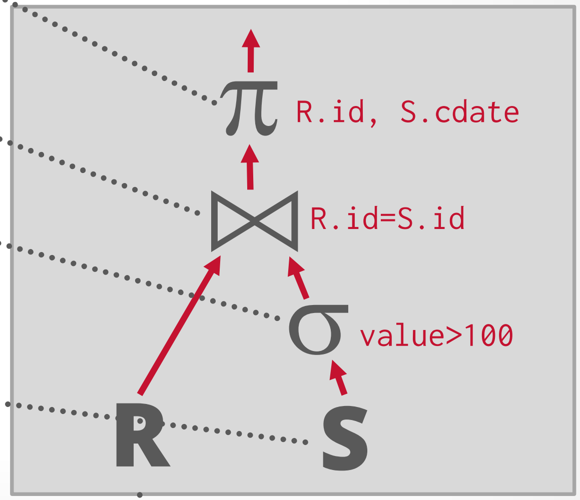
Next()
```
for t in child.Next():
  emit(projection(t))
```

Next()
```
for t1 in left.Next():
  buildHashTable(t1)
for t2 in right.Next():
  if probe(t2): emit(t1⋈t2)
```

Next()
```
for t in child.Next():
  if evalPred(t): emit(t)
```

Next()
```
for t in R:
  emit(t)
```

Next()
```
for t in S:
  emit(t)
```



Control Flow →
Data Flow →

1

```
for t in child.Next():
  emit(projection(t))
```

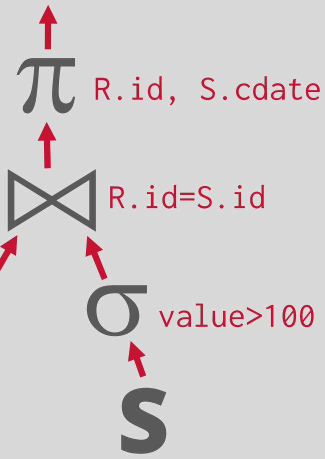
```
for t1 in left.Next():
  buildHashTable(t1)
for t2 in right.Next():
  if probe(t2): emit(t1⋈t2)
```

```
for t in child.Next():
  if evalPred(t): emit(t)
```

```
for t in R:
  emit(t)
```

```
for t in S:
  emit(t)
```

```sql
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Control Flow →
Data Flow →

1

```
for t in child.Next():
  emit(projection(t))
```

2

```
for t1 in left.Next():
  buildHashTable(t1)
for t2 in right.Next():
  if probe(t2): emit(t1⋈t2)
```

Single Tuple

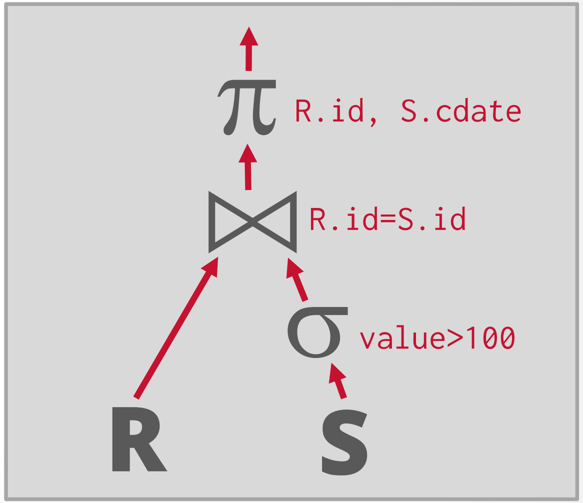
```
for t in child.Next():
  if evalPred(t): emit(t)
```

3

```
for t in R:
  emit(t)
```

```
for t in S:
  emit(t)
```

```sql
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Control Flow →
Data Flow →

1
```
for t in child.Next():
  emit(projection(t))
```

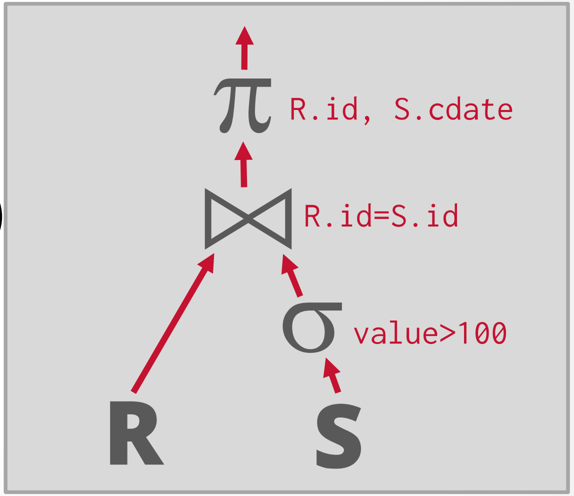
2
```
for t1 in left.Next():
  buildHashTable(t1)
for t2 in right.Next():
  if probe(t2): emit(t1⋈t2)
```

3
```
for t in R:
  emit(t)
```

4
```
for t in child.Next():
  if evalPred(t): emit(t)
```

5
```
for t in S:
  emit(t)
```

```sql
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Control Flow →
Data Flow →

1
```
for t in child.Next():
  emit(projection(t))
```

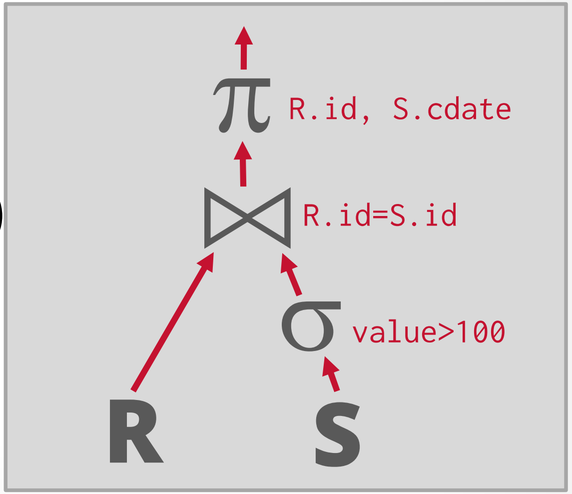
2
```
for t1 in left.Next():
  buildHashTable(t1)
for t2 in right.Next():
  if probe(t2): emit(t1⋈t2)
```

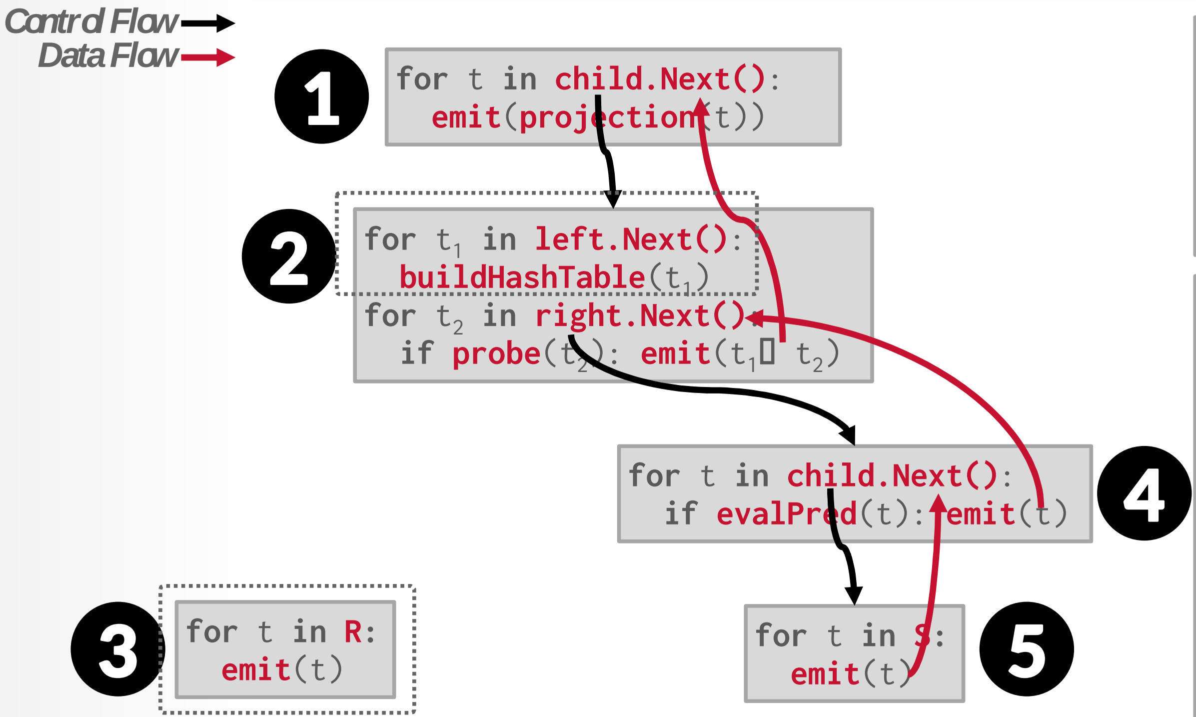
3
```
for t in R:
  emit(t)
```

4
```
for t in child.Next():
  if evalPred(t): emit(t)
```

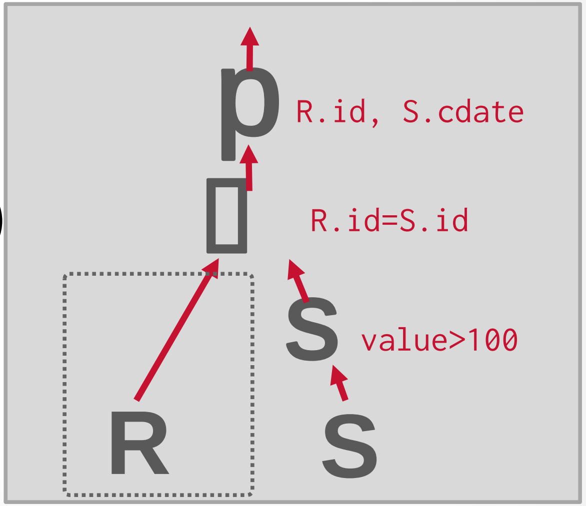
5
```
for t in S:
  emit(t)
```

```sql
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```






```
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Pipeline #1

Control Flow →
Data Flow →

1
```
for t in child.Next():
  emit(projection(t))
```

2
```
for t1 in left.Next():
  buildHashTable(t1)
for t2 in right.Next():
  if probe(t2): emit(t1⋈ t2)
```

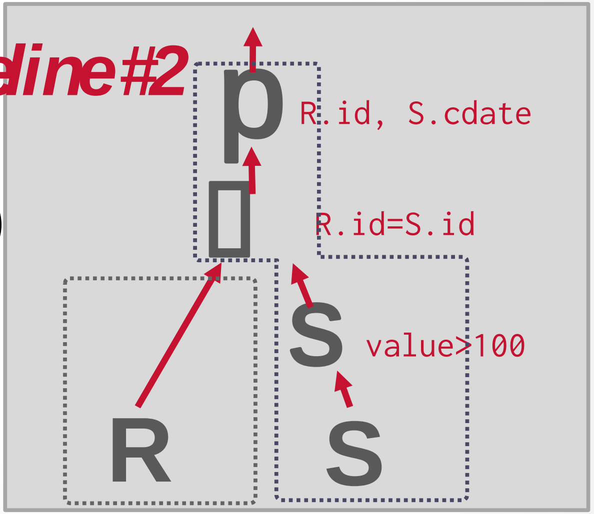
3
```
for t in R:
  emit(t)
```

4
```
for t in child.Next():
  if evalPred(t): emit(t)
```

5
```
for t in S:
  emit(t)
```

```
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```

Pipeline #2



Iterator Model

The Iterator model is used in almost every DBMS.

- Easy to implement / debug.
- Output control works easily with this approach.

Allows for pipelining

- where the DBMS tries to process each tuple through as many operators as possible before retrieving the next tuple.

A pipeline breaker

- is an operator that cannot finish until all its children emit all their tuples.
- → Joins (Build Side), Subqueries, Order By

Systems

SQLite, mongoDB, Microsoft SQL Server

IBM DB2, PostgreSQL, ORACLE

MySQL

Evolution of Processing Models

Iterator Model → Materialization Model → Batch Model

Materialization Model

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Description

- Each operator processes its input all at once and then emits its output all at once.
- The operator "materializes" its output as a single result.
- Can send either a materialized row or a single column.

Origin

- Originally developed in MonetDB in the 1990s to process entire columns at a time instead of single tuples.
- MonetDB = 1st pure database system with a columnar storage approach

Example

Control Flow
Data Flow

1

```
out = [ ]
for t in child.Output():
  out.add(projection(t))
return out
```

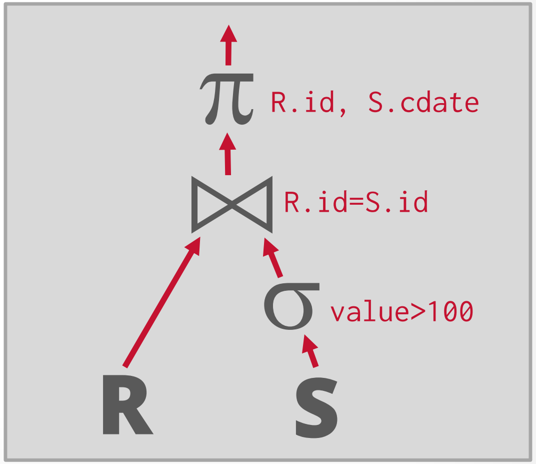
```
out = [ ]
for t1 in left.Output():
  buildHashTable(t1)
for t2 in right.Output():
  if probe(t2): out.add(t1⋈t2)
return out
```

```
out = [ ]
for t in child.Output():
  if evalPred(t): out.add(t)
return out
```

```
out = [ ]
for t in R:
  out.add(t)
return out
```

```
out = [ ]
for t in S:
  out.add(t)
return out
```

```sql
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Example

Control Flow
Data Flow

1

```
out = [ ]
for t in child.Output():
  out.add(projection(t))
return out
```

2

```
out = [ ]
for t₁ in left.Output():
  buildHashTable(t₁)
for t₂ in right.Output():
  if probe(t₂): out.add(t₁⋈t₂)
return out
```

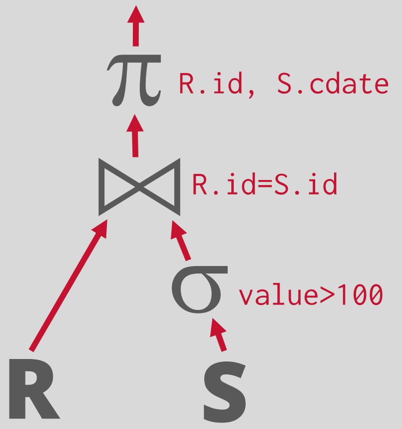
```
out = [ ]
for t in child.Output():
  if evalPred(t): out.add(t)
return out
```

3

```
out = [ ]
for t in R:
  out.add(t)
return out
```

```
out = [ ]
for t in S:
  out.add(t)
return out
```

```
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Example

Control Flow →
Data Flow →

❶
```
out = [ ]
for t in child.Output():
  out.add(projection(t))
return out
```

❷
```
out = [ ]
for t₁ in left.Output():
  buildHashTable(t₁)
for t₂ in right.Output():
  if probe(t₂): out.add(t₁⋈t₂)
return out
```

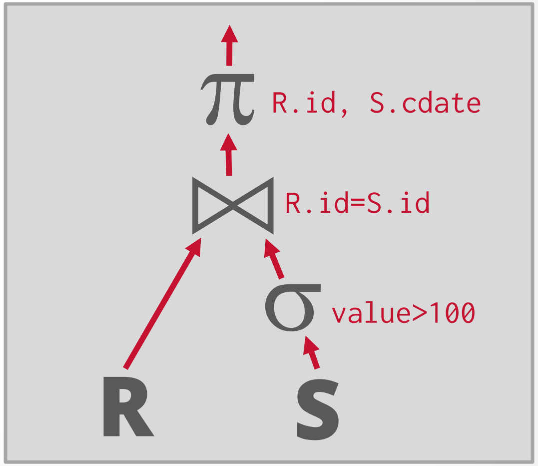
```
out = [ ]
for t in child.Output():
  if evalPred(t): out.add(t)
return out
```

All Tuples

❸
```
out = [ ]
for t in R:
  out.add(t)
return out
```

```
out = [ ]
for t in S:
  out.add(t)
return out
```

```
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Example

Control Flow
Data Flow

1
```
out = [ ]
for t in child.Output():
  out.add(projection(t))
return out
```

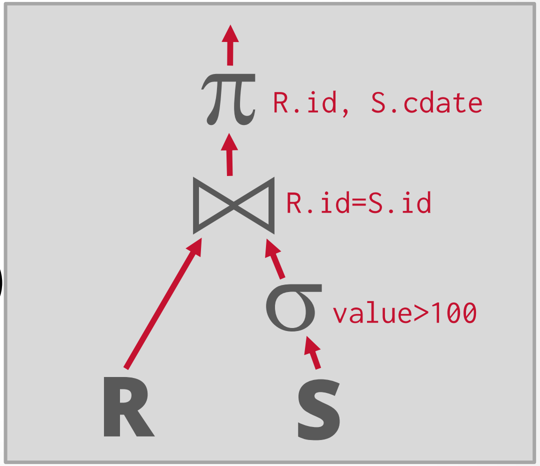
2
```
out = [ ]
for t1 in left.Output():
  buildHashTable(t1)
for t2 in right.Output():
  if probe(t2): out.add(t1⋈t2)
return out
```

4
```
out = [ ]
for t in child.Output():
  if evalPred(t): out.add(t)
return out
```

3
```
out = [ ]
for t in R:
  out.add(t)
return out
```

5
```
out = [ ]
for t in S:
  out.add(t)
return out
```

```sql
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Example

Control Flow →
Data Flow →

1
```
out = [ ]
for t in child.Output():
  out.add(projection(t))
return out
```

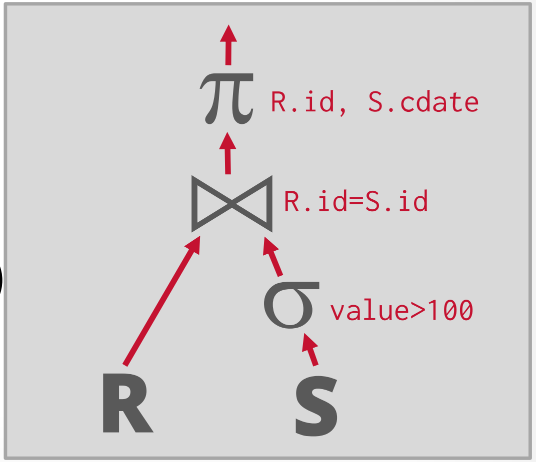
2
```
out = [ ]
for t1 in left.Output():
  buildHashTable(t1)
for t2 in right.Output():
  if probe(t2): out.add(t1⋈t2)
return out
```

3
```
out = [ ]
for t in R:
  out.add(t)
return out
```

4
```
out = [ ]
for t in child.Output():
  if evalPred(t): out.add(t)
return out
```

5
```
out = [ ]
for t in S:
  out.add(t)
return out
```

```sql
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Example

Control Flow →
Data Flow →

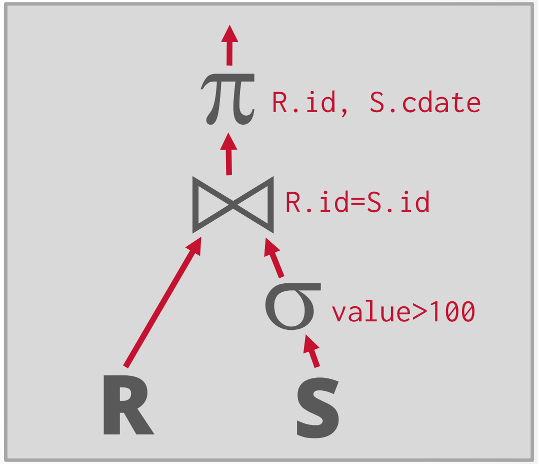
1
```
out = [ ]
for t in child.Output():
  out.add(projection(t))
return out
```

2
```
out = [ ]
for t₁ in left.Output():
  buildHashTable(t₁)
for t₂ in right.Output():
  if probe(t₂): out.add(t₁⋈t₂)
return out
```

```
out = [ ]
for t in S:
  if evalPred(t): out.add(t)
return out
```

3
```
out = [ ]
for t in R:
  out.add(t)
return out
```

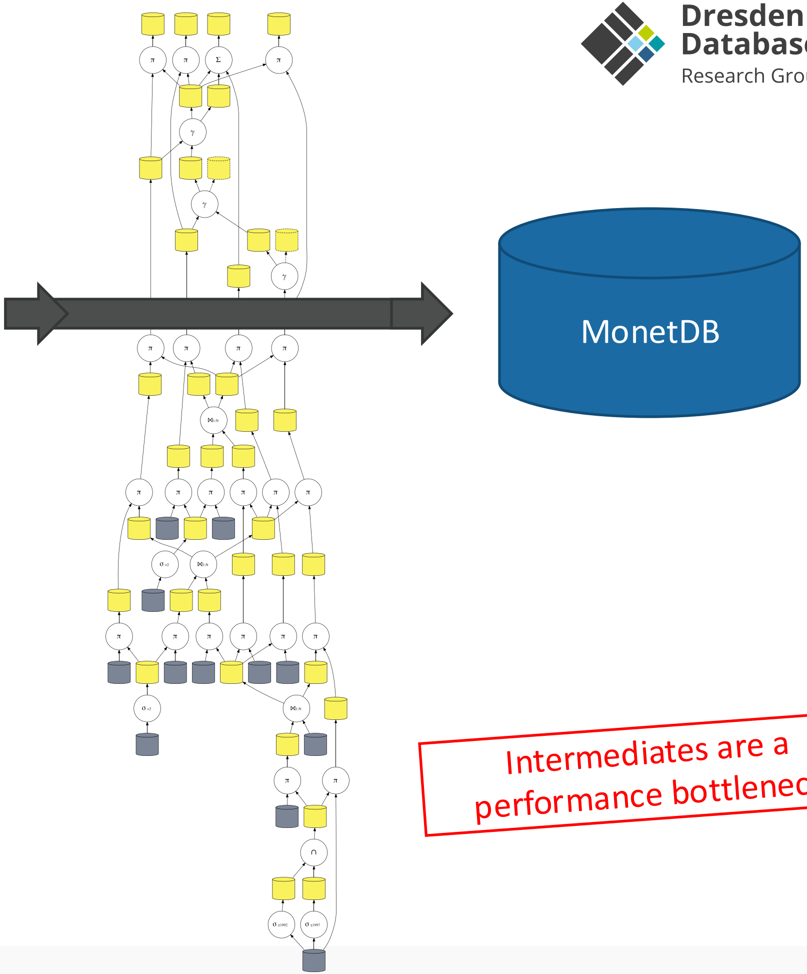
```
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Materialization Model

Example: Star Schema Benchmark (SSB) Query 3.1

```
SELECT c_nation, s_nation, d_year, SUM(lo_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;
```



Number of occurrences

33x operator

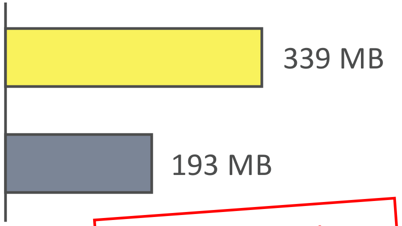
35x intermediate

12x base column

Many Intermediates

Total data size @sf 1

(64-bit per data element)



Large total size

Intermediates are a performance bottleneck

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Evolution of Processing Models

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Iterator Model

Materialization Model

Batch Model

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Batch Model

Like the Iterator Model where each operator implements a Next() function, but...

- Each operator emits a batch of tuples/columns instead of a single tuple.
- The operator's internal loop processes multiple tuples/column values at a time.
- The size of the batch can vary based on hardware or query properties.

Iterator Model

- Best-of-both- Worlds: Combination of Iterator Model and Materialization Model

Example

Control Flow →
Data Flow →

1

```
out = [ ]
for t in child.Next():
  out.add(projection(t))
  if |out|>n: emit(out)
```

2

```
out = [ ]
for t1 in left.Next():
  buildHashTable(t1)
for t2 in right.Next():
  if probe(t2): out.add(t1⋈t2)
  if |out|>n: emit(out)
```

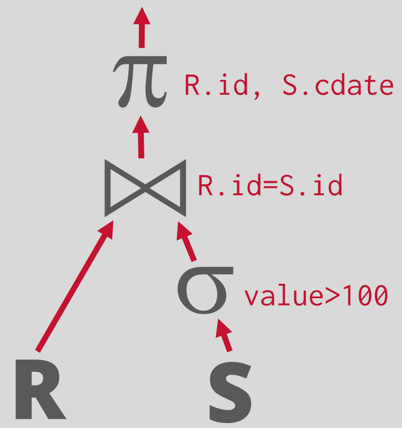
```
out = [ ]
for t in child.Next():
  if evalPred(t): out.add(t)
  if |out|>n: emit(out)
```

3

```
out = [ ]
for t in R:
  out.add(t)
  if |out|>n: emit(out)
```

```
out = [ ]
for t in S:
  out.add(t)
  if |out|>n: emit(out)
```

```sql
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Example

Control Flow →
Data Flow →

1
```
out = [ ]
for t in child.Next():
  out.add(projection(t))
  if |out|>n: emit(out)
```

2
```
out = [ ]
for t1 in left.Next():
  buildHashTable(t1)
for t2 in right.Next():
  if probe(t2): out.add(t1⋈t2)
  if |out|>n: emit(out)
```

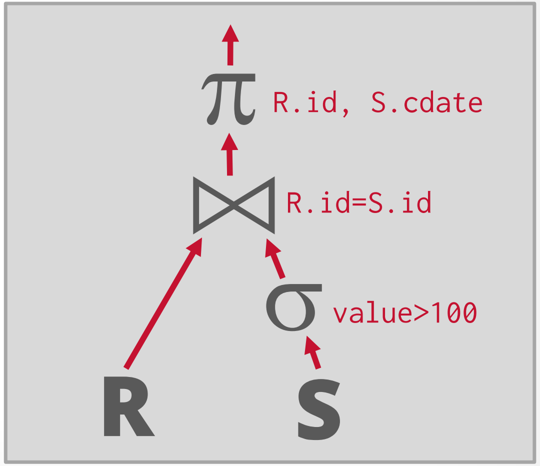
```
out = [ ]
for t in child.Next():
  if evalPred(t): out.add(t)
  if |out|>n: emit(out)
```

3
```
out = [ ]
for t in R:
  out.add(t)
  if |out|>n: emit(out)
```

Tuple Batch

```
out = [ ]
for t in S:
  out.add(t)
  if |out|>n: emit(out)
```

```sql
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Example

Control Flow →
Data Flow →

1
```
out = [ ]
for t in child.Next():
  out.add(projection(t))
  if |out|>n: emit(out)
```

2
```
out = [ ]
for t1 in left.Next():
  buildHashTable(t1)
for t2 in right.Next():
  if probe(t2): out.add(t1⋈t2)
  if |out|>n: emit(out)
```

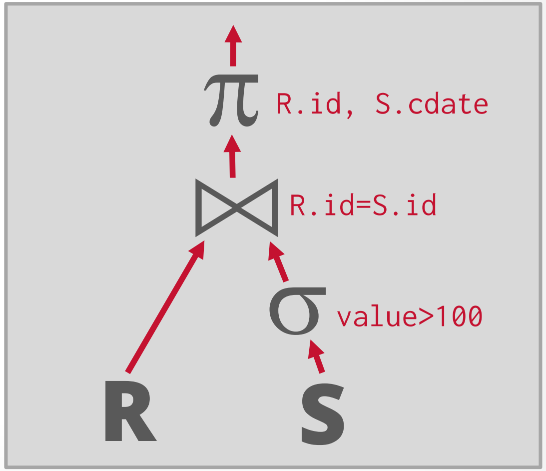
3
```
out = [ ]
for t in R:
  out.add(t)
  if |out|>n: emit(out)
```

Tuple Batch

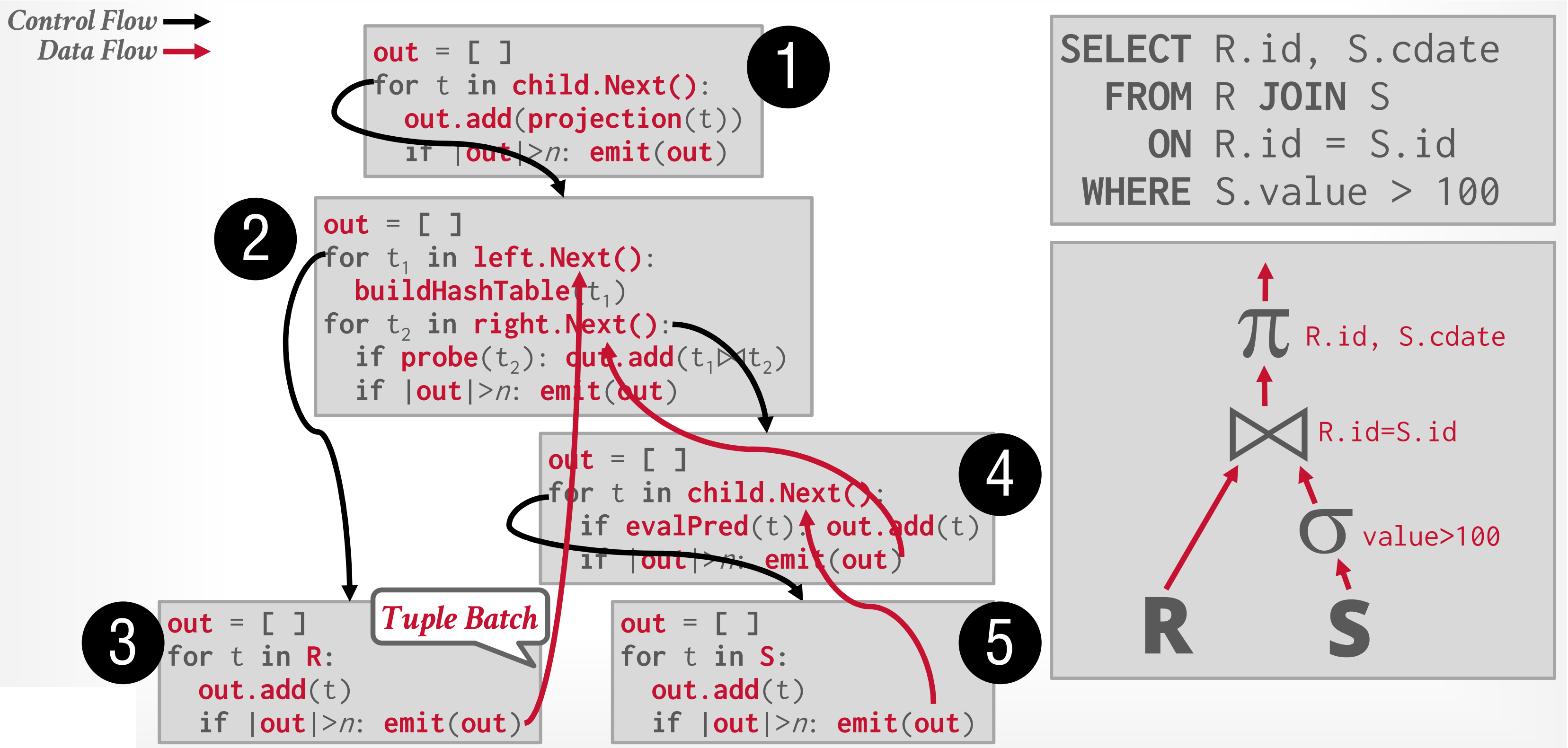
4
```
out = [ ]
for t in child.Next():
  if evalPred(t): out.add(t)
  if |out|>n: emit(out)
```

5
```
out = [ ]
for t in S:
  out.add(t)
  if |out|>n: emit(out)
```

```
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Example



Control Flow
Data Flow
out = [ ]
for t in child.Next():
out.add(projection(t))
if |out|>n: emit(out)
1
out = [ ]
for t_1 in left.Next():
buildHashTable(t_1)
for t_2 in right.Next():
if probe(t_2): out.add($t_1 \bowtie t_2$)
if |out|>n: emit(out)
2
out = [ ]
for t in child.Next():
if evalPred(t): out.add(t)
if |out|>n: emit(out)
4
3
out = [ ]
for t in R:
out.add(t)
if |out|>n: emit(out)
Tuple Batch
out = [ ]
for t in S:
out.add(t)
if |out|>n: emit(out)
5
SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100
π R.id, S.cdate
$\bowtie$ R.id=S.id
σ value>100
R
S

Batch Model

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Ideal for OLAP queries

- because it greatly reduces the number of invocations per operator.

Allows an out-of-order CPU

- to efficiently execute operators over batches of tuples.
- Operators perform work in tight for-loops over arrays, which compilers know how to optimize / vectorize.
- No data or control dependencies.
- Hot instruction cache.

Systems

presto
Google Big Query
ROCKSET
Yellowbrick
pinot
SingleStore
VERTICA
vectorwise
AlloyDB
ClickHouse
DuckDB
Velox
DATA FUSION

Processing Direction

Observation

- In the previous examples, the DBMS starts executing a query by invoking Next() at the root of the query plan and pulling data up from leaf operators.
- This is the how most DBMSs implement their execution engine.

Approach #1: Top-to-Bottom (Pull)

- Start with the root and "pull" data up from its children.
- Tuples are always passed between operators using function calls (unless it's a pipeline breaker).

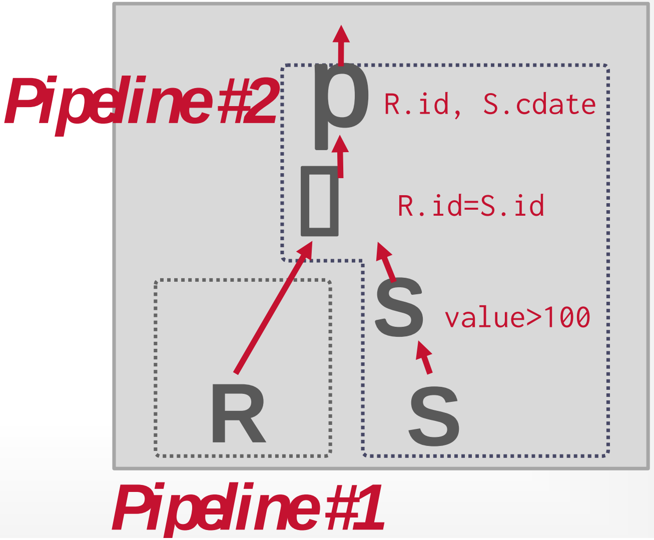
Approach #2: Bottom-to-Top (Push)

- Start with leaf nodes and "push" data to their parents.
- Can "fuse" operators together within a for-loop to minimize intermediate result staging.

Push-based Processing Direction

Control Flow →
Data Flow →

```
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



Push-based Processing Direction

Control Flow →
Data Flow →

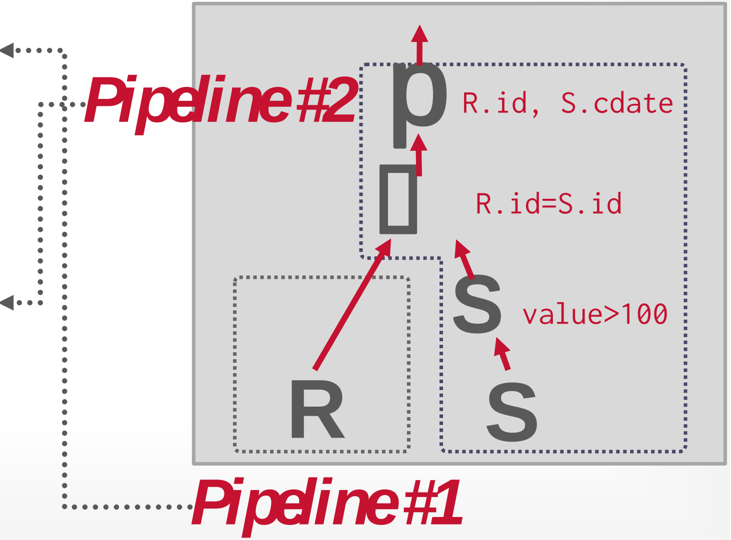
```sql
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```

1

```
for t1 in R:
  buildHashTable(t1)
```

2

```
for t2 in S:
  if evalPred(t):
    if probeHashTable(t2):
      emit(projection(t1⋈ t2))
```



Push-based Processing Direction

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Control Flow →
Data Flow →

Scheduler

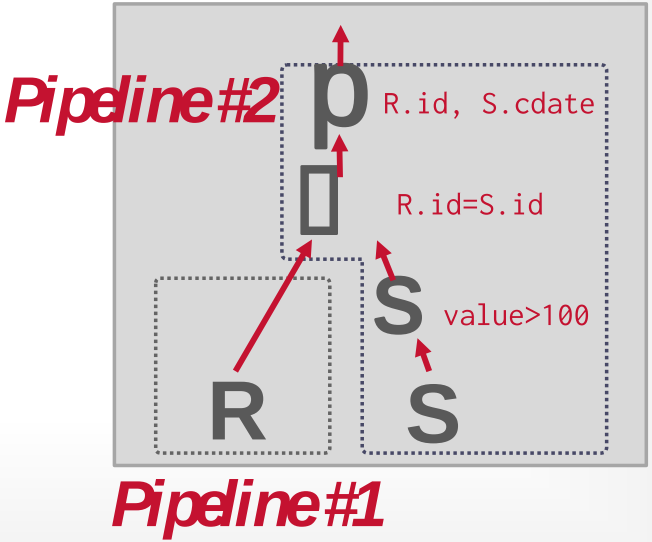
1

```
for t1 in R:
  buildHashTable(t1)
```

2

```
for t2 in S:
  if evalPred(t):
    if probeHashTable(t2):
      emit(projection(t1⨝ t2))
```

```
SELECT R.id, S.cdate
  FROM R JOIN S
    ON R.id = S.id
 WHERE S.value > 100
```



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Push-based Processing Direction

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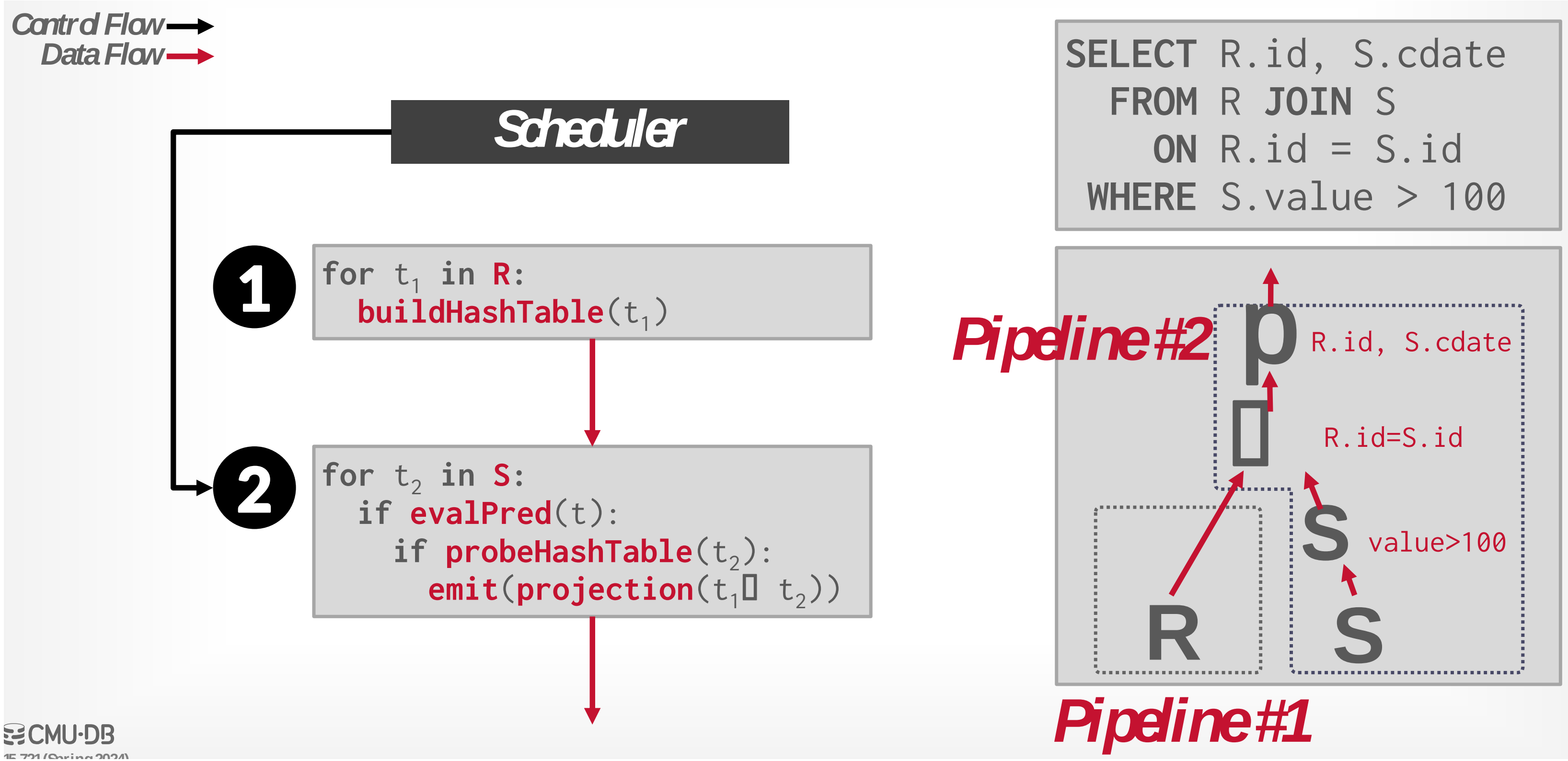

Summary

Modern In-Memory Database Systems

- Optimized for analytical queries
- Columnar Data Organization
- Batch-based Processing Model

Homework

- Please read the following paper (available on OPAL: 04-MonetDB.pdf)

DOI:10.1145/1409360.1409380

Breaking the Memory Wall in MonetDB

By Peter A. Boncz, Martin L. Kersten, and Stefan Manegold