Architecture of DB Systems
06 Query Processing

Matthias Boehm

Graz University of Technology, Austria
Computer Science and Biomedical Engineering
Institute of Interactive Systems and Data Science
BMK endowed chair for Data Management

Last update: Nov 05, 2021

SCIENCE
PASSION
TECHNOLOGY

Announcements/Org

- **#1 Video Recording**
  - Link in **TUbe** & **TeachCenter** (lectures will be public)
  - Optional attendance (independent of COVID)
  - **Hybrid**, in-person but video-recorded lectures
    - **HS i5** + Webex: https://tugraz.webex.com/meet/m.boehm
- **#2 COVID-19 Precautions** (HS i5)
  - Room capacity: 24/48 (green/yellow), 12/48 (orange/red)
  - TC lecture registrations (limited capacity, contact tracing)

max
24/90

- **#3 Course Evaluation and Exam**
  - Evaluation period: **Jan 01 – Feb 15**
  - Exam dates: **TBD** (virtual webex oral exams, 45min each)

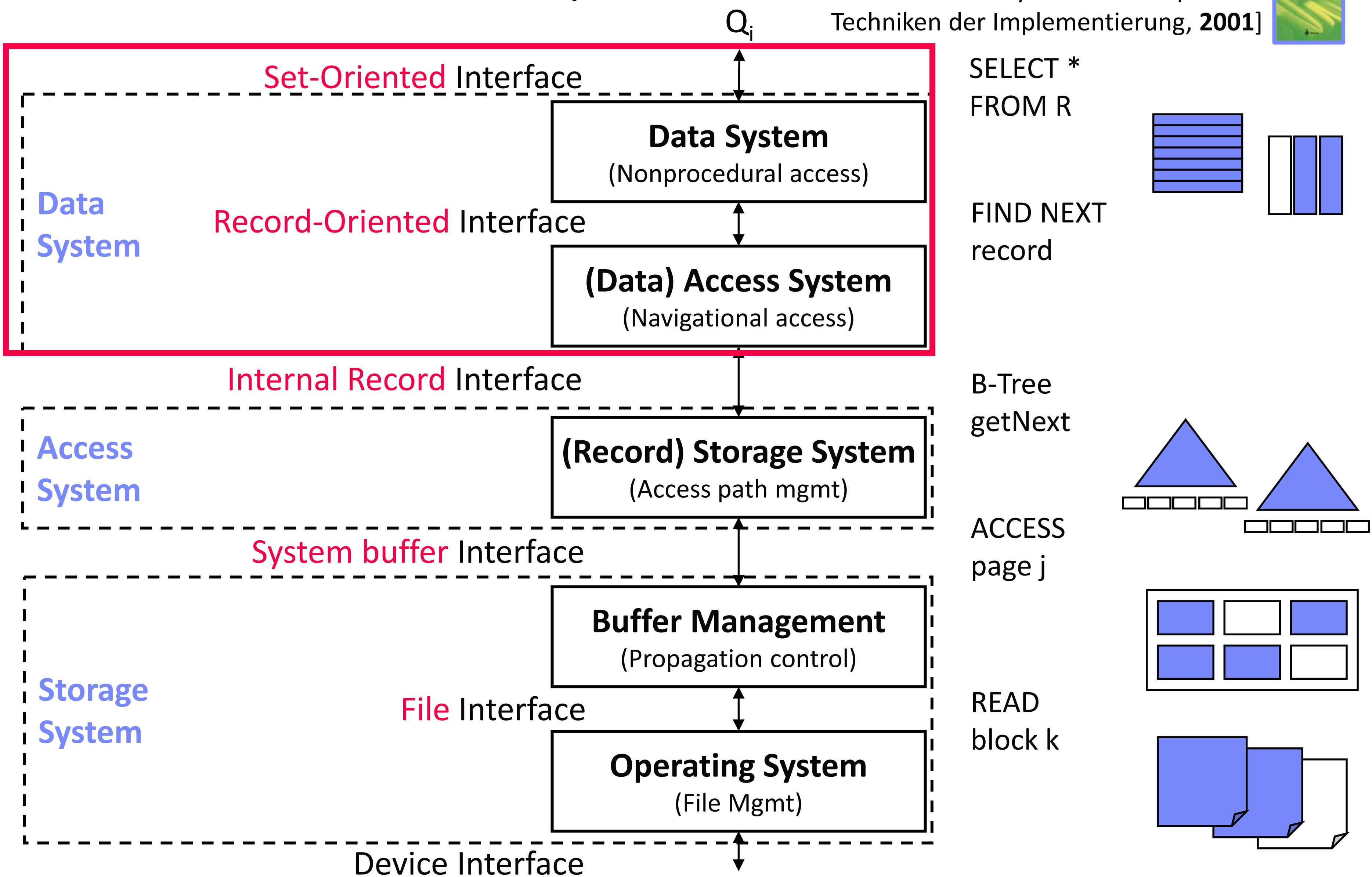
Agenda

- **Overview Query Processing**
- **Plan Execution Strategies**
- **Physical Plan Operators**

Overview Query Processing

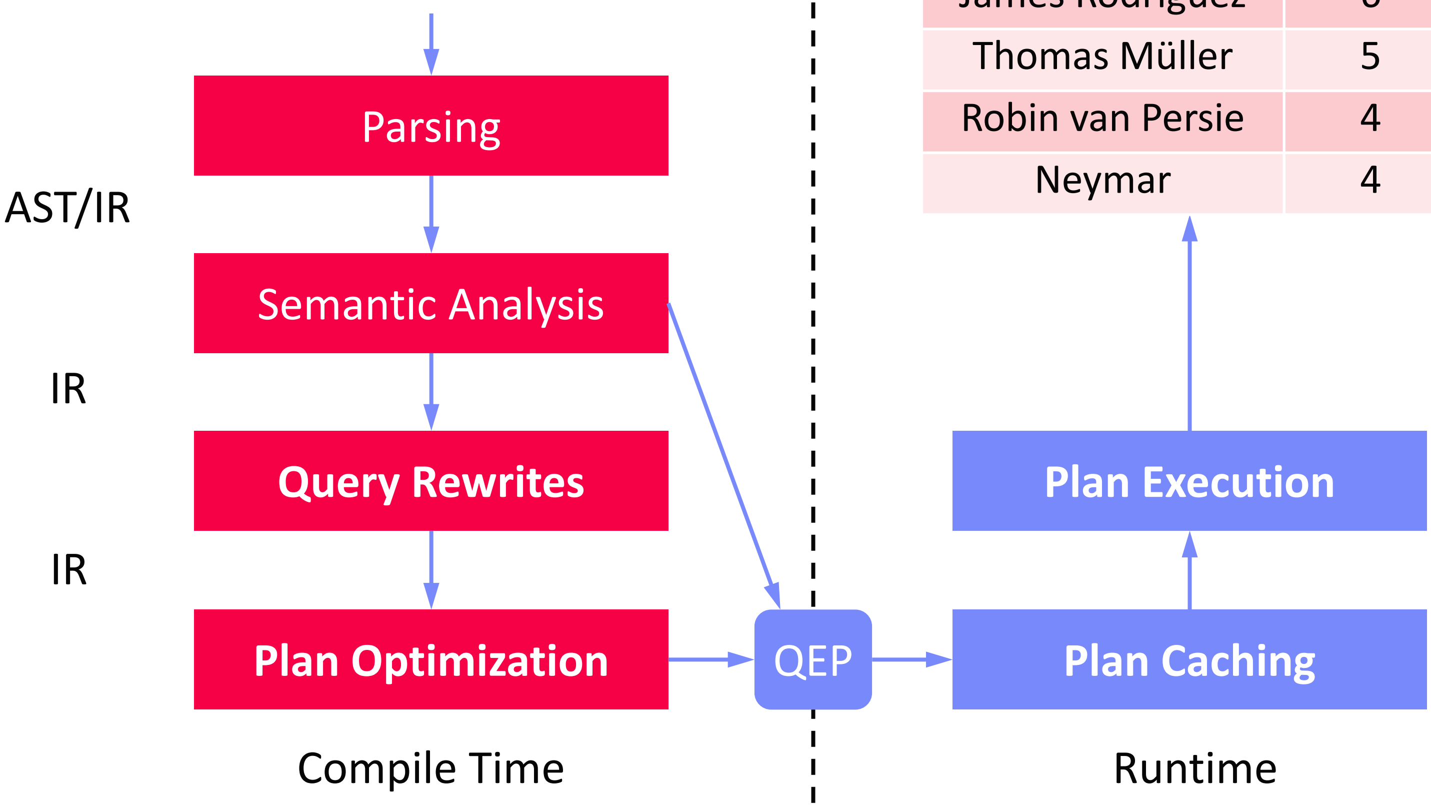
DBMS Architecture, cont.

[Theo Härder, Erhard Rahm: Datenbanksysteme: Konzepte und Techniken der Implementierung, **2001**]



Overview Query Processing

```
SELECT * FROM TopScorer
  WHERE Count>=4
```



Name	Count
James Rodríguez	6
Thomas Müller	5
Robin van Persie	4
Neymar	4

Database Catalog

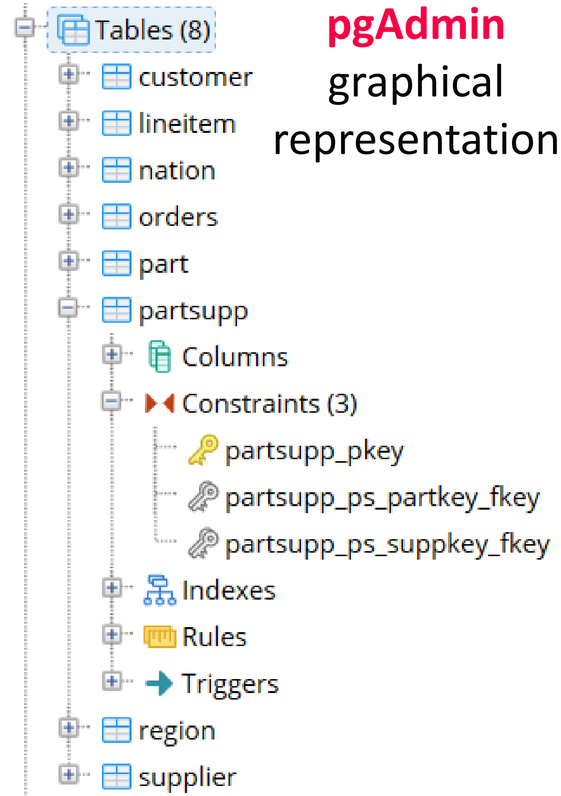
[Meikel Poess: TPC-H. **Encyclopedia of Big Data Technologies 2019**]

- **Catalog Overview**
  - **Meta data** of all database objects (tables, constraints, indexes) → **mostly read-only**
  - **Accessible through SQL**, but internal APIs
  - Organized by schemas (`CREATE SCHEMA tpch;`)

- **SQL `Information_Schema`**
  - Schema with tables for all tables, views, constraints, etc
  - **Example:** check for existence of accessible table

```
SELECT 1 FROM information_schema.tables
WHERE table_schema = 'tpch'
   AND table_name = 'customer'
```

(defined as views over PostgreSQL catalog tables)



pgAdmin graphical representation

Plan Caching

- **Motivation**
  - Query rewriting, optimization and plan generation is expensive
  - Cache and reuse compile plans
    (stored procedures, prepared/parameterized statements, ad-hoc queries)

- **Structure**
  - SQL query test
  - Compiled query plans
  - Statistics
    - Usage counts
    - Last run timestamp
    - Max/avg runtime
    - Compile time

#1 Probe Plan Cache

`hash(SQL)`

SQL	Plan	Stats
`SELECT * FROM`	QEP1: x-y-z	#5, 23ms
`SELECT a FROM`	QEP7: a-b	#100, 6ms
`CREATE PROC`	…	…

#2 Check schema valid, statistics up-to-date

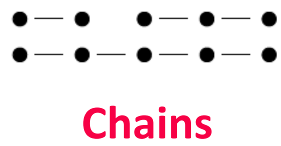
#3 Reuse or Recompilation

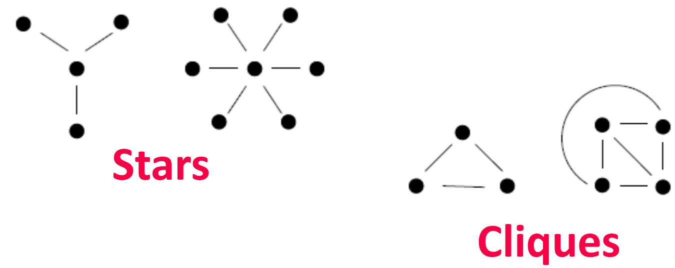
- **Examples:** MS SQL Server, IBM DB2

Query and Plan Types

[Guido Moerkotte, Building Query Compilers (Under Construction), **2020**, http://pi3.informatik.uni-mannheim.de/~moer/querycompiler.pdf]

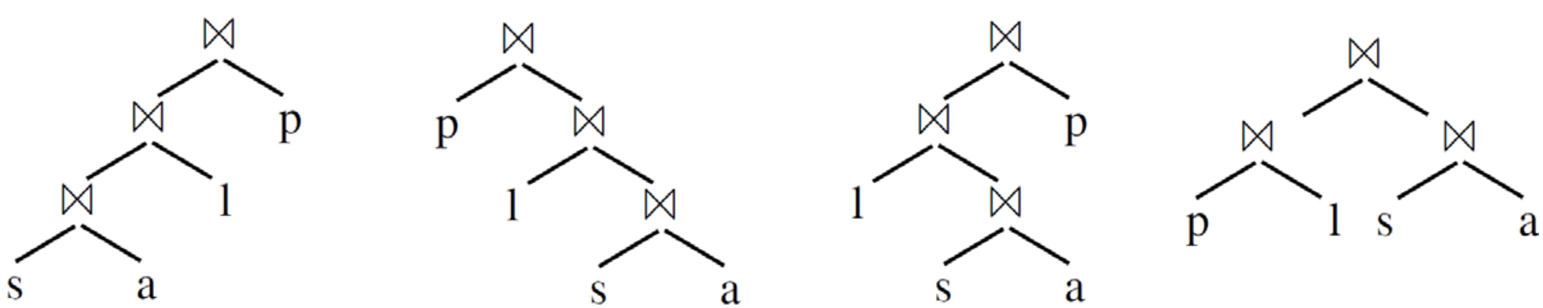
- **Query Types**
  - **Nodes:** Tables
  - **Edges:** Join conditions
  - Determine **hardness of query optimization** (w/o cross products)





- **Join Tree Types / Plan Types**
  - Data flow graph of tables and joins (logical/physical query trees)
  - **Edges:** data dependencies (fixed execution order: bottom-up)

Left-Deep Tree **Right-Deep Tree** **Zig-Zag Tree** **Bushy Tree**

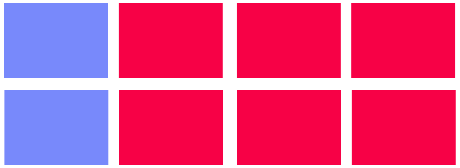


Result Caching

- **Motivation**
  - Read-mostly data and same queries over unchanged inputs
  - **Cache and reuse small result sets** (e.g., aggregation queries, distinct)

- **Structure**
  - Similar to materialized-views (cached intermediates)
  - Store results of queries w/ result_cache hint in subarea of buffer pool, reuse via hint
  - Drop cached results if underlying base data changes
  - Also: Function result cache (memoization)

```
SELECT /*+ result_cache*/ *
  FROM TopScorer
  WHERE Count>=4
```



Buffer pool pages

- **Examples: Oracle** (from 11g)
  [https://oracle.readthedocs.io/en/latest/plsql/cache/alternatives/result-cache.html]

Plan Execution Strategies

Overview Execution Strategies

- **Different execution strategies (processing models) with different pros/cons** (e.g., memory requirements, DAGs, efficiency, reuse)

- **#1 Iterator Model** (mostly row stores)
- **#2 Materialized Intermediates** (mostly column stores)
- **#3 Vectorized (Batched) Execution** (row/column stores)
- **#4 Query Compilation** (row/column stores)
- **#5 Data-Centric Processing** (row stores)

Query-centric

Data-centric

Iterator Model

Scalable (small memory)
High CPI measures

- **Volcano Iterator Model**
  - **Pipelined & no global knowledge**
  - **Open-Next-Close** (ONC) interface
  - Query execution from root node (pull-based)

[Goetz Graefe: Volcano - An Extensible and Parallel Query Evaluation System. **IEEE Trans. Knowl. Data Eng. 1994**]

- **Example $\sigma_{A=7}(R)$**

```
void open() { R.open(); }

void close() { R.close(); }

Record next() {
  while( (r = R.next()) != EOF )
    if( p(r) ) //A==7
      return r;
  return EOF;
}
```

```
open()
 next()
  next() → EOF
   close()
      |
open()
next()        σA=7  → EOF
next()
close()
      |
open()
next()         R
next()
next()
next()              → EOF
close()
```

- **Blocking Operators**
  - Sorting, grouping/aggregation, build-phase of (simple) hash joins

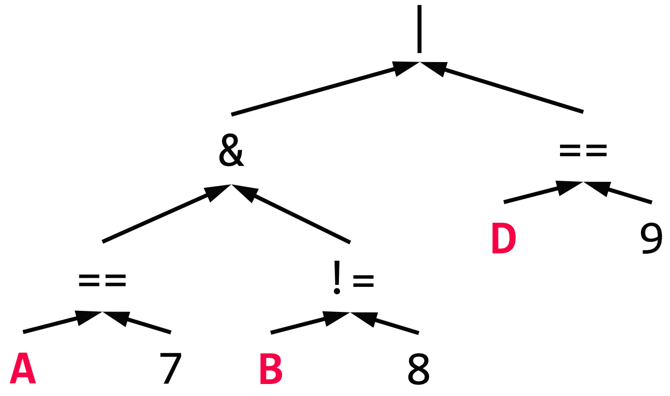
PostgreSQL: Init(), GetNext(), ReScan(), MarkPos(), RestorePos(), End()

Iterator Model – Predicate Evaluation

- **Operator Predicates**
  - Examples: arbitrary selection predicates and join conditions
  - Operators parameterized **with in-memory expression trees/DAGs**
  - **Expression evaluation engine** (interpretation)

- **Example Selection σ**
  - $(A = 7 \wedge B \neq 8) \vee D = 9$

A	B	C	D
7	8	Product 1	10
14	8	Product 3	11
7	3	Product 7	7
3	3	Product 2	1



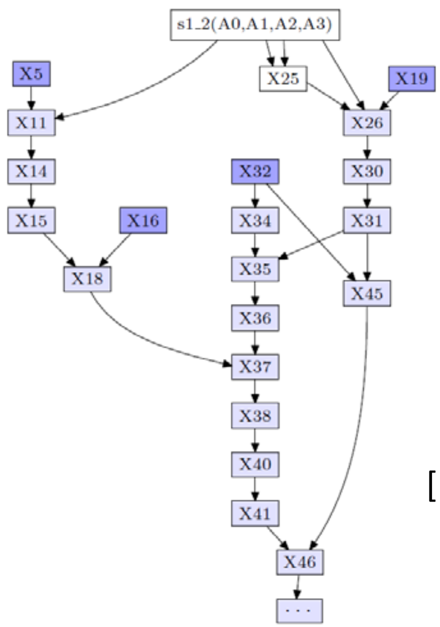
Materialized Intermediates (column-at-a-time)

```
SELECT count(DISTINCT o_orderkey)
  FROM orders, lineitem
  WHERE l_orderkey = o_orderkey
    AND o_orderdate >= date '1996-07-01'
    AND o_orderdate < date '1996-07-01'
      + interval '3' month
    AND l_returnflag = 'R';
```

```
function user.s1_2(A0:date,A1:date,A2:int,A3:str):void;
  X5 := sql.bind("sys","lineitem","l_returnflag",0);
  X11 := algebra.uselect(X5,A3);
  X14 := algebra.markT(X11,0@0);
  X15 := bat.reverse(X14);
  X16 := sql.bindIdxbat("sys","lineitem","l_orderkey_fkey");
  X18 := algebra.join(X15,X16);
  X19 := sql.bind("sys","orders","o_orderdate",0);
  X25 := mtime.addmonths(A1,A2);
  X26 := algebra.select(X19,A0,X25,true,false);
  X30 := algebra.markT(X26,0@0);
  X31 := bat.reverse(X30);
  X32 := sql.bind("sys","orders","o_orderkey",0);
  X34 := bat.mirror(X32);
  X35 := algebra.join(X31,X34);
  X36 := bat.reverse(X35);
  X37 := algebra.join(X18,X36);
  X38 := bat.reverse(X37);
  X40 := algebra.markT(X38,0@0);
  X41 := bat.reverse(X40);
  X45 := algebra.join(X31,X32);
  X46 := algebra.join(X41,X45);
  X49 := algebra.selectNotNil(X46);
  X50 := bat.reverse(X49);
  X51 := algebra.kunique(X50);
  X52 := bat.reverse(X51);
  X53 := aggr.count(X52);
  sql.exportValue(1,"sys.orders","L1","wrd",32,0,6,X53);
end s1_2;
```

Binary Association Tables (BATs:=OID/Val)

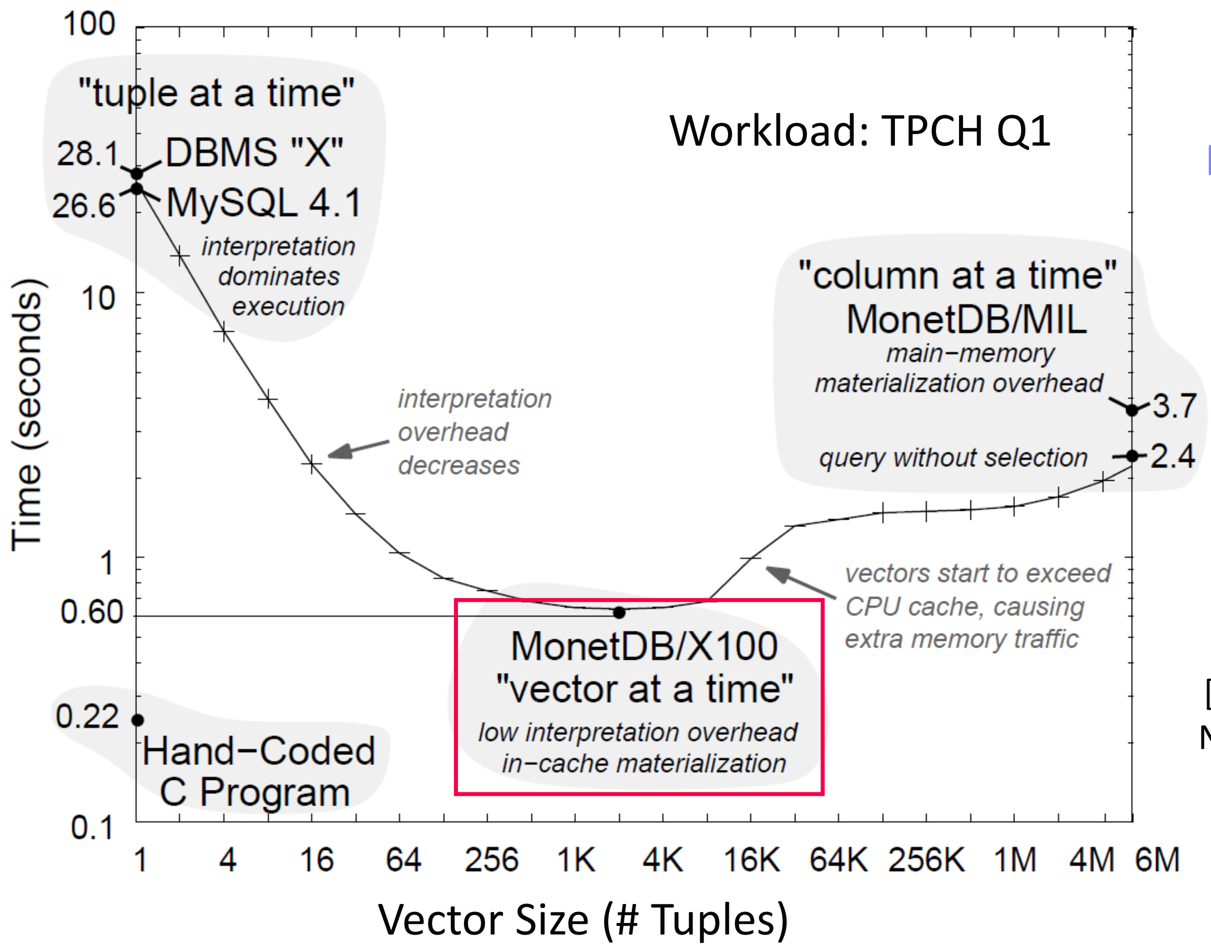
Column-oriented storage
Efficient array operations
DAG processing
Reuse of intermediates
Memory requirements
Unnecessary read/write from and to memory



[Milena Ivanova, Martin L. Kersten, Niels J. Nes, Romulo Goncalves: An architecture for recycling intermediates in a column-store. **SIGMOD 2009**]

Vectorized Execution (vector-at-a-time)

- **Idea: Pipelining of vectors (sub columns) s.t. vectors fit in CPU cache**



Column-oriented storage
Efficient array operations
Memory/cache efficiency
DAG processing
Reuse of intermediates

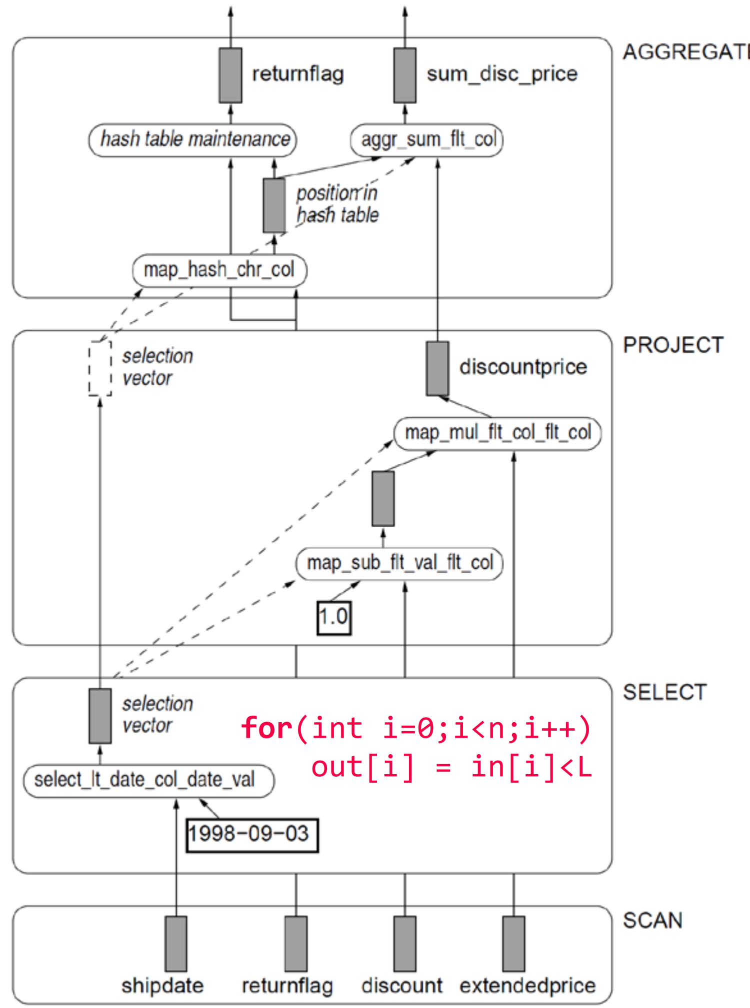
[Peter A. Boncz, Marcin Zukowski, Niels Nes: MonetDB/X100: Hyper-Pipelining Query Execution. **CIDR 2005**]

Vectorized Execution (vector-at-a-time), cont.

- **Motivation**
  - **Iterator Model:** many function calls, no instruction-level parallelism
  - **Materialized:** mem-bandwidth-bound
- **Hyper-Pipelining**
  - Operators work on vectors
  - Pipelining of vectors (sub-columns)
  - Vector sizes according to cache size
  - Pre-compiled function primitives
  - ➔ **Generalization of execution strategies**

[Peter A. Boncz, Marcin Zukowski, Niels Nes: MonetDB/X100: Hyper-Pipelining Query Execution. **CIDR 2005**]

[Marcin Zukowski, Peter A. Boncz, Niels Nes, Sándor Héman: MonetDB/X100 - A DBMS In The CPU Cache. **IEEE Data Eng. Bull. 28(2), 2005**]

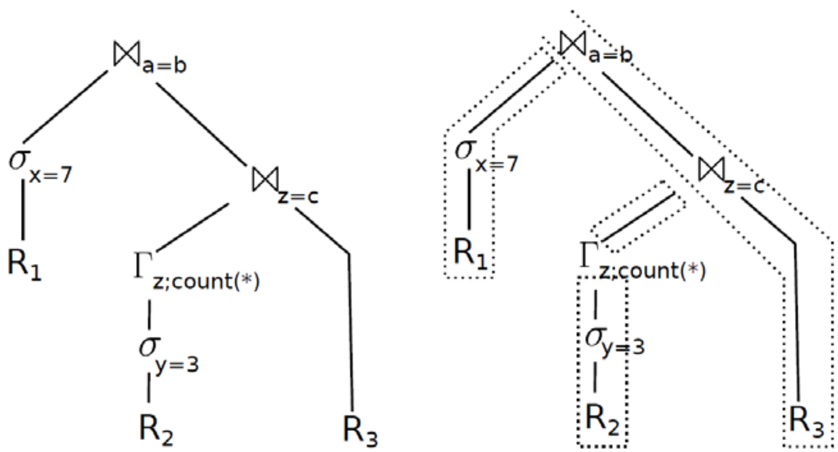


Query Compilation

07 Query Compilation and Parallelization

- **Idea: Data-centric, not op-centric processing + LLVM code generation**

Operator Trees
(w/o and w/ pipeline boundaries)



Compiled Query
(conceptual, not LLVM)

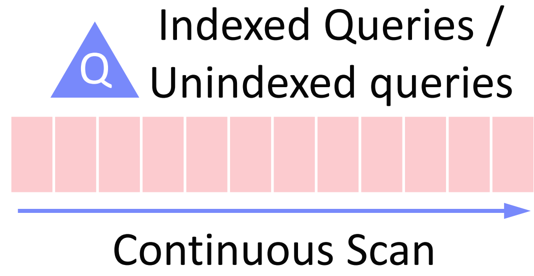
initialize memory of $\bowtie_{a=b}$, $\bowtie_{c=z}$, and Γ_z
for each tuple t in R_1
  if $t.x = 7$
    materialize t in hash table of $\bowtie_{a=b}$
for each tuple t in R_2
  if $t.y = 3$
    aggregate t in hash table of Γ_z
~~**for each** tuple t in Γ_z~~
  ~~materialize t in hash table of $\bowtie_{z=c}$~~
for each tuple t_3 in R_3
  for each match t_2 in $\bowtie_{z=c}[t_3.c]$
    for each match t_1 in $\bowtie_{a=b}[t_3.b]$
      output $t_1 \circ t_2 \circ t_3$

[Thomas Neumann: Efficiently Compiling Efficient Query Plans for Modern Hardware. **PVLDB 2011**]

Data-Centric / Continuous Scan Processing

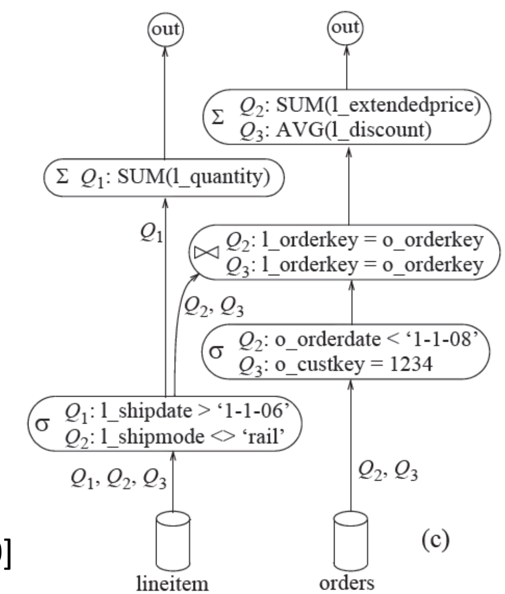
- **Crescando** (ETH Zurich)
  - **Amadeus use case:** latency <2s, freshness <2s, query diversity/update load, linear scale-out/scale-up
  - **ClockScan:** cooperative scan
  - **Index Union Update Join:** update-data join (write, and read cursor)

[Philipp Unterbrunner et al.: Predictable Performance for Unpredictable Workloads. **PVLDB 2(1) 2009**]



- **DataPath System** (Rice University)
  - Push-based, data-centric processing model
  - Multi-query optimization → DAG of operations (tuple bit-string to relate tuples to queries)
  - I/O system pushed chunks to operators
  - Load shedding on overload and explicit scheduling

[Subi Arumugam, Alin Dobra, Christopher M. Jermaine, Niketan Pansare, Luis Leopoldo Perez: The DataPath system: a data-centric analytic processing engine for large data warehouses. **SIGMOD 2010**]



Physical Plan Operators

Overview Plan Operators

- **Multiple Physical Operators**
  - **Different physical operators** for different data and query characteristics
  - Physical operators can have vastly different costs

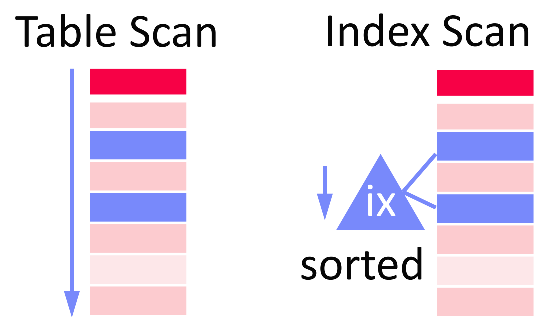
- **Examples** (supported in most DBMS)

	Selection	Projection	Grouping	Join
Logical Plan Operators	$\sigma_p(R)$	$\pi_A(R)$	$\gamma_{G:agg(A)}(R)$	$R \bowtie_{R.a=S.b} S$

Physical Plan Operators	`TableScan`
	`IndexScan`
	ALL
		ALL	`SortGB`
			`HashGB`
				`NestedLoopJN`
				`SortMergeJN`
				`HashJN`

Table and Index Scan

- **Table Scan vs Index Scan**
  - For highly selective predicates, index scan **asymptotically much better** than table scan
  - Index scan **higher per tuple overhead** (break even ~5% output ratio)



- **Index Scan**
  Example $\sigma_{7 \leq A \leq 106}(R)$
  - IX ASC on A

```
void open() { IX.open(); }

void close() { IX.close(); }

Record next() {
  if(r == null)
    return r=IX.get(Low);       // A=7
  if((r=IX.next()).K ≤ Upper) // A≤106
    return r;
  return EOF;
}
```

- **RID List Handling**
  - IX often returns TIDs
  - Fetch, Sort + Fetch
  - **AND:** RIDs(x) ∩ RIDs(y)
  - **OR:** RIDs(x) ∪ RIDs(y)

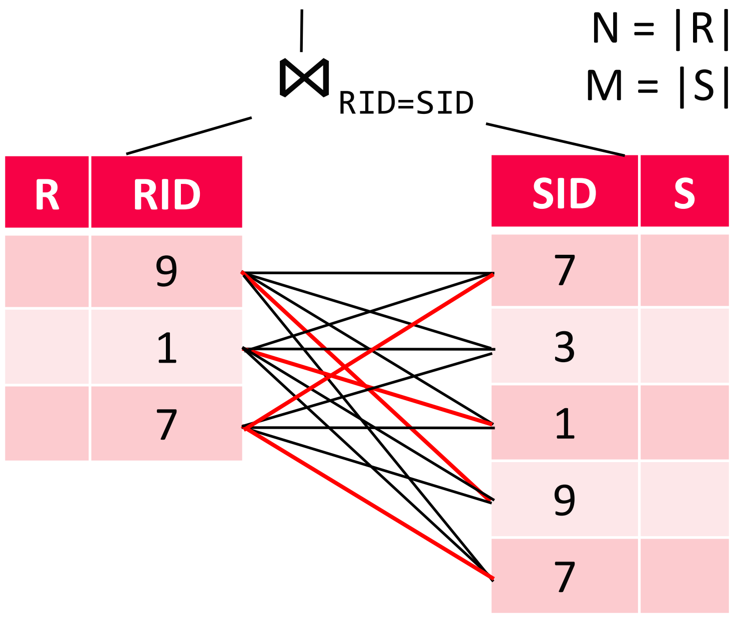
Nested Loop Join

- **Overview**
  - Most general join operator (no order, no indexes, arbitrary predicates θ)
  - Poor asymptotic behavior (very slow)

- **Algorithm** (pseudo code)

```
for each s in S
  for each r in R
    if( r.RID θ s.SID )
      emit concat(r, s)
```

How to implement **next()**?



- **Complexity**
  - Complexity: Time: **O(N * M)**, Space: **O(1)**
  - Pick smaller table as inner if it fits entirely in memory (buffer pool)

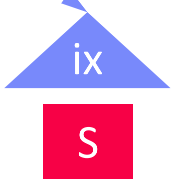
Block Nested Loop / Index Nested Loop Joins

- **Block Nested Loop Join**
  - Avoid I/O by blocked data access
  - Read blocks of b_R and b_S R and S pages
  - Complexity unchanged but potentially much fewer scans

```
for each block b_R in R
  for each block b_S in S
    for each r in b_R
      for each s in b_S
        if( r.RID θ s.SID )
          emit concat(r, s)
```

- **Index Nested Loop Join**
  - Use index to locate qualifying tuples (==, >=, >, <=, <)
  - Complexity (for equivalence predicates): Time: **O(N * log M)**, Space: **O(1)**

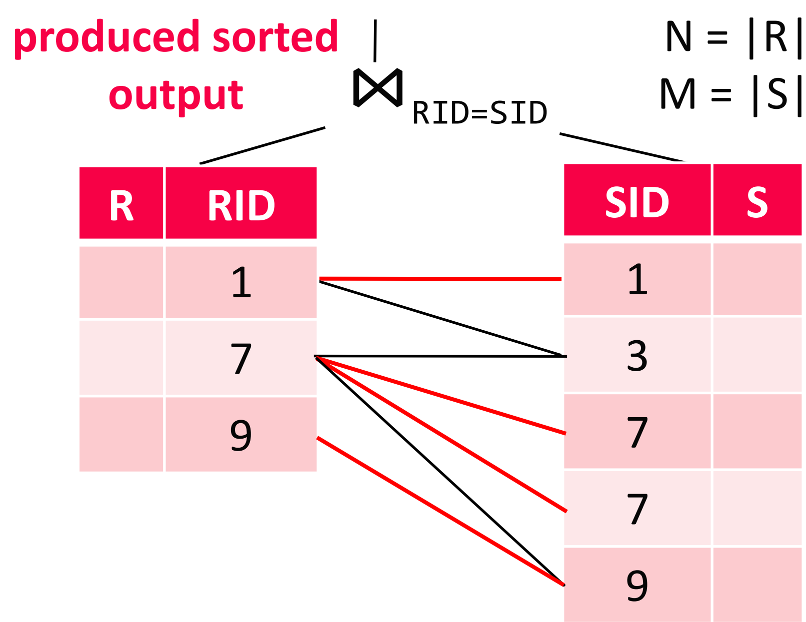
```
for each r in R
  for each s in S.IX(θ,r.RID)
    emit concat(r,s)
```



Sort-Merge Join

- **Overview**
  - **Sort Phase:** sort the input tables R and S (w/ external sort algorithm)
  - **Merge Phase:** step-wise merge with lineage scan
- **Algorithm** (Merge, PK-FK)

```
Record next() {
  while( curR!=EOF && curS!=EOF ) {
    if( curR.RID < curS.SID )
      curR = R.next();
    else if( curR.RID > curS.SID )
      curS = S.next();
    else if( curR.RID == curS.SID ) {
      t = concat(curR, curS);
      curS = S.next(); //FK side
      return t;
  } }
  return EOF;
}
```



- **Complexity**
  - Time (unsorted vs sorted): O(N log N + M log M) vs O(N + M)
  - Space (unsorted vs sorted): O(N + M) vs O(1)

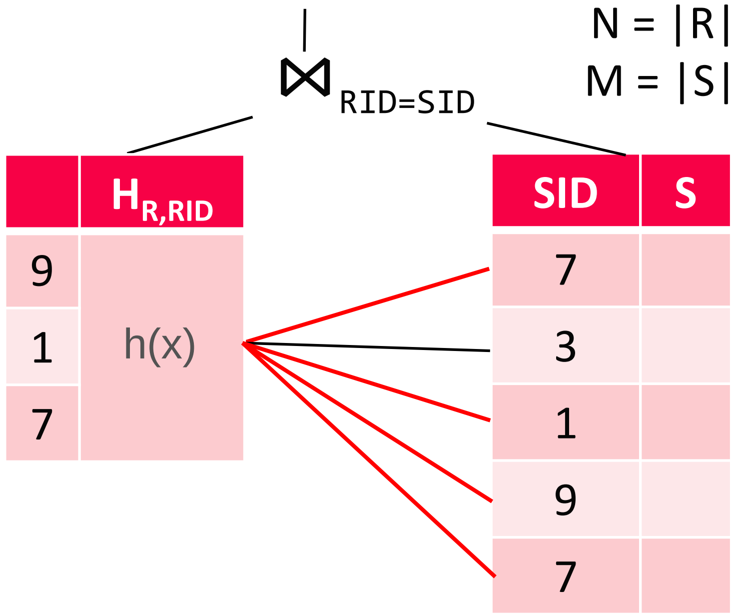
Hash Join

- **Overview**
  - **Build Phase:** read table S and build a hash table H_S over join key
  - **Probe Phase:** read table R and probe H_S with the join key
- **Algorithm** (Build+Probe, PK-FK)

```
Record next() {
  // build phase (first call)
  while( (r = R.next()) != EOF )
    Hr.put(r.RID, r);

  // probe phase
  while( (s = S.next()) != EOF )
    if( Hr.containsKey(s.SID) )
      return concat(Hr.get(s.SID), s);

  return EOF;
}
```

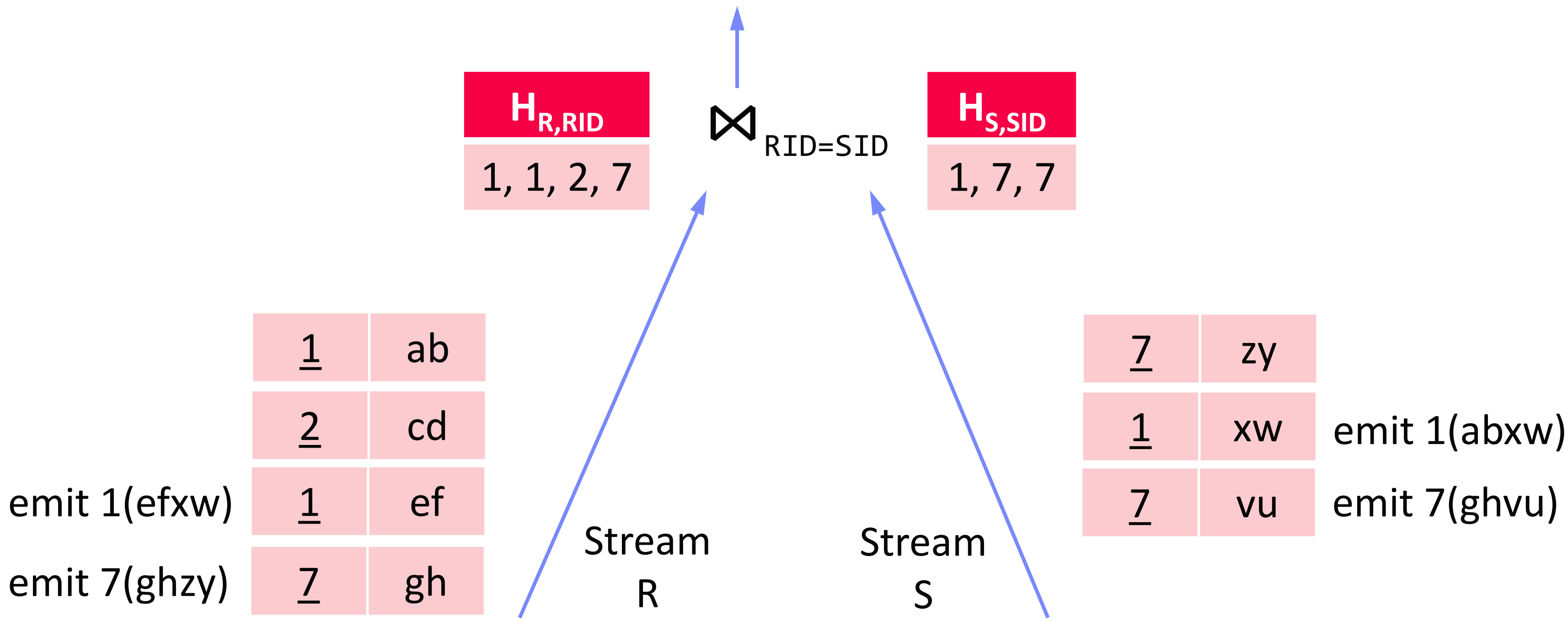


- **Complexity**
  - Time: O(N + M), Space: O(N)
  - Classic hashing: p in-memory partitions of Hr w/ p scans of R and S

Double-Pipelined Hash Join

[Zachary G. Ives, Daniela Florescu, Marc Friedman, Alon Y. Levy, Daniel S. Weld: An Adaptive Query Execution System for Data Integration. **SIGMOD 1999**]

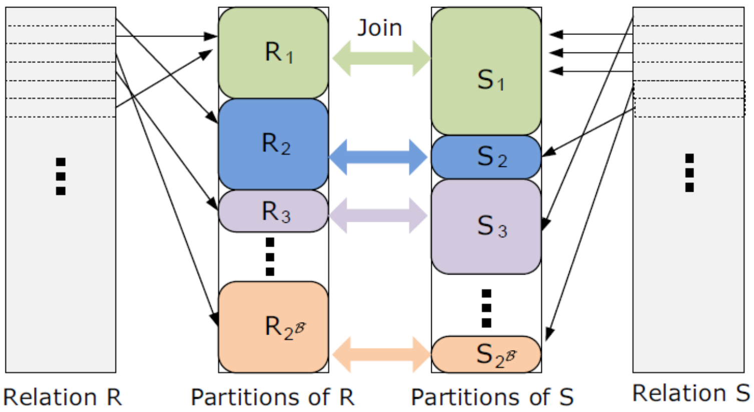
- **Overview and Algorithm**
  - Join of bounded streams (or unbounded w/ time-based invalidation)
  - **Equi join predicate**, **symmetric and non-blocking**
  - For every incoming tuple (e.g. left): probe (right)+emit, and build (left)



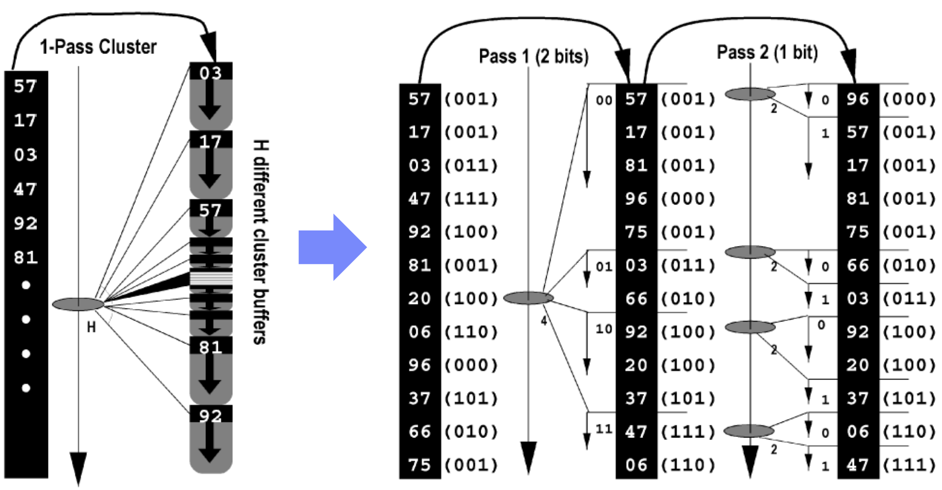
Partitioned Hash Join

[**Credit:** Changkyu Kim et al, VLDB'09]

- **Range-Partitioned**
  - Co-partitioning tuples from R and S into partitions defined by key ranges
  - Local hash join over partitions
  - Fit local hash table in caches
  - Partitioning shuffles rows/RIDs



- **Radix Hash Join**
  - Multi-pass radix partitioning (first 2,3,etc bits of hash)
  - Better locality during partitioning (TLB, L1/L2)



[Stefan Manegold, Peter A. Boncz, Martin L. Kersten: Optimizing Main-Memory Join on Modern Hardware. IEEE Trans. Knowl. **Data Eng. 14(4) 2002**]

Hash vs Sort-Merge Joins, Revisited … Revisited

- **PVLDB'09**

[Changkyu Kim et al: Sort vs. Hash **Revisited**: Fast Join Implementation on Modern Multi-Core CPUs. **PVLDB 2(2) 2009**]

- **PVDLB'12**

[Martina-Cezara Albutiu et al: Massively Parallel Sort-Merge Joins in Main Memory Multi-Core Database Systems. **PVLDB 5(10) 2012**]

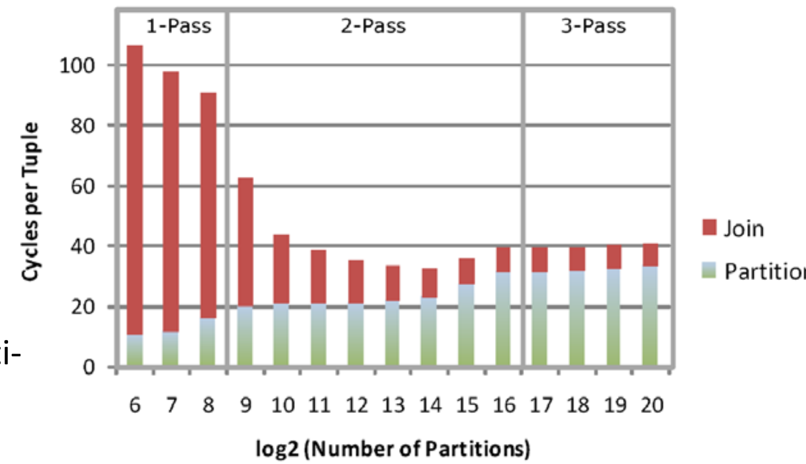
- **PVLDB'13 / TKDE'15**

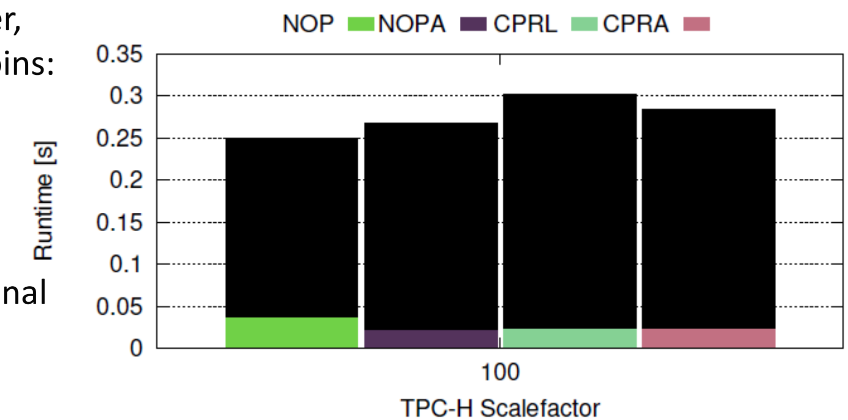
[Cagri Balkesen, Gustavo Alonso, Jens Teubner, M. Tamer Özsu: Multi-Core, Main-Memory Joins: Sort vs. Hash **Revisited**. **PVLDB 7(1) 2013**]

- **SIGMOD'16**

[Stefan Schuh, Xiao Chen, Jens Dittrich: An Experimental Comparison of **Thirteen** Relational Equi-Joins in Main Memory. **SIGMOD 2016**]

- **Interesting Perspective**
  - Large-small table joins
  - Comparison by query runtime



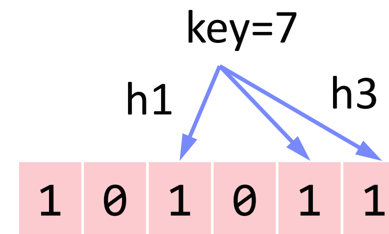


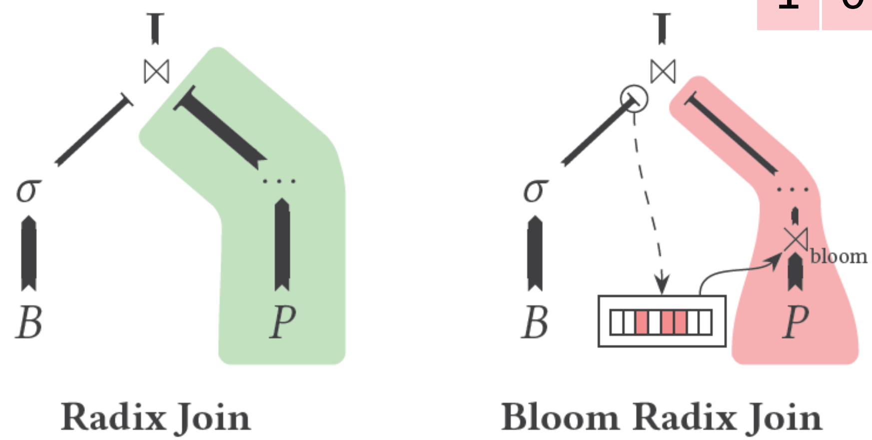
[Thomas Neumann: Comparing Join Implementations, http://databasearchitects.blogspot.com/2016/04/comparing-join-implementations.html, **04/2016**]

Bloom Filters

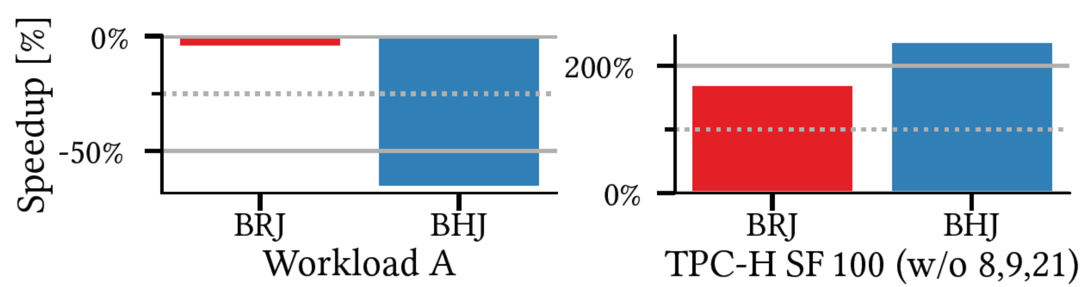
[Maximilian Bandle, Jana Giceva, Thomas Neumann: To partition, or not to partition, that is the join question in a real system, **SIGMOD 2021**]

- **Bloom Radix-Partitioned Join (BRJ)**
  - Motivation: partitioning probe side can be very expensive
  - Second partitioning pass of build side materializes the bloom filter
  - Filter probe side before partitioning



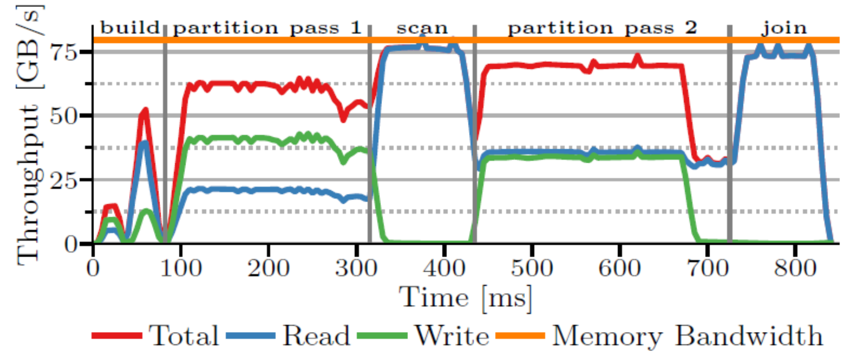


- **Comparison w/ Bloom Filter over RJ**
  - Micro: negative
  - TPC-H: positive

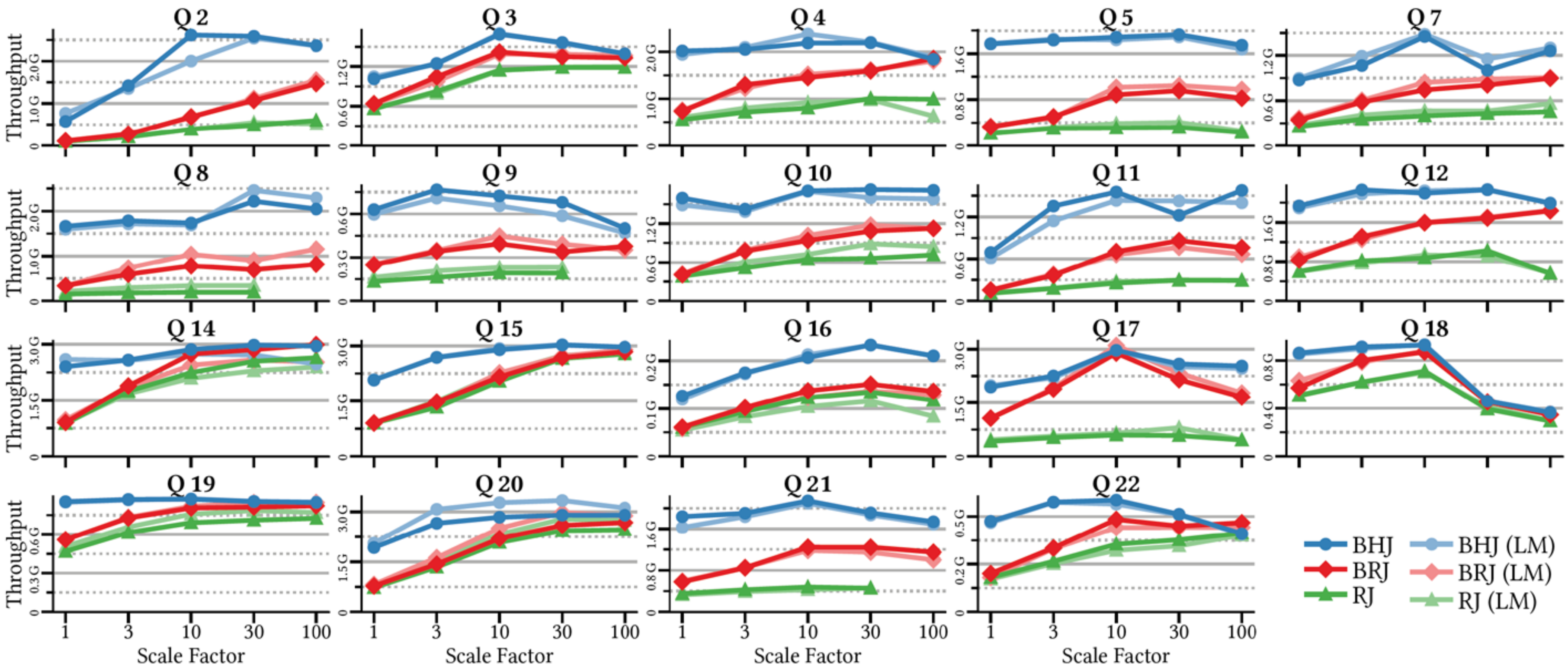


Experiments

- **Micro Benchmarks RJ, BRJ, BHJ**
  - https://github.com/opcm/pcm



- **TPC-H Benchmark**



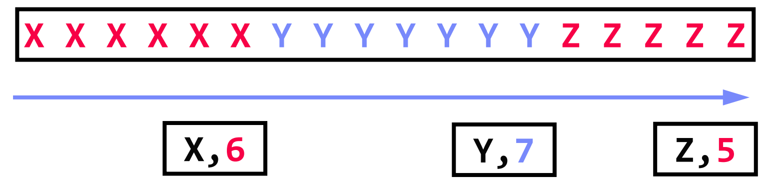
Sort-GroupBy and Hash-GroupBy

- **Recap: Classification of Aggregates (DM, DIA)**
  - Additive, semi-additive, additively-computable, others

$\gamma_{A,\texttt{count(*)}}(R)$

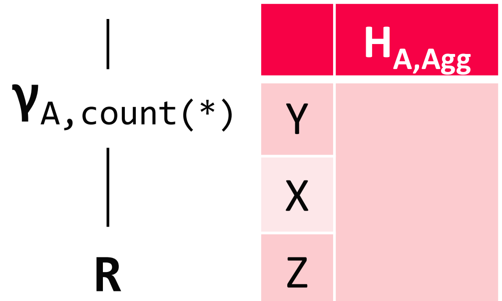
- **Sort Group-By**
  - Similar to sort-merge join (Sort, GroupAggregate)
  - Sorted group output

sort
O(N log N)
aggregate
O(N)



- **Hash Group-By**
  - Similar to hash join (HashAggregate)
  - Higher temporary memory consumption
  - Unsorted group output
  - **#1** w/ **tuple grouping**
  - **#2** w/ **direct aggregation** (e.g., count)
  - **Beware:** cache-unfriendly if many groups (size(H) > L2/L3 cache)

build & agg
O(N)



Summary and **Q&A**

- **Overview Query Processing**
- **Plan Execution Strategies**
- **Physical Plan Operators**

- **Next Lectures** (Part B)
  - **07 Query Compilation and Parallelization** [Nov 17]
  - **08 Query Optimization I** (rewrites, costs, join ordering) [Nov 24]
  - **09 Adaptive Query Processing** [Dec 01]