Programmierpraktikum: Datensysteme
02 Background Query Processing

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Announcements / Org

- **#1 Hybrid & Video Recording**
  - Hybrid lectures (in-person, zoom) with optional attendance
    https://tu-berlin.zoom.us/j/9529634787?pwd=R1ZsN1M3SC9BOU1OcFdmem9zT202UT09
  - Zoom **video recordings**, links from website
    https://mboehm7.github.io/teaching/ss26_ppds/index.htm

- **#2 Reminder Project Work**
  - Selection deadline passed **Apr 19**
  - Team assignments for DAMS groups (DAMS1-DAMS5) sent out **Apr 27**

Q&A

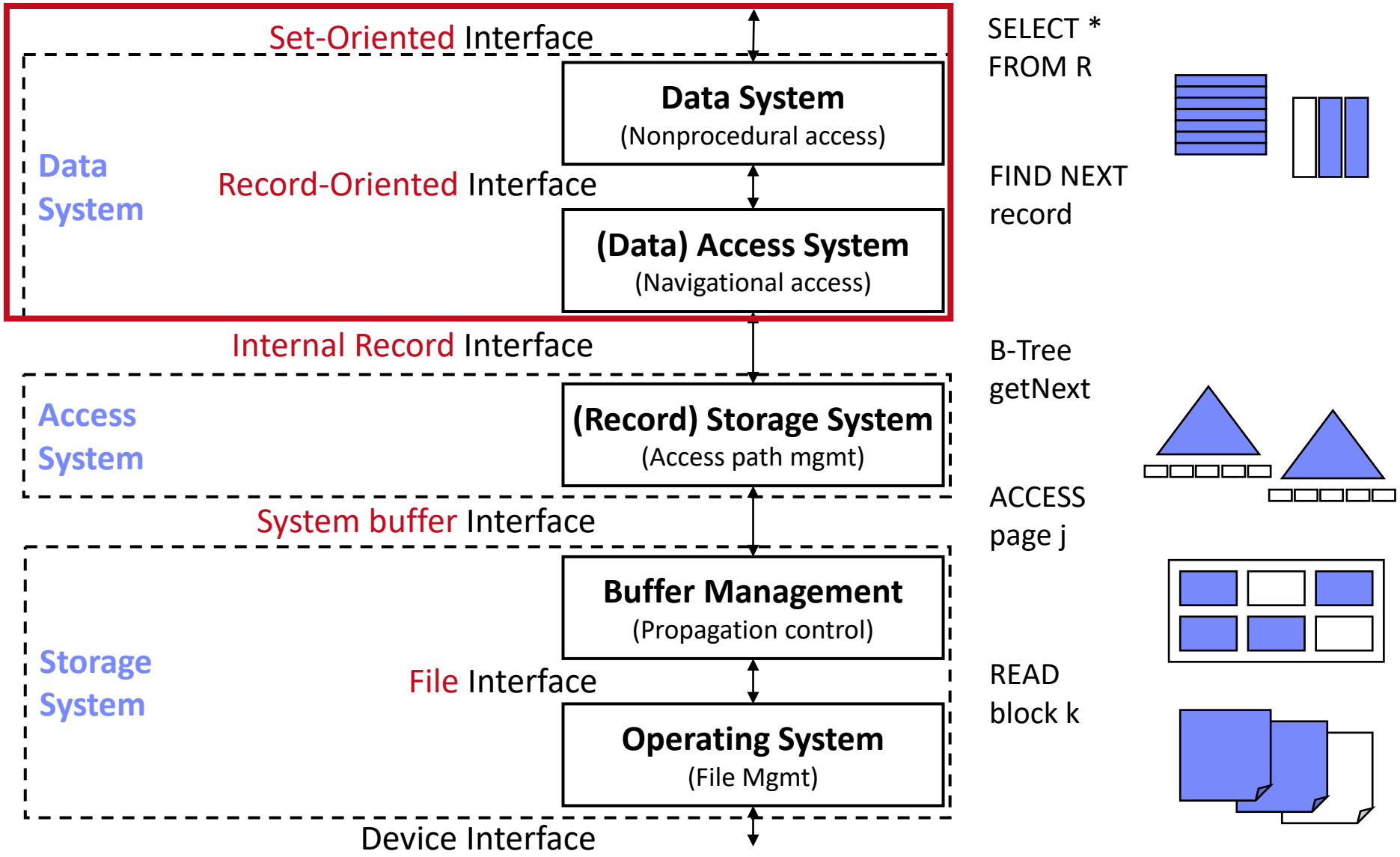
Agenda

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

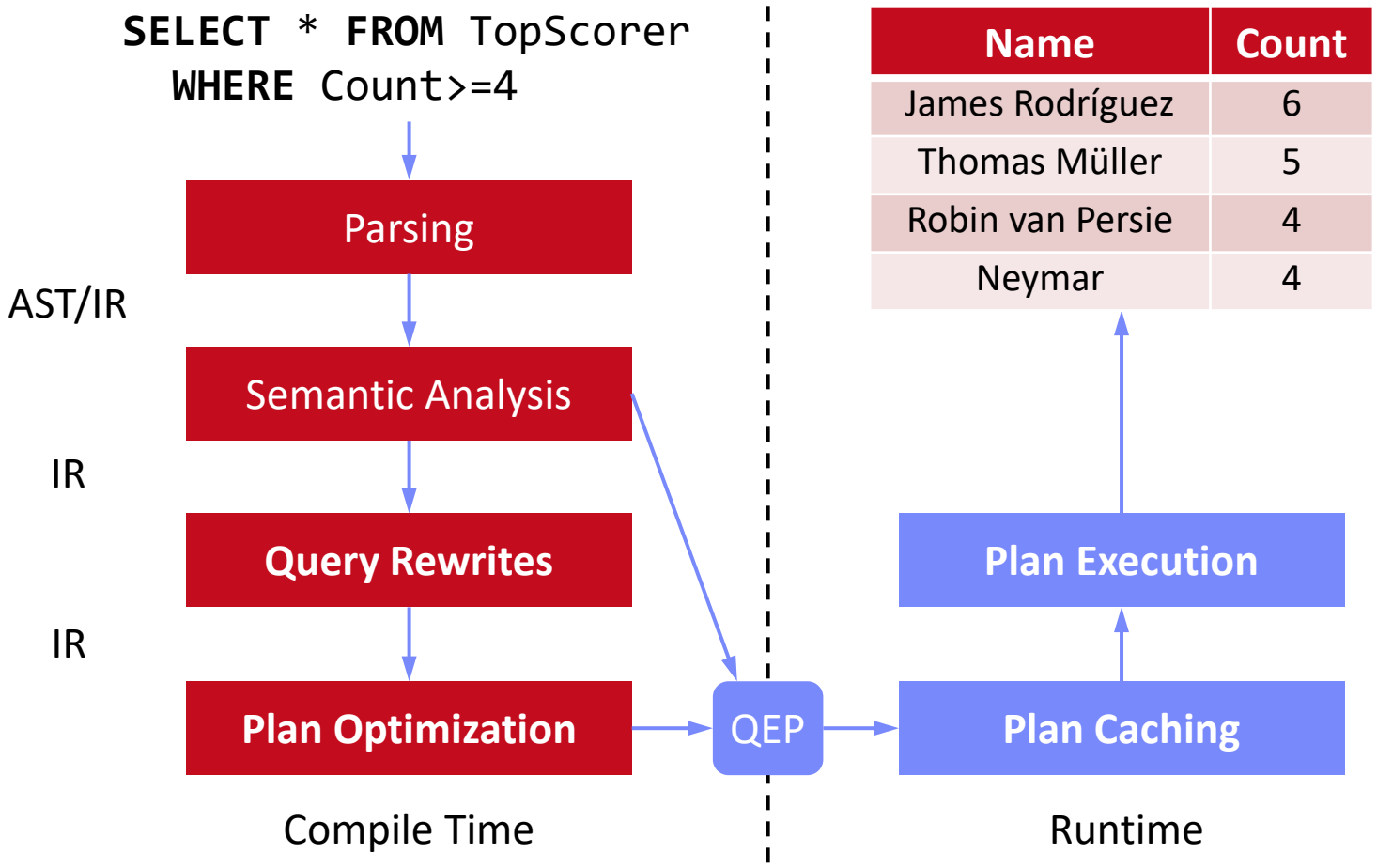
Overview Query Processing

DBMS System Architecture

[Theo Härder, Erhard Rahm: Datenbank-systeme: Konzepte und Techniken der Implementierung, **2001**]



Overview Query Processing



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

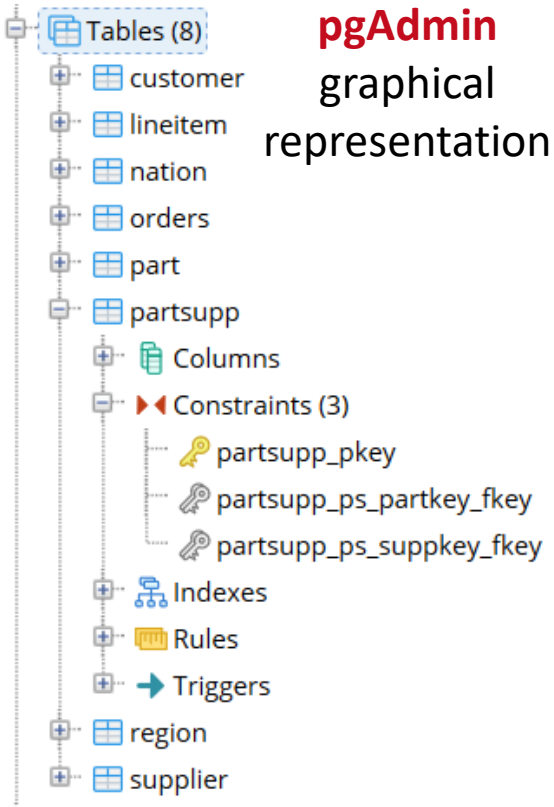
Database Catalog

[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
  - Defined as views over PostgreSQL catalog tables
  - **Example:** check for existence of accessible table

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



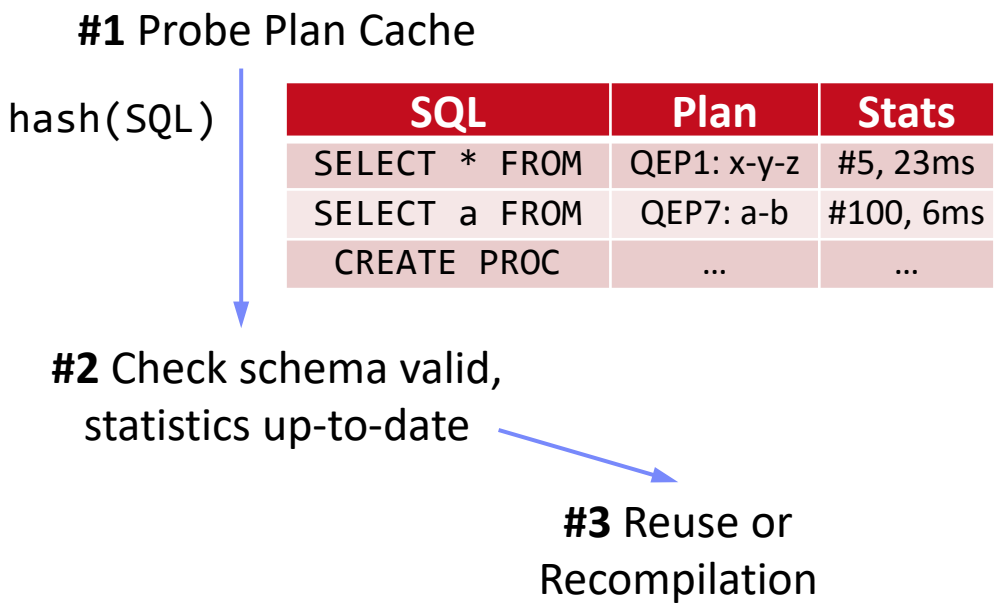
pgAdmin graphical representation

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

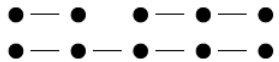
- **Examples:** MS SQL Server, IBM DB2



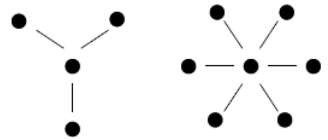
Query and Plan Types

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

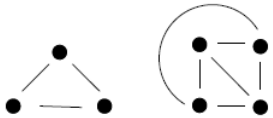
- **Query Types**
  - **Nodes:** Tables
  - **Edges:** Join conditions
  - Determine **hardness of query optimization** (w/o cross products)



Chains



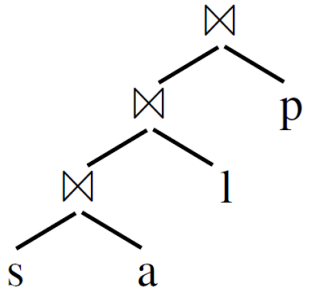
Stars



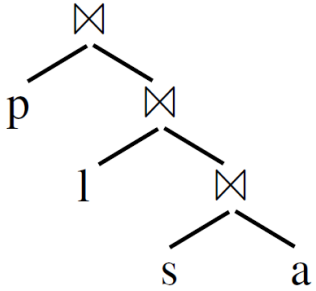
Cliques

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

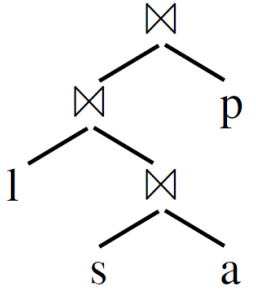
Left-Deep Tree



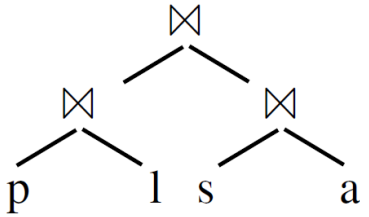
Right-Deep Tree



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 – Overview

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

- **Volcano Iterator Model**
  - **Open-Next-Close** (ONC) interface
  - Query execution from root node (pull-based) → **Pipelined**

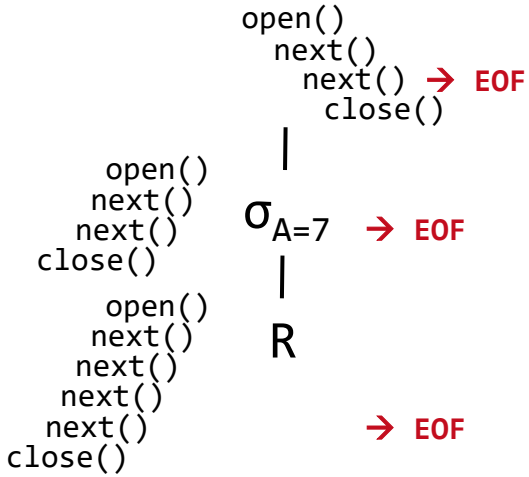
Scalable (small memory)
High CPI measures

- **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;
}
```



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

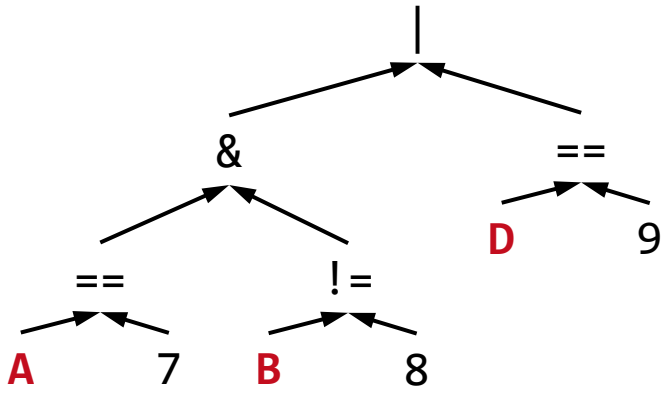
- **Blocking Operators**
  - Sorting, grouping/aggregation, build-phase of (simple) hash joins

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)

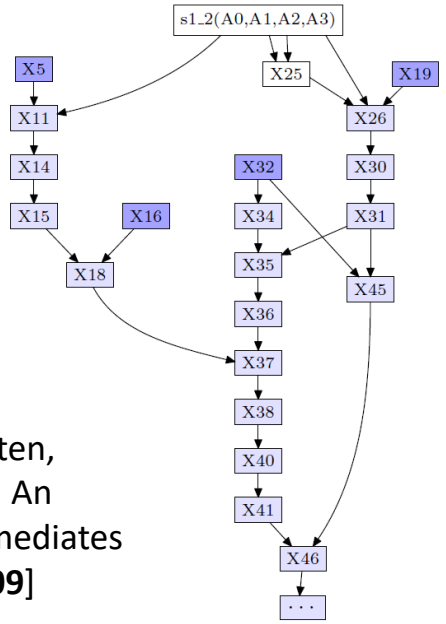
- **Example Selection σ**
  - $(A = 7 \wedge B \neq 8) \vee D = 9$

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;
```

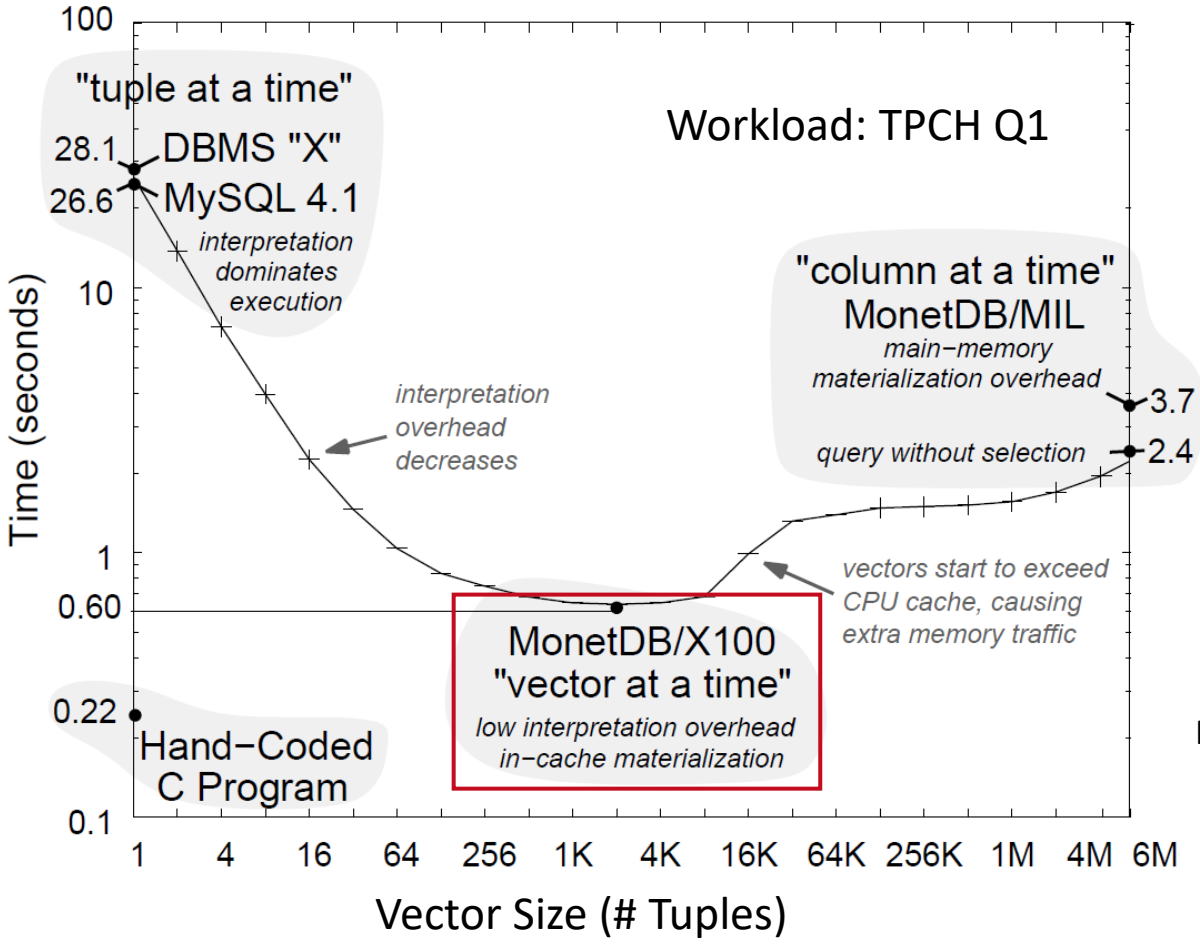
Binary Association Tables (BATs:=OID/Val)

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

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

Vectorized Execution (vector-at-a-time)

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



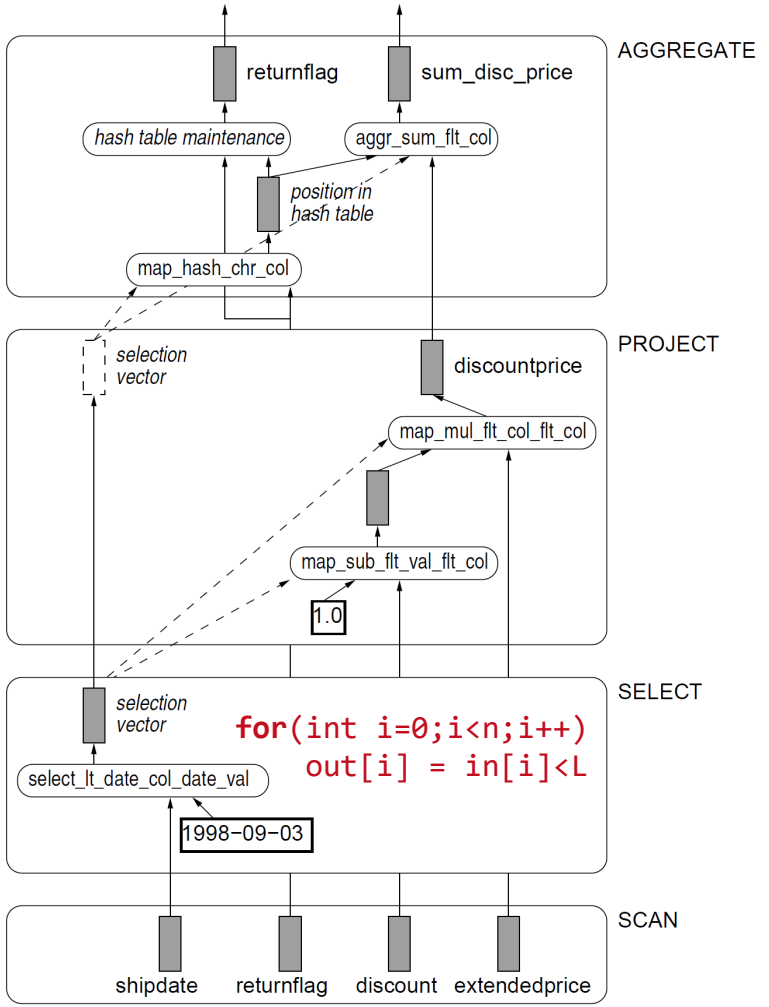
Column-oriented storage
Efficient array operations
Memory/cache efficiency
DAG processing
Reuse of intermediates

[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**



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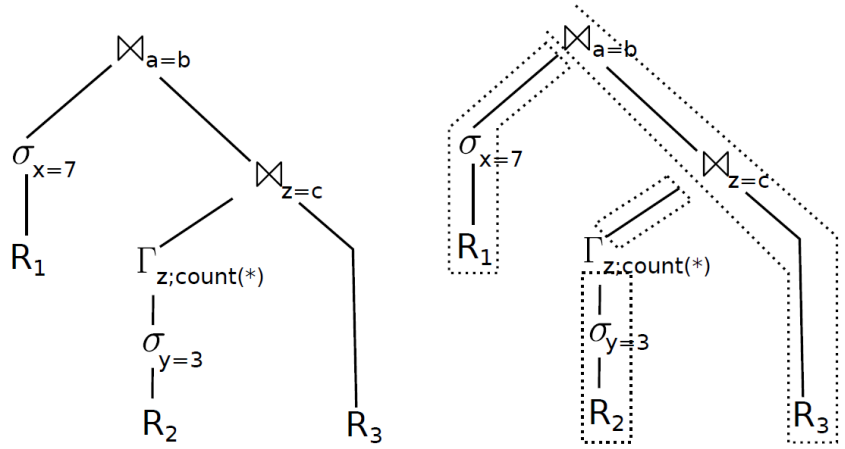
[Marcin Zukowski, Peter A. Boncz, Niels Nes, Sándor Héman: MonetDB/X100 - A DBMS In The CPU Cache. **IEEE Data Eng. Bull. 2005**]

Query Compilation

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

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



Compiled Query
(conceptual, not LLVM)

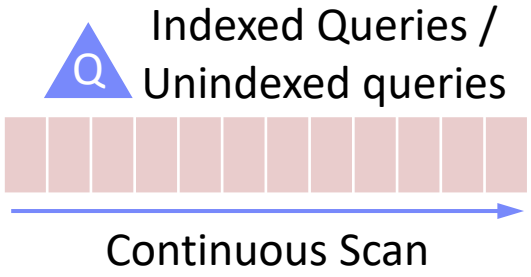
initialize memory of $\bowtie_{a=b}$, $\bowtie_{c=z}$, and Γ_z
for each tuple t in R_1
  if $t.x = 7$
    materialize t in hash table of $\bowtie_{a=b}$
for each tuple t in R_2
  if $t.y = 3$
    aggregate t in hash table of Γ_z
for each tuple t in Γ_z
  materialize t in hash table of $\bowtie_{z=c}$
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**]

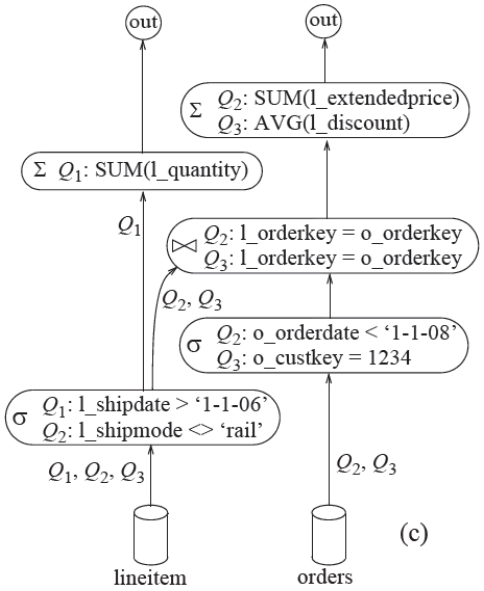
Data-Centric / Continuous Scan Processing

- **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 (bit-strings to map 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

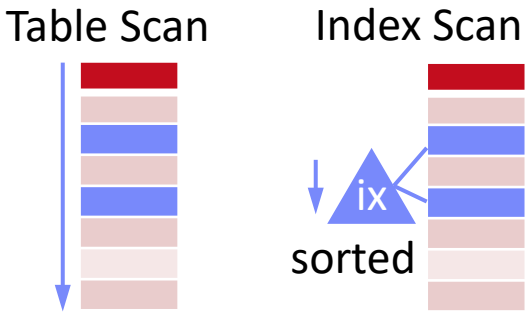
- **Examples** (supported in most DBMS)

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

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

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

```
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;
}
```

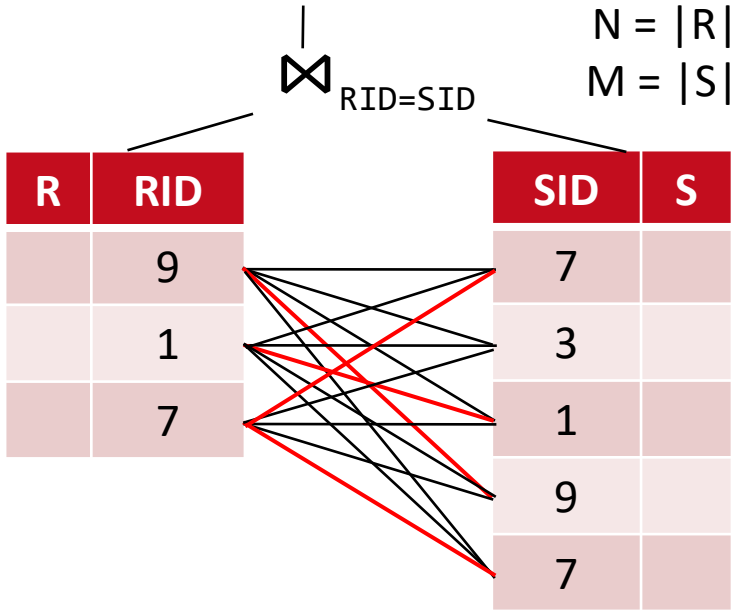
Nested Loop Join

- **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)

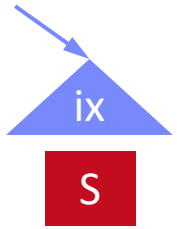
Block Nested Loop / Index Nested Loop Joins

- **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)
```

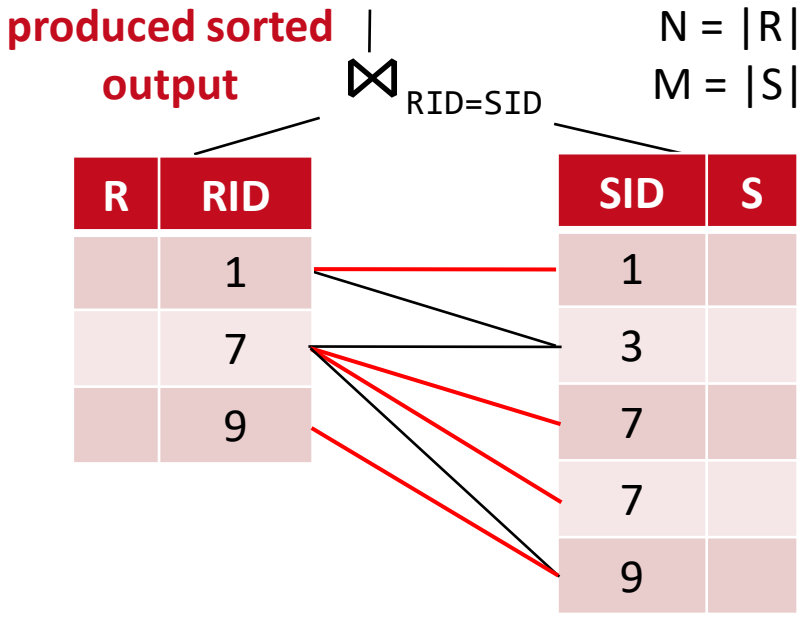


Sort-Merge Join

- **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

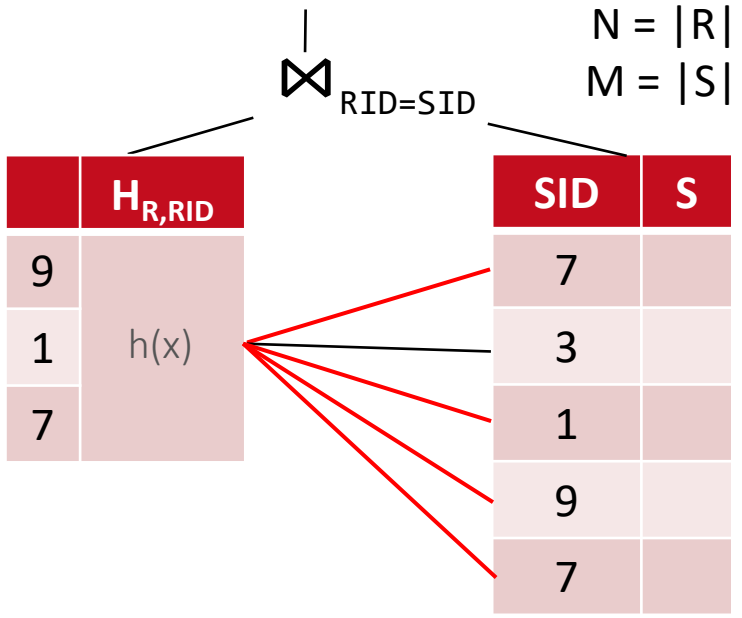
- **Overview**
  - **Build Phase:** read table S and build a hash table H_S over join key
  - **Probe Phase:** read table R and probe H_S with the join key

- **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;
}
```

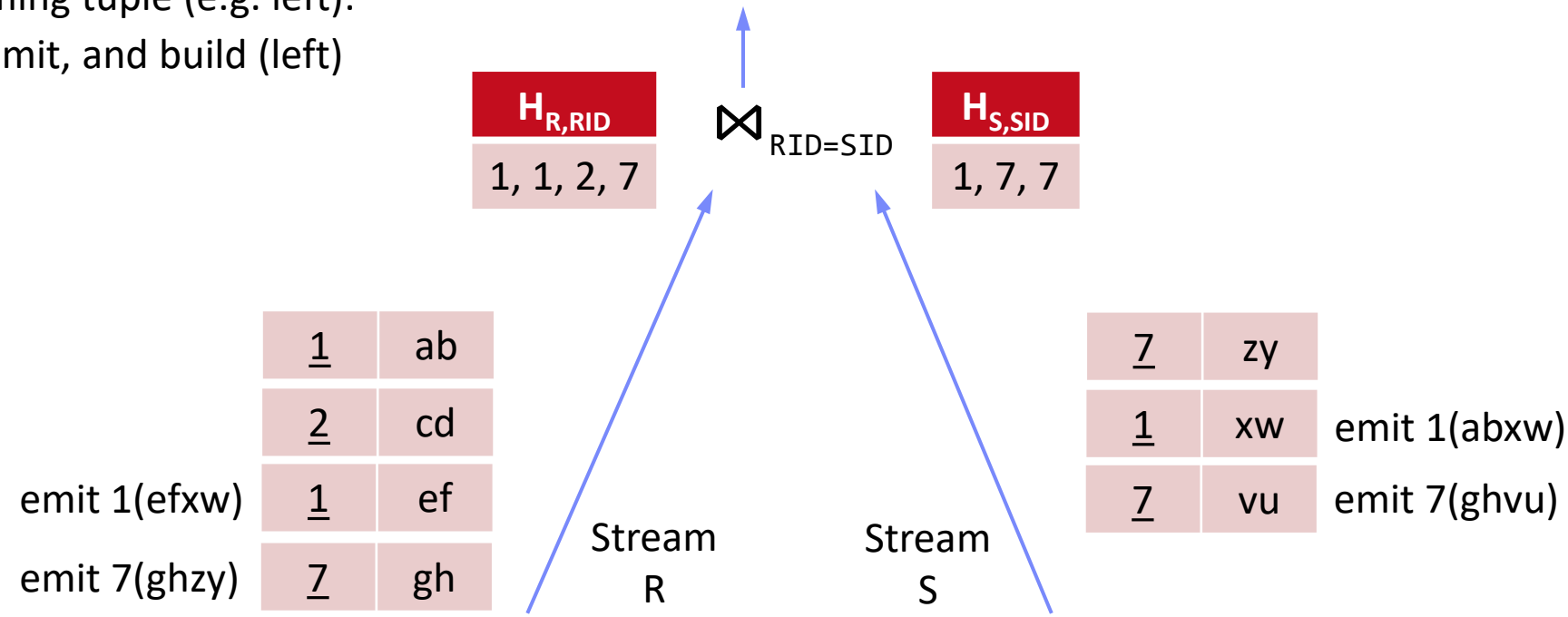


- **Complexity**
  - Time: O(N + M), Space: **O(N)**
  - Classic hashing: p in-memory partitions of Hr w/ p scans of R and S

Double-Pipelined Hash Join

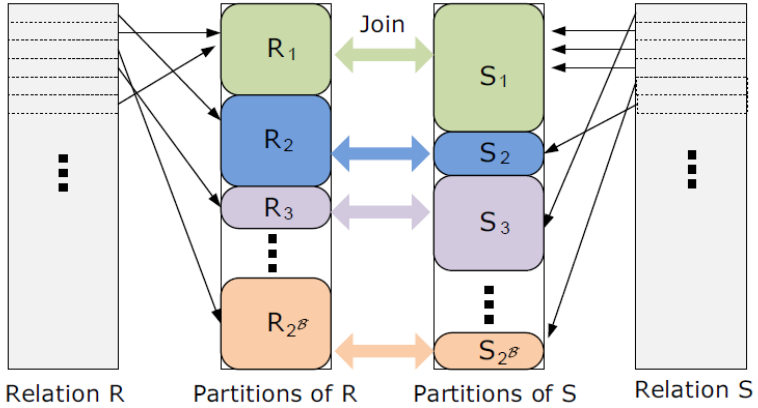
[Zachary G. Ives, Daniela Florescu, Marc Friedman, Alon Y. Levy, Daniel S. Weld: An Adaptive Query Execution System for Data Integration. **SIGMOD 1999**]

- **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)



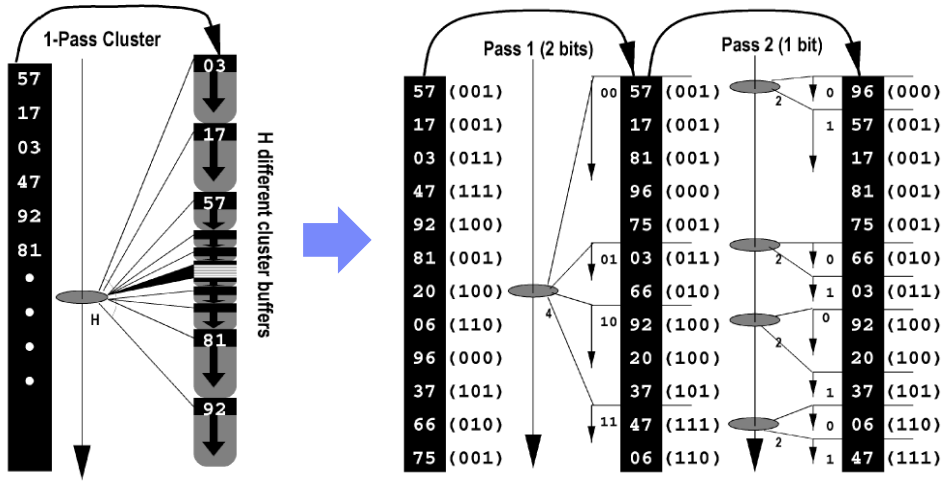
Partitioned Hash Join

- **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



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

- **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**

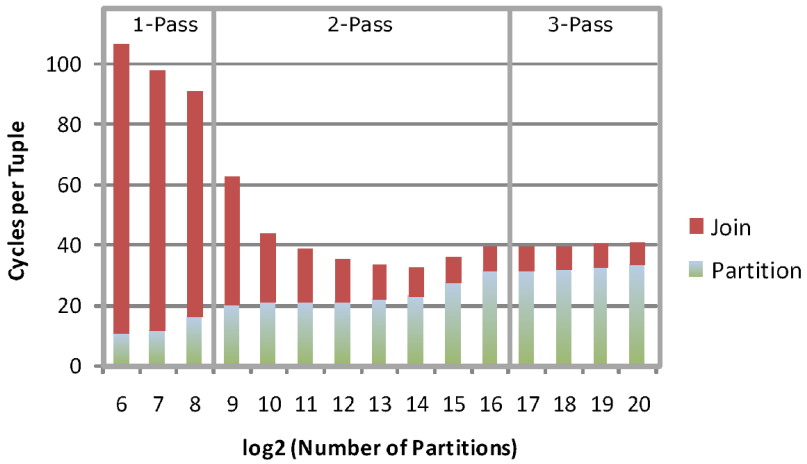
[Cagri Balkesen, Gustavo Alonso, Jens Teubner, M. Tamer Özsu: Multi-Core, Main-Memory Joins: Sort vs. Hash **Revisited**. **PVLDB 7(1) 2013**]

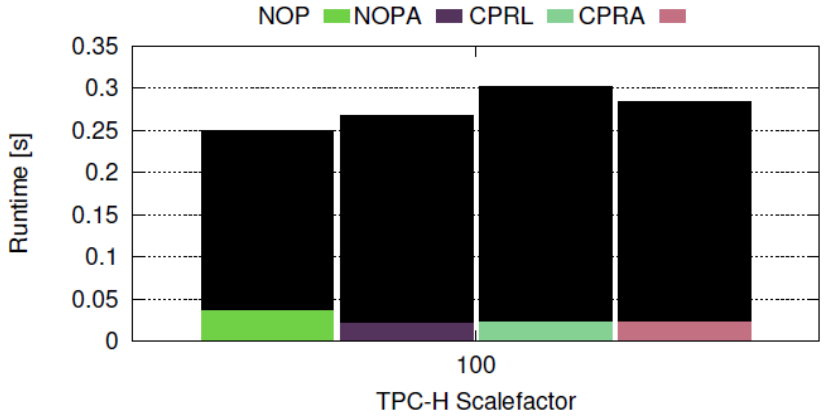
- **SIGMOD'16**

[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
  - Compare query runtime

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

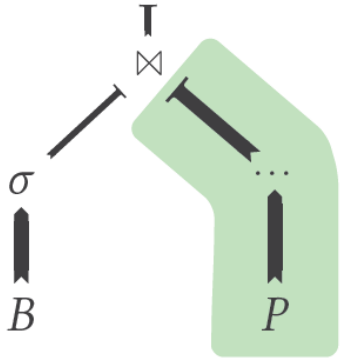




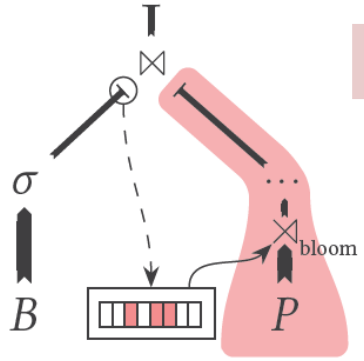
Bloom Filters

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

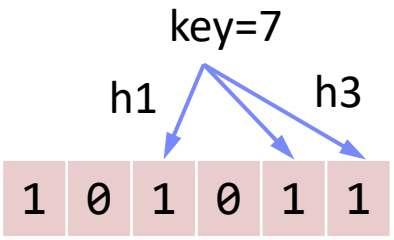
- **Bloom Radix-Partitioned Join (BRJ)**
  - **Motivation:** partitioning probe side can be very expensive
  - Second partitioning pass of build side materializes the **bloom filter**
  - Filter probe side before partitioning



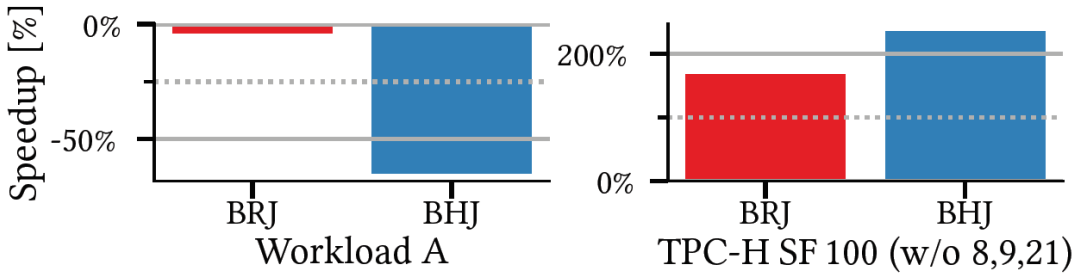
Radix Join



Bloom Radix Join

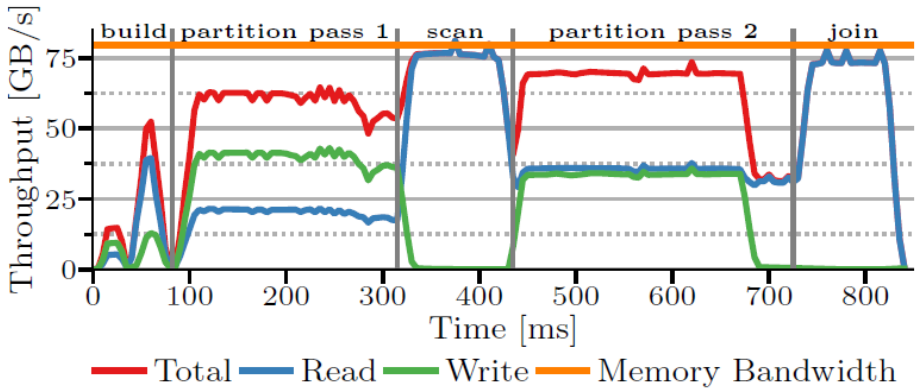


- **Comparison w/ Bloom Filter over RJ**
  - Micro: negative
  - TPC-H: positive

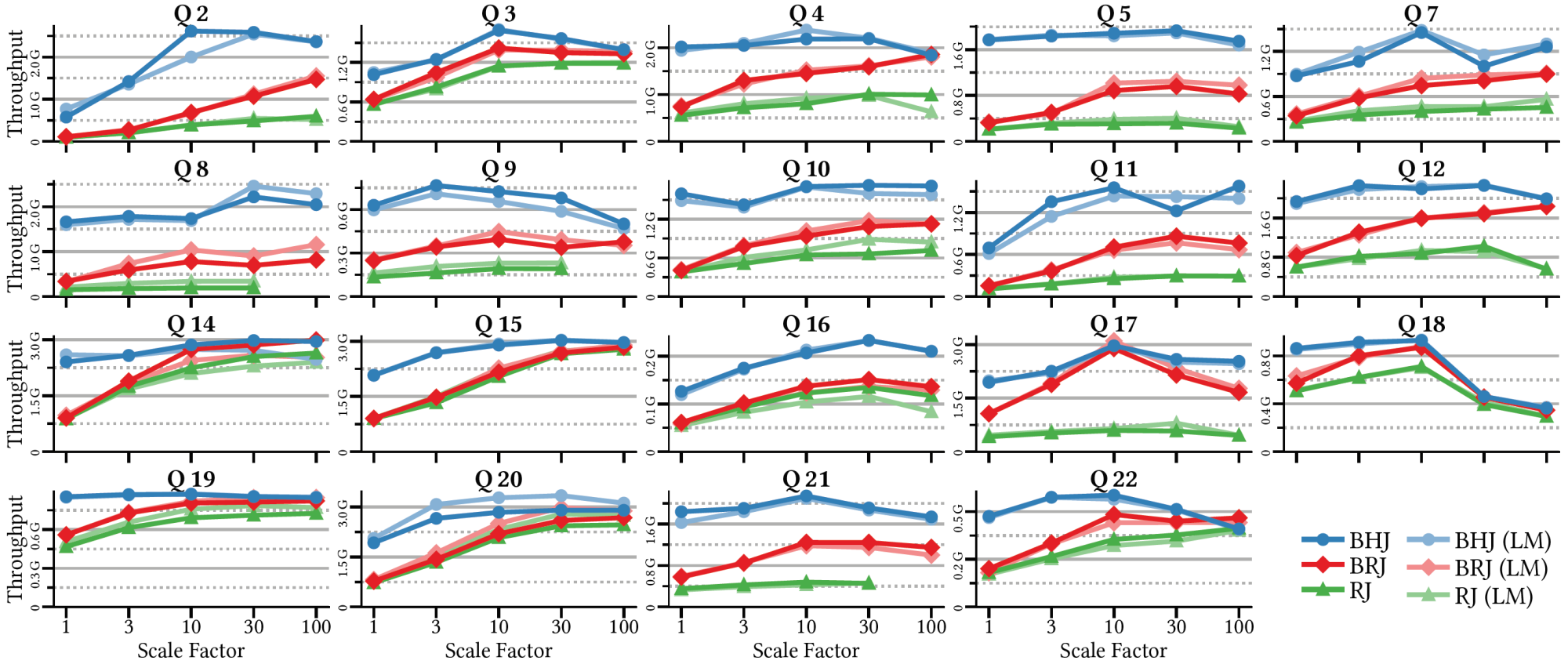


Experiments

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



- **TPC-H Benchmark**

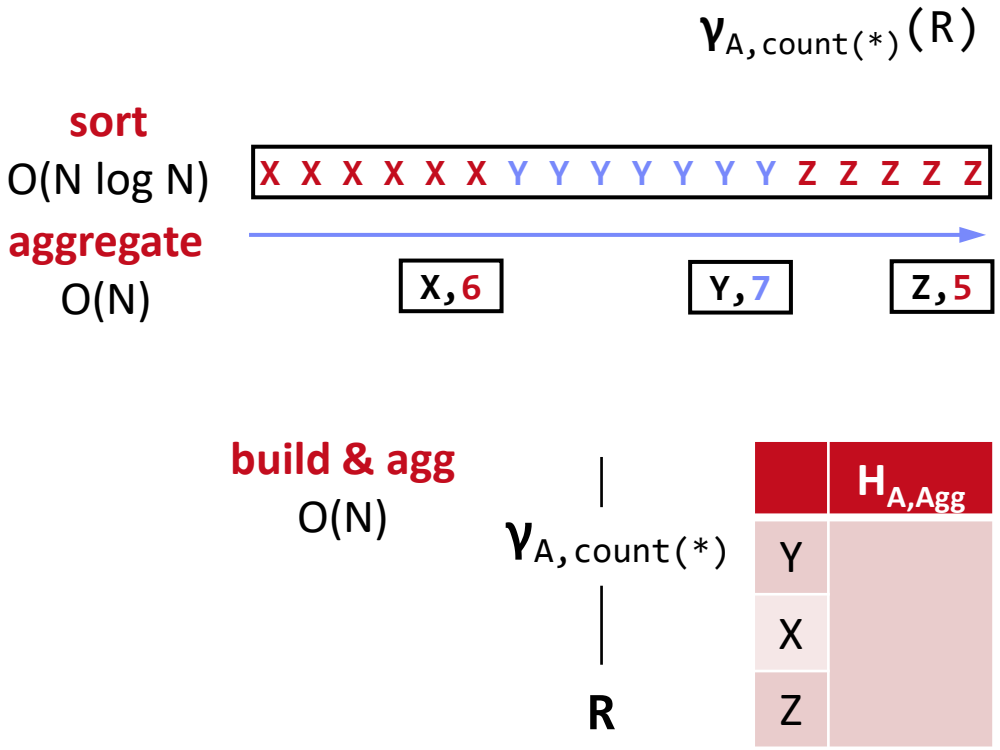


Sort-GroupBy and Hash-GroupBy

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

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

- **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)



Summary & QA

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

Thanks

- Next Lectures
  - **03** Background Query Compilation and Parallelization [May 11]
  - **04** Background Query Optimization [Jun 08]
  - **05** Experiments and Reproducibility [**Jun 22**]

➔ **Please contact your team members and get started**