Parallel Hash Join

Recap

Scheduling

- For each query plan, the DBMS must decide where, when, and how to execute it.
  - How many tasks should it use?
  - How many CPU cores should it use?
  - What CPU core should the tasks execute on?
  - Where should a task store its output?
- The DBMS always knows more than the OS.

Join Algorithms: Summary

Join Algorithm	IO Cost	Example
Simple Nested Loop Join	M + (m x N)	1.3 hours
Block Nested Loop Join	M + (M x N)	50 seconds
Index Nested Loop Join	M + (M x C)	Variable
Sort-Merge Join	M + N + (sort cost)	0.75 seconds
Hash Join	3 x (M + N)	0.45 seconds

Today's Agenda

- Background
- Partition Phase
- Build Phase
- Probe Phase
- Evaluation

Background

Parallel Join Algorithms

- Perform a join between two relations on multiple threads simultaneously to speed up operation.
- Two main approaches:
  - **Hash Join**
  - **Sort-Merge Join**
- We won't discuss nested-loop joins.

Observation

- Many OLTP DBMSs do **not** implement hash join.
- But an **index nested-loop join** with a small number of target tuples is at a high-level equivalent to a hash join.

Hashing vs. Sorting

- 1970s – Sorting (External Merge-Sort)
- 1980s – Hashing (Database Machines)
- 1990s – Equivalent
- 2000s – Hashing (For Unsorted Data)
- 2010s – Hashing (Partitioned vs. Non-Partitioned)
- 2020s – ???

Parallel Join Algorithms

SORT VS. HASH REVISITED: FAST JOIN IMPLEMENTATION ON MODERN MULTI-CORE CPUS
VLDB 2009
ORACLE intel

→ Hashing is faster than Sort-Merge.
→ Sort-Merge is faster w/ wider SIMD.

DESIGN AND EVALUATION OF MAIN MEMORY HASH JOIN ALGORITHMS FOR MULTI-CORE CPUS
SIGMOD 2011
WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

→ Trade-offs between partitioning & non-partitioning Hash-Join.

MASSIVELY PARALLEL SORT-MERGE JOINS IN MAIN MEMORY MULTI-CORE DATABASE SYSTEMS
VLDB 2012
HyPer

→ Sort-Merge is already faster than Hashing, even without SIMD.

MASSIVELY PARALLEL NUMA-AWARE HASH JOINS
IMDM 2013
HyPer

→ Ignore what we said last year.
→ You really want to use Hashing!

MAIN-MEMORY HASH JOINS ON MULTI-CORE CPUS: TUNING TO THE UNDERLYING HARDWARE
ICDE 2013
Systems@ETH zürich

→ New optimizations and results for Radix Hash Join.

AN EXPERIMENTAL COMPARISON OF THIRTEEN RELATIONAL EQUI-JOINS IN MAIN MEMORY
SIGMOD 2016
UNIVERSITÄT DES SAARLANDES

→ Hold up everyone! Let's look at everything more carefully!

Design Goals

- **Goal 1: Minimize Synchronization**
  - Avoid taking latches during execution.
- **Goal 2: Minimize Memory Access Cost**
  - Ensure that data is always local to worker thread.
  - Reuse data while it exists in CPU cache.

Improving Cache Behavior

- Factors that affect cache misses in a DBMS:
  - Cache + TLB capacity.
  - Locality (temporal and spatial).
- **Sequential Access (Scan):**
  - Clustering data to a cache line.
  - Execute more operations per cache line.
- **Random Access (Lookups):**
  - Partition data to fit in cache + TLB.

Parallel Hash Join

- Hash join is the most important operator in a DBMS for OLAP workloads.
- It is important that we speed up our DBMS's join algorithm by taking advantage of multiple cores.
- We will focus on in-memory DBMSs.
    - We want to keep all cores busy, without becoming memory bound.

Hash Join

- **Phase 1: Partition (optional)**
  - Divide the tuples of **R** and **S** into sets using a hash on the join key.
- **Phase 2: Build**
  - Scan relation **R** and create a hash table on join key.
- **Phase 3: Probe**
  - For each tuple in **S**, look up its join key in hash table for **R**. If a match is found, output combined tuple.
- Reference

Partition Phase

Partition Phase

- Split the input relations into partitioned buffers by hashing the tuples' join key(s).
  - Ideally the cost of partitioning is **less** than the cost of cache misses during build phase.
  - *a.k.a.*, **hybrid hash join** / **radix hash join**.
- Contents of buffers depends on storage model:
  - **NSM:** Usually the entire tuple.
  - **DSM:** Only the columns needed for the join + offset.

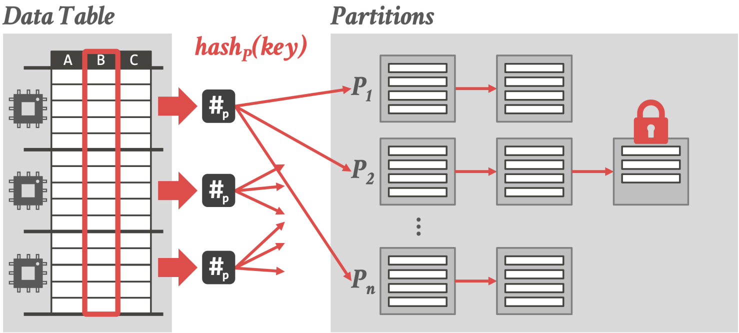
Partition Phase

- **Approach 1: Non-Blocking Partitioning**
  - Only scan the input relation once.
  - Produce output incrementally.
- **Approach 2: Blocking Partitioning (Radix)**
  - Scan the input relation multiple times.
  - Only materialize results all at once.
  - *a.k.a.*, radix hash join.

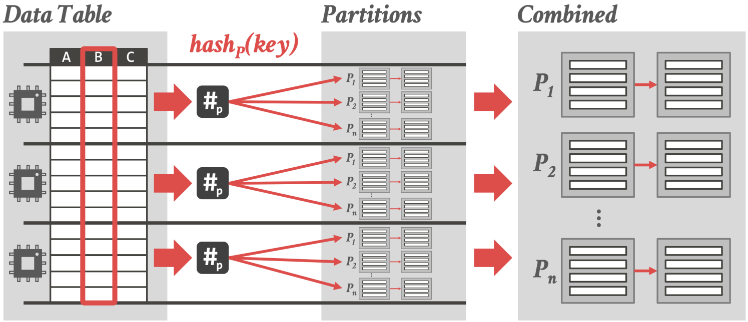
Non-Blocking Partitioning

- Scan the input relation only once and generate the output on-the-fly.
- **Approach 1: Shared Partitions**
  - Single global set of partitions that all threads update.
  - Must use a latch to synchronize threads.
- **Approach 2: Private Partitions**
  - Each thread has its own set of partitions.
  - Must consolidate them after all threads finish.

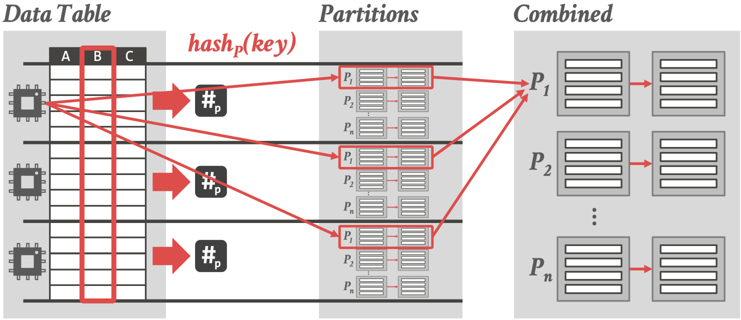
Shared Partitions



Private Partitions



Private Partitions

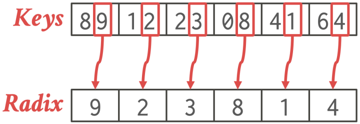


Blocking Partitioning (Radix Partitioning)

- Scan the input relation multiple times to generate the partitions.
- No need to synchronize.
- Multi-step pass over the relation:
  - Step 1: Scan **R** and compute a histogram of the number of tuples per hash key for the radix at some offset.
  - Step 2: Use this histogram to determine output offsets by computing the **prefix sum**.
  - Step 3: Scan **R** again and partition them according to the hash key.

Radix

- The radix of a key is the value of an integer at a position (using its base).



Radix

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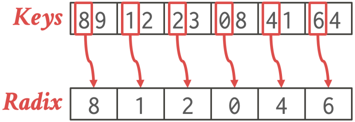
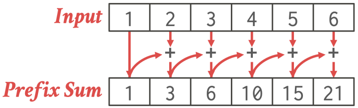
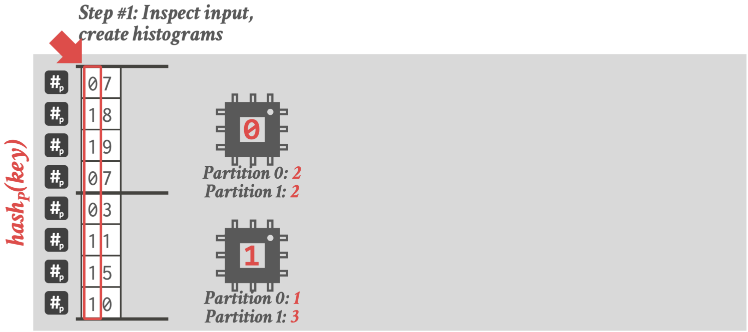


Prefix Sum

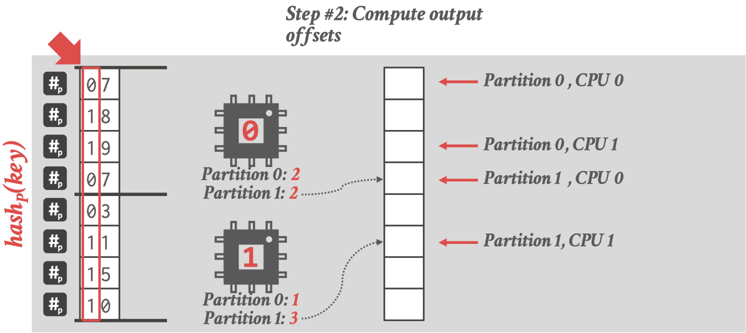
- The **prefix sum** of a sequence of numbers $(x_0, x_1, \ldots, x_n)$ is a second sequence of numbers $(y_0, y_1, \ldots, y_n)$ that is a running total of the input sequence.



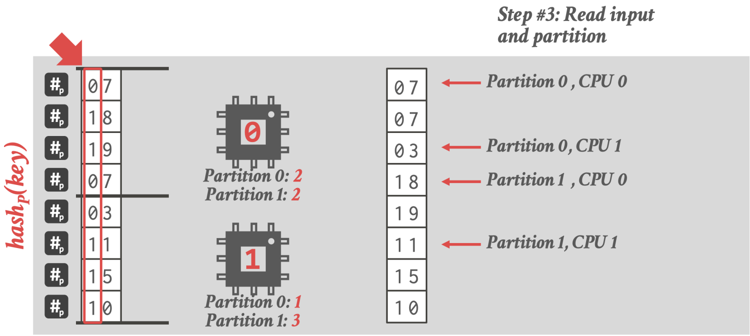
Radix Partitions



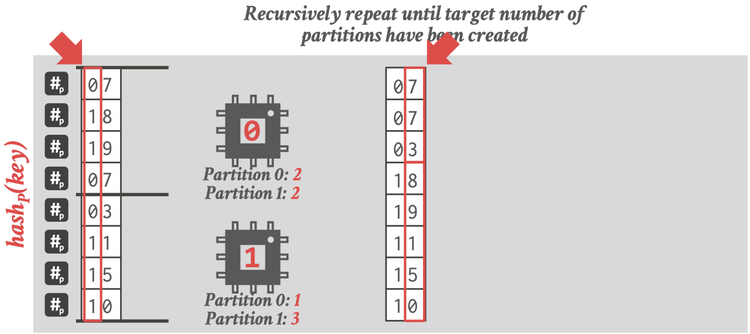
Radix Partitions



Radix Partitions



Radix Partitions



Build Phase

Build Phase

- The threads are then to scan either the tuples (or partitions) of **R**.
- For each tuple, hash the join key attribute for that tuple and add it to the appropriate bucket in the hash table.
  - The buckets should only be a few cache lines in size.

Hash Table

- **Design Decision 1: Hash Function**
  - How to map a large key space into a smaller domain.
  - Trade-off between being fast vs. collision rate.
- **Design Decision 2: Hashing Scheme**
  - How to handle key collisions after hashing.
  - Trade-off between allocating a large hash table vs. additional instructions to find/insert keys.

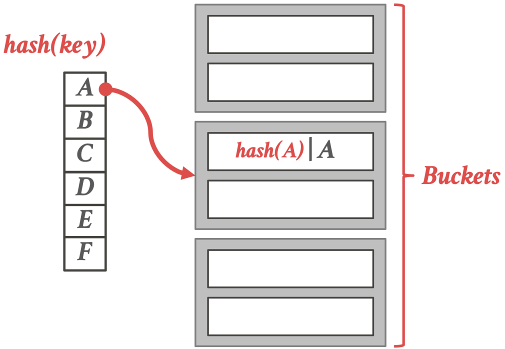
Hashing Schemes

- Approach 1: Chained Hashing (Dynamic)
- Approach 2: Linear Probe Hashing (Static)
- Approach 3: Robin Hood Hashing (Static)
- Approach 4: Hopscotch Hashing (Static)
- Approach 5: Cuckoo Hashing (Static)

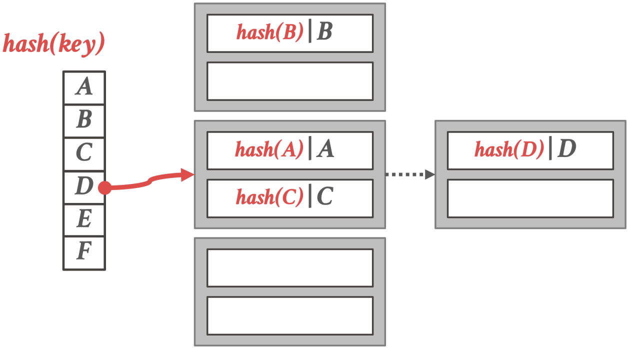
Chained Hashing

- Maintain a linked list of **buckets** for each slot in the hash table.
- Resolve collisions by placing all elements with the same hash key into the same bucket.
  - To determine whether an element is present, hash to its bucket and scan for it.
  - Insertions and deletions are generalizations of lookups.

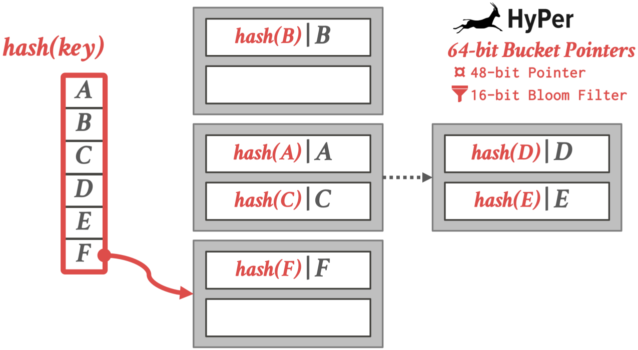
Chained Hashing



Chained Hashing



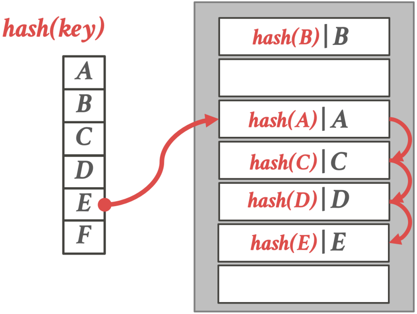
Chained Hashing



Linear Probe Hashing

- Single giant table of slots.
- Resolve collisions by linearly searching for the next free slot in the table.
  - To determine whether an element is present, hash to a location in the table and scan for it.
  - Must store the key in the table to know when to stop scanning.
  - Insertions and deletions are generalizations of lookups.

Linear Probe Hashing



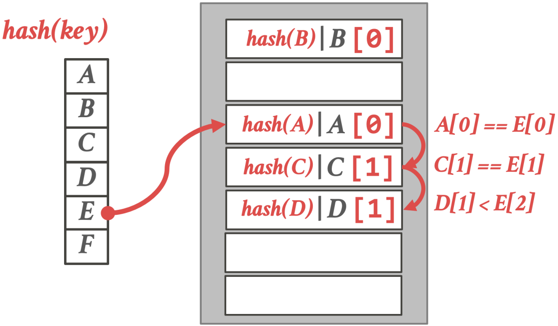
Observation

- To reduce the number of wasteful comparisons during the join, it is important to avoid collisions of hashed keys.
- This requires a chained hash table with $2\times$ the number of slots as the number of elements in $\underline{\mathbf{R}}$.

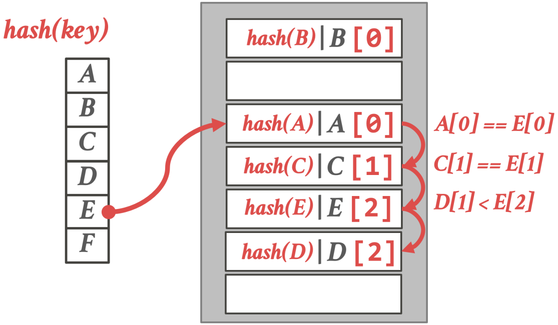
Robin Hood Hashing

- Variant of linear probe hashing that steals slots from **rich** keys and give them to **poor** keys.
  - Each key tracks the number of positions they are from where its optimal position in the table.
  - On insert, a key takes the slot of another key if the first key is farther away from its optimal position than the second key.

Robin Hood Hashing



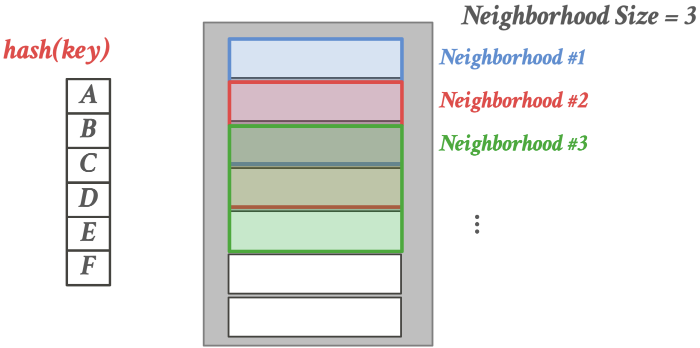
Robin Hood Hashing



Hopscotch Hashing

- Variant of linear probe hashing where keys can move between positions in a **neighborhood**.
  - A neighborhood is contiguous range of slots in the table.
  - The size of a neighborhood is a configurable constant.
- A key is guaranteed to be in its neighborhood or not exist in the table.

Hopscotch Hashing



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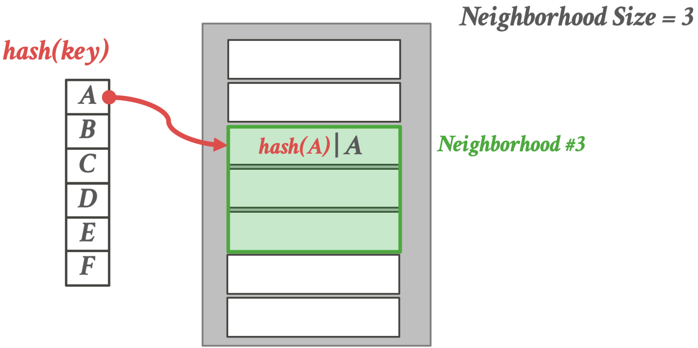

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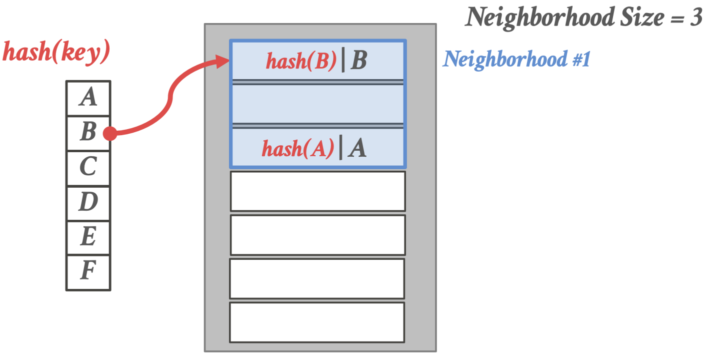

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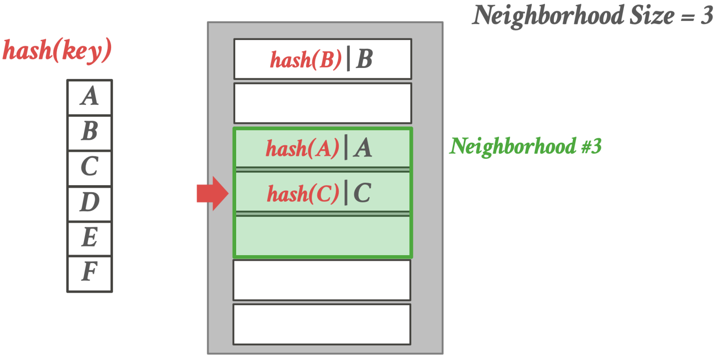

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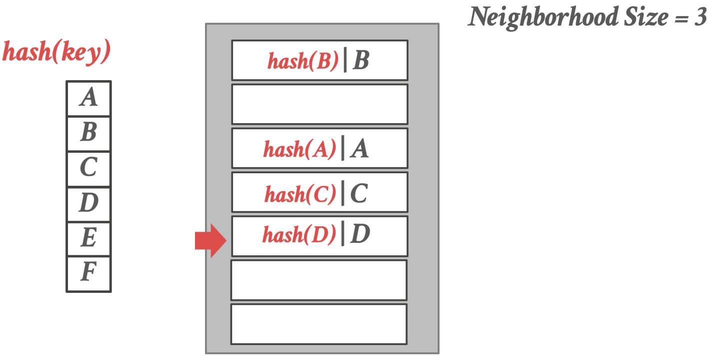

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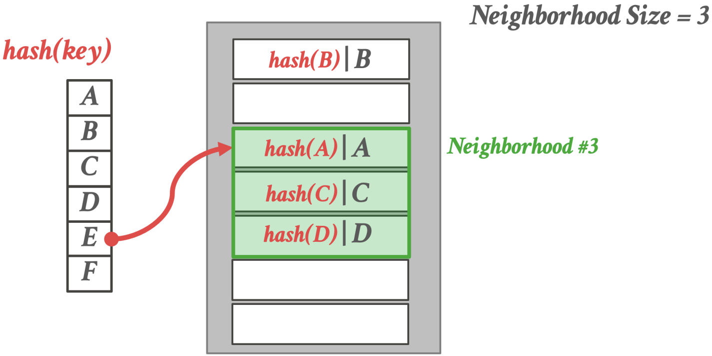

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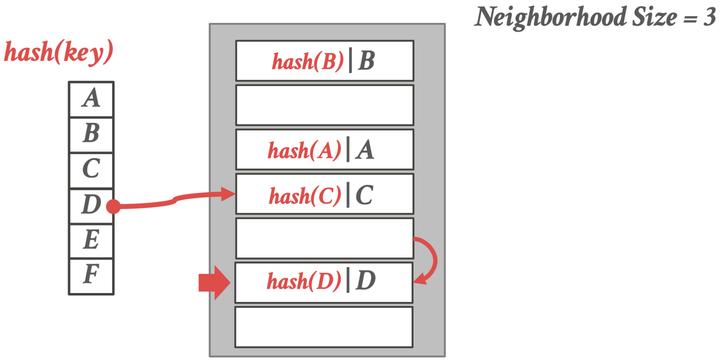

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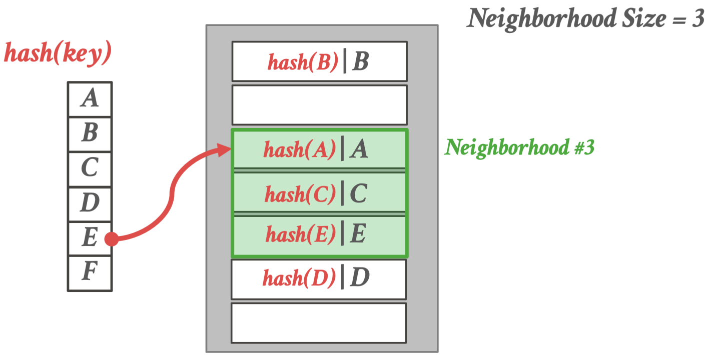
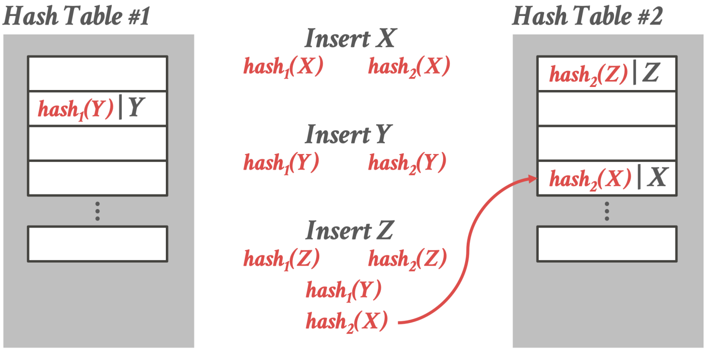


Cuckoo Hashing

- Use <u>**multiple tables**</u> with different hash functions.
  - On insert, check every table and pick anyone that has a free slot.
  - If no table has a free slot, evict the element from one of them and then re-hash it find a new location.
- Look-ups are always O(1) because only one location per hash table is checked.

Cuckoo Hashing



Probe Phase

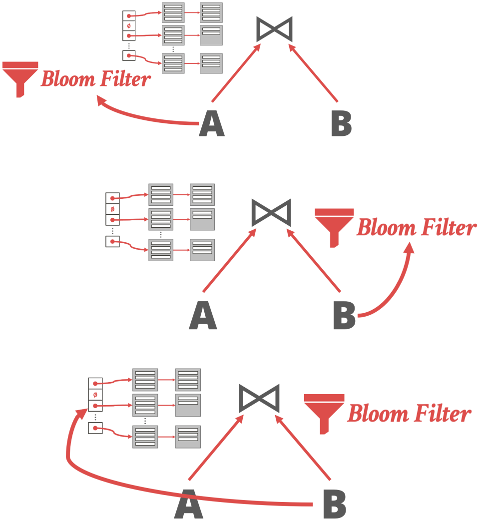
Probe Phase

- For each tuple in <u>**S**</u>, hash its join key and check to see whether there is a match for each tuple in corresponding bucket in the hash table constructed for <u>**R**</u>.
  - If inputs were partitioned, then assign each thread a unique partition.
  - Otherwise, synchronize their access to the cursor on <u>**S**</u>.

Probe Phase – Bloom Filter

- Create a Bloom Filter during the build phase when the key is likely to not **exist** in the hash table.
  - Threads check the filter before probing the hash table.
  - This will be faster since the filter will fit in CPU caches.
  - *a.k.a.*, called sideways information passing.

Probe Phase – Bloom Filter



Evaluation

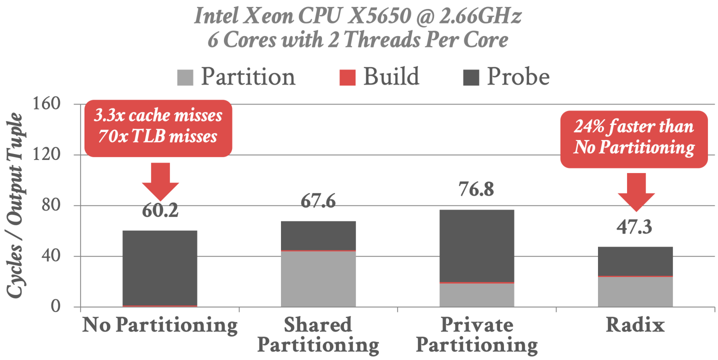
Hash Join Variants

	No-P	Shared-P	Private-P	Radix
Partitioning	No	Yes	Yes	Yes
Input scans	0	1	1	2
Sync during partitioning	–	Spinlock per tuple	Barrier	Barriers
Hash table	Shared	Private	Private	Private
Sync during build phase	Yes	No	No	No
Sync during probe phase	No	No	No	No

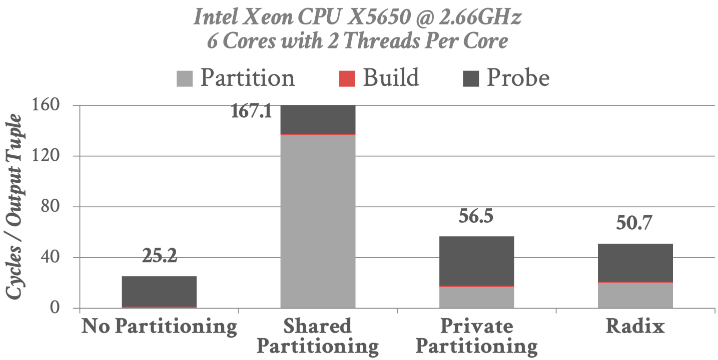
Benchmarks

- Primary key – foreign key join
  - Outer Relation (Build): 16 M tuples, 16 bytes each
  - Inner Relation (Probe): 256 M tuples, 16 bytes each
- Uniform and highly skewed (Zipf; s=1.25)
- No output materialization
- Reference

Hash Join - Uniform Dataset



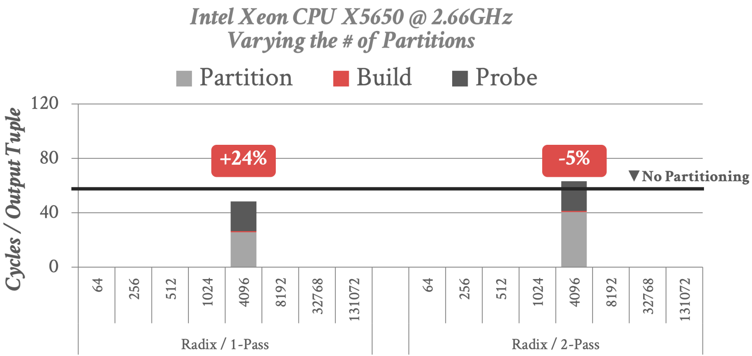
Hash Join - Skewed Dataset



Observation

- We have ignored a lot of important parameters for all these algorithms so far.
  - Whether to use partitioning or not?
  - How many partitions to use?
  - How many passes to take in partitioning phase?
- In a real DBMS, the optimizer will select what it thinks are good values based on what it knows about the data (and maybe hardware).

Radix Hash Join - Uniform Dataset



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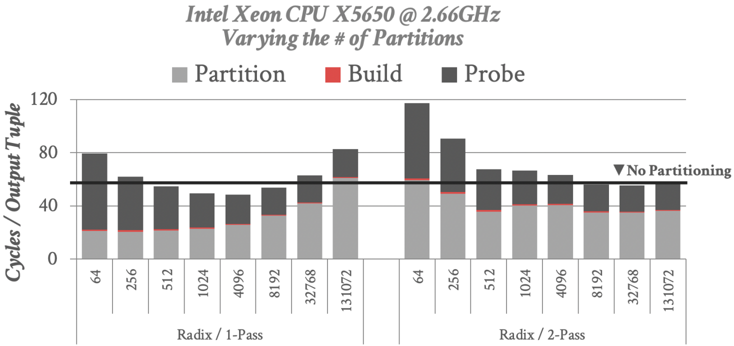

Conclusion

Conclusion

- Partitioned-based joins outperform no-partitioning algorithms in some settings, but it is non-trivial to tune it correctly.
- AFAIK, every DBMS vendor picks one hash join implementation and does not try to be adaptive.
- Next Class
  - Parallel Sort-Merge Join Algorithms