Track Join

Distributed Joins with Minimal Network Traffic

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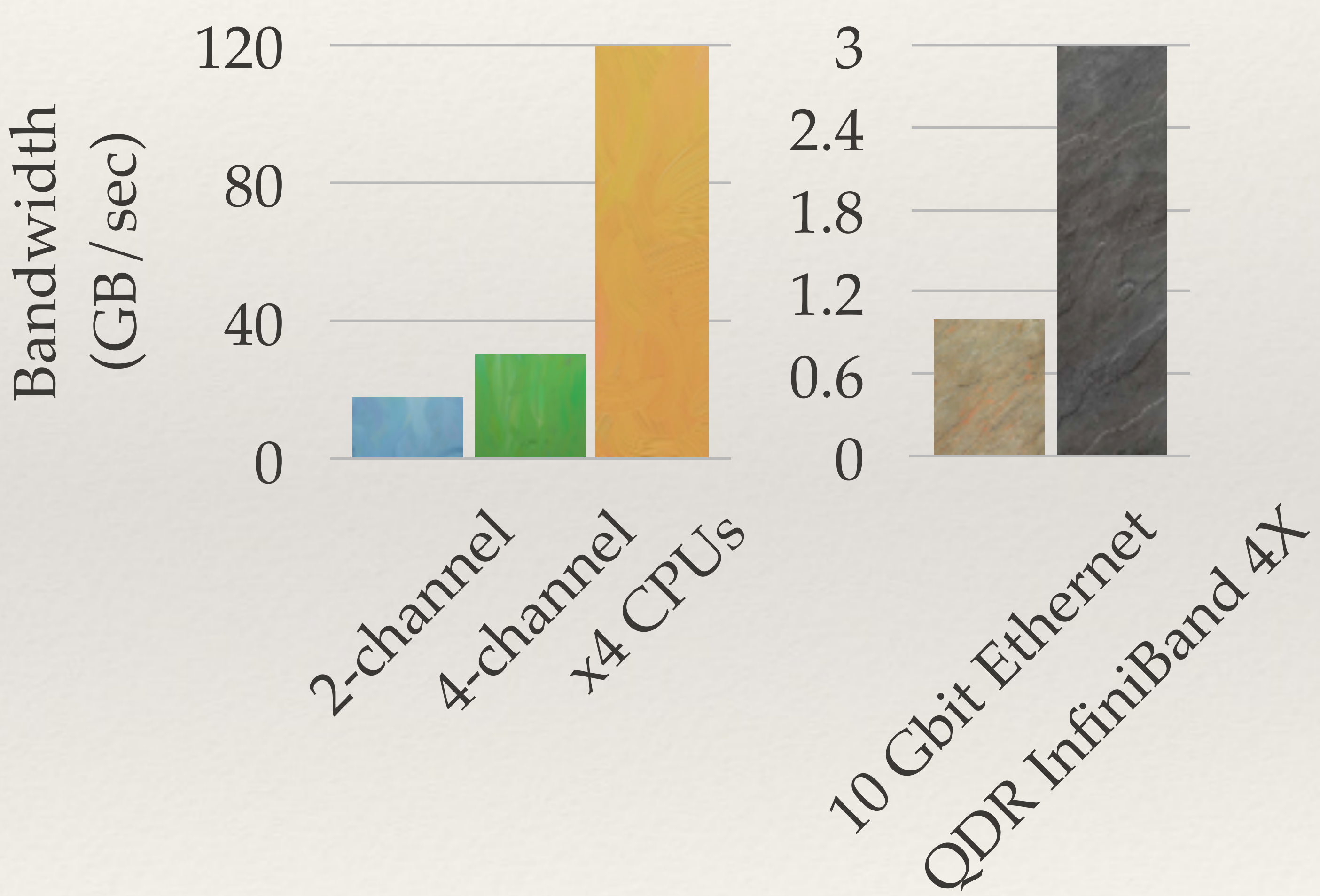
Local Joins

- Algorithms
  - Hash Join
  - Sort Merge Join
  - Index Join
  - Nested Loop Join

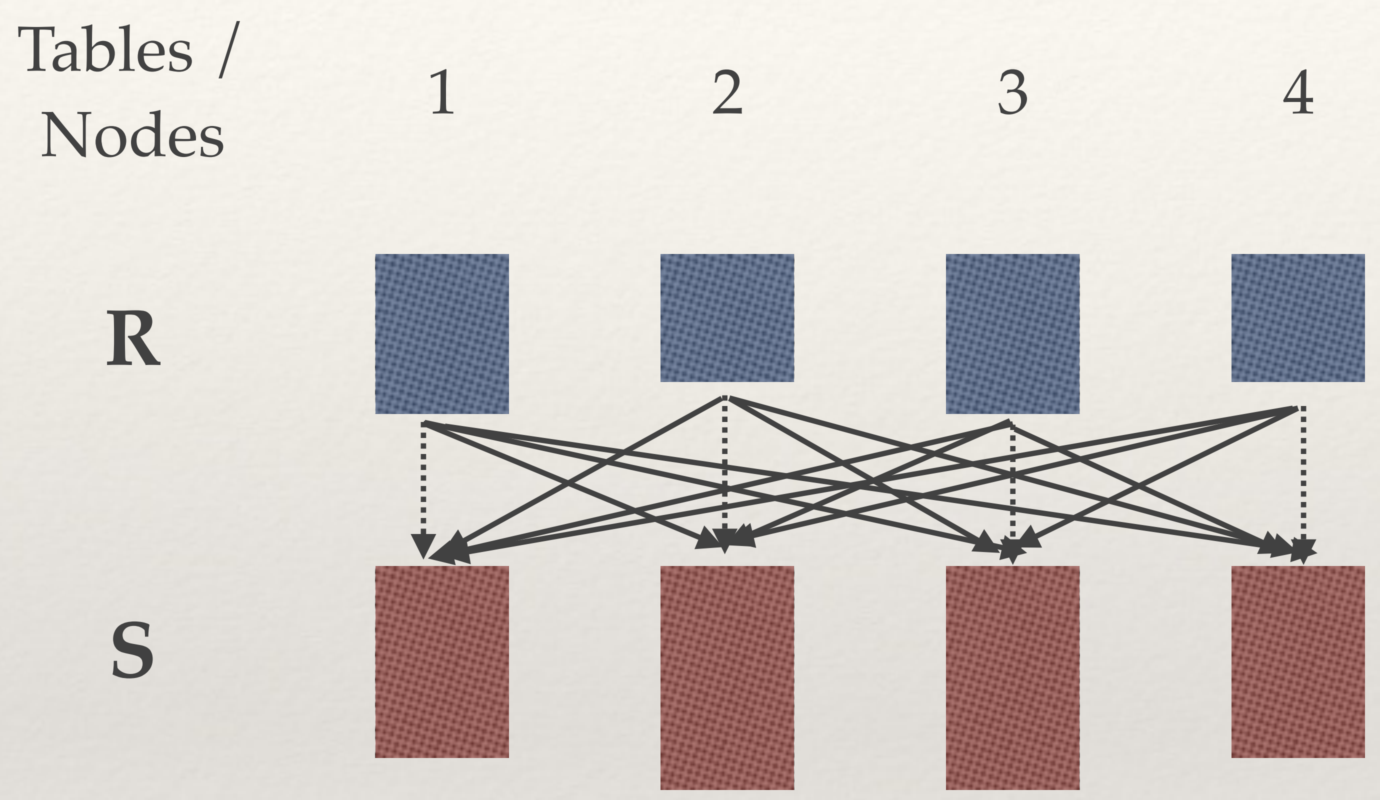
  - Spilling to disk
    - Bounded by disk bandwidth
  - When RAM resident
    - Scale by number of cores
    - Bounded by RAM **bandwidth**

RAM > Network

- RAM bandwidth ?
  - An example
    - 2-channel 1333 MHz RAM = ~18 GB/s
    - Add 4-channel RAM = ~30 GB/s
    - Add 4 CPUs = ~120 GB/s
  - Partition = ~1/3 of bandwidth
    - Partition = copy
      [Satish et.al. SIGMOD '10,
      Wassenberg et.al. EuroPar '11]
- Network bandwidth ?
  - Measure (partition) all-to-all
    - 10 Gbit Ethernet < 1 GB/s
    - QDR InfiniBand 4X < 3 GB/s

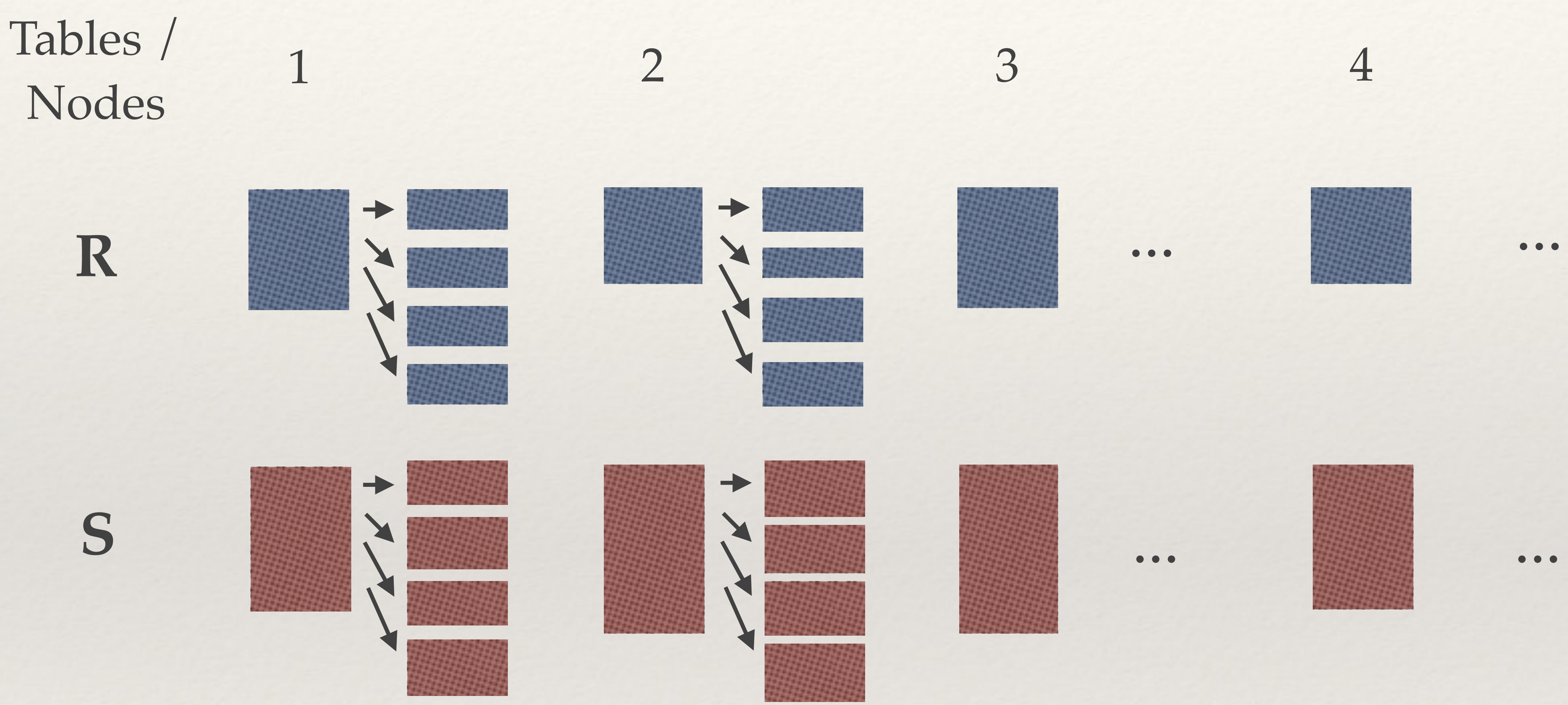


Broadcast Join



- Network cost
  - Transfer $min(|R|,|S|) * 3$
  - **Schedule** transfers optimally

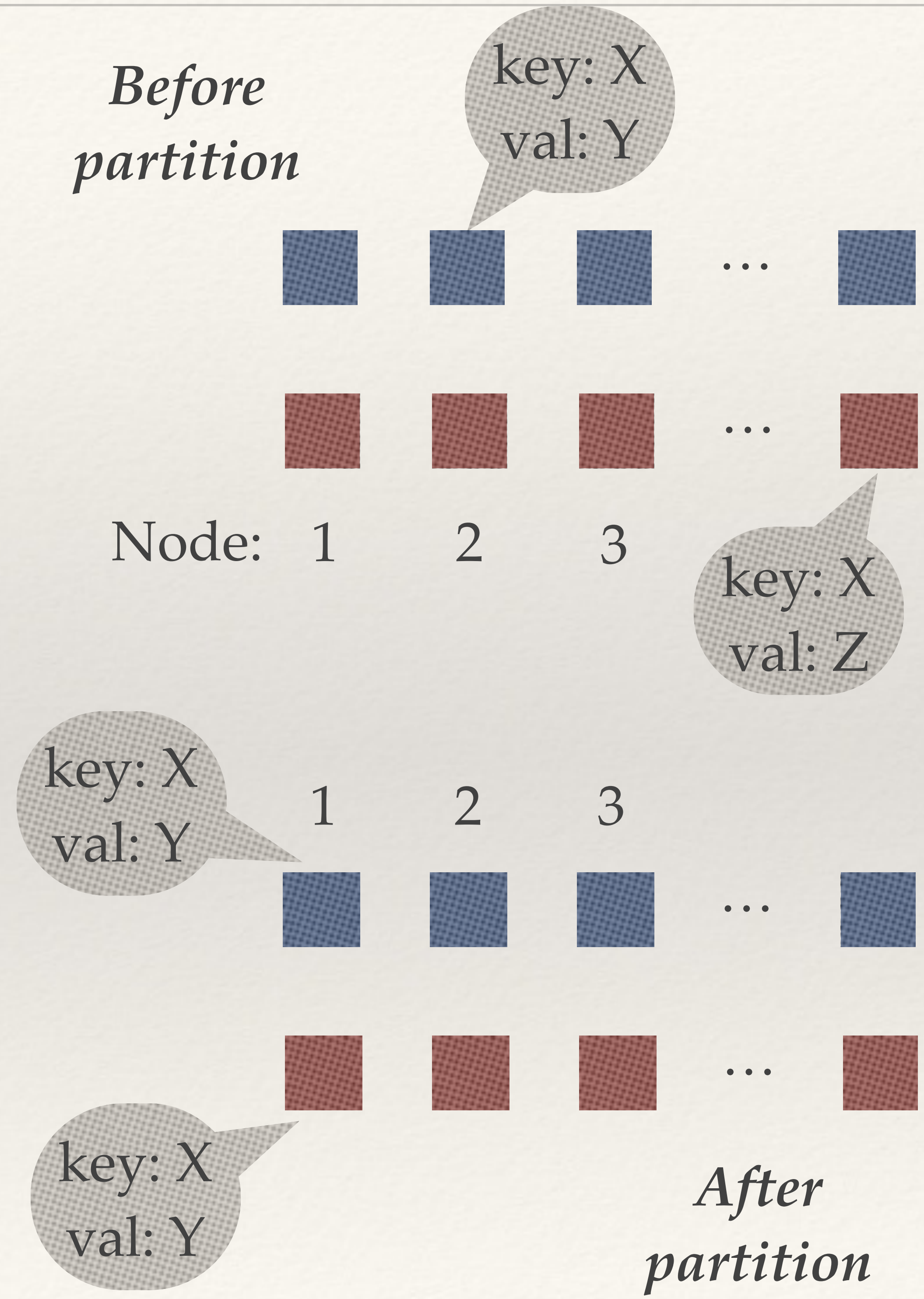
Hash Join



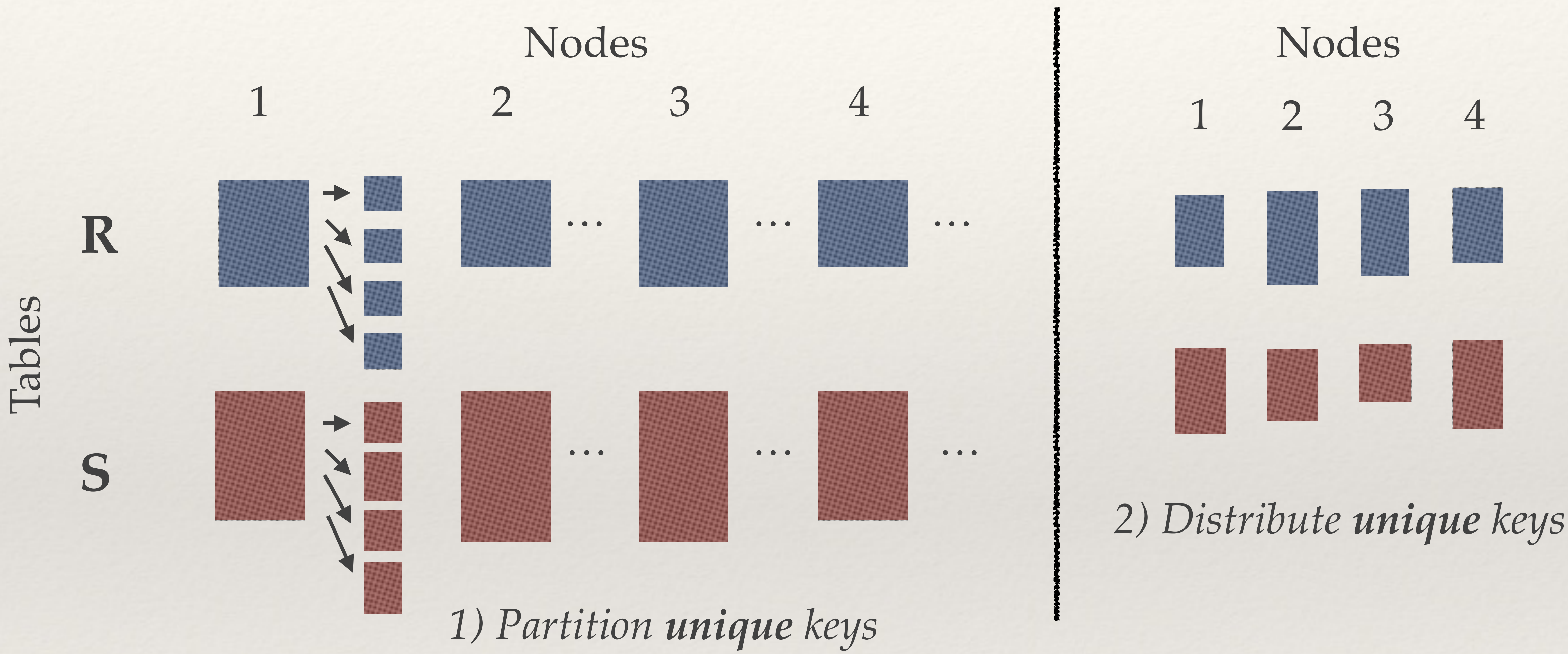
- Network cost
  - Transfer (|R|+|S|) * 3/4
  - **Distribution** of (almost) equal partitions

Hash Join

- Pros & cons
  - Broadcast join can be expensive
    - Useful only if |R| << |S|
  - Good for load balancing
    - Hashing randomizes the keys
  - Bad in locality awareness
    - (Again) Hashing randomizes the keys
  - Real datasets have locality
    - Deliberate clustering (optimization)
    - Time-based locality due to appends



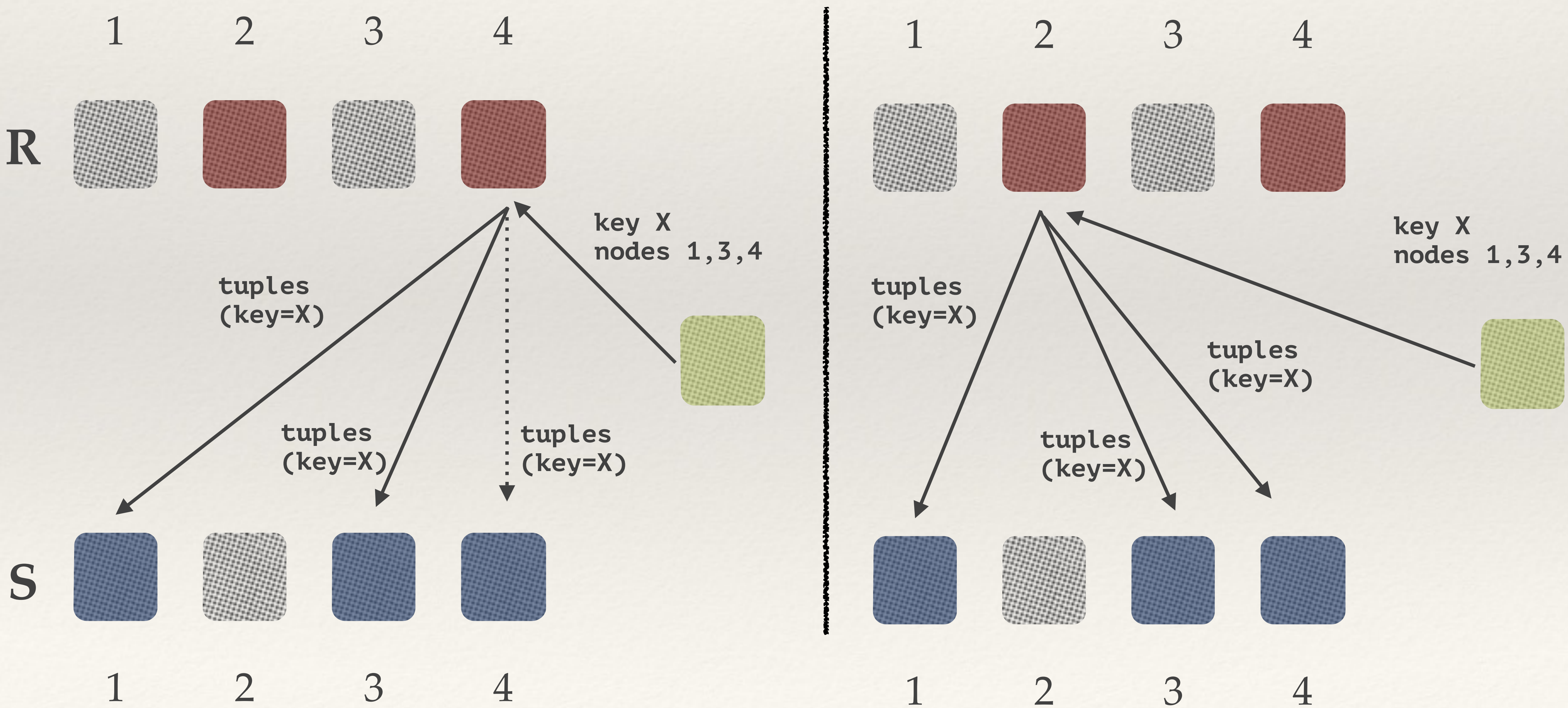
Track Join (2-phase)



- Tracking
  - Hash distribute join keys
  - Eliminate duplicates

Track Join (2-phase)

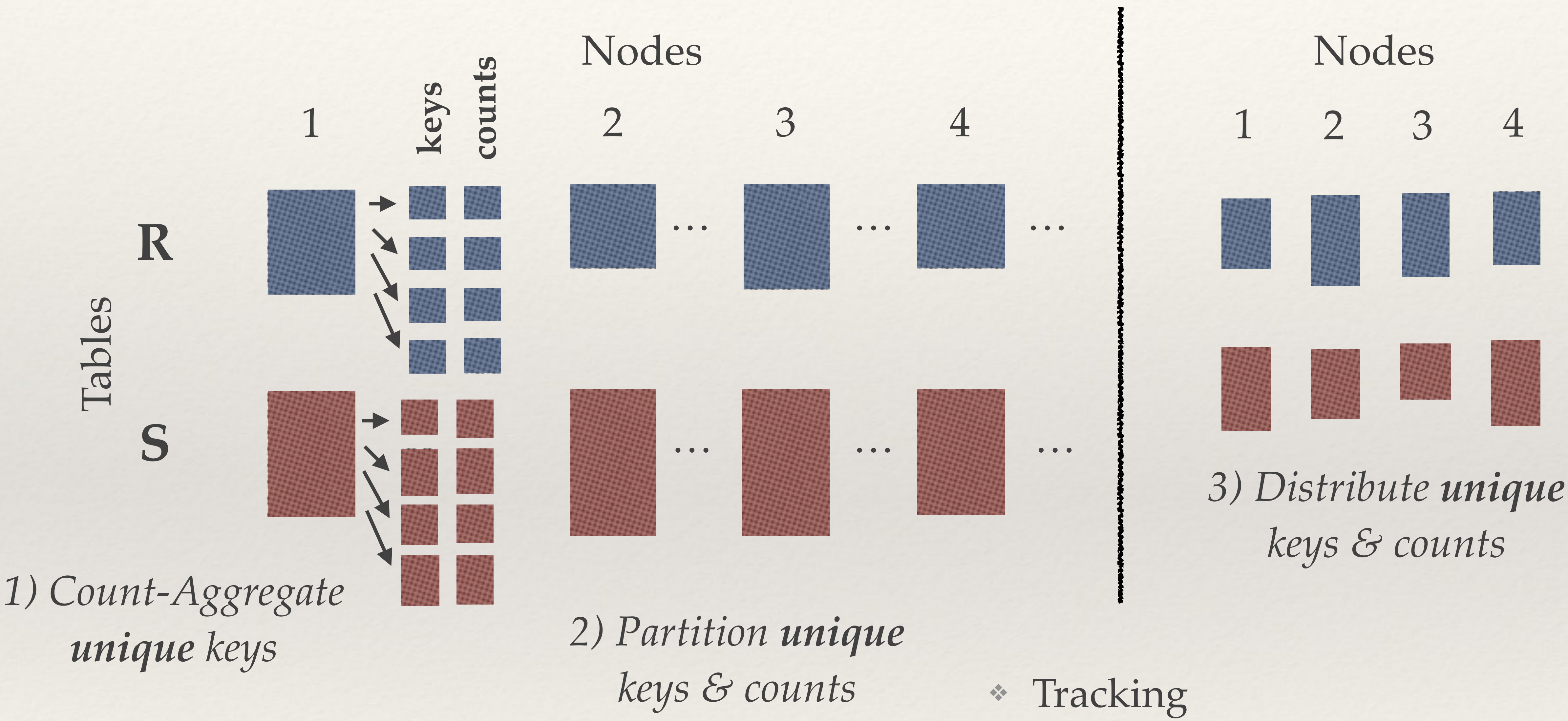
- Selective broadcast (last step)
  - For a single join key



Track Join (2-phase)

- 2-phase track join
  - Move *R* tuples to *S* tuple locations
    - *S* payloads stay in place: **never** move over the network
  - Cost: tracking + $min(|R|, |S|)$ * repeats
    - $min(|R|, |S|)$ decided by tuple **width (= payload width)**
- 3-phase track join
  - Decides tuple "direction" **dynamically**
    - Which table to move & which to keep in-place
  - **Augment** tracking with counts
    - **Counts** per unique key

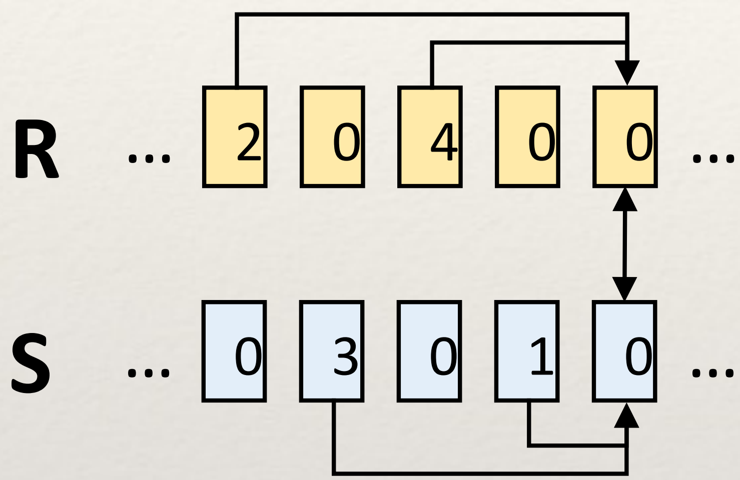
Track Join (3-phase)



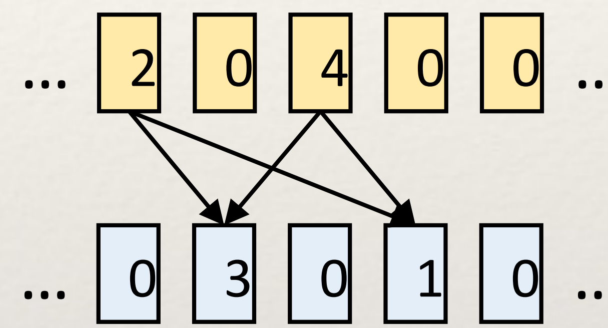
- Tracking
  - Count-aggregate keys
  - Hash distribute keys **& counts**

Schedules / Algorithm

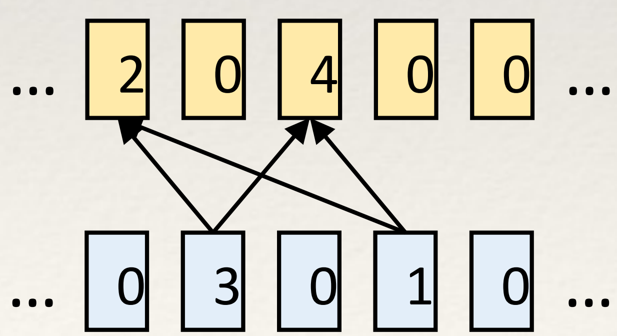
- Hash Join (cost = 10)



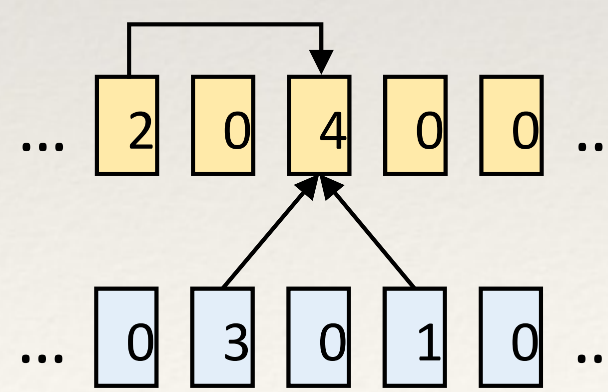
- 2-phase Track Join (cost = 12)



- 3-phase Track Join (cost = 8)



- 4-phase Track Join (cost = 6)

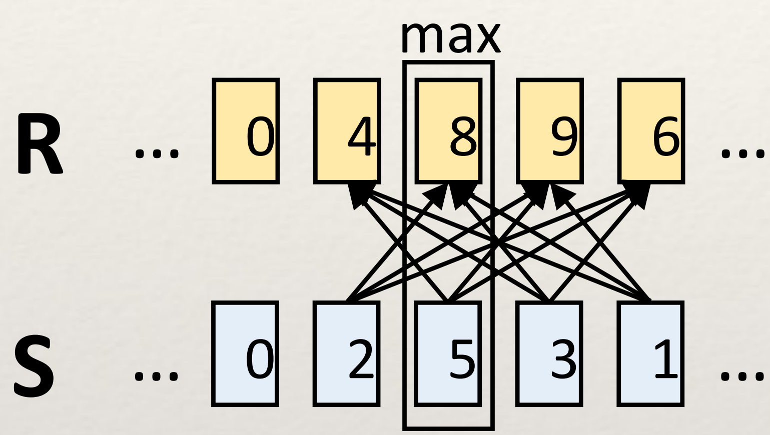


Track Join (4-phase)

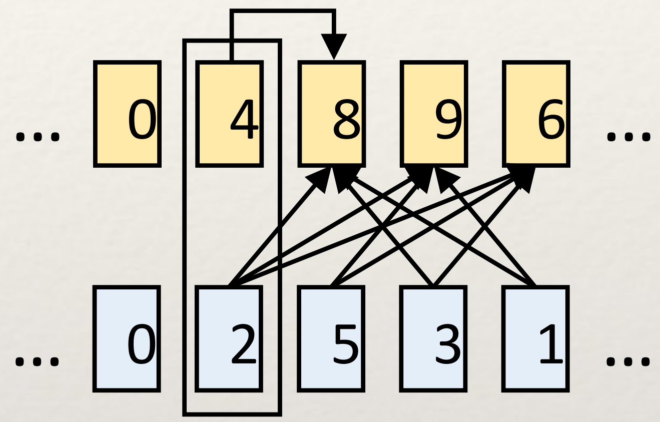
- Compute **optimal** Cartesian product join schedule
  - Track using keys & counts
    - As in 3-phase track join
  - Optimize R to S broadcast, and S to R
    - Compute R to S broadcast, and S to R
    - Allow **migration** of S tuples for R to S, and R tuples for S to R
    - Provably optimal in **linear** time
    - Pick best (optimized) direction for migrate & broadcast
  - Execute the optimal schedule
    - **First** migrate tuples from one table
    - **Then** broadcast tuples from the other table

Schedule Optimization

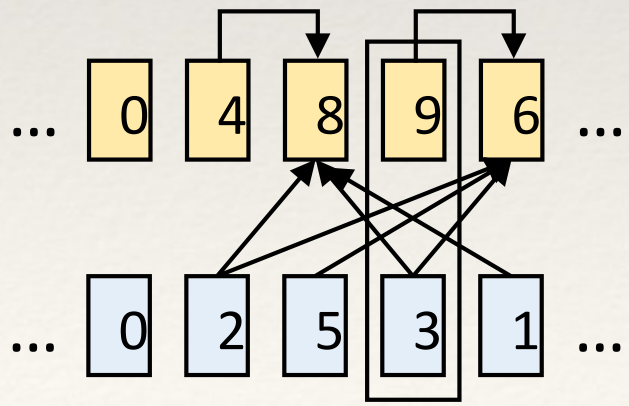
- Broadcast (cost = 0 + 33)



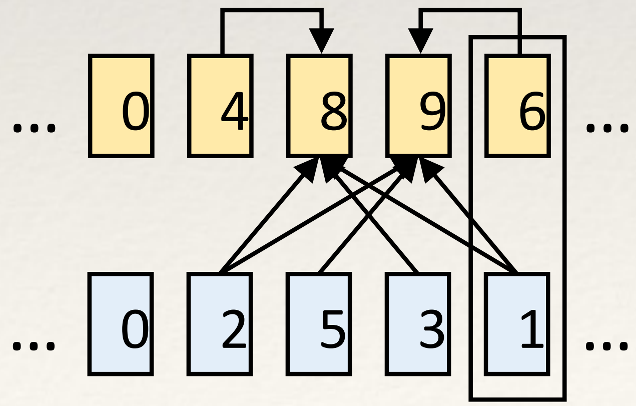
- Migrate 4? Yes (cost = 4 + 24 < 33)



- Migrate 9? No (cost = 13 + 16 > 28)



- Migrate 6? Yes (cost = 10 + 14 < 28)



Network Cost Approximation

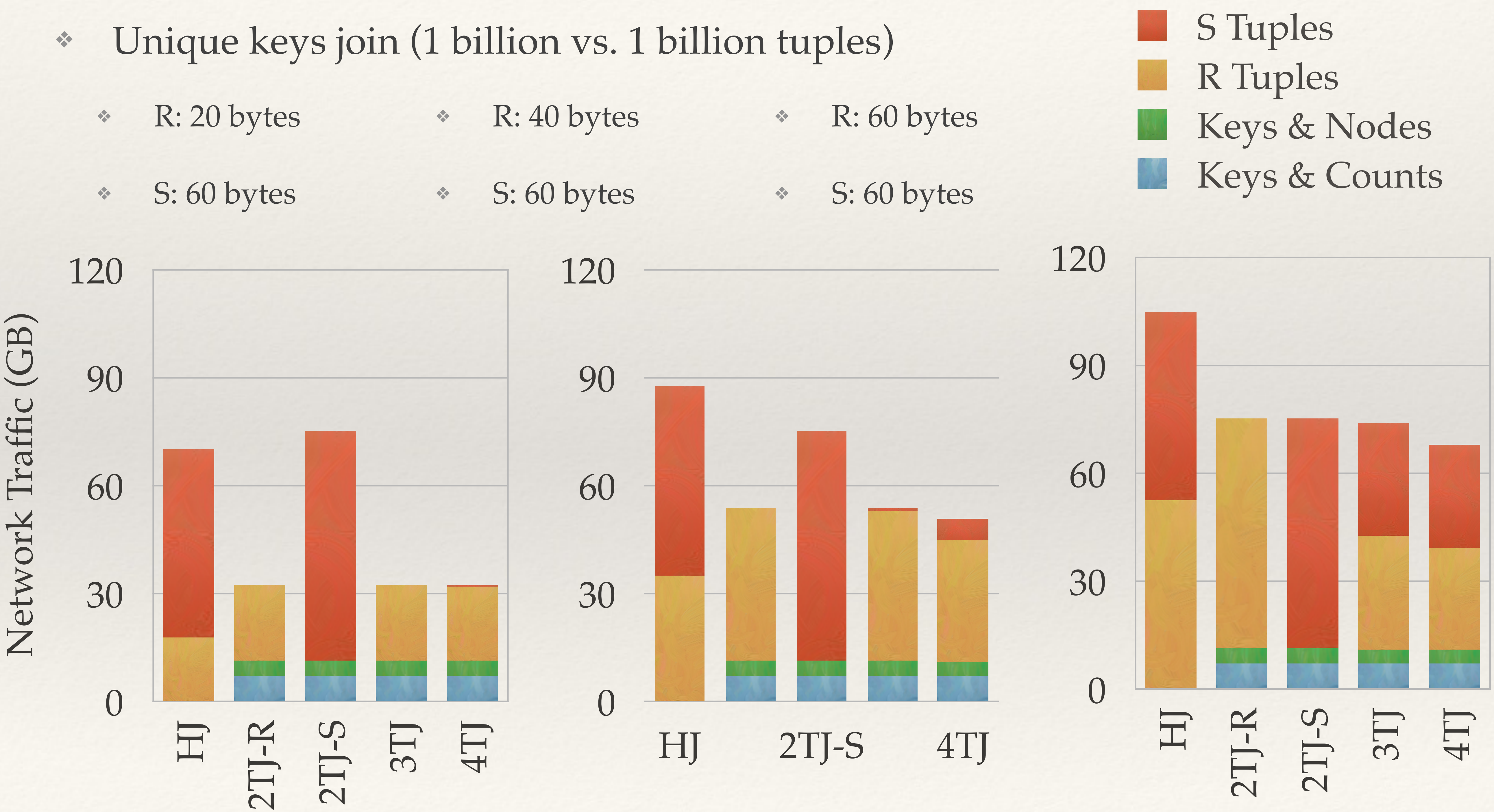
- When to use instead of hash join ?
  - Using standard statistics
    - # tuples
    - # distinct keys
  - Distinguish **classes** of correlation (= similar cartesian products)
    - Use correlated sampling [Yu et.al. SIGMOD '13]
  - Use track join
    - 2-phase if at least one table has **unique** keys
    - 4-phase if many **key repeats** or **locality** is expected
  - Use hash join
    - If payloads are **small** (e.g. key & record id only) and **no locality** exists

Track/Hash/Semi Joins

- Track join **is** a form of semi-join
  - Tracking generates schedules for **valid** Cartesian products **only**
    - Non-approximate like Bloom filter based semi-join (Bloom join)
    - Cost (of tracking) = distribute unique join keys (& counts)
  - Still may use semi-join on top of track join
    - Bloom filtering < tracking
  - However may **skip** semi-join unlike hash join
    - Tracking < Bloom filtering
- Hash join **can** become tracking-aware
  - Use record ids (**rids**) to track joining payloads
    - In the best case as good as 2-phase track join

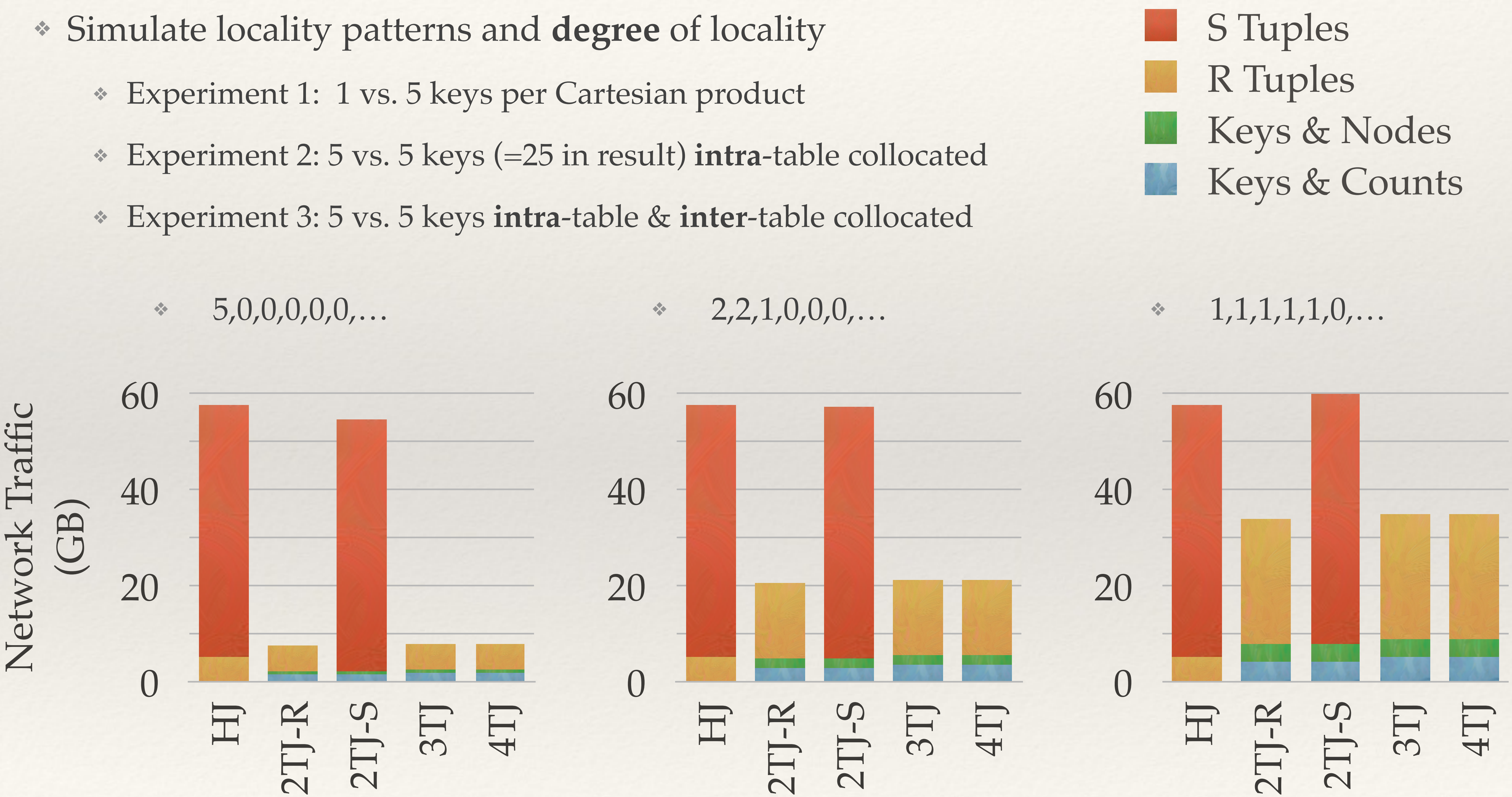
Network Traffic Simulations

- Unique keys join (1 billion vs. 1 billion tuples)
  - R: 20 bytes
  - S: 60 bytes
  - R: 40 bytes
  - S: 60 bytes
  - R: 60 bytes
  - S: 60 bytes

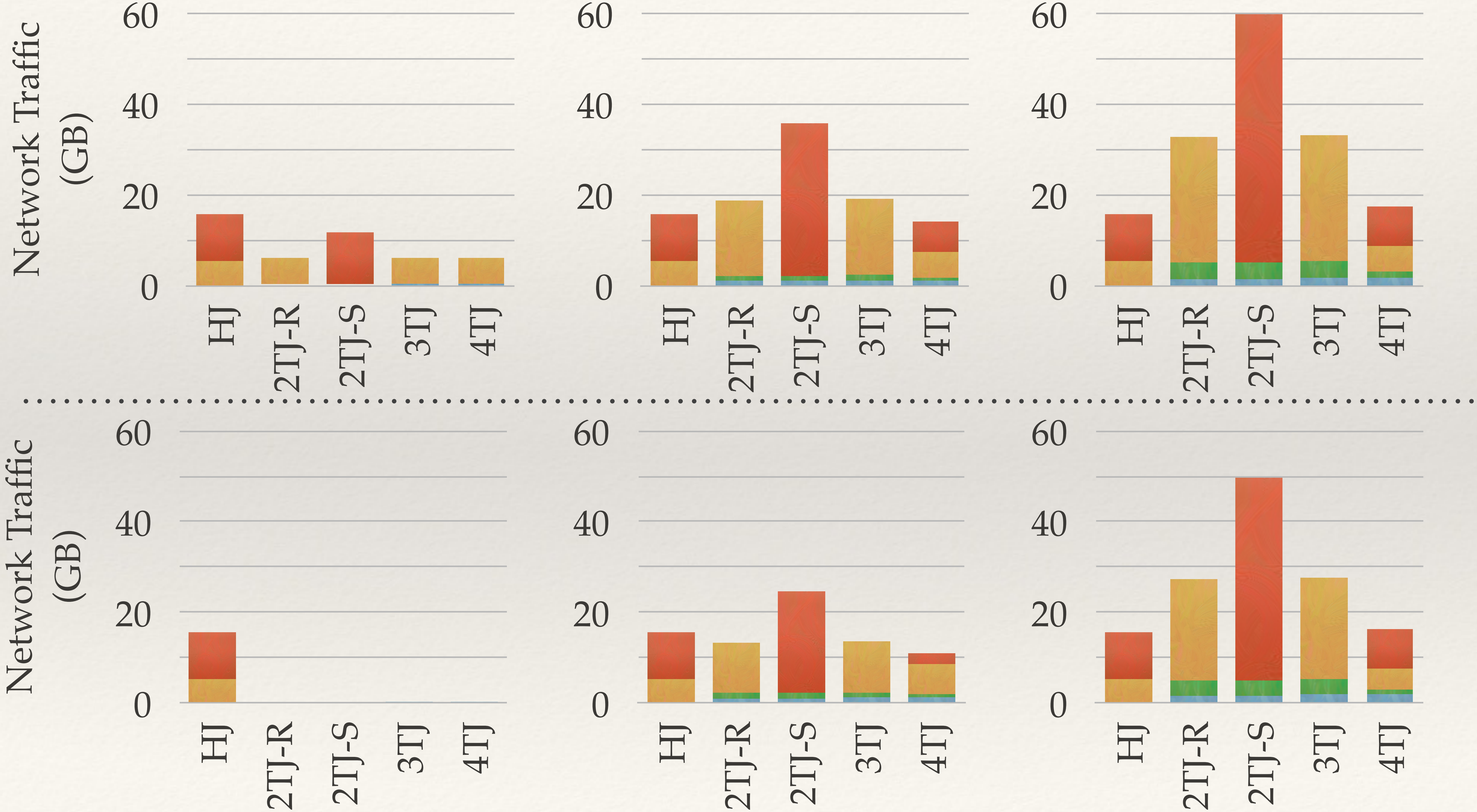


Simulating Locality

- Simulate locality patterns and **degree** of locality
  - Experiment 1: 1 vs. 5 keys per Cartesian product
  - Experiment 2: 5 vs. 5 keys (=25 in result) **intra**-table collocated
  - Experiment 3: 5 vs. 5 keys **intra**-table & **inter**-table collocated



Simulating Locality

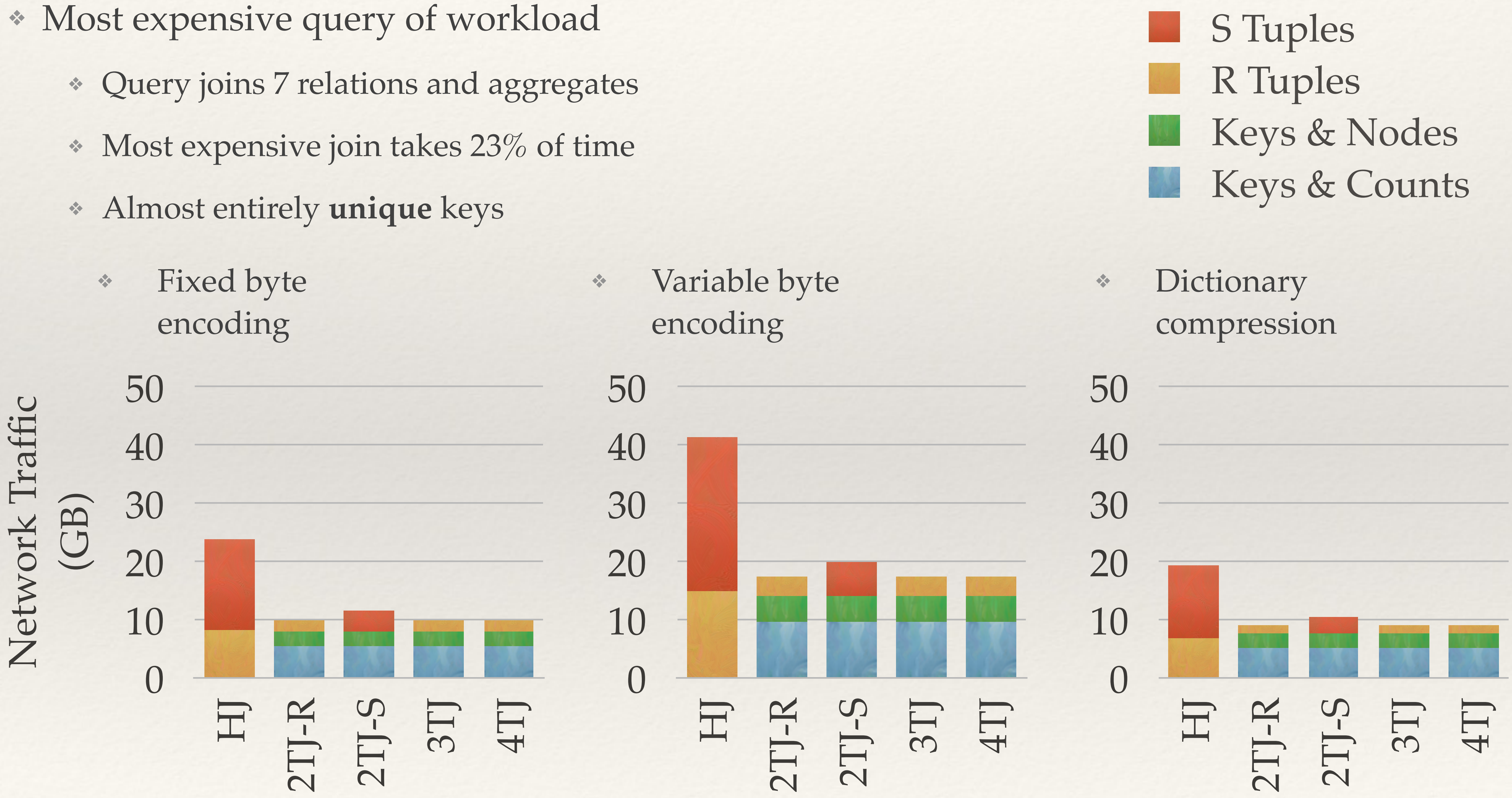


Real Workloads

- Real commercial vendor workloads
  - Profiled using commercial DBMS
    - 4 nodes x 2 CPUs (2.9 GHz) x 8 cores
    - QDR InfiniBand 4X
  - Extracted the **most expensive** queries
    - Extracted the **most expensive** join from them
    - Executed in the DBMS as a hash join
- Simulating track join
  - Multiple **encoding** schemes
    - **Variable** length types
    - Optimal **compression** schemes

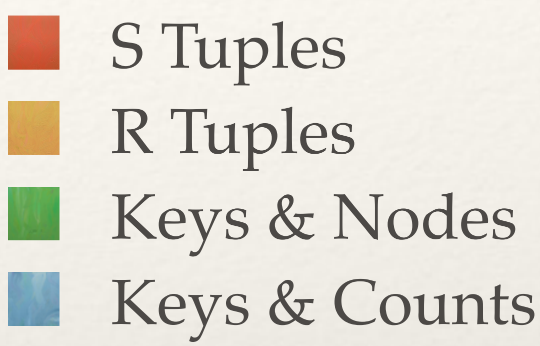
Real Workload 1 Traffic Simulation

- Most expensive query of workload
  - Query joins 7 relations and aggregates
  - Most expensive join takes 23% of time
  - Almost entirely **unique** keys

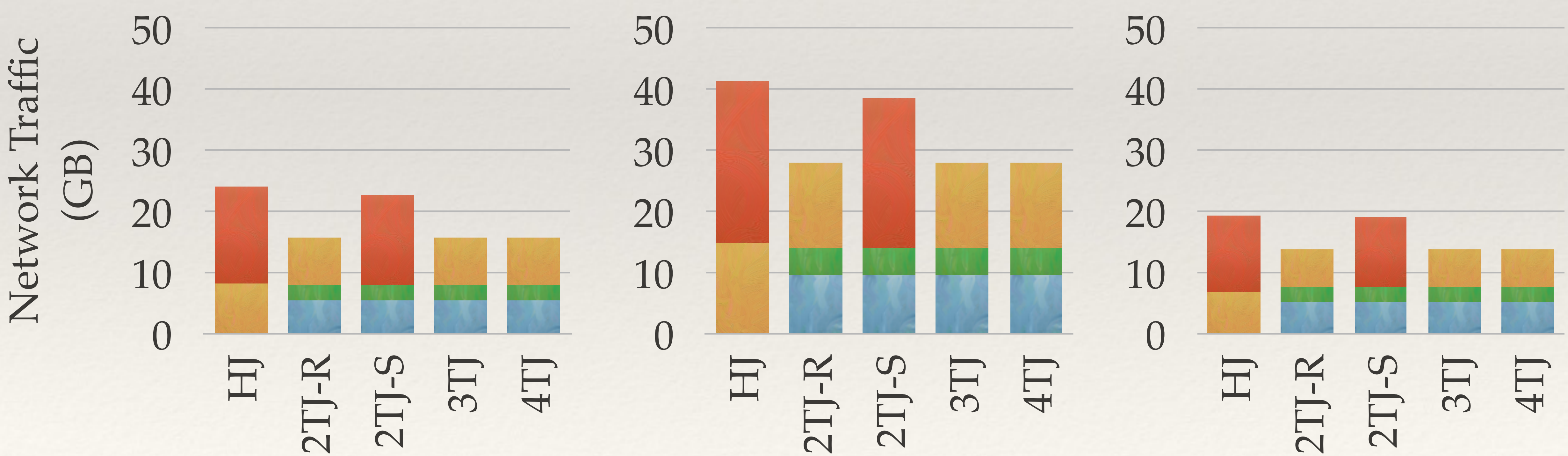


Real Workload 1 Traffic Simulation

- Most expensive query of workload
    - Exhibited significant **locality**
    - **Shuffle** the data randomly
    - **No** locality is possible now

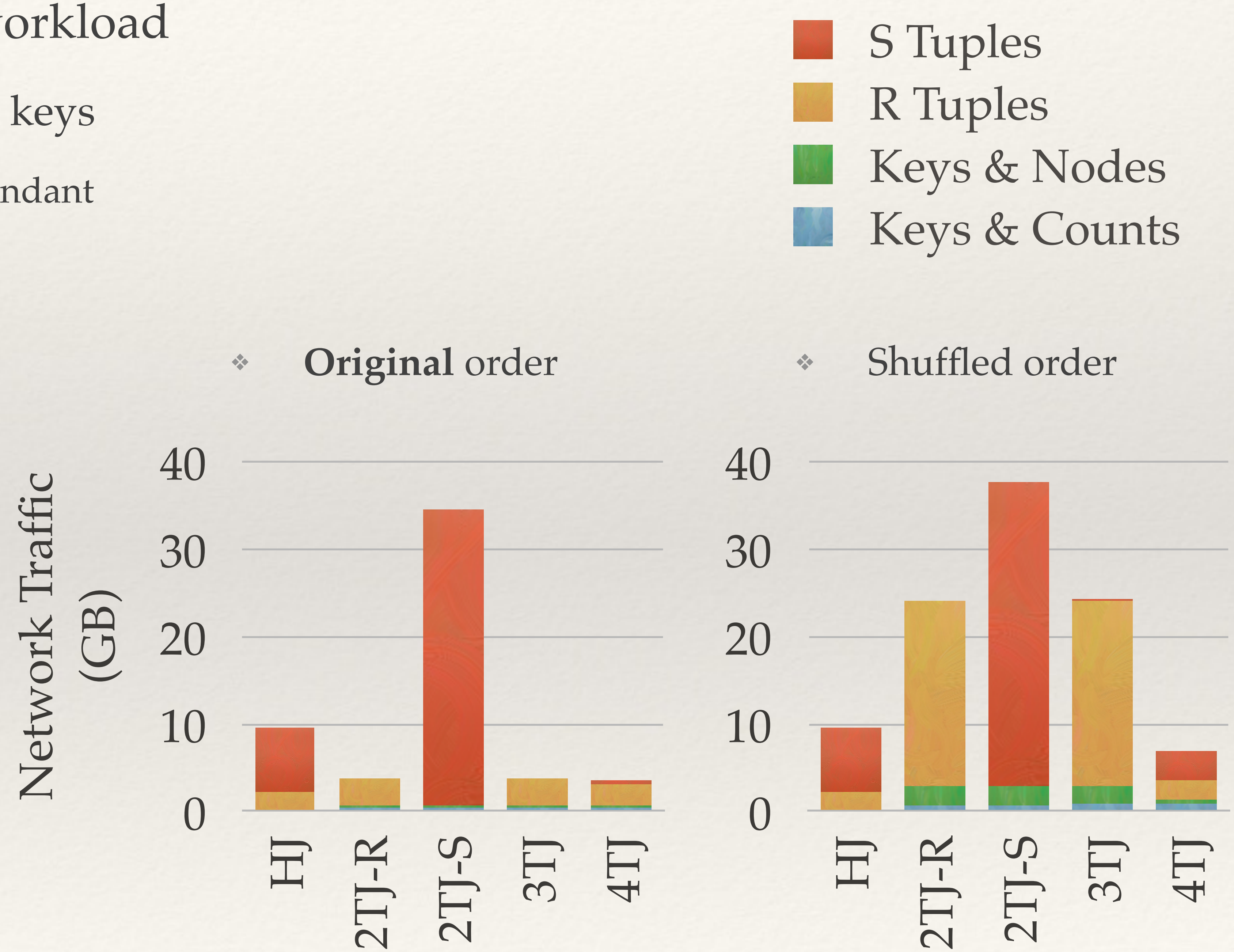


- Fixed byte encoding
- Variable byte encoding
- Dictionary compression



Real Workload 2 Traffic Simulation

- Most expensive query of workload
  - 2-phase suffices for unique keys
    - 3-phase / 4-phase are redundant
  - Workload 2 is different
    - No unique keys
  - **Very high** selectivity
    - R: ~40 million tuples
    - S: ~200 million tuples
    - RS: >1 billion tuples
  - Variable byte encoding
    - Base 100 / byte



Real Workload Experiments

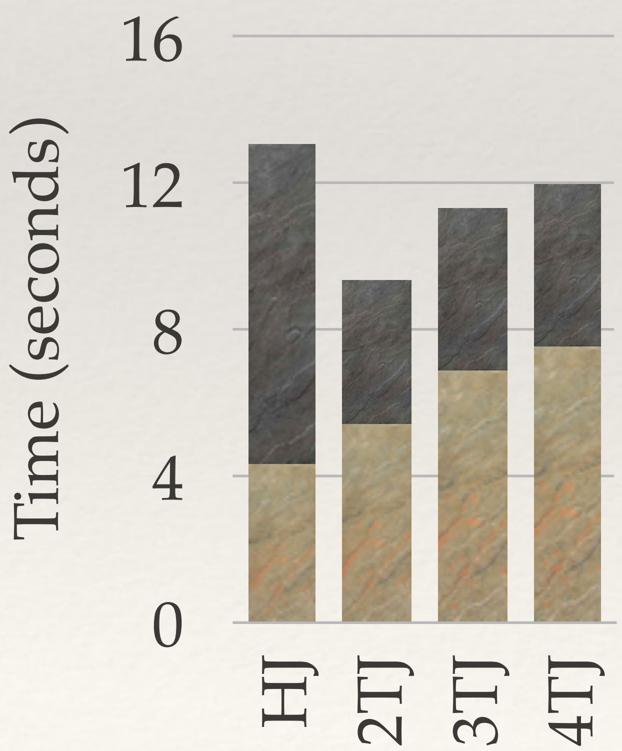
- Implementation
  - **Sort** for in-memory join
  - De-pipelined operators
    - De-couple network & CPU measurement
    - Experiments are invariant of network speed
  - Run on small private cluster
    - 4 nodes x 2 CPUs (2.66 GHz) x 4 cores
    - Accurately project any network speed
  - Evaluate real workloads
    - The same cases we simulated
    - On the same expensive join

Real Workload Time Experiments

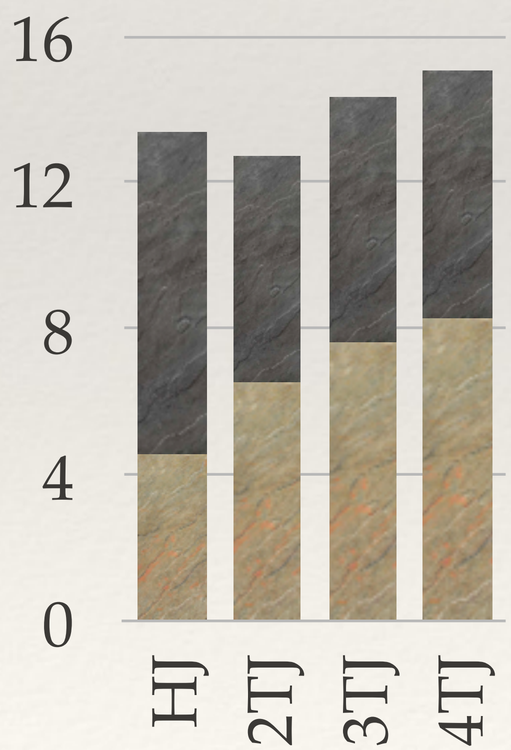
- Projected (accurately) to 10 Gbit Ethernet
  - CPU vs. network analogous to commercial platforms
  - DBMS profiling platform: ~2.8X network & ~2.2X CPU
  - Schedule generation is **fast** (insignificant in workload 2)

Network
CPU

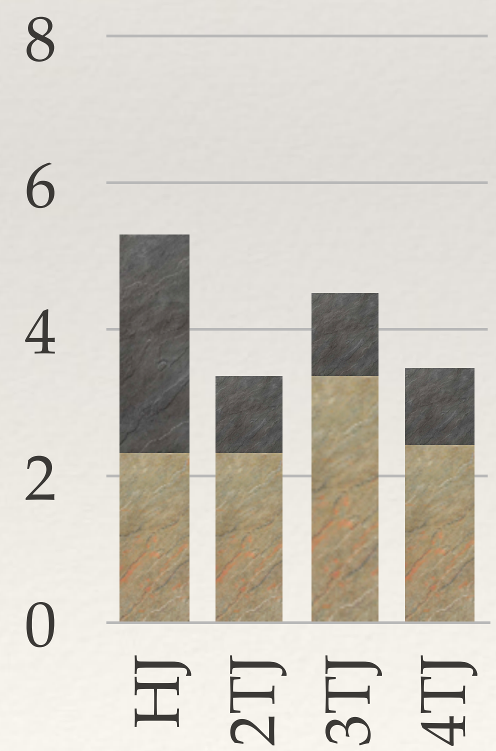
- **Original** real workload 1



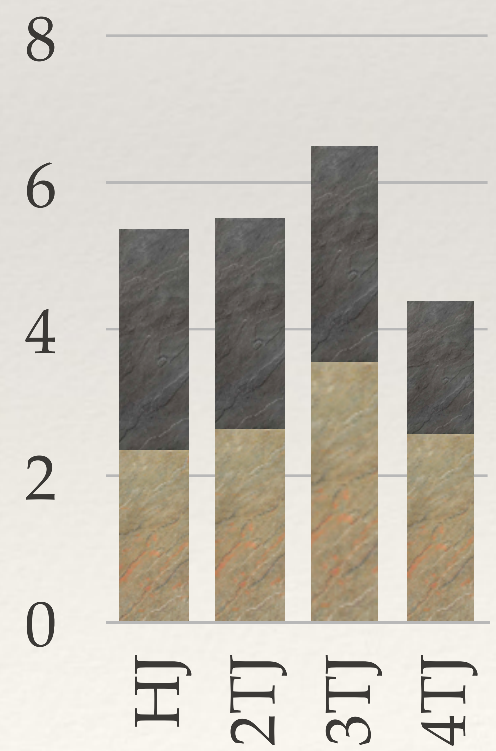
- Shuffled real workload 1



- **Original** real workload 2



- Shuffled real workload 2



Conclusions

- We introduced **Track Join**
  - For distributed joins
    - Not a hash join
    - Not a broadcast join
  - Optimize **network traffic**
    - **Track** matching keys using hash join
    - Works at join **key granularity** (not at hash groups)
    - Generate <u>optimal</u> Cartesian join schedules **fast** (and in linear time)
  - Experimental results
    - Reduces network traffic significantly
    - **CPU** time penalty is modest
    - Better with data **locality**

Questions