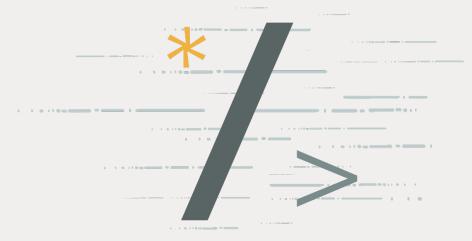
MySQL HeatWave A Deep Dive Into Architecture and Optimizations

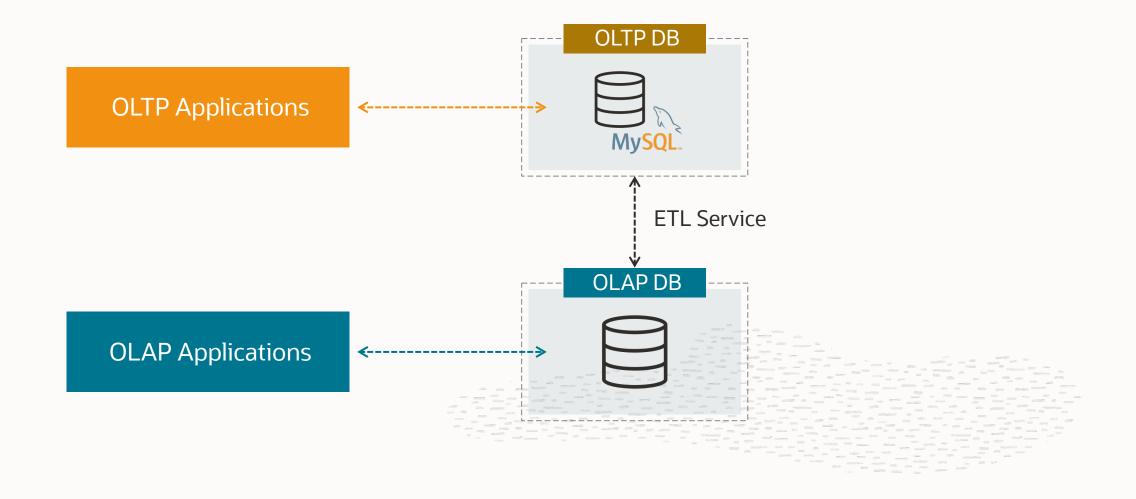
Cagri Balkesen, Ph.D. Architect, MySQL HeatWave January 31, 2025

Safe harbor statement

The following is intended to outline our general product direction. It is intended for information purposes only, and may not be incorporated into any contract. It is not a commitment to deliver any material, code, or functionality, and should not be relied upon in making purchasing decisions. The development, release, timing, and pricing of any features or functionality described for Oracle's products may change and remains at the sole discretion of Oracle Corporation.

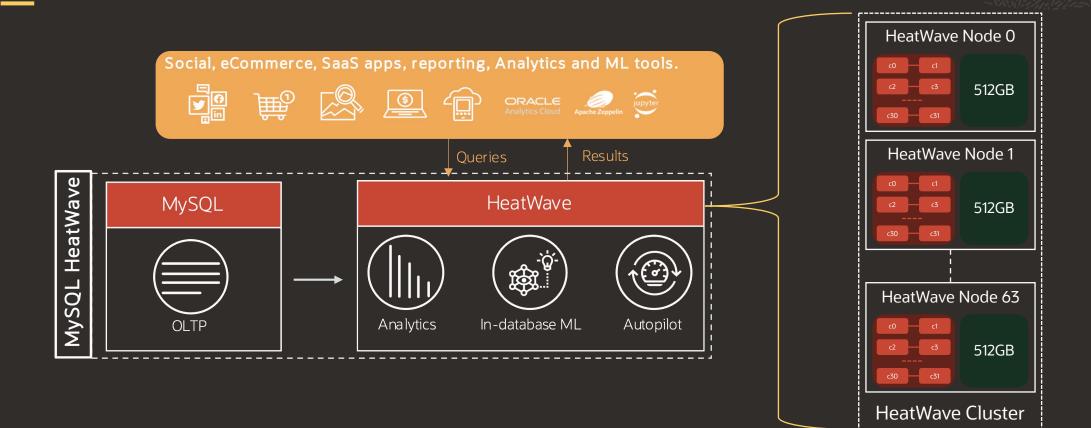


MySQL users have needed separate systems for OLTP and OLAP



MySQL HeatWave

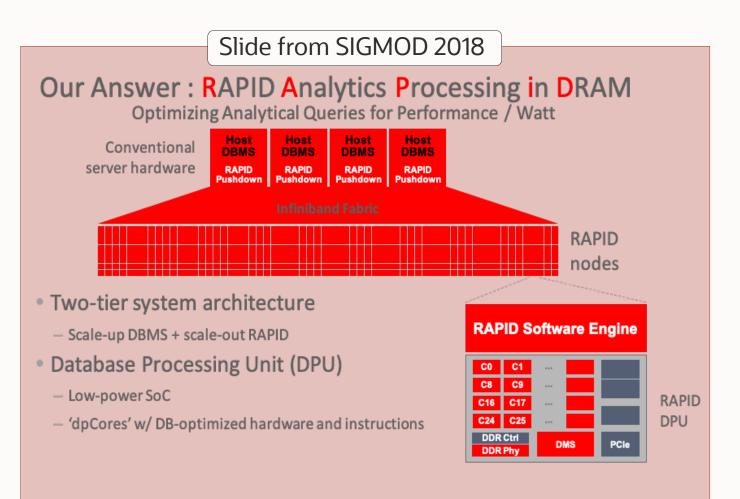
OLTP, OLAP/analytics, and ML in one cloud database service – without ETL



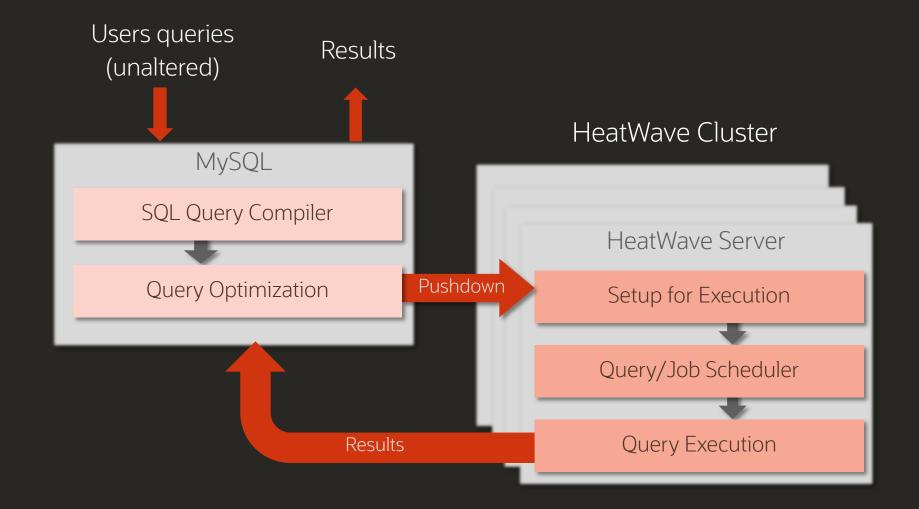
- Single MySQL database for OLTP & analytics applications
- Extreme performance & scalability to hundreds of nodes, thousands of cores

The Research Background on HeatWave

- Multi-year research project out of Oracle Labs with several publications (SIGMOD'18, MICRO'17, BigData'16, ICDE'16) and patents
- Project **RAPID**: Initial research project focused on software-hardware co-design with power/performance efficiency
- Scalable software design and architecture completely tech transferred to HeatWave
- Further SW enhancements and cloud tuning to compensate the lack of specialized hardware



Query Processing Architecture



MySQL HeatWave Analytics/OLAP Engine

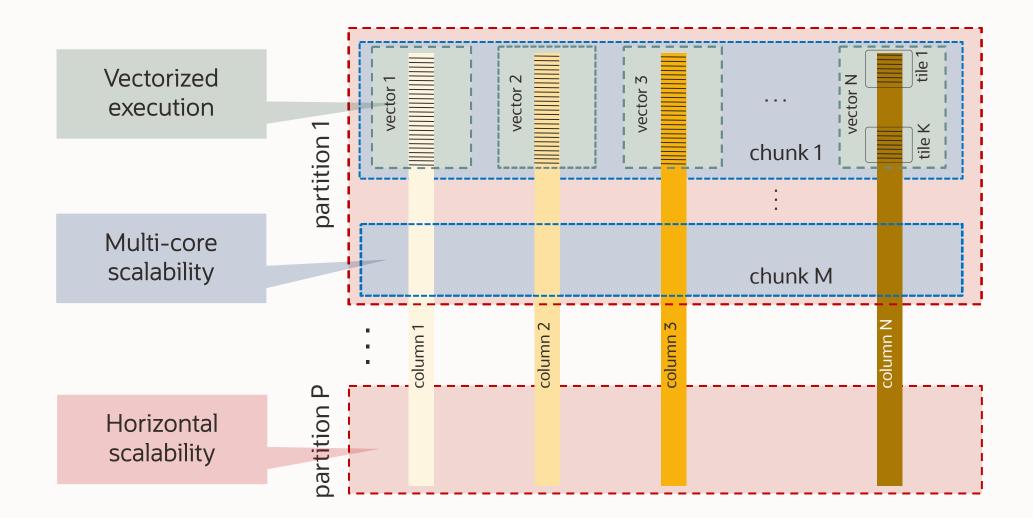
Architected for massive scale & performance

1 In-Memory, hybrid columnar processing

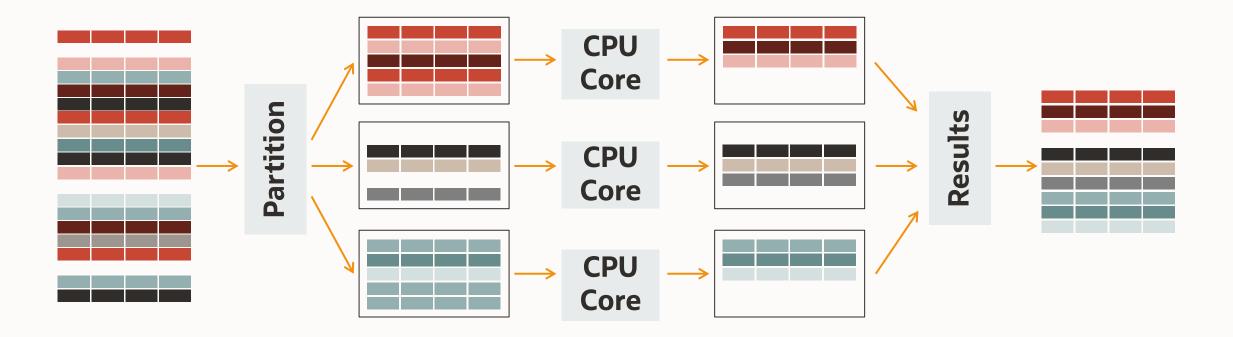
2 Massive inter- and intra-node parallelism optimized for cloud (OCI & AWS)

3 Distributed query processing algorithms (state-of-the art, based on research)

1. In-Memory hybrid columnar processing



2. Massively parallel architecture



- High-fanout workload-aware partitioning
- Machines & CPU cores can further process partitioned data in parallel
- Optimized for cache size and memory hierarchy of underlying hardware

3. Distributed algorithms optimized for cloud (OCI & AWS)

Partition data to fit into cache

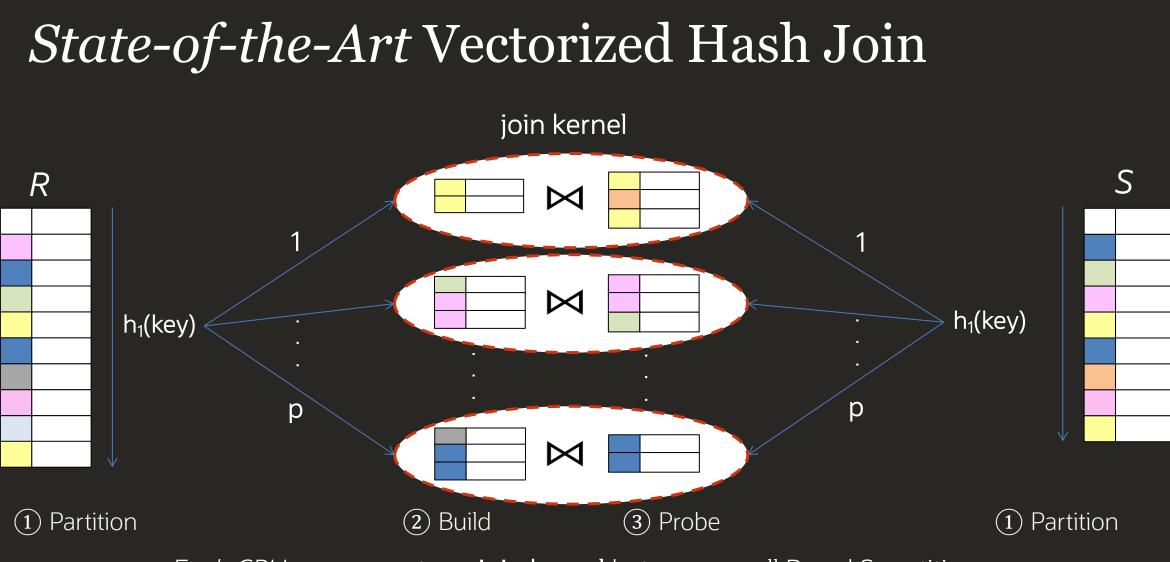
- Partition at near memory bandwidth with shape specific optimizations (e.g. hash computation)
- Ensure partitions reside in CPU cache

Process partitions as fast as possible

- Highly vectorized build & probe join kernels
- Hardware-conscious, hand-tuned primitives (e.g. using wide SIMD, AVX2 registers)

Overlap compute with communication

- Network optimizations for cloud (OCI) interconnect
- Intelligent scheduling of execute & transfer

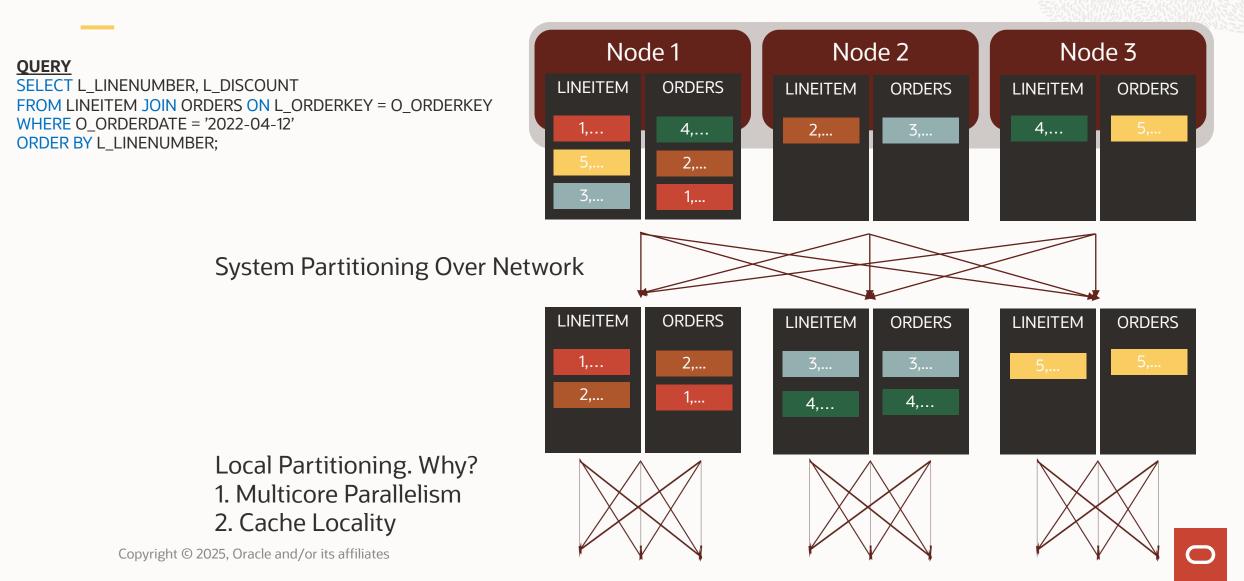


Each CPU core executes a **join kernel** between small R and S partitions Hash tables are typically compact and fits into lower level CPU caches

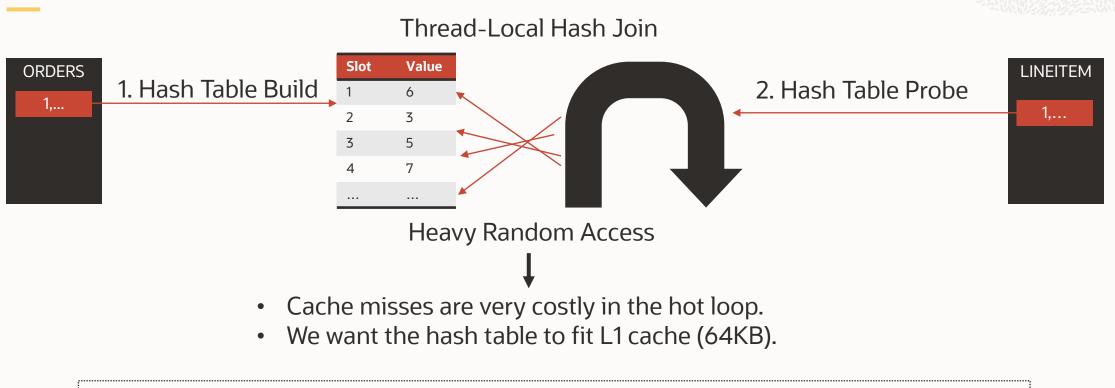
C. Balkesen; J. Teubner; G. Alonso; M. T. Özsu, Main-memory hash joins on multi-core CPUs: Tuning to the underlying hardware, IEEE ICDE 2013

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Distributed Relational Join using Vectorized Hash Join Kernels



How much do we need to partition?



Back of the envelope

- Orders Table: key column is 8B integers, 768 Billion rows: 6.1TB
- 6.1TB / 64KB = ~96 Million Partitions
- Next power of two: 2^27, a partitioning fanout of 134 Million

Data Partitioning Problem: Where is the bottleneck?

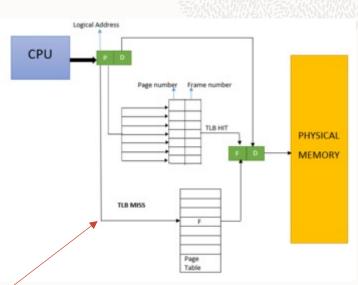
foreach tuple t in relation R:

```
p = hash(t.key)
partitions[p][counts[p]++] = t
```

- p is random and will cause heavy random access.
- In case the range of p is high (high fanout), chances of TLB misses are high.

TLB (Translation Lookaside Buffer)

- A specialized cache for virtual-to-physical address translation.
- If a virtual address is not found, expensive *page walk* occurs.
 - Can be even more expensive than simple cache miss; page walk might perform multiple memory accesses.
- Typical TLB has around 64-512 entries.
- Any partitioning fanout larger than 512 is likely to cause a huge performance impact.

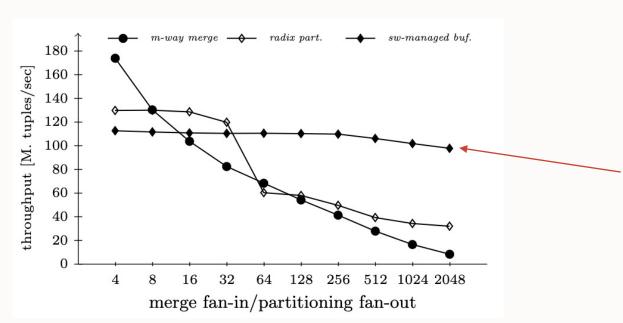


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Reducing the TLB bottleneck with SW-managed buffers [2]

foreach tuple t in relation R:

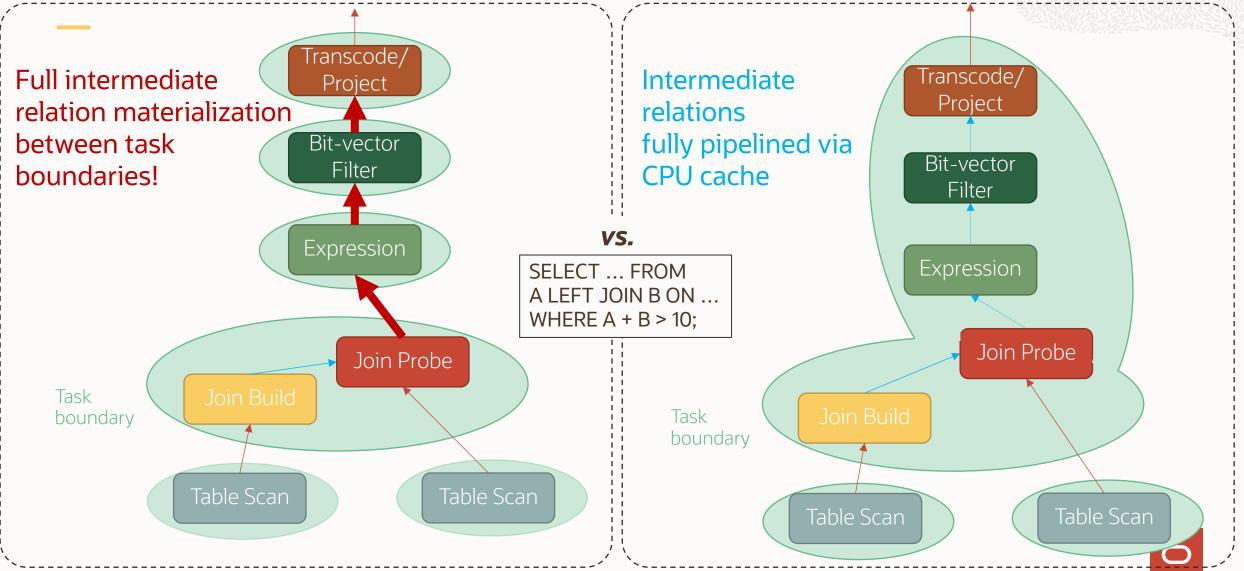
- Maintain smaller (i.e. cacheline size) buffers per partition.
- Most of the writes happen to a small number of pages; avoiding TLB misses.



• SW-managed buffers are a good optimization for the TLB bottleneck, yet higher partitioning fanout can still cause a problem.

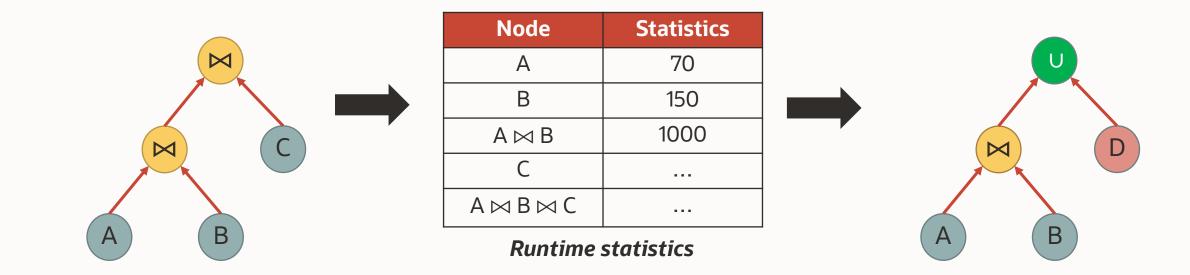
Memory-Conscious Query Processing

Operator Pipelining and Fusing



Auto Query Plan Improvement

Optimizer learns and improves query plan based on queries executed earlier

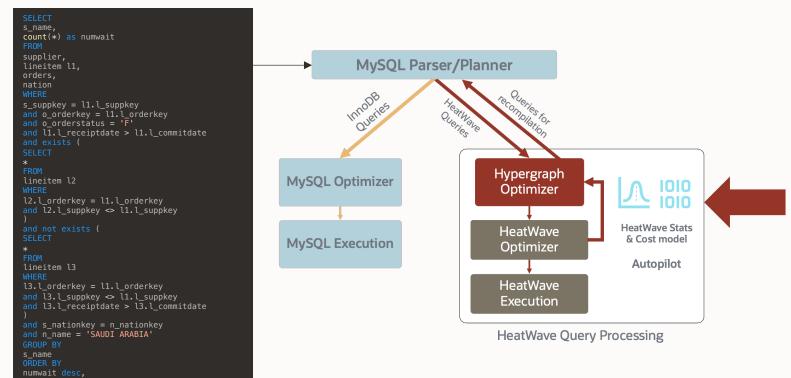


- Traditional caching techniques are not intelligent
- With Autopilot, system gets better as more queries are run
- 24TB TPC-H, TPC-DS performance improved by 40%

Query Optimization: Holistic Optimization

TPC-H Query 21

s_name

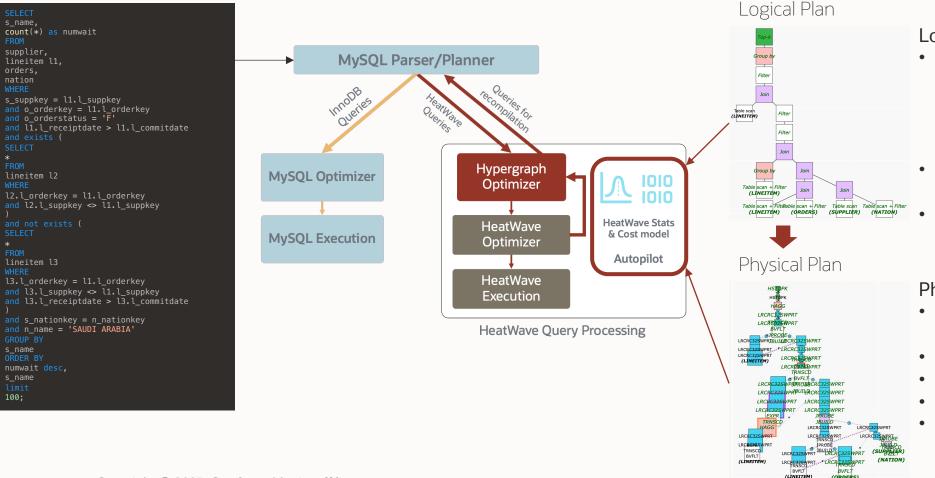


Hypergraph Optimizer gets information from HeatWave Optimizer per subgraph:

- Cardinality stats from previous runs.
- Cost model from HeatWave physical optimizer.

Query Optimization: A Detailed Overview

TPC-H Query 21



Logical plan decisions:

- Nodes are matched to previous runs to obtain accurate cardinality results (filter selectivity, join cardinality)
- Logical transformations (subquery pushdown)

Physical plan decisions:

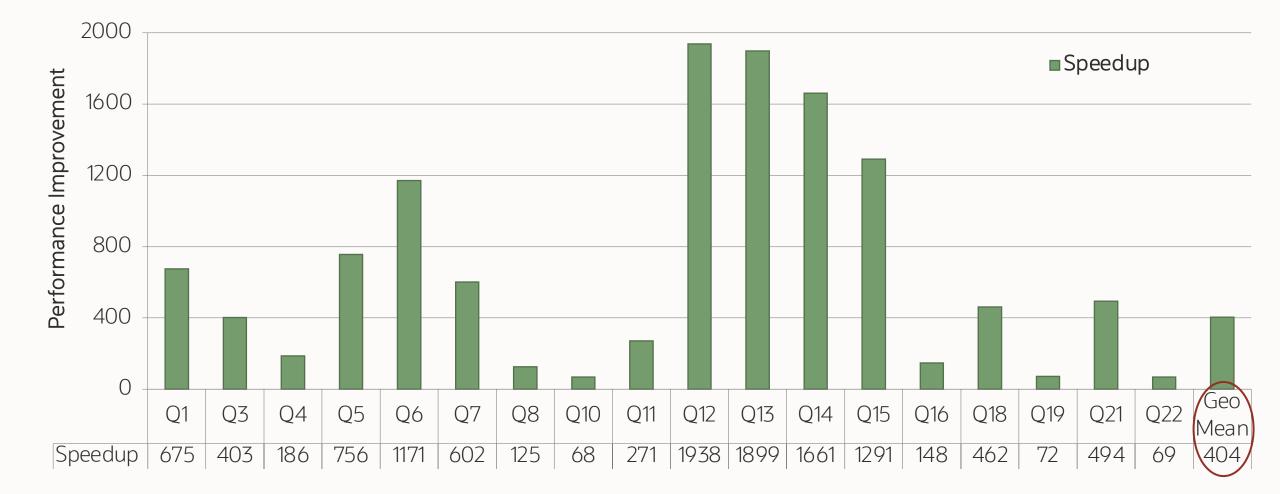
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- Join pattern (broadcast vs. partitioned)
- Partitioning fanout / rounds
- Bloom filter attachment
- Data placement key

HeatWave dramatically speeds up analytic queries: 400x Faster

Improvement over MySQL 8.0 on TPC-H queries (400G, 64 cores)



MySQL HeatWave

MySQL database service with a massively-scalable integrated analytics engine

Single MySQL database for OLTP & analytics applications

All existing applications work without changes

Extreme performance: Accelerates MySQL for OLAP queries by orders of magnitude, scales to thousands of cores

Dramatically faster and lower cost