Morsel-Driven Parallelism

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Problem

- Increasing multi-core parallelism > increasing single-thread performance
- Plan-driven parallelism/volcano-style parallelism
 - Bottlenecks and load balancing issues; not flexible
 - Parallelism hidden from operators; not optimal partitioning results due to lack of locality awareness.
 - Partitioning is static; load imbalances
 - Not NUMA aware; memory controllers decentralized to chips.
 - Main memory databases; many-core allows parallelization, but decentralization increases costs.

NUMA-Awareness

- Non-Uniform Memory Access
- Mem controllers \rightarrow chips.
- Access between cores and main memory not uniform.
- Access costs varied dependent on chip location (decentralized)
- Memory hierarchies need to be accounted for s.t. threads work on local data
 - Local data accessed faster than non-local data
 - Strategies: faster memory access > faster processors; limit memory accesses



Example

- Processors accessing non-local data increases latency
- Bus length increases with more processors
 - Scalability problems; increased latency; memory hierarchy is important.



Adaptive morsel-driven query execution

- Parallel query evaluation framework
- Task distribution at runtime; fully elastic
- Input processed by constant-sized work units
- NUMA-aware
- Morsel-wise scheduling for operators; hash-table sharing.
- Worker threads are equal to hardware threads.

Features

- Morsels (small fragments of input data) scheduled to threads.
 - Reduces load imbalances, workers finish on time.
 - Allocation of memory to decentralized chips; reduces access time; query cancelling
- Constant sized; facilitate work-stealing and preemption.
- Pipeless dependent
 - Volcano: oblivious to parallelism



Parallel Processing

- Hash table split to two pipelines. Thread local storage; avoid synch
- Scan and filter input T; build hash table HT(T) (Build and Probe Phases)



Figure 2: Parallellizing the three pipelines of the sample query plan: (left) algebraic evaluation plan; (right) three- respectively four-way parallel processing of each pipeline

Features

- Adaptive dispatcher
 - This allows adjusting of resources and reaction to execution speed during runtime.
 - Reallocates morsels and tasks if one finishes early (work-stealing)
 - Reduces/increases parallelism on threads
- NUMA-Aware; awareness of data locality
 - Process T morsel-wise; store NUMA-locally.
 - Pointers to hash table



Parallel Operators

- Need to accept tuples in parallel for pipeline parallelization
- Awareness of parallelism
- Dispatcher awareness of data
 - locality of morsels
 - Data and computation locations
 - Most execute on NUMA-local memory; faster accesses vs. non-local memory.
 - Operator pipelines for workers, still elastic

Hash Join

- Two tables (HT(T);HT(S))
- Build phase
 - Materialize input tuples to thread local storage
 - Input size known, empty table of input size constructed
- Probe phase
 - Inserts pointers to tuples
 - Check matches
 - Insert only; lookups after all inserts
 - Low synchronization costs



Build Phase



Probe Phase



Grouping/Aggregation

• Performance dependent on number of distinct keys; cache misses





Figure 9: Parallel merge sort



Figure 8: Parallel aggregation

Dispatcher

- Preserve NUMA locality
- Full elasticity
 - One morsel at a time
 - Priority scheduling of queries
- Load balancing
 - Prevent fast cores from waiting slow cores.



Example NUMA Multi-Core Server with 4 Sockets and 32 Cores

Figure 5: Dispatcher assigns pipeline-jobs on morsels to threads depending on the core

Dispatcher

- Assigns resources to parallel pipelines (tasks \rightarrow worker threads)
- Aware of data locality of NUMA-local morsels; allow local execution.
- Cores are in different clusters with their own local memory regions.
- Can still access memory in other clusters.
- Scheduling mechanism; allows flexible parallel execution (elasticity).



Figure 1: Idea of morsel-driven parallelism: $R \bowtie_A S \bowtie_B T$

Implementation

- HyPer
 - Main memory column database
 - No intra-query parallelism
 - JIT (Just-In-Time) Approach
 - Running during execution, schedule is morsel-wise.
- QEProject
 - Executable pipelines to dispatcher
 - Observes data dependencies
 - Temporary storage area for each thread/core

Implementation (Vectorwise)

- TPC-H
 - Vectorwise; competitor system
 - Not NUMA-aware
 - HyPer achieves 30x speed up
 - NUMA awareness important in some cases
 - Non-adaptivity reduces in most
 - All perform better than Vectorwise

system	geo. mean	sum	scal.
HyPer	0.45s	15.3s	28.1×
Vectorwise	2.84s	93.4s	9.3×
Vectorwise, full-disclosure settings	1.19s	41.2s	8.4×



Figure 11: TPC-H scalability on Nehalem EX (cores 1-32 are "real", cores 33-64 are "virtual")



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Implementation (NUMA awareness)



Figure 10: NUMA topologies, theoretical bandwidth

Implementation (NUMA awareness)

- NUMA-aware processing; lower latency and higher bandwidth
- Reducing of remote accesses in joins
- Alternatives
 - OS Default (OS placement)
 - Memory controller becomes a bottleneck
 - Interleaved (robin round allocation)
 - Reasonable not optimal

Irc-n.	Nehalem EX		Sandy Bridge EP			bandwidth [GB/s]		latency [ns]	
	geo. mean	max	geo. mean	max		local	mix	local	mix
OS default	1.57×	4.95×	2.40×	5.81×	Nehalem EX	93	60	161	186
interleaved	1.07×	1.24×	1.58×	5.01×	Sandy Bridge EP	121	41	101	257

Implementation (Elasticity)

- Parallelization shown to be fully elastic.
- TPC-H queries
- Threads can switch between queries dynamically.
 - Succeeded in reassigning threads in runtime and prioritizing.
- VS Static assignment in Volcano:
 - 2nd test: input/threads = morsel size.
 - Not too different w since query at once
 - Another single-threaded process reduces performance by 36.8%(vs 4.7%)





SSB #	time [s]	scal. [×]	read [GB/s]	write [GB/s]	remote [%]	QPI [%]
1.1	0.10	33.0	35.8	0.4	18	29
1.2	0.04	41.7	85.6	0.1	1	44
1.3	0.04	42.6	85.6	0.1	1	44
2.1	0.11	44.2	25.6	0.7	13	17
2.2	0.15	45.1	37.2	0.1	2	19
2.3	0.06	36.3	43.8	0.1	3	25
3.1	0.29	30.7	24.8	1.0	37	21
3.2	0.09	38.3	37.3	0.4	7	22
3.3	0.06	40.7	51.0	0.1	2	27
3.4	0.06	40.5	51.9	0.1	2	28
4.1	0.26	36.5	43.4	0.3	34	34
4.2	0.23	35.1	43.3	0.3	28	33
4.3	0.12	44.2	39.1	0.3	5	22



Implementation (Star Schema)

- Data warehousing scenario
- Speed up of 40x
- Large fact table, NUMA-local
- Faster aggregation
- Better scalability vs TPC-H
 - TPC-H more complex
 - Complex joins and aggregations
 - Single table

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Table 3: Star Schema Benchmark (scale 50) on Nehalem EX

Conclusion

- NUMA-awareness and runtime adaptivity is important; allows load balancing, elasticity and reduces latency in parallelism.
- Oblivious operators are not always the best solution. (parallel-aware)
- Splitting task and morsels carefully is important for analytical query performance.
- Possible to further reduce NUMA remote accesses.
- Morsel-driven parallelism performs better when handling multiple threads and queries where speed and workload vary throughout runtime.

Bibliography

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