A Distributed Hash Table for Shared Memory

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Distributed Hash Table

Main challenge

Building a *fast* and *CPU-efficient* shared hash table:

- Minimal latency
- Minimal memory overhead
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Specialized algorithms and data structures needed!

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- **Contribution**: Reducing roundtrips *while* CPU-efficient

High-performance Networking

Infiniband hardware

Specialized hardware used to construct high-performance networks:

- Comparable in price to Ethernet
- Supports bandwidths up to 100 Gb/s
- *Direct* access to memory via PCI-E bus

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RDMA: Remote Direct Memory Access

Directly access to remote memory *without* invoking remote CPUs

- Zero-copy networking
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Performance: *one-sided* RDMA vs TCP

Roundtrips latency: $< 3\mu s$ (Infiniband) vs $60\mu s$ (traditional Ethernet)

Hash Table: Challenges

Notation: Hash table

$T = \langle b_0, \ldots, b_{n-1} \rangle$ as a sequence of buckets b_i, where:

- n the hash table size and m the number of used entries
- $\alpha = \frac{m}{n}$ the load factor

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Takes a data element d as parameter, and:

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Design: Challenges

- How to *distribute* and access $T = \langle b_0, \ldots, b_{n-1} \rangle$ efficiently?
- How to *design* `find-or-put` to perform efficiently?

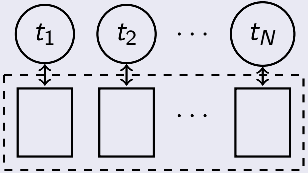
PGAS: Partitioned Global Address Space

Details

Assuming N participating threads:

PGAS: Partitioned Global Address Space

PGAS



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Assuming N participating threads:

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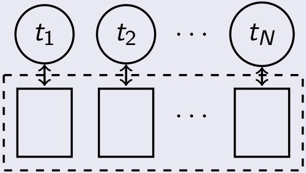
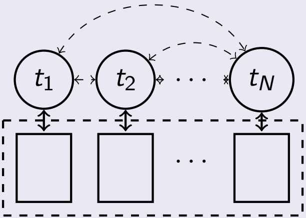


Hybrid PGAS



Details

Assuming N participating threads:

- **PGAS:** shared + distributed memory model
- **Hybrid PGAS:** PGAS + message passing *(dashed edges)*

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Hash Collisions

Efficiency: Resolving Hash Collisions

Occurs when $h(x) = h(y)$ for data elements $x \neq y$

- Efficiency of `find-or-put` depends on hashing strategy!

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Existing Work

- Pilaf, 2014 *(Cuckoo)*
- Nessie, 2014 *(Cuckoo)*
- FaRM, 2014 *(Hopscotch)*
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Best strategy for `find-or-put`

Which strategy requires the *least* number of roundtrips?

Comparing Hashing Strategies

Chained Hashing

- \+ Theoretical comp. $\Theta(1 + \alpha)$
- \- Dynamic mem. management
- \- Storing pointers

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Linear Probing

+ Buckets are consecutive
+ *No* locking or relocations
- Roundtrips for lookups?

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Linear Probing versus Hopscotch

- Due to Hopscotch invariant, lookups *may* be more expensive, but
- Inserts are arguably cheaper *(amortized complexity)*

Linear Probing: Efficiency Bounds

Knuth, 1997

The *expected* number of buckets to examine until the intended buckets is found is *at most*:

$$\frac{1}{2}\left(1 + \frac{1}{(1-\alpha)^2}\right)$$

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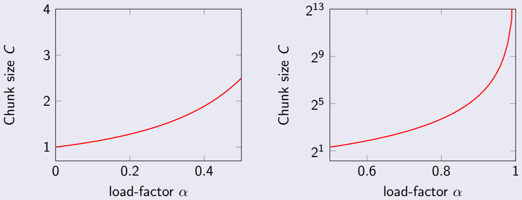

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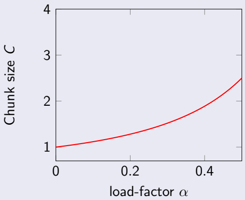

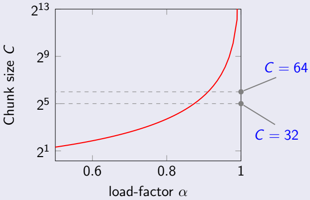

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Linear Probing: Hiding Latency

Contribution: Asynchronous queries

Before chunk iteration, first request the *next* chunk:

- Overlapping roundtrips with computational activity
- Find next chunk with *quadratic probing* to prevent clustering

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Obtains the i-th chunk, starting from bucket $b_{h(d)}$

- Returns a handle s

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Defining `query-chunk`(i, d)

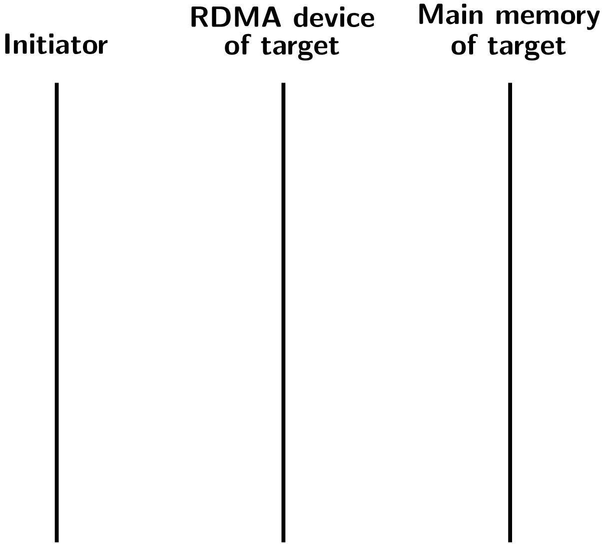
Obtains the i-th chunk, starting from bucket $b_{h(d)}$

- Returns a handle s

Defining `sync-chunk`(s)

Takes a handle s as parameter, waits until the *corresponding* query has been completed.

Linear Probing: Querying Visualized



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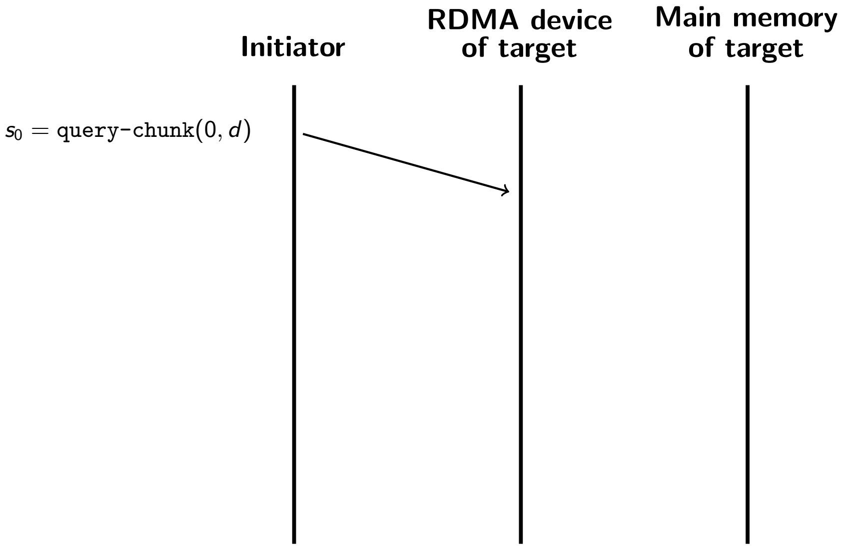

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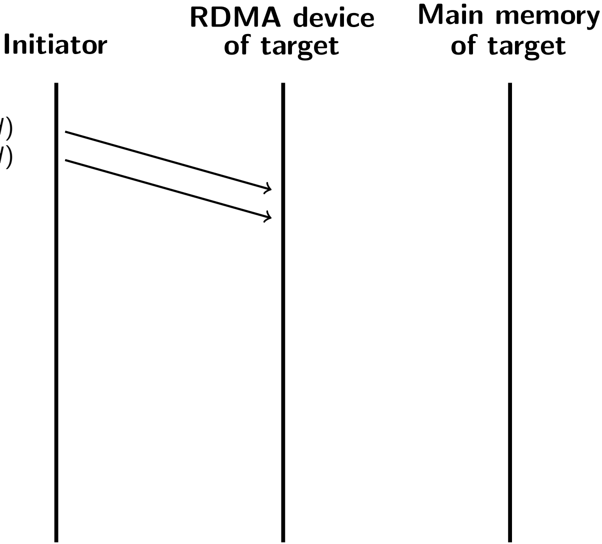
$s_0 = \texttt{query-chunk}(0, d)$
$s_1 = \texttt{query-chunk}(1, d)$



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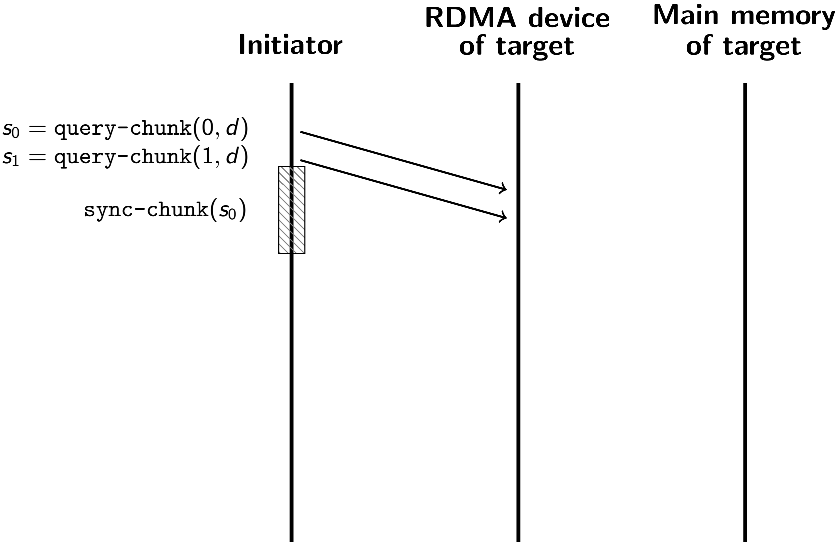

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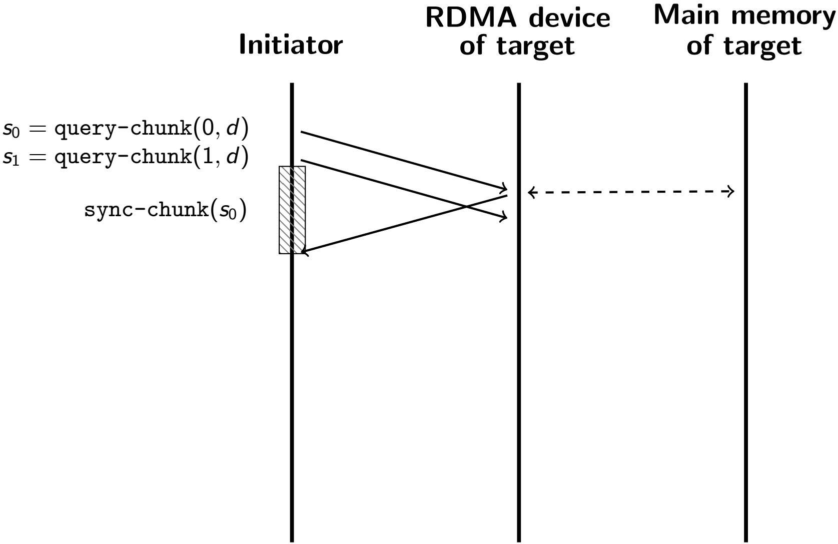

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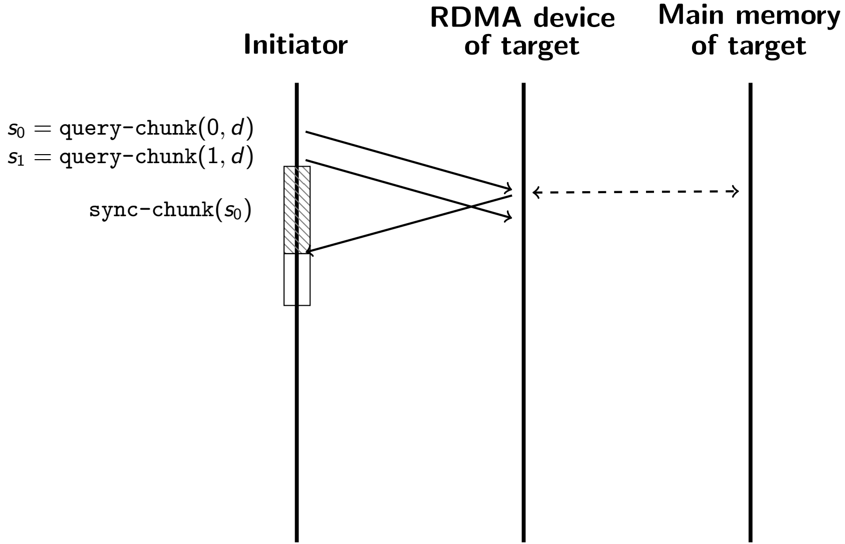

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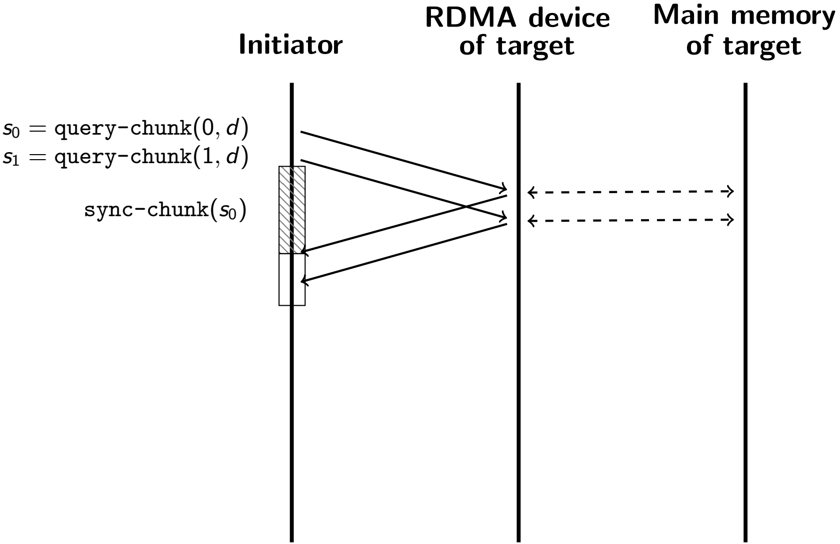

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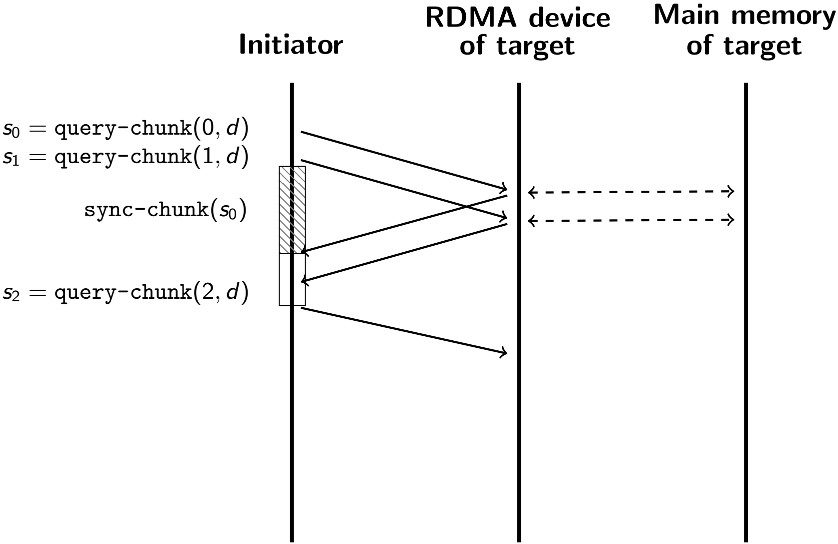

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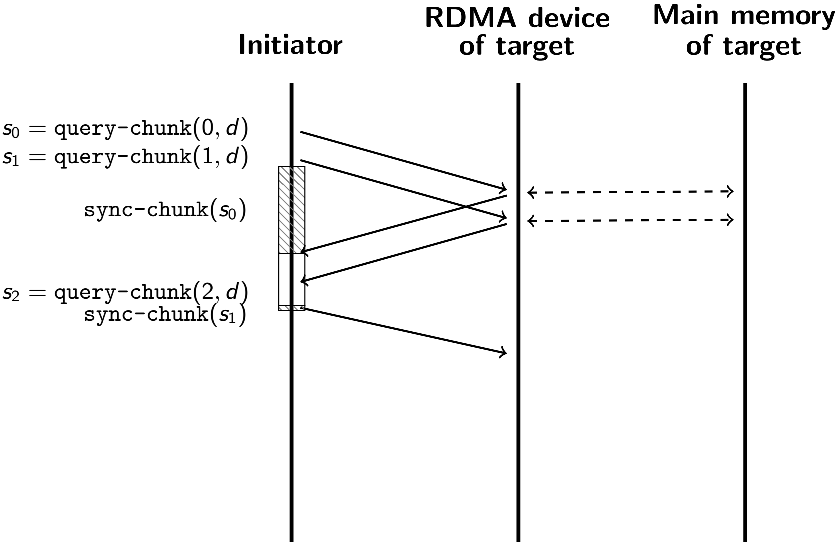

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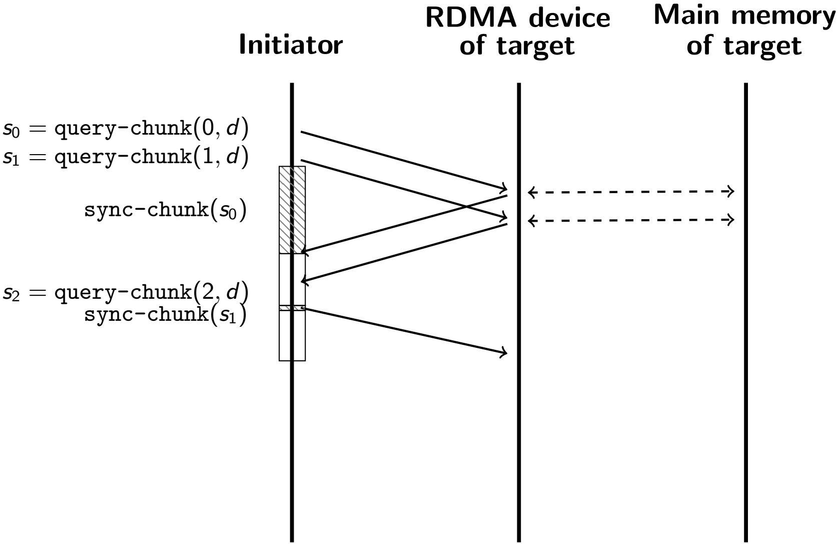

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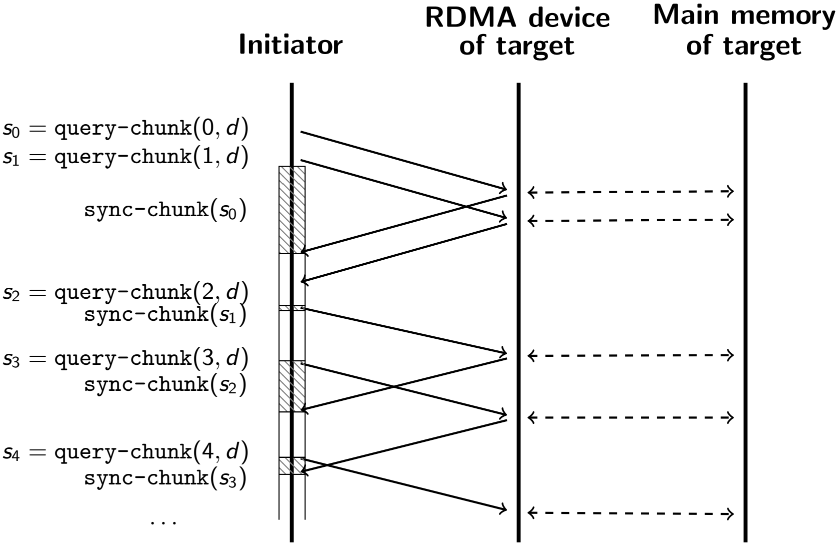

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Hash Table: Evaluation

Experimental Setup

All experiments have been perfomed on the *DAS-5* cluster:

- 66 machines
- 16 cores each (Intel E5-2630v3)
- 64 GB internal memory each
- connected via 48Gb/s Infiniband

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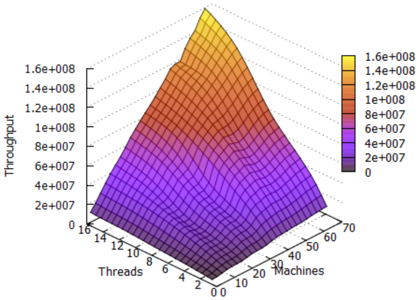
Benchmarks

Under different workloads, we measured:

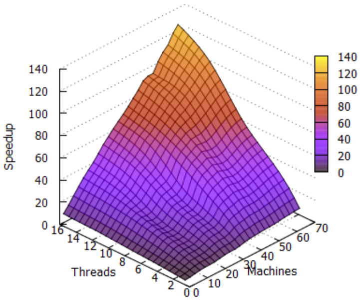
- Throughput of `find-or-put`
- Latency of `find-or-put`
- Roundtrips of `find-or-put`

Hash Table: Throughput

Total Throughput

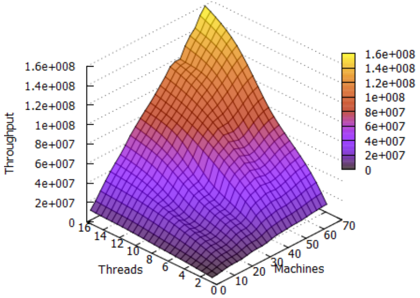


Speedup



Hash Table: Throughput

Total Throughput



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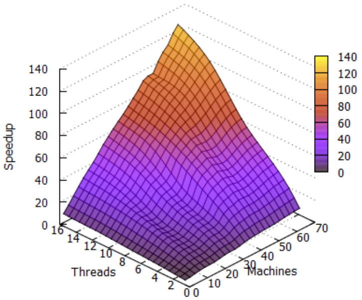
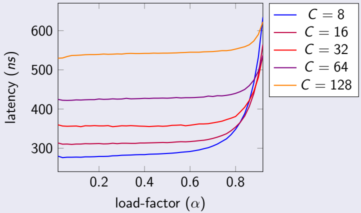


Observations

- Throughputs up to 140×10^6 reached (66 machines)
- Remote speedup up to 110 obtained
- Local throughput of 495×10^6 reached (1 threads)

Hash Table: Latency

Local latency



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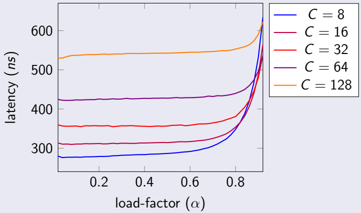
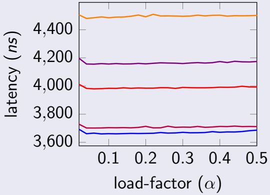
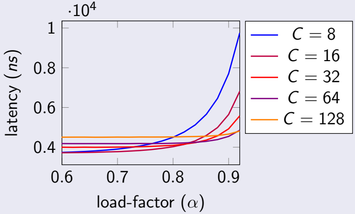


Remote latency





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Performance Indication

- **FaRM**: Inserts take $\sim 35\mu s$
- **Pilaf**: Operations take $\sim 30\mu s$
- **Nessie**: Inserts take $\sim 25\mu s$