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Phoenix Rebirth:
Scalable MapReduce on a Large-Scale Shared-Memory System

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Talk in a Nutshell

- ☐ Scaling a shared-memory MapReduce system on a 256-thread machine with NUMA characteristics

- ☐ Major challenges & solutions
  - Memory mgmt and locality => locality-aware task distribution
  - Data structure design => mechanisms to tolerate NUMA latencies
  - Interactions with the OS => thread pool and concurrent allocators

- ☐ Results & lessons learnt
  - Improved speedup by up to 19x (average 2.5x)
  - Scalability of the OS still the major bottleneck

Background

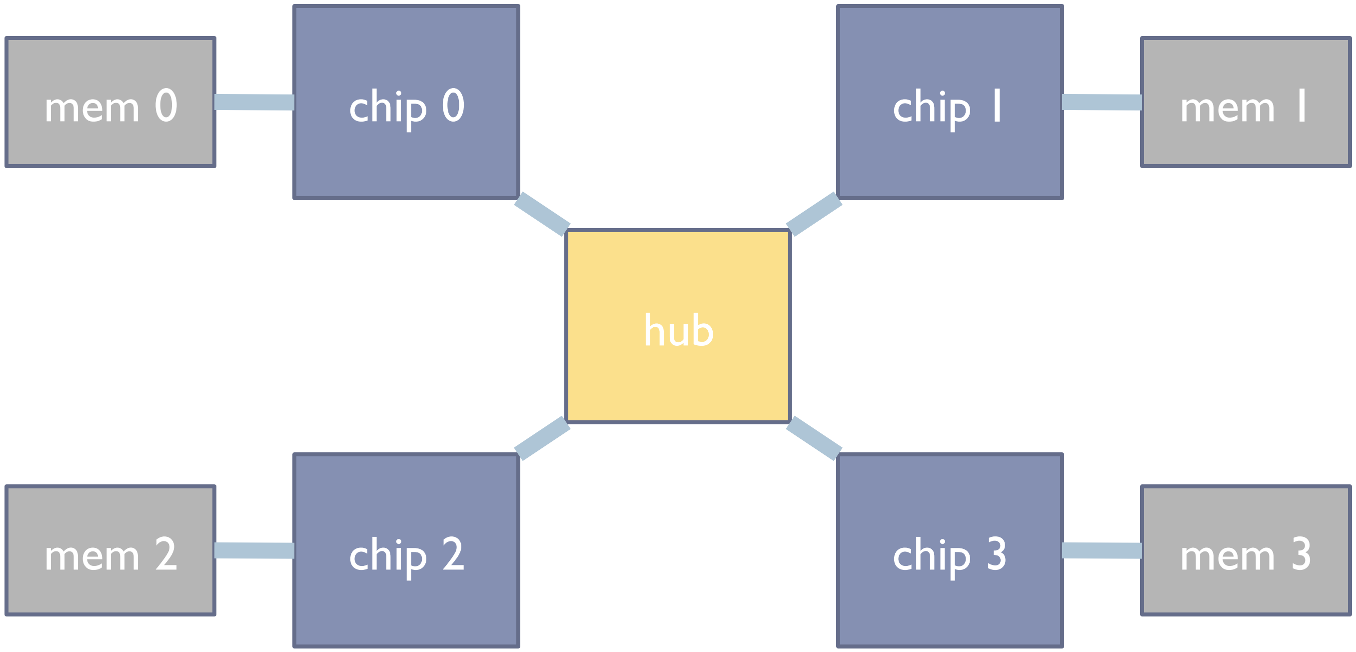
MapReduce and Phoenix

- MapReduce
  - A functional parallel programming framework for large clusters
  - Users only provide map / reduce functions
    - Map: processes input data to generate intermediate key / value pairs
    - Reduce: merges intermediate pairs with the same key
  - Runtime for MapReduce
    - Automatically parallelizes computation
    - Manages data distribution / result collection

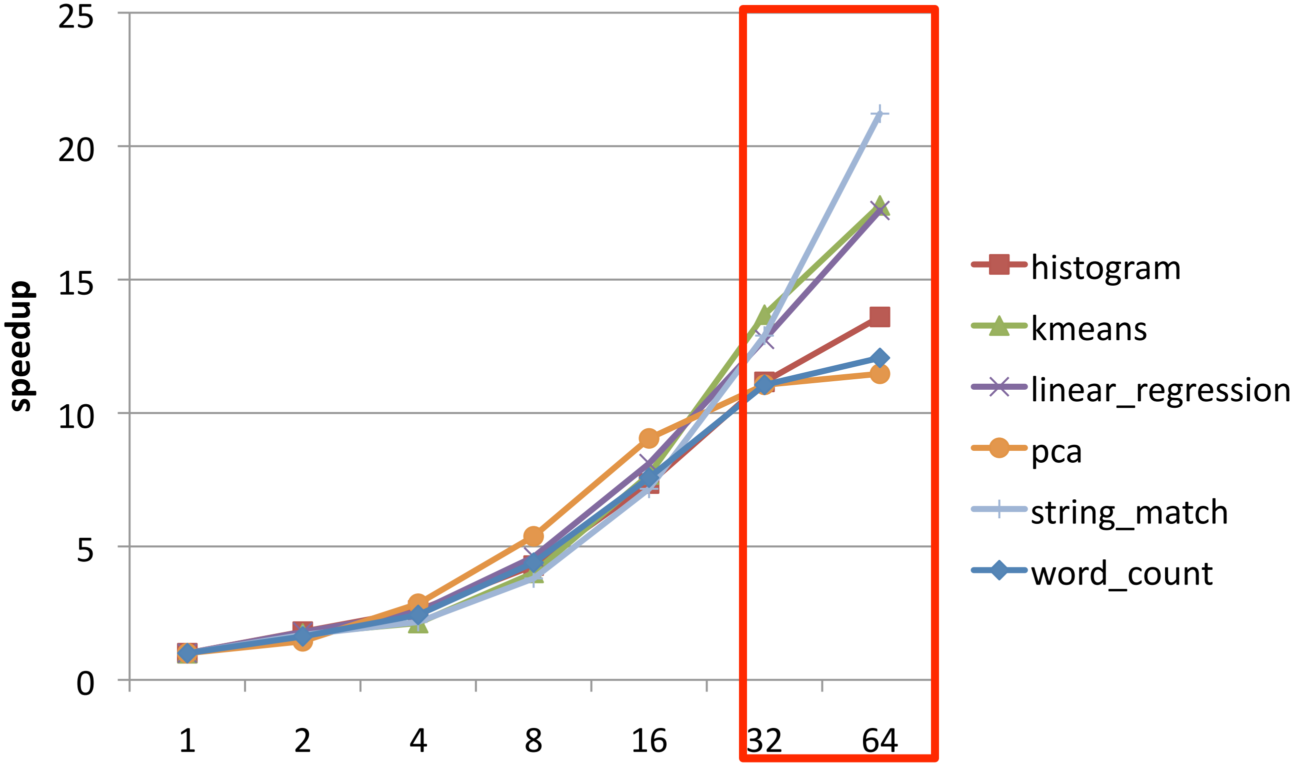
- Phoenix: shared-memory implementation of MapReduce
  - An efficient programming model for both CMPs and SMPs [HPCA'07]

Phoenix on a 256-Thread System

- ❑ 4 UltraSPARC T2+ chips connected by a single hub chip
  1. Large number of threads (256 HW threads)
  2. Non-uniform memory access (NUMA) characteristics
     - 300 cycles to access local memory, +100 cycles for remote memory



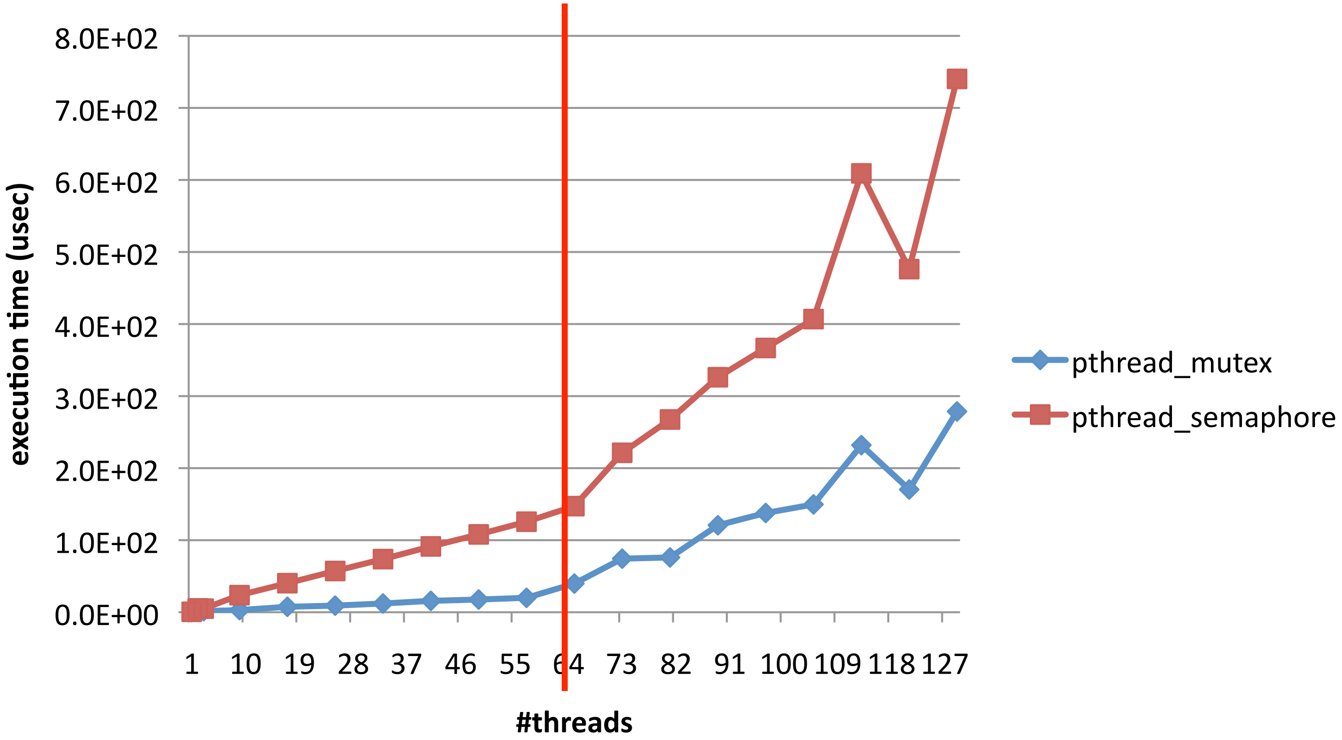
The Problem: Application Scalability



Speedup on a 4-Socket UltraSPARC T2+

- ❑ Baseline Phoenix scales well on a single socket machine
- ❑ Performance plummets with multiple sockets & large thread counts

The Problem: OS Scalability



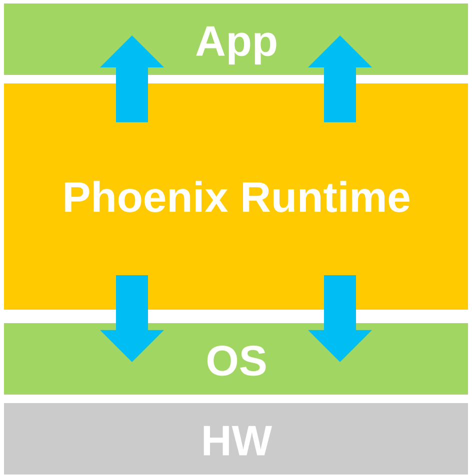
Synchronization Primitive Performance on the 4-Socket Machine

❑ OS / libraries exhibit NUMA effects as well

- Latency increases rapidly when crossing chip boundary
- Similar behavior on a 32-core Opteron running Linux

Optimizing the Phoenix Runtime on a Large-Scale NUMA System

Optimization Approach



Algorithmic Level

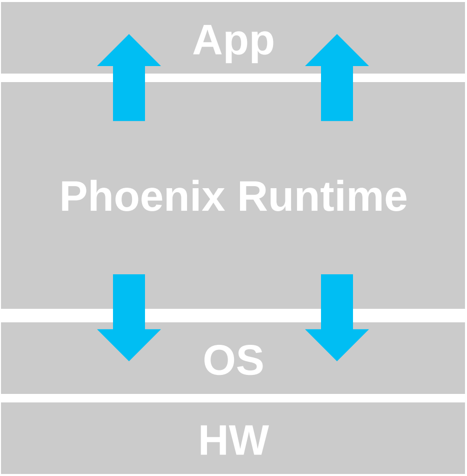
Implementation Level

OS Interaction Level

- ☐ Focus on the unique position of runtimes in a software stack
  - Runtimes exhibit complex interactions with user code & OS

- ☐ Optimization approach should be multi-layered as well
  - Algorithm should be NUMA aware
  - Implementation should be optimized around NUMA challenges
  - OS interaction should be minimized as much as possible

Algorithmic Optimizations



Algorithmic Level

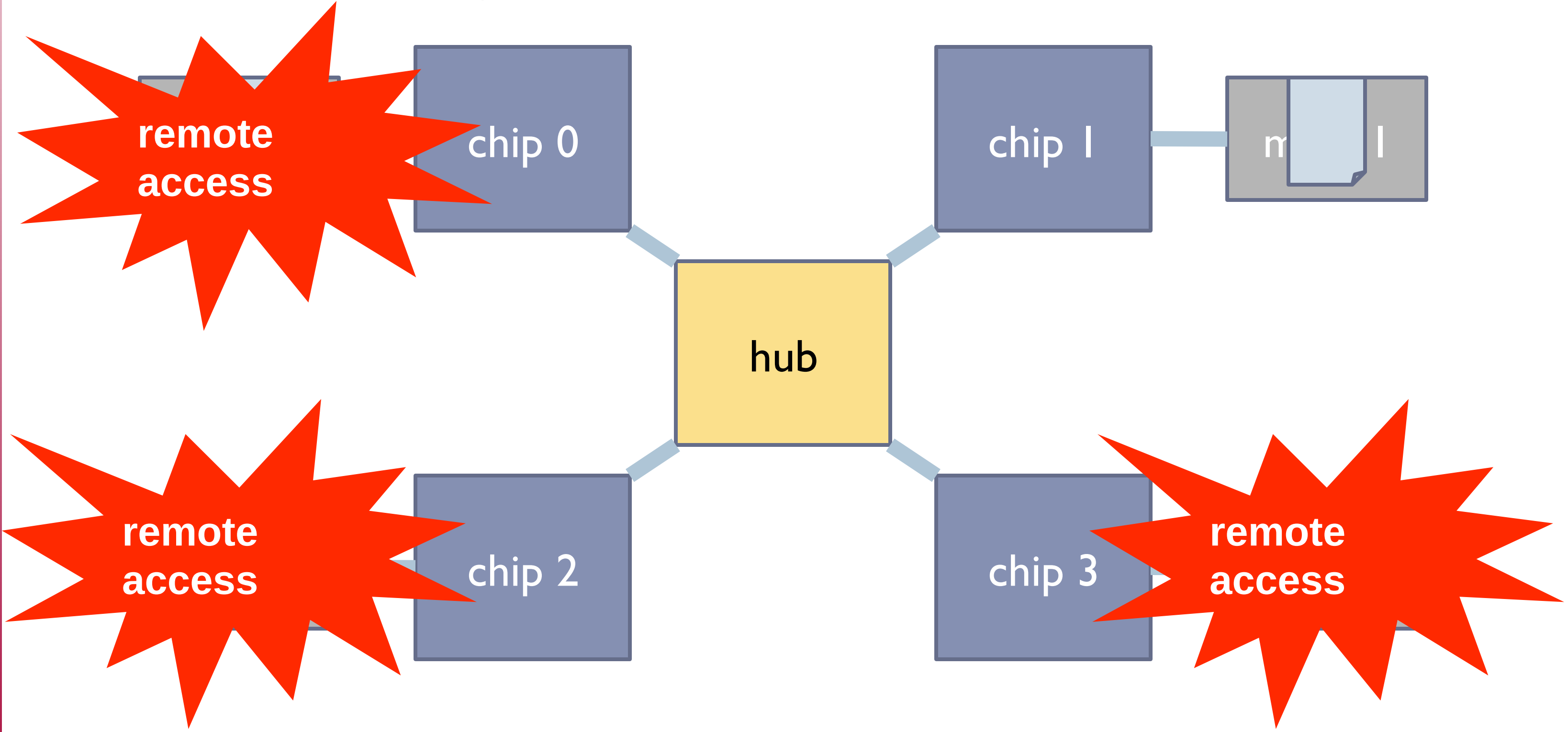
Implementation Level

OS Interaction Level

Algorithmic Optimizations (contd.)

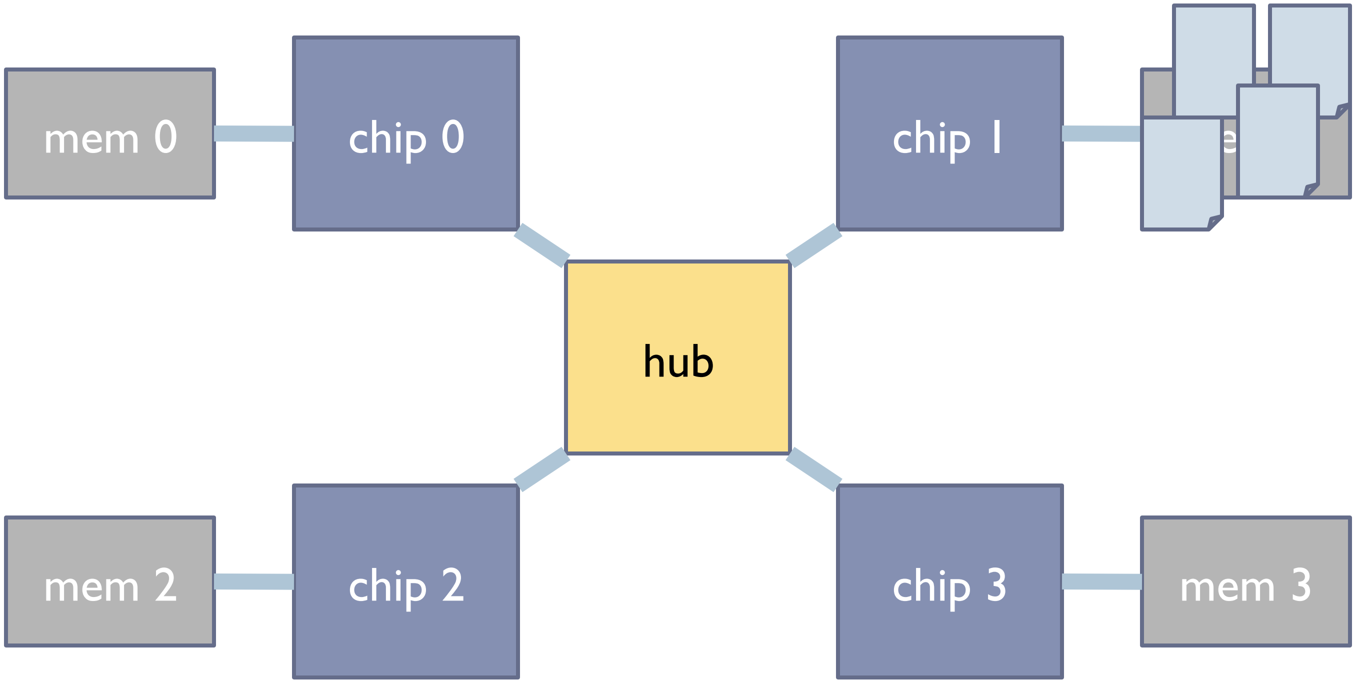
Runtime algorithm itself should be NUMA-aware

- Problem: original Phoenix did not distinguish local vs. remote threads
  - On Solaris, the physical frames for `mmap()`ed data spread out across multiple *locality groups* (a chip + a dedicated memory channel)
  - Blind task assignment can have local threads work on remote data

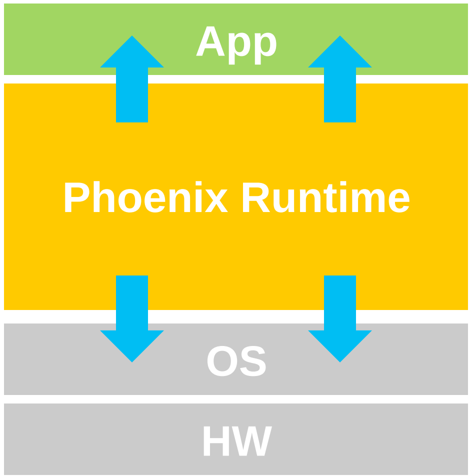


Algorithmic Optimizations (contd.)

- Solution: locality-aware task distribution
  - Utilize per-locality group task queues
  - Distribute tasks according to their locality group
  - Threads work on their local task queue first, then perform task stealing



Implementation Optimizations



Algorithmic Level

Implementation Level

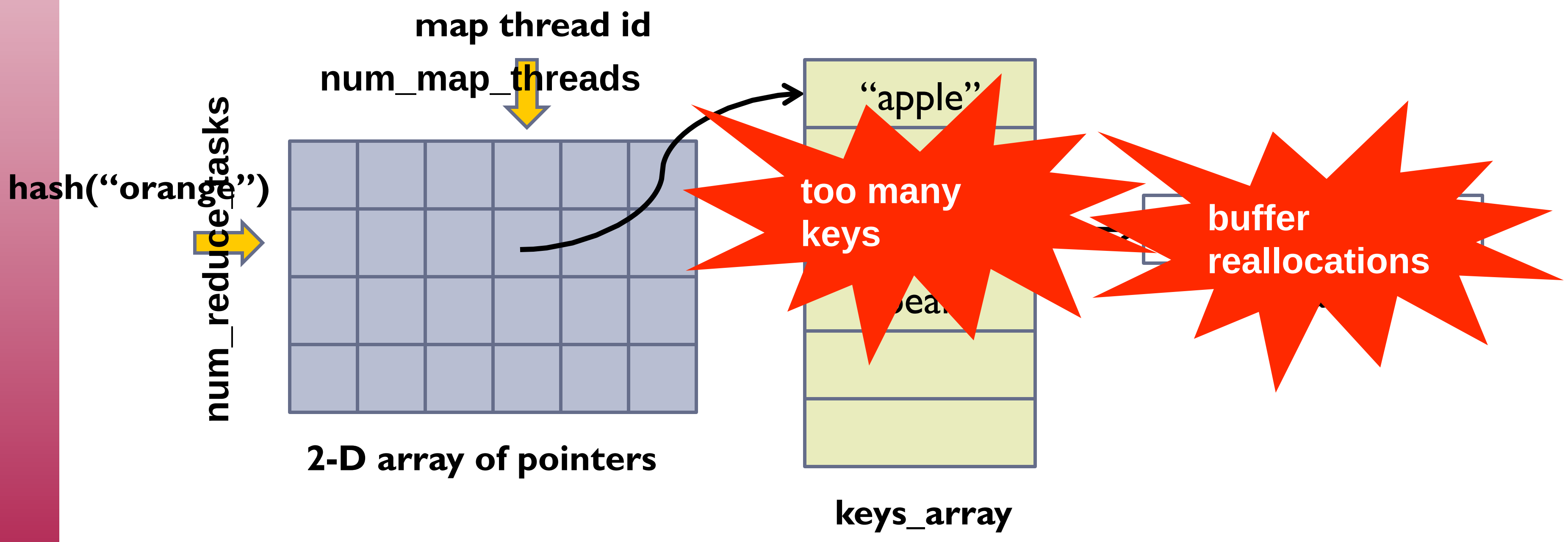
OS Interaction Level

Implementation Optimizations (contd.)

Runtime implementation should handle large data sets efficiently

- ❑ Problem: Phoenix core data structure not efficient at handling large-scale data

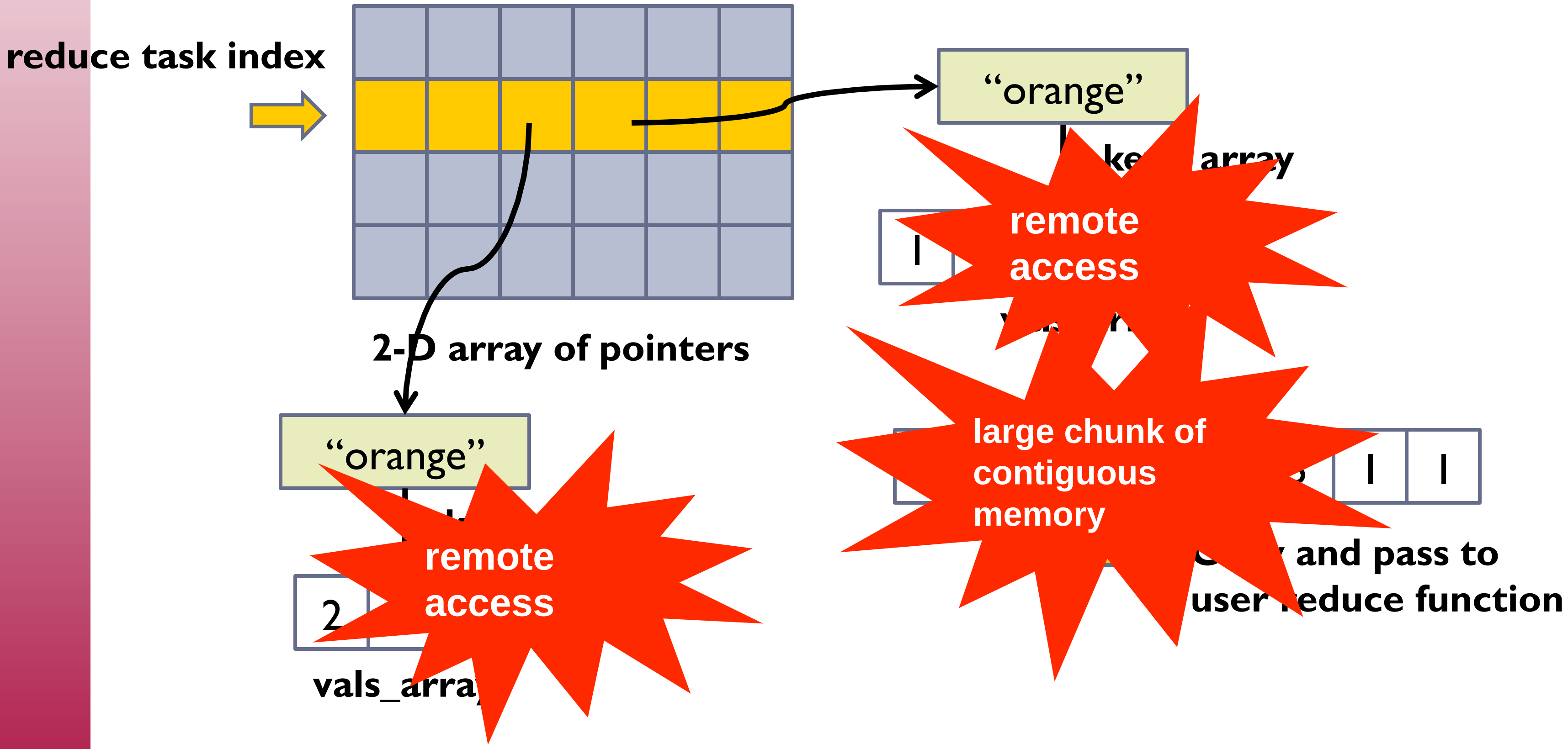
- ❑ Map Phase
  - Each column of pointers amounts to a fixed-size hash table
  - `keys_array` and `vals_array` all thread-local



Implementation Optimizations (contd.)

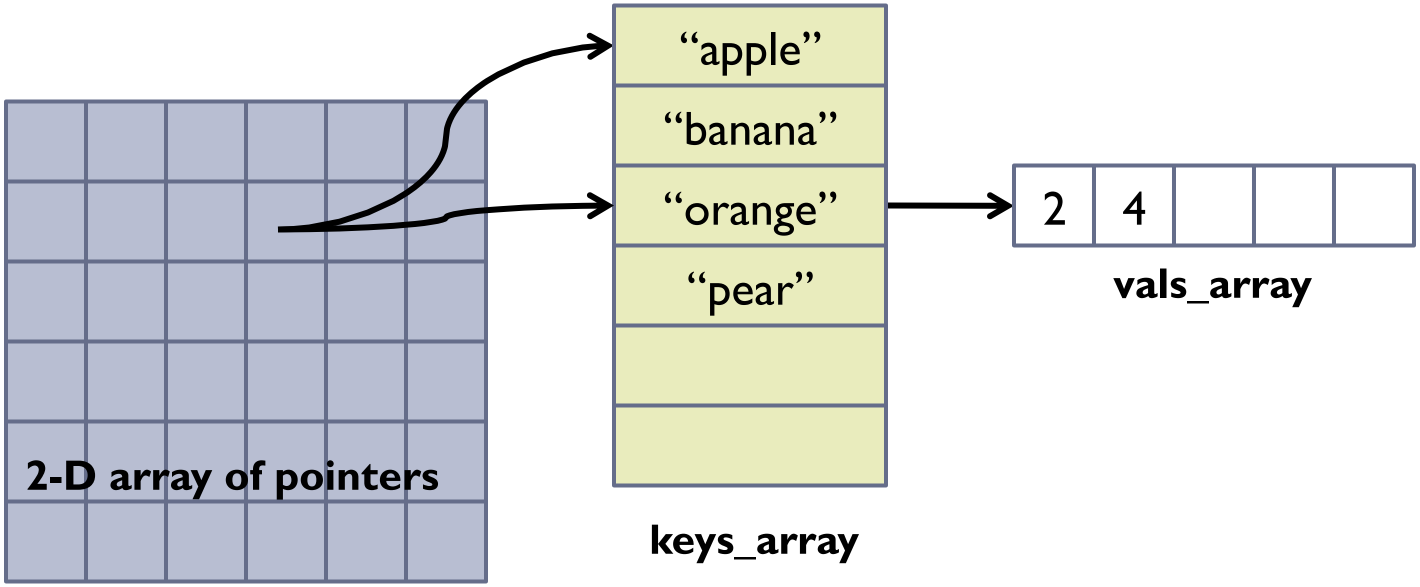
❑ Reduce Phase

- Each row amounts to one reduce task
- Mismatch in access pattern results in remote accesses



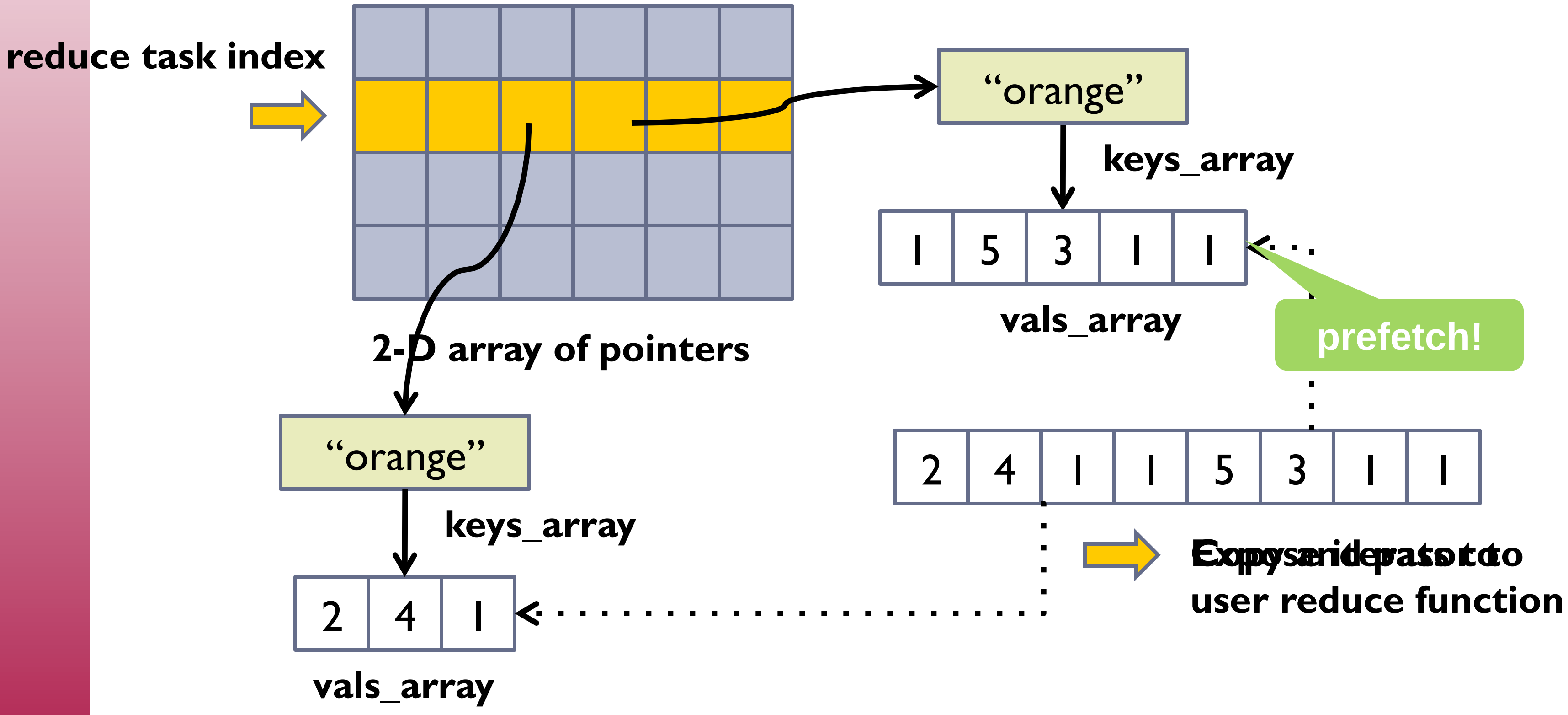
Implementation Optimizations (contd.)

- ❑ Solution 1: make the hash bucket count user-tunable
  - Adjust the bucket count to get few keys per bucket



Implementation Optimizations (contd.)

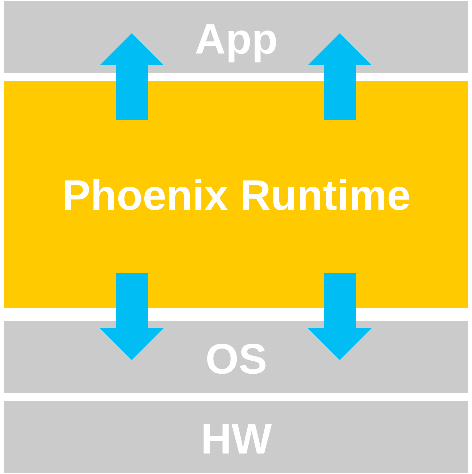
- Solution 2: implement iterator interface to `vals_array`
  - Removed copying / allocating the large value array
  - Buffer implemented as distributed chunks of memory
  - Implemented prefetch mechanism behind the interface



Other Optimizations Tried

- ☐ Replace hash table with more sophisticated data structures
  - Large amount of access traffic
  - Simple changes negated the performance improvement
    - E.g., excessive pointer indirection
- ☐ Combiners
  - Only works for commutative and associative reduce functions
  - Perform local reduction at the end of the map phase
  - Little difference once the prefetcher was in place
    - Could be good for energy
- ☐ See paper for details

OS Interaction Optimizations



Algorithmic Level

Implementation Level

OS Interaction Level

OS Interaction Optimizations (contd.)

Runtimes should deliberately manage OS interactions

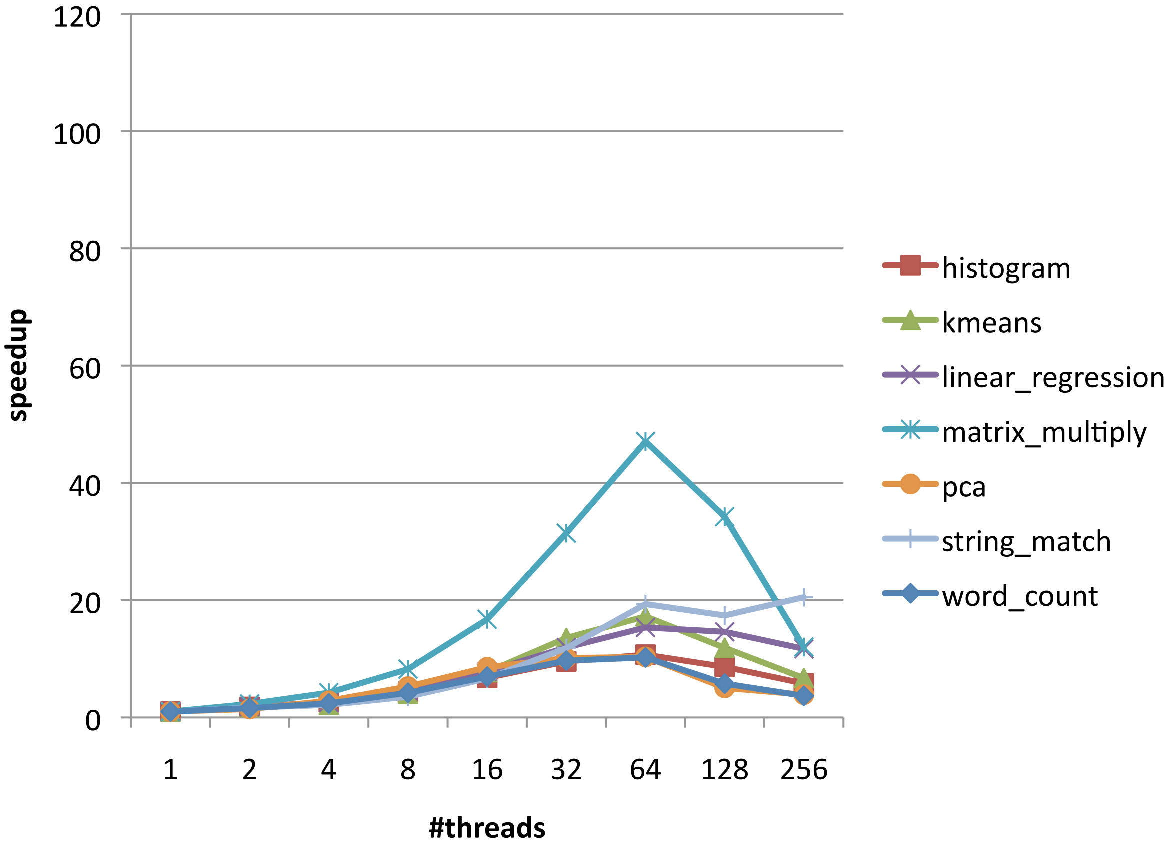
1. Memory management => memory allocator performance
   - Problem: large, unpredictable amount of intermediate / final data
   - Solution
     - Sensitivity study on various memory allocators
     - At high thread count, allocator performance limited by `sbrk()`
2. Thread creation => `mmap()`
   - Problem: stack deallocation (`munmap()`) in thread join
   - Solution
     - Implement thread pool
     - Reuse threads over various MapReduce phases and instances

Results

Experiment Settings

- ❑ 4-Socket UltraSPARC T2+
- ❑ Workloads released in the original Phoenix
  - Input set significantly increased to stress the large-scale machine
- ❑ Solaris 5.10, GCC 4.2.1 –O3
- ❑ Similar performance improvements and challenges on a 32-thread Opteron system (8-sockets, quad-core chips) running Linux

Scalability Summary

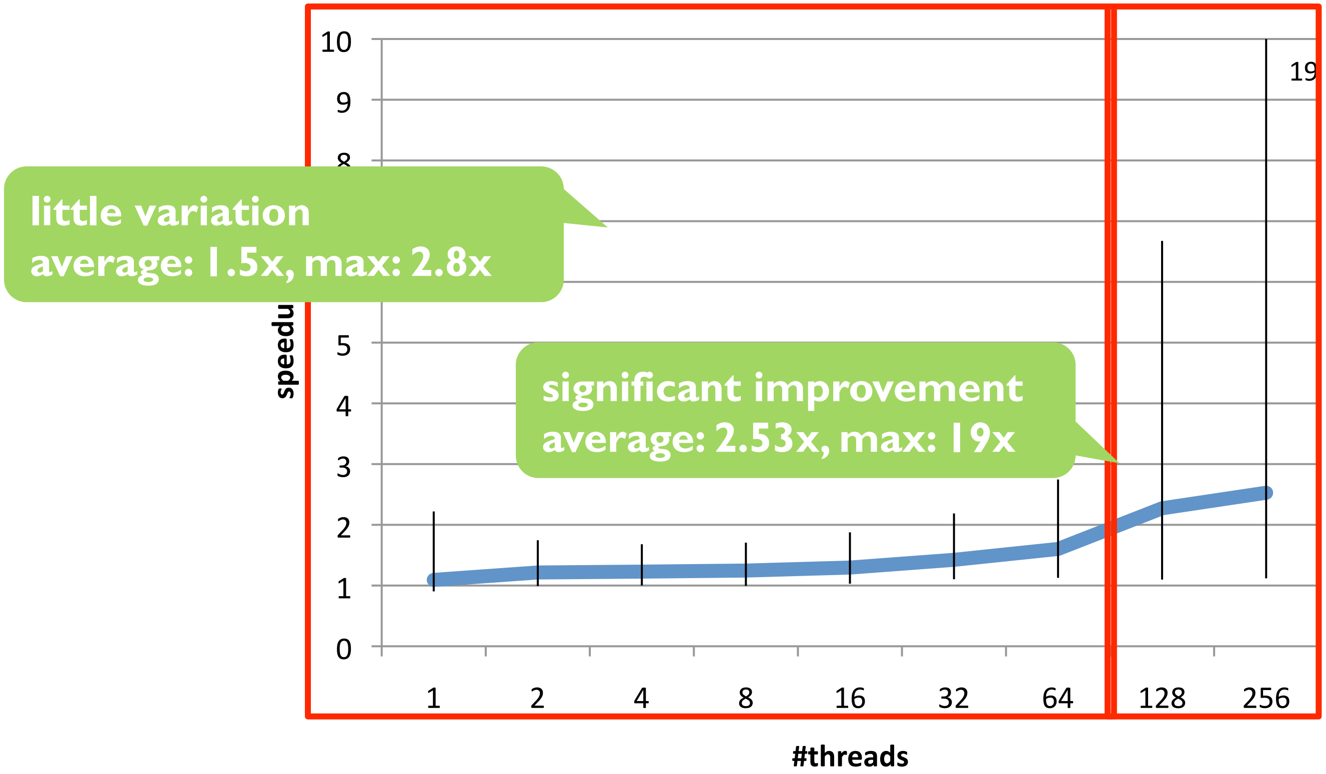


Scalability of the Optimized Version

Scalability of the Original Phoenix

- ☐ Significant scalability improvement

Execution Time Improvement



little variation
average: 1.5x, max: 2.8x

significant improvement
average: 2.53x, max: 19x

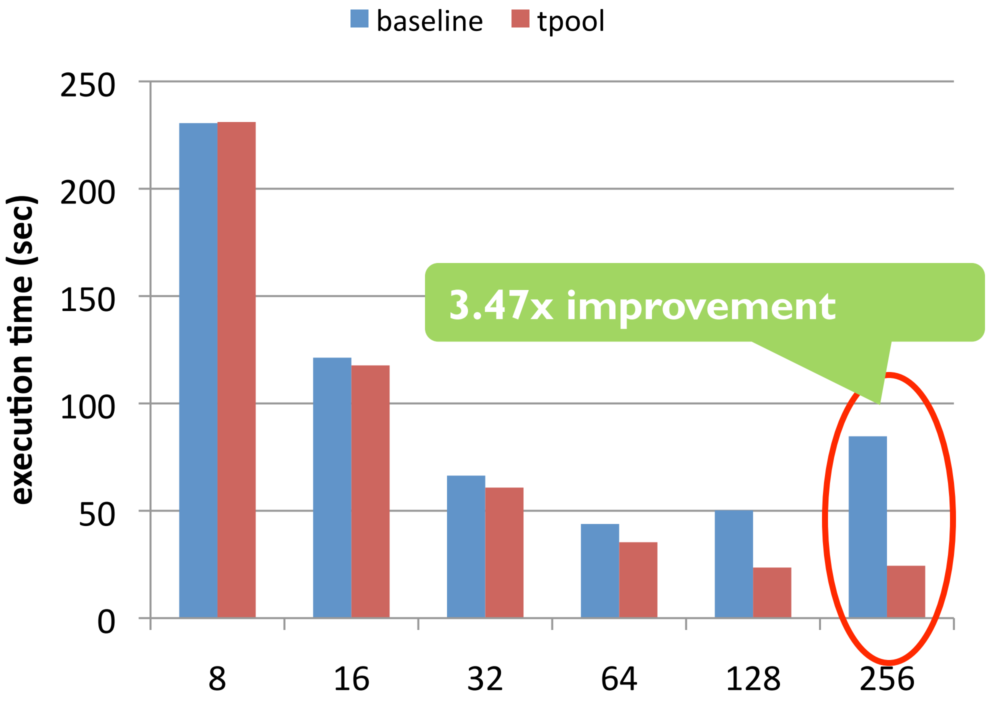
Relative Speedup over the Original Phoenix

- ❑ Optimizations more effective for NUMA

Analysis: Thread Pool

threads	before	after
8	20	10
16	1,947	13
32	4,499	18
64	9,956	33
128	14,661	44
256	14,697	102

Number of Calls to `munmap()` on `kmeans`

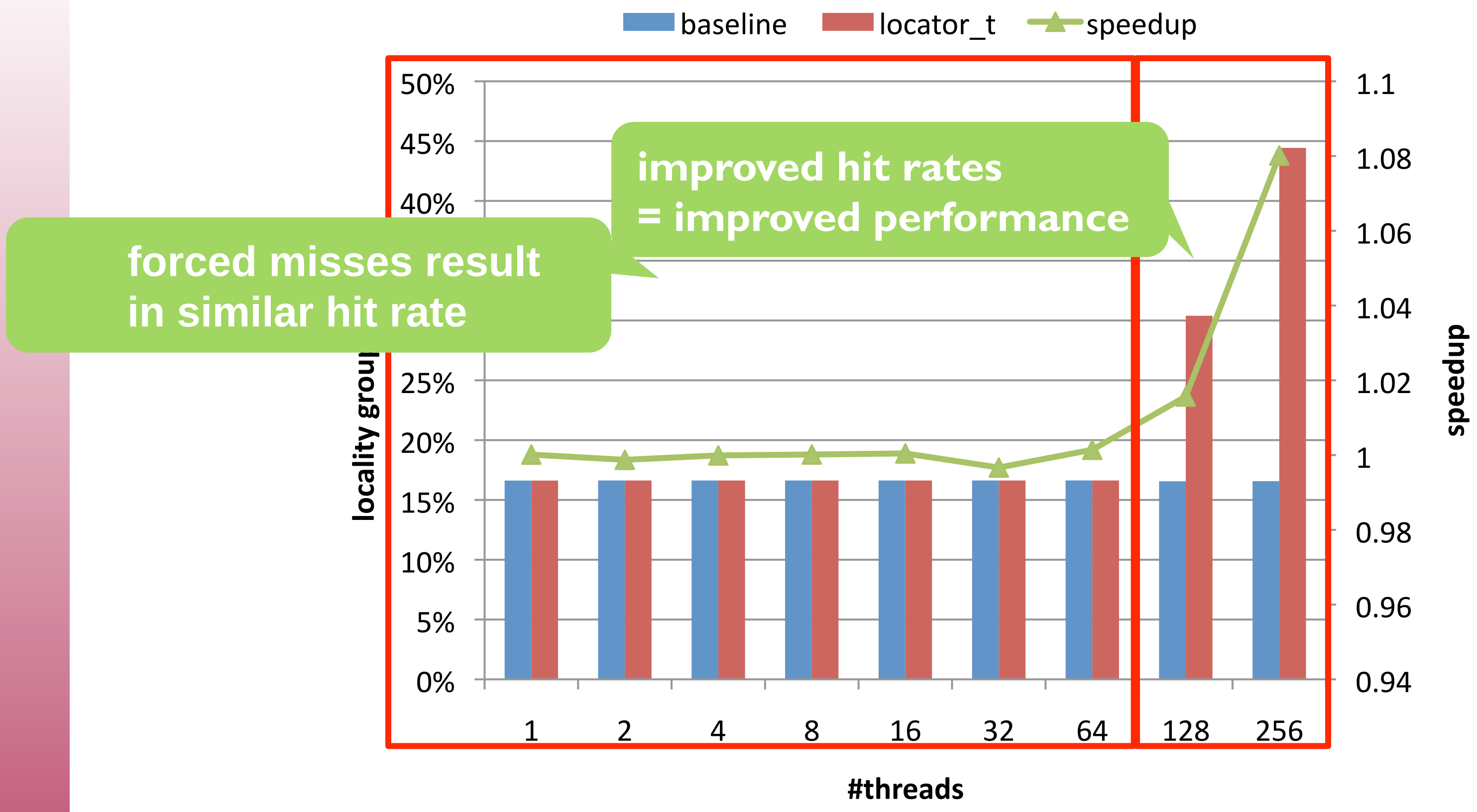


3.47x improvement

`kmeans` Performance Improvement due to Thread Pool

- `kmeans` performs a sequence of MapReduces
    - 160 iterations, 163,840 threads
- Thread pool effectively reduces the number of calls to `munmap()`

Analysis: Locality-Aware Task Distribution



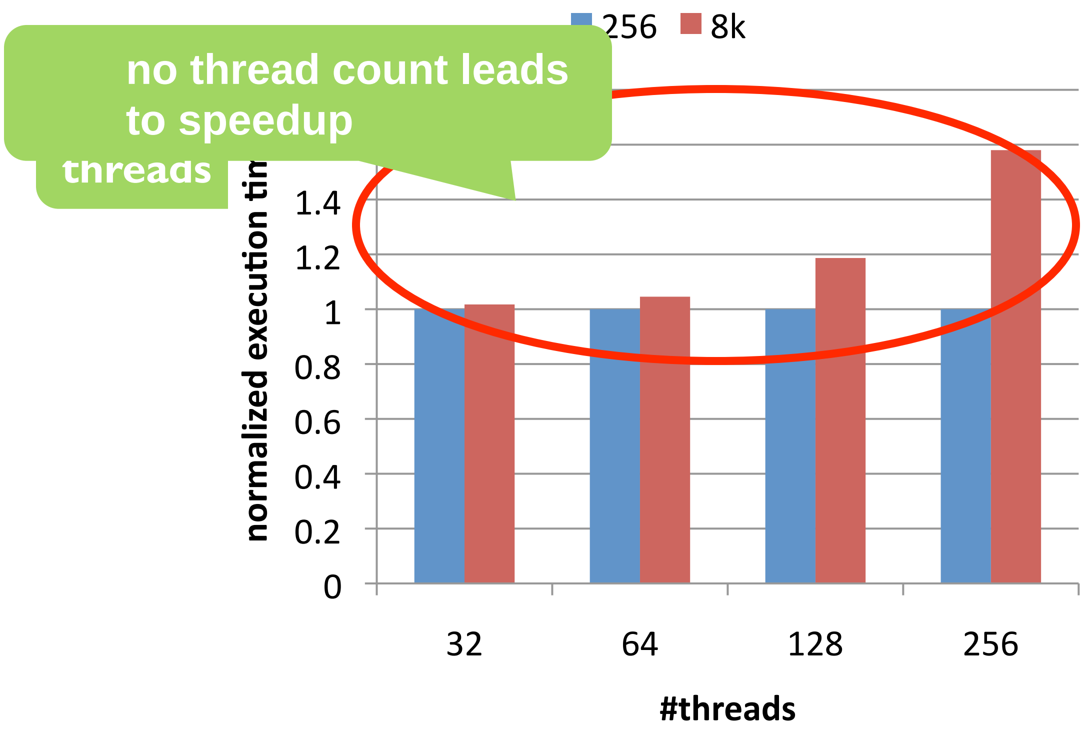
forced misses result in similar hit rate

improved hit rates = improved performance

Locality Group Hit Rate on `string_match`

- Locality group hit rate (% of tasks supplied from local memory)
- Significant locality group hit rate improvement under NUMA environment

Analysis: Hash Table Size



no thread count leads to speedup

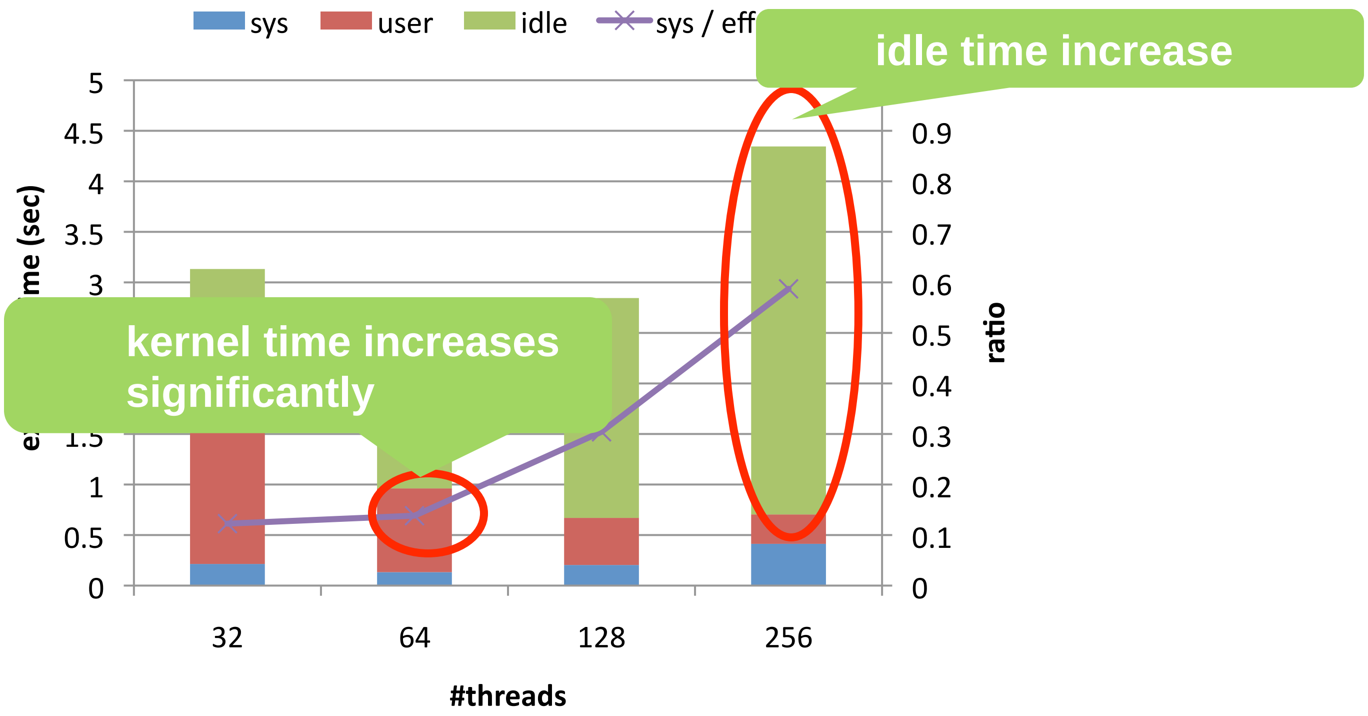
threads

kmeans Sensitivity to Hash Table Size

- ❑ No single hash table size worked for all the workloads
  - Some workloads generated only a small / fixed number of unique keys
  - For those that did benefit, the improvement was not consistent
- ❑ Recommended values provided for each application

Why Are Some Applications Not Scaling?

Non-Scalable Workloads



idle time increase

kernel time increases significantly

Execution Time Breakdown on `histogram`

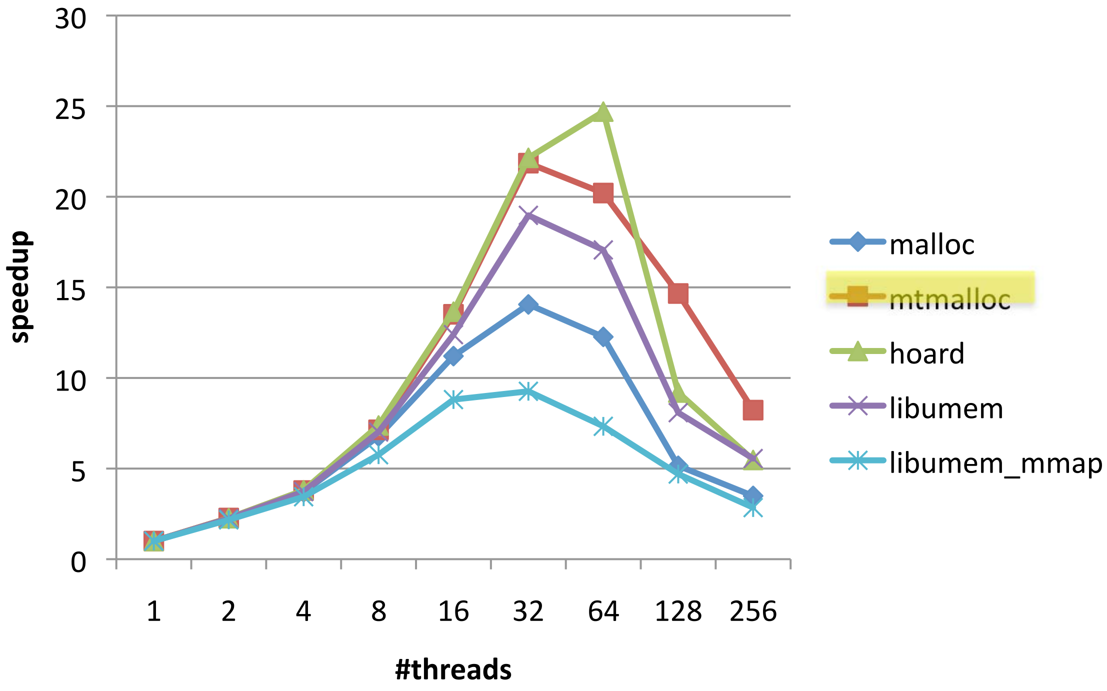
- ☐ Non-scalable workloads shared two common trends
  1. Significant idle time increase
  2. Increased portion of kernel time over total useful computation

Profiler Analysis

- ☐ `histogram`
  - 64 % execution time spent idling for data page fault
- ☐ `linear_regression`
  - 63 % execution time spent idling for data page fault
- ☐ `word_count`
  - 28 % of its execution time in `sbrk()` called inside the memory allocator
  - 27 % of execution time idling for data pages

- ☐ Memory allocator and `mmap()` turned out to be the bottleneck
- ☐ Not the physical I/O problem
  - OS buffer cache warmed up by repeating the same experiment with the same input

Memory Allocator Scalability



Memory Allocator Scalability Comparison on `word_count`

- ❑ `sbrk()` scalability a major issue
  - A single user-level lock serialized accesses
  - Per-address space locks protected in-kernel virtual memory objects
- ❑ `mmap()` even worse

`mmap()` Scalability

- ☐ Microbenchmark: `mmap()`user file and calculate the sum by streaming through data chunks

`mmap()` Microbenchmark Scalability

- ☐ `mmap()` alone does not scale
  - ☐ Kernel lock serialization on per process page table

Conclusion

- ❑ Multi-layered optimization approach proved to be effective
  - Average 2.5x speedup, maximum 19x
- ❑ OS scalability issues need to be addressed for further scalability
  - Memory management and I/O
  - Opens up a new research opportunity

Questions?

- ☐ The Phoenix System for MapReduce Programming, v2.0
  - Publicly available at http://mapreduce.stanford.edu