Optimizing Data Locality for Fork/Join Programs Using Constrained Work Stealing

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November 20, 2014

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  - Well-studied dynamic load balancing strategy
  - Provably efficient scheduling
  - Understandable bounds on time and space

Exploring the Problem

→ NUMA and Work Stealing

- Work stealing schedulers

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- Work stealing schedulers
  - A worker becomes a *thief* when it is idle
  - Randomly selects a victim
  - How might this degrade the performance in a NUMA environment?

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  - OpenMP: reuse schedules to improve memory affinity for looping constructs (Nikolopoulos, et al.)
  - OpenMP: explicit data placement and layout specification (Huang, et al., Bircsak, et al., Broquedis, et al.)

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(with and **without** explicit programmer mapping?)

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  - The *first time* memory is touched, the NUMA domain that the thread executes on determines the location of the page allocated
- Interleaved
  - Statically allocate pages in a round robin manner to the set of sockets specified

```
numactl --interleave=0,1,2,3,4,5,6,7
```

Motivating Example

→ Memory Copy: Adding Parallelism

```
#pragma omp parallel for schedule(static)
for (i = 0; i < size; i++)
  A[i] = B[i] = 0; // init
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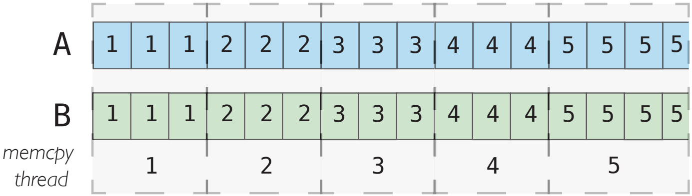

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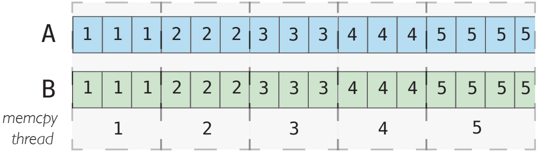

Loops are naturally matched, leading to good performance.

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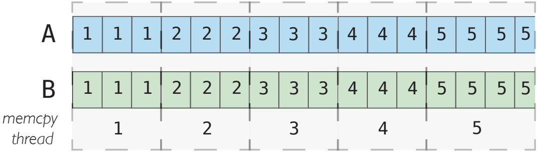

Empirical Study

- Parallel memory copy of 8GB of data, using OpenMP schedule static
- On an 80-core system with eight NUMA domains, first-touch policy
- Execution time: 169ms

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B	5	3	2	4	5	3	2	2	5	1	5	2	4	2	3	5
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Random work stealing mismatches the initialization and subsequent use, causing performance degradation.

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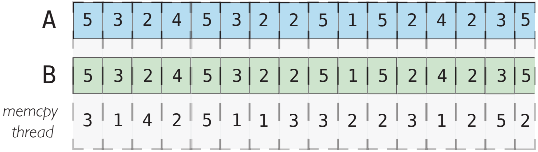

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- Parallel memory copy of 8GB, using MIT Cilk or OpenMP 3.0 Tasks
- Execution time: 436ms (Cilk/OMP task) vs. 169ms (OpenMP)

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OR

Build a user-specified schedule and constrain.

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- Using the theory in this paper, we can capture the work-stealing schedule
- Very low time and storage overhead
- Amount of information stored in practice is much smaller than $\mathcal{O}(\text{number of tasks})$

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    - ⋆ Reproduce the template schedule, but allow the order to deviate (respecting the application's dependencies)
  - Relaxed work stealing (RelWS)
    - ⋆ Reproduce the template schedule as much as possible, but allow workers to deviate when they are idle, by further stealing work

Experimental Setup

- Intel 80-core machine
  - Eight 2.27 GHz E7-8860 processors, each with 10 cores
  - Connected via Intel QPI 6.4 GT/s
  - 2 TB of DRAM
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  - All of our codes set the affinity of threads
    - First 10 threads always go to a single socket

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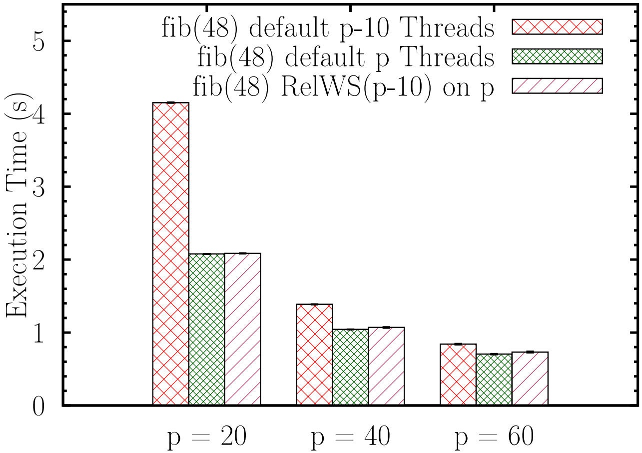
→ RELWS: **How well does it work?**



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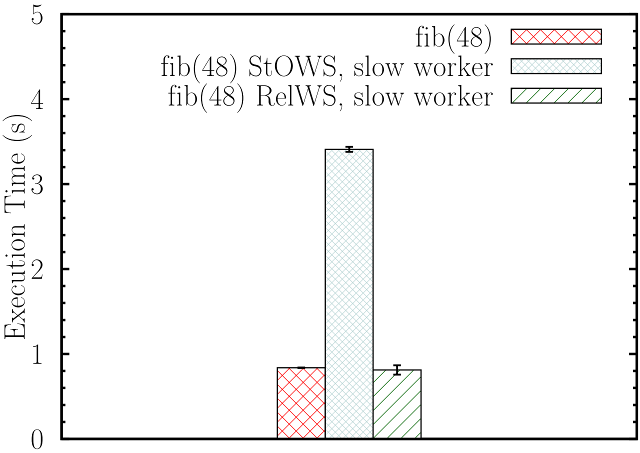
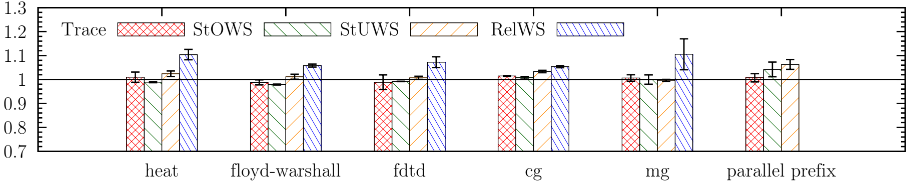


Benchmarks

Benchmark	Problem	Configuration	Tasks
heat	nx = ny = 32768	block = 64x8192	2k
floyd-warshall	n = 32768	block = 64x4096	4k
fdtd	ey = ex = hz = 32768	block = 64x8192	2k
NAS cg	NA=2^{21}, NNZ=15	rows = 1024	2k
NAS mg	N$\{$X,Y,Z$\}$=1024,LM=11	block=16x16x4MB	64–4k
parallel prefix	N = 256 MB	block = 512	512

(3) Re-using the Schedule

→ Overhead of Constrained Work Stealing (on 80 Cores)



Mean normalized ratio (y-axis) compared to default Cilk implementation. Error bars are relative standard deviation with a sample size of 5.

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  - The runtime builds a Steal Tree that is used as a template schedule

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  - Non-iterative, matching structure (parallel prefix)
    - ★ Re-use schedule from initialization for other phases with STUWS

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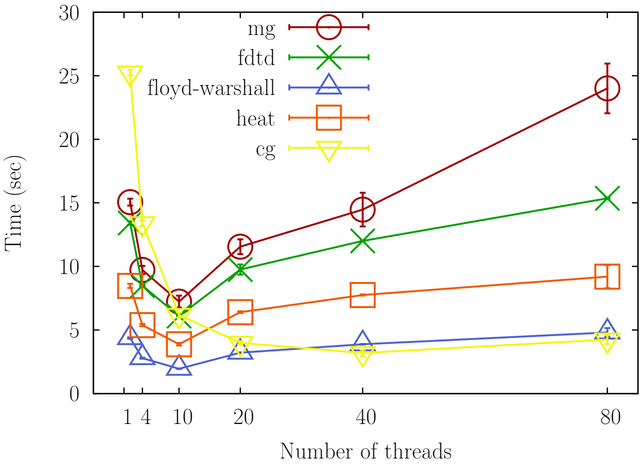
→ **Data redistribution cost (for the first few iterations)**



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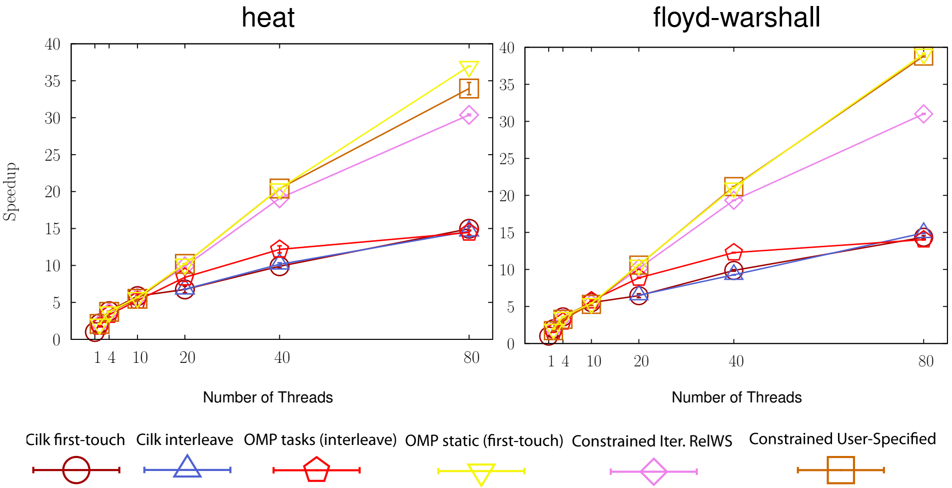

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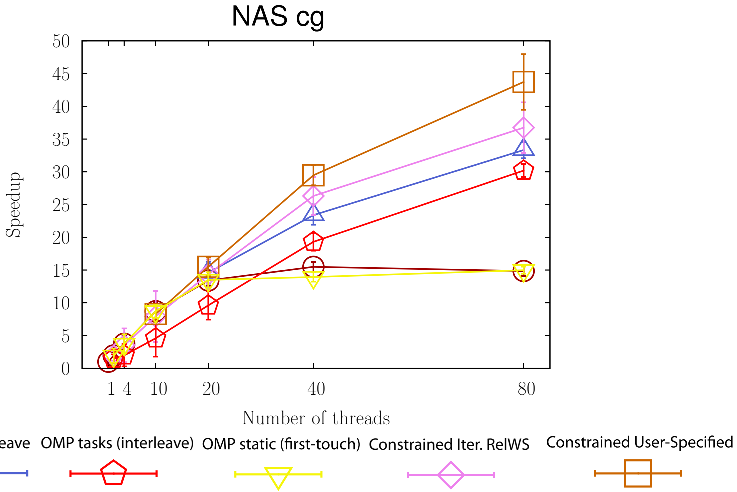

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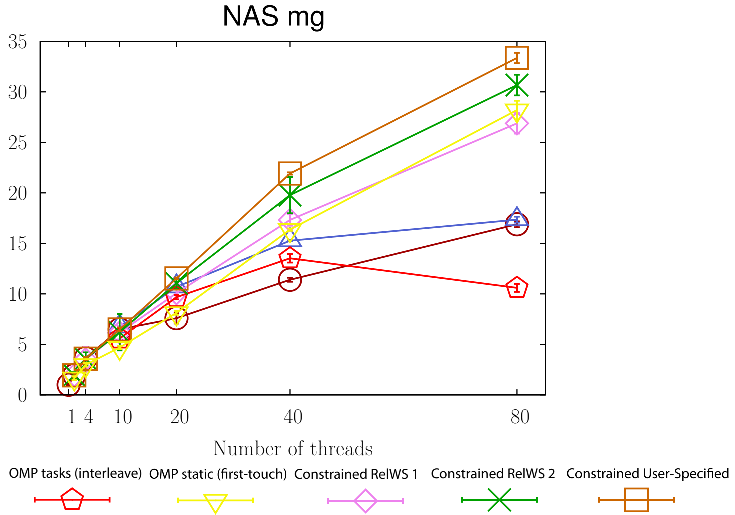

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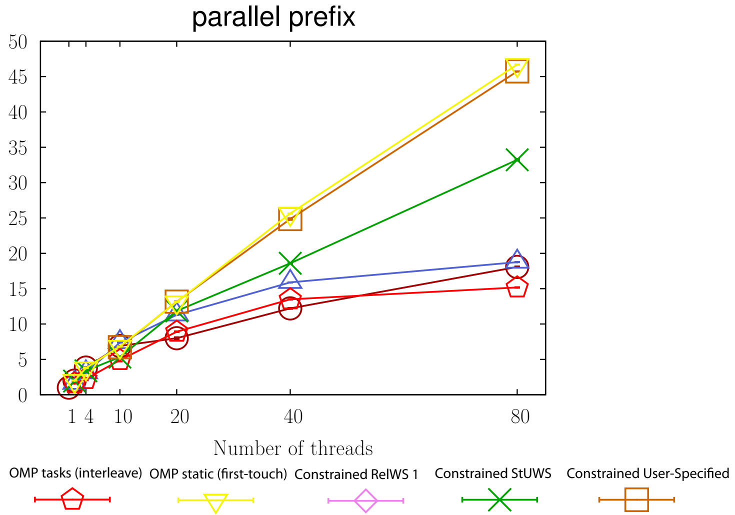

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  - Details are in the paper

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  - Up to 2.5x performance improvement on 80 cores compared to default Cilk!
- Future work
  - Can we use static compiler analysis to better match phases and understand access patterns?

Questions?

Evolving the Schedule

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