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Parallel Computing WS 2017/18

Session 10: OpenMP Tasks, Tracing, Scalability

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Smoke, Mirrors and NUMActl







Some irritating code



→ http://hpc.wiki/lab/session-10/omp-eztrace



Bringing it all together

Revisiting Profiling, Tracing, Scalability and Hardware Models





Profiling vs. Tracing



Profiling

- Aggregates performance events and timings for the execution as a whole.
- No chronology of the events (no timestamps).
- Some profilers record relative order of events.

Examples: IPM, ompP



Profiling vs. Tracing



Example of profiling output of IPM

call	orank	ncalls	<pre>buf_size</pre>	t_tot	t_min	t_max	%comm
MPI_Recv	2	17	131072	5.96e+00	6.43e-02	5.92e-01	75.5
MPI_Recv	7	18	4	1.82e+00	8.45e-06	4.17e-01	23.0
MPI_Barrier	*	2	*	1.04e-01	7.14e-05	1.03e-01	1.3
MPI_Sendrecv	/ 8	18	504	4.56e-03	6.31e-05	3.19e-04	0.1
MPI_Send	1	36	4	1.84e-03	1.75e-05	1.62e-04	0.0
MPI_Sendrecv	/ 16	18	504	1.55e-03	3.18e-05	2.80e-04	0.0

Here: 23% of communication time spent in 4 byte MPI_Recv.



Profiling vs. Tracing



Tracing

- Records the **chronology**, often with timestamps.
- **Extensive in time**: code is instrumented so all events are enclosed between timestamps.
- Extensive in data: amount of data in trace increases with runtime. Typically, trace data is periodically written to disk or network.

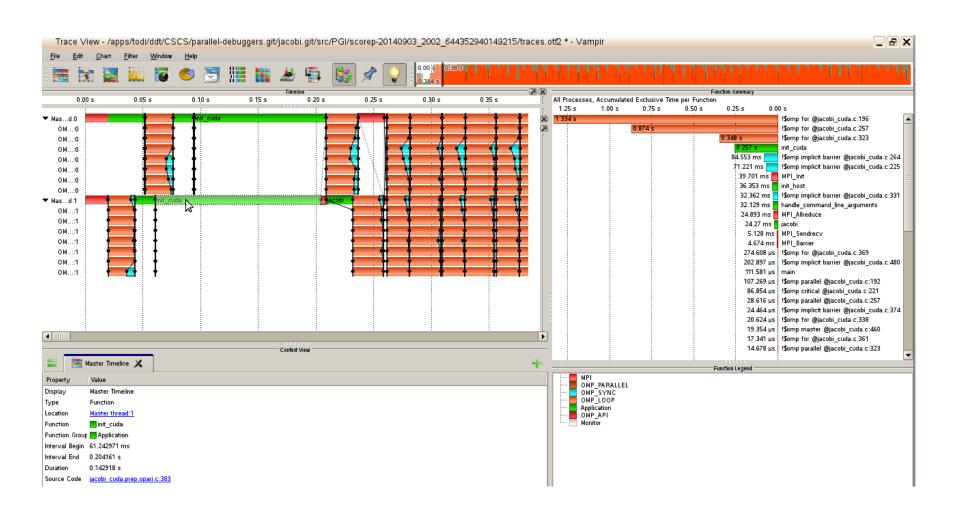
Example: Score-P (tracing) + Vampir (trace data viewer)



MAXIMILIANS-UNIVERSITÄT MÜNCHEN

Profiling vs. Tracing







Quickstart: eztrace



Free Open Source toolkit: eztrace

- Lightweight, portable and reasonably feature-rich (also an irritating sensation in the derrière to configure and build, a tad annoying to use and, of course, ugly as ten Scotsmen, probably just to remind you that it's free)
- Supports OpenMP, MPI, pthreads, CUDA, ...
- Plug-and-play build for SuperMuc provided for this course at http://hpc.wiki/lab/session-10/omp-eztrace/eztrace-supermuc-homeinst.tgz for your convenience (just unpack the tarball to ~/opt/eztrace)
- How-to and sources from this session: http://hpc.wiki/lab/session-10/



Example: openmp.03.map-ranges

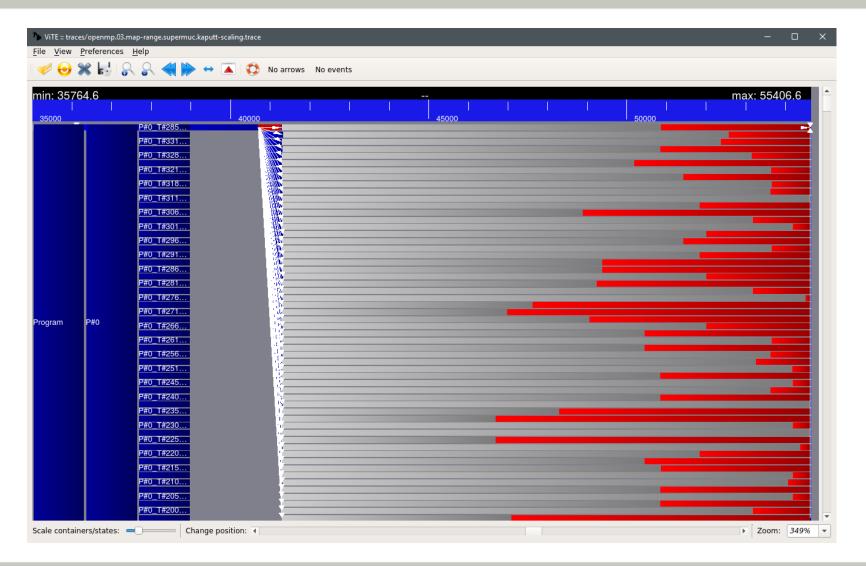


... now let's demystify the code examples we saw earlier (http://hpc.wiki/lab/session-10/omp-eztrace)



Example: openmp.03.map-ranges

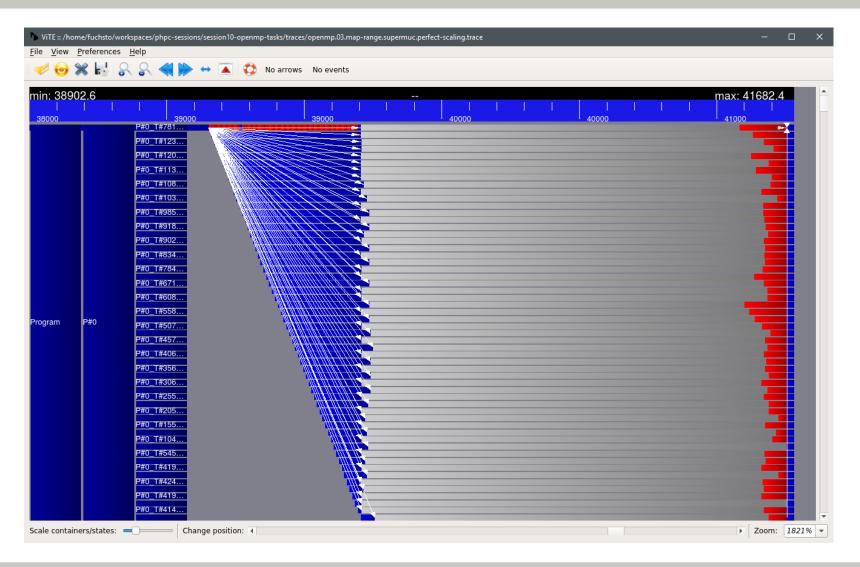






Example: openmp.03.map-ranges







OpenMP Solutions



False Sharing

Two or more threads write to seemingly unrelated variables:

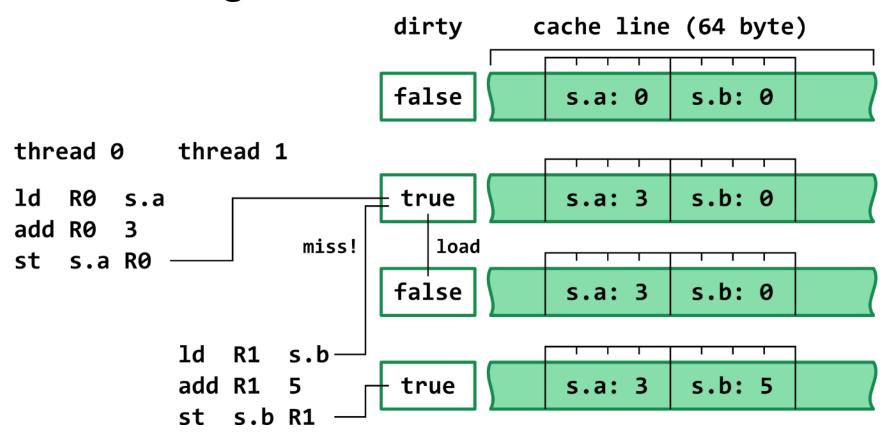
- Cache-miss in both threads:
 s.a and s.b are in same cache line, += is read and write.
- One of the most important usage patterns to spot.



OpenMP Solutions



False Sharing







OpenMP Solutions



False Sharing

Solution: alignment

```
shared: struct {
    aligned(c) int a;
    aligned(c) int b;
} s;
```

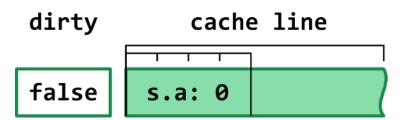
- Aligned variables (here: s.a, s.b) will be allocated and aligned at least on a c-byte boundary.
- If c = width of a cache line (typically 64 B): no false sharing.

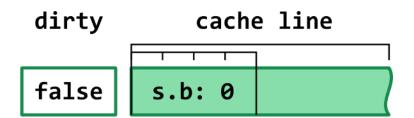






False Sharing







NUMA and numactl

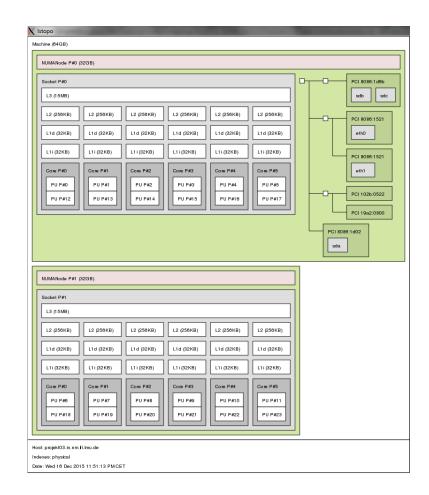




NUMA Nodes



Let's analyze this output from Istopo on a NUMA system ...

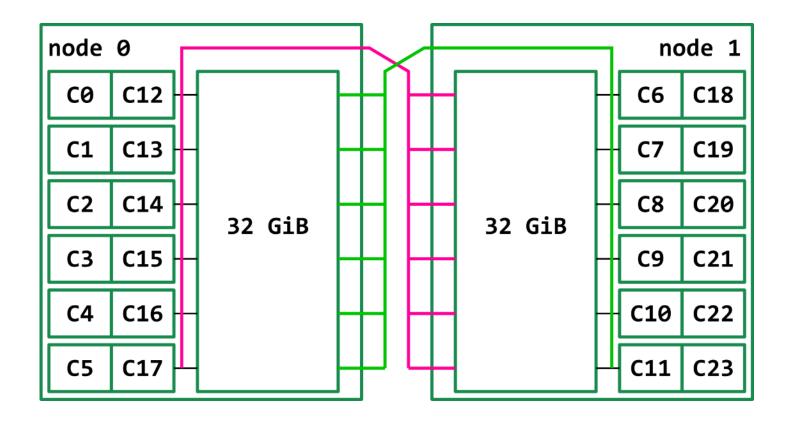




NUMA Nodes



Task- and Data Placement









What's the advantage of using

numactl --localalloc --physcpubind=0-11

compared to not specifying allocation policy / affinity?







What's the advantage of using

numactl --localalloc --physcpubind=0-11

compared to not specifying allocation policy / affinity?

- → Data placement:

 Nodes may only allocate in local memory (only 32 GiB available on each node)
- → Task placement:
 Hyperthreading cores disabled, every thread on dedicated physical core





numactl on SuperMUC Ph.2



SUPERMUC login22 \$ numactl --hardware

available: 4 nodes (0-3)

node 0 cpus: 0 1 2 3 4 5 6 28 29 30 31 32 33 34

--<SNIP>--

node distances:

node 0 1 2 3

0: 10 21 31 31

1: 21 10 31 31

2: 31 31 10 21

3: 31 31 21 10

This is obtained from **SLIT (System Locality Information Table)**

Three locality domains, here indicated by distances 10, 21, 31





Course Assignment



- Redesign partial sum algorithm variants (code: http://hpc.wiki/lab/session-09/) using OpenMP tasking
- Measure weak- and strong scaling as before (benchmark boilerplate available in code section)
- Visualize task dependencies using eztrace (or any other tracing tools, Vampir is available on SuperMUC)
- Use traces to explain scaling



Scalability

Example: OpenMP Matrix Multiplication



Matrix Product with OpenMP



```
void mmult_naive_par(double A[M][N], double B[N][K], double C[M][K]) {
    int
        i, j, k;
    double sum;
    #pragma omp parallel for private(j,k,sum)
   for (i = 0; i < M; i++) {
        for (j = 0; j < K; j++) {
            sum = 0.0;
            for (k = 0; k < N; k++) {
                sum += A[i][k] * B[k][j];
            C[i][j] = sum;
```







N/T	1	2	4	8	16	32
100	0.89	0.78	0.82	0.50	0.12	0.11
1000	14.12	19.90	32.91	32.32	26.22	21.66
2000	14.30	28.74	42.63	64.76	65.04	35.31
4000	14.68	29.09	57.93	82.64	156.84	138.94

These are actual measurements submitted for a highly optimized implementation of mmult.

Spot the effects of

- Amdahl's Law
- Gunther's Law
- Gustafson's Law





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Spot the effects of

Amdahl's Law

Performance increase (speedup) is **limited by sequential sections** and degree of parallelism.

Note that super-linear speedup is rare but possible!







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Spot the effects of

Gunther's Law

Performance may worsen if degree of parallelism is increased because contention rate increases.







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1000	14.12	19.90	32.91	32.32	26.22	21.66
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Spot the effects of

Gustafson's Law

Higher degree of parallelism can yield performance benefit **when problem size is increased**. For example:

 $N = 1000 \rightarrow GLFOPS$ drop from 8 to 16 threads.

 $N = 2000 \rightarrow GLFOPS$ saturated from 8 to 16 threads.

 $N = 4000 \rightarrow GFLOPS$ increased from 8 to 16 threads.







N/T	1	2	4	8	16	32
100	0.89	0.78	0.82	0.50	0.12	0.11
1000	14.12	19.90	32.91	32.32	26.22	21.66
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Spot the effects of

Gunther's Law + Gustafson's Law

Speedup saturation as predicted by Amdahl's and Gustafson's models shifted to higher degrees of parallelism with increasing problem size.

 $N = 1000 \rightarrow Saturates$ with 4 threads

 $N = 2000 \rightarrow Saturates with 8 threads$

 $N = 4000 \rightarrow Saturates$ with 16 threads





Vector Triad



We fail to achieve peak performance because we have the wrong problem. Bad luck.



Vector Triad



Vector Triad is a common benchmark, uses floating point addition and - multiplication as otherwise FLOPS peak performance could not be reached ("fused multiply-add", I prefer the term "multiply-accumulate")



Read this



Intel: "Optimizing Applications for NUMA"

https://software.intel.com/en-us/articles/optimizing-applications-for-numa

"What Every Programmer Should Know About Memory". Drepper, Ulrich. November 2007.

"Local and Remote Memory: Memory in a Linux/NUMA System". Lameter, Christoph. June 2006.



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