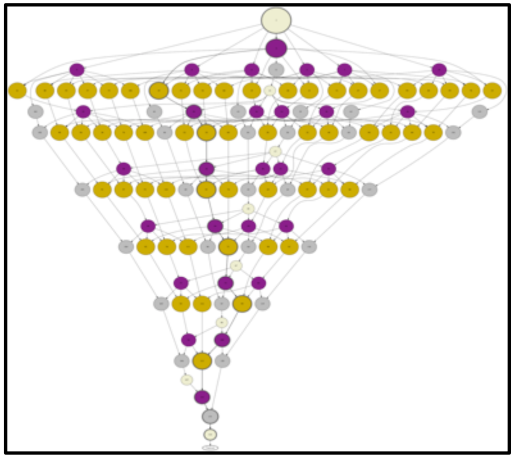
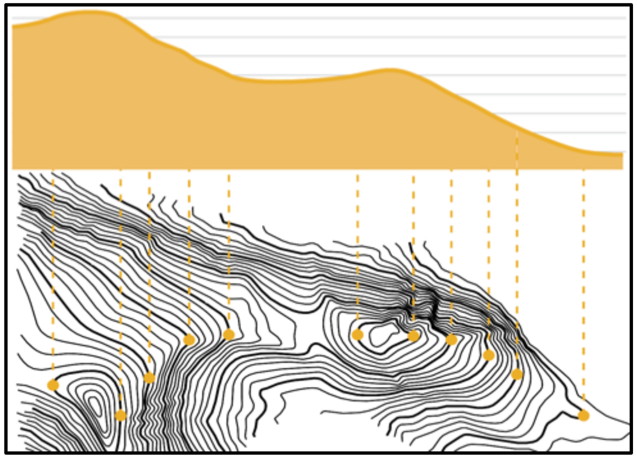
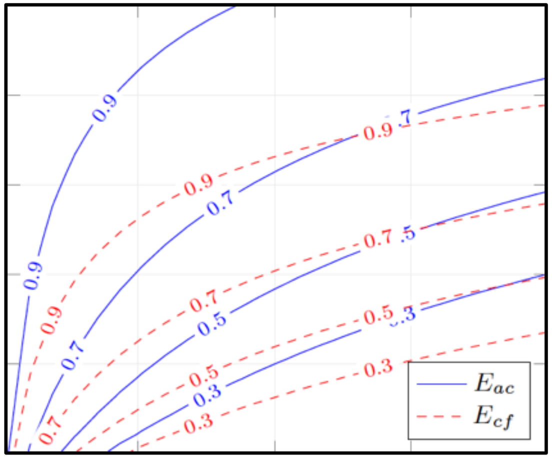
Isoefficiency in Practice: Configuring and Understanding the Performance of Task-based Applications

Sergei Shudler[1], Alexandru Calotoiu[1], Torsten Hoefler[2], Felix Wolf[1]







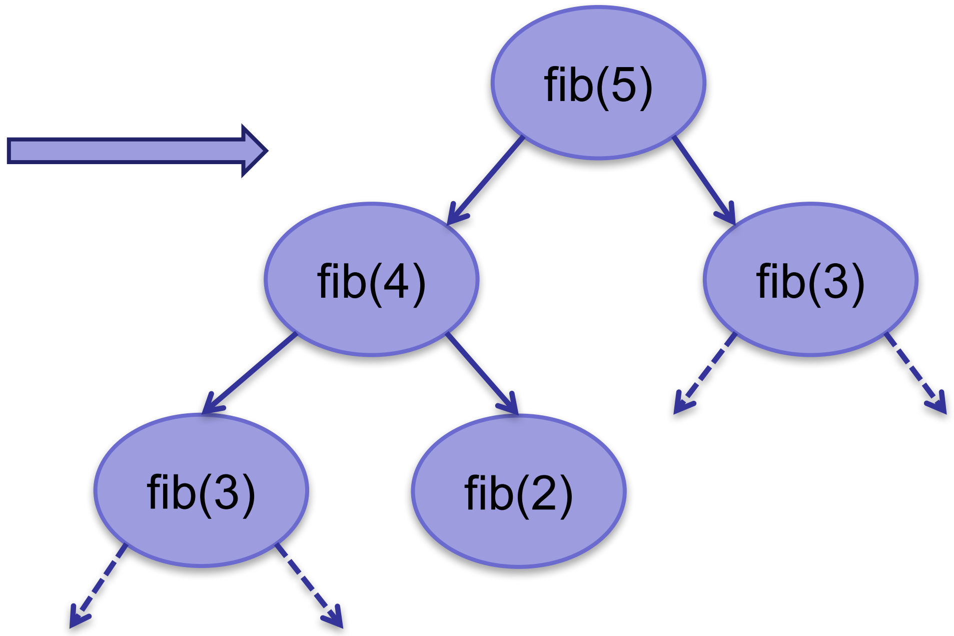
[1] TU Darmstadt, [2] ETH Zürich

Task-based programs

TECHNISCHE UNIVERSITÄT DARMSTADT

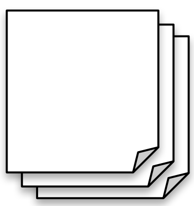
- Task-based paradigms: Cilk, OmpSs, OpenMP,…
- Scheduling managed by the runtime system
- Example:

```
#pragma omp task shared(x)
x = fib( n – 1 );
#pragma omp task shared(y)
y = fib( n – 2 );
#pragma omp taskwait
return x + y;
```



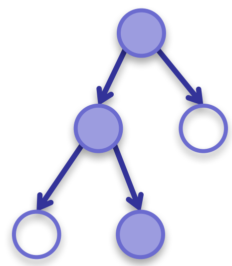
Efficiency of task-based applications – performance issues

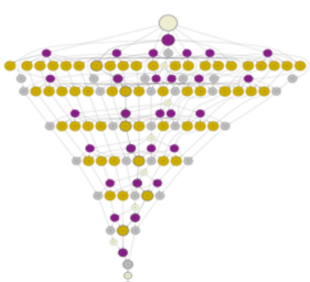
Input size



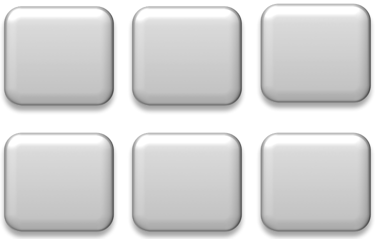
?

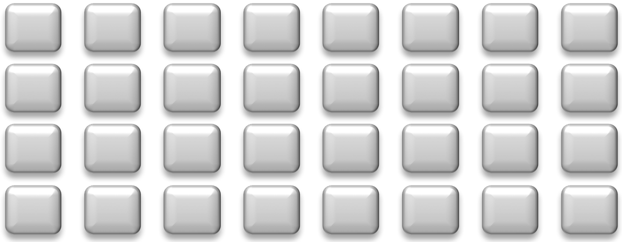
Task graph





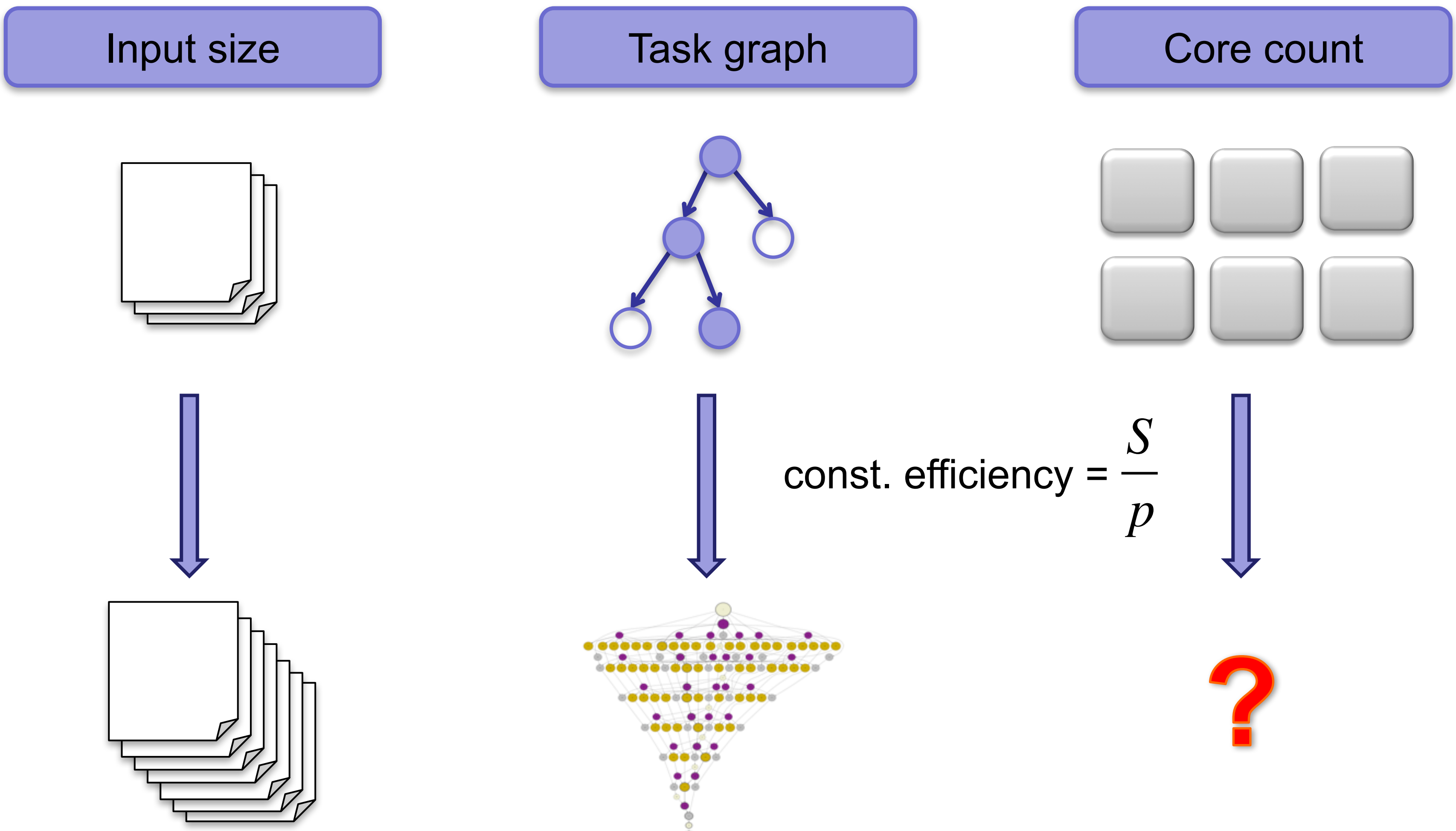
Core count





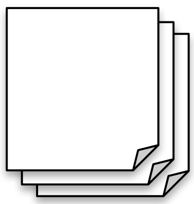
const. efficiency = $\frac{S}{p}$

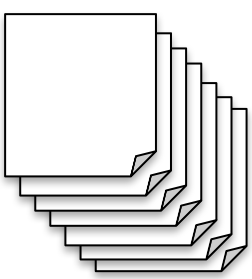
Efficiency of task-based applications – performance issues (2)



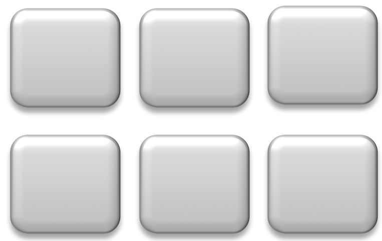
Efficiency of task-based applications – performance issues (3)

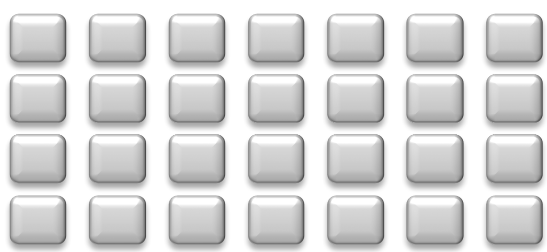
Input size





Core count



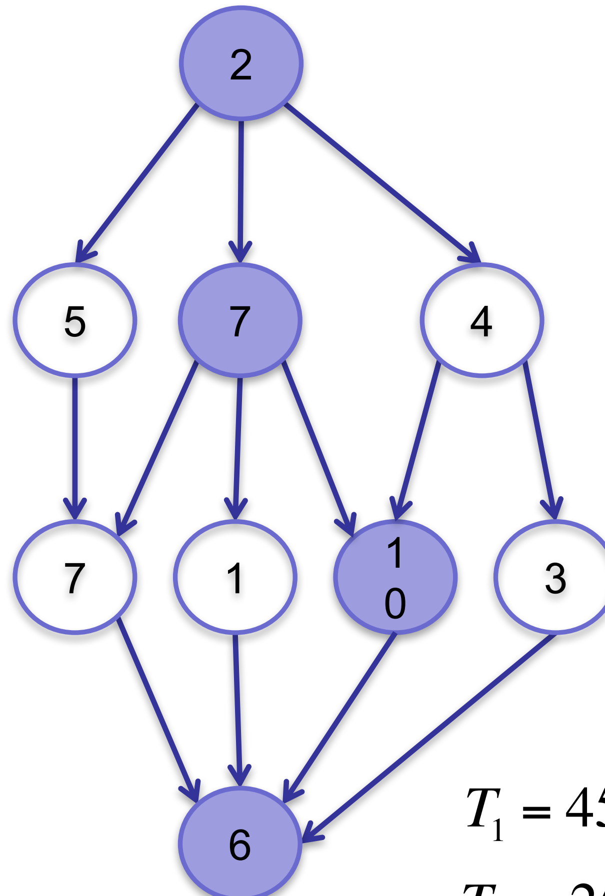


const. efficiency $= \frac{S}{p}$

Resource contention

Task dependency graph (TDG)

- Nodes – tasks, edges – dependencies
- p, n – processing elements, input size
- $T_1(n)$ – all the task times (*work*)
- $T_\infty(n)$ – longest path (*depth*)
- $\pi(n) = \frac{T_1(n)}{T_\infty(n)}$ – average parallelism
- $T_p(n)$ – execution time
- $S_p(n) = \frac{T_1(n)}{T_p(n)}$ – speedup



$T_1 = 45$

$T_\infty = 25$

TDG rules

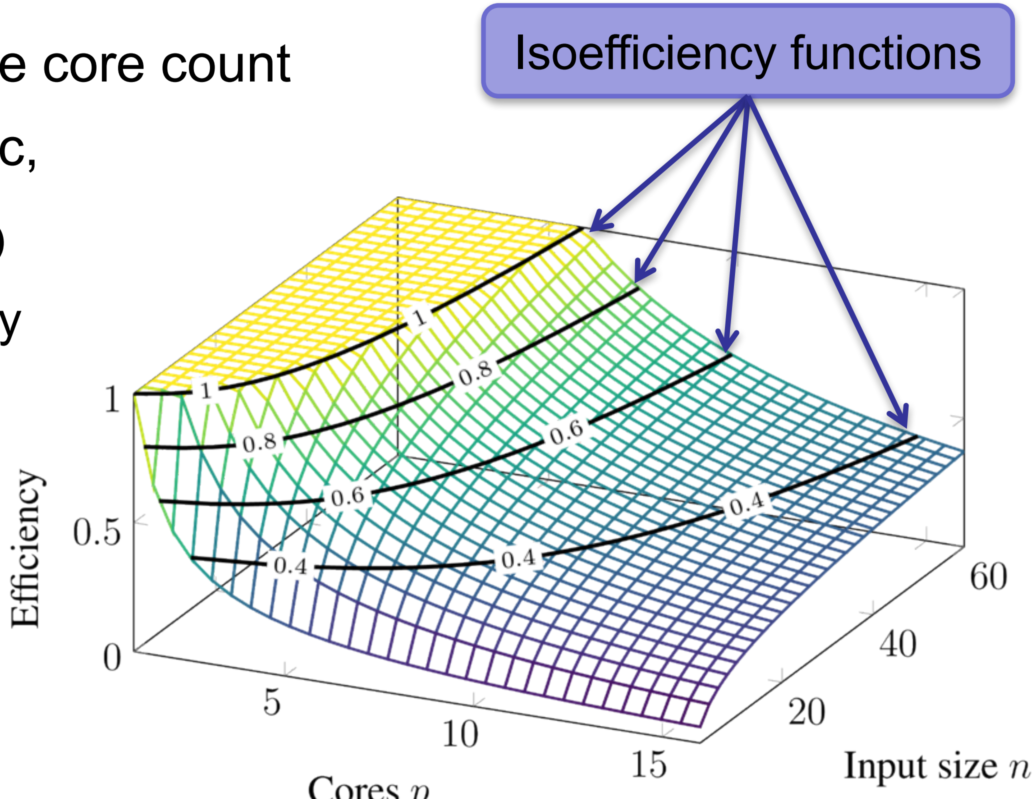
- Work rule: $T_p(n) \geq \frac{T_1(n)}{p}$ or: $S_p(n) \leq p$
  - Ignore super-linear speedups for simplicity
- Depth rule: $T_p(n) \geq T_\infty(n)$ or: $S_p(n) \leq \pi(n)$
  - Cannot execute faster than the critical path
- In summary: $S_p(n) \leq \min\{p, \pi(n)\}$

Efficiency & isoefficiency

- Efficiency is defined as: $E(p,n) = \frac{S_p(n)}{p} \leq \min\left\{1, \frac{\pi(n)}{p}\right\} = E_{ub}(p,n)$

- Isoefficiency binds together the core count and the input size for a specific, constant efficiency: $n = f_E(p)$
  - A contour line on the efficiency surface

- Example: Mergesort
  - $\pi(n) = \log n$
  - Surface depicts $E_{ub}(p,n)$



Modeled efficiency functions

$E_{ub}(p,n)$ – upper bound based on avg. parallelism

$$\Delta_{str} = E_{ub}(p,n) - E_{cf}(p,n)$$

$E_{cf}(p,n)$ – contention-free replays

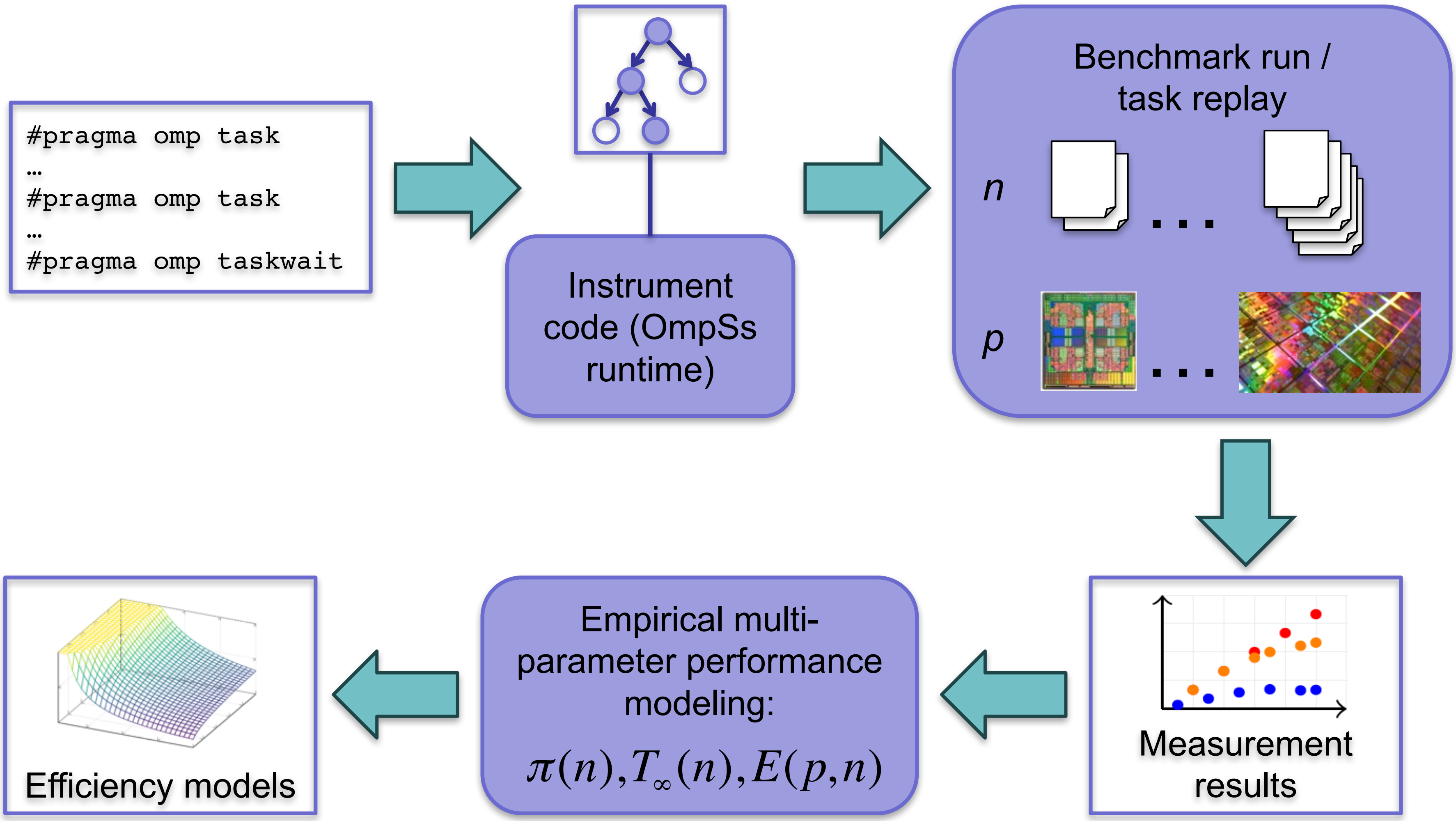
$$\Delta_{con} = E_{cf}(p,n) - E_{ac}(p,n)$$

$E_{ac}(p,n)$ – reflects actual performance

Structural discrepancy: characterizes the optimization potential

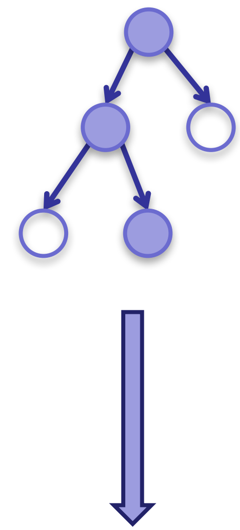
Contention discrepancy: shows how severe the resource contention is

Modeling workflow



Contention-free replay engine

- Uses OmpSs runtime API
- Replay on multiple threads
- No actual code execution (busy-waiting)
- Respects dependencies
- Same scheduling policy
- Minimum memory accesses

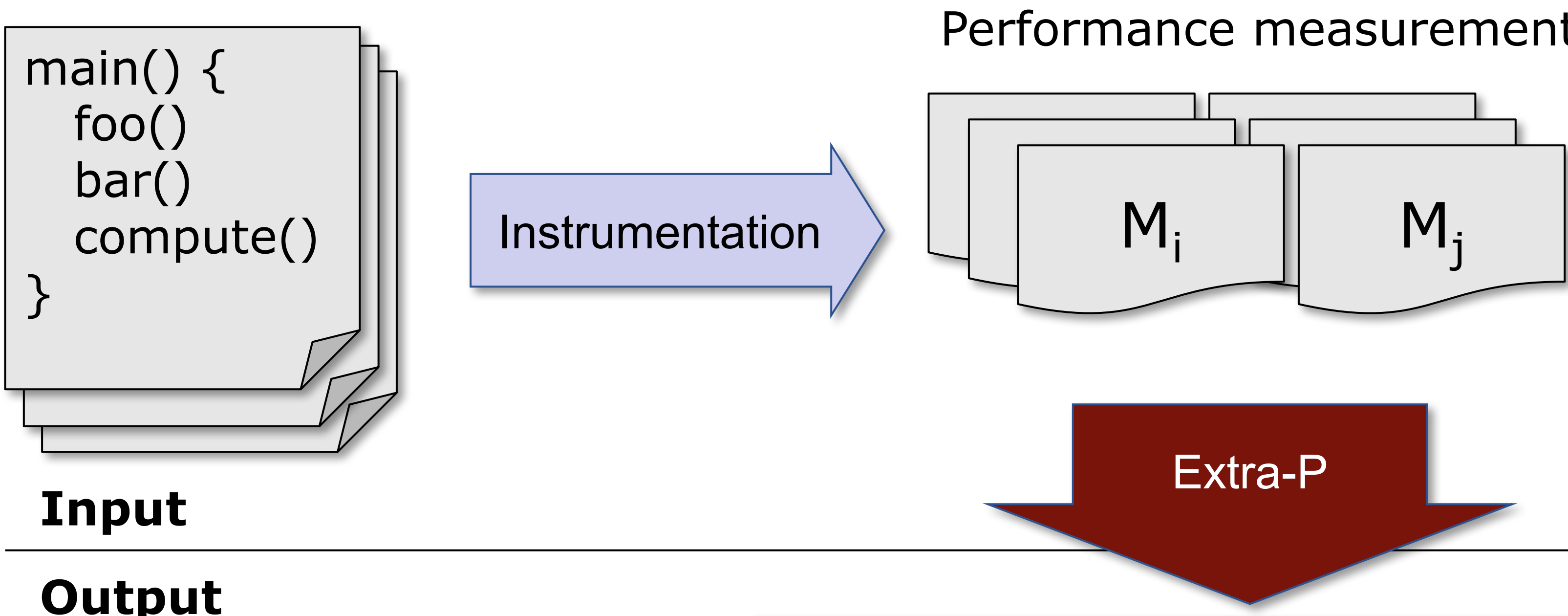


```
void execute_task( double t )
{
   double elapsed = 0;
   while( elapsed < t )
   //…
}

//…

nanos_create_wd_compact(…)
```

Performance modeling with Extra-P



Human-readable, multi-parameter performance models of all functions

$$f(x_1,\ldots,x_m)=\sum_{k=1}^{n} c_k \prod_{l=1}^{m} x_l^{i_{kl}} \cdot \log_2^{j_{kl}}(x_l)$$

A. Calotoiu, et al.: Fast Multi-Parameter Performance Modeling (*CLUSTER '16*)

www.scalasca.org/software/extra-p/download.html

Experiments setup

- Barcelona OpenMP Task Suite (BOTS) + Barcelona Application Repository (BAR)
  - Cholesky, FFT, Fib, NQueens, Sort, SparseLU, Strassen
- NUMA node with four Intel Xeon E7-4890 v2 processors
  - 60 cores in total

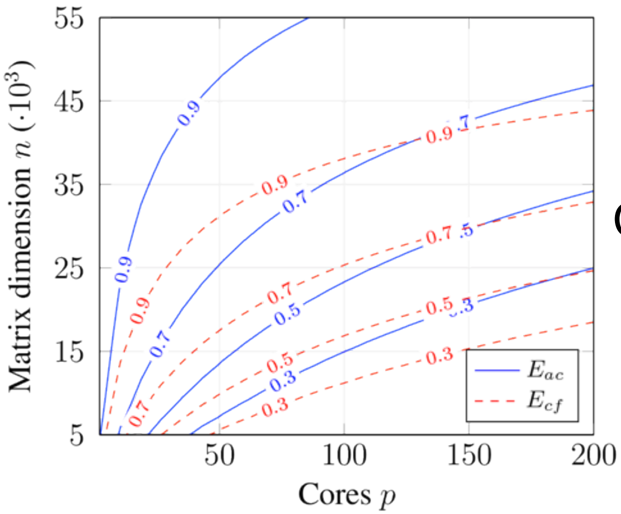
Depth and average parallelism models (excerpt)

Application (origin)	$T_\infty(n)$	$\pi(n)$
Cholesky (BAR)	$O(n^{1.75} \log n)$	$O(n)$
FFT (BAR)	$O(n^{2.75} \log n)$	$O(n^{0.67} \log n)$
Nqueens (BOTS)	$O(n^{2} \log n)$	$O(n^{2.875} \log n)$
Sort (BOTS)	$O(\sqrt{n})$	$O(\sqrt{n})$
SparseLU (BAR)	$O(n^{0.75} \log n)$	$O(n^{1.75} \log n)$
Strassen (BOTS)	$O(n^{2} \log n)$	$O(n^{0.75})$

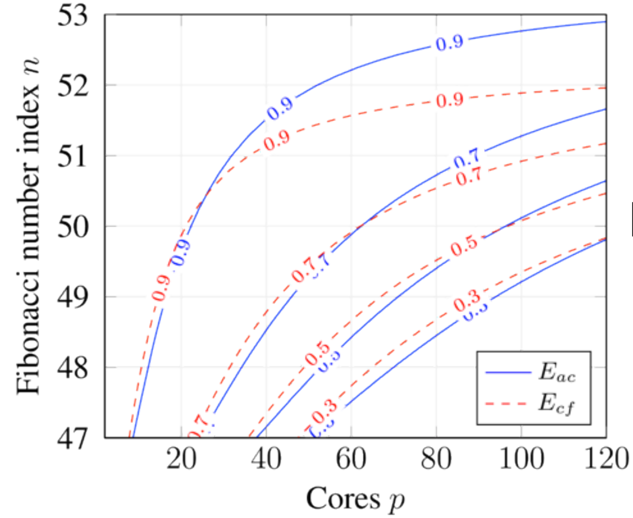
$T_\infty(n)$ grows faster or as fast as $\pi(n)$

Efficiency & isoefficiency models (excerpt)

TECHNISCHE UNIVERSITÄT DARMSTADT



Cholesky

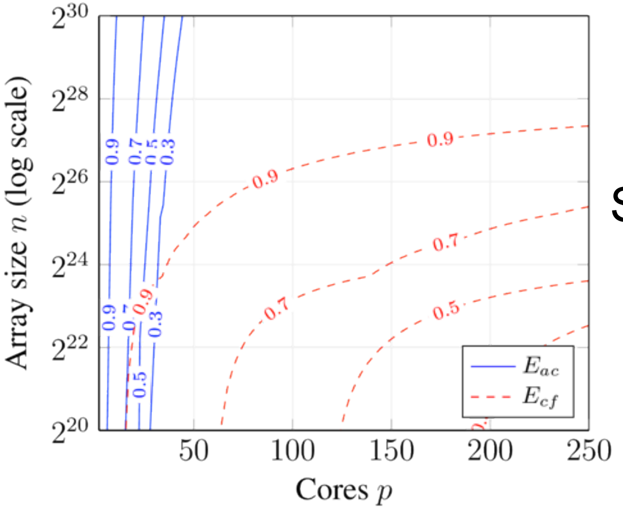


Fibonacci

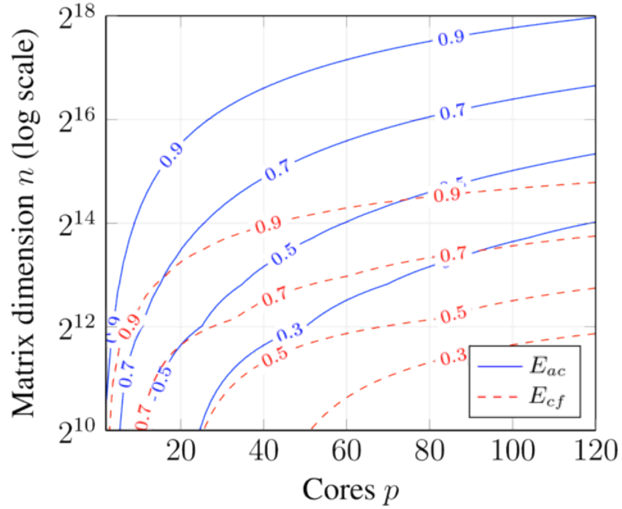
Cholesky models	**Fibonacci models**
$E_{ac} = 1.09 - 0.51\sqrt{p} + 3.11 \cdot 10^{-2}\sqrt{p}\log n$	$E_{ac} = 0.98 - 5.11 \cdot 10^{-3} p^{1.25} + 1.76 \cdot 10^{-3} p^{1.25} \log n$
$E_{cf} = 1.14 - 0.54\sqrt{p} + 3.4 \cdot 10^{-2}\sqrt{p}\log n$	$E_{cf} = 0.97 - 1.46 \cdot 10^{-2} p^{1.25} + 9.26 \cdot 10^{-3} p^{1.25} \log n$
$E_{ub} = \min\left\{1, \left(2.29 + 2.35 \cdot 10^{-3} n\right) p^{-1}\right\}$	$E_{ub} = \min\left\{1, \left(25.48 + 0.49 n^{2.75} \log n\right) p^{-1}\right\}$

$C - Af(p) + Bf(p)g(n)$ -- C: max, -Af(p): reduction, Bf(p)g(n): gain

Efficiency & isoefficiency models (excerpt)



Sort



Strassen

Sort models	Strassen models
$E_{ac} = 0.99 - 9.2 \cdot 10^{-3} p^{1.5} + 2.29 \cdot 10^{-4} p^{1.5} \log n$	$E_{ac} = 1.55 - 1.02 p^{0.25} + 4.59 \cdot 10^{-2} p^{0.25} \log n$
$E_{cf} = 1.0 - 4.61 \cdot 10^{-2} p^{0.75} + 1.62 \cdot 10^{-3} p^{0.75} \log n$	$E_{cf} = 1.26 - 0.65 p^{0.33} + 3.89 \cdot 10^{-2} p^{0.33} \log n$
$E_{ub} = \min\left\{1, \left(3.53 + 3.32 \cdot 10^{-2} \sqrt{n}\right) p^{-1}\right\}$	$E_{ub} = \min\left\{1, \left(0.25 n^{0.75}\right) p^{-1}\right\}$

$C - Af(p) + Bf(p)g(n)$ -- C: max, -A*f*(*p*): reduction, B*f*(*p*)*g*(*n*): gain

Co-design aspects

App.	Model	Input size for p = 60, E = 0.8
Fibonacci	$E_{ac} = 0.98 - 5.11 \cdot 10^{-3} p^{1.25} + 1.76 \cdot 10^{-3} p^{1.25} \log n$	51
	$E_{cf} = 0.97 - 1.46 \cdot 10^{-2} p^{1.25} + 9.26 \cdot 10^{-3} p^{1.25} \log n$	51
	$E_{ub} = \min\left\{1, \left(25.48 + 0.49 n^{2.75} \log n\right) p^{-1}\right\}$	49
Strassen	$E_{ac} = 1.55 - 1.02 p^{0.25} + 4.59 \cdot 10^{-2} p^{0.25} \log n$	83,600 x 83,600
	$E_{cf} = 1.26 - 0.65 p^{0.33} + 3.89 \cdot 10^{-2} p^{0.33} \log n$	12,680 x 12,680
	$E_{ub} = \min\left\{1, \left(0.25 n^{0.75}\right) p^{-1}\right\}$	1,200 x 1,200

For example (Strassen): $E_{ac} = 1.55 - 1.02 p^{0.25} + 4.59 \cdot 10^{-2} p^{0.25} \log n$

Let E = 0.8 and p = 60: $0.8 = 1.55 - 1.02 \cdot 60^{0.25} + 4.59 \cdot 10^{-2} \cdot 60^{0.25} \log n$

After solving: $n = 83,600$

Addressed questions

Input size for a given core count

Core count for a given input size

Fundamental scalability limitations in a task-based program

?!

Poor scaling caused by resource contention overhead

Further optimization potential: dependencies, scheduling, granularity

Acknowledgements

- Catwalk project within SPPEXA (DFG's Priority Program 1648 "Software for Exascale Computing")
- Score-E project (BMBF)
- Prima-X project (US DoE)
- TU Darmstadt University Computing Center
- OmpSs team at Barcelona Supercomputing Center

References (partial list)

[1] Sergei Shudler, Alexandru Calotoiu, Torsten Hoefler, Felix Wolf: Isoefficiency in Practice: Configuring and Understanding the Performance of Task-based Applications. *In Proc. of the ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming (PPoPP), Austin, TX, USA*, pages 1-13, ACM, February, 2017

2017

[2] Alexandru Calotoiu, David Beckingsale, Christopher W. Earl, Torsten Hoefler, Ian Karlin, Martin Schulz, Felix Wolf: Fast Multi-Parameter Performance Modeling. In *Proc. of the 2016 IEEE International Conference on Cluster Computing (CLUSTER), Taipei, Taiwan*, pages 1-10, IEEE Computer Society, September 2016

[3] Sergei Shudler, Alexandru Calotoiu, Torsten Hoefler, Alexandre Strube, Felix Wolf: Exascaling Your Library: Will Your Implementation Meet Your Expectations?. In *Proc. of the International Conference on Supercomputing (ICS), Newport Beach, CA, USA, pages 1-11, ACM, June 2015*

2015

[4] Alexandru Calotoiu, Torsten Hoefler, Marius Poke, Felix Wolf: Using Automated Performance Modeling to Find Scalability Bugs in Complex Codes. In Proc. of the ACM/IEEE Conference on Supercomputing (SC13), Denver, CO, USA, pages 1-12, ACM, November 2013

Thank you!