

DF00100 Advanced Compiler Construction

DF21500 Multicore Computing

Autotuning

A short introduction



Motivation

- Modern (high-end) computer architectures are (too) complex
 - Some final machine parameters may not be statically (well-)known
 - Caches (multiple levels, capacity, associativity, replacement policy)
 - Memory latency
 - ILP and pipelining: Dynamic dispatch, out-of-order execution, speculation, branching
 - Parallelism and contention for shared resources
 - OS scheduler
 - Paging
 - Performance not well predictable,
 e.g. for manual or compiler optimization
- Some program parameters (problem sizes, data locality etc.) may not be statically known
- Different algorithms / implementation variants may exist for a computation
- Hardcoded manual optimizations lead to non-performance-portable code
- Compiler optimizations are limited and may have unexpected side effects / interferences



Motivation (cont.)

- → Thousands of knobs that we could turn to tune performance!
 - Which ones and how?
 - Avoid hardcoding of performance tuning



Performance Portability for User-level code?

quicksort(a,n);

Avoid hard-coded adaptations / optimizations such as:

```
if (avail_num_threads() > 1)
  in_parallel {
    sort(a, n/2); // on first half of resources
                                                               NO!
    sort( &a[n/2], n-n/2); // on the other half
else ... (do it in serial)
if (available(GPU))
    gpusort(a,n);
                                                               NO!
else
    qsort(a,n);
if (n < CACHESIZE/4)
    mergesort(a,n);
else
```

Idea: Autotuning – Automatic optimization for unknown target system using Machine Learning

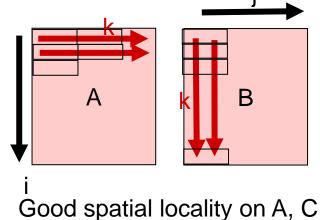
- Given: Training data and initial program version
 - → Observed performance on target
 - → Machine learning algorithm
 - → Optimization strategy (choice of some parameter(s))
 - → Automatic code generation / adaptation for target platform and possibly repeat this process
- for libraries: autotuning library generators,
 for compilers: iterative compilation
 for dynamic composition: context-aware composition
- Typical examples:
 - Find the best blocking factor(s) for loops or loop nests to automatically adapt to target cache behavior
 - Find the right sequence and settings of compiler optimizations
 - Select among different algorithms for same operation
 - How many cores/threads / which processors/accelerators to use?



Recall: Tiled Matrix-Matrix Multiplication (1)

- Matrix-Matrix multiplication C = A x B here for square (n x n) matrices C, A, B, with n large (~10³):
 - $C_{ij} = \sum_{k=1..n} A_{ik} B_{kj}$ for all i, j = 1...n
- Standard algorithm for Matrix-Matrix multiplication (here without the initialization of C-entries to 0):

```
for (i=0; i<n; i++)
  for (j=0; j<n; j++)
   for (k=0; k<n; k++)
        C[i][j] += A[i][k] * B[k][j];</pre>
```



Bad spatial locality on B (many capacity misses)

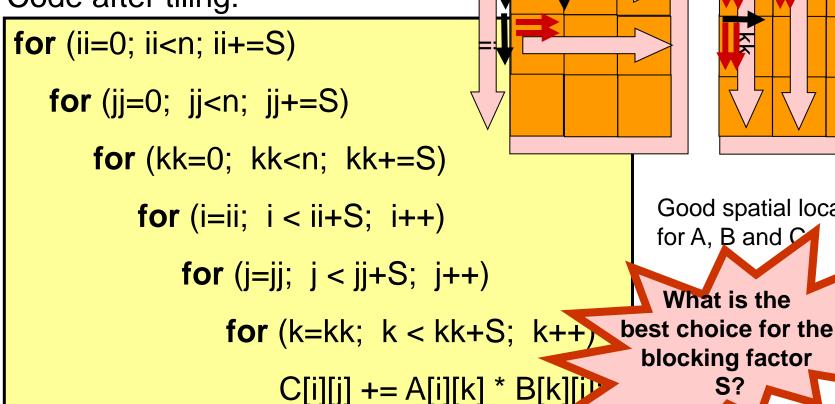


Recall: Tiled Matrix-Matrix Multiplication (2)

Block each loop by block size S (choose S so that a block of A, B, C fit in cache together)

then interchange loops

Code after tiling:



Good spatial locality for A, B and C

What is the blocking factor



Recall: Loop Unroll-And-Jam

unroll the outer loop and fuse the resulting inner loops:

```
\begin{array}{c} \textbf{for} \ i \ \textbf{from} \ \textbf{1} \ \textbf{to} \ N \ \textbf{do} \\ \quad \textbf{for} \ j \ \textbf{from} \ \textbf{1} \ \textbf{to} \ N \ \textbf{do} \\ \quad a[i] \leftarrow a[i] + b[j] \quad \textbf{unroll\&jam:} \\ \quad \textbf{od} \\ \textbf{od} \end{array}
```

```
for i from 1 to N step 2 do

for j from 1 to N do

a[i] \leftarrow a[i] + b[j]

a[i+1] \leftarrow a[i+1] + b[j]

od

od
```

The same conditions as for loop interchange (for the two innermost loops after the unrolling step) must hold (for a formal treatment see [Allen/Kennedy'02, Ch 24.1

- + increases reuse in inner loop
- + less overhead

What is the best choice for the unroll factor (here, 2)?



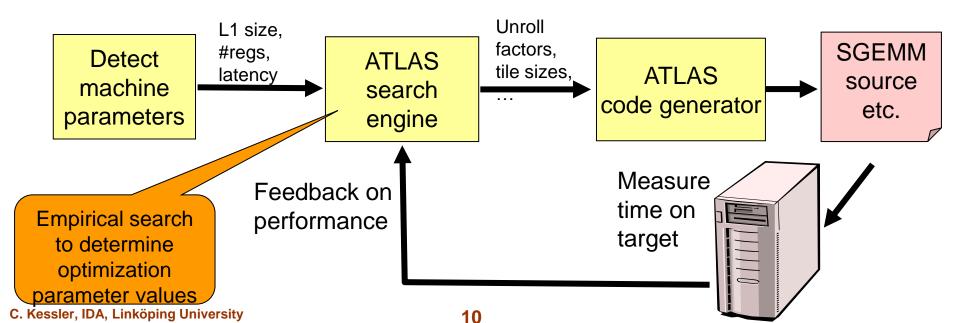
Auto-tuning linear algebra library ATLAS (1)

- BLAS = Basic Linear Algebra Subroutines
 - standard numerical library for Fortran, C
 - frequently used in high-performance applications
- Level-1 BLAS: Vector-vector operations e.g. dot product
- Level-2 BLAS: Matrix-vector operations
- Level-3 BLAS: Matrix-matrix operations, esp., generic versions of dense LU decomposition and Matrix mult.
 - SGEMM: $C := \alpha A * B + \beta C$ for matrices A,B,C, scalars α , β
 - is ordinary Matrix-Matrix multiplication for α =1, β =0



Auto-tuning linear algebra library ATLAS (2)

- ATLAS is a generator for optimized BLAS libraries
 - Tiling to address L1 cache
 - Unroll-and-jam / scalar replacement to exploit registers
 - Use multiply-accumulate and SIMD instructions where available
 - Schedule computation and memory accesses
- Outperforms vendor-specific BLAS implementations





Remark

- Off-line sampling and tuning by greedy heuristic search
 - Happens once for each new system at library deployment (generation) time
 - Can be expensive
- Not practical for less static scenarios or costly sampling
 - Fast predictors needed full execution or even simulation is not feasible
 - Usually constructed by machine learning
 - Shortens the feedback loop
 - Could be adapted dynamically (on-line sampling/tuning)



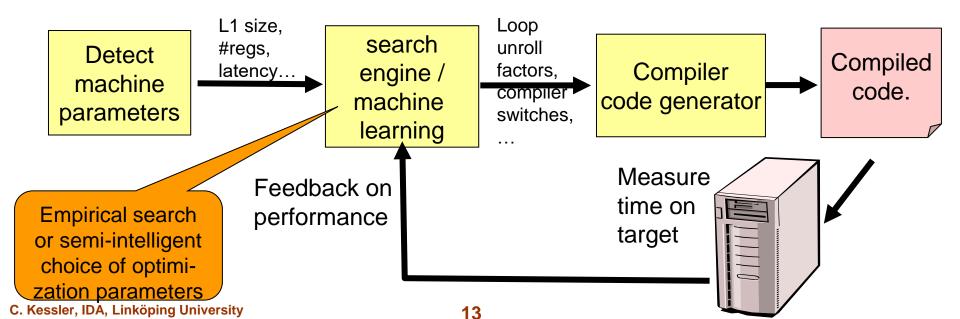
Further auto-tuning library generators

- Linear Algebra
 - ATLAS
 - PhiPAC
 - OSKI
- FFT and other signal processing
 - FFTW [Frigo'99]
 - SPIRAL [Püschel et al. 2005]
- Sorting, searching etc.
 - STAPL [Rauchwerger et al.]
 - [Li, Padua, Garzaran CGO'94]
 - [Brewer'95]
 - [Olszewski, Voss PDPTA-2004]



Generalize this in a compiler!

- Iterative compilation / autotuning compilers
 - Optimization of compiler transformation sequences
 - GCC MILEPOST project 2007-2008
 - CAPStuner, www.caps-entreprise.com
 - ActiveHarmony search engine + CHiLL source-to-source loop transformation framework
 - And many more recent works



One step further: Auto-tunable software components and run-time composition



- Component programmer exposes the knobs for optimization in a performance tuning interface
 - Tunable function parameters e.g. problem sizes
 - Equivalent implementation variants (different algorithms, ...) at calls
 - Possible loop transformations, code specializations
 - Resource allocation and scheduling for independent tasks
- At run time, automatically select
 - expected best implementation variant for each call,
 - expected best resource allocation and schedule for indep. subtasks,
 given run-time information on actual parameters and available resources.
 Look up model / dispatch tables prepared off-line (by machine learning)

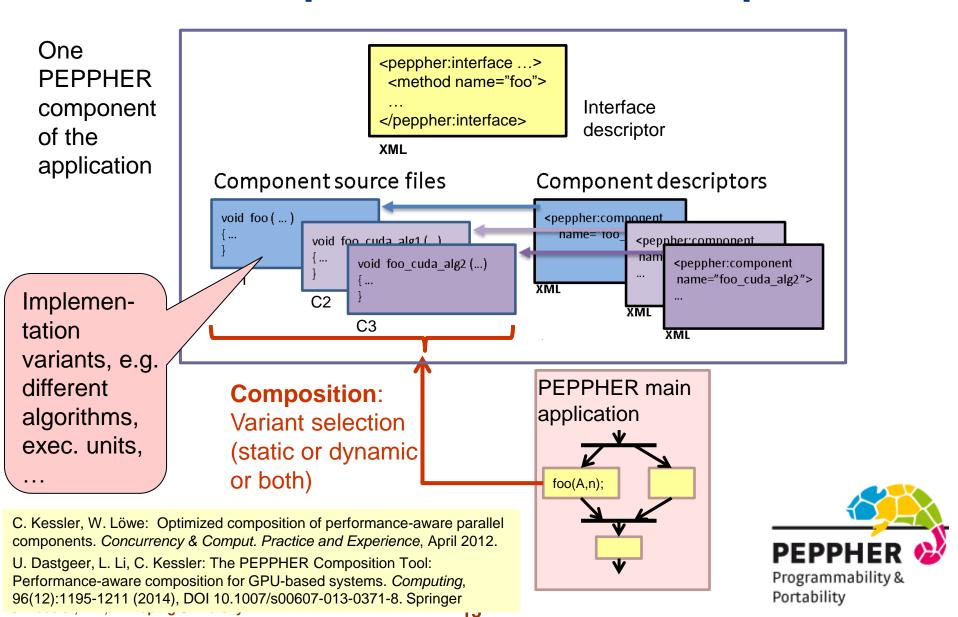
Examples

- Performance-aware parallel software components [K./Löwe 2007/2012]
- Autotuning SkePU (Dastgeer, Enmyren, K. 2011; Dastgeer, K. 2013)
- EU FP7 project PEPPHER (Benkner et al. IEEE Micro Sep/Oct. 2011)
- Related work: Merge, Elastic Functions, PetaBricks





Performance-aware components: Interfaces, implementations, descriptors



Summary: Auto-tuning

 Code optimization is difficult and very platform specific. Avoid hardcoding. Instead, expose what is tunable and let the system learn suitable configurations from training data.



Auto-tuning library generators

- Fixed domain, implicit or explicit human guidance of search space
- Auto-tuning compilers
 - General-purpose programs (HPC)
 - Program structure (loop nests) defines optimization search space
 - Limited influence by programmer (e.g., some #pragmas)
- Auto-tuning application-level software synthesis (software component composition)
 - Programmer-exposed performance tuning interfaces, install-time learning, run-time composition
- Can incorporate library and compiler based autotuning

References



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