TDDD56 Multicore and GPU Computing

Autotuning

A short introduction

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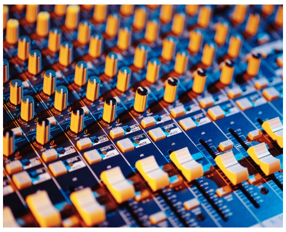
Motivation

- 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
  - → Perf. 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?

Avoid hard-coded adaptations / optimizations such as:

```
if (avail_num_threads() > 1)
   in_parallel {
      sort( a, n/2);   // on first half of resources
      sort( &a[n/2], n-n/2);   // on the other half
   }
else ... (do it in serial)
```

NO!

```
if (available(GPU))
      gpusort(a,n);
else
      qsort(a,n);
```

NO!

```
if (n < CACHESIZE/4)
      mergesort(a,n);
else
      quicksort(a,n);
```

NO!

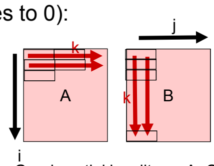
Idea: Autotuning – Automatic optimization for unknown target system using Machine Learning

- 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 $C = A \times B$
  here for square ($n \times n$) matrices C, A, B, with n large (~10^3):
  - $C_{ij} = \Sigma_{k=1..n} A_{ik} B_{kj}$ 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];
```



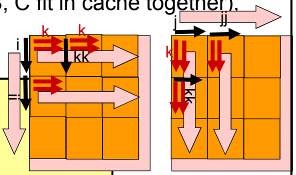
Good spatial locality on A, C

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:

```
for (ii=0; ii<n; ii+=S)
  for (jj=0;  jj<n;  jj+=S)
    for (kk=0;  kk<n;  kk+=S)
      for (i=ii;  i < ii+S;  i++)
        for (j=jj;  j < jj+S;  j++)
          for (k=kk;  k < kk+S;  k++)
            C[i][j] += A[i][k] * B[k][j];
```



Good spatial locality for A, B and C

What is the best choice for the blocking factor S?

Recall: Loop Unroll-And-Jam

unroll the outer loop
and fuse the resulting inner loops:

for i **from** 1 **to** N **do**
  for j **from** 1 **to** N **do**
    $a[i] \leftarrow a[i] + b[j]$
  od
od

unroll&jam:

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. 8.4.1])

+ increases reuse in inner loop
+ less overhead

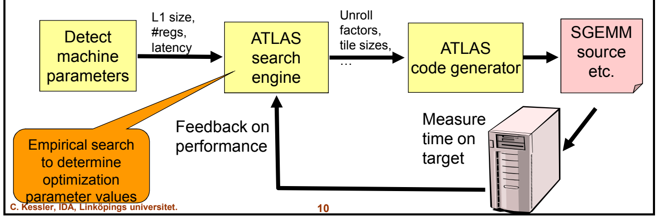
What is the best choice for the unroll factor (here, 2)?

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 := α A * B + β 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

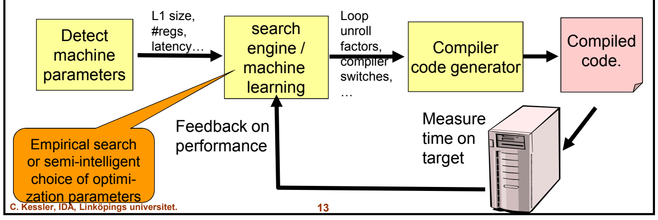
- Off-line sampling and tuning by greedy heuristic search
  - Happens once for each new system at library deployment (generation) time
  - Can be expensive
- Not practical for less static scenarios or costly sampling
  - Fast predictors needed – full execution or even simulation is not feasible
    - 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.
  - [Brewer'95]
  - STAPL [Rauchwerger et al.]
  - [Li, Padua, Garzaran CGO'04]
  - [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



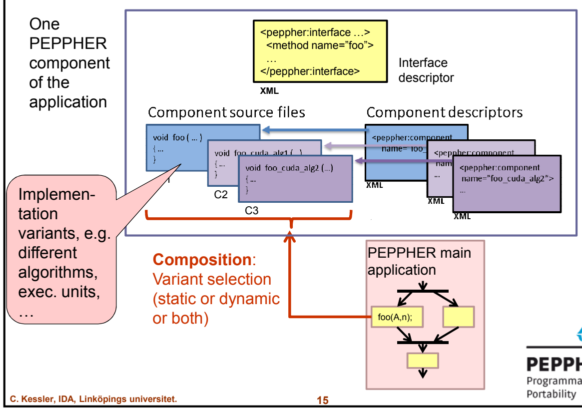
One step further: Multi-variant components and auto-tunable run-time composition

- (Application) component programmer exposes performance-relevant knobs for optimization *explicitly* in a **performance tuning interface**
  - Tunable function parameters e.g. problem sizes
  - Equivalent implementation variants (different algorithms, …)
  - 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 its execution,

  given run-time information on actual parameters and available resources.

  Look up dispatch tables prepared off-line (e.g. by machine learning)
- **Examples**
  - Performance-aware components [K./Löwe 2007/2012]
  - Autotuning SkePU [Dastgeer, K. 2011, 2013]
  - PEPPHER components and GCF [Dastgeer, K. 2014]
  - EU FP7 projects PEPPHER, EXCESS

Performance-aware components: Interfaces, implementations, descriptors

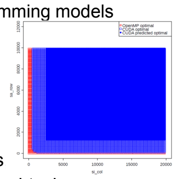


PEPPHER Programmability & Portability

Annotated Multi-Variant Components

- **User-level components**
  - Sequential or parallel implementations, possibly platform-specific
  - Internal parallelism encapsulated, multiple programming models
- **Performance-aware:**

  Annotate with performance prediction metadata, mark up performance-relevant variation points
  - Algorithmic variants
  - Operand data representation and storage
  - Tunable parameters: Buffer sizes, blocking factors
  - Schedule and resource allocation at independent subtasks
  - Portable composition and coordination of components



- Support by run-time system (StarPU)
- Goal: Performance Portability and Programmability
- Main target: heterogeneous multi-/manycore (esp. GPU) systems
- Details: [U. Dastgeer, PhD thesis 2014]

PEPPHER Programmability & Portability

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 multi-variant 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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