CS 380C: Advanced Topics in Compilers

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Administration

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Meeting times

- Lecture:
  - M 10AM-1PM, online
  - Short break of 5 minutes around 11:30AM
- Office hours:
  - Keshav Pingali: Monday 3-4PM, online
  - TA office hours: TBD

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Prerequisites

- Compilers and architecture
  - Some background in compilers
  - Basic computer architecture
- Machine learning
  - Basic knowledge of machine learning
- Software and math maturity
  - Able to implement large programs in C/C++
  - Comfortable with abstractions like graph theory
- Ability to read research papers and understand content

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Course material

- Website for course
  - http://www.cs.utexas.edu/users/pingali/CS380C/2020/index.html
- All lecture notes, announcements, papers, assignments, etc. will be posted there
- No assigned book for the course
  - post papers and other material as appropriate

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Coursework

- 4-5 programming assignments and problem sets
- Mid-semester exam
- Paper presentations
  - Second half of semester
- Term project
  - Substantial implementation project in area of compilers
- Final exam (at my discretion)

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Why do we need compilation technology?

- Traditional view:
  - Translation: high-level language (HLL) programs to low-level machine code
  - Optimization: reduce number of arithmetic operations by optimizations like common subexpression elimination
  - Ignore data structures: too complex to analyze
- Modern view:
  - Collection of automatic techniques for extracting meaning from and transforming programs
  - Useful for debugging, optimization, verification, detecting malware, translation, …..
  - Optimization:
    - Restructure (reorganize) computation to optimize locality and parallelism
    - Reducing amount of computation is useful but not critical
    - Optimizing data structure accesses is critical

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Why do we need translators?

- Bridge the "semantic gap"
  - Programmers prefer to write programs at a high level of abstraction
  - Modern architectures are very complex, so to get good performance, we have to worry about a lot of low-level details
  - Compilers let programmers write high-level programs and still get good performance on complex machine architectures
- Application portability
  - When a new ISA or architecture comes out, you only need to reimplement the compiler on that machine
  - Application programs should run without (substantial) modification
  - Saves programming effort
- Summary: performance + portability of HLL programs

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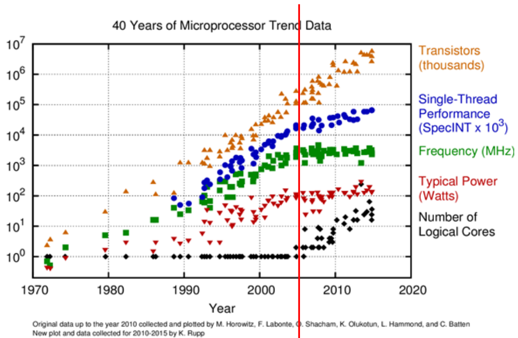
Microprocessor trend data



Before 2005 After 2005

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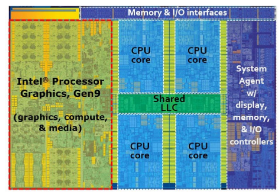
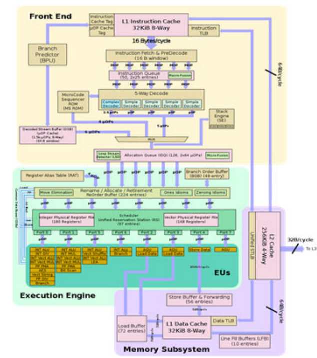
Intel Skylake chip



Chip



Block diagram of each core[10]

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Getting performance

- Programs must exploit
  - coarse-grain (thread-level) parallelism
  - memory hierarchy (L1,L2,L3,..)
  - instruction-level parallelism (ILP)
  - registers
  - ….
- How important is it to exploit these hardware features?
  - If you have n cores and you run on only one, you get at most 1/n of peak performance, so this is obvious
  - Memory hierarchy: typical latencies
    - L1 cache: ~ 1 cycle
    - L2 cache: ~ 10 cycles
    - Memory: ~ 500-1000 cycles
    - If most memory accesses hit in L1/L2 cache, performance is much better than if most of accesses go to memory

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Software problem

- Problem:
  - Programs obtained by expressing most algorithms in the straight-forward way perform poorly
  - Worrying about performance when coding algorithms complicates the software process greatly
- Let us study cache optimization to understand this
- Caches are useful only if programs have locality of reference
  - temporal locality: program references to given memory address are clustered together in time
  - spatial locality: program references clustered in address space are clustered in time

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Example: matrix multiplication

```
for I = 1, N    //assume arrays stored in row-major order
  for J = 1, N
    for K = 1, N
      C(I,J) = C(I,J) + A(I,K)*B(K,J)
```

- All six loop permutations are computationally equivalent (even modulo round-off error).
- Great algorithmic data reuse: each array element is touched O(N) times!
- However, execution times of the six versions can be very different if machine has a cache.

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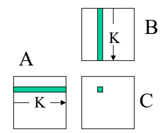
IJK version (large cache)

```
for I = 1, N
  for J = 1, N
    for K = 1, N
      C(I,J) = C(I,J) + A(I,K)*B(K,J)
```



- Large cache scenario: matrices are small enough to fit into cache
  - Assume only cold misses, no capacity or conflict misses
  - Miss ratio:
    - Data size = 3 N^2
    - Assume line size = b floating-point numbers
    - Miss ratio = 3 N^2 /b*4N^3 = 0.75/bN = 0.019 (b = 4,N=10)

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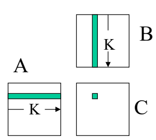
IJK version (small cache)

```
for I = 1, N
  for J = 1, N
    for K = 1, N
      C(I,J) = C(I,J) + A(I,K)*B(K,J)
```



- Small cache scenario: matrices are large compared to cache/row-major storage
  - Cold and capacity misses (ignore conflict misses)
  - Miss ratio:
    - C: N^2/b misses (good temporal locality)
    - A: N^3 /b misses (good spatial locality)
    - B: N^3 misses (poor temporal and spatial locality)
    - Miss ratio → 0.25 (b+1)/b = 0.3125 (for b = 4)

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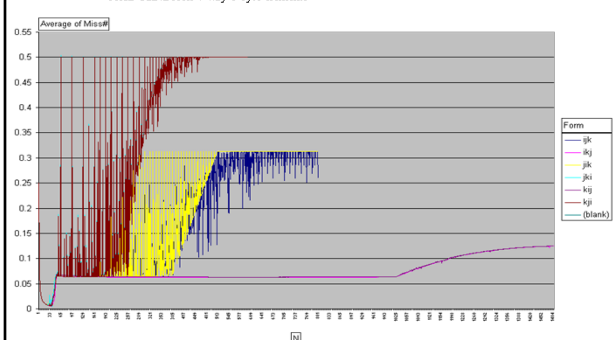
MMM Experiments

- Simulated L1 Cache Miss Ratio for Intel Pentium III
  - *MMM with N = 1…1300*
  - 16KB 32B/Block 4-way 8-byte elements



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Quantifying performance differences

```
for I = 1, N    //assume arrays stored in row-major order
  for J = 1, N
    for K = 1, N
      C(I,J) = C(I,J) + A(I,K)*B(K,J)
```

- Typical cache parameters:
  - L2 cache hit: 10 cycles, cache miss 70 cycles
- Time to execute IKJ version:
  $2N^3 + 70*0.13*4N^3 + 10*0.87*4N^3 = 73.2\ N^3$
- Time to execute JKI version:
  $2N^3 + 70*0.5*4N^3 + 10*0.5*4N^3 = 162\ N^3$
- Speed-up = 2.2
- Key transformation: loop permutation

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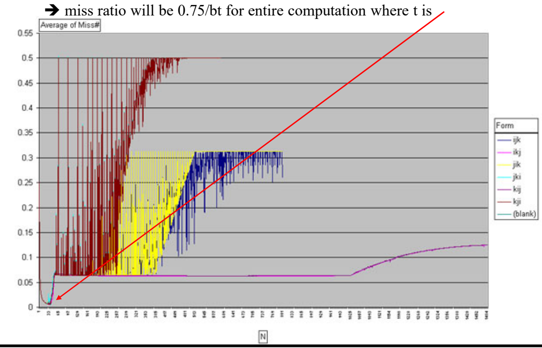
Even better.....

- Break MMM into a bunch of smaller MMMs so that large cache model is true for each small MMM
  ➔ large cache model is valid for entire computation
  ➔ miss ratio will be 0.75/bt for entire computation where t is



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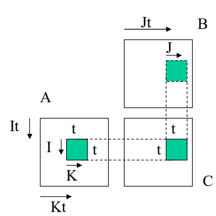
Loop tiling/blocking

```
for It = 1,N, t
  for Jt = 1,N,t
    for Kt = 1,N,t
      for I = It,It+t-1
        for J = Jt,Jt+t-1
          for K = Kt,Kt+t-1
            C(I,J) = C(I,J)+A(I,K)*B(K,J)
```



- Break big MMM into sequence of smaller MMMs where each smaller MMM multiplies sub-matrices of size txt.
- Parameter t (tile size) must be chosen carefully
  - as large as possible
  - working set of small matrix multiplication must fit in cache

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Speed-up from tiling/blocking

- Miss ratio for block computation
  = miss ratio for large cache model
  = 0.75/bt
  = 0.001 (b = 4, t = 200)
- Time to execute tiled version =
  $2N^3 + 70*0.001*4N^3 + 10*0.999*4N^3 = 42.3N^3$
- Speed-up over JKI version = 4

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Observations

- Locality optimized code is more complex than high-level algorithm.
- Locality optimization changed the order in which operations were done, not the number of operations
- "Fine-grain" view of data structures (arrays) is critical
- Loop orders and tile size must be chosen carefully
  - cache size is key parameter
  - associativity matters
- Actual code is even more complex: must optimize for processor resources
  - registers: register tiling
  - pipeline: loop unrolling
  - Optimized MMM code can be ~1000's of lines of C code
- Wouldn't it be nice to have all this be done automatically by a compiler?
  - Actually, it is done automatically nowadays…

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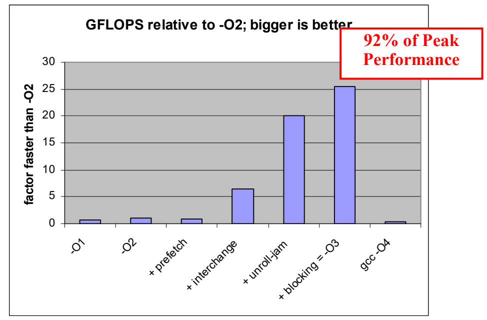
Performance of MMM code produced by Intel's Itanium compiler (-O3)



Goto BLAS obtains close to 99% of peak, so compiler is pretty good!

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Summary

- Exploiting parallelism, memory hierarchies etc. is very important
- If program uses only one core out of n cores in processors, you get at most 1/n of peak performance
- Memory hierarchy optimizations are very important
  - can improve performance by 10X or more
- Key points:
  - need to focus on data structure manipulation
  - reorganization of computations and data structure layout are key
  - few opportunities usually to reduce the number of computations except in address arithmetic

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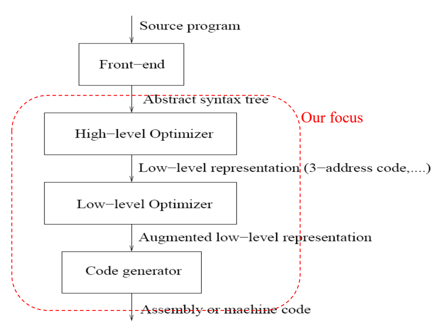
Organization of modern compiler



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Front-end

- Goal: convert linear representation of program to hierarchical representation
  - Input: text file
  - Output: abstract syntax tree + symbol table
- Key modules:
  - Lexical analyzer: converts sequence of characters in text file into sequence of tokens
  - Parser: converts sequence of tokens into abstract syntax tree + symbol table
  - Semantic checker: (eg) perform type checking

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High-level optimizer

- Goal: perform high-level analysis and optimization of program
- Input: AST + symbol table from front-end
- Output: Low-level program representation such as 3-address code
- Tasks:
  - Procedure/method inlining
  - Array/pointer dependence analysis
  - Loop transformations: unrolling, permutation, tiling, jamming,….

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Low-level optimizer

- Goal: perform scalar optimizations on low-level representation of program
- Input: low-level representation of program such as 3-address code
- Output: optimized low-level representation + additional information such as def-use chains
- Tasks:
  - Dataflow analysis: live variables, reaching definitions, …
  - Scalar optimizations: constant propagation, partial redundancy elimination, strength reduction, ….

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Code generator

- Goal: produce assembly/machine code from optimized low-level representation of program
- Input: optimized low-level representation of program from low-level optimizer
- Output: assembly/machine code for real or virtual machine
- Tasks:
  - Register allocation
  - Instruction selection

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JIT compilation

- Traditionally, all phases of compilation were completed before program was executed
- New twist: virtual machines
  - Offline compiler:
    - Generates code for virtual machine like JVM
  - Just-in-time compiler:
    - Generates code for real machine from VM code while program is executing
- Advantages:
  - Portability
  - JIT compiler can perform optimizations for particular input

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My lectures (scalar stuff)

- Introduction
  - compiler structure, architecture and compilation, sources of improvement
- Control flow analysis
  - basic blocks & loops, dominators, postdominators, control dependence
- Data flow analysis
  - lattice theory, iterative frameworks, reaching definitions, liveness
- Static-single assignment form (SSA)
  - static-single assignment, constant propagation.
- Global optimizations
  - loop invariant code motion, common subexpression elimination, strength reduction.
- Register allocation
  - coloring, allocation, live range splitting.
- Instruction scheduling (depending on schedule)
  - pipelined and VLIW architectures, list scheduling.

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My lectures (data structure stuff)

- Array dependence analysis
  - integer linear programming, dependence abstractions.
- Loop transformations for array programs
  - linear loop transformations, loop fusion/fission, enhancing parallelism and locality
- Self-optimizing programs
  - empirical search, ATLAS, FFTW
- Analysis of pointer-based programs
  - points-to and shape analysis
- Parallelizing graph programs
  - amorphous data parallelism, exploiting amorphous data-parallelism

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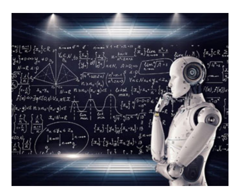
Advanced topics for CS 380C

- Optimizing machine learning programs
  - Training and testing times can be large
    - Models are getting more complex
    - Lot of training data
  - How for we optimize training and testing times on modern architectures?
- Exploiting machine learning in compilers
  - Some work in this area but no major breakthroughs yet
  - Active research topic
- Course
  - See website for partial list of papers we will study in this area
  - Papers will be presented by students
  - Ideally, your paper presentation and course project will be linked



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Schedule for lectures

- See
  - http://www.cs.utexas.edu/users/pingali/CS380C/2020/index.html
- Some lectures will be given by guest lecturers from my group and from industry

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Reading assignments for next class

- Lecture slides on SAM
  - Simple stack machine
- My SIGARCH blogpost:
  - Why has machine learning not had more impact on systems?
- Mike O'Boyle's survey article on using machine learning in compilers
  - Machine learning in compiler optimization
    Wang and O'Boyle, arXiv:1805.03441
- Eran Yahav's SIGPLAN blog post on machine learning in compilers
  - From-programs-to-deep-models-part-1

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