



UC Berkeley Teaching Professor Dan Garcia

CS61C

Great Ideas
in
Computer Architecture
(a.k.a. Machine Structures)



UC Berkeley Professor Bora Nikolić

Parallelism







New-School Machine Structures

Software

Parallel Requests

Assigned to computer e.g., Search "Cats"

Parallel Threads

Assigned to core e.g., Lookup, Ads

Parallel Instructions

>1 instruction @ one time e.g., 5 pipelined instructions

Parallel Data

>1 data item @ one time e.g., Add of 4 pairs of words

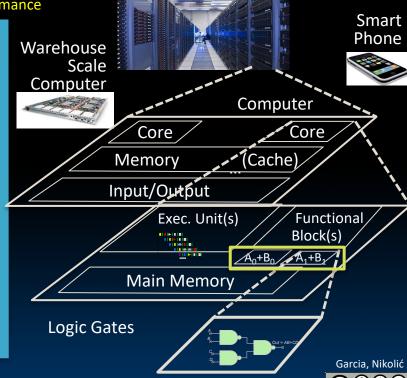
Hardware descriptions

All gates work in parallel at same time





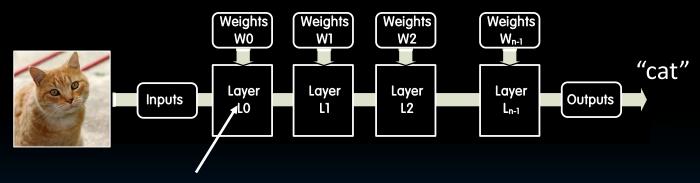
Hardware





Application: Machine Learning

• Inference in machine learning applications



Matrix-vector multiplications







Reference Problem: Matrix Multiplication

Matrix multiplication

- Basic operation in many engineering, data, and imaging processing tasks
- Image filtering, noise reduction, machine learning...
- Many closely related operations

dgemm

- double-precision floating-point matrix multiplication
 - In FORTRAN

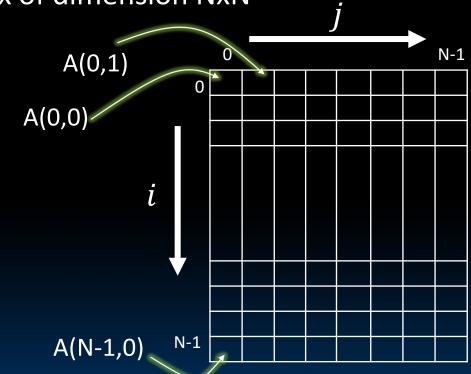






Matrices

Square matrix of dimension NxN

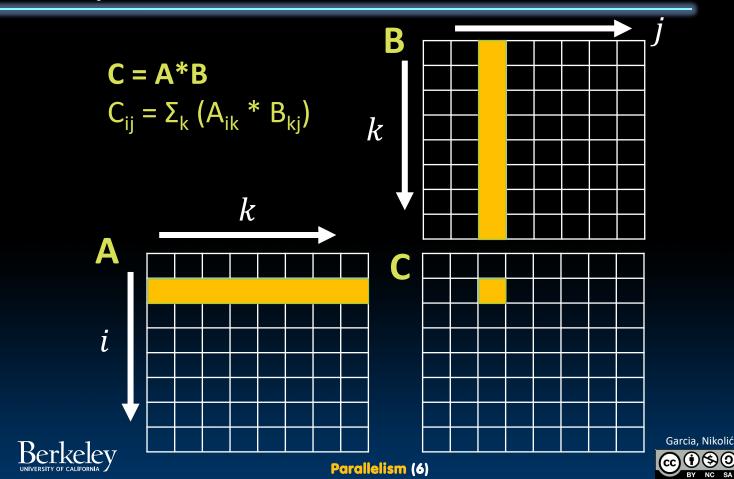








Matrix Multiplication



Matrix Multiplication



Matrix Multiply:

$$C_{i,j} = (A \times B)_{i,j} = \sum_{k=1}^{2} A_{i,k} \times B_{k,j}$$

$$\begin{bmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & A_{2,2} \end{bmatrix} \times \begin{bmatrix} B_{1,1} \\ B_{2,1} \end{bmatrix} \times \begin{bmatrix} B_{1,2} \\ B_{2,1} \end{bmatrix} = \begin{bmatrix} C_{1,1} = A_{1,1}B_{1,1} + A_{1,2}B_{2,1} \\ C_{2,1} = A_{2,1}B_{1,1} + A_{2,2}B_{2,1} \\ C_{2,1} = A_{2,1}B_{1,1} + A_{2,2}B_{2,1} \\ C_{2,1} = 1*1 + 0*2 = 1 \\ C_{1,2} = 1*3 + 0*4 = 3 \\ C_{2,1} = 0*1 + 1*2 = 2 \\ C_{2,2} = 0*3 + 1*4 = 4 \end{bmatrix}$$



Garcia, Nikolić



Reference: Python

Matrix multiplication in Python

```
def dgemm(N, a, b, c):
    for i in range(N):
        for j in range(N):
        c[i+j*N] = 0
        for k in range(N):
        c[i+j*N] += a[i+k*N] * b[k+j*N]
```

N	Python [MFLOPs]
32	5.4
160	5.5
480	5.4
960	5.3

- 1 MFLOP = 1 Million floatingpoint operations per second (fadd, fmul)
- dgemm(N ...) takes 2*N³ FLOPs





C

- c = a * b
- a, b, c are N x N matrices







Timing Program Execution

```
#include <stdio.h>
#include <stdlib.h>
#include <time.h>

int main(void) {
    // start time
    // Note: clock() measures execution time, not real time
    // big difference in shared computer environments
    // and with heavy system load
    clock_t start = clock();

    // task to time goes here:
    // dgemm(N, ...);

    // "stop" the timer
    clock_t end = clock();

    // compute execution time in seconds
    double delta_time = (double)(end-start)/CLOCKS_PER_SEC;
}
```







C vs. Python

N	C [GFLOPS]	Python [GFLOPS]	240x
32	1.30	0.0054	! ~
160	1.30	0.0055	
480	1.32	0.0054	
960	0.91	0.0053	

Which class gives you this kind of power? We could stop here ... but why? Let's do better!





Flynn's Taxonomy



Software vs. Hardware Parallelism

		Software		
		Sequential	Concurrent	
Hardware	Serial	Matrix Multiply written in MatLab running on an Intel Pentium 4	Windows Vista Operating System running on an Intel Pentium 4	
	Parallel	Matrix Multiply written in MATLAB running on an Intel Core i7	Windows Vista Operating System running on an Intel Core i7	

- Choice of hardware and software parallelism are independent
 - Concurrent software can also run on serial hardware
 - Sequential software can also run on parallel hardware
- Flynn's Taxonomy is for parallel hardware







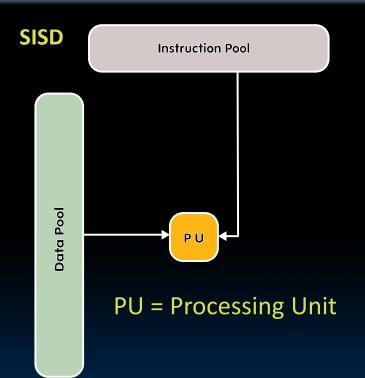
Flynn's Taxonomy



- SIMD and MIMD most commonly encountered today
- Most common parallel processing programming style: Single Program Multiple Data ("SPMD")
 - Single program that runs on all processors of an MIMD
 - Cross-processor execution coordination through conditional expressions (will see later in Thread Level Parallelism)
- SIMD: specialized function units (hardware), for handling lock-step calculations involving arrays
 - Scientific computing, machine learning, signal processing, multimedia
 (audio/video processing)



Single Instruction/Single Data Stream (SISD)



- Sequential computer that exploits no parallelism in either the instruction or data streams
- Examples of SISD

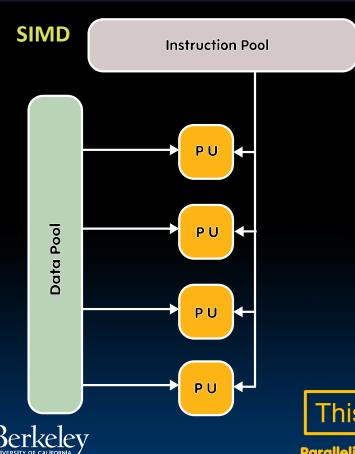
 architecture are
 traditional uniprocessor
 machines

This is what we did up to now in 61C





Single Instruction/Multiple Data Stream (SIMD)



Computer that applies a single instruction stream to multiple data streams for operations that may be naturally parallelized (e.g. SIMD instruction extensions or Graphics **Processing Unit)**

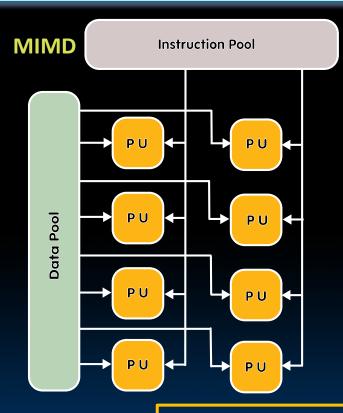
This segment







Multiple Instruction/Multiple Data Stream (MIMD)



- Multiple
 autonomous
 processors
 simultaneously
 executing different
 instructions on
 different data
- MIMD architectures include multicore and Warehouse Scale Computers

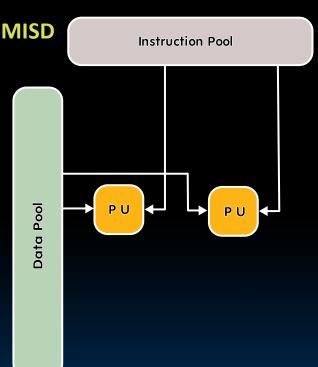


Later in this module





Multiple Instruction/Single Data Stream (MISD)



- instruction streams against a single data stream for data operations that can be naturally parallelized (e.g. certain kinds of array processors)
- MISD no longer commonly encountered, mainly of historical interest only

This has few applications. Not covered in 61C.



SIMD Architectures



SIMD Architectures

- Data-Level Parallelism (DLP): operation on multiple data streams
- Example: Multiplying a coefficient vector by a data vector (e.g. in filtering)

$$y[i] := c[i] \times x[i], 0 \le i < n$$

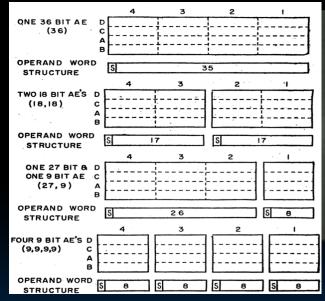
- Sources of performance improvement:
 - One instruction is fetched & decoded for entire operation
 - Multiplications are known to be independent
 - Pipelining/concurrency in memory access as well







First SIMD Extensions: MIT Lincoln Labs TX-2, 1957



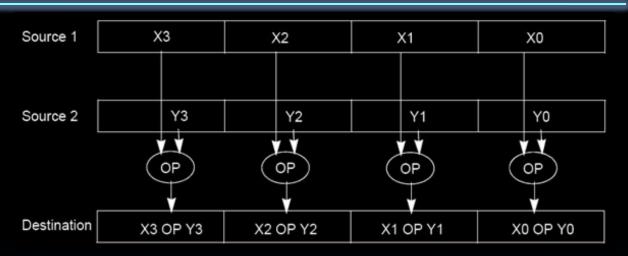








"Advanced Digital Media Boost"



- To improve performance, Intel's SIMD instructions
 - Fetch one instruction, do the work of multiple instructions
 - MMX (MultiMedia eXtension, Pentium II processor family)
 - SSE (Streaming SIMD Extension, Pentium III and beyond)

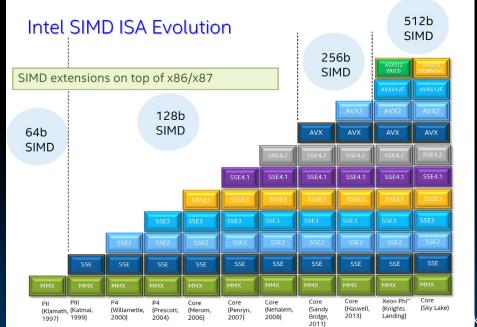






Intel x86 SIMD Evolution

- Started with multimedia extensions (MMX)
 - New instructions every few years
 - New and wider registers
 - More parallelism







C vs. Python

N	AVX [GFLOPS]	C [GFLOPS]	Python [GFLOPS]
32	4.56	1.30	0.0054
160	5.47	1.30	0.0055
480	5.27	1.32	0.0054
960	3.64	0.91	0.0053

Theoretical Intel i7-5557U performance is ~25 GFLOPS

3.1GHz x 2 instructions/cycle x 4 mults/inst = 24.8GFLOPS







XMM Registers in SSE

- Architecture extended with eight 128-bit data registers
 - 64-bit address architecture: available as 16 64-bit registers (XMM8 – XMM15)
 - e.g. 128-bit packed single-precision floating-point data type (doublewords), allows four single-precision operations to be performed simultaneously

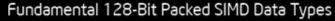
XMM7	
XMM6	
XMM5	
XMM4	
XMM3	
XMM2	
XMM1	
XMM0	

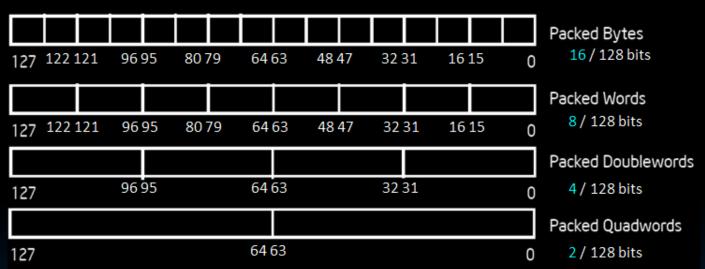






Intel Architecture SSE2+128-Bit SIMD Data Types





- Note: in Intel Architecture (unlike RISC V) a word is 16 bits
 - Single precision FP: Double word (32 bits)
 - Double precision FP: Quad word (64 bits)

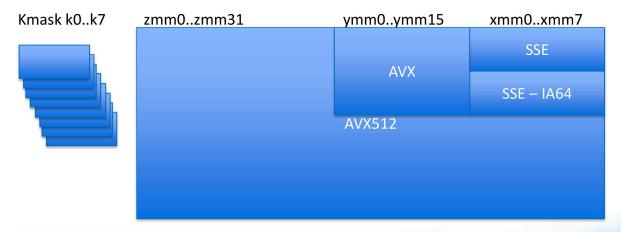






SIMD Registers in AVX512

AVX512 state



High amounts of compute need large amounts of state to compensate for memory BW AVX512 has 8x state compared to SSE (commensurate with its 8x flops level)

Intel confidential — presented under NDA only — under embargo until 6:01 a.m. PDT, June 19, 2017







Check Out My Laptop (1scpu)

```
Model:
                                 126
Model name:
                                 Intel(R) Core(TM) i7-1065G7 CPU @ 1.30GHz
Stepping:
CPU MHz:
                                 1497.605
BogoMIPS:
                                 2995,21
Hypervisor vendor:
                                 Microsoft
Virtualization type:
                                 full
L1d cache:
                                 192 KiB
L1i cache:
                                 128 KiB
L2 cache:
                                 2 MiB
L3 cache:
                                 8 MiB
Vulnerability Itlb multihit:
                                 KVM: Vulnerable
Vulnerability L1tf:
                                 Not affected
Vulnerability Mds:
                                 Not affected
Vulnerability Meltdown:
                                 Not affected
Vulnerability Spec store bypass: Mitigation; Speculative Store Bypass disabled via prctl and seccomp
Vulnerability Spectre v1:
                                 Mitigation; usercopy/swapgs barriers and user pointer sanitization
Vulnerability Spectre v2:
                                 Mitigation; Enhanced IBRS, IBPB conditional, RSB filling
Vulnerability Srbds:
                                 Not affected
Vulnerability Tsx async abort:
                                 Not affected
Flags:
                                 fpu vme de pse tsc msr pae mce cx8 apic sep mtrr pge mca cmov pat pse36 clflush mmx fxs
                                 r sse sse2 ss ht syscall nx pdpe1gb rdtscp lm constant tsc rep good nopl xtopology cpui
                                 d pni pclmulqdq ssse3 fma cx16 pcid sse4 1 sse4 2 movbe popcnt aes xsave avx f16c rdran
                                 d hypervisor lahf lm abm 3dnowprefetch invpcid single ssbd ibrs ibpb stibp ibrs enhance
                                 d fsgsbase bmil avx2 smep bmil erms invpcid avx512f avx512dq rdseed adx smap avx512ifma
                                  clflushopt avx512cd sha ni avx512bw avx512vl xsaveopt xsavec xgetbv1 xsaves avx512vbmi
                                  umip avx512 vbmi2 gfni vaes vpclmulqdq avx512 vnni avx512 bitalg avx512 vpopcntdq rdpi
                                 d flush l1d arch capabilities
```





SIMD Array Processing



Example: SIMD Array Processing

```
for each f in array:
                                                           pseudocode
  f = sqrt(f)
for each f in array {
  load f to the floating-point register
  calculate the square root
                                                          SISD
  write the result from the register to memory
for every 4 members in array {
  load 4 members to the SSE register
  calculate 4 square roots in one operation
                                                          SIMD
  write the result from the register to memory
```







Example: Add Single-Precision FP Vectors

```
Computation to be performed:
                               move from mem to XMM register
                               memory aligned, packed single precision
  vec res.x = v1.x + v2.x
  vec res.y = v1.y + y2.y;
                               add from mem to XMM register
  vec res.z = v1.z + v2.z
                               packed single precision
  vec res.w = v1.w + v2.w;
                               move from XMM register to mem
                               memory aligned, packed single precision
SSE Instruction Sequence:
movaps address-of-v1, %xmm0
  // v1.x | v1.z | v1.y | v1.x -> xmm0
addps address-of-v2, %xmm0
  // v1.w+y2.w + v1.z+v2.z + v1.y+v2.y + v1.x+v2.x
  -> xmm0
         %xmm0, address-of-vec res
movaps
```







Intel SSE Intrinsics

- Intrinsics are C functions and procedures for putting in assembly language, including SSE instructions
 - With intrinsics, can program using these instructions indirectly
 - One-to-one correspondence between SSE instructions and intrinsics

Instrinsics:

Corresponding SSE instructions:

Vector data type:

m128d

• Load and store operations:

mm load pd

mm store pd

• Arithmetic:

_mm_add_pd

mm mul pd

MOVAPD/aligned, packed double

MOVAPD/aligned, packed double

ADDPD/add, packed double

MULPD/multiple, packed double

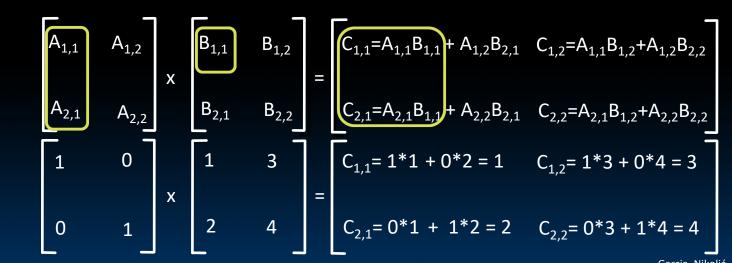


Matrix Multiply Example



Matrix Multiply:

$$C_{i,j} = (A \times B)_{i,j} = \sum_{k=1}^{2} A_{i,k} \times B_{k,j}$$







Initialization

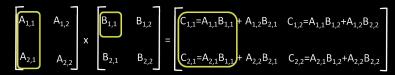
C_1	0	0
C_2	0	0







Initialization



$$\begin{array}{c|cccc}
C_1 & 0 & 0 \\
C_2 & 0 & 0
\end{array}$$

4	A _{1,1}	A _{2,1}	_mm_load_pd: Stored in memory in
		· · · · · · · · · · · · · · · · · · ·	Column order

B_1	B _{1,1}	B _{1,1}
B_2	B _{1,2}	B _{1.2}







$$\begin{bmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & A_{2,2} \end{bmatrix} \times \begin{bmatrix} B_{1,1} & B_{1,2} \\ B_{2,1} & B_{2,2} \end{bmatrix} = \begin{bmatrix} C_{1,1} = A_{1,1}B_{1,1} \\ C_{2,1} = A_{2,1}B_{1,1} \\ C_{2,1} = A_{2,1}B_{1,1} \\ C_{2,1} = A_{2,1}B_{1,1} \\ C_{2,2} = A_{2,1}B_{1,2} + A_{2,2}B_{2,2} \end{bmatrix}$$

$$\begin{array}{c|cccc} C_1 & O+A_{1,1}B_{1,1} & O+A_{2,1}B_{1,1} \\ C_2 & O+A_{1,1}B_{1,2} & O+A_{2,1}B_{1,2} \\ \end{array}$$

I = 1, intermediate result

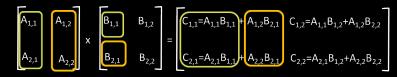
c1 = _mm_add_pd(c1,_mm_mul_pd(a,b1));
c2 = _mm_add_pd(c2,_mm_mul_pd(a,b2));
SSE instructions first do parallel multiplies
and then parallel adds in XMM registers











$$C_1$$
 $0+A_{1,1}B_{1,1}$ $0+A_{2,1}B_{1,1}$ C_2 $0+A_{1,1}B_{1,2}$ $0+A_{2,1}B_{1,2}$

c1 = _mm_add_pd(c1,_mm_mul_pd(a,b1));
c2 = _mm_add_pd(c2,_mm_mul_pd(a,b2));
SSE instructions first do parallel multiplies
and then parallel adds in XMM registers

■ I = 2, intermediate result

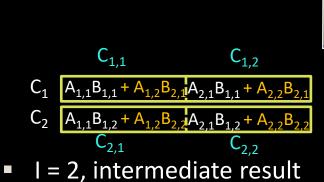


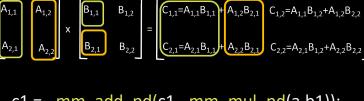
B_1	B _{2,1}	B _{2,1}
B ₂	B _{2,2}	B _{2,2}







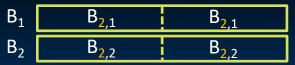




c1 = _mm_add_pd(c1,_mm_mul_pd(a,b1));
c2 = _mm_add_pd(c2,_mm_mul_pd(a,b2));
SSE instructions first do parallel multiplies
and then parallel adds in XMM registers



_mm_load_pd: Stored in memory in Column order









```
#include <stdio.h>
// header file for SSE compiler intrinsics
#include <emmintrin.h>
// NOTE: vector registers will be represented in
//comments as v1 = [a | b]
// where v1 is a variable of type m128d and
   a, b are doubles
int main(void) {
  // allocate A,B,C aligned on 16-byte boundaries
  double A[4] attribute ((aligned (16)));
  double B[4] attribute ((aligned (16)));
  double C[4] attribute ((aligned (16)));
  int Ida = 2;
  int i = 0;
  // declare several 128-bit vector variables
  m128d c1,c2,a,b1,b2;
```

```
// Initialize A, B, C for example
/* A =
                     (note column order!)
   10
   01
  A[0] = 1.0; A[1] = 0.0; A[2] = 0.0; A[3] = 1.0;
/* B =
                      (note column order!)
   13
   24
  B[0] = 1.0; B[1] = 2.0; B[2] = 3.0; B[3] = 4.0;
/* C =
                      (note column order!)
   00
   00
  C[0] = 0.0; C[1] = 0.0; C[2] = 0.0; C[3] = 0.0;
```







```
// used aligned loads to set
  //c1 = [\bar{c} \ 11 \mid c \ 21]
  c1 = mm load pd(C+0*lda);
  // c2 = [c \ 12 | c \ 22]
  c2 = mm load pd(C+1*lda);
  for (i = 0; i < 2; i++)
     i = 0: [a 11 | a 21]
     i = 1: [a 12 | a 22]
    a = mm load pd(A+i*lda);
    /* \overline{b1} =
     i = 0: [b 11 | b 11]
     i = 1: [b^{-}21] b^{-}21]
    b1 = mm load1 pd(B+i+0*lda);
    /* b2¯=
    i = 0: [b_12 | b_12]
i = 1: [b_22 | b_22]
   b2 = mm load1 pd(B+i+1*lda);
```

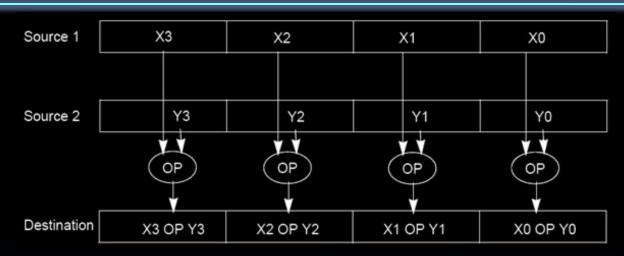
```
/* c1 =
   i = 0: [c 11 + a 11*b 11 | c 21 + a 21*b 11]
   i = 1: [c 11 + a 21*b 21 | c 21 + a 22*b 21]
  */
  c1 = mm add pd(c1, mm mul pd(a,b1));
  /* c2 =
   i = 0: [c 12 + a 11*b 12 | c 22 + a 21*b 12]
   i = 1: [c_12 + a_21*b_22 | c_22 + a_22*b_22]
  c2 = mm add pd(c2, mm mul pd(a,b2));
// store c1,c2 back into C for completion
mm store pd(C+0*lda,c1);
mm store pd(C+1*lda,c2);
// print C
printf("%g,%g\n\g,%g\n",C[0],C[2],C[1],\overline{C[3]);
return 0;
```







Back to RISC-V: Vector Extensions (Draft)



- To improve RISC-V performance, add SIMD instructions (and hardware) – V extension
 - Fetch one instruction, do the work of multiple instructions
 - OP denotes a vector instruction, prefix v vector register
 - vadd vd, vs1, vs2 (adds two vectors stored in vector registers)





"And in Conclusion..."

Flynn Taxonomy of Parallel Architectures

- SIMD: Single Instruction Multiple Data
- MIMD: Multiple Instruction Multiple Data
- SISD: Single Instruction Single Data
- MISD: Multiple Instruction Single Data (unused)

Intel AVX SIMD Instructions

- One instruction fetch that operates on multiple operands simultaneously
- 512/256/128/64-bit AVX registers
- Use C intrinsics



