

Computer Architecture A Quantitative Approach, Sixth Edition



#### Chapter 4

Data-Level Parallelism in Vector, SIMD, and GPU Architectures

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## **Contents**

- Vector Architecture
- SIMD Instruction Set Extensions for Multimedia
- Graphics Processing Units
- Fallacies and Pitfalls



- SIMD architectures can exploit significant datalevel parallelism for:
  - Matrix-oriented scientific computing
  - Media-oriented image and sound processing
- SIMD is more energy efficient than MIMD
  - Only needs to fetch one instruction per data operation
  - Makes SIMD attractive for personal mobile devices
- SIMD allows programmer to continue to think sequentially



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## **Contents**

#### Vector Architecture

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- RV64V Extensions
- RV64V Vector Instructions
- Example: DAXPY
- Vector Execution Time
- Challenges
- Improvements
  - 1. Multiple Lanes
  - 2. Vector-Length Registers
  - 3. Predicate Registers
  - 4. Memory Banks



## Vector Architectures

#### Basic idea

- Read sets of data elements into "vector registers"
- Operate on those registers
- Disperse the results back into memory
- Registers are controlled by compiler
  - Used to hide memory latency
  - Leverage memory bandwidth





## **RV64V Extension**

- Loosely based on Cray-1
- 32 64-bit vector registers
  - Register file has 16 read ports and 8 write ports
  - Elements per v. register depends on the configuration
- Vector functional units
  - Fully pipelined
  - Data and control hazards are detected
- Vector load-store unit
  - Fully pipelined
  - One word per clock cycle after initial latency
- Scalar registers
  - 32 general-purpose registers
  - 32 floating-point registers



## **RV64V Vector Instructions**

- Operate on vectors or vectors and scalars
- Examples: vadd, vmul, vld, vst
- Have suffixes
  - vv: two vector operands
  - .vs and .sv: vector and scalar operands
  - The compiler usually adds these suffixes according to the operands
  - Example: vmul v1,v0,fo is vmul.vs
- These instructions can operate on the following types:

Integer 8, 16, 32, and 64 bits	Floating point	16, 32, and 64 bits
--------------------------------	----------------	---------------------

- The operand type is implicit according to the register type.
- Registers are configurable at run time.



#### **Example: DAXPY**

- DAXPY: A times X plus Y
- C Code:
  for (i=0; i<32; i++)
  Y[i]=a\*X[i]+Y[i];
  </pre>

259 instructions

RISC-V Code:						
fld	f0,a					
addi	x28,x5,#256					
Loop:						
fld	f1,0(x5)					
fmul.d	f1,f1,f0					
fld	f2,0(x6)					
fadd.d	f2,f2,f1					
fsd	f2,0(x6)					
addi	x5,x5,#8					
addi	x6,x6,#8					
bne	x28,x5,Loop					



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#### **Example: DAXPY**

RV64V Code:

fld f0,a vld v0,x5 # Load vector X vmul v1, v0, f0vld v2,x6 vst v3,x6 vdisable

vsetdcfg 4\*FP64 # Enable 4 DP FP vregs # Load scalar a # Vector-scalar mult # Load vector Y vadd v3,v1,v2 # Vector-vector add # Store the sum # Disable vector regs

Only 8 instructions



#### **Vector Execution Time**

#### Execution time depends on three factors:

- Length of operand vectors
- Structural hazards
- Data dependencies
- RV64V functional units consume one element per clock cycle
  - Execution time is approximately the vector length
- Convey
  - Set of vector instructions that could potentially execute together



## **Chimes**

 Sequences with read-after-write dependency hazards placed in same convey via *chaining*

#### Chaining

 Allows a vector operation to start as soon as the individual elements of its vector source operand become available

#### Chime

- Unit of time to execute one convey
- *m* conveys executes in *m* chimes for vector length *n*
- For vector length of *n*, requires *m* x *n* clock cycles



#### Example

vld	v0,x5	
∨mul	v1,v0,f0	
vld	v2,x6	
vadd	v3,v1,v2	
vst	v3,x6	
Convo	bys:	
1	vld	vmul
2	vld	vadd
3	vst	

- # Load vector X
- # Vector-scalar multiply
- # Load vector Y
- # Vector-vector add
- # Store the sum



3 chimes, 2 FP ops per result, cycles per FLOP = 1.5

For 32 element vectors, requires  $32 \times 3 = 96$  clock cycles

## **Challenges**

- Start up time
  - Latency of vector functional unit
  - Assume the same as Cray-1
    - Floating-point add => 6 clock cycles
    - Floating-point multiply => 7 clock cycles
    - Floating-point divide => 20 clock cycles
    - Vector load => 12 clock cycles
- Improvements:
  - 1. > 1 element per clock cycle
  - 2. Non-32 wide vectors
  - 3. IF statements in vector code
  - 4. Memory system optimizations to support vector processors



## **Multiple Lanes**

- Beyond one element per clock cycle
- Element *i* of vector register A is "hardwired" to element *i* of vector register B
  - Allows for multiple hardware lanes





#### **Vector-Length Registers**

RV64V has two hardware registers:

- MVL: maximum vector-length register
- VL: vector-length register
- Vectors of arbitrary length are processed with *strip mining*. All blocks but the last are of length MVL, utilizing the full power of the vector processor. The last block contains the reminder elements.





#### **Vector-Length Registers**

Handling loo	ps not equal to	с 3	32.
vsetdo	cfg 2 DP FP	#	Enable 2 64b FP registers
fld	f0,a	#	Load scalar a
loop:			
setvl	t0,a0	#	vl = t0 = min(mvl,n)
vld	v0,x5	#	Load vector X
slli	t1,t0,3	#	t1 = v1 * 8 (in bytes)
add	x5,x5,t1	#	Increment pointer to X by vl*8
∨mul	v0,v0,f0	#	Vector-scalar mult
vld	v1,x6	#	Load vector Y
vadd	v1,v0,v1	#	Vector-vector add
sub	a0,a0,t0	#	n -= v1 (t0)
vst	v1,x6	#	Store the sum into Y
add	x6,x6,t1	#	Increment pointer to Y by v1*8
bnez	a0,loop	#	Repeat if n != 0
vdisat	ole	#	Disable vector regs



#### **Predicate Registers**

Consider: for (i = 0; i < 64; i=i+1)if (X[i] != 0) X[i] = X[i] - Y[i];

Use predicate register to "disable" elements:

vsetpcfgi 1 vld v1,x6 vst v0,x5 vdisable vpdisable

vsetdcfg 2\*FP64 # Enable 2 64b FP vector regs # Enable 1 predicate register vld v0,x5 # Load vector X into v0 # Load vector Y into v1 fmv.d.x f0,x0 # Put (FP) zero into f0 vpne p0,v0,f0 # Set p0(i) to 1 if v0(i)!=f0 vsub v0,v0,v1 # Subtract under vector mask # Store the result in X # Disable vector registers # Disable predicate registers



#### **Memory Banks**

- Memory system must be designed to support high bandwidth for vector loads and stores
- Spread accesses across multiple banks
  - Control bank addresses independently
  - Load or store non sequential words (need independent bank addressing)
  - Support multiple vector processors sharing the same memory





#### **Memory Banks**

#### Example: Cray T932

- 32 processors, each generating 4 loads and 2 stores/cycle
- Processor cycle time is 2.167 ns, SRAM cycle time is 15 ns
- How many memory banks needed?

SRAM cycle time = 15 / 2.167 = 7 cycles Access rate =  $32 \times (4+2) = 192$  access/cycle  $192 \times 7 = 1334$  banks



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#### SIMD Instruction Set Extensions for Multimedia

- Introduction
- Intel x86 SIMD Implementations
- DAXPY SIMD Example
- Roofline Performance Model



#### Introduction

 Media applications operate on data types narrower than the native word size



Limitations, compared to vector instructions:

- Number of data operands encoded into op code
- No predicate registers
- No sophisticated addressing (strided, scatter-gather)



## Intel x86 SIMD Implementations

- Intel MMX (1996)
  - Eight 8-bit integer ops or four 16-bit integer ops
- Streaming SIMD Extensions (SSE) (1999)
  - Eight 16-bit integer ops
  - Four 32-bit integer/fp ops or two 64-bit integer/fp ops
- Advanced Vector Extensions (2010)
  - Four 64-bit integer/fp ops
- AVX-512 (2017)
  - Eight 64-bit integer/fp ops
- Operands must be consecutive and aligned memory locations



#### **DAXPY SIMD Example**

	fld	f0,a	#	Load scalar a
	<pre>splat.4D</pre>	f0,f0	#	Make 4 copies of a
	addi	x28,x5,#256	#	Last address to load
_00	op:			
	fld.4D	f1,0(x5)	#	Load X[i] X[i+3]
	fmul.4D	f1,f1,f0	#	a x X[i] a x X[i+3
	fld.4D	f2,0(x6)	#	Load Y[i] Y[i+3]
	fadd.4D	f2,f2,f1	#	a x X[i]+Y[i]
			#	a x X[i+3]+Y[i+3]
	fsd.4D	f2,0(x6)	#	Store Y[i] Y[i+3]
	addi	x5,x5,#32	#	Increment index to X
	addi	x6,x6,#32	#	Increment index to Y
	bne	x28,x5,Loop	#	Check if done



## **Roofline Performance Model**

#### Basic idea:

- Plot peak floating-point throughput as a function of arithmetic intensity
- Ties together floating-point performance and memory performance for a target machine
- Arithmetic intensity
  - Floating-point operations per byte accessed

Attainable GPLOPs/sec = Min (Peak Memory BW × Arithmetic Intensity, Peak FP Performance )



#### **Example: Vector vs SIMD Ext.**

- NEC SX-9 is a vector supercomputer announced in 2008 that cost millions of dollars. It has a peak DP FP performance of 102.4 GFLOP/s and a peak memory bandwidth of 162 GB/s from the Stream benchmark.
  - 3.2 GHz, eight vector pipes, each having two multiply and two addition units; peak vector performance of 102.4 GFLOP/s
- Core i7 920 has a peak DP FP performance of 42.66 GFLOP/s and a peak memory bandwidth of 16.4 GB/s.
  - Peak Performance = 2.66 GHz \* 4 (cores/chip) \* 2 (ops/SIMD instr.) \* 2 (FP add-mul/op) = 42.66 GFLOP/s



#### **Example: Vector vs SIMD Ext.**

- Arith. Int. = 4 FLOP/byte: both processors operate at peak performance. SX-9 is 2.4 × faster than Core i7.
- Arith. Int. = 0.25 FLOP/byte: SX-9 is 10 × faster than Core i7.





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#### Graphics Processing Units

- Introduction
- CUDA GPU Programming
- NVIDIA GPU Architecture
- NVIDIA GPU ISA
- NVIDIA GPU Memory Structures
- NVIDIA GPU Memory Structures



- Heterogeneous execution model
  - CPU is the *host*, GPU is the *device*
- Develop a C-like programming language for GPU
- CUDA: Compute Unified Device Architecture
- Unify all forms of GPU parallelism as CUDA thread
- Programming model is "Single Instruction Multiple Thread"





## **CUDA GPU Programming**

- A thread is associated with each data element.
   Single instruction, multiple threads.
- C DAXPY function:

```
void daxpy(int n, double a, double *x, double *y) {
    int i;
    for(i=0; i<n; i++)
        y[i] = a*x[i] + y[i];</pre>
```

```
}
```

```
• CUDA DAXPY function:
void daxpy(int n, double a, double *x, double *y) {
    int i = blockIdx.x * blockDim.x + threadIdx.x;
    if (i < n) y[i] = a*x[i] + y[i];</pre>
```



## **CUDA GPU Programming**

- Code that works over all elements is the grid.
- Grids are broken into thread blocks of manageable sizes, e.g., 512 threads per block.
- SIMD instruction executes
   32 elements at a time (warp).
- Block = 512/32 = 16 warps.
- GPU hardware handles thread management, not applications or OS

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								-	****	0.5			
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			AL	32 ]	= B	L :	32	1	*	CL	32	1	
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	Thread	Thread1			•••		***						
	Block		A[	63 ]	= B	[	63	]	*	C[	63	]	
	0		A[	64 ]	= B	[	64	]	×	C[	64	]	
					****		****					***	
			A[	479]	= B	[ 4	79	]	×	C[	479	]	
			A[	480]	= B	[ 4	80	]	*	C[	480	]	
		SIMD	A[	481]	= B	[ 4	81	]	*	C[	481	]	
		Thread 15				-		_		_			
			A	511]	= B	[ 5	511	1	×	C[	511	1	
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		an m	A[	8160]	= B	[8]	160	]	*	C[	8160	]	
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		11100015			121								
			A[	8191]	= B	[8	191	]	*	C[	8191	]	



## **NVIDIA GPU Architecture**

- Current-generation GPUs have tens of multithreaded SIMD processors.
- Nvidia calls the multithreaded SIMD processor Streaming multiprocessor (SM).
- Blocks are assigned to a SMs by the Thread Block Scheduler.
- Each SM has SIMD Thread Scheduler (Warp scheduler) that schedules threads of SIMD instructions.





# NVIDIA GPU Architecture Pascal P100 GPU has 60 SMs, four spares.



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## **Simplified SM Processor**





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## **NVIDIA GPU Architecture**

- Similarities to vector machines:
  - Works well with data-level parallel problems
  - Scatter-gather transfers
  - Mask registers
  - Large register files
- Differences:
  - No scalar processor
  - Uses multithreading to hide memory latency
  - Has many functional units, as opposed to a few deeply pipelined units like a vector processor



#### **Terminology**

- Each thread is limited to 64 registers
- Groups of 32 threads combined into a SIMD thread or "warp"
  - Mapped to 16 physical lanes
- Up to 32 warps are scheduled on a single SIMD processor
  - Each warp has its own PC
  - Thread scheduler uses scoreboard to dispatch warps
  - By definition, no data dependencies between warps
  - Dispatch warps into pipeline, hide memory latency
- Thread block scheduler schedules blocks to SIMD processors
- Within each SIMD processor:
  - 32 SIMD lanes
  - Wide (16 lanes) and shallow (2 ops per lane) compared to vector processors
- See figure 4.14



#### **NVIDIA GPU ISA**

ISA is an abstraction of the hardware instruction set

- "Parallel Thread Execution (PTX)"
- Uses virtual registers
- Translation to machine code is performed in software
- Format of PTX instruction: opcode.type d,a,b,c;

Туре	.type specifier
Untyped bits 8, 16, 32, and 64 bits	.b8,.b16,.b32,.b64
Unsigned integer 8, 16, 32, and 64 bits	.u8,.u16,.u32,.u64
Signed integer 8, 16, 32, and 64 bits	.s8,.s16,.s32,.s64
Floating Point 16, 32, and 64 bits	.f16,.f32,.f64



## **NVIDIA GPU ISA**

#### DAXPY Example:

```
shl.s32 R8, blockIdx, 9 ; Block ID * Block size (512 or 2<sup>9</sup>)
add.s32 R8, R8, threadIdx ; R8 = i = my CUDA thread ID
ld.global.f64 RD0, [X+R8] ; RD0 = X[i]
ld.global.f64 RD2, [Y+R8] ; RD2 = Y[i]
mul.f64 RD0, RD0, RD4 ; Product in RD0 = RD0 * RD4 (scalar a)
add.f64 RD0, RD0, RD2 ; Sum in RD0 = RD0 + RD2 (Y[i])
st.global.f64 [Y+R8], RD0 ; Y[i] = sum (X[i]*a + Y[i])
```



## **NVIDIA GPU Memory Structures**

- Each SIMD Lane has private section of offchip DRAM
  - Contains stack frame, spilling registers, and private variables
- Each multithreaded SIMD processor also has local memory
  - Shared by SIMD lanes
     / threads within a
     block
- Memory shared by SIMD processors is GPU Memory
  - Host can read and write GPU memory











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## **Fallacies and Pitfalls**

- F: GPUs suffer from being coprocessors
  - GPUs have flexibility to change ISA
- P: Concentrating on peak performance in vector architectures and ignoring start-up overhead
  - Overheads require long vector lengths to achieve speedup
- P: Increasing vector performance without comparable increases in scalar performance
- F: You can get good vector performance without providing memory bandwidth
- F: On GPUs, just add more threads if you don't have enough memory performance
  - This works only if threads have good memory locality.

