

# **CS 152 Computer Architecture and Engineering**

## **CS252 Graduate Computer Architecture**

### **Lecture 09 – Multithreading/Vector/GPU**

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# Thread-Level Parallelism (TLP)

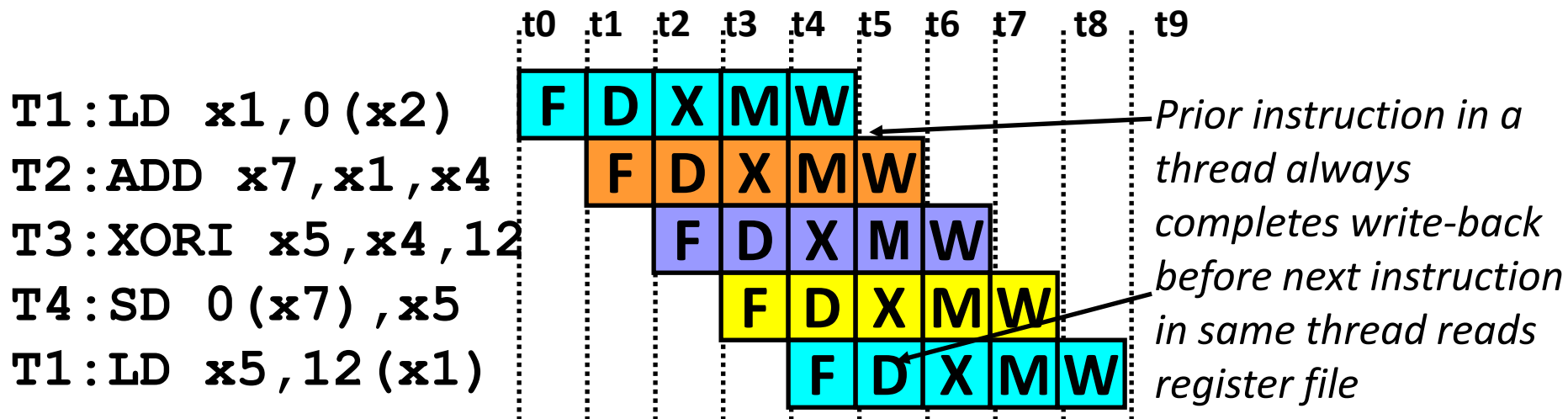
- Difficult to continue to extract instruction-level parallelism (ILP) from a single sequential thread of control
- Many workloads can make use of thread-level parallelism:
  - TLP from ***multiprogramming*** (run independent sequential jobs)
  - TLP from ***multithreaded*** applications (run one job faster using parallel threads)
- Multithreading uses TLP to improve utilization of a single processor

# Multithreading

How can we guarantee no dependencies between instructions in a pipeline?

One way is to interleave execution of instructions from different program threads on same pipeline

*Interleave 4 threads, T1-T4, on **non-bypassed** 5-stage pipe*



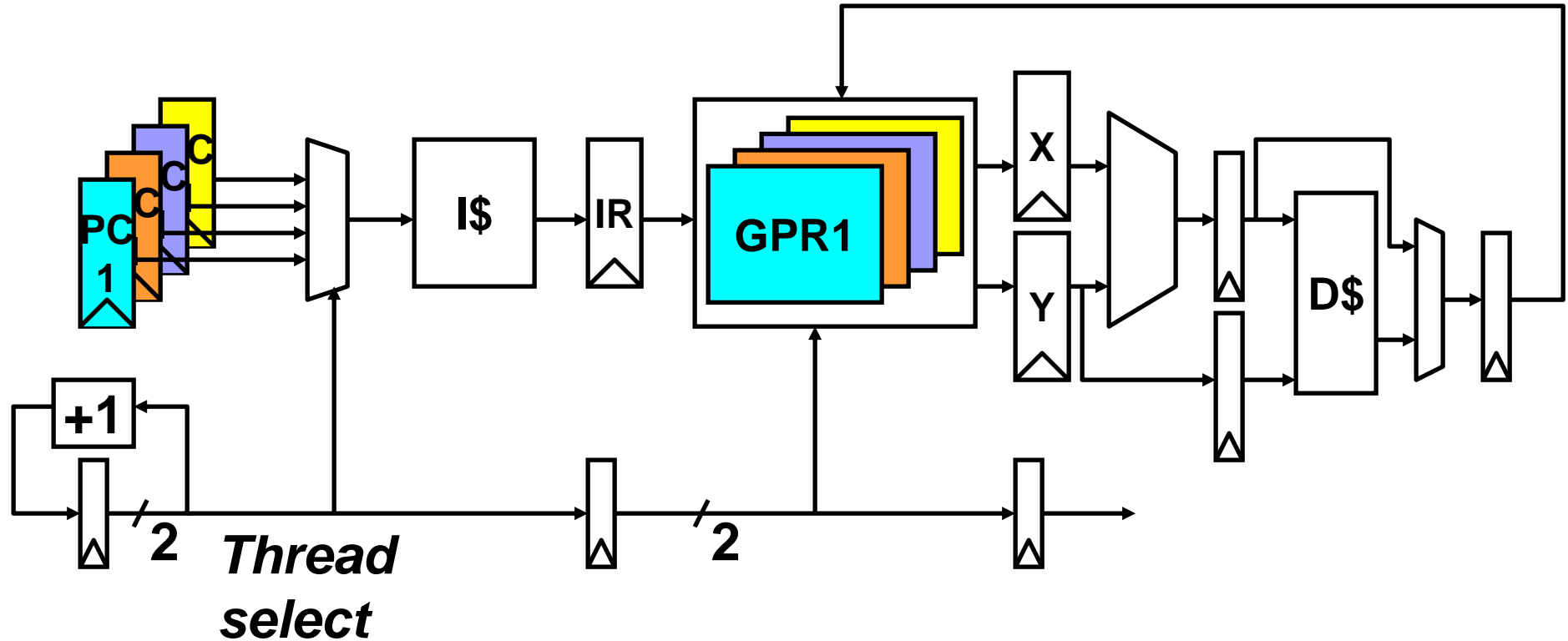
# CDC 6600 Peripheral Processors

(Cray, 1964)



- First multithreaded hardware
- 10 “virtual” I/O processors
- Fixed interleave on simple pipeline
- Pipeline has 100ns cycle time
- Each virtual processor executes one instruction every 1000ns
- Accumulator-based instruction set to reduce processor state

# Simple Multithreaded Pipeline



- Have to carry thread select down pipeline to ensure correct state bits read/written at each pipe stage
- Appears to software (including OS) as multiple, albeit slower, CPUs

# Multithreading Costs

- Each thread requires its own user state
  - PC
  - GPRs
- Also, needs its own system state
  - Virtual-memory page-table-base register
  - Exception-handling registers
- *Other overheads:*
  - Additional cache/TLB conflicts from competing threads
    - or add larger cache/TLB capacity
  - More OS overhead to schedule more threads (where do all these threads come from?)

# Thread Scheduling Policies

- Fixed interleave (*CDC 6600 PPU's, 1964*)
  - Each of N threads executes one instruction every N cycles
  - If thread not ready to go in its slot, insert pipeline bubble
- Software-controlled interleave (*TI ASC PPU's, 1971*)
  - OS allocates S pipeline slots amongst N threads
  - Hardware performs fixed interleave over S slots, executing whichever thread is in that slot



- Hardware-controlled thread scheduling (*HEP, 1982*)
  - Hardware keeps track of which threads are ready to go
  - Picks next thread to execute based on hardware priority scheme



# Denelcor HEP

(Burton Smith, 1982)



First commercial machine to use hardware threading in main CPU

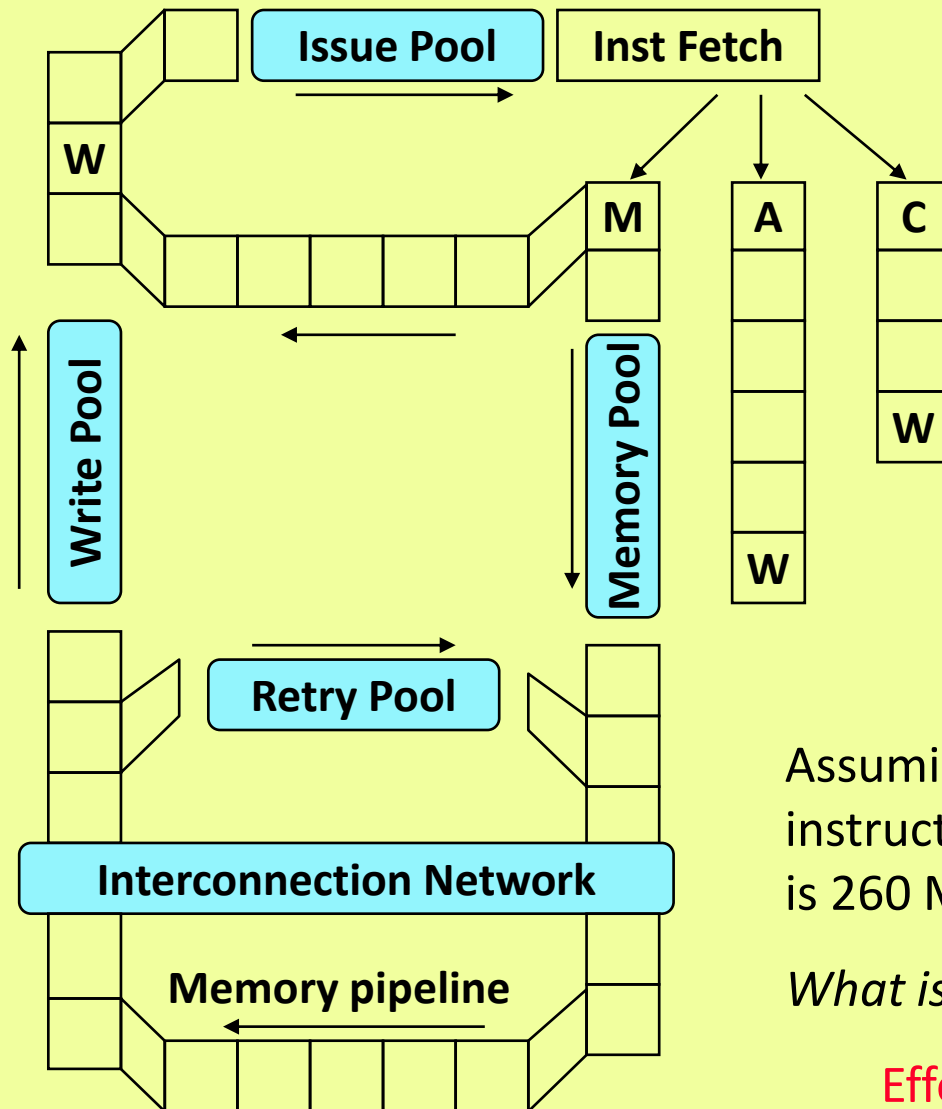
- 120 threads per processor
- 10 MHz clock rate
- Up to 8 processors
- precursor to Tera MTA (Multithreaded Architecture)

# Tera/Cray MTA (1990-2015)

- Up to 256 processors
- Up to 128 active threads per processor
- Processors and memory modules populate a sparse 3D torus interconnection fabric
- Flat, shared main memory
  - No data cache
  - Sustains one main memory access per cycle per processor
- GaAs logic in prototype, 1KW/processor @ 260MHz
  - Second version CMOS, MTA-2, 50W/processor
  - Newer version, XMT, fits into AMD Opteron socket, runs at 500MHz
  - Newer versions (2011), XMT-2, has higher memory bandwidth and capacity
  - Discontinued 2015?



# MTA Pipeline



- Every cycle, one VLIW instruction from one active thread is launched into pipeline
- Instruction pipeline is 21 cycles long
- Memory operations incur ~150 cycles of latency

Assuming a single thread issues one instruction every 21 cycles, and clock rate is 260 MHz...

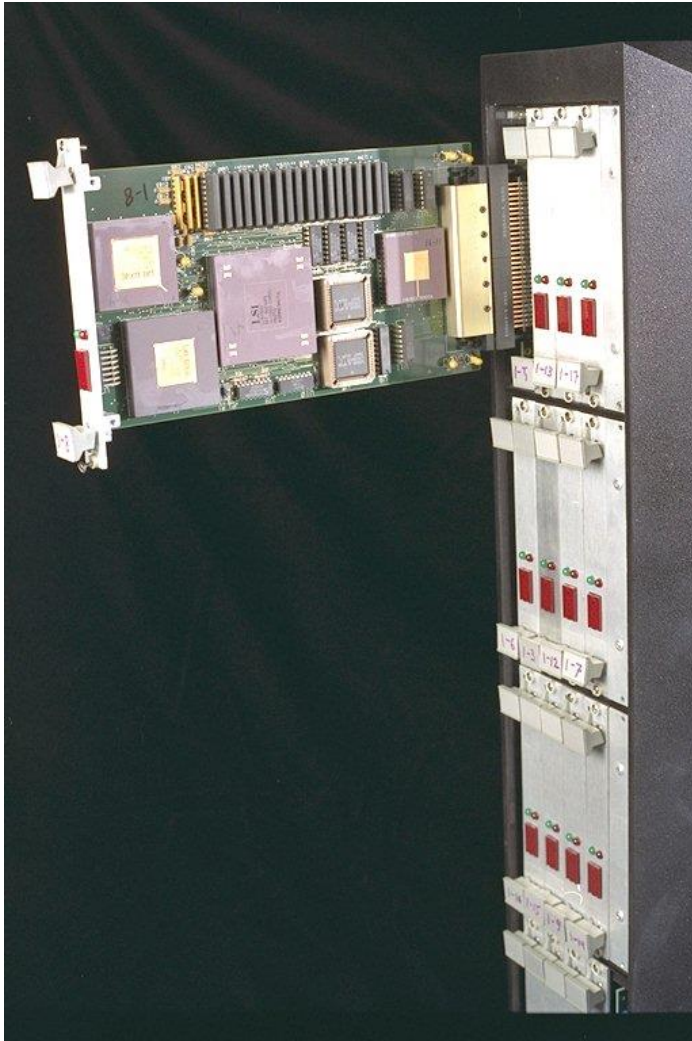
*What is single-thread performance?*

Effective single-thread issue rate is  
 $260/21 = 12.4$  MIPS

# Coarse-Grain Multithreading

- Tera MTA designed for supercomputing applications with large data sets and low locality
  - No data cache
  - Many parallel threads needed to hide large memory latency
- Other applications are more cache friendly
  - Few pipeline bubbles if cache mostly has hits
  - Just add a few threads to hide occasional cache miss latencies
  - Swap threads on cache misses

# MIT Alewife (1990)



- Modified SPARC chips
  - register windows hold different thread contexts
- Up to four threads per node
- Thread switch on local cache miss

# IBM PowerPC RS64-IV (2000)

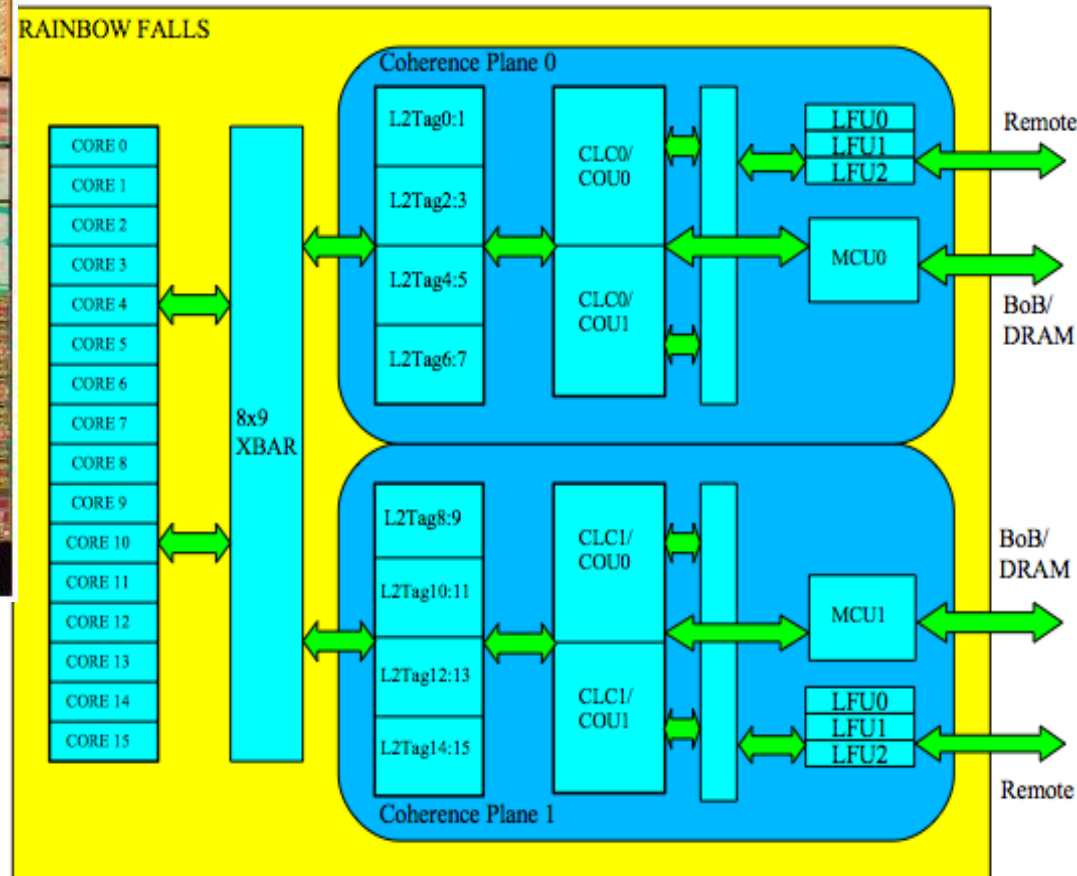
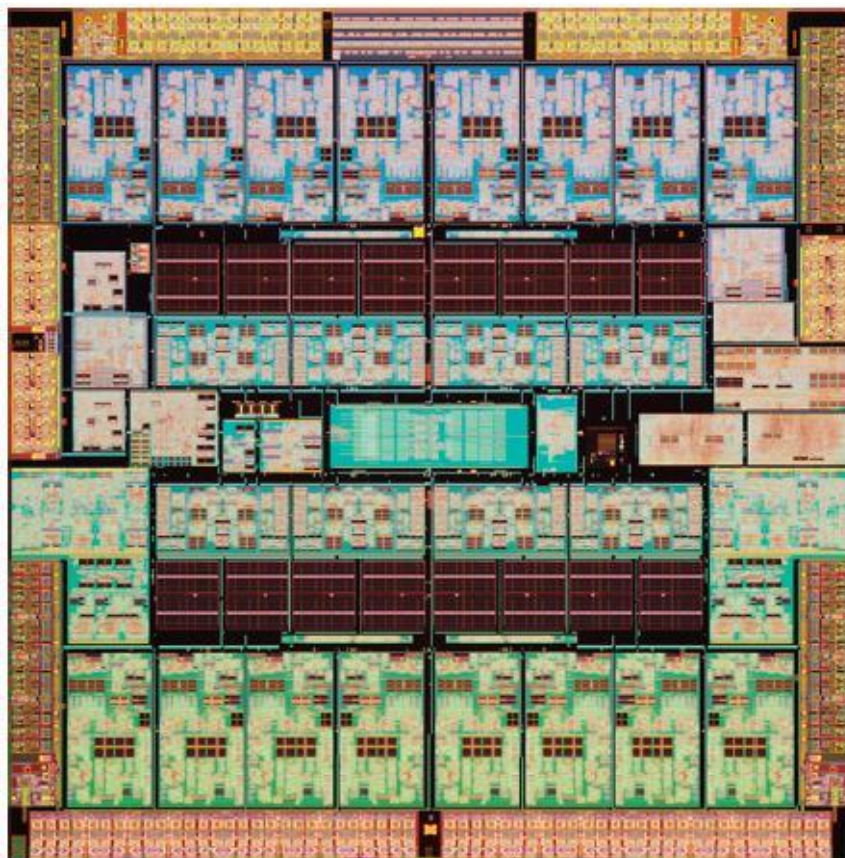
- Commercial coarse-grain multithreading CPU
- Based on PowerPC with quad-issue in-order five-stage pipeline
- Each physical CPU supports two virtual CPUs
- On L2 cache miss, pipeline is flushed and execution switches to second thread
  - short pipeline minimizes flush penalty (4 cycles), small compared to memory access latency
  - flush pipeline to simplify exception handling

# Oracle/Sun Niagara processors

- Target is datacenters running web servers and databases, with many concurrent requests
- Provide multiple simple cores each with multiple hardware threads, reduced energy/operation though much lower single thread performance
- Niagara-1 [2004], 8 cores, 4 threads/core
- Niagara-2 [2007], 8 cores, 8 threads/core
- Niagara-3 [2009], 16 cores, 8 threads/core
- T4 [2011], 8 cores, 8 threads/core
- T5 [2012], 16 cores, 8 threads/core
- M5 [2012], 6 cores, 8 threads/core
- M6 [2013], 12 cores, 8 threads/core



# Oracle/Sun Niagara-3, “Rainbow Falls” 2009





# Oracle SPARC M6 Processor (2013)

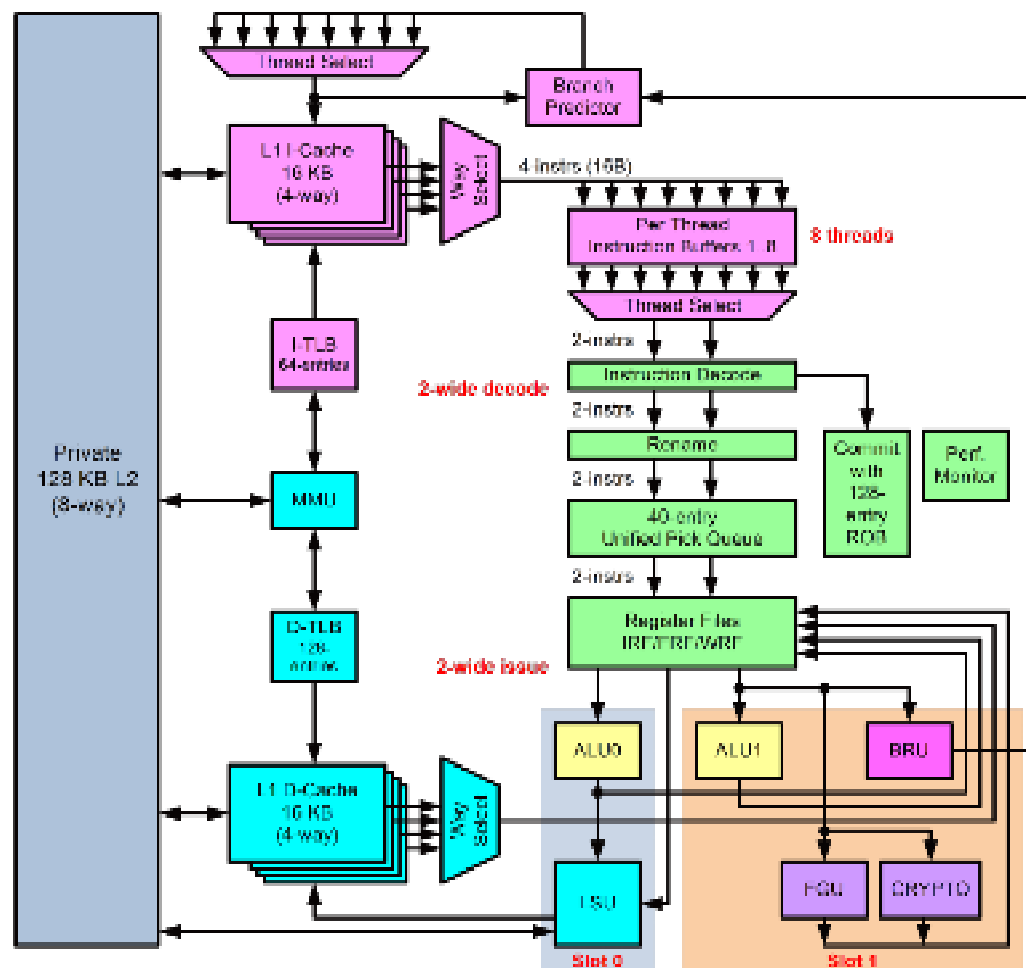
## The Next Oracle Processor: SPARC M6

	nm	Cores	Threads	L3\$	Memory per Socket	PCIe	Max. Sockets
T4	40	8	64	4MB	0.5TB	2*G2	4
T5	28	16	128	8MB	0.5TB	2*G3	8
M5	28	6	48	48MB	1TB	2*G3	32
M6	28	12	96	48MB	1TB	2*G3	96

# Oracle SPARC M6 Core (2013)

## SPARC S3 Core

- Dual-issue, out-of-order
- Integrated encryption acceleration instructions
- Enhanced instruction set to accelerate Oracle SW stack
- 1-8 strands, dynamically threaded pipeline

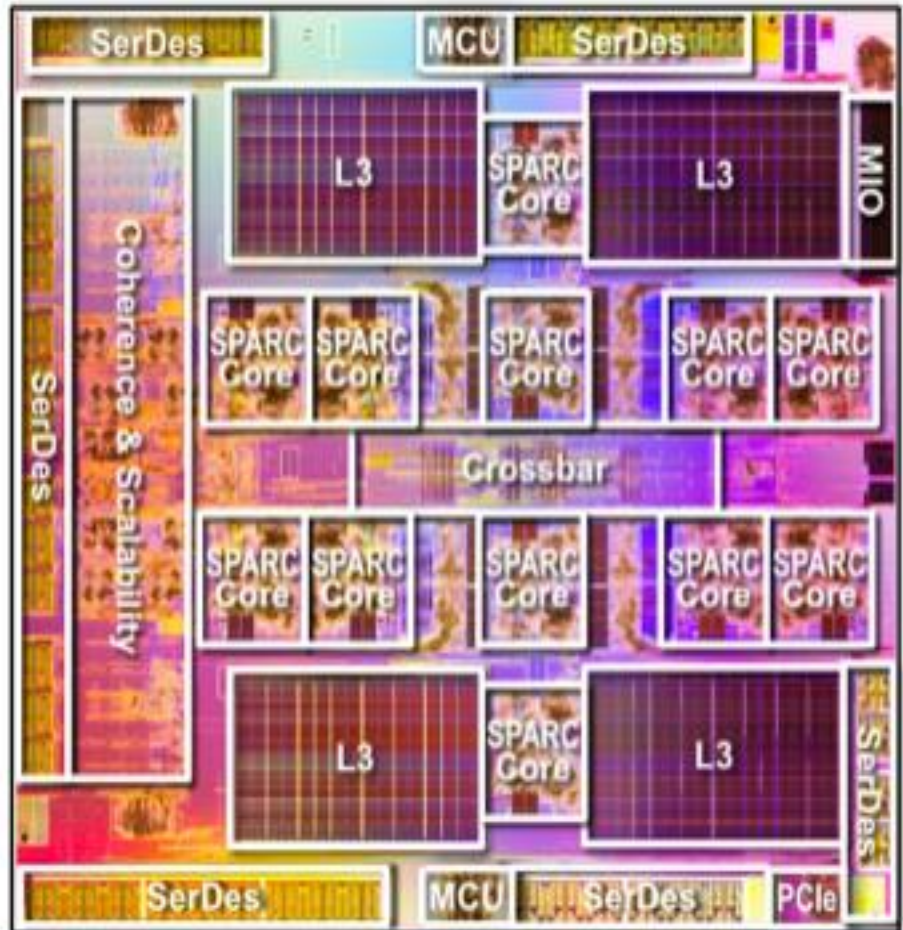


ORACLE

# Oracle SPARC M6 (2013)

## SPARC M6: Processor Overview

- 12 SPARC S3 cores, 96 threads
- 48MB shared L3 cache
- 4 DDR3 schedulers, maximum of 1TB of memory per socket
- 2 PCIe 3.0 x8 lanes
- Up to 8 sockets glue-less scaling
- Up to 96 sockets glued scaling
- 4.1 Tbps total link bandwidth
- 4.27 billion transistors

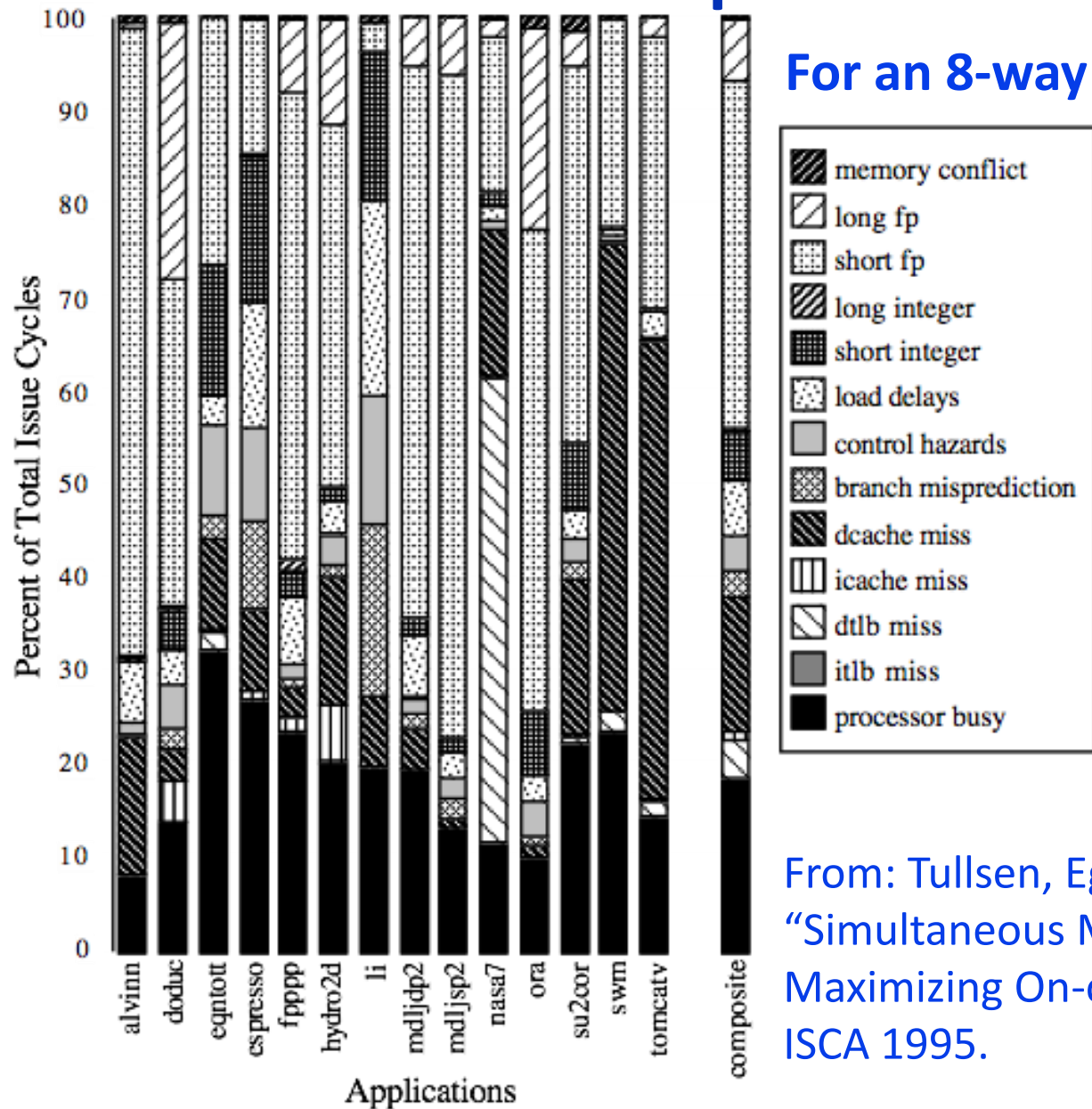


**Oracle ended SPARC programs after M8 in 2017**

# Simultaneous Multithreading (SMT) for OoO Superscalars

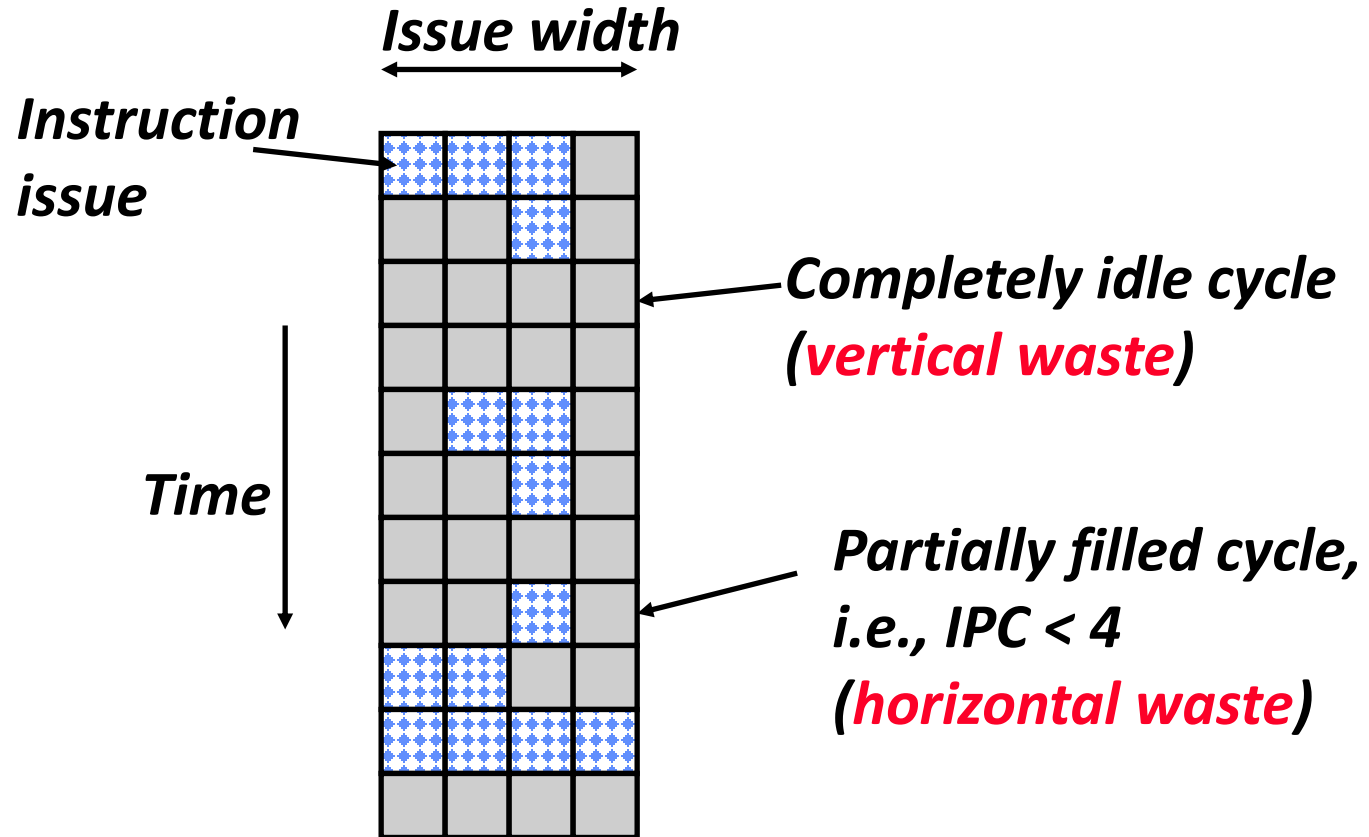
- Techniques presented so far have all been “vertical” multithreading where each pipeline stage works on one thread at a time
- SMT uses fine-grain control already present inside an OoO superscalar to allow instructions from multiple threads to enter execution on same clock cycle. Gives better utilization of machine resources.

# For most apps, most execution units lie idle in an OoO superscalar

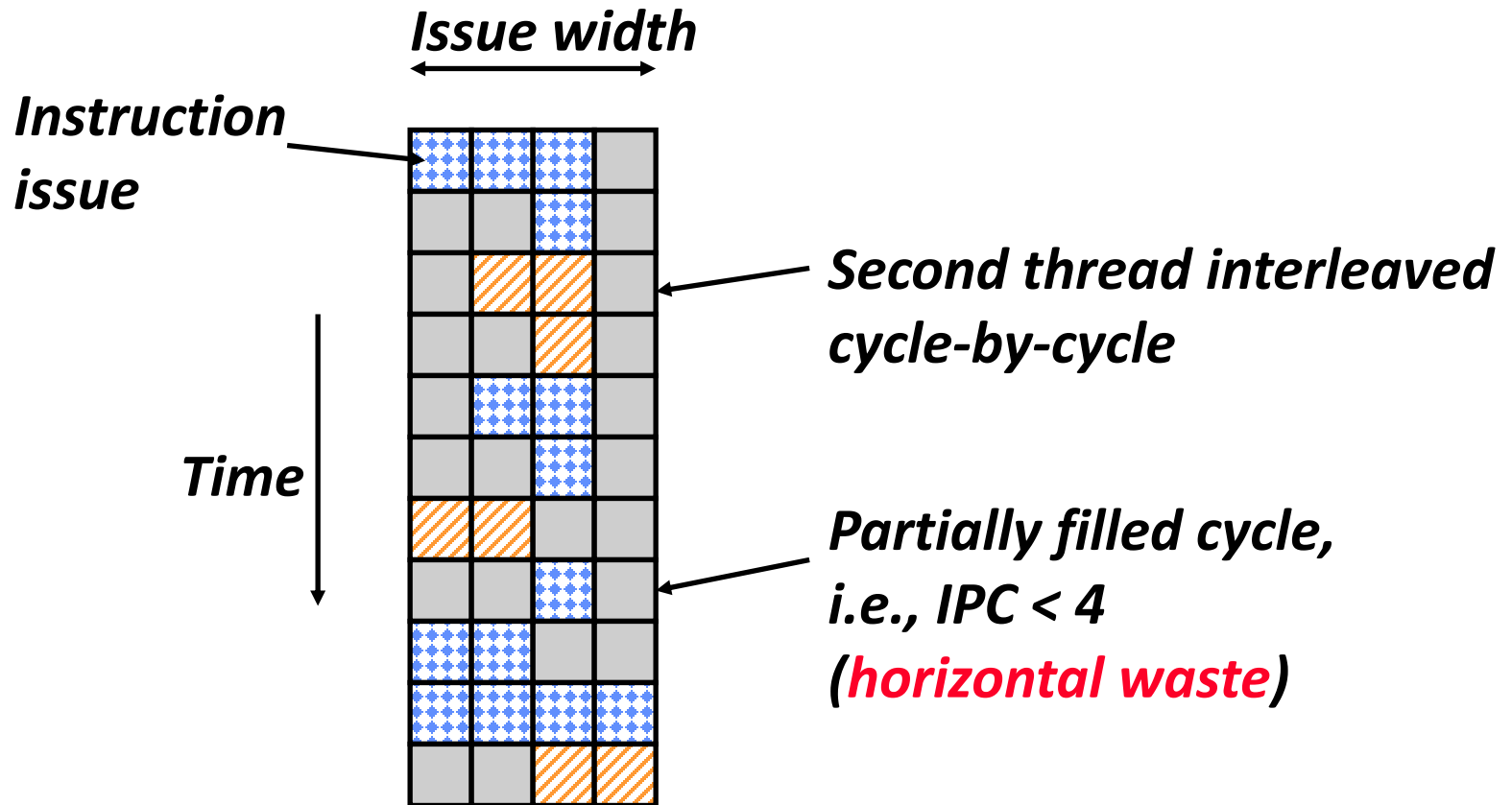


From: Tullsen, Eggers, and Levy, "Simultaneous Multithreading: Maximizing On-chip Parallelism", ISCA 1995.

# Superscalar Machine Efficiency

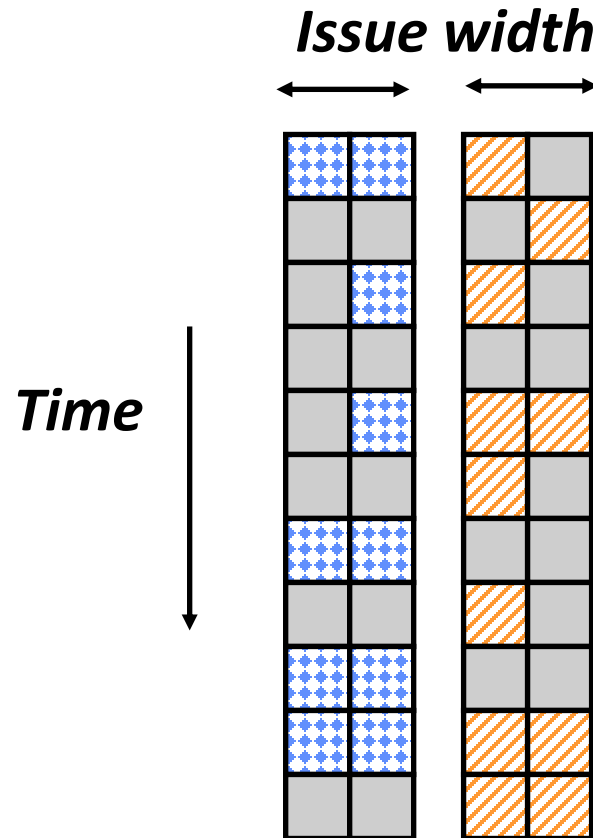


# Vertical Multithreading



- Cycle-by-cycle interleaving removes vertical waste, but leaves some horizontal waste

# Chip Multiprocessing (CMP)

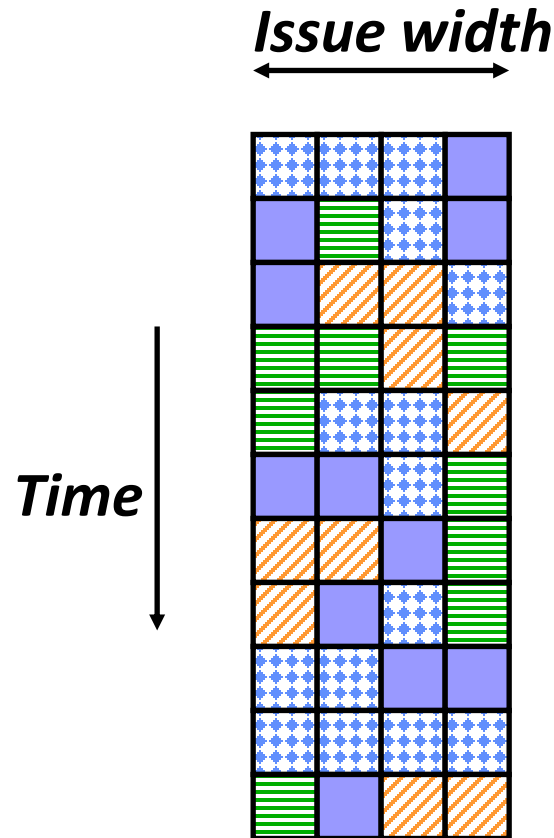


- What is the effect of splitting into multiple processors?
  - reduces horizontal waste,
  - leaves some vertical waste, and
  - puts upper limit on peak throughput of each thread.



# Ideal Superscalar Multithreading

[Tullsen, Eggers, Levy, UW, 1995]



- Interleave multiple threads to multiple issue slots with no restrictions

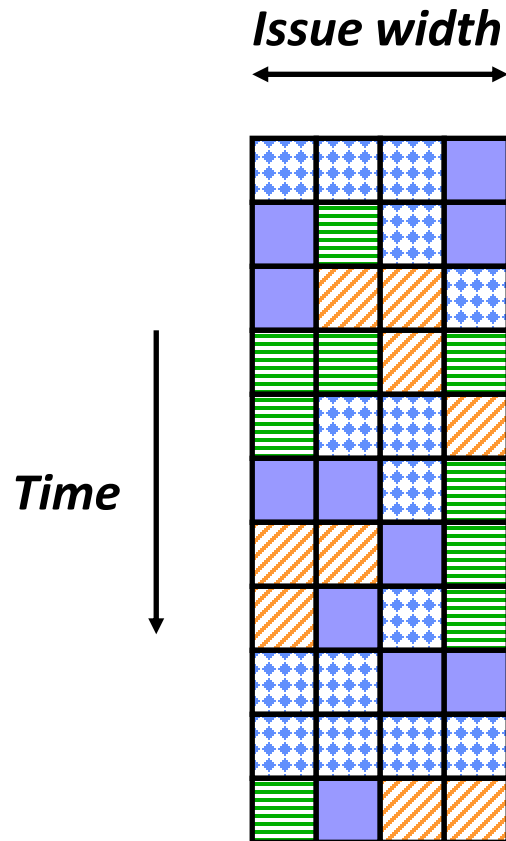
# O-o-O Simultaneous Multithreading

[Tullsen, Eggers, Emer, Levy, Stamm, Lo, DEC/UW, 1996]

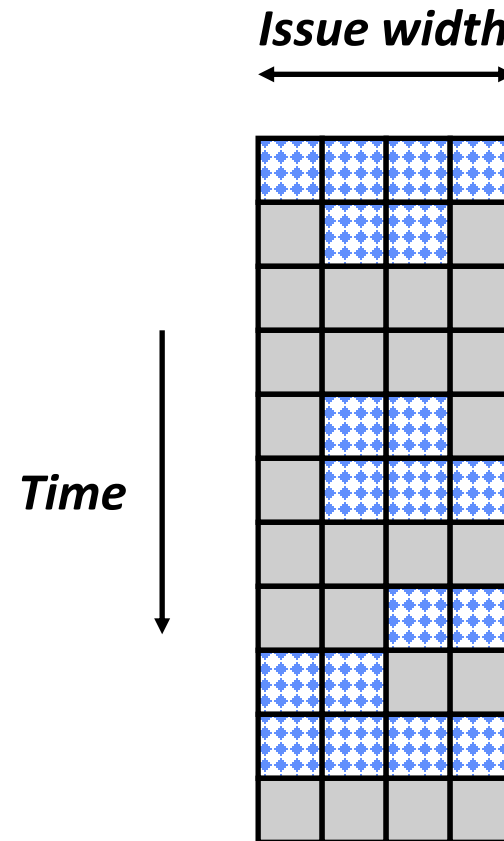
- Add multiple contexts and fetch engines and allow instructions fetched from different threads to issue simultaneously
- Utilize wide out-of-order superscalar processor issue queue to find instructions to issue from multiple threads
- OOO instruction window already has most of the circuitry required to schedule from multiple threads
- Any single thread can utilize whole machine

# SMT adaptation to parallelism type

For regions with high thread-level parallelism (TLP) entire machine width is shared by all threads



For regions with low thread-level parallelism (TLP) entire machine width is available for instruction-level parallelism (ILP)

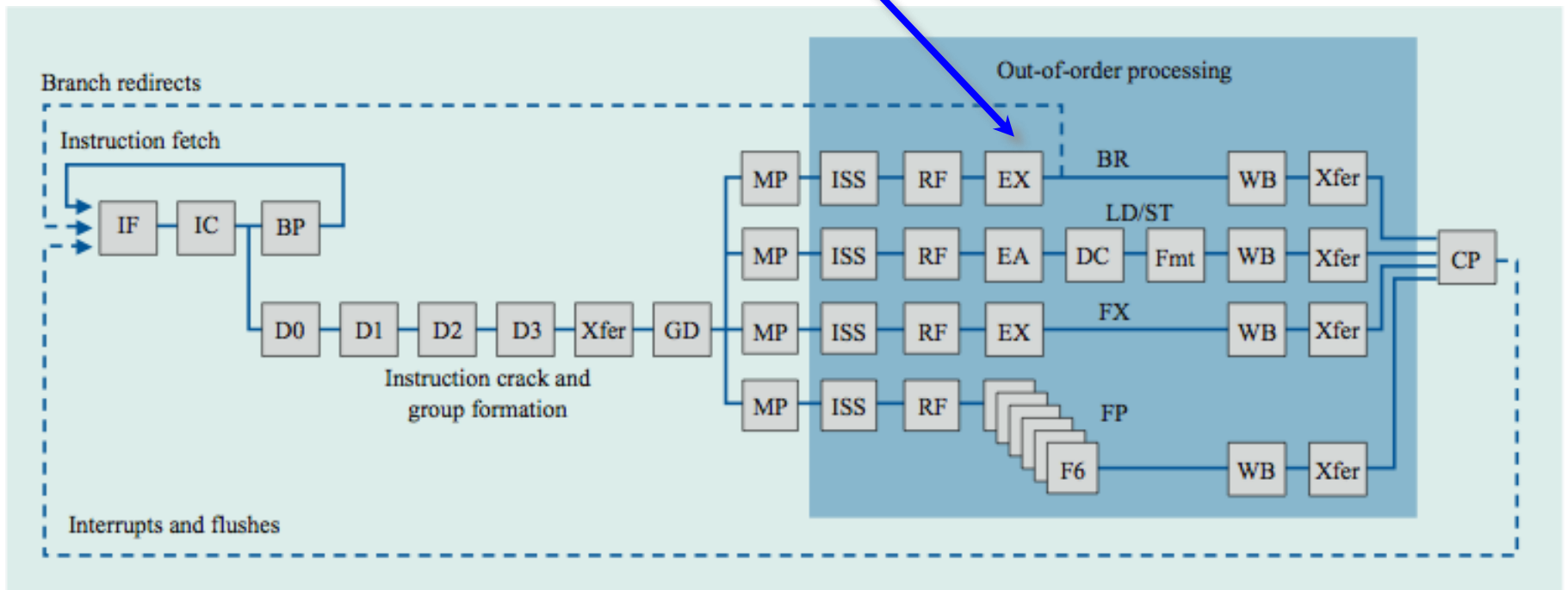
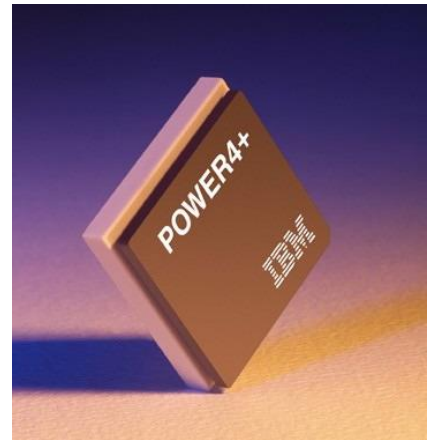


# Pentium-4 Hyperthreading (2002)

- First commercial SMT design (2-way SMT)
- Logical processors share nearly all resources of the physical processor
  - Caches, execution units, branch predictors
- Die area overhead of hyperthreading ~ 5%
- When one logical processor is stalled, the other can make progress
  - No logical processor can use all entries in queues when two threads are active
- Processor running only one active software thread runs at approximately same speed with or without hyperthreading
- Hyperthreading dropped on OoO P6-based followons to Pentium-4 (Pentium-M, Core Duo, Core 2 Duo), until revived with Nehalem generation machines in 2008.
- First Intel Atom (in-order x86 core) has two-way vertical multithreading
  - Hyperthreading == (SMT for Intel OoO & Vertical for Intel InO)

# IBM Power 4

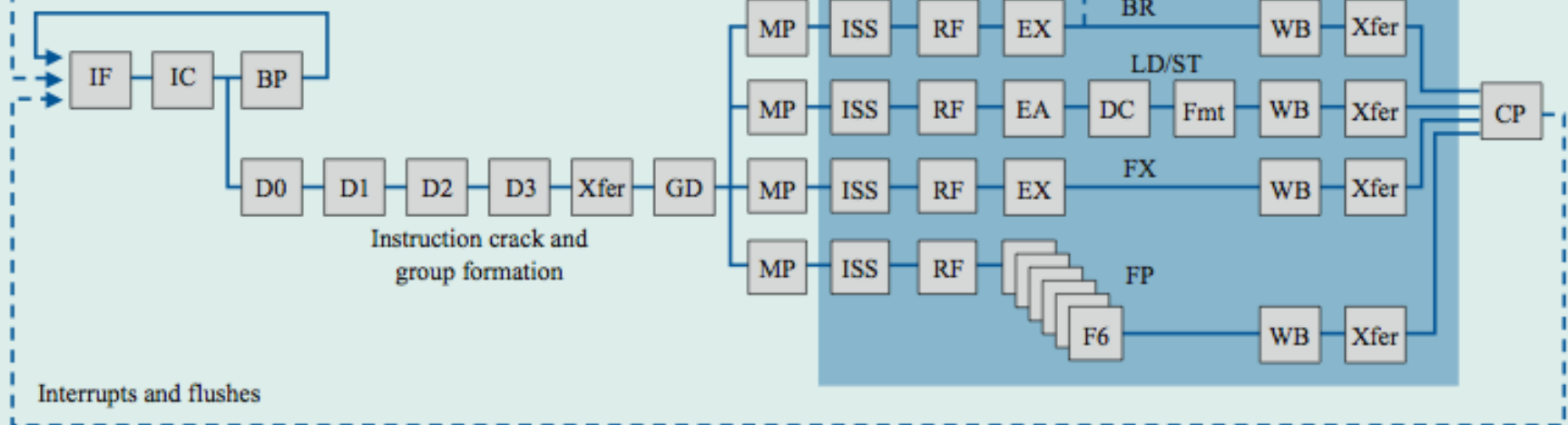
Single-threaded predecessor to Power 5.  
8 execution units in out-of-order engine,  
each may issue an instruction each cycle.



# Power 4

Branch redirects

Instruction fetch



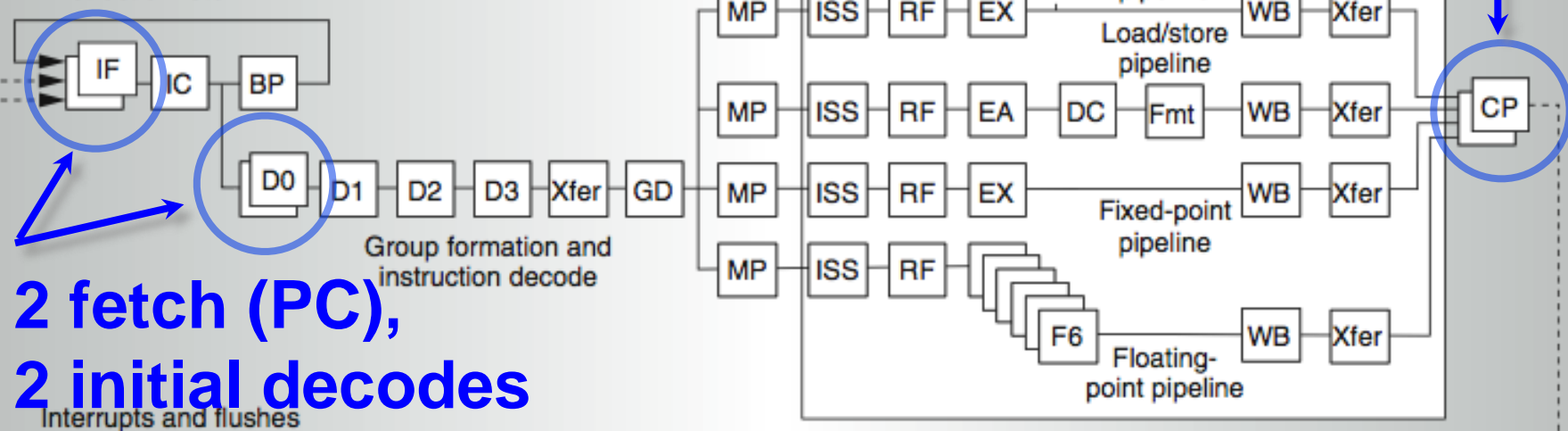
Out-of-order processing

2 commits  
(architected  
register sets)

# Power 5

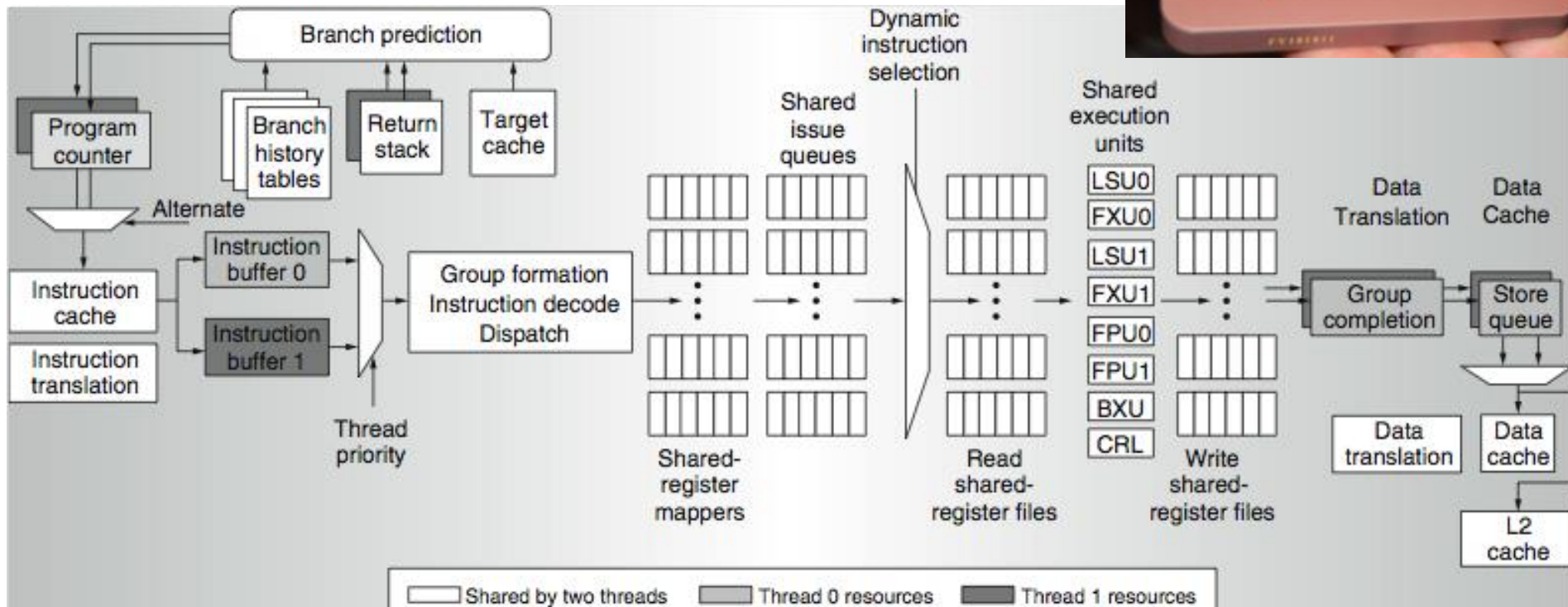
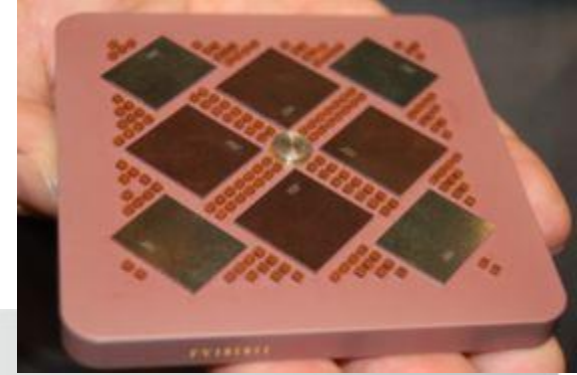
Branch redirects

Instruction fetch



2 fetch (PC),  
2 initial decodes

# Power 5 data flow ...



Why only 2 threads? With 4, one of the shared resources (physical registers, cache, memory bandwidth) would be prone to bottleneck

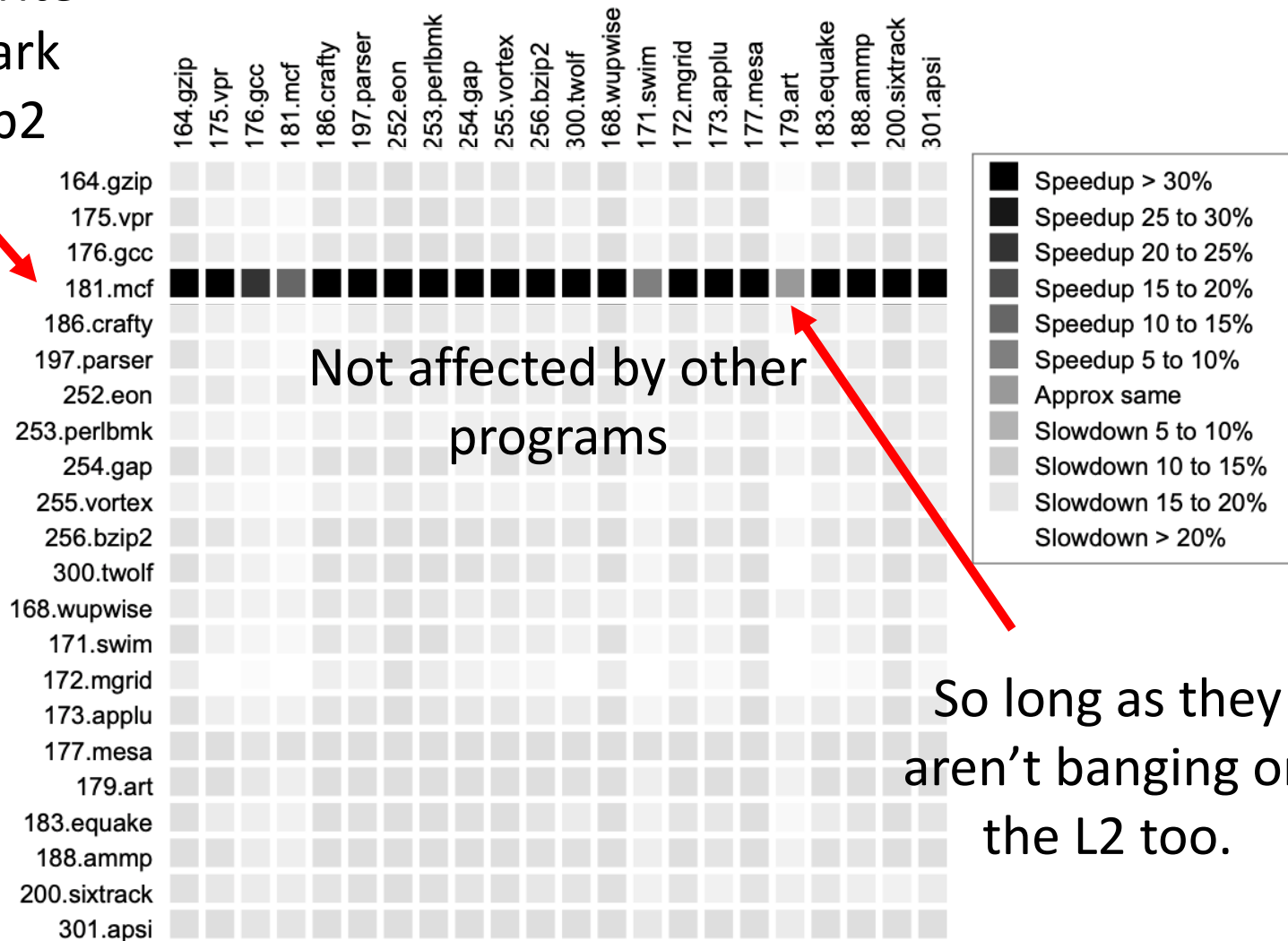
# Initial Performance of SMT

- Pentium-4 Extreme SMT yields 1.01 speedup for SPECint\_rate benchmark and 1.07 for SPECfp\_rate
  - Pentium-4 is dual-threaded SMT
  - SPECRate requires that each SPEC benchmark be run against a vendor-selected number of copies of the same benchmark
- Running on Pentium-4 each of 26 SPEC benchmarks paired with every other ( $26^2$  runs) speed-ups from 0.90 to 1.58; average was 1.20
- Power 5, 8-processor server 1.23 faster for SPECint\_rate with SMT, 1.16 faster for SPECfp\_rate
- Power 5 running 2 copies of each app speedup between 0.89 and 1.41
  - Most gained some
  - Fl.Pt. apps had most cache conflicts and least gains



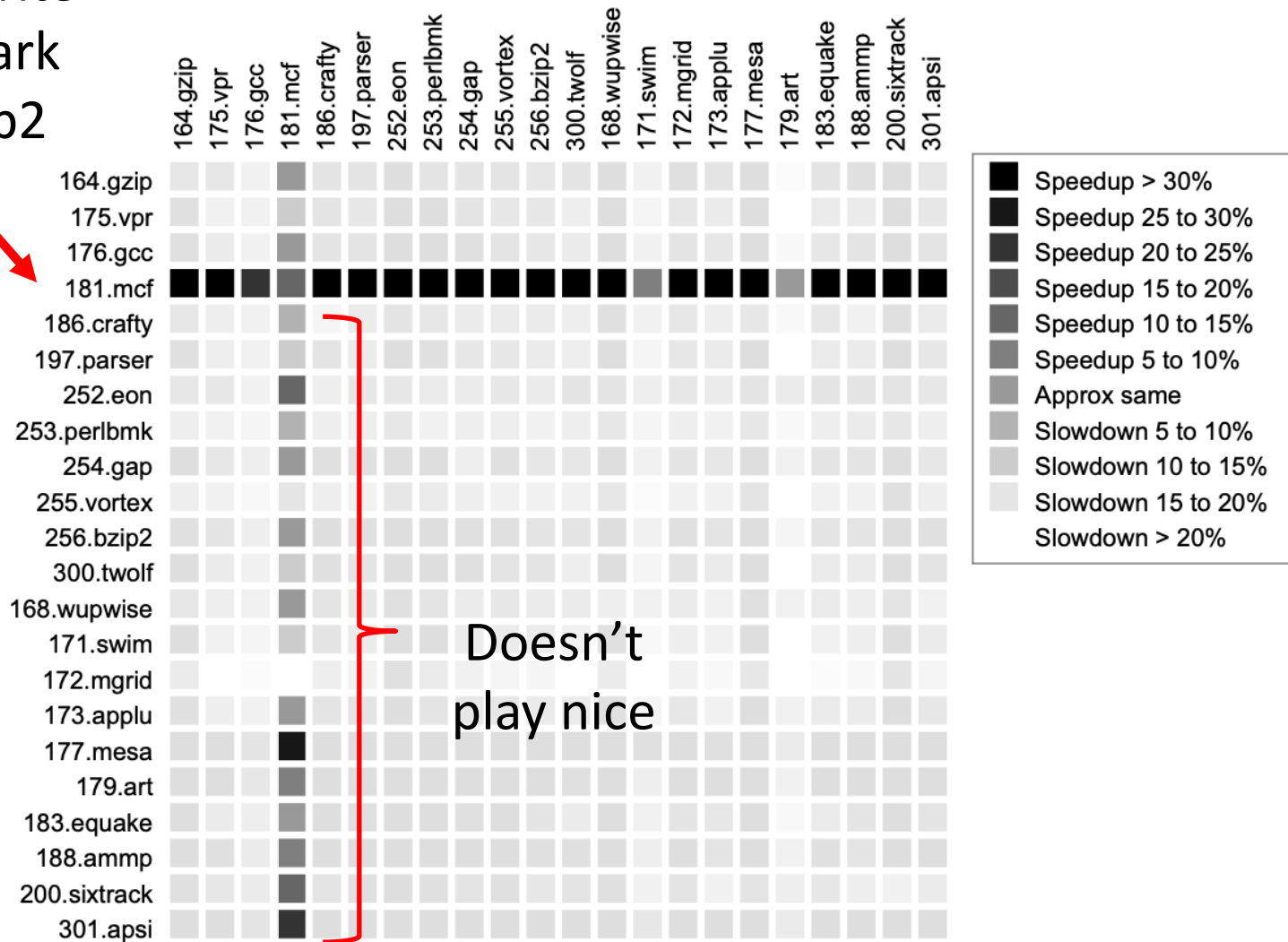
# SMT Performance: Application Interaction

Your favorite  
benchmark  
from Lab2

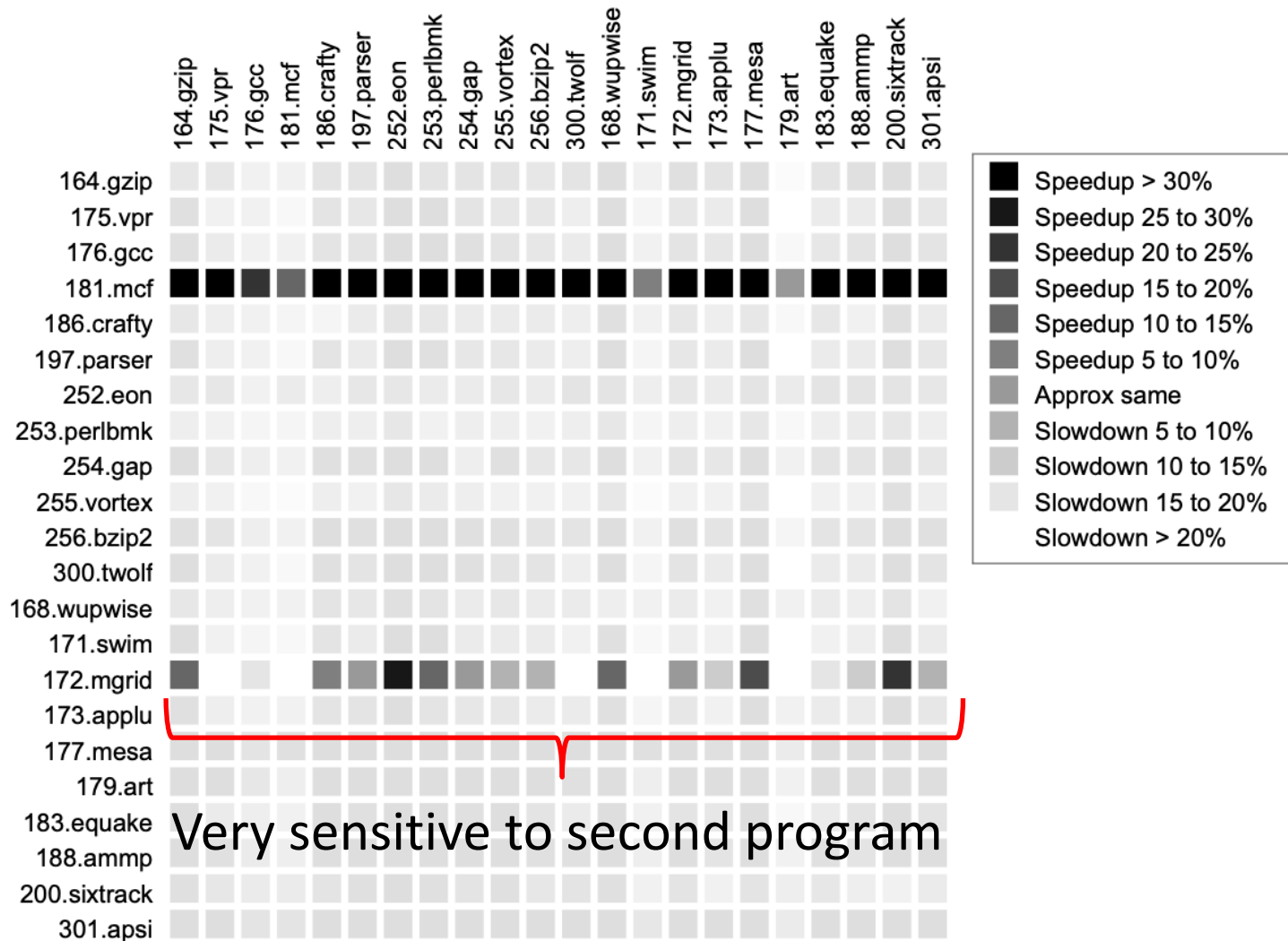


# SMT Performance: Application Interaction

Your favorite  
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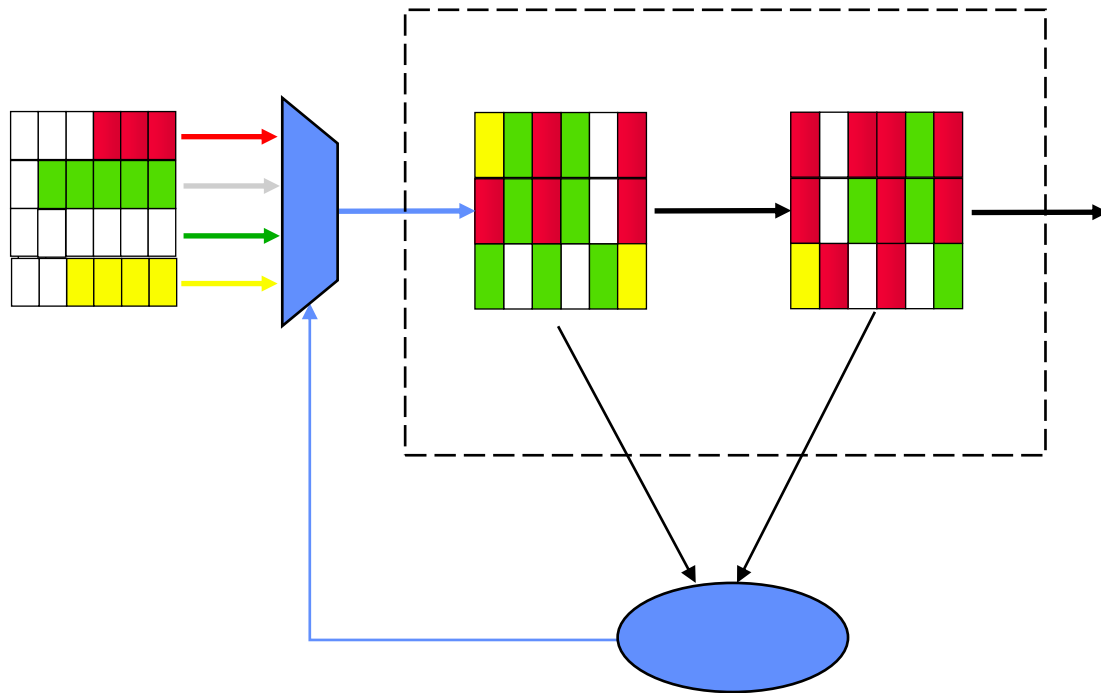


# SMT Performance: Application Interaction



# Icount Choosing Policy

Fetch from thread with the least instructions in flight.



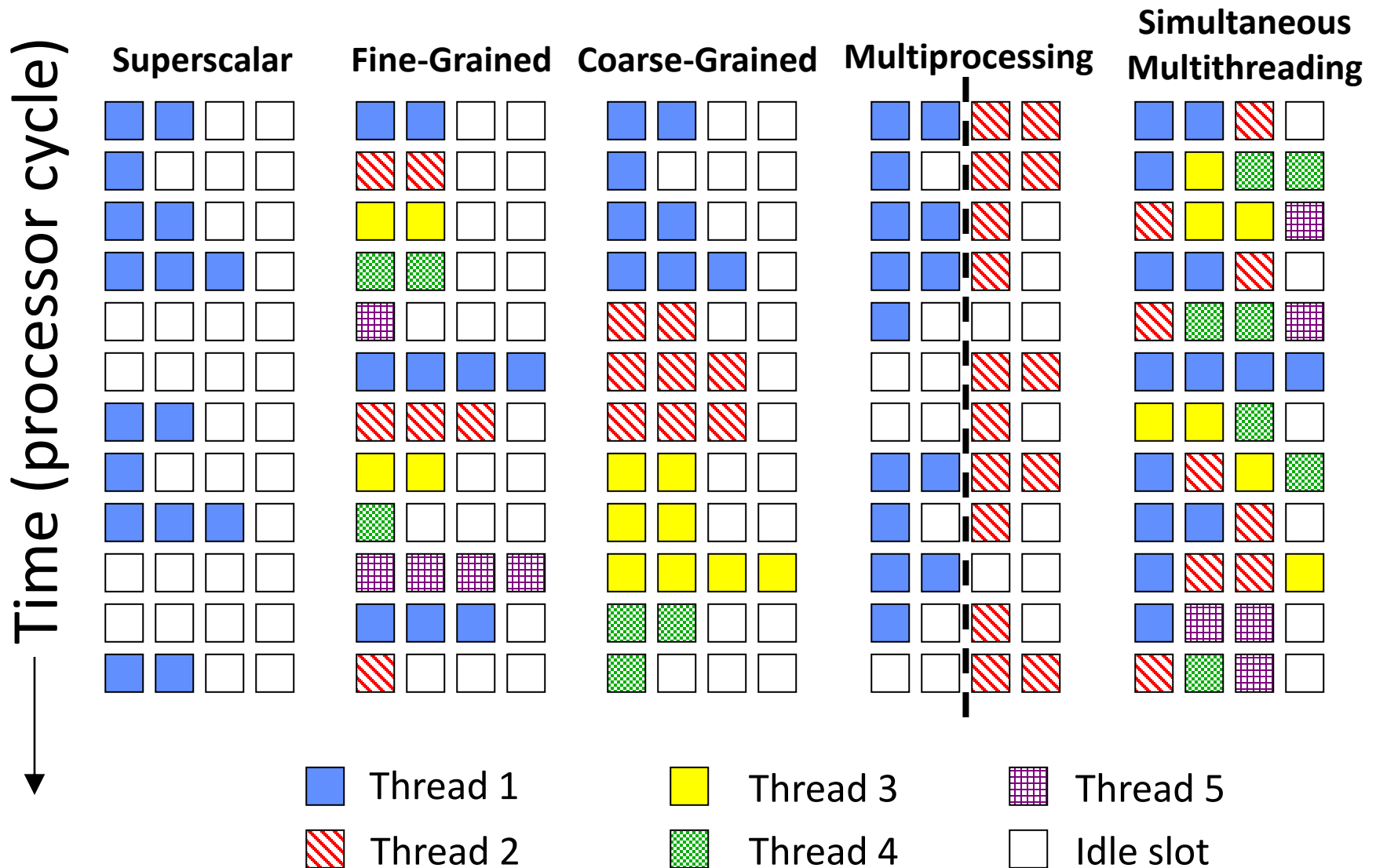
*Why does this enhance throughput?*

# SMT & Security

- Most hardware attacks rely on shared hardware resources to establish a side-channel
  - Eg. Shared outer caches, DRAM row buffers
- SMT gives attackers high-BW access to previously private hardware resources that are shared by co-resident threads:
  - TLBs: TLBleed (June, '18)
  - L1 caches: CacheBleed (2016)
  - Functional unit ports: PortSmash (Nov, '18)

OpenBSD 6.4 → Disabled HT in BIOS, AMD SMT to follow

# Summary: Multithreaded Categories



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# Supercomputer Applications

- Typical application areas
  - Military research (nuclear weapons, cryptography)
  - Scientific research
  - Weather forecasting
  - Oil exploration
  - Industrial design (car crash simulation)
  - Bioinformatics
  - Cryptography
- All involve huge computations on large data set
- Supercomputers: CDC6600, CDC7600, Cray-1, ...
- In 70s-80s, Supercomputer  $\equiv$  Vector Machine



# Vector Supercomputers

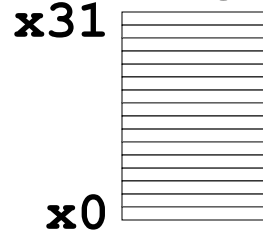


- Epitomized by Cray-1, 1976:
- Scalar Unit
  - Load/Store Architecture
- Vector Extension
  - Vector Registers
  - Vector Instructions
- Implementation
  - Hardwired Control
  - Highly Pipelined Functional Units
  - Interleaved Memory System
  - No Data Caches
  - No Virtual Memory

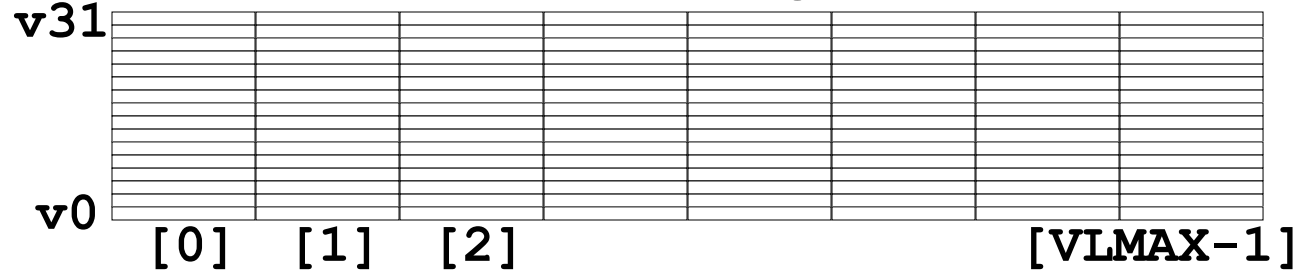
*[©Cray Research, 1976]*

# Vector Programming Model

Scalar Registers



Vector Registers

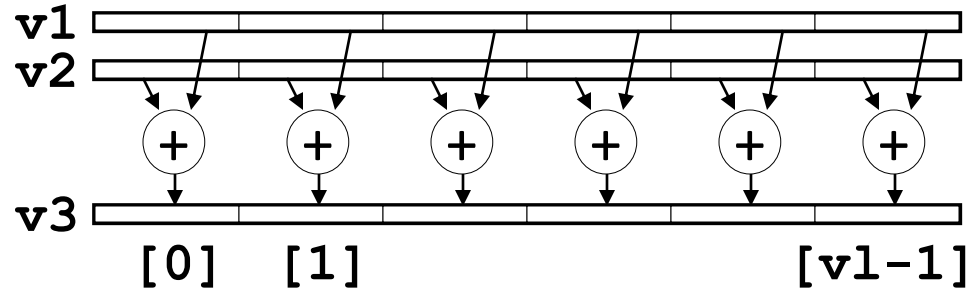


Vector Length Register

**v1**

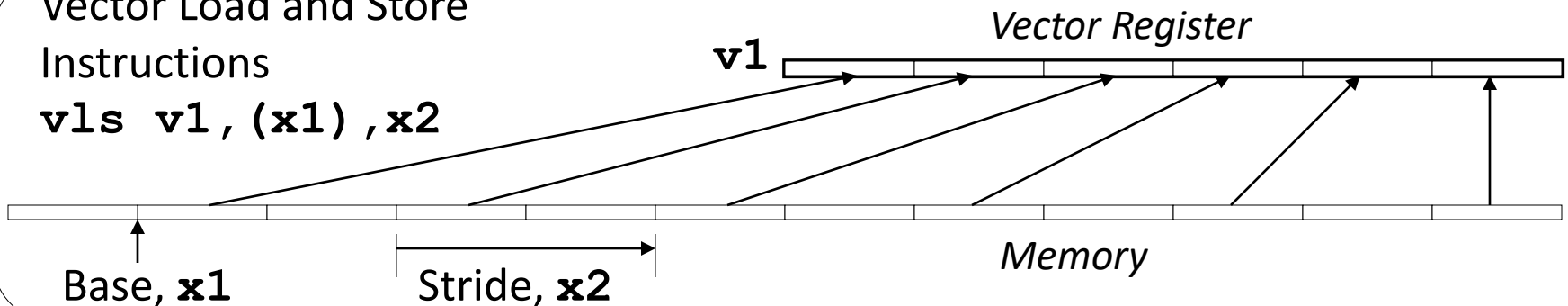
Vector Arithmetic  
Instructions

**vadd v3, v1, v2**



Vector Load and Store  
Instructions

**vls v1, (x1), x2**



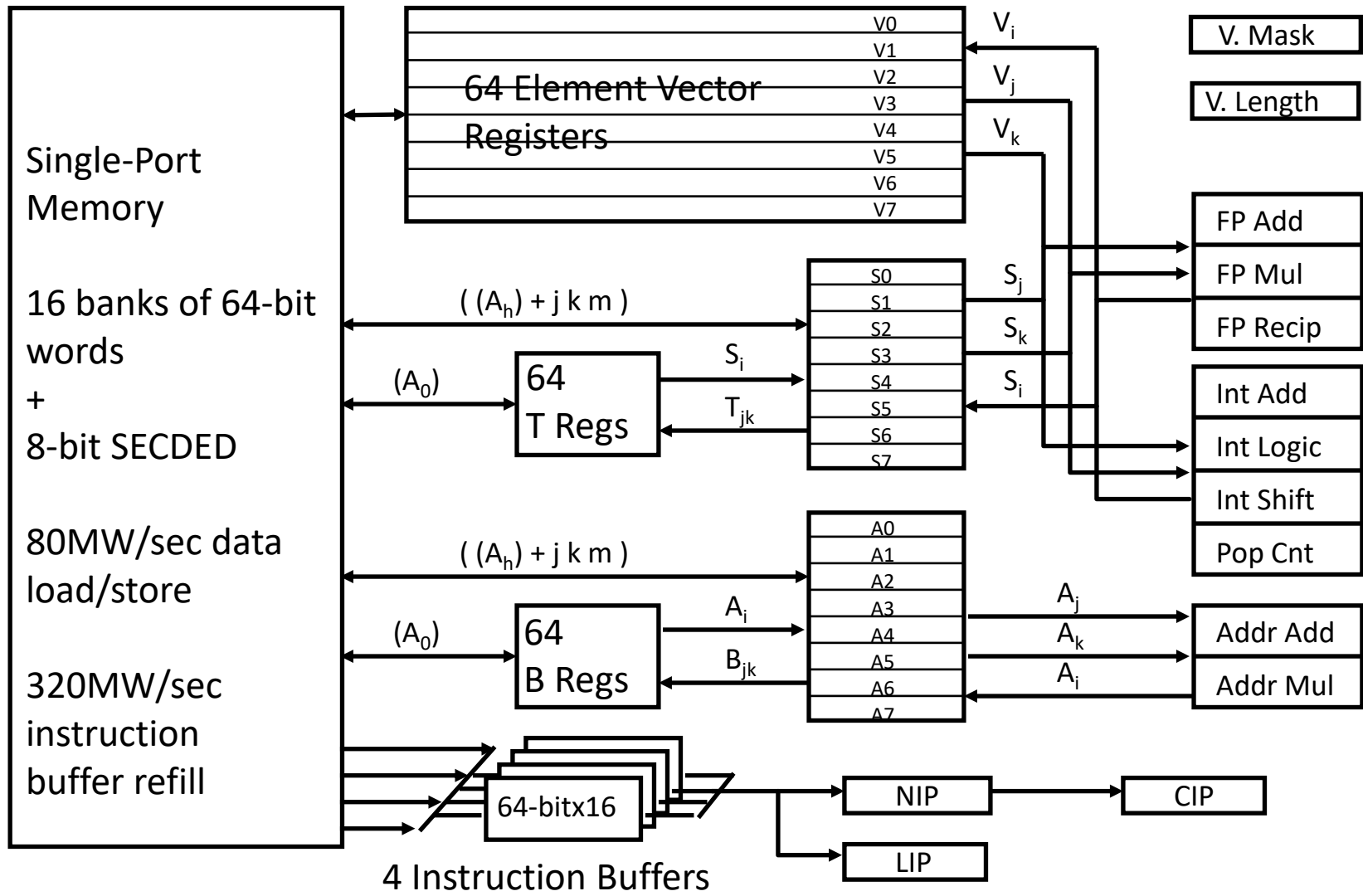
# Vector Code Example

```
# C code
for (i=0; i<64; i++)
    C[i] = A[i] + B[i];
```

```
# Scalar Code
    li x4, 64
loop:
    fld f1, 0(x1)
    fld f2, 0(x2)
    fadd.d f3, f1, f2
    fsd f3, 0(x3)
    addi x1, x1, 8
    addi x2, x2, 8
    addi x3, x3, 8
    subi x4, x4, 1
    bnez x4, loop
```

```
# Vector Code
    li x4, 64
    vsetv1 x4
    vld v1, (x1)
    vld v2, (x2)
    vadd v3, v1, v2
    vst v3, (x3)
```

# Cray-1 (1976)



*memory bank cycle 50 ns    processor cycle 12.5 ns (80MHz)*

# Vector Instruction Set Advantages

- Compact

- one short instruction encodes N operations

- Expressive, tells hardware that these N operations:

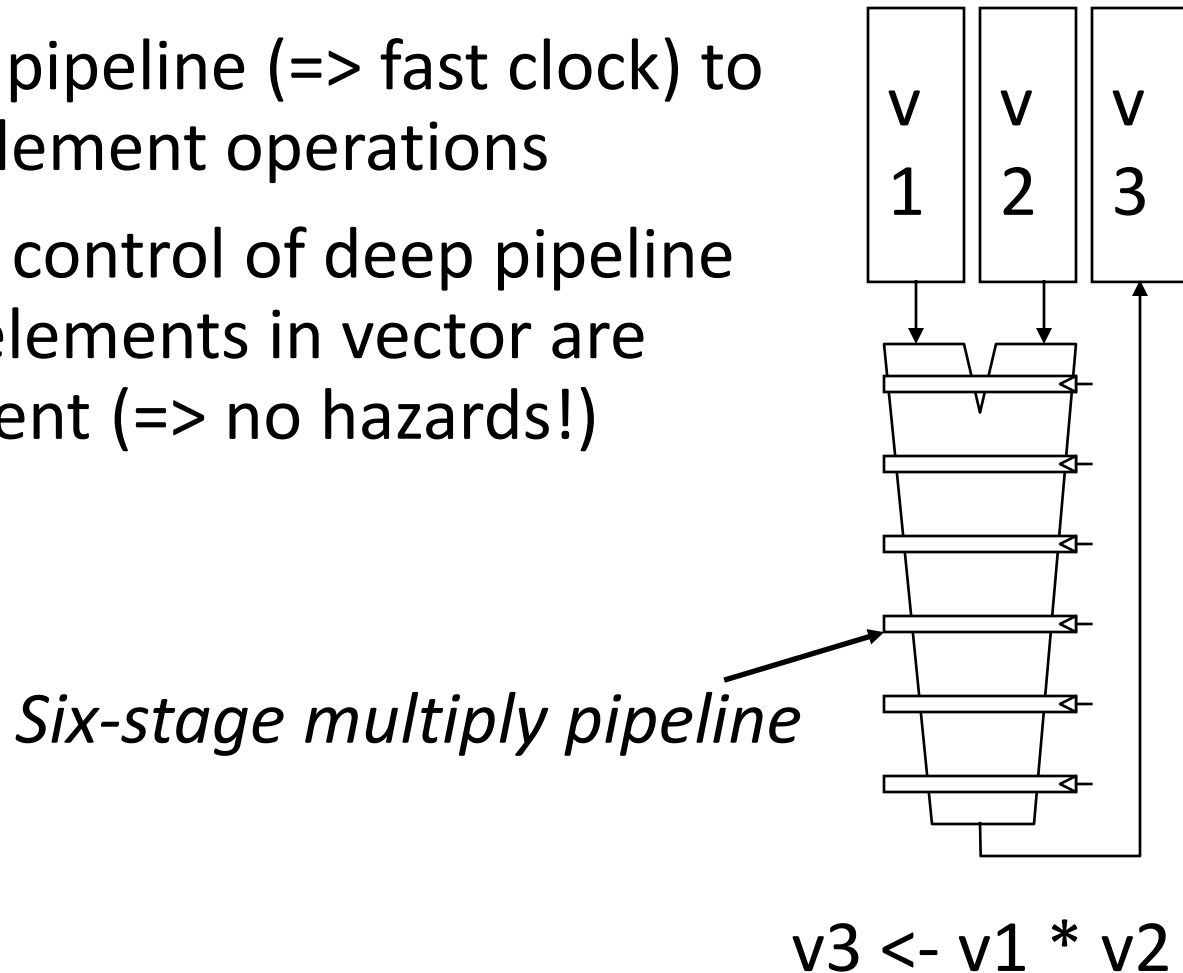
- are independent
- use the same functional unit
- access disjoint registers
- access registers in same pattern as previous instructions
- access a contiguous block of memory (unit-stride load/store)
- access memory in a known pattern (strided load/store)

- Scalable

- can run same code on more parallel pipelines (lanes)

# Vector Arithmetic Execution

- Use deep pipeline ( $\Rightarrow$  fast clock) to execute element operations
- Simplifies control of deep pipeline because elements in vector are independent ( $\Rightarrow$  no hazards!)

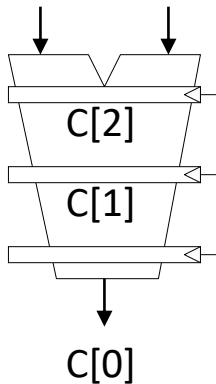


# Vector Instruction Execution

vadd vc, va, vb

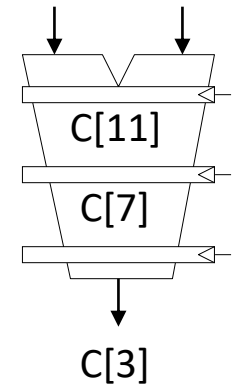
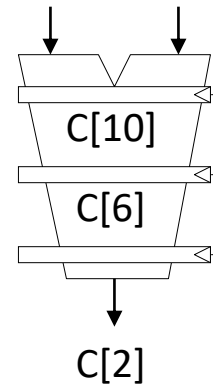
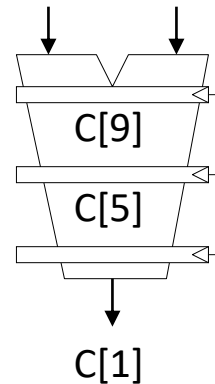
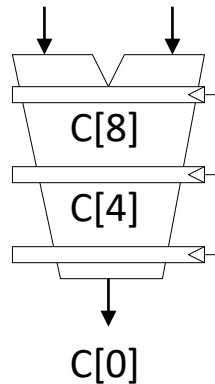
*Execution using  
one pipelined  
functional unit*

A[6] B[6]  
A[5] B[5]  
A[4] B[4]  
A[3] B[3]



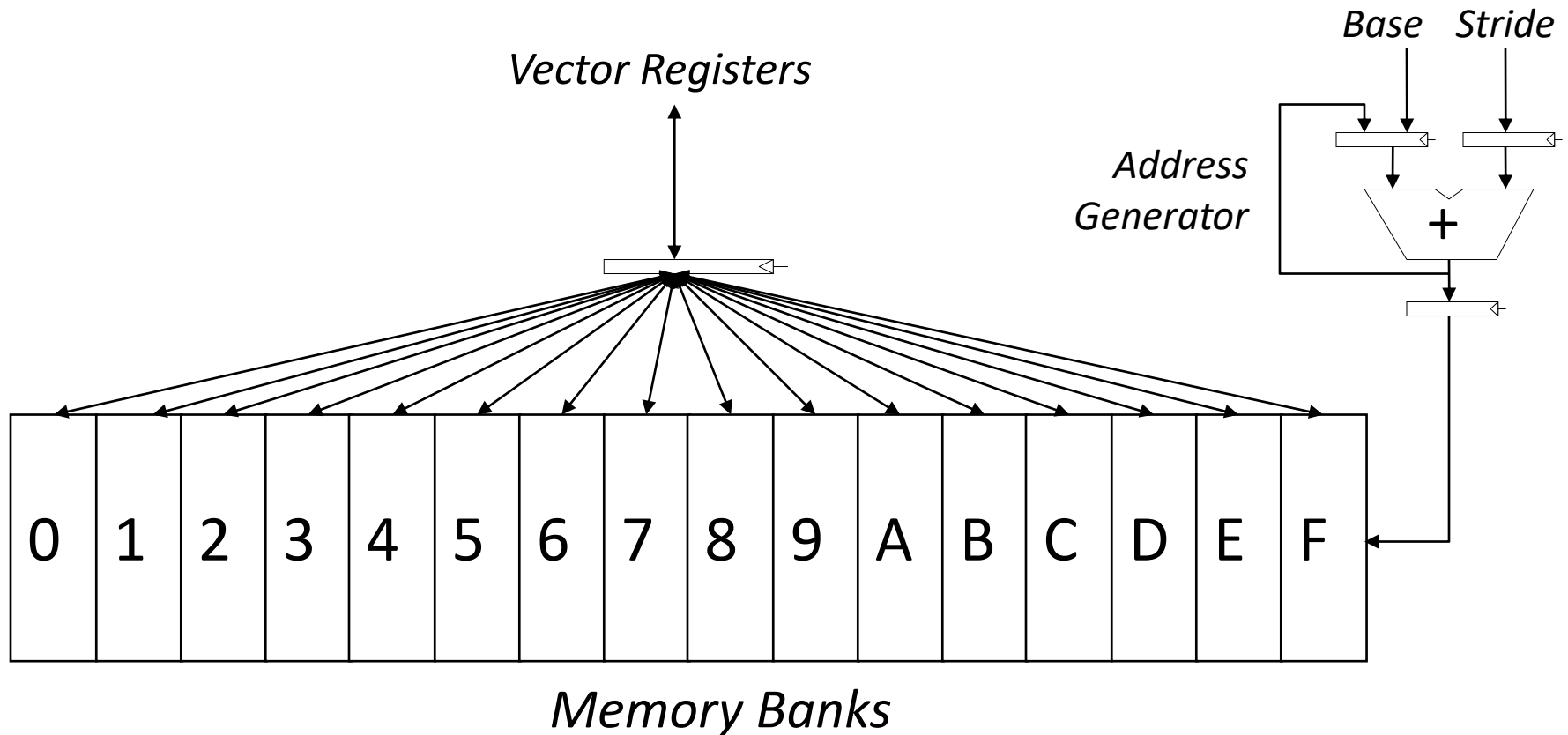
*Execution using  
four pipelined  
functional units*

A[24] B[24] A[25] B[25] A[26] B[26] A[27] B[27]  
A[20] B[20] A[21] B[21] A[22] B[22] A[23] B[23]  
A[16] B[16] A[17] B[17] A[18] B[18] A[19] B[19]  
A[12] B[12] A[13] B[13] A[14] B[14] A[15] B[15]



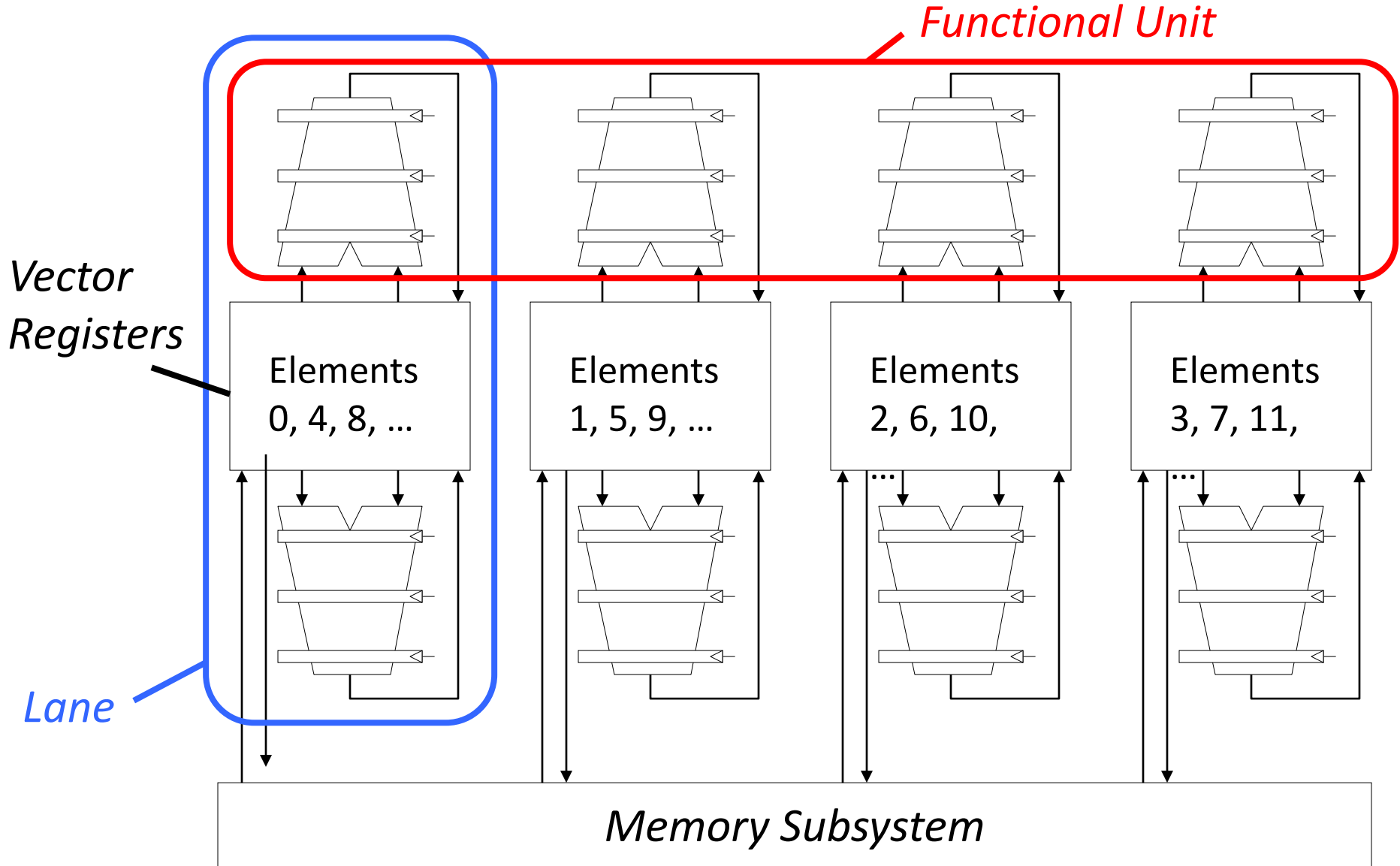
# Interleaved Vector Memory System

- Bank busy time: Time before bank ready to accept next request
- Cray-1, 16 banks, 4 cycle bank busy time, 12 cycle latency



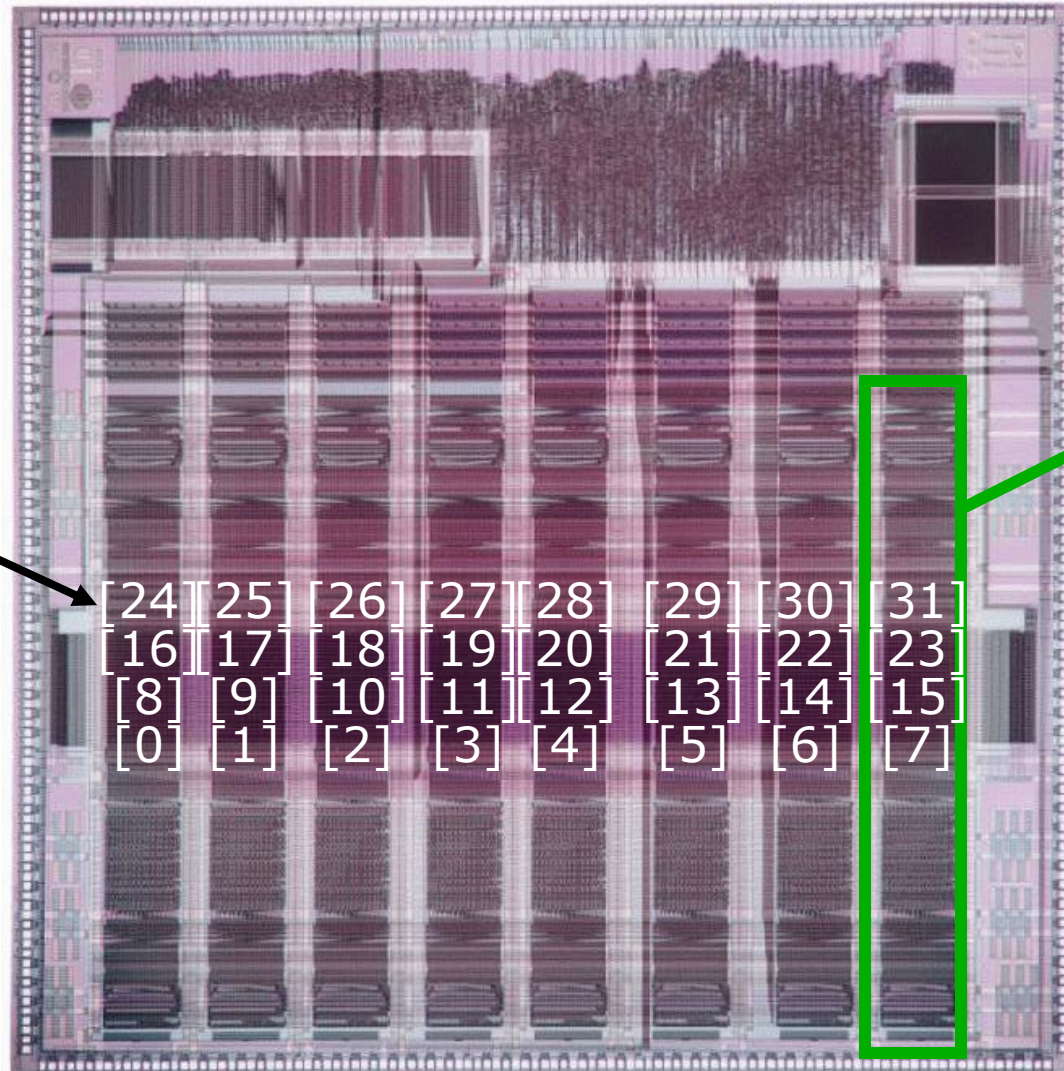


# Vector Unit Structure



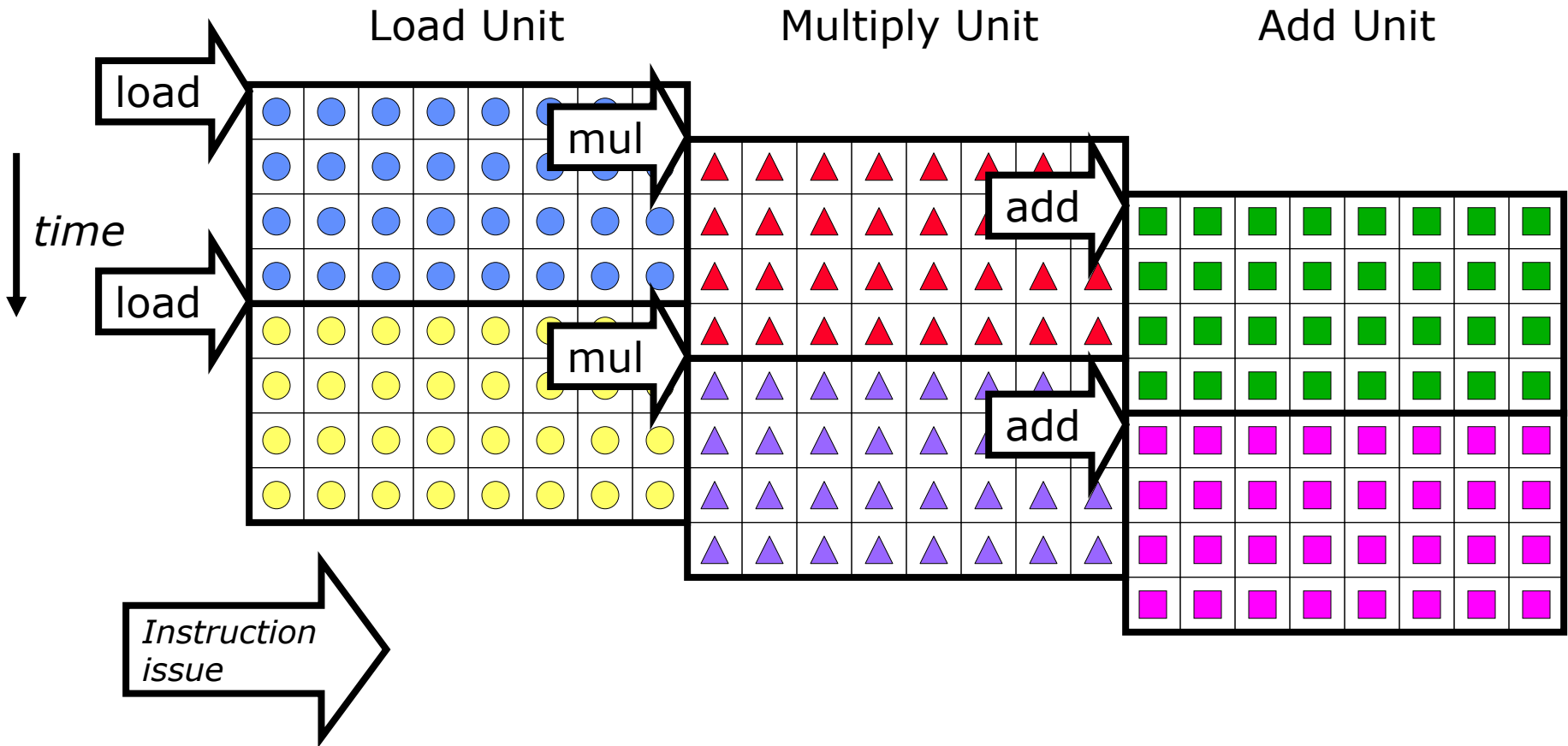
# T0 Vector Microprocessor (UCB/ICSI, 1995)

*Vector register  
elements striped  
over lanes*



# Vector Instruction Parallelism

- Can overlap execution of multiple vector instructions
  - example machine has 32 elements per vector register and 8 lanes

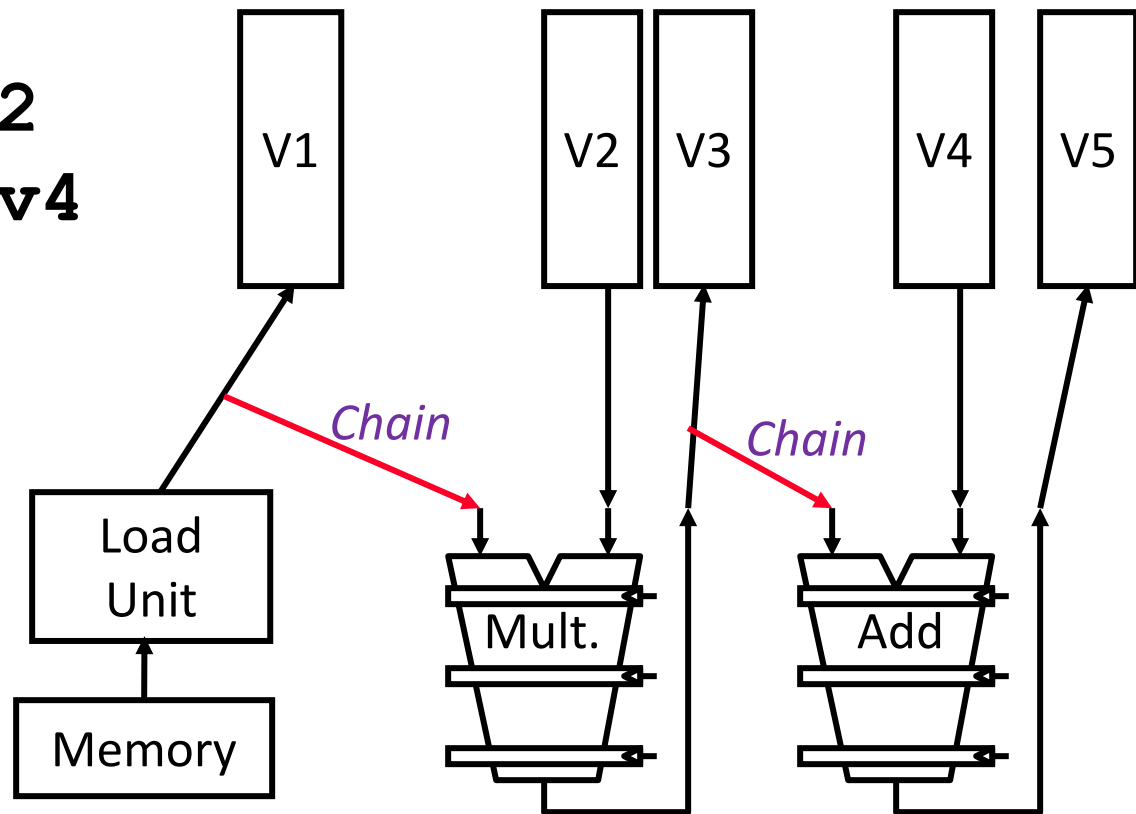


Complete 24 operations/cycle while issuing 1 short instruction/cycle

# Vector Chaining

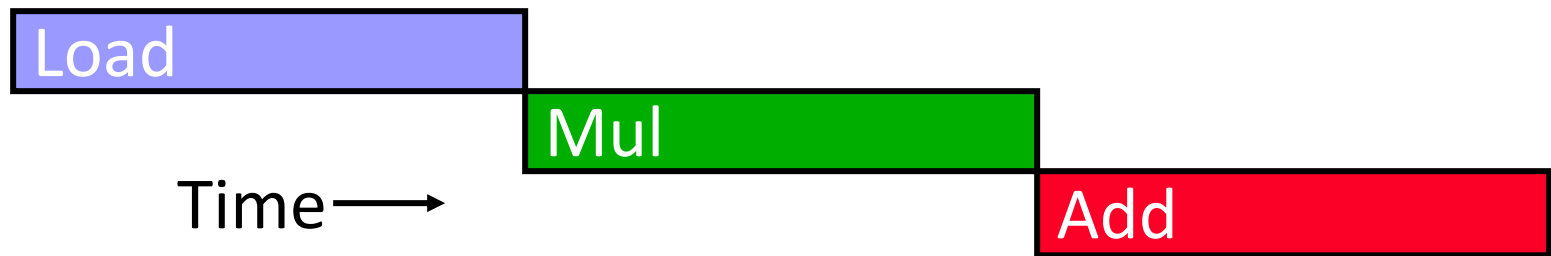
- Vector version of register bypassing
  - introduced with Cray-1

```
vld  v1  
vmul v3, v1, v2  
vadd v5, v3, v4
```



# Vector Chaining Advantage

- Without chaining, must wait for last element of result to be written before starting dependent instruction



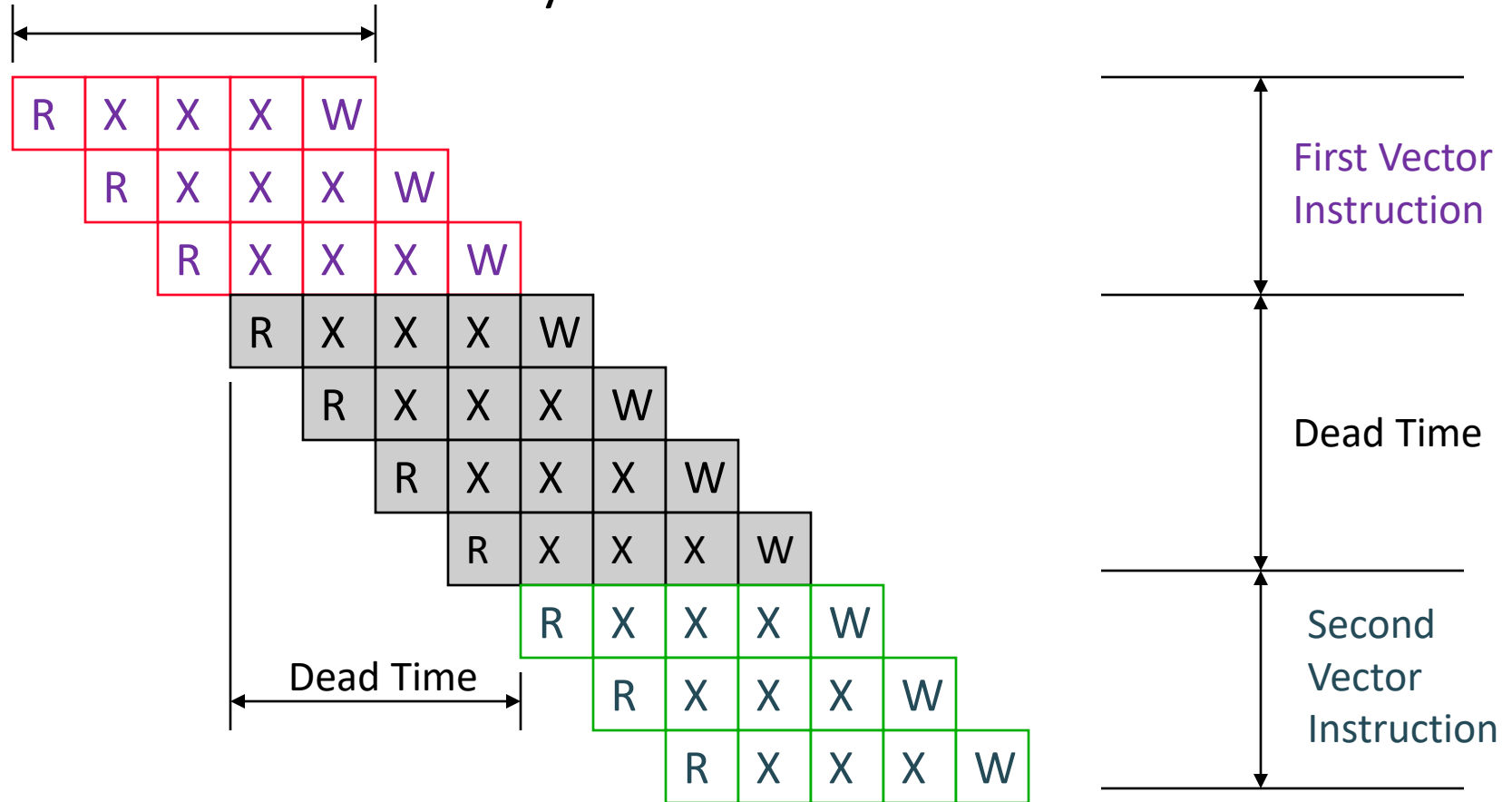
- With chaining, can start dependent instruction as soon as first result appears



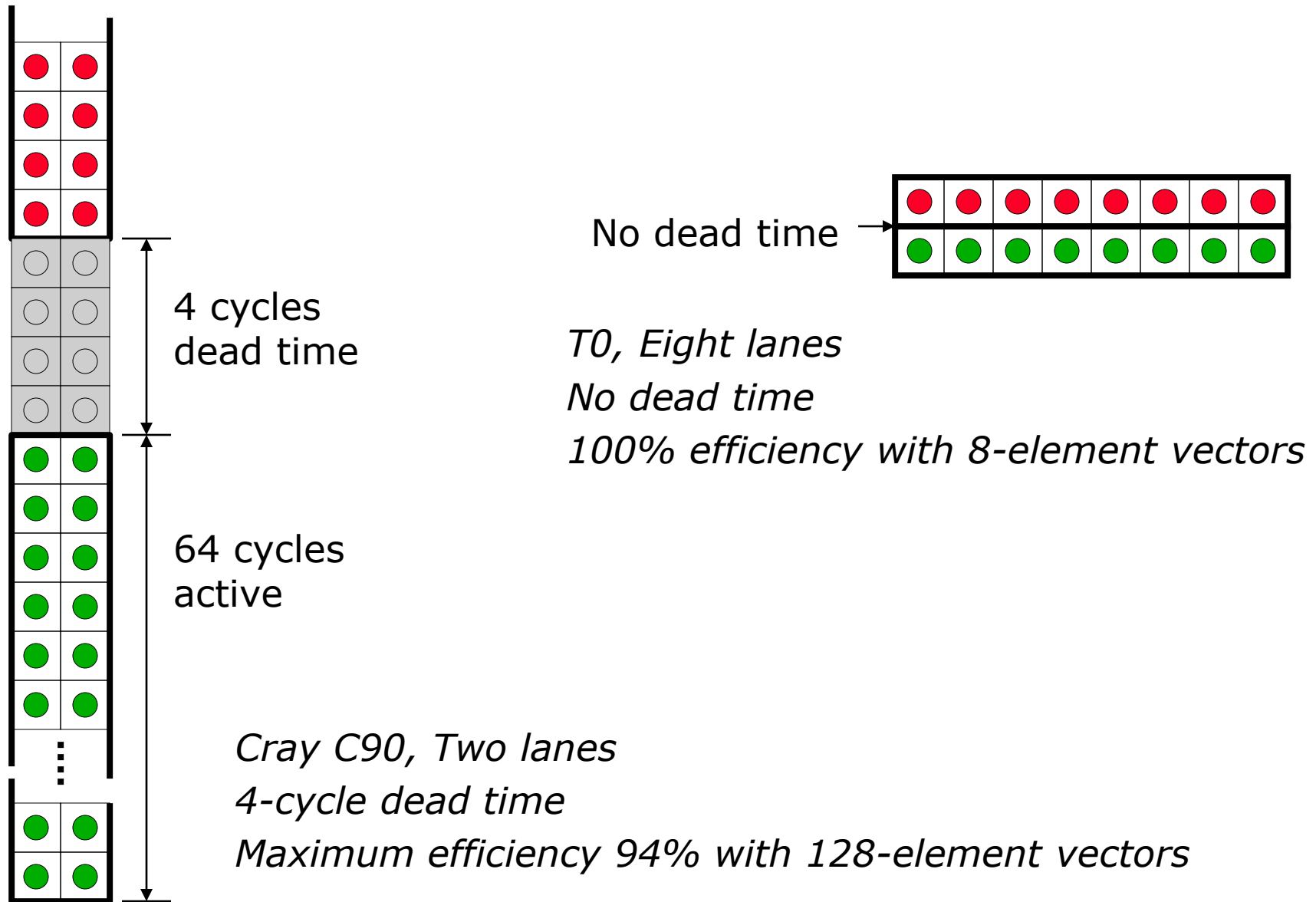
# Vector Startup

- Two components of vector startup penalty
  - functional unit latency (time through pipeline)
  - dead time or recovery time (time before another vector instruction can start down pipeline)

## Functional Unit Latency



# Dead Time and Short Vectors



# Vector Memory-Memory versus Vector Register Machines

- Vector memory-memory instructions hold all vector operands in main memory
- The first vector machines, CDC Star-100 ('73) and TI ASC ('71), were memory-memory machines
- Cray-1 ('76) was first vector register machine

## Example Source Code

```
for (i=0; i<N; i++)  
{  
    C[i] = A[i] + B[i];  
    D[i] = A[i] - B[i];  
}
```

## Vector Memory-Memory Code

```
vadd (C) , (A) , (B)  
vsub (D) , (A) , (B)
```

## Vector Register Code

```
vld V1, (A)  
vld V2, (B)  
vadd V3, V1, V2  
vst V3, (C)  
vsub V4, V1, V2  
vst V4, (D)
```



# Vector Memory-Memory vs. Vector Register Machines

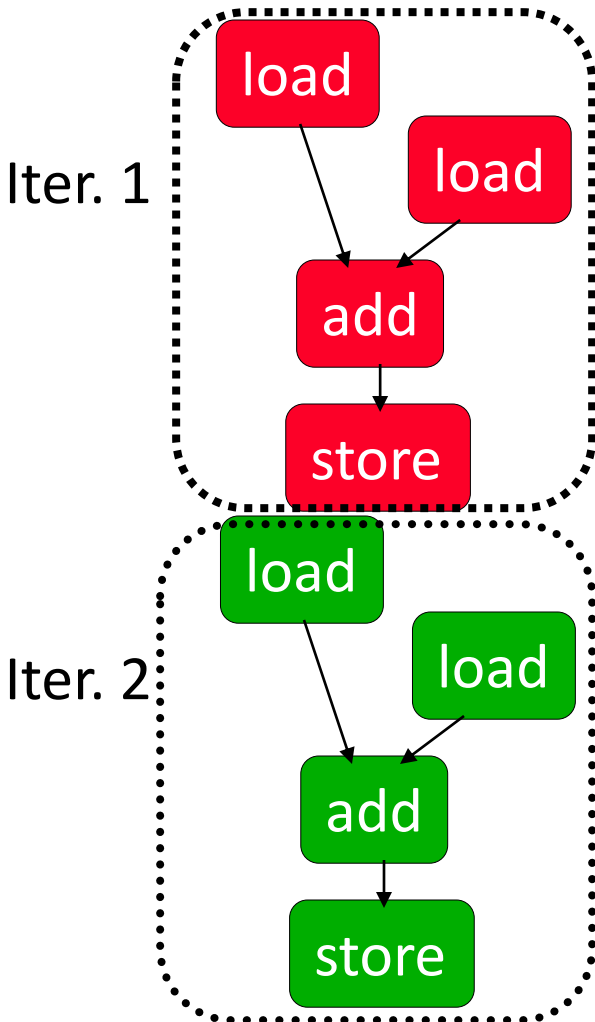
- Vector memory-memory architectures (VMMA) require greater main memory bandwidth, why?
  - All operands must be read in and out of memory
- VMMA make it difficult to overlap execution of multiple vector operations, why?
  - Must check dependencies on memory addresses
- VMMA incur greater startup latency
  - Scalar code was faster on CDC Star-100 for vectors < 100 elements
  - For Cray-1, vector/scalar breakeven point was around 2-4 elements
- Apart from CDC follow-ons (Cyber-205, ETA-10) all major vector machines since Cray-1 have had vector register architectures
- (we ignore vector memory-memory from now on)

# Automatic Code Vectorization

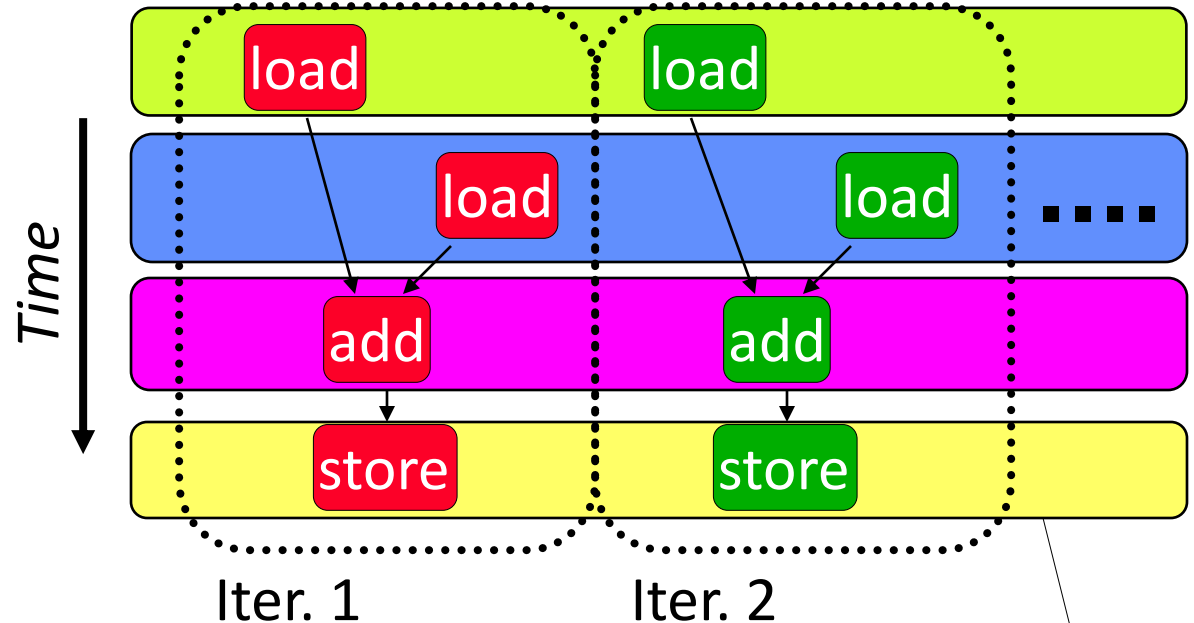
```
for (i=0; i < N; i++)
```

```
  C[i] = A[i] + B[i];
```

*Scalar Sequential Code*



*Vectorized Code*



*Vector Instruction*

Vectorization is a massive compile-time reordering of operation sequencing

⇒ requires extensive loop-dependence analysis

# Vector Stripmining

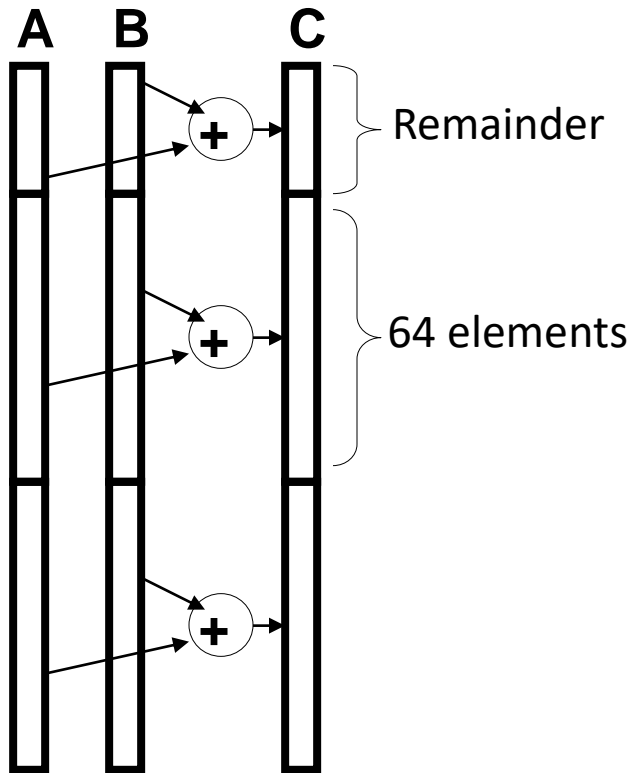
**Problem:** Vector registers have finite length

**Solution:** Break loops into pieces that fit in registers, “*Stripmining*”

```
andi x1, xN, 63 # N mod 64
vsetvl x1        # Do remainder
loop:
```

```
vld v1, (xA)
slli x2, x1, 3 # Multiply by 8
add xA, xA, x2 # Bump pointer
vld v2, (xB)
add xB, xB, x2
vadd v3, v1, v2
vst v3, (xC)
add xC, xC, x2
sub xN, xN, x1 # Subtract elements
li x1, 64
vsetvl x1      # Reset full length
bgtz xN, loop  # Any more to do?
```

```
for (i=0; i<N; i++)
    C[i] = A[i]+B[i];
```



# Vector Conditional Execution

Problem: Want to vectorize loops with conditional code:

```
for (i=0; i<N; i++)  
    if (A[i]>0) then  
        A[i] = B[i];
```

Solution: Add vector *mask* (or *flag*) registers

- vector version of predicate registers, 1 bit per element

...and *maskable* vector instructions

- vector operation becomes bubble (“NOP”) at elements where mask bit is clear

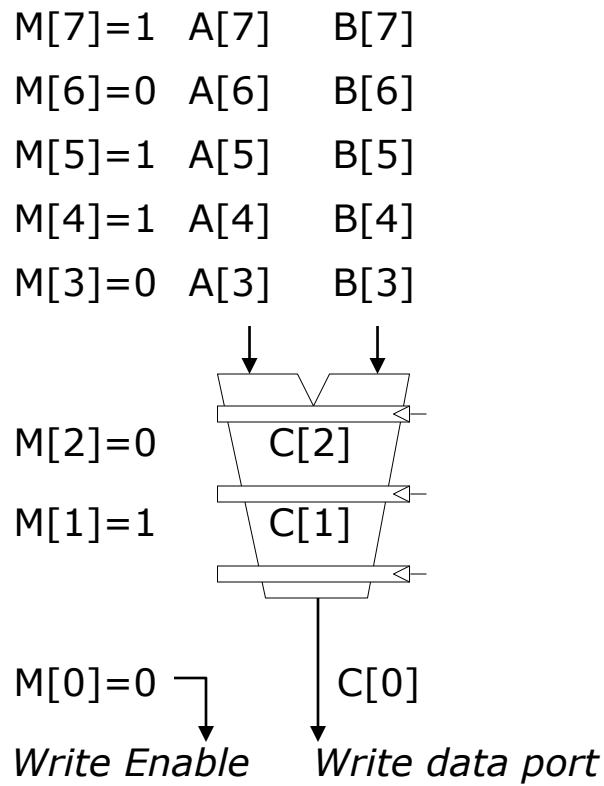
Code example:

```
cvm                # Turn on all elements  
vld vA, (xA)       # Load entire A vector  
vgt vA, f0         # Set bits in mask register where A>0  
vld vA, (xB)       # Load B vector into A under mask  
vst vA, (xA)       # Store A back to memory under mask
```

# Masked Vector Instructions

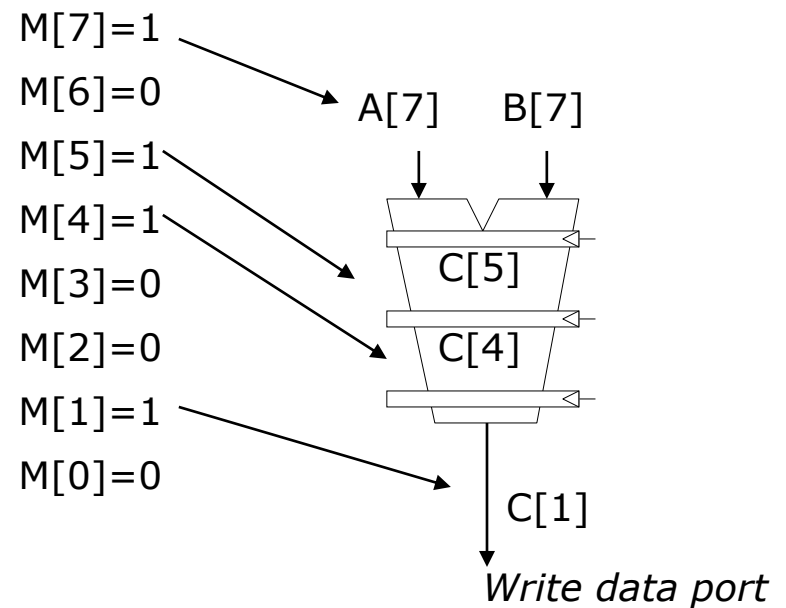
## Simple Implementation

- execute all N operations, turn off result writeback according to mask



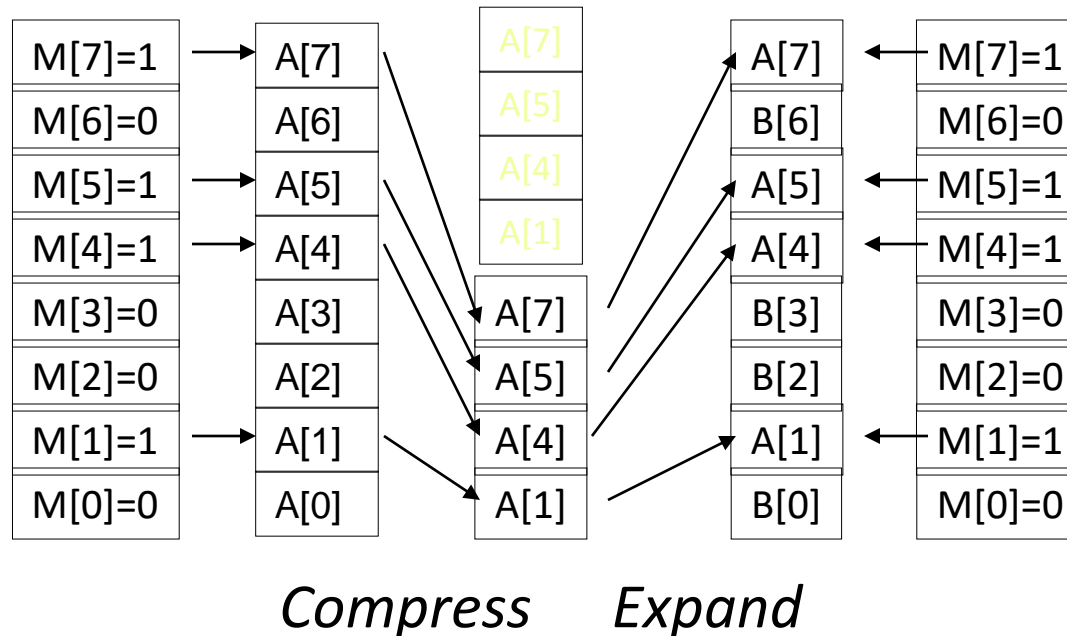
## Density-Time Implementation

- scan mask vector and only execute elements with non-zero masks



# Compress/Expand Operations

- Compress packs non-masked elements from one vector register contiguously at start of destination vector register
  - population count of mask vector gives packed vector length
- Expand performs inverse operation



Used for density-time conditionals and also for general selection operations

# Vector Reductions

**Problem:** Loop-carried dependence on reduction variables

```
sum = 0;
for (i=0; i<N; i++)
    sum += A[i];  # Loop-carried dependence on sum
```

**Solution:** Re-associate operations if possible, use binary tree to perform reduction

```
# Rearrange as:
sum[0:VL-1] = 0          # Vector of VL partial sums
for(i=0; i<N; i+=VL)     # Stripmine VL-sized chunks
    sum[0:VL-1] += A[i:i+VL-1]; # Vector sum
# Now have VL partial sums in one vector register
do {
    VL = VL/2;           # Halve vector length
    sum[0:VL-1] += sum[VL:2*VL-1] # Halve no. partials
} while (VL>1)
```

# Vector Scatter/Gather

Want to vectorize loops with indirect accesses:

```
for (i=0; i<N; i++)  
    A[i] = B[i] + C[D[i]]
```

Indexed load instruction (*Gather*)

```
vld vD, (xD)           # Load indices in D vector  
vlx vC, (xC), vD        # Load indexed from xC base  
vld vB, (xB)           # Load B vector  
vadd vA, vB, vC         # Do add  
vst vA, (xA)           # Store result
```



# Histogram with Scatter/Gather

Histogram example:

```
for (i=0; i<N; i++)  
    A[B[i]]++;
```

Is following a correct translation?

```
vld vB, (xB)          # Load indices in B vector  
vlx vA, (xA), vB      # Gather initial A values  
vadd vA, vA, 1        # Increment  
vsx vA, (xA), vB      # Scatter incremented values
```

# Vector Memory Models

- Some vector machines have a very relaxed memory model, e.g.

```
vst v1, (x1)    # Store vector to x1  
vld v2, (x1)    # Load vector from x1
```

- No guarantee that elements of v2 will have value of elements of v1 even when store and load execute by *same* processor!

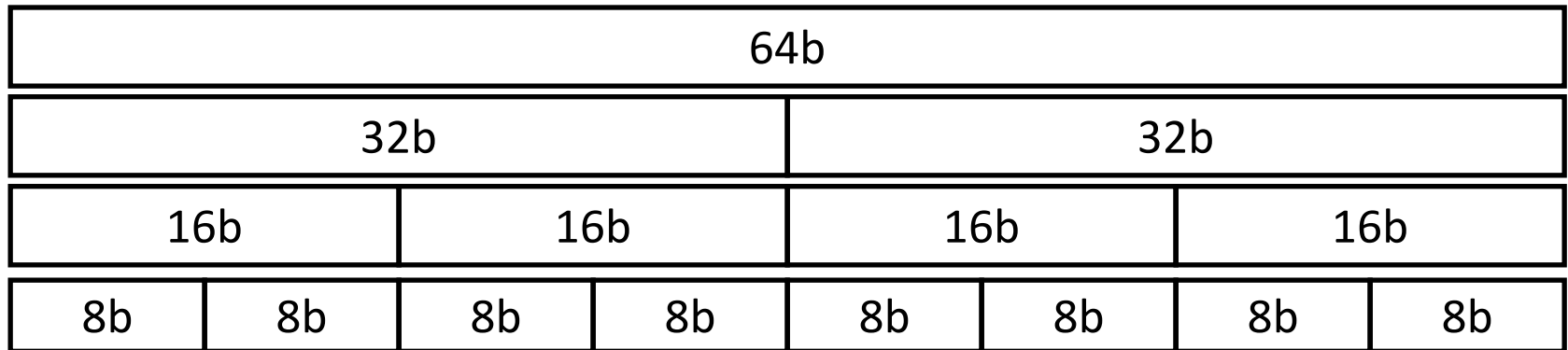
- So require explicit memory barrier or fence

```
vst v1, (x1)    # Store vector to x1  
fence           # Enforce ordering s->l  
vld v2, (x1)    # Load vector from x1
```

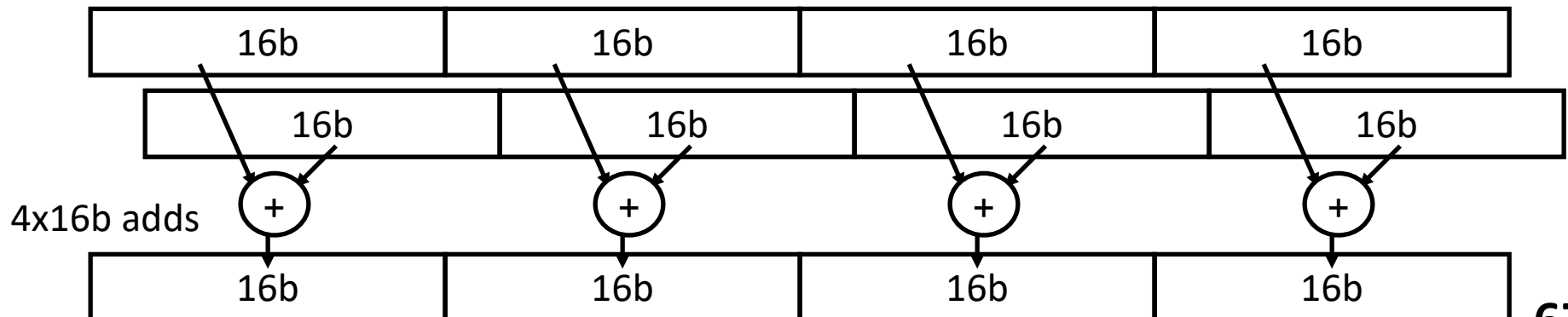
Vector machines support highly parallel memory systems (multiple lanes and multiple load and store units) with long latency (100+ clock cycles)

- hardware coherence checks would be prohibitively expensive
- vectorizing compiler can eliminate most dependencies

# Packed SIMD Extensions



- Very short vectors added to existing ISAs for microprocessors
- Use existing 64-bit registers split into 2x32b or 4x16b or 8x8b
  - Lincoln Labs TX-2 from 1957 had 36b datapath split into 2x18b or 4x9b
  - Newer designs have wider registers
    - 128b for PowerPC AltiVec, Intel SSE2/3/4
    - 256b/512b for Intel AVX
- Single instruction operates on all elements within register



# Packed SIMD versus Vectors

- Limited instruction set:
  - no vector length control
  - no strided load/store or scatter/gather
  - unit-stride loads must be aligned to 64/128-bit boundary
- Limited vector register length:
  - requires superscalar dispatch to keep multiply/add/load units busy
  - loop unrolling to hide latencies increases register pressure
- Trend towards fuller vector support in microprocessors
  - Better support for misaligned memory accesses
  - Support of double-precision (64-bit floating-point)
  - New Intel AVX spec (announced April 2008), 256b vector registers (expandable up to 1024b), gather added, scatter to follow
  - ARM Scalable Vector Extensions (SVE)

# **CS 152 Computer Architecture and Engineering**

## **CS252 Graduate Computer Architecture**

### **Lecture 09-3 GPUs**

#### **(Graphics Processing Units)**

Krste Asanovic

Electrical Engineering and Computer Sciences  
University of California at Berkeley

`http://www.eecs.berkeley.edu/~krste`  
`http://inst.eecs.berkeley.edu/~cs152`

# Types of Parallelism

- Instruction-Level Parallelism (ILP)
  - Execute independent instructions from one instruction stream in parallel (pipelining, superscalar, VLIW)
- Thread-Level Parallelism (TLP)
  - Execute independent instruction streams in parallel (multithreading, multiple cores)
- Data-Level Parallelism (DLP)
  - Execute multiple operations of the same type in parallel (vector/SIMD execution)
- Which is easiest to program?
- Which is most flexible form of parallelism?
  - i.e., can be used in more situations
- Which is most efficient?
  - i.e., greatest tasks/second/area, lowest energy/task

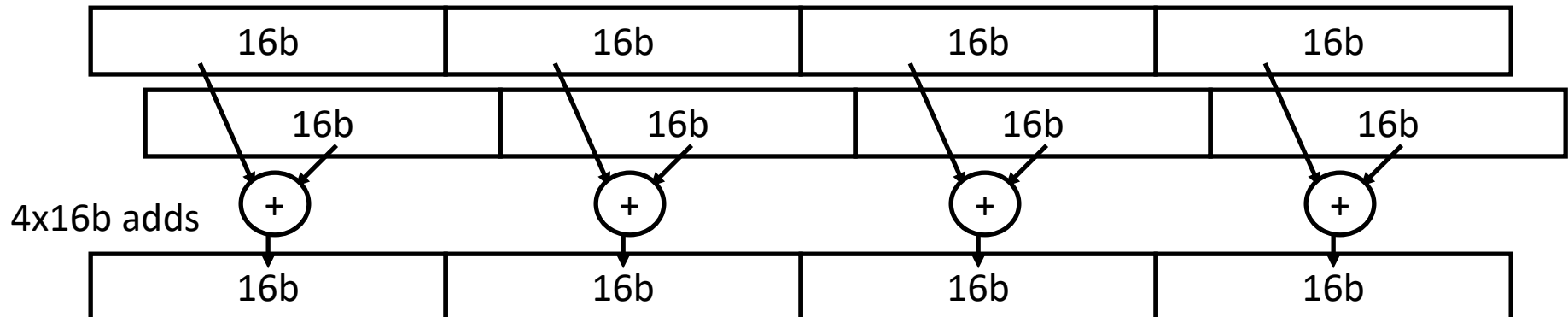
# Resurgence of DLP

- Convergence of application demands and technology constraints drives architecture choice
- New applications, such as graphics, machine vision, speech recognition, machine learning, etc. all require large numerical computations that are often trivially data parallel
- SIMD-based architectures (vector-SIMD, subword-SIMD, SIMT/GPUs) are most efficient way to execute these algorithms

# Packed SIMD Extensions



- Short vectors added to existing microprocessors ISAs, for multimedia
- Use existing 64-bit registers split into 2x32b or 4x16b or 8x8b
  - Lincoln Labs TX-2 from 1957 had 36b datapath split into 2x18b or 4x9b
  - Newer designs have wider registers
    - 128b for PowerPC AltiVec, Intel SSE2/3/4
    - 256b for Intel AVX
- Single instruction operates on all elements within register

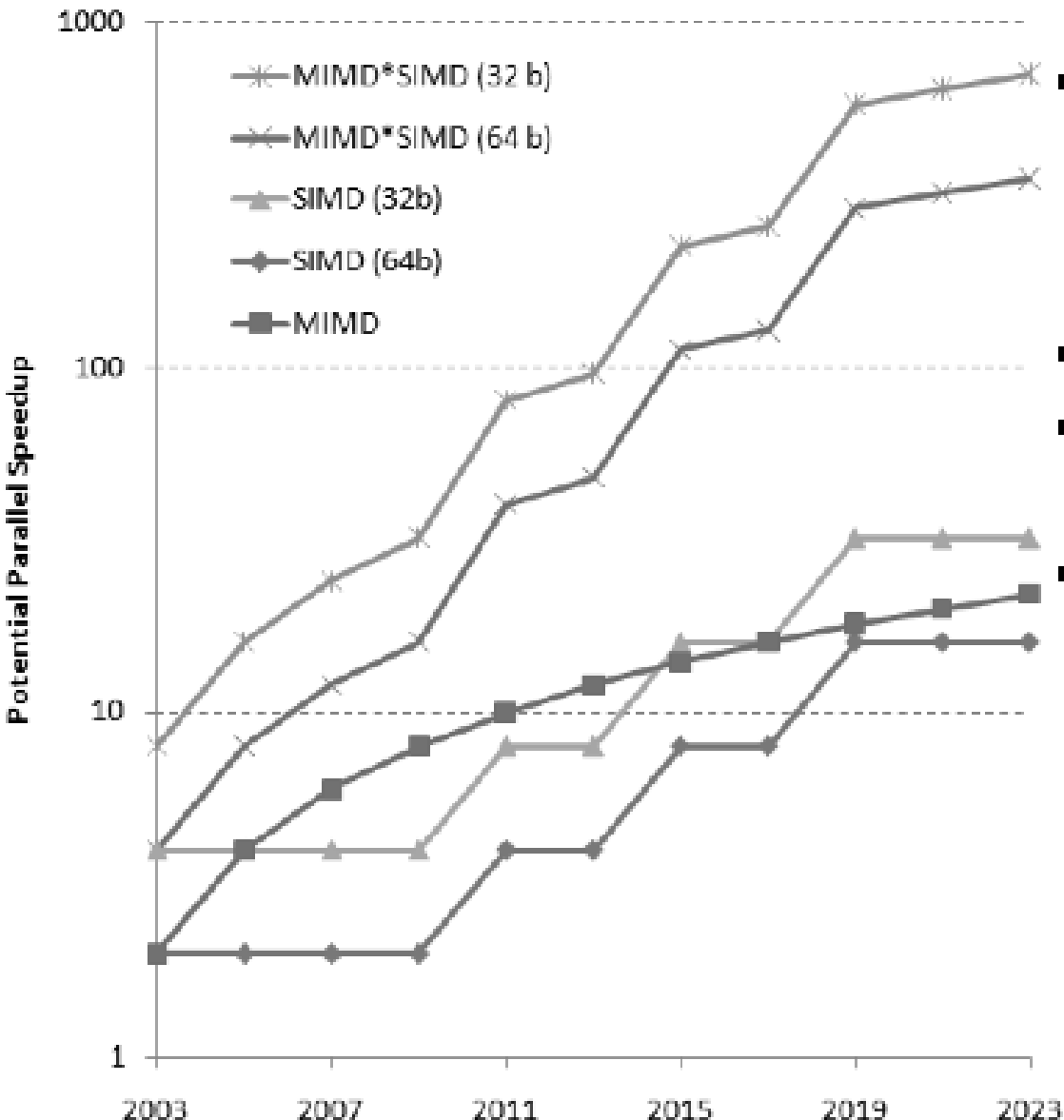




# Multimedia Extensions versus Vectors

- Limited instruction set
  - no vector length control
  - no strided load/store or scatter/gather
  - unit-stride loads must be naturally aligned to whole register width (e.g., 64 or 128-bit)
- Limited vector register length
  - requires superscalar issue to keep multiply/add/load units busy
  - loop unrolling to hide latencies increases register pressure
- Trend towards fuller vector support in microprocessors
  - Better support for misaligned memory accesses
  - Support of double-precision (64-bit floating-point)
  - New Intel AVX spec (announced April 2008), 256b vector registers (expandable up to 1024b) , adding scatter/gather
  - New ARM SVE/MVE vector ISA closer to traditional vector designs

# DLP important for conventional CPUs



- Prediction for x86 processors, from Hennessy & Patterson, 5<sup>th</sup> edition

– *Note: Educated guess, not Intel product plans!*

- TLP: 2+ cores / 2 years
- DLP: 2x width / 4 years

- DLP will account for more mainstream parallelism growth than TLP in next decade.

- SIMD –single-instruction multiple-data (DLP)
- MIMD- multiple-instruction multiple-data (TLP)

# Graphics Processing Units (GPUs)

- Original GPUs were dedicated fixed-function devices for generating 3D graphics (mid-late 1990s) including high-performance floating-point units
  - Provide workstation-like graphics for PCs
  - User could configure graphics pipeline, but not really program it
- Over time, more programmability added (2001-2005)
  - E.g., New language Cg for writing small programs run on each vertex or each pixel, also Windows DirectX variants
  - Massively parallel (millions of vertices or pixels per frame) but very constrained programming model
- Some users noticed they could do general-purpose computation by mapping input and output data to images, and computation to vertex and pixel shading computations
  - Incredibly difficult programming model as had to use graphics pipeline model for general computation

# General-Purpose GPUs (GP-GPUs)

- In 2006, Nvidia introduced GeForce 8800 GPU, which supported a new programming language CUDA (in 2007)
  - “Compute Unified Device Architecture”
  - Subsequently, broader industry pushing for OpenCL, a vendor-neutral version of same ideas.
- Idea: Take advantage of GPU computational performance and memory bandwidth to accelerate some kernels for general-purpose computing
- Attached processor model: Host CPU issues data-parallel kernels to GP-GPU for execution
- This lecture has a simplified version of Nvidia CUDA-style model and only considers GPU execution for computational kernels, not graphics
  - Would need whole other course to describe graphics processing

# Simplified CUDA Programming Model

- Computation performed by a very large number of independent small scalar threads (*CUDA threads* or *microthreads*) grouped into *thread blocks*.

```
// C version of DAXPY loop.
```

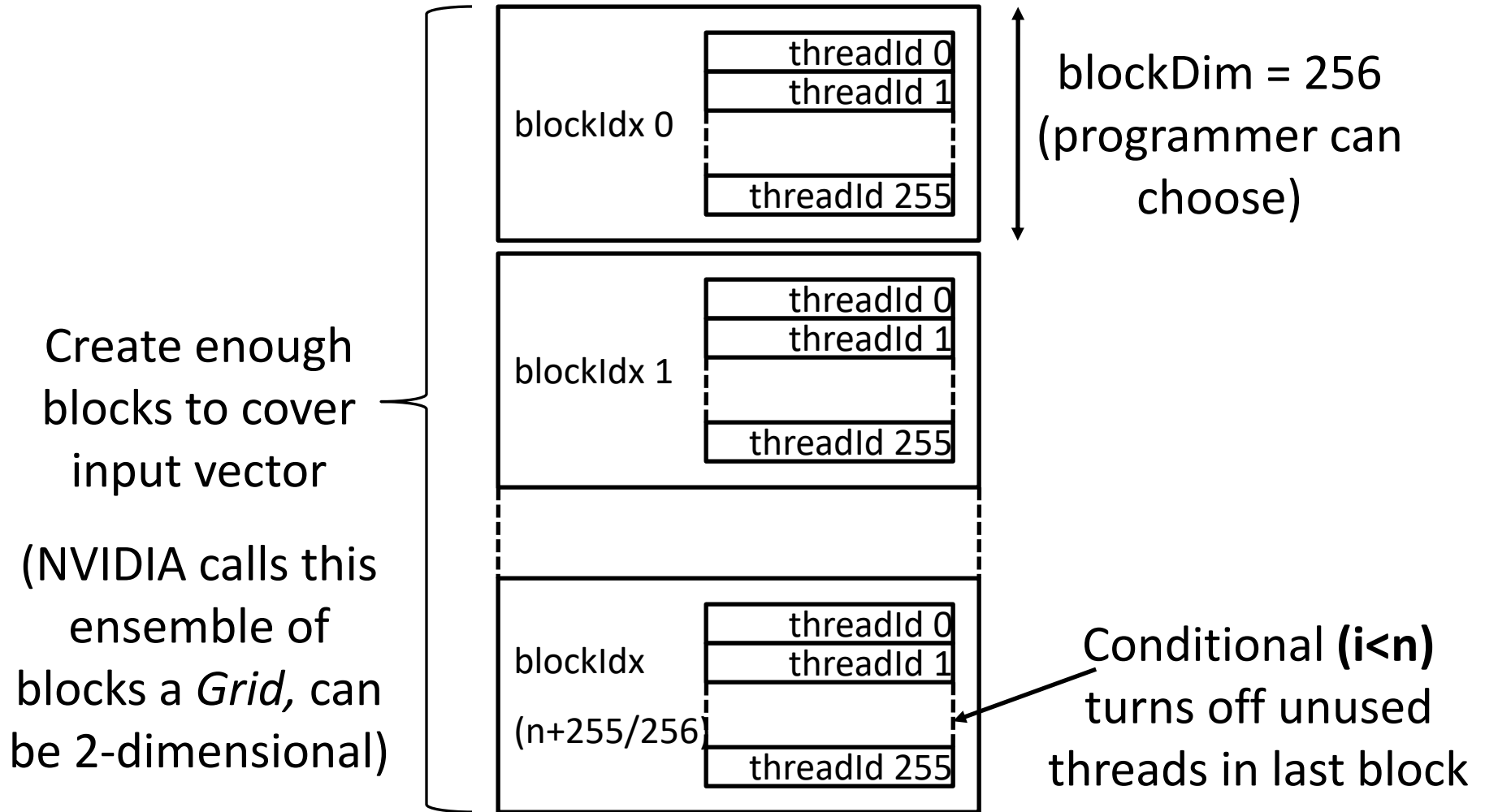
```
void daxpy(int n, double a, double*x, double*y)
{ for (int i=0; i<n; i++)
    y[i] = a*x[i] + y[i]; }
```

```
// CUDA version.
```

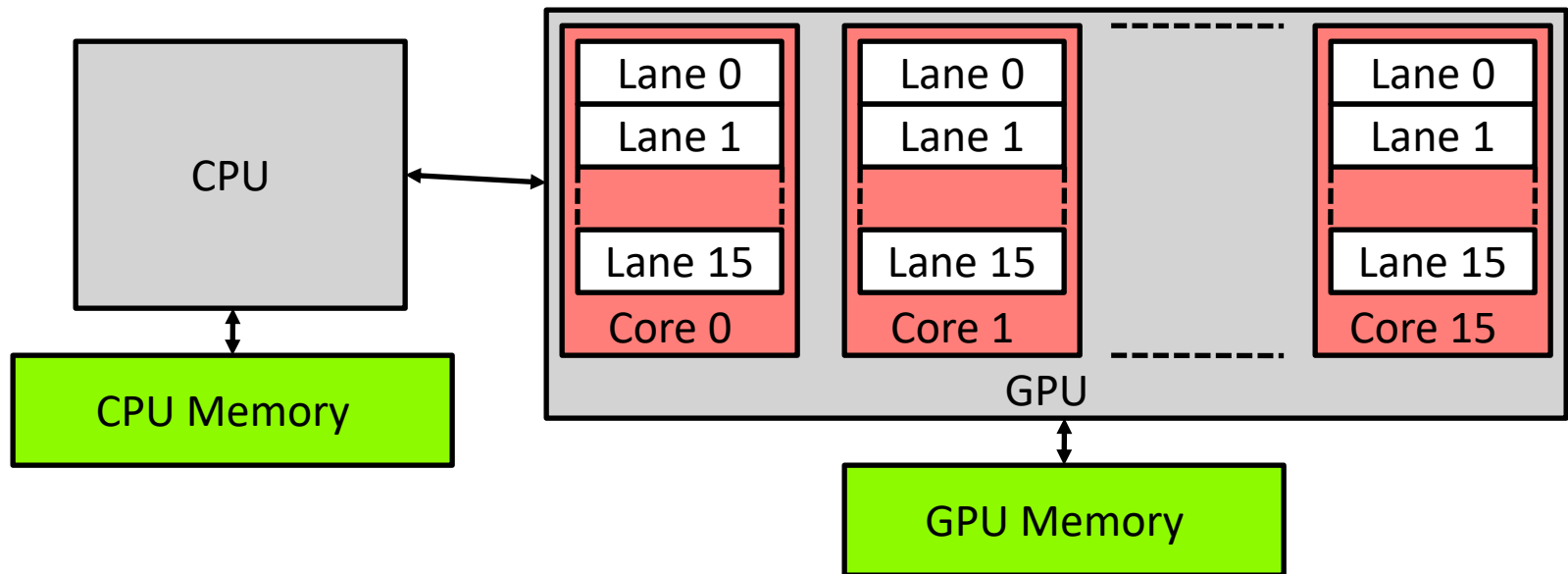
```
__host__ // Piece run on host processor.
int nblocks = (n+255)/256; //256 CUDA threads/block
daxpy<<<nblocks,256>>>(n,2.0,x,y);
```

```
__device__ // Piece run on GP-GPU.
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]; }
```

# Programmer's View of Execution



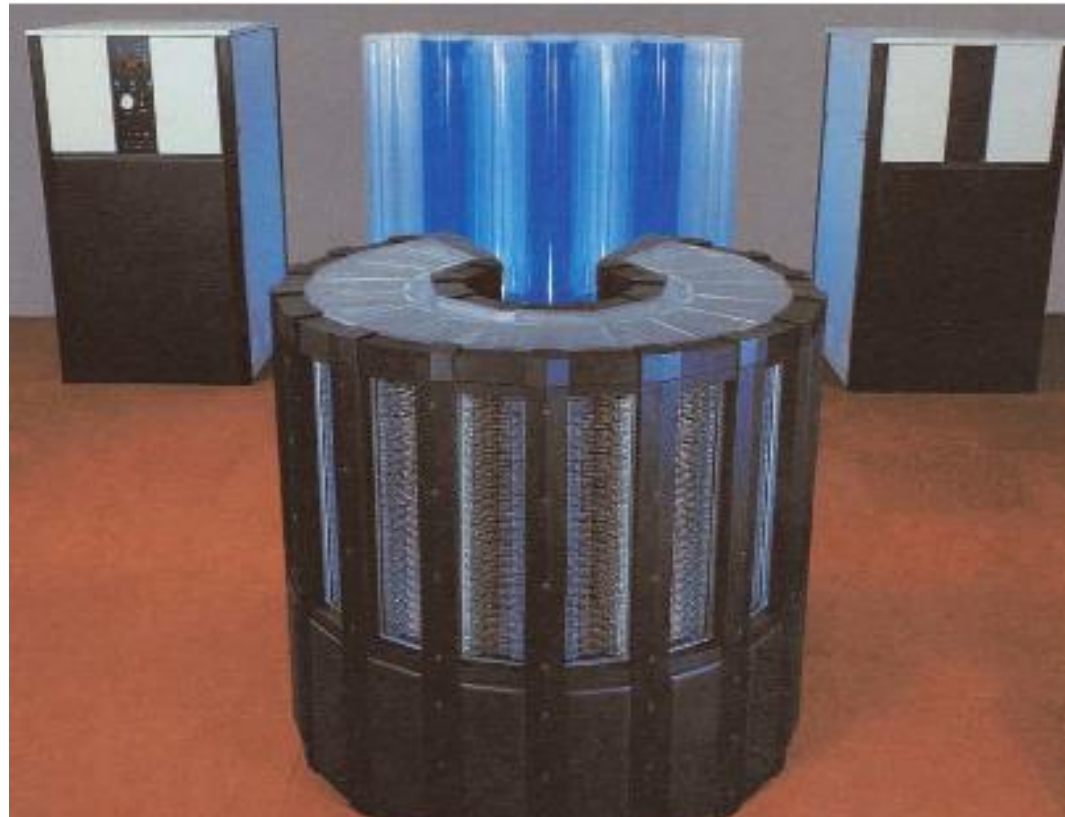
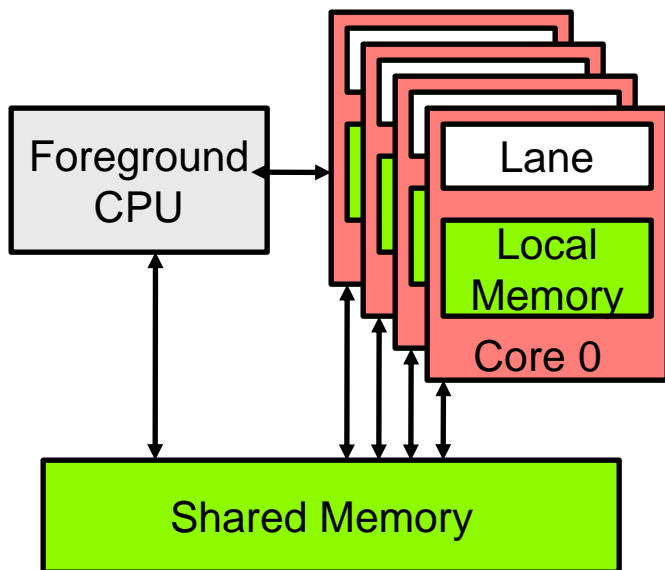
# Hardware Execution Model



- GPU is built from multiple parallel cores, each core contains a multithreaded SIMD processor with multiple lanes but with no scalar processor
  - some adding “scalar coprocessors” now
- CPU sends whole “grid” over to GPU, which distributes thread blocks among cores (each thread block executes on one core)
  - Programmer unaware of number of cores

# Historical Retrospective, Cray-2 (1985)

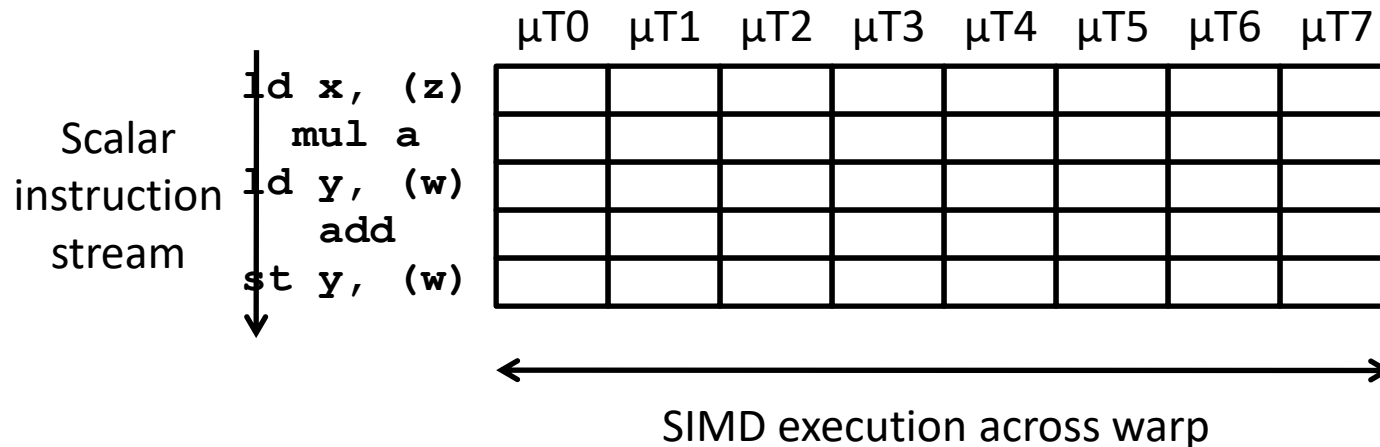
- 243MHz ECL logic
- 2GB DRAM main memory (128 banks of 16MB each)
  - Bank busy time 57 clocks!
- Local memory of 128KB/core
- 1 foreground + 4 background vector processors





# “Single Instruction, Multiple Thread” (SIMT)

- GPUs use a SIMT model, where individual scalar instruction streams for each CUDA thread are grouped together for SIMD execution on hardware (NVIDIA groups 32 CUDA threads into a *warp*)

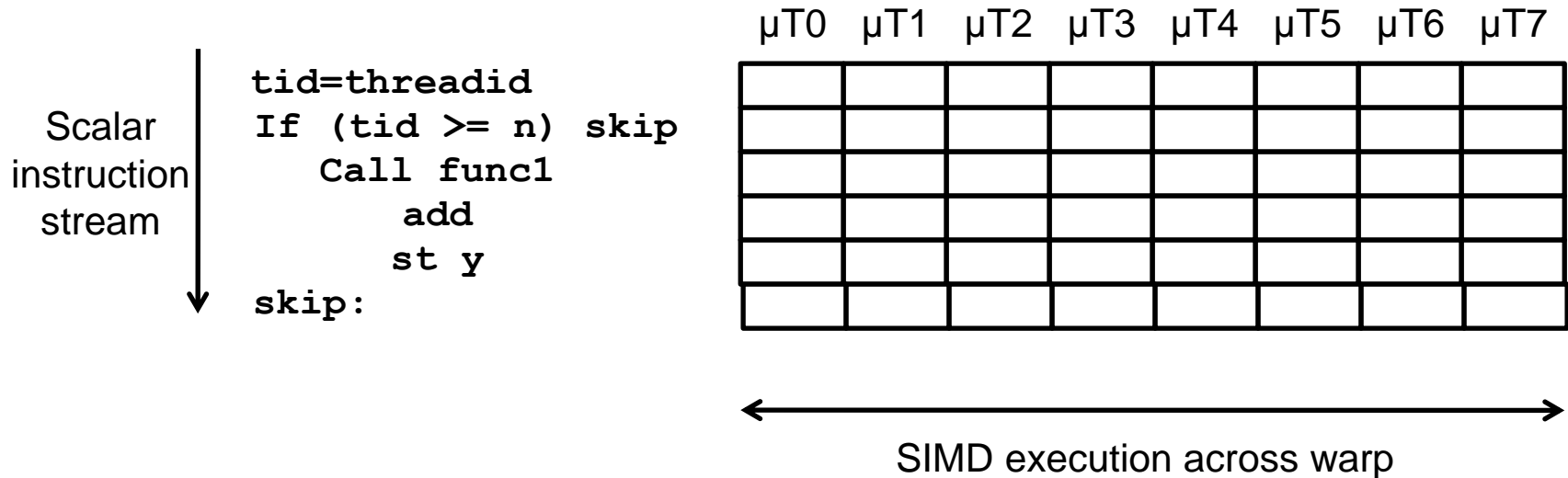


# Implications of SIMT Model

- All “vector” loads and stores are scatter-gather, as individual  $\mu$ threads perform scalar loads and stores
  - GPU adds hardware to dynamically coalesce individual  $\mu$ thread loads and stores to mimic vector loads and stores
- Every  $\mu$ thread has to perform stripmining calculations redundantly (“am I active?”) as there is no scalar processor equivalent

# Conditionals in SIMT model

- Simple if-then-else are compiled into predicated execution, equivalent to vector masking
- More complex control flow compiled into branches
- How to execute a vector of branches? Vector function calls?



# Branch Divergence

- Hardware tracks which  $\mu$ threads take or don't take branch
- If all go the same way, then keep going in SIMD fashion
- If not, create mask vector indicating taken/not-taken
- Keep executing not-taken path under mask, push taken branch PC+mask onto a hardware stack and execute later
- When can execution of  $\mu$ threads in warp reconverge?

# NVIDIA Instruction Set Arch.

- ISA is an abstraction of the hardware instruction set
  - “Parallel Thread Execution (PTX)”
    - opcode.type d,a,b,c;
  - Uses virtual registers
  - Translation to machine code is performed in software
  - Example:

```
shl.s32      R8, blockIdx, 9      ; Thread Block ID * Block size (512 or 29)
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 R0D, RD0, RD4             ; Product in RD0 = RD0 * RD4 (scalar a)
add.f64 R0D, RD0, RD2             ; Sum in RD0 = RD0 + RD2 (Y[i])
st.global.f64 [Y+R8], RD0         ; Y[i] = sum (X[i]*a + Y[i])
```

# Conditional Branching

- Like vector architectures, GPU branch hardware uses internal masks
- Also uses
  - Branch synchronization stack
    - Entries consist of masks for each SIMD lane
    - I.e. which threads commit their results (all threads execute)
  - Instruction markers to manage when a branch diverges into multiple execution paths
    - Push on divergent branch
  - ...and when paths converge
    - Act as barriers
    - Pops stack
- Per-thread-lane 1-bit predicate register, specified by programmer

# Example

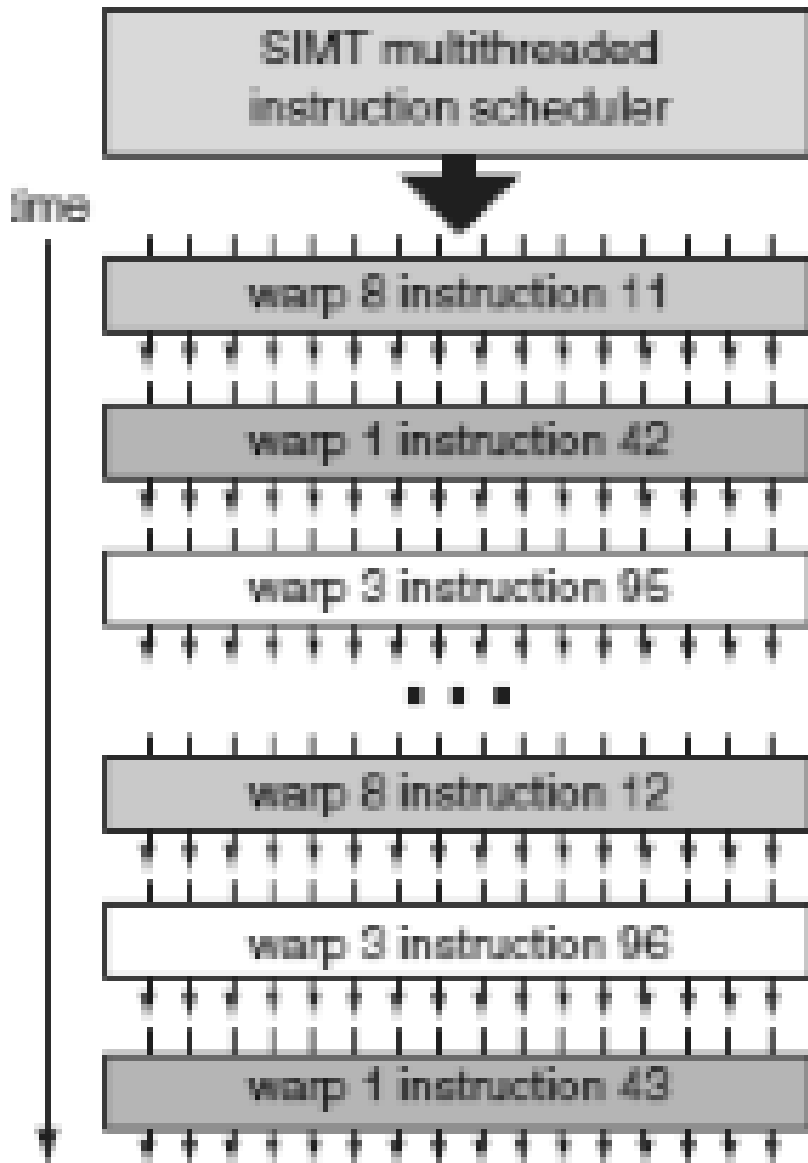
if (X[i] != 0)

    X[i] = X[i] - Y[i];

else X[i] = Z[i];

ld.global.f64	RD0, [X+R8]	; RD0 = X[i]
setp.neq.s32	P1, RD0, #0	; P1 is predicate register 1
@!P1, bra	ELSE1, *Push	; Push old mask, set new mask bits
		; if P1 false, go to ELSE1
ld.global.f64	RD2, [Y+R8]	; RD2 = Y[i]
sub.f64	RD0, RD0, RD2	; Difference in RD0
st.global.f64	[X+R8], RD0	; X[i] = RD0
@P1, bra	ENDIF1, *Comp	; complement mask bits
		; if P1 true, go to ENDIF1
ELSE1:	ld.global.f64 RD0, [Z+R8]	; RD0 = Z[i]
	st.global.f64 [X+R8], RD0	; X[i] = RD0
ENDIF1:	<next instruction>, *Pop	; pop to restore old mask

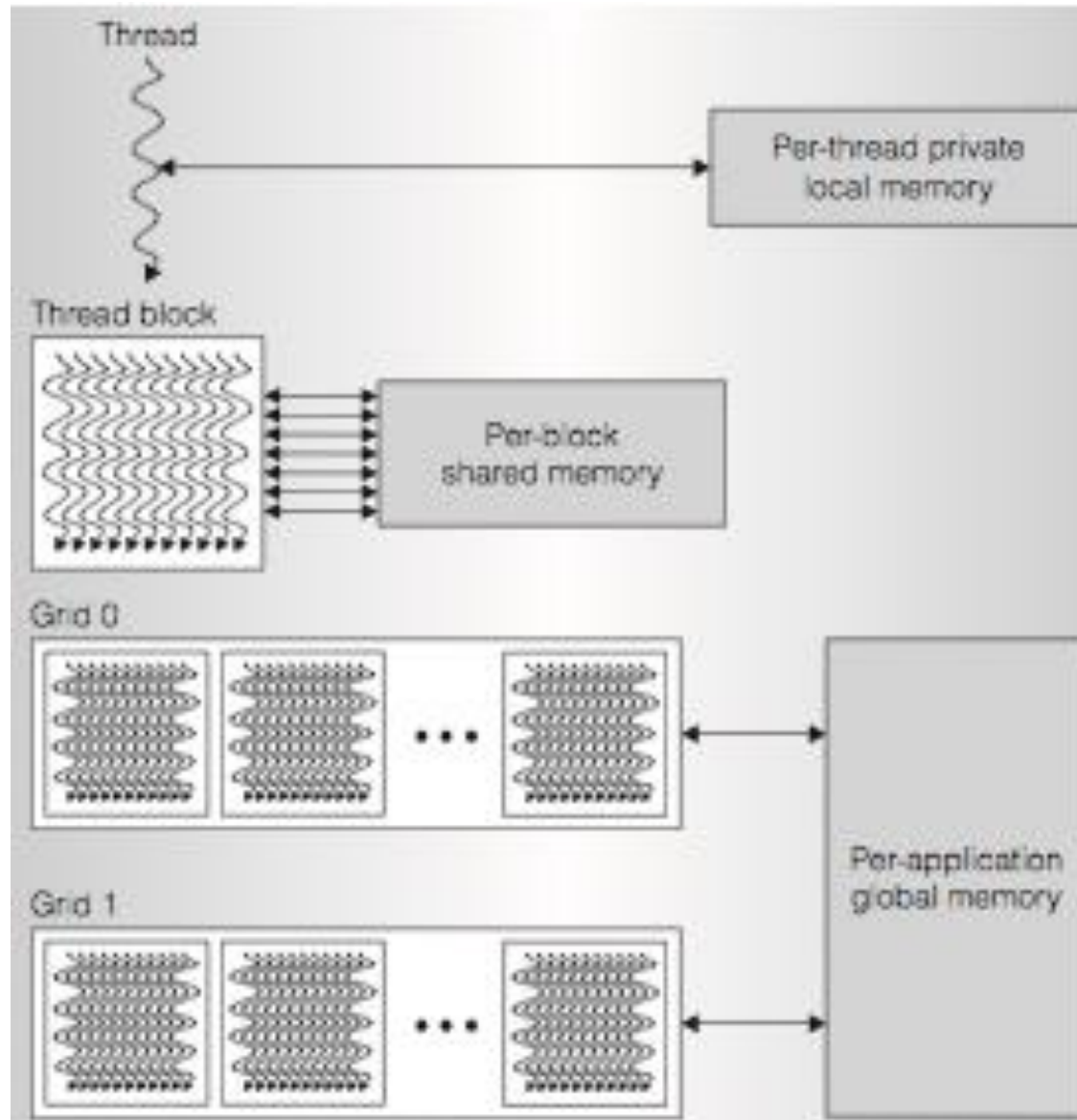
# Warps are multithreaded on core



- One warp of 32  $\mu$ threads is a single thread in the hardware
- Multiple warp threads are interleaved in execution on a single core to hide latencies (memory and functional unit)
- A single thread block can contain multiple warps (up to 512  $\mu$ T max in CUDA), all mapped to single core
- Can have multiple blocks executing on one core



# GPU Memory Hierarchy



[ Nvidia, 2010]

# SIMT

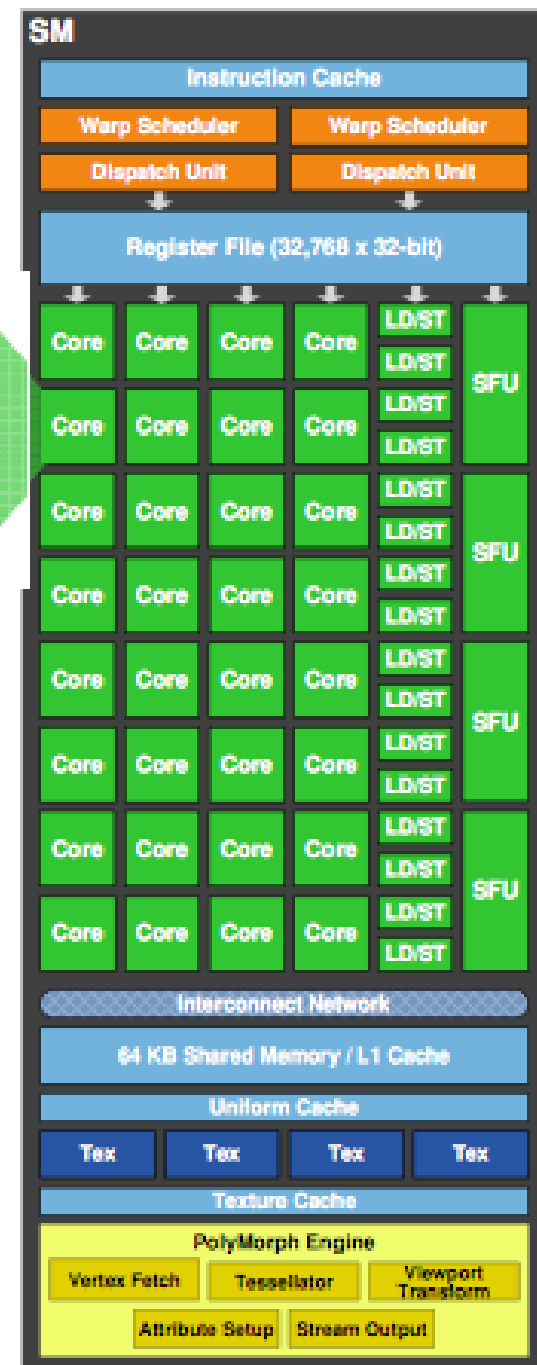
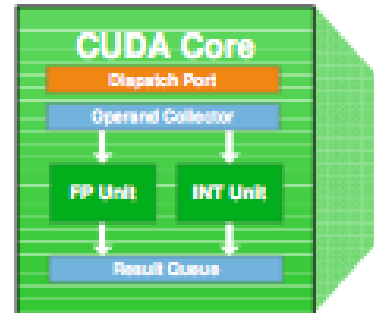
- Illusion of many independent threads
- But for efficiency, programmer must try and keep  $\mu$ threads aligned in a SIMD fashion
  - Try and do unit-stride loads and store so memory coalescing kicks in
  - Avoid branch divergence so most instruction slots execute useful work and are not masked off

# Nvidia Fermi GF100 GPU



[Nvidia,  
2010]

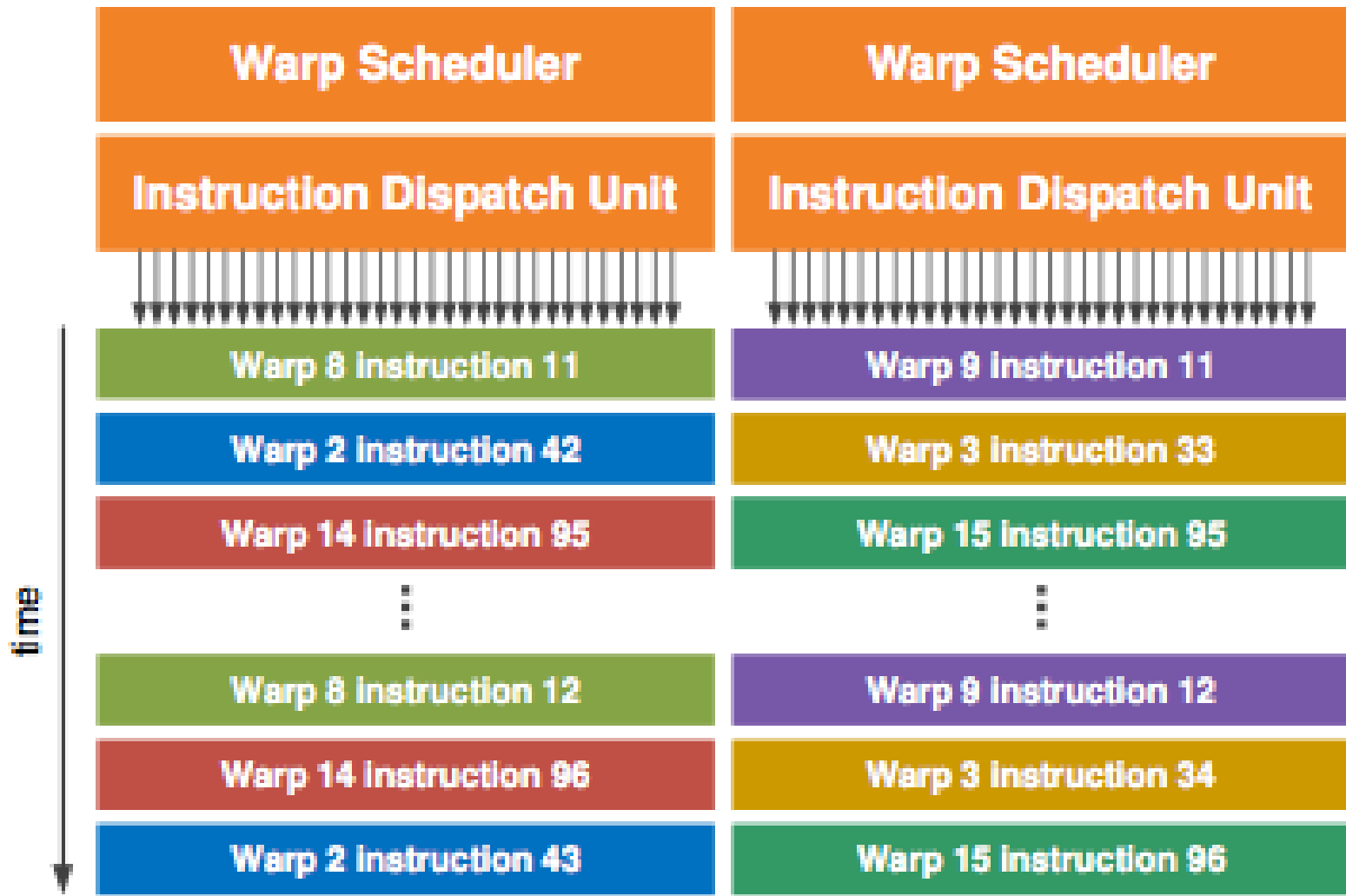
# Fermi “Streaming Multiprocessor” Core



# NVIDIA Pascal Multithreaded GPU Core



# Fermi Dual-Issue Warp Scheduler



# Important of Machine Learning for GPUs

NVIDIA Corporation

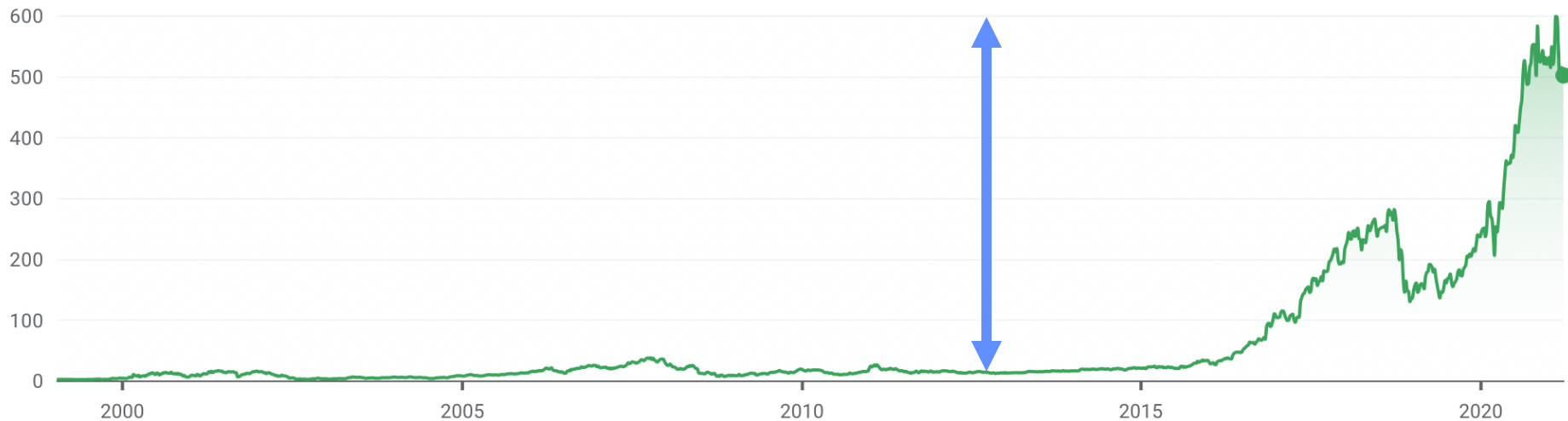
NVDA

**\$501.41** ↑ 30,473.78% +499.77 MAX

After Hours: **\$501.50** (↑ 0.018%) **+\$0.090**

Closed: Mar 25, 5:46:41 PM UTC-4 · USD · NASDAQ · Disclaimer

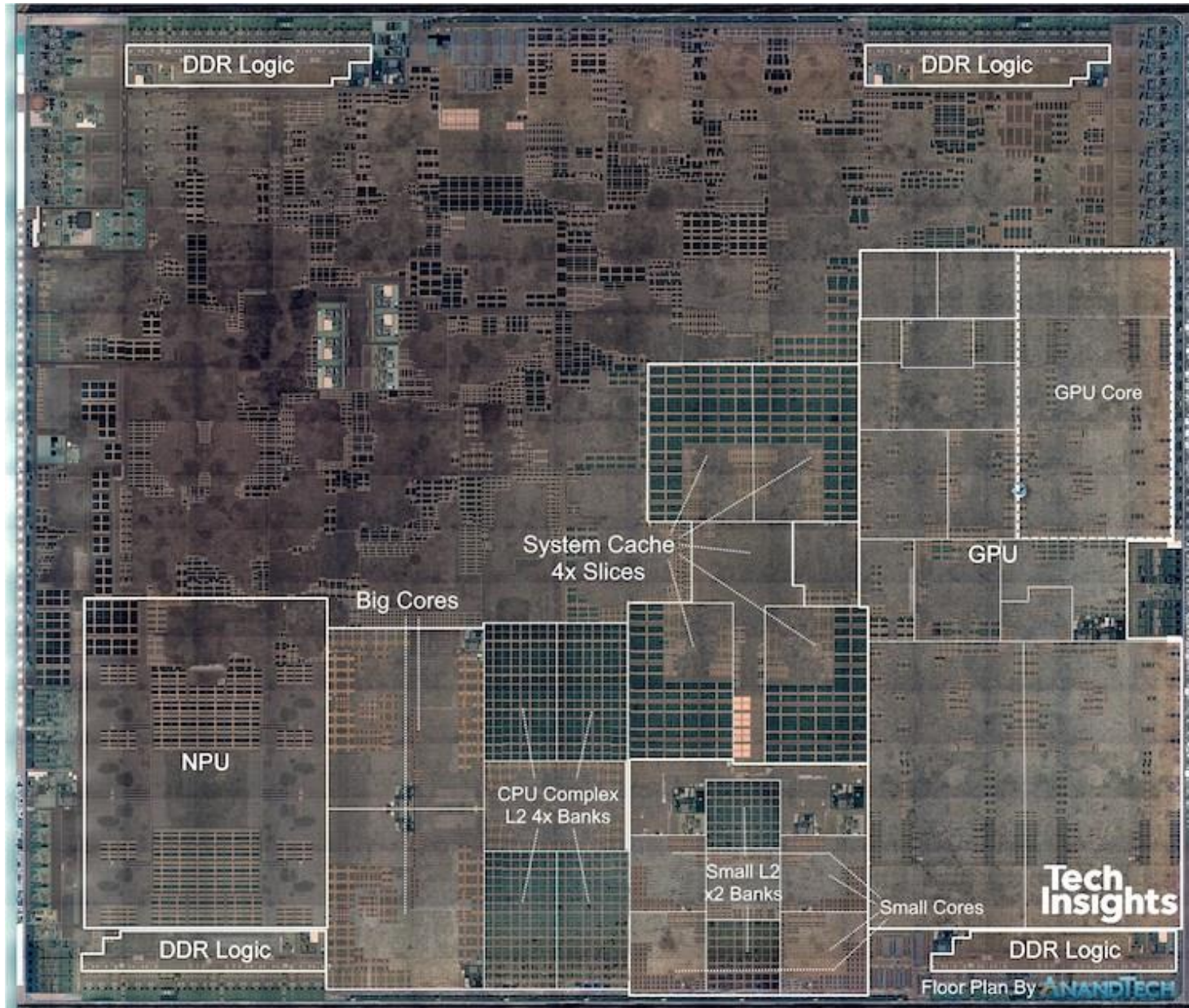
1D 5D 1M 6M YTD 1Y 5Y **MAX**



NVIDIA stock price 40x in 9 years (since deep learning became important)



# Apple A12 Processor (2018)



- 83.27mm<sup>2</sup>
- 7nm technology

**[Source: Tech Insights, AnandTech]**