

### **COMPUTER ORGANIZATION**

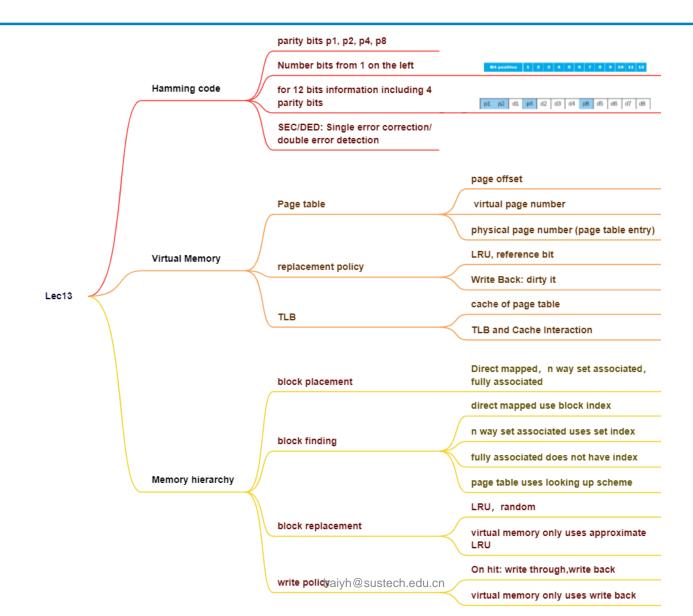
# Lecture 14 Parallel Processors from Client to Cloud

2025 Spring

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## Recap





### Introduction

- Goal: replacing large inefficient processors with many smaller, efficient processors to get better performance per joule
  - Multiprocessors, cluster
  - Scalability, availability, power efficiency
- Task-level (process-level) parallelism
  - High throughput for independent jobs
- Parallel processing program
  - Single program run on multiple processors
- Multicore microprocessors
  - Chips with multiple processors (cores)
  - Shared Memory Processors (SMP)



### **Hardware and Software**

- Challenge: hardware and software design that enables parallel processing programs, which can be efficiently executed (in performance and energy) when number of cores scales.
- Hardware
  - Serial: e.g., Pentium 4
  - Parallel: e.g., Core i7
- Software
  - Sequential: e.g., matrix multiplication
  - Concurrent: e.g., operating system
- Sequential/concurrent software can run on serial/parallel hardware



## **Parallel Programming**

- It's hard to create parallel software
- Parallel programming needs to achieve significant performance improvement
  - Otherwise, just use a faster uniprocessor, since it's easier!
- Difficulties of parallel programming:
  - Partitioning
  - Coordination
  - Communications overhead



### **Amdahl's Law**

- Sequential part can limit speedup
- Example: 100 processors, how to achieve 90× speedup?
  - 1 processor:  $T_{old} = T_{sequential} + T_{parallelizable}$
  - 100 processors:  $T_{new} = T_{sequential} + T_{parallelizable}/100$

Speedup = 
$$\frac{1}{(1-F_{\text{parallelizable}}) + F_{\text{parallelizable}}/100} = 90$$

- $\rightarrow$   $F_{parallelizable} = 0.999$
- sequential part should be no more than 0.1% of total task

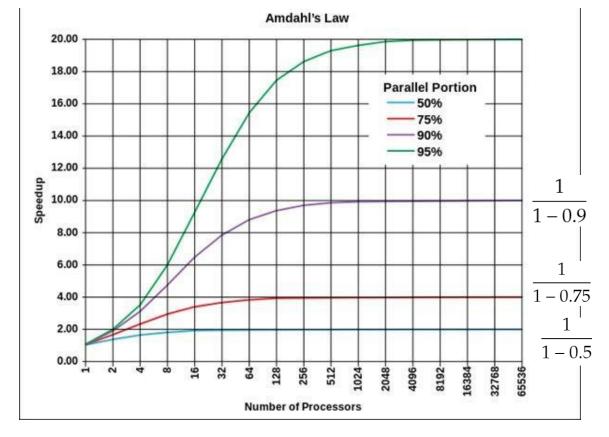
Speedup = 
$$\frac{1}{(1 - F_{parallelizable}) + \frac{1}{N}(F_{parallelizable})}$$

N = improve factor F = parallel portion



### **Amdahl's Law**

Speedup = 
$$\frac{T_1 + T_2}{T'} = \frac{T_1 + T_2}{\frac{T_1}{N} + T_2} = \frac{1}{\frac{1}{N} \left(\frac{T_1}{T_1 + T_2}\right) + \left(\frac{T_2}{T_1 + T_2}\right)} = \frac{1}{\frac{1}{N}(p) + (1 - p)}$$
(p: parallel portion)



$$T_1 = T_{affected}$$
 $T_2 = T_{unaffected}$ 
 $T' = T_{improved}$ 



## **Scaling Example**

- Workload: sum of 10 scalars, sum of two 10 × 10 matrix
  - Assume the sum of 10 scalars cannot be paralleled
  - What is the speedup of 10 processors and 40 processors?
- Single processor: Time =  $(10 + 100) \times t_{add}$
- 10 processors
  - Time =  $10 \times t_{add} + 100/10 \times t_{add} = 20 \times t_{add}$
  - Speedup = 110/20 = 5.5 (5.5/10=55% of potential)
- 40 processors
  - Time =  $10 \times t_{add} + 100/40 \times t_{add} = 12.5 \times t_{add}$
  - Speedup = 110/12.5 = 8.8 (8.8/40=22% of potential)
- Assumes load can be balanced across processors



## Scaling Example (cont.)

- What if matrix size is 20 × 20?
- Single processor: Time =  $(10 + 400) \times t_{add}$
- 10 processors
  - Time =  $10 \times t_{add} + 400/10 \times t_{add} = 50 \times t_{add}$
  - Speedup = 410/50 = 8.2 (8.2/10=82% of potential)
- 40 processors
  - Time =  $10 \times t_{add} + 400/40 \times t_{add} = 20 \times t_{add}$
  - Speedup = 410/20 = 20.5 (20.5/40=51% of potential)
- Assuming load balanced



## Strong vs Weak Scaling

- Strong scaling: problem size fixed
  - As in example
- Weak scaling: problem size proportional to number of processors
  - 10 processors, 10 × 10 matrix (100 elements)
    - Time =  $20 \times t_{add}$
  - 40 processors, 20 × 20 matrix (400 elements)
    - Time =  $10 \times t_{add} + 400/40 \times t_{add} = 20 \times t_{add}$
  - Constant performance in this example



## Strong vs Weak Scaling

Speedup:

No. of cores	10 scaler 10*10 matrix	10 scaler 20*20 matrix
10	5.5 (55% of potential)	8.2 (82% of potential)
40	8.8 (22% of potential)	20.5 (51% of potential)

- Strong scaling: keep problem size fixed, time is reverse proportional to number of processors: T(N,P)=T(1,P)/N
- Weak scaling: constant time cost when problem size is proportional to number of processors:  $T(N_1,P_1)=T(N_2,P_2)$



### **Load Balancing**

- In the above example
  - 40 processors are used to achieve 20.5 speedup
  - 40 processors are assumed to have balanced load (2.5% each)
- how about one processor with high load (5%)?
  - one processor takes 5%\*400=20 adds, the others takes the rest 400-20=380 adds
  - Time = max(380t/39, 20t/1)+10t = 30t
  - speedup = 410t/30t = 14, smaller than 20.5
- how about one processor with higher load (12.5%)?



### **Parallel Processing**

- The following techniques can enable parallel processing
  - SIMD, vector (section 6.3)
  - Multithreading (section 6.4)
  - SMPs and clusters (section 6.5)
  - GPUs (section 6.6)



### SISD, MIMD, SPMD, SIMD and vector

		Data Streams	
		Single	Multiple
Instruction Streams	Single	SISD: Intel Pentium 4	SIMD: SSE of ISA x86
	Multiple	MISD: No examples today	MIMD: Intel Core i7

- SISD: single instruction stream, single data stream
  - Uniprocessor
- MIMD : multiple instruction, multiple data
  - Multi-core processor
  - SPMD: single program, multiple data
    - A parallel program on a MIMD computer
    - Different processors execute on different sections of code



### SIMD

- Operate on vectors of data
  - Provide data level parallelism
  - E.g., MMX (MultiMedia eXtension) and SSE (Streaming SIMD Extension) instructions in x86
    - Multiple data elements in 128-bit wide registers
- All processors execute the same instruction at the same time
  - Each with different data address, etc.
- Simplifies synchronization
- Reduced instruction control hardware
- Works best for highly data-parallel applications



### **Vector Processors**

- Highly pipelined function units
- Stream data from/to vector registers to units
  - Data collected from memory into registers
  - Results stored from registers to memory
- Example: Vector extension to RISC-V
  - v0 to v31: 32  $\times$  64-element registers, (64-bit elements)
  - Vector instructions
    - fld.v, fsd.v: load/store vector
    - fadd.d.v: add vectors of double
    - fadd.d.vs: add scalar to each element of vector of double
- Significantly reduces instruction-fetch bandwidth





## An example using vector instruction

#### Conventional RISC-V code:

```
// load scalar a
      fld
             f0,a(x3)
      addi
           x5, x19, 512
                          // end of array X
loop: fld
          f_{1},0(x19)
                          // load x[i]
      fmul.d(f1,)f1,f0
                        // a * x[i]
             f2,0(x20)
      f1d
                          // load y[i]
      fadd.d(f2)f2(f1)
                          // a * x[i] + y[i]
            (f2)0(x20)
      fsd
                          // store y[i]
      addi
             x19, x19, 8
                          // increment index to x
      addi
             x20,x20,8
                          // increment index to y
      bltu
             x19, x5, loop
                          // repeat if not done
```

#### Vector RISC-V code:

```
fld f0,a(x3) // load scalar a
fld.v v0,0(x19) // load vector x
fmul.d.vs v0,v0,f0 // vector-scalar multiply
fld.v v1,0(x20) // load vector y
fadd.d.v v1,v1,v0 // vector-vector add
fsd.v v1,0(x20) // store vector y
```

#### Calculate:

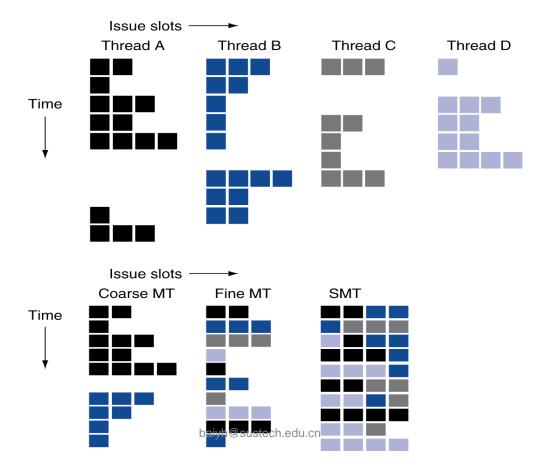
$$Y = a \times X + Y$$

➤ X and Y are vectors of 64 double precision numbers
 ➤ the starting addresses of X and Y are in x19 and x20



## Multithreading

- A related concept to MIMD, allows multiple threads to share a single processor
  - Threads: a lightweight process, share single address space





## Multithreading

- Coarse-grain multithreading
  - Only switch on long stall (e.g., L2-cache miss)
  - Simplifies hardware, but doesn't hide short stalls (eg, data hazards)
- Fine-grain multithreading
  - Switch threads after each cycle
  - Interleave instruction execution
  - If one thread stalls, others are executed



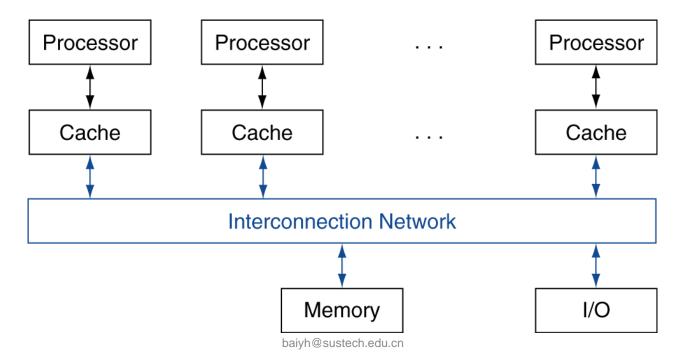
## Simultaneous Multithreading (SMT)

- In multiple-issue dynamically scheduled processor
  - Schedule instructions from multiple threads
  - Instructions from independent threads execute when function units are available
  - Within threads, dependencies handled by scheduling and register renaming
- Example: Intel Pentium-4 HT (Hyper Threading)
  - Two threads: duplicated registers, shared function units and caches



## **Shared Memory Multiprocessors**

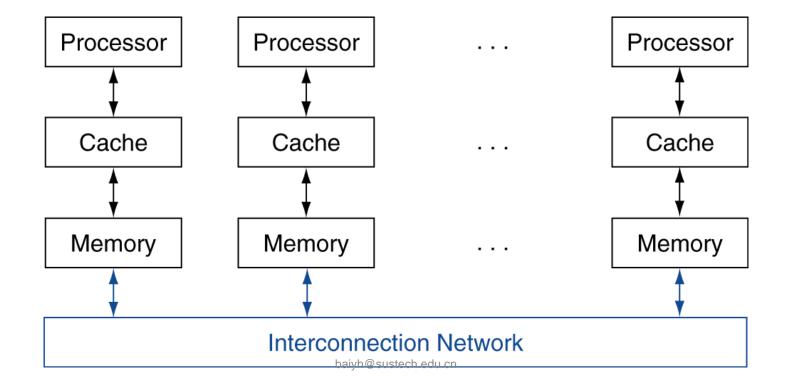
- Multithreading improves efficiency of one processor
- How to efficiently programming on multiprocessor?
  - Don't want to rewrite old programs in single processor
  - Share memory among multiple cores
- SMP: shared memory multiprocessor





## **Message Parsing Multiprocessors**

- Each processor has private physical address space
- Hardware sends/receives messages between processors





### **Loosely Coupled Clusters**

- Network of independent computers
  - Each has private memory and OS
  - Connected using I/O system
    - E.g., Ethernet/switch, Internet
- Suitable for applications with independent tasks
  - Web servers, databases, simulations, ...
- High availability, scalable, affordable
- Problems
  - Administration cost (prefer virtual machines)
  - Low interconnect bandwidth
    - c.f. processor/memory bandwidth on an SMP



## **Cloud Computing and Data Center**

### Cloud computing

- Warehouse Scale Computers (WSC)
- Software as a Service (SaaS)
- Portion of software run on a PMD (personal mobile device) and a portion run in the Cloud
- Amazon and Google

#### Data centers

 Millions of computers connected by off-theshelf networking devices

#### **Google Data Centers**







### Introduction of GPUs

### Development of GPU

- General-purpose CPU not suitable for graphic processing
- Game industry drive the improvement of graphic processing
- GPU (graphic processing unit) appear and developed faster than general-purpose CPU, high performance, low cost
- Easy-use programming language helps GPU's popularity
- Difference between GPU and CPU
  - GPU supplement CPU, doesn't replace it. GPU doesn't need to perform all tasks of CPU
  - GPU problem size is MB to GB, not hundreds of GB.



### **GPU Architectures**

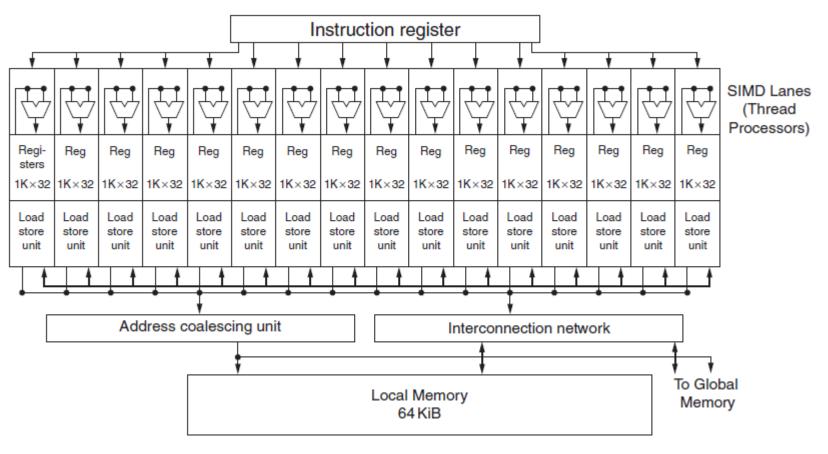
- Processing is highly data-parallel
  - GPUs are highly multithreaded, 16-32 threads
- GPU memory oriented towards bandwidth rather then latency
  - Graphics memory is wide and high-bandwidth
  - GPU memory is smaller than CPU. 4-6GB, instead of 256GB or above
    - Less reliance on multi-level caches
- Trend toward general purpose GPUs
  - Heterogeneous CPU/GPU systems
  - CPU for sequential code, GPU for parallel code
- Programming languages/APIs
  - DirectX, OpenGL
  - C for Graphics (Cg), High Level Shader Language (HLSL)
  - Compute Unified Device Architecture (CUDA)





## Block Diagram of a SIMD processor in GPU

A GPU consists of multiple multi-thread SIMD processors





## **Concluding Remarks**

- Goal: higher performance by using multiple processors
- Difficulties
  - Developing parallel software
  - Devising appropriate architectures
- From multicore to data centre
- Performance per dollar and performance per Joule drive both mobile and WSC



### **Summary for this course**

- Digital logic → computer organization → operating system/embedded system
- Main content:
  - Processor
  - Memory
  - Parallel
- Hardware thinking is important: resource tradeoff