

Future of Computing I: Diverging Computer System Design

15-213/18-213/15-513/18-613: Introduction to Computer Systems
28th Lecture, April 28, 2020

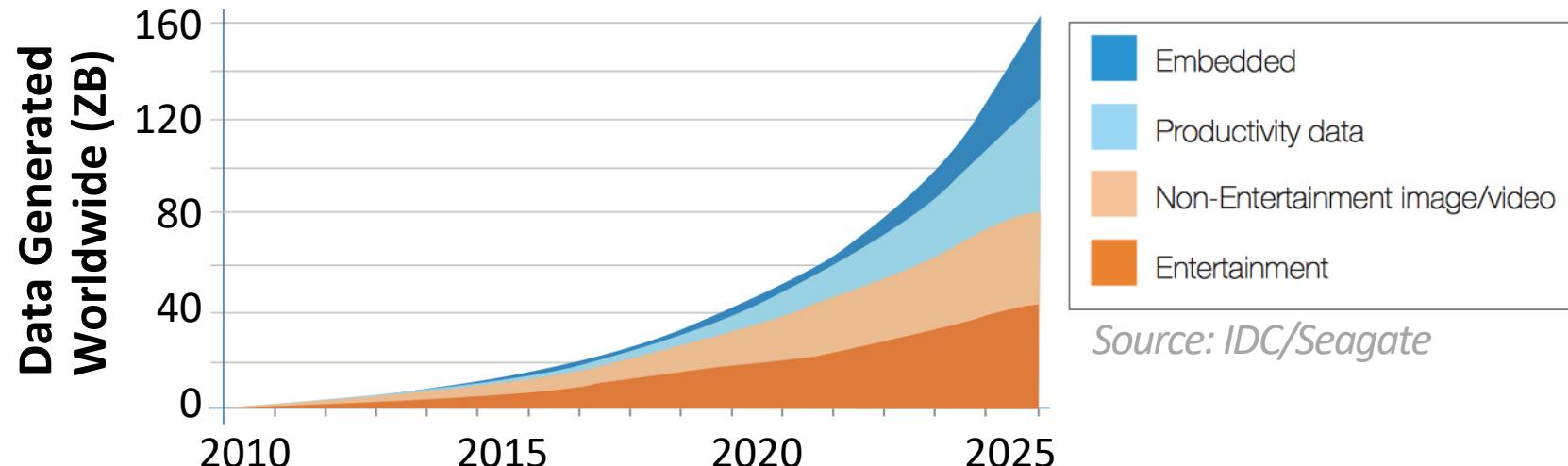
The Proliferation of Computing

■ Before 2000

- Personal computers: desktops (more predominant) and laptops
- Servers: delivered mostly static web pages (limited PHP/Perl/ASP)

■ Today

- Smartphones/tablets greatly outnumber desktops and laptops
- Servers and the cloud provide and store changing content
- Big data revolution: amount generated is growing exponentially



One-Size-Fits-All Is Going Away

- **Computers have very different needs and target metrics**
 - Used to be just performance
 - Power/energy matter greatly now
- **Specialization can help cut down energy**
 - Mobile devices use systems-on-chip (SoCs)
 - Servers use highly-multithreaded CPUs
- **x86 is no longer the dominant ISA**
 - Recall: RISC vs. CISC from the first machine programming lecture
 - ARM ISAs (which are RISC) are now used in the vast majority of mobile devices
 - x86 (which is CISC) still reigns supreme in servers, desktops, laptops

Computer System Design is Diverging

- **Several types of systems are becoming popular**
 - Graphics processing units (GPUs)
 - Mobile systems-on-chip (SoCs)
 - Data centers and cloud computing
 - Internet of things (IoT)/edge computing
- **A few promising designs may emerge in the future**
 - Processing-in-memory (PIM)
 - Neuromorphic computing

Computer System Design is Diverging

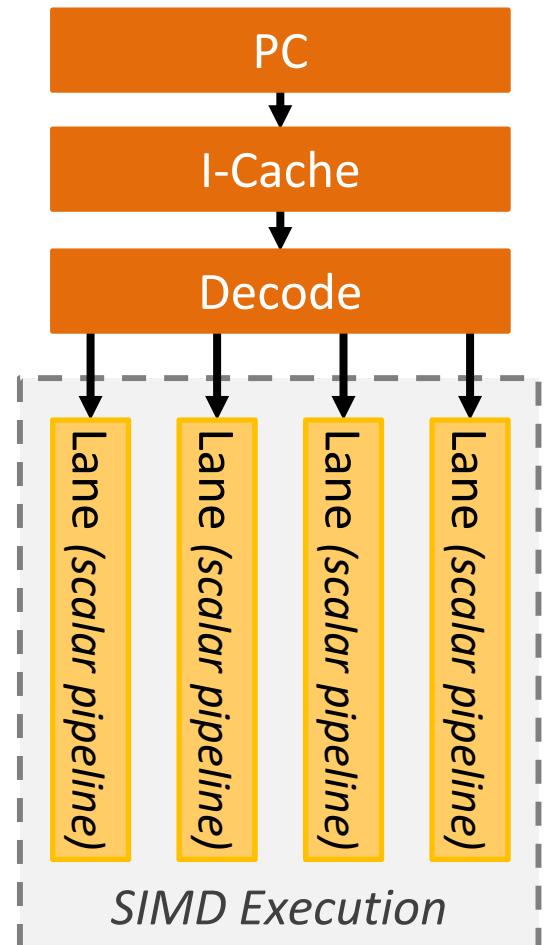
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How Do We Run Thousands of Threads?

- CPUs become increasingly inefficient
 - Small number of cores: need thousands of context switches
 - Large number of cores
 - Lots of hardware and power need to be used
 - How do we handle consistency and snooping?
- One option: **SIMT (single instruction, multiple thread)**
 - Run multiple copies of a single thread in **lockstep** (they all execute the *same* instruction at the *same* time) on different pieces of data
 - Programs use the **multithreaded** programming model (a.k.a. **single program, multiple data** or **SPMD**), but there are **key differences** from the multithreading you are used to

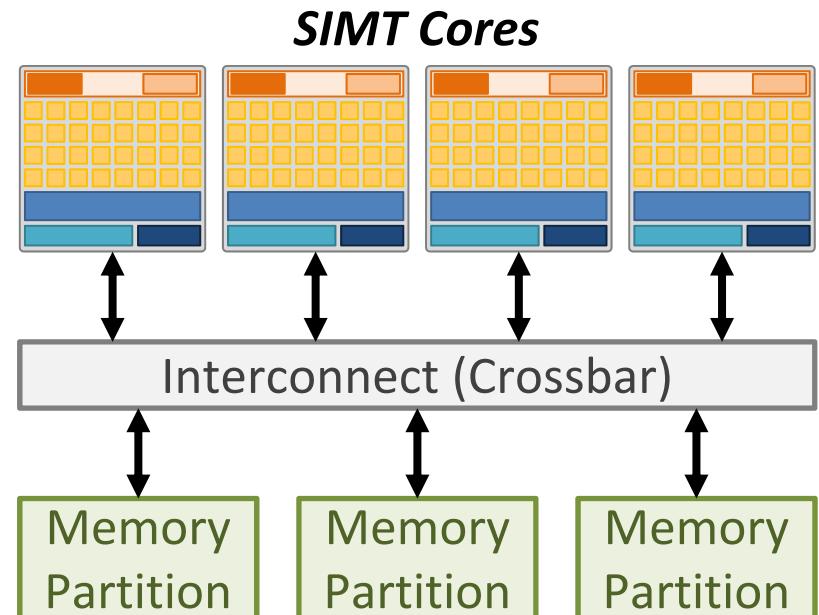
How to Implement SIMT

- Write a program using threads
 - Each thread executes the same code but operates on a different piece of data
 - Each thread has its own context (i.e., can be treated/restarted/executed independently)
- Group threads together dynamically (i.e., in hardware)
 - A group is known as a warp or a wavefront
 - Essentially a vector formed by hardware
- SIMT processors can share common control flow logic for a warp across a number of scalar execution lanes (one lane per thread)



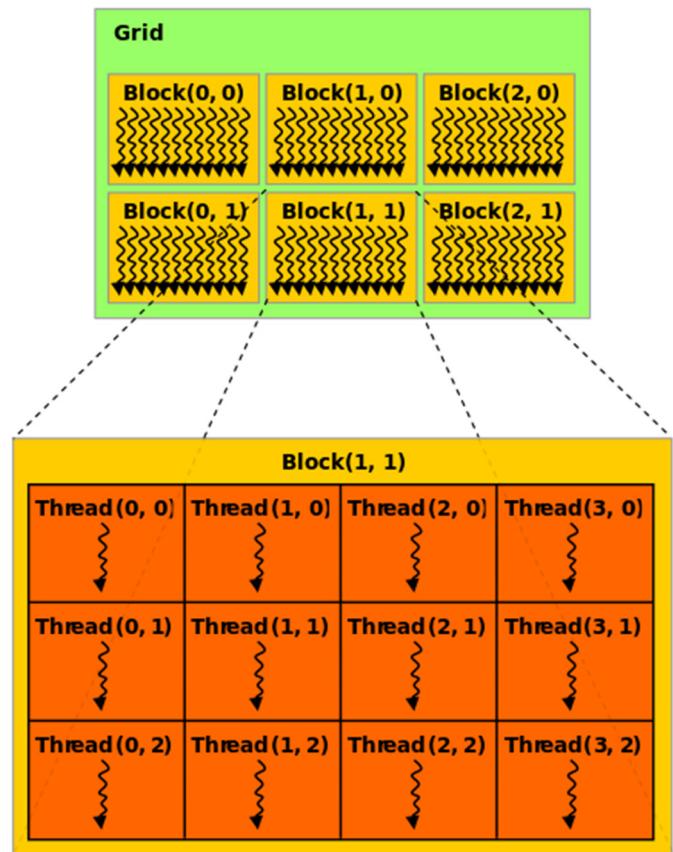
Graphics Processing Units (GPUs)

- A cluster of SIMT cores (known as SMs or shaders) that share a memory hierarchy
- Each SIMT core operates on one or more warps
- Original purpose was for graphics workloads
 - Designed to operate in parallel on thousands of pixels/vertices/fragments
 - Used to have special cores for each step of the graphics pipeline
 - SIMT cores now general purpose enough to execute all graphics pipeline stages (generically called a shader core)
- Now also used for general-purpose GPU (GPGPU) programming



Using a GPU: Program

- All terms here based on NVIDIA CUDA
- Basic unit of programming: **kernel**
 - A piece of code that can be run in parallel
 - A program consists of multiple kernels
 - Each kernel is assigned to a **grid** of threads
- Basic unit of execution: **thread block**
 - A group of threads that can be executed in parallel
 - Thread block is limited to 1024 threads
 - Multiple blocks (of the same thread count) can be combined to form a grid
- Kernels and thread blocks are managed by a **software runtime**



Using a GPU: Execution Flow

- 1. Host (i.e., CPU) sends a request to the GPU runtime to start a program**
- 2. Runtime copies memory from host address space to the GPU address space (separate memory in discrete GPUs)**
- 3. Runtime allocates per-thread resources (e.g., registers, scratchpad)**
- 4. GPU executes each kernel in the program**
- 5. Runtime copies results from GPU address space to host address space**

Common Issues in GPUs

■ Sharing memory with the CPU is challenging

- GPU has its own physical memory and address space
 - Not managed by the OS!
 - Requires program to copy data between the CPU and GPU
- **Unified Virtual Memory**
 - Shared address space between the CPU and the GPU
 - No more need to copy data back and forth
 - Big issue: coordinating virtual-to-physical page mappings

■ Thread divergence makes lockstep execution inefficient

- Each thread can have control flow instructions (e.g., branches)
- **Branch divergence** occurs when threads inside a warp branch to different execution paths
- **Memory divergence** occurs when some threads hit in a cache and others must go to main memory

Resource Allocation and Program Portability

- GPUs have several resources that must be allocated
 - Programmer dictates the resources needed per thread
 - Runtime simply provides what each thread/warp needs until it cannot fit any more threads on the SM
- How does a programmer know how to allocate resources?
 - Performance tuning: for each GPU architecture, test out different resource allocations and assign the best one
 - GPU architectures tend to keep the ratio of resources per warp context/per SM constant within a GPU generation
- Requires retuning every time a program is ported to a different architecture
- Auto-tuning tries to automate resource allocation (with mixed results)

Heterogeneous Computing

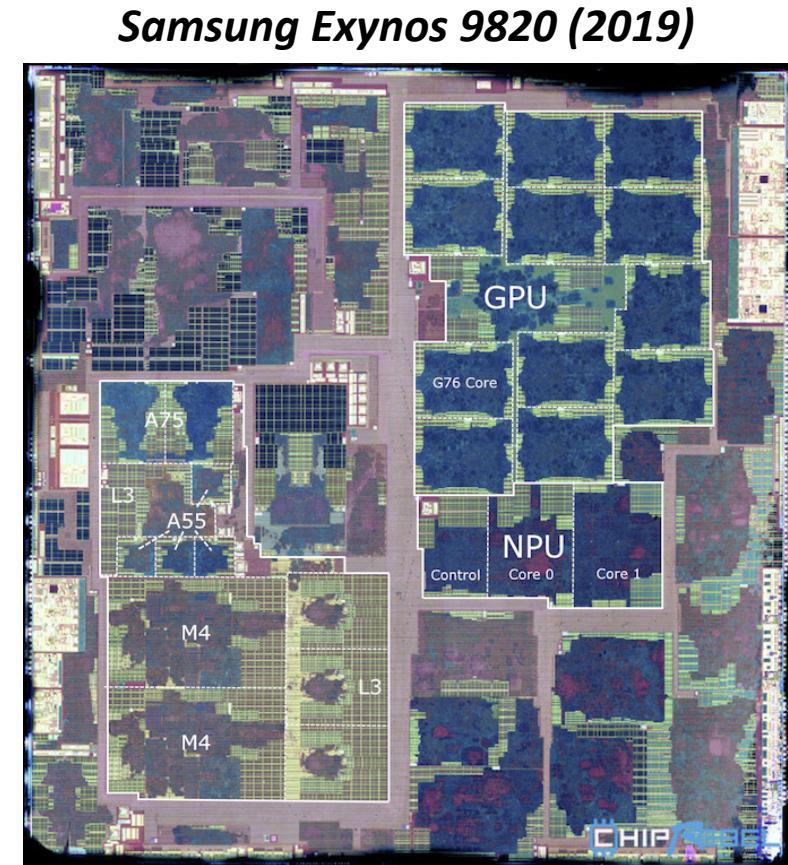
- While GPUs can help with massive multithreading, they clearly have their own challenges
- Reality: different types of compute require different types of hardware and systems
- Today: heterogeneous computing reigns supreme
 - CPUs handle more traditional workloads
 - GPUs handle highly parallel programs and graphics
 - Other hardware accelerators are designed for very common tasks
- We could just have separate chips for each...
- ... But today we put them all into a single **system-on-chip (SoC)**

Why a System-on-Chip?

- **There used to be separate chips for almost everything**
 - Floating-point units (e.g., the Intel x87)
 - Caches
 - Memory and I/O controllers
 - Discrete modems and accelerators (if present)
- **A few fundamental changes have made it more desirable to combine these on a single chip**
 - Smaller communication distances: faster latencies, higher bandwidth, and lower energy
 - Better use of the available transistors and chip area
- **CPUs integrated some, but not all, units (e.g., FPUs, caches, memory controllers) over the last few decades**
- **1970: the first SoC (used by Pulsar for the first digital watch)**
- **Mid-2000s: SoC development led to the smartphone revolution**

Common System-on-Chip Components

- Processor cores
- Graphics processing units (GPUs)
- Caches (L1/L2/L3 today)
- Digital signal processors (DSPs)
 - Accelerators that perform signal processing operations for sensors, multimedia processing
 - Often made up of vector extensions
- Networking modems
(e.g., WiFi, 4G LTE)
- AI/ML accelerators
(i.e., neural processing units)
- On-chip interconnect



Source: AnandTech/Chip Rebel

How Do We Use an SoC?

- **Each SoC can have a different set of components**
- **Before: one fixed set of resources, then write software for them**
- **Now: software informs the hardware design!**
 - Start with basic structures (e.g., CPU, cache, GPU)
 - Analyze software to find most common operations/tasks
 - Define an SoC architecture (using basic structures, premade blocks known as IP cores, and custom-designed logic)
 - Optimize your software for your SoC
- **System design can be challenging**
 - How do we manage and coordinate all of these components?
 - Burden often left on the systems programmer
 - Runtimes or APIs are commonly used by application developers

SoCs Have Helped Move Us to the Cloud

■ Traditional model

- Compute everything locally
- Worked great for small-data workloads of the past
- Difficult to shrink the size of a computer (e.g., an SoC)

■ Today: data centers and cloud computing

- Your computer sends a request across the network
- Giant “farms” of computers perform a significant portion of the computation
- Result is sent back to your computer
- A key enabler of smartphones
- These farms typically service billions of requests each second (think Google or Facebook)
- Requires highly-available, reasonably fast network



Cloud Computing vs. Data Centers

■ Data center

- The company providing a service owns and maintains its own servers for the service (or pays someone to do so)
- Machines are dedicated for that company
- Can (but don't always) run code natively

■ Cloud computing

- The company providing a service runs the service on someone else's servers
- Machines are shared across many companies and services
- Typically use **virtual machines** (VMs) or **containers** to allow multiple services to run on a single server without having access to each other's data, and to allow for job migration
- Examples: Amazon AWS, Microsoft Azure, Google GCP

Running Programs in the Cloud

- You wrote a program for OS G, but the cloud runs OS H 😞
- Virtual machines let you run your program inside OS H!
 - System virtual machines (i.e., full virtualization)
 - Hypervisor runs inside OS H (the host OS), provides an interface to emulate all of the hardware
 - OS G (the guest OS) runs inside the hypervisor, and *thinks* it is running directly on a machine (the one faked by the hypervisor)
 - Lots of overhead (e.g., 4-level page tables can require as many as 24 memory accesses!)
 - Process virtual machines (i.e., managed runtime environments)
 - Create a platform-independent environment for programs
 - Examples: Java VM, .NET framework
- Containers: one OS can run multiple isolated kernels

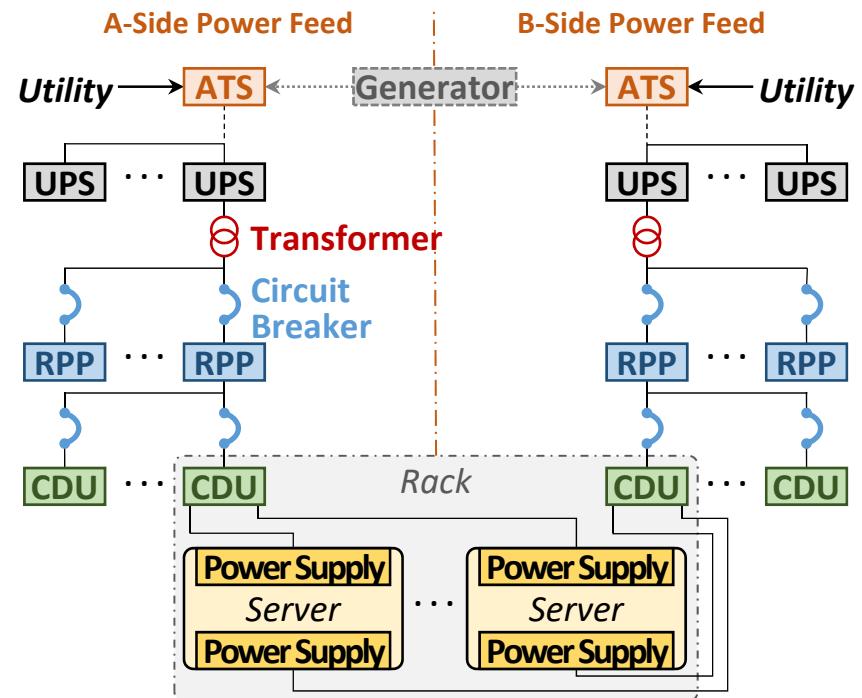
Data Centers Require Significant Power

- Globally, data centers consume 3% of the world's total power in 2017

- 2% of global emissions
- Projected to be as much as 20% by 2025

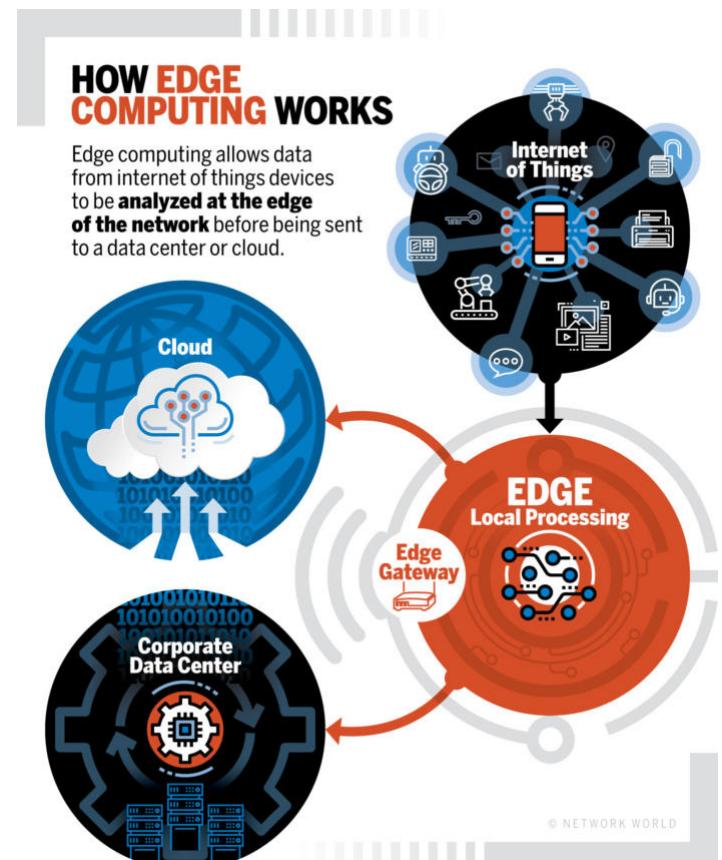
- Need to be efficient but reliable

- Redundant power feeds and infrastructure
- Load varies from day to day, and minute to minute in a day: data centers need to be overprovisioned, and must adjust based on the current load



Bringing Back Local Compute

- Large amounts of data sent to the cloud
- What if our devices could be smart and process (some of the) data for us?
- Internet of Things (IoT)
 - A very wide, distributed network of devices that can all talk with each other
 - Many IoT devices are simpler than smartphones (e.g., smart sensors) – designed to be deployed everywhere
- Edge computing
 - Cloud computing + IoT model pushed almost all compute from a smartphone to data centers
 - Now we're pushing back, because the Internet can't scale as rapidly as data: bandwidth limited, energy hungry



Source: Network World

Rethinking the Computer

- Today's computers are built off of assumptions made going back to the 1940s
 - Spatial/temporal locality
 - Instruction-based computation
 - Today's levels of abstractions
- Applications and use cases have changed significantly
 - Machine learning and data analytics
 - IoT and edge computing
 - Drones and autonomous vehicles
 - Precision medicine and bioinformatics
 - Mobile apps
- Shouldn't our computers change as well?

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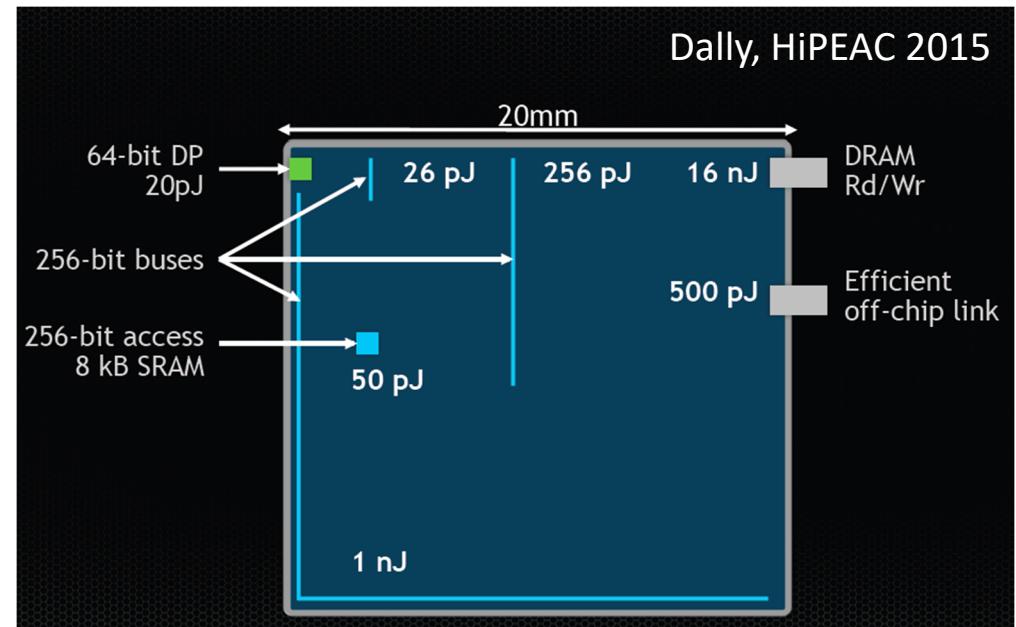
Hardware Hasn't Kept Up with the Times



- **Beefy processing engines (CPUs, GPUs, accelerators)**
 - Large numbers of cores, high degrees of multithreading
 - Out-of-order execution in CPUs
 - Many low-power optimizations
- **Designed for infrequent memory accesses**
 - Caches highly dependent on locality
 - Long, narrow off-chip memory channel to connect CPU with DRAM
- **While programs are becoming more data-centric, computer architectures remain compute-centric**

The Cost of Data Movement in Modern CPUs

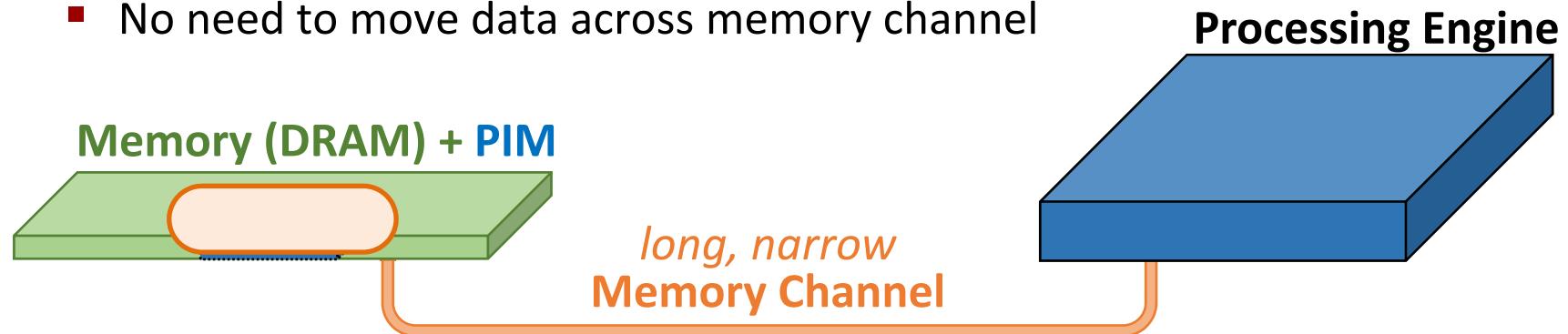
- In terms of energy costs, data movement dominates compute
- DRAM responsible for 25–50% of a computer's total energy
- Off-chip memory channel: ~30% of DRAM energy
- Data movement is a major bottleneck in modern systems
 - High energy spent on off-chip communication
 - Pin-limited bandwidth
 - High latency
 - Identified as the **von Neumann bottleneck** by Jim Backus in 1977



Can We Avoid Moving Data Around?

■ Processing-in-memory (PIM)

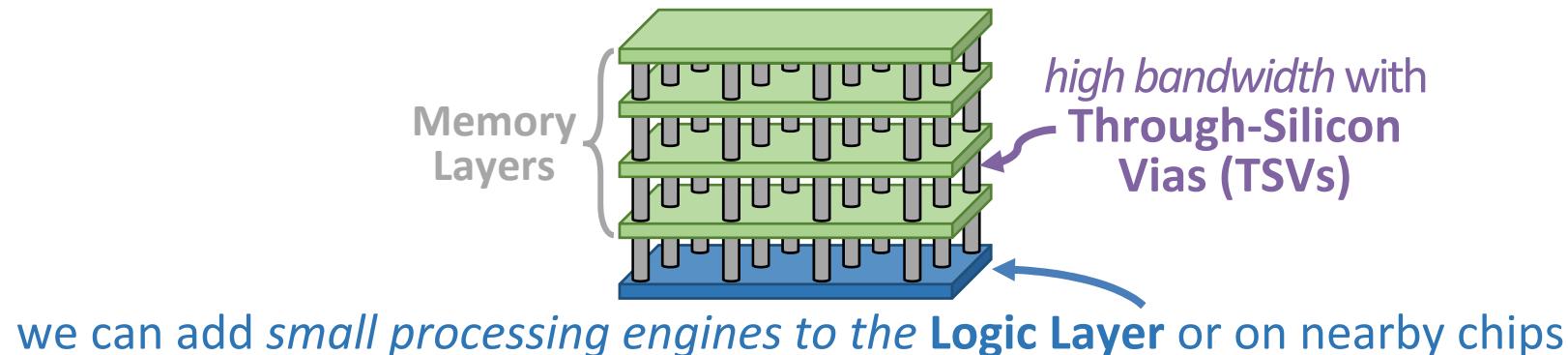
- Add some compute capability to memory
- No need to move data across memory channel



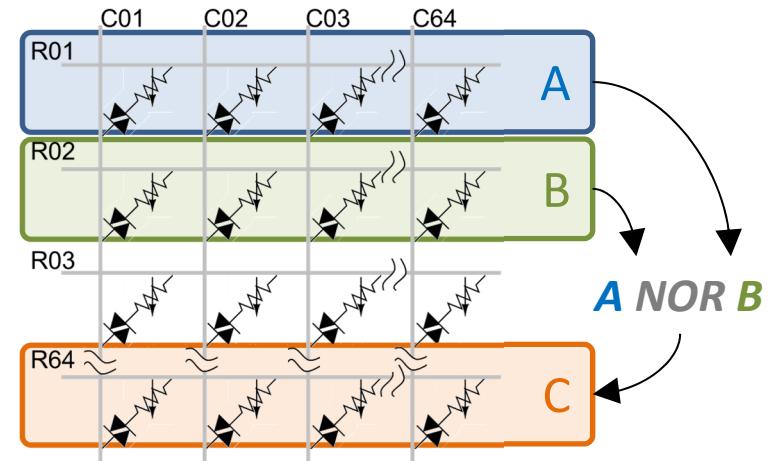
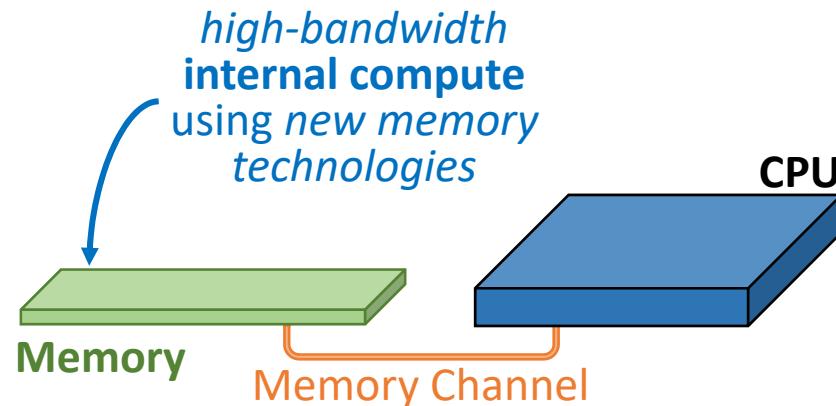
- PIM has been proposed as early as 1970
- New innovations in memory design have finally brought PIM close to a reality
- Kind of like an SoC: add new components/functionality, but this time near memory

Two Variants of PIM

■ Variant 1: Processing-Near-Memory



■ Variant 2: Processing-Using-Memory



Great... How Does This Affect Systems?

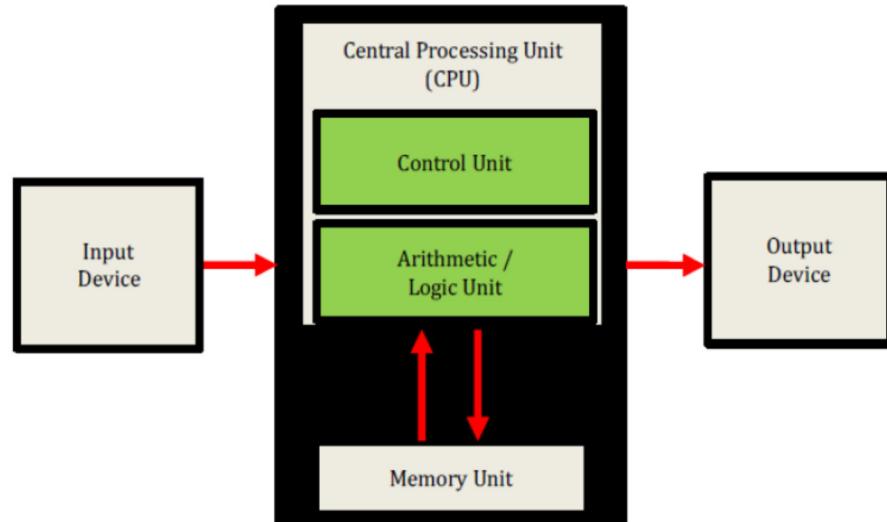
- Once PIM hardware exists, programmers must be able to use it
 - Tough sell: force them to **learn a new programming model**
 - Path to broad adoption: **adapt PIM to existing models**
- Unfortunately, PIM logic can't easily make use of a lot of systems essentials
 - Support for multithreading: OS needs to be exposed to PIM
 - Virtual memory: expensive for PIM to access TLBs in the CPU
 - Coherence/consistency: these can introduce a lot of traffic between the CPU and PIM
- How do compilers generate code for PIM logic?
- What about handling branches?
- Active research area: solving these challenges in the coming years

Motivating Neuromorphic Computing

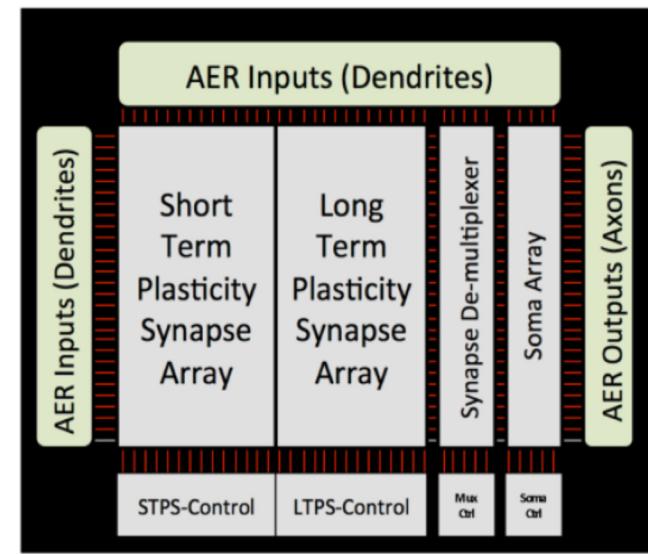
- **Artificial neural networks are the hot stud of computing now**
 - Forms implicit relationships between inputs and outputs
 - Can learn and represent very powerful models
 - However, ANNs are *not* accurate representations of our brain
- **What can our brain do?**
 - We can track things moving in real time as we see them
 - We can learn with uncertainty (ANNs need to experience everything)
 - And yet our brain runs at only a few Hz (vs. GHz for ANN accelerators)
- **Many applications can benefit from designing computers that look more like our brain**

Neuromorphic Architectures

von Neumann Architecture



Neuromorphic Architecture



Source: US DOE Report

- Several chips exist: IBM TrueNorth, Intel Loihi
- How do you use this?
 - Replace CPUs in existing systems? Add as accelerators?
 - IBM made its own object-oriented language (Corelet)

Summary

- **Computing is looking more and more heterogeneous**
 - Many different types of hardware
 - Many different types of use cases
- **There may be more radical hardware changes ahead**
 - Keeping up with significant shifts in applications
 - We need to think of what systems support will look like after these changes!
- **Does it mean that what you've learned in 213 is useless?**
 - No! Most of the core ideas will still stick around for decades
 - New systems are still built on the same underlying principles
- **It's an exciting time to be working in systems!**