GPUs

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CS 3410, Spring 2015
Computer Science
Cornell University

Announcements

Project3 Cache Race Games night Monday, May 4th, 5pm

- **Come, eat, drink, have fun and be merry!**
- **Location: B17 Upson Hall**

Prelim2: ***Thursday***, April 30th in evening

- Time and Location: ***7:30pm sharp*** in ***Statler Auditorium***
- Old prelims are online in CMS
- Prelim Review Session:

  TODAY, Tuesday, April 28, 7-9pm in B14 Hollister Hall

Project4:

- Design Doc due May 5th, bring design doc to mtg May 4-6
- Demos: May 12 and 13
- ***Will not be able to use slip days***

Announcements

Prelim2 Topics

- Lecture: Lectures 10 to 24
- Data and Control Hazards (Chapters 4.7-4.8)
- RISC/CISC (Chapters 2.16-2.18, 2.21)
- Calling conventions and linkers (Chapters 2.8, 2.12, Appendix A.1-6)
- Caching and Virtual Memory (Chapter 5)
- Multicore/parallelism (Chapter 6)
- Synchronization (Chapter 2.11)
- Traps, Exceptions, OS (Chapter 4.9, Appendix A.7, pp 445-452)

- HW2, Labs 3/4, C-Labs 2/3, PA2/3

- Topics from Prelim1 (not the focus, but some possible questions)

GPUs

The supercomputer in your laptop

GPU: Graphics processing unit

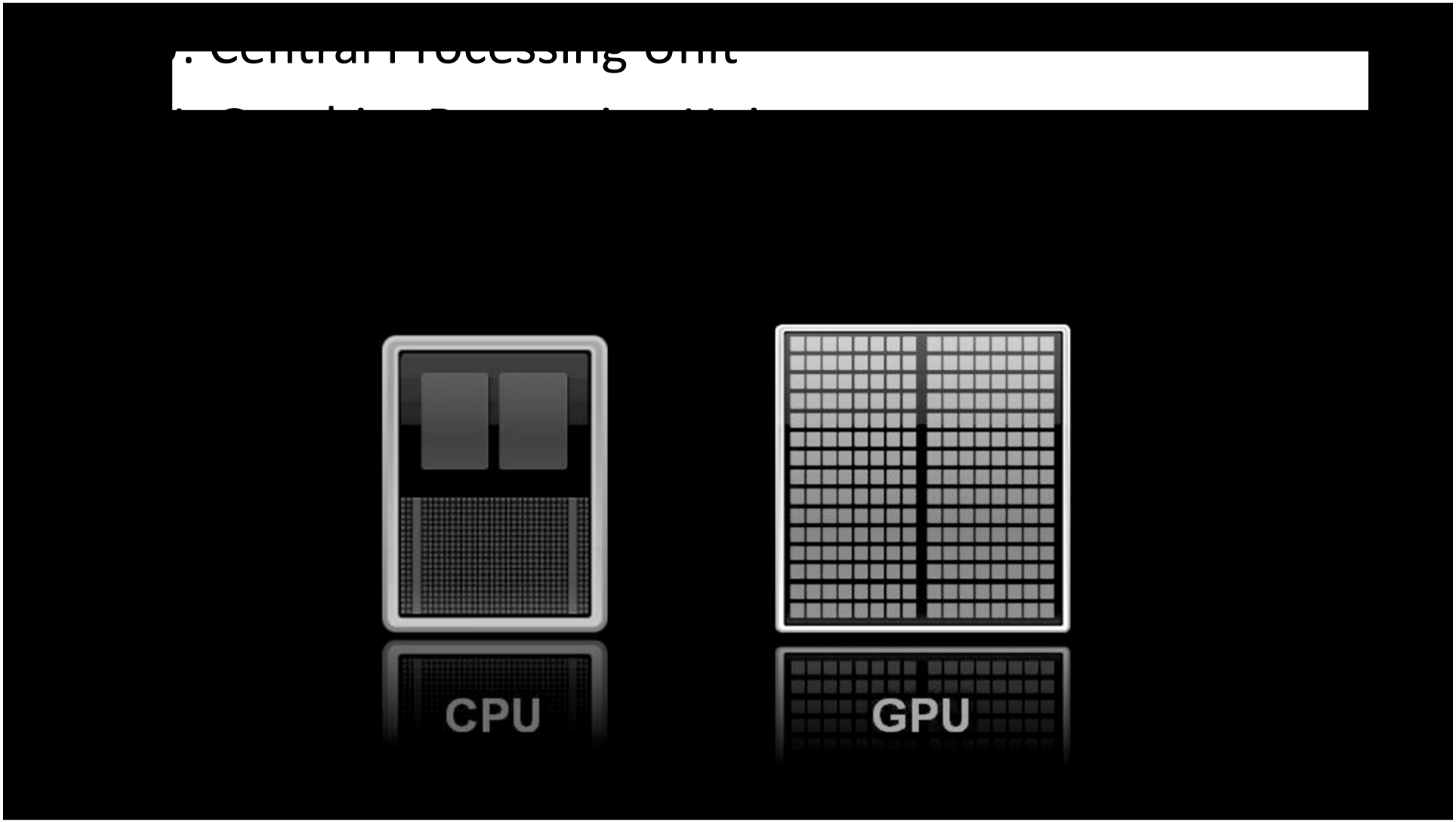
Very basic till about 1999

Specialized device to accelerate display

Then started changing into a full processor

2000-…: Frontier times

Parallelism



Parallelism

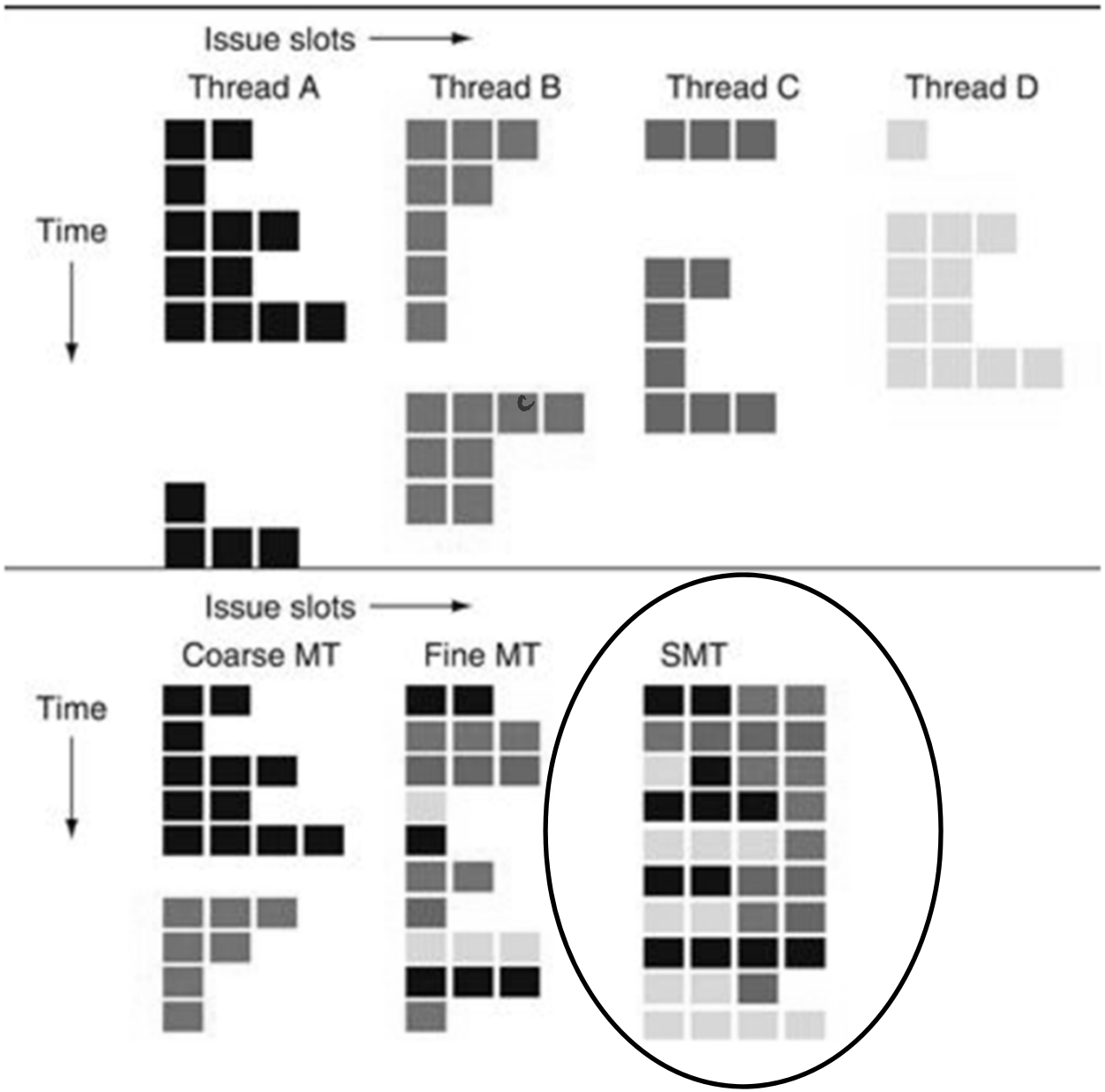
GPU parallelism is similar to multicore parallelism

Key: How to gang schedule thousands of threads on thousands of cores?

Hardware multithreading with thousands of register sets

GPU Hardware multithreads (like multicore Hyperthreads)

- MultiIssue + extra PCs and registers – dependency logic
- Illusion of thousands of cores
- Fine grain hardware multithreading - Easier to keep pipelines full


Issue slots
Thread A
Thread B
Thread C
Thread D
Time
Issue slots
Coarse MT
Fine MT
SMT
Time

GPU Architectures

Processing is highly data-parallel

- GPUs are highly multithreaded
- Use thread switching to hide memory latency
  - Less reliance on multi-level caches
- Graphics memory is wide and high-bandwidth

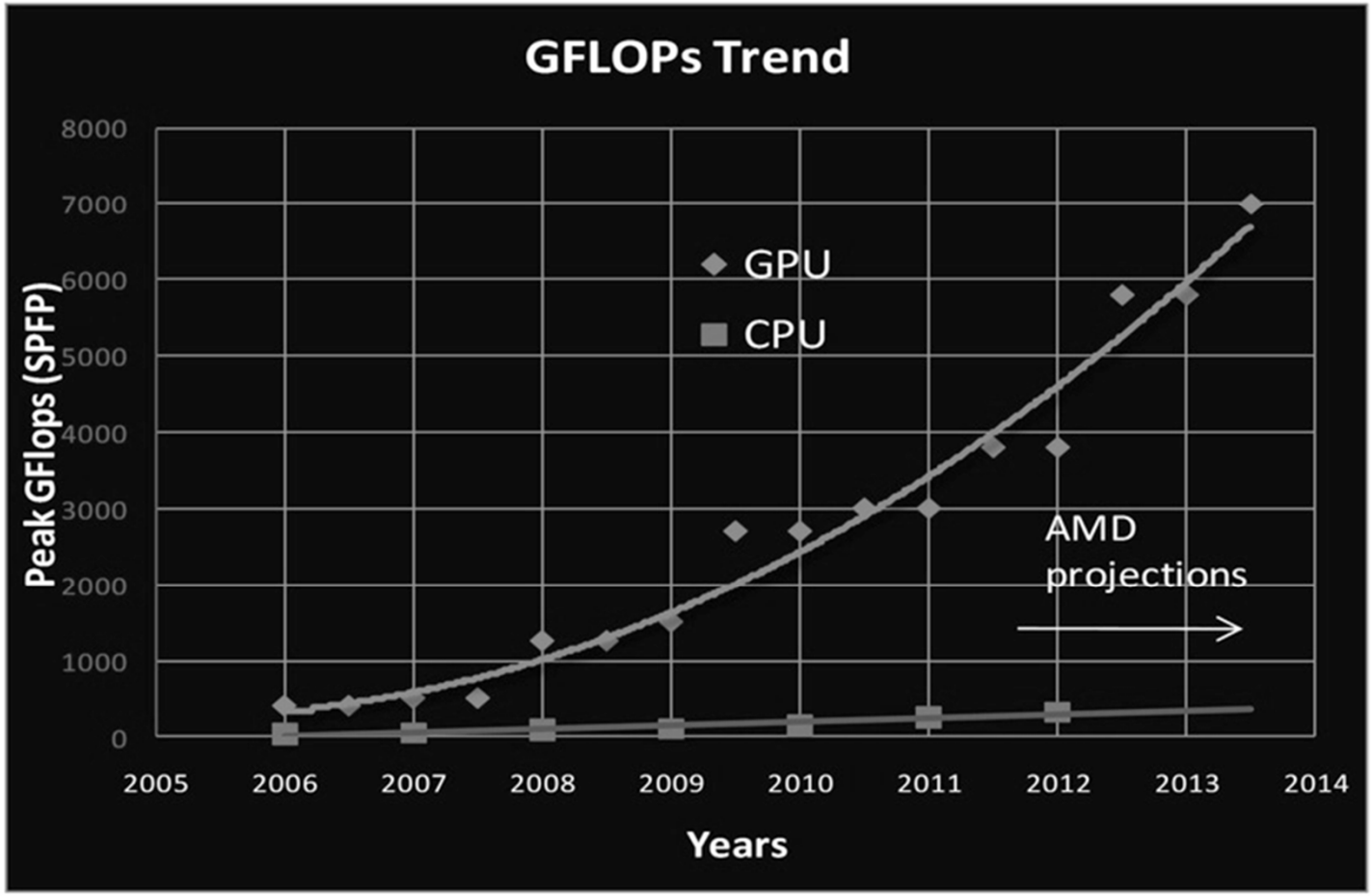
Trend toward general purpose GPUs

- Heterogeneous CPU/GPU systems
- CPU for sequential code, GPU for parallel code

Programming languages/APIs

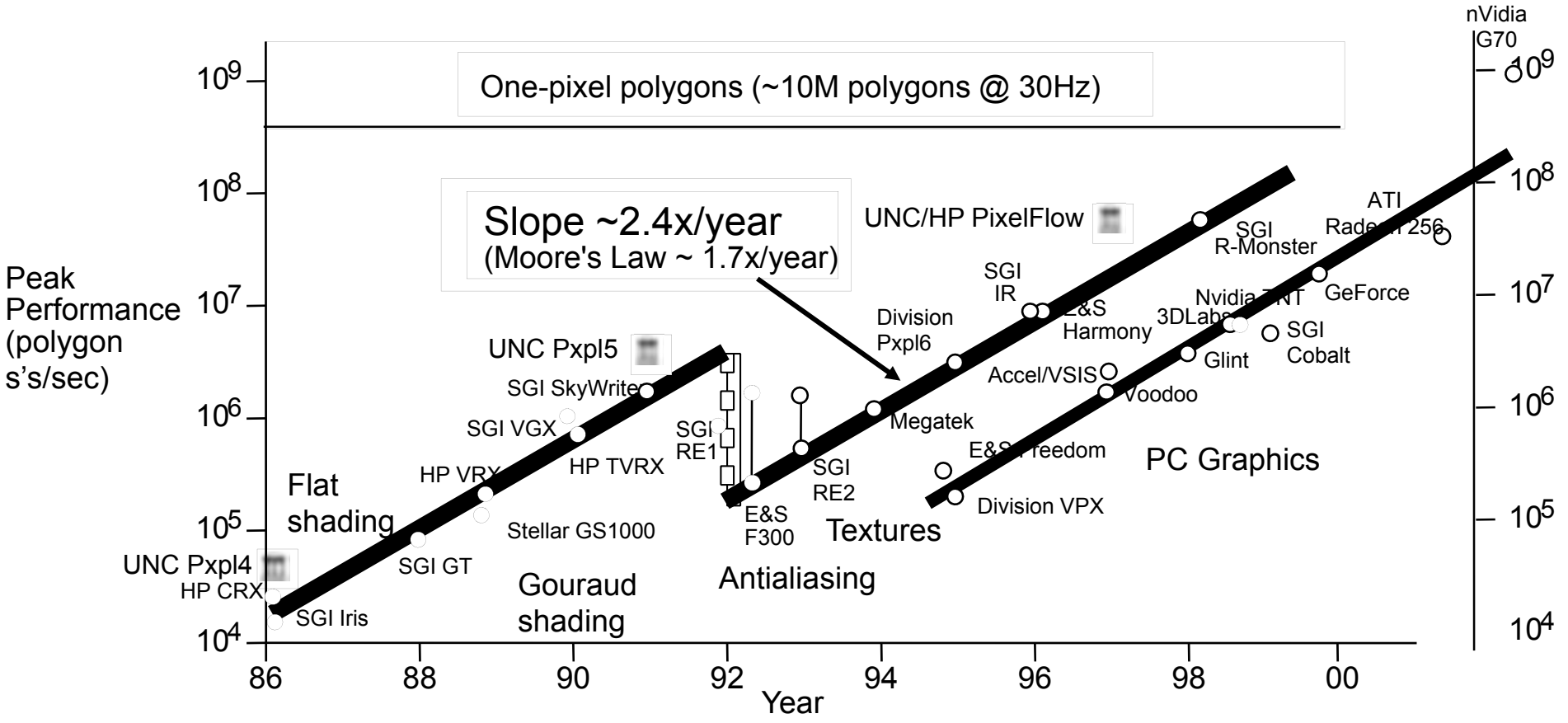
- DirectX, OpenGL
- C for Graphics (Cg), High Level Shader Language (HLSL)
- Compute Unified Device Architecture (CUDA)

GPU-type computation offers higher GFlops



(Source: Sam Naffziger, AMD)

GPUs: Faster than Moore's Law
Moore's Law is for Wimps?!

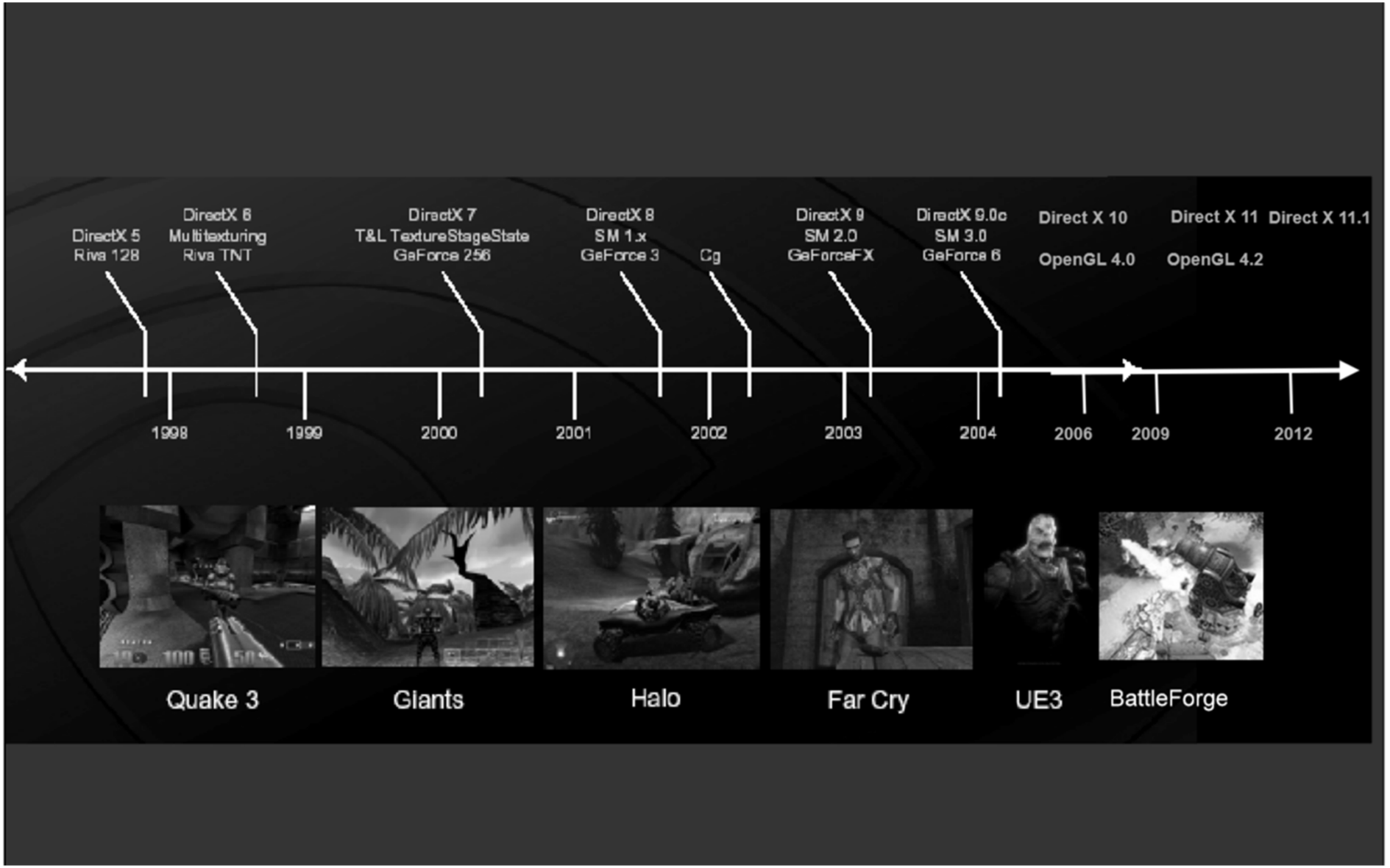


Graph courtesy of Professor John Poulton (from Eric Haines)

Programmable Hardware

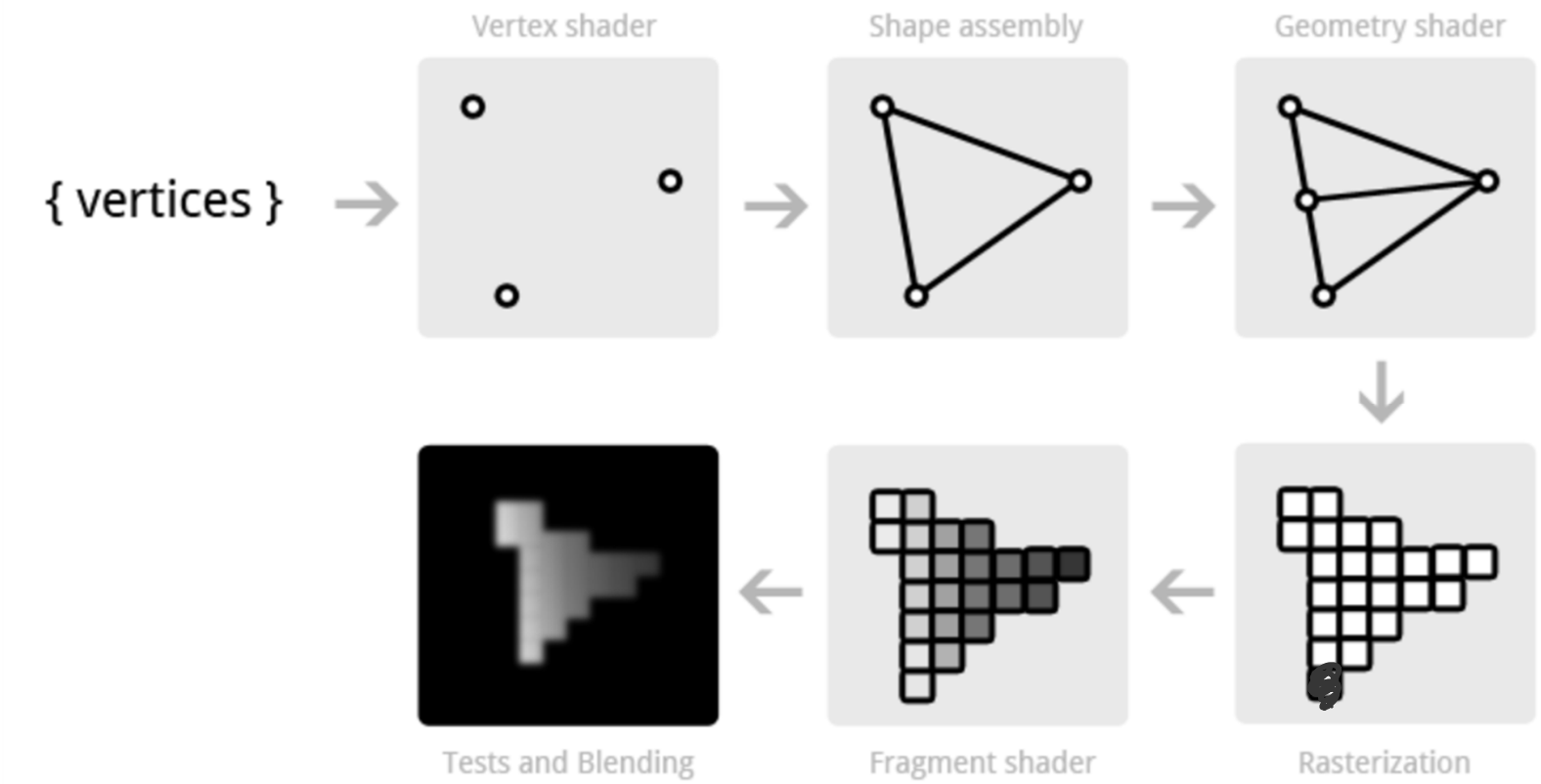
- Started in 1999
- Flexible, programmable
  - Vertex, Geometry, Fragment Shaders
- And much faster, of course
  - 1999 GeForce256: 0.35 Gigapixel peak fill rate
  - 2001 GeForce3: 0.8 Gigapixel peak fill rate
  - 2003 GeForceFX Ultra: 2.0 Gigapixel peak fill rate
  - ATI Radeon 9800 Pro : 3.0 Gigapixel peak fill rate
  - 2006 NV60: ... Gigapixel peak fill rate
  - 2009 GeForce GTX 285: 10 Gigapixel peak fill rate
  - 2011
    - GeForce GTC 590: 56 Gigapixel peak fill rate
    - Radeon HD 6990: 2x26.5
  - 2012
    - GeForce GTC 690: 62 Gigapixel/s peak fill rate

Evolution of GPU



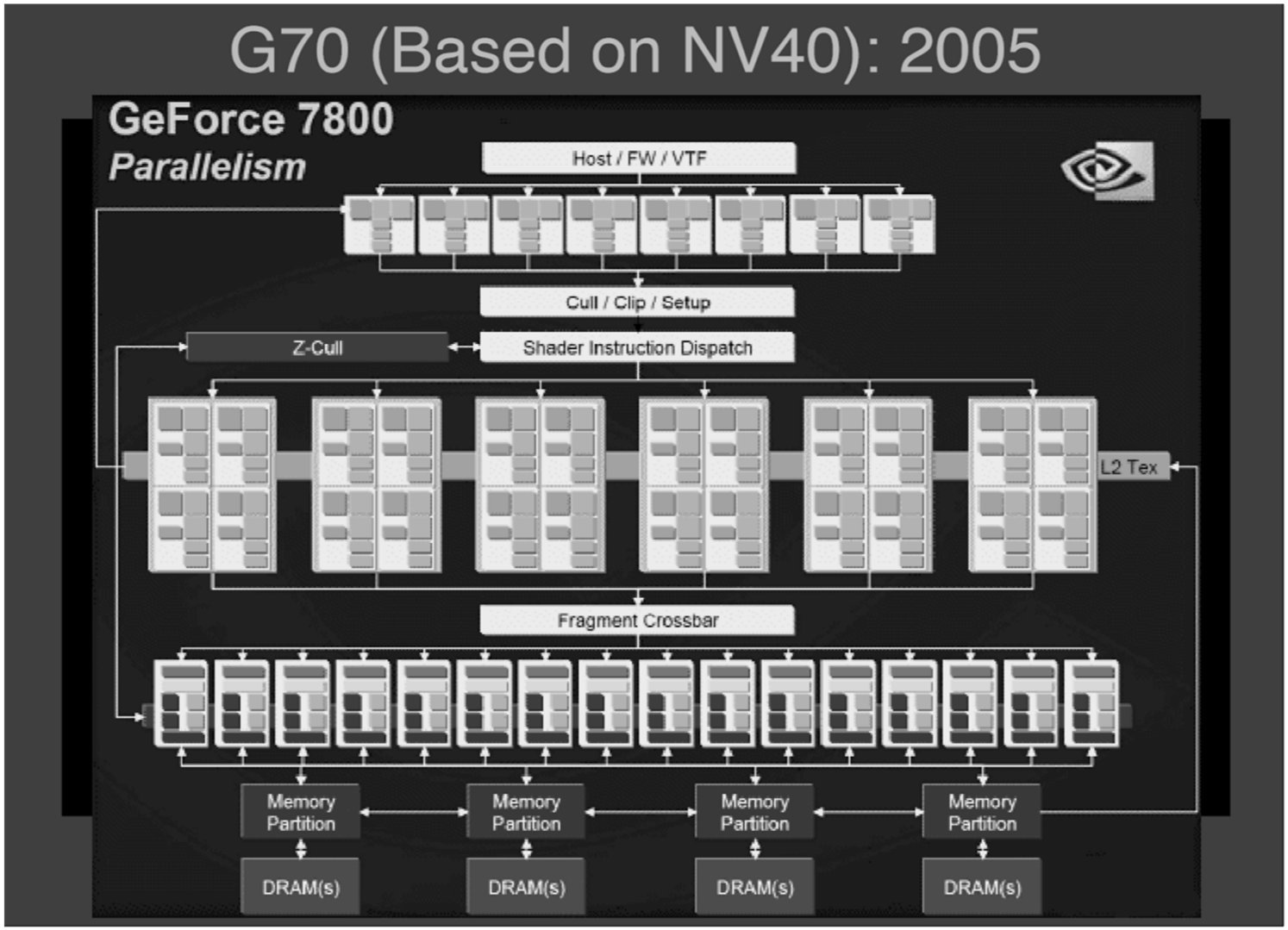
Around 2000

Fixed function pipeline

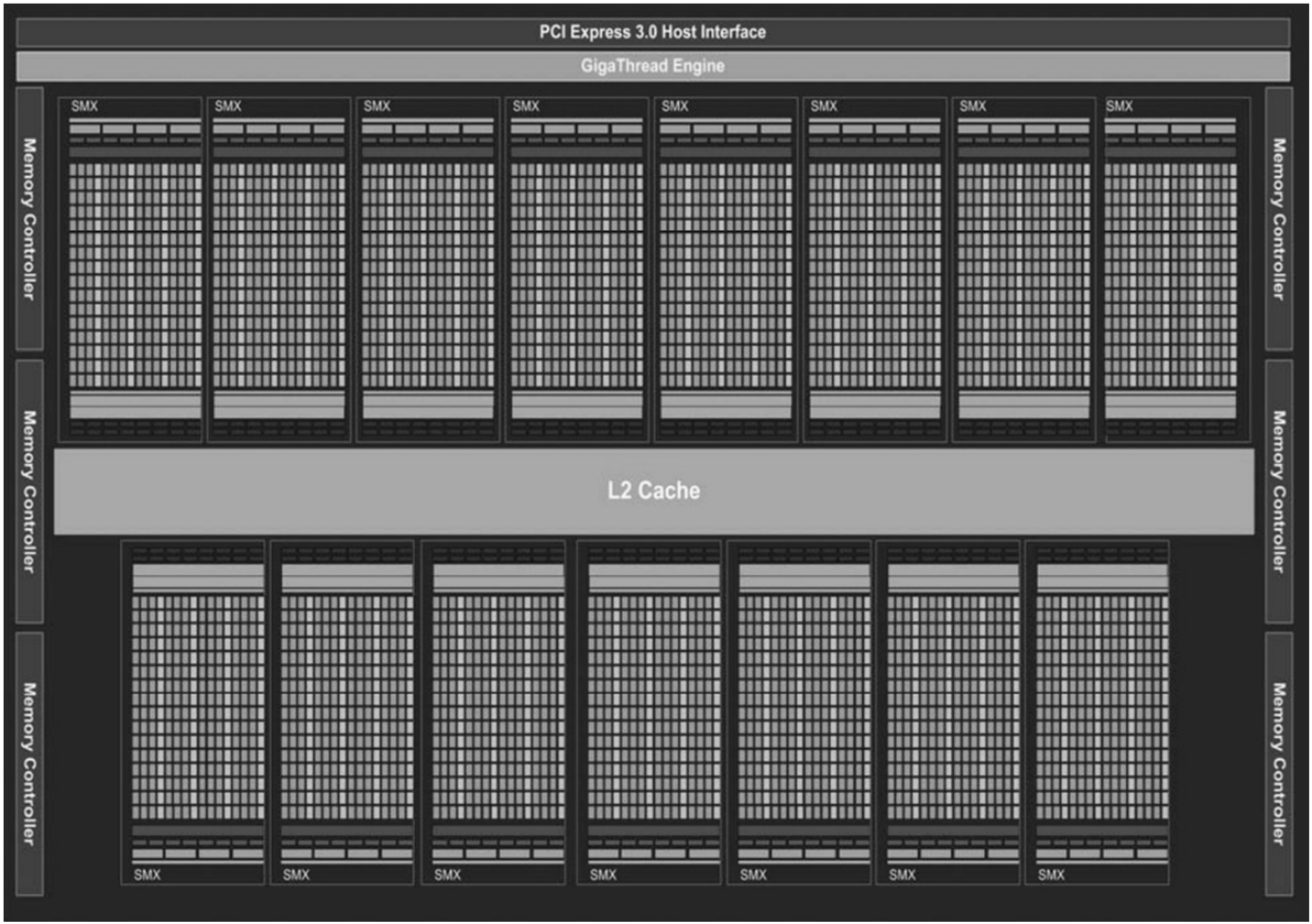


Around 2005

Programmable vertex and pixel processors



Post 2006: Unified Architecture



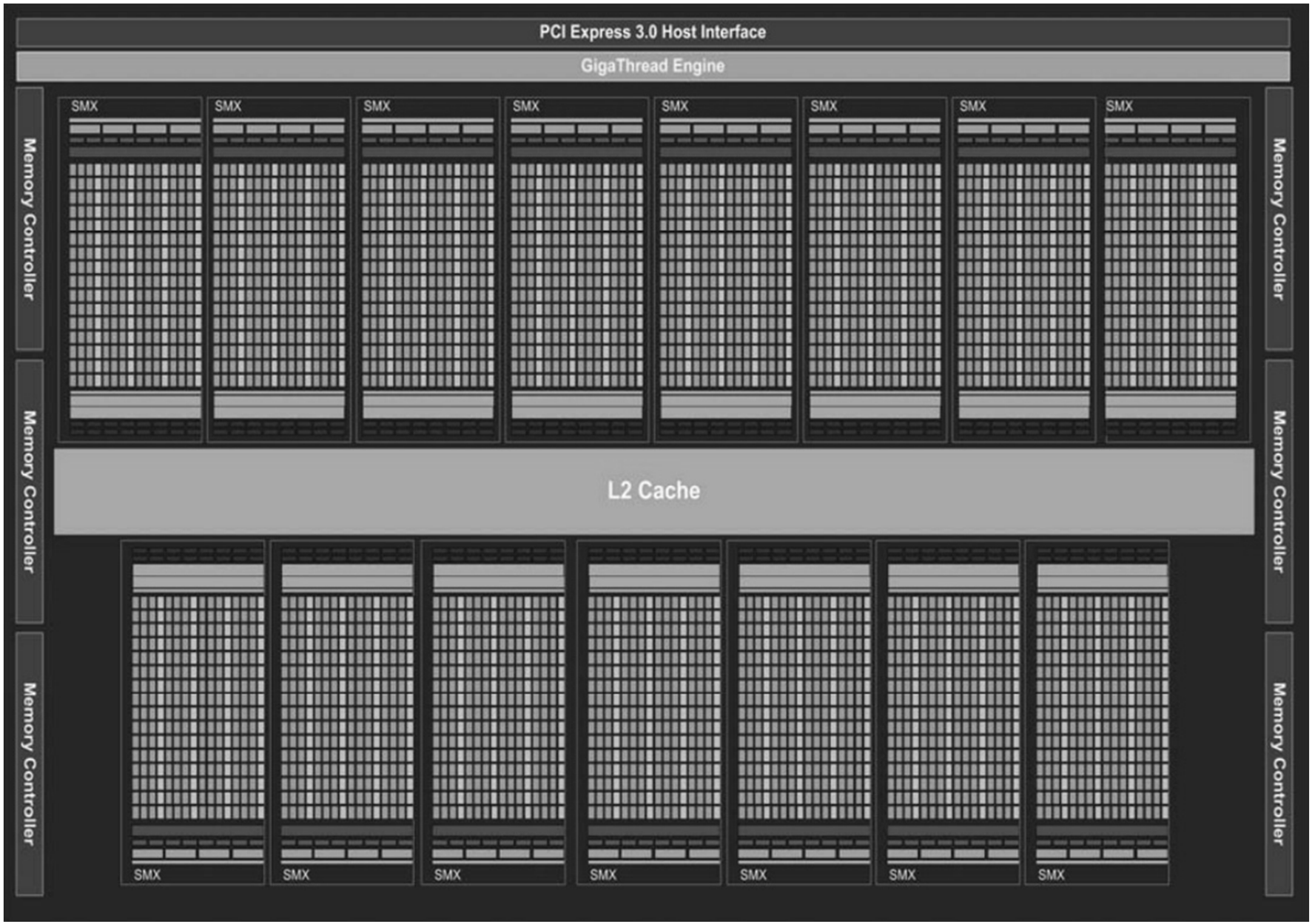
Why?

- Parallelism: thousands of cores
- Pipelining
- Hardware multithreading
- Not multiscale caching
    - Streaming caches
- Throughput, not latency

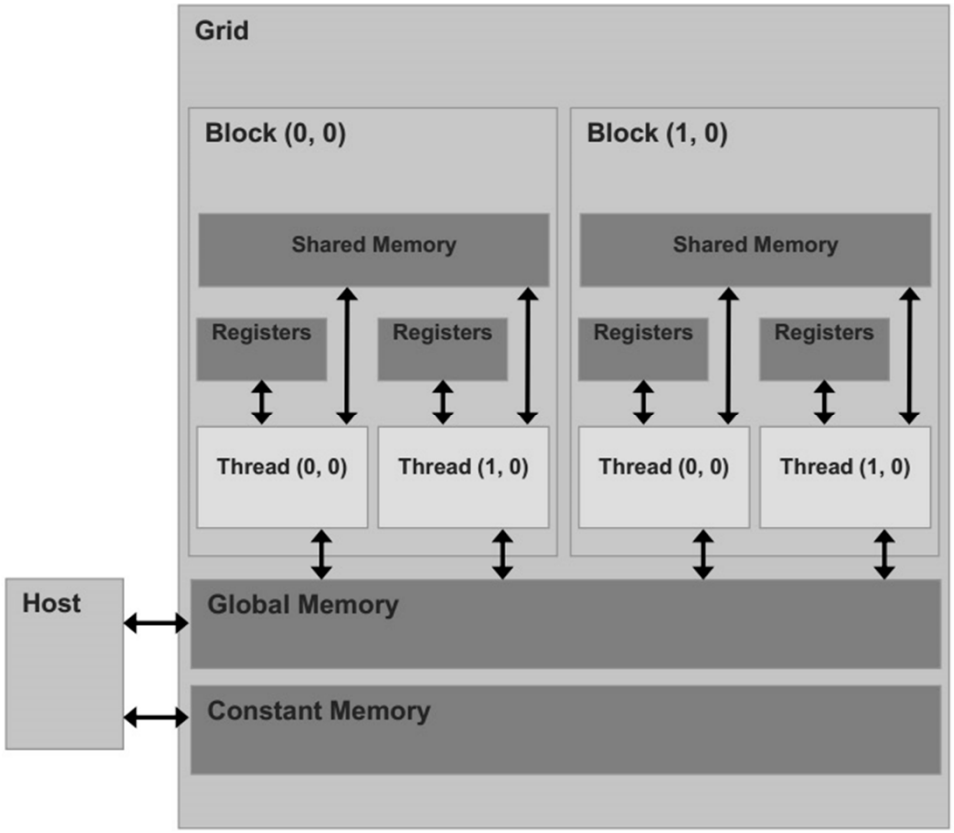
Flynn's Taxonomy

Single Instruction Single Data (SISD)	**Multiple Instruction Single Data (MISD)**
Single Instruction Multiple Data (SIMD)	Multiple Instruction Multiple Data (MIMD)

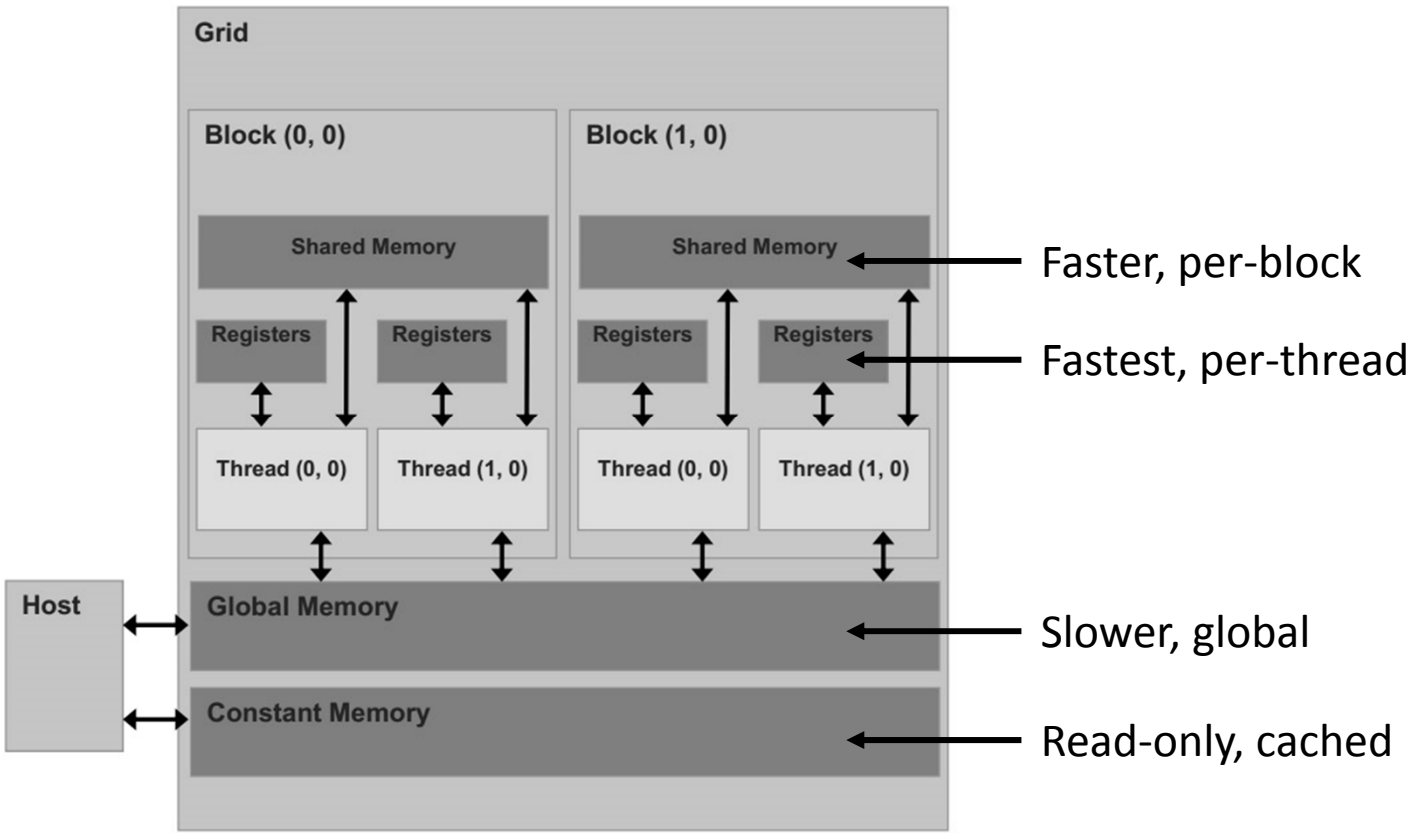
MIMD array of SIMD procs



Grids, Blocks, and Threads



CUDA Memory


Grid
Block (0, 0)
Block (1, 0)
Shared Memory
Shared Memory
Registers
Registers
Registers
Registers
Thread (0, 0)
Thread (1, 0)
Thread (0, 0)
Thread (1, 0)
Host
Global Memory
Constant Memory
Faster, per-block
Fastest, per-thread
Slower, global
Read-only, cached

Heterogeneous Computing

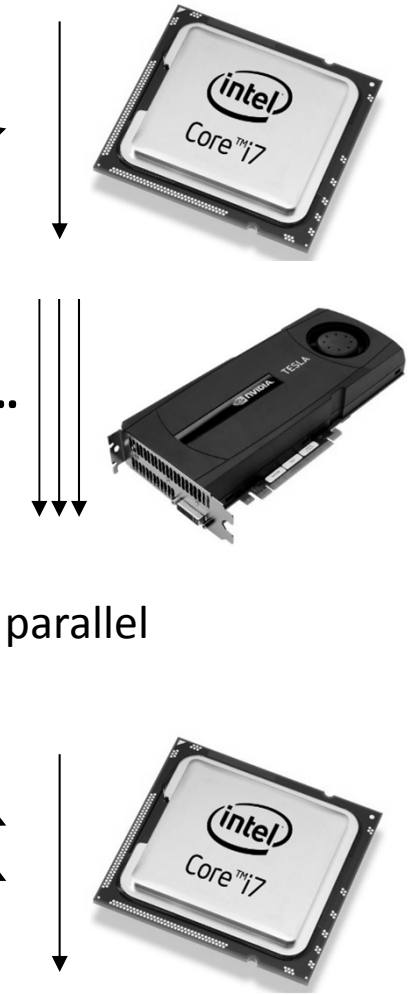
Host: the CPU and its memory

Device: the GPU and its memory

Programming using CUDA

Compute Unified Device Architecture

```
do_something_on_host();
kernel<<<nBlk, nTid>>>(args);
cudaDeviceSynchronize();
do_something_else_on_host();
```



Highly parallel

Hardware Thread Organization

Threads in a block are partitioned into warps

- All threads in a warp execute in a **S**ingle **I**nstruction **M**ultiple **D**ata, or SIMD, fashion
- All paths of conditional branches will be taken
- Warp size varies, many graphics cards have 32

NO guaranteed execution ordering between warps

Branch Divergence

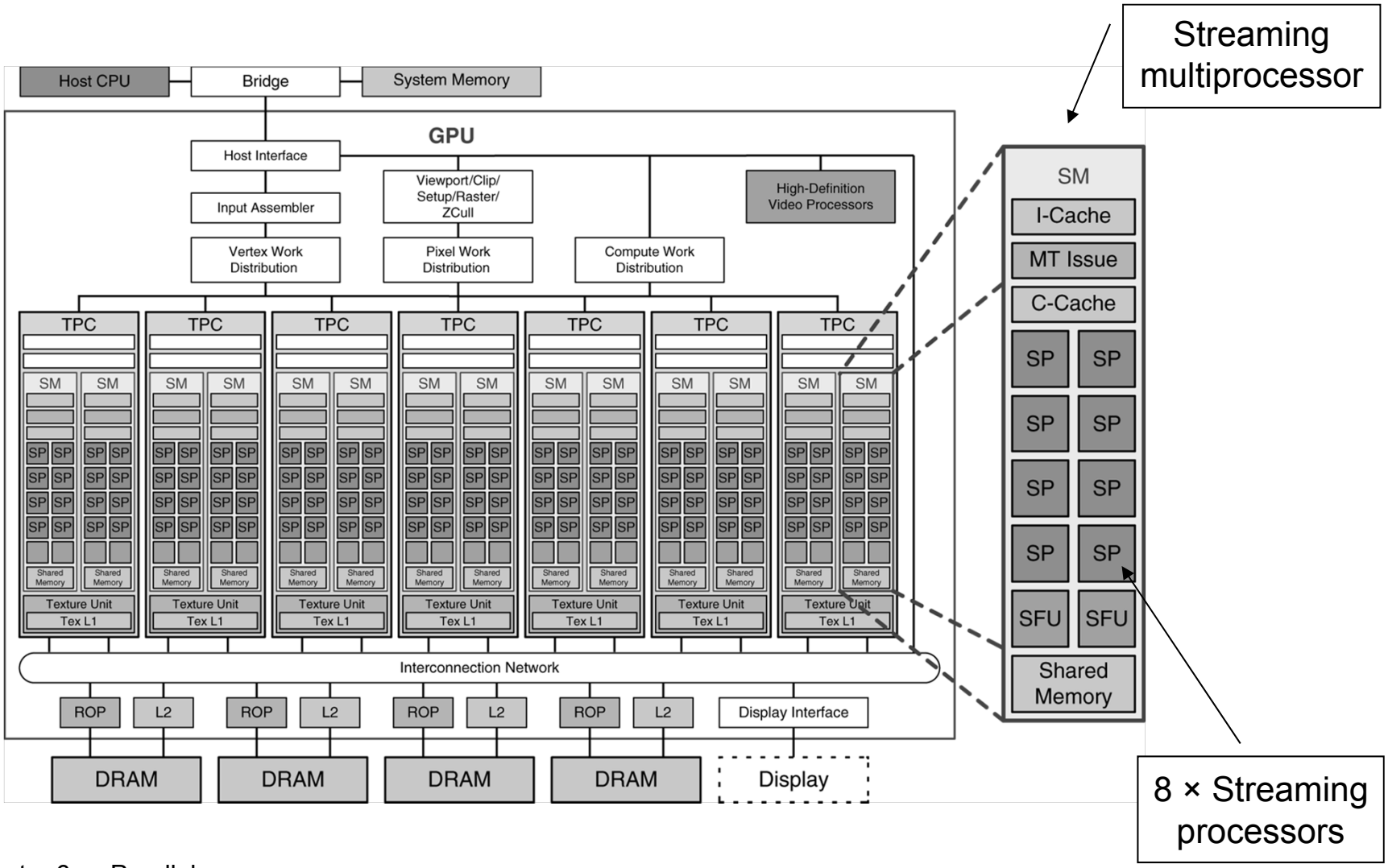
Threads in one warp execute very different branches

Significantly harms the performance!

Simple solution:

- Reordering the threads so that all threads in each block are more likely to take the same branch
- Not always possible

Example: NVIDIA Tesla



Example: NVIDIA Tesla

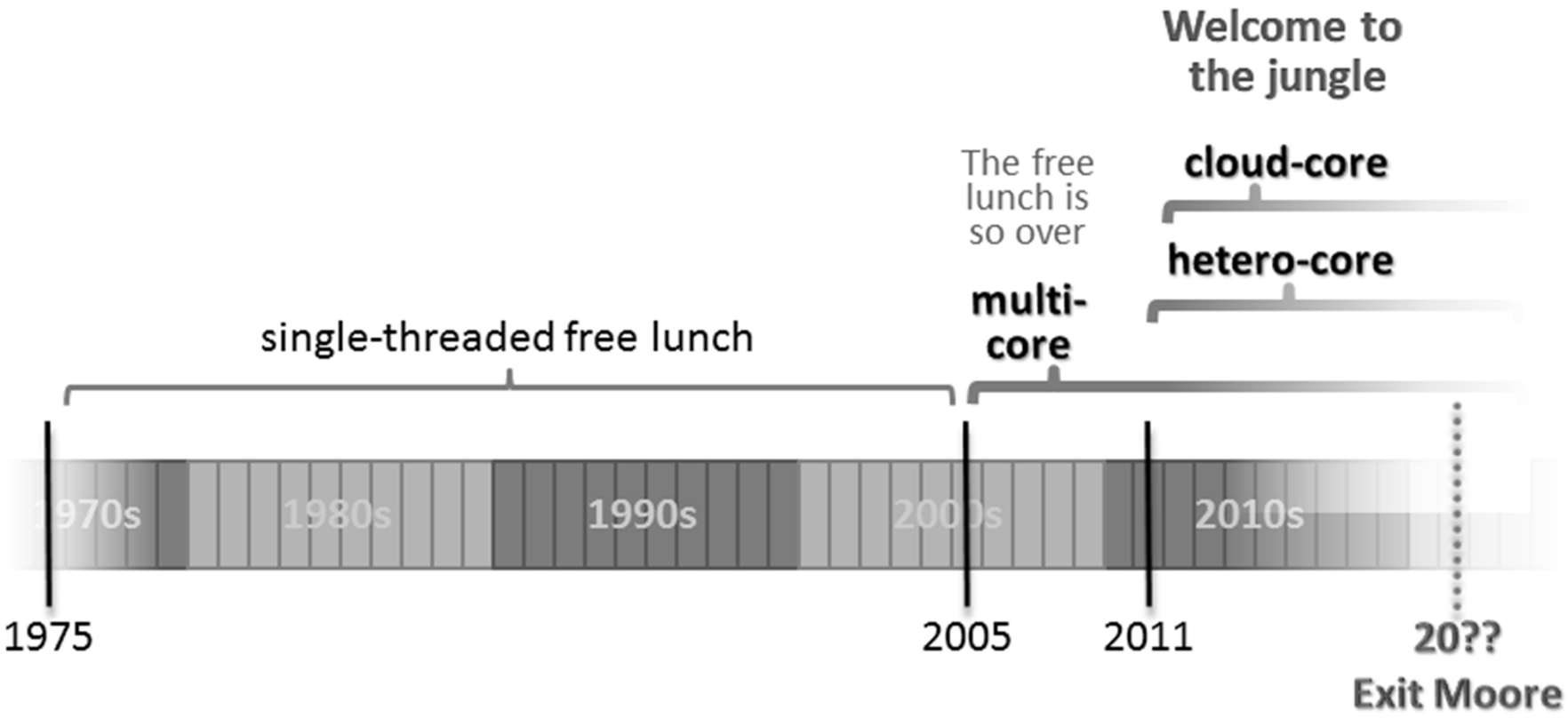
Streaming Processors

- Single-precision FP and integer units
- Each SP is fine-grained multithreaded

Warp: group of 32 threads

- Executed in parallel, SIMD style
  - 8 SPs
    × 4 clock cycles
- Hardware contexts for 24 warps
  - Registers, PCs, …


single-threaded free lunch
970s
1980s
1990s
200
1975
20


Welcome to the jungle
The free lunch is so over
cloud-core
hetero-core
multi-core
single-threaded free lunch
1970s
1980s
1990s
2000s
2010s
1975
2005
2011
20??
Exit Moore