# GPU Architecture (not covered on exam)

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#### Announcements

- Lab
  - Assignment due Wednesday
  - Canvas quiz by Thursday
  - Meet Fr/M
- Project 3
  - Checkpoint due Thursday 5%
  - Full project due next Thursday
- HW 3
  - Out later today
  - ~2 weeks to finish



#### Data-Level Parallelism (DLP)

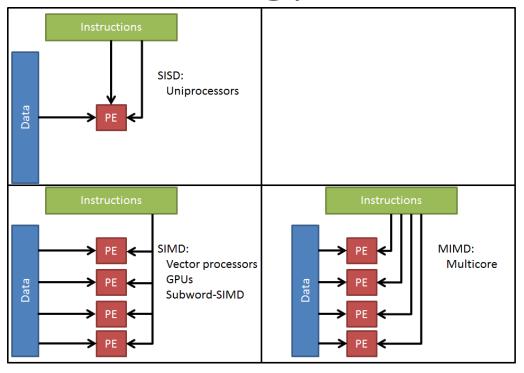
- Multiple instances of instructions that operate on different data
- Usually found across iterations of a "for" loop

```
for (I = 0; I < 100; I++)

Z[I] = A*X[I] + Y[I];
```



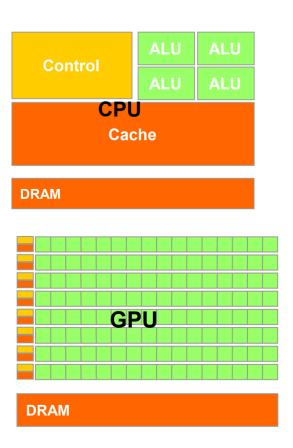
### SIMD Methodology





### SIMD Methodology

- Fetch / decode / schedule an instruction once
- Execute it several times
- Allows for much more of the die space to be dedicated to ALUs



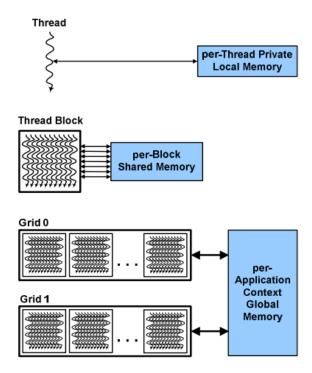


#### **CUDA Programming Model**

```
// CPU algorithm: sums two vectors sequentially
for(int a=0; a<size; a++)
         array1[a]+=array2[a];
// GPU algorithm: sums two vectors in parallel
  global void AddInts(int *a, int *b, int size) {
          int id = blockIdx.x * blockDim.x + threadIdx.x;
          if(id < size) {</pre>
                    a[id] += b[id];
                # thread blocks threads / block
AddInts <<< ceil(size / 256), 256 >>>(a, b, size);
```



### **CUDA Programming Model**





#### SIMT Model

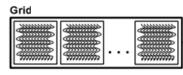
- Assumption: there are millions of elements in a vector to apply an operation to
  - Treat each element as a "thread"
- Fetch an instruction to operate on a ~10-100 elements at a time
  - SIMD
- Start fetching next instruction right away
  - Pipelining
- On the next cycle, fetch from a different bundle of 32 threads
  - That way, cache misses won't stall the program
  - Multi-threading
- Include 100s of these SIMD cores to execute different thread blocks
  - Multi-processing
- Result is "Single-Instruction-Multiple-Thread (SIMT)" computing



#### CUDA Hardware Hierarchy



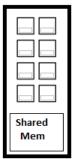




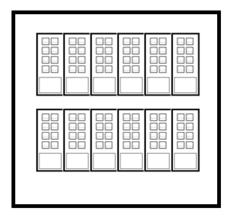




Streaming Multiprocessor



**Graphics Processing Unit** 







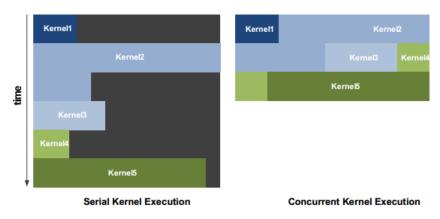
#### **CUDA** Architecture





#### GigaThread Scheduler

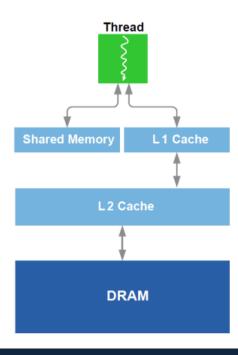
Concurrent Kernel Execution



10x Faster Context Switching between applications



### True Cache Hierarchy





### Shared Memory / L1 Cache

- Shared memory enables threads within same thread block to share data
  - Software controlled scratch pad
  - Typical in fairly deterministic GPU applications
- L1 beneficial for non-deterministic memory accesses



### General-Purpose GPUs

- GPUs were originally designed to accelerate graphics workloads
- Millions of vertexes on a screen
  - Most are independent, can be calculated as separate thread
- But tons of workloads match this level of parallelism
- GPUs are designed to be more "general purpose"



#### Irregular Parallelism

- Some "compute" operator performed over large elements of data
  - Data-level parallelism
- Which elements depends on specific structure
  - "Irregular" or "amorphous"
- Can often be represented as a graph
  - Breadth first search, n-body simulation, SGD



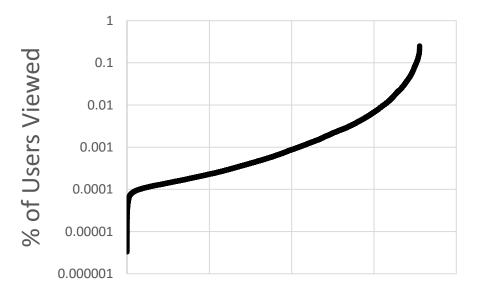
### Irregular Data

- Real world data sets becoming increasingly "sparse"
  - Fewer relative connections between data
- E.g. number of Facebook users grew 19.8% from 2017 to 2018
  - Average number of "friends" per user grew 11.2%
  - Average density of "friend" graph decreases by 7.2%



### Irregular Data

• E.g. number of Netflix users who've viewed content





#### Irregular Algorithm Implementations

#### Two common approaches:

#### 1. Topology-driven:

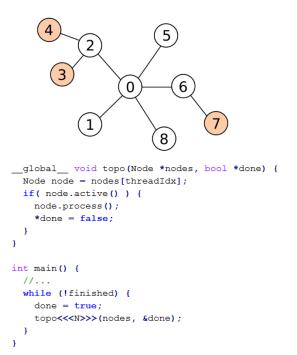
Every node is processed on each iteration until completion

#### 2. Data-driven:

 Active nodes are placed in a worklist, only visited when useful work to be done



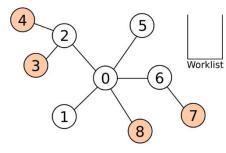
### Topology-Driven



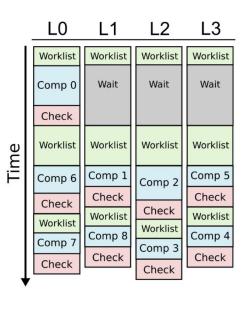
```
L0
        Check 1 | Check 2 | Check 3
Check 0
        Check 5 Check 6 Check 7
Comp 0
Check 4
Check 8
Check 0
        Check 1
                 Check 2
                         Check 3
         Comp 1
Check 4
                         Check 7
                 Comp 2
        Check 5
Check 8
                 Check 6
        Comp 5
Comp 8
                 Comp 6
Check 0
        Check 1
                 Check 2
                          Check 3
                          Comp 3
        Check 5 Check 6
Check 4
Comp 4
                          Check 7
                          Comp 7
Check 8
```



#### Data-Driven



```
__global__ void data(Node *nodes, WL *wl)
while(idx = wl->pop()) {
   Node node = nodes[idx];
   node.process();
   for(i=0; i<node.num_neighbors; i++) {
      wl->push(node.neighbor(i));
   }
}
int main() {
   //...
   init<<<N>>>>(nodes, wl);
   data<<<M>>>>(nodes, wl);
}
```





#### Why Have GPUs Been in the News?

- GPUs surged in popularity during the crypto-boom
- Cryptomining
  - A transaction is verified by someone performing "proof-of-work"
  - Basically, reversing a hash function
  - Whoever reverse-hashes first gets rewarded with currency
- GPUs can attempt multiple reverse-hashes simultaneously
- Power efficiency is more important than raw throughput
  - Easy to spend more money on electricity than what you earn



#### **GPU Costs**

#### **Graphics card prices continue to fall**



Credit: Sam Huitfeld, Viperlair



#### Why Have GPUs Been in the News?

- Al Boom
  - Spurred by bots like ChatGPT
- Large language models, deep learning, other AI/ML techniques rely on processing massive amounts of data
  - Language of linear algebra
  - Massive vectors and matrices
- GPUs can provide huge benefits over CPUs

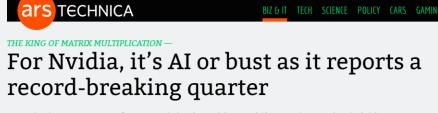


#### Will We See Another GPU Shortage?



## The AI boom could create a new crypto-style GPU shortage

Reports of huge GPU purchases from AI companies big and small are causing fears







Everybody wants GPUs for AI, and that's making Nvidia very happy (and rich).

#### Wanna Learn More?

- EECS 570 Parallel computer architecture
  - Learn more about how GPUs are designed (one topic in the class)
- EECS 471 Applied Parallel Programming with GPUs
  - How to efficiently program these things

