

# GPU CUDA Programming

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이 정 근 (Jeong-Gun Lee)

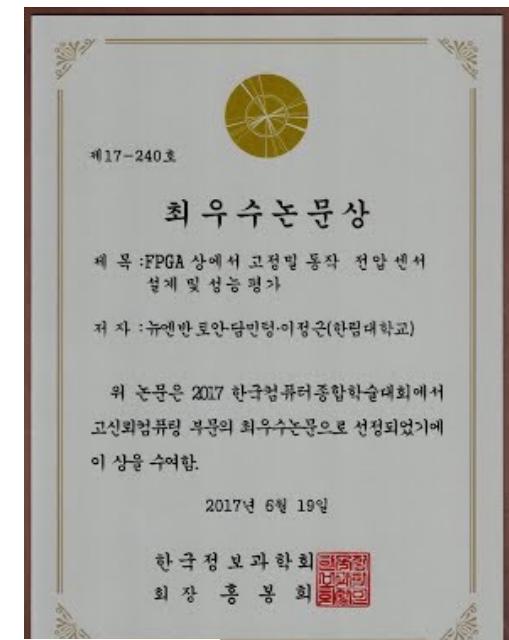
한림대학교 컴퓨터공학과, 임베디드 SoC 연구실

[www.onchip.net](http://www.onchip.net)

Email: [Jeonggun.Lee@hallym.ac.kr](mailto:Jeonggun.Lee@hallym.ac.kr)



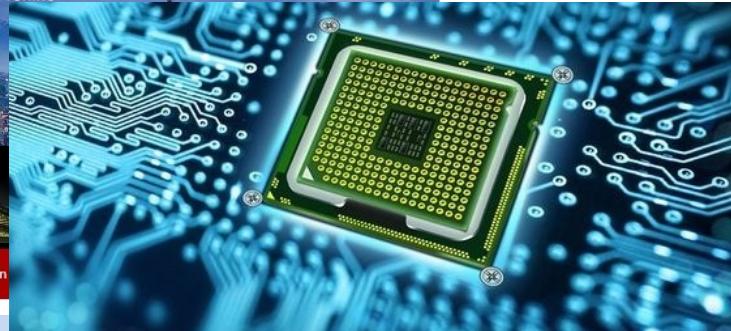
# ESoC Lab @ Hallym



60th IEEE International Midwest Symposium on Circuits and Systems  
Boston, MA, USA | A

**IMTC** 2017 IEEE International Instrumentation and Measurement Technology Conference  
May 22-25, 2017 | Politecnico di Torino | Torino, Italy

I2MTC 2017 AUTHORS PROGRAM REGISTRATION TRAVEL AND VENUE



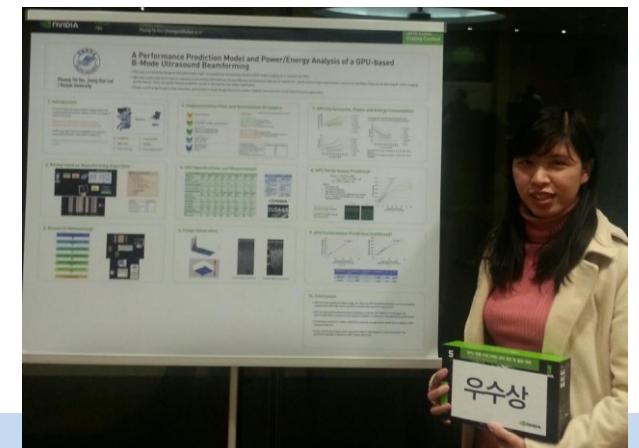
## APEMC 2017

2017 Asia-Pacific International Symposium on Electromagnetic Compatibility  
June 20-23, 2017 / The Commons, Yonsei University, Seoul, Korea

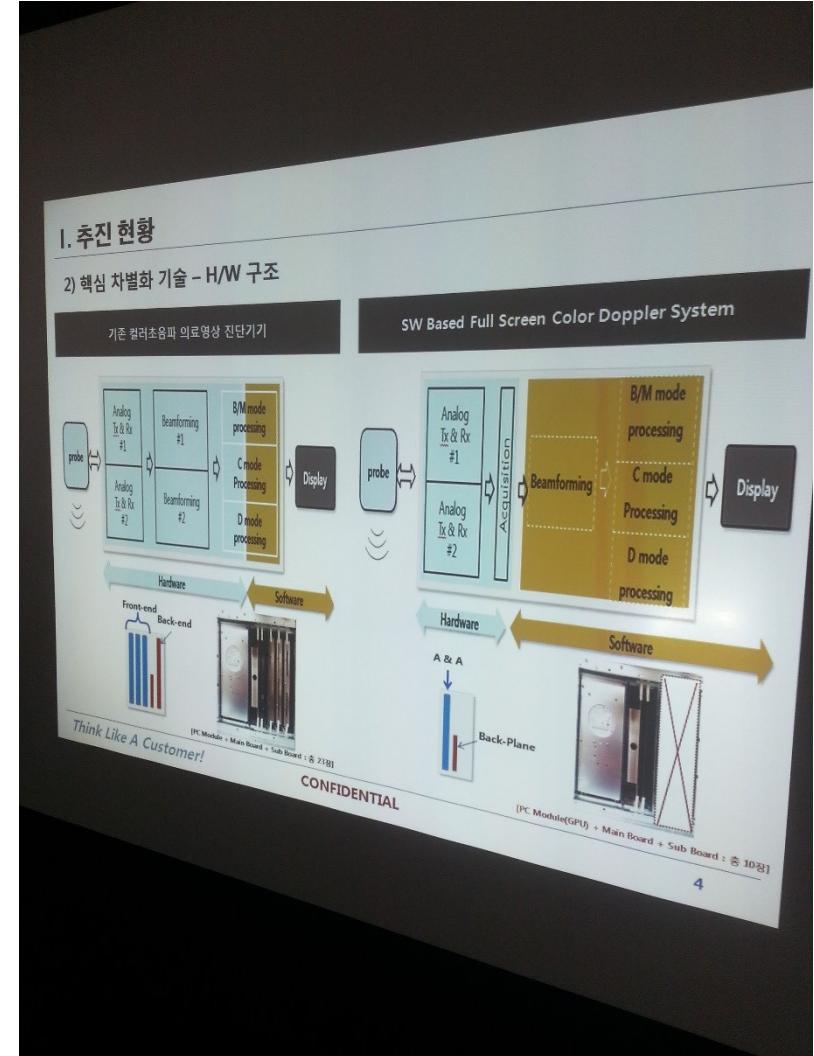
About APEMC 2017 ▾ Program ▾ Submission ▾ Exhibition/Sponsors ▾ Registration ▾ Venue/Accommodation ▾ Travel Information

# GPU Project

- The presented materials are based on the following three papers:
  - Thi Yen Phuong, Jeong-Gun Lee, "*Software Based Ultrasound B-mode/ Beamforming Optimization on GPU and its Performance Prediction*," In 21th IEEE International Conference on High Performance Computing, 2014
  - Thi Yen Phuong and Jeong-Gun Lee, "*Design Space Exploration of SW Beamformer on GPU*," in Concurrency and Computation: Practice and Experience, Volume 27, Issue 7, pages 1718–1733, May 2015 (R2 in JCR)
  - Thi Yen Phuong, Deok-Young Lee and Jeong-Gun Lee, "*A Performance, Power and Energy Analysis of Ultrasound B-Mode Imaging on a GPU with VFS*," in Concurrency and Computation: Practice and Experience. 2017
- The work was supported by “광역경제 선도산업 과제”
- The key researcher/developer:
  - Thi Yen Phuong



# Note



# eX NVIDIA GPU Education Center



모바일 · 온라인 프리미엄 교육전문 미디어

최신기사 대학·성인 중·고등 입시 유아·초등 교육정보 에듀포스트 기획·

2015 조선에듀 여름방학 캠프[학습/진로/디자인/독서/ 과학/해외]

수시의 모든 정보를 한눈에.

대학성인

## [조선에듀] 한림대 컴퓨터공학과, 엔비디아 GPU 교육 센터 국내 유일 지정

신혜민 조선에듀 기자



+/-

한림대학교는 "컴퓨터공학과가 비주얼 컴퓨팅 분야의 세계적인 선도 기업인 엔비디아로 지정됐다"고 5일 밝혔다.

GPU 교육센터는 최근 산업체 수요가 많은 고성능 GPU 컴퓨팅 기술을 학과 내 교과 과정하고 있는 대학 기관에 지정된다.

엔비디아 센터는 한림대를 포함해 국내에 5곳(서울시립대, 동명대, UNIST, 뉴욕주립대, GPU 교육센터는 한림대학교가 현재 유일하다.

컴퓨터공학과는 지난 3년간 학부 수업 및 대학원 수업에서 GPU에 대한 강의를 진행해 주최한 대회를 포함한 각종 학술대회에서 GPU 관련 연구로 다수 수상한 바 있다. 또한 소프트웨어 기반 의료초음파 영상 장치를 개발하고 있다.

한림대는 이러한 GPU 관련 연구 및 교육에 기여한 점을 인정받아 엔비디아 GPU 교육 센터 CUDA 클라우드 교육과 같은 다양한 엔비디아 자체 교육 프로그램과 함께 엔비디아 병렬 프로그래밍 전문가 및 교육에 대한 리소스에 접근할 수 있는 자격을 얻



GPU  
EDUCATION  
CENTER



뉴스 지역뉴스 스포츠·연예 라이프 오피니언 인물 어린이강원일보

속보 | 룹기사 모음 | 정치 | 경제 | 사회 | 문화 | 공연/전시 | 사설 | 칼럼 | 포토갤러리

인물 People

인물일반 | 인사 | 동정 | 부고 | 새얼굴 | 인터뷰 | 카데코리

## 엔비디아 GPU 교육센터 한림대 컴퓨터공학과 지정

2015-8-6 (목) 15면 - 장현정 기자

기자의 다른기사 보기

+

-

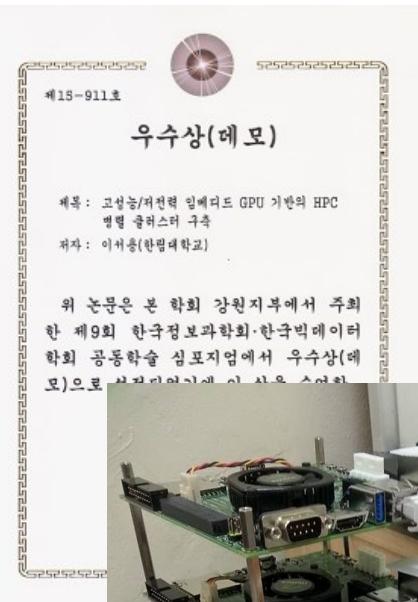
인쇄



▼ 지면보기

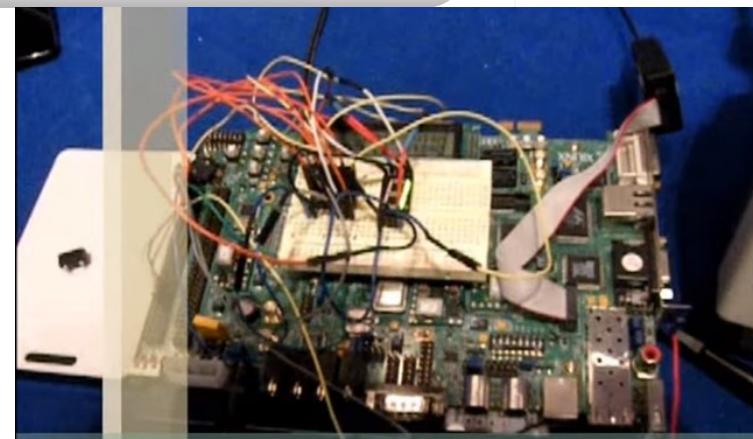
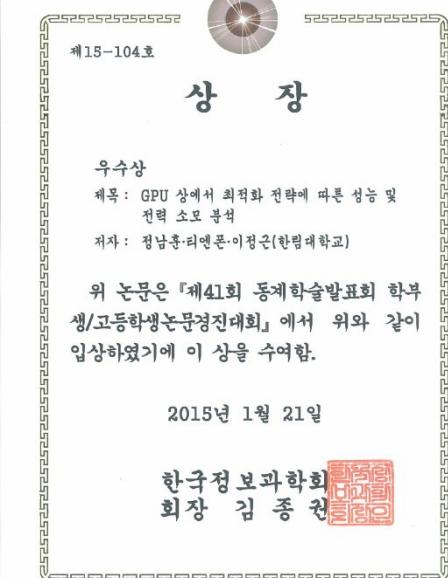
한림대 컴퓨터공학과가 비주얼 컴퓨팅 분야의 세계적 선도 기업인 엔비디아의 공식 GPU 교육 센터(PI 이정근 교수)로 지정됐다. GPU는 그래픽 처리를 위한 고성능 장치다. 엔비디아 센터는 한림대를 포함해 서울시립대, 동명대, UNIST, 뉴욕주립대 한국분교 등 국내 5곳에 불과하고 GPU 교육센터는 한림대가 유일하다. 한림대는 GPU 기술을 이용한 소프트웨어 기반 의료 초음파 영상 장치를 개발하고 있다.

# Undergraduate Researches



연구 개발:  
한림대학교 컴퓨터 공학과  
이승준 (학부 3학년)

지도:  
한림대학교 컴퓨터 공학과  
이정근 (지도 교수)  
한국전자통신연구원  
오명훈 (한이음 멘토)  
한국전자통신연구원  
신처훈 (인턴쉽 멘토)  
한국전자통신연구원  
김성남 (인턴쉽 멘토)



Asynchronous MIPS Processor  
@[Computer Engineering, Hallym Univ.]

<https://www.youtube.com/watch?v=N1PoNFW-aGg>

# 차례

- **Introduction**
  - Multicore/Manycore and GPU
  - GPU on Medical Applications
- **Parallel Programming on GPUs: Basics**
  - Conceptual Introduction
- **GPU Architecture Review**
- **Parallel Programming on GPUs: Practice**
  - Real programming
- **Conclusion**

DO YOU  
KNOW?



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DO YOU  
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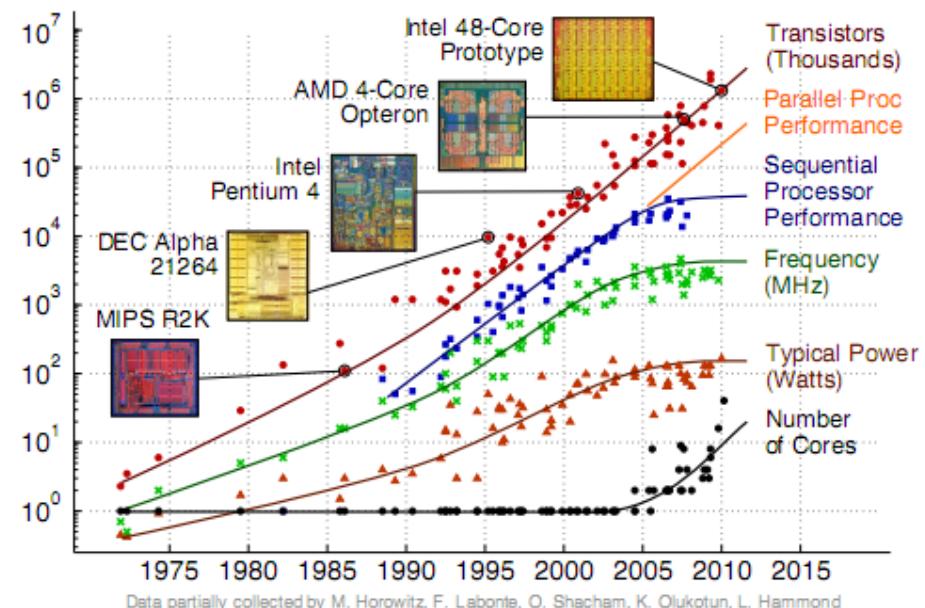
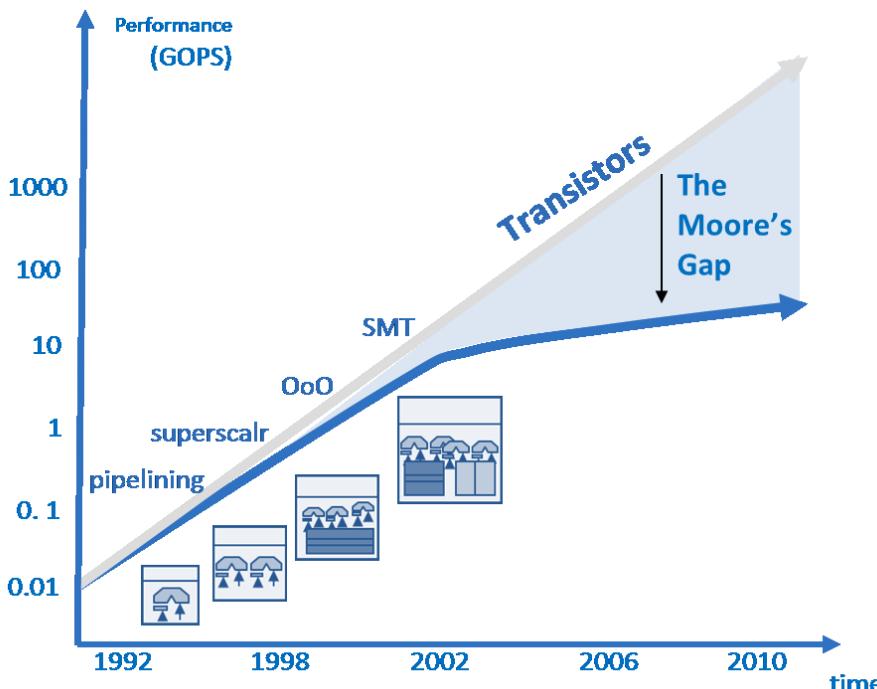


# Introduction

- Multicore/Manycore and GPU

A multi-core CPU (or chip-level multiprocessor, CMP) combines two or more independent cores into a single package composed of a single integrated circuit (IC), called a die, or more dies packaged together.

- Wikipedia



Prepared by C. Batten - School of Electrical and Computer Engineering - Cornell University - 2005 - retrieved Dec 12 2012 - <http://www.csl.cornell.edu/courses/ece5950/handouts/ece5950-overview.pdf>

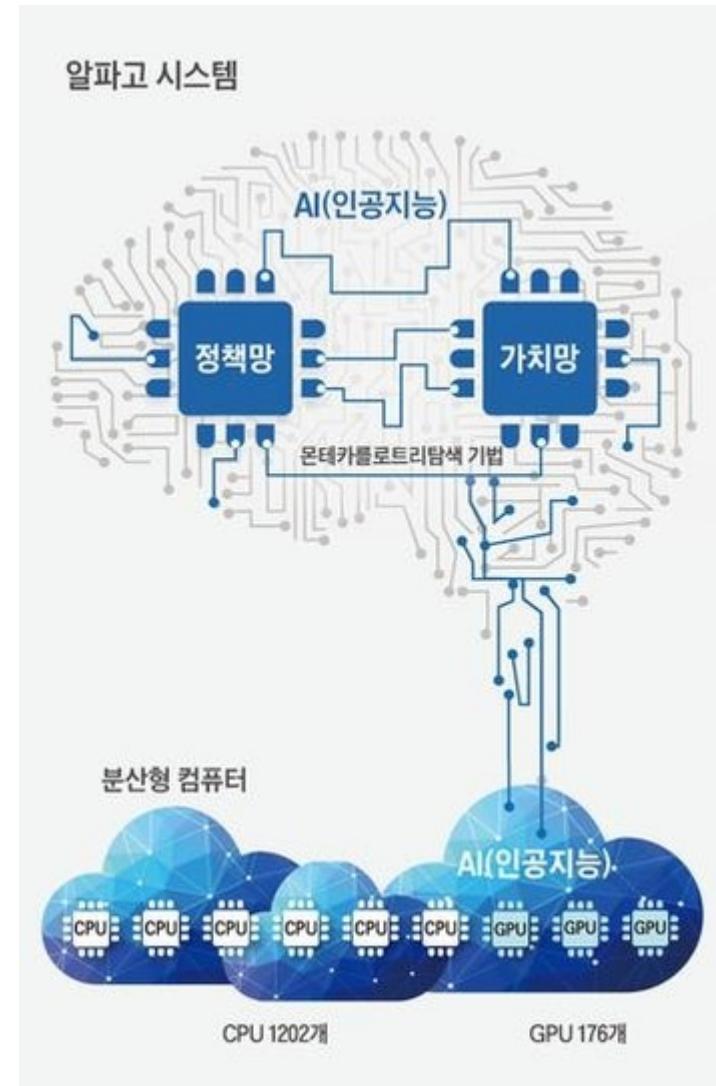
# Introduction

- Alpha-Go ?

구글의 DeepMind가 이렇게 강력한 인공지능을 개발할 수 있었던 바탕은 풍부한 계산자원에 있다. 판후이와 대국을 한 분산 AlphaGo의 경우 **1202개의 CPU와 176개의 GPU**가 사용됐다.

Deep learning is **HOT** !

Why now ?

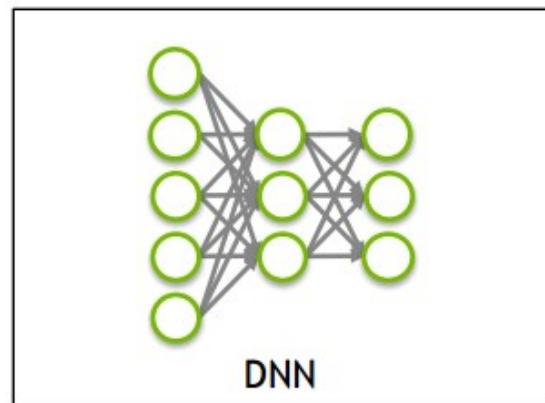


# Introduction

- Alpha-Go ?

구글의 DeepMind가 이렇게 강력한

## The Big Bang in Machine Learning



Why now ?



# Introduction: GPU ? Manycore ?

## NVIDIA TITAN Xp

GPU Engine Specs:

NVIDIA CUDA® Cores	3840
Boost Clock (MHz)	1582



April 6, 2017

 NVIDIA.

# Introduction: GPU ? Manycore ?

## 산업 사례 연구

NVIDIA® Tesla® GPU는 다양한 산업 영역에서 전 세계적으로 중요한 영향을 미치는 주요 컴퓨팅 과제들을 신속하고 정확하게 처리할 수 있도록 도와줍니다.

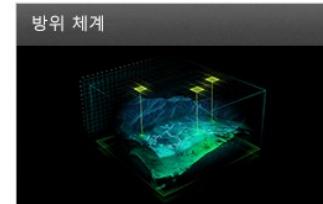
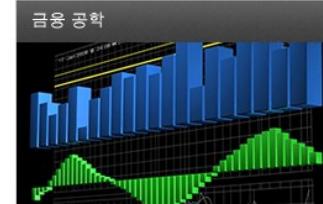
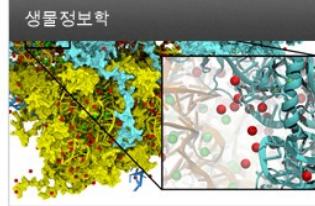
Tesla GPU 컴퓨팅 제품에 대한 정보가 궁금하시면 [Tesla GPU 컴퓨팅 브로셔](#)를 다운로드받아 보십시오 (PDF 1.63MB)



### 과학의 진보에 기여

이론에 컴퓨팅 성능이 뒷받침되어 과학적 발견을 어떻게 앞당기는지 알아봅니다. [동영상 보기 >](#)

# Grap nit ?



# Introduction: GPU ? Manycore ?

## 산업 사례 연구

NVIDIA® Tesla® GPU는 다양한 산업 영역에서 전 세계적으로 중요한 영향을 미치는 주요 컴퓨팅 과제들을 신속하고 정확하게 처리할 수 있도록 도와줍니다.

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의료 영상



생물 정보학



슈퍼컴퓨팅 센터

Gran | nit ?

# GPGPU

지진파 탐사

지리 정보 시스템 (GIS)

방위 체계

# General Purpose GPU



# Introduction: GPU ? Manycore ?

**GPU = SIMT**  
**Multi-threaded Vector Processing** on  
**Massively Parallel Many Cores**

SIMT was introduced by [Nvidia](#):

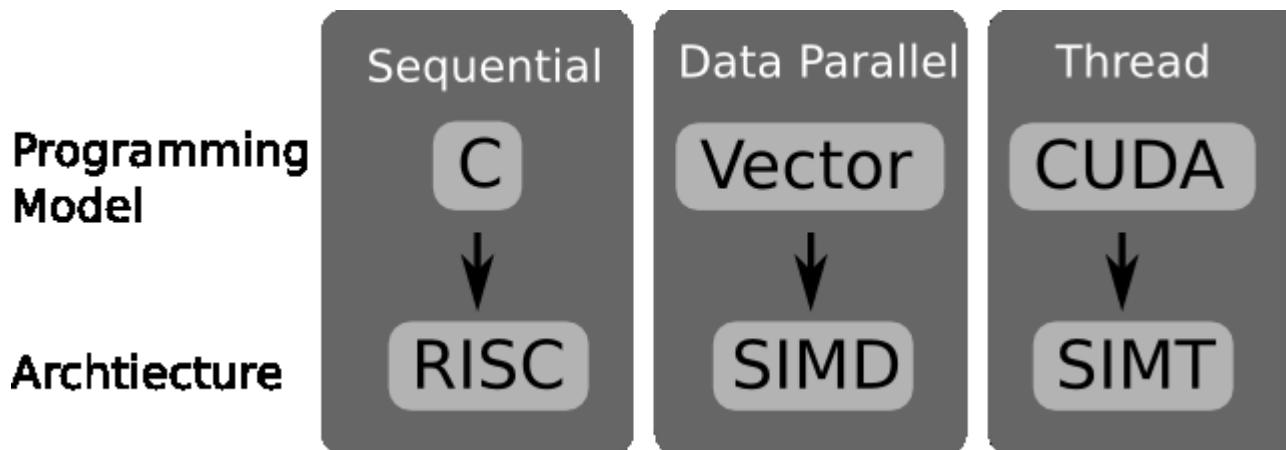
[The G80 Nvidia GPU architecture, [Tesla](#)] introduced the ***single-instruction multiple-thread (SIMT)*** execution model where multiple independent threads execute concurrently using a single instruction.

From [https://en.wikipedia.org/wiki/Single\\_instruction,\\_multiple\\_threads](https://en.wikipedia.org/wiki/Single_instruction,_multiple_threads)

**Pixel shaders : Vertex shaders → Unified Shader (GPGPU)**

# GPU and SIMT ?

- Multicore/Manycore and GPU

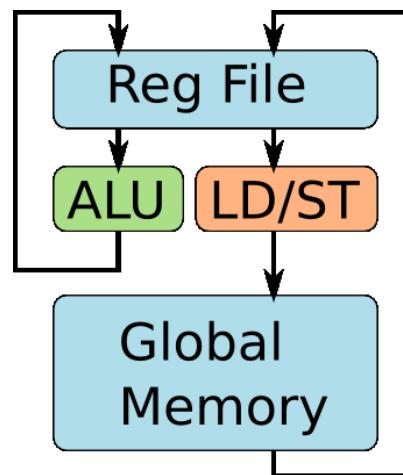


# Seq. vs Data Parallel vs Thread

```
int A[2][4];
for(i=0;i<2;i++){
    for(j=0;j<4;j++){
        A[i][j]++;
    }
}
```

Assembly  
code of  
inner-loop

```
lw r0, 4(r1)
addi r0, r0, 1
sw r0, 4(r1)
```



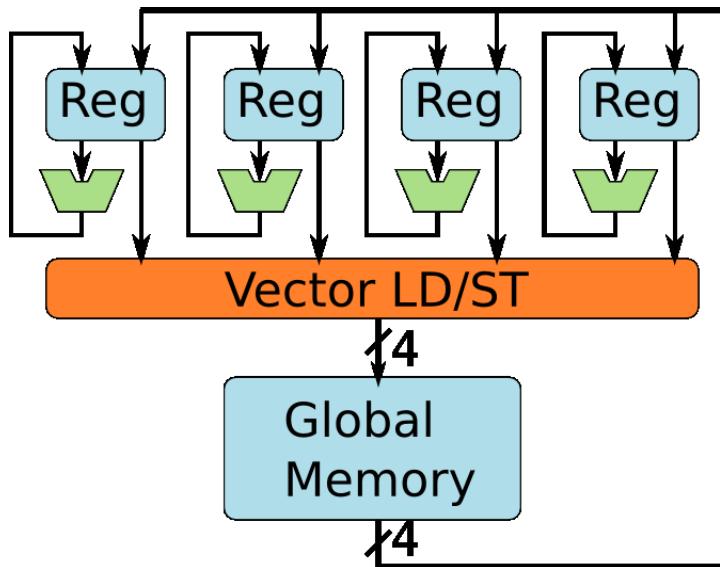
Programmer's  
view of RISC

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Most CPUs Have Vector SIMD Units

- Programmer's view of a vector SIMD, e.g. SSE.



참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Let's Program the Vector SIMD

- Unroll inner-loop

```
int A[2][4];
for(i=0;i<2;i++){
    for(j=0;j<4;j++){
        A[i][j]++;
    }
}
```



```
int A[2][4];
for(i=0;i<2;i++){
    movups  xmm0,      [ &A[i][0] ] // load
    addps   xmm0,      xmm1       // add 1
    movups  [ &A[i][0] ], xmm0    // store
}
```

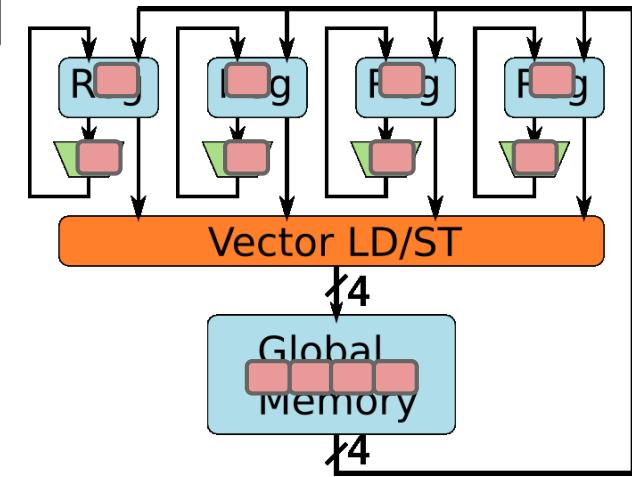
Looks like the previous example,  
but each SSE instruction executes on 4 ALUs.

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# How Do Vector Programs Run?

```
int A[2][4];
for(i=0;i<2;i++){
    movups xmm0,      [ &A[i][0] ] // load
    addps  xmm0,      xmm1       // add 1
    movups [ &A[i][0] ], xmm0   // store
}
```

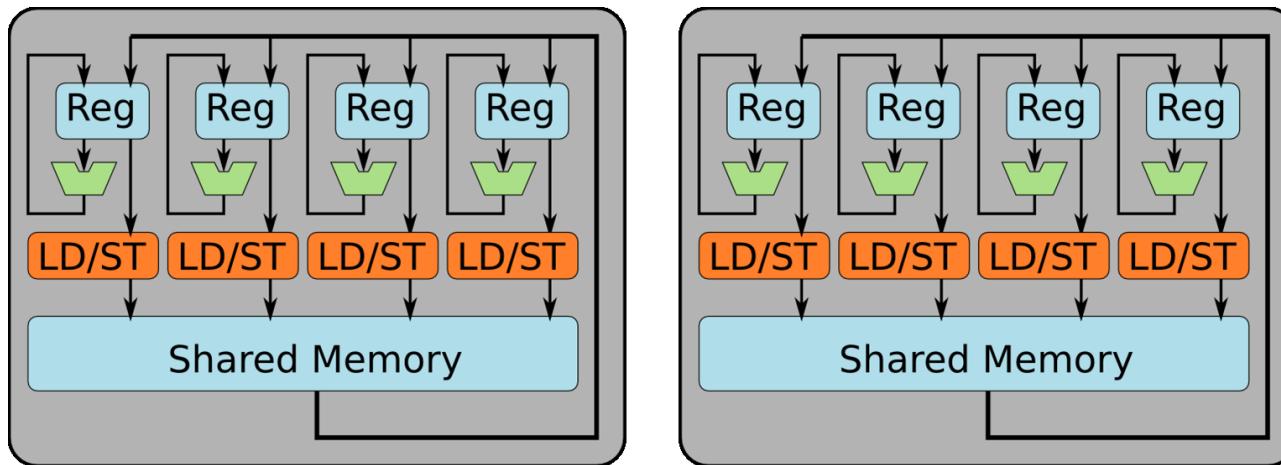


참조:

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# CUDA Programmer's View of GPUs

- A GPU contains multiple SIMD Units.

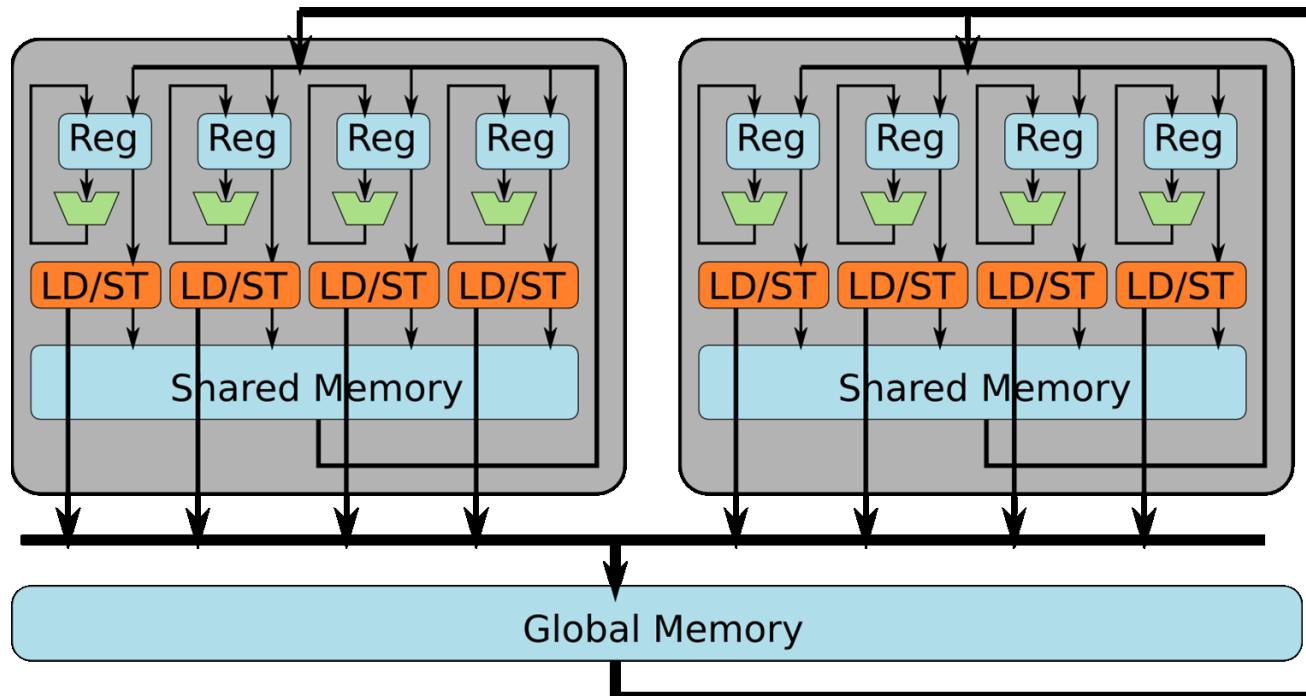


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# CUDA Programmer's View of GPUs

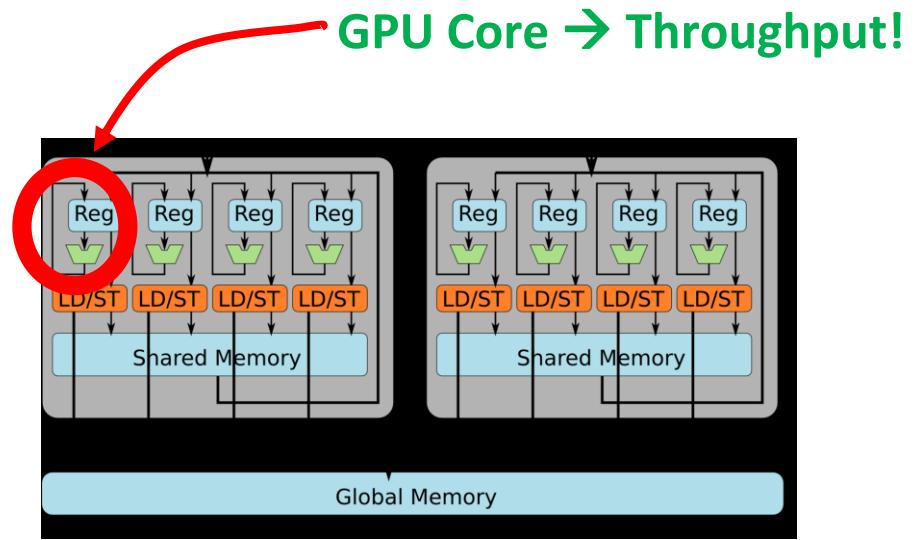
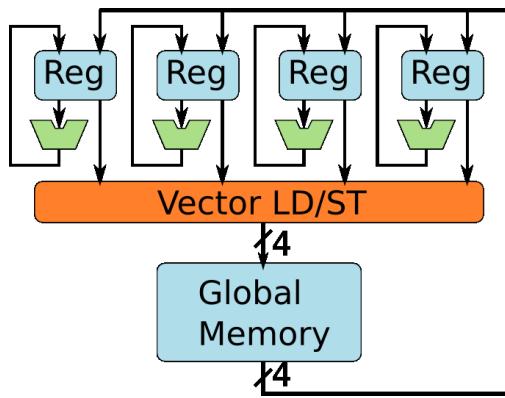
- A GPU contains multiple SIMD Units. All of them can access global memory.



참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# What Are the Differences?



Let's start with two important differences:

1. GPUs use **threads** instead of vectors
2. GPUs have the "**Shared Memory**" spaces

참조:

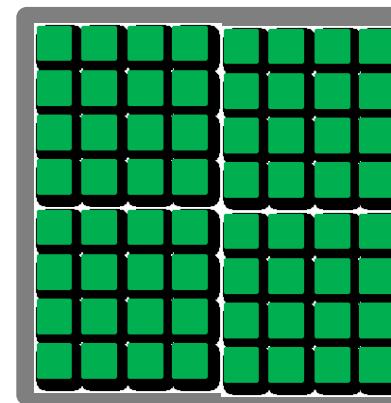
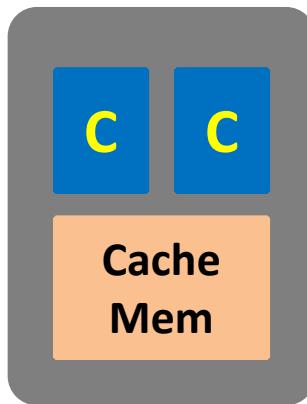
<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>



# CPU vs. GPU



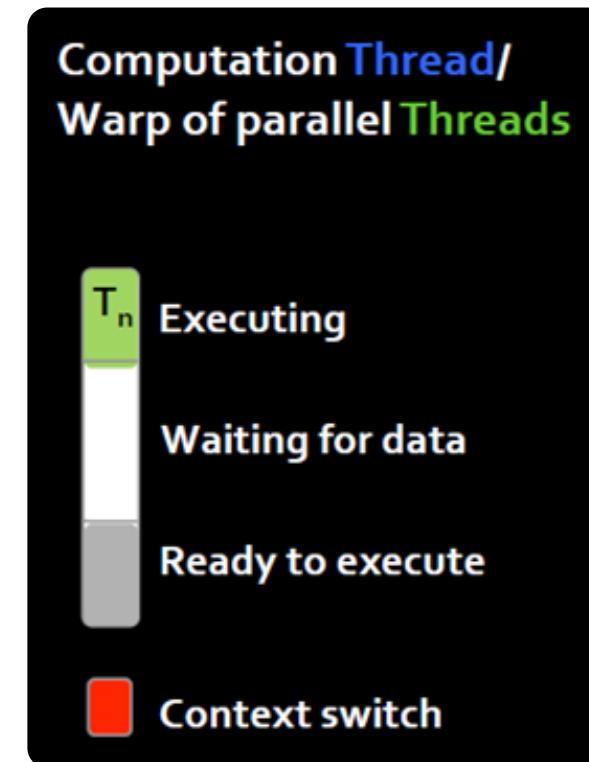
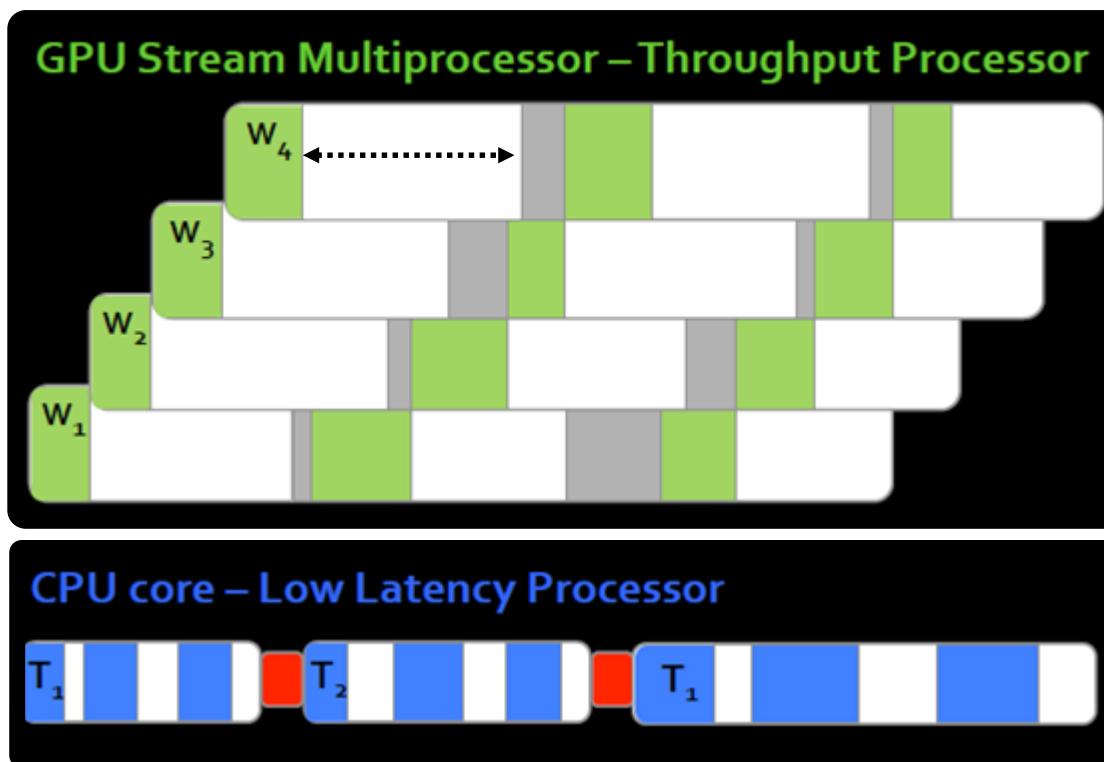
*Latency Processor + Throughput Processor*



*Heterogeneous Computing*

# CPU vs. GPU

- CPU architecture attempts to minimize latency within each thread with the help of CACHING
- GPU architecture hides latency with computation from other thread warps with the help of THREADING



# Introduction

## - Performance Gap

Conventional CPU computing architecture can no longer support the growing HPC needs.

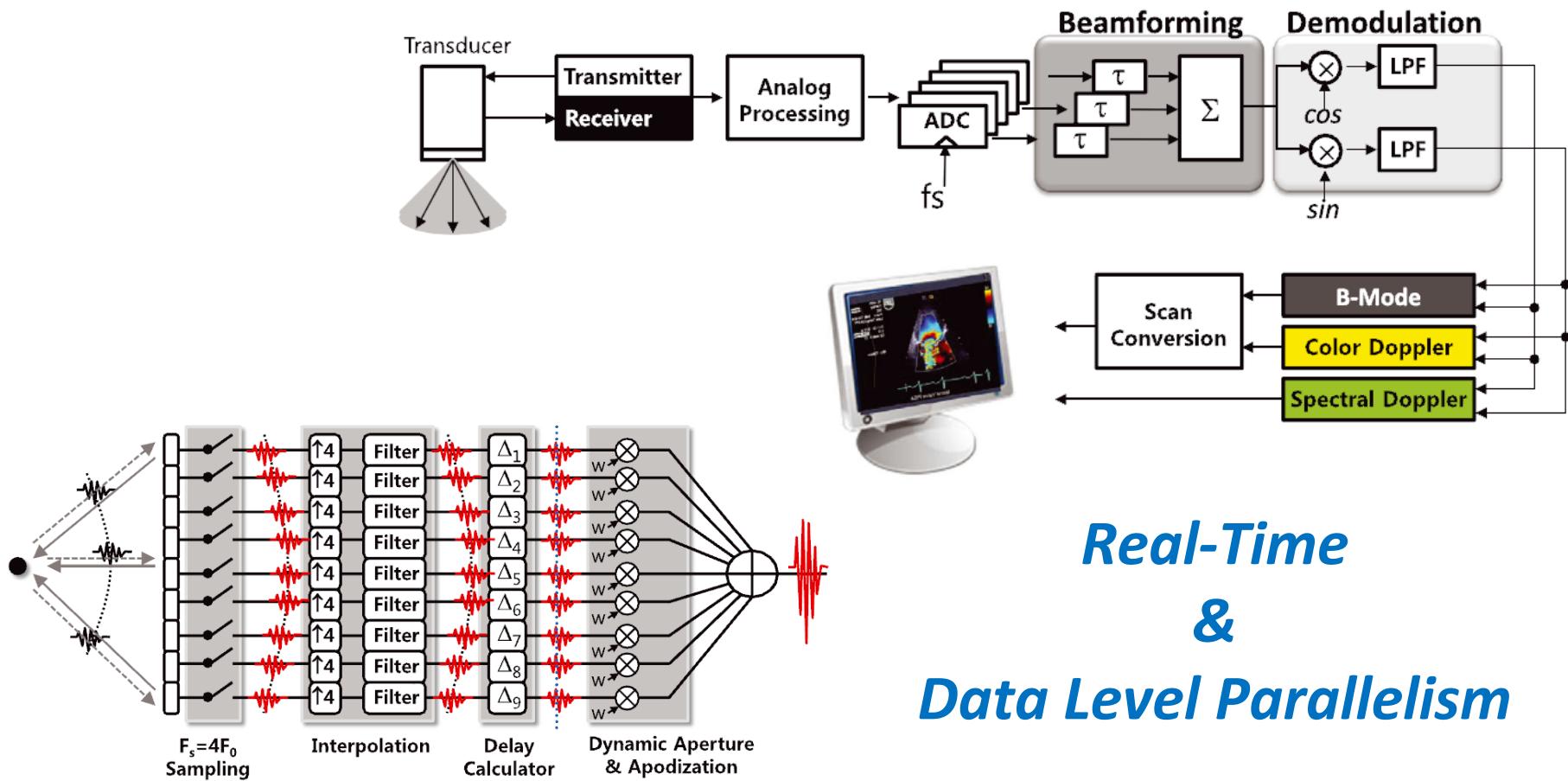
Source: Hennessy & Patterson, CAAQ, 4th Edition.



Ref: [Tesla GPU Computing Brochure](#)

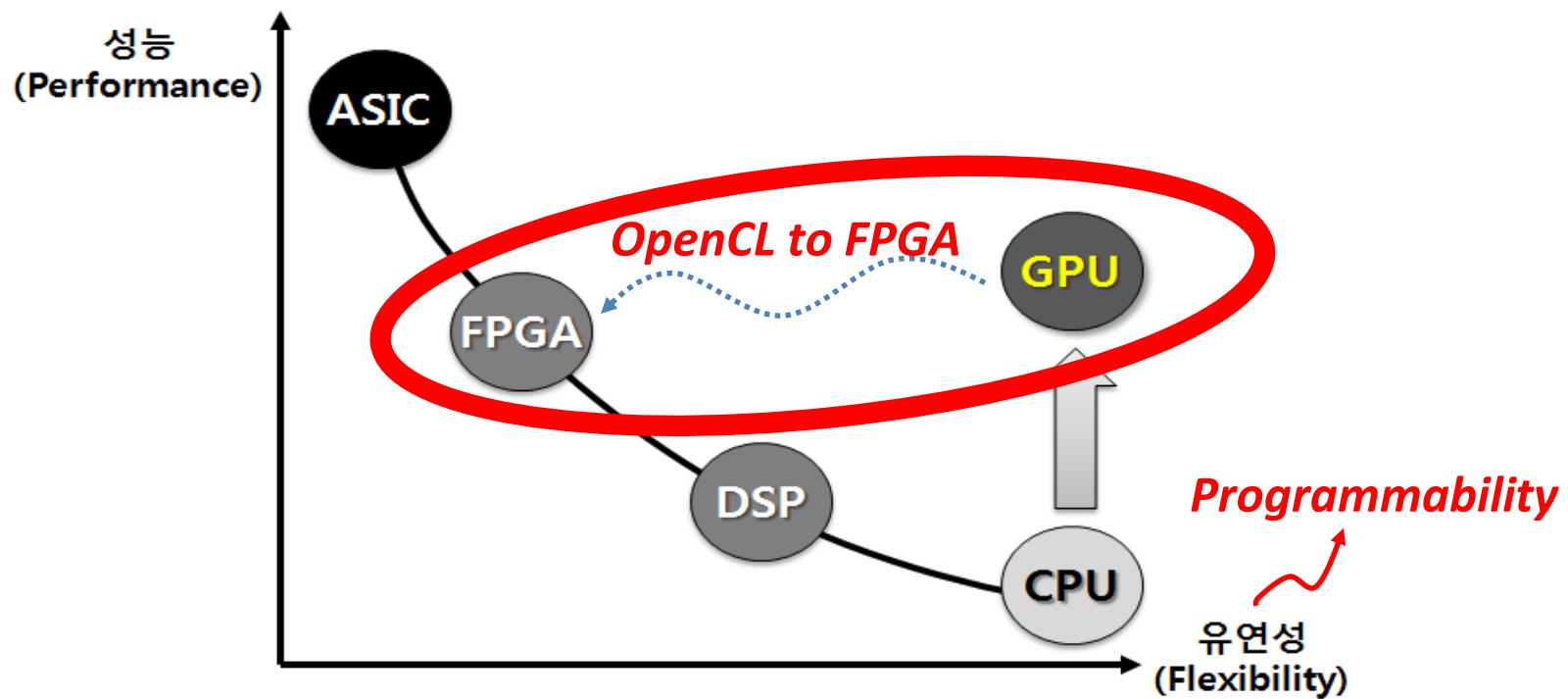
# Introduction

- GPU on **Medical Imaging** Applications
  - One of the **GOOD GPU APPLICATIONS**



# Introduction: *Programmable!*

- Implementation styles of conventional ***Medical Imaging*** Applications
  - ASIC / FPGA or DSP for high performance real-time computing



# 차례

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  - Real programming
- **Conclusion**

DO YOU  
KNOW?



# Parallel Programming on a GPU

We have one code part ...



```
for(i=0; i < 100; i++)  
    C[i] = A[i] + B[i];
```



Yes! It is simple !

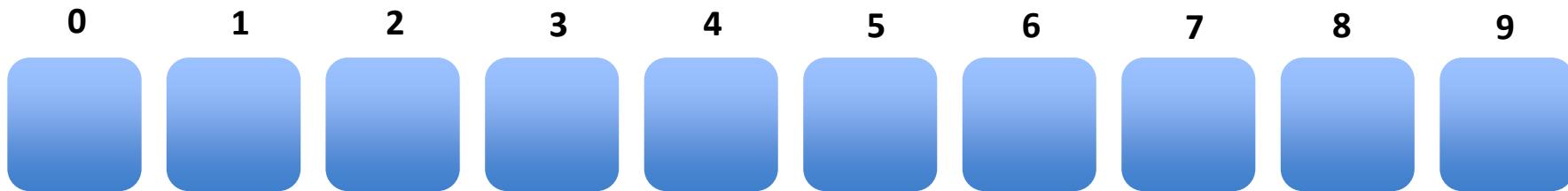
But what about on **10 cores** on-chip processor ?

# Parallel Programming on a GPU

But what about on 10 cores on-chip processor ?

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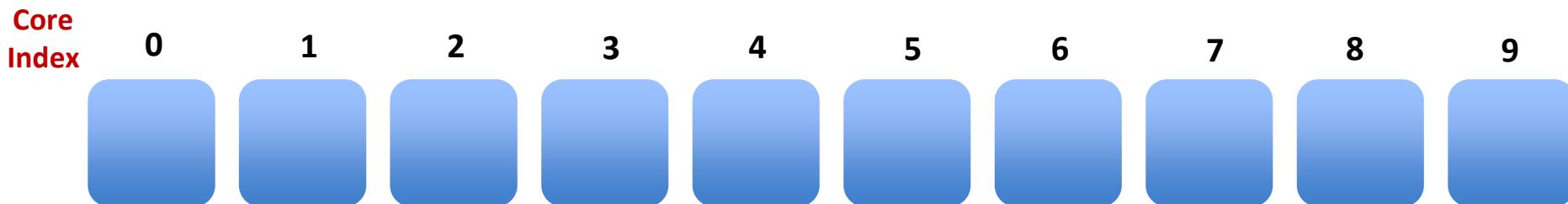
Core  
Index



# Parallel Programming on a GPU

But what about on 10 cores on-chip processor ?

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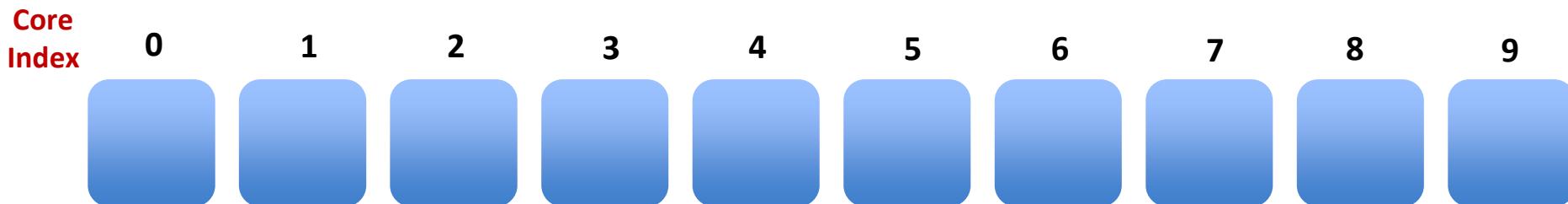
For each core

```
for(i=0; i < 10; i++)  
    C[      ?      ] = A[      ?      ] + B[      ?      ];
```

# Parallel Programming on a GPU

But what about on 10 cores on-chip processor ?

```
for(i=0; i < 100; i++)  
    C[i] = A[i] + B[i];
```



For each core

```
for(i=0; i < 10; i++)  
    C[CoreIndex*10+i] = A[CoreIndex*10+i] + B[CoreIndex*10+i];
```

# Parallel Programming on a GPU

What about Threading ?

```
for(i=0; i < 100; i++)  
    C[i] = A[i] + B[i];
```

Thread 0:  
 $C[0] = A[0] + B[0];$

Thread 1:  
 $C[1] = A[1] + B[1];$

...

Thread 98:  
 $C[98] = A[98] + B[98];$

Thread 99:  
 $C[99] = A[99] + B[99];$

# Parallel Programming on a GPU

What about Threading ?

```
for(i=0; i < 100; i++)  
    C[i] = A[i] + B[i];
```

Thread 0:  
 $C[0] = A[0] + B[0];$

Thread 1:  
 $C[1] = A[1] + B[1];$

...

Thread 98:  
 $C[98] = A[98] + B[98];$

Thread 99:  
 $C[99] = A[99] + B[99];$

Stream Processor (SP)

Schedule



# Parallel Programming on a GPU

Stream Multiprocessor (SM) 1

0

1

2

3

4

Shared Memory

Stream Multiprocessor (SM) 2

0

1

2

3

4

Shared Memory

?

Thread 0:  
 $C[0] = A[0] + B[0];$

Thread 1:  
 $C[1] = A[1] + B[1];$

...

Thread 98:  
 $C[98] = A[98] + B[98];$

Thread 99:  
 $C[99] = A[99] + B[99];$

# Parallel Programming on a GPU

Stream Multiprocessor (SM) 1

0

1

2

3

4

Shared Memory

Stream Multiprocessor (SM) 2

0

1

2

3

4

Shared Memory

Block 0

Thread 0:  
 $C[0] = A[0] + B[0];$

Thread 1:  
 $C[1] = A[1] + B[1];$

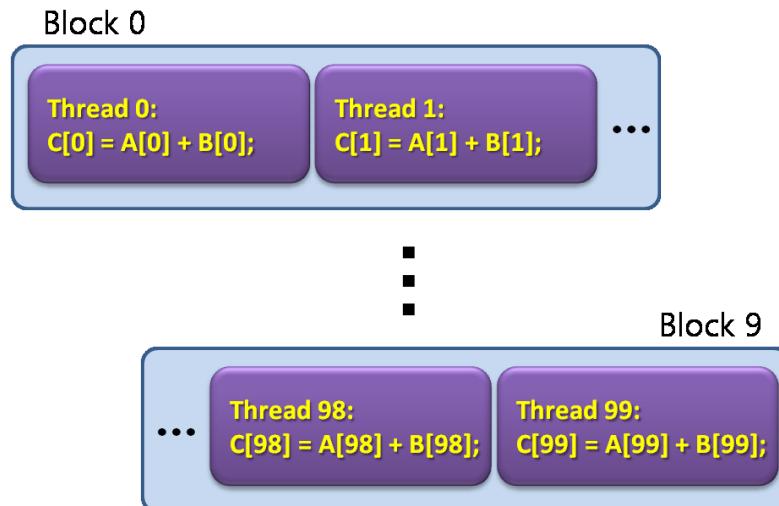
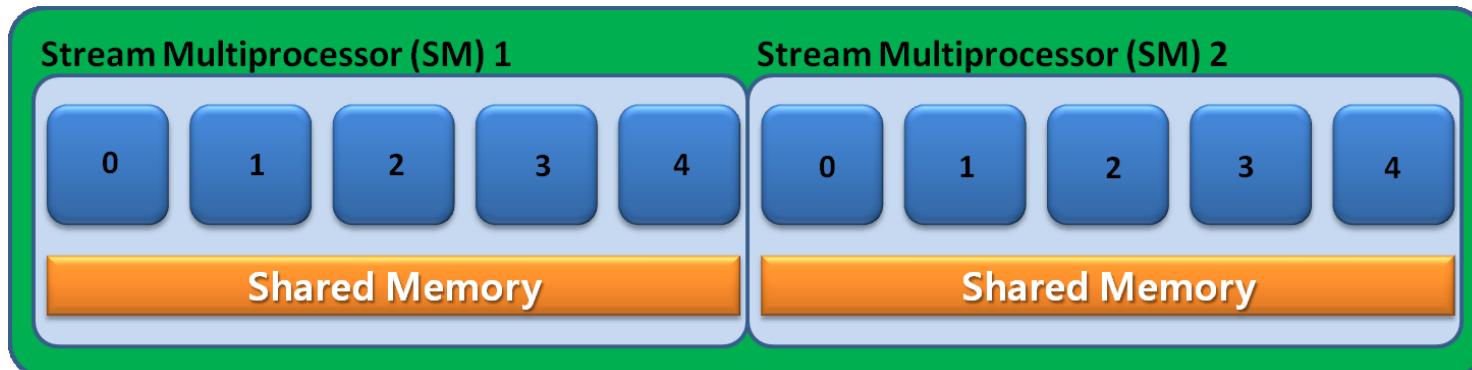
...

Block 9

Thread 98:  
 $C[98] = A[98] + B[98];$

Thread 99:  
 $C[99] = A[99] + B[99];$

# Parallel Programming on a GPU



1 Thread per block & 100 Blocks  
Or  
5 Thread per block & 20 Blocks  
Or  
**10 Thread per block & 10 Blocks**  
Or  
20 Thread per block & 5 Blocks  
...

# Parallel Programming on a **GPU**

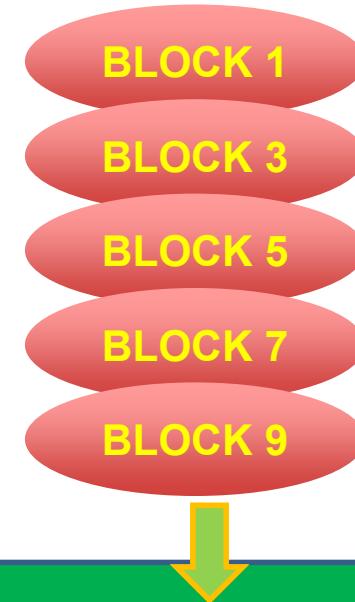
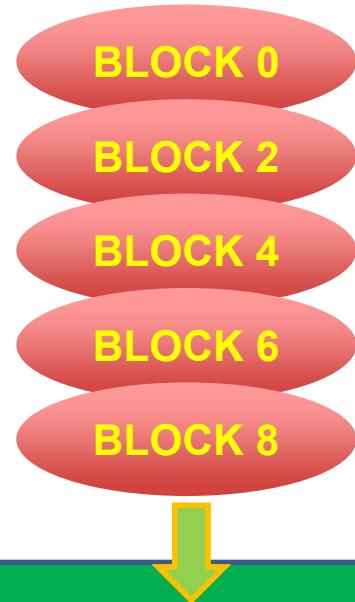
We have one code part ...

```
for(i=0; i < 100; i++)  
    C[i] = A[i] + B[i];
```

Now, **10 blocks** and **10 threads** per a block !

# Parallel Programming on a GPU

Now, **10 blocks** and **10 threads** per a block !



Stream Multiprocessor (SM) 1

Stream Multiprocessor (SM) 2

0

1

2

3

4

0

1

2

3

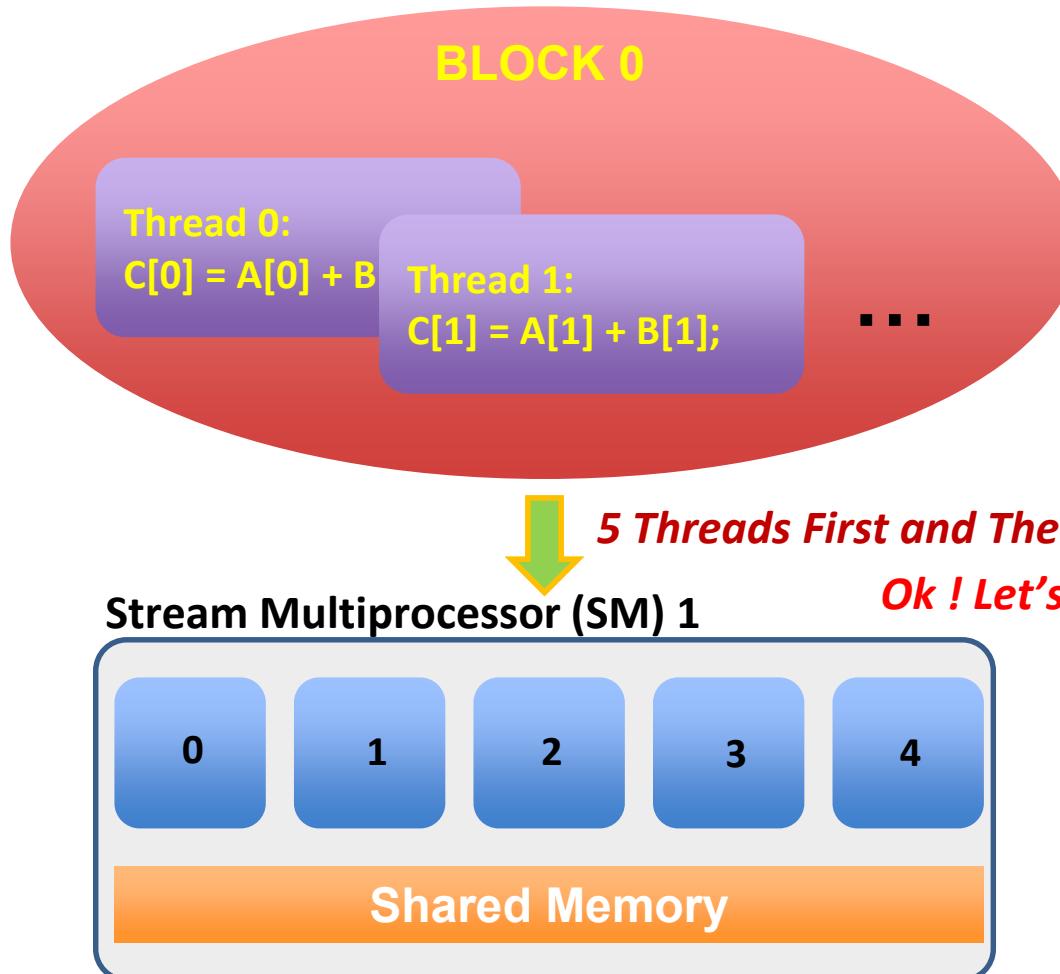
4

Shared Memory

Shared Memory

# Parallel Programming on a GPU

Now, **10 blocks** and **10 threads** per a block !



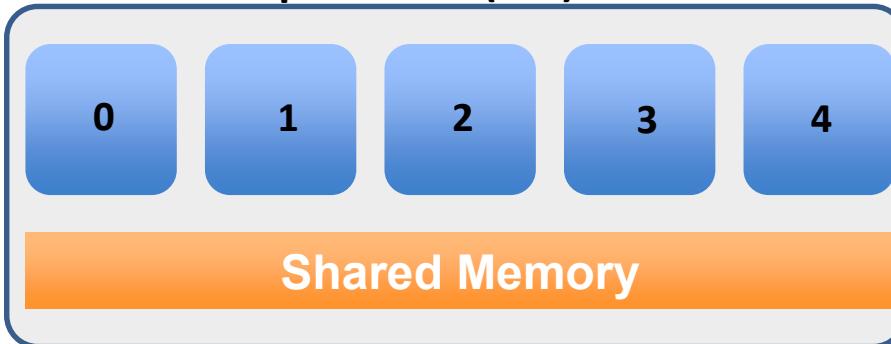
**WARP 0: thread 0 ... thread 4**

**WARP 1: thread 5 ... thread 9**

# Parallel Programming on a GPU

**Note:** Warp divergence

Stream Multiprocessor (SM) 1

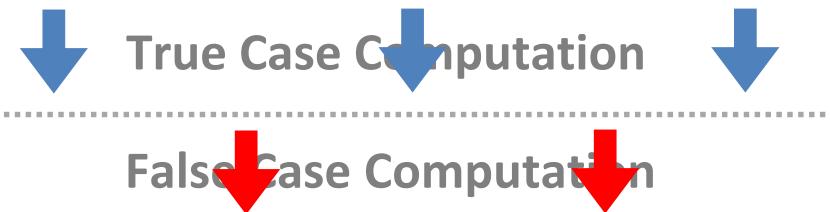


*WARP 0: thread 0 ... thread 4  
WARP 1: thread 5 ... thread 9*

```
__global__ warp_divergence( ... )  
{  
    ...  
    if ( condition )  
    { True Case Computation; }  
    else  
    { False Case Computation; }  
}
```

*WARP 0: thread0 thread1 thread2 thread3 thread4*

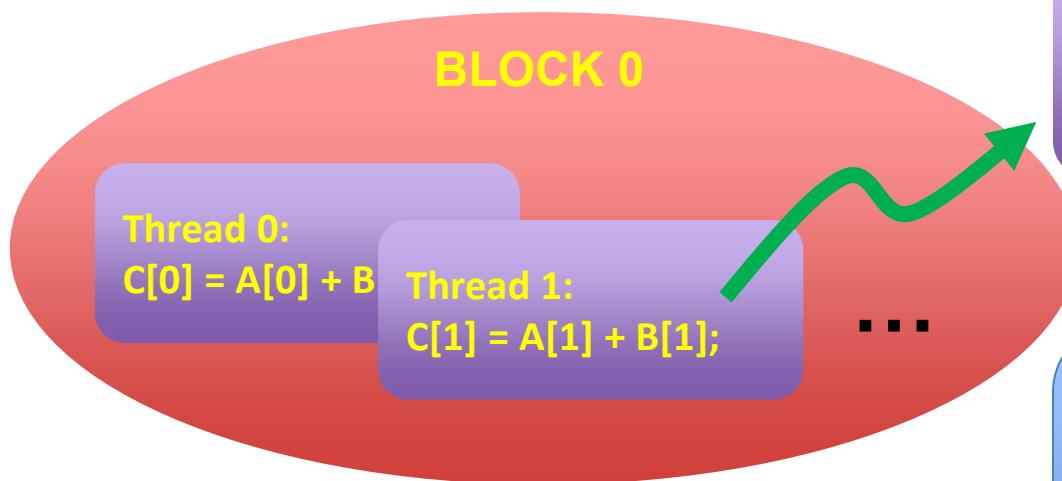
*Cond. : True      False      True      False      True*



# Parallel Programming on a GPU

Now, **10 blocks** and **10 threads** per a block !

→ We have two indexes: ***block index*** & ***thread index***



```
Block index ← 0; // blockIdx  
Thread index ← 1; // threadIdx  
C[0*10+1] = A[0*10+1] + B[0*10+1];
```

```
__global__ VectorAdd (A, B, C)  
{  
    C[blockIdx*10+threadIdx] =  
        A[blockIdx*10+threadIdx] +  
        B[blockIdx*10+threadIdx];  
}
```



# Parallel Programming on a **GPU**

---

Hm... Where are A, B, C arrays in a system ?

# Parallel Programming on a Manycore

Hm... Where are A, B, C arrays in a system ?

A system ?

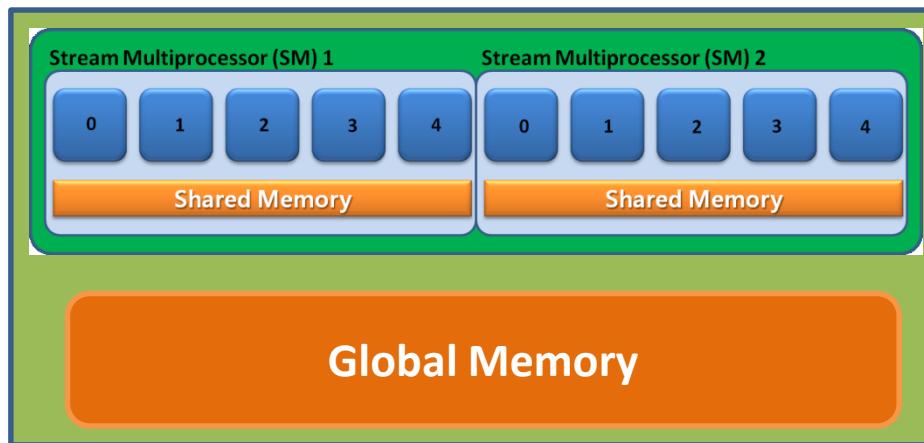


# Parallel Programming on a Manycore

Hm... Where are A, B, C arrays in a system ?

A system ?

GPU

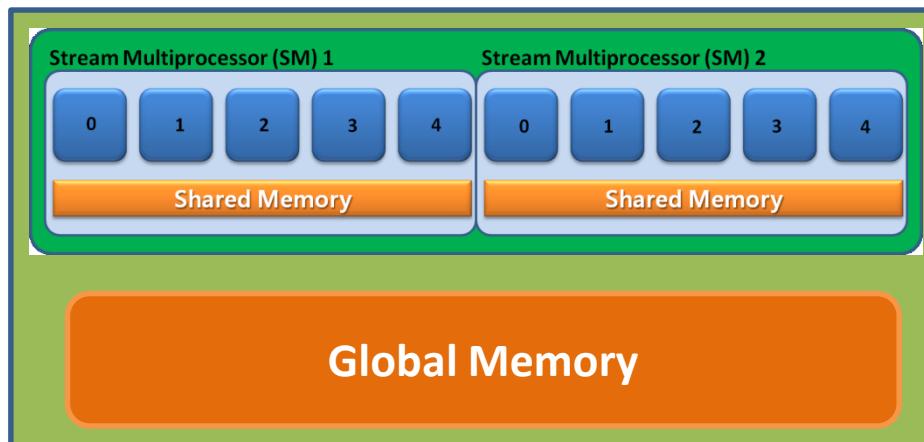


# Parallel Programming on a Manycore

Hm... Where are A, B, C arrays in a system ?

A system ?

**GPU**



PCI-E

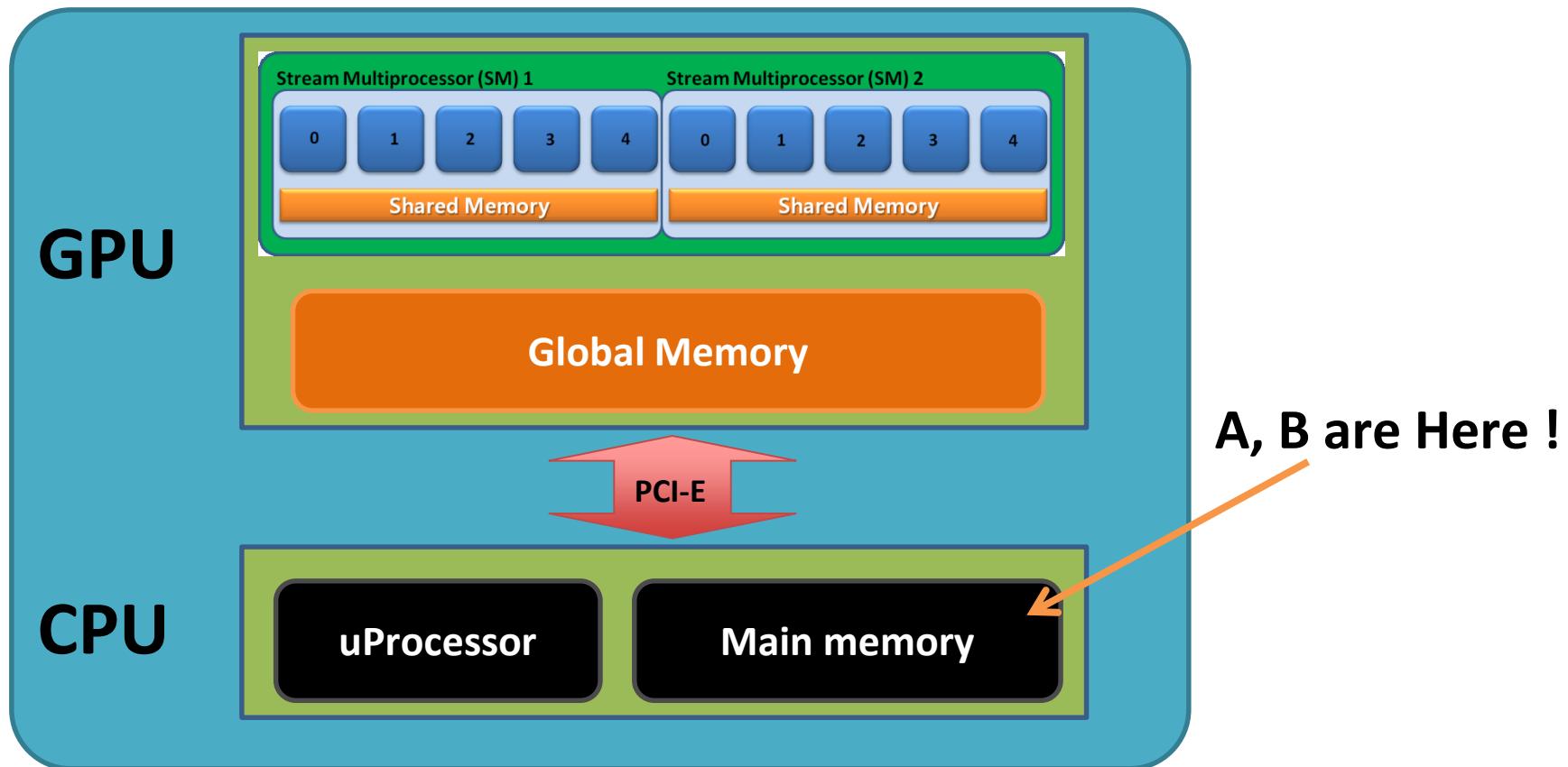
**CPU**



# Parallel Programming on a Manycore

Hm... Where are A, B, C arrays in a system ?

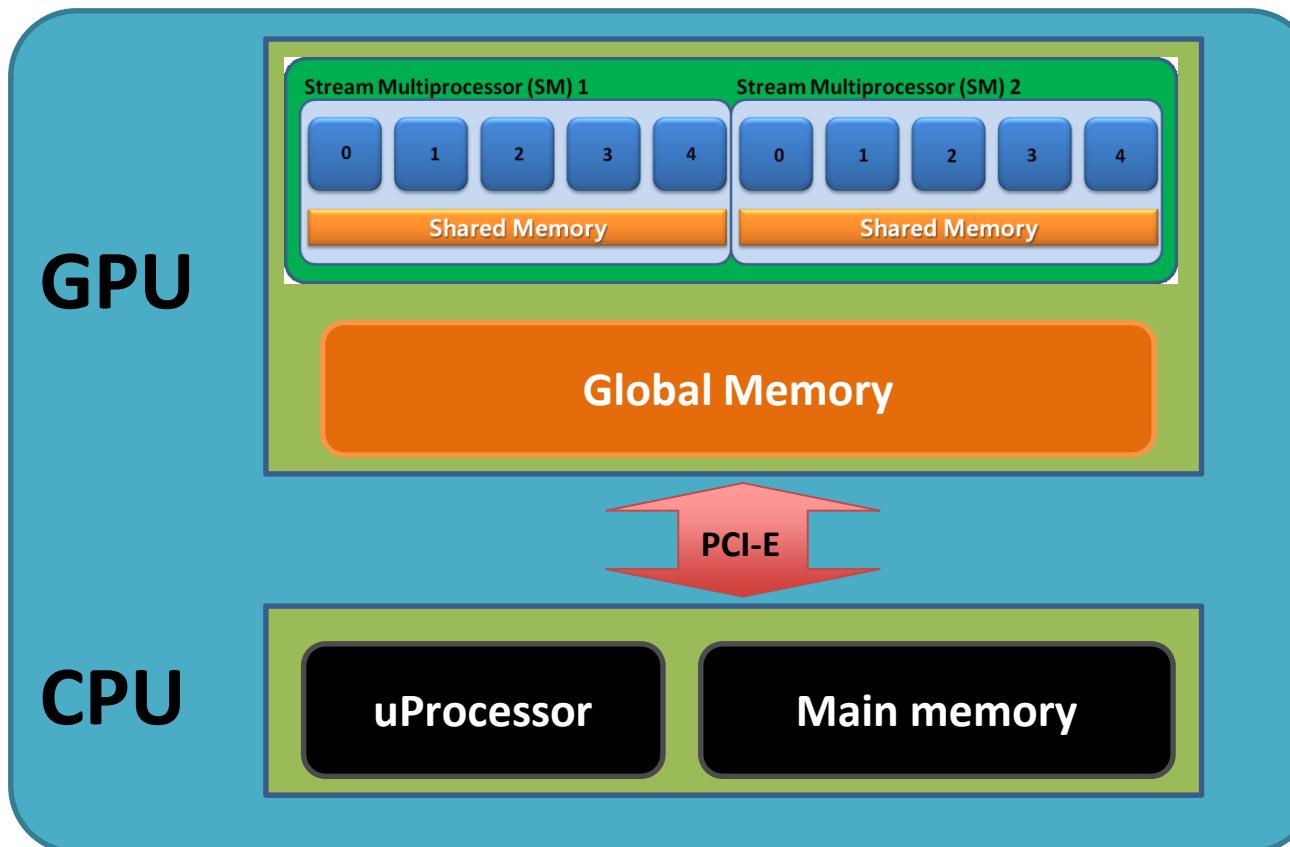
A system !



# Parallel Programming on a Manycore

Hm... Where are A, B, C arrays in a system ?

A system !



1. `cudaMalloc`
2. `cudaMemcpy`
3. Kernel launch
4. `cudaMemcpy`

# 차례

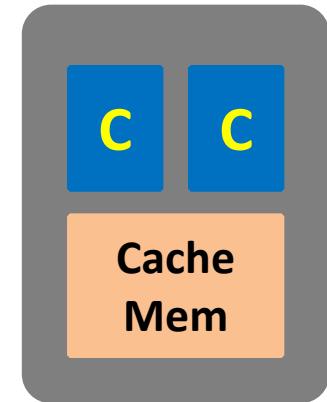
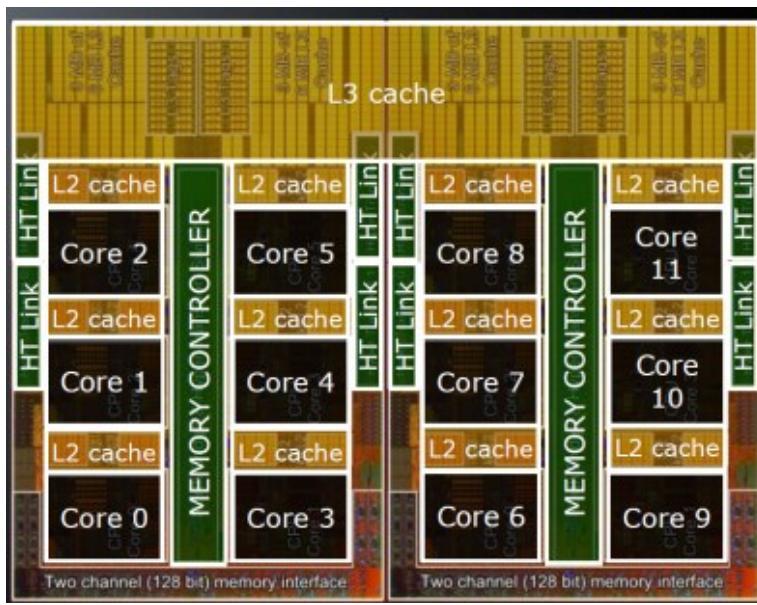
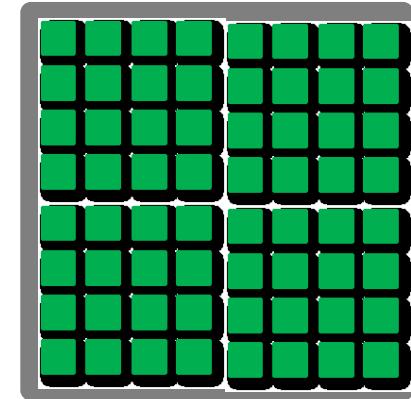
- **Introduction**
  - Multicore/Manycore and GPU
  - GPU on Medical Applications
- **Parallel Programming on GPUs: Basics**
  - Conceptual Introduction
- **GPU Architecture Review**
- **Parallel Programming on GPUs: Practice**
  - Real programming
- **Conclusion**

DO YOU  
KNOW?



# GPU Architecture

- The **architecture** of GPUs
  - Single Instruction Multiple Thread (SIMT)
  - Manycore Vector Processing
  - **Throughput**-Oriented Accelerating Architecture
- First See a **CPU Case**: AMD 12 Core CPU

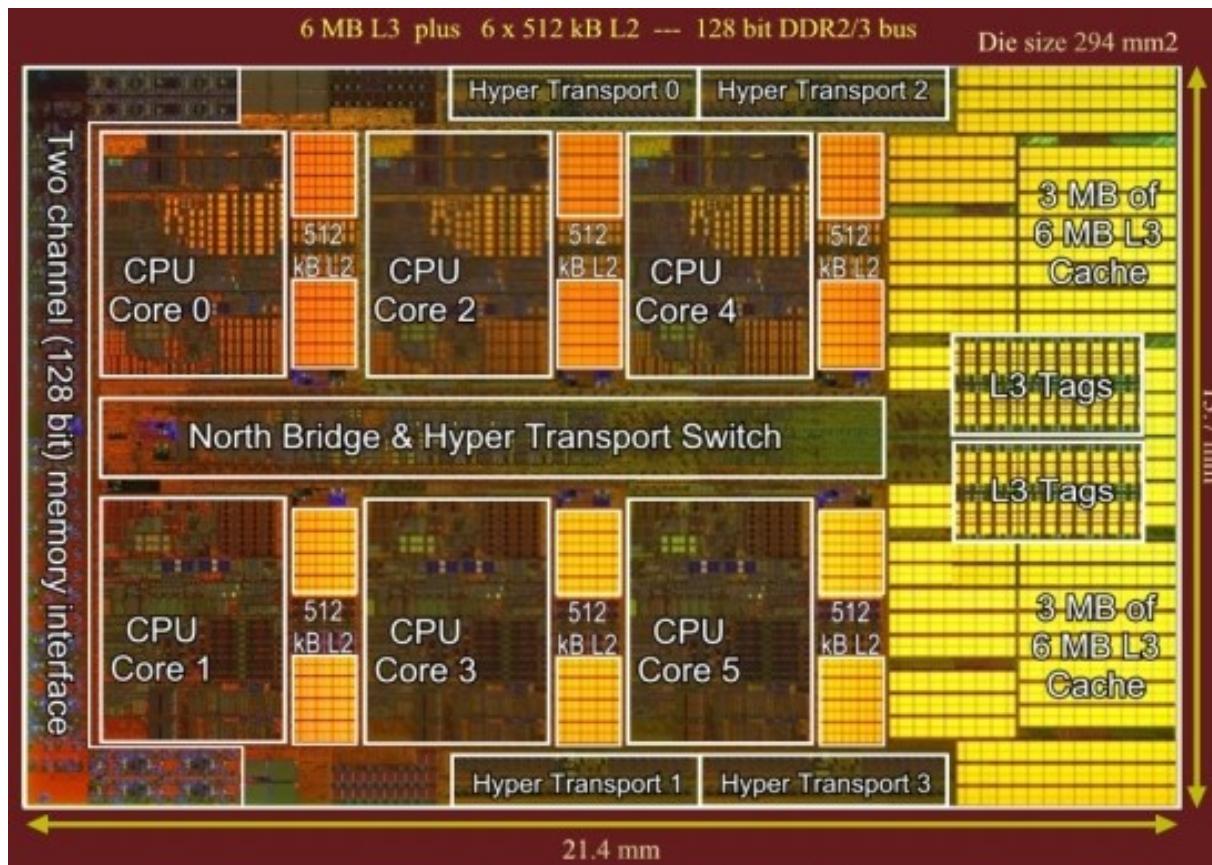


**Many on-chip Cache: L1/L2/L3**

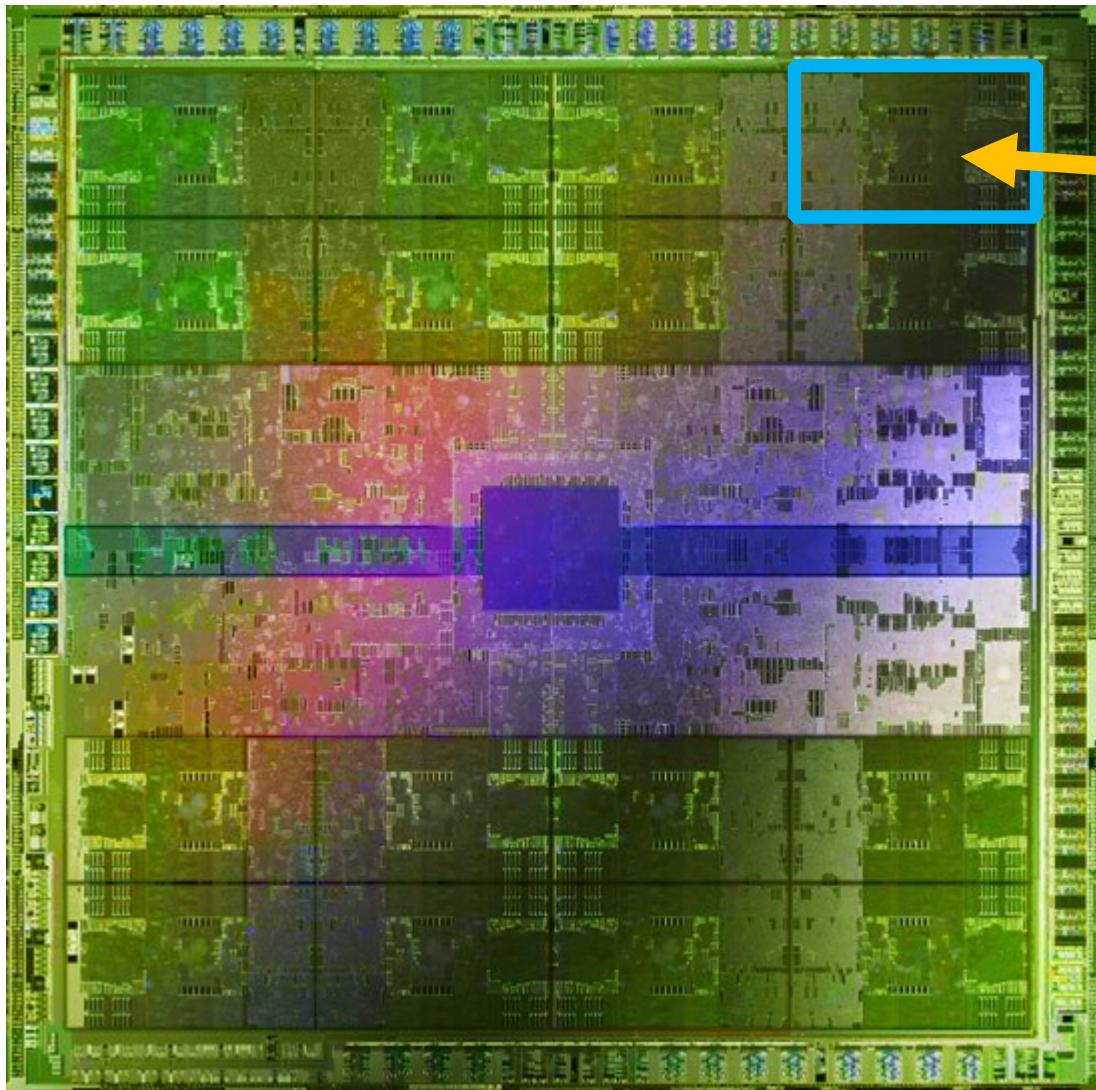
\* HT: HyperTransport - low-latency point-to-point link - <https://en.wikipedia.org/wiki/HyperTransport>

# One More ?

- Another AMD 6-core CPU



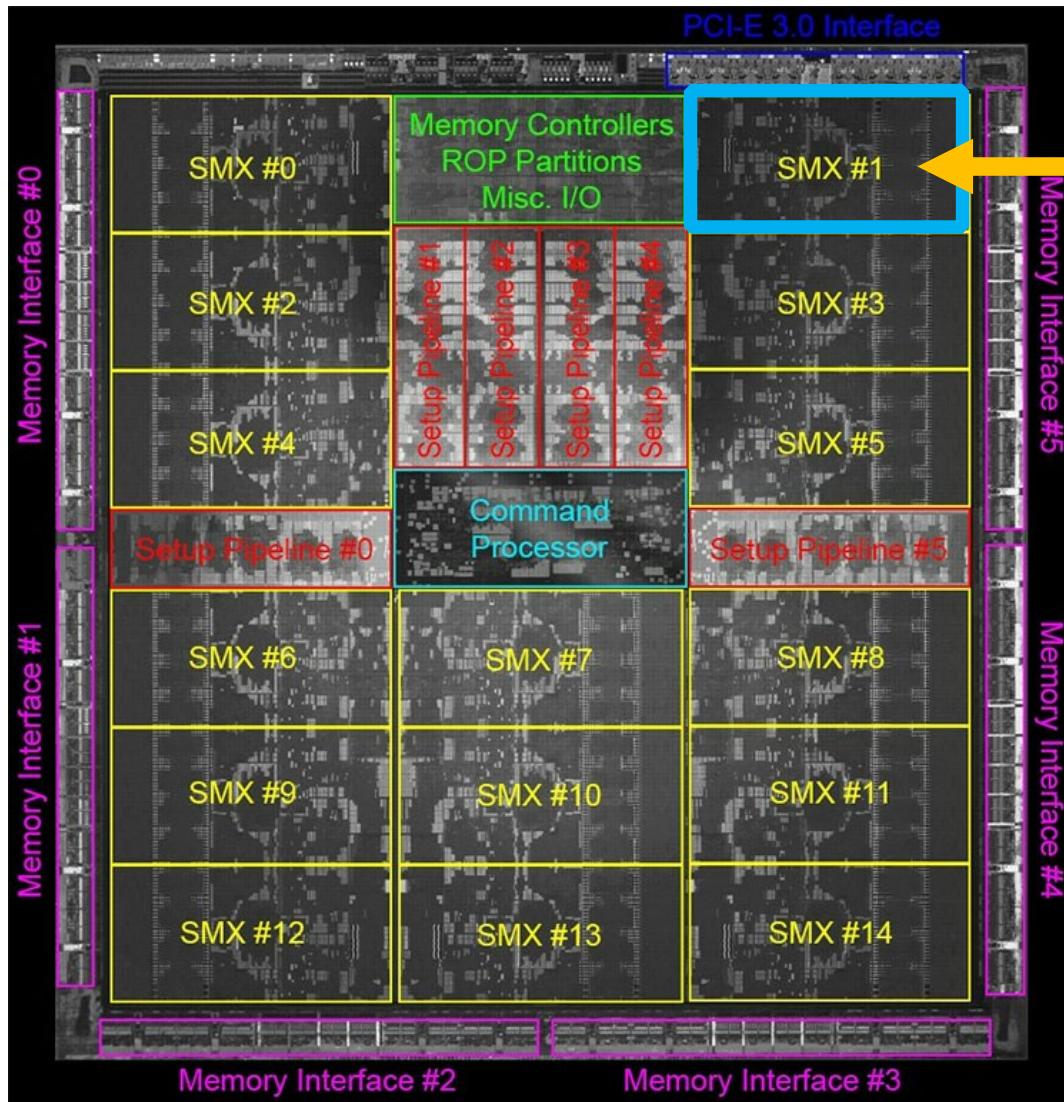
# Then, Fermi GPU ?



Compute Unit  
(SM = 32 CUDA cores)

16 SM = 512 Cores

# Then, Kepler GPU ?

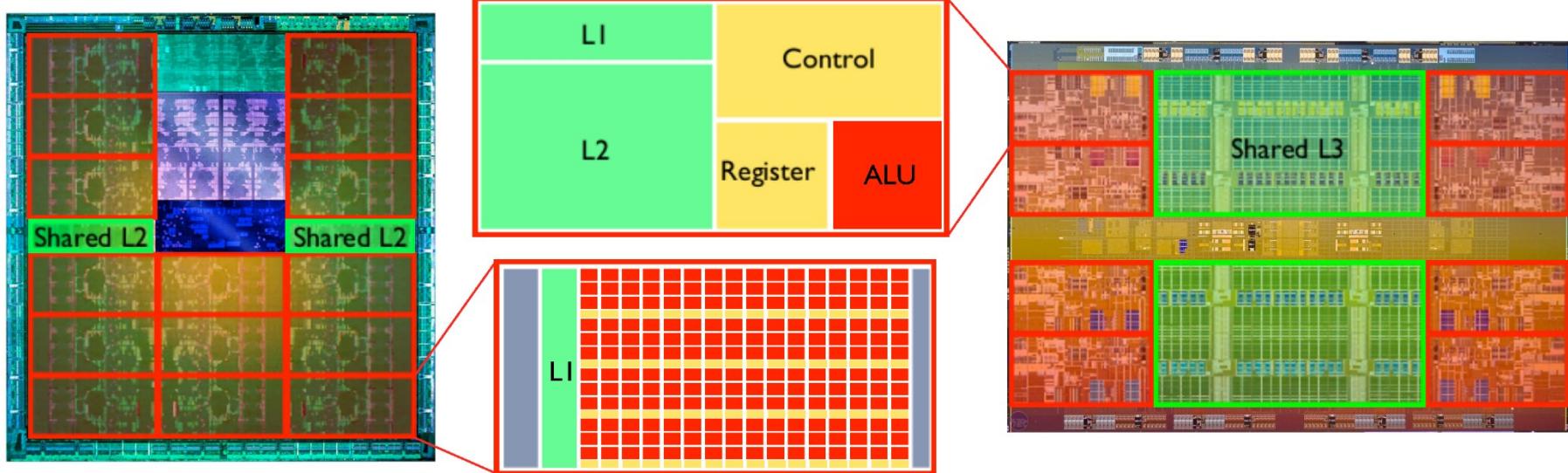


Compute Unit  
(SMX = 192 CUDA cores)

16 SMX = 2880 Cores

GK110 Packs 2880 CUDA Cores, 384-bit Memory Interface

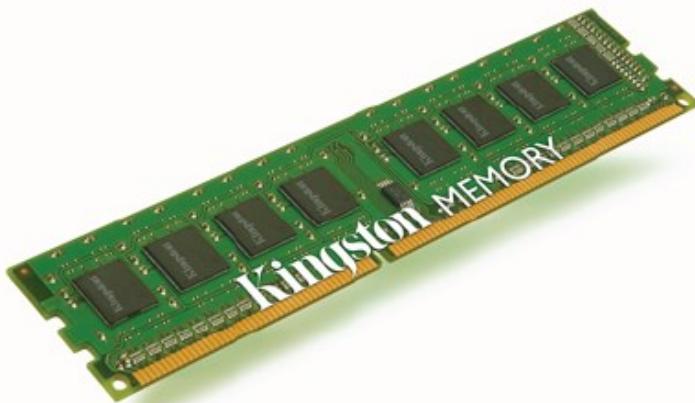
# Cache in CPU & GPU



- Die shots of **NVIDIA's GK110 GPU** (left) and **Intel's Nehalem Beckton 8 core CPU** (right) with block diagrams for the GPU streaming multiprocessor and the CPU core.

# One more thing in GPU

- Special Memory in GPU
  - **Graphics memory**: much **higher bandwidth** than standard CPU memory (QDR)



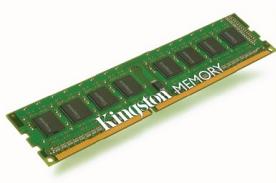
CPUs use DRAM



GPUs use Graphics DRAM

# One more thing in GPU

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  - **Graphics memory**: much **higher bandwidth** than standard CPU memory (QDR)



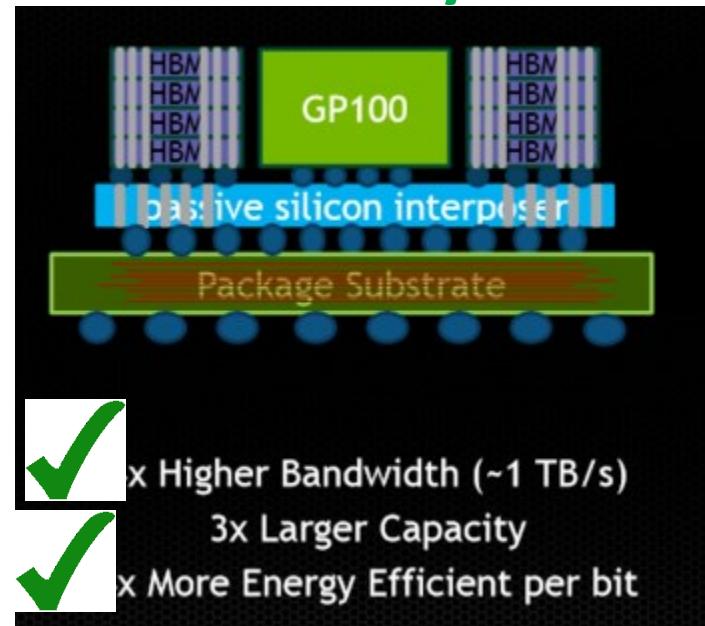
CPUs use DRAM



GPUs use Graphics DRAM

**HBM2**  
**High Bandwidth Memory**

## Stacked Memory in Pascal





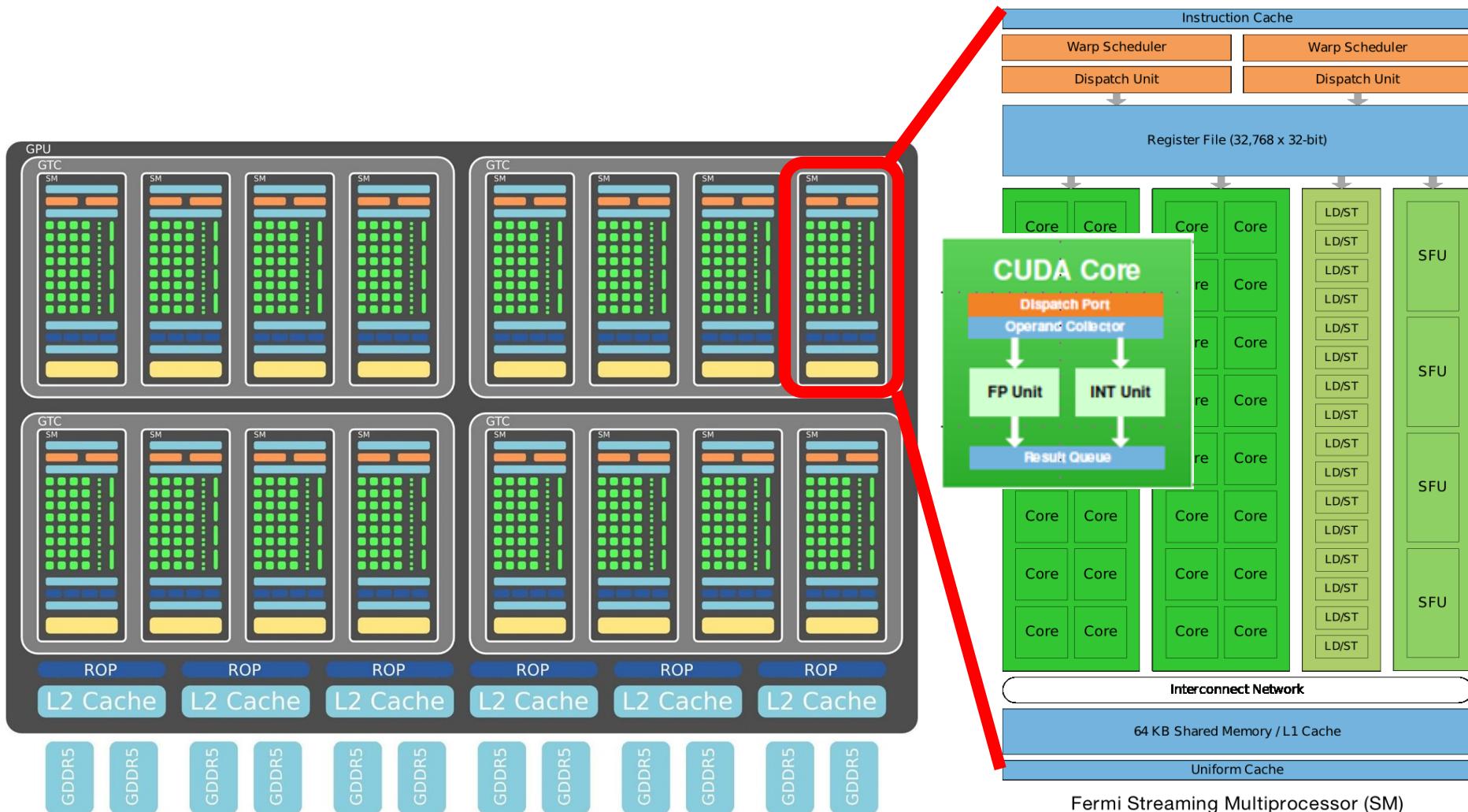
# Simple Comparison

- GPU vs CPU: **Theoretical** Peak capabilities

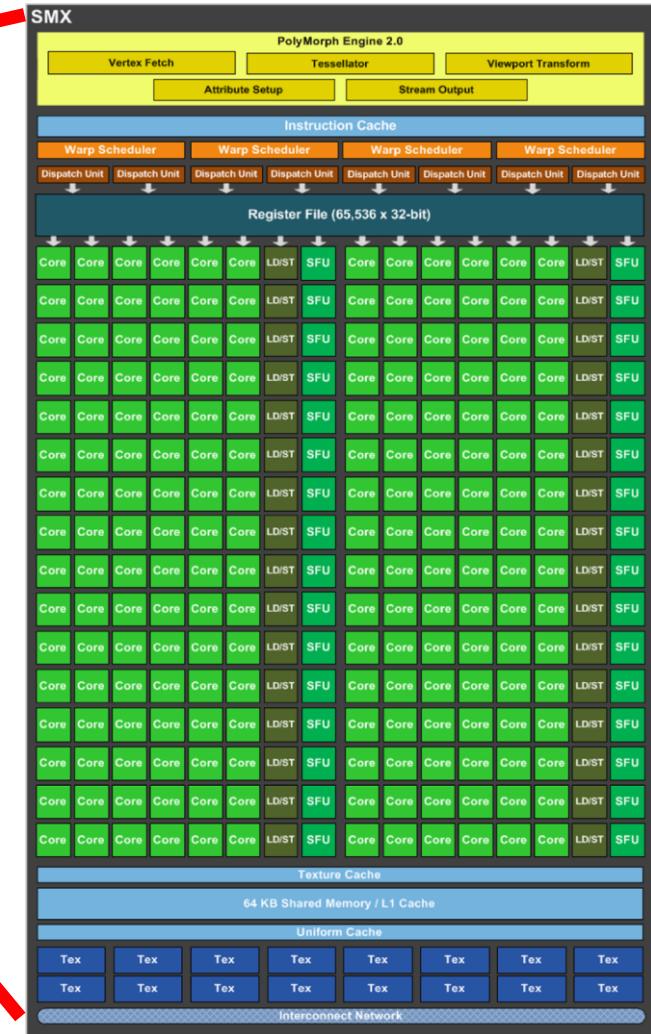
	NVIDIA Fermi	AMD Magny-Cours (6172)
Cores	448 (1.15GHz)	12 (2.1GHz)
Operations/cycle	1	4
DP Performance (peak)	515 GFlops	101 GFlops
Memory Bandwidth (peak)	144 GB/s	27.5 GB/s

- For these particular example, GPU's theoretical advantage is ~5x for both compute and main memory bandwidth
- Performance very much depends on applications
  - Depends on how well a target application is suited to/tuned for architecture

# Nvidia GPU: Fermi (2009)

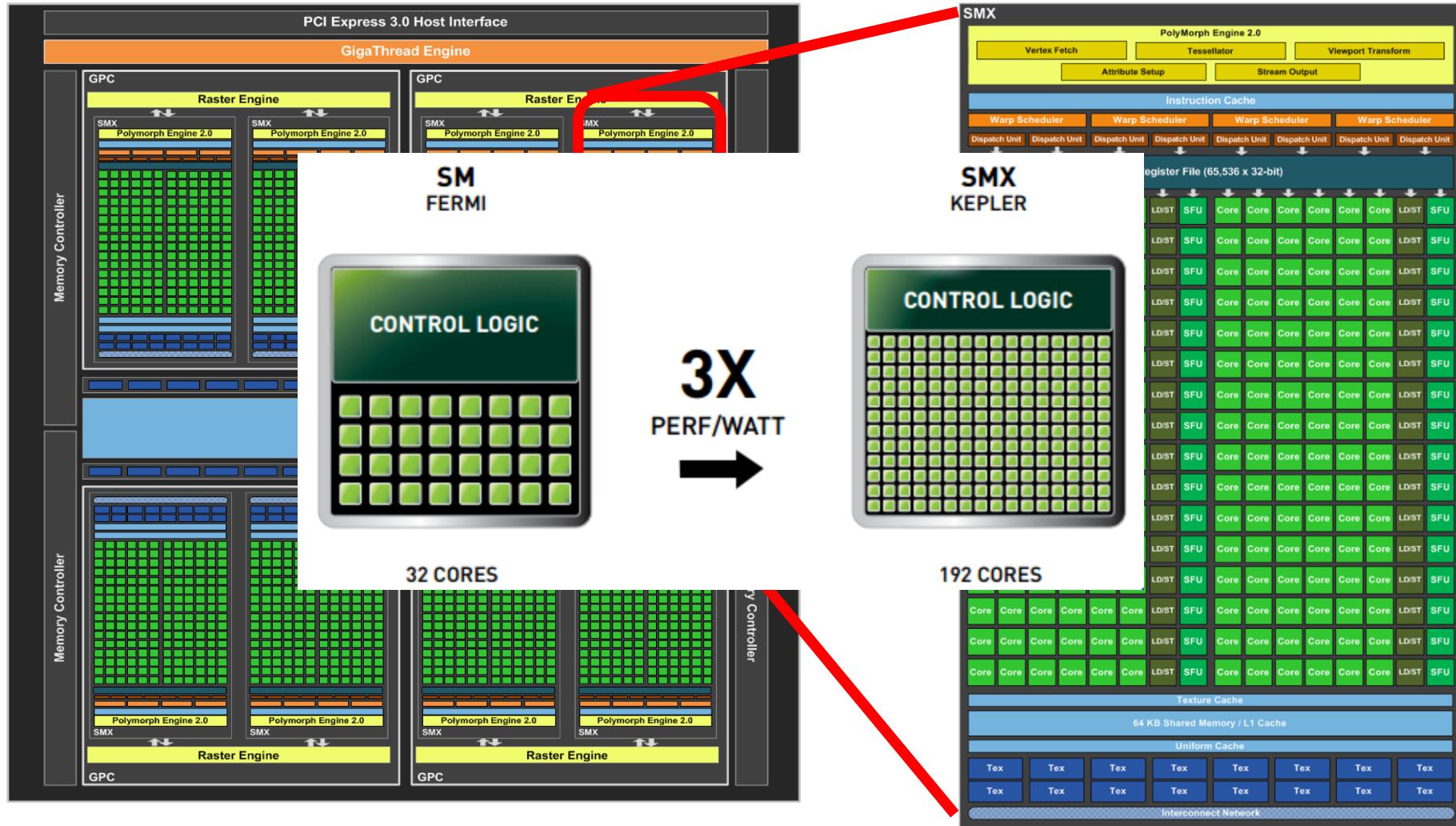


# Nvidia GPU: Kepler (2012)



ref: <http://www.nvidia.com/object/nvidia-kepler.html>

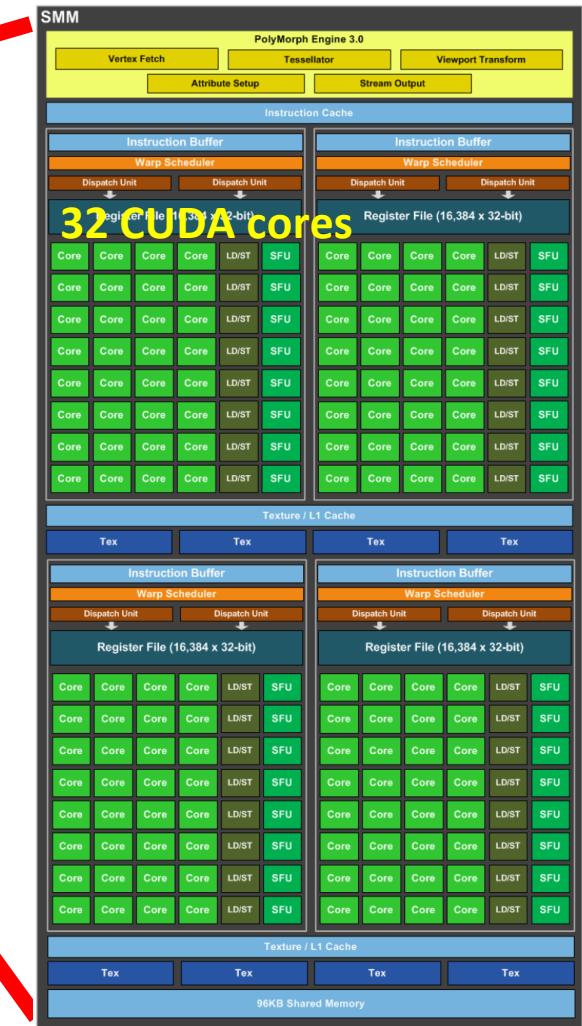
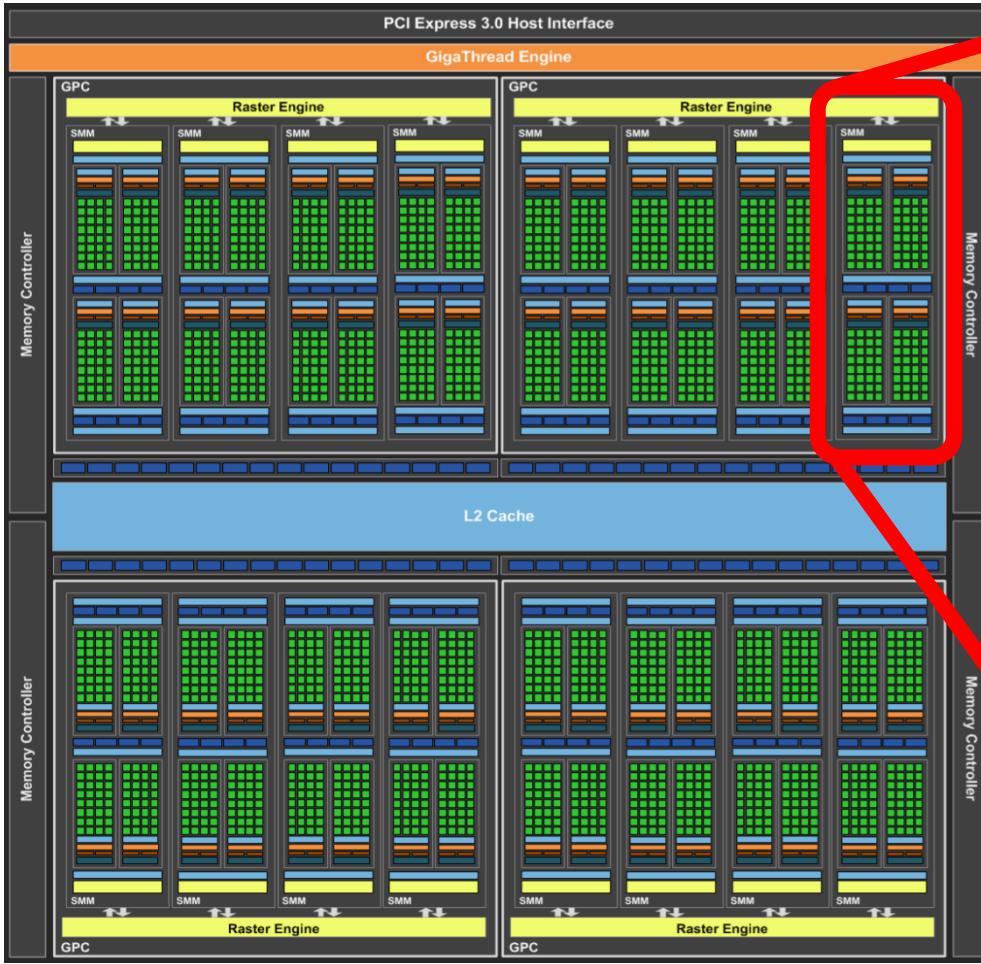
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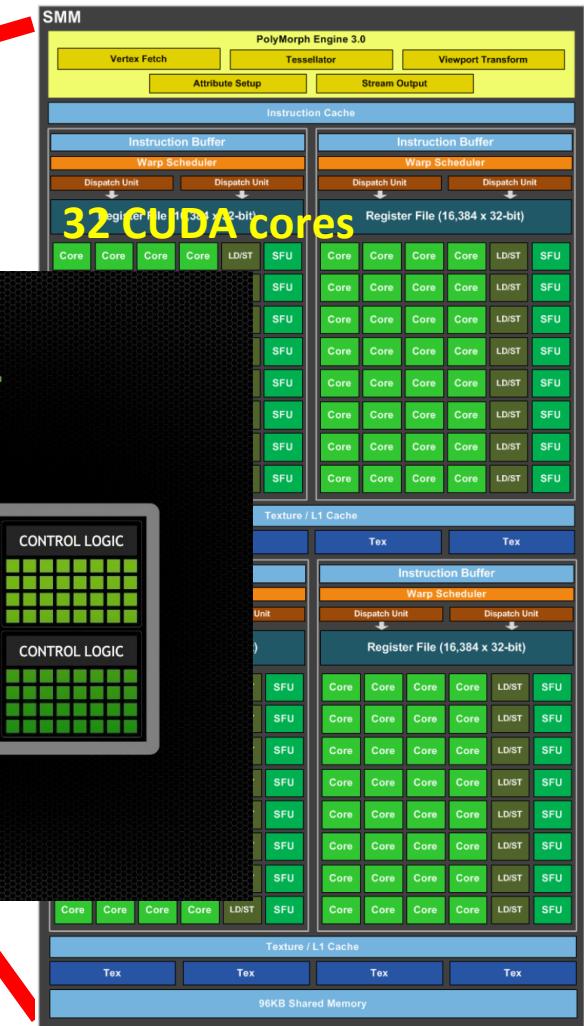
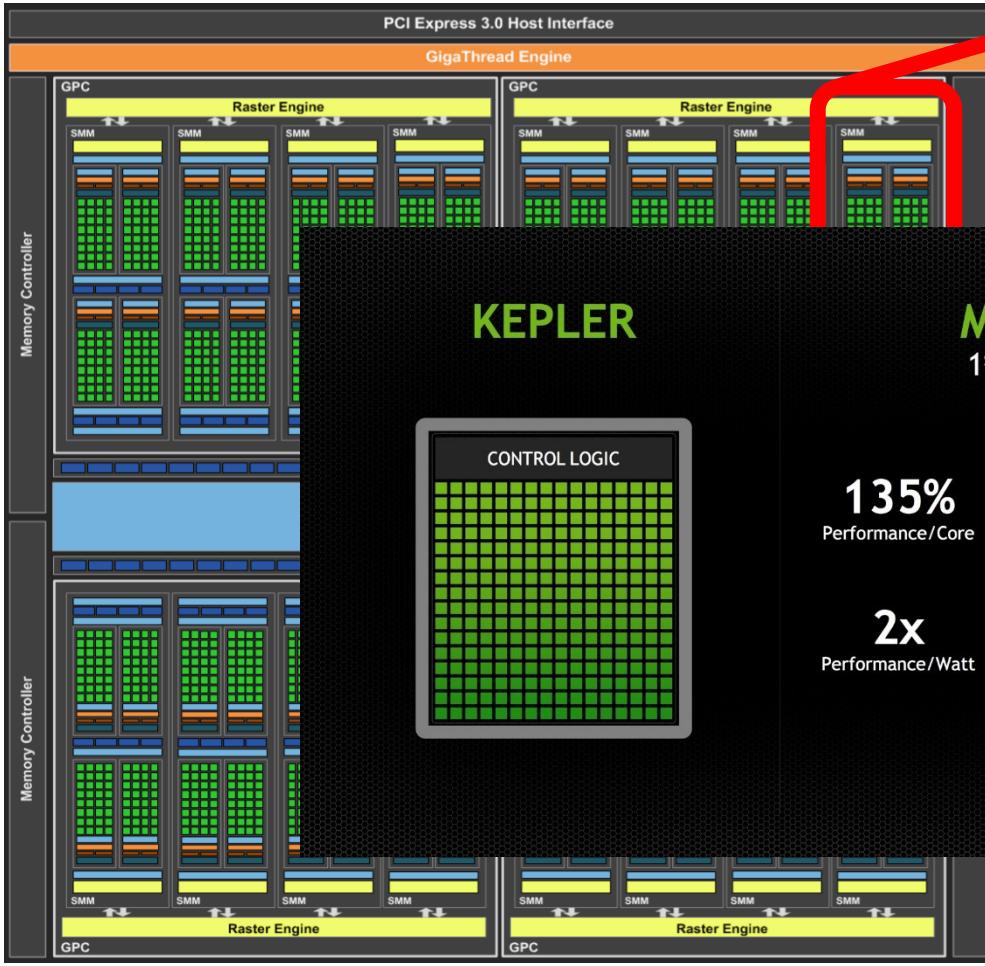
# Nvidia GPU: Maxwell (2014)

128 CUDA cores/SMM



# Nvidia GPU: Maxwell (2014)

128 CUDA cores/SMM



# Nvidia GPU: Pascal (2016)

## TESLA P100 GPU: GP100

56 SMs

3584 CUDA Cores

5.3 TF Double Precision

10.6 TF Single Precision

21.2 TF Half Precision

16 GB HBM2

720 GB/s Bandwidth



Looking at an individual SM, there are 64 CUDA cores, and each SM has a 256K register file, which is four times the size of the shared L2 cache size. In total, the GP100 has 14,336K of register file space. Compared to Maxwell, each core in Pascal has twice as many registers, 1.33 times more shared memory

# Nvidia GPU: Pascal (2016)

## GP100 SM

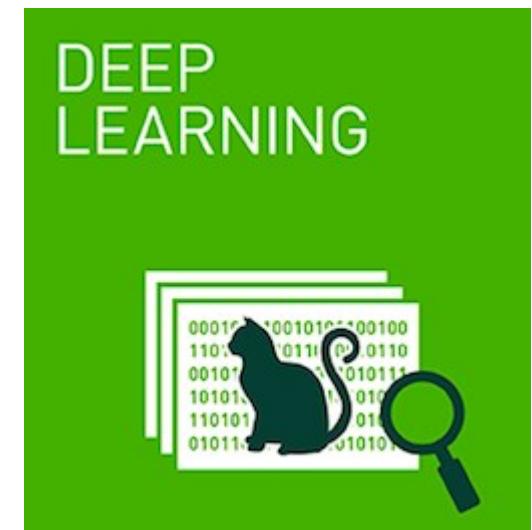
GP100	
CUDA Cores	64
Register File	256 KB
Shared Memory	64 KB
Active Threads	2048
Active Blocks	32



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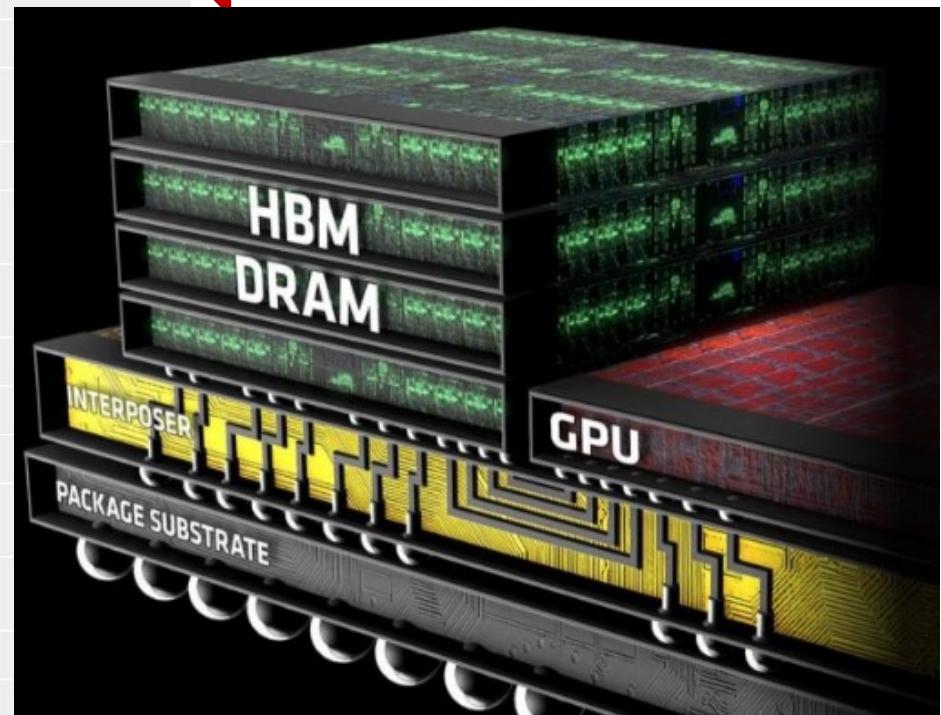
# Nvidia GPU: Pascal (2016)

	Tesla P100	Tesla K80	Tesla K40	Tesla M40
Stream Processors	3584	2 x 2496	2880	3072
Core Clock	1328MHz	562MHz	745MHz	948MHz
Boost Clock(s)	1480MHz	875MHz	810MHz, 875MHz	1114MHz
Memory Clock	1.4Gbps HBM2	5GHz GDDR5	6GHz GDDR5	6GHz GDDR5
Memory Bus Width	4096-bit	2 x 384-bit	384-bit	384-bit
Memory Bandwidth	720GB/sec	2 x 240GB/sec	288GB/sec	288GB/sec
VRAM	16GB	2 x 12GB	12GB	12GB
Half Precision	21.2 TFLOPS	8.74 TFLOPS	4.29 TFLOPS	6.8 TFLOPS
Single Precision	10.6 TFLOPS	8.74 TFLOPS	4.29 TFLOPS	6.8 TFLOPS
Double Precision	5.3 TFLOPS (1/2 rate)	2.91 TFLOPS (1/3 rate)	1.43 TFLOPS (1/3 rate)	213 GFLOPS (1/32 rate)
GPU	GP100 (610mm <sup>2</sup> )	GK210	GK110B	GM200
Transistor Count	15.3B	2 x 7.1B(?)	7.1B	8B
TDP	300W	300W	235W	250W
Cooling	N/A	Passive	Active/Passive	Passive
Manufacturing Process	TSMC 16nm FinFET	TSMC 28nm	TSMC 28nm	TSMC 28nm
Architecture	Pascal	Kepler	Kepler	Maxwell 2

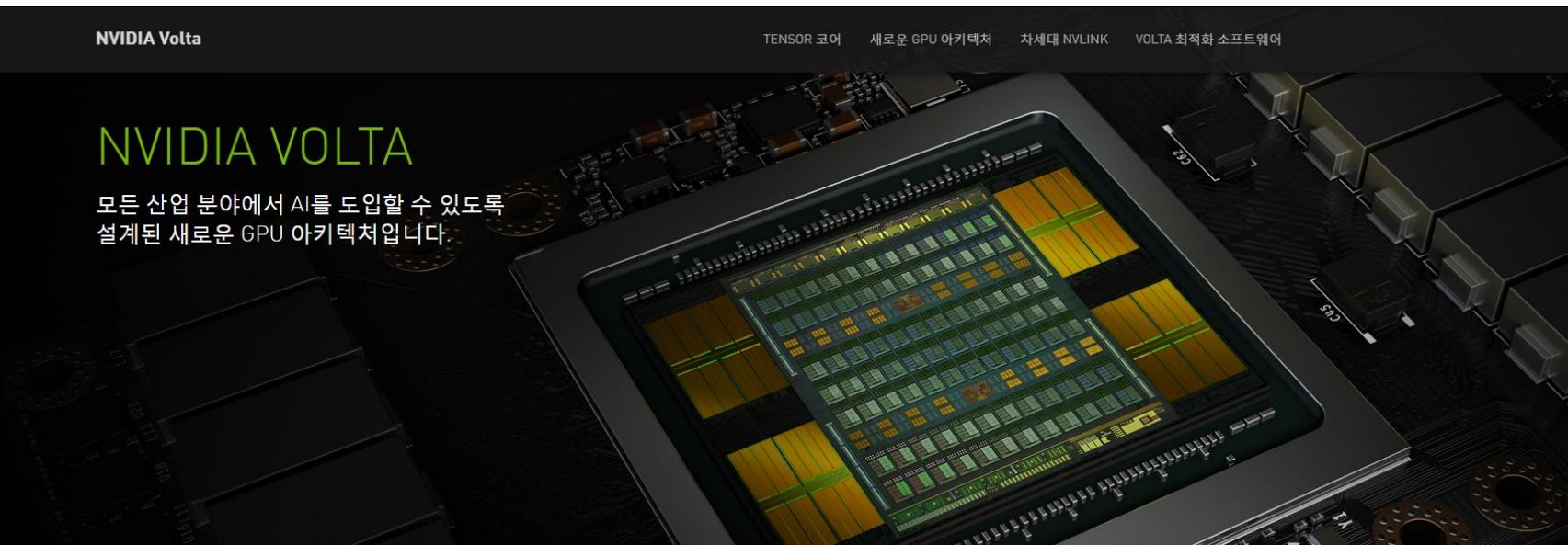


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VRAM	16GB	2 x 12GB	12GB	
Half Precision	21.2 TFLOPS	8.74 TFLOPS	4.29 TFLOPS	
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Architecture	Pascal	Kepler	Kepler	Maxwell 2



# Nvidia GPU: Volta (2017)



# Nvidia GPU: Volta (2017)



Volta GV100 Full GPU with 84 SM Units



# Nvidia GPU: Volta (2017)

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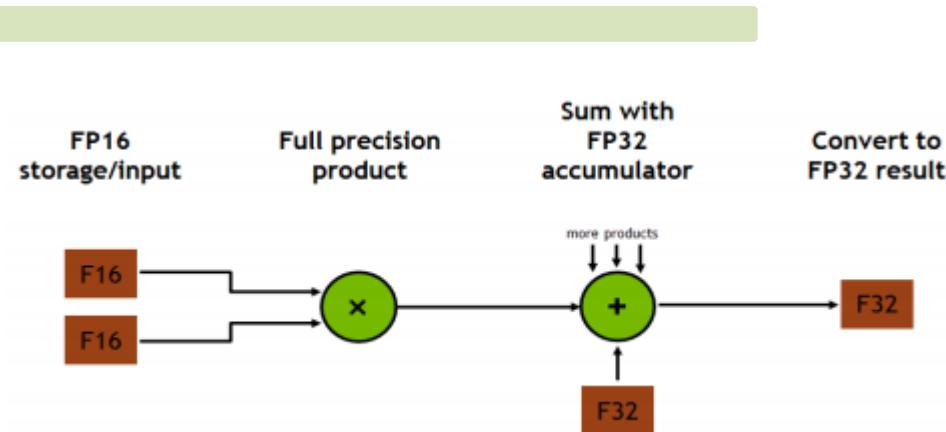
- Volta uses a **12 nm FinFET** process.
- Architectural improvements of the Volta architecture include the following:
  - **CUDA Compute Capability 7.0 ~~~> 9.0**
  - **High Bandwidth Memory 2** <https://en.wikipedia.org/wiki/CUDA>
  - **NVLink 2.0**: a high-bandwidth bus between the CPU and GPU, and between multiple GPUs. Allows much higher transfer speeds than those achievable by using PCI Express; estimated to provide **25 Gbit/s per lane**.[7] (Disabled for Titan V)
  - **Tensor cores**: A tensor core is a unit that multiplies two  $4 \times 4$  FP16 matrices, and then adds a third FP16 or FP32 matrix to the result by using fused multiply-add (fma) operations, and obtains an FP32 result that could be optionally demoted to an FP16 result. Tensor cores are intended to speed up the training of neural networks.

# Volta: Tensor Core

- **Tensor cores:** A tensor core is a unit that multiplies two  $4 \times 4$  FP16 matrices, and then adds a third FP16 or FP32 matrix to the result by using **fused multiply-add (fma) operations**, and obtains an FP32 result that could be optionally demoted to an FP16 result. Tensor cores are intended to speed up the training of neural networks.

$$D = A \times B + C$$

$D = \begin{pmatrix} A_{0,0} & A_{0,1} & A_{0,2} & A_{0,3} \\ A_{1,0} & A_{1,1} & A_{1,2} & A_{1,3} \\ A_{2,0} & A_{2,1} & A_{2,2} & A_{2,3} \\ A_{3,0} & A_{3,1} & A_{3,2} & A_{3,3} \end{pmatrix}_{\text{FP16 or FP32}} \begin{pmatrix} B_{0,0} & B_{0,1} & B_{0,2} & B_{0,3} \\ B_{1,0} & B_{1,1} & B_{1,2} & B_{1,3} \\ B_{2,0} & B_{2,1} & B_{2,2} & B_{2,3} \\ B_{3,0} & B_{3,1} & B_{3,2} & B_{3,3} \end{pmatrix}_{\text{FP16}} + \begin{pmatrix} C_{0,0} & C_{0,1} & C_{0,2} & C_{0,3} \\ C_{1,0} & C_{1,1} & C_{1,2} & C_{1,3} \\ C_{2,0} & C_{2,1} & C_{2,2} & C_{2,3} \\ C_{3,0} & C_{3,1} & C_{3,2} & C_{3,3} \end{pmatrix}_{\text{FP16 or FP32}}$



# Nvidia GPU: Volta (2017)

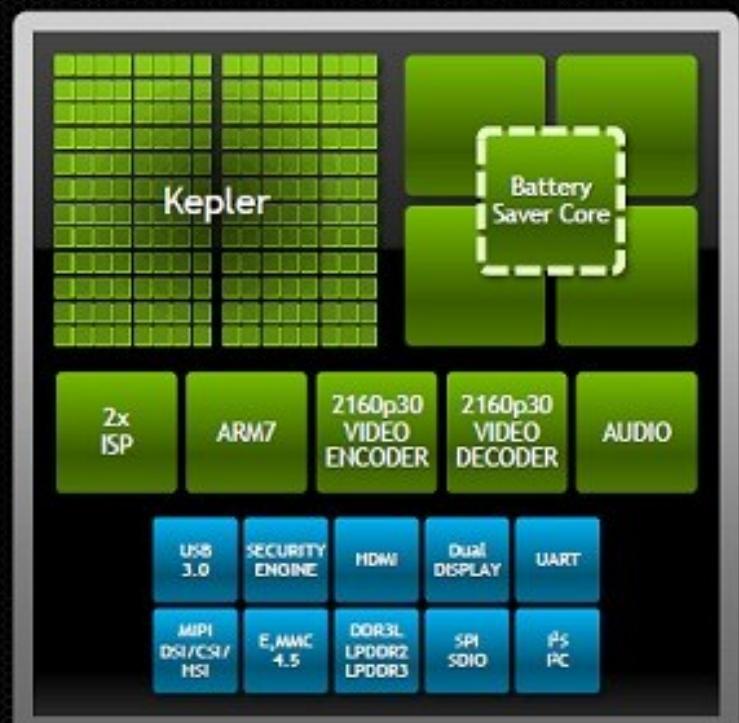
Table 1. Comparison of NVIDIA Tesla GPUs

Tesla Product	Tesla K40	Tesla M40	Tesla P100	Tesla V100
GPU	GK180 (Kepler)	GM200 (Maxwell)	GP100 (Pascal)	GV100 (Volta)
SMs	15	24	56	80
TPCs	15	24	28	40
FP32 Cores / SM	192	128	64	64
FP32 Cores / GPU	2880	3072	3584	5120
FP64 Cores / SM	64	4	32	32
FP64 Cores / GPU	960	96	1792	2560
Tensor Cores / SM	NA	NA	NA	8
Tensor Cores / GPU	NA	NA	NA	640
GPU Boost Clock	810/875 MHz	1114 MHz	1480 MHz	1530 MHz
Peak FP32 TFLOPS <sup>1</sup>	5	6.8	10.6	15.7
Peak FP64 TFLOPS <sup>1</sup>	1.7	.21	5.3	7.8
Peak Tensor TFLOPS <sup>1</sup>	NA	NA	NA	125
Texture Units	240	192	224	320
Memory Interface	384-bit GDDR5	384-bit GDDR5	4096-bit HBM2	4096-bit HBM2
Memory Size	Up to 12 GB	Up to 24 GB	16 GB	16 GB
L2 Cache Size	1536 KB	3072 KB	4096 KB	6144 KB
Shared Memory Size / SM	16 KB/32 KB/48 KB	96 KB	64 KB	Configurable up to 96 KB
Register File Size / SM	256 KB	256 KB	256 KB	256KB
Register File Size / GPU	3840 KB	6144 KB	14336 KB	20480 KB
TDP	235 Watts	250 Watts	300 Watts	300 Watts
Transistors	7.1 billion	8 billion	15.3 billion	21.1 billion
GPU Die Size	551 mm <sup>2</sup>	601 mm <sup>2</sup>	610 mm <sup>2</sup>	815 mm <sup>2</sup>
Manufacturing Process	28 nm	28 nm	16 nm FinFET+	12 nm FFN

<sup>1</sup> Peak TFLOPS rates are based on GPU Boost Clock

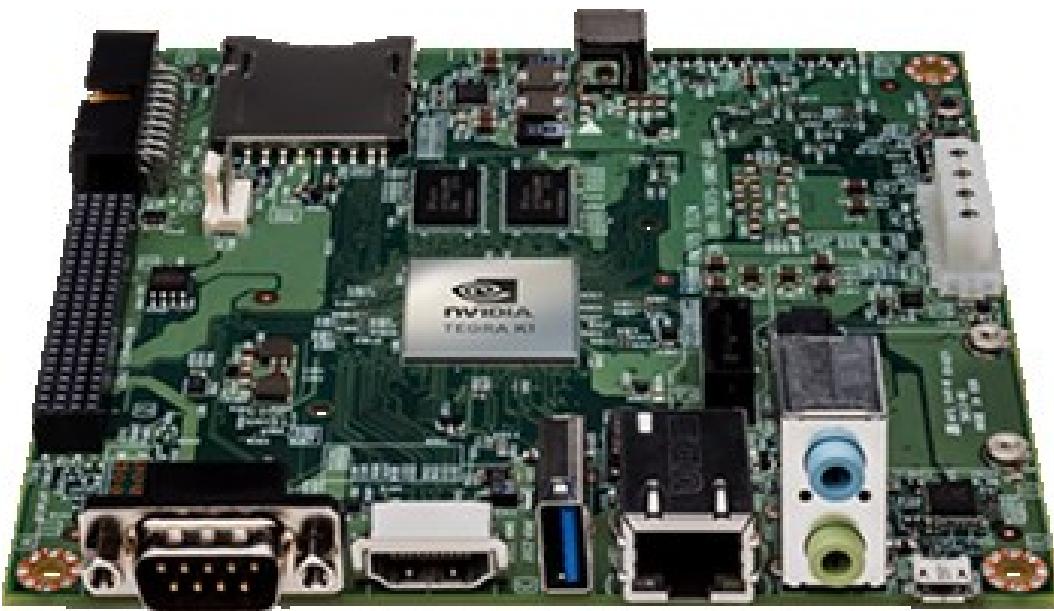
# Embedded Mobile ?

## Tegra K1

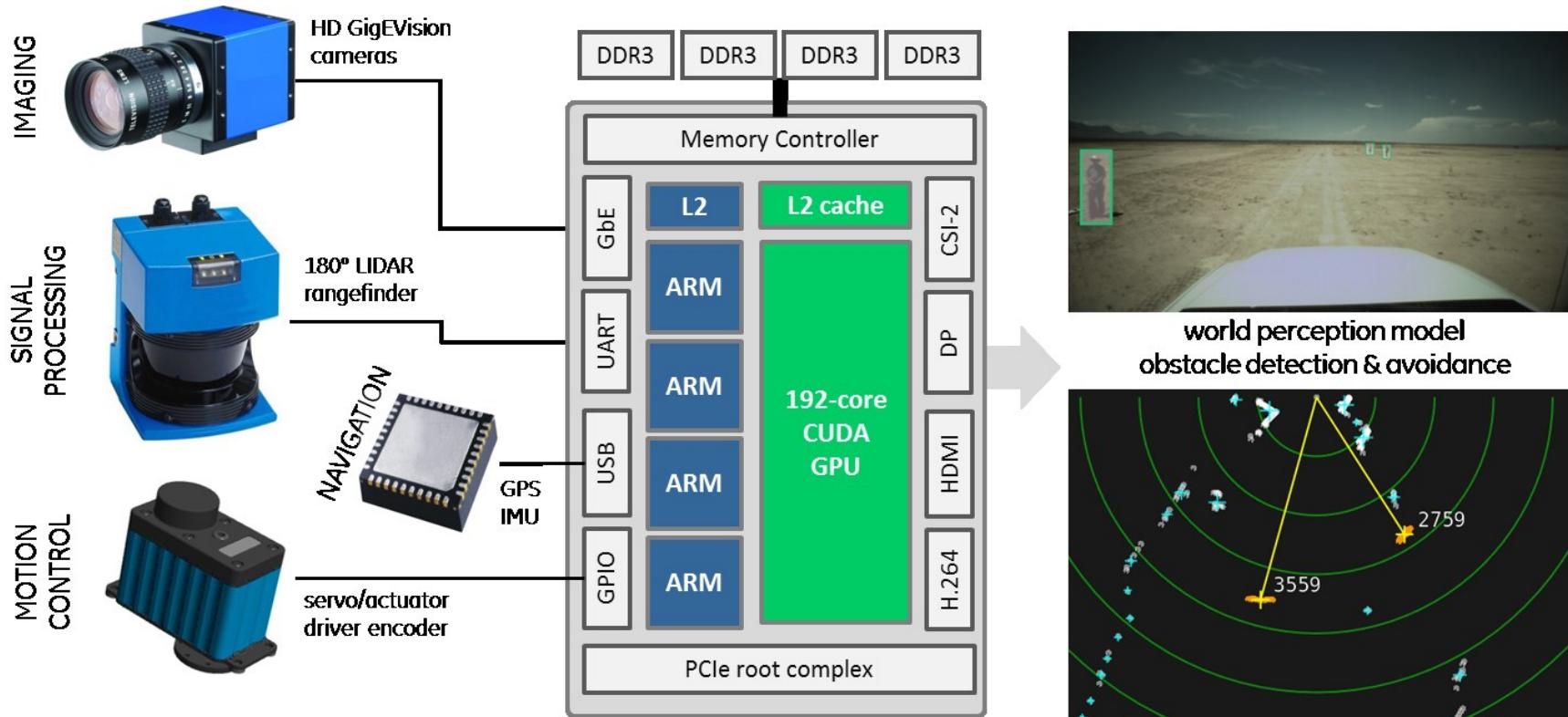


GPU	Kepler GPU (192 CUDA Cores) OpenGL 4.4, OpenGL ES3.0, DX11, CUDA 6
CPU	Quad Core Cortex A15 "r3" With 5th Battery-Saver Core; 2MB L2 cache
CAMERA	Dual High Performance ISP 1.2 Gigapixel throughput, 100MP sensor
POWER	Lower Power 28HPM, Battery Saver Core
DISPLAY	4K panel, 4K HDMI DSI, eDP, LVDS, High Speed HDMI 1.4a

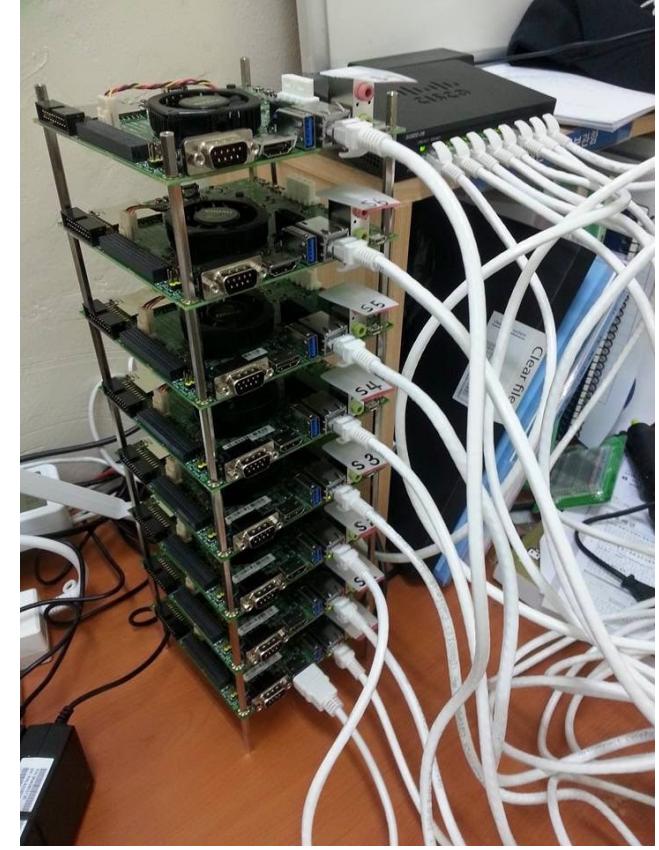
# Embedded Mobile ?



# Embedded Mobile ?



# Jetson TK1 Micro Server Cluster



# Our Lab: Jetson TK1

```
ubuntu@tegra-ubuntu: ~/NVIDIA_CUDA-6.5_Samples/1_Utils/deviceQuery
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/1_Utils/deviceQuery$ ./deviceQuery
./deviceQuery Starting...

CUDA Device Query (Runtime API) version (CUDART static linking)

Detected 1 CUDA Capable device(s)

Device 0: "GK20A"
  CUDA Driver Version / Runtime Version      6.5 / 6.5
  CUDA Capability Major/Minor version number: 3.2
  Total amount of global memory:            1892 MBytes (1984385024 bytes)
    ( 1) Multiprocessors, (192) CUDA Cores/MP: 192 CUDA Cores
    GPU Clock rate:                         852 MHz (0.85 GHz)
    Memory Clock rate:                      924 Mhz
    Memory Bus Width:                      64-bit
    L2 Cache Size:                          131072 bytes
    Maximum Texture Dimension Size (x,y,z): 1D=(65536), 2D=(65536, 65536), 3D=(4096, 4096, 4096)
    Maximum Layered 1D Texture Size, (num) layers 1D=(16384), 2048 layers
    Maximum Layered 2D Texture Size, (num) layers 2D=(16384, 16384), 2048 layers
    Total amount of constant memory:          65536 bytes
    Total amount of shared memory per block:   49152 bytes
    Total number of registers available per block: 32768
    Warp size:                            32
    Maximum number of threads per multiprocessor: 2048
    Maximum number of threads per block:       1024
    Max dimension size of a thread block (x,y,z): (1024, 1024, 64)
    Max dimension size of a grid size (x,y,z): (2147483647, 65535, 65535)
    Maximum memory pitch:                   2147483647 bytes
    Texture alignment:                     512 bytes
    Concurrent copy and kernel execution: Yes with 1 copy engine(s)
    Run time limit on kernels:             No
    Integrated GPU sharing Host Memory: Yes
    Support host page-locked memory mapping: Yes
    Alignment requirement for Surfaces: Yes
    Device has ECC support:               Disabled
    Device supports Unified Addressing (UVA): Yes
    Device PCI Bus ID / PCI location ID: 0 / 0
    Compute Mode:
      < Default (multiple host threads can use ::cudaSetDevice() with device simultaneously) >

deviceQuery, CUDA Driver = CUDART, CUDA Driver Version = 6.5, CUDA Runtime Version = 6.5, NumDevs = 1, Device0 = GK20A
Result = PASS
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/1_Utils/deviceQuery$
```

# Demos on Jetson TK1

- Vision



Face detection: [http://elinux.org/Jetson/Tutorials/Vision-controlled\\_GPIO](http://elinux.org/Jetson/Tutorials/Vision-controlled_GPIO)

Bgfg segm: <http://pages.hmc.edu/jspjut/class/s2015/e190u/lab/lab5.html>

GPIO: <http://www.jetsonhacks.com/2015/09/17/gpio-nvidia-jetson-tk1/>



# Demos on Jetson TK1

---

- Machine Learning
  - Try **YOLO** (You only look once) on your Jetson TK1!
- Follow Steps:
  - git clone <https://github.com/pjreddie/darknet>
  - cd darknet
  - make
  - wget <https://pjreddie.com/media/files/yolo.weights>
  - ./darknet detect cfg/yolo.cfg yolo.weights data/dog.jpg

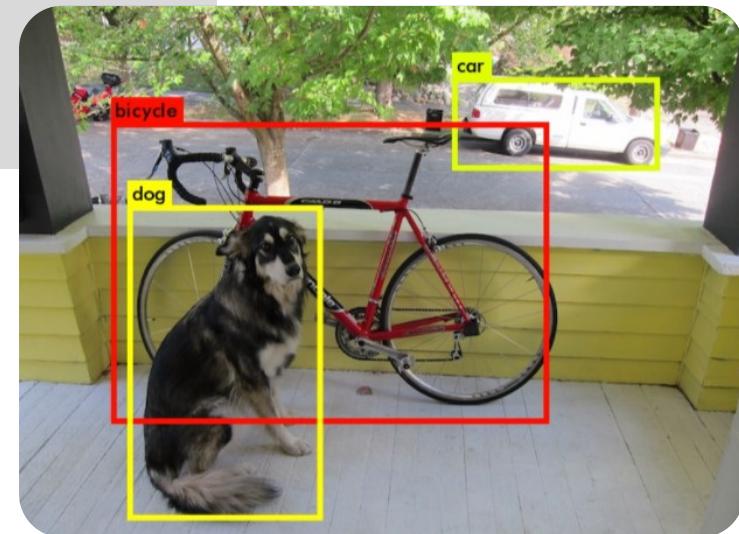
# Demos on Jetson TK1

- Machine Learning

```
layer  filters  size      input        output
  0 conv   32 3 x 3 / 1  416 x 416 x 3 -> 416 x 416 x 32
  1 max     2 x 2 / 2  416 x 416 x 32 -> 208 x 208 x 32
  .....
 29 conv   425 1 x 1 / 1  13 x 13 x1024 -> 13 x 13 x 425
 30 detection
Loading weights from yolo.weights...Done!
data/dog.jpg: Predicted in 0.016287 seconds.
car: 54%
bicycle: 51%
dog: 56%
```

- Try **data/eagle.jpg**

- **data/dog.jpg**
- **data/person.jpg**
- **data/horses.jpg !**



<https://devtalk.nvidia.com/default/topic/975387/fastest-framework-for-object-detection-on-jetson-tk1-/>



# Demos on Jetson TK1

---

- Machine Learning
- Real-Time Detection on a Webcam
  - Install Tiny YOLO
    - Tiny YOLO is based off of the Darknet reference network and is much faster but less accurate than the normal YOLO model.

```
wget https://pjreddie.com/media/files/tiny-yolo-voc.weights
```

```
./darknet detector test cfg/voc.data cfg/tiny-yolo-voc.cfg tiny-yolo-voc.weights data/dog.jpg
```



# Demos on Jetson TK1

---

- Machine Learning
- Real-Time Detection on a Webcam
  - Install Tiny YOLO
    - Tiny YOLO is based off of the Darknet reference network and is much faster but less accurate than the normal YOLO model.

```
wget https://pjreddie.com/media/files/tiny-yolo-voc.weights
```

```
./darknet detector demo cfg/voc.data cfg/tiny-yolo-voc.cfg tiny-yolo-voc.weights
```

<https://devtalk.nvidia.com/default/topic/975387/fastest-framework-for-object-detection-on-jetson-tk1-/>

<https://groups.google.com/forum/#topic/darknet/of0cKVPF7gM>

# Demos on Jetson TK1

- Machine Learning

• R

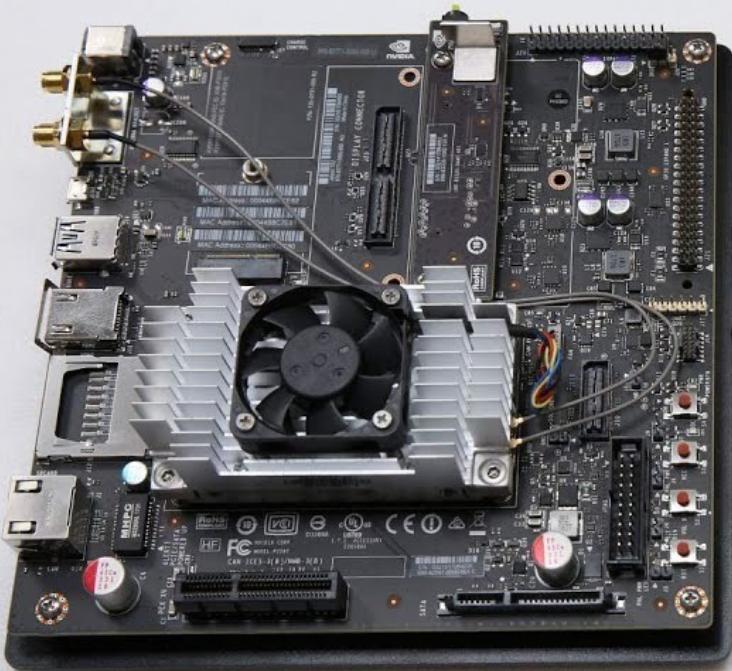


<https://devtalk.nvidia.com/default/topic/975387/fastest-framework-for-object-detection-on-jetson-tk1/>  
<https://groups.google.com/forum/#topic/darknet/of0cKVPF7gM>



# Jetson TX1 and TX2

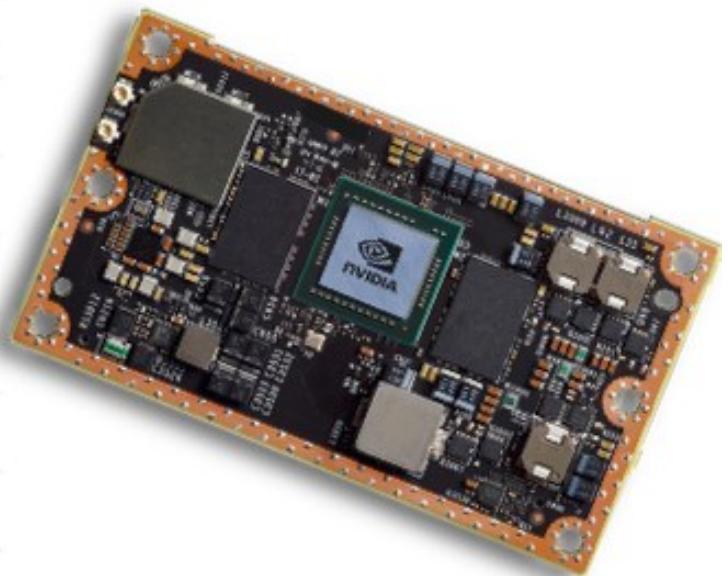
## Comparing the NVIDIA Jetson TX1 and TX2



arrow | [arrow.com](http://arrow.com)

# Jetson TX1 and TX2

	JETSON TX1	JETSON TX2
<b>GPU</b>	Maxwell	Pascal
<b>CPU</b>	64-bit A57 CPUs	64-bit Denver 2 and A57 CPUs
<b>Memory</b>	4 GB 64 bit LPDDR4 25.6 GB/s	8 GB 128 bit LPDDR4 58.4 GB/s
<b>Storage</b>	16 GB eMMC	32 GB eMMC
<b>Wi-Fi/BT</b>	802.11 2x2 ac/BT Ready	802.11 2x2 ac/BT Ready
<b>Video Encode</b>	2160p @ 30	2160p @ 60
<b>Video Decode</b>	2160p @ 60	2160p @ 60 12 bit support for H.265, VP9
<b>Camera</b>	1.4Gpix/s Up to 1.5Gbps per lane	1.4Gpix/s Up to 2.5Gbps per lane
<b>Mechanical</b>	50mm x 87mm 400-pin Compatible Board to Board Connector	



# 차례

- **Introduction**
  - Multicore/Manycore and GPU
  - GPU on Medical Applications
- **Parallel Programming on GPUs: Basics**
  - Conceptual Introduction
- **GPU Architecture Review**
- **Parallel Programming on GPUs: Practice**
  - Real programming
- **Conclusion**

DO YOU  
KNOW?



# CUDA Kernels

- Parallel portion of application: execute as a **kernel**
  - Entire GPU executes kernel
  - Kernel launches create thousands of CUDA threads efficiently

CPU	Host	Executes functions
GPU	Device	Executes kernels

- CUDA threads
  - Lightweight
  - Fast switching: Hardware
  - 1000s execute simultaneously
- Kernel launches create **hierarchical** groups of threads
  - Threads are grouped into **Blocks**, and Blocks into **Grids**
  - Threads and Blocks represent different levels of parallelism

Kernel Thread !  
 $C[i] = A[i] + B[i];$

# CUDA C : C with a few keywords

- **Kernel**: function that executes on device (**GPU**) and can be called from host (**CPU**)
  - Can only access GPU memory
  - No variable number of arguments
  - No static variables
- Functions must be declared with a qualifier
  - global**: GPU kernel function launched by CPU, must return void
  - device**: can be called from GPU functions
  - host**: can be called from CPU functions (default)
- Qualifiers determines how functions are compiled
  - Controls which compilers are used to compile functions

Kernel Thread !  
 $C[i] = A[i] + B[i];$

**device** add(...)  
{ ...  
 $C[i] = A[i] + B[i];$

# CUDA C : C with a few keywords

- **Kernel**: function that executes on device (**GPU**) and can be called from host (**CPU**)
- Functions must be declared with a qualifier
  - global**: **GPU** kernel function launched by **CPU**, must return void
  - device**: can be called from **GPU** functions
  - host**: can be called from **CPU** functions (default)

```
#include <stdio.h>

__device__ void hiDeviceFunction(void)
{ printf("Hello! This is in hiDeviceFunction. \n"); }

__global__ void helloCUDA(void)
{
    printf("Hello thread %d\n", threadIdx.x);
    hiDeviceFunction();
}

int main()
{
    helloCUDA<<<1, 1>>>();
    return 0;
}
```

```
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/MYCODE/lab1$ nvcc hello.cu
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/MYCODE/lab1$ ./a.out
Hello thread 0
Hello! This is in hiDeviceFunction.
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/MYCODE/lab1$ █
```

# CUDA C : C with a few keywords

- Functions must be declared with a qualifier

`__global__`: GPU kernel function launched by CPU, must return void

`__device__`: can be called from GPU functions

`__host__`: can be called from CPU functions (default)

```
#include <stdio.h>

__global__ void helloCUDA(void)
{
    printf("Hello thread %d\n", threadIdx.x);
}

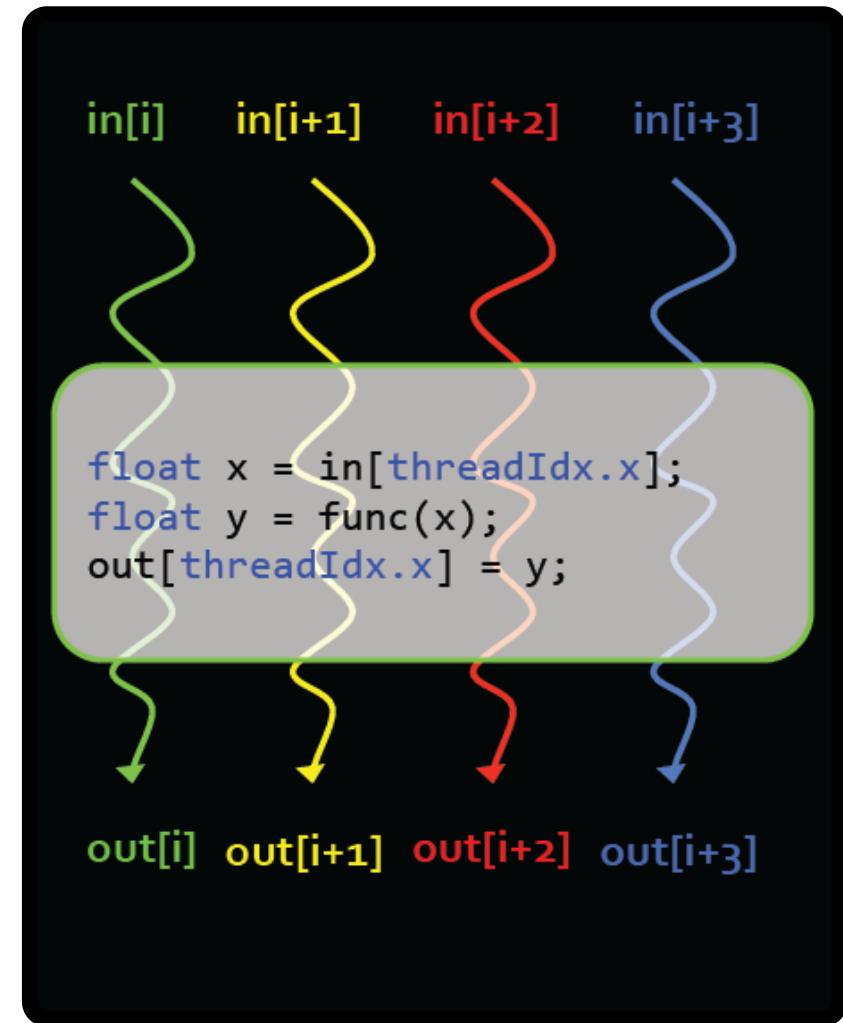
int main()
{
    helloCUDA<<<1, 4>>>();
    cudaDeviceReset();
    return 0;
}
```

```
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/MYCODE/lab1$ nvcc hello.cu
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/MYCODE/lab1$ ./a.out
Hello thread 0
Hello thread 1
Hello thread 2
Hello thread 3
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/MYCODE/lab1$
```

# CUDA Kernels : Parallel Threads

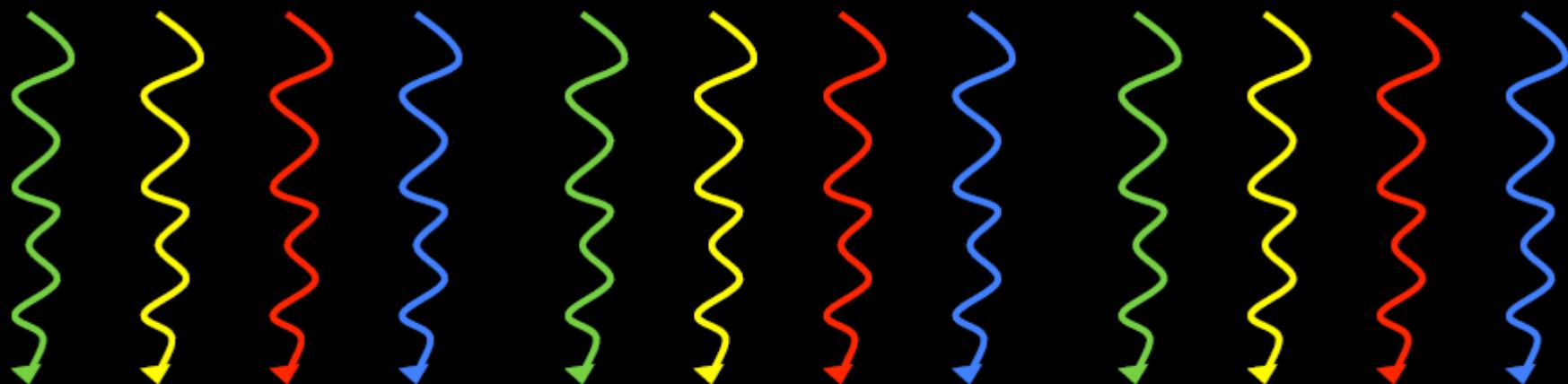
- A **kernel** is a function executed on a GPU as an **array** of parallel threads
- All threads execute the same kernel code, but can take different paths
- **Each thread has an ID**
  - Select input/output data
  - Control decisions

```
__device__ add(...)  
{  ...  
  i = threadIdx.x;  
  C[i] = A[i] + B[i];  
  ...
```



# CUDA Thread Organization

- GPUs can handle thousands of concurrent threads
- CUDA programming model supports even more
  - Allows a kernel launch to specify more threads than the GPU can execute concurrently
  - Helps to amortize kernel launch times

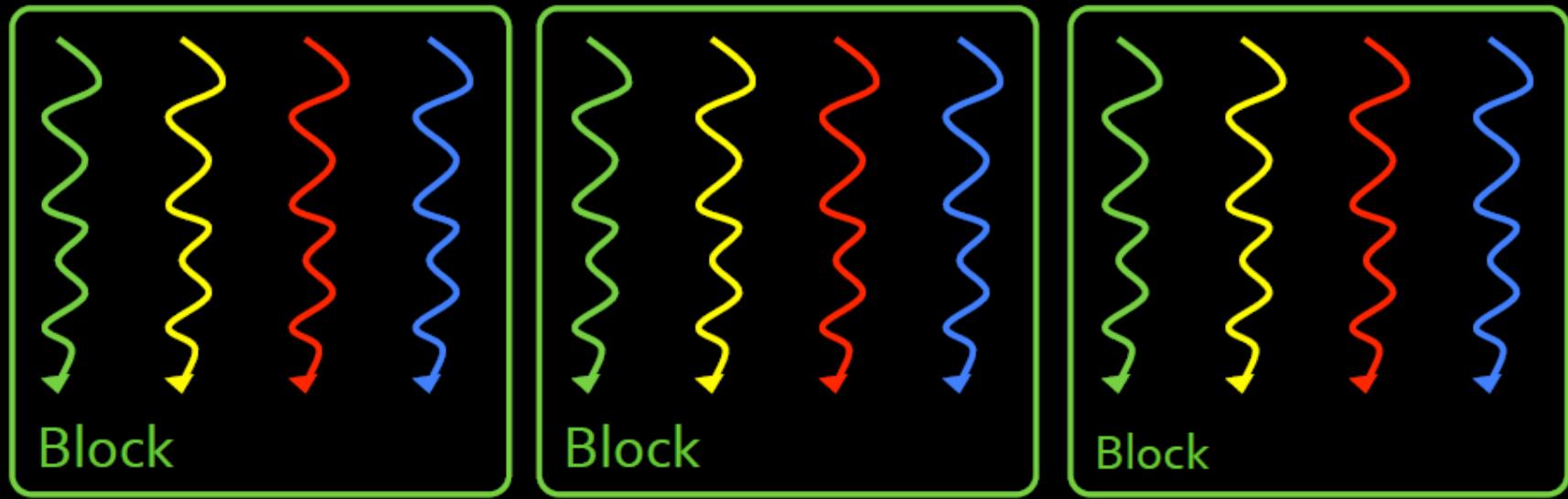




# Blocks of threads

---

- Threads are grouped into blocks

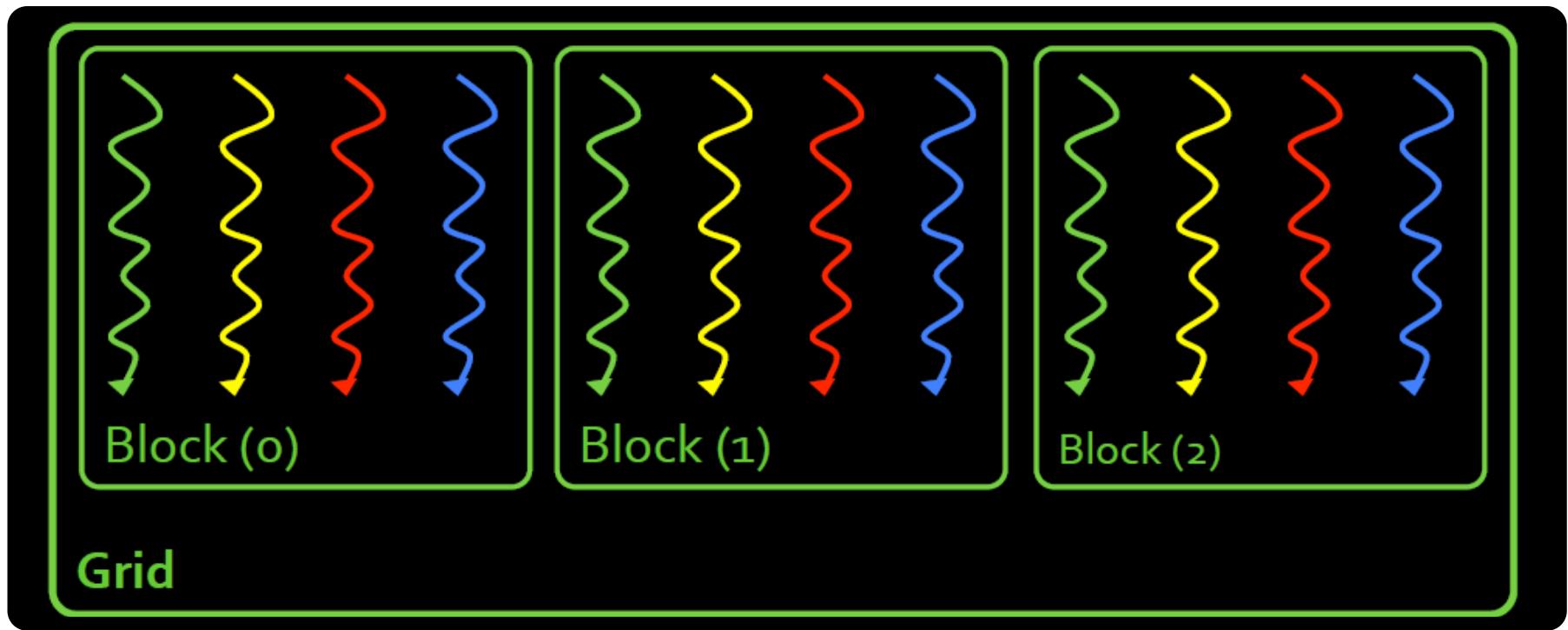




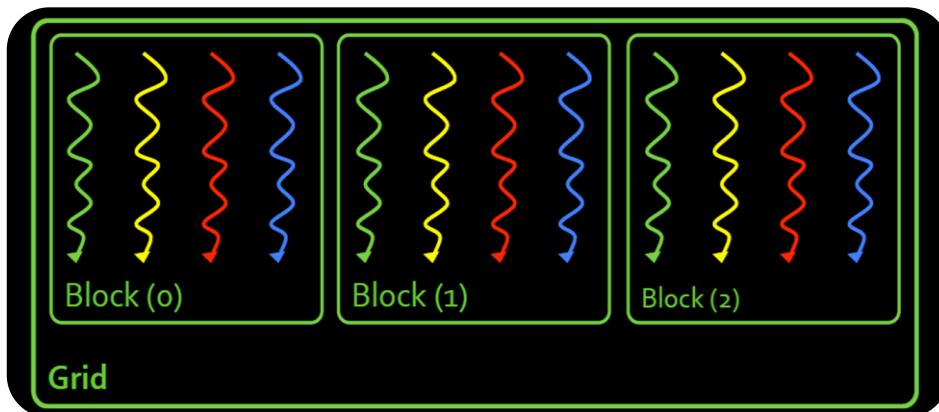
# Grids of blocks

---

- Threads are grouped into **blocks**
- Blocks are grouped into a **grid**
- A **kernel** is executed as a **grid of blocks of threads**



# Grids of blocks



```
#include <stdio.h>

__global__ void helloCUDA(void)
{
    printf("Hello thread %d in block %d\n",
           threadIdx.x, blockIdx.x);
}

int main()
{
    helloCUDA<<<3, 4>>>();
    cudaDeviceReset();
    return 0;
}
```

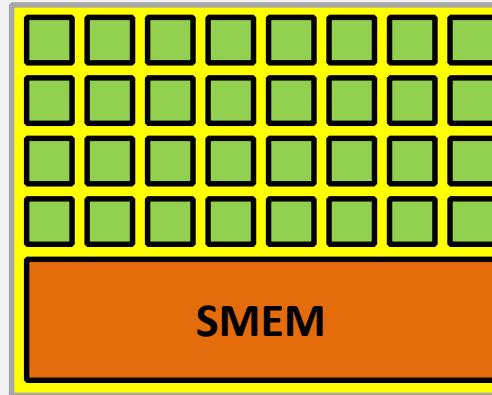
```
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/MYCODE/lab1$ nvcc hello.cu
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/MYCODE/lab1$ ./a.out
Hello thread 0 in block 1
Hello thread 1 in block 1
Hello thread 2 in block 1
Hello thread 3 in block 1
Hello thread 0 in block 2
Hello thread 1 in block 2
Hello thread 2 in block 2
Hello thread 3 in block 2
Hello thread 0 in block 0
Hello thread 1 in block 0
Hello thread 2 in block 0
Hello thread 3 in block 0
```

# Blocks execute on SM

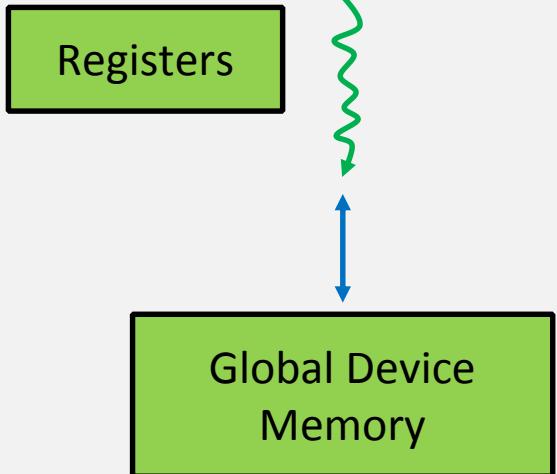
## Streaming Processor



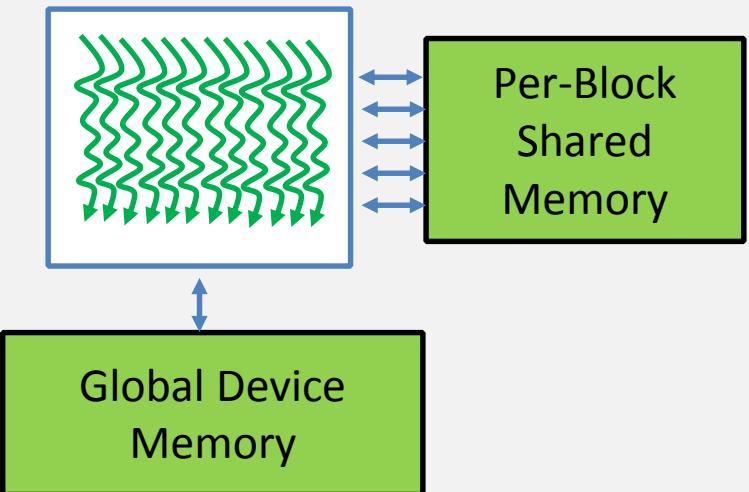
## Streaming Multiprocessor



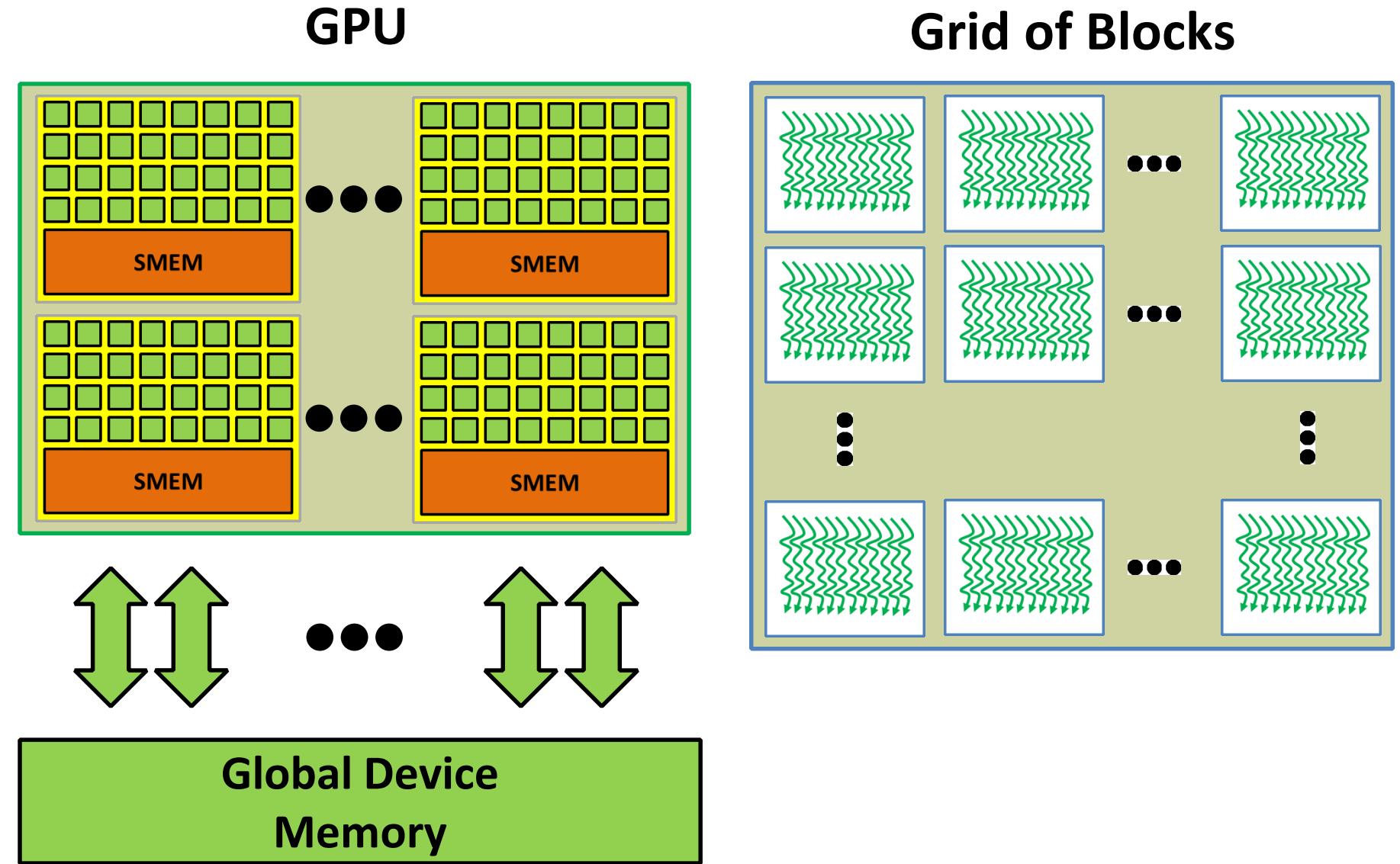
## Thread



## Thread block



# Grids of blocks executes across GPU





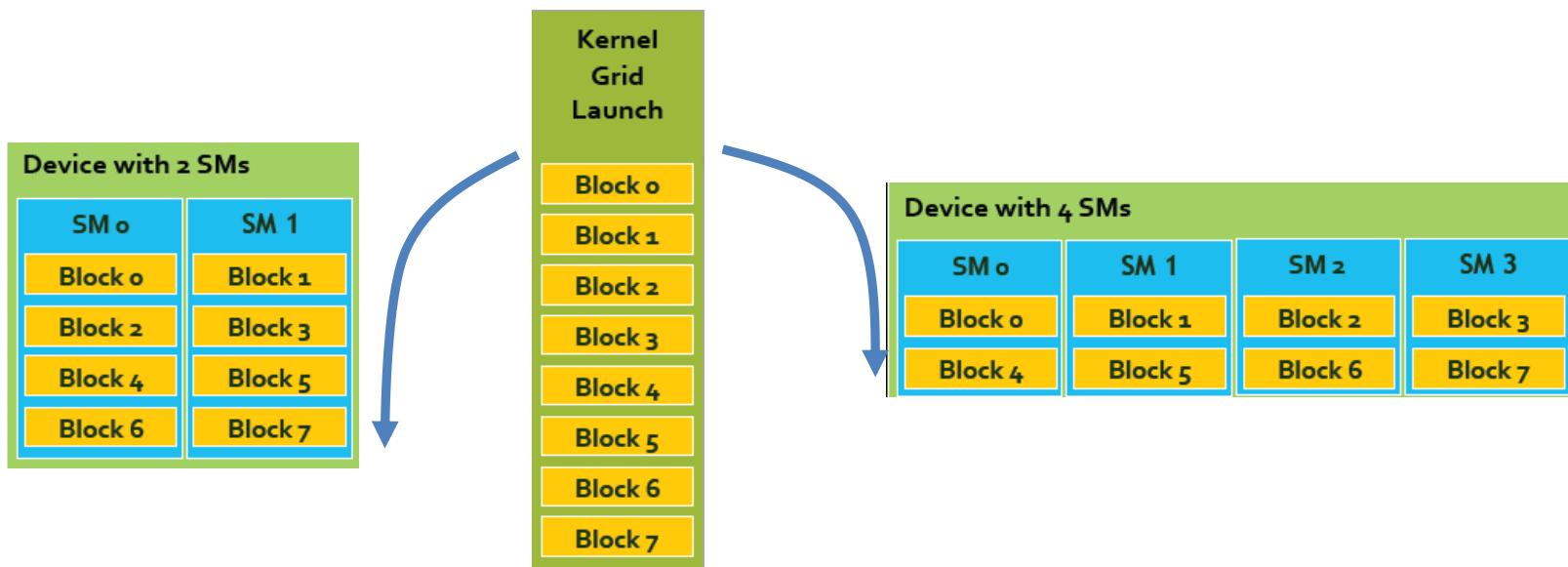
# Kernel Execution

---

- A **thread** executes on a **single** streaming processor
  - Allows use of a familiar scalar code within a kernel
- A **block** executes on a **single** streaming **multiprocessor**
  - Threads and blocks do not migrate to different SMs
  - All threads within block execute in concurrently, in parallel
- A streaming multiprocessor may execute **multiple** blocks
  - Must be able to satisfy aggregate register and memory demands

# Block abstraction provides scalability

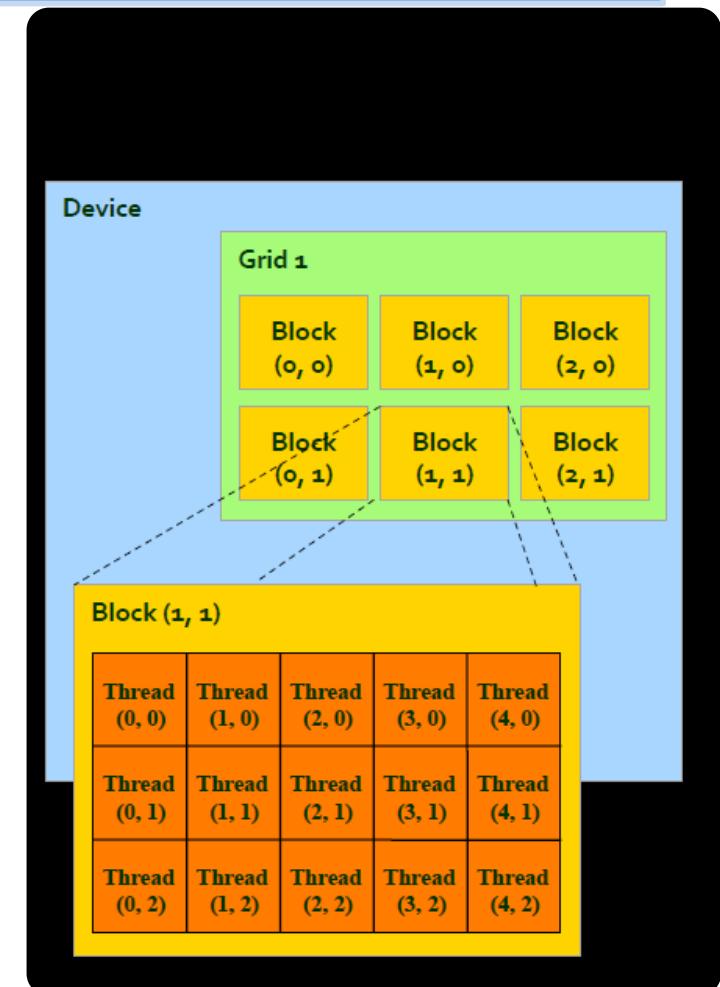
- Blocks may execute in **arbitrary order**, concurrently or sequentially and parallelism increases with resources
  - Depends on when execution resources become available
- Independent execution of blocks provides scalability
  - Blocks can be distributed across any number of SMs



# Thread and Block ID and Dimensions

- **Threads**
  - 3D IDs, unique within a block
- **Thread Blocks**
  - 2D IDs, unique within a grid
- Build-in variables

- **threadIdx**
- **blockIdx**
- **blockDim**
- **gridDim**



- Programmers usually select dimensions that simplify the mapping of the application data to CUDA threads

# Examples of Indexes and Indexing

```
__global__ void kernel( int *a )  
{  
    int idx = blockIdx.x*blockDim.x + threadIdx.x;  
    a[idx] = 7;           // output: 7777 7777 7777 7777  
}
```

```
__global__ void kernel( int *a )  
{  
    int idx = blockIdx.x*blockDim.x + threadIdx.x;  
    a[idx] = blockIdx.x; // output: 0000 1111 2222 3333  
}
```

```
__global__ void kernel( int *a )  
{  
    int idx = blockIdx.x*blockDim.x + threadIdx.x;  
    a[idx] = threadIdx.x; // output: 0123 1234 0123 0123  
}
```



# Example of 2D indexing

---

```
__global__ void kernel( int *a )
{
    int ix = blockIdx.x*blockDim.x + threadIdx.x;
    int iy = blockIdx.y*blockDim.y + threadIdx.y;
    int idx = iy * dimx + ix;

    a[idx] = a[idx] + 1;
}
```

# Let's Start Again from C

OPTIONAL

SKIP

```
int A[2][4];
for(i=0;i<2;i++)
    for(j=0;j<4;j++)
        A[i][j]++;
```

*convert into CUDA*

```
int A[2*4];
kernelF<<<(2,1),(4,1)>>>(A); // define 2x4=8 threads
__device__ kernelF(A){           // all threads run same kernel
    i = blockIdx.x;              // each thread block has its id
    j = threadIdx.x;             // each thread has its id
    A[i*2+j]++;                 // each thread has different i and j
}
```

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Thread Hierarchy

Example:

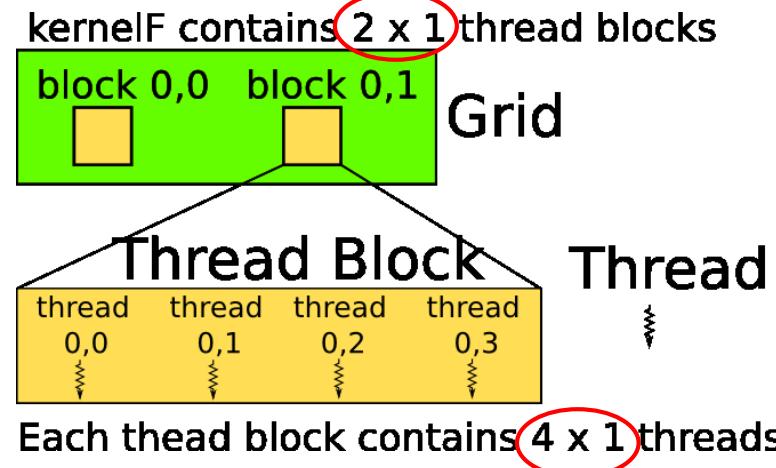
thread 3 of block 1 operates  
on element A[1][3]

```
int A[2*4];
kernelF<<<(2,1),(4,1)>>>(A); // define 2x4=8 threads
__device__ kernelF(A){
    i = blockIdx.x;
    j = threadIdx.x;
    A[i*2+j]++;
}
```

*// all threads run same kernel*  
*// each thread block has its id*  
*// each thread has its id*  
*// each thread has different i and j*

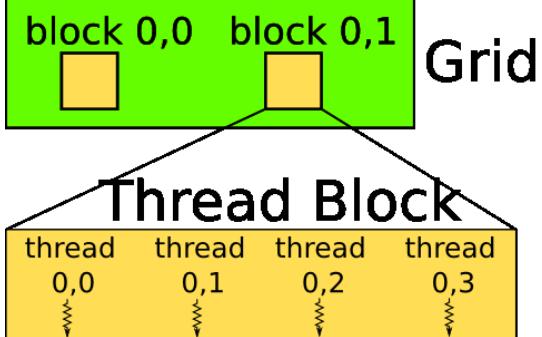
참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

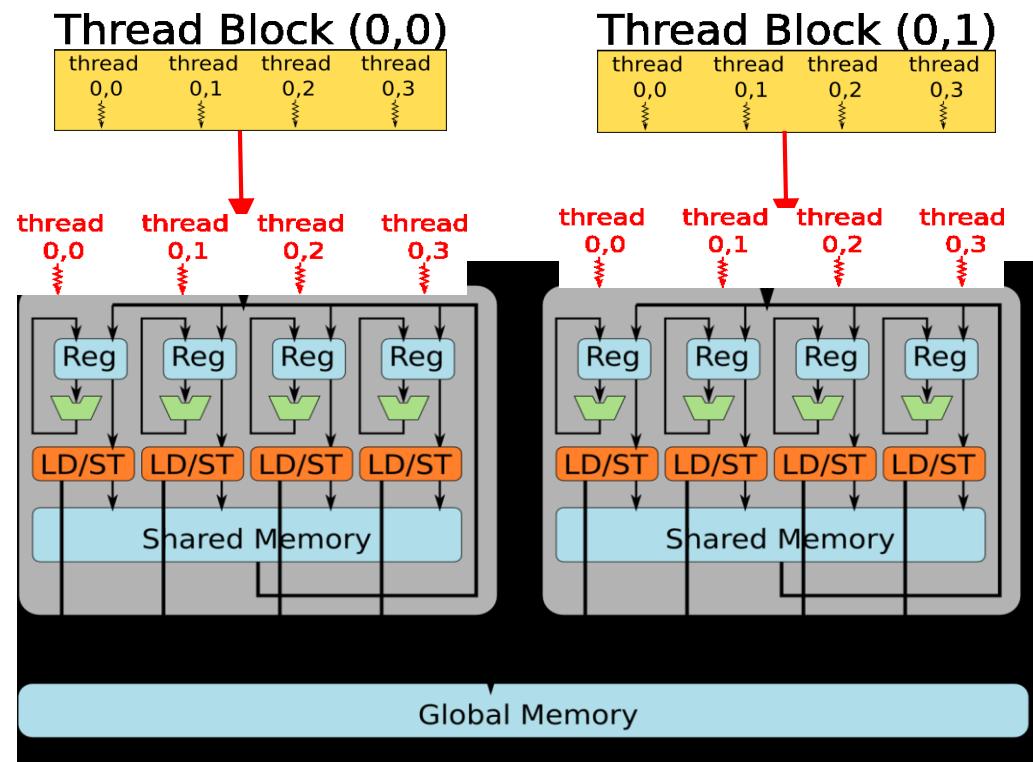


# How Are Threads Scheduled?

kernelF contains  $2 \times 1$  thread blocks



Each thread block contains  $4 \times 1$  threads



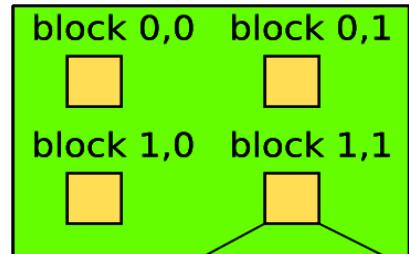
참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

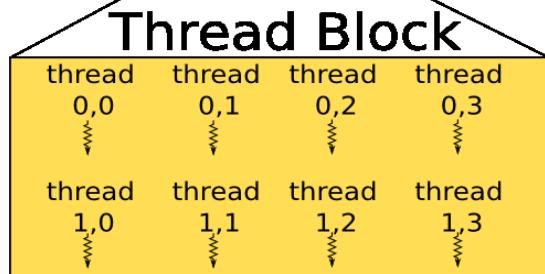
# Blocks Are Dynamically Scheduled

## Grid

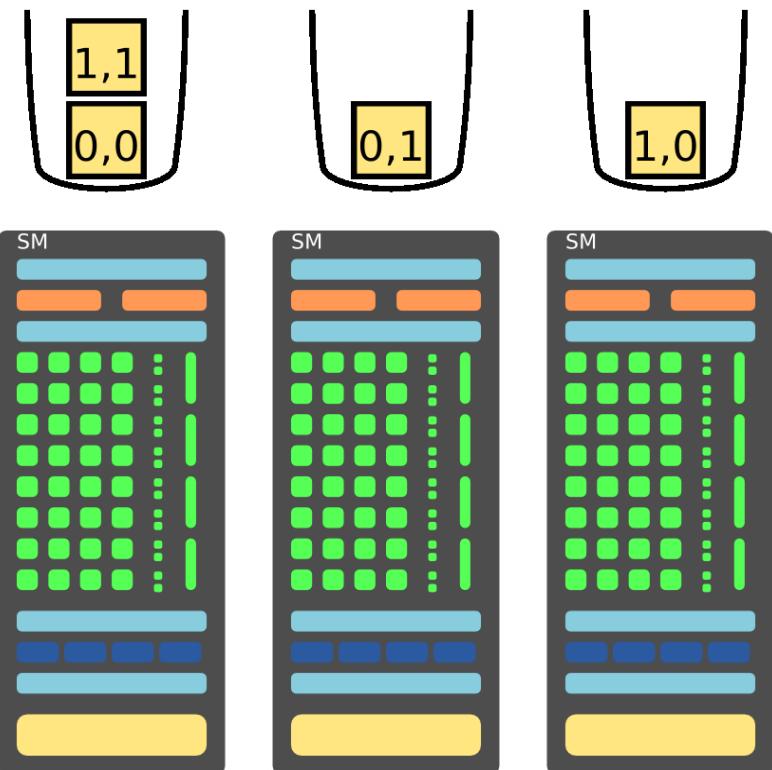
kernelF contains  $2 \times 2$  thread blocks



Thread ↴



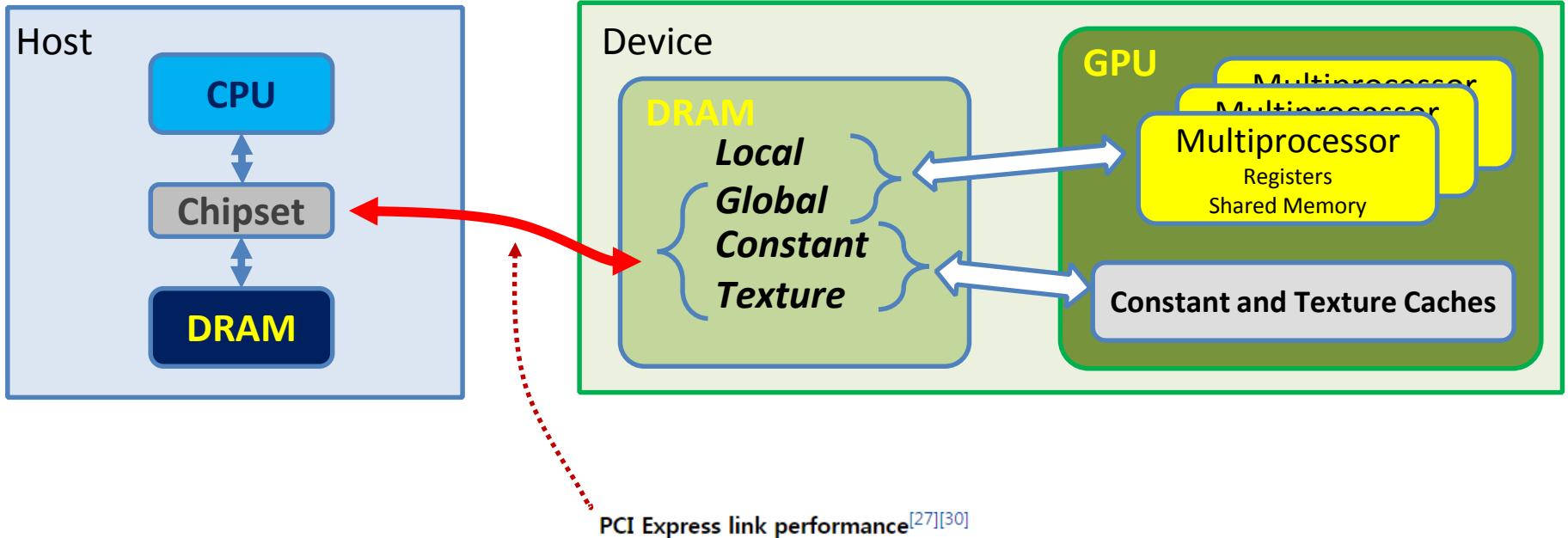
Each thread block contains  $4 \times 2$  threads



참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Memory Architecture



PCI Express version	Line code	Transfer rate <sup>[i]</sup>	Throughput <sup>[i]</sup>			
			×1	×4	×8	×16
1.0	8b/10b	2.5 GT/s	250 MB/s	1 GB/s	2 GB/s	4 GB/s
2.0	8b/10b	5 GT/s	500 MB/s	2 GB/s	4 GB/s	8 GB/s
3.0	128b/130b	8 GT/s	984.6 MB/s	3.938 GB/s	7.877 GB/s	15.754 GB/s
4.0 (expected in 2017)	128b/130b	16 GT/s	1.969 GB/s	7.877 GB/s	15.754 GB/s	31.508 GB/s
5.0 (far future) <sup>[28][29]</sup>	128b/130b	32 or 25 GT/s <sup>[ii]</sup>	3.9, or 3.08 GB/s	15.8, or 12.3 GB/s	31.5, or 24.6 GB/s	63.0, or 49.2 GB/s

# Memory Architecture

ubuntu@tegra-ubuntu:~/NVIDIA  
bandwidthTest bandwidthTest  
bandwidthTest.cu Makefile  
ubuntu@tegra-ubuntu:~/NVIDIA  
[CUDA Bandwidth Test] - Star  
Running on...

Device 0: GK20A  
Quick Mode

PCI Express version	Line code	Transfer rate <sup>[i]</sup>	PCI Express link performance <sup>[27][30]</sup>			
			×1	×4	×8	×16
1.0	8b/10b	2.5 GT/s	250 MB/s	1 GB/s	2 GB/s	4 GB/s
2.0	8b/10b	5 GT/s	500 MB/s	2 GB/s	4 GB/s	8 GB/s
3.0	128b/130b	8 GT/s	984.6 MB/s	3.938 GB/s	7.877 GB/s	15.754 GB/s
4.0 (expected in 2017)	128b/130b	16 GT/s	1.969 GB/s	7.877 GB/s	15.754 GB/s	31.508 GB/s
5.0 (far future) <sup>[28][29]</sup>	128b/130b	32 or 25 GT/s <sup>[ii]</sup>	3.9, or 3.08 GB/s	15.8, or 12.3 GB/s	31.5, or 24.6 GB/s	63.0, or 49.2 GB/s

[https://en.wikipedia.org/wiki/PCI\\_Express](https://en.wikipedia.org/wiki/PCI_Express)

## Host to Device Bandwidth, 1 Device(s)

### PINNED Memory Transfers

Transfer Size (Bytes)	Bandwidth(MB/s)
33554432	988.7

## Device to Host Bandwidth, 1 Device(s)

### PINNED Memory Transfers

Transfer Size (Bytes)	Bandwidth(MB/s)
33554432	3793.5

## Device to Device Bandwidth, 1 Device(s)

### PINNED Memory Transfers

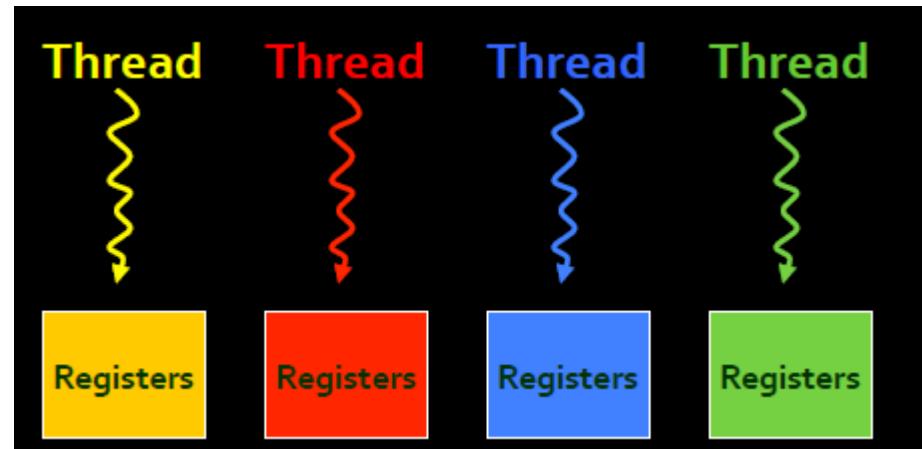
Transfer Size (Bytes)	Bandwidth(MB/s)
33554432	11805.1

Result = PASS

ubuntu@tegra-ubuntu:~/NVIDIA\_CUDA-6.5\_Samples/1\_Utils/bandwidthTest\$

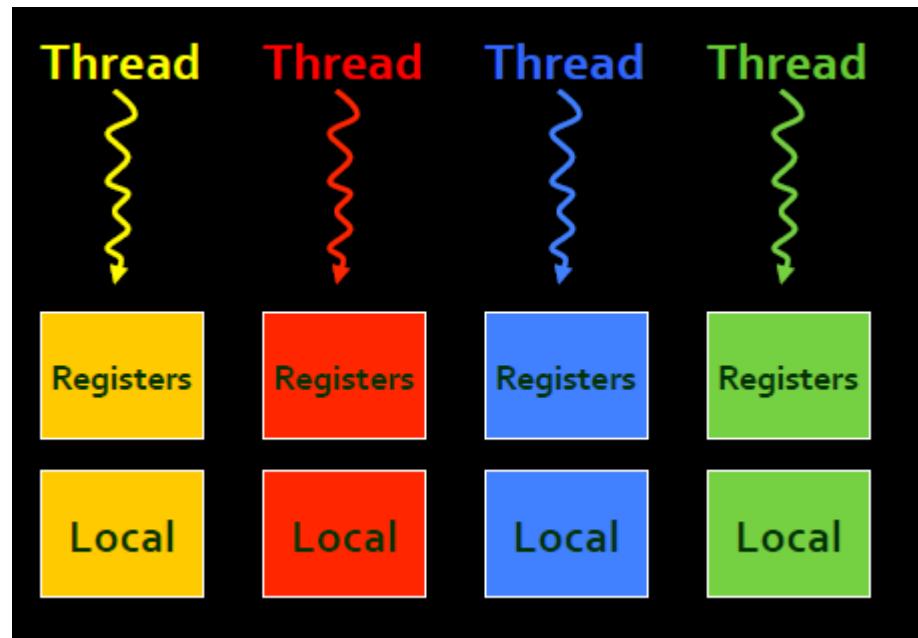
# CUDA Memory Hierarchy

- Thread
  - Registers



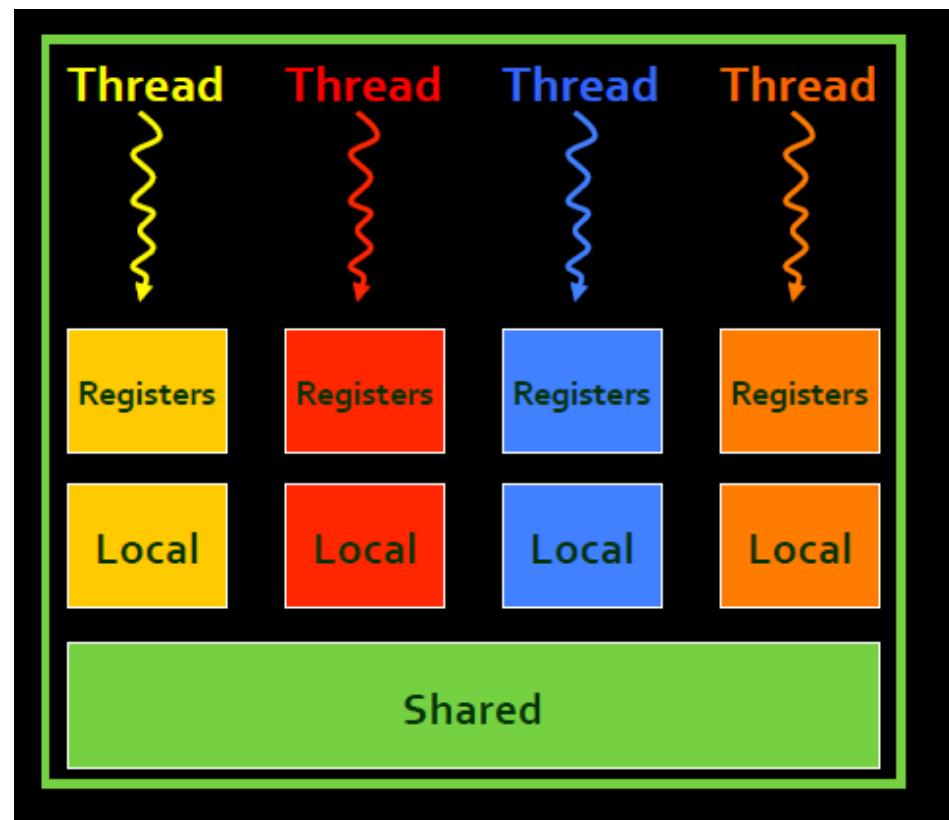
# CUDA Memory Hierarchy

- Thread
  - Registers
  - Local memory



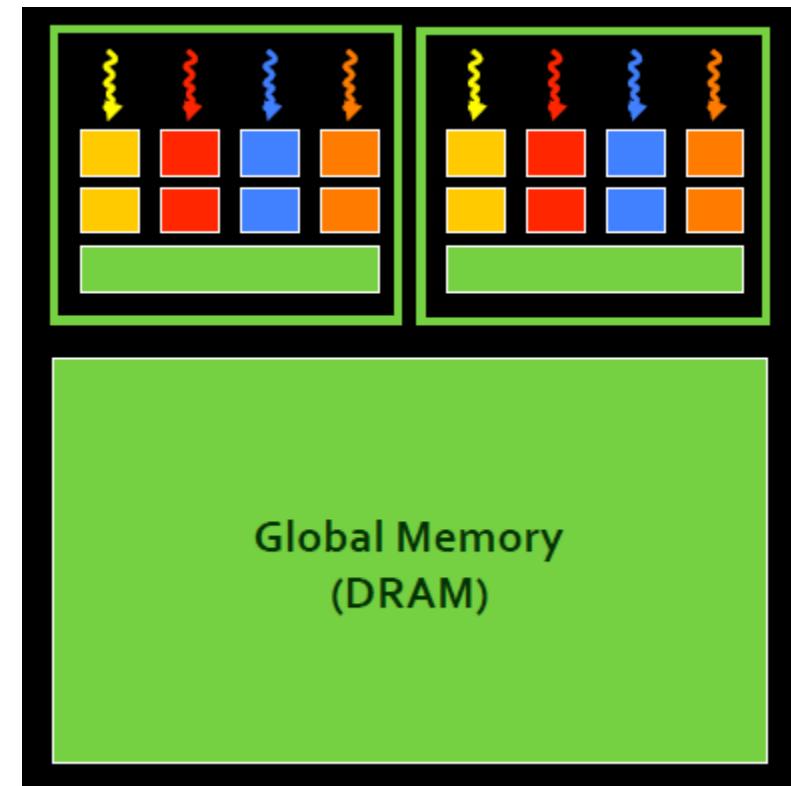
# CUDA Memory Hierarchy

- Thread
  - Registers
  - Local memory
- Thread Block
  - Shared memory



# CUDA Memory Hierarchy

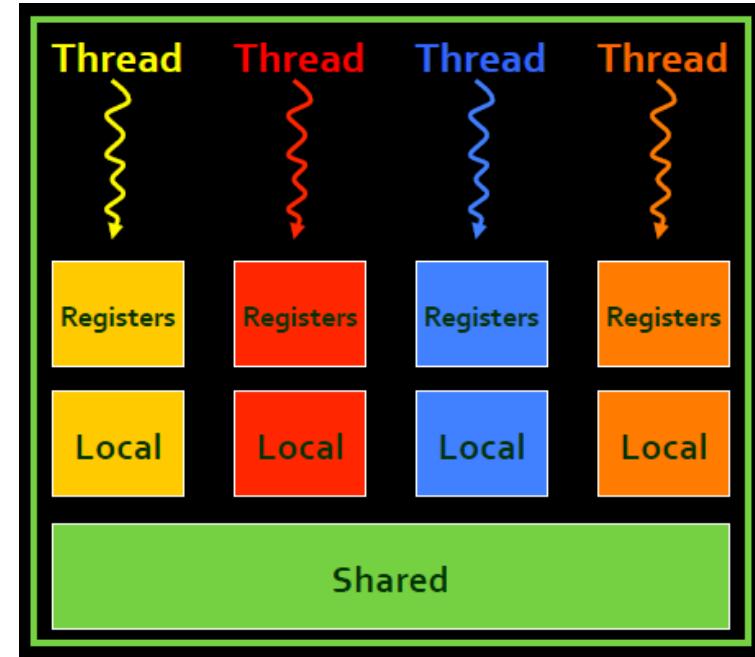
- Thread
  - Registers
  - Local memory
- Thread Block
  - Shared memory
- All Thread Blocks
  - Global memory



# Shared Memory

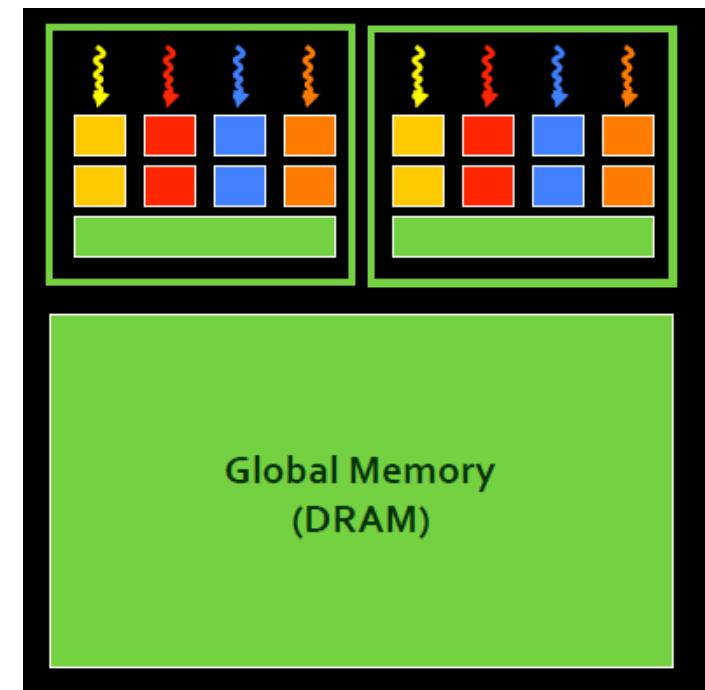
`__shared__ <type> x[<elements>];`

- Allocated per thread block
- Scope: threads in block
- Data lifetime: same as block
- Capacity: small (about 48kB)
- Latency: a few cycles
- Bandwidth: very high
  - SM:  $32 * 4B * 1.15\text{GHz} / 2 = 73.6 \text{ GB/s}$
  - GPU:  $14 * 32 * 4B * 1.15\text{GHz} / 2 = 1.03 \text{ TB/s}$
- Common uses
  - Sharing data among threads in a block
  - User-managed cache (to reduce global memory accesses)



# Global Memory

- Allocated explicitly by host (CPU) thread
- Scope: all threads of all kernels
- Data lifetime: determined by host (CPU) thread
  - `cudaMalloc(void **pointer, size_t nbytes)`
  - `cudaFree(void* pointer)`
- Capacity: large (1-12GB)
- Latency: 400-800 cycles
- Bandwidth: 156 GB/s, → 1TB/s
  - Data access patterns will limit bandwidth achieved in practice
- Common uses
  - Staging data transfers to/from CPU
  - Staging data between kernel launches



# Global Memory

```
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/1_Utils.../bandwidthTest$ ls  
bandwidthTest      bandwidthTest.o  NsightEclipse.xml  
bandwidthTest.cu   Makefile       readme.txt  
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/1_Utils.../bandwidthTest$ ./bandwidthTest  
[CUDA Bandwidth Test] - Starting...  
Running on...
```

Device 0: GK20A  
Quick Mode

**Host to Device Bandwidth, 1 Device(s)**

PINNED Memory Transfers

Transfer Size (Bytes)	Bandwidth(MB/s)
33554432	988.7

**Device to Host Bandwidth, 1 Device(s)**

PINNED Memory Transfers

Transfer Size (Bytes)	Bandwidth(MB/s)
33554432	3793.5

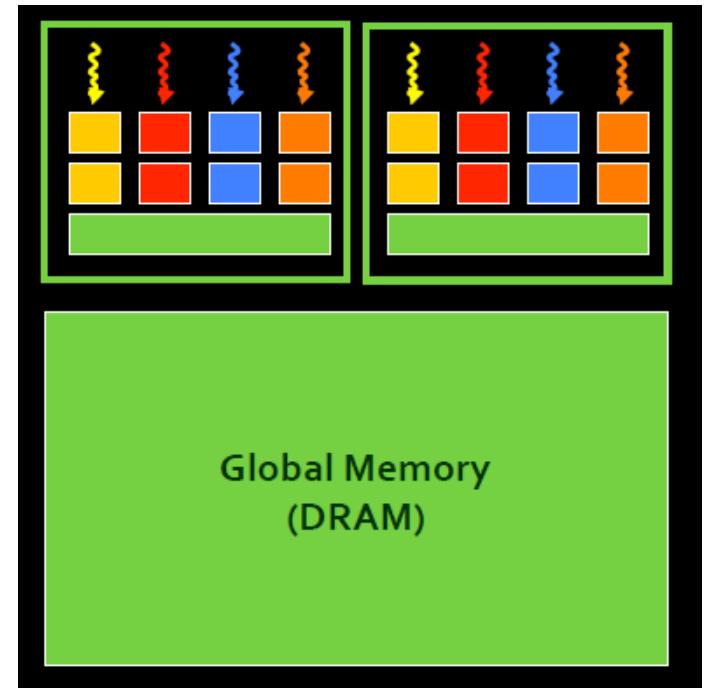
**Device to Device Bandwidth, 1 Device(s)**

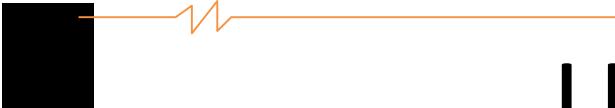
PINNED Memory Transfers

Transfer Size (Bytes)	Bandwidth(MB/s)
33554432	11805.1

**Result = PASS**

```
ubuntu@tegra-ubuntu:~/NVIDIA_CUDA-6.5_Samples/1_Utils.../bandwidthTest$
```

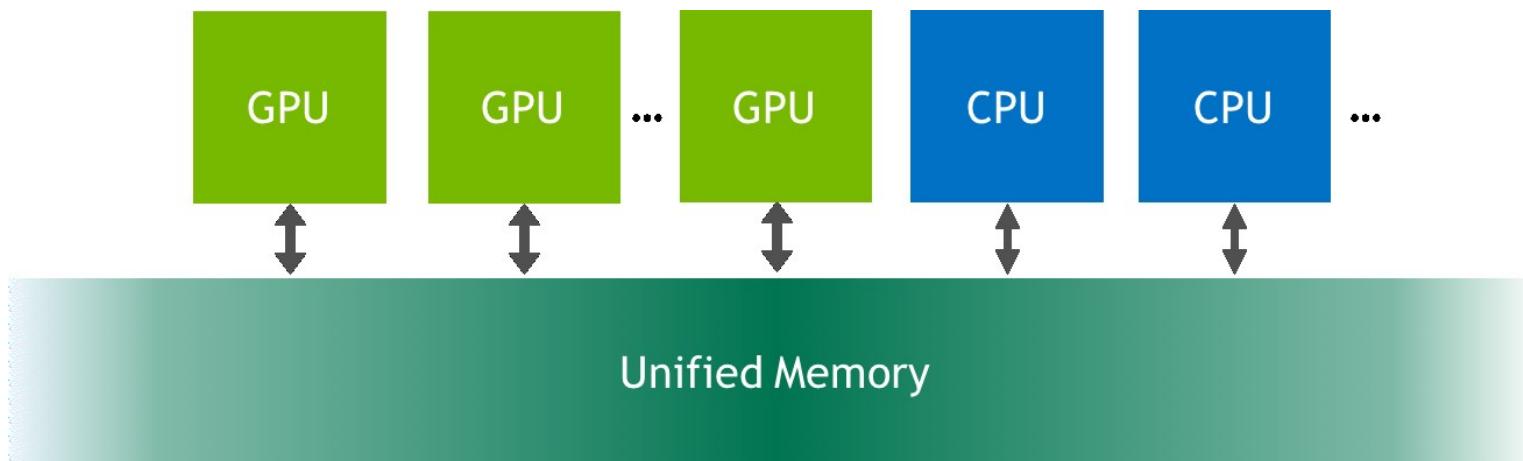




# Unified Memory

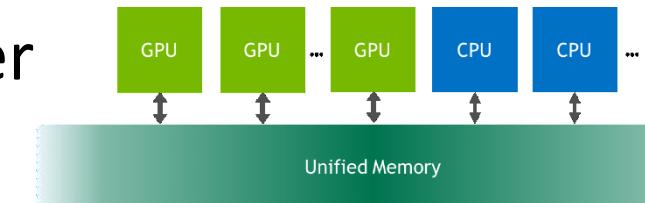
---

- Unified Memory for CUDA Beginners



# Unified Memory

- Unified Memory for CUDA Beginner



## On-Demand Paging

```
__global__
void setValue(int *ptr, int index, int val)
{
    ptr[index] = val;
}
```

```
void foo(int size) {
    char *data;
    cudaMallocManaged(&data, size);
    memset(data, 0, size);
    setValue<<<...>>>(data, size/2, 5);
    cudaDeviceSynchronize();
    useData(data);
    cudaFree(data);
}
```

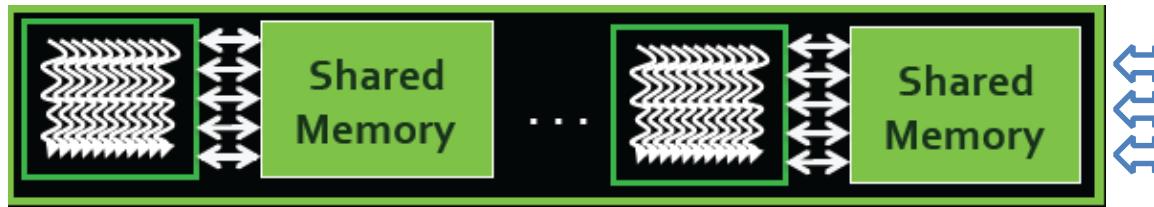
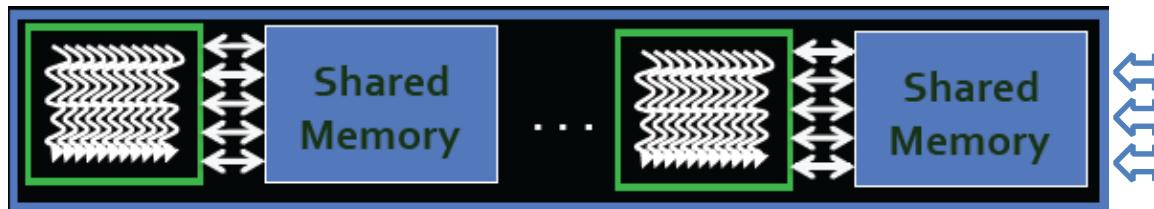
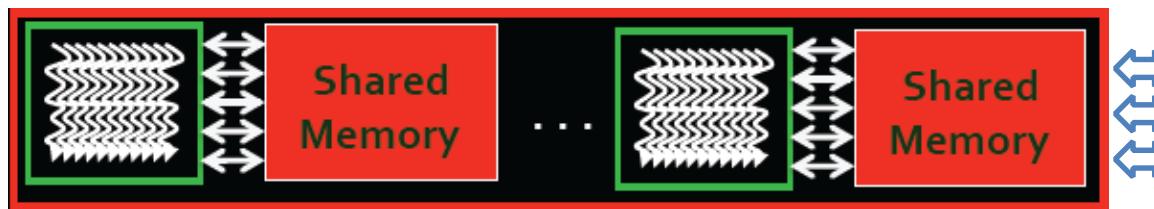
Unified Memory allocation

Access all values on CPU

Access one value on GPU

# Communication and Data Persistence

sequential  
kernels



# Managing Device (GPU) Memory

- Host (CPU) manage device (GPU) memory
  - `cudaMalloc(void** pointer, size_t num_bytes)`
  - `cudaMemset(void** pointer, int value, size_t count)`
  - `cudaFree(void* pointer)`
- Ex.: allocate and initialize array of 1024 ints on device

```
// allocate and initialize int x[1024] on device
```

```
int n = 1024;  
  
int num_bytes = 1024*sizeof(int);  
  
int* d_x = 0; // holds device pointer  
  
cudaMalloc((void**)&d_x, num_bytes);  
  
cudaMemset(d_x, 0, num_bytes);  
  
cudaFree(d_x);
```



# Transferring Data

- `cudaMemcpy(void* dst, void* src, size_t num_bytes, enum cudaMemcpyKind direction);`
  - Returns to host thread after the copy completes
  - **Block** CPU thread until all bytes have been copied
  - Doesn't start copying until previous CUDA calls complete
- Direction controlled by `num cudaMemcpyKind`
  - `cudaMemcpyHostToDevice`
  - `cudaMemcpyDeviceToHost`
  - `cudaMemcpyDeviceToDevice`
- CUDA also provides **non-blocking**
  - Allows program to **overlap** data transfer with concurrent computation on host and device



# Example: SAXPY Kernel

```
// [compute] for(i=0; i<n; i++) y[i] = a*x[i] + y[i];  
// Each thread processes one element  
__global__ void saxpy(int n, float a, float* x, float* y)
```

?

```
int main()
```

?



# Example: SAXPY Kernel

```
// [compute] for(i=0; i<n; i++) y[i] = a*x[i] + y[i];
// Each thread processes one element
__global__ void saxpy(int n, float a, float* x, float* y)
{
    int i = threadIdx.x + blockDim.x * blockIdx.x;
    if( i < n ) y[i] = a*x[i] + y[i];
}

int main()
```



?

# Example: SAXPY Kernel

```
// [compute] for(i=0; i<n; i++) y[i] = a*x[i] + y[i];
// Each thread processes one element
__global__ void saxpy(int n, float a, float* x, float* y)
{
    int i = threadIdx.x + blockDim.x * blockIdx.x;
    if( i < n ) y[i] = a*x[i] + y[i];
}

int main()
{
    ...
    // invoke parallel SAXPY kernel with 256 threads / block
    int nblocks = (n + 255)/256;
    saxpy<<<nblocks, 256>>>(n, 2.0, d_x, d_y);
}
```





# Example: SAXPY Kernel

```
// [compute] for(i=0; i<n; i++) y[i] = a*x[i] + y[i];
// Each thread processes one element
__global__ void saxpy(int n, float a, float* x, float* y)
{
    int i = threadIdx.x + blockDim.x * blockIdx.x;
    if( i<n ) y[i] = a*x[i] + y[i];
}
```

Device Code

```
int main()
{
    ...
    // invoke parallel SAXPY kernel with 256 threads / block
    int nblocks = (n + 255)/256
    saxpy<<<nblocks, 256>>>(n, 2.0, d_x, d_y);
}
```



# Example: SAXPY Kernel

```
// [compute] for(i=0; i<n; i++) y[i] = a*x[i] + y[i];
// Each thread processes one element
__global__ void saxpy(int n, float a, float* x, float* y)
{
    int i = threadIdx.x + blockDim.x * blockIdx.x;
    if( i<n ) y[i] = a*x[i] + y[i];
}
```

```
int main()
{
    ...
    // invoke parallel SAXPY kernel with 256 threads / block
    int nblocks = (n + 255)/256
    saxpy<<<nblocks, 256>>>(n, 2.0, d_x, d_y);
}
```

Host Code

# Example: SAXPY Kernel

```
int main()
{
    // allocate and initialize host (CPU) memory
    float* x = ...;
    float* y = ...;

    // allocate device (GPU) memory
    float *d_x, *d_y;
    cudaMalloc((void**) &d_x, n*sizeof(float));
    cudaMalloc((void**) &d_y, n*sizeof(float));
    // copy x and y from host memory to device memory
    cudaMemcpy(d_x, x, n*sizeof(float), cudaMemcpyHostToDevice);
    cudaMemcpy(d_y, y, n*sizeof(float), cudaMemcpyHostToDevice);
    // invoke parallel SAXPY kernel with 256 threads / block
    int nblocks = (n + 255)/256
    saxpy<<<nblocks, 256>>>(n, 2.0, d_x, d_y);
```



# Example: SAXPY Kernel

```
int main()
{
    // allocate and initialize host (CPU) memory
    float* x = ...;
    float* y = ...;
```

```
// allocate device (GPU) memory
float *d_x, *d_y;
cudaMalloc((void**) &d_x, n*sizeof(float));
cudaMalloc((void**) &d_y, n*sizeof(float));
```

```
// copy x and y from host memory to device memory
cudaMemcpy(d_x, x, n*sizeof(float), cudaMemcpyHostToDevice);
cudaMemcpy(d_y, y, n*sizeof(float), cudaMemcpyHostToDevice);
```

```
// invoke parallel SAXPY kernel with 256 threads / block
int nblocks = (n + 255)/256
saxpy<<<nblocks, 256>>>(n, 2.0, d_x, d_y);
```



# Example: SAXPY Kernel

```
// invoke parallel SAXPY kernel with 256 threads / block  
int nblocks = (n + 255)/256;  
saxpy<<<nblocks, 256>>>(n, 2.0, d_x, d_y);
```

```
// copy y from device (GPU) memory to host (CPU) memory  
cudaMemcpy(d_y, y, n*sizeof(float), cudaMemcpyDeviceToHost);
```

```
// do something with the result ...
```

```
// free device (GPU) memory  
cudaFree(d_x);  
cudaFree(d_y);
```

```
return 0;  
}
```



# Example: Check the Differences

```
void saxpy_serial(int n, float a, float* x, float* y)
{
    for(int i = 0; i < n; i++)
        y[i] = a*x[i] + y[i];
}
// invoke host SAXPY function
saxpy_serial(n, 2.0, x, y);
}
```

**O(n)**

**Standard C Code**

```
__global__ void saxpy(int n, float a, float* x, float* y)
{
    int i = threadIdx.x + blockDim.x * blockIdx.x;
    if( i < n ) y[i] = a*x[i] + y[i];
}
// invoke parallel SAXPY kernel with 256 threads / block
int nblocks = (n + 255)/256;
saxpy<<<nblocks, 256>>>(n, 2.0, d_x, d_y);
}
```

**O(1)**

**CUDA C Code**

# One More: multiplication table

- Parallel construction of multiplication table

```
// multiplication table using CUDA
...
#include <cuda_runtime.h>

#define BLOCK_SIZE 8
#define THREAD_SIZE 9

int main()
{
    int *host_Result; //Save result data of host
    int *device_Result; //Save result data of device

    int i=0, j=0;

    //Allocate host memory
    host_Result = (int *)malloc( BLOCK_SIZE * THREAD_SIZE * sizeof(int) );

    //Allocate device memory
    cudaMalloc( (void**)&device_Result, sizeof(int) * BLOCK_SIZE * THREAD_SIZE);

    //Function name <<BLOCK_SIZE, THREAD_SIZE>>> parameters
    test <<<BLOCK_SIZE, THREAD_SIZE>>>(device_Result); //Execute Device code
```



# One More: multiplication table

- Parallel construction of multiplication table

```
//Function name <<BLOCK_SIZE, THREAD_SIZE>>> parameters
test <<<BLOCK_SIZE, THREAD_SIZE>>>(device_Result); //Execute Device code

//Copy device result to host result
cudaMemcpy( host_Result,
            device_Result, sizeof(int) * BLOCK_SIZE * THREAD_SIZE,
            cudaMemcpyDeviceToHost );

//Print result
for(j=0; j<BLOCK_SIZE; j++)
{
    printf("%3d step\n", (j + 2));
    for(i=0; i<THREAD_SIZE; i++)
    {
        printf("%3d X %3d = %3d\n", j+2, i+1, host_Result[j * THREAD_SIZE + i]);
    }
    printf("\n");
}

free(host_Result); //Free host memory
cudaFree(device_Result); //Free device memory

return 1;
}
```



# One More: multiplication table

- Parallel construction of multiplication table

```
// Device code
__global__ void test(int *result)
{
    int tidx, bidx;
    tidx = threadIdx.x;          //x-coordinate of thread
    bidx = blockIdx.x;          //x-coordinate of block

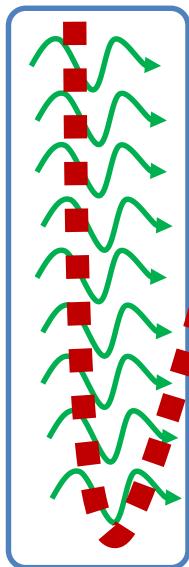
    result[_____] = _____
}
```



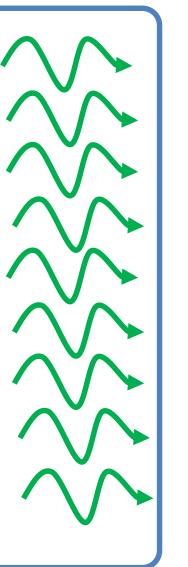
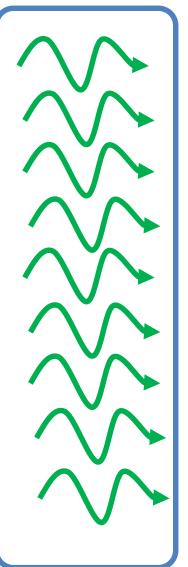
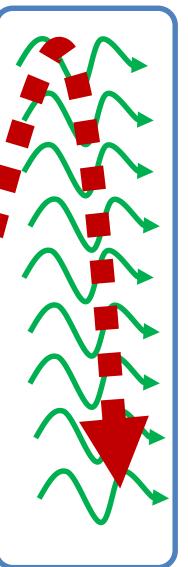
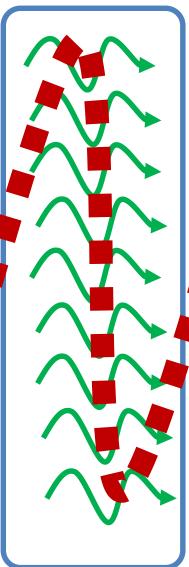
# One More: multiplication table

- Parallel construction of multiplication table

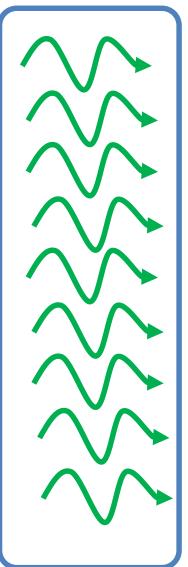
Block 0



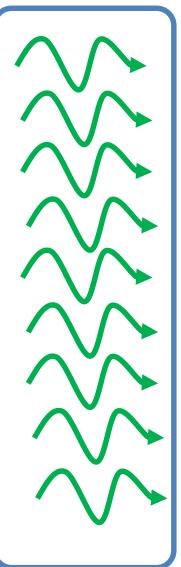
2단



Block 7



9단



# One More: multiplication table

- Parallel construction of multiplication table

```
// Device code
__global__ void test(int *result)
{
    int tidx, bidx;
    tidx = threadIdx.x;          //x-coordinate of thread
    bidx = blockIdx.x;          //x-coordinate of block

    result[THREAD_SIZE * bidx + tidx] = (bidx + 2) * (tidx + 1);
}
```



# One more: Utilizing Memory Hierarchy

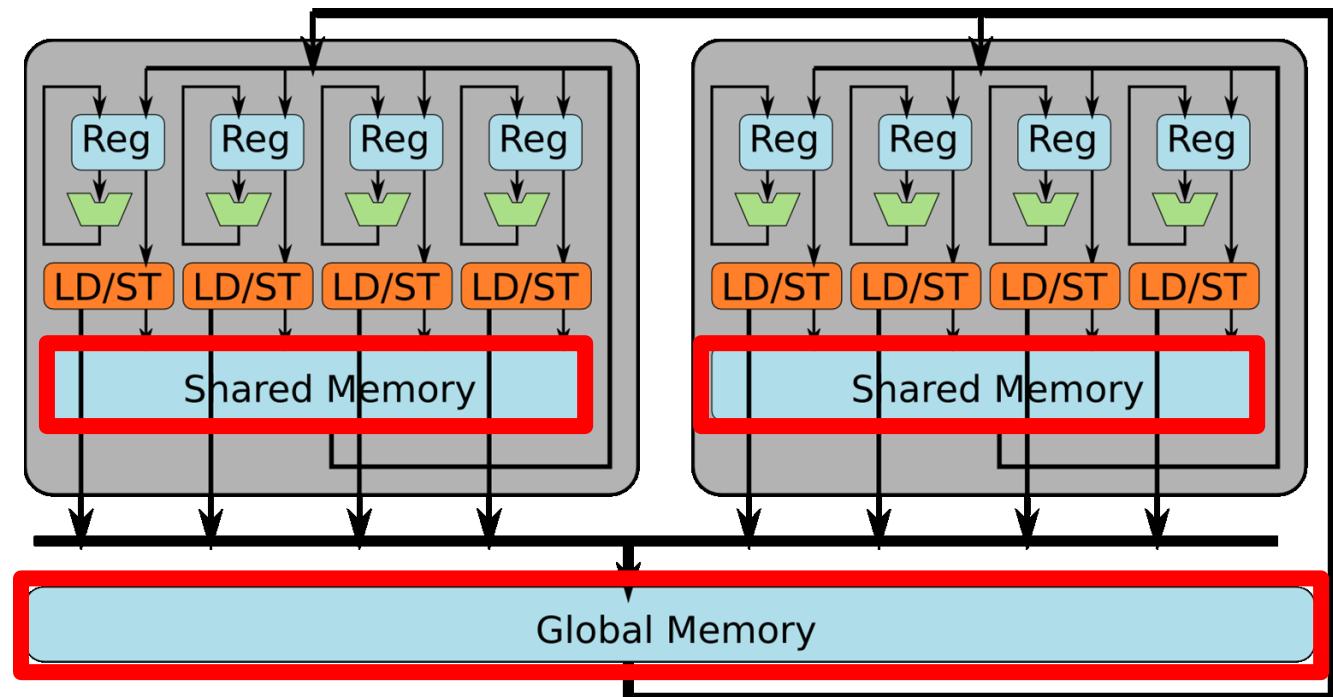
Memory access latency

several cycles

100+ cycles

OPTIONAL

SKIP

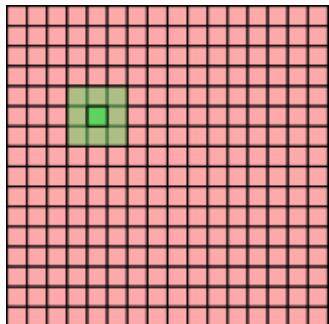


참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Example: Average Filters

Average over a  
3x3 window for  
a 16x16 array



```
kernelF<<<(1,1),(16,16)>>>(A);  
__device__ kernelF(A){  
    i = threadIdx.y;  
    j = threadIdx.x;  
    tmp = (A[i-1][j-1] + A[i-1][j] +  
           ... + A[i+1][j+1] ) / 9;  
    A[i][j] = tmp;  
}
```

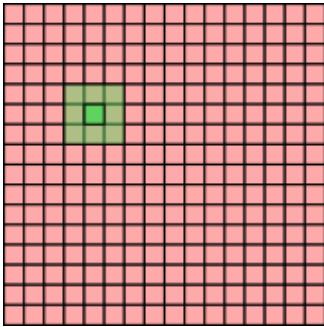
Each thread loads 9 elements  
from global memory.  
It takes hundreds of cycles.

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Utilizing the Shared Memory

Average over a  
3x3 window for  
a 16x16 array

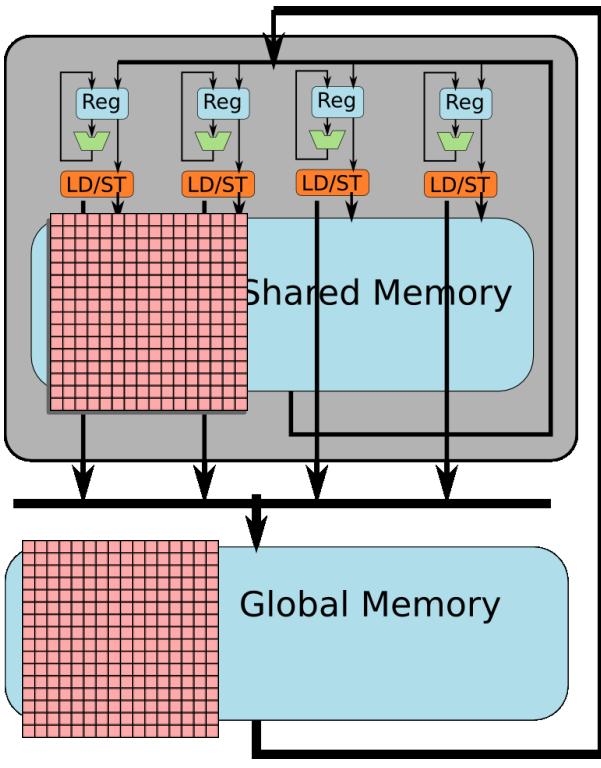


```
kernelF<<<(1,1),(16,16)>>>(A);  
  
__device__  kernelF(A){  
    __shared__ smem[16][16];  
    i = threadIdx.y;  
    j = threadIdx.x;  
    smem[i][j] = A[i][j]; // load to smem  
    A[i][j] = ( smem[i-1][j-1] + smem[i-1][j] +  
                ... + smem[i+1][j+1] ) / 9;  
}
```

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Utilizing the Shared Memory



```
kernelF<<<(1,1),(16,16)>>>(A);  
__device__ kernelF(A){  
    __shared__ smem[16][16];  
    i = threadIdx.y;  
    j = threadIdx.x;    Each thread loads one element  
    smem[i][j] = A[i][j]; // load to smem  
    A[i][j] = ( smem[i-1][j-1] + smem[i-1][j] +  
                ... + smem[i+1][i+1] ) / 9;  
}
```

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# However, the Program Is Incorrect

```
kernelF<<<(1,1),(16,16)>>>(A);
__device__ kernelF(A){
    __shared__ smem[16][16];
    i = threadIdx.y;
    j = threadIdx.x;
    smem[i][j] = A[i][j]; // load to smem
    A[i][j] = ( smem[i-1][j-1] + smem[i-1][j] +
                ... + smem[i+1][j+1] ) / 9;
}
```

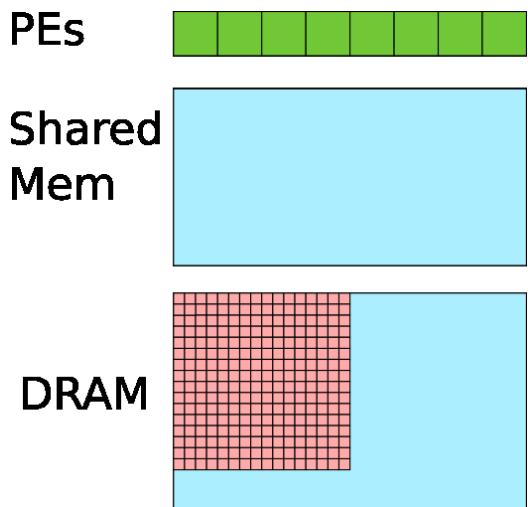
Hazards!

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Let's See What's Wrong

Assume 256 threads are scheduled on 8 PEs.



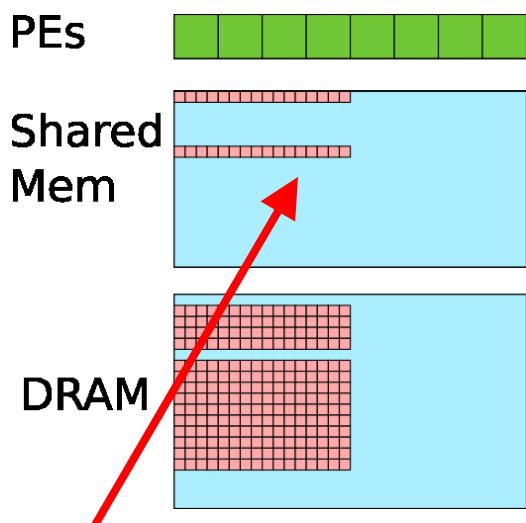
```
__device__ kernelF(A){  
    __shared__ smem[16][16];  
    i = threadIdx.y;  
    j = threadIdx.x; Before load instruction  
    smem[i][j] = A[i][j]; // load to smem  
    A[i][j] = ( smem[i-1][j-1] + smem[i-1][j] +  
                ... + smem[i+1][i+1] ) / 9;  
}
```

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Let's See What's Wrong

Assume 256 threads are scheduled on 8 PEs.



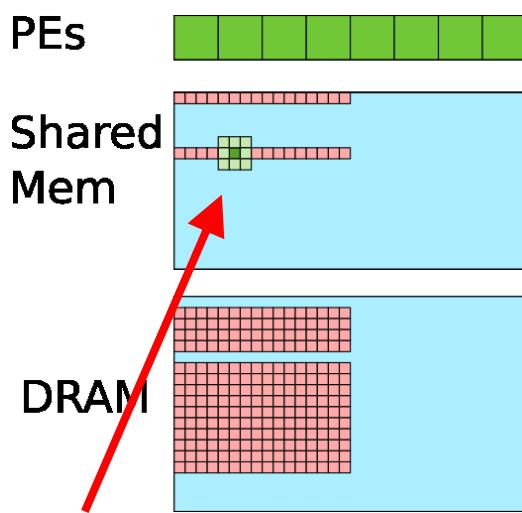
```
kernelF<<<(1,1),(16,16)>>>(A);  
__device__ kernelF(A){  
    __shared__ smem[16][16];  
    i = threadIdx.y;  
    j = threadIdx.x;  
    smem[i][j] = A[i][j]; // load to smem  
    A[i][j] = ( smem[i-1][j-1] + smem[i-1][j] +  
                ... + smem[i+1][j+1] ) / 9;  
}
```

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Let's See What's Wrong

Assume 256 threads are scheduled on 8 PEs.



Some elements in the window are not yet loaded by other threads. Error!

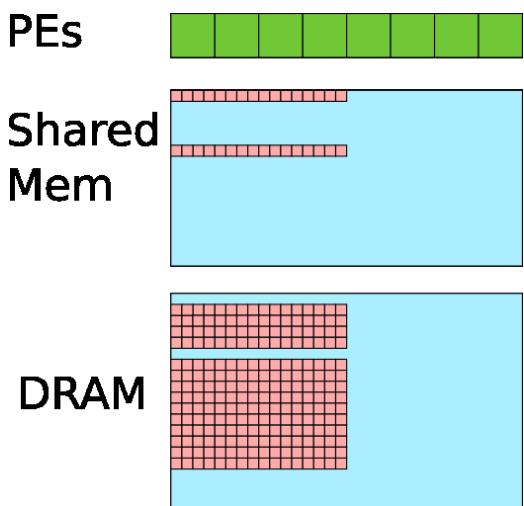
```
__device__ kernelF(A){  
    __shared__ smem[16][16];  
    i = threadIdx.y;  
    j = threadIdx.x;  
    smem[i][j] = A[i][j]; // load to smem  
    A[i][j] = ( smem[i-1][j-1] + smem[i-1][j] +  
                ... + smem[i+1][j+1] ) / 9;  
}
```

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# How To Solve It?

Assume 256 threads are scheduled on 8 PEs.



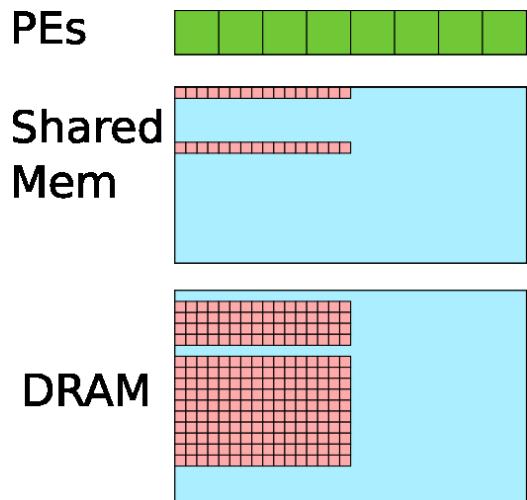
```
__device__ kernelF(A){  
    __shared__ smem[16][16];  
    i = threadIdx.y;  
    j = threadIdx.x;  
    smem[i][j] = A[i][j]; // load to smem  
    A[i][j] = ( smem[i-1][j-1] + smem[i-1][j] +  
                ... + smem[i+1][j+1] ) / 9;  
}
```

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Use a "SYNC" barrier

Assume 256 threads are scheduled on 8 PEs.



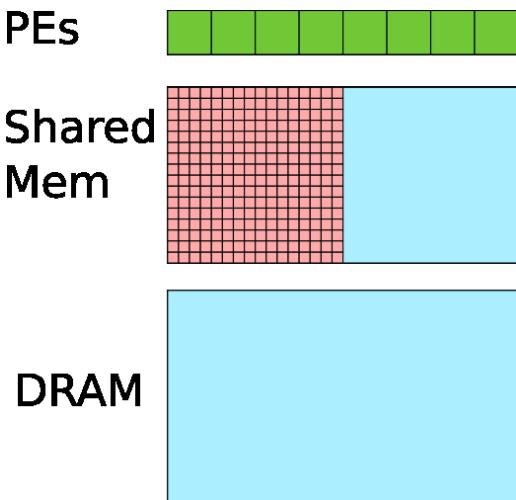
```
kernelF<<<(1,1),(16,16)>>>(A);  
__device__ kernelF(A){  
    __shared__ smem[16][16];  
    i = threadIdx.y;  
    j = threadIdx.x;  
    smem[i][j] = A[i][j]; // load to smem  
    __SYNC();  
    A[i][j] = ( smem[i-1][j-1] + smem[i-1][j] +  
                ... + smem[i+1][i+1] ) / 9;  
}
```

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Use a "SYNC" barrier

Assume 256 threads are scheduled on 8 PEs.



```
kernelF<<<(1,1),(16,16)>>>(A);  
__device__ kernelF(A){  
    __shared__ smem[16][16];  
    i = threadIdx.y;  
    j = threadIdx.x;  
    smem[i][j] = A[i][j]; // load to smem  
    __SYNC();  
    A[i][j] = ( smem[i-1][j-1] + smem[i-1][j] +  
                ... + smem[i+1][j+1] ) / 9;  
}
```

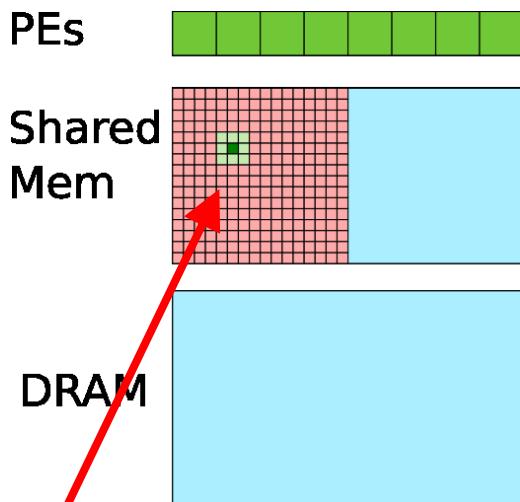
Wait until all threads hit barrier

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>

# Use a "SYNC" barrier

Assume 256 threads are scheduled on 8 PEs.



All elements in the window  
are loaded when each thread  
starts averaging.

```
kernelF<<<(1,1),(16,16)>>>(A);  
__device__ kernelF(A){  
    __shared__ smem[16][16];  
    i = threadIdx.y;  
    j = threadIdx.x;  
    smem[i][j] = A[i][j]; // load to smem  
    SYNC();  
    A[i][j] = ( smem[i-1][j-1] + smem[i-1][j] +  
                ... + smem[i+1][j+1] ) / 9;  
}
```

참조:

<http://www.es.ele.tue.nl/~heco/courses/EmbeddedComputerArchitecture/>



# Simple Profile

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- <http://docs.nvidia.com/cuda/profiler-users-guide/index.html#summary-mode>
- <https://devblogs.nvidia.com/parallelforall/cuda-pro-tip-nvprof-your-handy-universal-gpu-profiler/>

# 차례

- **Introduction**
  - Multicore/Manycore and GPU
  - GPU on Medical Applications
- **Parallel Programming on GPUs: Basics**
  - Conceptual Introduction
- **GPU Architecture Review**
- **Parallel Programming on GPUs: Practice**
  - Real programming
- **Conclusion**

DO YOU  
KNOW?





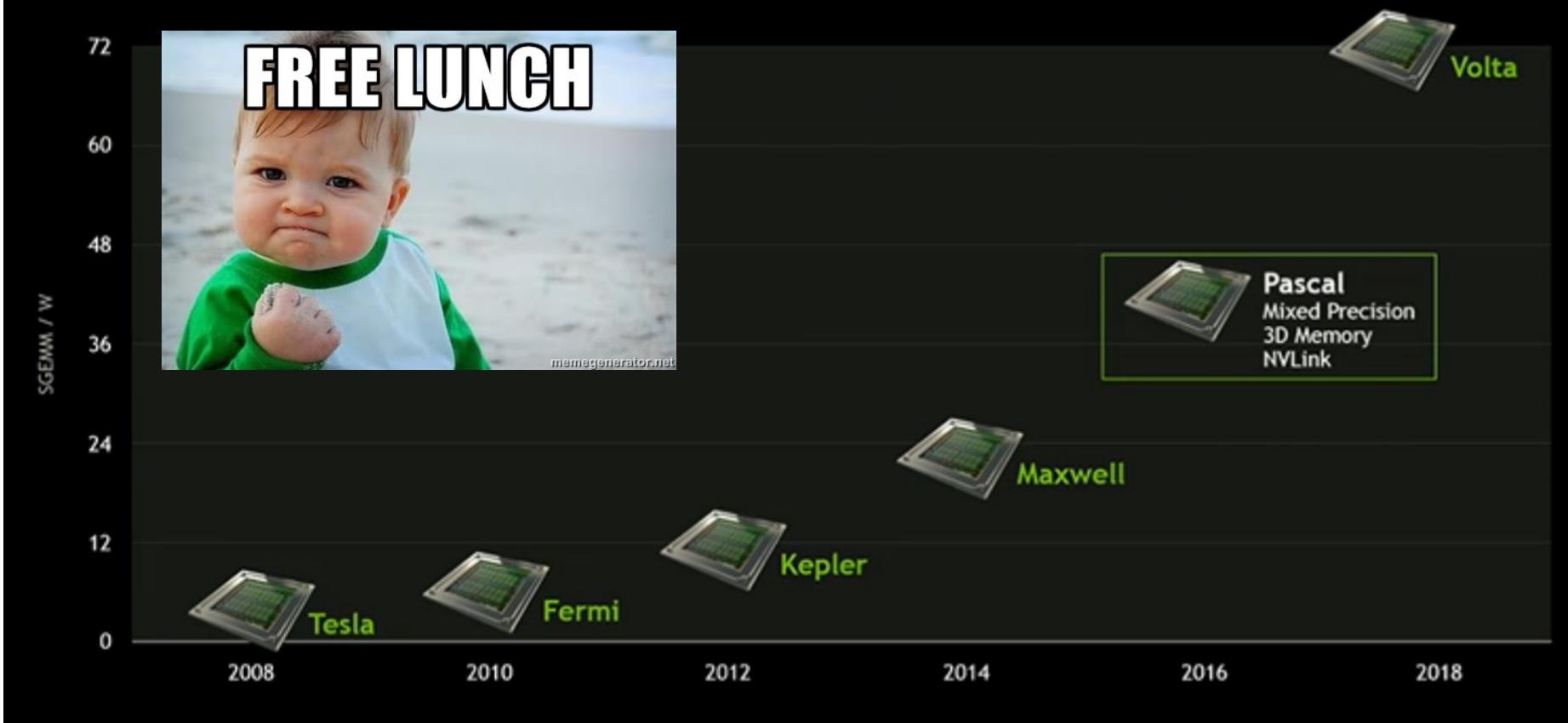
# Conclusion

---

- GPU is still ***evolving*** for even much higher performance
  - **Stacked DRAM**
  - **NVLINK**
- ***Free Lunch*** ?
  - GPU continue to improve performance and power with more advanced GPU hardware/software features
- Mobile / portable medical system & Car system
  - **Tegra K1/X1**

# Conclusion

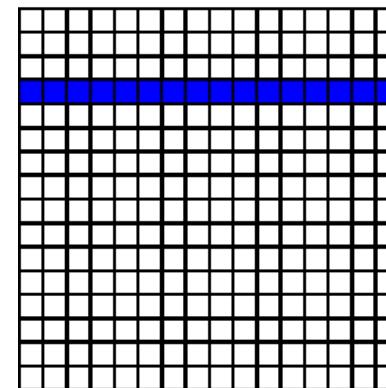
- GPU is still *evolving* for even much higher performance  
Single precision floating General Matrix Multiply (**SGEMM**)



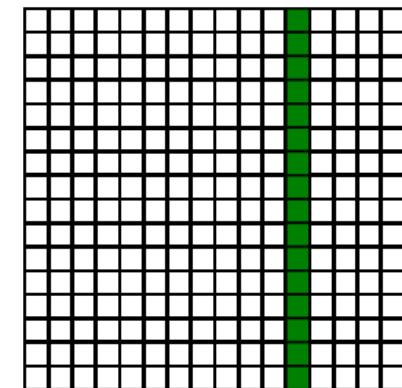
# Final Questions: Matrix Multiplication

```
void main(){  
  
    define A, B, C  
    for i = 0 to M do  
        for j = 0 to N do  
            /* compute element C(i,j) */  
            for k = 0 to K do  
                C(i,j) <= C(i,j) + A(i,k) * B(k,j)  
            end  
        end  
    end  
}
```

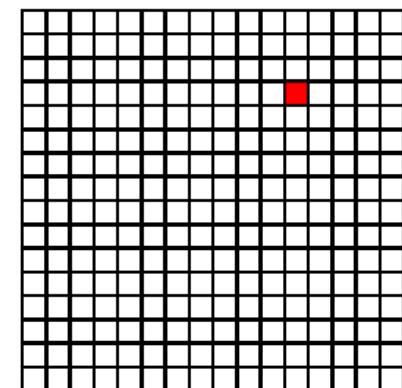
A



B



C (i,j)

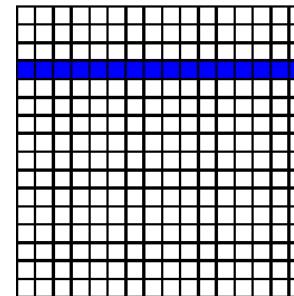


# Final Questions: Matrix Multiplication

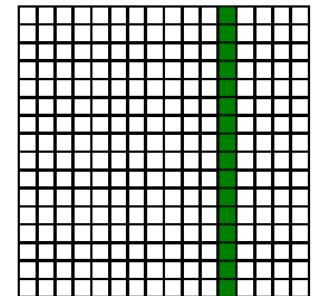
main:

```
define A_cpu, B_cpu, C_cpu in the CPU memory;  
define A_gpu, B_gpu, C_gpu in the GPU memory;  
memcpy A_cpu to A_gpu;  memcpy B_cpu to B_gpu;  
dim3 dimBlock(16, 16);  dim3 dimGrid(N/dimBlock.x, M/dimBlock.y);  
...
```

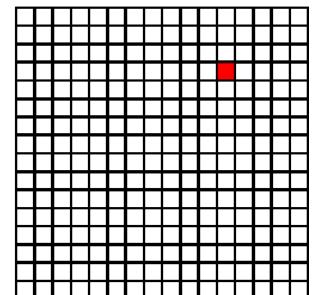
A



B



C



```
__global__ void matrixMul(A_gpu,B_gpu,C_gpu,K){  
    temp <= 0
```

```
    C_gpu(i,j) <= accu
```

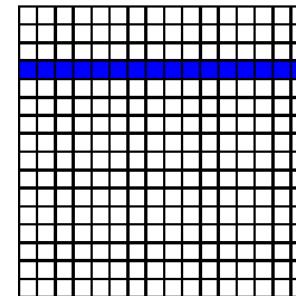
```
}
```

# Final Questions: Matrix Multiplication

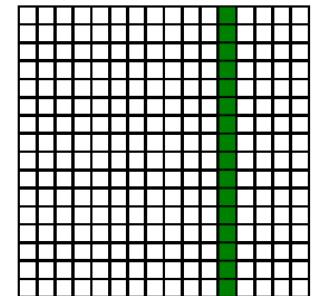
main:

```
define A_cpu, B_cpu, C_cpu in the CPU memory;  
define A_gpu, B_gpu, C_gpu in the GPU memory;  
memcpy A_cpu to A_gpu;  memcpy B_cpu to B_gpu;  
dim3 dimBlock(16, 16);  dim3 dimGrid(N/dimBlock.x, M/dimBlock.y);  
...
```

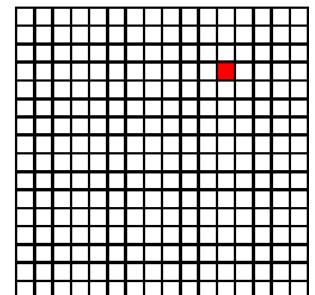
A



B



C



```
__global__ void matrixMul(A_gpu,B_gpu,C_gpu,K){
```

```
    temp <= 0
```

```
    i <= blockIdx.y * blockDim.y + threadIdx.y // Row i of matrix C
```

```
    j <= blockIdx.x * blockDim.x + threadIdx.x // Column j of matrix C
```

```
    for k = 0 to K-1 do
```

```
        accu <= accu + A_gpu(i,k) * B_gpu(k,j)
```

```
    end
```

```
    C_gpu(i,j) <= accu
```

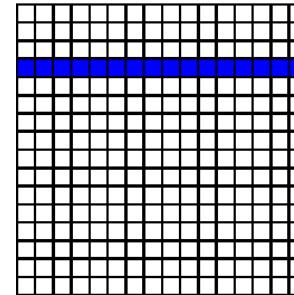
```
}
```

# Final Questions: Matrix Multiplication

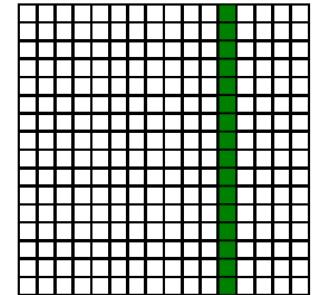
main:

```
define A_cpu, B_cpu, C_cpu in the CPU memory;  
define A_gpu, B_gpu, C_gpu in the GPU memory;  
memcpy A_cpu to A_gpu;  memcpy B_cpu to B_gpu;  
dim3 dimBlock(16, 16);  dim3 dimGrid(N/dimBlock.x, M/dimBlock.y);  
...
```

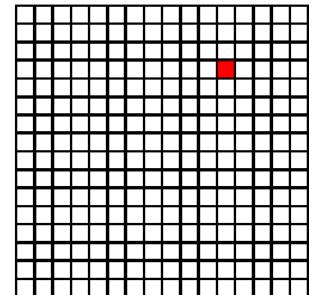
A



B



C



```
__global__ void matrixMul(A_gpu,B_gpu,C_gpu,K){
```

```
    temp <= 0
```

```
    i <= blockIdx.y * blockDim.y + threadIdx.y // Row i of matrix C
```

```
    j <= blockIdx.x * blockDim.x + threadIdx.x // Column j of matrix C
```

```
    for k = 0 to K-1 do
```

```
        accu <= accu + A_gpu(i,k) * B_gpu(k,j)
```

```
    end
```

```
    C_gpu(i,j) <= accu
```

```
}
```

Thanks !

