

CS 380 - GPU and GPGPU Programming Lecture 8: GPU Architecture, Pt. 6

Markus Hadwiger, KAUST

Reading Assignment #4 (until Sep 29)



Read (required):

Get an overview of NVIDIA Ampere (GA102 and A100) GPU white papers:

```
https://www.nvidia.com/content/PDF/
nvidia-ampere-ga-102-gpu-architecture-whitepaper-v2.pdf
https://www.nvidia.com/content/dam/en-zz/Solutions/Data-Center/
nvidia-ampere-architecture-whitepaper.pdf
```

Get an overview of NVIDIA Hopper (H100) Tensor Core GPU white paper:

https://resources.nvidia.com/en-us-hopper-architecture/nvidia-h100-tensor-c

• Get an overview of NVIDIA Blackwell (GB202) GPU white papers:

```
https://images.nvidia.com/aem-dam/Solutions/geforce/blackwell/
nvidia-rtx-blackwell-gpu-architecture.pdf
```

https://www.nvidia.com/content/dam/en-zz/Solutions/design-visualization/quadro-product-literature/NVIDIA-RTX-Blackwell-PRO-GPU-Architecture-v1.0.pdf

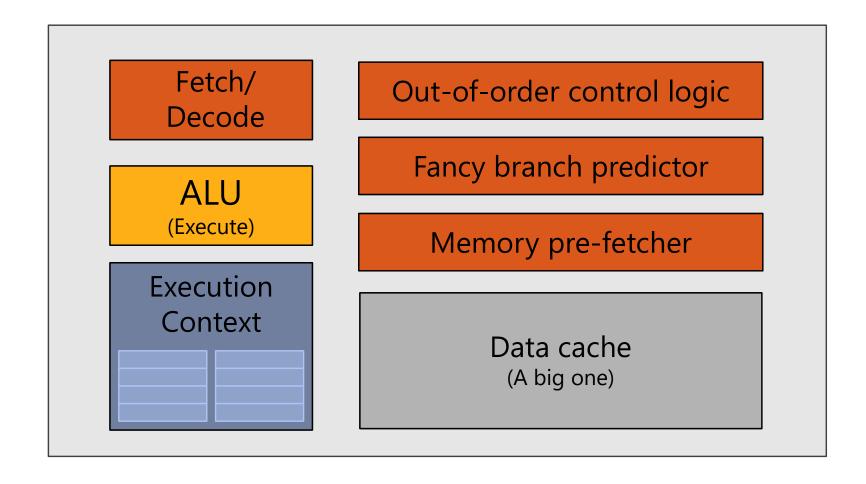
Read (optional):

- Look at the "Tuning Guides" for different architectures in the CUDA SDK
- PTX Instruction Set Architecture (9.0): https://docs.nvidia.com/cuda/parallel-thread-execution/ Read Chapters 1 – 3; get an overview of Chapter 9; browse through the other chapters to get a feeling for what PTX looks like
- CUDA SASS ISA (13.0), Chap. 6: https://docs.nvidia.com/cuda/pdf/CUDA Binary Utilities.pdf

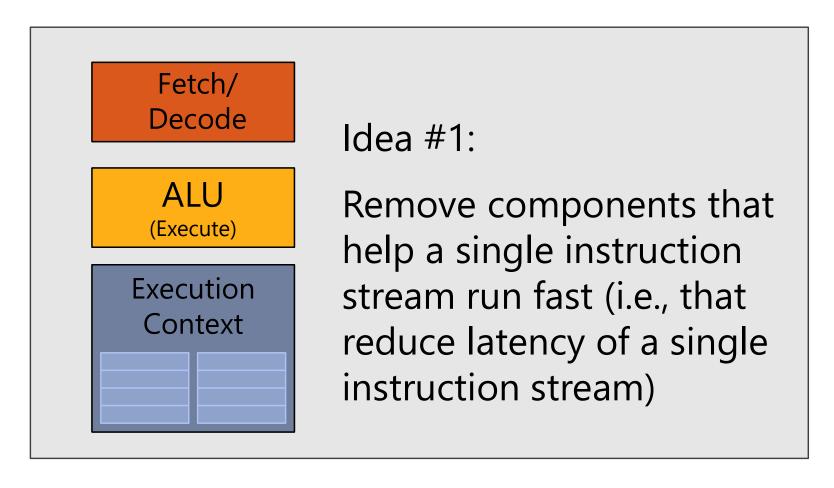
GPU Architecture: General Architecture

GPU Architecture Big Idea #1

CPU-"style" cores



Idea #1: Slim down

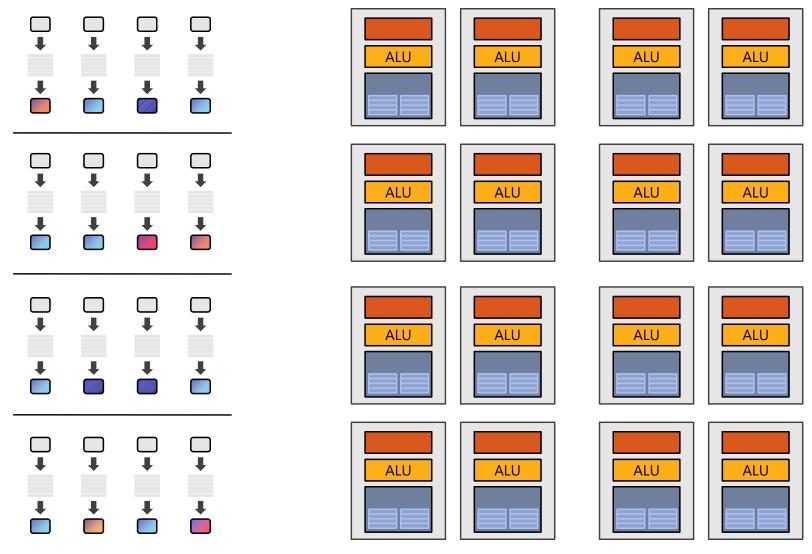


Goal: Increase (peak) throughput

Sixteen cores

(sixteen fragments in parallel)

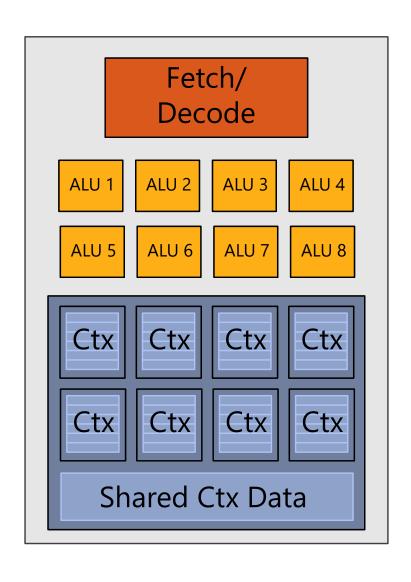
→ 16x peak throughput!



16 cores = 16 simultaneous instruction streams

GPU Architecture Big Idea #2

Idea #2: Add ALUs



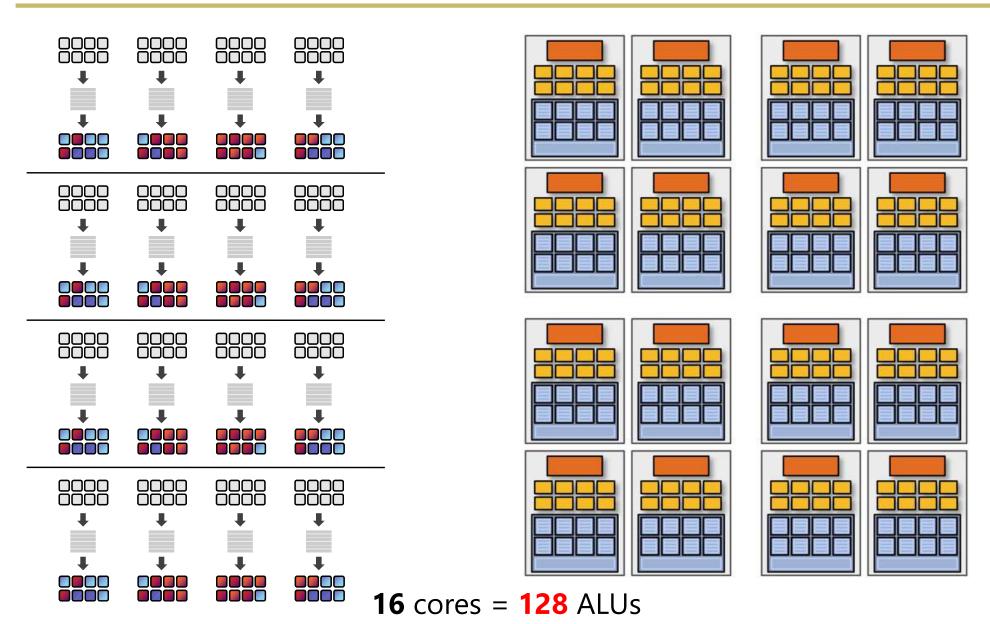
Idea #2:

Amortize cost/complexity of managing an instruction stream across many ALUs

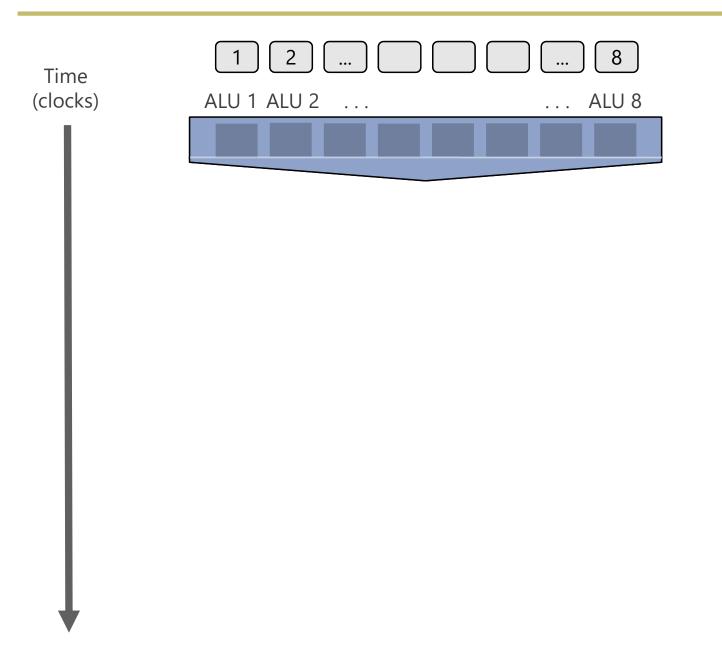
SIMD processing

(or SIMT, SPMD)

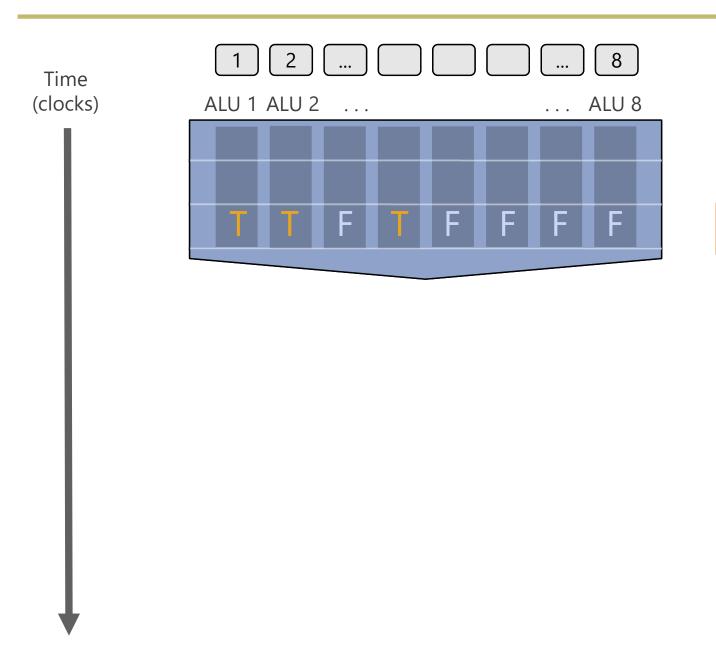
128 fragments in parallel → 128x peak throughput!



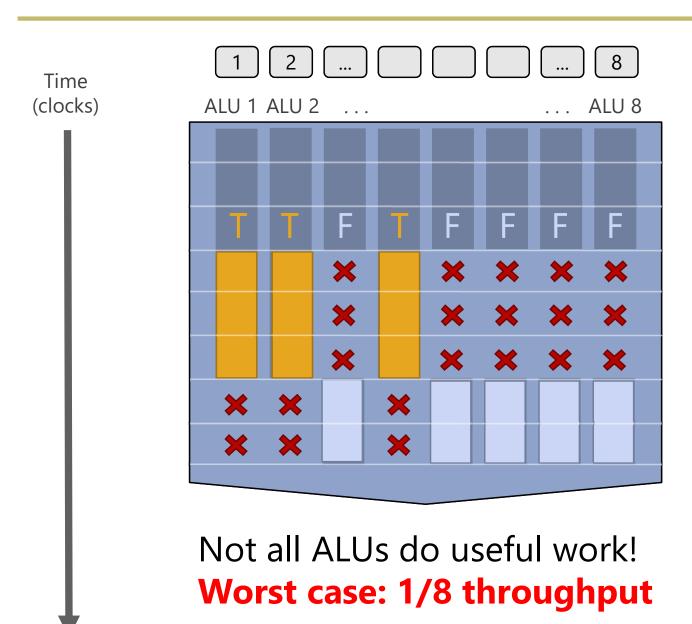
= 16 simultaneous instruction streams



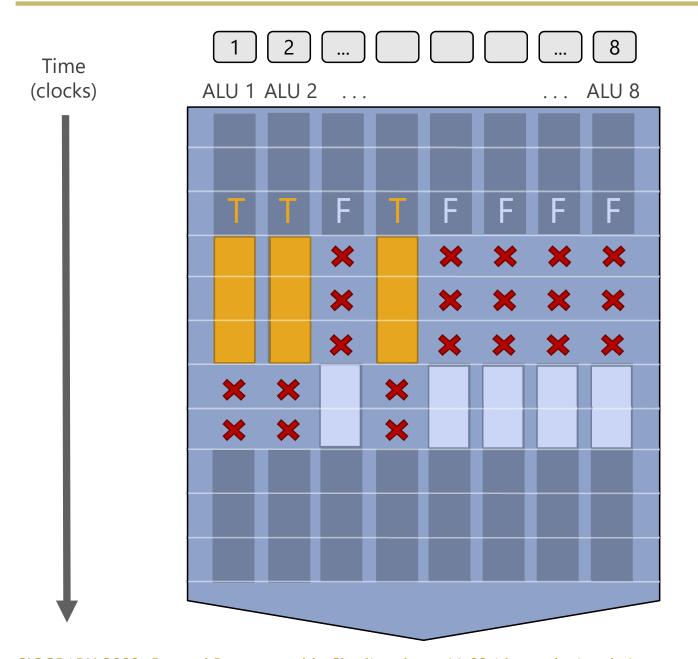
```
<unconditional</pre>
shader code>
if (x > 0) {
    y = pow(x, exp);
    y *= Ks;
     refl = y + Ka;
} else {
    x = 0;
    refl = Ka;
<resume unconditional</pre>
shader code>
```



```
<unconditional</pre>
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shader code>
```

GPU Architecture Big Idea #3

Idea #3: Interleave execution of groups

But we have LOTS of independent fragments.

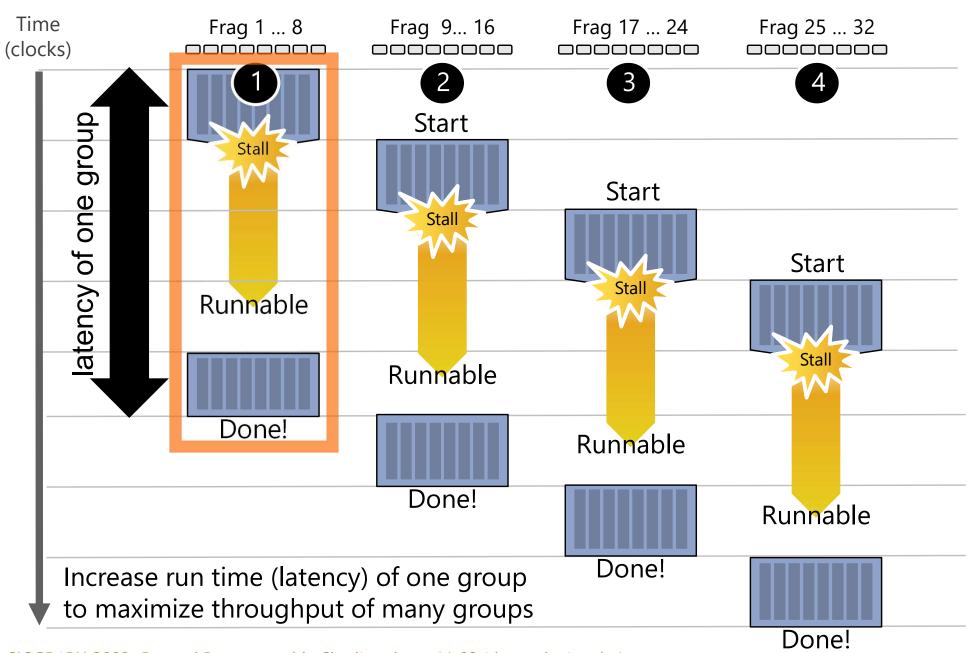
Idea #3:

Interleave processing of many fragments on a single core to avoid stalls caused by high latency operations.

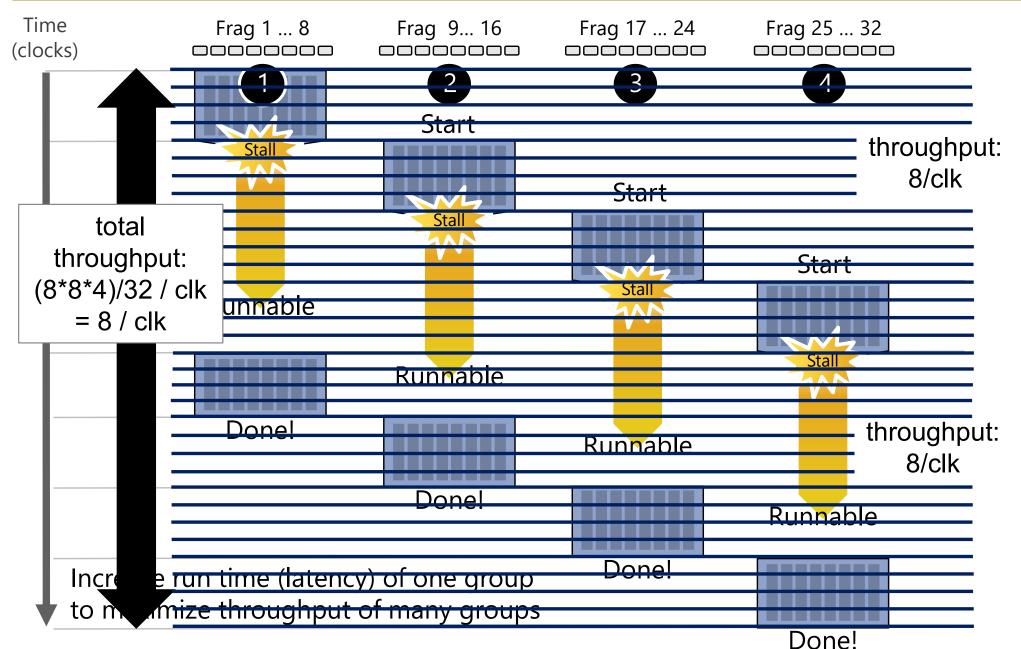
(including instruction pipeline hazards)

Increases the latency of a single group of fragments, but keeps the throughput as close to peak as possible!

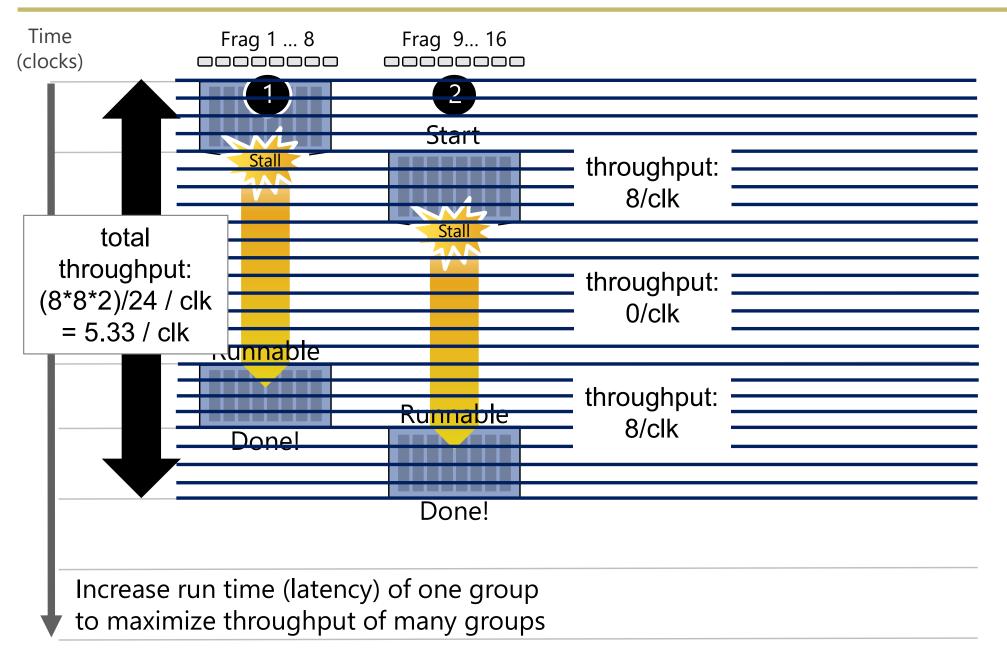
Hiding shader stalls



Throughput! (4 groups of threads)



Throughput! (2 groups of threads)



Concepts: Types of Parallelism



Instruction level parallelism (ILP)

- In single instruction stream: Can consecutive instructions/operations be executed in parallel? (Because they don't have a dependency)
- Exploit ILP: Execute independent instructions (1) via pipelined execution (instr. pipe), or even (2) in multiple parallel instruction pipelines (superscalar processors)
- On GPUs: also important, but much less than TLP (compare, e.g., Kepler with current GPUs)

Thread level parallelism (TLP)

- Exploit that by definition operations in different threads are independent (if no explicit communication/synchronization is used, which should be minimized)
- Exploit TLP: Execute operations/instructions from multiple threads in parallel (which also needs multiple parallel instruction pipelines)
- On GPUs: main type of parallelism

more types:

- Bit-level parallelism (processor word size: 64 bits instead of 32, etc.)
- Data parallelism (SIMD/vector instructions), task parallelism, ...

Concepts: Latency Hiding



Not about latency of single operation or group of operations: It's about avoiding that the *throughput* goes below peak

Hide latency that *does* occur for one instruction (group) by executing a different instruction (group) as soon as current one stalls:

→ Total throughput does not go down

In GPUs, hide latencies via:

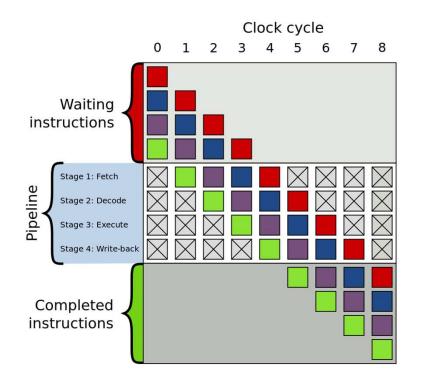
- TLP: pull independent, not-stalling instruction from other thread group
- ILP: pull independent instruction from down the inst. stream in same thread group
- Depending on GPU: TLP often sufficient, but sometimes also need ILP
- However: If in one cycle TLP doesn't work, ILP can jump in or vice versa

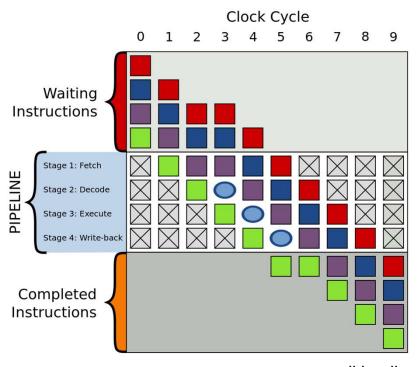
Interlude: Instruction Pipelining



Most common way to exploit instruction-level parallelism (ILP)

Problem: hazards (different solutions: bubbles, forwarding, ...)





wikipedia

https://en.wikipedia.org/wiki/Instruction_pipelining https://en.wikipedia.org/wiki/Classic RISC pipeline

Concepts: SM Occupancy in CUDA (TLP!)



We need to hide latencies from

- Instruction pipelining hazards (RAW read after write, etc.)
 (also: branches; behind branch, fetch instructions from different instruction stream)
- Memory access latency

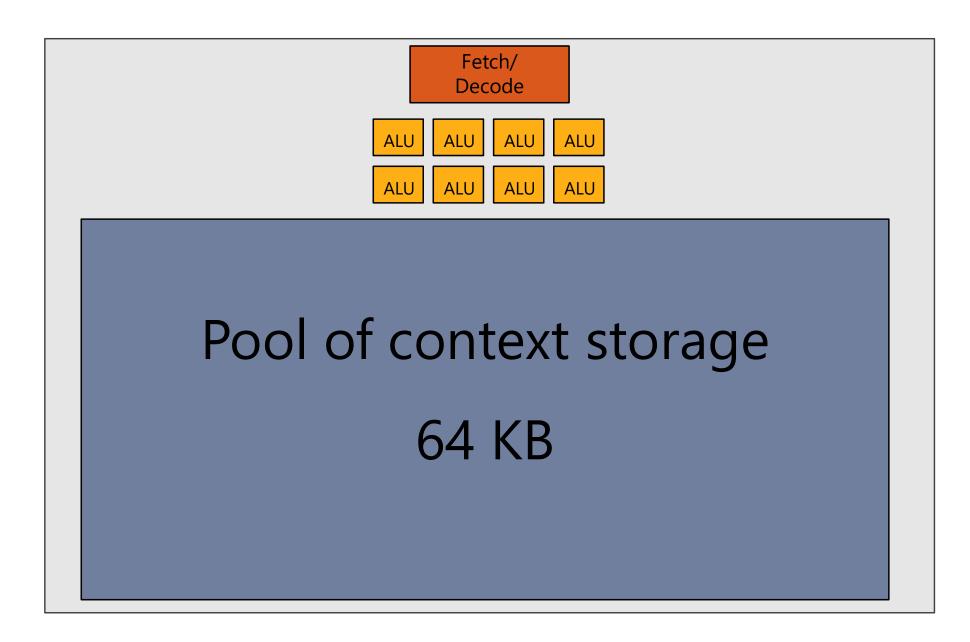
First type of latency: Definitely need to hide! (it is always there)

Second type of latency: only need to hide if it does occur (of course not unusual)

Occupancy: How close are we to maximum latency hiding ability? (how many threads are resident vs. how many could be)

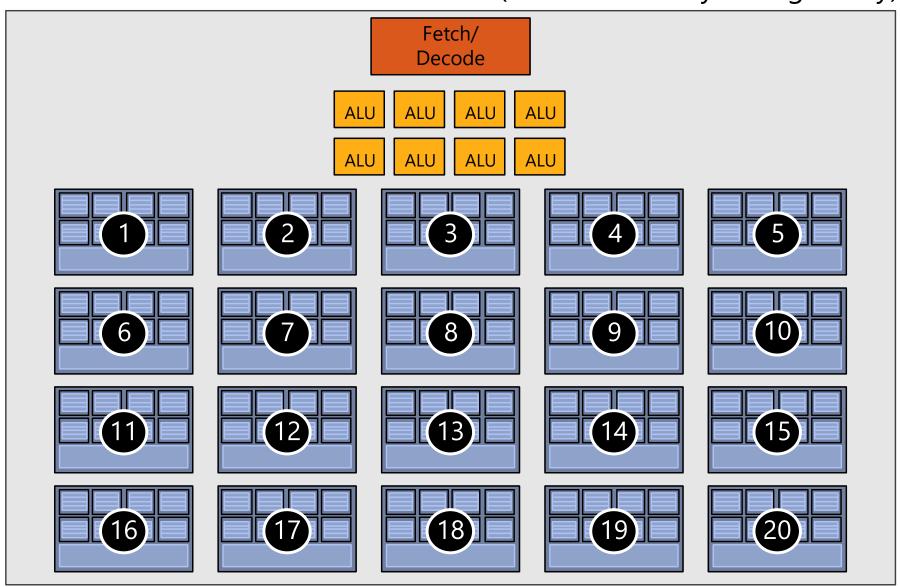
See run time occupancy API, or Nsight Compute: https://docs.nvidia.com/nsight-compute/NsightCompute/index.html#occupancy-calculator

Storing contexts

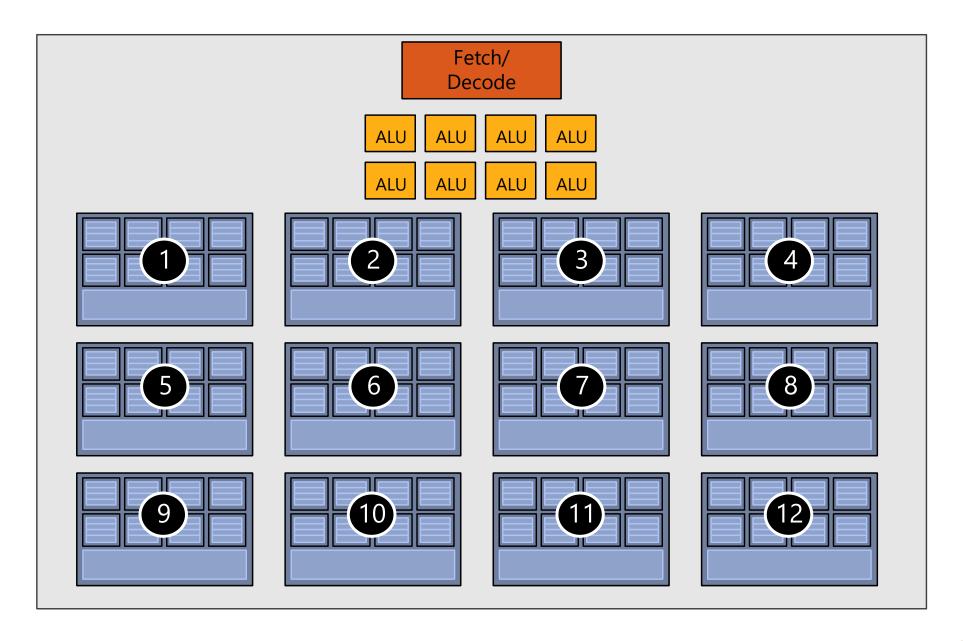


Twenty small contexts (few regs/thread)

(maximal latency hiding ability)

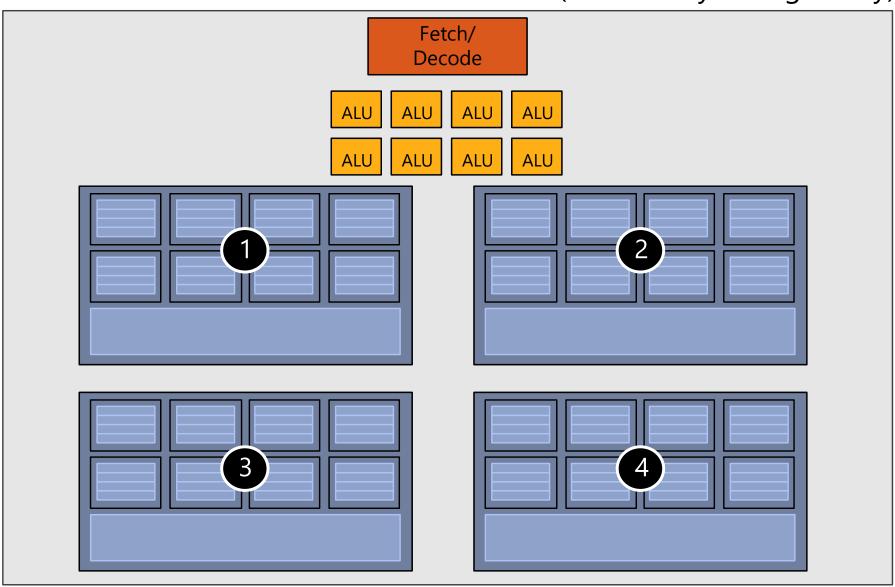


Twelve medium contexts (more regs/th.)



Four large contexts (many regs/thread)

(low latency hiding ability)



Complete GPU

16 cores

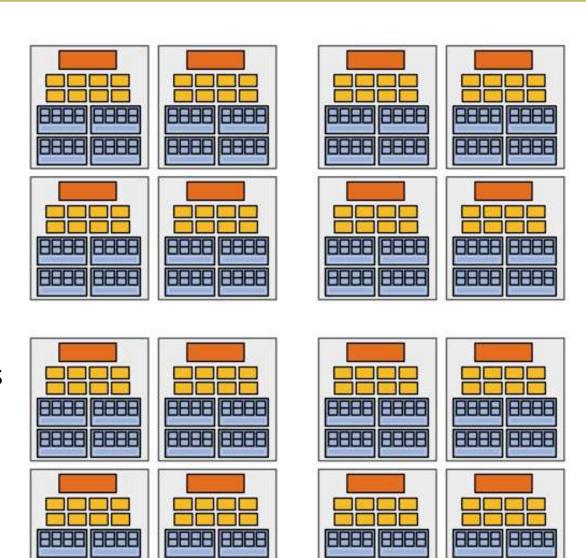
8 mul-add [mad] ALUs per core (8*16 = 128 total)

16 simultaneous instruction streams

64 (4*16) concurrent (but interleaved) instruction streams

512 (8*4*16) concurrent fragments (resident threads)

= **256 GFLOPs** (@ 1GHz) (**128** * 2 [mad] * 1G)



Complete GPU

16 cores

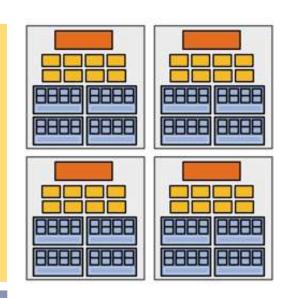
8 mul-add [mad] ALUs per core (8*16 = 128 total)

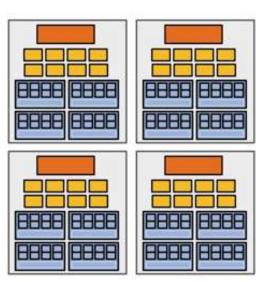
16 simultaneous instruction streams

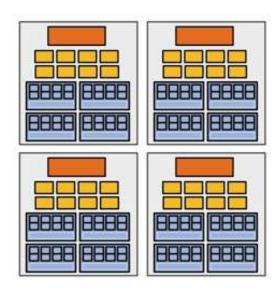


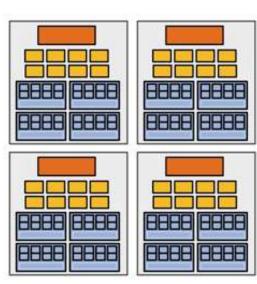
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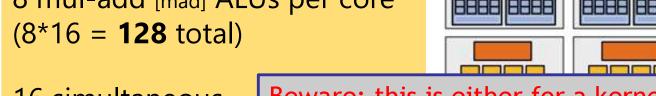


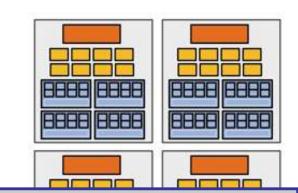


Complete GPU

16 cores

8 mul-add [mad] ALUs per core





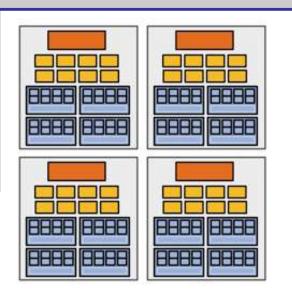
16 simultaneous instruction streams

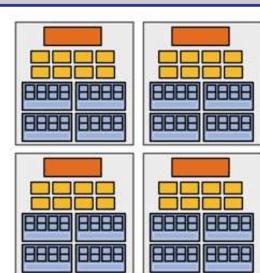
Beware: this is either for a kernel that happens to have the occupancy shown here (4 groups of threads per core), or: the diagram could show maximum occupancy

64 (4*16) concurrent (but interleaved) instruction streams

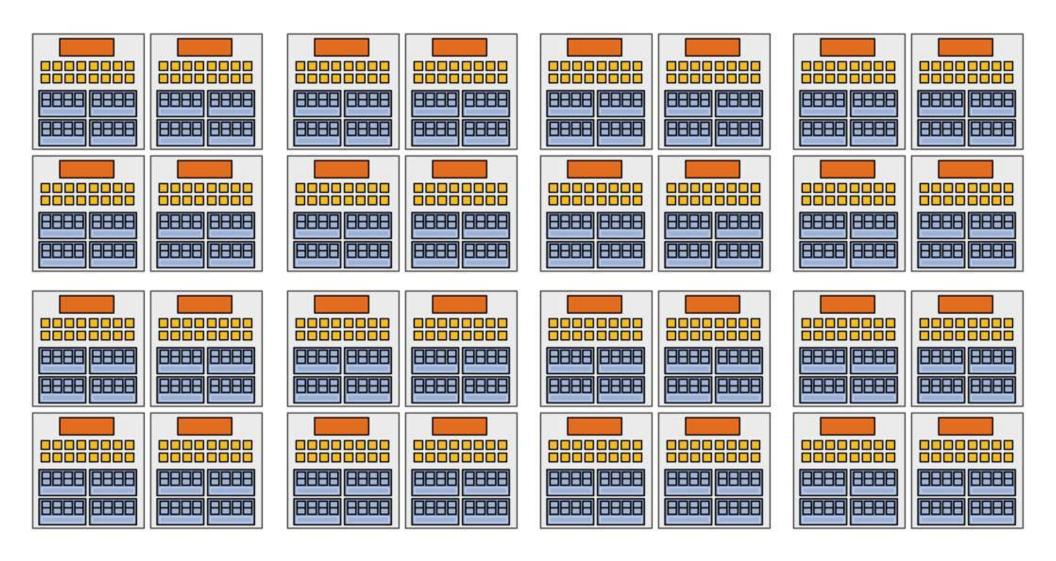
512 (8*4*16) concurrent fragments (resident threads)

= **256 GFLOPs** (@ 1GHz) (**128** * 2 [mad] * 1G)





"Enthusiast" GPU (Some time ago :)



32 cores, 16 ALUs per core (512 total) = 1 TFLOP (@ 1 GHz)

Where We've Arrived...



Summary: three key ideas for high-throughput execution

- 1. Use many "slimmed down cores," run them in parallel
- 2. Pack cores full of ALUs (by sharing instruction stream overhead across groups of fragments)
 - Option 1: Explicit SIMD vector instructions
 - Option 2: Implicit sharing managed by hardware

GPUs are here! (usually)

- 3. Avoid latency stalls by interleaving execution of many groups of fragments
 - When one group stalls, work on another group

GPU Architecture:Real Architectures

NVIDIA Architectures (since first CUDA GPU)



Tesla [CC 1.x]: 2007-2009

• G80, G9x: 2007 (Geforce 8800, ...) GT200: 2008/2009 (GTX 280, ...)

Fermi [CC 2.x]: 2010 (2011, 2012, 2013, ...)

• GF100, ... (GTX 480, ...) GF104, ... (GTX 460, ...) GF110, ... (GTX 580, ...)

Kepler [CC 3.x]: 2012 (2013, 2014, 2016, ...)

• GK104, ... (GTX 680, ...) GK110, ... (GTX 780, GTX Titan, ...)

Maxwell [CC 5.x]: 2015

GM107, ... (GTX 750Ti, ...); [Nintendo Switch]
 GM204, ... (GTX 980, Titan X, ...)

Pascal [CC 6.x]: 2016 (2017, 2018, 2021, 2022, ...)

- GP100 (Tesla P100, ...)
- GP10x: x=2,4,6,7,8, ... (GTX 1060, 1070, 1080, Titan X *Pascal*, Titan Xp, ...)

Volta [CC 7.0, 7.2]: 2017/2018

 GV100, ... (Tesla V100, Titan V, Quadro GV100, ...)

Turing [CC 7.5]: 2018/2019

• TU102, TU104, TU106, TU116, TU117, ... (Titan RTX, RTX 2070, 2080 (Ti), GTX 1650, 1660, ...)

Ampere [CC 8.0, 8.6, 8.7, 8.8]: 2020

 GA100, GA102, GA104, GA106, ...; [Nintendo Switch 2] (A100, RTX 3070, 3080, 3090 (Ti), RTX A6000, ...)

Hopper [CC 9.0], Ada Lovelace [CC 8.9]: 2022/23

 GH100, AD102, AD103, AD104, AD106, AD107, ...
 (H100, L40, RTX 4080 (12/16 GB), RTX 4090, RTX 6000 (Ada), ...)

Blackwell [CC 10.0, 10.1(11.0), 10.3, 12.0, 12.1]: 2024/2025

 GB100/102, GB200, GB202/203/205/206/207, ...
 (RTX 5080/5090, GB100/GB200 NVL72, HGX B100/B200, RTX 4000/5000/6000 PRO Blackwell, ...)

Concepts: Latency Hiding (Latency Tolerance)



Main goal: Avoid that instruction throughput goes below peak

ILP: Hide instruction pipeline latency of one instruction by pipelined execution of *independent* instruction from same thread

TLP: Hide any latency occurring for one thread (group/warp/wavefront) by executing a different thread (group/warp/wavefront) as soon as current thread (group/warp/wavefront) stalls:

→ Total throughput does not go down

GPUs

- TLP: pull independent, not-stalling instruction from other thread group
- ILP: pull independent instruction from same thread group (instruction stream)
- Depending on GPU: TLP often sufficient, but sometimes also need ILP
- However: If in one cycle TLP doesn't work, ILP can jump in or vice versa*

(*depending on actual microarchitecture)

ILP vs. TLP on GPUs



Main observations

- Each time unit (usually one clock cycle), a new instruction without dependencies should be dispatched to functional units (ALUs, SFUs, ...)
- *Instruction* is a *group of threads* that is executing the same instruction: CUDA warp (32 threads), wavefront (32 or 64 threads), ...
- Where can this instruction come from?
 - TLP: from another runnable warp (i.e., different instruction stream)
 - ILP: from the same warp (i.e., the same instruction stream)

How many instructions/warps per time unit (clock cycle)?

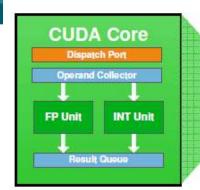
- "Scalar" pipeline (CPI=1.0): **TLP sufficient** (if enough warps); **can exploit ILP** (next instruction either from different warp, or from same warp)
- "Superscalar" (*CPI<1.0*) pipeline: dispatch more than one instruction per cycle, (#dispatchers > #warp schedulers): **need ILP!**

(CPI = clocks per instruction)

Example: "Scalar" GF100

Main concept here:

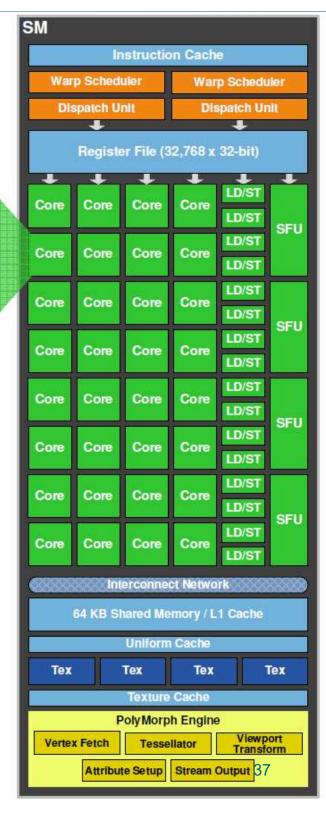
There is one instruction dispatcher (dispatch unit / fetch/decode unit)
per warp scheduler (warp selector)



Details later...

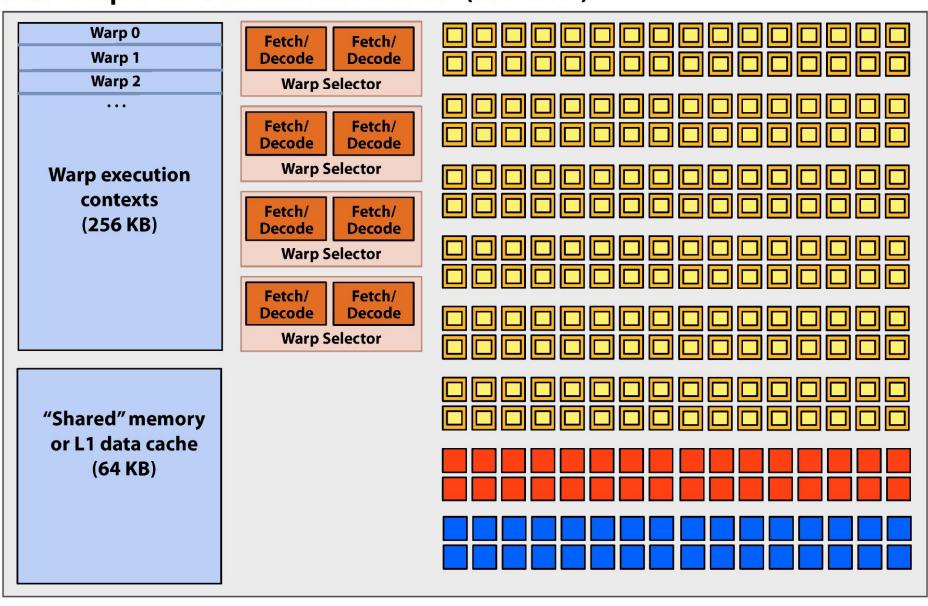
Ignore less important subtleties... GF100 has two warp schedulers, not one, and each 32-thread instruction is executed over two clock cycles, not one, etc.

Caveat on NVIDIA diagrams: if two dispatchers per warp scheduler are shown, it still doesn't mean that the ALU pipeline is "superscalar" (often, the second dispatcher dispatches to a *non-ALU* pipeline) ... need to look at CUDA programming guide info, also given in our tables in row "# ALU dispatch / warp sched."

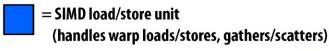


Example: "Superscalar" ALUs in SM Architecture

NVIDIA Kepler GK104 architecture SMX unit (one "core")



= SIMD function unit, control shared across 32 units (1 MUL-ADD per clock) = "special" SIMD function unit, control shared across 32 units (operations like sin/cos)



Instruction Throughput



Instruction throughput numbers in older (<13) CUDA C Programming Guide (Chapter 8.4)

					Comp	ute Cap	ability				
	3.5, 3.7	5.0, 5.2	5.3	6.0	6.1	6.2	7.x	8.0	8.6	8.9	9.0
16-bit floating- point add, multiply, multiply- add		/A	256	128	2	256	128	25 128 for	56 nv_bfloat16	128	256
32-bit floating- point add, multiply, multiply- add	192	12	28	64	12	28	6	54		128	
64-bit floating- point add, multiply, multiply-	64	2	4	32	2	4	32	32	2	2	64
add	8 for GeFor	ce GPUs, exc	cept for Titar	GPUs			2 for comp	ute capabilit	y 7.5 GPUs		

Instruction Throughput



Instruction throughput numbers in older (<13) CUDA C Programming Guide (Chapter 8.4)

					Comp	ute Cap	ability				
	3.5, 3.7	5.0, 5.2	5.3	6.0	6.1	6.2	7.x	8.0	8.6	8.9	9.0
32-bit floating-point reciprocal square root, base-2 logarithm [_log2f] base 2 exponentia [exp2f], sine [_sinf] cosine [_cosf]	l I	32		16	,	32			16		
32-bit integer add, extended- precision add, subtract, extended- precision subtract	160	1	28	64	1	28			64		
32-bit integer multiply, multiply- add, extended- precision multiply- add	32		Mul	tiple inst	ruct.		3	2 for ex	64 tended-	precisio	n

list continues...

Instruction Throughput



Instruction throughput numbers in CUDA 13 C Best Practices Guide (Chapter 12.1, Table 5)

Compute Capabil-	7.5	8.0	8.6	8.9	9.0	10.0	12.0
ity	Turing	Amı	pere	Ada	Hopper	Blac	kwell
16-bit floating- point add, multiply, multiply- add (2-way SIMD): add. f16x2	64 ³ ³ multiple	128 ⁴ ⁴ 64 for e instruction	64 nv_bfloat10 s fornv_bf		128	64	
32-bit floating- point add, multiply, multiply- add: add.f32	64		128				
64-bit floating- point add, multiply, multiply- add: add.f64	2	32	2		64	64	2



CC	2.0 (Fermi)	2.1 (Fermi)	3.x (Kepler)	5.x (Maxwell)	6.0 (Pascal)	6.1/6.2 (Pascal)	7.x (Volta, Turing)	8.0/8.6 (Ampere)	8.9/9.0 (Ada, Hopper)	10.x/12.x (Blackwell)
# warp sched. / SM	2	2	4	4	2	4	4	4	4	4
# ALU dispatch / warp sched.	1 (over 2 clocks)	2 (over 2 clocks)	2	1	1	1	1	1	1	1
SM busy with # warps + inst	L	2L	8L	4L	2L	4L	4L	4L	4L	4L
inst. pipe latency (L)	22	22	11	9	6	6	4	4	4	4
SM busy with # warps	22	22 + ILP	44 + ILP	36	12	24	16	16	16	16

see NVIDIA CUDA C Programming Guides (different versions) performance guidelines/multiprocessor level; compute capabilities



CC	2.0 (Fermi)	2.1 (Fermi)	3.x (Kepler)	5.x (Maxwell)	6.0 (Pascal)	6.1/6.2 (Pascal)	7.x (Volta, Turing)	8.0/8.6 (Ampere)	8.9/9.0 (Ada, Hopper)	10.x/12.x (Blackwell)
# warp sched. / SM	2	2	4	4	2	4	4	4	4	4
# ALU dispatch / warp sched.	1 (over 2 clocks)	2 (over 2 clocks)	2	1	1	1	1	1	1	1
SM busy with # warps + inst	L	2L	8L	4L	2L	4L	4L	4L	4L	4L
inst. pipe latency (L)	22	22	11	9	6	6	4	4	4	4
SM busy with #warps	22	22 + ILP	44 + ILP	36	12	24	16	16	16	16

IF no other stalls occur! (i.e., except inst. pipe hazards)

see NVIDIA CUDA C Programming Guides (different versions) performance guidelines/multiprocessor level; compute capabilities



CC	2.0 (Fermi)	2.1 (Fermi)	3.x (Kepler)	5.x (Maxwell)	6.0 (Pascal)	6.1/6.2 (Pascal)	7.x (Volta, Turing)	8.0/8.6 (Ampere)	8.9/9.0 (Ada, Hopper)	10.x/12.x (Blackwell)
# warp sched. / SM	2	2	4	4	2	4	4	4	4	4
# ALU dispatch / warp sched.	1 (over 2 clocks)	2 (over 2 clocks)	2) 1	1	1	1	1	1	1
SM busy with # warps + inst	L	2L	8L	4L	2L	4L	4L	4L	4L	4L
inst. pipe latency (L)	22	22	11	9	6	6	4	4	4	4
SM busy with # warps	22	22 + ILP	44 + ILP	36	12	24	16	16	16	16

IF no other stalls occur! "State (i.e., except inst. pipe hazards)

"superscalar" see NVIDIA CUDA C Programming Guides (different versions)
s) performance guidelines/multiprocessor level; compute capabilities



cc	2.0 (Fermi)	2.1 (Fermi)	3.x (Kepler)	5.x (Maxwell)	6.0 (Pascal)	6.1/6.2 (Pascal)	7.x (Volta, Turing)	8.0/8.6 (Ampere)	8.9/9.0 (Ada, Hopper)	10.x/12.x (Blackwell)
# warp sched. / SM	2	2	4	4	2	4	4	4	4	4
# ALU dispatch / warp sched.	1 (over 2 clocks)	2 (over 2 clocks)	2	1	1	1	1	1	1	1
SM busy with # warps + inst	L	2L	8L	4L	2L	4L	4L	4L	4L	4L
inst. pipe latency (L)	22	22	11	9	6	6	4	4	4	4
SM busy with # warps	22	22 + ILP	44 + ILP	36	12	24	16	16	16	16

IF no other stalls occur! "Solite., except inst. pipe hazards)

"superscalar" see NVIDIA CUDA C Programming Guides (different versions)
s) performance guidelines/multiprocessor level; compute capabilities

