Agenda

- 3:20 to 3:40: Coffee Break
- 3:40 to 4:00: Brief Introduction to CUDA Programming
- 4:00 to 5:00: Build Tensor Programs with Hidet in Python
  - Part 1: Introduction to Deep Learning Compiler Hidet
  - Part 2: Interactive Demos on how to use Hidet (with Jupyter Notebooks)

Tutorial Website

UNIVERSITY OF TORONTO

CentML

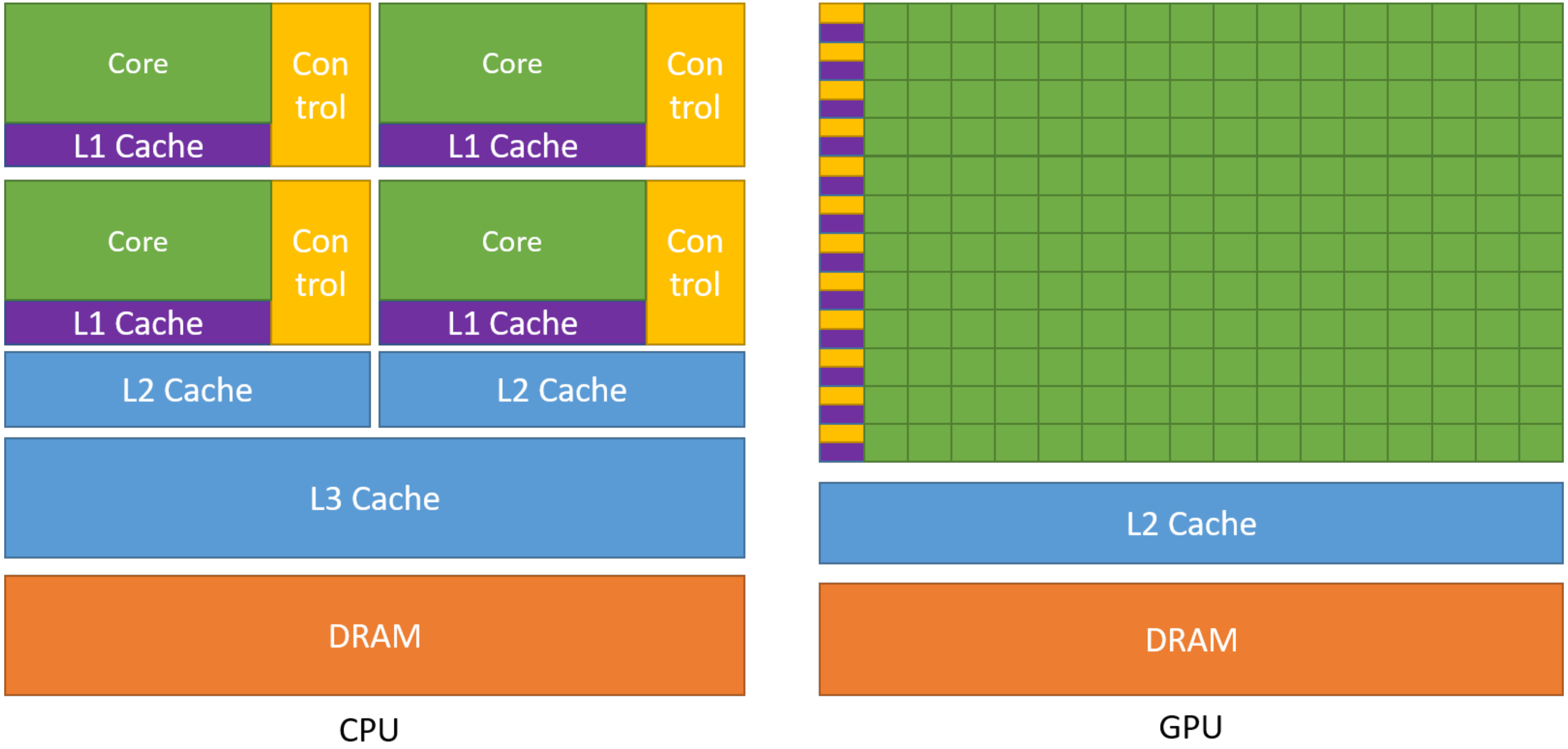
A Brief Introduction to CUDA Programming

Yaoyao Ding

yaoyao@cs.toronto.edu

Contents are adopted from NVIDIA's CUDA C++ Programming Guide

CPU vs. GPU


Core
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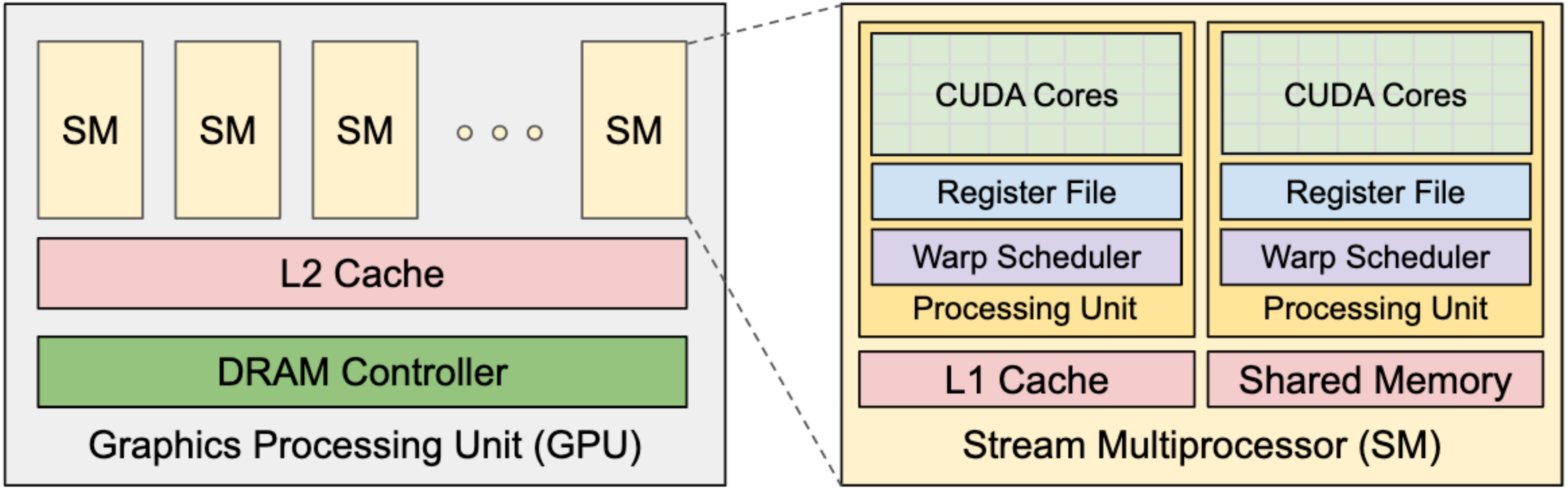
L3 Cache
DRAM
CPU
L2 Cache
DRAM
GPU

Inside a NVIDIA GPU



CUDA Kernel and Its Invocation

```
// Kernel definition
__global__ void VecAdd(float* A, float* B, float* C)
{
    int i = threadIdx.x;
    C[i] = A[i] + B[i];
}

int main()
{
    ...
    // Kernel invocation with N threads
    VecAdd<<<1, N>>>(A, B, C);
    ...
}
```

Something New:

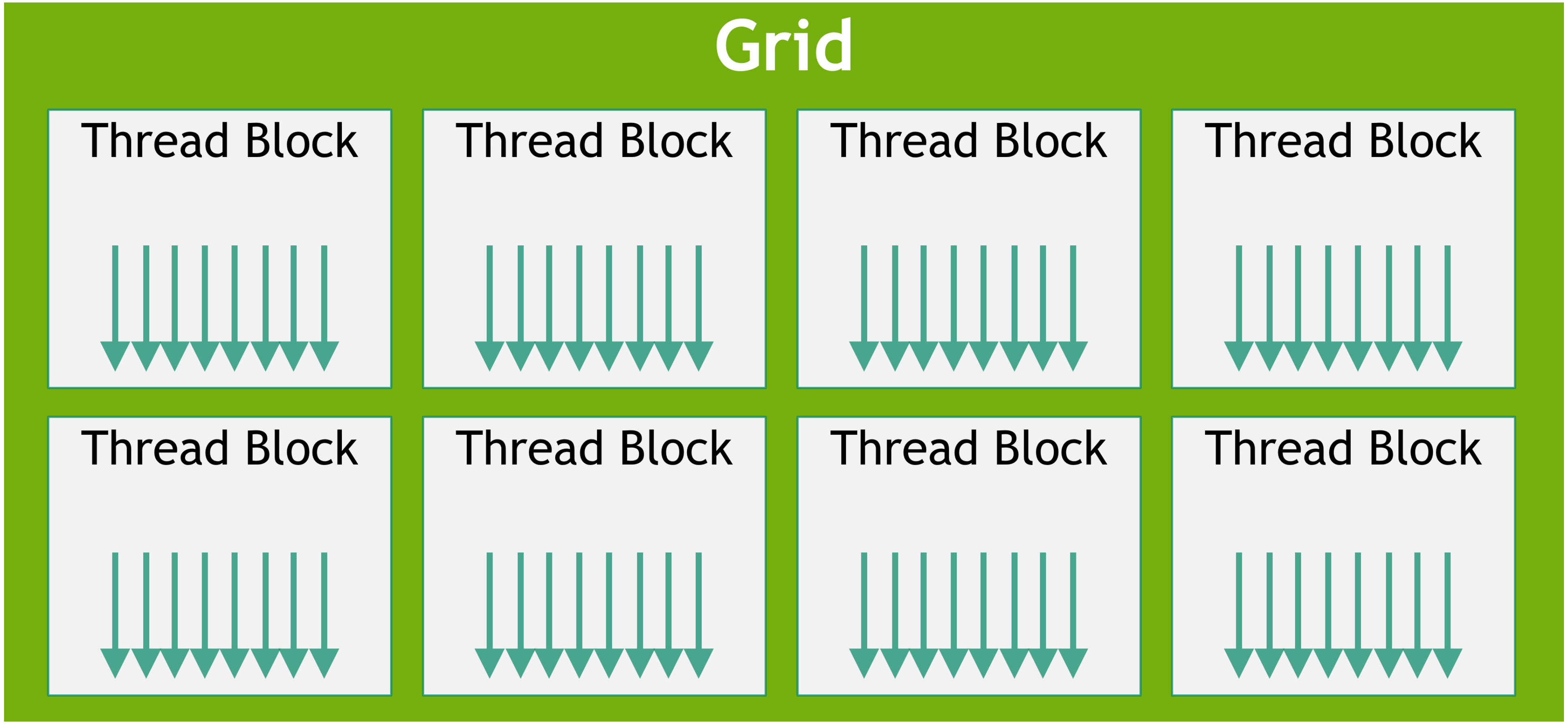
- `__global__`
- `threadIdx.x`
- `<<<1, N>>>`

Thread Hierarchy: Up to 3 dimensions

```
// Kernel definition
__global__ void MatAdd(float A[N][N], float B[N][N],
                       float C[N][N])
{
    int i = threadIdx.x;
    int j = threadIdx.y;
    C[i][j] = A[i][j] + B[i][j];
}

int main()
{
    ...
    // Kernel invocation with one block of N * N * 1 threads
    int numBlocks = 1;
    dim3 threadsPerBlock(N, N);
    MatAdd<<<numBlocks, threadsPerBlock>>>(A, B, C);
    ...
}
```

Thread Hierarchy: Thread, Thread Block, Grid



Thread Hierarchy

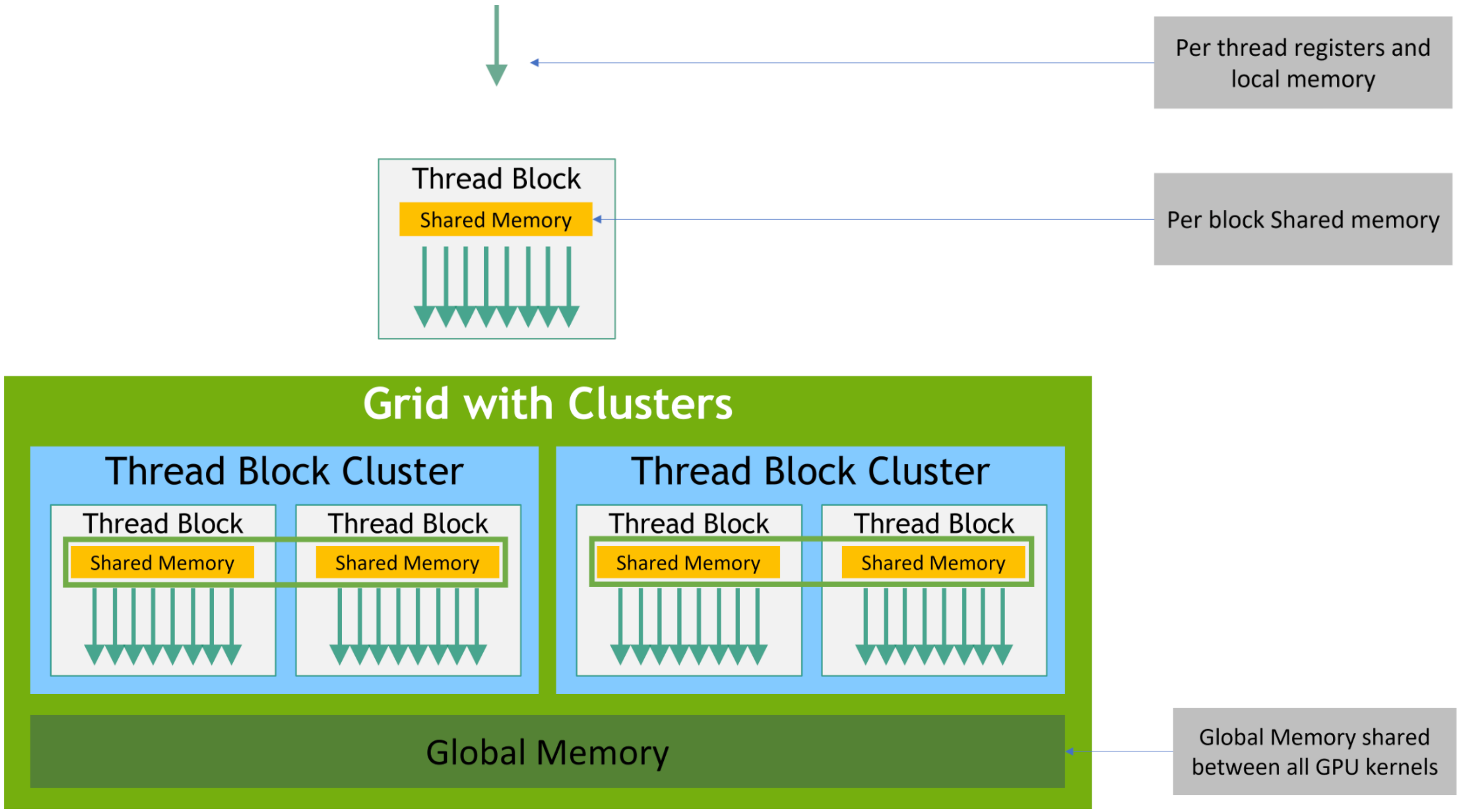
```
// Kernel definition
__global__ void MatAdd(float A[N][N], float B[N][N],
float C[N][N])
{
    int i = blockIdx.x * blockDim.x + threadIdx.x;
    int j = blockIdx.y * blockDim.y + threadIdx.y;
    if (i < N && j < N)
        C[i][j] = A[i][j] + B[i][j];
}

int main()
{
    ...
    // Kernel invocation
    dim3 threadsPerBlock(16, 16);
    dim3 numBlocks(N / threadsPerBlock.x, N / threadsPerBlock.y);
    MatAdd<<<numBlocks, threadsPerBlock>>>(A, B, C);
    ...
}
```

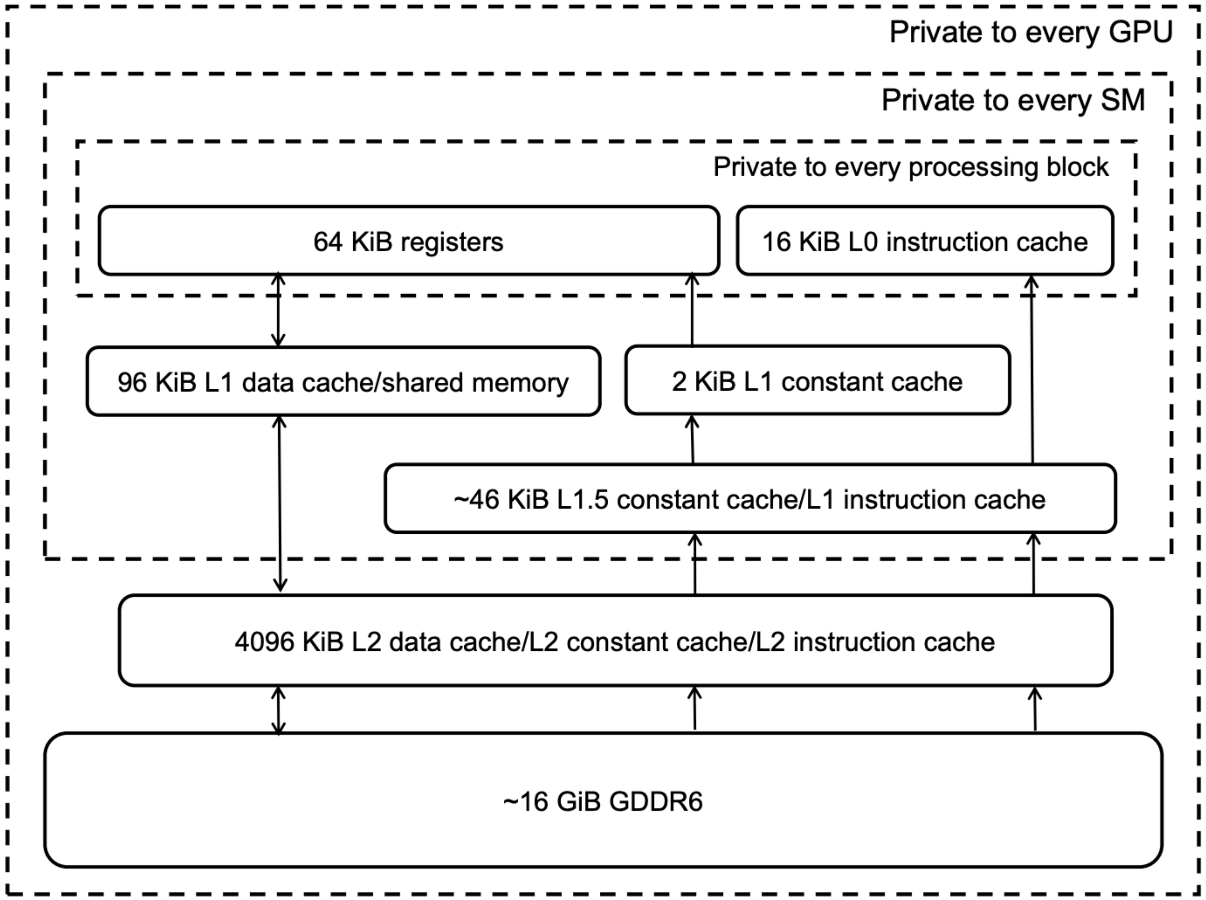
Threads in a block can cooperate by:

- Shared memory, and
- Synchronizing their execution via `__syncthreads()`

Memory Hierarchy



Memory Hierarchy



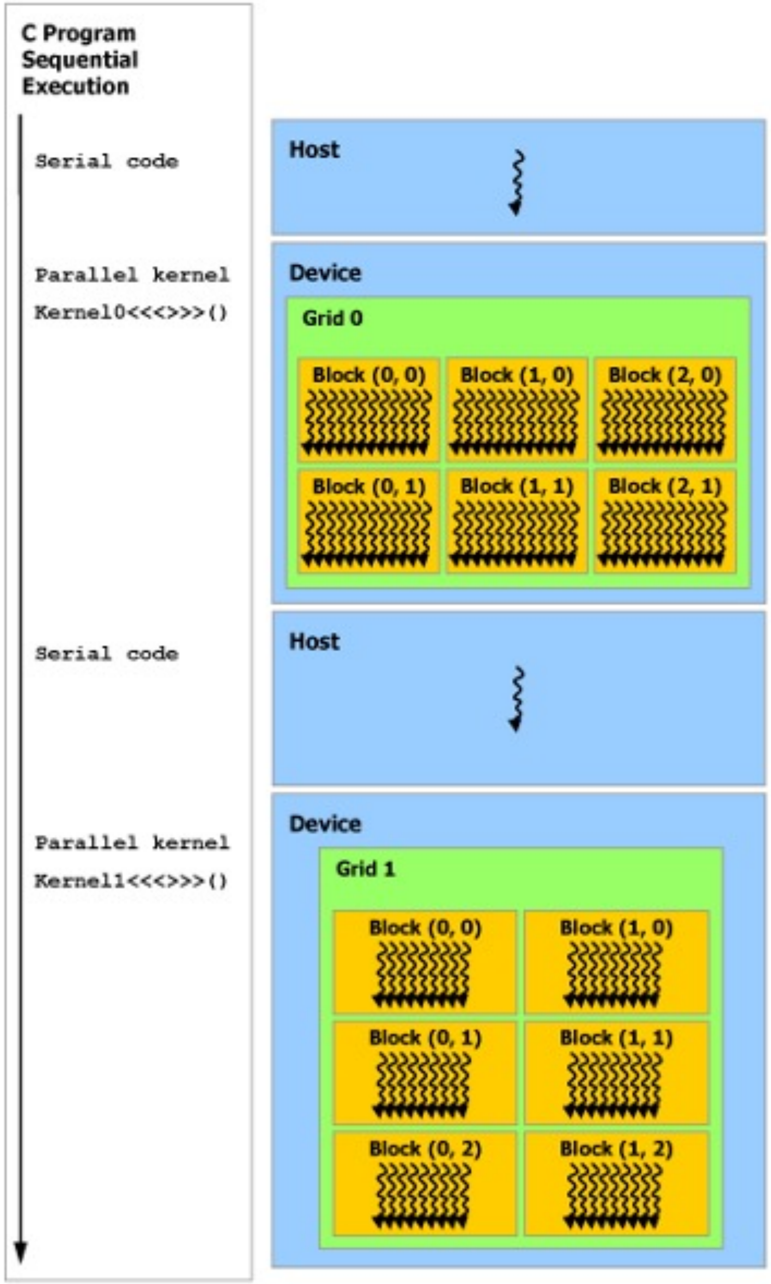
Memory hierarchy of the Turing T4 GPU (TU104)

NVIDIA T4 GPU Latency:

- Shared memory: 19 cycles
- Global memory:
  - L1 hit: 32 cycles
  - L2 hit: ~188 cycles
  - L2 miss & TLB hit: 296 cycles
  - L2 miss & TLB miss: 616 cycles

Reference: Dissecting the NVidia Turing T4 GPU via Microbenchmarking

Heterogeneous Programming



Device Memory

Host Memory

Device Memory

Example: Vector Addition

```
__global__ void add_kernel(int *a, int *b, int *c, int n) {
    int i = blockIdx.x * blockDim.x + threadIdx.x;
    if (i < n) {
        c[i] = a[i] + b[i];
    }
}
```

Example: Matrix Multiplication (Matmul)

```
__global__ void matmul_kernel(float *a, float *b, float *c, int n) {
    int i = blockIdx.x * blockDim.x + threadIdx.x;
    int j = blockIdx.y * blockDim.y + threadIdx.y;
    if (i < n && j < n) {
        float acc = 0.0;
        for (int k = 0; k < n; k++) {
            acc += a[i * n + k] * b[k * n + j];
        }
        c[i * n + j] = acc;
    }
}
```

GitHub: www.github.com/hidet-org/hidet
Installation: `pip install hidet`
Usage: `torch.compile(model, backend='hidet')`

Hidet:
An Open-Source Deep Learning Compiler

Yaoyao Ding

yaoyao@cs.toronto.edu

Tensor Programs are Everywhere

Paradise cosmic beach

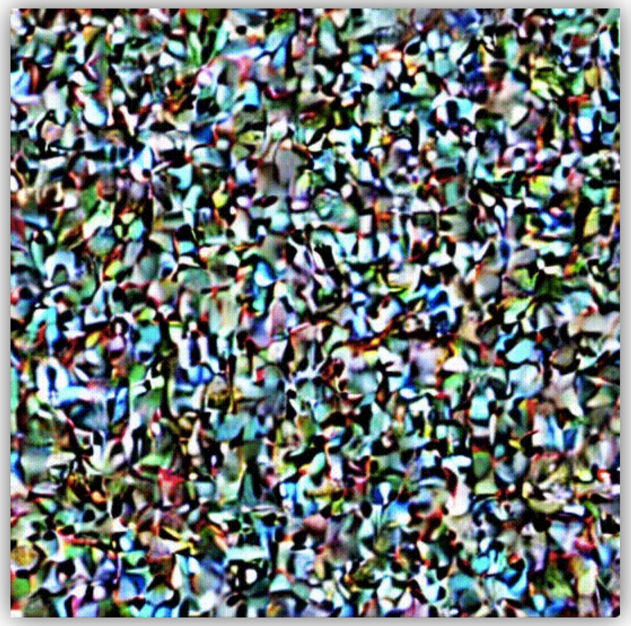


Image Generation [1]

Compose a funny rap for yourself in 5 lines

Yo, it's ChatGPT, the AI sensation
Here to answer your every question
I may be digital, but don't you worry
My rhymes are fire, they'll make you hurry
So come on and ask, let's make history!

Chat Bot

$694K per day [2]

```
void conv2d(
    float32 image[N, Ci, H, W],
    float32 filter[Co, Ci, Kx, Ky],
    float32 output[N, Co, H, W]
) {...}
```

Tensor Programs

Run fast

Reduce cost

[1] The Illustrated Stable Diffusion, by Jay Alammar
[2] https://www.semianalysis.com/p/the-inference-cost-of-search-disruption

Tensor Program Generation & Optimization

- Vendor Library (Manually optimization)
- State-of-the-art Tensor Compiler: Apache TVM

Limited Support for
Non-Loop-Oriented Optimizations

Sub-Optimal Performance

Long Optimization Time (e.g., hours)

- **Task-Mapping Programming Paradigm (ours)**

Good Support for
Non-Loop-Oriented Optimizations

Up to 1.4x Better Performance

11x Less Optimization Time

Deep Learning Compiler: TVM

Computation

```
C = compute([M, N], lambda i, j: reduce([K], A[i, k] * B[k, j]))
```

❶ Generate Default Tensor Program

Default Program

```
for i in range(M):
  for j in range(N):
    for k in range(K):
      C[i, j] += A[i, k] * B[k, j]
```

❷ Apply **Declarative** Scheduling Primitives

Schedule Primitives	Original Program	Scheduled Program

fuse(i, j)	for i in range(128):
	  for j in range(4):
	    body(i, j)
		for ij in range(512):
		  body(ij / 4, ij % 4)

split(i, 128)	for i in range(512):
	  body(i)
		for oi in range(4):
		  for ii in range(128):
		    body(oi * 128 + ii)

reorder(i, j)	for i in range(128):
	  for j in range(4):
	    body(i, j)
		for j in range(4):
		  for i in range(128):
		    body(i, j)

bind(i, threadIdx.x)	for i in range(128): body(i)	body(threadIdx.x)

Apply Declarative Scheduling Primitives

```
for i in range(M):
  for j in range(N):
    for k in range(K):
      C[i, j] += A[i, k] * B[k, j]
```

Default Program

1

```
oi, ii = split(i, 64)
oj, ij = split(j, 64)
```

```
for io in range(M/64):
  for ii in range(64):
    for oj in range(N/64):
      for ij in range(64):
        for k in range(K):
          i, j = io * 64 + ii, jo * 64 + ij
          C[i, j] += A[i, k] * B[k, j]
```

2

```
reorder(oi, oj, ii, ij)
```

```
for io in range(M/64):
  for oj in range(N/64):
    for ii in range(64):
      for ij in range(64):
        for k in range(K):
          i, j = io * 64 + ii, jo * 64 + ij
          C[i, j] += A[i, k] * B[k, j]
```

3

```
bind(oi, blockIdx.x)
bind(oj, blockIdx.y)
```

```
for ii in range(64):
  for ij in range(64):
    for k in range(K):
      i = blockIdx.x * 64 + ii
      j = blockIdx.y * 64 + ij
      C[i, j] += A[i, k] * B[k, j]
```

Scheduled Program

github.com/hidet-org/hidet

For simplicity, we assume M and N are a multiple of 64.

Deep Learning Compiler: TVM

Computation

```
C = compute([M, N], lambda i, j: reduce([K], A[i, k] * B[k, j]))
```

1 Generate Default Tensor Program

Default Program

```
for i in range(M): for j in range(N): for k in range(K):
  C[i, j] += A[i, k] * B[k, j]
```

2 Apply **Declarative** Scheduling Primitives (called Scheduling)

```
1. oi, ii = split(i, 64)      4. bind(oi, blockIdx.x)
2. oj, ij = split(j, 64)      5. bind(oj, blockIdx.y)
3. reorder(oi, oj, ii, ij)    6. ...
```

Two Scheduling Methods:

- Template-based: AutoTVM [1]
- Rule-based: Ansor [2]

Kernel Tuning:
Search best schedule hyper-parameter

Scheduled Program

```
for ii in range(64):
  for ij in range(64):
    for k in range(K):
      C[i, j] += A[ii + blockIdx.x * 64, k] * B[k, ij + blockIdx.y * 64]
```

Declarative Loop-Oriented Scheduling

github.com/hidet-org/hidet

[1] Chen, Tianqi, et al. "Learning to optimize tensor programs." NeurIPS 2018.
[2] Zheng, Lianmin, et al. "Ansor: Generating high-performance tensor programs for deep learning." *OSDI* 2020.

Limitation of Loop-Oriented Scheduling

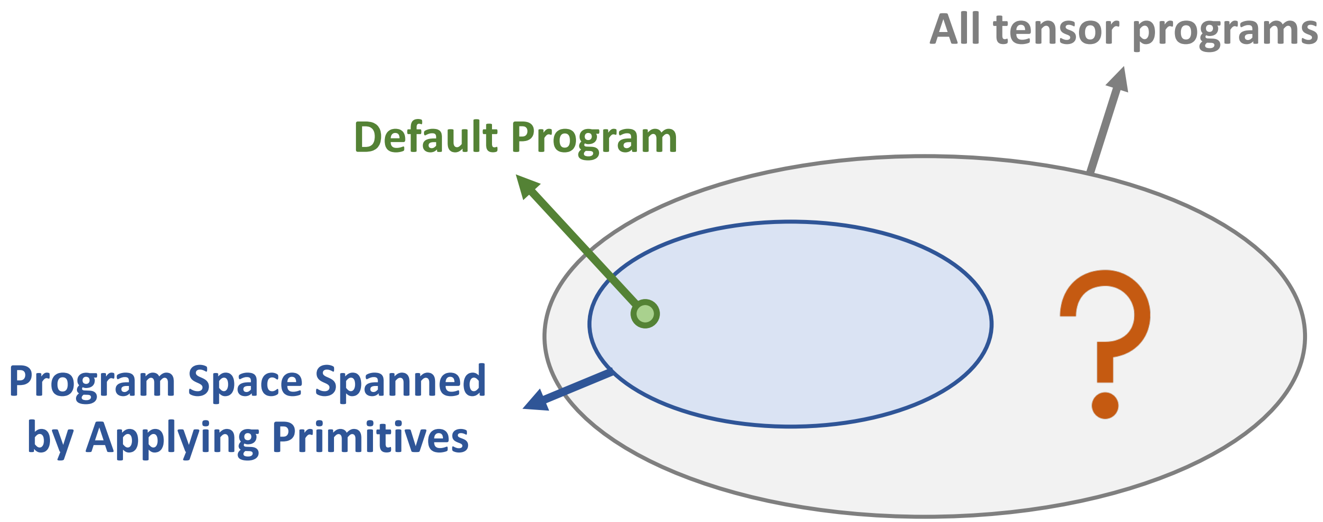
Computation

❶ Generate Default Tensor Program

Default Program

❷ Apply **Declarative** Scheduling Primitives

Scheduled Program



Limited Expressiveness of Loop-Oriented Scheduling ➡

Sub-Optimal Performance

(e.g., can not express double buffering opt.)

Long Optimization Time

(4-6 hours on average)

An Example of Non-Loop-Oriented Optimization

```
def matmul(A: fp32[M, K], B: fp32[K, N],
           C: fp32[M, N]):
  SmemA, SmemB = shared fp32[64, 8], fp32[8, 64]
  RegsC = local fp32[...]

  for k0 in range(128):
    # Load A and B fragments
    # from global memory to shared memory
    SmemA, SmemB = cooperative_load(A, B, k0)
    sync_threads()
    # RegsC = SmemA * SmemB + RegsC
    RegsC = block_mma(SmemA, SmemB, RegsC)
    sync_threads()
  ...
```

Matrix Multiplication without Double Buffering

```
RegsA, RegsB = register fp32[...], fp32[...]
SmemA, SmemB = shared fp32[2, 64, 8], fp32[2, 8, 64]
SmemA[0], SmemB[0] = cooperative_load(A, B, 0)
sync_threads()

for k0 in range(127):
  p, q = k0 % 2, (k0 + 1) % 2
  RegsA, RegsB = cooperative_load(A, B, k0 + 1)
  RegsC = block_mma(SmemA[p], SmemB[p], RegsC)
  SmemA[q], SmemB[q] = RegsA, RegsB
  sync_threads()
...
```

Two buffers for A/B

Preloading **Next** Tile of A/B into Registers

Computation of **Current** Tile

Store Next Tile of A/B into Shared Memory

Matrix Multiplication with Double Buffering

Key Idea: Task Mapping Programming Paradigm

```
Smem = compute([64, 8], lambda i, j => Gmem[i, j])
```

1 Default Program

```
for i in range(64):
  for j in range(8):
    Smem[i, j] = Gmem[i, j]
```

2 Schedule

```
io, ii = split(i, 16)
iik = fuse(ii, k)
bind(iik, threadIdx.x)
```

3 Lower Primitives

Declarative Loop-Oriented Scheduling

1 Write Program with Task Mapping

```
mapping = repeat(4, 1).spatial(16, 8)
for i, j in mapping(threadIdx.x):
  Smem[i, j] = Gmem[i, j]
```

2 Lower Task Mappings

Task Mapping replaces **Schedule Primitives**

```
for io in range(4):
  t = threadIdx.x
  i, j = io * 16 + t / 8, t % 8
  Smem[i, j] = Gmem[i, j]
```

Task-Mapping Programming Paradigm

github.com/hidet-org/hidet

Definition, Usage and Pros of Task Mapping

Iterate the Assigned Tasks

Define Task Mapping

```
...
mapping = repeat(4, 1).spatial(16, 8)

for  i, k  in mapping( threadIdx.x ):
  SmemA[i, k] = A[i, k]
```

Task Index

Worker Index

Implementation of a task

```
mapping = repeat(4, 1).spatial(2, 64)

for  i, j  in mapping( threadIdx.x ):

  SmemB[i, j] = B[i, j]

...
```

- **High Flexibility:**
  Allow developer to manipulate tensor programs in fine granularity
  => More Optimizations and Better Performance

- **Efficient Partial Tile:**
  Add the predicate inside the loop body
  => Reduce Tuning Space & Optimization Time

- **Post Scheduling Fusion:**
  Automatically fuse surrounding operators
  => Less Memory Transfer and Better Performance

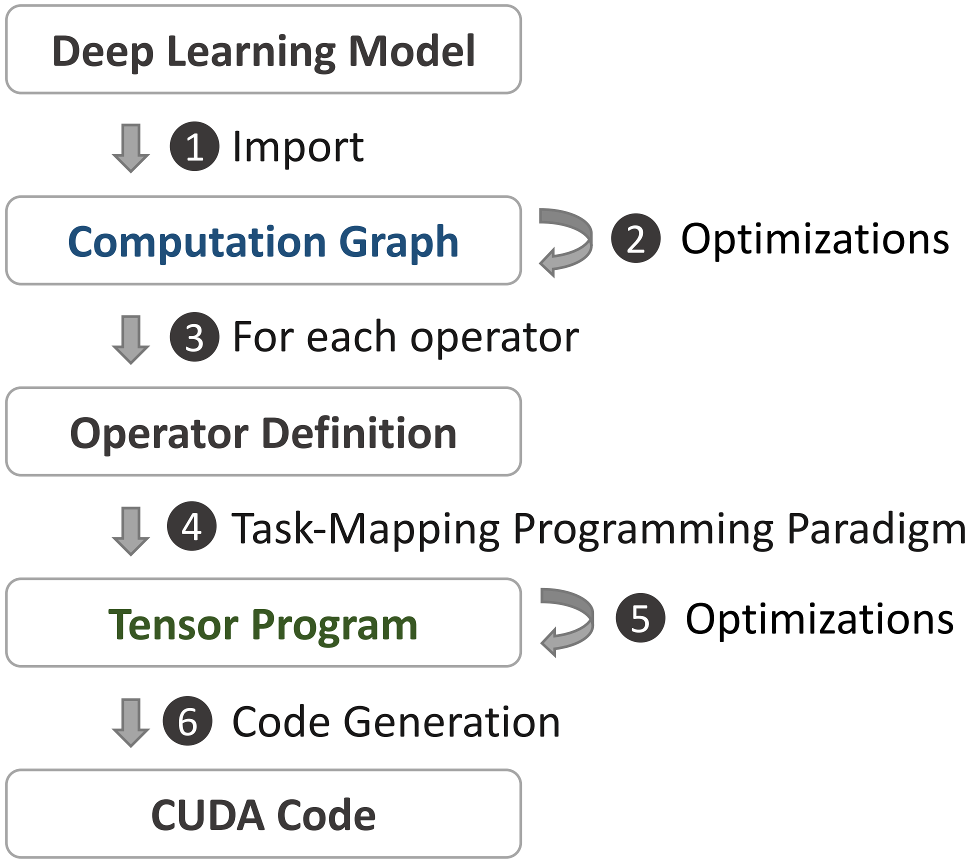
Implementation

GitHub: www.github.com/hidet-org/hidet
Installation: `pip install hidet`
Usage: `torch.compile(model, backend='hidet')`

- **Hidet**
  A Deep Learning Compiler from Scratch

- **Intermediate Representations (IRs)**
  - High Level: Computation Graph IR
  - Low Level: Tensor Program IR

- **Two Scheduling Machanisms at ④**
  - Template-based Scheduling
  - Rule-based Scheduling



Hidet Compilation Flow

Practice Session

Tutorial Website