Decoupled Triton: A Block-Level Decoupled Language for Writing and Exploring Efficient Machine-Learning Kernels

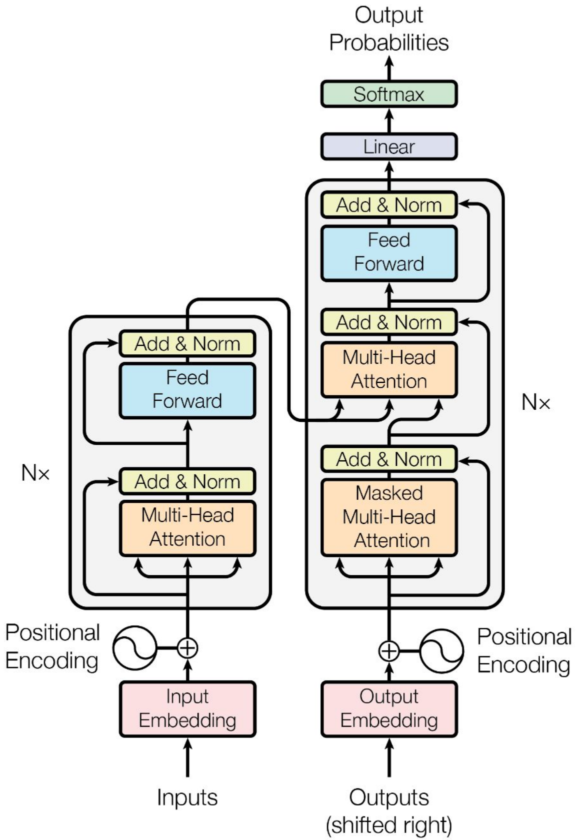
Quinn Pham

Machine-Learning (ML) Kernels

Machine-learning kernels

Machine-learning kernels

- Specialized functions for tensor operations.



Vaswani *et al.*

Machine-learning kernels

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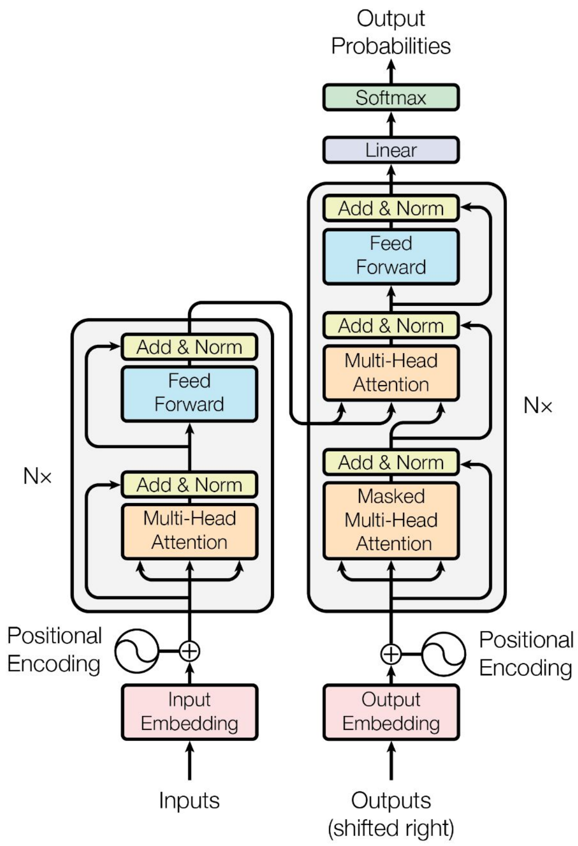
  - Matrix multiplication



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Machine-learning kernels

- Specialized functions for tensor operations.
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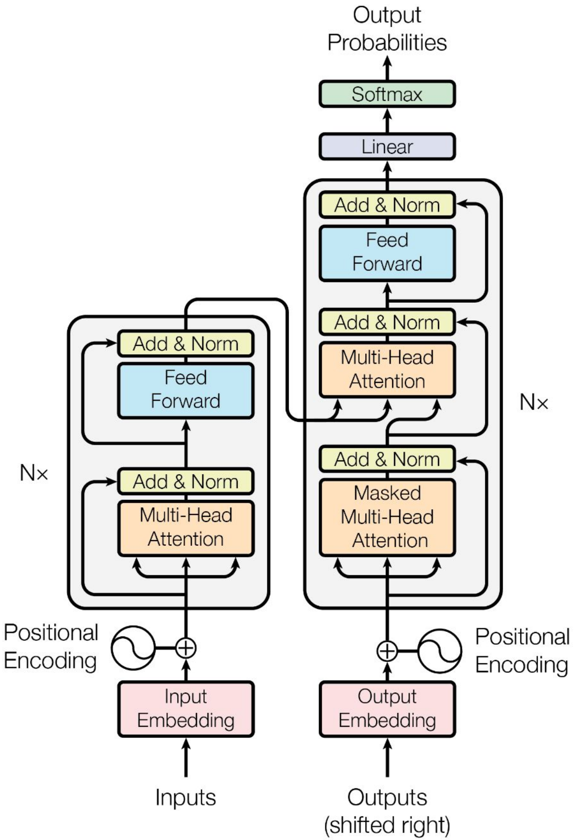

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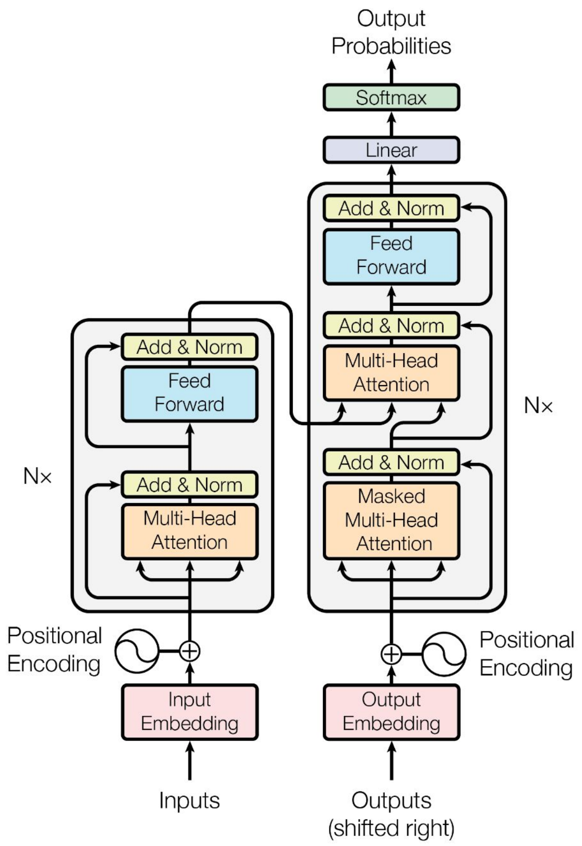

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Machine-learning kernels

- Specialized functions for tensor operations.
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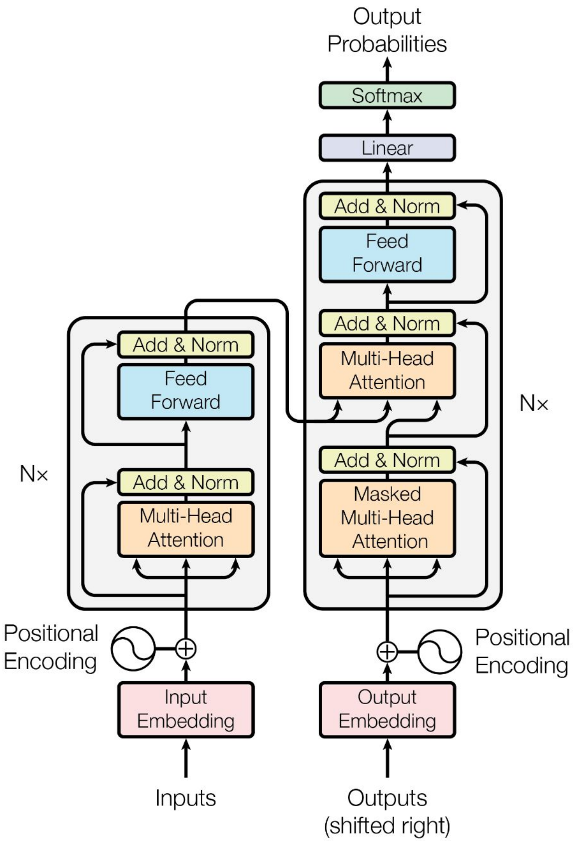
  - LayerNorm



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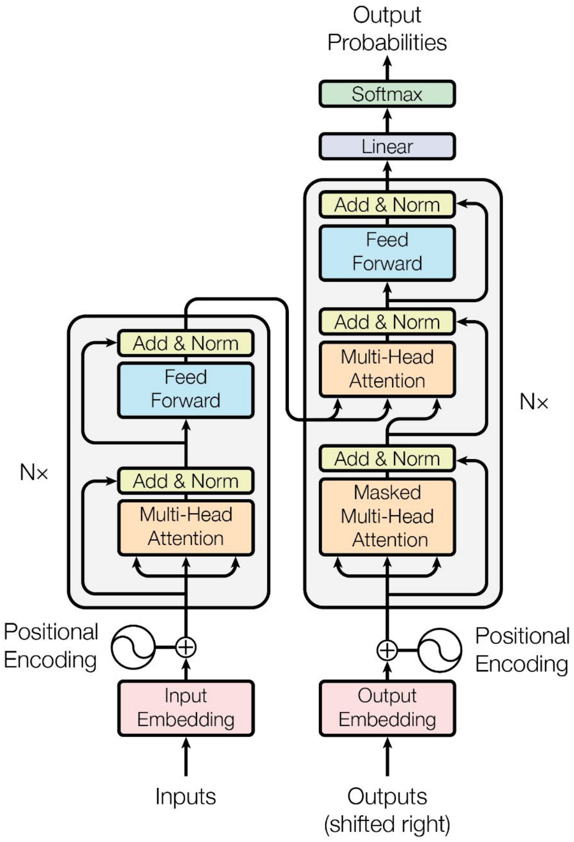
  - Fused operations (*e.g.* matmul + sigmoid)



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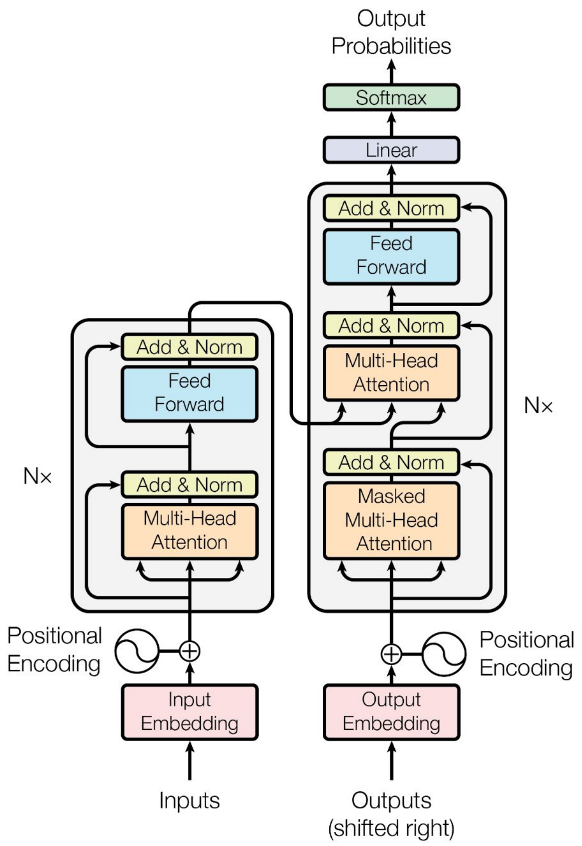

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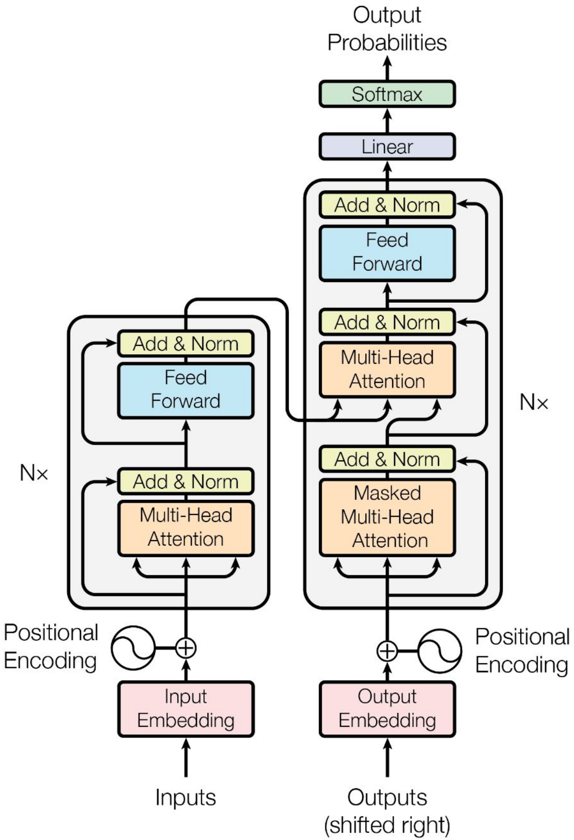

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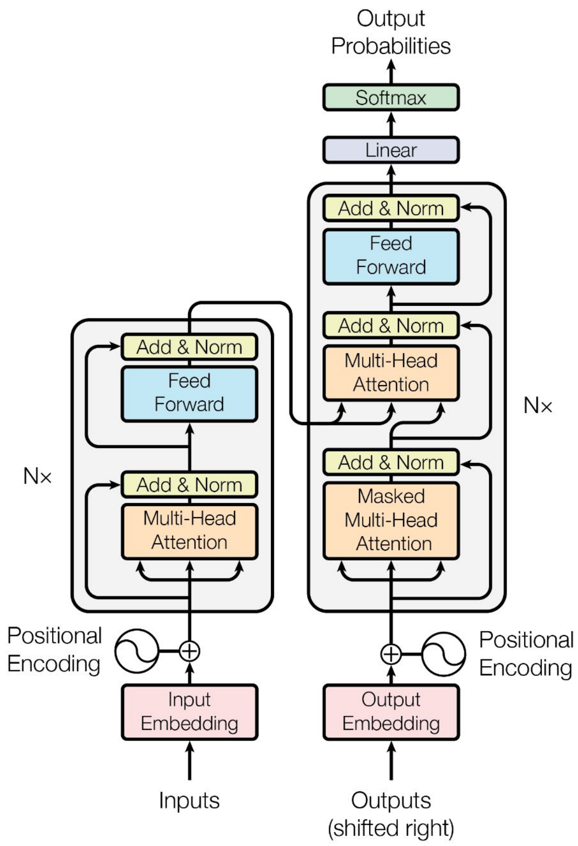
  - Efficient models require efficient kernels



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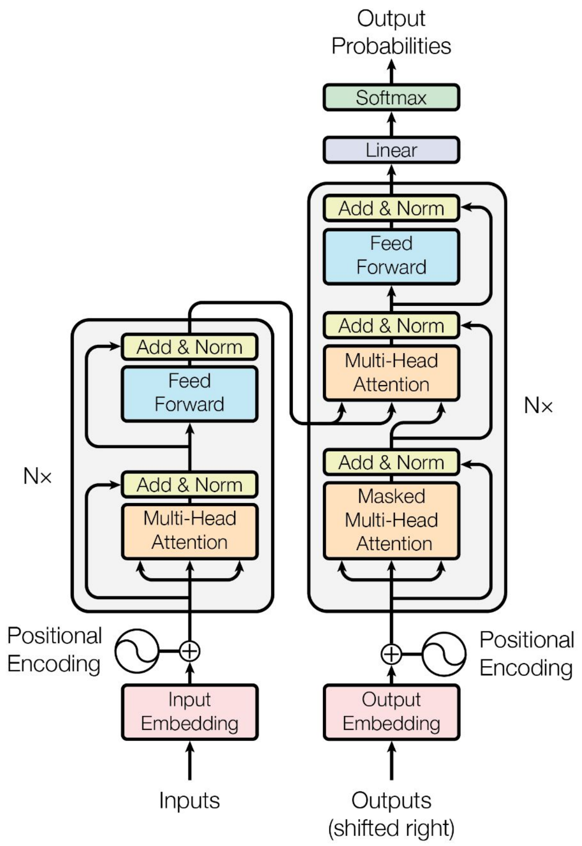

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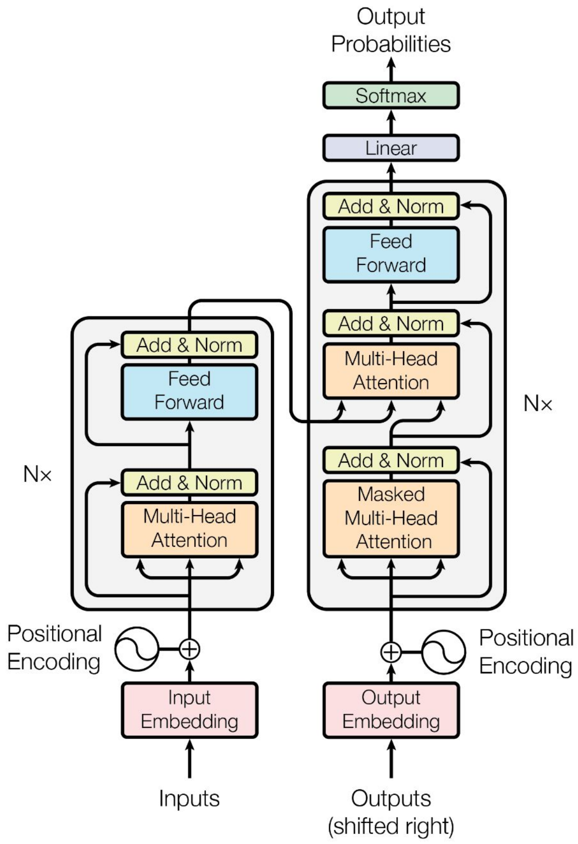

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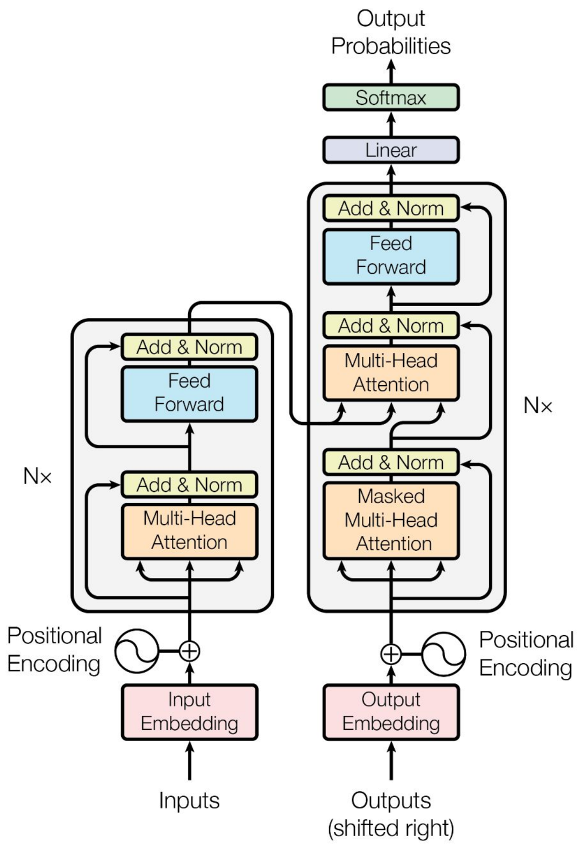
- Building blocks of deep-learning models.
    - Efficient models require efficient kernels
- Executed on parallel hardware (GPUs, TPUs).
- High-performance kernel libraries (cuBLAS, cuDNN).
    - Provide kernels for common tensor operations



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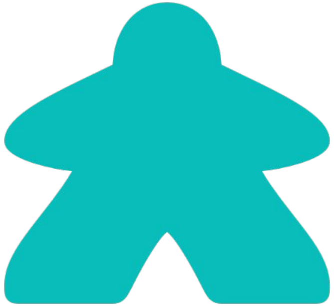
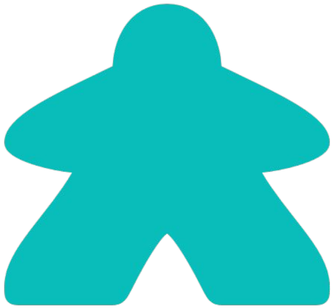
Building the motivation for Decoupled Triton.



Deep Learning Researcher

I created an amazing
Deep Learning model
that demonstrates AGI.



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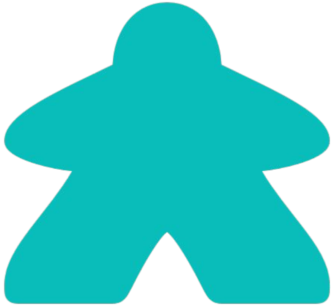

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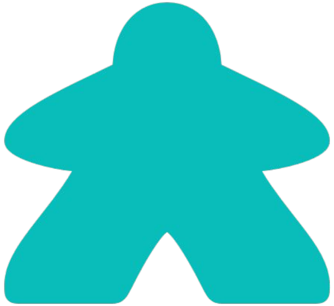

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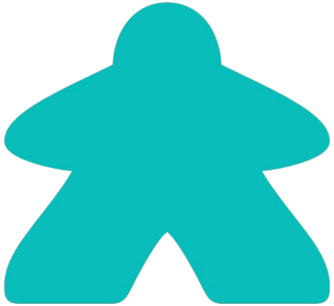

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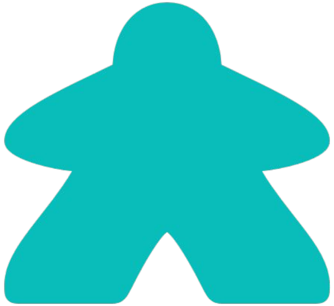

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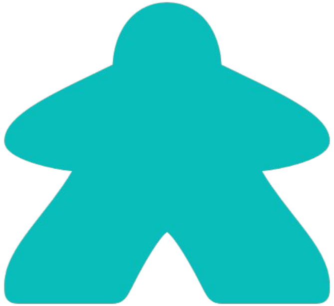

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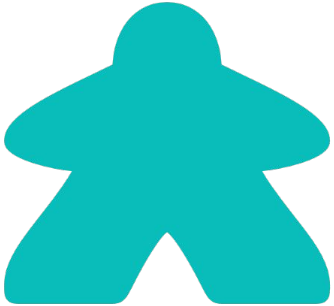

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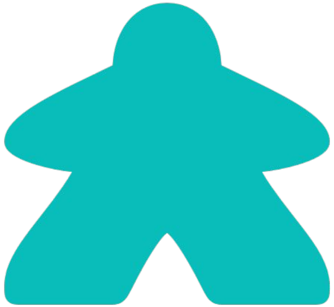
An efficient op kernel will not be provided by high-performance kernel libraries!

Writing efficient machine-learning kernels



Writing efficient machine-learning kernels

- Low-abstraction parallel-programming languages (CUDA, OpenCL, HIP).

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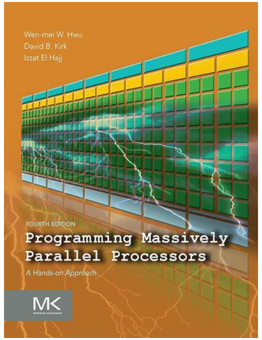
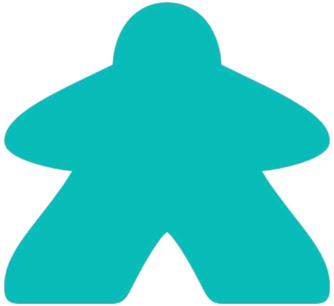
    - Require strong understanding of parallel architectures and parallel programming patterns





Triton

Triton: An Intermediate Language and Compiler for Tiled Neural Network Computations

Philippe Tillet
Harvard University
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Maintained by OpenAI

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A @ B = C

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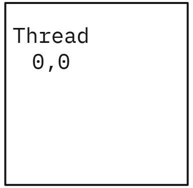

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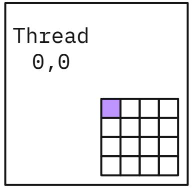

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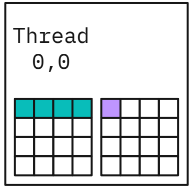

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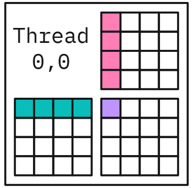

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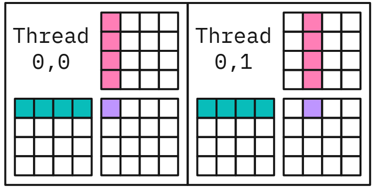

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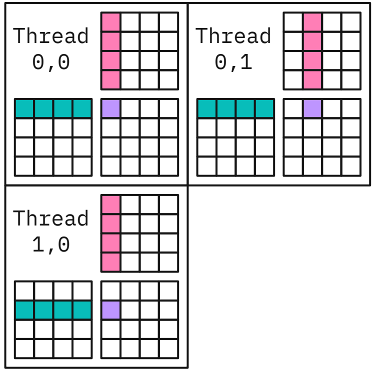

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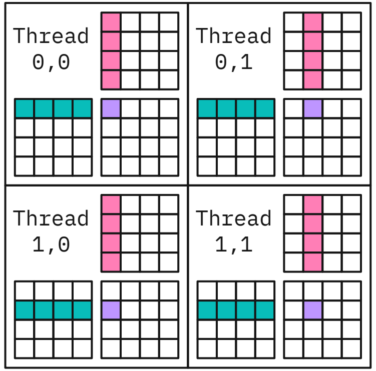

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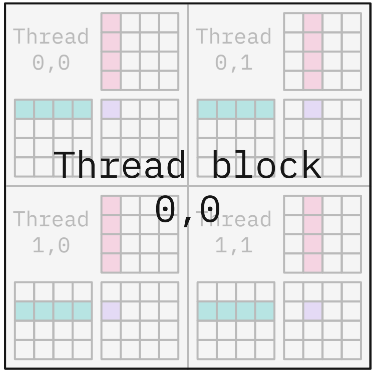

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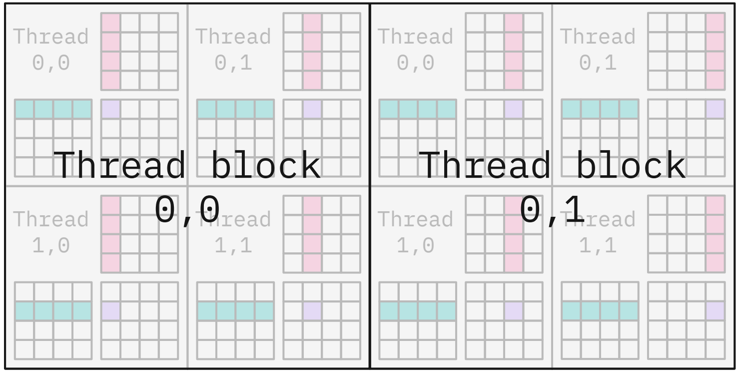

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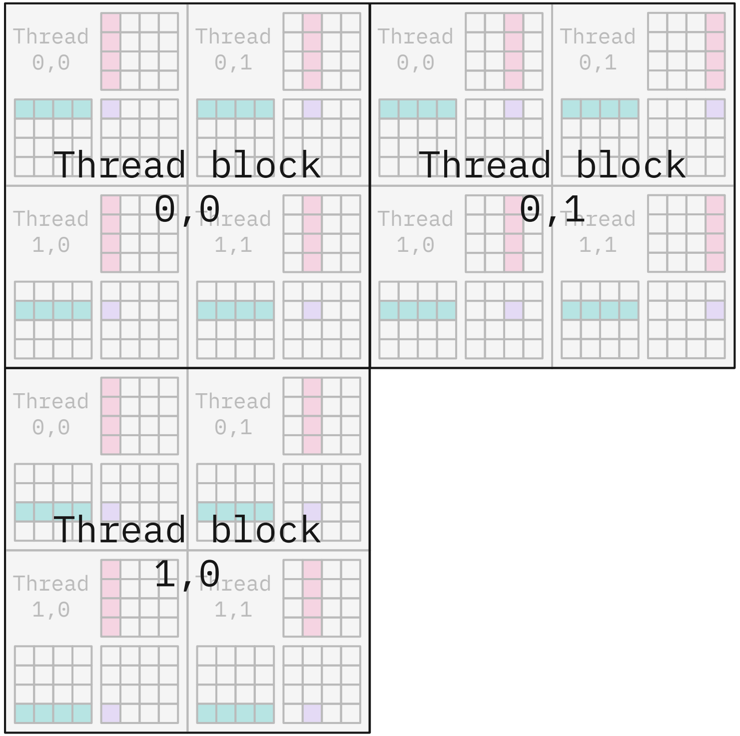

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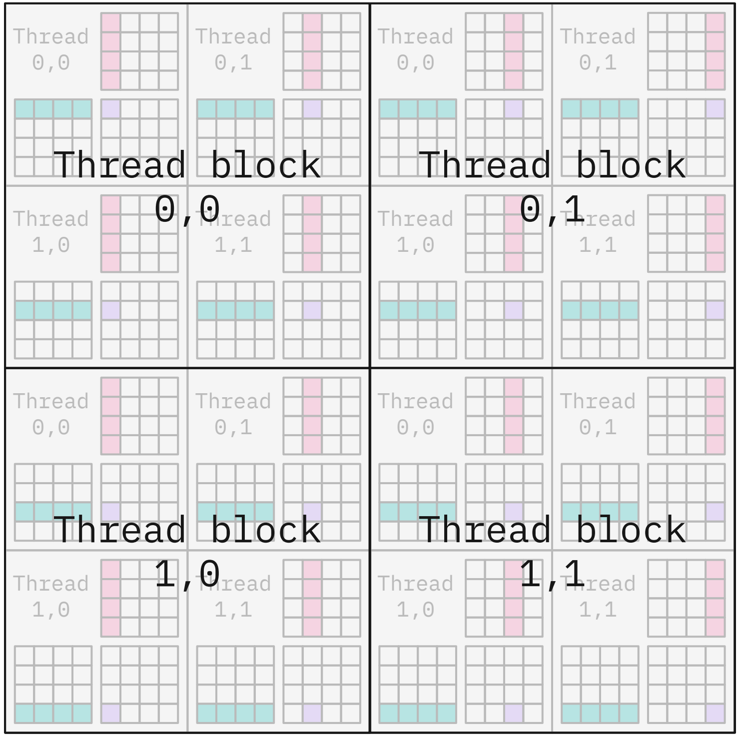

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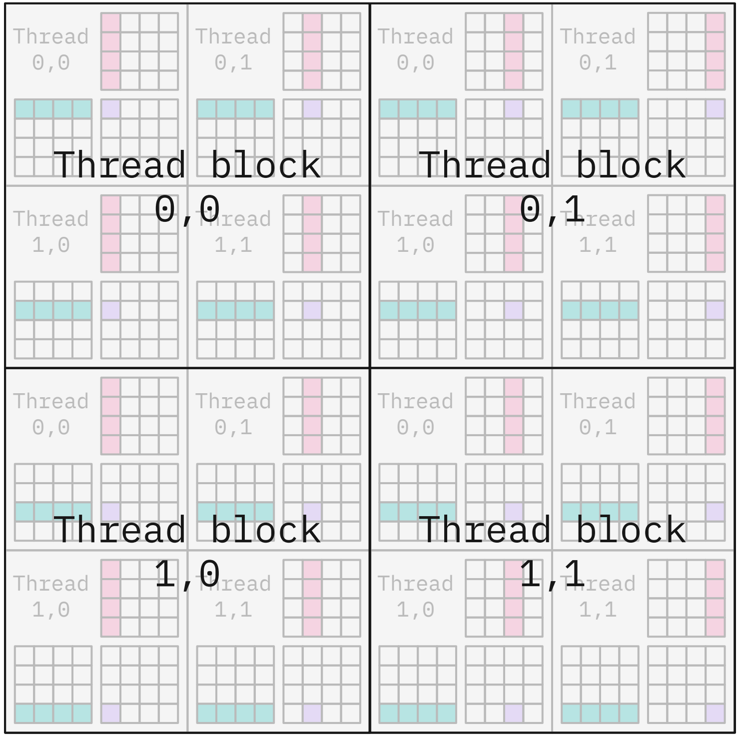

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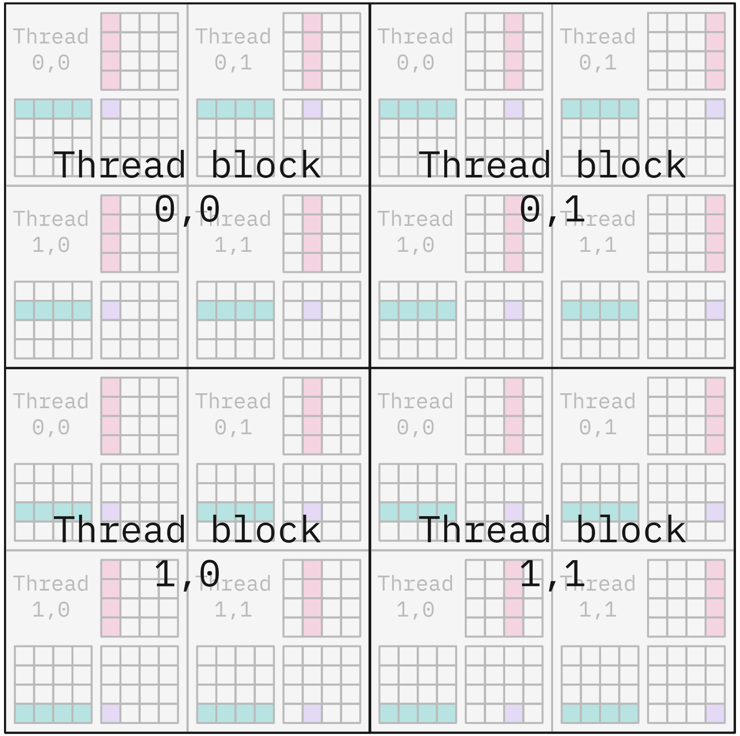

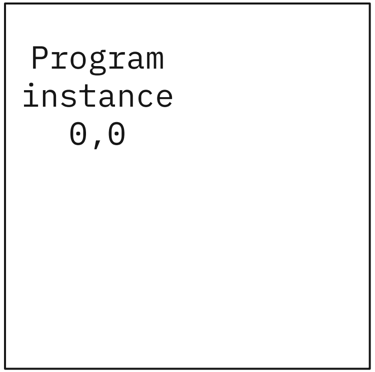

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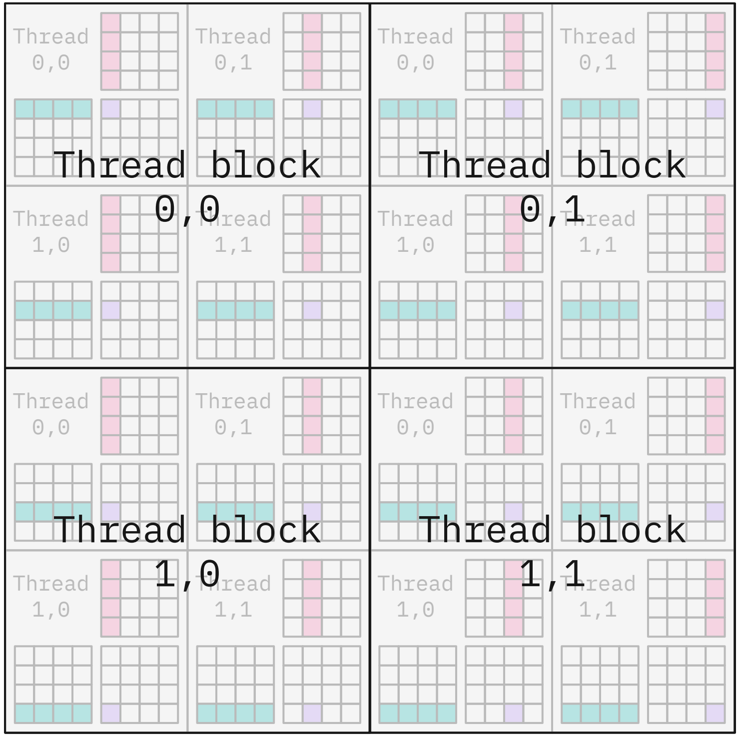

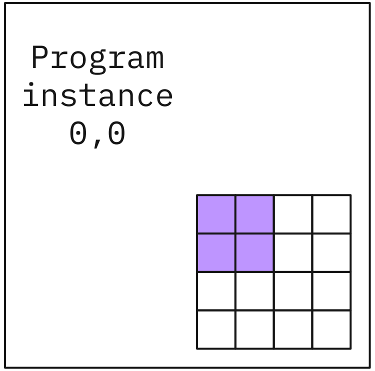

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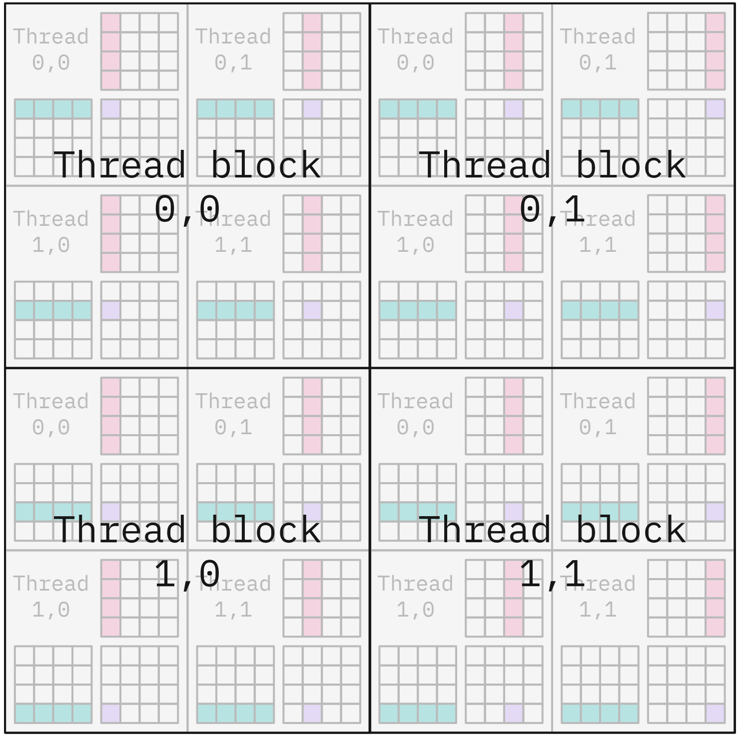

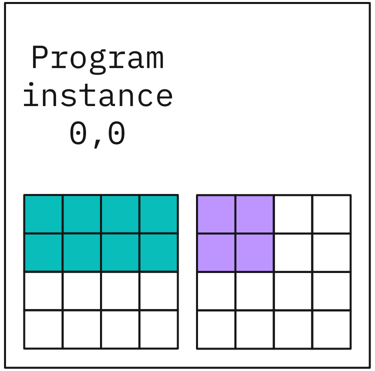

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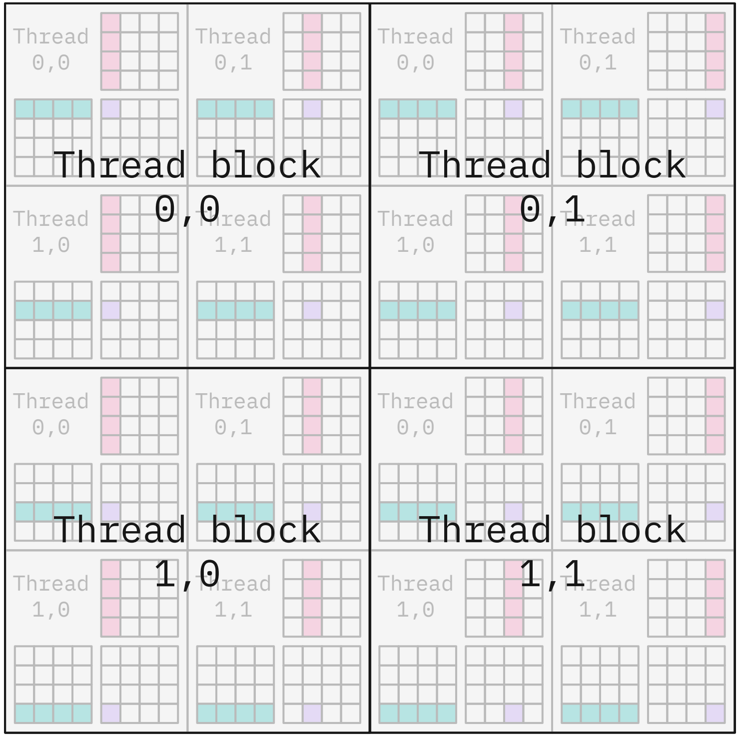

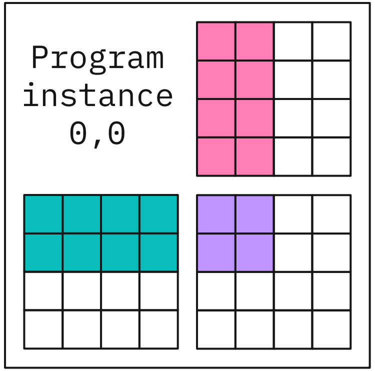

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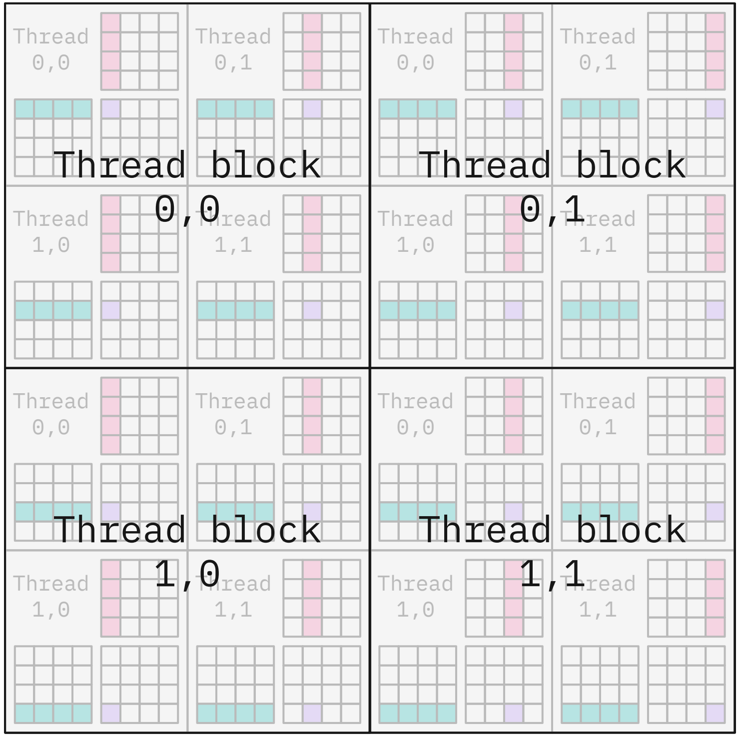

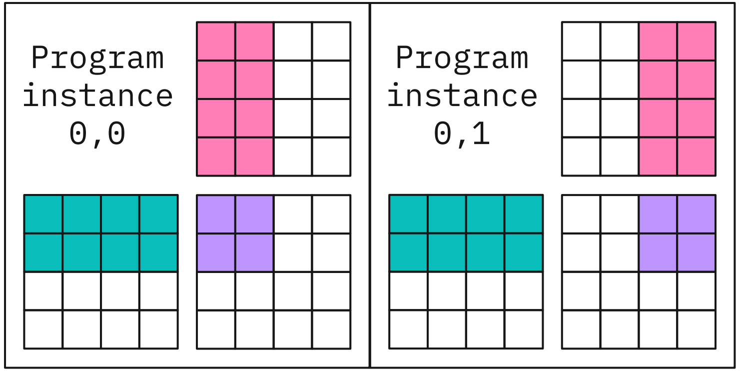

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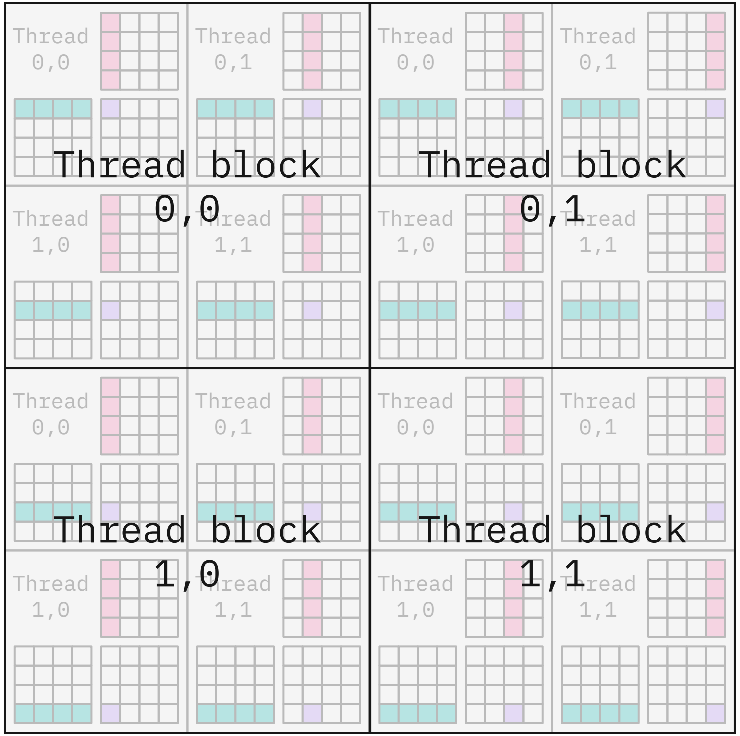

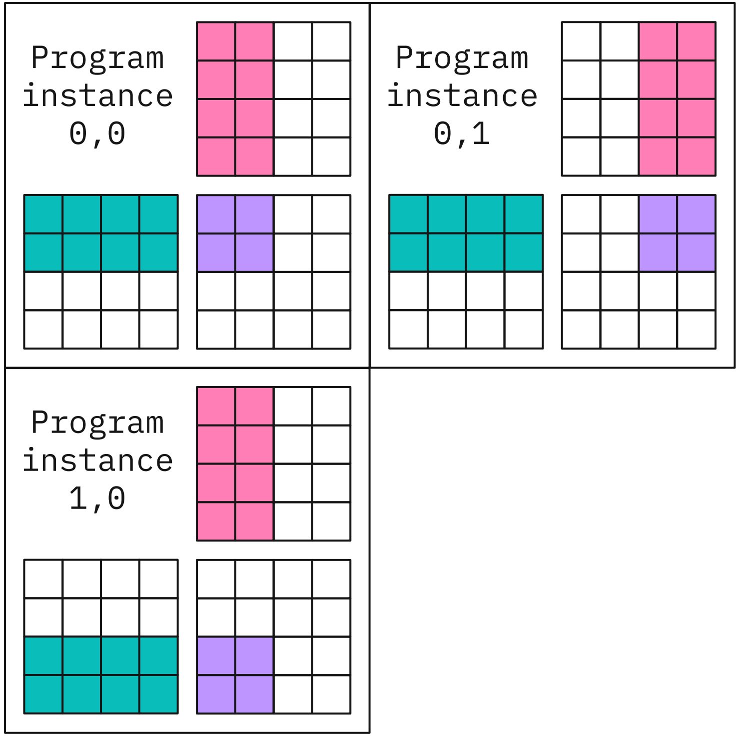

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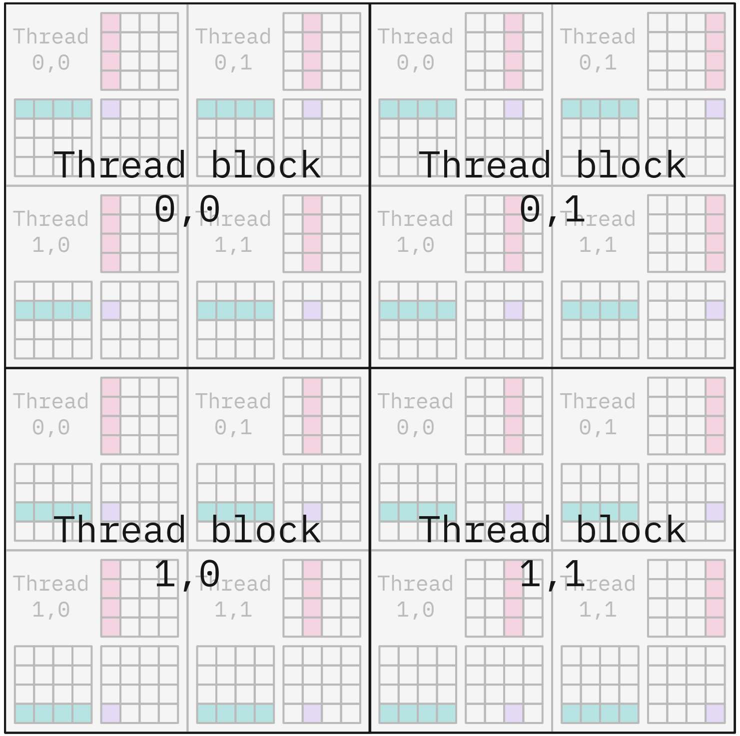
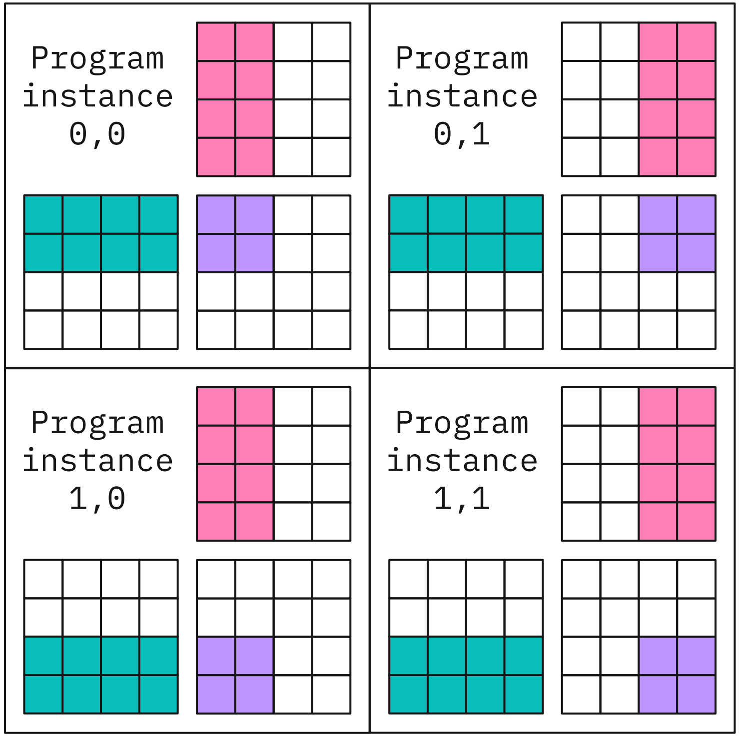
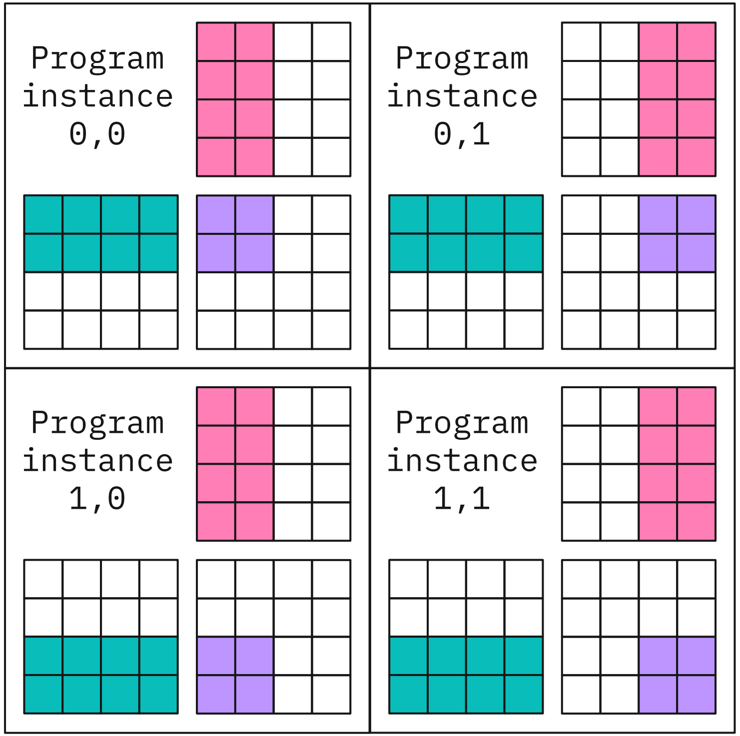




Block-level programming model

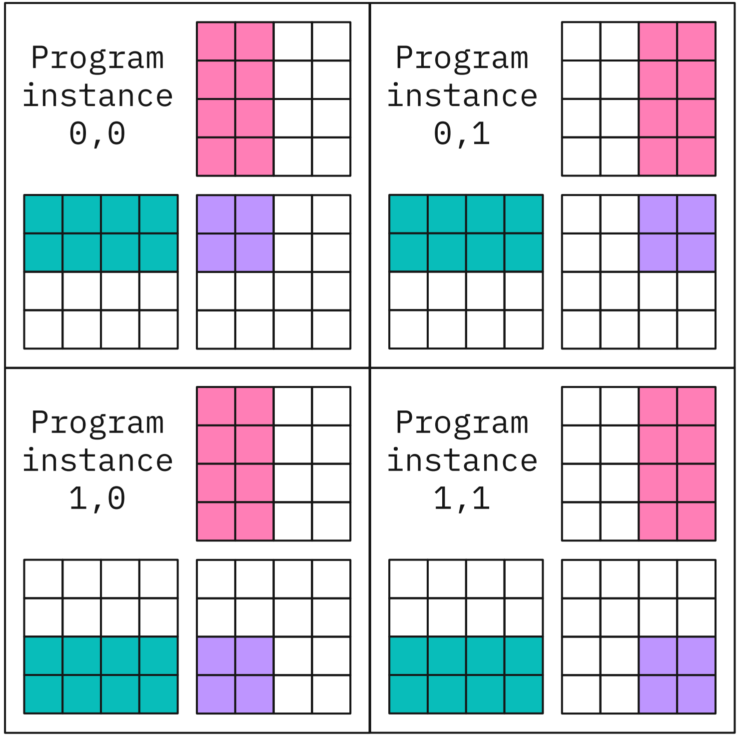
A @ B = C



Block-level programming model

A @ B = C

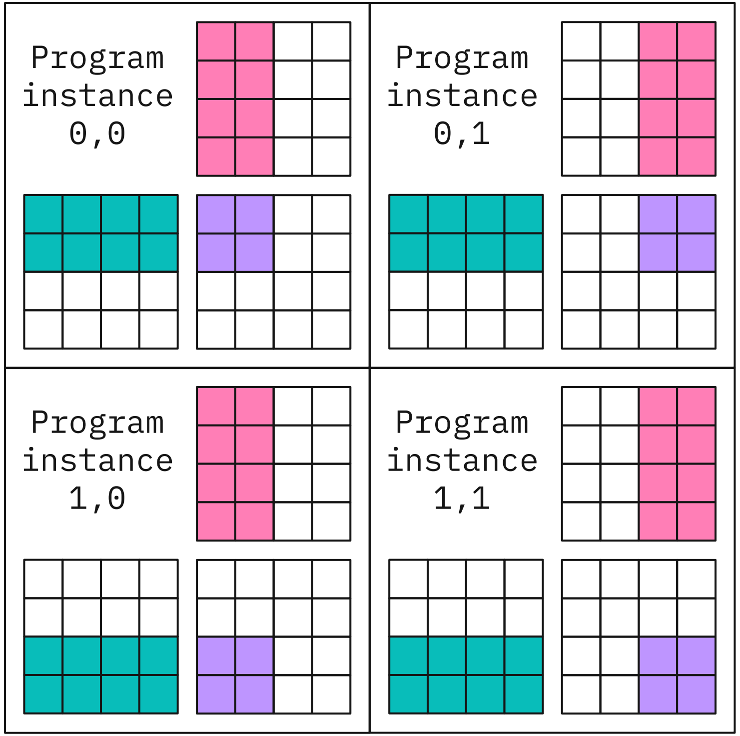
- Programmers define parallel computations using a block-level abstraction.



Block-level programming model

A @ B = C

- Programmers define parallel computations using a block-level abstraction.
  - Above the thread-level programming model (CUDA, OpenCL, HIP)



Block-level programming model

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- Programmers define parallel computations using a block-level abstraction.
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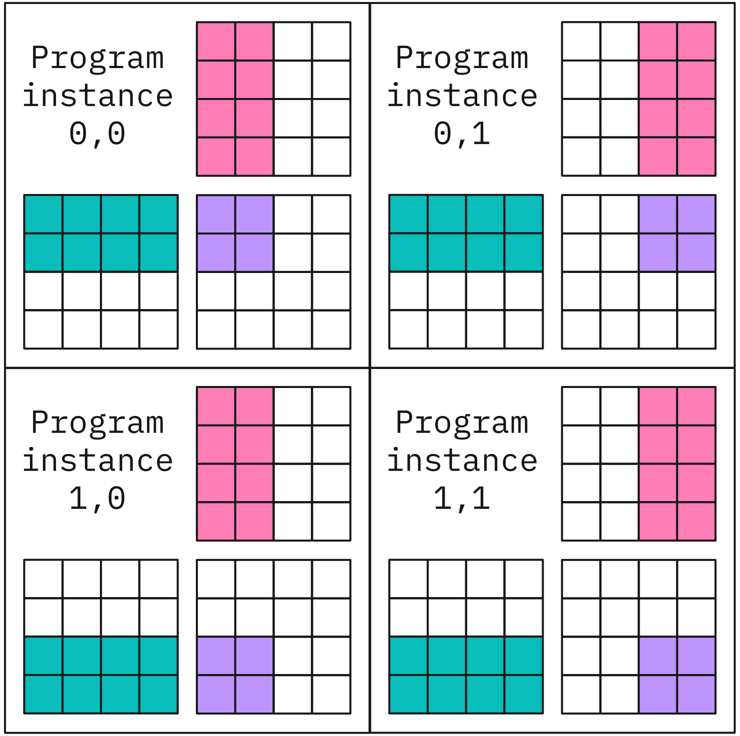
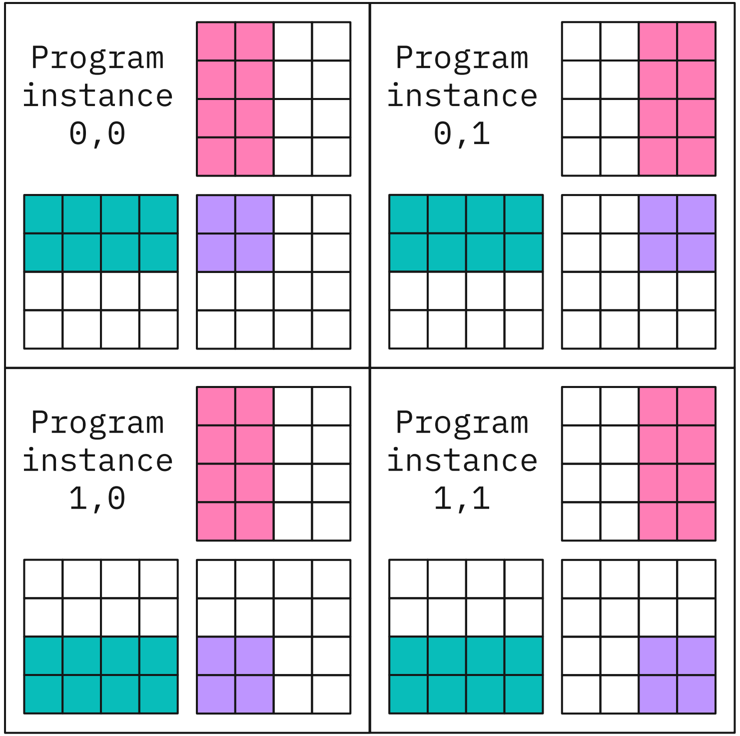
- Partition output tensor into blocks (tiles).



Block-level programming model

A @ B = C

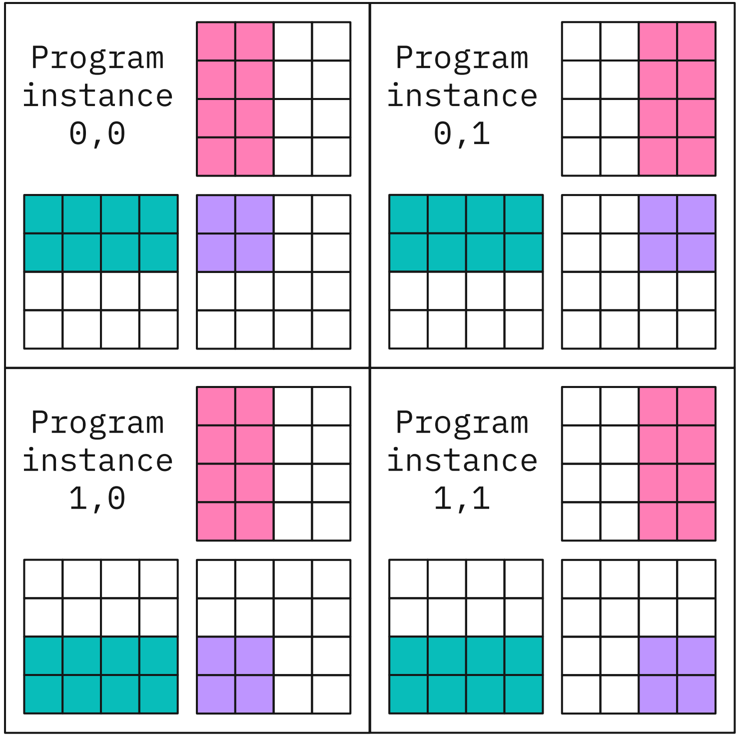
- Programmers define parallel computations using a block-level abstraction.
  - Above the thread-level programming model (CUDA, OpenCL, HIP)
- Partition output tensor into blocks (tiles).
  - Many program instances are launched in parallel from a kernel grid.



Block-level programming model

A @ B = C

- Programmers define parallel computations using a block-level abstraction.
  - Above the thread-level programming model (CUDA, OpenCL, HIP)
- Partition output tensor into blocks (tiles).
  - Many program instances are launched in parallel from a kernel grid.
  - Each program computes a different block of the output



Matmul Triton kernel

Matmul Triton kernel

```
@triton.jit
def matmul_kernel(a_ptr, b_ptr, c_ptr, M, N, K,
                  stride_am, stride_ak, stride_bk, stride_bn, stride_cm, stride_cn,
                  BLOCK_SIZE_M: tl.constexpr, BLOCK_SIZE_N: tl.constexpr, BLOCK_SIZE_K: tl.constexpr):
    pid_m = tl.program_id(axis=0)
    pid_n = tl.program_id(axis=1)
    offs_am = (pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M))
    offs_bn = (pid_n * BLOCK_SIZE_N + tl.arange(0, BLOCK_SIZE_N))
    offs_k = tl.arange(0, BLOCK_SIZE_K)
    a_ptrs = a_ptr + (offs_am[:, None] * stride_am + offs_k[None, :] * stride_ak)
    b_ptrs = b_ptr + (offs_k[:, None] * stride_bk + offs_bn[None, :] * stride_bn)
    accumulator = tl.zeros((BLOCK_SIZE_M, BLOCK_SIZE_N), dtype=tl.float32)
    for k in range(0, tl.cdiv(K, BLOCK_SIZE_K)):
        a = tl.load(a_ptrs, mask=offs_k[None, :] < K - k * BLOCK_SIZE_K, other=0.0)
        b = tl.load(b_ptrs, mask=offs_k[:, None] < K - k * BLOCK_SIZE_K, other=0.0)
        accumulator = tl.dot(a, b, accumulator)
        a_ptrs += BLOCK_SIZE_K * stride_ak
        b_ptrs += BLOCK_SIZE_K * stride_bk
    c = accumulator.to(tl.float16)
    offs_cm = pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M)
    offs_cn = pid_n * BLOCK_SIZE_N + tl.arange(0, BLOCK_SIZE_N)
    c_ptrs = c_ptr + stride_cm * offs_cm[:, None] + stride_cn * offs_cn[None, :]
    c_mask = (offs_cm[:, None] < M) & (offs_cn[None, :] < N)
    tl.store(c_ptrs, c, mask=c_mask)
```

Matmul Triton kernel

```
@triton.jit
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    pid_m = tl.program_id(axis=0)
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    offs_am = (pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M))
    offs_bn = (pid_n * BLOCK_SIZE_N + tl.arange(0, BLOCK_SIZE_N))
    offs_k = tl.arange(0, BLOCK_SIZE_K)
    a_ptrs = a_ptr + (offs_am[:, None] * stride_am + offs_k[None, :] * stride_ak)
    b_ptrs = b_ptr + (offs_k[:, None] * stride_bk + offs_bn[None, :] * stride_bn)
    accumulator = tl.zeros((BLOCK_SIZE_M, BLOCK_SIZE_N), dtype=tl.float32)
    for k in range(0, tl.cdiv(K, BLOCK_SIZE_K)):
        a = tl.load(a_ptrs, mask=offs_k[None, :] < K - k * BLOCK_SIZE_K, other=0.0)
        b = tl.load(b_ptrs, mask=offs_k[:, None] < K - k * BLOCK_SIZE_K, other=0.0)
        accumulator = tl.dot(a, b, accumulator)
        a_ptrs += BLOCK_SIZE_K * stride_ak
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    c = accumulator.to(tl.float16)
    offs_cm = pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M)
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    c_ptrs = c_ptr + stride_cm * offs_cm[:, None] + stride_cn * offs_cn[None, :]
    c_mask = (offs_cm[:, None] < M) & (offs_cn[None, :] < N)
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    pid_m = tl.program_id(axis=0)
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    a_ptrs = a_ptr + (offs_am[:, None] * stride_am + offs_k[None, :] * stride_ak)
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    accumulator = tl.zeros((BLOCK_SIZE_M, BLOCK_SIZE_N), dtype=tl.float32)
    for k in range(0, tl.cdiv(K, BLOCK_SIZE_K)):
        a = tl.load(a_ptrs, mask=offs_k[None, :] < K - k * BLOCK_SIZE_K, other=0.0)
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        accumulator = tl.dot(a, b, accumulator)
        a_ptrs += BLOCK_SIZE_K * stride_ak
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    c = accumulator.to(tl.float16)
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    c_ptrs = c_ptr + stride_cm * offs_cm[:, None] + stride_cn * offs_cn[None, :]
    c_mask = (offs_cm[:, None] < M) & (offs_cn[None, :] < N)
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    pid_m = tl.program_id(axis=0)
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    a_ptrs = a_ptr + (offs_am[:, None] * stride_am + offs_k[None, :] * stride_ak)
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        a_ptrs += BLOCK_SIZE_K * stride_ak
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    offs_k = tl.arange(0, BLOCK_SIZE_K)
    a_ptrs = a_ptr + (offs_am[:, None] * stride_am + offs_k[None, :] * stride_ak)
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    c_ptrs = c_ptr + stride_cm * offs_cm[:, None] + stride_cn * offs_cn[None, :]
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    tl.store(c_ptrs, c, mask=c_mask)
```

Matmul Triton kernel launch

Matmul Triton kernel launch

```
def matmul(a, b):
    M, K = a.shape
    K, N = b.shape
    c = torch.empty((M, N), device=a.device, dtype=torch.float16)
    grid = lambda META: (triton.cdiv(M, META['BLOCK_SIZE_M']), triton.cdiv(N, META['BLOCK_SIZE_N']), )
    matmul_kernel[grid](
        a, b, c,
        M, N, K,
        a.stride(0), a.stride(1),
        b.stride(0), b.stride(1),
        c.stride(0), c.stride(1)
    )
    return c
```

Matmul Triton kernel launch

```
def matmul(a, b):
    M, K = a.shape
    K, N = b.shape
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Matmul Triton kernel launch

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        a.stride(0), a.stride(1),
        b.stride(0), b.stride(1),
        c.stride(0), c.stride(1)
    )
    return c
```

What is abstracted away by Triton’s block-level programming model?

Matmul CUDA kernel

Matmul CUDA kernel

```
template <int BLOCK_SIZE> __global__ void MatrixMulCUDA(float *C, float *A, float *B, int wA, int wB) {
    int bx = blockIdx.x;
    int by = blockIdx.y;
    int tx = threadIdx.x;
    int ty = threadIdx.y;
    int aBegin = wA * BLOCK_SIZE * by;
    int aEnd = aBegin + wA - 1;
    int aStep = BLOCK_SIZE;
    int bBegin = BLOCK_SIZE * bx;
    int bStep = BLOCK_SIZE * wB;
    float Csub = 0;
    for (int a = aBegin, b = bBegin; a <= aEnd; a += aStep, b += bStep) {
        __shared__ float As[BLOCK_SIZE][BLOCK_SIZE];
        __shared__ float Bs[BLOCK_SIZE][BLOCK_SIZE];
        As[ty][tx] = A[a + wA * ty + tx];
        Bs[ty][tx] = B[b + wB * ty + tx];
        __syncthreads();
        #pragma unroll
        for (int k = 0; k < BLOCK_SIZE; ++k) {
            Csub += As[ty][k] * Bs[k][tx];
        }
        __syncthreads();
    }
    int c               = wB * BLOCK_SIZE * by + BLOCK_SIZE * bx;
    C[c + wB * ty + tx] = Csub;
}
```

Matmul CUDA kernel

```
template <int BLOCK_SIZE> __global__ void MatrixMulCUDA(float *C, float *A, float *B, int wA, int wB) {
    int bx = blockIdx.x;
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    int aBegin = wA * BLOCK_SIZE * by;
    int aEnd = aBegin + wA - 1;
    int aStep = BLOCK_SIZE;
    int bBegin = BLOCK_SIZE * bx;
    int bStep = BLOCK_SIZE * wB;
    float Csub = 0;
    for (int a = aBegin, b = bBegin; a <= aEnd; a += aStep, b += bStep) {
        __shared__ float As[BLOCK_SIZE][BLOCK_SIZE];
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        As[ty][tx] = A[a + wA * ty + tx];
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        __syncthreads();
        #pragma unroll
        for (int k = 0; k < BLOCK_SIZE; ++k) {
            Csub += As[ty][k] * Bs[k][tx];
        }
        __syncthreads();
    }
    int c               = wB * BLOCK_SIZE * by + BLOCK_SIZE * bx;
    C[c + wB * ty + tx] = Csub;
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```

- Thread- & thread-block-level program mapping

Matmul CUDA kernel

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template <int BLOCK_SIZE> __global__ void MatrixMulCUDA(float *C, float *A, float *B, int wA, int wB) {
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    int aBegin = wA * BLOCK_SIZE * by;
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    int aStep = BLOCK_SIZE;
    int bBegin = BLOCK_SIZE * bx;
    int bStep = BLOCK_SIZE * wB;
    float Csub = 0;
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```

- Thread- & thread-block-level program mapping
- Shared memory

Matmul CUDA kernel

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    int aStep = BLOCK_SIZE;
    int bBegin = BLOCK_SIZE * bx;
    int bStep = BLOCK_SIZE * wB;
    float Csub = 0;
    for (int a = aBegin, b = bBegin; a <= aEnd; a += aStep, b += bStep) {
        __shared__ float As[BLOCK_SIZE][BLOCK_SIZE];
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        As[ty][tx] = A[a + wA * ty + tx];
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        __syncthreads();
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        for (int k = 0; k < BLOCK_SIZE; ++k) {
            Csub += As[ty][k] * Bs[k][tx];
        }
        __syncthreads();
    }
    int c               = wB * BLOCK_SIZE * by + BLOCK_SIZE * bx;
    C[c + wB * ty + tx] = Csub;
}
```

- Thread- & thread-block-level program mapping
- Shared memory
- Thread coalescence

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    int aStep = BLOCK_SIZE;
    int bBegin = BLOCK_SIZE * bx;
    int bStep = BLOCK_SIZE * wB;
    float Csub = 0;
    for (int a = aBegin, b = bBegin; a <= aEnd; a += aStep, b += bStep) {
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- Thread- & thread-block-level program mapping
- Shared memory
- Thread coalescence
- Thread synchronization

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    int tx = threadIdx.x;
    int ty = threadIdx.y;
    int aBegin = wA * BLOCK_SIZE * by;
    int aEnd = aBegin + wA - 1;
    int aStep = BLOCK_SIZE;
    int bBegin = BLOCK_SIZE * bx;
    int bStep = BLOCK_SIZE * wB;
    float Csub = 0;
    for (int a = aBegin, b = bBegin; a <= aEnd; a += aStep, b += bStep) {
        __shared__ float As[BLOCK_SIZE][BLOCK_SIZE];
        __shared__ float Bs[BLOCK_SIZE][BLOCK_SIZE];
        As[ty][tx] = A[a + wA * ty + tx];
        Bs[ty][tx] = B[b + wB * ty + tx];
        __syncthreads();
        #pragma unroll
        for (int k = 0; k < BLOCK_SIZE; ++k) {
            Csub += As[ty][k] * Bs[k][tx];
        }
        __syncthreads();
    }
    int c               = wB * BLOCK_SIZE * by + BLOCK_SIZE * bx;
    C[c + wB * ty + tx] = Csub;
}
```

- Thread- & thread-block-level program mapping
- Shared memory
- Thread coalescence
- Thread synchronization
- ...

Matmul CUDA kernel

```
template <int BLOCK_SIZE> __global__ void MatrixMulCUDA(float *C, float *A, float *B, int wA, int wB) {
    int bx = blockIdx.x;
    int by = blockIdx.y;
    int tx = threadIdx.x;
    int ty = threadIdx.y;
    int aBegin = wA * BLOCK_SIZE * by;
    int aEnd = aBegin + wA - 1;
    int aStep = BLOCK_SIZE;
    int bBegin = BLOCK_SIZE * bx;
    int bStep = BLOCK_SIZE * wB;
    float Csub = 0;
    for (int a = aBegin, b = bBegin; a <= aEnd; a += aStep, b += bStep) {
        __shared__ float As[BLOCK_SIZE][BLOCK_SIZE];
        __shared__ float Bs[BLOCK_SIZE][BLOCK_SIZE];
        As[ty][tx] = A[a + wA * ty + tx];
        Bs[ty][tx] = B[b + wB * ty + tx];
        __syncthreads();
        #pragma unroll
        for (int k = 0; k < BLOCK_SIZE; ++k) {
            Csub += As[ty][k] * Bs[k][tx];
        }
        __syncthreads();
    }
    int c               = wB * BLOCK_SIZE * by + BLOCK_SIZE * bx;
    C[c + wB * ty + tx] = Csub;
}
```

- Thread- & thread-block-level program mapping
- Shared memory
- Thread coalescence
- Thread synchronization
- ...

Handled by the Triton compiler!

What wrong with Triton?

Matmul Triton kernel

```
@triton.jit
def matmul_kernel(a_ptr, b_ptr, c_ptr, M, N, K,
                  stride_am, stride_ak, stride_bk, stride_bn, stride_cm, stride_cn,
                  BLOCK_SIZE_M: tl.constexpr, BLOCK_SIZE_N: tl.constexpr, BLOCK_SIZE_K: tl.constexpr):
    pid_m = tl.program_id(axis=0)
    pid_n = tl.program_id(axis=1)
    offs_am = (pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M))
    offs_bn = (pid_n * BLOCK_SIZE_N + tl.arange(0, BLOCK_SIZE_N))
    offs_k = tl.arange(0, BLOCK_SIZE_K)
    a_ptrs = a_ptr + (offs_am[:, None] * stride_am + offs_k[None, :] * stride_ak)
    b_ptrs = b_ptr + (offs_k[:, None] * stride_bk + offs_bn[None, :] * stride_bn)
    accumulator = tl.zeros((BLOCK_SIZE_M, BLOCK_SIZE_N), dtype=tl.float32)
    for k in range(0, tl.cdiv(K, BLOCK_SIZE_K)):
        a = tl.load(a_ptrs, mask=offs_k[None, :] < K - k * BLOCK_SIZE_K, other=0.0)
        b = tl.load(b_ptrs, mask=offs_k[:, None] < K - k * BLOCK_SIZE_K, other=0.0)
        accumulator = tl.dot(a, b, accumulator)
        a_ptrs += BLOCK_SIZE_K * stride_ak
        b_ptrs += BLOCK_SIZE_K * stride_bk
    c = accumulator.to(tl.float16)
    offs_cm = pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M)
    offs_cn = pid_n * BLOCK_SIZE_N + tl.arange(0, BLOCK_SIZE_N)
    c_ptrs = c_ptr + stride_cm * offs_cm[:, None] + stride_cn * offs_cn[None, :]
    c_mask = (offs_cm[:, None] < M) & (offs_cn[None, :] < N)
    tl.store(c_ptrs, c, mask=c_mask)
```

Matmul Triton kernel

```
@triton.jit
def matmul_kernel(a_ptr, b_ptr, c_ptr, M, N, K,
                  stride_am, stride_ak, stride_bk, stride_bn, stride_cm, stride_cn,
                  BLOCK_SIZE_M: tl.constexpr, BLOCK_SIZE_N: tl.constexpr, BLOCK_SIZE_K: tl.constexpr):
    pid_m = tl.program_id(axis=0)
    pid_n = tl.program_id(axis=1)
    offs_am = (pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M))
    offs_bn = (pid_n * BLOCK_SIZE_N + tl.arange(0, BLOCK_SIZE_N))
    offs_k = tl.arange(0, BLOCK_SIZE_K)
    a_ptrs = a_ptr + (offs_am[:, None] * stride_am + offs_k[None, :] * stride_ak)
    b_ptrs = b_ptr + (offs_k[:, None] * stride_bk + offs_bn[None, :] * stride_bn)
    accumulator = tl.zeros((BLOCK_SIZE_M, BLOCK_SIZE_N), dtype=tl.float32)
    for k in range(0, tl.cdiv(K, BLOCK_SIZE_K)):
        a = tl.load(a_ptrs, mask=offs_k[None, :] < K - k * BLOCK_SIZE_K, other=0.0)
        b = tl.load(b_ptrs, mask=offs_k[:, None] < K - k * BLOCK_SIZE_K, other=0.0)
        accumulator = tl.dot(a, b, accumulator)
        a_ptrs += BLOCK_SIZE_K * stride_ak
        b_ptrs += BLOCK_SIZE_K * stride_bk
    c = accumulator.to(tl.float16)
    offs_cm = pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M)
    offs_cn = pid_n * BLOCK_SIZE_N + tl.arange(0, BLOCK_SIZE_N)
    c_ptrs = c_ptr + stride_cm * offs_cm[:, None] + stride_cn * offs_cn[None, :]
    c_mask = (offs_cm[:, None] < M) & (offs_cn[None, :] < N)
    tl.store(c_ptrs, c, mask=c_mask)
```

- Pointer arithmetic

Matmul Triton kernel

```
@triton.jit
def matmul_kernel(a_ptr, b_ptr, c_ptr, M, N, K,
                  stride_am, stride_ak, stride_bk, stride_bn, stride_cm, stride_cn,
                  BLOCK_SIZE_M: tl.constexpr, BLOCK_SIZE_N: tl.constexpr, BLOCK_SIZE_K: tl.constexpr):
    pid_m = tl.program_id(axis=0)
    pid_n = tl.program_id(axis=1)
    offs_am = (pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M))
    offs_bn = (pid_n * BLOCK_SIZE_N + tl.arange(0, BLOCK_SIZE_N))
    offs_k = tl.arange(0, BLOCK_SIZE_K)
    a_ptrs = a_ptr + (offs_am[:, None] * stride_am + offs_k[None, :] * stride_ak)
    b_ptrs = b_ptr + (offs_k[:, None] * stride_bk + offs_bn[None, :] * stride_bn)
    accumulator = tl.zeros((BLOCK_SIZE_M, BLOCK_SIZE_N), dtype=tl.float32)
    for k in range(0, tl.cdiv(K, BLOCK_SIZE_K)):
        a = tl.load(a_ptrs, mask=offs_k[None, :] < K - k * BLOCK_SIZE_K, other=0.0)
        b = tl.load(b_ptrs, mask=offs_k[:, None] < K - k * BLOCK_SIZE_K, other=0.0)
        accumulator = tl.dot(a, b, accumulator)
        a_ptrs += BLOCK_SIZE_K * stride_ak
        b_ptrs += BLOCK_SIZE_K * stride_bk
    c = accumulator.to(tl.float16)
    offs_cm = pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M)
    offs_cn = pid_n * BLOCK_SIZE_N + tl.arange(0, BLOCK_SIZE_N)
    c_ptrs = c_ptr + stride_cm * offs_cm[:, None] + stride_cn * offs_cn[None, :]
    c_mask = (offs_cm[:, None] < M) & (offs_cn[None, :] < N)
    tl.store(c_ptrs, c, mask=c_mask)
```

- Pointer arithmetic
- Load/store masking

Matmul Triton kernel

```
@triton.jit
def matmul_kernel(a_ptr, b_ptr, c_ptr, M, N, K,
                  stride_am, stride_ak, stride_bk, stride_bn, stride_cm, stride_cn,
                  BLOCK_SIZE_M: tl.constexpr, BLOCK_SIZE_N: tl.constexpr, BLOCK_SIZE_K: tl.constexpr):
    pid_m = tl.program_id(axis=0)
    pid_n = tl.program_id(axis=1)
    offs_am = (pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M))
    offs_bn = (pid_n * BLOCK_SIZE_N + tl.arange(0, BLOCK_SIZE_N))
    offs_k = tl.arange(0, BLOCK_SIZE_K)
    a_ptrs = a_ptr + (offs_am[:, None] * stride_am + offs_k[None, :] * stride_ak)
    b_ptrs = b_ptr + (offs_k[:, None] * stride_bk + offs_bn[None, :] * stride_bn)
    accumulator = tl.zeros((BLOCK_SIZE_M, BLOCK_SIZE_N), dtype=tl.float32)
    for k in range(0, tl.cdiv(K, BLOCK_SIZE_K)):
        a = tl.load(a_ptrs, mask=offs_k[None, :] < K - k * BLOCK_SIZE_K, other=0.0)
        b = tl.load(b_ptrs, mask=offs_k[:, None] < K - k * BLOCK_SIZE_K, other=0.0)
        accumulator = tl.dot(a, b, accumulator)
        a_ptrs += BLOCK_SIZE_K * stride_ak
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    c = accumulator.to(tl.float16)
    offs_cm = pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M)
    offs_cn = pid_n * BLOCK_SIZE_N + tl.arange(0, BLOCK_SIZE_N)
    c_ptrs = c_ptr + stride_cm * offs_cm[:, None] + stride_cn * offs_cn[None, :]
    c_mask = (offs_cm[:, None] < M) & (offs_cn[None, :] < N)
    tl.store(c_ptrs, c, mask=c_mask)
```

- Pointer arithmetic
- Load/store masking
- Hard to find an efficient schedule

Matmul Triton kernel

```
@triton.jit
def matmul_kernel(a_ptr, b_ptr, c_ptr, M, N, K,
                  stride_am, stride_ak, stride_bk, stride_bn, stride_cm, stride_cn,
                  BLOCK_SIZE_M: tl.constexpr, BLOCK_SIZE_N: tl.constexpr, BLOCK_SIZE_K: tl.constexpr):
    pid_m = tl.program_id(axis=0)
    pid_n = tl.program_id(axis=1)
    offs_am = (pid_m * BLOCK_SIZE_M + tl.arange(0, BLOCK_SIZE_M))
    offs_bn = (pid_n * BLOCK_SIZE_N + tl.arange(0, BLOCK_SIZE_N))
    offs_k = tl.arange(0, BLOCK_SIZE_K)
    a_ptrs = a_ptr + (offs_am[:, None] * stride_am + offs_k[None, :] * stride_ak)
    b_ptrs = b_ptr + (offs_k[:, None] * stride_bk + offs_bn[None, :] * stride_bn)
    accumulator = tl.zeros((BLOCK_SIZE_M, BLOCK_SIZE_N), dtype=tl.float32)
    for k in range(0, tl.cdiv(K, BLOCK_SIZE_K)):
        a = tl.load(a_ptrs, mask=offs_k[None, :] < K - k * BLOCK_SIZE_K, other=0.0)
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    c_ptrs = c_ptr + stride_cm * offs_cm[:, None] + stride_cn * offs_cn[None, :]
    c_mask = (offs_cm[:, None] < M) & (offs_cn[None, :] < N)
    tl.store(c_ptrs, c, mask=c_mask)
```

- Pointer arithmetic
- Load/store masking
- Hard to find an efficient schedule

Decoupled Languages

Decoupling Algorithms from Schedules for Easy Optimization of Image Processing Pipelines

Jonathan Ragan-Kelley[*] Andrew Adams[*] Sylvain Paris[†] Marc Levoy[‡] Saman Amarasinghe[*] Frédo Durand[*]

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Decoupling the algorithm from the schedule

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Decoupling the algorithm from the schedule

- Halide introduced the concept of algorithm and schedule in a programming language.

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Decoupling the algorithm from the schedule

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  - Algorithm: what to compute

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Decoupling the algorithm from the schedule

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  - Algorithm: what to compute
  - Schedule: how to compute

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Decoupling the algorithm from the schedule

- Halide introduced the concept of algorithm and schedule in a programming language.
  - Algorithm: what to compute
  - Schedule: how to compute
- A function is defined by the composition of these two independent components.

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Decoupling the algorithm from the schedule

- Halide introduced the concept of algorithm and schedule in a programming language.
  - Algorithm: what to compute
  - Schedule: how to compute
- A function is defined by the composition of these two independent components
- Decoupled Triton applies this concept to block-level machine learning kernels.

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Efficient schedules

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Efficient schedules

- The schedule determines performance factors.

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Efficient schedules

- The schedule determines performance factors.
  - *E.g.* memory access pattern

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Efficient schedules

- The schedule determines performance factors.
  - *E.g.* memory access pattern
- The most efficient schedule will depend on:

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Efficient schedules

- The schedule determines performance factors.
  - *E.g.* memory access pattern
- The most efficient schedule will depend on:
  - Algorithm

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Efficient schedules

- The schedule determines performance factors.
  - *E.g.* memory access pattern
- The most efficient schedule will depend on:
  - Algorithm
  - Workload size

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Efficient schedules

- The schedule determines performance factors.
  - *E.g.* memory access pattern
- The most efficient schedule will depend on:
  - Algorithm
  - Workload size
  - Hardware architecture

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Decoupled Triton example

Decoupled Triton example

```
# Declarations
Func mm;
In A, B;
Var x, y;
RVar k;

# Algorithm
mm[x, y] = rdot(A[x, k], B[k, y], k);

# Schedule
mm.tensorize(x:128, k:32, y:128);
mm.block(x:128, y:128);
mm.map(x:x1/8, y, x1);
mm.num_warps(4);
mm.num_stages(3);
mm.compile();
```

Decoupled Triton example

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mm.map(x:x1/8, y, x1);
mm.num_warps(4);
mm.num_stages(3);
mm.compile();
```

```
@triton.jit
def mm_kernel(A_ptr, A_x_stride: tl.constexpr, A_k_stride:
tl.constexpr, B_ptr, B_k_stride: tl.constexpr, B_y_stride:
tl.constexpr, mm_ptr, mm_x_stride: tl.constexpr, mm_y_stride:
tl.constexpr, y_SIZE: tl.constexpr, x_SIZE: tl.constexpr, k_SIZE:
tl.constexpr):
  y_BLOCK_COUNT = y_SIZE // 128
  x_BLOCK_COUNT = x_SIZE // 128
  x_pid = tl.program_id(0).to(tl.int64) // (y_BLOCK_COUNT * 8) %
(x_BLOCK_COUNT // 8)
  y_pid = tl.program_id(0).to(tl.int64) // 8 % y_BLOCK_COUNT
  x1_pid = tl.program_id(0).to(tl.int64) % 8
  x_pid_ = x_pid * 8 + x1_pid
  y_block_start = y_pid * 128
  x_block_start = x_pid_ * 128
  k_arange = tl.arange(0, 32)
  y_arange = tl.arange(0, 128)
  x_arange = tl.arange(0, 128)
  k_accumulator = tl.zeros((128, 128,), tl.float32)
  for k_iter in range(0, k_SIZE, 32):
    A = tl.load(A_ptr + (x_block_start + x_arange[:, None]) *
A_x_stride + (k_iter + k_arange[None, :]) * A_k_stride)
    B = tl.load(B_ptr + (k_iter + k_arange[:, None]) * B_k_stride +
(y_block_start + y_arange[None, :]) * B_y_stride)
    k_accumulator = tl.dot(A, B, k_accumulator)
  k_reduction_result = k_accumulator
  mm = k_reduction_result
  tl.store(mm_ptr + (x_block_start + x_arange[:, None]) * mm_x_stride +
(y_block_start + y_arange[None, :]) * mm_y_stride, mm)

def mm(B, A, y, x, k):
  A_x_stride, A_k_stride, = A.stride()
  B_k_stride, B_y_stride, = B.stride()
  mm = torch.empty(x, y, dtype=torch.float32, device='cuda')
  mm_x_stride, mm_y_stride, = mm.stride()
  mm_grid = (triton.cdiv(x, 128) * triton.cdiv(y, 128)),
  mm_kernel[mm_grid](A, A_x_stride, A_k_stride, B, B_k_stride,
B_y_stride, mm, mm_x_stride, mm_y_stride, y, x, k, num_stages=3,
num_warps=4)
  return mm
```

Decoupled Triton example

```
# Declarations
Func mm;
In A, B;
Var x, y;
RVar k;

# Algorithm
mm[x, y] = rdot(A[x, k], B[k, y], k);

# Schedule
mm.tensorize(x:128, k:32, y:128);
mm.block(x:128, y:128);
mm.map(x:x1/8, y, x1);
mm.num_warps(4);
mm.num_stages(3);
mm.compile();
```

More readable!

```
@triton.jit
def mm_kernel(A_ptr, A_x_stride: tl.constexpr, A_k_stride: tl.constexpr, B_ptr, B_k_stride: tl.constexpr, B_y_stride: tl.constexpr, mm_ptr, mm_x_stride: tl.constexpr, mm_y_stride: tl.constexpr, y_SIZE: tl.constexpr, x_SIZE: tl.constexpr, k_SIZE: tl.constexpr):
  y_BLOCK_COUNT = y_SIZE // 128
  x_BLOCK_COUNT = x_SIZE // 128
  x_pid = tl.program_id(0).to(tl.int64) // (y_BLOCK_COUNT * 8) % (x_BLOCK_COUNT // 8)
  y_pid = tl.program_id(0).to(tl.int64) // 8 % y_BLOCK_COUNT
  x1_pid = tl.program_id(0).to(tl.int64) % 8
  x_pid_ = x_pid * 8 + x1_pid
  y_block_start = y_pid * 128
  x_block_start = x_pid_ * 128
  k_arange = tl.arange(0, 32)
  y_arange = tl.arange(0, 128)
  x_arange = tl.arange(0, 128)
  k_accumulator = tl.zeros((128, 128,), tl.float32)
  for k_iter in range(0, k_SIZE, 32):
    A = tl.load(A_ptr + (x_block_start + x_arange[:, None]) * A_x_stride + (k_iter + k_arange[None, :]) * A_k_stride)
    B = tl.load(B_ptr + (k_iter + k_arange[:, None]) * B_k_stride + (y_block_start + y_arange[None, :]) * B_y_stride)
    k_accumulator = tl.dot(A, B, k_accumulator)
  k_reduction_result = k_accumulator
  mm = k_reduction_result
  tl.store(mm_ptr + (x_block_start + x_arange[:, None]) * mm_x_stride + (y_block_start + y_arange[None, :]) * mm_y_stride, mm)

def mm(B, A, y, x, k):
  A_x_stride, A_k_stride, = A.stride()
  B_k_stride, B_y_stride, = B.stride()
  mm = torch.empty(x, y, dtype=torch.float32, device='cuda')
  mm_x_stride, mm_y_stride, = mm.stride()
  mm_grid = (triton.cdiv(x, 128) * triton.cdiv(y, 128)),
  mm_kernel[mm_grid](A, A_x_stride, A_k_stride, B, B_k_stride, B_y_stride, mm, mm_x_stride, mm_y_stride, y, x, k, num_stages=3, num_warps=4)
  return mm
```

Decoupled Triton example

```
# Declarations
Func mm;
In A, B;
Var x, y;
RVar k;

# Algorithm
mm[x, y] = rdot(A[x, k], B[k, y], k);

# Schedule
mm.tensorize(x:128, k:32, y:128);
mm.block(x:128, y:128);
mm.map(x:x1/8, y, x1);
mm.num_warps(4);
mm.num_stages(3);
mm.compile();
```

```
@triton.jit
def mm_kernel(A_ptr, A_x_stride: tl.constexpr, A_k_stride:
tl.constexpr, B_ptr, B_k_stride: tl.constexpr, B_y_stride:
tl.constexpr, mm_ptr, mm_x_stride: tl.constexpr, mm_y_stride:
tl.constexpr, y_SIZE: tl.constexpr, x_SIZE: tl.constexpr, k_SIZE:
tl.constexpr):
  y_BLOCK_COUNT = y_SIZE // 128
  x_BLOCK_COUNT = x_SIZE // 128
  x_pid = tl.program_id(0).to(tl.int64) // (y_BLOCK_COUNT * 8) %
(x_BLOCK_COUNT // 8)
  y_pid = tl.program_id(0).to(tl.int64) // 8 % y_BLOCK_COUNT
  x1_pid = tl.program_id(0).to(tl.int64) % 8
  x_pid_ = x_pid * 8 + x1_pid
  y_block_start = y_pid * 128
  x_block_start = x_pid_ * 128
  k_arange = tl.arange(0, 32)
  y_arange = tl.arange(0, 128)
  x_arange = tl.arange(0, 128)
  k_accumulator = tl.zeros((128, 128,), tl.float32)
  for k_iter in range(0, k_SIZE, 32):
    A = tl.load(A_ptr + (x_block_start + x_arange[:, None]) *
A_x_stride + (k_iter + k_arange[None, :]) * A_k_stride)
    B = tl.load(B_ptr + (k_iter + k_arange[:, None]) * B_k_stride +
(y_block_start + y_arange[None, :]) * B_y_stride)
    k_accumulator = tl.dot(A, B, k_accumulator)
  k_reduction_result = k_accumulator
  mm = k_reduction_result
  tl.store(mm_ptr + (x_block_start + x_arange[:, None]) * mm_x_stride +
(y_block_start + y_arange[None, :]) * mm_y_stride, mm)

def mm(B, A, y, x, k):
  A_x_stride, A_k_stride, = A.stride()
  B_k_stride, B_y_stride, = B.stride()
  mm = torch.empty(x, y, dtype=torch.float32, device='cuda')
  mm_x_stride, mm_y_stride, = mm.stride()
  mm_grid = (triton.cdiv(x, 128) * triton.cdiv(y, 128)),
  mm_kernel[mm_grid](A, A_x_stride, A_k_stride, B, B_k_stride,
B_y_stride, mm, mm_x_stride, mm_y_stride, y, x, k, num_stages=3,
num_warps=4)
  return mm
```

Decoupled Triton example

```
# Declarations
Func mm;
In A, B;
Var x, y;
RVar k;

# Algorithm
mm[x, y] = rdot(A[x, k], B[k, y], k);

# Schedule
mm.tensorize(x:128, k:32, y:128);
mm.block(x:128, y:128);
mm.map(x:x1/8, y, x1);
mm.num_warps(4);
mm.num_stages(3);
mm.compile();
```

Modular algorithm and schedule!

```
@triton.jit
def mm_kernel(A_ptr, A_x_stride: tl.constexpr, A_k_stride:
tl.constexpr, B_ptr, B_k_stride: tl.constexpr, B_y_stride:
tl.constexpr, mm_ptr, mm_x_stride: tl.constexpr, mm_y_stride:
tl.constexpr, y_SIZE: tl.constexpr, x_SIZE: tl.constexpr, k_SIZE:
tl.constexpr):
  y_BLOCK_COUNT = y_SIZE // 128
  x_BLOCK_COUNT = x_SIZE // 128
  x_pid = tl.program_id(0).to(tl.int64) // (y_BLOCK_COUNT * 8) %
(x_BLOCK_COUNT // 8)
  y_pid = tl.program_id(0).to(tl.int64) // 8 % y_BLOCK_COUNT
  x1_pid = tl.program_id(0).to(tl.int64) % 8
  x_pid_ = x_pid * 8 + x1_pid
  y_block_start = y_pid * 128
  x_block_start = x_pid_ * 128
  k_arange = tl.arange(0, 32)
  y_arange = tl.arange(0, 128)
  x_arange = tl.arange(0, 128)
  k_accumulator = tl.zeros((128, 128,), tl.float32)
  for k_iter in range(0, k_SIZE, 32):
    A = tl.load(A_ptr + (x_block_start + x_arange[:, None]) *
A_x_stride + (k_iter + k_arange[None, :]) * A_k_stride)
    B = tl.load(B_ptr + (k_iter + k_arange[:, None]) * B_k_stride +
(y_block_start + y_arange[None, :]) * B_y_stride)
    k_accumulator = tl.dot(A, B, k_accumulator)
  k_reduction_result = k_accumulator
  mm = k_reduction_result
  tl.store(mm_ptr + (x_block_start + x_arange[:, None]) * mm_x_stride +
(y_block_start + y_arange[None, :]) * mm_y_stride, mm)

def mm(B, A, y, x, k):
  A_x_stride, A_k_stride, = A.stride()
  B_k_stride, B_y_stride, = B.stride()
  mm = torch.empty(x, y, dtype=torch.float32, device='cuda')
  mm_x_stride, mm_y_stride, = mm.stride()
  mm_grid = (triton.cdiv(x, 128) * triton.cdiv(y, 128)),
  mm_kernel[mm_grid](A, A_x_stride, A_k_stride, B, B_k_stride,
B_y_stride, mm, mm_x_stride, mm_y_stride, y, x, k, num_stages=3,
num_warps=4)
  return mm
```

Decoupled Triton example

```
# Declarations
Func mm;
In A, B;
Var x, y;
RVar k;

# Algorithm
mm[x, y] = rdot(A[x, k], B[k, y], k);

# Schedule
mm.tensorize(x:128, k:32, y:128);
mm.block(x:128, y:128);
mm.map(x:x1/8, y, x1);
mm.num_warps(4);
mm.num_stages(3);
mm.compile();
```

Modular algorithm and schedule!
Rapidly iterate and explore schedules!

```
@triton.jit
def mm_kernel(A_ptr, A_x_stride: tl.constexpr, A_k_stride:
tl.constexpr, B_ptr, B_k_stride: tl.constexpr, B_y_stride:
tl.constexpr, mm_ptr, mm_x_stride: tl.constexpr, mm_y_stride:
tl.constexpr, y_SIZE: tl.constexpr, x_SIZE: tl.constexpr, k_SIZE:
tl.constexpr):
  y_BLOCK_COUNT = y_SIZE // 128
  x_BLOCK_COUNT = x_SIZE // 128
  x_pid = tl.program_id(0).to(tl.int64) // (y_BLOCK_COUNT * 8) %
(x_BLOCK_COUNT // 8)
  y_pid = tl.program_id(0).to(tl.int64) // 8 % y_BLOCK_COUNT
  x1_pid = tl.program_id(0).to(tl.int64) % 8
  x_pid_ = x_pid * 8 + x1_pid
  y_block_start = y_pid * 128
  x_block_start = x_pid_ * 128
  k_arange = tl.arange(0, 32)
  y_arange = tl.arange(0, 128)
  x_arange = tl.arange(0, 128)
  k_accumulator = tl.zeros((128, 128,), tl.float32)
  for k_iter in range(0, k_SIZE, 32):
    A = tl.load(A_ptr + (x_block_start + x_arange[:, None]) *
A_x_stride + (k_iter + k_arange[None, :]) * A_k_stride)
    B = tl.load(B_ptr + (k_iter + k_arange[:, None]) * B_k_stride +
(y_block_start + y_arange[None, :]) * B_y_stride)
    k_accumulator = tl.dot(A, B, k_accumulator)
  k_reduction_result = k_accumulator
  mm = k_reduction_result
  tl.store(mm_ptr + (x_block_start + x_arange[:, None]) * mm_x_stride +
(y_block_start + y_arange[None, :]) * mm_y_stride, mm)

def mm(B, A, y, x, k):
  A_x_stride, A_k_stride, = A.stride()
  B_k_stride, B_y_stride, = B.stride()
  mm = torch.empty(x, y, dtype=torch.float32, device='cuda')
  mm_x_stride, mm_y_stride, = mm.stride()
  mm_grid = (triton.cdiv(x, 128) * triton.cdiv(y, 128)),
  mm_kernel[mm_grid](A, A_x_stride, A_k_stride, B, B_k_stride,
B_y_stride, mm, mm_x_stride, mm_y_stride, y, x, k, num_stages=3,
num_warps=4)
  return mm
```

Why decouple the algorithm from the schedule?

```
# Declarations
Func mm;
In A, B;
Var x, y;
RVar k;

# Algorithm
mm[x, y] = rdot(A[x, k], B[k, y], k);

# Schedule
mm.tensorize(x:128, k:32, y:128);
mm.block(x:128, y:128);
mm.map(x:x1/8, y, x1);
mm.num_warps(4);
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- More readable kernel definitions.

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```

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- Modular algorithm and schedule definition.
    - Enables rapid kernel schedule iteration and exploration

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mm.num_stages(3);
mm.compile();
```

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- Modular algorithm and schedule definition.
  - Enables rapid kernel schedule iteration and exploration
- Allows users to explicitly define their own kernel scheduling (user-schedulable-language).

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mm.num_stages(3);
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```

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Decoupled Triton

Decoupled Triton

An abstraction layer on top of Triton that decouples the algorithm from the schedule.

Decoupled Triton

Decoupled Triton

DT File

Decoupled Triton

DT File

DT Compiler

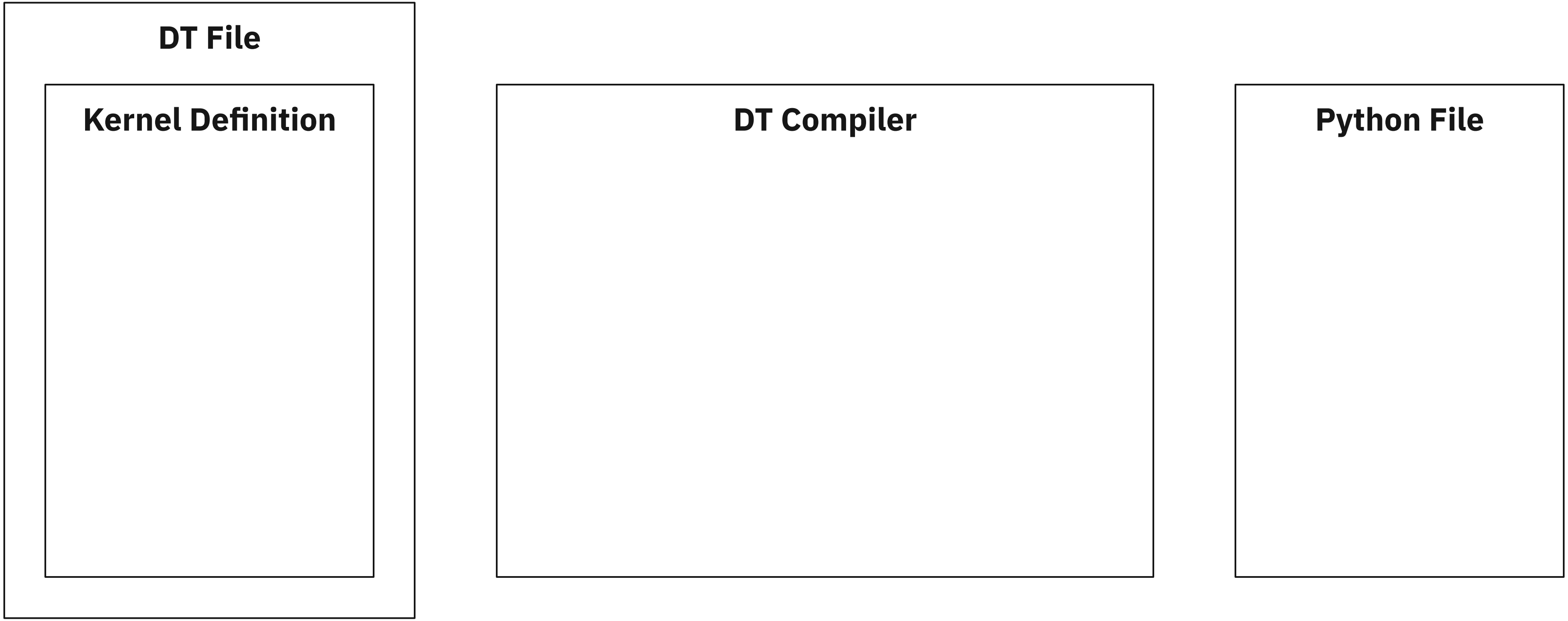
Decoupled Triton

DT File

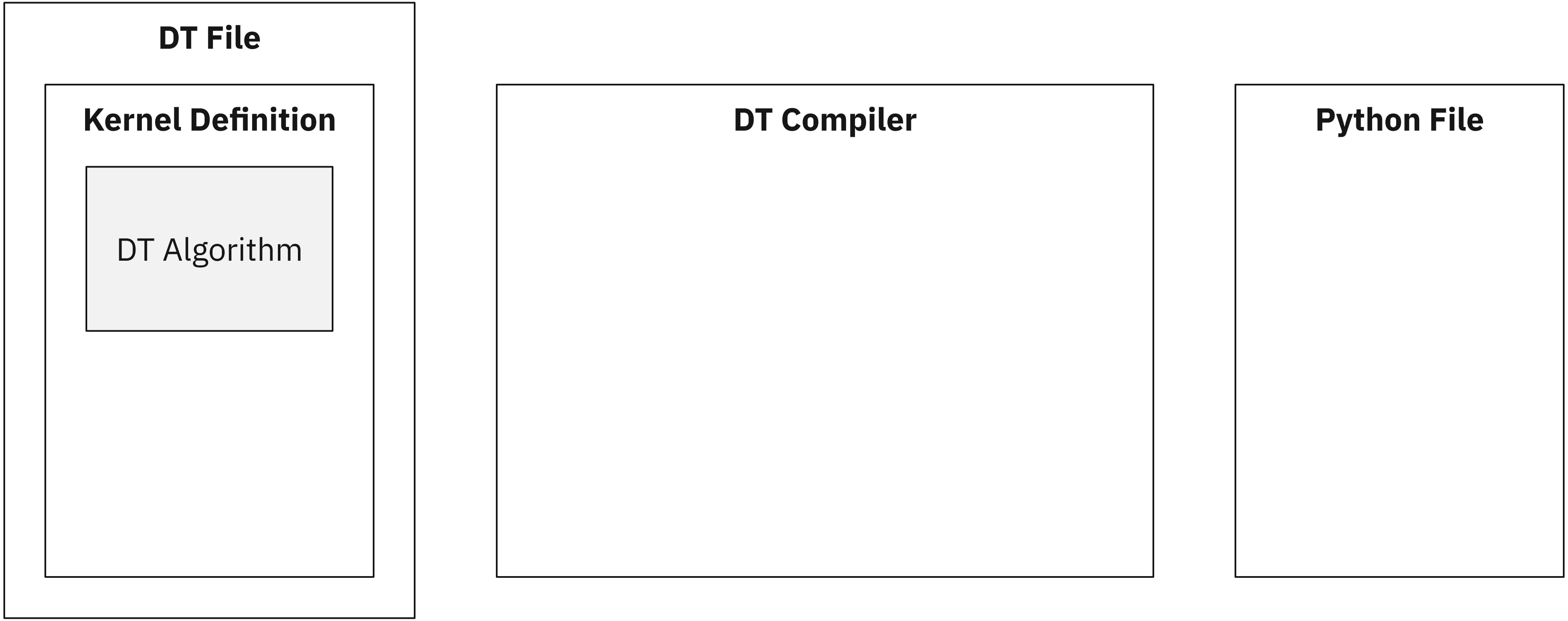
DT Compiler

Python File

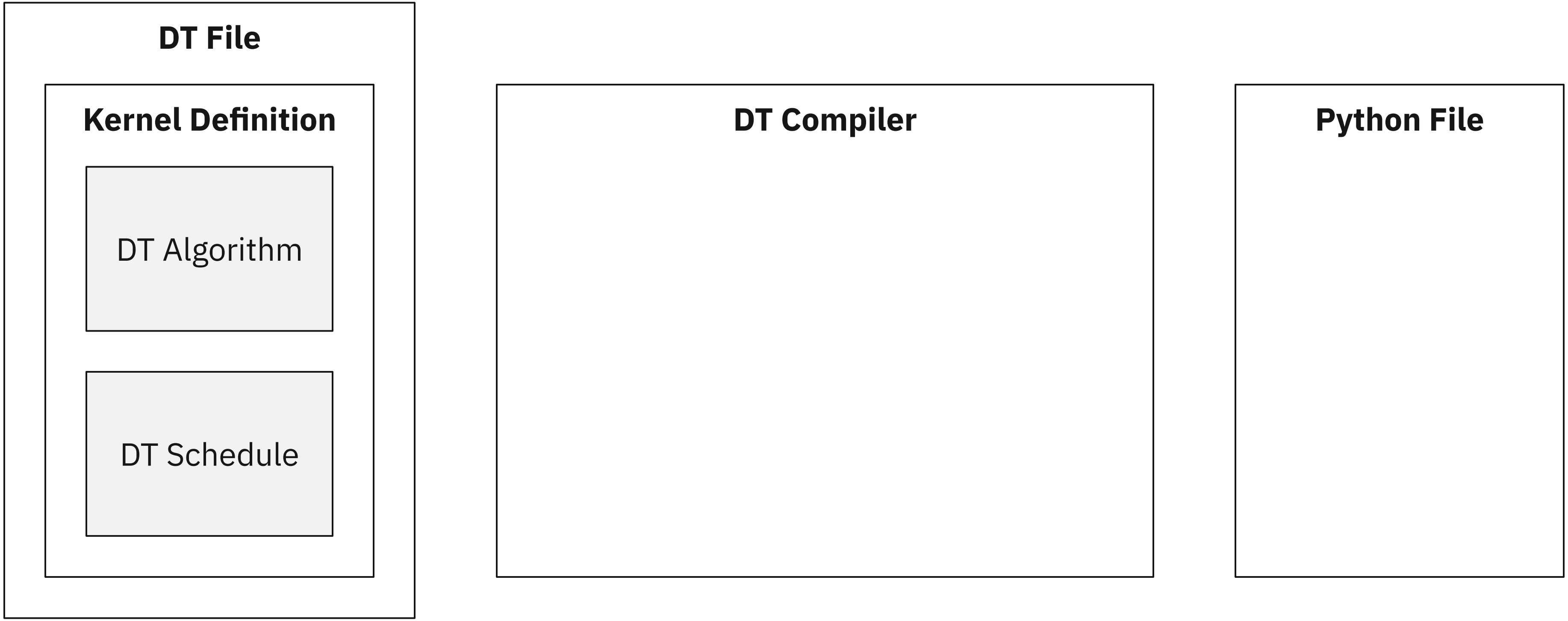
Decoupled Triton



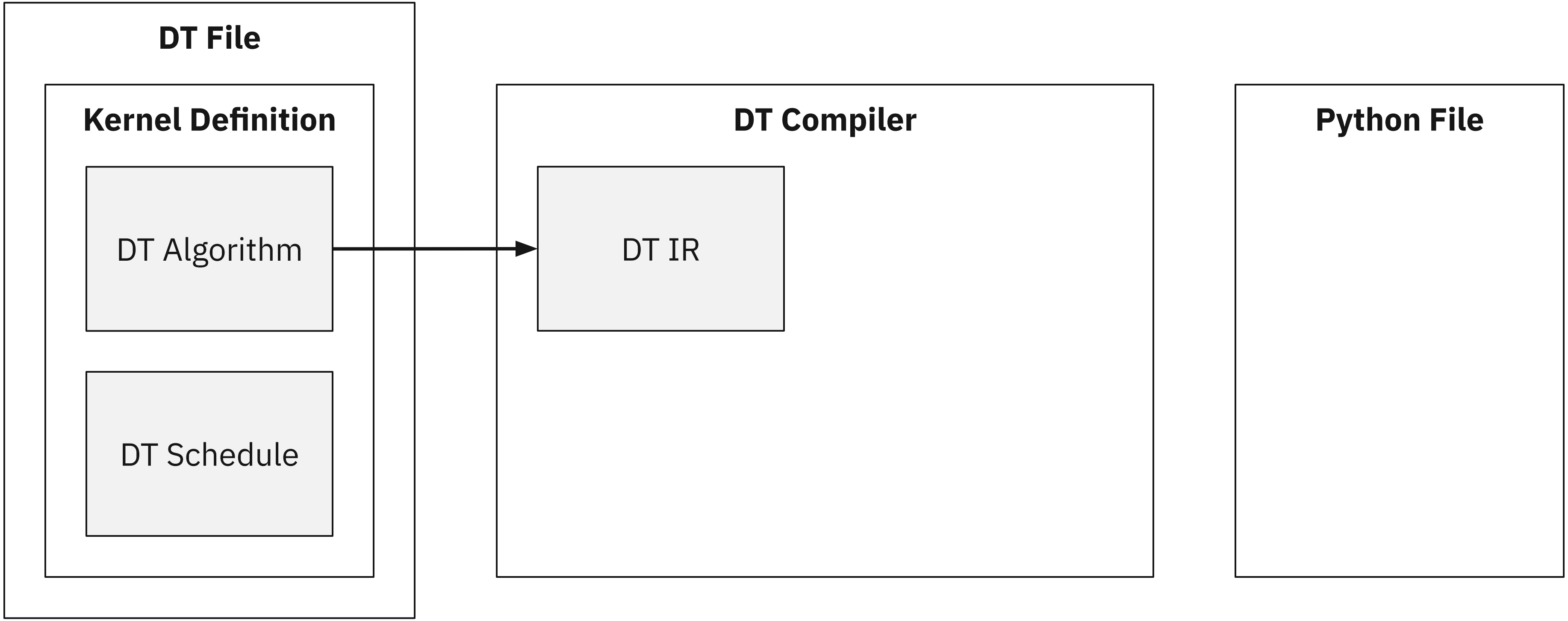
Decoupled Triton



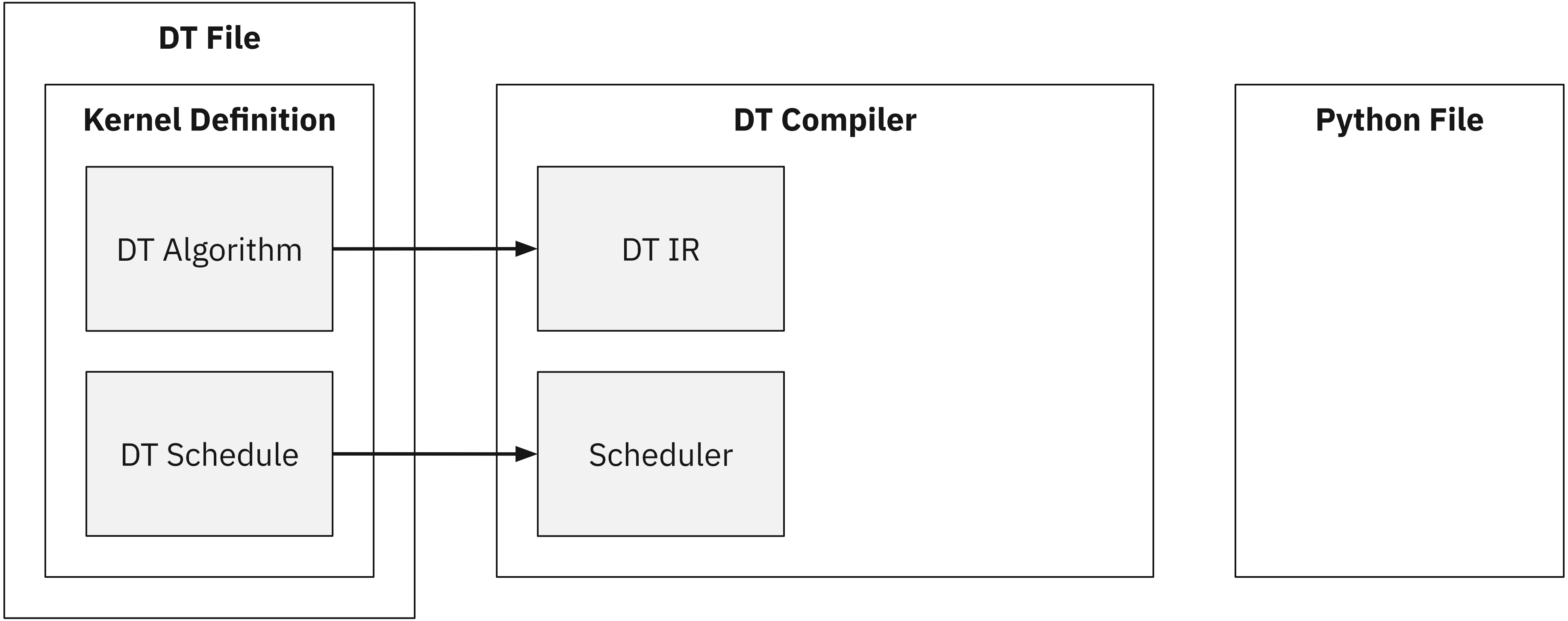
Decoupled Triton



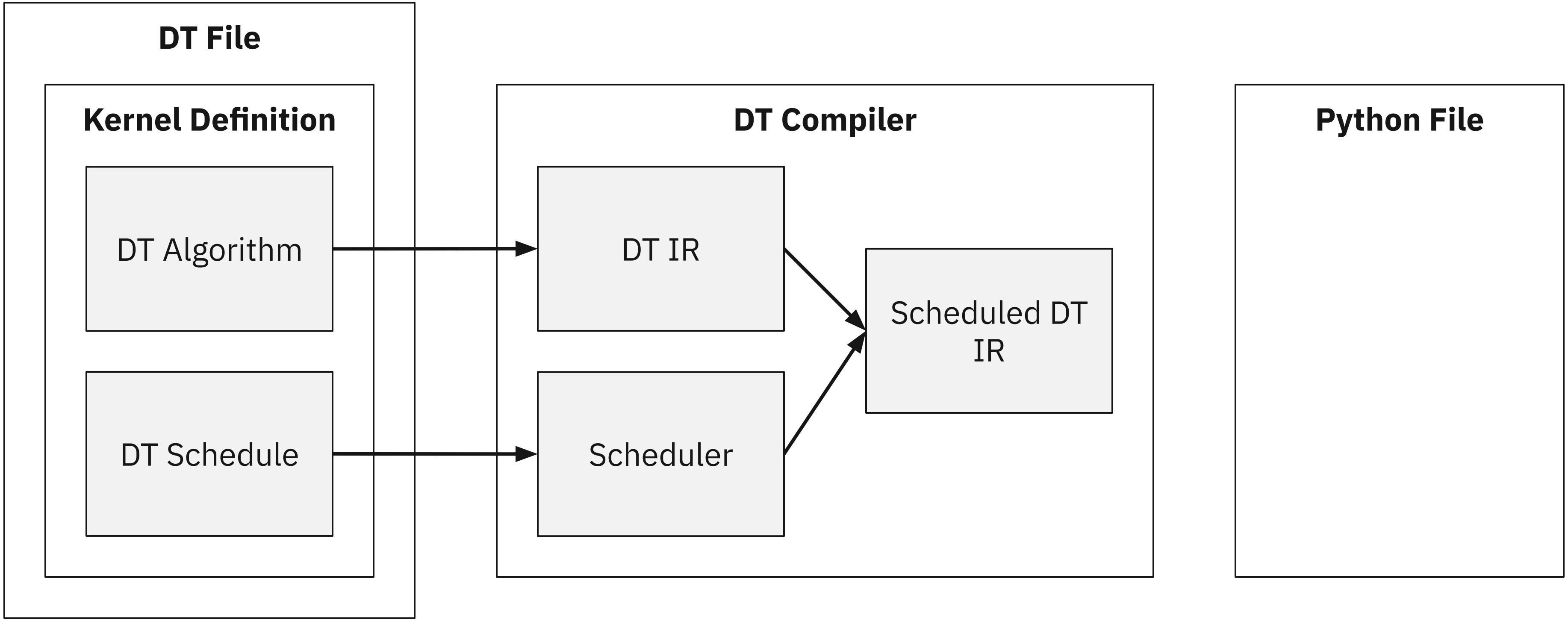
Decoupled Triton



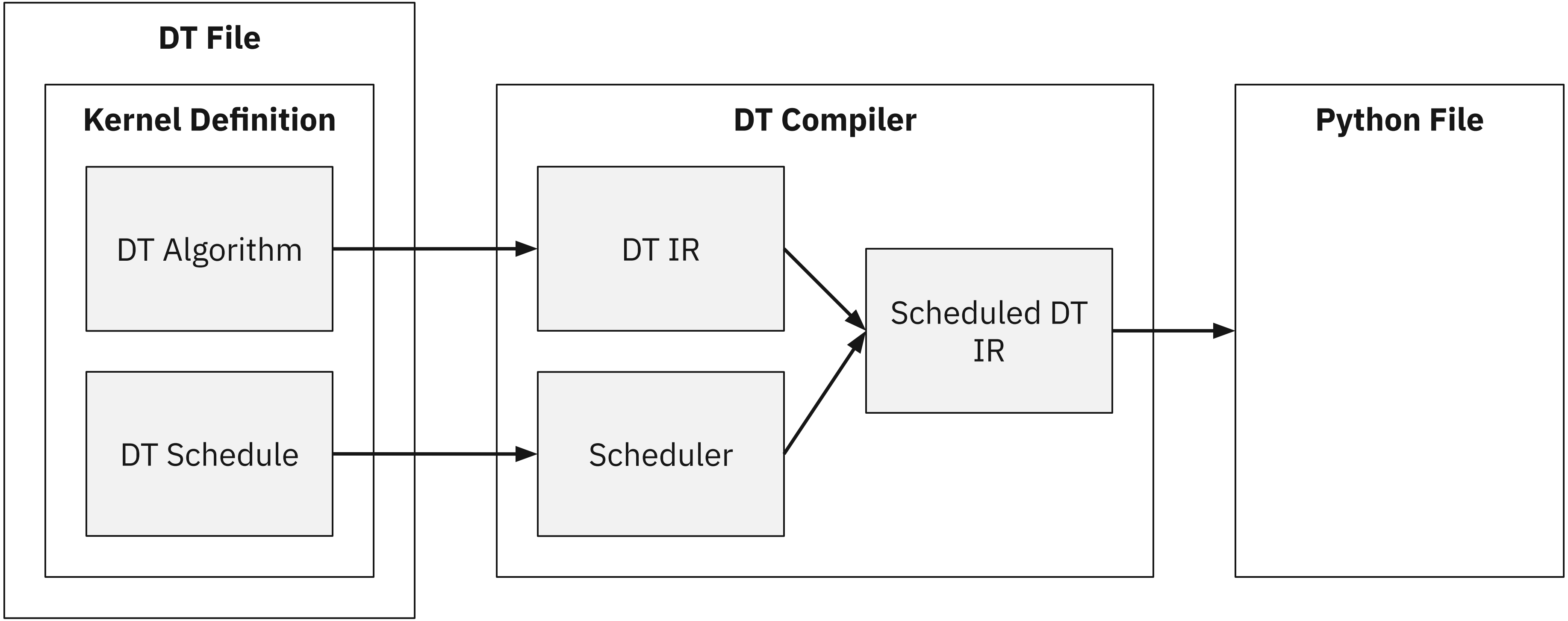
Decoupled Triton



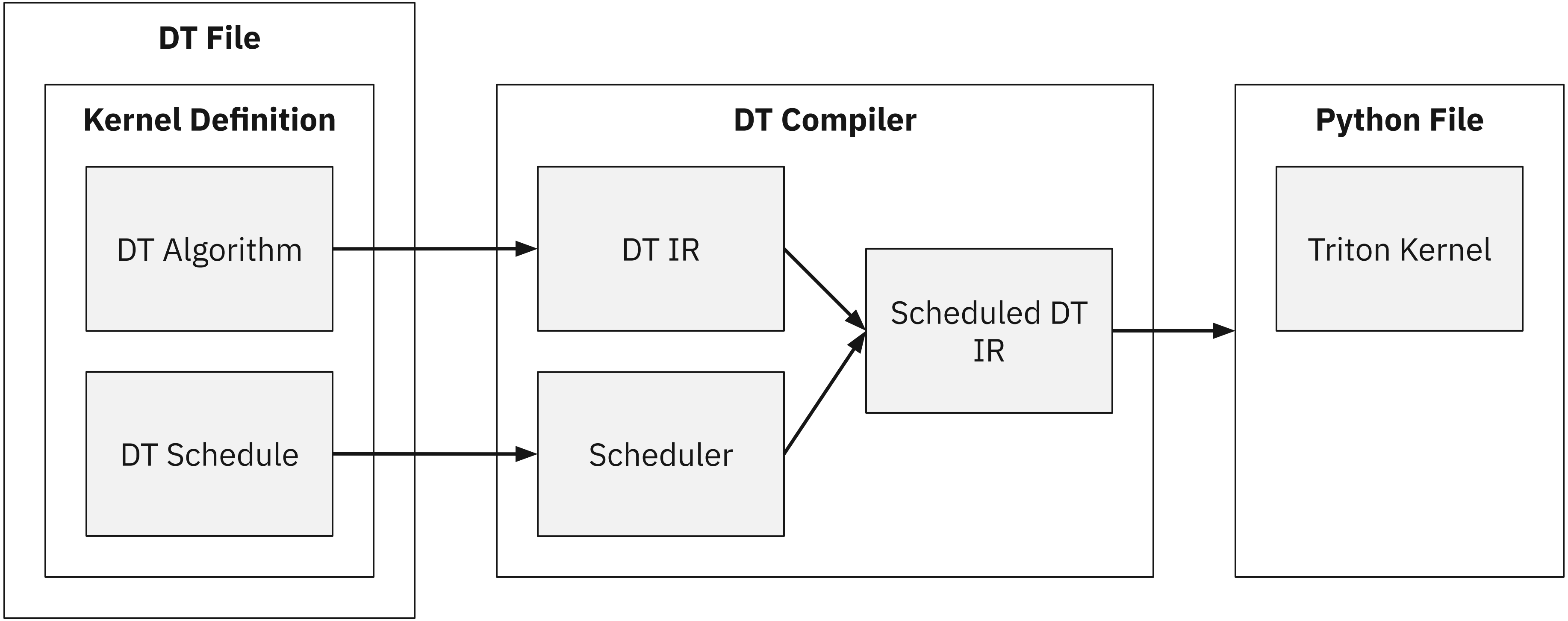
Decoupled Triton



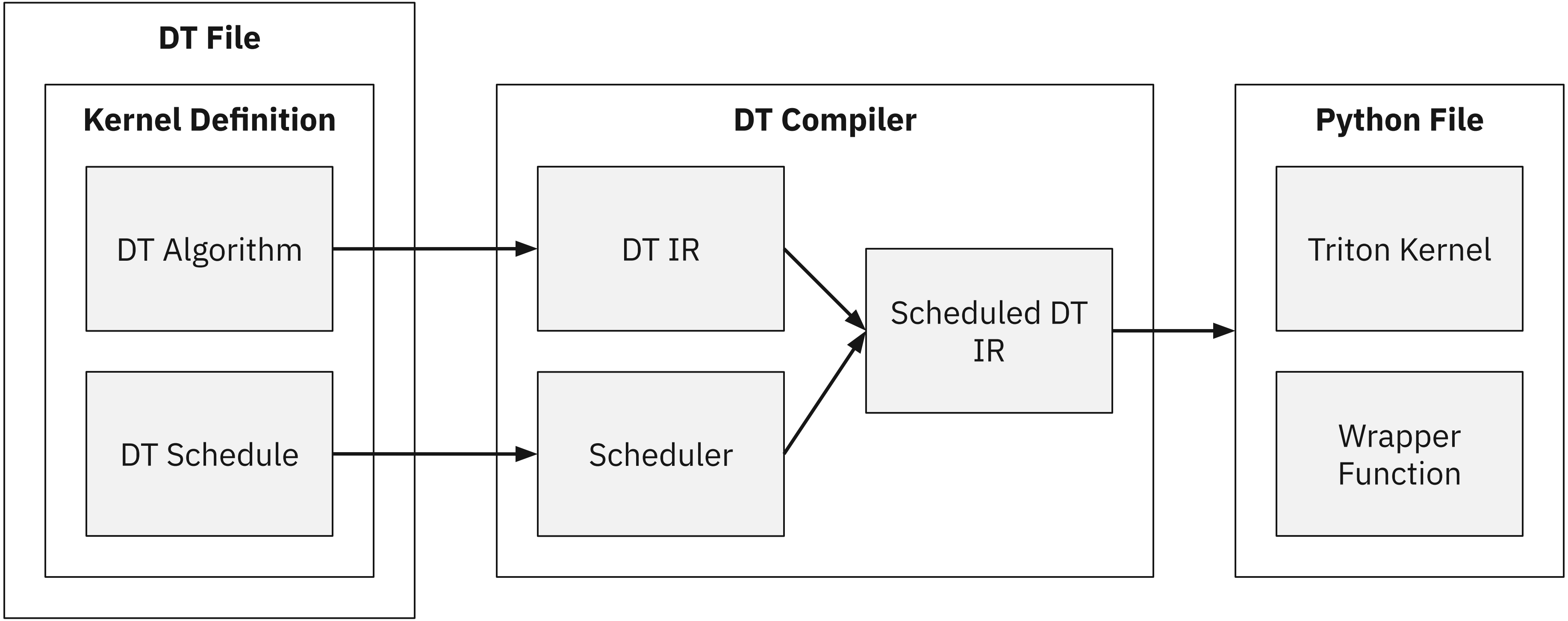
Decoupled Triton



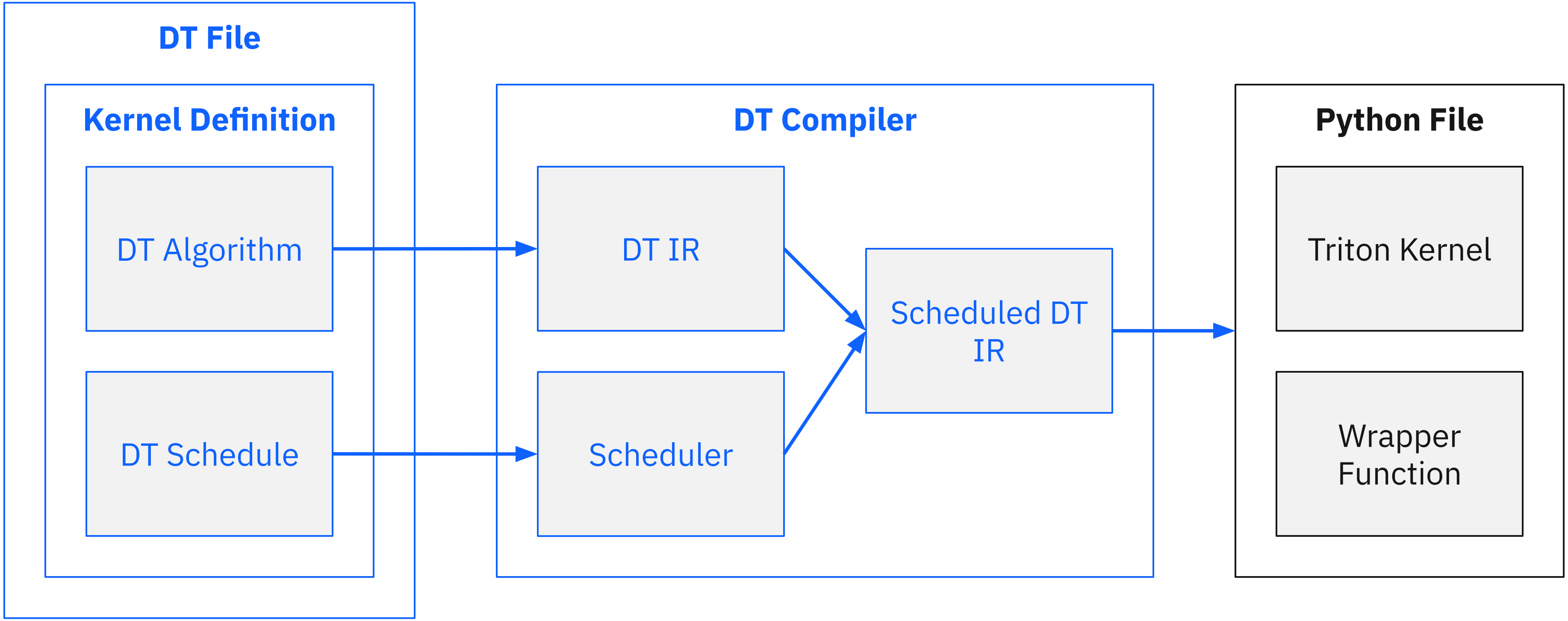
Decoupled Triton



Decoupled Triton

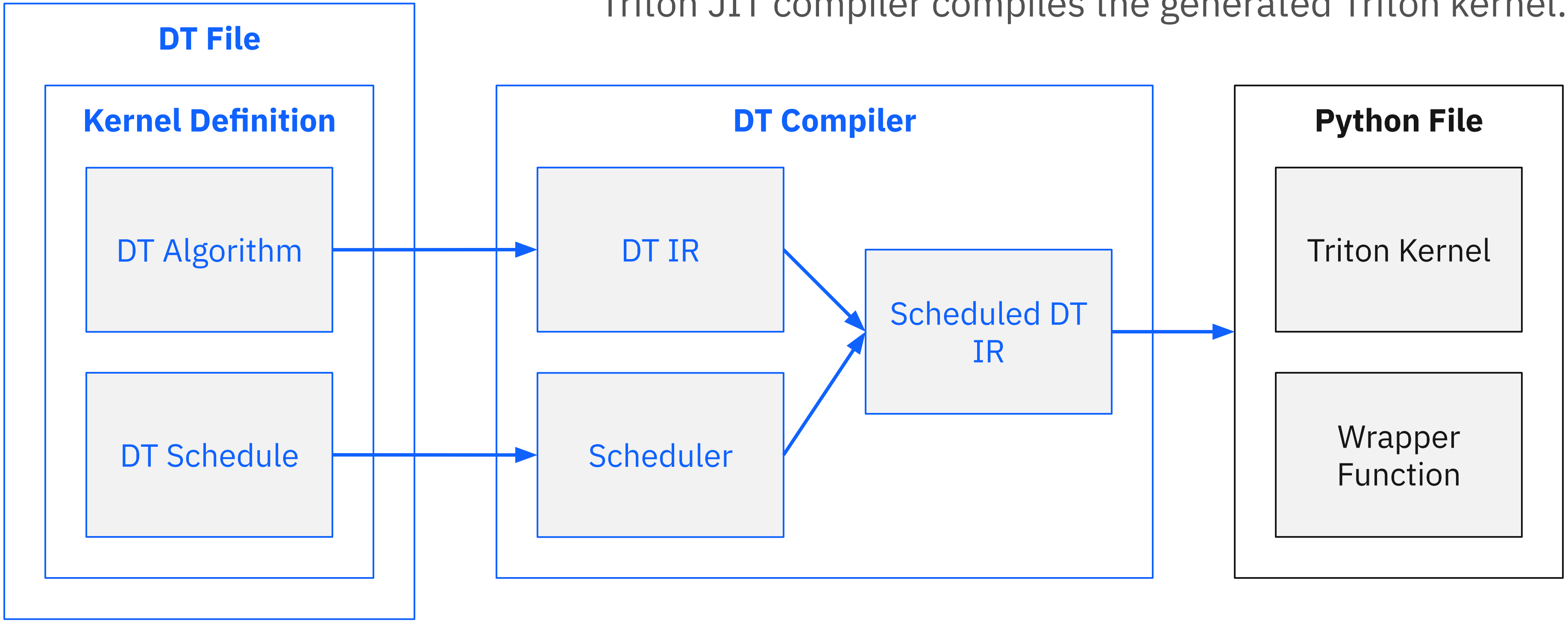


Decoupled Triton

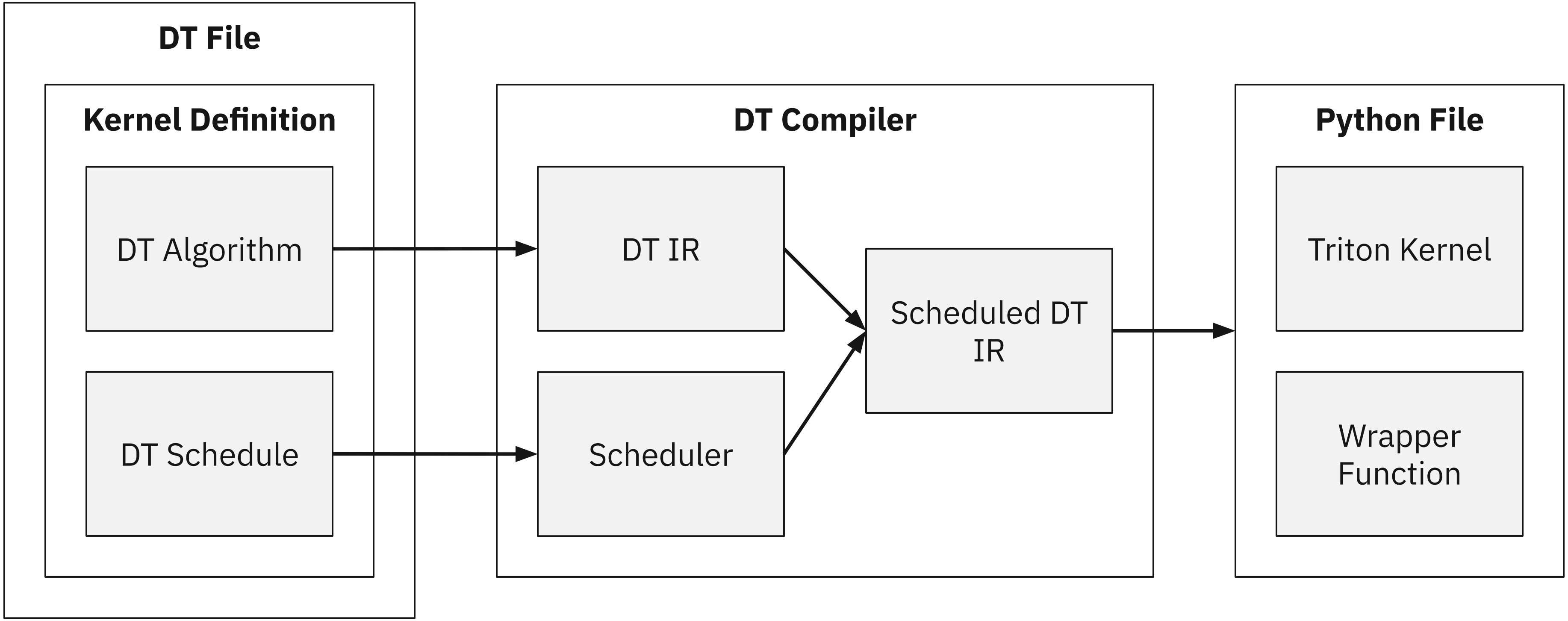


Decoupled Triton

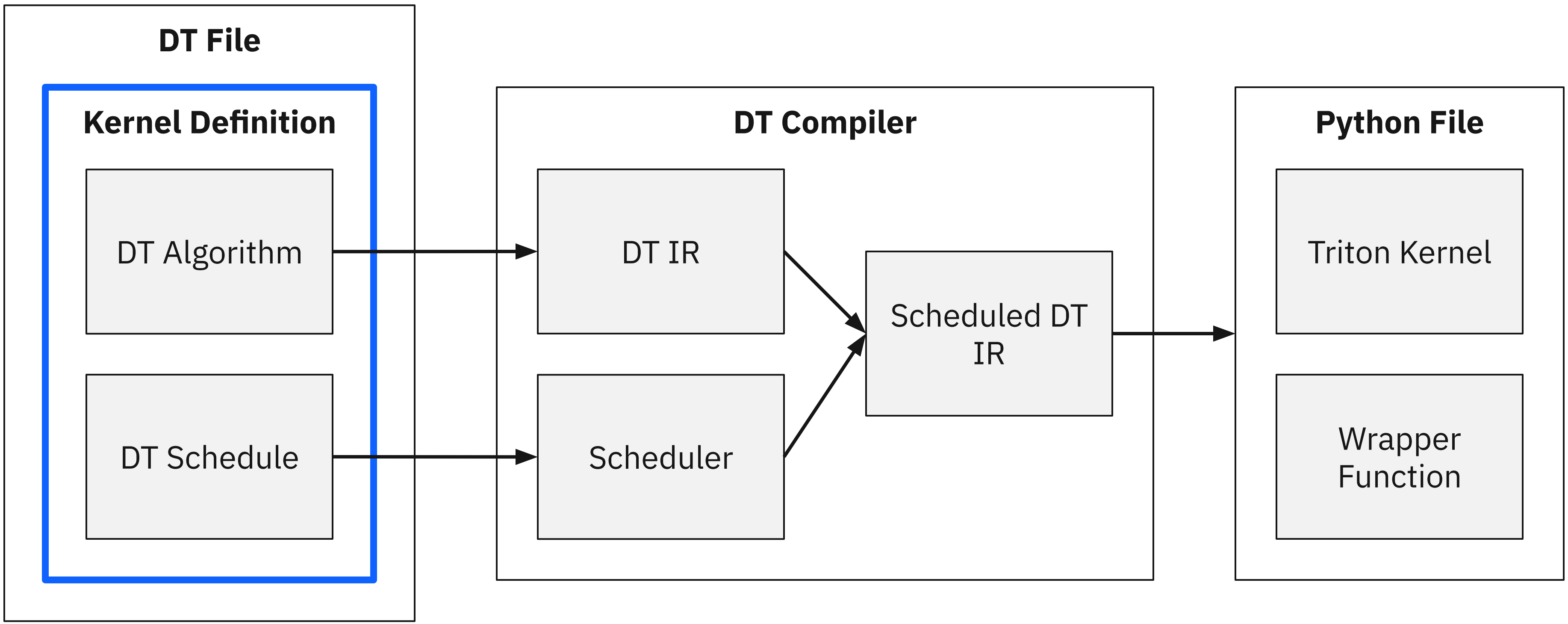
Triton JIT compiler compiles the generated Triton kernel.



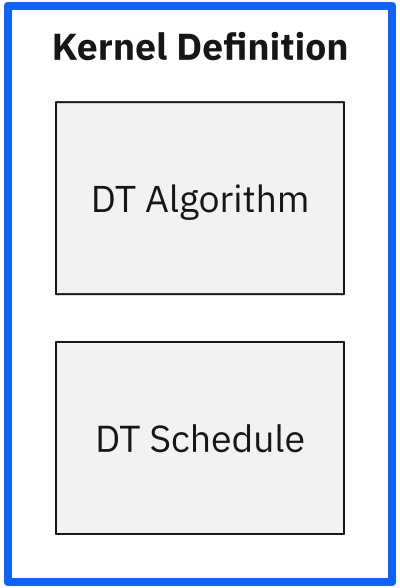
Decoupled Triton



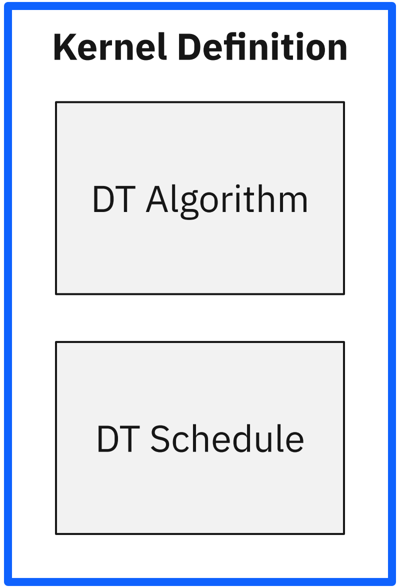
Decoupled Triton



Scaled vector addition kernel definition in DT



Scaled vector addition kernel definition in DT

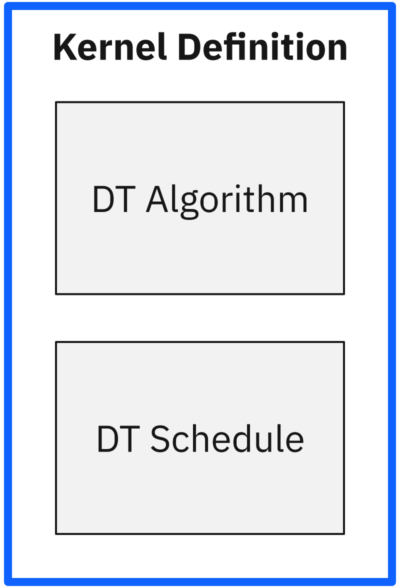



```
# Declarations
Func add_out; # Tensor function to be defined
In   A, B;    # Input tensors
SIn  alpha;   # Input scalar
Var  x, y;    # Dimensions labels

# Algorithm
add_out[x, y] = alpha * (A[x, y] + B[x, y]);

# Schedule
add_out.block(x:1, y:256);
add_out.tensorize(y:64);
add_out.compile();
```

Scaled vector addition kernel definition in DT




```
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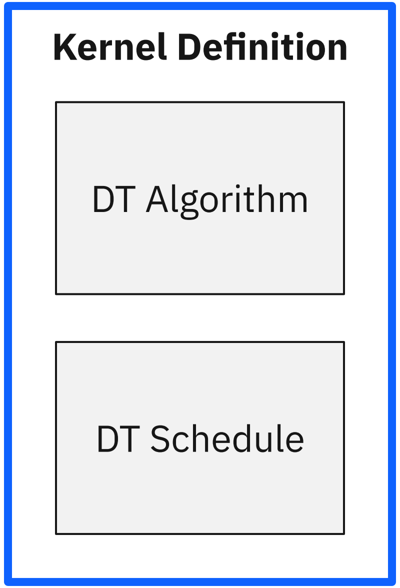
SIn  alpha;   # Input scalar
Var  x, y;    # Dimensions labels

# Algorithm
add_out[x, y] = alpha * (A[x, y] + B[x, y]);

# Schedule
add_out.block(x:1, y:256);
add_out.tensorize(y:64);
add_out.compile();
```

Scaled vector addition kernel definition in DT

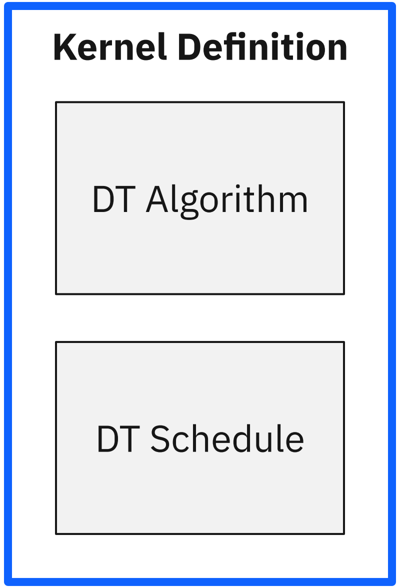



```
# Declarations
Func add_out; # Tensor function to be defined
In   A, B;    # Input tensors
SIn  alpha;   # Input scalar
Var  x, y;    # Dimensions labels

# Algorithm
add_out[x, y] = alpha * (A[x, y] + B[x, y]);

# Schedule
add_out.block(x:1, y:256);
add_out.tensorize(y:64);
add_out.compile();
```

Scaled vector addition kernel definition in DT

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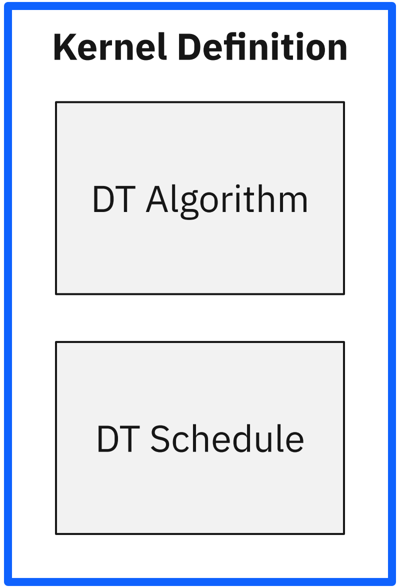


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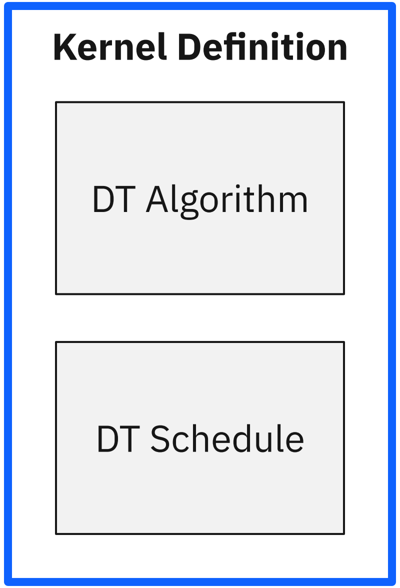


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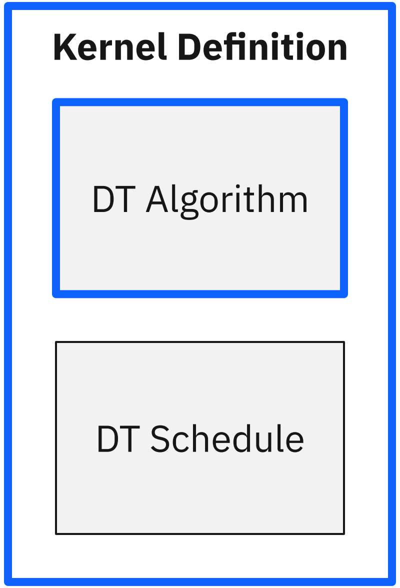


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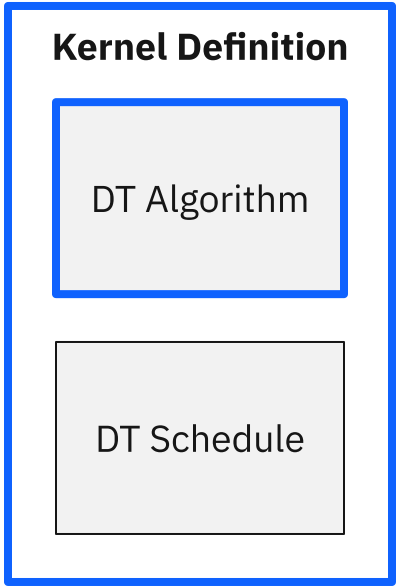


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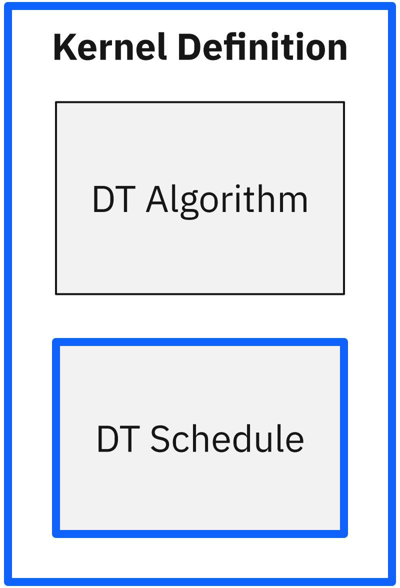
Scaled vector addition kernel definition in DT

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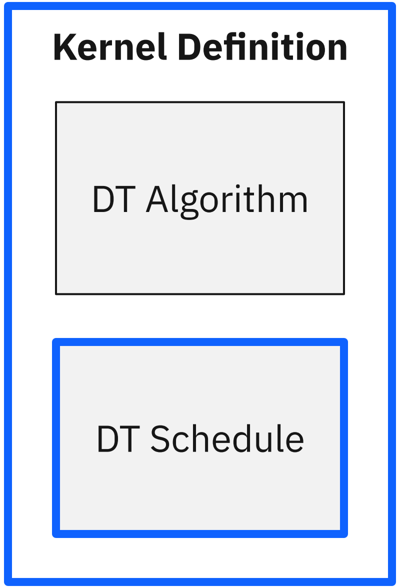
Scaled vector addition kernel definition in DT

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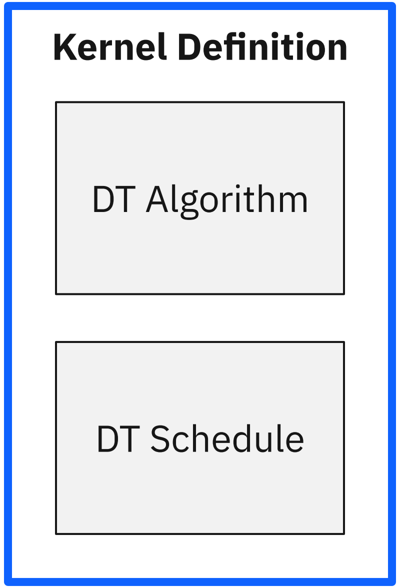
Scaled vector addition kernel definition in DT

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add_out.block(x:1, y:256);
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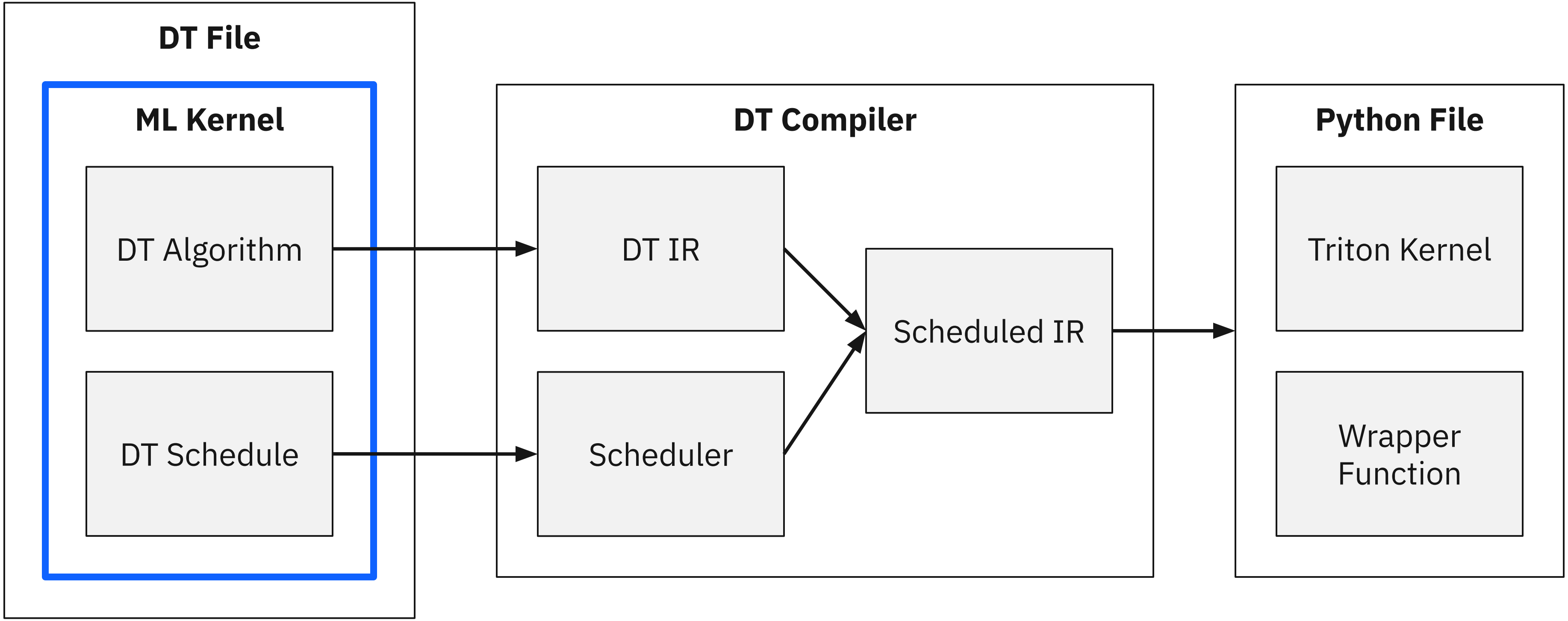
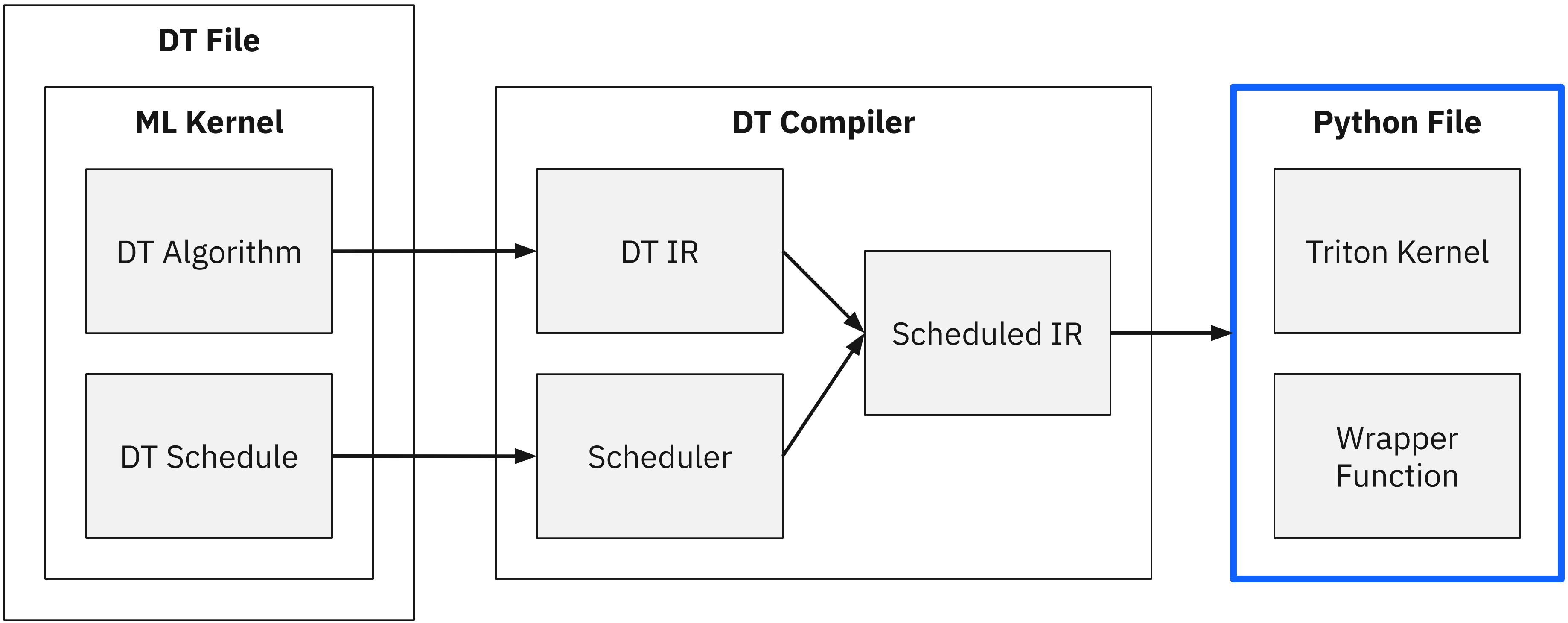
```

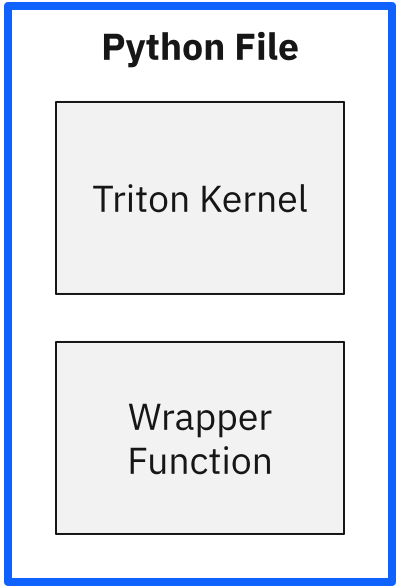
Decoupled Triton



Decoupled Triton



Generated Python file

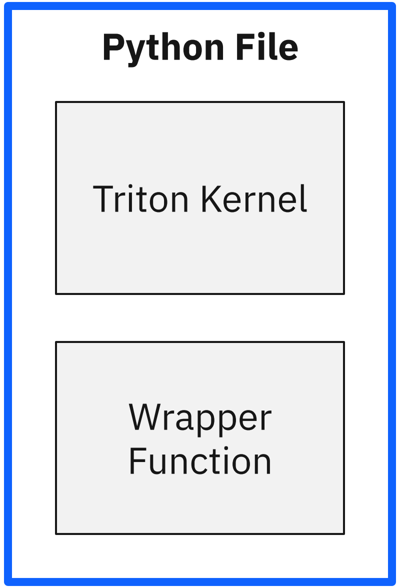


Generated Python file

```
import torch
import triton
import triton.language as tl

@triton.jit
def add_out_kernel(A_ptr, A_x_stride: tl.constexpr, A_y_stride: tl.constexpr, B_ptr,
                   B_x_stride: tl.constexpr, B_y_stride: tl.constexpr, alpha, add_out_ptr,
                   add_out_x_stride: tl.constexpr, add_out_y_stride: tl.constexpr, y_SIZE: tl.constexpr,
                   x_SIZE: tl.constexpr):
  y_BLOCK_COUNT = y_SIZE // 256
  x_BLOCK_COUNT = x_SIZE // 1
  y_pid = tl.program_id(0).to(tl.int64) // x_BLOCK_COUNT % y_BLOCK_COUNT
  x_pid = tl.program_id(0).to(tl.int64) % x_BLOCK_COUNT
  y_block_start = y_pid * 256
  x_block_start = x_pid * 1
  y_arange = tl.arange(0, 64)
  for y_iter in range(0, 256, 64):
    A = tl.load(A_ptr + x_block_start * A_x_stride + (y_block_start + y_iter + y_arange) * A_y_stride)
    B = tl.load(B_ptr + x_block_start * B_x_stride + (y_block_start + y_iter + y_arange) * B_y_stride)
    add_out = alpha * (A + B)
    tl.store(add_out_ptr + x_block_start * add_out_x_stride + (y_block_start + y_iter + y_arange) *
add_out_y_stride, add_out)

def add_out(B, A, alpha, y, x):
  A_x_stride, A_y_stride, = A.stride()
  B_x_stride, B_y_stride, = B.stride()
  add_out = torch.empty(x, y, dtype=torch.float32, device='cuda')
  add_out_x_stride, add_out_y_stride, = add_out.stride()
  add_out_grid = (triton.cdiv(x, 1) * triton.cdiv(y, 256)),
  add_out_kernel[add_out_grid](A, A_x_stride, A_y_stride, B, B_x_stride, B_y_stride, alpha,
                               add_out, add_out_x_stride, add_out_y_stride, y, x, num_stages=3, num_warps=4)
  return add_out
```



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import torch
import triton
import triton.language as tl

@triton.jit
def add_out_kernel(A_ptr, A_x_stride: tl.constexpr, A_y_stride: tl.constexpr, B_ptr,
                   B_x_stride: tl.constexpr, B_y_stride: tl.constexpr, alpha, add_out_ptr,
                   add_out_x_stride: tl.constexpr, add_out_y_stride: tl.constexpr, y_SIZE: tl.constexpr,
                   x_SIZE: tl.constexpr):
  y_BLOCK_COUNT = y_SIZE // 256
  x_BLOCK_COUNT = x_SIZE // 1
  y_pid = tl.program_id(0).to(tl.int64) // x_BLOCK_COUNT % y_BLOCK_COUNT
  x_pid = tl.program_id(0).to(tl.int64) % x_BLOCK_COUNT
  y_block_start = y_pid * 256
  x_block_start = x_pid * 1
  y_arange = tl.arange(0, 64)
  for y_iter in range(0, 256, 64):
    A = tl.load(A_ptr + x_block_start * A_x_stride + (y_block_start + y_iter + y_arange) * A_y_stride)
    B = tl.load(B_ptr + x_block_start * B_x_stride + (y_block_start + y_iter + y_arange) * B_y_stride)
    add_out = alpha * (A + B)
    tl.store(add_out_ptr + x_block_start * add_out_x_stride + (y_block_start + y_iter + y_arange) *
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def add_out(B, A, alpha, y, x):
  A_x_stride, A_y_stride, = A.stride()
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  add_out = torch.empty(x, y, dtype=torch.float32, device='cuda')
  add_out_x_stride, add_out_y_stride, = add_out.stride()
  add_out_grid = (triton.cdiv(x, 1) * triton.cdiv(y, 256)),
  add_out_kernel[add_out_grid](A, A_x_stride, A_y_stride, B, B_x_stride, B_y_stride, alpha,
                               add_out, add_out_x_stride, add_out_y_stride, y, x, num_stages=3, num_warps=4)
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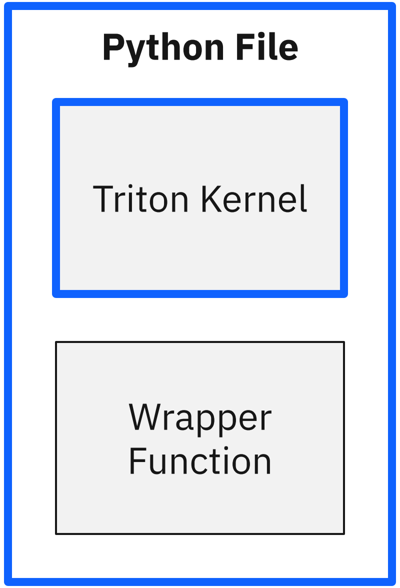

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                   add_out_x_stride: tl.constexpr, add_out_y_stride: tl.constexpr, y_SIZE: tl.constexpr,
                   x_SIZE: tl.constexpr):
  y_BLOCK_COUNT = y_SIZE // 256
  x_BLOCK_COUNT = x_SIZE // 1
  y_pid = tl.program_id(0).to(tl.int64) // x_BLOCK_COUNT % y_BLOCK_COUNT
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  y_block_start = y_pid * 256
  x_block_start = x_pid * 1
  y_arange = tl.arange(0, 64)
  for y_iter in range(0, 256, 64):
    A = tl.load(A_ptr + x_block_start * A_x_stride + (y_block_start + y_iter + y_arange) * A_y_stride)
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  add_out = torch.empty(x, y, dtype=torch.float32, device='cuda')
  add_out_x_stride, add_out_y_stride, = add_out.stride()
  add_out_grid = (triton.cdiv(x, 1) * triton.cdiv(y, 256)),
  add_out_kernel[add_out_grid](A, A_x_stride, A_y_stride, B, B_x_stride, B_y_stride, alpha,
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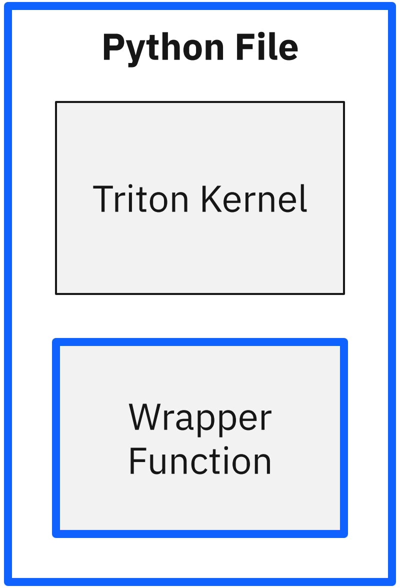

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                   add_out_x_stride: tl.constexpr, add_out_y_stride: tl.constexpr, y_SIZE: tl.constexpr,
                   x_SIZE: tl.constexpr):
  y_BLOCK_COUNT = y_SIZE // 256
  x_BLOCK_COUNT = x_SIZE // 1
  y_pid = tl.program_id(0).to(tl.int64) // x_BLOCK_COUNT % y_BLOCK_COUNT
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  y_block_start = y_pid * 256
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  add_out_kernel[add_out_grid](A, A_x_stride, A_y_stride, B, B_x_stride, B_y_stride, alpha,
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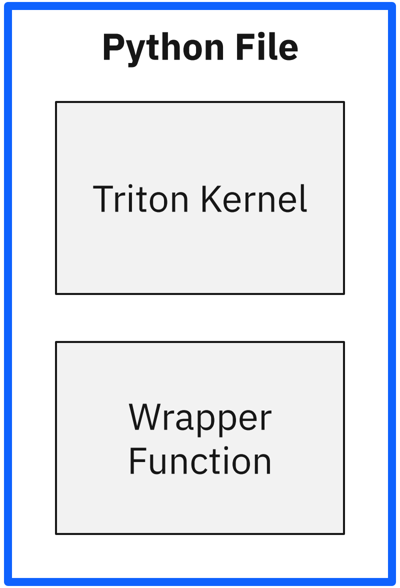
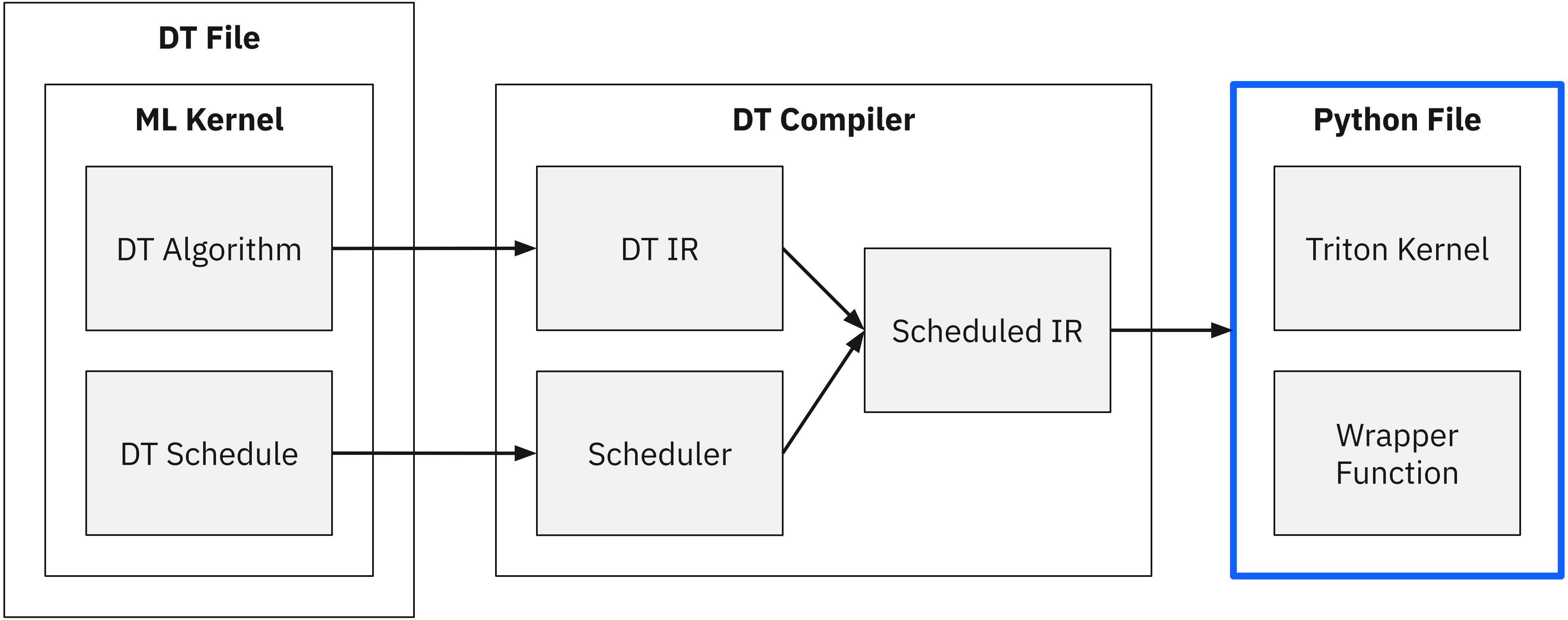
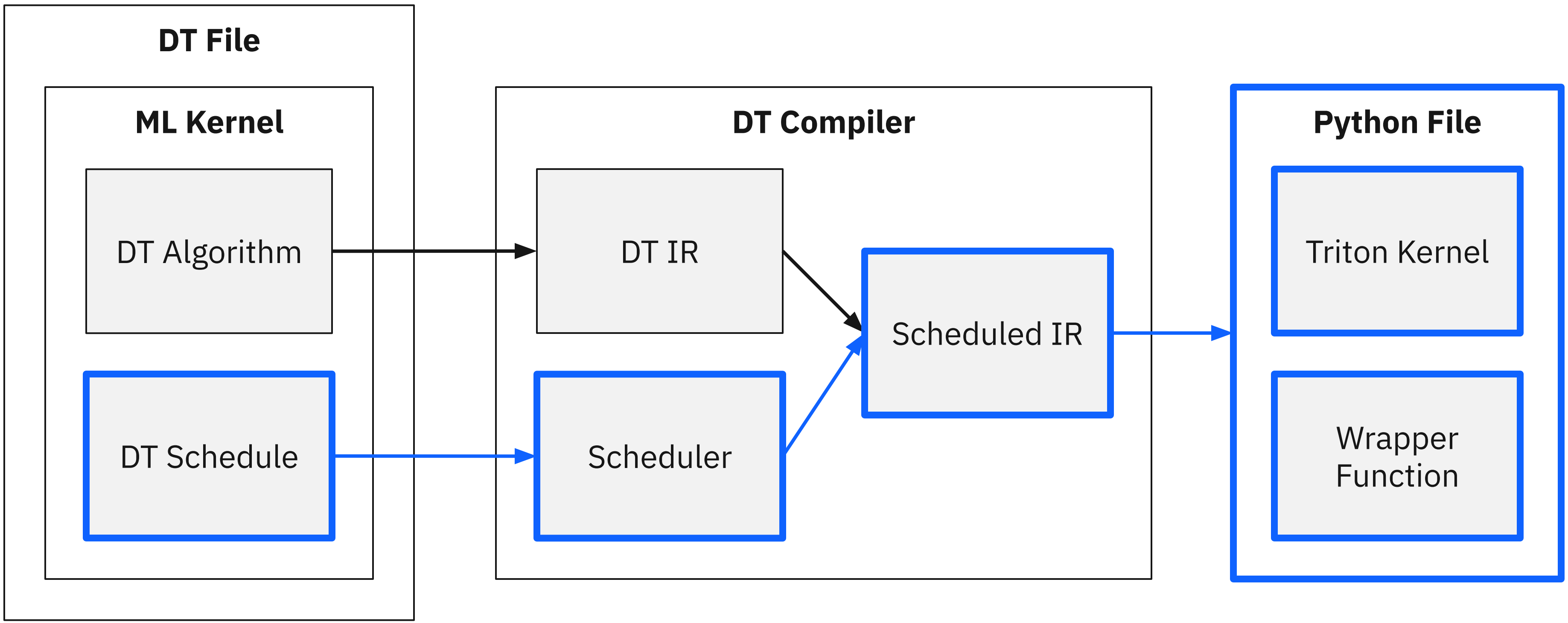
```



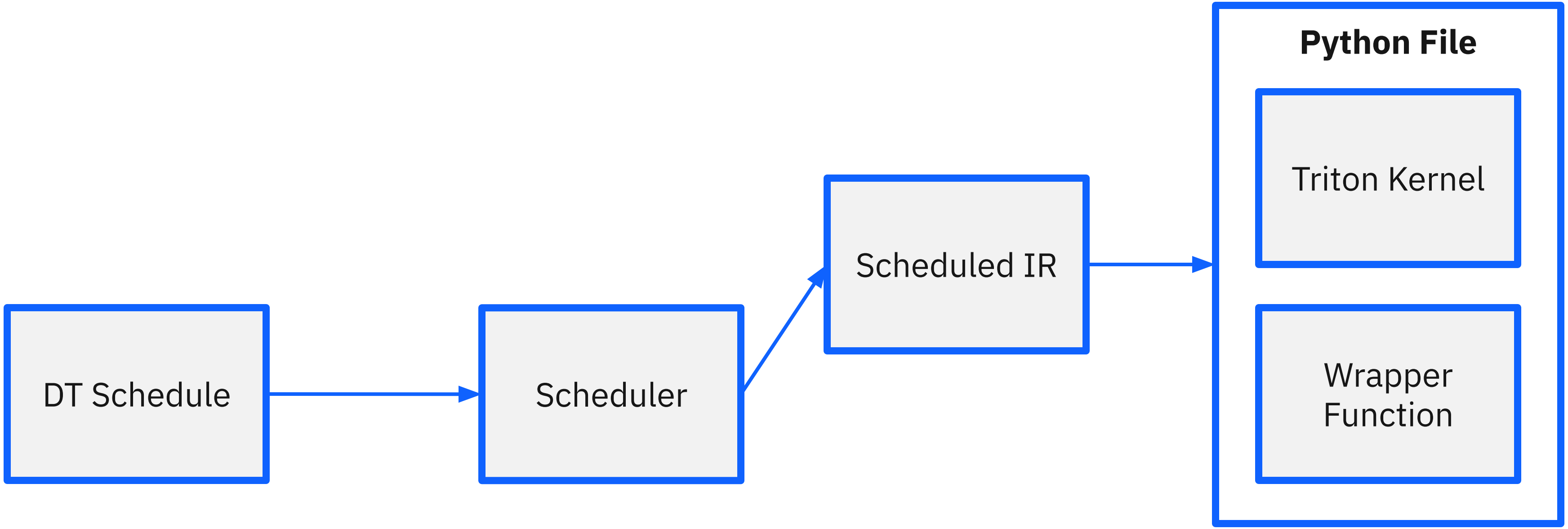
Decoupled Triton



Decoupled Triton



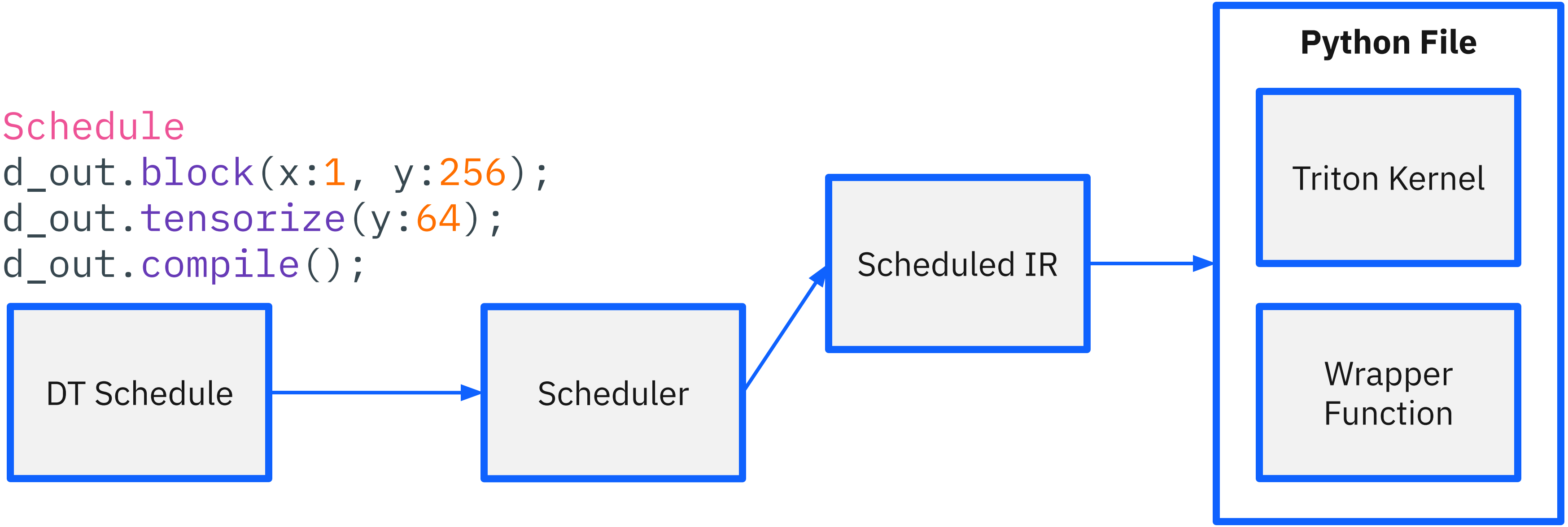
Scheduling



DT Schedule
Scheduler
Scheduled IR
Python File
Triton Kernel
Wrapper Function

Scheduling

```
# Schedule
add_out.block(x:1, y:256);
add_out.tensorize(y:64);
add_out.compile();
```



Scheduling

```
# Schedule
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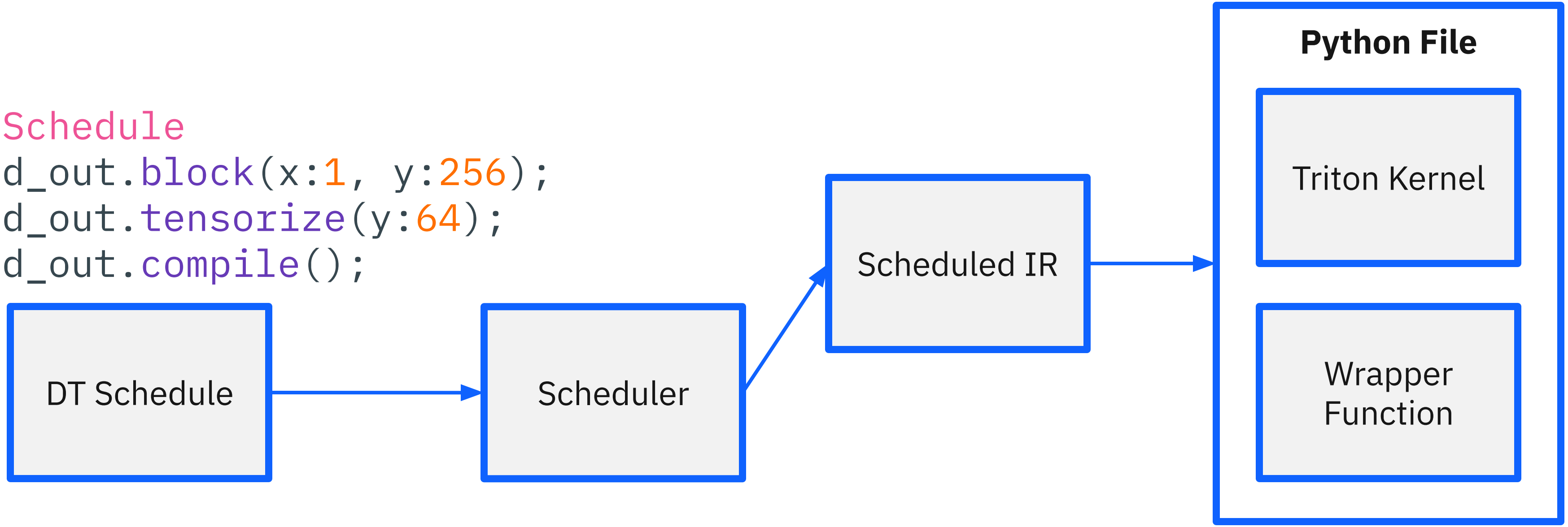

Scheduling primitives transform the kernel's schedule.

Default schedule

Default schedule

```
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In   A, B;
SIn  alpha;
Var  x, y;

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add_out.compile();
```

Default schedule

```
Func add_out;
In   A, B;
SIn  alpha;
Var  x, y;

add_out[x,y] = alpha * (A[x,y] + B[x,y]);

add_out.compile();
```

```
@triton.jit
def add_out_kernel(...):
  for x_iter in range(0, x_SIZE, 1):
    for y_iter in range(0, y_SIZE, 1):
      A = tl.load(A_ptr + x_iter * A_x_stride + y_iter * A_y_stride)
      B = tl.load(B_ptr + x_iter * B_x_stride + y_iter * B_y_stride)
      add_out = alpha * (A + B)
      tl.store(add_out_ptr + x_iter * add_out_x_stride +
                             y_iter * add_out_y_stride, add_out)

def add_out(...):
  ...
  add_out_grid = (1,)
  add_out_kernel[add_out_grid](...)
  ...
```

Default schedule

```
Func add_out;
In   A, B;
SIn  alpha;
Var  x, y;

add_out[x,y] = alpha * (A[x,y] + B[x,y]);

add_out.compile();
```

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      B = tl.load(B_ptr + x_iter * B_x_stride + y_iter * B_y_stride)
      add_out = alpha * (A + B)
      tl.store(add_out_ptr + x_iter * add_out_x_stride +
                             y_iter * add_out_y_stride, add_out)

def add_out(...):
  ...
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```

Default schedule

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Func add_out;
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add_out.compile();
```

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      B = tl.load(B_ptr + x_iter * B_x_stride + y_iter * B_y_stride)
      add_out = alpha * (A + B)
      tl.store(add_out_ptr + x_iter * add_out_x_stride +
                             y_iter * add_out_y_stride, add_out)

def add_out(...):
  ...
  add_out_grid = (1,)
  add_out_kernel[add_out_grid](...)
  ...
```

Default schedule

```
Func add_out;
In   A, B;
SIn  alpha;
Var  x, y;

add_out[x,y] = alpha * (A[x,y] + B[x,y]);

add_out.compile();
```

```
@triton.jit
def add_out_kernel(...):
  for x_iter in range(0, x_SIZE, 1):
    for y_iter in range(0, y_SIZE, 1):
      A = tl.load(A_ptr + x_iter * A_x_stride + y_iter * A_y_stride)
      B = tl.load(B_ptr + x_iter * B_x_stride + y_iter * B_y_stride)
      add_out = alpha * (A + B)
      tl.store(add_out_ptr + x_iter * add_out_x_stride +
                             y_iter * add_out_y_stride, add_out)

def add_out(...):
  ...
  add_out_grid = (1,)
  add_out_kernel[add_out_grid](...)
  ...
```

Default schedule

```
Func add_out;
In   A, B;
SIn  alpha;
Var  x, y;

add_out[x,y] = alpha * (A[x,y] + B[x,y]);

add_out.compile();
```

```
@triton.jit
def add_out_kernel(...):
  for x_iter in range(0, x_SIZE, 1):
    for y_iter in range(0, y_SIZE, 1):
      A = tl.load(A_ptr + x_iter * A_x_stride + y_iter * A_y_stride)
      B = tl.load(B_ptr + x_iter * B_x_stride + y_iter * B_y_stride)
      add_out = alpha * (A + B)
      tl.store(add_out_ptr + x_iter * add_out_x_stride +
                             y_iter * add_out_y_stride, add_out)

def add_out(...):
  ...
  add_out_grid = (1,)
  add_out_kernel[add_out_grid](...)
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Default schedule

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Var  x, y;

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@triton.jit
def add_out_kernel(...):
  for x_iter in range(0, x_SIZE, 1):
    for y_iter in range(0, y_SIZE, 1):
      A = tl.load(A_ptr + x_iter * A_x_stride + y_iter * A_y_stride)
      B = tl.load(B_ptr + x_iter * B_x_stride + y_iter * B_y_stride)
      add_out = alpha * (A + B)
      tl.store(add_out_ptr + x_iter * add_out_x_stride +
                             y_iter * add_out_y_stride, add_out)

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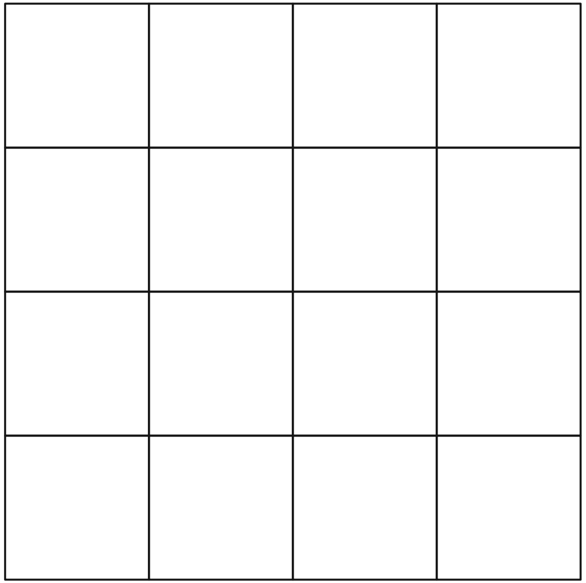

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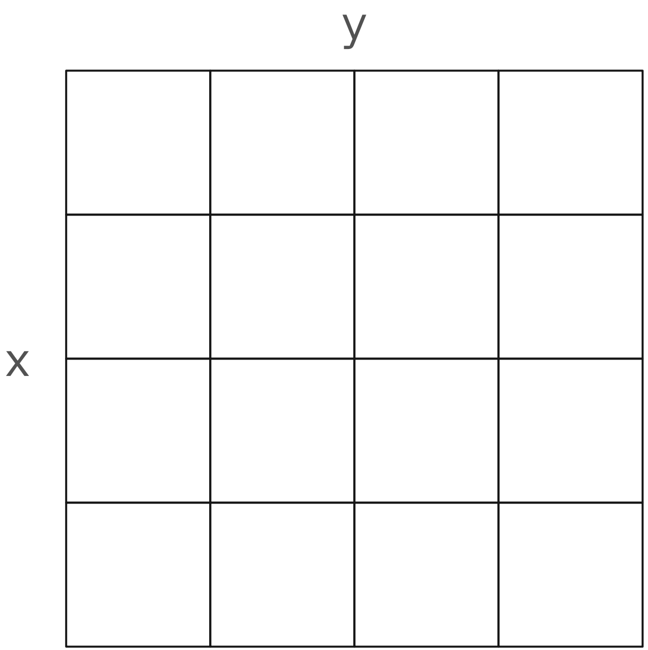

Block

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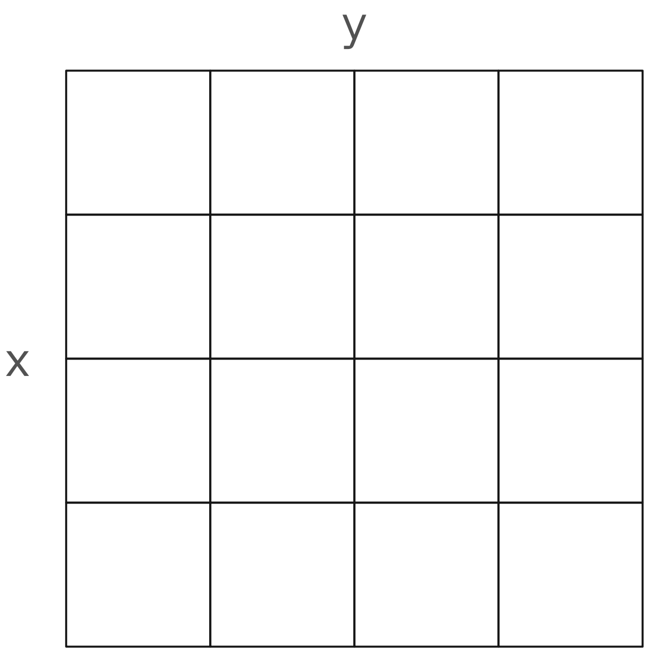
```
out.block(x:1, y:2)
```



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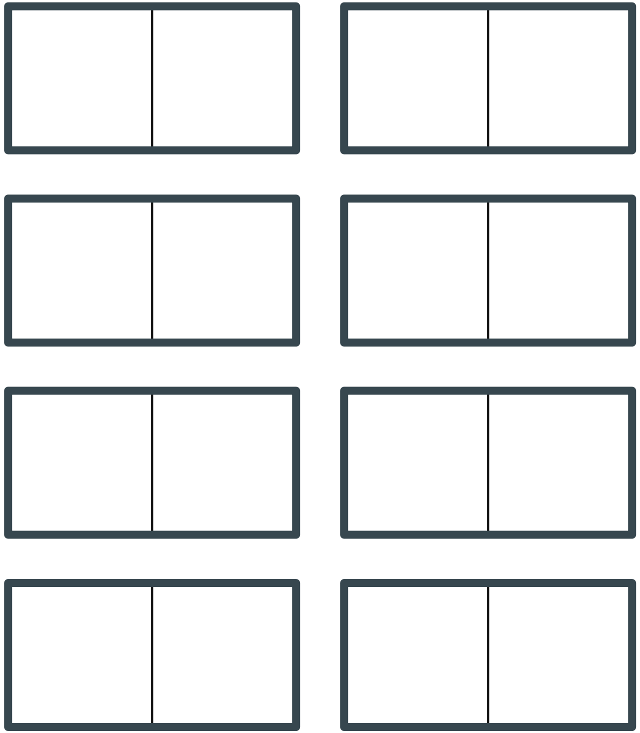

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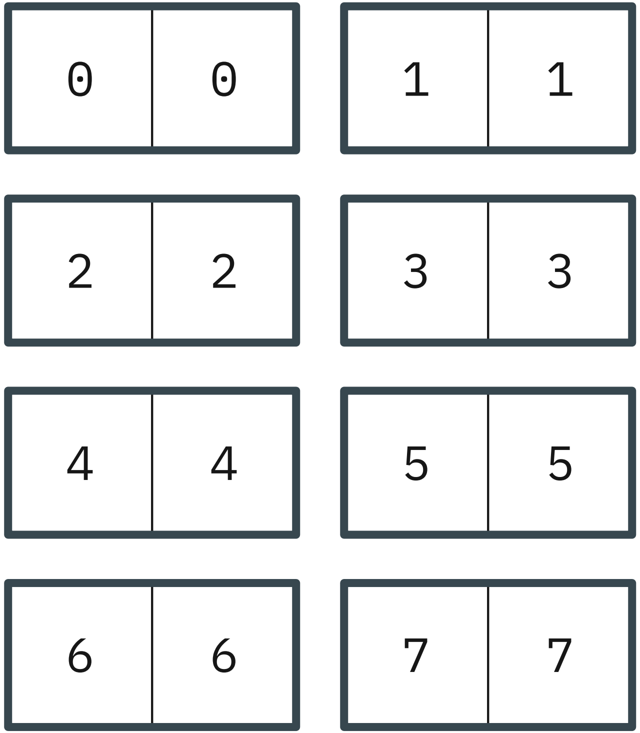

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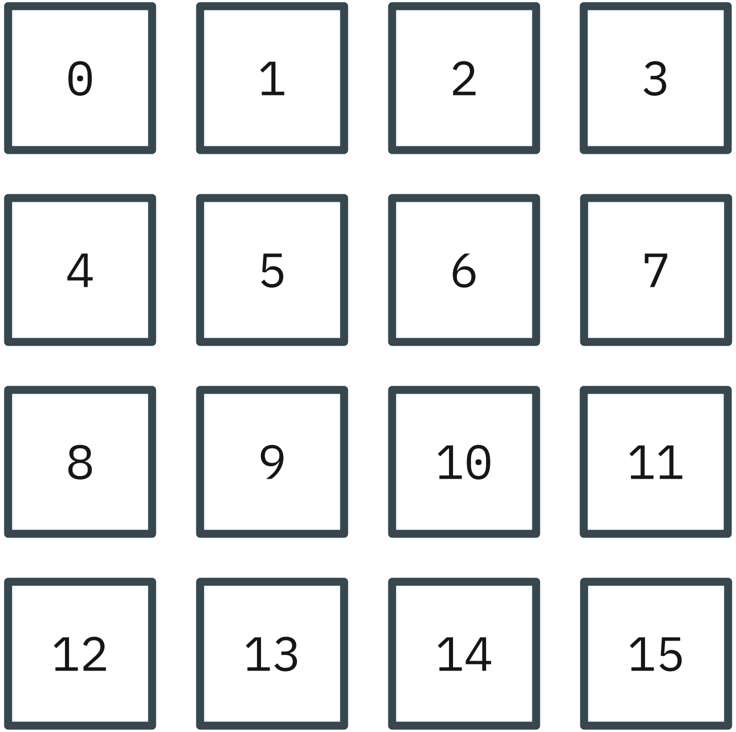

Block

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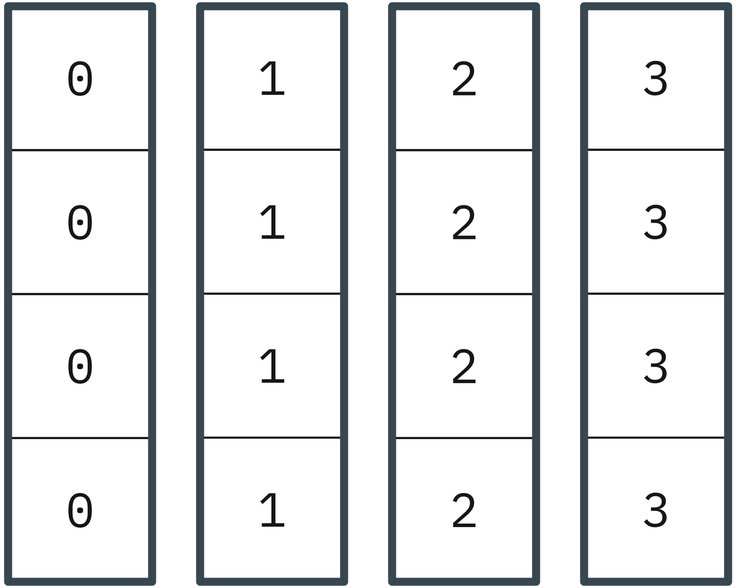
  - Each block is computed by a separate program instance in the kernel launch grid

```
out.block(x:4, y:1)
```



Block

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```
out.block(x:4, y:4)
```

0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0

Block

```
Func add_out;
In   A, B;
SIn  alpha;
Var  x, y;

add_out[x,y] = alpha * (A[x,y] + B[x,y]);

add_out.block(x:4, y:64);
add_out.compile();
```

Block

```
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add_out.block(x:4, y:64);
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```

```
@triton.jit
def add_out_kernel(...):
  y_BLOCK_COUNT = y_SIZE // 64
  x_BLOCK_COUNT = x_SIZE // 4
  y_pid = tl.program_id(0).to(tl.int64) //
          x_BLOCK_COUNT % y_BLOCK_COUNT
  x_pid = tl.program_id(0).to(tl.int64) % x_BLOCK_COUNT
  y_block_start = y_pid * 64
  x_block_start = x_pid * 4
  for x_iter in range(0, 4, 1):
    for y_iter in range(0, 64, 1):
      A = tl.load(A_ptr + (x_block_start + x_iter) * A_x_stride +
                          (y_block_start + y_iter) * A_y_stride)
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      add_out = alpha * (A + B)
      tl.store(add_out_ptr + (x_block_start + x_iter) *
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def add_out(...):
  ...
  add_out_grid = (triton.cdiv(x, 4) * triton.cdiv(y, 64)),
  add_out_kernel[add_out_grid](...)
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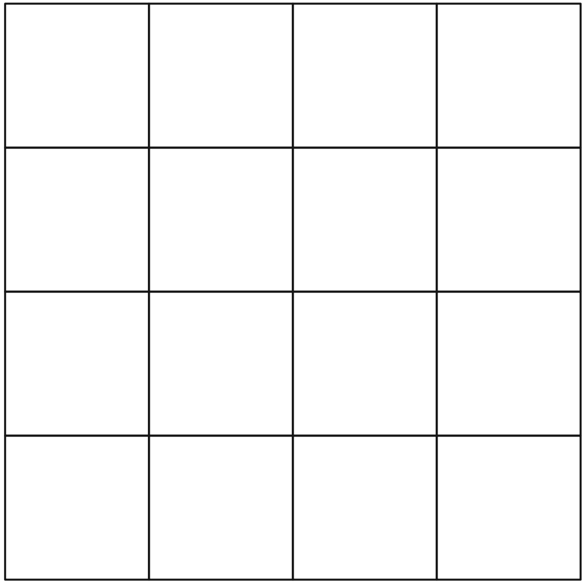

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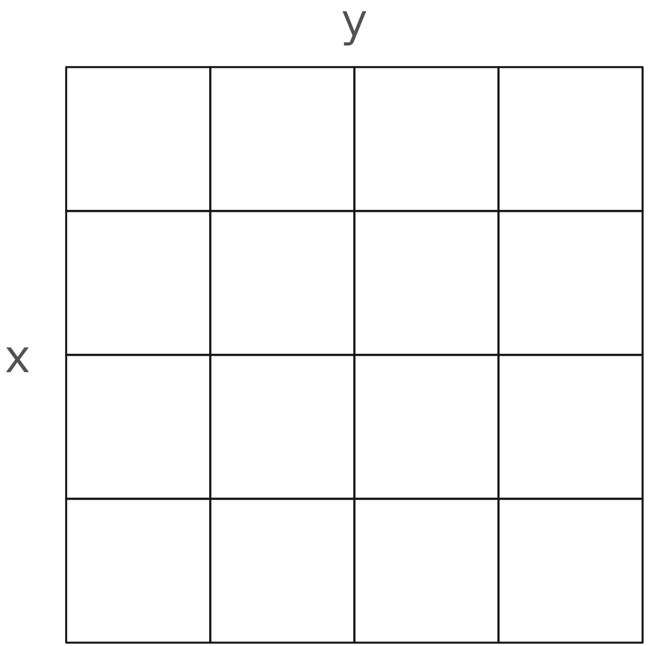

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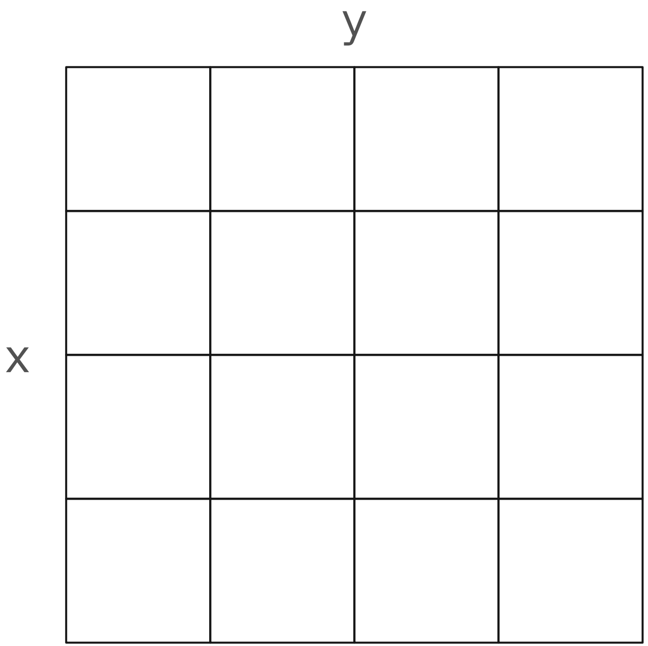
```
out.tensorize(x:2, y:2)
```



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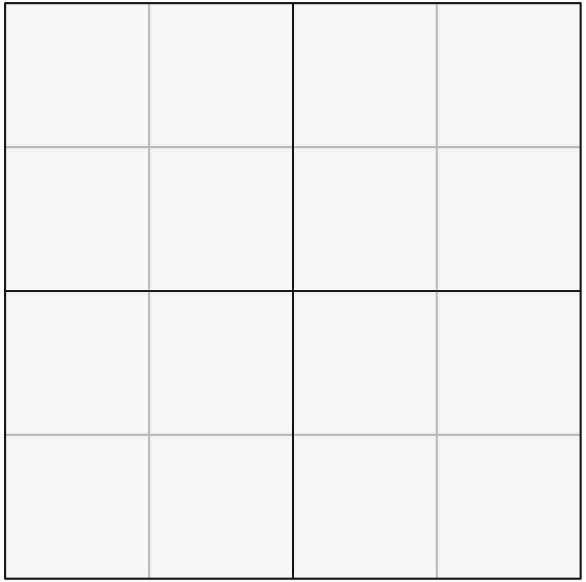

Tensorize

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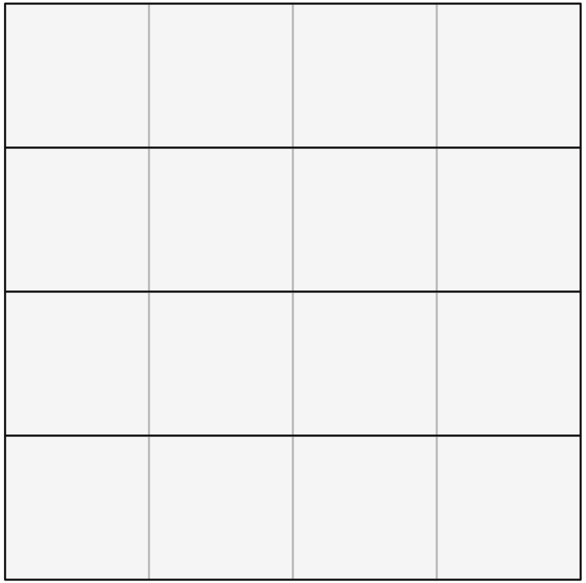
```
out.tensorize(x:1, y:4)
```



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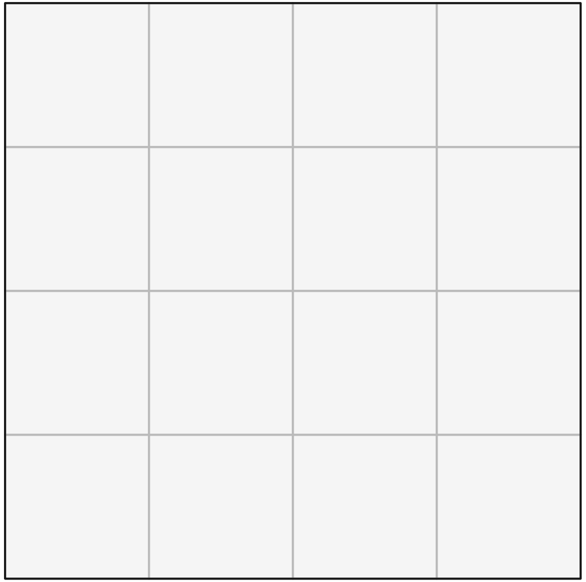

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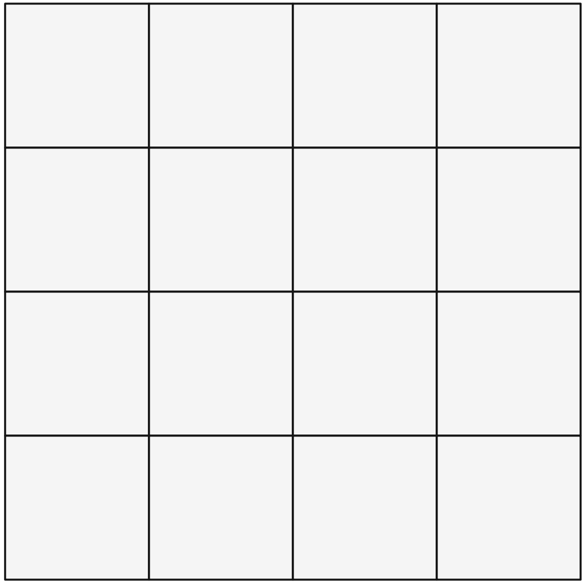

Tensorize

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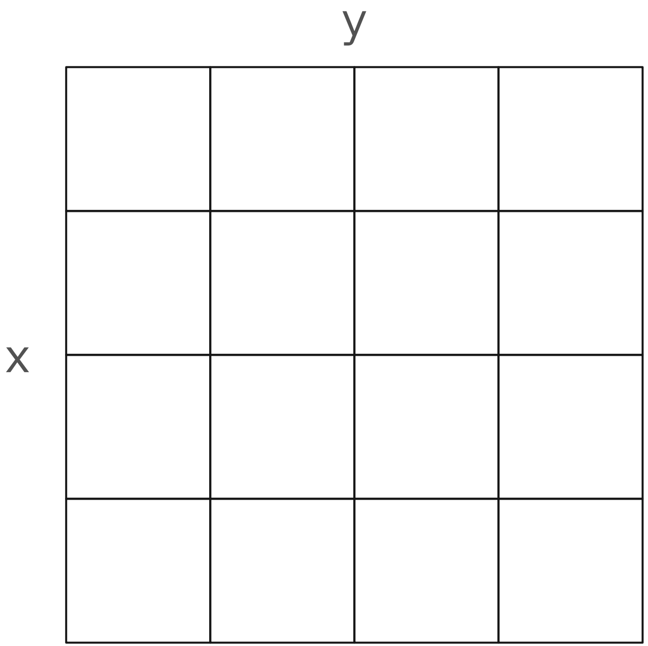
```
out.block(x:2, y:4)
out.tensorize(x:2, y:1)
```



Tensorize

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```
out.block(x:2, y:4)
out.tensorize(x:2, y:1)
```

0	0	0	0
0	0	0	0

1	1	1	1
1	1	1	1

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out.block(x:2, y:4)
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```

0	0	0	0
0	0	0	0

1	1	1	1
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Tensorize

```
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In   A, B;
SIn  alpha;
Var  x, y;

add_out[x,y] = alpha * (A[x,y] + B[x,y]);

add_out.block(x:4, y:64);
add_out.tensorize(x:2, y:64);
add_out.compile();
```

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  x_pid = tl.program_id(0).to(tl.int64) % x_BLOCK_COUNT
  y_block_start = y_pid * 64
  x_block_start = x_pid * 4
  y_arange = tl.arange(0, 64)
  x_arange = tl.arange(0, 2)
  for x_iter in range(0, 4, 2):
    A = tl.load(A_ptr + (x_block_start + x_iter + x_arange[:, None])
                * A_x_stride + (y_block_start + y_arange[None, :])
                * A_y_stride)
    B = tl.load(B_ptr + (x_block_start + x_iter + x_arange[:, None])
                * B_x_stride + (y_block_start + y_arange[None, :])
                * B_y_stride)
    add_out = alpha * (A + B)
    tl.store(add_out_ptr +
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  y_block_start = y_pid * 64
  x_block_start = x_pid * 4
  y_arange = tl.arange(0, 64)
  x_arange = tl.arange(0, 2)
  for x_iter in range(0, 4, 2):
    A = tl.load(A_ptr + (x_block_start + x_iter + x_arange[:, None])
                * A_x_stride + (y_block_start + y_arange[None, :])
                * A_y_stride)
    B = tl.load(B_ptr + (x_block_start + x_iter + x_arange[:, None])
                * B_x_stride + (y_block_start + y_arange[None, :])
                * B_y_stride)
    add_out = alpha * (A + B)
    tl.store(add_out_ptr +
             (x_block_start + x_iter + x_arange[:, None]) *
             add_out_x_stride + (y_block_start + y_arange[None, :]) *
             add_out_y_stride, add_out)

def add_out(...):
  ...
  add_out_grid = (triton.cdiv(x, 4) * triton.cdiv(y, 64)),
  add_out_kernel[add_out_grid](...)
  ...
```

Tensorize

```
Func add_out;
In   A, B;
SIn  alpha;
Var  x, y;

add_out[x,y] = alpha * (A[x,y] + B[x,y]);

add_out.block(x:4, y:64);
add_out.tensorize(x:2, y:64);
add_out.compile();
```

```
@triton.jit
def add_out_kernel(...):
  y_BLOCK_COUNT = y_SIZE // 64
  x_BLOCK_COUNT = x_SIZE // 4
  y_pid = tl.program_id(0).to(tl.int64) //
          x_BLOCK_COUNT % y_BLOCK_COUNT
  x_pid = tl.program_id(0).to(tl.int64) % x_BLOCK_COUNT
  y_block_start = y_pid * 64
  x_block_start = x_pid * 4
  y_arange = tl.arange(0, 64)
  x_arange = tl.arange(0, 2)
  for x_iter in range(0, 4, 2):
    A = tl.load(A_ptr + (x_block_start + x_iter + x_arange[:, None])
                * A_x_stride + (y_block_start + y_arange[None, :])
                * A_y_stride)
    B = tl.load(B_ptr + (x_block_start + x_iter + x_arange[:, None])
                * B_x_stride + (y_block_start + y_arange[None, :])
                * B_y_stride)
    add_out = alpha * (A + B)
    tl.store(add_out_ptr +
             (x_block_start + x_iter + x_arange[:, None]) *
             add_out_x_stride + (y_block_start + y_arange[None, :]) *
             add_out_y_stride, add_out)

def add_out(...):
  ...
  add_out_grid = (triton.cdiv(x, 4) * triton.cdiv(y, 64)),
  add_out_kernel[add_out_grid](...)
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Tensorize

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add_out.tensorize(x:2, y:64);
add_out.compile();
```

```
@triton.jit
def add_out_kernel(...):
  y_BLOCK_COUNT = y_SIZE // 64
  x_BLOCK_COUNT = x_SIZE // 4
  y_pid = tl.program_id(0).to(tl.int64) //
          x_BLOCK_COUNT % y_BLOCK_COUNT
  x_pid = tl.program_id(0).to(tl.int64) % x_BLOCK_COUNT
  y_block_start = y_pid * 64
  x_block_start = x_pid * 4
  y_arange = tl.arange(0, 64)
  x_arange = tl.arange(0, 2)
  for x_iter in range(0, 4, 2):
    A = tl.load(A_ptr + (x_block_start + x_iter + x_arange[:, None])
            * A_x_stride + (y_block_start + y_arange[None, :])
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            * B_y_stride)
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Tensorize

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  y_block_start = y_pid * 64
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              * B_y_stride)
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    tl.store(add_out_ptr +
             (x_block_start + x_iter + x_arange[:, None]) *
             add_out_x_stride + (y_block_start + y_arange[None, :]) *
             add_out_y_stride, add_out)

def add_out(...):
  ...
  add_out_grid = (triton.cdiv(x, 4) * triton.cdiv(y, 64)),
  add_out_kernel[add_out_grid](...)
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```

Map

Map

- Specifies the mapping from program instance in the kernel launch grid to output block.

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  - Requires blocking

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out.block(x:..., y:...)
```

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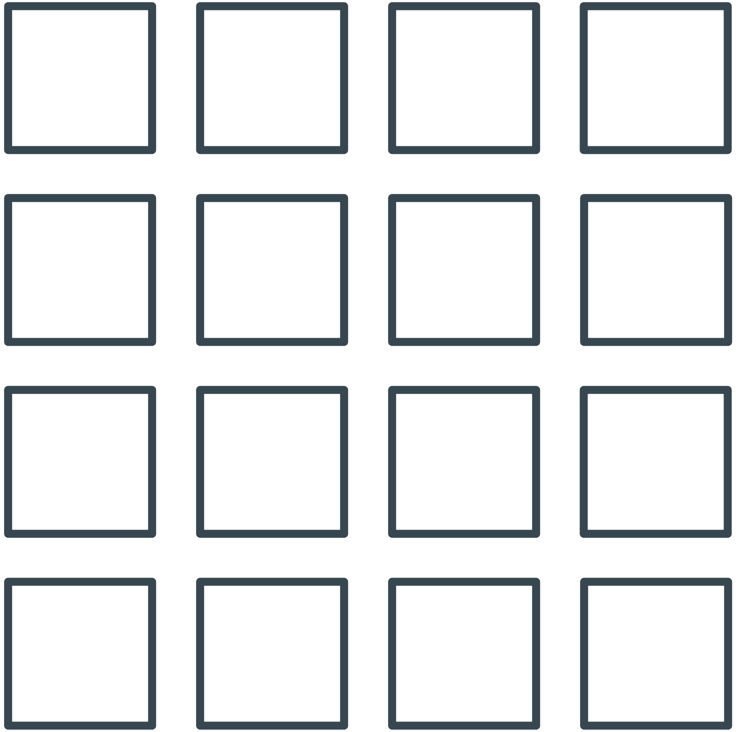

Map

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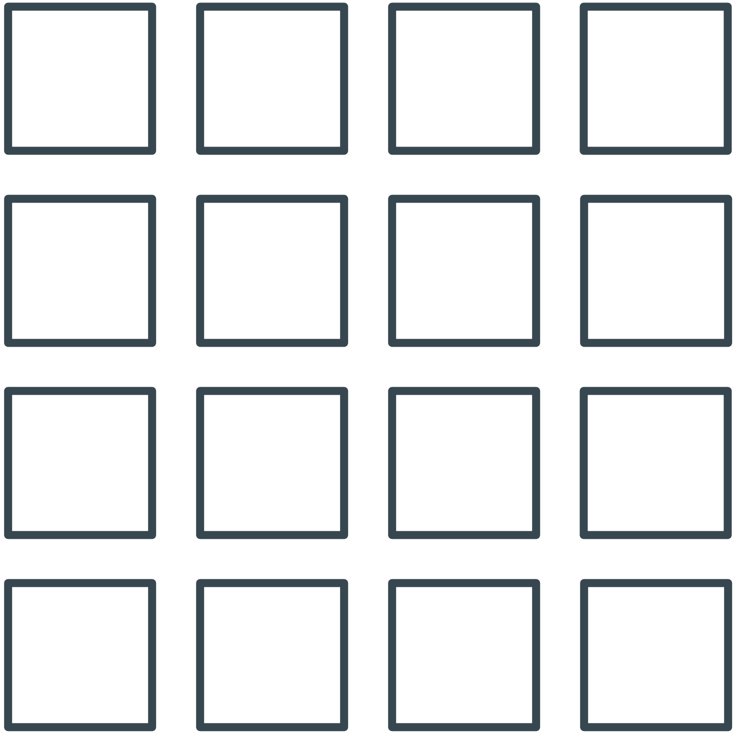
  - Requires blocking

```
out.block(x:..., y:...)

    out.map(x, y)
```



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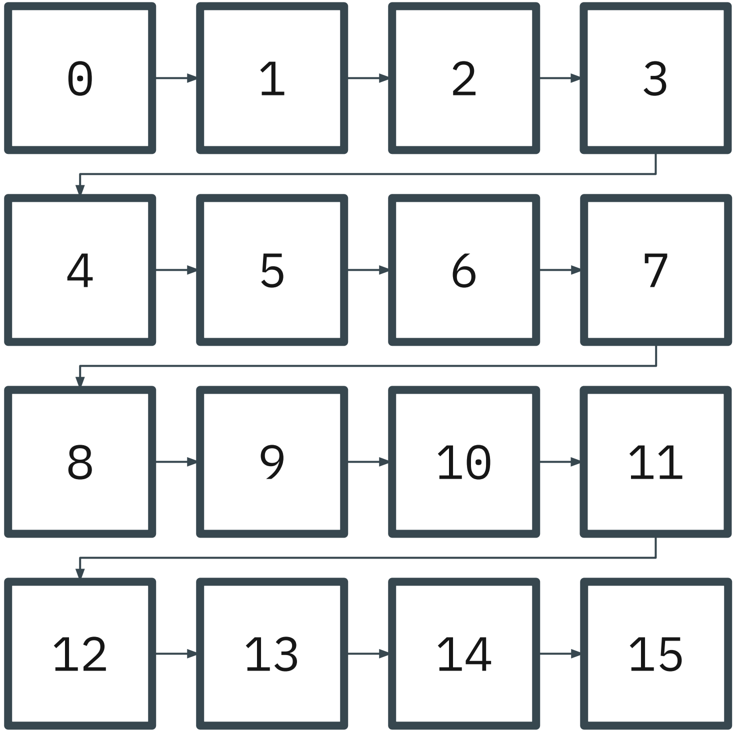
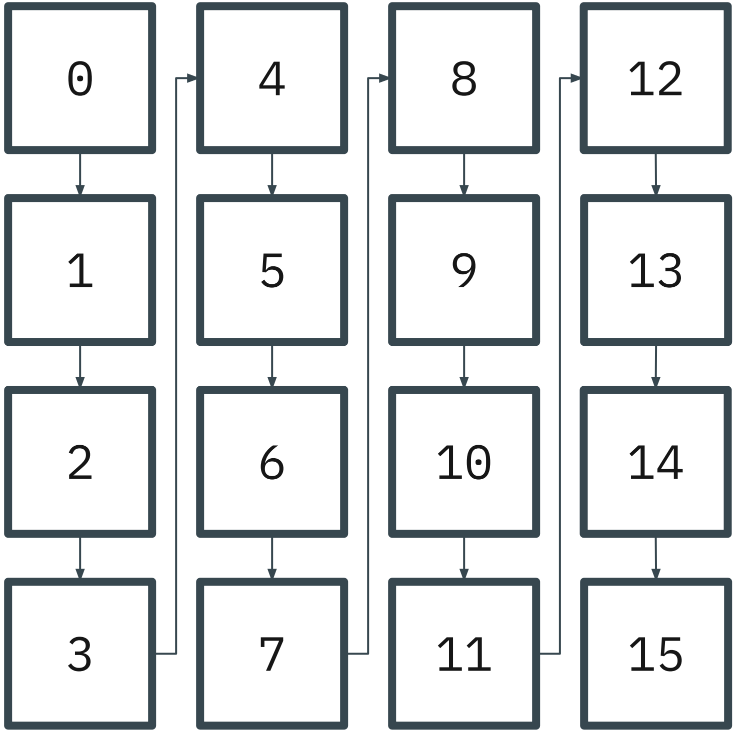


Map

- Specifies the mapping from program instance in the kernel launch grid to output block.
  - Requires blocking

```
out.block(x:..., y:...)
```

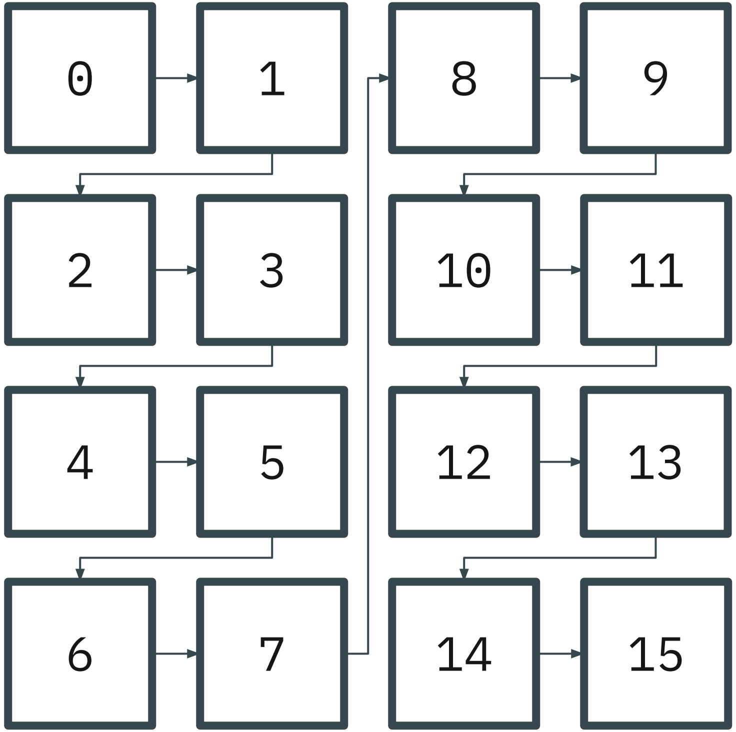
```
out.map(y, x)
```



Map

- Specifies the mapping from program instance in the kernel launch grid to output block.
  - Requires blocking

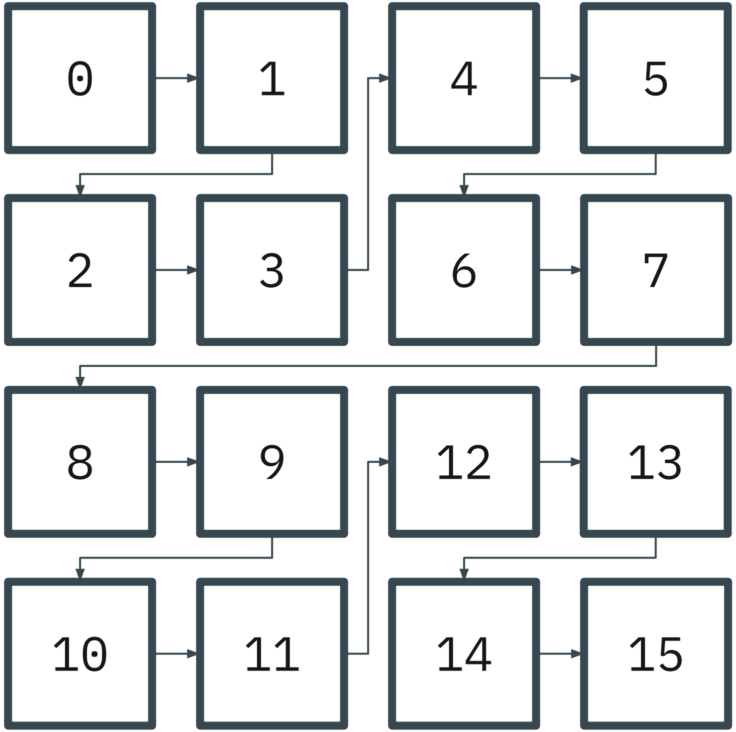
```
out.block(x:..., y:...)
out.map(y:yi/2, x, yi)
```



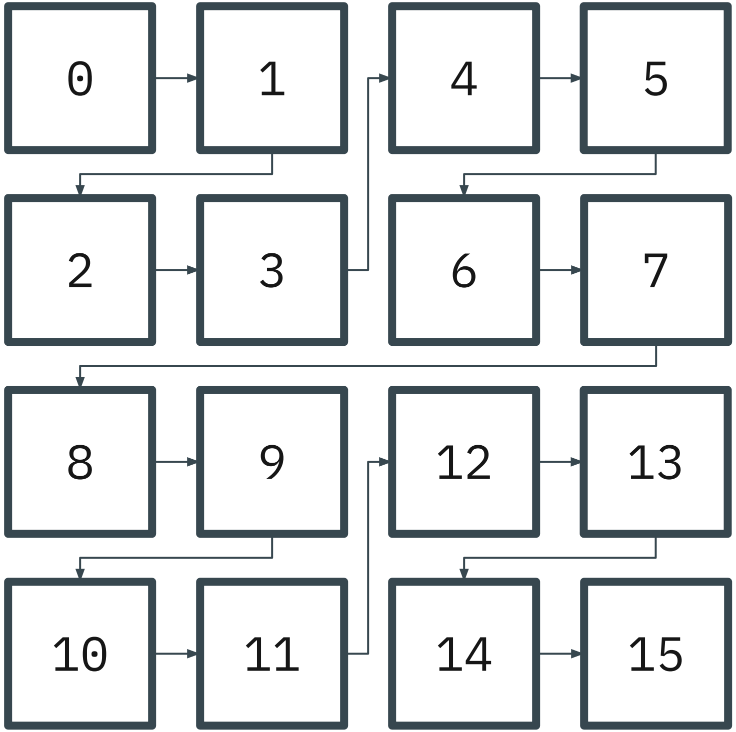
Map

- Specifies the mapping from program instance in the kernel launch grid to output block.
  - Requires blocking

```
out.block(x:..., y:...)
out.map(x:xi/2, y:yi/2, xi, yi)
```

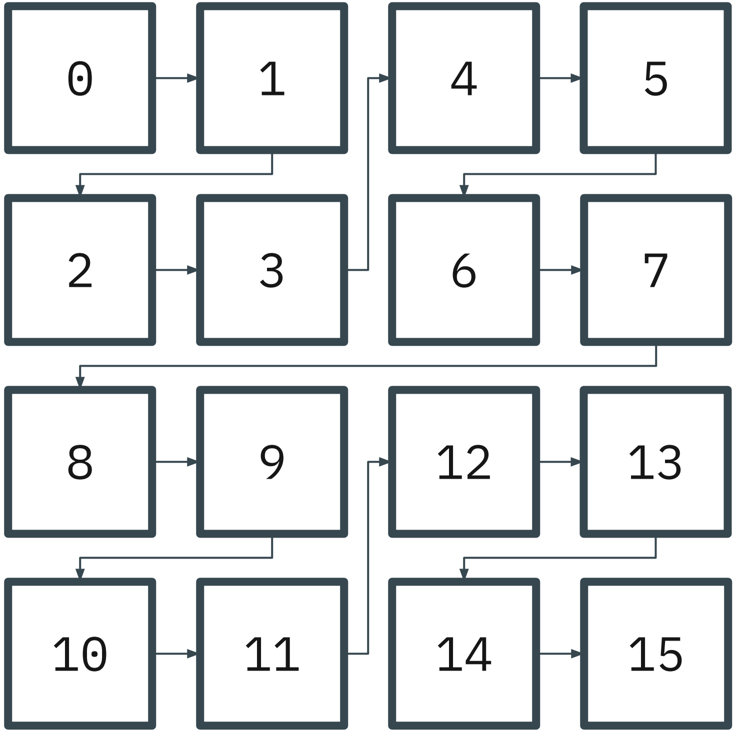


Why map?



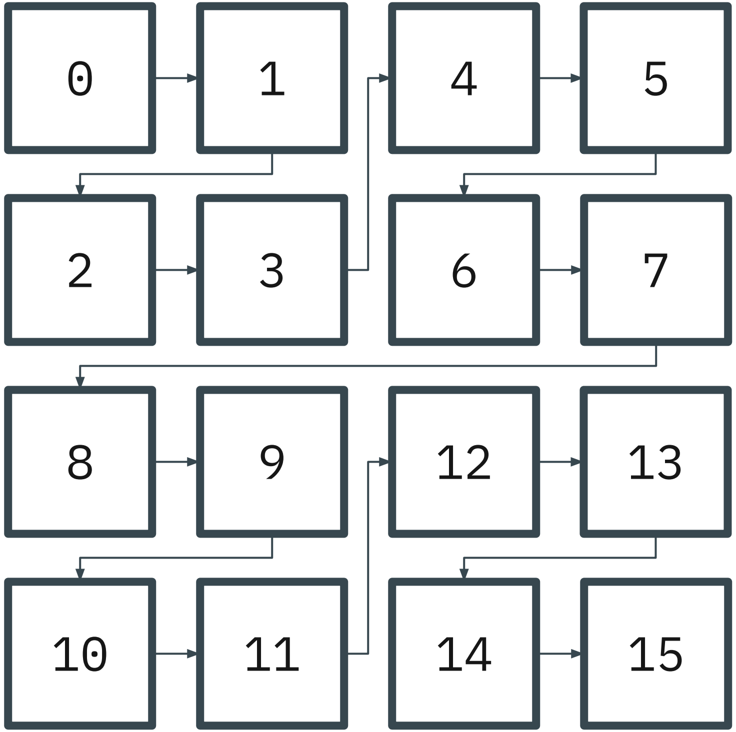
Why map?

- Hardware resources constrain program instance parallelism.



Why map?

- Hardware resources constrain program instance parallelism.
- Program instances may reuse data loaded into the cache by others.



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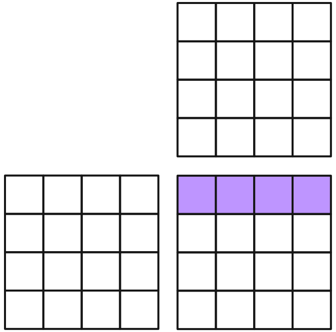

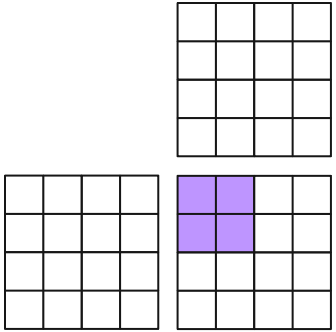

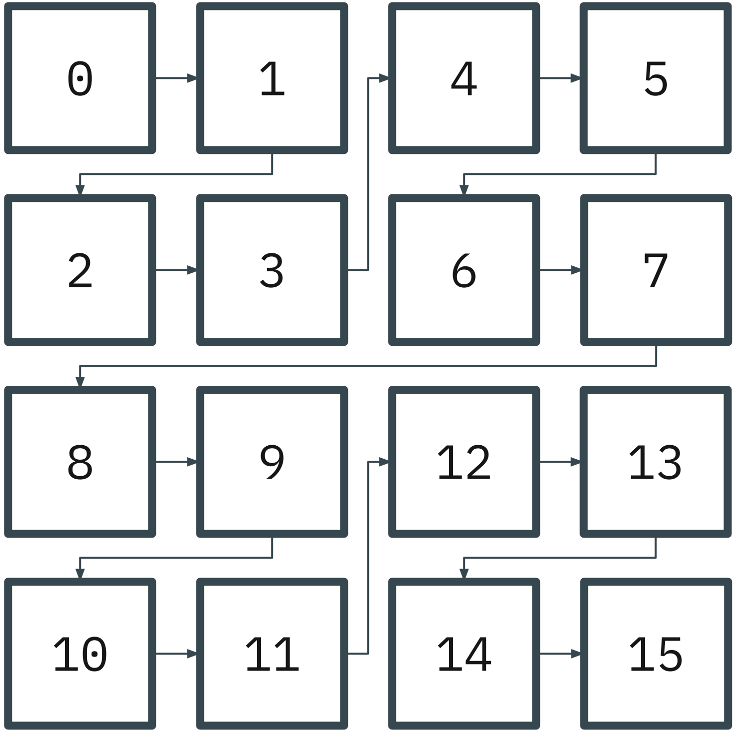

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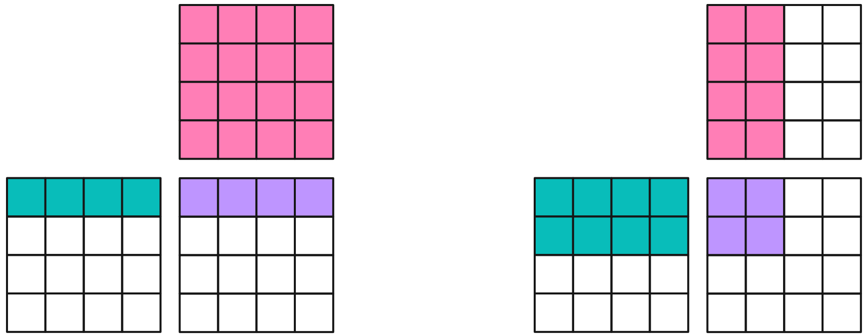
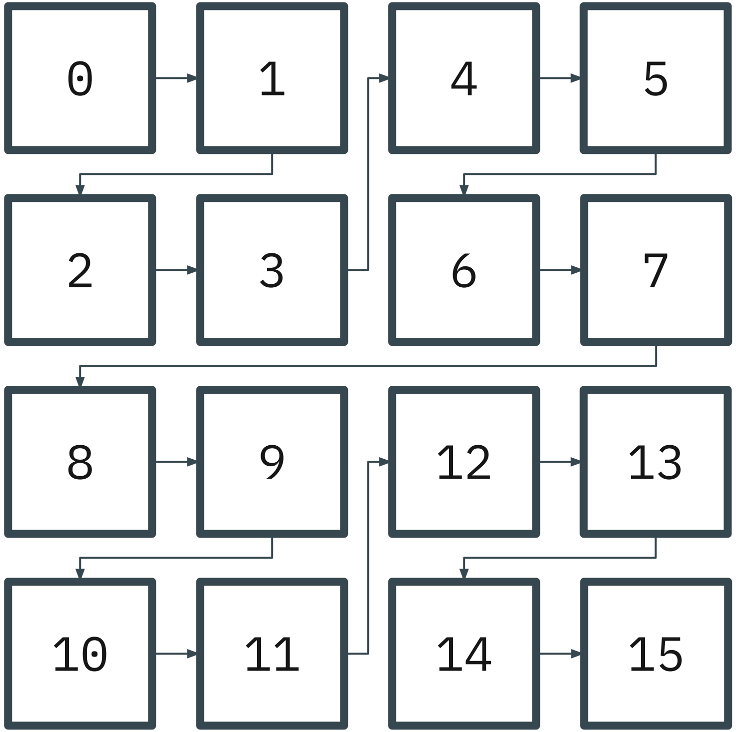
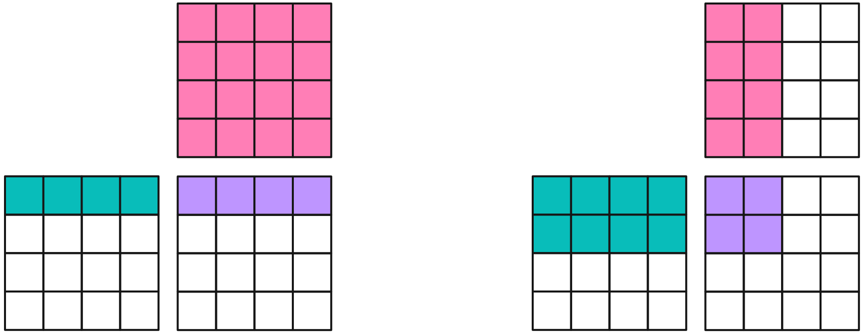


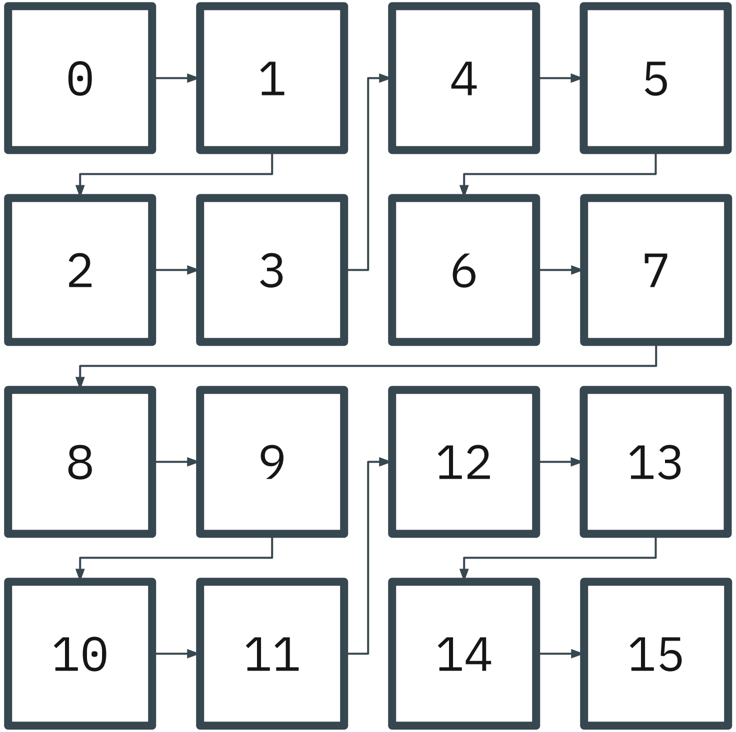


Why map?

- Hardware resources constrain program instance parallelism.
- Program instances may reuse data loaded into the cache by others.

Program instance mapping matters!





Fuse at

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- Fuse a target func into a destination func at a particular loop level.

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  - Same as successive loop fusions

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- Fuse a target func into a destination func at a particular loop level.
    - Same as successive loop fusions

```
Func swish_out, tmp;
In A;
SIn beta;
Var x, y;

tmp[x, y] = sigmoid(beta * A[x, y]);
swish_out[x, y] = A[x, y] * tmp[x, y];

tmp.fuse_at(swish_out, y)
swish_out.compile();
```

Evaluation

Research Questions

Research Questions

1. How **expressive** are DT’s scheduling primitives for generating efficient ML kernels?

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2. Is finding efficient schedules with DT **feasible** for most ML operations?

Research Questions

1. How **expressive** are DT's scheduling primitives for generating efficient ML kernels?

2. Is finding efficient schedules with DT **feasible** for most ML operations?

3. Are there **opportunities** for DT to generate ML kernels that outperform expert-written Triton kernels and ML frameworks?

Experimental Methodology

Experimental Methodology

DT
Algorithm

Experimental Methodology

DT Algorithm

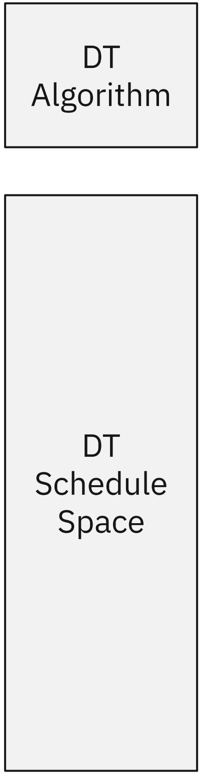
```
Func relu_out;
In   A;
Var  x, y;

relu_out[x, y] = maximum(0, A[x, y]);
```

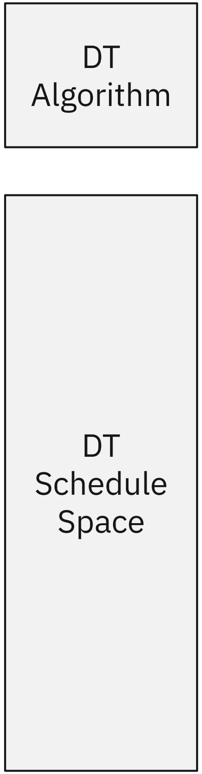
Experimental Methodology

DT
Algorithm

Experimental Methodology

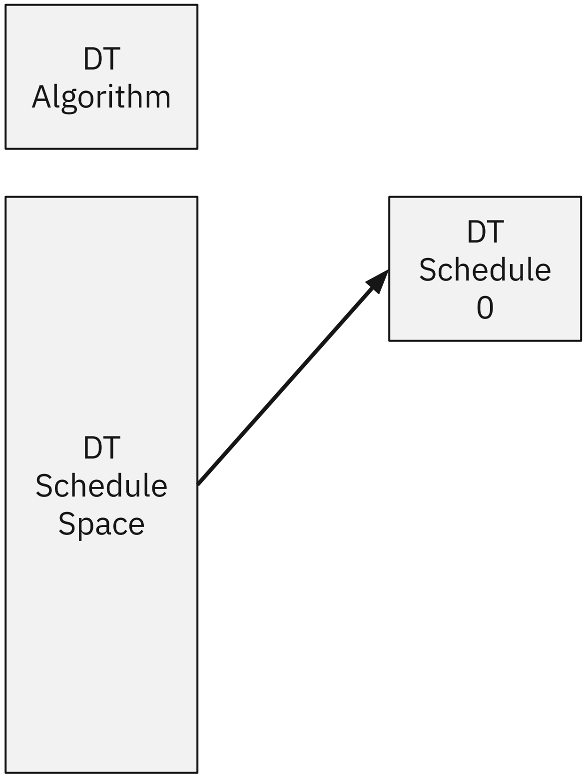


Experimental Methodology

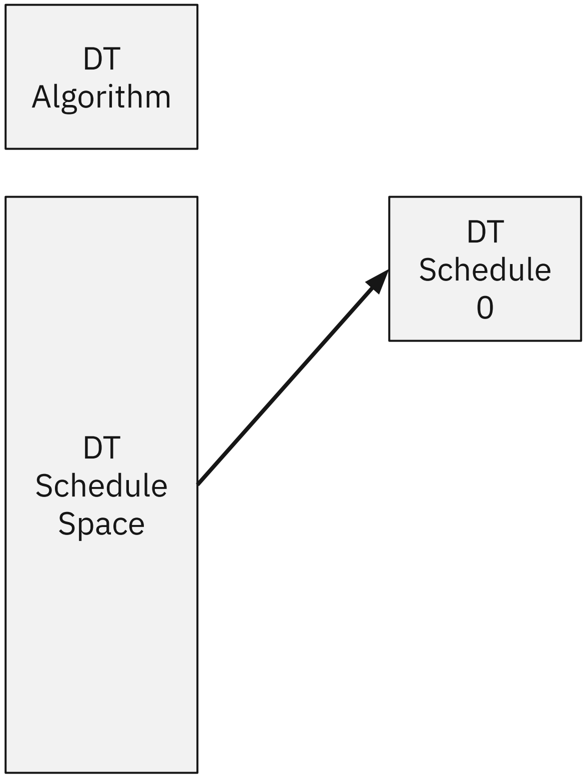


To define a schedule space, a small manual exploration is performed.

Experimental Methodology

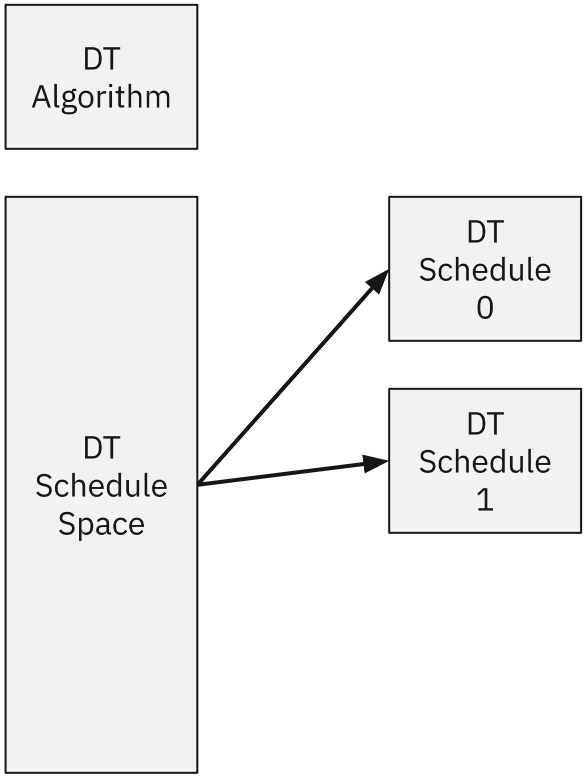


Experimental Methodology




```
relu_out.block(x:8, y:16);
relu_out.map(x:xi/4, y, xi);
relu_out.compile();
```

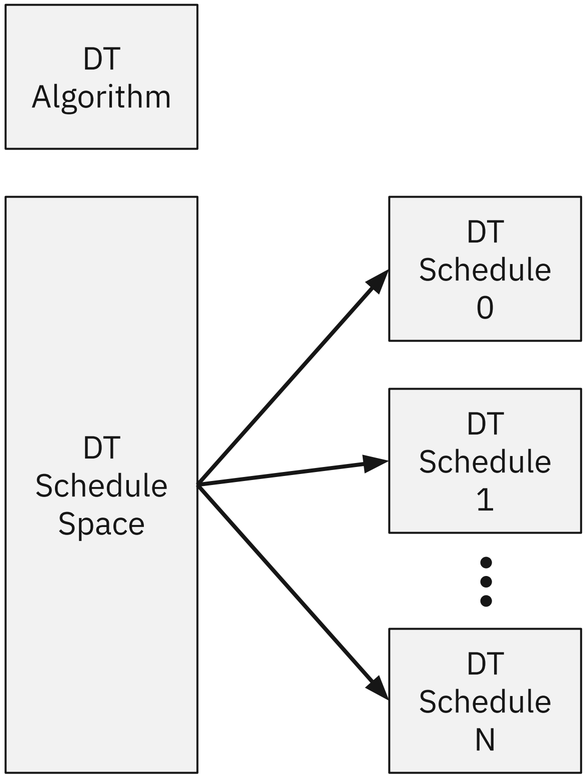
Experimental Methodology




```
relu_out.block(x:8, y:16);
relu_out.map(x:xi/4, y, xi);
relu_out.compile();
```

```
relu_out.block(x:1, y:128);
relu_out.tensorize(y:128);
relu_out.map(y, x);
relu_out.compile();
```

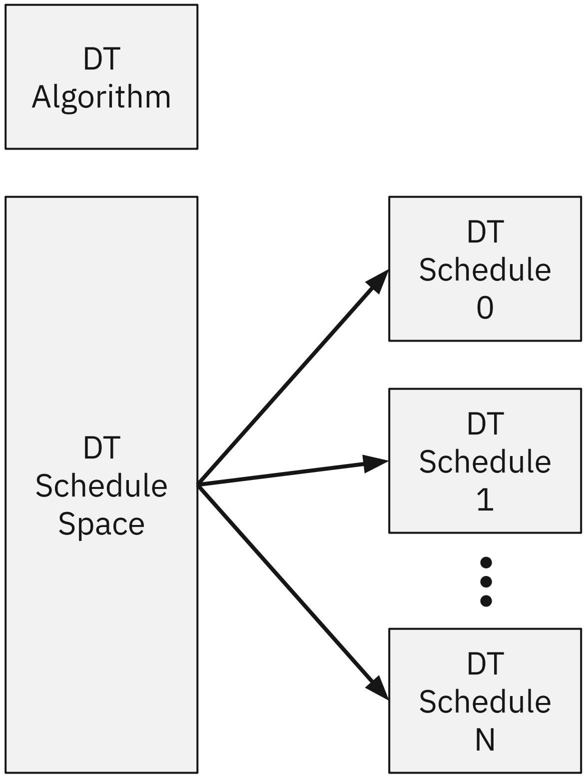
Experimental Methodology



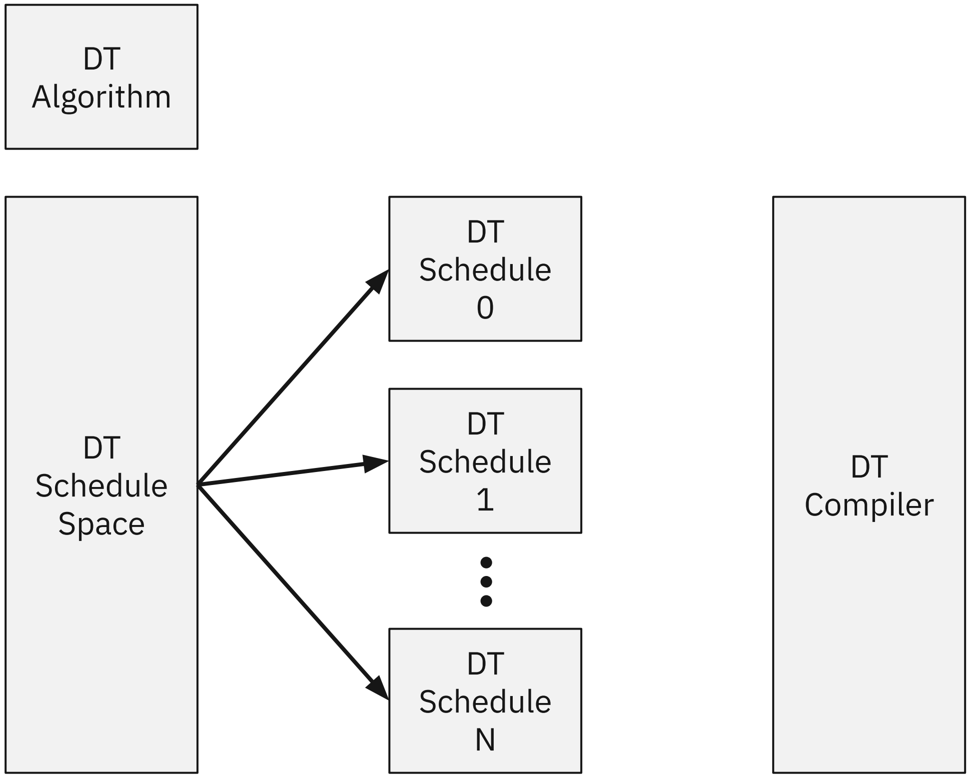

```
relu_out.block(x:8, y:16);
relu_out.map(x:xi/4, y, xi);
relu_out.compile();
```

```
relu_out.block(x:1, y:128);
relu_out.tensorize(y:128);
relu_out.map(y, x);
relu_out.compile();
```

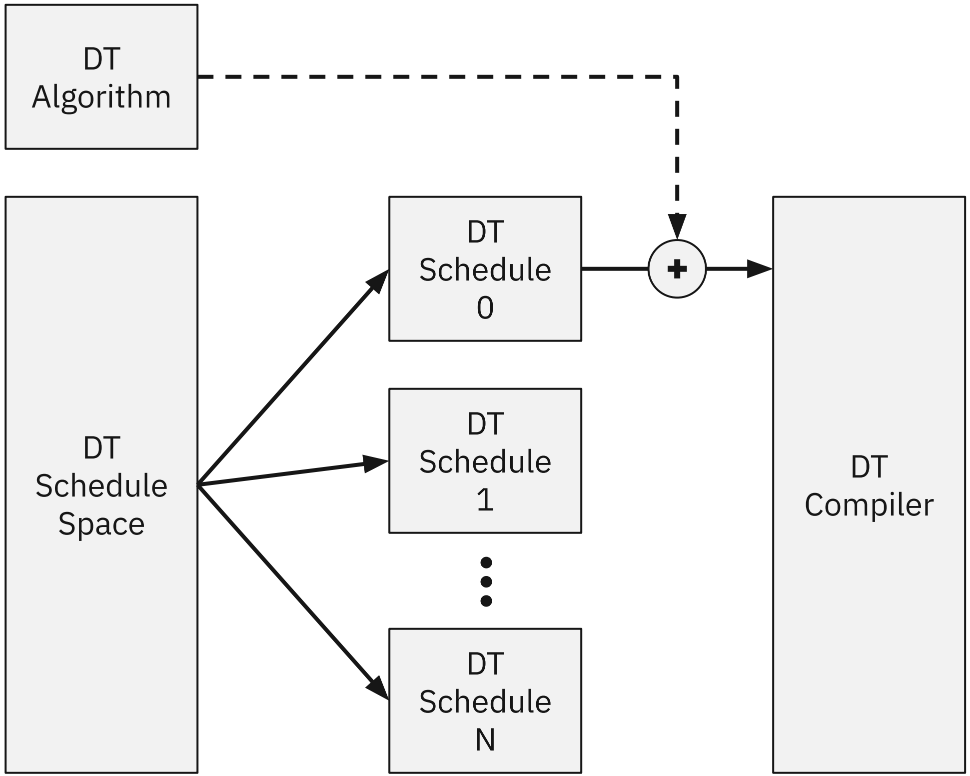
Experimental Methodology



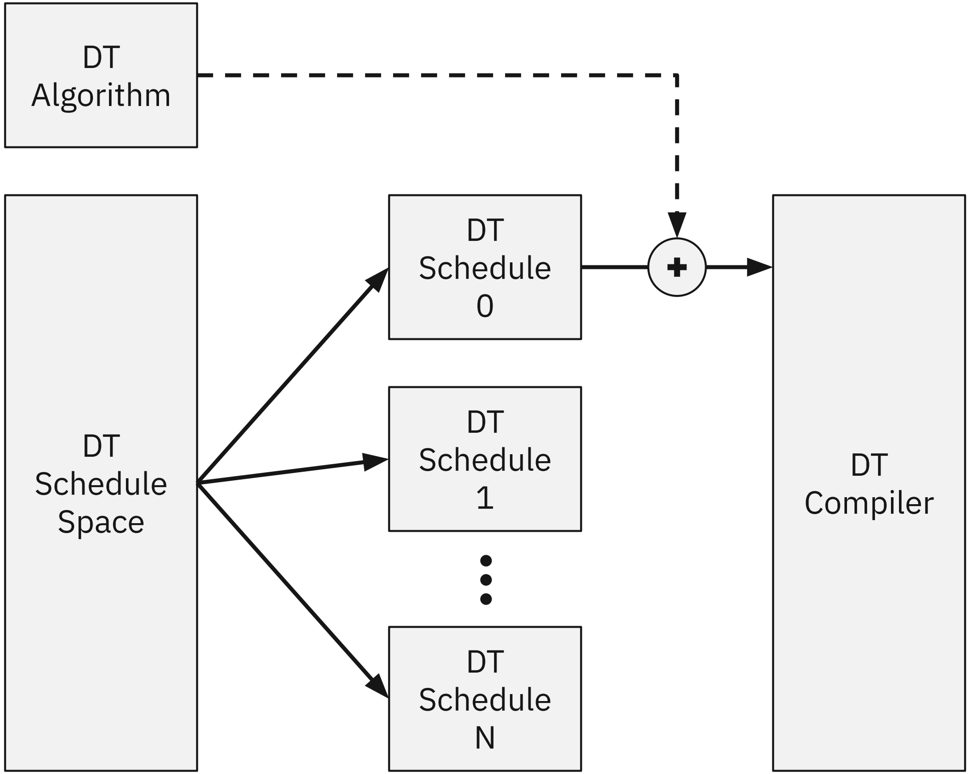
Experimental Methodology



Experimental Methodology



Experimental Methodology

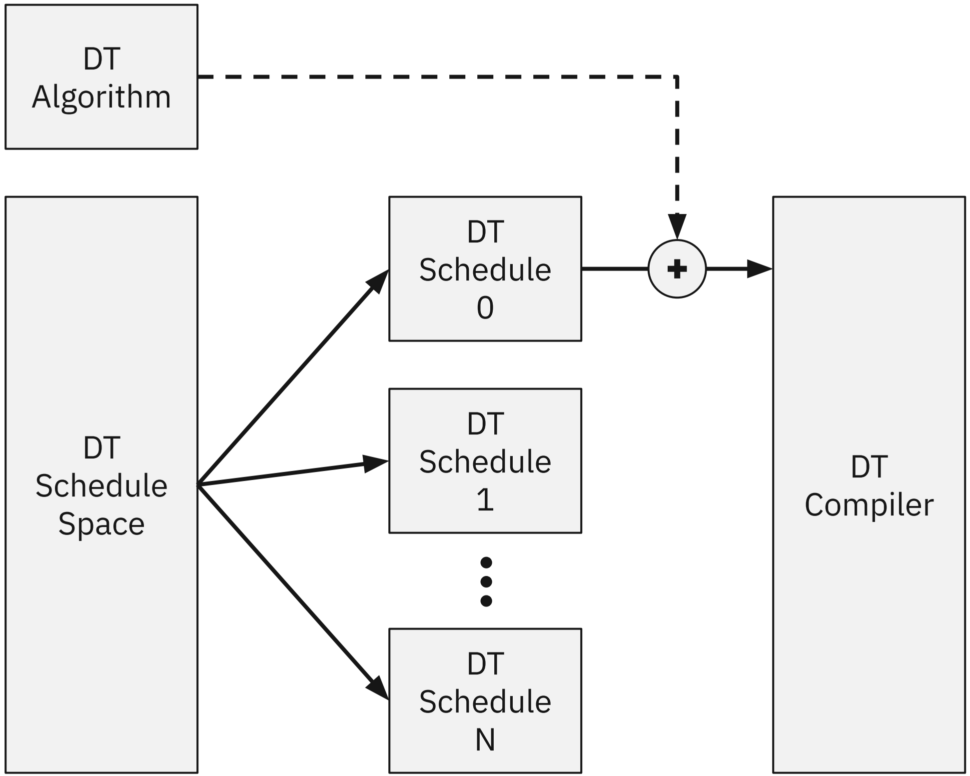



```
Func relu_out;
In   A;
Var  x, y;

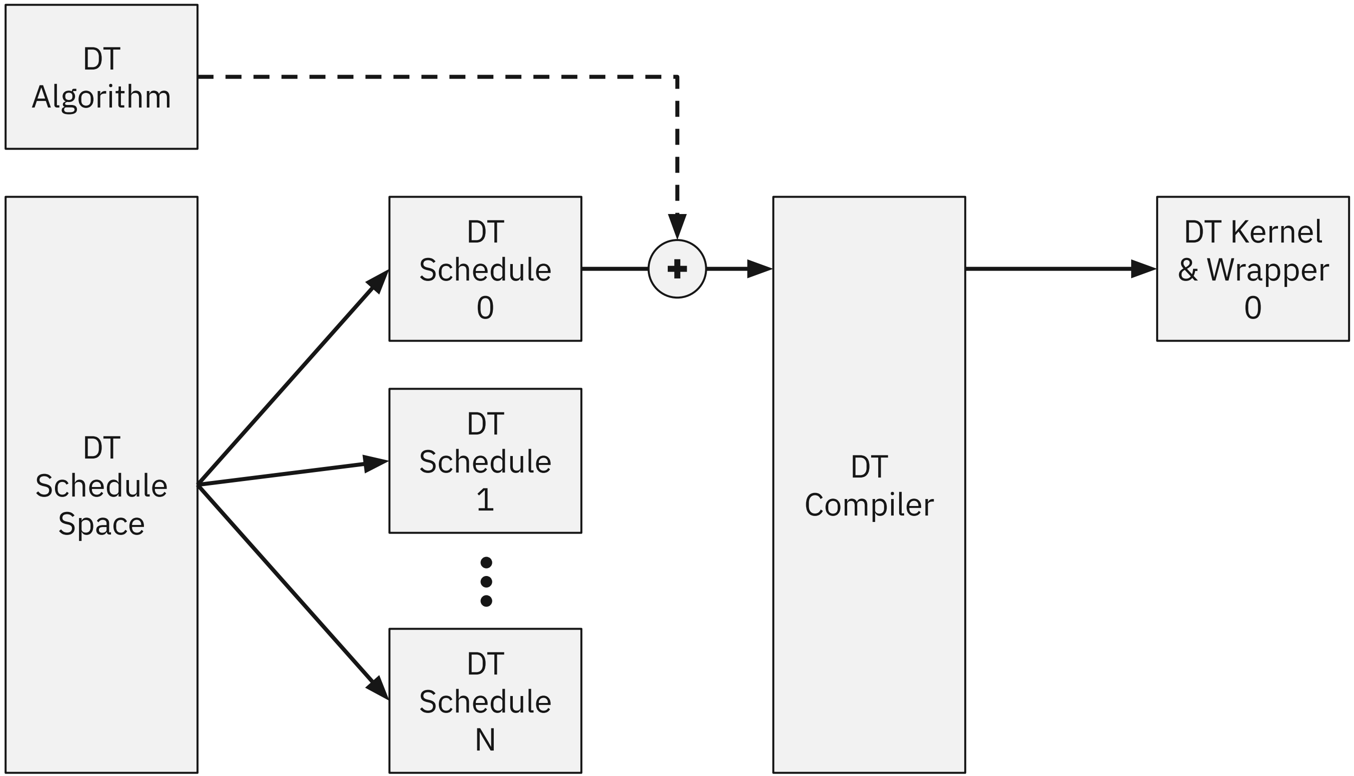
relu_out[x, y] = maximum(0, A[x, y]);

relu_out.block(x:8, y:16);
relu_out.map(x:xi/4, y, xi);
relu_out.compile();
```

Experimental Methodology



Experimental Methodology



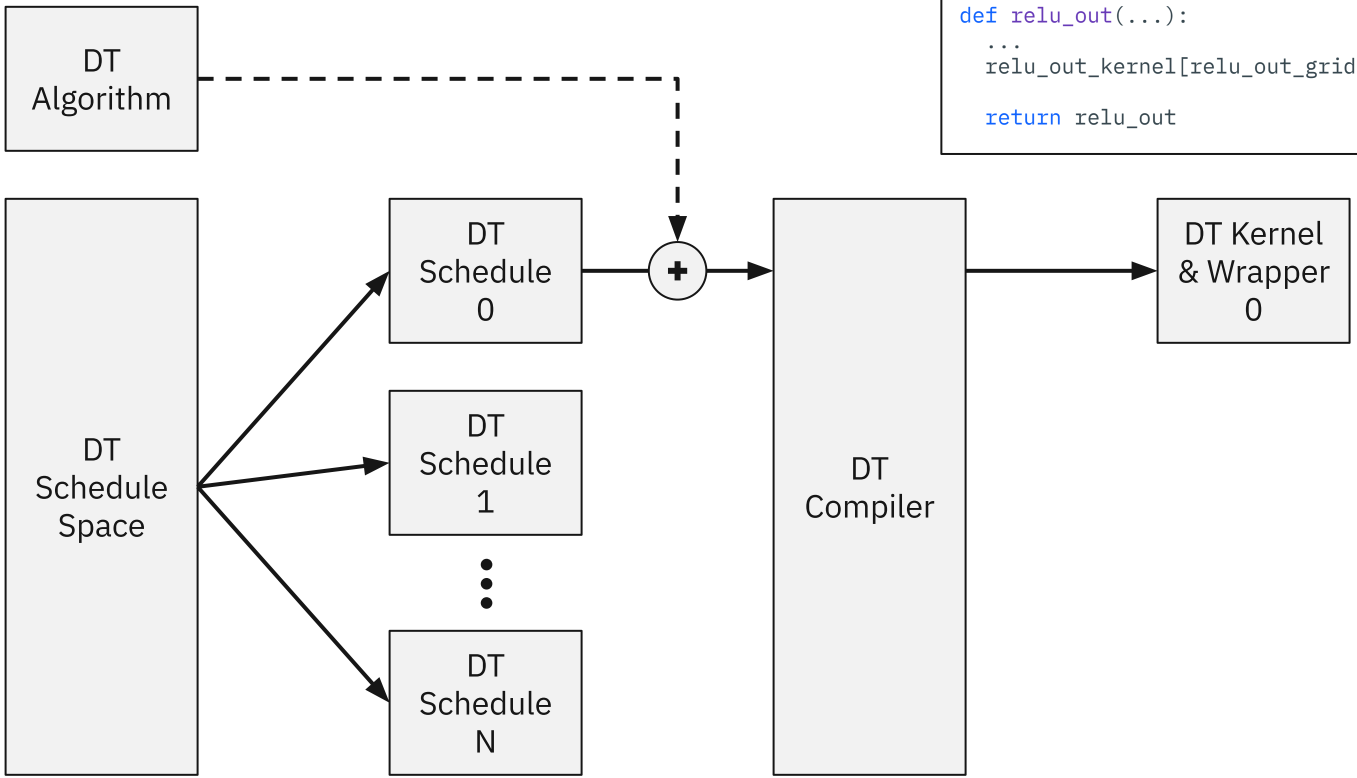
Experimental Methodology

```python
import torch
import triton
import triton.language as tl

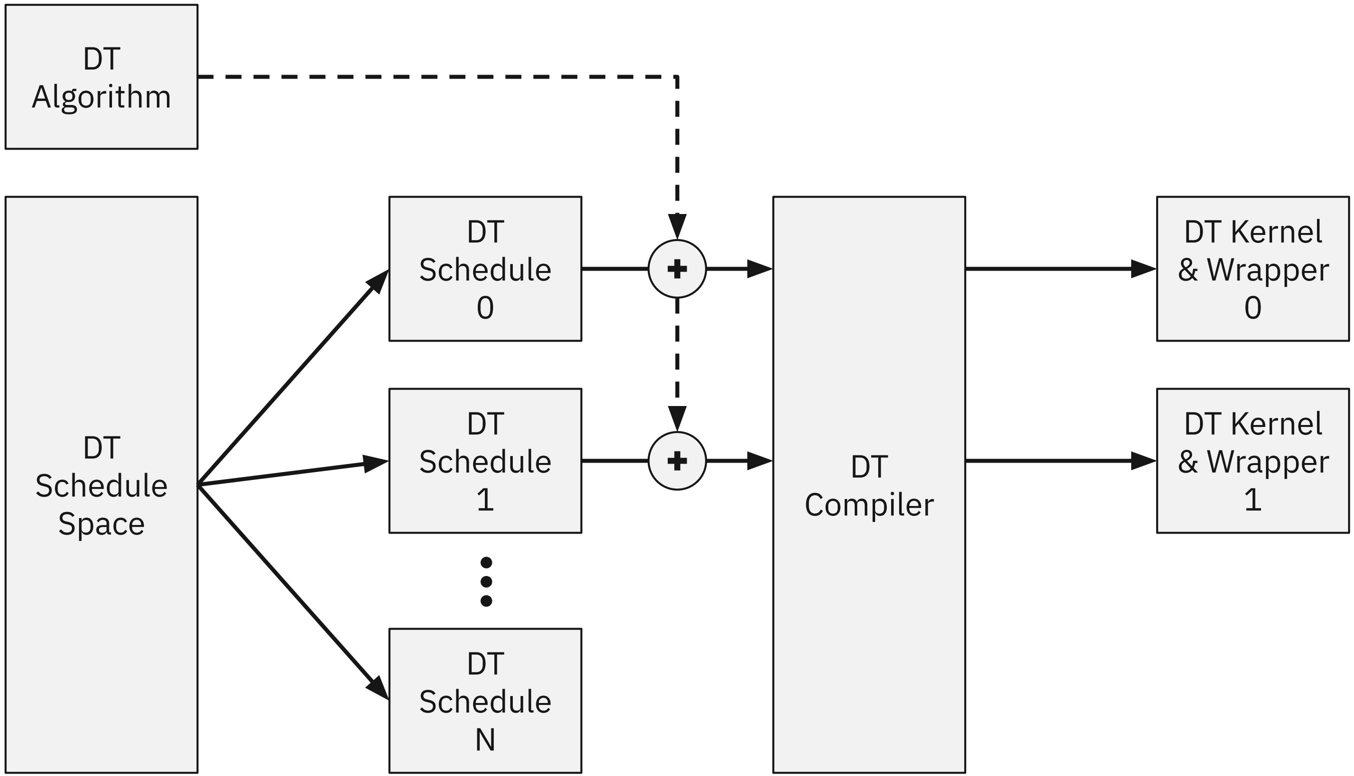
@triton.jit
def relu_out_kernel(...):
  ...

def relu_out(...):
  ...
  relu_out_kernel[relu_out_grid](...)

  return relu_out
```



Experimental Methodology



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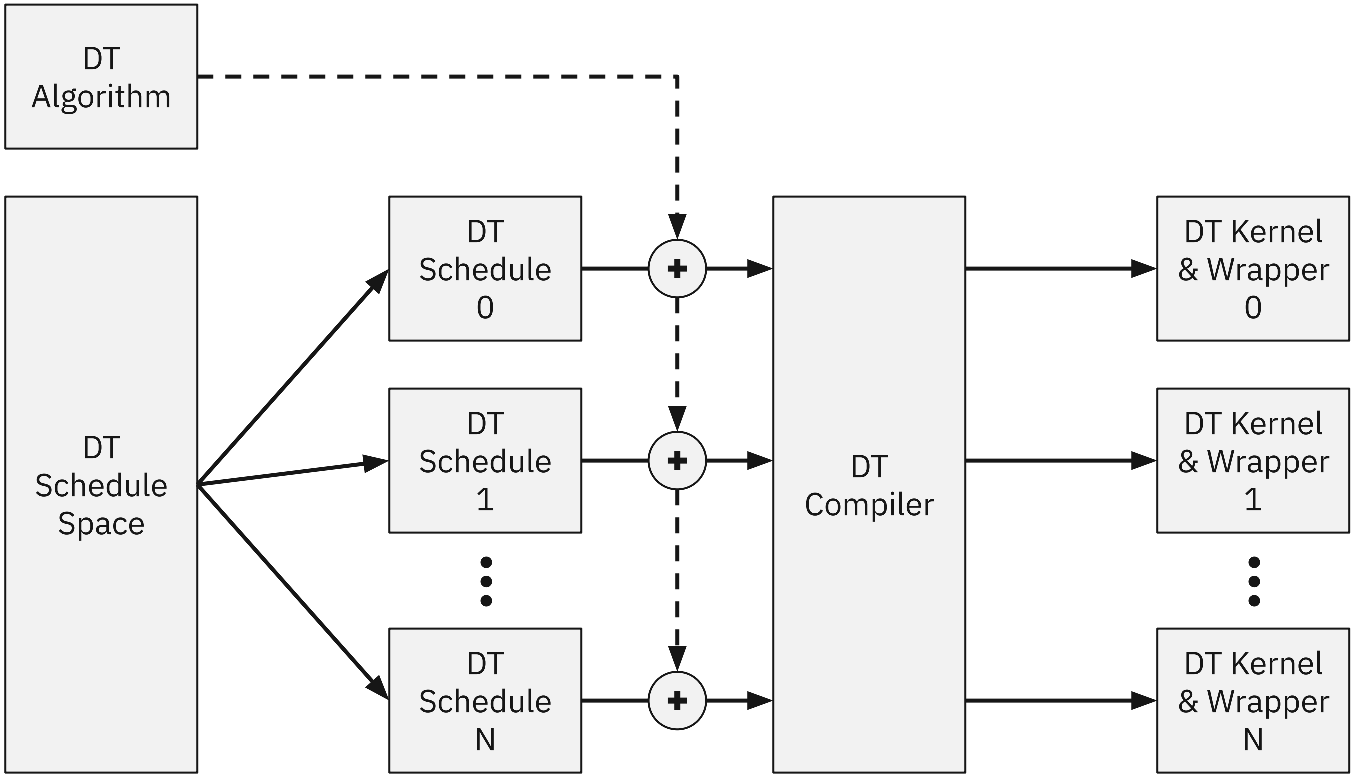
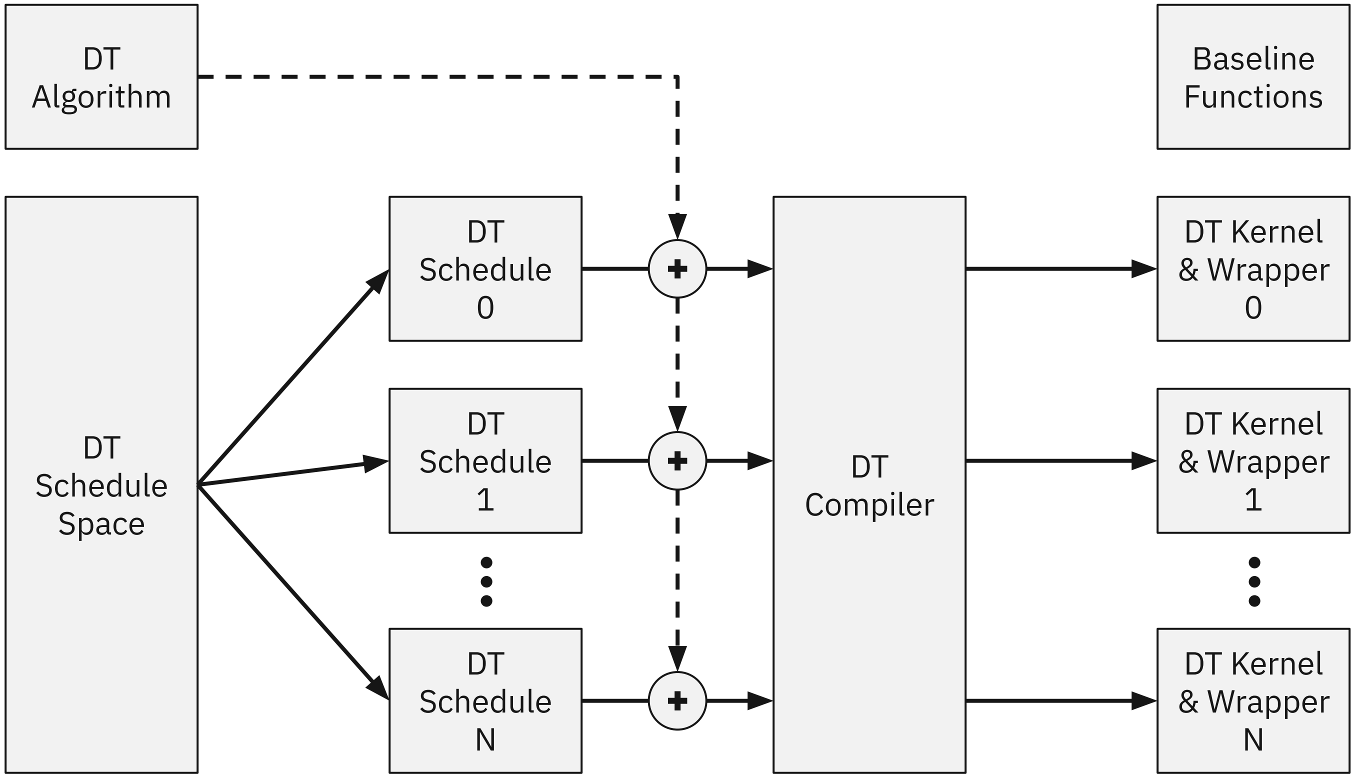


Experimental Methodology



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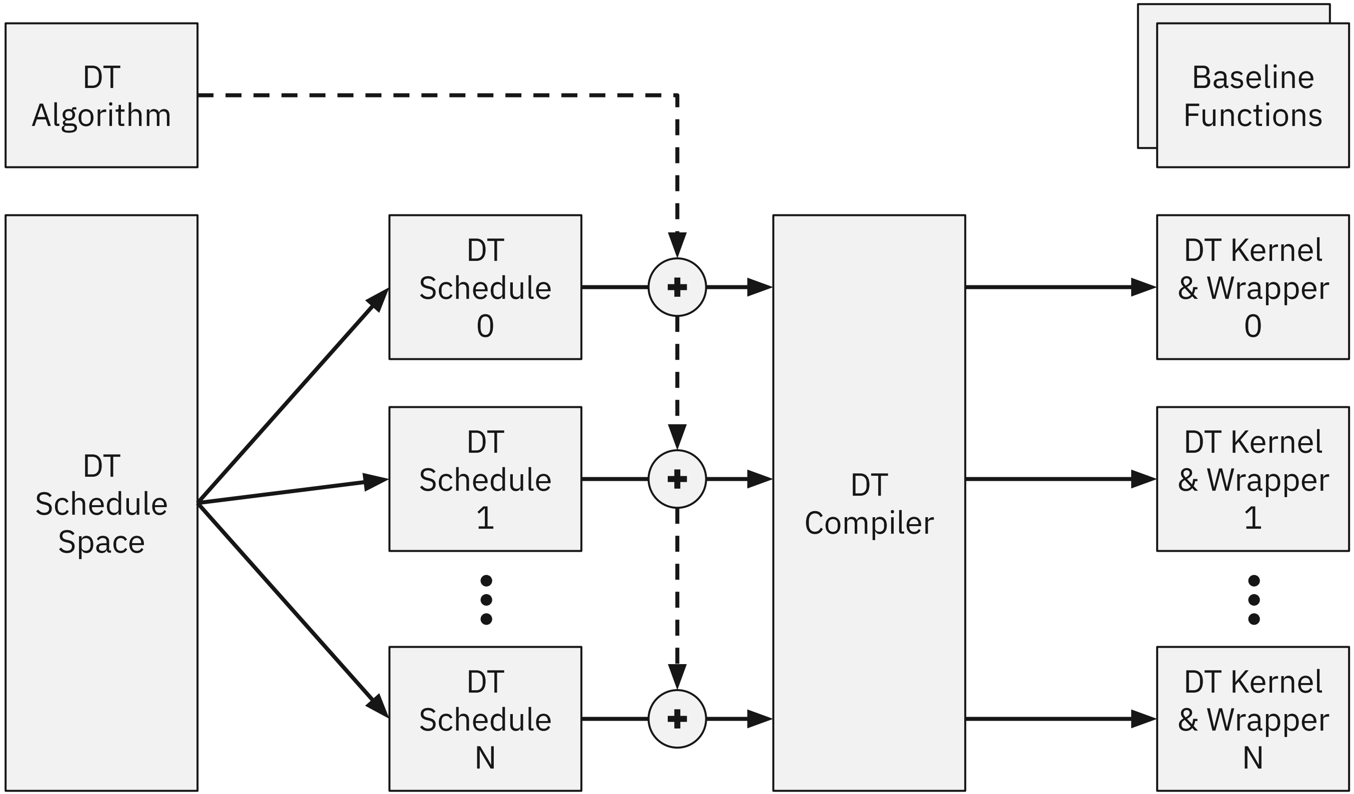
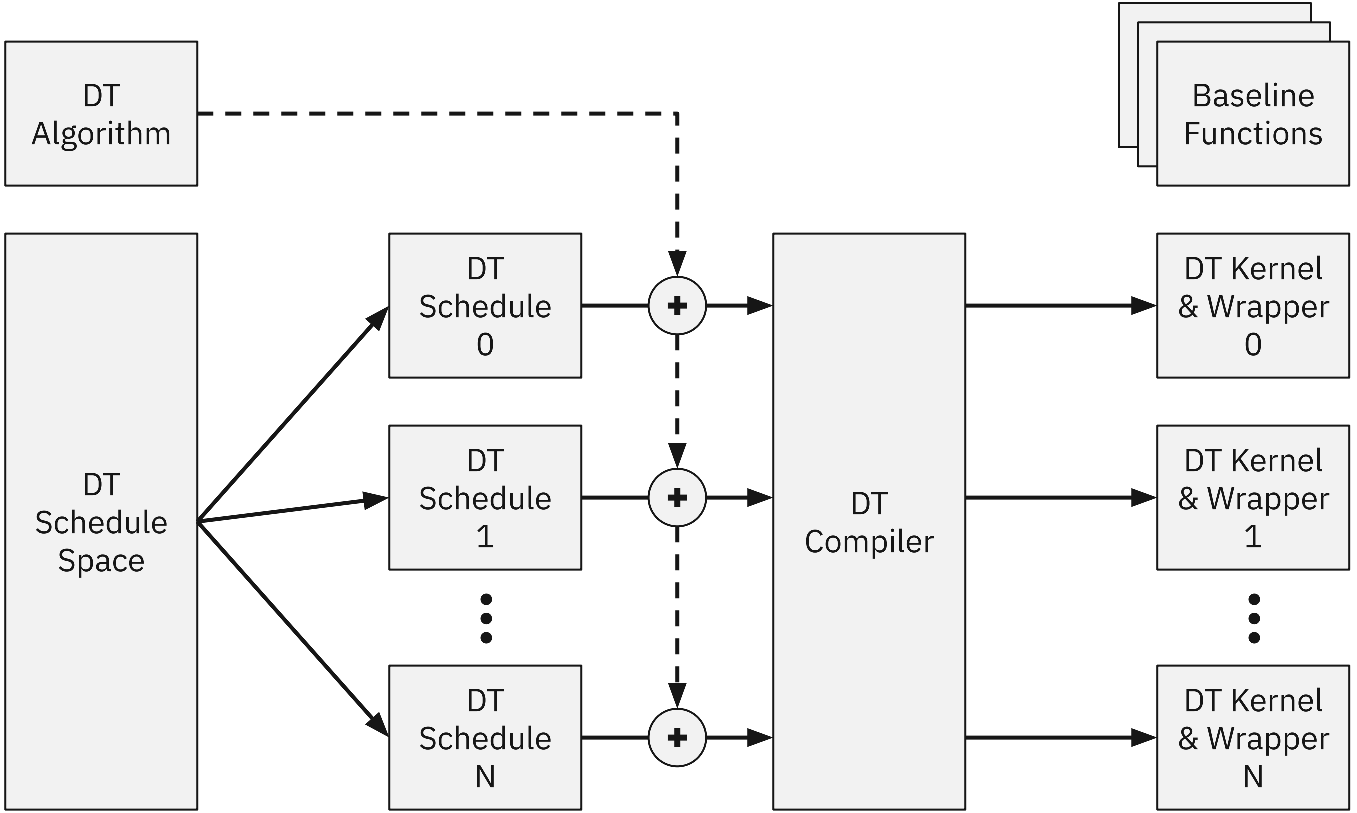
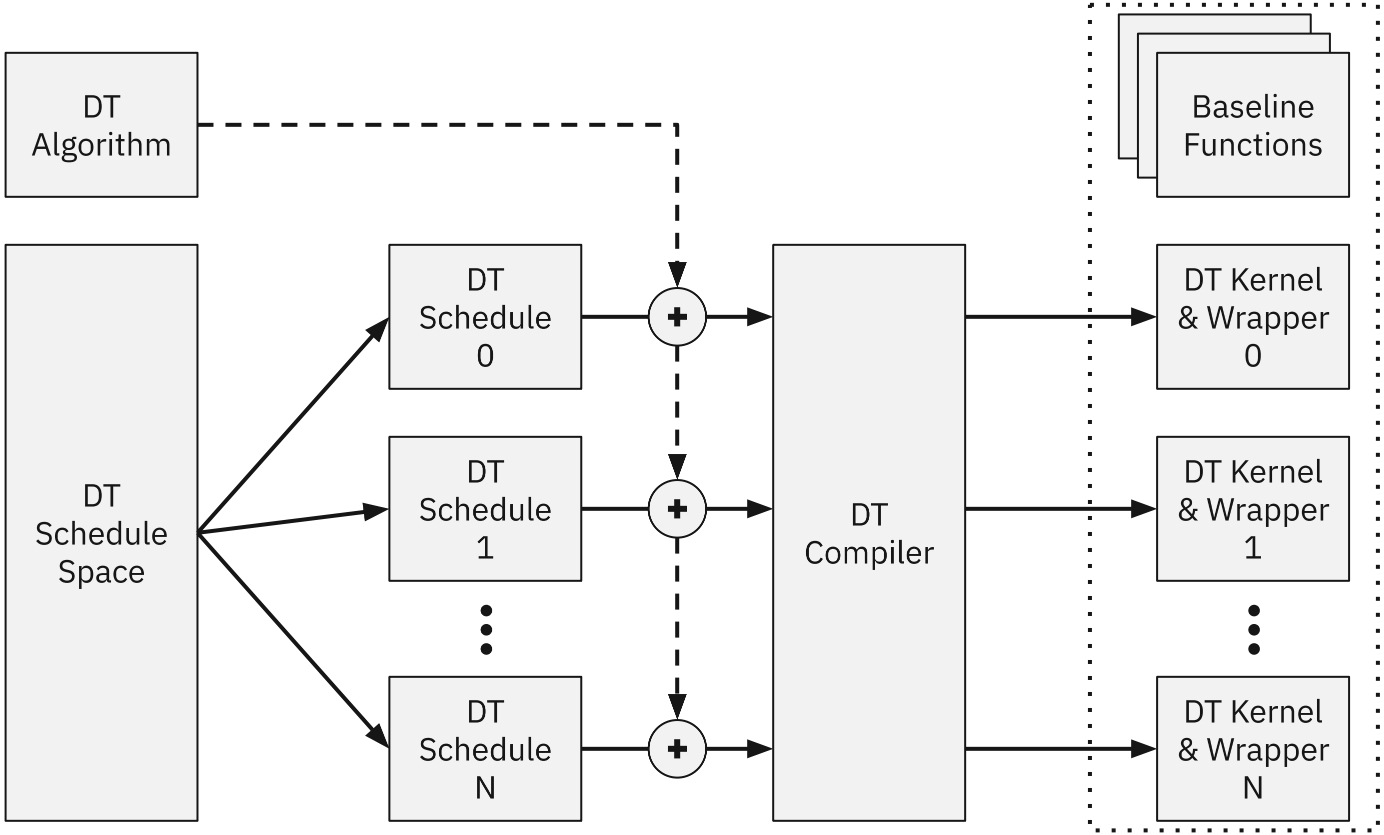


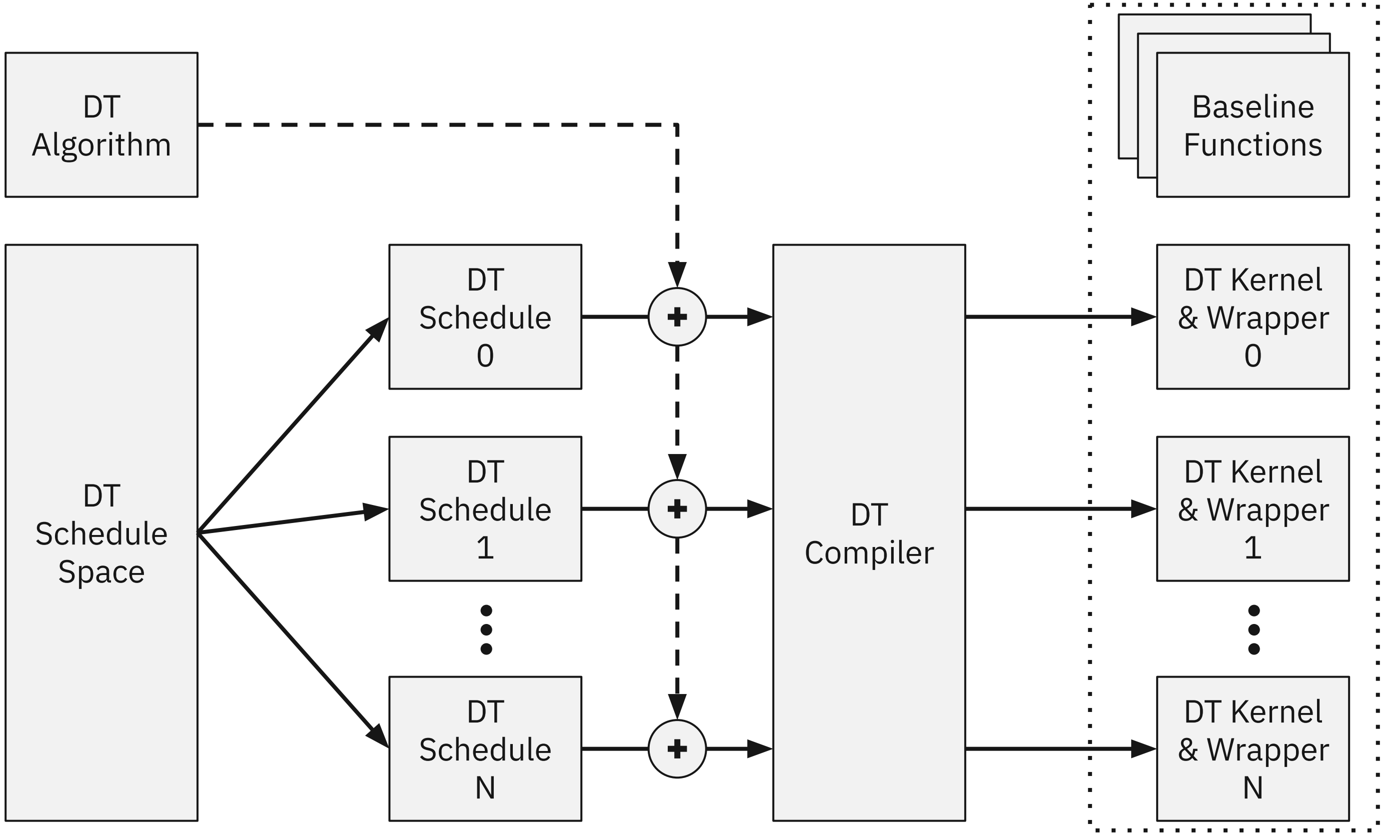
Experimental Methodology



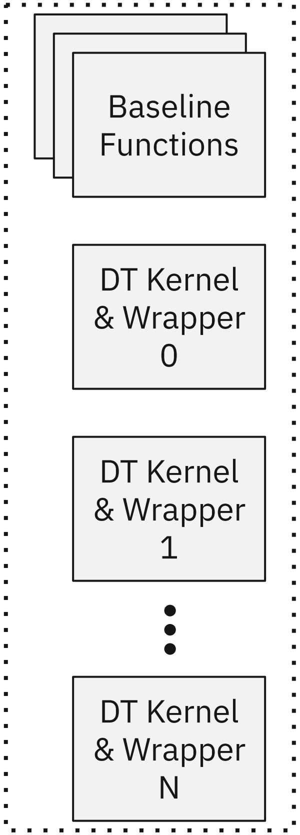
Experimental Methodology



Experimental Methodology

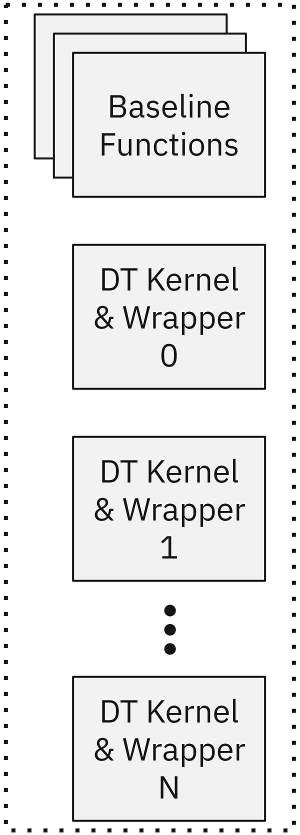


Experimental Methodology



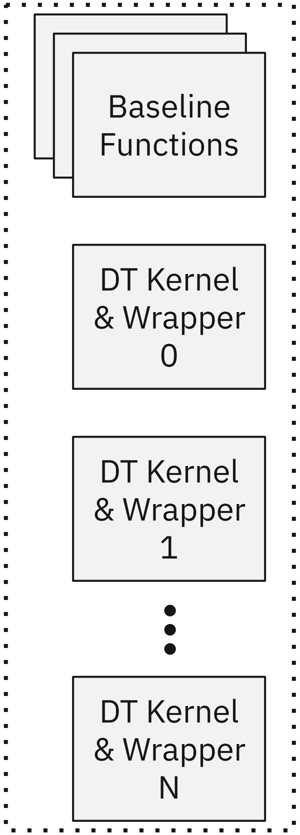
Experimental Methodology

- Same inputs



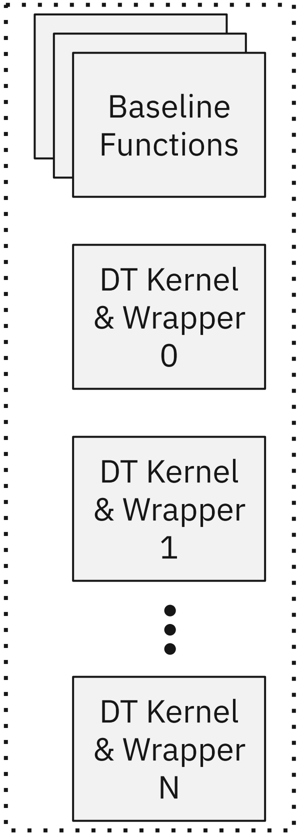
Experimental Methodology

- Same inputs
- Measure run time



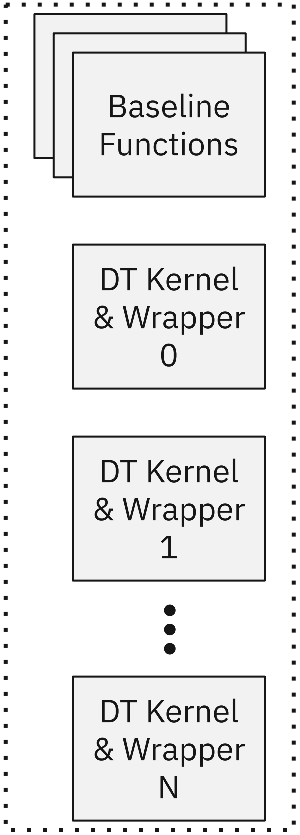
Experimental Methodology

- Same inputs
- Measure run time
  - `triton.testing.do_bench()`



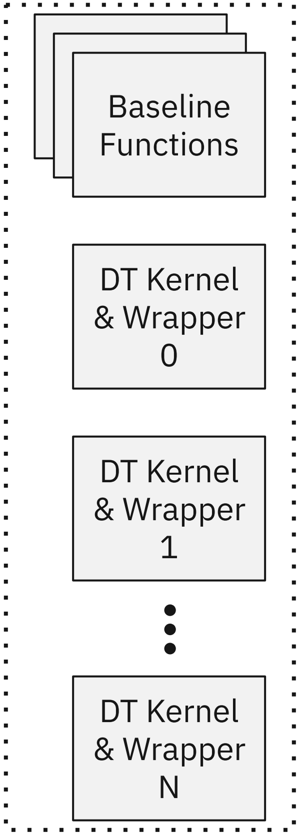
Experimental Methodology

- Same inputs
- Measure run time
    - `triton.testing.do_bench()`
        - 25 ms warmup



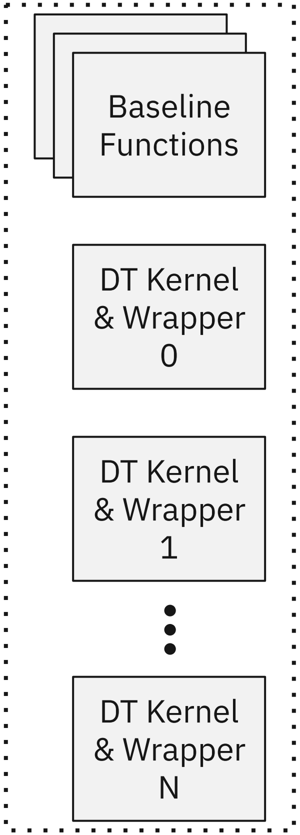
Experimental Methodology

- Same inputs
- Measure run time
  - `triton.testing.do_bench()`
    - 25 ms warmup
    - 100 ms repetition



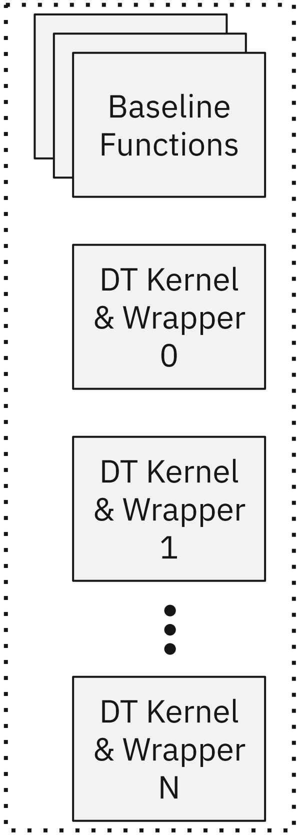
Experimental Methodology

- Same inputs
- Measure run time
  - `triton.testing.do_bench()`
    - 25 ms warmup
    - 100 ms repetition
  - Mean of 5 iterations



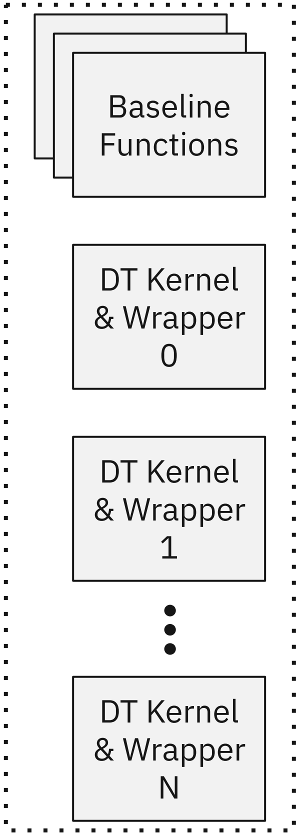
Experimental Methodology

- Same inputs
- Measure run time
    - `triton.testing.do_bench()`
        - 25 ms warmup
        - 100 ms repetition
    - Mean of 5 iterations
        - Random order within iteration



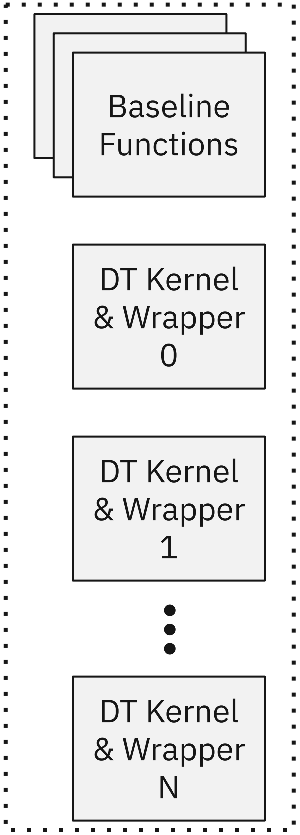
Experimental Methodology

- Same inputs
- Measure run time
  - `triton.testing.do_bench()`
    - 25 ms warmup
    - 100 ms repetition
  - Mean of 5 iterations
    - Random order within iteration
- Correctness



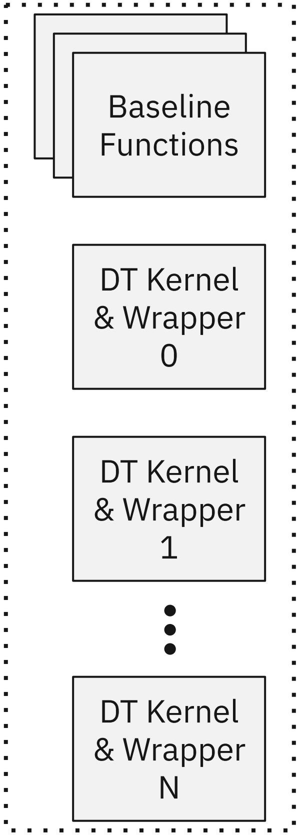
Experimental Methodology

- Same inputs
- Measure run time
    - `triton.testing.do_bench()`
        - 25 ms warmup
        - 100 ms repetition
    - Mean of 5 iterations
        - Random order within iteration
- Correctness
    - `torch.allclose()`

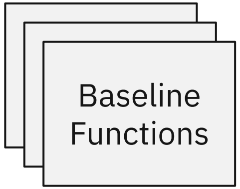


Experimental Methodology

- Same inputs
- Measure run time
  - `triton.testing.do_bench()`
    - 25 ms warmup
    - 100 ms repetition
  - Mean of 5 iterations
    - Random order within iteration
- Correctness
  - `torch.allclose()`
- NVIDIA RTX 5000 Ada Generation GPU

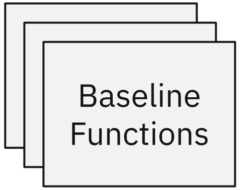


Baselines



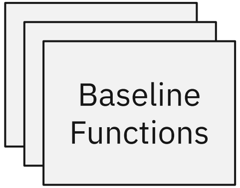
Baselines

- PyTorch



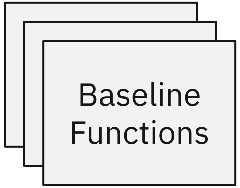
Baselines

- PyTorch
  - `torch.compile()`



Baselines

- PyTorch
  - `torch.compile()`
  - `torch.compile(mode=”max-autotune”)`



Baselines

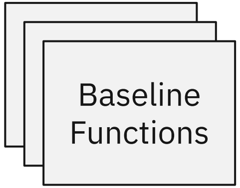
- PyTorch
    - `torch.compile()`
    - `torch.compile(mode=”max-autotune”)`

- Liger Kernels

Baseline Functions

Baselines

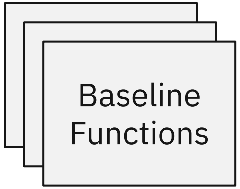
- PyTorch
  - `torch.compile()`
  - `torch.compile(mode="max-autotune")`
- Liger Kernels
  - Open source collection of efficient triton kernels



Baselines

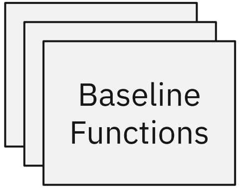
- PyTorch
  - `torch.compile()`
  - `torch.compile(mode="max-autotune")`

- Liger Kernels
  - Open source collection of efficient triton kernels
  - Common LLM operations



Baselines

- PyTorch
  - `torch.compile()`
  - `torch.compile(mode="max-autotune")`
- Liger Kernels
  - Open source collection of efficient triton kernels
  - Common LLM operations
- Other Triton Kernel



Baselines

- PyTorch
  - `torch.compile()`
  - `torch.compile(mode="max-autotune")`
- Liger Kernels
  - Open source collection of efficient triton kernels
  - Common LLM operations
- Other Triton Kernel
  - Expert-written Triton kernel

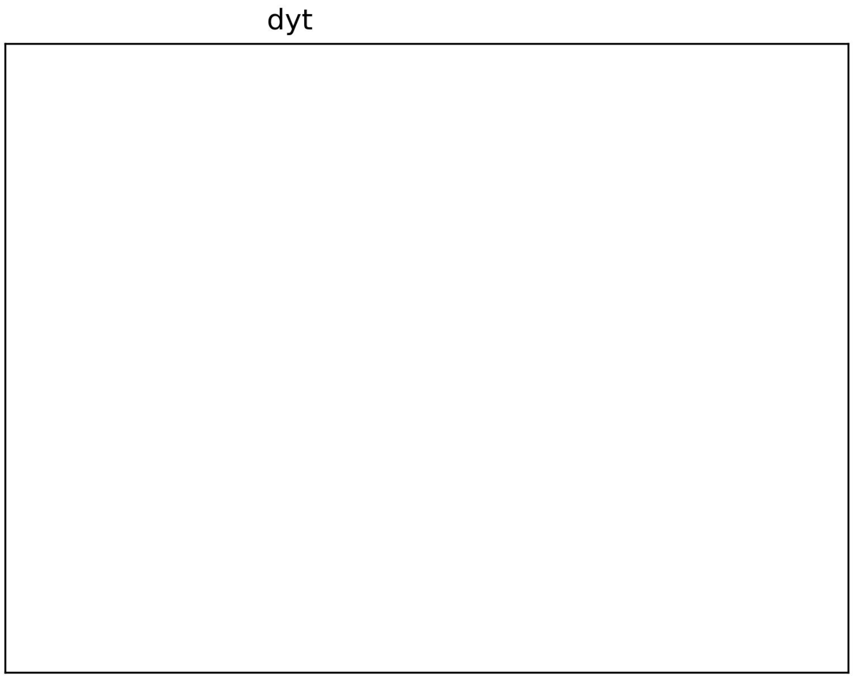
Baseline Functions

Results

Graphs

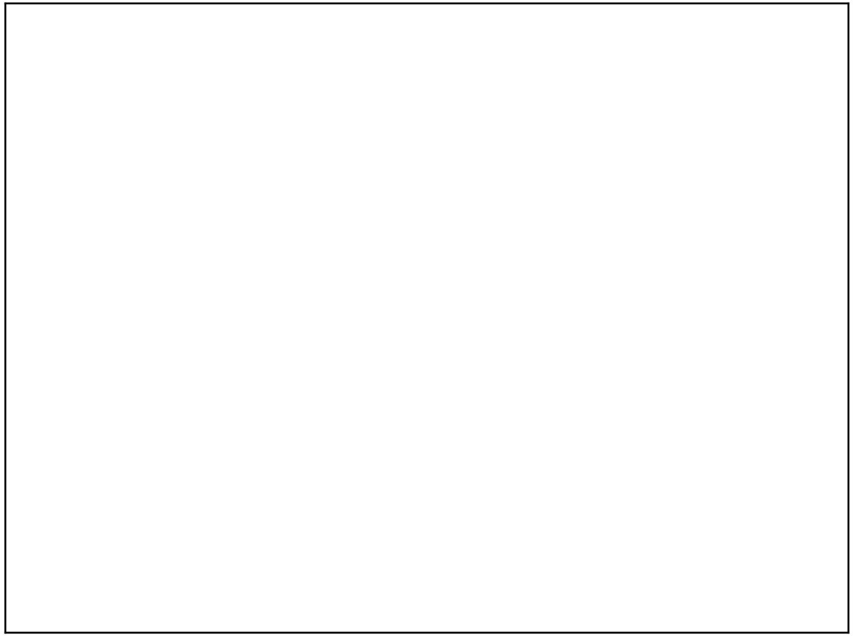
Graphs

Graphs

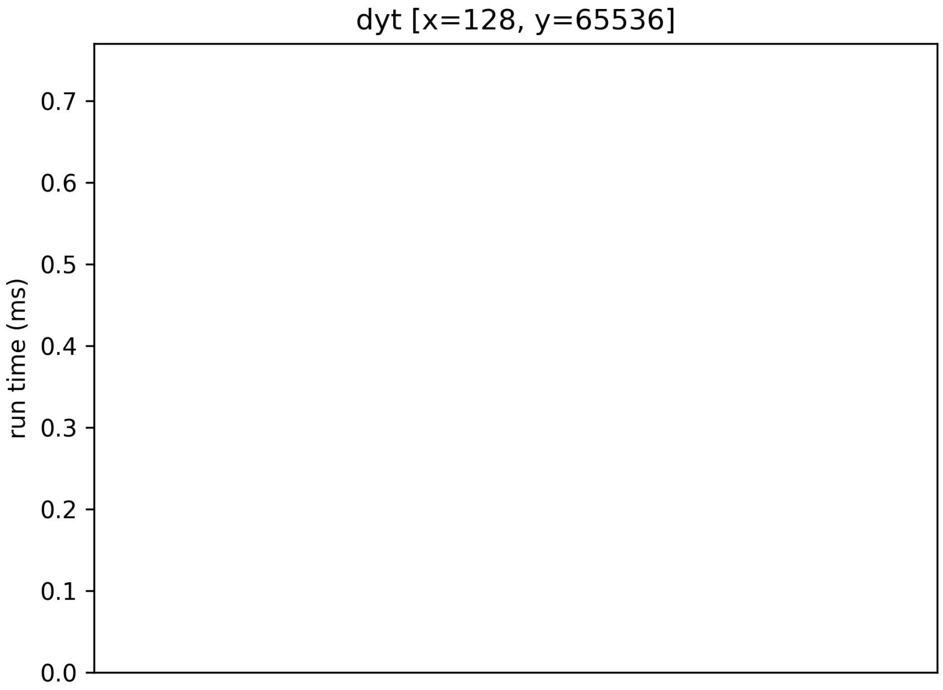


Graphs

dyt [x=128, y=65536]

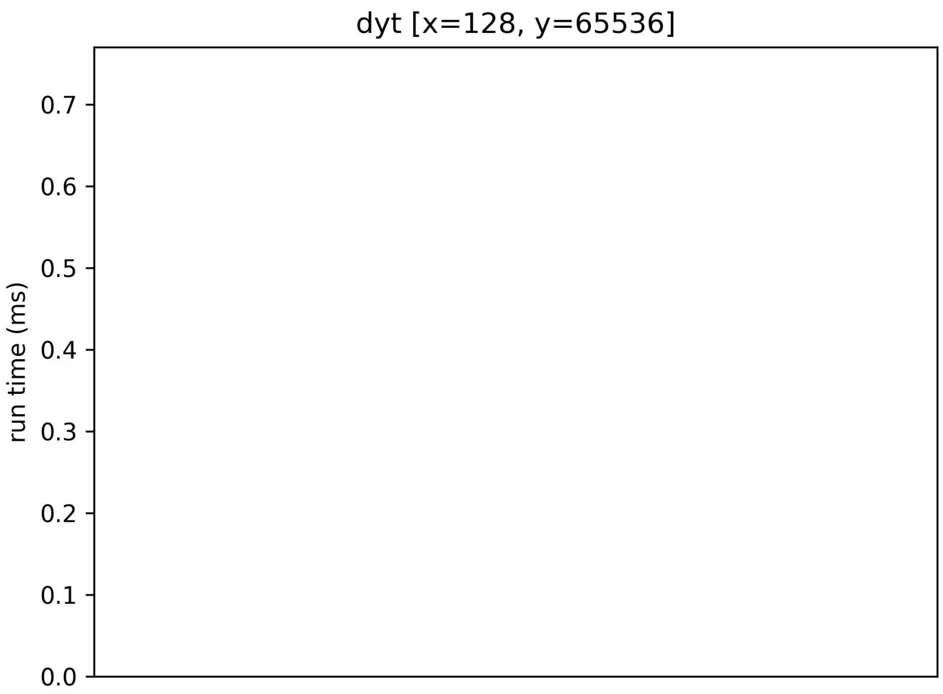


Graphs

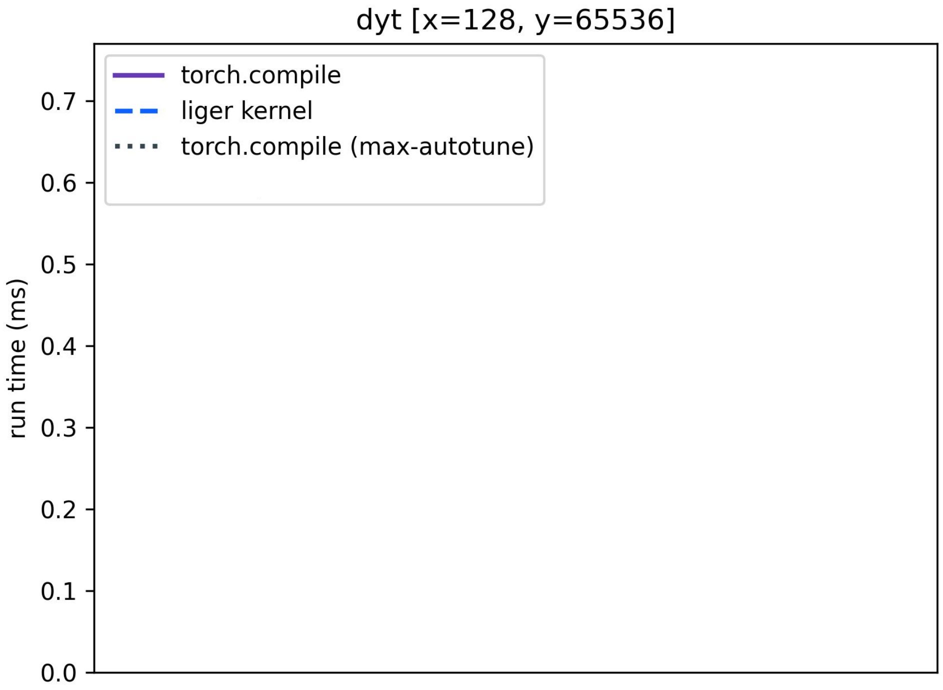


Graphs

Lower is better!

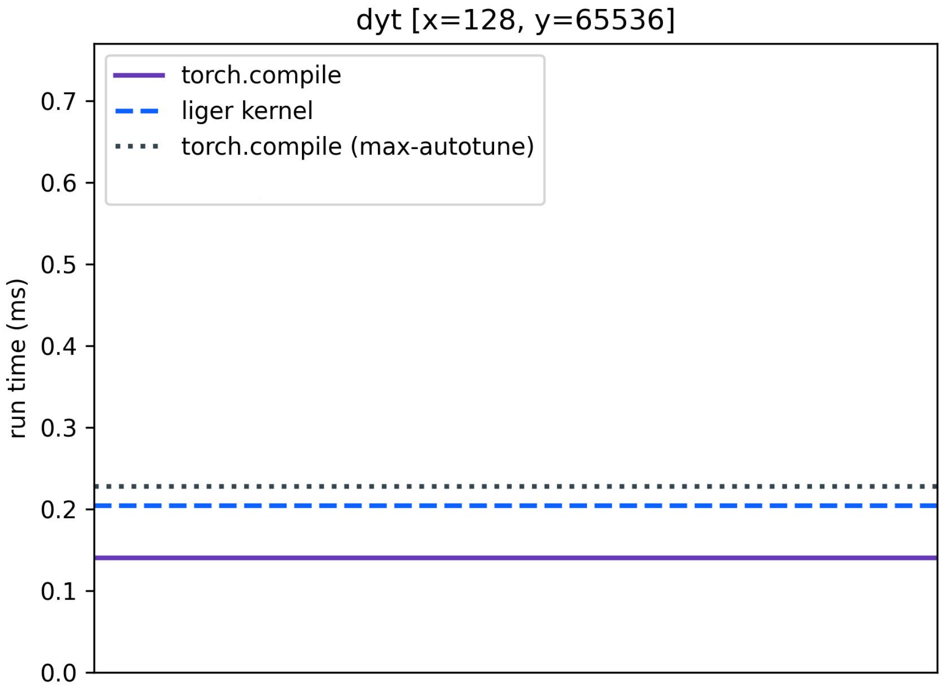


Graphs



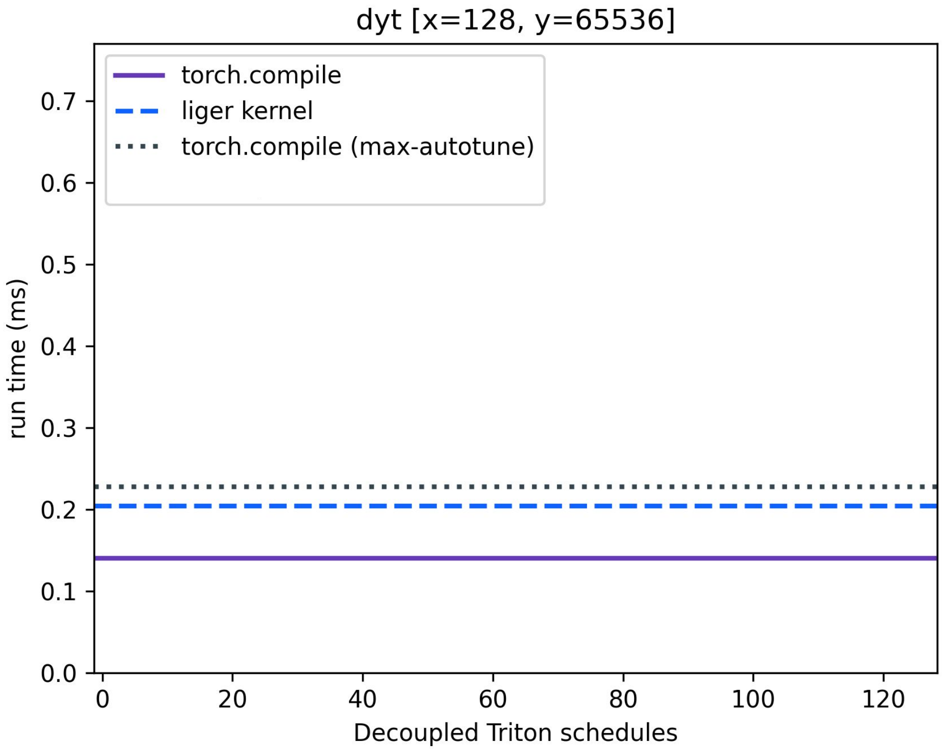
dyt [x=128, y=65536]
torch.compile
liger kernel
torch.compile (max-autotune)
run time (ms)
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0

Graphs

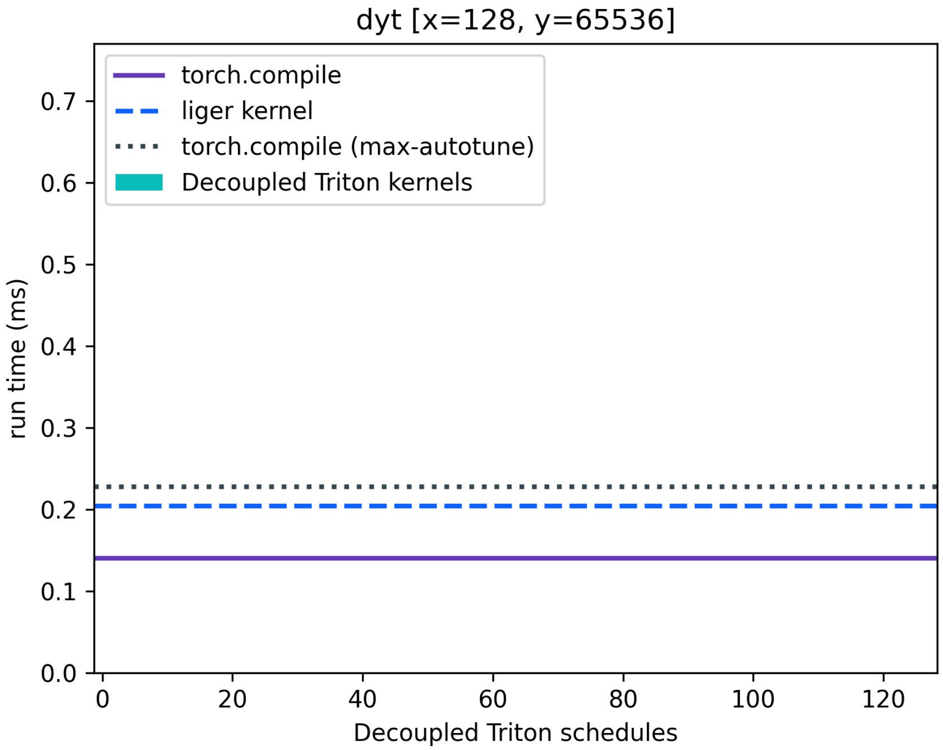


dyt [x=128, y=65536]
torch.compile
liger kernel
torch.compile (max-autotune)
run time (ms)
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7

Graphs

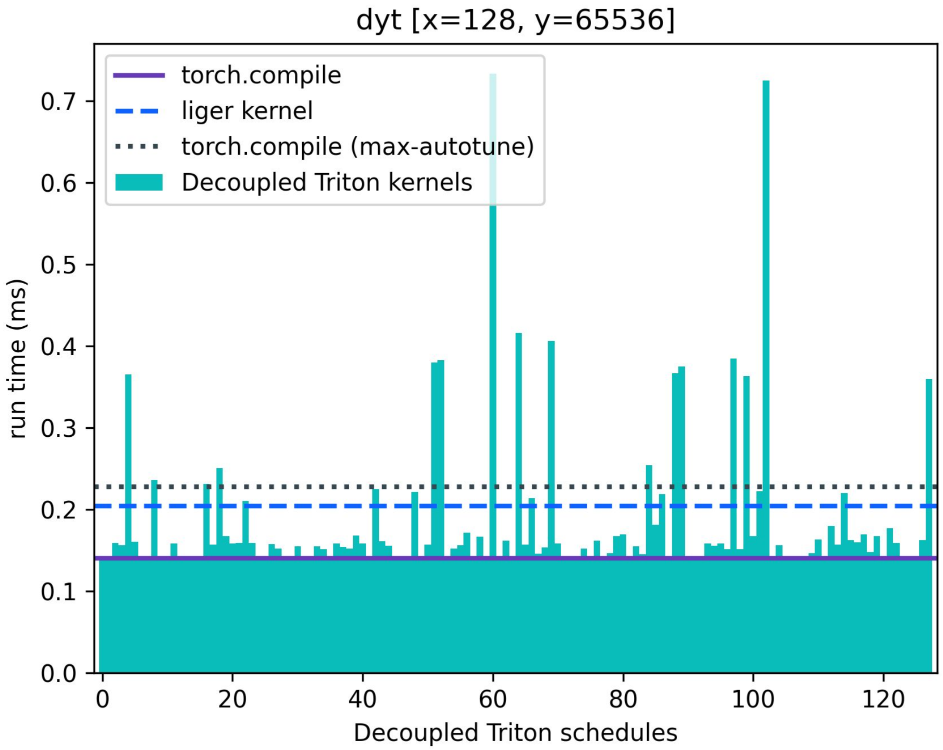

dyt [x=128, y=65536]
torch.compile
liger kernel
torch.compile (max-autotune)
run time (ms)
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
20
40
60
80
100
120
Decoupled Triton schedules

Graphs



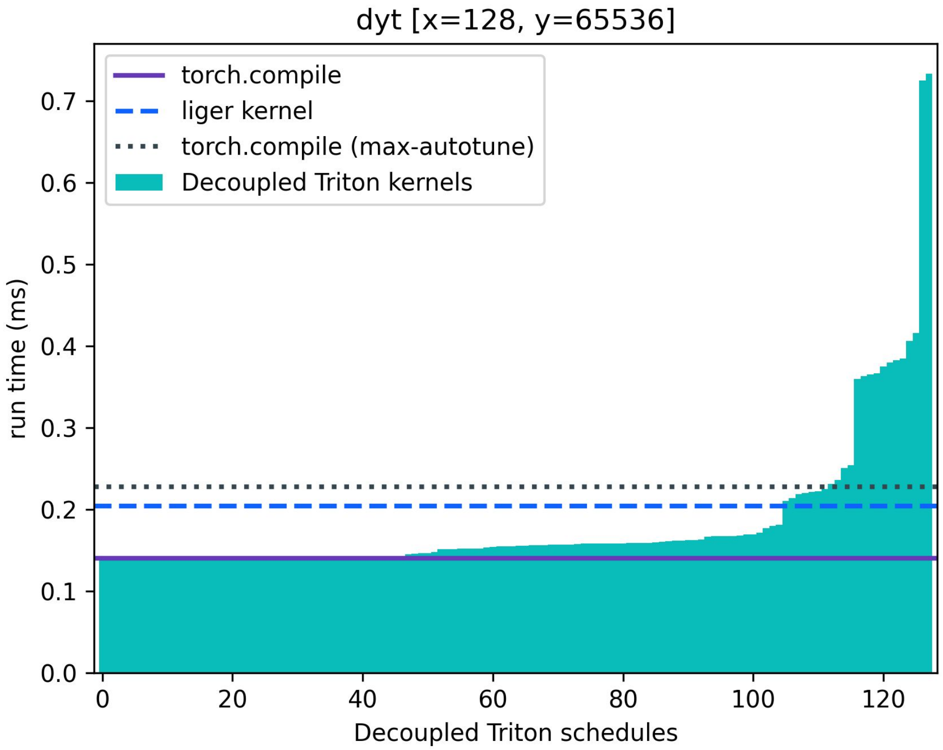
dyt [x=128, y=65536]
torch.compile
liger kernel
torch.compile (max-autotune)
Decoupled Triton kernels
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
run time (ms)
0
20
40
60
80
100
120
Decoupled Triton schedules

Graphs



dyt [x=128, y=65536]
torch.compile
liger kernel
torch.compile (max-autotune)
Decoupled Triton kernels
run time (ms)
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
20
40
60
80
100
120
Decoupled Triton schedules

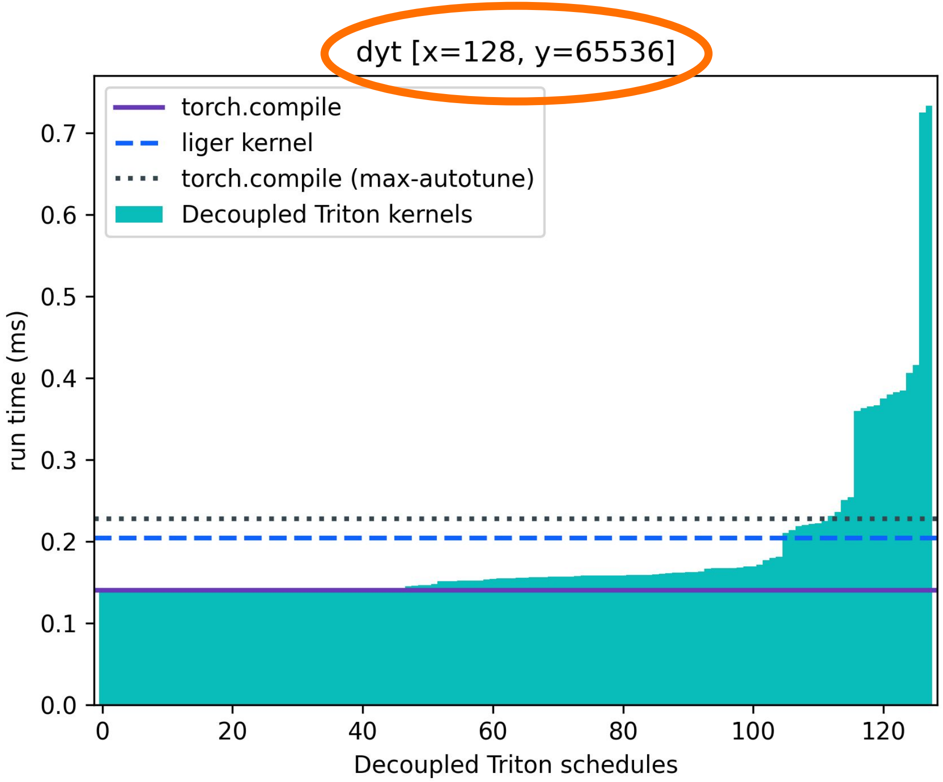
Graphs



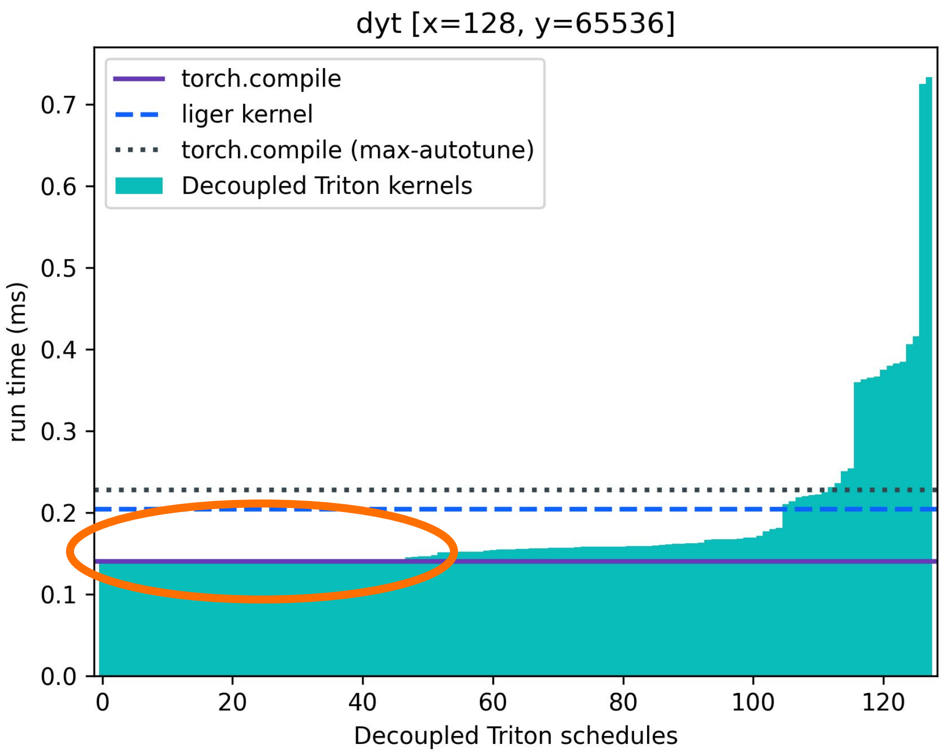
dyt [x=128, y=65536]
torch.compile
liger kernel
torch.compile (max-autotune)
Decoupled Triton kernels
run time (ms)
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
20
40
60
80
100
120
Decoupled Triton schedules

Graphs

What operation and dimension sizes?

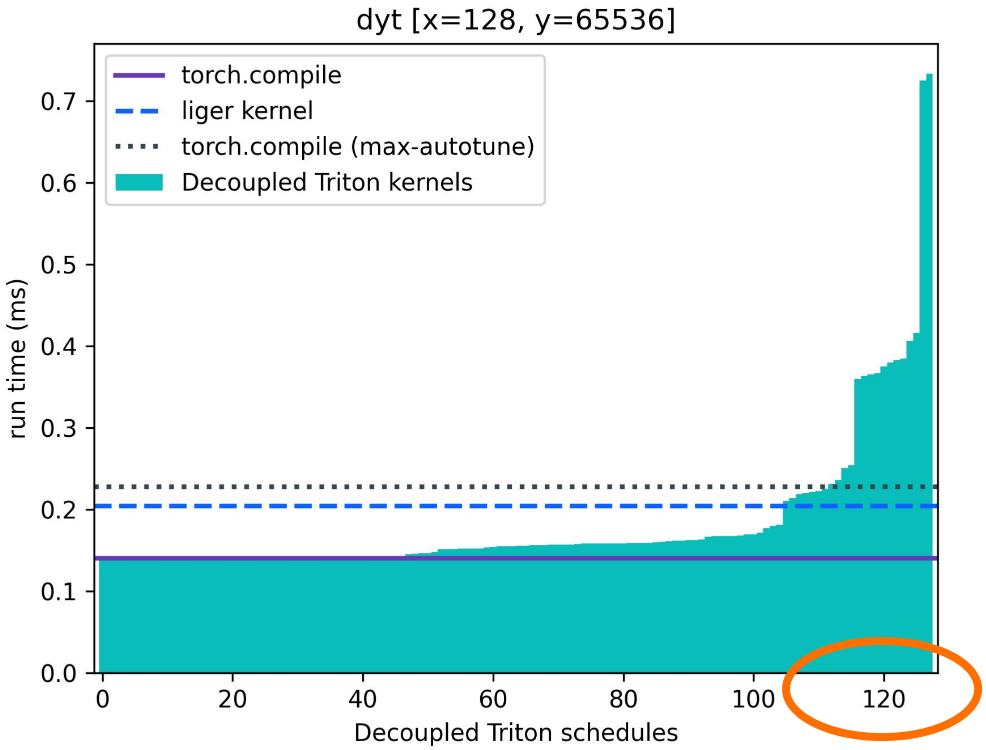


Graphs



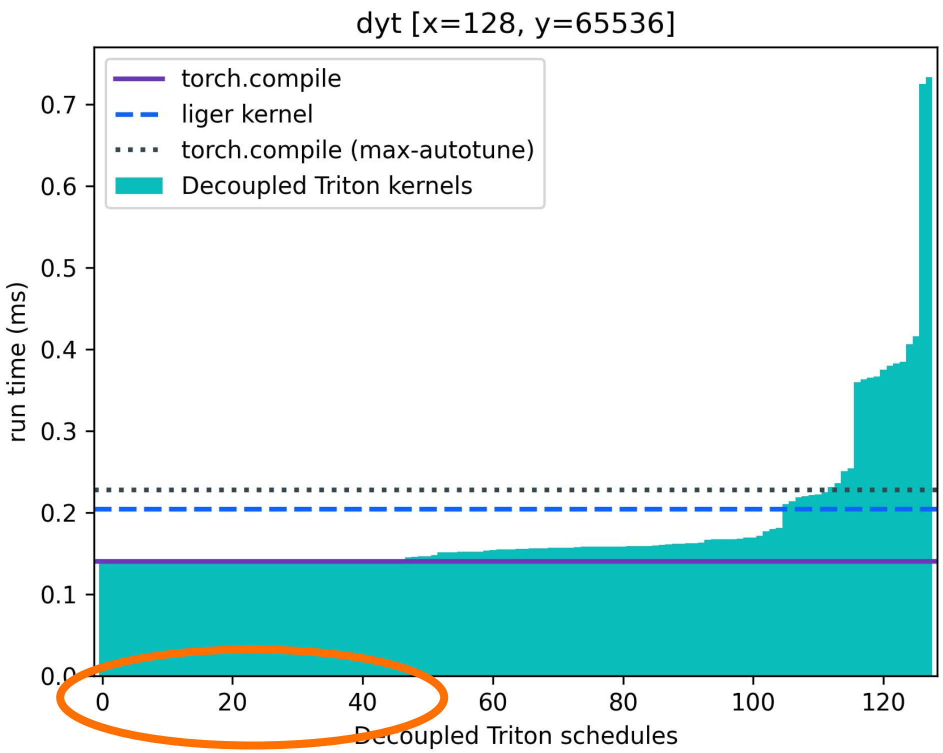
Competitive with the baselines?

Graphs



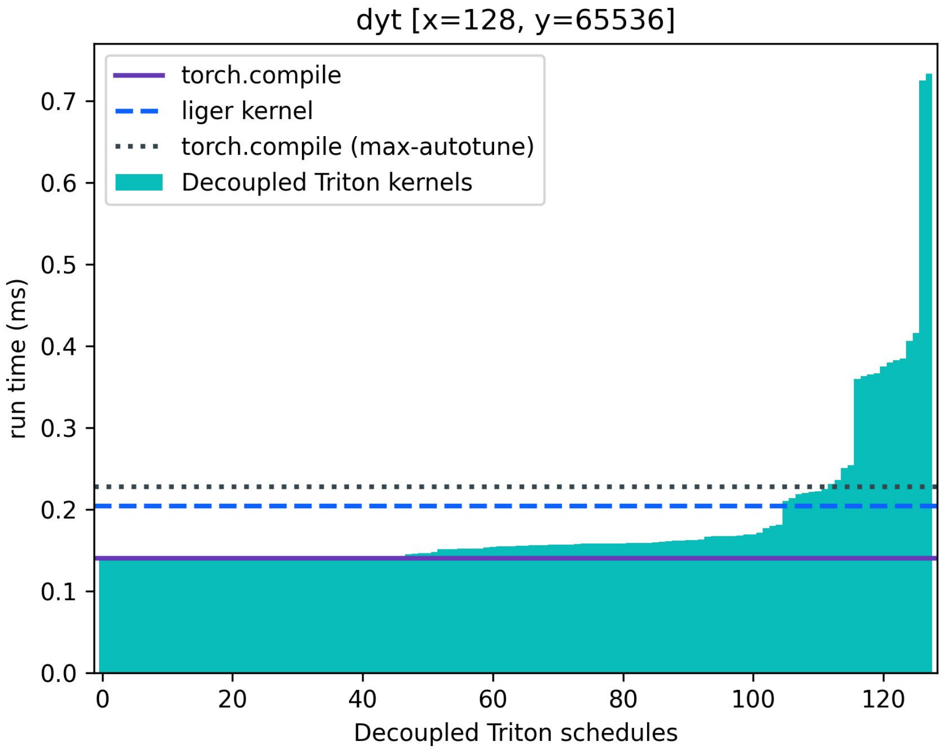
How many schedules in search space?

Graphs



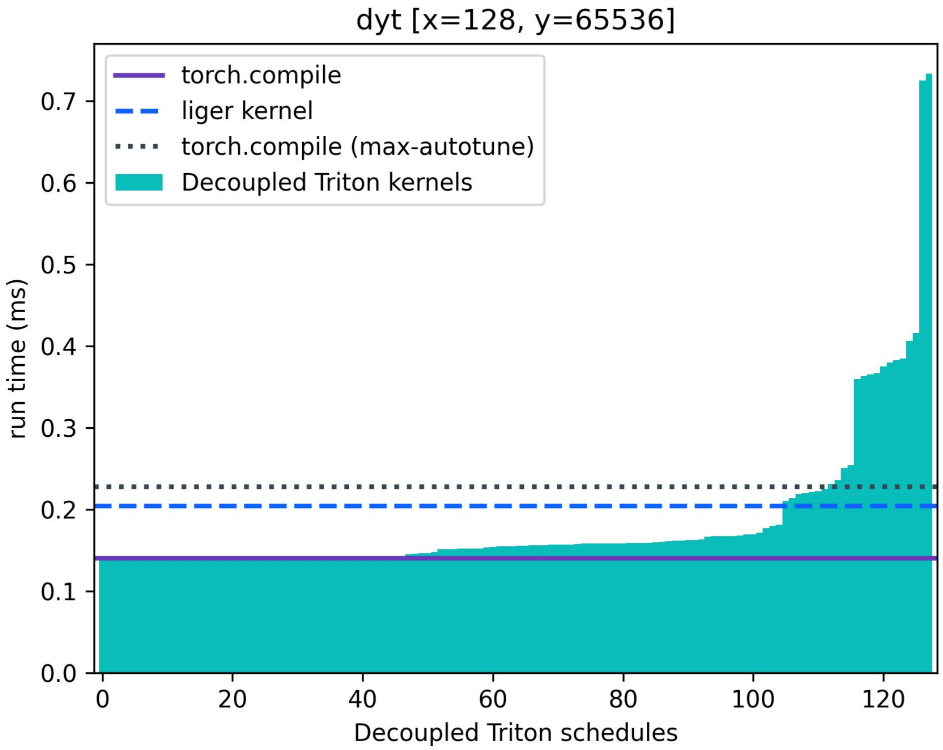
How many schedules are competitive?

DyT



dyt [x=128, y=65536]
torch.compile
liger kernel
torch.compile (max-autotune)
Decoupled Triton kernels
run time (ms)
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
20
40
60
80
100
120
Decoupled Triton schedules

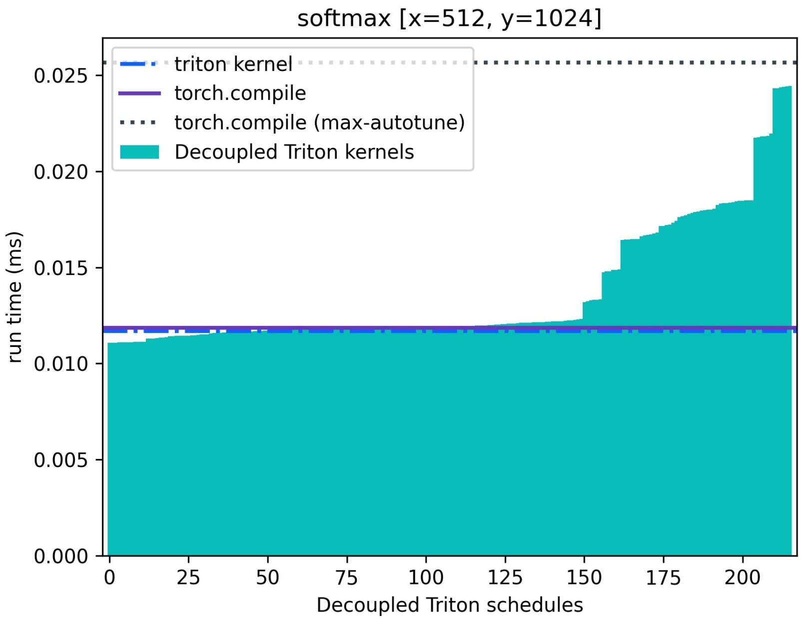
DyT



Many liger kernels have a limitations about the innermost dimension size!

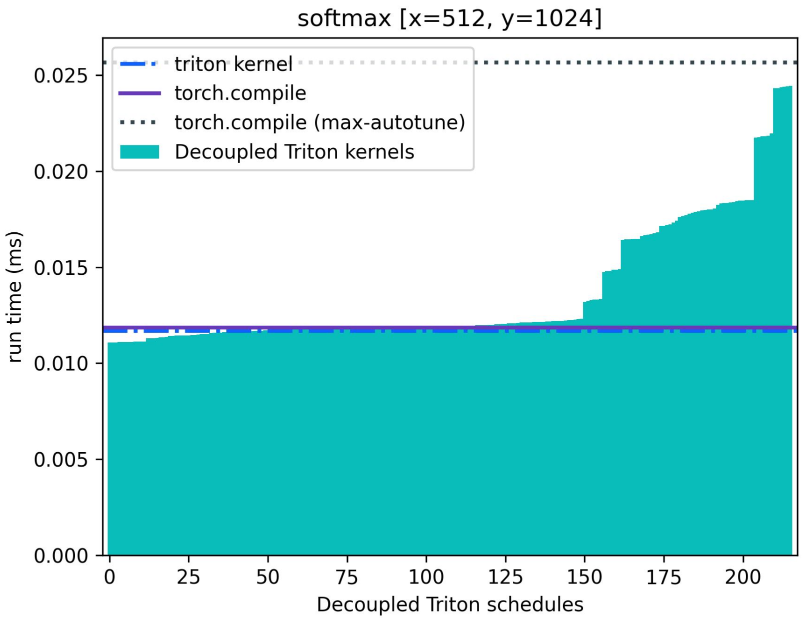
Softmax

Softmax

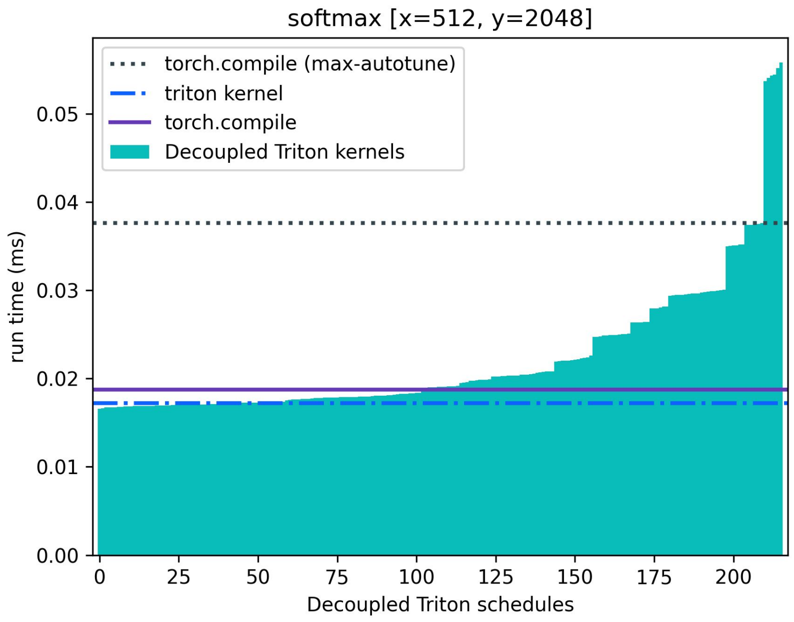


softmax [x=512, y=1024]
triton kernel
torch.compile
torch.compile (max-autotune)
Decoupled Triton kernels
run time (ms)
0.000
0.005
0.010
0.015
0.020
0.025
0
25
50
75
100
125
150
175
200
Decoupled Triton schedules

Softmax

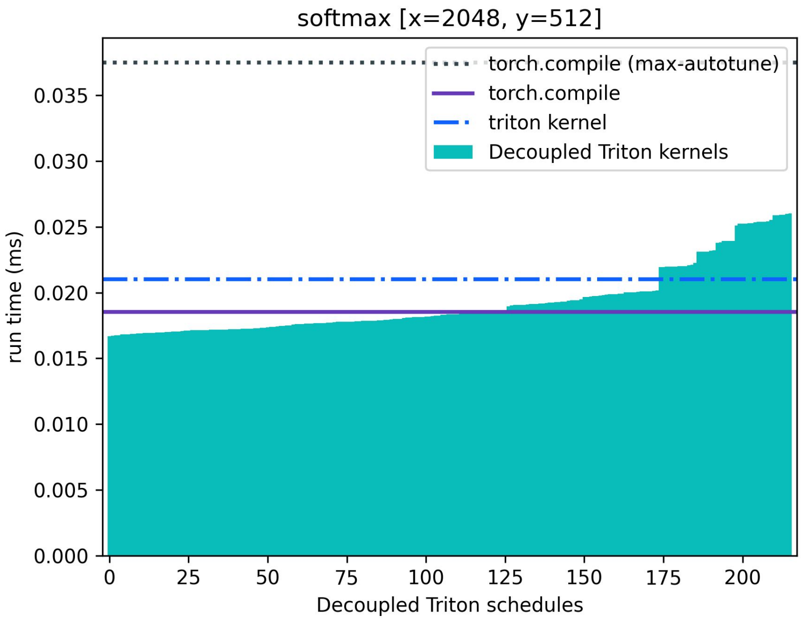


softmax [x=512, y=1024]
triton kernel
torch.compile
torch.compile (max-autotune)
Decoupled Triton kernels
run time (ms)
0.000
0.005
0.010
0.015
0.020
0.025
0
25
50
75
100
125
150
175
200
Decoupled Triton schedules



softmax [x=512, y=2048]
torch.compile (max-autotune)
triton kernel
torch.compile
Decoupled Triton kernels
run time (ms)
0.00
0.01
0.02
0.03
0.04
0.05
0
25
50
75
100
125
150
175
200
Decoupled Triton schedules

Softmax



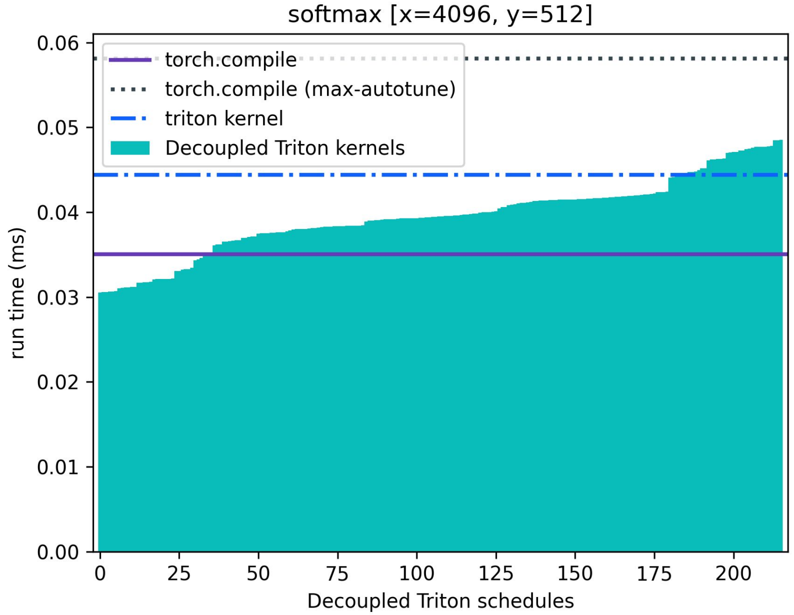
softmax [x=2048, y=512]
torch.compile (max-autotune)
torch.compile
triton kernel
Decoupled Triton kernels
run time (ms)
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
0
25
50
75
100
125
150
175
200
Decoupled Triton schedules

Softmax

```
Func _softmax, _sum;
In   A;
Var  x;
RVar y;

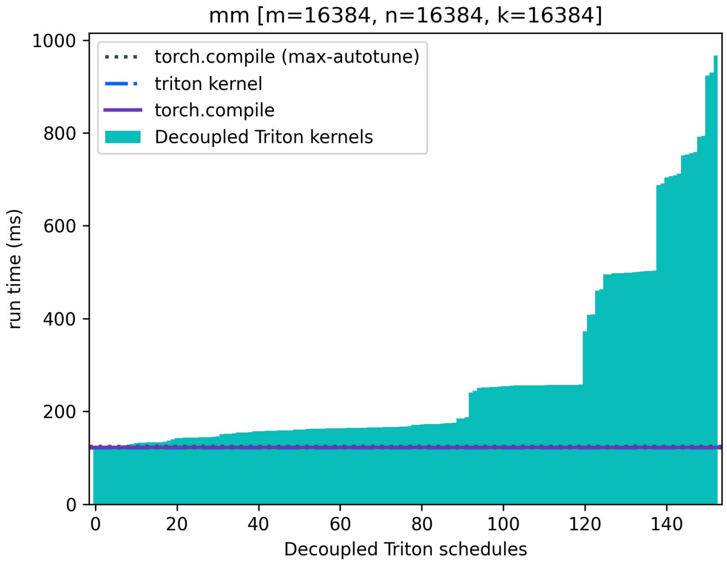
_sum[x]         = rsum(exp(A[x, y]), y);
_softmax[x, y] = exp(A[x, y]) / reshape(_sum[x], x, 1);

_softmax.block(x:4);
_softmax.tensorize(y:512);
_softmax.tensorize(x:0);
_softmax.num_warps(32);
_sum.fuse_at(_softmax, x);
_softmax.compile_to_kernel();
```

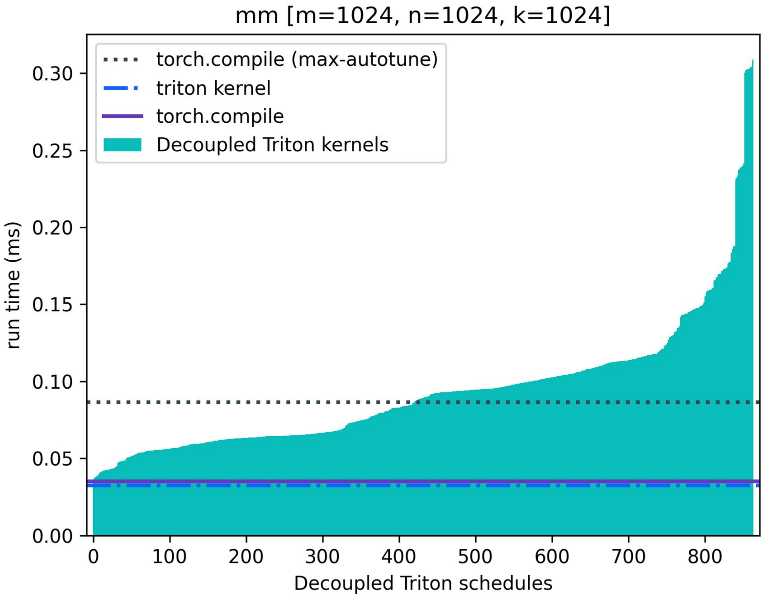


Matmul

Matmul

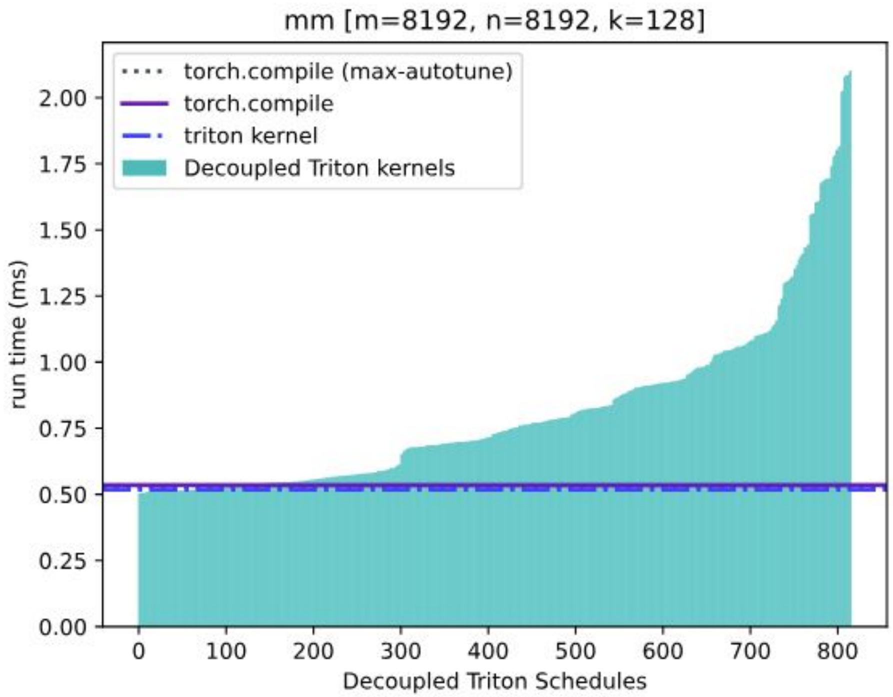


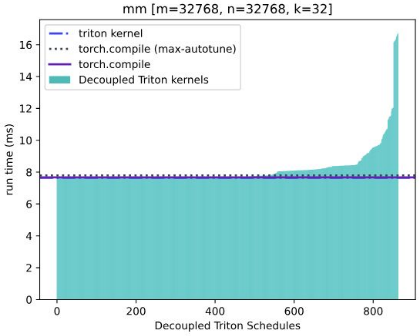
mm [m=16384, n=16384, k=16384]
torch.compile (max-autotune)
triton kernel
torch.compile
Decoupled Triton kernels
run time (ms)
0
200
400
600
800
1000
0
20
40
60
80
100
120
140
Decoupled Triton schedules

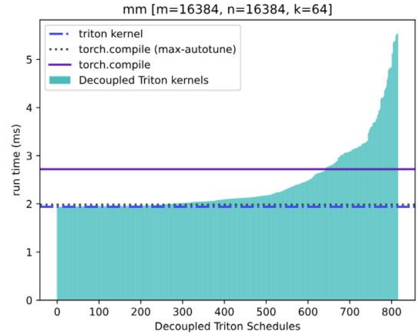


mm [m=1024, n=1024, k=1024]
torch.compile (max-autotune)
triton kernel
torch.compile
Decoupled Triton kernels
run time (ms)
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0
100
200
300
400
500
600
700
800
Decoupled Triton schedules

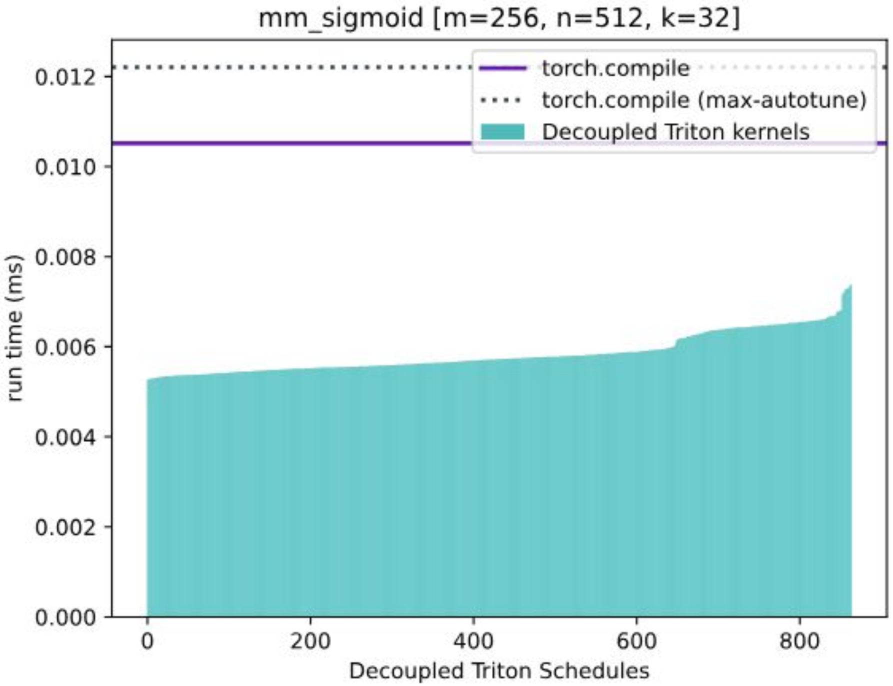
Matmul


mm [m=8192, n=8192, k=128]
torch.compile (max-autotune)
torch.compile
triton kernel
Decoupled Triton kernels
run time (ms)
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0
100
200
300
400
500
600
700
800
Decoupled Triton Schedules

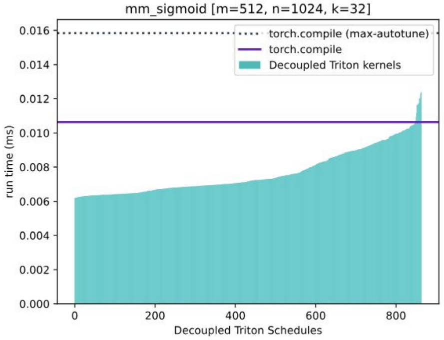

mm [m=32768, n=32768, k=32]
triton kernel
torch.compile (max-autotune)
torch.compile
Decoupled Triton kernels
run time (ms)
16
14
12
10
8
6
4
2
0
0
200
400
600
800
Decoupled Triton Schedules


mm [m=16384, n=16384, k=64]
triton kernel
torch.compile (max-autotune)
torch.compile
Decoupled Triton kernels
run time (ms)
5
4
3
2
1
0
0
100
200
300
400
500
600
700
800
Decoupled Triton Schedules

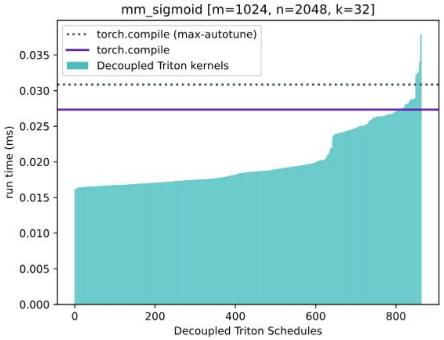
mmsigmoid



mm_sigmoid [m=256, n=512, k=32]
torch.compile
torch.compile (max-autotune)
Decoupled Triton kernels
run time (ms)
0.000
0.002
0.004
0.006
0.008
0.010
0.012
0
200
400
600
800
Decoupled Triton Schedules



mm_sigmoid [m=512, n=1024, k=32]
torch.compile (max-autotune)
torch.compile
Decoupled Triton kernels
run time (ms)
0.000
0.002
0.004
0.006
0.008
0.010
0.012
0.014
0.016
0
200
400
600
800
Decoupled Triton Schedules



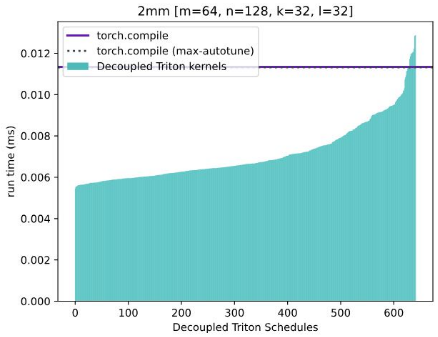
mm_sigmoid [m=1024, n=2048, k=32]
torch.compile (max-autotune)
torch.compile
Decoupled Triton kernels
run time (ms)
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
0
200
400
600
800
Decoupled Triton Schedules

2mm (outer-loop fusion)

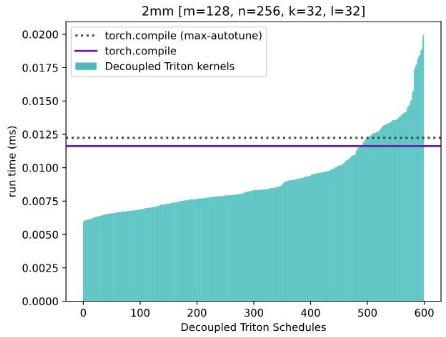
```
Func _2mm, mm;
In   A, B, C;
Var  m, n;
RVar k, l;

mm[m, l]   = rdot(A[m, k], B[k, l], k);
_2mm[m, n] = rdot(mm[m, l], C[l, n], l);

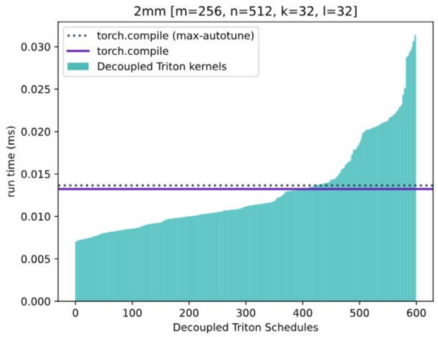
_2mm.block(m:16);
_2mm.tensorize(m:16);
_2mm.tensorize(n:64);
_2mm.tensorize(k:32);
_2mm.tensorize(l:0);
_2mm.num_stages(4);
_2mm.num_warps(4);
mm.fuse_at(_2mm, m);
_2mm.compile_to_kernel();
```



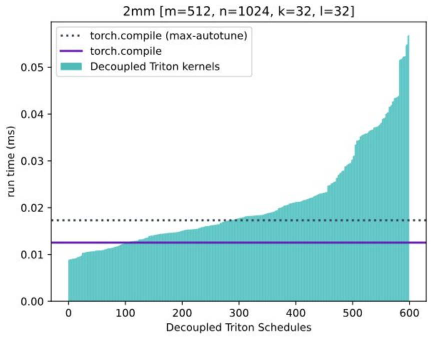
(a) `m=64, n=128, k=32, l=32`



(b) `m=128, n=256, k=32, l=32`

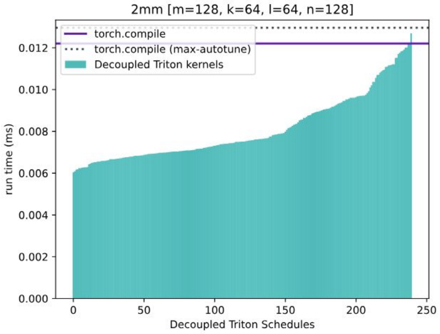


(c) `m=256, n=512, k=32, l=32`

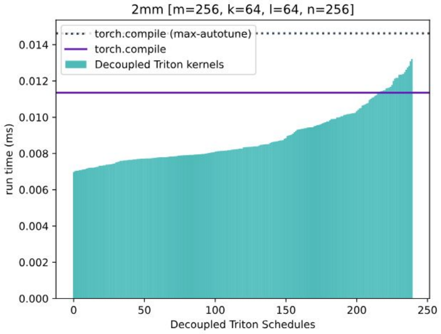


(d) `m=512, n=1024, k=32, l=32`

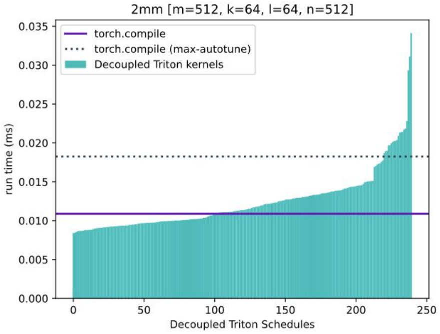
2mm (inner-loop fusion)



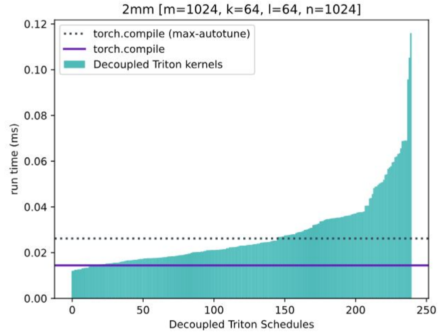
(a) m=128, k=64, l=64, n=128



(b) m=256, k=64, l=64, n=256



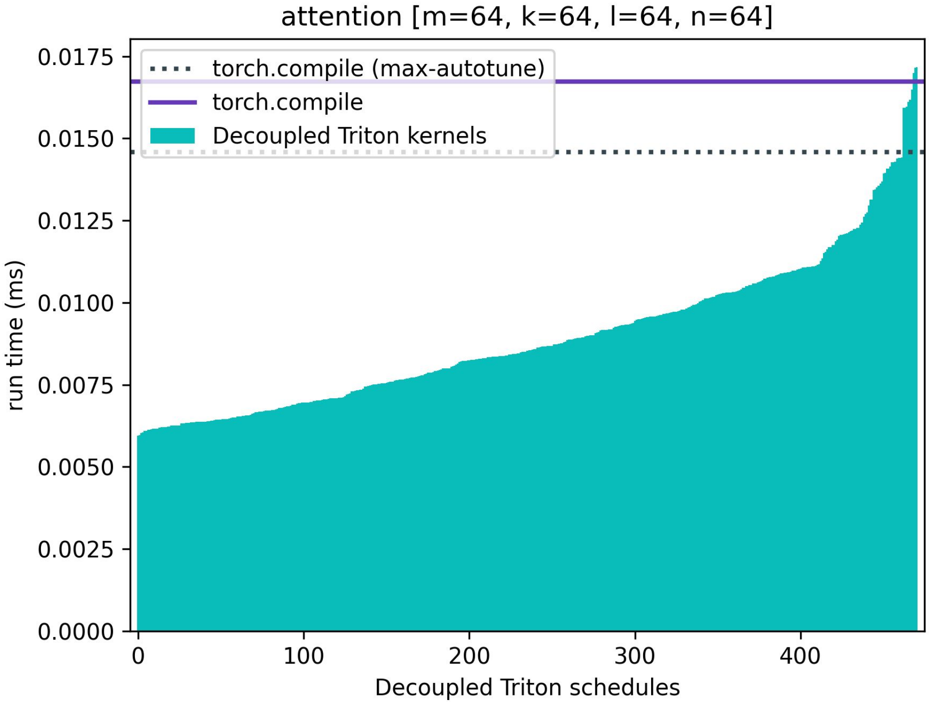
(c) m=512, k=64, l=64, n=512



(d) m=1024, k=64, l=64, n=1024

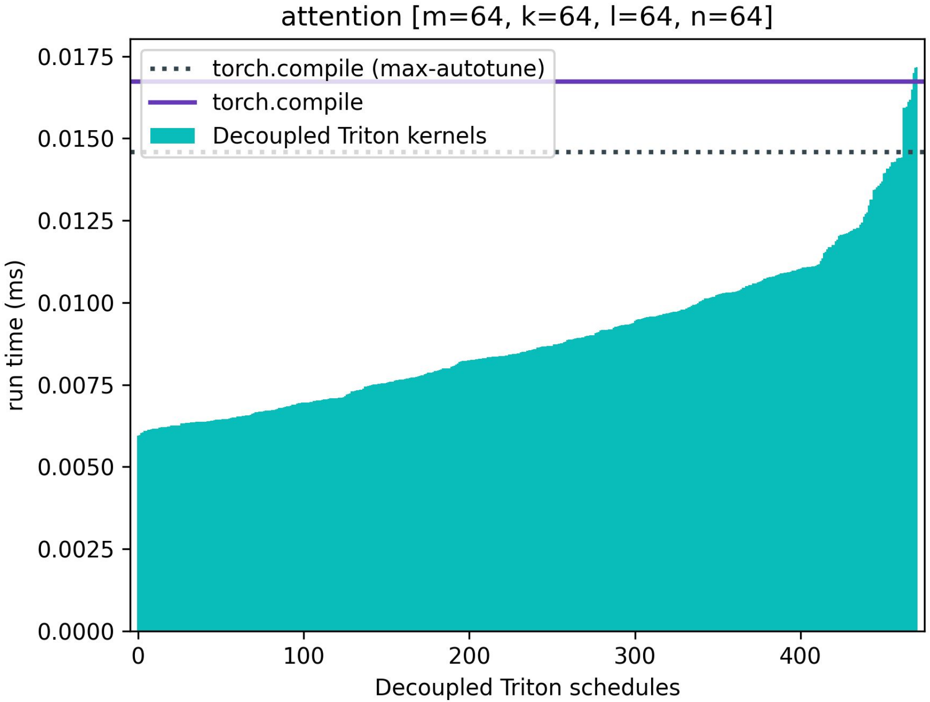
Attention

Attention

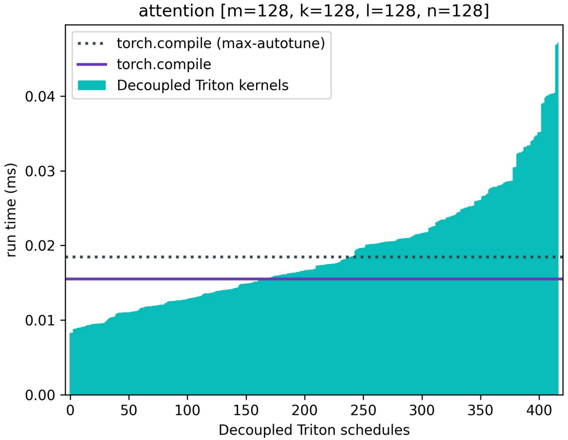


attention [m=64, k=64, l=64, n=64]
torch.compile (max-autotune)
torch.compile
Decoupled Triton kernels
run time (ms)
0.0175
0.0150
0.0125
0.0100
0.0075
0.0050
0.0025
0.0000
0
100
200
300
400
Decoupled Triton schedules

Attention

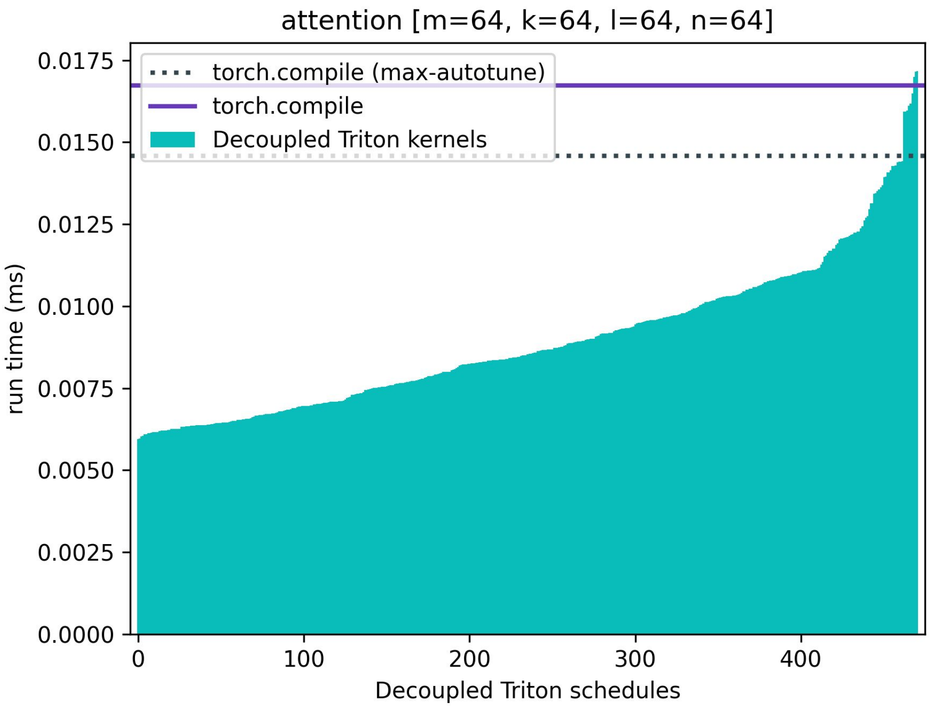


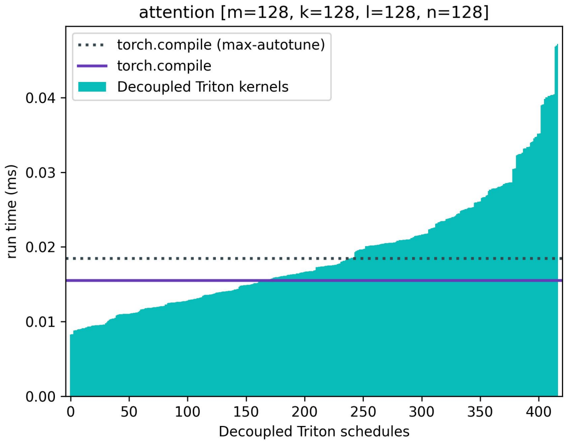
attention [m=64, k=64, l=64, n=64]
torch.compile (max-autotune)
torch.compile
Decoupled Triton kernels
run time (ms)
0.0000
0.0025
0.0050
0.0075
0.0100
0.0125
0.0150
0.0175
0
100
200
300
400
Decoupled Triton schedules

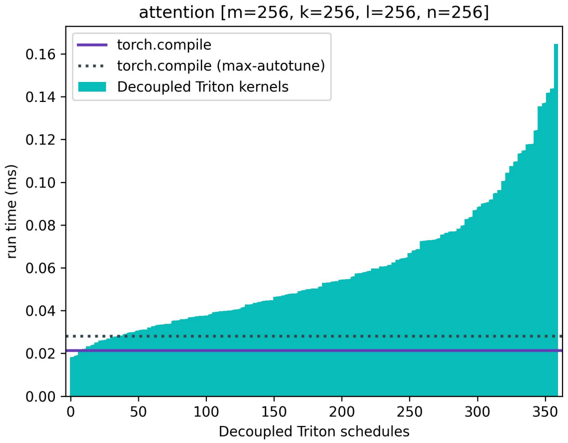


attention [m=128, k=128, l=128, n=128]
torch.compile (max-autotune)
torch.compile
Decoupled Triton kernels
run time (ms)
0.00
0.01
0.02
0.03
0.04
0
50
100
150
200
250
300
350
400
Decoupled Triton schedules

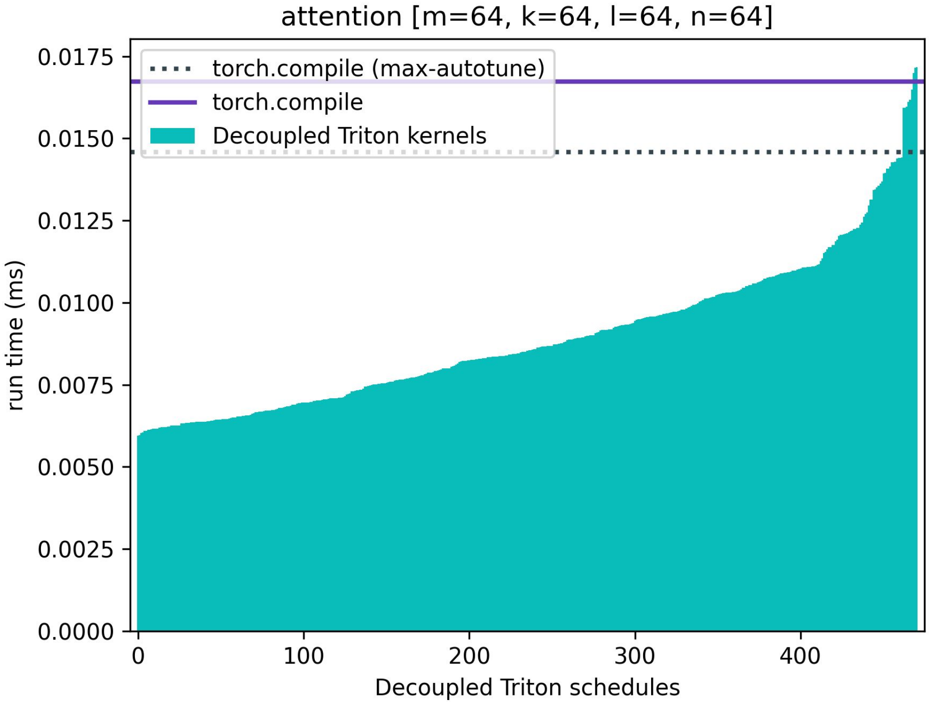
Attention


attention [m=64, k=64, l=64, n=64]
torch.compile (max-autotune)
torch.compile
Decoupled Triton kernels
run time (ms)
0.0000
0.0025
0.0050
0.0075
0.0100
0.0125
0.0150
0.0175
0
100
200
300
400
Decoupled Triton schedules


attention [m=128, k=128, l=128, n=128]
torch.compile (max-autotune)
torch.compile
Decoupled Triton kernels
run time (ms)
0.00
0.01
0.02
0.03
0.04
0
50
100
150
200
250
300
350
400
Decoupled Triton schedules


attention [m=256, k=256, l=256, n=256]
torch.compile
torch.compile (max-autotune)
Decoupled Triton kernels
run time (ms)
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
0
50
100
150
200
250
300
350
Decoupled Triton schedules

Attention




```
Func attention, mm, e, sm, dvsr;
In   A, B, C;
Var  m, n;
RVar k, l;

mm[m, l]        = rdot(A[m, k], B[k, l], k) / sqrt(len(l));
e[m, l]         = exp(mm[m, l]);
dvsr[m]         = rsum(e[m, l], l);
sm[m, l]        = e[m, l] / reshape(dvsr[m], m, 1);
attention[m, n] = rdot(sm[m, l], C[l, n], l);

attention.tensorize(m:16);
attention.block(m:16);
attention.tensorize(n:64);
attention.tensorize(k:16);
attention.tensorize(l:0);
attention.num_stages(8);
attention.num_warps(8);
mm.fuse_at(e, l);
dvsr.fuse_at(sm, m);
sm.fuse_at(attention, m);
e.fuse_at(attention, m);
attention.compile();
```

Discussion

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- Decoupled Triton can always compete with expert-written Triton kernels and PyTorch.

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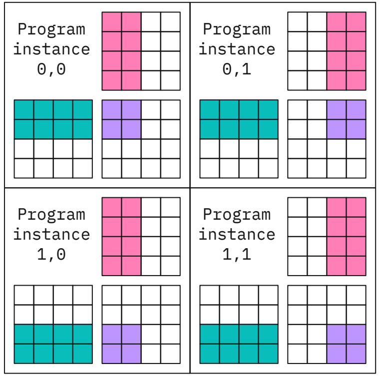
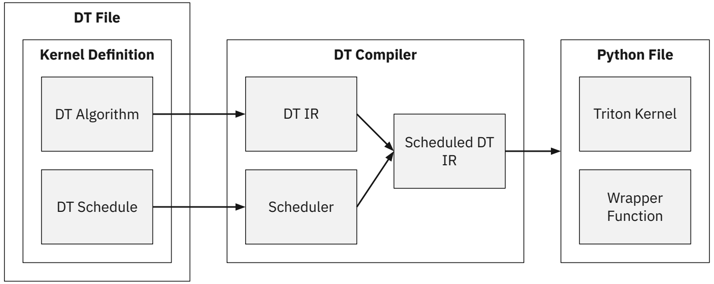
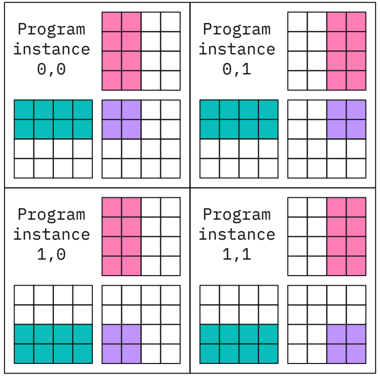
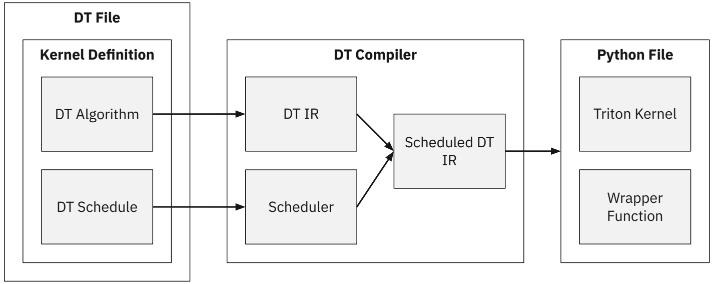
- Generally, it is easy to find an efficient schedule for an operation.

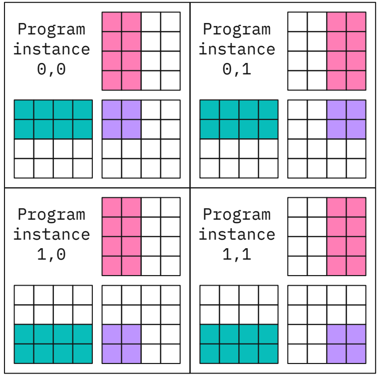
- Decoupled Triton can outperform expert-written Triton kernels and PyTorch when the shapes are unusual or when the existing solutions cannot implement efficient fusions.


Program instance 0,0
Program instance 0,1
Program instance 1,0
Program instance 1,1


DT File
Kernel Definition
DT Algorithm
DT Schedule
DT Compiler
DT IR
Scheduler
Scheduled DT IR
Python File
Triton Kernel
Wrapper Function


Program instance 0,0
Program instance 0,1
Program instance 1,0
Program instance 1,1

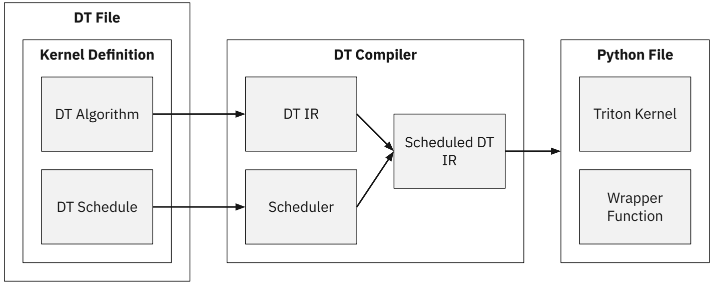


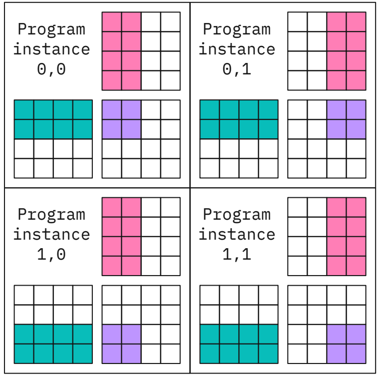



```
# Declarations
Func mm;
In A, B;
Var x, y;
RVar k;

# Algorithm
mm[x, y] = rdot(A[x, k], B[k, y], k);

# Schedule
mm.tensorize(x:128, k:32, y:128);
mm.block(x:128, y:128);
mm.map(x:x1/8, y, x1);
mm.num_warps(4);
mm.num_stages(3);
mm.compile();
```





0	0	0	0
0	0	0	0

1	1	1	1
1	1	1	1

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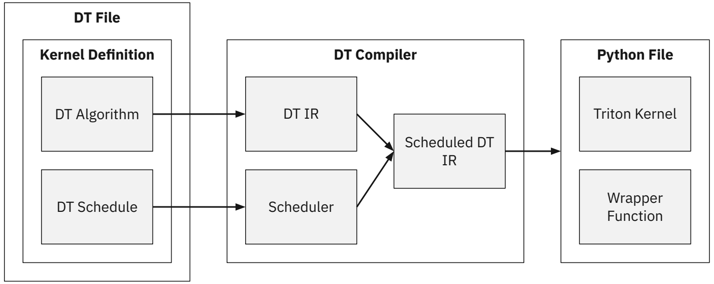

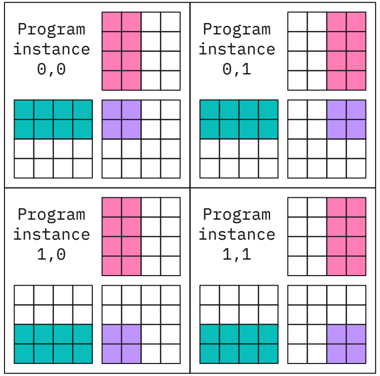

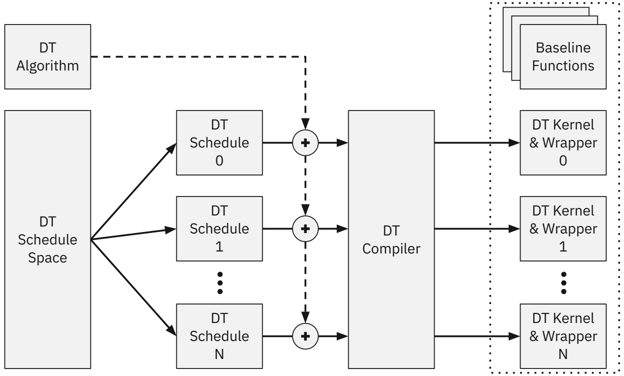

0	0	0	0
0	0	0	0

1	1	1	1
1	1	1	1

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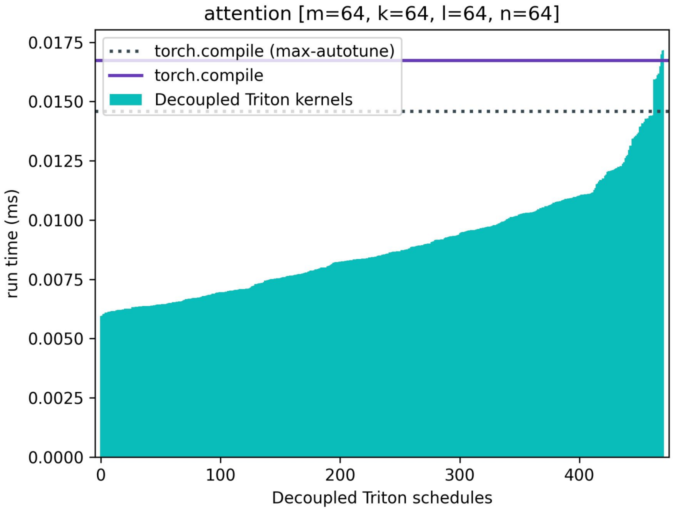
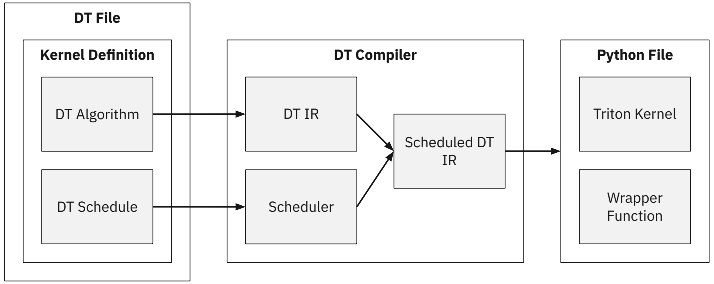
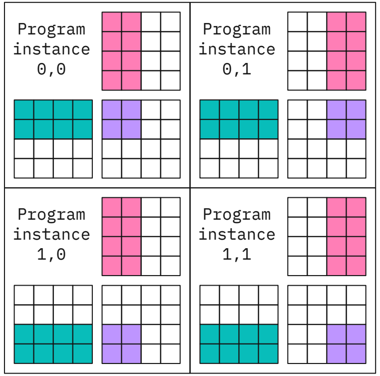
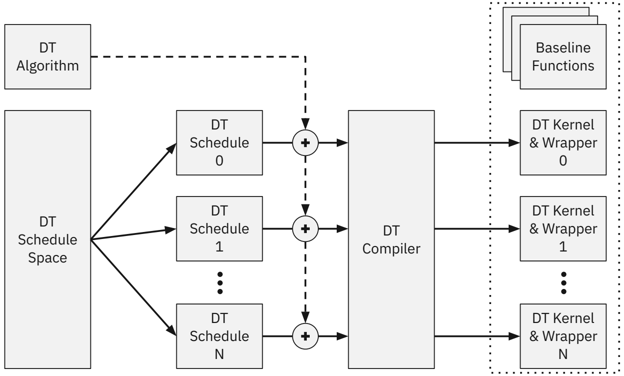
```









0	0	0	0
0	0	0	0

1	1	1	1
1	1	1	1

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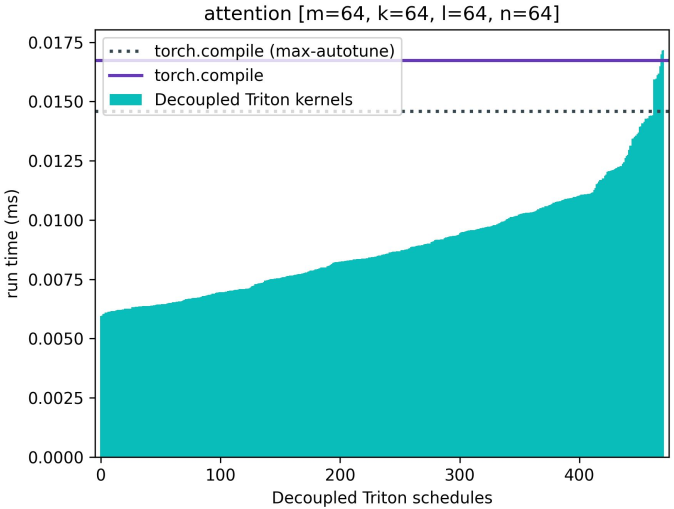
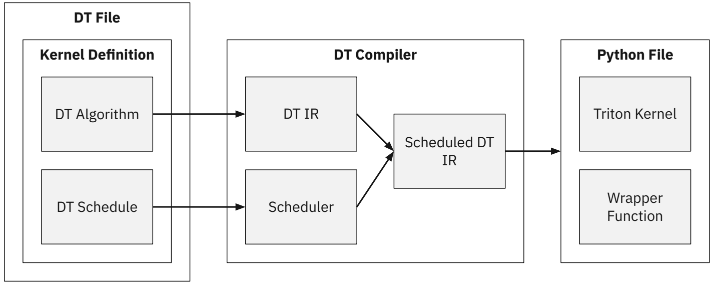
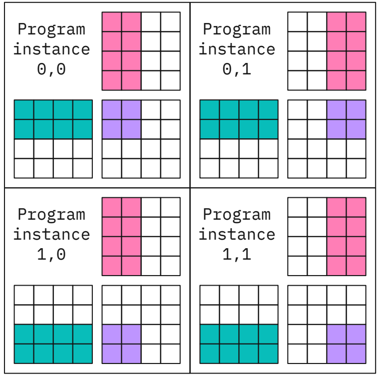
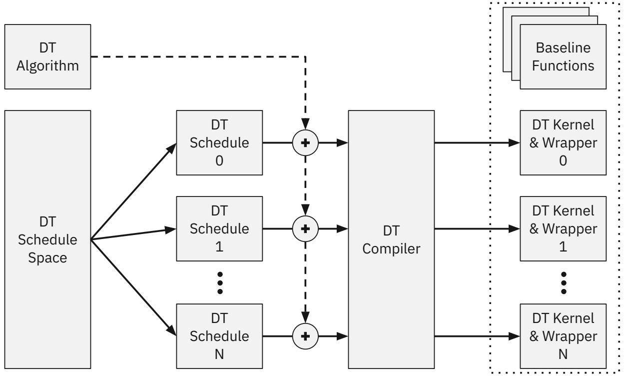
```







Thank you :)



0	0	0	0
0	0	0	0

1	1	1	1
1	1	1	1

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```