https://hao-ai-lab.github.io/dsc291-s24/

DSC 291: ML Systems
Spring 2024

LLMs

Parallelization

Single-device Optimization

Basics

GPU and CUDA

- Basic concepts and Architecture
  - Concepts
  - Execution Model
  - Memory
- Programming abstraction
- **Case study: Matmul**

Case study: GPU Matmul

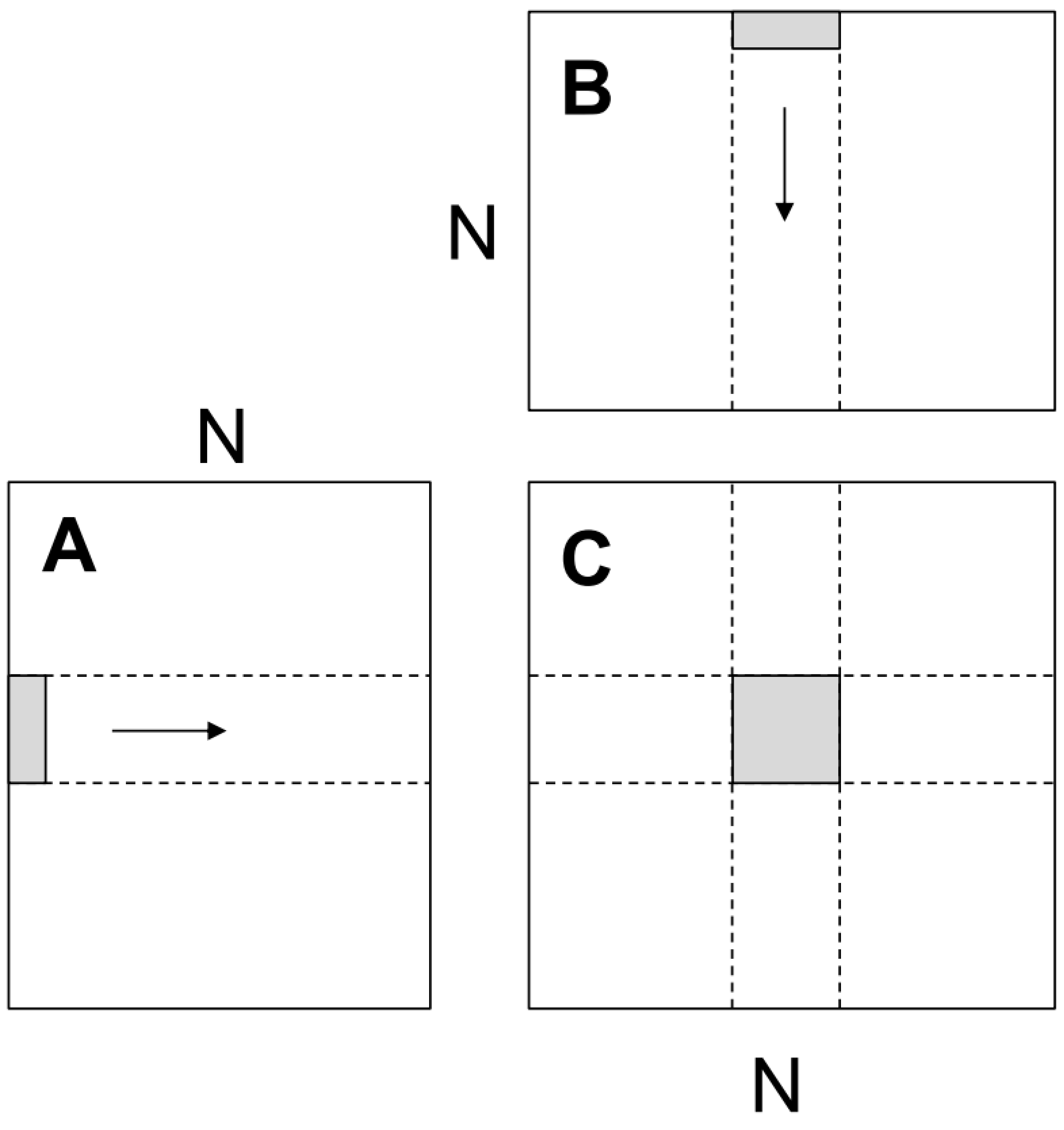
- Strawman solution:
  - C = A x B
  - Each thread computes one element

```
int N = 1024;
dim3 threadsPerBlock(32, 32, 1);
dim3 numBlocks(N/32, N/32, 1);

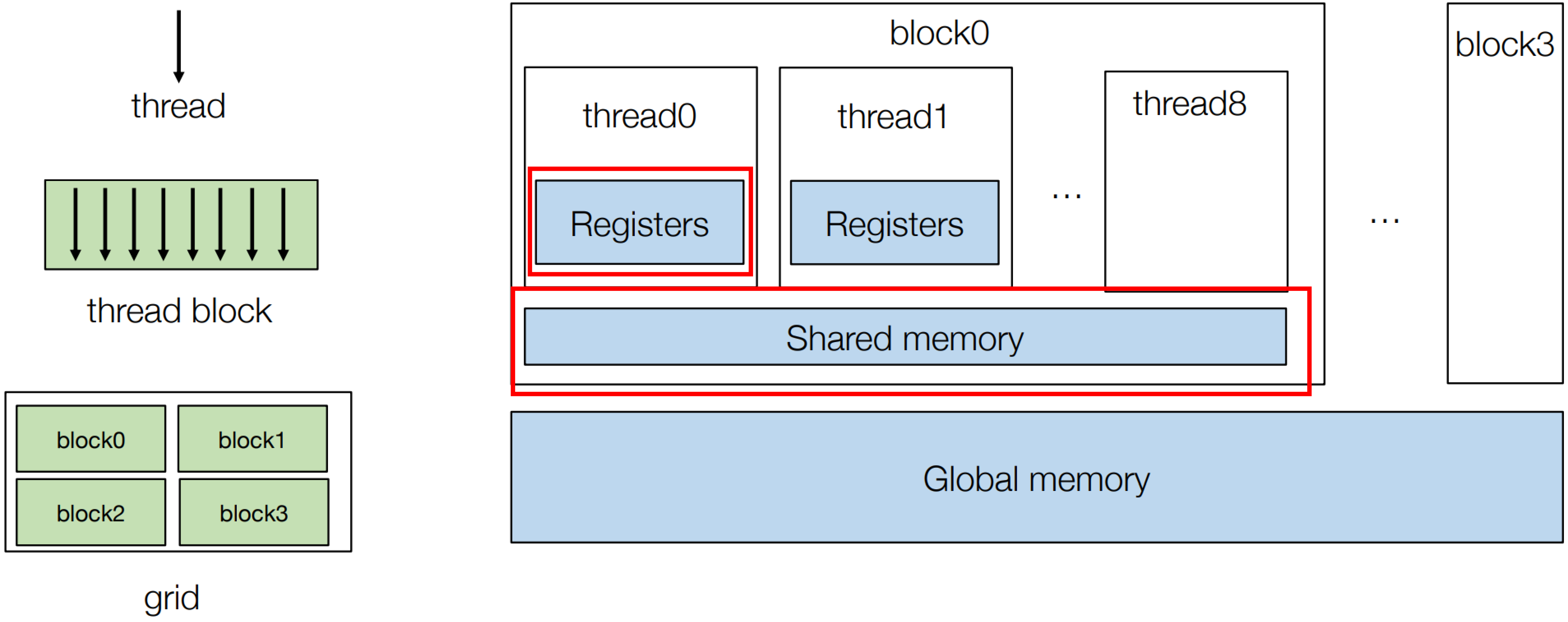
matmul<<<numBlocks, threadsPerBlock>>>(A, B, C);
```

```
__global__ void mm(float A[N][N], float B[N][N], float C[N][N]) {
  int x = blockIdx.x * blockDim.x + threadIdx.x;
  int y = blockIdx.y * blockDim.y + threadIdx.y;

  result = 0;
  for (int k = 0; k < N; ++k) {
    result += A[x][k] * B[k][y];
  }
  C[x][y] = result;
}
```



High-level Opt Idea: Recall Memory Hierarchy

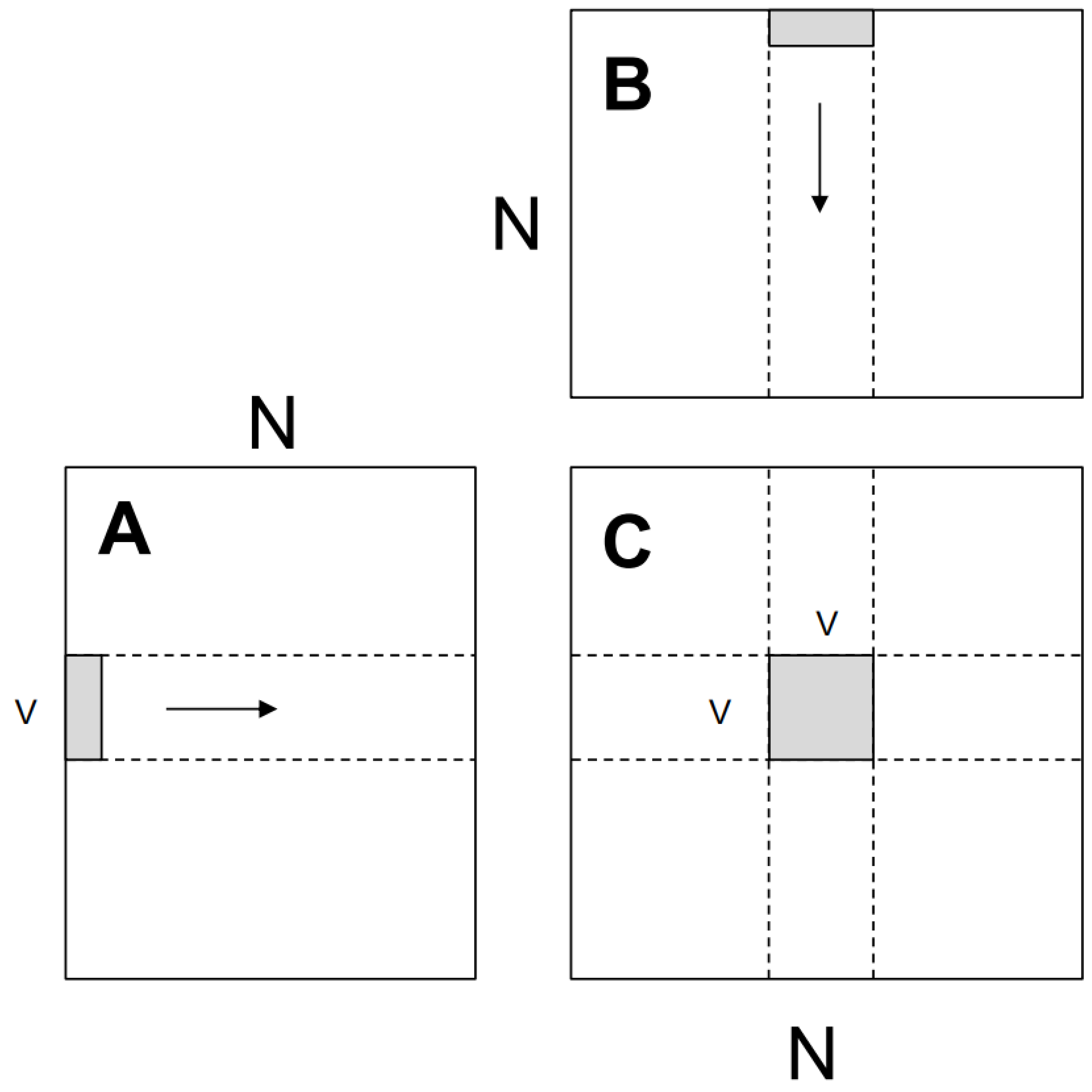


Recall register tiling -> thread tiling

- Each thread computes a VxV submatrix

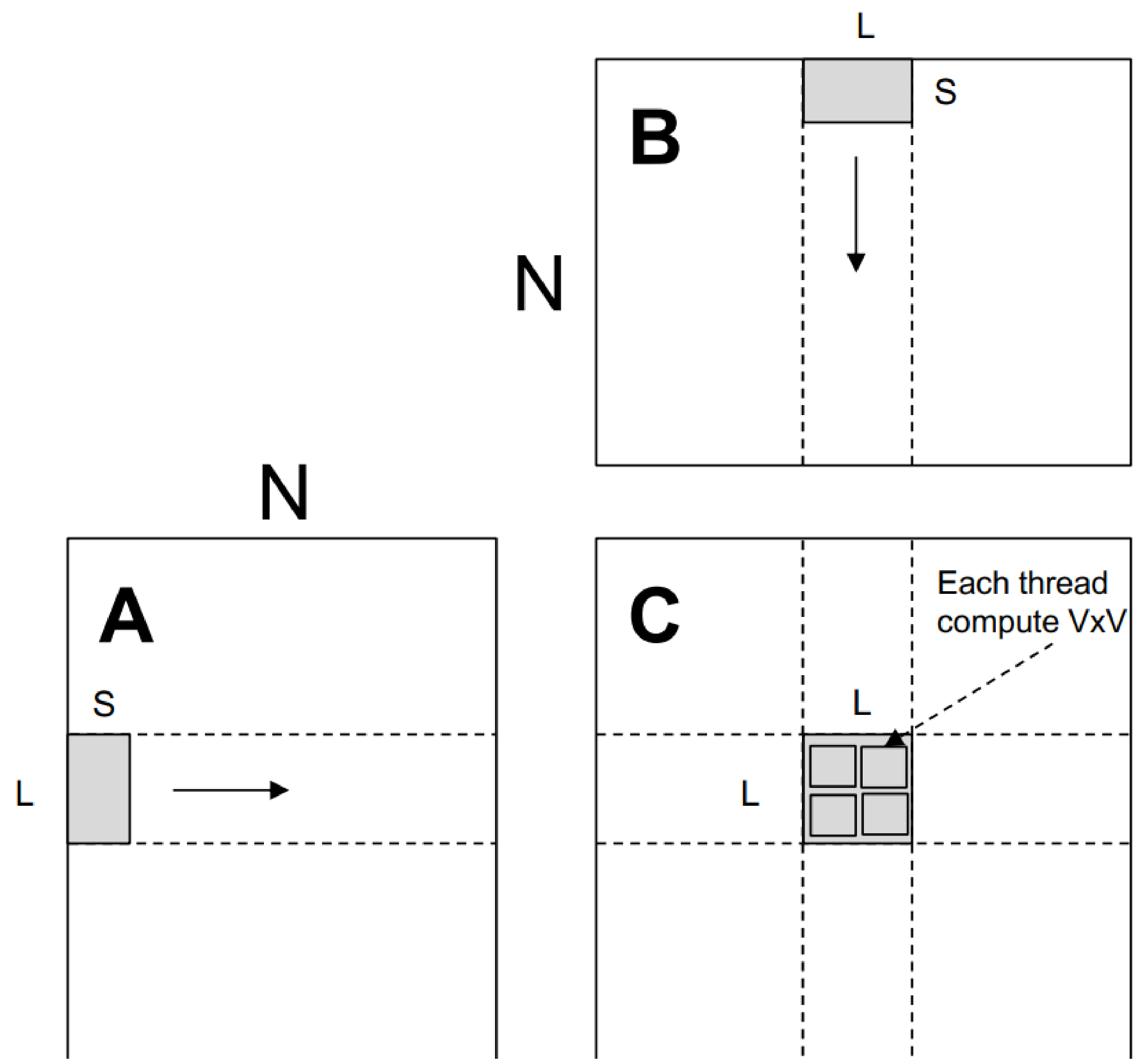
```
__global__ void mm(float A[N][N], float B[N][N], float C[N][N]) {
  int ybase = blockIdx.y * blockDim.y + threadIdx.y;
  int xbase = blockIdx.x * blockDim.x + threadIdx.x;

  float c[V][V] = {0};
  float a[V], b[V];
  for (int k = 0; k < N; ++k) {
    a[:] = A[xbase*V : xbase*V + V, k];
    b[:] = B[k, ybase*V : ybase*V + V];
    for (int y = 0; y < V; ++y) {
      for (int x = 0; x < V; ++x) {
        c[x][y] += a[x] * b[y];
      }
    }
  }
  C[xbase * V : xbase*V + V, ybase*V : ybase*V + V] = c[:];
}
```



Recall Cache-aware tiling -> block-level tiling

- Use block shared mem
- A block computes a L x L submatrix
- Then a thread computes a V x V submatrix and reuses the matrices in shared block memory




```
__global__ void mm(float A[N][N], float B[N][N], float C[N][N]) {
  __shared__ float sA[S][L], sB[S][L];
  float c[V][V] = {0};
  float a[V], b[V];
  int yblock = blockIdx.y;
  int xblock = blockIdx.x;

  for (int ko = 0; ko < N; ko += S) {
    __syncthreads();
    // needs to be implemented by thread cooperative fetching
    sA[:, :] = A[k : k + S, yblock * L : yblock * L + L];
    sB[:, :] = B[k : k + S, xblock * L : xblock * L + L];
    __syncthreads();
    for (int ki = 0; ki < S; ++ ki) {
      a[:] = sA[ki, threadIdx.y * V : threadIdx.y * V + V];
      b[:] = sA[ki, threadIdx.x * V : threadIdx.x * V + V];
      for (int y = 0; y < V; ++y) {
        for (int x = 0; x < V; ++x) {
          c[y][x] += a[y] * b[x];
        }
      }
    }
  }
  int ybase = blockIdx.y * blockDim.y + threadIdx.y;
  int xbase = blockIdx.x * blockDim.x + threadIdx.x;
  C[ybase * V : ybase*V + V, xbase*V : xbase*V + V] = c[:];
}
```

Memory overhead?

- Global memory access per threadblock
  - 2LN
- Number of threadblocks:
  - N^2 / L^2
- Total global memory access:
  - 2N^3 / L
- Shared memory access per thread:
  - 2VN
- Number of threads
  - N^2 / V^2
- Total shared memory access:
  - 2N^3 / V

```
__global__ void mm(float A[N][N], float B[N][N], float C[N][N]) {

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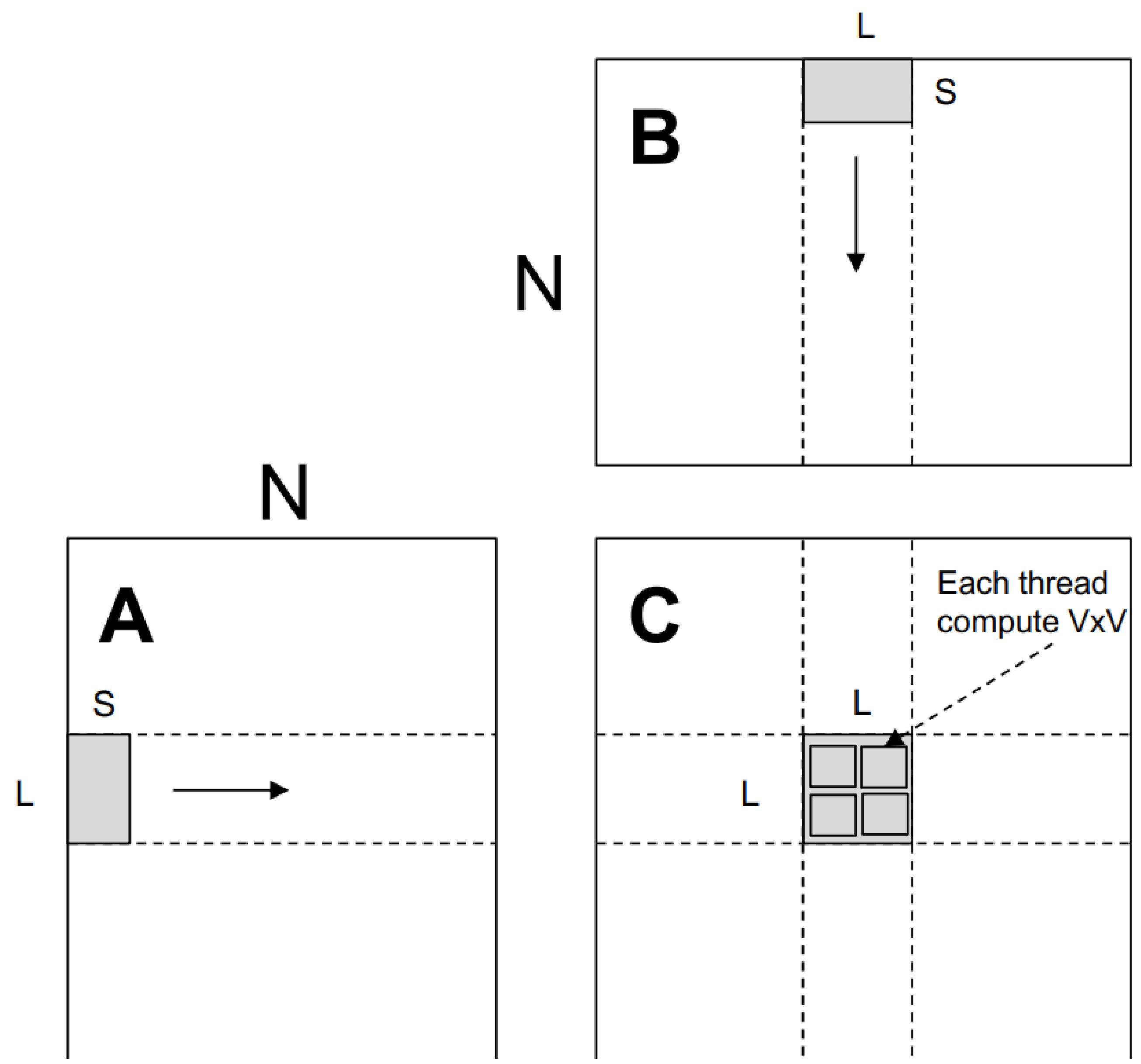
      a[:] = sA[ki, threadIdx.y * V : threadIdx.y * V + V];
      b[:] = sA[ki, threadIdx.x * V : threadIdx.x * V + V];
      for (int y = 0; y < V; ++y) {
        for (int x = 0; x < V; ++x) {
          c[y][x] += a[y] * b[x];
        }
      }
    }
  }
  int ybase = blockIdx.y * blockDim.y + threadIdx.y;
  int xbase = blockIdx.x * blockDim.x + threadIdx.x;
  C[ybase * V : ybase*V + V, xbase*V : xbase*V + V] = c[:];
}
```

Core Problems Here

- How to choose L/V? Tradeoffs:
  - #threads
  - #registers
  - Amount of shared memory

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      b[:] = sA[ki, threadIdx.x * V : threadIdx.x * V + V];
      for (int y = 0; y < V; ++y) {
        for (int x = 0; x < V; ++x) {
          c[y][x] += a[y] * b[x];
        }
      }
    }
  }
  int ybase = blockIdx.y * blockDim.y + threadIdx.y;
  int xbase = blockIdx.x * blockDim.x + threadIdx.x;
  C[ybase * V : ybase*V + V, xbase*V : xbase*V + V] = c[:];
}
```

More GPU Optimizations

- Global memory continuous read
- Shared memory bank conflict
- Pipelining
- Tensor core
- Etc.

Next Topic:

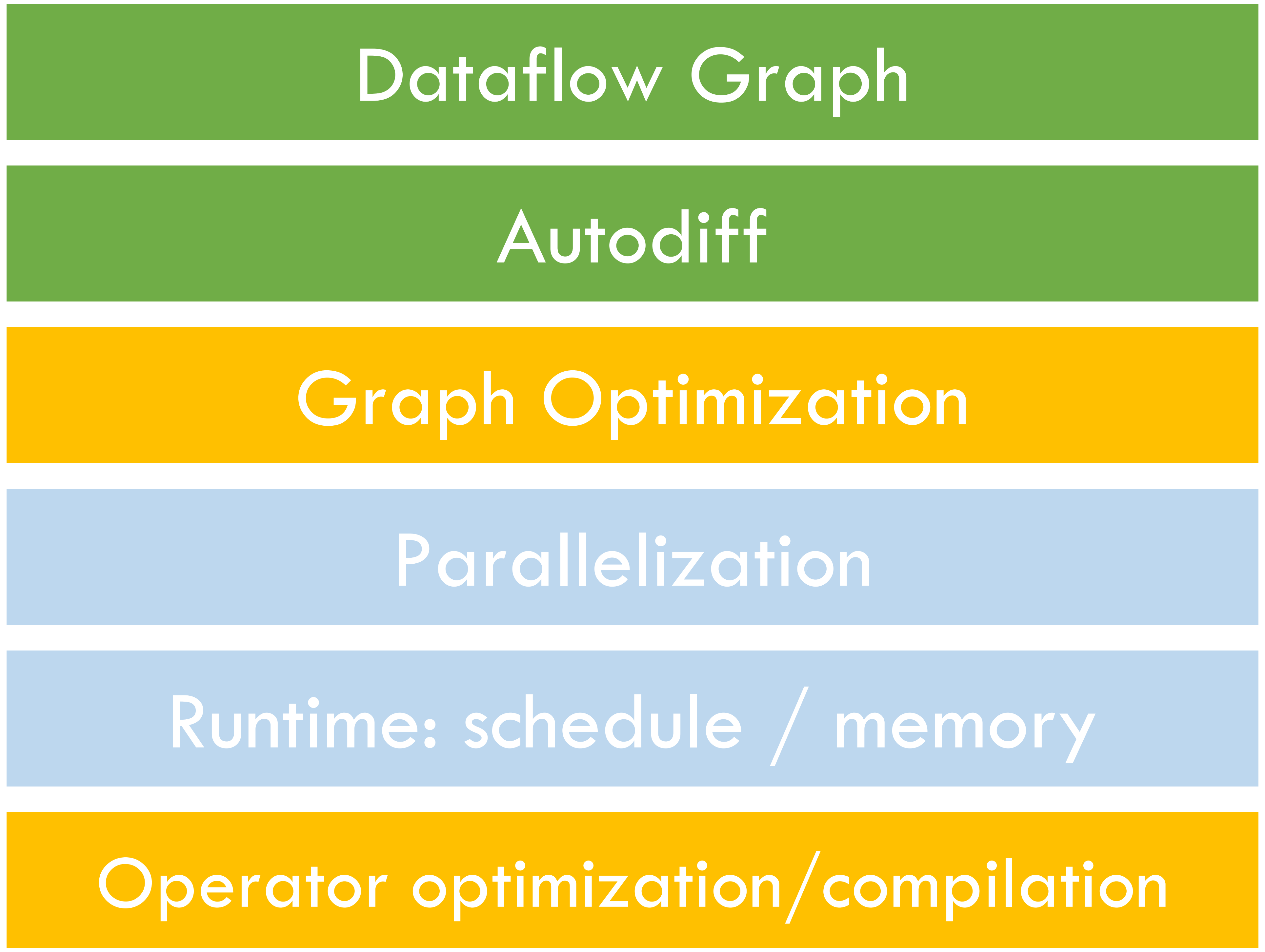
LLMs

Parallelization

Single-device Optimization

Basics

Orange are parts of ML Compilation



Agenda on this part

- ML Compilation Overview
  - Compiler
  - Graph optimization
- Memory Optimization
  - Activation checkpointing
  - Quantization and Mixed precision
- Two Guest Talks covering details in compilation, JIT, graph fusion, and beyond:
  - Meta PyTorch lead developer: Jason Ansel
  - Google JAX/XLA lead developer: Jinliang Wei

ML Compilation Overview

ML Models

Transformer, ResNet, LSTM ...

Data

IMAGENET ...

WIKIPEDIA
The Free Encyclopedia

Diverse and fast evolving models

Big data

Specialized compute acceleration

Compute

In Reality

ML Models

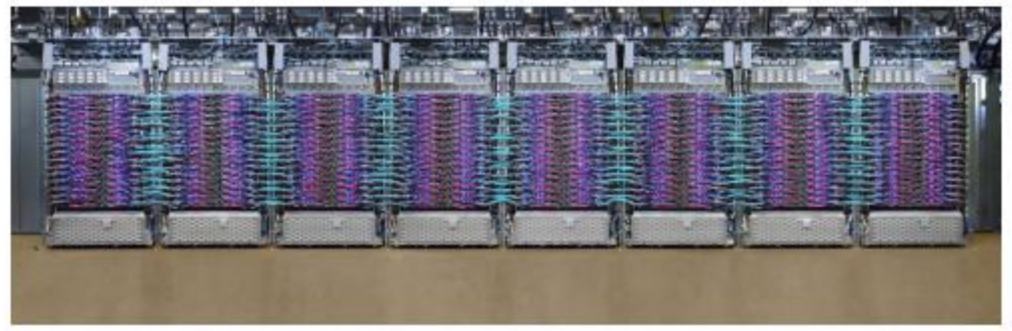
Transformer, ResNet, LSTM ...

MKL-DNN

cuDNN

ARM-Compute

TPU Backends



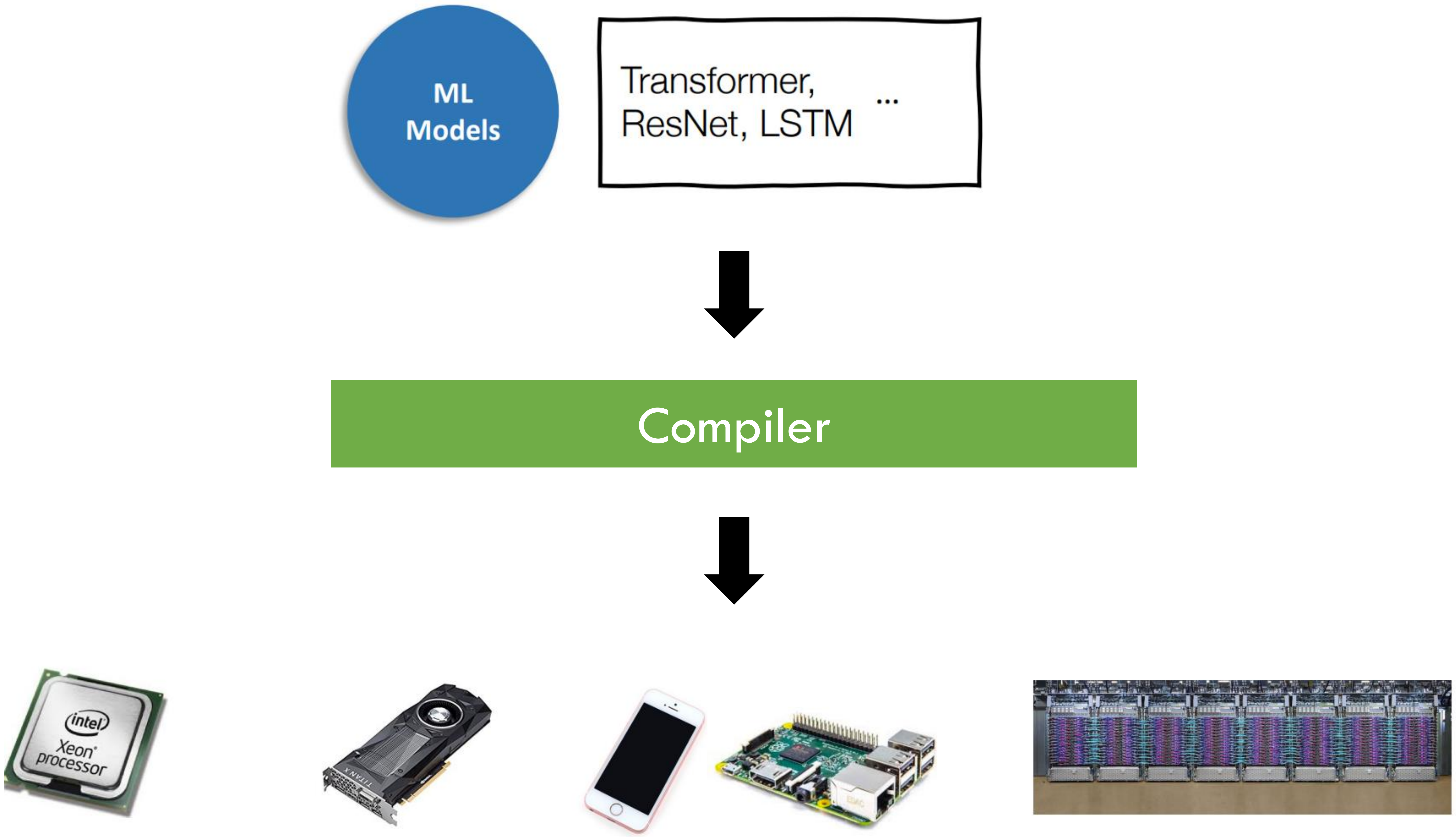
Goals

There are many equivalent ways to run the same model execution.

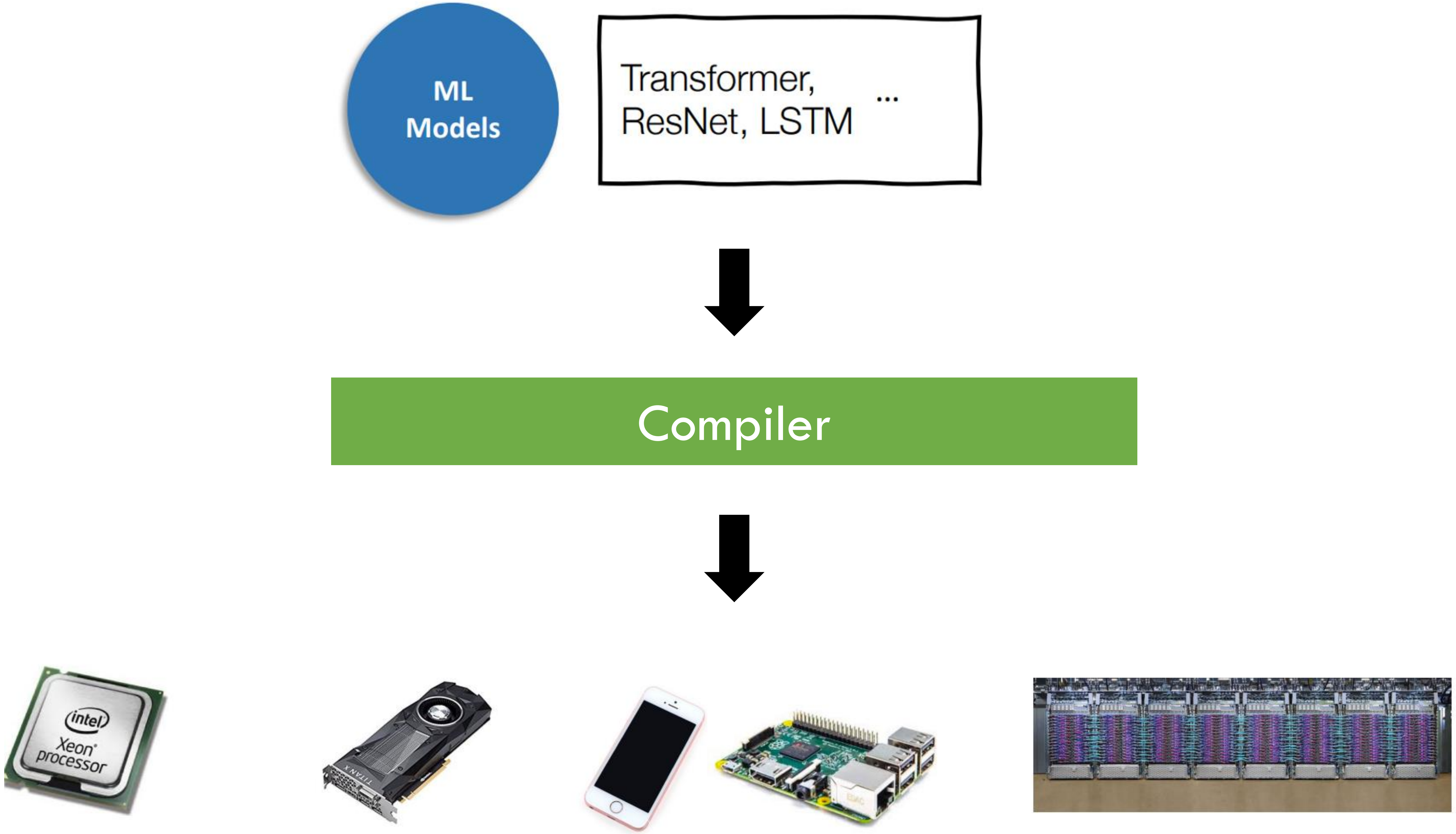
The common theme of MLC is optimization in different forms:

- Minimize memory usage
- Maximize execution efficiency
- Scaling to heterogeneous devices
- Minimize developer overhead

ML Compilation Goals



ML Compilation Goals



What is a Traditional Compiler?

Human
Code (e.g., cpp)

↓

Compiler

↓

Machine
code

ML Models

Transformer,
ResNet, LSTM
...

Dataflow Graph

Transformed Dataflow Graph

Efficient Kernel code

Machine code

↓

Problems:

- Op-level: How to make operator fast on different hardware?
  - Tiling Based on register/cache/shared mem sizes
  - Use target device-specific accelerations
  - Generate the operator implementations automatically
- Graph-level: graph transformations to make it faster
- Programming-level:
  - How to transform an imperative code (by developers) into a compile-able code?

Compilation Process Today

ML Models

Transformer, ResNet, LSTM ...

Lowering

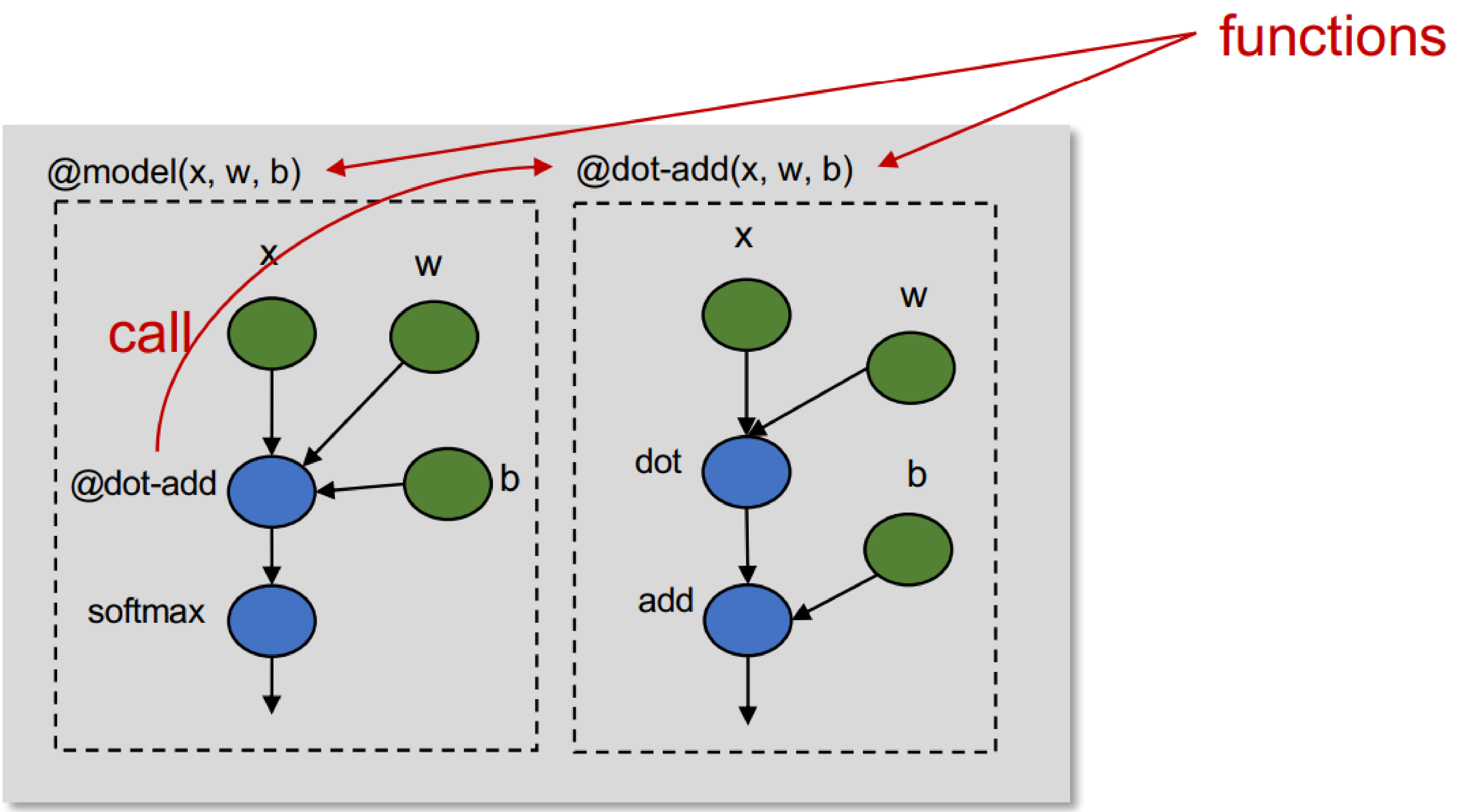
IR and transformers

Op-level optimizations

CodeGen

IR: Intermediate representation

- What is the difference between this IR and the dataflow graph?



IRModule: a collection if interdependent functions

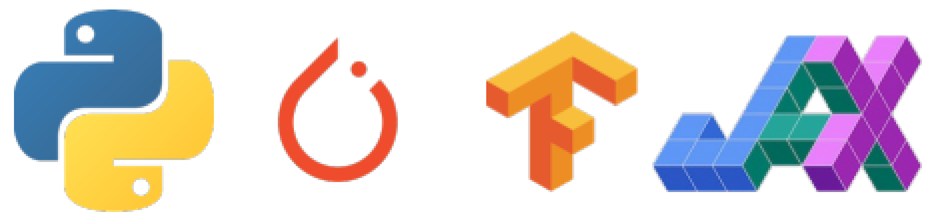
Notable Compilers

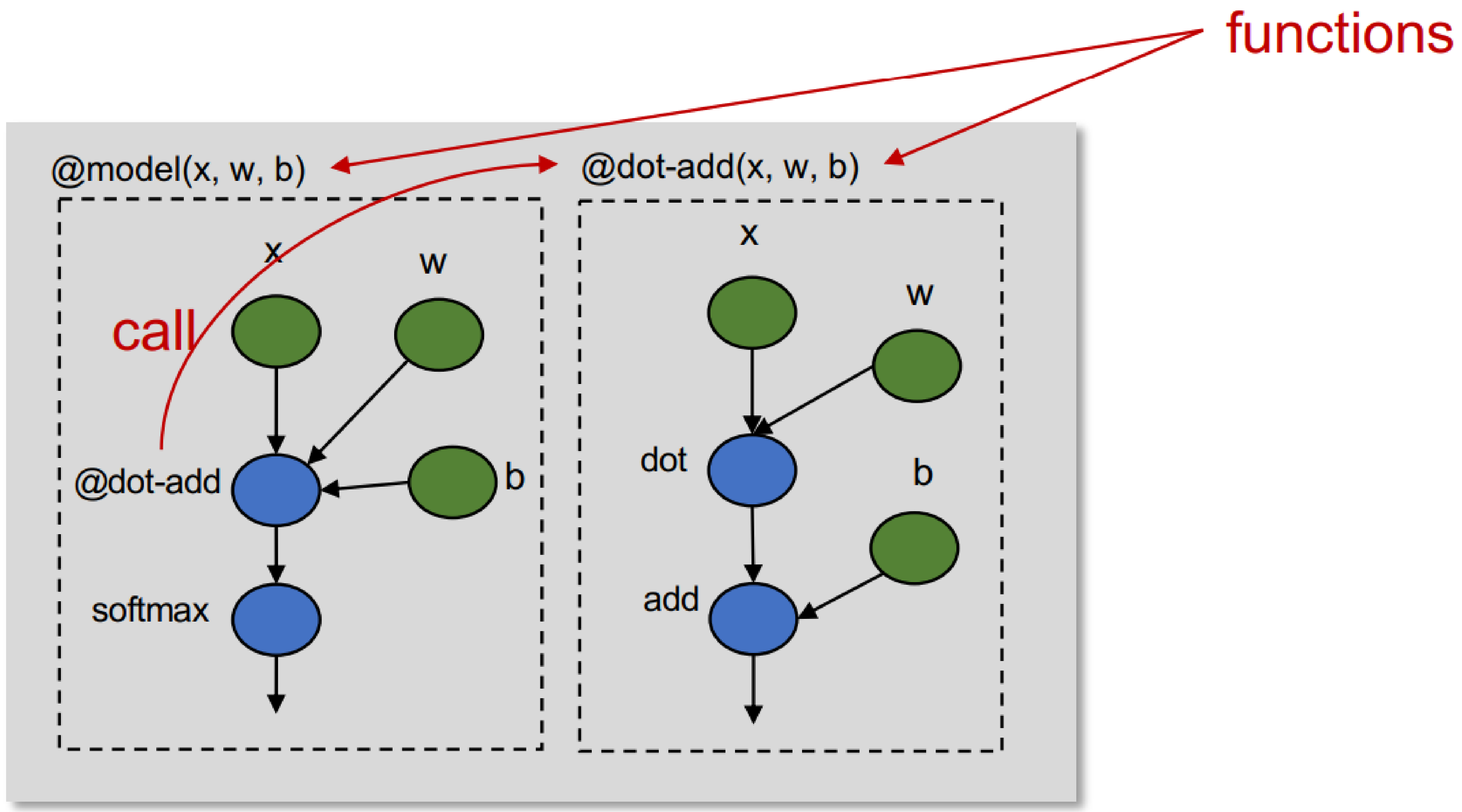
There are many different IRs by different compilers

- XLA: Accelerated Linear Algebra
  - HLO
- TVM: tensor virtual machine
  - IRModule (we used this on in class)
- Torch.compile: PyTorch
- Modular: Chris Lattner’s startup

User Code transformations

- What are potential challenges of user code parsing?

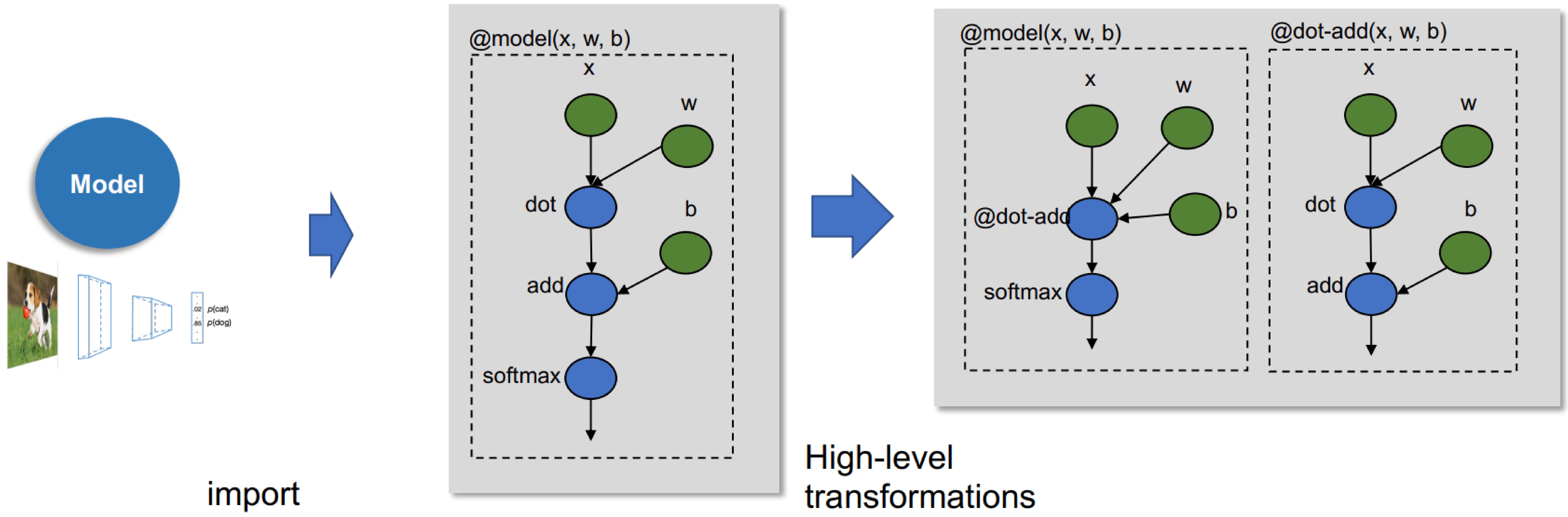




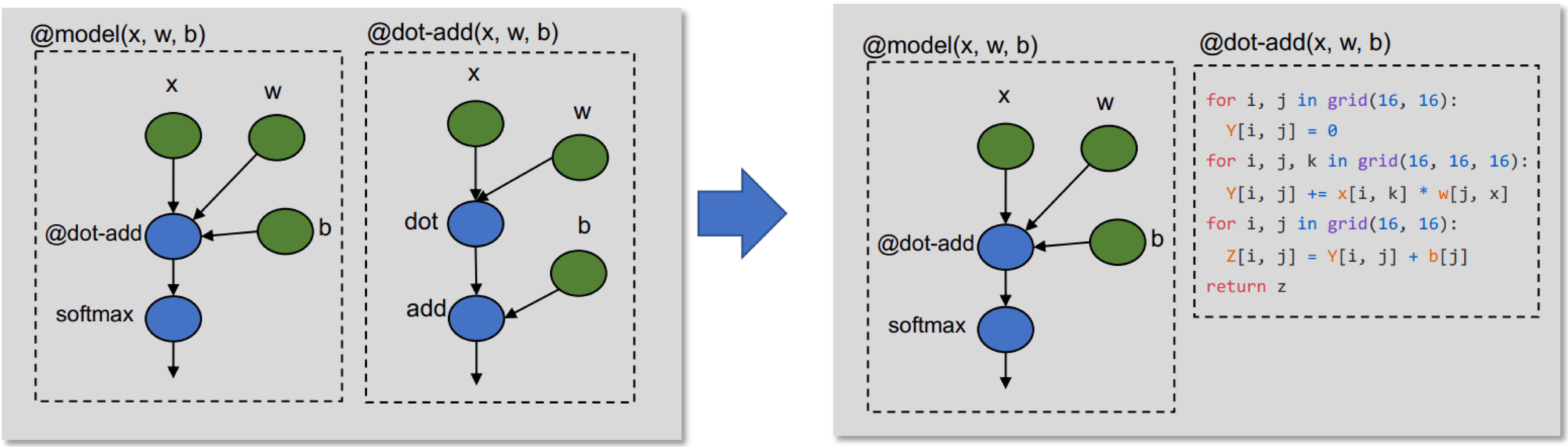
IRModule: a collection if interdependent functions

Example Compile flow: high-level transformations

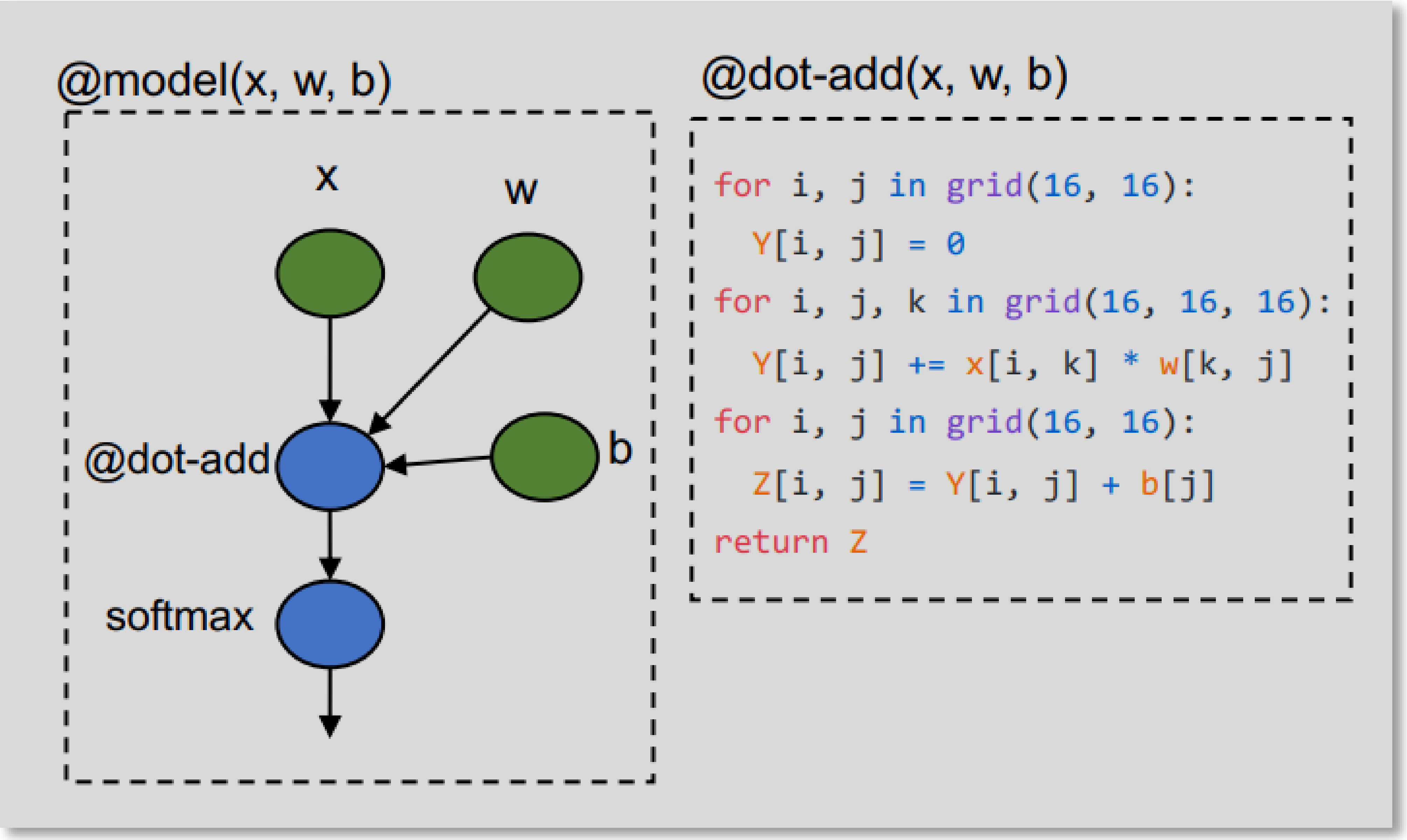
- We'll talk about some techniques here next week

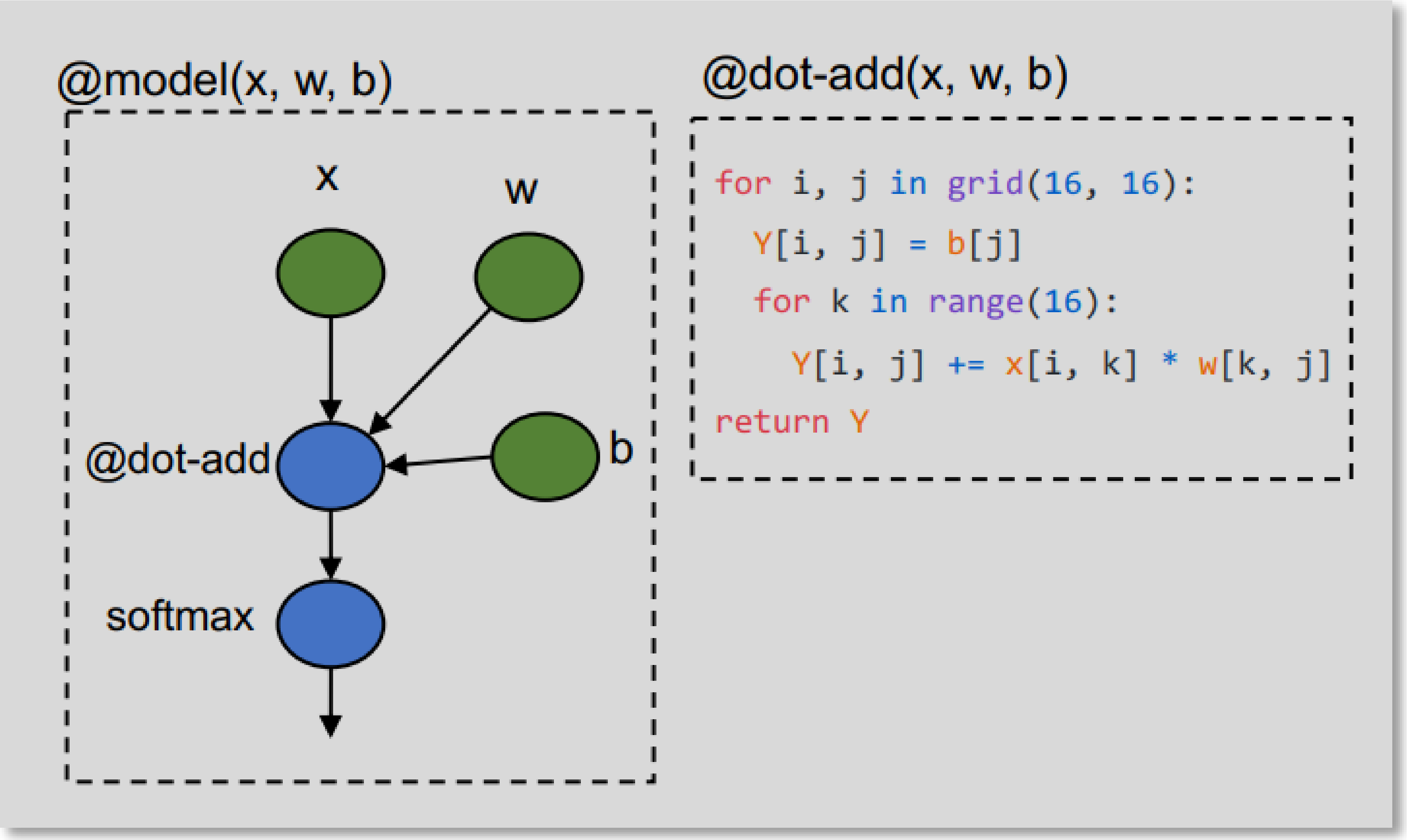


Example Compile flow: lowering to loop IR



Example Compile flow: Loop transformers





Low-level transformations

Example Compilation: CodeGen

Eventually, we transform a user code into some binary artifacts