

# 15-884: Machine Learning Systems

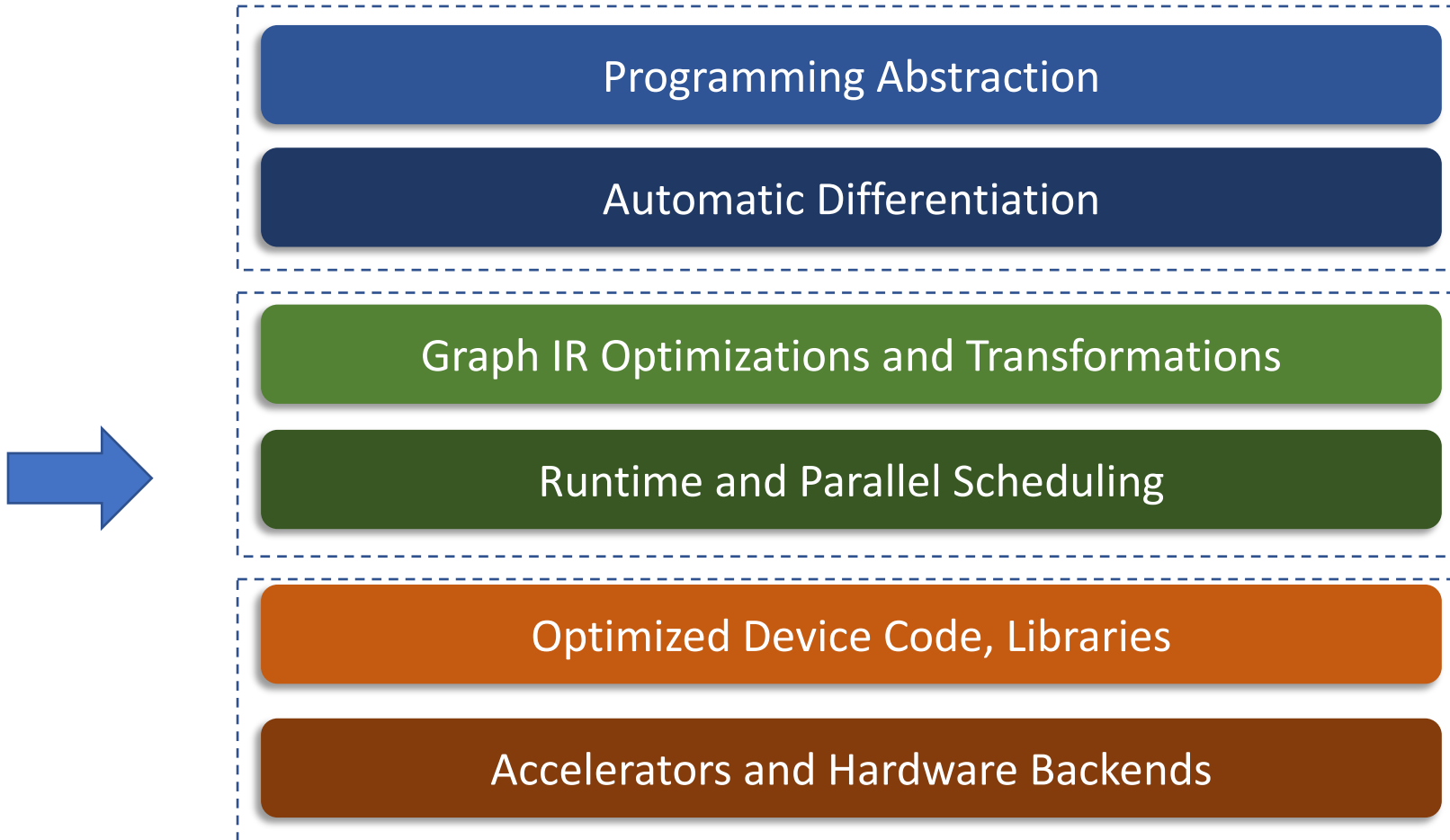
## Parallel Scheduling

Instructor: Tianqi Chen

# Logistics

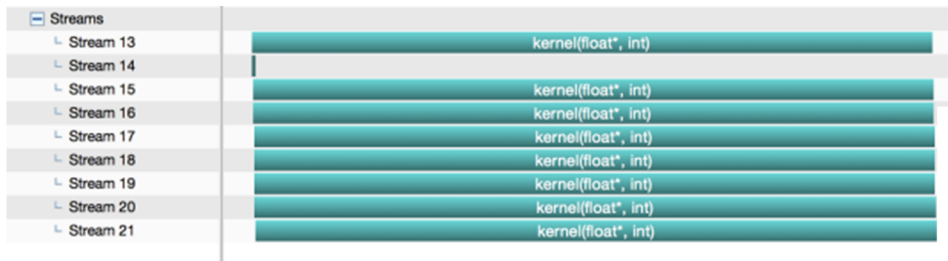
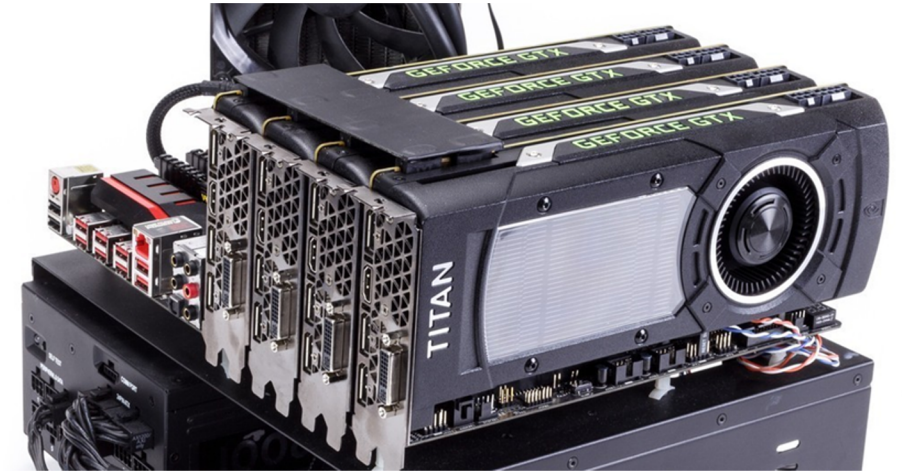
- Project Proposal on Friday
  - Talk to us if you any questions
- Guest lectures in the later part of the semester
  - Separate zoom links, we will post announcements to the piazza

# A Typical Deep Learning System Stack

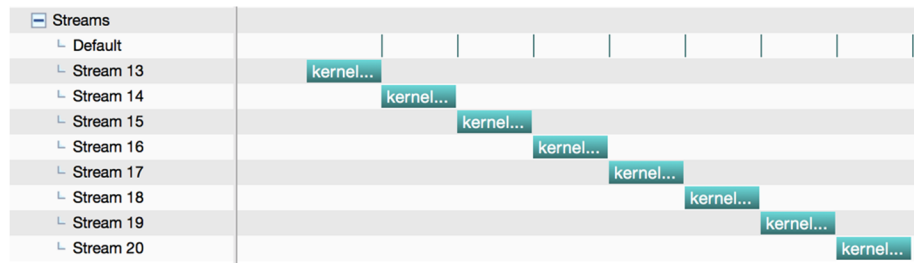


# Parallelization Problem

- Parallel execution of concurrent kernels
- Overlap compute and data transfer



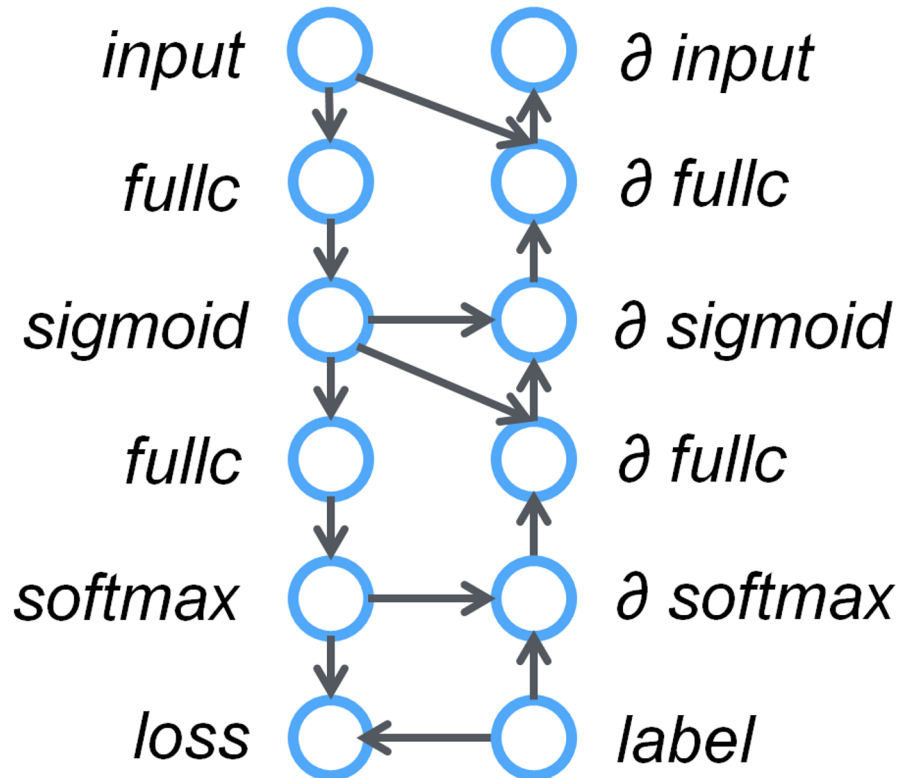
Parallel over multiple streams



Serial execution

# Recap: Training Workflow

## Gradient Calculation



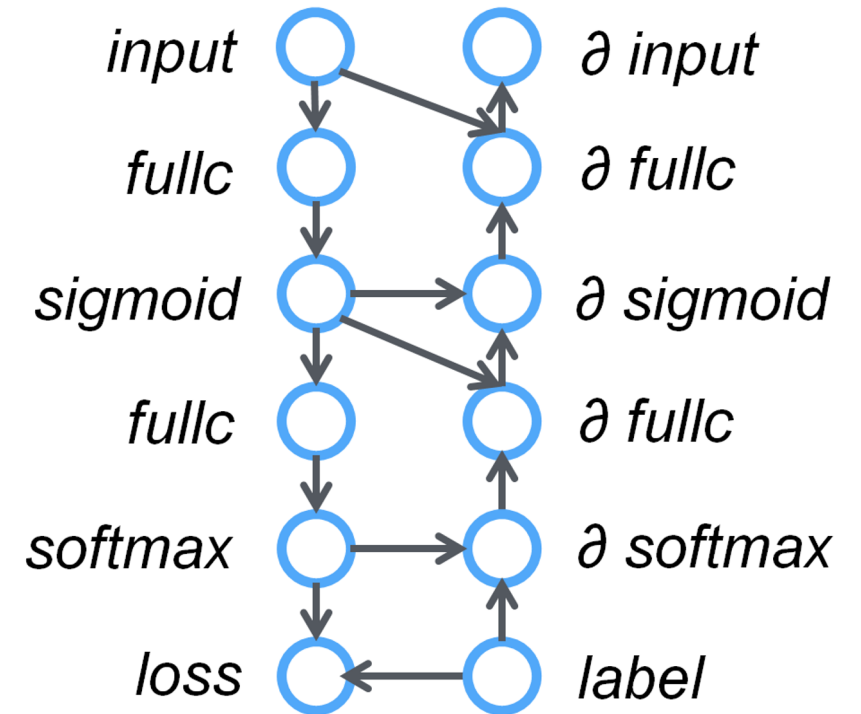
## Interactions with Model

Parameter Update

$$w = w - \eta \partial f(w)$$

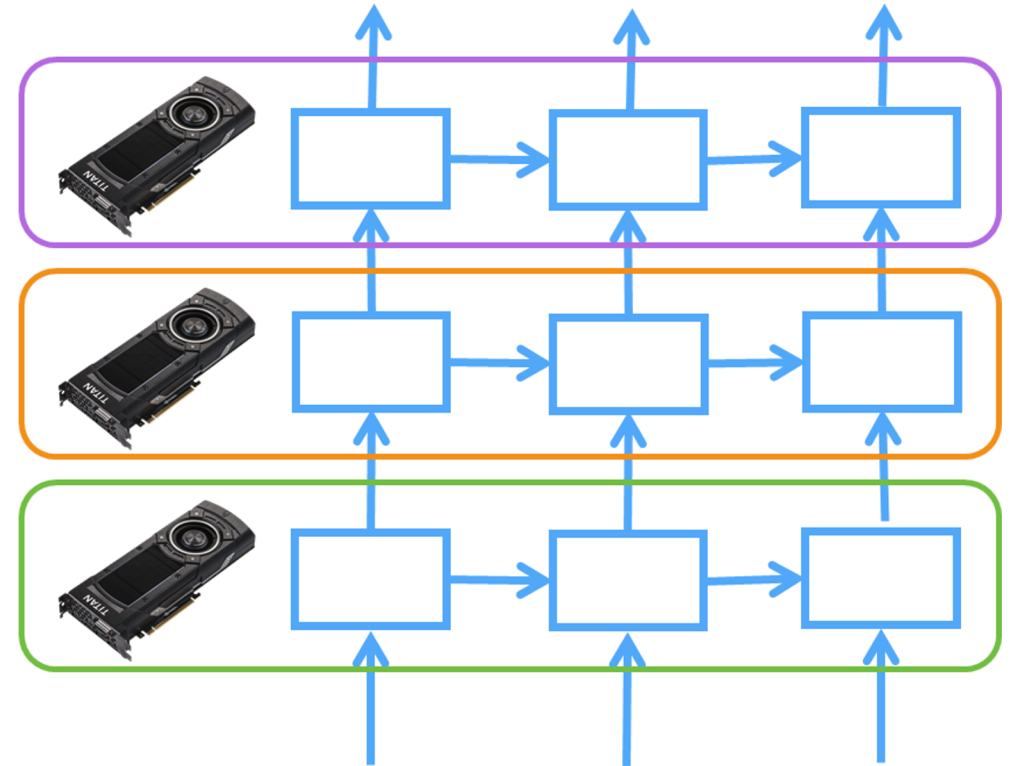
# Discussions

- What are common parallelization patterns
- How to build system support for these patterns
- How to handle dynamic computations



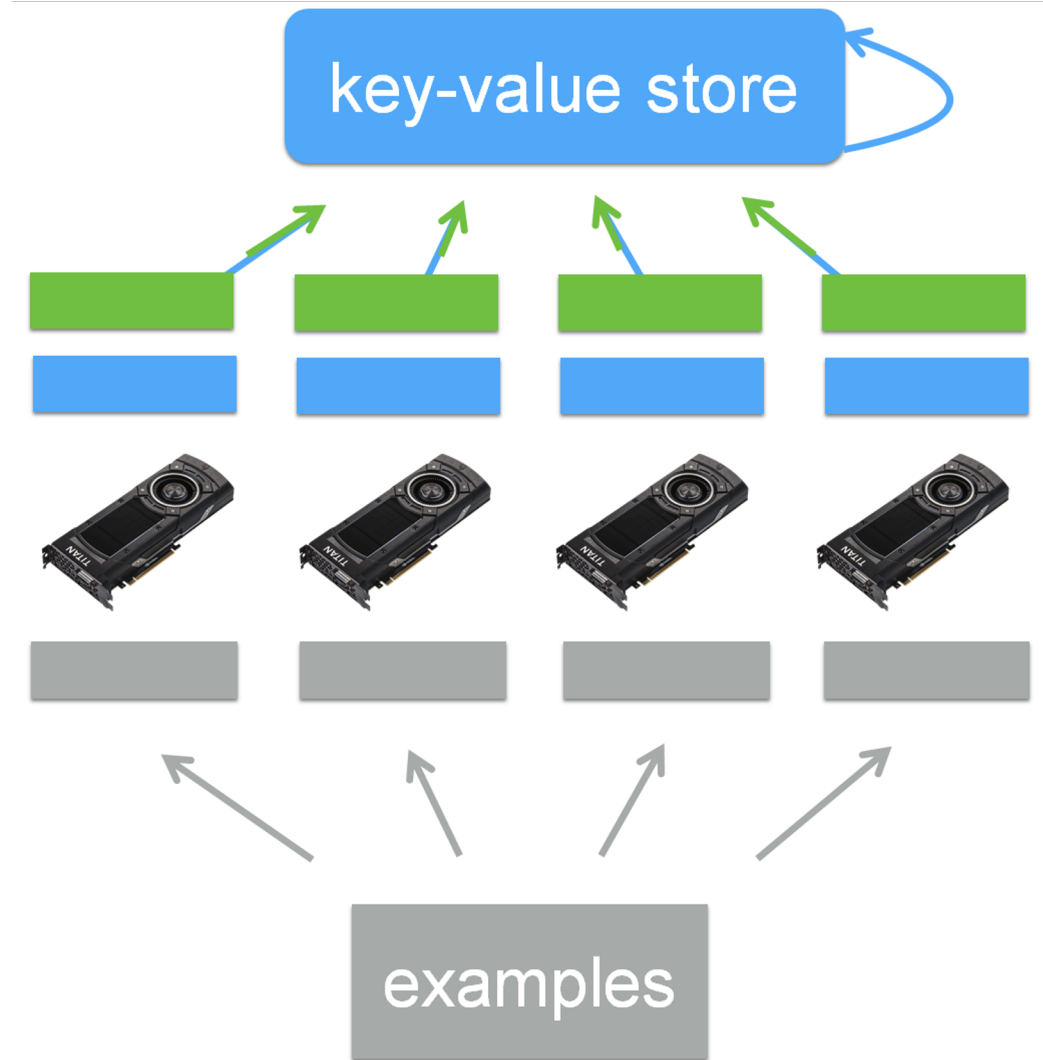
# Model Parallel Training

- Map parts of workload to different devices
- Benefit from special dependency patterns (wave style)
  - e.g. LSTM



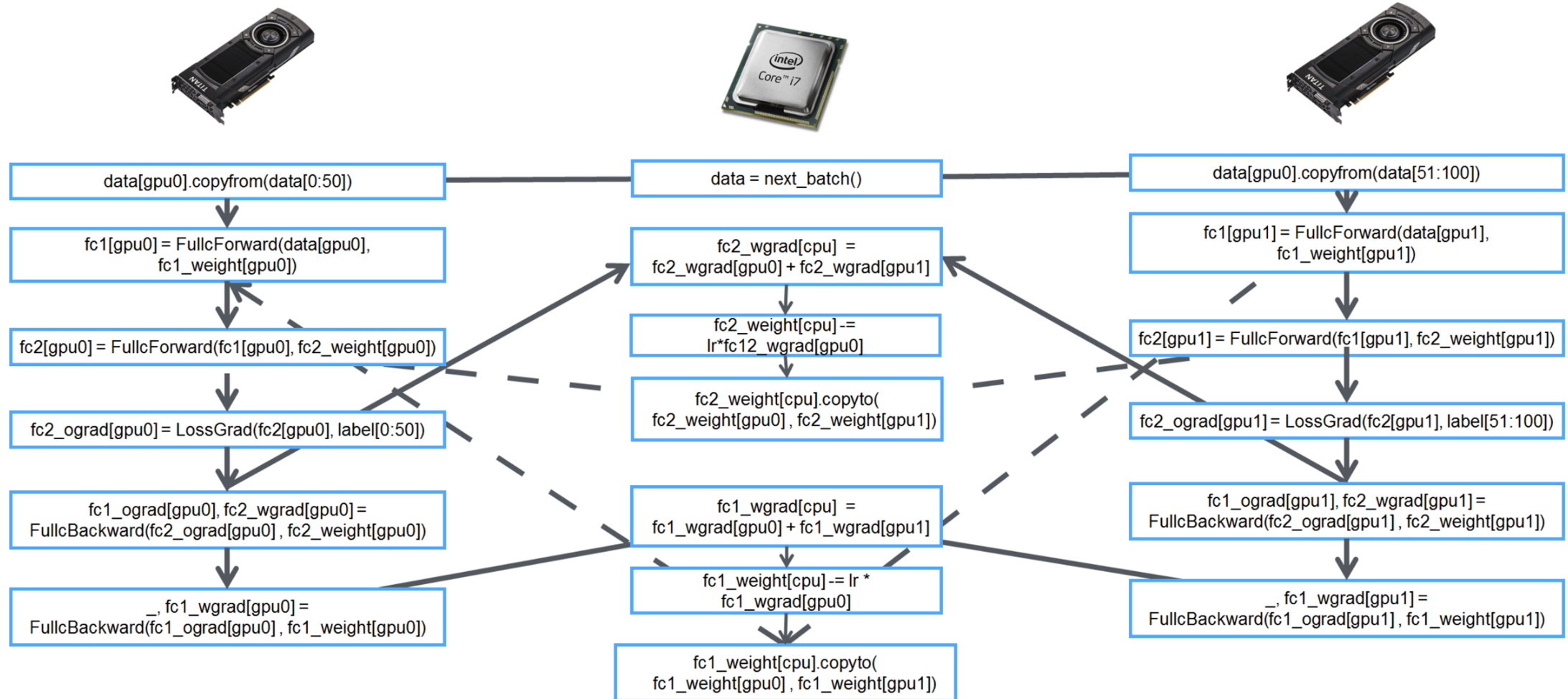
# Data Parallelism

- Train replicated version of model in each machine
- Synchronize the gradient

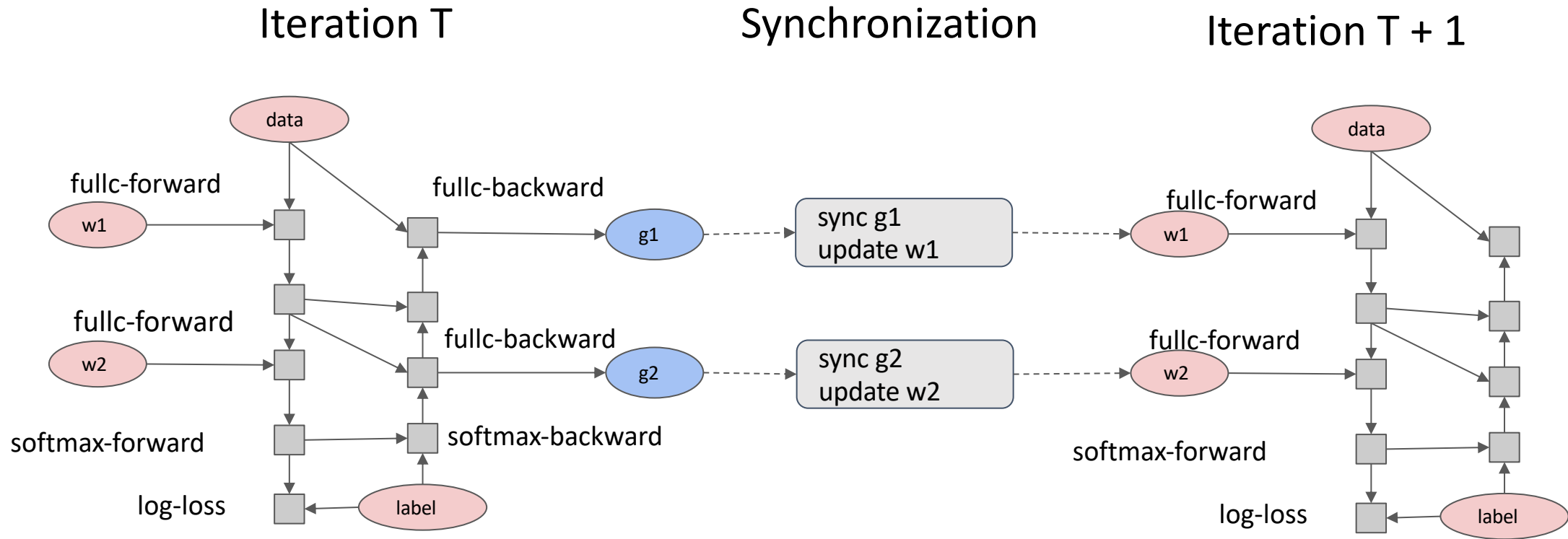




# Data Parallel Training on Two GPUs

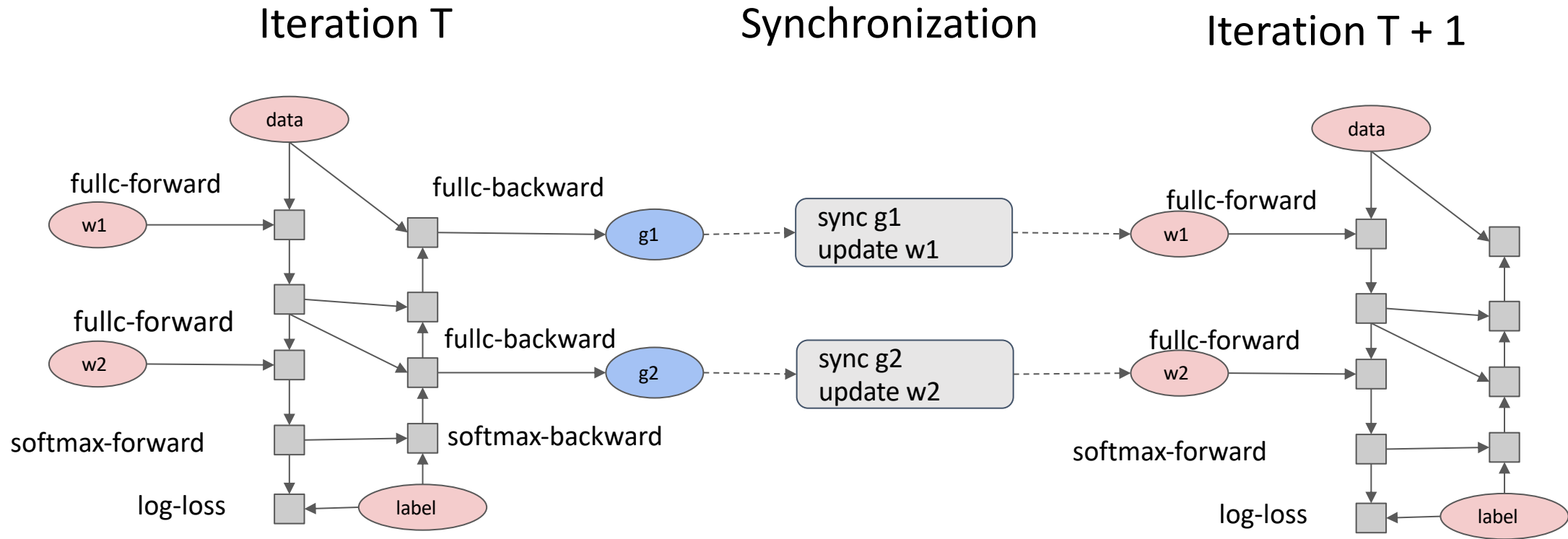


# The Communication Bottleneck



Which operations can run in concurrent with synchronization of g2/w2?

# Parallel Programs are Hard to Write



Need some way to automate the runtime scheduling

# Introducing a Generic Scheduler

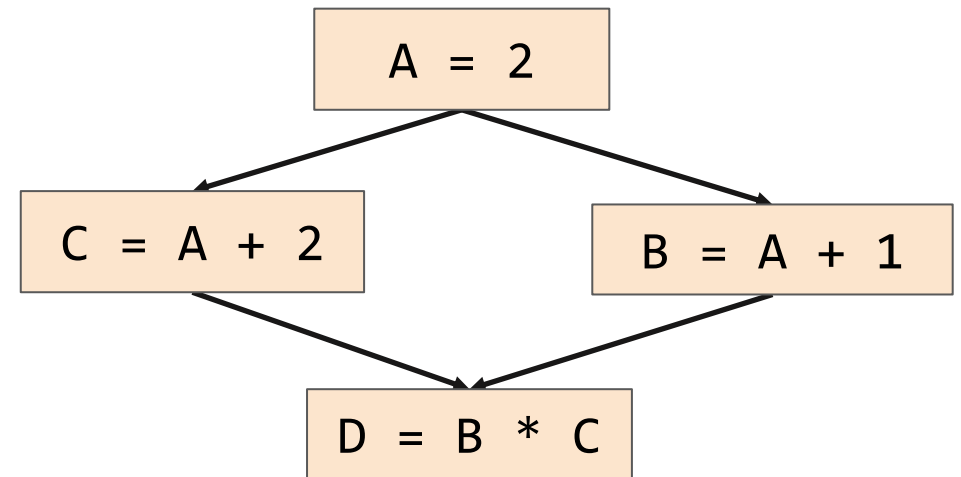
- Case study a runtime parallel scheduler
- Similar design variants in many systems (e.g. TFRT)

# Goal of the Scheduler Interface

- Write Serial-style Program
- Possibly dynamically (not declare graph beforehand)

```
>>> import mxnet as mx
>>> A = mx.nd.ones((2,2)) *2
>>> C = A + 2
>>> B = A + 1
>>> D = B * C
```

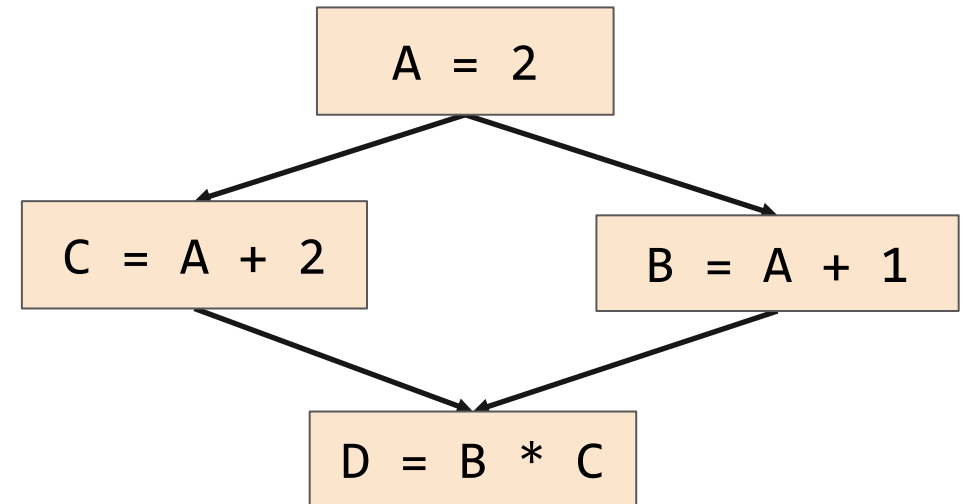
- Run in Parallel
- Respect serial execution order



Like out of order execution in modern CPUs but happens across multiple devices

# Discussion: How to schedule the following ops

- Random number generator
- Memory recycling
- Cross device copy
- Send data over network channel

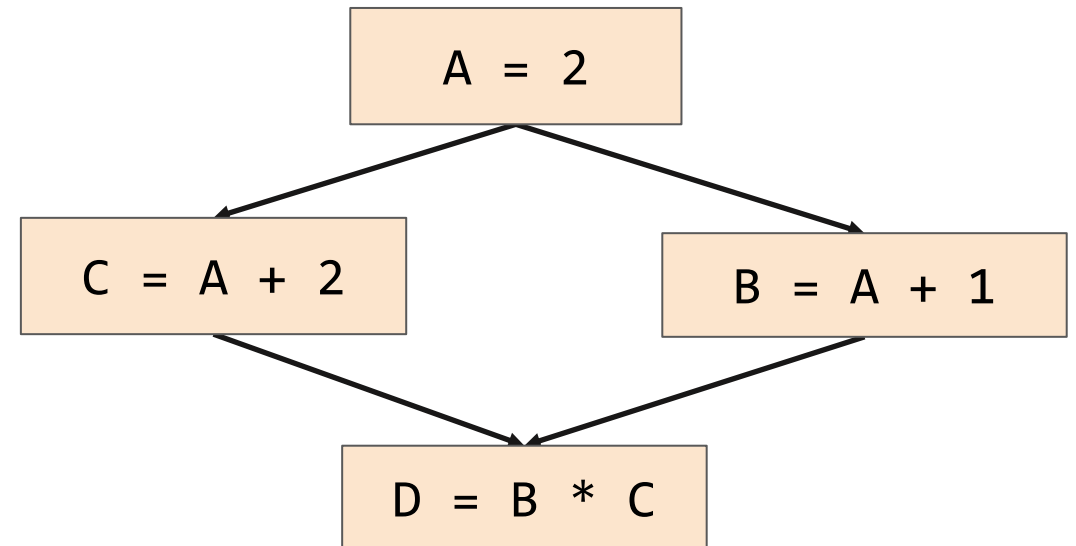


# Data Flow Dependency

Code

```
A = 2  
B = A + 1  
C = A + 2  
D = B * C
```

Dependency

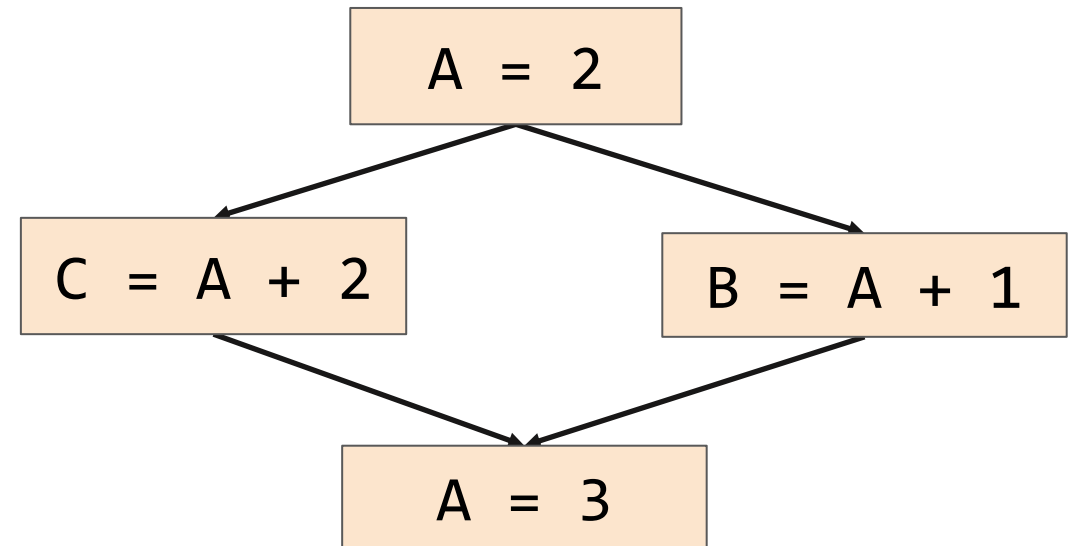


# Write After Read Mutation

Code

```
A = 2  
B = A + 1  
C = A + 2  
A = 3
```

Dependency





# Memory Recycle

Code

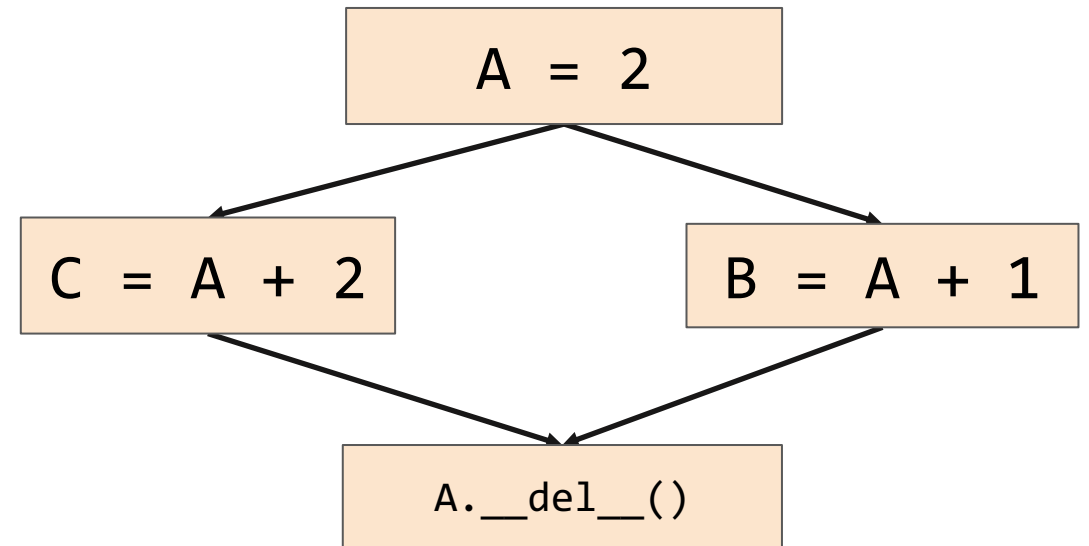
`A = 2`

`B = A + 1`

`C = A + 2`

`A.__del__()`

Dependency



# Random Number Generator

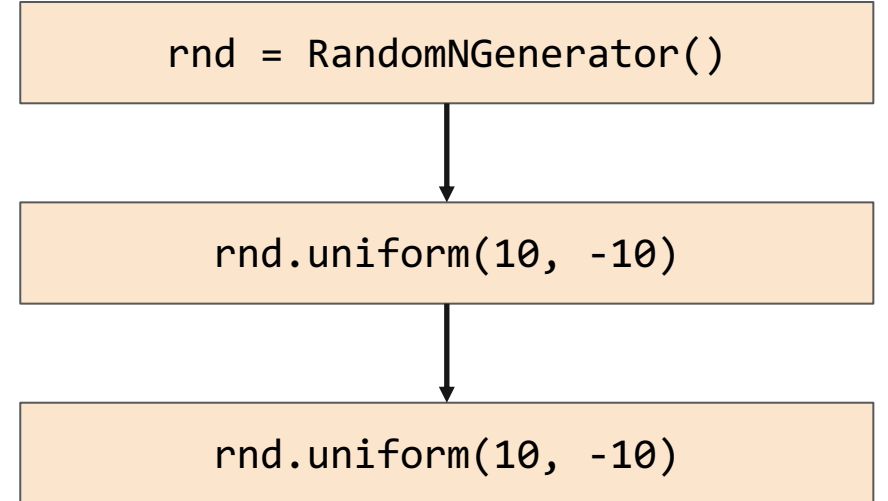
Code

```
rnd = RandomNumberGenerator()
```

```
B = rnd.uniform(10, -10)
```

```
C = rnd.uniform(10, -10)
```

Dependency



# Goal of Scheduler Interface

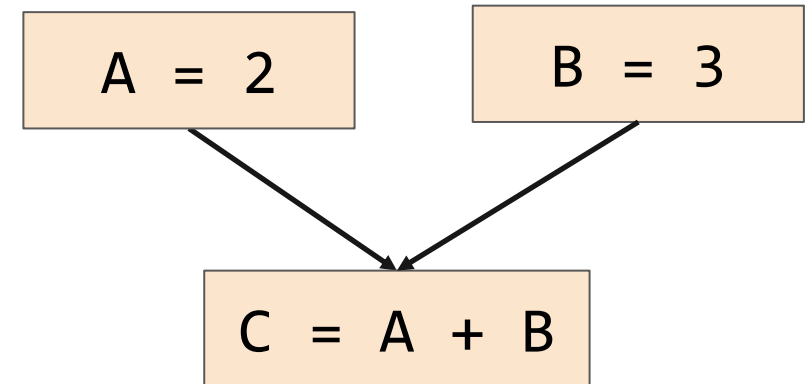
- Schedule any resources
  - Data
  - Random number generator
  - Network communicator
- Schedule any operation

# DAG Graph based scheduler

## Interface:

```
engine.push(lambda op, deps=[])
```

- Explicit push operation and its dependencies
- Can reuse the computation graph structure
- Useful when all results are immutable
- Used in typical frameworks (e.g. TensorFlow)
- What are the drawbacks?



# Pitfalls when using Scheduling Mutations

## Write after Read

```
tf.assign(A, B + 1)
tf.assign(T, B + 2)
tf.assign(B, 2)
```

## Read after Write

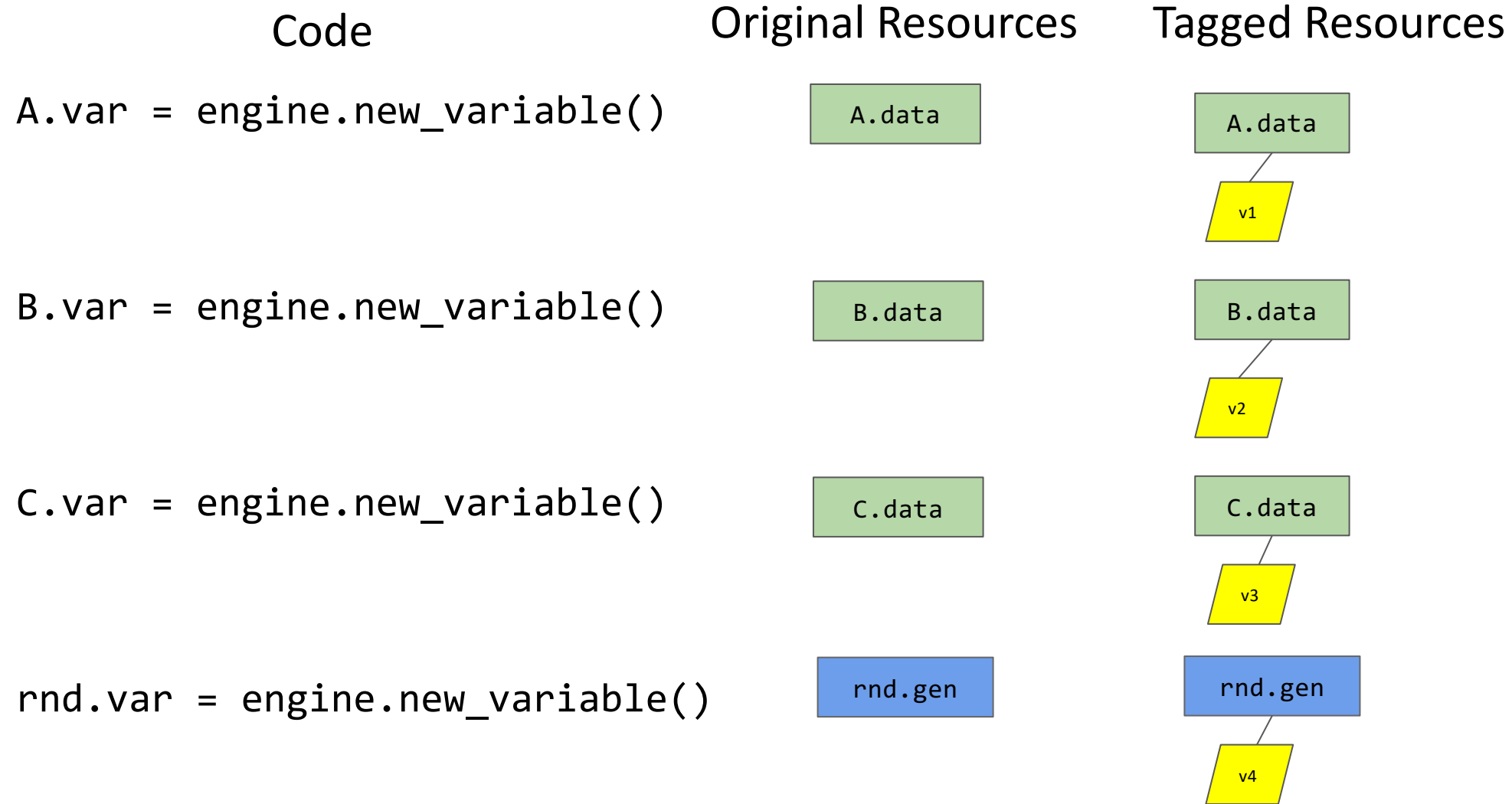
```
T = tf.assign(B, B + 1)
tf.assign(A, B + 2)
```

A **mutation aware** scheduler can solve these problems much easier than DAG based scheduler

# MXNet Program for Data Parallel Training

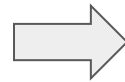
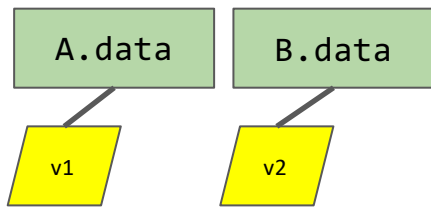
```
for dbatch in train_iter:
    % iterating on GPUs
    for i in range(ngpu):
        % pull the parameters
        for key in update_keys:
            kvstore.pull(key, execs[i].weight_array[key])
        % compute the gradient
        execs[i].forward(is_train=True)
        execs[i].backward()
        % push the gradient
        for key in update_keys:
            kvstore.push(key, execs[i].grad_array[key])
```

# Mutation aware Scheduler: Tag each Resource

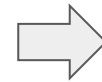
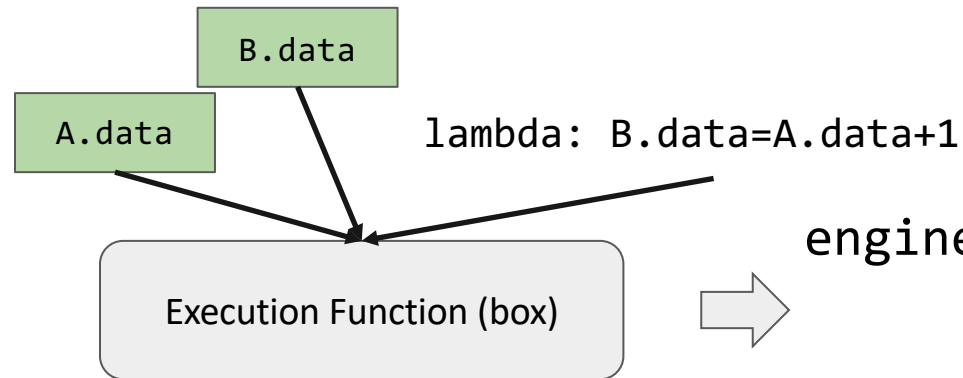


# Mutation aware Scheduler: Push Operation

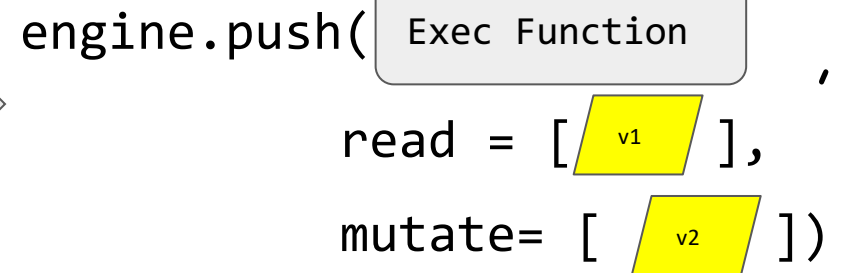
The Tagged Data



Pack Reference to Related Things into Execution Function (via Closure)



Push the Operation to Engine









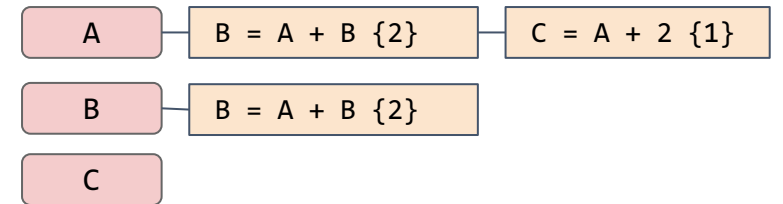
# Example Scheduling: Random Number Generator

```
B = rnd.uniform(10, -10) → engine.push(lambda:  
    B.data = rnd.gen.uniform(10,-10),  
    read=[], mutate= [rnd.var, B.var])
```

```
C = rnd.uniform(10, -10) → engine.push(lambda:  
    C.data = rnd.gen.uniform(10,-10),  
    read=[], mutate= [rnd.var, C.var])
```

# Queue based Implementation of scheduler

- Like scheduling problem in OS or out of order execution in CPUs
- Maintain a pending operation queue
- Schedule new operations with event update



# Enqueue Demonstration

$B = A + 1$  (reads A, mutates B)

$C = A + 2$  (reads A, mutates C)

$A = C * 2$  (reads C, mutates A)

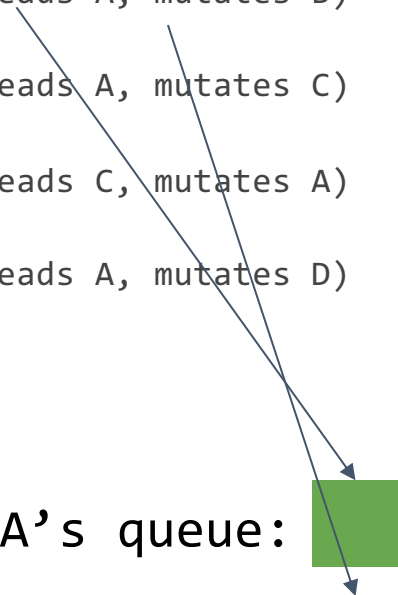
$D = A + 3$  (reads A, mutates D)

A's queue: 

B's queue: 

C's queue:

D's queue:



# Enqueue Demonstration

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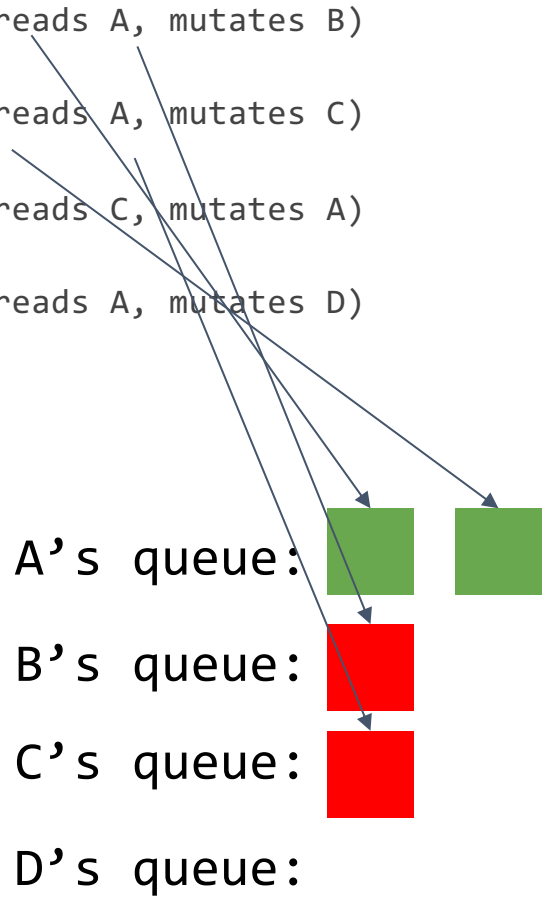
$D = A + 3$  (reads A, mutates D)

A's queue: 

B's queue: 

C's queue: 

D's queue:



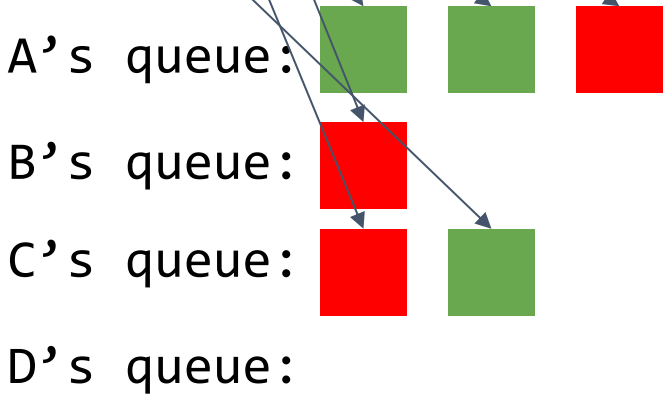
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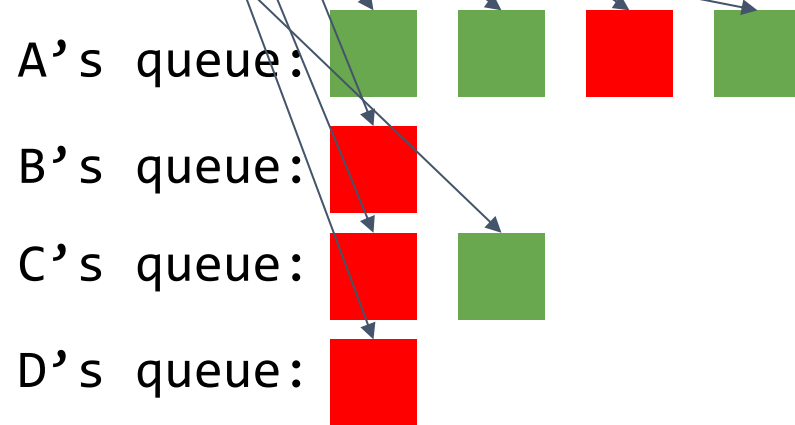
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$A = C * 2$  (reads C, mutates A)

$D = A + 3$  (reads A, mutates D)



**Discuss: What is the update policy of queue when an operation finishes?**



# Update Policy

Request

A = 2 {1}

B = 2 {1}

Queue

A

B

C

Ready/Running Ops

Two operations are pushed. Because A and B are ready to write, we decrease the pending counter to 0. The two ops are executed directly.

operation {wait counter}

operation and the number of pending dependencies it need to wait for

var

ready to read and mutate

var

ready to read, but still have uncompleted reads. Cannot mutate

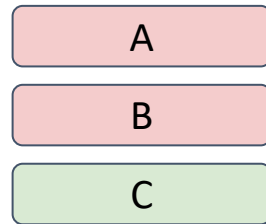
var

still have uncompleted mutations. Cannot read/write

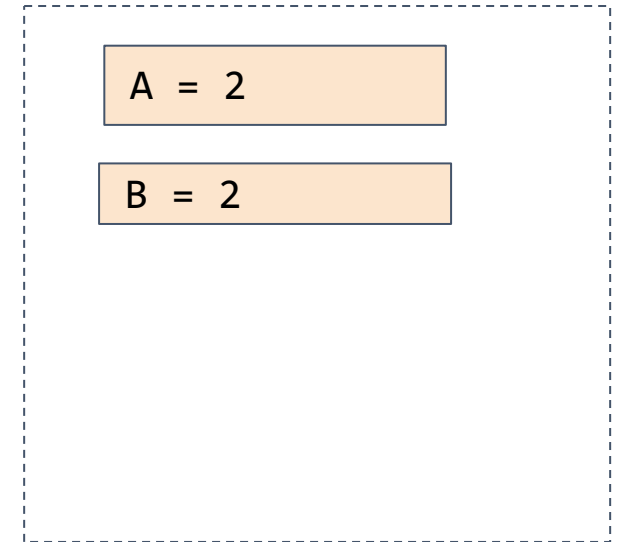
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Request

Queue



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var

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# Update Policy

## Request

B = A + B {2}

C = A + 2 {2}

## Queue

A

B

C

## Ready/Running Ops

A = 2

B = 2

Another two operations are pushed. Because A and B are not ready to read. The pushed operations will be added to the pending queues of variables they wait for.

operation {wait counter}

operation and the number of pending dependencies it need to wait for

var

ready to read and mutate

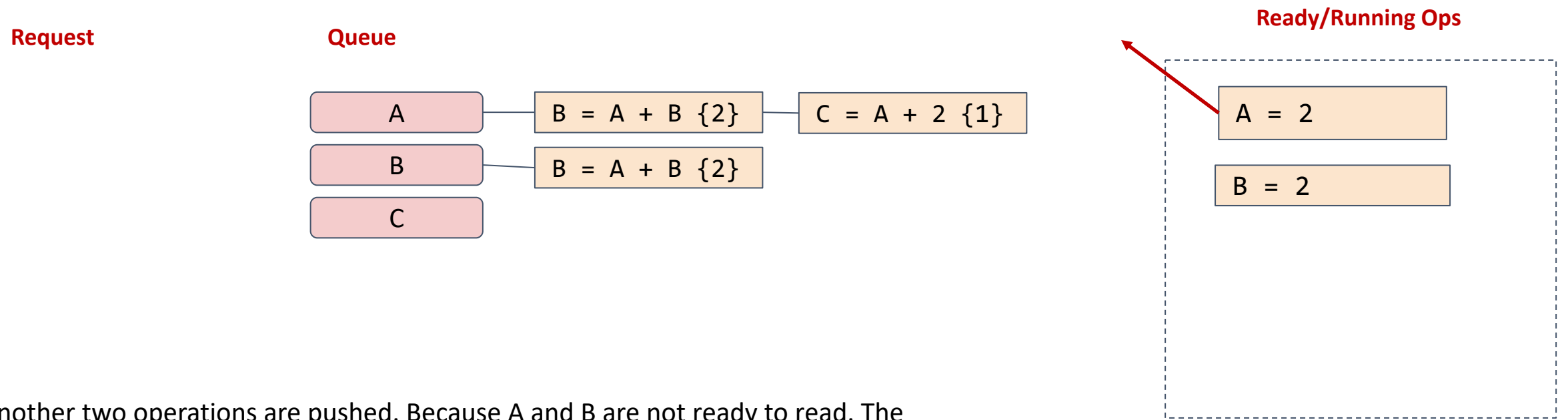
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# Update Policy



Another two operations are pushed. Because A and B are not ready to read. The pushed operations will be added to the pending queues of variables they wait for.

operation {wait counter}

operation and the number of pending dependencies it need to wait for

var

ready to read and mutate

var

ready to read, but still have uncompleted reads. Cannot mutate

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still have uncompleted mutations. Cannot read/write

# Update Policy

## Request

A.del() {1}

## Queue

A

B

C

B = A + B {1}

## Ready/Running Ops

B = 2

C = A + 2

A=2 finishes, as a result, the pending reads on A are activated. B=A+B still cannot run because it is still wait for B.

operation {wait counter}

operation and the number of pending dependencies it need to wait for

var

ready to read and mutate

var

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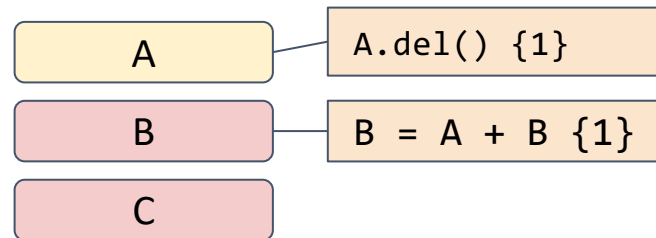
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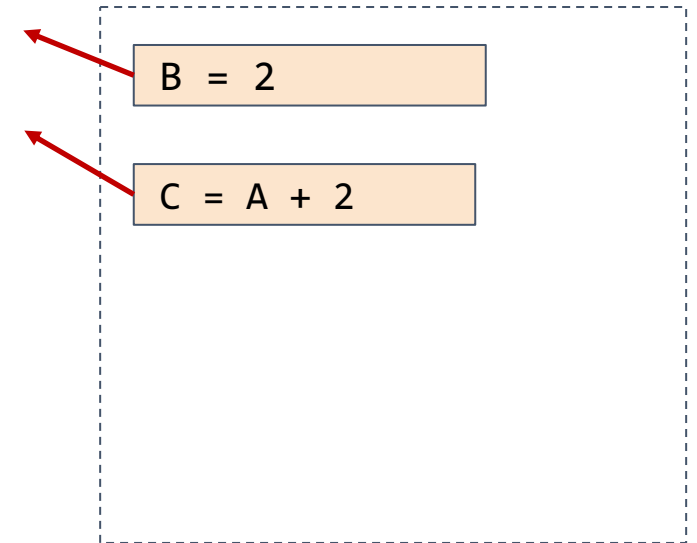
# Update Policy

Request

Queue



Ready/Running Ops



A.del() is a mutate operation. So it need to wait on A until all previous reads on A finishes.

operation {wait counter}

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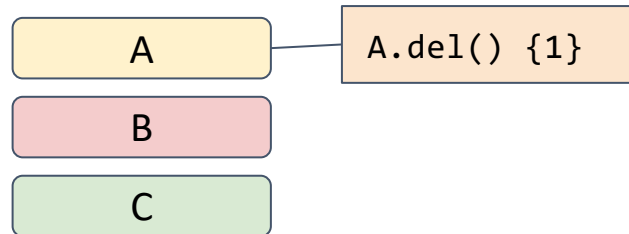
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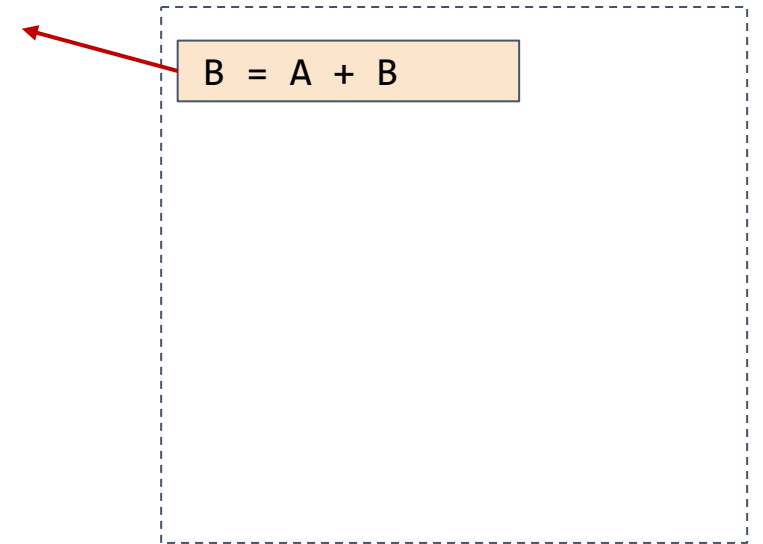
# Update Policy

Request

Queue



Ready/Running Ops



B=2 finishes running. B=A+B is able to run because all its dependencies are satisfied. A.del() still need to wait for B=A+B to finish for A to turn green

operation {wait counter}

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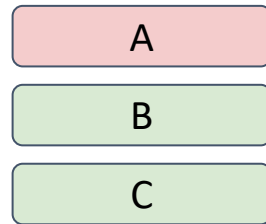
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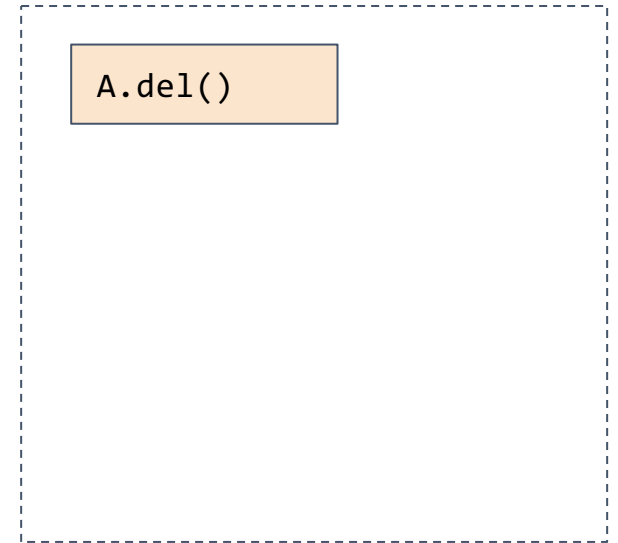
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var

ready to read and mutate

var

ready to read, but still have uncompleted reads. Cannot mutate

var

still have uncompleted mutations. Cannot read/write



# Summary

- Automatic scheduling makes parallelization easier
- Mutation aware interface to handle resource contention
- Queue based scheduling algorithm