ESPRESSO

Hi-Speed DNN Training with Espresso: Unleashing the Full Potential of Gradient Compression

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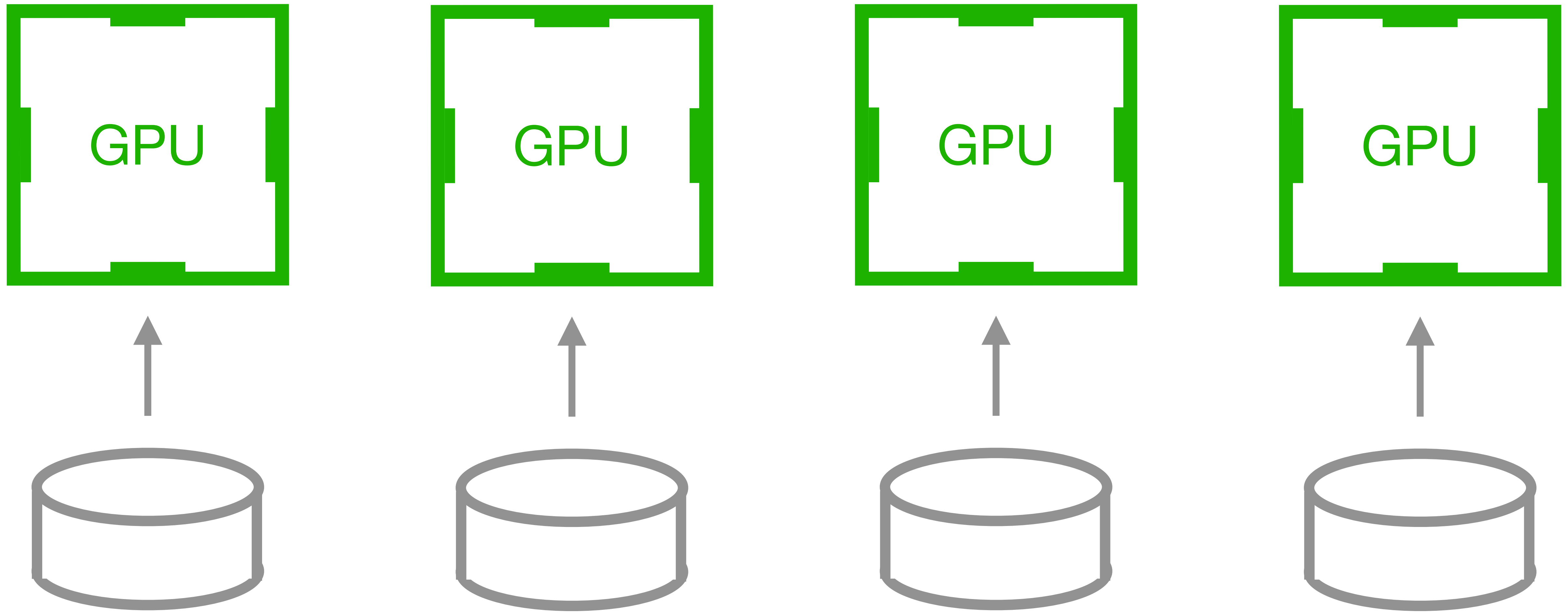
RICE

*ByteDance

Distributed deep learning

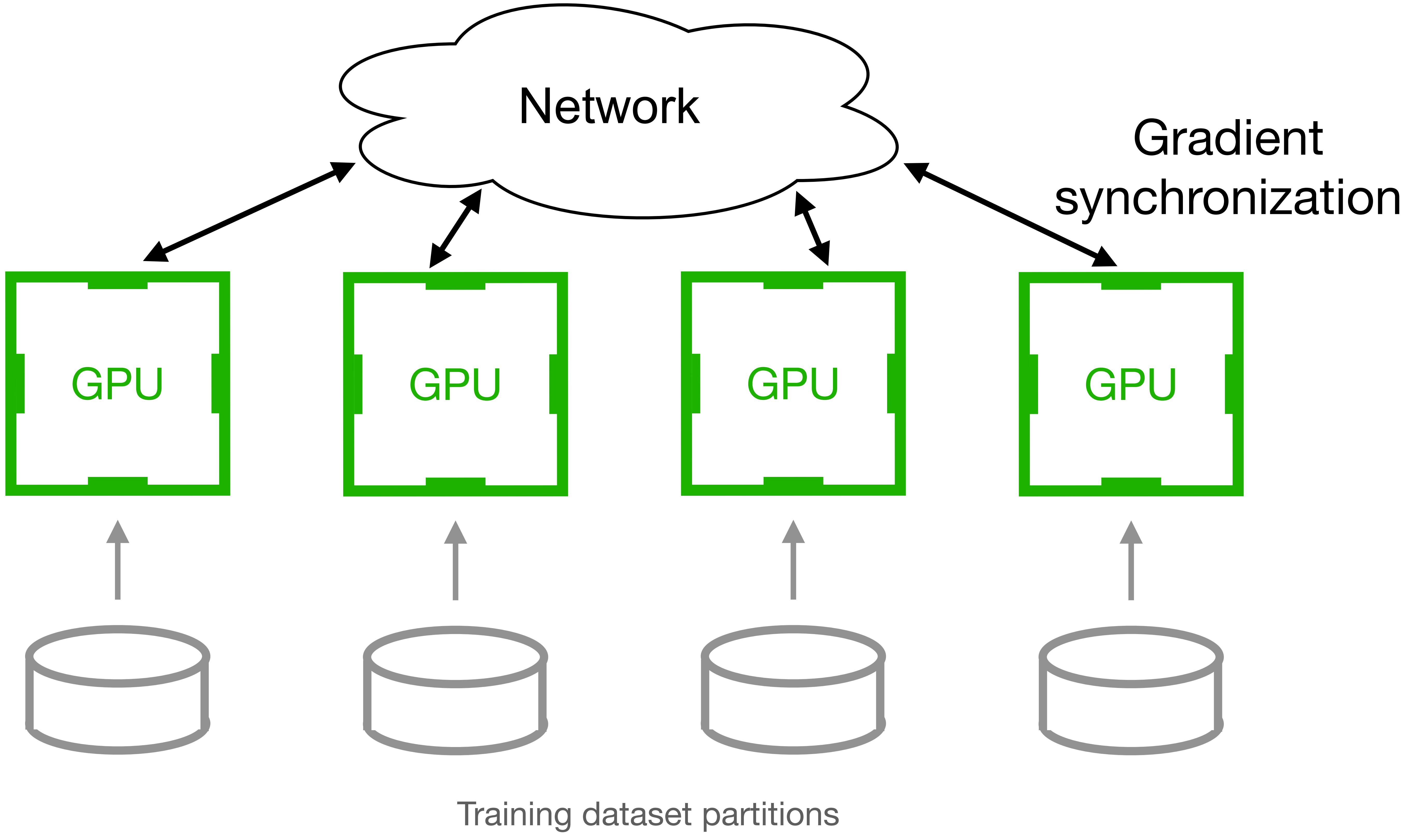
- Scale out training with multiple GPUs



Training dataset partitions

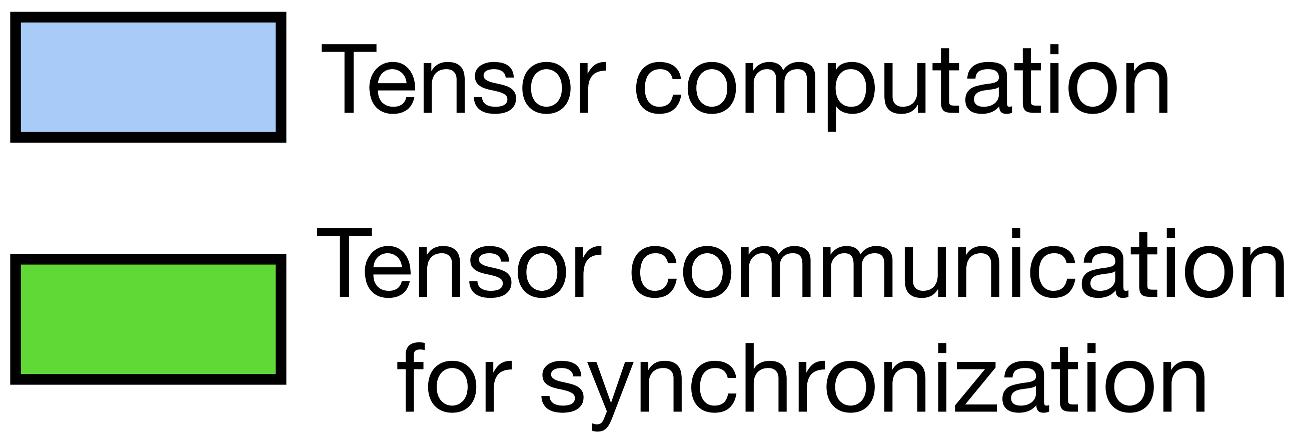
Distributed deep learning

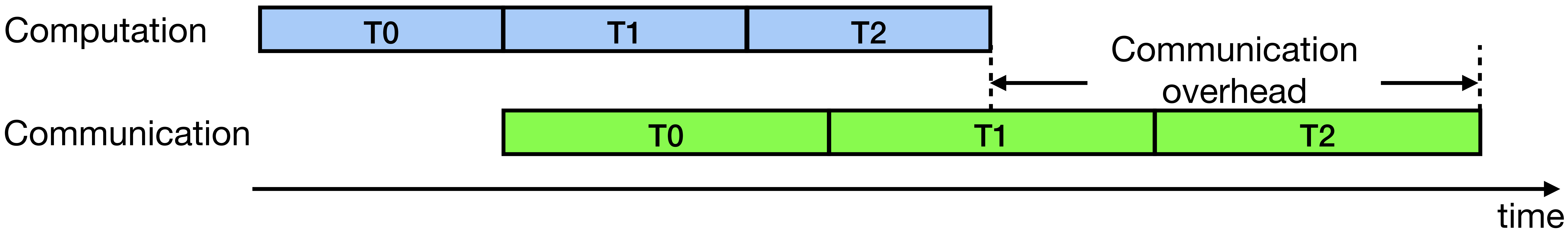
- Gradient synchronization among GPUs



Communication is bottleneck

- Communication cannot fully overlap with computation





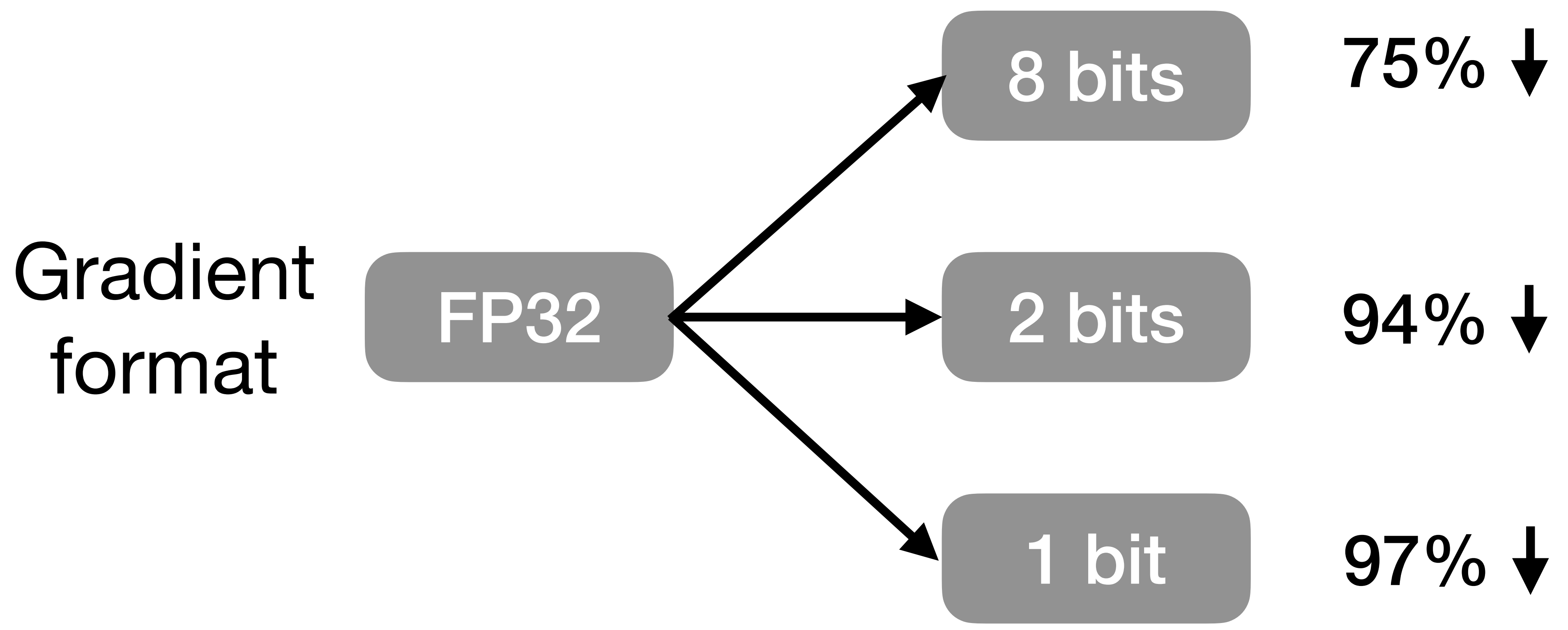
- Communication overhead can account for more than **50%** of training time [1]

[1] Gradient Compression Supercharged High-Performance Data Parallel DNN Training, SOSP ’21

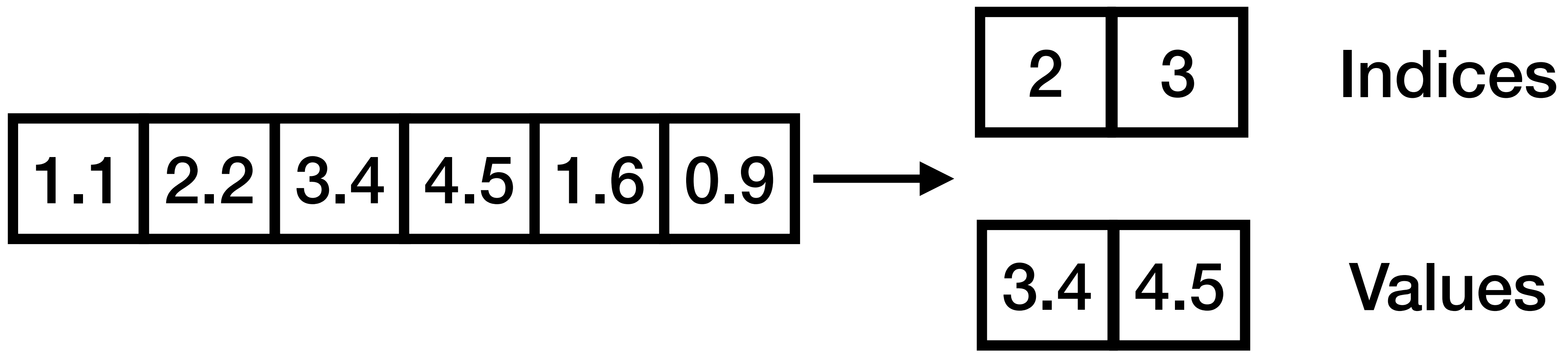
Gradient compression (GC)

- GC shrinks communicated traffic volume
  - has negligible impact on model accuracy [1]

- Quantization



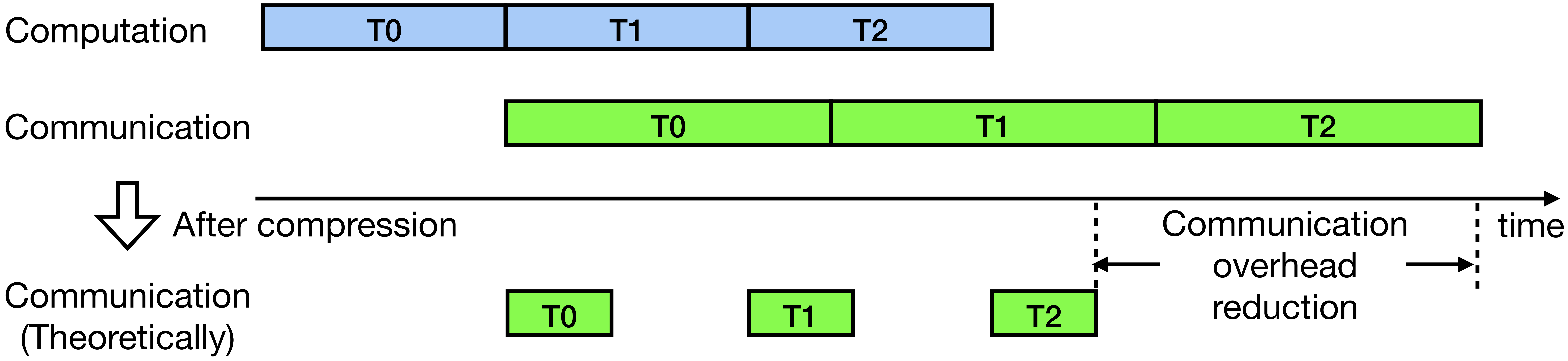
- Sparsification
  - A subset of gradients
  - Save > 99% traffic volume [2]



[1] GRACE: A compressed communication framework for distributed machine learning, ICDCS ‘21
[2] DRAGONN: Distributed Randomized Approximate Gradients of Neural Networks, ICML ‘22

Gradient compression (GC) in theory

- GC reduces communication overhead

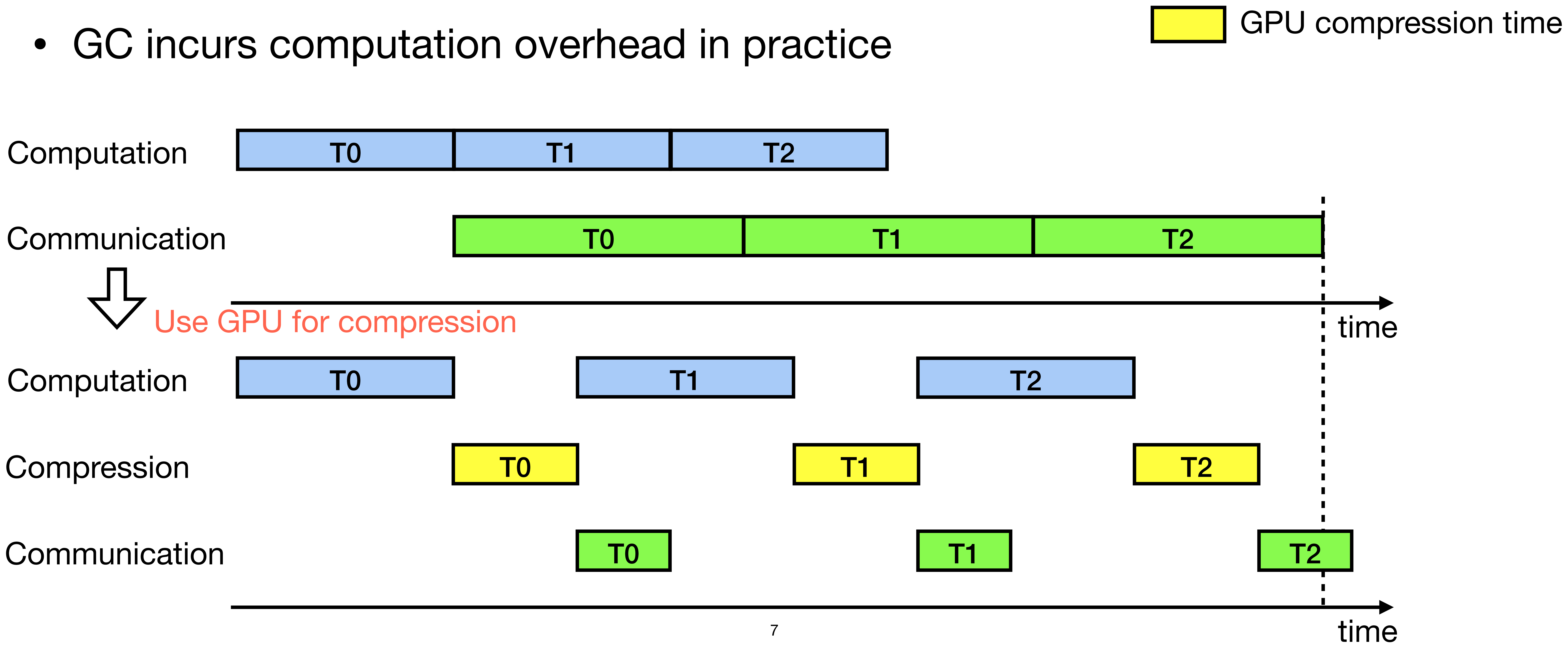


- However, GC algorithms are designed from an algorithmic perspective

Gradient compression (GC) in reality

Use GPU for compression

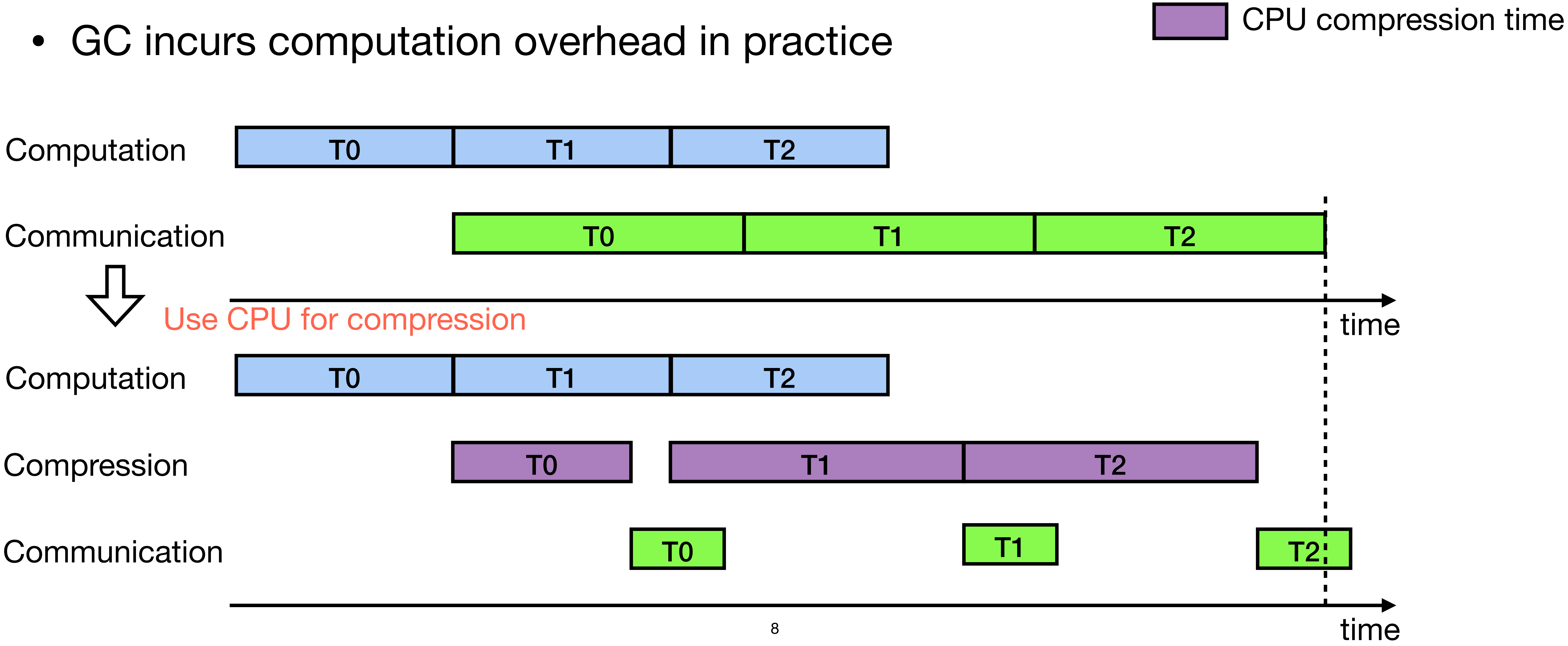
- GC incurs computation overhead in practice



Gradient compression (GC) in reality

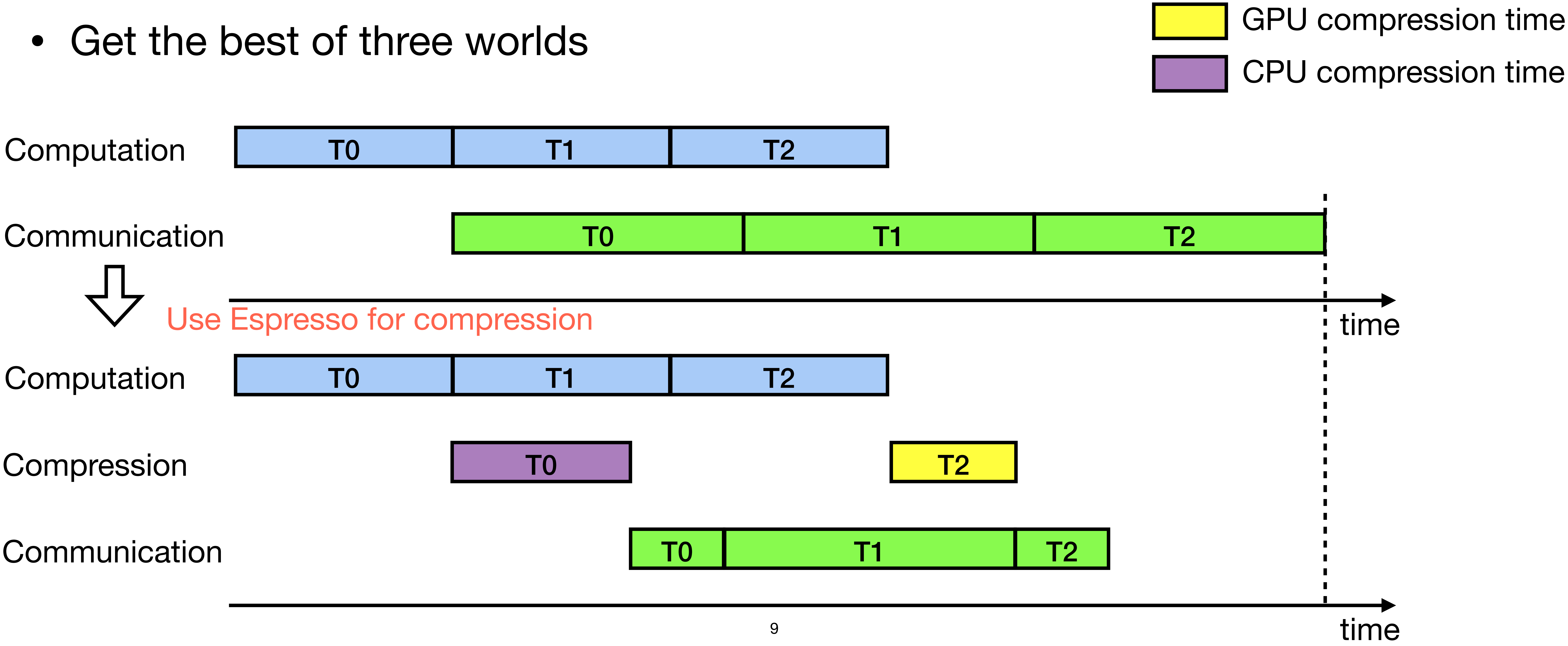
Use CPU for compression

- GC incurs computation overhead in practice



Gradient compression (GC) with Espresso

- Get the best of three worlds

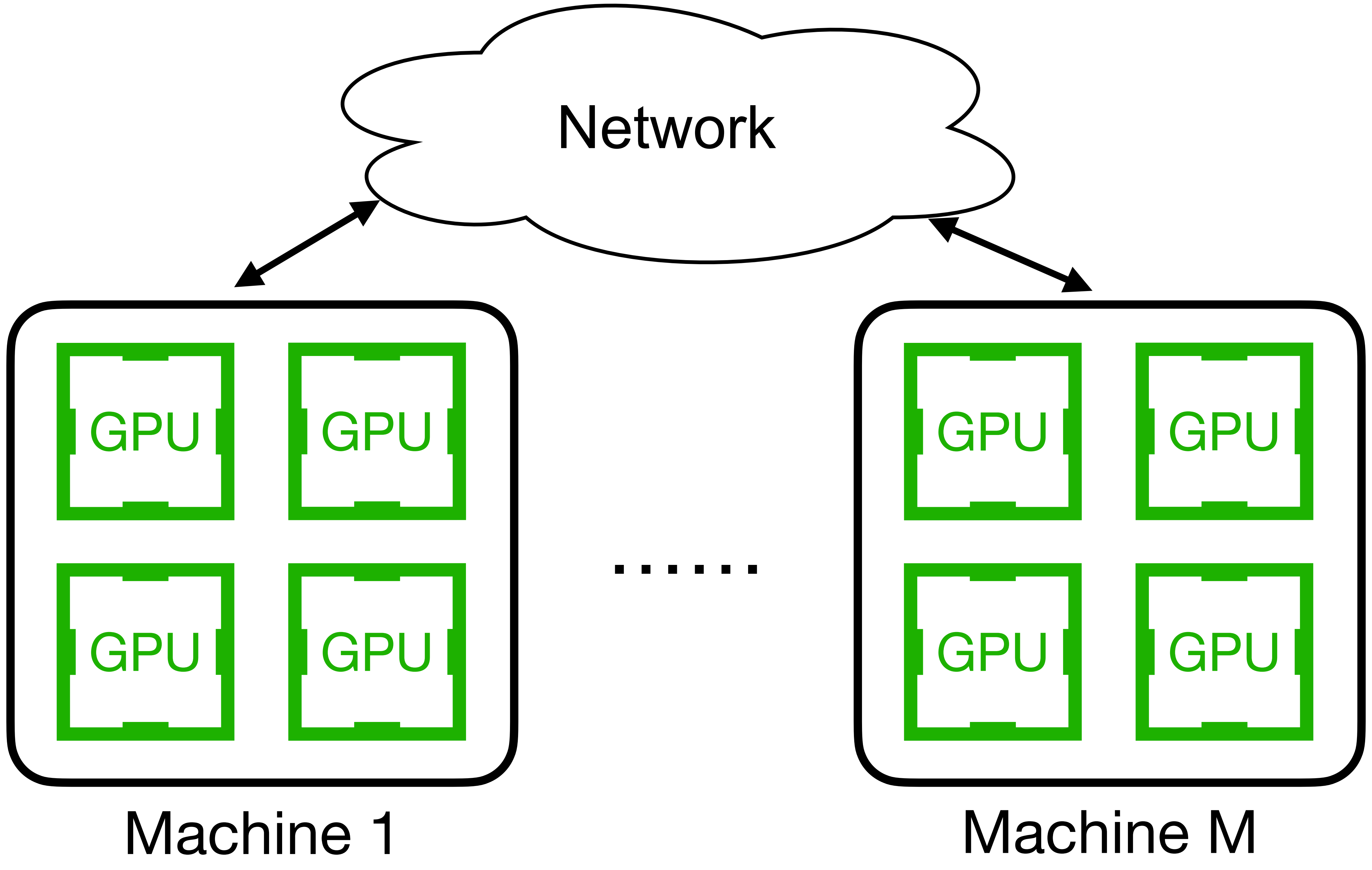


How to choose communication schemes?

- Dimensions of communication schemes

Hierarchical communication	?	Flat communication
Indivisible communication	?	Divisible communication

Which communication operation to use?



- These decisions have critical impacts on training throughput

How to find the optimal compression strategy?

Maximize the training throughput

- Challenges

#1: How to describe the search space of compression strategies?

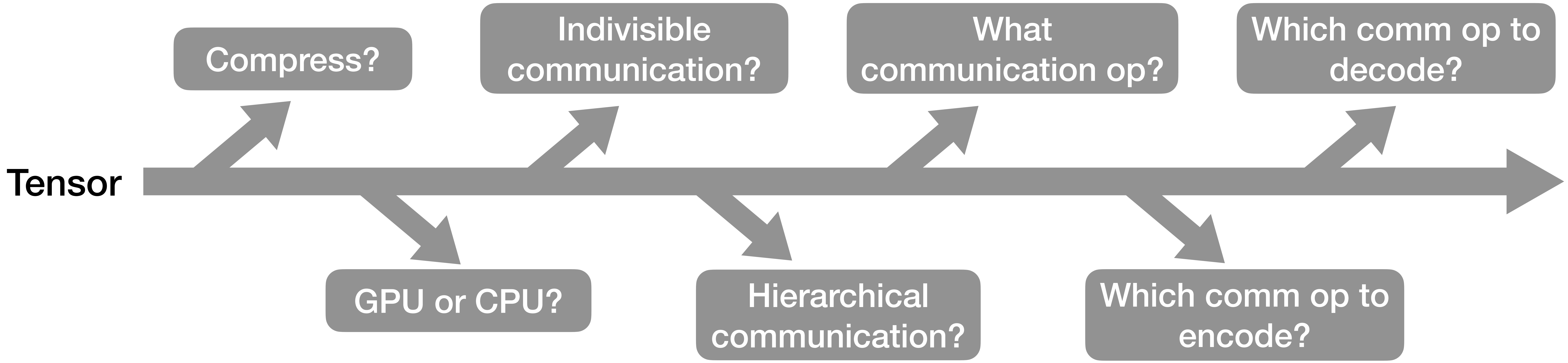
#2: How to evaluate the performance of a compression strategy?

#3: How to quickly determine a good compression strategy?

Challenge #1

Describe the search space of compression strategies

- Many dimensions of decisions for each tensor

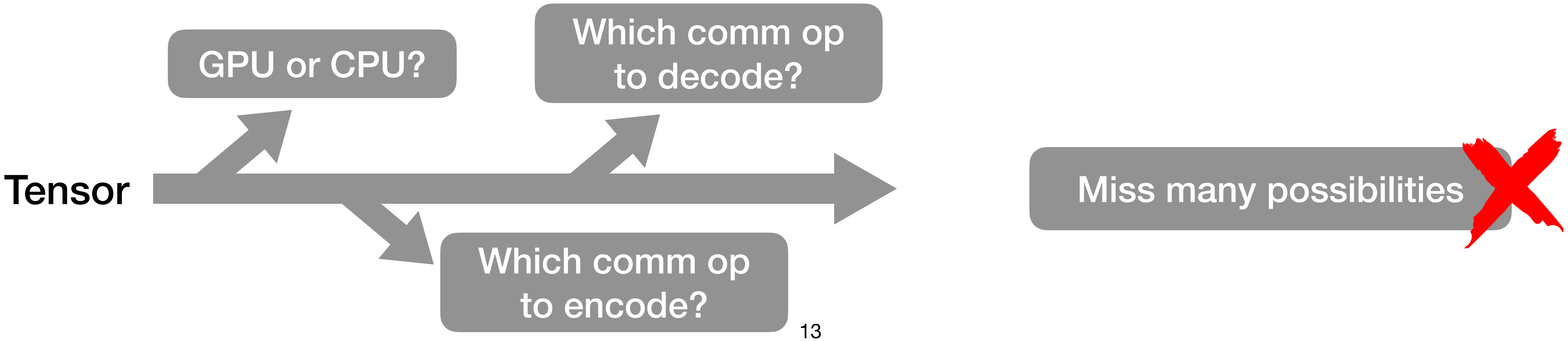


Challenge #1 (cont'd)

The decision order matters

- Some decisions have strict logical dependencies

- Some decision orders lead to bad choices



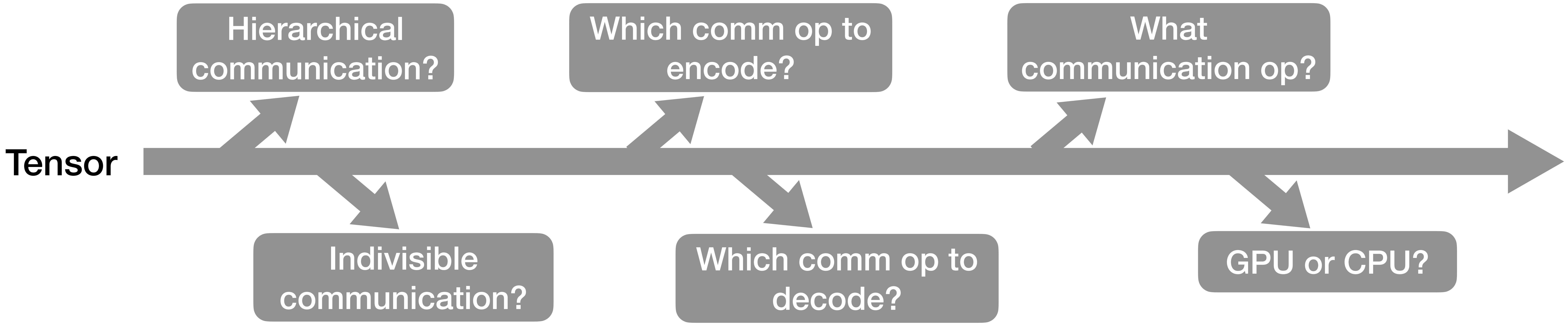
Solution

A decision order to maximize the number of possibilities

- Four steps
  - Step 1: determine the number of communication operations
  - Step 2: determine which operations for encoding and decoding
  - Step 3: determine what specific communication operations to use
  - Step 4: determine GPU or CPU for compression

Consider the dependencies

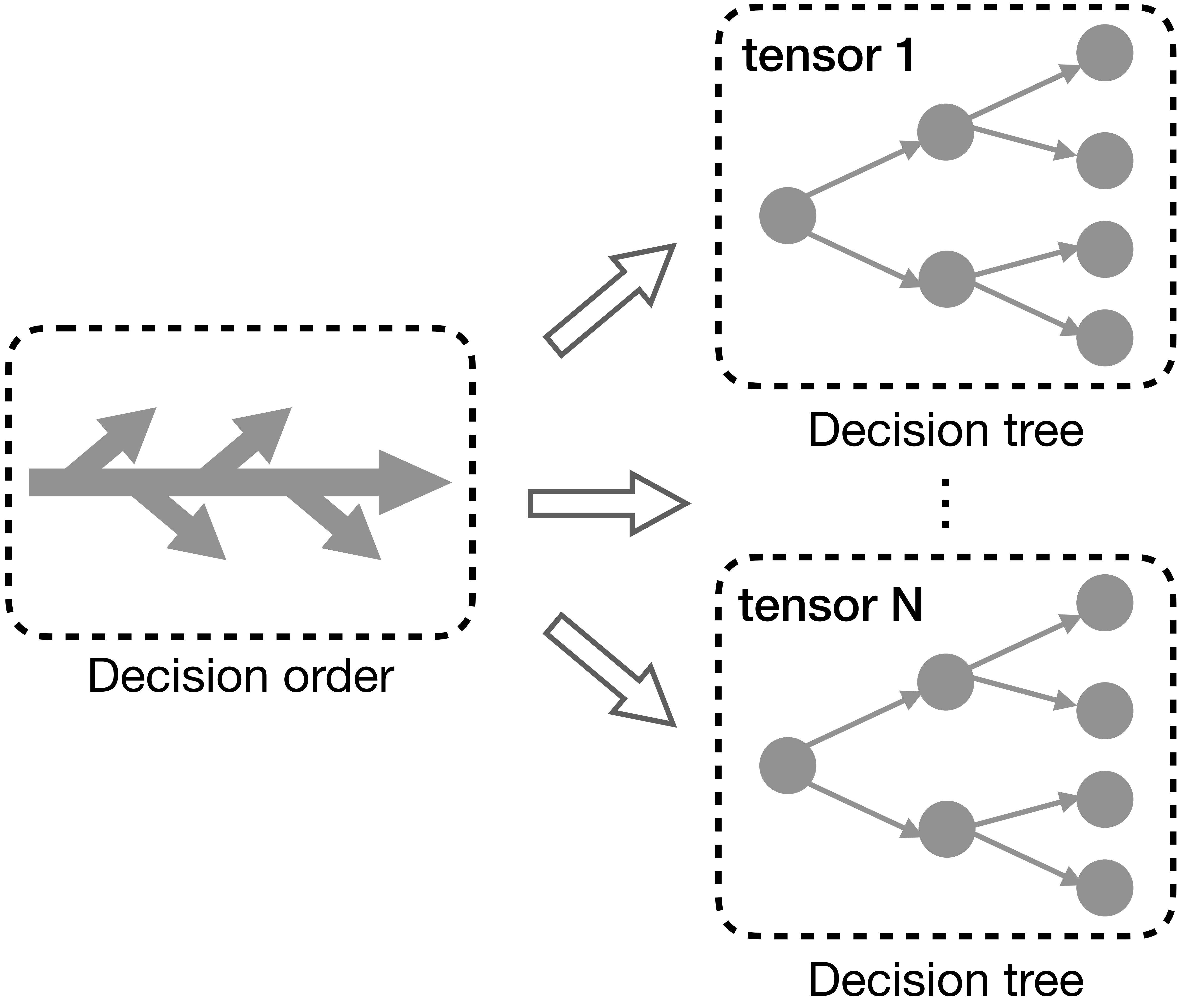
Consider all possibilities



Compress? is implies by which comm op to encode?

Solution (cont'd)

A tree abstraction



A decision tree describe all possible compression options of each tensor

The compression options of all tensors form a compression strategy

All decision trees together describe the search space of strategies

Challenge #2

Evaluate the performance of a compression strategy

- Compare different compression strategies
  - Expensive to run end-to-end training with compression strategies
- Our solution
  - Use measurements from real testbed to model training process

Tensor computation time | Tensor compression time | Tensor communication time

  - Derive the timeline of training with any strategy
  - More details in the paper

Challenge #3

Quickly determine a good compression strategy

- Extremely large search space

Thousands of compression options for each tensor

Hundreds of tensors in a DNN training model

- Different training jobs have different optimal strategies

Different training models

Different GC algorithms

Different hardware settings

- How to avoid searching the whole search space?
  - Minimize the computational time to determine a good strategy

Solution

Compression with GPUs or CPUs?

- Compressing with GPUs and CPUs have different properties

Compress tensors with GPUs
- Fast compression
- Delay computation

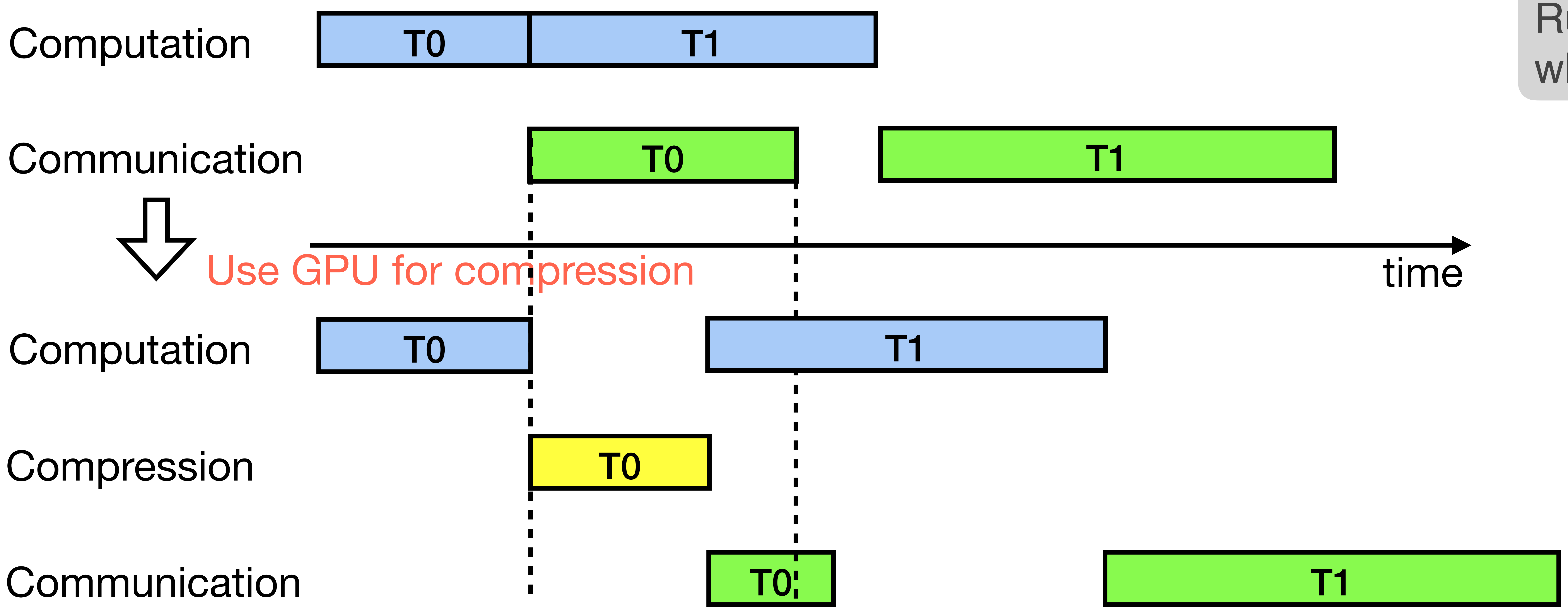
Compress tensors with CPUs
- Slow compression
- Delay communication

- A two-step decision algorithm
  - Step 1: compress tensors with GPU only
  - Step 2: offload GPU compression to CPUs to minimize compression overheads

Solution (cont'd)

Rule out sub-optimal strategies

- Step 1: Compress tensors with GPU only



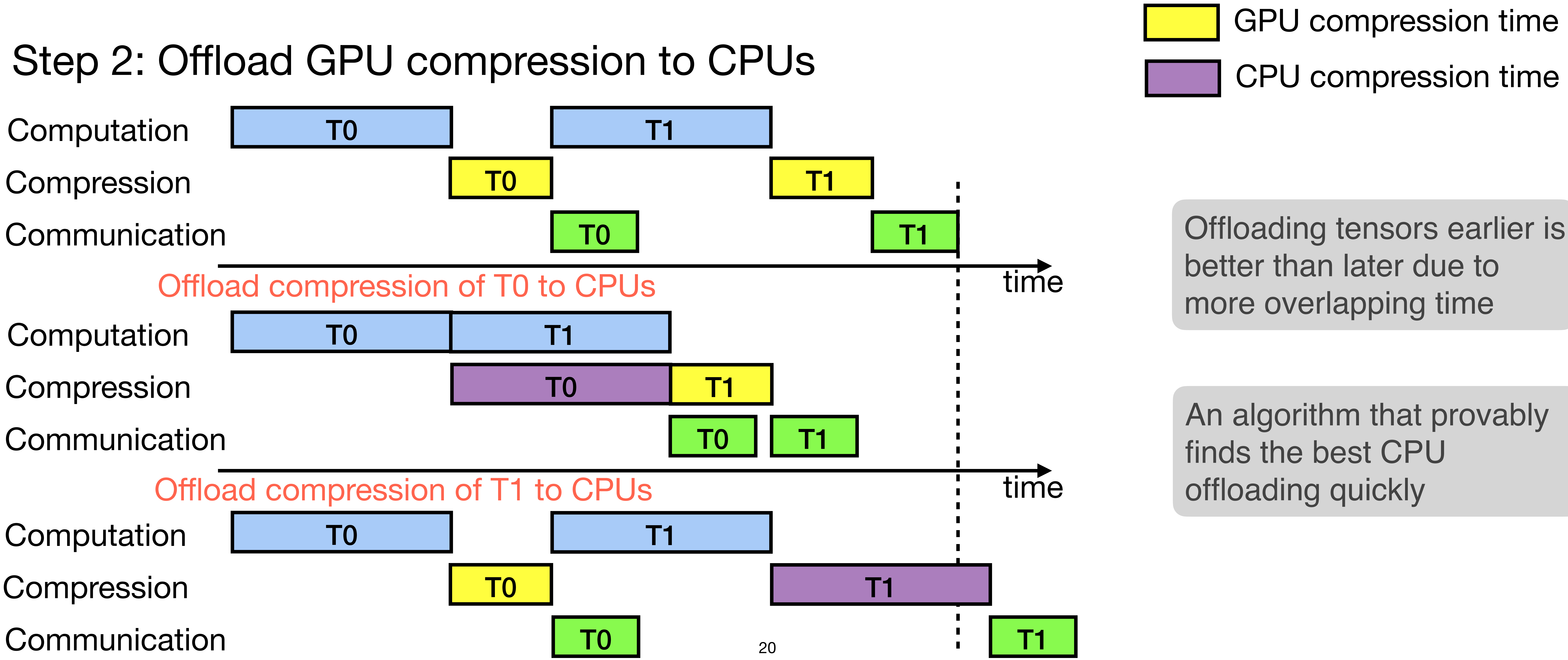
Rule out tensors with which GC cannot benefit

Compressing T0 with GPU is sub-optimal

Solution (cont'd)

Rule out sub-optimal strategies

- Step 2: Offload GPU compression to CPUs

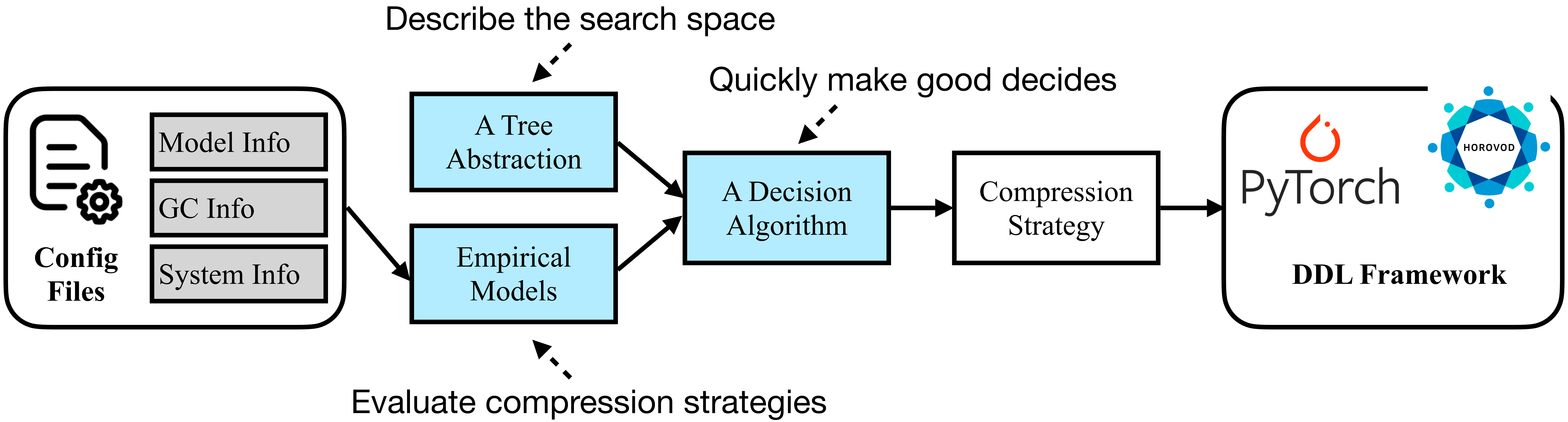


Offloading tensors earlier is better than later due to more overlapping time

An algorithm that provably finds the best CPU offloading quickly

Espresso

- System implementation



Results

25Gbps network, PCIe

- Each machine has 8 V100 GPUs

(a) VGG16+Randomk (b) LSTM+EFSignSGD (c) ResNet101+DGC

Up to 77% improvement

More evaluations in the paper

Summary

- Fundamentally analyze the challenges of applying GC
- A tree abstraction to express the search space of compression strategies
  - Expressiveness
  - Extensibility
- A two-step decision algorithm to determine compression strategies
  - Select a near-optimal strategy in milliseconds

Thank you!

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https://github.com/zhuangwang93/Espresso