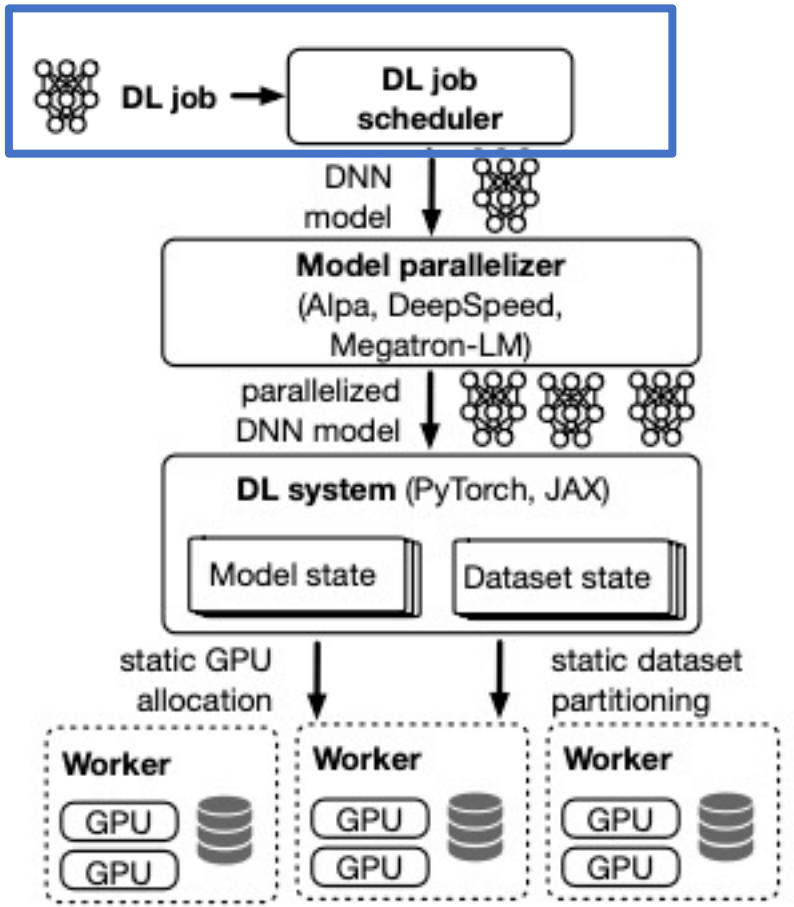
Dynamic Training Parallelization

Zhanghan Wang

2024/12/02

What can we do on top of them?



Dynamic Training Parallelization

Auto parallelization (Haitian/Hexu)

Torch Tensor Implementation (Haitian)

Collective Communication Lib (Tao)
DL Compilers (David)

Tenplex: Dynamic Parallelism for Deep Learning using Parallelizable Tensor Collections

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Enabling Parallelism Hot Switching for Efficient Training of Large Language Models

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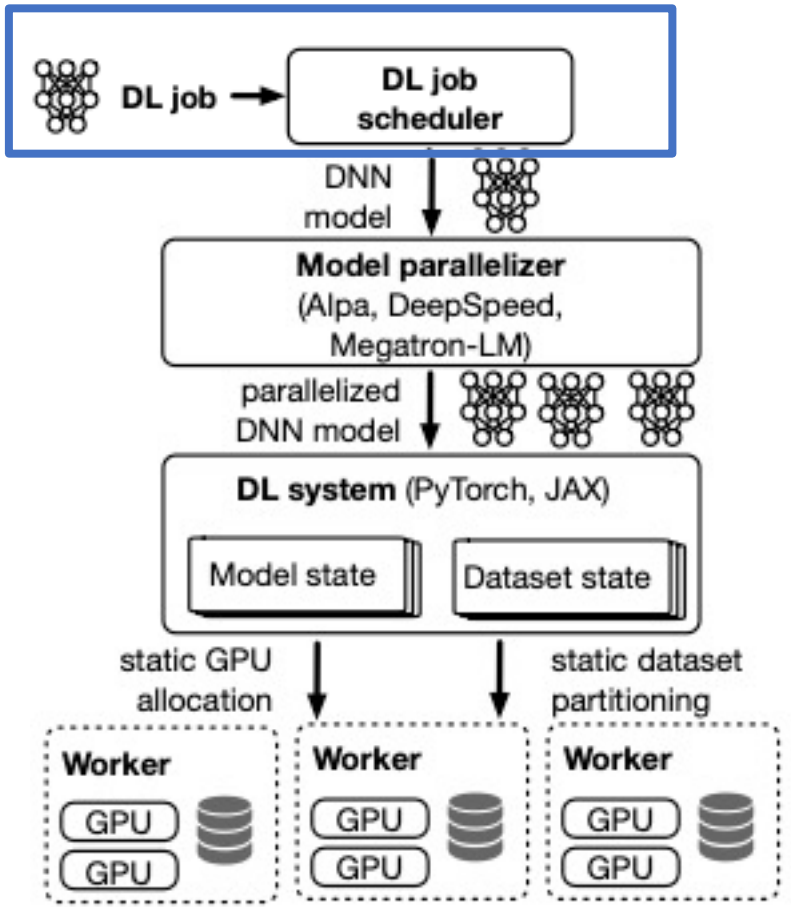
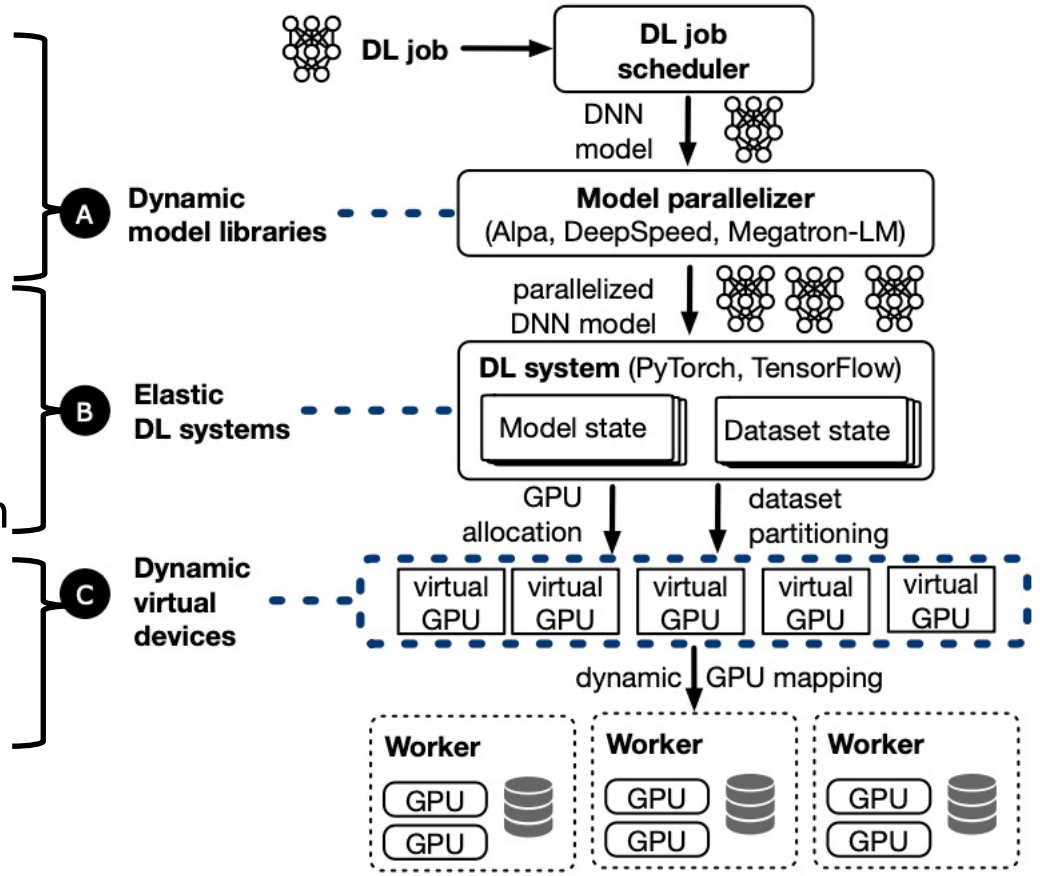
Dynamic Training Parallelization



- Why?
  - Tenplex (resource changes)
    - Elasticity (cloud)
    - Redeployment (hardware maintenance)
    - Failure recovery (GPU failure)
  - HotSPa
    - The optimal parallelism strategies varies for different sequence lengths.
- Thus, we may require changing parallelism strategy dynamically.

Dynamic Training Parallelization

- How is dynamic parallelization supported now?
  - Model parallelizers
    - Alpa, MegatronLM, DeepSpeed…
    - Can re-plan upon resource changing;
    - But require manual re-partitioning.
  - Elastic DL Systems
    - Elastic Horovod, Torch Distributed…
    - Require manual re-partitioning
    - No support for full multi-dimensional parallelism
  - Virtual Devices (Virtualize GPUs)
    - VirtualFlow, EasyScale, Singularity…
    - Only supports dynamic DP



Dynamic Training Parallelization

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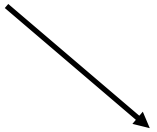
Challenges or Missing parts

- Auto re-partition
- Full multi-dim parallelism
- Low reconfiguration overhead



Means changing from a parallelism strategy to another

Dynamic Training Parallelization

Challenges or Missing parts

- Auto re-partition
- Full multi-dim parallelism
- Low reconfiguration overhead

} **States Abstraction** of model/data tensors and their transformation

} **Reconfig Planning**: find low-cost reconfig plan to transfer or re-load tensors.

TENPLEX: Dynamic Parallelism for Deep Learning using Parallelizable Tensor Collections

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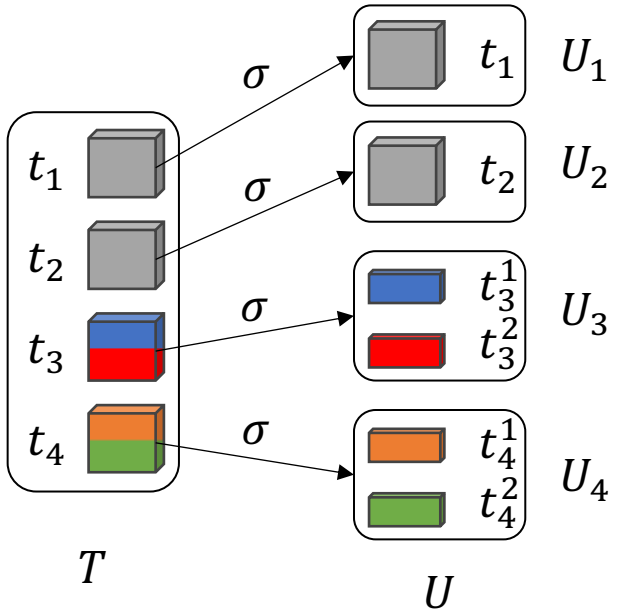
Tenplex – State Abstraction

- Parallelizable Tensor Collection (PTC)

$$\text{PTC} = (T, \sigma, \phi, \alpha)$$

  - $T = D \cup M = \{t_1, \ldots, t_n\}$. Here, D for dataset tensors and M for model tensors.
  - σ slices a tensor $t_i \in T$ into sub-tensors $U_1 = \sigma(t_i) = \{t_i^1, \ldots, t_i^m\}$.

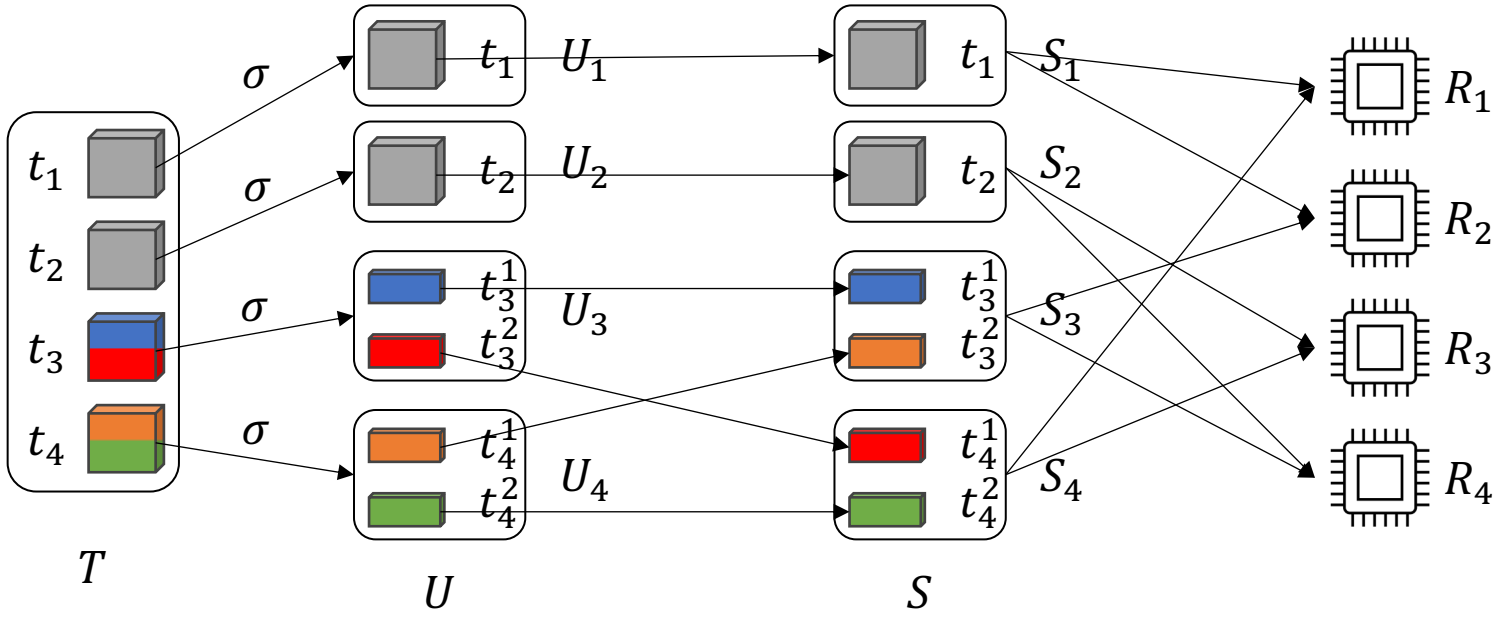


Tenplex – State Abstraction

- Parallelizable Tensor Collection (PTC)

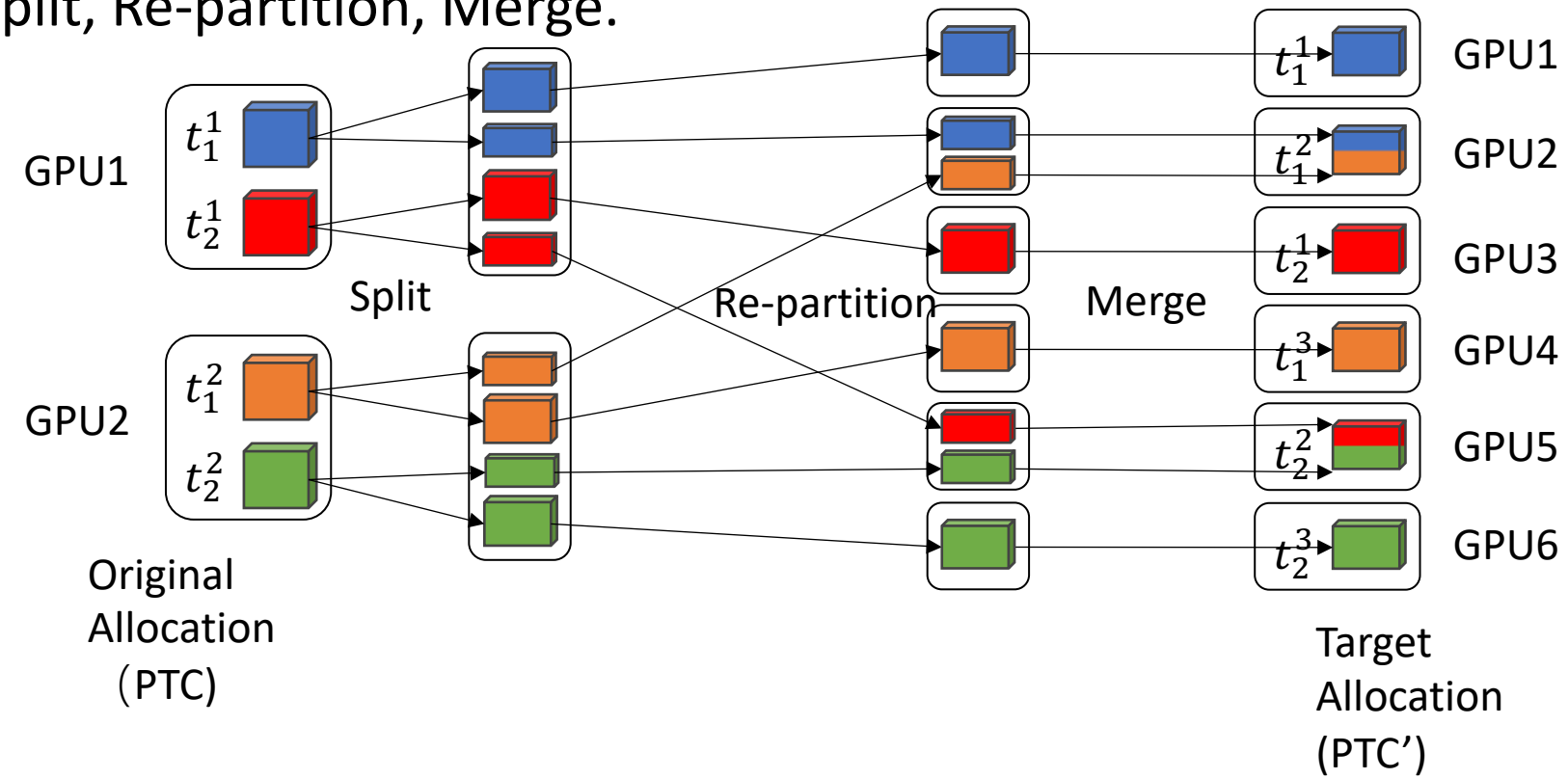
$$\text{PTC} = (T, \sigma, \phi, \alpha)$$

  - ϕ partitions U into sub-collections $S = \phi(U) = \{S_1, \ldots, S_p\}$
  - α allocates the sub-collections to GPUs. (A sub-collection can be allocated to multiple GPUs)



Tenplex – Reconfig Planning

- Reconfigure PTC $= (T, \sigma, \phi, \alpha)$ into PTC' $= (T, \sigma', \phi', \alpha')$
- Steps:
  - Split, Re-partition, Merge.



Tenplex workflow

- Tensor Store
  - Numpy to support most DL Systems
- State Transformer
  - 3. Reconfig Plan Generation
  - 4. Execute the plan
- Fault tolerance
  - If at least one DP replica survives, Tenplex retrieves updated states from GPU (instead of loading checkpoint and starting from previous step).

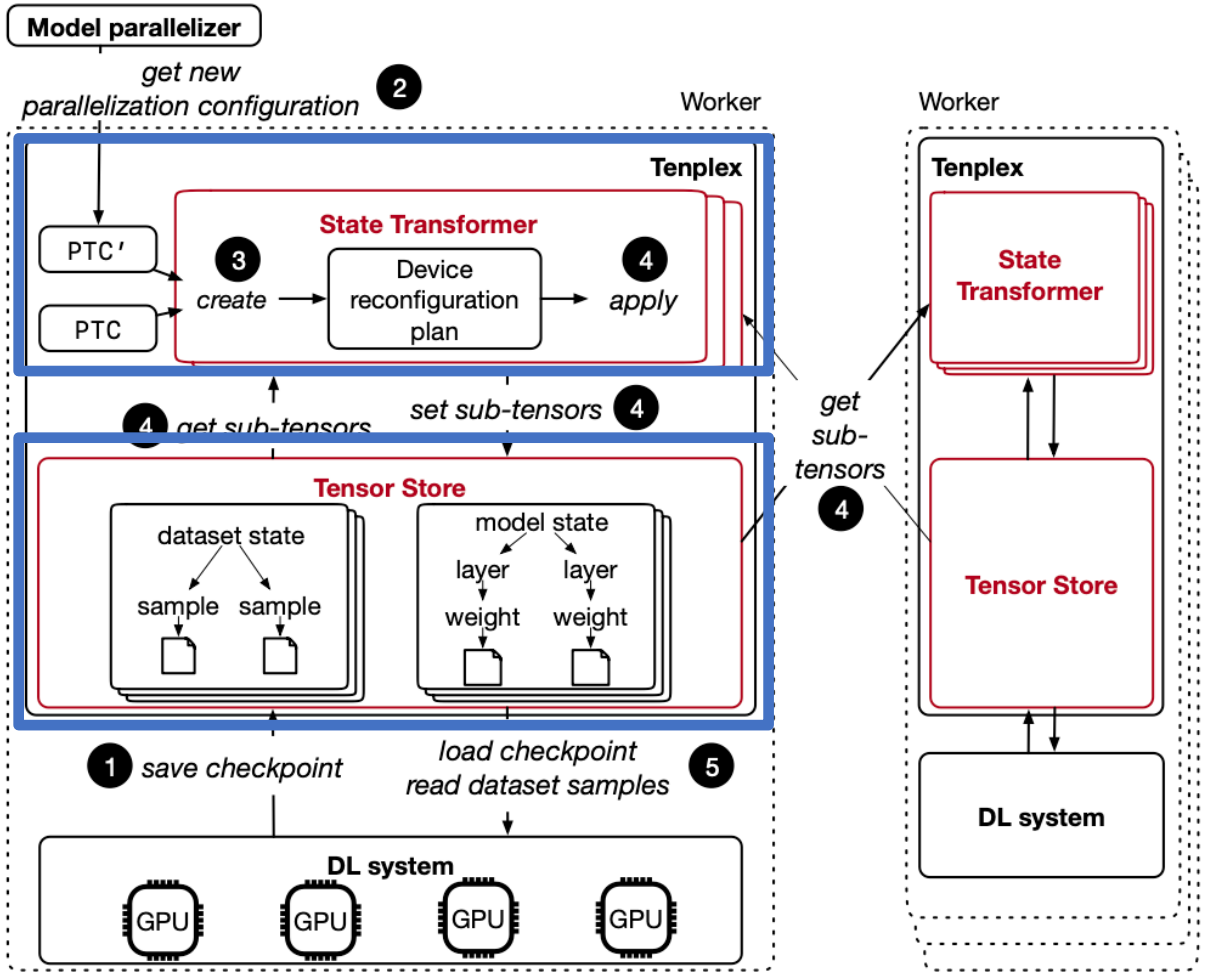
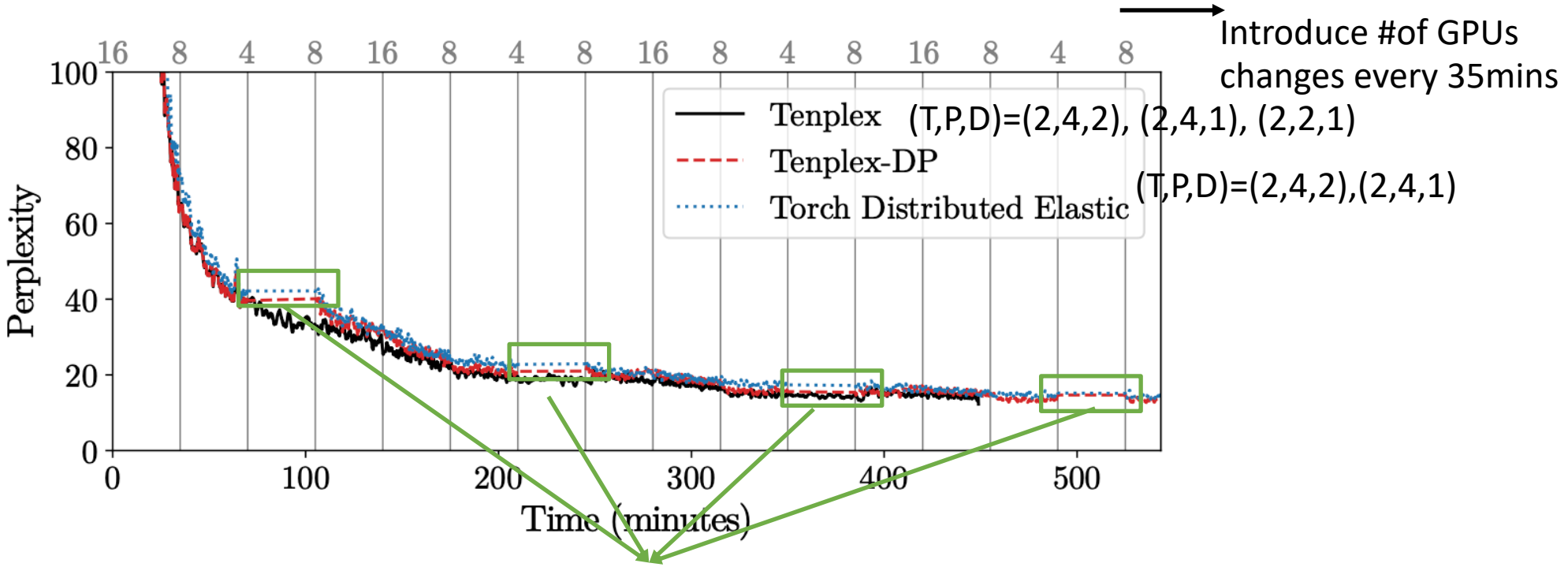


Fig. 8. TENPLEX architecture

Tenplex Evaluation - Speedup

- To run to the same step, Tenplex takes 298 mins, Tenplex-DP takes 576mins, Torch takes 548mins.
  - Torch only supports dynamic DP; Tenplex-DP only reconfigures DP.



Tenplex-DP and Torch paused. This is 35*4=140mins

Tenplex Evaluation - Others

- Redeployment time. E.g., migrating from one set of 8 GPUs to another set of 8 GPUs.
- Failure recovery time.
- Reconfiguration time.
- …

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HotSPa

- Tenplex is for handling resources changing.
- HotSPa actively find best parallelization strategy given different sequence lengths.
  - Their observation:

> In this paper, we first reveal the under-explored fact that the optimal parallelism strategy varies even for the sequences within a single mini-batch. Motivated by this, we present

Why Sequence Length Matters?

The maximum supported seq len of the model

- Longer sequence requires higher context length and more memory
- More memory requires higher TP degree (or other parallelism)
- Higher TP means lower DP degree, increasing latency due to communication.

Table 1. Running time (in seconds) of different tensor parallelism degrees (LLaMA2-7B, 8GPUs, *DP=8/TP*) when processing the same amount of tokens.

Seq Len	# Seqs	*TP=1*	*TP=2*	*TP=4*	*TP=8*
1K	512	**13.9**	14.7	16.2	19.5
2K	256	**14.2**	15.1	16.6	19.8
4K	128	**14.9**	15.8	17.4	20.6
8K	64	OOM	**17.4**	19.1	22.1
16K	32	OOM	OOM	**21.8**	25.0
32K	16	OOM	OOM	OOM	**30.8**

Why Sequence Length Matters?

- Distribution of sequence lengths is skewed.
- Thus, a randomly sampled mini-batch usually contains few long sequences with a lot of short sequences.

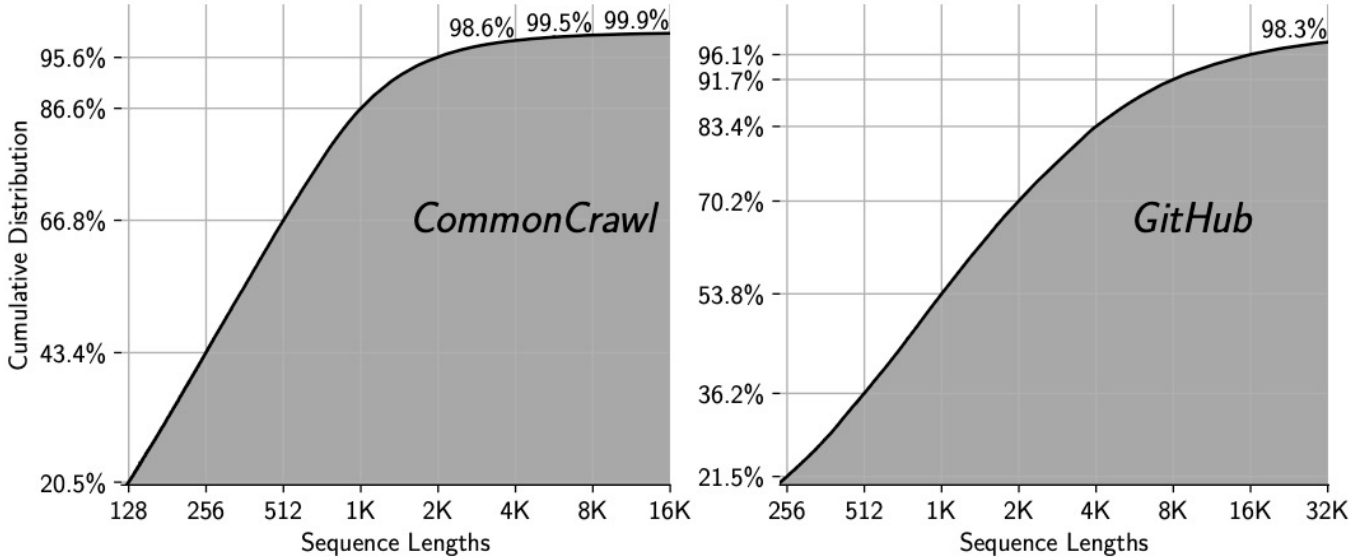
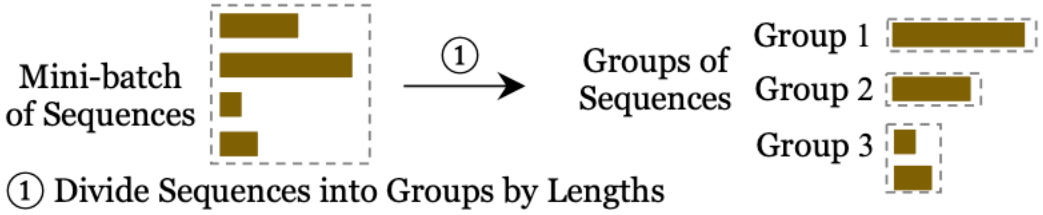


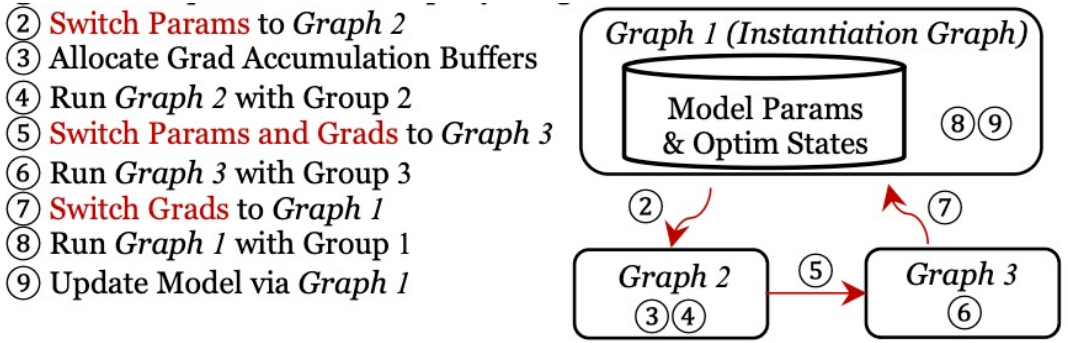
Figure 3. Cumulative distributions of sequence lengths.

How to solve this?

- Partition sequences into multiple groups,



- For each group, use different parallelism strategies.



Dynamic Training Parallelization (Revisit)

- Challenges or Missing parts
  - Auto re-partition
  - Full multi-dim parallelism
  - Low reconfiguration overhead

LogicGraph + ***DistConfig*** + ***Graph Compiler***

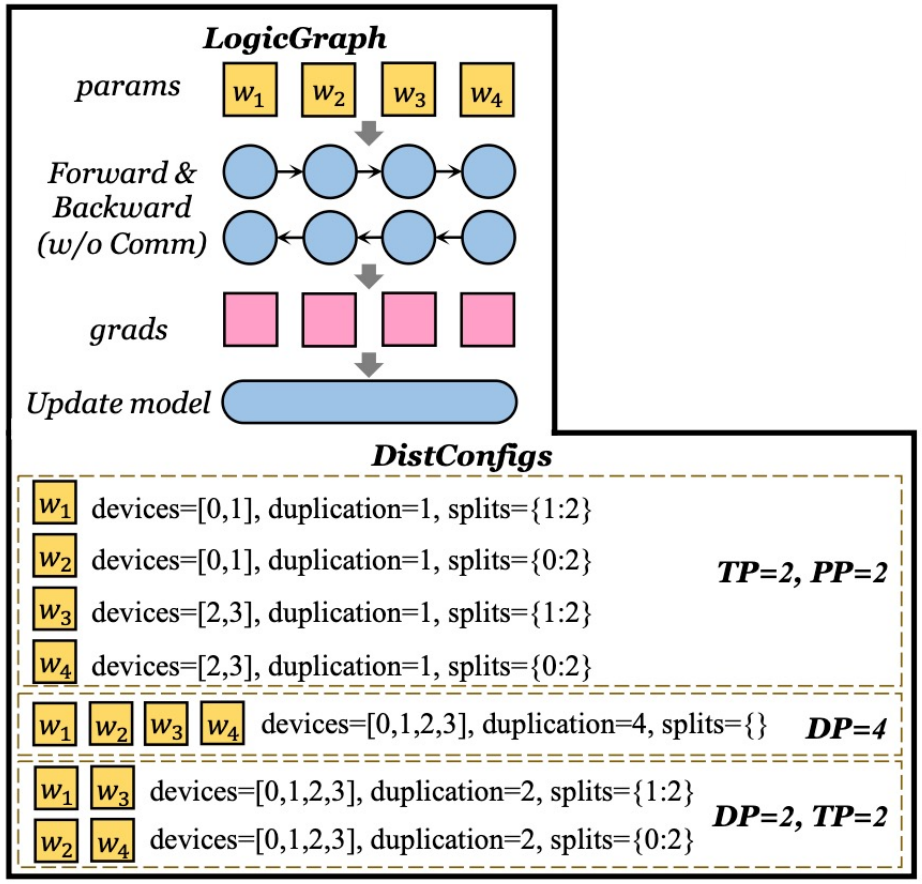
States Abstraction of model/data tensors and their transformation

Reconfig Planning: find low-cost reconfig plan to transfer or re-load tensors.

Hot Switch Planner

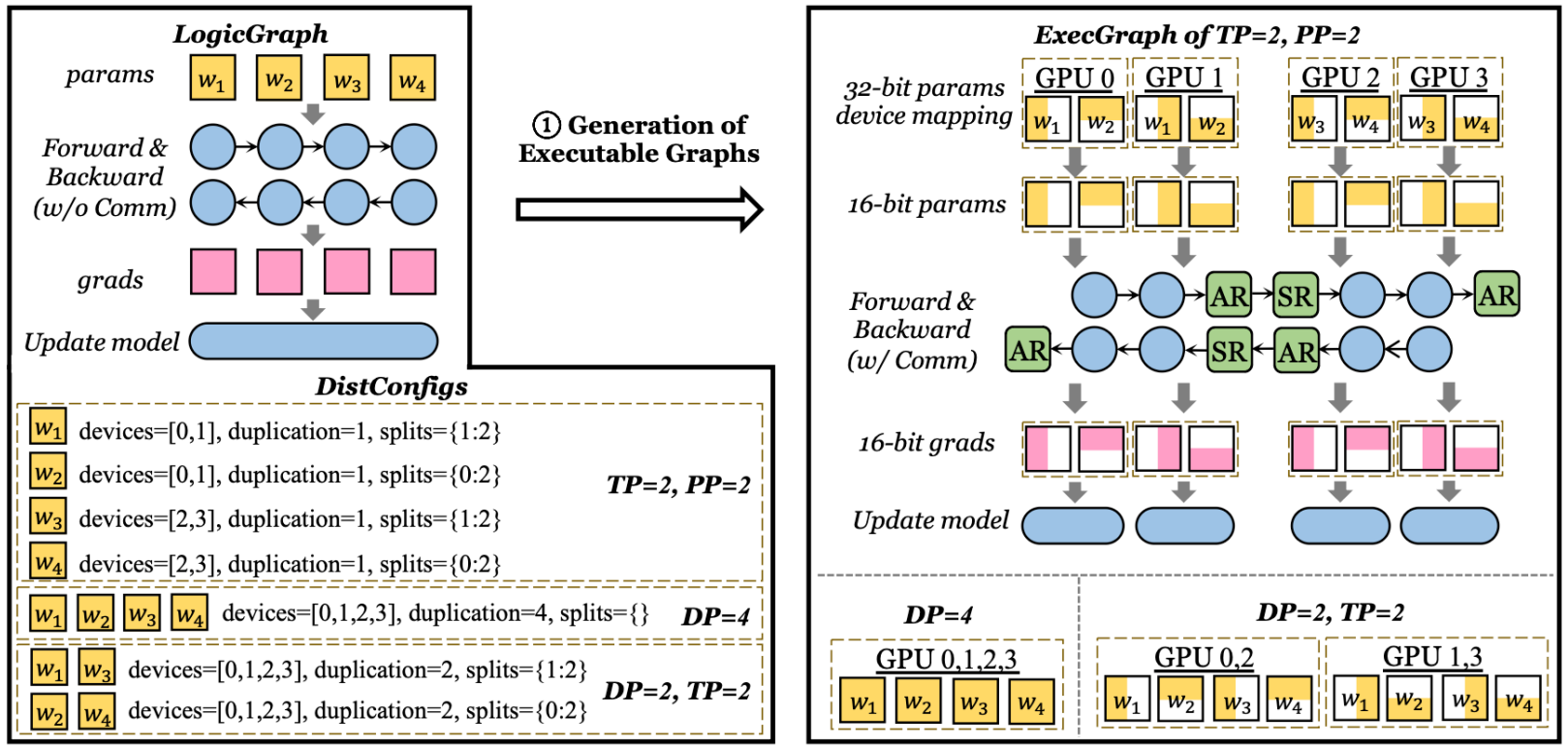
HotSPa – State Abstraction

- LogicGraph
  - No communication
- DistConfig
  - Annotate each tensor (manually)
    - Assigned devices
    - DP degree
    - How to Split ({dim: #of splits})
      - For TP…



HotSPa – State Abstraction

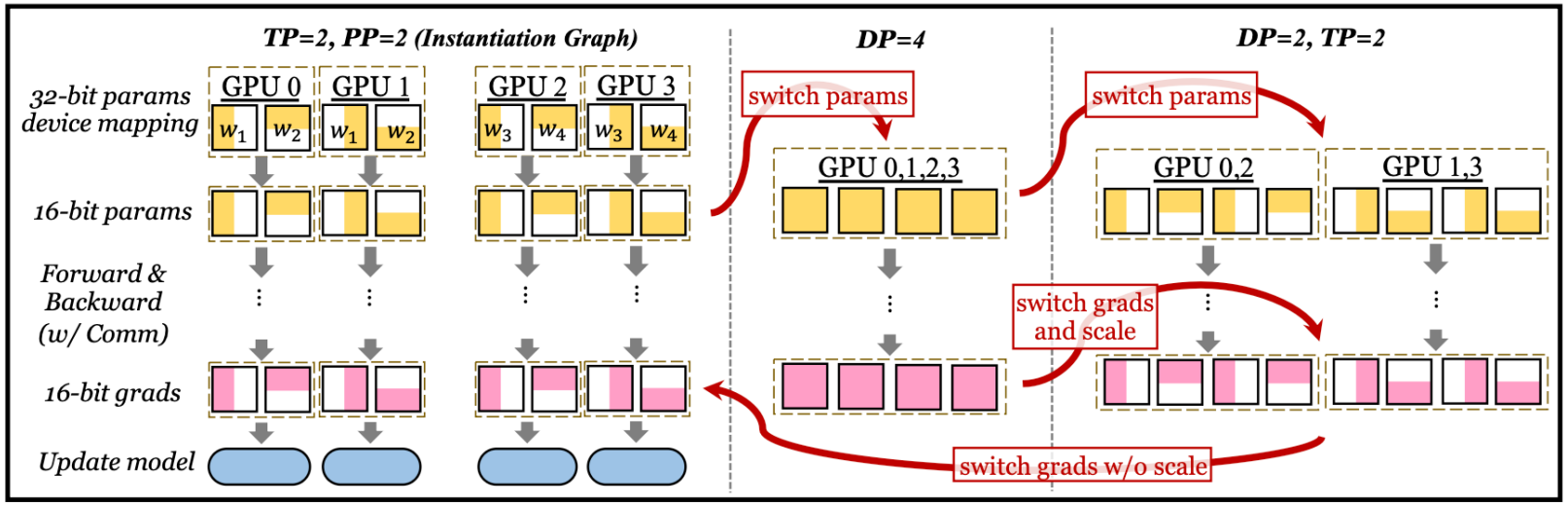
- Graph Compiler (LogicGraph + DistConfig → ExecGraph)
  - Insert type casting, communication, accumulation.



- Order?
- Transfer?

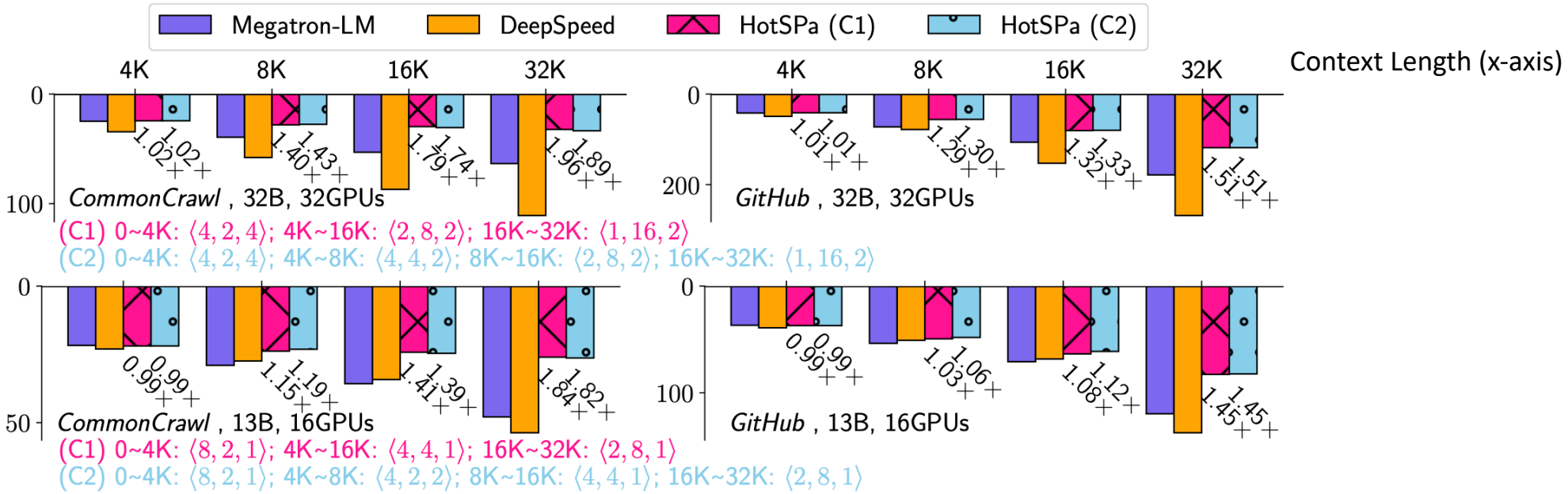
HotSPa – Reconfig Planning

- Instantiation Base Graph (for mixed-precision training)
  - Minimize memory occupation
- Order of ExecGraph
  - Minimize total switching cost
- Switching plan and its cost (Heuristic Greedy Algorithm)
  - Metrics: Total volume of inter/intra-node transferring.
  - Prefer intra-node communication and minimize the maximum sending volume of all devices.



HotSPa Evaluation

- Running time of Megatron-LM and DeepSpeed increases as context length increases;
- Running time of HotSPa increases much slower.



Part of evaluation results.

Conclusion

- Different motivation
  - Tenplex: resource changes
  - HotSPa: sequences can be re-grouped to use better parallelization
- Similar state abstraction
  - Tenplex also records dataset read position
  - HotSPa maintains LogicGraph for GraphCompiler to compile into ExecGraph
- Reconfig planning
  - Tenplex is more passive
    - Just moves tensors from source to destination.
  - HotSPa is more active
    - Finds a set of DistConfigs in advance and orchestrates them in a good order.
    - Also uses some heuristics.
- Results
  - Tenplex allows resource changes
  - HotSPa optimizes specifically for the skewed sequence lengths.