WLB-LLM: Workload-Balanced 4D Parallelism for Large Language Model Training

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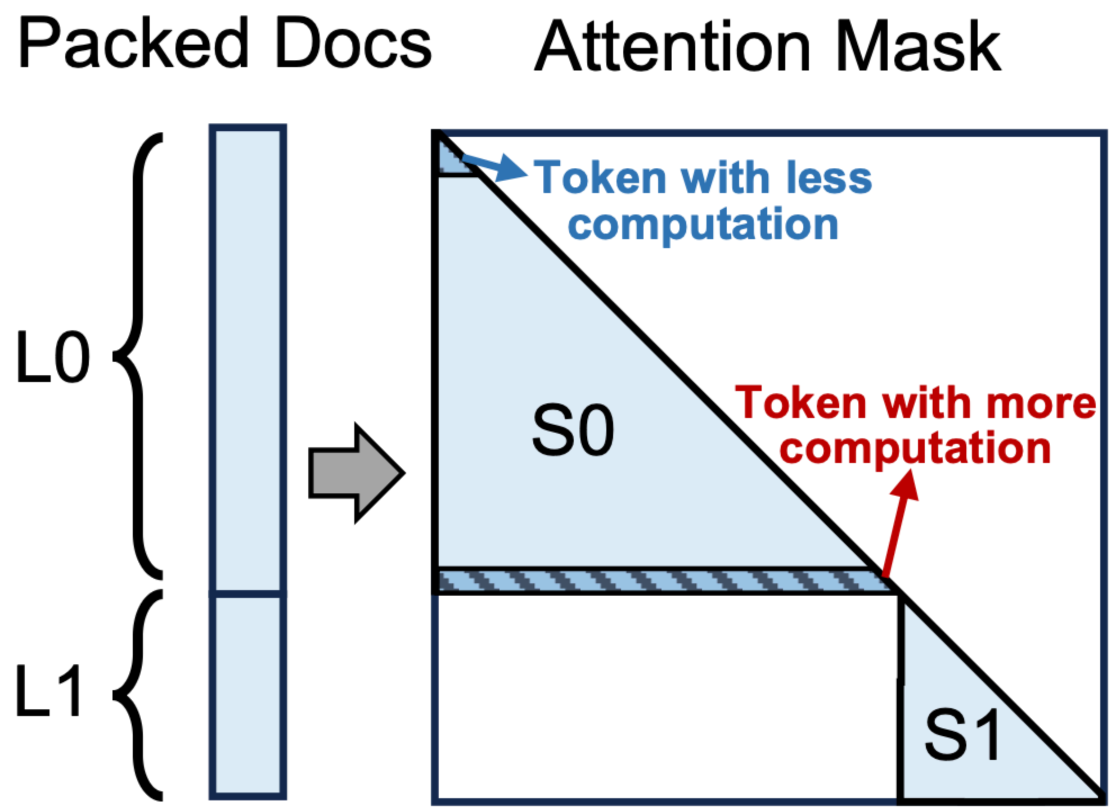
Introduction

- Llama 3.1 405B trained over 16k GPUs for 30M H100 hours.
- Using AWS H100 pricing **$212M**.
- A 1.2x increase in training speed would have saved **$36M** in cloud costs.
- WLLB-LLM is a work from Meta and UCSD, released ~6 months after their training Llama 3 that achieves this.

Self Attention

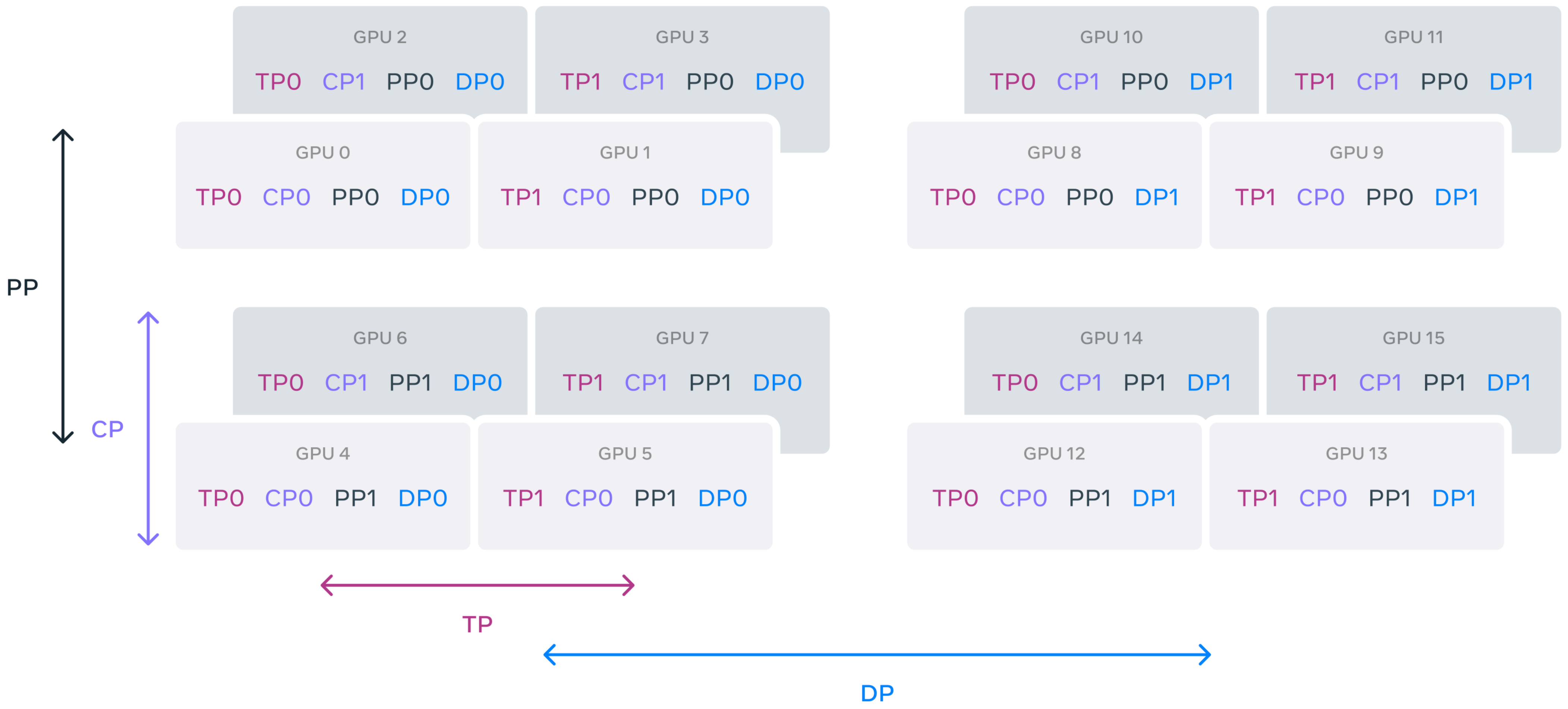
- Attention scales quadratically with the number of past tokens $O(T^2)$
- Not all tokens are equal: Processing later tokens in a document require more computation than earlier.
- When packing multiple documents for training, control attention span using masks.



4D Parallelism

- Huge models are trained on huge clusters because of scale and necessity.
- Tensor shape $[B, T, H]$ across several layers.
- 4D Parallelism splits this shape in various ways.
    - Data - Split B across replicated model.
    - Pipeline - Split model into groups of layers.
    - Context - Split along sequence length T
    - Tensor - Split across the H.

4D Parallelism



$$DP > PP > CP > TP$$

Key Takeaways

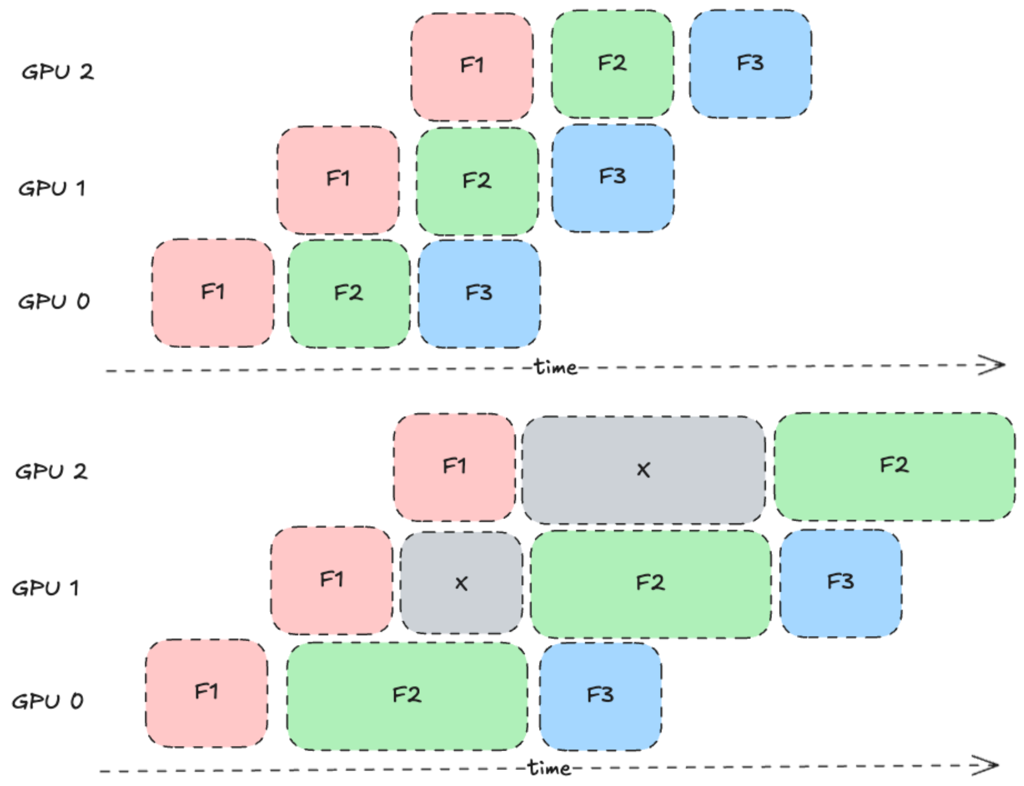
Problem: In long-context 4D training, token count is a weak proxy for compute; attention cost is highly non-uniform.

- **Core idea #1 (PP)**: Reduce PP imbalance via attention-aware micro-batch packing.
- **Core idea #2 (CP)**: Reduce CP imbalance via fine-grained per-document sharding.

Bottom line: WLB-LLM improves training throughput ($\approx 1.23x$) without hurting convergence.

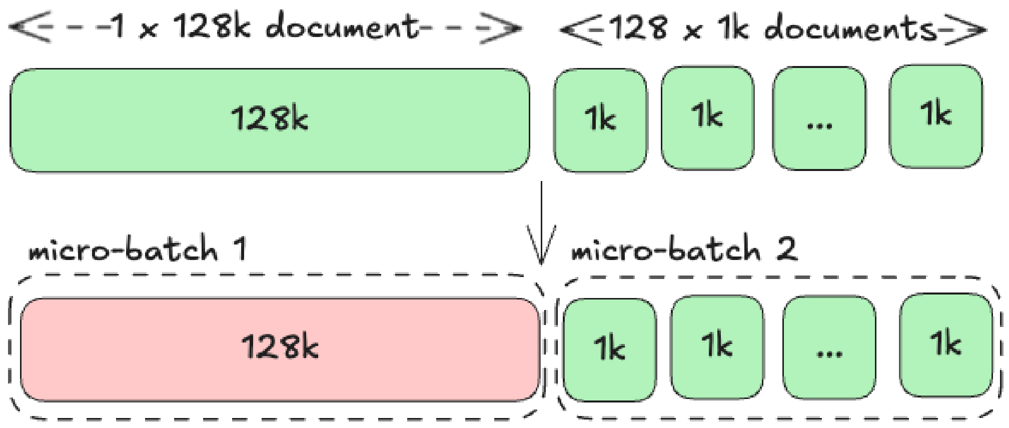
Motivation #1 - Pipeline Imbalance

- Pipeline Parallelism splits B into N μB to hide delays.
- Balanced Batches $\rightarrow$ Higher throughput



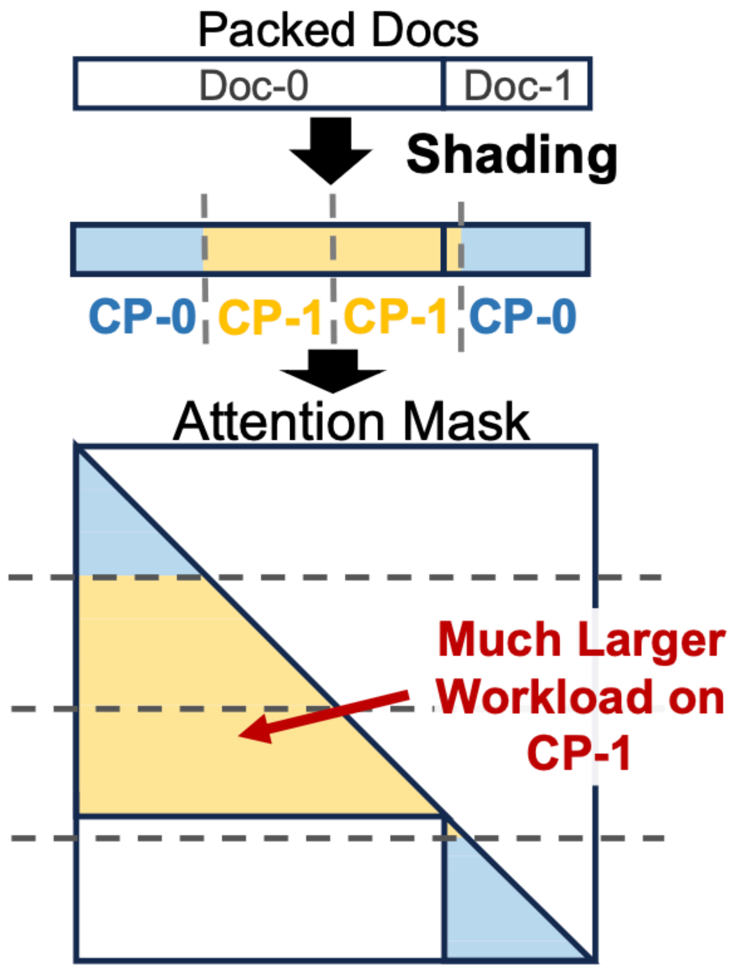
Motivation #1 - Pipeline Imbalance

- Naive approach $\longrightarrow$ split by tokens.
- Each μB has uniform sequence length = `CONTEXT_WINDOW_SIZE`
- Does this balance LLM workload?
- $k.128^2 >> k.128 * 1^2$



Motivation #2 - Context Imbalance

- Workload across CP workers should be balanced.
- After packing, split the sequence into $2.CP$ parts and assign one from front and one from back to balance attention.
- Good heuristic, fails for multiple packed documents. Common in long context training.
- Every small delay adds up to higher-order delays.



Baseline: Attention-Aware packing.

Idea: Divide B into μB by estimating d_i^2 as attention cost for each document.

- It works, but limited balancing improvements $\rightarrow$ limited speedup.
- Higher balancing across μB requires balancing across multiple global B. This disturbs the random order of training and loss convergence.
- It might be impossible to come up with such a μB construction, if there are no candidates.

$$\begin{aligned} \text{minimize} \quad & \max(\boxed{\sum_{i=1}^{N} x_{ij} \cdot d_i^2)}, \; j = 1, \cdots, M \\ \text{subject to} \quad & \sum_{j=1}^{M} x_{ij} = 1, \qquad i = 1, \cdots, N \\ & \sum_{i=1}^{N} x_{ij} \cdot d_i \leq L, \qquad j = 1, \cdots, M \\ & x_{ij} \in \{0, 1\} \end{aligned}$$

Attention Cost

Each Document is present in only one batch

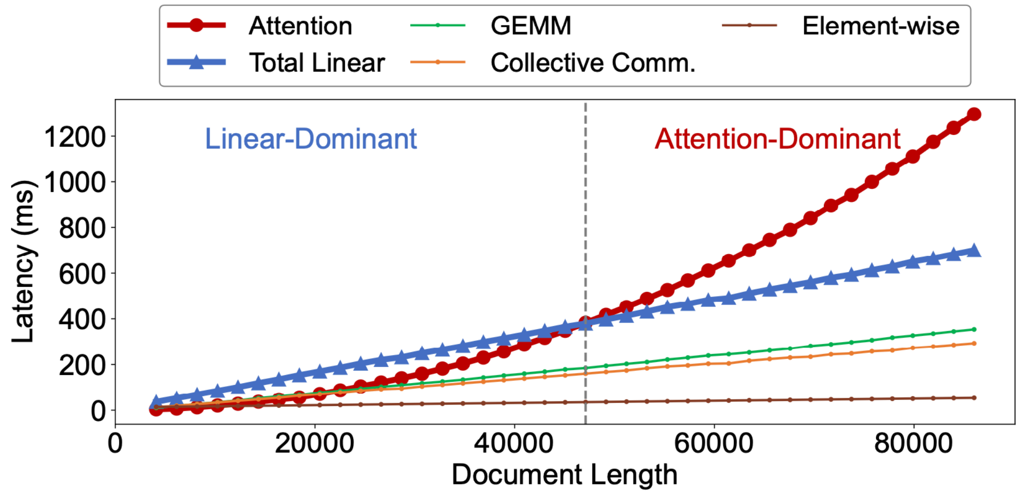
L = Context Size

Variable-Length Packing

Idea: Allow $len(\mu B) > \texttt{CONTEXT\_SIZE}$ for weaker μB

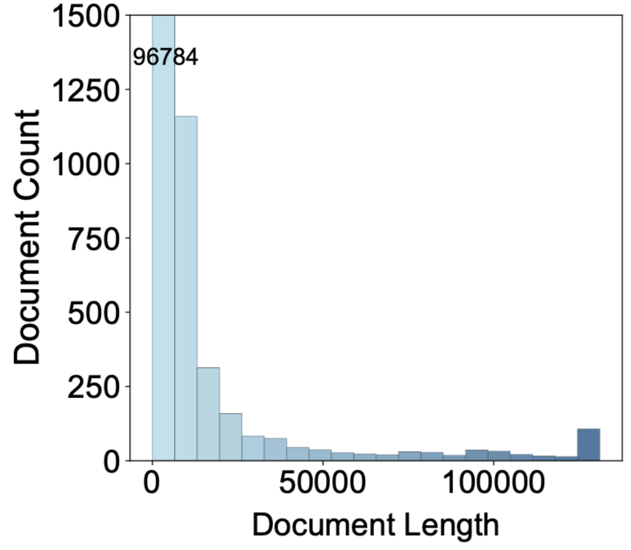
- Attention is Quadratic, but other operations are linear (feed-forward, comms etc.)
- Balance the total workload, not just attention.
- Balance long documents against many shorter documents.

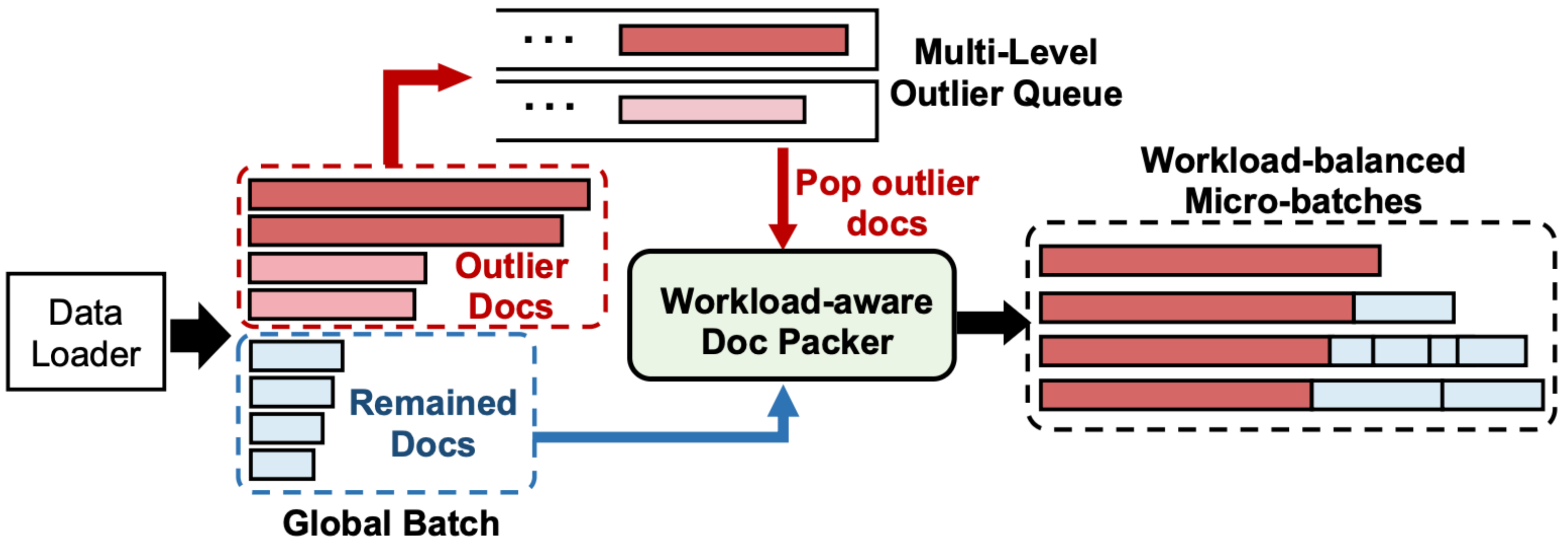
$$\min\left(\max\left(\sum_{i=1}^{N}\left(W_a(x_{ij}\cdot d_i)+W_l(x_{ij}\cdot d_i)\right)\right)\right)$$



Outlier document detection

- Still, you might not have sufficient smaller documents to balance the load of a long document.
- Observe: there aren't that many ultra-long documents.
- Instead of balancing across multiple batches, delay the few long documents.
- Model convergence should not hurt significantly.

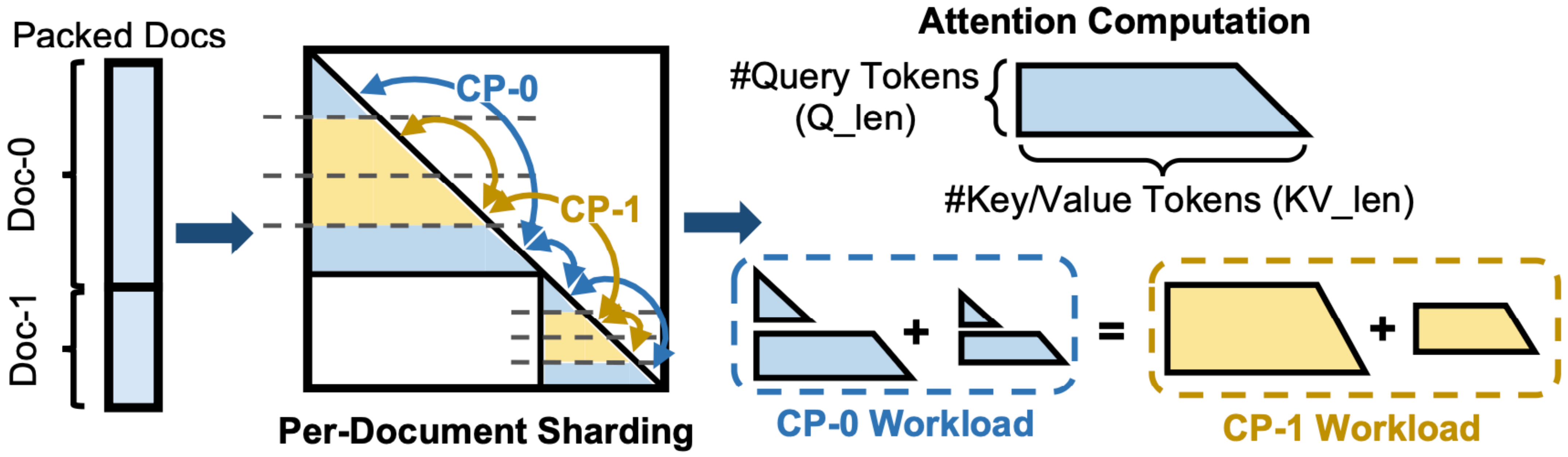



Multi-Level Outlier Queue
Pop outlier docs
Workload-balanced Micro-batches
Outlier Docs
Data Loader
Workload-aware Doc Packer
Remained Docs
Global Batch

Improved CP sharding

Idea: Apply CP indexing logic to each individual document.

- This should yield a more balanced workload across multiple CP workers.
- They also implement an optimization to avoid padding tokens.

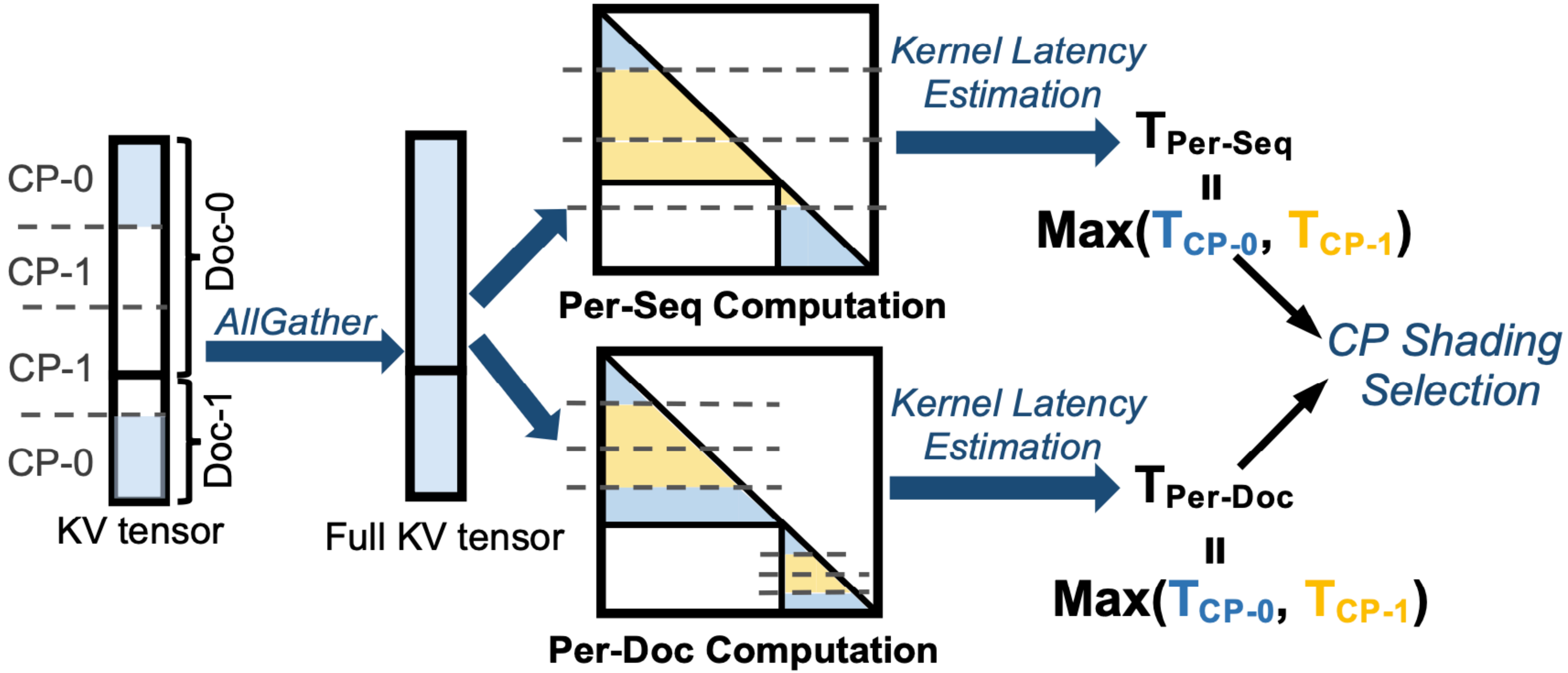


Kernel inefficiencies

- Per-Document sharding achieves better balance, but it does not always guarantee better performance.
- Smaller per-rank attention problems reduce kernel efficiency:
    - Poor tile utilization → padding overhead for short sequences (<128 tokens).
    - Lower effective FLOPs utilization → higher time per token.
    - Reduced KV tile reuse → weaker Hopper TMA multicast benefits

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Kernel Inefficiencies



Experimental Setup

- **Cluster**: 32 nodes, each with 8x NVIDIA H100 SXM 80GB GPUs.
- **Interconnect**: NVLink intra-node, RoCE inter-node.
- **Models**: LLaMA-like 550M, 7B, 30B, 70B; each tested at 64K and 128K context.
- **Training config**: 4D parallelism, global batch size = `PP_size x DP_size`, `bfloat16` precision.
- **Baselines**:
  - `Plain-4D`: default 4D training with per-sequence CP sharding.
  - `Fixed-4D`: fixed-length packing + fixed CP sharding (per-sequence or per-document).

Speedup Breakdown

Which optimization helps us the most?

- `PP-Var-Len` alone $\rightarrow$ 1.28x
- Orthogonal optimizations that combine well.
- Every second counts!

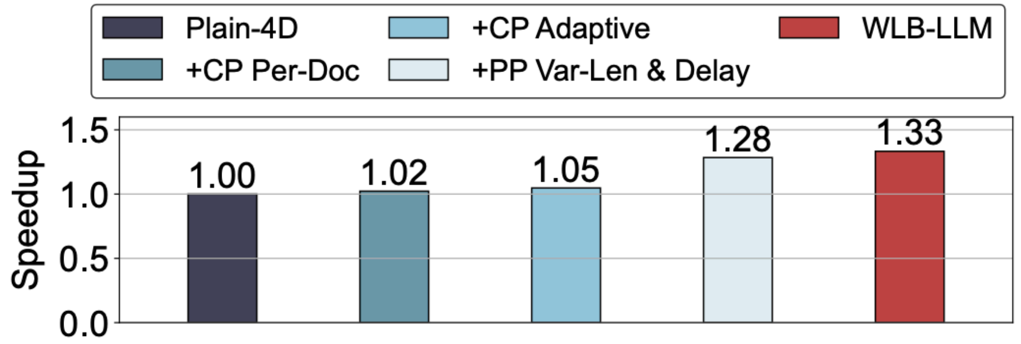


Figure 13: Performance breakdown of *WLB-LLM* on the 7B model with a 128K context window.

Speedup across Model + Context

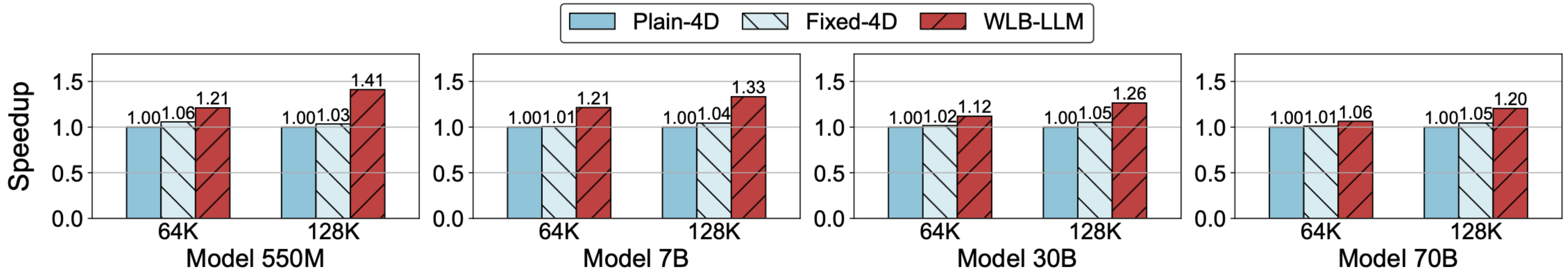


Figure 12: Training performance speedups of *WLB-LLM* and *Fixed-4D* over *Plain-4D* across various configurations.

- WLB-LLM consistently outperforms baseline for all tested configurations.
- Naive attention balancing is insufficient.
- Relative speedup decreases with increased model size.

Other Experiments (Summary)

- **Context sensitivity (Fig. 14)**: Speedup increases with context length (about `1.07x @64K` to `1.40x @160K` on 7B), consistent with worse imbalance at longer contexts.
- **Packing overhead vs balance (Table 2)**: WLB-LLM reaches near-optimal imbalance with low runtime overhead (tens of ms), while solver-based packing can be prohibitively slow.
- **CP sharding ablation (Fig. 15)**: Adaptive sharding consistently outperforms always-per-sequence or always-per-document sharding.
- **Convergence / quality**: Their training-loss curves indicate no clear quality regression from the system optimizations.

Discussion & Critique

Strengths

- Identifies and fixes a bottleneck for training long-context Llama models with 4D parallelism.
- Joint PP+CP optimization gives meaningful real-system gains, especially as context windows grow.
- Engineering is practical: low overhead and no obvious convergence regression in their reported runs.

Weaknesses

- Workload dependence and limited generalization evidence outside their evaluated distribution.
- Strong dependence on a small number of extreme outliers; unclear benefit when length distributions are flatter.
- Heavy use of heuristics (packing + sharding selection) without strong guarantees in worst-case settings.

Related Work

(1) Efficient Long-context Language Model Training by Core Attention Disaggregation (DistCA)

- Split out “core attention” ($\mathrm{softmax}(QK^\top)V$) as a weightless compute service, separate from the rest of the transformer.
- Better than WLB-style baselines at scale: reports ~1.15–1.35× throughput gains over their WLB “ideal” baseline in 4D (with PP), depending on workload.

(2) ByteScale Efficient Scaling of LLM Training with a 2048K Context Length on More Than 12,000 GPUs

- Hybrid Data Parallelism (HDP): unify DP + CP into one dynamic device mesh.
- Length-aware sharding: use the minimum number of devices per sequence.
- Short sequences stay local (skip CP comm), long sequences shard across more GPUs.

(3) Ordering efficiency

- Reduce pipeline bubbles by optimizing scheduling.
- PipeDream, 1F1B, Seq1F1B.

What did you think?

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Packing Method		Imbalance Degree	Packing Overhead (ms)
Method	Config		
Original Packing	/	1.44	0
Fixed-Len Greedy	#global batch=1	1.41	4
	#global batch=2	1.22	5
	#global batch=4	1.11	5
	#global batch=8	1.08	5
Fixed-Len Solver	#global batch=1	1.40	467
	#global batch=2	1.18	1488
	#global batch=4	1.09	25313
WLB-LLM	#queue=1	1.24	8
	#queue=2	1.05	20
	#queue=3	1.05	23

Table 2: Packing imbalance degree and overhead analysis.