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

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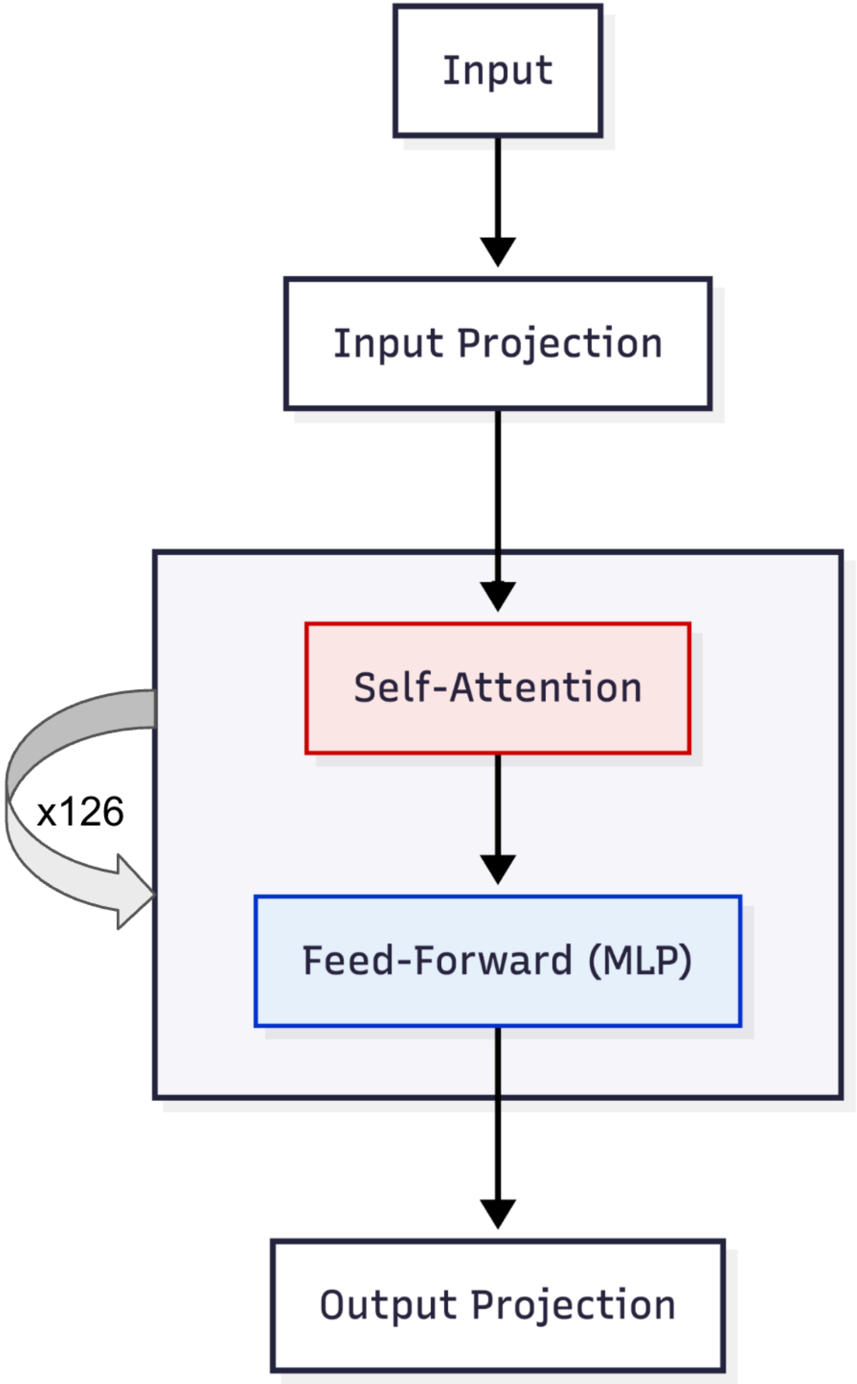
Introduction

- 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.
- WLLM is a work from Meta and UCSD, released ~6 months after their training Llama 3 that achieves this.

Background - Model Architecture

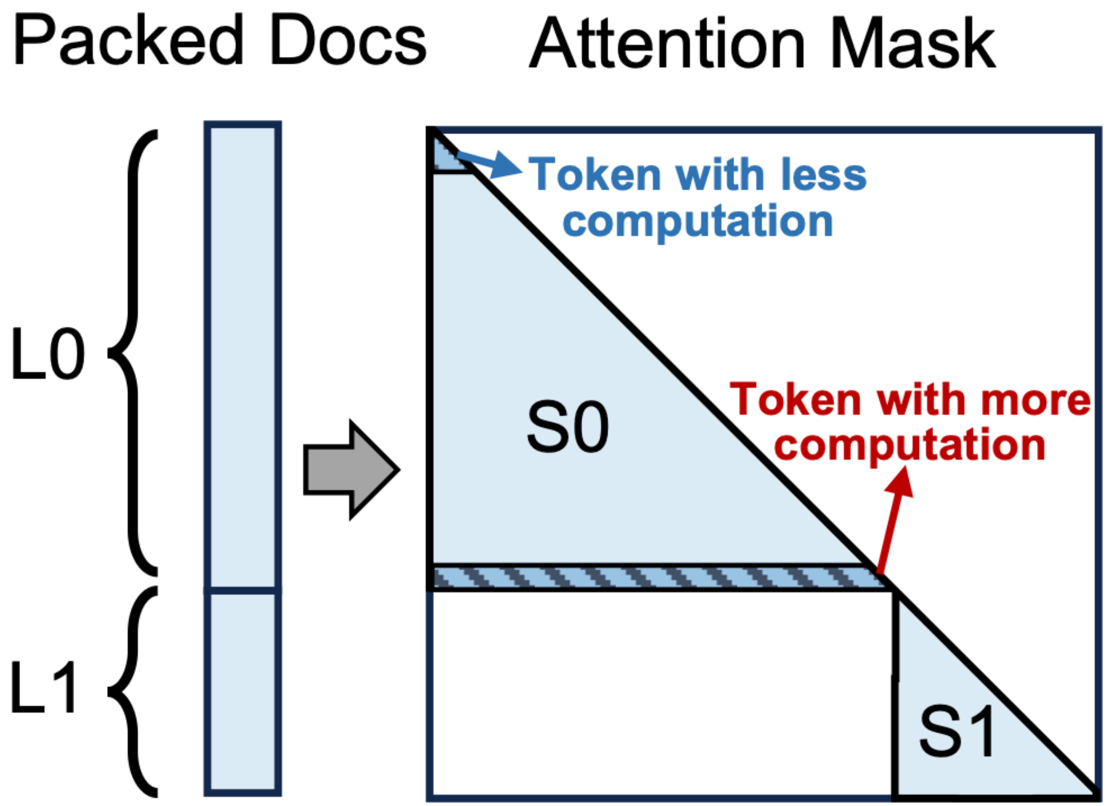
Things to keep in mind:

- Really big models, 405B = 910GB with 126 transformer blocks.
- Self-Attention, a layer that enriches tokens in a sequence with other token information.
- Feed-Forward, a linear matrix multiplication layer.



Self Attention

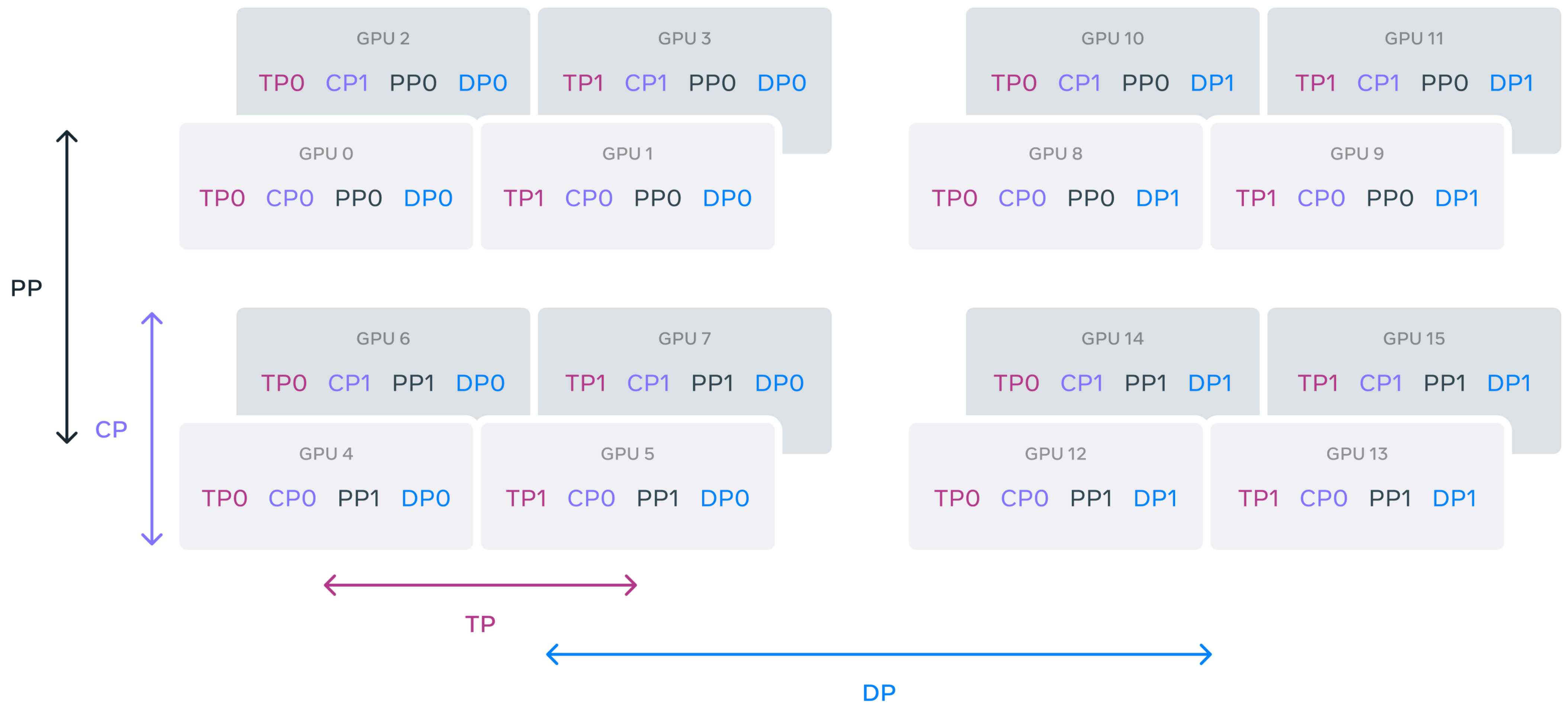
- Attention scales quadratically with the number of past tokens $O(T^2)$
- Not all tokens are equal: Processing later tokens in a document require more computation than earlier.
- When packing multiple documents for training, control attention span using masks.



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.

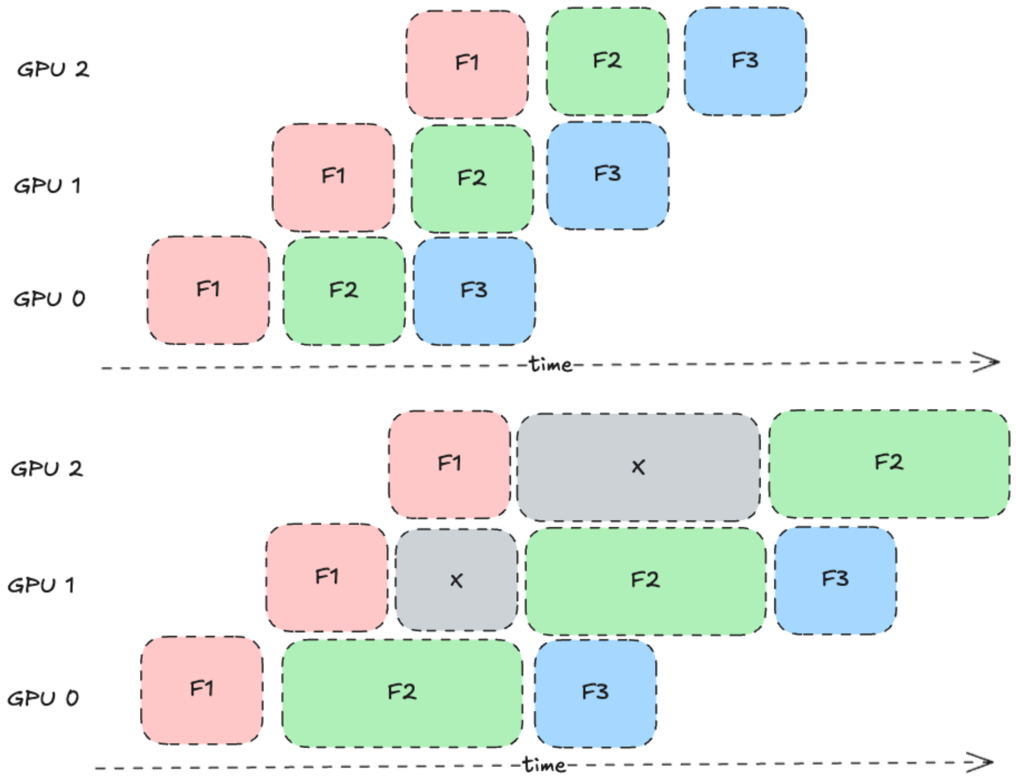
4D Parallelism



$$DP > PP > CP > TP$$

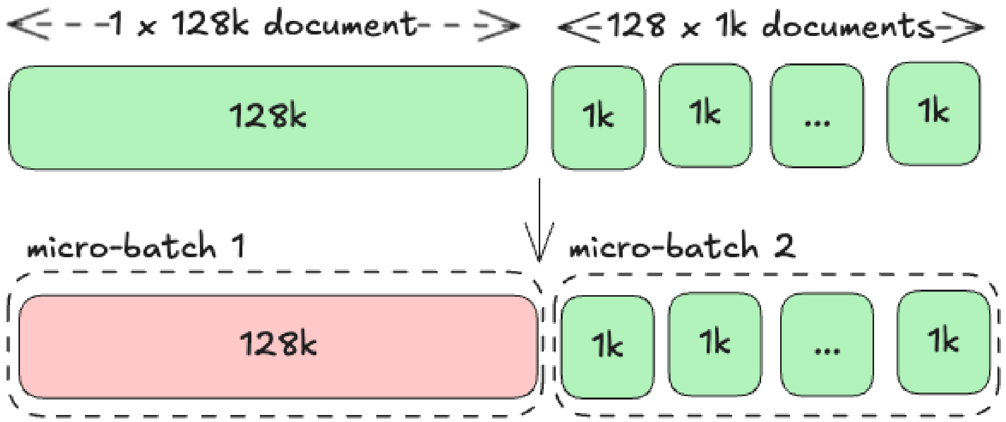
Motivation #1 - Pipeline Imbalance

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



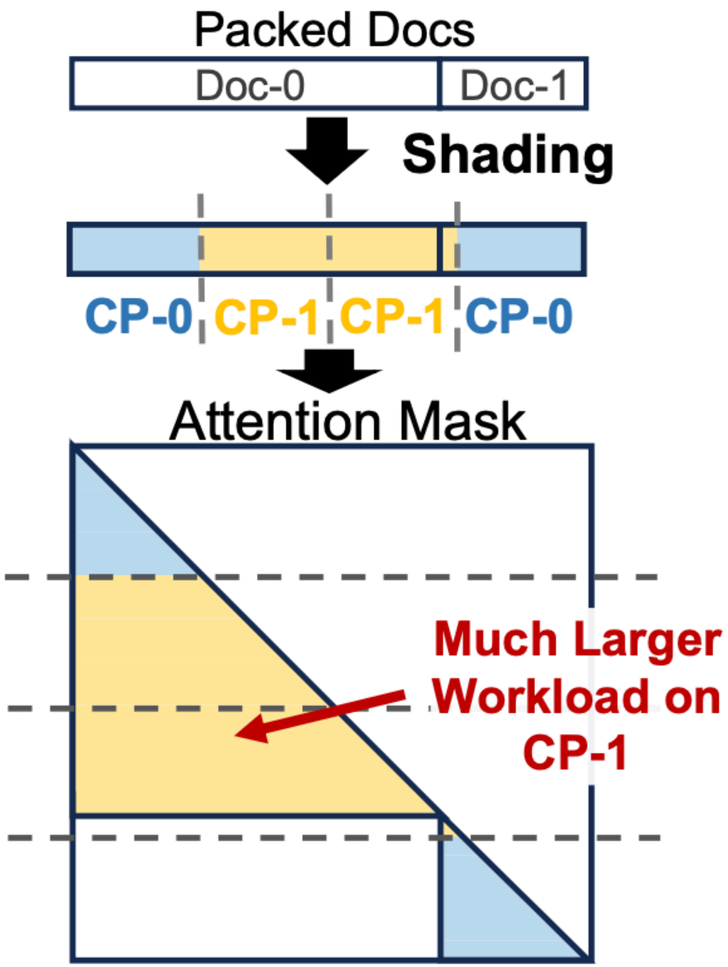
Motivation #1 - Pipeline Imbalance

- Naive approach $\rightarrow$ split by tokens.
- Each μB has uniform sequence length = `CONTEXT_WINDOW_SIZE`
- Does this lead to equal attention?
- $k.128^2 >> k.128 * 1^2$



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.
- Not a huge problem, but every millisecond adds up!



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 improvemnts $\rightarrow$ 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.

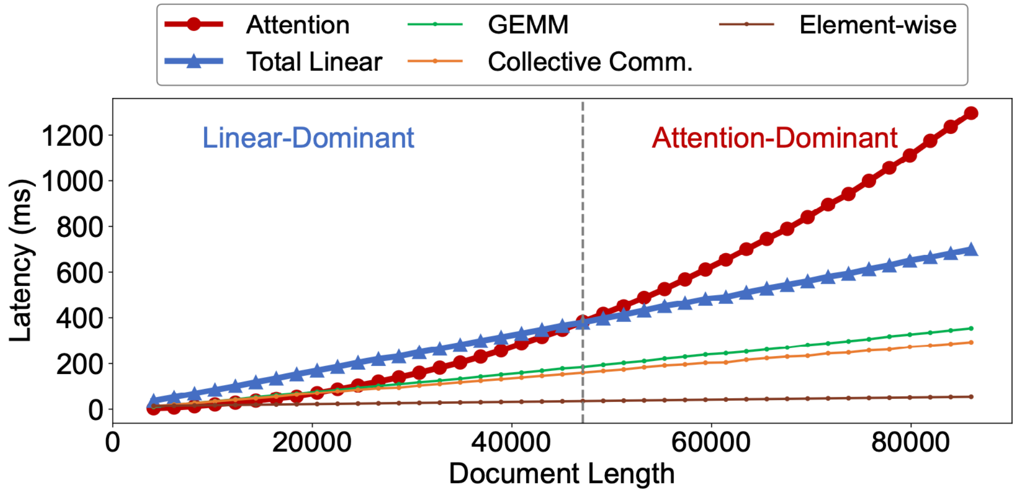
$$
\begin{aligned}
\text{minimize} \quad & \max\left(\sum_{i=1}^{N} x_{ij} \cdot d_i^2\right), \; j = 1, \cdots, M \\
\text{subject to} \quad & \sum_{j=1}^{M} x_{ij} = 1, \qquad\qquad i = 1, \cdots, N \\
& \sum_{i=1}^{N} x_{ij} \cdot d_i \leq L, \qquad j = 1, \cdots, M \\
& x_{ij} \in \{0, 1\}
\end{aligned}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

Variable-Length Packing

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

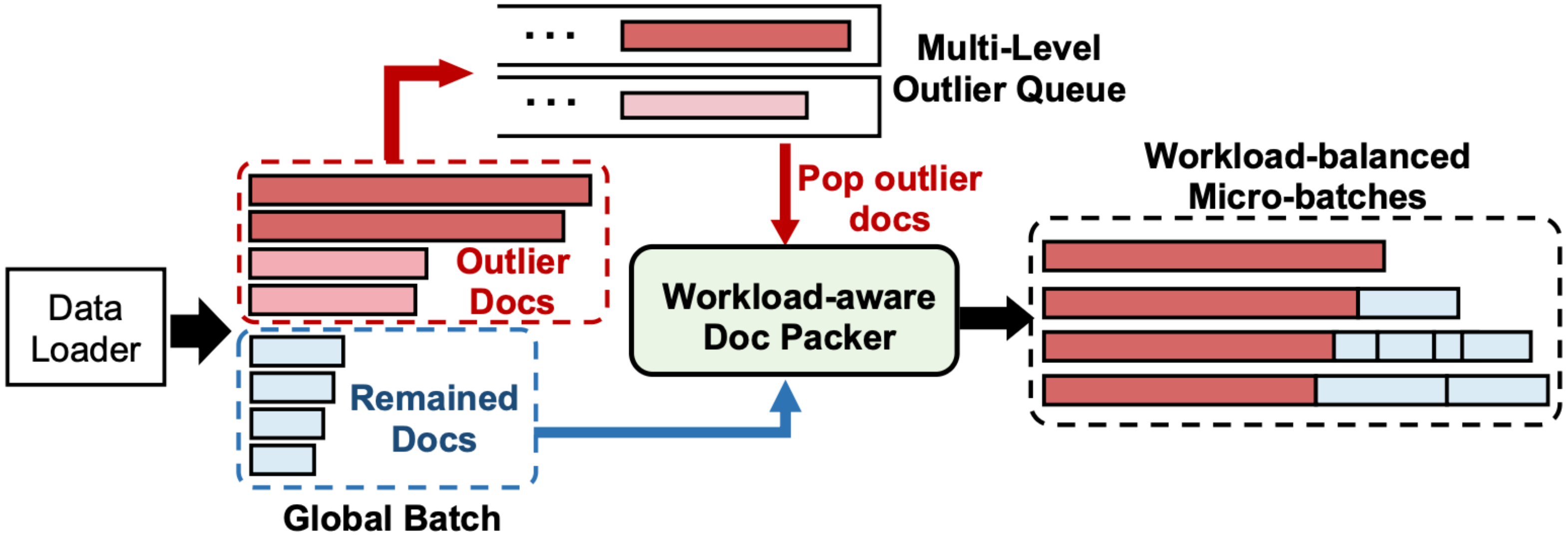
- Attention is Quadratic, but other operations are linear (feed-forward, comms etc.)
- Balance the total workload, not just attention.
- Balance long documents against many shorter documents.

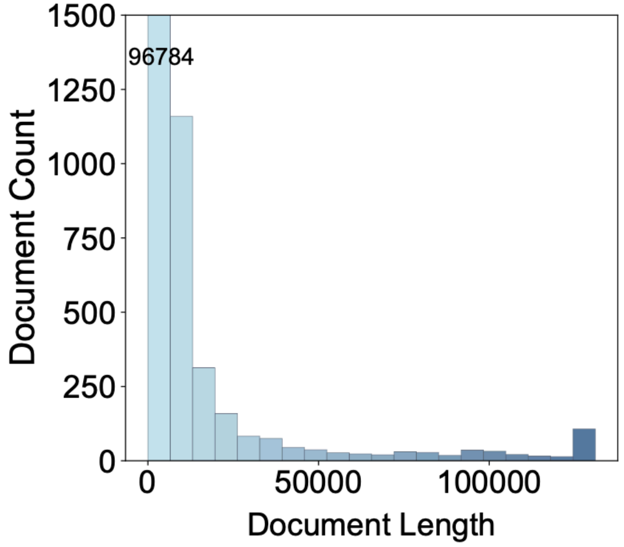
$$\min\left(\max\left(\textstyle\sum_{i=1}^{N}\left(W_a(x_{ij}\cdot d_i)+W_l(x_{ij}\cdot d_i)\right)\right)\right)$$



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.





Main Algorithm

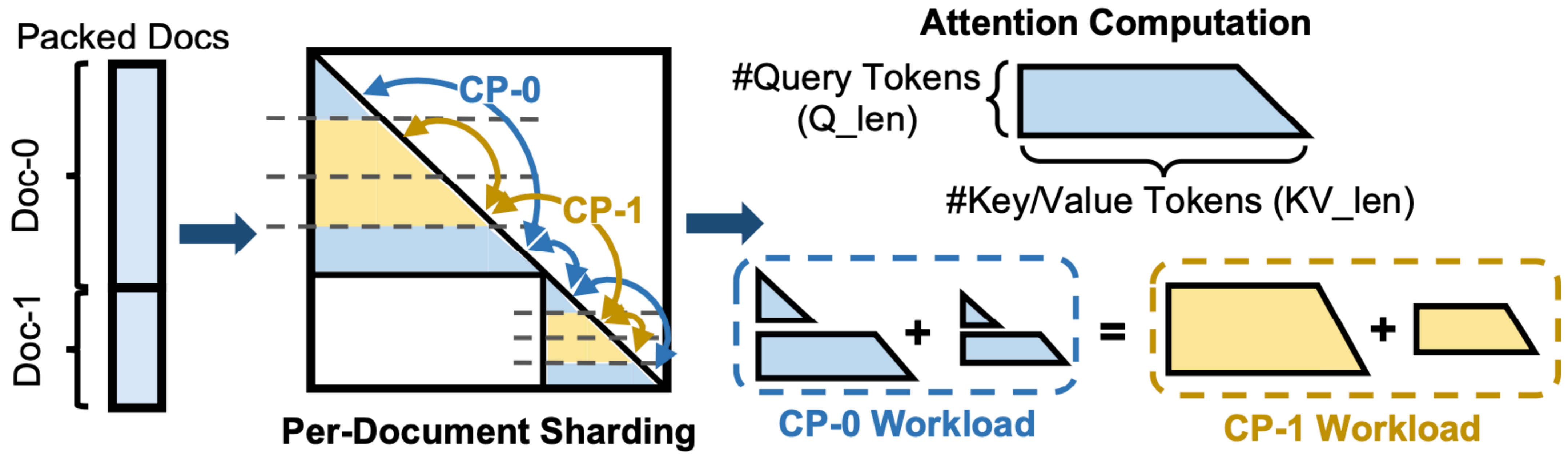
Given a DP bach

- construct a document set by removing the outlier documents, filling from the queue, and rolling over any documents from the previous iteration.
- now you effectively have a set of documents that you solved for using an ILP in S3.3, however they claim that it would take too long.
- so they instead pack greedily into an array of N micro-batches. sort the documents in reverse by length, and for each document:
    - find the least loaded microbatch (first by load, next by length)
    - if it can fit this current document, great.
    - else reserve this document for a later stage.

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.

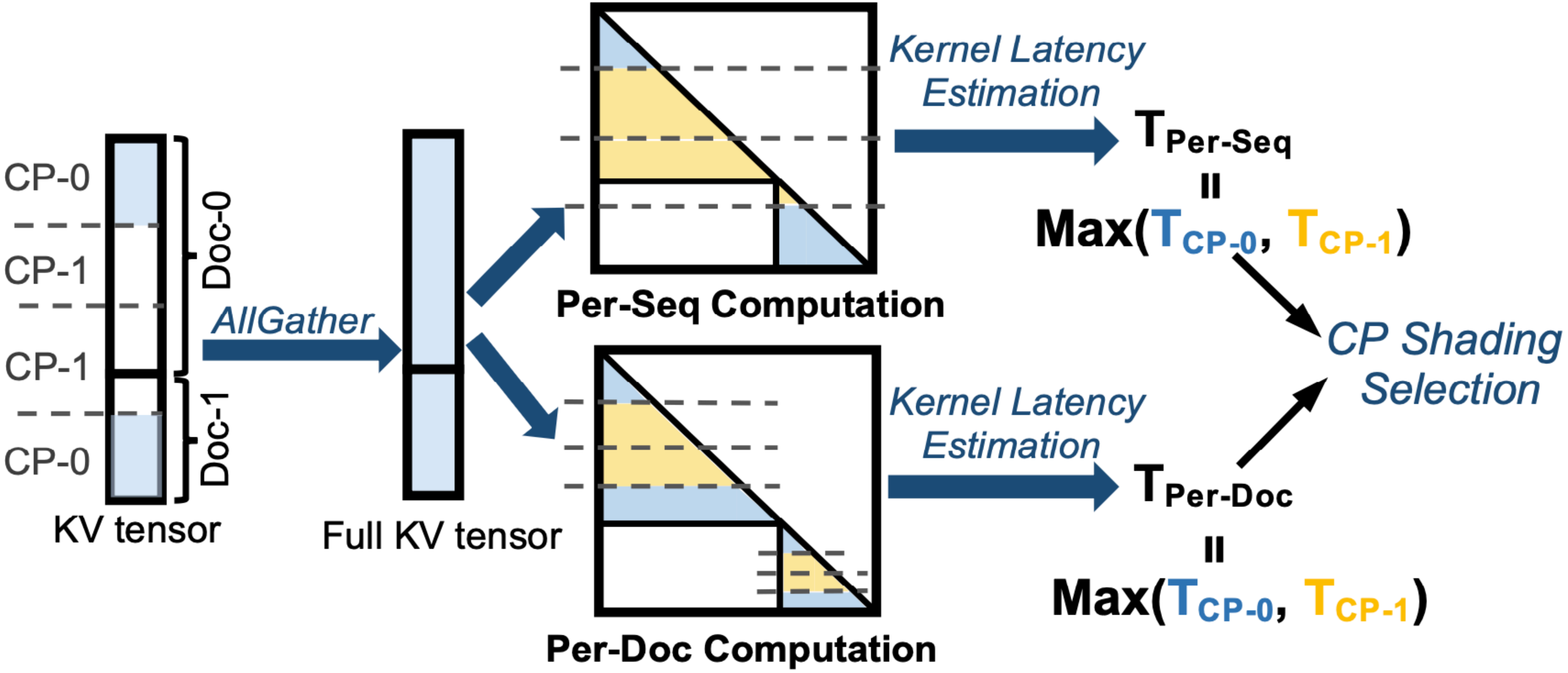


Kernel inefficiencies

- Per-Document sharding achieves better balance, but it does not guarantee better performance.
- The attention kernel might become less efficient for smaller documents.
- Sharding lowers the Q dimension, which might cause:
  - Longer kernel time due to redundant computations (padding < 128 tokens)
  - Decreased throughput (unable to leverage TMA)

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

Kernel Inefficiences



Evaluation

- their contributions are in PP and CP balancing. Let's think, when would PP and CP imbalance hurt most?
  - CP: longer context, more chance of long document being assigned to imbalanced worker.
  - PP: larger model, micro-batch imbalance adds more to the latency.

Speedup Breakdown

Which optimization helps us the most?

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

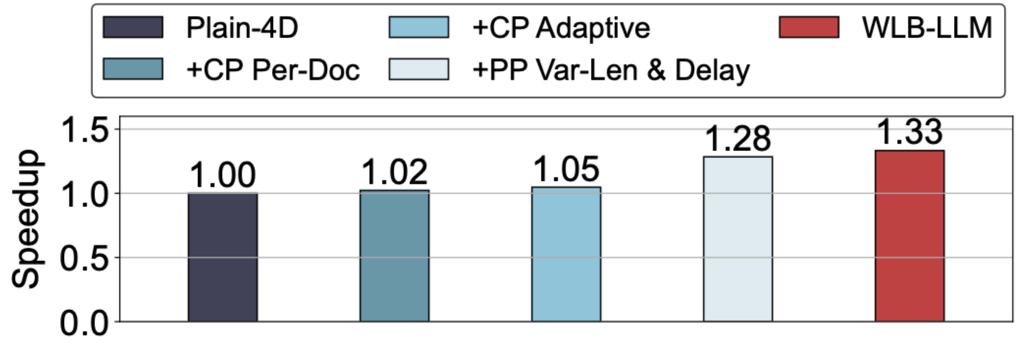


Figure 13: Performance breakdown of *WLB-LLM* on the 7B model with a 128K context window.

Speedup across Model + Context

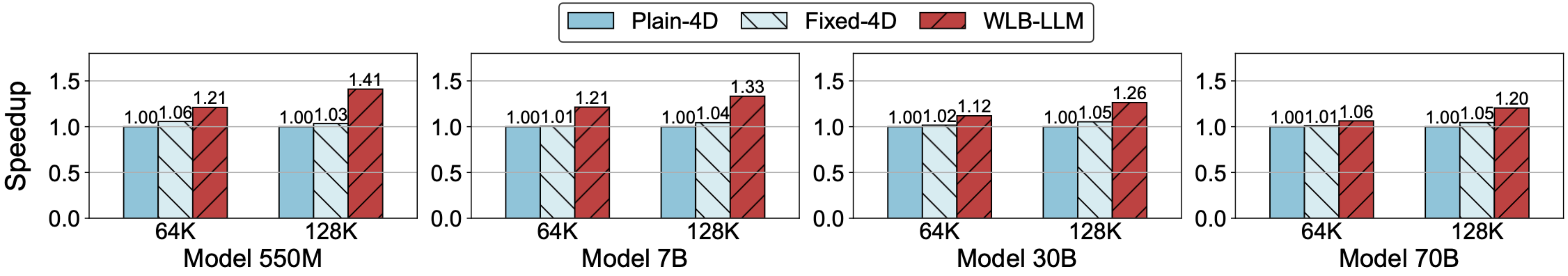


Figure 12: Training performance speedups of *WLB-LLM* and *Fixed-4D* over *Plain-4D* across various configurations.

Speedup vs Context Window

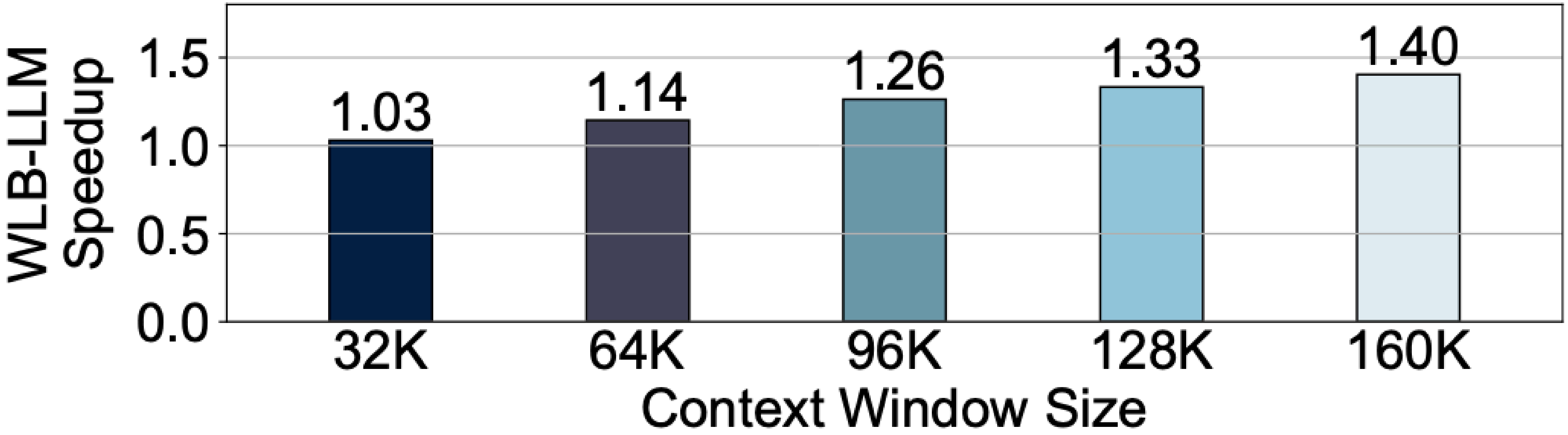


Figure 14: Speedups of *WLB-LLM* on the 7B model across context window sizes.

Ablation - Packing Overhead

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.

Ablation - CP Sharding

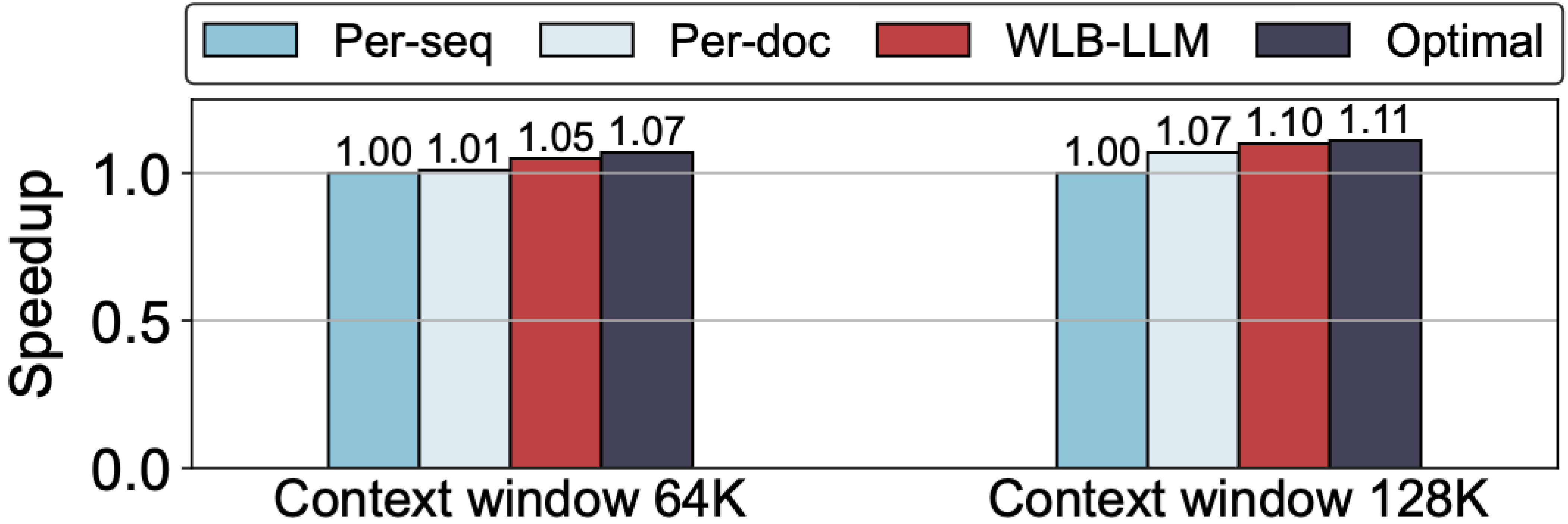


Figure 15: CP sharding performance comparison.

Discussion & Critique

Strengths:

- Clear bottleneck identification with evidence and analysis.
- Practical, deployable solution that demonstrates measurable gains.
- Careful consideration of overheads and convergence.

Questions:

- Larger models show smaller relative gains due to communication overhead, do gains vanish at extreme scale?
- How does this approach scale to MoE models?

Key Takeaway

Batch compute, not tokens.