TrainVerify: Equivalence-Based Verification for Distributed LLM Training

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Enabling large models through scaling that are prone to silent errors

Llama 3.1
405 B

deepseek
671 B

Don't fit on one GPU

Model

Data

GPU 0

Single device

GPU 0 GPU 1 GPU 2 GPU 3

Tensor Parallelism (TP)

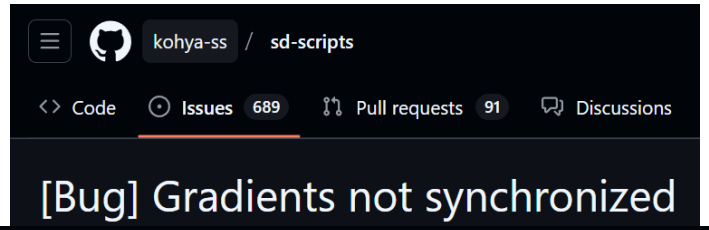
Scaling techniques are complex

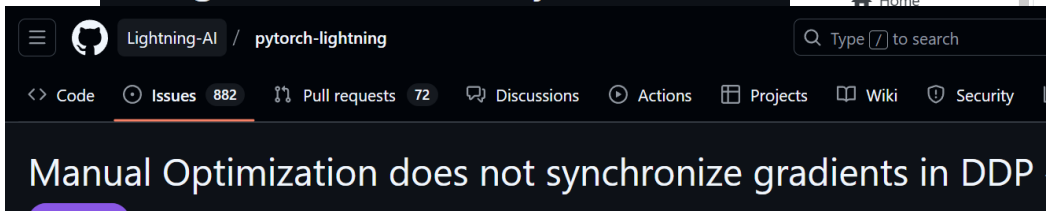
Sharding Communication

Optimizer Schedule

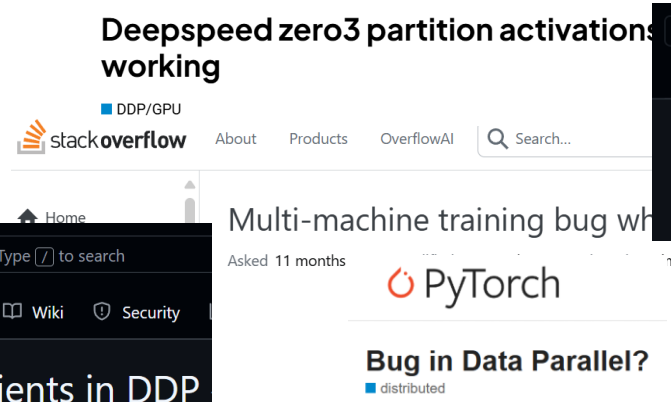
Prone to silent errors

Wrong communication operations

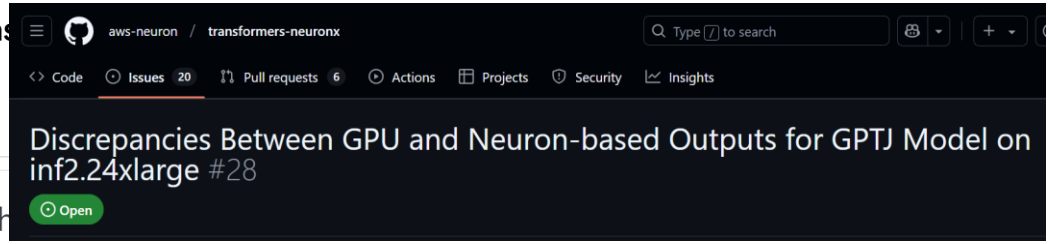




Wrong sharding



Wrong calculation



Behavior not like single-device pipeline, loss value not decreasing or garbage outputs

Model quality to drop

Example: Missing all-reduce (Megatron-LM)

LinearWithFrozenWeight backward fix when TP > 1, bug leads to non-decreasing loss

```
271  272          def backward(ctx, grad_output):
272  273              (weight,) = ctx.saved_tensors
273  274              grad_input = grad_output.matmul(weight)
274       -          return grad_input, None, None
     275  +
     276  +          if ctx.allreduce_dgrad:
     277  +              # All-reduce. Note: here async and sync are effectively the same.
     278  +              torch.distributed.all_reduce(grad_input, group=get_tensor_model_parallel_group())
     279  +
     280  +          return grad_input, None, None, None
```

Detecting when to do the all-reduce is difficult when manually looking through large ml-systems codebase

Silent bugs are tricky since they are subtle

Runtime recovery

CheckFreq [FAST ‘21], Varuna [EuroSys ‘22], GEMINI [SOSP ‘23], Oobleck [SOSP ‘23], Bamboo [NSDI ‘23], ReCycle [SOSP ‘24]

- ⊕ Fault-tolerant to failures
- ⊖ Relies on explicit error signals

Position: Expose silent errors before deployment

Testing frameworks

DeepXplore [SOSP ‘17], DeepTest [ICSE ‘18], Eagle [ICSE ‘22], NNSmith [ASPLOS ‘23], MLIRSmith [ASE ‘23], PolyJuice [OOPSLA ‘24]

- ⊕ Detects many bugs
- ⊖ No guarantee of absence of bugs

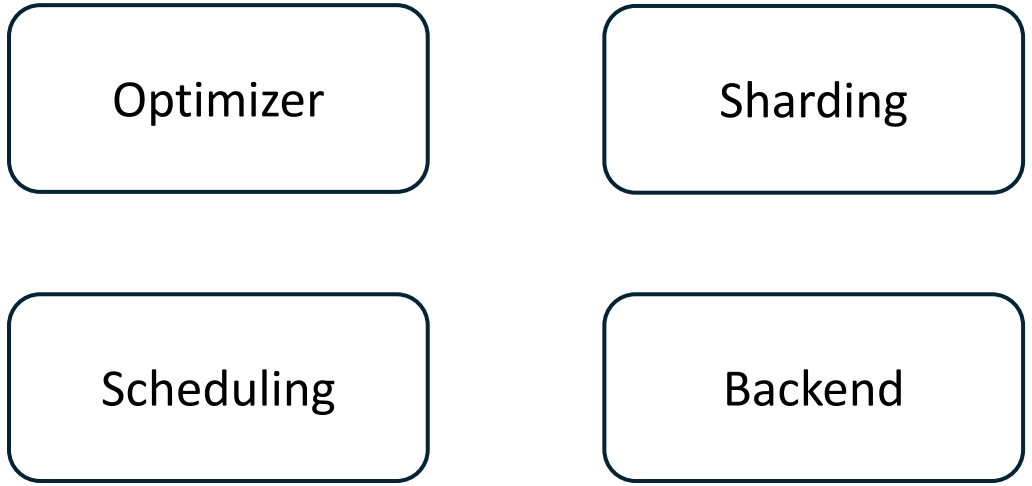
Position: Guarantee absence of errors in pipelines

Developers approach in debugging is ad-hoc

Examine intermediate tensor values in the entire huge code space manually

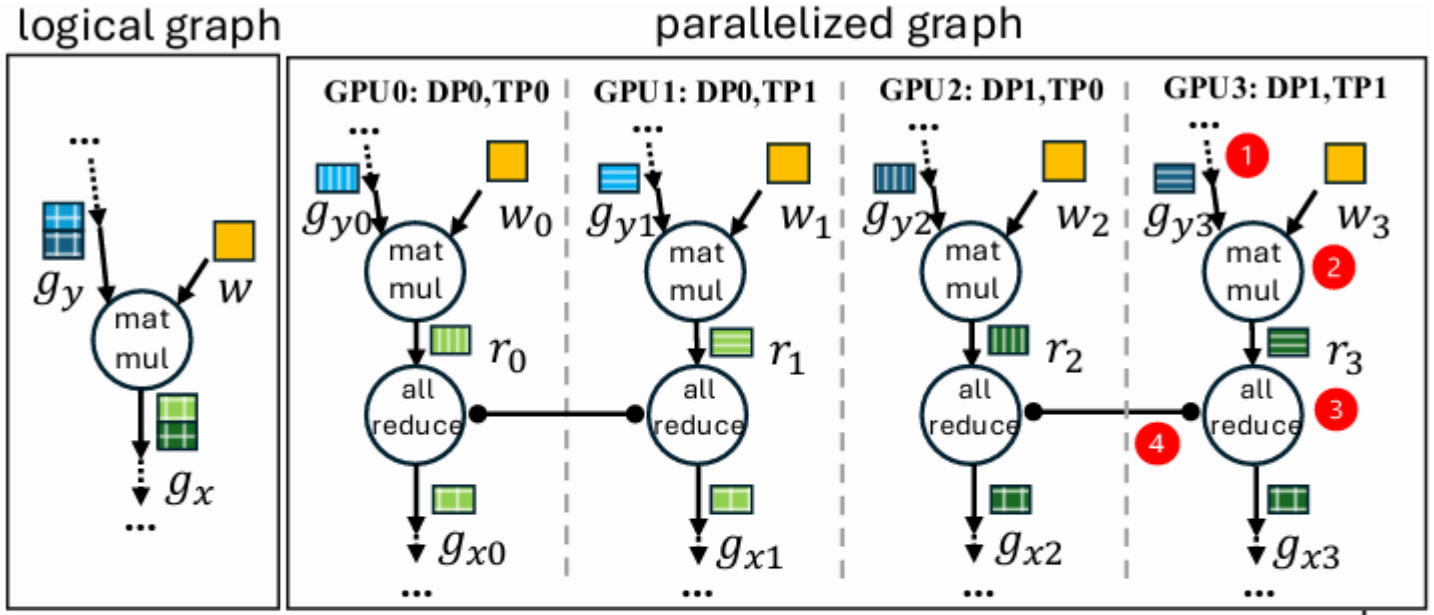
attention.py

```
print(...)
result = hlo.reshape(result, (n_seqs,
n_active_tokens, hidden_size))
print(...)
```



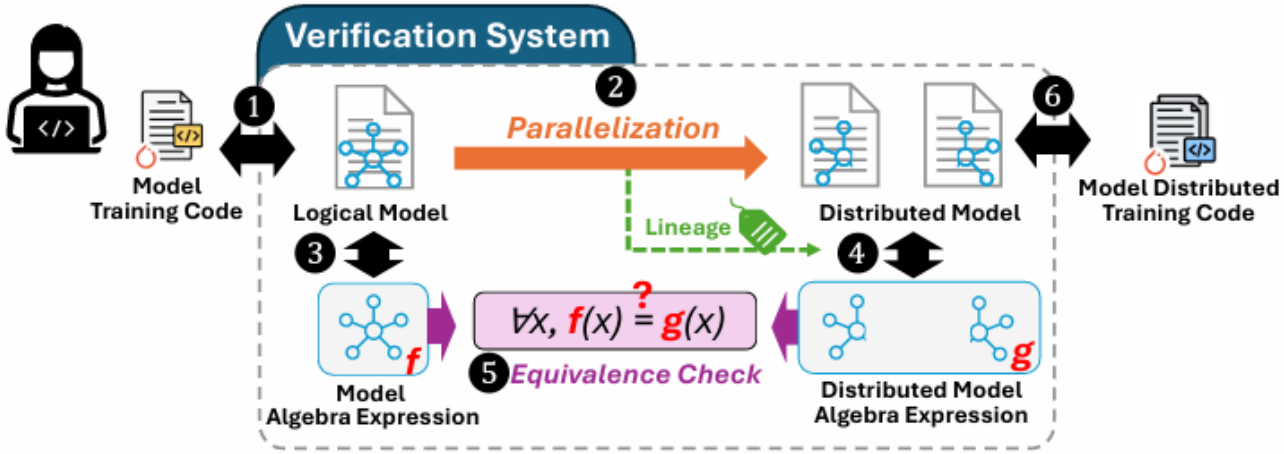
- Numerous amount of phases
- Hard to differentiate correct and wrong tensors due to floating-point round-off errors
- Tedious to manually piece tensors on multiple devices to match single on

Expose silent errors without explicit signals




```
def training_code_gpu3():
    model_tp_group = dist.new_group(ranks=[2,3])
 1  ... # upstream model code
    gy3 = ...
    w3  = ...
    gx3 = gy3.matmul(w3) 2
 3  dist.all_reduce(gx3,group=model_tp_group) 4
    ... # downstream model code
```

TrainVerify Workflow

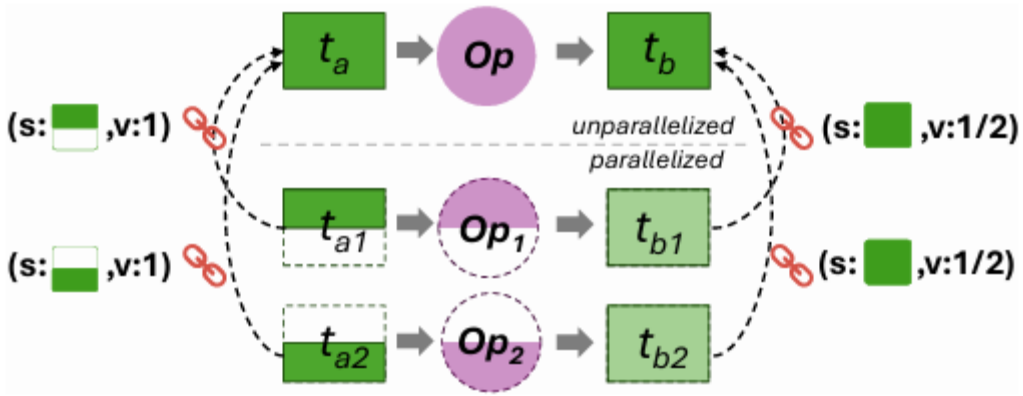


- Extract DFGs from logical and distributed (1) and (6)
- Symbolize DFGs from concrete tensors (3) (4) using lineage metadata (2) to track dependencies between logical and distributed
- Check equivalence using SMT solver (5)

Symbolic DFGs

- Construct manually DFG that represents the logical and distributed model which represent the forward and backward pass
- Define manually formal definition of operators in DNN frameworks
- Lineage: Tracks how tensors are related between single-device and distributed tensors

Lineage


t_a
Op
t_b
(s: ,v:1)
unparallelized
parallelized
(s: ,v:1/2)
t_{a1}
Op_1
t_{b1}
(s: ,v:1)
(s: ,v:1/2)
t_{a2}
Op_2
t_{b2}

Shape reduction

$$c_{1,1} = a_{1,1} \cdot b_{1,1} + a_{1,2} \cdot b_{2,1} + a_{1,3} \cdot b_{3,1}$$
$$c_{2,2} = a_{2,1} \cdot b_{1,2} + a_{2,2} \cdot b_{2,2} + a_{2,3} \cdot b_{3,2}$$

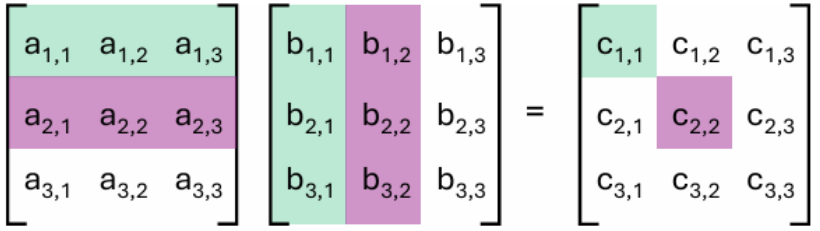


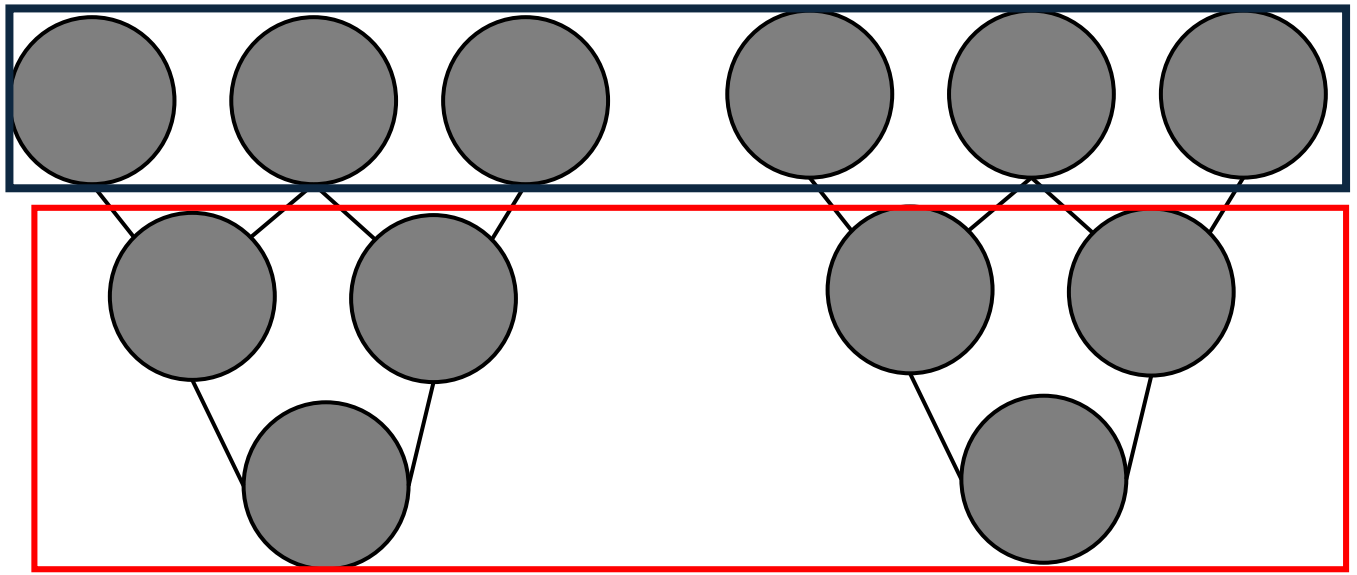
Figure 5. DNN operator `MatMul`: different output elements $c_{1,1}$ and $c_{2,2}$ are calculated using the same function but on different inputs.

- Operating on per-element values in tensor is expensive
- DNN operators have the SIMD (Single Instruction, Multiple Data) property, apply same computation across different data elements

Minimum shapes

- Shape alignment: reshape (M,N) to (M,P,Q) where N = PxQ
- Semantic intact: avoid reducing shape to 1 to avoid incorrectness in matmul

Stage-Parallel Verification



- Divide model into multiple stages and verify them in parallel
- Each stage consists of aligned subgraphs from single-device and distributed graphs, where each stage’s boundary is defined as tensors with lineage information

Implementation

- 6000 lines of code in Python
- Built on nnScaler, a distributed training framework from Microsoft
- Builds the single-device and distributed plans from generated IR graphs in nnScaler
- Tensor lineage is built using nnScaler’s indexing metadata and source code

Evaluation (Real-world models)

Exp. ID	Model	Layers	DP	TP	PP	NM
L1	Llama3-8B	32	512	1	1	1
L2	Llama3-70B	80	16	8	4	32
L3	Llama3-405B	126	64	8	16	16
D1	DS-V3-16B	27	16	4	2	16
D2	DS-V3-236B	60	16	8	4	16
D3	DS-V3-671B	61	32	8	8	16

Table 2. Evaluated real-world large models.

	L1	L2	L3	D1	D2	D3
Solver Parallelism	30	30	4	30	16	8
End-to-end Time	0.5h	7.5h	47h	0.5h	3.5h	31h

Table 3. Verification time for the evaluated models.

Evaluation (Setup)

- Dataflow graphs generated from machines with 4 A6000 GPUs
- Execution plans scaling up to 8192 GPUs

Evaluation (Scalability)

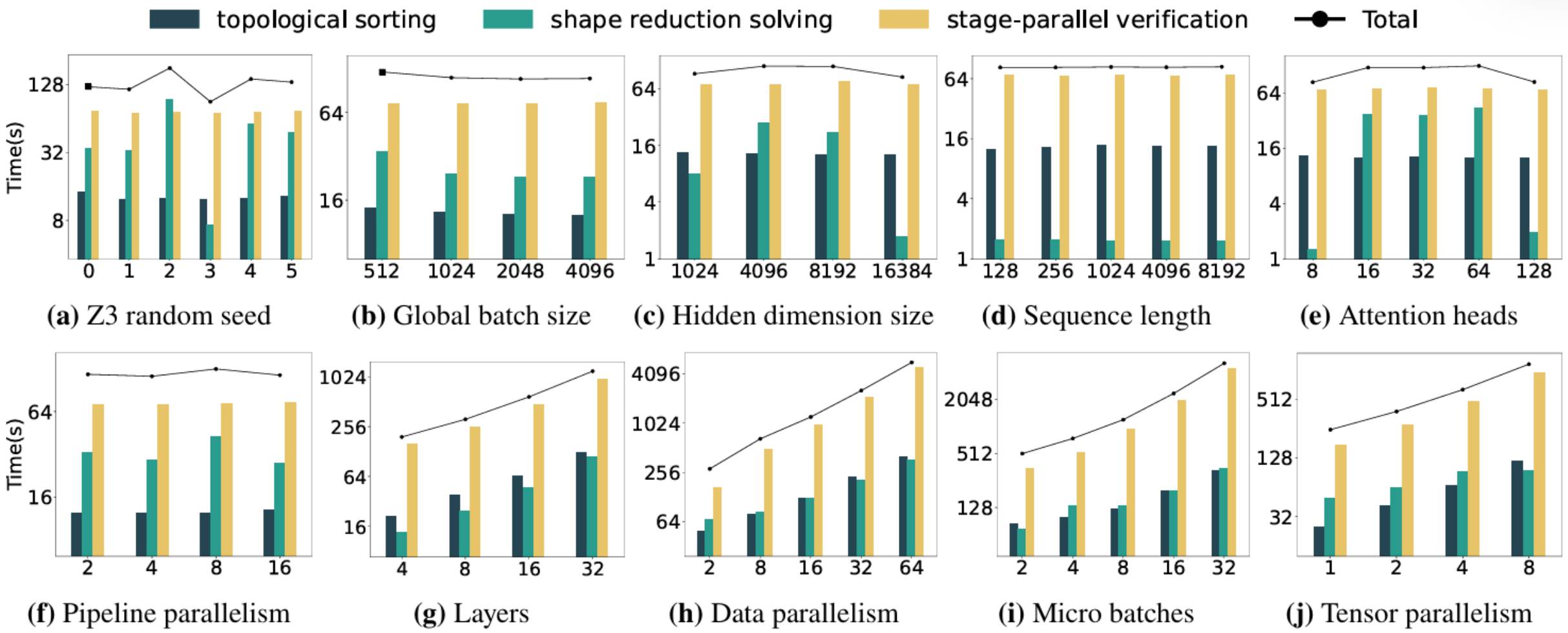


Figure 7. TrainVerify's performance trends regarding different training configurations. The y-axes use a $\log_2$ scale. Bars indicate the time breakdown by component, while lines represent the end-to-end verification time.

Evaluation (Scalability)

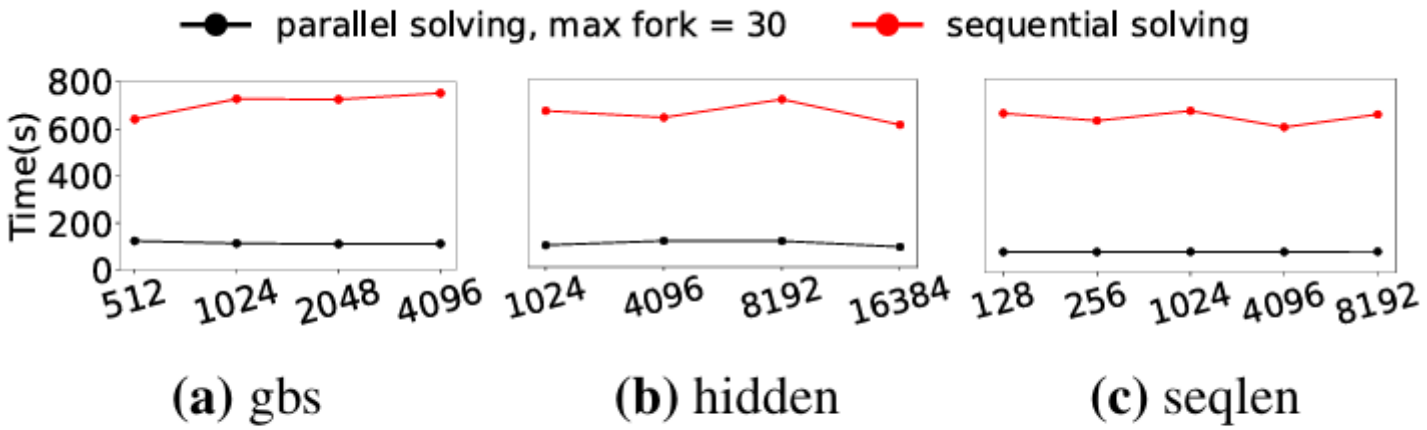


Figure 8. Verification time with vs. without stage parallelism.

Evaluation (Bugs eliminated)

- Incorrect communication operators
- Incorrect device assignment
- Incorrect partitioning
- Incorrect scaling
- Incorrect pipeline scheduling

- First four bugs are completely eliminated in TrainVerify, for the 5th bug, TrainVerify eliminates through early data dependency analysis

Evaluation (Bugs eliminated)

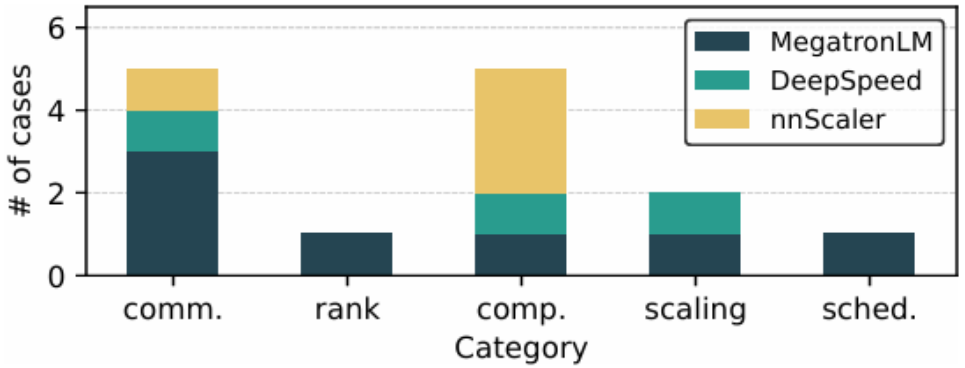


Figure 9. Reproduced incorrect parallelization cases.

- The bugs are reproduced in nnScaler, a machine learning training framework developed by Microsoft Research

Evaluation (New bugs)

- C1: Sharding a non-partitionable dimension
- C2: Dangling tensors in backward pass

Limitations

- Heavy reliance on graph-based execution plans
- Shape reduction assumes linearity on DNN operators
- Lineage information might be needed to be added manually

Conclusion

- Silent errors exist in many distributed training frameworks which are difficult to detect using existing work
- TrainVerify argues using the generated graphs, these errors can be exposed by verifying their equivalence
- TrainVerify scales to large models and exposes 14 old bugs and 2 new categories of bugs in machine learning training frameworks