## Memory-Efficient Pipeline-Parallel DNN Training

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### State-of-the-art models are becoming larger!



## Model parallelism can alleviate memory pressure



Time —

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## This work: memory-efficient pipeline parallelism

- High throughput
- Low memory footprint
- Strong weight update semantics (same weight version used in both the forward and backward pass for a given batch)

## **Double-buffered weight updates**

#### Stashed state



 $W_i^{(j)} \longrightarrow$  Version number (incorporates gradients from inputs  $\leq j$ )  $W_i^{(j)} \longrightarrow$  Stage or worker ID

#### Generate a new weight version every 4 inputs $(1 \rightarrow 4, 5 \rightarrow 8, etc.)$

## Semantics of double-buffered weight updates

• Vanilla weight update semantics:  $W^{(t+1)} = W^{(t)} - \nu \cdot \nabla f(W^{(t)})$ 

• Weight update semantics with 2BW almost **unchanged** (note additional delay term of 1 in gradient computation):  $W^{(t+1)} = W^{(t)} - v \cdot \nabla f(W^{(t-1)})$ 

## **Evaluation**

### 2BW has weight update semantics similar to vanilla



BERT model with 355 million parameters

Accuracy on downstream MNLI and RACE tasks unchanged

## **PipeDream-2BW** is faster than baselines



8 p3.16xlarge instances (64 GPUs) on AWS 3.8-billion parameter GPT model

## Conclusion

- Pipeline parallelism can be used to train large models, but can suffer from low resource utilization or high memory footprint
- PipeDream-2BW accelerates training by up to 3.2x compared to baselines that use pipelining, and 20x compared to other baselines

# Code open sourced at <u>https://github.com/msr-fiddle/pipedream/tree/pipedream\_2bw</u>



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