

Check-N-Run: a Checkpointing System for Training Deep Learning Recommendation Models

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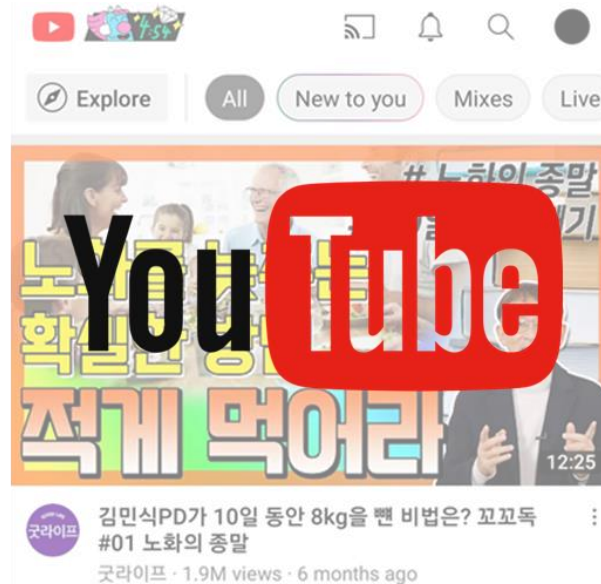
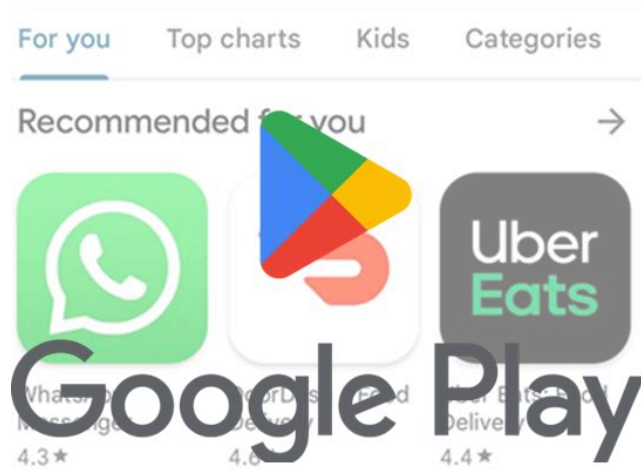
Introduction

- Personalized recommendation is everywhere



Introduction

- Recommendation models are important
 - 40% of apps installs on Google Play
 - 60% of watch time on YouTube
 - 35% of purchase on Amazon
 - 75% of movie watches on Netflix



What is Recommendation Model?

- Recommendation model
 - Updates only a small fraction of the model during each iteration
 - Exceed Terabytes, which stress planetary scale storage system

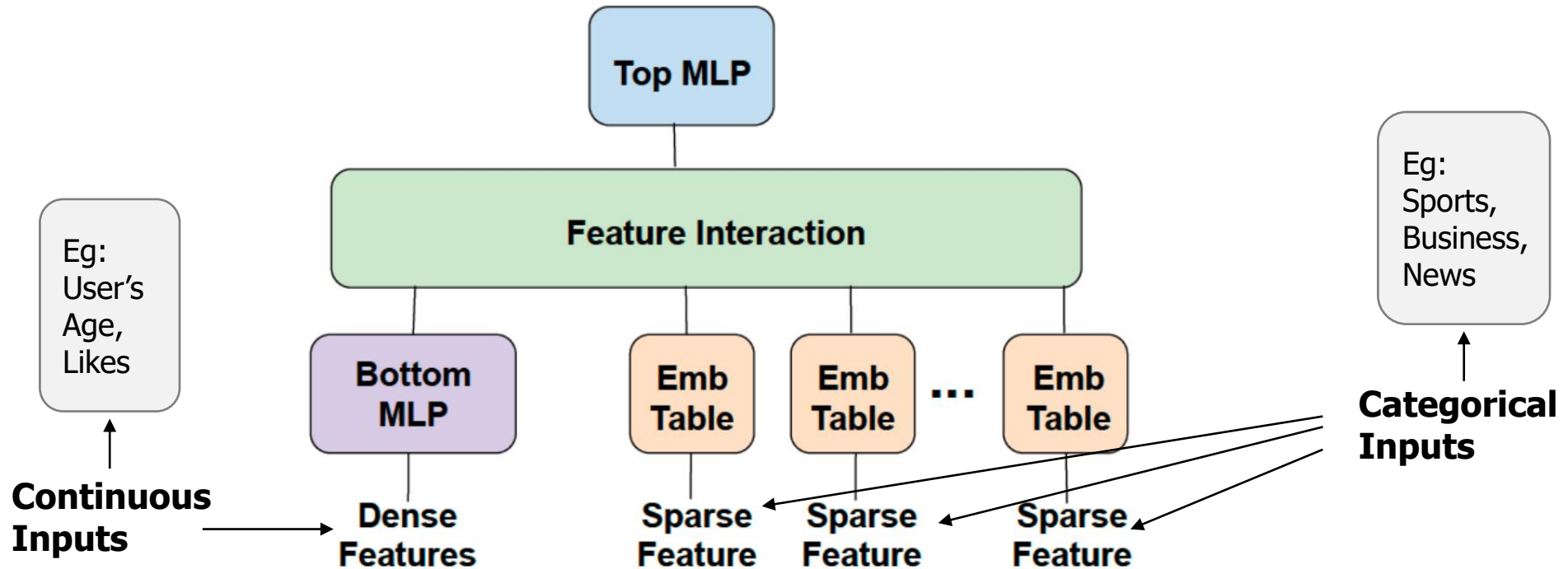


Figure 1: A typical recommendation model

Background

- High performance training at Facebook

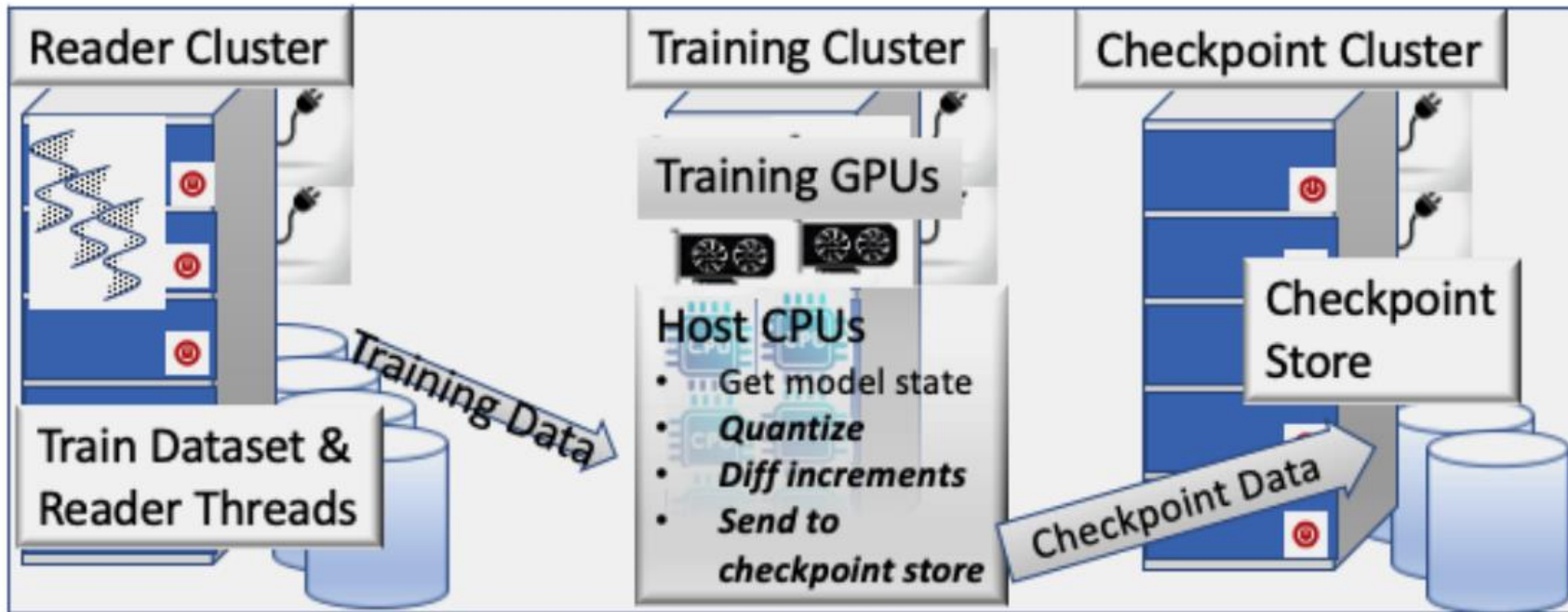


Figure 2: An Overview of Training and Checkpoint Systems

Why do we need checkpoints?

- Failure recovery
- Migrating training processes
- Publishing snapshots in real time
- Transfer learning

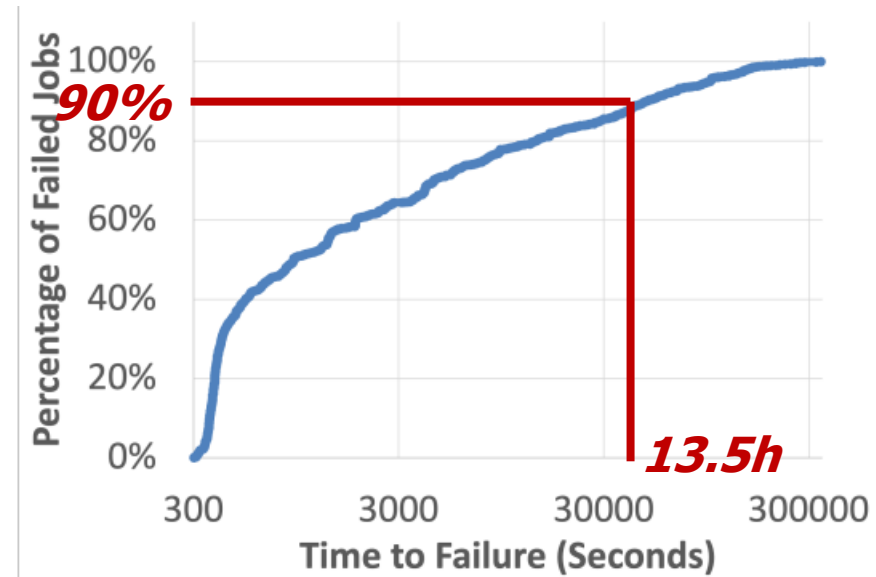


Figure 3: Training job failure CDF in our cluster. Jobs that fail within 5 minutes are removed since they are usually simple user setup errors.

What are the checkpoint challenges?

- Accuracy
- Frequency
- Write bandwidth
- Storage capacity

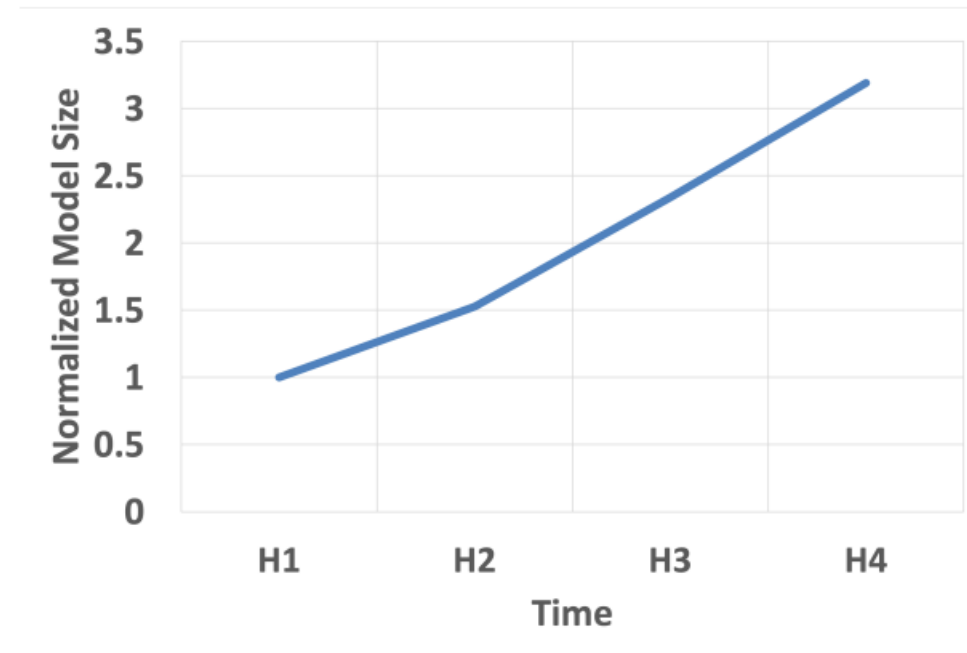


Figure 4: The normalized model size over the past 2 years

Check-N-Run

- Checkpointing workflow

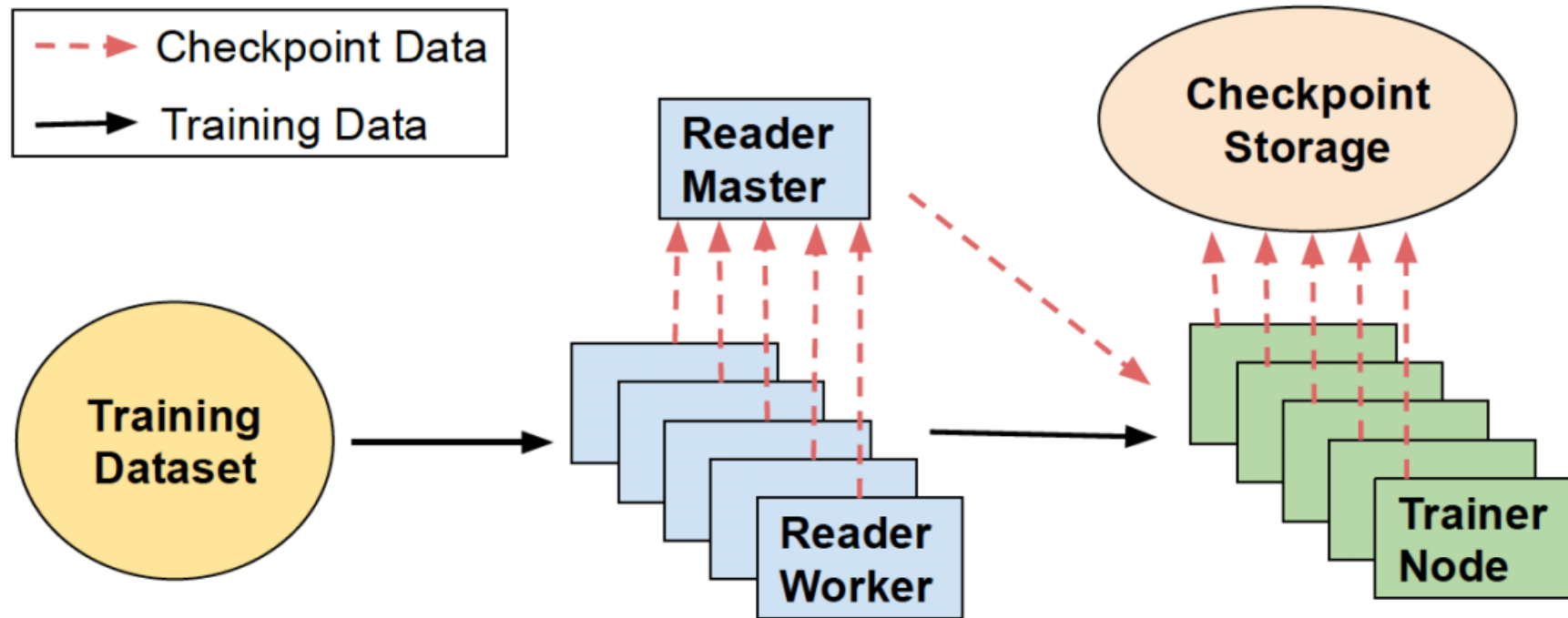


Figure 8: High-level data flow during training

Differential Checkpointing

- One-Shot Differential Checkpointing
 - Takes single checkpointing as a full baseline checkpoint
 - Stores modified vectors since the baseline checkpoint
- Consecutive Incremental Checkpointing
 - Stores the vectors that were modified only during the last interval
 - Requires keeping all previous incremental checkpoints for reconstructing the model
- Intermittent Differential Checkpointing
 - Does a full model checkpointing intermittently
 - Decides when to take a full checkpoint using a simple history based predictor

Evaluation

- Differential Checkpointing Policy Comparison

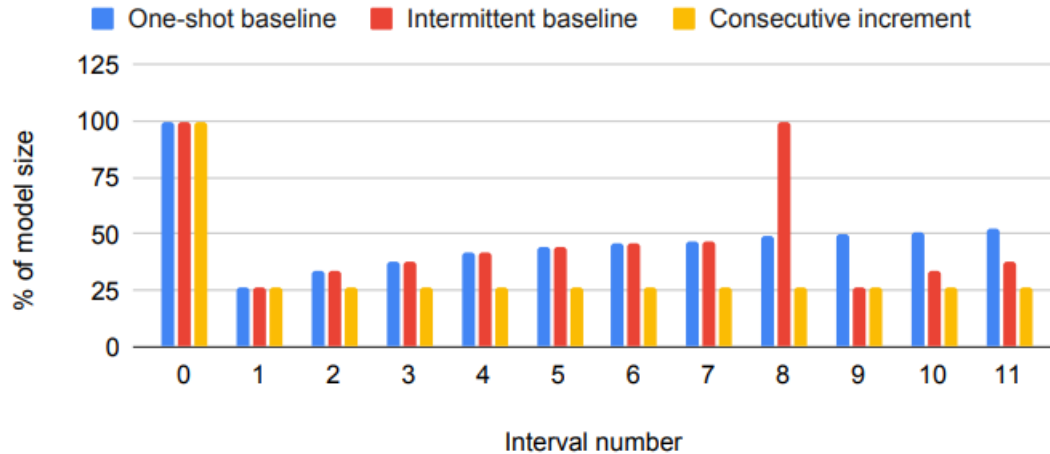


Figure 15: Bandwidth measure: checkpoint size per interval of 30 minutes, for different checkpoint policies

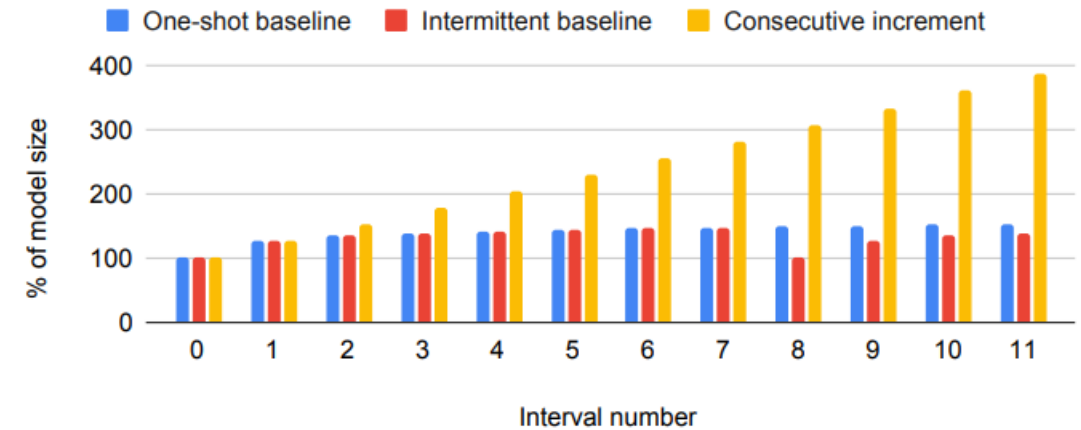
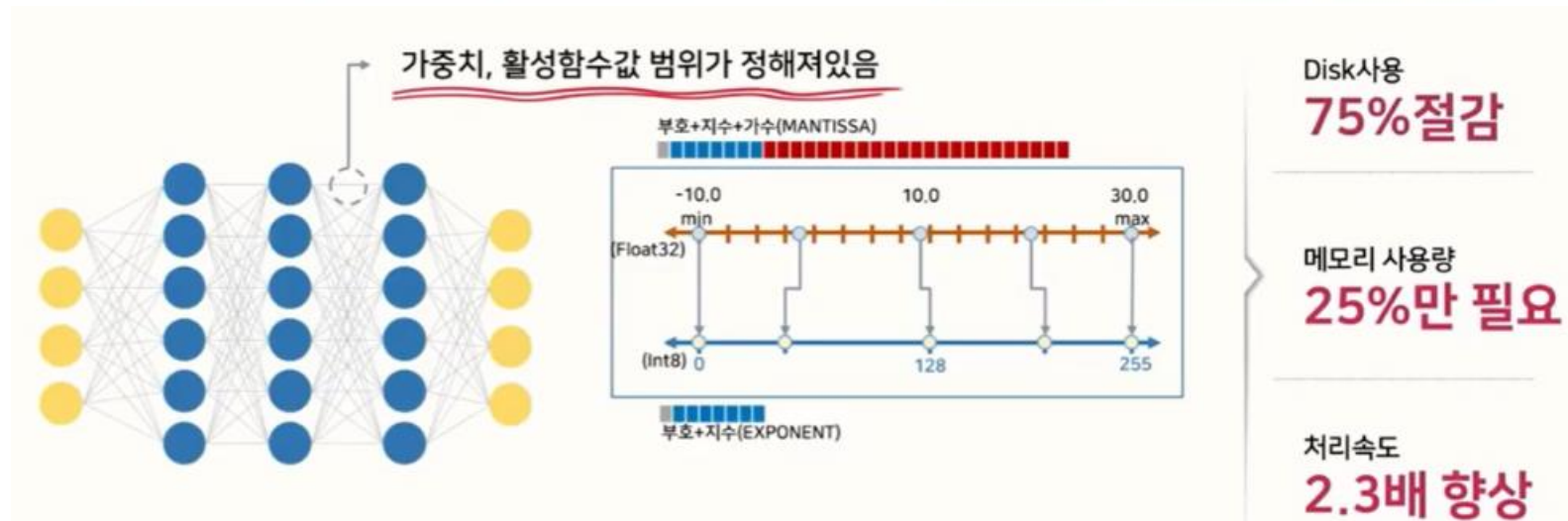


Figure 16: Storage measure: the required storage capacity at each interval of 30 minutes, for different checkpoint policies

Checkpoint quantization

- Compress checkpoint without degrading training accuracy

FP32			INT8		
-3.57	4.67	-3.97	33	255	22
-1.74	2.34	-1.76	82	192	81
-4.75	-0.06	3.07	1	127	212



(source: <https://gaussian37.github.io/dl-concept-quantization/>)

Quantization strategies

- Uniform quantization
 - Symmetric, Asymmetric uniform quantization
- Non-uniform quantization using k-means
 - Embedding vectors are not all mapped into equally spaced buckets
- Adaptive uniform quantization
 - Leverage a greedy search algorithm to select the Xmin and Xmax values

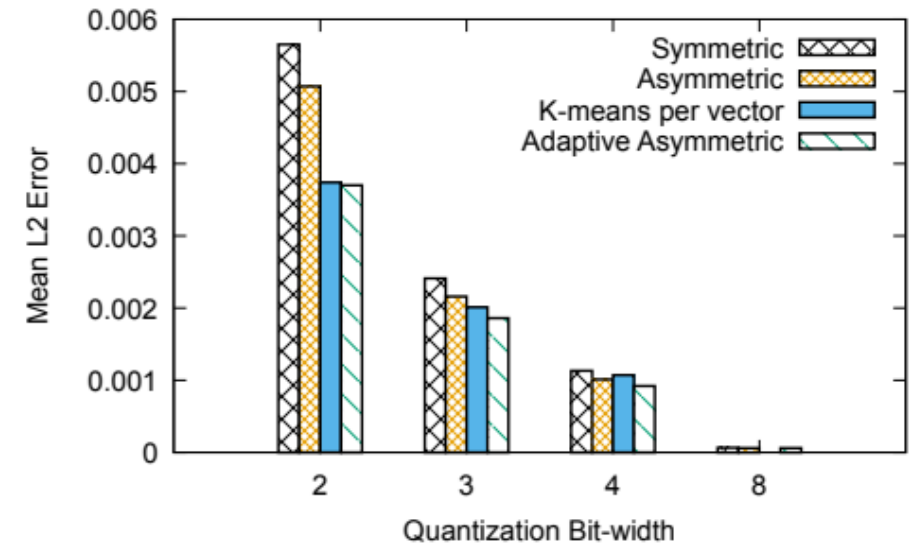
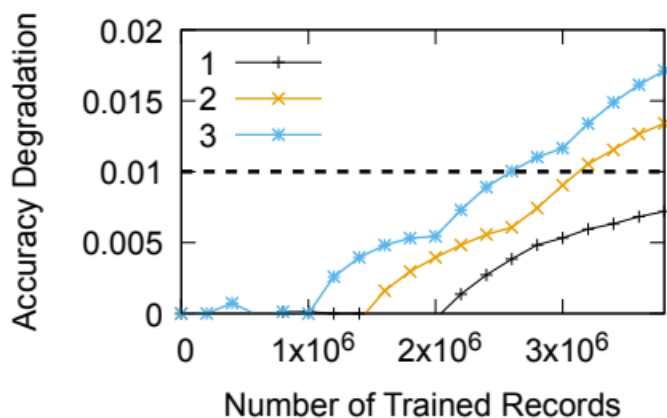


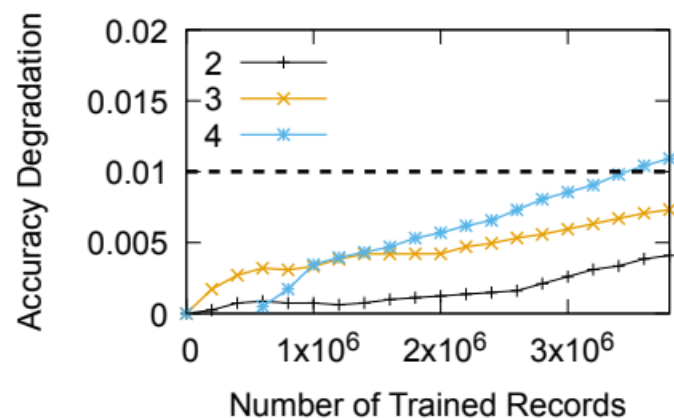
Figure 9: Mean ℓ_2 error of a quantized checkpoint for different quantization approaches

Evaluation

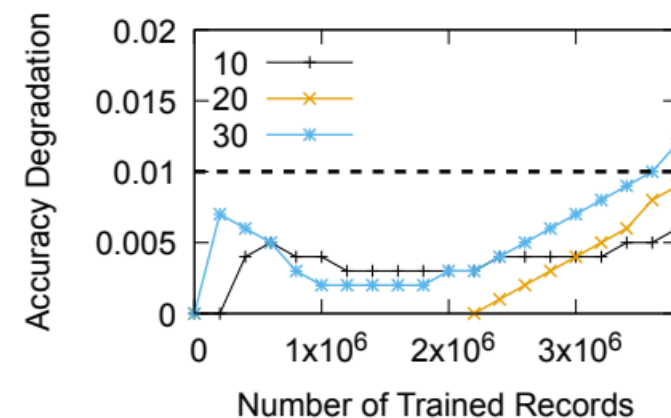
- The training accuracy



(a)



(b)



(c)

Figure 14: Lifetime accuracy degradation in a training job of 4 billion training samples, when using: (a) 2-bit, (b) 3-bit, and (c) 4bit quantized checkpoints. The lines represent the number of times the job had to resume from a quantized checkpoint

Evaluation

- Overall reduction in write bandwidth and storage capacity

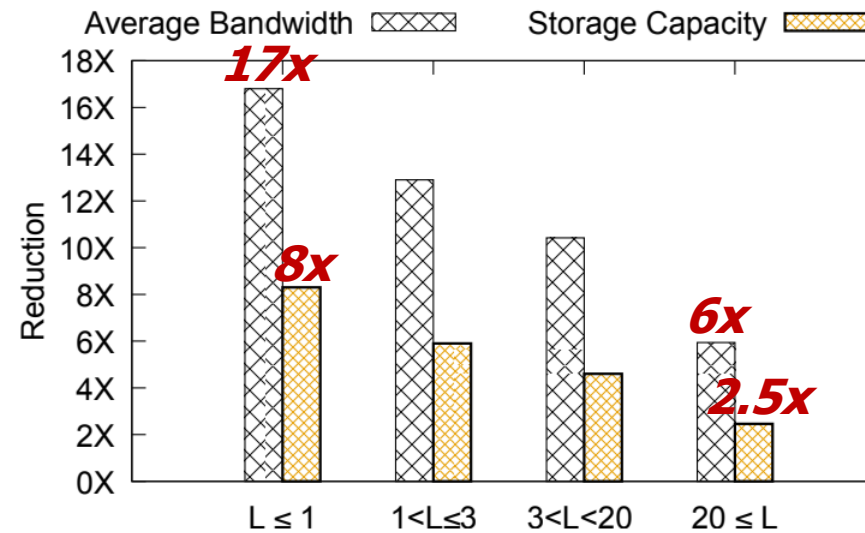


Figure 17: Overall reduction of the checkpoint average write bandwidth and storage capacity. L represents the number of times the training job had to resume from a checkpoint.

Conclusion

- The checkpointing of large recommendation systems at scale is challenging
- Check-N-Run uses strategies of differential checkpointing and quantization
- Check-N-Run significantly reduces the required write-bandwidth and storage capacity



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Thank You !

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