Distributed Parameter Server for Massive Ads System

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Joint work with

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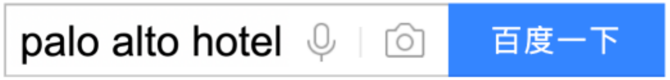
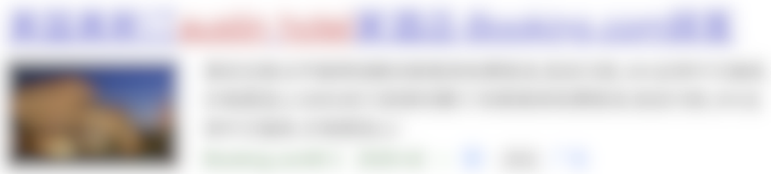
Sponsored Online Advertising

Sponsored Online Advertising

Query



Ad



User portrait

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Neural Network

Click-through Rate

$$\mathbf{CTR} = \frac{\#Click\text{−}throughs}{\#Impressions} \times 100\%$$

High-dimensional sparse vectors (10^{11} dimensions)

CTR Prediction Models at Baidu

2009 and earlier: Single machine CTR models

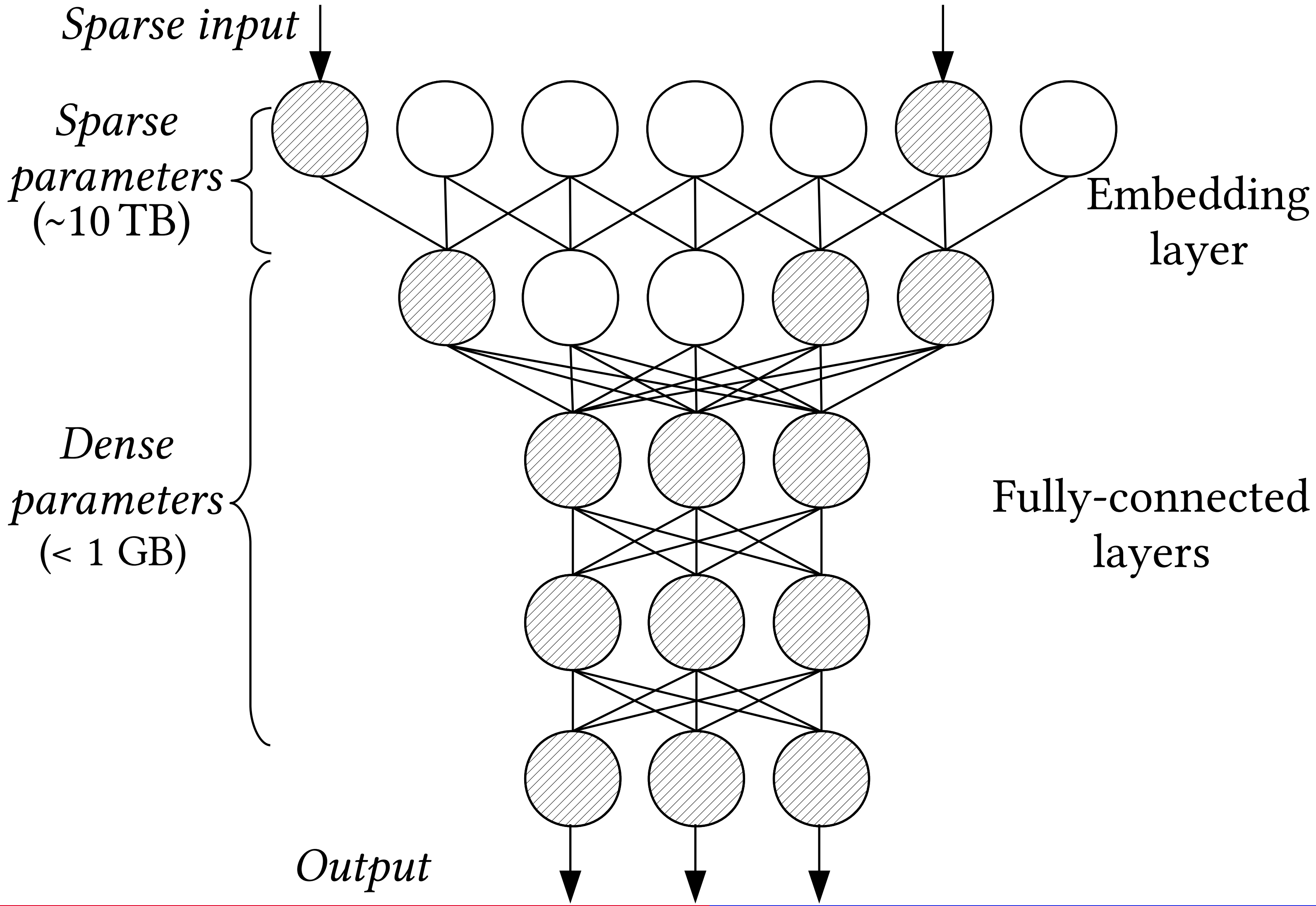
2010: Distributed logistic regression (LR) and distributed parameter server

2013: Distributed deep neural networks (DNN) , extremely large models

Since 2017: Single GPU AIBox, Multi-GPU Hierarchical Parameter Sever, Approx. near neighbor (ANN) search, Maximum inner product search (MIPS)

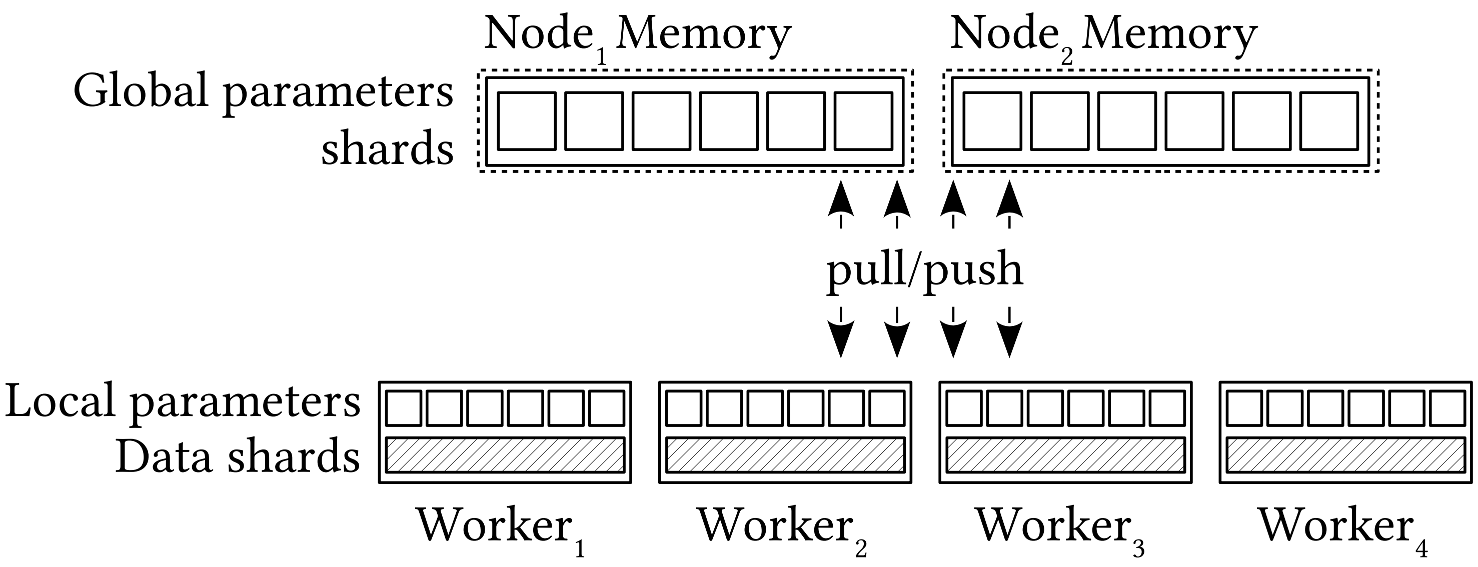
ANN and MIPS have become increasingly important in the whole pipeline of CTR prediction, due to the popularity & maturity of embedding learning and improved ANN/MIPS techniques

A Visual Illustration of CTR Models



MPI Cluster Solution

Distributed Parameter Server



Wait! Why do We Need Such a Massive Model?

Hashing For Reducing CTR Models

One permutation + one sign random projection (work done in 2015)

Image search ads is typically a small source of revenue

Table 1. OP+OSRP for Image Search Sponsored Ads Data

	# Nonzero Weights	Test AUC
Baseline LR	31,949,213,205	0.7112
Baseline DNN		0.7470
Hash+DNN ($k = 2^{34}$)	6,439,972,994	0.7407
Hash+DNN ($k = 2^{23}$)	3,903,844,565	0.7388
Hash+DNN ($k = 2^{22}$)	2,275,442,496	0.7370
Hash+DNN ($k = 2^{31}$)	1,284,025,453	0.7339
Hash+DNN ($k = 2^{30}$)	707,983,366	0.7310
Hash+DNN ($k = 2^{29}$)	383,499,175	0.7278
Hash+DNN ($k = 2^{28}$)	203,864,439	0.7245
Hash+DNN ($k = 2^{27}$)	106,824,123	0.7208
Hash+DNN ($k = 2^{26}$)	55,363,771	0.7175
Hash+DNN ($k = 2^{25}$)	28,479,330	0.7132
Hash+DNN ($k = 2^{24}$)	14,617,324	0.7113

1. Hashing + DNN significantly improves over LR (logistic regression)!
2. A fine solution if the goal is to use **single-machine** to achieve good accuracy!

Hashing For Reducing CTR Models

One permutation + one sign random projection (work done in 2015)

Table 2. OP+OSRP for Web Search Sponsored Ads Data

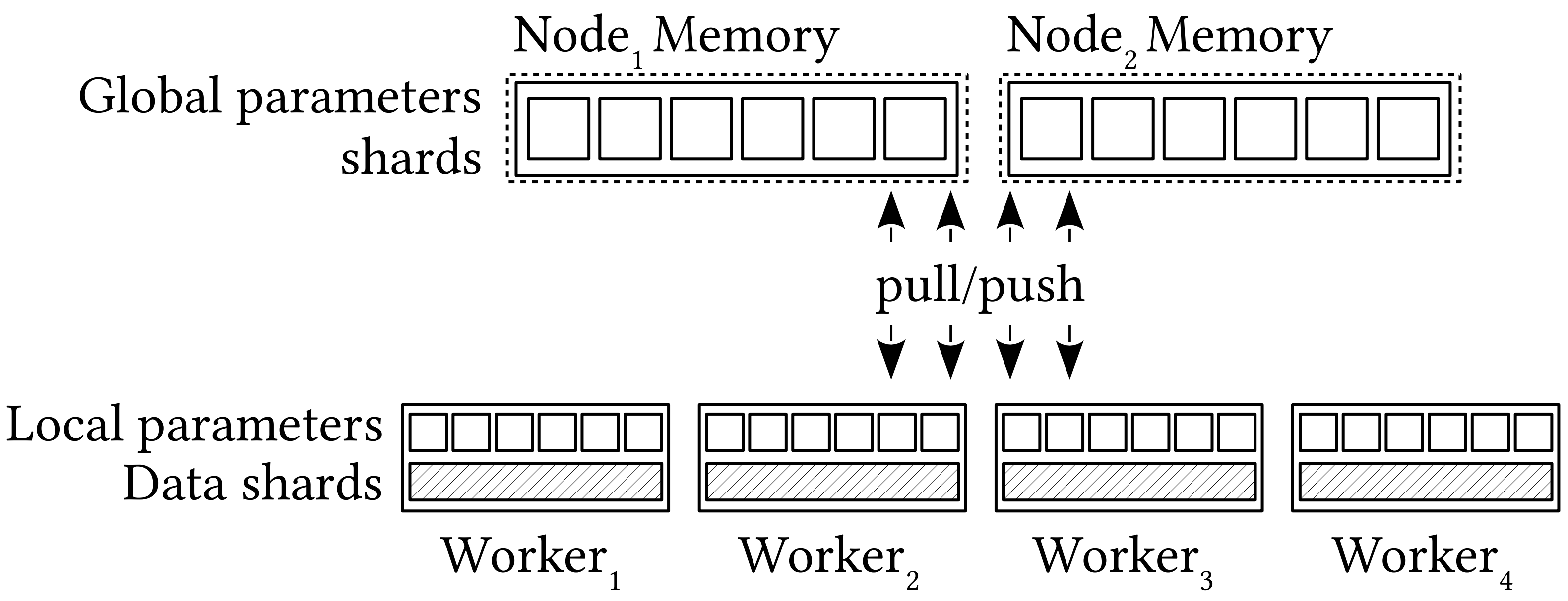
	# Nonzero Weights	Test AUC
Baseline LR	199,359,034,971	0.7458
Baseline DNN		0.7670
Hash+DNN ($k = 2^{32}$)	3,005,012,154	0.7556
Hash+DNN ($k = 2^{31}$)	1,599,247,184	0.7547
Hash+DNN ($k = 2^{30}$)	838,120,432	0.7538
Hash+DNN ($k = 2^{29}$)	433,267,303	0.7528
Hash+DNN ($k = 2^{28}$)	222,780,993	0.7515
Hash+DNN ($k = 2^{27}$)	114,222,607	0.7501
Hash+DNN ($k = 2^{26}$)	58,517,936	0.7487
Hash+DNN ($k = 2^{24}$)	15,410,799	0.7453
Hash+DNN ($k = 2^{22}$)	4,125,016	0.7408

Web search ads
use more features
and larger models

1. Even a 0.1% decrease in AUC would result in a noticeable decrease in revenue
2. Solution of using hashing + DNN + single machine is typically not acceptable

MPI Cluster Solution

Distributed Parameter Server

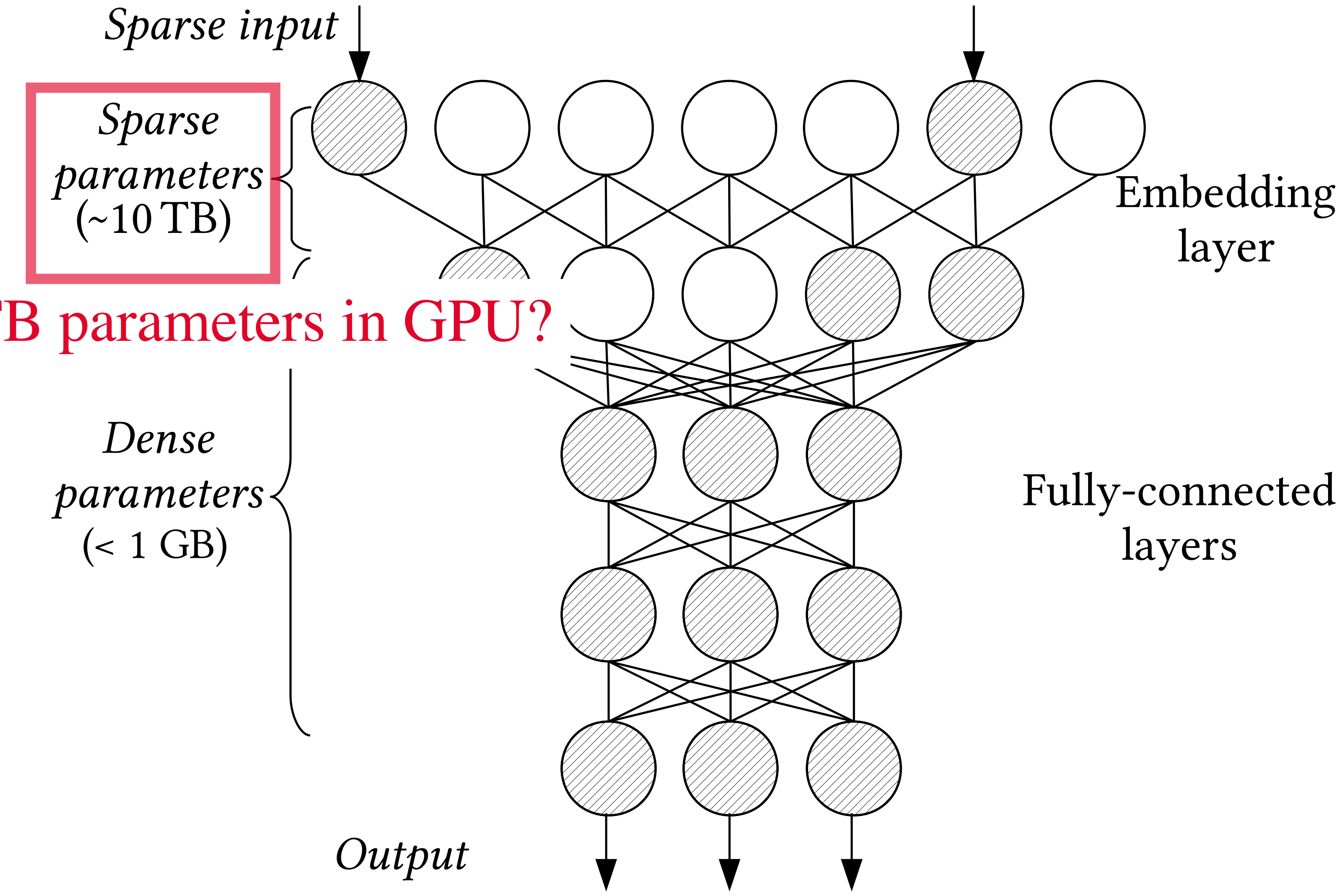


10-TB model parameters ⟶ Hundreds of computing nodes

- Hardware and maintenance cost
- Communication cost

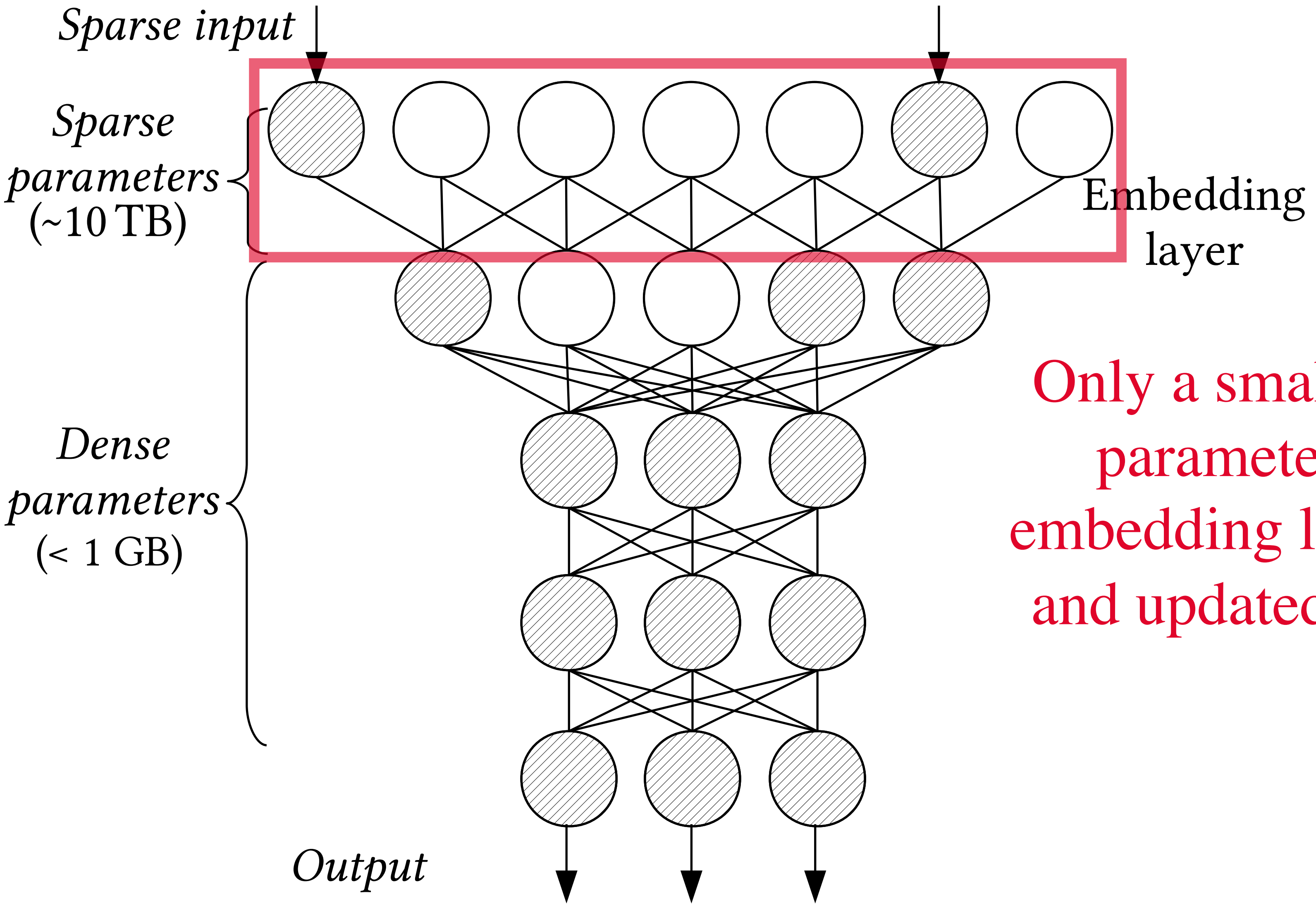
But all the cool kids use GPUs!

Let's train the 10-TB Model with GPUs!



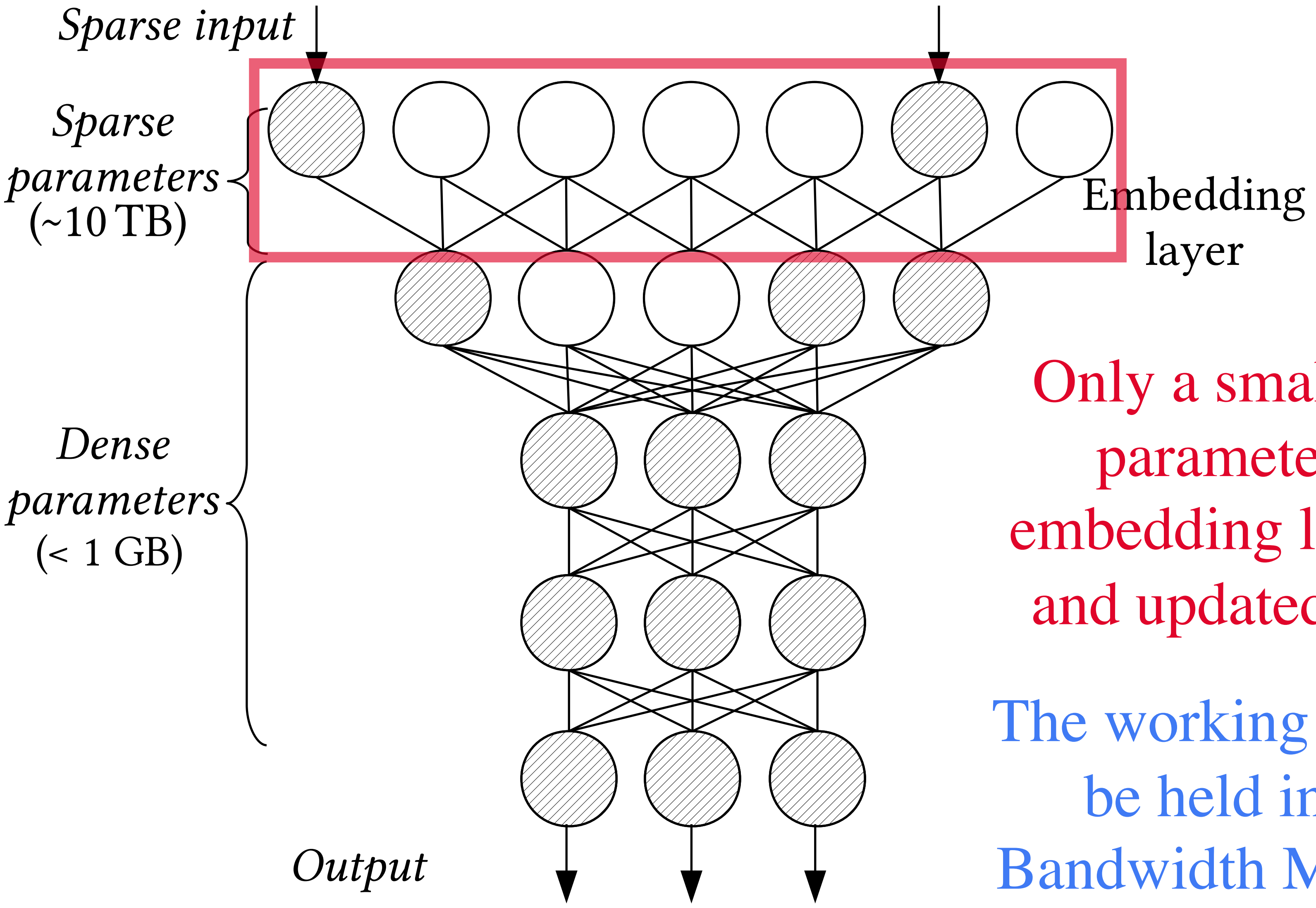
Hold 10 TB parameters in GPU?

A few hundreds of non-zeros



Only a small subset of parameters in the embedding layer is used and updated in a batch

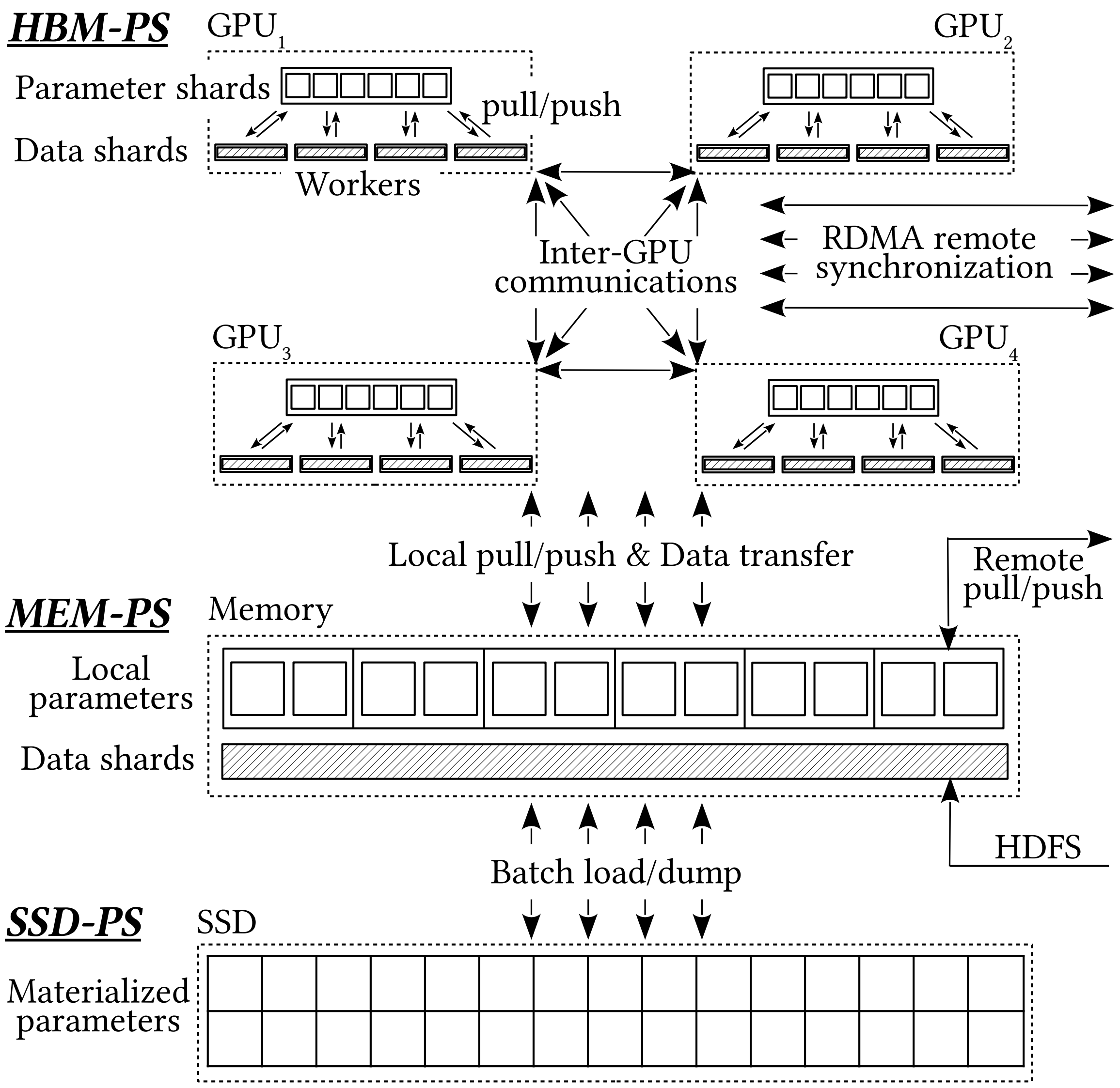
A few hundreds of non-zeros

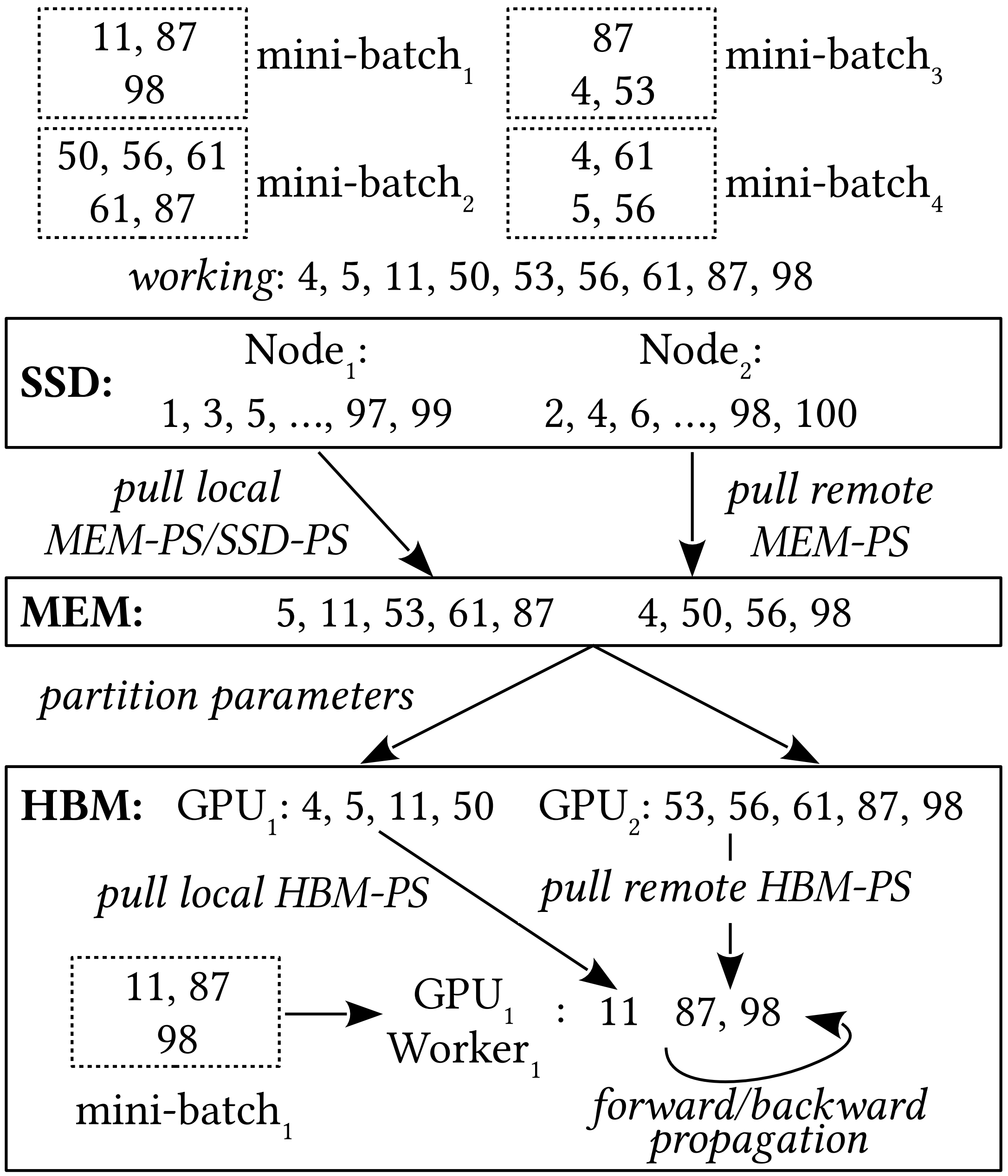


Only a small subset of parameters in the embedding layer is used and updated in a batch

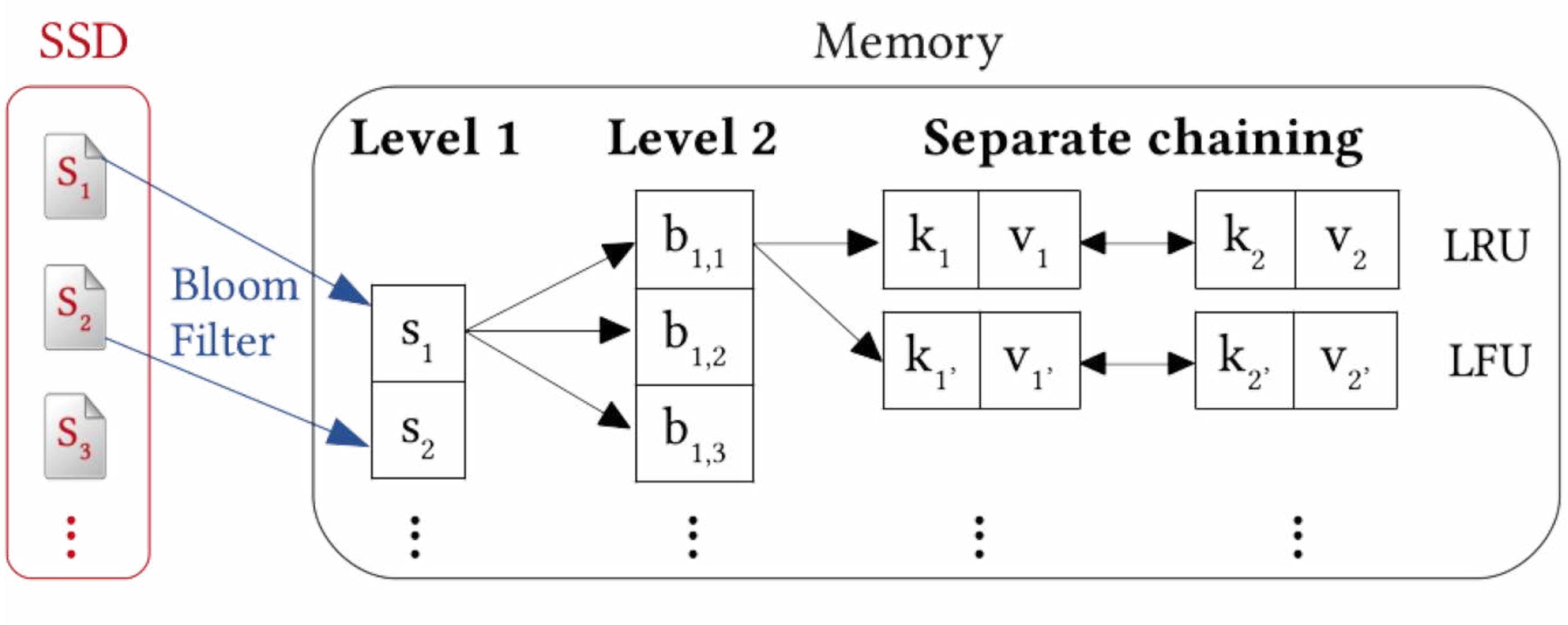
The working parameters can be held in GPU High Bandwidth Memory (HBM)

Solve the Machine Learning Problem in a System Way!




11, 87
98
mini-batch1
87
4, 53
mini-batch3
50, 56, 61
61, 87
mini-batch2
4, 61
5, 56
mini-batch4
working: 4, 5, 11, 50, 53, 56, 61, 87, 98
SSD:
Node1:
1, 3, 5, ..., 97, 99
Node2:
2, 4, 6, ..., 98, 100
pull local MEM-PS/SSD-PS
pull remote MEM-PS
MEM:
5, 11, 53, 61, 87
4, 50, 56, 98
partition parameters
HBM:
GPU1: 4, 5, 11, 50
GPU2: 53, 56, 61, 87, 98
pull local HBM-PS
pull remote HBM-PS
11, 87
98
mini-batch1
GPU1
Worker1
: 11 87, 98
forward/backward propagation

MEM-PS and SSD-PS



[1] Weijie Zhao, Deping Xie, Ronglai Jia, Yulei Qian, Ruiquan Ding, Mingming Sun, and Ping Li. 2020. "Distributed Hierarchical GPU Parameter Server for Massive Scale Deep Learning Ads Systems". MLSys '20.
[2] Weijie Zhao, Jingyuan Zhang, Deping Xie, Yulei Qian, Ronglai Jia, and Ping Li. 2019. "AIBox: CTR Prediction Model Training on a Single Node". CIKM '19.

Experimental Evaluation

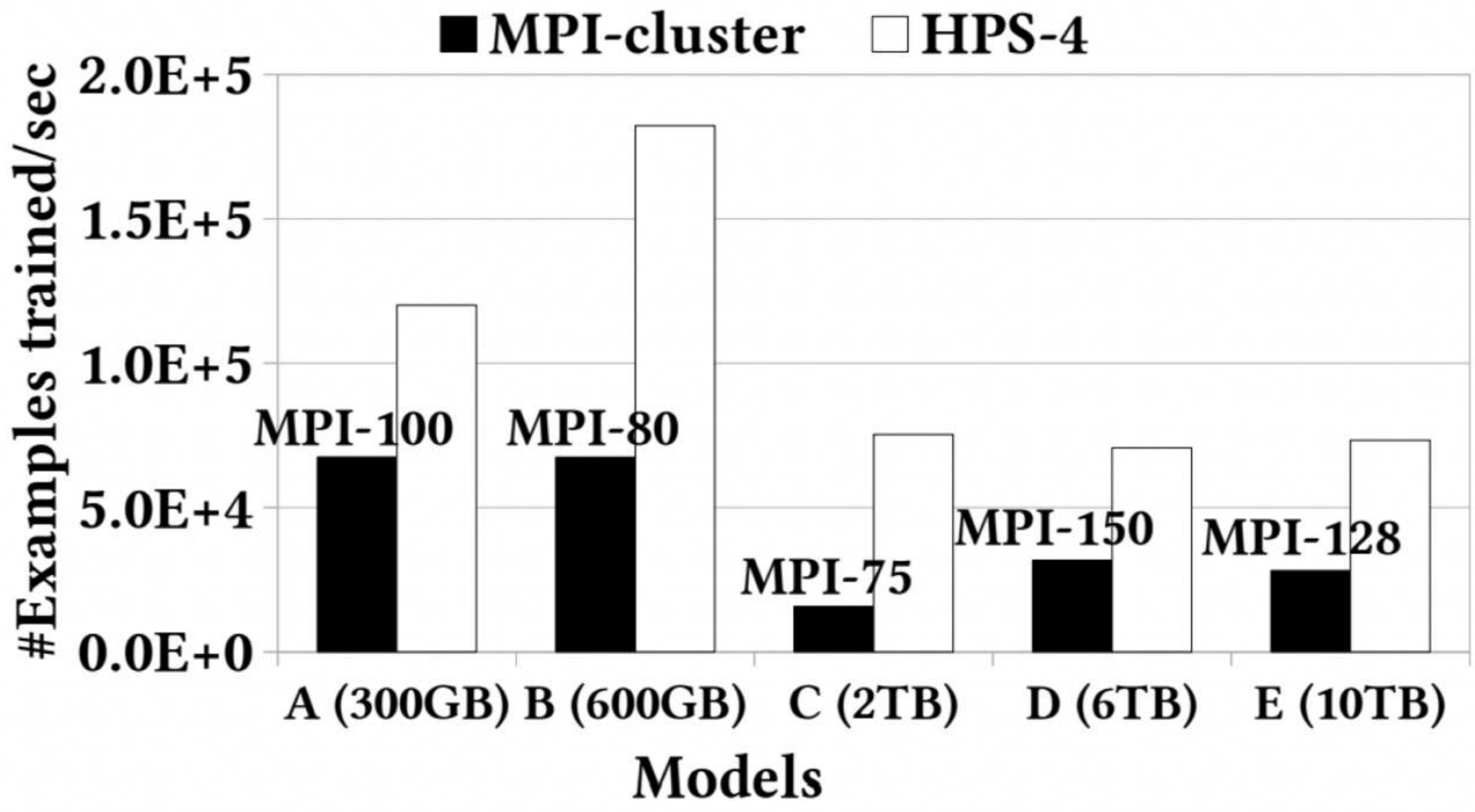
- 4 GPU computing nodes
- 8 cutting-edge 32 GB HBM GPUs
- Server-grade CPUs with 48 cores (96 threads)
- ~1 TB of memory
- ~20 TB RAID-0 NVMe SSDs
- 100 Gb RDMA network adaptor

Experimental Evaluation

Table 3. Model specifications.

	#Non-zeros	#Sparse	#Dense	Size (GB)	MPI
A	100	8×10^9	7×10^5	300	100
B	100	2×10^{10}	2×10^4	600	80
C	500	6×10^{10}	2×10^6	2,000	75
D	500	1×10^{11}	4×10^6	6,000	150
E	500	2×10^{11}	7×10^6	10,000	128

Execution Time



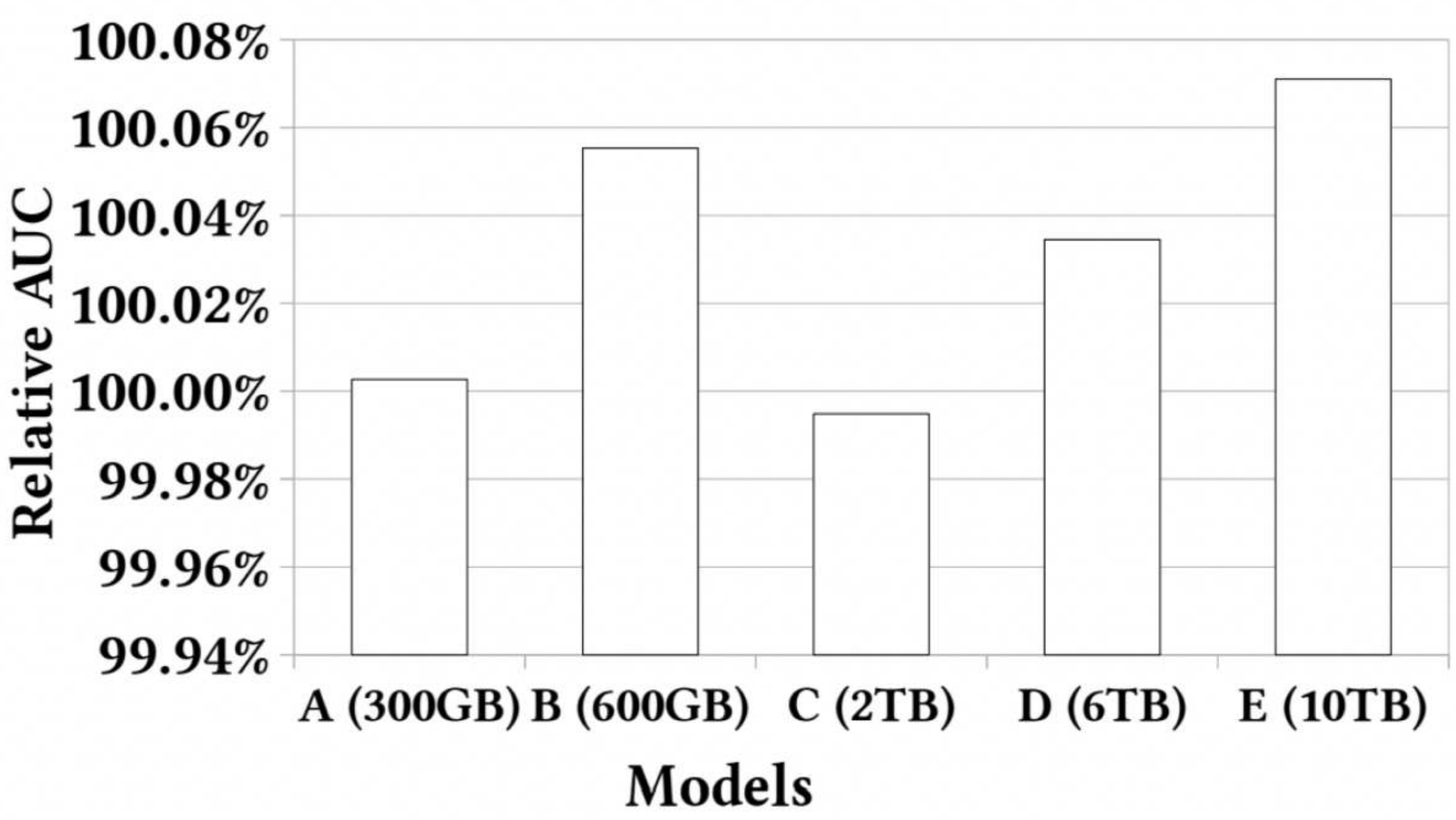
Price-Performance Ratio

- Hardware and maintenance cost: 1 GPU node ~ 10 CPU-only nodes
- 4 GPU node vs. 75-150 CPU nodes

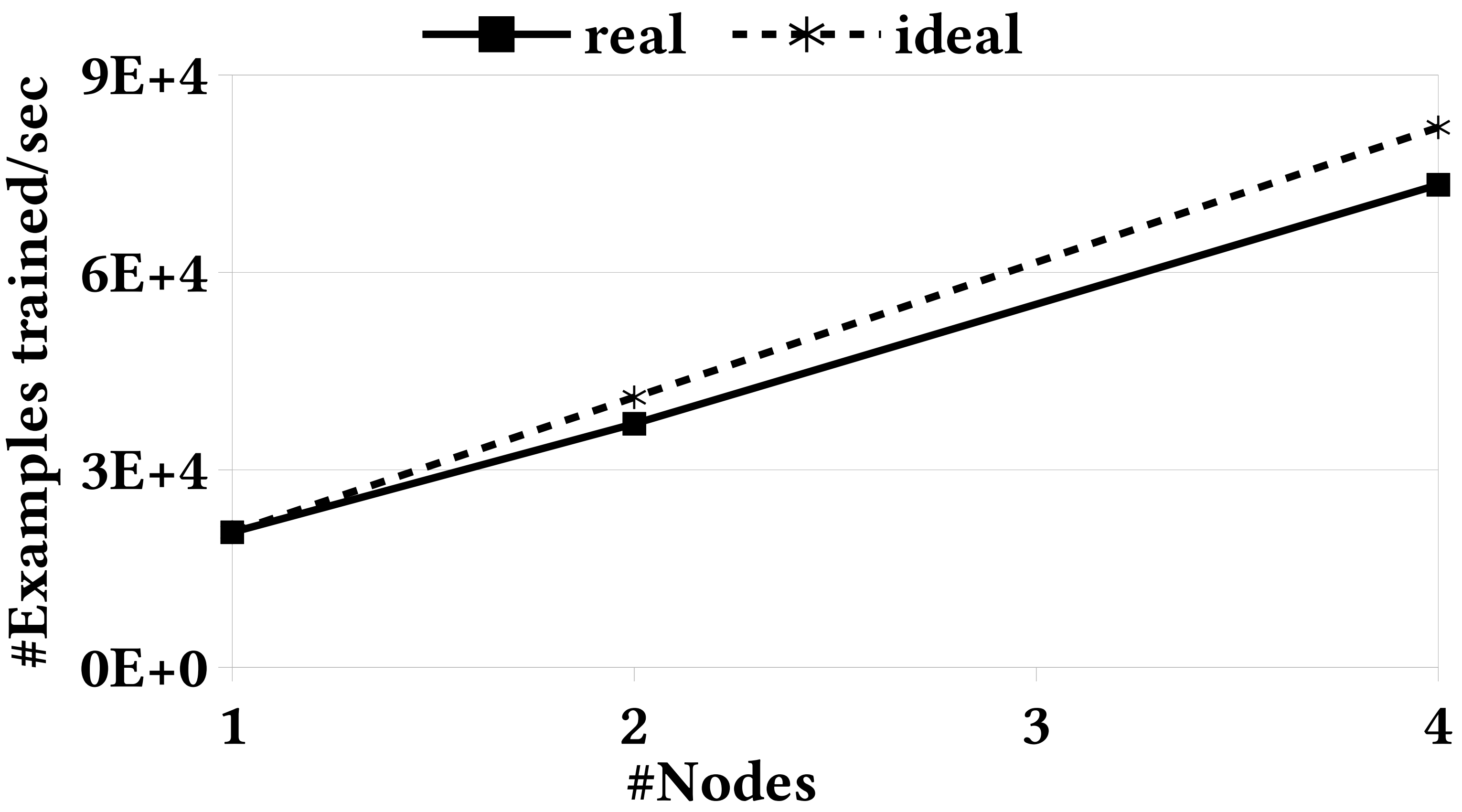
Table 4. The speedup over the MPI-cluster solution and the normalized speedup at the same hardware and maintenance cost.

	A	B	C	D	E
Speedup over MPI-cluster	1.8	2.7	4.8	2.2	2.6
Cost-normalized speedup	4.4	5.4	9.0	8.4	8.3

AUC


100.08%
100.06%
100.04%
100.02%
100.00%
99.98%
99.96%
99.94%
Relative AUC
A (300GB)
B (600GB)
C (2TB)
D (6TB)
E (10TB)
Models

Scalability



Conclusions

- We introduce the architecture of a distributed hierarchical GPU parameter server for massive deep learning ads systems.
- We perform an extensive set of experiments on 5 CTR prediction models in real-world online sponsored advertising applications.
- A 4-node hierarchical GPU parameter server can train a model more than 2X faster than a 150-node in-memory distributed parameter server in an MPI cluster.
- The cost of 4 GPU nodes is much less than the cost of maintaining an MPI cluster of 75-150 CPU nodes.
- The price-performance ratio of this proposed system is 4.4-9.0X better than the previous MPI solution.
- This system is being integrated with the **PaddlePaddle** deep learning platform (https://www. paddlepaddle.org.cn) to become **PaddleBox**.