A Novel Inference Algorithm for Large Sparse Neural Network using Task Graph Parallelism

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SNIG

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Inference Engine MIT/IEEE/Amazon HPEC Graph Challenge https://github.com/dian-lun-lin/SNIG



Challenges: Performance and Memory Constraint

> 4 billion nonzero parameters

Neurons/Layers	120	480	1920	Bias	Size	Image Nonzeros	
1024	3,932,160	15,728,640	62,914,560	-0.30	1.25 GB	6,374,505	
4096	15,728,640	62,914,560	251,658,240	-0.35	5.40 GB	25,019,051	
16384	62,914,560	251,658,240	1,006,632,960	-0.40	22.70 GB	98,858,913	
65536	251,658,240	1,006,632,960	4,026,531,840	-0.45	94.70 GB	392,191,985	

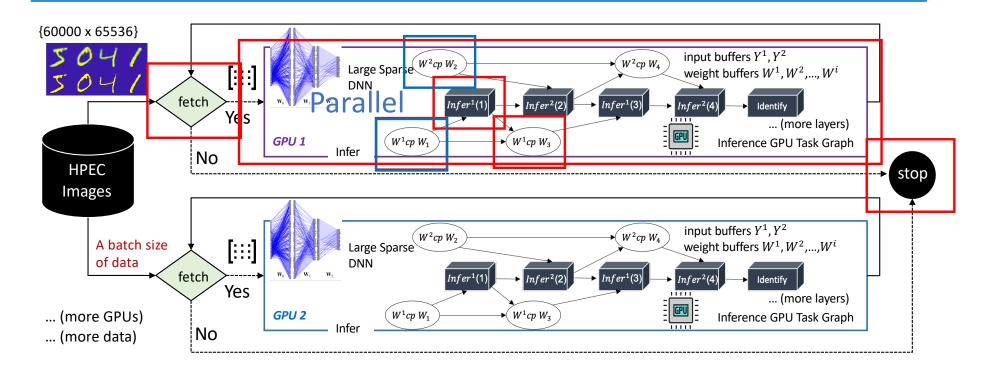
Previous year's champion (Bisson and Fatica, IEEE HPEC 2020, BF for short)

- Require the entire input data to sit in the GPUs under unified memory addressing
- Synchronize computation at each layer for load balancing

Pipeline parallelism (Yanping Huang et al., NIPS 2019, GPipe for short)

- Require the entire model to sit in GPUs
- Synchronize computation at each pipeline stage

Key Solution: Task Graph Parallelism (CUDA Graph)



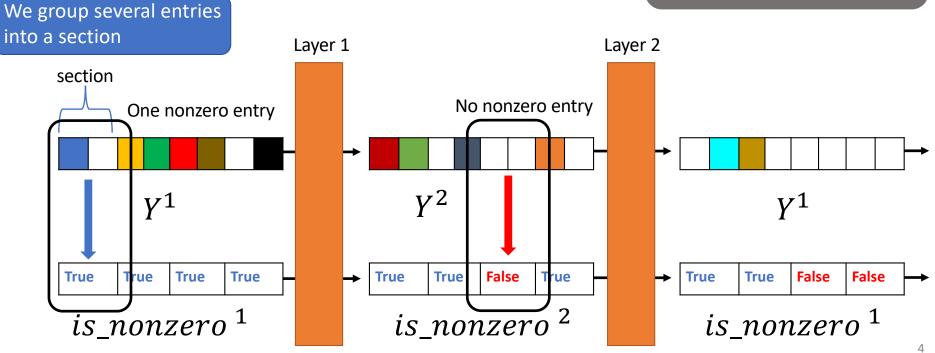
End-to-end parallelism

Extensible to arbitrary LSNNs and input data under different numbers of GPUs

Reduce Memory Usage

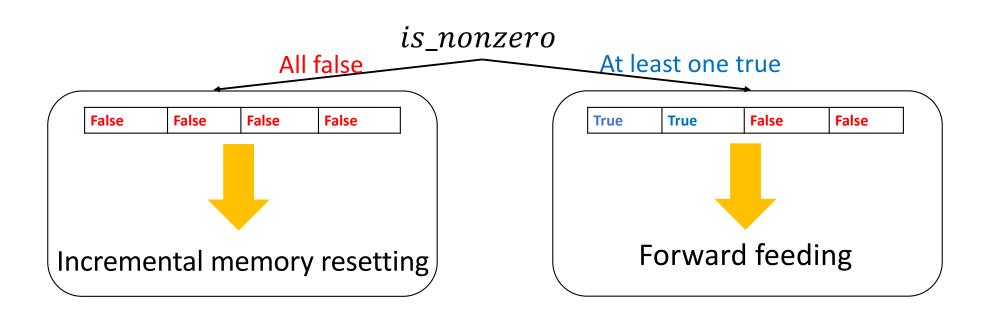
During the inference, each GPU allocates

- two input buffers Y^1 , Y^2
- two Boolean arrays *is_nonzero*¹, *is_nonzero*²
- Layer 1 takes Y^1 as input and outputs to the Y^2 ; Layer 2 takes Y^2 as input and outputs to the Y^1
- White entries represent zeros

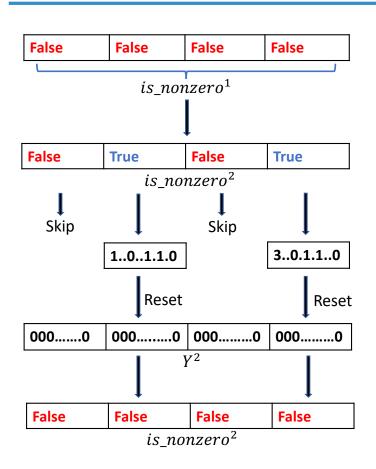


Two Key Components in Our Kernel

Our Goal: avoid unwanted computation on zero entries



Component #1: Incremental Memory Resetting



Observation:

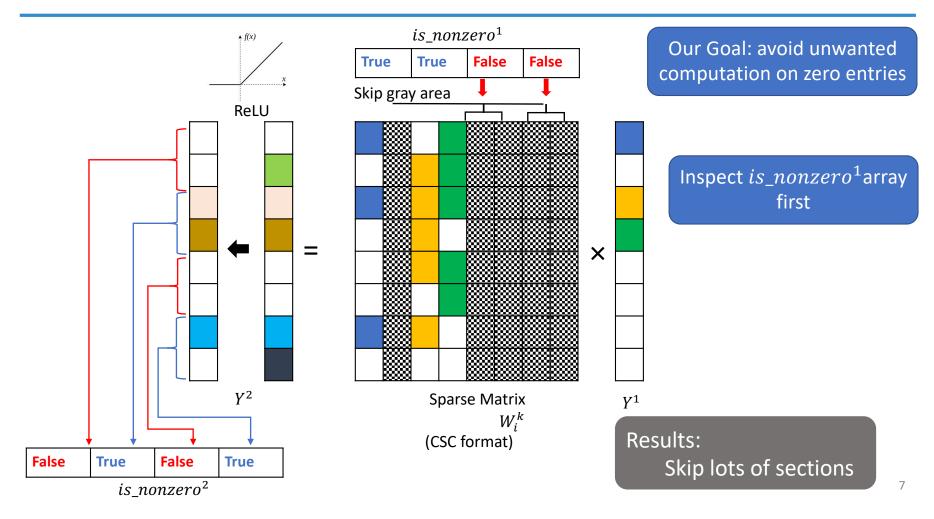
If inputs are all zeros, outputs are still all zeros

Contains at least one nonzero entry

Results:

- 1. Skip lots of sections
- 2. Resetting rather than computing

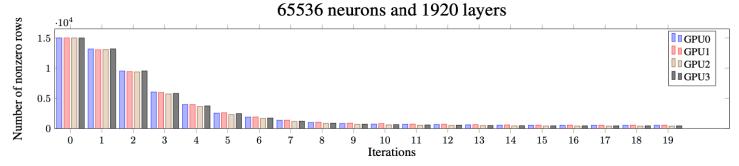
Component #2: Forward Feeding



Experimental Results

Baseline

- https://github.com/dian-lun-lin/SNIG
- o BF (Bisson and Fatica, IEEE HPEC 2019) without NVLink (Doesn't affect performance)



- GPipe (Yanping Huang et al., NIPS 2019)
- Software
 - Ubuntu Linux 5.0.0-21-generic x86 64-bit machine
 - C++14 and CUDA NVCC 10.1 (CUDA Graph Library)
- Hardware
 - 40 Intel Xeon Gold 6138 CPU cores at 2.00 GHz
 - 4 GeForce RTX 2080 Ti GPUs with 11 GB memory
 - o 256 GB RAM

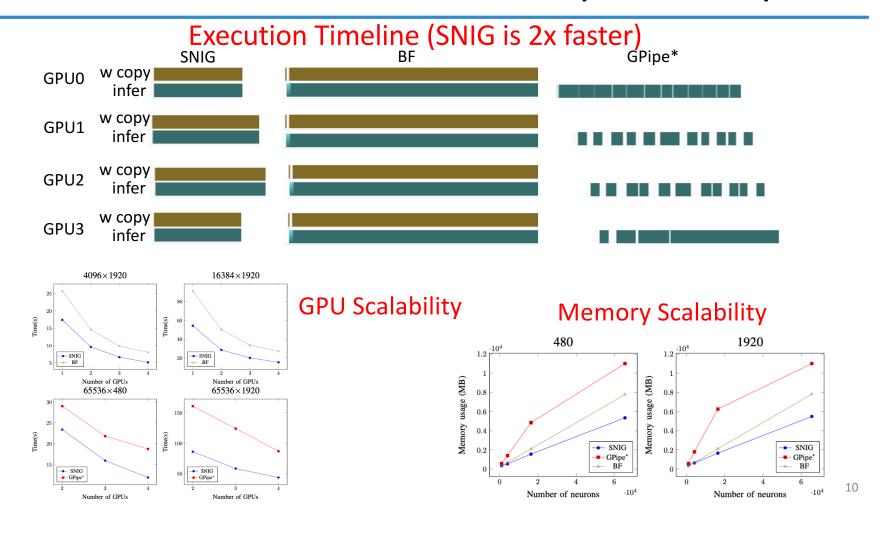
Our implementation of BF method:

- Only partition at the beginning
- The number of non-empty rows per iteration remains balanced at each GPU

Overall runtime results of SNIG, BF, and GPipe

Bold text r	renresent	·s	Reported in seconds									onds
the best s	•	Number of GPUs										
		1			2			3			4	
Neurons	Layers	BF	SNIG	BF	GPipe*	SNIG	BF	GPipe*	SNIG	BF	GPipe*	SNIG
	120	0.682	0.799	0.409	0.400	0.518	0.310	0.339	0.342	0.272	0.307	0.189
1024 480 1920 120	480	1.975	1.609	1.178	0.928	1.019	0.889	0.741	0.700	0.848	0.636	0.476
	1920	7.197	5.252	4.428	3.178	3.187	3.330	2.396	2.291	3.093	2.012	1.748
	120	2.305	1.609	1.265	1.010	0.962	0.853	0.896	0.646	0.681	0.810	0.421
4096 480 1920 120 16384 480 1920	480	6.932	4.696	3.921	2.742	2.695	2.637	2.136	1.830	2.165	1.824	1.367
	1920	25.75	17.41	14.63	9.732	9.584	9.817	7.278	6.610	8.035	6.023	5.121
	120	8.165	4.433	4.283	2.925	2.538	2.896	2.481	1.729	2.328	2.241	1.295
	480	24.50	14.02	13.28	7.999	7.683	8.997	6.151	5.346	7.286	5.217	4.041
	1920	91.05	54.22	50.01	28.68	28.39	33.39	21.44	19.98	27.08	17.70	15.24
65536 4	120	524.3	14.78	262.5	11.41	8.073	11.33	10.16	5.581	9.136	9.643	4.394
	480	>1800	43.00	1027	28.99	23.38	33.23	21.82	15.96	26.94	18.74	11.91
	1920	>1800	162.2	>1800	160.9	85.96	123.2	124.0	58.22	98.59	86.77	43.44

Execution Timeline & GPU/Memory Scalability



Thanks!



https://github.com/dian-lun-lin/SNIG dian-lun.lin@utah.edu