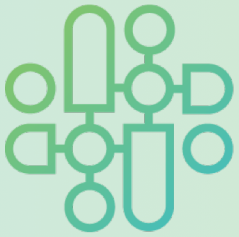


SC23

Denver, CO | i am hpc.

Programming Novel AI Accelerators for Scientific Computing – Cerebras Wafer Scale Cluster

Claire Zhang (claire.zhang@cerebras.net)

Cerebras Systems

November 12, 2023

Cerebras Wafer-Scale Engine (WSE-2)

Still the Largest Chip Ever Made

850,000 cores optimized for sparse linear algebra

46,225 mm^2 silicon

2.6 trillion transistors

40 gigabytes of on-chip memory

20 PByte/s memory bandwidth

220 Pbit/s fabric bandwidth

7nm process technology

Cluster-scale performance in a single chip

cerebras

Cerebras CS-2 System

The world's fastest AI accelerator

- ✓ Deploy easily into existing racks
- ✓ Cluster-scale in a single system
- ✓ Datacenter-scale in a cluster
- ✓ Available on-prem or remote / in cloud

Condor Galaxy 1 “CG-1” AI Supercomputer

64 Cerebras CS-2 systems, linked together with “*SwarmX*” for 4 ExaFLOPS of AI Compute

64
CS-2 nodes

54 million
AI cores

4 exaFLOPS
AI compute
at FP16

82 TB
parameter memory

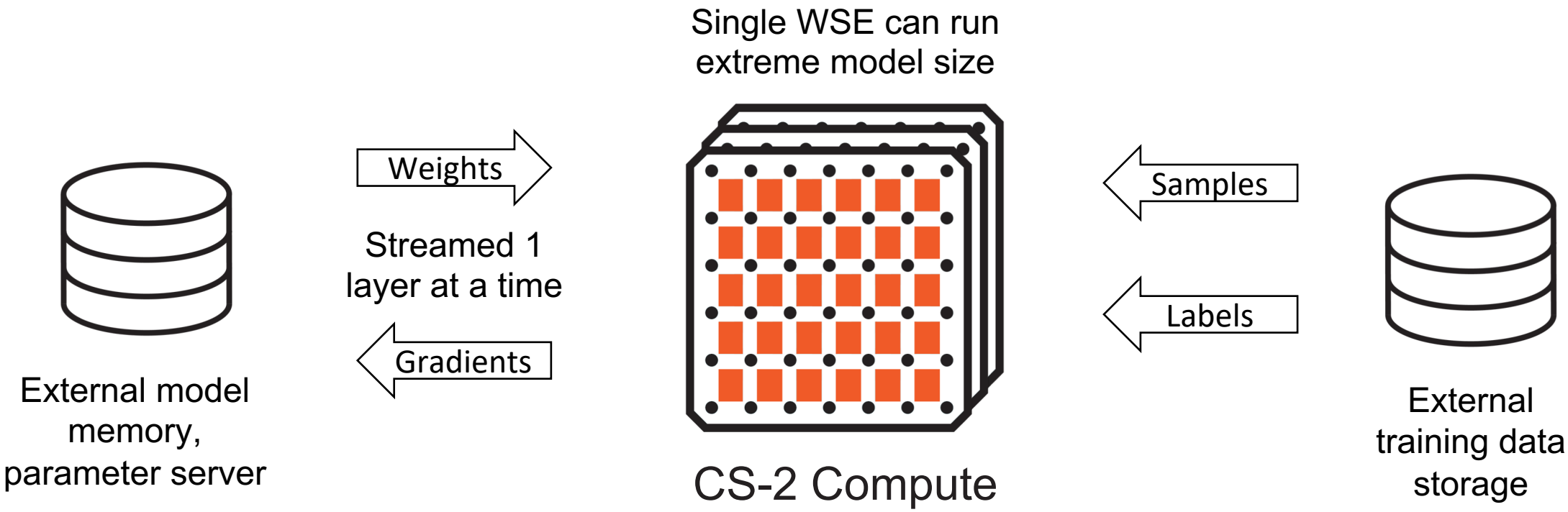
388 Tbps
internal bandwidth

72,704
AMD EPYC™ cores

10 days
to first training run

cerebras

Weight Streaming technology disaggregates storage and compute to enable trillion parameter model training

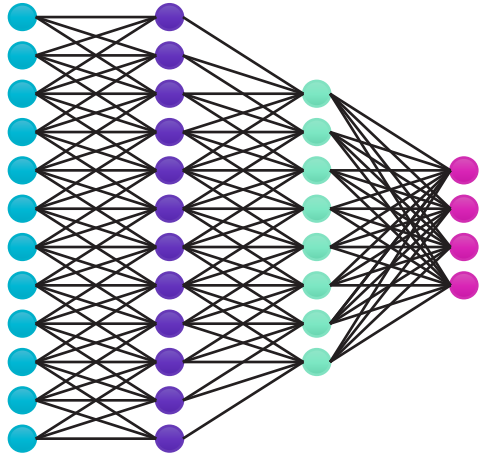


Scale model size and training speed independently

Weight Streaming Execution Model

Built for extreme-scale neural networks:

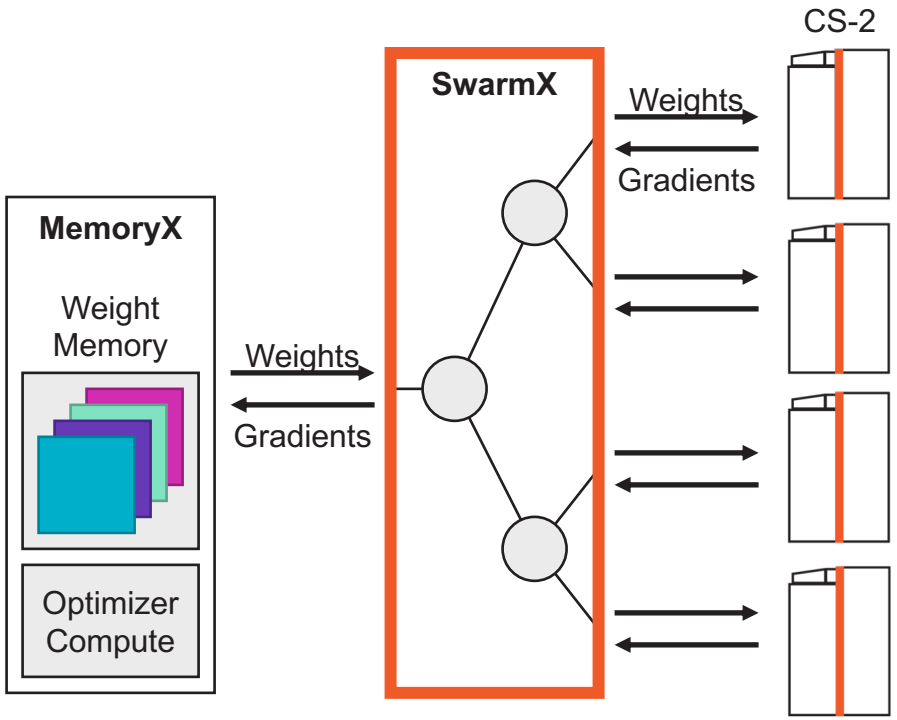
- Weights stored externally off-wafer
- Weights streamed onto wafer to compute layer
- Activations only are resident on wafer
- Execute one layer at a time



Decoupling weight optimizer compute

- Gradients streamed out of wafer
- Weight update occurs in MemoryX

Simple Scaling to Multiple CS-2s



- Data parallel training across CS-2s
- Weights are **broadcast** to all CS-2s
- Gradients are **reduced** on way back
- **Multi-system scaling with the same execution model as single system**
  - Same system architecture
  - Same network execution flow
  - Same software user interface

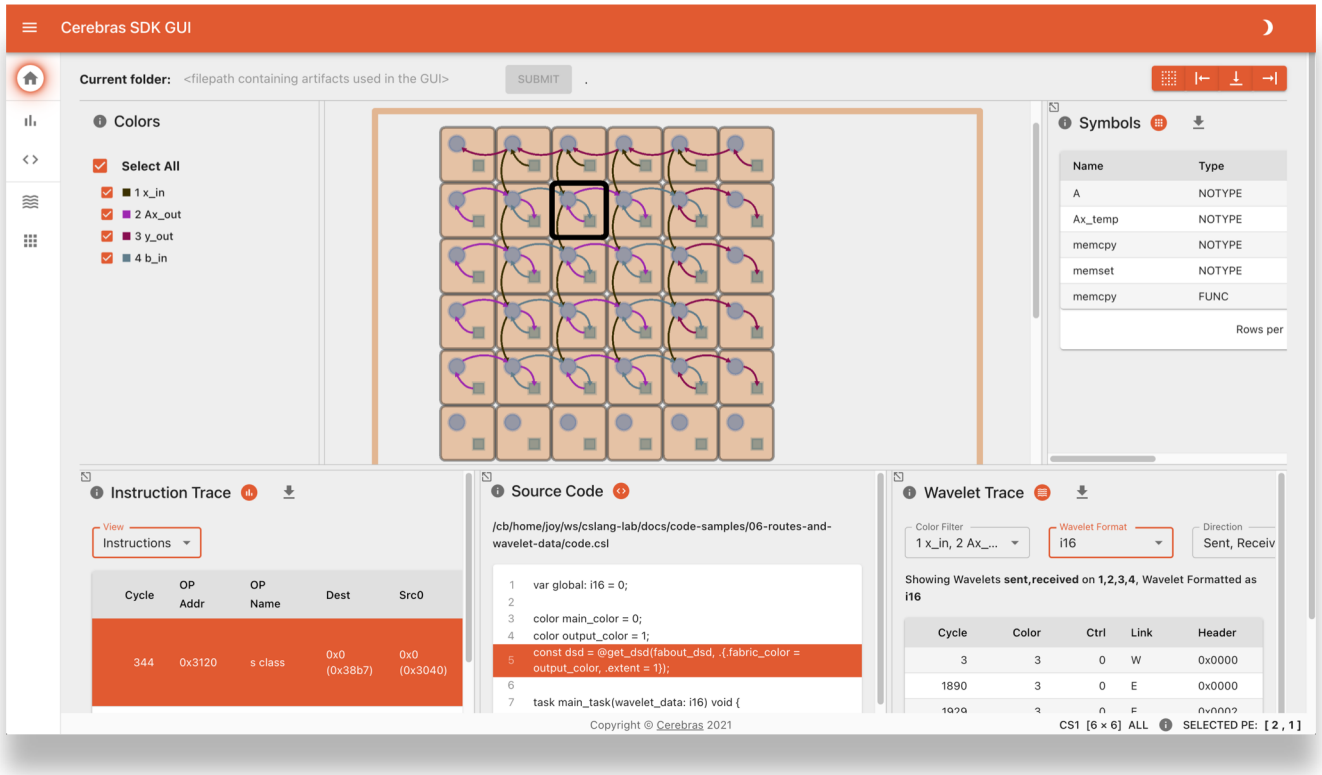
Scalable to extreme model sizes

Compute scaling independent from capacity

Cerebras SDK

A general-purpose parallel-computing platform and API allowing software developers to write custom programs (“kernels”) for Cerebras systems.

Language	CSL: Cerebras Software Language
	Host APIs with Python
Libraries	Optimized primitives
Tools	Simulator, Debugger
	Performance profiler, Visualization



AI Case Study – Award-Winning COVID Research Accomplished on Cerebras 16-node Cluster

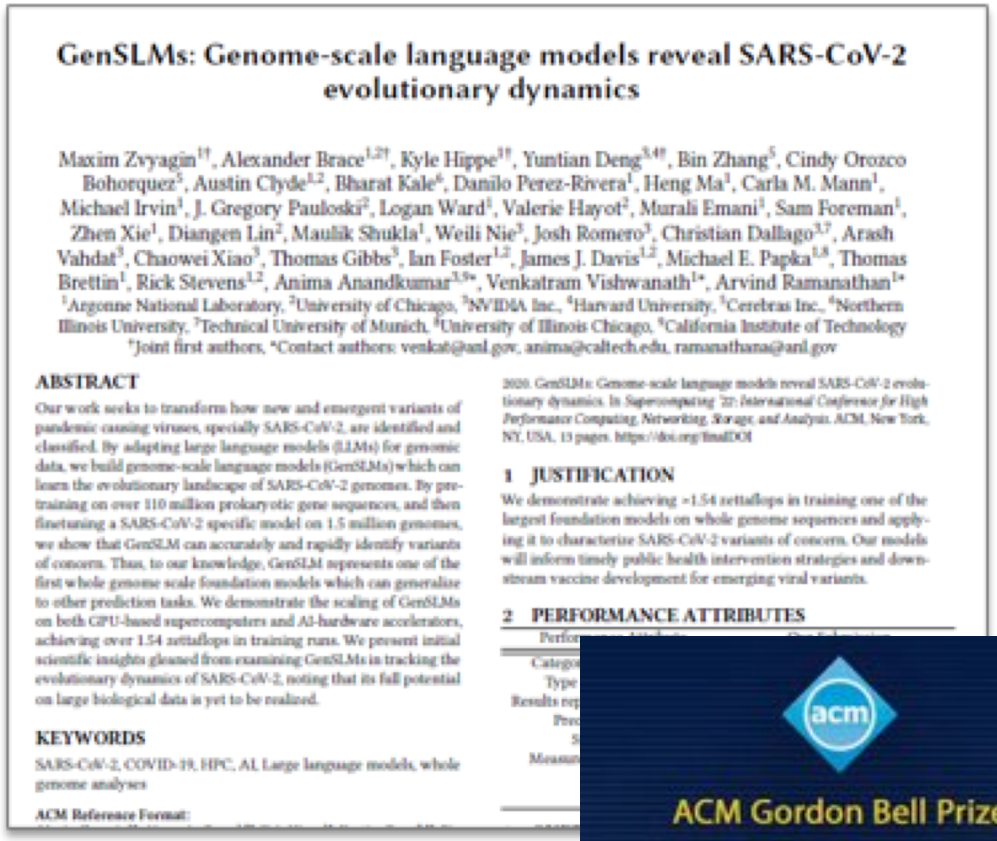
Collaborator: Argonne National Labs is a U.S. Department of Energy's national laboratory for science and engineering research

The Ask: Accelerate COVID-19 understanding by training 250M-25B GPT models on full-length SARS-CoV-2 genome data, using 10,240 token sequence length

Challenge: At the project's timeframe, team found pre-training LLMs with long sequence lengths intractable using conventional hardware, making experimentation difficult due to long training time.

What we did: We leveraged our CS-2 cluster and effortless programming model to pre-train the models of interest. No code changes or specialized expertise was required.

Outcome: The collaborative project won the ACM Gordon Bell Special Prize for High Performance Computing-Based COVID-19 Research



GenSLMs: Genome-scale language models reveal SARS-CoV-2 evolutionary dynamics

Maxim Zvyagin[1†], Alexander Brace[1,2†], Kyle Hippe[1†], Yuntian Deng[3,4†], Bin Zhang[5], Cindy Orozco Bohorquez[5], Austin Clyde[1,2], Bharat Kale[6], Danilo Perez-Rivera[1], Heng Ma[1], Carla M. Mann[1], Michael Irvin[1], J. Gregory Pauloski[2], Logan Ward[1], Valerie Hayot[2], Murali Emani[1], Sam Foreman[1], Zhen Xie[1], Diangen Lin[2], Maulik Shukla[1], Weili Nie[3], Josh Romero[3], Christian Dallago[3,7], Arash Vahdat[3], Chaowei Xiao[3], Thomas Gibbs[3], Ian Foster[1,2], James J. Davis[1,2], Michael E. Papka[1,8], Thomas Brettin[1], Rick Stevens[1,2], Anima Anandkumar[3,9*], Venkatram Vishwanath[1*], Arvind Ramanathan[1*]

[1]Argonne National Laboratory, [2]University of Chicago, [3]NVIDIA Inc., [4]Harvard University, [5]Cerebras Inc., [6]Northern Illinois University, [7]Technical University of Munich, [8]University of Illinois Chicago, [9]California Institute of Technology

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ABSTRACT

Our work seeks to transform how new and emergent variants of pandemic causing viruses, specially SARS-CoV-2, are identified and classified. By adapting large language models (LLMs) for genomic data, we build genome-scale language models (GenSLMs) which can learn the evolutionary landscape of SARS-CoV-2 genomes. By pre-training on over 110 million prokaryotic gene sequences, and then finetuning a SARS-CoV-2 specific model on 1.5 million genomes, we show that GenSLM can accurately and rapidly identify variants of concern. Thus, to our knowledge, GenSLM represents one of the first whole genome scale foundation models which can generalize to other prediction tasks. We demonstrate the scaling of GenSLMs on both GPU-based supercomputers and AI-hardware accelerators, achieving over 1.54 zettaflops in training runs. We present initial scientific insights gleaned from examining GenSLMs in tracking the evolutionary dynamics of SARS-CoV-2, noting that its full potential on large biological data is yet to be realized.

KEYWORDS

SARS-CoV-2, COVID-19, HPC, AI, Large language models, whole genome analyses

ACM Reference Format:

2020. GenSLMs: Genome-scale language models reveal SARS-CoV-2 evolutionary dynamics. In *Supercomputing '22: International Conference for High Performance Computing, Networking, Storage, and Analysis.* ACM, New York, NY, USA, 13 pages. https://doi.org/finalDOI

1 JUSTIFICATION

We demonstrate achieving ~1.54 zettaflops in training one of the largest foundation models on whole genome sequences and applying it to characterize SARS-CoV-2 variants of concern. Our models will inform timely public health intervention strategies and downstream vaccine development for emerging viral variants.

2 PERFORMANCE ATTRIBUTES

2022 Gordon Bell Special Prize Winner

HPC Case Study – King Abdullah University of Science and Technology (KAUST) Breaks Record on Seismic Processing

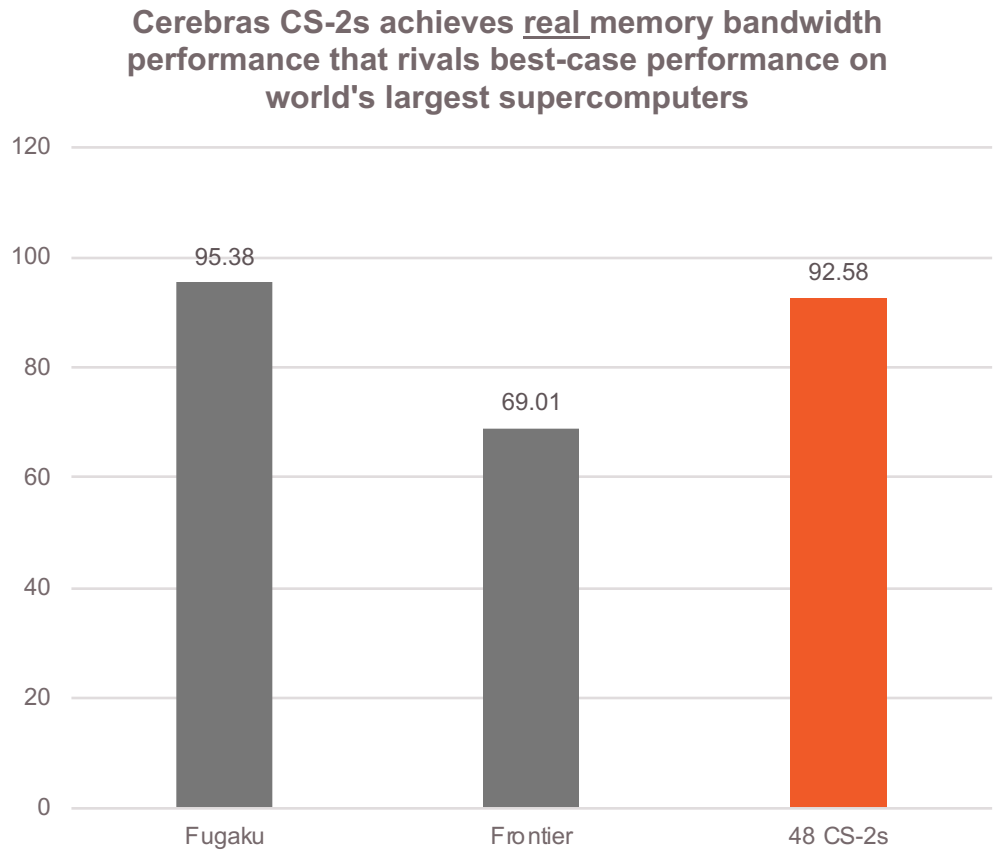
Collaborator: KAUST is a world-renowned university that was ranked as one of the fastest-rising universities for high-quality research output.

The Ask: Deliver improved performance on seismic processing workload by leveraging Cerebras System's unique architecture and massive on-chip memory.

Challenge: Seismic processing algorithms are typically memory-bound problems, limited by the memory access speeds of other architectures. Researchers were challenged to re-design an algorithm to take advantage of Cerebras hardware to improve performance.

What we did: Provided researchers with Cerebras SDK to re-design a Tile Low-Rank Matrix-Vector Multiplication (TLR-MVM) algorithm to be optimized for Cerebras CS-2. We also provided researchers with CG-1, our AI Supercomputer, to run this simulation.

Outcome: Achieved a record sustained memory bandwidth of 92.58 Petabytes per second (PB/s) through the implementation of a TLR-MVM kernel that is uniquely tailored to exploit the advanced architecture of Cerebras CS-2 systems.

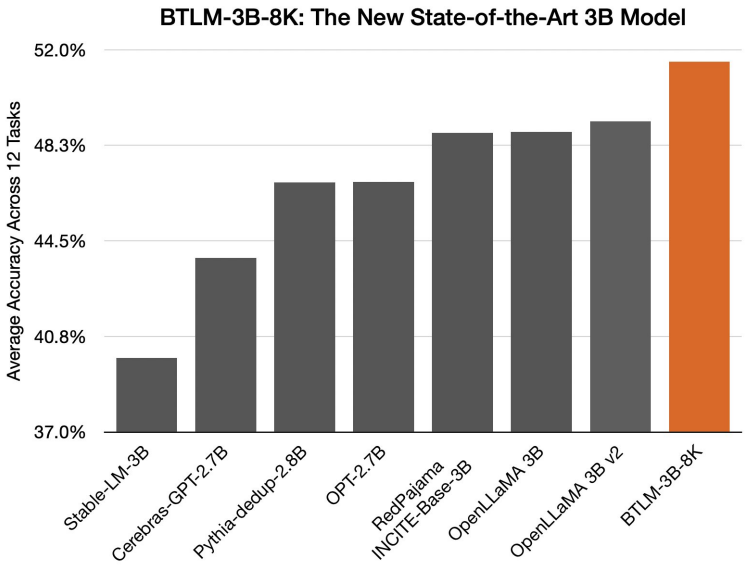


2023 Gordon Bell Prize Finalist

Cerebras Open-Source Models

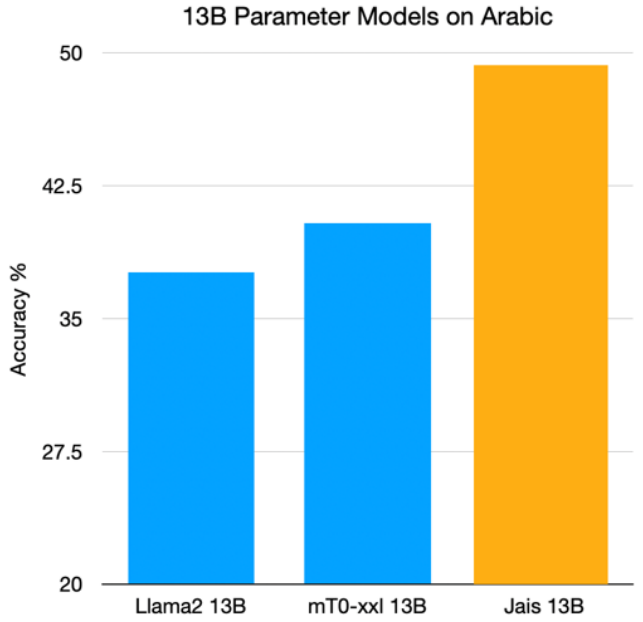
Cerebras-GPT

A family of open, compute efficient, large language models



BTLM-3B-8K

The state-of-the-art 3B open-source language model, in partnership with OpenTensor

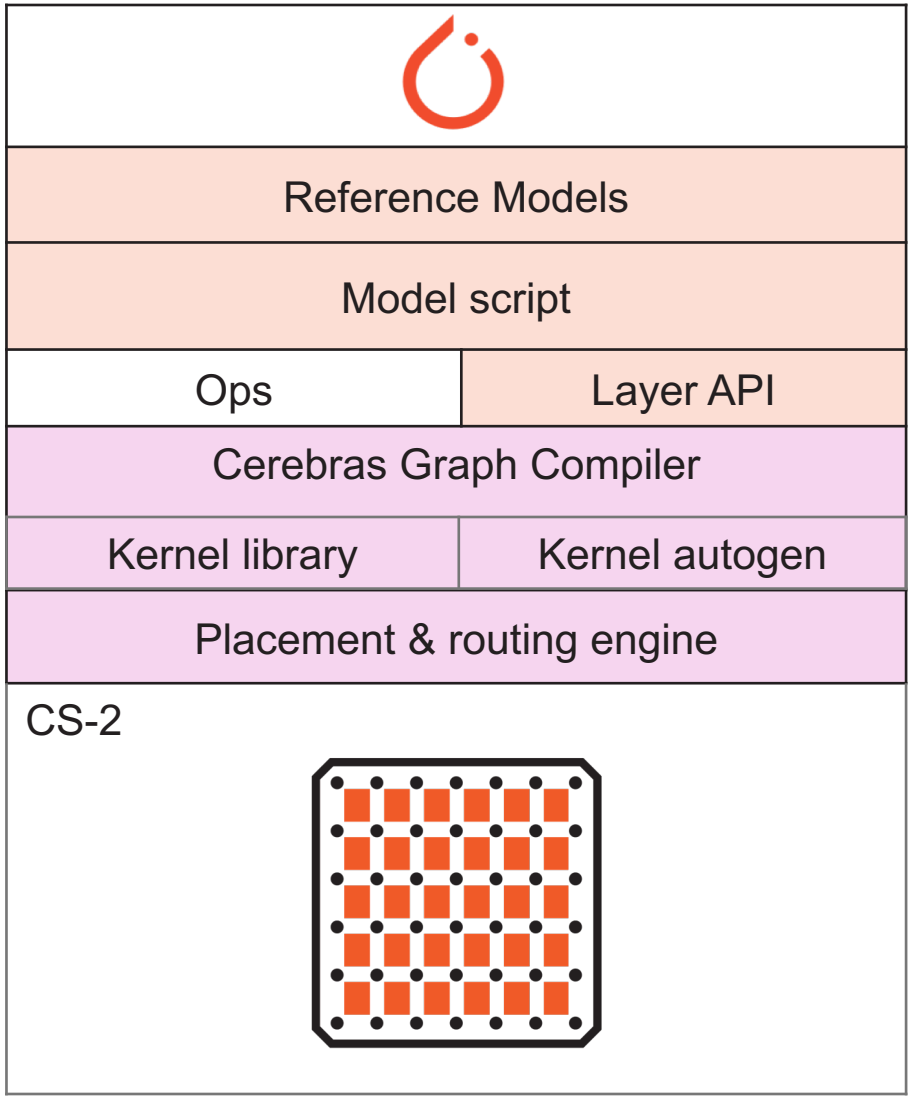


Jais

The World's Best Arabic-English Language Model, in partnership with G42

Develop in PyTorch, Execute on CS

- Dead-simple to run
- Program the same way as you would with a single GPU
- User does not worry about distributed compute or parallelism



Introducing: Cerebras Model Zoo Repository

github.com/Cerebras/modelzoo

As a **starting** point	Reference model implementations (PyTorch): GPT-2, GPT-3, GPT-J, BERT and much more Data preparation scripts Configurations for multiple model sizes
For **benchmarking**	Tuned implementations for optimal performance
To **develop** new models	Cerebras PyTorch APIs File organization as a template to start your own models

Typical Anatomy of a model in Model Zoo

run.py	Main script to execute train, eval in CS-2
configs/	Folder with different parametrizations of the model in .yaml files
model.py	Creation of the NN model function
utils.py	Helper functions to set up run.py
data.py	Helper functions to prepare data

github.com/Cerebras/modelzoo

Programming / training with the cluster is simple

Define the model

- Write in PyTorch
- Parameterize based on yaml file
- Write *logical* model for *single* device

Train the model

- Point to the model parameters
- Specify the number of CS-2s
- Specify the number of steps
- Run!

params_gpt3xl.yaml

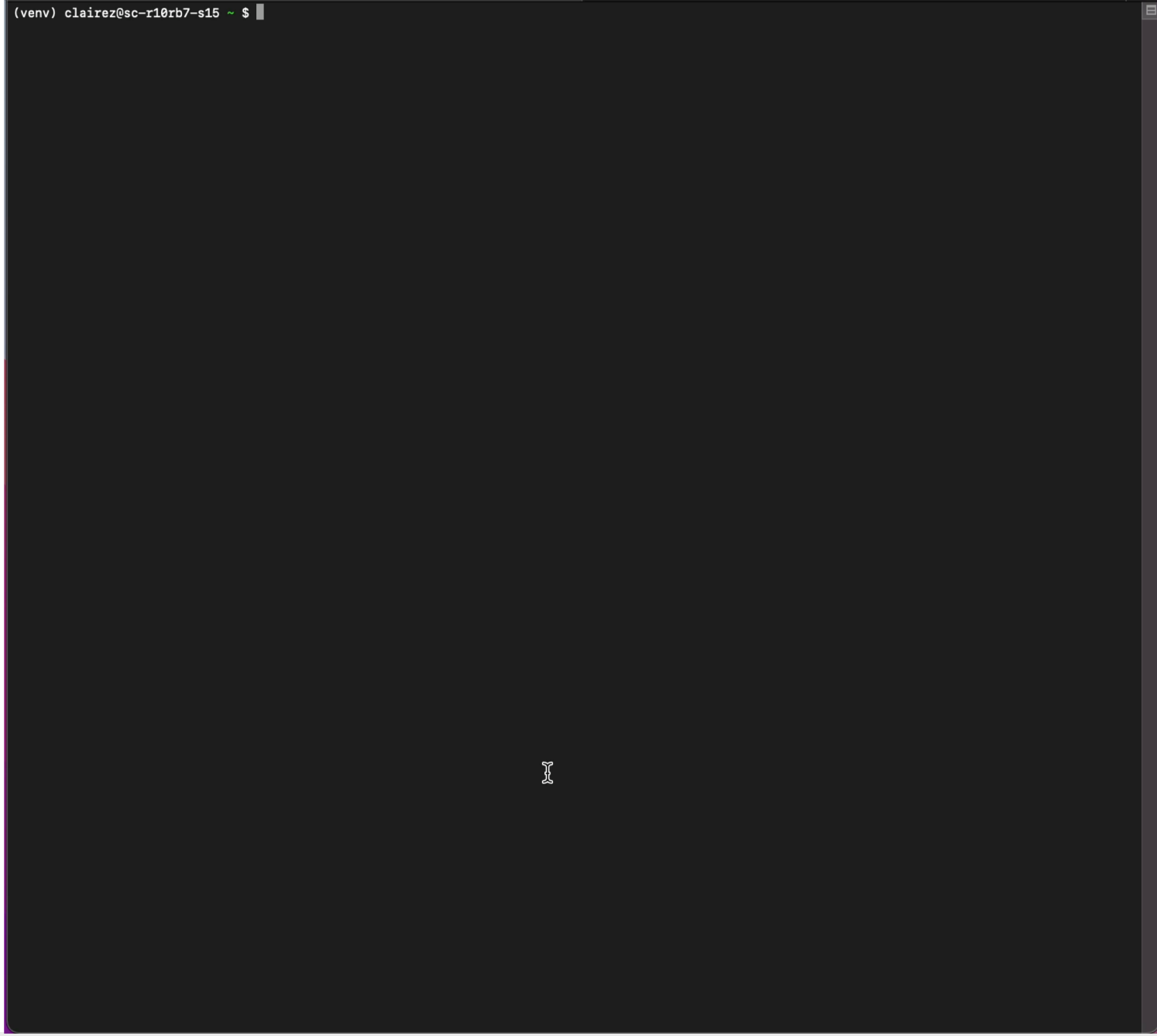
```
### GPT-3 XL 1.3B

hidden_size: 2048
num_hidden_layers: 24
num_heads: 16
```

training:

```
python run.py \
--params params_gpt3xl.yaml \
--num_csx 1 \
--num_steps 100 \
--model_dir model_dir \
--mode train
```

Demo

1.3B GPT Model Training on 1 CS-2

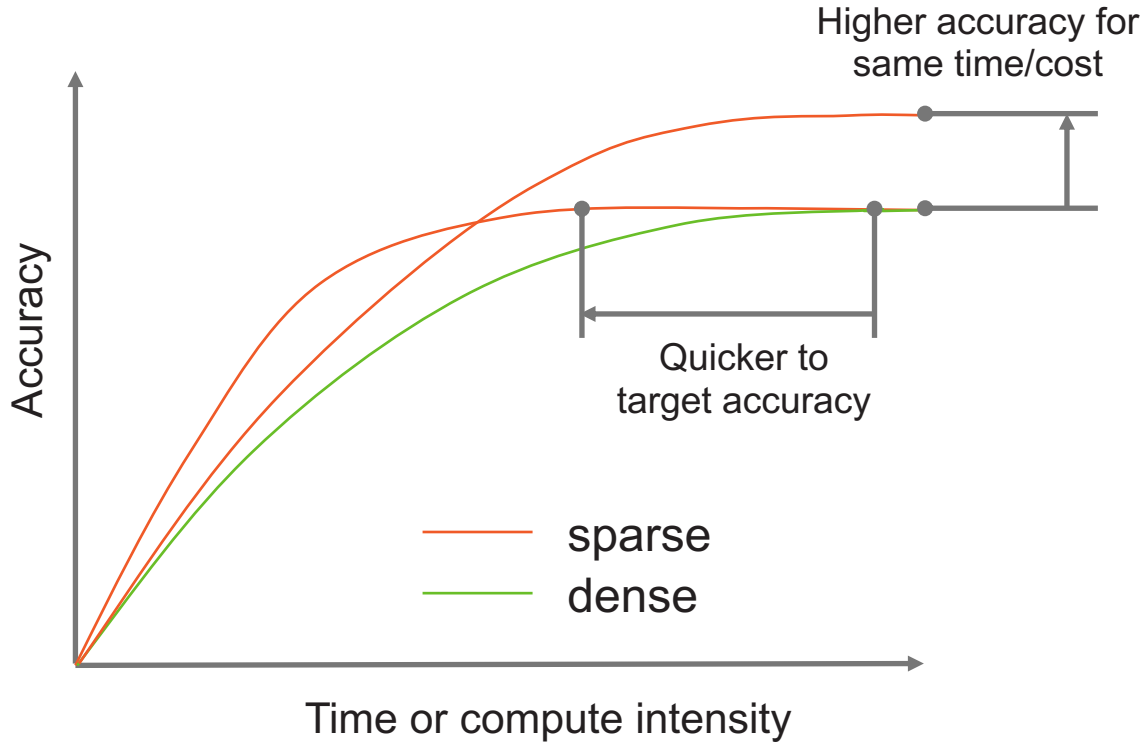


Sparsity Accelerated Training

- Unstructured sparsity acceleration opens up another dimension of advancement beyond improving model architecture
- Sparsity improves training efficiency:
  1. Same accuracy, less training effort
  2. Higher accuracy, same training effort
- The ideal method would achieve both!

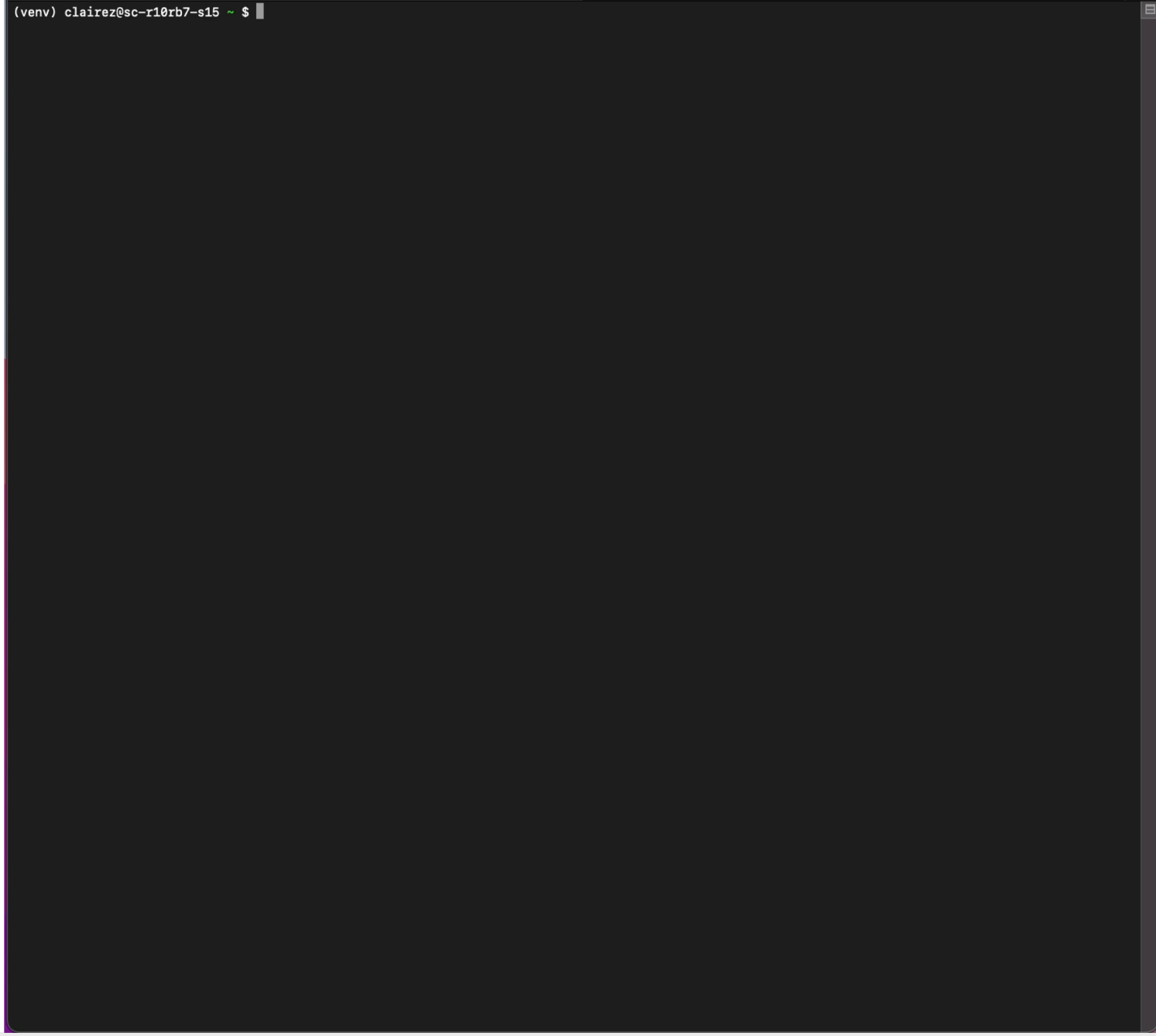
Puts control of compute performance into hands of ML practitioner

- This is an active research area in the ML community and at Cerebras



Demo

1.3B GPT with Sparsity Training on 1 CS-2

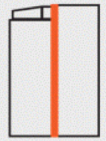


Scaling compute to more CS-2s is simple

Scaling compute

- Change the number of CS-2s
- Fully data-parallel training
- Run!

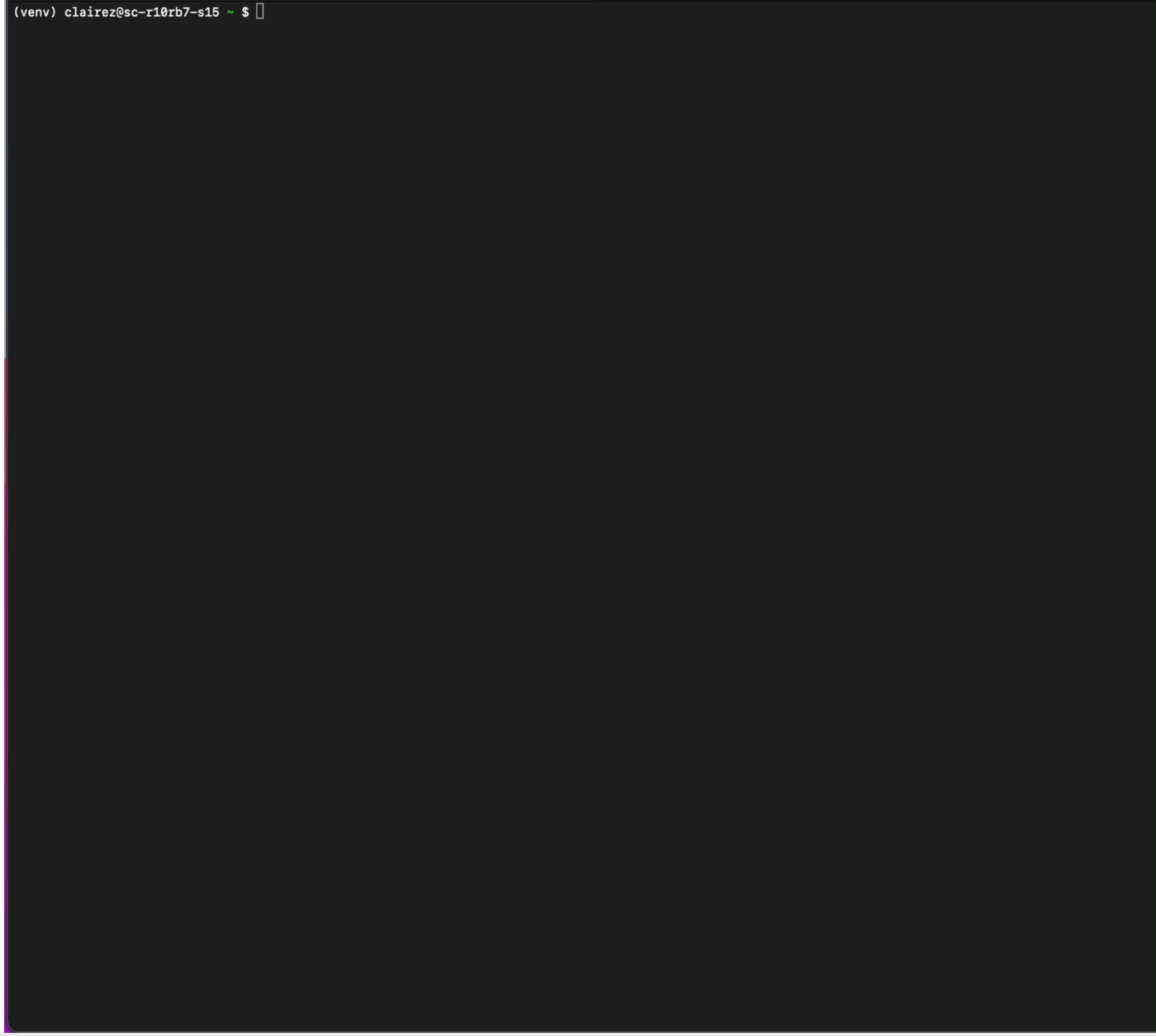
```
python run.py
--params params.yaml        <-- Where's your dataset?
--num_csx = 1               <-- How many nodes?
--model_dir = model_dir     <-- Where to store weights?
--num_steps = 1000          <-- How many training steps?
--mode=train                <-- Train, evaluate or infer?
```



cerebras

Demo

1.3B GPT Training on 16 CS-2s



Data Parallel Models Enables Near Linear Scaling

- Even the largest state-of-the-art models can train on a single CS-2
- Near-linear time to solution scaling across multiple CS-2s in a wafer-scale cluster

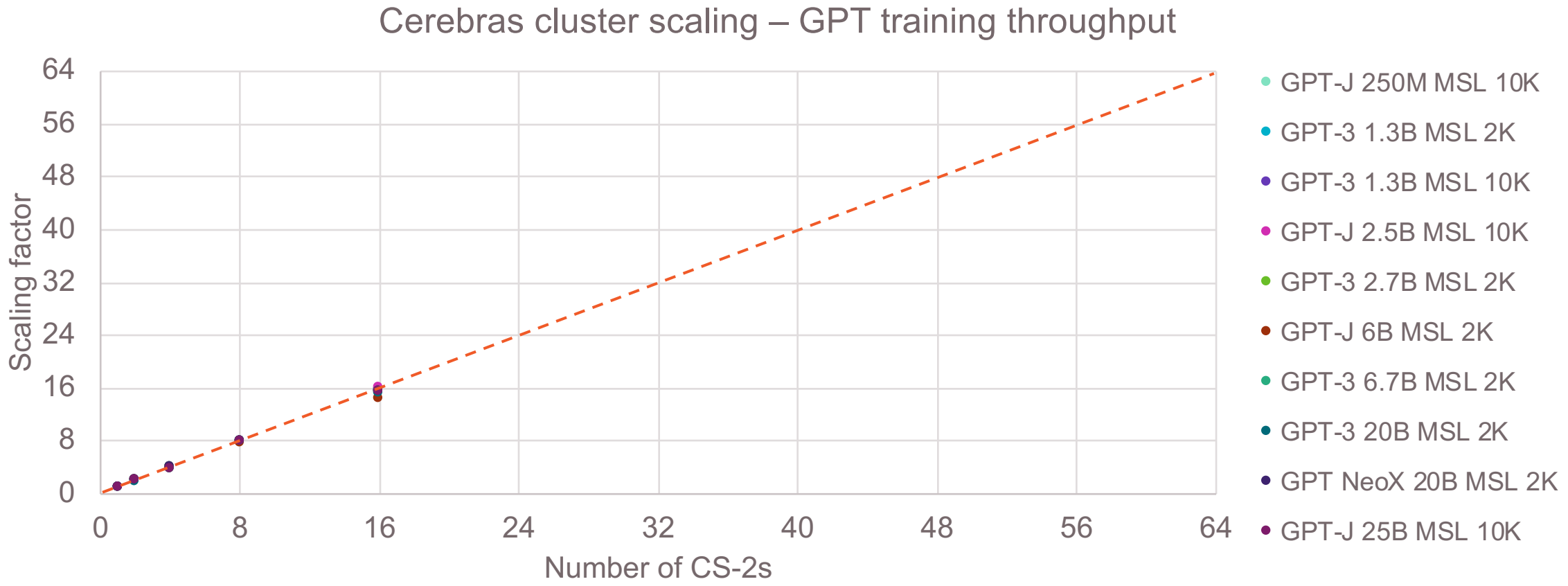


Figure. Measured training throughput scaling for 250M-20B GPT models over 1-16 CS-2 systems; projected scaling to 64 systems.

Scaling to larger models is simple

Scaling the model

- Change the model parameters in yaml
- Fully data-parallel training
- Run!

params_gptneox.yaml

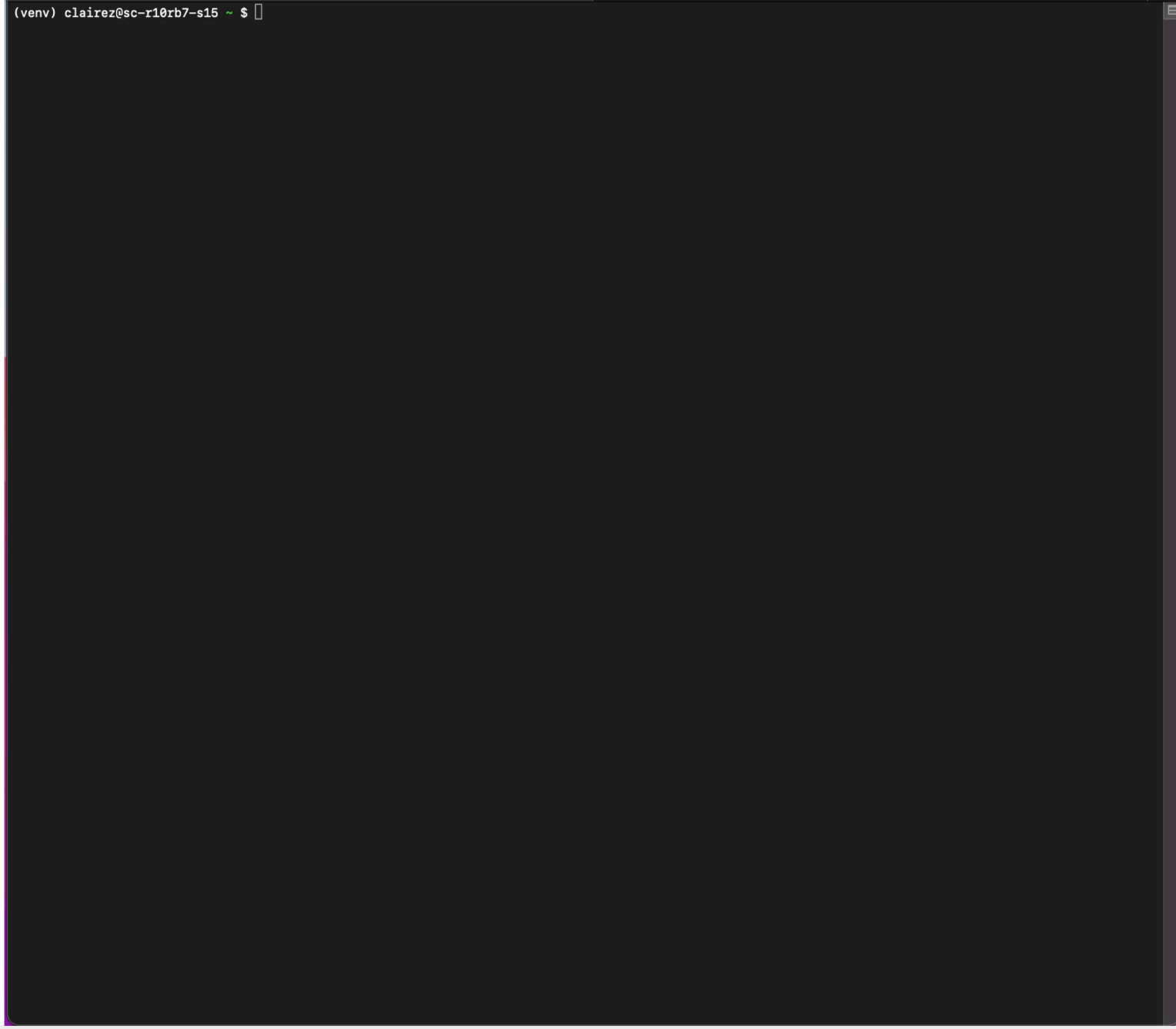
```
### GPT-NeoX 20B

hidden_size: 6144
num_hidden_layers: 44
num_heads: 64
```

training:

```
python run.py \
--params params_gptneox.yaml \
--num_csx 16 \
--num_steps 100 \
--model_dir model_dir \
--mode train
```

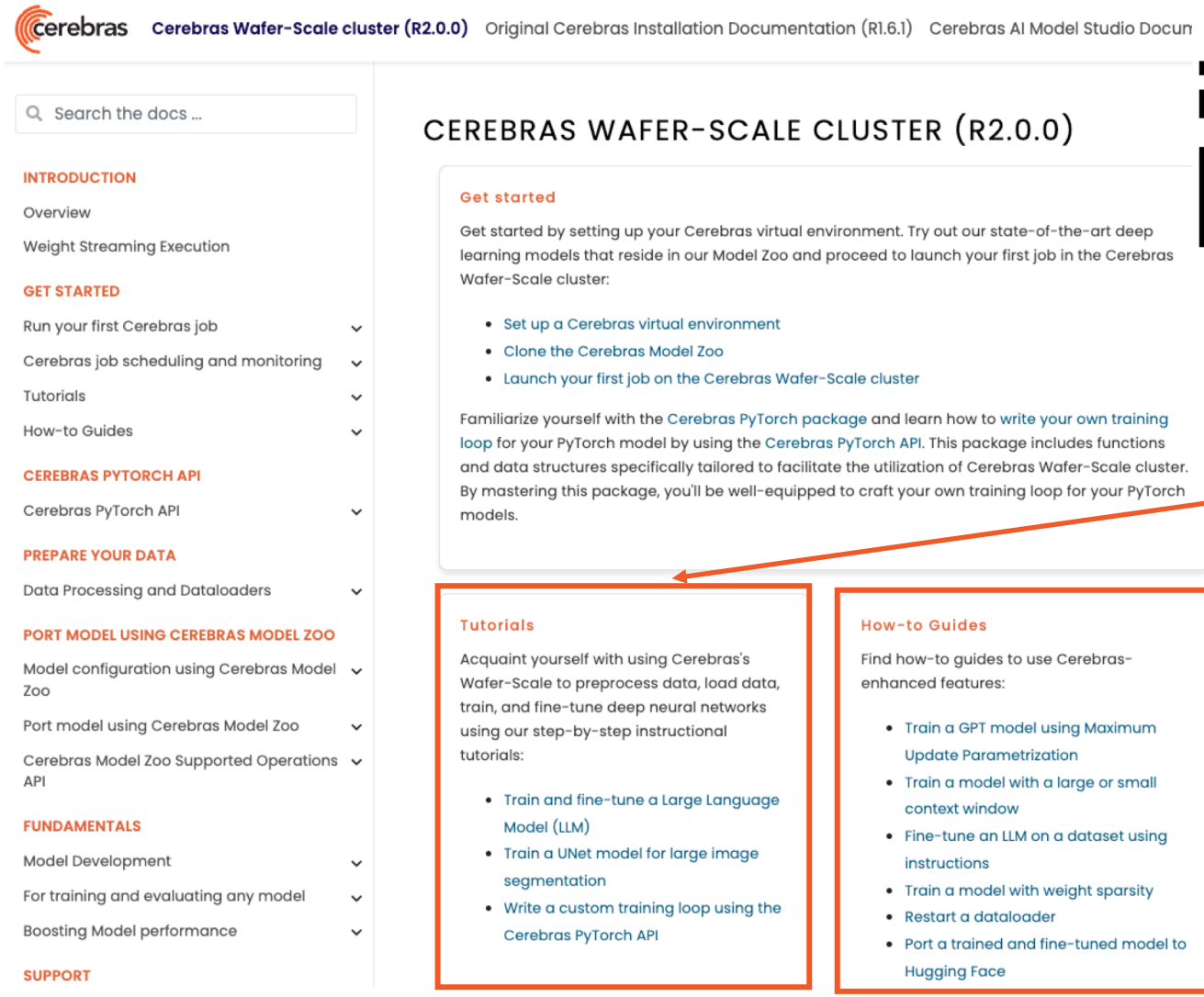
Demo

20B GPT NeoX Training on 16 CS-2s



Cerebras Documentation

docs.cerebras.net/



Using Cerebras for your entire training workflow

Comprehensive tutorials

Quick "how-to" walkthroughs

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- Sign up for our monthly newsletter at info.cerebras.net/subscribe
- Join our Discord at discord.gg/hZp5MUyw
- Join our Discourse at discourse.cerebras.net/
- LinkedIn - linkedin.com/company/cerebras-systems/
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Thank you