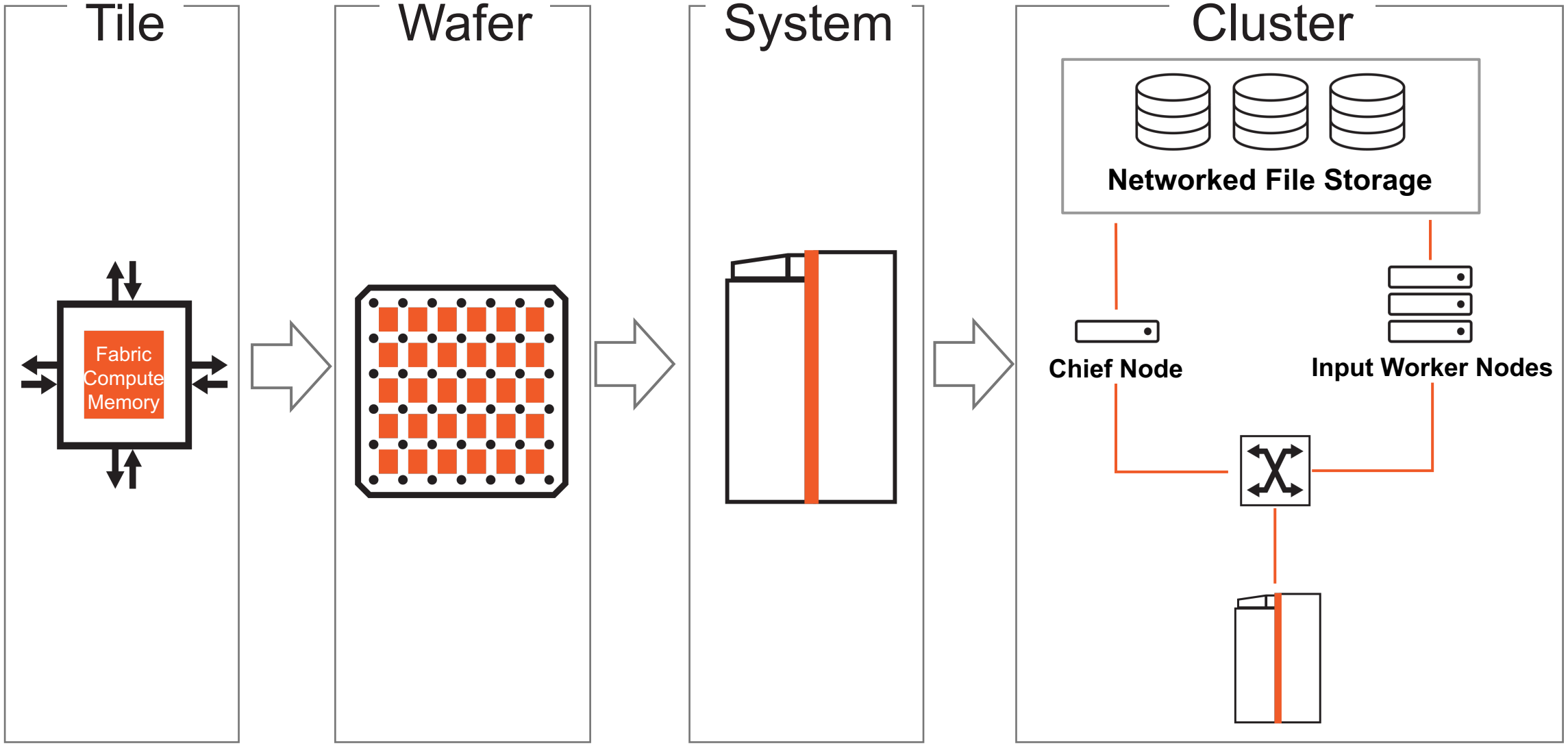
Cerebras CS-2: the AI Compute Engine for Neocortex

June 1, 2022

Outline

- CS-2 overview
- CS-2 for Deep Learning
  - PyTorch and TF integration
  - Reference implementations, docs, supported layers
  - Examples of successful DL projects
  - DL topics of interest
- CS-2 for HPC
  - Programming with the Software Development Kit (SDK) and Cerebras Software Language (CSL)
  - Examples of successful HPC projects
  - HPC topics of interest

CS-2 Overview



Cerebras Wafer Scale Engine (WSE-2)

The Most Powerful Processor for HPC & AI

850,000	cores optimized for sparse linear algebra
46,225 mm²	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

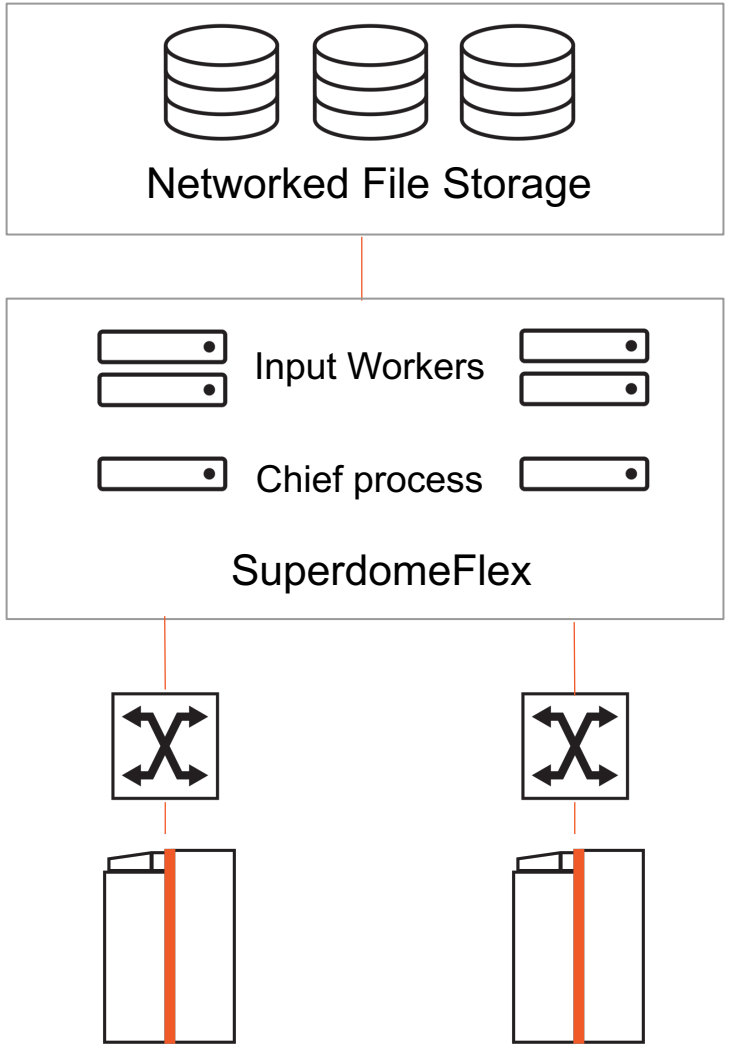
The world's fastest AI & HPC accelerator

- ✓ **Deploy easily into existing racks**
- ✓ **Cluster-scale in a single system**
- ✓ **Datacenter-scale in a cluster**

- 15 RU, standard data center rack
- 12 x 100 GbE IO
- Closed-Loop Water Cooling
- 28 kW max power

Deployment and job execution within Neocortex

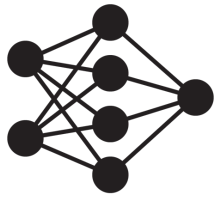
- CS-2 is a **network-attached accelerator**
- Cerebras SW runs on CS-2 and on the SuperdomeFlex
  - Chief compiles the code and manages CS-2
  - Input workers read data, run the input pipeline, and stream data to CS-2
- Loss output, summaries, checkpoints are streamed from CS-2 to SuperdomeFlex
- Jobs are managed by slurm



Developer Resources

For ML developers

Cerebras Implementations
(Public References and Private Model Zoo)



Cerebras ML Software

For kernel developers

Cerebras SDK

CS-2 for Deep Learning

Frameworks supported

TensorFlow

Class:

CerebrasEstimator

- Based on TF Estimator, takes over executions after XLA compilation
- TensorFlow 2.2

PyTorch

Python Module:

cerebras.framework.torch

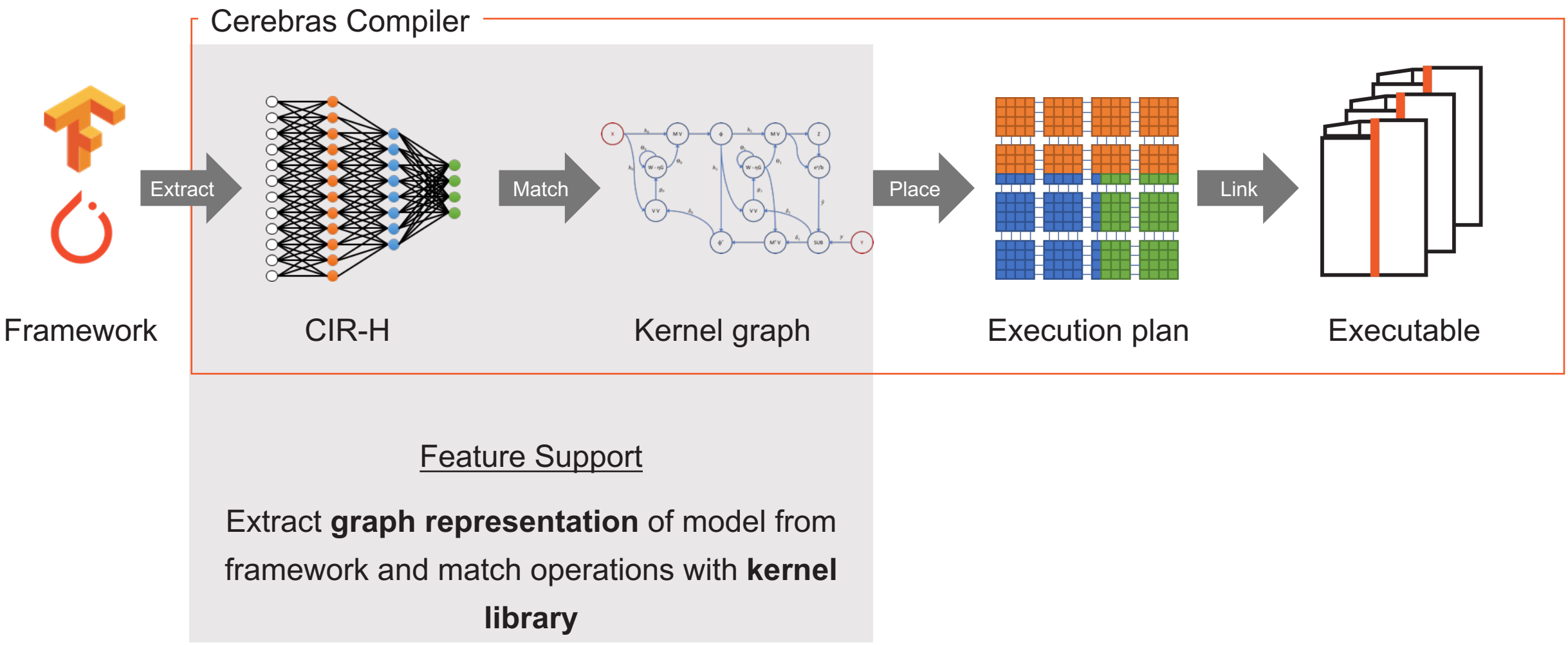
- Based on PyTorch XLA
- Wrappers for Dataloader, Module, Session
- PyTorch 1.11

How do we translate a model into a CS executable?

Framework

CS-2

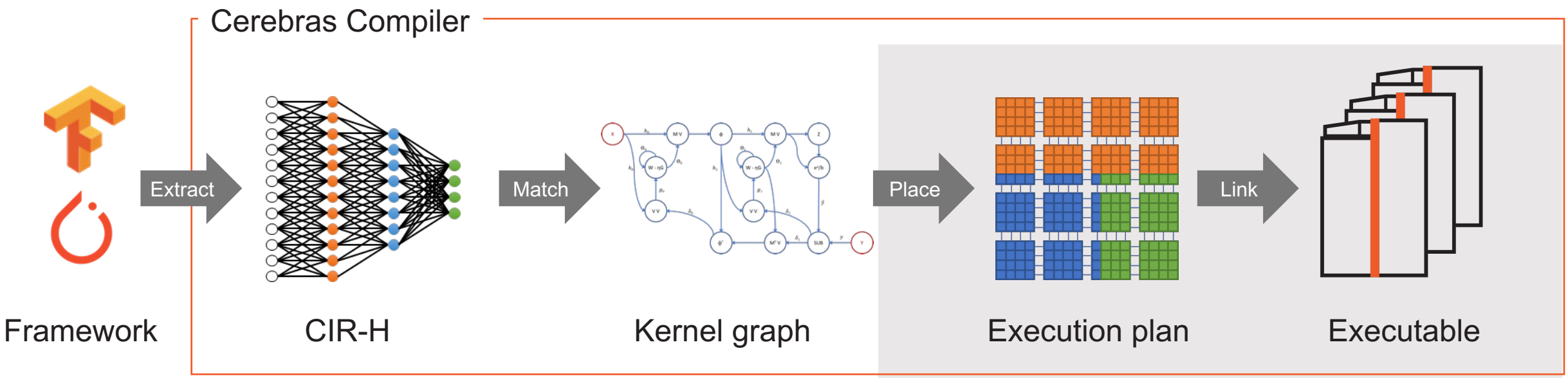
The Cerebras Software Platform



Feature Support

Extract **graph representation** of model from framework and match operations with **kernel library**

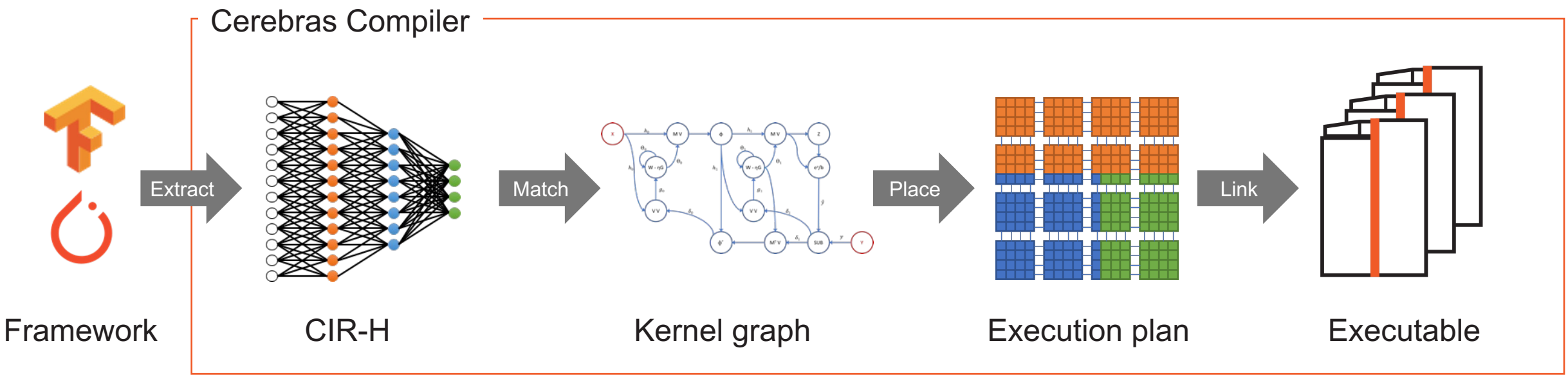
The Cerebras Software Platform



Hardware Placement

Assign kernels to **regions of fabric** and create **executable** to be run by CS-2.

The Cerebras Software Platform



Program a cluster-scale resource with the ease of a single node

ML Software Key Features

Network Architectures

- Transformers (TF and PyT)
  - E.g., BERT, RoBERTa, AIAYN, T5, GPT
- Multi-layer Perceptrons (MLP) (TF and PyT)
- Experimental (in Beta, TF only)
  - Recurrent Neural Networks (LSTMs)
  - Graph Neural Networks (GNN's)
  - Convolutional Variational Autoencoders
  - UNet

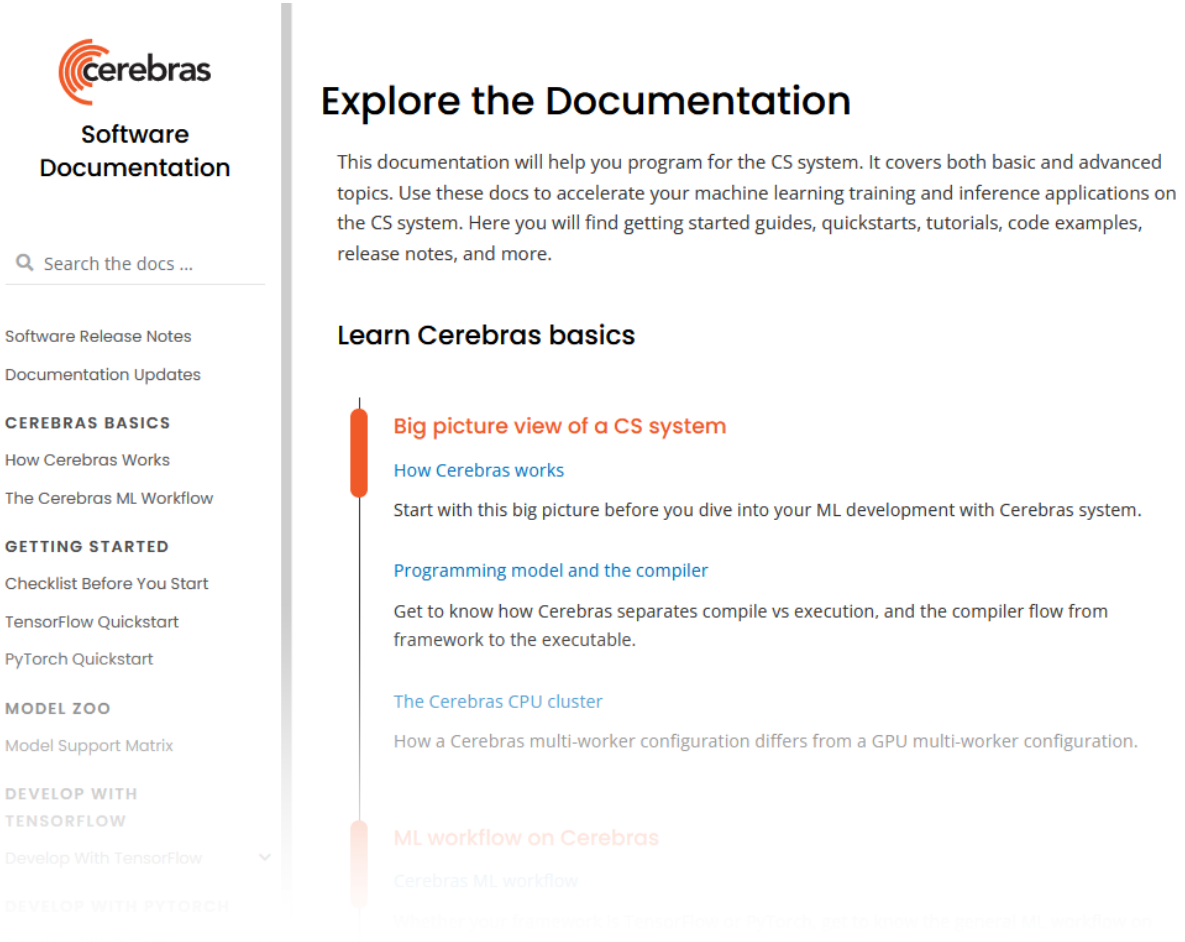
General features

- Supports Train, Eval and Predict
- Trained weights in standard TF and PyT formats
- Monitor your runs with TensorBoard
- Automatic input pipeline optimization
- Automatic kernel generation for non-linears and losses
  - E.g., SeLU, Softmax Cross Entropy, etc.
- Multi-replica support for smaller models

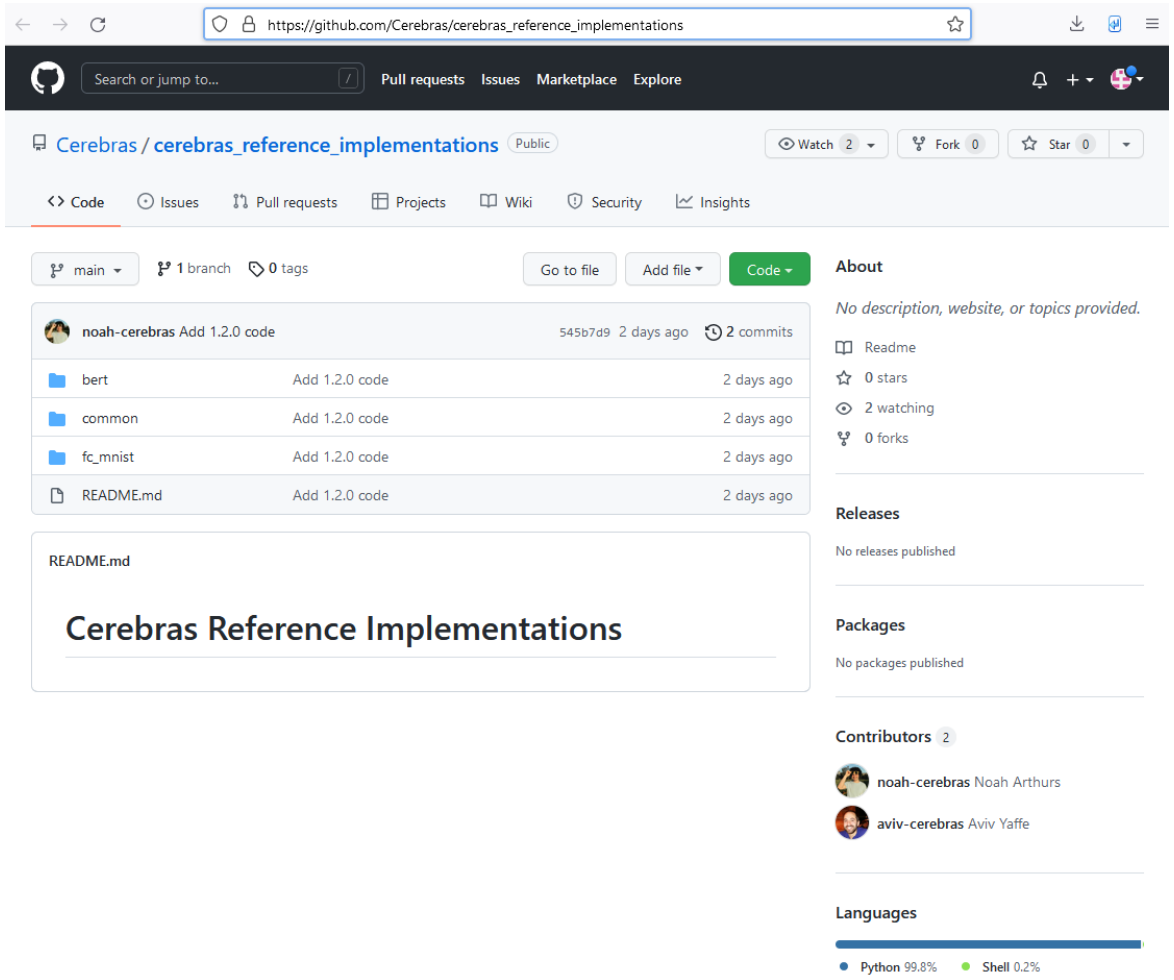
Poll: What types of models are you working with?

Resources

Documentation : docs.cerebras.net



Cerebras Reference Implementations

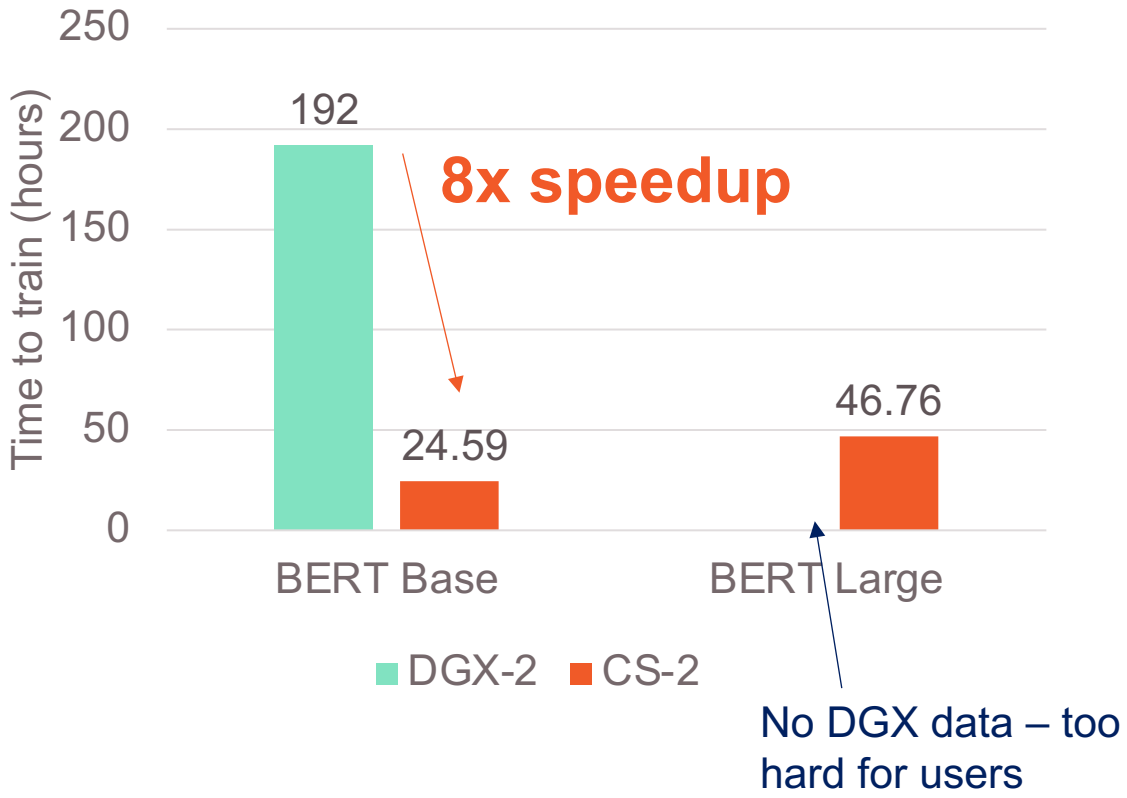


BERT on PubMed

Objective:
Retrain BERT Base and train BERT Large from scratch on PubMed abstracts + PMC full texts
13.9B words: **4.2x larger than BERT dataset**

Target:
Converge to published accuracy
(Eval metrics after pre-training and accuracy on BLURB NER and BioASQ after fine-tuning)

Challenge:
Very long time-to-train
Difficult for team to iterate
High complexity involved with building larger GPU cluster



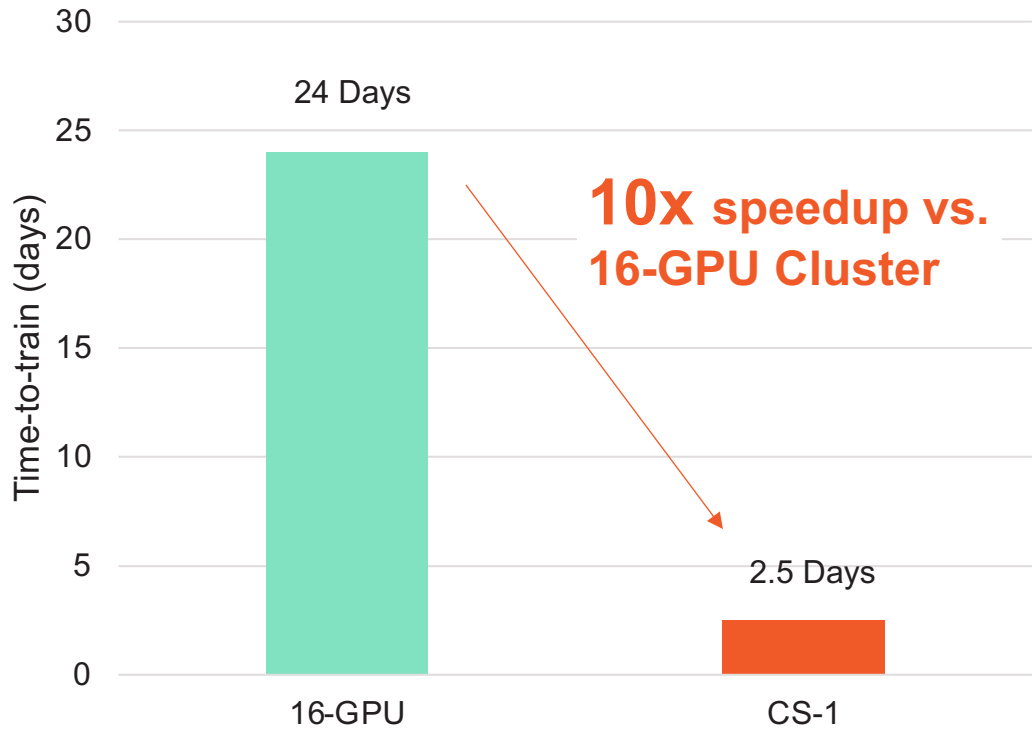
DGX scaling is sublinear. Requires > 10 systems to achieve 8x acceleration.
~4x faster to train Bert LARGE on CS-2 than Bert BASE on DGX.

Epigenomic Language Model Developed by GSK

Objective: Accelerate genetic validation of drug targets using novel technique that includes epigenomic data in NLP models, rather than genome-only models

Challenge: Training this complex model with massive datasets would take several weeks on a 16-GPU cluster, making rapid experimentation impractical

Outcome: ~10X training speedup empowered researchers to experiment with epigenomic data and demonstrate superior results to DNA-only datasets



"The training speedup afforded by the Cerebras system enabled us to explore architecture variations in a way that would have been prohibitively time and resource intensive on a typical GPU cluster"

"Epigenomic Language Models Powered by Cerebras", Dec 2021. arxiv.org/abs/2112.07571

BERT on Pfam for TAPE

Task:
Explore semi-supervised NLP models to learn representations for proteins, evaluate with Tasks Assessing Protein Embeddings (TAPE)

Target:
Converge to published accuracy on downstream tasks

Challenge:
Very long time-to-train
Difficult for team to iterate
High complexity involved with building larger GPU cluster

Outcome:
CS-1 reduced training time to from a week to less than a day
The system enables dramatic acceleration in experimentation pace

Poll: What are the typical model sizes you work with?

Topics of interest for ML applications

- Domain-specific large-scale transformer-style language models
- Transfer learning with large-scale transformer-style language models
- Multilingual models, machine translation
- Learning representations for DNA and RNA sequences, proteins
- Training extreme-scale language models with sparse weights
- Training transformer-style models with long sequences
- Scaling laws, efficient training regimes for transformer models
- Image segmentation with high-resolution images

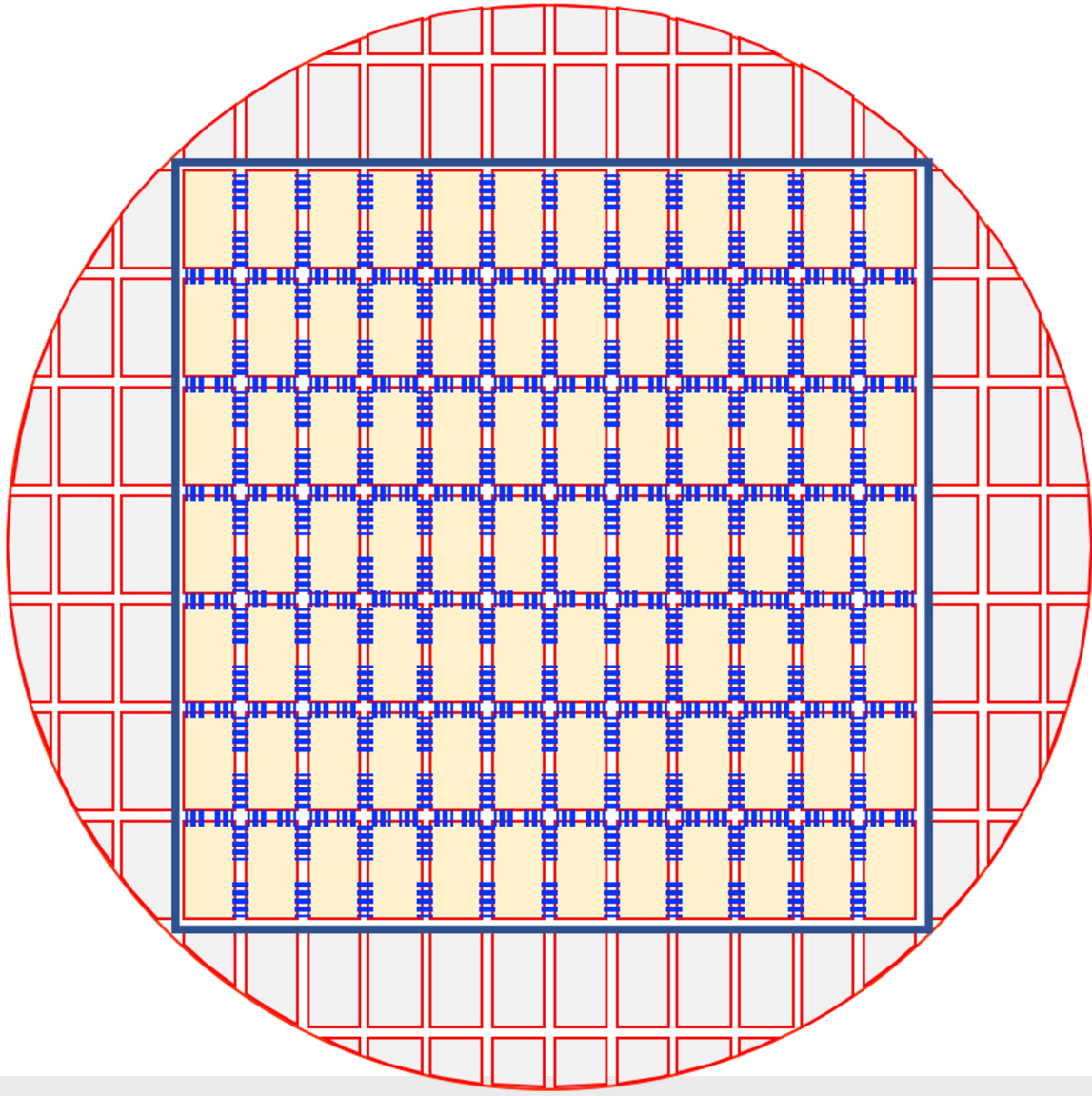
CS-2 for HPC

Does your application scale poorly across nodes?

Examples: *FFT-based solvers, particle simulators, non-linear problems with iterative solvers*

The Cerebras solution:

- The WSE-2 has a fabric that is **high bandwidth** and **low-latency**, allowing for excellent parallel efficiency for non-linear and highly communicative codes
- The CS-2 system has **850k cores** and can fit problems on an individual chip that take tens to hundreds of traditional small compute nodes.
  - Each core is individually programmable



Is your application constrained by data access?

Examples: *Stencil based PDE solvers, linear algebra solvers, signal processing, sparse tensor math, big data analysis*

The Cerebras solution:

- The CS-2 system has **40 GB of SRAM** uniformly distributed across the wafer that is **1 cycle** away from the processing element
  - Speeds up memory access by orders of magnitude
- The CS-2 system is capable of **1.2 Tb/s bandwidth** onto the chip
  - Stream data onto the chip as required

Poll: What type of HPC algorithms do you use?

Cerebras SDK

Language

CSL: Cerebras Software Language

Host APIs with Python

Libraries

Optimized primitives

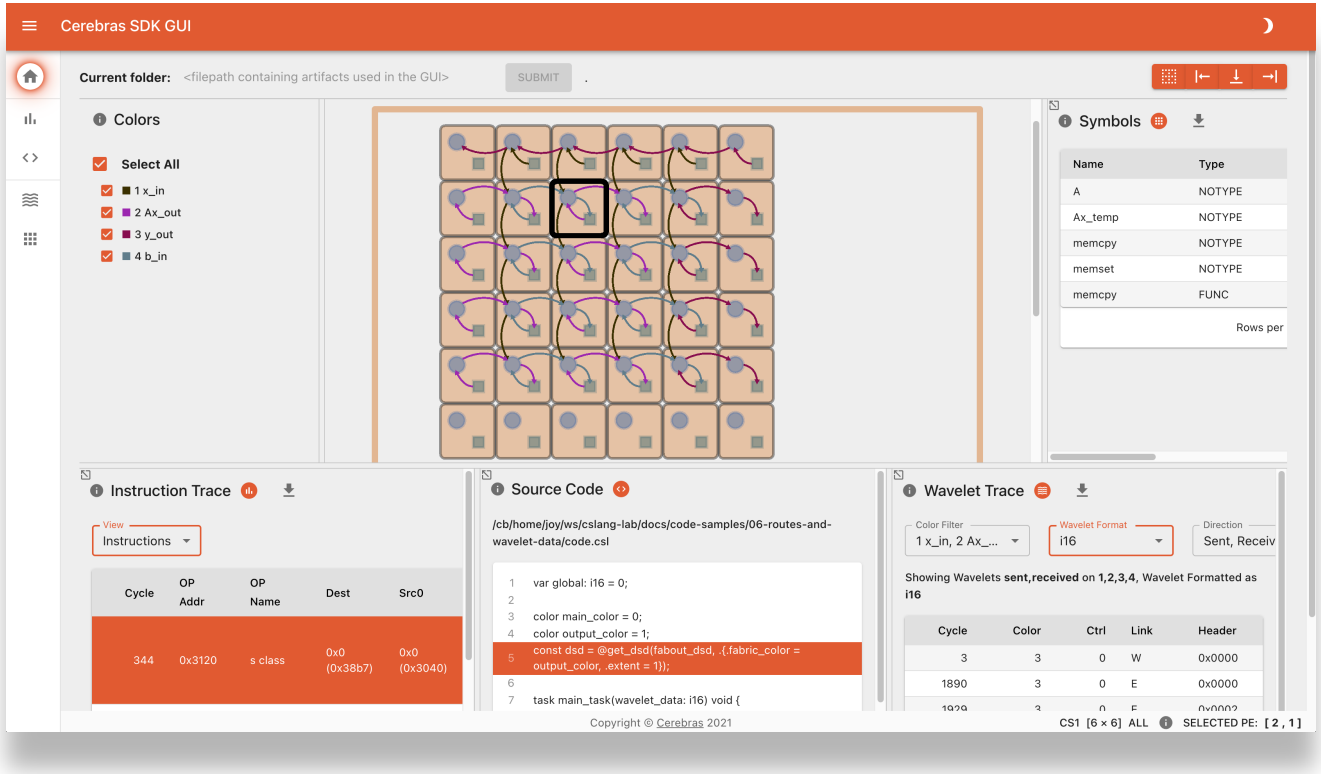
Tools

Simulator

Debugger

Performance profiler

Visualization



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

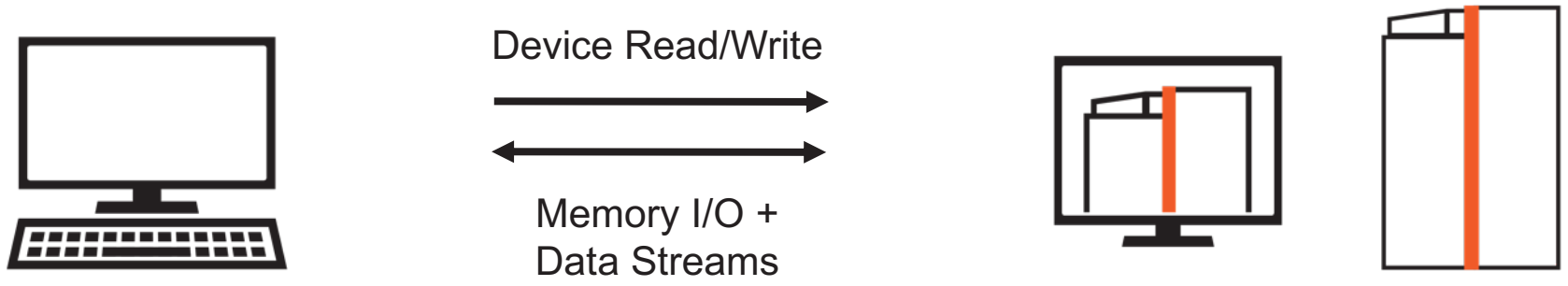
From a Programmer's Perspective

Host CPU(s): Python

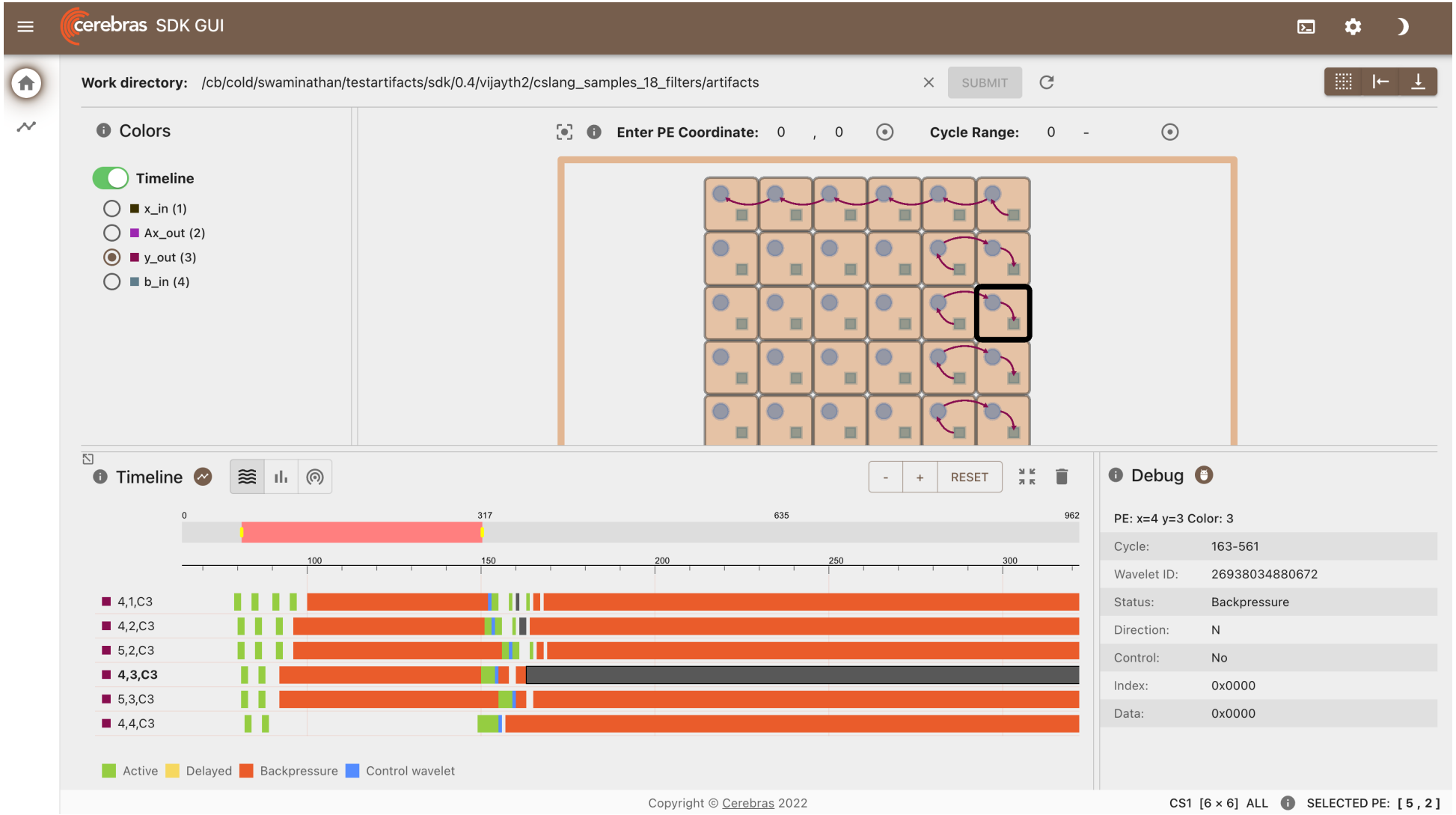
- Loads program onto simulator or CS-2 system
- Streams in/out data from one or more workers
- Reads/writes device memory

Device: CSL

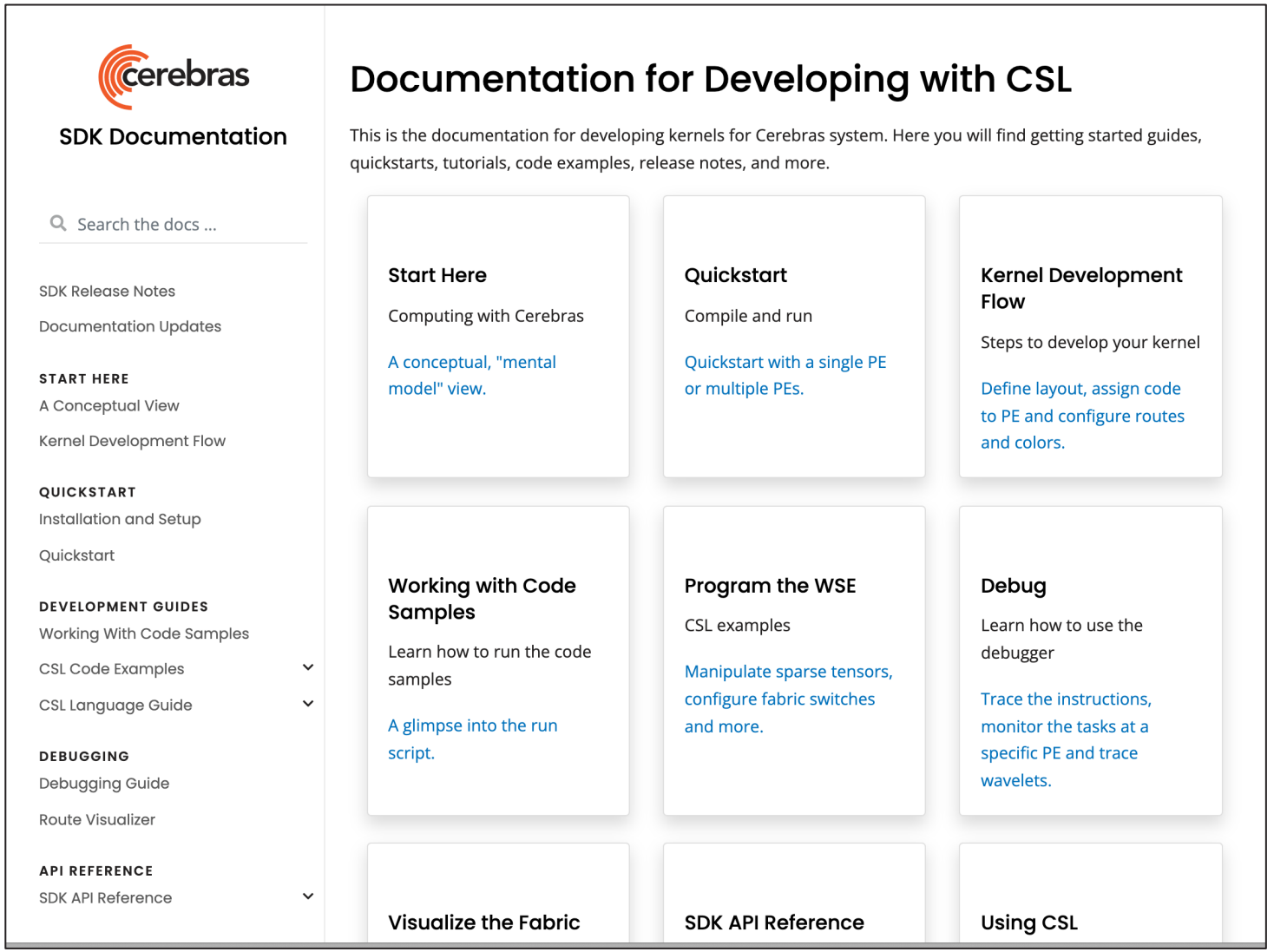
- Target software simulator or CS-2
- CSL programs run on groups of cores on the WSE, specified by programmer
- Executes dataflow programs



Simulation Debug Tools



Private Documentation: sdk.cerebras.net



Examples Included in the SDK

- Basic tasks and colors
- Multiple source files
- Multi-PE kernel
- Basic parameters
- Wavelet-triggered Tasks
- Arrays and Pointers
- Sparse Tensors
- Memory DSDs
- Fabric DSDs
- Reduction
- Basic Branches
- Initializers
- Modules
- Loops
- Kernel Parameterization
- Fabric Switches
- GEMV
- FFT
- Stencil (Finite Differences)
- Shift-Add Multiply

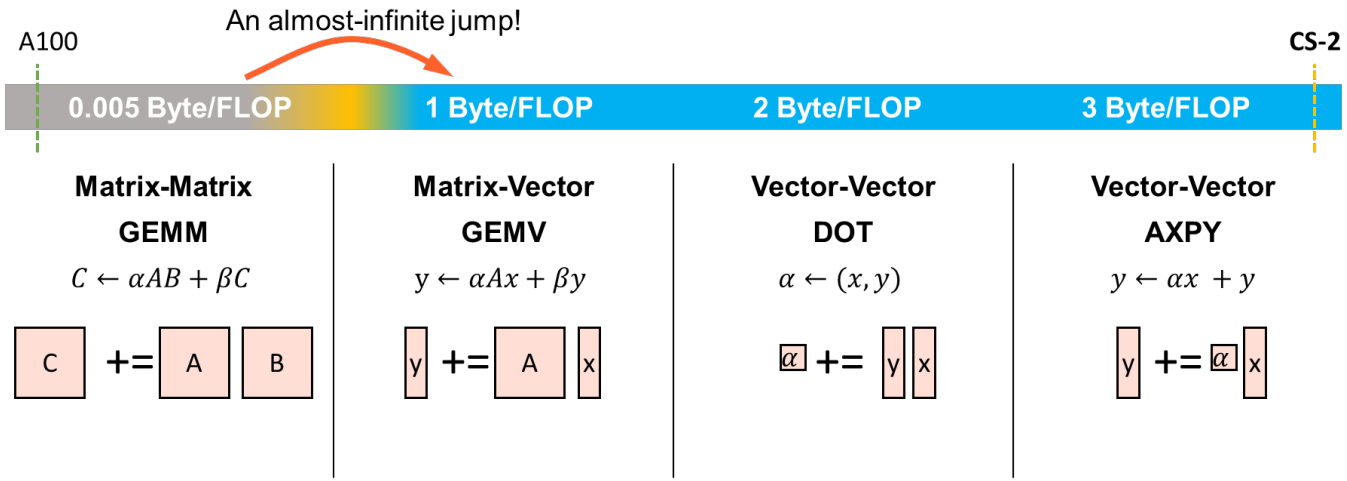
Poll: What hardware do you use today for your HPC work?

National Energy Technology Laboratory

Towards Real-Time CFD

Cerebras system solves sparse linear equations 200X faster than Joule 2.0 supercomputer[1]

Sparse GEMM performance enabled by massive memory bandwidth



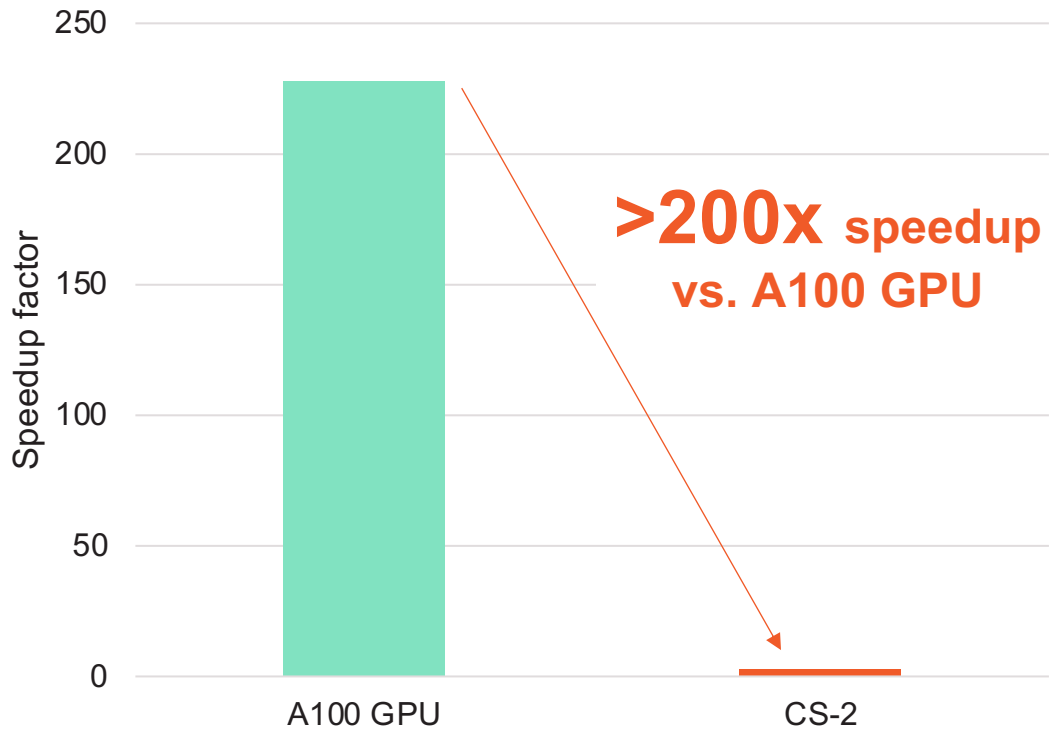
1. Rocki et al., “Fast Stencil-Code Computation on a Wafer-Scale Processor” SC20. arxiv.org/abs/2010.03660

Accelerated energy research at TotalEnergies

Objective: Enable order-of-magnitude speedups on a wide range of simulations: batteries, biofuels, wind flows, drillings, and CO2 storage

Challenge: Participate in Total study to evaluate hardware architectures, using finite difference seismic modelling code as a benchmark

Outcome: Cerebras CS-2 system outperformed a A100 AI GPU by >200X using code written in the Cerebras Software Language (CSL). System now installed and running at customer facility in Houston, TX



"We count on the CS-2 system to boost our multi-energy research and give our research 'athletes' that extra competitive advantage."

Dr. Vincent Saubestre, CEO and President, TotalEnergies Research & Technology USA

TotalEnergies

Mathias Jacquelin, Mauricio Araya-Polo, Jie Meng, "Massively Scalable Stencil Algorithm" Submitted to SuperComputing 2022, https://arxiv.org/abs/2204.03775

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Topics of interest for HPC applications

- Structured grid based PDE and ODE solvers
- Dense linear algebra
- Sparse linear algebra
- Spectral analyses for streaming data
- Particle methods with regular communication
- Monte Carlo type problems that can fill the wafer

In conclusion

- CS-2 is a dense and powerful single system, powered by 1 enormous chip
  - Cluster-scale compute on a single device => good fit for large DL models
  - 40GB SRAM with massive memory bandwidth => good fit for sparse problems
- CS-2 for Deep Learning
  - Via integration with TensorFlow and PyTorch
  - No low-level programming required
  - Cerebras Software takes care of distributing computations across 850,000 cores
- CS-2 for HPC
  - Via SDK and CSL
  - Users decide how to distribute the computations
- Faster experiments = more ideas tested!

Thank you! Questions?

https://cerebras.net/