

AI and ML at Capital One

Leveraging standardized cloud platforms for data management, model development, and operationalization, we use AI and ML to look out for our customers' financial well-being, help them become more financially empowered, and better manage their spending.



LEARN MORE

AI RESEARCH PRIORITIES Anomaly Detection Natural Language Processing Behavior Models Deep Learning for Event Prediction Foundation Models Privacy & Accessibility Graph Networks Large Language Models



MatX: high throughput chips for LLMs

Reiner Pope, cofounder and CEO

MatX focuses on:

maximizing **performance/\$** on **large models**

MatX does not focus on:

small models small deployments

This saves a lot of silicon!

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ML/HW codesign



ML research is critical to the company:

- numerics
- memory bandwidth
- ...

Great research needs a great codebase:

• matx.com/seqax

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matx.com/jobs

Meet the team **Tuesday, May 14th from 5-8pm** at the Hyatt for drinks and food!

Visit <u>matx.com/meetmatx</u> to register and get more information

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Transforming Generative Al from Unsustainable to Attainable

Sree Ganesan Vice President of Product, d-matrix.ai

• d-Matrix

Unique Challenges of Generative Inference



Models are large (billions of parameters) and context lengths are growing

→ Requires *more* memory capacity and *more* compute capacity

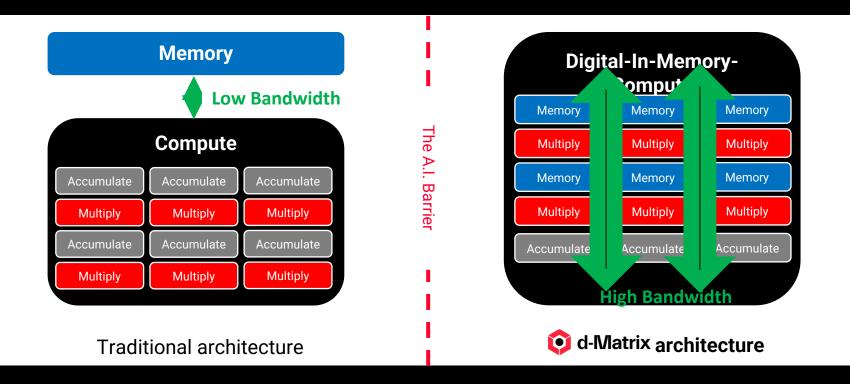
Prompt processing is compute bound & token generation is memory bound
 Requires high memory bandwidth and high peak compute capability

These exacerbate the pain points of cost, power and performance

The d-matrix inference solution is built from the ground-up to accelerate generative inference



A New Computing Paradigm is Needed



The d-Matrix Advantage



Attainable

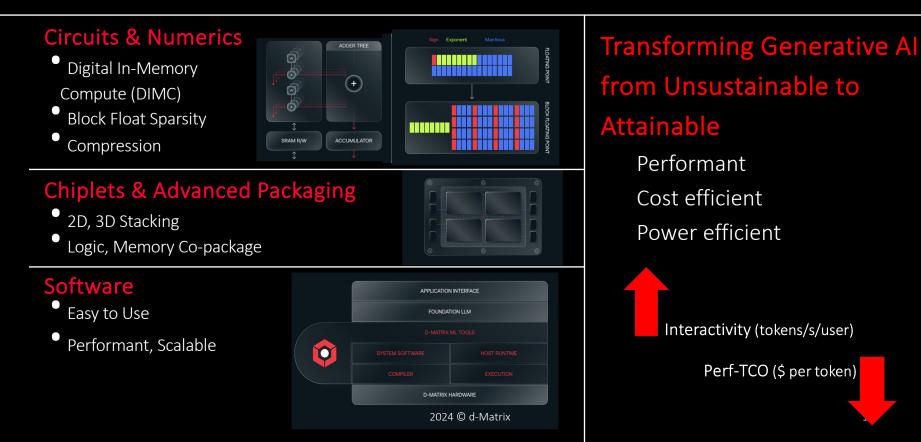
Performant

Cost efficient

Power efficient

Interactivity (tokens/s/user)

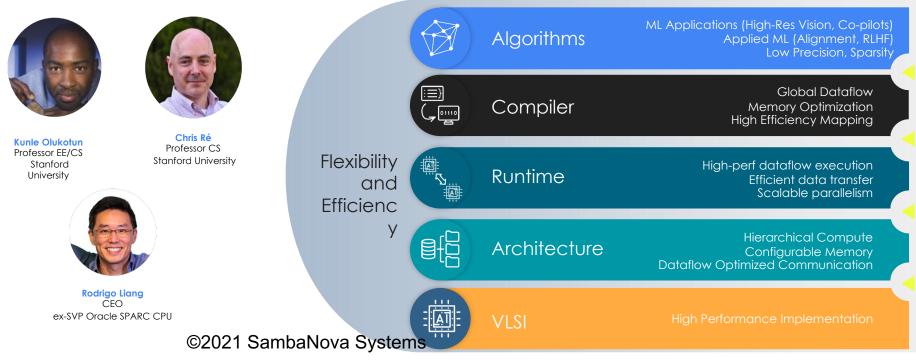
Perf-TCO (\$ per token)



SambaNova Systems Overview

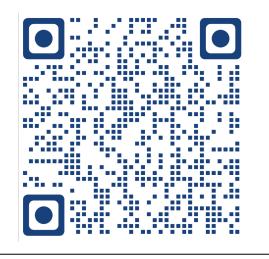
Full stack co-engineering yields optimizations where best delivered with the highest impact

Reconfigurable Dataflow Architecture (RDA)



Resources

Developer Website and Past Publications



VB VentureBeat

SambaNova announces new AI Samba-CoE v0.2 that already beats Databricks DBRX

SiliconANGLE

SambaNova debuts 'composition of experts' AI model with 1T+ parameters

MarkTechPost

This AI Paper from SambaNova Presents a Machine Learning Method to Adapt Pretrained LLMs to New Languages

The rapid advancement of large language models has ushered in a new era of natural language processing capabilities.

SambaNova

https://sambanova.ai > blog > using-mixed-precision-on-...

Using Mixed Precision on RDUs

Job Opportunities

- Computer Vision
- Large Language Models (LLMs)
- Multimodality
- Compiler
- System Software
- Computer Architecture
- Physical Design / VLSI





Databricks Mosaic Research: MLSys 2024

Abhi Venigalla, NLP Architect

Databricks Mosaic Research

- Help orgs build+serve custom AI models ...
- ... Using their own unique data ...
- ... As efficiently as possible.



- What do we need? Reusable tools, infrastructure, recipes.
 - DBRX: <u>https://huggingface.co/databricks/dbrx-instruct</u>
 - Composer: <u>https://github.com/mosaicml/composer</u>
 - Megablocks: <u>https://github.com/databricks/megablocks</u>
 - StreamingDataset: <u>https://github.com/mosaicml/streaming</u>
 - Lilac: <u>https://www.lilacml.com/</u>



• Why open-source software/models? Feedback, testing, trust, ownership.

Research -> Production Idea #1: Hardware is changing rapidly, check assumptions!

- What networking bandwidths / block sizes are available in the cloud today?
 - H100: 3200 Gbps/Node, in blocks of 2k+ GPUs
- How much memory, memBW is there?
 - 8xH100: 640 GB HBM
 - 8xB100, 8xMI300X: 1.5 TB HBM
 - 72xB2OO (NVL72): 13.5 TB HBM, + another 17 TB LPDDR5X
- What data types are being hardware accelerated?
 - **Today:** BF16, FP8
 - Soon: BF16, FP8, MXFP4
- If you see an excess of a quantity (FLOPs/BW/compute/memory), can you modify the workload to take advantage of that excess to deliver better quality/latency/something else?





Research -> Production Idea #2: Work together with scaling laws

- Show that an idea scales well at small budgets (0.01 -> 0.1 -> 1)
- To convince folks that it will work at larger budgets (1 -> 10 -> 100)
- Might require new metrics continuous rather than discrete scores
- Also: good tools/models/simulators are useful at every scale
 - Personal request: Please build an LLM online inference simulator!!

- E.g. many-shot ICL, why didn't we catch this sooner? 1 -> 10 -> 100 -> (today) 1000 shot
 - In-Context Learning with Long-Context Models: An In-Depth Exploration: https://arxiv.org/pdf/2405.00200

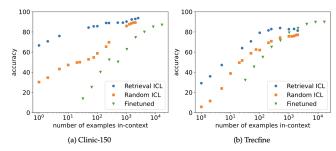


Figure 2: Comparing retrieval ICL, random selection ICL, and finetuning on two representative datasets. Finetuning sometimes, but not always, exceeds ICL at high numbers of demonstrations. Note that, while retrieval ICL uses the listed number of examples in context, it assumes access to the larger test set to draw examples from (Perez et al., 2021). Results on other datasets are in Appendix C.

THE FASTEST **CLOUD FOR** GEN AI BUILT ON LEADING AI RESEARCH

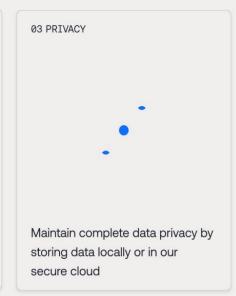
together.ai

WE BELIEVE THE FUTURE OF AI IS

OPEN SOURCE

01 TRANSPARENCY

02 CONTROL ... Customize models with proprietary data to build applications that serve your needs



Innovations

Products

FLASH ATTENTION 2

COCKTAIL SGD

SUB-QUADRATIC ARCHITECTURES

REDPAJAMA OPEN DATA & MODELS

TOGETHER INFERENCE

TOGETHER FINE-TUNING

TOGETHER GPU CLUSTERS

TOGETHER CUSTOM MODELS



OctoAl's mission is to enable customers to benefit from the latest Al innovations by offering efficient, customizable, and reliable Al systems.



Founded 2019 in Seattle, WA UW-CSE Spin-off 100 employees, 50% in Seattle, rest across the globe

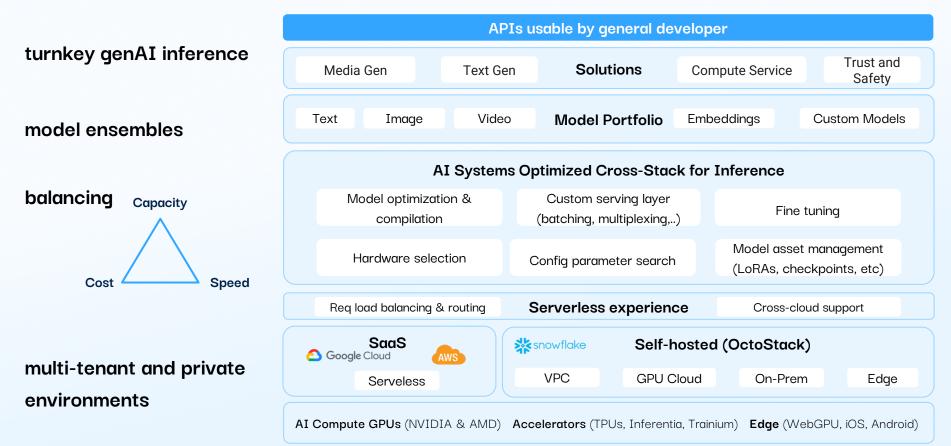
Built on deep expertise in AI systems, with foundational open source traction (Apache TVM, MLC-LLM, etc)

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\$132M seed/A/B/C from Madrona, Amplify, Addition, Qualcomm and Tiger Global 26

OctoAI Stack: Integrated and Composable



OctoAl.

AI Systems Stack for User Outcomes

Our goal: flexible, fast inference stack with rapid time-to-market

Achieved by:

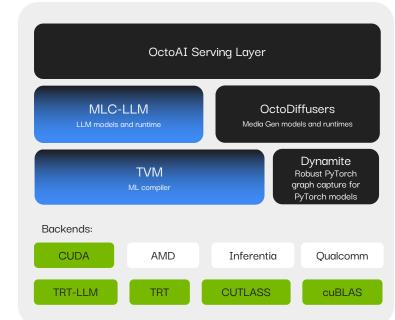
- Leveraging and extending native SW software stack
- Building graph capture, compiler, and runtime systems
- Open source TVM and MLC-LLM w/ community

Example: Enabled high-value use cases on NVIDIA ahead of native support:

- Large-scale LoRA for image gen
- High-performance structured JSON output
- Mixtral and Llama3 on OctoAI

100+ customers in production, 10s of B of tokens/day, millions of images/wk, exciting customer use cases.

OctoAI Optimized Inference Stack



Our stack enables broad hardware target coverage and

Fast time-to-market through:

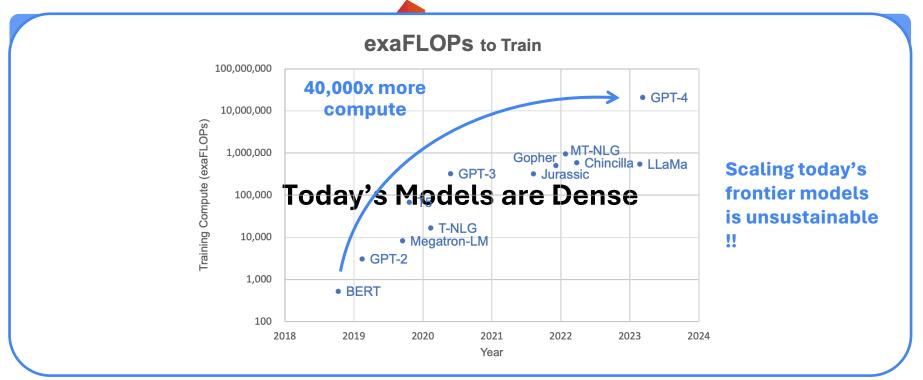
- $\,\circ\,$ Combining existing kernels, libraries, and compilers
- $\,\circ\,$ More robust graph capture of PyTorch Ops



Accelerating AI with Wafer-Scale Computing

ML on Cerebras

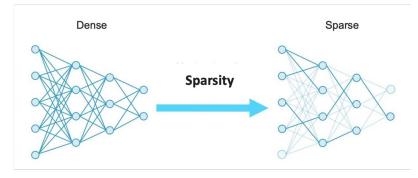
From multi-lingual LLMs to healthcare chatbots to code models. State-of-the-Art quality

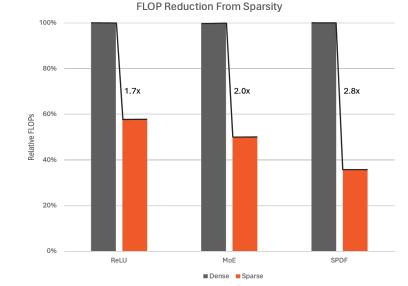


WSE: Co-designed with Sparsity for Scale

Sparsity opportunities are everywhere

- e.g. ReLU, Mixture of Experts, Weight Sparsity
- Not all HW can take advantage of all forms of sparsity





Recent Sparsity Publications

- **Sparse-IFT**: Sparse Iso-FLOP Transformations for Maximizing Training Efficiency (to appear at ICML, 2024)
- Enabling **High-Sparsity Foundational Llama** Models with Efficient Pretraining and Deployment (*arXiv*, 2024)
- **SPDF**: Sparse Pre-training and Dense Fine-tuning for Large Language Models (UAI, 2023)

Find out more at our Booth

Li et al., The Lazy Neuron Phenomenon: On Emergence of Activation Sparsity in Transformers, 2023
 Jiang et al., Mixtral of Experts, 2024
 Thangarasa et al., SPDF: Sparse Pre-training and Dense Fine-tuning for Large Language Models, 2023

Wafer-Scale Memory Bandwidth built for Sparsity

- Low data reuse \Rightarrow high mem bw
- WSE accelerates all forms of sparsity
 - Static and dynamic sparsity
 - Structured and unstructured sparsity
 - Weight and activation sparsity



