Why JAX and Flax NNX?

A High-Performance, Flexible Platform for Advanced Computation

Leveraging composable transformations, modern hardware, and a Pythonic neural network API for demanding AI/ML and scientific workloads

Developer Love

"There's a sense of tranquility when I nuke my code and rewrite it in JAX. Not only does it become faster, all my horrible code is rewritten better"

- Stone Tao (UCSD, Co-Founder of Lux AI Challenge)

Source: https://twitter.com/Stone_Tao/status/1555394550092353537

Why did Google develop JAX?

- Google learned from years of experience
  - DistBelief
  - TensorFlow
- Google needed high performance to scale efficiently
- Google needed flexibility and modularity to innovate quickly

High performance, flexibility, and modularity became the guiding principles for the development of JAX

Performance: JAX versus NumPy

```
def jax_batch(W, b, x):
  for i in range(10000):
    result = jax_predict(W, b, x)
  return 0

def np_batch(W, b, x):
  for i in range(10000):
    result = np_predict(W, b, x)
  return 0

jit_predict = jax.jit(jax_batch)
```

Colab CPU Instance:

NumPy: `np_batch(W, b, x)`
92.7 ms ± 22.7 ms per loop

JAX (with compile): `jit_predict(W, b, x)`
34.6 µs ± 41.8 µs per loop

JAX (after compile): `jit_predict(W, b, x)`
17.3 µs ± 6.83 µs per loop

~5,300X speedup versus NumPy

Performance: NNX versus PyTorch

```
def nnx_batch(W, b, x):
  for i in range(10000):
    result = nnx_predict(W, b, x)
  return 0

def pt_batch(W, b, x):
  for i in range(10000):
    result = pt_predict(W, b, x)
  return 0

nnx_jit_predict = nnx.jit(nnx_batch)
```

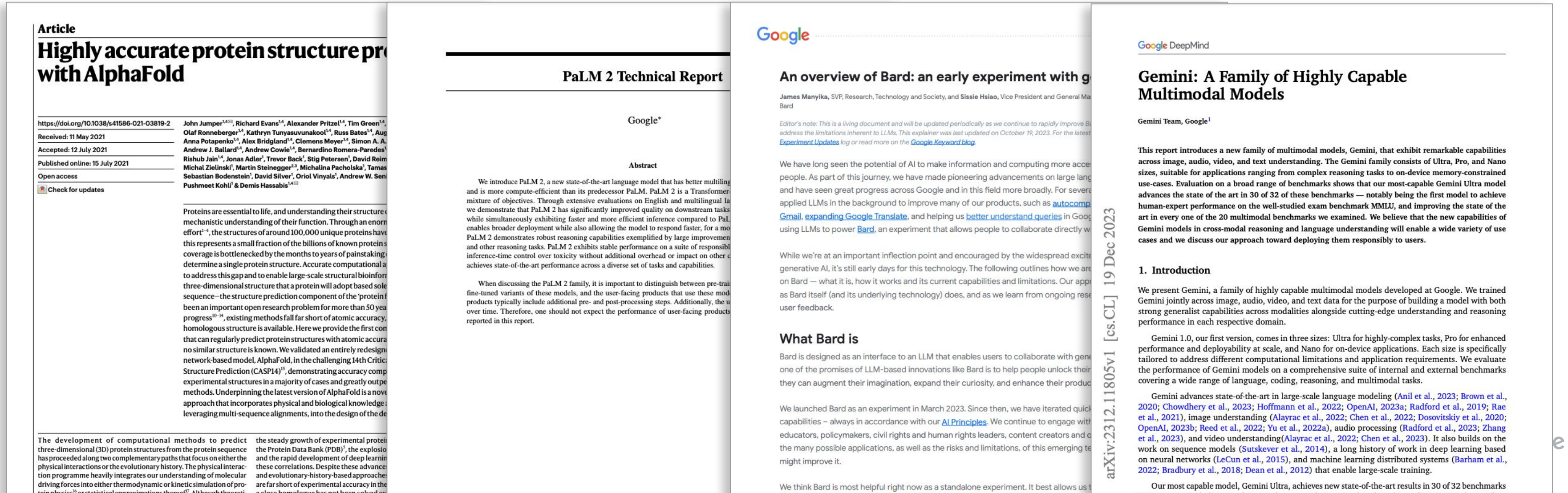
Colab CPU Instance:

```
PyTorch: pt_batch(W, b, x)
82.2 ms ± 18.8 ms per loop

NNX (with compile): nnx_jit_predict(W, b, x)
83.1 µs ± 76.3 µs per loop

NNX (after compile): nnx_jit_predict(W, b, x)
37.2 µs ± 1.42 µs per loop
```

~2,200X speedup versus PyTorch

Flexibility and Modularity

- You’ve seen results generated with JAX
- Google uses JAX for nearly all of its research and GenAI development
- Gemini, Gemma, Imagen, Veo, Waymo, etc. are all created using JAX



JAX: High-Performance Foundation

- **Accelerated Numerical Computing**: JAX is a platform built on Python and NumPy syntax, designed for high performance on accelerators like GPUs and TPUs.
- **Function Transformations**: Its core power lies in composable function transformations (`jit()`, `grad()`, `vmap()`) that automatically differentiate, compile, and vectorize standard Python code.
- **Beyond ML**: While powerful for ML, JAX is also a foundational library for any domain requiring accelerated numerical operations.

JAX Strength: Scalability & Portability

- **Designed for Scale**: Engineered for speed on single devices and scalability across multiple devices.
- **Simplified Distributed Parallelism**: Leveraging XLA, distributing computations often involves minimal boilerplate; users specify data partitioning (sharding), and XLA handles communication/synchronization.

JAX Strength: Scalability & Portability

- **Automatic Scaling**: Code often scales effectively across different hardware configurations (e.g., single GPU to TPU pods) with minimal changes, as XLA adjusts the execution plan.
- **Hardware Agnosticism**: JAX code typically runs without modification on CPUs, NVIDIA GPUs, and Google TPUs, thanks to XLA abstracting hardware specifics.

Developer Love

"I used to write custom CUDA kernels and optimize my code to stuff large GNNs into GPU memory. So I decide to profile some common GNN operations with JAX and PyTorch. It turns out that the JIT of JAX always outperforms PyTorch in both time and mem."

- Zhaocheng Zhu (PhD @ MilaQuebec)

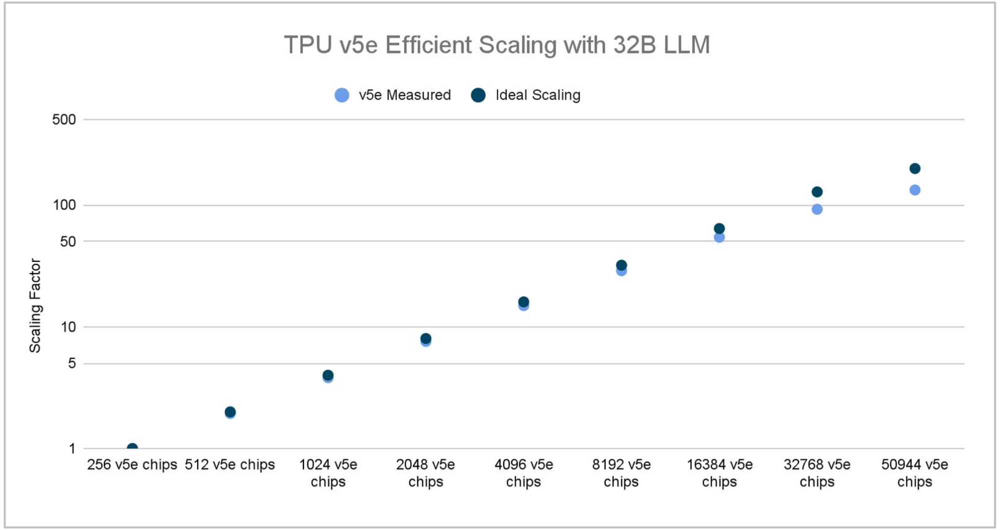
Source: https://twitter.com/zhu_zhaocheng/status/1656372666582827008

JAX Scalability: Scaling to 50,944 TPUs with JAX

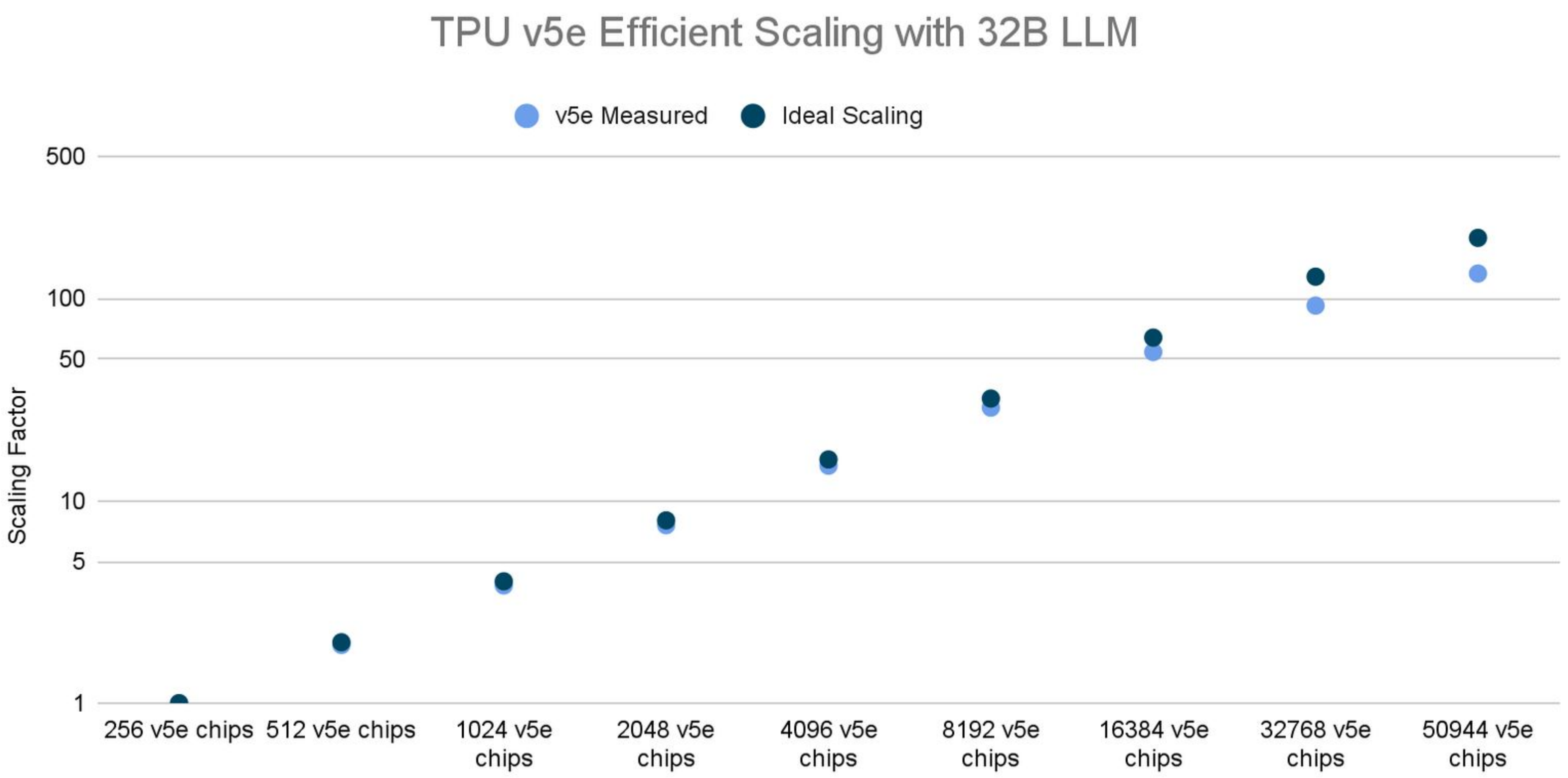
JAX Scalability: TPUs

In November 2023, we used Multislice Training to run an extremely large LLM distributed training job

- 50,944 Cloud TPU v5e chips (spanning 199 Cloud TPU v5e pods)
- Near ideal scaling



Source: https://cloud.google.com/blog/products/compute/the-worlds-largest-distributed-llm-training-job-on-tpu-v5e

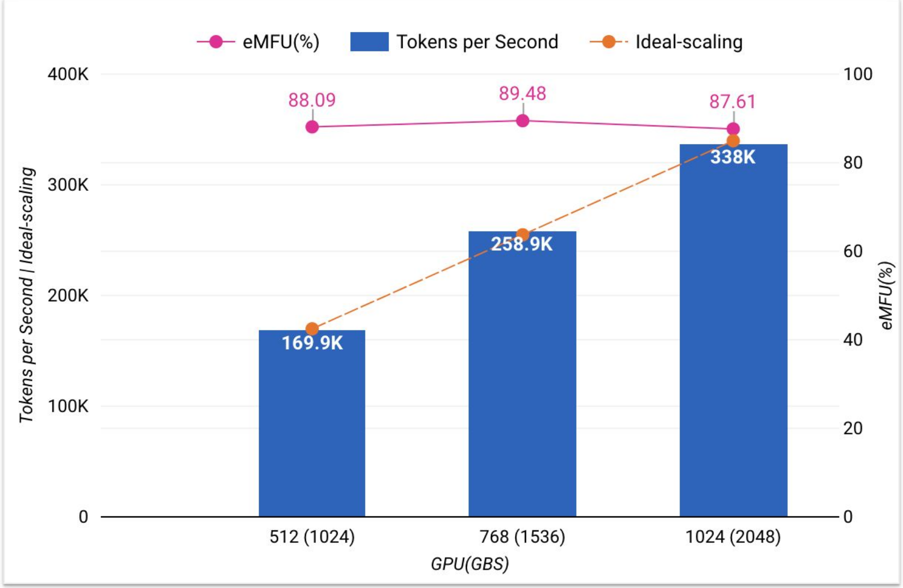


TPU v5e Efficient Scaling with 32B LLM
v5e Measured
Ideal Scaling
Scaling Factor
500
100
50
10
5
1
256 v5e chips
512 v5e chips
1024 v5e chips
2048 v5e chips
4096 v5e chips
8192 v5e chips
16384 v5e chips
32768 v5e chips
50944 v5e chips

JAX Scalability: GPUs

Training Performance Results : A3 Ultra

Llama3.1-405B (JAX, MaxText, FP8) Benchmark



High Performance at Scale

> 80% EMFU FP8 at 1000 NVIDIA GPU scale

Near linear scaling upto 1024 GPU scale

MaxText + JAX/XLA stack allows ease of performance optimization

Close partnership with NVIDIA

Reproducible recipes
https://github.com/AI-Hypercomputer/gpu-recipes/

seq-len=8192. emfu= (observed flops throughput/bf16 peak flops). Google internal data for A3 Ultra as of February, 2025. Performance numbers subject to continuous updates

Google

Developer Love

“Personally, I've decided to switch to JAX due to its modern approach to parallelism, which can be automatic or semi-automatic. The JAX compiler takes care of many demanding tasks, such as managing the communication of activations and gradients.”

- Luyu Gao (PhD candidate @CarnegieMellon)

Source: https://twitter.com/luyu_gao/status/1768276177448567142

Hardware Portability: JAX v PyTorch v TF Failure Rates

Comparison of TPU and GPU Failure and Success Rates						
	GPUs			TPUs		
	Success	Failure		Success	Failure	
	Pass	Partial	Complete	Pass	Partial	Complete
TensorFlow	78%	8%	14%	71%	15%	14%
PyTorch	92%	3%	5%	57%	27%	17%
JAX	98%	0%	2%	97%	0%	3%

Source:
[The Grand Illusion: The Myth of Software Portability and Implications for ML Progress (Cohere/MIT Sept 2023)]

Flax NNX

Flax NNX: Intuitive Neural Network Development

Modular, layered design

Flax NNX

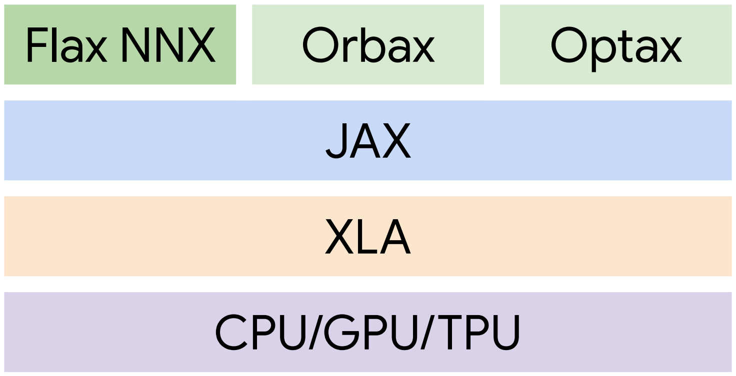
- Neural network library for JAX that is designed for ease of use

Orbax

- Checkpointing and export

Optax

- Gradient processing and optimization



Flax NNX: Intuitive Neural Network Development

- **Modern JAX API**: Flax NNX is a neural network library within the Flax ecosystem, specifically designed for JAX.
- **Simplified & Flexible**: Introduced in 2024, NNX is engineered for simplicity, flexibility, and an enhanced developer experience, making it easier to create, inspect, debug, and analyze models.
- **First-Class Pytree Integration:** NNX Modules are now native JAX Pytrees, allowing direct use with `jax.jit`, `jax.vmap`, and other transformations.
- **Builds on Experience**: Incorporates learnings from previous JAX libraries for a more user-friendly interface.

Developer Love

“The jit'd JAX (Flax in this case) impl ran circles around familiar PyTorch and TF impl of similar algos (CPU or GPU). And that's without taking the time to vectorize the eval envs. I was using https://github.com/ikostrikov/jaxrl as my starting point.”

- Ross Wightman

Source: https://twitter.com/wightmanr/status/1417616247118733313

Flax NNX Strength: Pythonic Design

- **Familiar Object Semantics**: Embraces standard Python object concepts like classes, inheritance, attributes, methods, and reference semantics. Allows natural patterns like weight sharing.
- **Intuitive Module Definition**: Define layers/models by subclassing `nnx.Module`, defining sub-layers as attributes in `__init__`, and logic in `__call__`. Uses standard layers like `nnx.Linear`, `nnx.Conv`, `nnx.BatchNorm`, etc.
- **Seamless JAX Integration:** As native Pytrees, NNX modules work directly with JAX's function transformations.
- **Easier Adoption**: Lowers the barrier for developers familiar with object-oriented frameworks (like PyTorch/Keras) to leverage JAX.

JAX Ecosystem

JAX Ecosystem: Breadth & Flexibility

- **Large and Growing**: A major strength is the large, diverse ecosystem of libraries, tools, and projects built upon JAX.
- **Testament to Power**: This vibrant activity showcases JAX's flexibility and applicability across a wide array of domains, far beyond conventional deep learning.
- **Modular Philosophy**: JAX core remains lean, encouraging domain-specific innovation in independent libraries.
- **Curated Neural Network Stack**: The JAX AI Stack provides a tested set of core libraries (JAX, Flax, Optax, Orbax) for compatibility and easier onboarding.

JAX Ecosystem: Representative Examples

- **Neural Networks**: Flax NNX, Equinox, Penzai, Scenic, Objax, EasyDeL.
- **Foundation Models**: MaxText, Levanter, EasyLM, Marin.
- **Reinforcement Learning**: RLax, BRAX (physics), gymnax (envs), Jumanji (envs), Mctx (search), Pgx (games).
- **Probabilistic Programming**: NumPyro, Oryx, Distrax, BlackJAX (samplers), GPJax (Gaussian Processes).

JAX Ecosystem: Representative Examples

- **Scientific Computing**: JAX M.D. (molecular dynamics), NetKet (quantum physics), jax-cosmo (cosmology), Diffrax (diff eq solvers), delta PV (photovoltaics), dynamiqs (quantum dynamics), XLB (fluid dynamics).
- **Optimization**: Optax, JAXopt, Optimistix.
- **Utilities**: Chex (testing), Orbax (checkpointing), SafeJax (serialization).

Conclusion

Conclusion: Premier Choice for Advanced Computation

- **JAX Foundation**: Provides exceptional performance via XLA, **`jit()`**, **`grad()`**, **`vmap()`**, enhanced by a functional paradigm promoting composability and reproducibility.
- **Flax NNX Usability**: Offers an intuitive, Pythonic API for building, debugging, and managing neural networks, with native Pytree integration that connects seamlessly with JAX.
- **Powerful Combination**: Together, JAX's performance and Flax NNX's usability, amplified by the vast and diverse ecosystem, create a leading platform for tackling complex challenges in AI/ML and scientific discovery.

Learning Resources

Code Exercises, Quick References, and Slides

- https://goo.gle/learning-jax

Learn JAX

Community and Docs

Community:

- https://goo.gle/jax-community

Docs

- JAX AI Stack: https://jaxstack.ai
- JAX: https://jax.dev
- Flax NNX: https://flax.readthedocs.io