Leveraging the JAX AI Stack

A High-Performance Journey for PyTorch Developers

Why Consider JAX? Performance

Performance: NNX versus PyTorch

Colab CPU Instance:

- **PyTorch:** `pt_batch(W, b, x)`
  82.2 ms ± 18.8 ms per loop
- **NNX (after compile):** `nnx_jit_predict(W, b, x)`
  37.2 µs ± 1.42 µs per loop

~2,200X speedup versus PyTorch

> “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)

Why Consider JAX? Scalability

JAX Scalability: Scaling to 50,944 TPUs with JAX

- In November 2023, Google used JAX for an extremely large LLM training job
- **50,944 Cloud TPU v5e chips**
- Demonstrated **near-ideal linear scaling**

JAX is the foundation for Google's largest models, including **Gemini, Gemma, Imagen, and Veo**.

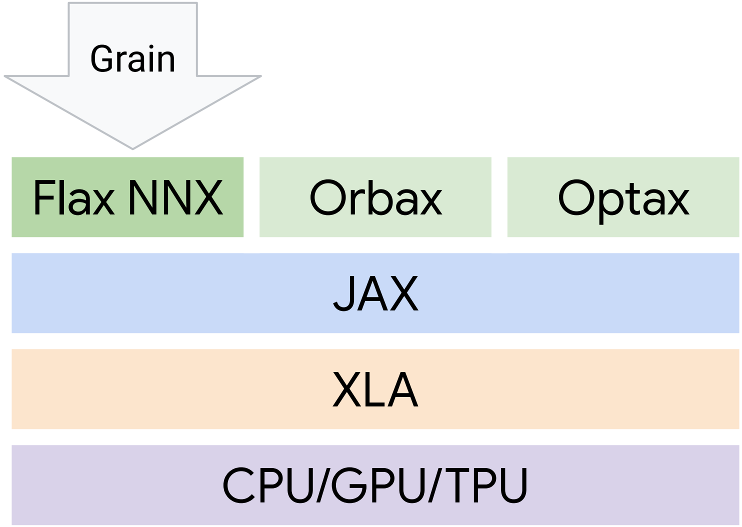
What is the JAX AI Stack?

A curated set of interoperable libraries for high-performance ML research and development.

- **Core Philosophy:** Achieve Performance, Flexibility, and Scalability using **function transformations**.
- **Engine:** Uses the **XLA (Accelerated Linear Algebra)** compiler to generate highly optimized code for the target hardware.
- **Portability:** Enables running the same code, often without modification, across **CPUs, GPUs, and TPUs**.

The Full Stack: A Modular, Layered Design

- **Grain:** Data Loading (optional)
- **Flax NNX:** Neural Networks
- **Optax:** Optimizers
- **Orbax:** Checkpointing
- **JAX:** Function Transformations & NumPy API
- **XLA:** Compiler



Roles of the Core Libraries

- **JAX:** The foundation. Provides a NumPy-like API and the core function transformations (`jit`, `grad`, `vmap`).
- **Flax NNX:** The model builder. A Pythonic neural network library, analogous to `torch.nn.Module`, for defining models.
- **Optax:** The optimizer. A library for gradient processing and optimization, analogous to `torch.optim`.
- **Orbax:** The checkpointer. A library for saving and restoring training state (`model params`, `optimizer state`), analogous to `torch.save` and `torch.load` but built for distributed systems.
- **Grain:** The data loader. A high-performance, deterministic data loading library, analogous to `torch.utils.data.DataLoader`

The JAX Engine: Composable Function Transformations

JAX's power comes from wrapping Python functions in transformations that change *how* they execute.

- `jax.jit()` -> **Compiles** the function with XLA for high speed.
- `jax.grad()` -> Creates a new function that computes **gradients**.
- `jax.vmap()` -> **Vectorizes** or "auto-batches" the function.

These transformations can be arbitrarily composed, e.g., `jax.jit(jax.grad(loss_fn))`.

Key Transform: jax.jit (Compilation)

The `jit` (Just-In-Time) transform uses XLA to compile a JAX-compatible Python function into highly optimized machine code for the target accelerator.

- Dramatically speeds up execution compared to standard Python by fusing operations, optimizing memory use, and avoiding interpreter overhead.
- Conceptually similar to `torch.compile()`, but `jit` is the fundamental and standard way to get performance in JAX.

Key Transform: jax.grad (Differentiation)

`grad` provides powerful and flexible automatic differentiation.

- It is a **transformation** that takes a numerical function (e.g., a loss function) and returns a *new function* that computes its gradient.
- This is different from PyTorch's `loss.backward()`, which computes gradients and stores them as side-effects on `.grad` attributes.
- It composes seamlessly with `jit` and other JAX transforms.

Flax NNX: Pythonic Models

Flax NNX provides structure for defining Neural Networks, giving you a familiar object-oriented experience on top of JAX's functional core.

- **Pythonic Feel:** Define models by subclassing **`nnx.Module`**, making them feel like regular Python objects. Analogous to **`torch.nn.Module`**.
- **Manages State:** While it provides this convenient object-style, it is designed to work correctly with JAX's functional nature, managing the model's state (parameters, batch stats) in a way that is compatible with **`jit`** and **`grad`**.

Optax: Composable Optimizers

Optax is the gradient processing and optimization library, analogous to `torch.optim`.

- **Composable:** Build optimizers by chaining smaller, independent transformation blocks (e.g., `add_momentum`, `scale_by_adam`).
- **Stateful but Functional:** An optimizer's state is handled explicitly.
  1. `init()` function creates the optimizer's state.
  2. `update()` function takes gradients and the current state, and returns the parameter updates and the *new* optimizer state.

Orbax: Robust Checkpointing

Orbax handles saving and loading of training state (model params, optimizer state, etc.), designed specifically for the JAX ecosystem.

- **Distributed-Aware:** Manages saving/restoring JAX PyTrees, even when state is sharded across many accelerators and hosts.
- **Fault-Tolerance:** Critical for long-running jobs on preemptible infrastructure.
- **Asynchronous:** Can save checkpoints in the background to minimize impact on training throughput.

Grain: High-Performance Data Loading

Grain is Google's library for efficient data reading and preprocessing, designed for JAX.

- **Purpose-Built for JAX:** Solves data bottlenecks to keep fast accelerators fed with data.
- **Parallel Processing:** Uses multiprocessing to prepare batches in parallel, bypassing Python's GIL.
- **Distributed Sharding:** Integrates with JAX's distributed environment to automatically provide each process with a unique slice of the data.

Comparison: Training Loop & Backpropagation

```python
# PyTorch
import torch
import torch.nn as nn
import torch.optim as optim


# Define a simple model
class SimpleModel_Torch(nn.Module):
    def __init__(self):
        super().__init__()
        self.linear = nn.Linear(1, 1)

    def forward(self, x):
        return self.linear(x)
```

```python
# Flax NNX
from flax import nnx
import jax
import jax.numpy as jnp
from optax import sgd
from typing import Any


# Define a simple model
class SimpleModel_NNX(nnx.Module):
    def __init__(self, *, rngs: nnx.Rngs):
        self.linear = nnx.Linear(1, 1, rngs=rngs)

    def __call__(self, x: jnp.ndarray):
        return self.linear(x)
```

Comparison: Training Loop & Backpropagation

```python
# PyTorch
model_torch = SimpleModel_Torch()

optimizer_torch = \
  optim.SGD(model_torch.parameters(), lr=0.01)
loss_fn = nn.MSELoss()


# Dummy data
x_torch = torch.tensor(
          [[2.0]], requires_grad=True)
y_torch = torch.tensor([[4.0]])
```

```python
# Flax NNX
model_nnx = SimpleModel_NNX(rngs=nnx.Rngs(0))

# Optimizer
optimizer = nnx.Optimizer(
              model_nnx,
              tx=sgd(learning_rate=0.01),
              wrt=nnx.Param)

# Dummy data
x_nnx = jnp.array([[2.0]])
y_nnx = jnp.array([[4.0]])
```

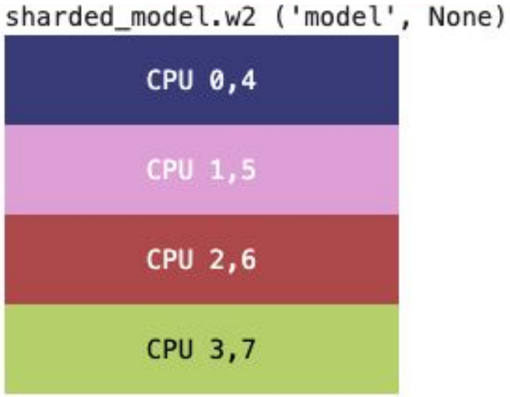
Comparison: Training Loop & Backpropagation

```python
# PyTorch Training step

# Zero the gradients
optimizer_torch.zero_grad()
output_torch = model_torch(x_torch)
loss_torch = loss_fn(
               output_torch, y_torch)
loss_torch.backward()  # Compute gradients

# Update parameters
optimizer_torch.step()

print("PyTorch Loss:", loss_torch.item())
```

```python
# Flax NNX Training step
@nnx.jit
def train_step(model, optimizer, x, y):
  def loss_fn(model):
    return jnp.mean((model(x) - y) ** 2)

  loss, grads = \
        nnx.value_and_grad(loss_fn)(model)
  # in-place updates
  optimizer.update(model, grads)

  return loss

# Pass the optimizer
loss_nnx = train_step(model_nnx,
                  optimizer, x_nnx, y_nnx)

print("Flax NNX Loss:", loss_nnx)
```

JAX Superpower: Flexible Parallelism

JAX offers powerful, flexible ways to scale across multiple accelerators, driven by the compiler.



PyTorch: Library-Based

- You wrap your single-device model in a library object like `DDP` or `FSDP`.
- The library manages communication behind the scenes.
- `model = DDP(model)`

JAX: Compiler-Driven (SPMD)

- You describe the desired parallel *layout* of your data and parameters using sharding annotations.
- `jax.jit` compiles a new, optimized parallel program from scratch based on these annotations.
- This provides a more unified and flexible approach to different parallelism strategies (Data, Model, etc.).

Summary & The Full Workflow

- The JAX AI Stack provides a complete, high-performance workflow: **Grain (data) -> Flax (model) -> Optax (optimization) -> Orbax (checkpointing)**.
- JAX enables high-performance via composable **function transforms** (**jit**, **grad**, **vmap**).
- **Flax NNX** provides a familiar, Pythonic, object-oriented way to define models (`torch.nn.Module-like`).
- The functional paradigm makes state explicit — passing models and state into functions — which is key to performance, reproducibility, and scalability.
- JAX supports compiler-driven **parallelism** for unparalleled scaling.

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