Google

Debugging JAX & Flax NNX:

A Guide for PyTorch Users

Leveraging Familiar Concepts and Mastering New Tools

Why is JAX Debugging Different? The JIT Impact

- **PyTorch**: Mostly eager execution. `print()`, `pdb` work directly on runtime values.
- **JAX**: Relies heavily on Just-In-Time (JIT) compilation (`@jax.jit`) for performance.
    - **Tracing Phase**: Python code runs once with abstract tracers (shapes/types) to build a computation graph. Standard `print()` or `pdb` only see these tracers. However tracers can be useful, since they carry shapes and `dtypes`.
    - **Execution Phase**: Compiled graph (e.g., XLA) runs later on CPU/GPU/TPU with concrete values. Standard tools can't inspect this directly.
- **Challenge**: How to inspect *runtime* values inside JIT-compiled code?

"`printf` Debugging" in JAX: `jax.debug.print()`

- The JAX equivalent of `print()` for use inside transformed functions (`jit, vmap, grad`).
- Embeds the print operation into the compiled computation graph.
- Outputs concrete runtime values during execution.
- Use `ordered=True` to ensure prints appear sequentially as written.

"`printf` Debugging" in JAX: `jax.debug.print()`

```
@jax.jit
def compute_intermediate(x):
  y = x * 2
  print("Standard print (tracer):", y)   # Sees tracers during compilation
  # Sees runtime values
  jax.debug.print("jax.debug.print (runtime value): {y}", y=y, ordered=True)
  z = y + 1
  return z

compute_intermediate(jnp.array(5.0))
# Output:
# Standard print (tracer): Traced<ShapedArray(float32)...>
# jax.debug.print (runtime value): 10.0
```

Interactive Debugging in JIT: `jax.debug.breakpoint()`

- The JAX equivalent of **`pdb.set_trace()`** or **`breakpoint()`** for use inside transformed functions.
- Pauses execution at runtime within the compiled code.
- Provides a (**`jaxdb`**) prompt similar to **`pdb`**.
- Allows inspecting runtime values of variables in the JAX context (**`p variable_name`**).
- Use **`c`** to continue, **`q`** to quit.
- Can be made conditional using **`jax.lax.cond()`**.

Interactive Debugging in JIT: `jax.debug.breakpoint()`

```
@jax.jit
def check_value(x):
  y = jnp.sin(x)
  jax.debug.print("Value before breakpoint: {y}", y=y)
  jax.debug.breakpoint() # Execution pauses here
  z = jnp.cos(y)
  return z

check_value(jnp.array(0.5))
# Output: Value before breakpoint: 0.47942555
# (jaxdb) p y
# Array(0.47942555, dtype=float32)
# (jaxdb) c
```

Visualizing Data Layout: `jax.debug.visualize_array_sharding`

- **Problem**: Need to verify data layout across devices in distributed settings with sharding.
- **Tool**: `jax.debug.visualize_array_sharding(array)` prints text diagram of layout.
- **How it Works**: Shows which data slice is on which device ID at runtime.
- **Usage**: Call inside JIT/distributed functions to check sharding from `Mesh/PartitionSpec`.

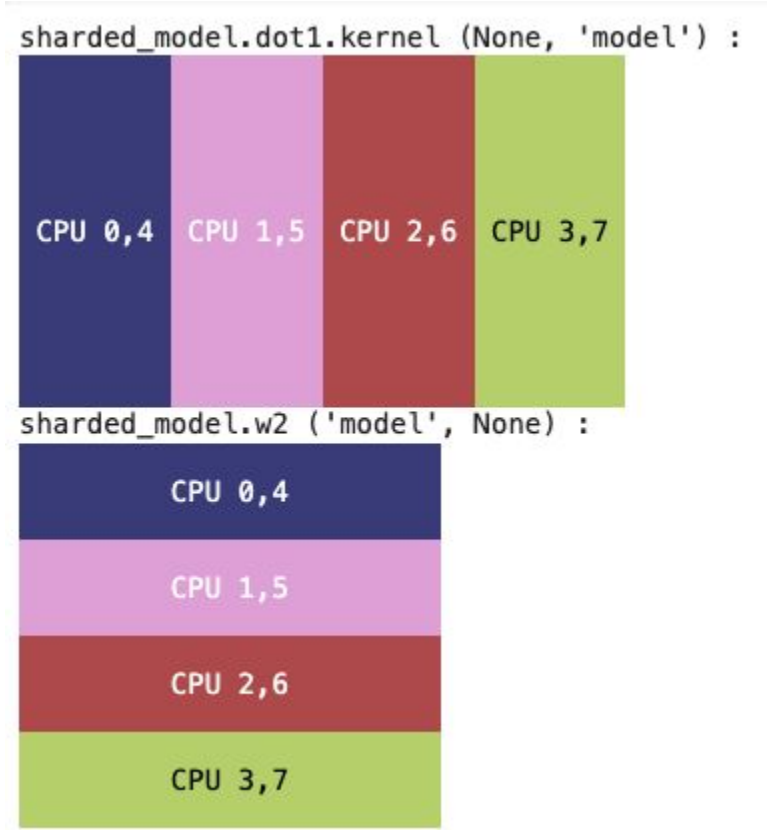
`visualize_array_sharding` Code Example

```
# --- Assume mesh setup (e.g., 2x2) ---
# mesh = Mesh(devices, ('data', 'model'))
# P = PartitionSpec

@jax.jit
def my_distributed_func(x_sharded):
  # Visualize input array layout
  print("--- Input Sharding ---")
  jax.debug.visualize_array_sharding(x_sharded) # <<< Visualize

  y = x_sharded * 2 # Computation
  print("--- Output Sharding ---")
  jax.debug.visualize_array_sharding(y) # <<< Visualize
  return y
```

Visualizing Data Layout: `jax.debug.visualize_array_sharding`



Back to Basics: Temporarily Disabling JIT

Sometimes you just want standard Python debugging.

- **`jax.disable_jit()`** forces JAX functions to execute eagerly (like PyTorch/NumPy).
- Allows standard **`print()`** and **`pdb/breakpoint()`** to work as expected, inspecting runtime values directly.
- Also enables IDE debuggers like VS Code

Back to Basics: Temporarily Disabling JIT

- How to use:
  - **Context Manager**: `with jax.disable_jit()`: ... (Recommended for locality)
  - **Globally**: `jax.config.update("jax_disable_jit", True)`
  - **Environment Var**: `JAX_DISABLE_JIT=1`
- **Major Drawback**: Disables JIT optimizations -> significantly slower execution. Use temporarily for debugging!

Back to Basics: Temporarily Disabling JIT

```
@jax.jit
def problematic_function(x):
  y = jnp.log(x)
  # pdb works here ONLY if JIT is disabled
  pdb.set_trace()
  return y * 2

# Execute with JIT disabled for this block
with jax.disable_jit():
  print("Running with JIT disabled...")
  result_no_jit = problematic_function(jnp.array(5.0)) # pdb triggers
```

Back to Basics: Temporarily Disabling JIT

Limits on `jax.disable_jit()`:

- If you're using functional transforms, like **`jax.vmap`** and **`jax.scan`**, you won't be able to break into the function to inspect values
- But tools like **`sow`** from NNX are designed to be compatible with these transforms

Automatic NaN Hunting: The `jax_debug_nans` Flag

Problem: Numerical instability leading to **NaNs** inside JITted code can be hard to trace.

Solution: Enable the `jax_debug_nans` configuration flag.

- `jax.config.update("jax_debug_nans", True)` (in Python)
- Environment Variable: `JAX_DEBUG_NANS=1`

Automatic NaN Hunting: The `jax_debug_nans` Flag

How it Works:

- Monitors JIT computations for **`NaN`** outputs.
- If a **`NaN`** is detected, JAX automatically re-runs the function in eager mode (like **`disable_jit`**) to pinpoint the exact operation causing the **`NaN`** and raise an error there.

Automatic NaN Hunting: The `jax_debug_nans` Flag

Limitations:

- Can significantly slow down execution due to checks and potential eager re-runs.
- Might raise errors on intentionally created `NaNs`.
- Best used during debugging, disable for production/performance runs.

Inspecting Flax NNX Models: `nnx.display()`

Understanding Your NNX Model: `nnx.display()`

Flax NNX is designed with inspectability in mind (uses standard Python objects)

- `nnx.display()` provides a clear view of NNX objects:
  - `nnx.Module` (models, layers)
  - `nnx.Optimizer`
  - `nnx.State`
  - Other contained JAX arrays/objects

Understanding Your NNX Model: `nnx.display()`

- Shows structure, parameters, state variables, shapes, types, and values.
- Creates a rich, interactive tree view in notebooks/Colab. Falls back to standard print otherwise.
- Analogous to `print(pytorch_model)` but often more detailed and interactive.

```
Linear( # Param: 15 (60 B)
  w=Param(value=<jax.Array float32(2, 5) ≈0.42 ±0.34 [≥0.029, ≤0.95] nonzero:10>),
  b=Param(value=<jax.Array float32(5,) ≈0.0 ±0.0 [≥0.0, ≤0.0] zero:5>),
  din=2,
  dout=5,
)
```

Capturing Intermediate Values: `nnx.sow()`

Flax NNX `Module.sow()` - Capturing Intermediate Values

What is `Module.sow()`?

- A method within **`flax.nnx.Module`** designed to capture and store intermediate values computed during a module's forward pass.
- **Purpose**: Simplifies tracking internal computations (e.g., activations, gradients) without manually passing data structures through the call stack.
- Useful for:
  - Debugging model behavior.
  - Visualizing intermediate layer outputs.
  - Implementing custom loss functions based on internal states.

Flax NNX `Module.sow()` - Capturing Intermediate Values

How it Works: Core Arguments

```
self.sow(variable_type, name, value, *, reduce_fn=None, init_fn=None)
```

- **`variable_type:`** Specifies the variable wrapper (e.g., **`nnx.Intermediate`**). Used for later filtering/retrieval.
- **`name (str):`** The attribute name under which the value will be stored on the module instance.
- **`value:`** The actual JAX array or Python object to be stored.
- **`(Optional) reduce_fn, init_fn:`** Customize how values are stored/aggregated if **`sow`** is called multiple times with the same name

Using `Module.sow()` - Storage, Retrieval & Customization

```python
class SimpleModel(nnx.Module):
  def __init__(self, rngs):
    self.dense = nnx.Linear(2, 3, rngs=rngs)
  def __call__(self, x):
    x = self.dense(x)
    # Sow the output of the dense layer
    self.sow(nnx.Intermediate, 'dense_output', x)
    return x * 2

model = SimpleModel(rngs=nnx.Rngs(0))
y = model(jnp.ones((1, 2)))

# Retrieve the sown value
intermediate_val = model.dense_output.value
# Output: (array([[...]]),) - A tuple containing the value
print(intermediate_val)
```

Flax NNX `Module.sow()` - Capturing Intermediate Values

Storage and Retrieval

- Sown values are stored as attributes on the module instance, named according to the name argument.
- The actual data is accessed via the `.value` property of this attribute (e.g., `model.dense_output.value`).
- **Default Behavior:** Calling `sow` multiple times with the same name appends the new value to a tuple stored in `.value`. Be mindful of potential memory growth with frequent calls.

Flax NNX `Module.sow()` - Capturing Intermediate Values

Advanced Features

- **Custom Aggregation:** Use `init_fn` and `reduce_fn` to define custom logic for combining multiple sown values (e.g., sum, product, average) instead of appending to a tuple.
- **State Management:** Sown variables (typed by `variable_type`) integrate with NNX graph utilities like `nnx.split()`, `nnx.state()`, and `nnx.pop()` for extracting or managing specific types of intermediate values from the module state.

Robustness with Chex Assertions

Note:
This section is optional if you have already gone through the Chex module.

Catching Errors Early: Chex Assertions

Chex: A library from DeepMind for reliable JAX code (testing, debugging)

- Provides powerful assertion functions.
- Static Assertions: Check properties independent of runtime values (shapes, dtypes, rank, structure).
- Work seamlessly inside `@jax.jit()` because they operate on traced information.

Catching Errors Early: Chex Assertions

Examples (static assertions):

- `chex.assert_shape(array, (batch, features))`
- `chex.assert_rank(array, 2)`
- `chex.assert_type(array, jnp.float32)`
- `chex.assert_trees_all_equal_shapes(tree1, tree2)`

Monitoring with TensorBoard

Visualizing Training: TensorBoard Integration (Setup)

TensorBoard works well with JAX/Flax for monitoring experiments.

Setup:

1. **Install**: `pip install tensorboard` (You might need tensorflow or torch[tensorboard] for the writer).
2. **Create Summary Writer**: Points to a log directory. Can use TensorBoardX, or TensorFlow, or PyTorch utilities.
3. **Launch TensorBoard**: From terminal: `tensorboard --logdir logs`
4. **Access in browser** (usually `http://localhost:6006`).

TensorBoard: Create Summary Writer

```
# Option 1: TensorBoardX
from tensorboardX import SummaryWriter
writer = SummaryWriter("logs/my_run_1")

# Option 2: TensorFlow writer
import tensorflow as tf
writer = tf.summary.create_file_writer("logs/my_run_1")

# Option 3: PyTorch writer (if torch installed)
from torch.utils.tensorboard import SummaryWriter
writer = SummaryWriter("logs/my_run_1")
```

Visualizing Training: TensorBoard Integration (Logging)

- Log metrics, images, etc., from your training loop.
- **Scalars** (Loss, Accuracy):
  - Use `tf.summary.scalar(...)` (TF writer, or PyTorch writer)
  - **Crucial**: Convert JAX arrays to Python scalars using `.item()` before logging.
- **Images**: Visualize inputs, predictions, attention maps (`writer.add_image(...)`).
- **Profiling**: JAX profiling (`jax.profiler`) can also output data viewable in TensorBoard for performance analysis.

Code Example (Logging Scalars with TensorBoardX Writer)

```
# Inside training loop (epoch = current step)
# Assume train_loss, val_accuracy are JAX arrays

writer.add_scalar('Loss/train', train_loss.item(), global_step=epoch)
writer.add_scalar('Accuracy/validation', val_accuracy.item(), global_step=epoch)

# Remember writer.close() when done
```

TensorBoard TIME SERIES SCALARS INACTIVE

Show data download links

Ignore outliers in chart scaling

Tooltip sorting method: default

Smoothing

0.6

Horizontal Axis

STEP RELATIVE WALL

Runs

Write a regex to filter runs

TOGGLE ALL RUNS

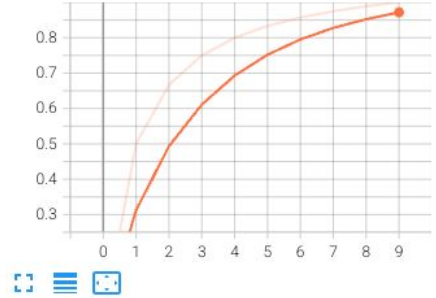
logs/jax_debug_run_solution

Filter tags (regular expressions supported)

Accuracy

Accuracy/validation

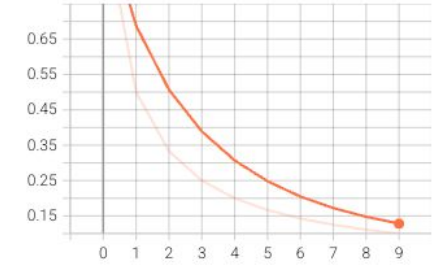
tag: Accuracy/validation



Loss

Loss/train

tag: Loss/train



Profiling with XProf, aka JAX Profiler

Installing and Enabling XProf

Installing and enabling XProf in TensorBoard is easy!

XProf includes:

- Overview Page, Framework Op Stats, Graph Viewer, HLO Op Stats, Memory Profile, Memory Viewer, HLO Op Profile, Roofline Model, Trace Viewer

```
!pip install -Uq tensorboard tensorboard_plugin_profile

jax.profiler.start_trace(LOG_DIR) # Capturing trace for xprof

// Some training loop code

jax.profiler.stop_trace()
```

TensorBoard PROFILE INACTIVE

XProf

CAPTURE PROFILE

Runs (1)

tpu-training

Tools (9)

Overview Page

Hosts (1)

gke-tpu-b309f56b-rq5s

Performance Summary

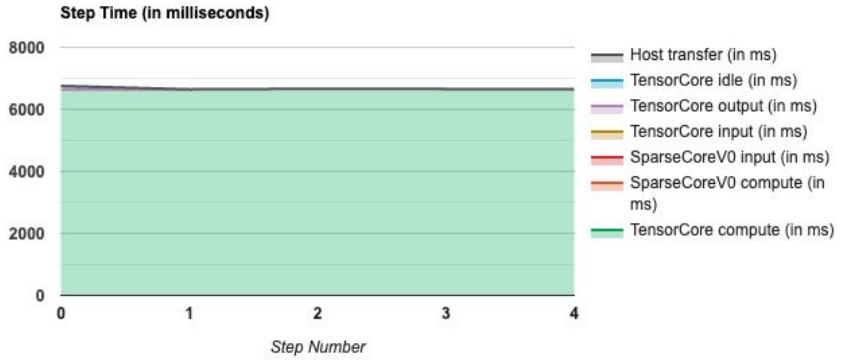
Average Step Time
(σ = 45.5 ms)
lower is better.
6676.2 ms

FLOPS Utilization
higher is better.
Utilization of TPU Matrix Units: 30.6%
Compared to Program's Optimal FLOPS: 0.0%
see roofline_model

TPU Duty Cycle
higher is better.
0.0%

Memory Bandwidth Utilization
higher is better.
0.0%

Step-time Graph



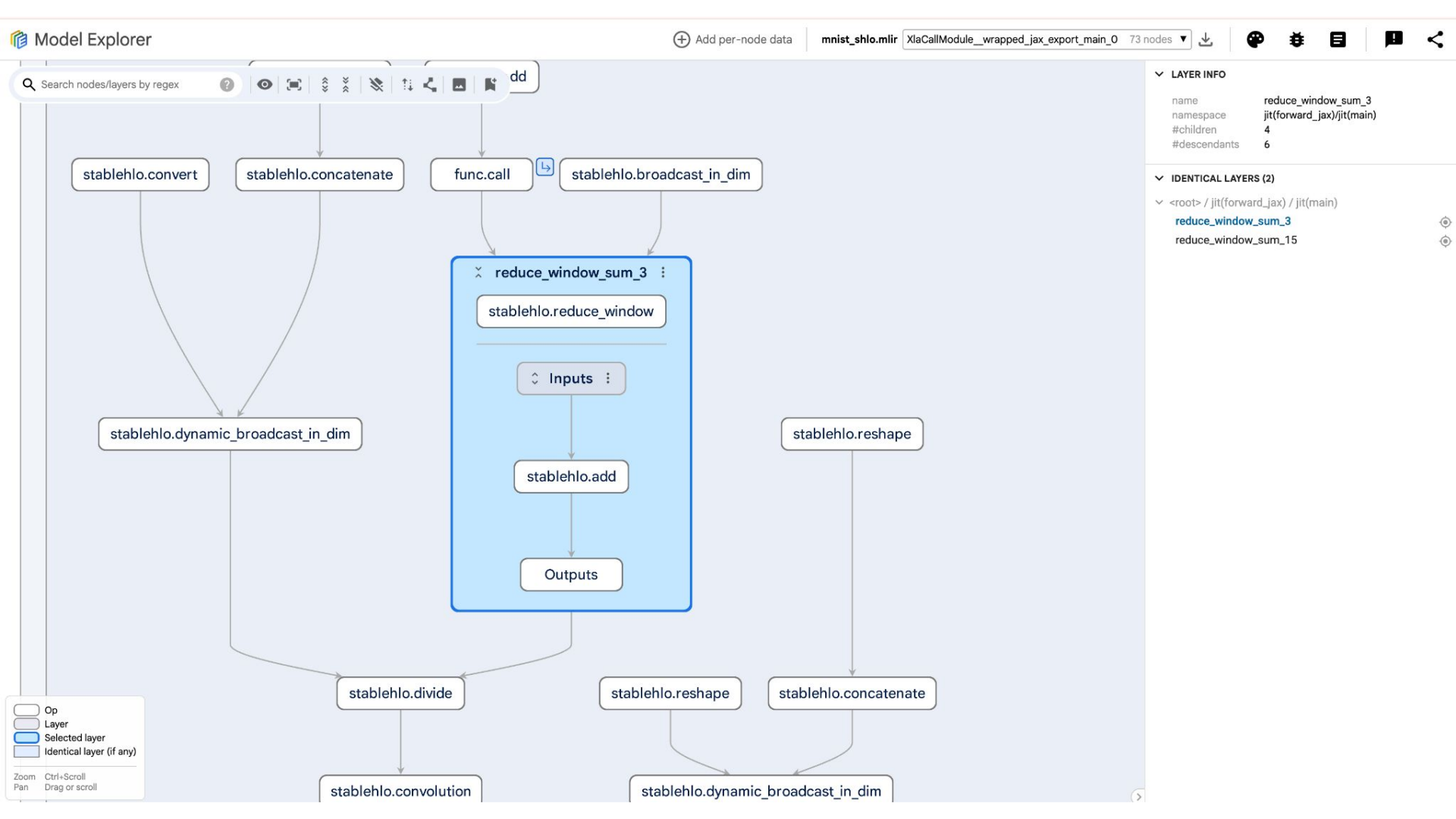
Digging into your model with Model Explorer

Google

Exploring the Model with Model Explorer

Model Explorer is a powerful graph visualization tool designed to help you understand and debug your ML models.

- Hierarchical Layout
  - View your model's structure clearly with nested layers that you can expand and collapse as needed.
- Metadata Overlays
  - Gain insights by overlaying metadata (e.g., attributes, inputs/outputs, etc) and custom data (e.g. performance) on nodes.
- Powerful Interactive Features
  - Focus on specific areas with search, navigate graphs smoothly with bookmarks and layer popups, customize node styles with queries, compare graphs side-by-side, and more.


Model Explorer
Add per-node data
mnist_shlo.mlir
XlaCallModule__wrapped_jax_export_main_0
73 nodes
Search nodes/layers by regex
stablehlo.convert
stablehlo.concatenate
func.call
stablehlo.broadcast_in_dim
reduce_window_sum_3
stablehlo.reduce_window
Inputs
stablehlo.add
Outputs
stablehlo.dynamic_broadcast_in_dim
stablehlo.reshape
stablehlo.divide
stablehlo.reshape
stablehlo.concatenate
stablehlo.convolution
stablehlo.dynamic_broadcast_in_dim
Op
Layer
Selected layer
Identical layer (if any)
Zoom Ctrl+Scroll
Pan Drag or scroll
LAYER INFO
name reduce_window_sum_3
namespace jit(forward_jax)/jit(main)
#children 4
#descendants 6
IDENTICAL LAYERS (2)
<root> / jit(forward_jax) / jit(main)
reduce_window_sum_3
reduce_window_sum_15

Bridging from PyTorch:
Similarities, Key Differences, & Adaptations

Google

Mapping Your PyTorch Skills to JAX/NNX

Your PyTorch Toolkit:

- `print()` for values
- `pdb / breakpoint()` for interactive steps
- Manual `NaN/Inf` checks
- `print(model)` for structure
- TensorBoard
- Hooks for intermediate values
- Profiler

Mapping Your PyTorch Skills to JAX/NNX

JAX/Flax NNX Analogues:

- **Value Inspection**: `jax.debug.print()` (in JIT), `print()` (if using `jax.disable_jit`)
- **Interactive Debugging**: `jax.debug.breakpoint` (in JIT), `pdb` or IDE (if using `jax.disable_jit`)
- **`NaN/Inf` Checks**: `chex.assert_tree_all_finite` (with `chex.chexify`)
- **Structure Inspection**: `nnx.display(model)`
- **Monitoring**: TensorBoard (similar setup/usage)
- **Assertions**: Chex (`assert_shape`, etc.)

Key Differences & Necessary Adaptations

- JIT is King: The biggest change. Debugging often means choosing:
  - Use JAX-specific tools (`jax.debug.*`, Chex + `chex.chexify`) to work within JIT.
  - Temporarily disable JIT (`jax.disable_jit`) to use standard tools, sacrificing performance.

Key Differences & Necessary Adaptations

- Hooks vs. Functional Style: PyTorch uses hooks heavily. JAX/NNX leans towards:
  - Returning intermediate values explicitly from functions (e.g., using `has_aux=True` in `jax.grad`).
  - Using `jax.debug.callback` for more complex host interactions.
  - Transforming functions (like gradient transforms) instead of in-place modification.

Key Differences & Necessary Adaptations

- **State Management:** NNX uses explicit state. Optimizer updates are now more functional (`optimizer.update(model, grads)`), making data flow clearer and easier to debug.
- **Error Messages**: JIT compilation can sometimes obscure error origins. Using `jax_debug_nans`, Chex, or `jax.disable_jit` helps pinpoint issues more accurately.

Recommended Debugging Workflow

A Systematic Approach to JAX/NNX Debugging

Static Checks First:

- Use `nnx.display()` to verify model/optimizer structure and initial state.
- Add Chex static assertions (`assert_shape, assert_type`) liberally.
- Manually check input/output shapes outside JIT.

A Systematic Approach to JAX/NNX Debugging

Runtime Issues within JIT:

- **`NaN/Inf`**? Use **`chex.assert_tree_all_finite(model)`** + **`@chex.chexify`**, or enable **`jax_debug_nans.`**
- Inspect values: Use **`jax.debug.print`**.
- Interactive step-through: Use **`jax.debug.breakpoint`**.

A Systematic Approach to JAX/NNX Debugging

Complex Issues / Need Standard Tools:

- Temporarily use with **`jax.disable_jit()`**: around the problematic code.
- Use standard **`print()`** and **`pdb/breakpoint()`**, or IDE debugger.

A Systematic Approach to JAX/NNX Debugging

Performance Issues:

- Suspect re-compilation? Use **`chex.assert_max_traces`**.
- Bottlenecks? Use **`jax.profiler`** (+ TensorBoard).

A Systematic Approach to JAX/NNX Debugging

Monitor Continuously:

- Integrate TensorBoard early for logging metrics and visualization.

Conclusion

- Debugging JAX/NNX requires adapting from PyTorch's eager-first model due to JIT.
- Master the JAX toolkit: `jax.debug.print, jax.debug.breakpoint`.
- Know when to use the "escape hatch": `jax.disable_jit`.
- Leverage Flax NNX's inspectability: `nnx.display()`.
- Build robustness with Chex assertions (static, value + `chex.chexify`).
- Monitor effectively with TensorBoard.
- Choose the right tool for the specific debugging task.

Learning Resources

Code Exercises, Quick References, and Slides

- https://goo.gle/learning-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