AXLearn

Modular, Hardware-Agnostic Large Model Training

Apple

MLSys 2026 `github.com/apple/axlearn`

The Problem

At Apple, we train AI models for products serving **billions of users** — on a fleet that spans **GPU, TPU, and AWS Trainium**, with **hundreds** of architecture variants.

Existing training systems force a costly trade-off:

- Most are tied to a single backend (Megatron-LM → GPU; MaxText → TPU).
- Most rely on **subtyping**, which forces cascading edits whenever a feature lands.
- No system delivers both first-class **modularity** *and* **hardware-agnostic** training.

> **We need both, at once.**
> Minimal-code architecture changes *and* the same model running across every accelerator we own.

Why Subtyping Hurts

Replacing an FFN with MoE *looks* like 4 lines (DeepSpeed):

```
- self.fc3 = nn.Linear(84, 10)
+ self.fc3 = nn.Linear(84, 84)
+ self.fc3 = deepspeed.moe.layer.MoE(...)
+ self.fc4 = nn.Linear(84, 10)
```

Every **parent** layer instantiates the child — so a child change forces a new parent subtype. By induction, the change propagates to *every ancestor module*.

4 LoC
the diff in isolation

200+ LoC
actual QwenV2→MoE diff

4,000 LoC
at Apple's variant scale

LoC-Complexity: the Right Metric

Plain LoC is a snapshot. We need to measure how a system *evolves*.

LoC-Complexity

The *asymptotic* LoC required to add a new feature variant, as a function of N (modules) and M (variants).

System	LoC-Comp(RoPE)	LoC-Comp(MoE)	RoPE LoC	MoE LoC
Megatron-LM	$O(NM)$	$O(N)$	400	20
DeepSpeed	$O(NM)$	$O(NM)$	320	4,000
TorchTitan	$O(NM)$	$O(NM)$	240	400
Praxis (Pax)	$O(NM)$	$O(M)$	300	5
MaxText	$O(NM)$	$O(NM)$	200	300
AXLearn (Ours)	$\mathbf{O(1)}$	$\mathbf{O(1)}$	**0**	**0**

Related Work: No System Has All Three

Existing systems each give up something — backend coverage, architectural agility, or both.

System	Model-Agn.	Modular	3D Par.	GPU	TPU	Trainium
Megatron-LM	–	–	✓	✓	–	–
DeepSpeed	✓	–	✓	✓	–	–
PyTorch FSDP	✓	–	–	✓	–	–
PyTorch XLA FSDP	✓	–	–	✓	✓	–
TorchTitan	–	partial	✓	✓	–	–
Flax / Haiku / Pax	✓	partial	✓	✓	✓	–
MaxText	–	partial	✓	✓	✓	–
AXLearn (Ours)	✓	✓	✓	✓	✓	✓

The gap we close

First system that is **model-agnostic**, **modular**, and runs across **GPU, TPU, and Trainium**.

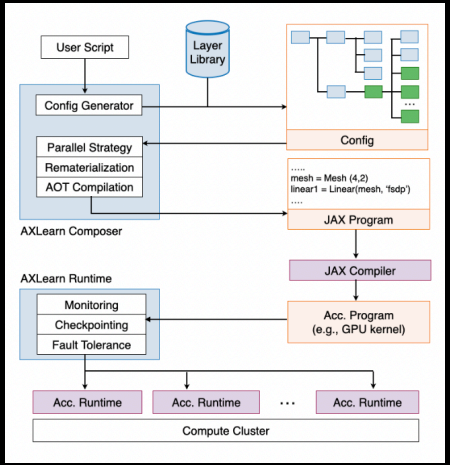
Key Idea: Strict Encapsulation

- **Every** module is replaceable: input pipeline, model, optimizer, checkpointer, trainer loop.
- **Configs compose hierarchically as a tree.** A parent never inspects its child's hyperparameters — it only agrees on input/output shapes.
- A **config modifier** traverses the tree and rewrites targeted subtrees *without touching parents*.

Drop-in replacement, by construction.

Swap an FFN for an MoE; switch the attention kernel; change the optimizer — the surrounding architecture is untouched.

System Architecture



Composer *(config → JAX program)*

- Mesh selection & sharding annotations
- Rematerialization, AOT compilation
- Per-backend kernel selection

Runtime *(orchestration on the cluster)*

- Async checkpointing (S3 / GCS)
- Watchdog & fault tolerance
- Slice-level hot-swap on Kubernetes

Built on **JAX + XLA + GSPMD** — one program, every backend.

Config Modifier: 10 LoC, 1,000+ Experiments

```
def replace_config(cfg, tgt, new_cfg):        # the modifier (10 LoC)
  def enter_fn(child):
    for k, v in child.items():
      if isinstance(v, tgt.Config):
        new_cfg.set(**v.items())
        child.set(k, new_cfg)
  cfg.visit(enter_fn=enter_fn)
```

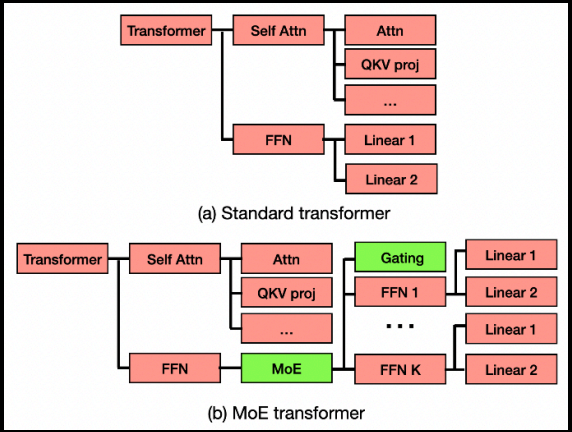
Apply MoE to every experiment config in production:

```
replace_config(trainer_cfg, target=FeedForwardLayer,
               new_cfg=MoELayer.default_config().set(...))
```

Reused 1,000+ times in production

No edits to `TransformerLayer`, `Llama`, or any other ancestor module.

Modularity in One Picture



The **green** nodes are the *only* changes from the standard Transformer to the MoE Transformer.

DeepSpeed: 4,000+ LoC in existing files.

AXLearn: **0** — only the new module is added.

Hardware-Agnostic via XLA + GSPMD

One JAX program, four backends. But XLA alone isn't enough.

- **Native config-based parallelism** — FSDP, pipeline, expert, sequence, tensor parallelism, no model code edits.
- **Mesh rules** apply per-backend modifiers automatically: FSDP within TPU v5e slices + DP across; 8-way TP within H100 nodes + FSDP across.
- **Rematerialization tags** let users save/recompute specific activations per hardware (HBM-bound vs compute-bound).
- **Custom kernels** (FlashAttention, etc.) drop in as black-box nodes — without breaking encapsulation.
- **First training system** to support AWS Trainium2 *at scale*.

Same Llama2-70B config trains on H100, TPU-v5p, *and* Trainium2 — only the mesh shape changes.

Performance: Matches or Exceeds SOTA on Every Backend

Identical hardware, batch size 1024. **The only system on all four backends.**

Model	Hardware	System	MFU	Tok/s
Llama2-7B	32× H100-8	MaxText	54.7%	3.0M
	32× H100-8	**AXLearn**	**54.2%**	**3.0M**
	tpu-v5p-512	**AXLearn**	**66.2%**	**1.7M**
	64× Trainium2-16	**AXLearn**	**24.2%**	**3.5M**
Llama2-70B	64× H100-8	Megatron-LM	47.2%	538K
	64× H100-8	**AXLearn**	**40.0%**	**456K**
	tpu-v5p-1024	**AXLearn**	**68.0%**	**360K**
	64× Trainium2-16	**AXLearn**	**25.0%**	**374K**
Qwen-3 30B-A3B	tpu-v5p-1024	**AXLearn**	**31.6%**	**1.3M**
	64× B200-8	**AXLearn**	**19.2%**	**3.9M**

Near-linear scaling: 150B model holds **37.6% MFU at 32,768 chips**.

Runtime: Built for Failures

At 32,768 chips, hardware breaks every few hours — recovery is everything.

- **Async checkpointing** to S3 / GCS with bandwidth- and memory-aware sharding.
- **Watchdog** on step time + utilization triggers restart, on-call alert, or stack-trace dump.
- **Multi-tier checkpoints** on node-local memory/disk; weights restored in-replica then broadcast over fast interconnect.
- **Slice-level hot-swap** on Kubernetes: over-provisioned spares replace failed nodes in seconds.

4 min
slice hot-swap

9 min
checkpoint restore

21 min
total time lost*

*downtime + lost progress since last checkpoint, on a 32,768-chip job

A Surprise: Training Modules → SOTA Inference

Encapsulated KV-cache layouts let us drop in continuous batching, disaggregated prefill/decode, and paged caches *without* re-implementing models or layers.

Model	System	TTFT	TPOT	Throughput
Llama2-7B	vLLM	538.6 ms	22.4 ms	1,117 tok/s
	AXLearn	**40.1 ms**	**9.1 ms**	**3,125 tok/s**
Llama2-70B	vLLM	80 s	189.8 ms	705 tok/s
	AXLearn	**150.5 ms**	**28.1 ms**	**1,139 tok/s**

500× TTFT, up to 6.7× TPOT, 1.6–2.8× throughput

On TPU. Inference performance was *not* the design goal — it fell out of strict encapsulation.

Deployed at Apple

- One codebase across **AWS, GCP, Azure, on-premises** — GPU, TPU, Trainium2.
- **Thousands of models** trained by **hundreds of engineers** over several years.
- **Apple Intelligence** runs on top.
- Open source under Apache 2.0.

Open source — `github.com/apple/axlearn`

`pip install axlearn` Apache 2.0 · JAX · XLA · GSPMD

Takeaways

1. **Strict encapsulation** unlocks modularity — configs as trees, modules as drop-ins.
2. **LoC-Complexity** captures what plain LoC misses: how a system *evolves*.
3. **One codebase, every backend** — GPU, TPU, B200, Trainium2 — via XLA + custom kernels + mesh rules.
4. **Bet on a compiler-first design** (XLA + GSPMD) paid off: layers stay modular as new hardware arrives.

Open source — `github.com/apple/axlearn`

`pip install axlearn` Apache 2.0 · JAX · XLA · GSPMD