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Optimizing Transformer-based Sequential Recommender Systems

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Executive Summary

Goal:
To evaluate how model scaling and optimization strategies affect training efficiency and performance of BERT4Rec for sequential recommendation.

Approach:
Scaled BERT4Rec from 5M to 430M parameters and applied multiple optimization techniques across three hardware platforms (NVIDIA A100, V100, L4).

Value / Benefit:
Demonstrated how modern ML optimization techniques can dramatically reduce training time and resource cost while improving throughput for large models.

Technical Challenges

- Model instability with scaling (sensitive to LR, exploding gradients) => Hyperparameter sweeps
- Memory bottlenecks during training larger models (430M) => Distributed training
- Instability in training with mixed precision (AMP) => use GradScaler for gradient scaling
- Slower training on V100, L4 => did not use L4 for the largest model
- GPU availability on HPC
- Tuning iLoRA

Approach

Baseline Setup

- **Dataset**: MovieLens-20M (initial), Amazon Electronics (for scaled up variants)
  - Preprocessed to filter users/items with fewer than 5 interactions
  - Created input sequences for masked item prediction (like MLM)

- **Base model**: BERT4Rec (originally 5M parameters, scaled up to 85M for new baseline)

- **Scaled variants**: 130M, 430M

- **Framework**: PyTorch 2.1
  - Mixed Precision using torch.cuda.amp
  - Model Optimization using torch.compile, torch.jit
  - iLoRA integration via manual LoRA injection into transformer layers

- **Baseline metrics**: Hit Rate at 10, epoch time, throughput

- **Experiment Tracking & Profiling**: Weights & Biases (WandB), PyTorch Profiler

- **Multi-GPU scaling**: DistributedDataParallel

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Approach

Optimization Techniques

- Hyperparameter sweeps: LR, dropout, weight decay
- Mixed precision training: AMP
- torch.compile & torch.jit: runtime graph optimizations
- iLoRA (Instance-wise LoRA): parameter-efficient tuning
- Metrics recorded: Accuracy, Time/epoch, Throughput (samples/sec)

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Summary of Main Results

Model Size	Accuracy (Hit Rate@10)	Hardware (GPU)	Time/Epoch	Throughput (samples/sec)
5M : original model on MovieLens-20M	0.0745	T4	~17 min	3378.37
85.11 M	0.0818	A100	~2.5 min	19659.98
130.10 M	0.0855	A100	~4 min	11630.68
429.15 M	0.0910	A100	~9 min	3805.26

- AMP & torch.compile halved training time for larger models
- iLoRA achieved similar accuracy with <1% of trainable params

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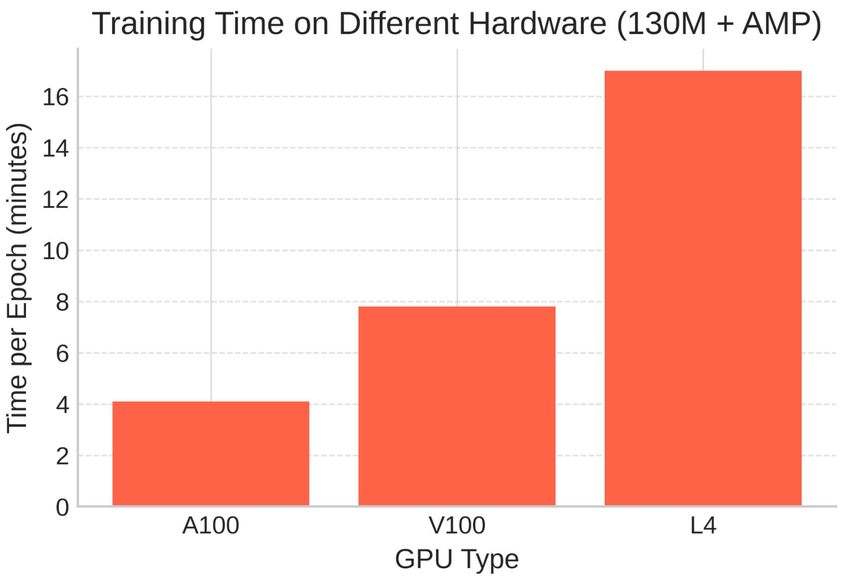
Experimental Evaluation:

I. Hardware Comparison: NVIDIA A100, V100, L4

- A100: Fastest
- V100: Takes double the time.
  2x V100 equal to 1x A100 in time.
- L4: Takes almost 4x of A100



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Experimental Evaluation:

II. JIT + AMP

- torch.compile reduced Python overhead significantly
- AMP improved speed almost 2x with negligible loss in accuracy

III. iLoRA

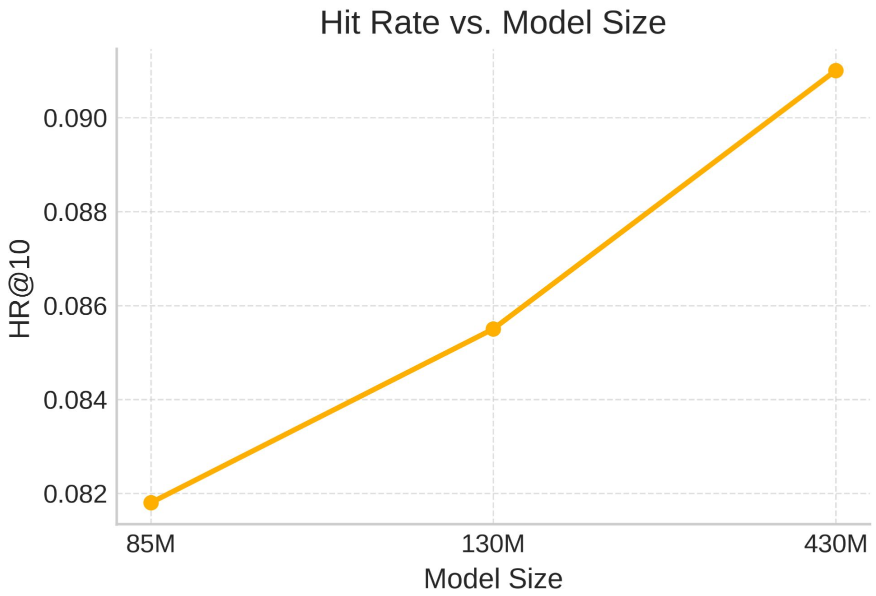
- Applied on 130M (trainable 0.55%) & 430M (trainable 0.96%) models
- Retained accuracy while reducing trainable parameters by 99.4%
- Tradeoff: iLoRA bit slower per epoch, but saves memory and compute

Experimental Evaluation

Performance vs Model size:

Hit Rate@10: a measure of evaluating the performance of recommender systems.

We observe that the hit rate improves with increasing model size due to higher capacity of the model to learn dependencies.



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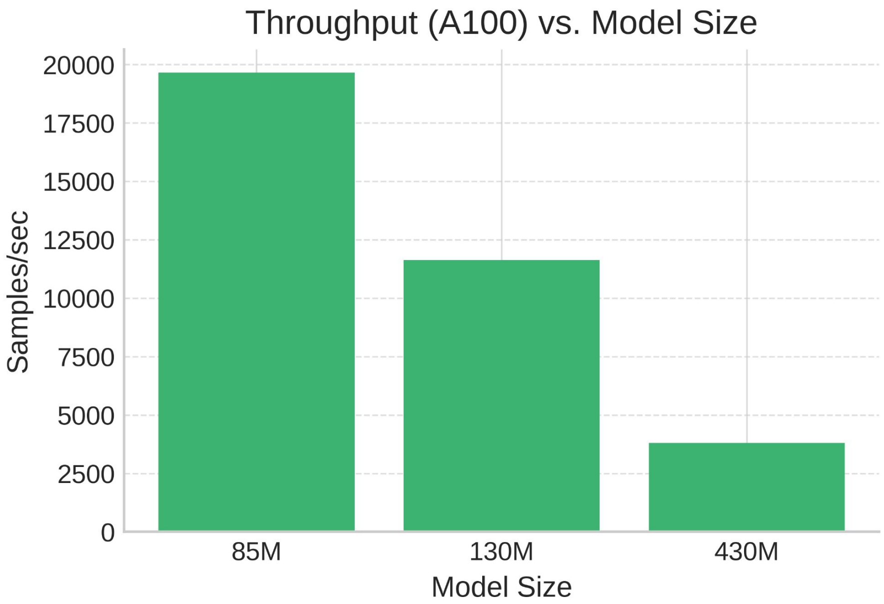
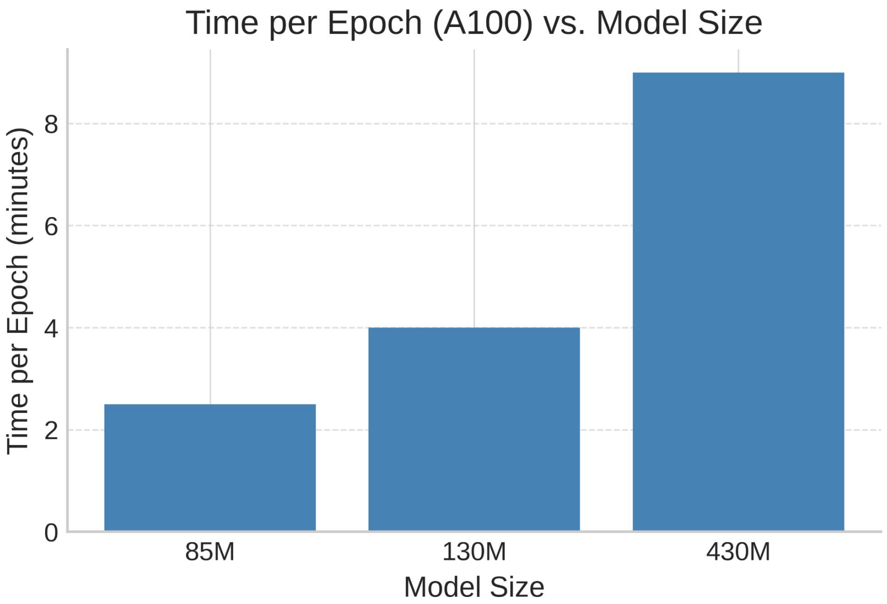
Training efficiency vs Model size:

- Throughput drops as model size increases due to higher compute and memory demand.
- Training time increases sharply as model size grows, especially beyond 130M.





Profiling Insights with PyTorch Profiler: 130M model

Metric	No Opt	AMP Only	Compile Only	AMP+Compile
Self CUDA Time Total	201.2 ms	204.4 ms	203.5 ms	32.6ms
Peak CUDA Memory	~11.2GB	~7.2GB	~11.2GB	~7.2GB
Top Op by CUDA %	aten::mm	aten::mm	aten::mm	CompiledFunction + mm
Launch Overhead	High	High	Lower	Lowest

*these experiments were done on the 130M model on A100 GPU

- **AMP + Compile drastically reduces Self CUDA time** (6× faster), due to op fusion + FP16 acceleration.
- **AMP alone reduces memory usage** (~4 GB saved), enabling larger batch sizes.
- torch.compile introduces minor CPU overhead but eliminates redundant kernel launches.
- aten::mm remains dominant, but fused CompiledFunction replaces many smaller ops.

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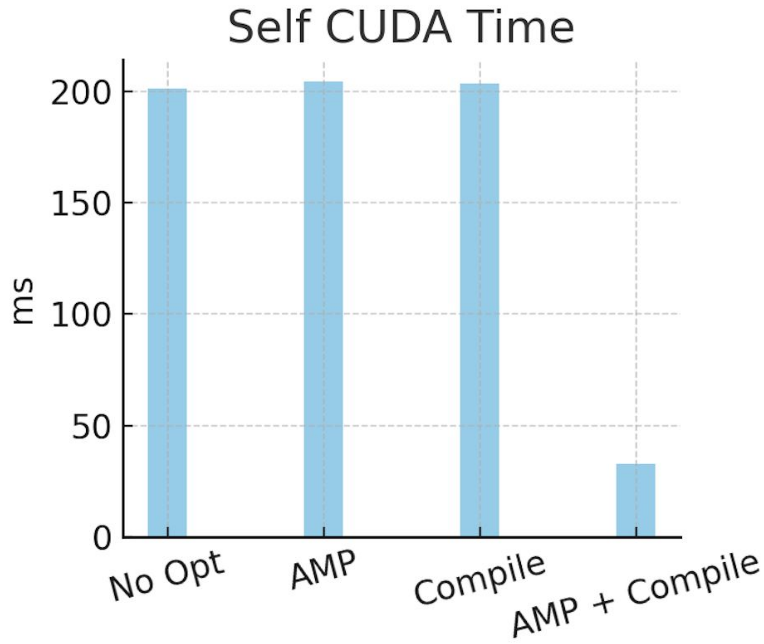
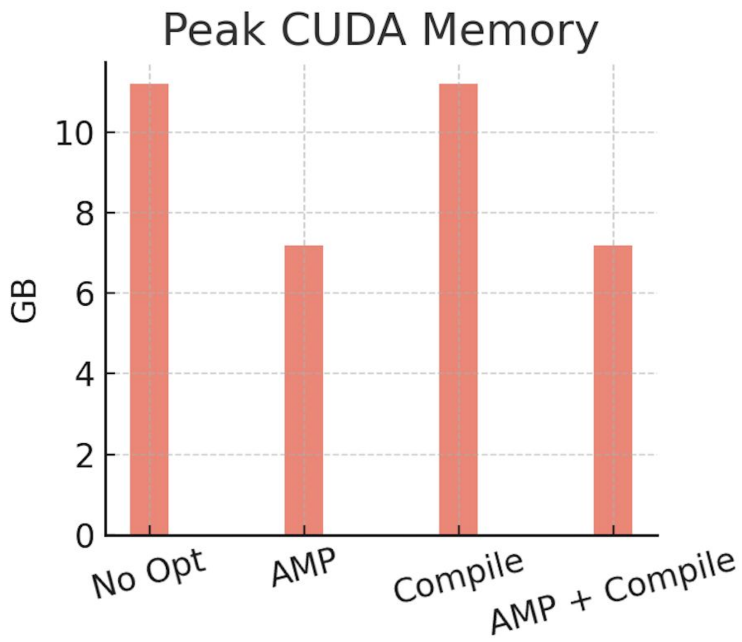
Profiling Insights with PyTorch Profiler





Combining AMP and torch.compile reduces step time by 75% and memory by 40%, giving the most optimized BERT4Rec training setup

Profiling Insights with PyTorch Profiler

Configuration	Step Time	Self CUDA	Memory
iLORA	~470ms	~470ms	10.4GB
iLORA+AMP	~173ms	100.7ms	2.9GB
iLORA+AMP+Compile	~975ms	908ms	8.1GB
iLORA+AMP+Compile(Reduced)	~130ms	~76ms	2.85GB

*these experiments were done on the 430M model on A100 GPU

- The **baseline iLoRA** shows the slowest execution, with high memory demands and over 470 ms per training step.
- Adding **AMP** drastically reduces both step time and memory consumption, dropping usage from ~10.4 GB to ~2.9 GB.
- However, using **default torch.compile** with AMP introduces significant overhead due to dynamic adapter logic, increasing step time to nearly 1 second.
- Switching to **torch.compile(mode='reduce-overhead')** recovers performance — achieving the **fastest iLoRA configuration**, with ~130 ms step time and only 2.85 GB memory usage.

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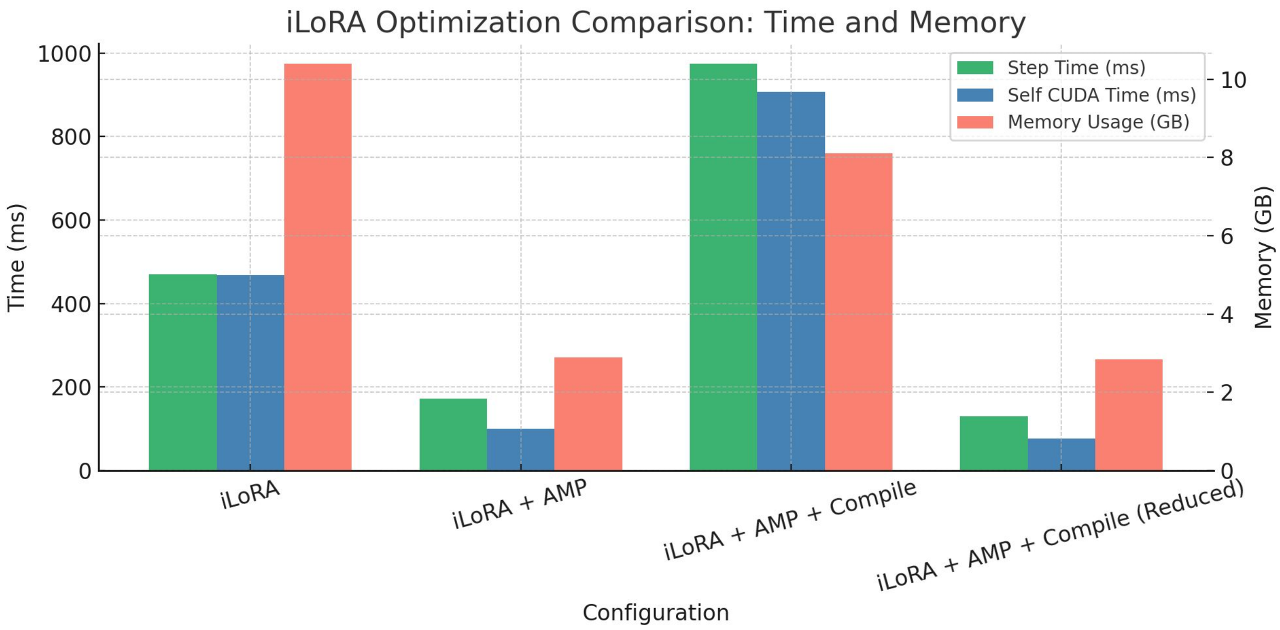
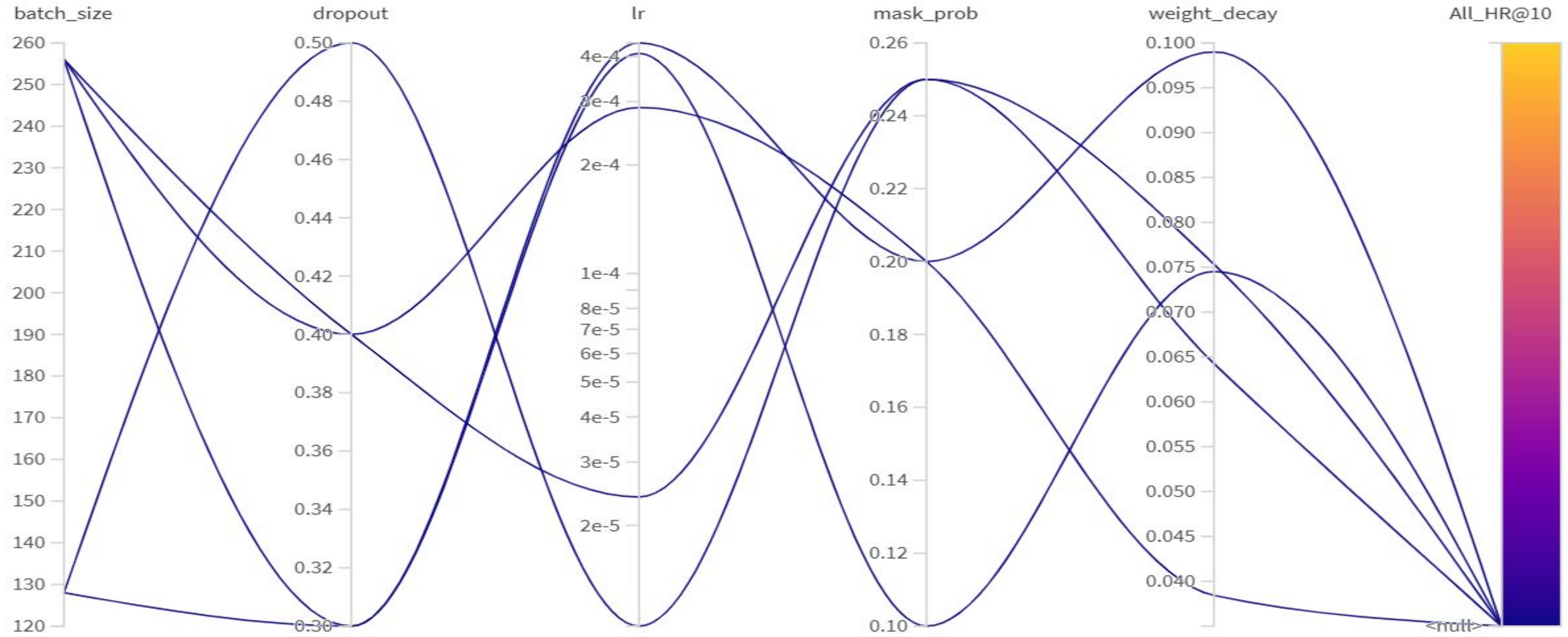
Profiling Insights with PyTorch Profiler



By switching to reduce-overhead, we retain AMP's memory and speed gains while avoiding compile overhead — achieving the best iLoRA performance.

WandB Sweeps



Observation and Conclusion

- Scaling BERT4Rec improves performance but at high compute cost
- AMP + torch.compile offers best speedup across all sizes
- iLoRA is a promising technique for training large models with limited resources
- Optimization needs to be hardware-aware for best results

GitHub Repository

GitHub:
https://github.com/mahi397/Optimizing-Transformer-based-Sequential-RecommenderSystems

WandB: https://wandb.ai/ms15532-new-york-university/BERT4Rec

WandB: https://wandb.ai/tt2884-new-york-university/BERT4Rec

THANK YOU

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