Feature-Aware Pruning in MLPs

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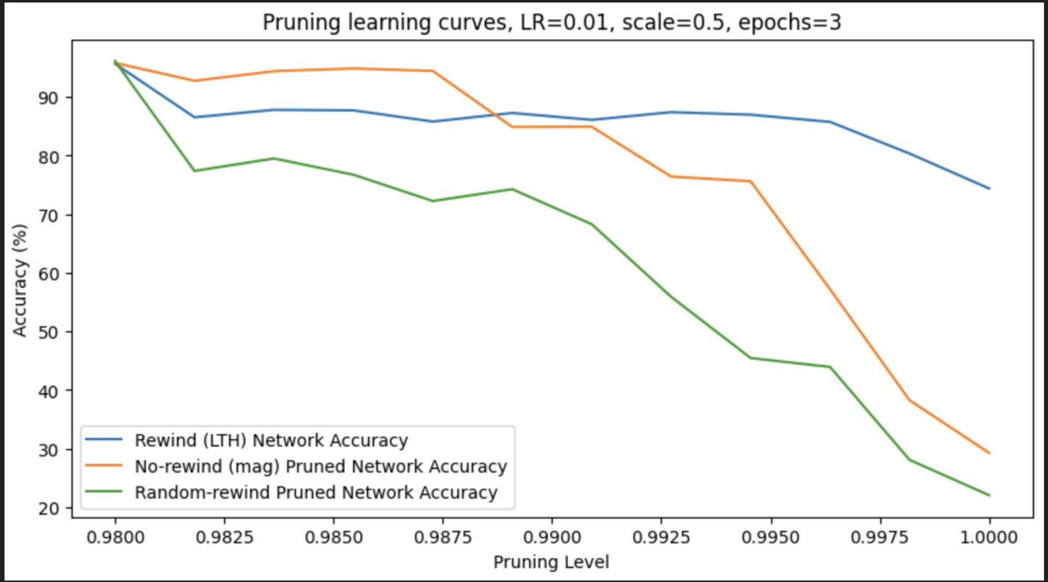
Levels of pruning

1) Before training, at init (SNIP, GraSP, SynFlow) [1, 2, 3]
2) **During training (lottery tickets)** [4]
3) After training, before inference (magnitude-based pruning) [5]

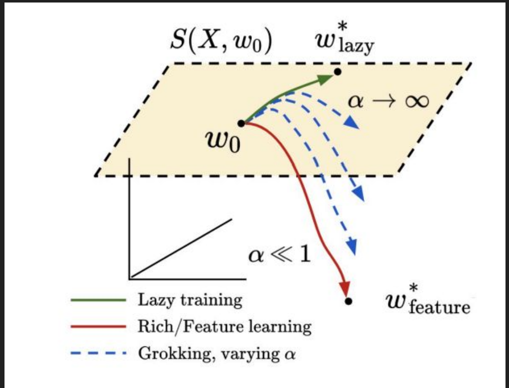
Lottery Ticket Hypothesis



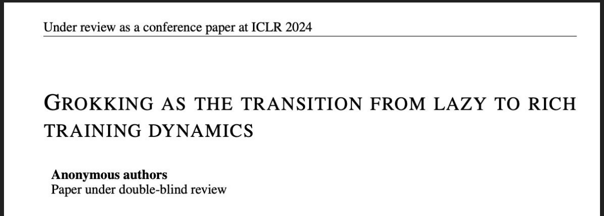
30 seconds of ML theory: lazy and rich training regimes

- Networks are powerful *nonlinear* models.

- ML theorists have discovered ways to modify any neural network to *continuously linearize it* [6, 7].
  - One such way, by tuning a parameter “alpha,” is given on the right
  - Highly nonlinear (small alpha) = “**rich training**,” vs highly linearized (large alpha) = “**lazy training**”
  - **Amount of feature learning = deviation from linearized model (tuned by alpha)**



(c) α Alters Dynamics



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GROKKING AS THE TRANSITION FROM LAZY TO RICH TRAINING DYNAMICS

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Paper under double-blind review

Feature-Learning Networks Are Consistent Across Widths At Realistic Scales

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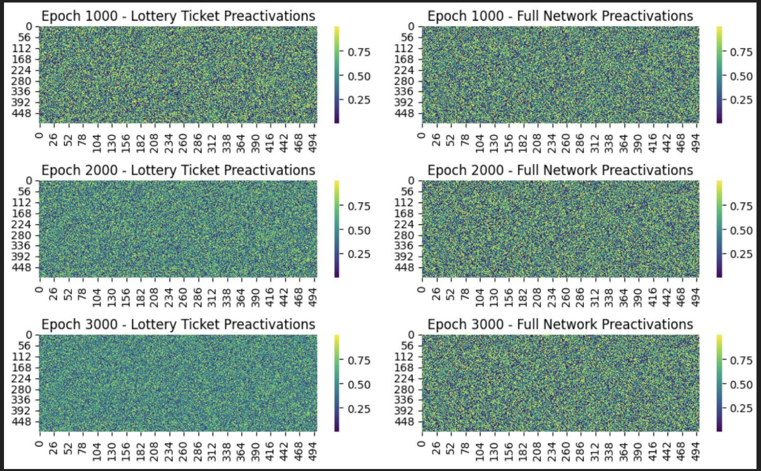
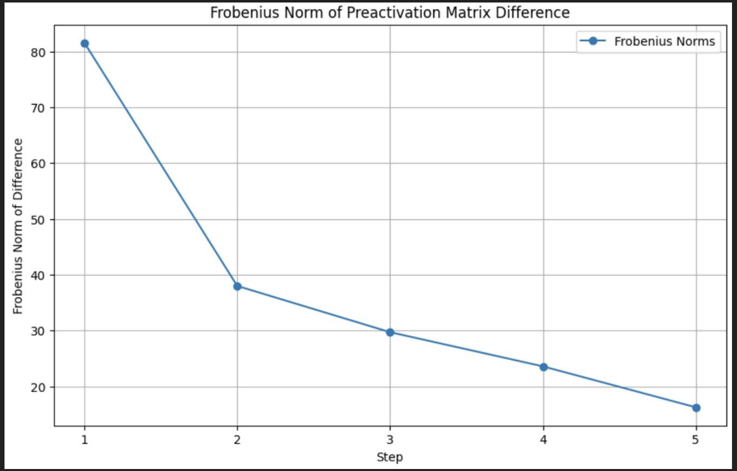
Toy model

- One hidden-layer MLP student-teacher task [8, 9]
- Find lottery ticket on this model, then train lottery ticket and full network
- Compare preactivation matrices for lottery ticket and full net during training
  - Visual way to compare “learned features”





Take-away from toy model

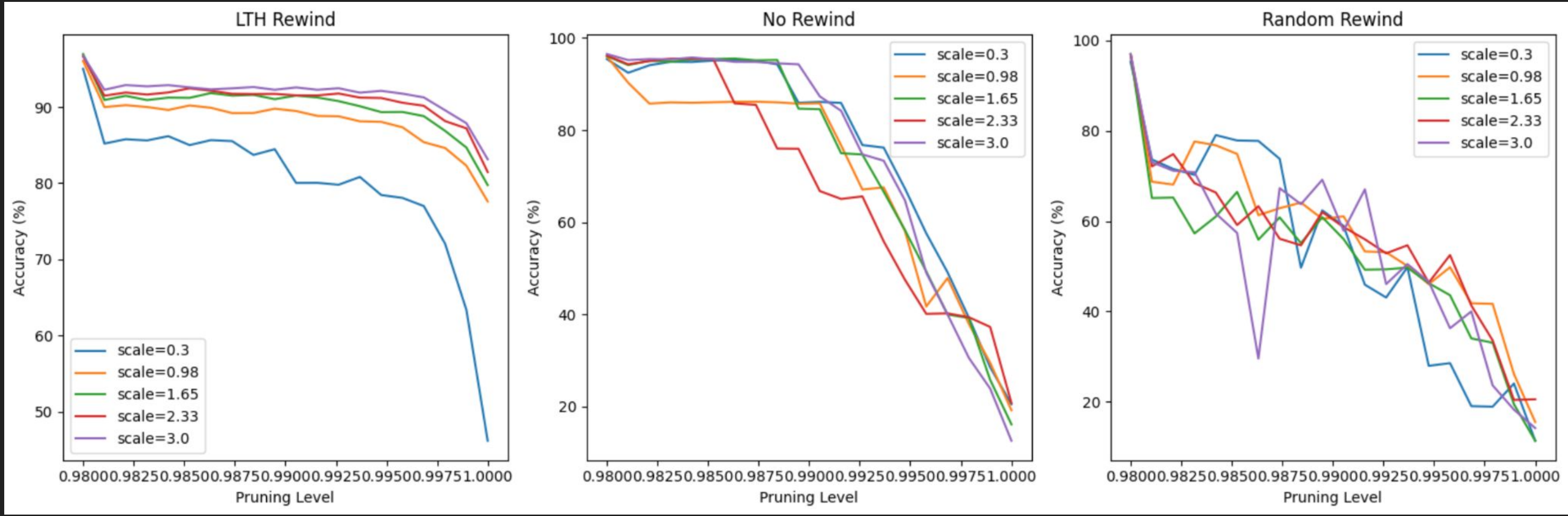
LTH:

1. Pruned networks reach same end-time test error as full network
2. (Stronger) Pruned networks reach same end-time *features* as full network
3. (Strongest) Pruned networks have same *feature dynamics* as full network

Conjecture: LTH paper shows (1). Toy model suggests (3). This property *does not hold for pruning with random rewinding or no rewinding*!

Hypothesis: sweeping over rate of feature learning should change performance of lottery tickets *uniformly*, but performance of random/no rewind in a complicated, *messy* way (features are not necessarily the same over sweep).

Testing conjecture **on MNIST**



Punchline: *we can beat the state of the art in pruning* by using tricks from theory.

Left (orange) is MLP on MNIST from LTH paper. Purple is **(ours).**

References

Before Training, at Initialization:

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After Training, Before Inference:

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Appendix: additional experiments (explained in report)