Learning Dynamic Networks

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Problem Statement

Overparameterized models have led to many **breakthroughs** in machine learning.

Challenges:
- Larger Models:
  - Efficient **storage** and inference.
  - **Efficient training** of large models.
  - **Overfitting**, regularization and generalization.
- Train Longer:
  - Handle **temporal** dynamics of training.

Overparameterization - Sparsity/Pruning

Common method to handle challenges of overparatermization - **Pruning**.

Benefits - similar performance, with a **fraction of the weights** , **faster training** and more **robust** to noise.

Our Approach - Can we learn these schedules using RL

Algorithm 1 Learning Sparsity Schedules using Reinforcement Learning

Input: train dataset X_{train_set}, test dataset X_{test_set}, train network f_{train}, eval network f_{eval}, agent a, number of episodes N, minimum density per layer min_d and maximum density per layer max_d.

$a \leftarrow init(min_d, max_d)$ ▷ Initialize agent a.

$X_{train\_split}, X_{val\_split} \leftarrow split(X_{train\_set})$ ▷ Split train dataset.

for episode=1,N **do**

  $a \leftarrow train\_loop(a, X_{train\_split}, X_{val\_split}, f_{train})$ ▷ Run train loop and retrieve trained agent a.

  eval_loop$(a, X_{train_set}, X_{val_set}, f_{eval})$ ▷ Run evaluation loop on unseen network f_{eval} using trained agent a.

end for

- Agent - PPO.
- Dataset - Cifar10.
- Sparsity:
  - Random Pruning, with Random Regrowth (**RP-RR**)
  - Magnitude Pruning, with Random Regrowth (**MP-RR**)

Train Longer - Schedules

When we train longer -> more **critical temporal decisions** to make.

Temporal Decisions (examples include):
- Learning Rate - Initial Learning Rat & **LR Schedule**.
- Sparsity - Initial Sparsity & **Sparsity Schedule**.

What about these choices per layer?! - **Layerwise Schedules.**
Standard approach - choose these schedules through **trial-and-error**.

Question

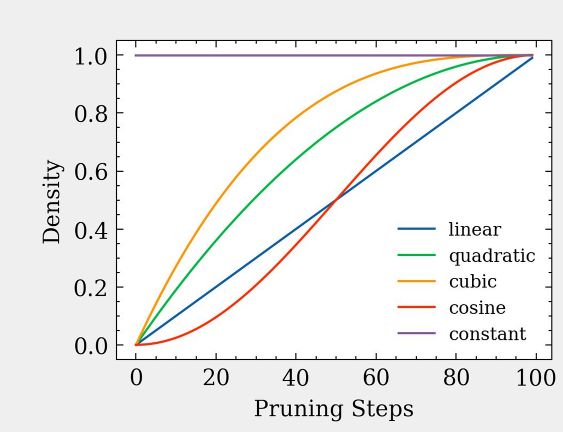
Can we learn **temporal** (possibly **layerwise**) **schedules** in a principled manner?

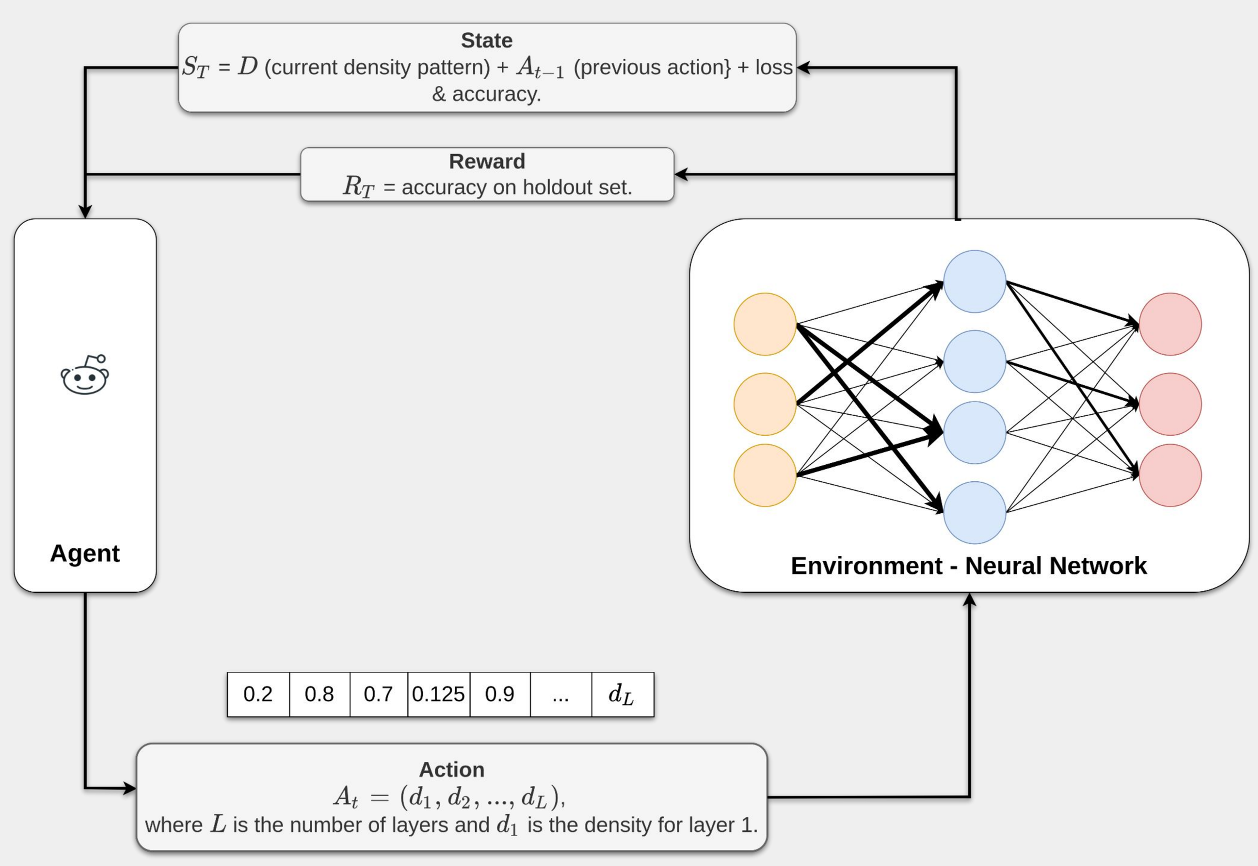
Related Work

Handcrafted schedules.

- ***Constant*** - SET [1], Deep Rewiring (DeepR) [2] and Neural Network Synthesis Tool (NEST) [3].
- ***Cosine*** - RigL [4] and Sparse Network From Scratch (SNFS) [5]
- ***Cubic*** - [6],[7].

Examples of Simple Schedules:





Results

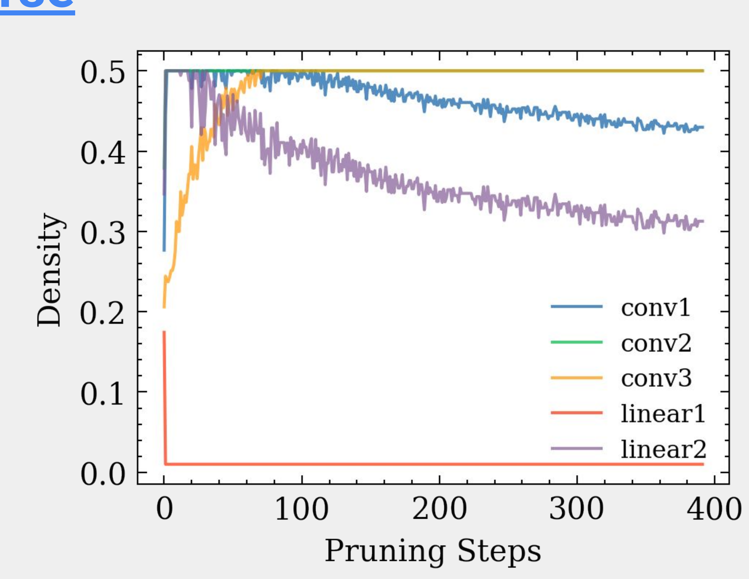
Simple CNN - 5 Layers

1. Learned Schedules are Competitive

Table 1: Test Accuracy (mean and standard deviation) of different schedules on CIFAR-10, using Simple-CNN.

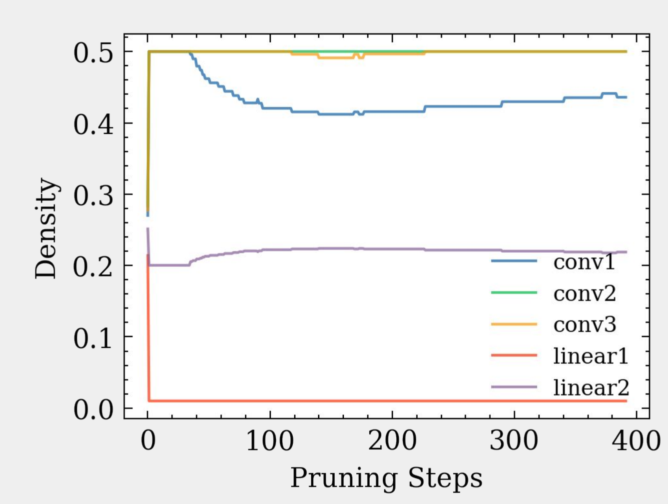
Target Density (%)	Schedule	Random Pruning with Random Regrowth (RP-RR)	Magnitude Pruning with Random Regrowth (MP-RR)
10	Linear	20.365 +- 17.952	60.418 +- 1.362
	Quadratic	23.15 +- 20.043	61.259 +- 1.485
	Cubic	33.721 +- 21.693	60.396 +- 0.832
	Cosine	18.302 +- 14.379	59.807 +- 0.384
	Constant	**61.475 +- 0.731**	62.536 +- 0.314
	Learned (Ours)	61.071 +- 1.574	**63.191 +- 0.810**
50	Linear	64.54 +- 0.477	64.78 +- 0.464
	Quadratic	64.987 +- 0.86	63.933 +- 0.431
	Cubic	65.31 +- 0.49	64.315 +- 0.437
	Cosine	64.672 +- 0.771	64.737 +- 0.345
	Constant	65.1 +- 0.283	65.388 +- 0.375
	Learned (Ours)	**65.655 +- 0.515**	**65.686 +- 0.284**
100	Linear	66.228 +- 0.691	66.711 +- 0.423
	Quadratic	66.947 +- 0.749	67.25 +- 0.578
	Cubic	66.857 +- 0.627	67.395 +- 0.547
	Cosine	66.074 +- 0.282	66.18 +- 1.027
	Full Dense	**67.815 +- 0.146**	67.878 +- 0.482
	Learned (Ours)	67.534 +- 0.174	**67.908 +- 0.162**

2. Learned Schedules are Layerwise Diverse



3. Learned a Handcrafted Schedule!

Piecewise Schedule for Random Pruning- [8].



ResNet-18

Schedule	Test Accuracy
Linear	93.019 +- 0.024
Quadratic	93.106 +- 0.107
Cubic	**93.148 +- 0.156**
Cosine	92.916 +- 0.105
Constant (Fully Dense)	92.481 +- 0.641
Learned (Ours)	92.818 +- 0.048

Challenges:
1. **Non-stationarity** environment.
   a. Our environment (the network we are learning a schedule for) is learning and adapting while our agent is learning to model the environment.
   b. Worse for challenging networks - use techniques like **data augmentation** and **learning rate decay** (e.g. ResNet-18).
2. **High dimension** action and (possibly) state space.
3. **Slow convergence** - 25-50 episodes.

Conclusion:

In this work, we demonstrate that it is **possible** to learn **well performing dynamic sparsity schedules** using reinforcement learning. The schedules learned are not arbitrary and are distinct per layer and pruning method.

References

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ICML Workshop Paper- Workshop on Dynamic Neural Networks.