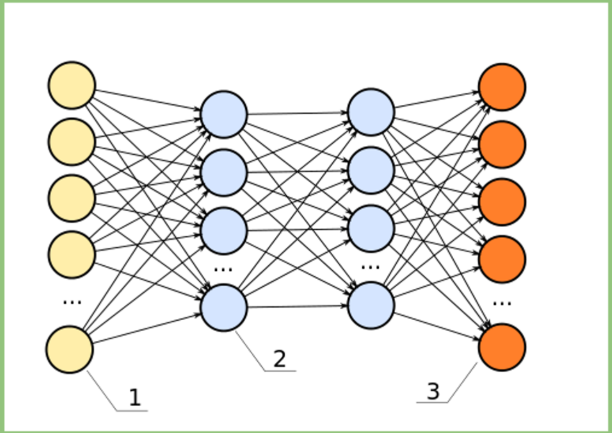
The Lottery Ticket Hypothesis

paper by Jonathan Frankle and Michael Carbin
@ MIT CSAIL [link]

presentation by **Jack Morris**
12/1/19



https://qdata.github.io/deep2Read/

Background: **Pruning**

- To reduce the size of a neural network by removing unwanted parts

- People have been trying to **prune** neural networks for awhile
  - Idea originated into 1990s

The Pruning Process

1. Train the network
2. Remove superfluous structure
3. Fine-tune the network
4. [optional] iteratively repeat steps 2 and 3

<u>What structure?</u>

Weights? Neurons? Filters? Channels? Layers?

<u>What does "superfluous" mean?</u>

Magnitudes? Gradients? Activations?

Motivation

As you may imagine, lots of groups have tried something like this before

"Training a pruned model from scratch performs worse than retraining a pruned model, …, which may be due to the difficulty of training small networks from scratch" – Pruning Filters for Efficient ConvNets

Motivating Questions

Can we train sparsely pruned networks from scratch? **Yes**

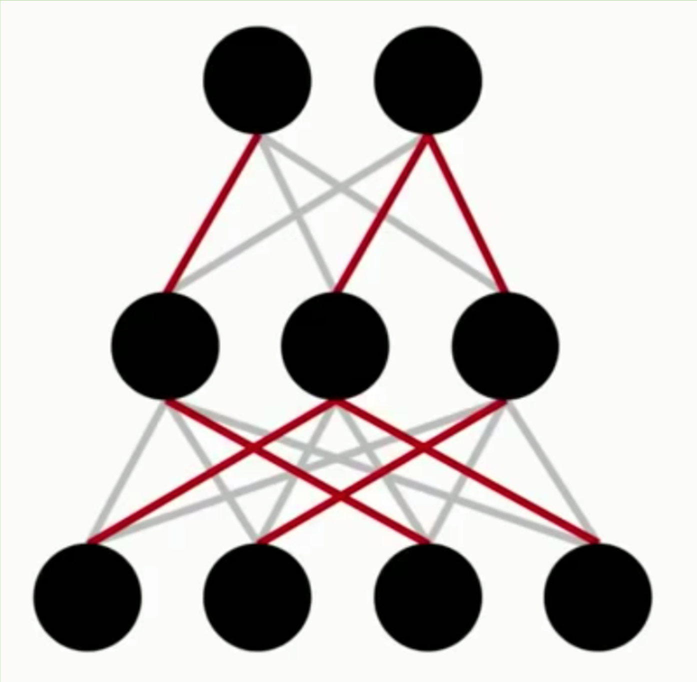
Corollary: Do networks have to be overparameterized to learn? **No**

There's a catch: **Need to reuse the weight initializations from the original training process**.

Training Pruned Networks

1. Randomly initialize the network's weights
2. Train it and prune superfluous structure
3. Reset each remaining weight to its value from 1
4. Repeat and 💰 **PROFIT** 💰

Training Pruned Networks



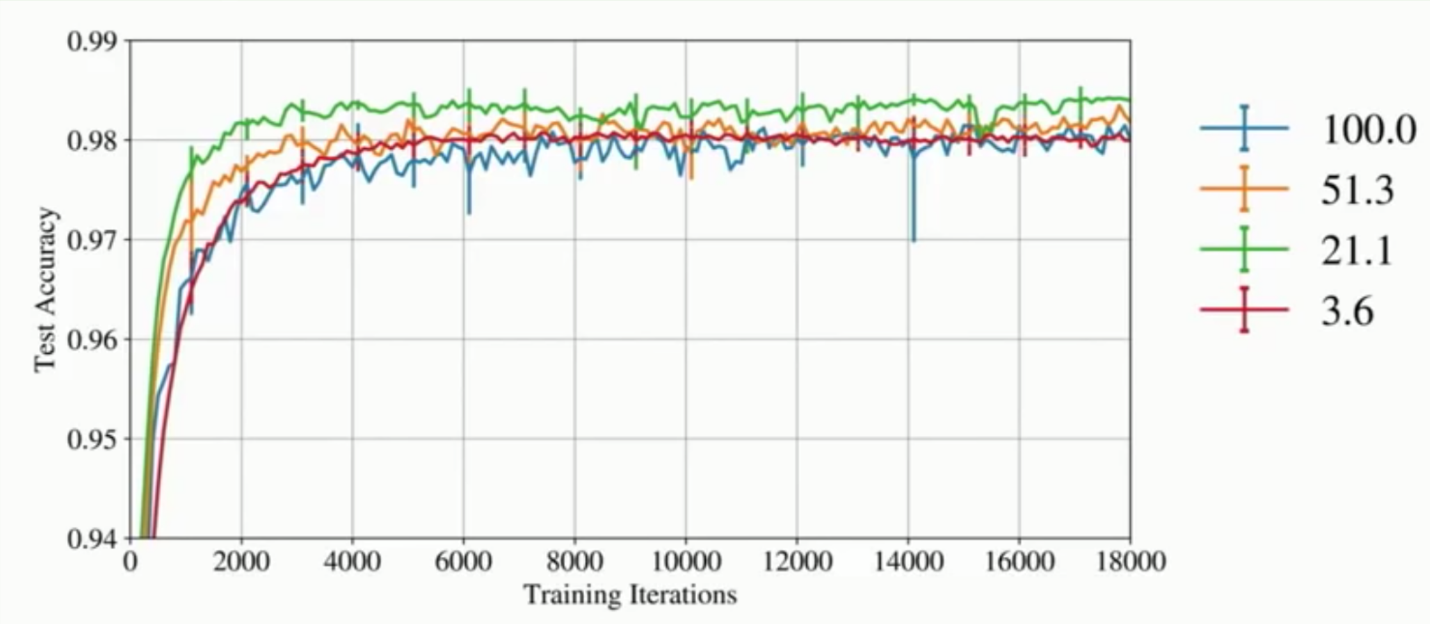
Training Pruned Networks

- Giant appendix shows that this works with batch normalization, dropout, convolutional layers, weight decay, residual connections, optimizers, etc. for any hyperparameter choices
- ***Caveats:***
  - 1. If you randomly reinitialize the network, this won’t work
  - 2. You still have to train the network first (so it’s not a particularly efficient process)

Training Pruned Networks

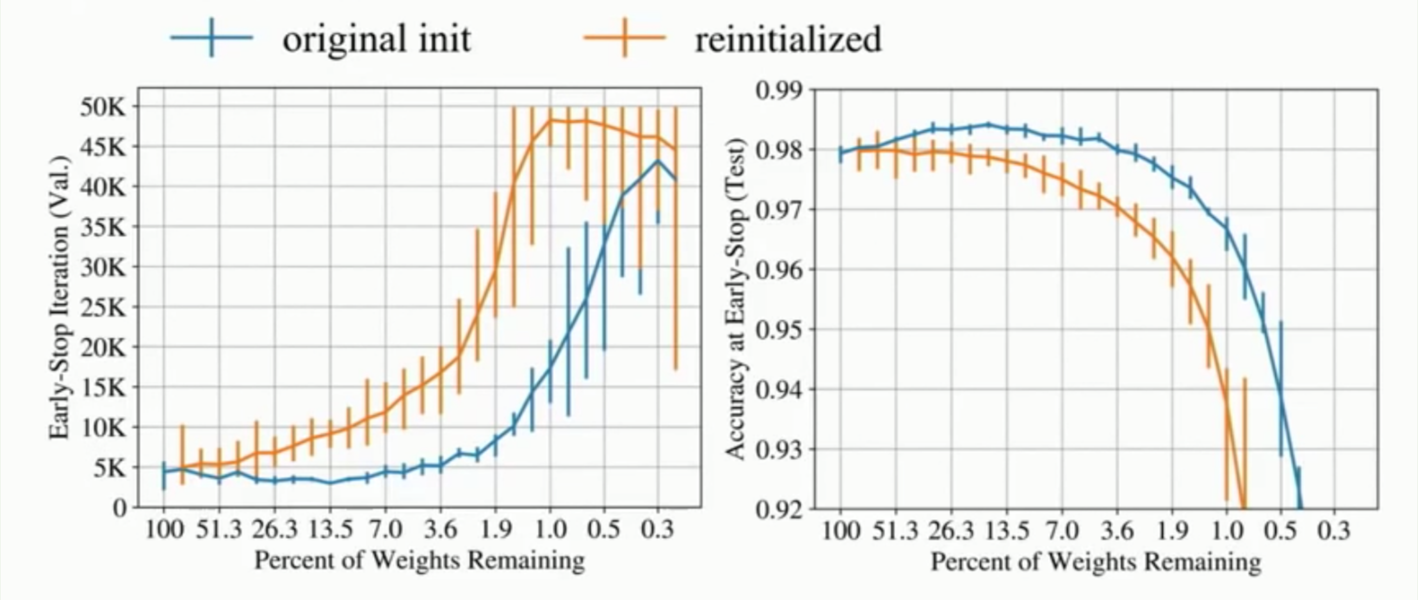
- So to recap, these small subnetworks:
  - 1. Are between 15% and 1% of the original size
  - 2. Learn faster than the original network
  - 3. Reach the same or higher test accuracy

Results



LeNet 300-100-10 for MNIST / fully-connected / 300k parameters

Results



LeNet 300-100-10 for MNIST / fully-connected / 300k parameters

The Lottery Ticket Hypothesis

Plain English:
Dense, trainable networks have sparse trainable subnetworks that are equally capable

Formally:
$f(x; W)$ reaches accuracy **a** in **t** iterations
$f(x; m \circ W)$ reaches accuracy **a'** in **t'** iterations

$\exists m \mid \quad \sum m \ll w \quad a' \geq a \quad t' \leq t$

Possible future work

- Finding a way to prune networks early in training

- Examining these subnetworks to see what works– use this info to develop better architectures and initializations

- Make good subnetworks and reuse them on tasks
    - (A good test for overfitting, too)

- *Stabilizing the Lottery Ticket Hypothesis* (Frankle, 2019)
    - Prune after a few iterations, not at t=0
    - Compress ResNet-50, Inception-v3 in one shot by over 50%!

Questions?