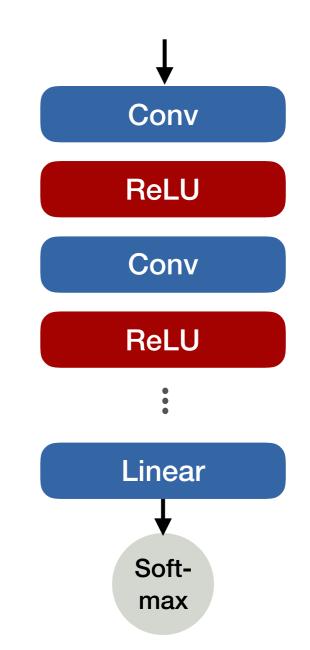
# Open Problem: Understanding generalization

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# Generalization in deep learning

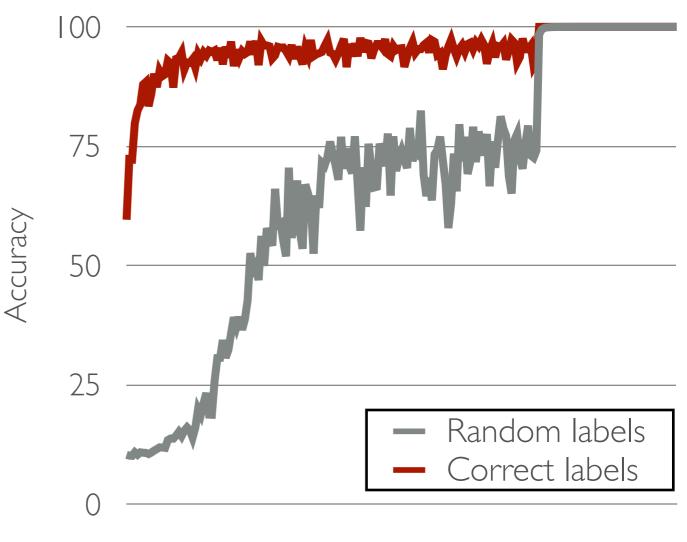
- Standard wisdom
  - Bigger/wider models overfit more



### Deep networks are big enough to remember all training data

Deep networks easily fit random labels

- Memorize all data
- Works even for random noise inputs



wide resnet on cifar-10

Epochs

Understanding deep learning requires rethinking generalization, Zhang etal. 2017

# Why does SGD still work?

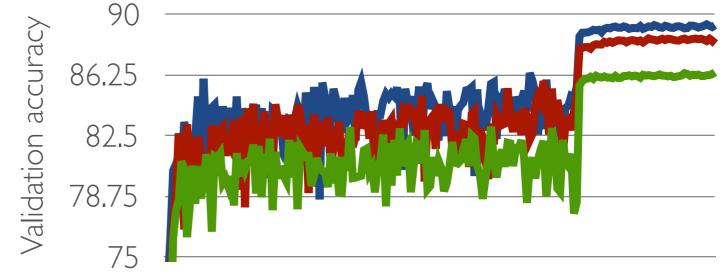
- SGD gradually minimizes objective
- Prefers solutions close to initialization
- Implicitly regularizes
- Random labels take SGD on a longer path

Exploring generalization in Deep Learning, Neyshabur etal. 2017

### Larger networks overfit less

#### wide resnet on cifar-10

- Without data augmentation
  100
  93.75
  87.5
  81.25
  100% training accuracy
  75
  - Larger models generalize better
  - Hence overfit less



Epochs

Understanding deep learning requires rethinking generalization, Zhang etal. 2017

### Larger networks overfit less

#### wide resnet on cifar-10

width 16 **Fraining loss** 0.75 width 32 width 48 0.5 0.25 /alidation loss 0.75 0.5 0.25 Epochs

On Calibration of Modern Neural Networks, Guo etal. 2017

 All models overfit massively on loss (log likelihood)

### Larger networks overfit less

- Do we need a new learning theory?
- Do we need new intuitions?

### In summary

- Models can overfit, but do not with SGD and data augmentation
  - Implicit regularization
  - How to do make it explicit?
  - Overfitting is dependent on learning algorithms (e.g. Adam overfits more)
- How can we measure overfitting?