## Feed-forward Neural Networks (Part 2: learning)

## Outline (part 2)

- Learning feed-forward neural networks
- SGD and back-propagation


## csall <br> Learning neural networks



## Simple example

- A long chain like neural network



## 540 <br> C S A I L <br> 2 hidden units: training

Initial network (hidden units)
Average hinge loss per epoch


C S A I L

## 2 hidden units: training

- After $\sim 10$ passes through the data
hidden unit activations




## 10 hidden units

- Randomly initialized weights (zero offset) for the hidden units



## 10 hidden units

- After ~ 10 epochs the hidden units are arranged in a manner sufficient for the task (but not otherwise perfect)




## 

- 2 hidden units can no longer solve this task



## 

- 2 hidden units can no longer solve this task

I 0 hidden units



## 用解 Decisions (and a harder task)

10 hidden units


100 hidden units


## Decision boundaries

- Symmetries introduced in initialization can persist...

100 hidden units
(zero offset initialization)


100 hidden units
(random offset initialization)


## Size, optimization

- Many recent architectures use ReLU units (cheap to evaluate, sparsity)
- Easier to learn as large models...

10 hidden units


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## 500 hidden units



## Summary (part 2)

- Neural networks can be learned with SGD similarly to linear classifiers
- The derivatives necessary for SGD can be evaluated effectively via back-propagation
- Multi-layer neural network models are complicated... we are no longer guaranteed to reach global (only local) optimum with SGD
- Larger models tend to be easier to learn ... units only need to be adjusted so that they are, collectively, sufficient to solve the task

