Feed-forward Neural Networks (Part 2: learning)

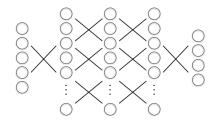


Outline (part 2)

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



Learning neural networks





Simple example

• A long chain like neural network

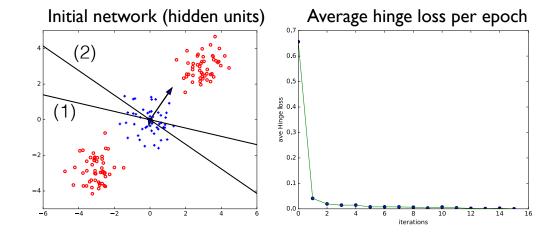








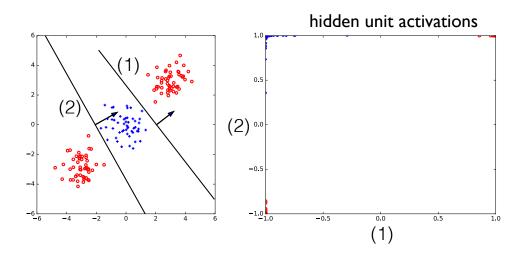
2 hidden units: training





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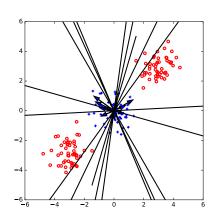
→ After ~10 passes through the data





10 hidden units

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



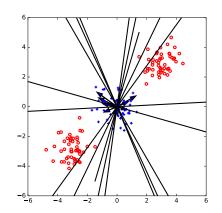


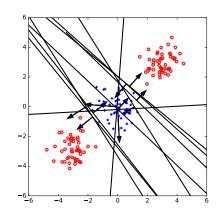
10 hidden units

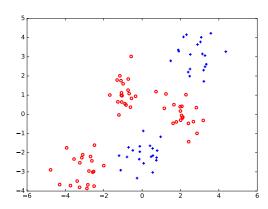
Decisions (and a harder task)

ightharpoonup 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



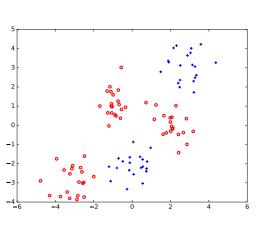


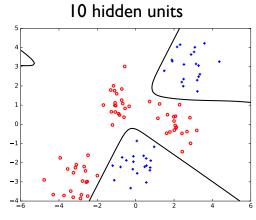


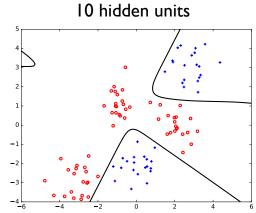
Decisions (and a harder task)

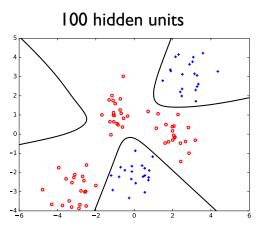
Decisions (and a harder task)

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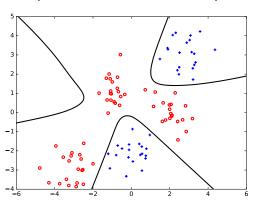




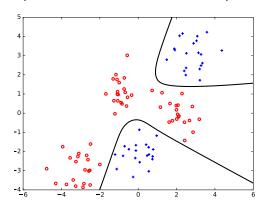
Decision boundaries

Symmetries introduced in initialization can persist...

100 hidden units (zero offset initialization)



100 hidden units (random offset initialization)

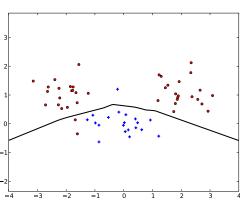


CSALL

Size, optimization

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

10 hidden units





Size, optimization

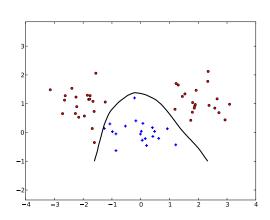
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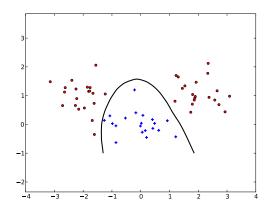
Size, optimization

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

100 hidden units



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