



COMP9444: Neural Networks and Deep Learning

Week 3b. Hidden Unit Dynamics

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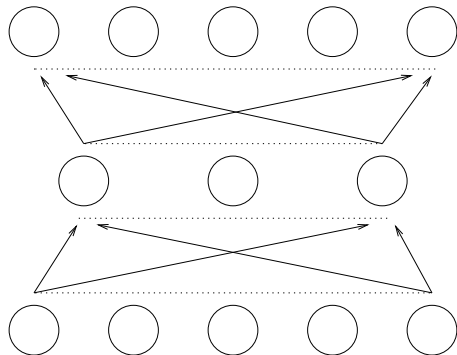
Outline

- geometry of hidden unit activations (8.2)
- limitations of 2-layer networks
- vanishing / exploding gradients
- alternative activation functions (6.3)
- ways to avoid overfitting in neural networks (5.2-5.3)

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Encoder Networks

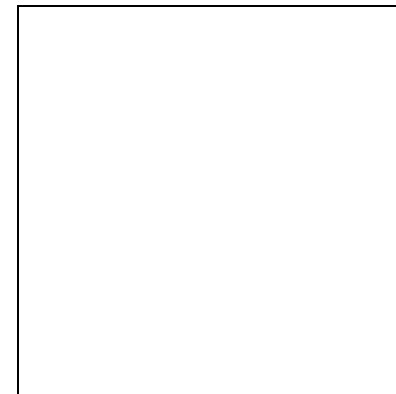


Inputs	Outputs
10000	10000
01000	01000
00100	00100
00010	00010
00001	00001

- identity mapping through a bottleneck
- also called N–M–N task
- used to investigate hidden unit representations

N–2–N Encoder

Hidden Unit Space:



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8-3-8 Encoder

Exercise:

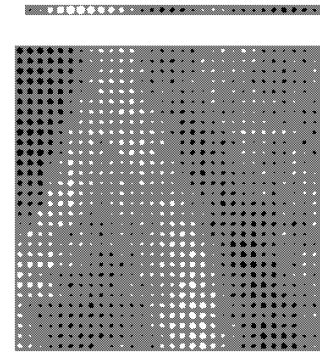
- Draw the hidden unit space for 2-2-2, 3-2-3, 4-2-4 and 5-2-5 encoders.
- Represent the input-to-hidden weights for each input unit by a point, and the hidden-to-output weights for each output unit by a line.
- Now consider the 8-3-8 encoder with its 3-dimensional hidden unit space.
 - what shape would be formed by the 8 points representing the input-to-hidden weights for the 8 input units?
 - what shape would be formed by the planes representing the hidden-to-output weights for each output unit?

Hint: think of two platonic solids, which are “dual” to each other.

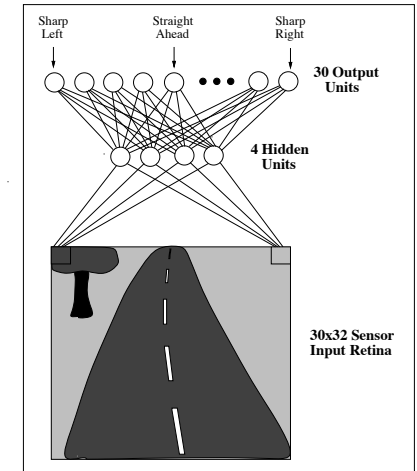
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Hinton Diagrams



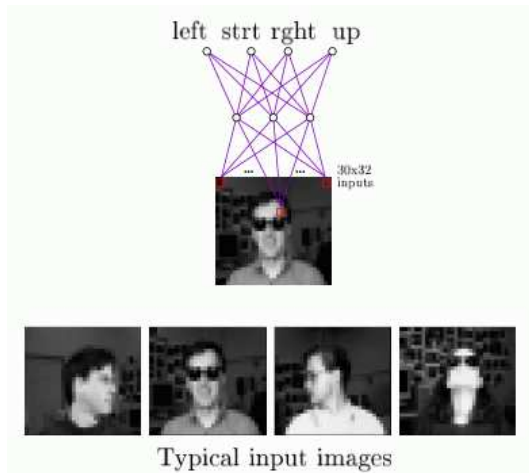
- used to visualize higher dimensions
- white = positive, black = negative



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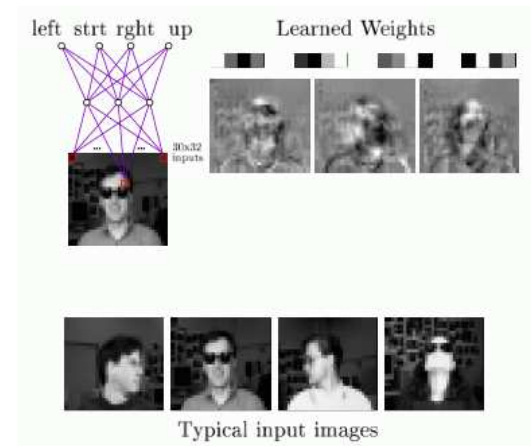
Learning Face Direction



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Learning Face Direction



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Weight Space Symmetry (8.2)

- swap any pair of hidden nodes, overall function will be the same
- on any hidden node, reverse the sign of all incoming and outgoing weights (assuming symmetric transfer function)
- hidden nodes with identical input-to-hidden weights in theory would never separate; so, they all have to begin with different random weights
- in practice, all hidden nodes may try to do similar job at first, then gradually specialize.

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Controlled Nonlinearity

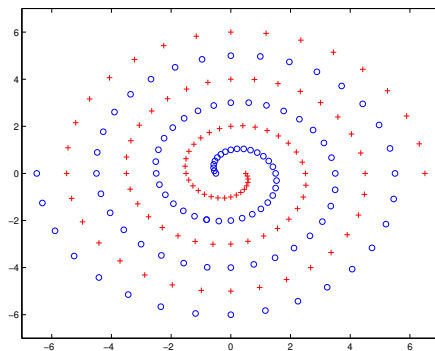
- for small weights, each layer implements an approximately linear function, so multiple layers also implement an approximately linear function.
- for large weights, transfer function approximates a step function, so computation becomes digital and learning becomes very slow.
- with typical weight values, two-layer neural network implements a function which is close to linear, but takes advantage of a limited degree of nonlinearity.

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Limitations of Two-Layer Neural Networks

Some functions are difficult for a 2-layer network to learn.

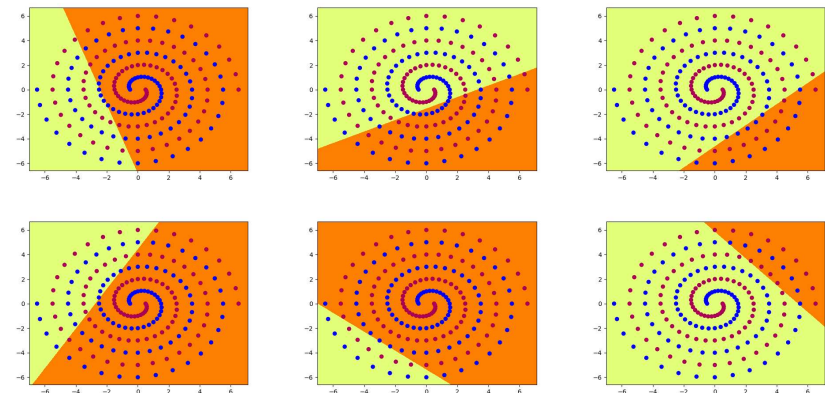


For example, this Twin Spirals problem is difficult to learn with a 2-layer network, but it can be learned using a 3-layer network.

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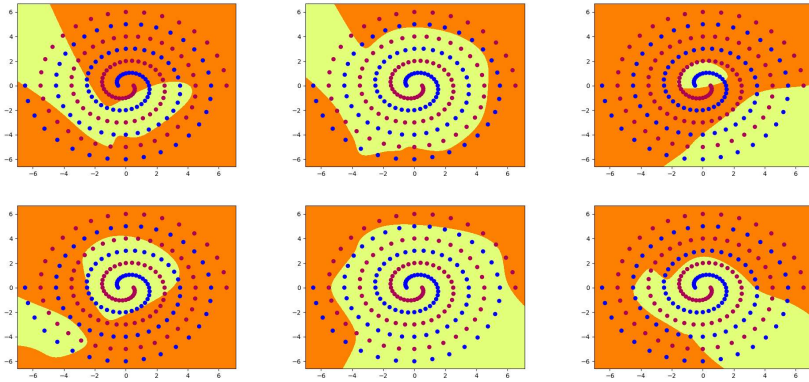
First Hidden Layer



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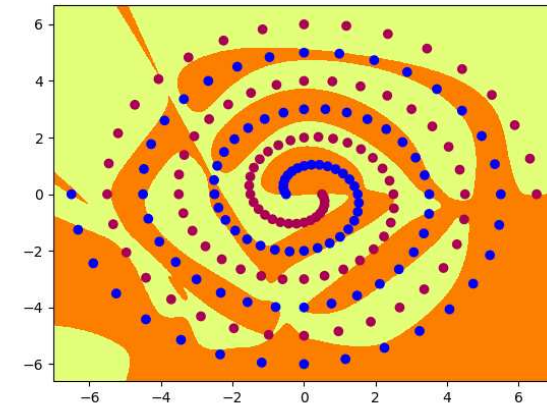
Second Hidden Layer



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Network Output



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Adding Hidden Layers

- twin spirals can be learned by 3-layer network
- first hidden layer learns linearly separable features
- second hidden layer combines these to produce more complex features
- learning rate and initial weight values must be small
- learning can be improved using the Adam optimizer

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Vanishing / Exploding Gradients

- training by backpropagation in networks with many layers is difficult
- when the weights are small, the differentials become smaller and smaller as we backpropagate through the layers, and end up having no effect
- when the weights are large, the activations in the higher layers may saturate to extreme values
- when the weights are large, the differentials may sometimes get multiplied twice in succession in places where the transfer function is steep, causing them to blow up to large values

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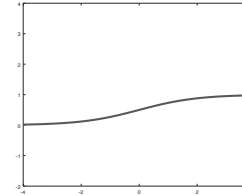


Vanishing / Exploding Gradients

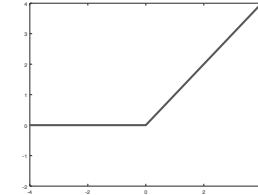
Ways to avoid vanishing / exploding gradients:

- new activations functions
- weight initialization (Week 4)
- batch normalization (Week 4)
- skip connections (Week 4)
- long short term memory (LSTM) (Week 5)

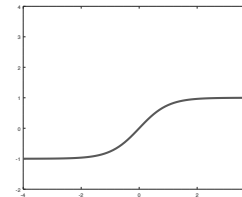
Activation Functions (6.3)



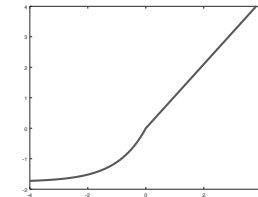
Sigmoid



Rectified Linear Unit (ReLU)



Hyperbolic Tangent



Scaled Exponential Linear Unit (SELU)

Activation Functions

- sigmoid and hyperbolic tangent traditionally used for 2-layer networks, but suffer from vanishing gradient problem in deeper networks.
- rectified linear units (ReLUs) are popular for deep networks (including convolutional networks); gradients will not vanish because derivative is either 0 or 1.