Block Practical: Connectionist models and cognitive processes

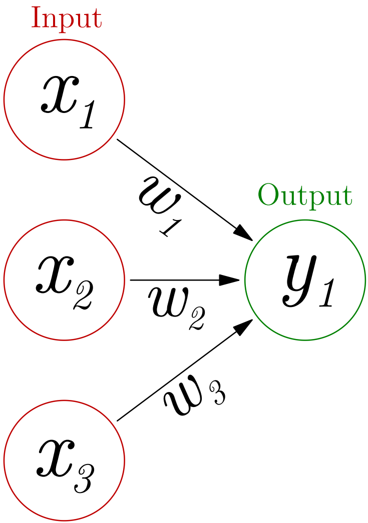
Part 3: **Feedforward Networks**

Olivia Guest

2-layer Perceptron

Simplest form of network

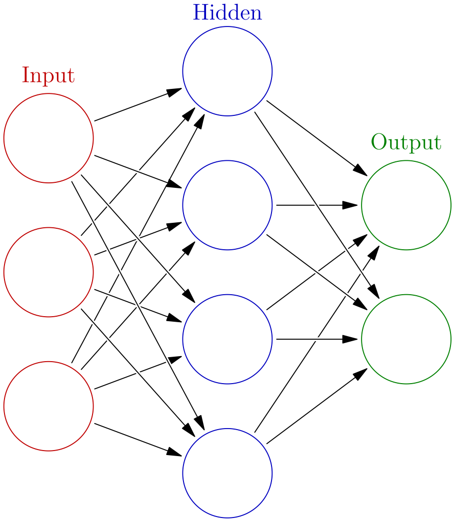
- Linearly separable datasets only
- Cannot solve XOR-like problems
- We need something more human-like in problem solving abilities!



3-layer Perceptron

Just add hidden units!

- Can solve most problems



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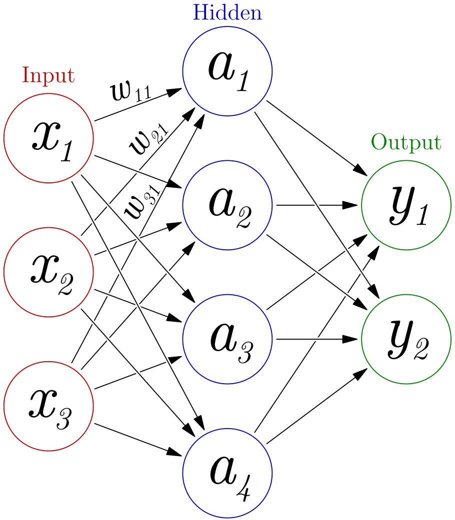
- As before we use targets to find the error for the output states...
  $\delta_i = y_i - t_i$



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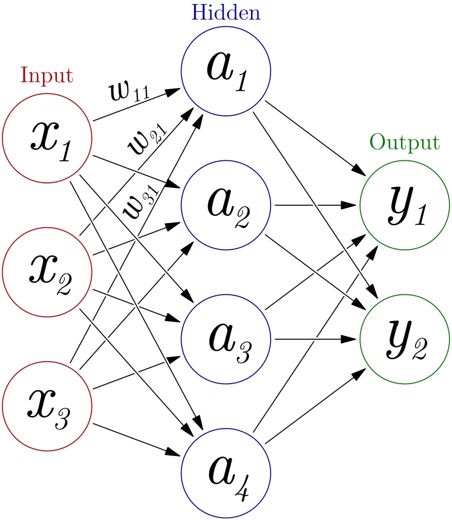
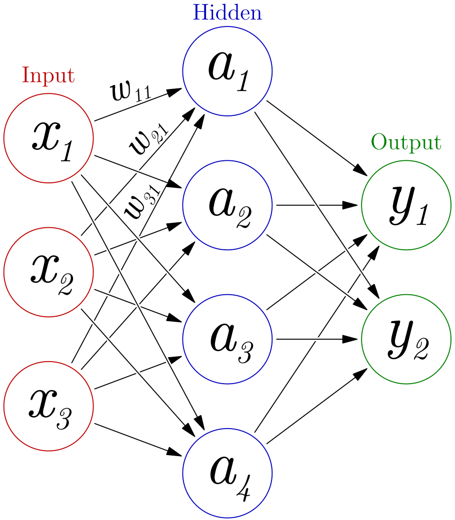
- But how do we train the hidden units?



3-layer Perceptron

Feedforward phase

- Run network as normal, i.e., feed activations forwards
- When at output calculate error: $\delta_i = y_i - t_i$
- But how do we calculate error for the hidden units?



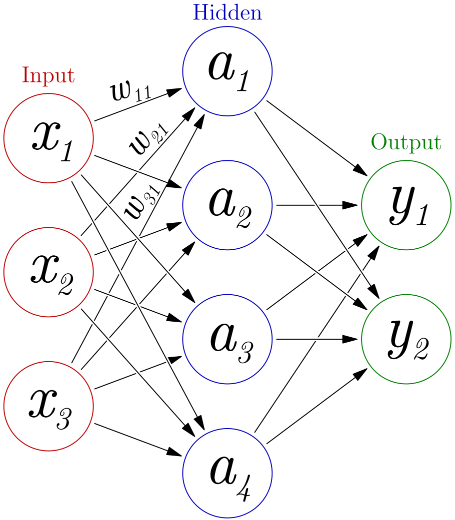
3-layer Perceptron

Backpropagation phase

- Now the output is the starting point
- When at output calculate error:

$$\delta_i = y_i - t_i$$

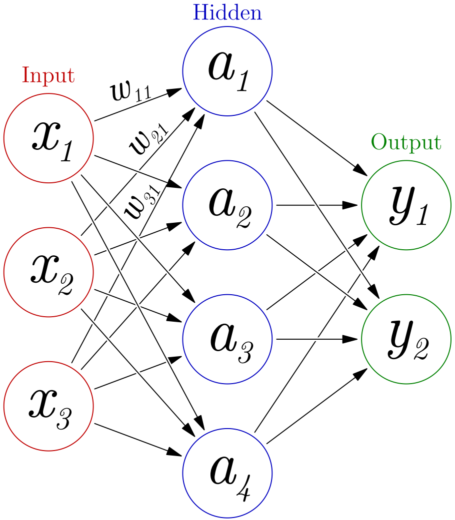
- Now run the network backwards!



3-layer Perceptron

Backpropagation phase

- The hidden targets are:
  $t_i = \sum_j \delta_j w_{ij}$



3-layer Perceptron

Backpropagation phase

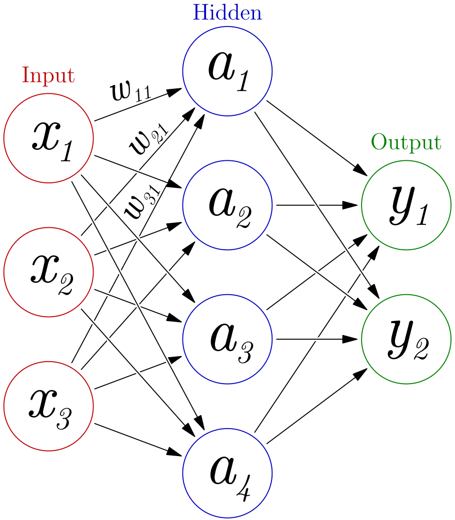
- The hidden targets are: $t_i = \sum_j \delta_j w_{ij}$
- Now we can calculate errors!

  Output error:

  $\delta_i = y_i - t_i$

  Hidden error:

  $\delta_i = a_i(1 - a_i)t_i$



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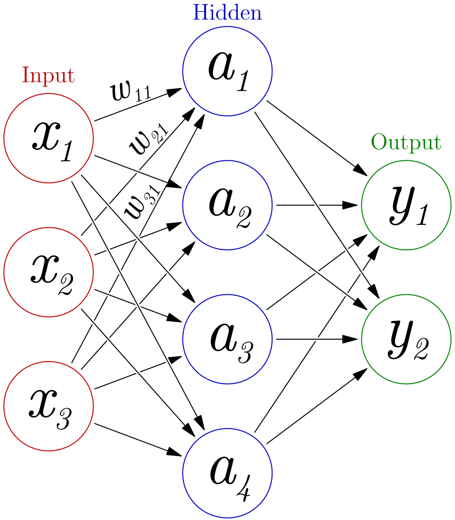
Backpropagation phase

- Now we have our δ_is, we can calculate weight updates!



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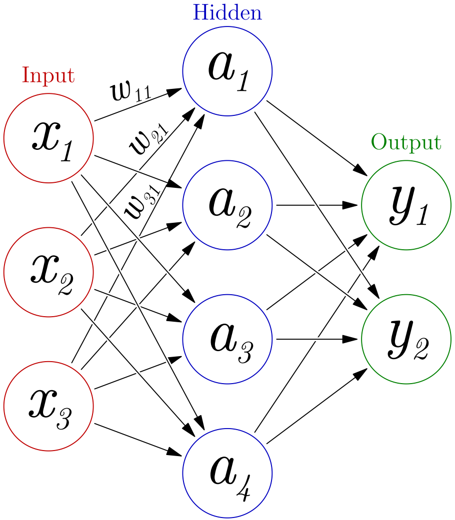

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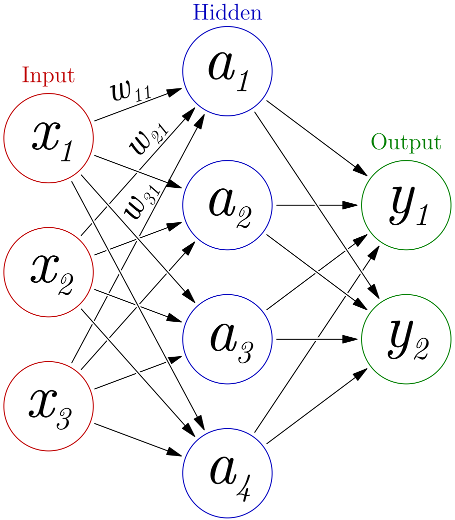

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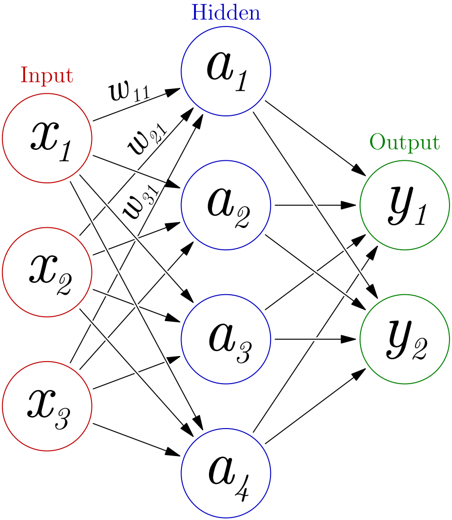

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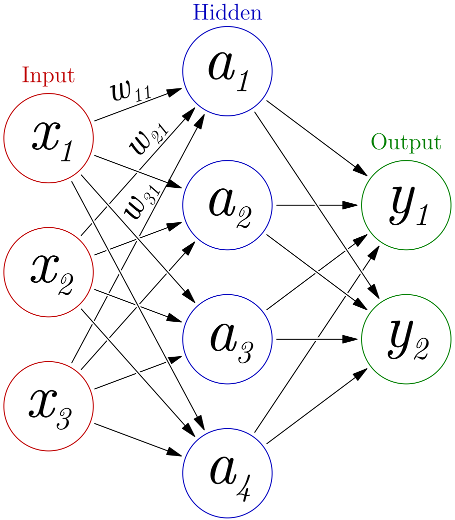

3-layer Perceptron

Backpropagation phase

- Now we have our δ_is, we can calculate weight updates!

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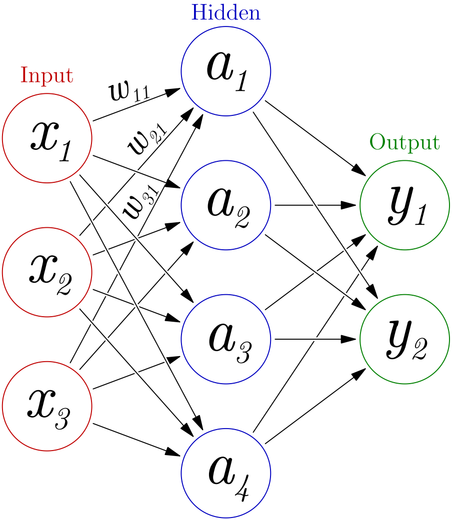
- But — before applying these updates — we want to avoid local minima, so we have a few options...



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Just before applying Δw_{ij}s consider...

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- Patternwise or in a batch? How to define a training epoch?
- How to present patterns? In a random order? Serially?

3-layer Perceptron

Applying weight changes!

- General equation for learning:

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$$w_{ij}^{\varepsilon+1} = w_{ij}^{\varepsilon} + \nu \Delta w_{ij}^{\varepsilon-1} - \mu \Delta w_{ij}^{\varepsilon}$$

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Applying weight changes!

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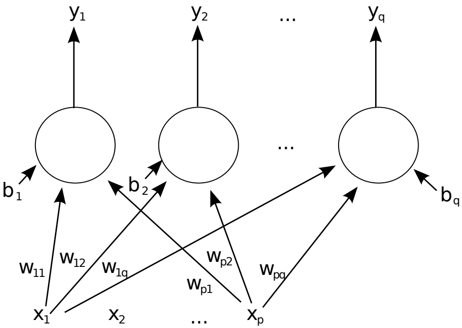
where ε denotes the epoch, the momentum is ν, and the learning rate is μ — latter two can be either variable or constant.

Bias Units aka Thresholds

What is it?

- A weight attached to a "unit" that is always on



Bias Units aka Thresholds

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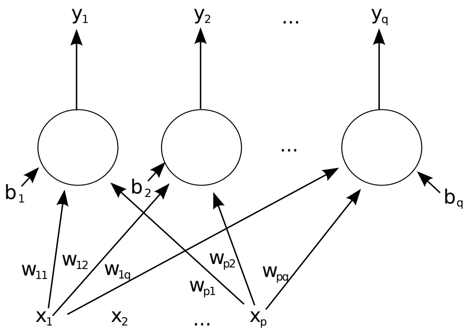

Bias Units aka Thresholds

What is it?

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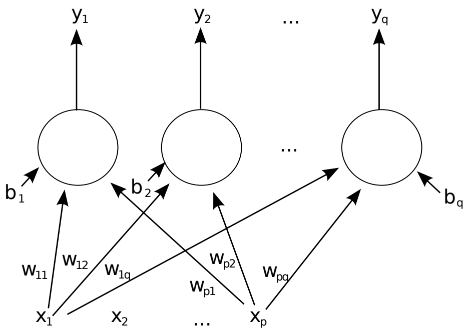
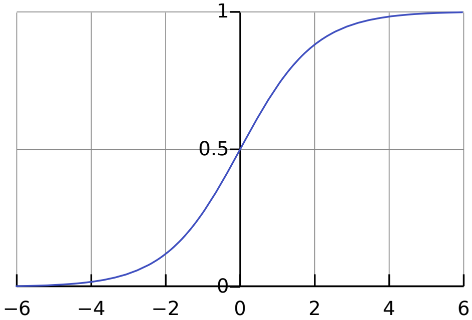
- Trained identically to the weights
- Moves activation function left and right



Activation Function

Logistic, squashing, sigmoid, activation, step, etc., functions

- Generic names: f, activation function, etc.



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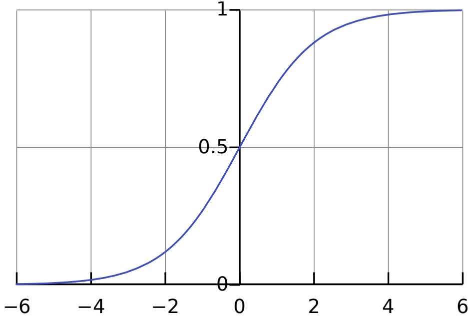

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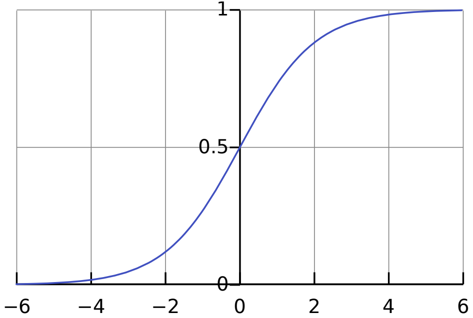

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- More on this in exercises!