Neural Learning

COMP9417, 23T1

1. Neural Learning
2. Recap: The Perceptron
3. Multi-layer Perceptron
4. Back-propagation
5. Reminder: Revision

Section 1

Neural Learning

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You'll typically see this field referred to as *deep learning*.

Deep learning has become the forefront of modern machine learning. With it comes many challenges and intricacies which are out of the scope of this course (see COMP9444, *Deep Learning Book* by Goodfellow et al).

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This course discuses what makes up neural networks, partially why they are effective and how they work.

Section 2

Recap: The Perceptron

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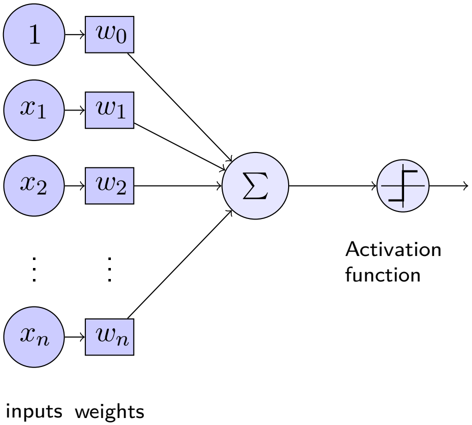

Section 3

Multi-layer Perceptron

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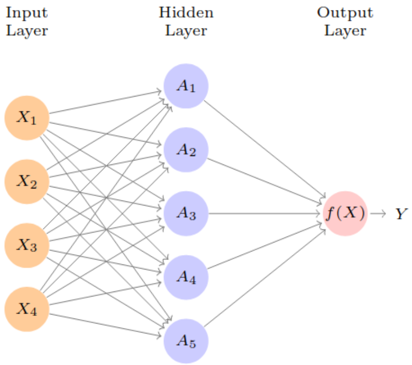

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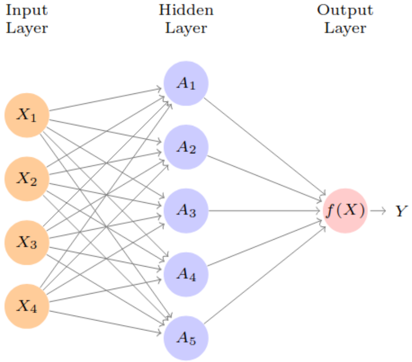

If we define the activation function used for the hidden layer as g and the weights for input features as β:

$$
\begin{aligned}
f(X) &= w_0 + \sum_{i=1}^{n} w_i A_i \\
&= w_0 + \sum_{i=1}^{n} w_i g(X_i)
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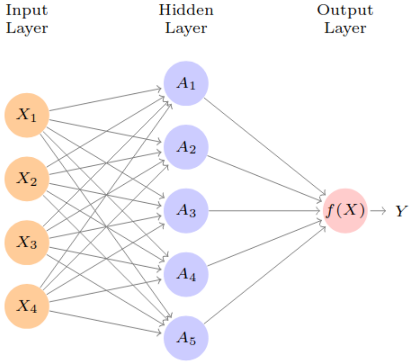

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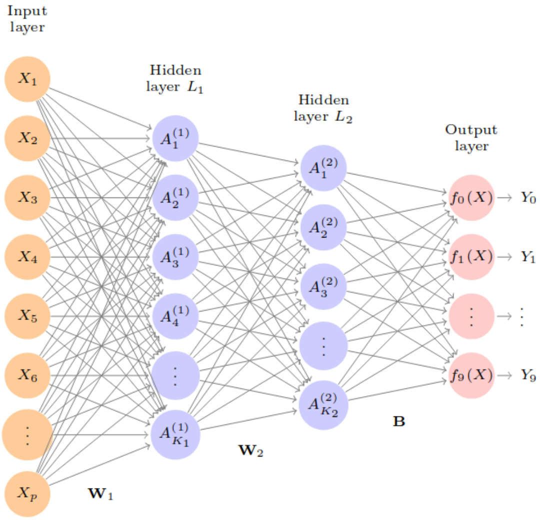
f(X) &= w_0 + \sum_{i=1}^{n} w_i A_i \\
&= w_0 + \sum_{i=1}^{n} w_i g(\beta_0 + \sum_{j=1}^{p} \beta_j X_i)
\end{aligned}
$$


Input layer
X_1
X_2
X_3
X_4
X_5
X_6
$\vdots$
X_p
Hidden layer L_1
$A_1^{(1)}$
$A_2^{(1)}$
$A_3^{(1)}$
$A_4^{(1)}$
$\vdots$
$A_{K_1}^{(1)}$
Hidden layer L_2
$A_1^{(2)}$
$A_2^{(2)}$
$A_3^{(2)}$
$\vdots$
$A_{K_2}^{(2)}$
Output layer
$f_0(X) \to Y_0$
$f_1(X) \to Y_1$
$\vdots \to \vdots$
$f_9(X) \to Y_9$
$\mathbf{W}_1$
$\mathbf{W}_2$
$\mathbf{B}$

Section 4

Back-propagation

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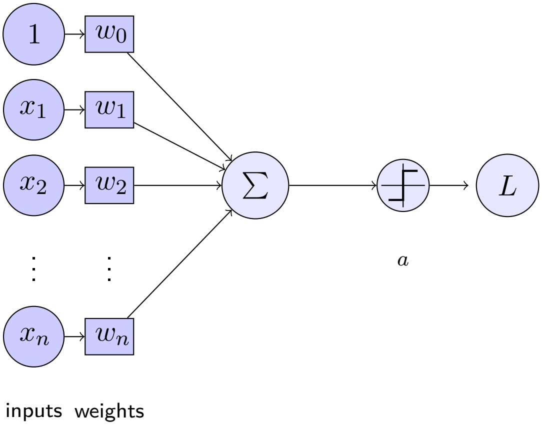
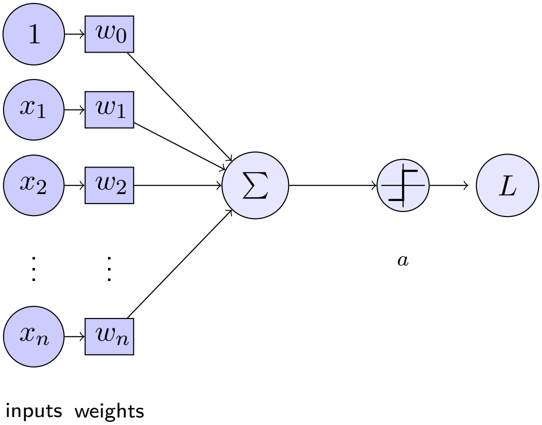
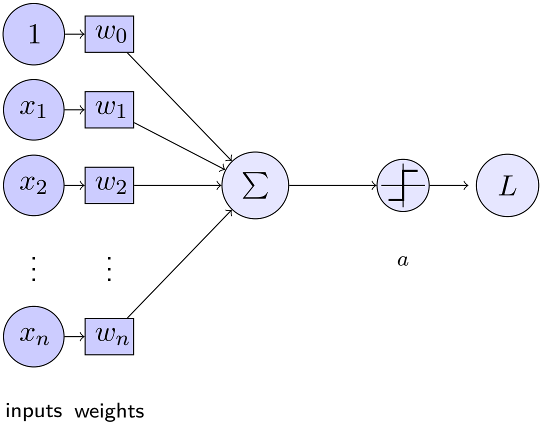
But how do we even calculate the gradient?


1
w_0
x_1
w_1
x_2
w_2
x_n
w_n
Σ
a
L
inputs
weights



The loss is a function of the activation:

$$L(a, y)$$



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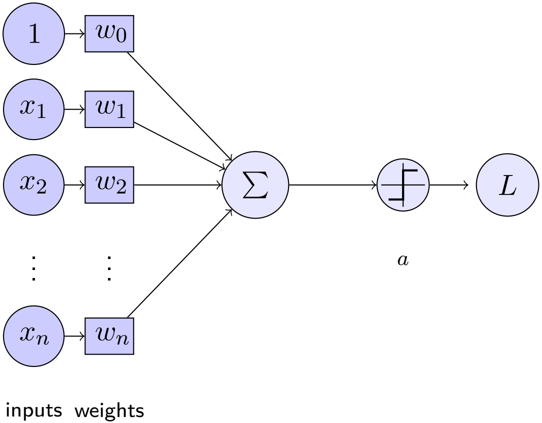
The activation is a function of the inputs, the weights and the bias:

$$a(x_1, \ldots, x_n, w_0, \ldots, w_n)$$



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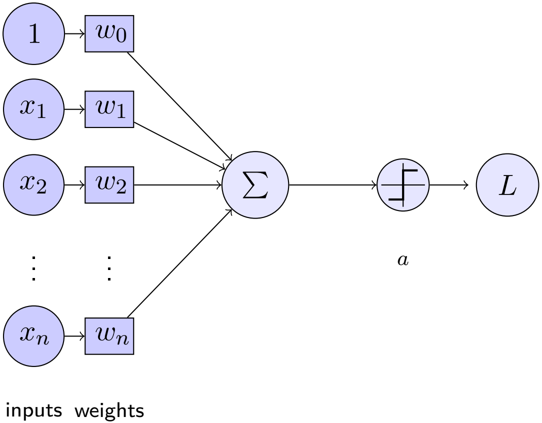

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The activation is a function of the inputs, the weights and the bias:

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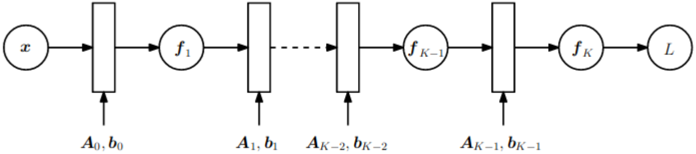
What we want to optimise the loss function is:

$$\frac{\partial L}{\partial w_i} = \frac{\partial L}{\partial a} \frac{\partial a}{\partial w_i}$$

Say we have the following network architecture, where A represents the weights and b the bias:



If we say that $\theta_K = \{A_K, b_K\}$ for a layer k. The gradient of our coefficients looks like this:

$$\frac{\partial L}{\partial \theta_{K-1}} = \frac{\partial L}{\partial f_K} \frac{\partial f_K}{\partial \theta_{K-1}}$$

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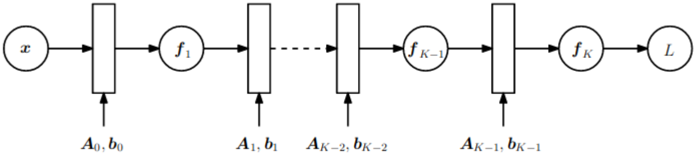

If we say that $\theta_K = \{A_K, b_K\}$ for a layer k. The gradient of our coefficients looks like this:

$$\frac{\partial L}{\partial \theta_{K-2}} = \frac{\partial L}{\partial f_K} \frac{\partial f_K}{\partial f_{K-1}} \frac{\partial f_{K-1}}{\partial \theta_{K-2}}$$

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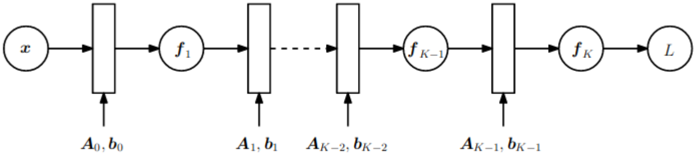

If we say that $\theta_K = \{A_K, b_K\}$ for a layer k. The gradient of our coefficients looks like this:

$$\frac{\partial L}{\partial \theta_{K-3}} = \frac{\partial L}{\partial f_K} \frac{\partial f_K}{\partial f_{K-1}} \frac{\partial f_{K-1}}{\partial f_{K-2}} \frac{\partial f_{K-2}}{\partial \theta_{K-3}}$$

Using back-propagation, we can therefore calculate:

$$\nabla L(\theta, y) = \left[\frac{\partial L}{\partial \theta_1}, \frac{\partial L}{\partial \theta_2}, \dots, \frac{\partial L}{\partial \theta_K}\right]$$

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We can then all of our parameters (in the basic case):

$$\theta^{(t)} = \theta^{(t-1)} - \nabla L(\theta, y)$$

Typically, the optimiser will be some form of stochastic gradient descent (minibatch in some cases) as classic gradient descent is expensive for a large number of parameters and data points.

Let's visualise a neural network working:

Tensorflow Playground

Section 5

Reminder: Revision

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Next week is the last week of tutorials!

Are there any specific topics you want resources or revision on?