

## Model Representation II

To re-iterate, the following is an example of a neural network:

$$a_1^{(2)} = g(\Theta_{10}^{(1)}x_0 + \Theta_{11}^{(1)}x_1 + \Theta_{12}^{(1)}x_2 + \Theta_{13}^{(1)}x_3) \ a_2^{(2)} = g(\Theta_{20}^{(1)}x_0 + \Theta_{21}^{(1)}x_1 + \Theta_{22}^{(1)}x_2 + \Theta_{23}^{(1)}x_3) \ a_3^{(2)} = g(\Theta_{30}^{(1)}x_0 + \Theta_{31}^{(1)}x_1 + \Theta_{32}^{(1)}x_2 + \Theta_{33}^{(1)}x_3) \ h_{\Theta}(x) = a_1^{(3)} = g(\Theta_{10}^{(2)}a_0^{(2)} + \Theta_{11}^{(2)}a_1^{(2)} + \Theta_{12}^{(2)}a_2^{(2)} + \Theta_{13}^{(2)}a_3^{(2)})$$

In this section we'll do a vectorized implementation of the above functions. We're going to define a new variable  $z_k^{(j)}$  that encompasses the parameters inside our g function. In our previous example if we replaced by the variable z for all the parameters we would get:

$$egin{aligned} a_1^{(2)} &= g(z_1^{(2)}) \ a_2^{(2)} &= g(z_2^{(2)}) \ a_3^{(2)} &= g(z_3^{(2)}) \end{aligned}$$

In other words, for layer j=2 and node k, the variable z will be:

$$z_k^{(2)} = \Theta_{k,0}^{(1)} x_0 + \Theta_{k,1}^{(1)} x_1 + \dots + \Theta_{k,n}^{(1)} x_n$$

The vector representation of x and  $z^j$  is:

$$x = egin{bmatrix} x_0 \ x_1 \ \cdots \ x_n \end{bmatrix} \, z^{(j)} = egin{bmatrix} z_1^{(j)} \ z_2^{(j)} \ \cdots \ z_n^{(j)} \end{bmatrix}$$

Setting  $x=a^{\left(1\right)}$  , we can rewrite the equation as:

$$z^{(j)} = \Theta^{(j-1)} a^{(j-1)}$$



We are multiplying our matrix  $\Theta^{(j-1)}$  with dimensions  $s_j \times (n+1)$  (where  $s_j$  is the number of our activation nodes) by our vector  $a^{(j-1)}$  with height (n+1). This gives us our vector  $z^{(j)}$  with height  $s_j$ . Now we can get a vector of our activation nodes for layer j as follows: