

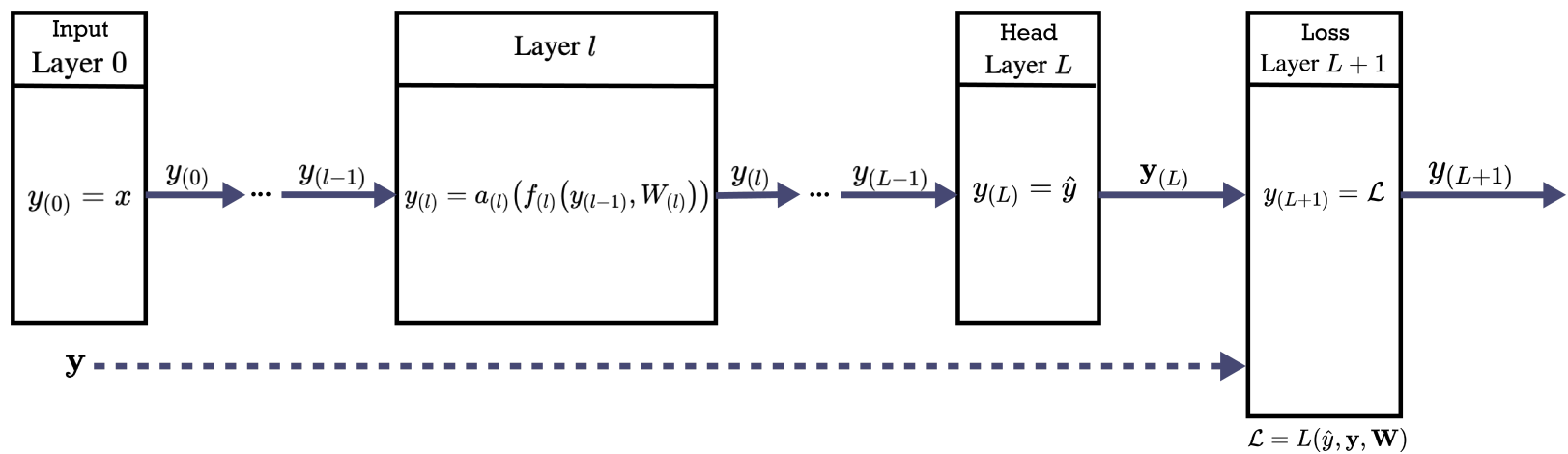
Inside a layer: Units/Neurons

Notation 1

Layer l , for $1 \leq l \leq L$:

- Produces output vector $\mathbf{y}_{(l)}$
- $\mathbf{y}_{(l)}$ is a vector of $n_{(l)}$ synthetic features
$$n_{(l)} = \|\mathbf{y}_{(l)}\|$$
- Takes as input $\mathbf{y}_{(l-1)}$, the output of the preceding layer

- Layer L will typically implement Regression or Classification
- The first $(L - 1)$ layers create synthetic features of increasing complexity
- We will use layer $(L + 1)$ to compute a Loss



The input \mathbf{x}

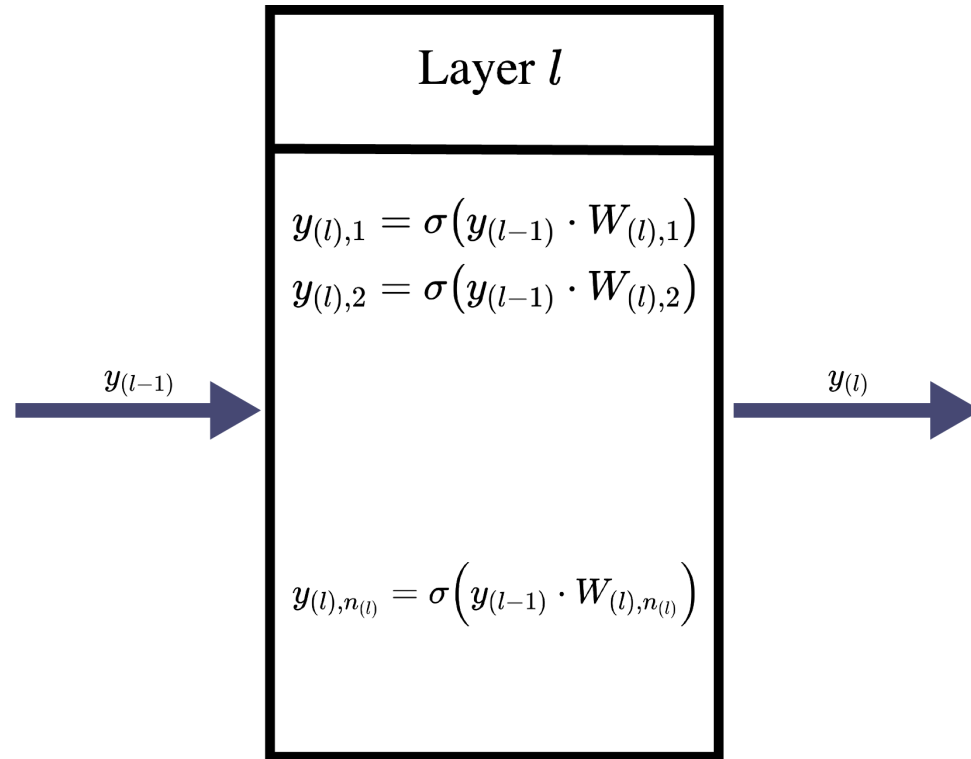
- Is called "layer 0"
- $\mathbf{y}_{(0)} = \mathbf{x}$

The output $\mathbf{y}_{(L-1)}$ of the penultimate layer ($L - 1$)

- Becomes the input of a Classifier/Regression model at layer L

Let's look inside layer l (of a particular type called *Fully Connected* or *Dense*)

Layer



- Input vector of $n_{(l-1)}$ features: $\mathbf{y}_{(l-1)}$
- Produces output vector or $n_{(l)}$ features $\mathbf{y}_{(l)}$
- Feature j defined by the function

$$\mathbf{y}_{(l),j} = \sigma(\mathbf{y}_{(l-1)} \cdot \mathbf{W}_{(l),j})$$

Each feature $\mathbf{y}_{(l),j}$ is produced by a *unit (neuron)*

- There are $n_{(l)}$ units in layer l
- The units are *homogenous*
 - same input $\mathbf{y}_{(l-1)}$ to every unit
 - same functional form for every unit
 - units differ only in $\mathbf{W}_{(l),j}$

Units are also sometimes referred to as *Hidden Units*

- They are internal to a layer.
- From the standpoint of the Input/Output behavior of a layer, the units are "hidden"

The functional form

$$\mathbf{y}_{(l),j} = \sigma(\mathbf{y}_{(l-1)} \cdot \mathbf{W}_{(l),j})$$

is called a *Dense* or *Fully Connected* unit.

It is called Fully connected since

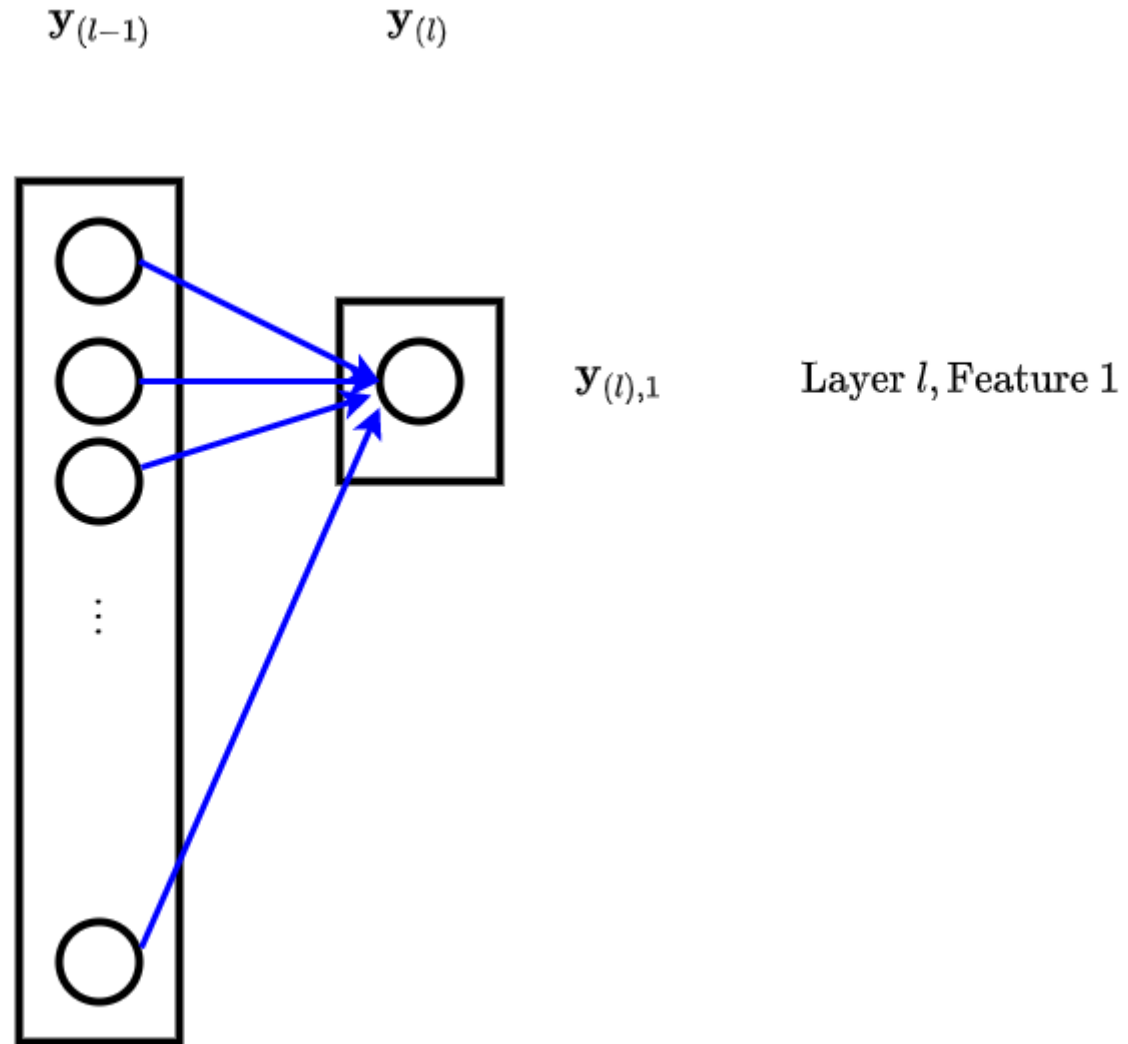
- each unit takes as input $\mathbf{y}_{(l-1)}$, **all** $n_{(l-1)}$ outputs of the preceding layer

The *Fully Connected* part can be better appreciated by looking at a diagram of the connectivity of a *single* unit producing a *single* feature.

A Fully Connected/Dense Layer producing a *single* feature at layer l computes

$$\mathbf{y}_{(l),1} = a_{(l)}(\mathbf{y}_{(l-1)} \cdot \mathbf{W}_{(l),1})$$

Fully connected unit, single feature

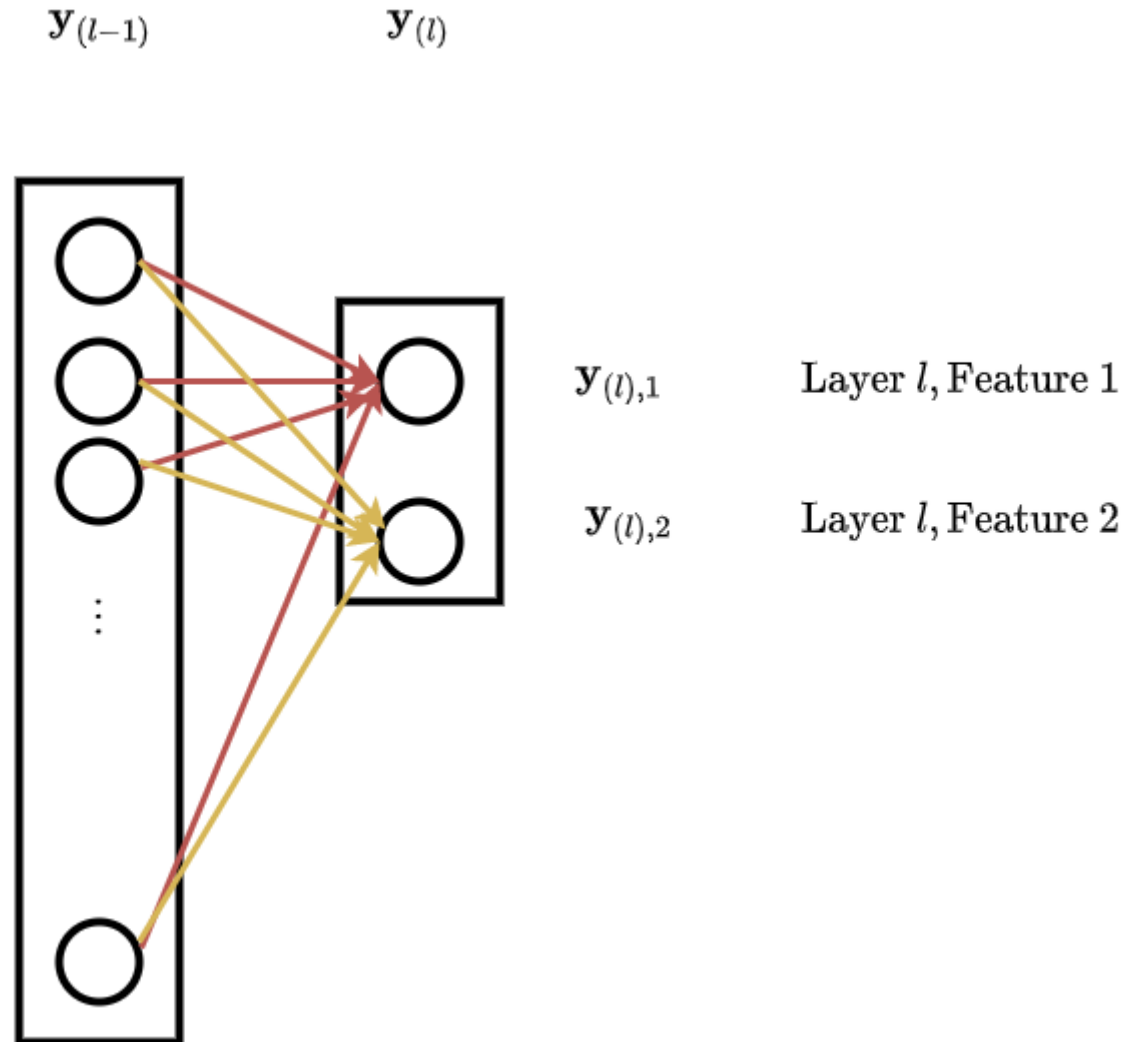


The edges into the single unit of layer l correspond to $\mathbf{W}_{(l),1}$.

A Fully Connected/Dense Layer with multiple units producing *multiple* feature at layer l computes

$$\mathbf{y}_{(l),j} = a_{(l)}(\mathbf{y}_{(l-1)} \cdot \mathbf{W}_{(l),j})$$

Fully connected, two features



The edges into each unit of layer l correspond to

- $\mathbf{W}_{(l),1}, \mathbf{W}_{(l),2} \dots$
- Separate colors for each units/row of \mathbf{W}

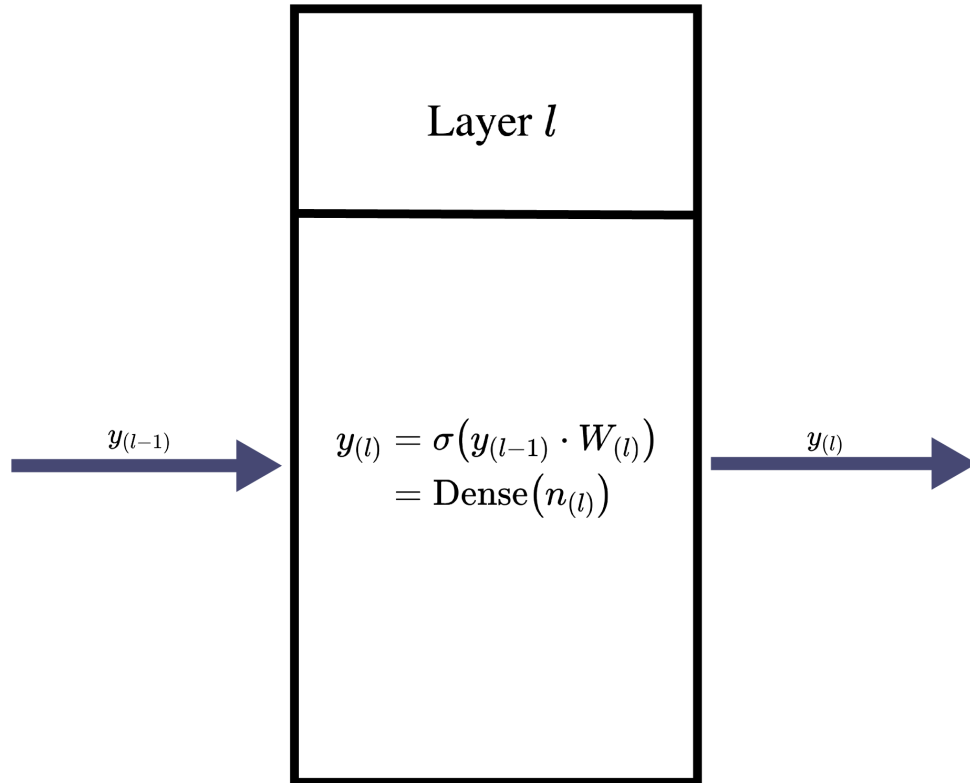
Each unit $\mathbf{y}_{(l),j}$ in layer l creates a new feature using pattern $\mathbf{W}_{(l),j}$

The functional form is of

- A dot product $\mathbf{y}_{(l-1)} \cdot \mathbf{W}_{(l),j}$
 - Which can be thought of matching input $\mathbf{y}_{(l-1)}$ against pattern $\mathbf{W}_{(l),j}$
- Fed into σ , the *sigmoid* function we have previously encountered in Logistic Regression.

Because the units are homogeneous, we can depict it as

Layer



where

- $\mathbf{y}_{(l)}$ is a vector of length $n_{(l)}$
- $\mathbf{W}_{(l)}$ is a matrix
 - $n_{(l)}$ rows
 - $\mathbf{W}_{(l)}^{(j)}$
 $= \mathbf{W}_{(l),j}$

Written with the shorthand $\text{Dense}(n_l)$

We will introduce other types of layers.

- Most will be homogeneous
- Not all will be fully Connected
- The dot product will play a similar role

The sigmoid function σ may be the *most significant part* of the functional form

- The dot product is a *linear* operation
- The outputs of sigmoid are *non-linear* in its inputs

So the sigmoid induces a non-linear transformation of the features $\mathbf{y}_{(l-1)}$

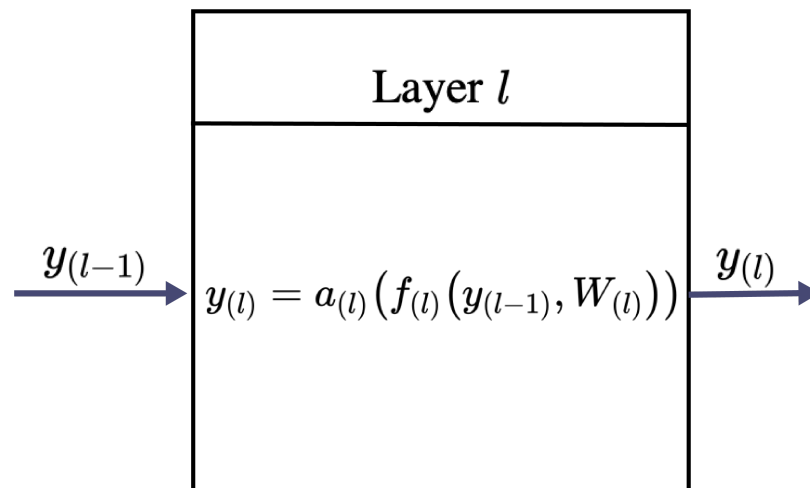
The outer function which applies a non-linear transformation to linear inputs

- Is called an *activation function*
- Sigmoid is one of several activation functions we will study

- The operation of a layer does not always need to be a dot production
- The activation function of a layer need not always be the sigmoid

More generically we write a layer as

Layers



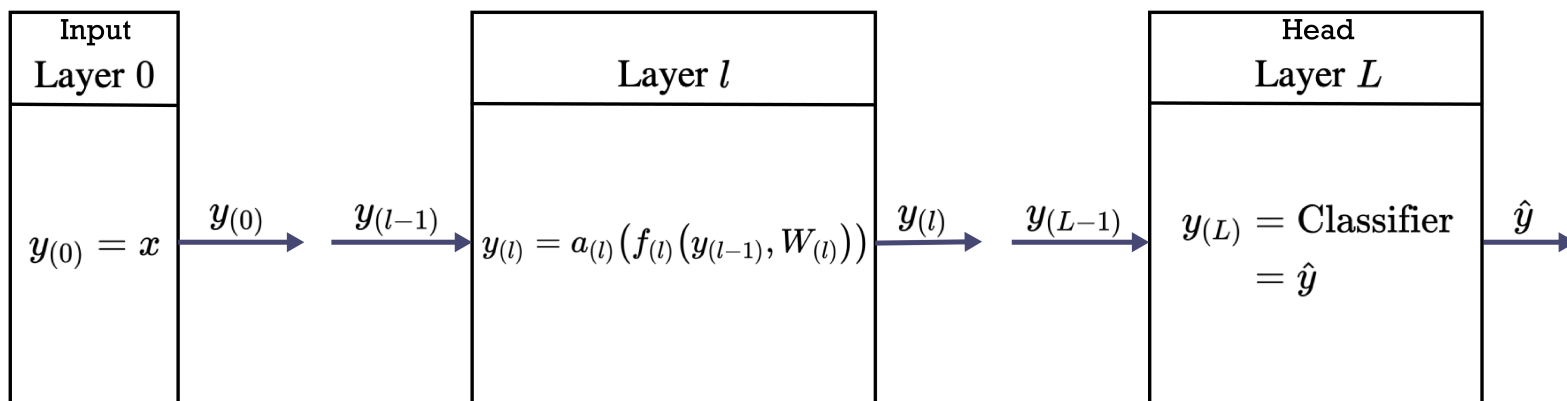
$$\mathbf{y}_{(l)} = \mathbf{a}_{(l)} \left(\mathbf{f}_{(l)} (\mathbf{y}_{(l-1)}, \mathbf{W}_{(l)}) \right)$$

where

- $\mathbf{f}_{(l)}$ is a function of $\mathbf{y}_{(l-1)}$ and $\mathbf{W}_{(l)}$
- $\mathbf{a}_{(l)}$ is an activation function

So our multi-layer Neural Network (using Dense layers) looks like

Layers



In slightly more mathematical terms: Layer l is computing a function $y_{(l)} = F_{(l)}$

$$F_{(l)}(y_{(l-1)}; \mathbf{W}_{(l)}) = y_{(l)}$$

$$F_{(l)} : \mathcal{R}^{\|y_{(l-1)}\|} \mapsto \mathcal{R}^{\|y_{(l)}\|}$$

If we expand $F_{(l)}$, we see that it is the l -fold composition of functions $F_{(1)}, \dots, F_{(l)}$

$$\begin{aligned} y_{(l)} &= F_{(l)}(y_{(l-1)}; \mathbf{W}_{(l)}) \\ &= F_{(l)}(F_{(l-1)}(y_{(l-2)}; \mathbf{W}_{(l-1)}); \mathbf{W}_{(l)}) \\ &= F_{(l)}(F_{(l-1)}(F_{(l-2)}(y_{(l-3)}; \mathbf{W}_{(l-2)}); \mathbf{W}_{(l-1)}); \mathbf{W}_{(l)}) \\ &= \vdots \end{aligned}$$

So the layer-wise architecture is nothing more than a way of computing a nested (composed) function.

In [4]: `print("Done")`

Done