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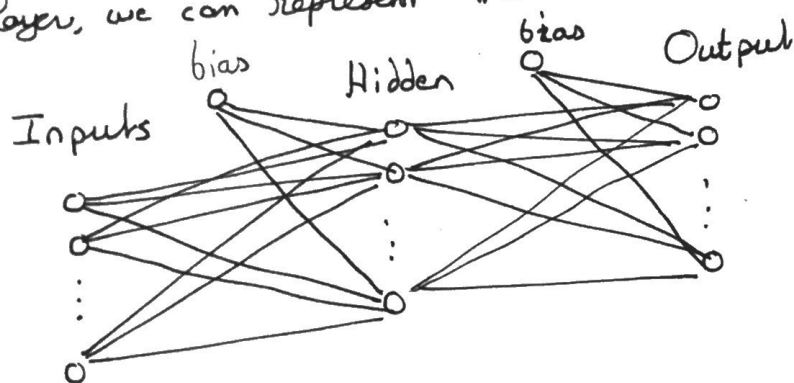
Deep Learning - HW1

Problem 1: Let's show that any feedforward neural network (FNN) with

linear activation function is equivalent to a FNN with no hidden layers.

Let's proceed by induction. For the case $k=1$, where k is the number of

hidden layers, we can represent the FNN as:



- Let's define:
- X any vector of inputs
 - H the vector of hidden layer's values from X
 - Y the vector of outputs' values from X
 - $W_{i \rightarrow h}$ the vector of weights from the input layer to the hidden layer
 - $B_{i \rightarrow h}$ the vector of biases from the input layer to the hidden layer
 - F_h the activation function of the hidden layer.
 - $W_{h \rightarrow o}$ the vector of weights from the hidden layer to the output layer
 - $B_{h \rightarrow o}$ the vector of biases from the hidden layer to the output layer
 - F_o the activation function of the output layer.

With these notations, we are able to write:

$$\begin{cases} H = F_h(W_{i \rightarrow h} X + B_{i \rightarrow h}) \\ Y = F_o(W_{h \rightarrow o} H + B_{h \rightarrow o}) \end{cases}$$

We further assumed that f_h and f_o are linear. So we can define their coefficients

as:

$$\begin{cases} f_h(u) = \alpha_h u + \beta_h \\ f_o(u) = \alpha_o u + \beta_o \end{cases}$$

In that case:

$$\begin{aligned} y &= f_o(w_{h \rightarrow o} h + b_{h \rightarrow o}) \\ &= \alpha_o w_{h \rightarrow o} f_h(w_{i \rightarrow h} x + b_{i \rightarrow h}) + \alpha_o b_{h \rightarrow o} + \beta_o \\ &= \alpha_o w_{h \rightarrow o} [\alpha_h w_{i \rightarrow h} x + \alpha_h b_{i \rightarrow h} + \beta_h] + \alpha_o b_{h \rightarrow o} + \beta_o \\ &= (\alpha_o w_{h \rightarrow o} \alpha_h w_{i \rightarrow h}) x + (\alpha_o w_{h \rightarrow o} \alpha_h b_{i \rightarrow h} + \alpha_o w_{h \rightarrow o} \beta_h + \alpha_o b_{h \rightarrow o} + \beta_o) \end{aligned}$$

w.l.o.g. we can define

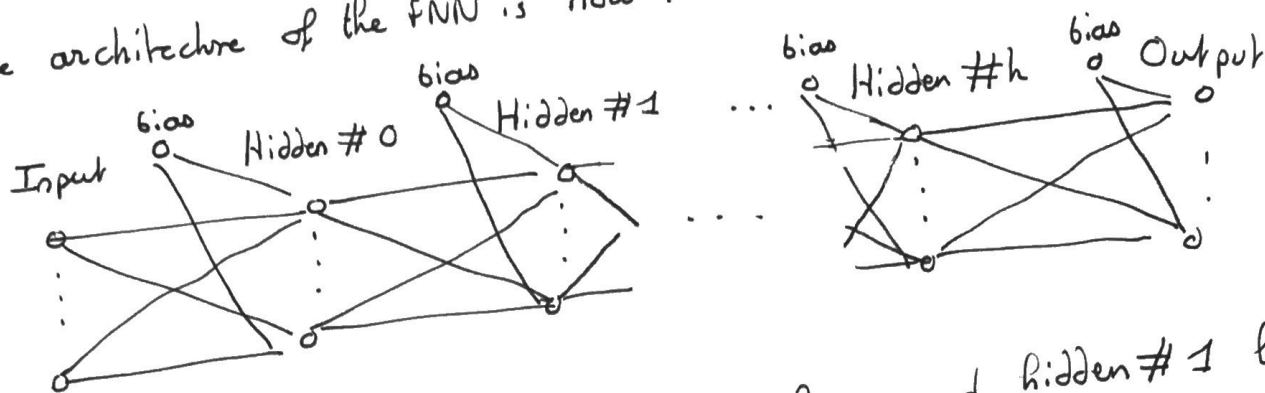
$$\begin{aligned} W &= \alpha_o w_{h \rightarrow o} + \alpha_h w_{i \rightarrow h} \\ B &= \alpha_o w_{h \rightarrow o} \alpha_h b_{i \rightarrow h} + \alpha_o w_{h \rightarrow o} \beta_h + \alpha_o b_{h \rightarrow o} + \beta_o \end{aligned}$$

so that $\boxed{y = Wx + B}$, this is the equation of a FNN with no hidden layers (and the identity as the activation function).

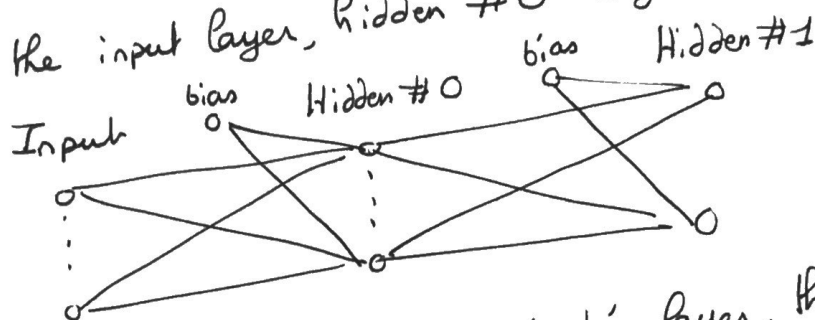
$\boxed{\text{So the result holds true for } k=1}$

Let's assume the result holds true for $k \in \mathbb{N}^*$, let's prove it remains true for $(k+1)$ hidden layers with linear activation function.

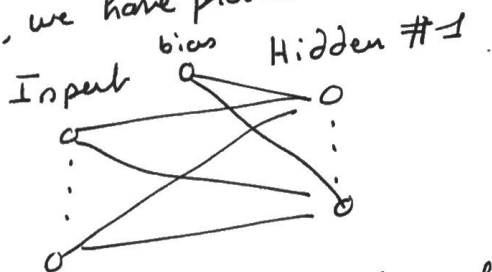
The architecture of the FNN is now:



Let's consider the input layer, Hidden #0 layer and Hidden #1 layer in a vacuum:



If we consider the Hidden #1 as an 'output' layer, this is exactly the case $k=1$, we have proven that it is equivalent to:



If we substitute in the initial architecture, the FNN is equivalent to:



which go back to the case of a FNN with k hidden layers. As we assumed in our induction, it is equivalent to a FNN with no hidden layers.

So we have proven that any FNN with linear activation function is equivalent to a FNN with no hidden layer.