# **Q & A: Neural Networks**

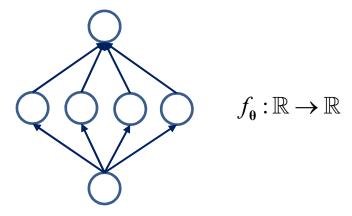
Lecture series "Machine Learning"

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## **Quiz: Number of parameters in MLP**

 Assume a multilayer perceptron for regression, with a one-dimensional input and a one-dimensional output and a single hidden layer with 4 nodes:



- Question: how many model parameters does this model have, that is, what is  $|\theta|$ ? Remember to include the bias parameters.
  - 6 parameters
  - 7 parameters
  - 12 parameters
  - 13 parameters
  - 17 parameters
  - 20 parameters



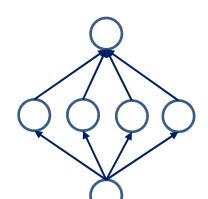
## **Quiz: Number of parameters in MLP**

- **Solution:** the MLP has  $|\theta| = 13$  parameters
- To see that, let's look at the parameters for each layer:
  - The input layer has no parameters
  - In the intermediate layer, we have a matrix  $\mathbf{W}_1 \in \mathbb{R}^{4 \times 1}$  and a bias vector  $\mathbf{b}_1 \in \mathbb{R}^4$ , so eight parameters overall
  - In the final layer, we have a matrix  $\mathbf{W}_2 \in \mathbb{R}^{1 \times 4}$  and a bias term  $\mathbf{b}_2 \in \mathbb{R}^1$ , so five parameters overall

$$f_{\boldsymbol{\theta}}(\mathbf{x}) = \mathbf{W}_2 \mathbf{z}_1 + \mathbf{b}_2$$

$$\mathbf{z}_1 = \sigma(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1)$$

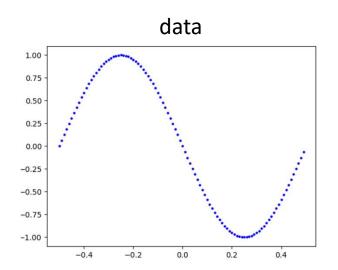
$$\mathbf{x} \in \mathbb{R}^M$$



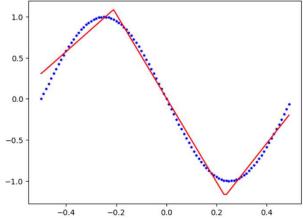
$$\mathbf{W}_2 \in \mathbb{R}^{1 \times 4}, \quad \mathbf{b}_2 \in \mathbb{R}^1$$

$$\mathbf{W}_1 \in \mathbb{R}^{4 \times 1}, \ \mathbf{b}_1 \in \mathbb{R}^4$$

- We can use the MLP from the previous slide to solve a simple toy regression problem
  - Inputs: 100 data points uniformly spaced in interval [-0.5,0.5]
  - Targets: obtained from sine function,  $y = \sin((x+0.5) \cdot 2\pi)$
- Fitting the MLP from last slide using squared loss to this data set results in:





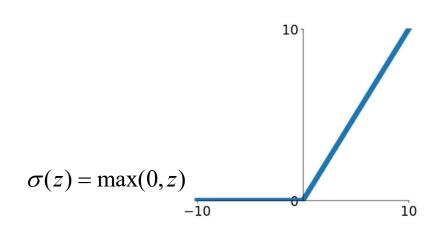


• Question: which nonlinear activation function did I use? ReLU, sigmoid, or tanh?



- Solution: ReLU activations.
  - For ReLU activations, the only operations used in the model are linear operations and maximum
  - Therefore, the final function stays piecewise linear

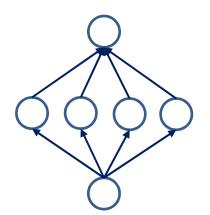
#### **ReLU: Rectified linear unit**



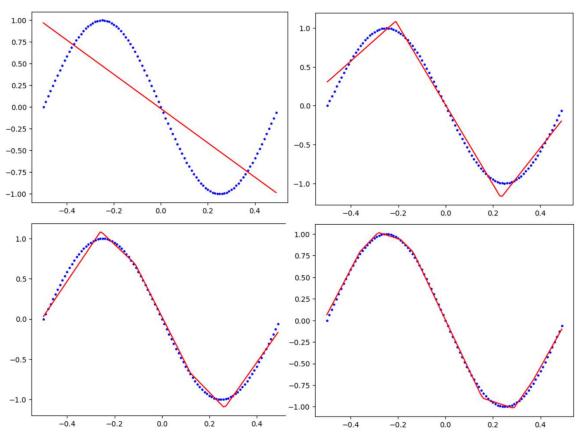
$$f_{\theta}(\mathbf{x}) = \mathbf{W}_2 \mathbf{z}_1 + \mathbf{b}_2$$

$$\mathbf{z}_1 = \sigma(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1)$$

$$\mathbf{x} \in \mathbb{R}^M$$



 We now study variants of the MLP. In the figures below, we see results of fitting four different variants of the MLP given above to the same sine data set:



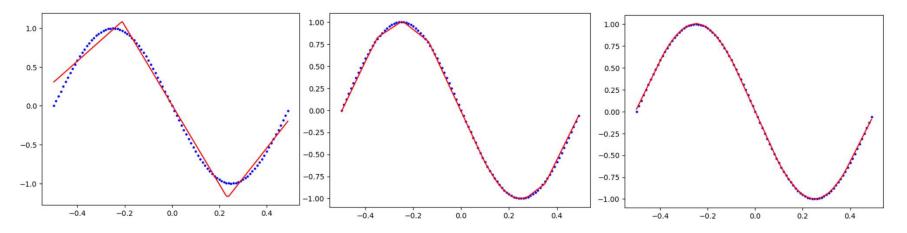
**Question**: what was changed between the different variants?

- The number of nodes in the hidden layer: 2, 4, 40, 400
- The nonlinear activation function: leaky ReLU, ReLu, sigmoid, tanh
- The number of hidden layers:0, 1, 2, 3 hidden layers
- The regularizer of the model



- **Solution**: Number of hidden layers changes
  - This is most easily seen in the first plot: without a hidden layer, the model is linear
  - The more hidden layers we have, the more expressive/flexible the model becomes, so it can fit the training data more accurately

 We now study variants of the MLP. In the figures below, we see results of fitting four different variants of the MLP given above to the same sine data set:



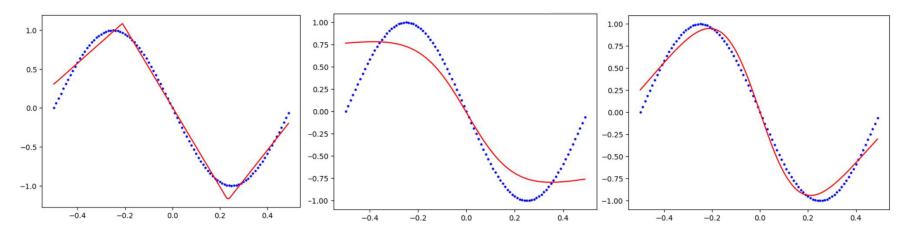
**Question**: what was changed between the different variants?

- The number of nodes in the hidden layer: 4, 40, 400
- The nonlinear activation function: ReLU, sigmoid, tanh
- The regularizer of the model
- The number of data points



- **Solution**: Number of nodes in hidden layer changes (4, 40, 400 nodes)
  - As the number of nodes changes, the model becomes more expressive/flexible and therefore can fit the training data more accurately
  - Changing the activation function or the regularizer or the number of data points would not affect the representational capacity of the model
  - Note that the model stays piecewise linear, but with more segments in the piecewise linear function, making it appear smoother

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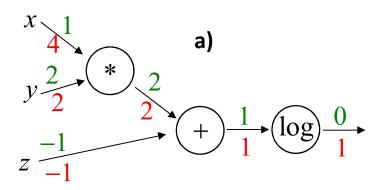
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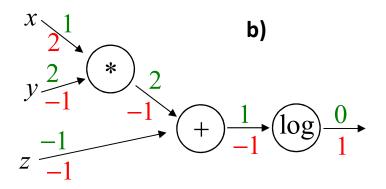
- The number of nodes in the hidden layer: 4, 40, 400
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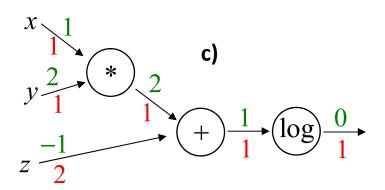
- **Solution**: The activation function (ReLU, sigmoid, tanh)
  - In the second and third plot, the functions are smooth (not piecewise linear anymore)
  - However, the number of parameters and therefore the representational capacity of the model has not really increased: the learned function is smoother but not really a better fit to training data

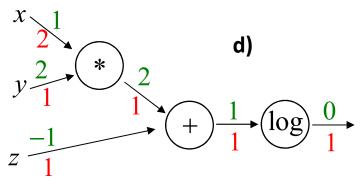
#### **Quiz: Automatic Differentiation**

- Assume  $f: \mathbb{R}^3 \to \mathbb{R}$  with  $f(x, y, z) = \log(x \cdot y + z)$ , where log denotes natural logarithm
- **Question**: Which is the correct compute graph and corresponding backpropagation result for the gradient  $\nabla f$  at the point (x, y, z) = (1, 2, -1)?



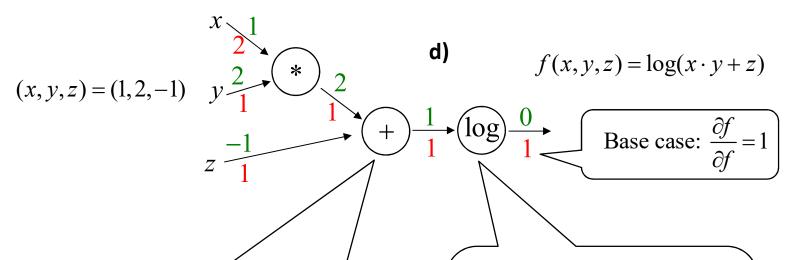






### **Quiz: Automatic Differentiation**

• **Solution**: the correct backpropagation procedure is d)



Upstream gradient: 1

Local gradient: 
$$\frac{\partial}{\partial a}[a+b]=1$$
,  $\frac{\partial}{\partial b}[a+b]=1$ 

Downstream gradients:  $1 \cdot 1 = 1$ ,  $1 \cdot 1 = 1$ 

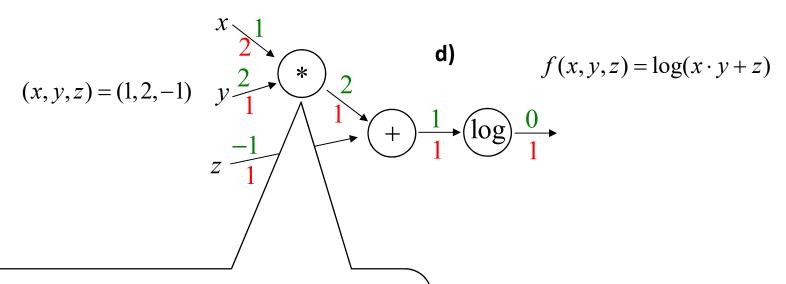
Upstream gradient: 1

Local gradient: 
$$\frac{\partial}{\partial x} \log x = \frac{1}{x}$$

Downstream gradient:  $\frac{1}{1} \cdot 1 = 1$ 

#### **Quiz: Automatic Differentiation**

• **Solution**: the correct backpropagation procedure is d)



Upstream gradient: 1

Local gradient:  $\frac{\partial}{\partial a}[a \cdot b] = b$ ,  $\frac{\partial}{\partial b}[a \cdot b] = a$ 

Downstream gradients:  $1 \cdot 2 = 1$ ,  $1 \cdot 1 = 1$