IN5550: Neural Methods in Natural Language Processing
Sub-lecture 3.2
Basics of deep learning

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What exactly is ‘deep’ in deep neural networks?

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- ...but followed with some non-linear operation g at each layer.
- At the last layer, the prediction $\hat{\boldsymbol{y}}$ is produced.
- The whole system is trained simultaneously, end-to-end.

$$\phi(\boldsymbol{x}) = g(\boldsymbol{x}\boldsymbol{W}') \tag{1}$$

$$\hat{\boldsymbol{y}} = \phi(\boldsymbol{x})\boldsymbol{W} \tag{2}$$

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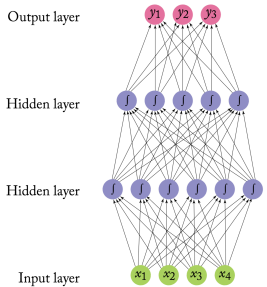
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Feed-forward neural networks

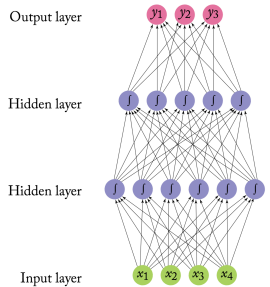
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3. all layers in between (hidden layers) contain hidden units, which form hidden representations of the input data.

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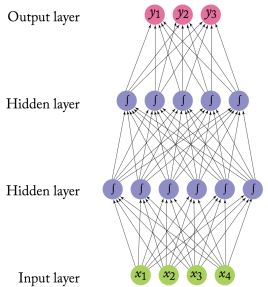


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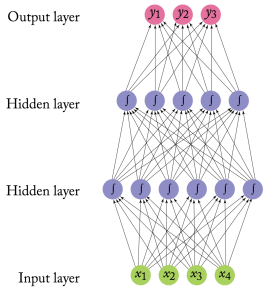
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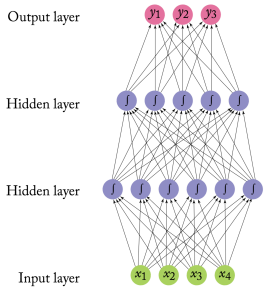
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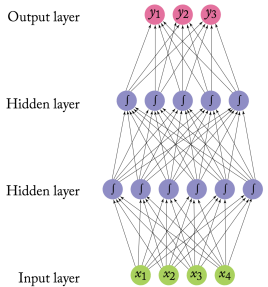
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Enters deep learning



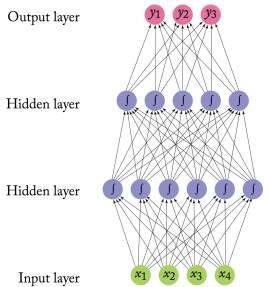
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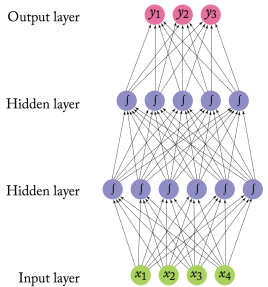
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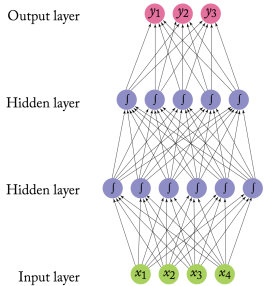
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- NB: not all neural architectures are fully connected (more on that in the next lectures).

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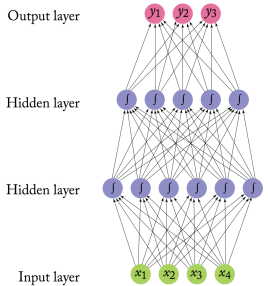
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- NB: not all neural architectures are fully connected (more on that in the next lectures).
- Question: **total number of trainable weights in the network depicted above?**

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- Bias is added trivially to each layer (often except the last one).

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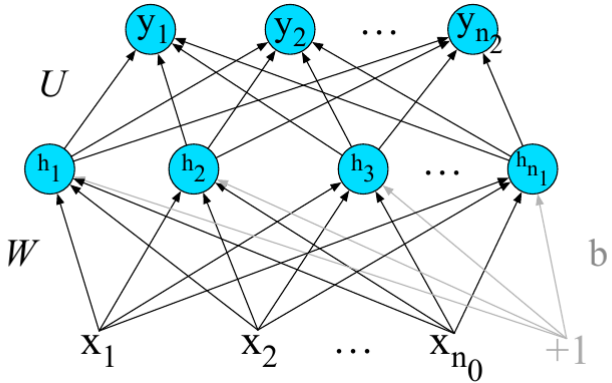


- Bias is added trivially to each layer (often except the last one).
- Then, such a neural network is described with:

$$\hat{\boldsymbol{y}} = g^2(g^1(\boldsymbol{x}\boldsymbol{W^1} + \boldsymbol{b^1})\boldsymbol{W^2} + \boldsymbol{b^2})\boldsymbol{W^3} \tag{3}$$

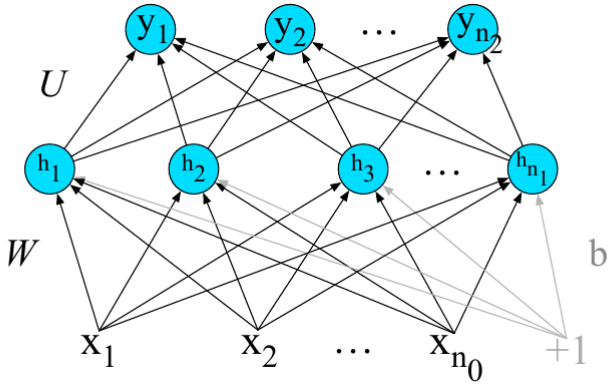
- $\boldsymbol{x} \in \mathbb{R}^4, \boldsymbol{W^1} \in \mathbb{R}^{4\times6}, \boldsymbol{b^1} \in \mathbb{R}^6, \boldsymbol{W^2} \in \mathbb{R}^{6\times5}, \boldsymbol{b^1} \in \mathbb{R}^5, \boldsymbol{W^3} \in \mathbb{R}^{5\times3}$
- g^1, g^2 are non-linear activation functions.

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Feed-forward network with one hidden layer and bias
(from Jurafsky and Martin, 2026)

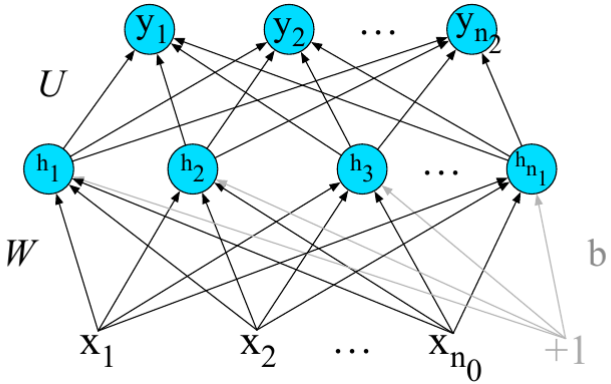
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Thus, what is 'deep'?

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Feed-forward network with one hidden layer and bias
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Thus, what is 'deep'? Multiple layers and non-linearities between them.

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Important: **feed-forward neural networks with multiple layers and non-linear transformations can theoretically approximate any function** (given enough layers and neurons).

[Leshno et al., 1993].

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Unfortunately, that gives no guarantees to real world problems:

- Is such a network learnable?
- Can we approximate the true function given non-infinite amounts of training data?
- Anyway, multi-layered perceptrons (MLPs) are still good baselines for many tasks.

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  - ...and reflect this in its hidden representations.

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2 Play with a demo

Play with a demo

There is a cool interactive visualization from Andrei Karpathy (Stanford) which can give you some clue about how different variables in deep networks interact and influence learned decision boundaries.

Let's look at it to develop intuitions.

`https://cs.stanford.edu/people/karpathy/convnetjs/demo/classify2d.html`

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The next sub-lecture 3.3: practicalities of training deep neural nets.

References I



Leshno, M., Lin, V. Y., Pinkus, A., and Schocken, S. (1993).
Multilayer feedforward networks with a nonpolynomial activation function can approximate any function.
Neural Networks, 6(6):861–867.