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

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- At the last layer, the prediction $\hat{\boldsymbol{y}}$ is produced.
- The whole system is trained simultaneously.

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

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

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1. The first layer contains input units,
2. the last layer contains output units,
3. all layers in between (hidden layers) contain hidden units, which form hidden representations of the input data.

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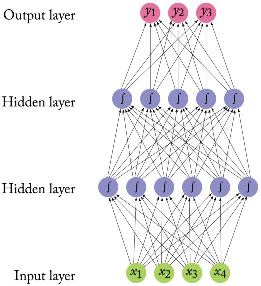

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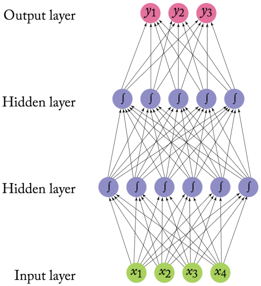

- Feed-forward network with 2 hidden layers;

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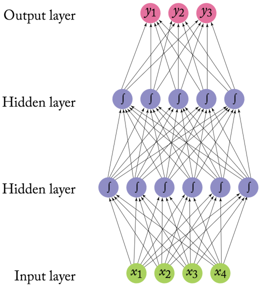

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- Before the transition to the l^{n+1}, the output vector of l^n goes through a non-linear function (instead of simple weighted sum).

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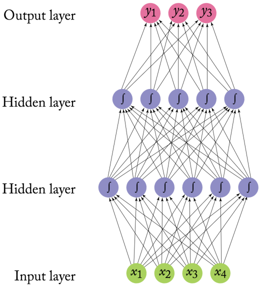

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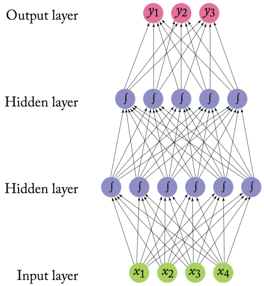

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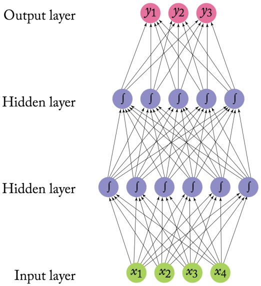

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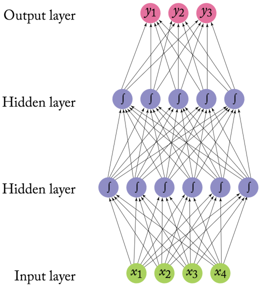

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- NB: not all neural architectures are fully connected (more on that in the next lectures).

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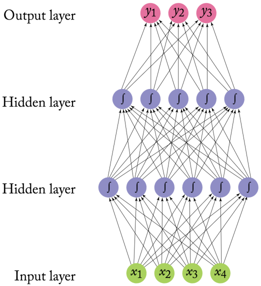

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  - ... mathematically, a vector-matrix multiplication $\boldsymbol{x^n} \cdot \boldsymbol{W^n} = \boldsymbol{x^{n+1}}$
- NB: not all neural architectures are fully connected (more on that in the next lectures).
- Question: **total number of trainable weights in this network?**

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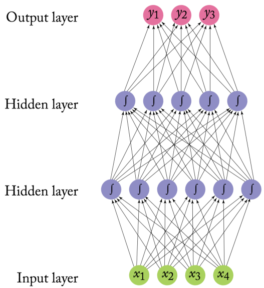

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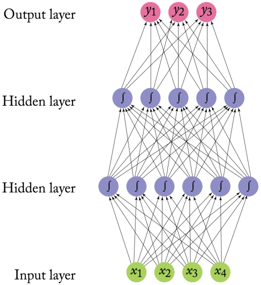

- Bias is added trivially to each layer (often except the last one).
- Then, such a neural network is described with:

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

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

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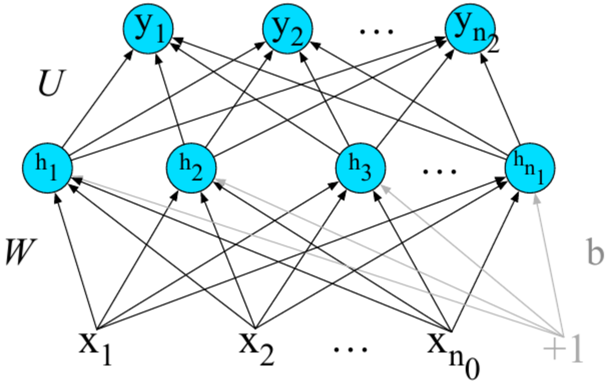

Feed-forward network with one hidden layer and bias
(from Jurafsky and Martin, 2023)

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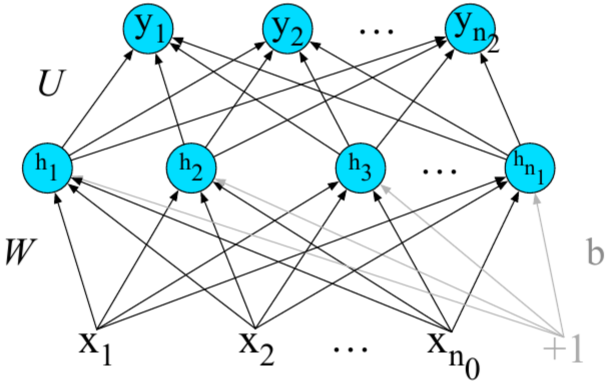

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Thus, what is 'deep'?

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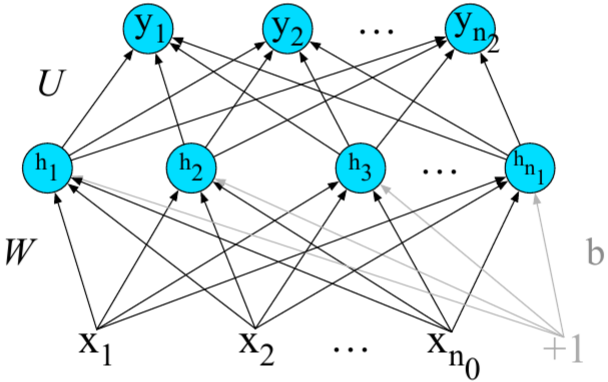

Feed-forward network with one hidden layer and bias
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Thus, what is 'deep'? Multiple layers and non-linearities between them.

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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 word problems:

- Is such a network learnable?
- Can we approximate the true function given only limited amounts of training data?
- Anyway, MLPs are still good baselines for many tasks.

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- a.k.a. θ;

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  - the network is able to learn that '*not*' and '*good*' co-occurrence in a text is a powerful feature in itself...
  - ...and reflect this in its hidden representations.

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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`

Play with the demo (will discuss at the Q&A / group session as well)

1. Use a 2 layer linear classifier for the spiral data (change '*tanh*' to '*linear*' for all layers). What happens?

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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.