IN5550: Neural Methods in Natural Language Processing
Sub-lecture 2.4
From linear models to neural networks

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Advantages and limitations of linear models

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Unfortunately, linear models can represent only linear relations in the data

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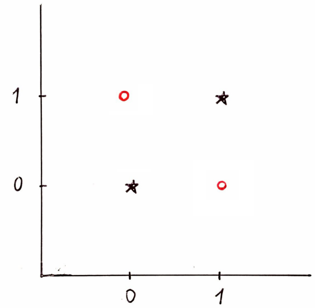
- One example is the XOR ('excluding OR') function:



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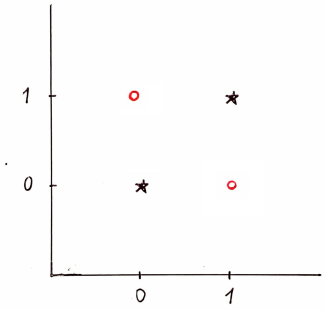

It is clearly not linearly separable.

Possible solutions

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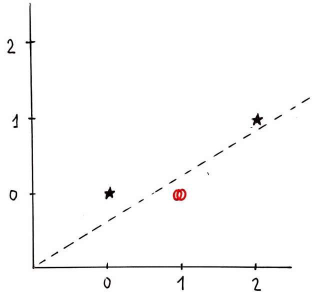
For example, $\phi(x_1, x_2) = [x_1 + x_2, x_1 \times x_2]$ maps the instances to another representation and makes the XOR problem linearly separable:



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- Support Vector Machines (SVM) classifiers handle this to some extent...
  [Cortes and Vapnik, 1995]
- ...but they scale linearly in time on the size of the training data (slow!).

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Training mapping functions

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

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- The equation above defines a simple multi-layer perceptron (MLP): our first neural model.

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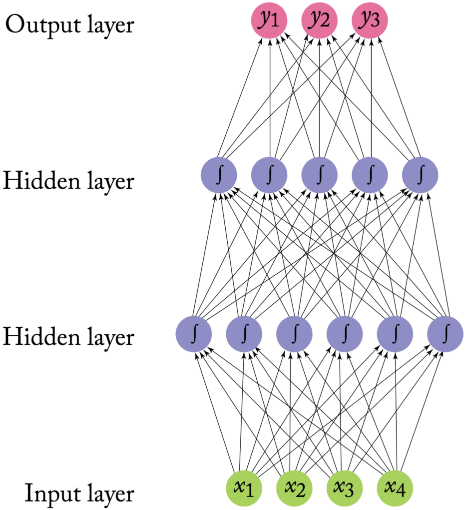

Perceptron with 2 hidden layers

Going deeply non-linear: multi-layered perceptrons

The nature of perceptrons

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Important: **neural networks with hidden layers can theoretically approximate any function** [Leshno et al., 1993].

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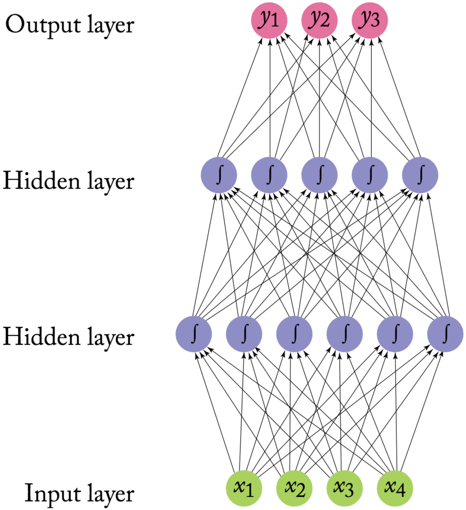

A simple feed-forward neural network. More next week!

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- Ask questions about the pre-recorded lectures published on January 27
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Next week: Training Deep Neural Networks

- More on multi-layer perceptrons and feed-forward neural networks.
- Are they really like brain?
- Common activation functions.
- Regularizing neural networks with dropout.
- Computation graphs.

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Obligatory assignment

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References I

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In Machine Learning, pages 273–297.

Leshno, M., Lin, V. Y., Pinkus, A., and Schocken, S. (1993).
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