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

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2. Going deeply non-linear: multi-layered perceptrons
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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

Advantages and limitations of linear models



- Are there non-linear functions that linear models can't deal with?

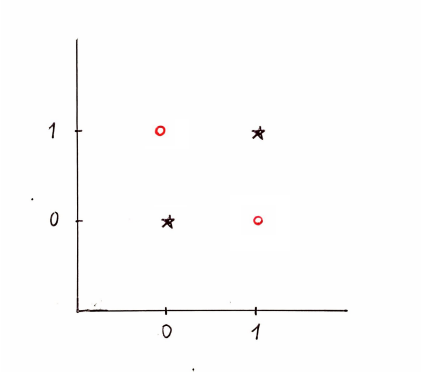
Advantages and limitations of linear models



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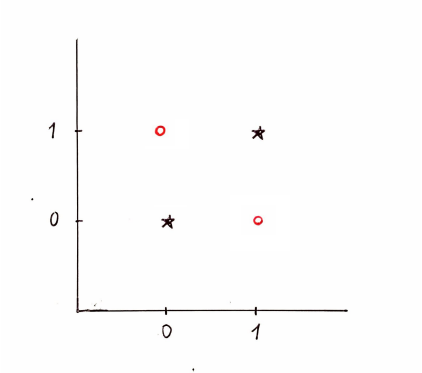
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It is clearly not linearly separable.

Advantages and limitations of linear models



Possible solutions

- We can transform the input so that it becomes linearly separable.

Advantages and limitations of linear models



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Advantages and limitations of linear models



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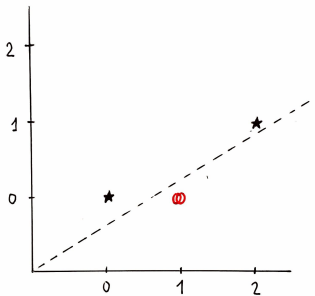
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For example, $\phi(x_1, x_2) = [x_1 + x_2, x_1 \times x_2]$ maps the instances to another representation and makes the XOR problem linearly separable:



Advantages and limitations of linear models



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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!).

Advantages and limitations of linear models



Training mapping functions

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

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- ...where g is a non-linear activation function, and $\boldsymbol{W}', \boldsymbol{b}'$ are its trainable parameters.
- The equation above defines a simple multi-layer perceptron (MLP): our first neural model.

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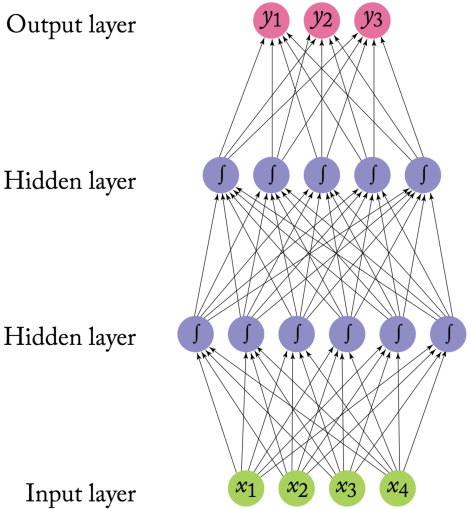


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Going deeply non-linear: multi-layered perceptrons



Perceptron with 2 hidden layers

Going deeply non-linear: multi-layered perceptrons



The nature of perceptrons

- Input data goes through successive transformations at each layer.

Going deeply non-linear: multi-layered perceptrons



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Going deeply non-linear: multi-layered perceptrons

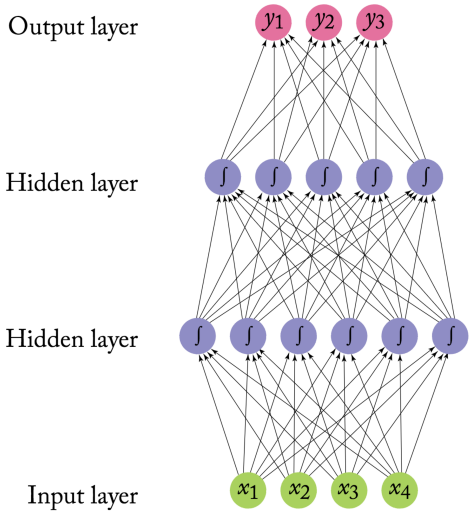


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Important: **neural networks with hidden layers can theoretically approximate any function** [Leshno et al., 1993].

Going deeply non-linear: multi-layered perceptrons



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

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Q&A session, January 27

- Ask questions about the pre-recorded lectures published on January 23
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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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- Due February 28.
- Look it up on the course page.

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Group session January 28th

- Hands-on: Computing setup and *Fox* basics
- Make sure you have access to *Fox*!

References I

Cortes, C. and Vapnik, V. (1995).
Support-vector networks.
In Machine Learning, pages 273–297.

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.