IN5550: Neural Methods in Natural Language Processing
Sub-lecture 3.1
Multi-layered neural networks

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Contents

Obligatory assignment

Time to get your hands dirty!

- Obligatory assignment 1 is published.
- Will work on related topics at the group sessions February 8 and 15.

IN5550 – Spring 2023

1. Bag of Words Document Classification

UiO Language Technology Group

Deadline: 16 February, at 21:59 (Devilry)

Goals

1. Learn how to use the Fox cluster to train deep learning models.
2. Get familiar with the *PyTorch* library
3. Learn how to use *PyTorch* to train and evaluate neural classifiers in NLP tasks.

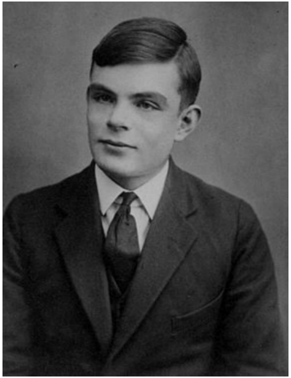
Contents

Multi-layered neural networks

'Machines of this character can behave in a very complicated manner when the number of units is large.'

Alan Turing, 'Intelligent Machinery'

[Turing, 1948]



Brain metaphor

- Why 'artificial neural networks'?

Multi-layered neural networks

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Multi-layered neural networks

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Multi-layered neural networks

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  - the whole system is distributed across many neurons.

Multi-layered neural networks

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- Thus, it's less cool but more convenient to think about artificial neural networks in terms of linear algebra concepts:
  - vectors,
  - matrices,
  - sequential algebraic operations on them.

The most basic neuron...

Multi-layered neural networks

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Multi-layered neural networks

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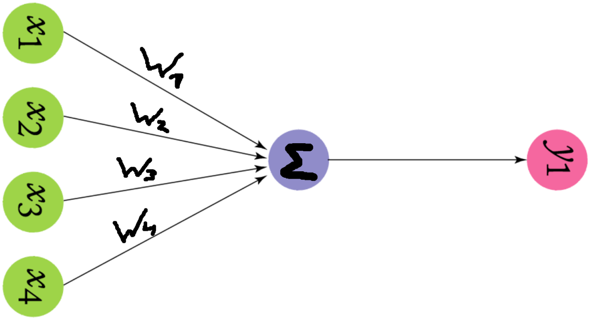

Multi-layered neural networks

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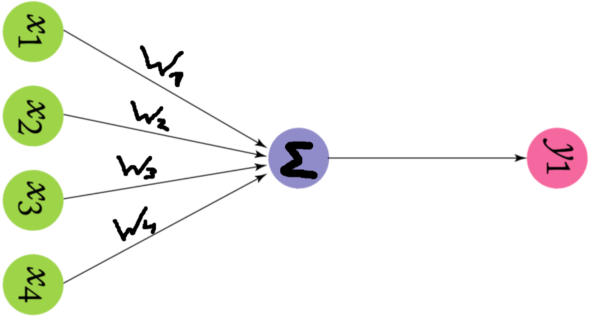

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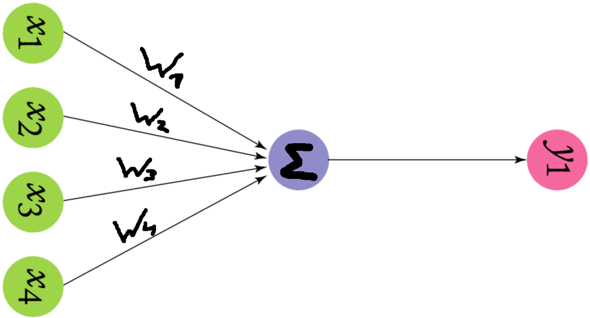
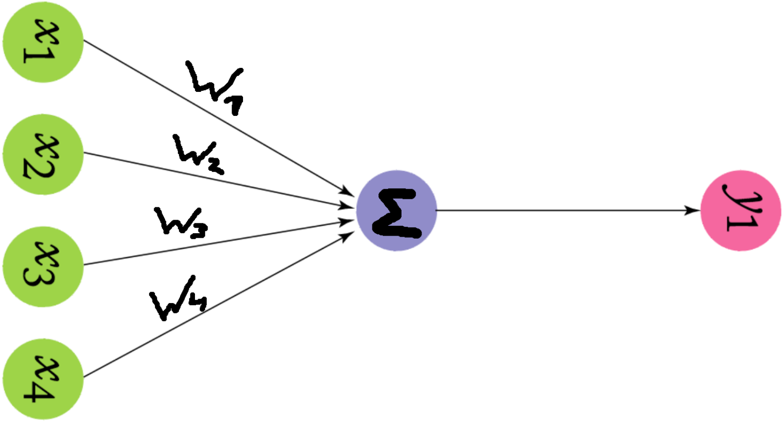


- input feature vector $\boldsymbol{x}$ is multiplied by the weights $\boldsymbol{W}$;
- here, $\boldsymbol{W}$ is a vector, so the result is a scalar value $\hat{y}_1$.

Multi-layered neural networks



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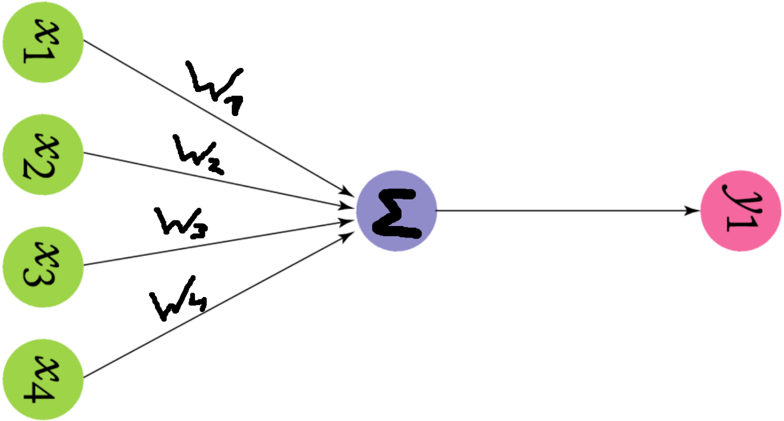

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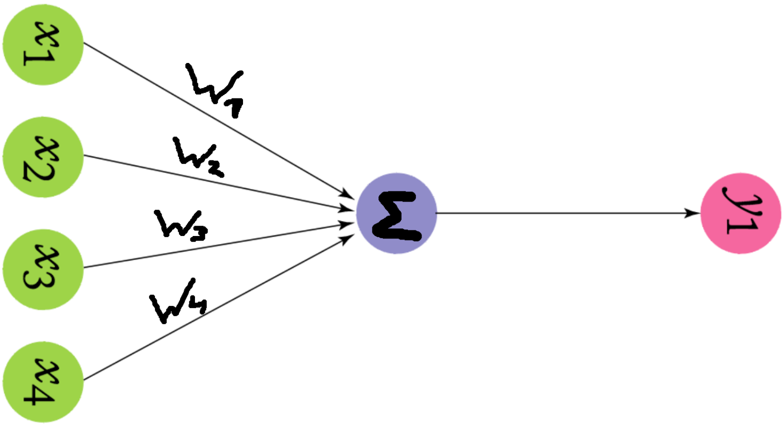
Multi-layered neural networks



- In fact this is already a simple neural network...
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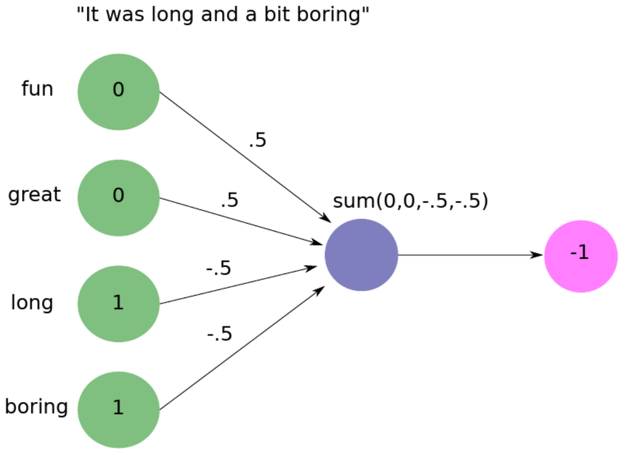
- Σ takes 4 input values and returns their weighted sum as output value.

Multi-layered neural networks



Sentiment analysis with only one neuron and binary bag-of-words.

Multi-layered neural networks

Stack of linear classifiers

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  $\hat{\boldsymbol{y}} = \boldsymbol{x} \cdot \boldsymbol{W}$
- We can make this classifier predict vectors instead of scalars...
  - ...by making $\boldsymbol{W}$ a matrix;
  - ...and thus using a row of several neurons, instead of only one.

Multi-layered neural networks

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Multi-layered neural networks

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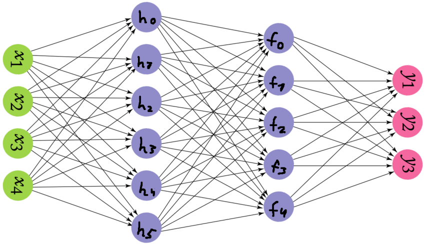
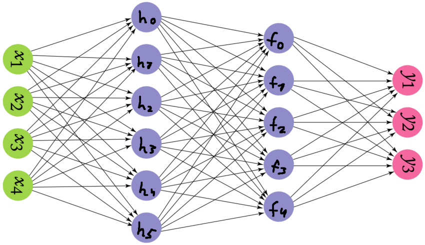
Can even use both multiple neurons and multiple layers.

Multi-layered neural networks



Multi-layered neural networks



Looks much like a 'deep neural network'

Stacked linear classifier with multiple computational units at each layer:

$$h = \boldsymbol{x} \cdot \boldsymbol{W^0} \tag{2}$$

$$f = \boldsymbol{h} \cdot \boldsymbol{W^1} \tag{3}$$

$$\hat{\boldsymbol{y}} = \boldsymbol{f} \cdot \boldsymbol{W^2} \tag{4}$$

Multi-layered neural networks

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Multi-layered neural networks

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- Still can't handle XOR and other non-linear problems.

Multi-layered neural networks

Non-linear transformations of the input data make the desired difference.

Multi-layered neural networks

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- Hyperbolic tangent:

$$\tanh(x) = \frac{e^{2x} - 1}{e^{2x} + 1} \rightarrow [-1, 1]$$

Multi-layered neural networks

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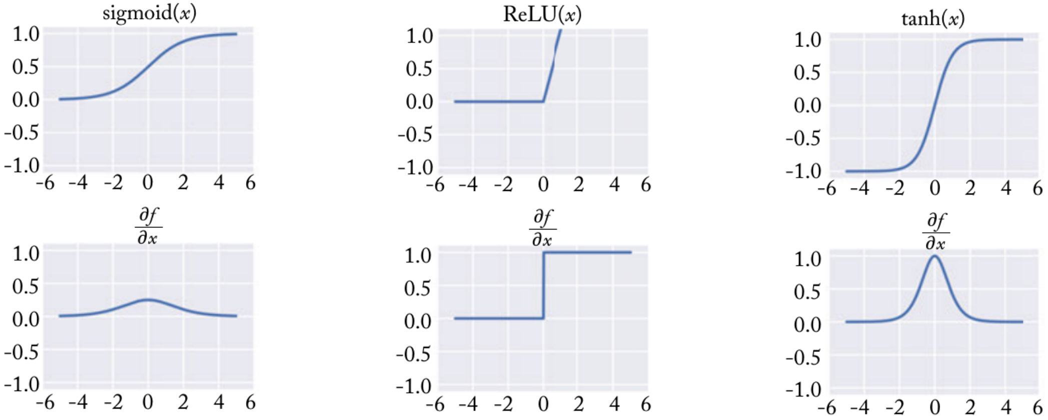
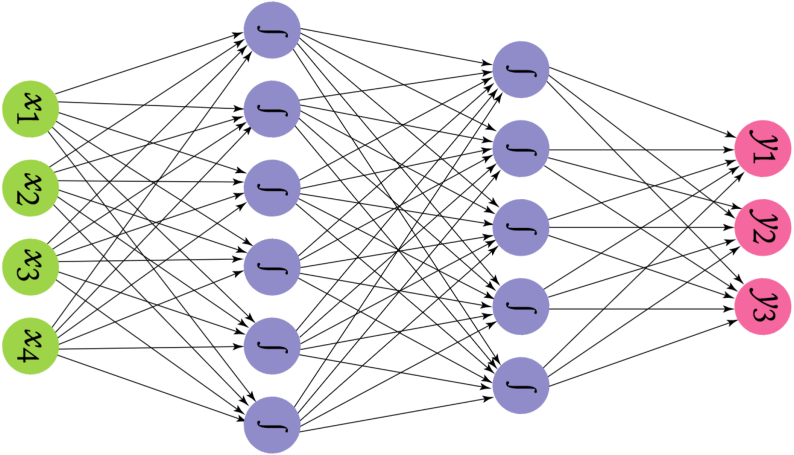


...and their derivatives.

Multi-layered neural networks



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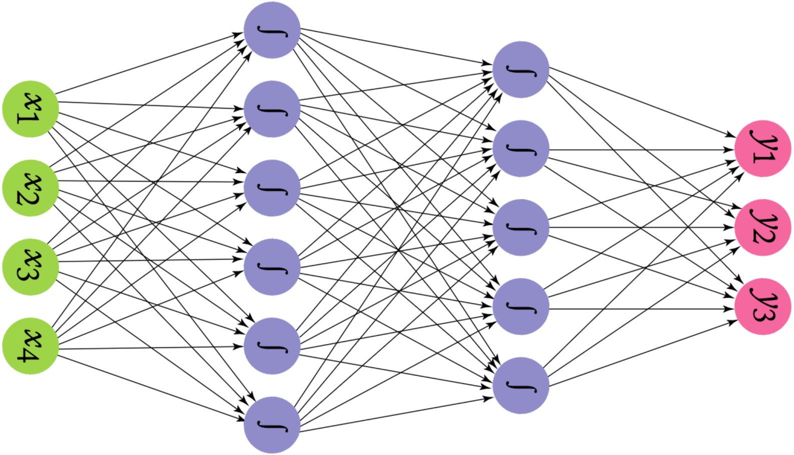

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In the next sub-lecture 3.2: why 'feed-forward' and 'fully connected'?

References I

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