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- Visit the lesson website to see some interesting alternatives

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+ You could turn a COLI star!


L'algoritmo di Arianna: "Così su Twitter do la caccia ai post contro le donne"

di Emanuela Giampaoli

La Repubblica (Bologna); 31 March, 2021

RAI News 24; 8 April, 2021

92586 Computational Linguistics

Lesson 12. "More than One" Neuron

Alberto Barrón-Cedeño

Alma Mater Studiorum-Università di Bologna
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30/03/2022

Previously

- The perceptron
- Intro to neural networks

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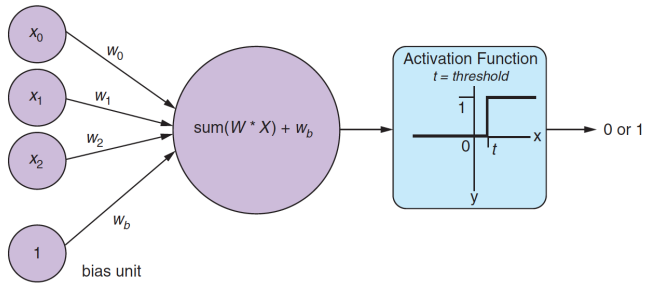
Backpropagation (brief)

Weight Updating

Learning in a "simple" perceptron[1] vs a fully-connected network



(?, p. 158, 168)

[1] Remember: aka linear regression

Weight Updating

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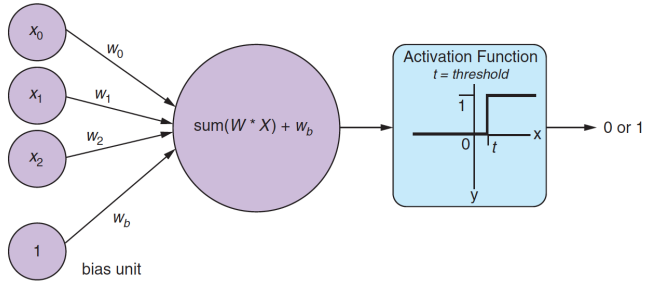

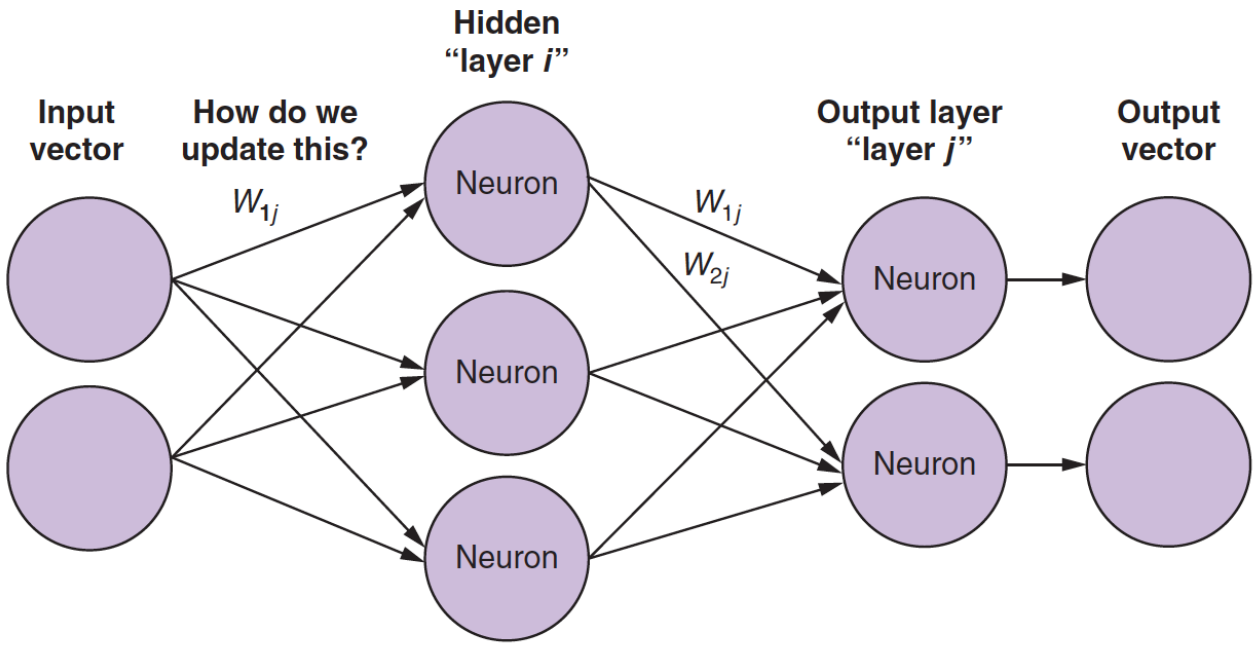

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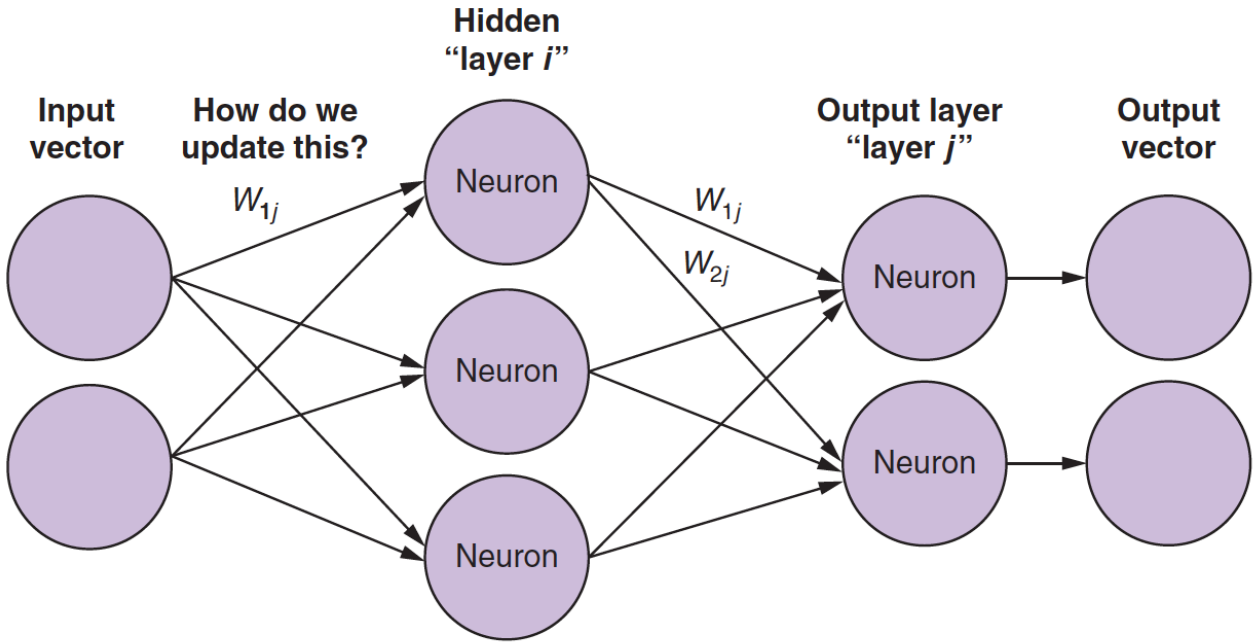
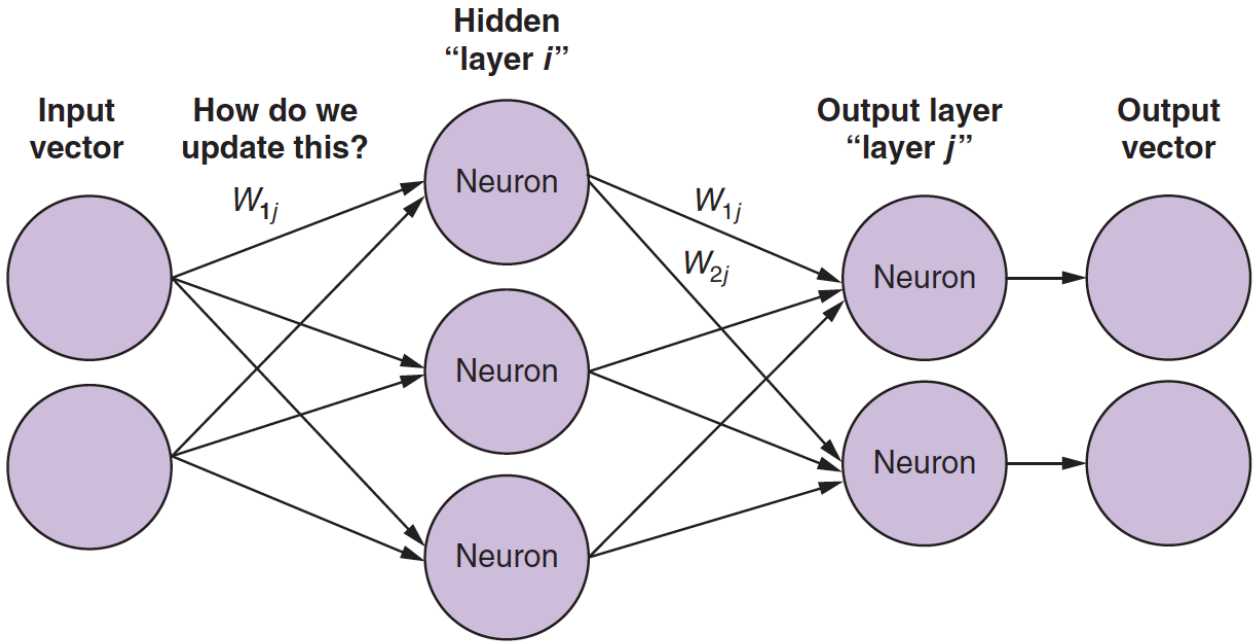
[1] Remember: aka linear regression

Backpropagation (of the errors)



[2] Notice that the first W_{1j} should be W_{1i}

Backpropagation (of the errors)



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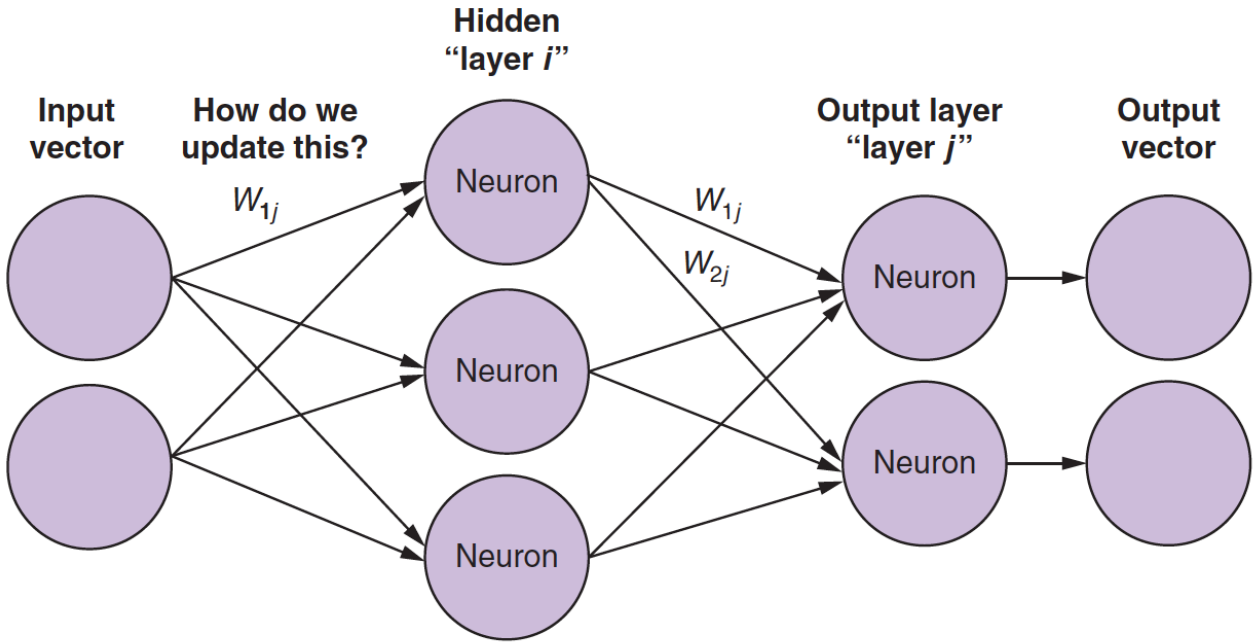

- The error is computed on the output vector
- How much error did W_{1i} "contribute"?[2]
- "Path": $W_{1i} \rightarrow [W_{1j}, W_{2j}] \rightarrow output$

[2] Notice that the first W_{1j} should be W_{1i}

Backpropagation (of the errors)

A better activation function

Step function: $f(\vec{x}) = \begin{cases} 1 & \text{if } \sum_{i=0}^{n} x_i w_i > \mathit{threshold} \\ 0 & \text{otherwise} \end{cases}$

[3] The change of the output is not proportional to the change of the input.

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Sigmoid function: non-linear[3] and continuously differentiable

$$S(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

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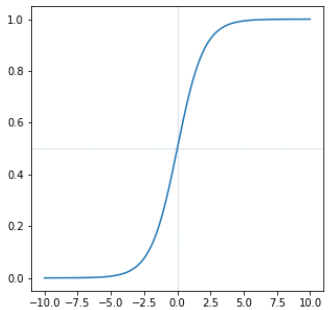

Non-linear $\rightarrow$ model non-linear relationships

Continuously differentiable $\rightarrow$ partial derivatives wrt various variables to update the weights

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Backpropagation

Differentiating to adjust

Squared error (in (**?**, p. 171) they say this is MSE; wrong)

$$SE = (y - f(x))^2 \tag{2}$$

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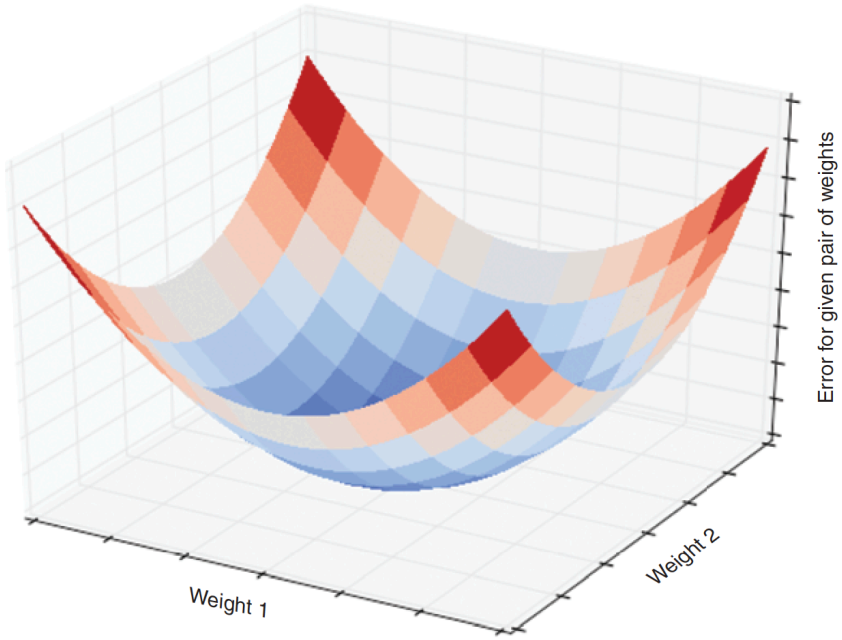
With (4) we can find the derivative of the actfunct $\forall$ neuron wrt its input.
Plain words: find the contribution of a weight to the error and adjust it!

(no further math)

Backpropagation (of the errors)

∼Gradient descent: minimising the error



Convex error curve

(**?**, p. 173–174)

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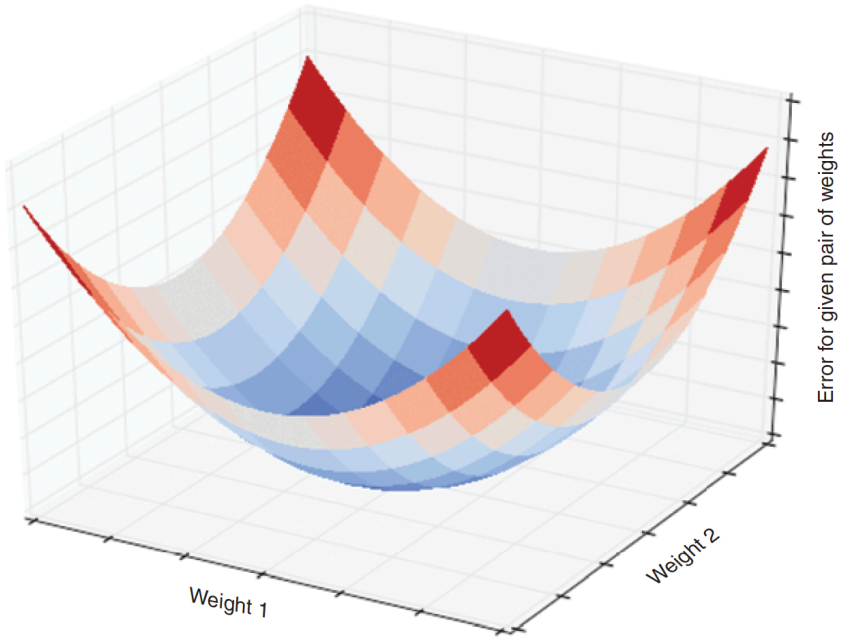

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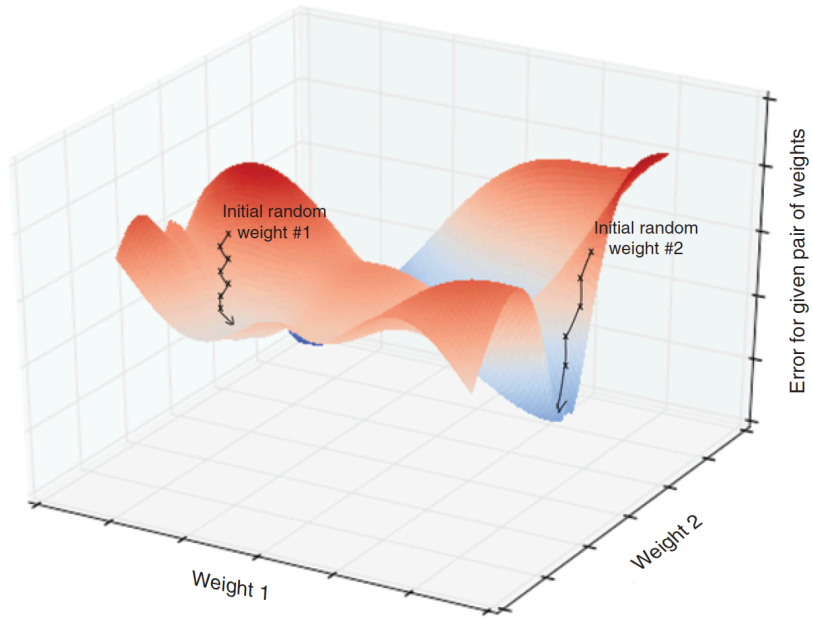

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(**?**, p. 173–174)

Addressing Local minima

Batch learning

- Aggregate the error for the batch
- Update the weight at the end

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- Look at the error for each single instance
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Mini-batch

- Much smaller batch, combining the best of the two worlds
- $\rightarrow$ Fast as batch, resilient as stochastic gradient descent

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Important parameter: learning rate α
A parameter to define at what extent should we "correct" the error

Keras

Some Available Libraries

There are many high- and low-level libraries in many languages

- **PyTorch**
  Community-driven; `https://pytorch.org/`
- **Theano**
  MILA (UdeM); `www.deeplearning.net/software/theano/`[4]
- **TensorFlow**
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We will use **Keras**; `https://keras.io/`

[4] Non active

What is Keras

- High-level wrapper with an accessible API for Python

What is Keras

- High-level wrapper with an accessible API for Python
- Gives access to three alternative backends
  - Theano
  - TensorFlow
  - CNTK (MS)

Keras

Logical exclusive OR in Keras

input		**output**
0	0	0
0	1	1
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  - First dense layer
    - 2 inputs, 10 neurons
    - 30 parameters

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Now we can compile the model

📖 Let us see

Some Guidelines

Design Decisions

Activation functions

- Sigmoid
- ReIU Rectified linear unit (and variations)
- tanh Hyperbolic tangent

Figure source: (?)

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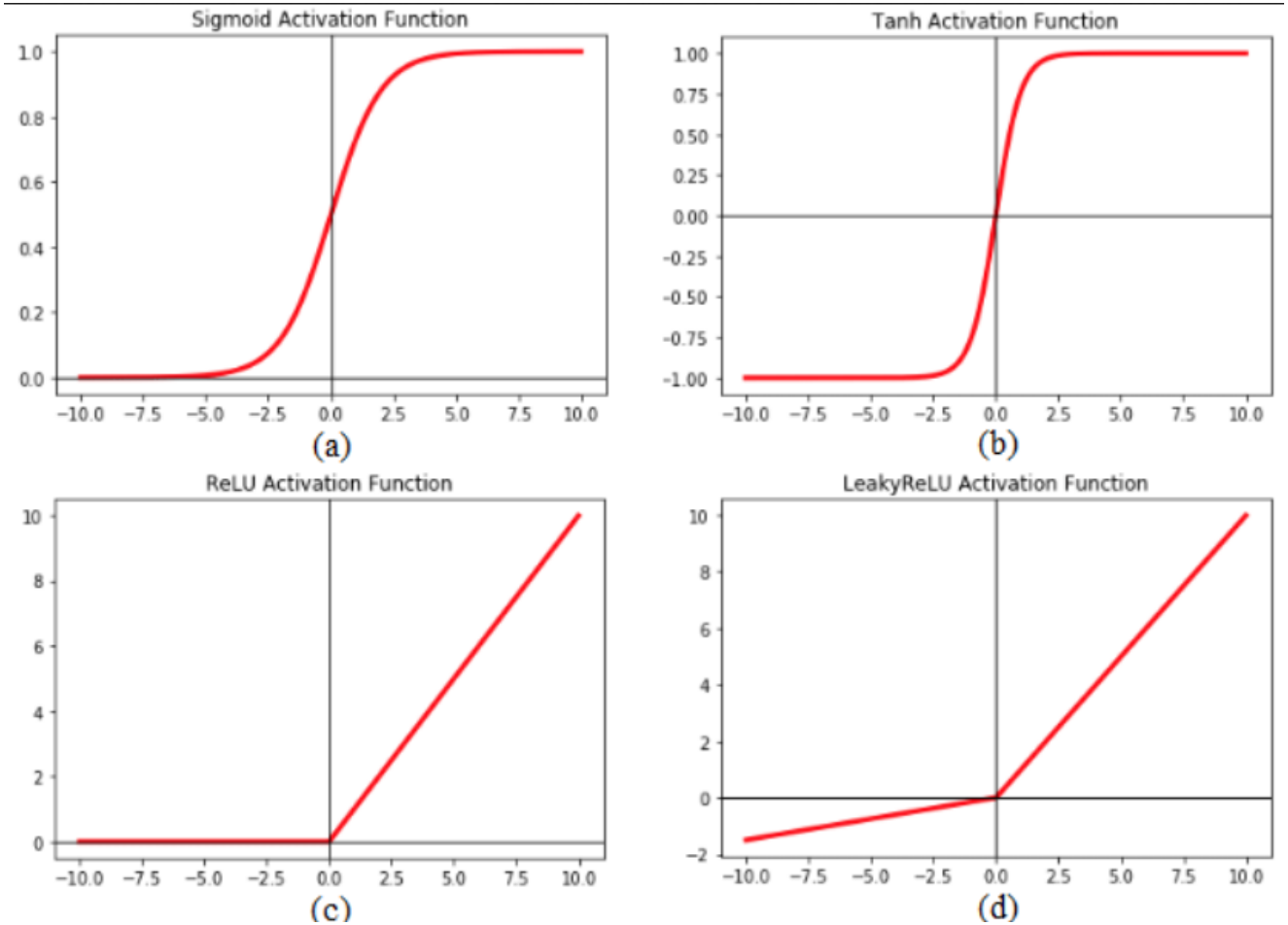

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Regularisation

- Dampen a weight from growing/shrinking too far from the rest to prevent overfitting

Normalisation

Example House classification.

Input	number of bedrooms, last selling price
Output	Likelihood of selling
Vector	`input_vec = [2, 90000]`

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NLP uses TF-IDF, one-hot encoding, word2vec (already normalised!)

References

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2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.