Feedforward Neural Networkss: Revisiting Word Vectors and Text Classification

COM6513 Natural Language Processing

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Computer Science Department

Week 6
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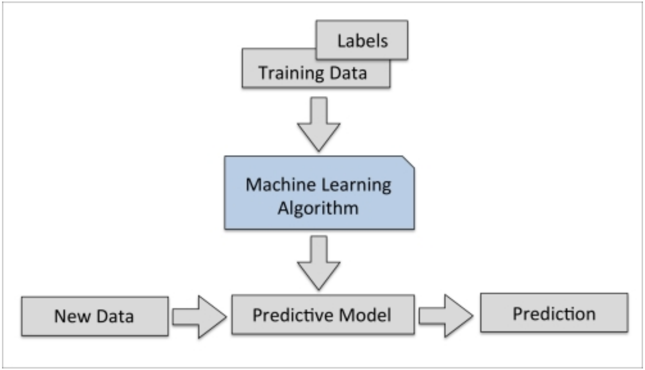
The University Of Sheffield.

In lecture 2...



Supervised ML

In lecture 2...

- **Machine Learning Algorithm:** Logistic Regression
- Binary and Multi-class

Logistic Regression recap

- Compute the dot product z between the input vector $\mathbf{x}$ and the weight vector $\mathbf{w}$, and add a bias term b (often ignored):

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- Predict the class with the highest probability:

$$\hat{y} := \begin{cases} 0 & \text{if } P(y = 1|\mathbf{x}; \mathbf{w}) < 0.5 \\ 1 & \text{otherwise} \end{cases}$$

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- LR directly maps input to output and only captures linear relationships in the data

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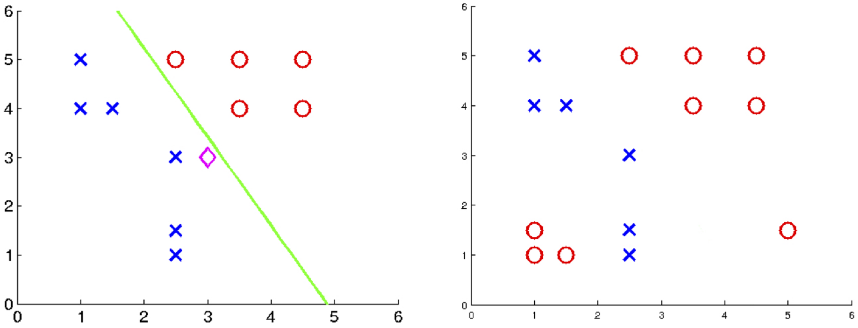
- Pass input through a series of intermediate computations (**hidden layers**) to capture **non-linear relationships** a.k.a. **deep learning**
- Train with **SGD** and **Backpropagation** (for computing the gradients)
- NLP applications: word vectors and text classification

Limitations of linear models



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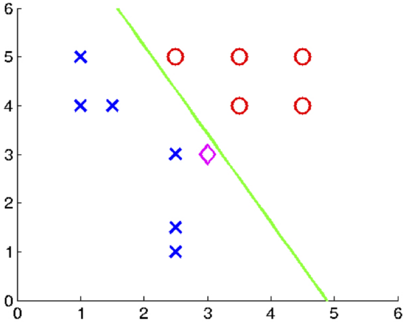

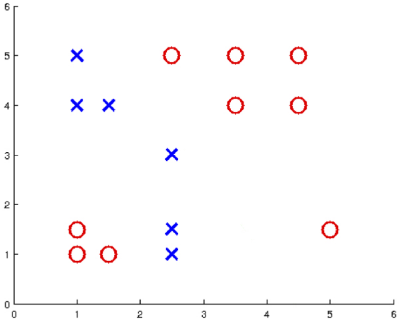

The righthand dataset is not linearly separable and cannot be learned with a linear model.

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- The final layer to obtain the prediction is called the **output** layer (e.g. sigmoid, softmax)

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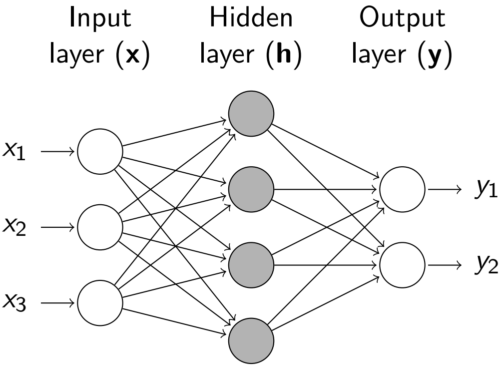

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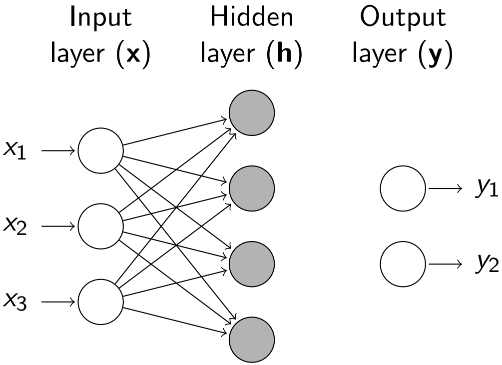

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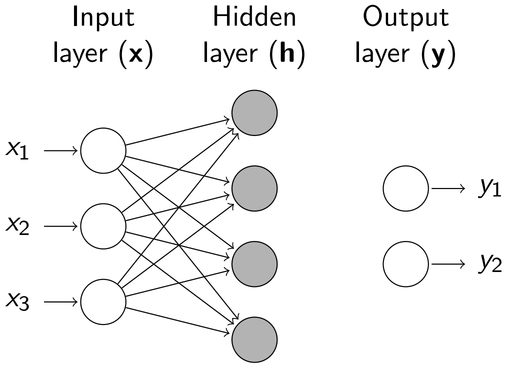

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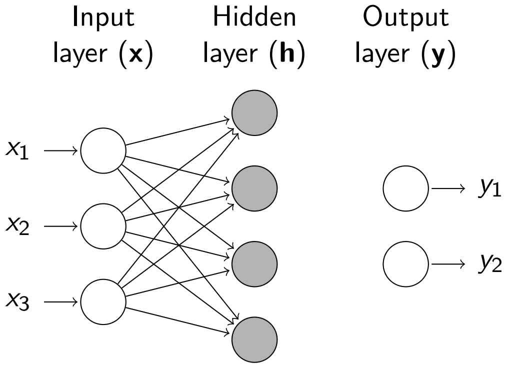

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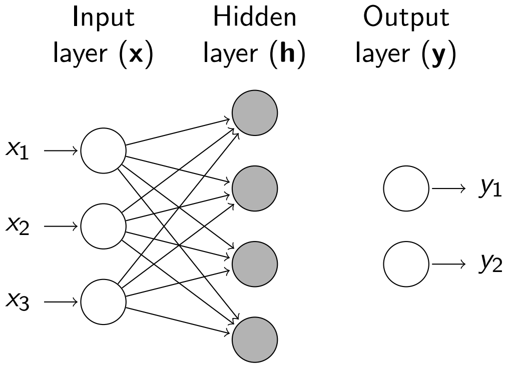

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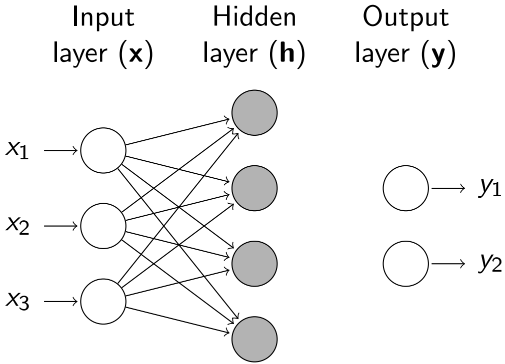

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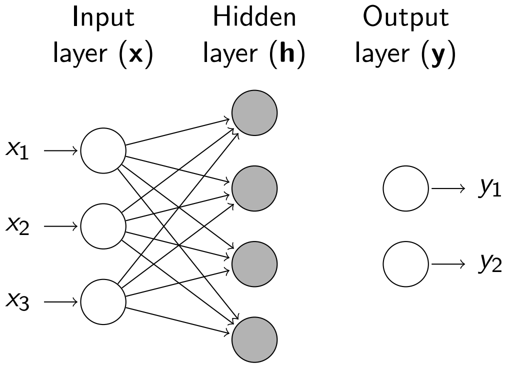

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Extended to deeper architectures:

$$\mathbf{h_i} = g(\mathbf{h}_{i-1}^T \mathbf{W}_{h_i})$$

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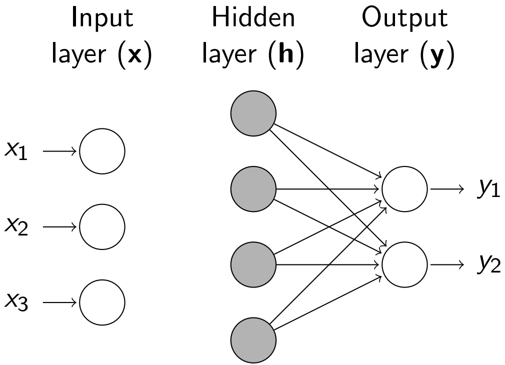

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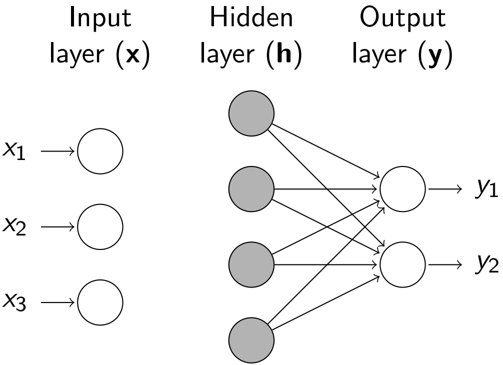

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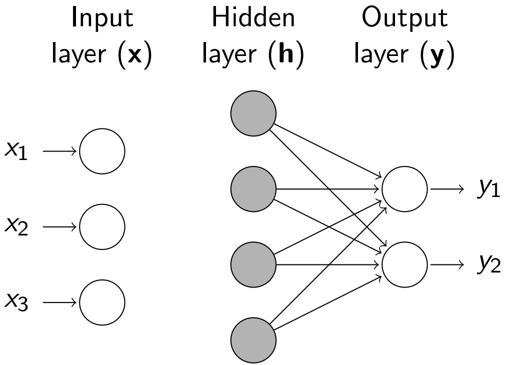

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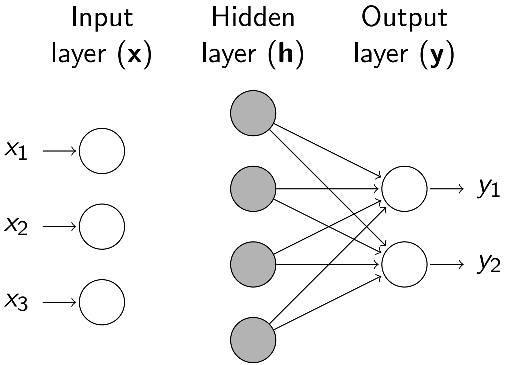

$$\begin{cases} \mathbf{h} = g(\mathbf{x}^T \mathbf{W}_h) \\ \mathbf{y} = softmax(\mathbf{h}^T \mathbf{W}_o) \\ \mathbf{W}_o \in \mathcal{R}^{h \times y} \end{cases}$$

But what is $g(\cdot)$?

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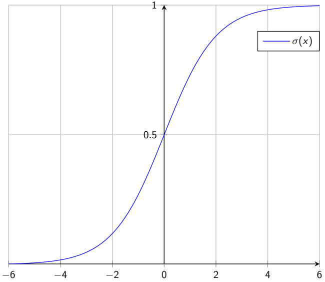
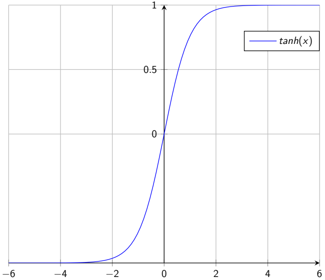
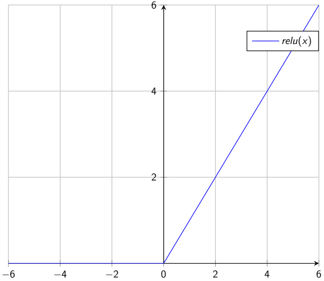
- And many more...

Activation Functions







Training: Stochastic Gradient Descent (SGD) recap

Input: $D_{train} = \{(x_1, y_1)...(x_M, y_M)\}, D_{val} = \{(x_1, y_1)...(x_D, y_D)\},$
$\quad$ *learning rate* η, *epochs* e, *tolerance* t

initialize $\mathbf{w}$ *with zeros*

for each *epoch* e **do**

randomise order in D_{train}

for each (x_i, y_i) *in* D_{train} **do**

update $\mathbf{w} = \mathbf{w} - \eta \nabla_{\mathbf{w}} L(\mathbf{w}; x_i; y_i)$

monitor training and validation loss

if *previous validation loss* $-$ *current validation loss*; *smaller than* t

break

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How to compute the gradient for the weights of the hidden layers?

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- **Forward Pass:** Compute and store all the output values of all the hidden units (for each hidden layer) and the output layer

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- **Forward Pass:** Compute and store all the output values of all the hidden units (for each hidden layer) and the output layer
- **Backward Pass:** Compute the gradients for the output and hidden layers with respect to the cost function L and update the weights for each layer

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initialise $W_i \in W = \{W_1, ..., W_l\}$ *for each layer (small random values)*

for each *epoch* e **do**

randomise order in D_{train}

for each (x_i, y_i) *in* D_{train} **do**

layer_outputs = *forward_pass*$((x_i, y_i), W)$

$W =$ *backward_pass*$((x_i, y_i), W, L,$ **layer_outputs**$)$

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end for
Get prediction $\hat{\mathbf{y}} = \mathbf{h}_l$
Compute cross-entropy loss $L(\hat{y}, y)$
return $\mathbf{h}$, $\mathbf{z}$ for all layers

Backward Pass

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  Update current weights:
  $W_k \leftarrow W_k - \eta \nabla_{W_k} L$
end for
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  - Apply a random binary mask after the activation function, i.e. elementwise multiplication with vector containing %20 0s in random positions

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- Architecture engineering vs feature engineering
- Theory says that we can approximate any function with one hidden layer, practice says different architectures work well for different problems

Implementation tips

- Learning objective non-convex: initialisation matters
  - start with small non-zero values
  - random restarts to escape local optima
- Greater learning capacity makes overfitting more likely: regularise
- Many open libraries are available: PyTorch, Tensorflow, MxNet, Keras etc.

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- Instead, use a feedforward network to **predict** a context word for a given word (and vice versa)
- **Word2Vec (Mikolov et al., 2013)** family, more recently supporting char n-grams (e.g. FastText)

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AS2

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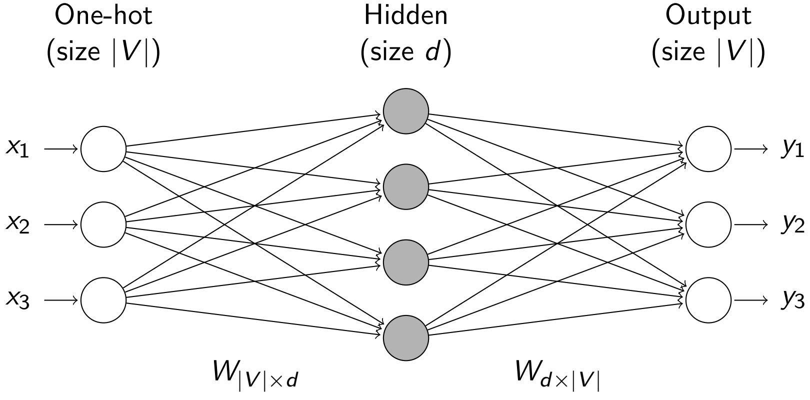
- **Output:** softmax over the vocabulary to predict the correct context/target words respectively

Word2Vec Architecture



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- Evaluation: standard approaches for word representation (see Lecture 1)
- Pre-trained word embeddings are widely re-used in other NLP tasks, i.e. transfer learning (more in Lecture 10)

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  - **Subsampling frequent words** to decrease the number of training examples

Applications: Text Classification

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Applications: Text Classification

- **Approach 1:** Pass BOW vectors into a series of hidden layers (extending the LR model in Lecture 2)
- **Approach 2:** Pass one-hot word vectors through an **embedding layer** to obtain embeddings for each word in a document which are subsequently **concatenated (or added/averaged) and passed through a series of hidden layers**
- Approach 2 is more contemporary and usually the embedding layer is pre-trained (e.g. using Word2Vec) and is not updated during training

Bibliographhy

- Chapters 6-8 from Goodfellow et al.
- Sections 3-6 from Goldberg
- Tutorial on backprop by D. Stansbury
- Word2vec tutorial by Chris McCormick

Coming up next..

- Recurrent Networks and Neural Language Modelling