Natural Language Processing (CS-472) Spring-2023

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Overview of this week's lecture

Review of Neural Networks

- Recap of fundamentals of neural networks
- Forward and backpropagation in MLPs
- Activation functions
- Improving network training

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Let’s establish some notation for neural networks

- In supervised learning, the training dataset consists of input/output pairs.

$$\{\boldsymbol{x_i}, y_i\}, for\ i = 1, \dots, N$$

  - In NLP, $\boldsymbol{x_i}$ are inputs representing words (indices or vectors), sentences, or documents etc.
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  - y_i denotes labels (one type/class of word from C classes).
- The task of Deep Neural Networks (DNNs) applied to NLP is normally prediction for,
  - Classes: sentiment, Named Entity, buy/sell decision, etc.
  - Other words: Masked Natural Language Understanding.
  - Multi-word sequences: Translation, Question/Answering, etc.

Training data for a binary classification may be visualised on a 2D plane

- For the given $2D$ vector space, learn a decision boundary to separate the two classes.

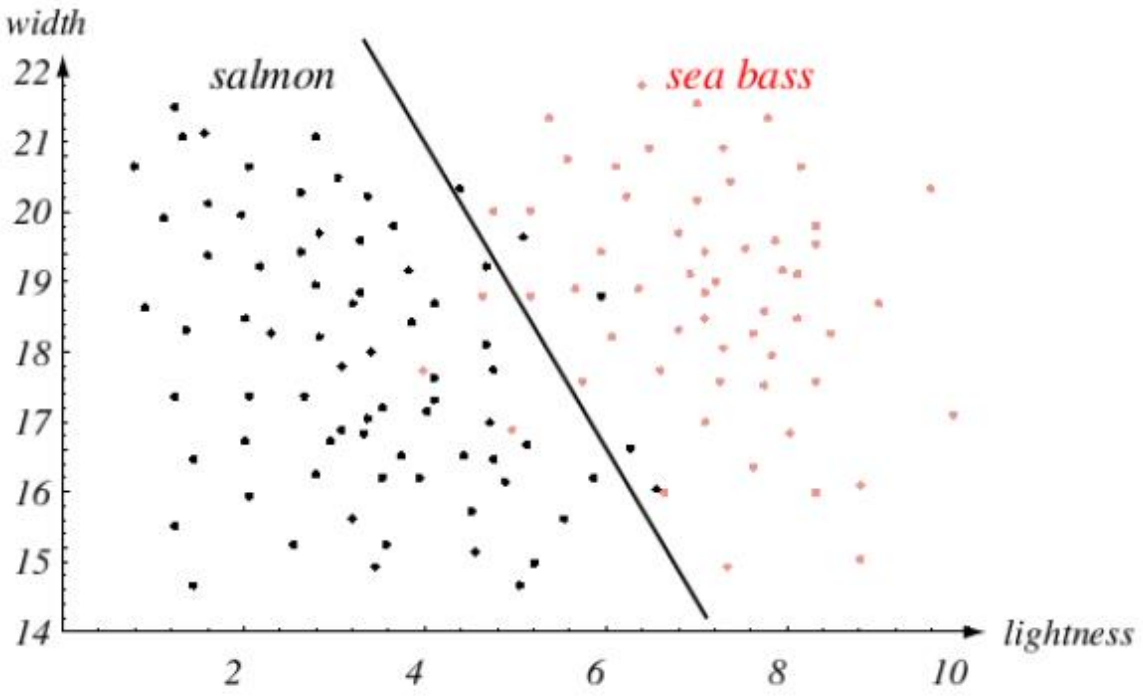

FIGURE 1.4. The two features of lightness and width for sea bass and salmon. The dark line could serve as a decision boundary of our classifier. Overall classification error on the data shown is lower than if we use only one feature as in Fig. 1.3, but there will still be some errors. From: Richard O. Duda, Peter E. Hart, and David G. Stork, *Pattern Classification*. Copyright © 2001 by John Wiley & Sons, Inc.

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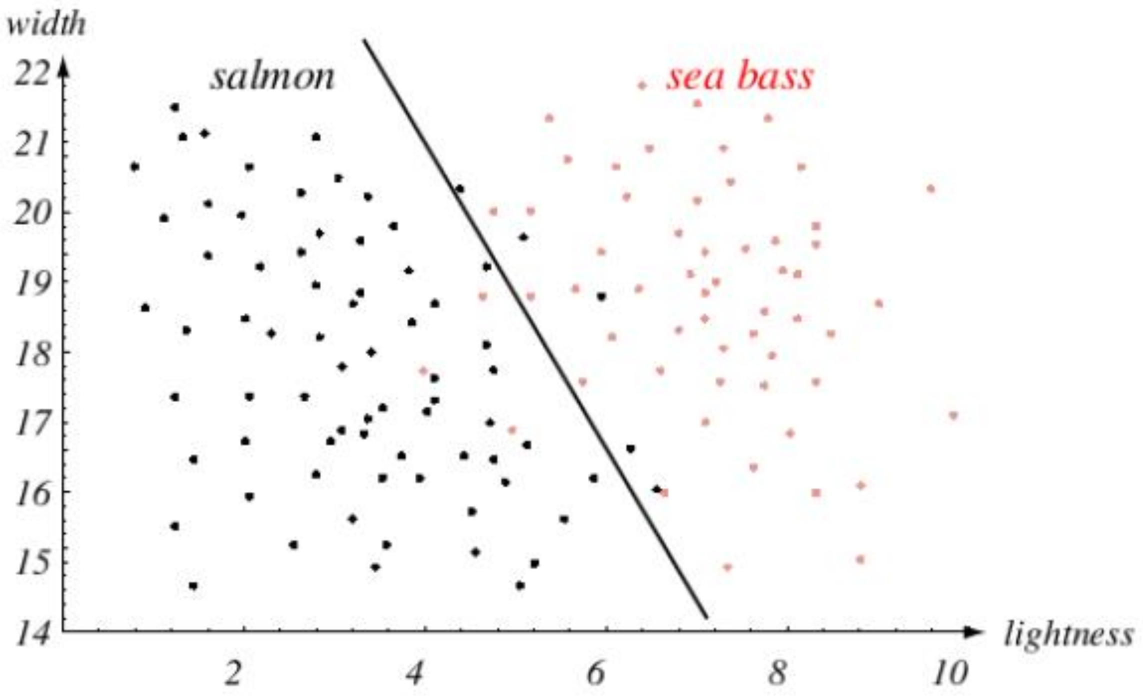

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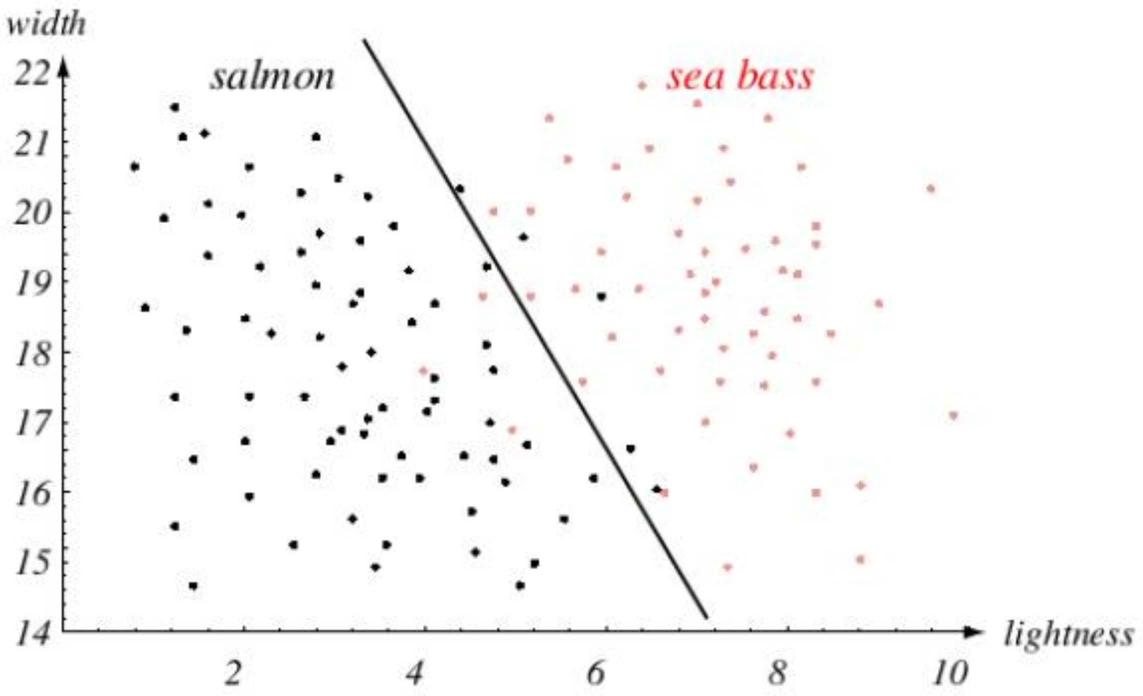
    - Set weights $\boldsymbol{W} \in \mathbb{R}^{c \times d}$ to find a **hyperplane** the fits the data.



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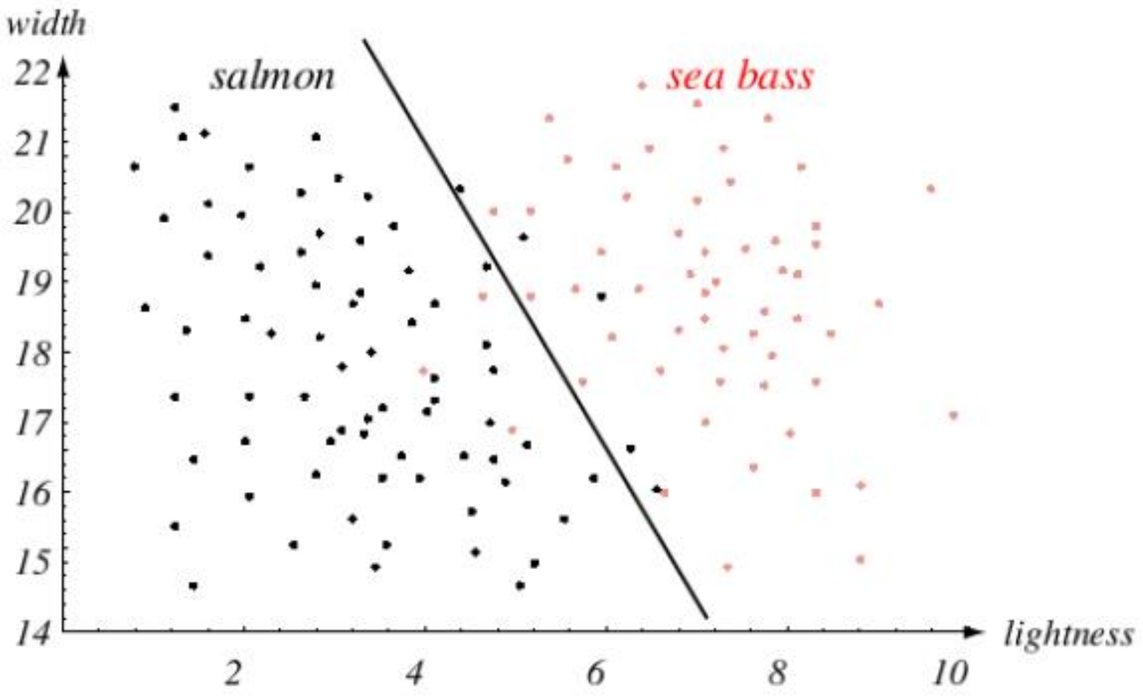
- Method?

  For each input x_i, predict $P(y|x)$.



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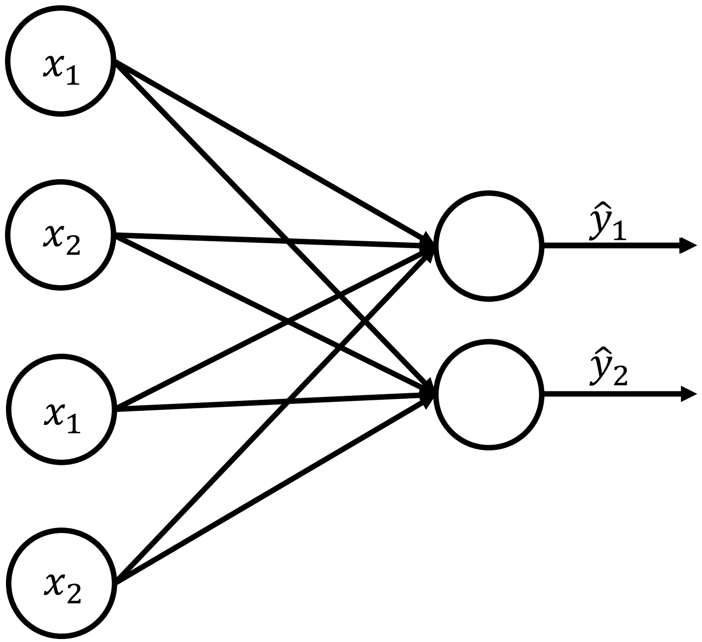

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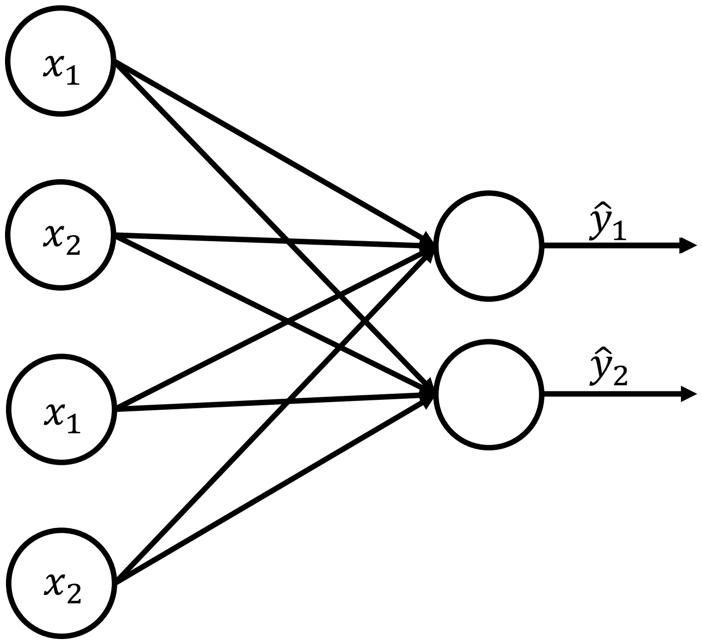

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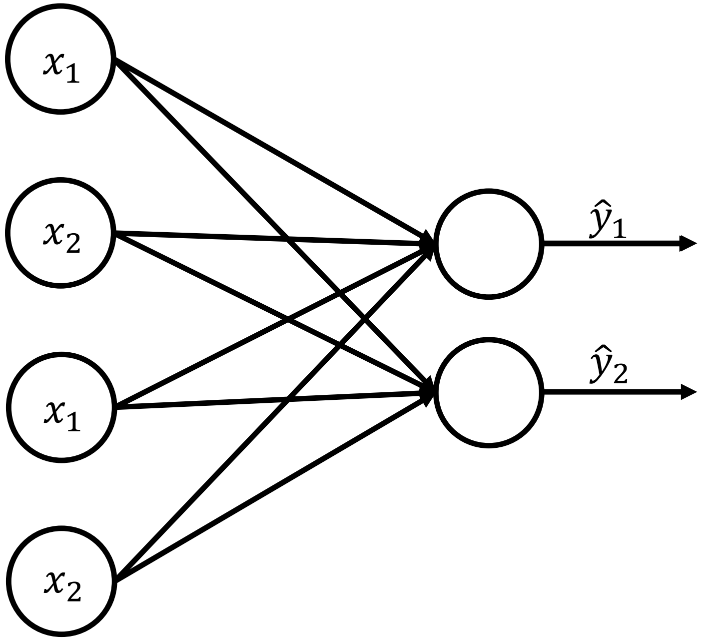

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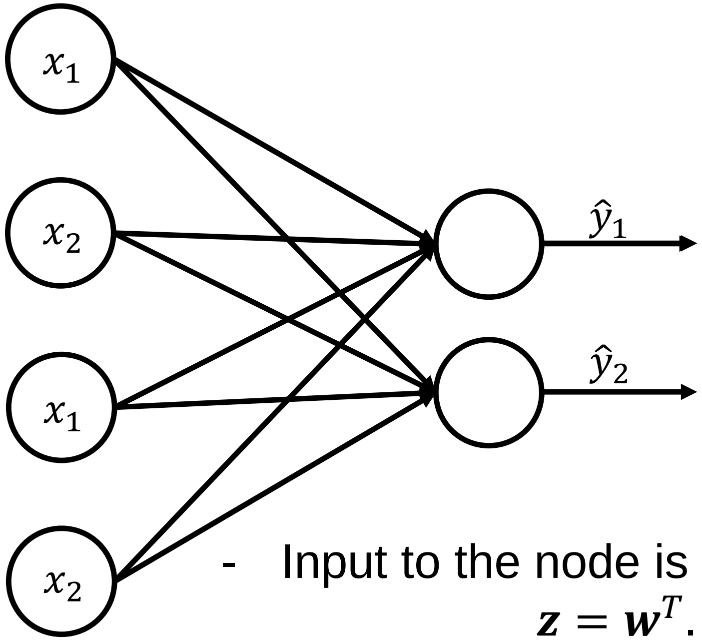

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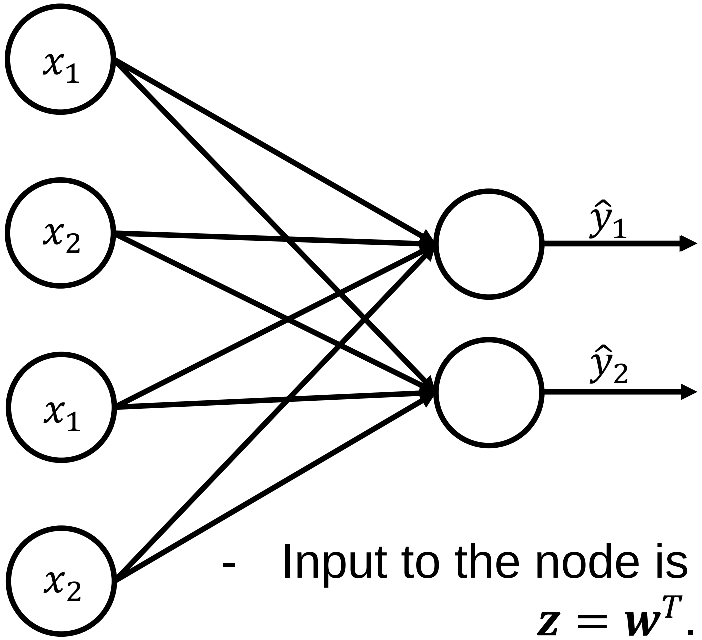

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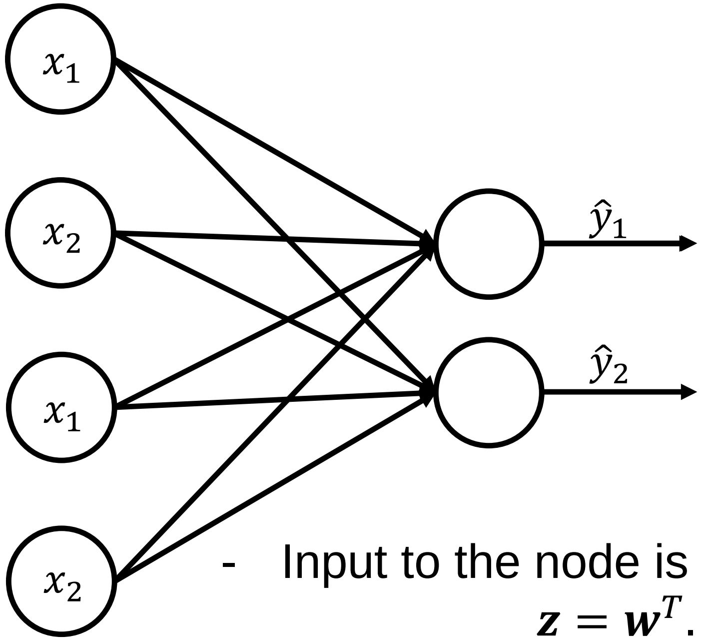

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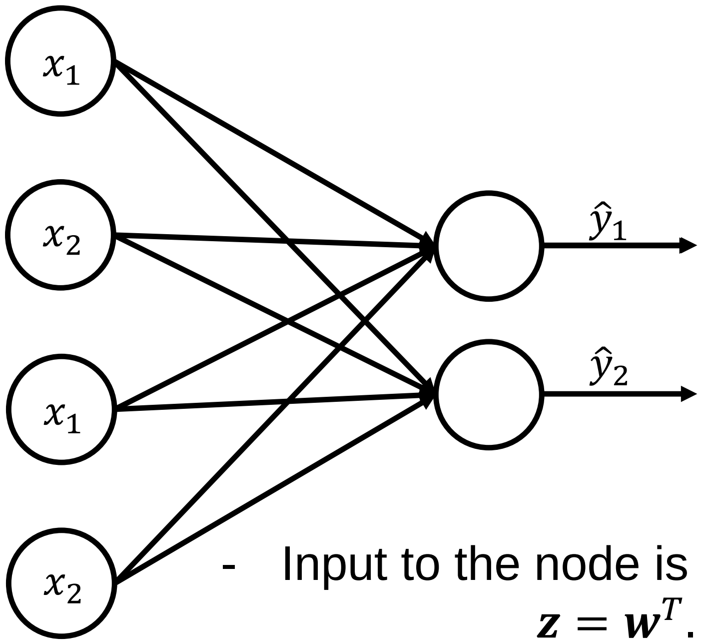

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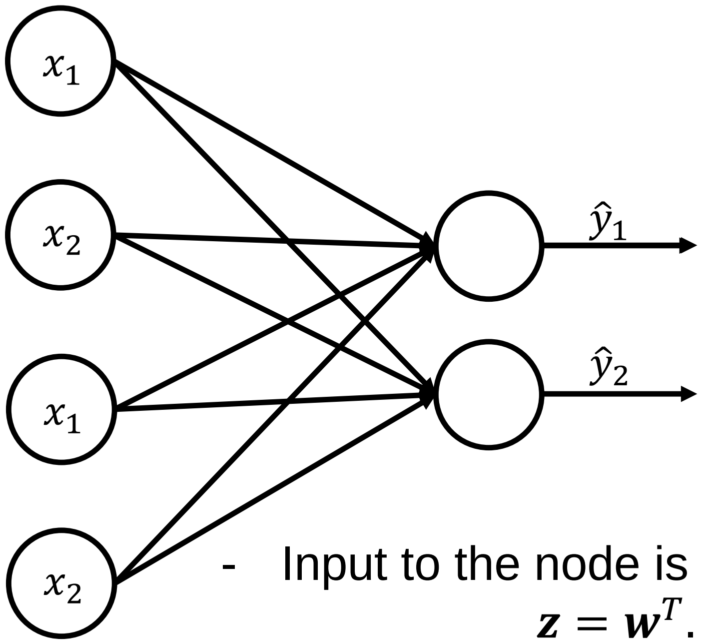

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$$softmax = \frac{\exp z_i}{\sum_{c=1}^{C} \exp z_c}$$

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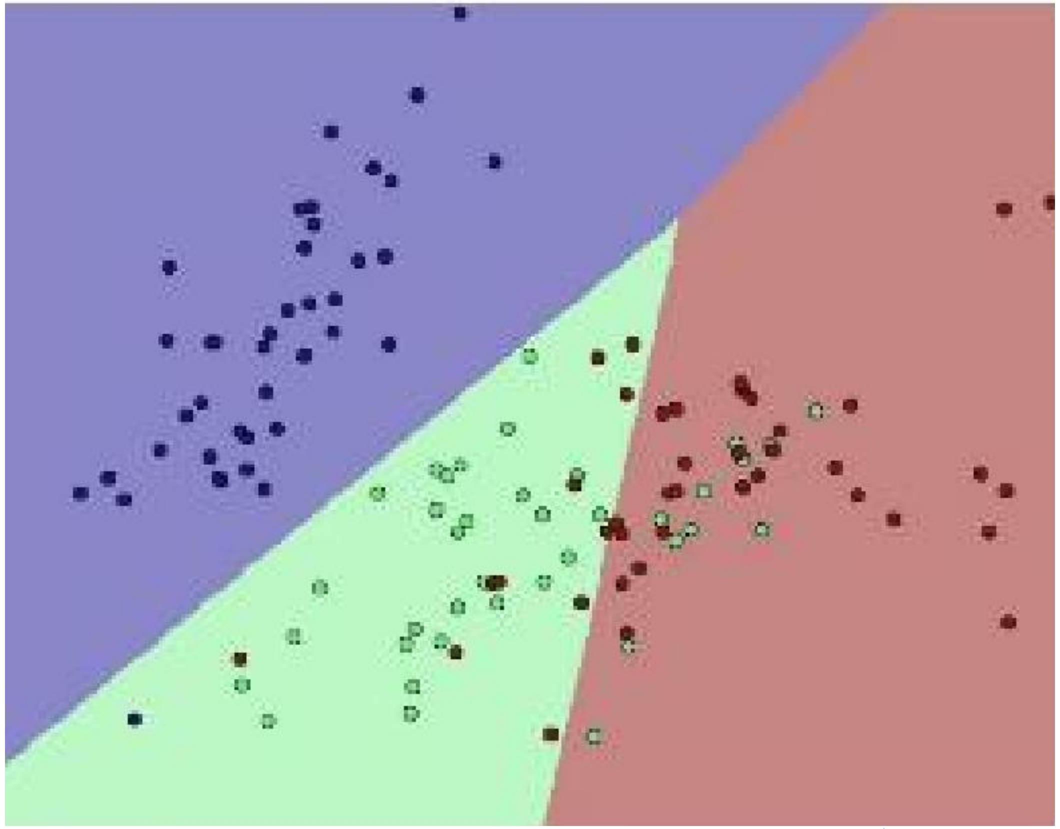

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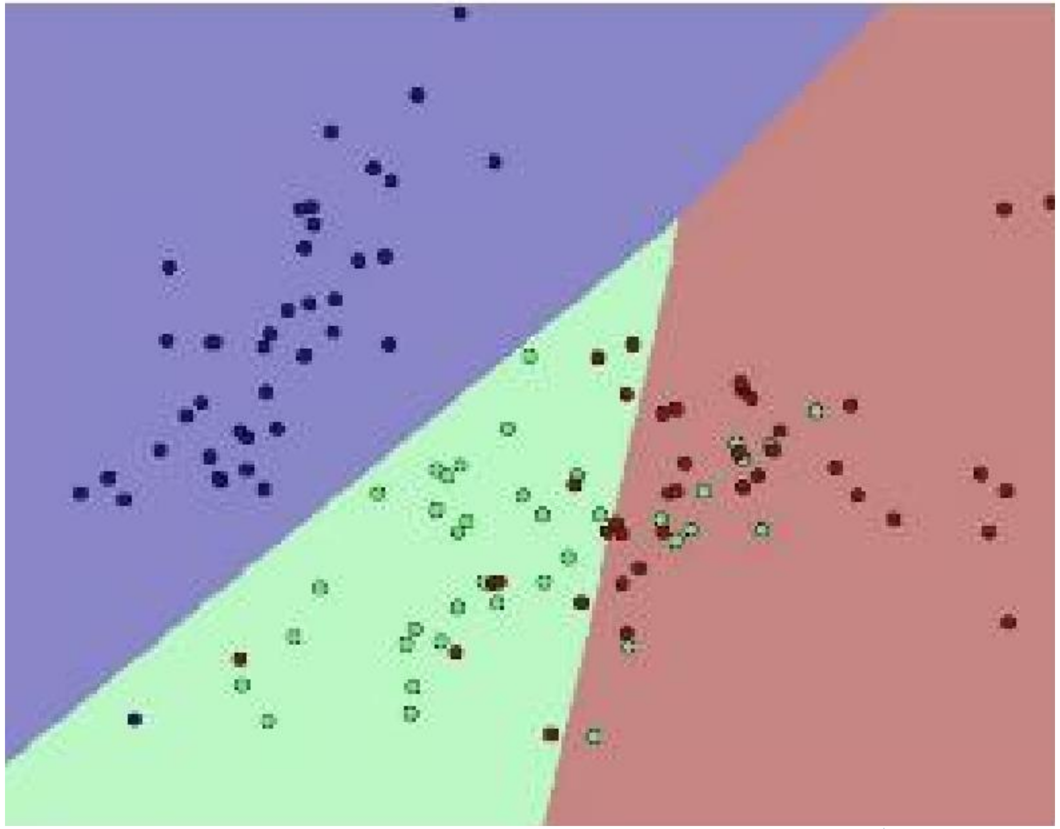
- Naïve Bayes, SVM, Logistic Regression are examples of linear classifiers.



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    - Assuming a ground truth probability distribution that is 1 at the right class, and 0 elsewhere, or

$$P_{GT} = [0,0,\dots,0,1,0,\dots,0],$$

the only term left is the negative log probability of the true class $(-\log q(c))$

Average loss over all training samples gives cost function

- Cross entropy over the whole dataset gives the cost function.

$$J(\theta) = \sum_{j=1}^{N} -\log\left(\frac{e^{z_{ij}}}{\sum_{c=1}^{C} e^{z_c}}\right)$$

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- What if labels are not truly one hot encoded?

$$P_{GT} = [0,0, \dots, 0.7, 0.3, 0, \dots, 0]$$

Optimisation of networks parameters is done by calculating gradients

- Usually, θ only consists of columns of W matrix,

$$\theta = \begin{bmatrix} w_1 \\ w_2 \\ . \\ . \\ . \\ w_d \end{bmatrix} \in \mathbb{R}^{c \times d}$$

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- Update in decision boundary is done via,

$$\nabla_\theta J(\theta) = \begin{bmatrix} \nabla w_1 \\ \nabla w_2 \\ . \\ . \\ . \\ \nabla w_d \end{bmatrix} \in \mathbb{R}^{c \times d}$$

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- One hot encoded word vectors can be considered as another layer in the neural network.

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- What's the need for activation function?
  - Introduce non-linearity and scale the activation. Why non-linearity?
  - Which activation function is better?

Do Deep Neural Networks really perform better?

- If you can satiate their appetite.
    - Data for starter
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- Deep Neural Networks are much more to just larger number of layers.
  - What is wide neural network?
  - What happens to gradients in DNNs?
  - Impact of input scale in the DNNs?

A Multi Layer Perceptron (MLP) is a deep neural network

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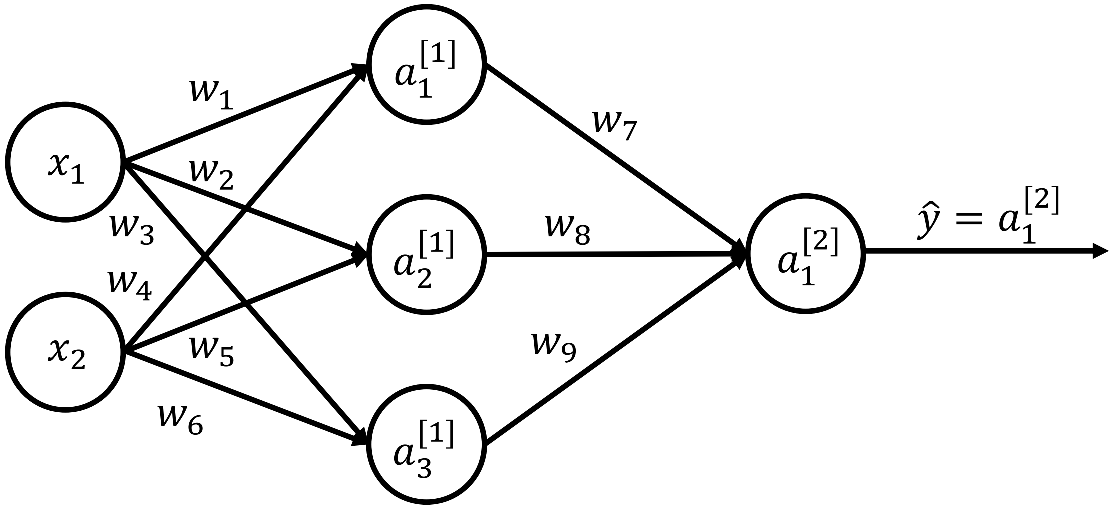

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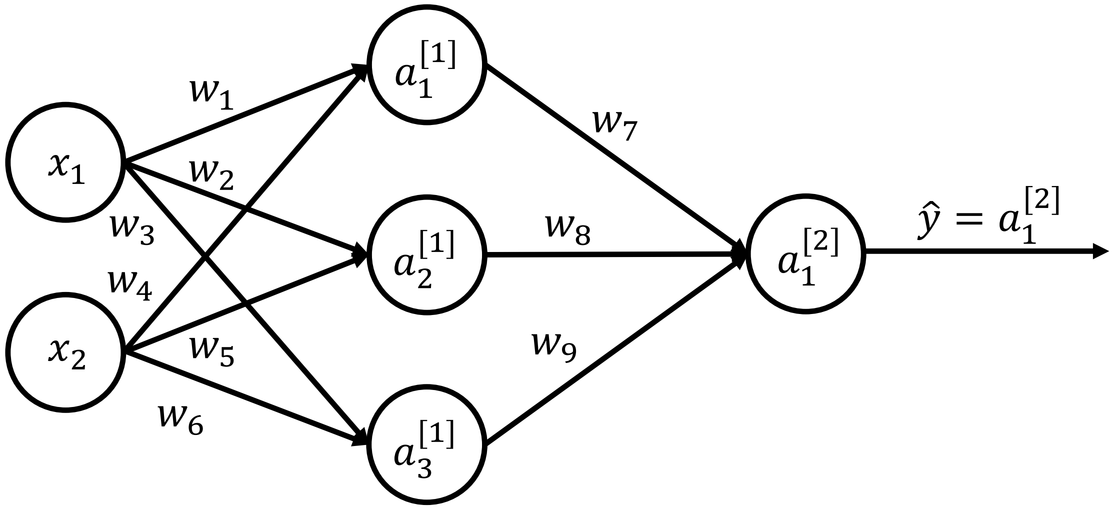

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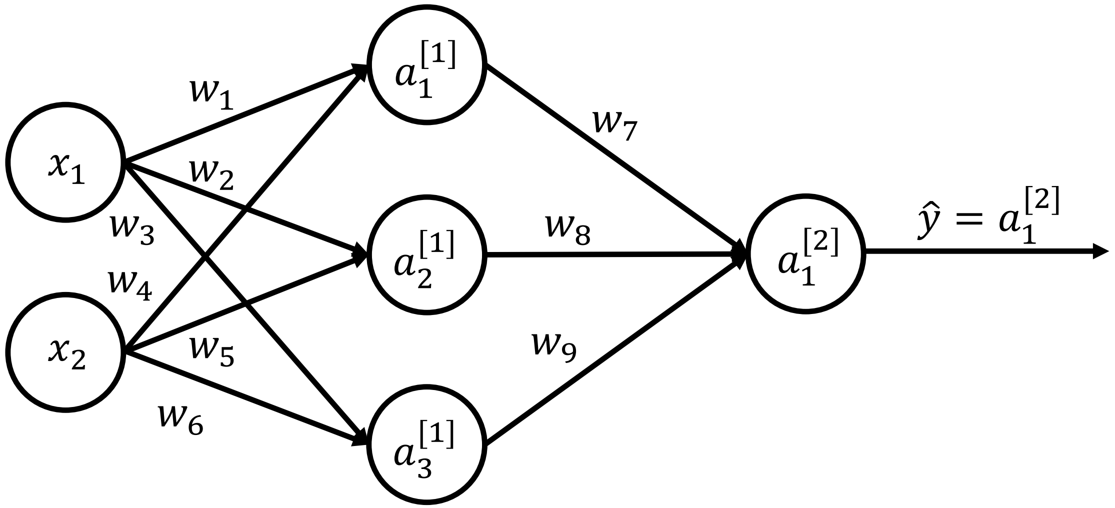

- Backward Pass: for update in w_1, for instance.

$$\frac{\partial L}{\partial\, w_1} = \frac{\partial L}{\partial\, a_1^{[2]}} \times \frac{\partial a_1^{[2]}}{\partial z_1^{[2]}} \times \frac{\partial z_1^{[2]}}{\partial a_1^{[1]}} \times \frac{\partial a_1^{[1]}}{\partial z_1^{[1]}} \times \frac{\partial z_1^{[1]}}{\partial w_1}$$

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    - Learning non-linear functions helps neural networks fit complex data.
- Various applications call for different activation functions better suited to the tasks.

Sigmoid function is one of the oldest activation functions

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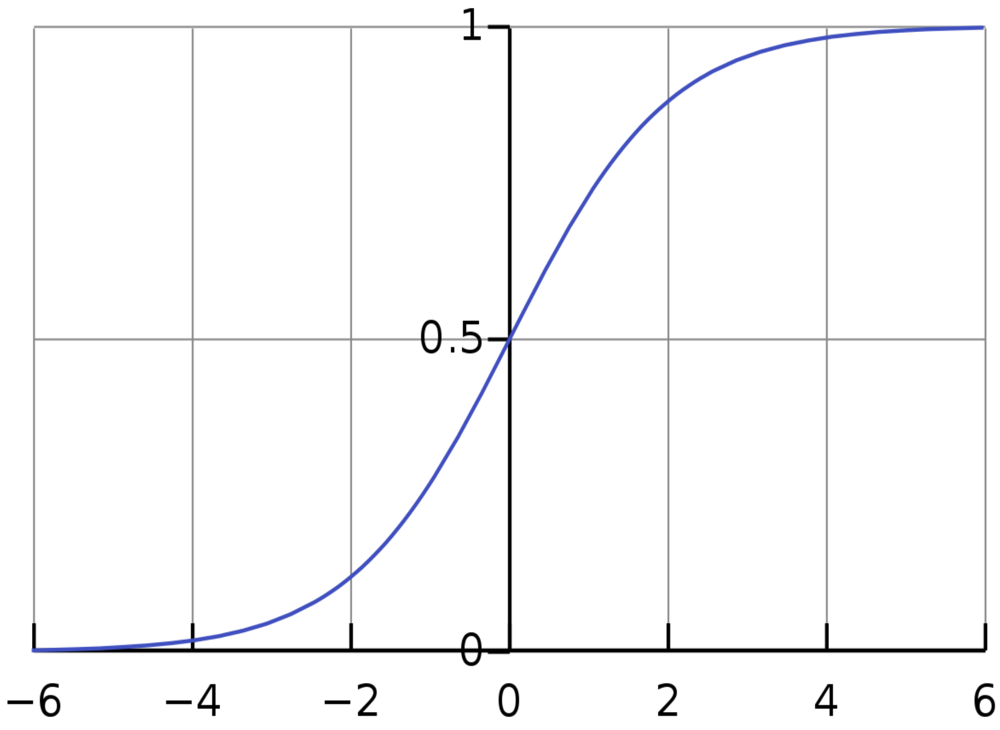
- Normalises inputs between $(0,1)$ giving psudoprobability.
- Maximum gradient is 0.25 at $x = 0$.



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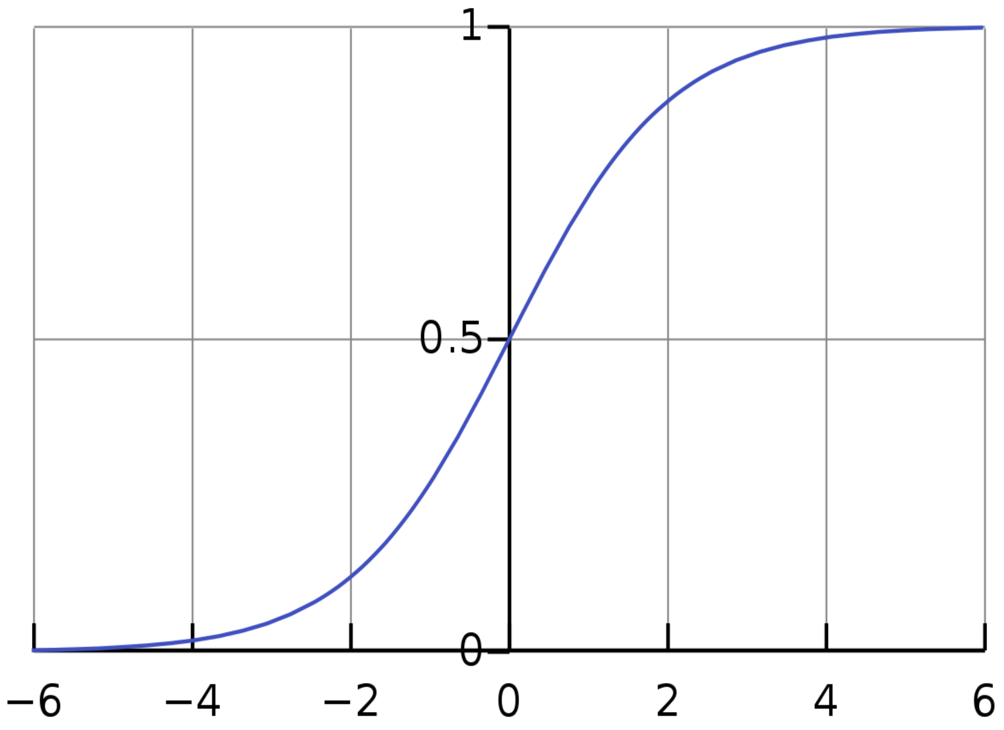

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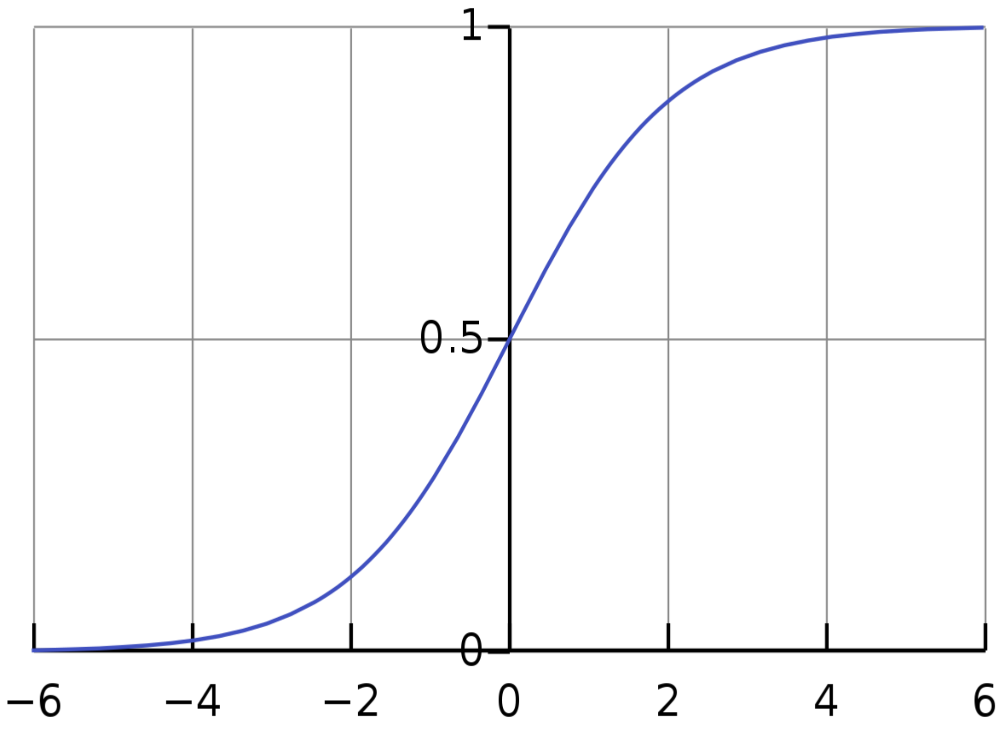
- Very narrow linear range.
- Severely prone to vanishing gradient resulting in slow learning.
- Its output is not zero-centred. May cause inefficient weight updates
- Exponential operations are computationally expensive.



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

$$f'(x) = f(x)(1 - f(x))$$

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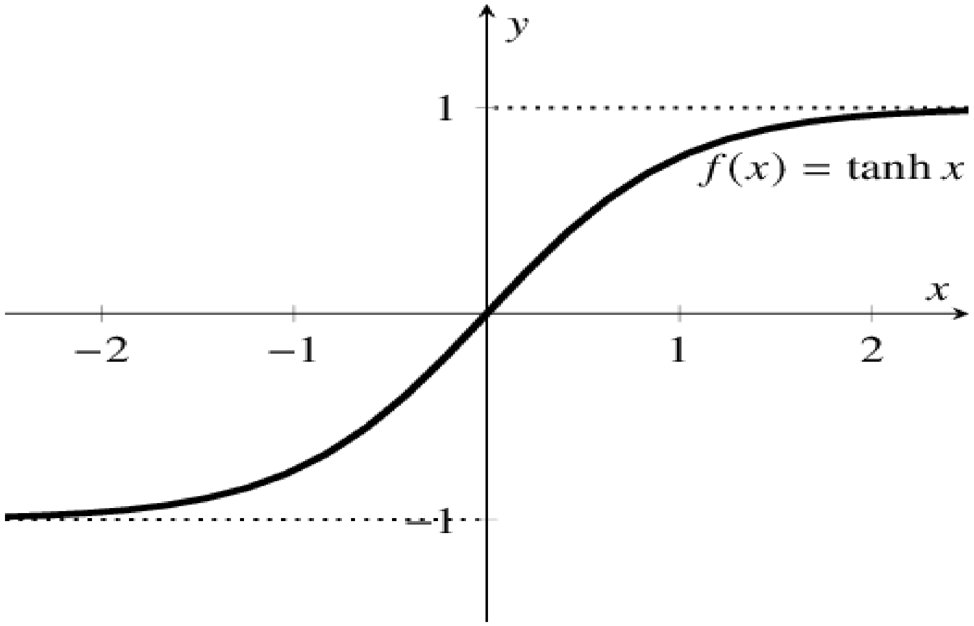
Hyperbolic Tangent is a better alternative to sigmoid in hidden layers

- A shifted and scaled version of sigmoid.

$$\tanh(z) = 2\,sigmoid(2z) - 1$$

- Most common activation function in RNNs.



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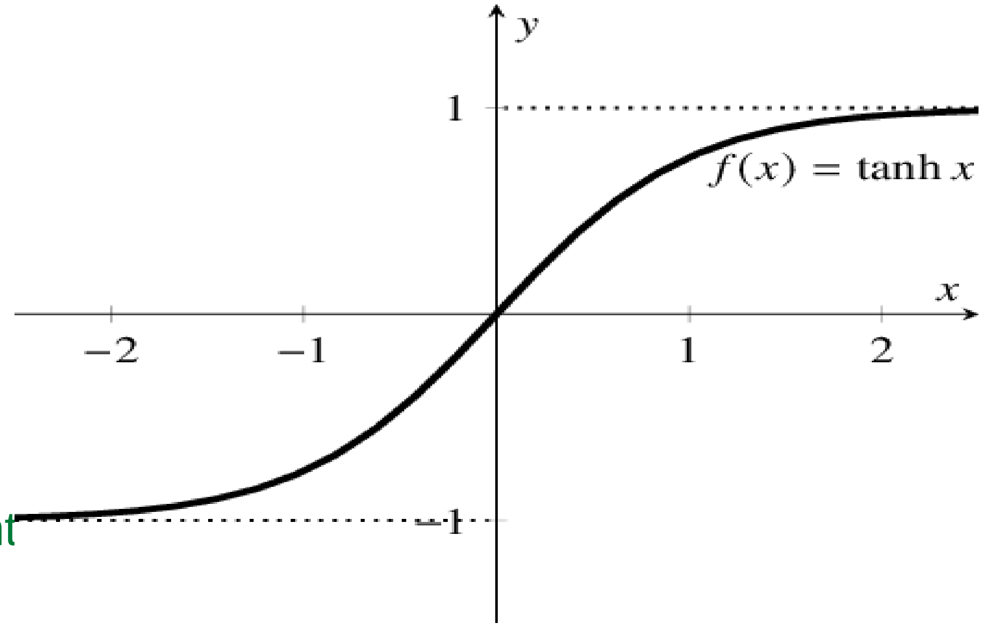

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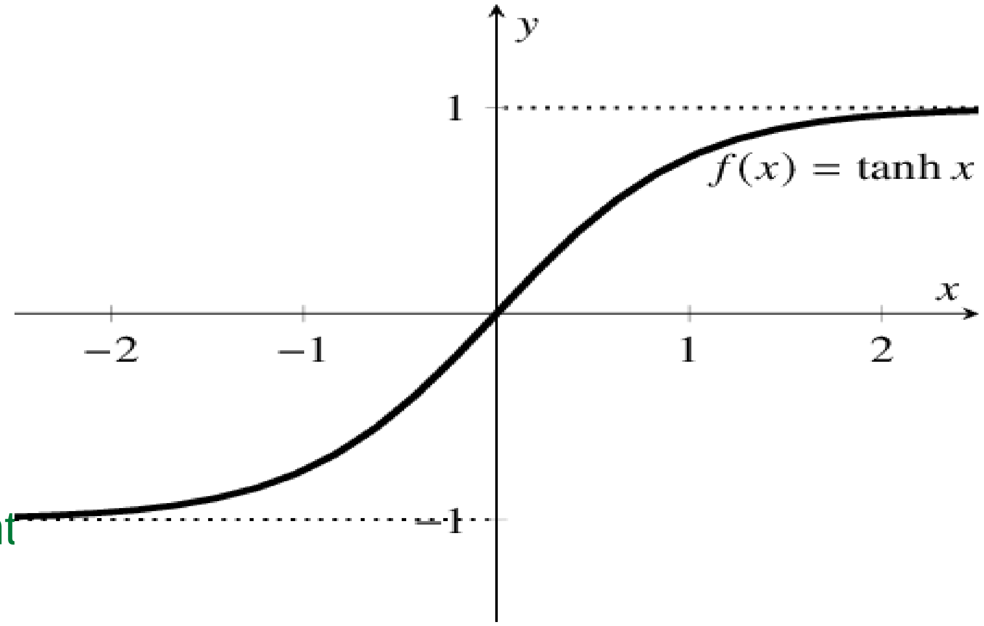

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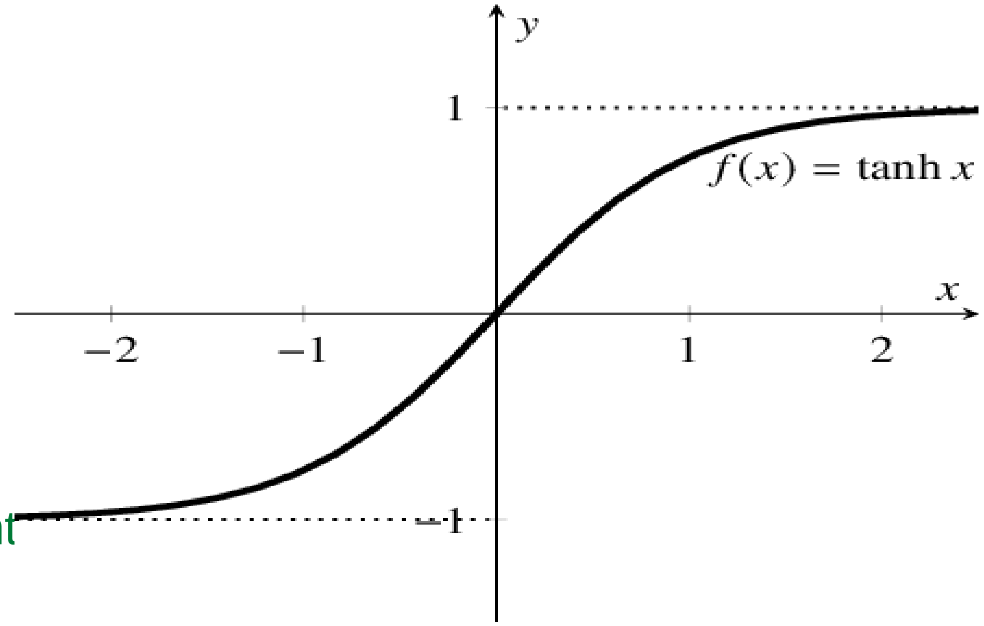
- Variant: Hard tanh.



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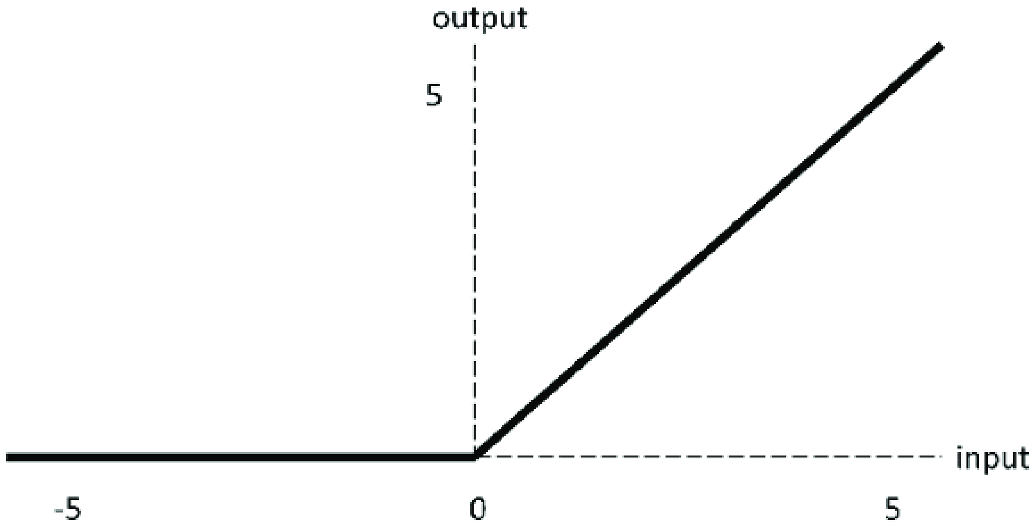
Rectified Linear Unit is the most popular activation function in hidden layers

- Better substitute for $\tanh$ and $sigmoid$ functions for hidden layers.
- May also be used in output layer.
- Probability of having x exactly equal to 0 is very small.



$$f(x) = \max(0, x)$$

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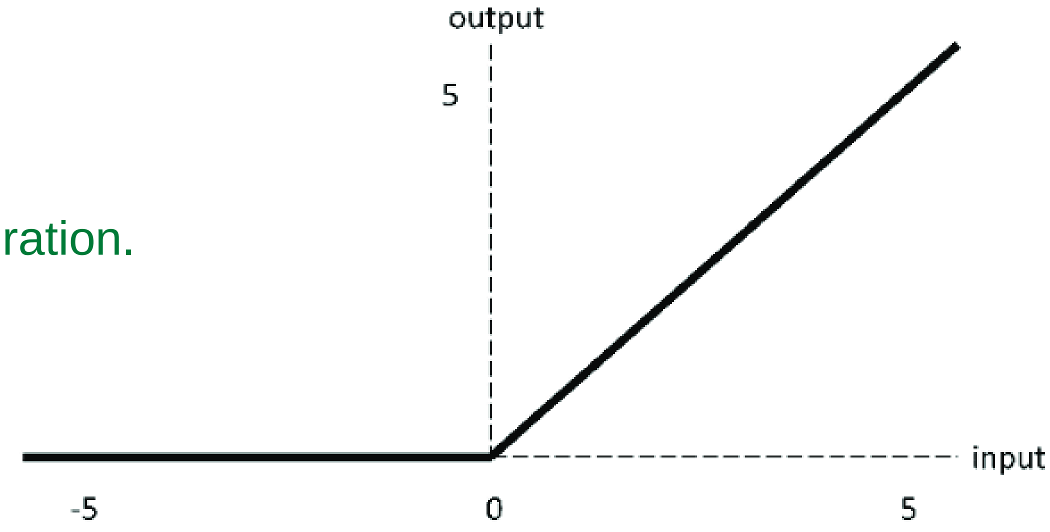

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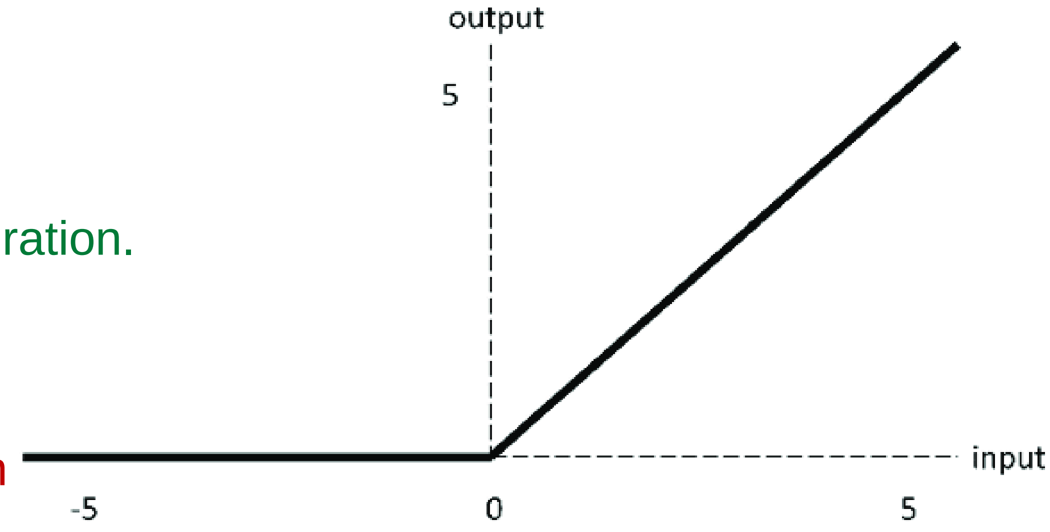

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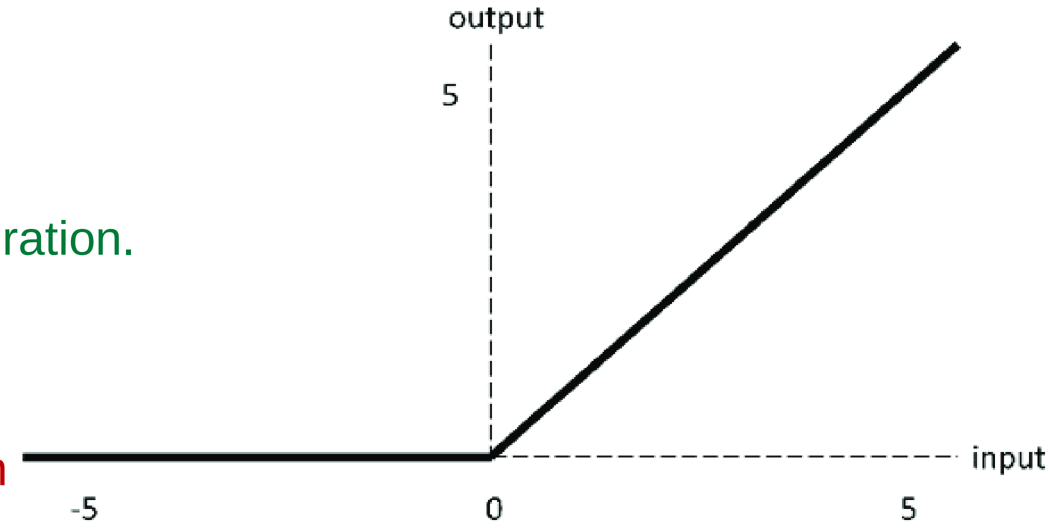
- Variants: Leaky ReLU, Parametric ReLU, Swish



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How to initialise network parameters?

- Initialise all weights and biases with zero?
  - For biases, initialising with zero is fine but not for weights.
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https://www.deeplearning.ai/ai-notes/initialization/index.html

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- Initialise all weights and biases with a constant?
  - Same thing will happen as initialising with all zeros.
- Initialise all weights and biases randomly. Following what distribution?
  - Uniform distribution $[0, 1]$
  - Uniform distribution $[-0.5, 0.5]$
  - Gaussian distribution with mean 0 and small variance. Why?

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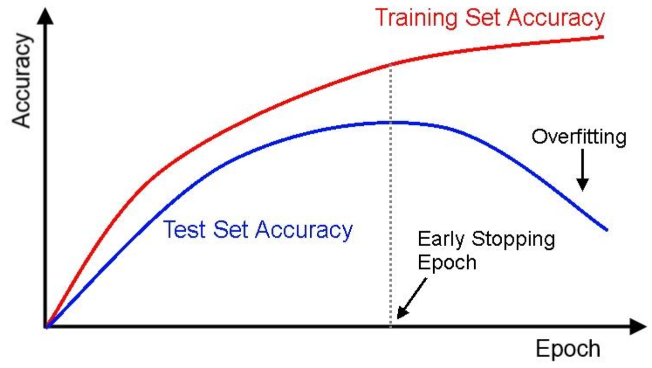
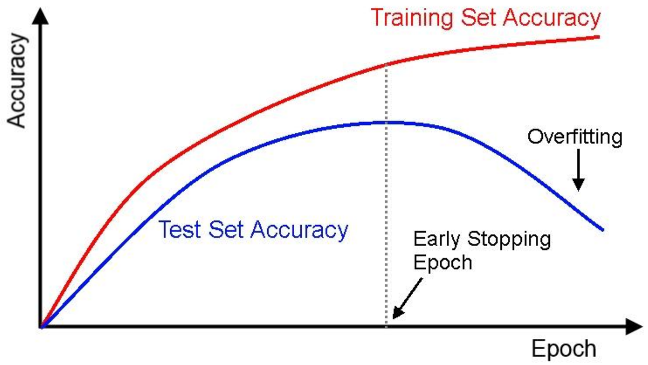
Regularisation prevents overfitting



Regularisation prevents overfitting

- L2 Regularisation is a common and useful method to prevent overfitting.

$$J(w,b) = \frac{1}{m}\sum_{i=0}^{m}\mathcal{L}(y^i,\hat{y}^i) + \frac{\lambda}{2m}\sum_{j=0}^{L}\left\|w^{[l]}\right\|^2$$



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- Dropouts are used only at training time.

$$r^{[l-1]} \sim Bernoulli\ (p)$$
$$\tilde{a}^{[l-1]} = r^{[l-1]} * a^{[l-1]}$$
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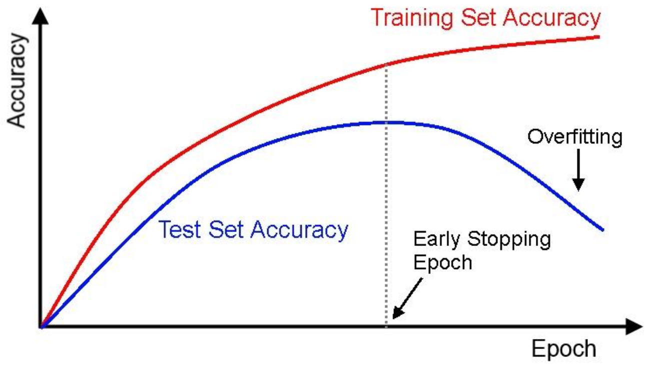

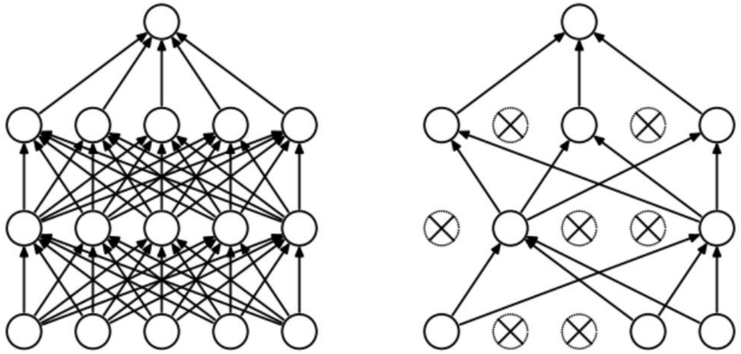

(a) Standard Neural Net

(b) After applying dropout.

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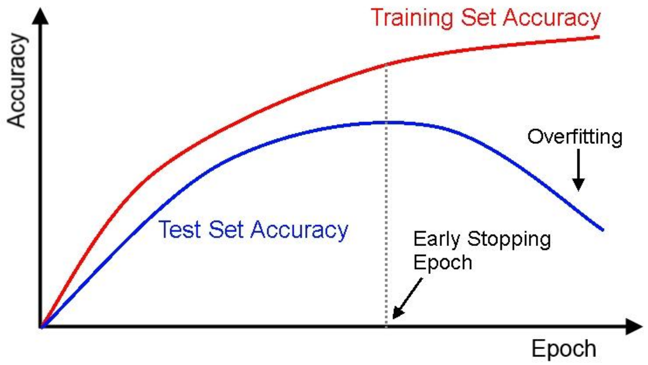

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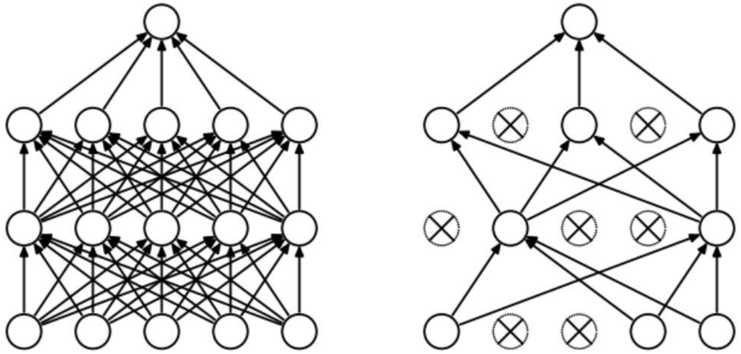

(a) Standard Neural Net (b) After applying dropout.

- Early Stopping is not a regularisation technique per se but helps *evade* overfitting.

Learning rate decay helps adjust speed of convergence

- Manual Decay: Can only work with smaller models.

- Discrete Staircase Decay: Divide learning rate by a constant every fixed number of epochs.

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$$\alpha = \frac{\alpha_o}{1 + decayFactor \ * epoch}$$

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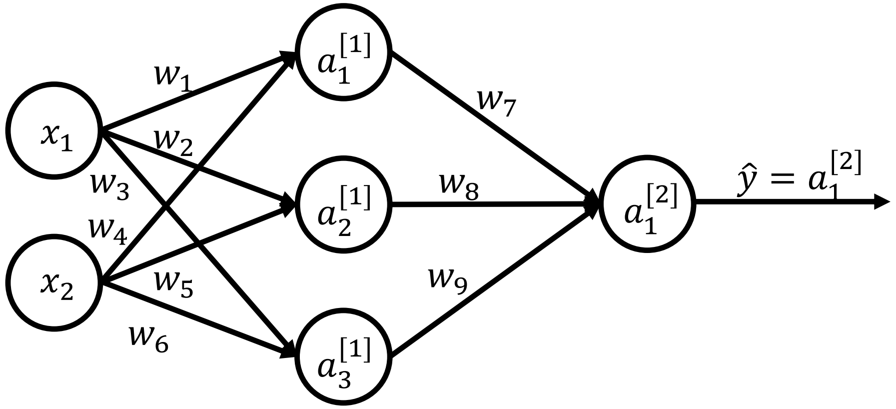
- Conditional Decay

  - Reduce α only if and when necessary.

Batch Normalisation helps with training stability and convergence

- Normalises the hidden activations.



Ioffe, Sergey, and Christian Szegedy. "Batch normalization: Accelerating deep network training by reducing internal covariate shift." International conference on machine learning. PMLR, 2015.

Batch Normalisation helps with training stability and convergence

- Normalises the hidden activations.

- Batch Norm takes two steps.

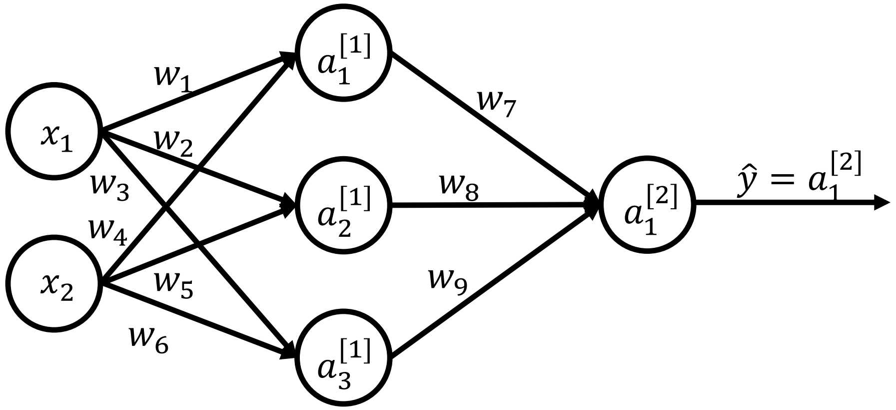
  - Standardise the activations.

$$z'^{(i)}_j = \frac{z^{(i)}_j - \mu}{\sigma}, i \in \{1, \dots, n\}, j \in \{1, \dots, d\}$$

    Here n is minibatch size, and d is the size of the layer.

  - Pre-activation scaling of net inputs.

$$\tilde{z}^{(i)}_j = \gamma_j . z'^{(i)}_j + \beta_j$$



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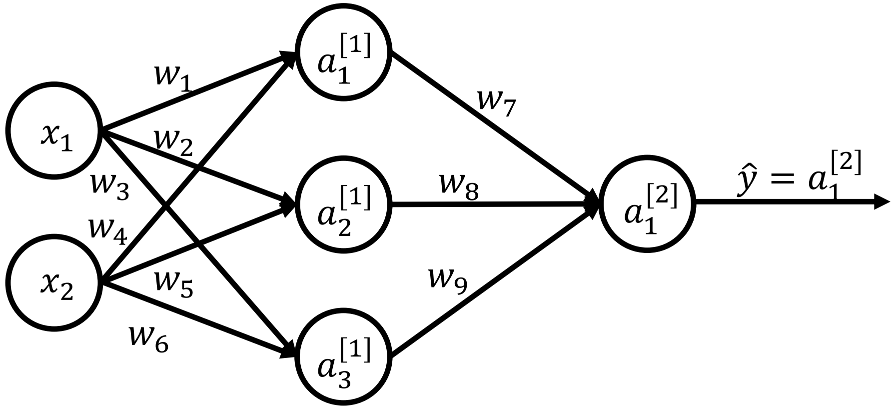
- Batch Norm parameters have the same size as the bias vector.

- Batch Normalisation of layer l helps in faster training of layer $l + 1$.



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Do you have any question?

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