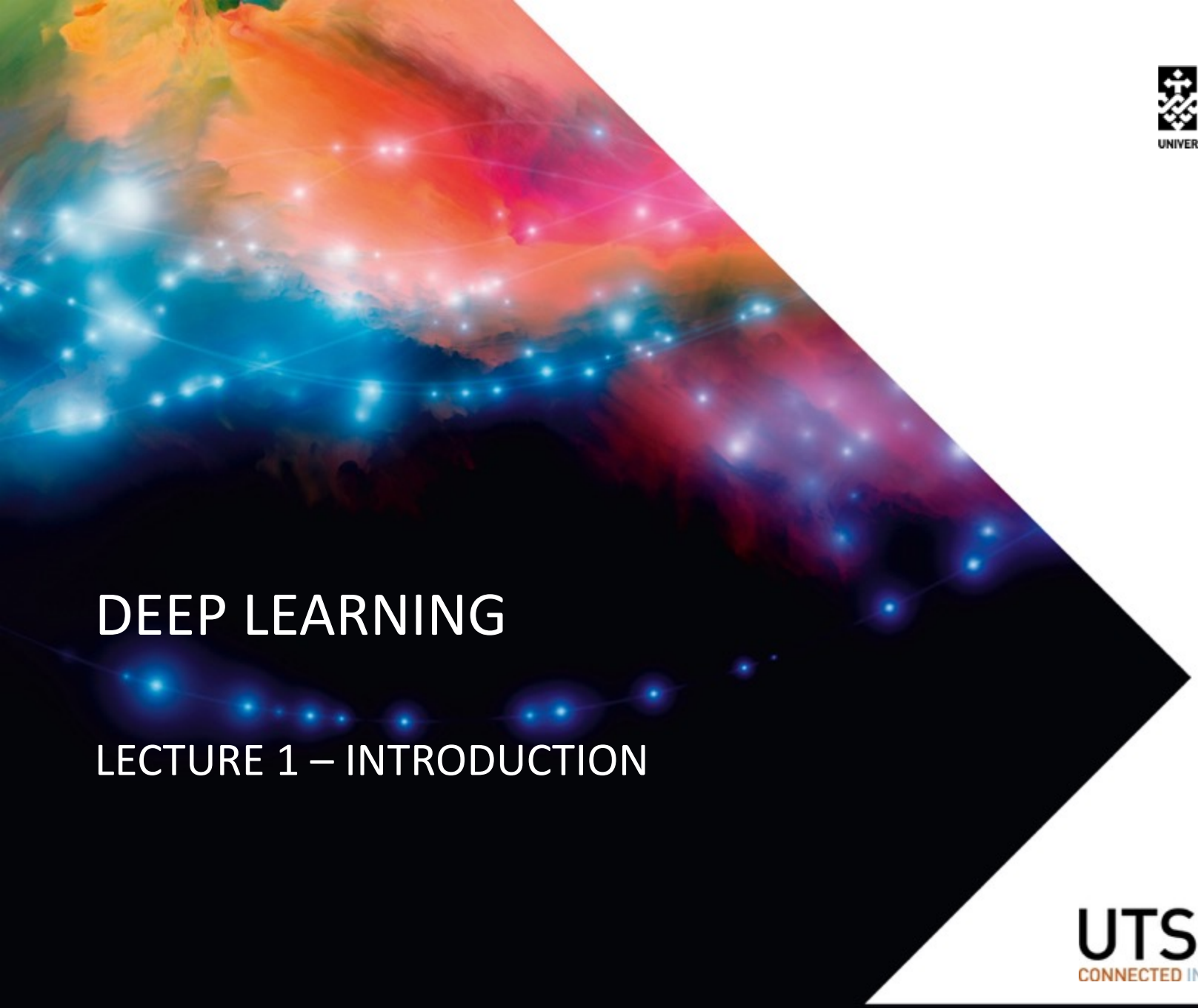


UTS
UNIVERSITY OF TECHNOLOGY SYDNEY

DEEP LEARNING

LECTURE 1 – INTRODUCTION

UTS:CIC
CONNECTED INTELLIGENCE CENTRE

TEACHING TEAM

Instructors:

Kailash Awati

> Office: Rm 37, Level 3, Building 5D (Quay St)

> Email: kailash.awati@uts.edu.au

> Phone: 9514 4708

Alex Scriven

> Email: Alexander.Scriven@uts.edu.au

OVERVIEW OF SUBJECT

This subject gives students a holistic understanding of deep learning, based on readings of research papers, coding exercises and practical assignments.

Three pillars:

> (Some) mathematics

> (skimming of) academic papers

> (coding) coding

What's not included:

> Deep analysis of any particular architecture

> Too much emphasis on deployment

OVERVIEW OF SUBJECT

The SLOs:

- Form an intuitive and mathematical understanding of Vanilla Neural Networks
- Articulate the strengths, weaknesses and use cases of a variety of Deep Learning neural network architectures.
- Implement and optimise a variety of Deep Learning neural network architectures
- Communicate the selection, training & analysis of deep learning models for business use cases in a context-appropriate manner
- Synthesise and interpret relevant academic papers as well as other sources of knowledge relating to deep learning to build a model for current progress and potential future directions, commercial applications and ethical implications
- Understand and utilise the latest work towards visualising and uncovering insights from traditionally ‘black-box’ models.

BLOCK SESSIONS OUTLINE

Block Session	Details
1 – 4th April	• Course introduction • Introduction to neural networks, building a vanilla neural network from scratch
2 – 11th April	• Software and hardware • Training and optimization in depth
3 – 2nd May	• Computer vision: types of tasks, CNNs in depth, classic to advanced architectures.
4 – 9th May	• Sequence models: RNN, LSTM, Transformers & Attention • Guest lecture & Lab: NLP in action
5 – 16th May	• Generative Adversarial Networks • Deep Reinforcement Learning (time permitting)
6 – 30th May	• Model deployment. Interactive lecture-lab building and deploying a simple webapp for your model.

ASSIGNMENTS

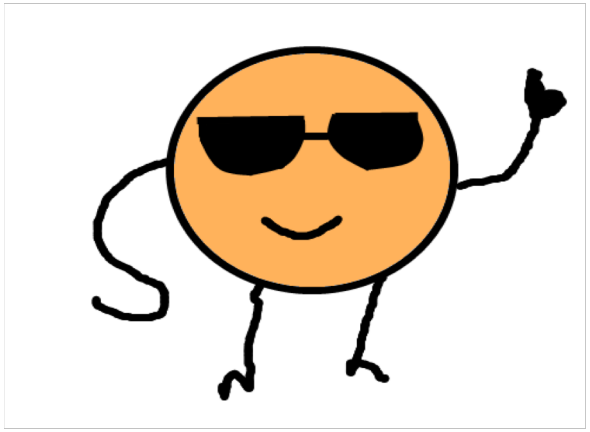
AT	Details	Release	Due	Days
1A	• Build and optimize a vanilla neural network from scratch (no frameworks)	02/04/2019	21/04/2019	17
1B	• Build and optimize an image classifier for a business use case	02/05/2019	26/05/2019	24
2A	• Literature review of key historic and modern academic papers on a chosen deep learning architecture.	16/05/2019	02/06/2019	17
2B	• Propose application of research undertaken in 2A to an industry problem	16/05/2019	02/06/2019	17
3	• Build and optimize a sequence-based model for a business use case	30/05/2019	20/06/2019	21

AT3 is groupwork. You may propose a more interesting project (*conditions apply!)

OVERVIEW OF SUBJECT

Important notes:

- Nobody (including me) knows everything about every architecture. Just like ‘classic’ ML, we have areas we know better than others.
- Diving deep into a particular branch you may very well end up more well versed than me.
- *Facilitator* more than teacher
- This course will focus on breadth rather than depth



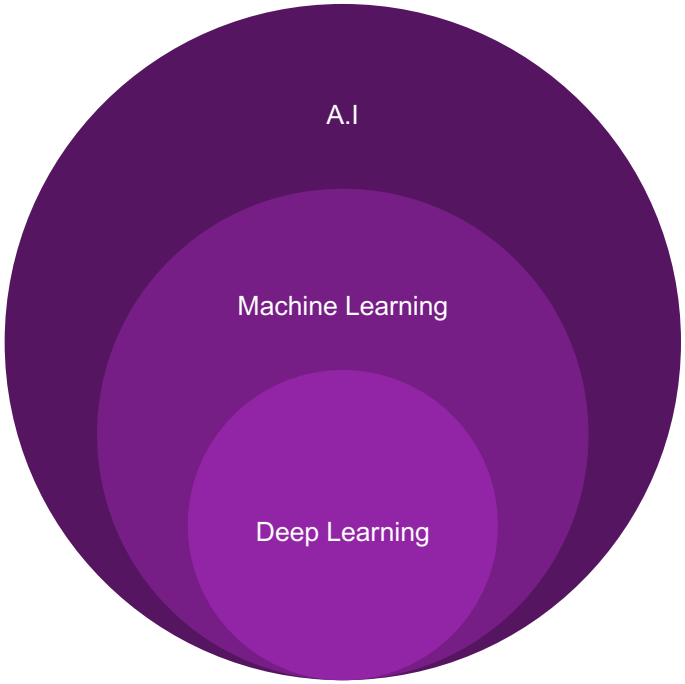
A note on ‘A.I’

This graph appears often, though different people will have different views.

Be aware that **most often** these days when people say ‘A.I’ they either mean:

A. Software, that is distinctly none of the above (like rule-based systems)

B. A neural net architecture (CNN, RNN, DRL, GAN)



‘A.I’ is ‘locally’ smart

All you’re seeing now — all these feats of AI like self-driving cars, interpreting medical images, beating the world champion at Go and so on — these are very narrow intelligences, and ***they’re really trained for a particular purpose****. They’re situations where we can collect a lot of data…*

-Yann Lecun (Creator of CNN, Facebook Chief AI)

Key Take away: ‘Generalised A.I’ is a very different concept. Most A.I models break if taken slightly outside of what they are trained for

An A.I Example

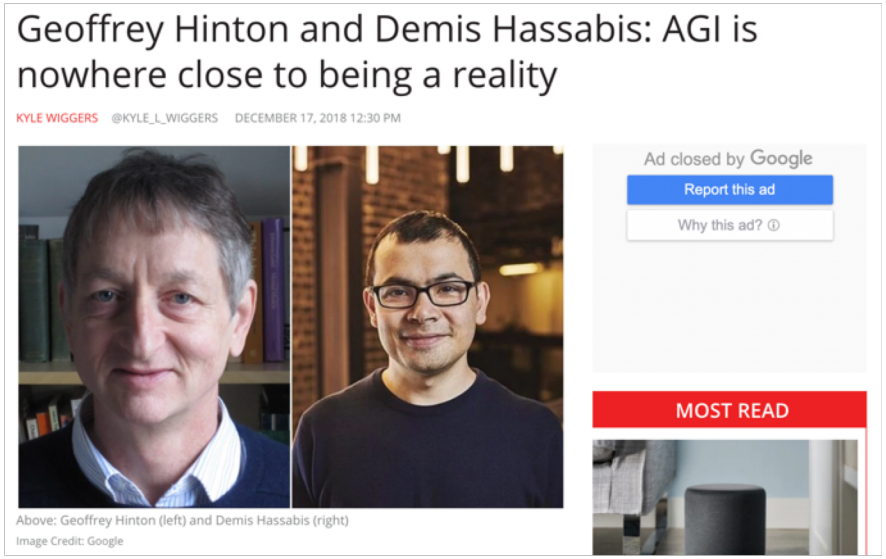
Google Duplex (Voice assistant booking stunt)

'Enter Duplex
Google Duplex's conversations sound natural thanks to advances in understanding, interacting, timing, and speaking.

At the core of Duplex is a recurrent neural network (RNN) designed to cope with these challenges, built using TensorFlow Extended (TFX). To obtain its high precision, ***we trained Duplex's RNN on a corpus of anonymized phone conversation data****.*

https://ai.googleblog.com/2018/05/duplex-ai-system-for-natural-conversation.html

In other words…..



Hassabis cautions that they by no means suggest AGI is around the corner — far from it. Unlike the AI systems of today, he says, people draw on intrinsic knowledge about the world to perform prediction and planning….

https://venturebeat.com/2018/12/17/geoffrey-hinton-and-demis-hassabis-agi-is-nowhere-close-to-being-a-reality/

We don't have systems that can transfer in an efficient way knowledge they have from one domain to the next. I think you need things like concepts or extractions to do that

To be perfectly blunt…..

"All the impressive achievements of deep learning amount to just curve fitting"

– Judea Pearl

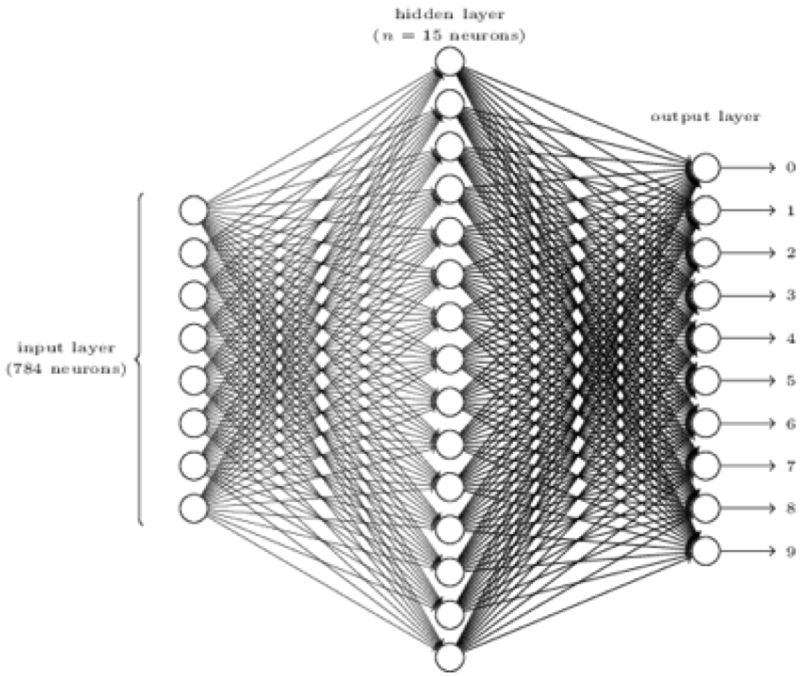
Visually speaking…

(An introduction to)

Neural Networks

Neural Networks

1. **WHAT** are Neural Networks
2. **WHY** are Neural Networks
3. **HOW** do we ‘Neural Networks’

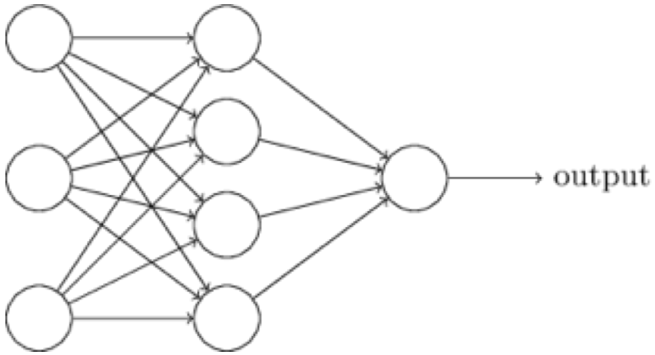


[WHAT] Neural Networks

neural network

noun
plural noun: **neural networks**

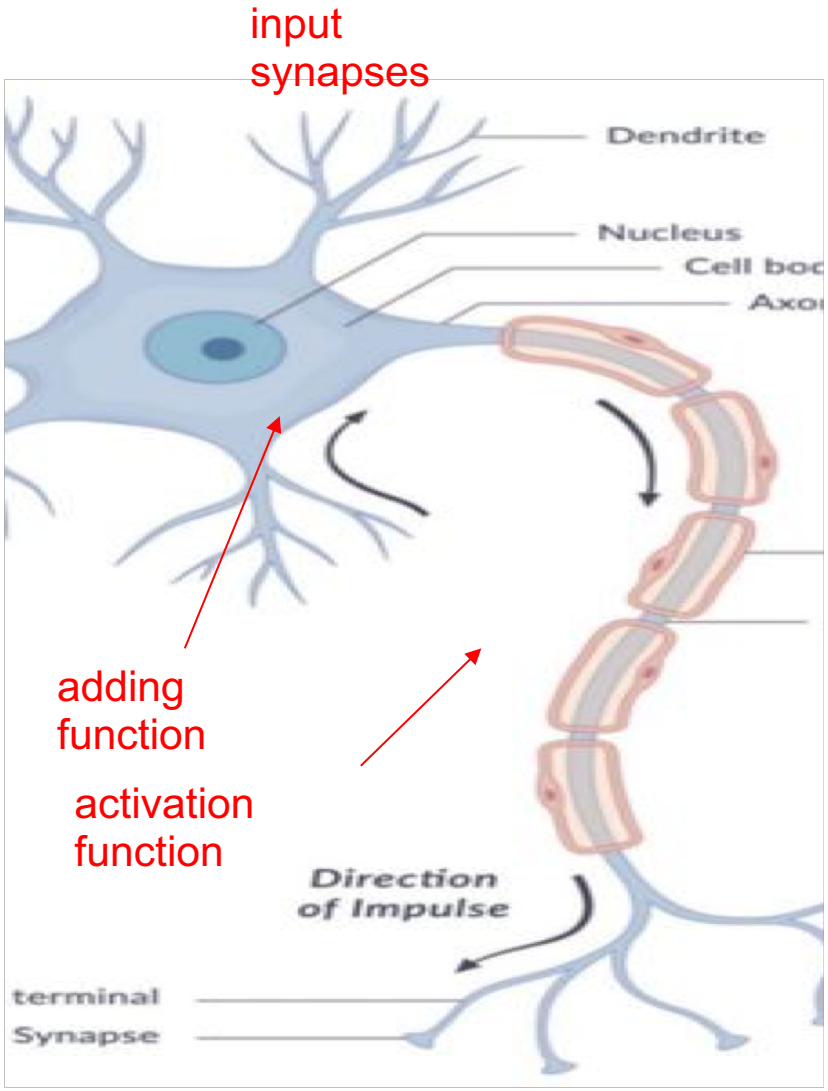
a computer system modelled on the human brain and nervous system.



MODEL OF A NEURON

The neuron is an information processing unit fundamental to a neural network. Neurons have three characteristics:

1. A set of input *synapses (connecting links)*, each with a weight
2. An *adding function* to sum the input signals
3. An *activation function* to limit the output range of the neuron



Limitations of ‘Brain’ Model

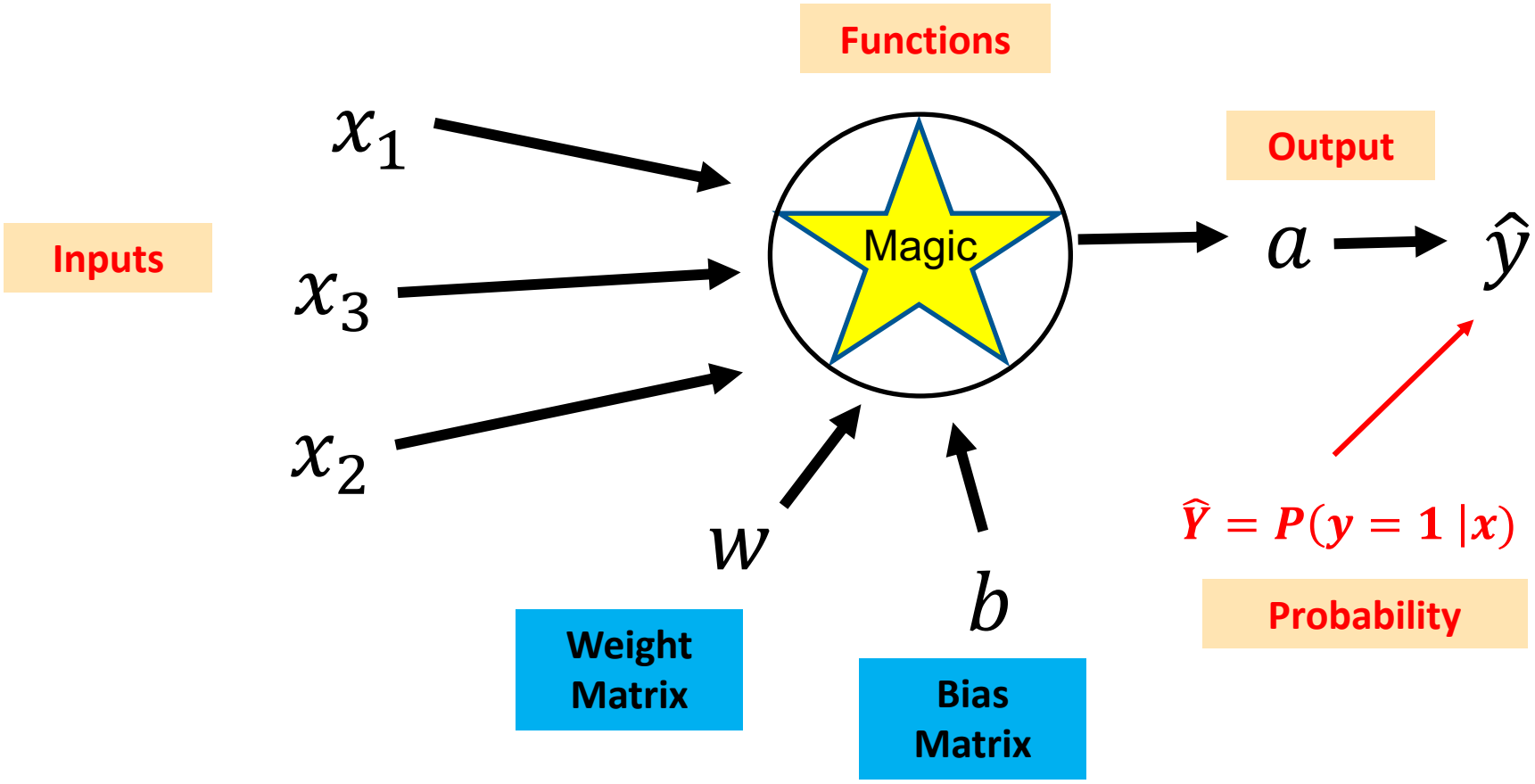
The ‘Brain’ model is more of a historical name that has stuck around (probably because it sounds cooler than ‘multi-layer perceptron’) but has little *real* relation to our understanding of the brain today*.

In real life, ‘Neurons’:

1. Have many **different types** that are quite distinct from each other
2. The computations at the dendrites can be **very complex** functions
3. The simple weight-matrix approach is a vast simplification of the non-linear, **dynamic system** of interactions of our synapses.

*In computer-vision, the techniques hold closer semblance to real human cognition.

Let's start with a neuron

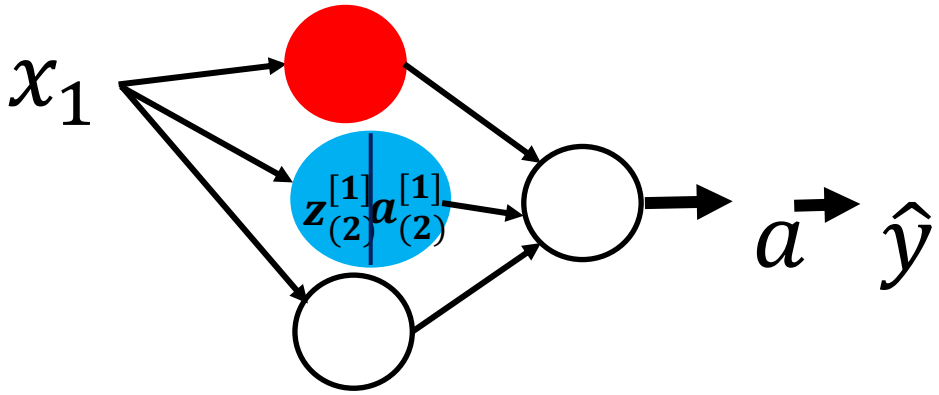


Some notation

- Let us use superscript with square brackets to denote which layer we are referring to

- Let us us subscript with round brackets to denote which neuron (top to bottom) in a layer we are referring to

- So $z_{(2)}^{[1]}$ is the 'adding' function of the second neuron in the 1st layer.



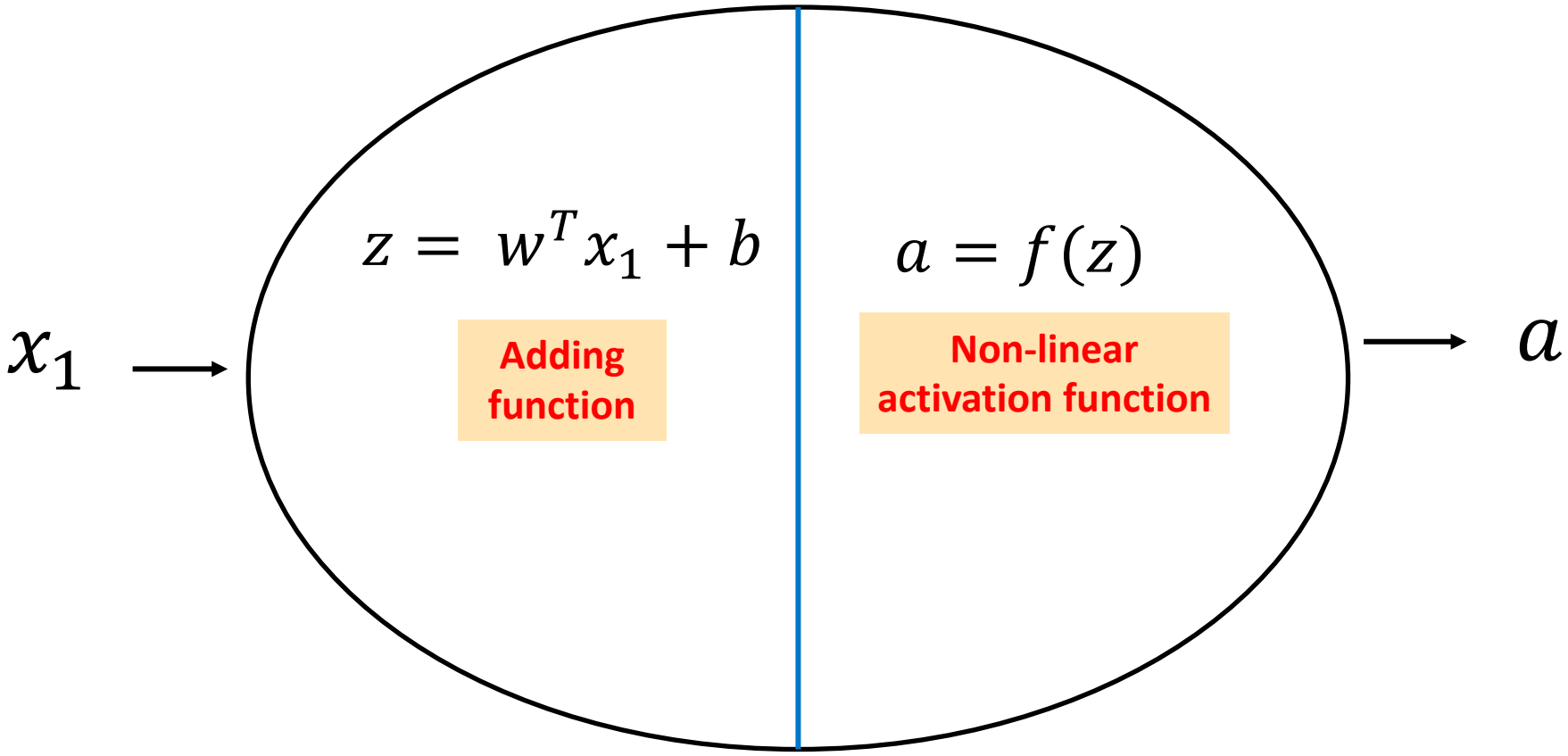
‘W’ AND ‘B’

- **‘w’** is our matrix of weights that we will apply to each of our input data points.

(This becomes our hyperparameter to ‘tune’)

- **‘b’** is our bias term.
  - Similar to intercept in linear regression and serve much the same function (allows us to shift the function above the origin)
  - Has a value of 1 and is not connected to other nodes.
  - Without it, we are assuming our activation is through the origin
    - $Y = mx + \mathbf{b}$

Inside a Neuron



Why transpose W?

Why transpose W?

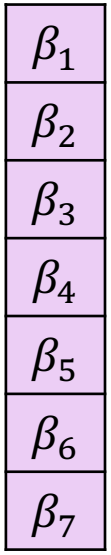
- **Recall: 'w'** is our matrix of weights that we will apply to each of our input data points.

w will therefore have a weight per variable

- We have $w \in \mathbb{R}^{n_x}$ where n_x is the number of features of x

Consider 1 training example of 10 features

x_1



w_1

Can I multiply these together currently?

No!

We must have form

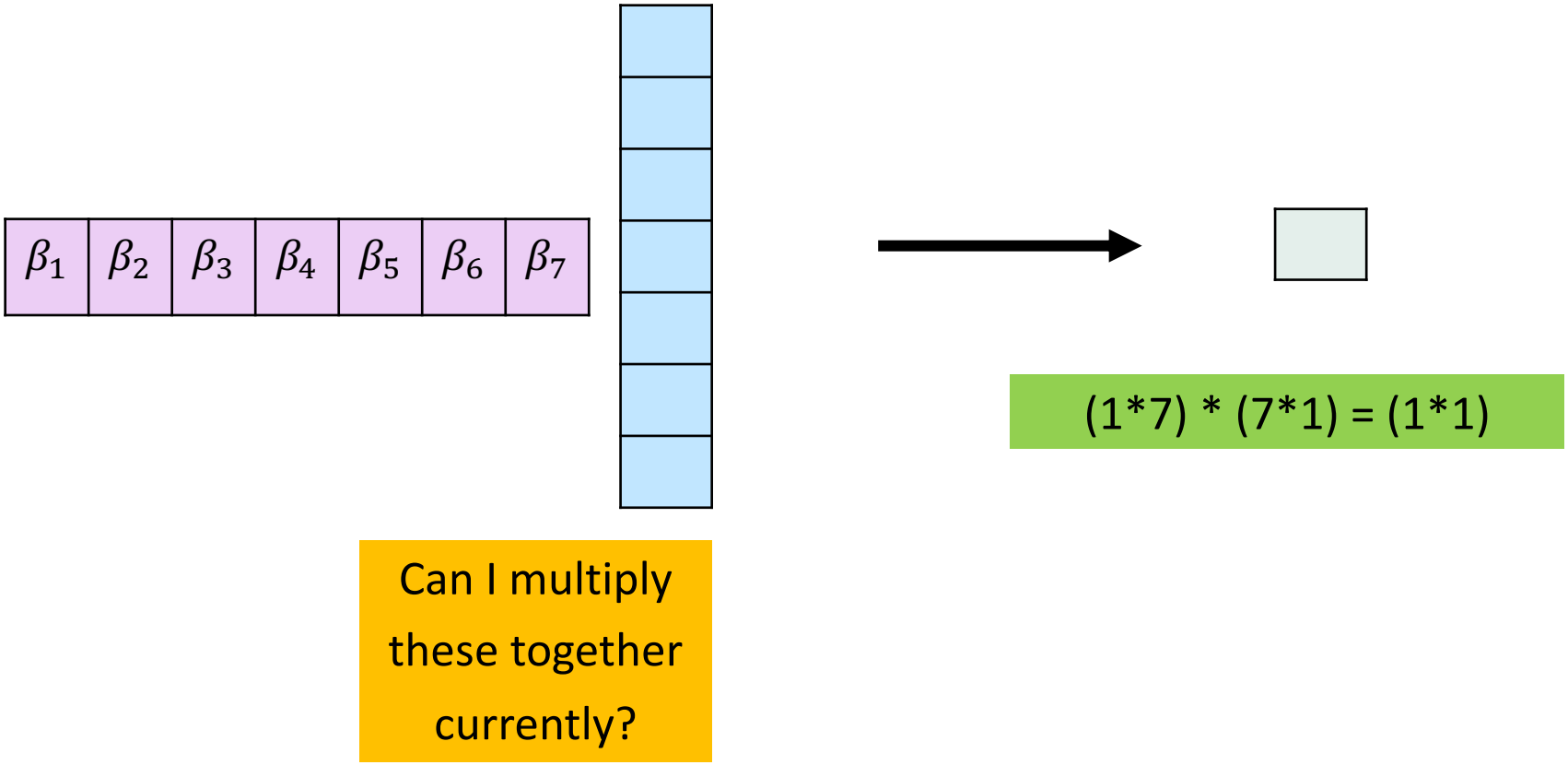
$\mathbb{R}^{n_x} * \boldsymbol{m} * \mathbb{R}^{\boldsymbol{m}} * a$

Or (m*n) * (n*p) = m*p

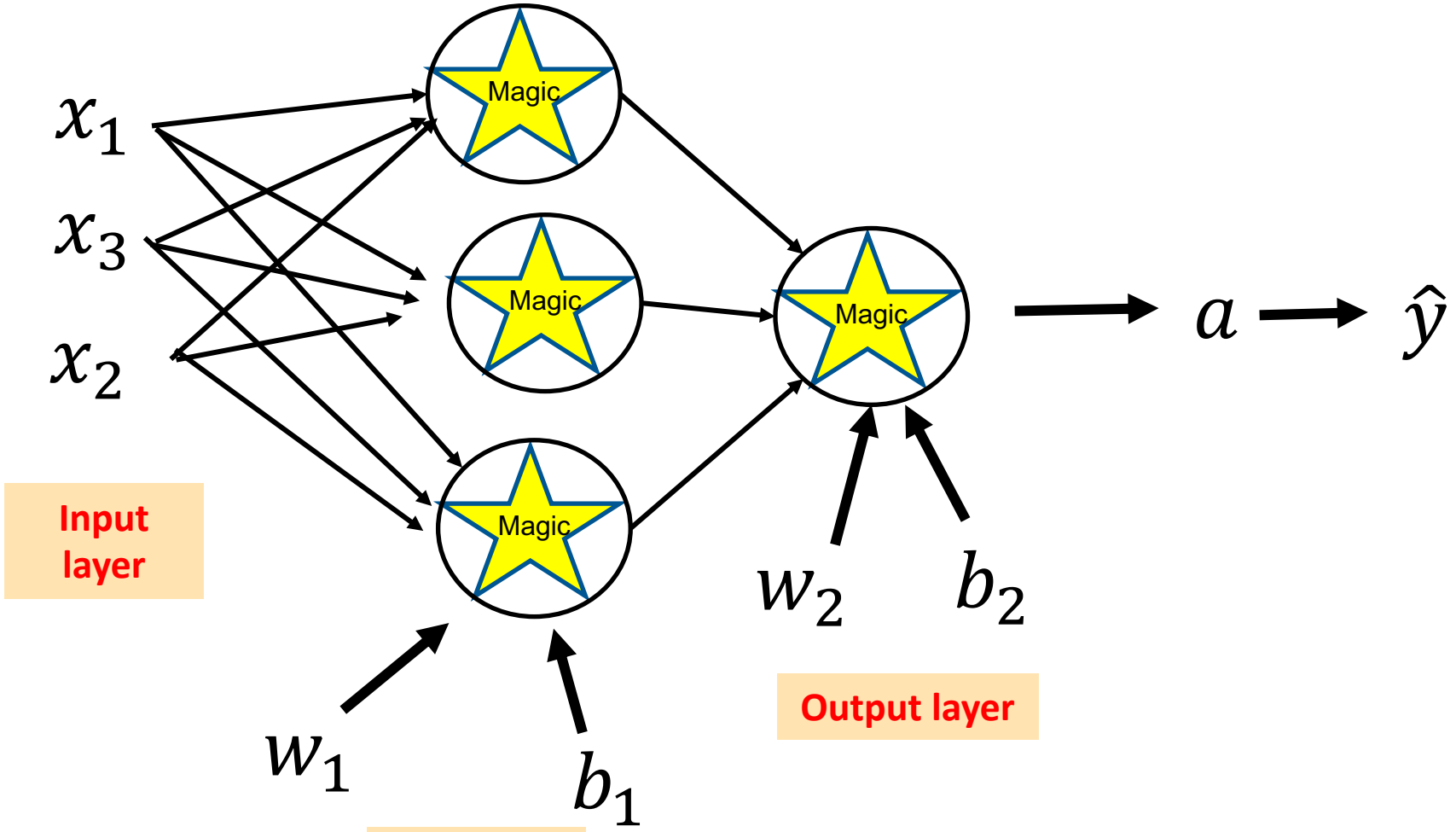
Where m = rows, n= columns

Why transpose W?

- To allow us to undertake matrix calculus we must transpose something



Neuron to ‘network’



RELATION TO LINEAR MODELS

- A single neuron is effectively a generalised linear model, i.e. a linear regression model inside a function *f*
- If the activation function (*f)* is the logistic function, then our single neuron model is the same as logistic regression
- Neural networks go much further than linear models, due to the *network* of neurons

ACTIVATION FUNCTIONS

- What is the activation for?
  - These are to scale our output and add non-linear properties
- Why non-linear?
  - Consider if we we only undertook ‘adding’ functions at each node.
  - Then we are only making linear transformations. Linear-by-linear-by-linear.
  - Hence this is no more powerful than one linear node!

Let's prove that!

- Consider a NN with no activation function, we just do the multiplication step:
  - $\boldsymbol{a^l} = z^l = w_l^T x_l + b_l$
  - $a^{l+1} = z^{l+1} = w_{l+1}^T \boldsymbol{a^l} + b_l$

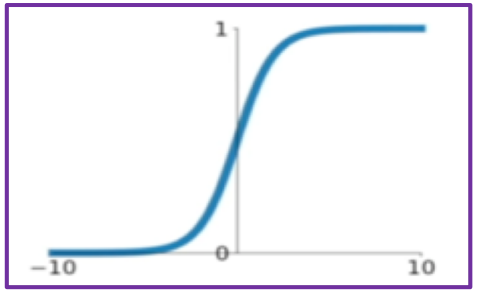
Substitute Line 1 into Line 2

- $a^{l+1} = z^{l+1} = w_{l+1}^T * (\boldsymbol{w_l^T x_l + b_l}) + b_l$

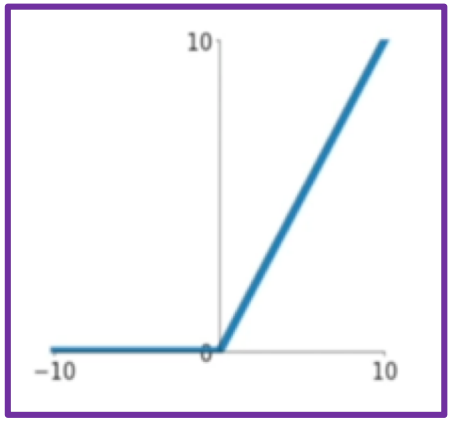
We are just making linear transformations, no 'curve' to our function!

Some common activation functions

- Sigmoid
  - $\sigma(x) = \frac{1}{1+e^{-x}}$
  - Historically popular, not anymore (except for last layer)



- ReLU (Rectified linear unit) (Krizchevsky et al. 2012)
  - $\max(0, x)$
  - Safe, very popular these days. Fixes a number of problems with sigmoid to do with gradient flow.

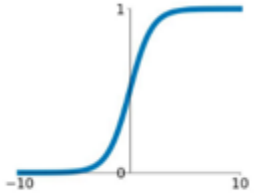


Other Activation Functions

Activation Functions

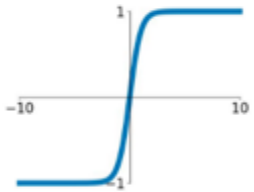
Sigmoid

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



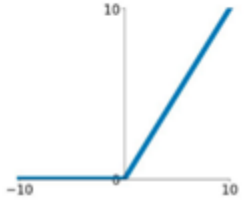
tanh

$$\tanh(x)$$



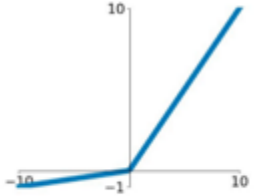
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

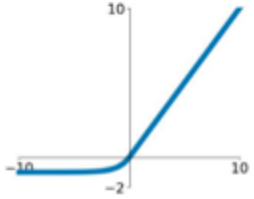


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



From instances to vectors

- To ease the maths in our networks, we like to operate in vectors and matrixes.
- This means that rather than a ‘for loop’ we can simply undertake efficient matrix calculations.
- So let us take all our weights and stack them:
  - $W^{[1]T} = \begin{bmatrix} - & w_1{}^{[1]T} & - \\ - & w_2{}^{[1]T} & - \\ - & w_3{}^{[1]T} & - \end{bmatrix}$
- And the same for our Z, A and X (now using capital letters to denote a matrix).

$$\boldsymbol{X} = \begin{bmatrix} | & | & | \\ \boldsymbol{x_1} & \boldsymbol{x_2} & \boldsymbol{x_3} \\ | & | & | \end{bmatrix}$$

$X \in \mathbb{R}^{n_x * m}$
(Features high, samples long)

From instances to vectors

- Given X is of the form:

$$\boldsymbol{X} = \begin{bmatrix} | & | & | \\ \boldsymbol{x_1} & \boldsymbol{x_2} & \boldsymbol{x_3} \\ | & | & | \end{bmatrix}$$

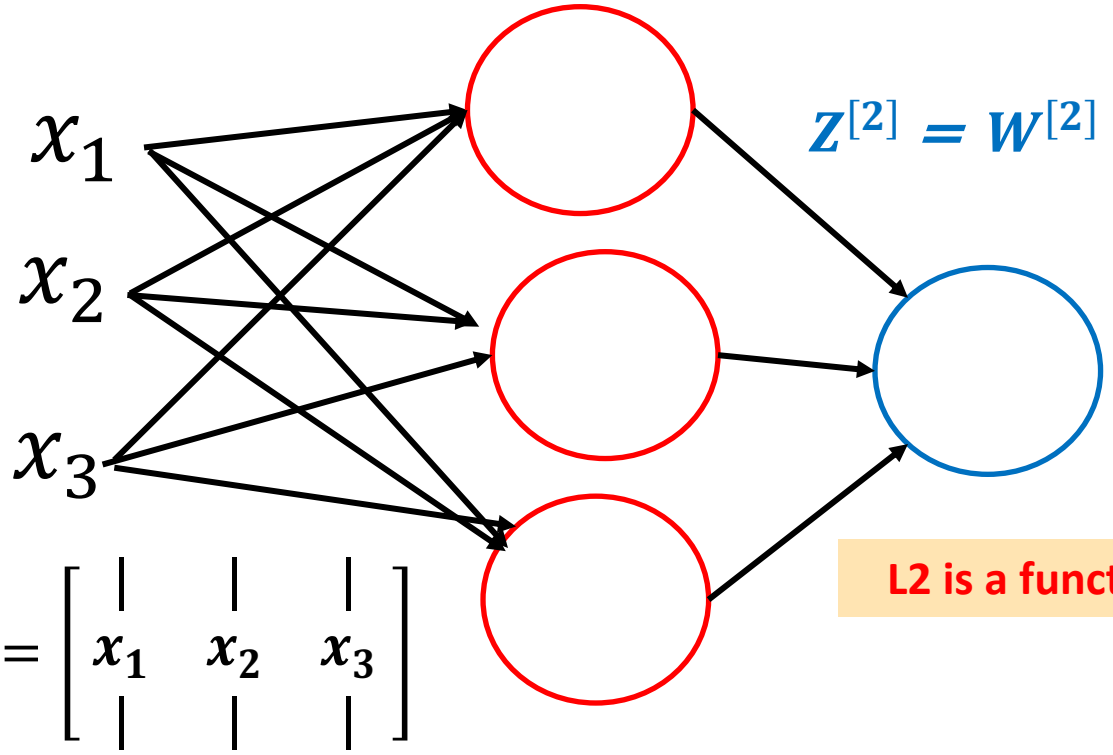
$X \in \mathbb{R}^{n_x * m}$
(Features high, samples long)

- What is Y's dimension?

$$\boldsymbol{Y} = [\, \boldsymbol{y_1} \quad \boldsymbol{y_2} \quad \boldsymbol{y_3} \,]$$

$Y \in \mathbb{R}^{1 * m}$
(Features high, samples long)

The matrix algebra through our network



$$Z^{[2]} = W^{[2]} \cdot A^{[1]} + b^{[2]} \mid A^{[2]} = \sigma(Z^{[2]})$$

$$A^{[2]} \rightarrow \hat{y}$$

L2 is a function of L1

$$X = \begin{bmatrix} | & | & | \\ x_1 & x_2 & x_3 \\ | & | & | \end{bmatrix}$$

Note what are the later layers are modelling?

$$Z^{[1]} = W^{[1]} \cdot X + b^{[1]} \rightarrow A^{[1]} = \sigma(Z^{[1]})$$

L1 is a function of L0

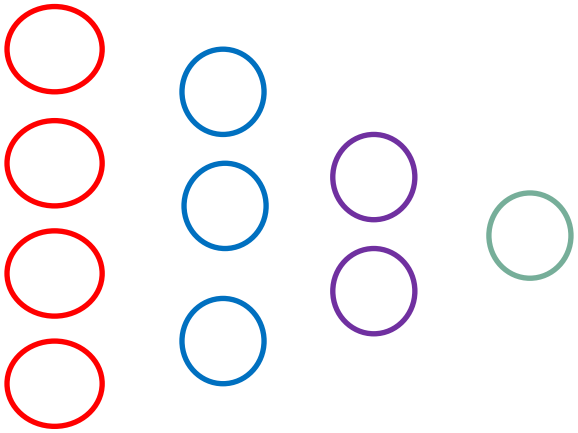
Generalizing the algebra

- The ‘Z’ of any given layer, L, can be found with the following formula:
  - $Z^{[L]} = W^{[L]}.A^{[L-1]} + b^{[L]}$
- And the ‘A’ (activation matrix) of any given layer, L, is found by:
  - $A^{[L]} = g^{[L]}(Z^{[L]})$
    - Where g is the activation function (sigmoid, ReLU, Tanh etc)

The size of our matrices

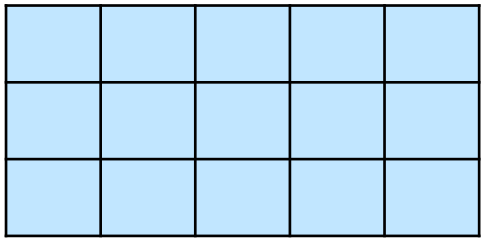
- Given the relationships between layers, our different matrices will have defined, relative sizes.

$$X = \begin{bmatrix} | & | & | & | & | \\ x_1 & x_2 & x_3 & x_4 & x_5 \\ | & | & | & | & | \end{bmatrix}$$

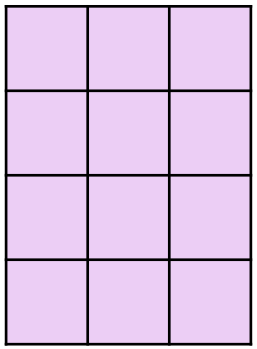


- Example above where x_n = (1,3) : What is the dimensions of each step?
  - $W^{[l]} = (n^{[l]}, n^{[l-1]}) = dW^{[l]}$
  - $Z^{[l]} = A^{[l]} = (n^{[l]}, m) = dZ^{[l]} = dA^{[l]}$
  - $b^{[l]} = (n^{[l]}, 1) = db^{[l]}$

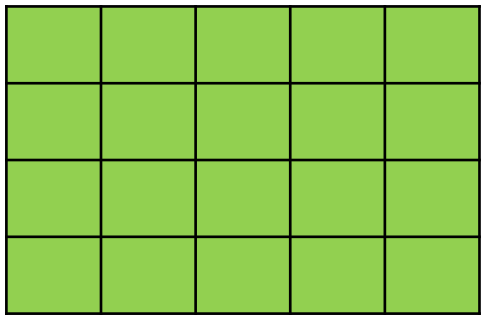
The size of our matrices



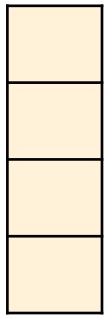
$A^{[0]}$ = (3,5)



$W^{[1]}$ = (4,3)



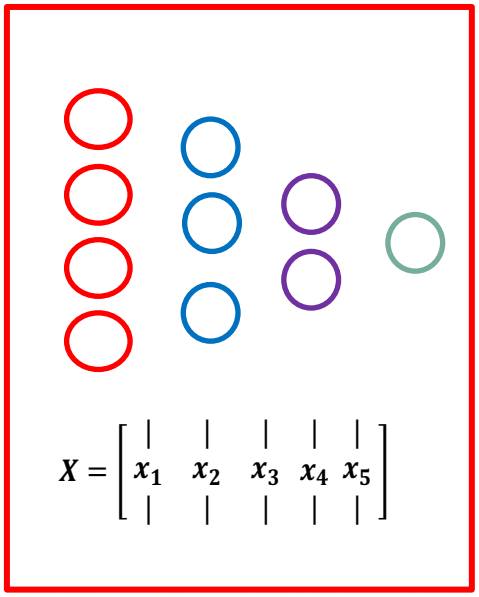
$Z^{[1]}$ = (4,5)



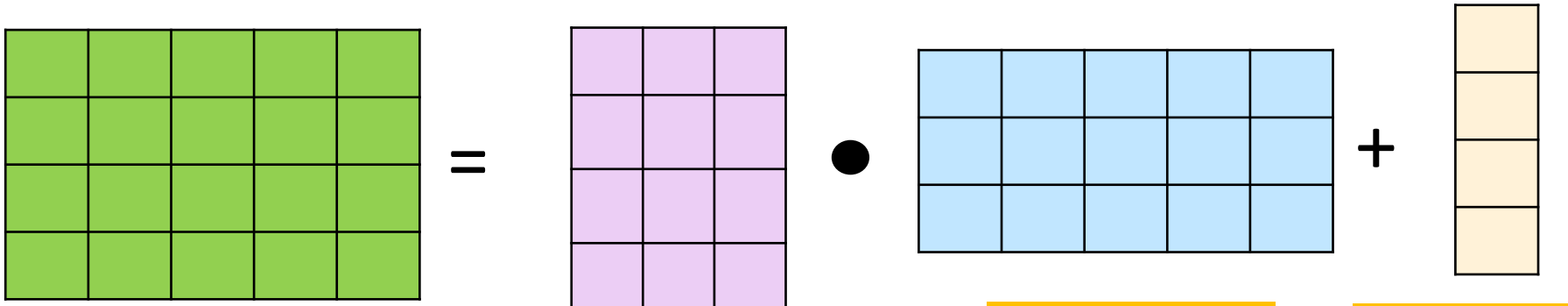
$b^{[1]}$ = (4,1)

- Let's calculate the sizes:
  - $W^{[l]} = (n^{[l]}, n^{[l-1]}) = \boldsymbol{dW^{[l]}}$

    $Z^{[l]} = A^{[l]} = (n^{[l]}, m) = \boldsymbol{dZ^{[l]} = dA^{[l]}}$
  - $b^{[l]} = (n^{[l]}, 1) = \boldsymbol{db^{[l]}}$



Our matrices (formulas)



$Z^{[1]}$ = (4,5)

$W^{[1]}$ = (4,3)

$A^{[0]}$ = (3,5)

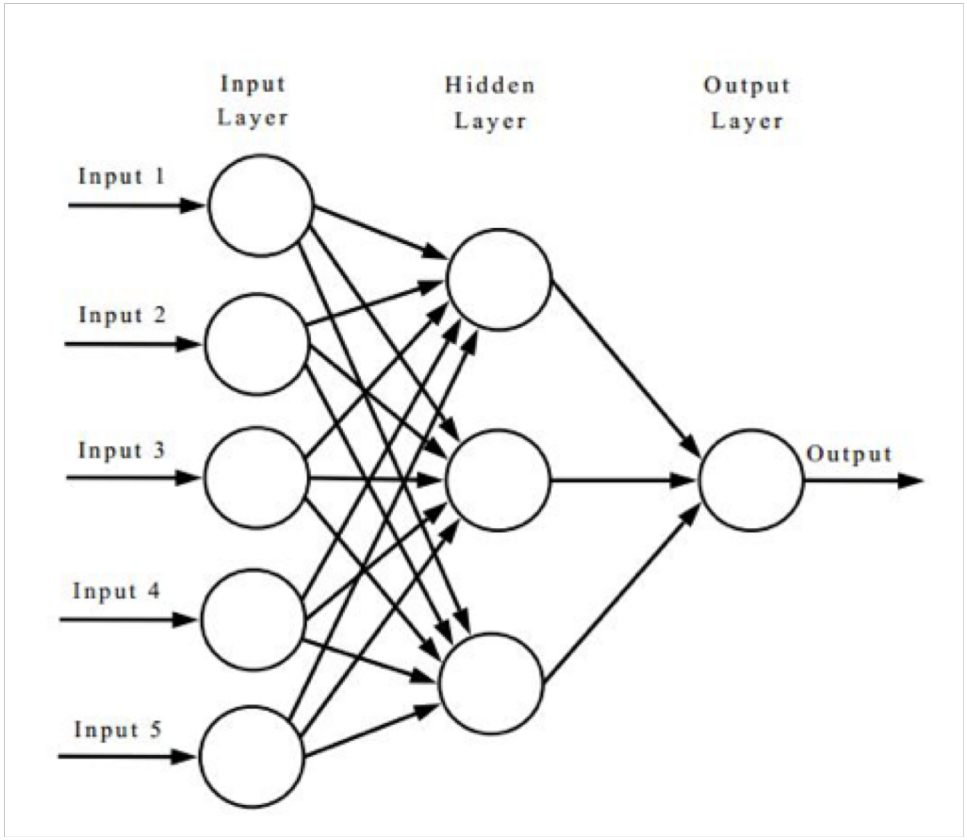
$b^{[1]}$ = (4,1)

$$Z^{[L]} = W^{[L]}.A^{[L-1]} + b^{[L]}$$

FEEDFORWARD NEURAL NETWORKS

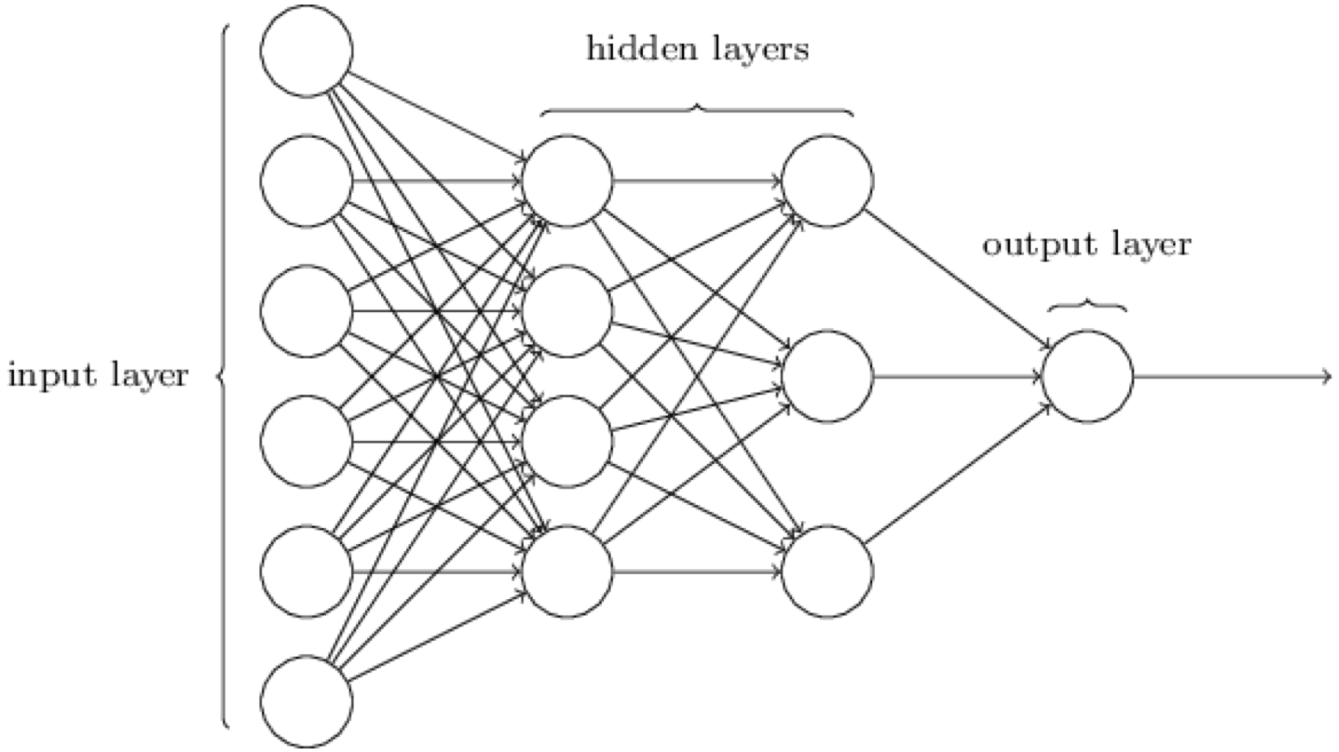
- What we have just seen is called a ‘feedforward neural network’
- It is *feedforward* because information passes through in one direction only, from inputs, through the hidden layer and to the output
- To simplify the matrix algebra we had before:

$$f(x) = f^{(2)}(f^{(1)}(x))$$



FEEDFORWARD NEURAL NETWORKS

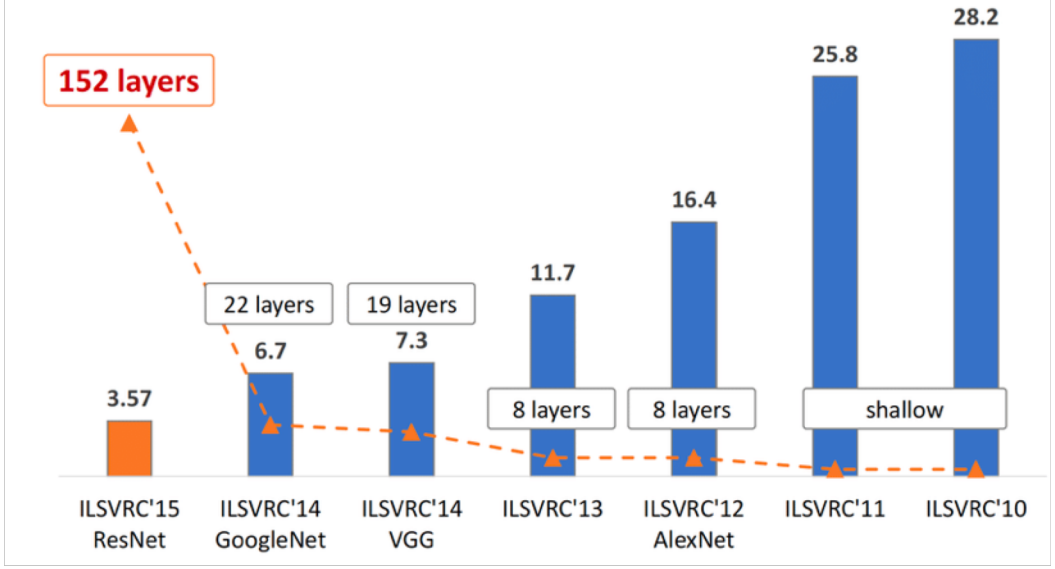
- It is common to have many hidden layers (a deeper neural network)



$$f(x) = f^{(3)}\left(f^{(2)}\left(f^{(1)}(x)\right)\right)$$

From NN to ‘DEEP LEARNING’

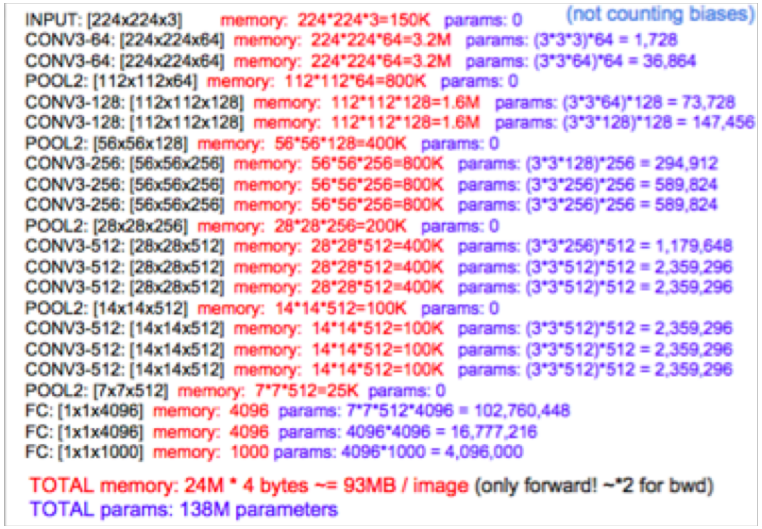
- Primarily uses deep neural network architectures
- More layers (deeper) allows for more flexible models
- Requires much more computing power and larger data sets
- Can learn non-linear transformations of data as features, and hierarchies of features



How big do these networks get?

https://vimeo.com/154085950

Alexnet (2012) had around 138M parameters,

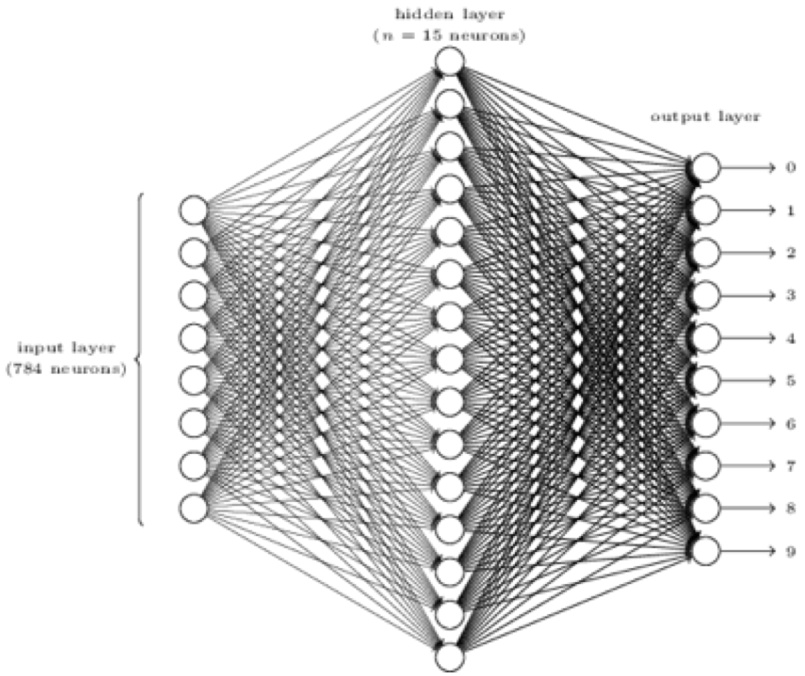


Confused? – Key Takeaways

- Lots of little ‘Neurons’ made up of:
  - A linear function (weight multiplication + bias)
  - A non-linear activation function
- We stack lots of these to be able to be able to map complex data relationships and ‘weird’ data types that conventional models cannot.
  - $f_3 = f_2(f_1(x))$
- To really appreciate how it works and the *beauty* of the different models, make sure you understand the linear algebra occurring

Neural Networks

1. ~~**WHAT** are Neural Networks~~
2. **WHY** are Neural Networks
3. **HOW** do we ‘Neural Networks’

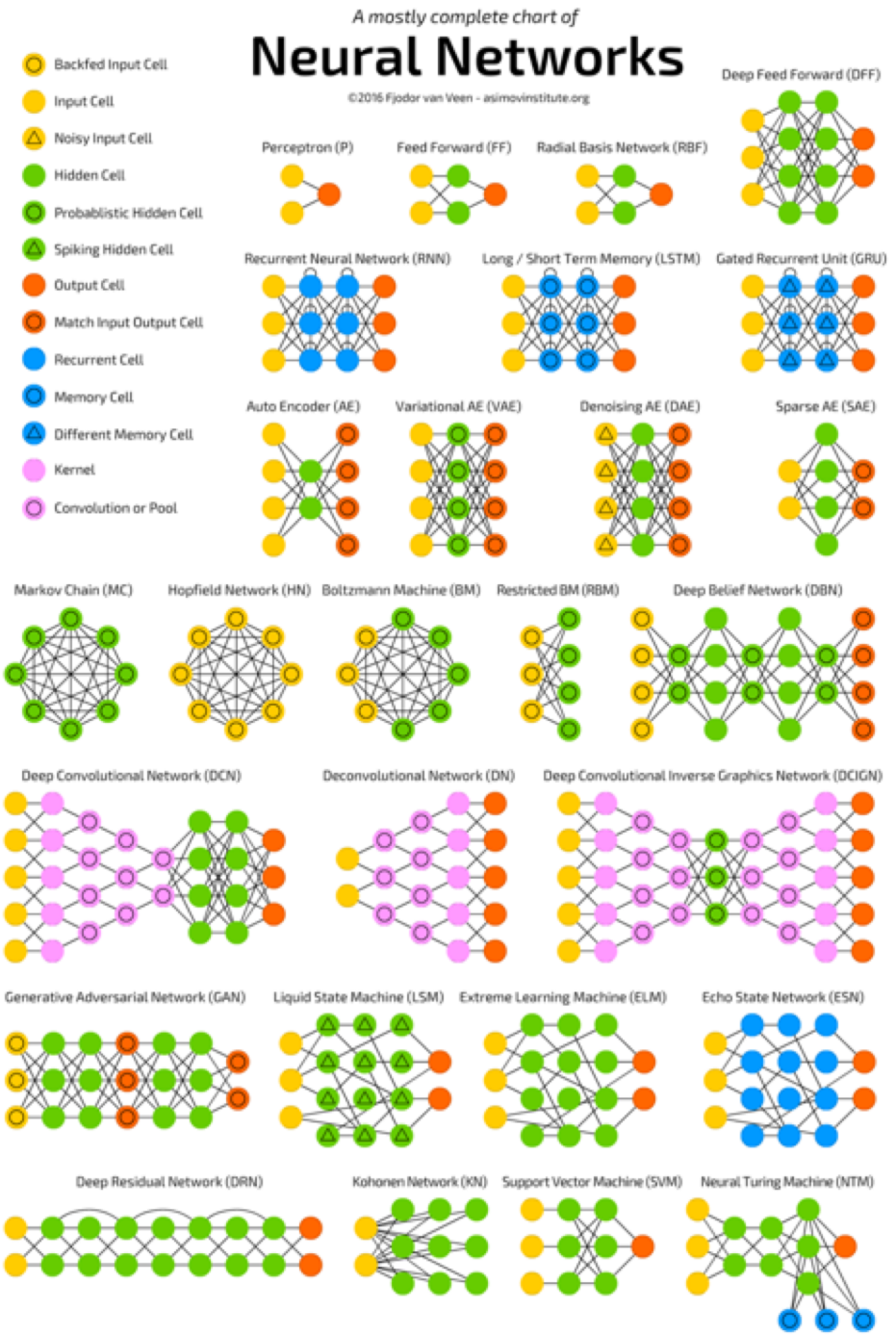


WHY IT WORKS

- With a sufficiently large (or deep) hidden layer(s), it is possible to represent *any continuous* function of the inputs with arbitrary accuracy
- Think back to the bias-variance trade-off:
  - By using a network of neurons (think *nested GLMs*), we are providing a great deal more flexibility
  - The catch is that we are increasing variance – the model is more likely to overfit to our training data
- One issue is that there is no clear guidance on selecting the width of each hidden layer (number of neurons) or the depth (number of hidden layers) for a given problem

OTHER TYPES

- **Convolutional neural network**
  - Used in computer vision
- **Recurrent neural network**
  - Sequence Data
- **LSTM**
  - Sequence data (Time series)
- **Auto-encoder**
  - Unsupervised learning
- **Deep Reinforcement Learning**
  - ‘Games’



Neural Networks

1. ~~**WHAT** are Neural Networks~~

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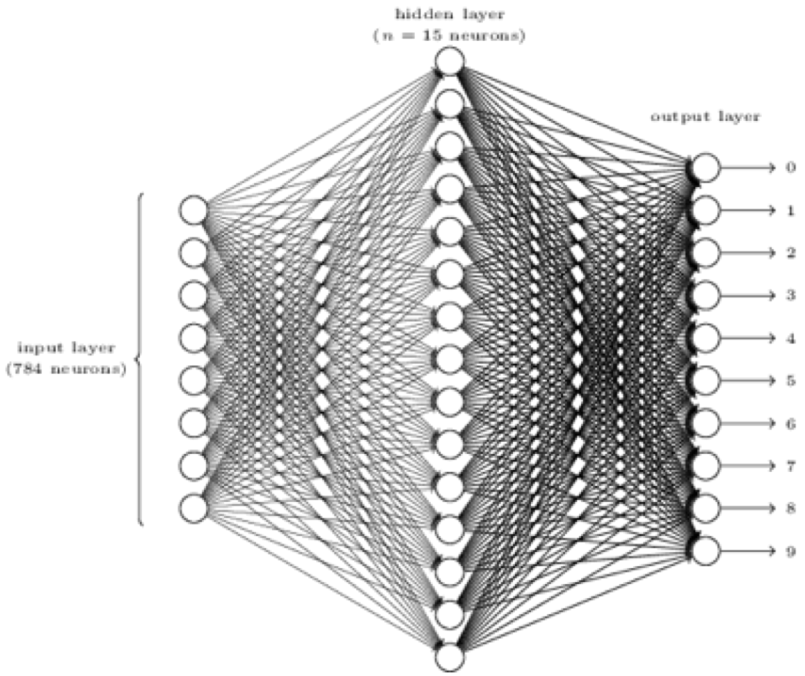
3. **HOW** do we ‘Neural Networks’



How to ‘A.I’ in (6) simple steps

1. **Initialize your network**
   - **Select number of hidden layers, number of hidden units per layer, activation functions**
2. **‘Feed Forward’**
   - **We have covered this essentially!**
3. Calculate a loss
   - How bad did our model do?
4. ‘Back propagate’
   - This will allow us to see how our weights affect our loss
5. Update weights
6. Repeat
7. (Optional – regularize)

One thing we missed! (Data Preparation)

- We want to **zero-center/ zero-mean** the data.

Why?

- So our output is not too sensitive to small changes in weight matrix.
- To assist the gradient optimization path (link to *sigmoid* decline

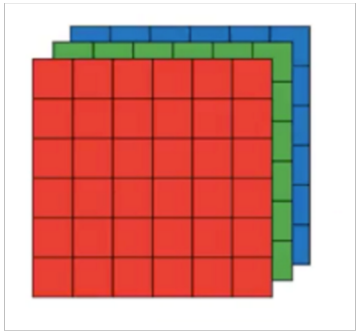
- We want to **normalize** the data.

Why?

- So our variables can equally contribute

  Different scales will make an *elongated* cost function and hence need a small learning rate step – training takes longer.

Not really needed for images – why?



Data Preparation: Extra

- Look up *whitening* (Kessy et al., 2016)
  - Similar to PCA but components have unit variance
  - Can first perform PCA, then divide principal components by sqrt(eigenvalues)
- Additional step could be ZCA ('Mahalanobis whitening')
  - Whitened data has minimal adjustments to the 'space' of the original data.

Generally for images, only zero-mean. For other DNN tasks, consider more pre-processing

Weight initialization

- Proposition 1: Simply initialize the weights to zero?

Bad Idea – Why?

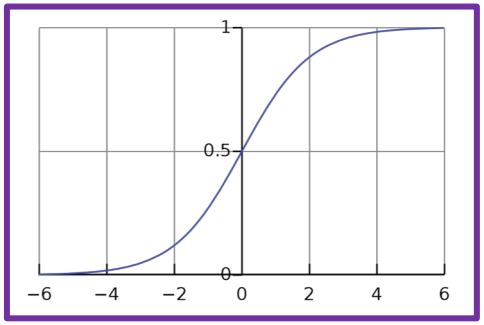
- The weights would all do the same thing, output same values, receive same gradient etc.
- Proposition 2: Add a small non-zero value

Ok – but has some issues
(See AT1)

- Proposition 3: Other, advanced methods

(See AT1)

Creating a loss function (cross-entropy)



- Let us consider a binary outcome, then we can use a sigmoid loss function

$$L(\hat{Y}, y) = -(y log \hat{Y}) + (1 - y) \log(1 - \hat{Y})$$

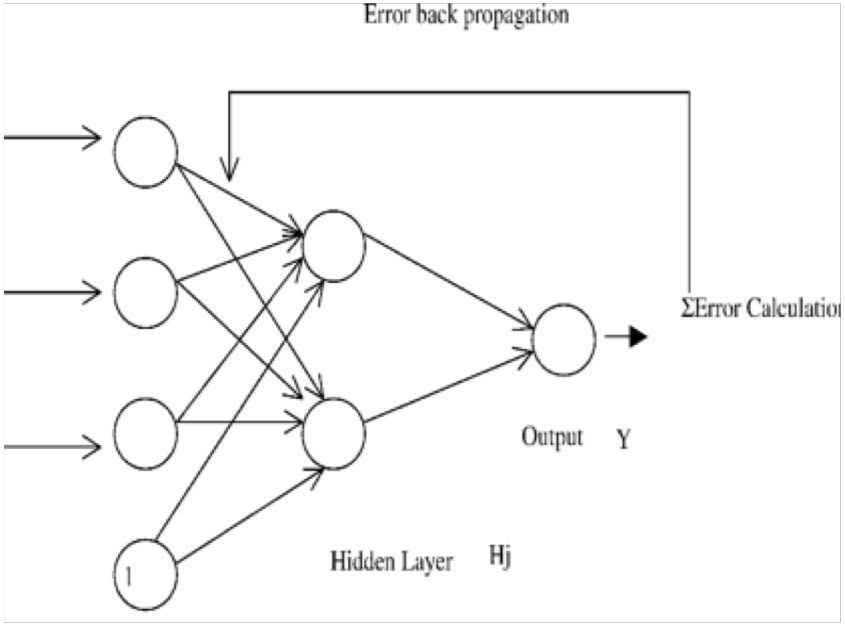
- Consider if Y=1
  - $(1 - y)\, log(1 - \hat{Y})$ becomes 0
  - We are left with $-(1)\, log(\hat{Y})$
  - What would be $\hat{Y}$ when we are really sure it IS? (0.999?)
    - log(0.990) = Zero!
- Consider if Y=0
  - $-(y log\, \hat{Y})$ becomes 0
  - We are left with $(1)\, log(1 - \hat{Y})$
  - What would be $\hat{Y}$ when we are really sure it ISN'T? (0.001?)
    - log(0.999) = Zero!

BACK-PROPAGATION

- Once we have decided on a neural network architecture, the model boils down to a set of weights
- We cannot use optimisation methods from linear models to determine all these weights. Why?
- We use the back-propagation algorithm instead:
  1. Find the error at the output layer (i.e. classification error, MSE)
  2. Use this error to adjust the weight between the last hidden layers and the output layer ➔ we *back-propagate* the error at the output layer to the hidden layer
  3. Repeat 1 and 2 until all hidden layers are updated

BACK-PROPAGATION

- The idea is that each hidden node is ‘responsible’ for some fraction of the error.
- We divide the error according to the weight of the connection between each hidden node and the output – hidden nodes with a greater reduction in error get more weight



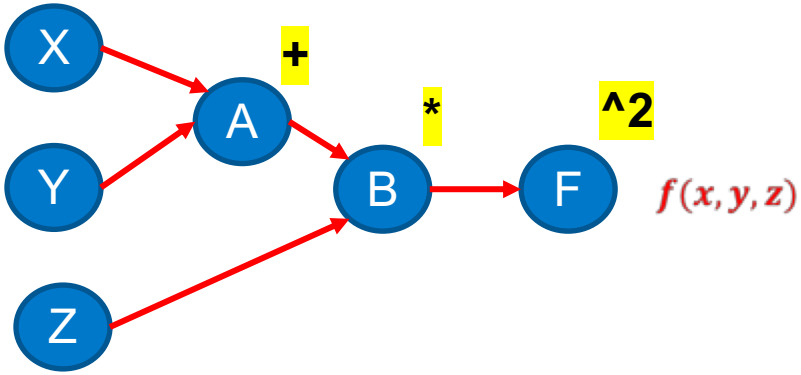
BACK-PROPAGATION

- Consider a simple computational graph made from the function

$$f(x, y, z) = ((x + y)z)^2$$

- How does A affect $f(x, y, z)$?

$$\frac{df}{dA} \; ??$$

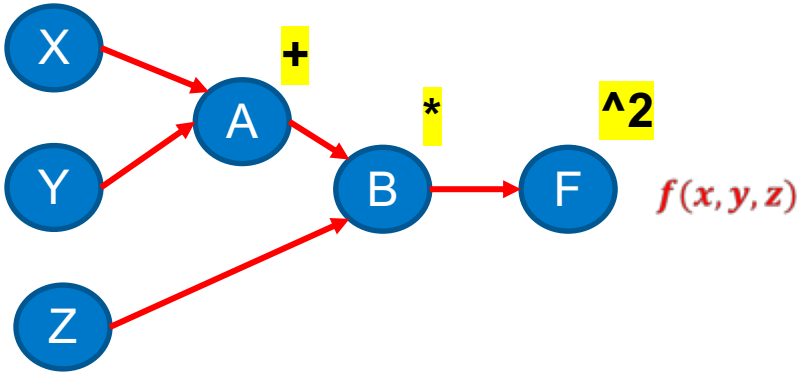


BACK-PROPAGATION

- How does A affect $f(x, y, z)$?

  $\frac{df}{dA}$??
- Hint: What we have are intermediary functions:

  $A = x + y$



Luckily calculus has a neat trick called the 'chain rule'

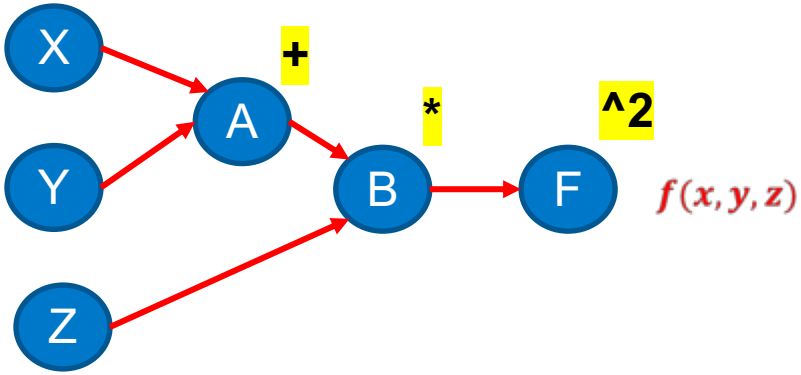
$$\frac{df}{dA} = \frac{\partial f}{\partial B} * \frac{\partial B}{\partial A}$$

So what is $\frac{\partial f}{\partial B}$?

$$\frac{\partial f}{\partial B} = 2B \text{ and } \frac{\partial B}{\partial A} = Z$$

$$\text{so } \frac{df}{dA} = 2BZ$$

BACK-PROPAGATION

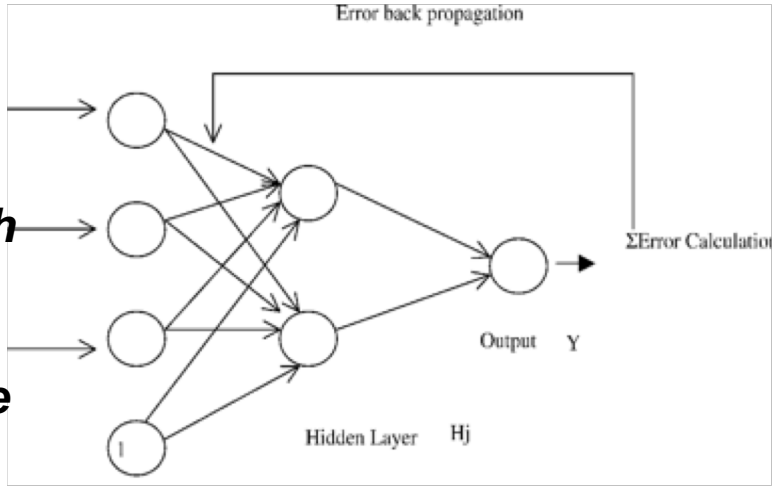


- How does X affect $f(x, y, z)$?

  $\frac{df}{dX}$??
- What is the chain rule for this?

$$\frac{d\,f}{dX} = \frac{\partial f}{\partial B} * \frac{\partial B}{\partial A} * \frac{\partial A}{\partial X}$$

The idea is that each hidden node is 'responsible' for some fraction of the error



BACK-PROPAGATION for Matrices

- What if we don't have scalars but have matrices?

Everything holds true, except we now get a **jacobian matrix** (first order partial derivatives of the weight matrices with respect to the loss function)

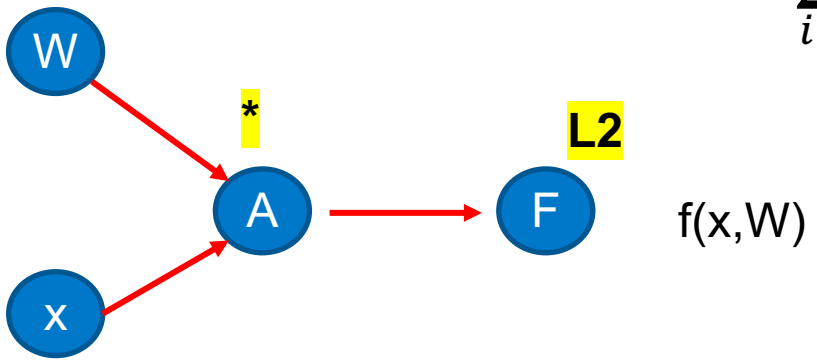
- An example computational graph:
  - **Matrix multiplication** (then)
  - **L2 transformation** (sum of the square of each element) v

$$f(x, W) = ||W.x||^2 = \sum_{i=1}^{n} (W.x)_i^2$$

Jacobian walkthrough

$$\begin{matrix} 0.1 & 0.5 \\ -0.3 & 0.8 \end{matrix}$$

$$f(x, W) = ||W.x||^2 = \sum_{i=1}^{n} (W.x)_i^2$$



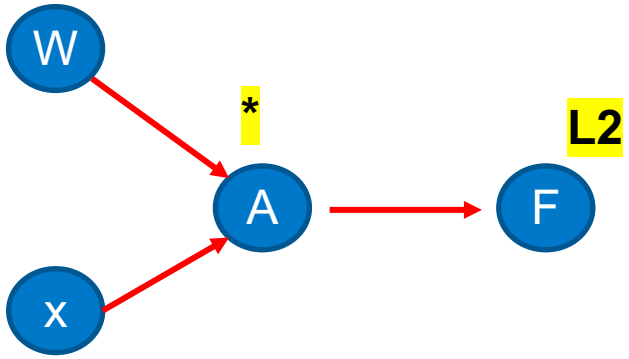
$$\begin{matrix} 0.2 \\ 0.4 \end{matrix}$$

$$\begin{matrix} 0.1 & 0.5 \\ -0.3 & 0.8 \end{matrix} \bullet \begin{matrix} 0.2 \\ 0.4 \end{matrix} = ????$$

Jacobian walkthrough

$$\begin{matrix} 0.1 & 0.5 \\ -0.3 & 0.8 \end{matrix}$$

$$f(x, W) = ||W.x||^2 = \sum_{i=1}^{n} (W.x)_i^2$$



$$\begin{matrix} 0.2 \\ 0.4 \end{matrix}$$

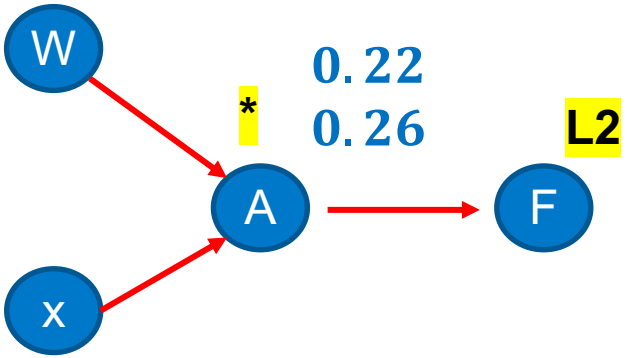
$$\begin{matrix} 0.1 & 0.5 \\ -0.3 & 0.8 \end{matrix} \bullet \begin{matrix} 0.2 \\ 0.4 \end{matrix} =$$

(0.1*0.22)+(0.5*0.4) = 0.22
(-0.3*0.2)+(0.8*0.4) = 0.26

Jacobian walkthrough

$$\begin{matrix}0.1 & 0.5 \\ -0.3 & 0.8\end{matrix}$$

$$f(x, W) = ||W.x||^2 = \sum_{i=1}^{n} (W.x)_i^2$$



$$\begin{matrix}0.22 \\ 0.26\end{matrix}$$

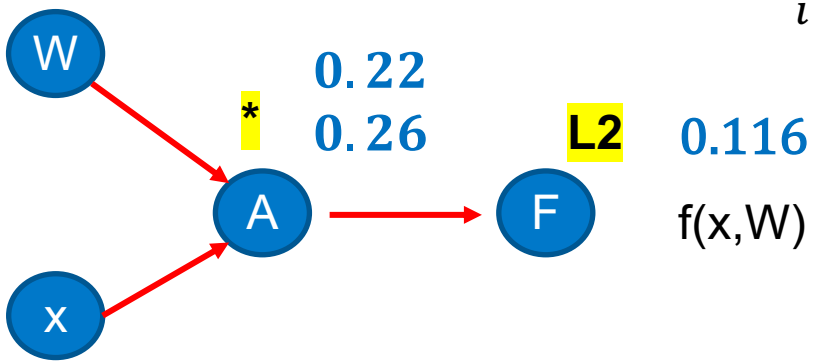
$$\begin{matrix}0.2 \\ 0.4\end{matrix}$$

$$\left|\left|\begin{matrix}0.22 \\ 0.26\end{matrix}\right|\right|^2 = ????$$

Jacobian walkthrough

$$\begin{matrix} 0.1 & 0.5 \\ -0.3 & 0.8 \end{matrix}$$

$$f(x, W) = ||W.x||^2 = \sum_{i=1}^{n} (W.x)_i^2$$



$$\begin{matrix} 0.22 \\ 0.26 \end{matrix}$$

0.116

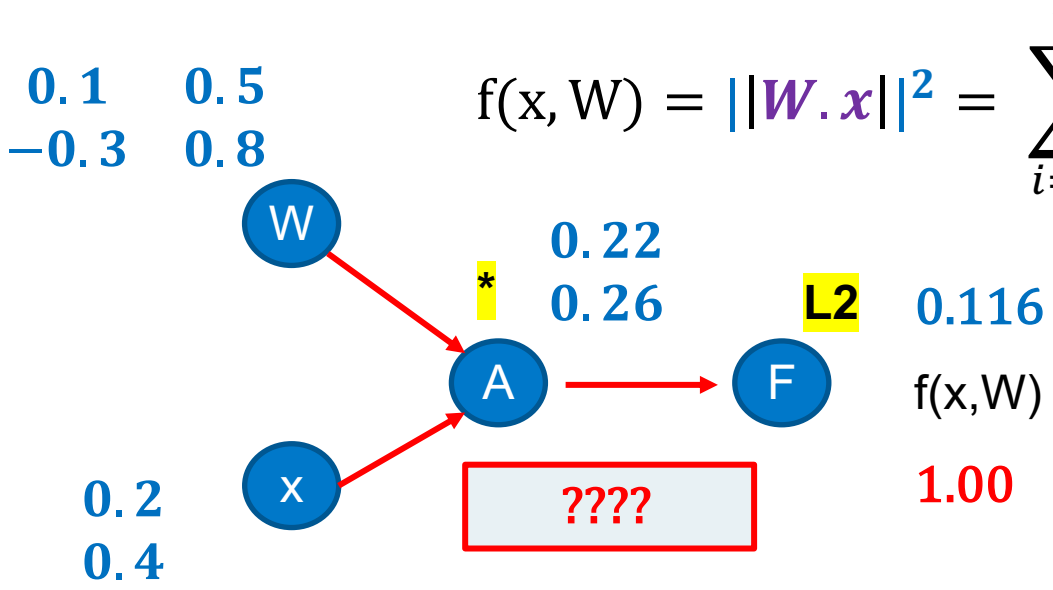
f(x,W)

$$\begin{matrix} 0.2 \\ 0.4 \end{matrix}$$

$$||\begin{matrix} 0.22 \\ 0.26 \end{matrix}||^2 =$$

(0.22*0.22)+(0.26*0.26) = 0.116

Jacobian walkthrough (backwards)

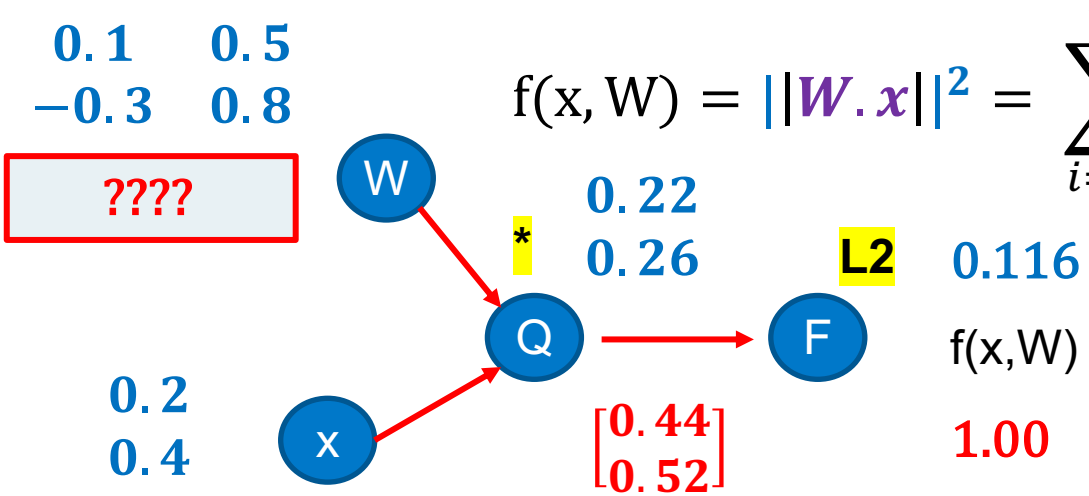


$$f(x, W) = ||W.x||^2 = \sum_{i=1}^{n} (W.x)_i^2$$

- First (1) is derivative of the output with itself.
  - Roll back one layer, what's the function – how do we differentiate it?

$$\frac{df(x)}{dx} where\ f(x) = x^{(2)} \gg f'(x) = 2x = \begin{bmatrix} 2 * 0.22 \\ 2 * 0.26 \end{bmatrix} (1.00) = \begin{bmatrix} 0.44 \\ 0.52 \end{bmatrix}$$

Jacobian walkthrough (backwards)



$$f(x, W) = ||W.x||^2 = \sum_{i=1}^{n} (W.x)_i^2$$

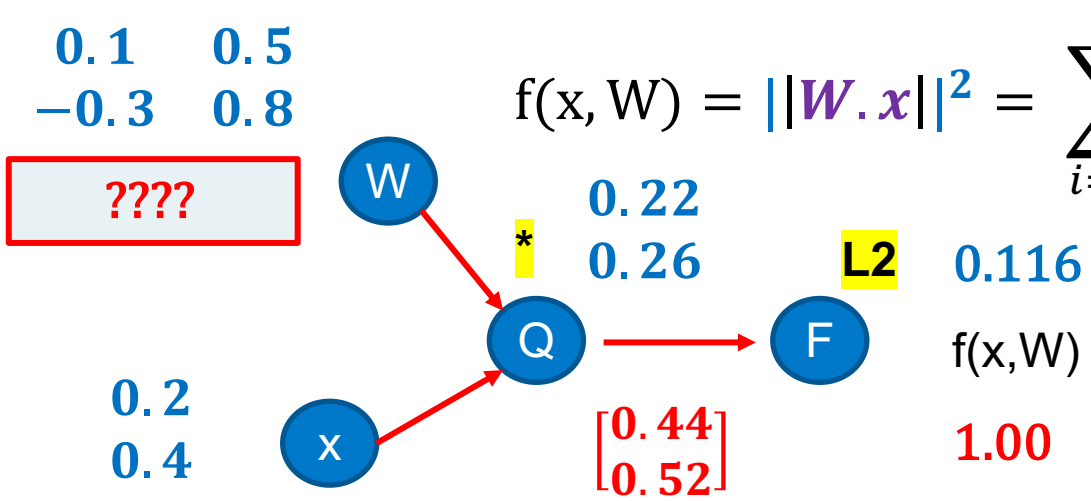
- Roll back another layer, how do we do this?
  - We need to create our **jacobian** to do this.

$$\frac{dq}{dw} \; where \; \begin{bmatrix} q_{11} \\ q_{21} \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} * \begin{bmatrix} x_{11} \\ x_{21} \end{bmatrix} = \begin{bmatrix} w_{11}x_{11} + & w_{12}x_{21} \\ w_{21}x_{11} + & w_{22}x_{21} \end{bmatrix}$$

(We can also use a shortcut)

$\frac{d(b^T x)}{dx} = b$ where our (b=X) and (X=W)

Jacobian walkthrough (backwards)



$$f(x, W) = ||W.x||^2 = \sum_{i=1}^{n} (W.x)_i^2$$

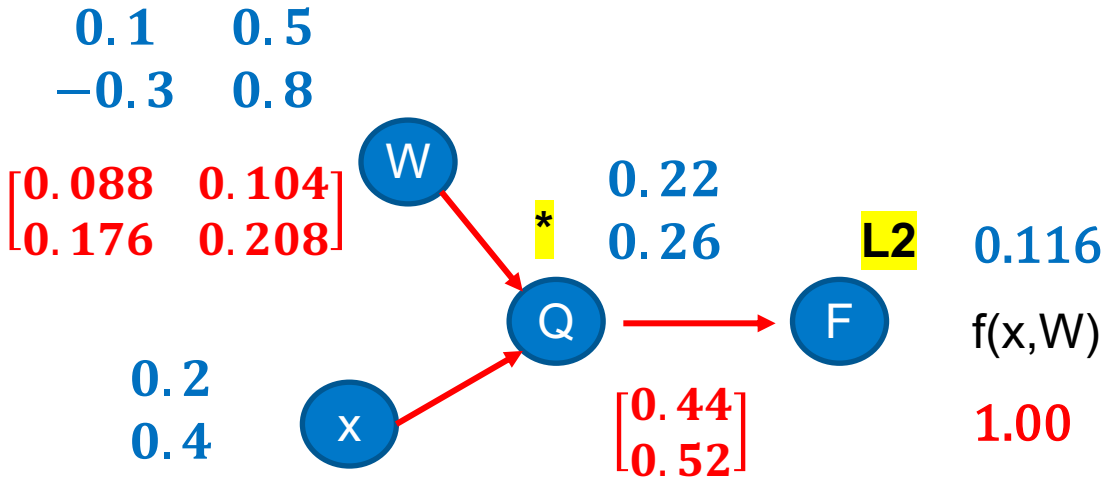
$$\frac{dq}{dw} \; where \; \begin{bmatrix} q_{11} \\ q_{21} \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} * \begin{bmatrix} x_{11} \\ x_{21} \end{bmatrix} = \begin{bmatrix} w_{11}x_{11} + & w_{12}x_{21} \\ w_{21}x_{11} + & w_{22}x_{21} \end{bmatrix}$$

$\frac{d(b^T x)}{dx} = b$ where our (b=X) and (X=W)

$$\begin{bmatrix} 0.2 & 0.4 \end{bmatrix} * \begin{bmatrix} 0.44 \\ 0.52 \end{bmatrix} = \begin{bmatrix} 0.088 & 0.104 \\ 0.176 & 0.208 \end{bmatrix}$$

Jacobian walkthrough (backwards)

$$f(x, W) = ||W.x||^2 = \sum_{i=1}^{n} (W.x)_i^2$$

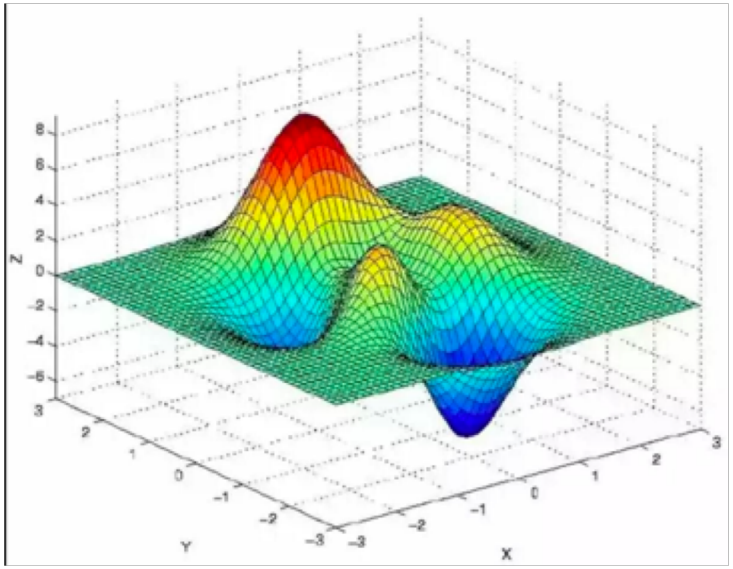


Key takeaway:

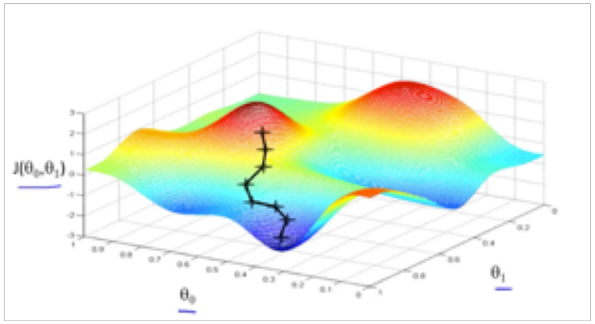
- The fundamental principle of the 'Chain Rule' can be applied to matrices in order to determine the influence of weight matrix elements on final output (loss)

UPDATING THE WEIGHTS - GRADIENT DESCENT

- In multiple dimensions, the **gradient** is the vector of **partial derivatives** along each dimension.
- Think of it like a person standing somewhere in a valley of lots of ups and downs. Your goal is to find the lowest point (and efficiently!)
  - The height is the loss function, X-Y-Z are your parameters



(do we have only 3 parameters? How many do we have?)

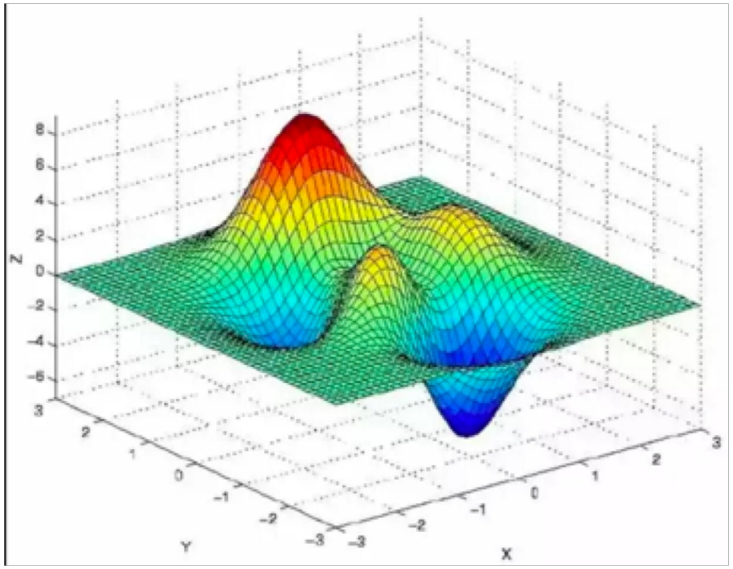


1. Start somewhere
2. Take a bunch of little steps around us and see where is the steepest slope (negative derivative)
3. Then take a small step in that direction
4. Repeat

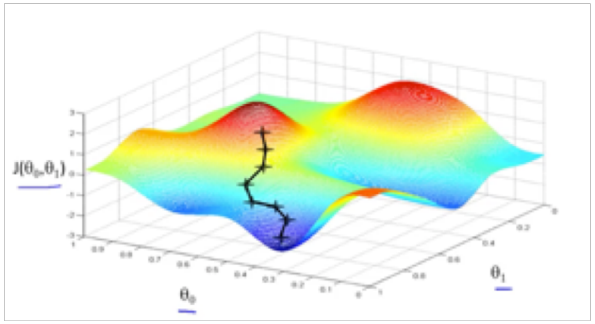
UPDATING THE WEIGHTS - GRADIENT DESCENT

The small step is termed the learning rate:

- If α is too small, gradient descent will take a long time
- If α is too large, you can fail to converge or overshoot the minimum (diverge)



https://www.youtube.com/watch?v=WnqQrPNYz5Q



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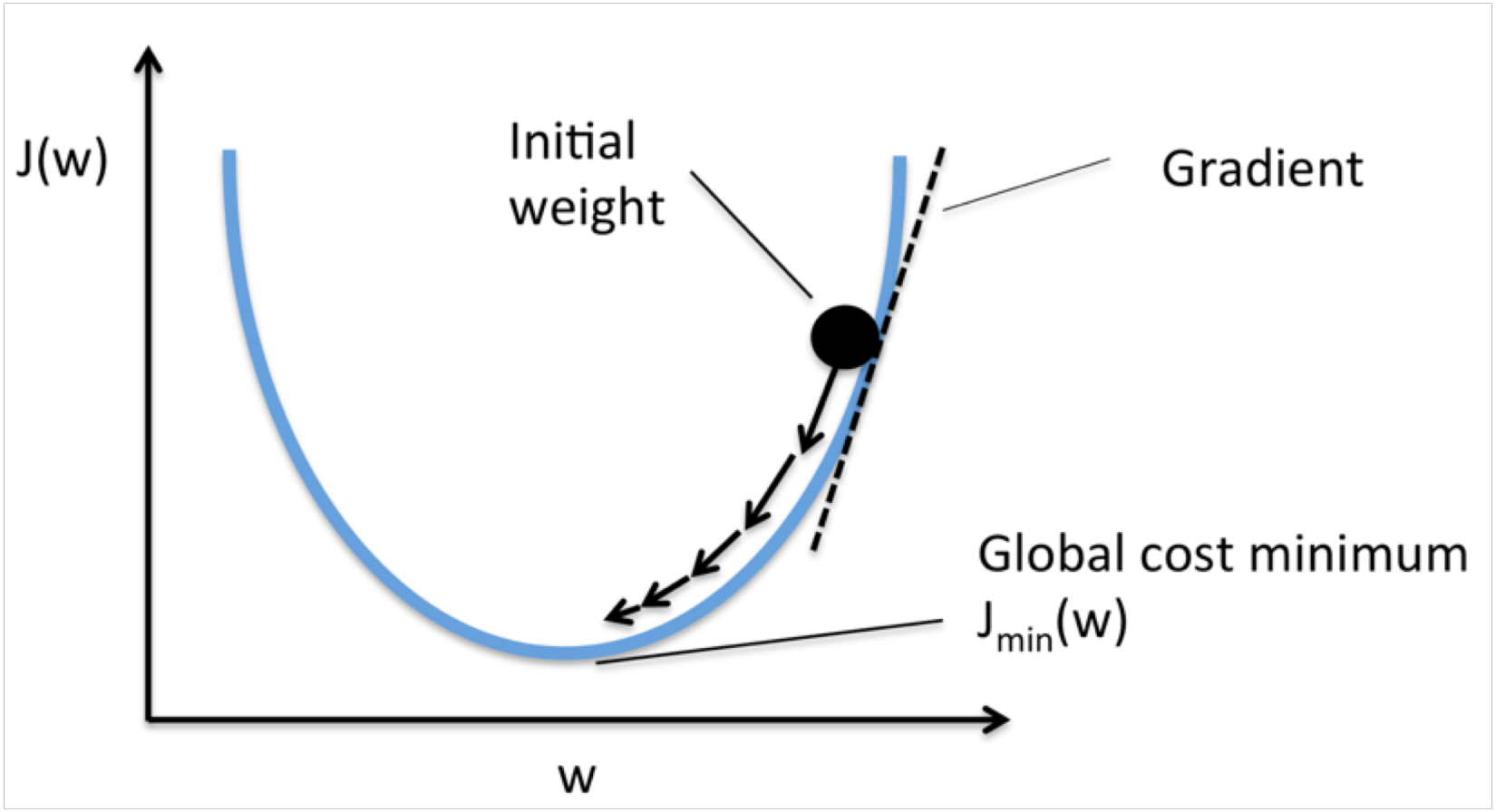
GRADIENT DESCENT



AT1 BRIEFING + LAB

Walkthrough briefing PDF and notebook