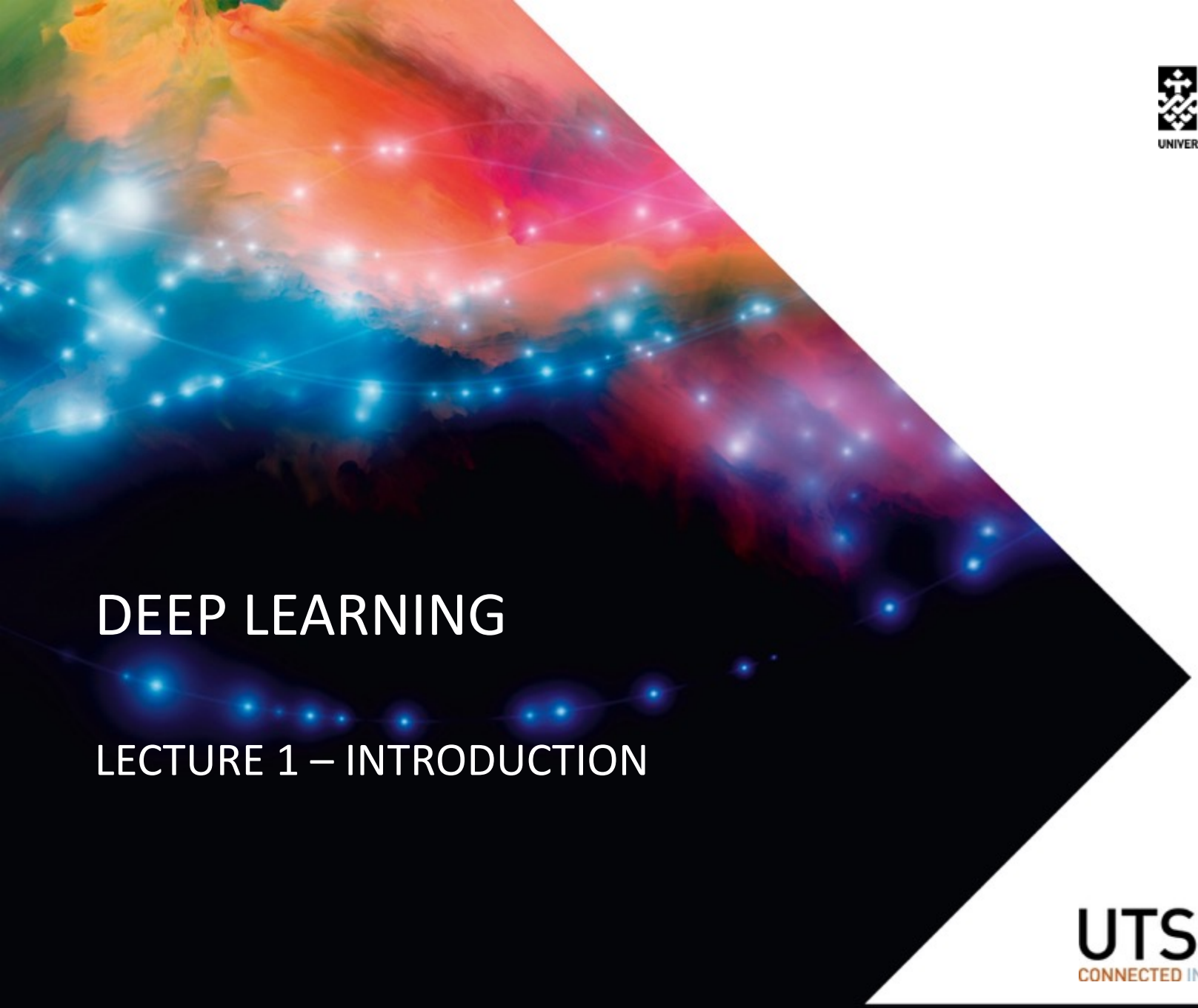


UTS
UNIVERSITY OF TECHNOLOGY SYDNEY

DEEP LEARNING

LECTURE 1 – INTRODUCTION

UTS:CIC
CONNECTED INTELLIGENCE CENTRE

OVERVIEW OF TODAY

Schedule:

> Review of last week

> A bit more maths (Finish last week)

> Optimisation algorithms

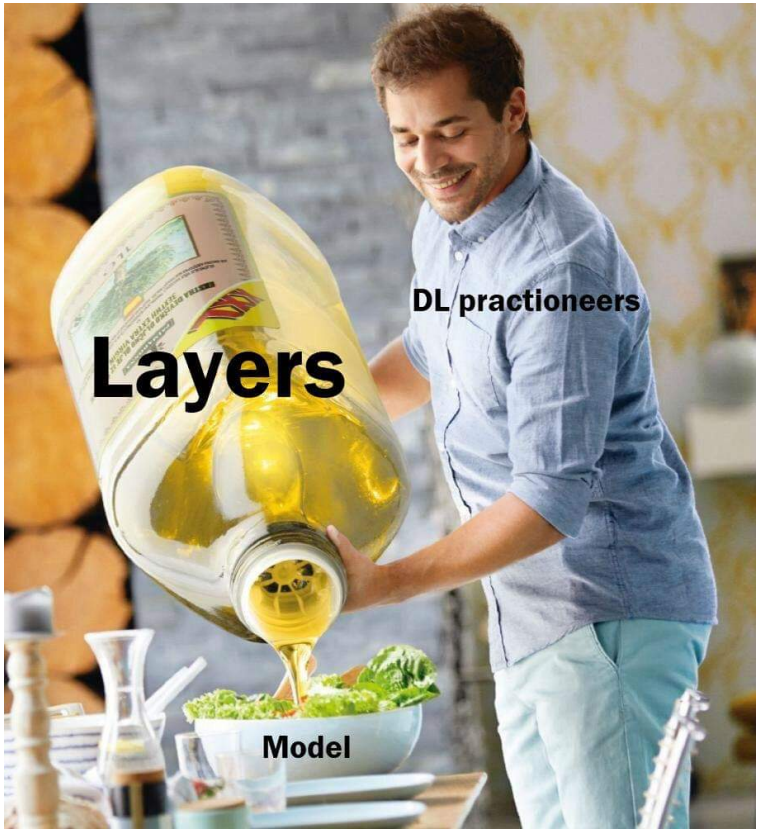
> Regularisation methods

> Software & Hardware

Lab:

> Introduction to Tensorflow **& Keras**

HOW IS AT1 GOING?



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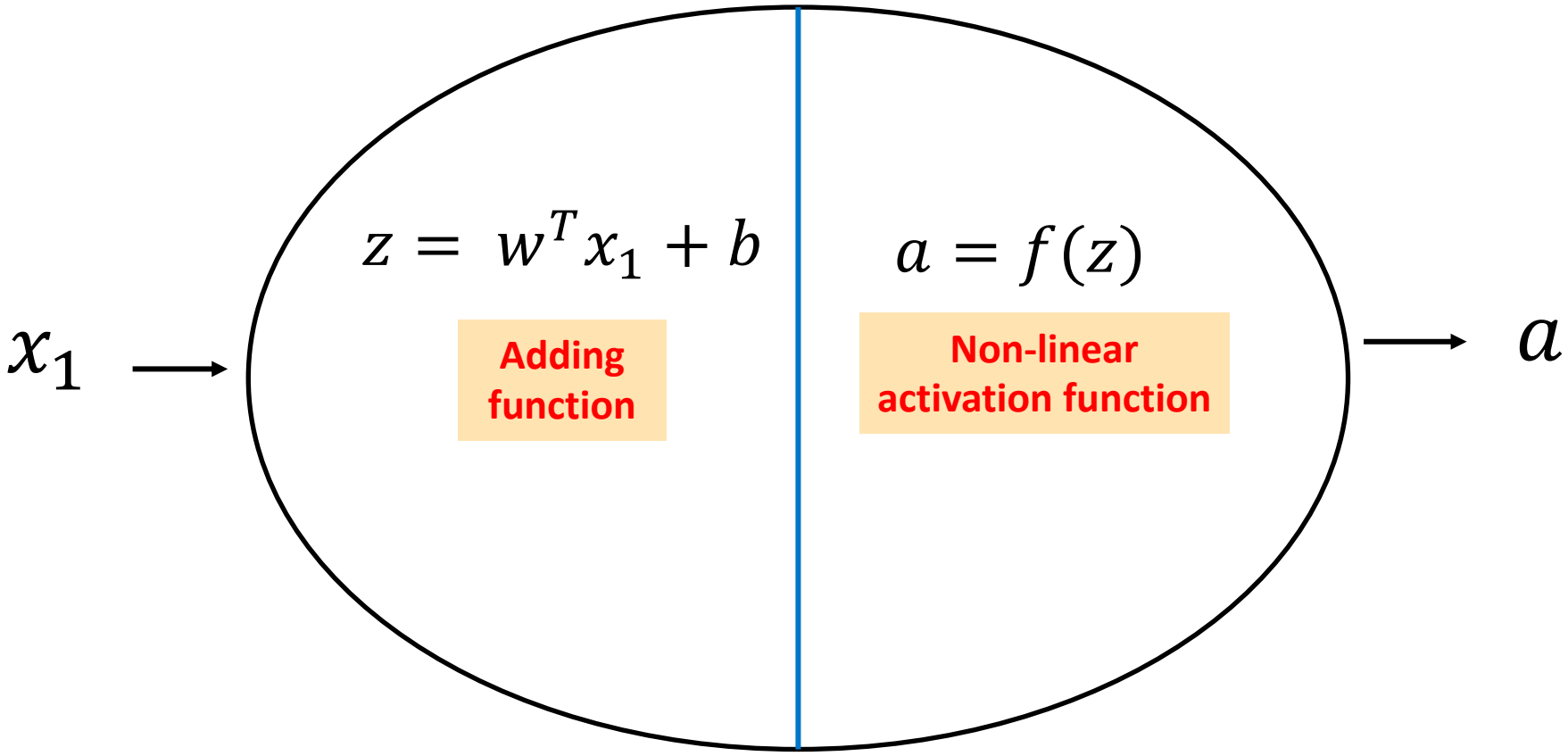
To be perfectly blunt…..

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

– Judea Pearl

Be careful…

Inside a Neuron



Why transpose W?

Why transpose W?

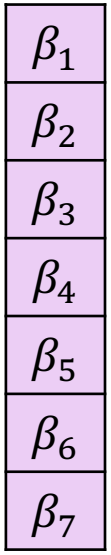
- **Recall: 'w'** is our matrix of weights that we will apply to each of our input data points.

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

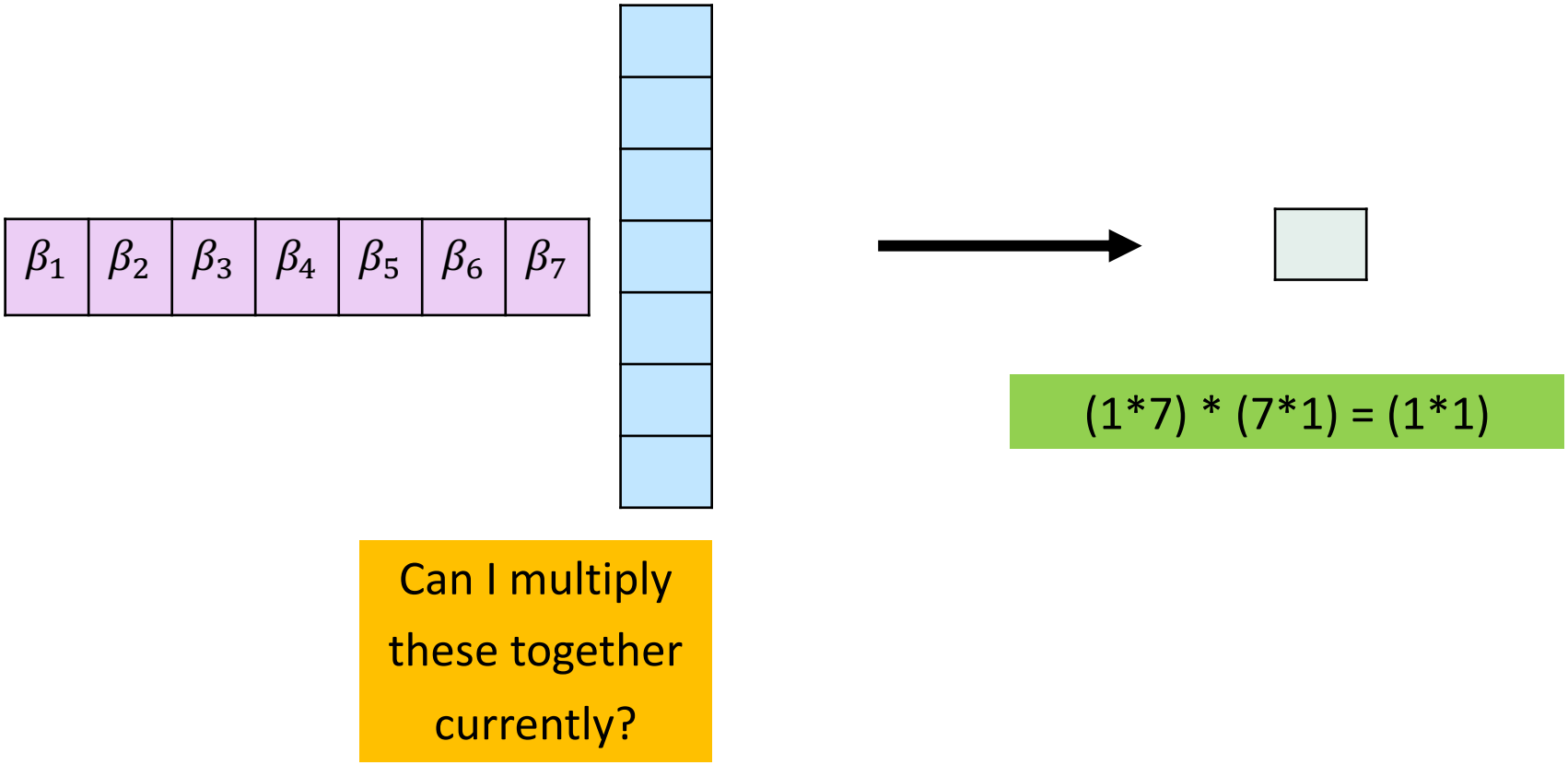
$\mathbb{R}^{n_x} * \boldsymbol{m} * \mathbb{R}^{\boldsymbol{m}} * a$

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

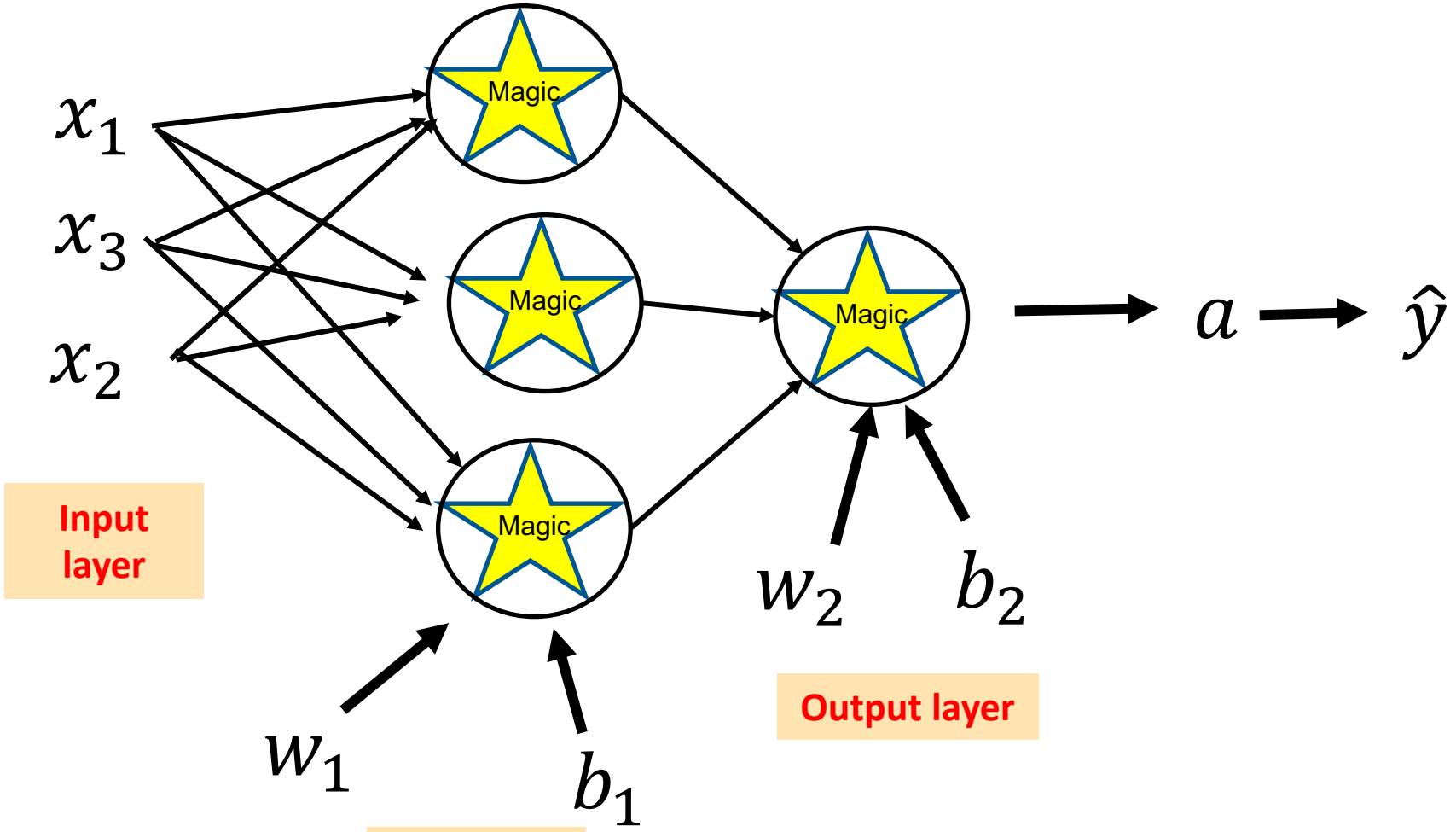
Where m = rows, n= columns

Why transpose W?

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



Neuron to ‘network’

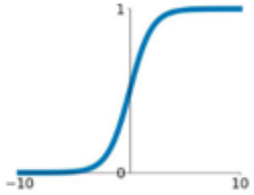


Other Activation Functions

Activation Functions

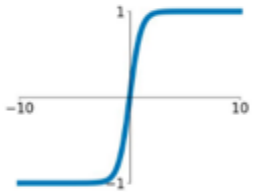
Sigmoid

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



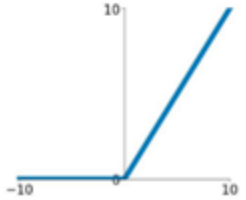
tanh

$$\tanh(x)$$



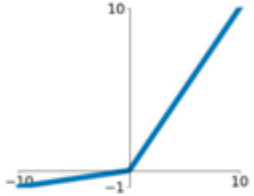
ReLU

$$\max(0, x)$$



Leaky ReLU

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

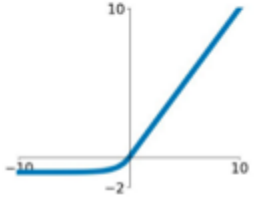


Maxout

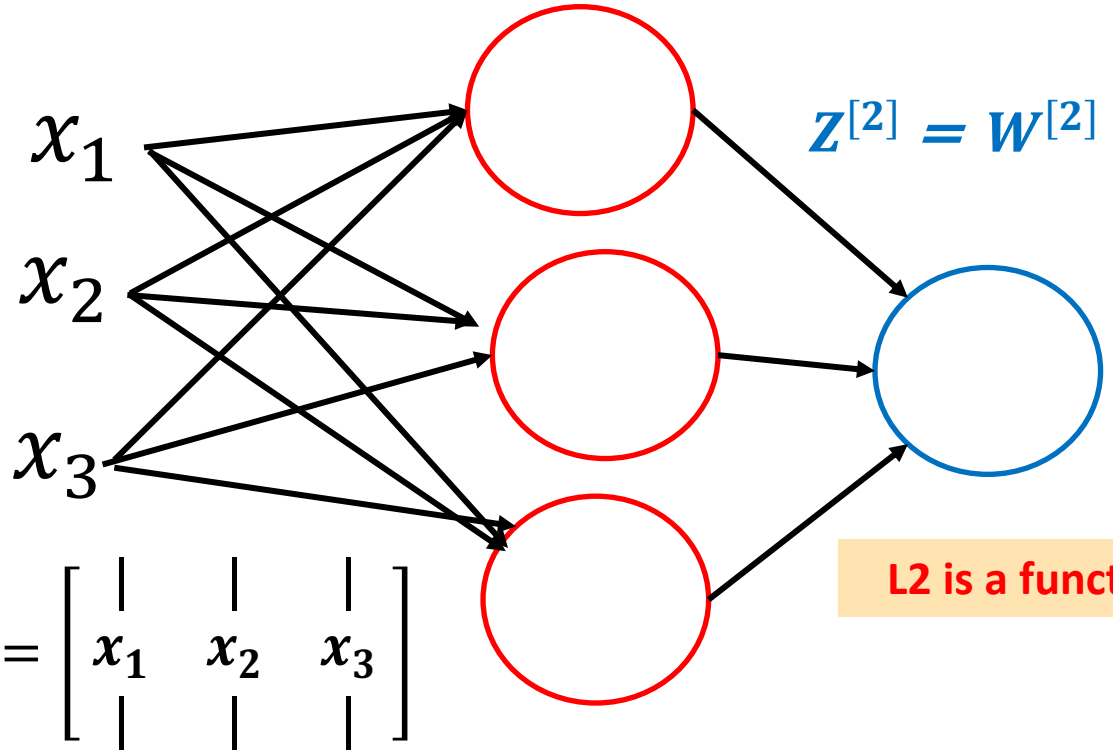
$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

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



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

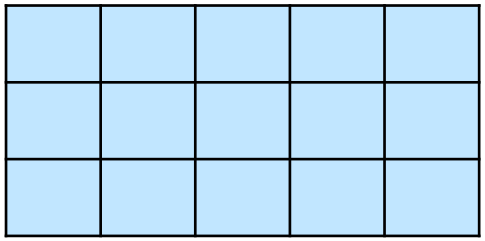
$$X = \begin{bmatrix} | & | & | \\ x_1 & x_2 & x_3 \\ | & | & | \end{bmatrix}$$

Note what are the later layers are modelling?

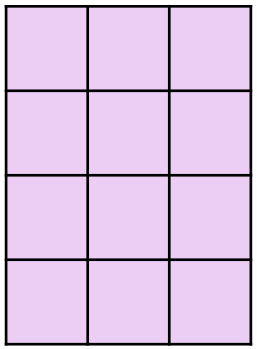
$$Z^{[1]} = W^{[1]} \cdot X + b^{[1]} \rightarrow A^{[1]} = \sigma(Z^{[1]})$$

L1 is a function of L0

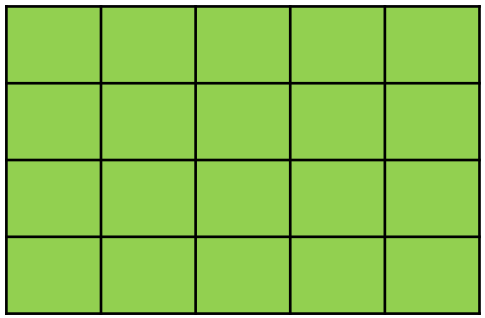
The size of our matrices



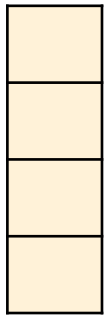
$A^{[0]}$ = (3,5)



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



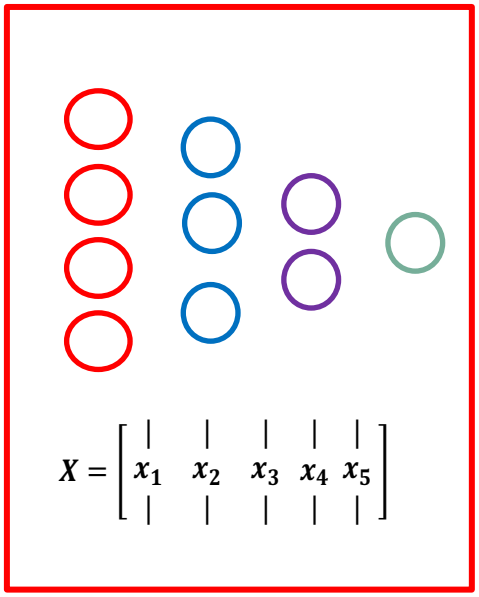
$Z^{[1]}$ = (4,5)



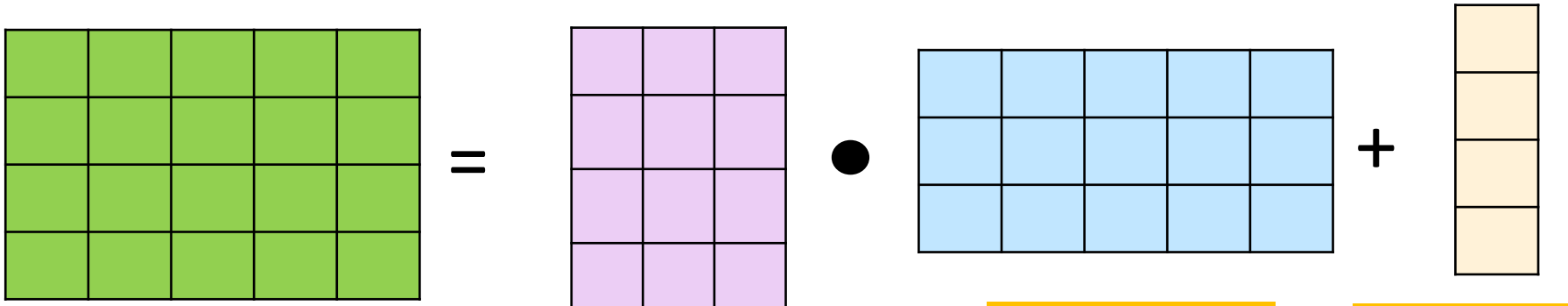
$b^{[1]}$ = (4,1)

- 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)

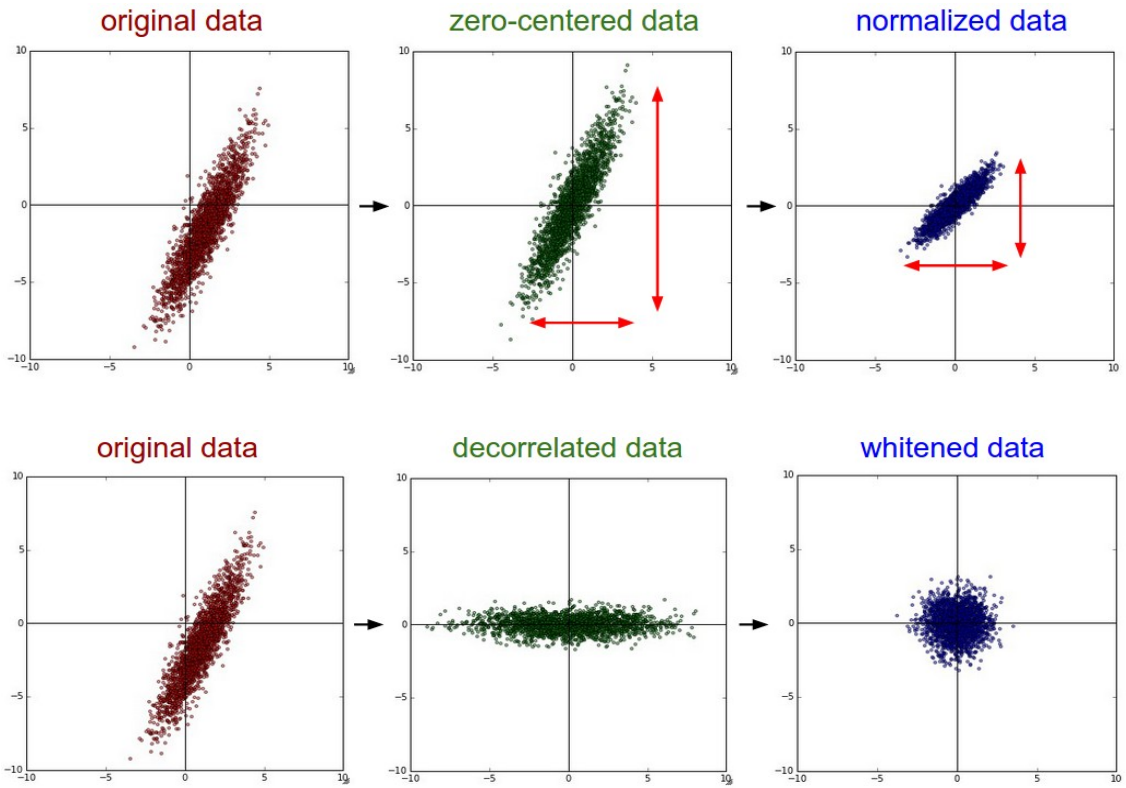
$$Z^{[L]} = W^{[L]}.A^{[L-1]} + b^{[L]}$$

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)

Data Preparation:

- **zero-center/ zero-mean** the data
- **normalize** the data.
- Whitening/sphering
  - zCA whitening



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)

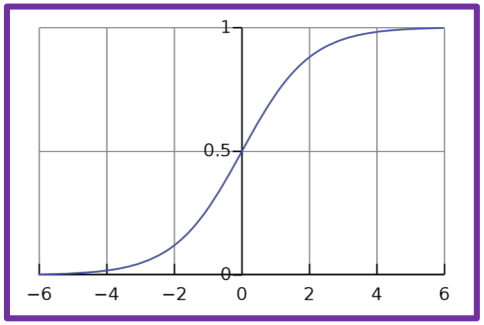
- Proposition 3: Other, advanced methods

(See AT1)

Weight initialization Part 2

- **Xavier initialisation (Good for Tanh activations)**
  - (Source, Glorot & Bengio et al, 2010)
  - Initialize weights from distribution with zero mean and variance.
  - Multiply by $\sqrt{\frac{1}{ni+no}}$ (number input, output units)
- **He initialisation (Good for Relu activations)**
  - (Source He at al., 2015)
  - Similar to above but multiply by $\sqrt{\frac{2}{ni}}$

Creating a loss function (cross-entropy)



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

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

- 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
  - $-(ylog\,\hat{Y})$ 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

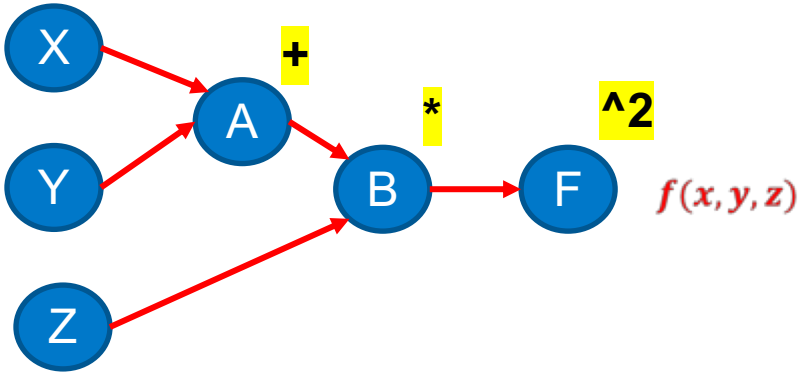
- Once we have decided on a neural network architecture, the model boils down to a set of weights
- We cannot use optimisation methods from linear models to determine all these weights. Why?
- We use the back-propagation algorithm instead:
  1. Find the error at the output layer (i.e. classification 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

- 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 for Matrices

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

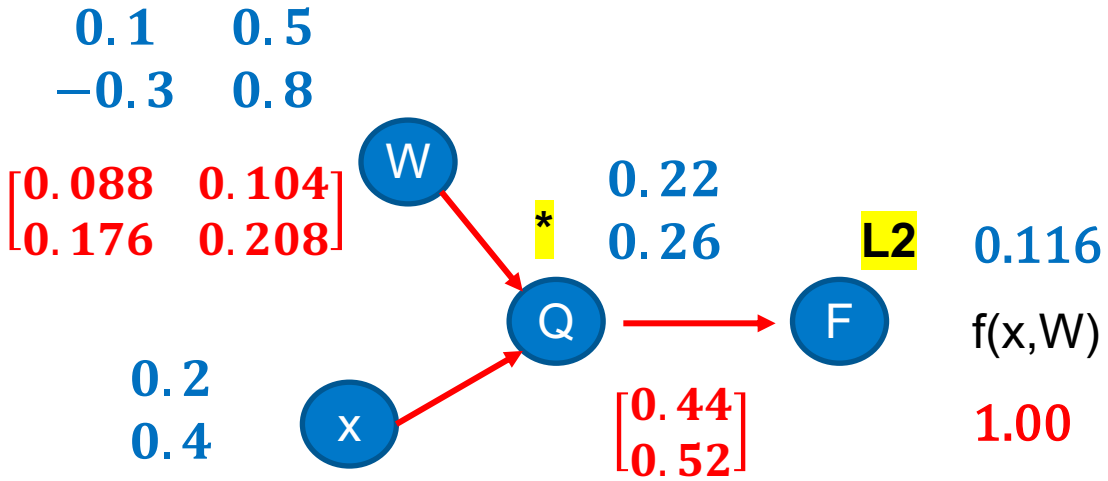
Everything holds true, except we now get a **jacobian matrix** (first order partial derivatives of the weight matrices with respect to the loss function)

- 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 (backwards)

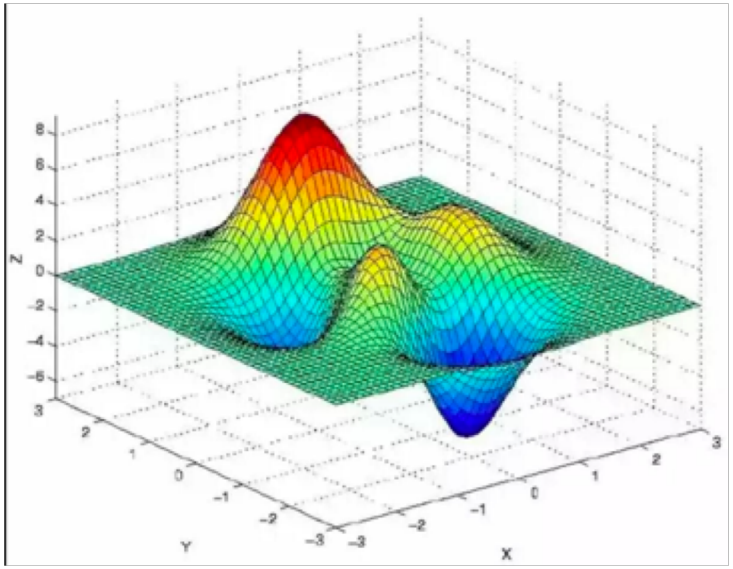
$$f(x, W) = ||W.x||^2 = \sum_{i=1}^{n} (W.x)_i^2$$



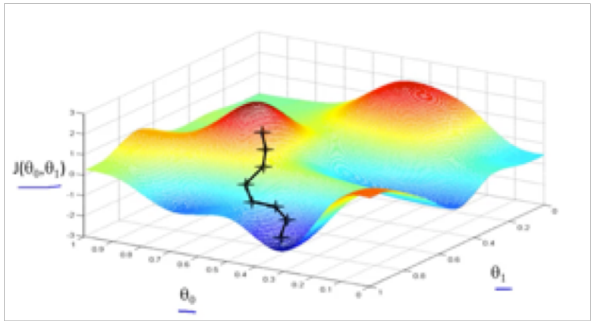
Key takeaway:
The fundamental principle of the 'Chain Rule' can be applied to matrices in order to determine the influence of weight matrix elements on final output (loss)

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?)

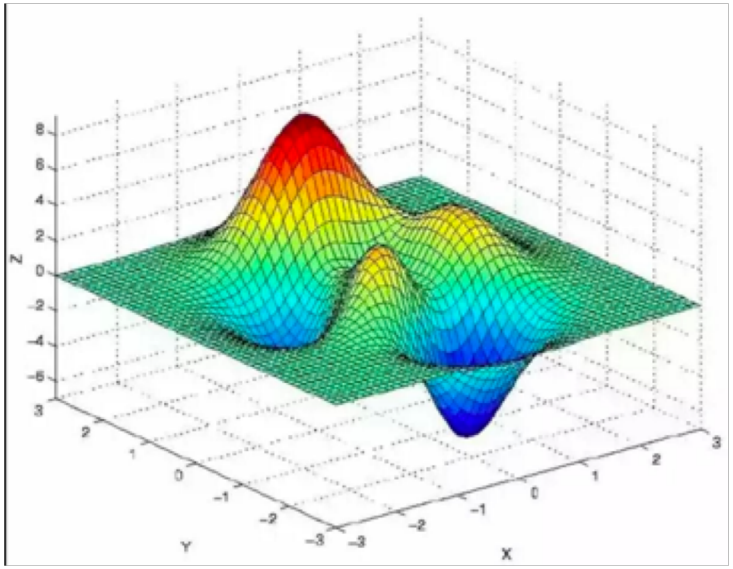


1. Start somewhere
2. Take a bunch of little steps around us and see where is the steepest slope (negative derivative)
3. Then take a small step in that direction
4. Repeat

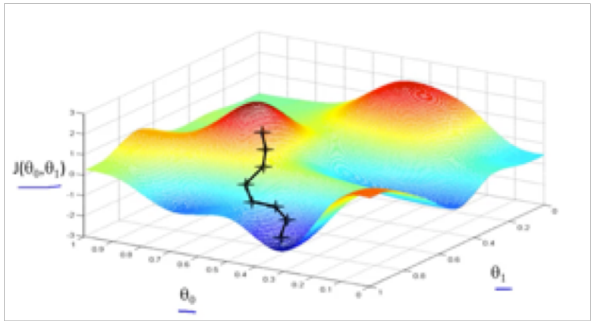
UPDATING THE WEIGHTS - GRADIENT DESCENT

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)

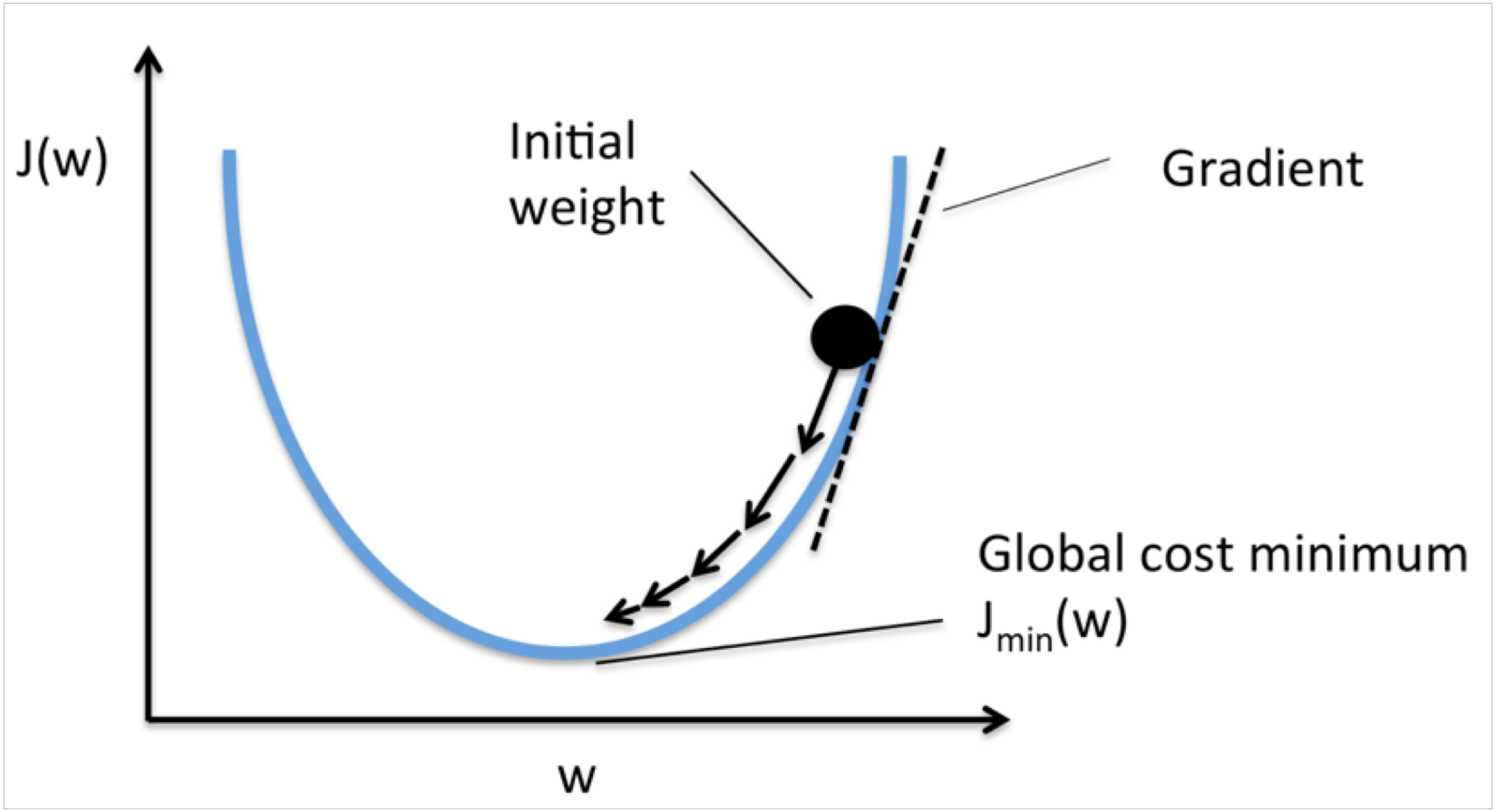


https://www.youtube.com/watch?v=WnqQrPNYz5Q



https://www.youtube.com/watch?v=IHZwWFHWa-w

GRADIENT DESCENT



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FORWARD PROP (SUMMARY)

- For the first and second layers:
  - $Z^{[1]} = W^{[1]} \cdot A^{[0]} + b^{[1]}$
    - $A^{[1]} = g^{[1]}(Z^{[1]})$
  - $Z^{[2]} = W^{[1]} \cdot A^{[1]} + b^{[1]}$
    - $A^{[2]} = g^{[2]}(Z^{[2]})$
- For some layer l:
  - $Z^{[l]} = W^{[l]} \cdot A^{[l-1]} + b^{[l]}$
    - $A^{[l]} = g^{[l]}(Z^{[l]})$

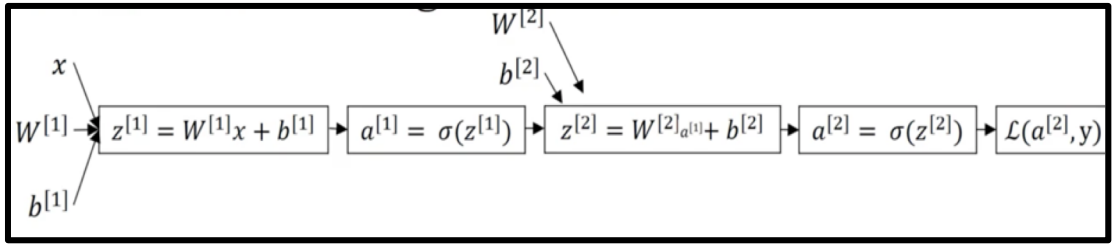
Matrix Sizes

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

BACK PROP MATHS

$$L(a^{[2]}, y) = -((y log a^{[2]}) + (1 - y) \log(1 - a^{[2]}))$$

(1/m) *



Let's go backwards on this computational graph

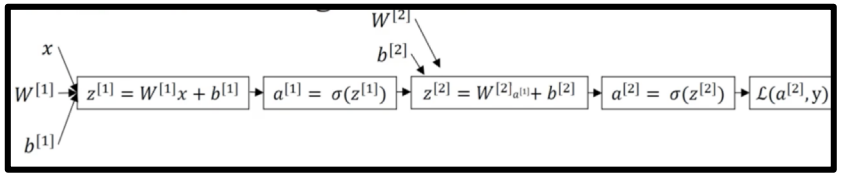
- Differentiate loss w.r.t $a^{[2]}$

$$da^{[2]} = \frac{dl}{\partial a^{[2]}} = -\frac{y}{a^{[2]}} + \frac{1-y}{1-a^{[2]}} \left(Note: \frac{dln(x)}{dx} = \frac{1}{x}\right)$$

- Differentiate loss w.r.t $z^{[2]}$

$$\boldsymbol{dz^{[2]}} = \frac{\boldsymbol{\partial l}}{\boldsymbol{\partial z^{[2]}}} = \frac{\boldsymbol{\partial l}}{\boldsymbol{\partial a^{[2]}}} * \frac{\boldsymbol{da^{[2]}}}{\boldsymbol{dz}}$$

BACK PROP MATHS



- Differentiate loss w.r.t $a^{[2]}$

$$da^{[2]} = \frac{dl}{\partial a^{[2]}} = -\frac{y}{a^{[2]}} + \frac{1-y}{1-a^{[2]}} \quad \left(Note: \frac{dln(x)}{dx} = \frac{1}{x}\right)$$

- Differentiate loss w.r.t $z^{[2]}$

$$\boldsymbol{dz^{[2]}} = \frac{\boldsymbol{\partial l}}{\boldsymbol{\partial z^{[2]}}} = \frac{\boldsymbol{\partial l}}{\boldsymbol{\partial a^{[2]}}} * \frac{\boldsymbol{da^{[2]}}}{\boldsymbol{dz}}$$

$$\frac{\partial l}{\partial a^{[2]}} = -\frac{y}{a^{[2]}} + \frac{1-y}{1-a^{[2]}} \;\&\; \frac{\boldsymbol{da^{[2]}}}{\boldsymbol{dz}} = \boldsymbol{a^{[2]}\left(1 - a^{[2]}\right)} \quad \left(Note: \frac{d\sigma(x)}{dx} = \sigma(x) * (1 - \sigma(x))\right)$$

$$\therefore \frac{\boldsymbol{\partial l}}{\boldsymbol{\partial z^{[2]}}} = a^{[2]} - y$$

- Differentiate loss w.r.t $w^{[2]}$

$$dw^{[2]} = \frac{\partial l}{\partial w^{[2]}} = \frac{\partial l}{\partial z^{[2]}} * \frac{dz^{[2]}}{dw^{[2]}} = \boldsymbol{a^{[2]} - y} * a^{[1]T}$$

$$\therefore = dz^{[2]}a^{[1]T}$$

+ Bias

$$db^{[2]} = dz^{[2]}$$

DIFFERENTIATE SIGMOID

https://towardsdatascience.com/derivative-of-the-sigmoid-function-536880cf918e

Let's say we want to find the derivative of $y = \sigma(x) = (1 + \exp(-x))^{-1}$. So we have:

$$\frac{dy}{dx} = (-1)(1 + \exp(-x))^{-2} \frac{d}{dx}(1 + \exp(-x))$$

$$= (-1)(1 + \exp(-x))^{-2}(0 + \frac{d}{dx}\exp(-x))$$

$$= (-1)(1 + \exp(-x))^{-2}(\exp(-x))\frac{d}{dx}(-x)$$

$$= (-1)(1 + \exp(-x))^{-2}(\exp(-x))(-1)$$

$$= \frac{\exp(-x)}{(1 + \exp(-x))^2}$$

$$= \frac{1 + \exp(-x) - 1}{(1 + \exp(-x))^2}$$

$$= \frac{1 + \exp(-x)}{(1 + \exp(-x))^2} - \frac{1}{(1 + \exp(-x))^2}$$

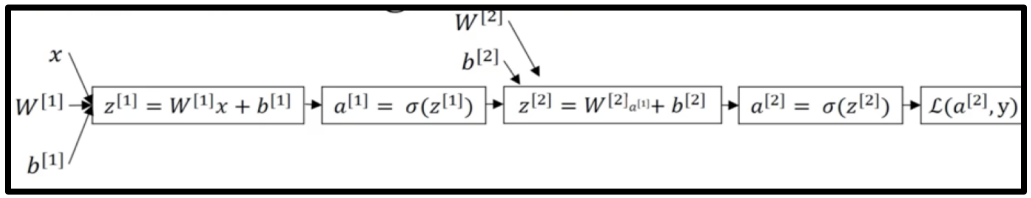
$$= \sigma(x) - (\sigma(x))^2$$

$$= \sigma(x) \cdot (1 - \sigma(x))$$

https://math.stackexchange.com/questions/78575/derivative-of-sigmoid-function-sigma-x-frac11e-x

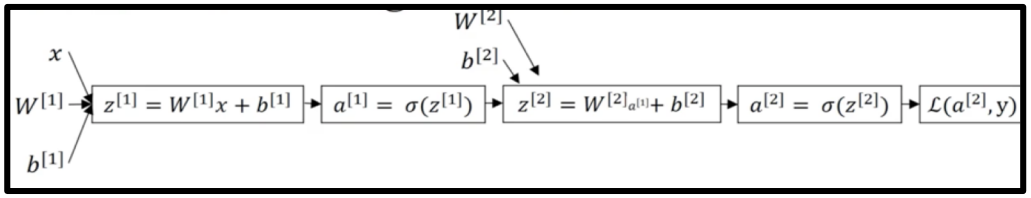
CONT.....

- Back to our data:



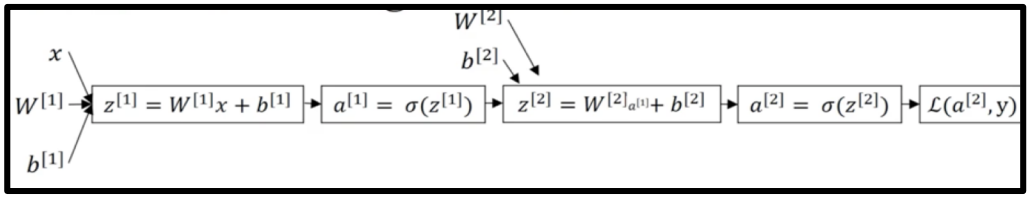
- Third step back:
  - $\boldsymbol{da^{[1]}} = \frac{\boldsymbol{dl}}{\boldsymbol{\partial a^{[1]}}} = \frac{\boldsymbol{\partial l}}{\boldsymbol{\partial z^{[2]}}} * \frac{dz^{[2]}}{da^{[1]}} = \boldsymbol{dz^{[2]} W^{[2]}}$
- Fourth step back:
  - $\boldsymbol{dz^{[1]}} = \frac{\partial l}{\partial z^{[1]}} = \frac{\boldsymbol{\partial l}}{\boldsymbol{\partial a^{[1]}}} * \frac{da^{[1]}}{dz^{[1]}}$
    - $\left(\boldsymbol{dz^{[2]} W^{[2]T}}\right) a^{[1]}\left(1 - a^{[1]}\right)$
      - $\frac{da^{[1]}}{dz^{[1]}}$ is $g^{[1]'}\left(z^{[1]}\right)$ as we won't always activate with σ
  - $dw^{[1]} = \frac{\partial l}{\partial w^{[1]}} = \frac{\boldsymbol{\partial l}}{\boldsymbol{\partial z^{[1]}}} * \frac{\boldsymbol{dz^{[1]}}}{\boldsymbol{dw^{[1]}}}$
    - $\boldsymbol{dz^{[1]} a^{[0]T}}$ recalling $\boldsymbol{a^{[0]}} = x$
  - $db^{[1]} = dz^{[1]}$

LET'S VECTORISE!



- $dZ^{[2]} = A^{[2]} - Y$
- $dW^{[2]} = \frac{1}{m} dZ^{[2]} A^{[1]T}$
- $db^{[2]} = \frac{1}{m} * \sum dZ^{[2]}$
  - $dZ^{[1]} = \left(W^{[2]T} dZ^{[2]}\right) * g^{[1]'}\left(Z^{[1]}\right)$
  - $dW^{[1]} = \frac{1}{m} dZ^{[1]} A^{[0]T}$ noting ($A^{[0]} = X$)
  - $db^{[1]} = \frac{1}{m} * \sum dZ^{[1]}$

LET'S GENERALISE!



- $dW^{[l]} = \frac{1}{m} dZ^{[l]} A^{[l-1]T}$
- $db^{[l]} = \frac{1}{m} * \sum dZ^{[l]}$
- $dZ^{[l]} = \left(W^{[l+1]T} dZ^{[l+1]}\right) * g^{[l]'}\left(Z^{[l]}\right)$
  - **OR >>>** $\left(dA^{[l]}\right) * g^{[l]'}\left(Z^{[l]}\right)$
- $dA^{[l-1]} = W^{[l]T} dZ^{[l]}$

Loss functions – Softmax

- What if we have multiple classes? Introducing Softmax function

$$P(Y = k \mid X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$

- Probability Y is some class (given the network) is equal to e-to-the-power of the 'score' for that class divided by the sum of each other 'score' to the other classes, raised by e

- We are essentially computing a probability distribution over our classes

- Therefore the loss can be seen as the ***negative log likelihood of the correct class***

In Math:

$$L_i = -\log P(Y = y_i \mid X = x_i)$$

$$L_i = -\log\left(\frac{e^{y_i}}{\sum_j e^{s_j}}\right)$$

Loss = -log(**Probability of true class**)

(Consider –log(**1**))

Loss functions – Softmax

$$P(Y = k \mid X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}} \qquad \text{Thus } L_i = -\log\left(\frac{e^{s_{y_i}}}{\sum_j e^{s_j}}\right)$$

- Probability Y is some class (given the network) is equal to e-to-the-power of the 'score' for that class divided by the sum of each other 'score' to the other classes, raised by e

'Score'
3.2
5.1
-1.7

→

Raise e
24.5
164.0
0.18

$e^{3.2} = 24.5$

→

Divide
0.13
0.87
0.00095

$\frac{24.5}{(24.5 + 164 + 0.18)} = 0.13$

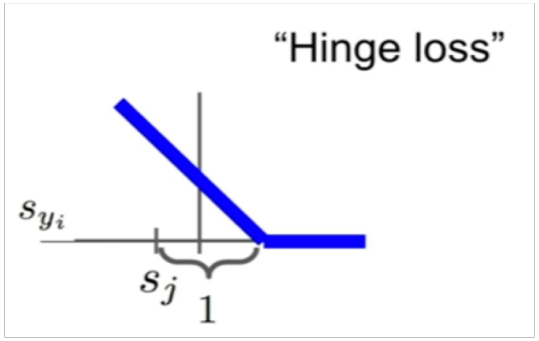
→

Loss
0.89
0.06
6.96

$-\log(0.13) = 0.89$

Loss functions – Other

- Hinge loss (Multi-class SVM)



- Regression (MSE, MAE, RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}}$$

Others

https://towardsdatascience.com/common-loss-functions-in-machine-learning-46af0ffc4d23

OVERVIEW OF TODAY

Schedule:

> Review of last week

> A bit more (maths) from last week

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> Introduction to Tensorflow **& Keras**

OPTIMISATION: (MINI)BATCH, STOCHASTIC GD

- The problem: If we have many training examples, our input matrix becomes huge!
  - Consider X where we have 5 or 10 or 15 million examples….

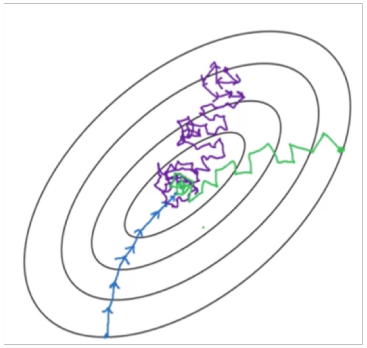
$$X = \begin{bmatrix} | & | & | & | & | \\ x_1 & x_2 & x_3 & x_4 & \dots & x_n \\ | & | & | & | & | \end{bmatrix}$$

  - A solution is to undertake **minibatch** gradient descent, so splitting our dataset into size of 256 samples, our cost function becomes:
    - $J^{\{t\}}(w, b) = \frac{1}{256} \sum_{i=1}^{256} L\left(\widehat{Y^{(i)}}, y^{(i)}\right)$
      - **Where {t}** is our minibatch
  - Simply loop through all minibatches, forward-backprop as normal
  - One round (minibatch) is considered an **epoch**

OPTIMISATION: (MINI)BATCH, STOCHASTIC GD

- If you have:
  - minibatch size is **m** then you have **batch** gradient descent. This can take huge processing power, though will step and converge nicely.
  - Minibatch size is **1** then you have **stochastic** gradient descent. You lose the vectorisation speedup and is quite noisy.
  - If minibatch size is **>1<m** then you have **minibatch** gradient descent

- Common minibatch sizes are 64, 128, 256, 512
  - Technically also a hyperparameter (though not a primary one)



OPTIMISATION ALGORITHMS: MOMENTUM

- Consider the formula for and exponentially weighted moving averages:
  - $V_t = \beta V_{t-1} + (1-\beta)x_t$ where $\beta \in [0,1]$ and x_t is some value at the current time.
    - We can approximate that V_t is averaging over $\frac{1}{1-\beta}$ days
- We are computing an average that takes into account **n** number of trailing days. Consider **0.9** for β
  - V_{100} = $\mathbf{0.9}V_{99} + (1-\mathbf{0.9})\, x_{100}$
    - V_{99} itself = $\mathbf{0.9}V_{98}$ and $(1-\mathbf{0.9})x_{99}$ etc
- Therefore V_{100} is a small weight $(0.1)\, x_{100}$ of the current value and a **sum of all previous temperatures**
  - multiplied by an **exponentially decaying function**
    - So $0.1x_{100} + 0.1 * 0.9x_{99} + 0.1 * (0.9)^2 x_{98}$…etc

OPTIMISATION ALGORITHMS: MOMENTUM

- (From source)
- Adjust β to be lower, you get a more noisy graph as you let local effects be more powerful.
- Larger β smooths more but will respond slower.

OPTIMISATION ALGORITHMS: MOMENTUM

- How does this work for us?
  - Initialise $V_{dW}, V_{db} = 0$ where V_{dW} is the same dimensions as W and V_{db} has same dimensions as b
- On iteration t:
  - Compute dW, db as usual on the current mini-batch
  - $V_{dW} = \beta V_{dW} + (1 - \beta) dW$
  - $V_{db} = \beta V_{db} + (1 - \beta) db$
  - Update:
    - $W := W - \alpha * V_{dW}$
    - $b := b - \alpha * V_{db}$

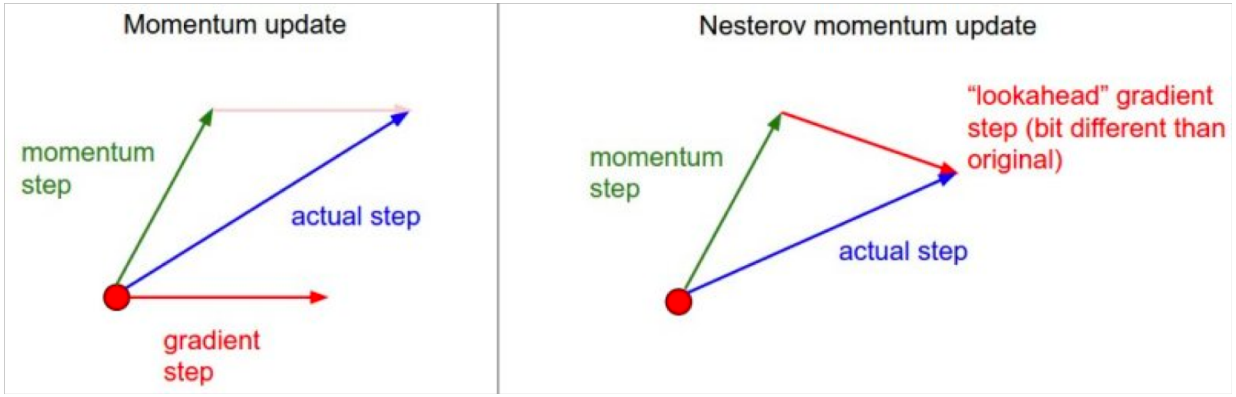
Best β?

Commonly 0.9 is used ('Averaging over the last 10 gradients' β) but perhaps try others?

- An extension to this (nesterov momentum) does a 'step forward backwards' alteration (often oversteps)

OPTIMISATION ALGORITHMS: NESTEROV

- An extension to momentum does a ‘step forward backwards’ alteration (often oversteps) (source in notes)
- Rather than taking a weighted average of Velocity and Gradient (at current point) to make our actual step, we instead:
  - Step in direction of velocity
  - Take gradient at that point
  - Go back to original point and mix together these two for the actual step.

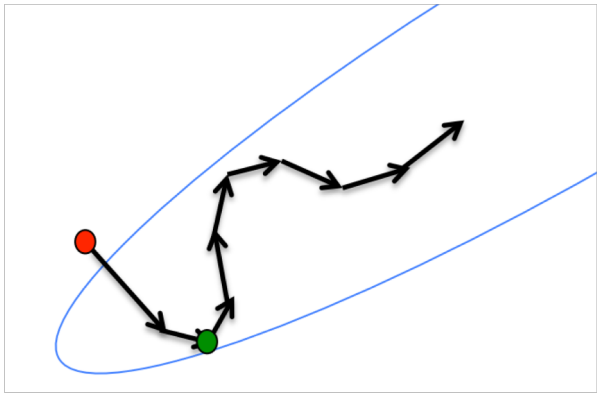


OPTIMISATION ALGORITHMS: RMSPROP

- Source (Hinton on coursera…)
- Stands for 'Root Mean Squared' Prop
  - Initialise $S_{dW}, S_{db} = 0$
- On iteration t:
  - Compute dW, db as usual on the current mini-batch
  - $S_{dW} = \beta S_{dW} + (1-\beta) dW^2$
  - $S_{db} = \beta S_{db} + (1-\beta) db^2$
  - Update:
    - $W := W - \alpha * \frac{dW}{\sqrt{S_{dW} + \varepsilon}}$
    - $b := b - \alpha * \frac{db}{\sqrt{S_{db} + \varepsilon}}$

Why?

This keeps a moving average of the squared gradient of each weight. This should 'squash' high oscillating training run.



OPTIMISATION ALGORITHMS: ADAM

- 'Adaptive Moment Estimation' (Momentum + RMSProp)
  - β_m (momentum β) as first 'moment' and β_r (rmsprop β) as second 'moment'
  - Initialise $S_{dW}, S_{db}, V_{dW}, V_{db} = 0$
- On iteration t:
  - Compute dW, db as usual on the current mini-batch
  - $V_{dW} = \beta_m V_{dW} + (1-\beta_m)dW$ & $V_{db} = \beta_m V_{db} + (1-\beta_m)db$
    - Add a bias correction ${V_{dW}}^c = \frac{V_{dW}}{1-{\beta_m}^t}$ & ${V_{db}}^c = \frac{V_{db}}{1-{\beta_m}^t}$
  - $S_{dW} = \beta_r S_{dW} + (1-\beta_r)dW^2$ & $S_{db} = \beta_r S_{db} + (1-\beta_r)db^2$
    - Add a bias correction ${S_{dW}}^c = \frac{S_{dW}}{1-{\beta_r}^t}$ & ${S_{db}}^c = \frac{S_{db}}{1-{\beta_r}^t}$
  - Update:
    - $W := W - \alpha * \frac{{V_{dW}}^c}{\sqrt{{S_{dW}}^c + \varepsilon}}$
    - $b := b - \alpha * \frac{{V_{db}}^c}{\sqrt{{S_{db}}^c + \varepsilon}}$

Commonly:

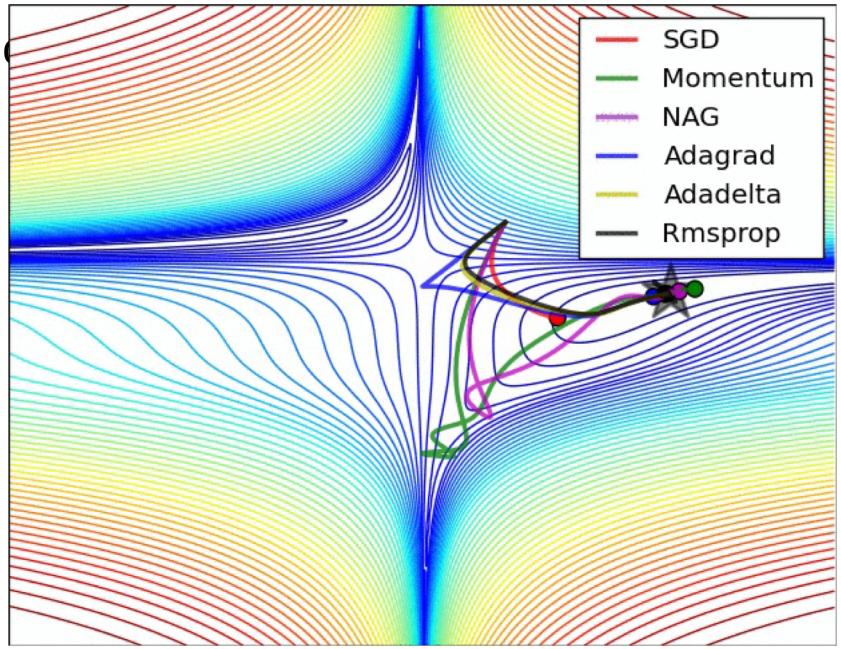
- β_m = 0.9
- β_r = 0.999
- α (start) 1e-3 or 5e-4

Why bias correct?

Moments are biased towards zero during initial time steps (especially with small β)

OPTIMISATION ALGORITHMS: MORE??

- ‘Nesterov-accelerated Adaptive Moment Estimation’ (Nesterov momentum + Adam) (source) (NADAM)
- Even more????
  - https://arxiv.org/pdf/1609.04747.pdf
  - Adagrad, Ada



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REGULARISATION: L2 (WEIGHT DECAY)

- L2 regularization can be used in neural networks as well. We add a small penalty term to our loss function which becomes a hyperparameter to tune.

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

$$\text{Where } \left\|w^{[l]}\right\|_F^2 = \sum_{i=1}^{n^{[l-1]}} \sum_{j=1}^{n^{[l]}} (w_{ij})^2$$

- That is, for each weight matrix in the NN we simply add the square of each element in those matrices.
- Note the F rather than 2 since this is called the Frobenius Norm rather than L2 norm for matrices.
- This ‘zeros out’ some hidden units with smaller weights

REGULARISATION: L2 & BACK PROP

- We will need to adjust our backprop formulas slightly:

$$dw^{[l]} = \frac{1}{m} dZ^{[l]} A^{[l-1]T} + \boldsymbol{\frac{\lambda}{m} w^{[l]}}$$

Therefore our update step can remain the same as:

$$w^{[l]} := w^{[l]} - \alpha * dw$$

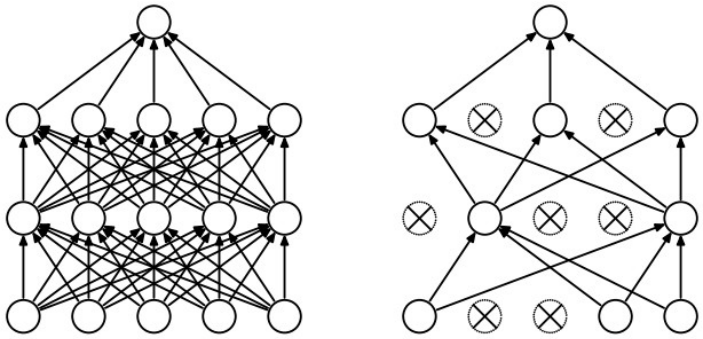
Or expanding is:

- $w^{[l]} := w^{[l]} - \alpha * \left(\frac{1}{m} dZ^{[l]} A^{[l-1]T}\right) \boldsymbol{- \alpha * (\frac{\lambda}{m} w^{[l]})}$
- Rearranging: $w^{[l]} := \boldsymbol{w^{[l]} - \alpha * (\frac{\lambda}{m} w^{[l]})} - \alpha * \left(\frac{1}{m} dZ^{[l]} A^{[l-1]T}\right)$
- Rearranging the first part : $\boldsymbol{w^{[l]}(1 - \frac{\alpha\lambda}{m})}$

See how we are 'decaying' the weight matrix?

REGULARISATION: DROPOUT

- (Source, Srivastava et al, 2014) Or (Source Hinton, Srivastava et all 2012) Or (Source Farley, Goodfellow et al 2014)
- We will need to adjust our backprop formulas slightly:
- On each forward pass (Training example), randomly set some neurons to zero So remove all the ingoing and outgoing links to that node
- The probability of dropping is a hyperparameter, p
    - You could also set this differently depending on the layer. So perhaps your last 1 or 2 layers don't need dropout if they are (n=2) or (n=3) but for more dense layers in the middle you set a higher p.

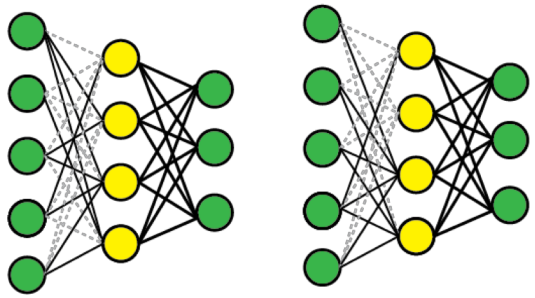


(a) Standard Neural Net (b) After applying dropout.

REGULARISATION: DROPOUT

REGULARISATION: DROPOUT

- Why does it work?
  - Forces the network to have ***redundant representation***
  - Can theoretically show it is a version of L2
- A **Problem**:
  - Our output is random and may take longer to train.
- A **Solution** ('Inverted Dropout'):
  - At training time, divide by P so that at test time there is no difference.
  - For example, if we have a 50 unit layer and drop (0.2 = 10 units), we scale the output (A) by (A/0.8)
  - Some nice code here
- There is also 'DropConnect' (a generalization of dropout where you zero out some of the weight matrix)



EXTRA: LEARNING RATE DECAY

- This technique can speed up training and prevent the 'bounce' around as the model converges towards an optimum.
- We can thus implement **standard learning rate decay** as follows:

$$\boldsymbol{\alpha = \frac{1}{1 + d * n} * \alpha_0}$$

- Where d is the decay rate and n is the epoch number
- Other variations:
  - Exponential decay: $\alpha = 0.95^n * \alpha_0$
  - K decay: $\alpha = \frac{k}{\sqrt{n}} * \alpha_0$ OR $\alpha = \frac{k}{t} * \alpha_0$ where t is minibatch number
  - Discrete ('staircase'/ 'half-life') decay = half α at certain t's
  - Manual

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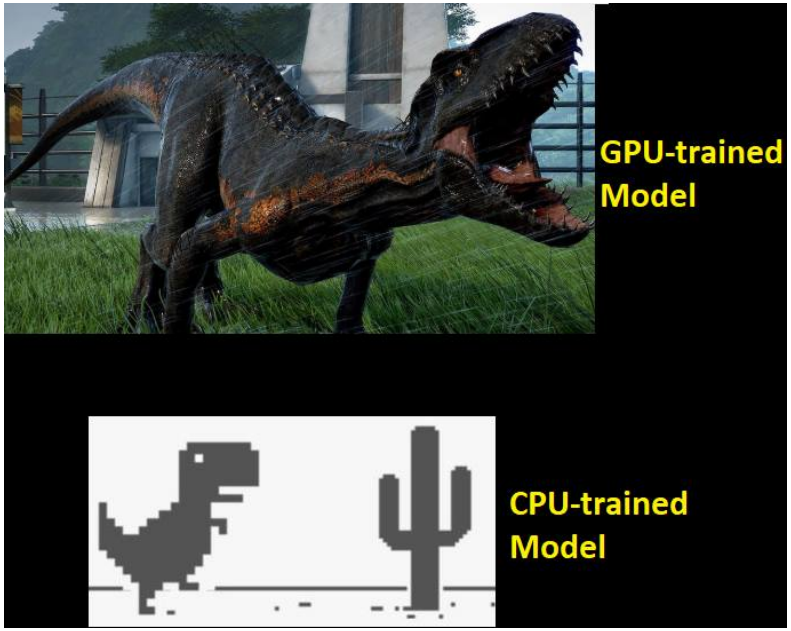
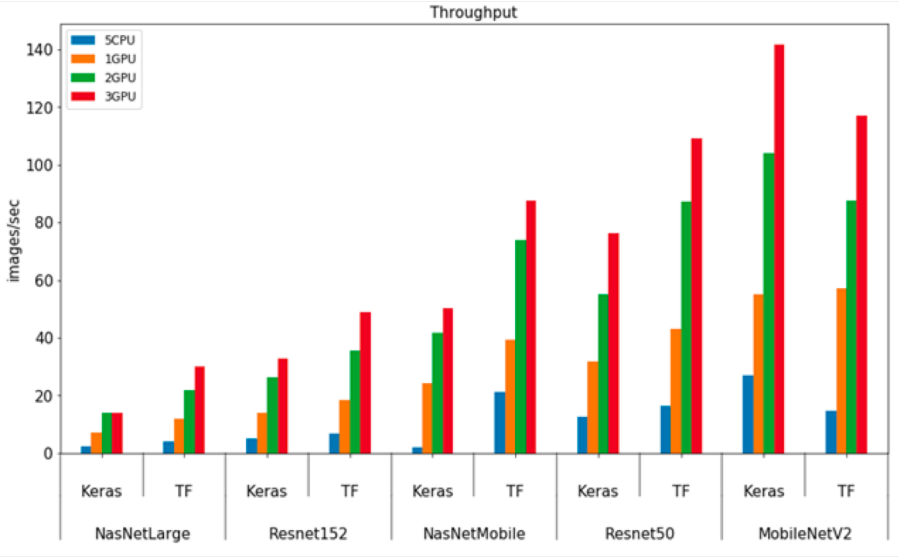
GPU - CPU – TPU?

- CPUs are a few very complex cores (General processing core)
- GPUs are hundreds/thousands of simpler cores (can run thousands of concurrent threads)
  - Uses parallel processing of the matrix work in NN
  - (NVIDIA GPU required for CUDA)
- TPU is a special custom build by Google specifically for deep learning.





GPU - CPU – TPU?

CPU vs GPU

	# Cores	Clock Speed	Memory	Price
CPU (Intel Core i7-7700k)	4 (8 threads with hyperthreading)	4.4 GHz	Shared with system	$339
CPU (Intel Core i7-6950X)	10 (20 threads with hyperthreading)	3.5 GHz	Shared with system	$1723
GPU (NVIDIA Titan Xp)	3840	1.6 GHz	12 GB GDDR5X	$1200
GPU (NVIDIA GTX 1070)	1920	1.68 GHz	8 GB GDDR5	$399

CPU: Fewer cores, but each core is much faster and much more capable; great at sequential tasks

GPU: More cores, but each core is much slower and "dumber"; great for parallel tasks

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture8.pdf

WHAT'S IN A FRAMEWORK?

- Tensorflow the most popular and has all the bells and whistles
- Keras is 'syntactic sugar' (a wrapper) for tensorflow.
- Caffe2 not used as much (from facebook)
- Pytorch recently becoming more popular. Very fast.
- Others (not as popular):
  - CNTK (Microsoft), MXNet (Amazon)

https://www.youtube.com/watch?v=SJldOOs4vB8

LAB – TENSORFLOW **& KERAS**