DL week2

Hello!

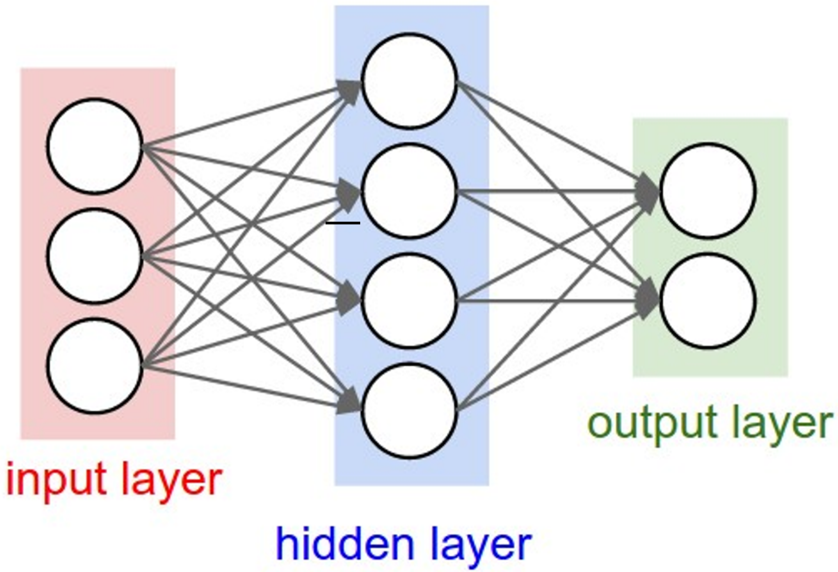
I am Maria Tikhonova

Graduated from Mech-Math MSU & YSDA

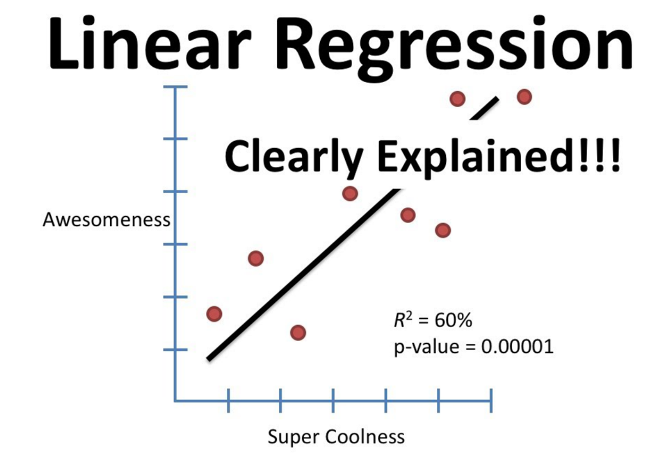
Work in R’n’D NLP team in SBER DEVICES

Teach in

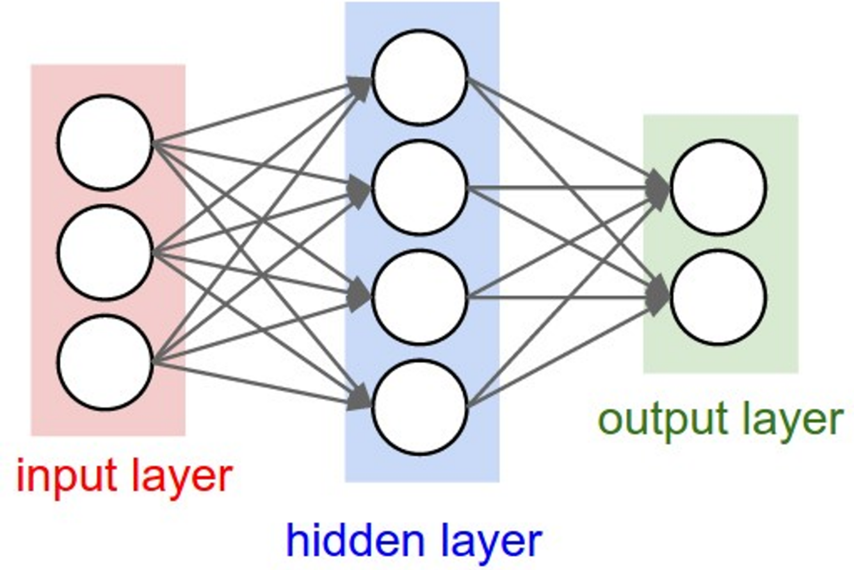
simple **deep** NN



LR vs 1-FC layer net



vs.

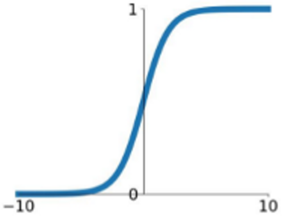


Which is better? Why?

Activation functions

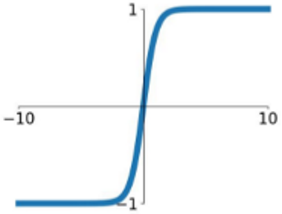
Sigmoid

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



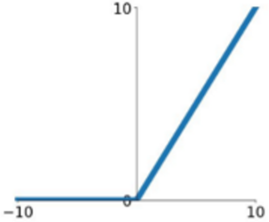
tanh

$\tanh(x)$



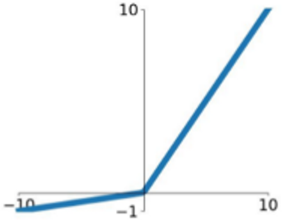
ReLU

$\max(0, x)$



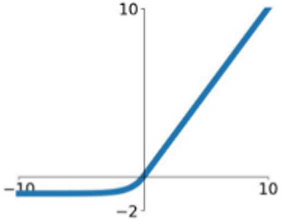
Leaky ReLU

$\max(0.1x, x)$

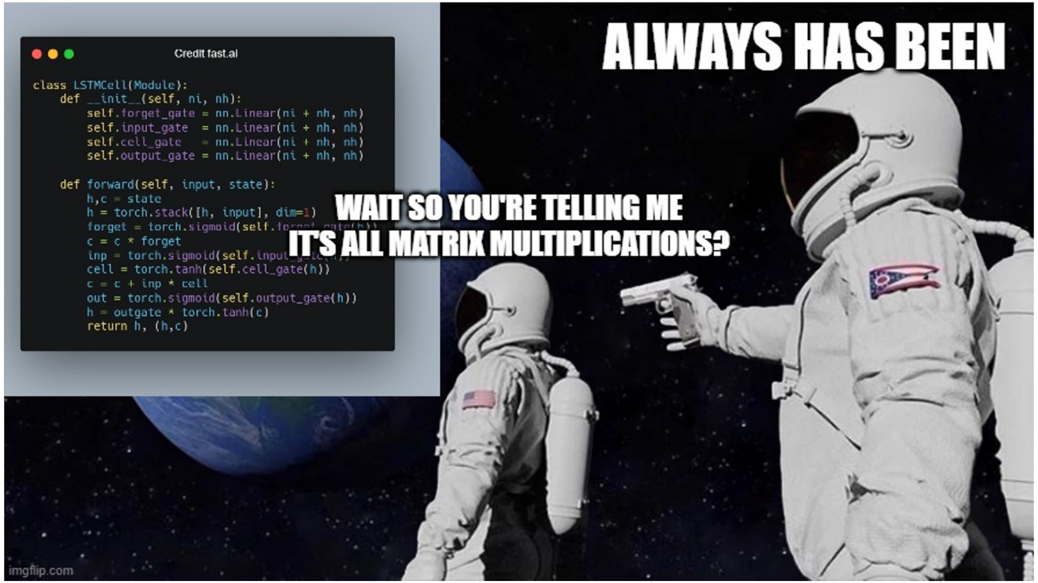


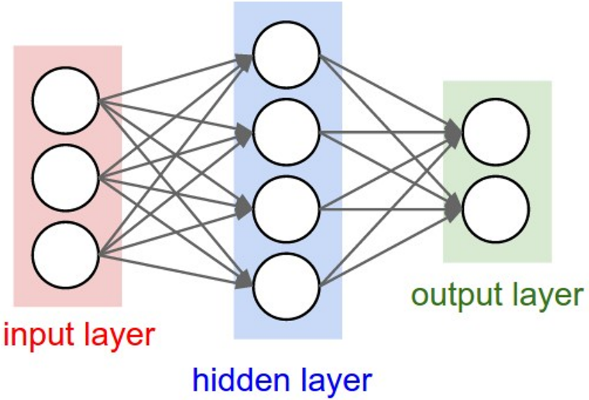
ELU

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



FC layer matrix form

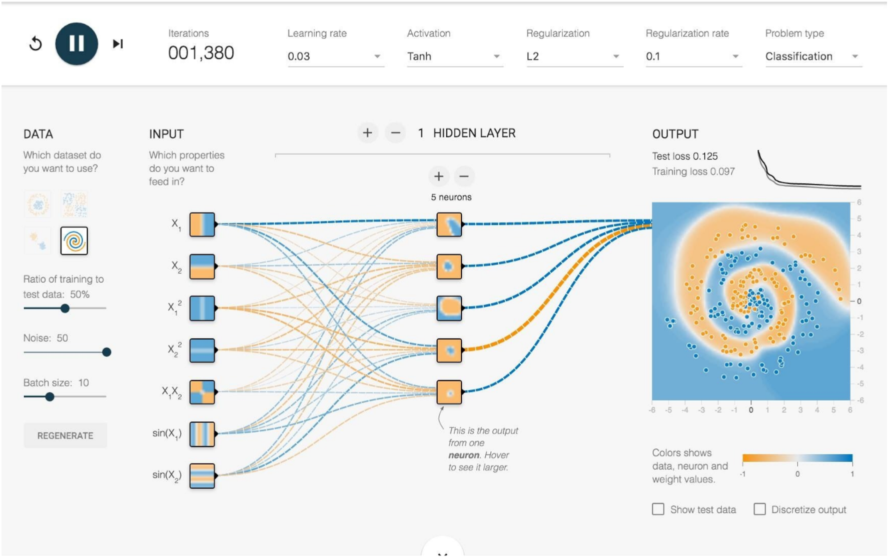


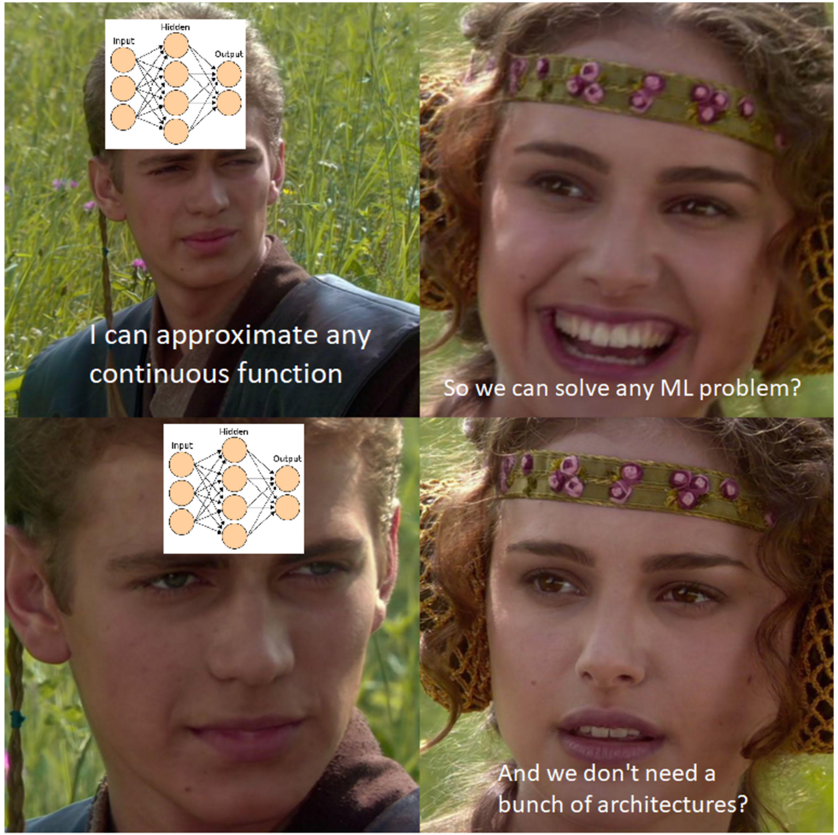


$$Y = X * W + b$$

Universal approximation theorem

In simple words: *the universal approximation theorem says that neural networks can approximate any continuous function.*





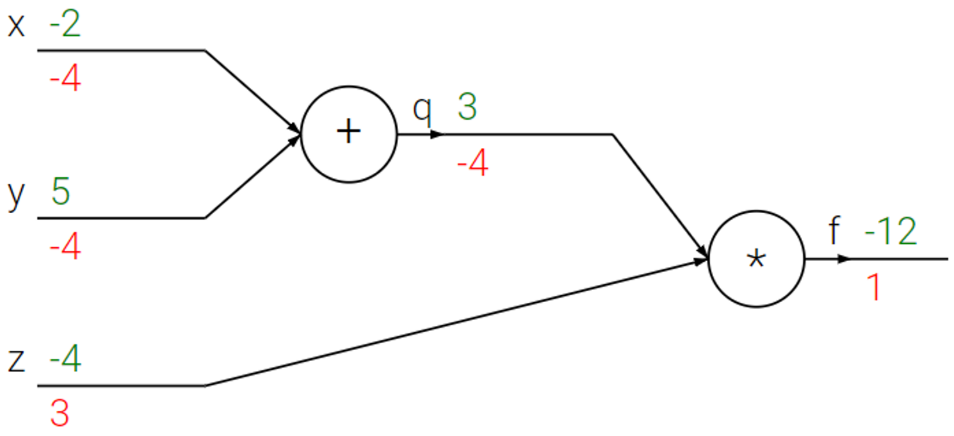
Backprop Basics and Chain Rule

$$f(x, y, z) = (x + y)z.$$

$q = x + y$ and $f = qz.$

chain rule $$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial x}.$$

Forward and Backward Pass



https://cs231n.github.io/optimization-2/

Backprop Basics and total derivative

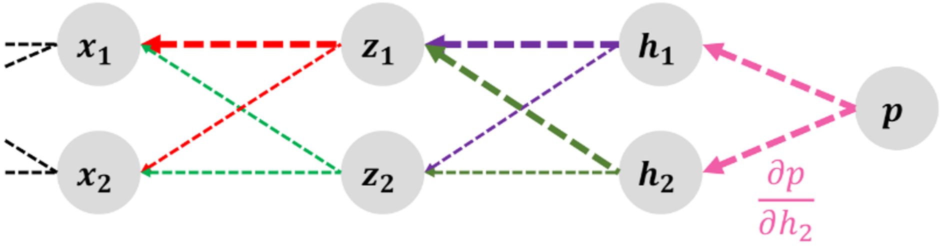
3: $\frac{\partial p}{\partial h_1}$ $\frac{\partial p}{\partial h_2}$

2: $\frac{\partial p}{\partial z_1} = \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_1} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_1}$ $\frac{\partial p}{\partial z_2} = \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_2} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_2}$

1:

$$\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_1}\frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_1}\frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_2}\frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_2}\frac{\partial z_2}{\partial x_1}$$

$$\frac{\partial p}{\partial x_2} = \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_1}\frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_1}\frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_2}\frac{\partial z_2}{\partial x_2} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_2}\frac{\partial z_2}{\partial x_2}$$



$$\frac{dL}{dt} = \frac{d}{dt}L\big(t, x_1(t), \ldots, x_n(t)\big).$$

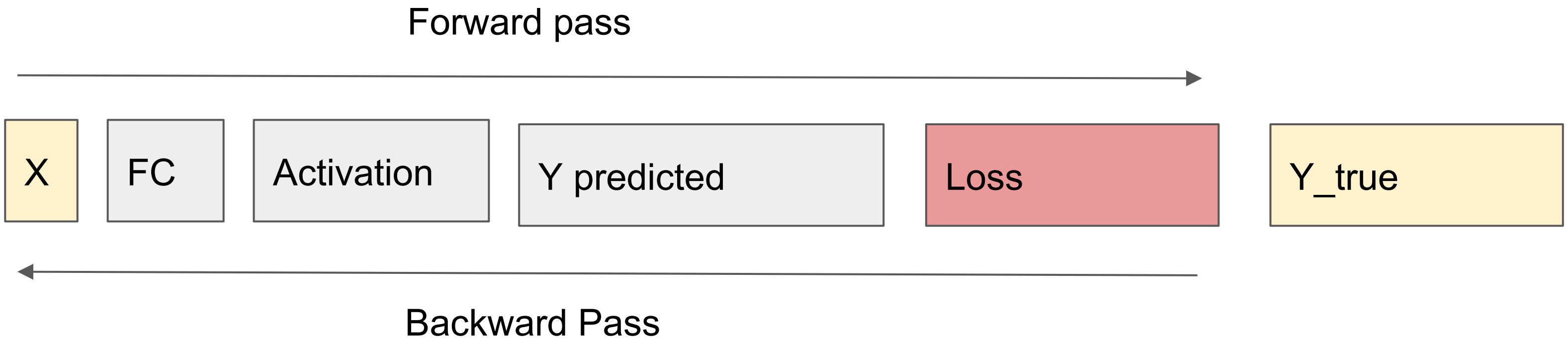
$$\frac{dL}{dt} = \frac{\partial L}{\partial t} + \sum_{i=1}^{n} \frac{\partial L}{\partial x_i}\frac{dx_i}{dt}$$

https://github.com/hse-ds/iad-deep-learning/blob/master/2021/lectures/lecture02-convnets.pdf

Backprop Basics: Simple FC net in matrix form

FC = X * W1 + b1
Activation = your_activation_function(FC)
Y_predicted = Activation * W2 + b2

X [batch size, features]
W [features, outputs]
b [outputs]

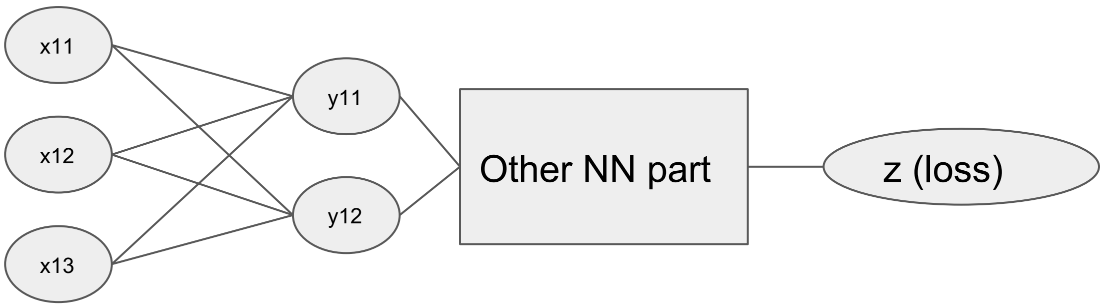


$$\frac{\partial Loss}{\partial W1} = \frac{\partial Loss}{\partial Y predicted} * \frac{\partial Y predicted}{\partial Activation} * \frac{\partial Activation}{\partial W1}$$

$$\frac{\partial Loss(X * W + b))}{\partial X} = \frac{\partial Loss}{\partial X * W + b} * W^T$$ [batch size, features]

$$\frac{\partial Loss(X * W + b))}{\partial W} = X^T * \frac{\partial Loss}{\partial X * W + b}$$ [batch size, outputs]

Backprop Basics: Simple FC net in matrix form



$$\begin{pmatrix} y_{11} \\ y_{12} \end{pmatrix} = \begin{pmatrix} x_{11} & x_{12} & x_{13} \end{pmatrix} \begin{pmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \end{pmatrix} = \begin{pmatrix} w_{11}x_{11} + w_{21}x_{12} + w_{31}x_{13} \\ w_{12}x_{11} + w_{22}x_{12} + w_{32}x_{13} \end{pmatrix}^T$$

$$\frac{dz}{dx_{11}} = \frac{dz}{dy_{11}} * \frac{dy_{11}}{dx_{11}} + \frac{dz}{dy_{12}} * \frac{dy_{12}}{dx_{11}} = \frac{dz}{dy_{11}} * w_{11} + \frac{dz}{dy_{12}} * w_{12}$$

$$\frac{dz}{dw_{11}} = \sum_j \frac{dz}{dy_{j1}} * \frac{dy_{j1}}{dw_{11}} = \sum_j \frac{dz}{dy_{j1}} * x_{j1}$$

$$\frac{\partial Loss(X * W + b))}{\partial X} = \frac{\partial Loss}{\partial X * W + b} * W^T$$

$$\frac{\partial Loss(X * W + b))}{\partial W} = X^T * \frac{\partial Loss}{\partial X * W + b}$$

Now, coding :)

Me
Lin Alg, Stats,
Probability Theory
in FreshmanYear
Me
Graduate Level
Machine Learning