

# 6COSCO20W: APPLIED AI

# WEEK 8: ARTIFICIAL NEURAL NETWORKS (ANNs)

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# **NOTES**

- We will use PollEverywhere multiple times during the lecture: polleverywhere.com/esterbonmati
- It may be useful to have a notebook and pen/pencil (or your preferred method) to take some notes.

Before session: What do you think machine learning is?

# FROM LAST SESSION...

output(s) classifications hard-coded predictions methodsalgorithm's machines k-means science input(s) learning data algorithm know test given Set adapt. algorithm know idealused SOLITANS humans gradually able Learn makes omething method cuses models instead

#### **LEARNING OUTCOMES OF THIS SESSION**

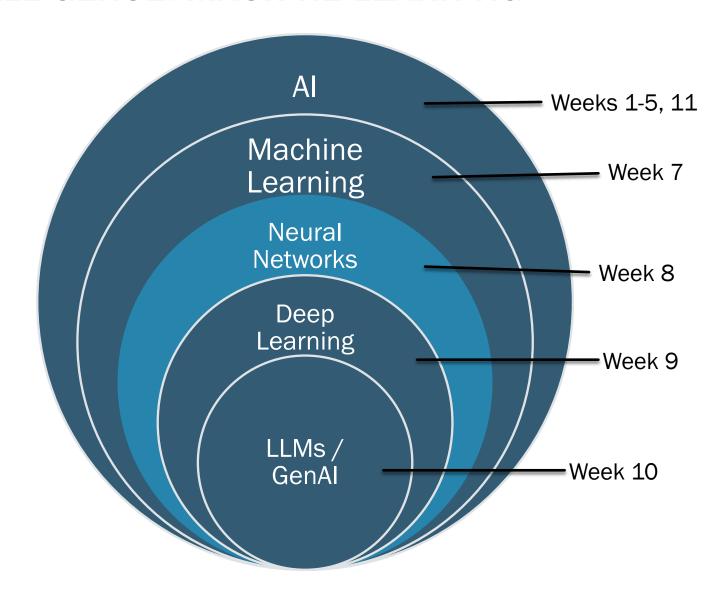
#### **Perceptron**

- Explain the perceptron
- Inputs and outputs
- Weights
- Forward propagation
- Explain what is an activation functions
- Be able to calculate the output of a perceptron

#### **Neural Networks**

- Be able to list the name of the different layers
- Be able to describe how neural networks work in your own words
- Explain problems with data
- Explain what are hyperparameters
- Be able to evaluate performance and calculate accuracy

# **ARTIFICIAL INTELLIGENCE: MACHINE LEARNING**



#### Before: what is an artificial neural network?

pollev.com/esterbonmati

Nobody has responded yet.

Hang tight! Responses are coming in.

# Do you know any examples of applications using a neural network?

pollev.com/esterbonmati

Nobody has responded yet.

Hang tight! Responses are coming in.

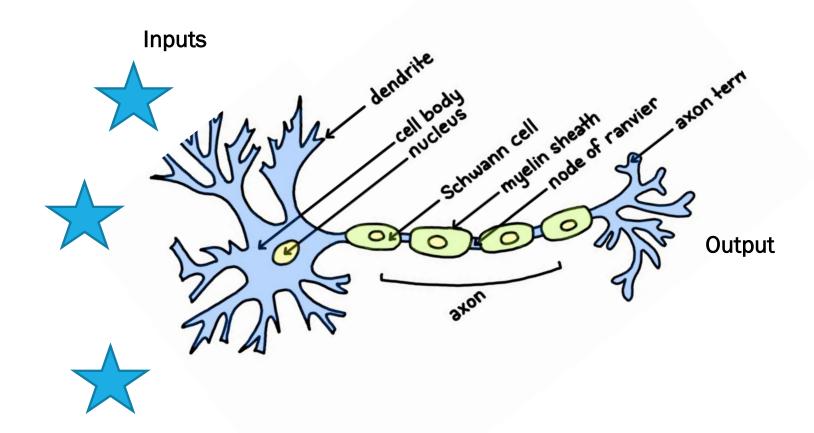
# ARTIFICIAL NEURAL NETWORKS (ANNs)

Why are they important?
ANN can help computers
make intelligent
decisions with limited
human assistance.

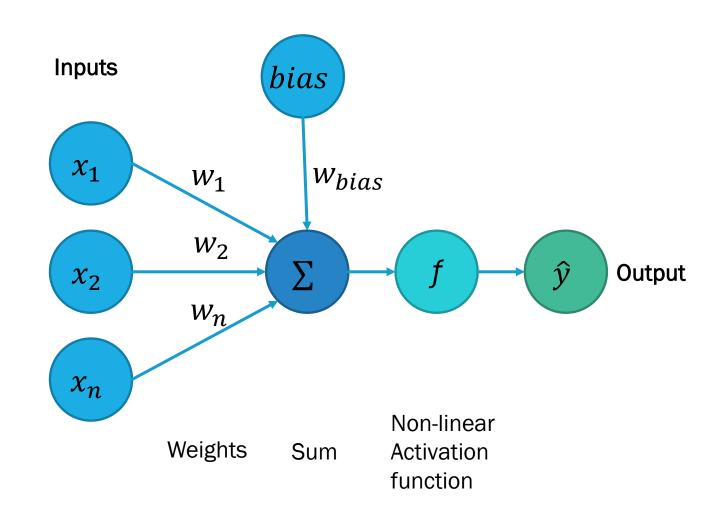
They can learn and model the **relationships** between input and output data that are nonlinear and complex.



# **NEURON**

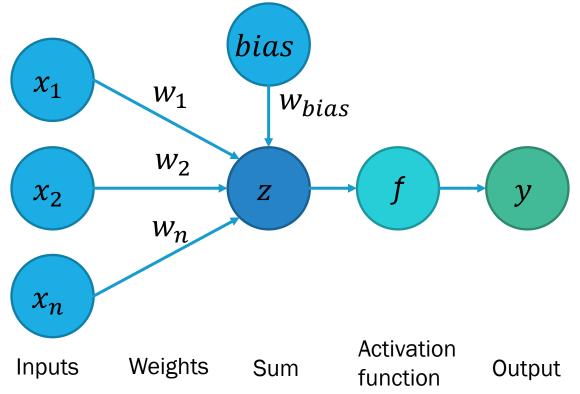


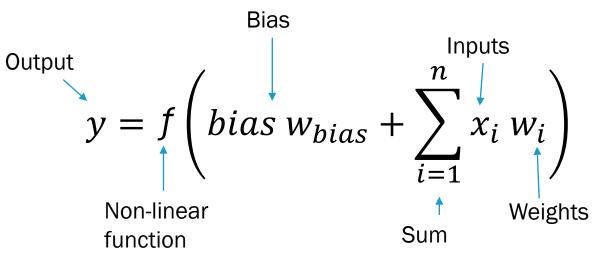
# THE PERCEPTRON



#### THE PERCEPTRON

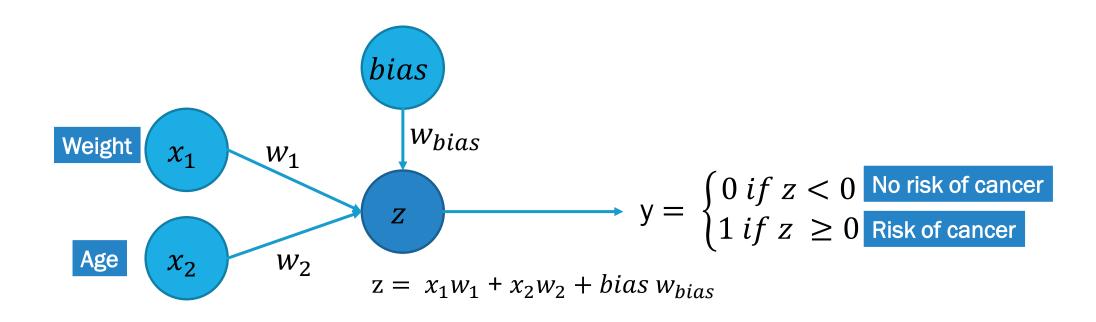
- Building block of neural networks (single neuron)
- Mimics the neuron in the human brain
- Forward propagation (input → neuron → output)





$$z=x_1\ w_1+x_2\ w_2+...+x_n\ w_n+bias\ w_{bias}$$
 
$$y=f(z)$$
 
$$\text{Example: y}=\begin{cases} 0\ if\ z<0\\ 1\ if\ z\geq 0 \end{cases}$$

#### PERCEPTRON: FORWARD PROPAGATION EXAMPLE

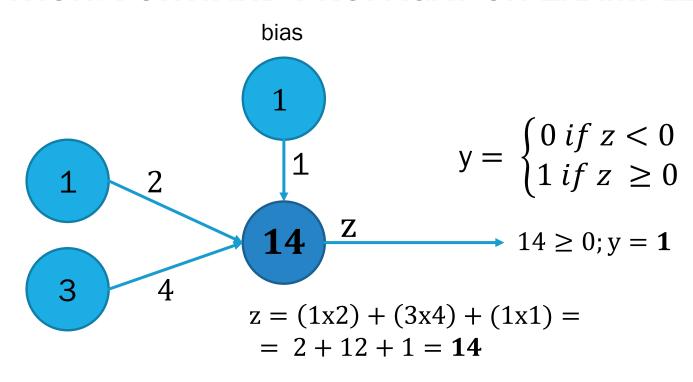


# Do you know another example of a perceptron?

- Logic operations (except XOR)
- Linear seperation
- Predict who is going to pass this module based on the number of lectures and tutorials attended



#### PERCEPTRON: FORWARD PROPAGATION EXAMPLE



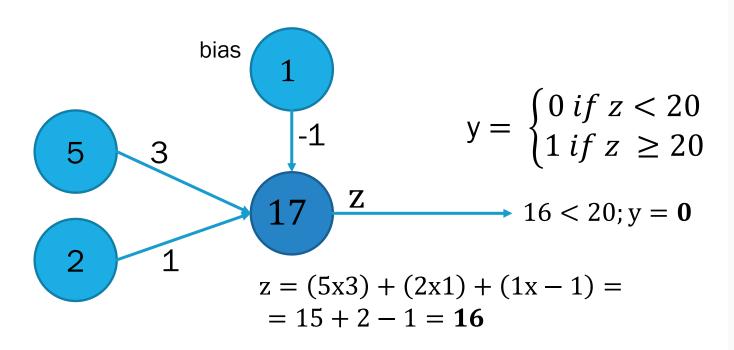








# PERCEPTRON: FEEDBACK





pollev.com/esterbonmati
When poll is PollEv.com active respond

/esterbonma



#### Result perceptron 1

Nobody has responded yet.

Hang tight! Responses are coming in.

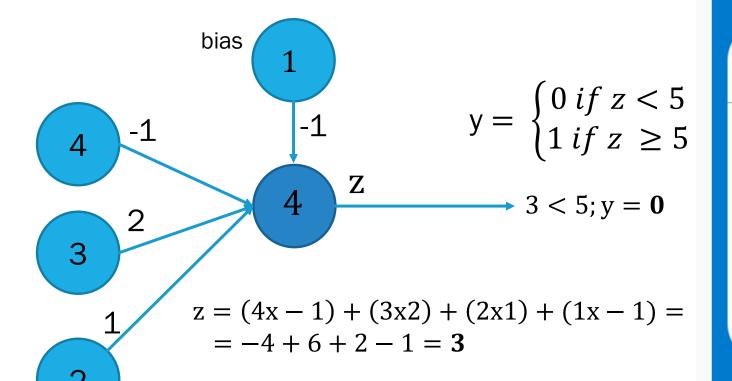








# **PERCEPTRON: FEEDBACK**





# pollev.com/esterbonmati When poll is PollEv.com

active respond

PollEv.com /esterbonmat



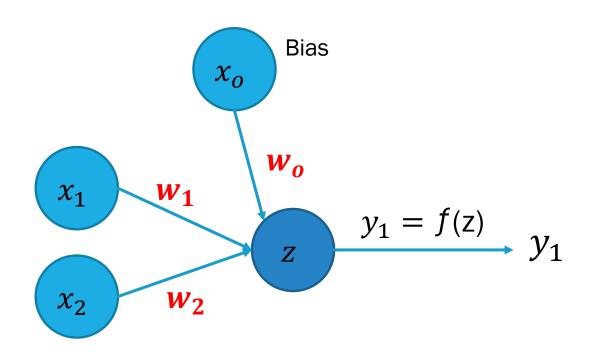
#### Results perceptron 2

Nobody has responded yet.

Hang tight! Responses are coming in.

#### PERCEPTRON: HOW DO WE FIND THE WEIGHTS?

Problem: we want to train a perceptron to classify points in 2 classes.

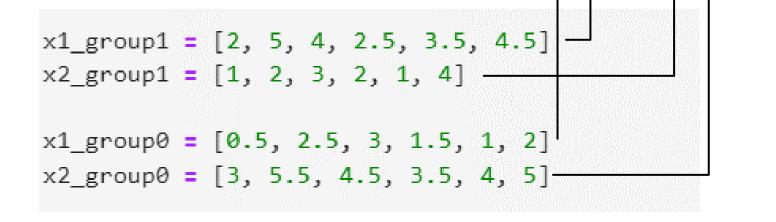


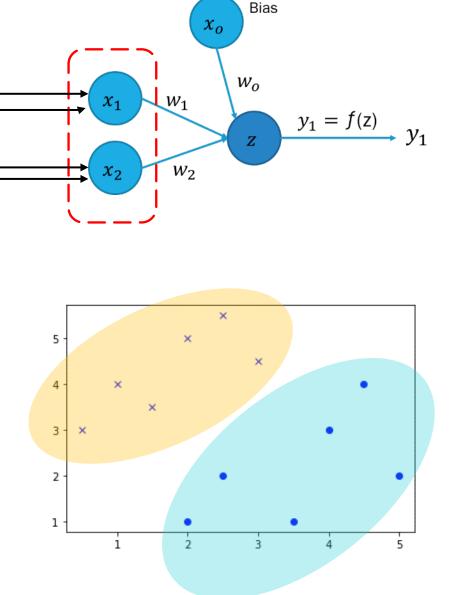
How do we find the weights to classify the points?

$$z = x_1 w_1 + x_2 w_2 + x_0 w_0$$

# **PERCEPTRON: INPUT DEFINITION**

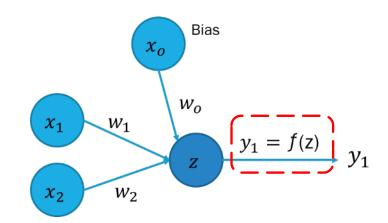
<u>Problem</u>: We have 2 groups of samples, each of them defined by 2 values, and we want to use a perceptron to classify them into their group.





#### PERCEPTRON: ACTIVATION FUNCTION

$$y = \begin{cases} -1 & \text{if } z \le 0 \\ 1 & \text{if } z > 0 \end{cases}$$

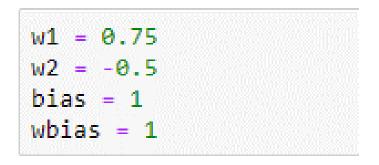


If the sum is is greater than 0 we return 1, otherwise we return 0

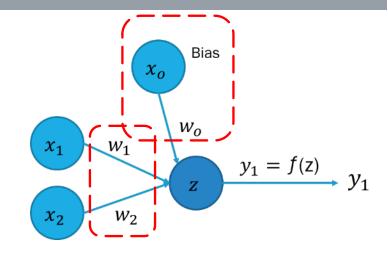
```
In [112]: def activation_function(value):
    if value > 0: return 1
    else: return -1
```

# PERCEPTRON: WEIGHTS AND BIAS DEFINITION

Some random weights...



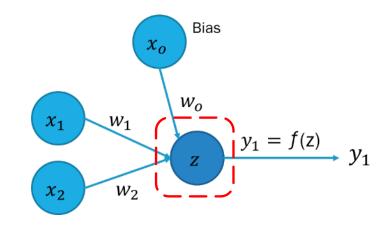
How good are these weights in grouping the input data?



#### PERCEPTRON: FORWARD PROPAGATION

We need to find z in order to calculate the output y ...

```
def perceptron(x1, x2, bias):
   z = x1*w1 + x2*w2 + bias*wbias
   return z
```



Then we can calculate the output y using the perceptron and the activation function:

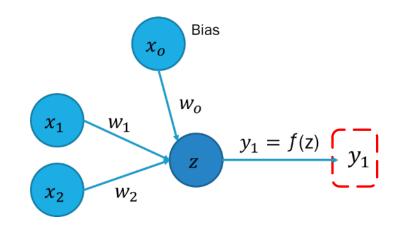
```
for i in range(len(x1_group0)):
    z = perceptron(x1_group0[i], x2_group0[i], bias)
    group = activation_function(z)
    print('Point ' + str(i) + ' in group 0 returned ' + str(group))
```

#### PERCEPTRON: PREDICTION AND RESULTS

We calculate the output for each group, so we know which is the prediction:

```
group = activation_function(2)
print('Point ' + str(i) + ' in group 1 returned ' + str(group))

for i in range(len(x1_group0)):
    z = perceptron(x1_group0[i], x2_group0[i], bias)
    group = activation_function(z)
    print('Point ' + str(i) + ' in group 0 returned ' + str(group))
```



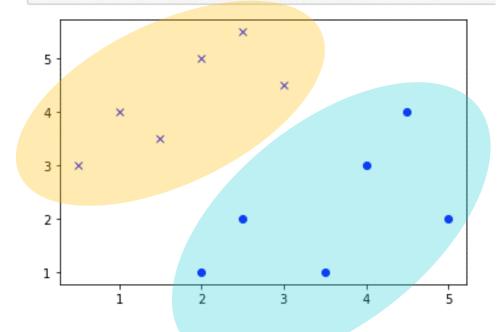
$$accuracy = \frac{number\ correct\ samples}{total\ number\ of\ samples} = \frac{9}{12} = 0.75 \rightarrow 75\ \%$$

Can we improve the accuracy if we change the weights?

# **PERCEPTRON: VISUALISATION**

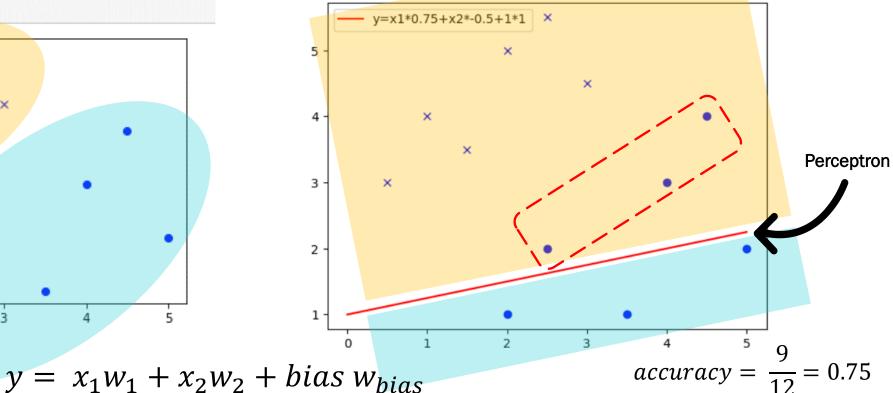
#### Plot the points

```
In [117]: fig = plt.figure()
    ax = plt.axes()
    plt.plot(x1_group1, x2_group1, 'ob')
    plt.plot(x1_group0, x2_group0, 'xb')
    plt.show()
```



```
[7]: x1 = np.linspace(0,5,100)
    x2 = np.linspace(0,5,100)
    y_1 = w1*x1 + w2*x2 + 1

plt.plot(x1_group1, x2_group1, 'ob')
    plt.plot(x1_group0, x2_group0, 'xb')
    plt.plot(x1, y_1, '-r', label='y=x1*0.75+x2*-0.5+1*1')
    plt.legend(loc='upper left')
    plt.show()
```



# **PERCEPTRON: UPDATE WEIGHTS**

To change the prediction output, we need to change the weights

```
In [102]: w1 = 1
    w2 = 1
    bias = 1

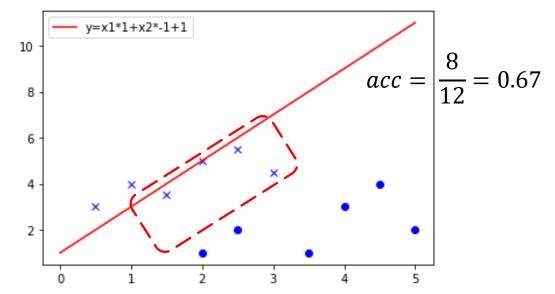
y_1 = w1*x1 + w2*x2 + bias*wbias

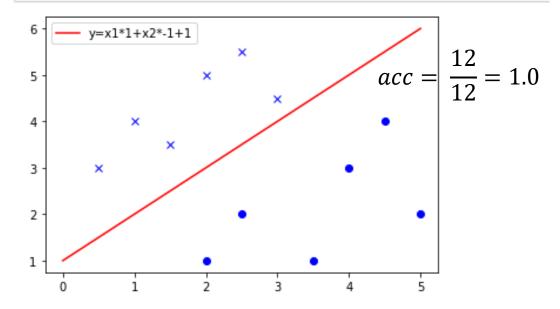
plt.plot(x1_group1, x2_group1, 'ob')
    plt.plot(x1_group0, x2_group0, 'xb')
    plt.plot(x1, y_1, '-r', label='y=x1*1+x2*1+1*1')
    plt.legend(loc='upper left')
    plt.show()
```

```
In [103]: w1 = 3
    w2 = -2
    bias = 1
    wbias = -1

y_1 = x1*w1 + x2*w2 + bias*bias

plt.plot(x1_group1, x2_group1, 'ob')
    plt.plot(x1_group0, x2_group0, 'xb')
    plt.plot(x1, y_1, '-r', label='y=x1*3+x2*-2+1*-1')
    plt.legend(loc='upper left')
    plt.show()
```

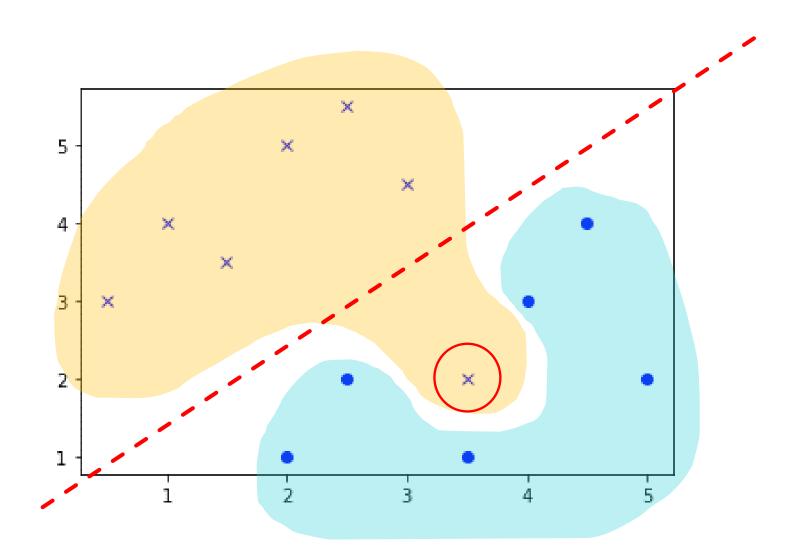




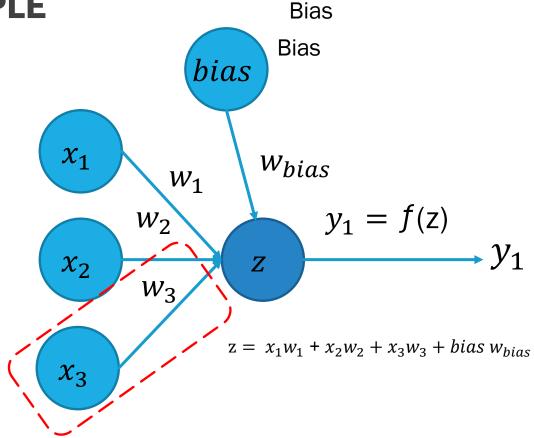
#### PERCEPTRON: NEW PREDICTION

```
In [104]: for i in range(len(x1 group1)):
               sum = perceptron(x1 group1[i], x2 group1[i], bias)
               group = activation function(sum)
               print('Point ' + str(i) + ' in group 1 returned ' + str(group))
           for i in range(len(x1 group0)):
               sum = perceptron(x1_group0[i], x2_group0[i], bias)
               group = activation function(sum)
               print('Point ' + str(i) + ' in group 0 returned ' + str(group))
          Point 0 in group 1 returned 1
          Point 1 in group 1 returned 1
          Point 2 in group 1 returned 1
          Point 3 in group 1 returned 1
                                                               acc = \frac{12}{12} = 1.0 \rightarrow 100 \%
          Point 4 in group 1 returned 1
          Point 5 in group 1 returned 1
          Point 0 in group 0 returned -1
          Point 1 in group 0 returned -1
          Point 2 in group 0 returned -1
          Point 3 in group 0 returned -1
          Point 4 in group 0 returned -1
          Point 5 in group 0 returned -1
```

# **NEURAL NETWORKS: ANOTHER EXAMPLE**

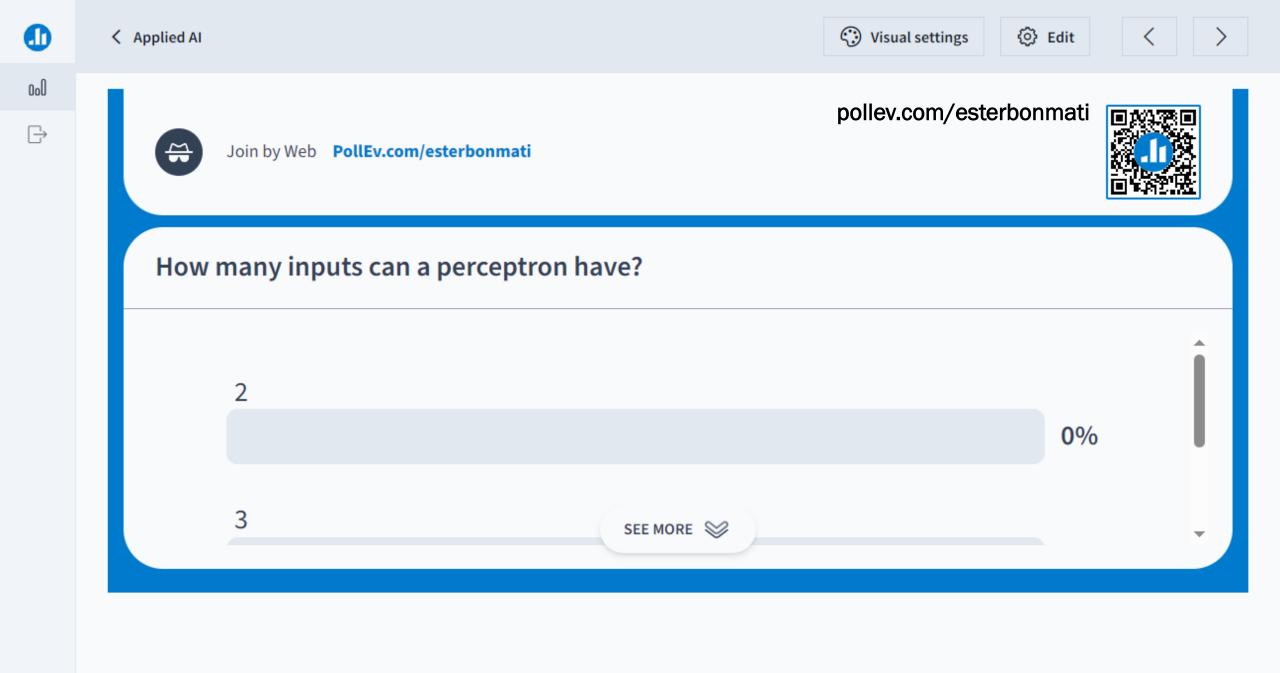


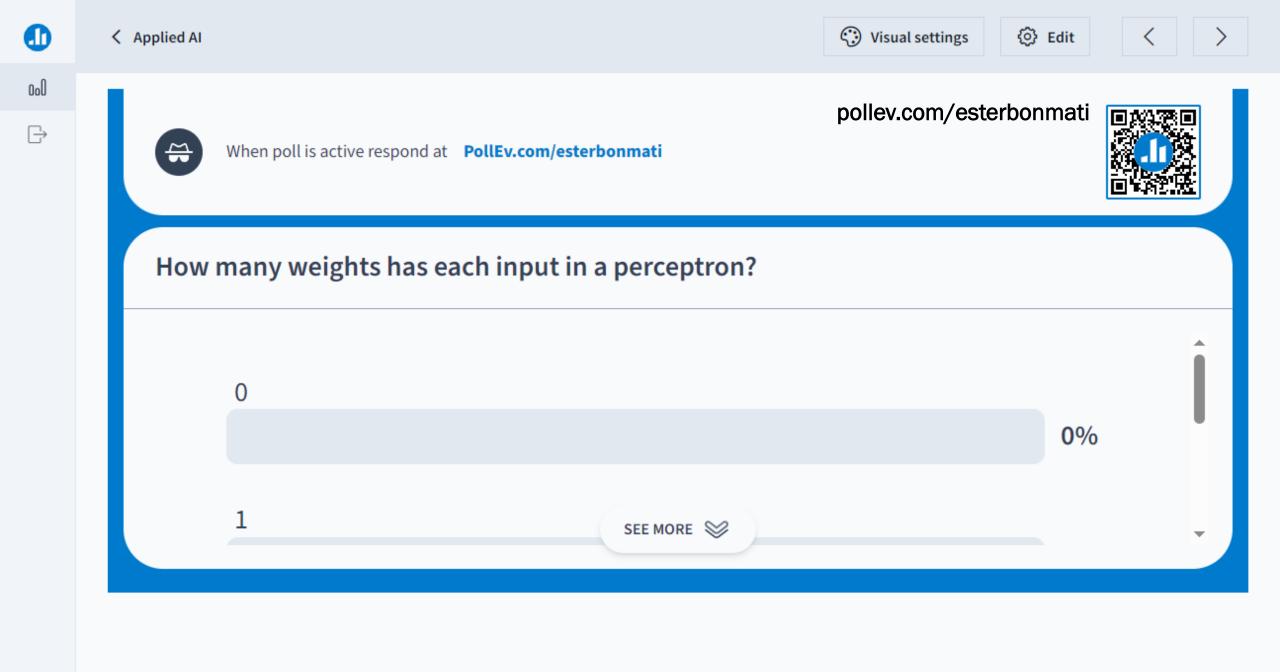
# **NEURAL NETWORKS: ANOTHER EXAMPLE**

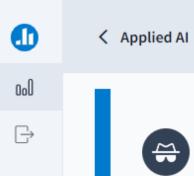


[For reference only] Equation of a plane = ax + by + cz + d

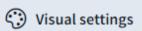










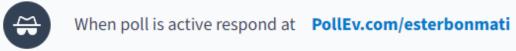








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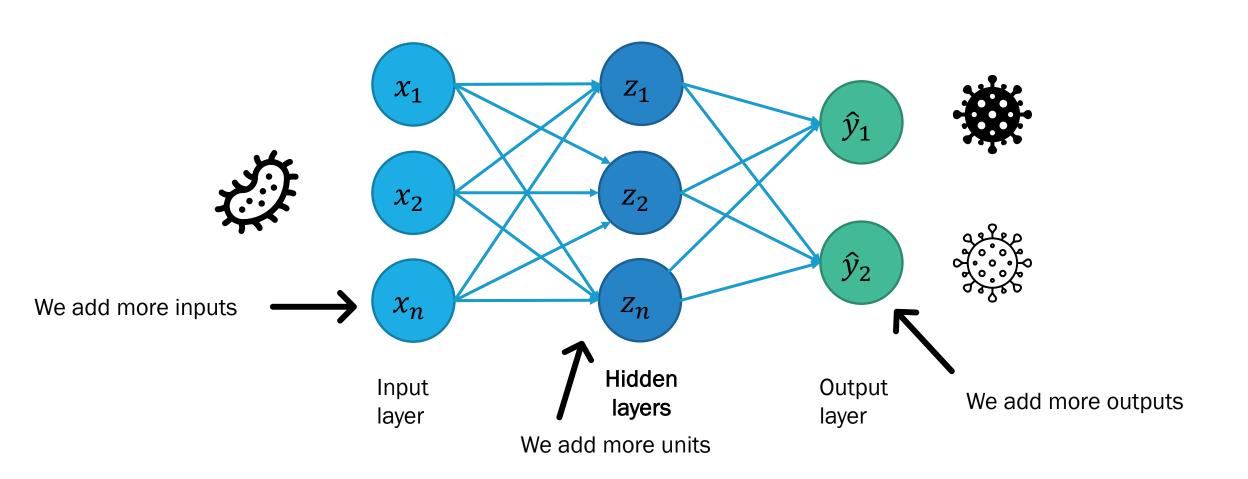


Q&A

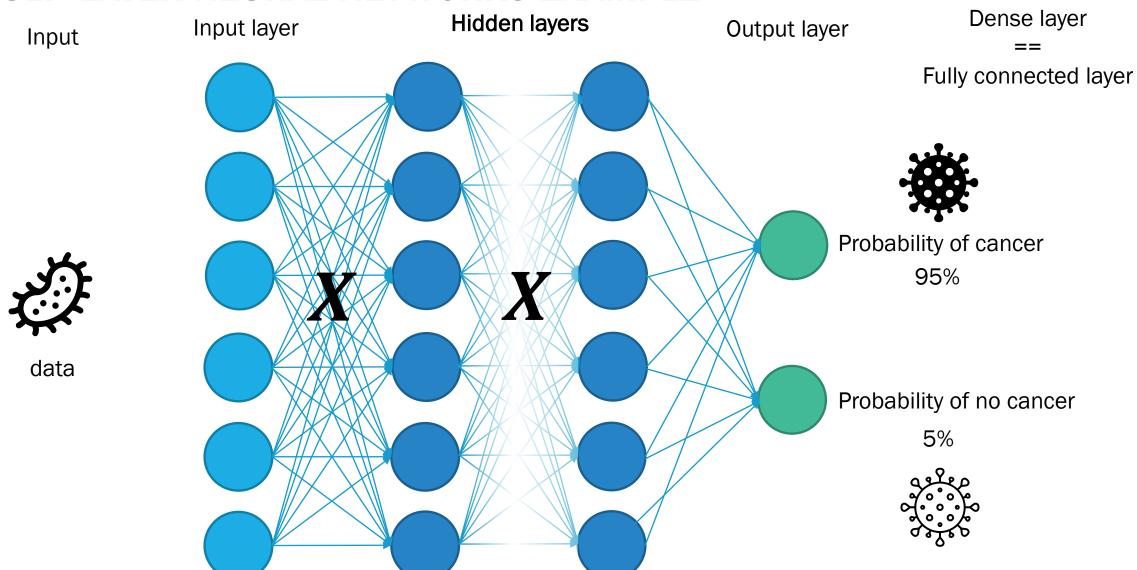
Nobody has responded yet.

Hang tight! Responses are coming in.

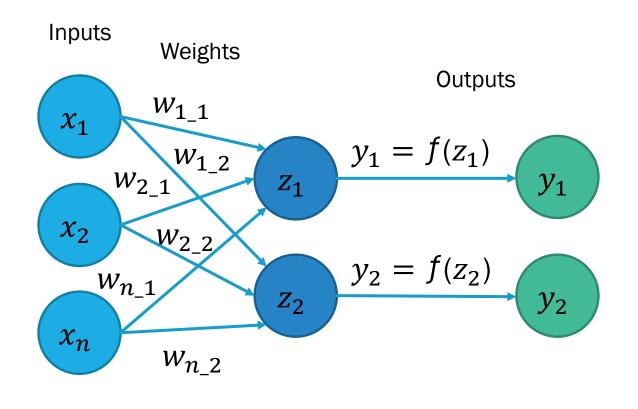
# **MULTI-LAYER NEURAL NETWORKS**



# **MULTI-LAYER NEURAL NETWORKS EXAMPLE**



# **ARTIFICIAL NEURAL NETWORKS (ANN)**



Each output has its own weight for each input

$$z = w_0 + \sum_{i=1}^{n} x_i w_i$$

$$\hat{y} = f\left(w_0 + \sum_{i=1}^{n} x_i w_i\right)$$

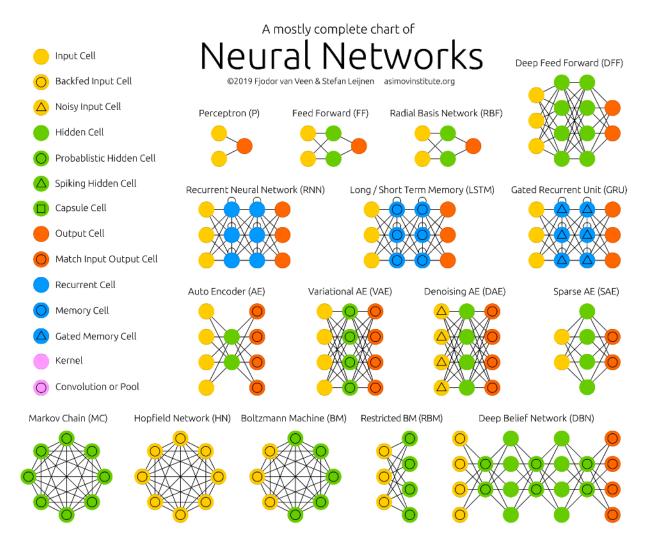
# FOR REFERENCE ONLY: ACTIVATION FUNCTIONS

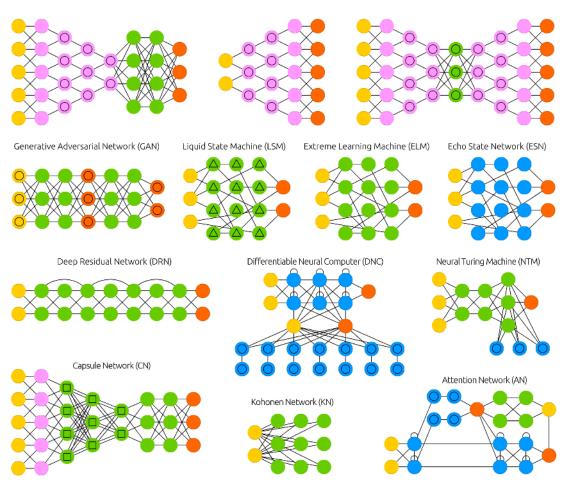
Activation function	Equation	Example	1D Graph
Linear	$\phi(z) = z$	Adaline, linear regression	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	-
Hyperbolic tangent (Tanh)	$\phi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	Multi-layer Neural Networks	-
Rectifier, ReLU (Rectified Linear Unit)	$\phi(z) = \max(0, z)$	Multi-layer Neural Networks	-
Copyright © Sebastian Raschka 2016 (http://sebastianraschka.com)			

Non-linear

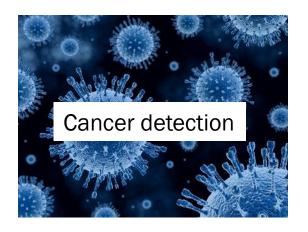
Non-linear activation functions allow to learn more complex mappings

#### **EXAMPLES OF NEURAL NETWORKS**





#### WHAT CAN WE DO WITH ANN?









Recognition/Classification



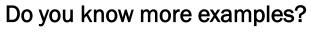








Stock market prediction





#### RESEARCH

#### Forecasting Climatic Trends Using Neural Networks: An Experimental Study Using Global Historical Data

Takeshi Ise 1,2\* and Yurika Oba

<sup>1</sup> Field Science Education and Research Center (FSERC), Kyoto University, Kyoto, Japan, <sup>2</sup> Japan Science and Technology Agency (JST), Kawaguchi, Japan

#### **Review Article**

4291

#### Artificial neural networks in the cancer genomics frontier

Andrew Oustimov<sup>1</sup>, Vincent Vu<sup>2</sup>

<sup>1</sup>Department of Epidemiology & Biostatistics, College of Public Health, University of South Florida, Tampa, FL 33620, USA; <sup>2</sup>Department of Mathematics and Statistics, University of California, Los Angeles, CA, USA

Correspondence to: Andrew Oustimov, MPH. Department of Epidemiology & Biostatistics, College of Public Health, University of South Florida, 13201 Bruce B Downs Blvd, Tampa, FL 33620, USA. Email: aoustimo@mail.usf.edu.

IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS, VOL. 32, NO. 10, OCTOBER 2021

#### Attention in Natural Language Processing

Andrea Galassi<sup>®</sup>, Marco Lippi<sup>®</sup>, and Paolo Torroni<sup>®</sup>

Tran et al. Genome Medicine (2021) 13:152 https://doi.org/10.1186/s13073-021-00968-x

#### Genome Medicine

#### AUTOMATIC LANGUAGE IDENTIFICATION USING DEEP NEURAL NETWORKS

Ignacio Lopez-Moreno<sup>1</sup>, Javier Gonzalez-Dominguez<sup>1,2</sup>, Oldrich Plchot<sup>3</sup>, David Martinez<sup>4</sup>, Joaquin Gonzalez-Rodriguez<sup>2</sup>, Pedro Moreno<sup>1</sup>

<sup>1</sup>Google Inc., New York, USA
<sup>2</sup>ATVS-Biometric Recognition Group, Universidad Autonoma de Madrid, Spain
<sup>3</sup>Brno University of Technology, Czech Republic
<sup>4</sup>Aragon Institute for Engineering Research (I3A), University of Zaragoza, Spain

{elnota, jgd}@google.com

REVIEW Open Access

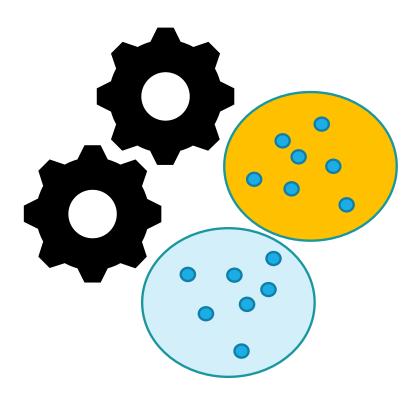
# Deep learning in cancer diagnosis, prognosis and treatment selection



Khoa A. Tran<sup>1,2</sup>, Olga Kondrashova<sup>1</sup>, Andrew Bradley<sup>4</sup>, Elizabeth D. Williams<sup>2,3</sup>, John V. Pearson<sup>1</sup> and Nicola Waddell<sup>1\*</sup>

#### **SUPERVISED VS UNSUPERVISED**

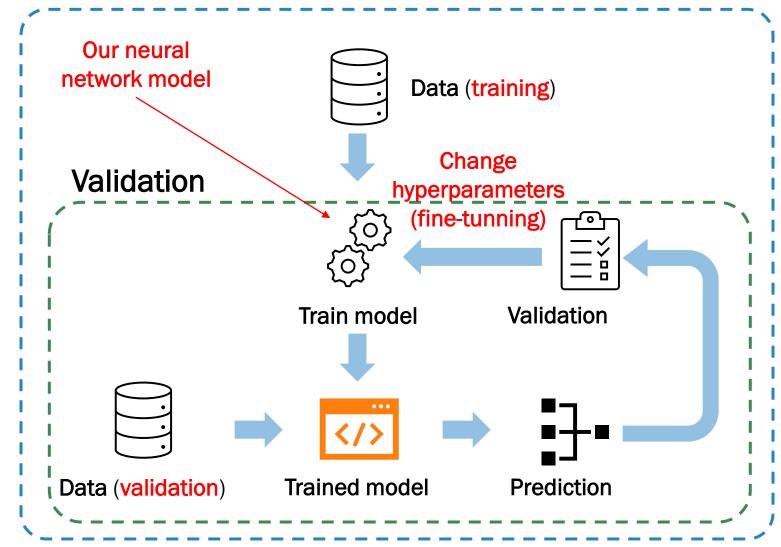


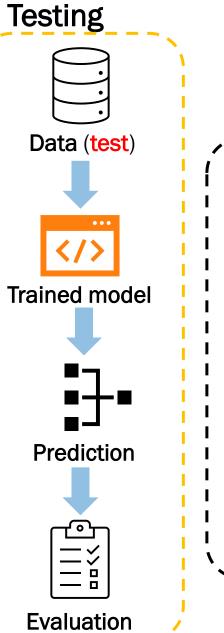


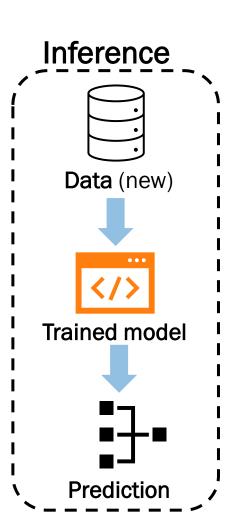
We have both **supervised** and **unsupervised** neural networks. We will focus the rest of the lecture on **supervised** learning.

#### **MACHINE LEARNING**

## **Training**







#### **DATA SPLIT**

Data split

Training set	Validation set	Test set	
80%	10%	10%	(small datasets)
60%	20%	20%	(larger datasets)

Imbalanced dataset

Know your data:

Balanced dataset

50% data

50% data

Cat Dog

80% data

20% data

Cat Dog

#### **NEURAL NETWORK EXAMPLE**

Input

Input layer Multiple hidden layers **Output layer** 

How do we initialise weights?

How can we find the optimum weights so that the error is minimal?

#### TRAINING A NEURAL NETWORK

Train model

- Objective: find the optimum weights that will give the lowest error [loss]
- Optimisation (Gradient Descent)
  - 1. Randomly initialise weights
  - 2. Find how much the weights need to change (by computing the derivates)
  - 3. Update weights by taking a small step [learning rate]
  - 4. Repeat until convergence (until there is no improvement) [number of epochs]

#### FOR REFERENCE ONLY: LOSS OPTIMISATION

- Identify (train) a set of weights that will give us the minimum error
- Loss functions: Cross entropy, Mean Squared Error, Mean Absolute Error.
- Needs to be differentiable (the derivative of the function exists for all points).

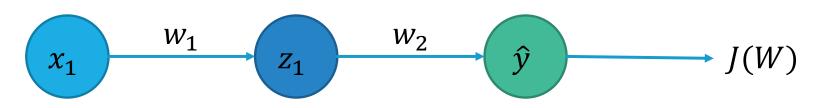
Binary classification	Multiclass classification	Regression
Loss: Cross Entropy	Loss: Cross Entropy	Loss: Mean Squared Error
Activation: Sigmoid	Activation: Softmax	

#### **BACKPROPAGATION: BACKWARD PROPAGATION OF ERRORS**

Train model

Compute the gradients (computationally expensive!)

How does a small change on the weights affect the final loss J(W)?



Watch:
<a href="https://www.youtube.co">https://www.youtube.co</a>
<a href="mailto:m/watch?v=IN2XmBhILt4">m/watch?v=IN2XmBhILt4</a>
<a href="mailto:list=PLbIh5JKOoLUIxGD">&list=PLbIh5JKOoLUIxGD</a>
<a href="mailto:Qs4LFFD--41Vzf-">Qs4LFFD--41Vzf-</a>
<a href="mailto:ME1&index=4">ME1&index=4</a>

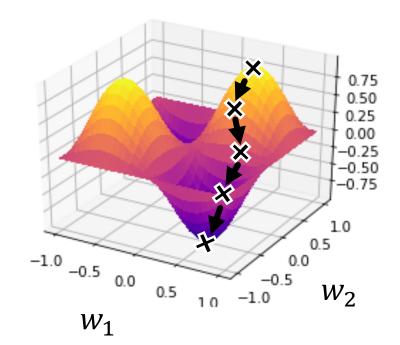
How much a change in  $w_2$  will affect the total error (loss) J(W)?

The partial derivative of the loss with respect to  $w_2$ 

$$\frac{\partial J(W)}{\partial w_2} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial w_2}$$

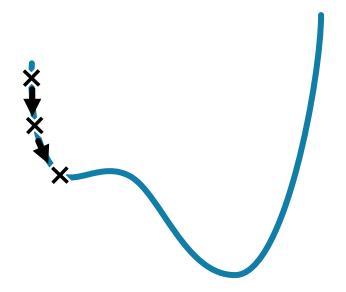
How much a change in  $w_1$  will affect the total error (loss) J(W)?

$$\frac{\partial J(W)}{\partial w_1} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial z_1} * \frac{\partial z_1}{\partial w_1}$$

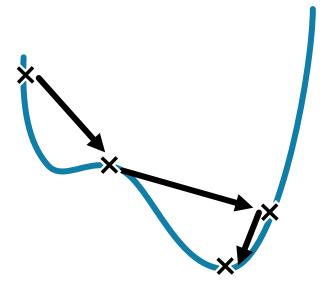


Train model

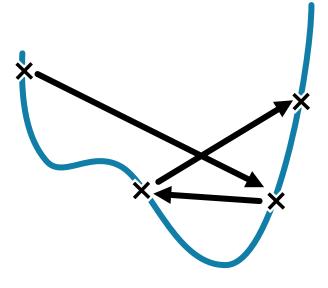
How much step we take in the gradient?



Small learning rate



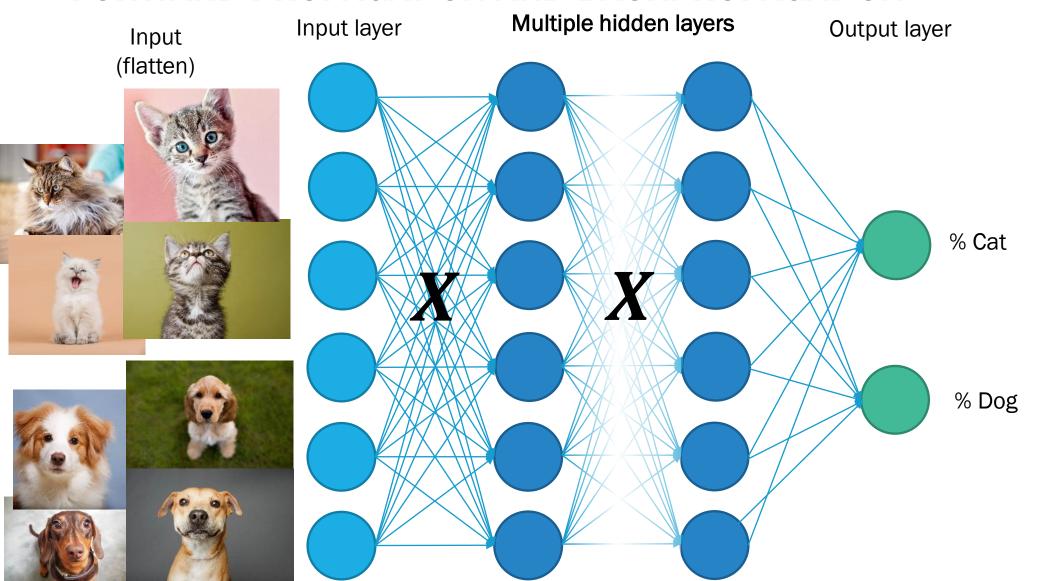
Good learning rate



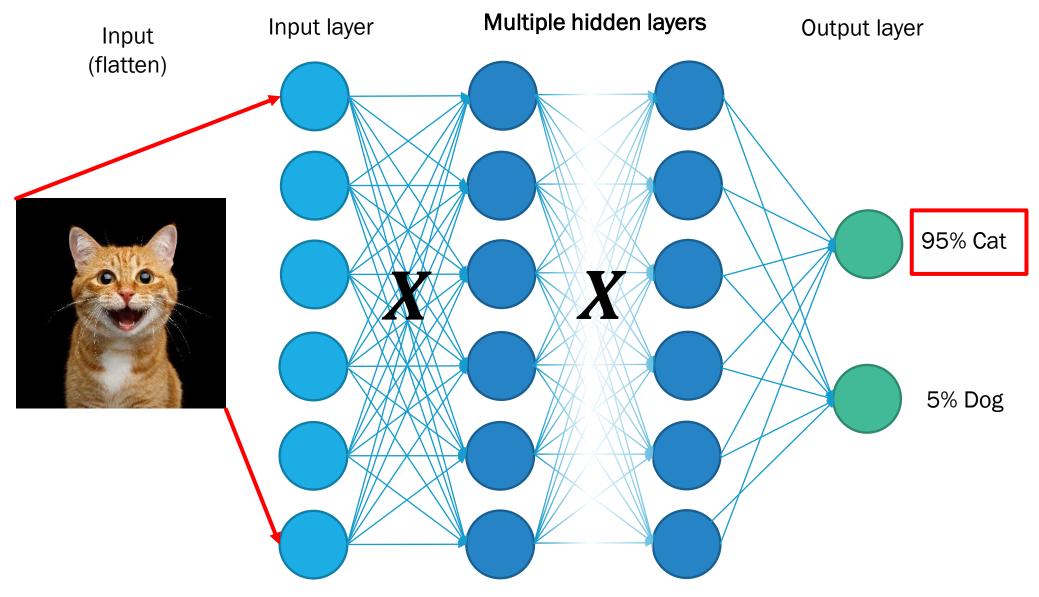
Large learning rate

#### FORWARD PROPAGATION AND BACKPROPAGATION

Train model

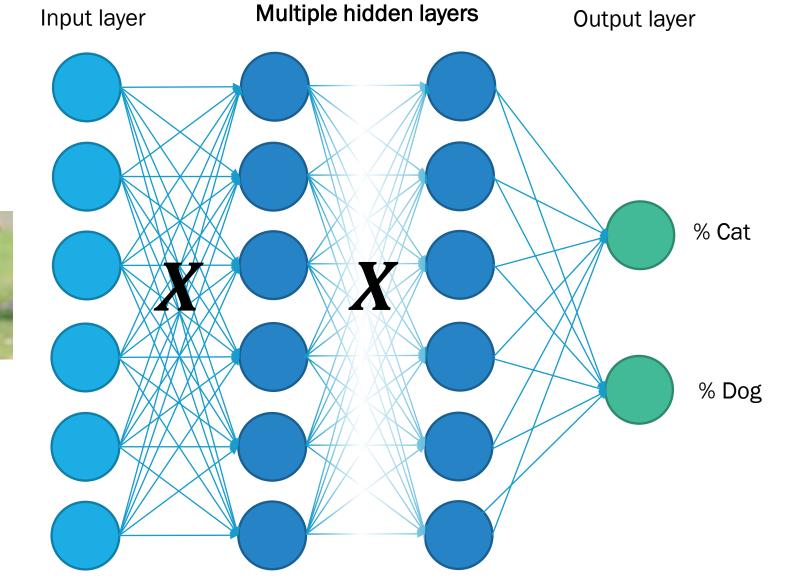


## FORWARD PROPAGATION AND BACKPROPAGATION

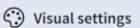


# FORWARD PROPAGATION AND BACKPROPAGATION

Input (flatten)













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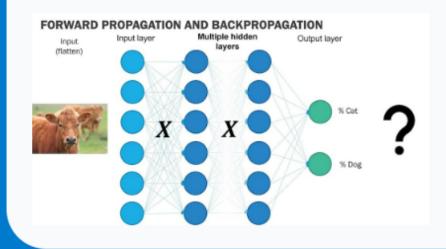






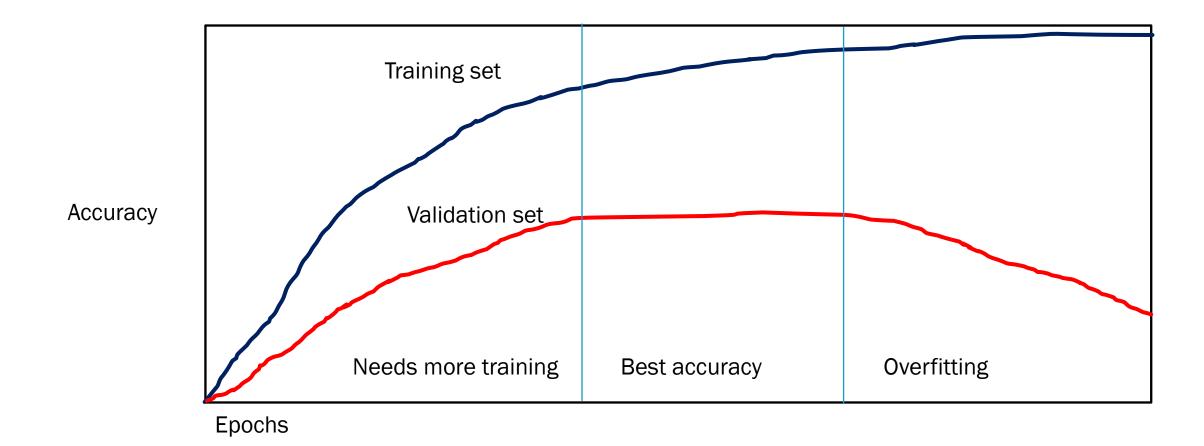


#### What will the NN predict?



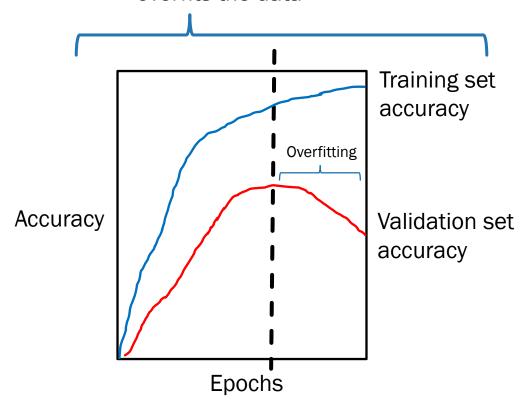
Will predict cow

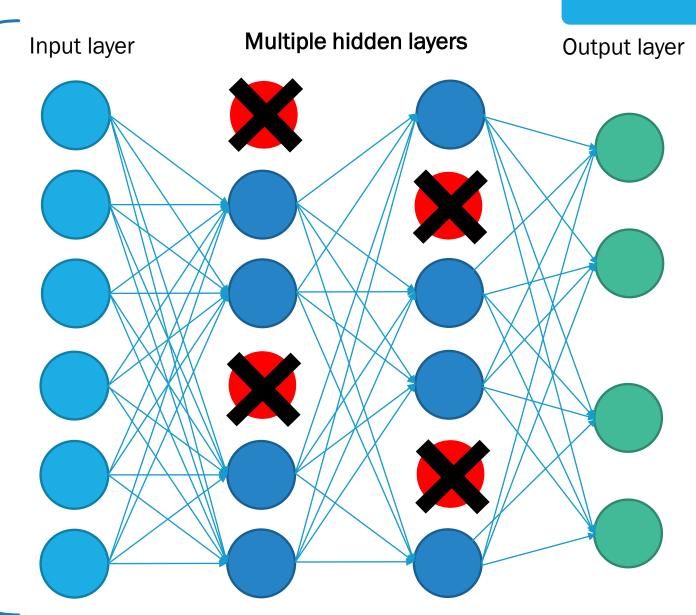
0%



## **PROBLEMS: OVERFITTING**

- Regularisation
  - Dropout: During training, we set some activation to 0 (usually 50%)
  - Early stopping: stop training before it overfits the data



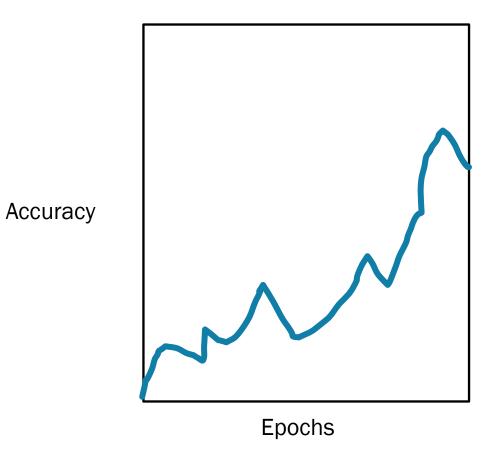


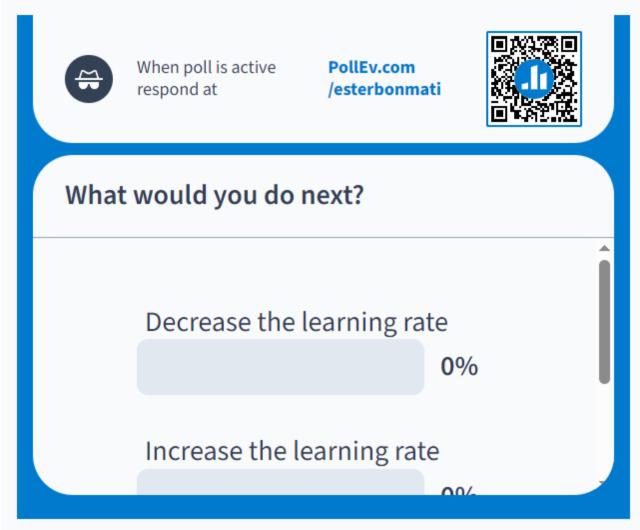


 $\Box$ 



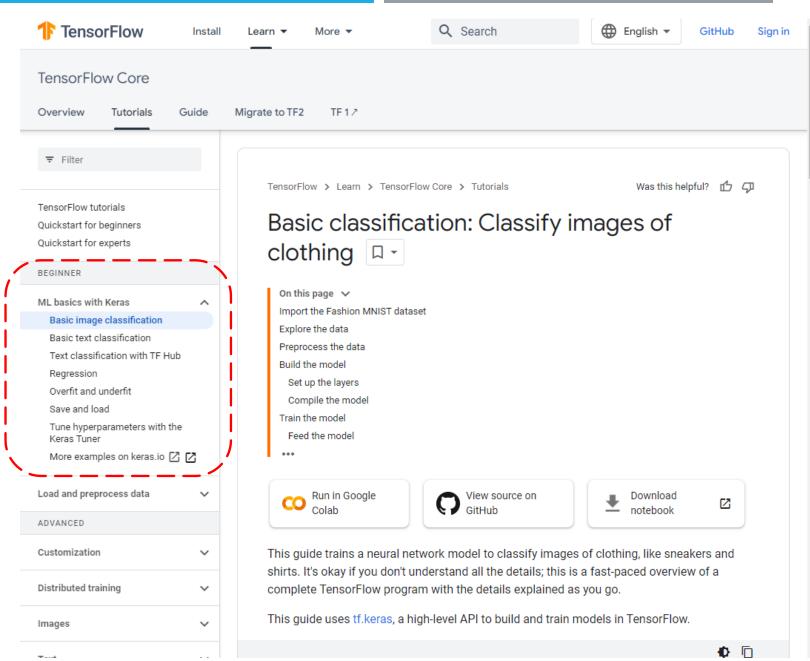
#### **TRAINING**





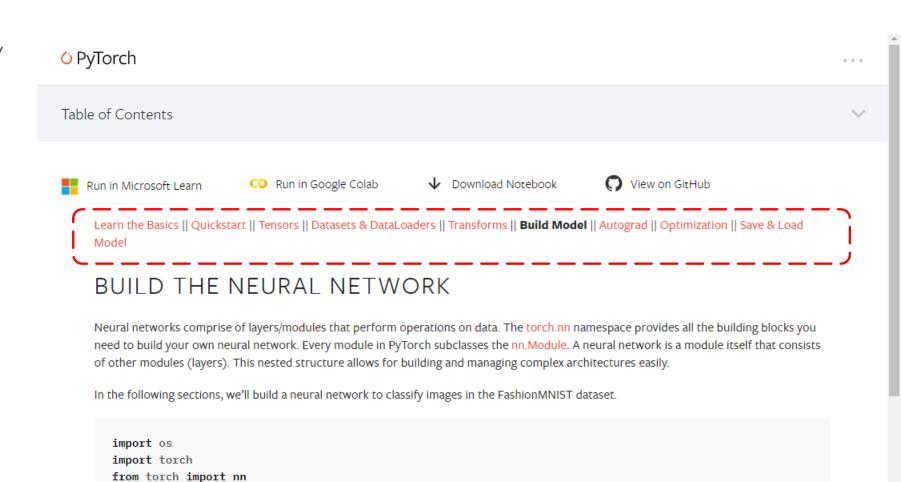
#### **TENSORFLOW & KERAS**

 https://www.tensorflow.org/ tutorials/keras/classification



#### **PYTORCH**

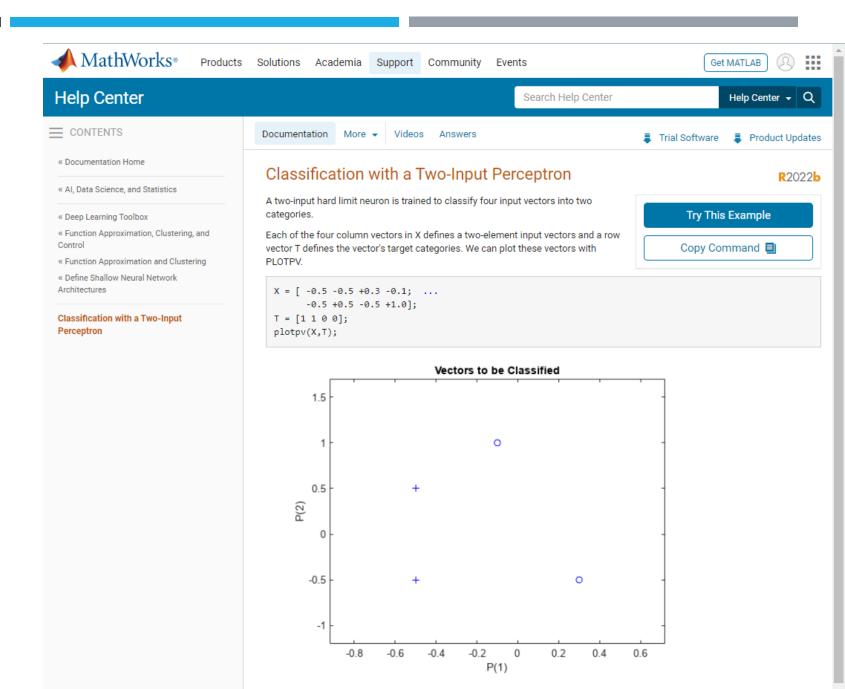
https://pytorch.org/tutorials/ beginner/basics/buildmodel \_tutorial.html



from torch.utils.data import DataLoader
from torchvision import datasets, transforms

#### **ALSO IN MATLAB**

 https://uk.mathworks.com/help /deeplearning/ug/classificationwith-a-2-input-perceptron.html













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When poll is active respond at **PollEv.com/esterbonmati** 



After: what is a neural network or artificial neural network?

Nobody has responded yet.

Hang tight! Responses are coming in.

#### **ACKNOWLEDGEMENTS**

Acknowledgements: This lecture was inspired by the following material:

- http://introtodeeplearning.com/: MIT Introduction to Deep Learning | 6.S191
- Neural Networks (Applied Al 21/22 Dr. Artie Basukoski)