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Deep Learning & Neural Networks

Dr. Shahira Ahmed

DS710

Lecture 3

Deep Learning & Neural Networks DS710

Lecture 3
Training the Network-Part(1)

Dr. Shahira Ahmed

Lecture Outline

- Linear Algebra Review
- What is Vectorization?
- How Vectorization is important in Machine learning?
- Advantages of Vectorized Implementation
- Demonstration on Colab
- Representing Neural Network weighted sum as vectors
- Training Network

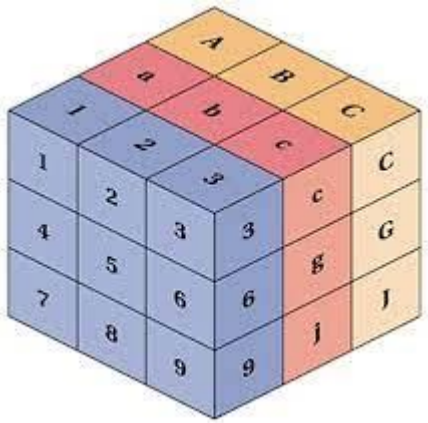
Linear Algebra Review

- Scalars is only a Single numbers
- Vectors: A vector is an array of numbers

$$\boldsymbol{x} = \begin{bmatrix} x_1 \\ x_2 \\ \cdots \\ x_n \end{bmatrix}$$

- Matrix:

$$\boldsymbol{A} = \begin{bmatrix} A_{1,1} & A_{1,2} & \cdots & A_{1,n} \\ A_{2,1} & A_{2,2} & \cdots & A_{2,n} \\ \cdots & \cdots & \cdots & \cdots \\ A_{m,1} & A_{m,2} & \cdots & A_{m,n} \end{bmatrix}$$



- A tensor is a n-dimensional array with n>2

Linear Algebra Review

Grayscale Image

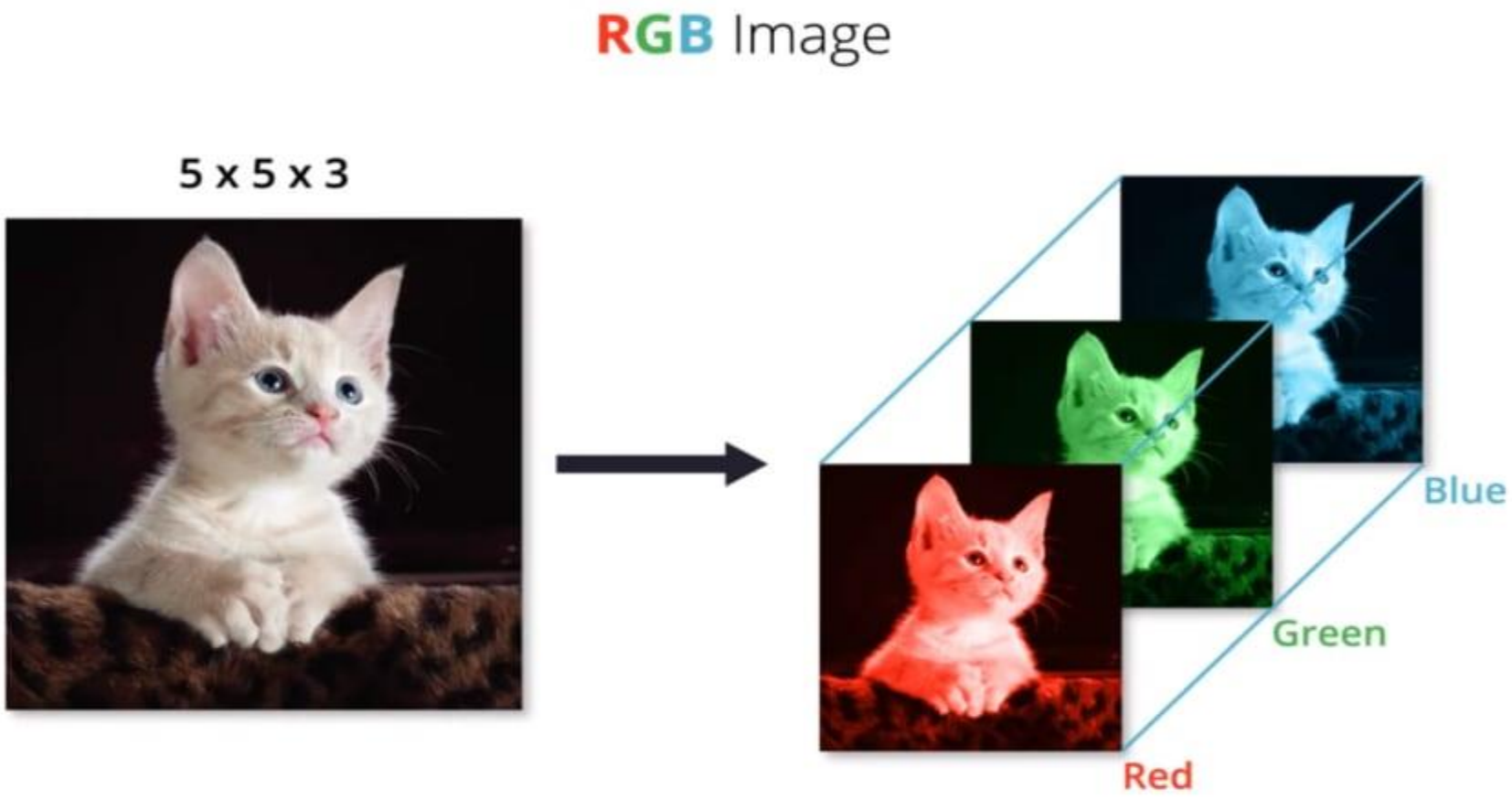
6 x 6

6 x 6

1	0	4	2	125	67
8	2	5	4	34	12
20	13	25	15	240	2
76	8	6	6	100	76
34	66	134	223	201	3
255	123	89	55	32	2

https://dev.to/sandeepbalachandran/machine-learning-going-furthur-with-cnn-part-2-41km

Linear Algebra Review



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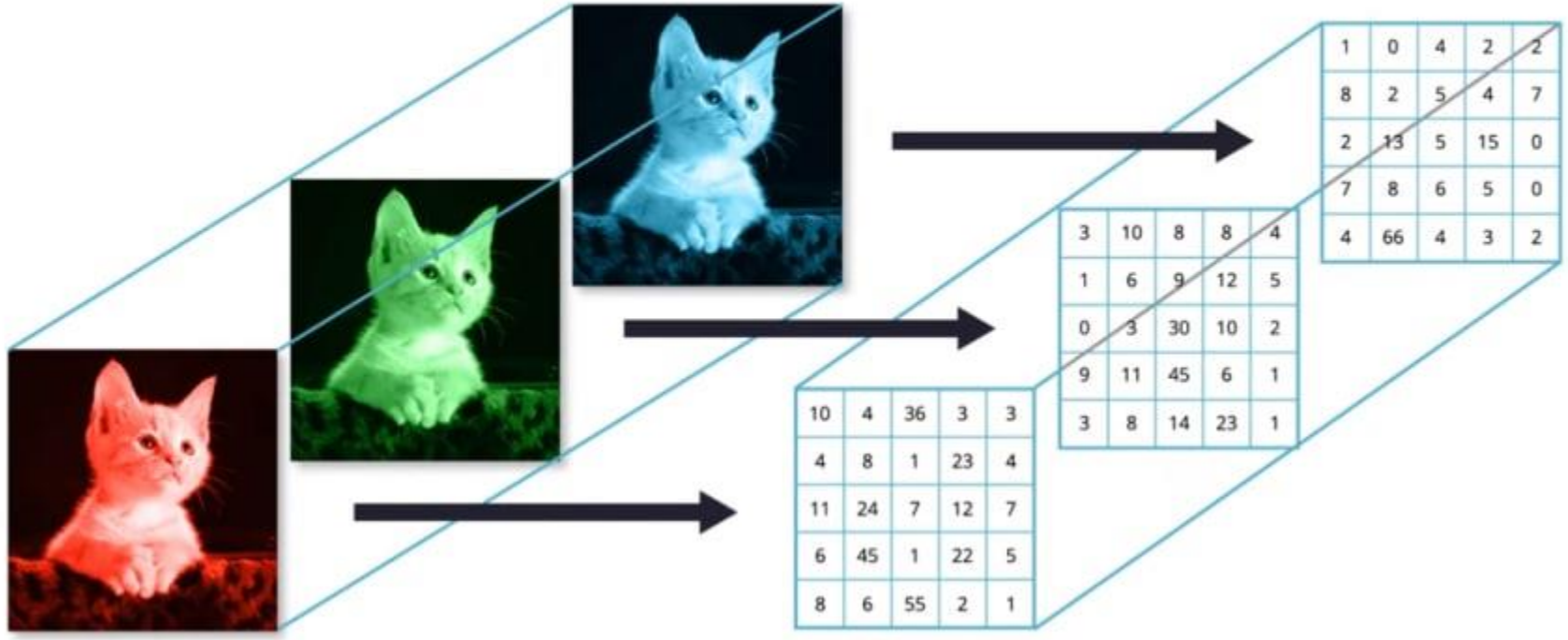

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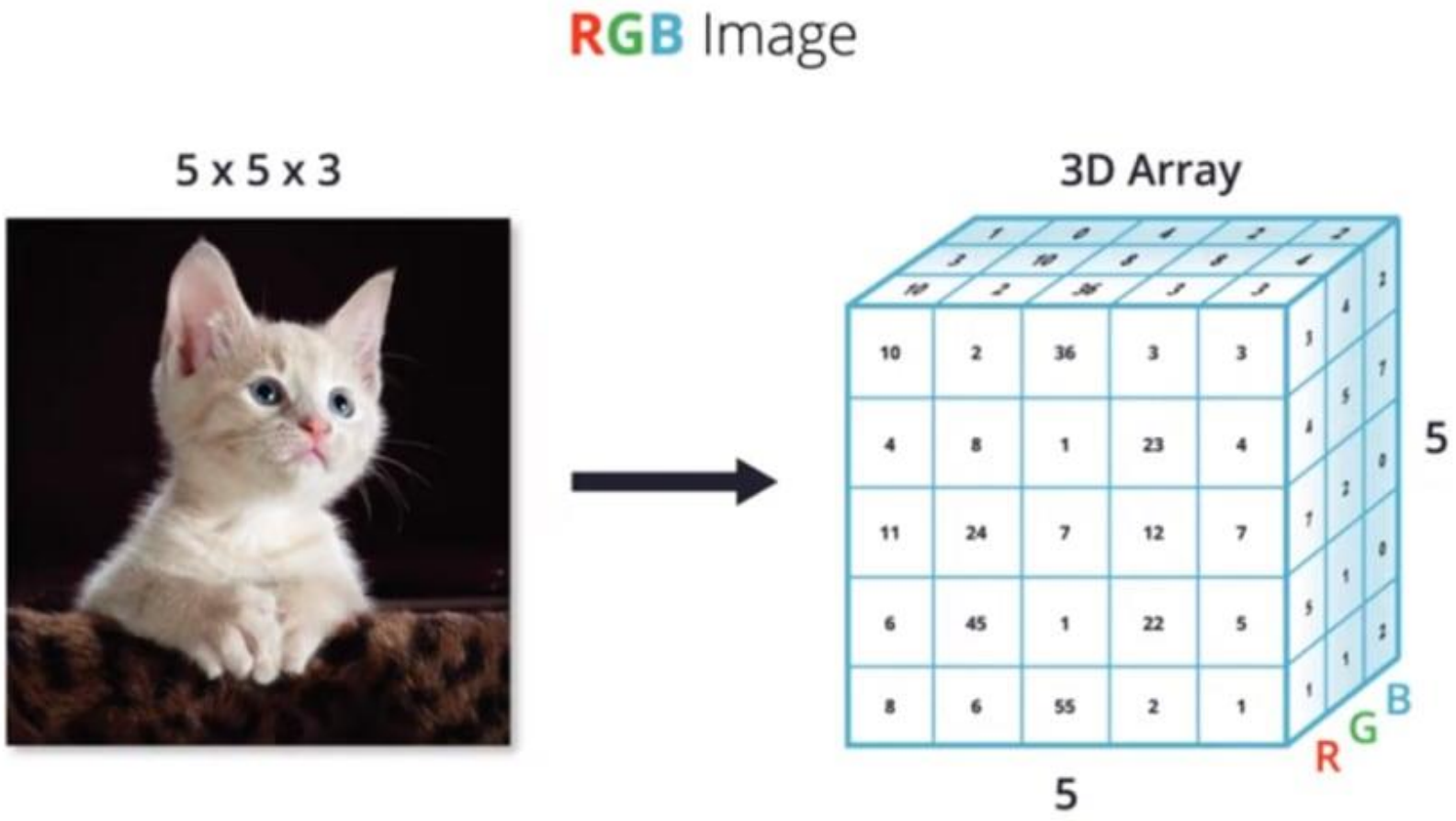

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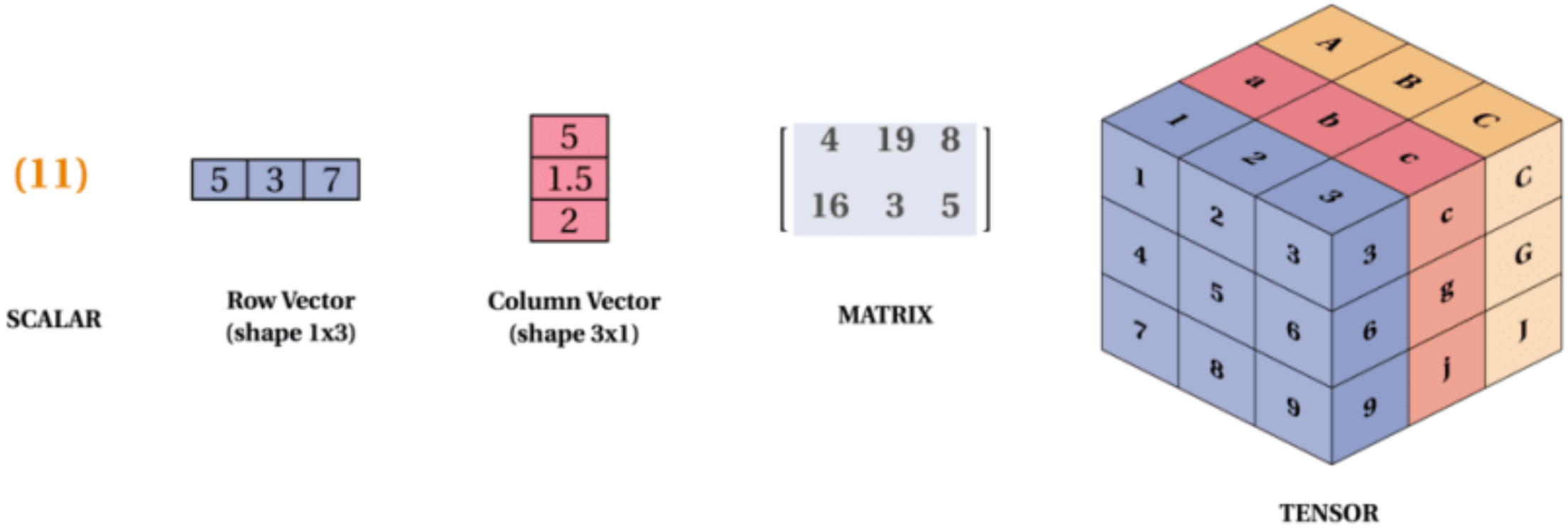

https://dev.to/mmithrakumar/scalars-vectors-matrices-and-tensors-with-tensorflow-2-0-1f66

Dot Product

- An algebraic operation in which two equal length vectors are being multiplied such that it produces a single number. Dot Product often called as inner product. This product results in a scalar number

$$a \cdot b = \underset{(1 \times n)}{\begin{bmatrix} a_1 & a_2 & a_3 & a_4 & a_5 \end{bmatrix}} \underset{(n \times 1)}{\begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}} = \left\{ a_1b_1 + a_2b_2 + a_3b_3 + a_4b_4 + a_5b_5 \right\}$$

Dot Product

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Dot Product

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \bullet \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix} = \begin{bmatrix} (1\cdot 5)+(2\cdot 7) & (1\cdot 6)+(2\cdot 8) \\ (3\cdot 5)+(4\cdot 7) & (3\cdot 6)+(4\cdot 8) \end{bmatrix}$$

$$= \begin{bmatrix} 5+14 & 6+16 \\ 15+28 & 18+32 \end{bmatrix} = \begin{bmatrix} 19 & 22 \\ 43 & 50 \end{bmatrix}$$

Outer Product

- Multiply two vectors a and b with dimension n x 1 and m x 1 then the outer product of the vector results in a rectangular matrix of n x m.

$$a \otimes b = ab^T = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{bmatrix}_{(n \times 1)} \begin{bmatrix} b_1 & b_2 & b_3 & b_4 & b_5 \end{bmatrix}_{(1 \times n)} = \begin{Bmatrix} a_1b_1 & a_1b_2 & a_1b_3 & a_1b_4 & a_1b_5 \\ a_2b_1 & a_2b_2 & a_2b_3 & a_2b_4 & a_2b_5 \\ a_3b_1 & a_3b_2 & a_3b_3 & a_3b_4 & a_3b_5 \\ a_4b_1 & a_4b_2 & a_4b_3 & a_4b_4 & a_4b_5 \\ a_5b_1 & a_5b_2 & a_5b_3 & a_5b_4 & a_5b_5 \end{Bmatrix}_{(n \times n)}$$

Outer Product

Element wise Product

Element-wise multiplication of two matrices is the algebraic operation in which each element of first matrix is multiplied by its corresponding element in the later matrix. Dimension of the matrices should be same.

$$a \circ b = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{bmatrix}_{(n \times 1)} \circ \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}_{(n \times 1)} = \begin{bmatrix} a_1b_1 \\ a_2b_2 \\ a_3b_3 \\ a_4b_4 \\ a_5b_5 \end{bmatrix}_{(n \times 1)}$$

Element wise Product

Transpose

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$$

Input

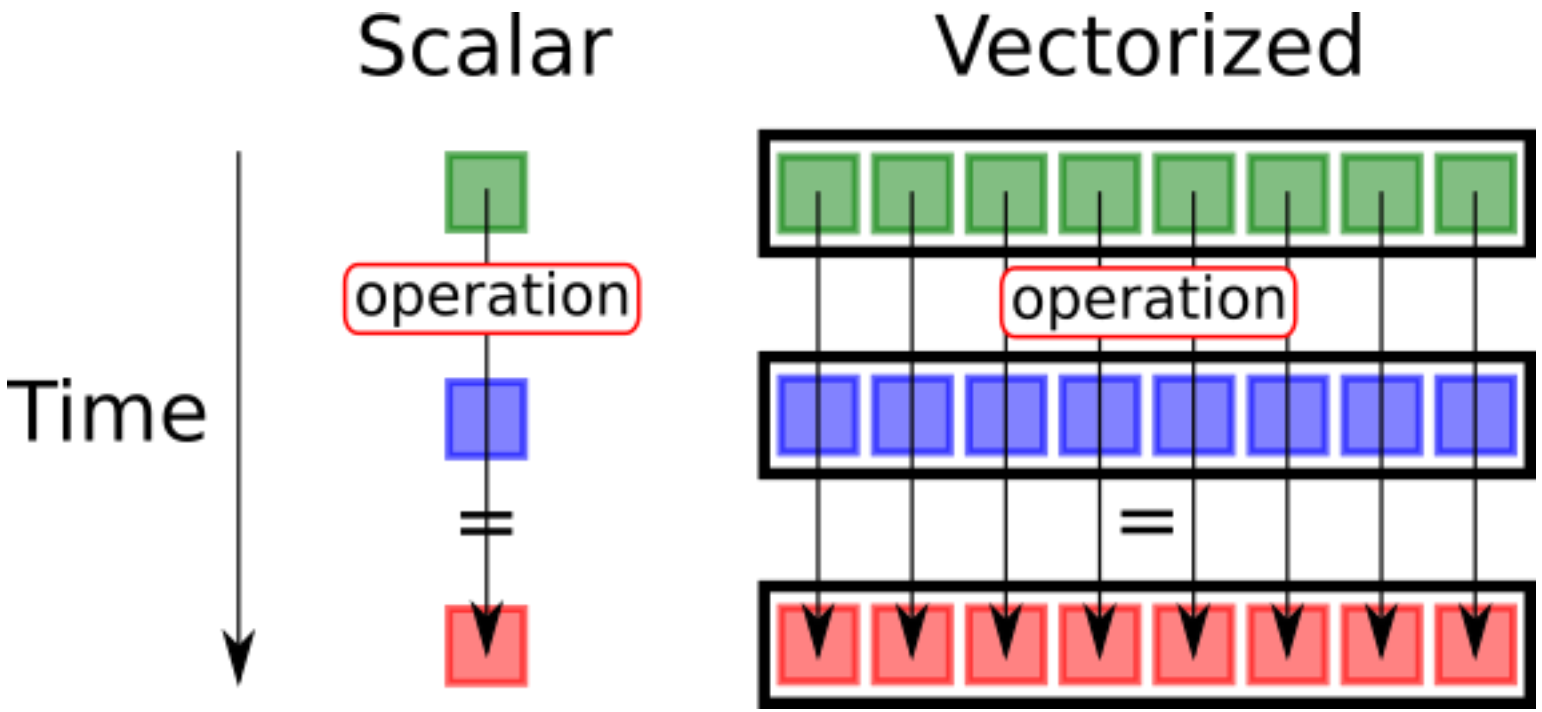
$$\begin{bmatrix} 1 & 4 & 7 \\ 2 & 5 & 8 \\ 3 & 6 & 9 \end{bmatrix}$$

Output

What is Vectorization?

- Vectorization in machine learning refers to the process of represents data into Vectors, Matrices, and Tensors.
- Process data without using loops

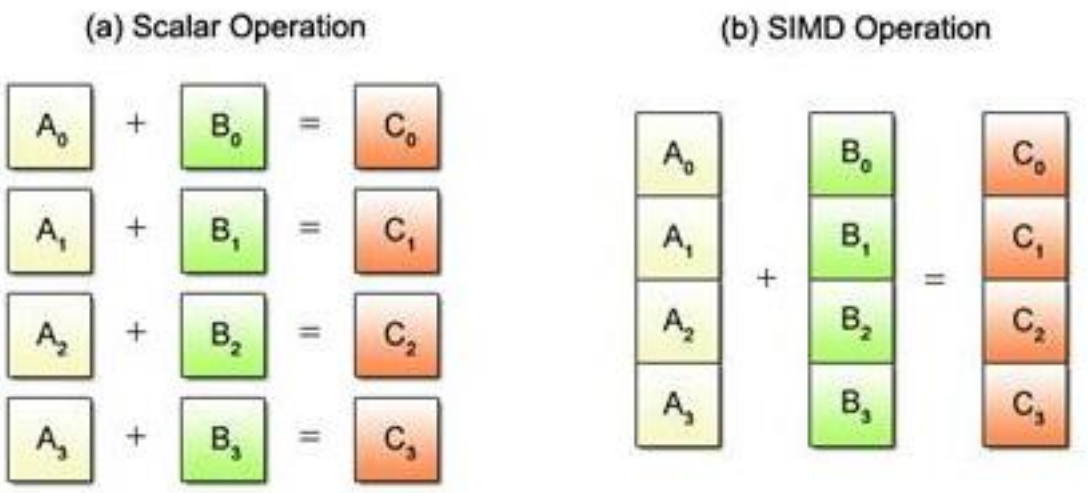
Why Vectorization



https://medium.com/@jwbtmf/vectorization-in-deep-learning-c47f0d171d0a

Why Vectorization?

SIMD is short for Single Instruction/Multiple Data, while the term SIMD operations refer to a computing method that enables the processing of multiple data with a single instruction



https://medium.com/@jwbtmf/vectorization-in-deep-learning-c47f0d171d0a

Why Vectorization?

- Efficiency : Due to the fact that they make use of the parallel processing capability of contemporary CPUs and GPUs, vectorized operations are often performed significantly quicker than their non-vectorized equivalents. This can lead to significant speed-ups in training and inference.
- Memory : Vectorized operations can also reduce memory usage.

Why Vectorization

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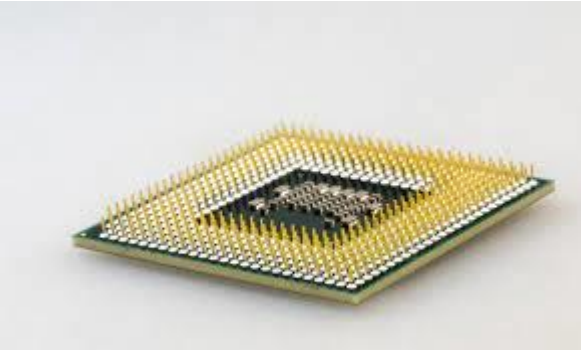
- Express data as matrices
- Perform computations on multiple data points simultaneously
- Performing parallel computations using matrix operations
- Hardware accelerators like GPUs
- Efficient memory utilization
- Less Time- more speed

CPU vs GPU vs TPU

- **CPU (Central Processing Unit):**
  - A CPU is the primary processing unit in a computer system. CPUs excel at sequential processing and are optimized for tasks that require high single-threaded performance. They are commonly found in desktop and laptop computers, servers, and mobile devices.

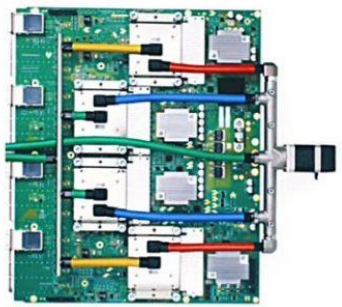


CPU vs GPU vs TPU

- https://www.youtube.com/watch?v=-P28LKWTzrI

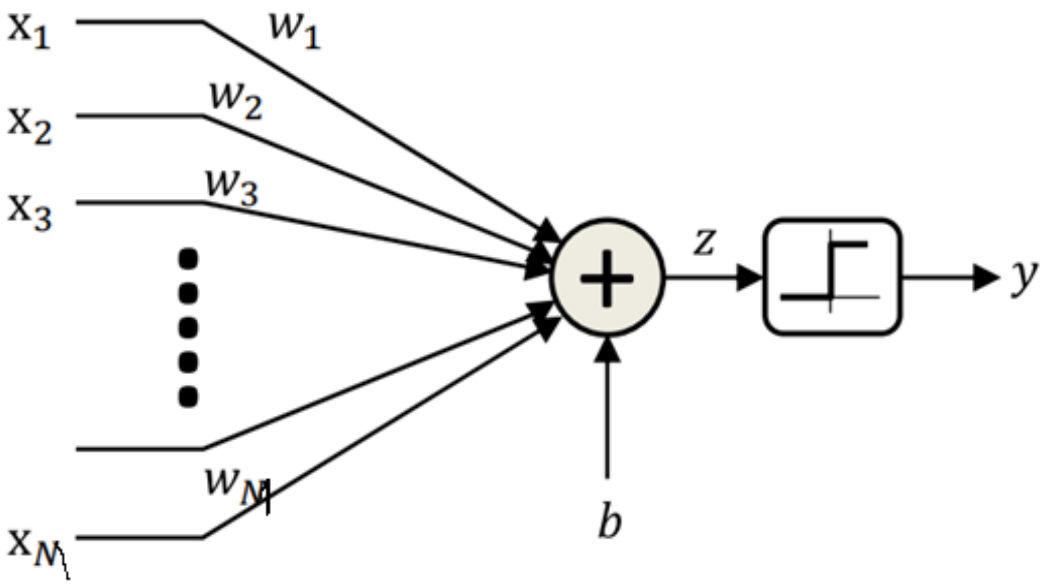
CPU vs GPU vs TPU

- **TPU (Tensor Processing Unit):**
  - A TPU is a specialized application-specific integrated circuit (ASIC) developed by Google for accelerating machine learning workloads.
  - It is specifically designed to perform tensor operations, which are fundamental to many machine learning algorithms.
  - TPUs are highly optimized for matrix multiplication and are capable of delivering significantly higher performance compared to CPUs and GPUs for deep learning tasks.
  - They are commonly used in data centers and cloud computing platforms to accelerate machine learning training and inference.



TPU V4

Recap: the perceptron



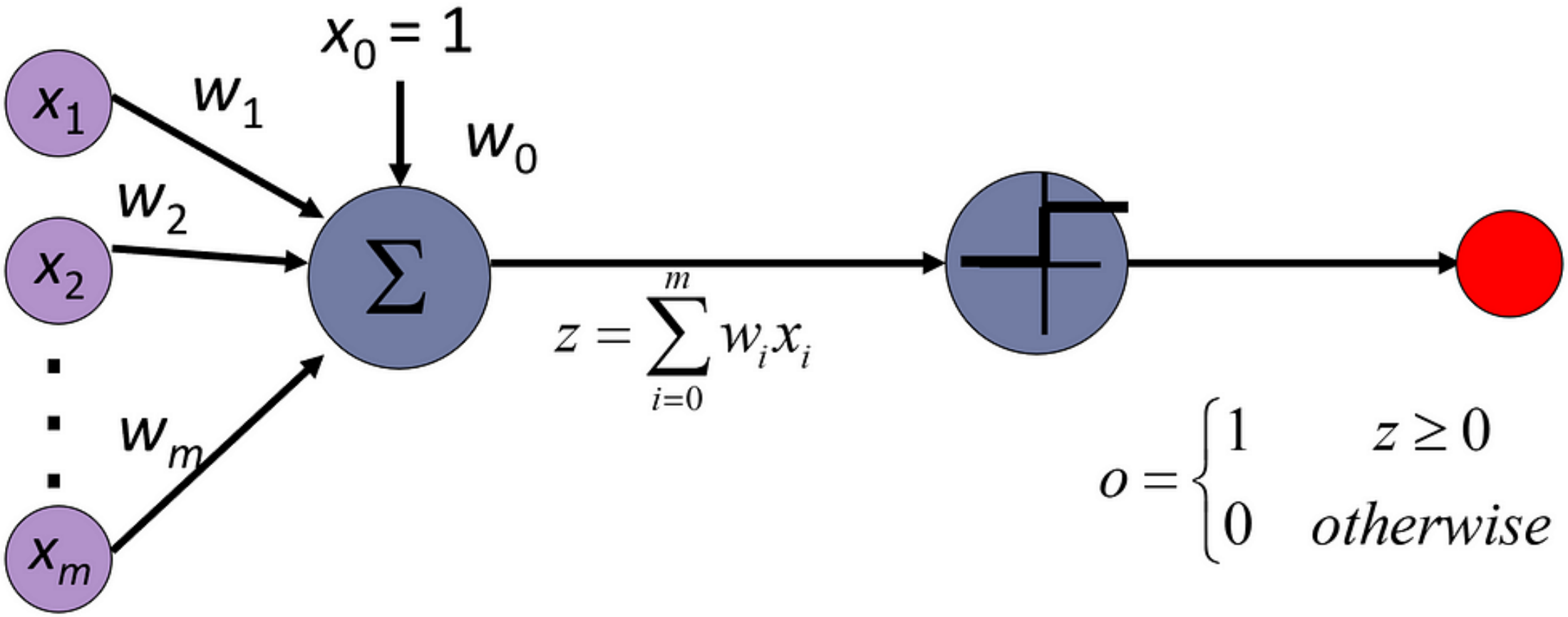
Linear vs Affine?

$$z = \sum_i w_i x_i + b$$

$$y = \begin{cases} 1 \; if \; z \geq 0 \\ 0 \; else \end{cases}$$

- – “Fires” if the affine function of inputs is positive

Recap: the perceptron

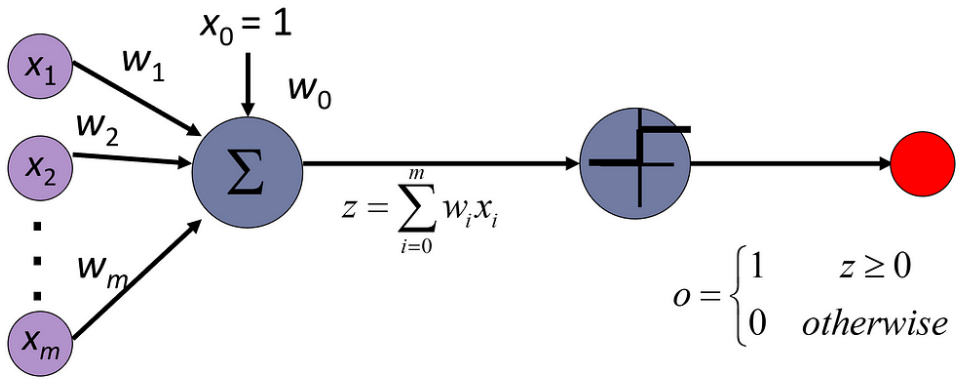


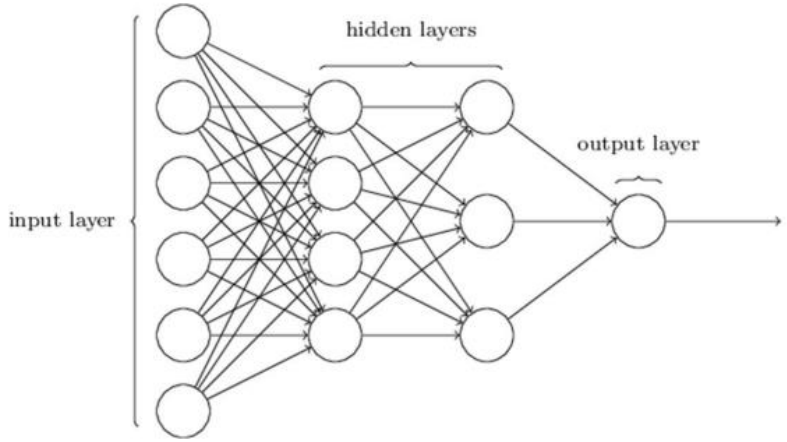
$$z = \sum_{i=0}^{m} w_i x_i$$

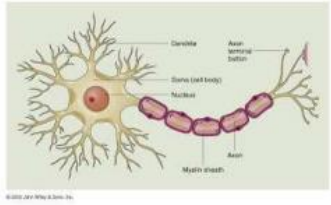
$$o = \begin{cases} 1 & z \geq 0 \\ 0 & otherwise \end{cases}$$

https://towardsdatascience.com/perceptrons-the-first-neural-network-model-8b3ee4513757

Recap : Nnets and the brain



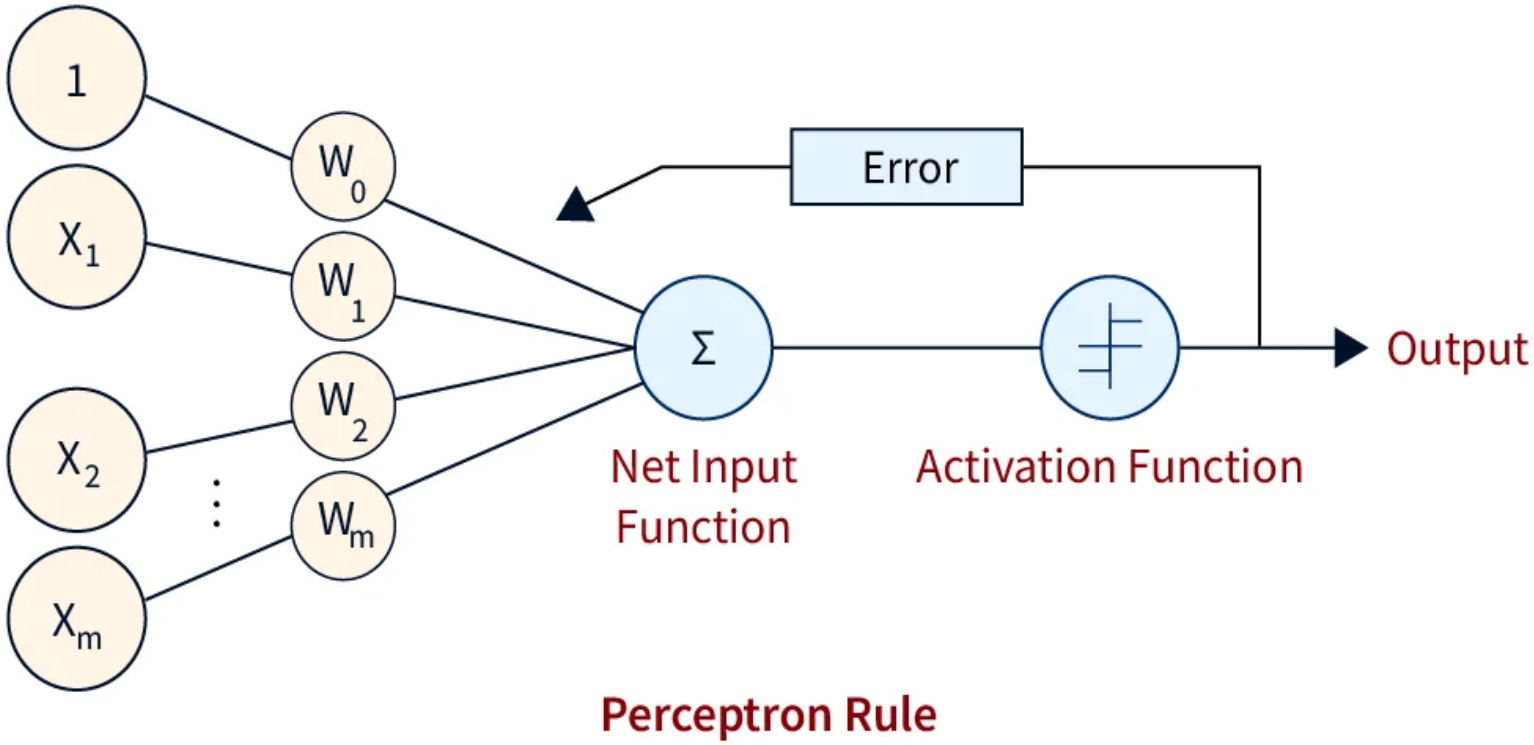




- Neural nets are composed of networks of computational models of neurons called perceptrons

https://deeplearning.cs.cmu.edu/S23/document/slides/lec2.universal.pdf

Learning the Network

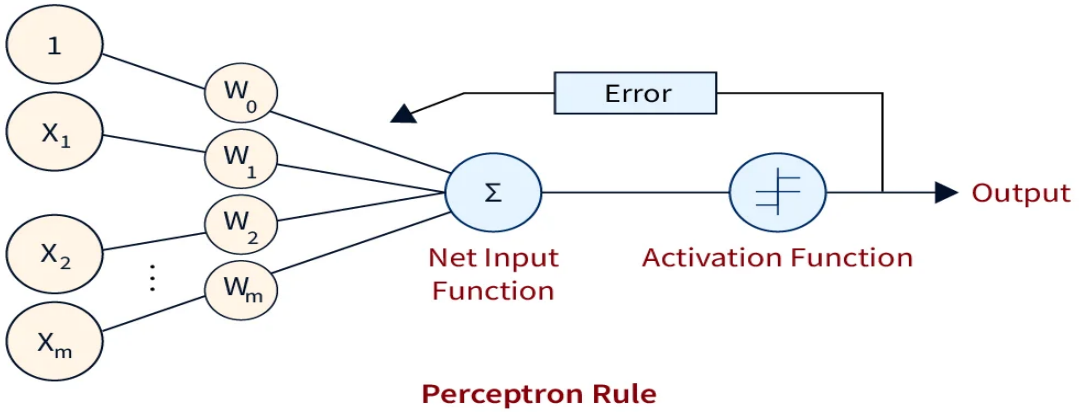


Calculate Weights

https://www.scaler.com/topics/machine-learning/perceptron-learning-algorithm/

Perceptron learning algorithm

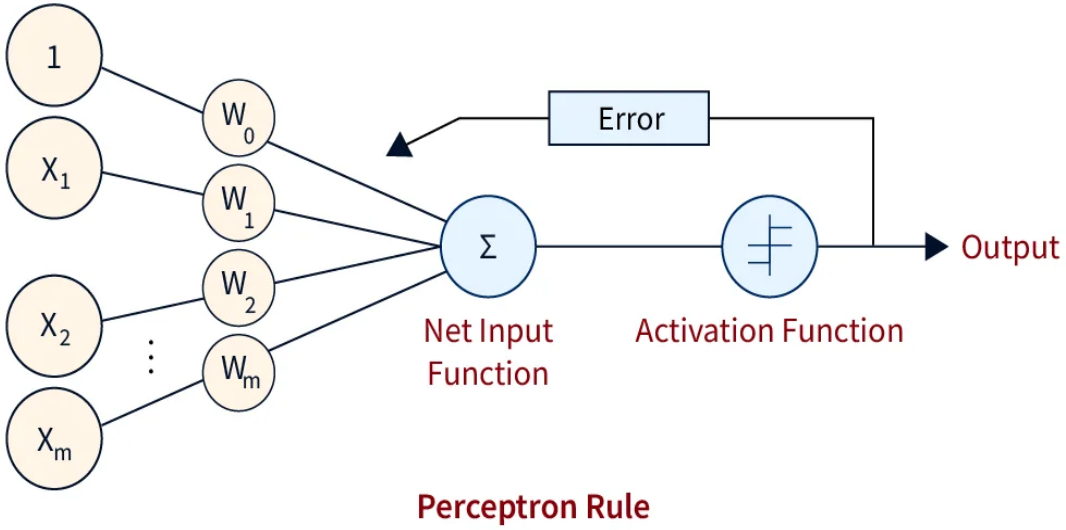
- (1) Calculate Weighted Sum: multiply all input values with corresponding weight values and then add them to determine the weighted sum. Mathematically, we can calculate the weighted sum as follows:
- $\sum wi * xi = x1 * w1 + x2 * w2 + \cdots + wm * xm$. Add another term called bias 'b' to the weighted sum to improve the model performance.

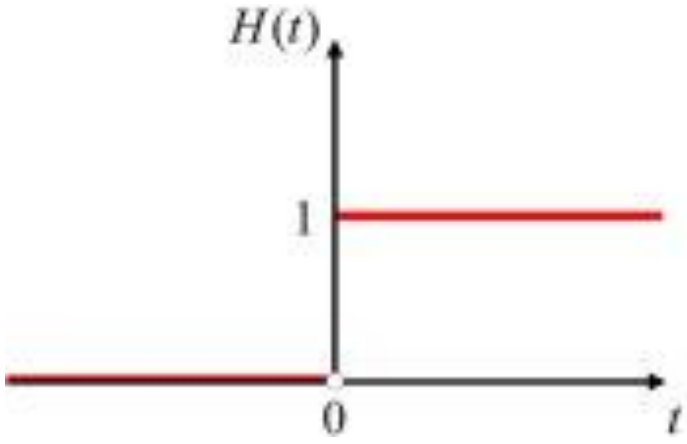


$$= \sum_{i=0}^{m} w_i x_i$$

Perceptron learning algorithm

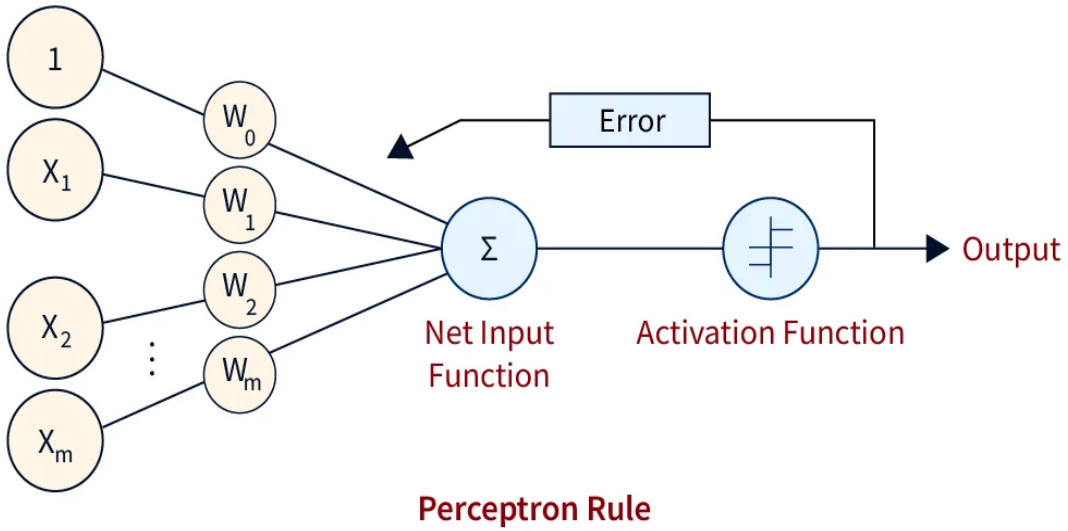
- (2) an activation function is applied to this weighed sum, producing a binary or a continuous-valued output. $Y = f(\sum_{i=0}^{m} w_i x_i)$



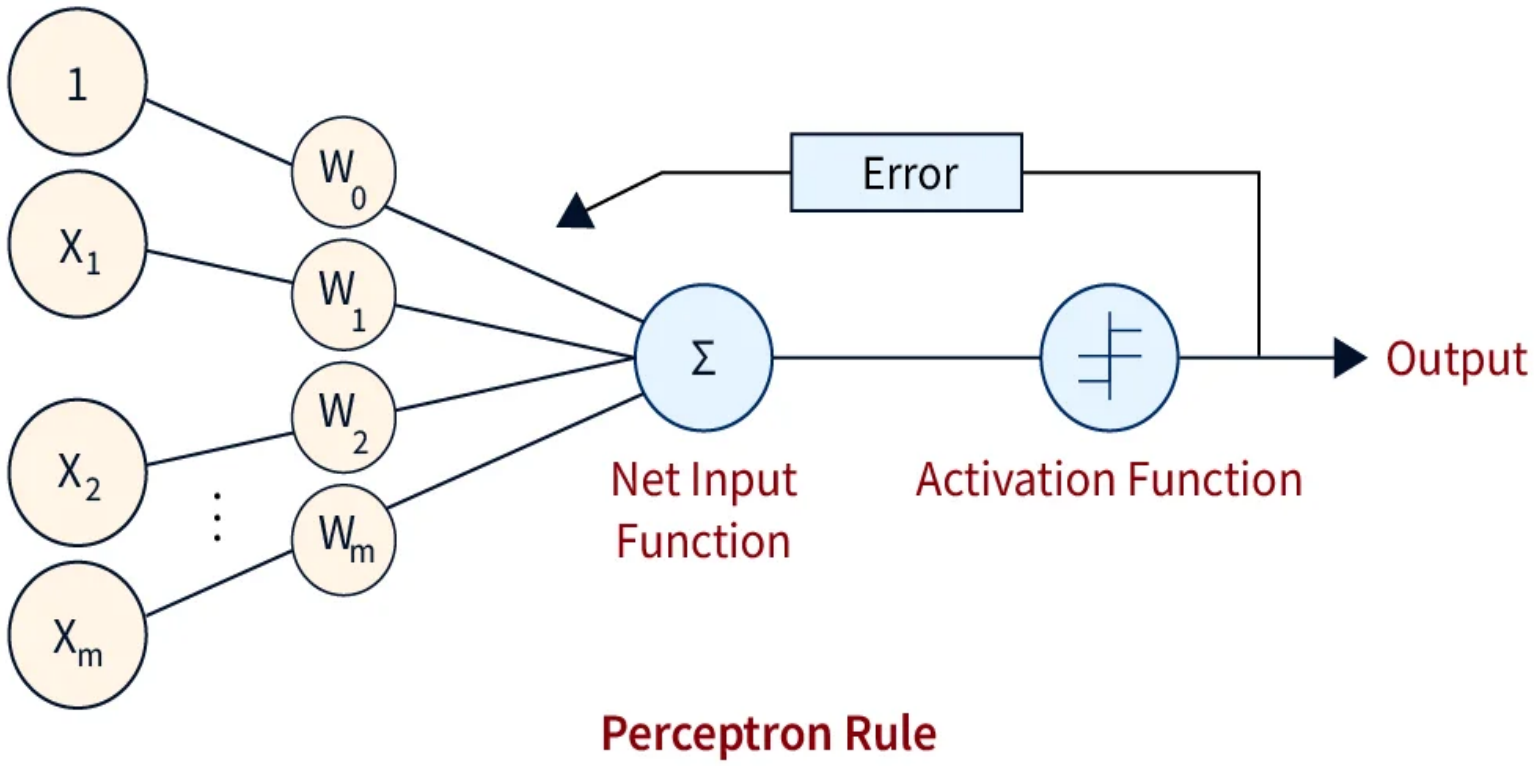


Perceptron learning algorithm

- (3) Evaluate
  - The difference between this output and the actual target value is computed to get the error term, E, generally in terms of mean squared error. The steps up to this form the forward propagation part of the algorithm(Predicted -Acual)^2.



Perceptron learning algorithm



Matrix Operations

$$w_1, w_2, w_3, \dots \dots \dots \dots \dots \dots \dots \dots \dots . w_m$$

Variables

Samples

	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6	.....	Variable m
Sample 1	29	31	34	36	39	48	.....	48
Sample 2	27	29	31	34	36	45	.....	45
Sample 3	25	27	29	31	34	42	.....	42
Sample 4	23	25	27	29	31	39	.....	39
⋮	⋮	⋮	⋮	⋮	⋮	⋮	.....	⋮
Sample n	18	20	21	23	24	26	.....	20

Matrix Operations

$$w_1, w_2, w_3, \dots \dots \dots \dots \dots \dots \dots \dots \dots . w_m$$

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⋮	⋮	⋮	⋮	⋮	⋮	⋮	.....	⋮
Sample n	18	20	21	23	24	26	.....	20

Matrix Operation

- The **dimensions** of a matrix give the number of rows and columns of the matrix *in that order*.

3 columns

$$A = \begin{bmatrix} -2 & 5 & 6 \\ 5 & 2 & 7 \end{bmatrix}$$

2 rows

2*3
Matrix

https://www.khanacademy.org/

Matrix Operation

$$A = \begin{bmatrix} 1 & 3 \\ 2 & 4 \\ 2 & 5 \end{bmatrix} \text{ and } B = \begin{bmatrix} 1 & 3 & 2 & 2 \\ 2 & 4 & 5 & 1 \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & 3 \\ 2 & 4 \\ 2 & 5 \end{bmatrix} \text{ and } B = \begin{bmatrix} 1 & 3 & 2 & 2 \\ 2 & 4 & 5 & 1 \end{bmatrix}$$

2 row entries
= 2 columns

2 column entries
= 2 rows

$$A = \begin{bmatrix} 1 & 3 \\ 2 & 4 \\ 2 & 5 \end{bmatrix} \qquad B = \begin{bmatrix} 1 & 3 & 2 & 2 \\ 2 & 4 & 5 & 1 \end{bmatrix}$$

$$(m \times n) \cdot (n \times k)$$

product is defined

Matrix Operation

Is CD defined?

$$C = \begin{bmatrix} 5 & 3 & 6 & 1 \\ 6 & 8 & 5 & 3 \end{bmatrix} \text{ and } D = \begin{bmatrix} 2 & 1 & 8 \\ 7 & 5 & 5 \end{bmatrix}.$$

CD UnDefined

Matrix Operation

A is a 4×2 matrix and B is a 2×3 matrix.

- IS AB Defined?
- IS BA Defined?

- IS AB Defined?Yes
- IS BA Defined?NO

Matrix Operations

$$w_1, w_2, w_3, \dots \dots \dots \dots \dots \dots \dots \dots \dots . w_m$$

1*m

Variables

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	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6	.....	Variable m
Sample 1	29	31	34	36	39	48	.....	48
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⋮	⋮	⋮	⋮	⋮	⋮	⋮	.....	⋮
Sample n	18	20	21	23	24	26	.....	20

n*m

Matrix Operations

$$w_1, w_2, w_3, \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . w_m$$

1*m

$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ \\ w_m \end{bmatrix}$$

m*1

Variables

Samples

	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6	.....	Variable m
Sample 1	29	31	34	36	39	48	.....	48
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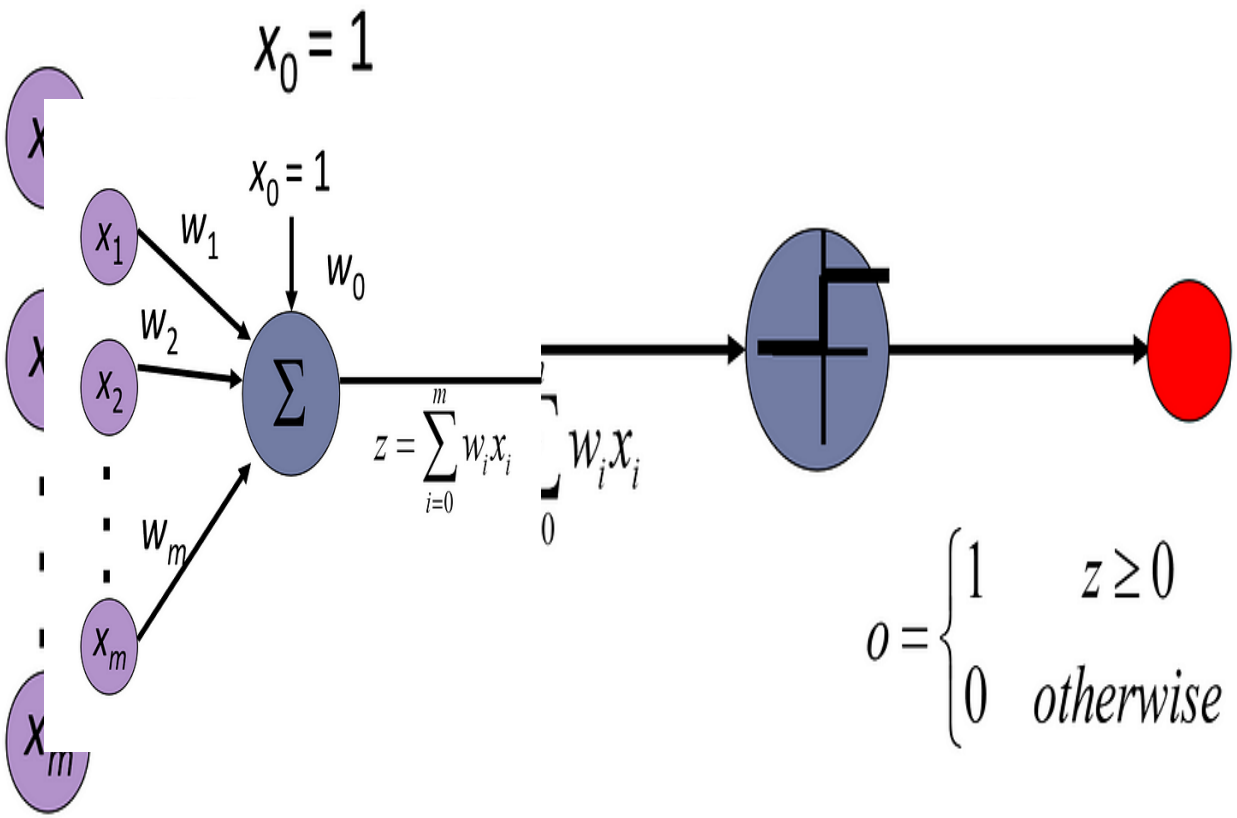
⋮	⋮	⋮	⋮	⋮	⋮	⋮	.....	⋮
Sample n	18	20	21	23	24	26	.....	20

n*m

Matrix Operations

- Weighted Sum
  - $\sum_{i=1}^{m} w_i x_i + b$
  - $\sum_{i=0}^{m} w_i x_i$
  - $\boldsymbol{w}^T \boldsymbol{x}$



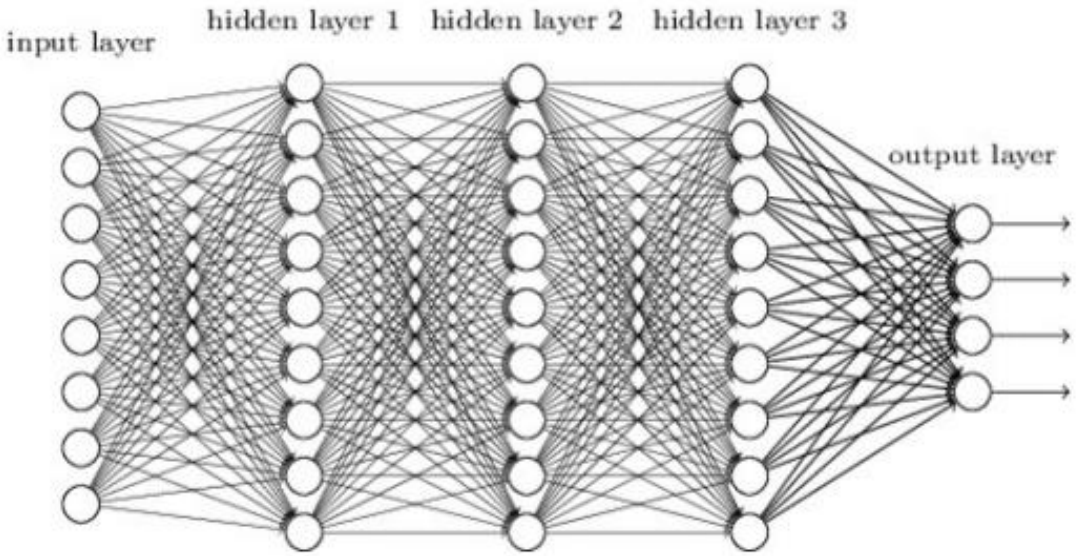
Learning the Network

Dr. Shahira Ahmed

Limitation of Perceptron

- A perceptron model's output can only be a binary number i.e. "0" or "1" because of activation function.
- The perceptron model can only be used to categorize the input vectors' linearly separable sets. If input vectors are non-linear, they can't be properly classified.

The multi-layer perceptron

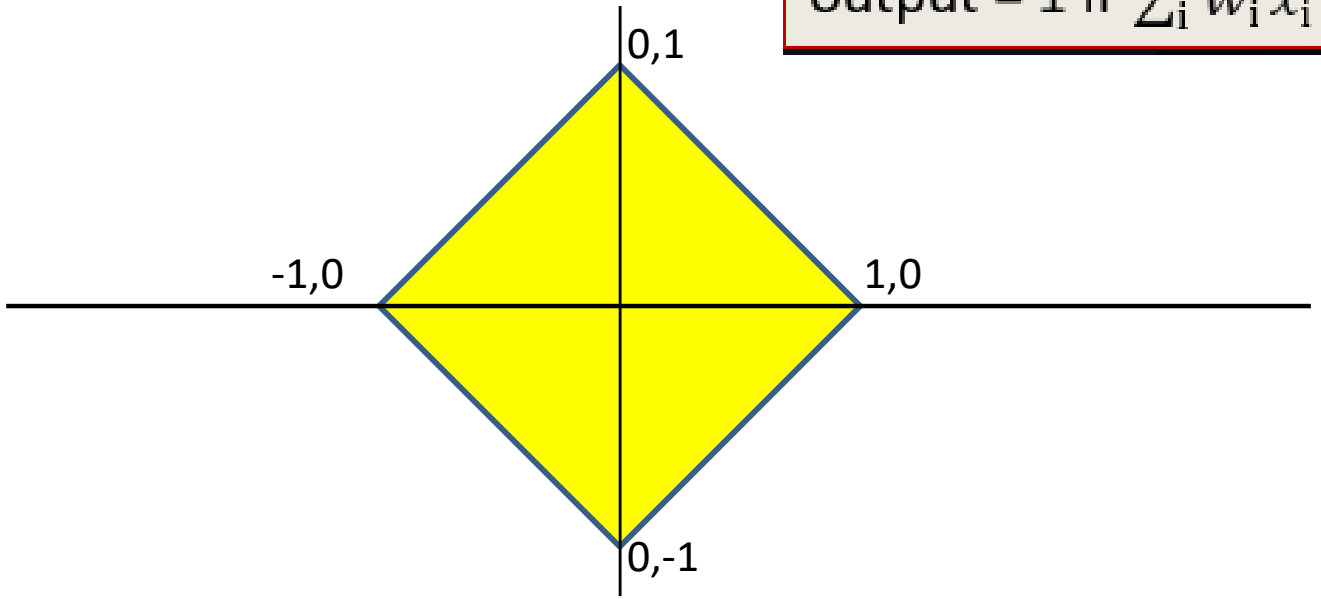


- A network of perceptrons
  - Perceptrons “feed” other perceptrons.

https://deeplearning.cs.cmu.edu/S23/document/slides/lec2.universal.pdf

Option 1: Construct by hand

Assuming simple perceptrons:
output = 1 if $\sum_i w_i x_i + b_i \geq 0, else\ 0$



- Given a function, *handcraft* a network to satisfy it
- E.g.: Build an MLP to classify this decision boundary

https://deeplearning.cs.cmu.edu/S23/

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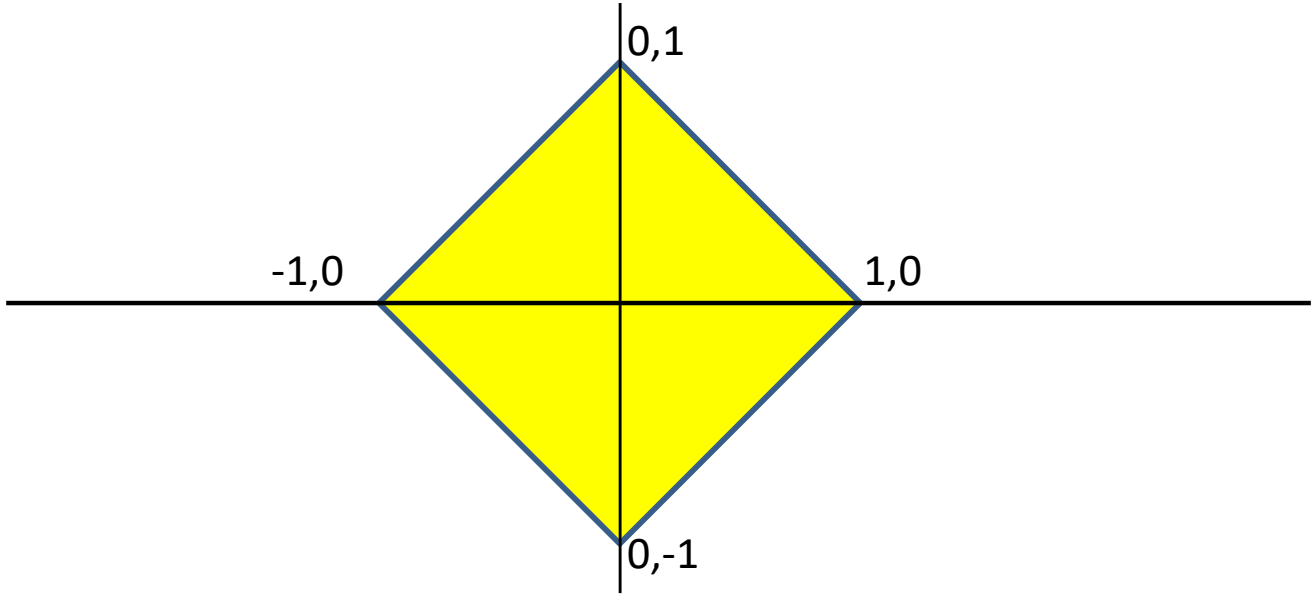

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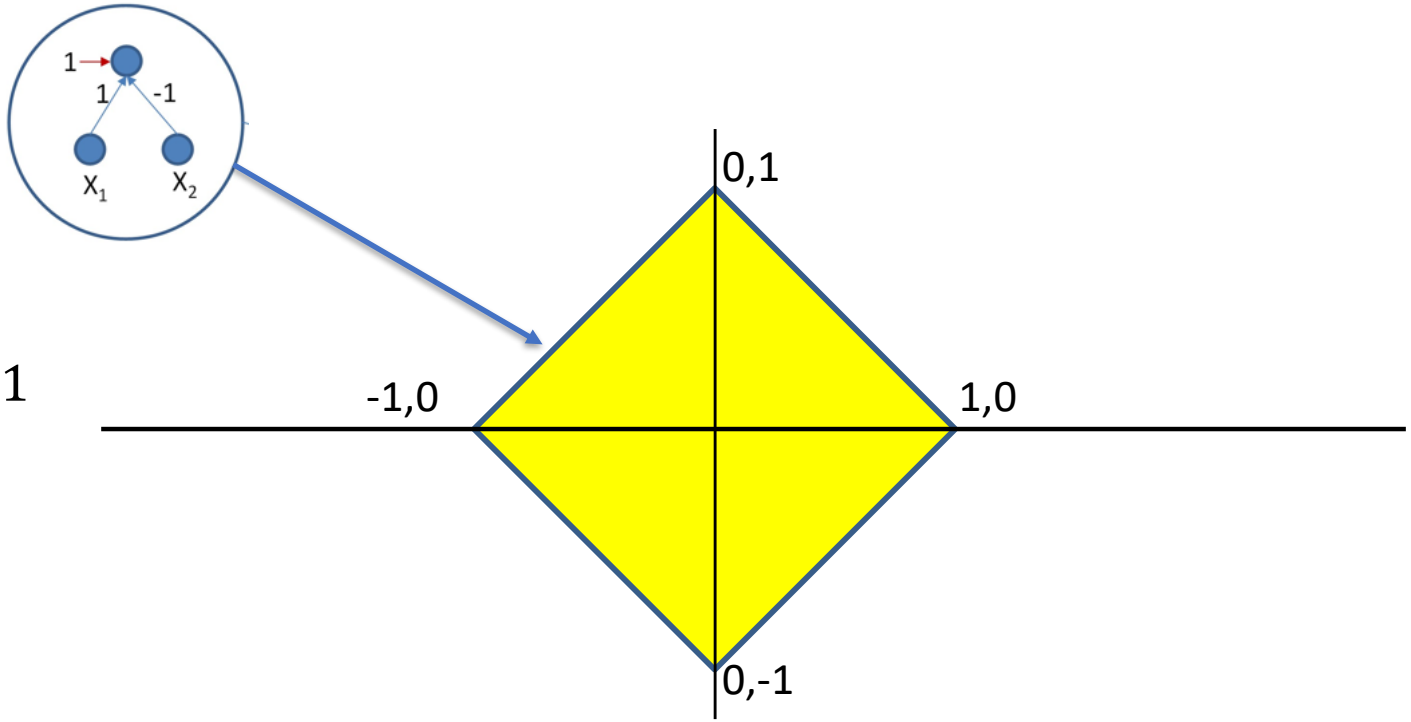

$x_1 - x_2 + 1$

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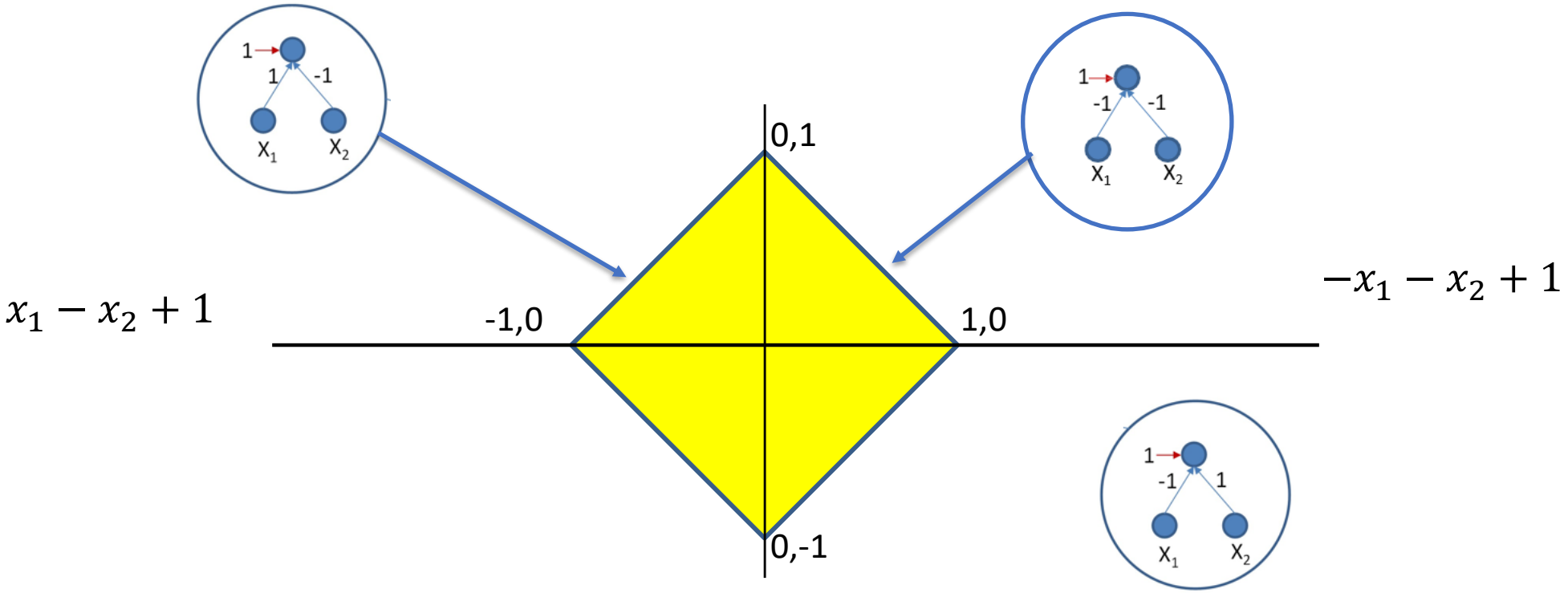

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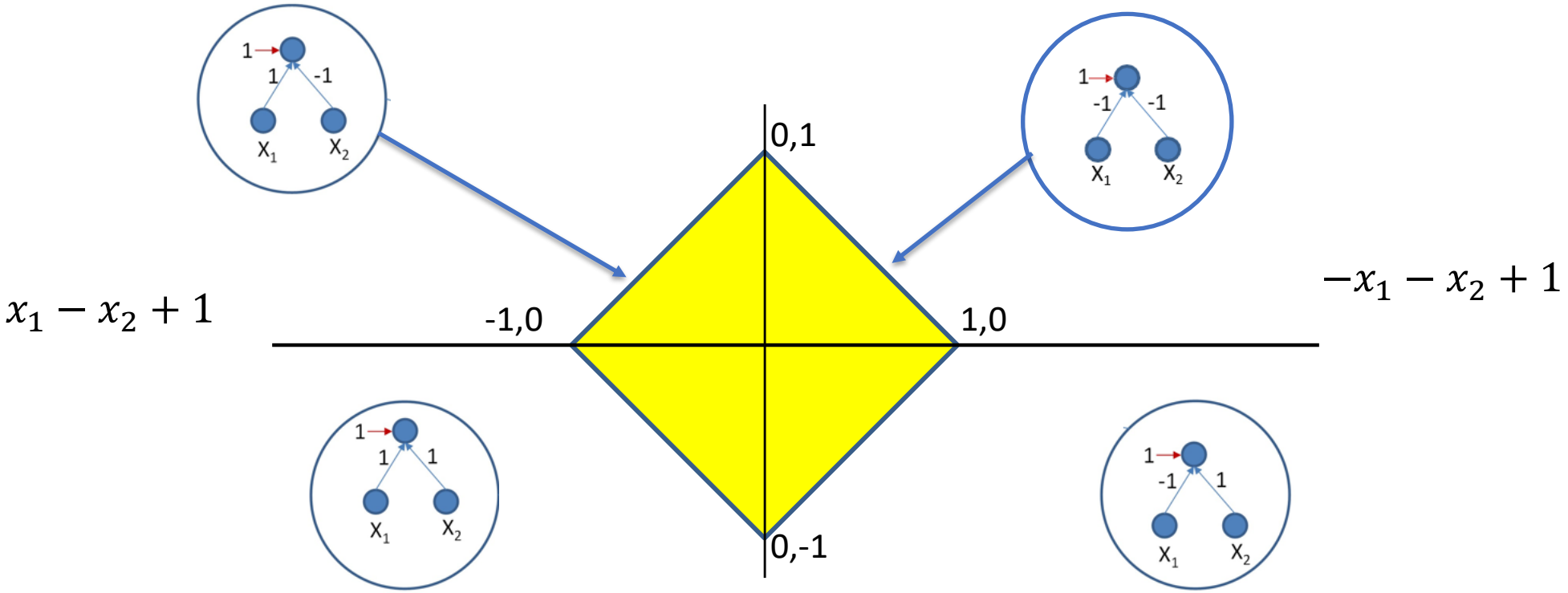
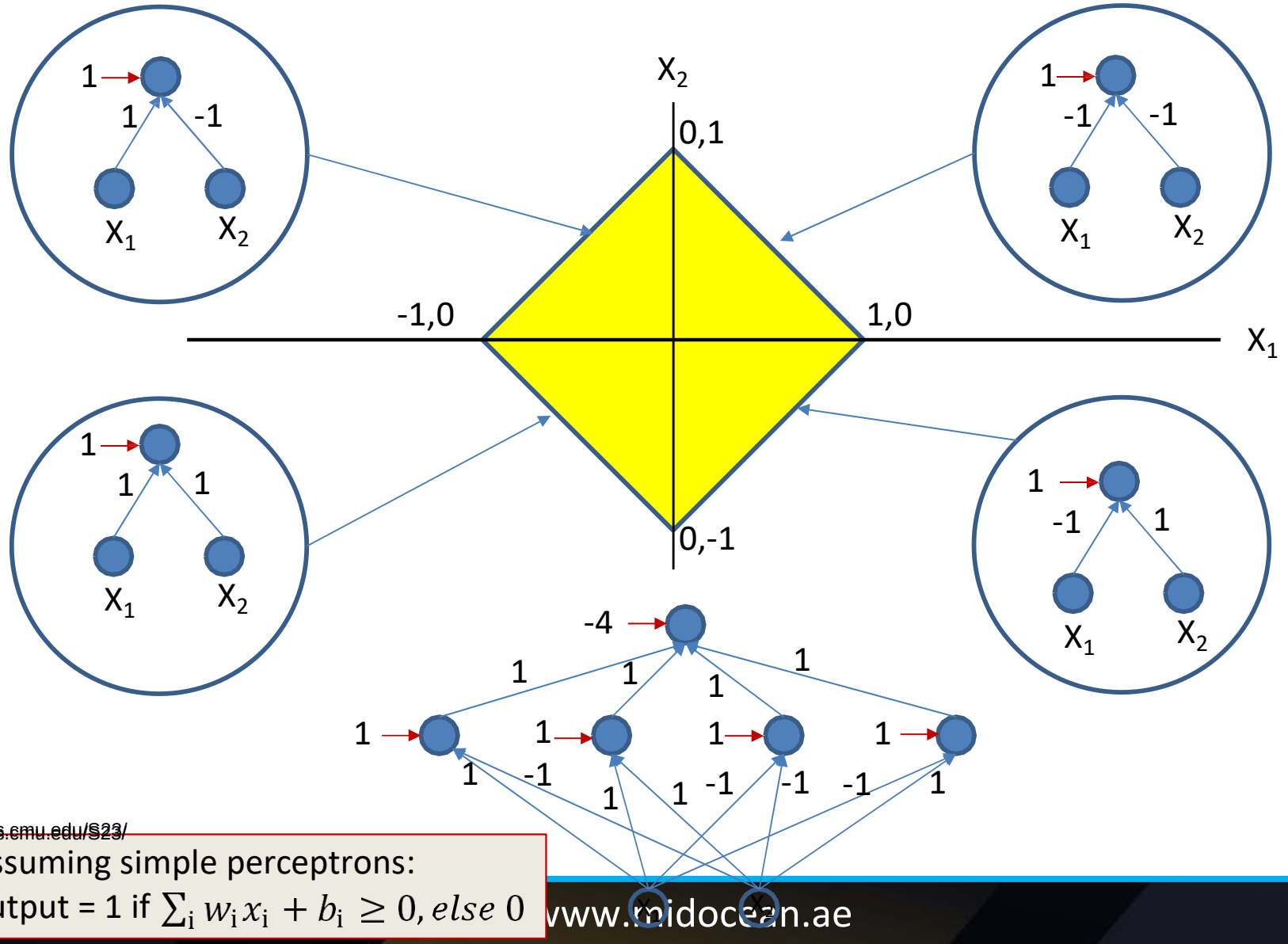


- Given a function, *handcraft* a network to satisfy it
- E.g.: Build an MLP to classify this decision boundary

Option 1: Construct by hand



https://deeplearning.cs.cmu.edu/S23/

Assuming simple perceptrons:
output = 1 if $\sum_i w_i x_i + b_i \geq 0, else\ 0$

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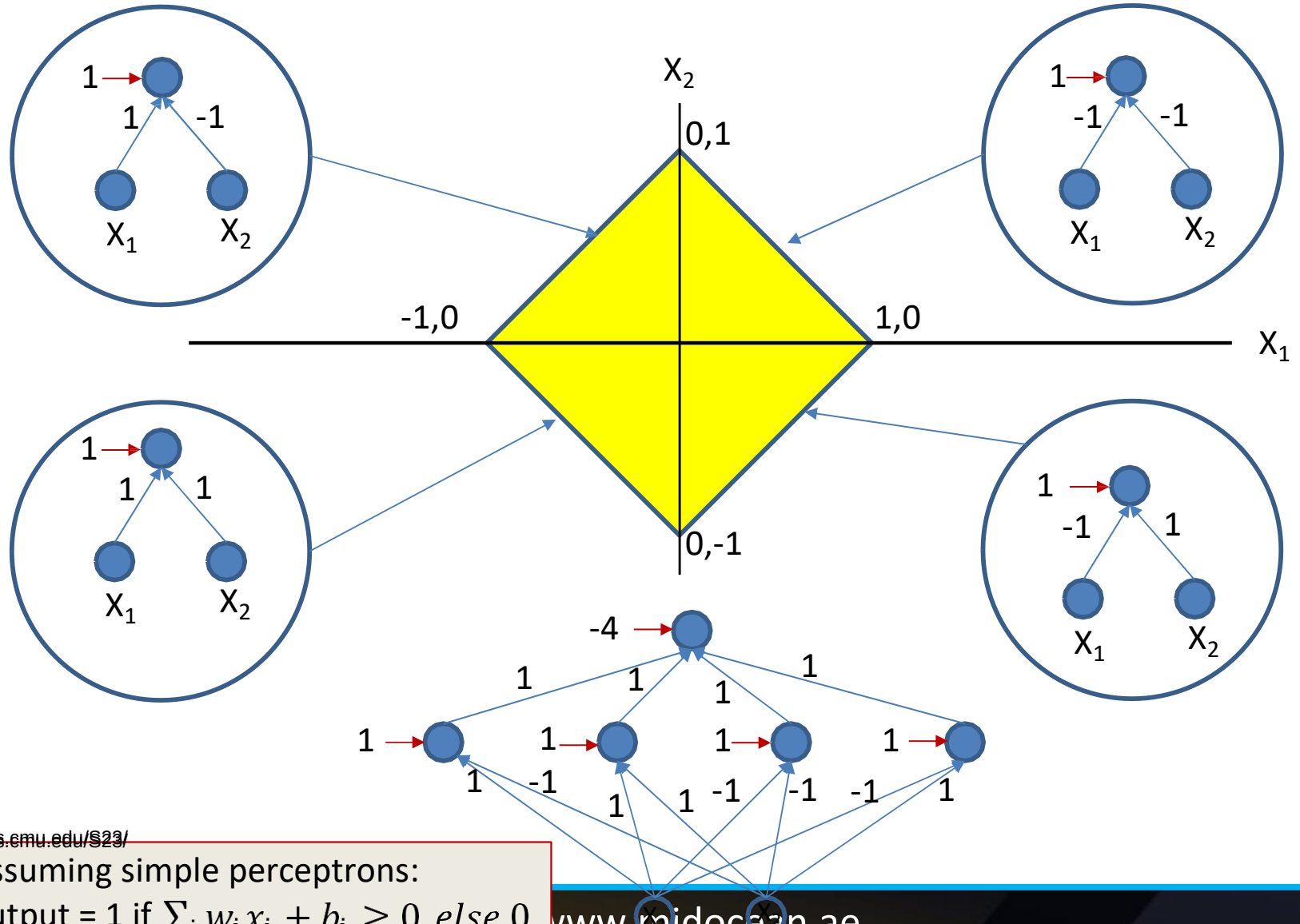

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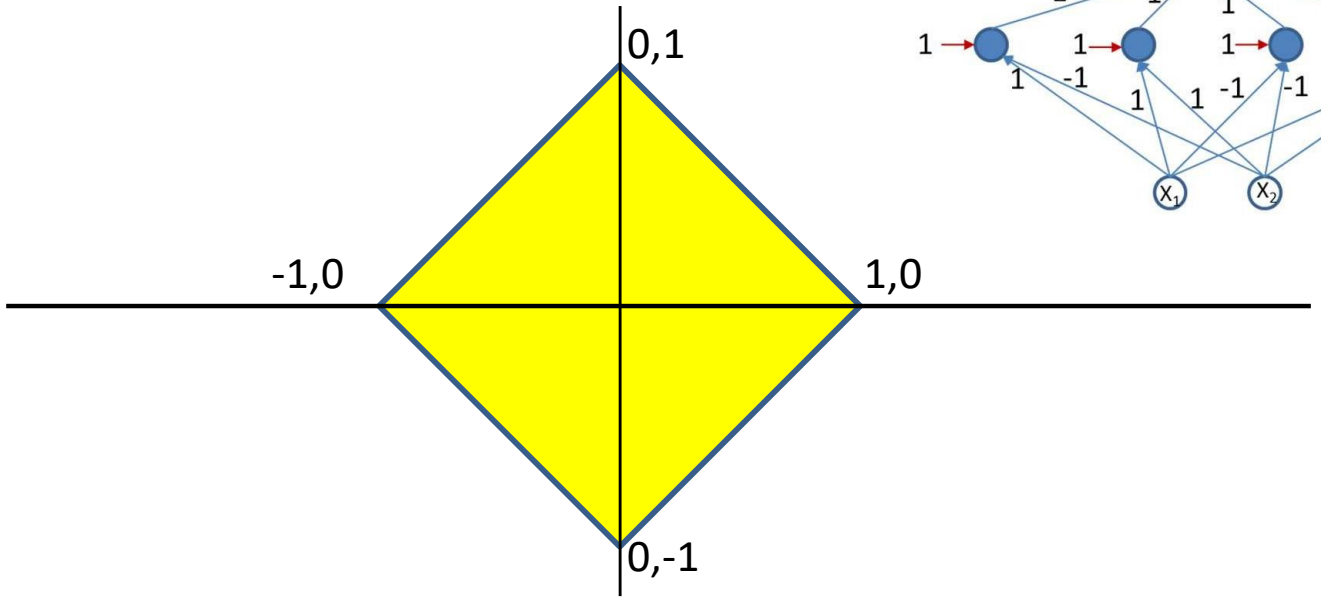

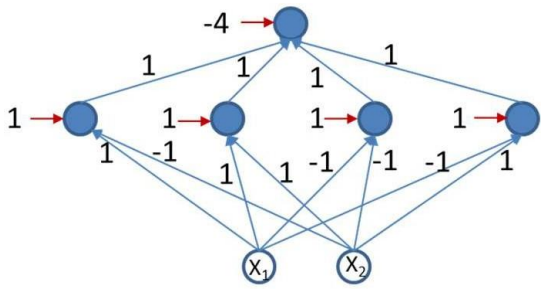

- Given a function, *handcraft* a network to satisfy it
- E.g.: Build an MLP to classify this decision boundary
- Not possible for all but the simplest problems..

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Summary

- Vectorization
- Advantages of Vectorized Implementation
- Single vs Multilayer perceptron
- Training Network by hand

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