

Module 2.3: Perceptron

The story ahead ...

- What about non-boolean (say, real) inputs ?

The story ahead ...

- What about non-boolean (say, real) inputs ?
- Do we always need to hand code the threshold ?

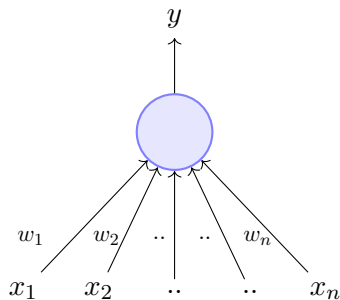
The story ahead ...

- What about non-boolean (say, real) inputs ?
- Do we always need to hand code the threshold ?
- Are all inputs equal ? What if we want to assign more weight (importance) to some inputs ?

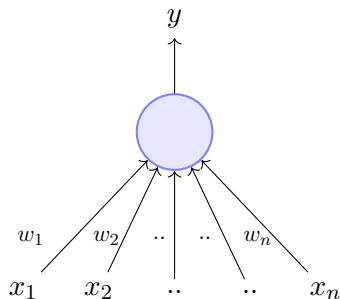
The story ahead ...

- What about non-boolean (say, real) inputs ?
- Do we always need to hand code the threshold ?
- Are all inputs equal ? What if we want to assign more weight (importance) to some inputs ?
- What about functions which are not linearly separable ?

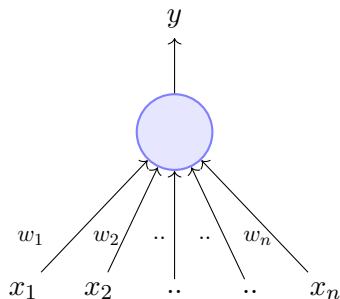
- Frank Rosenblatt, an American psychologist, proposed the **classical perceptron** model (1958)



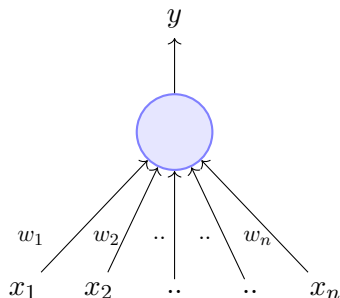
- Frank Rosenblatt, an American psychologist, proposed the **classical perceptron** model (1958)



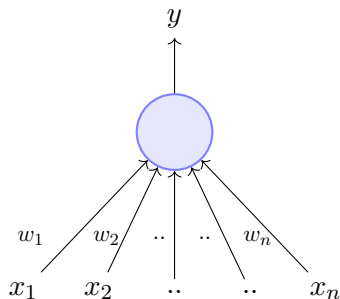
- Frank Rosenblatt, an American psychologist, proposed the **classical perceptron** model (1958)
- A more general computational model than McCulloch–Pitts neurons



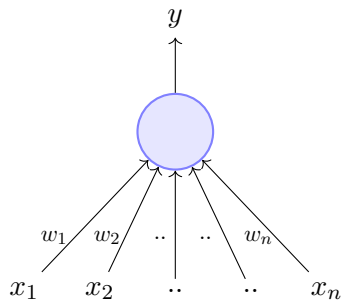
- Frank Rosenblatt, an American psychologist, proposed the **classical perceptron** model (1958)
- A more general computational model than McCulloch–Pitts neurons
- **Main differences:** Introduction of numerical weights for inputs and a mechanism for learning these weights

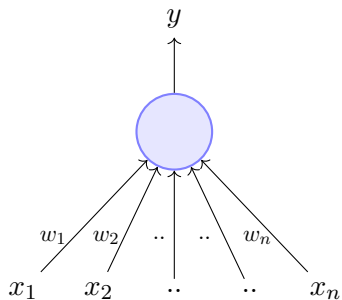


- Frank Rosenblatt, an American psychologist, proposed the **classical perceptron** model (1958)
- A more general computational model than McCulloch–Pitts neurons
- **Main differences:** Introduction of numerical weights for inputs and a mechanism for learning these weights
- Inputs are no longer limited to boolean values

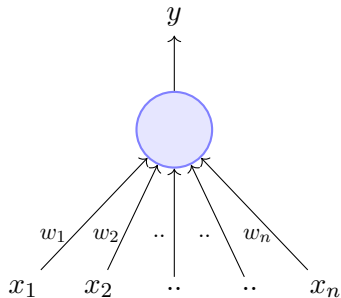


- Frank Rosenblatt, an American psychologist, proposed the **classical perceptron** model (1958)
- A more general computational model than McCulloch–Pitts neurons
- **Main differences:** Introduction of numerical weights for inputs and a mechanism for learning these weights
- Inputs are no longer limited to boolean values
- Refined and carefully analyzed by Minsky and Papert (1969) - their model is referred to as the **perceptron** model here



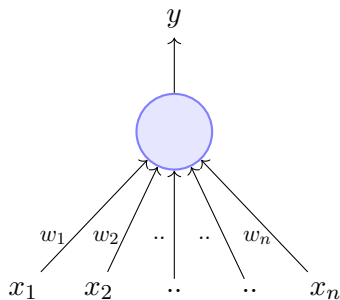


$$y = 1 \quad \text{if} \sum_{i=1}^n w_i * x_i \geq \theta$$



$$y = 1 \quad \text{if} \sum_{i=1}^n w_i * x_i \geq \theta$$

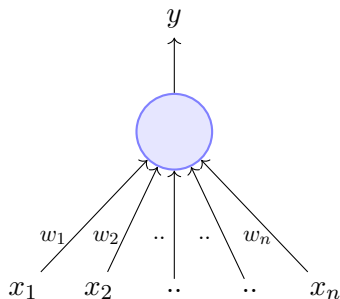
$$= 0 \quad \text{if} \sum_{i=1}^n w_i * x_i < \theta$$



$$y = 1 \quad \text{if} \sum_{i=1}^n w_i * x_i \geq \theta$$

$$= 0 \quad \text{if} \sum_{i=1}^n w_i * x_i < \theta$$

Rewriting the above,

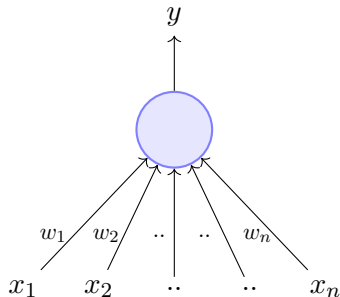


$$y = 1 \quad \text{if} \sum_{i=1}^n w_i * x_i \geq \theta$$

$$= 0 \quad \text{if} \sum_{i=1}^n w_i * x_i < \theta$$

Rewriting the above,

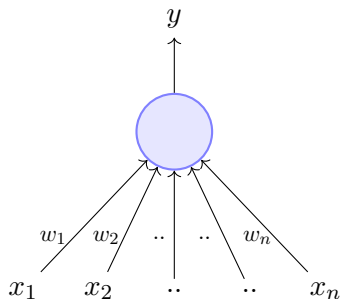
$$y = 1 \quad \text{if} \sum_{i=1}^n w_i * x_i - \theta \geq 0$$



$$\begin{aligned}
 y &= 1 && \text{if } \sum_{i=1}^n w_i * x_i \geq \theta \\
 &= 0 && \text{if } \sum_{i=1}^n w_i * x_i < \theta
 \end{aligned}$$

Rewriting the above,

$$\begin{aligned}
 y &= 1 && \text{if } \sum_{i=1}^n w_i * x_i - \theta \geq 0 \\
 &= 0 && \text{if } \sum_{i=1}^n w_i * x_i - \theta < 0
 \end{aligned}$$

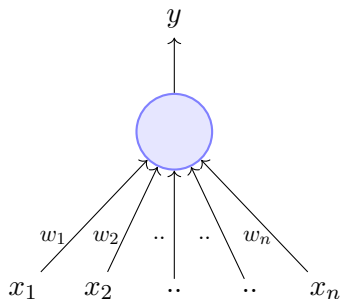


A more accepted convention,

$$\begin{aligned}
 y &= 1 && \text{if } \sum_{i=1}^n w_i * x_i \geq \theta \\
 &= 0 && \text{if } \sum_{i=1}^n w_i * x_i < \theta
 \end{aligned}$$

Rewriting the above,

$$\begin{aligned}
 y &= 1 && \text{if } \sum_{i=1}^n w_i * x_i - \theta \geq 0 \\
 &= 0 && \text{if } \sum_{i=1}^n w_i * x_i - \theta < 0
 \end{aligned}$$



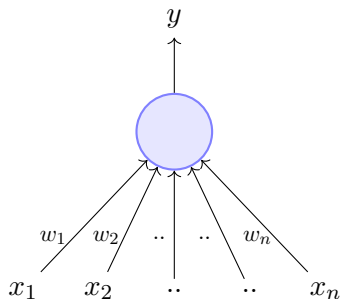
A more accepted convention,

$$y = 1 \quad \text{if} \sum_{i=0}^n w_i * x_i \geq 0$$

$$\begin{aligned} y &= 1 && \text{if} \sum_{i=1}^n w_i * x_i \geq \theta \\ &= 0 && \text{if} \sum_{i=1}^n w_i * x_i < \theta \end{aligned}$$

Rewriting the above,

$$\begin{aligned} y &= 1 && \text{if} \sum_{i=1}^n w_i * x_i - \theta \geq 0 \\ &= 0 && \text{if} \sum_{i=1}^n w_i * x_i - \theta < 0 \end{aligned}$$



$$\begin{aligned}
 y &= 1 && \text{if } \sum_{i=1}^n w_i * x_i \geq \theta \\
 &= 0 && \text{if } \sum_{i=1}^n w_i * x_i < \theta
 \end{aligned}$$

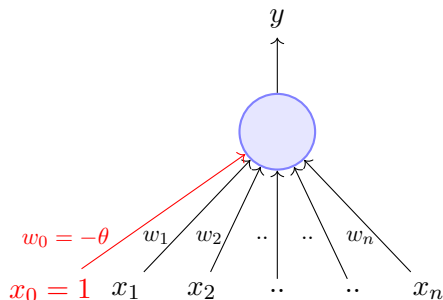
Rewriting the above,

A more accepted convention,

$$y = 1 \quad \text{if } \sum_{i=0}^n w_i * x_i \geq 0$$

$$\begin{aligned}
 y &= 1 && \text{if } \sum_{i=1}^n w_i * x_i - \theta \geq 0 \\
 &= 0 && \text{if } \sum_{i=1}^n w_i * x_i - \theta < 0
 \end{aligned}$$

where, $x_0 = 1$ and $w_0 = -\theta$



A more accepted convention,

$$y = 1 \quad \text{if} \quad \sum_{i=0}^n w_i * x_i \geq 0$$

where, $x_0 = 1$ and $w_0 = -\theta$

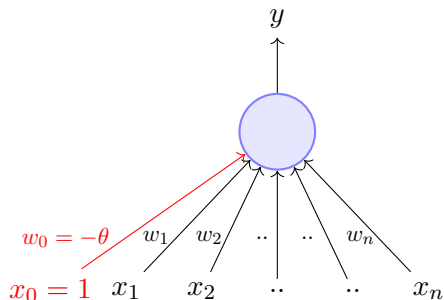
$$y = 1 \quad \text{if} \quad \sum_{i=1}^n w_i * x_i \geq \theta$$

$$= 0 \quad \text{if} \quad \sum_{i=1}^n w_i * x_i < \theta$$

Rewriting the above,

$$y = 1 \quad \text{if} \quad \sum_{i=1}^n w_i * x_i - \theta \geq 0$$

$$= 0 \quad \text{if} \quad \sum_{i=1}^n w_i * x_i - \theta < 0$$



A more accepted convention,

$$\begin{aligned}
 y &= 1 && \text{if } \sum_{i=0}^n w_i * x_i \geq 0 \\
 &= 0 && \text{if } \sum_{i=0}^n w_i * x_i < 0
 \end{aligned}$$

where, $x_0 = 1$ and $w_0 = -\theta$

$$\begin{aligned}
 y &= 1 && \text{if } \sum_{i=1}^n w_i * x_i \geq \theta \\
 &= 0 && \text{if } \sum_{i=1}^n w_i * x_i < \theta
 \end{aligned}$$

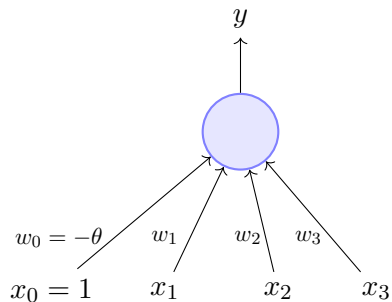
Rewriting the above,

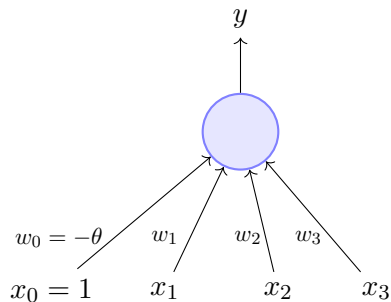
$$\begin{aligned}
 y &= 1 && \text{if } \sum_{i=1}^n w_i * x_i - \theta \geq 0 \\
 &= 0 && \text{if } \sum_{i=1}^n w_i * x_i - \theta < 0
 \end{aligned}$$

We will now try to answer the following questions:

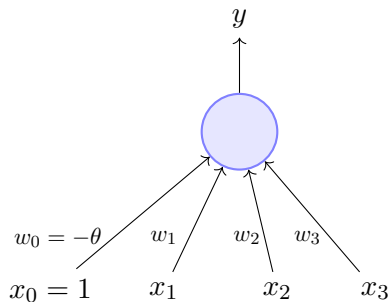
- Why are we trying to implement boolean functions?
- Why do we need weights ?
- Why is $w_0 = -\theta$ called the bias ?

- Consider the task of predicting whether we would like a movie or not





- Consider the task of predicting whether we would like a movie or not
- Suppose, we base our decision on 3 inputs (binary, for simplicity)

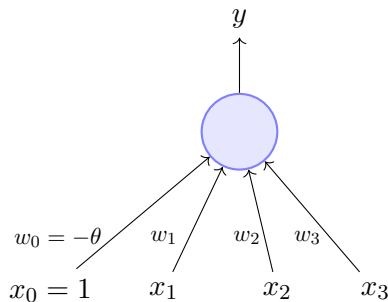


- Consider the task of predicting whether we would like a movie or not
- Suppose, we base our decision on 3 inputs (binary, for simplicity)
- Based on our past viewing experience (**data**), we may give a high weight to *isDirectorNolan* as compared to the other inputs

$x_1 = isActorDamon$

$x_2 = isGenreThriller$

$x_3 = isDirectorNolan$



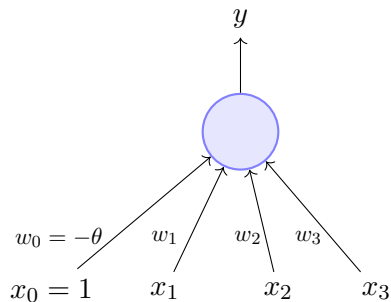
$x_1 = isActorDamon$

$x_2 = isGenreThriller$

$x_3 = isDirectorNolan$

- Consider the task of predicting whether we would like a movie or not
- Suppose, we base our decision on 3 inputs (binary, for simplicity)
- Based on our past viewing experience (**data**), we may give a high weight to *isDirectorNolan* as compared to the other inputs
- Specifically, even if the actor is not *Matt Damon* and the genre is not *thriller* we would still want to cross the threshold θ by assigning a high weight to *isDirectorNolan*

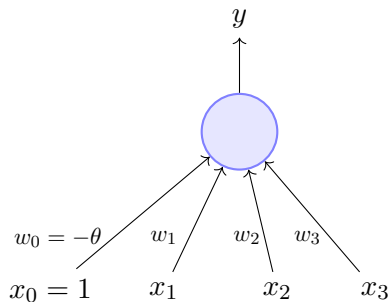
- w_0 is called the bias as it represents the prior (prejudice)



$x_1 = isActorDamon$

$x_2 = isGenreThriller$

$x_3 = isDirectorNolan$

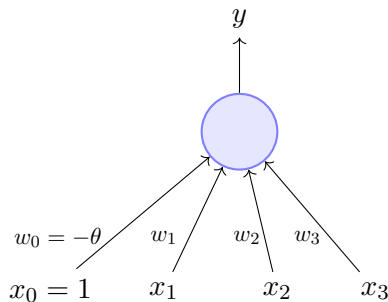


- w_0 is called the bias as it represents the prior (prejudice)
- A movie buff may have a very low threshold and may watch any movie irrespective of the genre, actor, director [$\theta = 0$]

$x_1 = isActorDamon$

$x_2 = isGenreThriller$

$x_3 = isDirectorNolan$

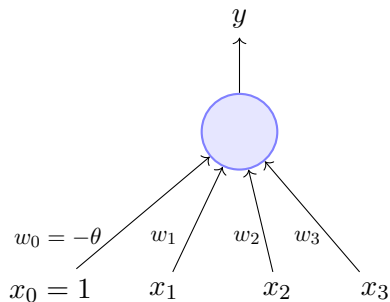


- w_0 is called the bias as it represents the prior (prejudice)
- A movie buff may have a very low threshold and may watch any movie irrespective of the genre, actor, director [$\theta = 0$]
- On the other hand, a selective viewer may only watch thrillers starring Matt Damon and directed by Nolan [$\theta = 3$]

$x_1 = isActorDamon$

$x_2 = isGenreThriller$

$x_3 = isDirectorNolan$



$x_1 = isActorDamon$
 $x_2 = isGenreThriller$
 $x_3 = isDirectorNolan$

- w_0 is called the bias as it represents the prior (prejudice)
- A movie buff may have a very low threshold and may watch any movie irrespective of the genre, actor, director [$\theta = 0$]
- On the other hand, a selective viewer may only watch thrillers starring Matt Damon and directed by Nolan [$\theta = 3$]
- The weights (w_1, w_2, \dots, w_n) and the bias (w_0) will depend on the data (viewer history in this case)

What kind of functions can be implemented using the perceptron? Any difference from McCulloch Pitts neurons?

McCulloch Pitts Neuron

(assuming no inhibitory inputs)

$$y = 1 \quad \text{if } \sum_{i=0}^n x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n x_i < \theta$$

Perceptron

$$y = 1 \quad \text{if } \sum_{i=0}^n w_i * x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n w_i * x_i < \theta$$

McCulloch Pitts Neuron

(assuming no inhibitory inputs)

$$y = 1 \quad \text{if } \sum_{i=0}^n x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n x_i < \theta$$

- From the equations it should be clear that even a perceptron separates the input space into two halves

Perceptron

$$y = 1 \quad \text{if } \sum_{i=0}^n w_i * x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n w_i * x_i < \theta$$

McCulloch Pitts Neuron

(assuming no inhibitory inputs)

$$y = 1 \quad \text{if } \sum_{i=0}^n x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n x_i < \theta$$

- From the equations it should be clear that even a perceptron separates the input space into two halves
- All inputs which produce a 1 lie on one side and all inputs which produce a 0 lie on the other side

Perceptron

$$y = 1 \quad \text{if } \sum_{i=0}^n w_i * x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n w_i * x_i < \theta$$

McCulloch Pitts Neuron

(assuming no inhibitory inputs)

$$y = 1 \quad \text{if } \sum_{i=0}^n x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n x_i < \theta$$

Perceptron

$$y = 1 \quad \text{if } \sum_{i=0}^n w_i * x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n w_i * x_i < \theta$$

- From the equations it should be clear that even a perceptron separates the input space into two halves
- All inputs which produce a 1 lie on one side and all inputs which produce a 0 lie on the other side
- In other words, a single perceptron can only be used to implement linearly separable functions

McCulloch Pitts Neuron

(assuming no inhibitory inputs)

$$y = 1 \quad \text{if } \sum_{i=0}^n x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n x_i < \theta$$

Perceptron

$$y = 1 \quad \text{if } \sum_{i=0}^n w_i * x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n w_i * x_i < \theta$$

- From the equations it should be clear that even a perceptron separates the input space into two halves
- All inputs which produce a 1 lie on one side and all inputs which produce a 0 lie on the other side
- In other words, a single perceptron can only be used to implement linearly separable functions
- Then what is the difference?

McCulloch Pitts Neuron

(assuming no inhibitory inputs)

$$y = 1 \quad \text{if } \sum_{i=0}^n x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n x_i < \theta$$

Perceptron

$$y = 1 \quad \text{if } \sum_{i=0}^n w_i * x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n w_i * x_i < \theta$$

- From the equations it should be clear that even a perceptron separates the input space into two halves
- All inputs which produce a 1 lie on one side and all inputs which produce a 0 lie on the other side
- In other words, a single perceptron can only be used to implement linearly separable functions
- Then what is the difference? The weights (including threshold) can be learned and the inputs can be real valued

McCulloch Pitts Neuron

(assuming no inhibitory inputs)

$$y = 1 \quad \text{if } \sum_{i=0}^n x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n x_i < \theta$$

Perceptron

$$y = 1 \quad \text{if } \sum_{i=0}^n w_i * x_i \geq \theta$$
$$= 0 \quad \text{if } \sum_{i=0}^n w_i * x_i < \theta$$

- From the equations it should be clear that even a perceptron separates the input space into two halves
- All inputs which produce a 1 lie on one side and all inputs which produce a 0 lie on the other side
- In other words, a single perceptron can only be used to implement linearly separable functions
- Then what is the difference? The weights (including threshold) can be learned and the inputs can be real valued
- We will first revisit some boolean functions and then see the perceptron learning algorithm (for learning weights)

x_1	x_2	OR
0	0	
0	1	
1	0	
1	1	

x_1	x_2	OR
0	0	0

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i$

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
0	1	1	

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
0	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
0	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
1	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
0	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
1	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 0 < 0 \implies w_0 < 0$$

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
0	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
1	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 0 < 0 \implies w_0 < 0$$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 1 \geq 0 \implies w_2 > -w_0$$

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
0	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
1	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 0 < 0 \implies w_0 < 0$$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 1 \geq 0 \implies w_2 > -w_0$$

$$w_0 + w_1 \cdot 1 + w_2 \cdot 0 \geq 0 \implies w_1 > -w_0$$

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
0	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
1	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 0 < 0 \implies w_0 < 0$$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 1 \geq 0 \implies w_2 > -w_0$$

$$w_0 + w_1 \cdot 1 + w_2 \cdot 0 \geq 0 \implies w_1 > -w_0$$

$$w_0 + w_1 \cdot 1 + w_2 \cdot 1 \geq 0 \implies w_1 + w_2 > -w_0$$

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
0	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
1	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 0 < 0 \implies w_0 < 0$$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 1 \geq 0 \implies w_2 > -w_0$$

$$w_0 + w_1 \cdot 1 + w_2 \cdot 0 \geq 0 \implies w_1 > -w_0$$

$$w_0 + w_1 \cdot 1 + w_2 \cdot 1 \geq 0 \implies w_1 + w_2 > -w_0$$

- One possible solution to this set of inequalities is $w_0 = -1, w_1 = 1.1, w_2 = 1.1$ (and various other solutions are possible)

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
0	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
1	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$

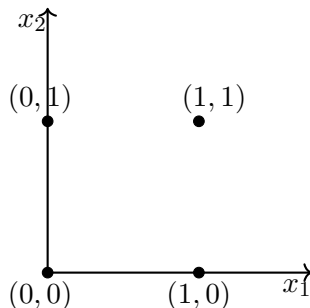
$$w_0 + w_1 \cdot 0 + w_2 \cdot 0 < 0 \implies w_0 < 0$$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 1 \geq 0 \implies w_2 > -w_0$$

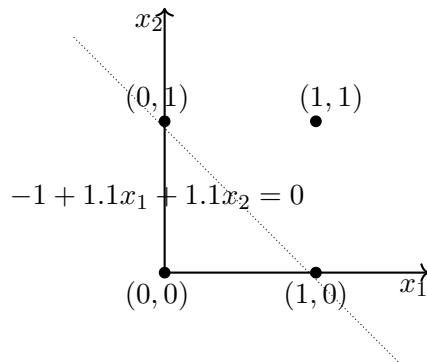
$$w_0 + w_1 \cdot 1 + w_2 \cdot 0 \geq 0 \implies w_1 > -w_0$$

$$w_0 + w_1 \cdot 1 + w_2 \cdot 1 \geq 0 \implies w_1 + w_2 > -w_0$$

- One possible solution to this set of inequalities is $w_0 = -1, w_1 = 1.1, w_2 = 1.1$ (and various other solutions are possible)



x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
0	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
1	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$



$$\begin{aligned}
 w_0 + w_1 \cdot 0 + w_2 \cdot 0 < 0 &\implies w_0 < 0 \\
 w_0 + w_1 \cdot 0 + w_2 \cdot 1 \geq 0 &\implies w_2 > -w_0 \\
 w_0 + w_1 \cdot 1 + w_2 \cdot 0 \geq 0 &\implies w_1 > -w_0 \\
 w_0 + w_1 \cdot 1 + w_2 \cdot 1 \geq 0 &\implies w_1 + w_2 > -w_0
 \end{aligned}$$

- One possible solution to this set of inequalities is $w_0 = -1, w_1 = 1.1, w_2 = 1.1$ (and various other solutions are possible)

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
0	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
1	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$

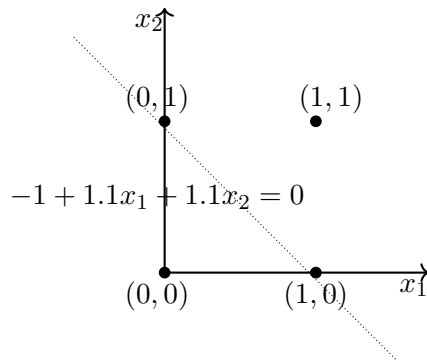
$$w_0 + w_1 \cdot 0 + w_2 \cdot 0 < 0 \implies w_0 < 0$$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 1 \geq 0 \implies w_2 > -w_0$$

$$w_0 + w_1 \cdot 1 + w_2 \cdot 0 \geq 0 \implies w_1 > -w_0$$

$$w_0 + w_1 \cdot 1 + w_2 \cdot 1 \geq 0 \implies w_1 + w_2 > -w_0$$

- One possible solution to this set of inequalities is $w_0 = -1, w_1 = 1.1, w_2 = 1.1$ (and various other solutions are possible)



- Note that we can come up with a similar set of inequalities and find the value of θ for a McCulloch Pitts neuron also

x_1	x_2	OR	
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
0	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$
1	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$

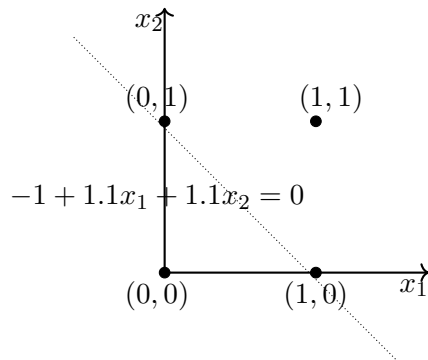
$$w_0 + w_1 \cdot 0 + w_2 \cdot 0 < 0 \implies w_0 < 0$$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 1 \geq 0 \implies w_2 > -w_0$$

$$w_0 + w_1 \cdot 1 + w_2 \cdot 0 \geq 0 \implies w_1 > -w_0$$

$$w_0 + w_1 \cdot 1 + w_2 \cdot 1 \geq 0 \implies w_1 + w_2 > -w_0$$

- One possible solution to this set of inequalities is $w_0 = -1, w_1 = 1.1, w_2 = 1.1$ (and various other solutions are possible)



- Note that we can come up with a similar set of inequalities and find the value of θ for a McCulloch Pitts neuron also (Try it!)