

Lecture 3

Sigmoid Neurons, Gradient Descent, Feedforward Neural Networks,
Representation Power of Feedforward Neural Networks

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- For Module 3.4, I have borrowed ideas from the videos by Ryan Harris on "visualize backpropagation" (available on youtube)
- For Module 3.5, I have borrowed ideas from this excellent book * which is available online
- I am sure I would have been influenced and borrowed ideas from other sources and I apologize if I have failed to acknowledge them

*<http://neuralnetworksanddeeplearning.com/chap4.html>

Module 3.1: Sigmoid Neuron

The story ahead ...

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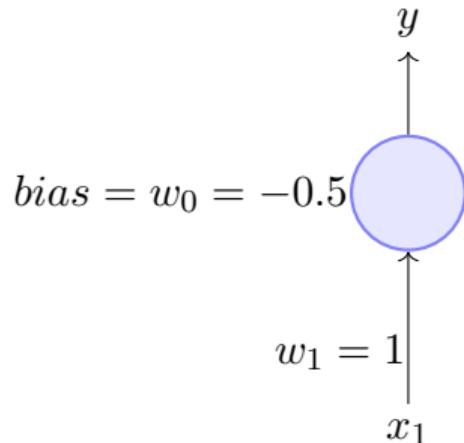
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- Can we have a network which can (approximately) represent such functions ?

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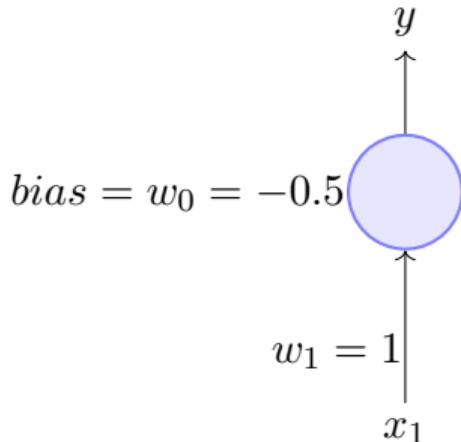
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- Can we have a network which can (approximately) represent such functions ?
- Before answering the above question we will have to first graduate from *perceptrons* to *sigmoidal neurons* ...

Recall

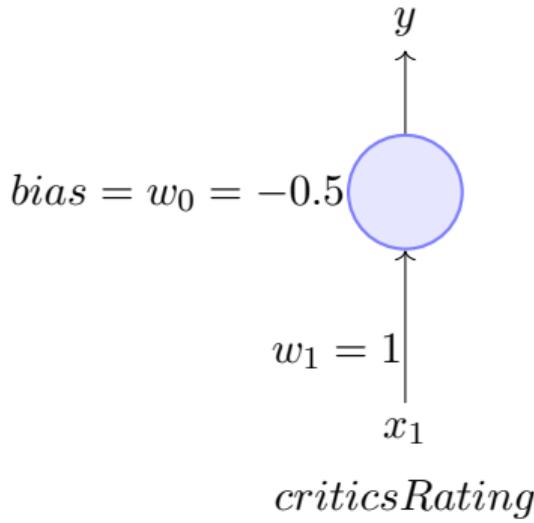
- A perceptron will fire if the weighted sum of its inputs is greater than the threshold ($-w_0$)



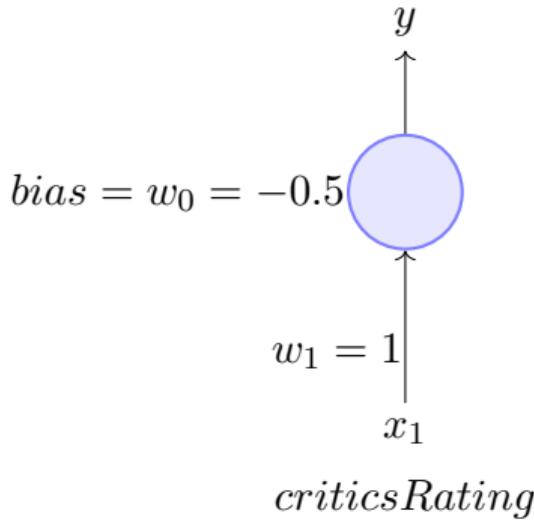
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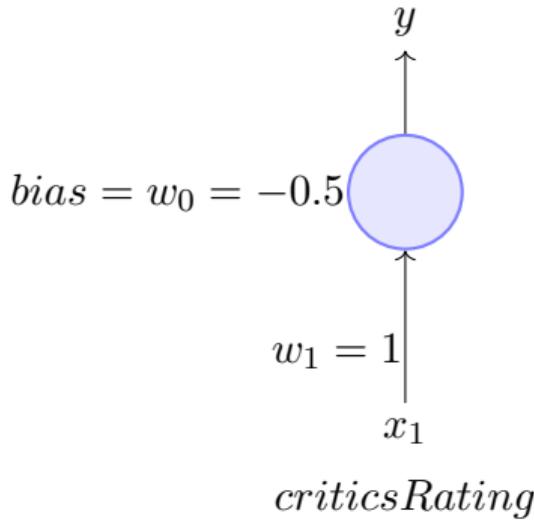
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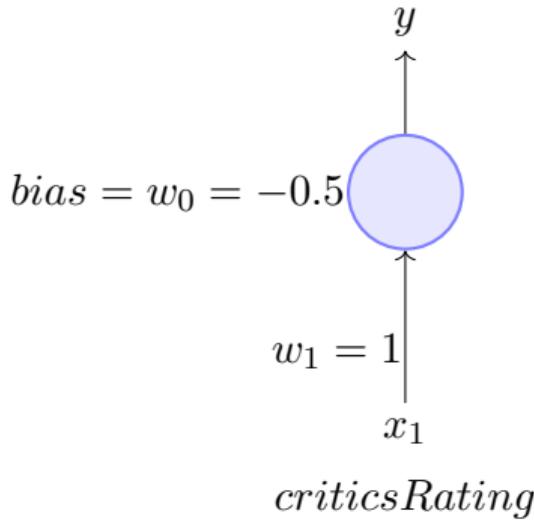
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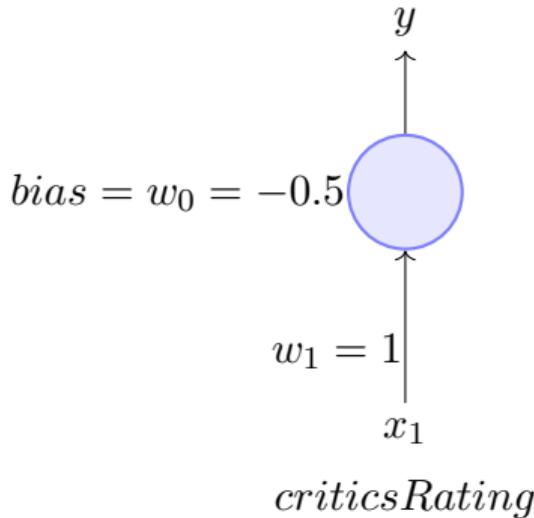
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- If the threshold is 0.5 ($w_0 = -0.5$) and $w_1 = 1$ then what would be the decision for a movie with $criticsRating = 0.51$?



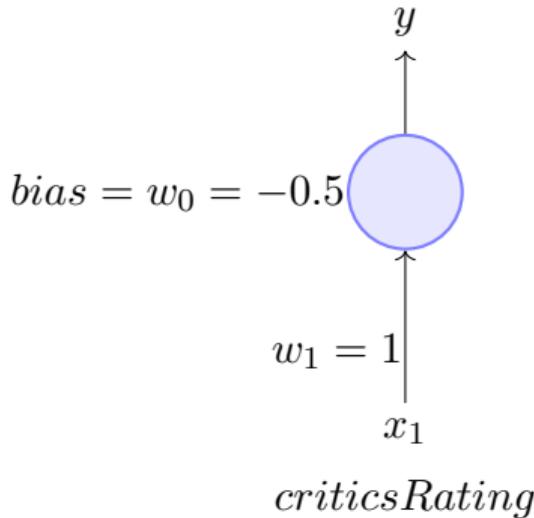
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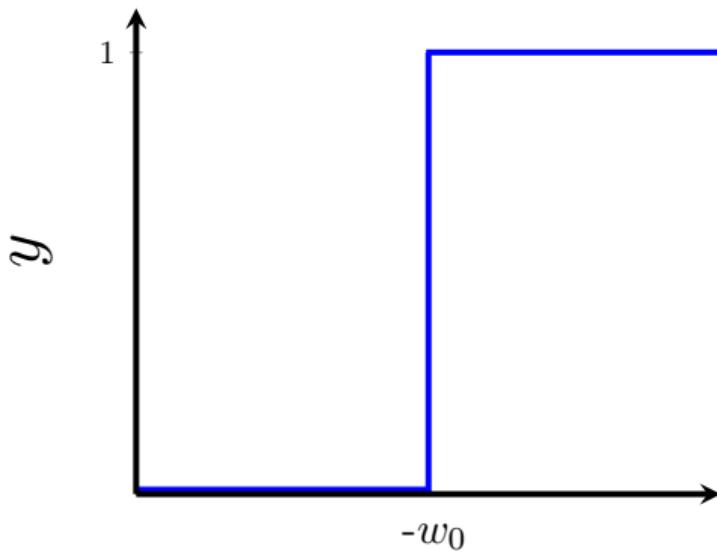


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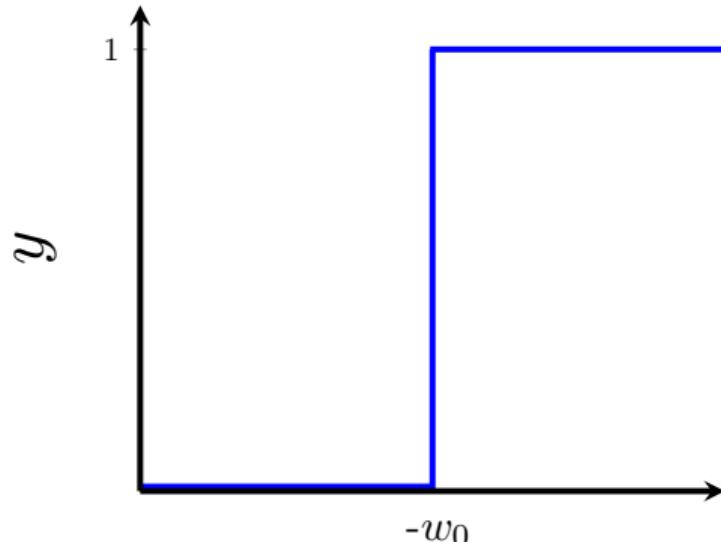
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- For example, let us return to our problem of deciding whether we will like or dislike a movie
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- What about a movie with $\text{criticsRating} = 0.49$? (dislike)
- It seems harsh that we would like a movie with rating 0.51 but not one with a rating of 0.49

- This behavior is not a characteristic of the specific problem we chose or the specific weight and threshold that we chose



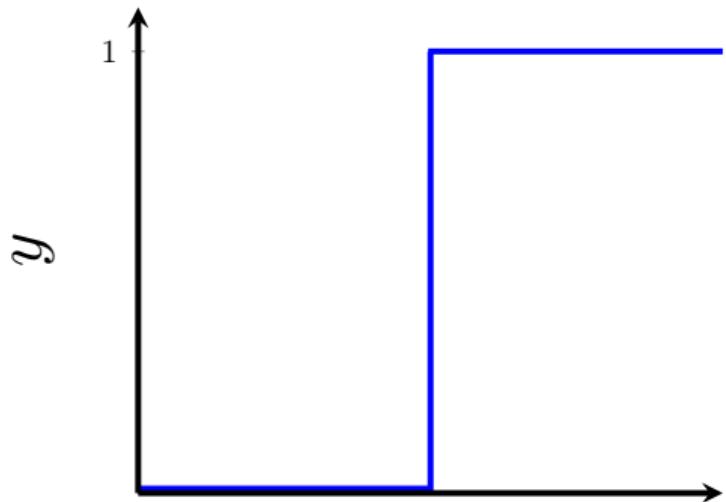
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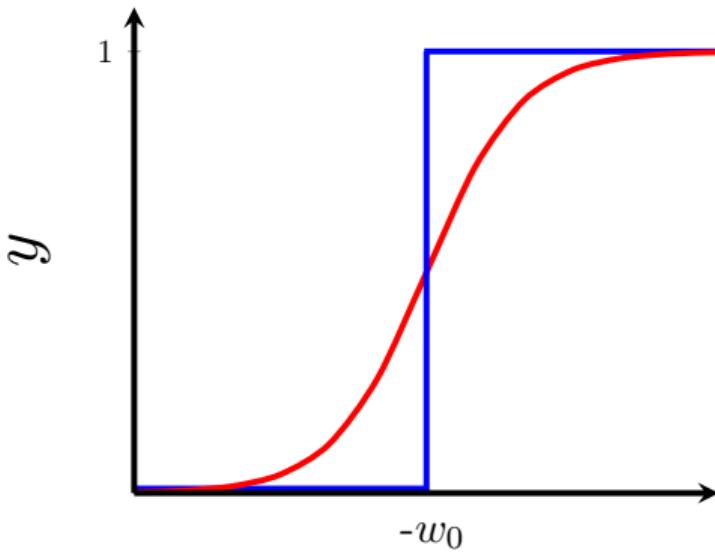


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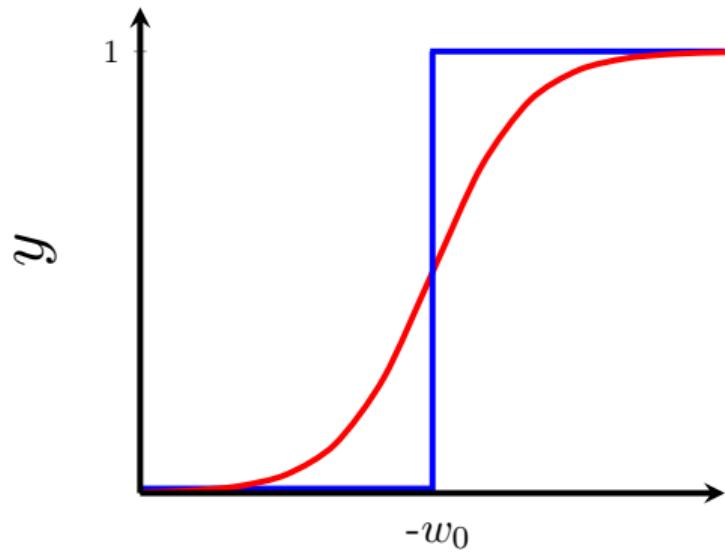


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- There will always be this sudden change in the decision (from 0 to 1) when $\sum_{i=1}^n w_i x_i$ crosses the threshold ($-w_0$)
- For most real world applications we would expect a smoother decision function which gradually changes from 0 to 1



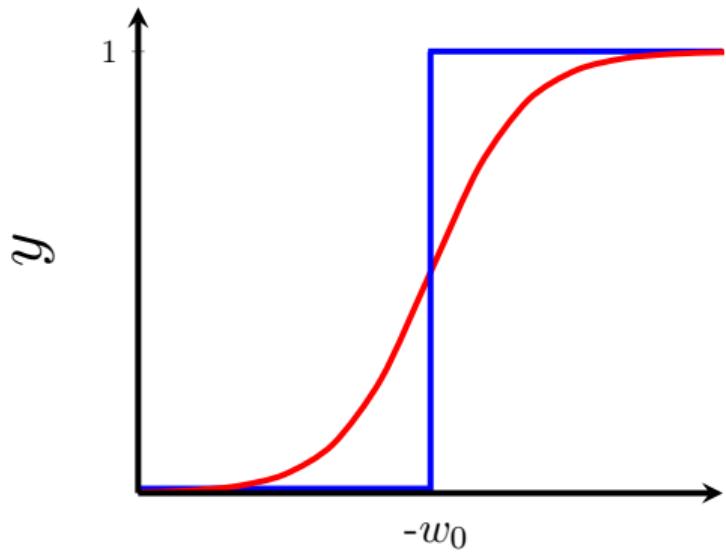
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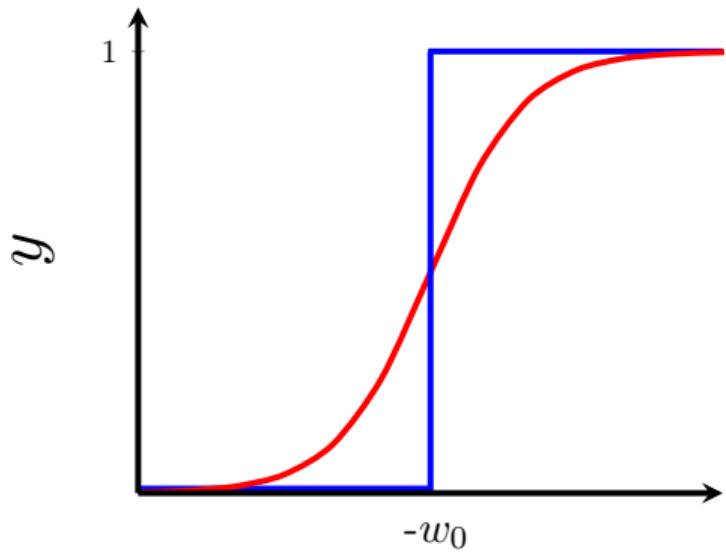
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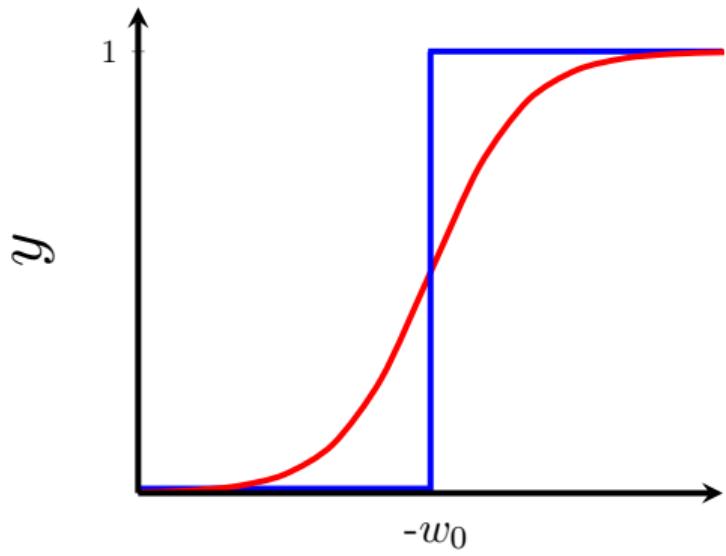


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- Also the output y is no longer binary but a real value between 0 and 1 which can be interpreted as a probability



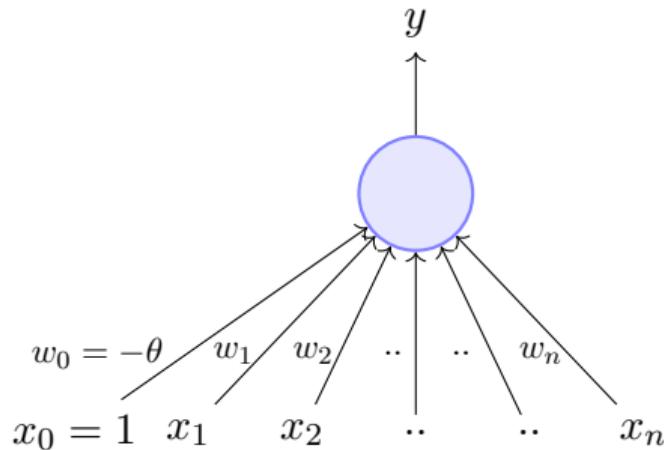
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- Instead of a like/dislike decision we get the probability of liking the movie

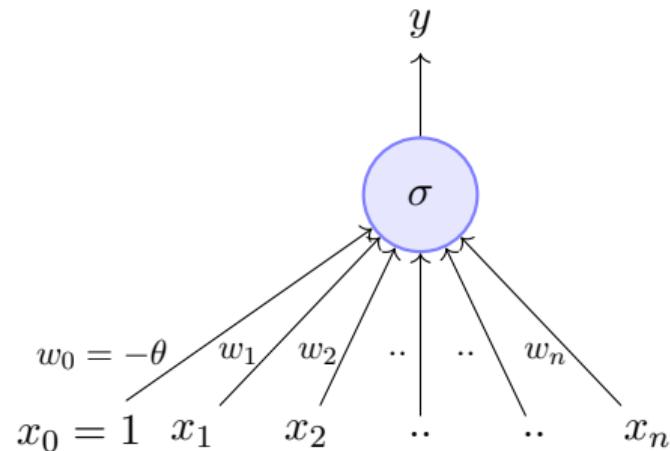
Perceptron



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

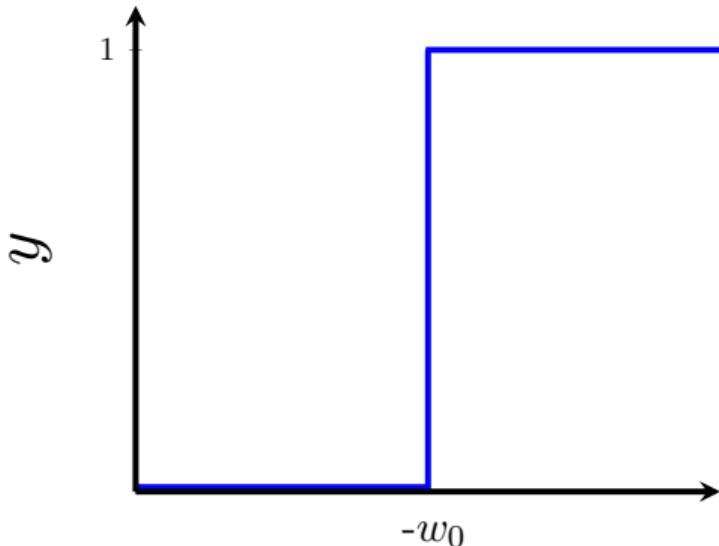
$$= 0 \quad if \sum_{i=0}^n w_i * x_i < 0$$

Sigmoid (logistic) Neuron



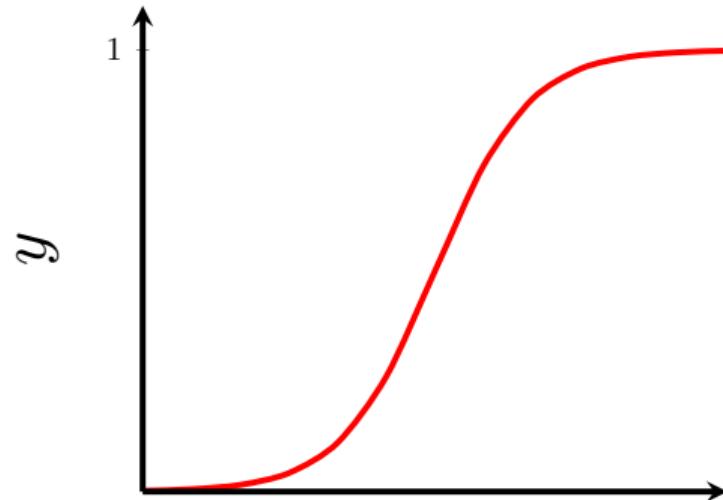
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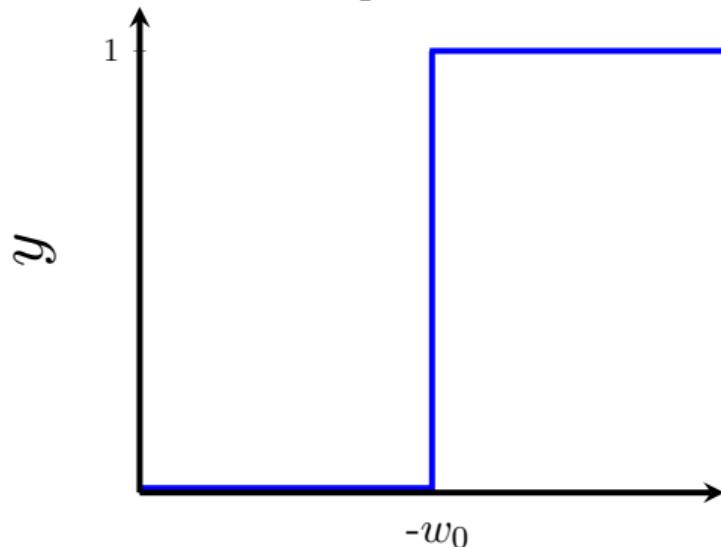
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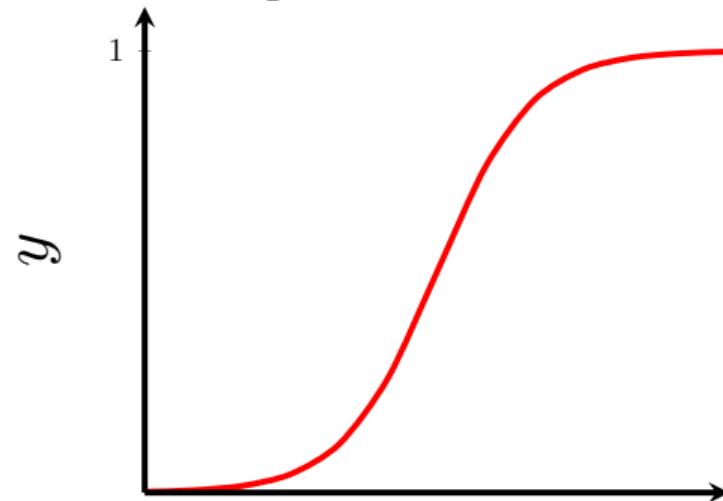
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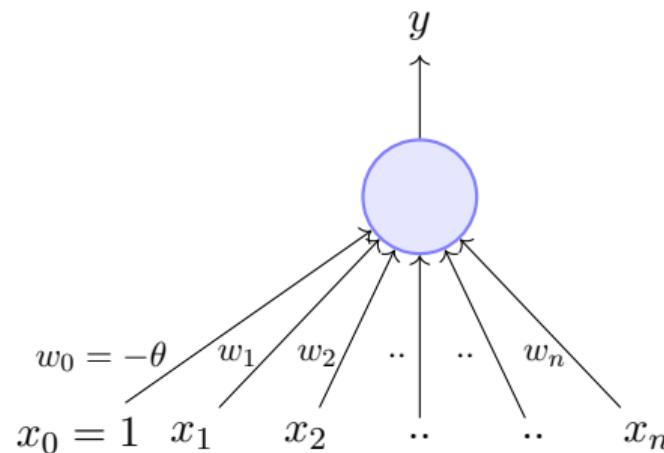
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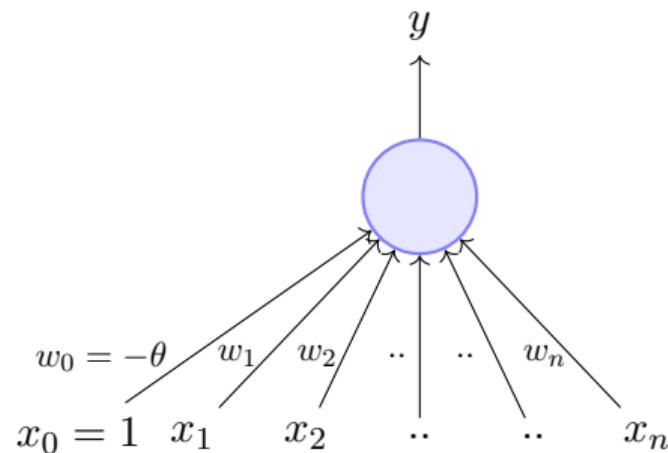
Module 3.2: A typical Supervised Machine Learning Setup

- What next ?

Sigmoid (logistic) Neuron

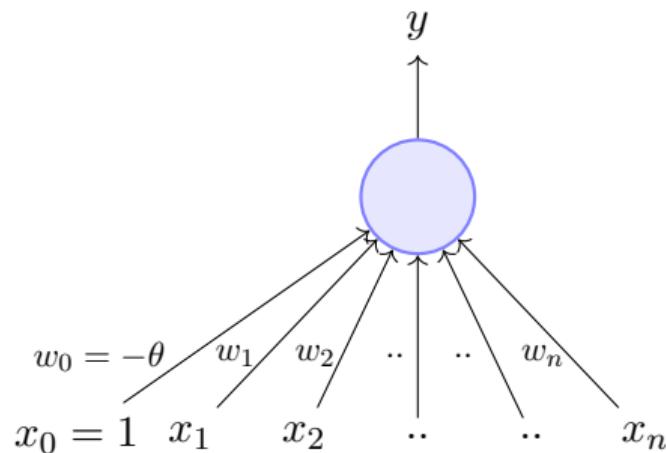


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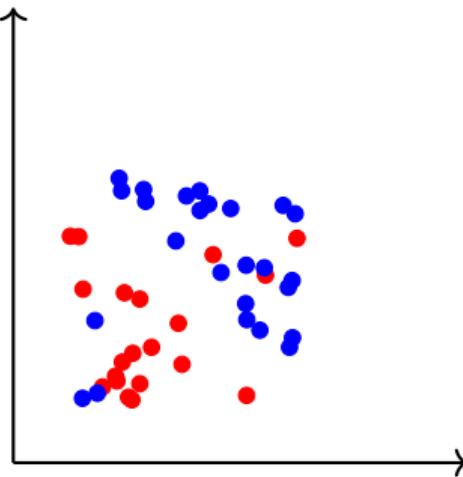


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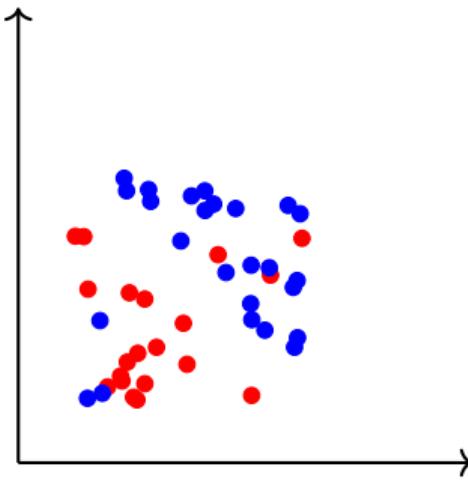
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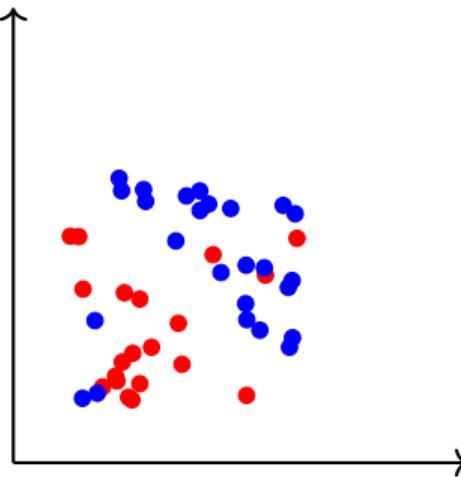
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- Before we see such an algorithm we will revisit the concept of **error**



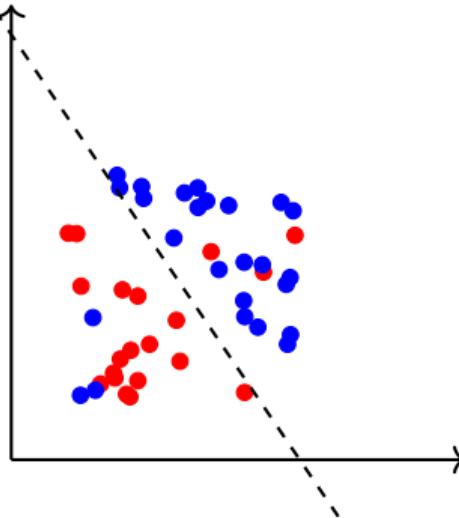
- Earlier we mentioned that a single perceptron cannot deal with this data because it is not linearly separable



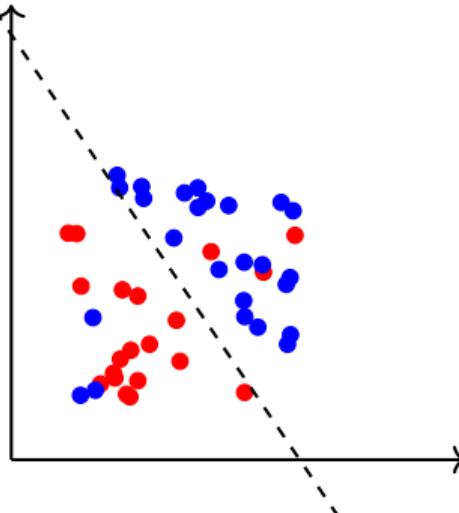
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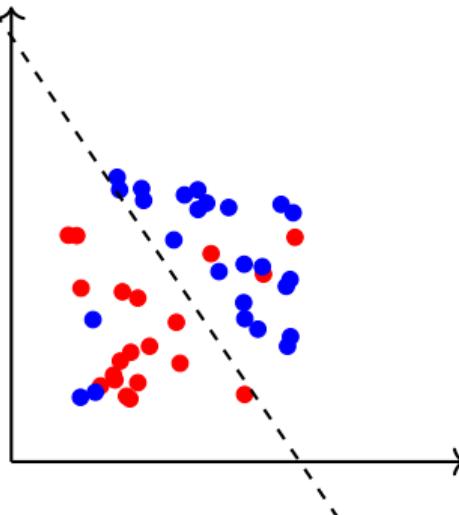
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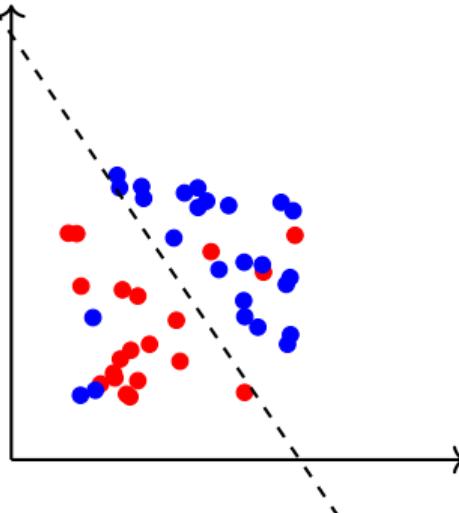
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- From now on, we will accept that it is hard to drive the error to 0 in most cases and will instead aim to reach the minimum possible error

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- **Objective/Loss/Error function:** One possibility is

$$\mathcal{L}(\mathbf{W}) = \sum_{i=1}^n (\hat{y}_i - y_i)^2$$

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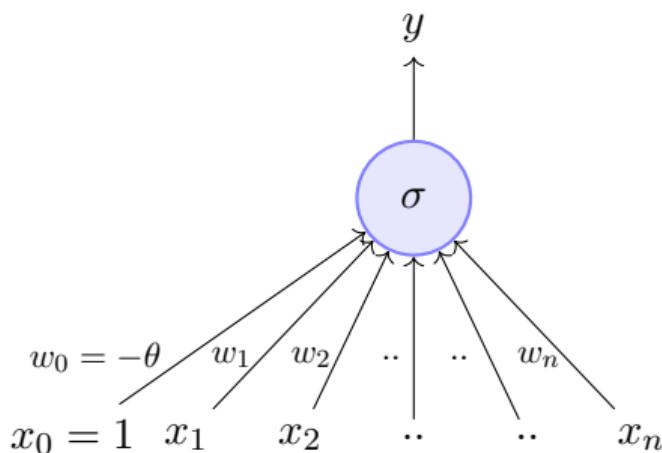
$$\hat{y} = \frac{1}{1 + e^{-(\mathbf{W}^T \mathbf{x})}}$$

- **Parameter:** \mathbf{W}
- **Learning algorithm:** Gradient Descent [we will see soon]
- **Objective/Loss/Error function:** One possibility is

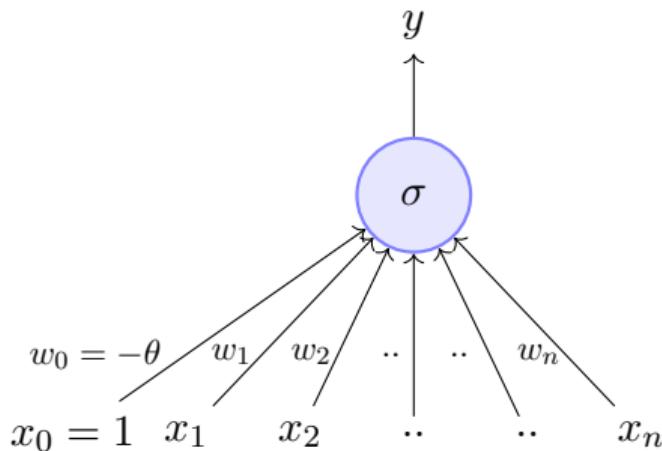
$$\mathcal{L}(\mathbf{W}) = \sum_{i=1}^n (\hat{y}_i - y_i)^2$$

The learning algorithm should aim to find a \mathbf{W} which minimizes the above function (squared error between y and \hat{y})

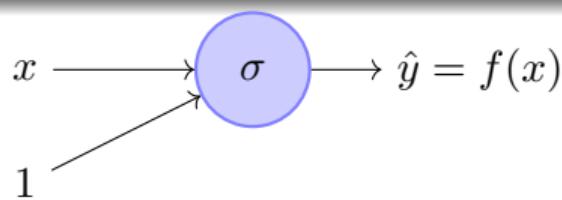
Module 3.3: Learning Parameters: (Infeasible) guess work



- Keeping this supervised ML setup in mind, we will now focus on this **model** and discuss an **algorithm** for learning the **parameters** of this model from some given **data** using an appropriate **objective function**

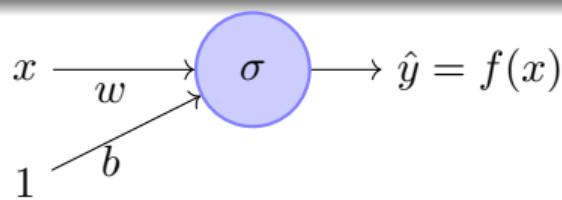


- Keeping this supervised ML setup in mind, we will now focus on this **model** and discuss an **algorithm** for learning the **parameters** of this model from some given **data** using an appropriate **objective function**
- σ stands for the sigmoid function (logistic function in this case)



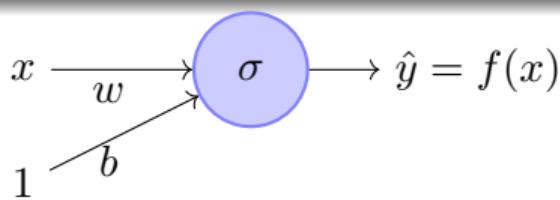
$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$

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- For ease of explanation, we will consider a very simplified version of the model having just 1 input



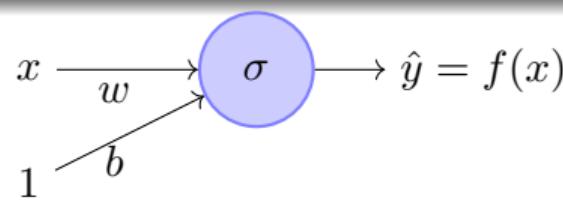
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- Keeping this supervised ML setup in mind, we will now focus on this **model** and discuss an **algorithm** for learning the **parameters** of this model from some given **data** using an appropriate **objective function**
- σ stands for the sigmoid function (logistic function in this case)
- For ease of explanation, we will consider a very simplified version of the model having just 1 input
- Further to be consistent with the literature, from now on, we will refer to w_0 as b (bias)

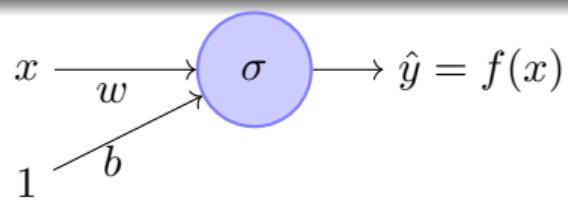


$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$

- Keeping this supervised ML setup in mind, we will now focus on this **model** and discuss an **algorithm** for learning the **parameters** of this model from some given **data** using an appropriate **objective function**
- σ stands for the sigmoid function (logistic function in this case)
- For ease of explanation, we will consider a very simplified version of the model having just 1 input
- Further to be consistent with the literature, from now on, we will refer to w_0 as b (bias)
- Lastly, instead of considering the problem of predicting like/dislike, we will assume that we want to predict $\text{criticsRating}(y)$ given $\text{imdbRating}(x)$ (for no particular reason)



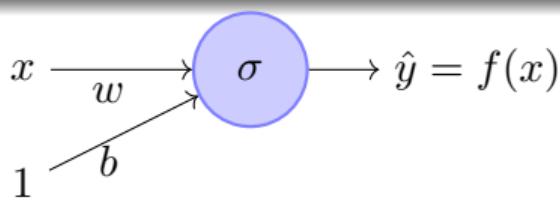
$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$



Input for training

$\{x_i, y_i\}_{i=1}^N \rightarrow N$ pairs of (x, y)

$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$



$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$

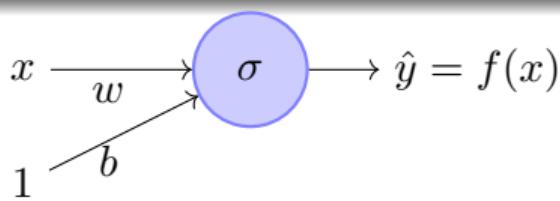
Input for training

$\{x_i, y_i\}_{i=1}^N \rightarrow N$ pairs of (x, y)

Training objective

Find w and b such that:

$$\underset{w,b}{\text{minimize}} \mathcal{L}(w, b) = \sum_{i=1}^N (y_i - f(x_i))^2$$



$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$

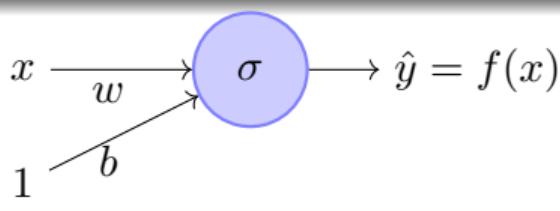
Input for training

$\{x_i, y_i\}_{i=1}^N \rightarrow N$ pairs of (x, y)

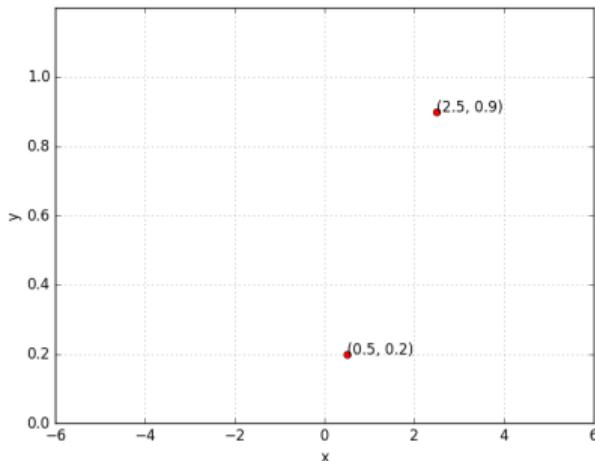
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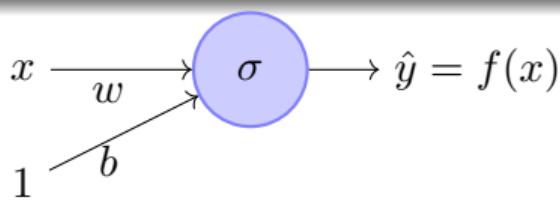


$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$

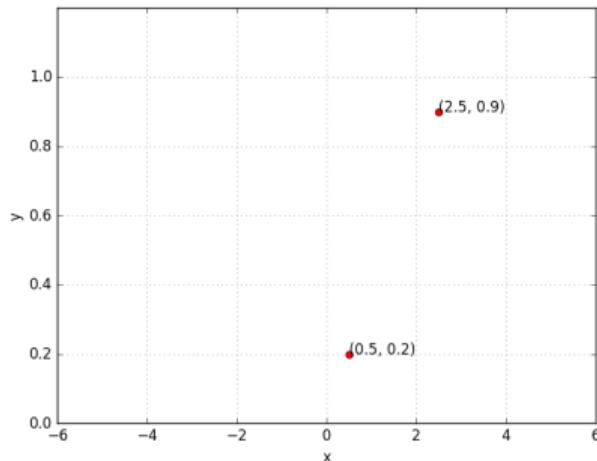


What does it mean to train the network?

- Suppose we train the network with $(x, y) = (0.5, 0.2)$ and $(2.5, 0.9)$

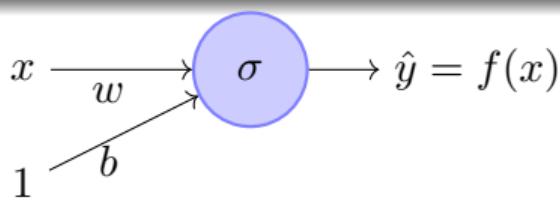


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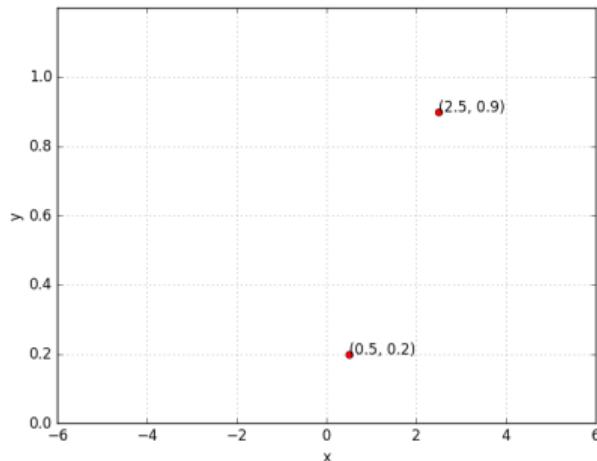


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- Suppose we train the network with $(x, y) = (0.5, 0.2)$ and $(2.5, 0.9)$
- At the end of training we expect to find w^* , b^* such that:

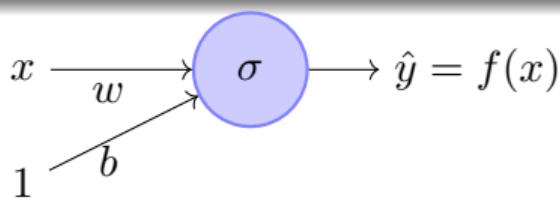


$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$

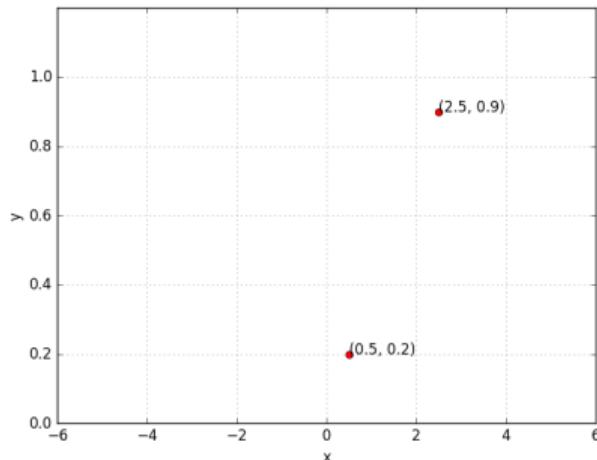


What does it mean to train the network?

- Suppose we train the network with $(x, y) = (0.5, 0.2)$ and $(2.5, 0.9)$
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- $f(0.5) \rightarrow 0.2$ and $f(2.5) \rightarrow 0.9$



$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$

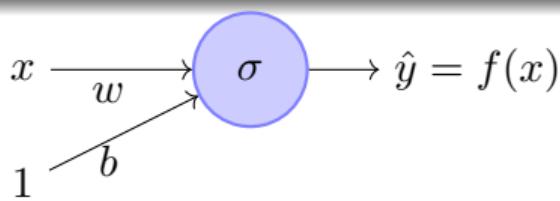


What does it mean to train the network?

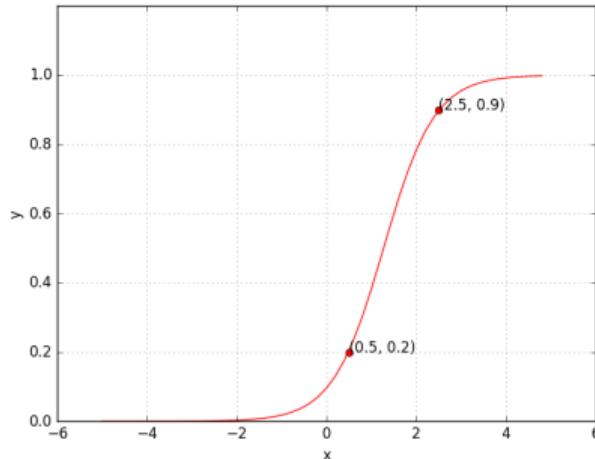
- Suppose we train the network with $(x, y) = (0.5, 0.2)$ and $(2.5, 0.9)$
- At the end of training we expect to find w^* , b^* such that:
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In other words...

- We hope to find a sigmoid function such that $(0.5, 0.2)$ and $(2.5, 0.9)$ lie on this sigmoid



$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$



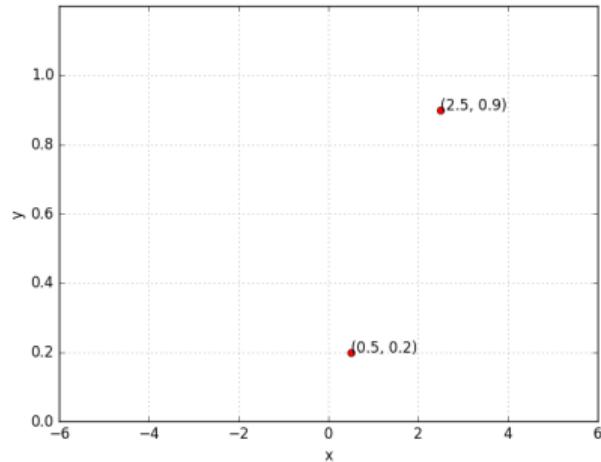
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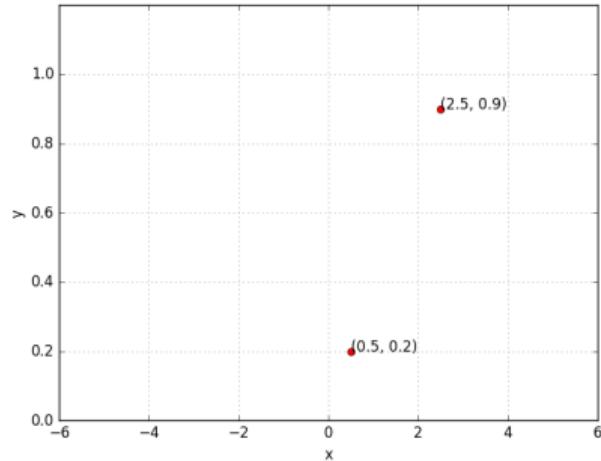
In other words...

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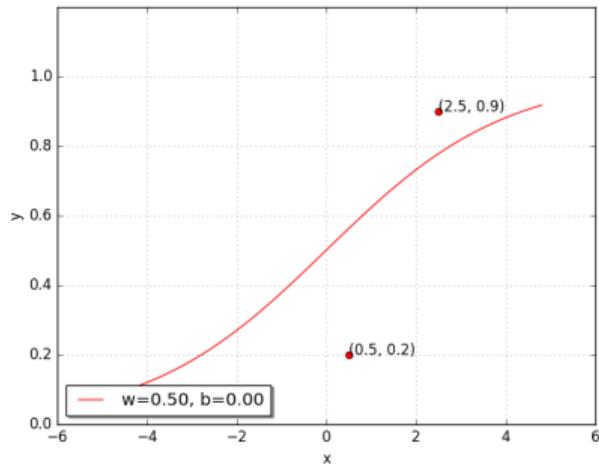
Let us see this in more detail....



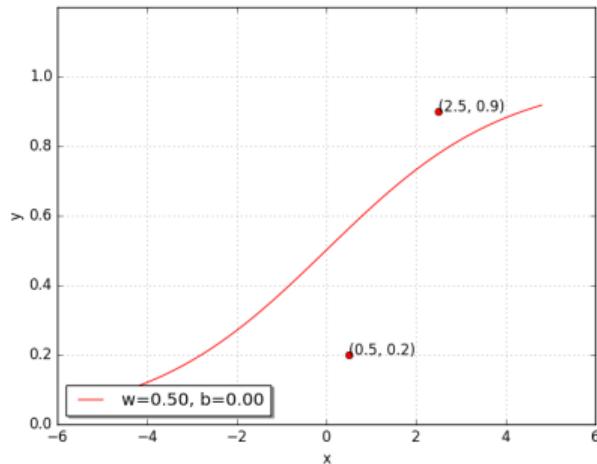
- Can we try to find such a w^*, b^* manually



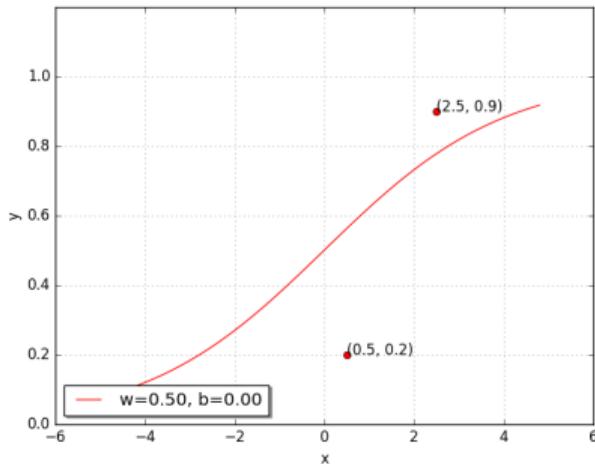
- Can we try to find such a w^*, b^* manually
- Let us try a random guess.. (say, $w = 0.5, b = 0$)

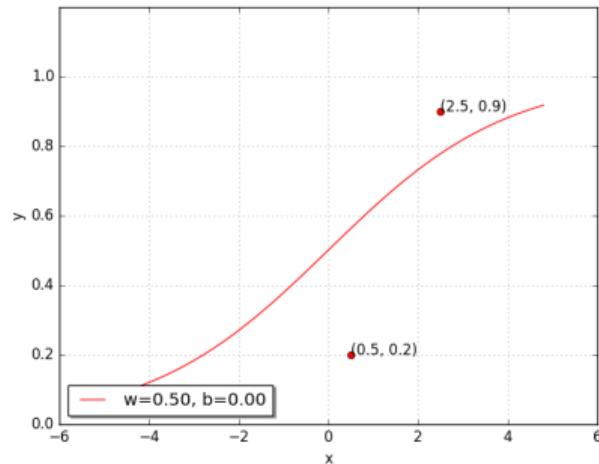


- Can we try to find such a w^*, b^* manually
- Let us try a random guess.. (say, $w = 0.5, b = 0$)
- Clearly not good, but how bad is it ?

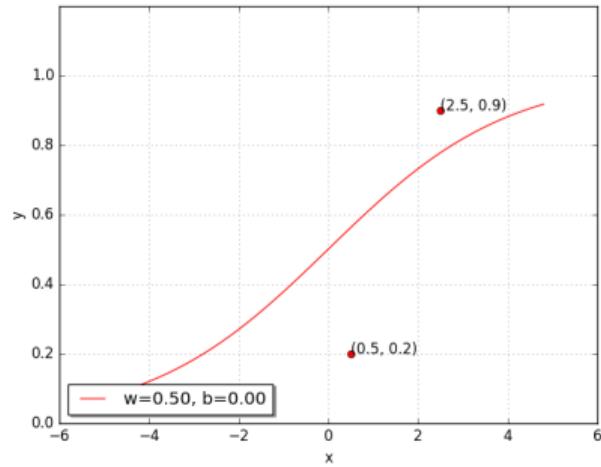


- Can we try to find such a w^*, b^* manually
- Let us try a random guess.. (say, $w = 0.5, b = 0$)
- Clearly not good, but how bad is it ?
- Let us revisit $\mathcal{L}(w, b)$ to see how bad it is ...

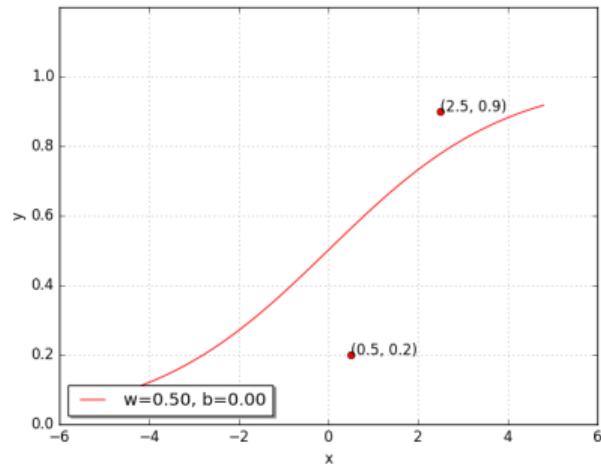




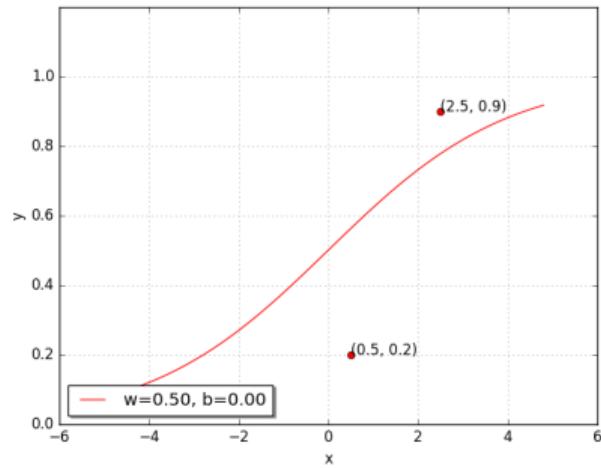
$$\mathcal{L}(w, b) = \frac{1}{2} * \sum_{i=1}^N (y_i - f(x_i))^2$$



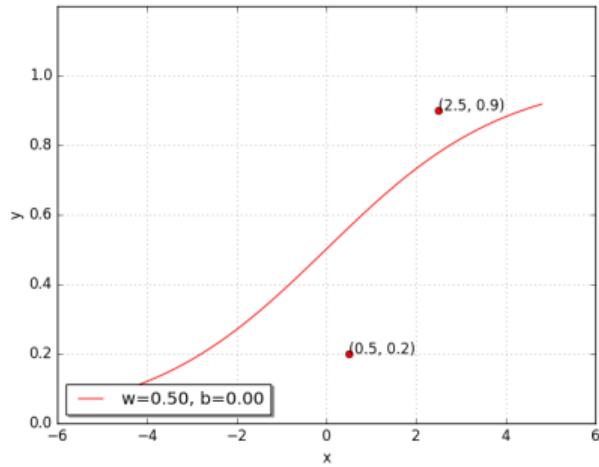
$$\begin{aligned}\mathcal{L}(w, b) &= \frac{1}{2} * \sum_{i=1}^N (y_i - f(x_i))^2 \\ &= \frac{1}{2} * (y_1 - f(x_1))^2 + (y_2 - f(x_2))^2\end{aligned}$$



$$\begin{aligned}
 \mathcal{L}(w, b) &= \frac{1}{2} * \sum_{i=1}^N (y_i - f(x_i))^2 \\
 &= \frac{1}{2} * (y_1 - f(x_1))^2 + (y_2 - f(x_2))^2 \\
 &= \frac{1}{2} * (0.9 - f(2.5))^2 + (0.2 - f(0.5))^2
 \end{aligned}$$



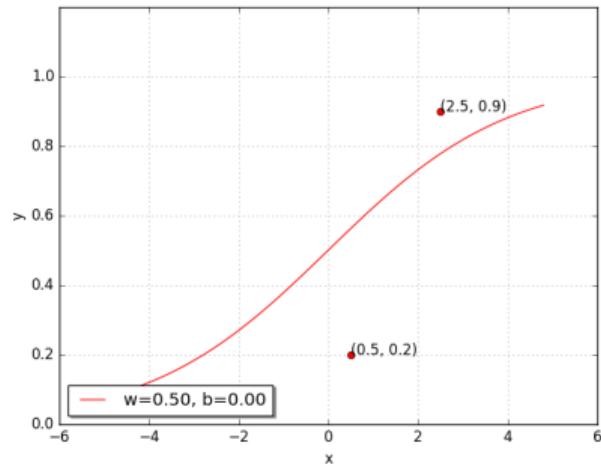
$$\begin{aligned}
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 &= 0.073
 \end{aligned}$$



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 \mathcal{L}(w, b) &= \frac{1}{2} * \sum_{i=1}^N (y_i - f(x_i))^2 \\
 &= \frac{1}{2} * (y_1 - f(x_1))^2 + (y_2 - f(x_2))^2 \\
 &= \frac{1}{2} * (0.9 - f(2.5))^2 + (0.2 - f(0.5))^2 \\
 &= 0.073
 \end{aligned}$$

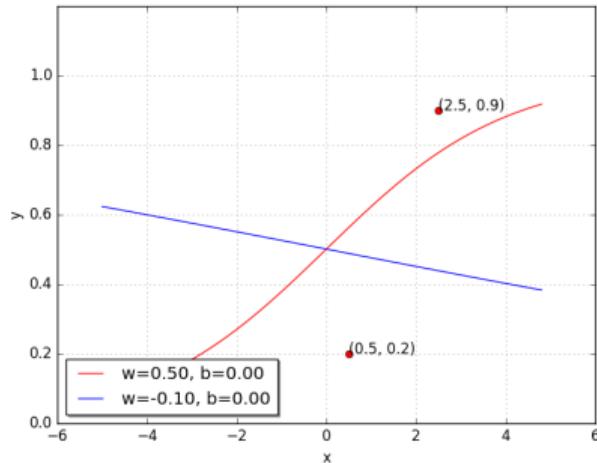
We want $\mathcal{L}(w, b)$ to be as close to 0 as possible

Let us try some other values of w, b



w	b	$\mathcal{L}(w, b)$
0.50	0.00	0.0730

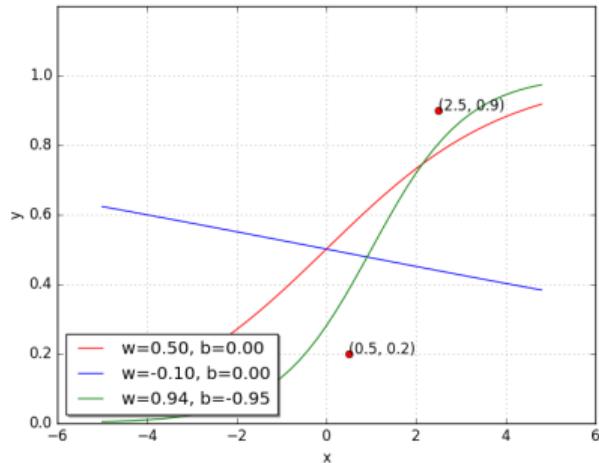
Let us try some other values of w, b



w	b	$\mathcal{L}(w, b)$
0.50	0.00	0.0730
-0.10	0.00	0.1481

Oops!! this made things even worse...

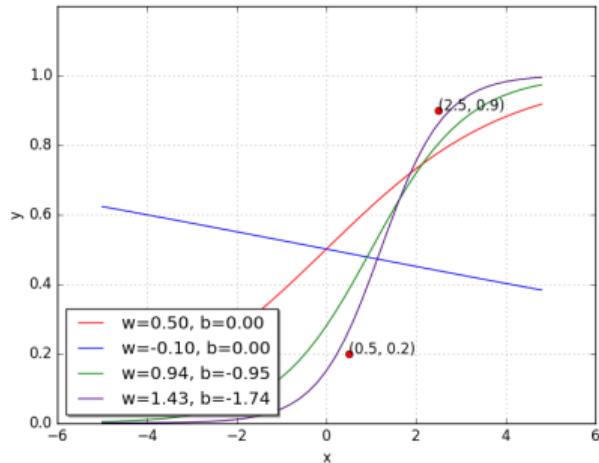
Let us try some other values of w , b



w	b	$\mathcal{L}(w, b)$
0.50	0.00	0.0730
-0.10	0.00	0.1481
0.94	-0.94	0.0214

Perhaps it would help to push w and b in the other direction...

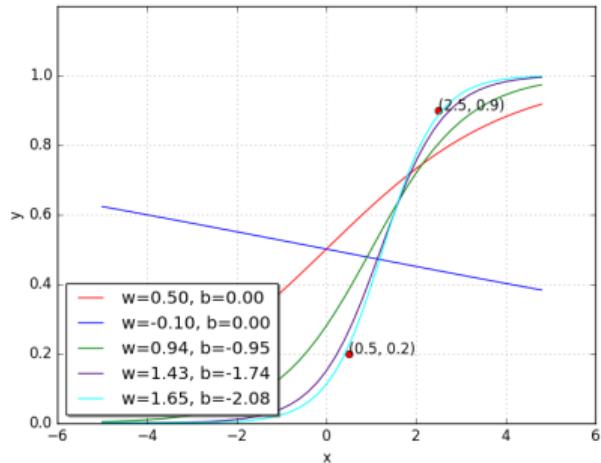
Let us try some other values of w , b



w	b	$\mathcal{L}(w, b)$
0.50	0.00	0.0730
-0.10	0.00	0.1481
0.94	-0.94	0.0214
1.43	-1.73	0.0028

Let us keep going in this direction, *i.e.*, increase w and decrease b

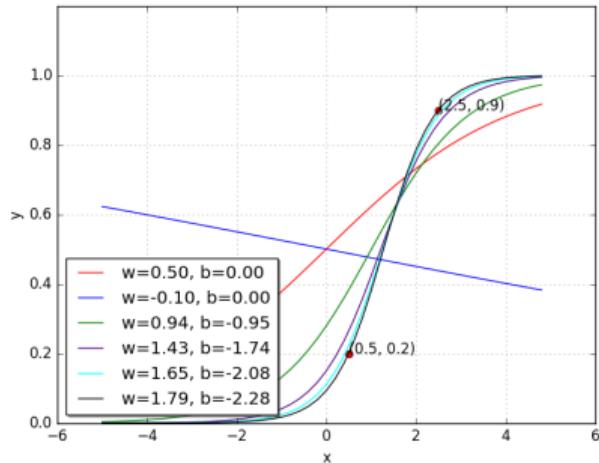
Let us try some other values of w , b



w	b	$\mathcal{L}(w, b)$
0.50	0.00	0.0730
-0.10	0.00	0.1481
0.94	-0.94	0.0214
1.42	-1.73	0.0028
1.65	-2.08	0.0003

Let us keep going in this direction, *i.e.*, increase w and decrease b

Let us try some other values of w , b



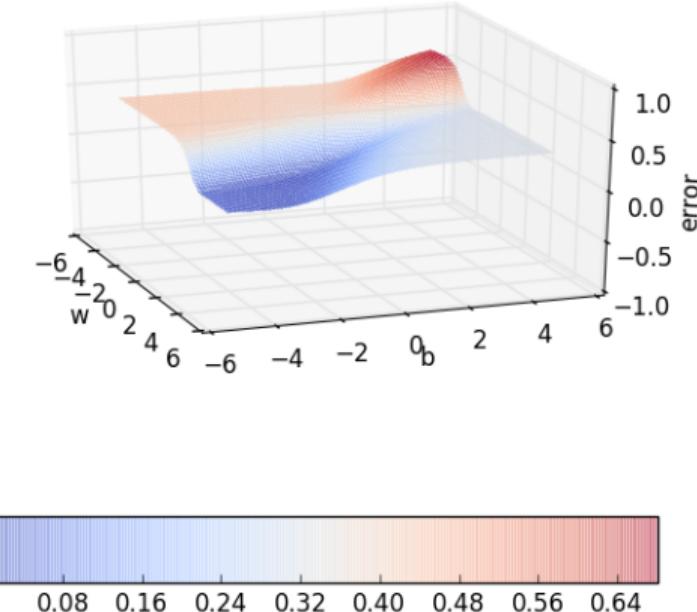
w	b	$\mathcal{L}(w, b)$
0.50	0.00	0.0730
-0.10	0.00	0.1481
0.94	-0.94	0.0214
1.42	-1.73	0.0028
1.65	-2.08	0.0003
1.78	-2.27	0.0000

With some guess work and intuition we were able to find the right values for w and b

Let us look at something better than our “guess work” algorithm....

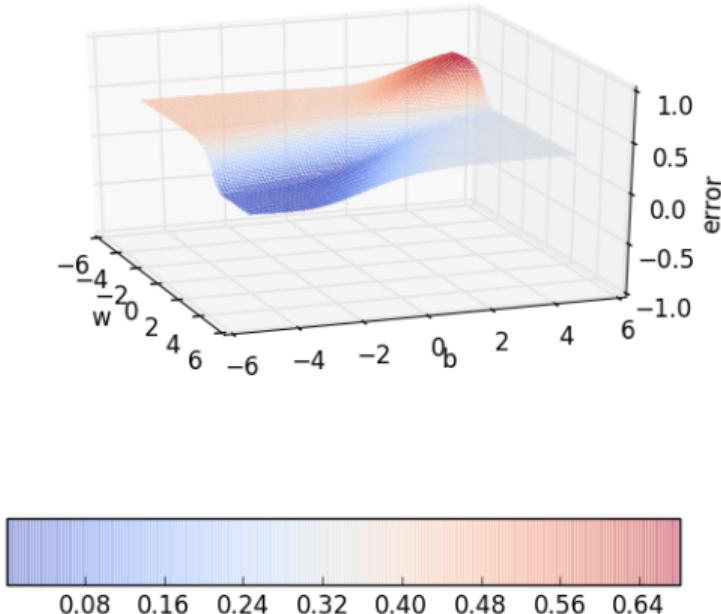
- Since we have only 2 points and 2 parameters (w , b) we can easily plot $\mathcal{L}(w, b)$ for different values of (w, b) and pick the one where $\mathcal{L}(w, b)$ is minimum

Random search on error surface



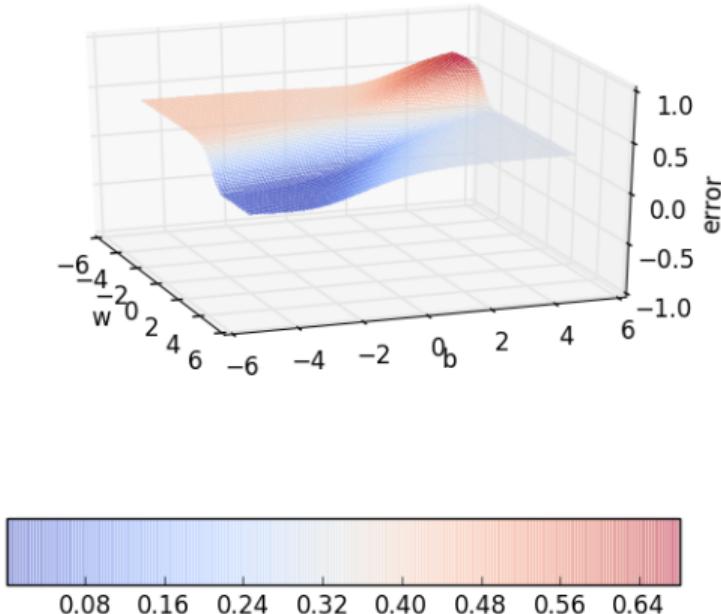
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Random search on error surface



- Since we have only 2 points and 2 parameters (w, b) we can easily plot $\mathcal{L}(w, b)$ for different values of (w, b) and pick the one where $\mathcal{L}(w, b)$ is minimum
- But of course this becomes intractable once you have many more data points and many more parameters !!

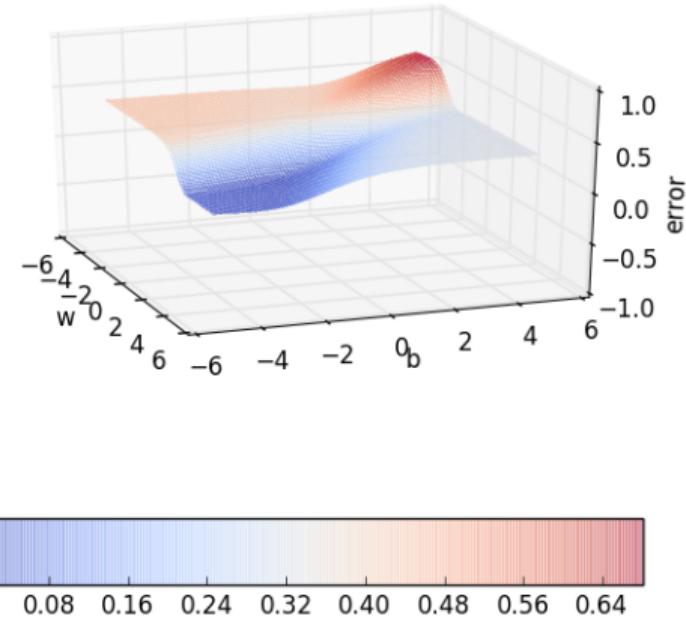
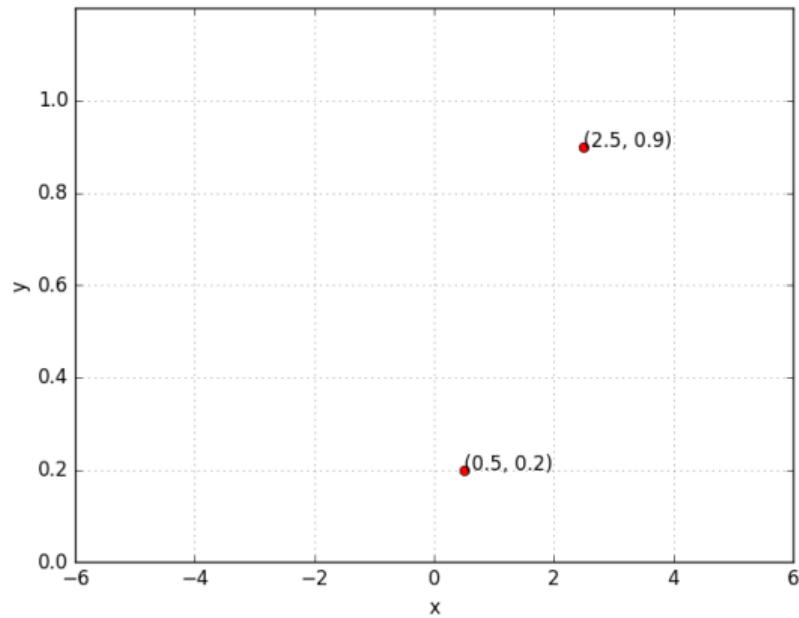
Random search on error surface

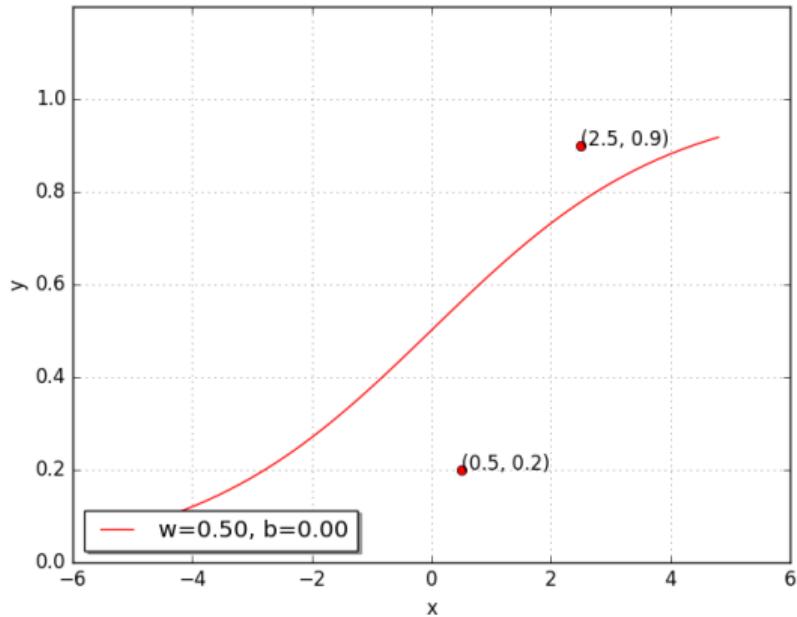


- Since we have only 2 points and 2 parameters (w, b) we can easily plot $\mathcal{L}(w, b)$ for different values of (w, b) and pick the one where $\mathcal{L}(w, b)$ is minimum
- But of course this becomes intractable once you have many more data points and many more parameters !!
- Further, even here we have plotted the error surface only for a small range of (w, b) [from $(-6, 6)$ and not from $(-\infty, \infty)$]

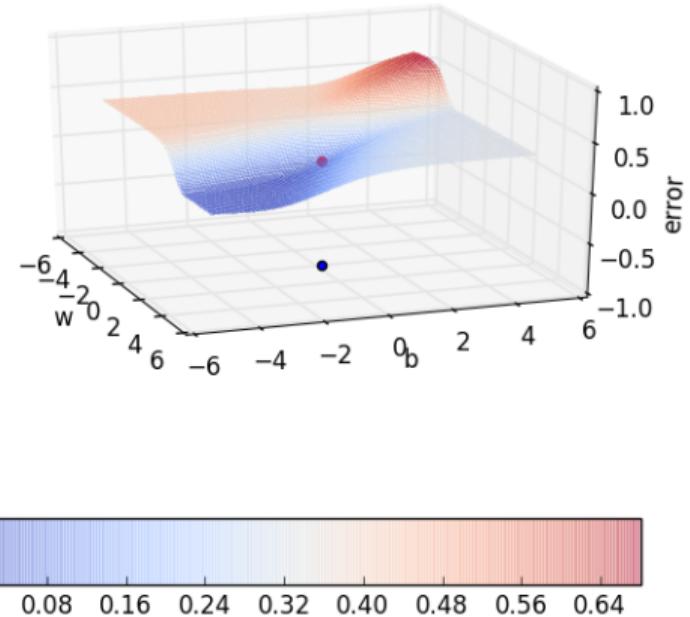
Let us look at the geometric interpretation of our “guess work” algorithm in terms of this error surface

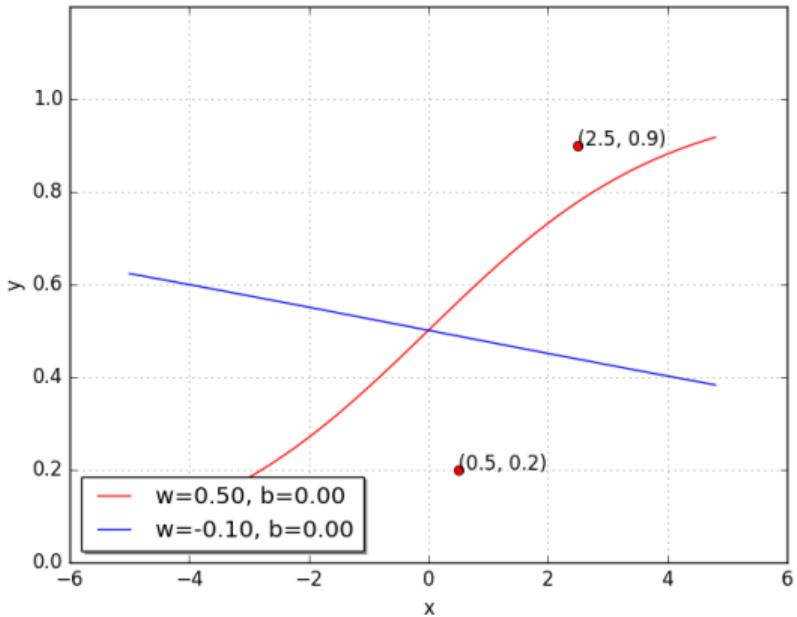
Random search on error surface



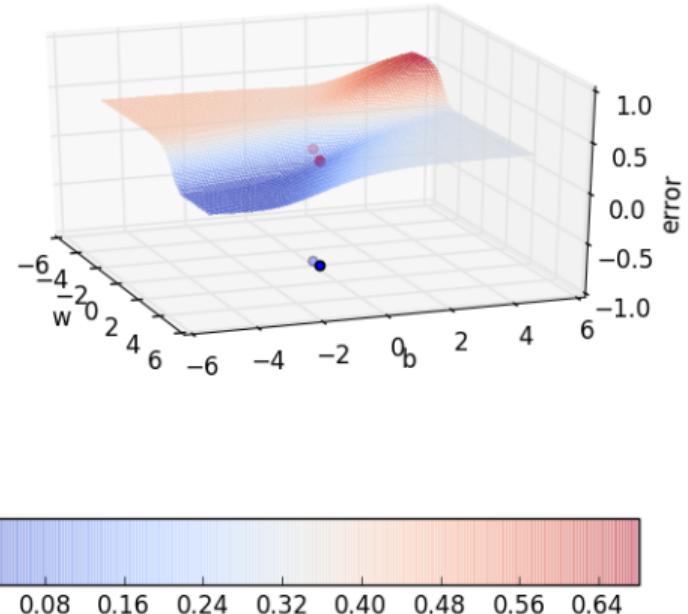


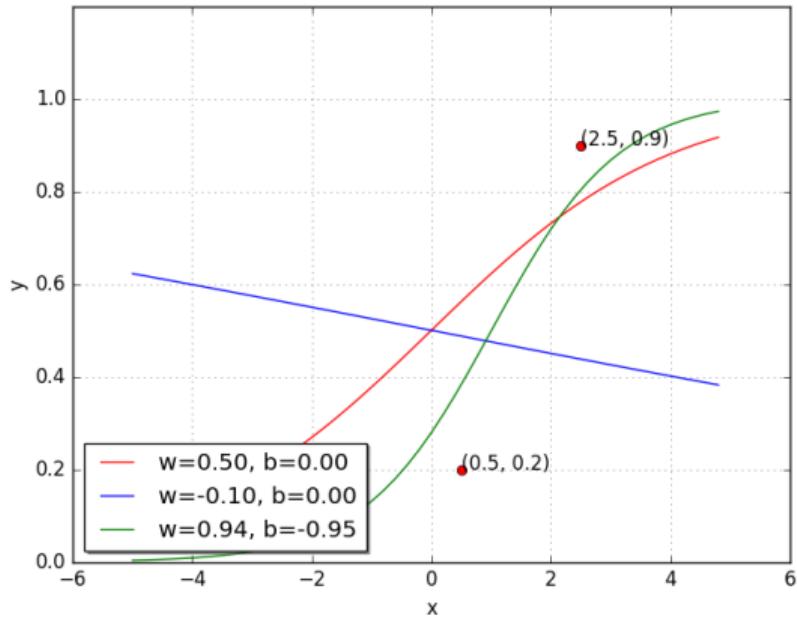
Random search on error surface



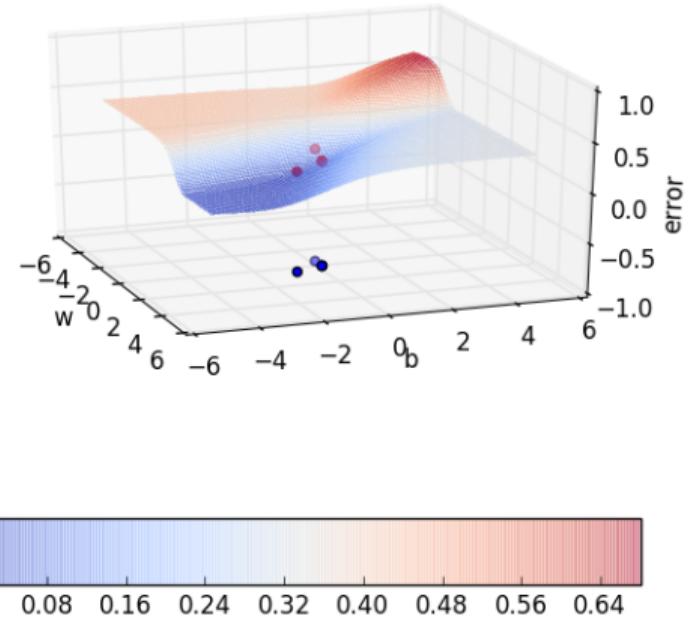


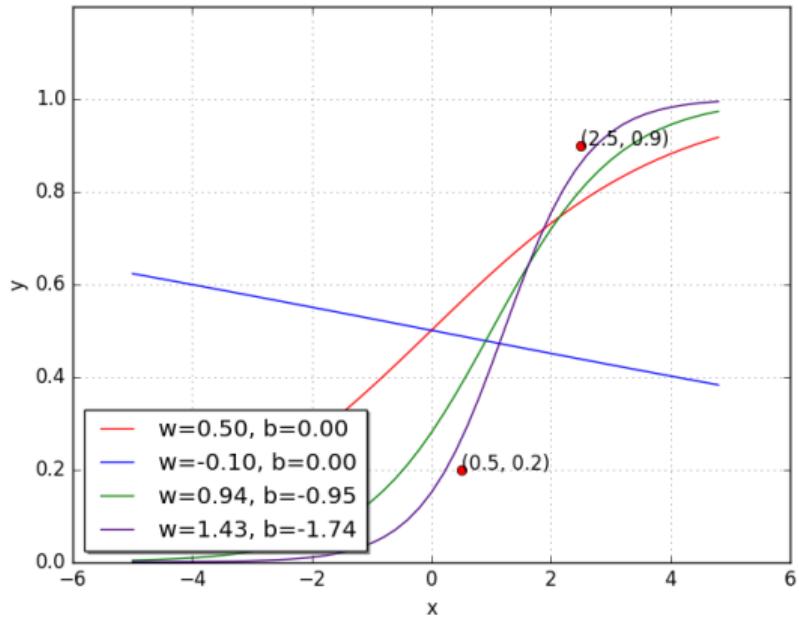
Random search on error surface



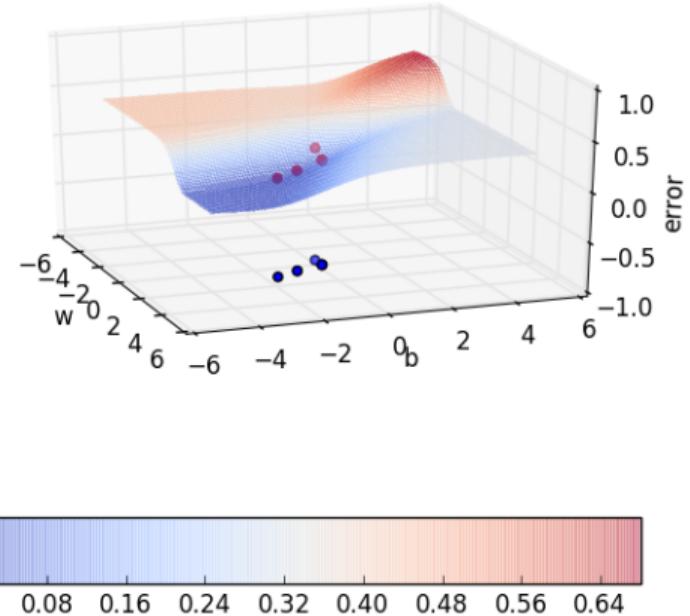


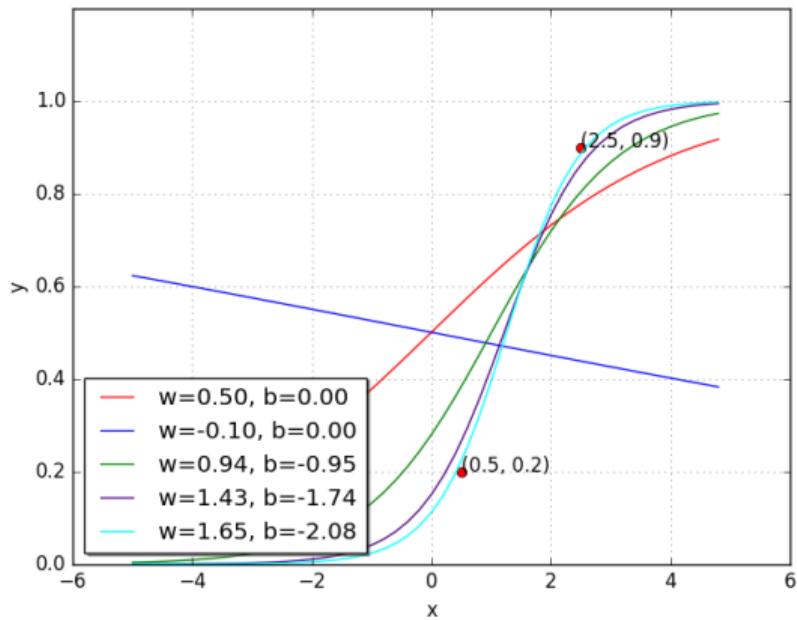
Random search on error surface



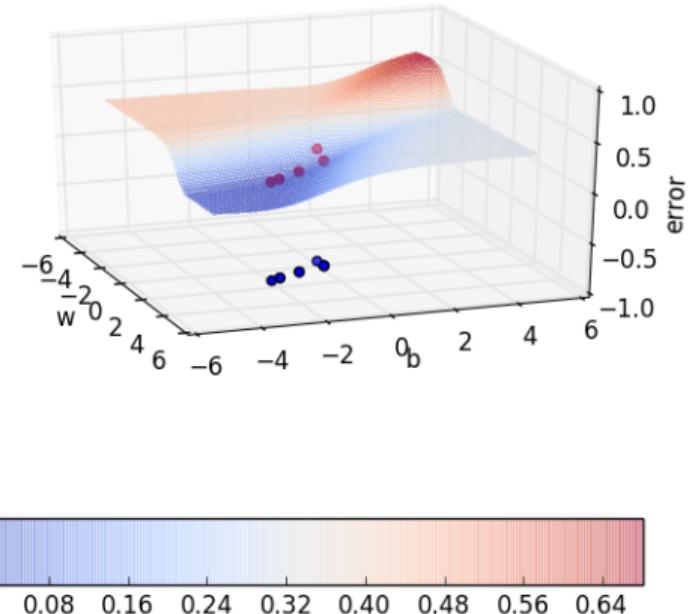


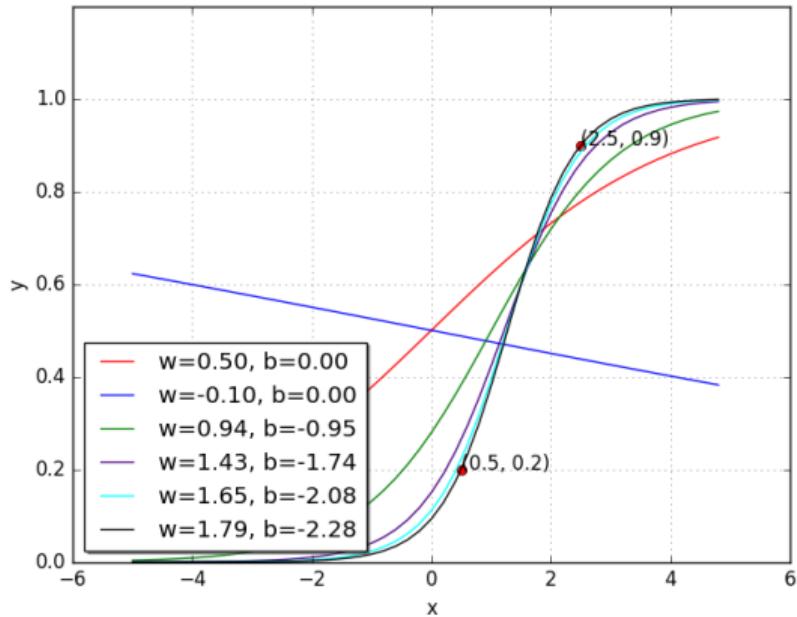
Random search on error surface



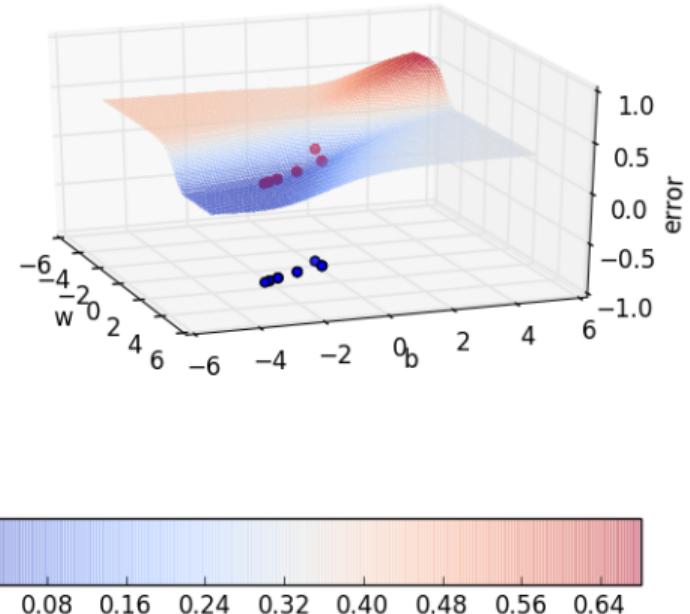


Random search on error surface





Random search on error surface



Module 3.4: Learning Parameters : Gradient Descent

Now let us see if there is a more efficient and principled way of doing this

Goal

Find a better way of traversing the error surface so that we can reach the minimum value quickly without resorting to brute force search!

vector of parameters,
say, randomly initialized

$$\theta = [w, b]$$

vector of parameters,
say, randomly initial-
ized

$$\theta = [w, b]$$

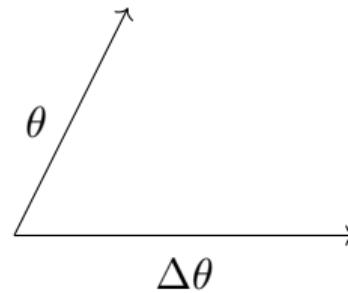
$$\Delta\theta = [\Delta w, \Delta b]$$

change in the
values of w, b

vector of parameters,
say, randomly initial-
ized

$$\theta = [w, b]$$

change in the
values of w, b

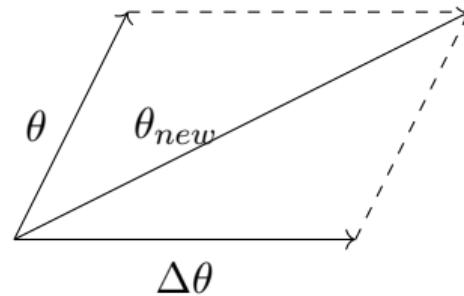


vector of parameters,
say, randomly initialized

$$\theta = [w, b]$$

$$\Delta\theta = [\Delta w, \Delta b]$$

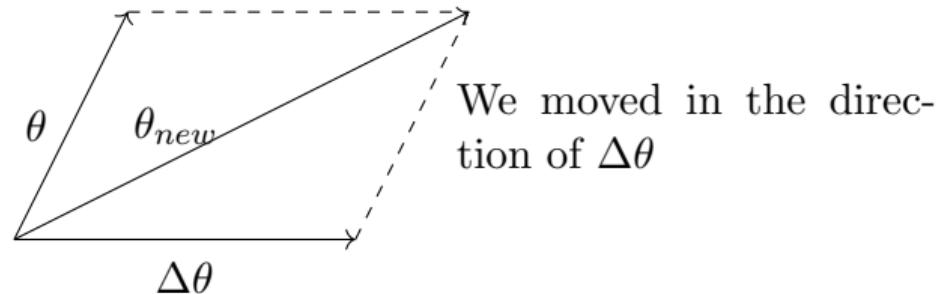
change in the
values of w, b



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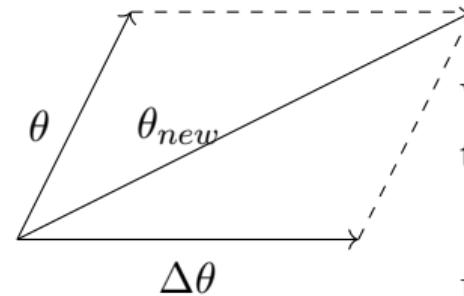
change in the
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We moved in the direction of $\Delta\theta$

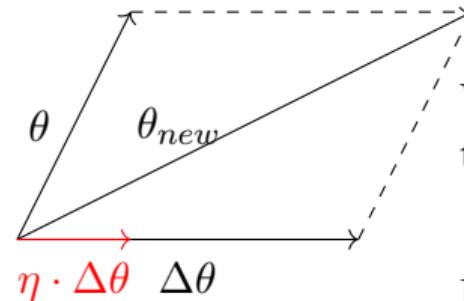
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$$\Delta\theta = [\Delta w, \Delta b]$$



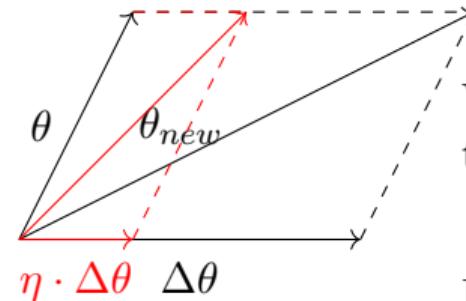
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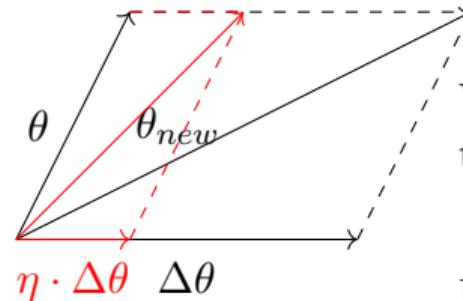
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$$\theta_{new} = \theta + \eta \cdot \Delta\theta$$



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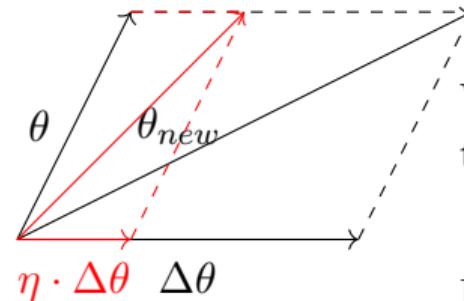
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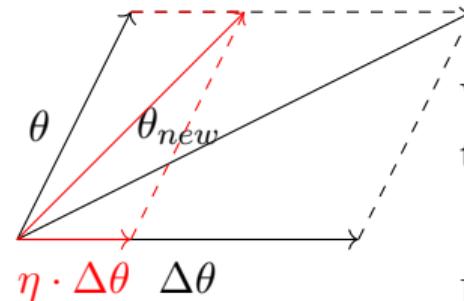
Question: What is the right $\Delta\theta$ to use ?

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The answer comes from Taylor series

For ease of notation, let $\Delta\theta = u$, then from Taylor series, we have,

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$$\mathcal{L}(\theta + \eta u) - \mathcal{L}(\theta) < 0 \text{ [i.e., if the new loss is less than the previous loss]}$$

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This implies,

$$u^T \nabla \mathcal{L}(\theta) < 0$$

Okay, so we have,

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$$-1 \leq \cos(\beta) = \frac{u^T \nabla \mathcal{L}(\theta)}{\|u\| * \|\nabla \mathcal{L}(\theta)\|} \leq 1$$

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multiply throughout by $k = \|u\| * \|\nabla \mathcal{L}(\theta)\|$

$$-k \leq k * \cos(\beta) = u^T \nabla \mathcal{L}(\theta) \leq k$$

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Thus, $\mathcal{L}(\theta + \eta u) - \mathcal{L}(\theta) = u^T \nabla \mathcal{L}(\theta) = k * \cos(\beta)$ will be most negative when $\cos(\beta) = -1$ i.e., when β is 180°

Gradient Descent Rule

- The direction u that we intend to move in should be at 180° w.r.t. the gradient

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Parameter Update Equations

$$w_{t+1} = w_t - \eta \nabla w_t$$

$$b_{t+1} = b_t - \eta \nabla b_t$$

where, $\nabla w_t = \frac{\partial \mathcal{L}(w, b)}{\partial w}$ at $w = w_t, b = b_t$, $\nabla b = \frac{\partial \mathcal{L}(w, b)}{\partial b}$ at $w = w_t, b = b_t$

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So we now have a more principled way of moving in the w - b plane than our “guess work” algorithm

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Algorithm: gradient_descent()

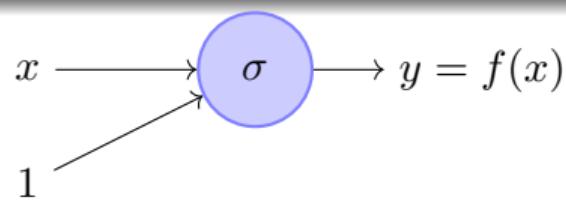
```
t ← 0;  
max_iterations ← 1000;  
while  $t < max\_iterations$  do  
    |  $w_{t+1} \leftarrow w_t - \eta \nabla w_t;$   
    |  $b_{t+1} \leftarrow b_t - \eta \nabla b_t;$   
end
```

- Let us create an algorithm from this rule ...

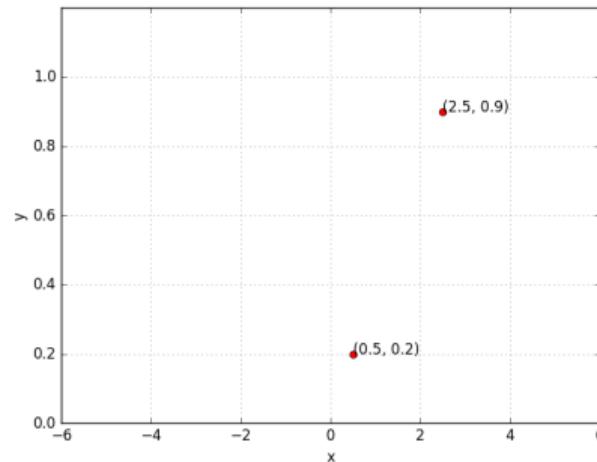
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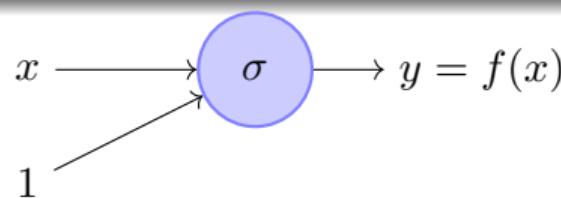
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- To see this algorithm in practice let's first derive ∇w and ∇b for our toy neural network



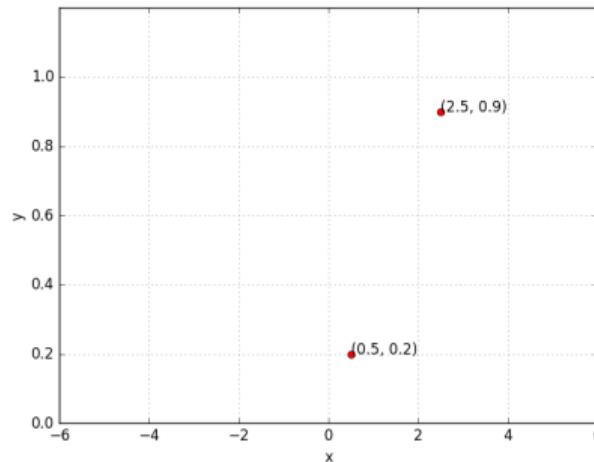
$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$

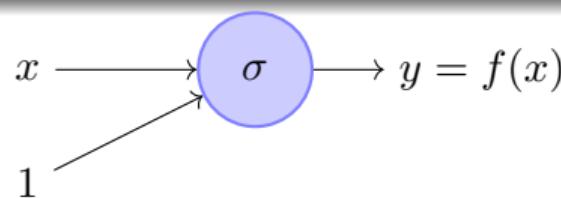




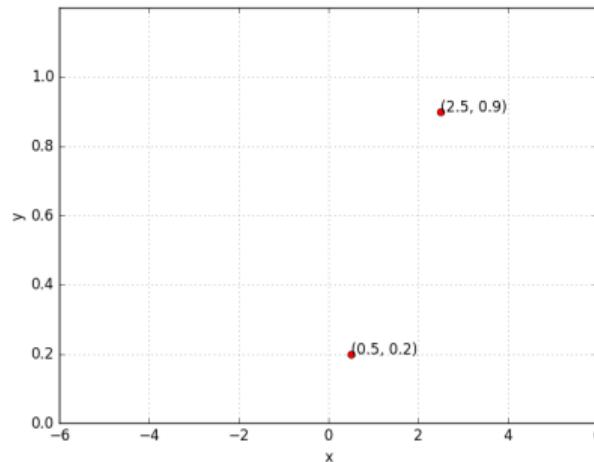
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Let's assume there is only 1 point to fit
(x, y)



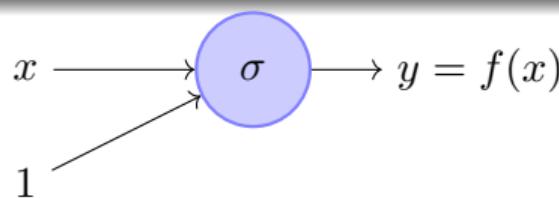


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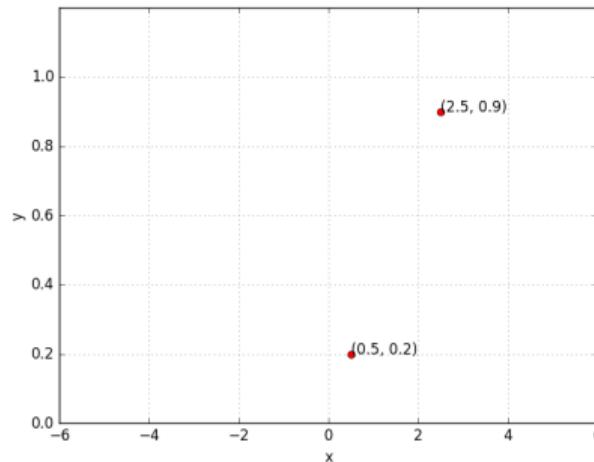


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$$\mathcal{L}(w, b) = \frac{1}{2} * (f(x) - y)^2$$



$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$



Let's assume there is only 1 point to fit
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$$\begin{aligned}\mathcal{L}(w, b) &= \frac{1}{2} * (f(x) - y)^2 \\ \nabla w &= \frac{\partial \mathcal{L}(w, b)}{\partial w} = \frac{\partial}{\partial w} \left[\frac{1}{2} * (f(x) - y)^2 \right]\end{aligned}$$

$$\nabla w = \frac{\partial}{\partial w} \left[\frac{1}{2} * (f(x) - y)^2 \right]$$

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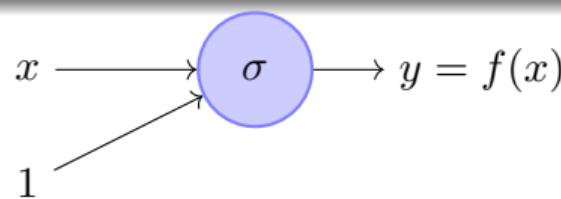
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 &= f(x) * (1 - f(x)) * x
 \end{aligned}$$

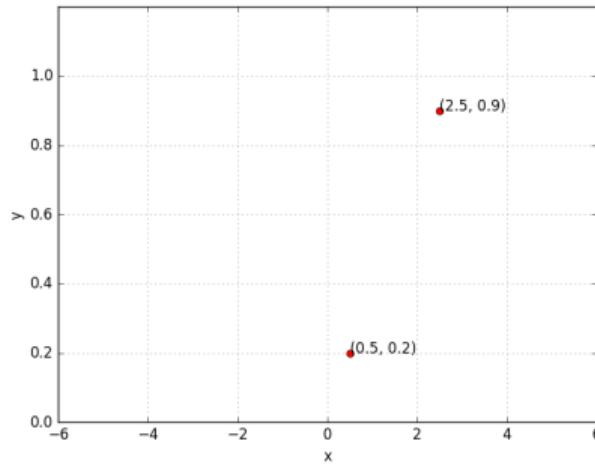
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 &= \color{red}{(f(x) - y) * f(x) * (1 - f(x)) * x}
 \end{aligned}$$

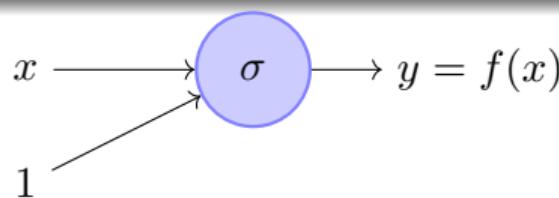
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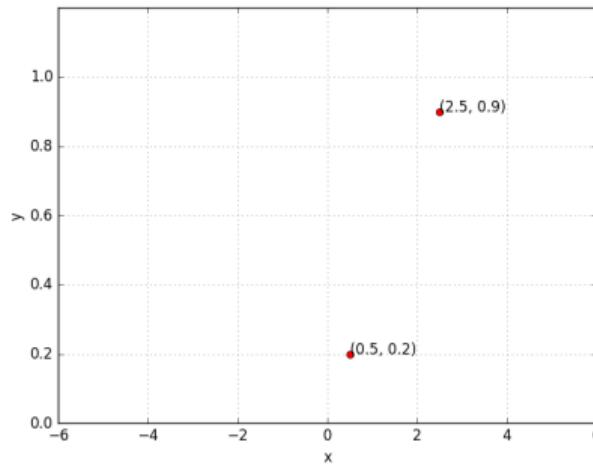
$$f(x) = \frac{1}{1+e^{-(w \cdot x + b)}}$$

So if there is only 1 point (x, y) , we have,



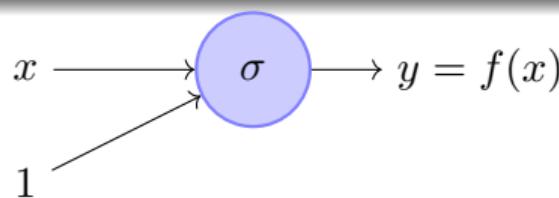


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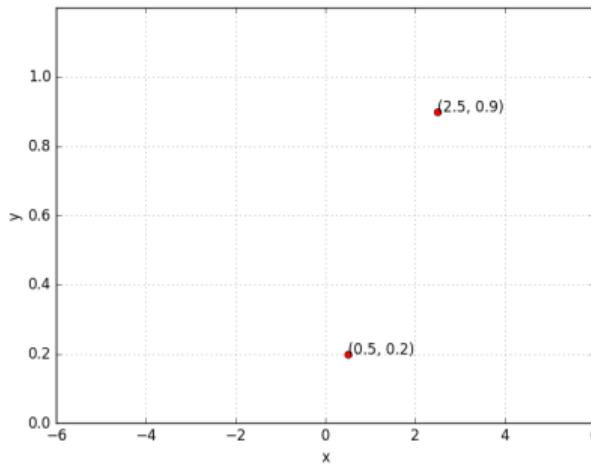


So if there is only 1 point (x, y) , we have,

$$\nabla w = (f(x) - y) * f(x) * (1 - f(x)) * x$$



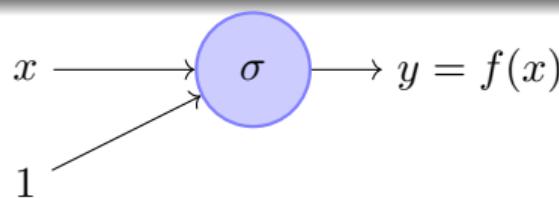
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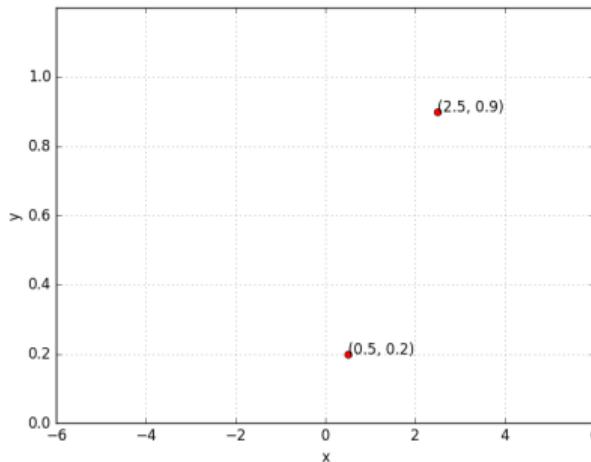
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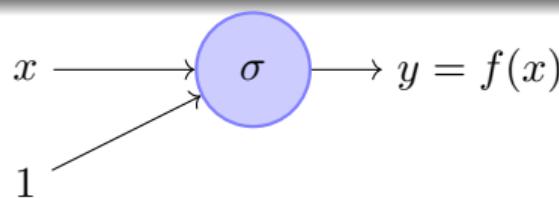


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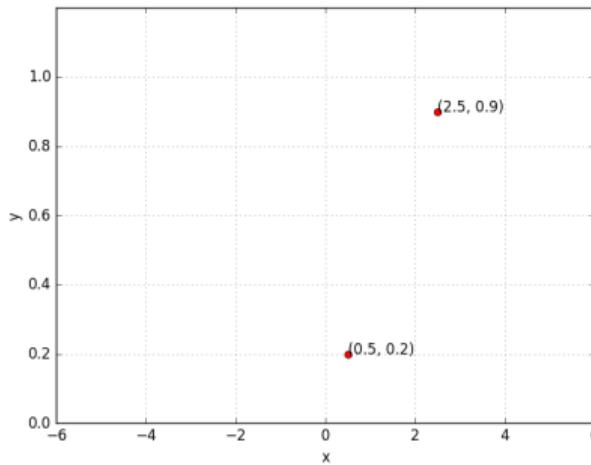
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$$\nabla w = \sum_{i=1}^2 (f(x_i) - y_i) * f(x_i) * (1 - f(x_i)) * x_i$$



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For two points,

$$\nabla w = \sum_{i=1}^2 (f(x_i) - y_i) * f(x_i) * (1 - f(x_i)) * x_i$$

$$\nabla b = \sum_{i=1}^2 (f(x_i) - y_i) * f(x_i) * (1 - f(x_i))$$

```
X = [0.5, 2.5]  
Y = [0.2, 0.9]
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def error (w, b) :
    err = 0.0
    for x,y in zip(X,Y) :
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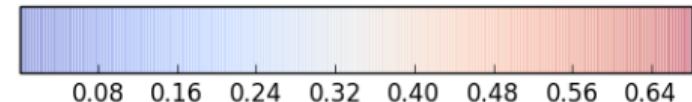
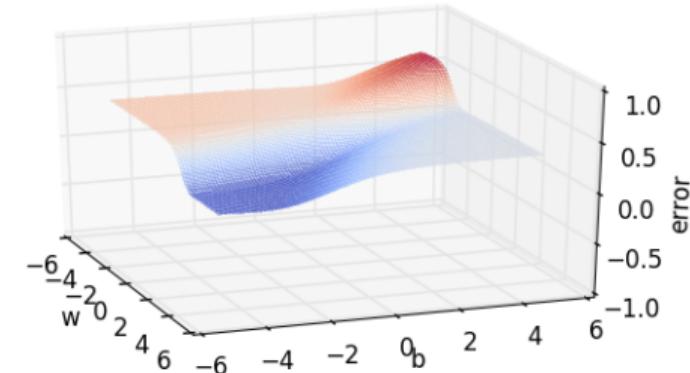
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Random search on error surface



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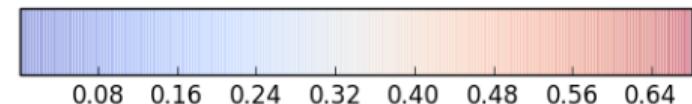
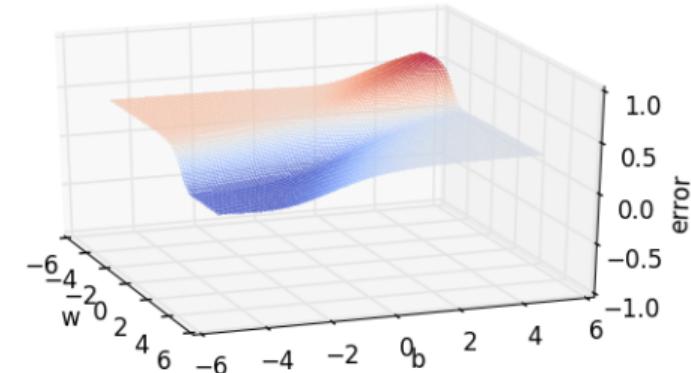
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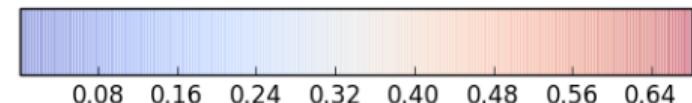
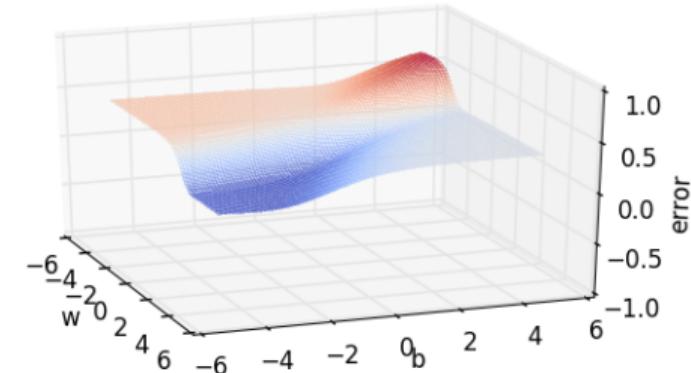
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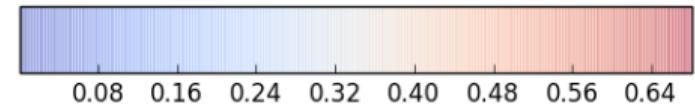
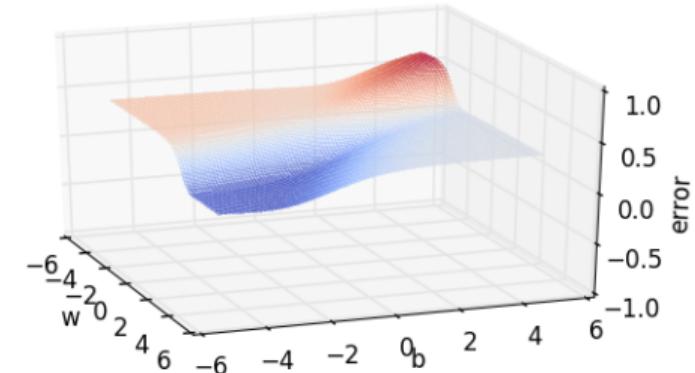
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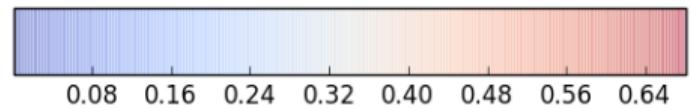
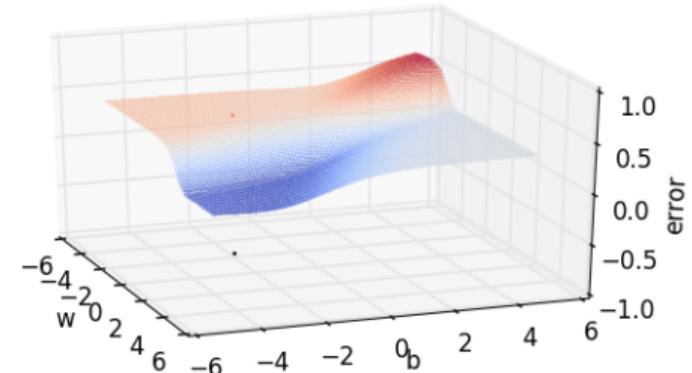
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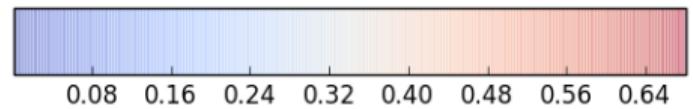
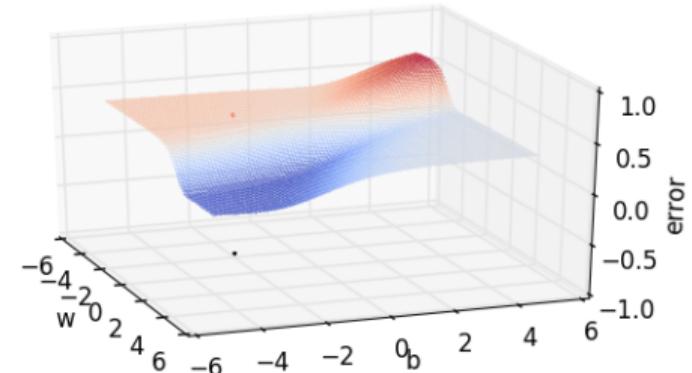
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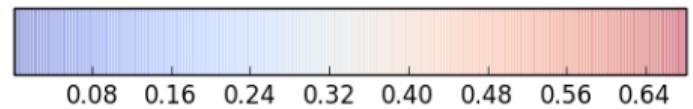
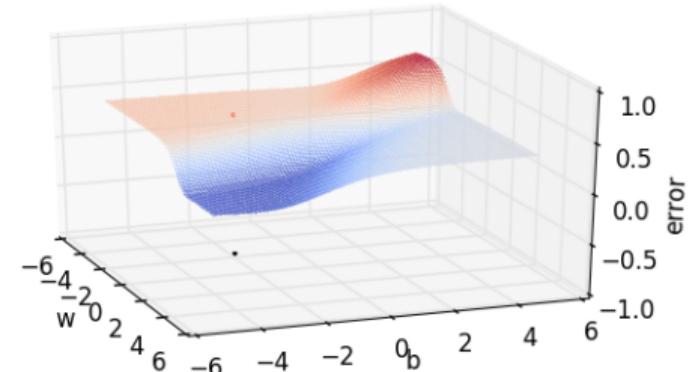
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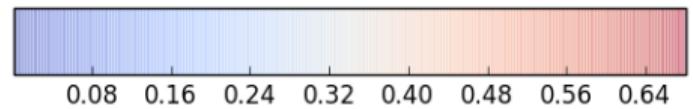
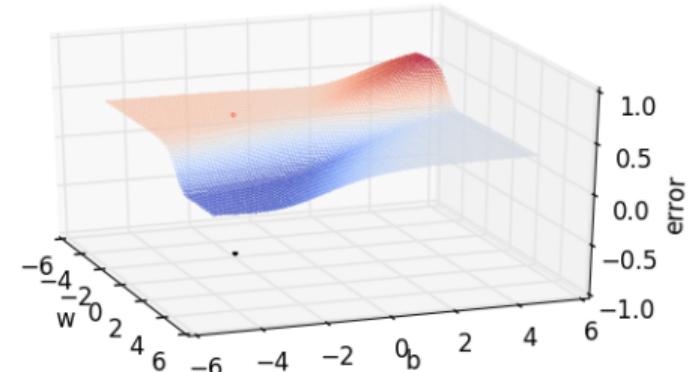
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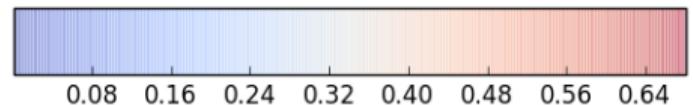
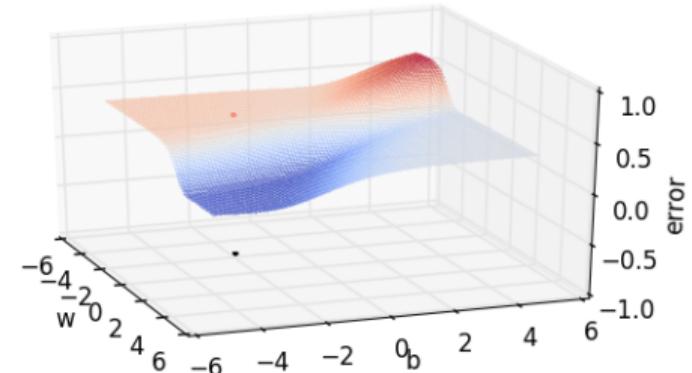
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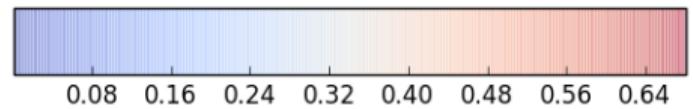
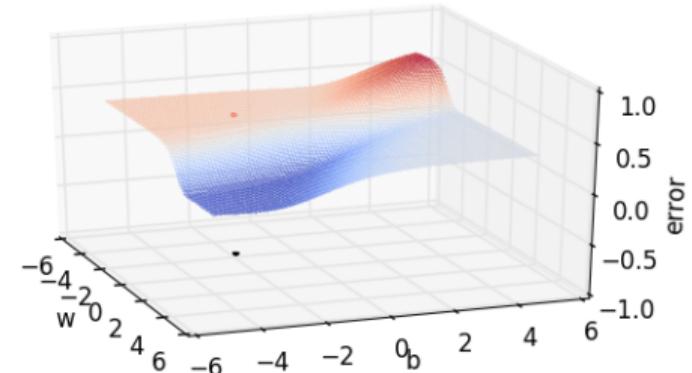
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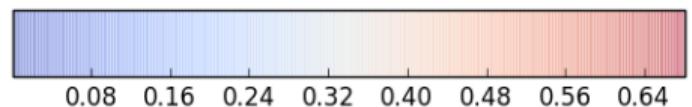
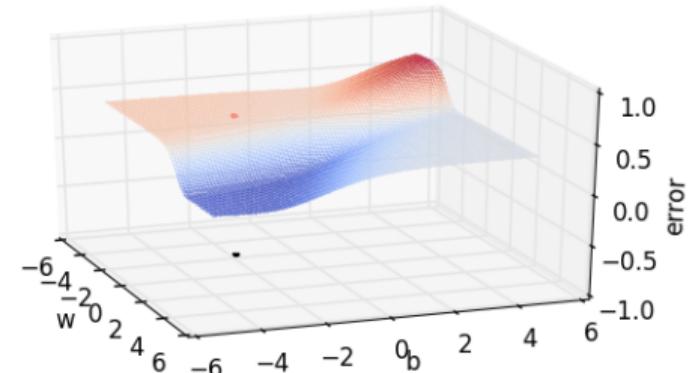
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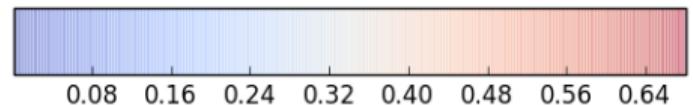
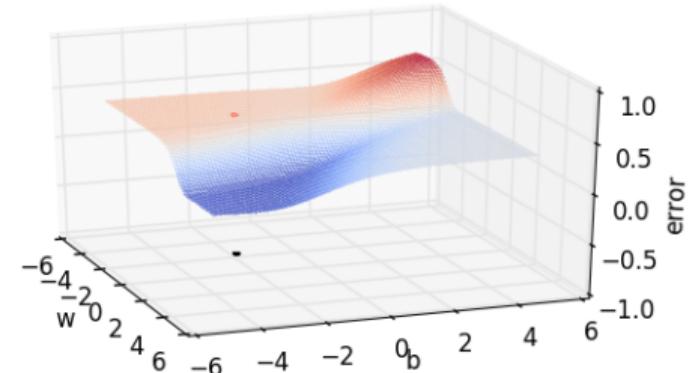
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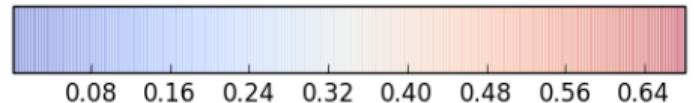
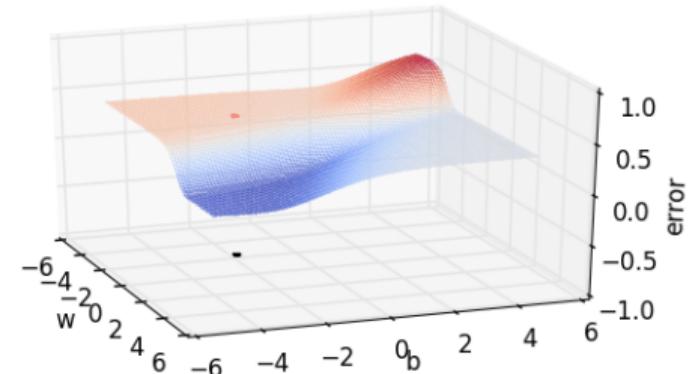
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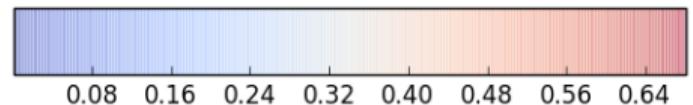
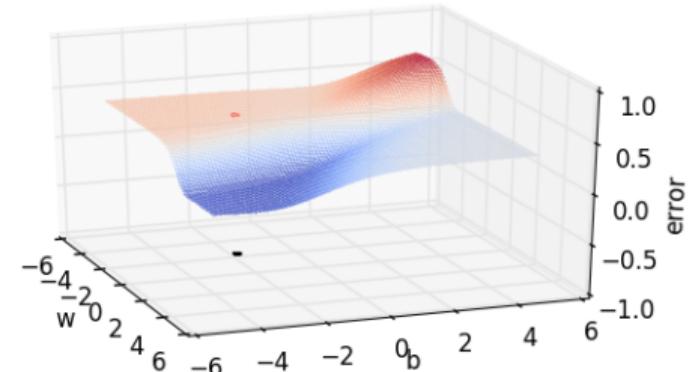
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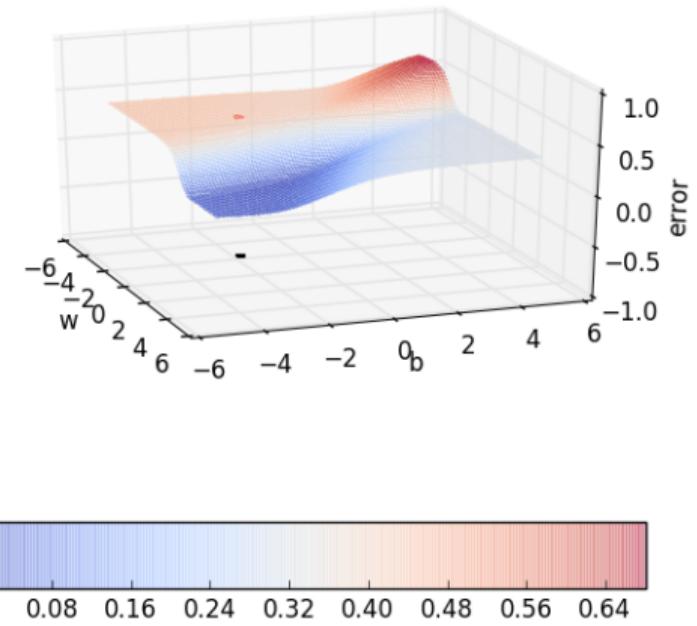
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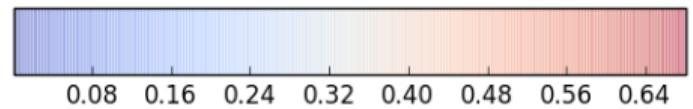
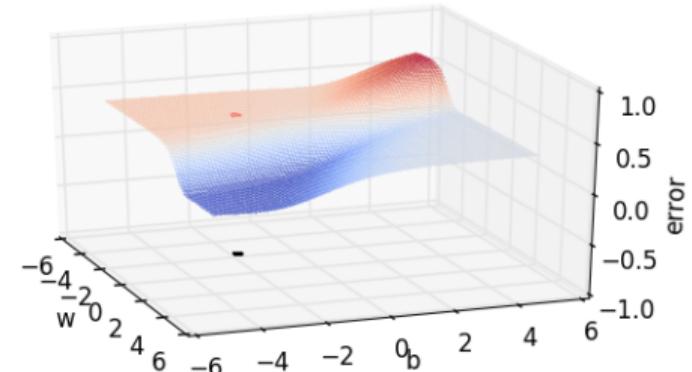
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Gradient descent on the error surface



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X = [0.5, 2.5]
Y = [0.2, 0.9]

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    return 1.0 / (1.0 + np.exp(-(w*x + b)))

def error (w, b) :
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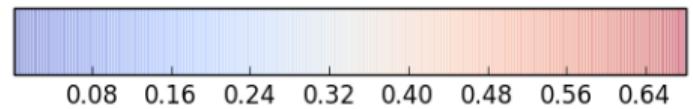
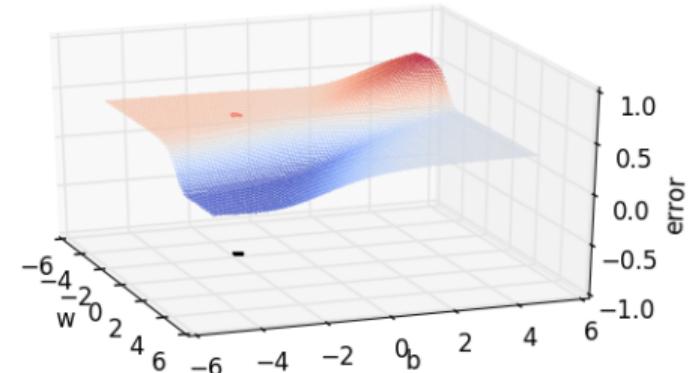
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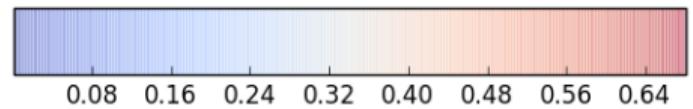
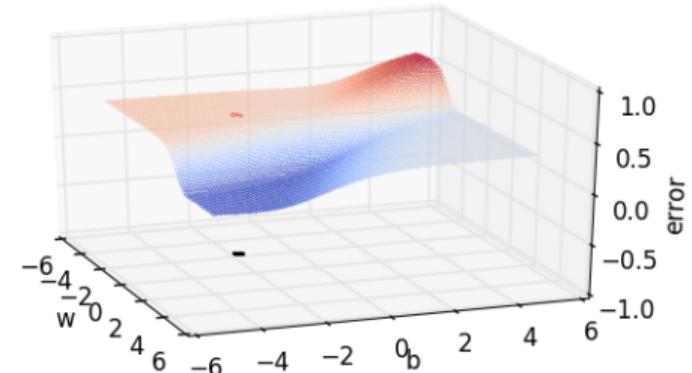
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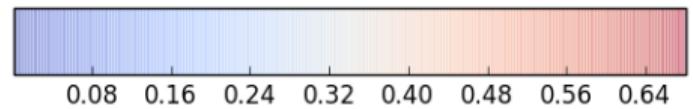
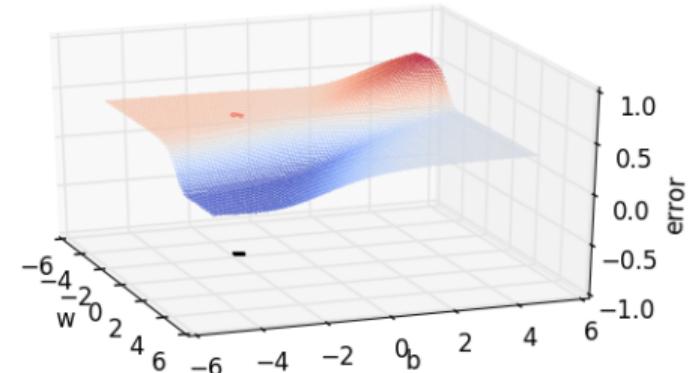
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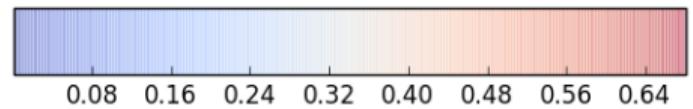
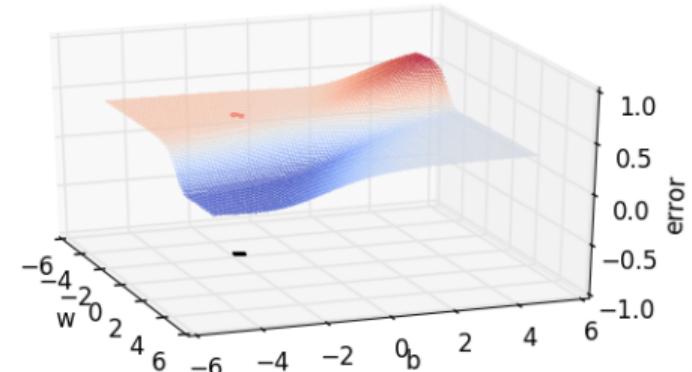
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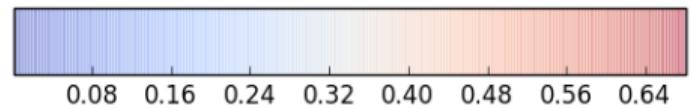
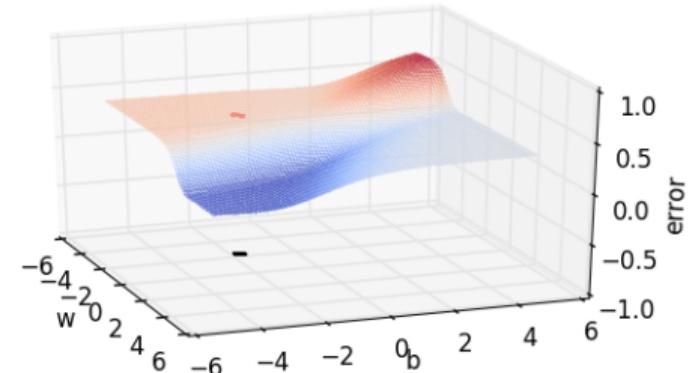
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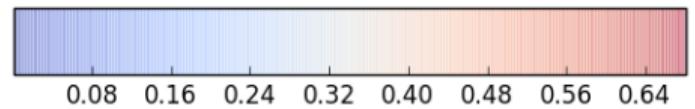
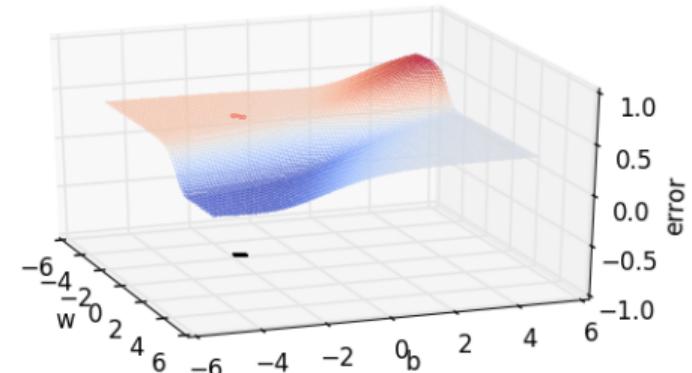
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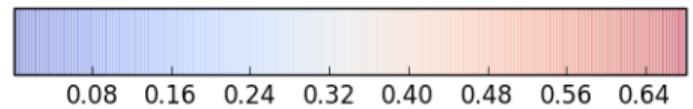
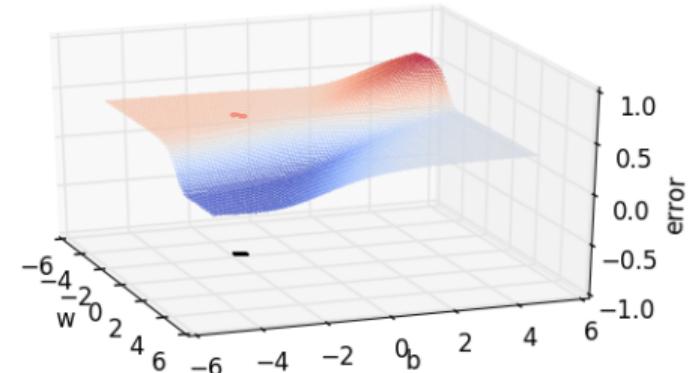
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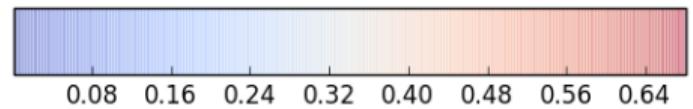
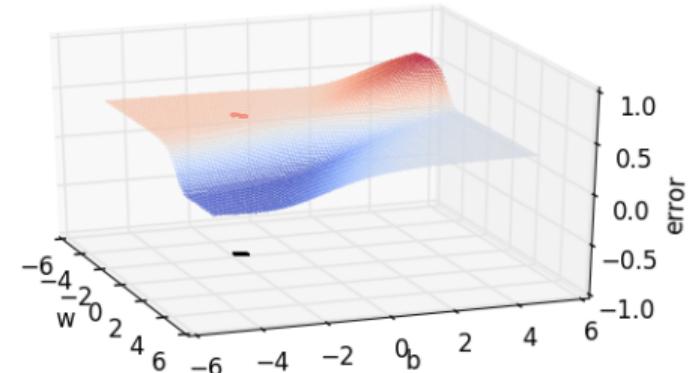
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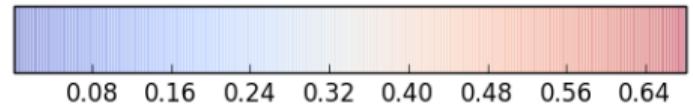
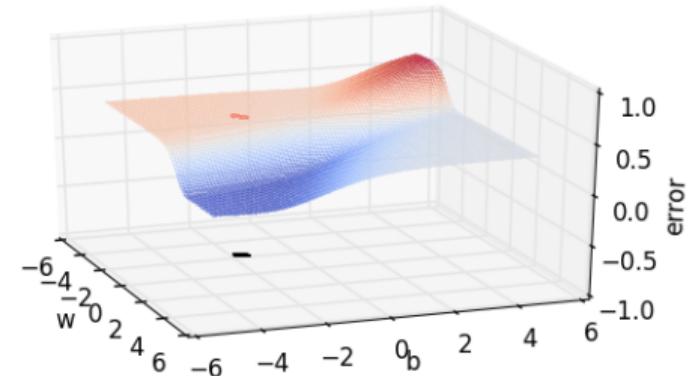
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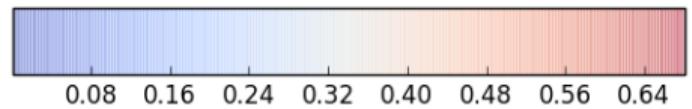
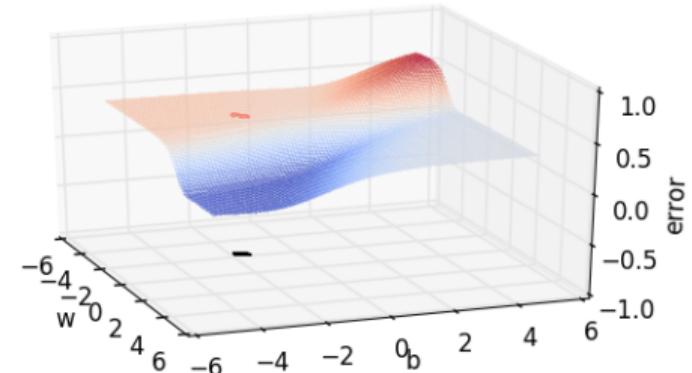
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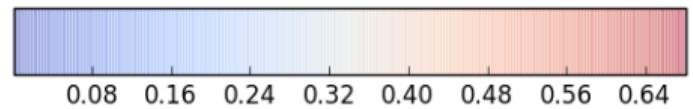
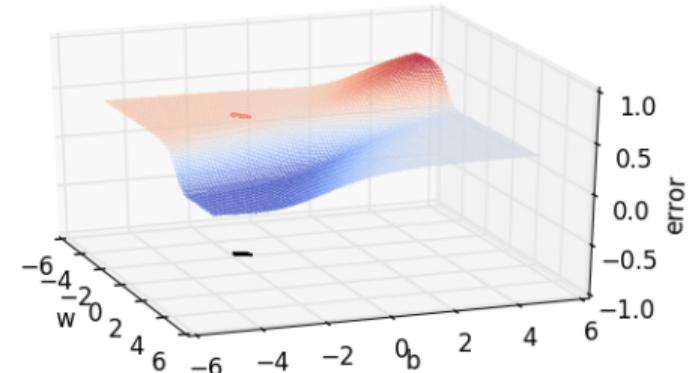
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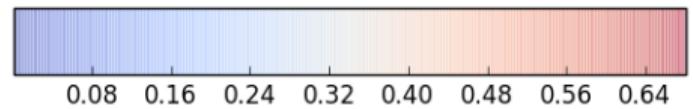
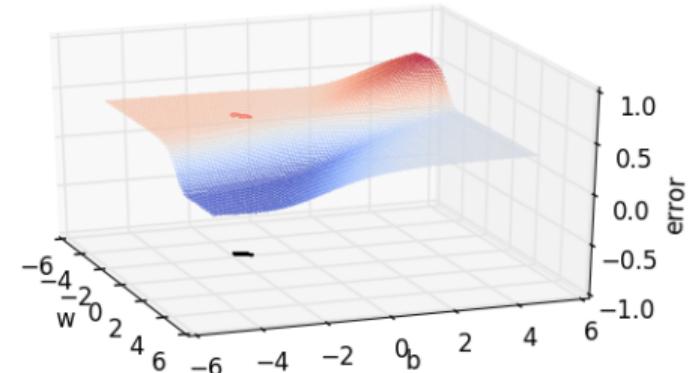
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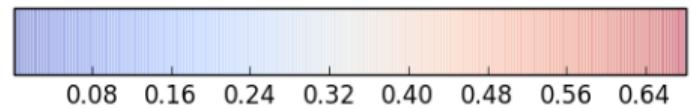
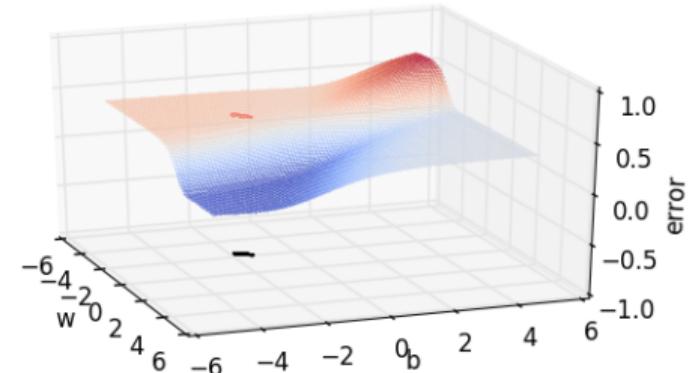
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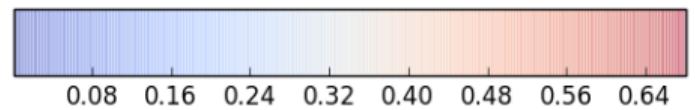
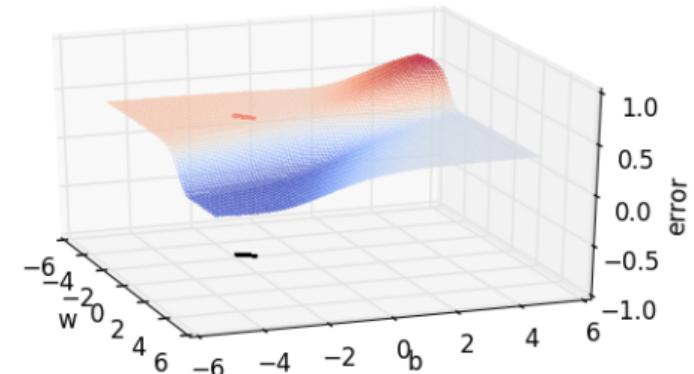
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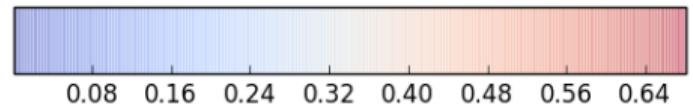
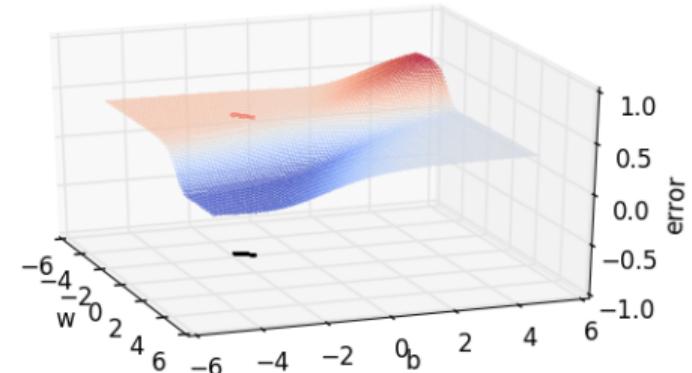
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Gradient descent on the error surface



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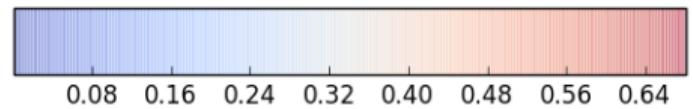
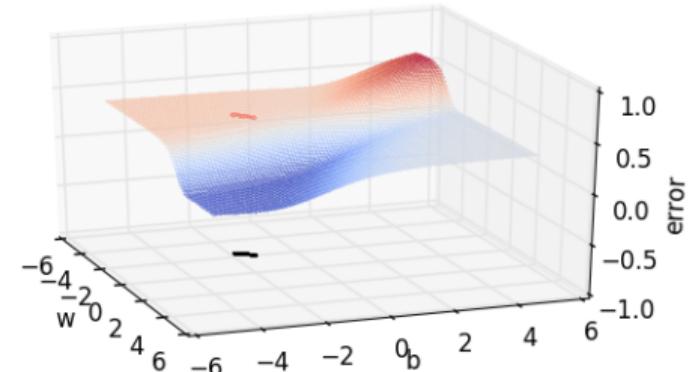
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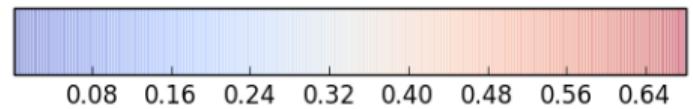
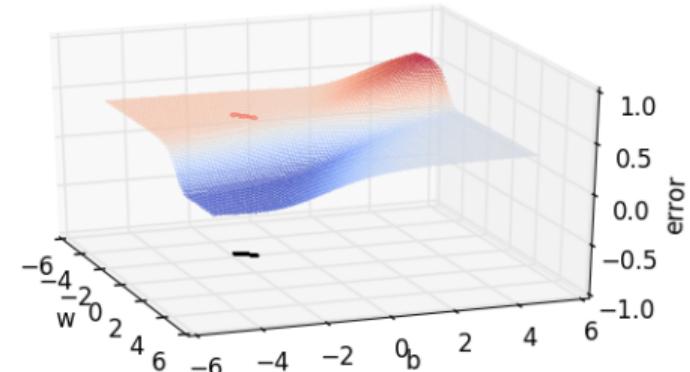
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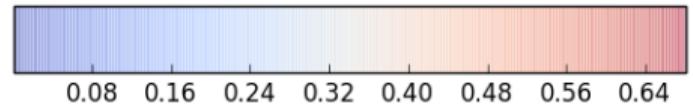
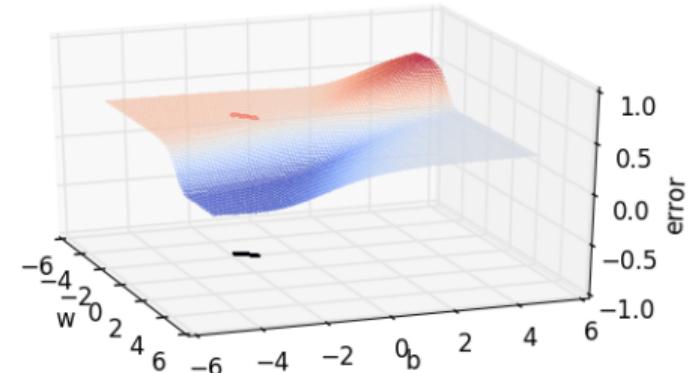
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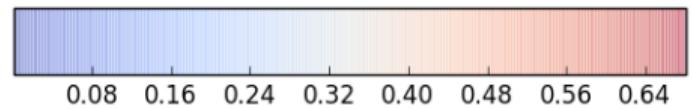
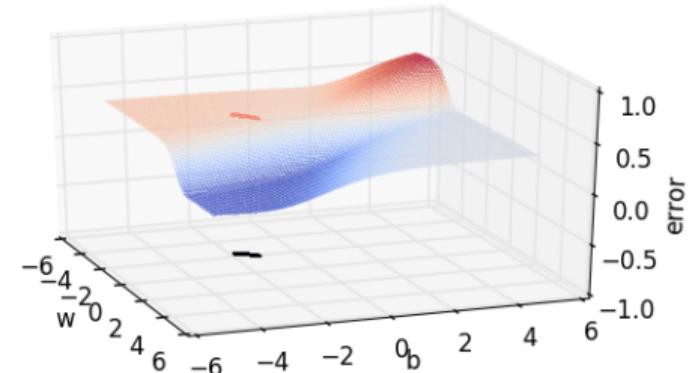
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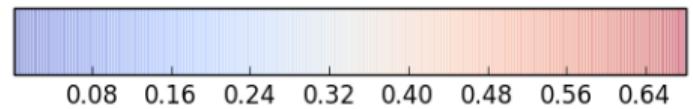
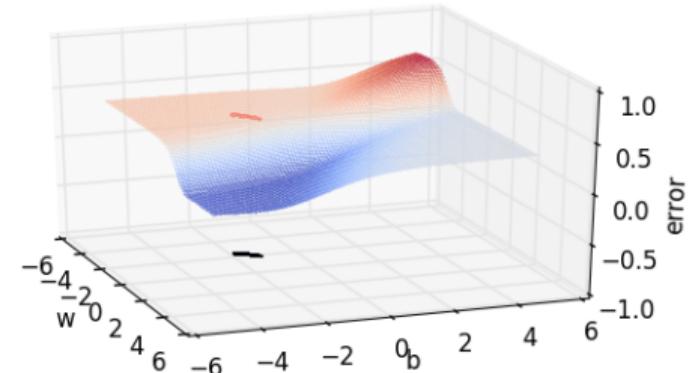
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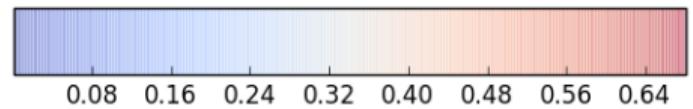
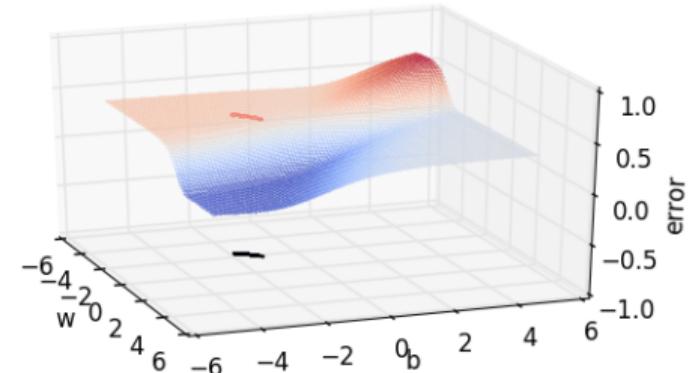
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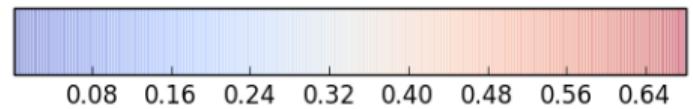
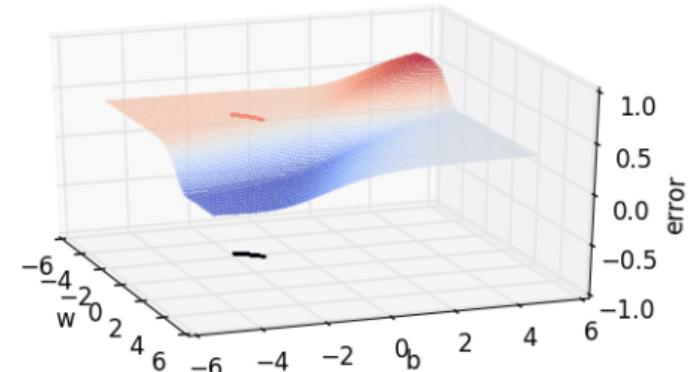
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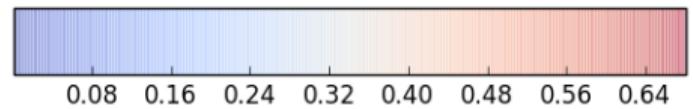
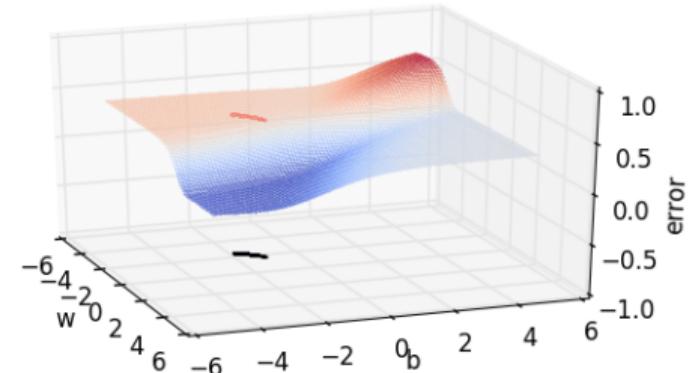
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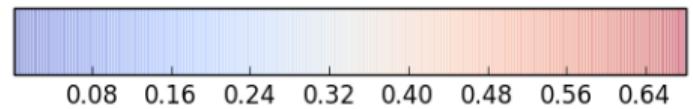
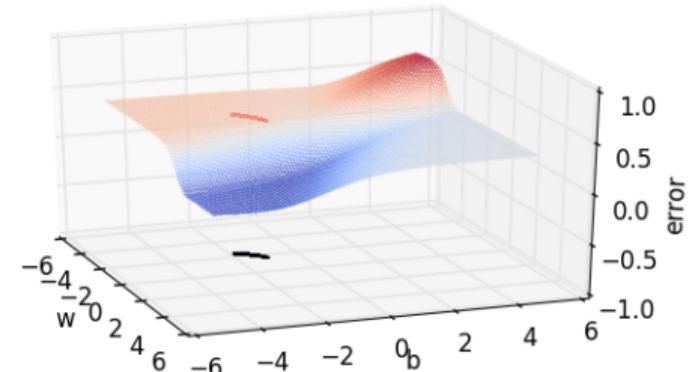
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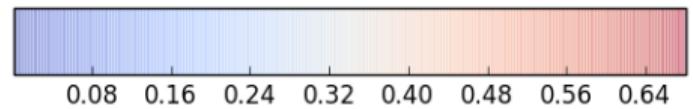
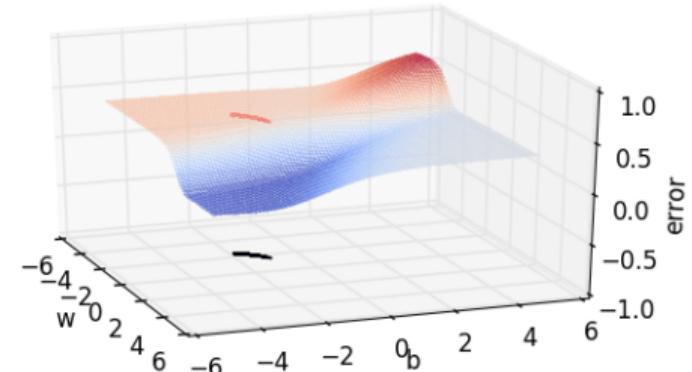
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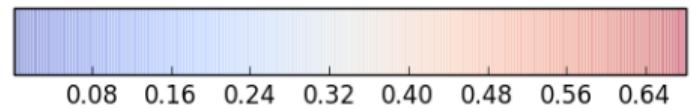
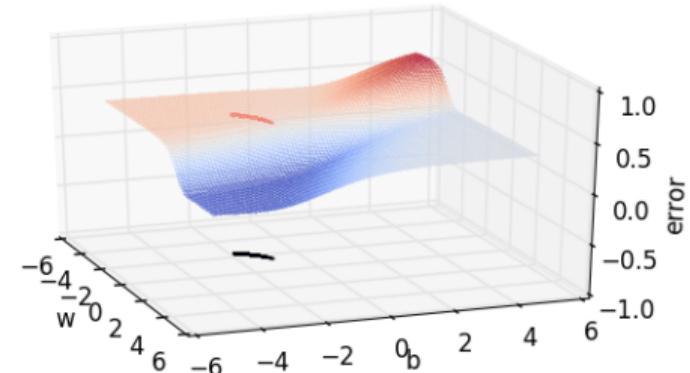
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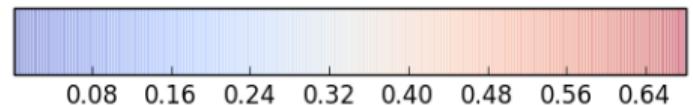
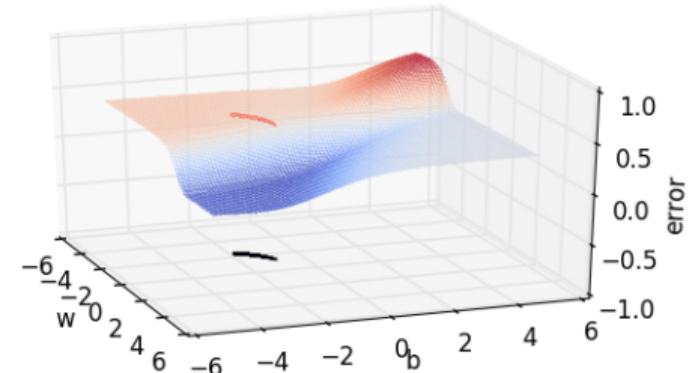
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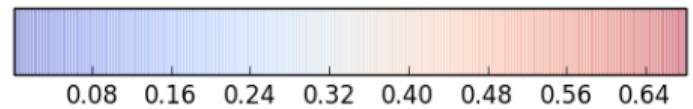
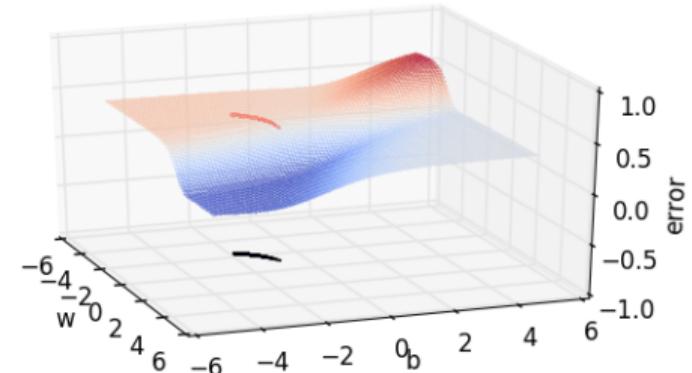
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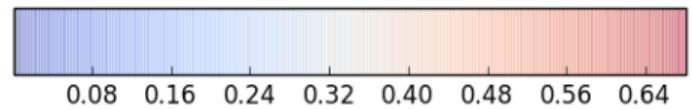
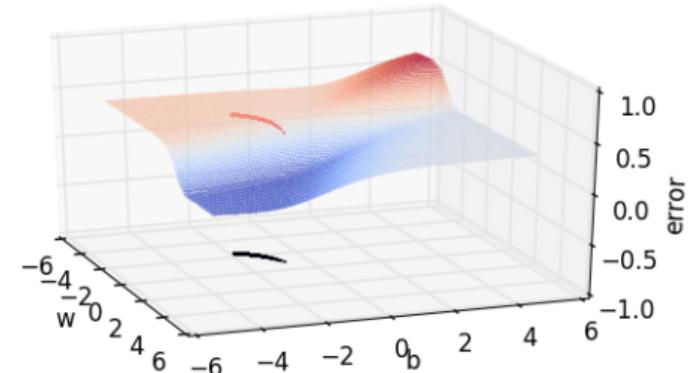
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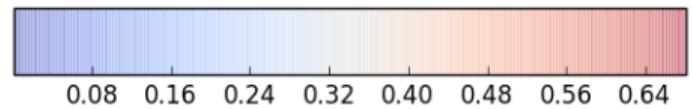
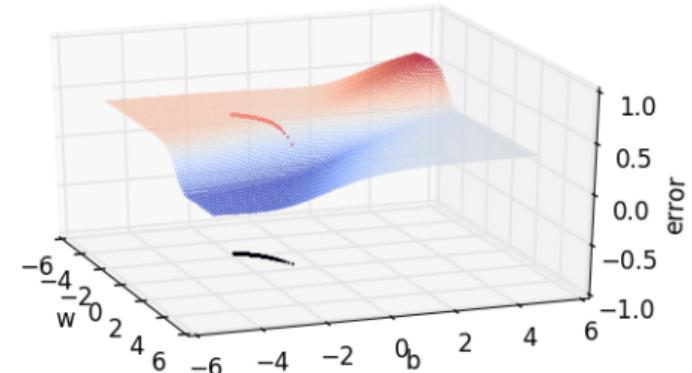
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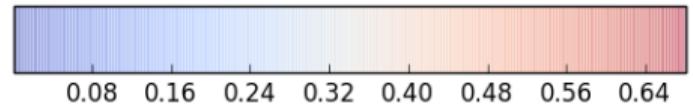
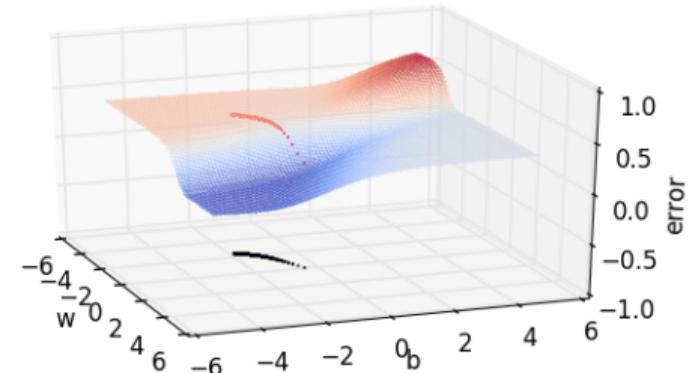
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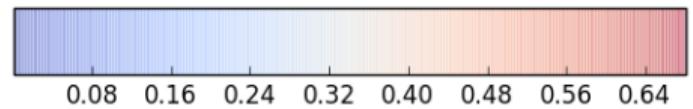
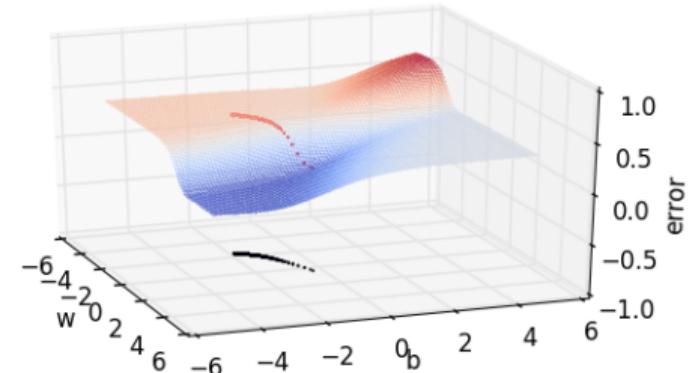
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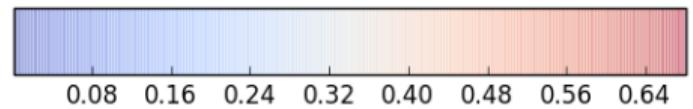
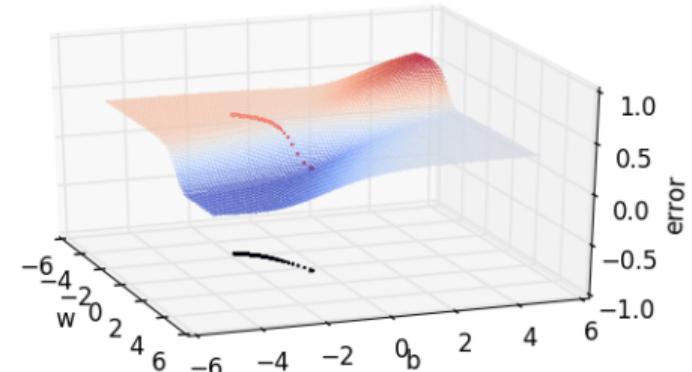
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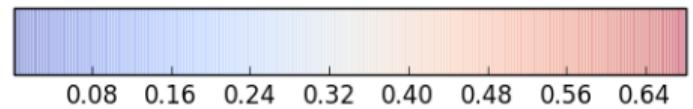
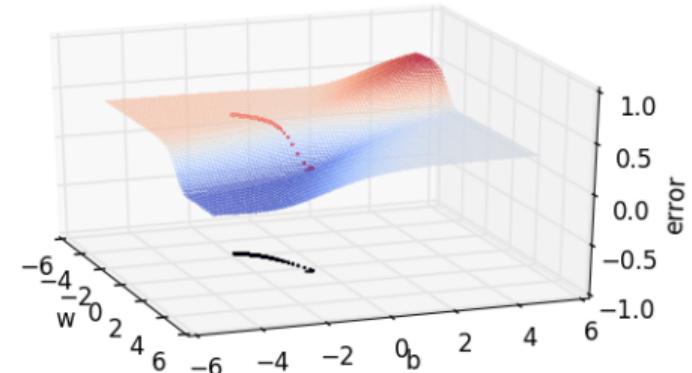
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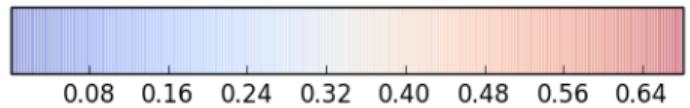
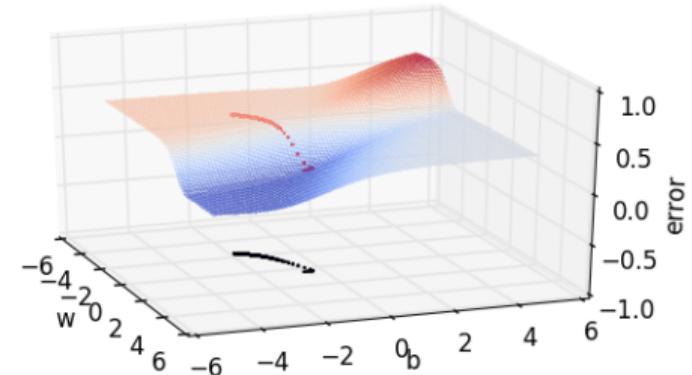
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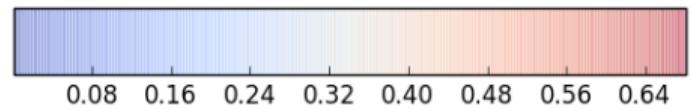
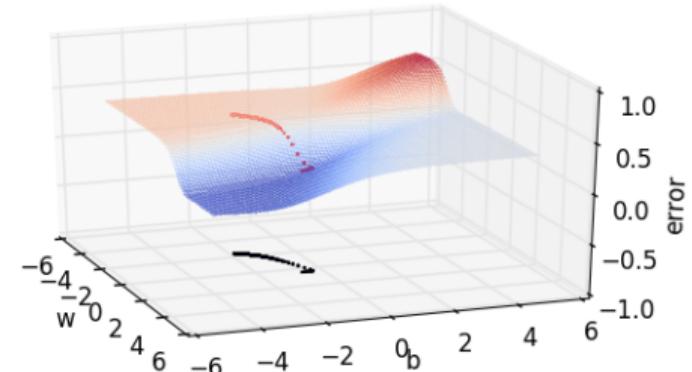
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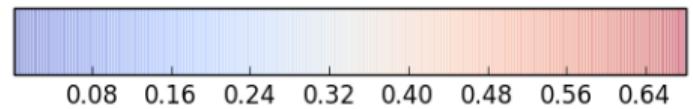
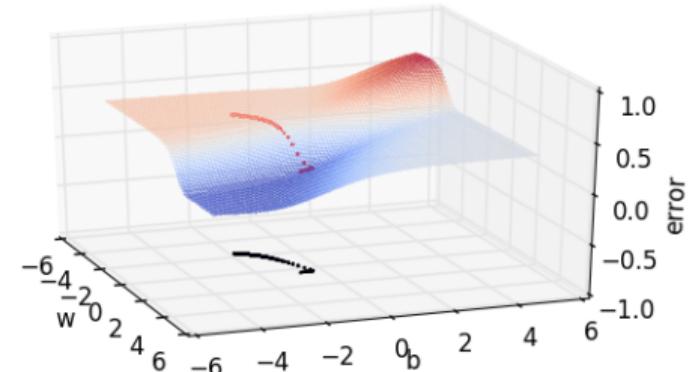
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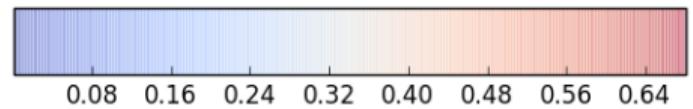
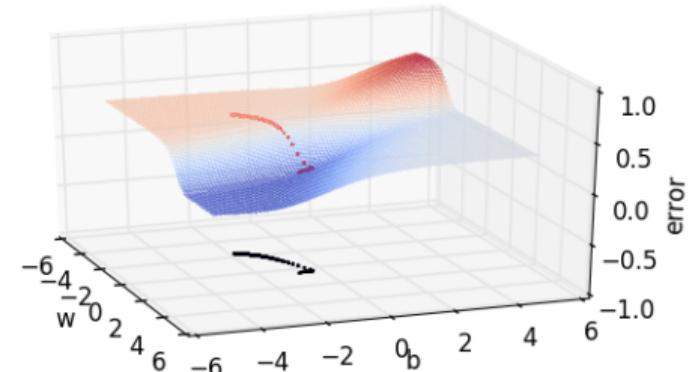
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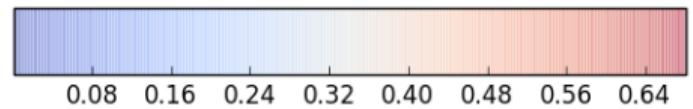
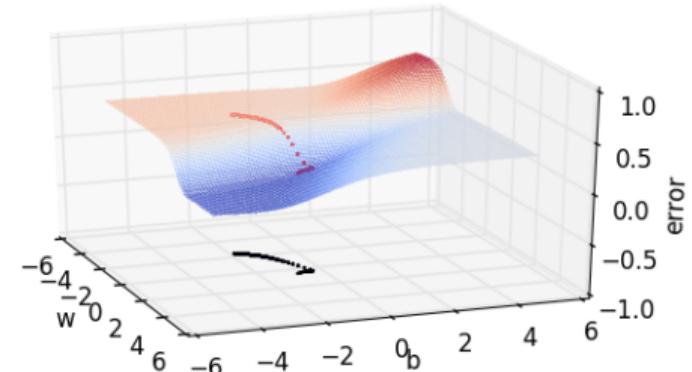
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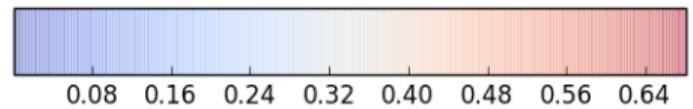
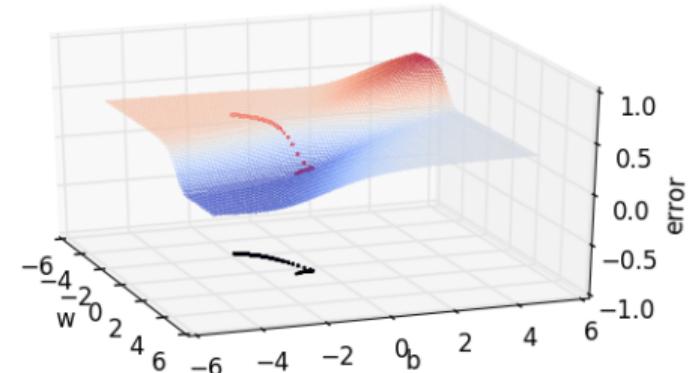
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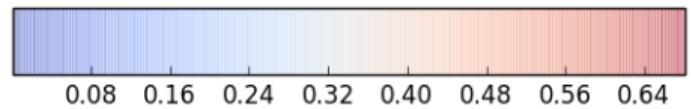
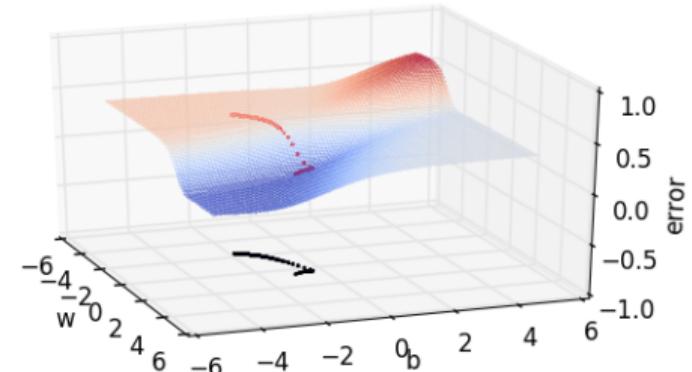
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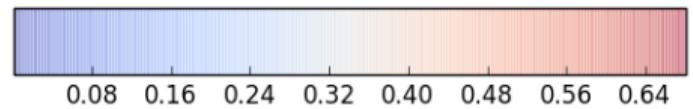
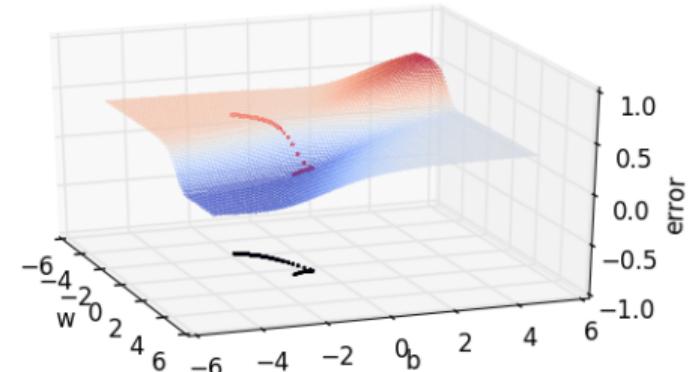
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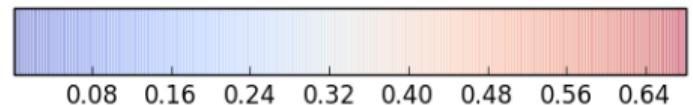
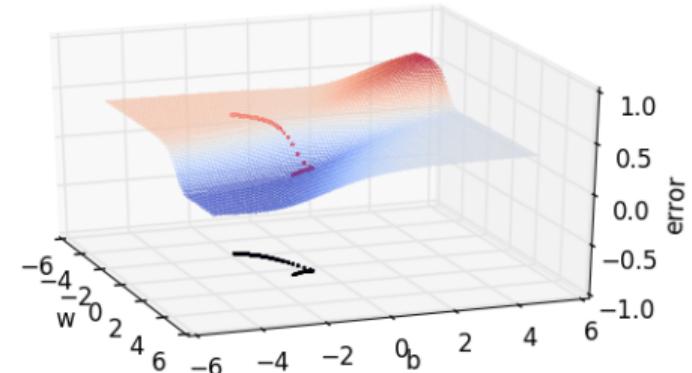
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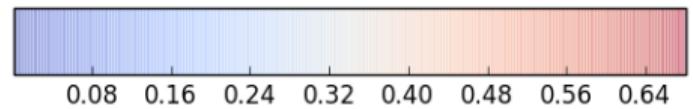
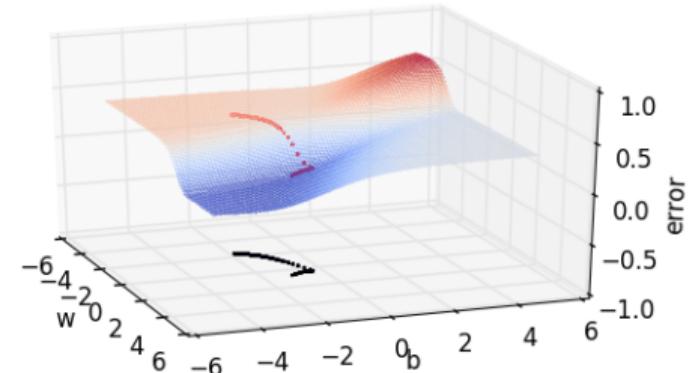
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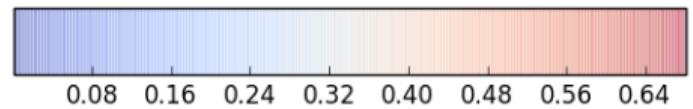
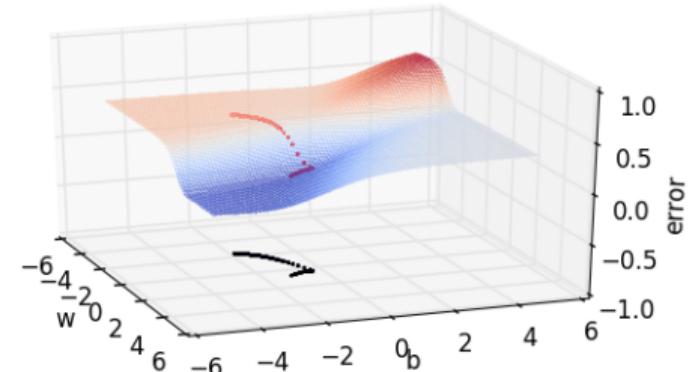
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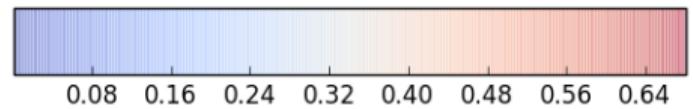
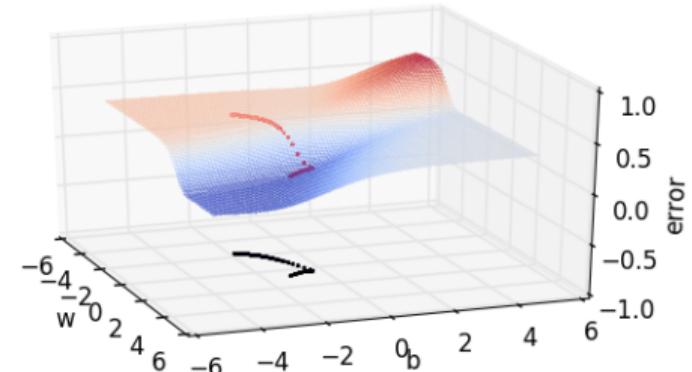
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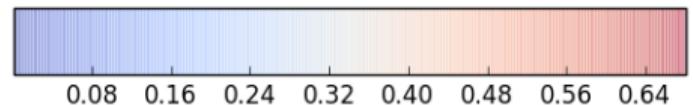
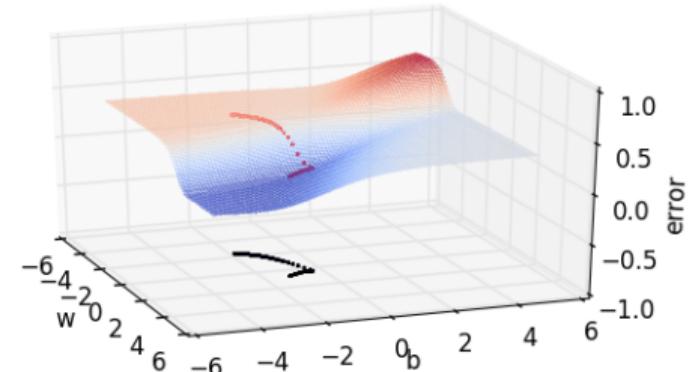
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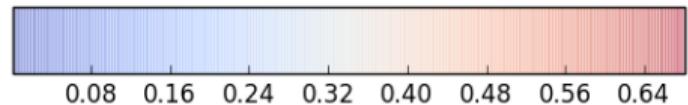
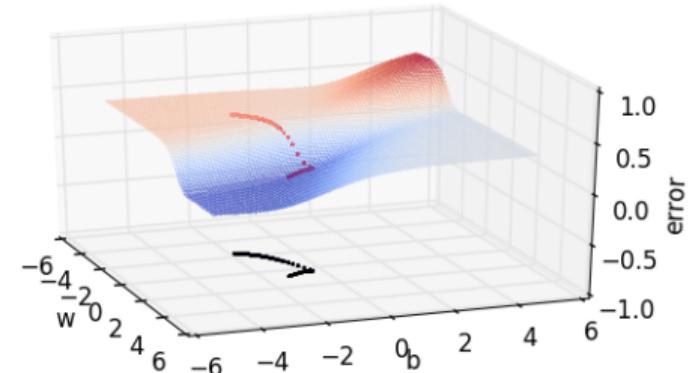
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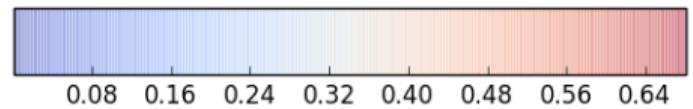
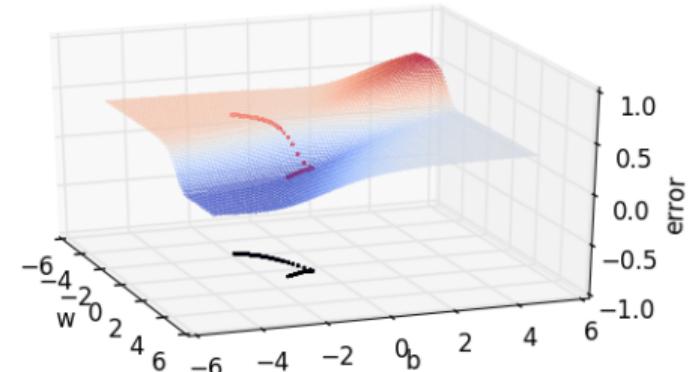
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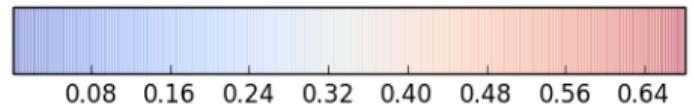
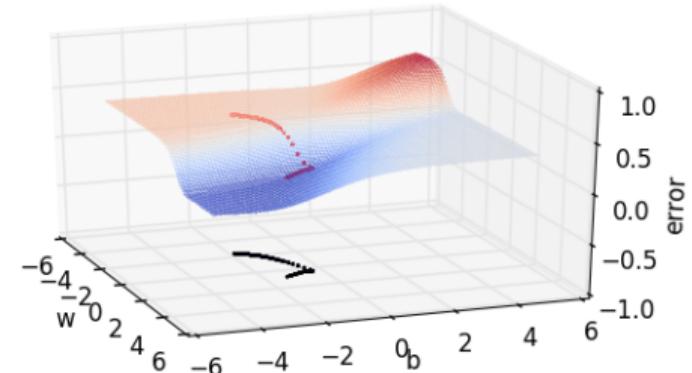
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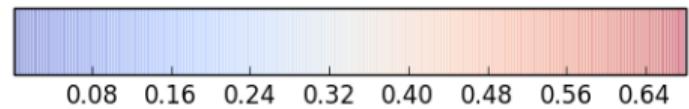
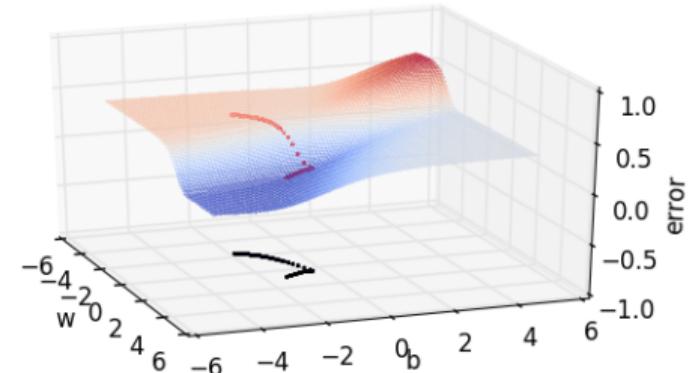
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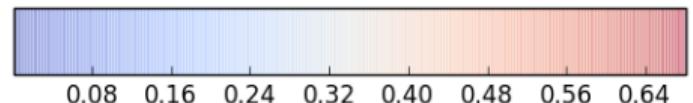
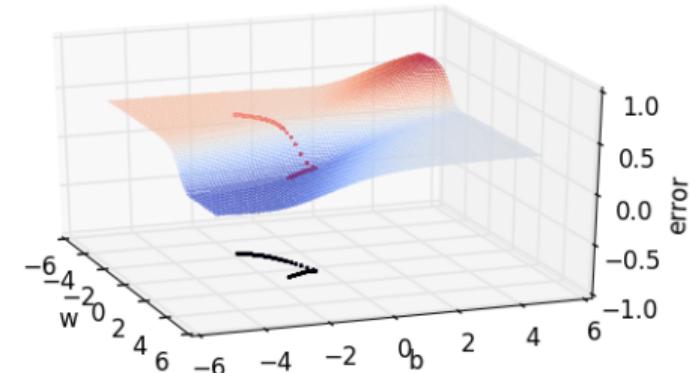
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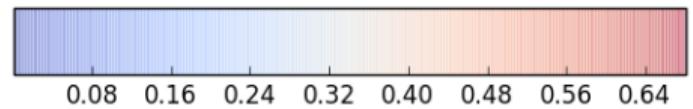
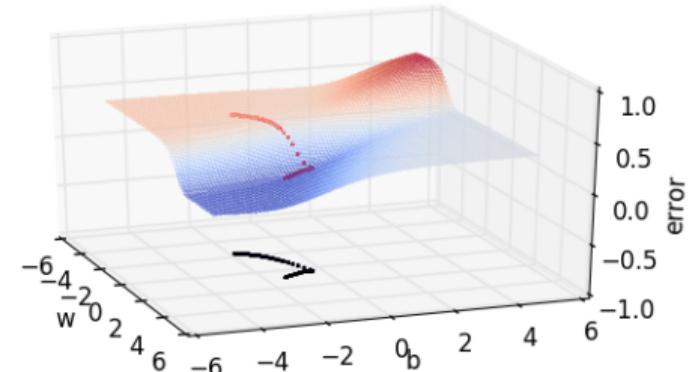
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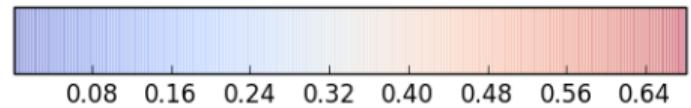
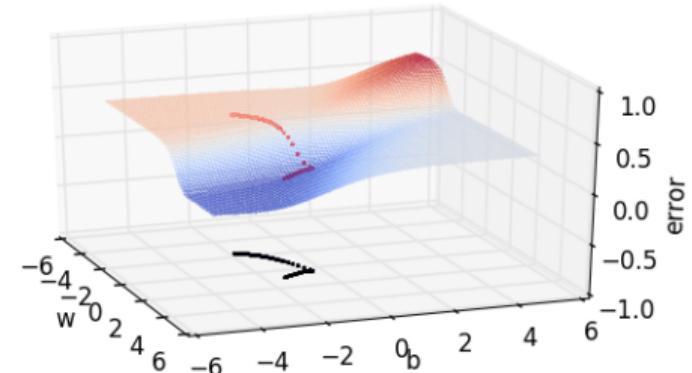
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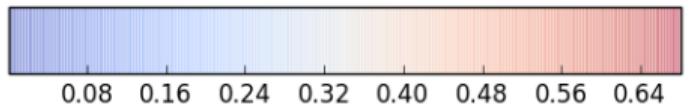
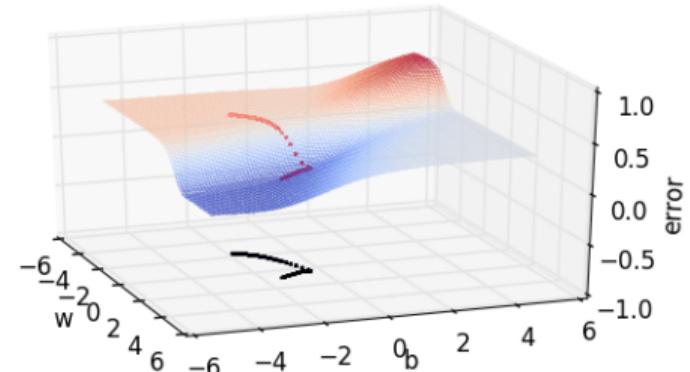
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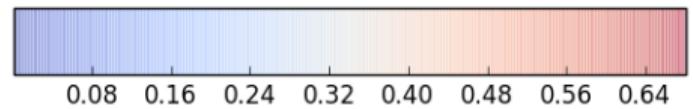
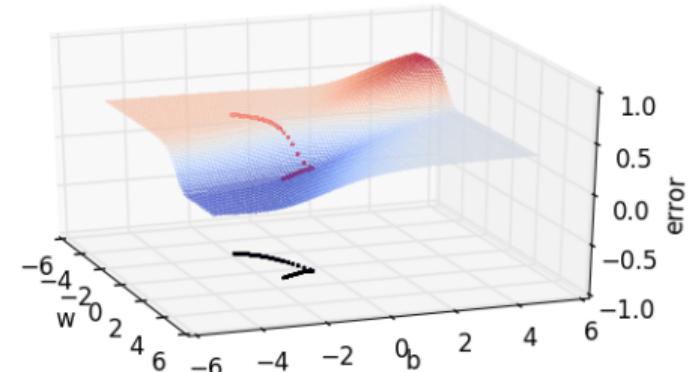
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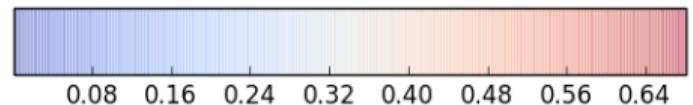
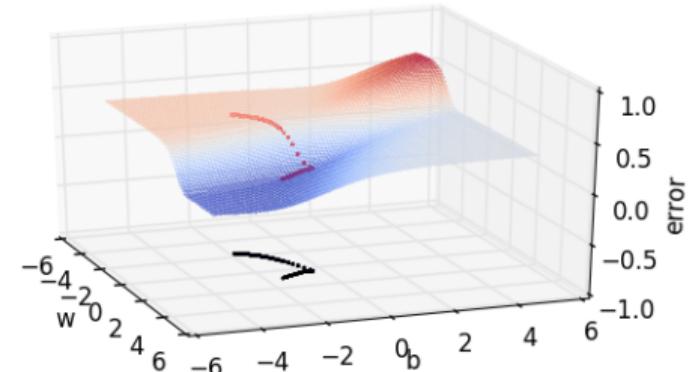
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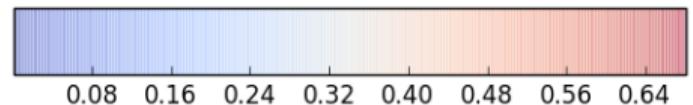
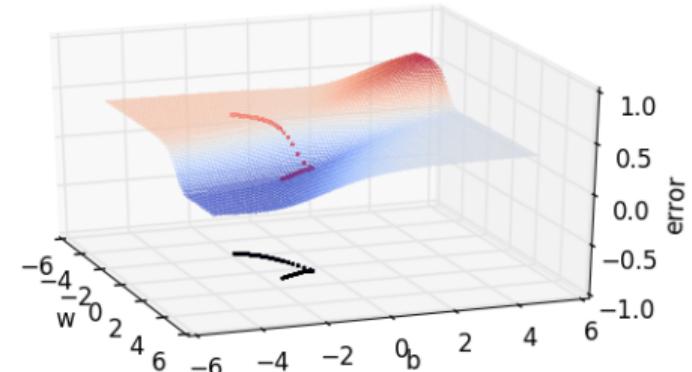
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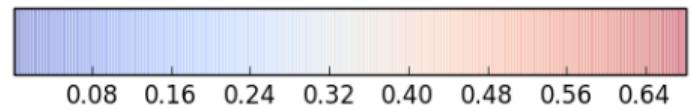
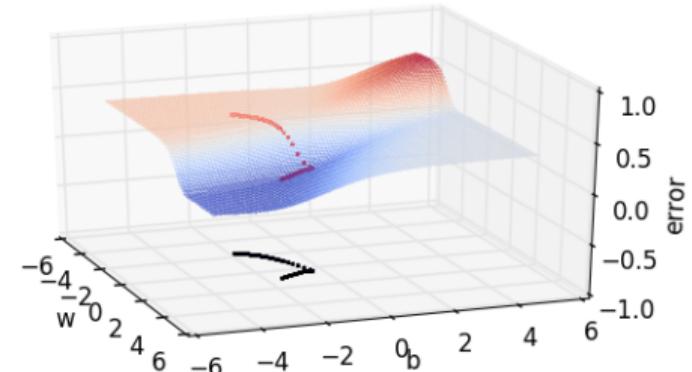
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Gradient descent on the error surface



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Y = [0.2, 0.9]

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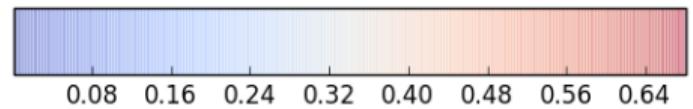
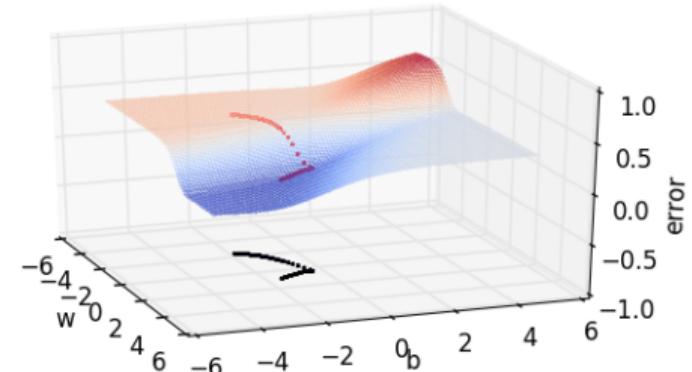
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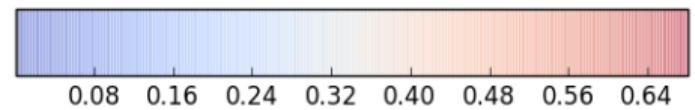
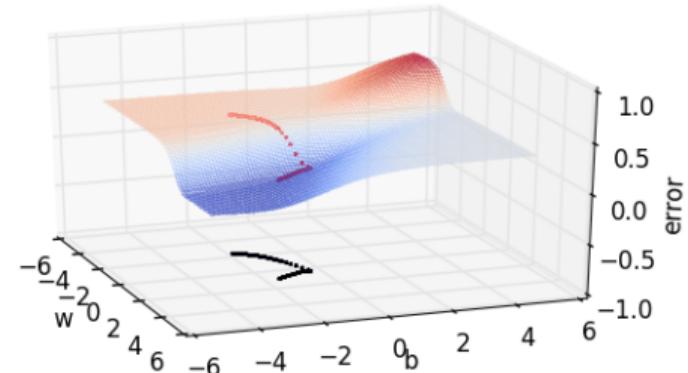
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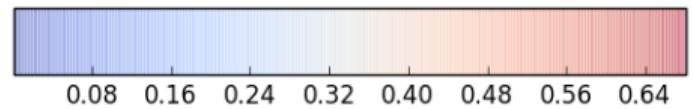
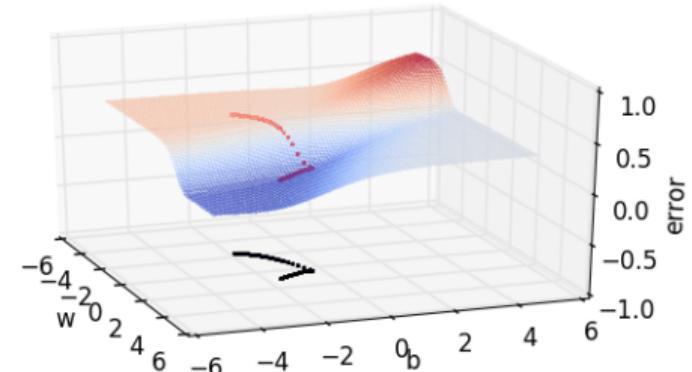
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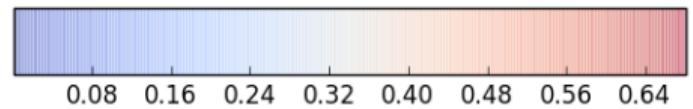
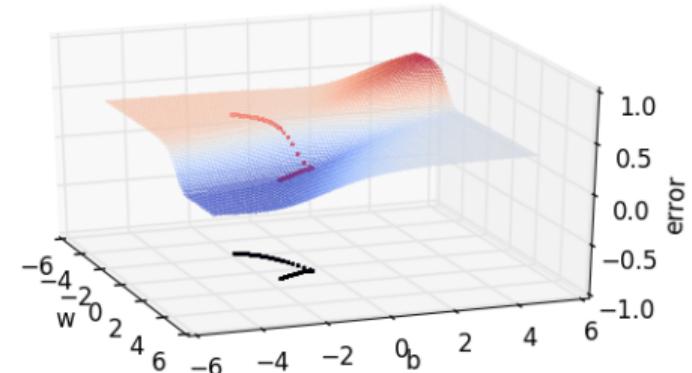
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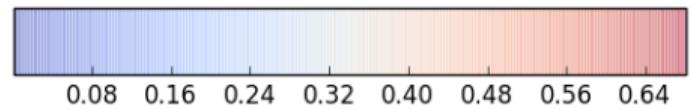
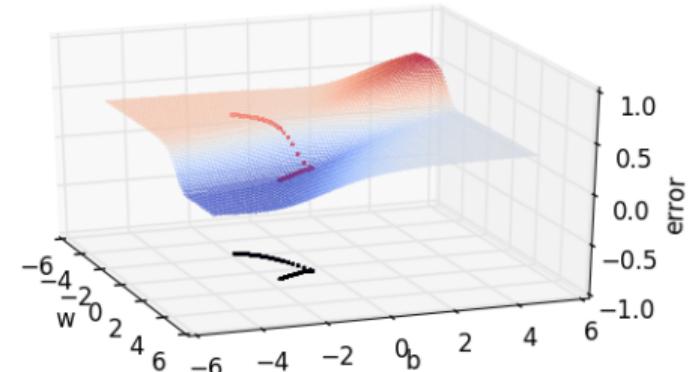
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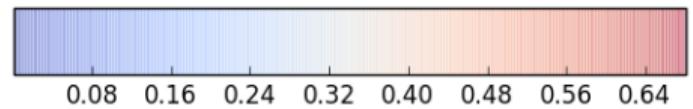
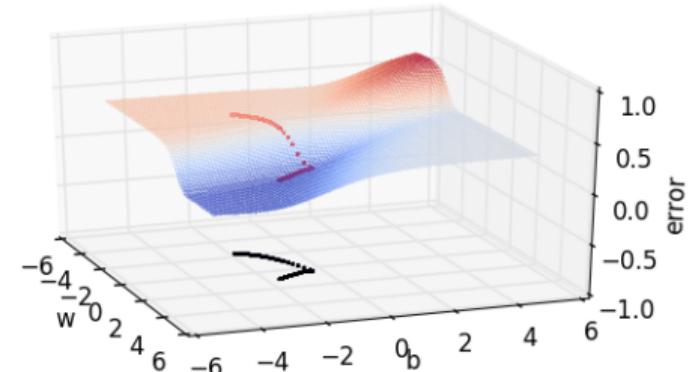
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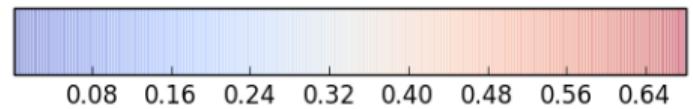
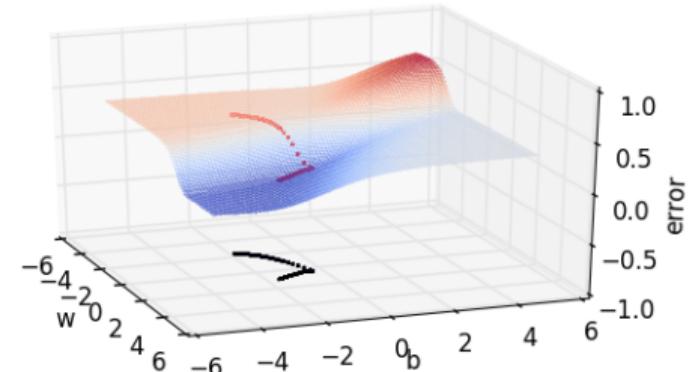
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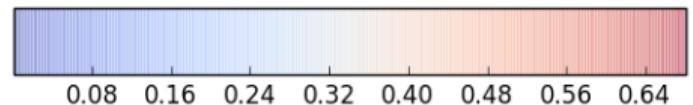
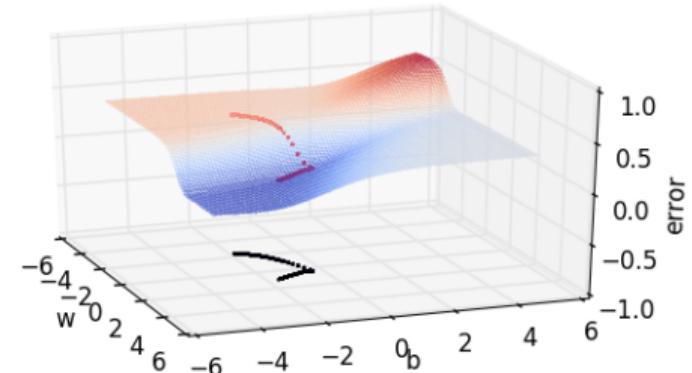
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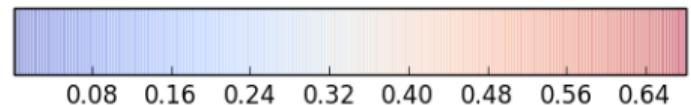
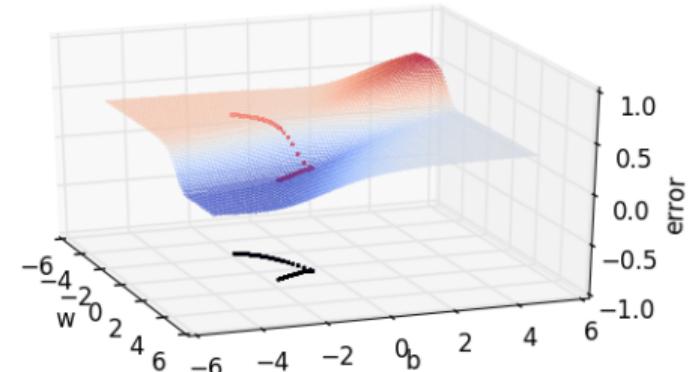
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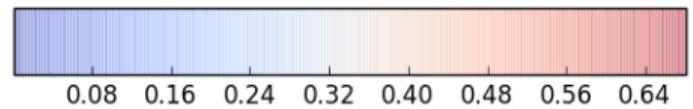
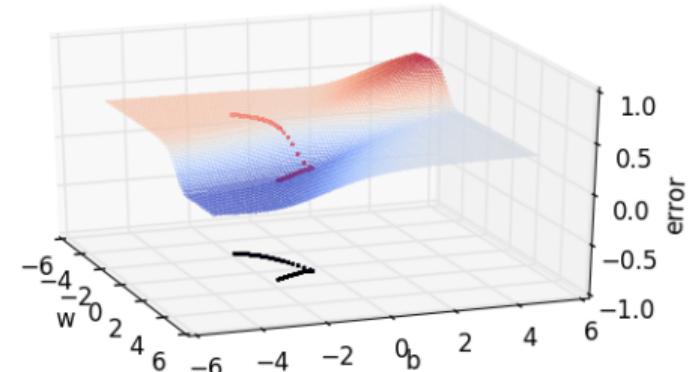
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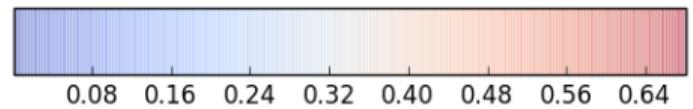
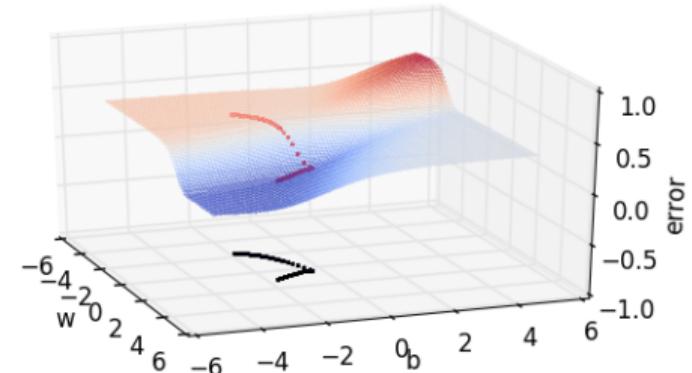
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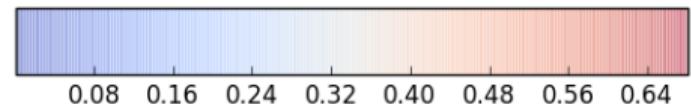
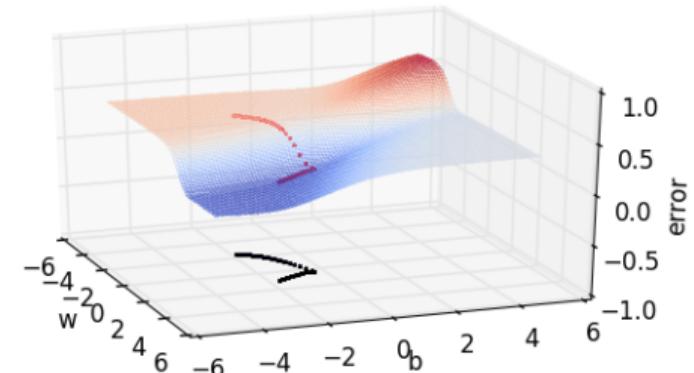
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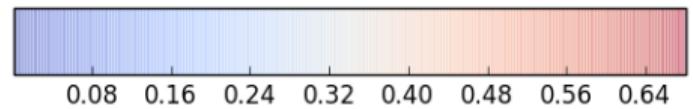
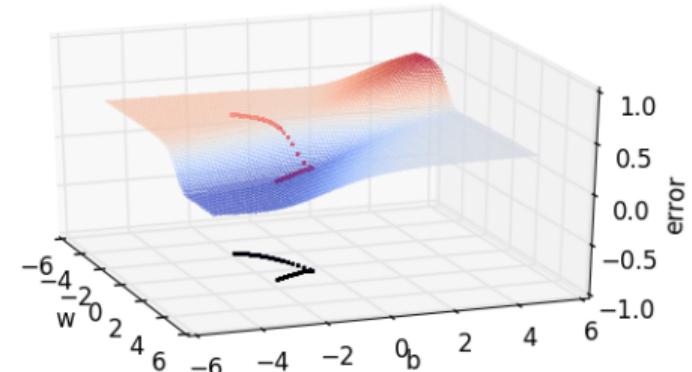
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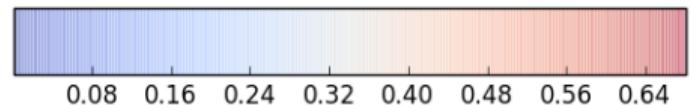
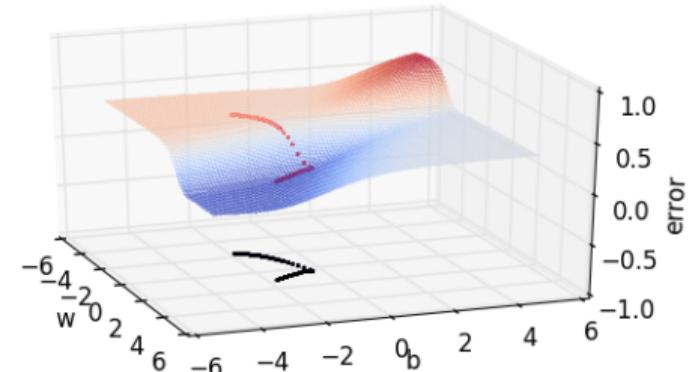
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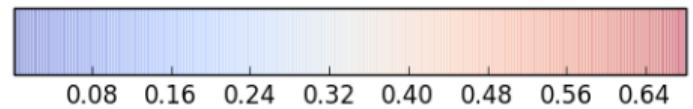
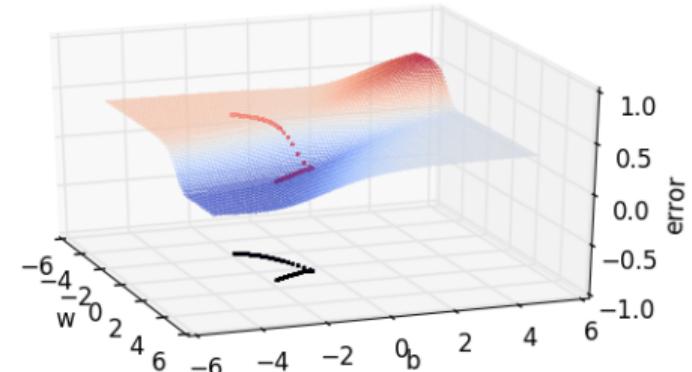
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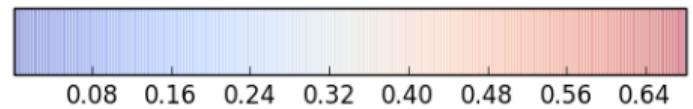
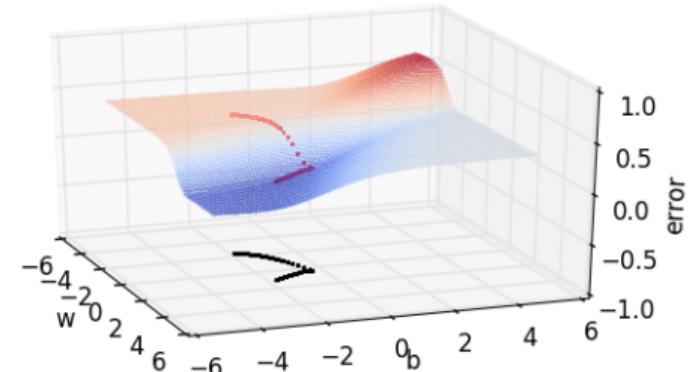
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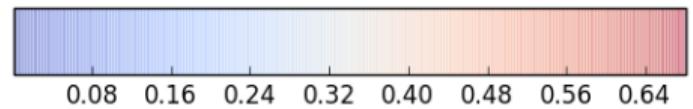
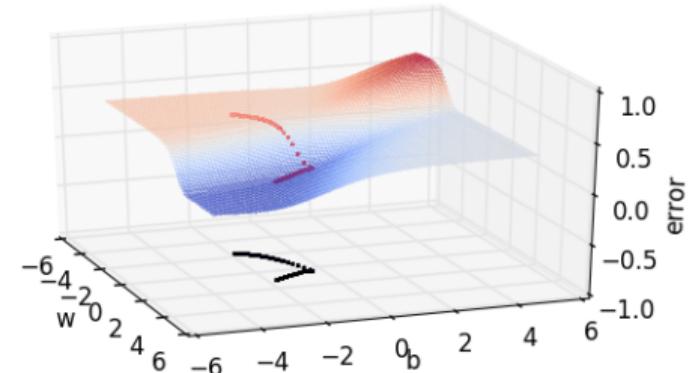
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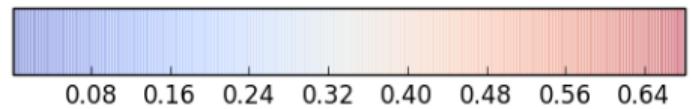
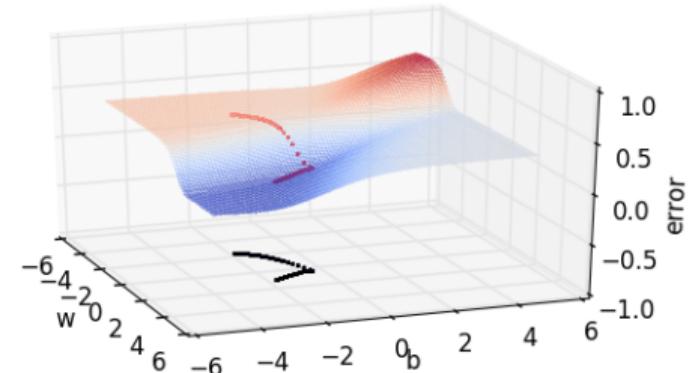
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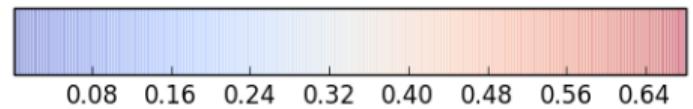
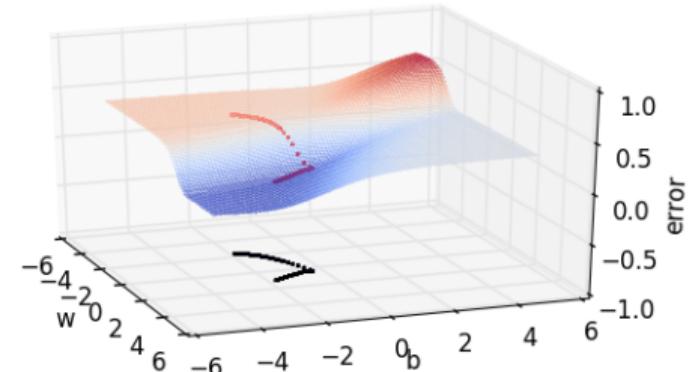
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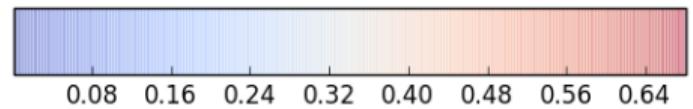
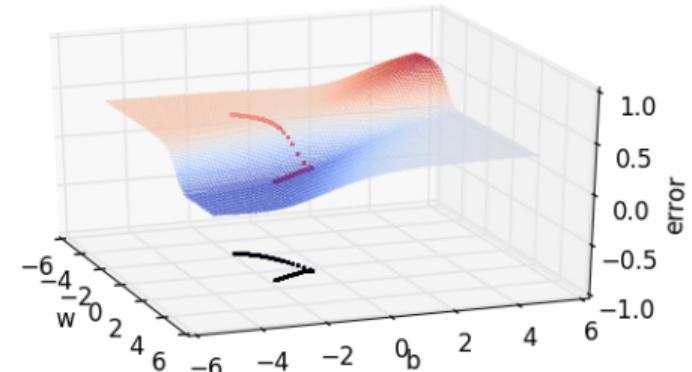
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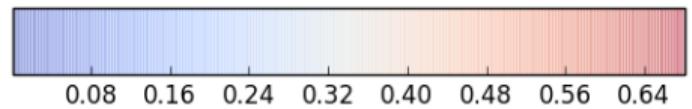
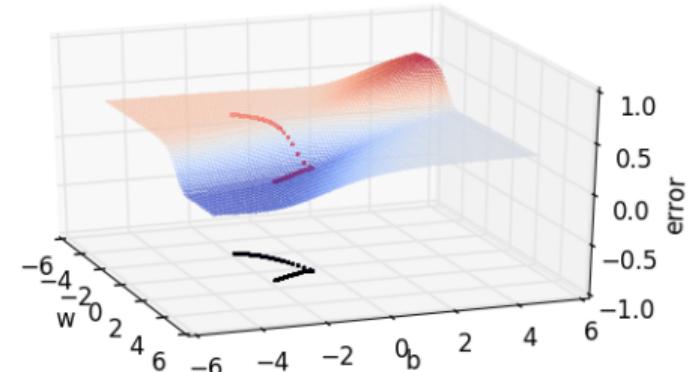
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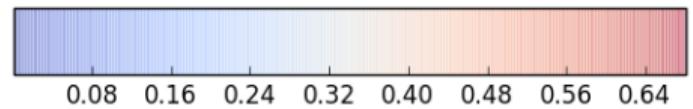
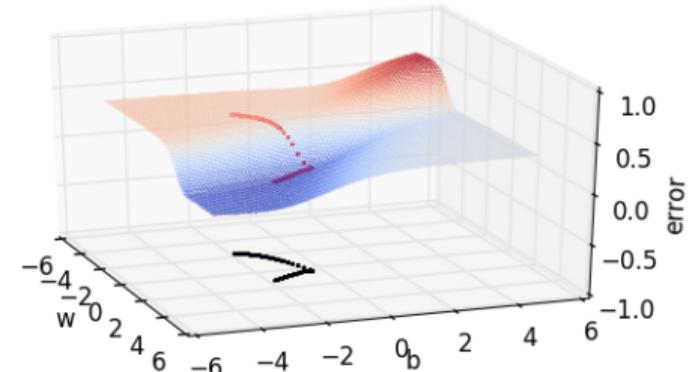
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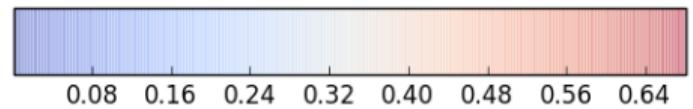
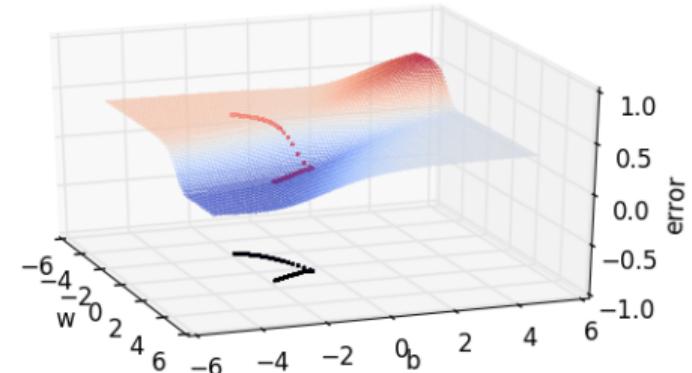
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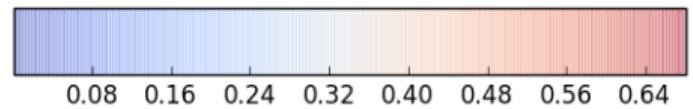
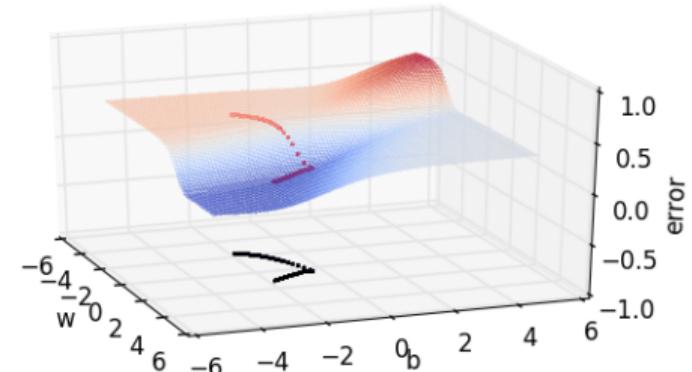
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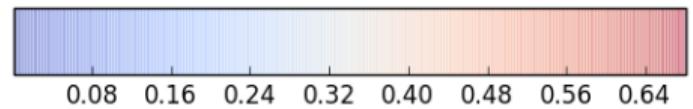
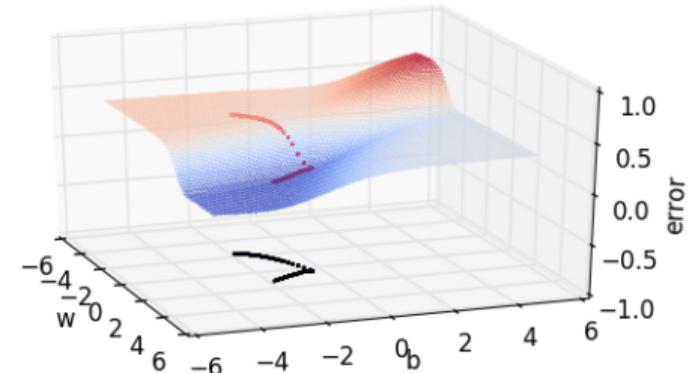
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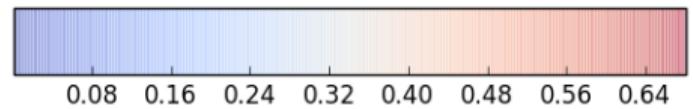
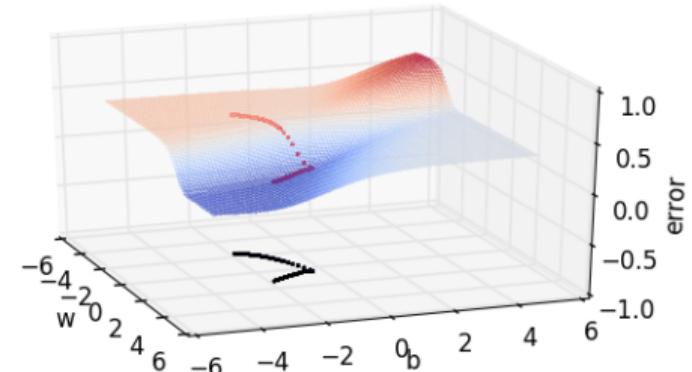
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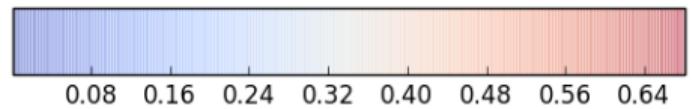
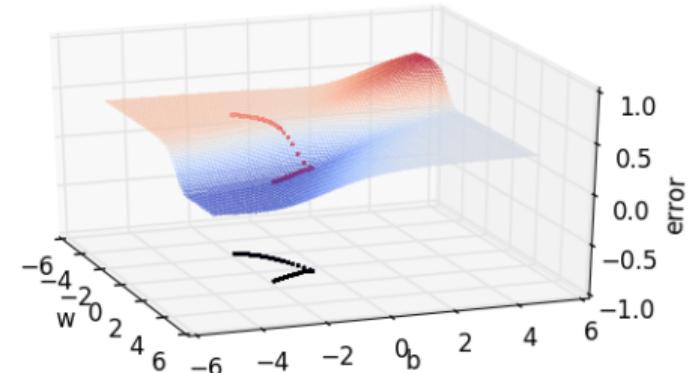
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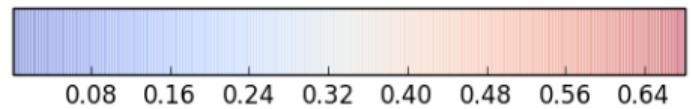
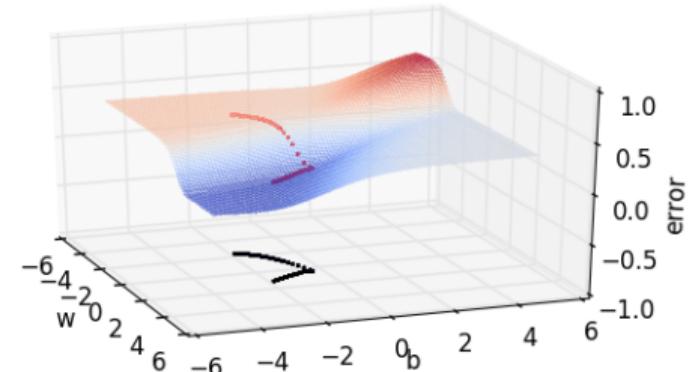
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- For the time being it suffices to know that we have an algorithm for learning the parameters of a sigmoid neuron
- So where do we head from here ?

Module 3.5: Representation Power of a Multilayer Network of Sigmoid Neurons

Representation power of a multilayer network of perceptrons

Representation power of a multilayer network of sigmoid neurons

Representation power of a multilayer network of perceptrons

A multilayer network of perceptrons with a single hidden layer can be used to represent any boolean function precisely (no errors)

Representation power of a multilayer network of sigmoid neurons

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A multilayer network of neurons with a single hidden layer can be used to approximate any continuous function to any desired precision

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Representation power of a multilayer network of sigmoid neurons

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In other words, there is a guarantee that for any function $f(x) : \mathbb{R}^n \rightarrow \mathbb{R}^m$, we can always find a neural network (with 1 hidden layer containing enough neurons) whose output $g(x)$ satisfies $|g(x) - f(x)| < \epsilon$!!

Representation power of a multilayer network of perceptrons

A multilayer network of perceptrons with a single hidden layer can be used to represent any boolean function precisely (no errors)

Representation power of a multilayer network of sigmoid neurons

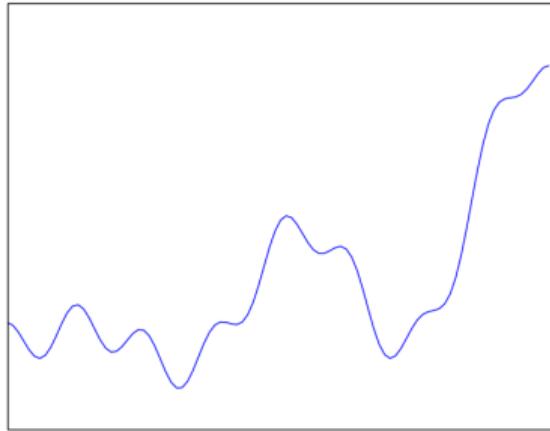
A multilayer network of neurons with a single hidden layer can be used to approximate any continuous function to any desired precision

In other words, there is a guarantee that for any function $f(x) : \mathbb{R}^n \rightarrow \mathbb{R}^m$, we can always find a neural network (with 1 hidden layer containing enough neurons) whose output $g(x)$ satisfies $|g(x) - f(x)| < \epsilon$!!

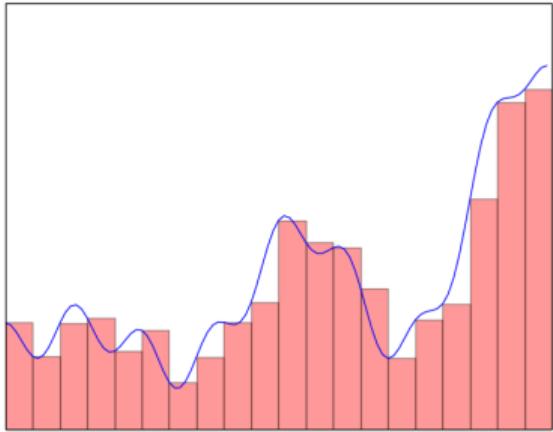
Proof: We will see an illustrative proof of this... [Cybenko, 1989], [Hornik, 1991]

- See this link* for an excellent illustration of this proof
- The discussion in the next few slides is based on the ideas presented at the above link

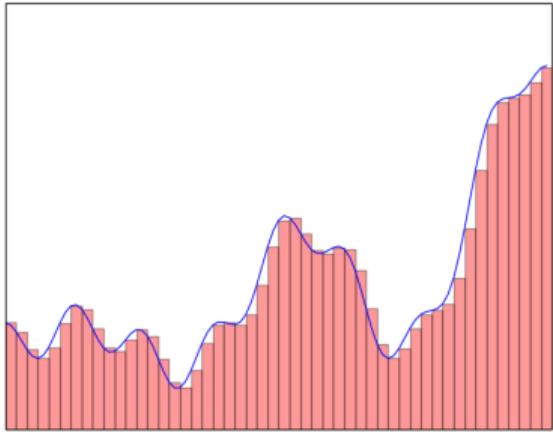
*<http://neuralnetworksanddeeplearning.com/chap4.html>



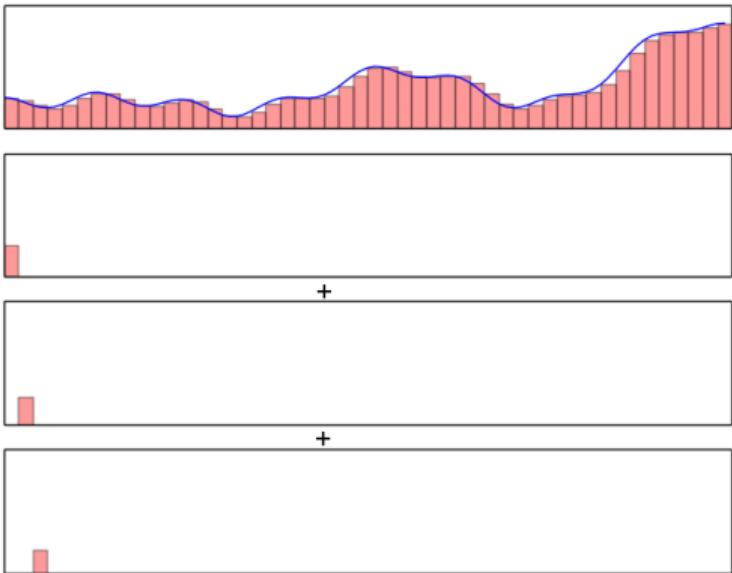
- We are interested in knowing whether a network of neurons can be used to represent an arbitrary function (like the one shown in the figure)



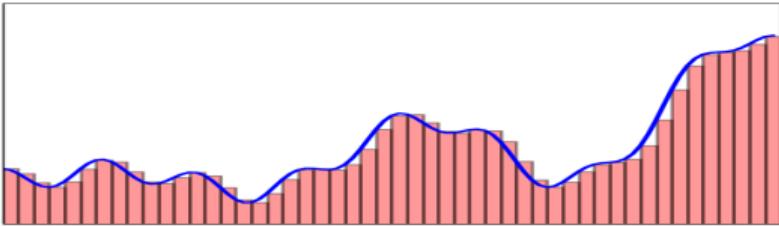
- We are interested in knowing whether a network of neurons can be used to represent an arbitrary function (like the one shown in the figure)
- We observe that such an arbitrary function can be approximated by several “tower” functions



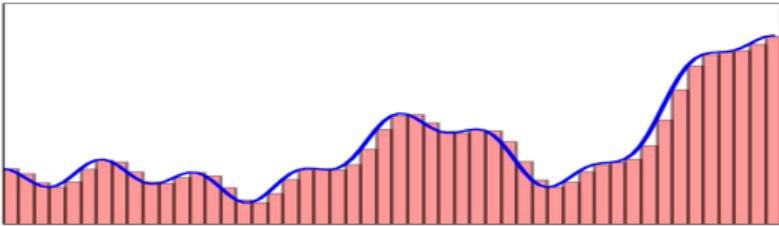
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- More the number of such “tower” functions, better the approximation



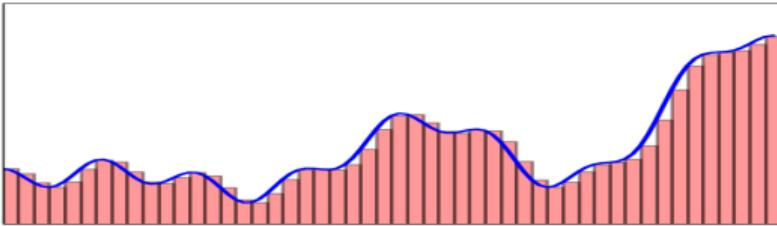
- We are interested in knowing whether a network of neurons can be used to represent an arbitrary function (like the one shown in the figure)
- We observe that such an arbitrary function can be approximated by several “tower” functions
- More the number of such “tower” functions, better the approximation
- To be more precise, we can approximate any arbitrary function by a sum of such “tower” functions



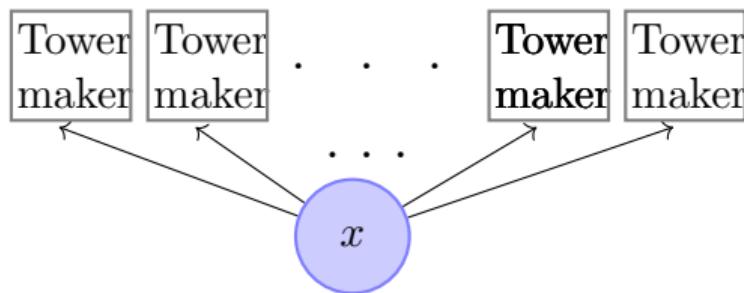
- We make a few observations

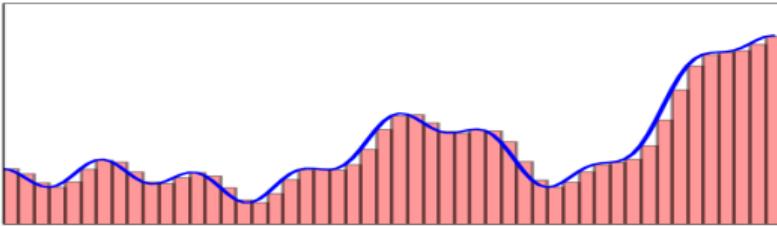


- We make a few observations
- All these “tower” functions are similar and only differ in their heights and positions on the x-axis

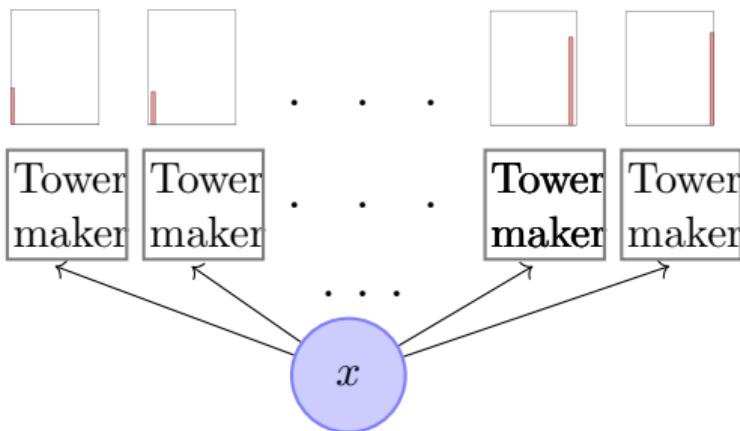


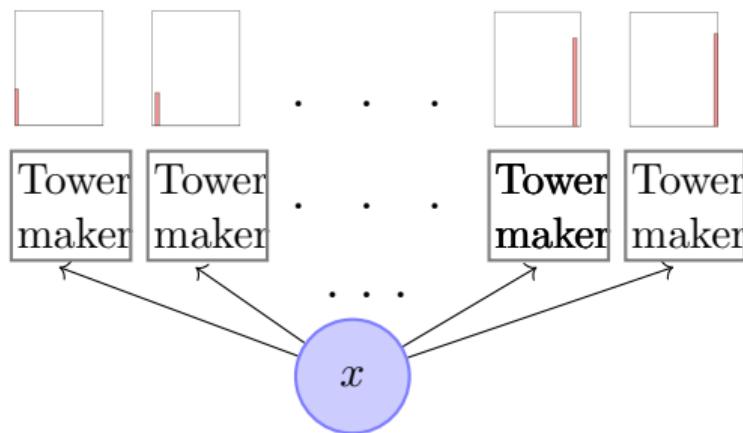
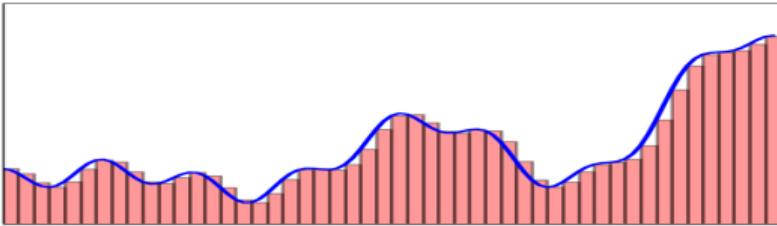
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- Suppose there is a black box which takes the original input (x) and constructs these tower functions



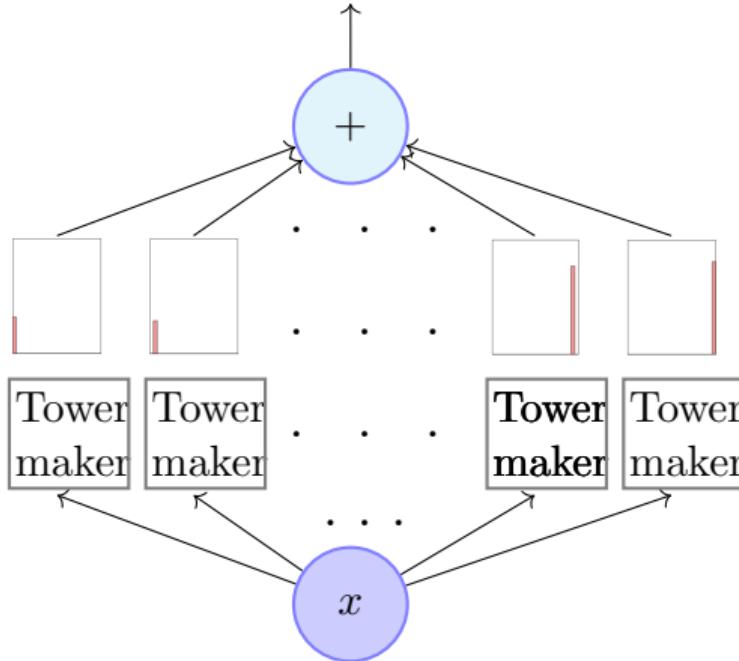
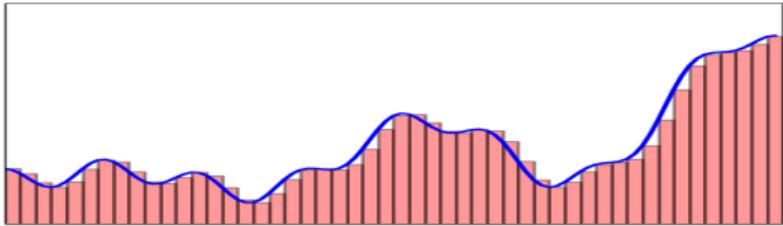


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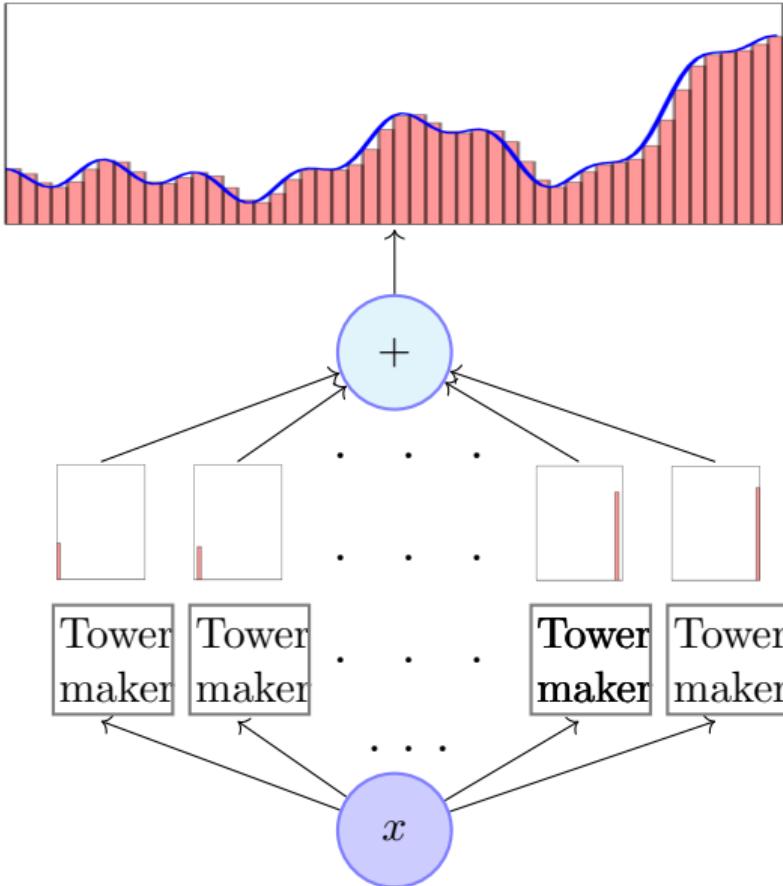




- We make a few observations
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- Suppose there is a black box which takes the original input (x) and constructs these tower functions
- We can then have a simple network which can just add them up to approximate the function

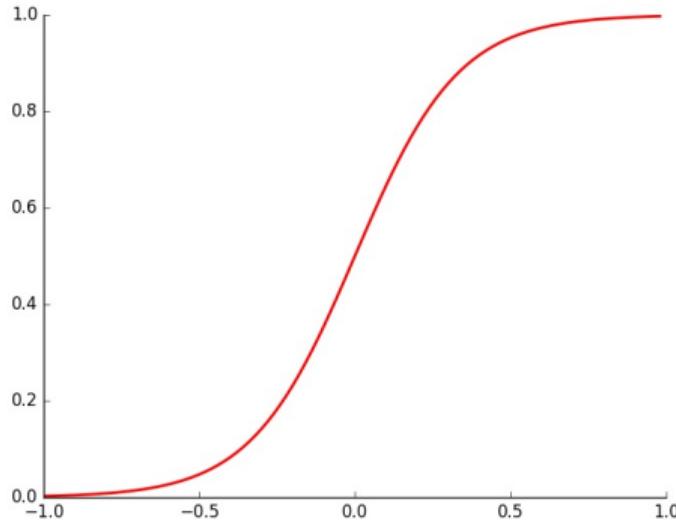


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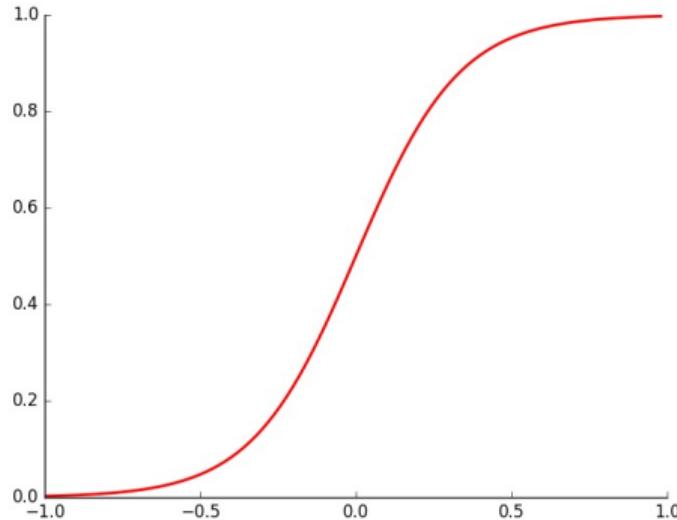


- We make a few observations
- All these “tower” functions are similar and only differ in their heights and positions on the x-axis
- Suppose there is a black box which takes the original input (x) and constructs these tower functions
- We can then have a simple network which can just add them up to approximate the function
- Our job now is to figure out what is inside this blackbox

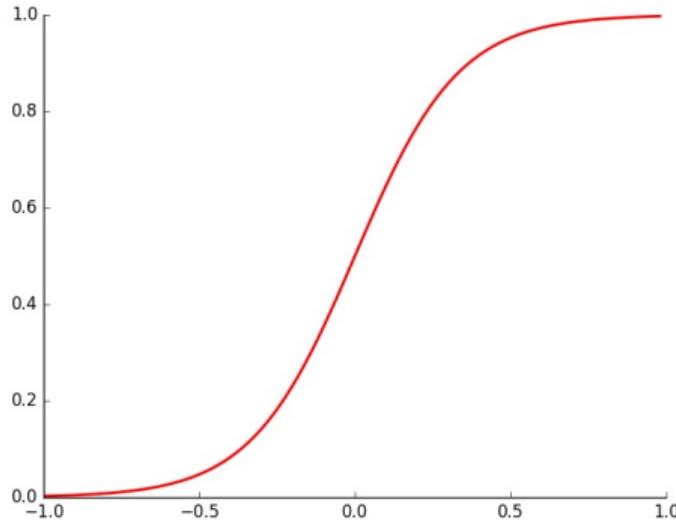
We will figure this out over the next few slides ...



- If we take the logistic function and set w to a very high value we will recover the step function

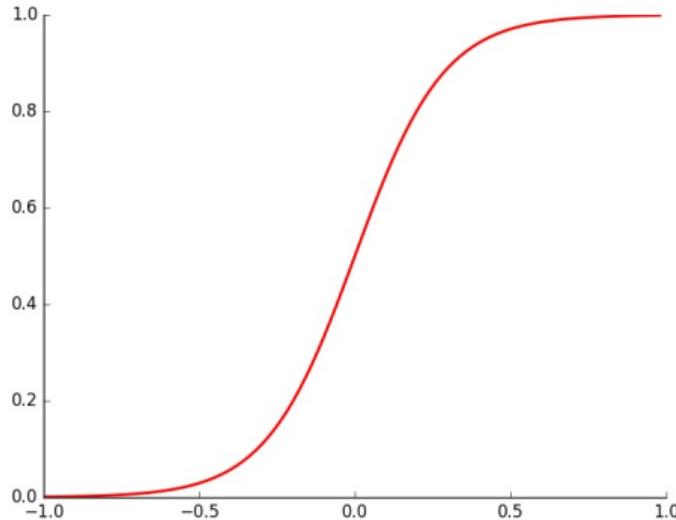


- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



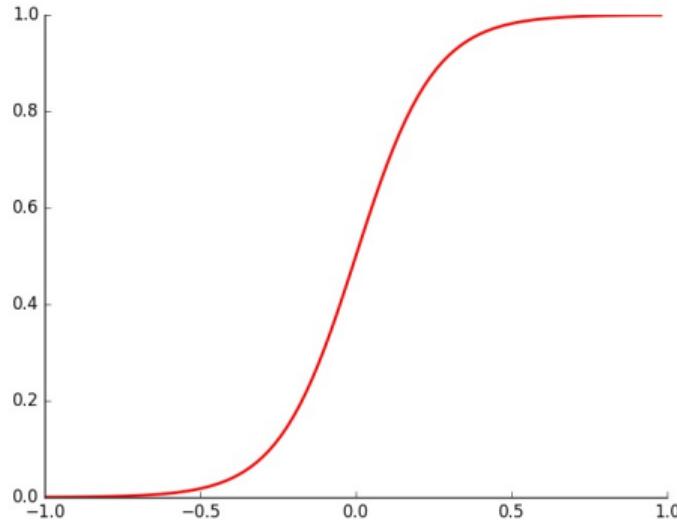
$$w = 6, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



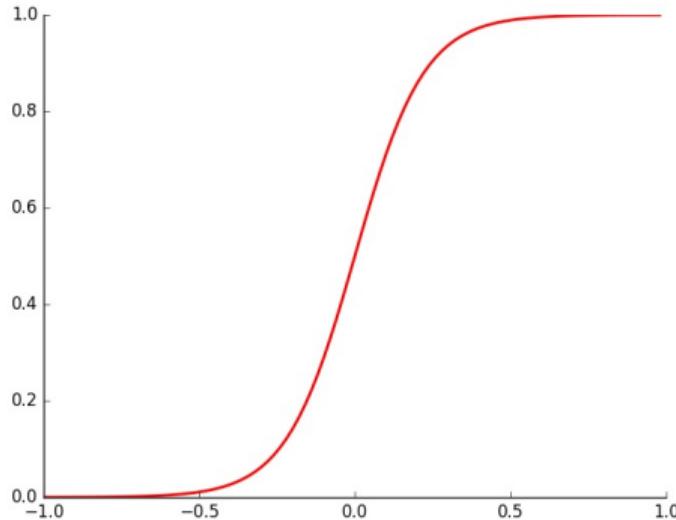
$$w = 7, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



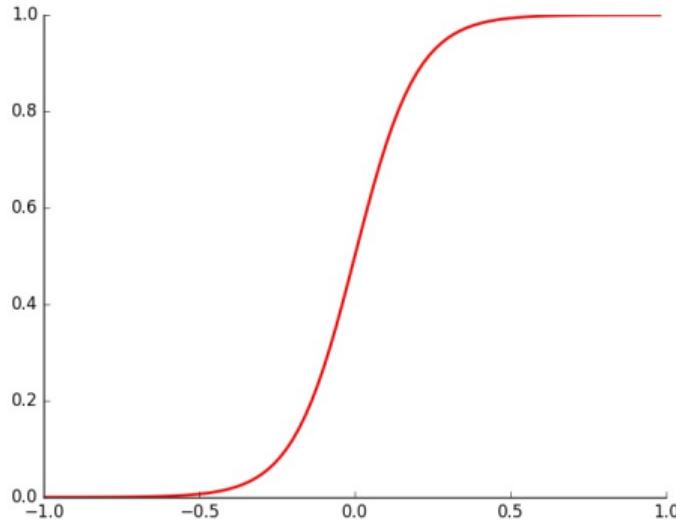
$$w = 8, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



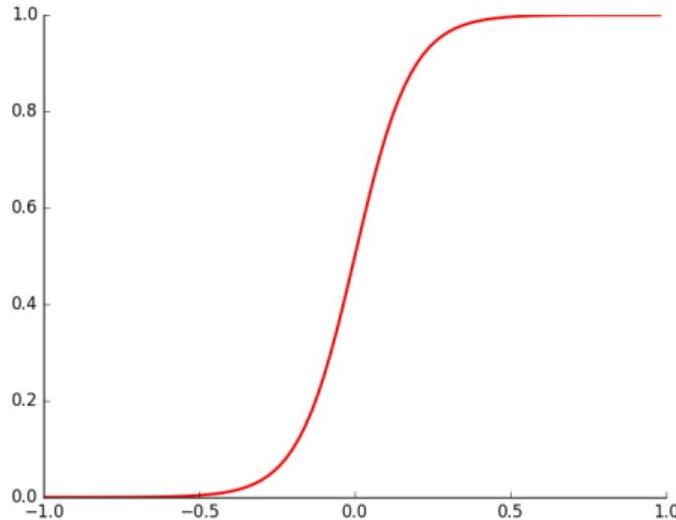
$$w = 9, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



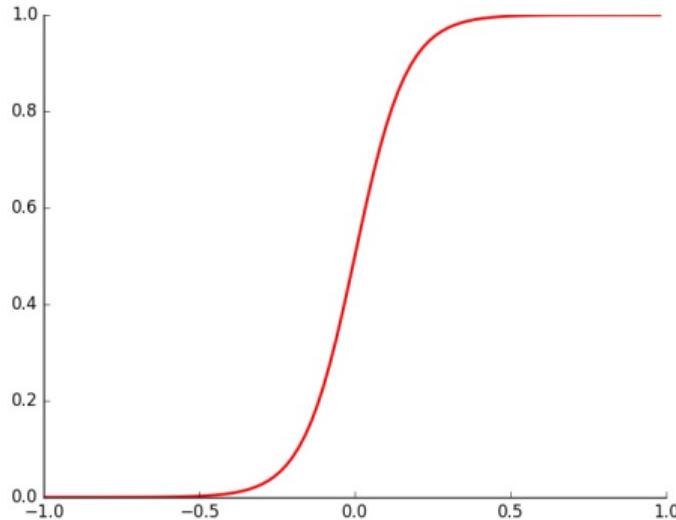
$$w = 10, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



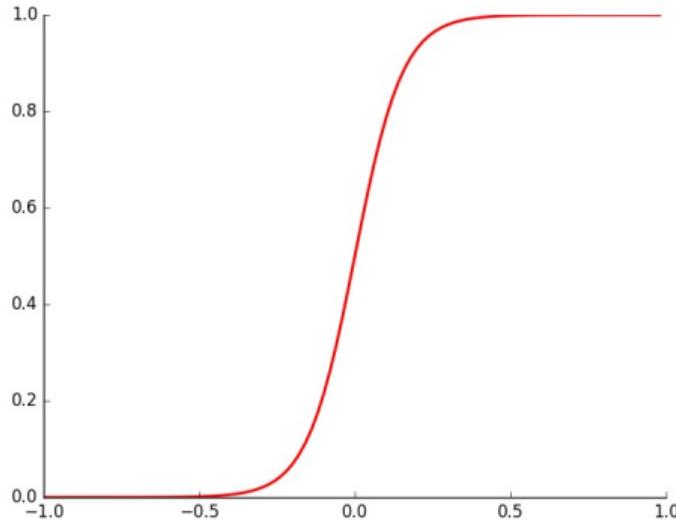
$$w = 11, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



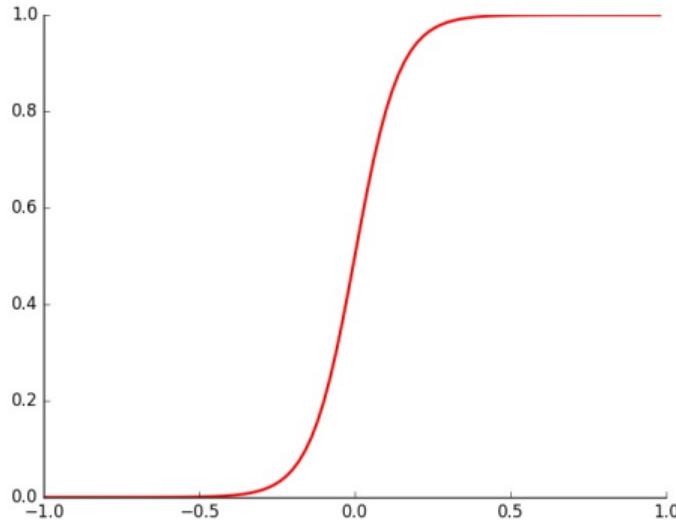
$$w = 12, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



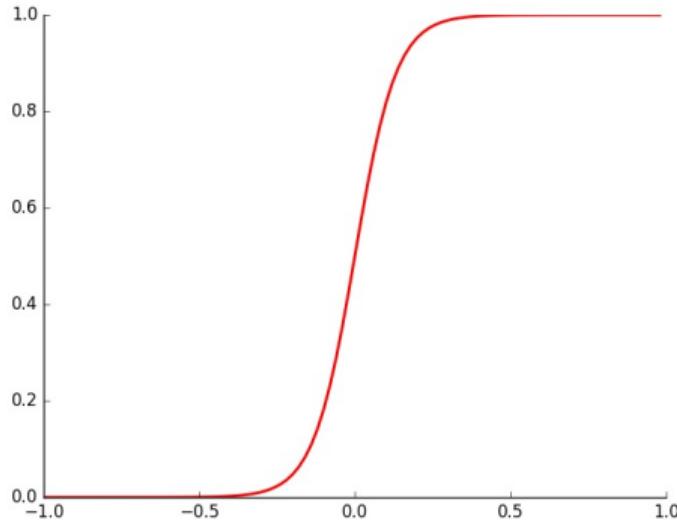
$$w = 13, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



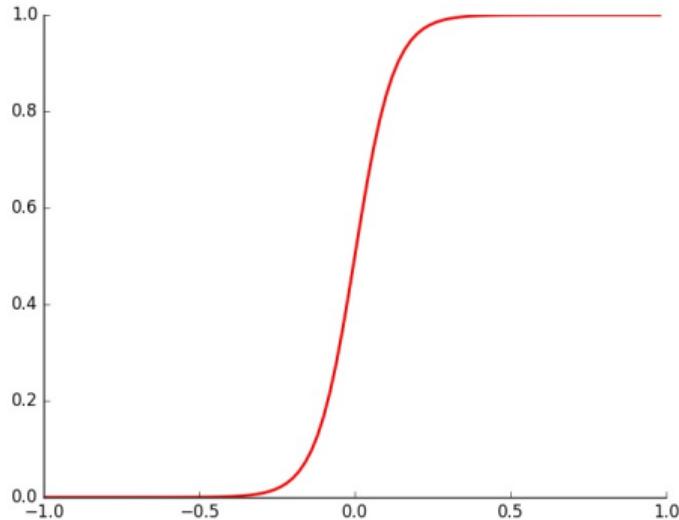
$$w = 14, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



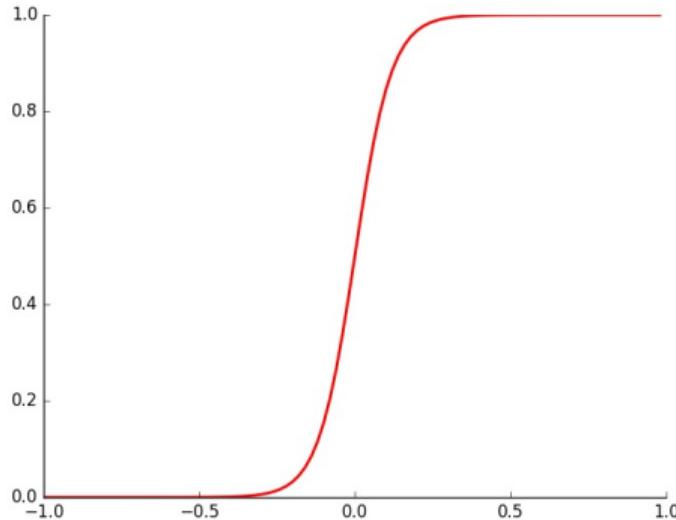
$$w = 15, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



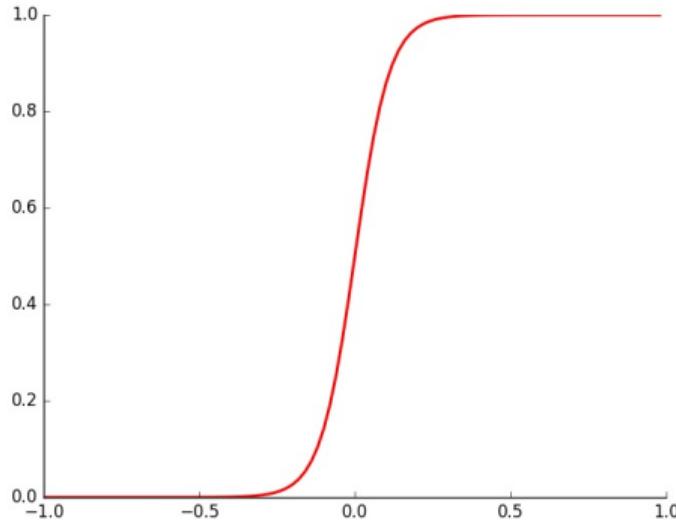
$$w = 16, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



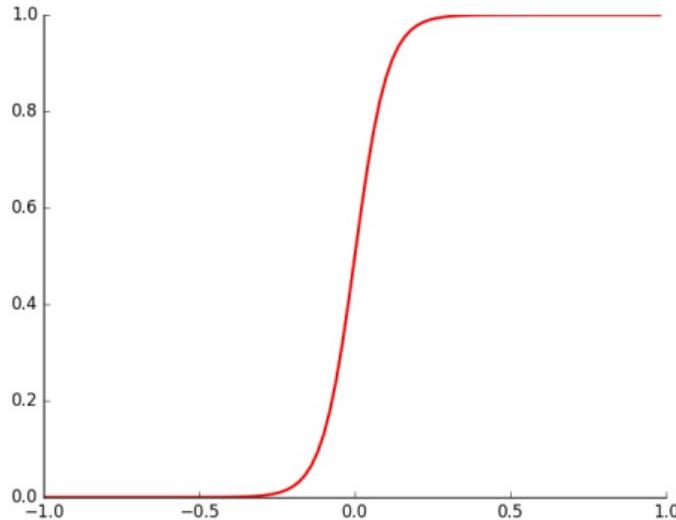
$$w = 17, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



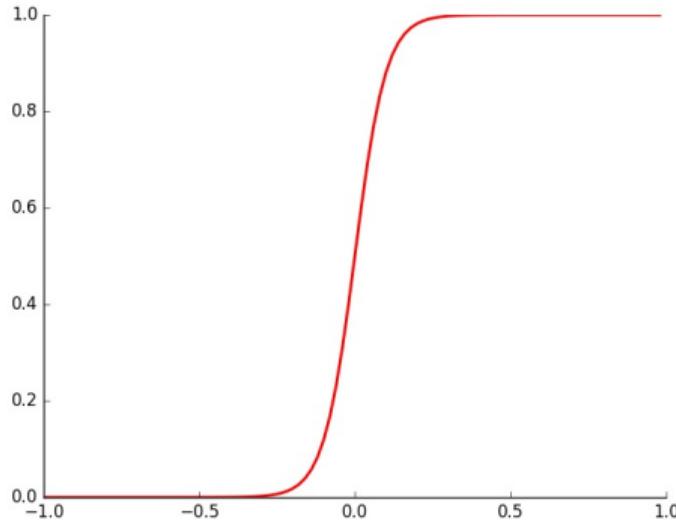
$$w = 18, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



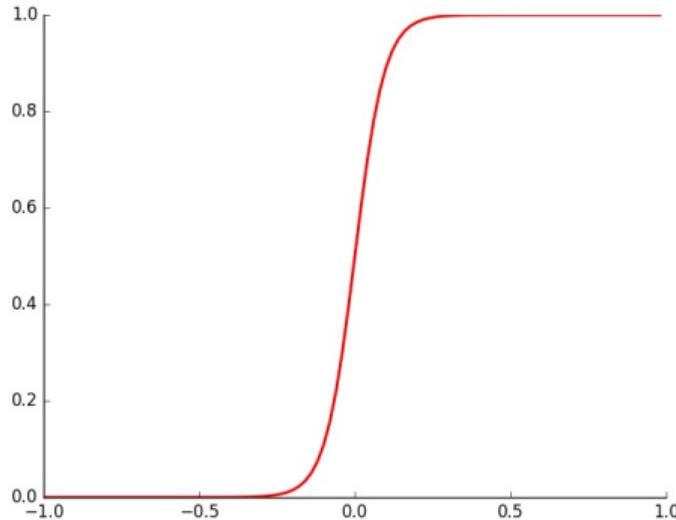
$$w = 19, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



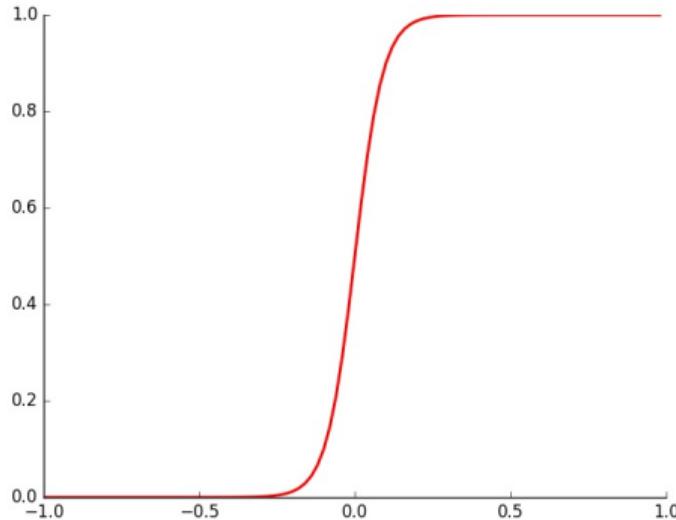
$$w = 20, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



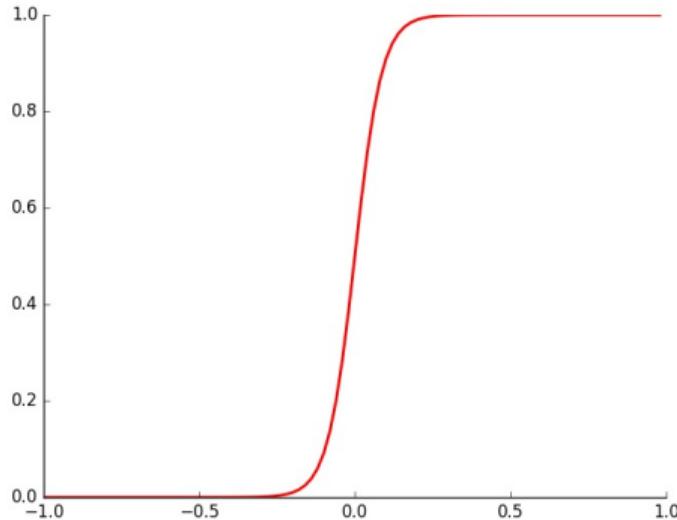
$$w = 21, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



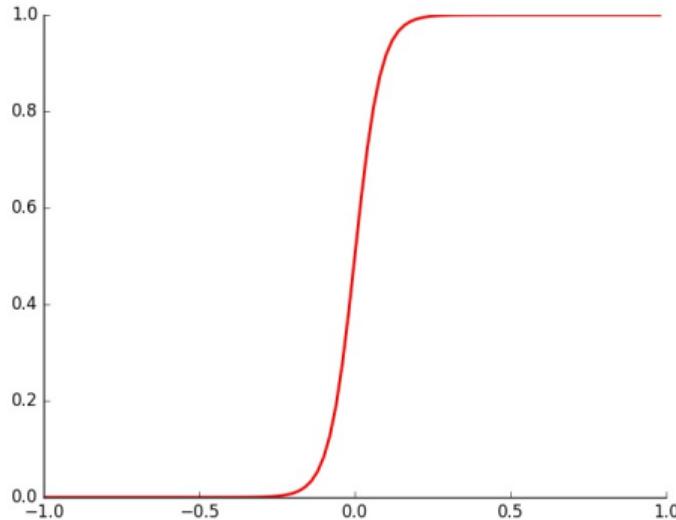
$$w = 22, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



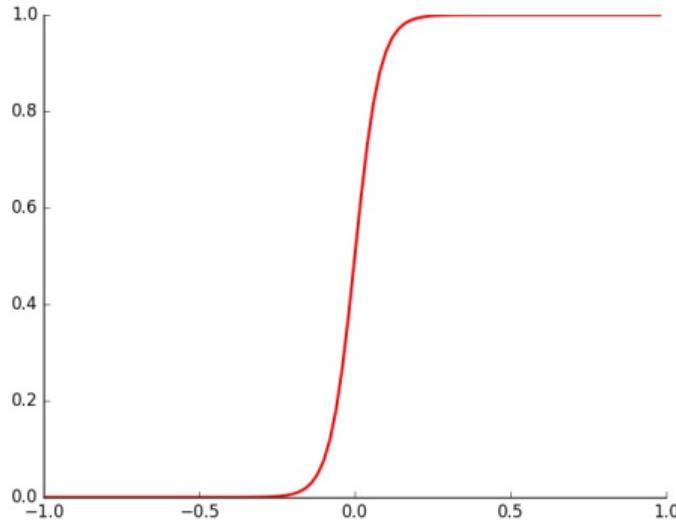
$$w = 23, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



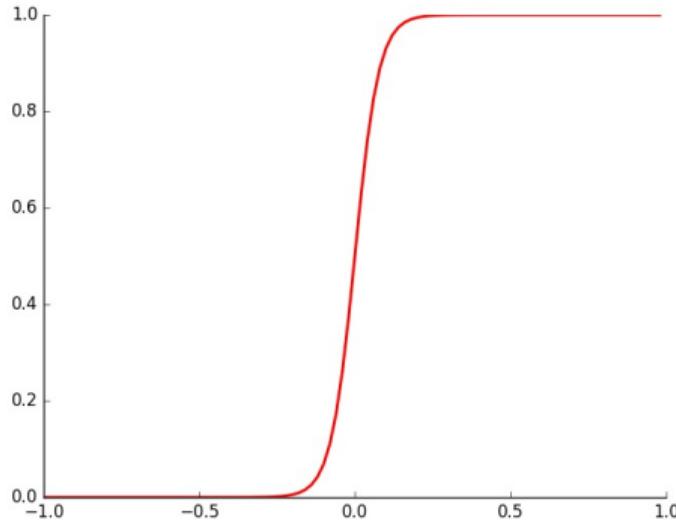
$$w = 24, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



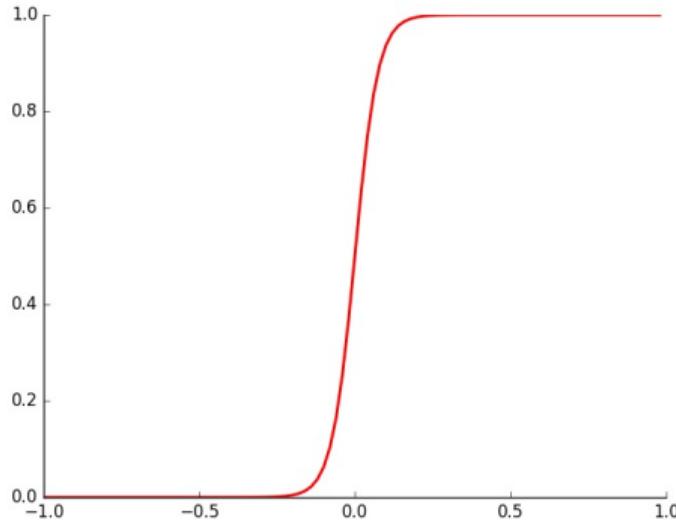
$$w = 25, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



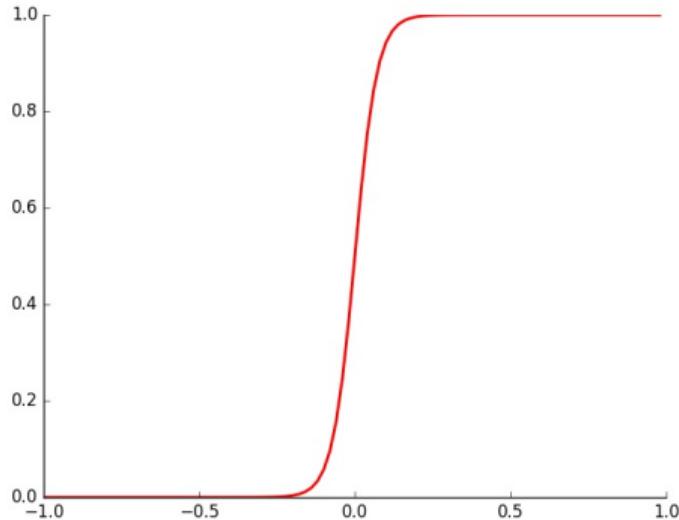
$$w = 26, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



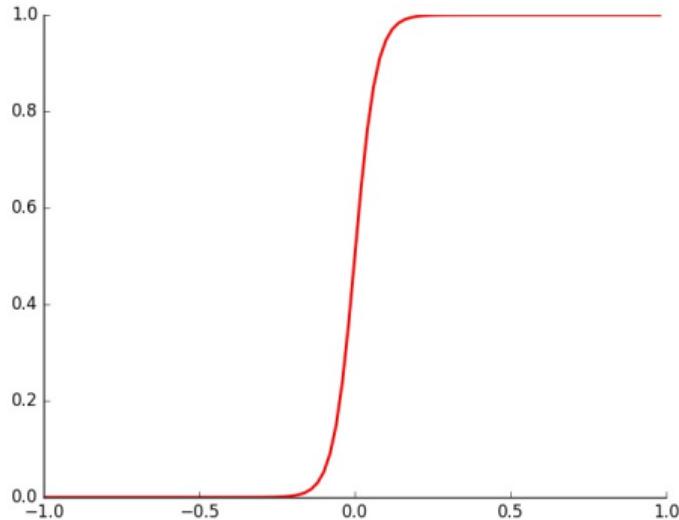
$$w = 27, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



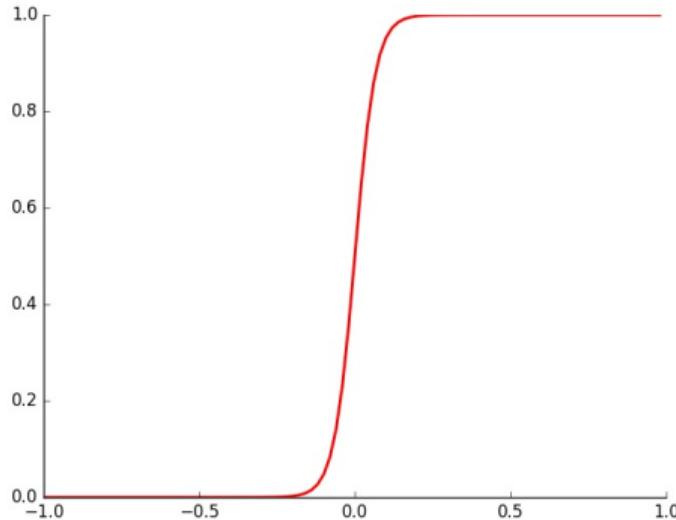
$$w = 28, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



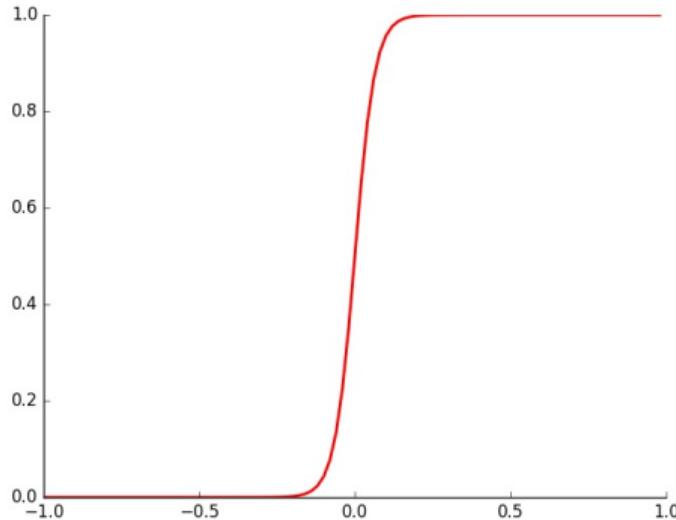
$$w = 29, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



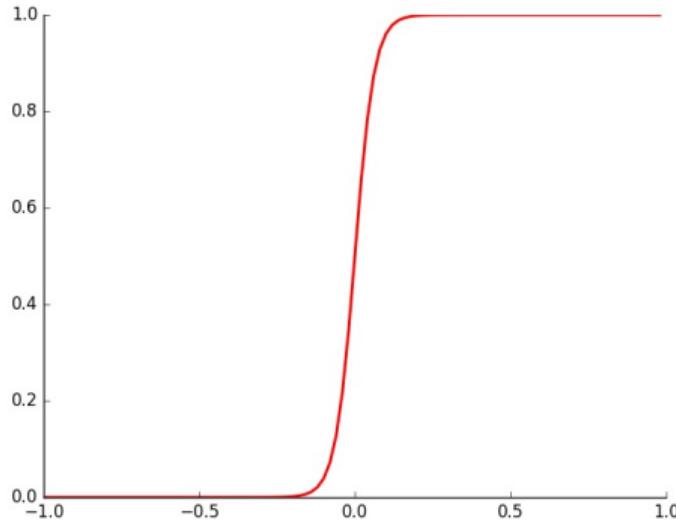
$$w = 30, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



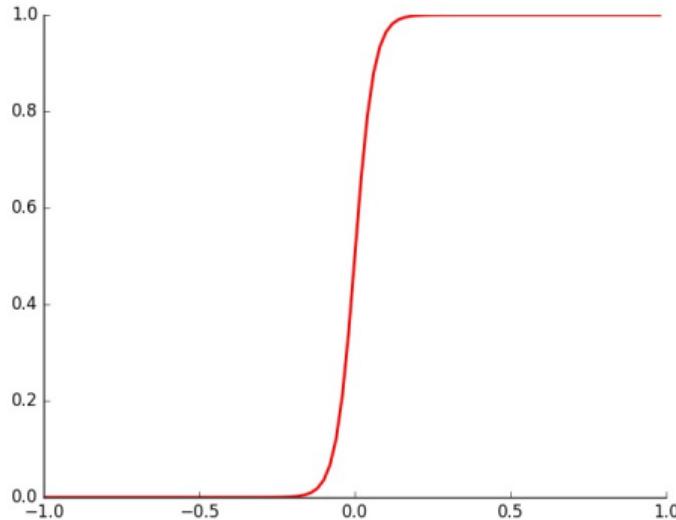
$$w = 31, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



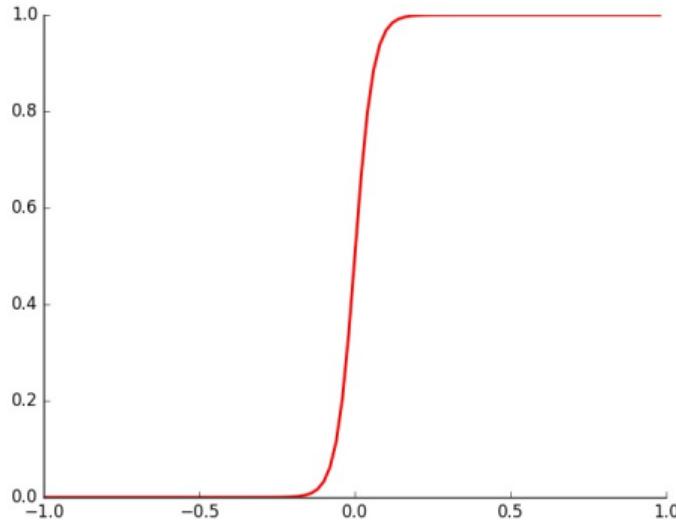
$$w = 32, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



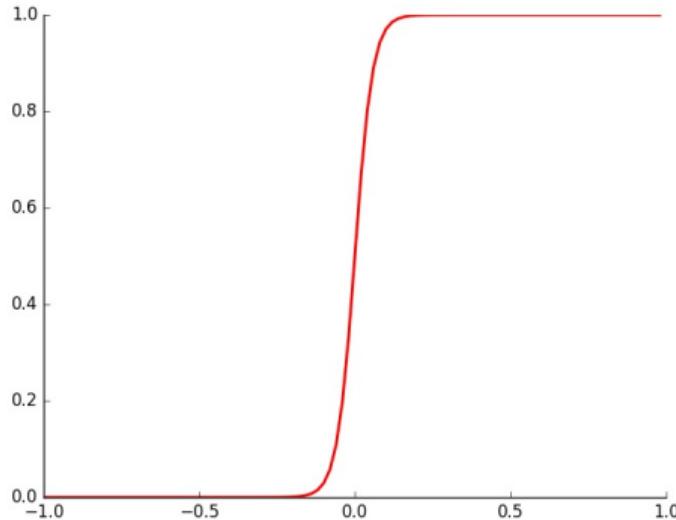
$$w = 33, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



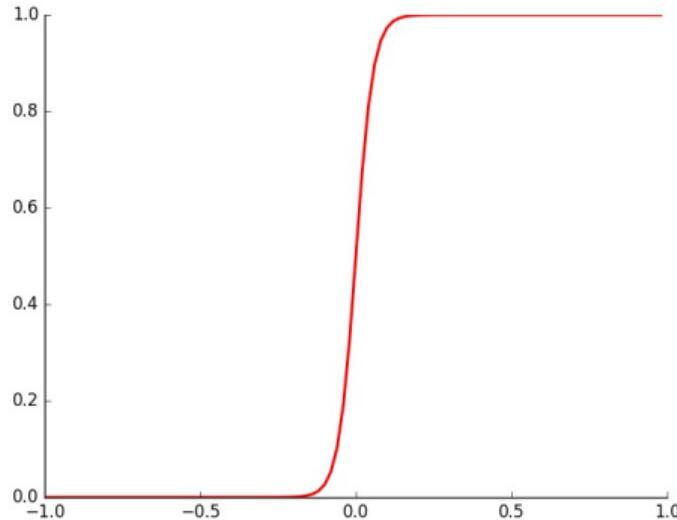
$$w = 34, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



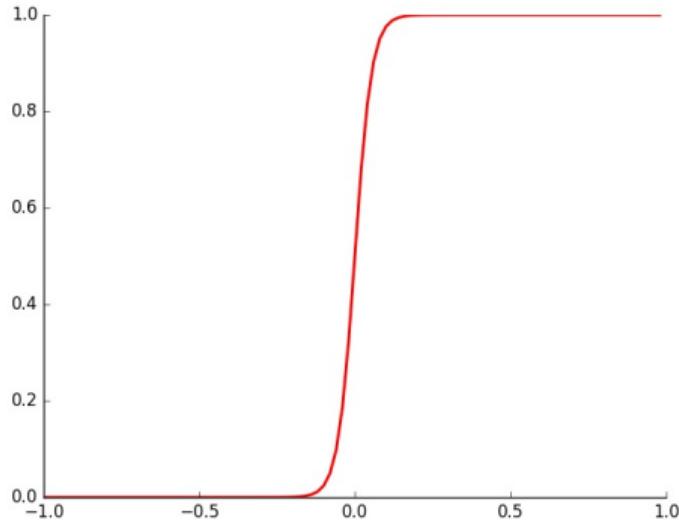
$$w = 35, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



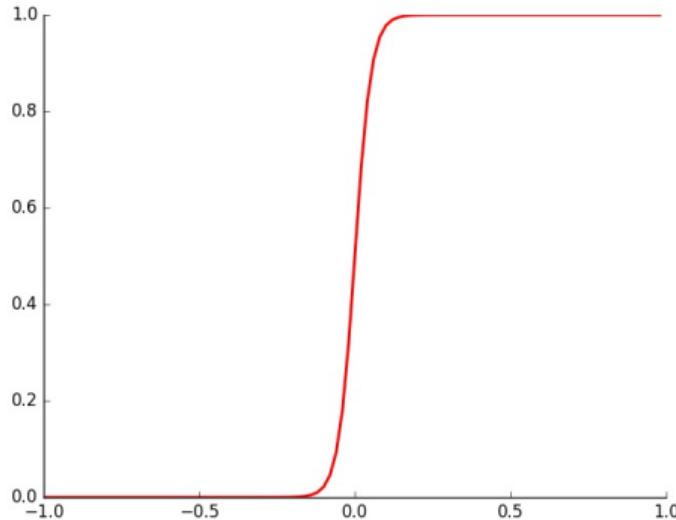
$$w = 36, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



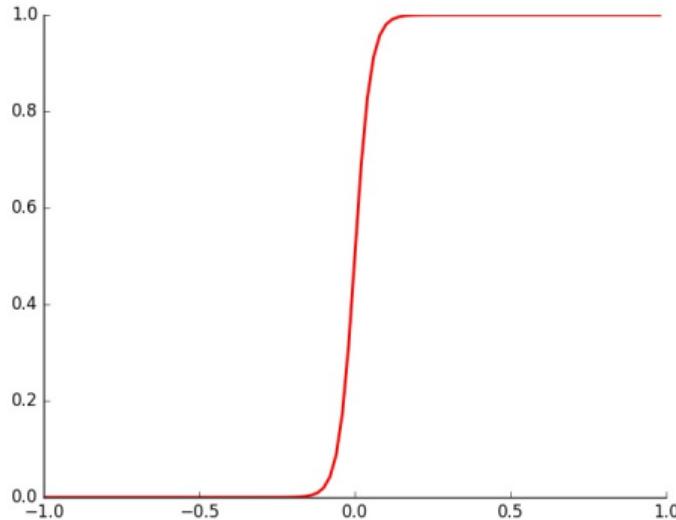
$$w = 37, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



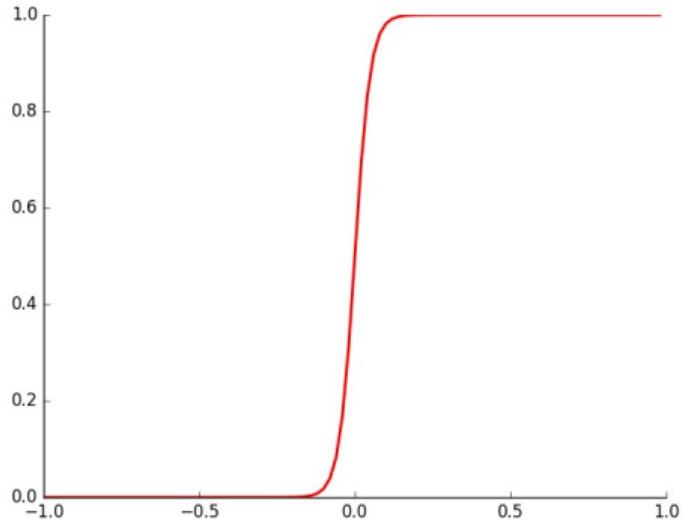
$$w = 38, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



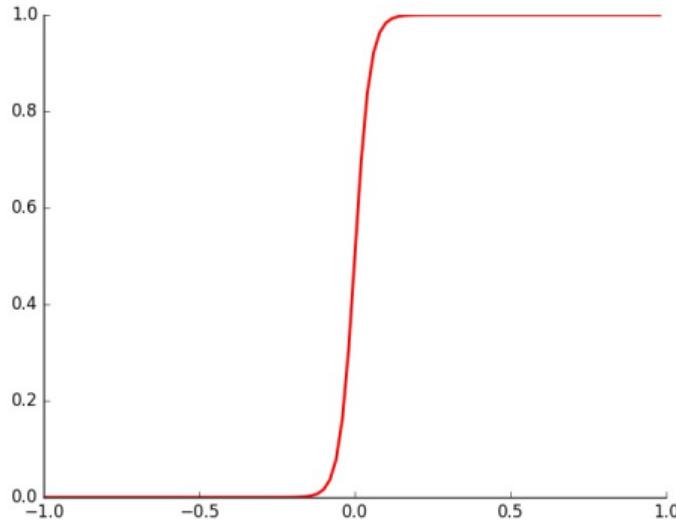
$$w = 39, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



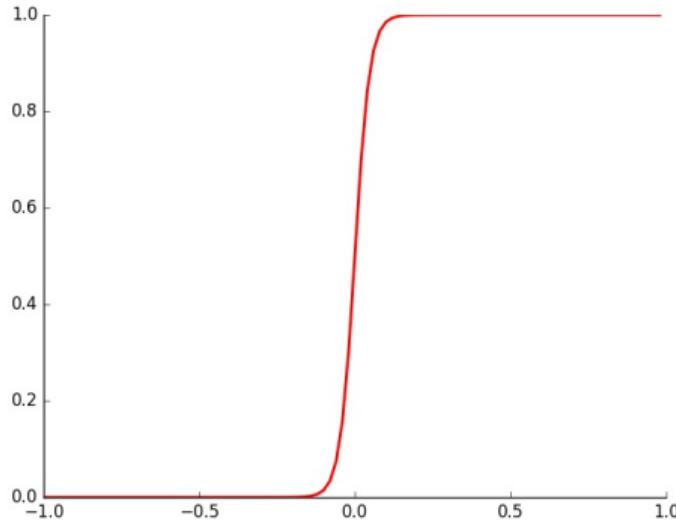
$$w = 40, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



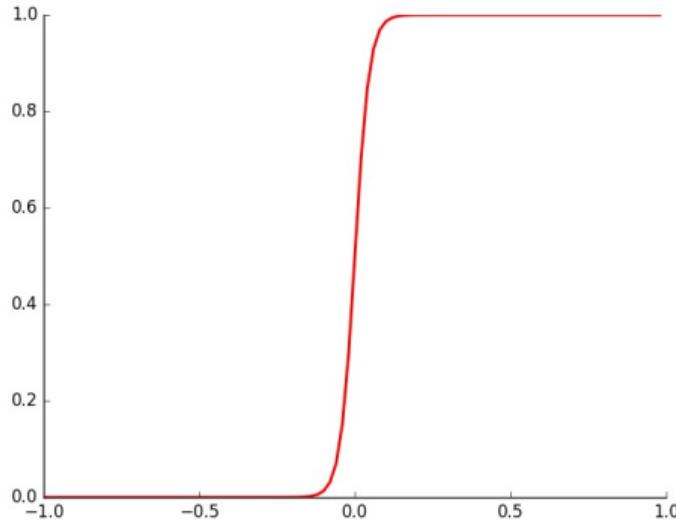
$$w = 41, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



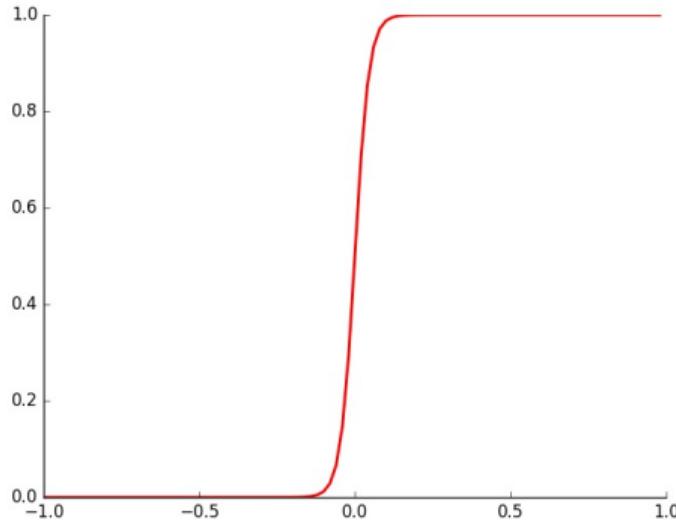
$$w = 42, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



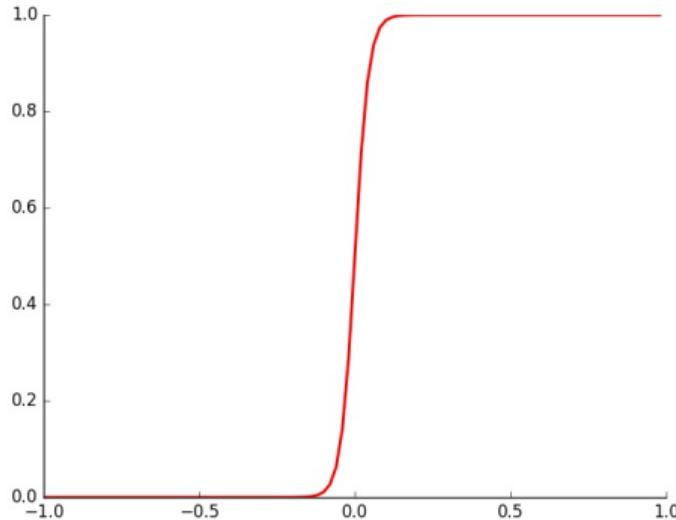
$$w = 43, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



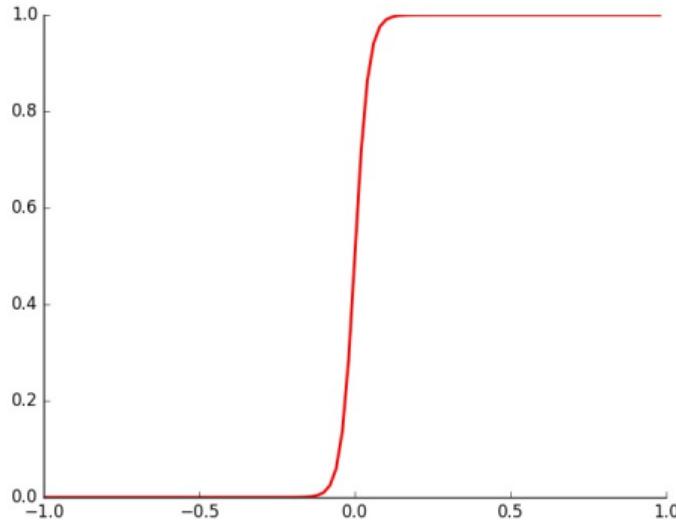
$$w = 44, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



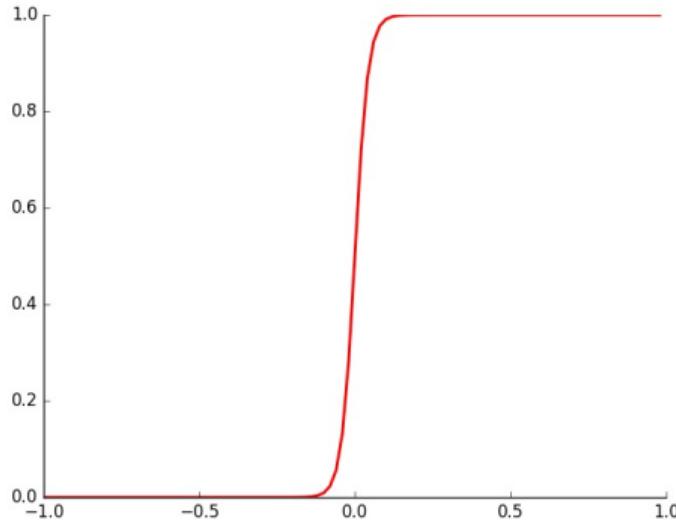
$$w = 45, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



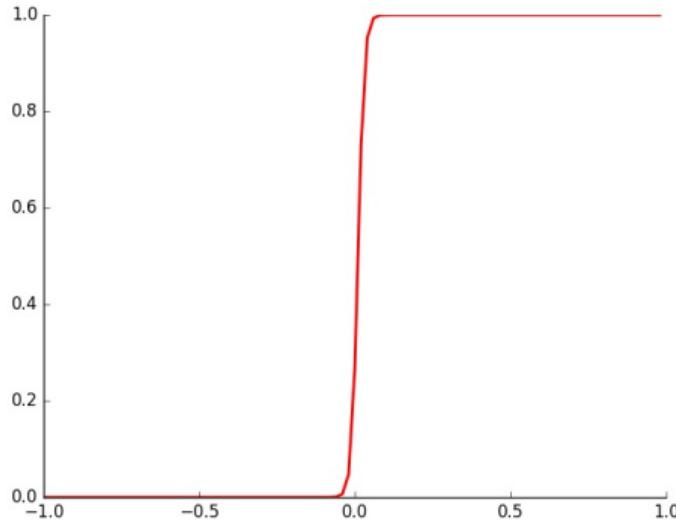
$$w = 46, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



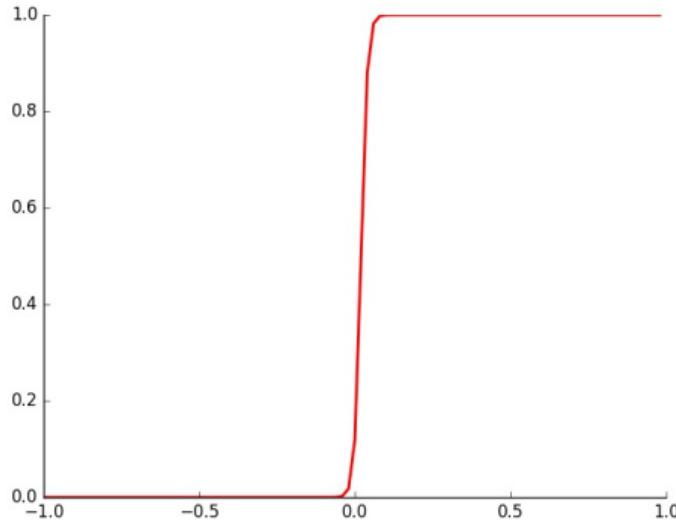
$$w = 47, b = 0$$

- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w



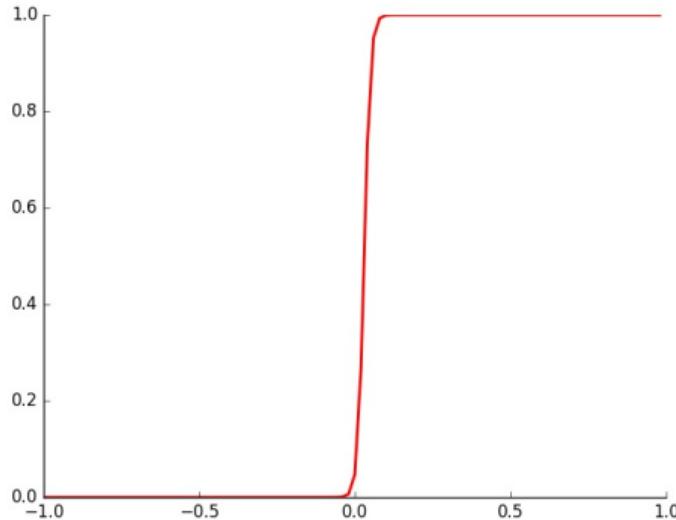
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 1, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



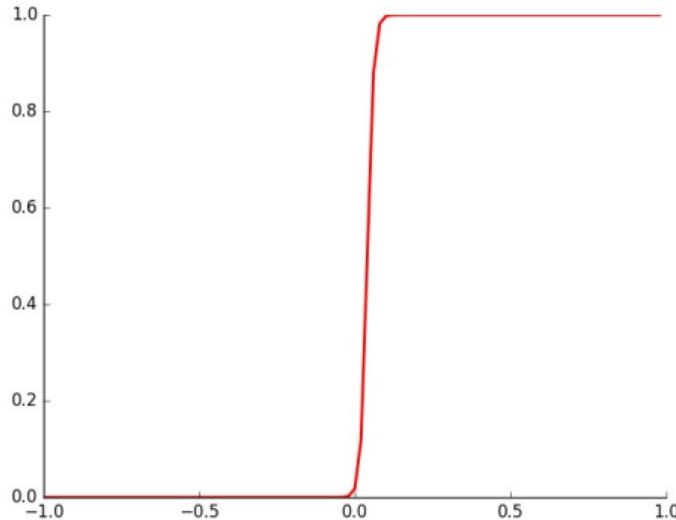
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 2, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



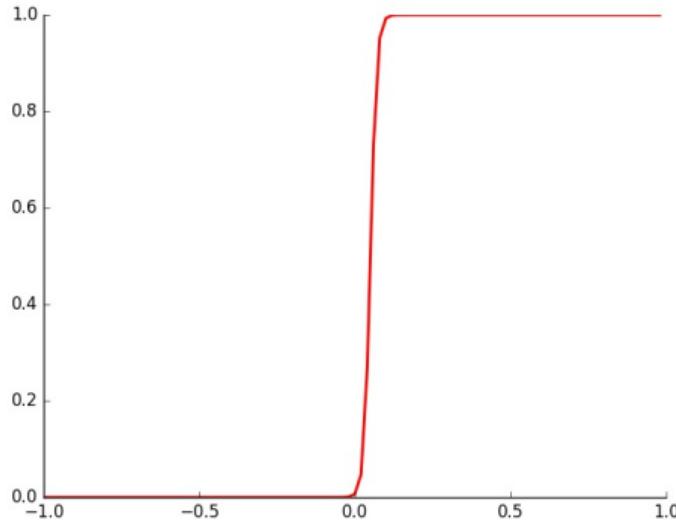
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 3, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



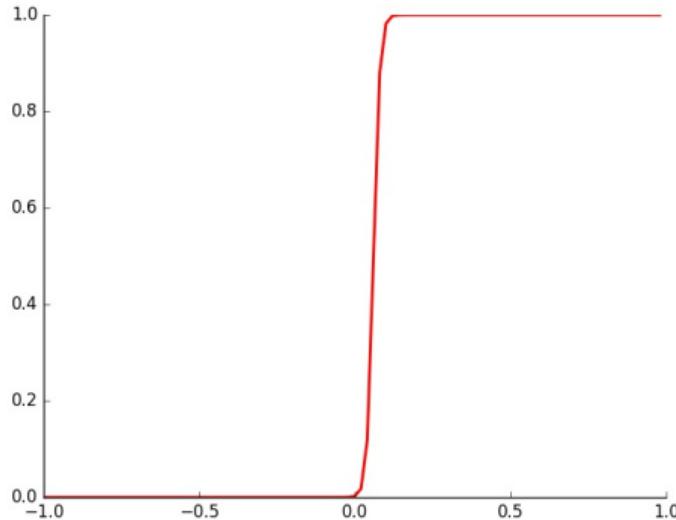
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 4, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



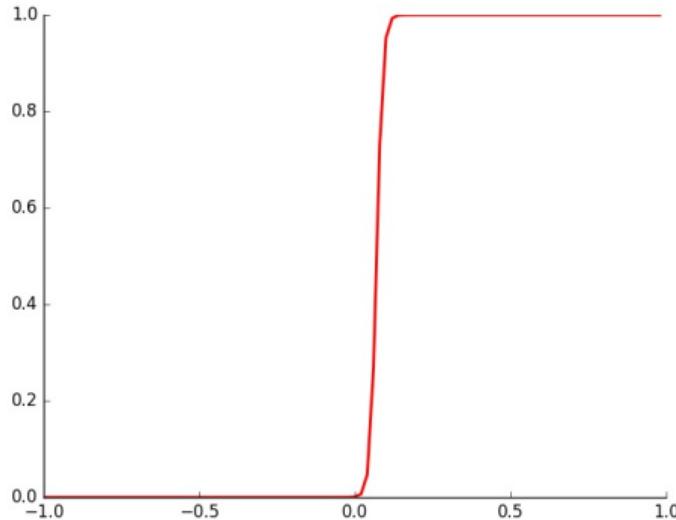
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 5, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



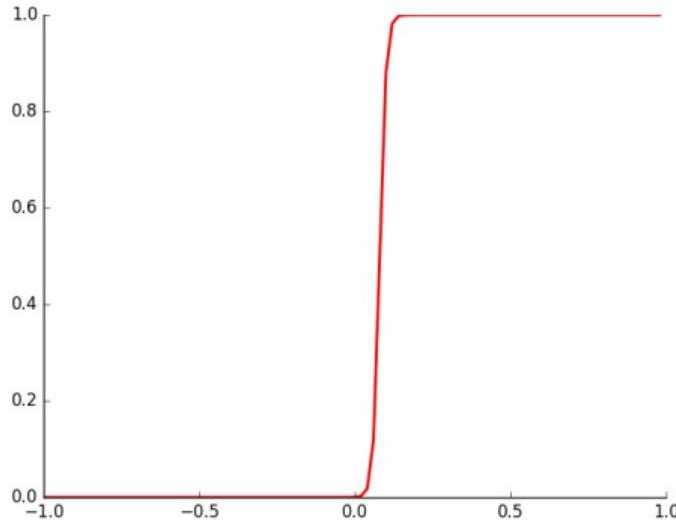
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 6, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



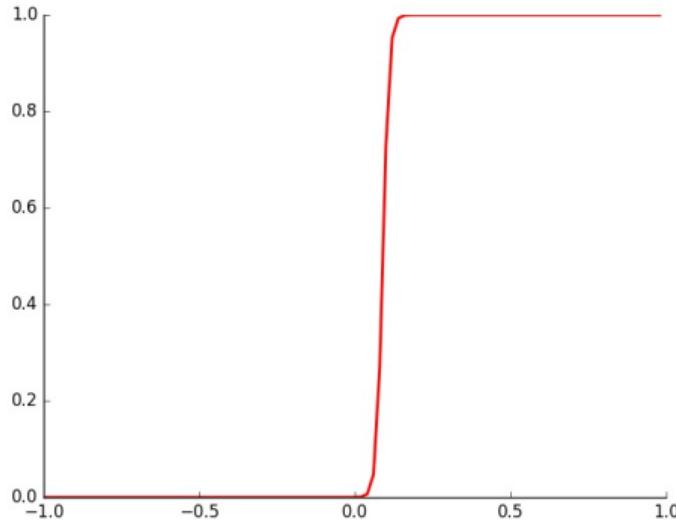
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 7, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



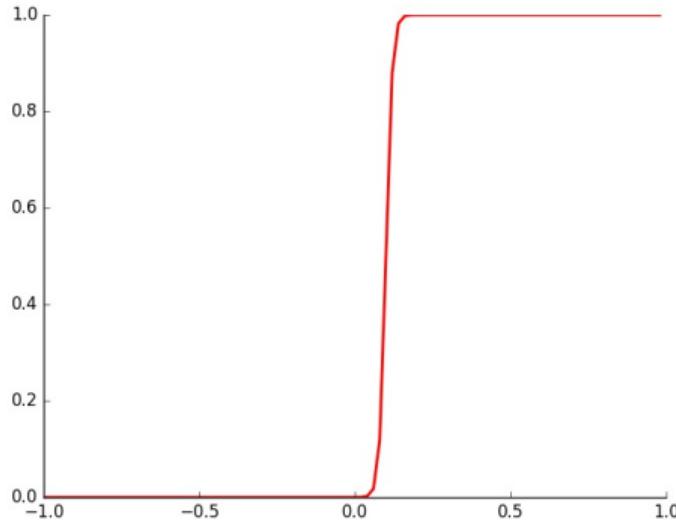
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 8, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



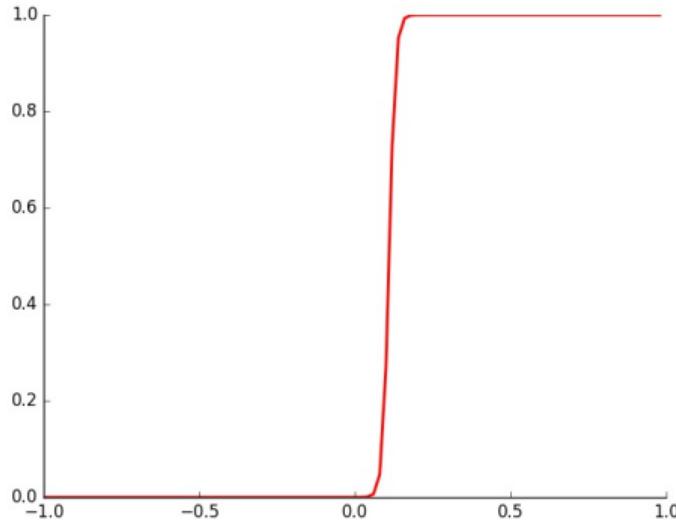
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 9, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



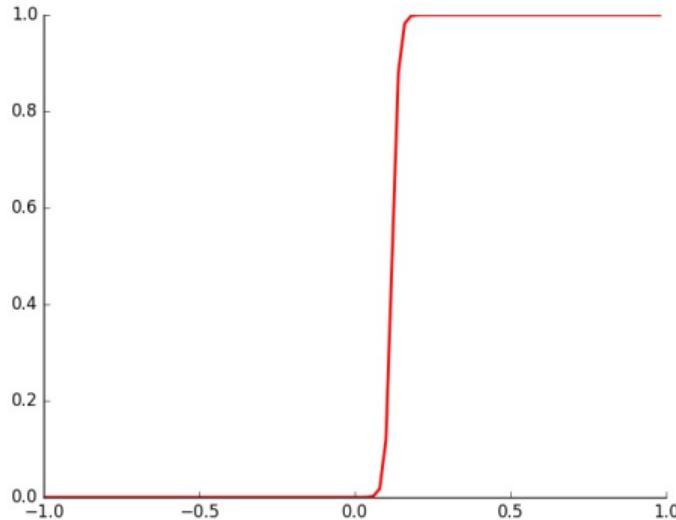
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 10, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



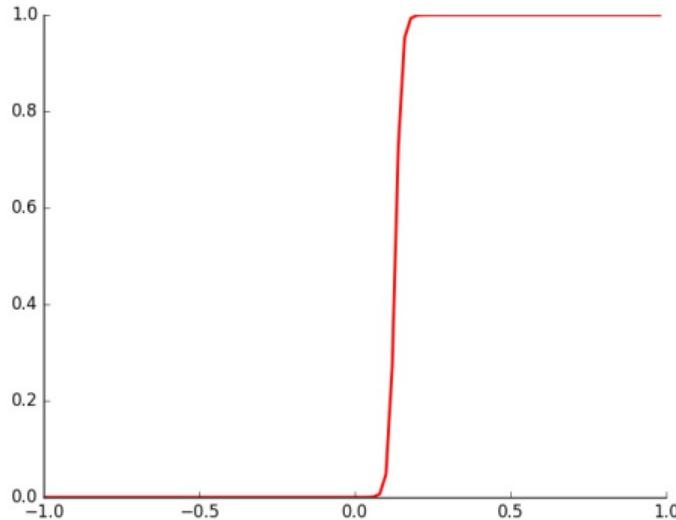
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 11, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



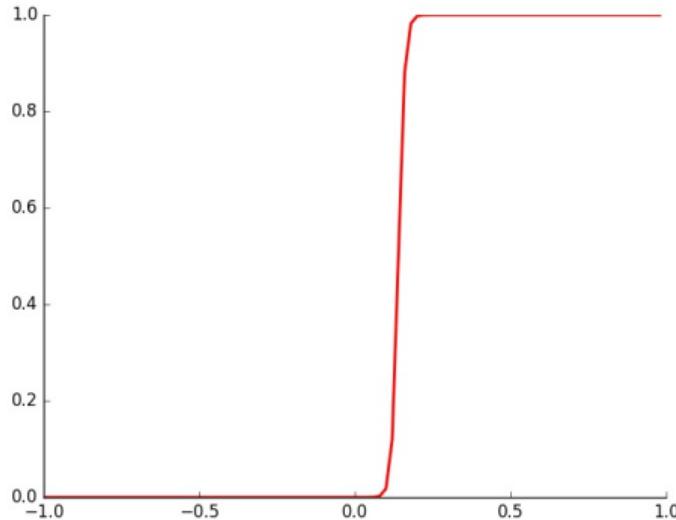
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 12, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



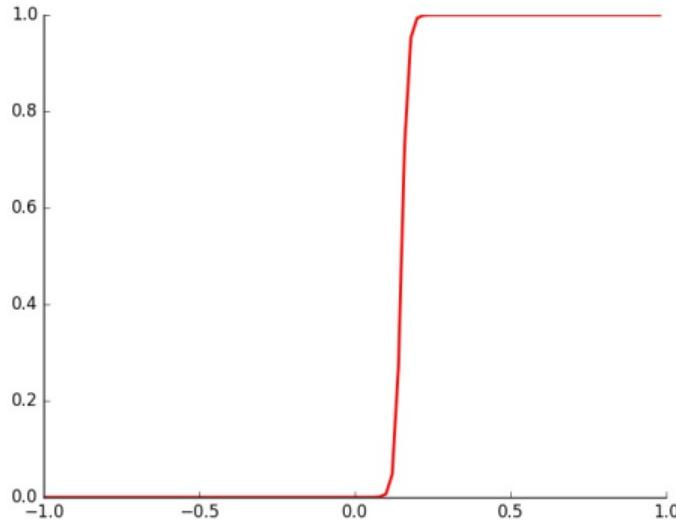
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 13, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



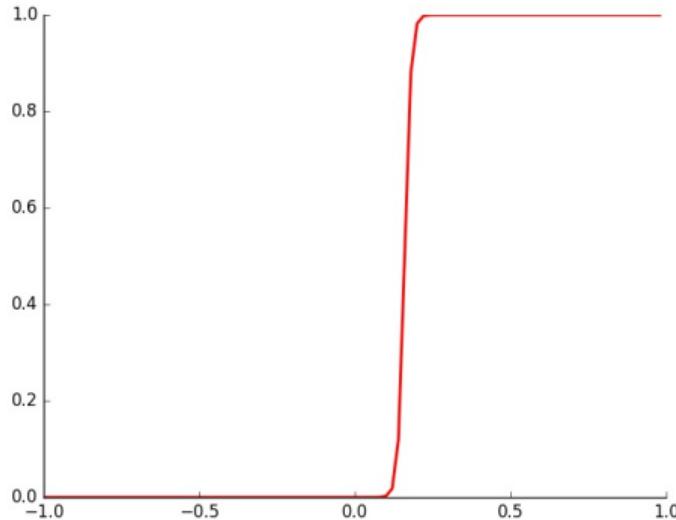
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 14, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



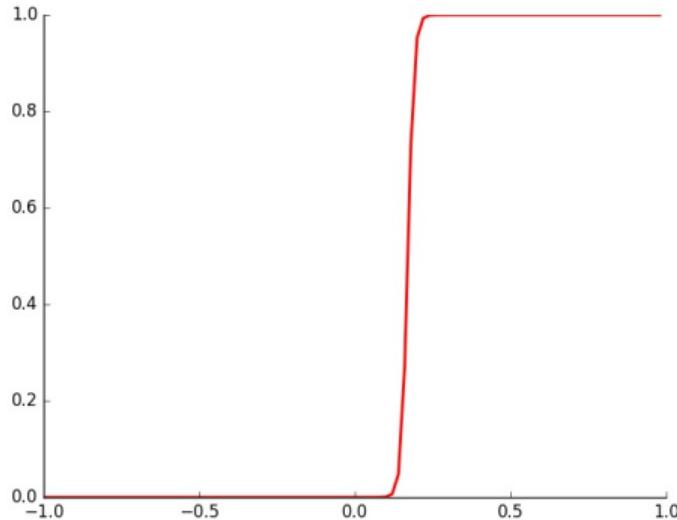
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 15, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



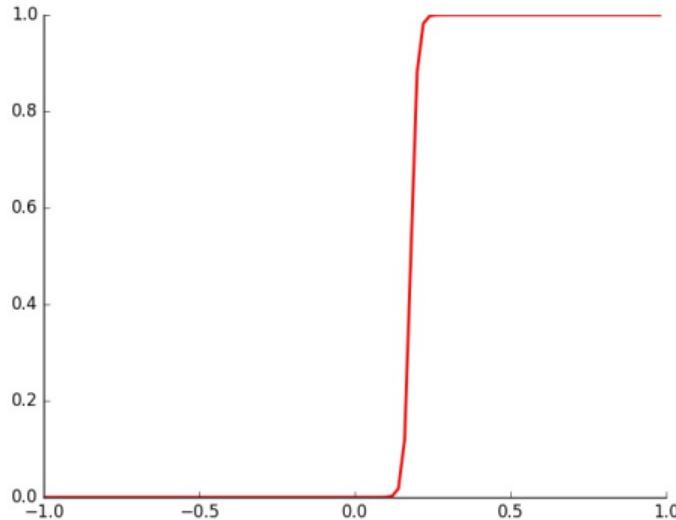
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 16, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



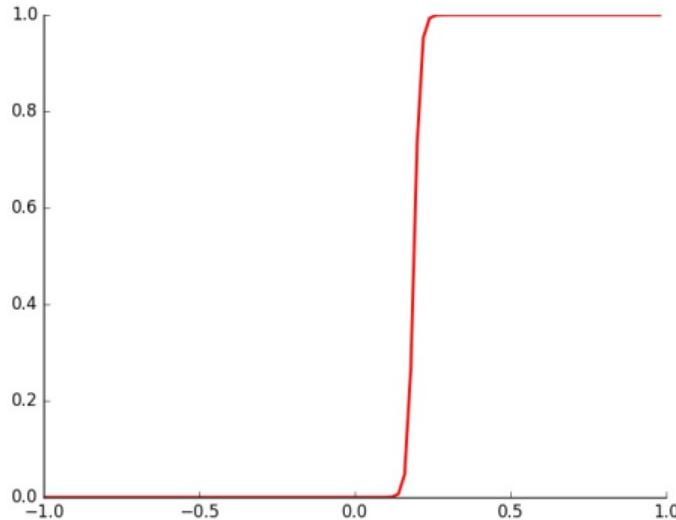
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 17, \sigma(x) = \frac{1}{1 - \exp^{(wx+b)}}$$



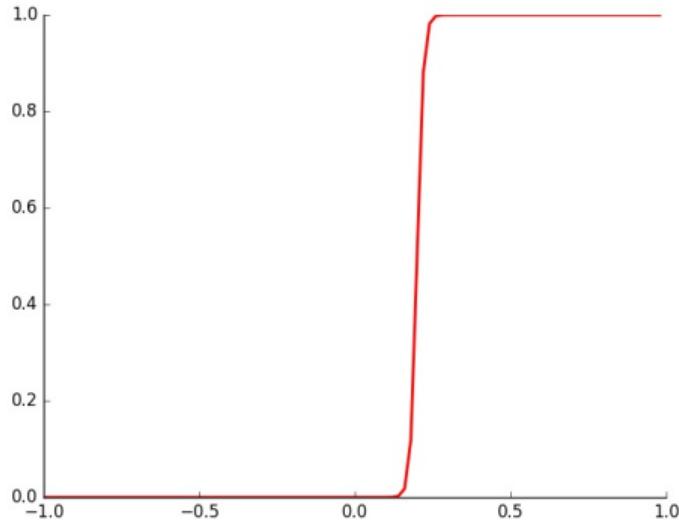
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 18, \sigma(x) = \frac{1}{1 - \exp^{(wx+b)}}$$



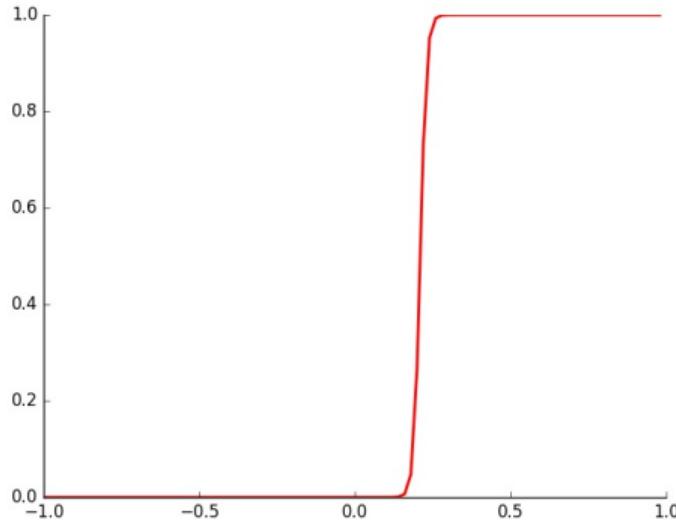
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 19, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



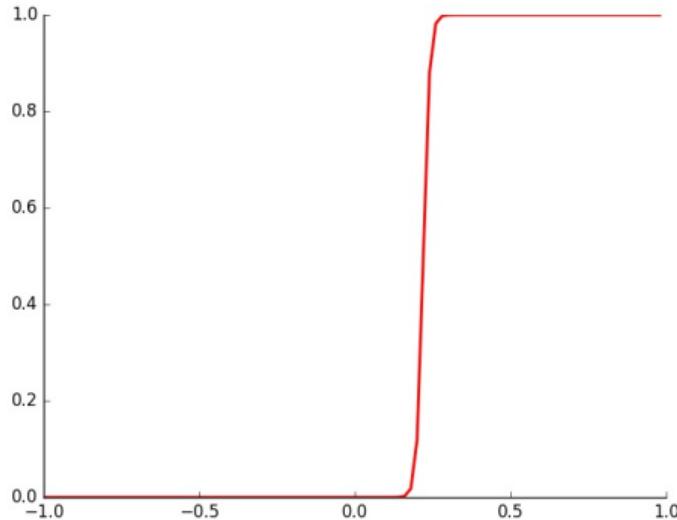
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 20, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



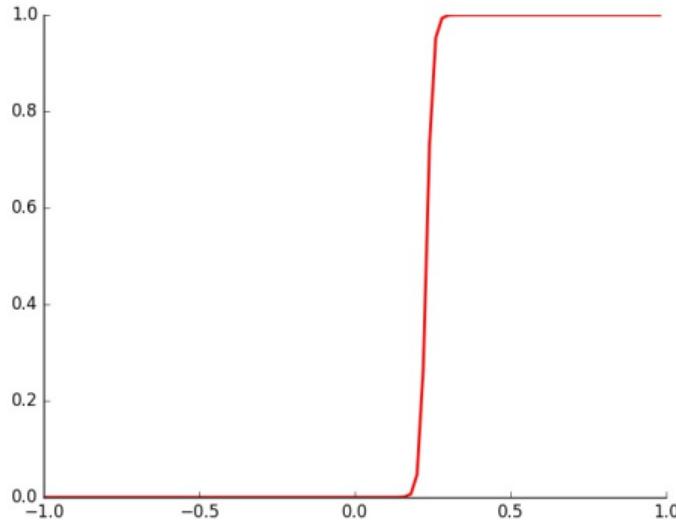
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 21, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



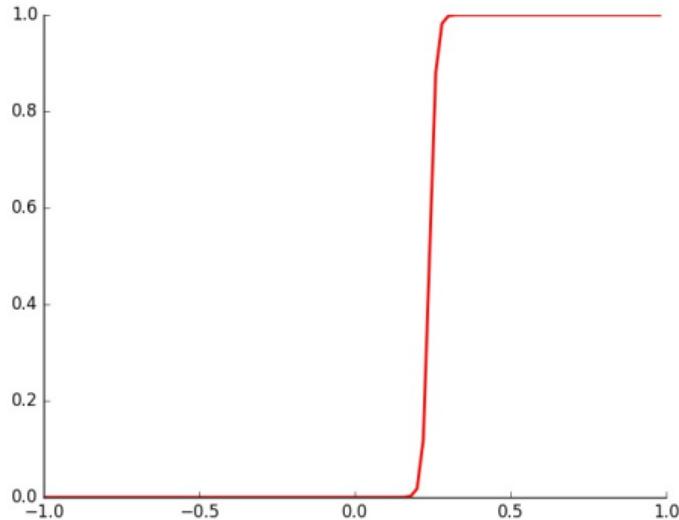
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 22, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



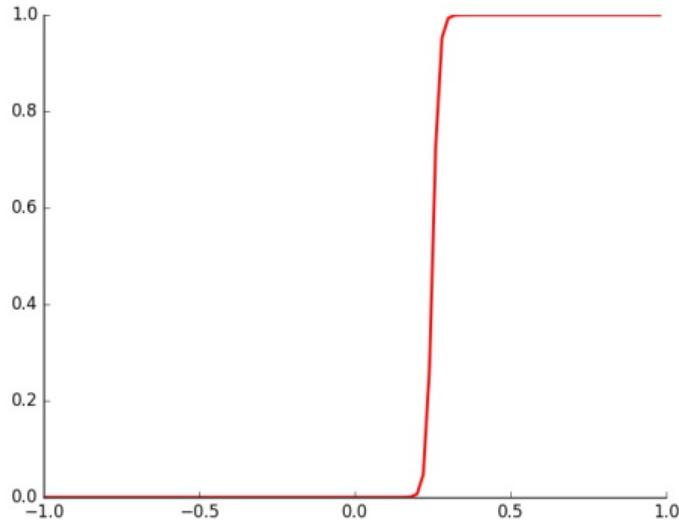
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 23, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



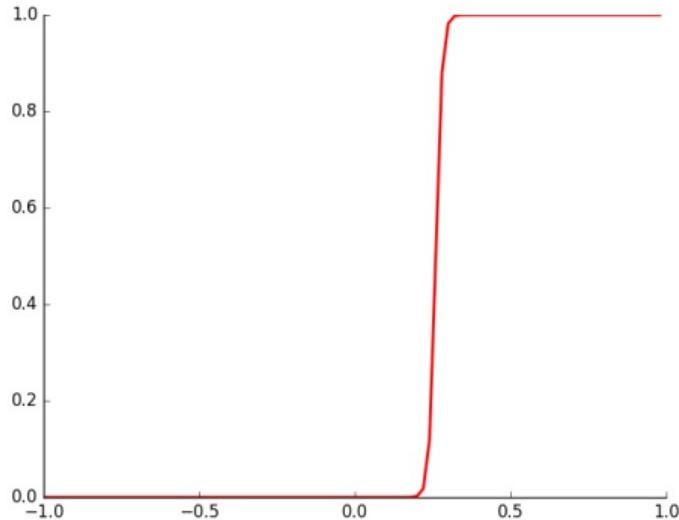
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 24, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



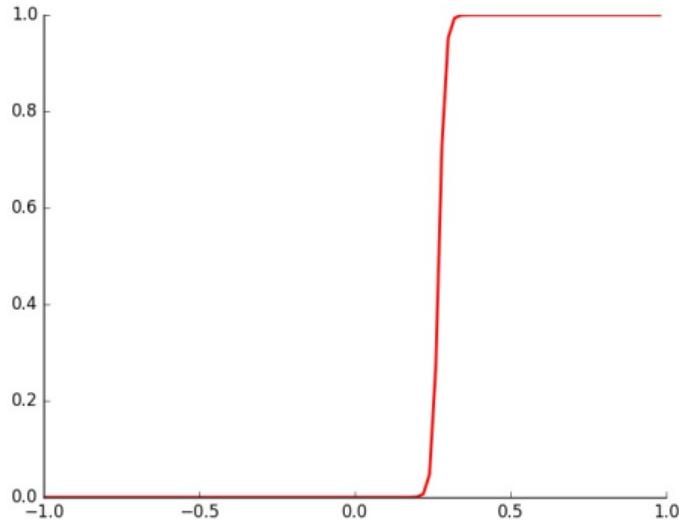
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 25, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



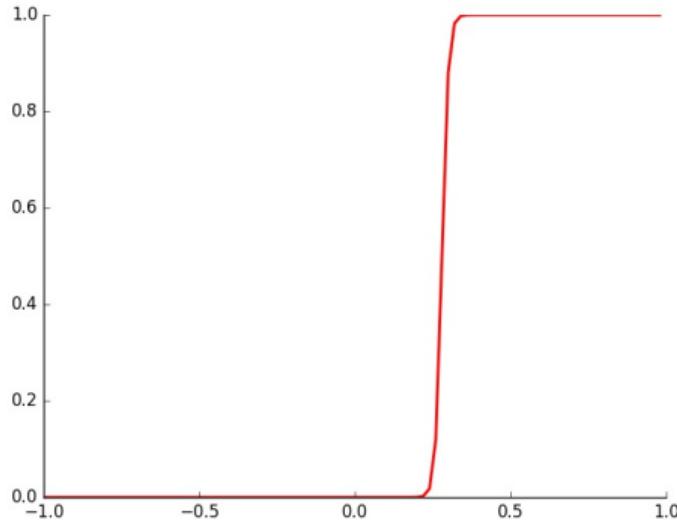
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 26, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



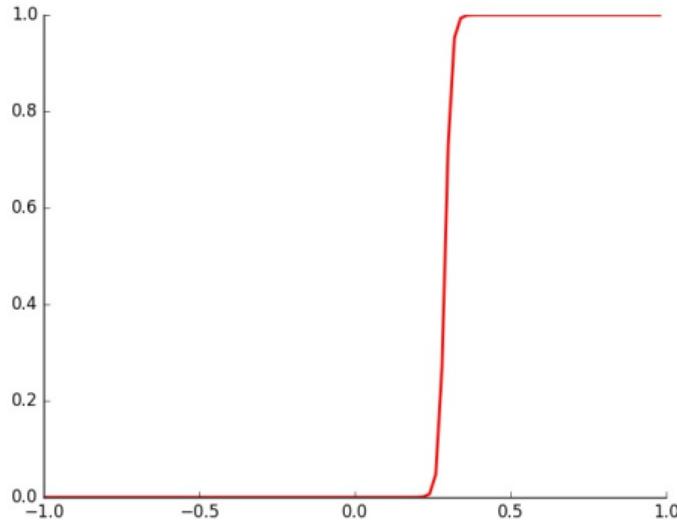
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 27, \sigma(x) = \frac{1}{1 - \exp^{(wx+b)}}$$



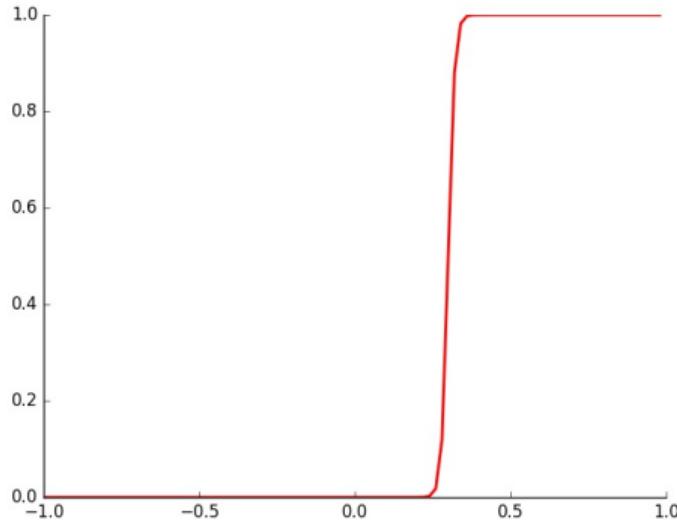
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 28, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



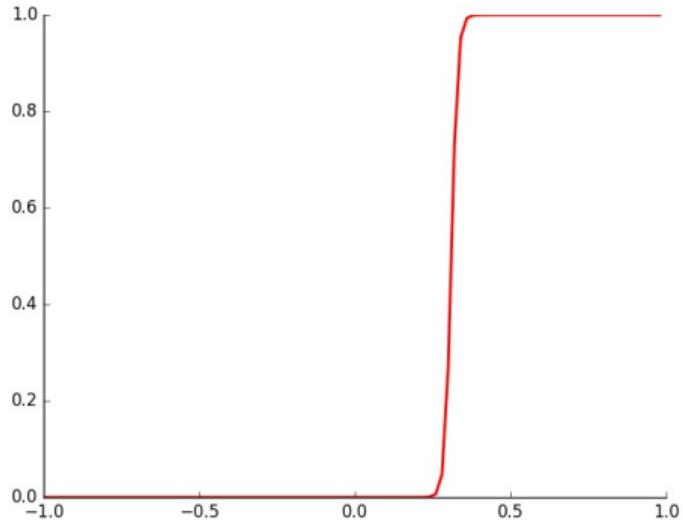
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 29, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



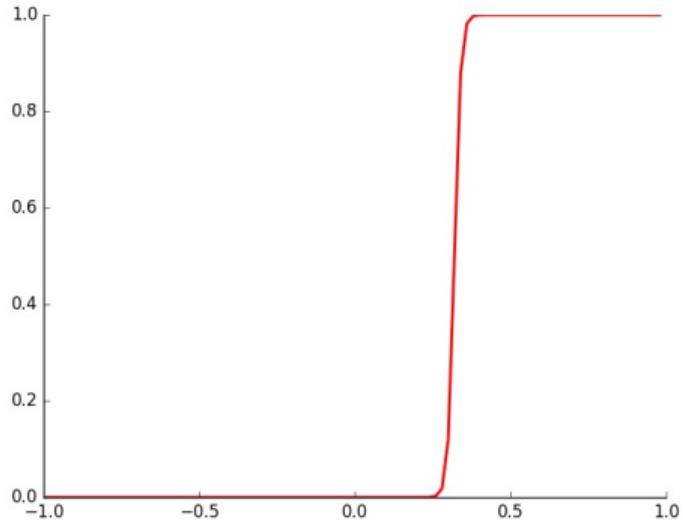
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 30, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



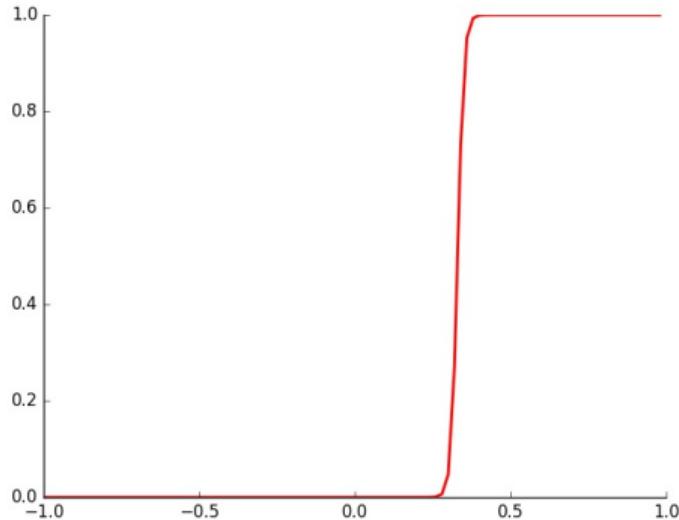
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 31, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



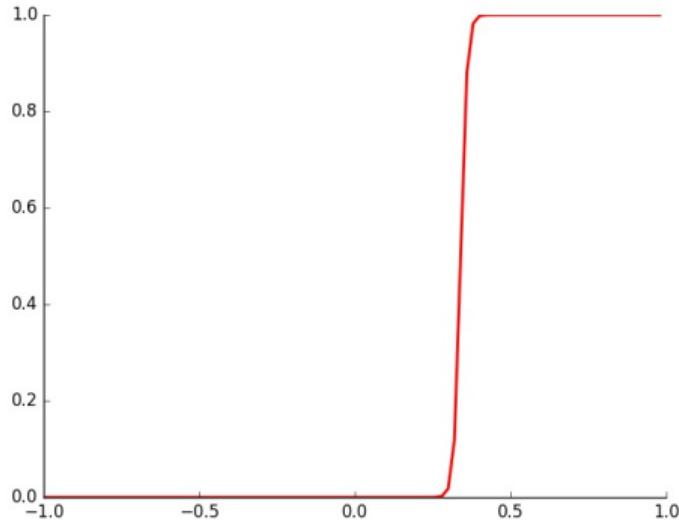
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 32, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



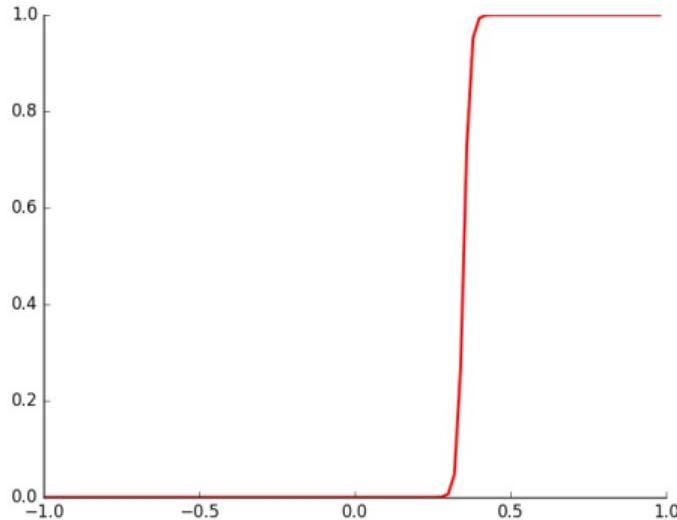
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 33, \sigma(x) = \frac{1}{1 - \exp^{(wx+b)}}$$



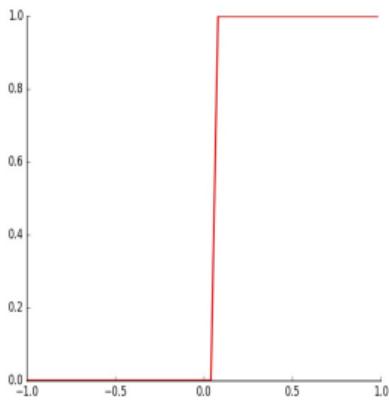
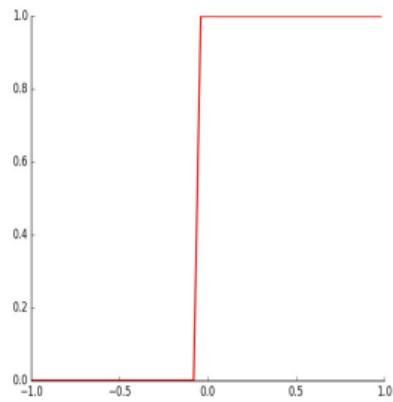
- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

$$w = 50, b = 34, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$

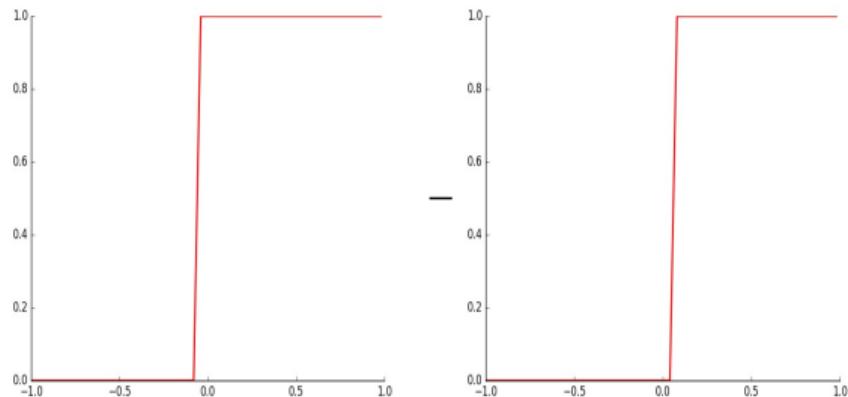


- If we take the logistic function and set w to a very high value we will recover the step function
- Let us see what happens as we change the value of w
- Further we can adjust the value of b to control the position on the x-axis at which the function transitions from 0 to 1

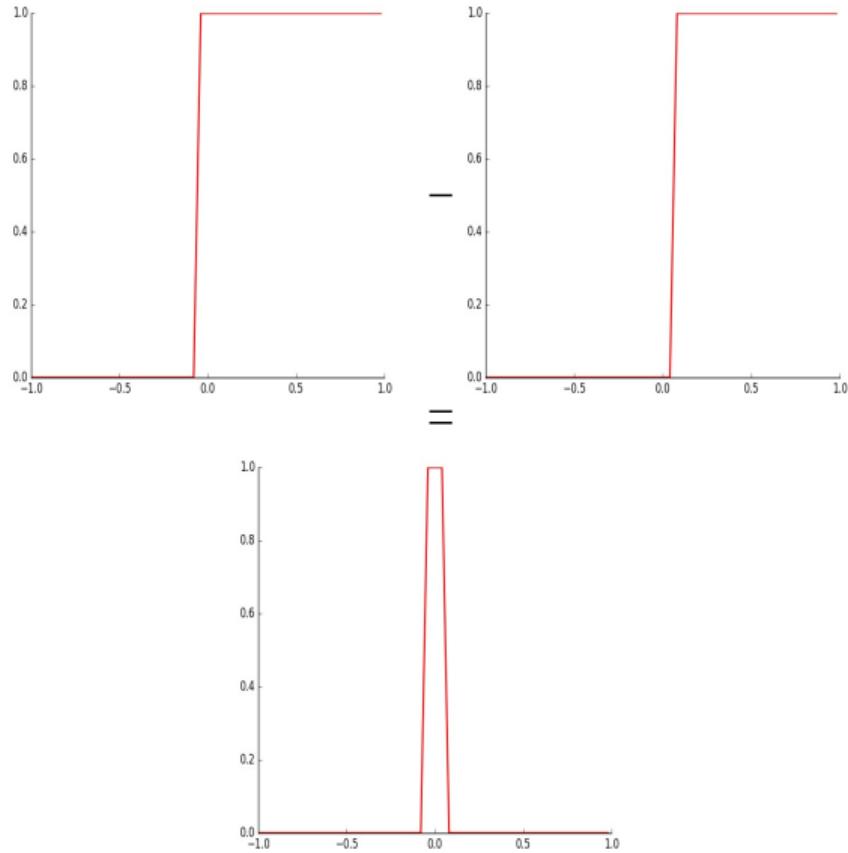
$$w = 50, b = 35, \sigma(x) = \frac{1}{1-\exp^{(wx+b)}}$$



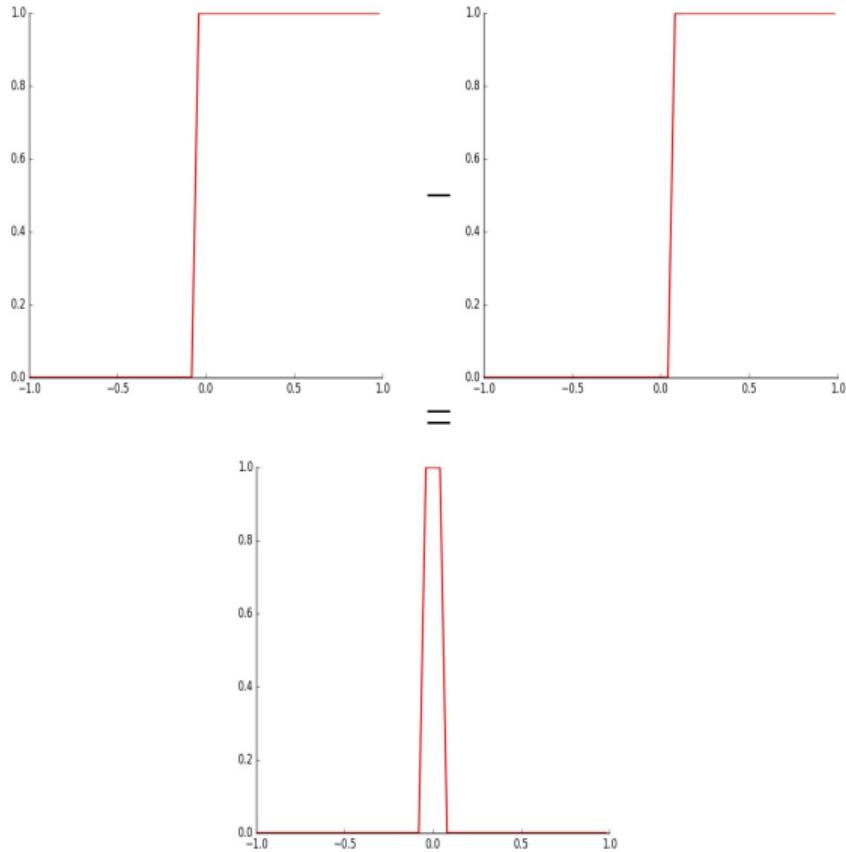
- Now let us see what we get by taking two such sigmoid functions (with different b 's) and subtracting one from the other



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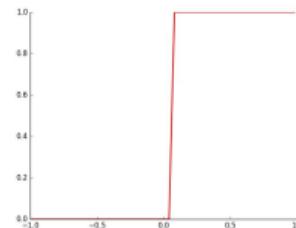
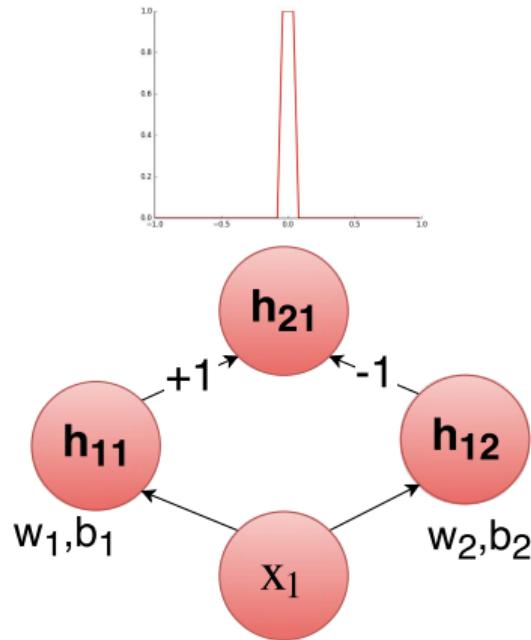
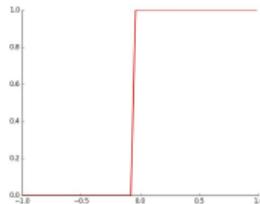


- Now let us see what we get by taking two such sigmoid functions (with different b 's) and subtracting one from the other

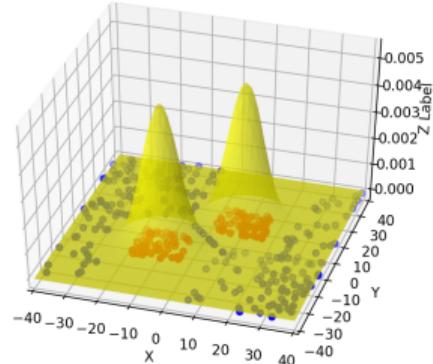


- Now let us see what we get by taking two such sigmoid functions (with different b 's) and subtracting one from the other
- Voila! We have our tower function !!

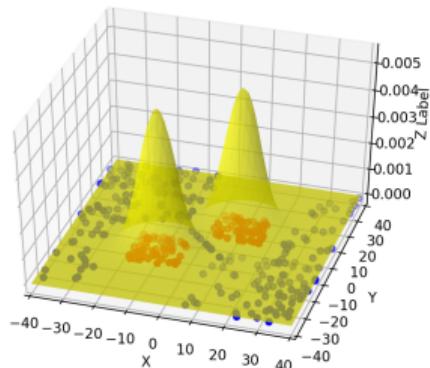
- Can we come up with a neural network to represent this operation of subtracting one sigmoid function from another ?



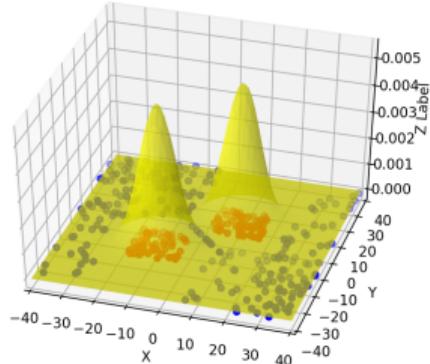
- What if we have more than one input?

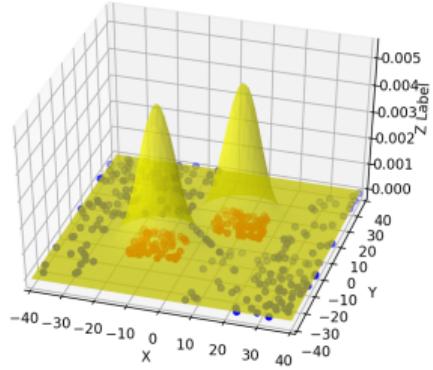


- What if we have more than one input?
- Suppose we are trying to take a decision about whether we will find oil at a particular location on the ocean bed(Yes/No)

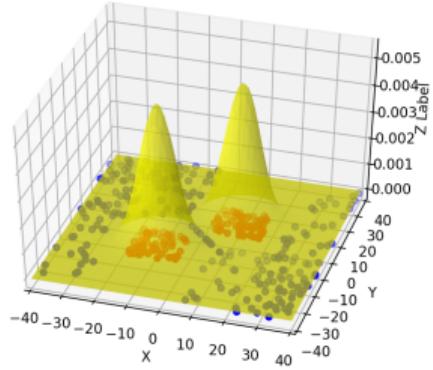


- What if we have more than one input?
- Suppose we are trying to take a decision about whether we will find oil at a particular location on the ocean bed(Yes/No)
- Further, suppose we base our decision on two factors: Salinity (x_1) and Pressure (x_2)





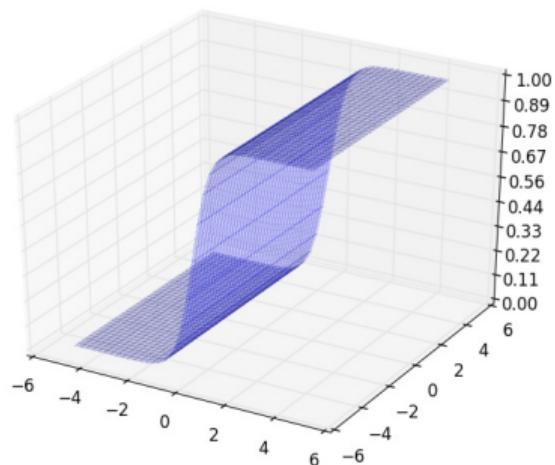
- What if we have more than one input?
- Suppose we are trying to take a decision about whether we will find oil at a particular location on the ocean bed(Yes/No)
- Further, suppose we base our decision on two factors: Salinity (x_1) and Pressure (x_2)
- We are given some data and it seems that $y(oil|no - oil)$ is a complex function of x_1 and x_2



- What if we have more than one input?
- Suppose we are trying to take a decision about whether we will find oil at a particular location on the ocean bed(Yes/No)
- Further, suppose we base our decision on two factors: Salinity (x_1) and Pressure (x_2)
- We are given some data and it seems that $y(oil|no-oil)$ is a complex function of x_1 and x_2
- We want a neural network to approximate this function

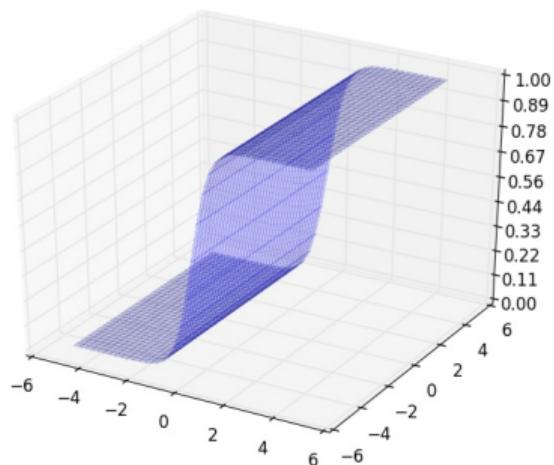
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

- This is what a 2-dimensional sigmoid looks like

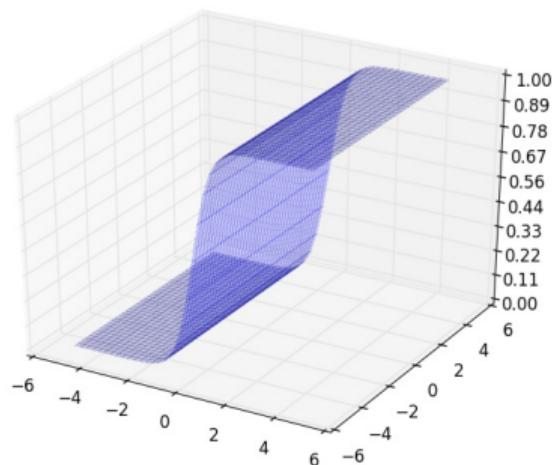


$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case



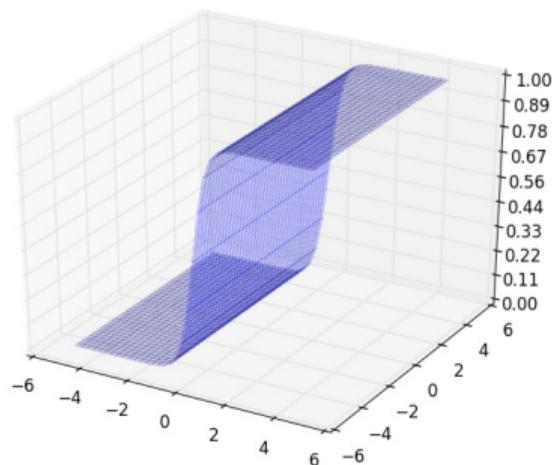
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 2, w_2 = 0, b = 0$$

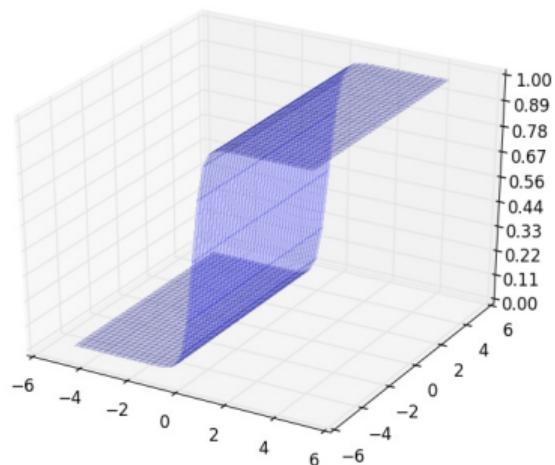
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 3, w_2 = 0, b = 0$$

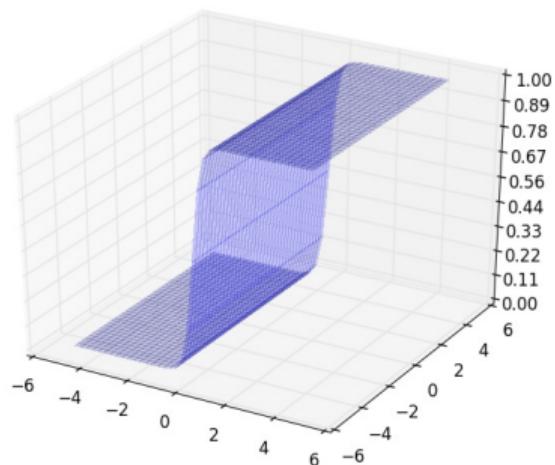
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 4, w_2 = 0, b = 0$$

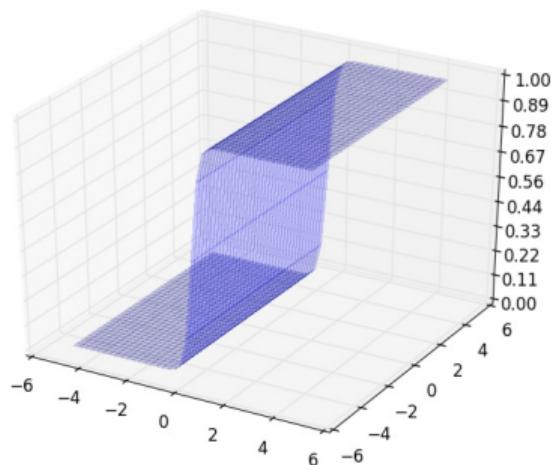
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 5, w_2 = 0, b = 0$$

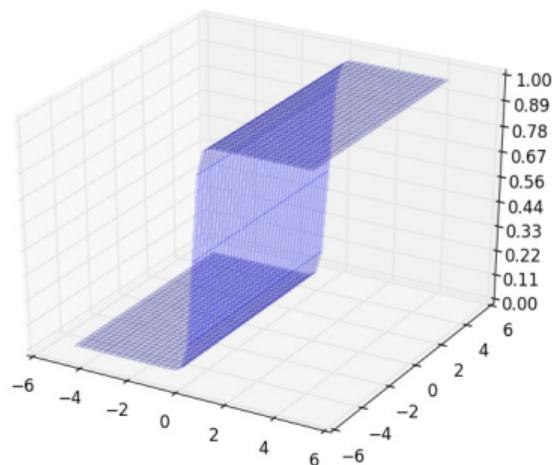
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 6, w_2 = 0, b = 0$$

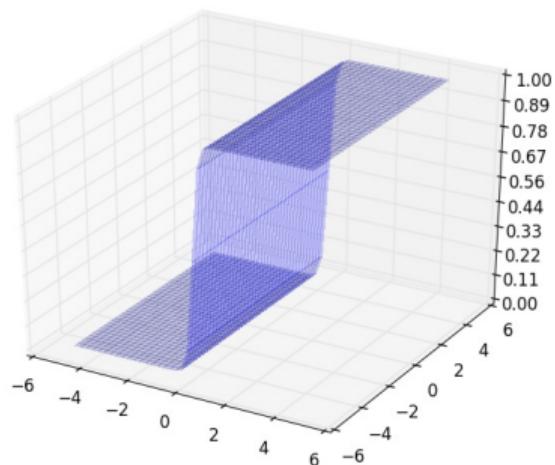
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 7, w_2 = 0, b = 0$$

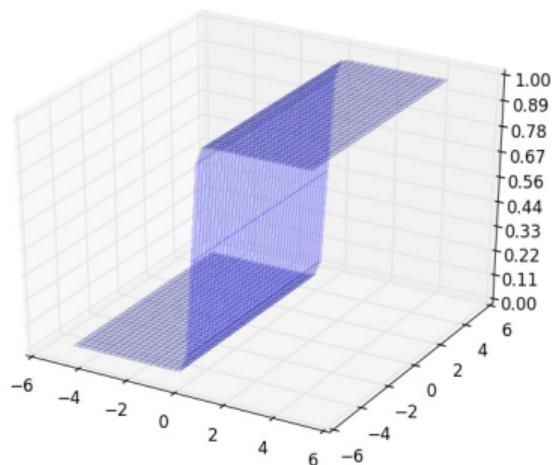
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 8, w_2 = 0, b = 0$$

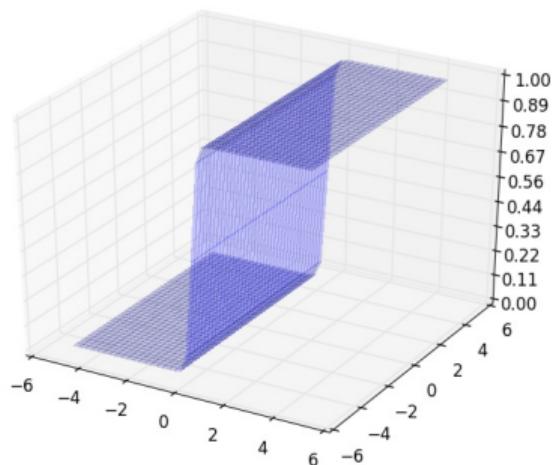
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 9, w_2 = 0, b = 0$$

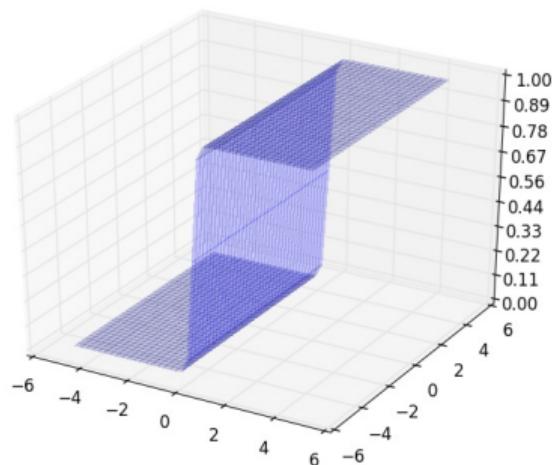
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



$$w_1 = 10, w_2 = 0, b = 0$$

- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

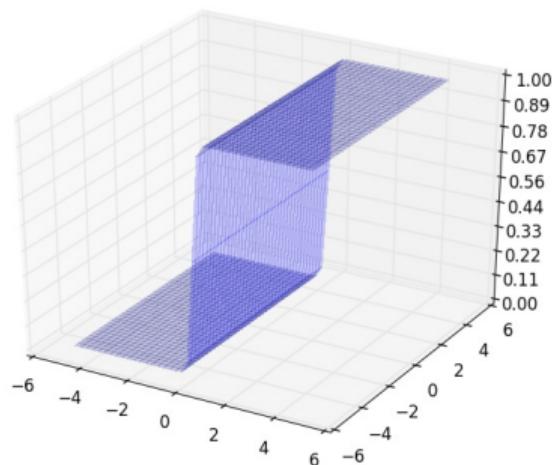
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 11, w_2 = 0, b = 0$$

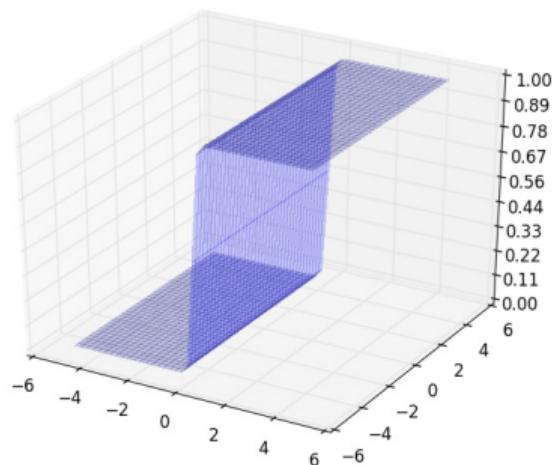
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 12, w_2 = 0, b = 0$$

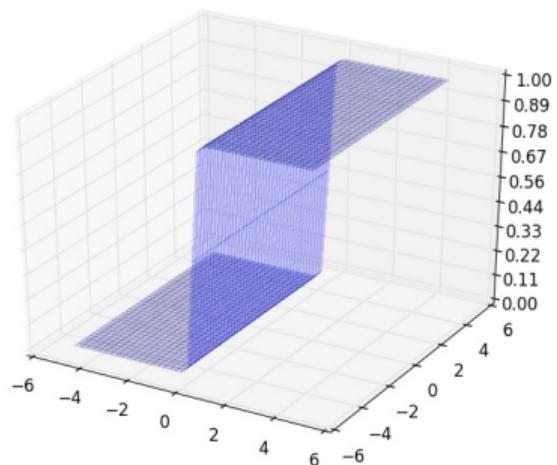
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 13, w_2 = 0, b = 0$$

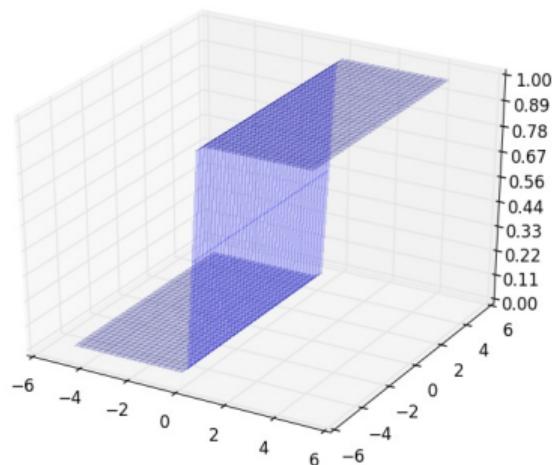
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 14, w_2 = 0, b = 0$$

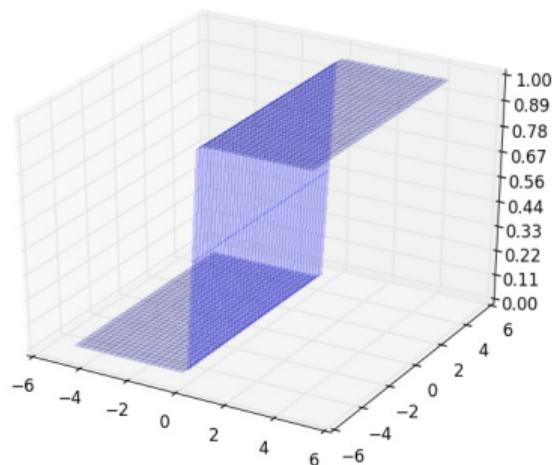
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 15, w_2 = 0, b = 0$$

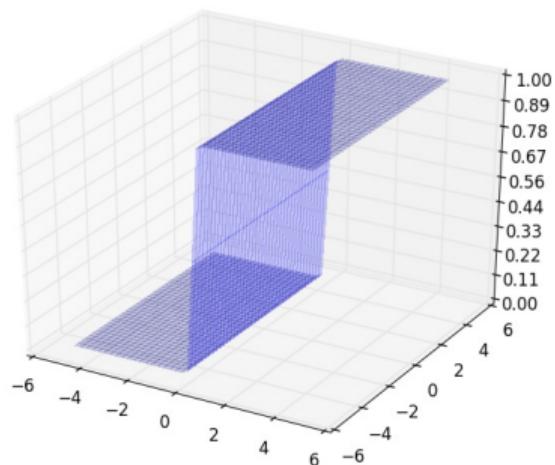
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



$$w_1 = 16, w_2 = 0, b = 0$$

- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

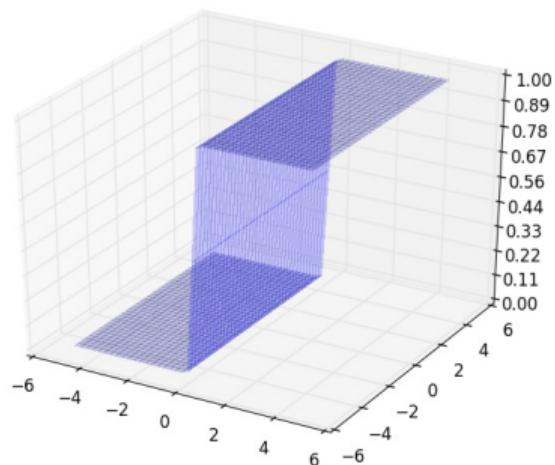
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 17, w_2 = 0, b = 0$$

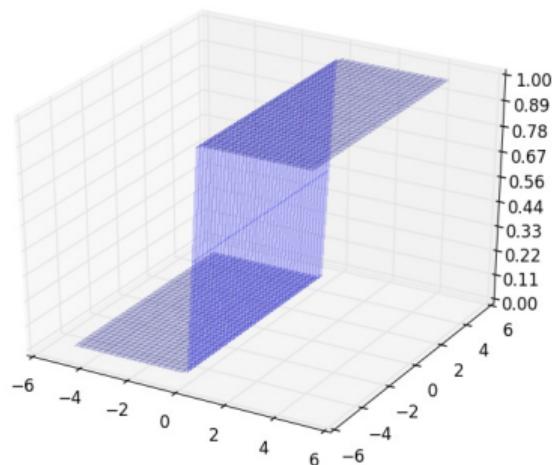
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 18, w_2 = 0, b = 0$$

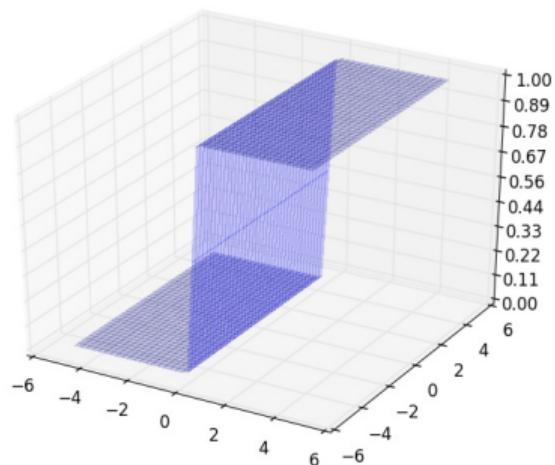
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 19, w_2 = 0, b = 0$$

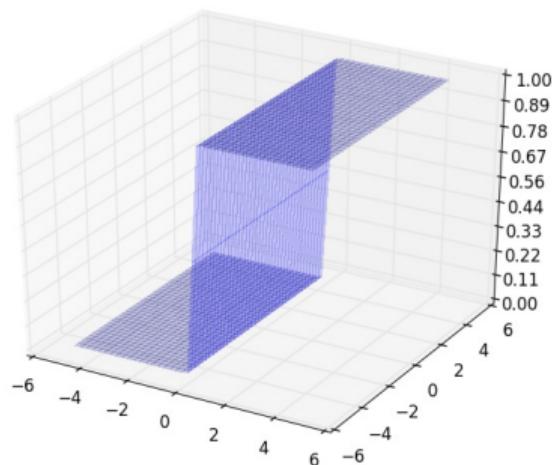
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 20, w_2 = 0, b = 0$$

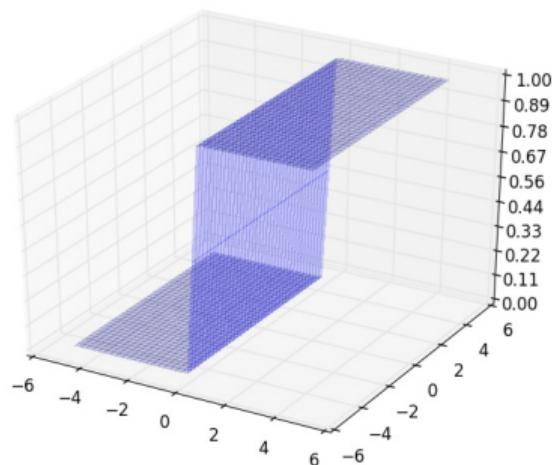
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 21, w_2 = 0, b = 0$$

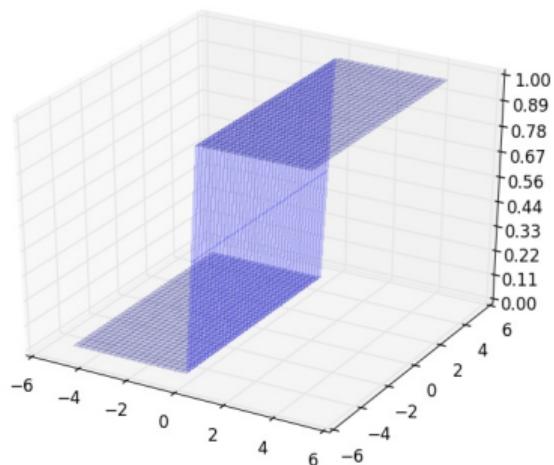
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 22, w_2 = 0, b = 0$$

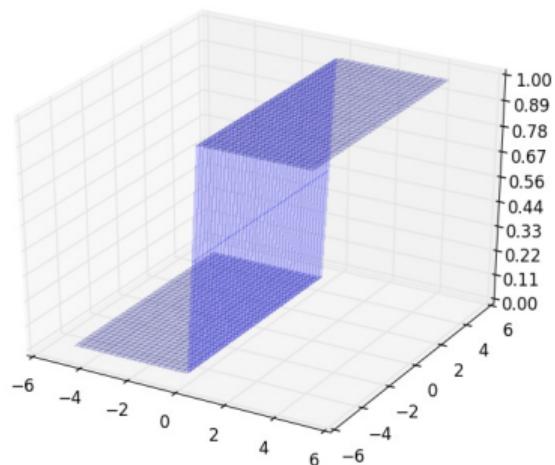
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

$$w_1 = 23, w_2 = 0, b = 0$$

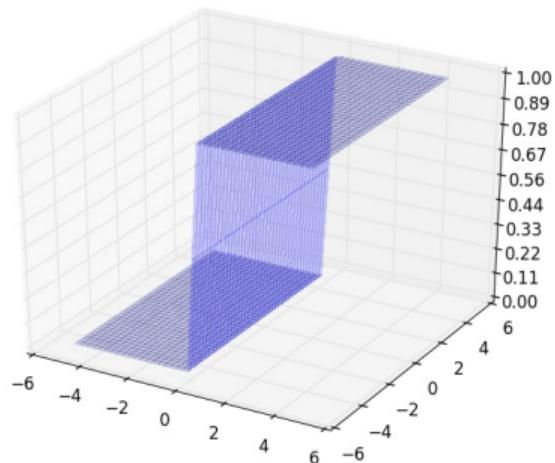
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function

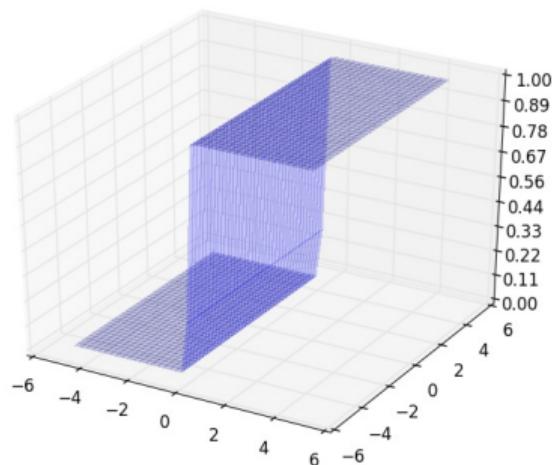
$$w_1 = 24, w_2 = 0, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function
- What would happen if we change b ?

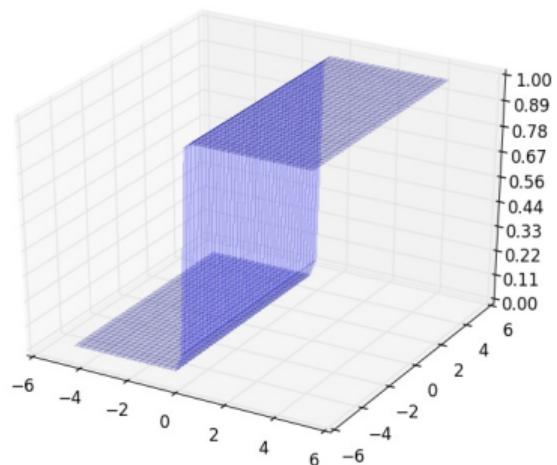
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



$$w_1 = 25, w_2 = 0, b = 5$$

- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function
- What would happen if we change b ?

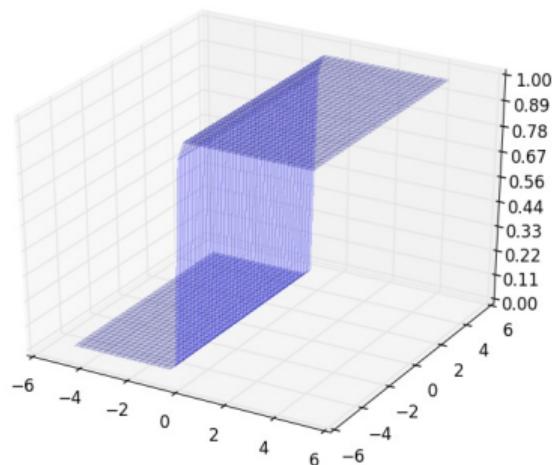
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



$$w_1 = 25, w_2 = 0, b = 10$$

- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function
- What would happen if we change b ?

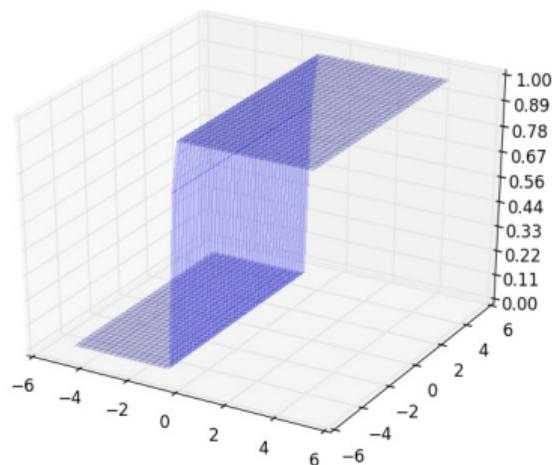
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



$$w_1 = 25, w_2 = 0, b = 15$$

- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function
- What would happen if we change b ?

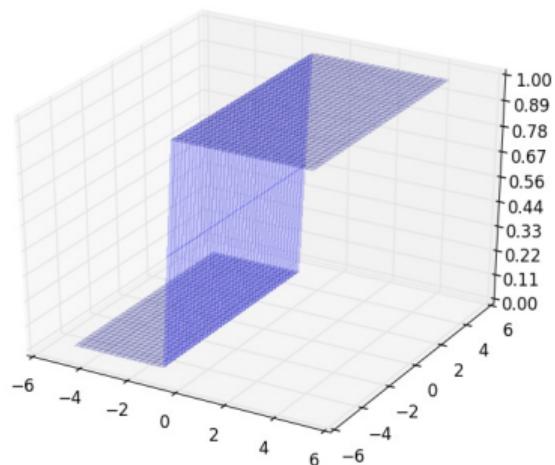
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



$$w_1 = 25, w_2 = 0, b = 20$$

- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function
- What would happen if we change b ?

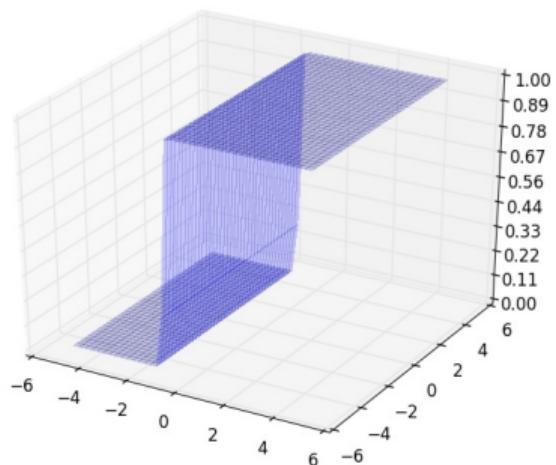
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



$$w_1 = 25, w_2 = 0, b = 25$$

- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function
- What would happen if we change b ?

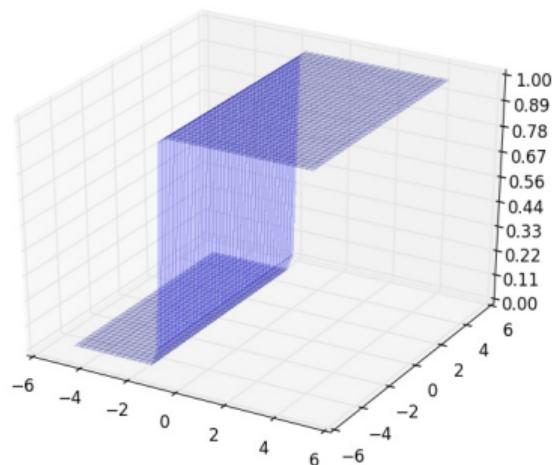
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function
- What would happen if we change b ?

$$w_1 = 25, w_2 = 0, b = 30$$

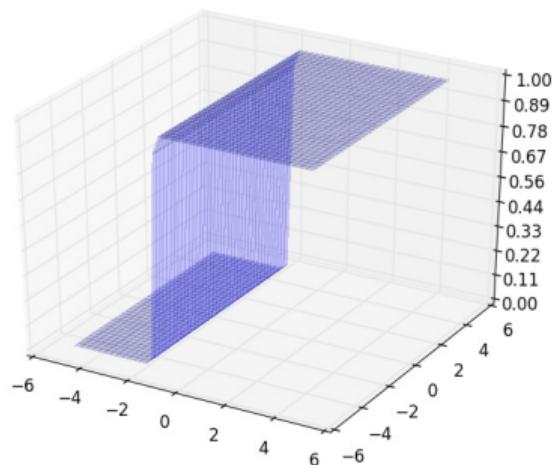
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



$$w_1 = 25, w_2 = 0, b = 35$$

- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function
- What would happen if we change b ?

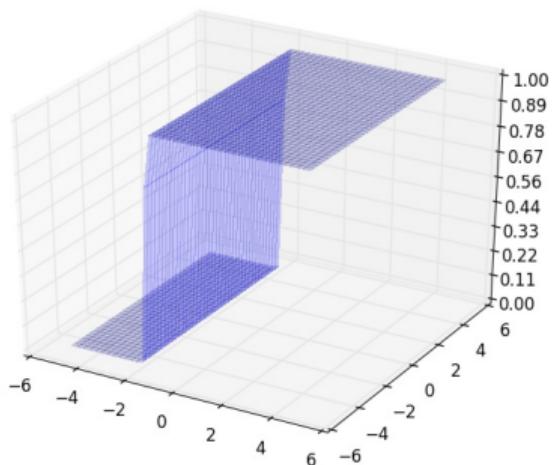
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$



$$w_1 = 25, w_2 = 0, b = 40$$

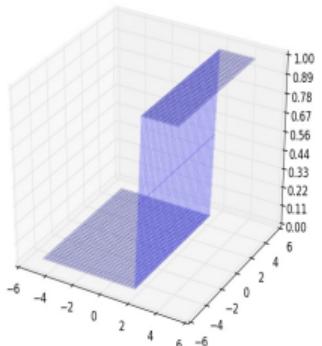
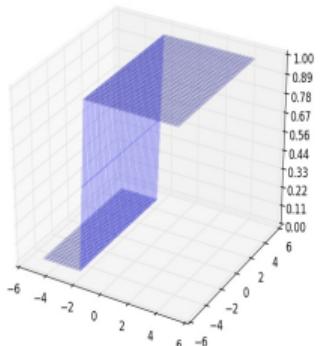
- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function
- What would happen if we change b ?

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

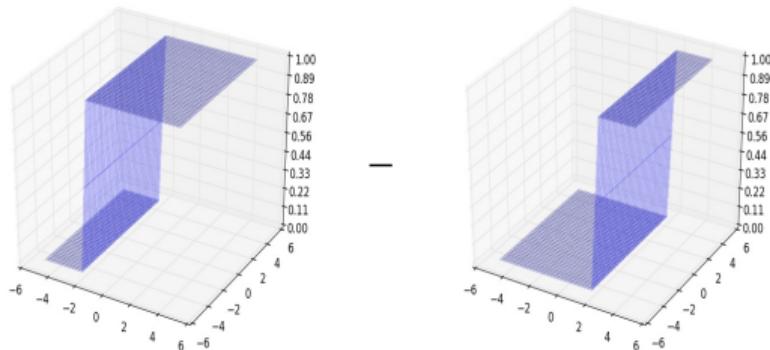


$$w_1 = 25, w_2 = 0, b = 45$$

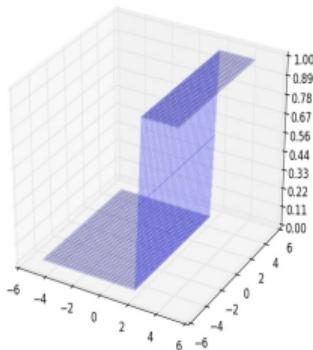
- This is what a 2-dimensional sigmoid looks like
- We need to figure out how to get a tower in this case
- First, let us set w_2 to 0 and see if we can get a two dimensional step function
- What would happen if we change b ?



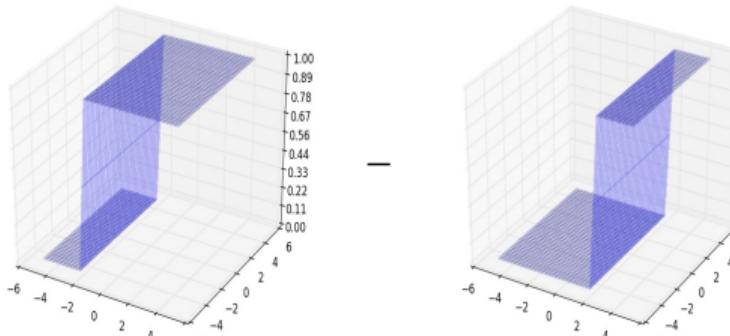
- What if we take two such step functions (with different b values) and subtract one from the other



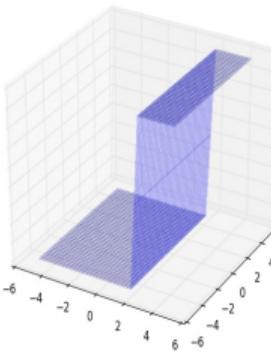
- What if we take two such step functions (with different b values) and subtract one from the other



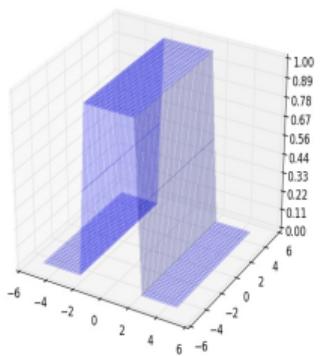
- What if we take two such step functions (with different b values) and subtract one from the other

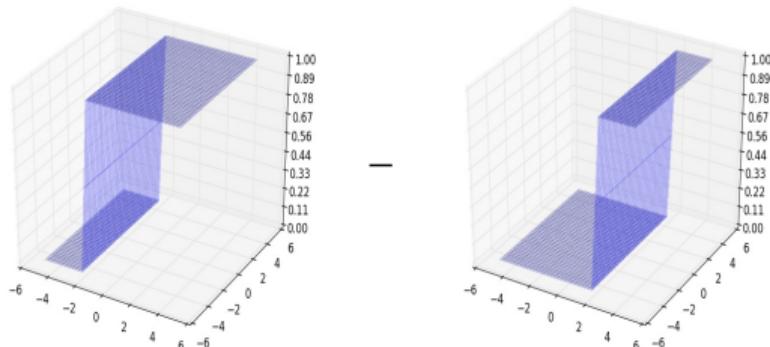


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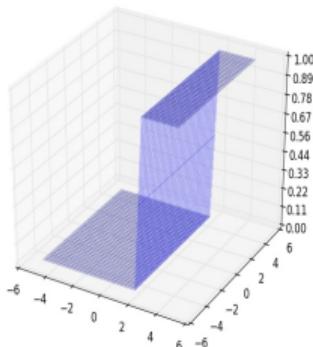


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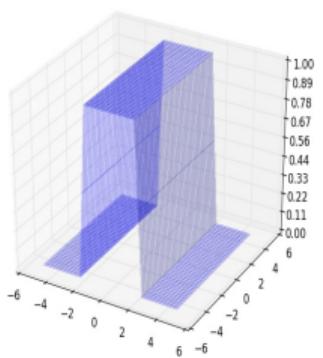


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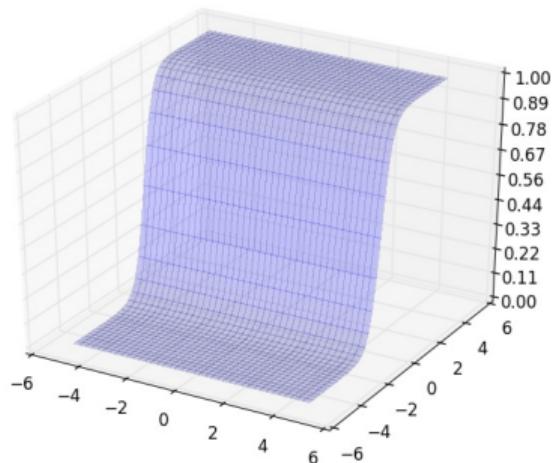
- What if we take two such step functions (with different b values) and subtract one from the other
- We still don't get a tower (or we get a tower which is open from two sides)

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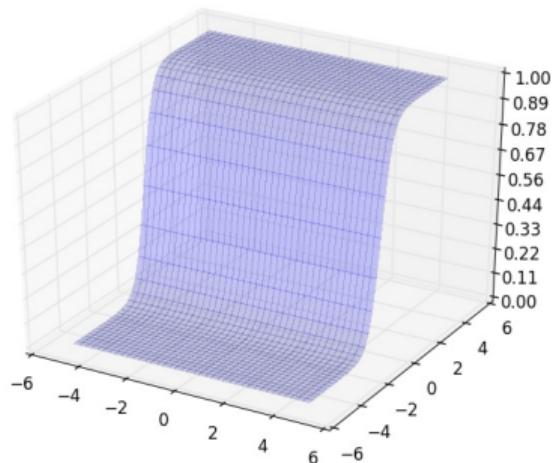
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



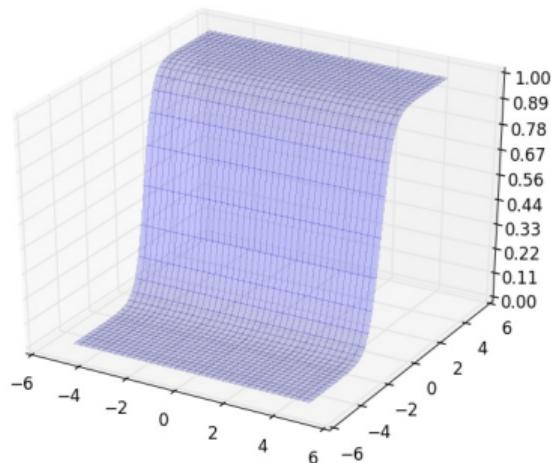
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

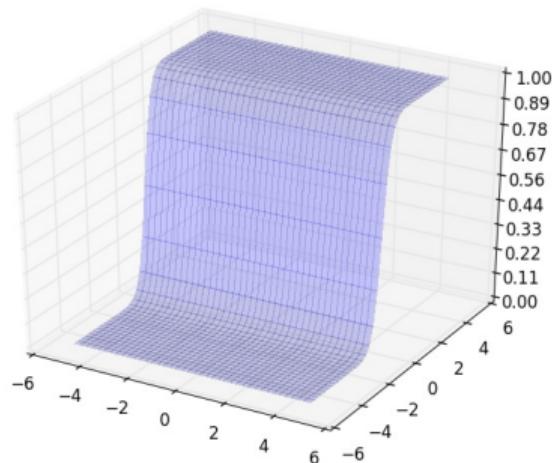
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 2, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

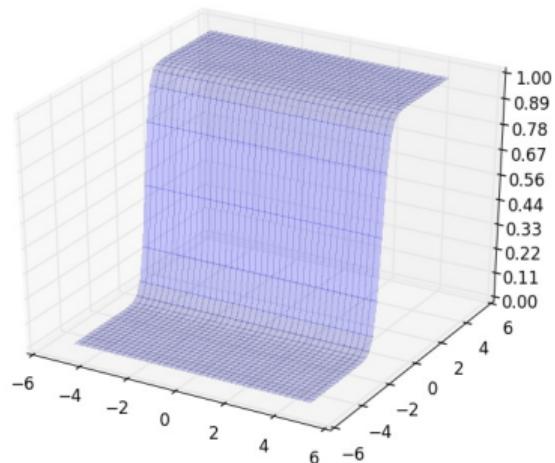
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 3, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

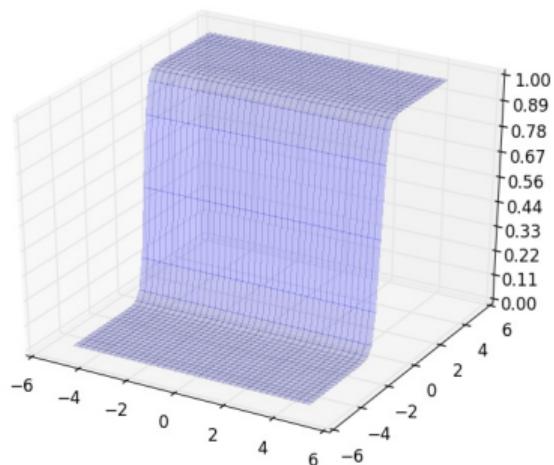
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 4, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

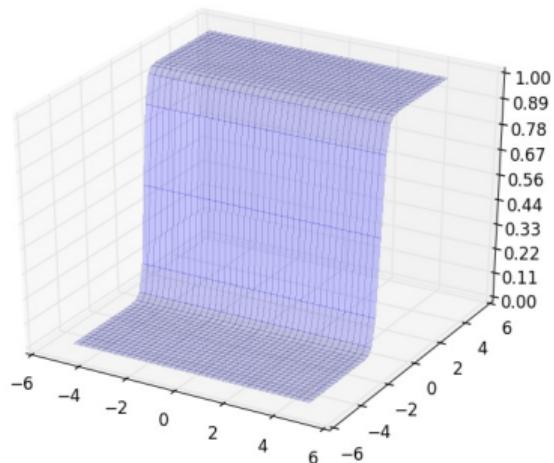
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 5, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

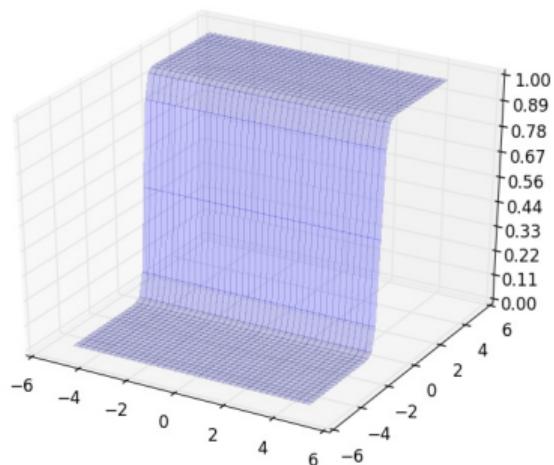
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 6, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

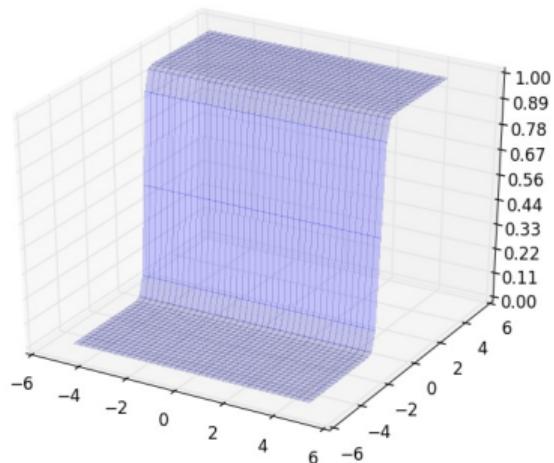
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 7, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

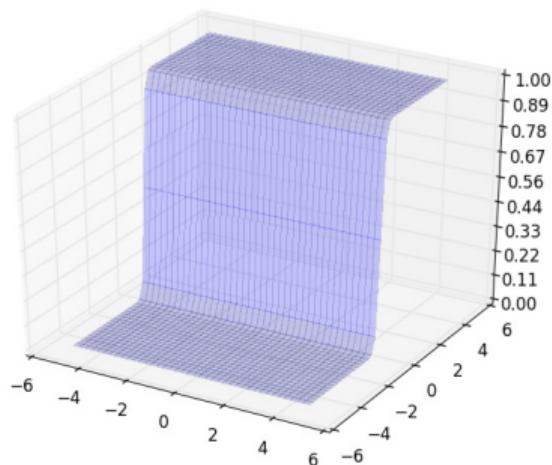
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 8, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

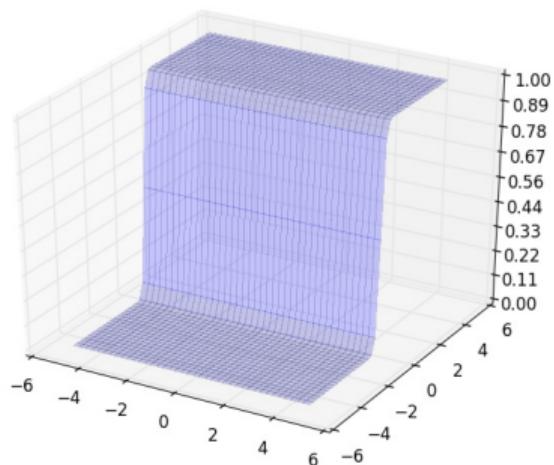
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 9, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

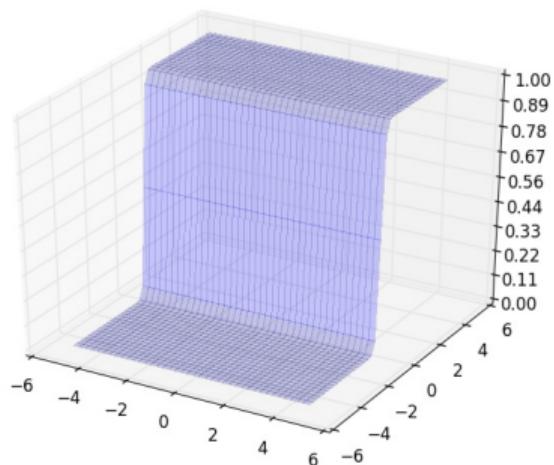
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 10, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

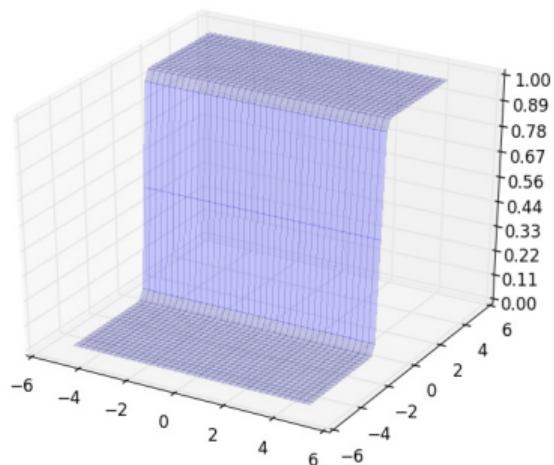
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 11, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

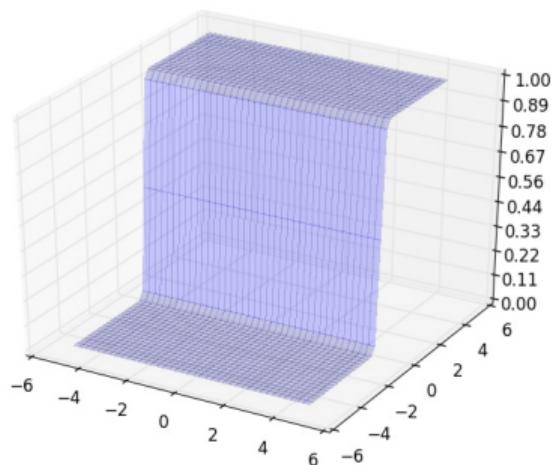
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 12, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

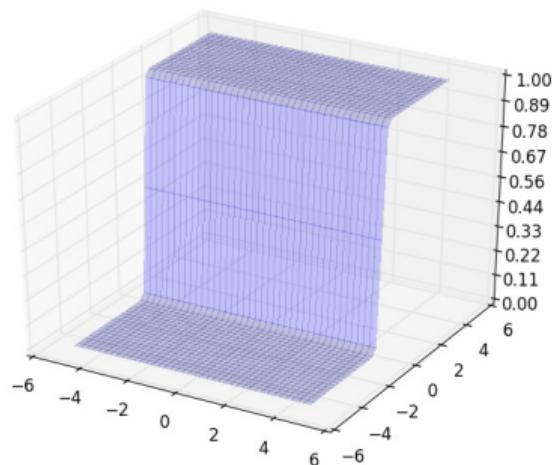
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 13, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

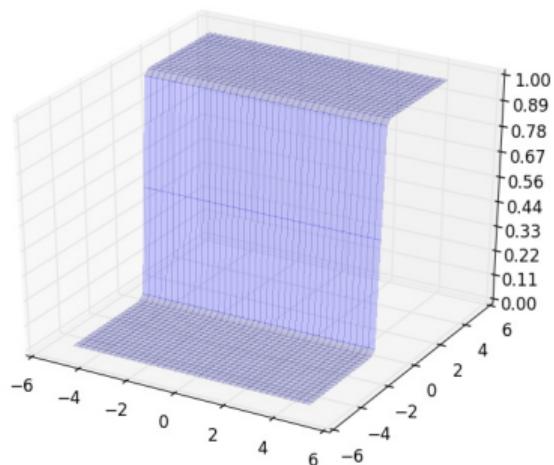
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 14, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

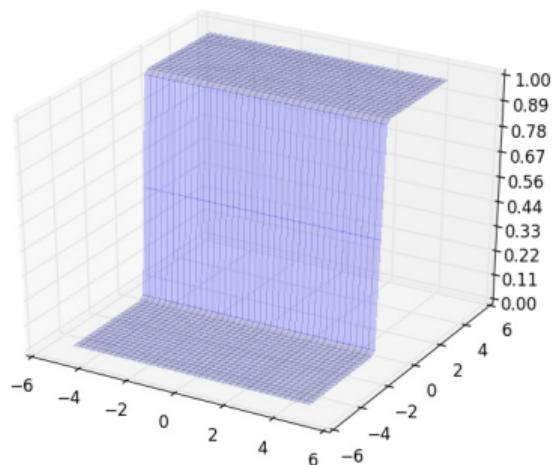
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 15, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

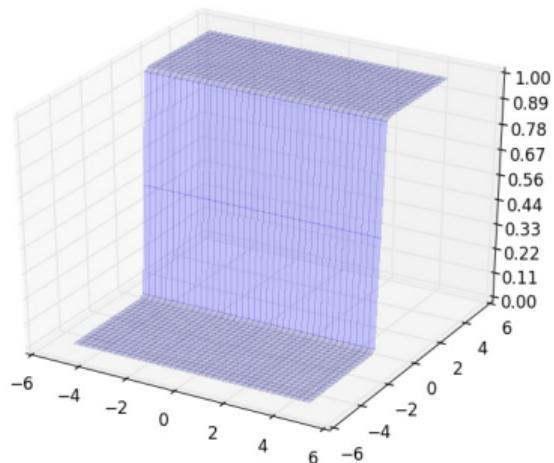
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 16, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

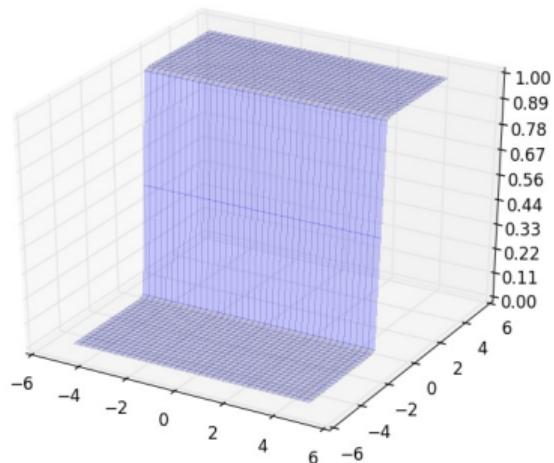
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 17, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

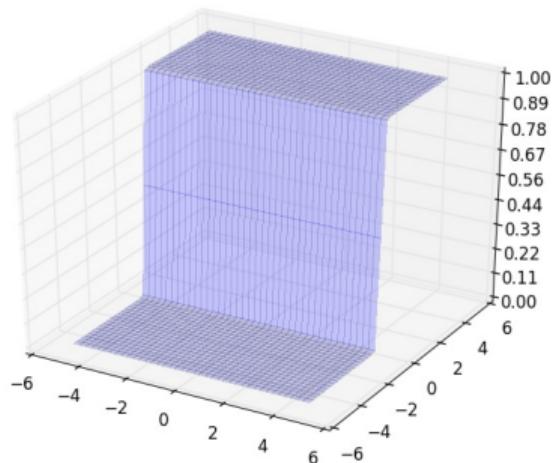
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 18, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

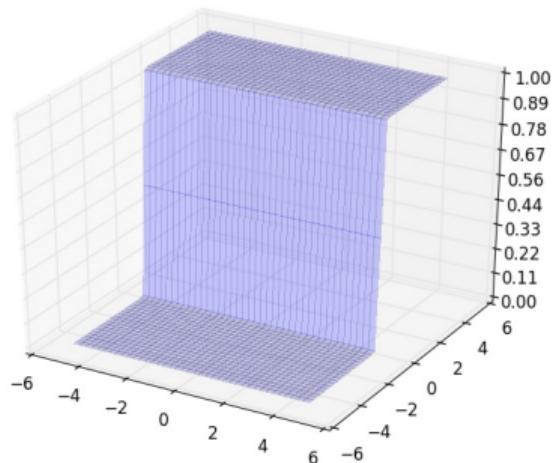
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 19, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

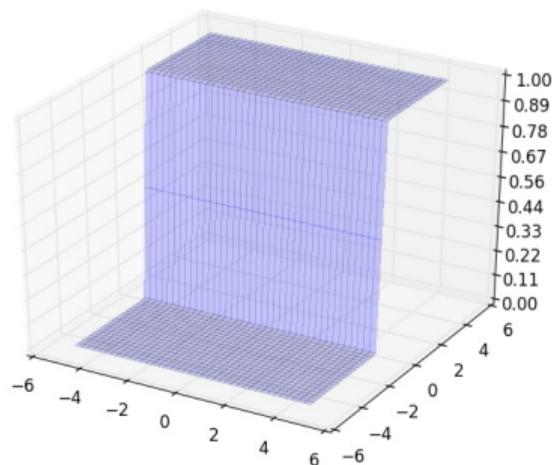
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 20, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

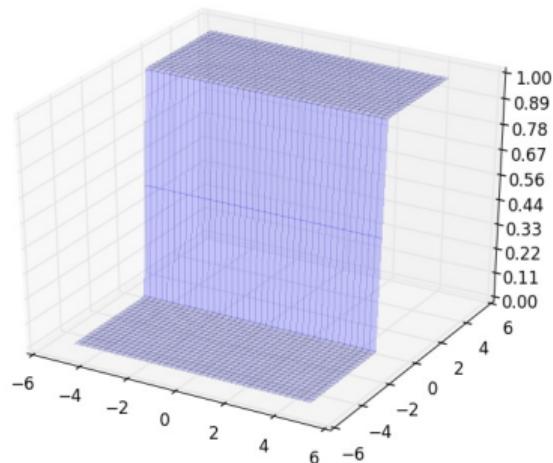
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 21, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

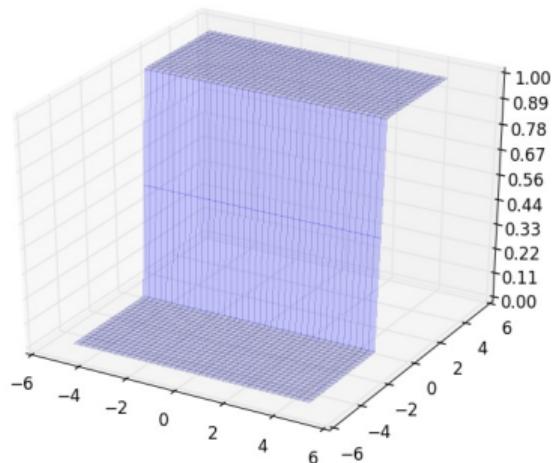
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 22, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

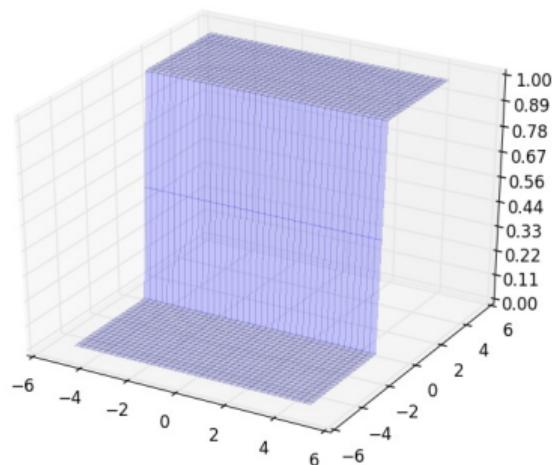
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 23, b = 0$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

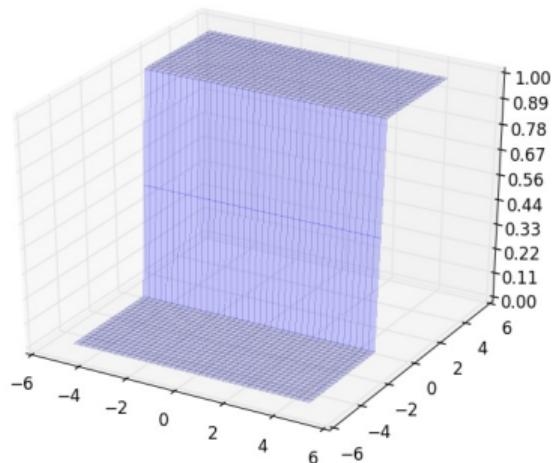
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation



$$w_1 = 0, w_2 = 24, b = 0$$

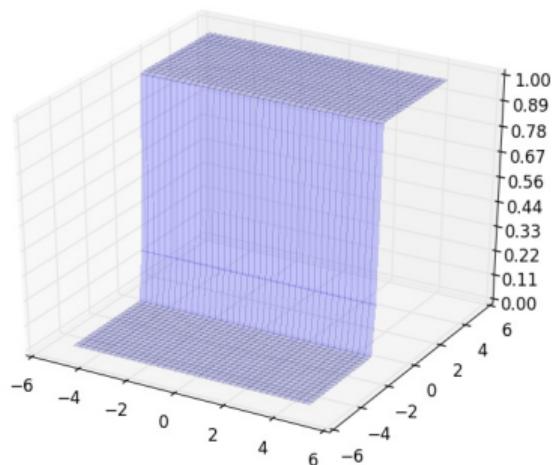
$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation
- And now we change b



$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

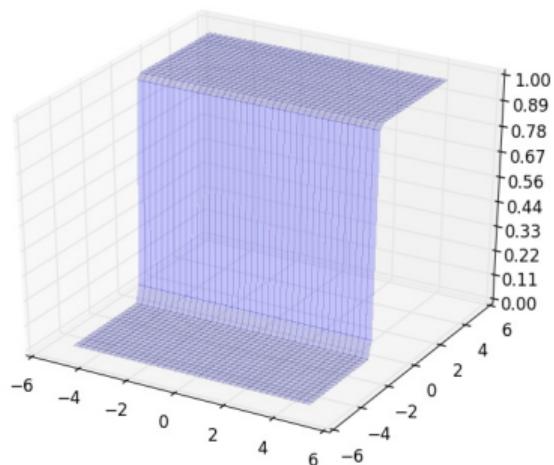
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation
- And now we change b



$$w_1 = 0, w_2 = 25, b = 5$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

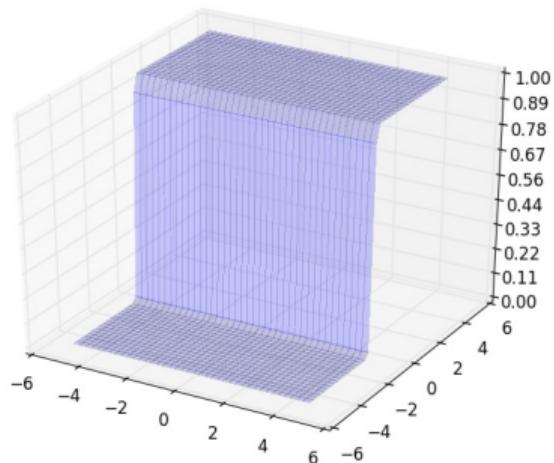
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation
- And now we change b



$$w_1 = 0, w_2 = 25, b = 10$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

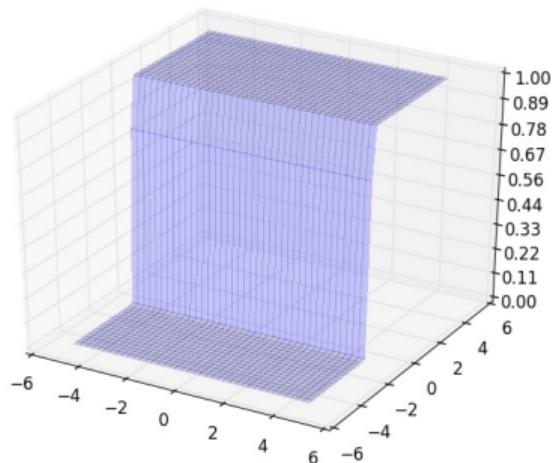
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation
- And now we change b



$$w_1 = 0, w_2 = 25, b = 15$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

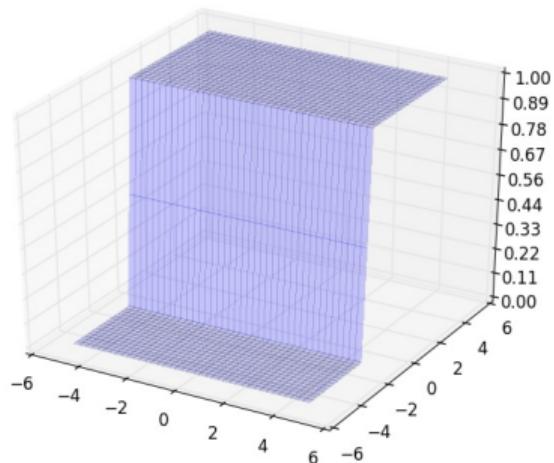
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation
- And now we change b



$$w_1 = 0, w_2 = 25, b = 20$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

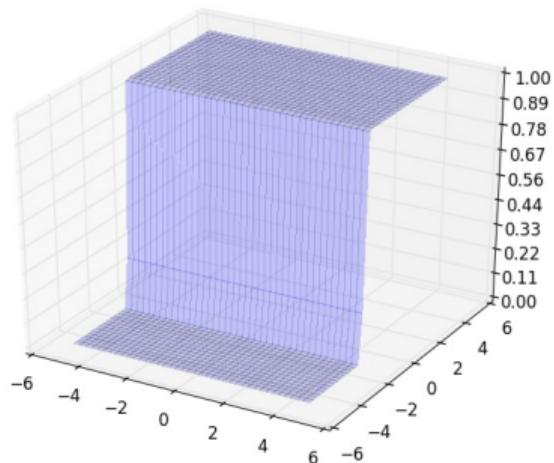
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation
- And now we change b



$$w_1 = 0, w_2 = 25, b = 25$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

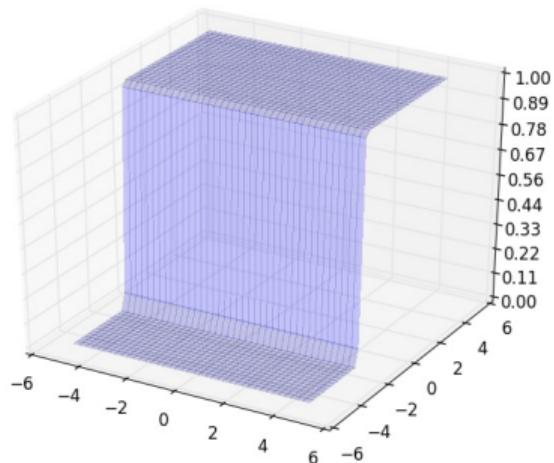
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation
- And now we change b



$$w_1 = 0, w_2 = 25, b = 30$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

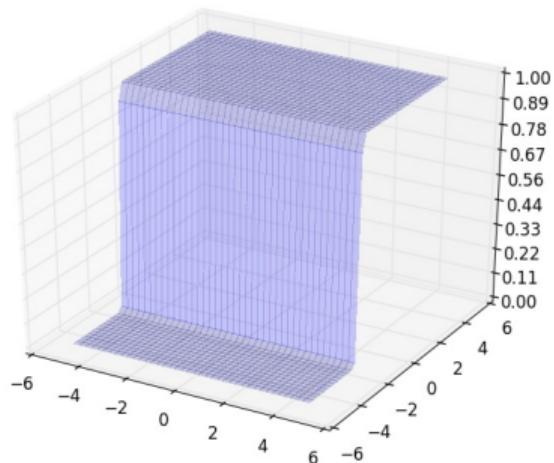
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation
- And now we change b



$$w_1 = 0, w_2 = 25, b = 35$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

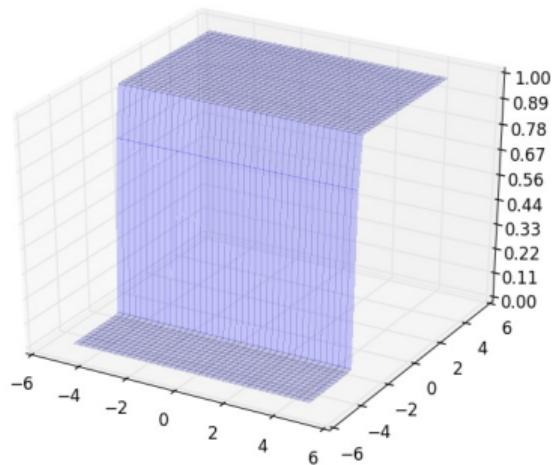
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation
- And now we change b



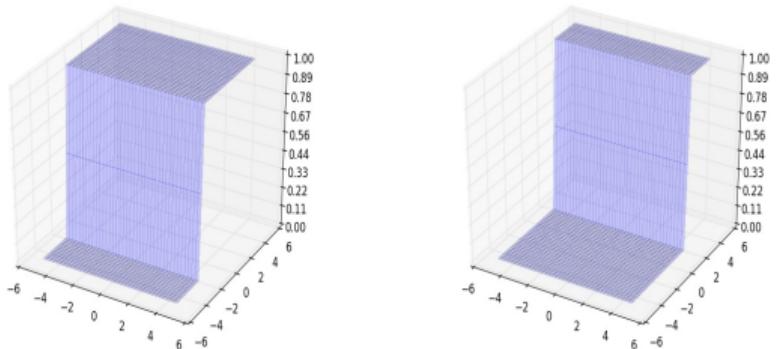
$$w_1 = 0, w_2 = 25, b = 40$$

$$y = \frac{1}{1 + \exp^{-(w_1x_1 + w_2x_2 + b)}}$$

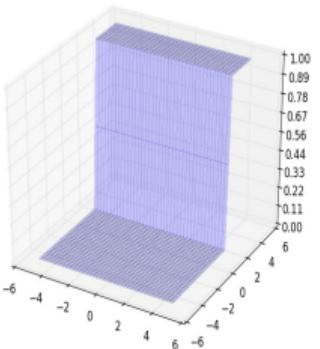
- Now let us set w_1 to 0 and adjust w_2 to get a 2-dimensional step function with a different orientation
- And now we change b

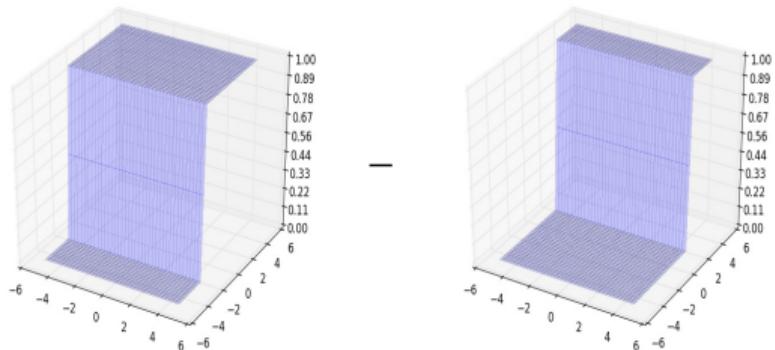


$$w_1 = 0, w_2 = 25, b = 45$$



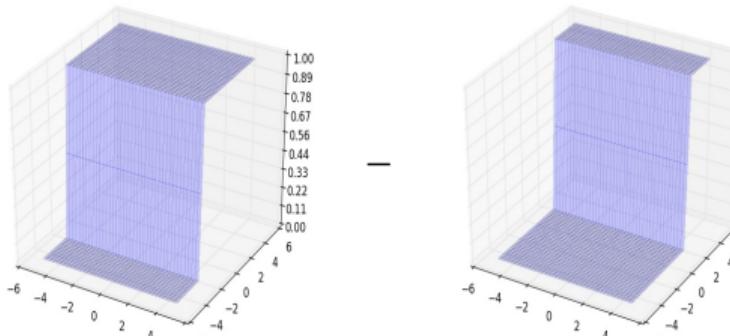
- Again, what if we take two such step functions (with different b values) and subtract one from the other



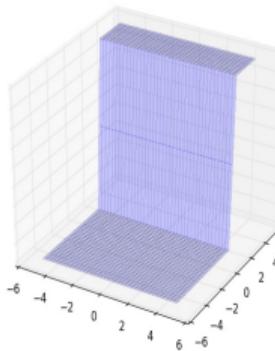


- Again, what if we take two such step functions (with different b values) and subtract one from the other

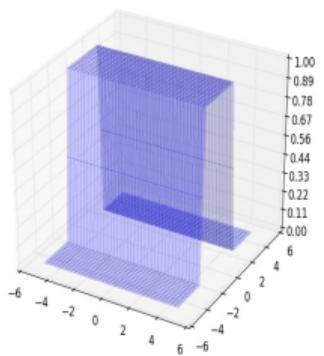
- Again, what if we take two such step functions (with different b values) and subtract one from the other

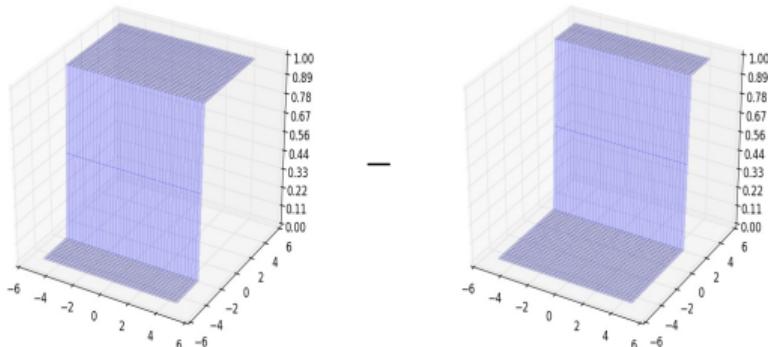


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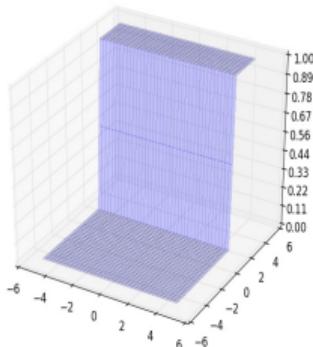


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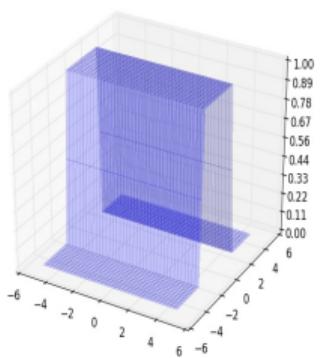




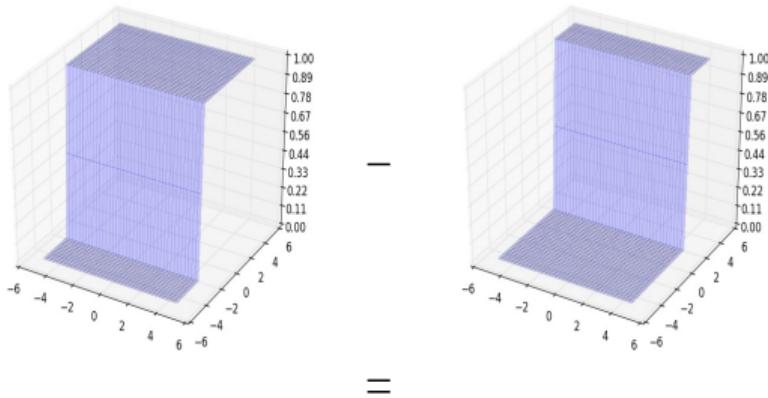
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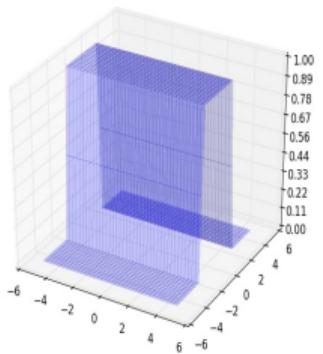
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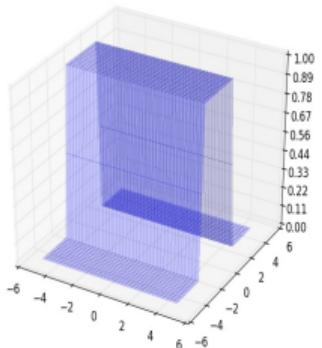
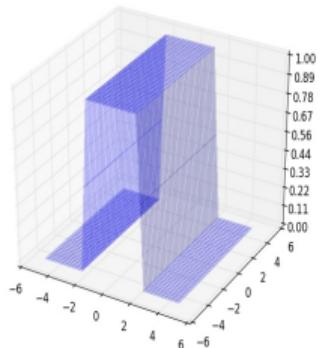
- Again, what if we take two such step functions (with different b values) and subtract one from the other
- We still don't get a tower (or we get a tower which is open from two sides)

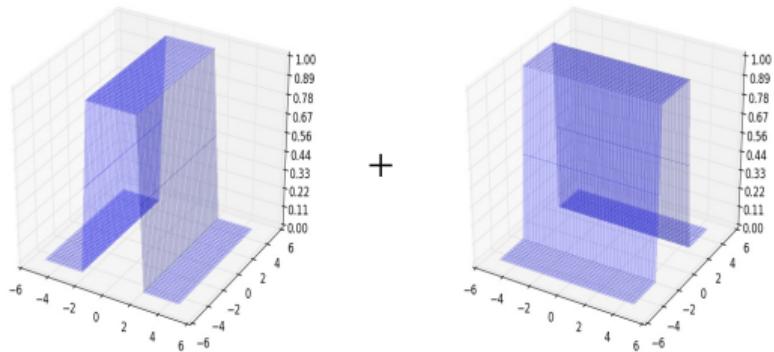


- Again, what if we take two such step functions (with different b values) and subtract one from the other
- We still don't get a tower (or we get a tower which is open from two sides)
- Notice that this open tower has a different orientation from the previous one



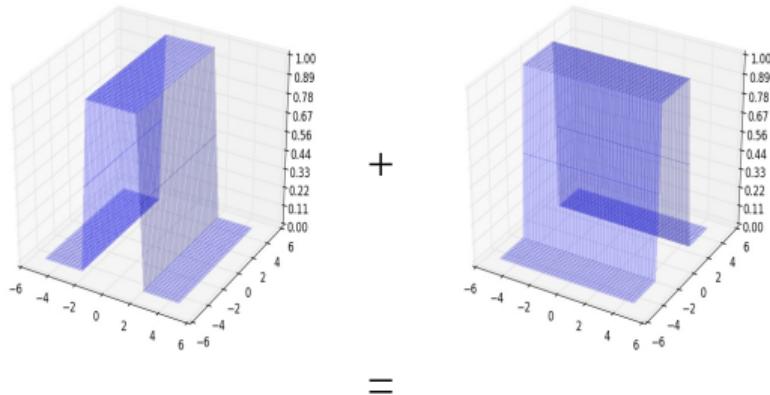
- Now what will we get by adding two such open towers ?





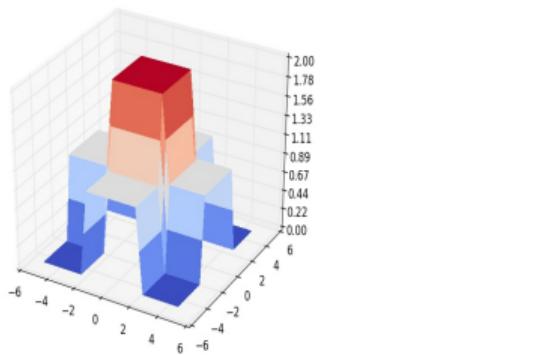
- Now what will we get by adding two such open towers ?

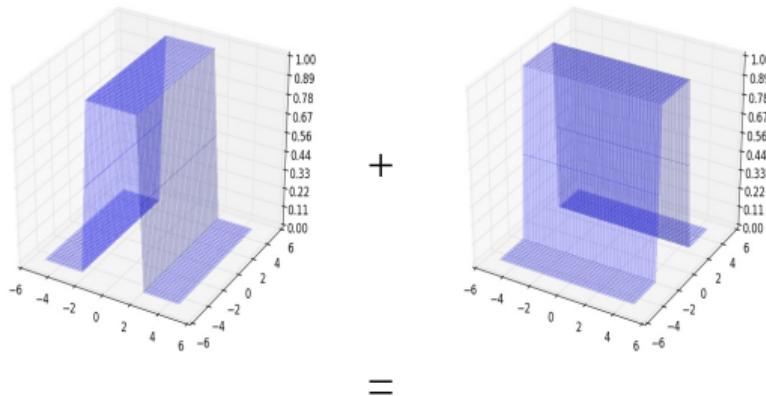
- Now what will we get by adding two such open towers ?



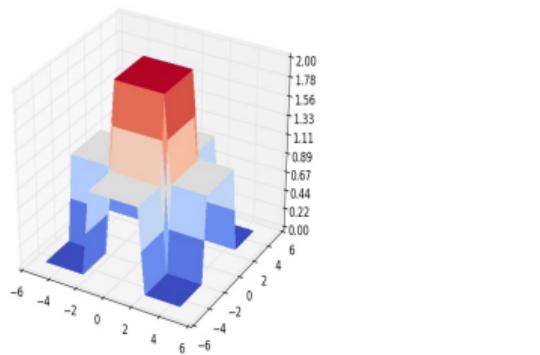
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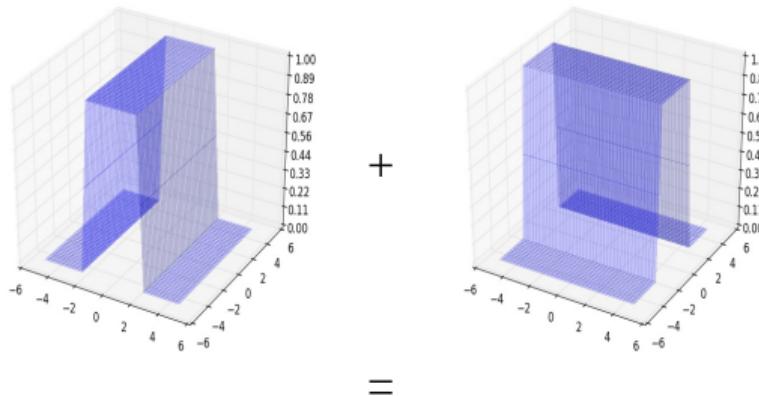
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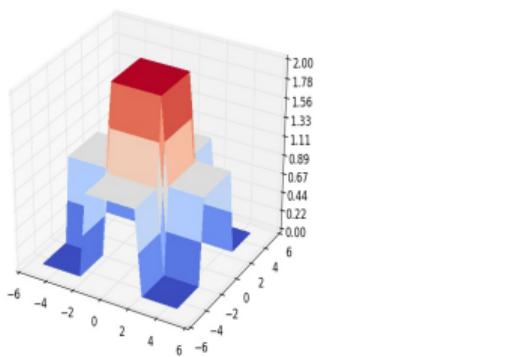


- Now what will we get by adding two such open towers ?
- We get a tower standing on an elevated base

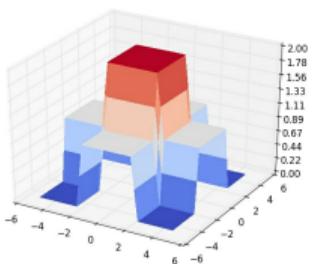
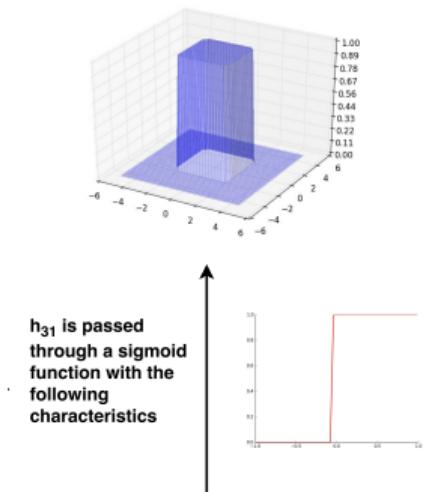




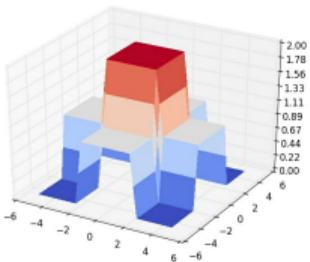
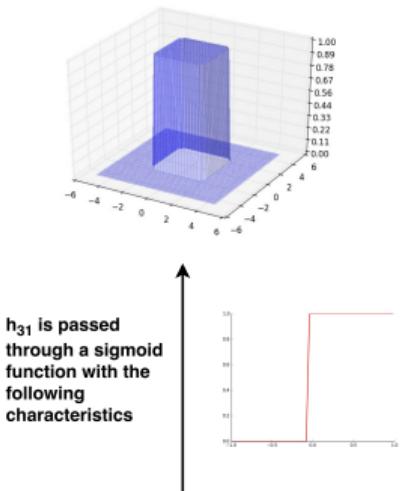
- Now what will we get by adding two such open towers ?
- We get a tower standing on an elevated base
- We can now pass this output through another sigmoid neuron to get the desired tower !



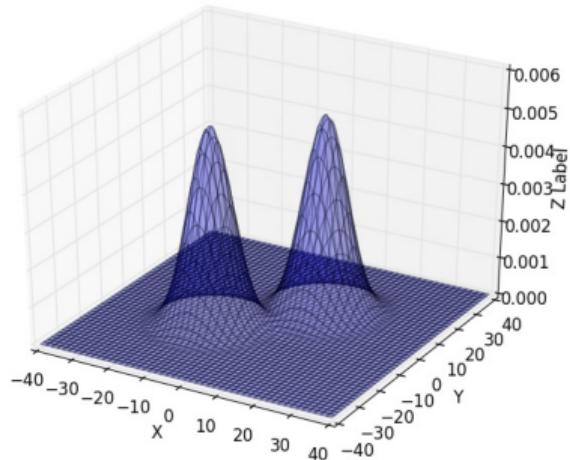
- Now what will we get by adding two such open towers ?
- We get a tower standing on an elevated base
- We can now pass this output through another sigmoid neuron to get the desired tower !



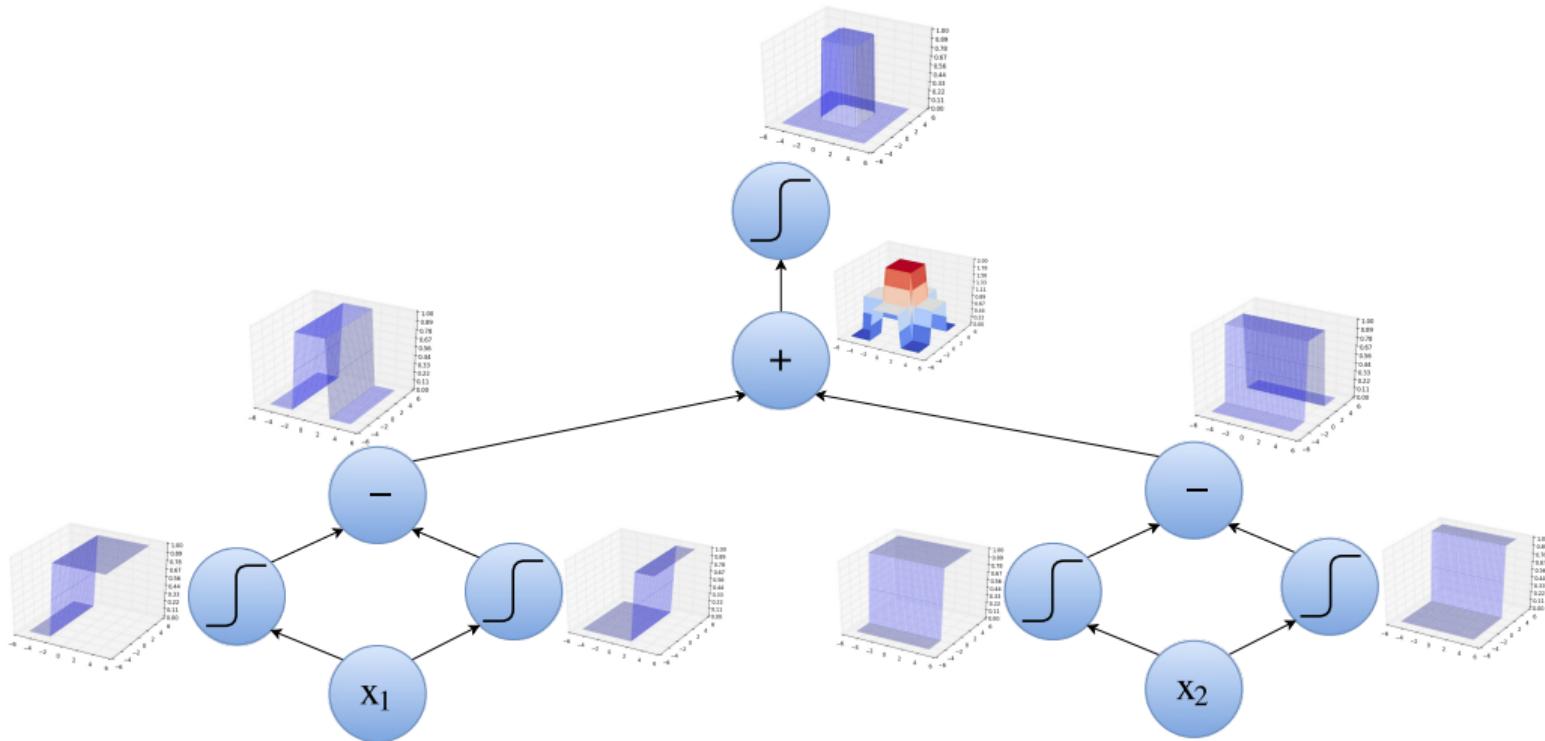
- Now what will we get by adding two such open towers ?
- We get a tower standing on an elevated base
- We can now pass this output through another sigmoid neuron to get the desired tower !
- We can now approximate any function by summing up many such towers

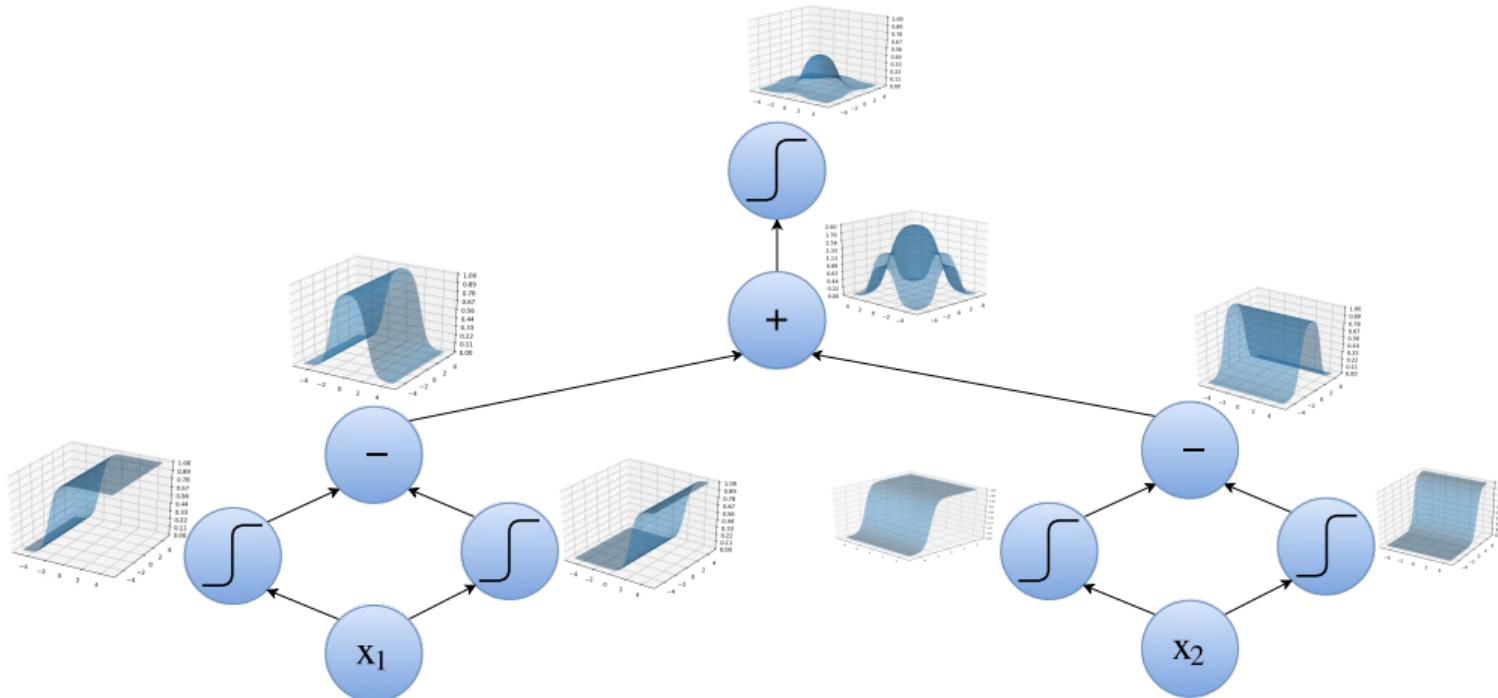


- For example, we could approximate the following function using a sum of several towers



- Can we come up with a neural network to represent this entire procedure of constructing a 3 dimensional tower ?



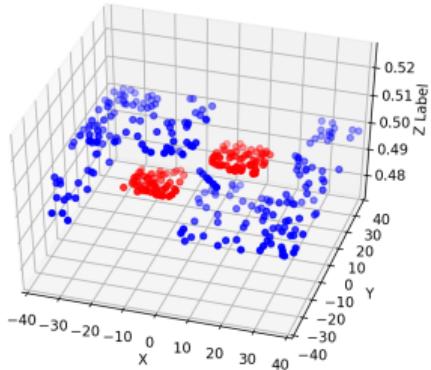


Think

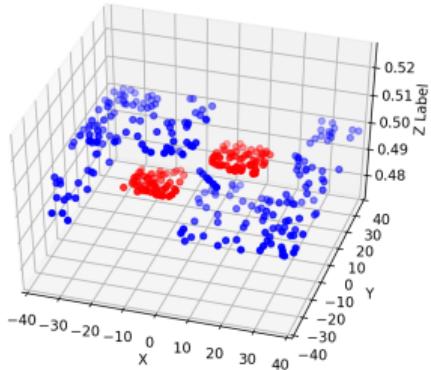
- For 1 dimensional input we needed 2 neurons to construct a tower
- For 2 dimensional input we needed 4 neurons to construct a tower
- How many neurons will you need to construct a tower in n dimensions ?

Time to retrospect

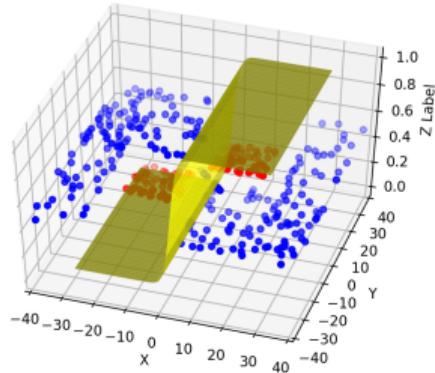
- Why do we care about approximating any arbitrary function ?
- Can we tie all this back to the classification problem that we have been dealing with ?



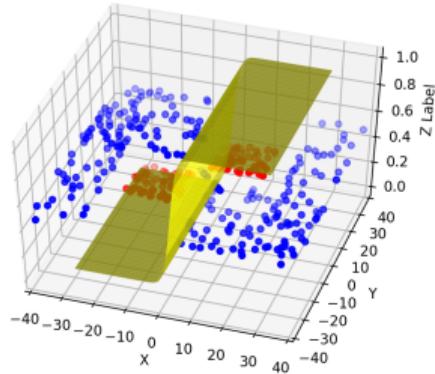
- We are interested in separating the blue points from the red points



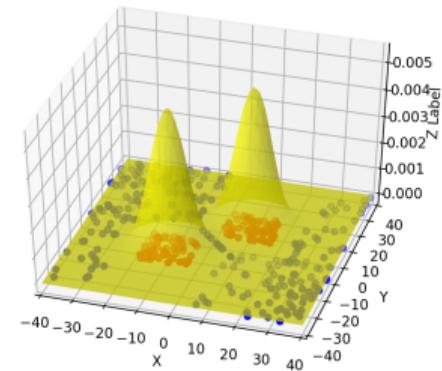
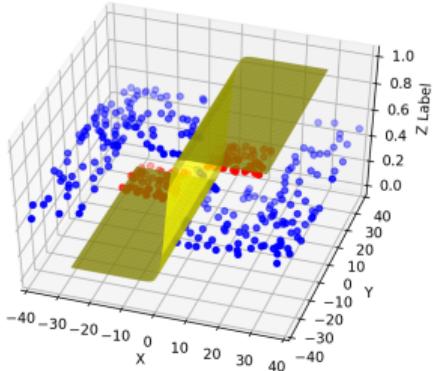
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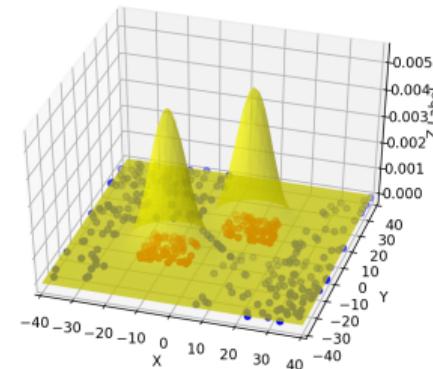
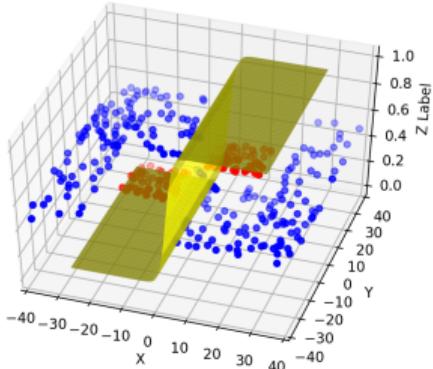
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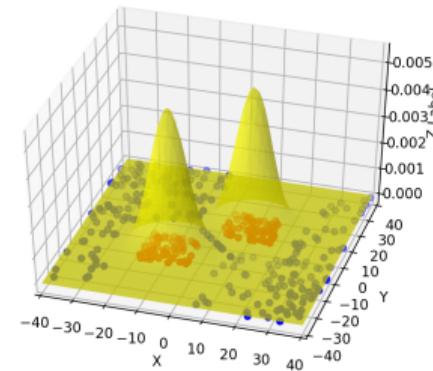
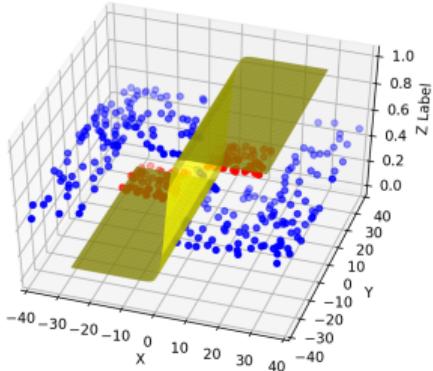


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- This is what we actually want
- The illustrative proof that we just saw tells us that we can have a neural network with two hidden layers which can approximate the above function by a sum of towers
- Which means we can have a neural network which can exactly separate the blue points from the red points !!