When we look at stock prices, they tend to change over time.

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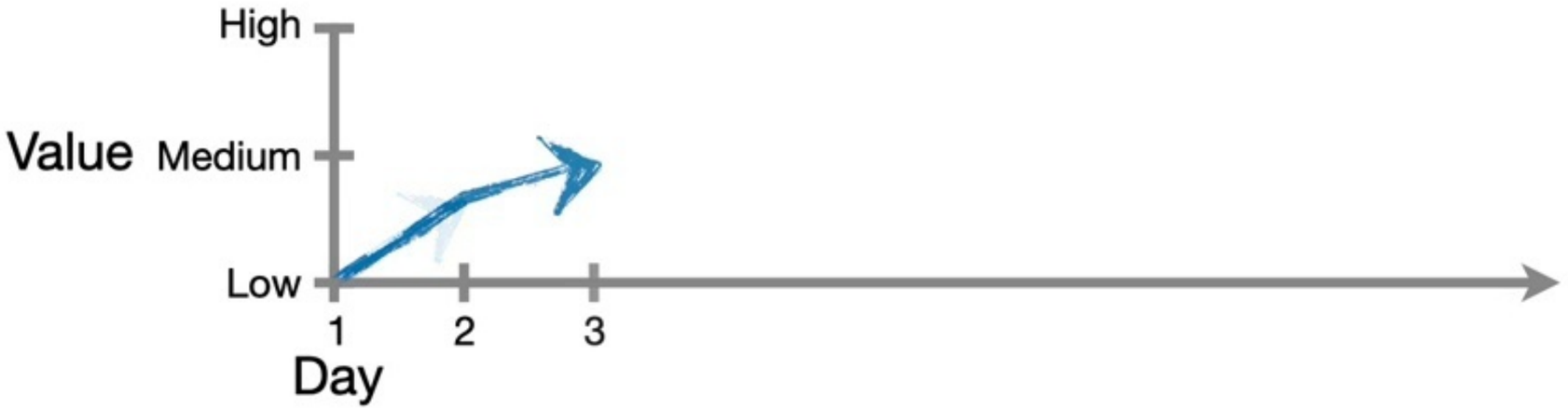

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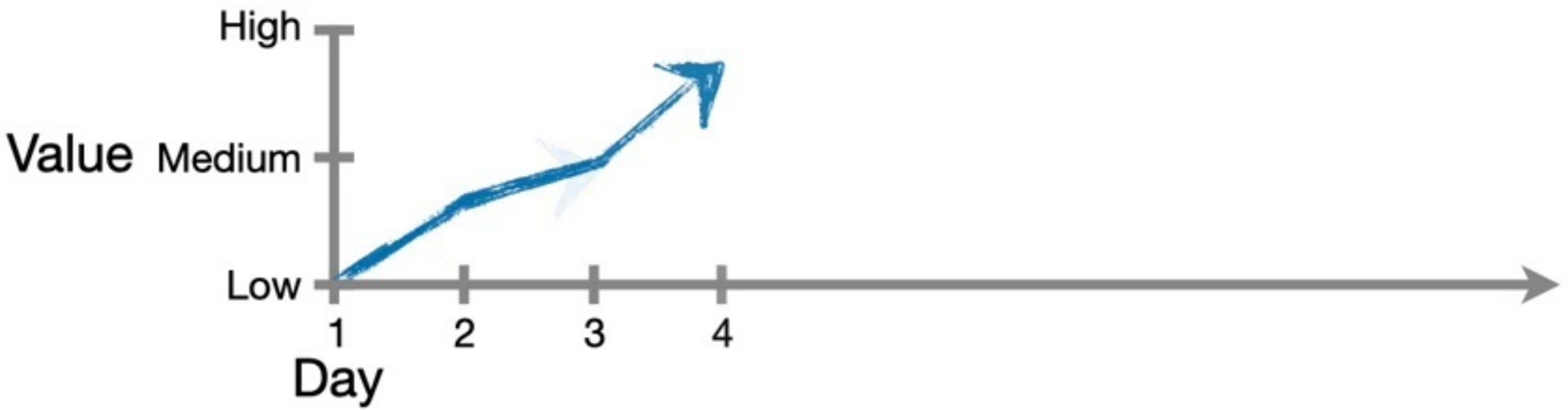

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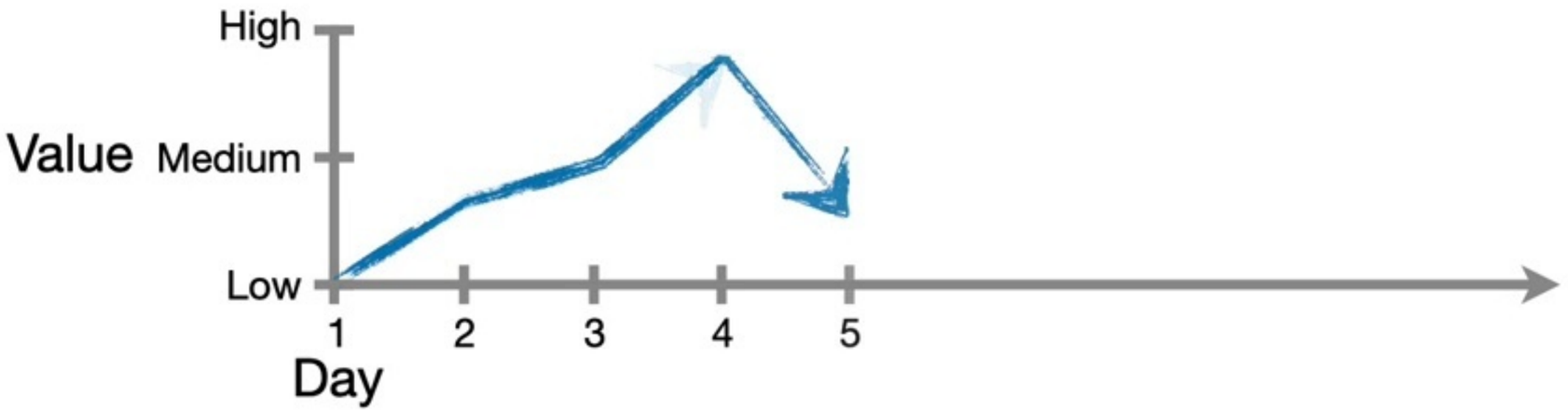
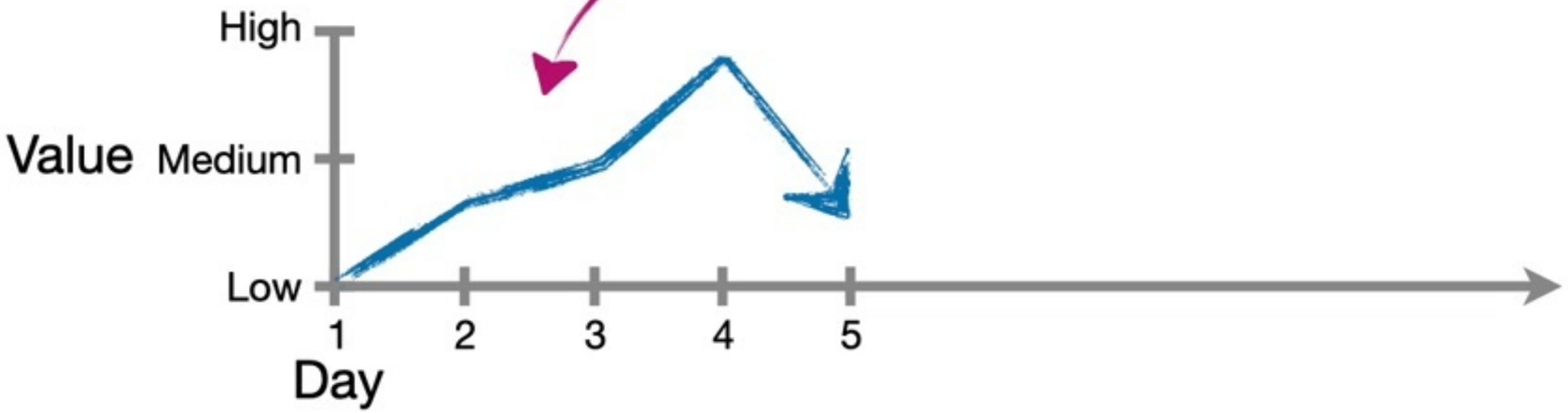


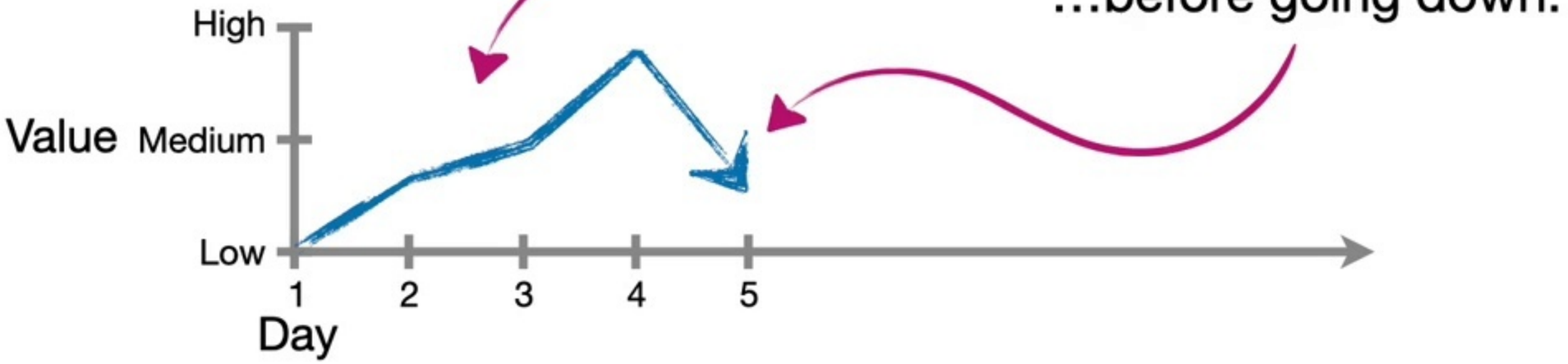
For example, the price of this stock went up for **4** days…

Hooray!

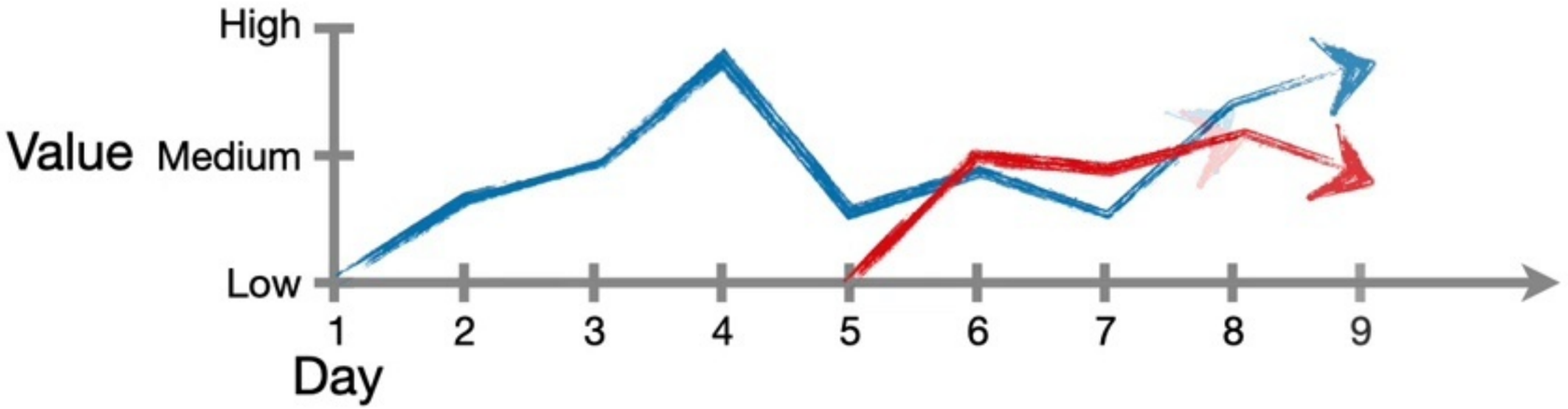


For example, the price of this stock went up for **4** days…

…before going down.

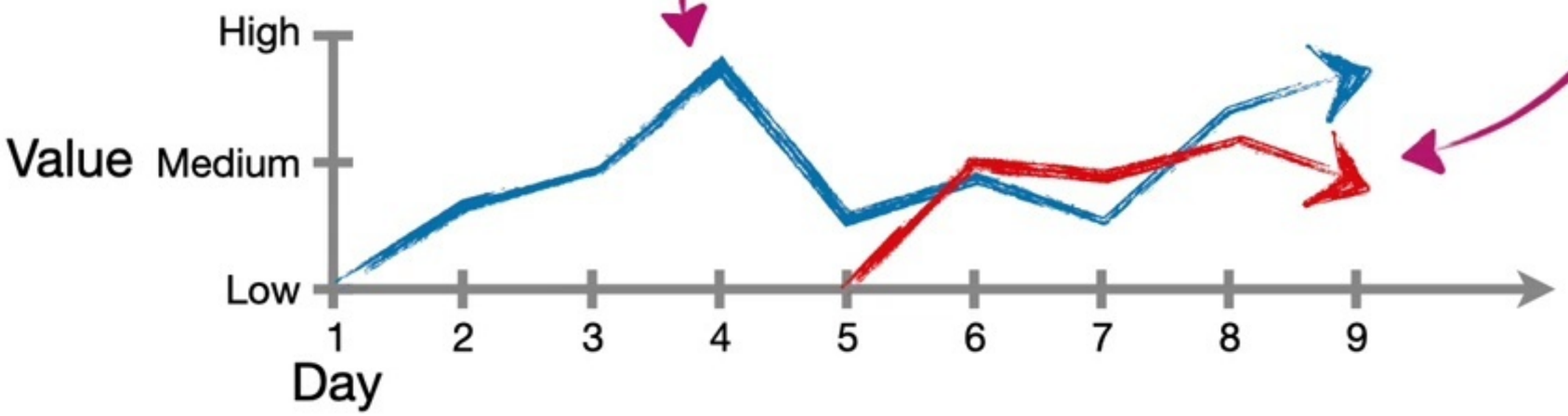


Also, the longer a company has been traded on the stock market, the more data we'll have for it.

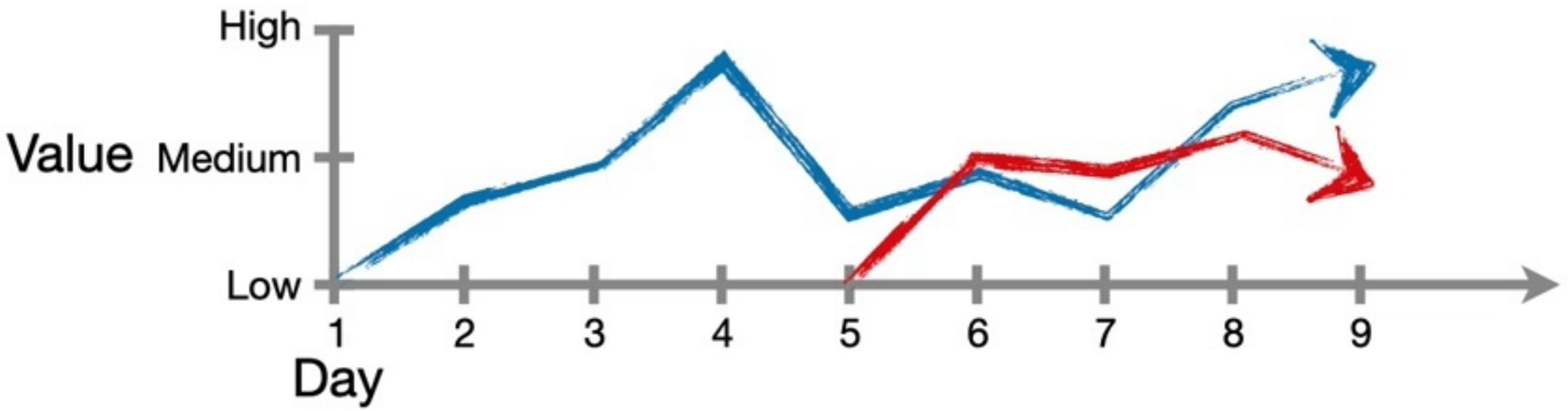


For example, we have more time points for the company represented by the **blue line**…

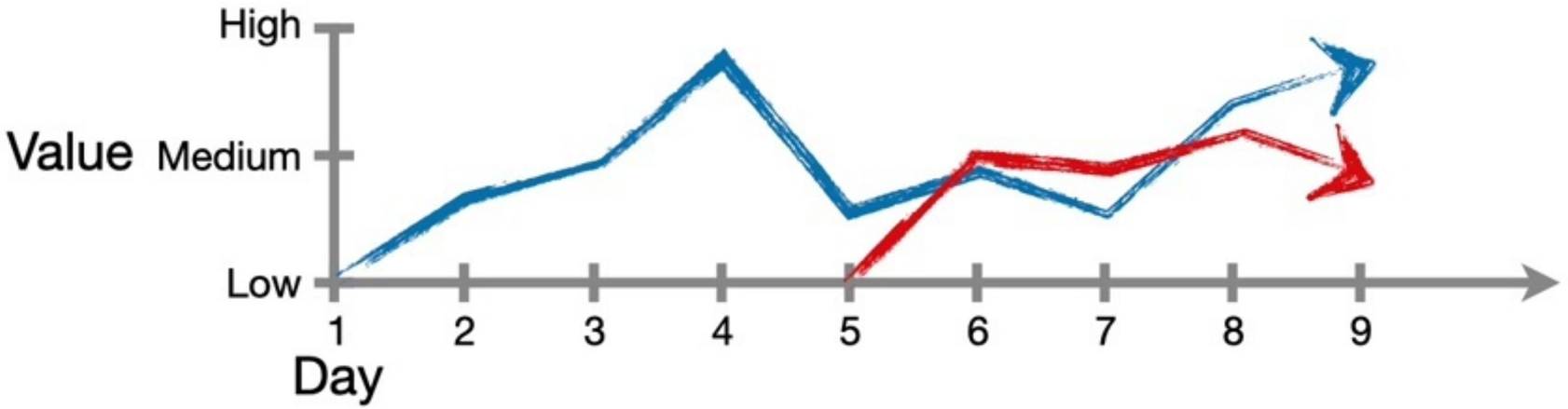
…then we have for the company represented by the **red line**.



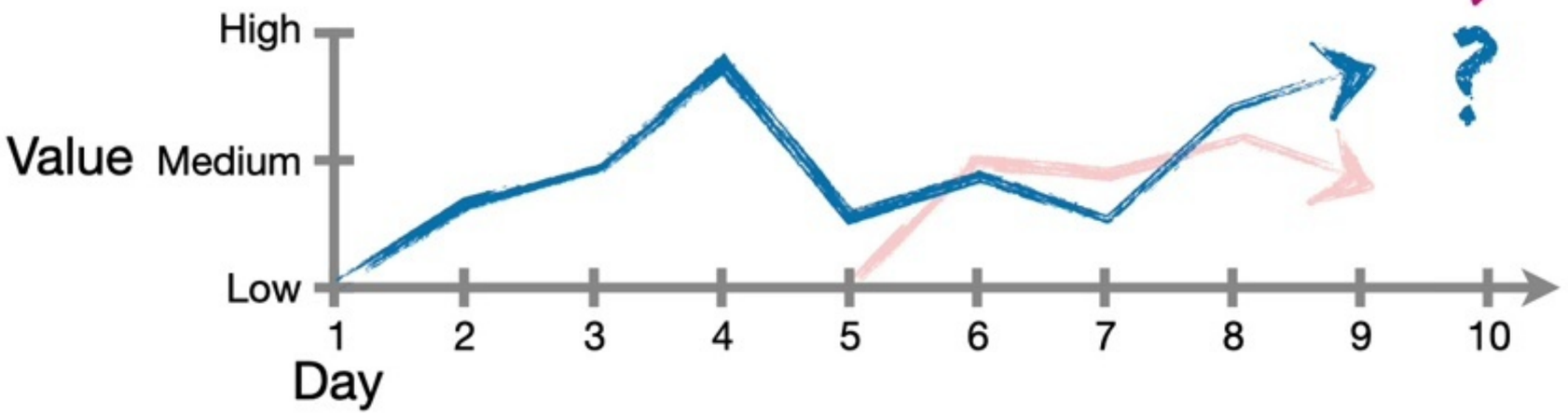
What this means is, if we
want to use a neural network
to predict stock prices…

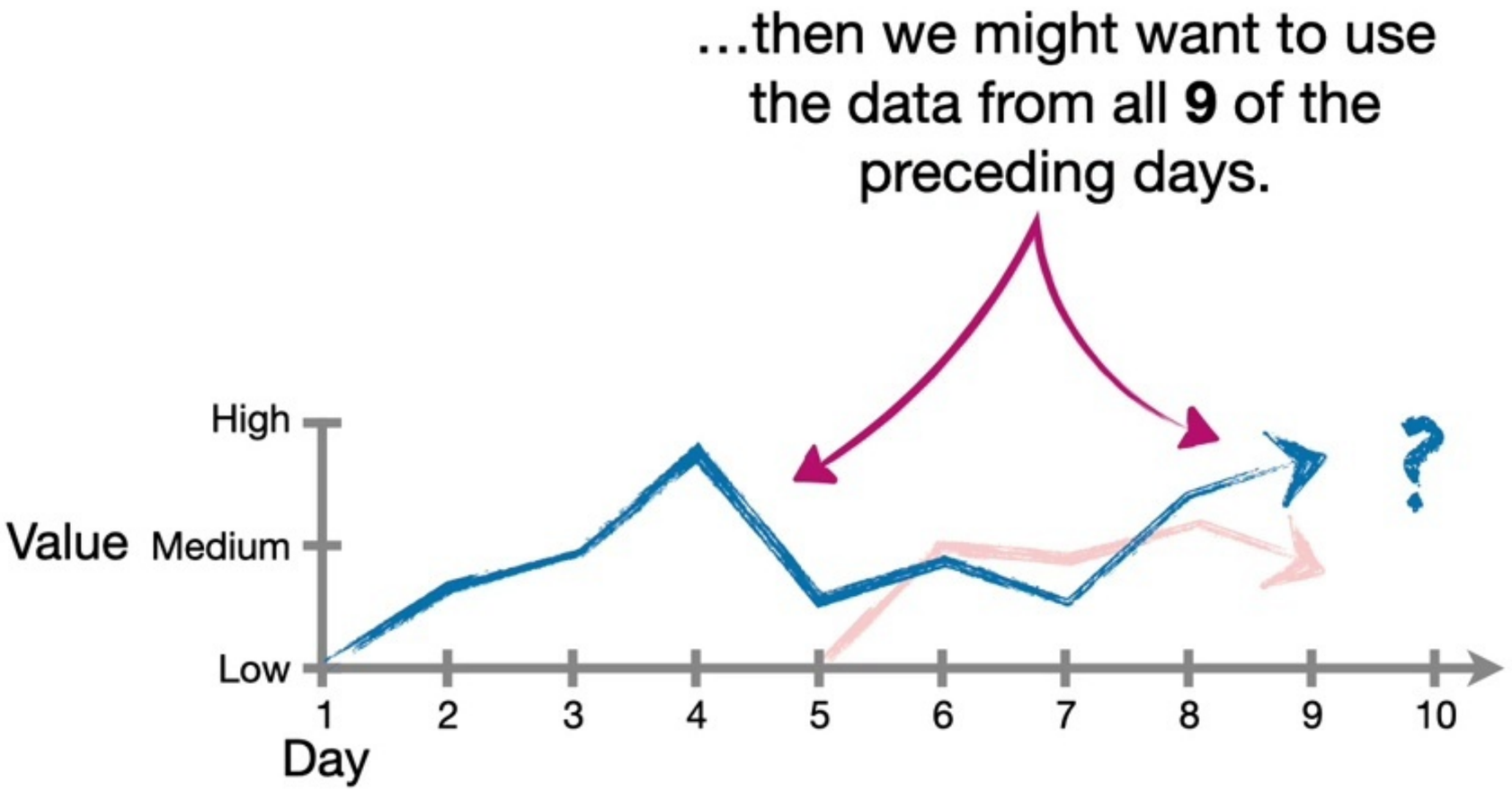


…then we need a neural network that works with different amounts of sequential data.

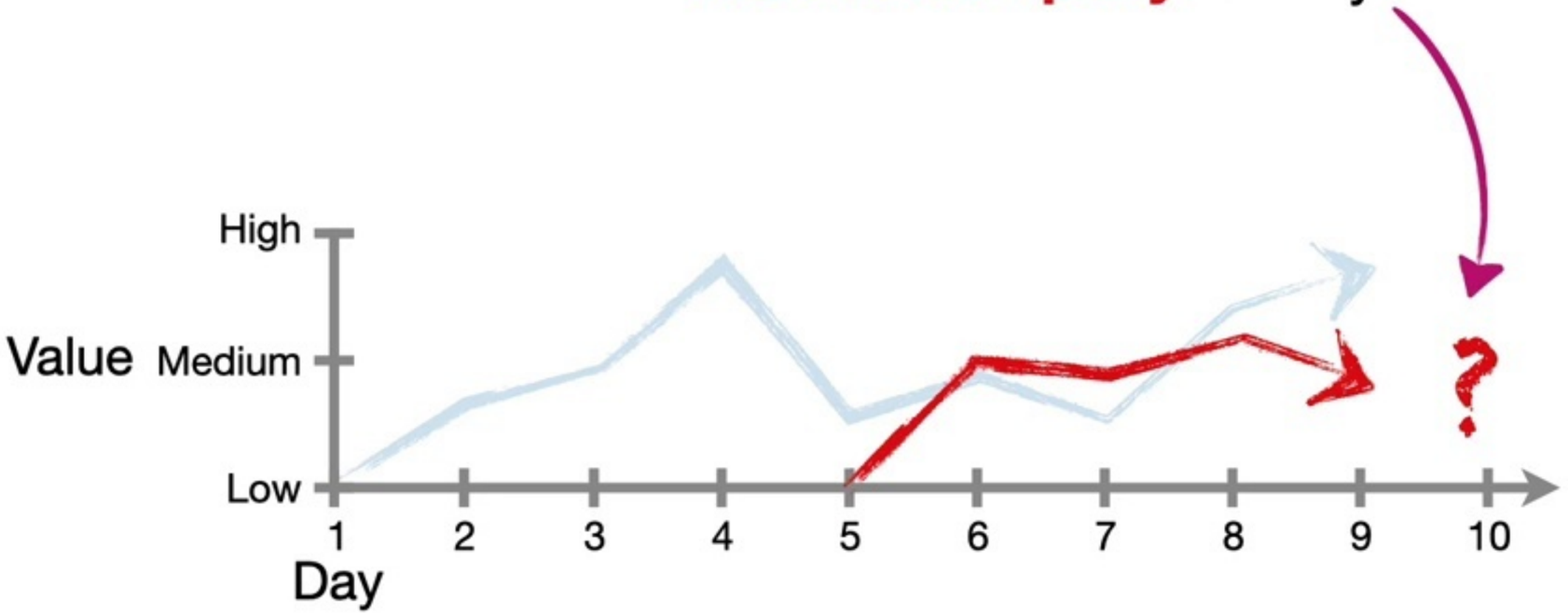


In other words, if we want to predict the stock price for the **blue line company** on day **10**…

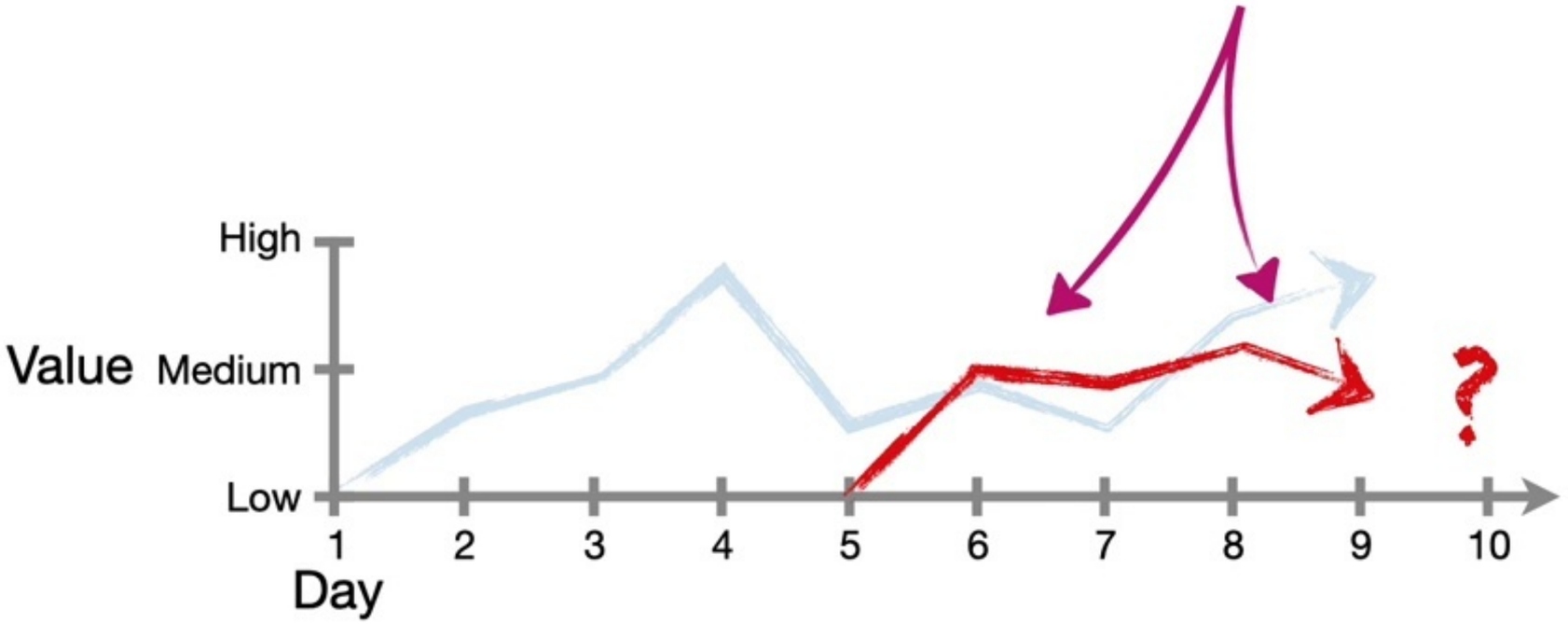



…then we might want to use the data from all 9 of the preceding days.
High
Value
Medium
Low
1
2
3
4
5
6
7
8
9
10
Day
?

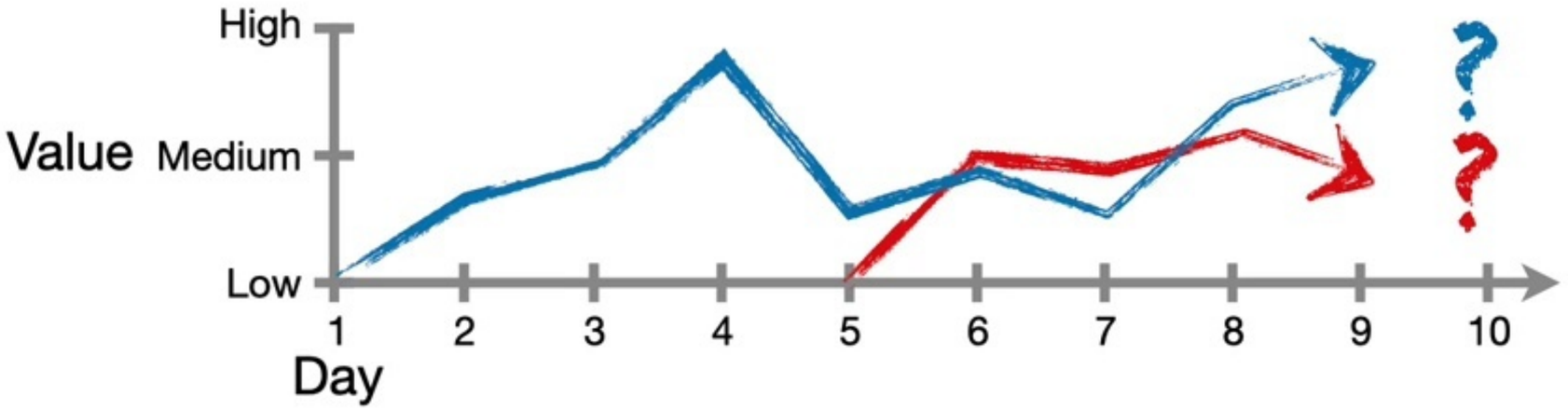
In contrast, if we wanted to predict the stock price for the **red line company** on day **10**…



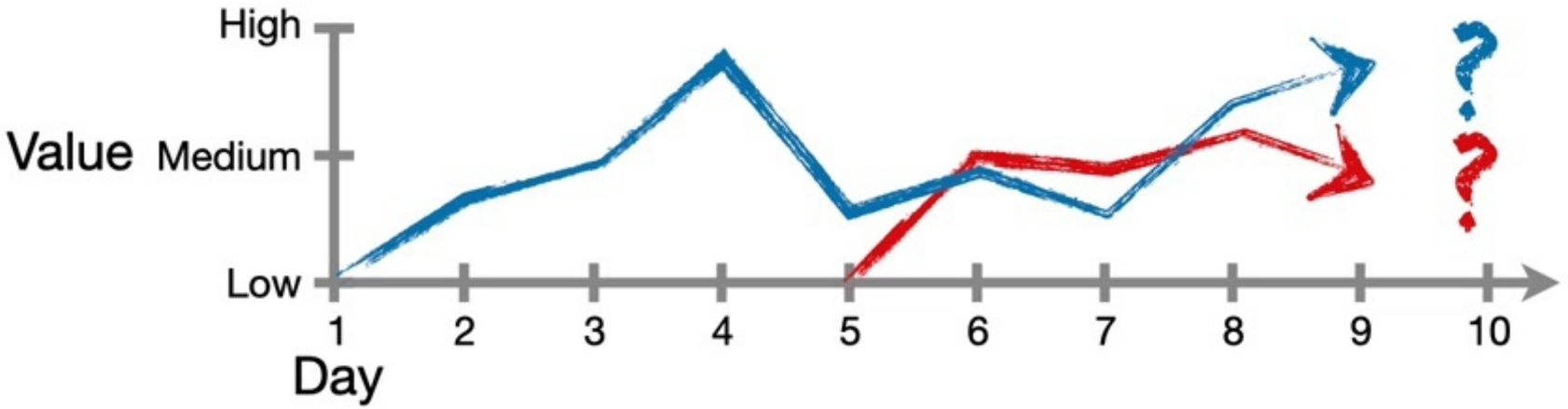
…then we would only have data for the preceding **5** days.



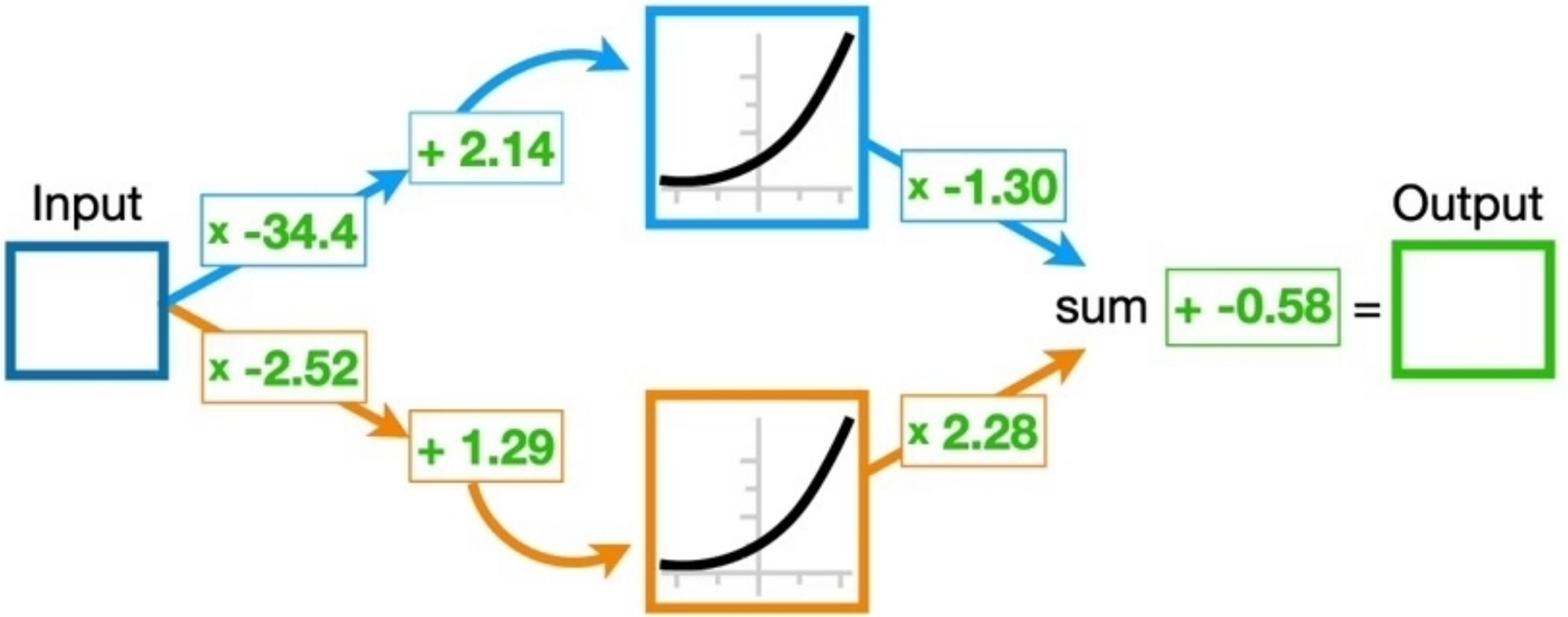
So we need the neural network
to be flexible in terms of how
much sequential data we use
to make a prediction.



This is a big difference compared
to the other neural networks
we've looked at in this series.



For example, in **Neural Networks Clearly Explained**, we examined a neural network that made predictions using **1** input value, no more and no less.



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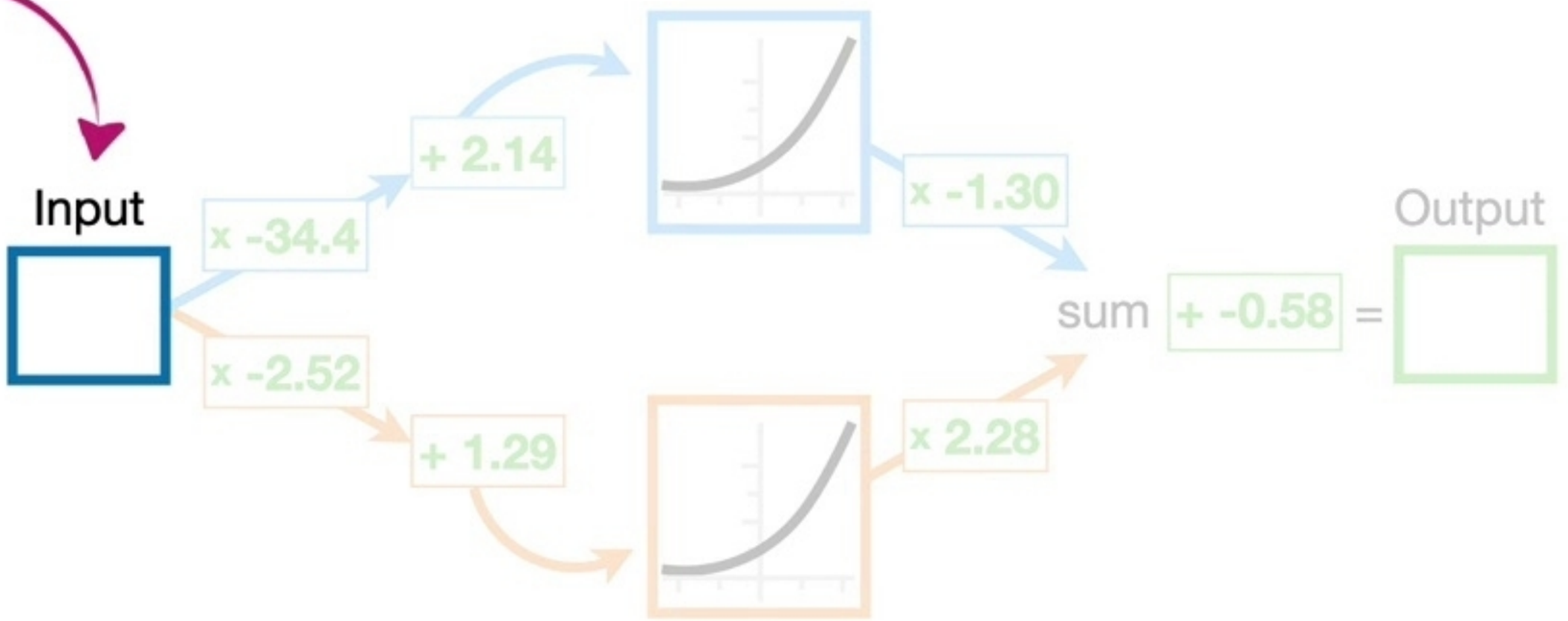
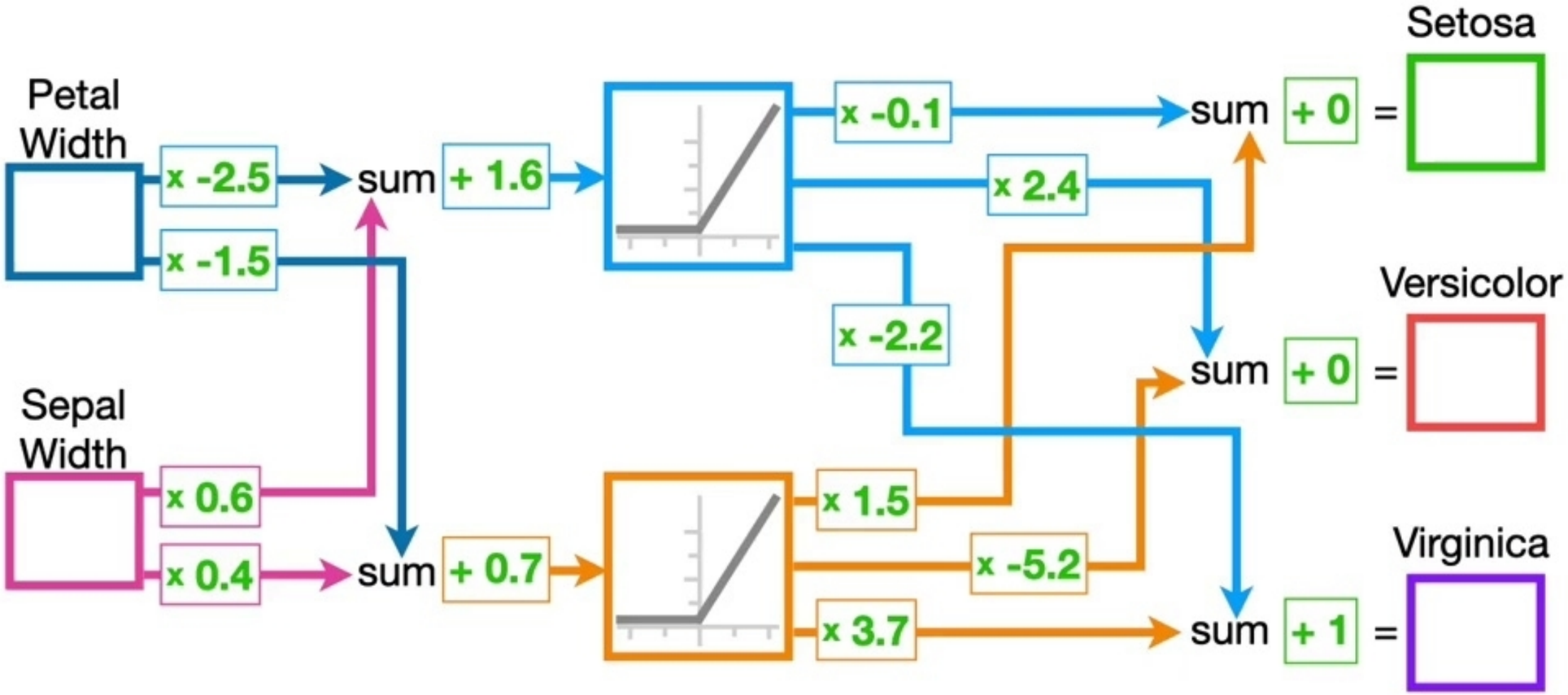


And if you saw the **StatQuest** on **Neural Networks with Multiple Inputs and Outputs**, you saw this neural network that made predictions using **2** input values, no more and no less.



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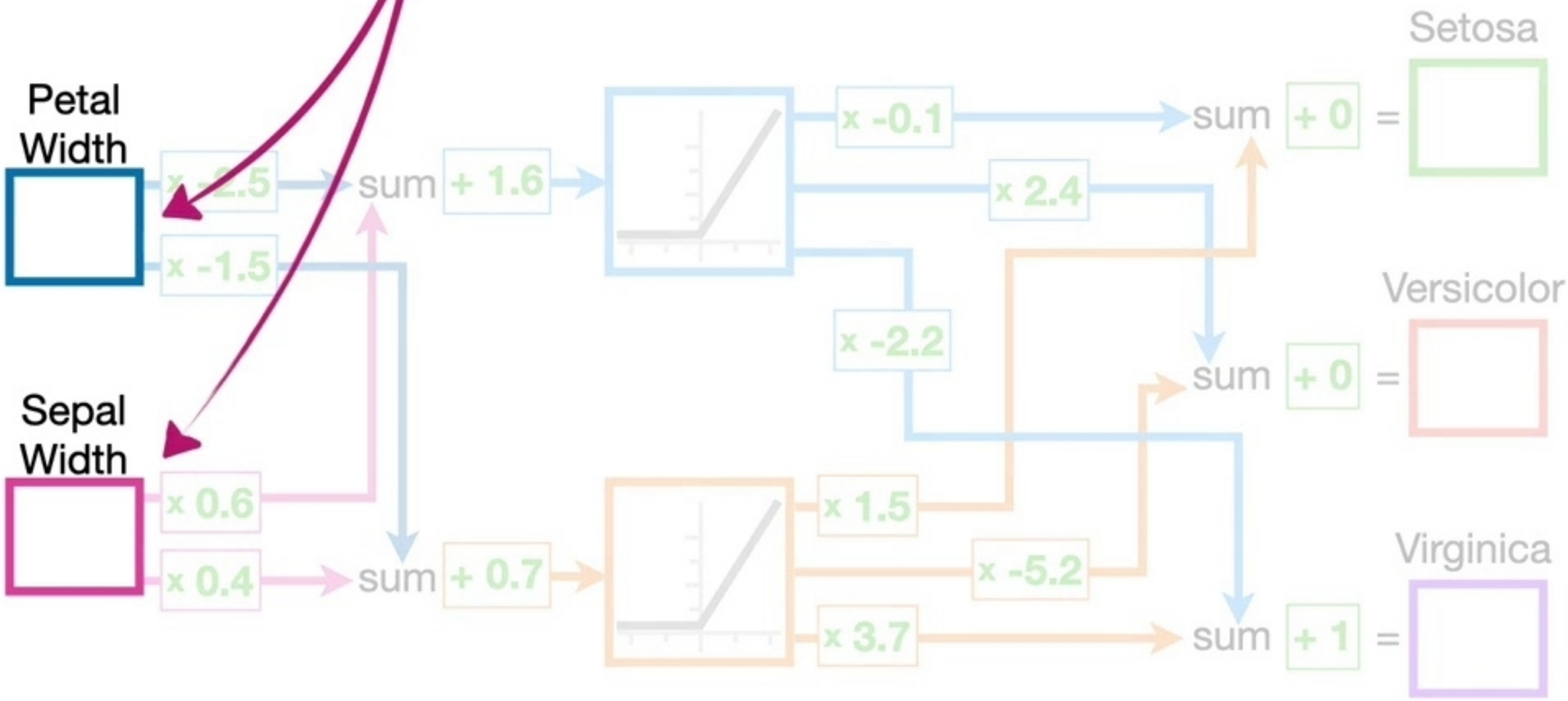
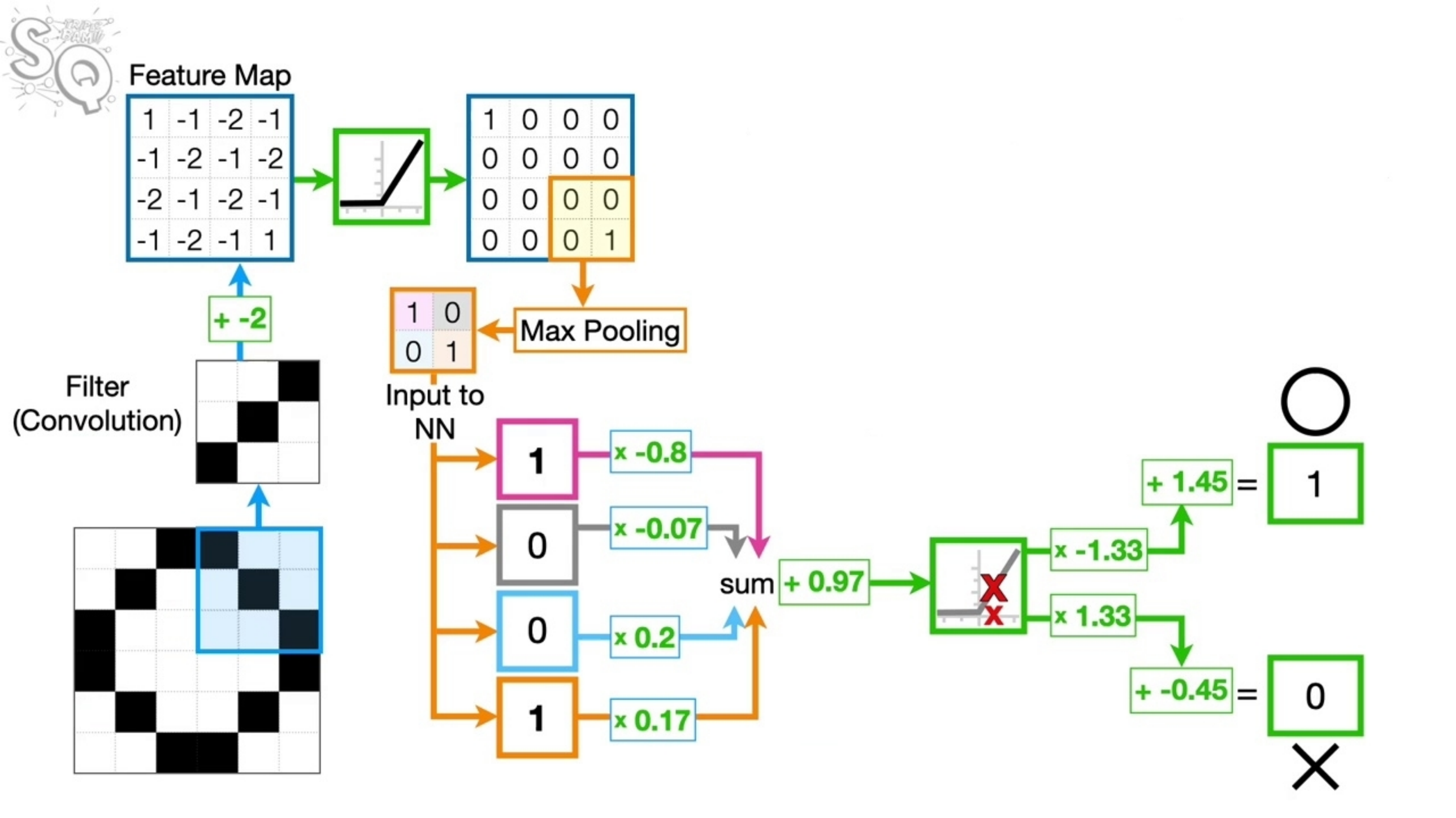
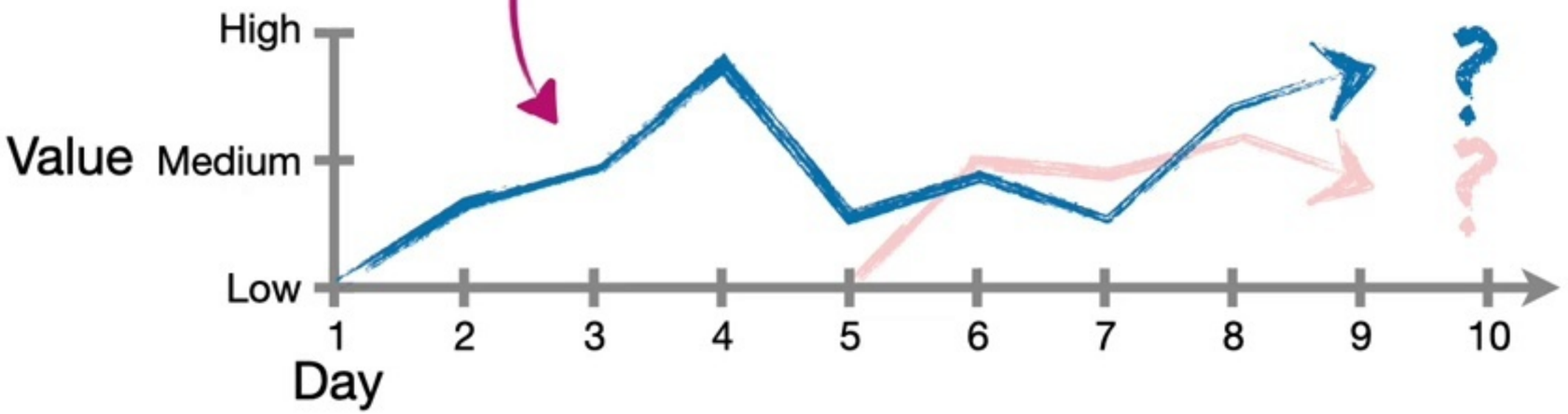
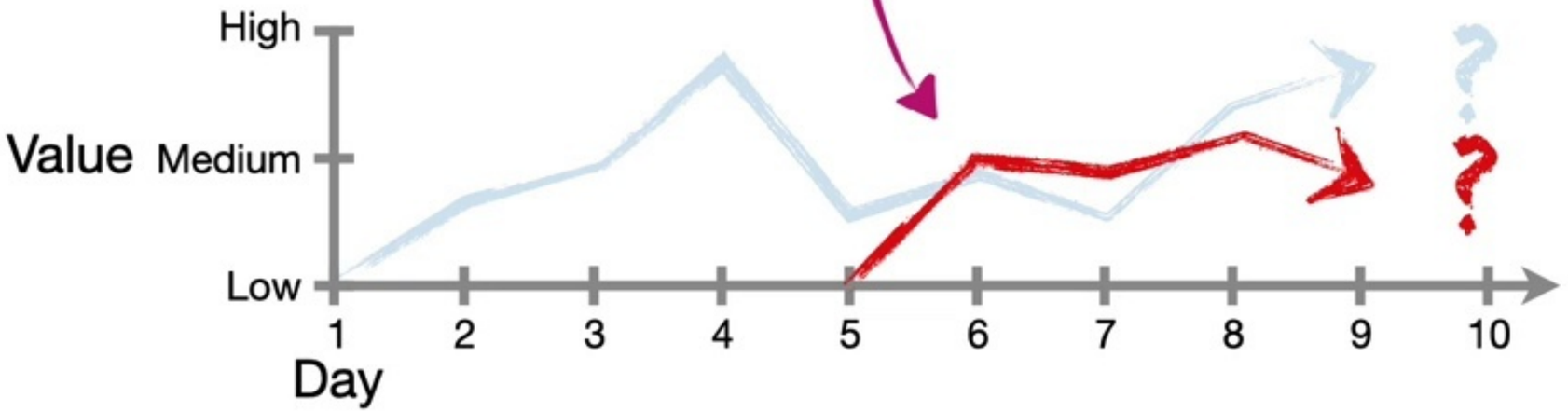



Feature Map
1 -1 -2 -1
-1 -2 -1 -2
-2 -1 -2 -1
-1 -2 -1 1
1 0 0 0
0 0 0 0
0 0 0 0
0 0 0 1
Max Pooling
1 0
0 1
Input to NN
+ -2
Filter (Convolution)
1
0
0
1
x -0.8
x -0.07
x 0.2
x 0.17
sum
+ 0.97
x -1.33
x 1.33
+ 1.45 =
+ -0.45 =
1
0

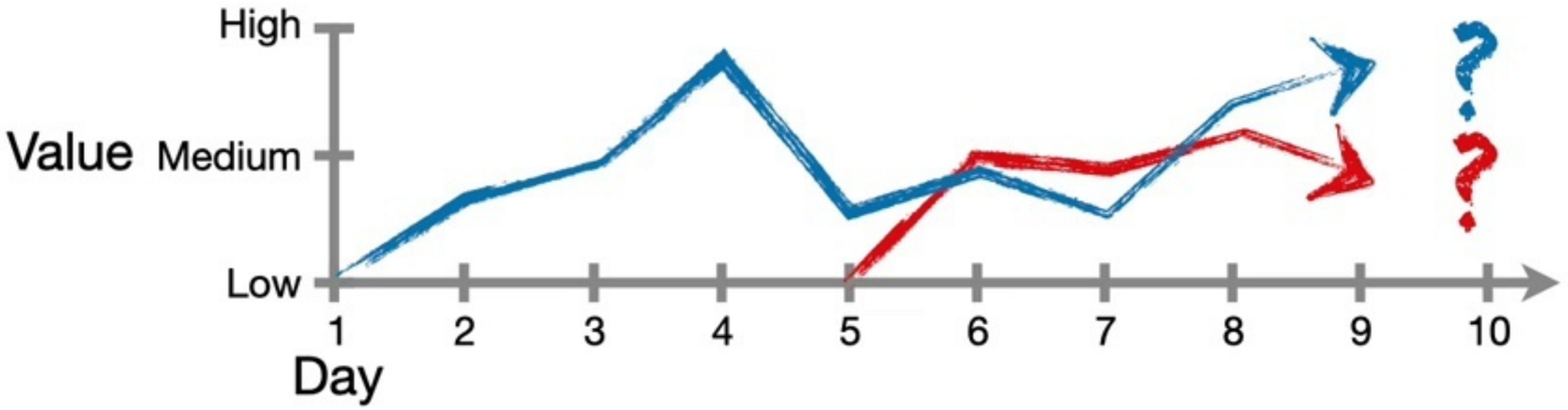
However, now we need a neural network that can make a prediction using the **9** values we have for the **blue company**…



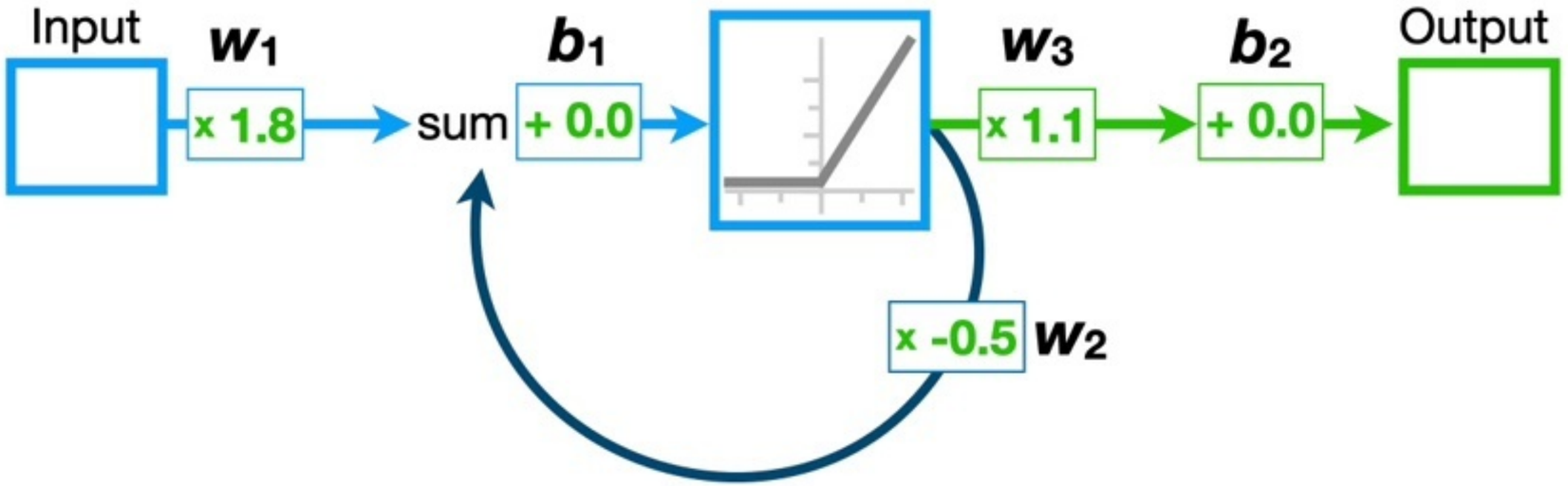
…and make a prediction using the **5** values we have for the **red company**.



The good news is that one way to deal with the problem of having different amounts of input values is to use a **Recurrent Neural Network (RNN)**.



Just like the other neural networks that we've seen before, **Recurrent Neural Networks** have **weights**, **biases**,



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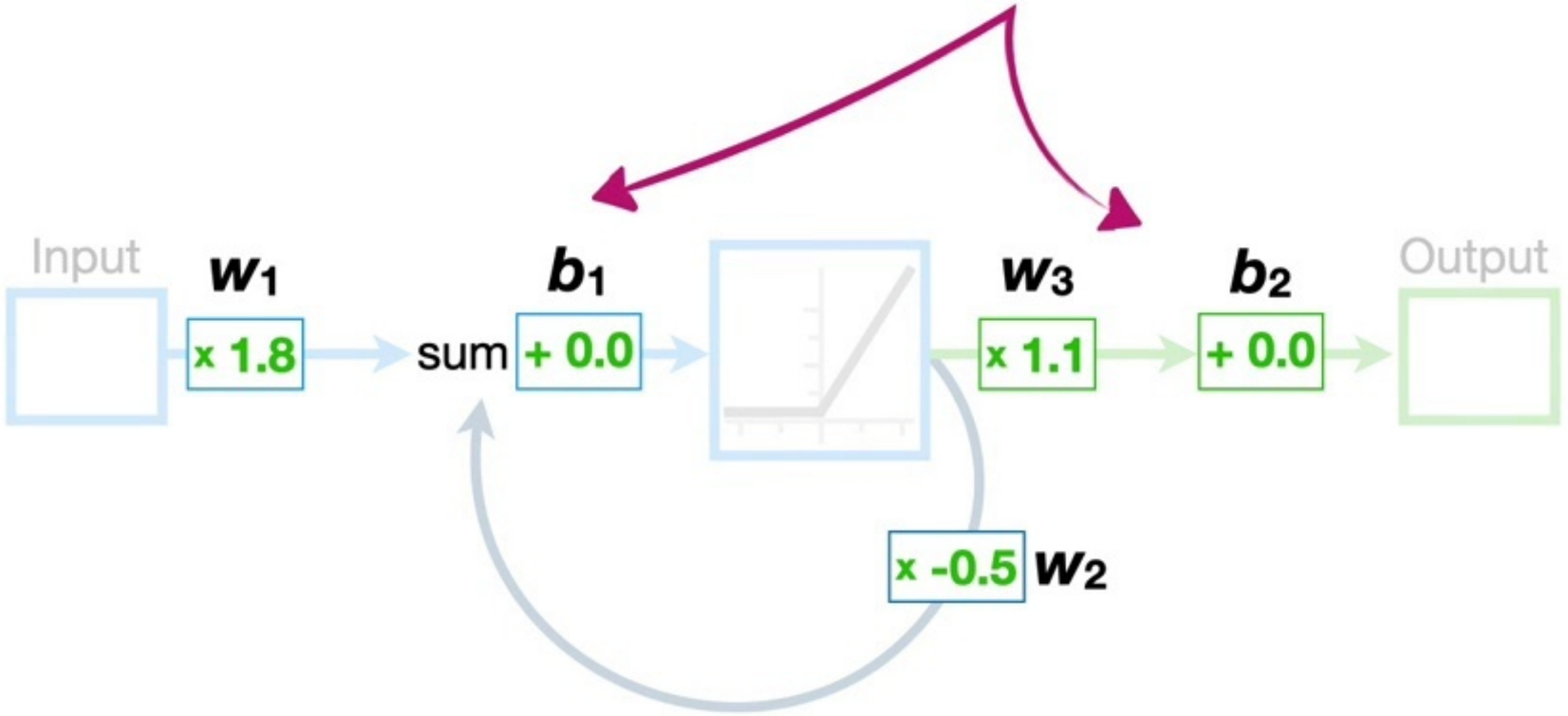
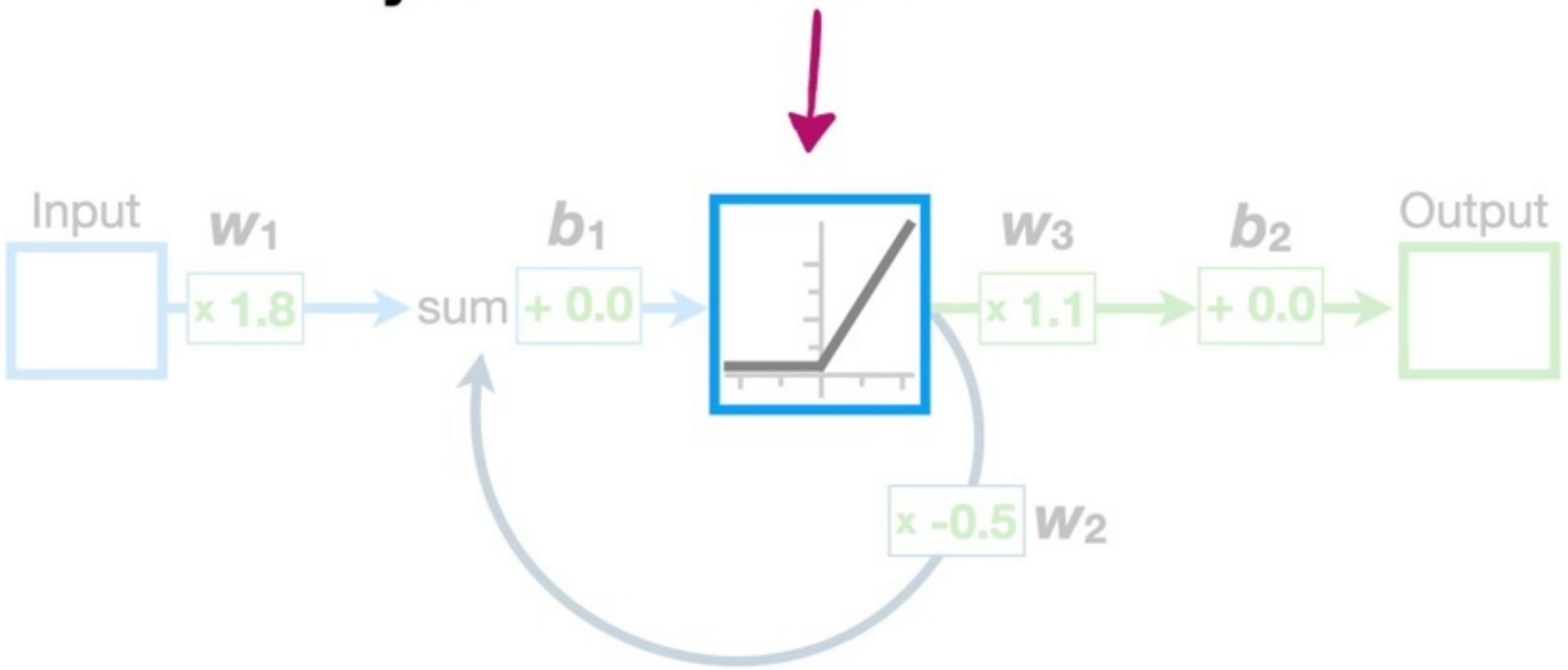
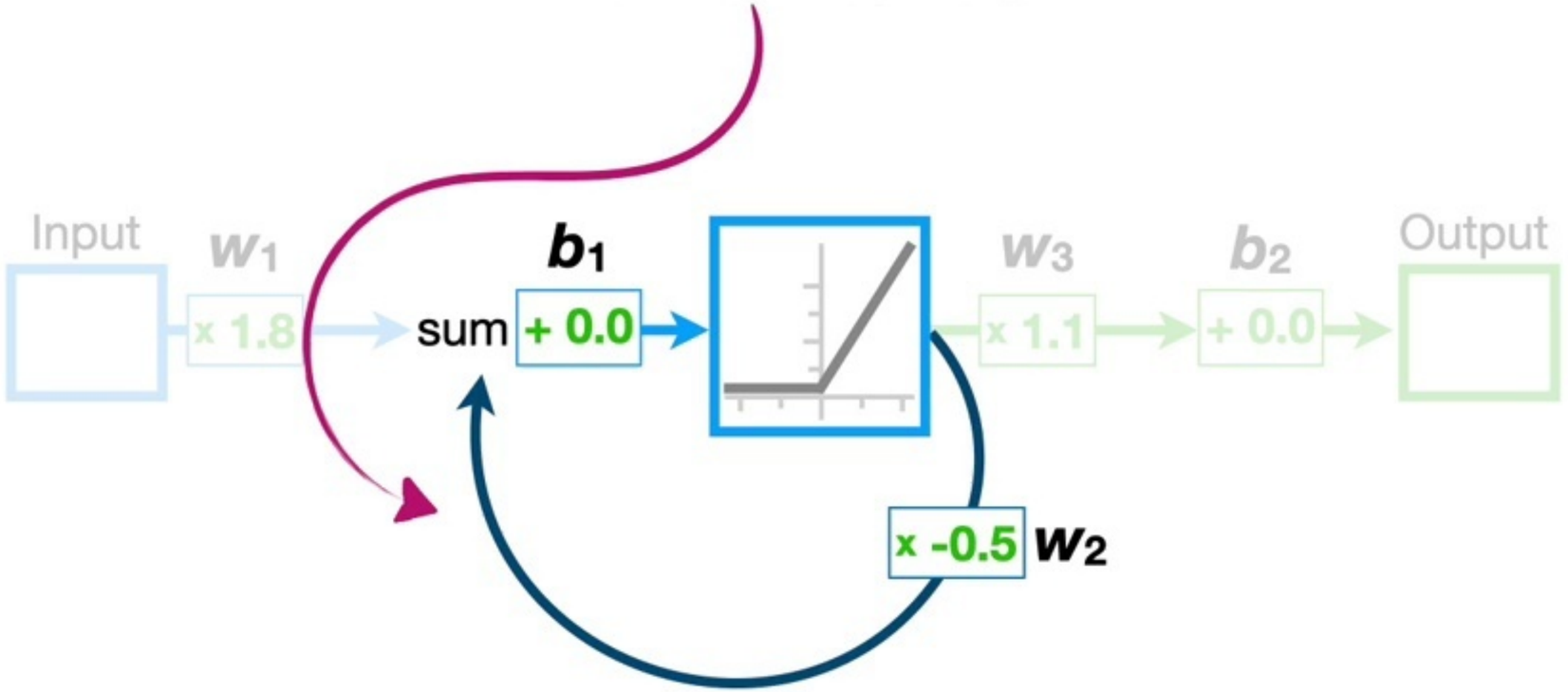


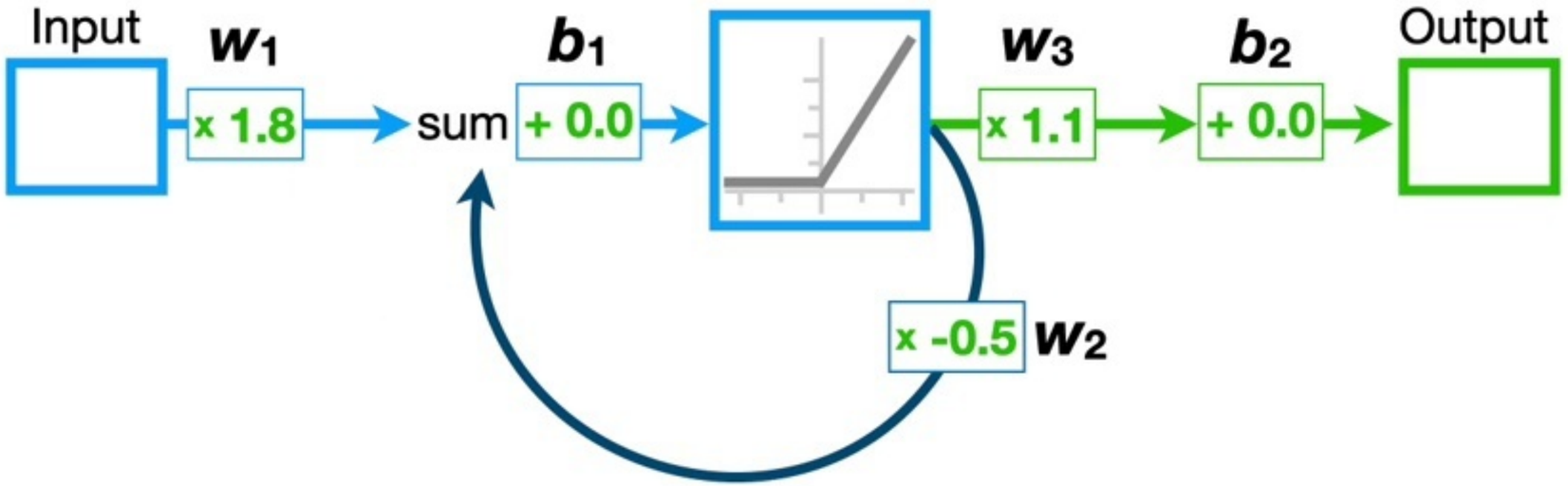
Just like the other neural networks that we've seen before, **Recurrent Neural Networks** have **weights**, **biases**, **layers** and **activation functions**.



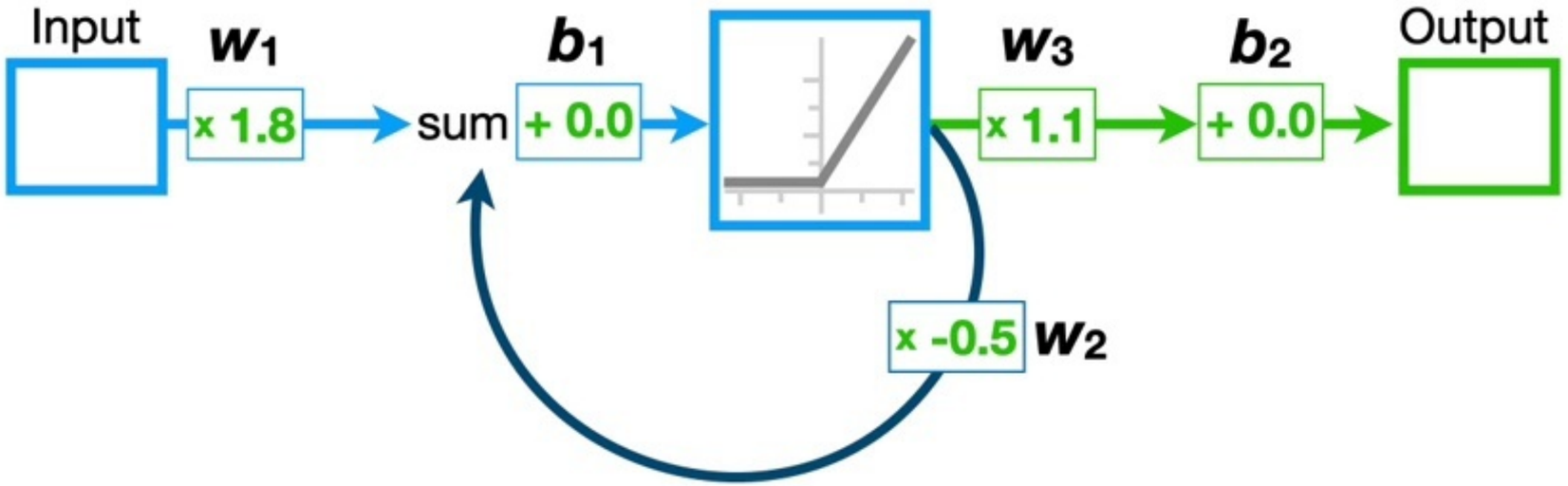
The big difference is that
Recurrent Neural Networks also
have **feedback loops.**



And, although this neural network may look like it only takes a single input value…



…the **feedback loop** makes it possible to use *sequential* input values, like stock market prices collected over time, to make predictions.



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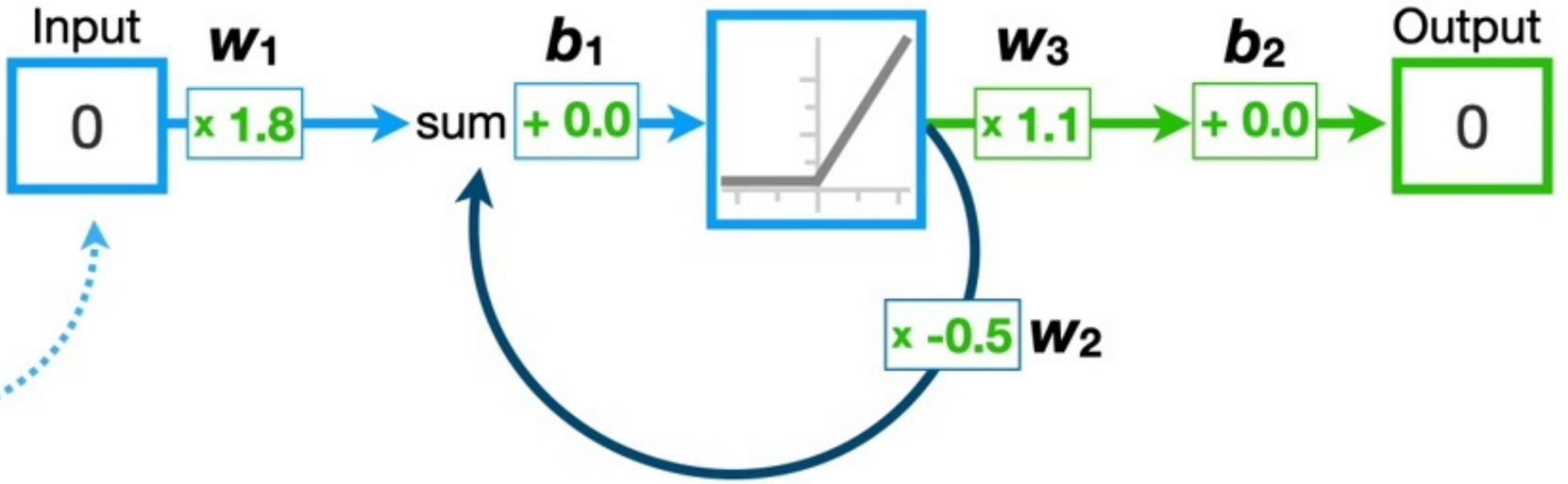

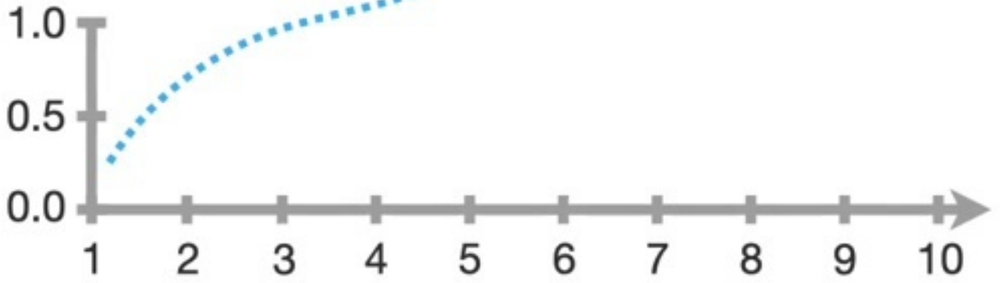

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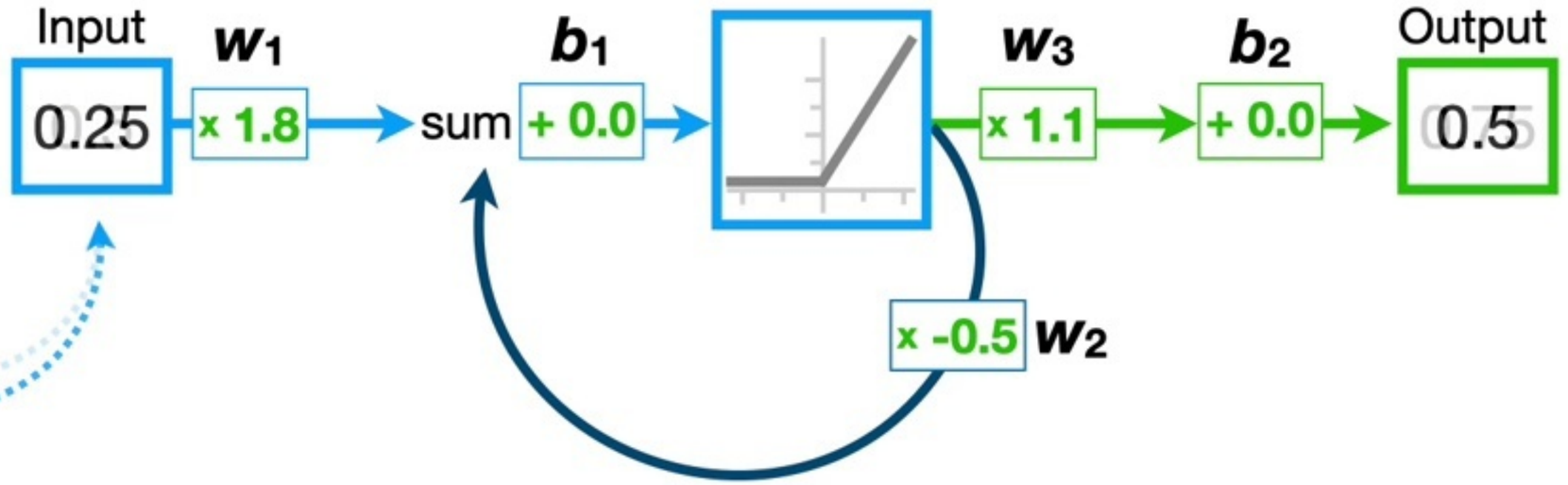

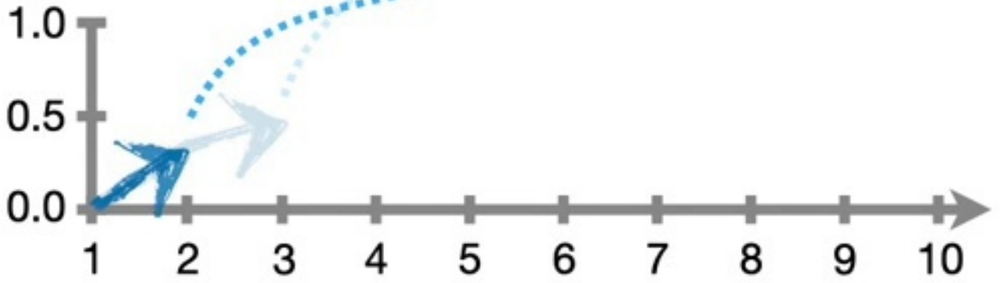

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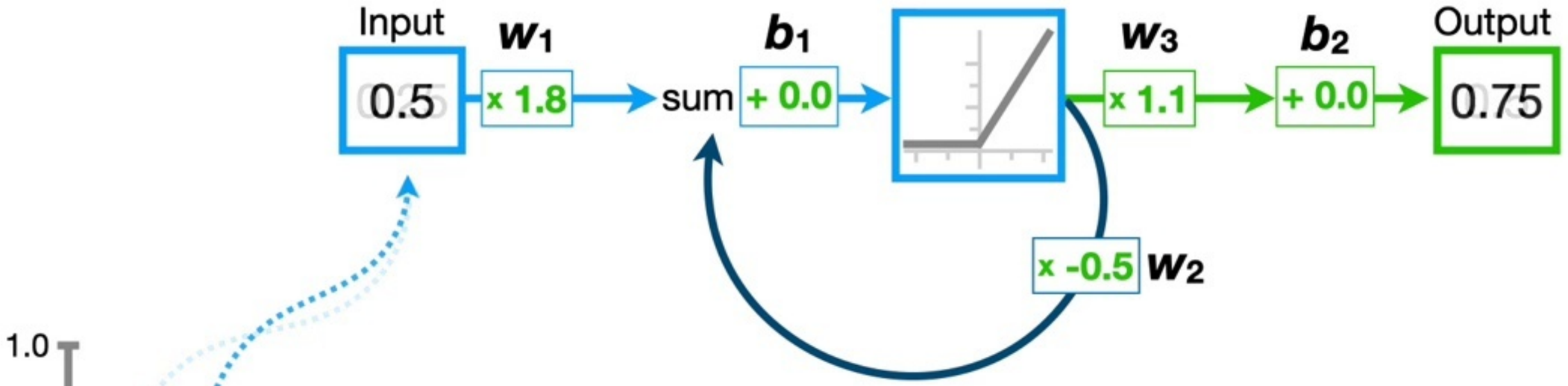

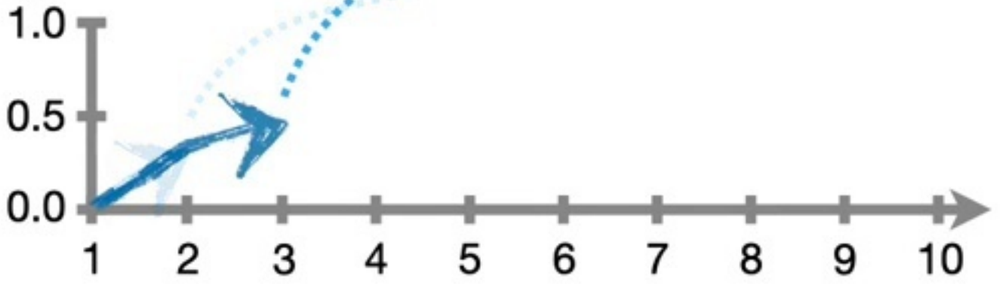

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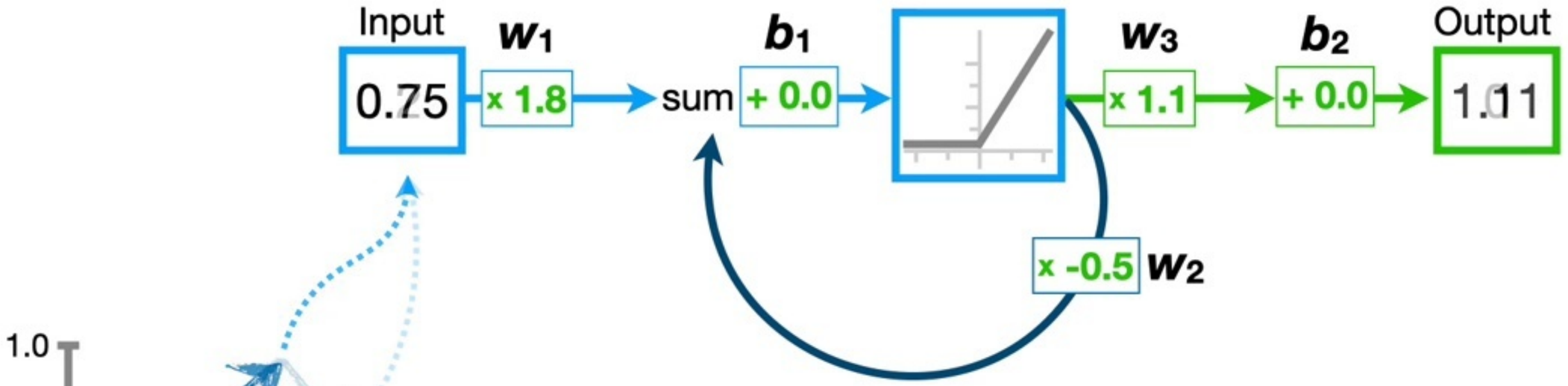

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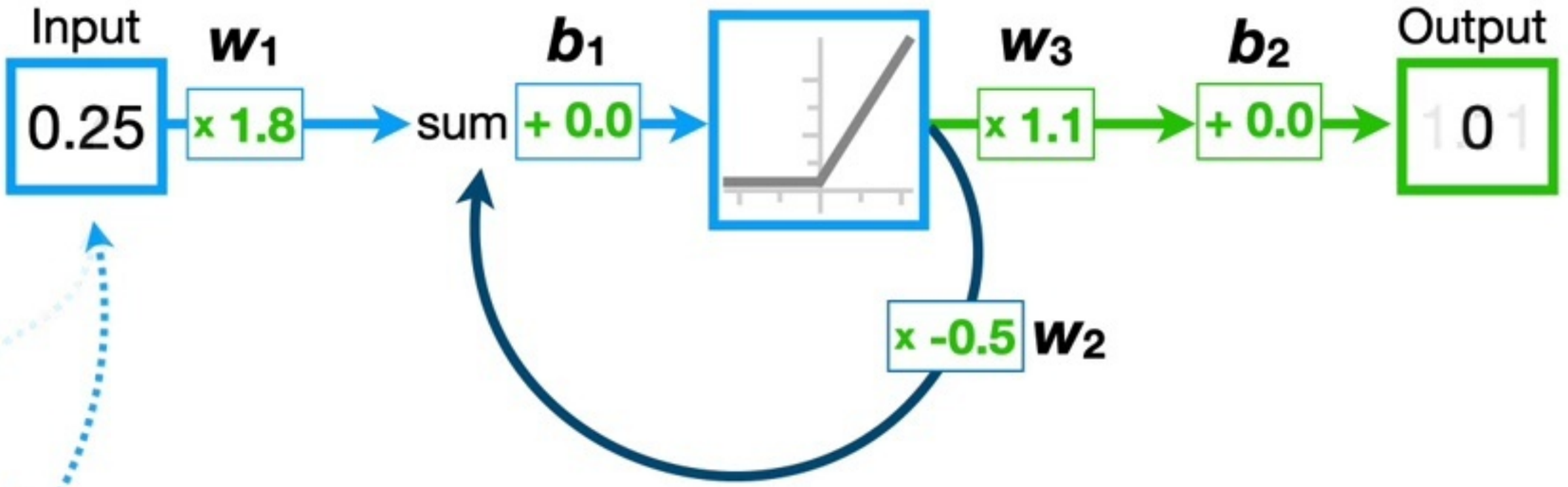

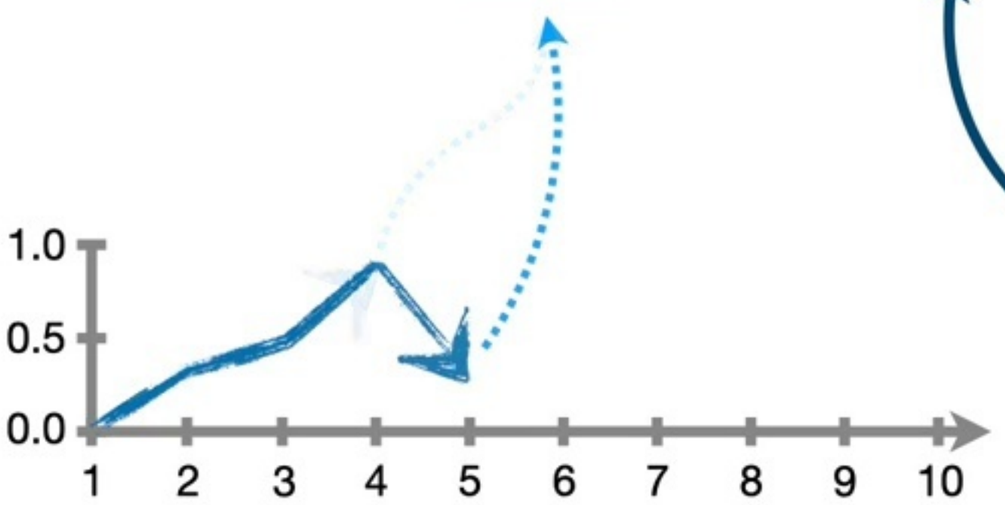

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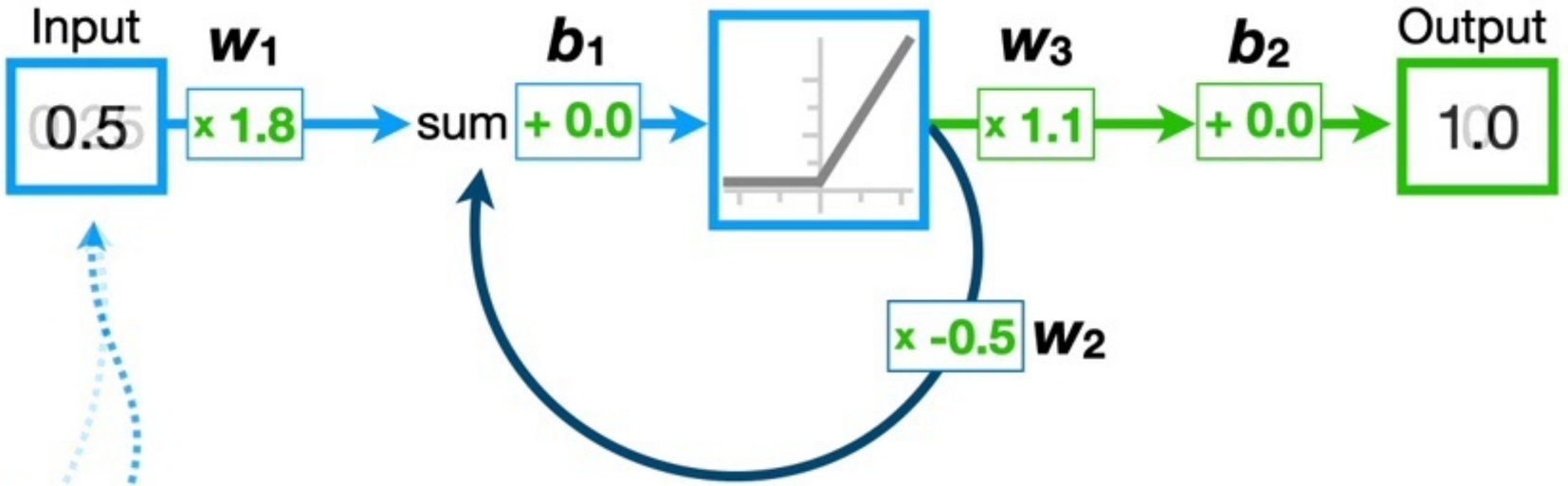

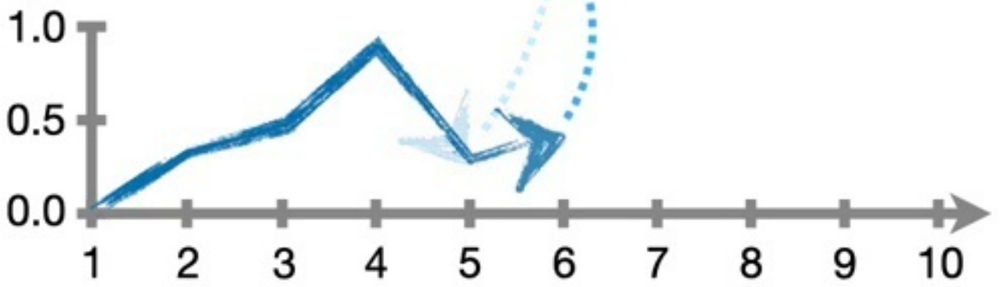

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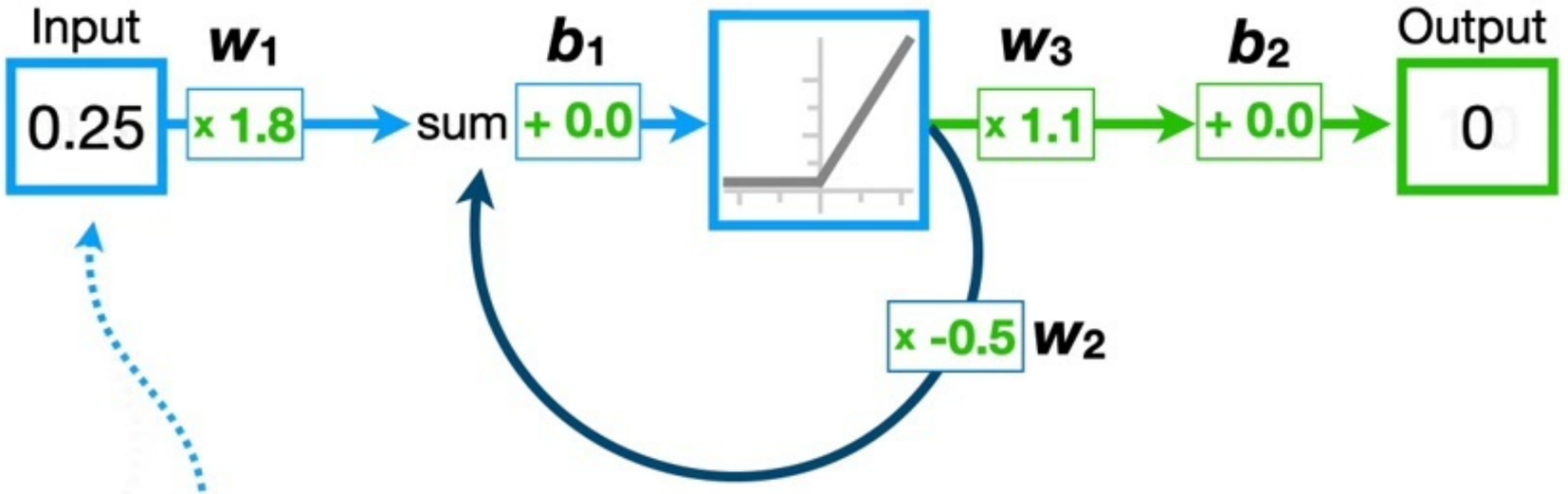

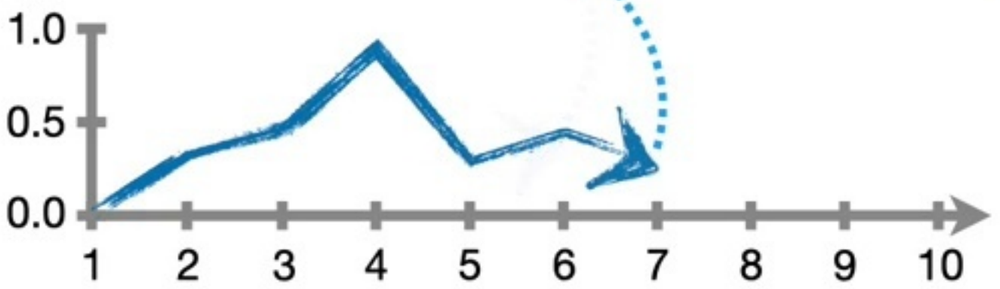

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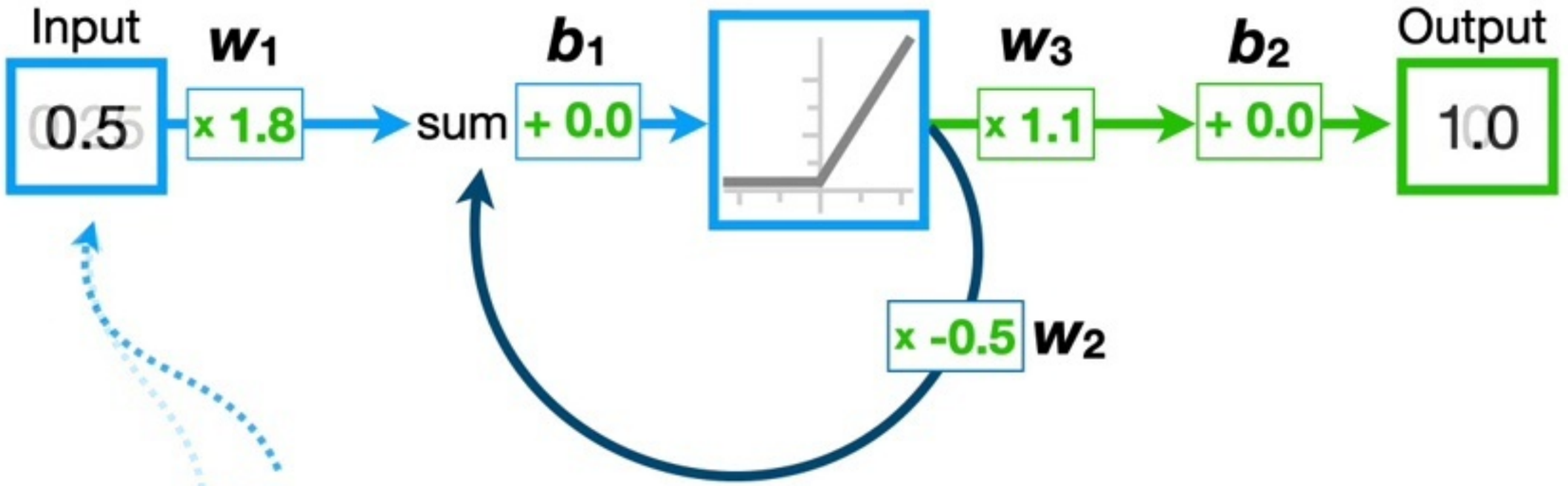

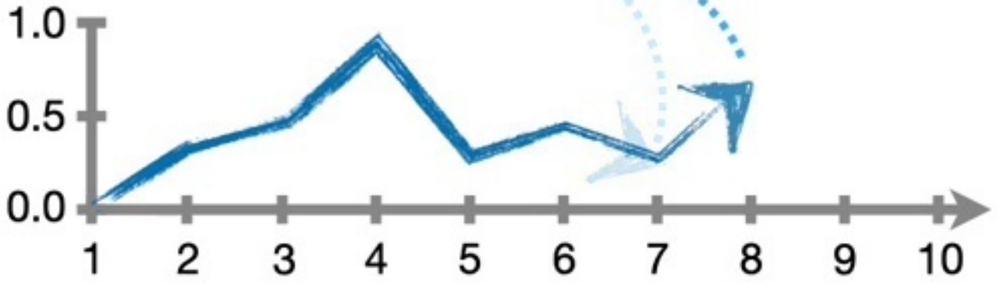

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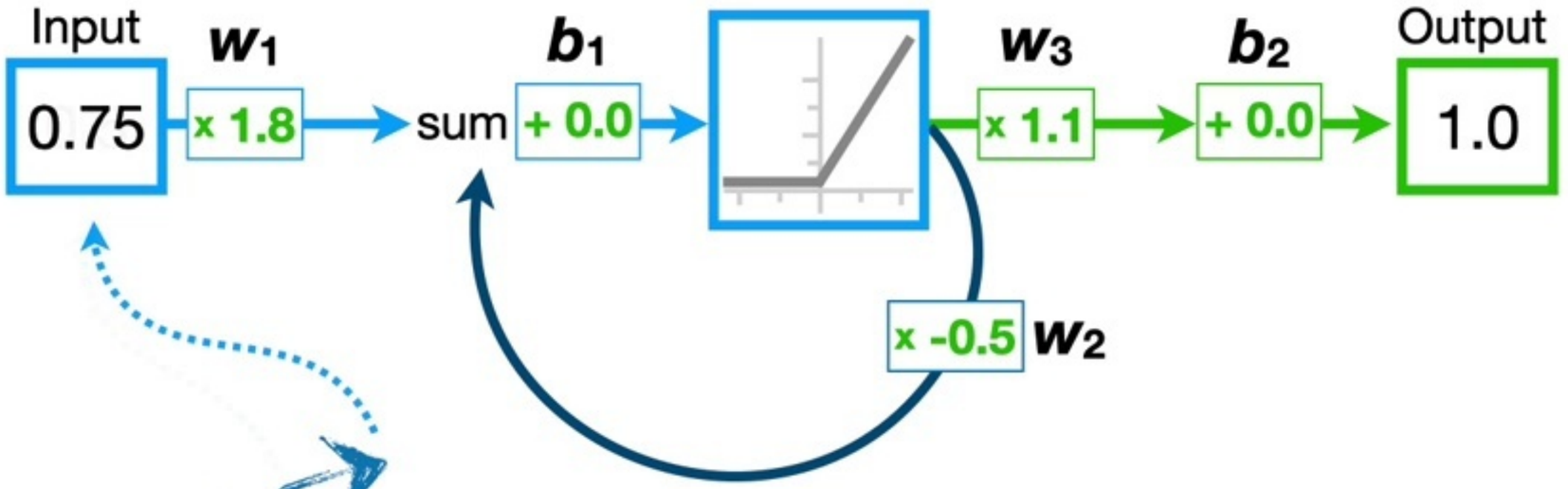
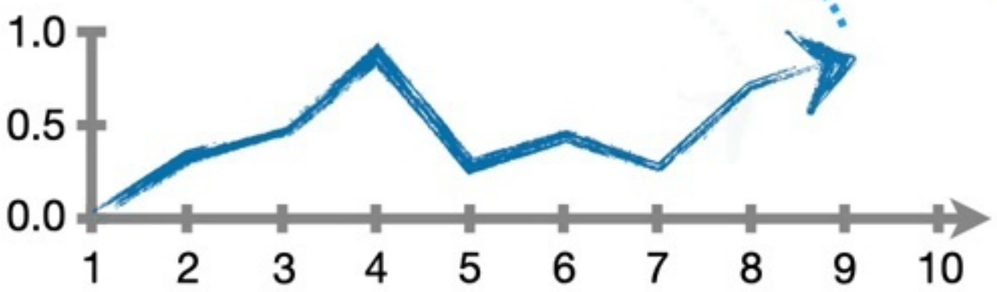
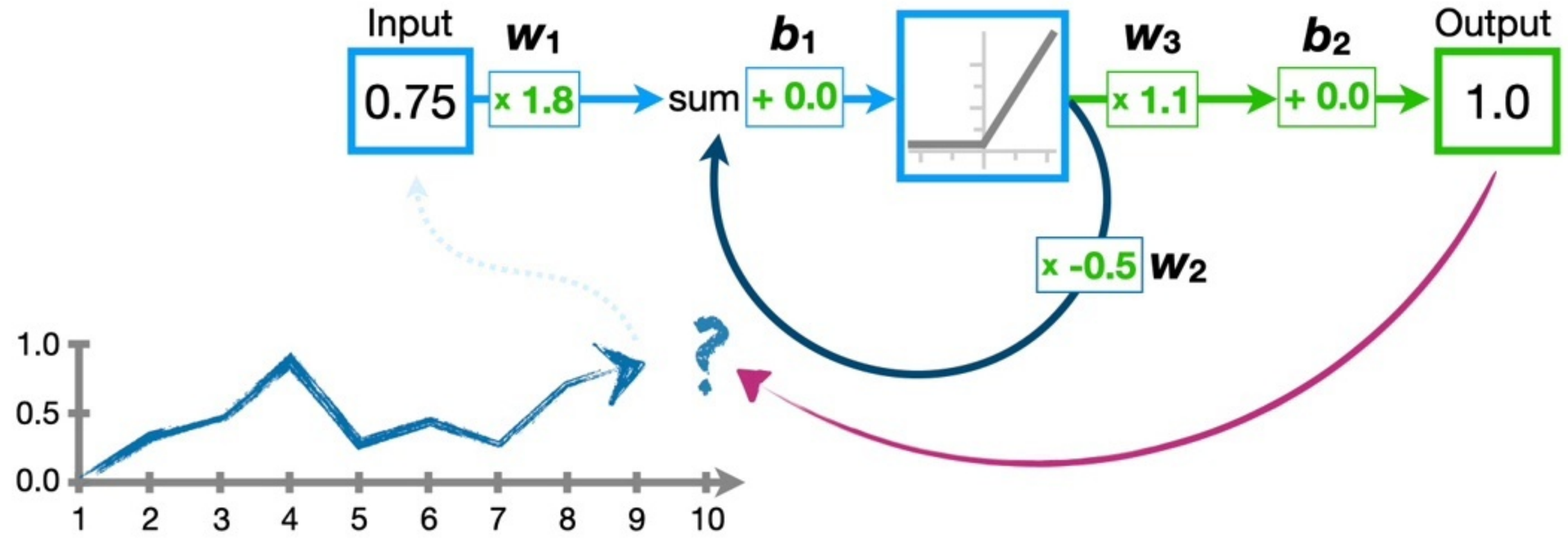
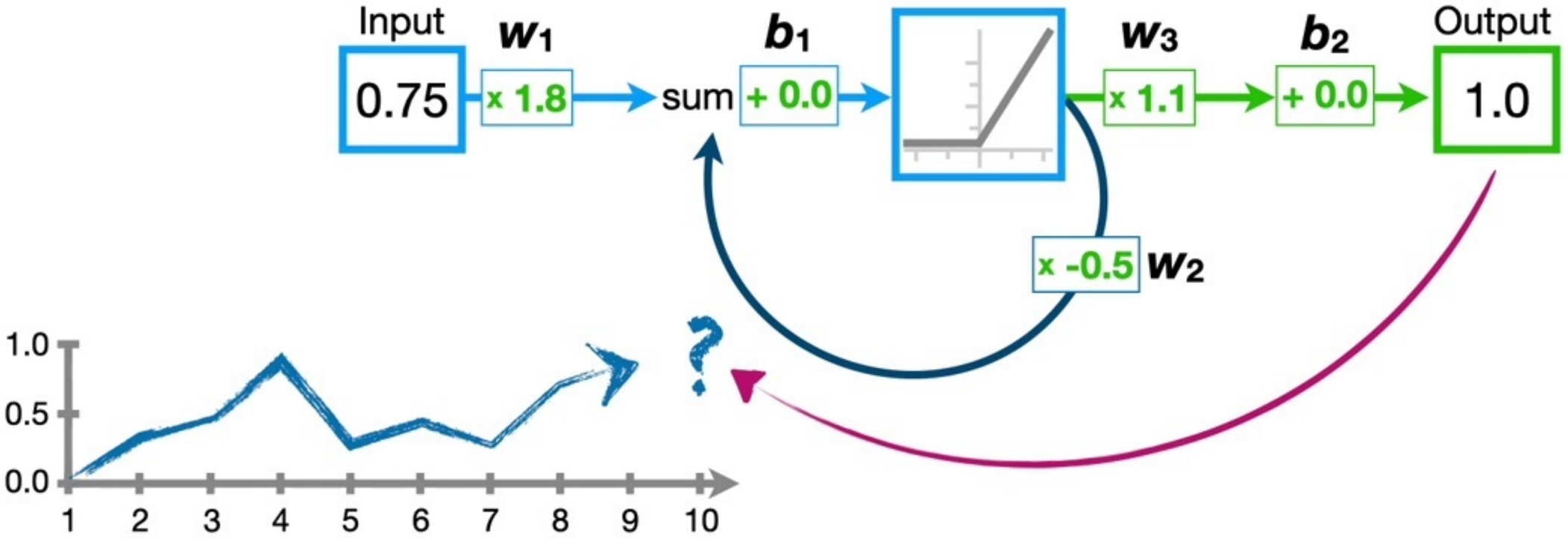


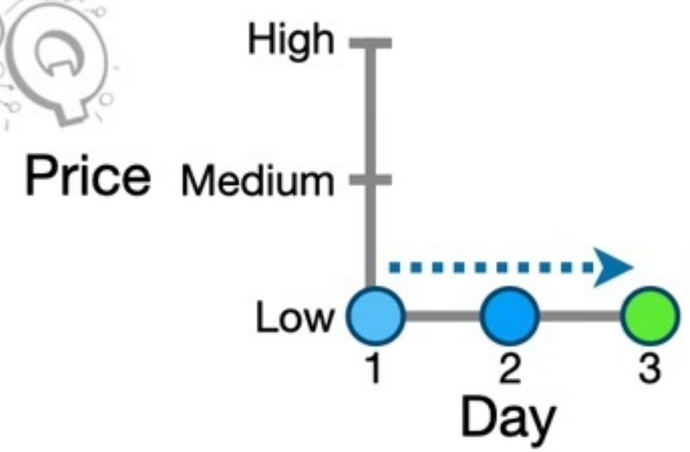


…the **feedback loop** makes it possible to use *sequential* input values, like stock market prices collected over time, to make predictions.

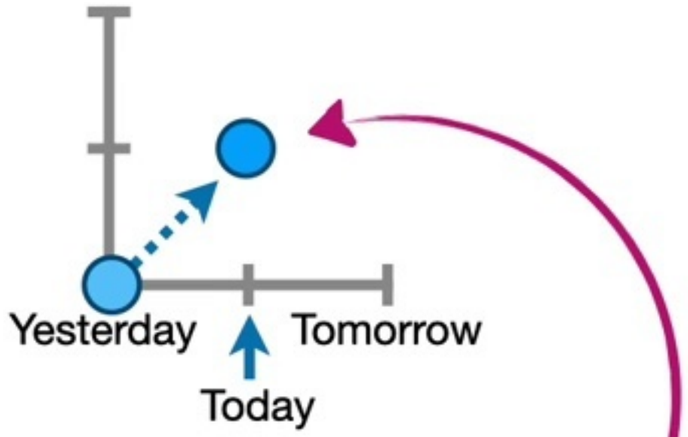


To understand how, exactly, this
Recurrent Neural Network can make
predictions with sequential input values…

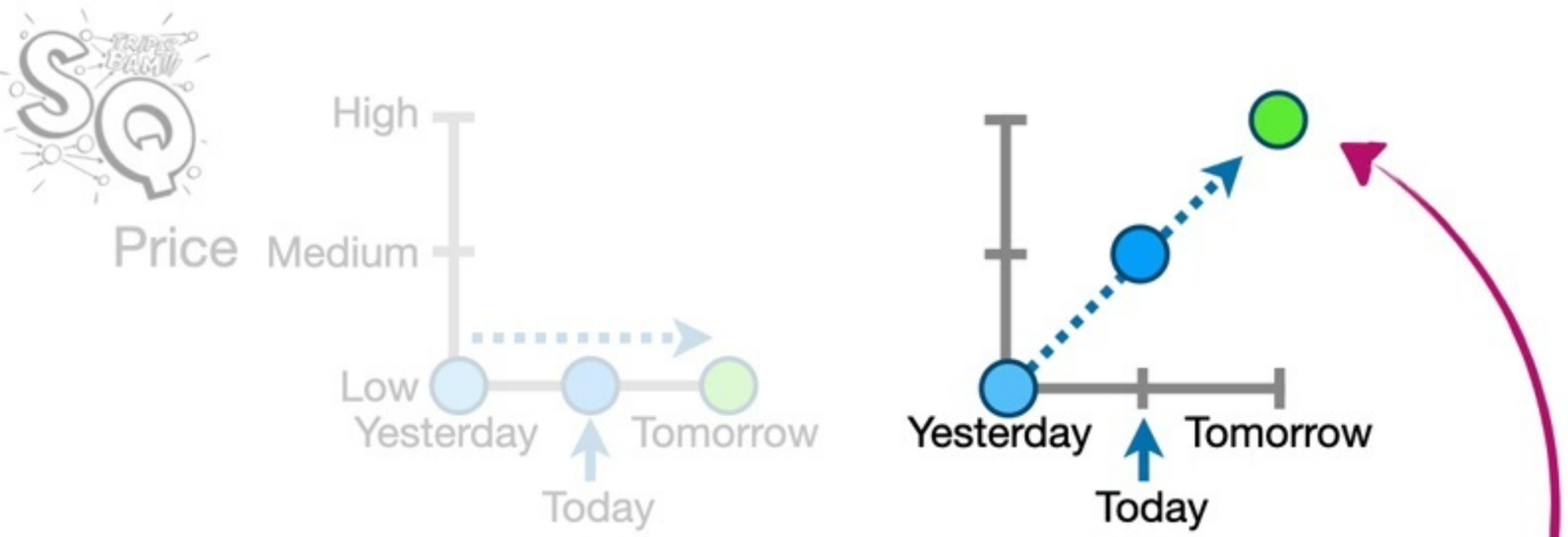




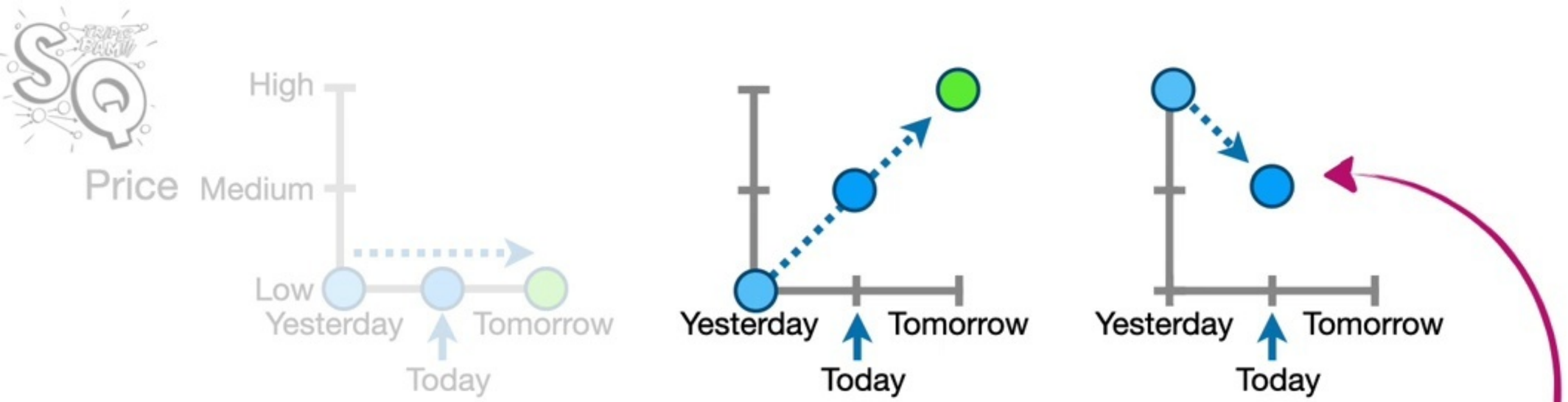
…then, more often than not, the price remains low on the next day.



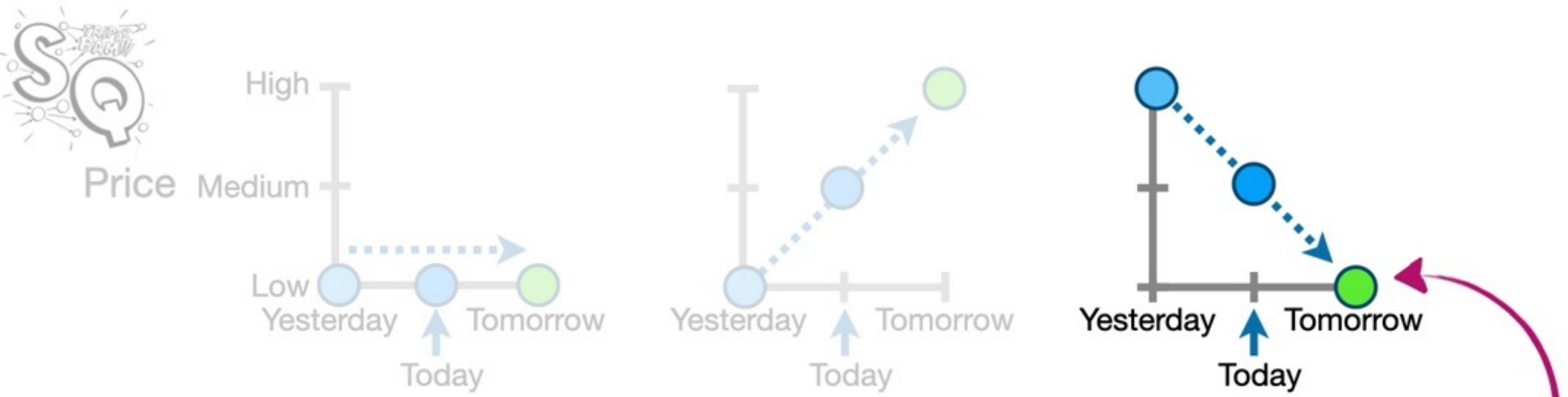
In contrast, if **yesterday's** price was low and **today's** price is medium…



…then **tomorrow's** price should be even higher.



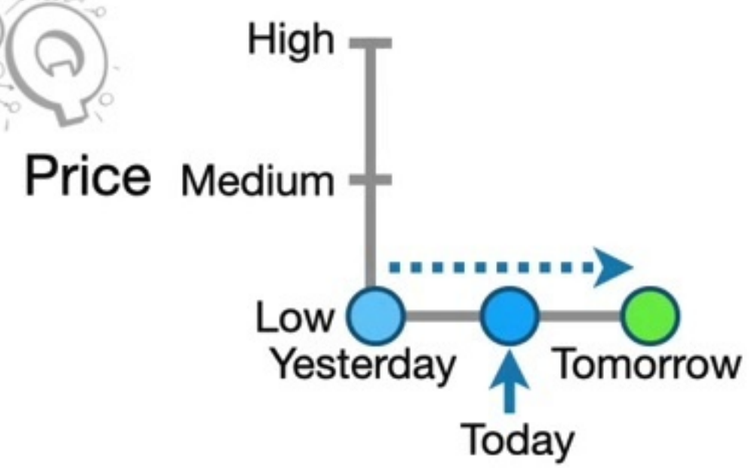
And when the price decreases from high to medium…

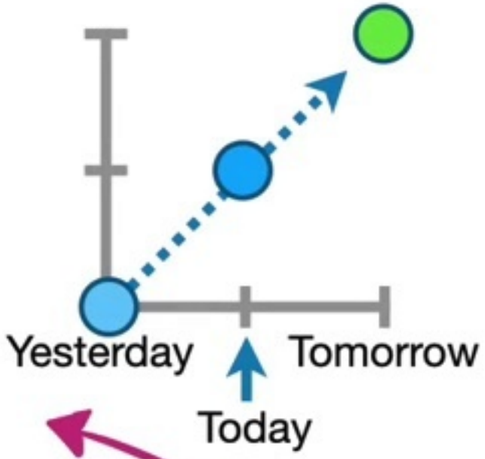


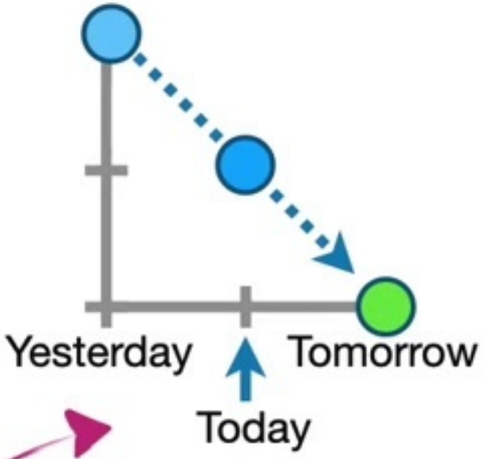
…then **tomorrow's** price will be even lower.

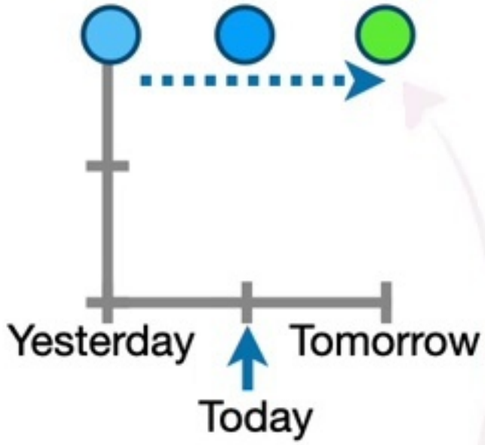
Lastly, if the price stays high for two days in a row…

…then the price will be high **tomorrow**.



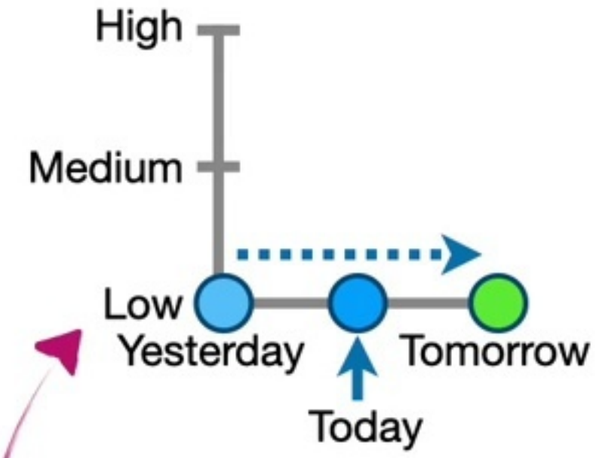


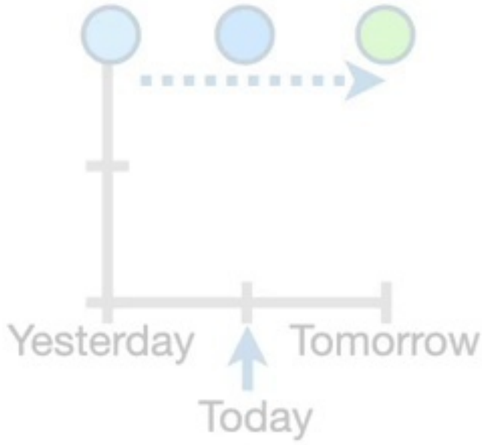




Now that we see the general trends in stock prices in **StatLand**…

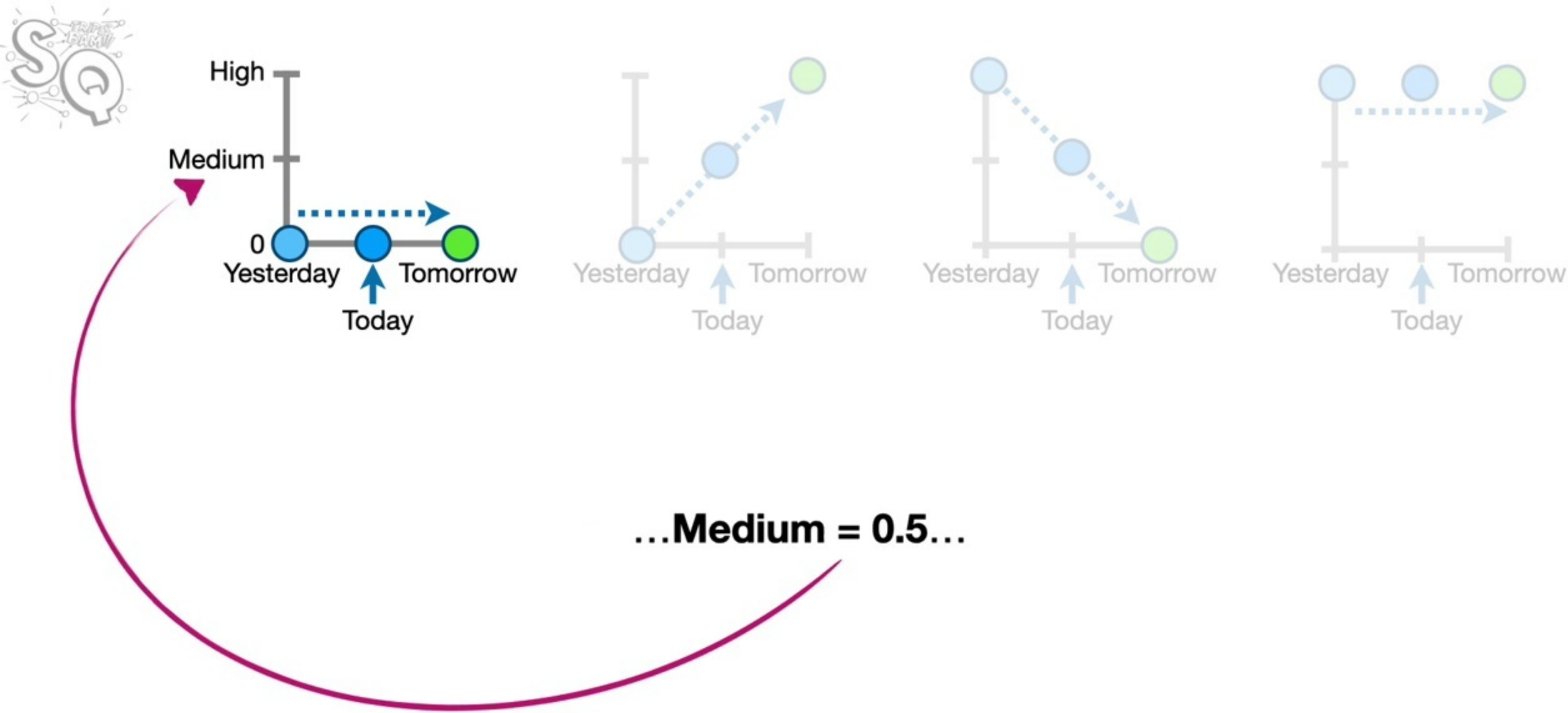
…then the price will be high **tomorrow**.



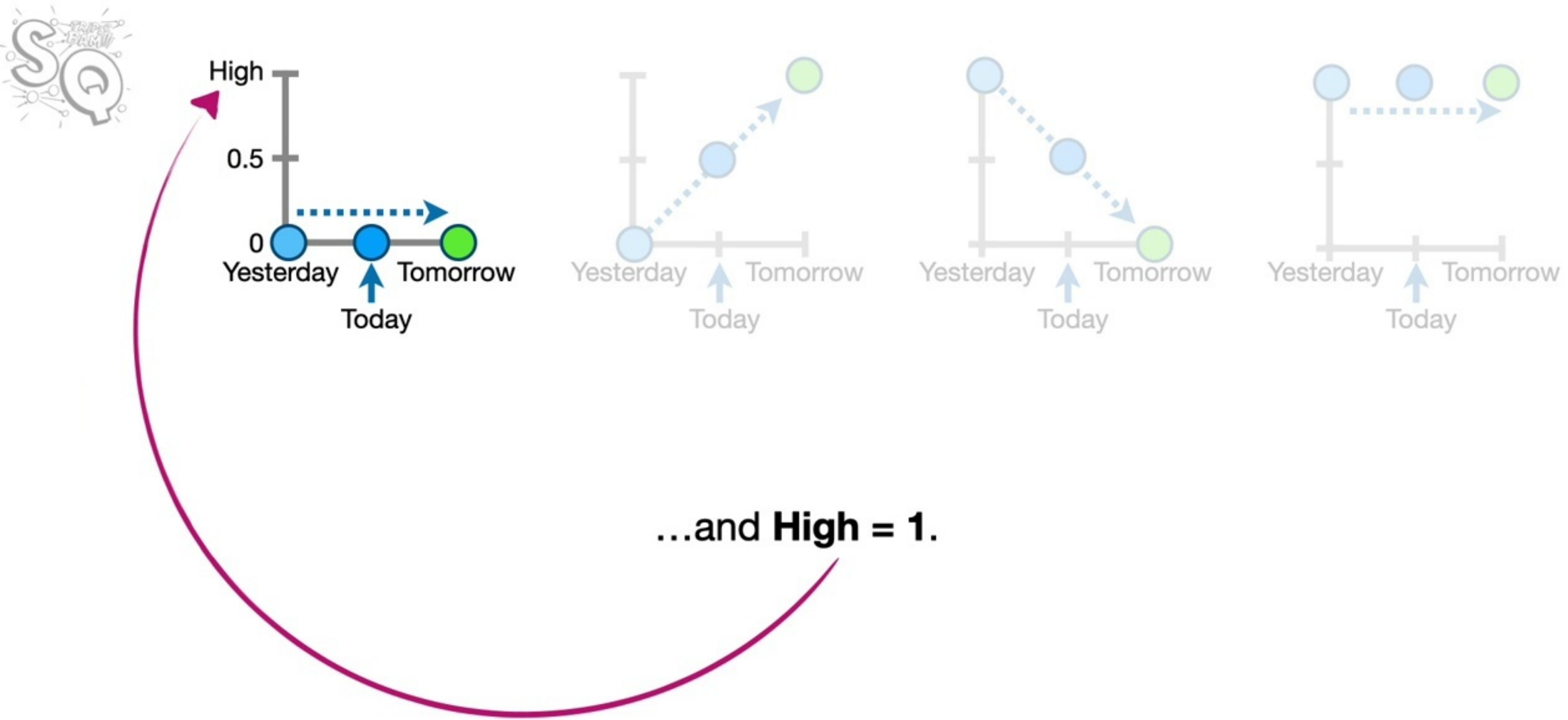


The first thing we'll do scale the prices so that **Low = 0**…

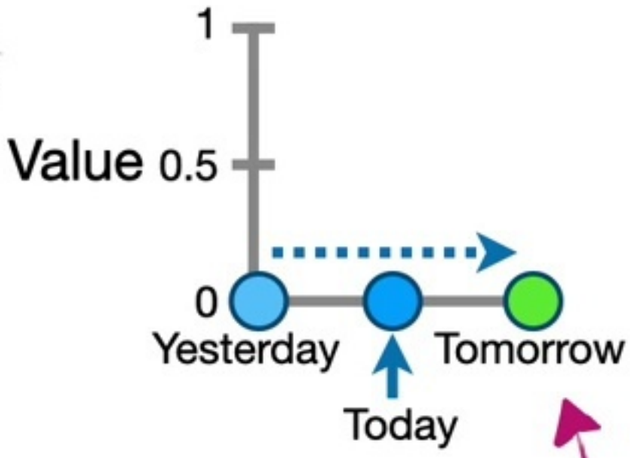
The first thing we'll do scale the prices so that **Low = 0**…


High
Medium
0
Yesterday
Today
Tomorrow
Yesterday
Today
Tomorrow
Yesterday
Today
Tomorrow
Yesterday
Today
Tomorrow

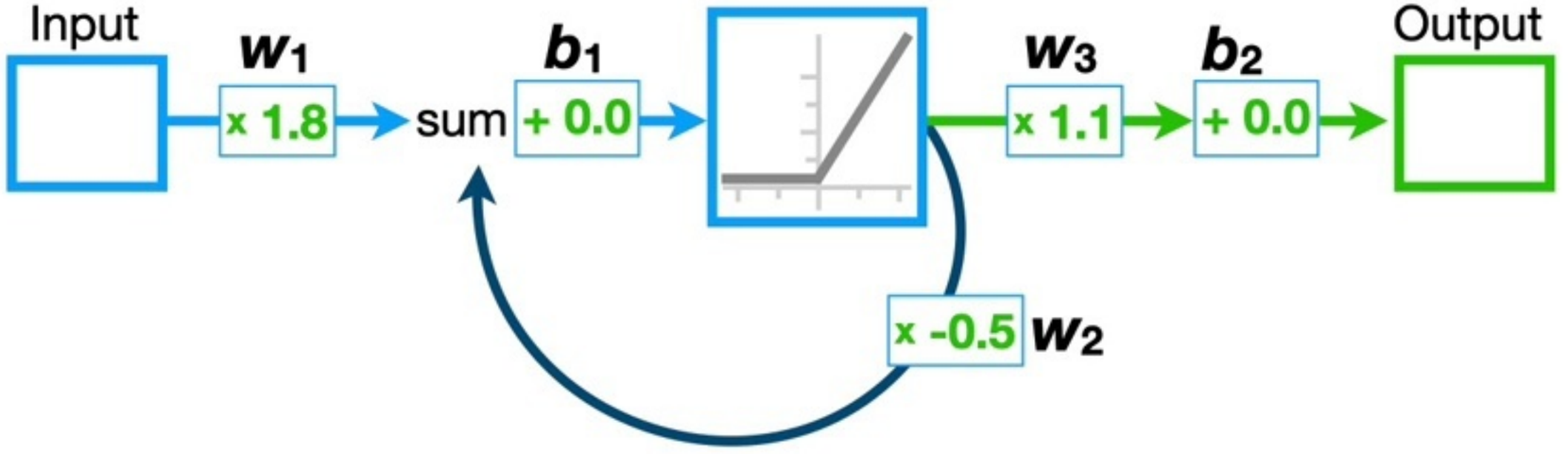
…Medium = 0.5…

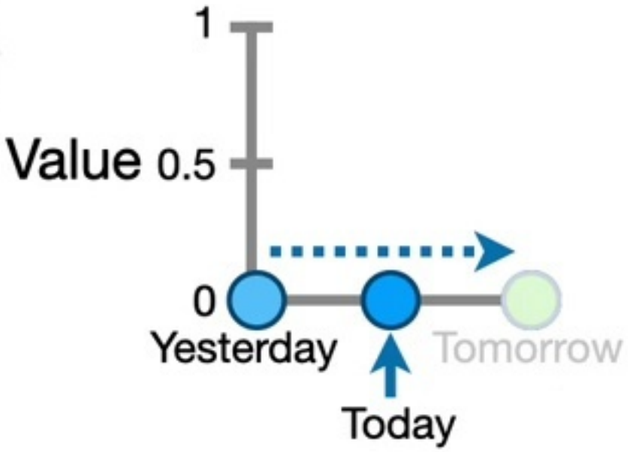

High
0.5
0
Yesterday
Today
Tomorrow
Yesterday
Today
Tomorrow
Yesterday
Today
Tomorrow
Yesterday
Today
Tomorrow

…and **High = 1**.

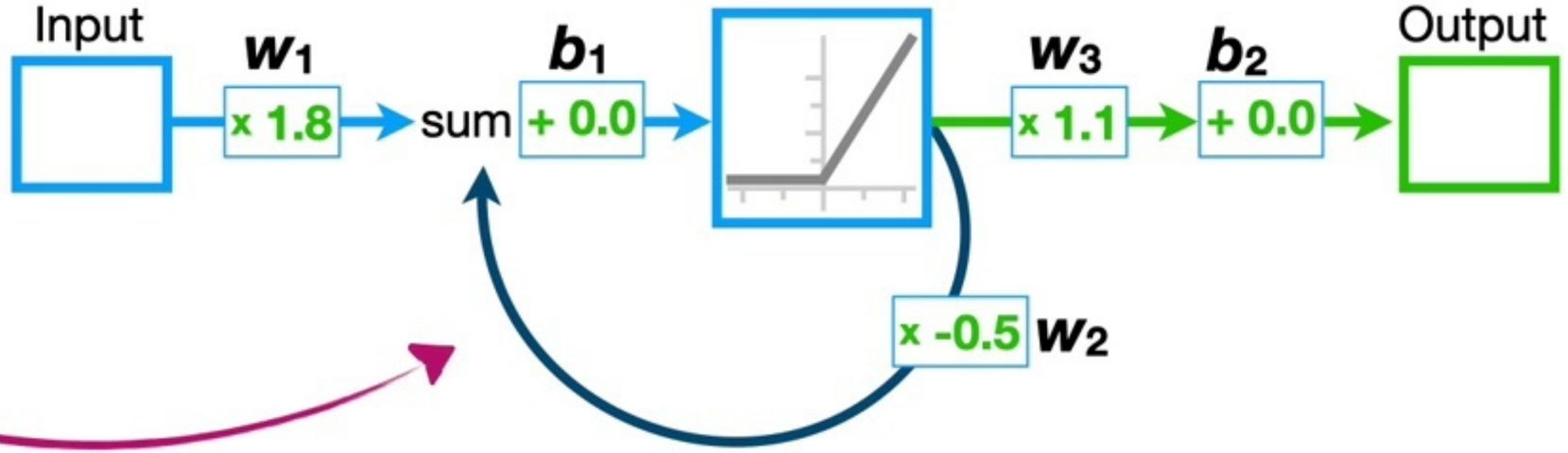


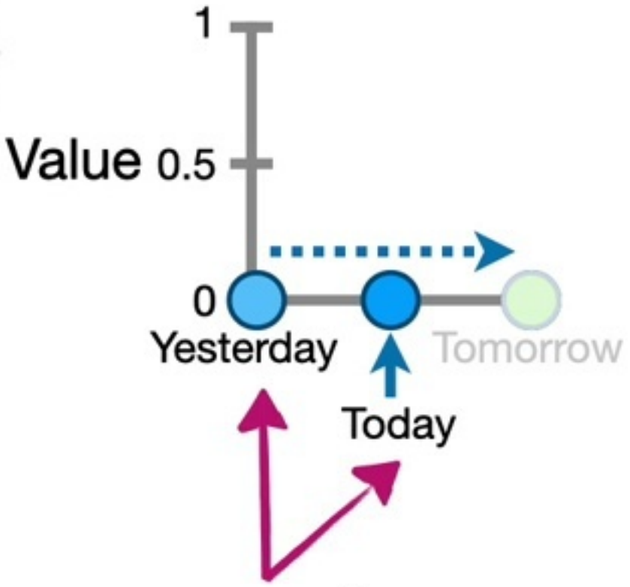
…and see if it can correctly predict **tomorrow's** value.



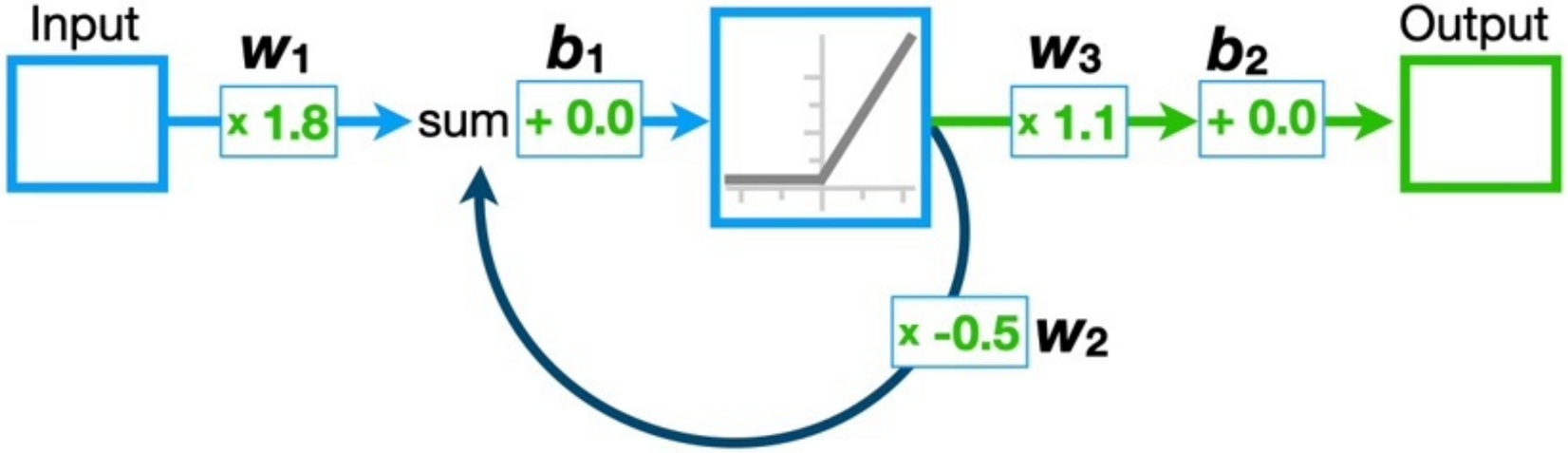


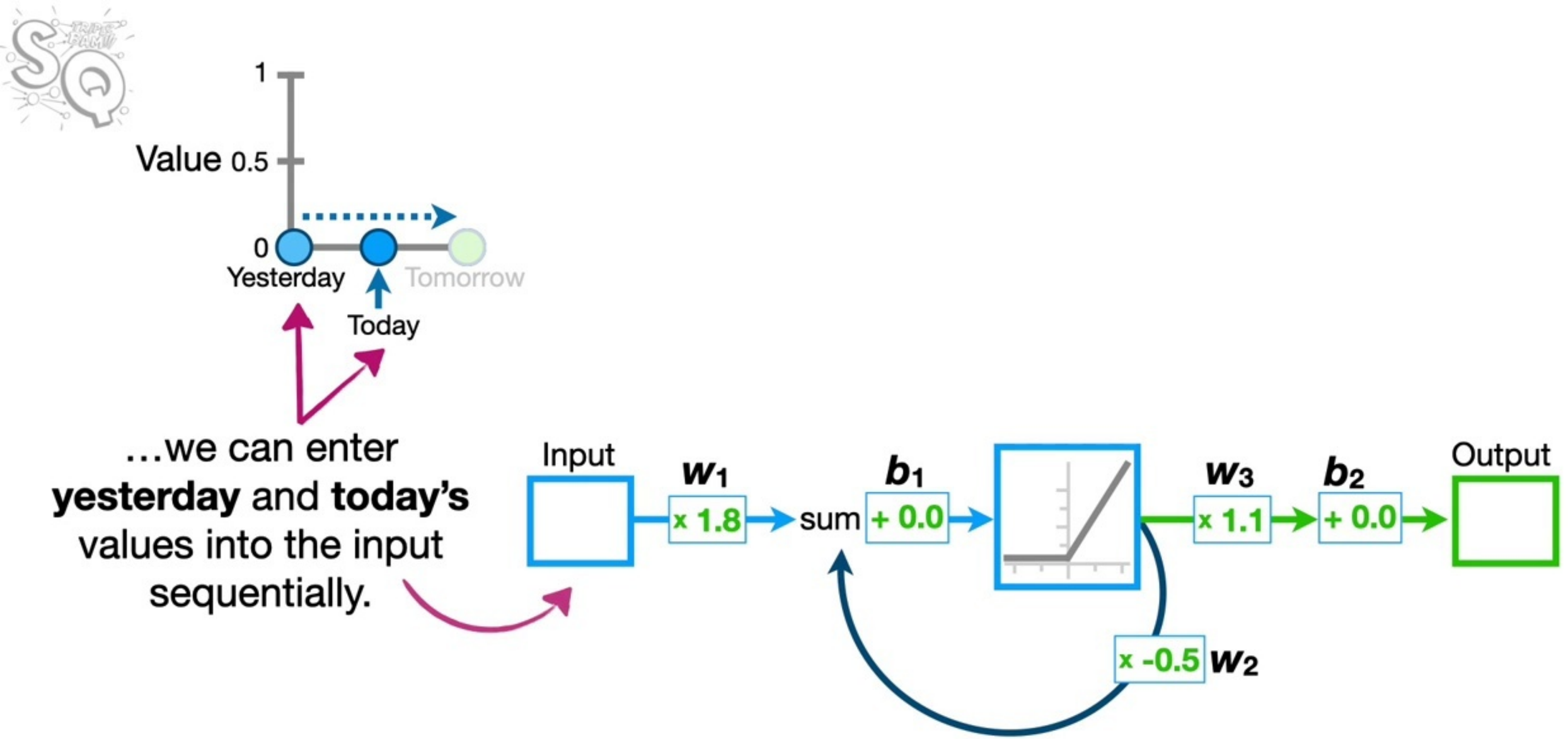
Now, because the recurrent neural network has a **feedback loop**…

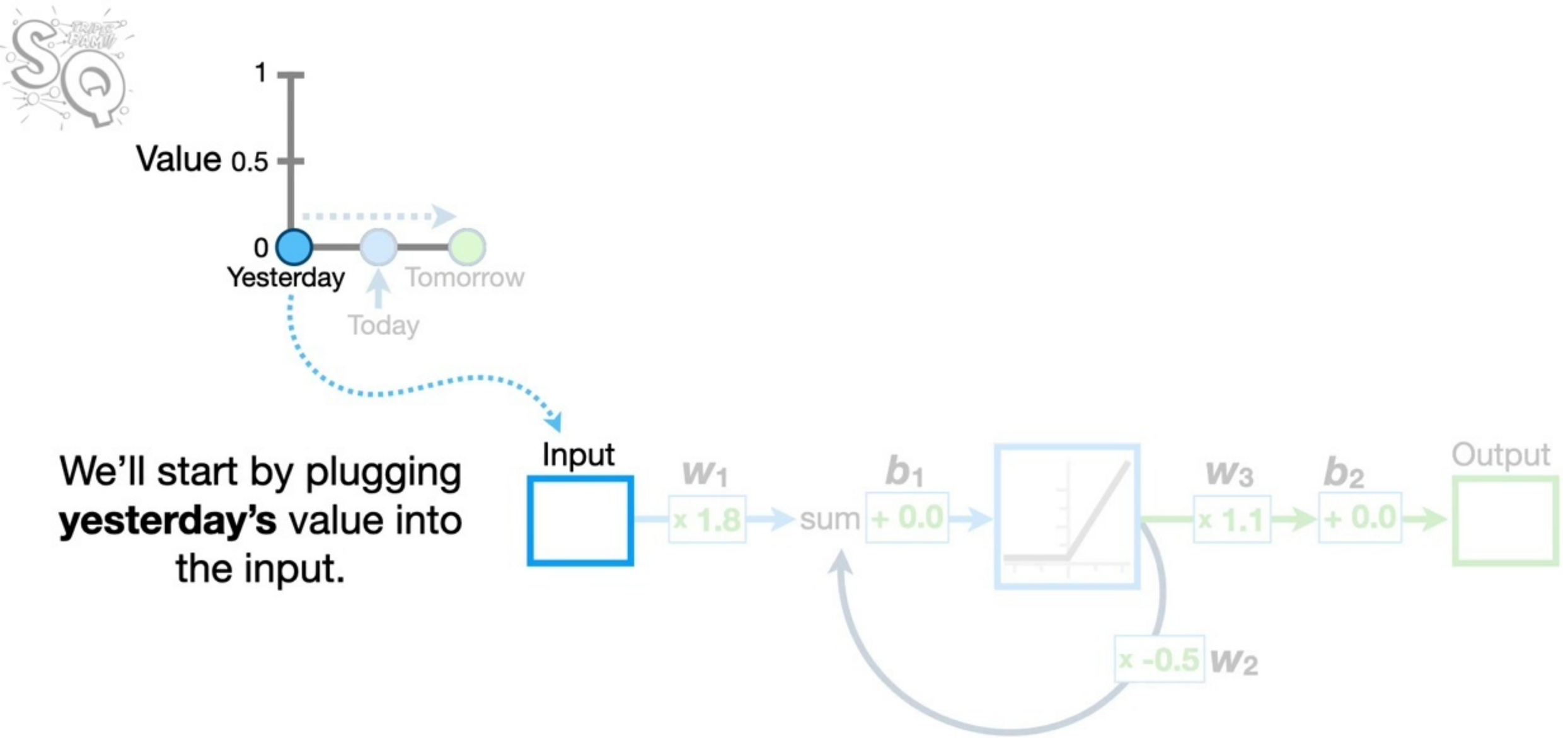




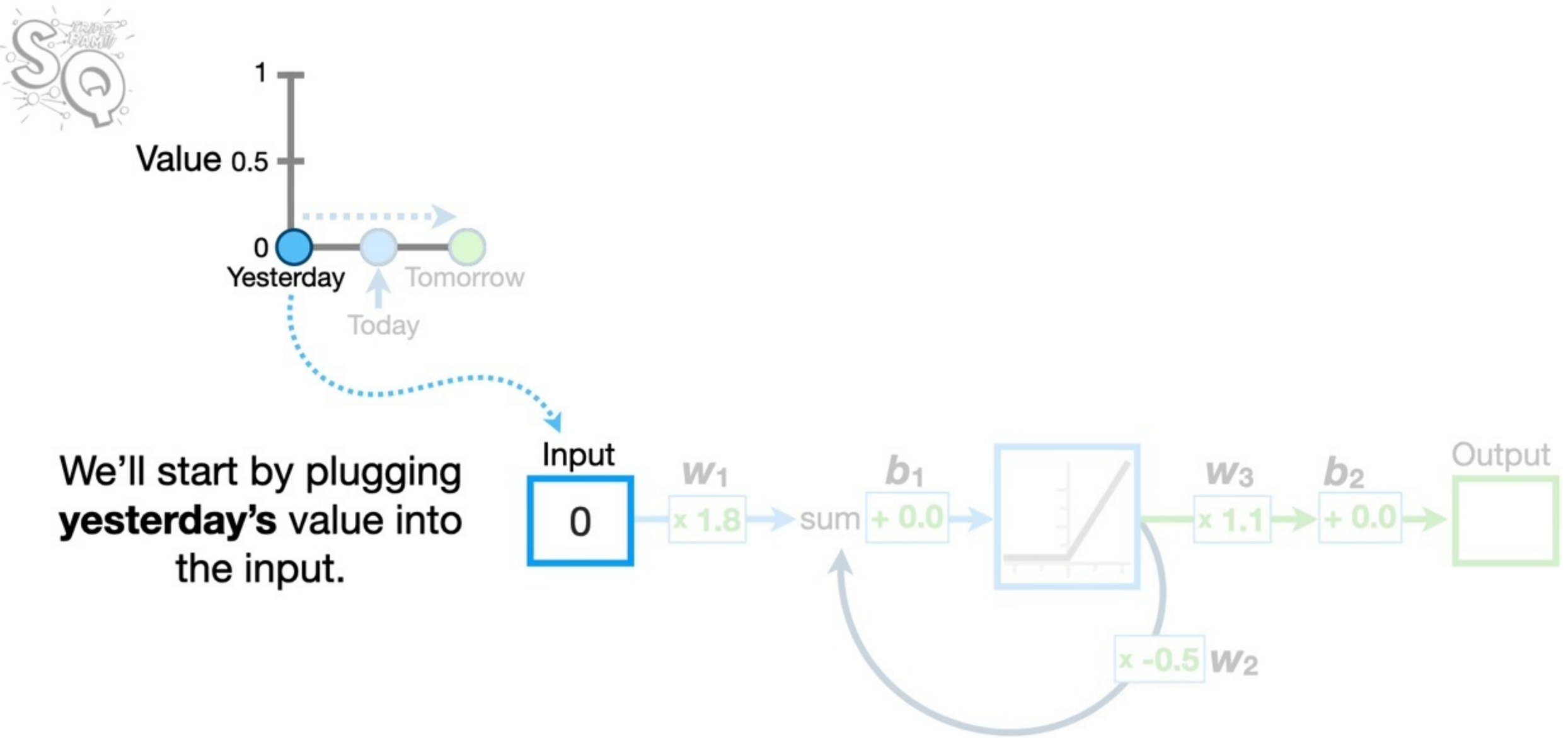
…we can enter **yesterday** and **today's** values into the input sequentially.



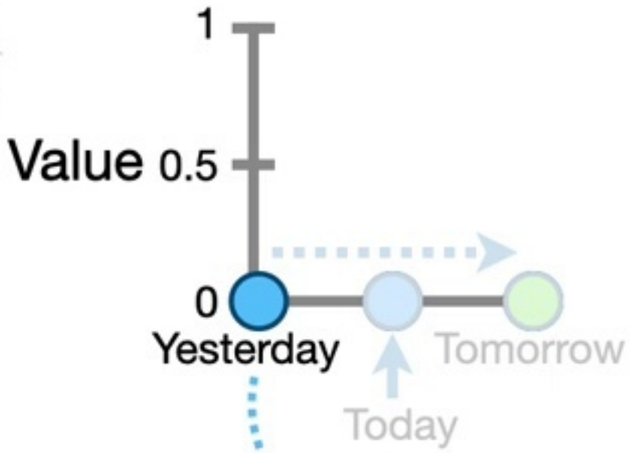

1
Value 0.5
0
Yesterday
Today
Tomorrow
…we can enter **yesterday** and **today's** values into the input sequentially.
Input
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2



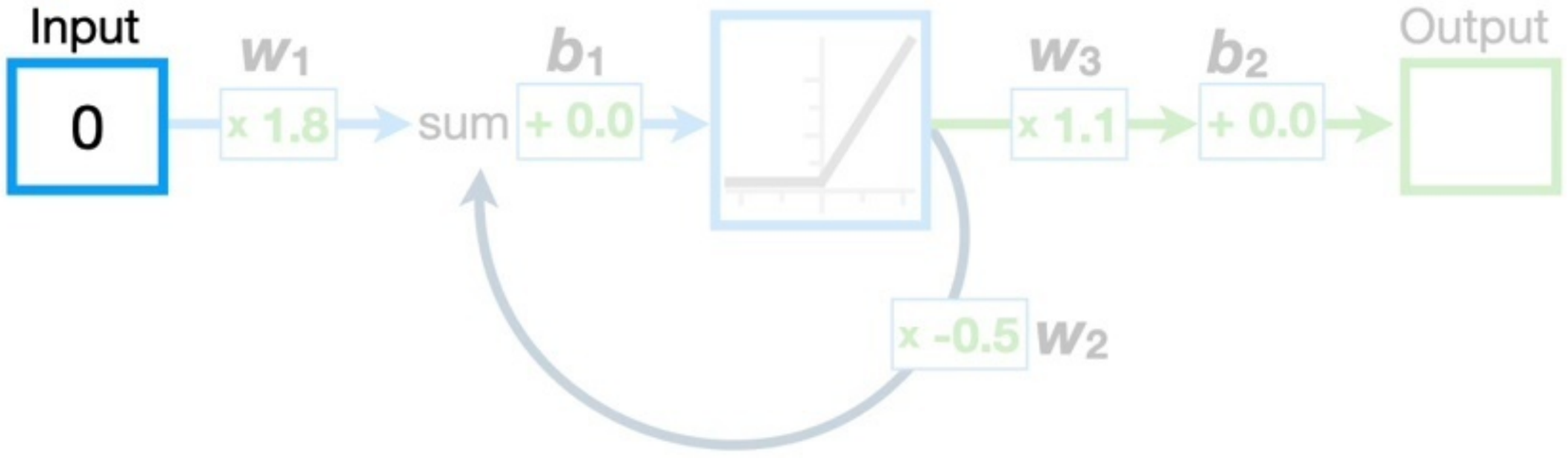
We'll start by plugging **yesterday's** value into the input.

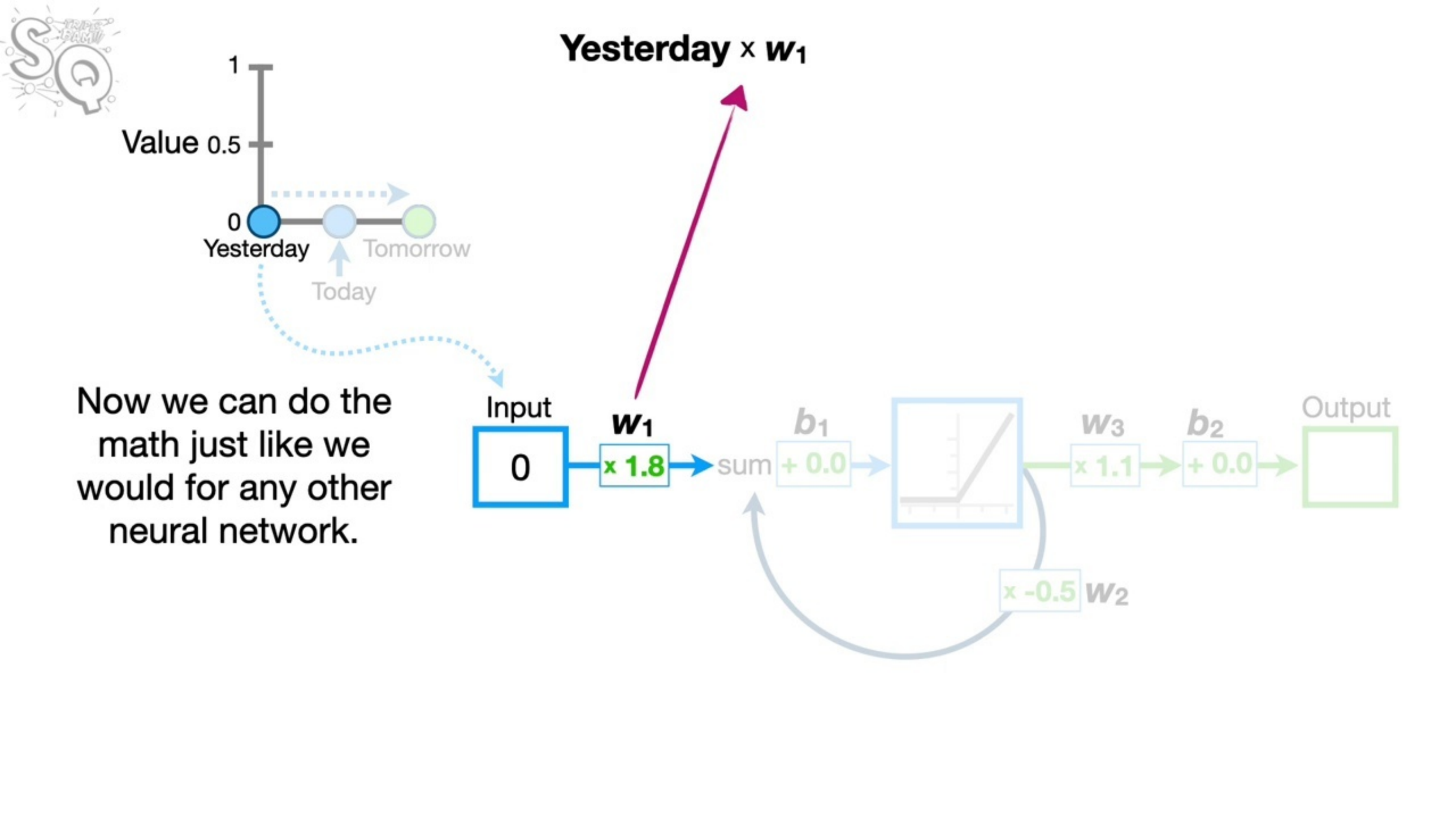


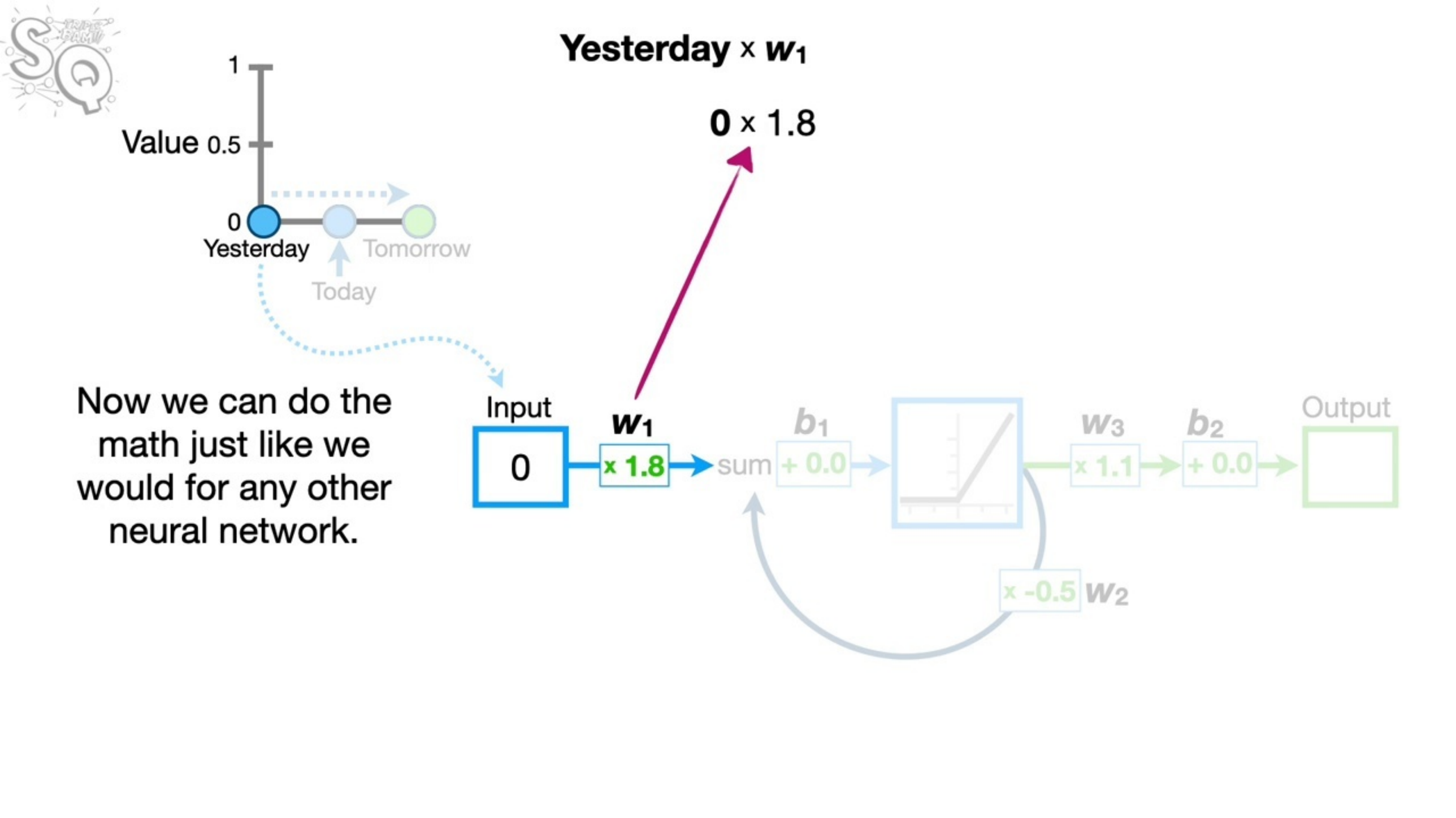
We'll start by plugging **yesterday's** value into the input.

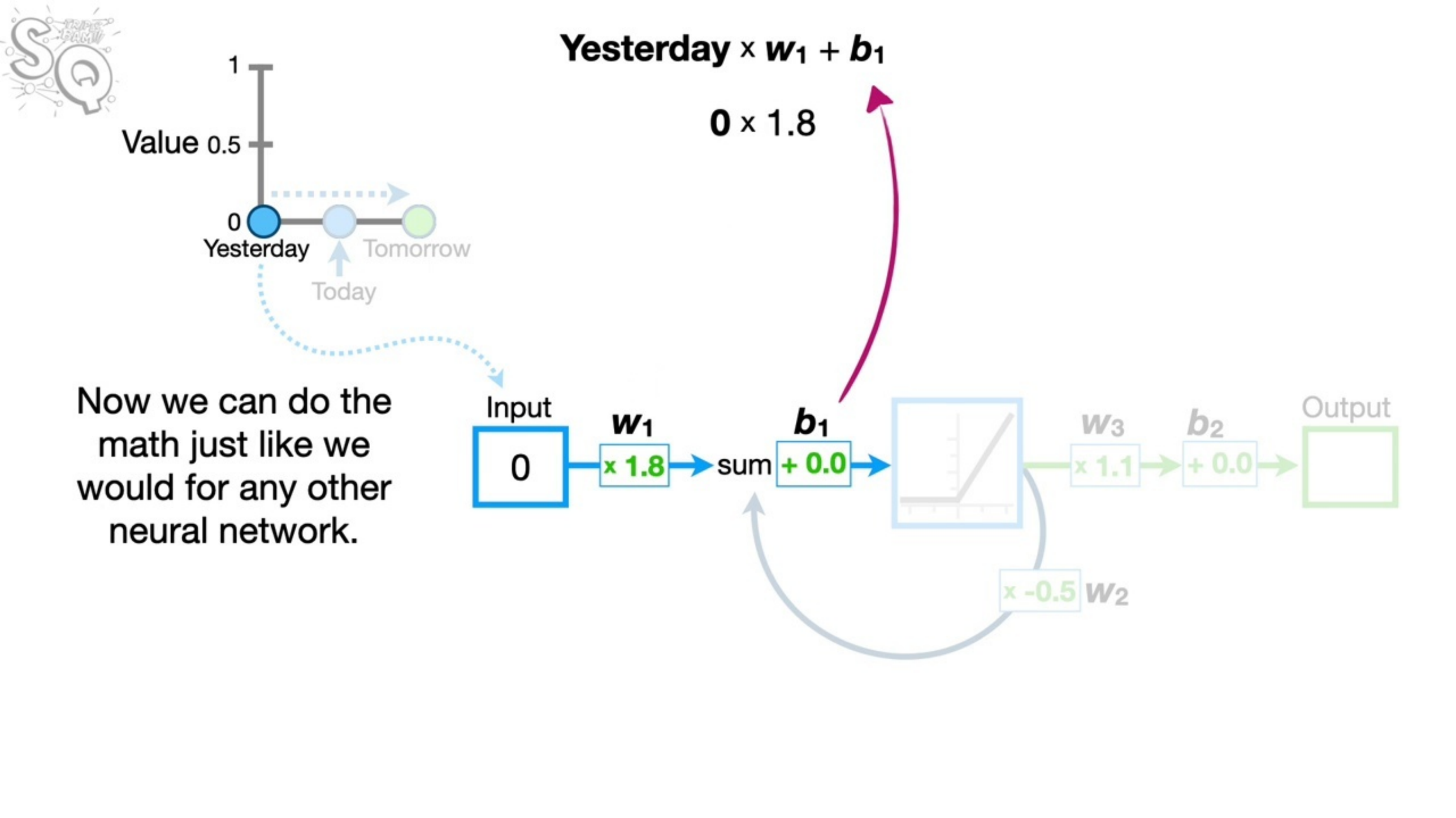


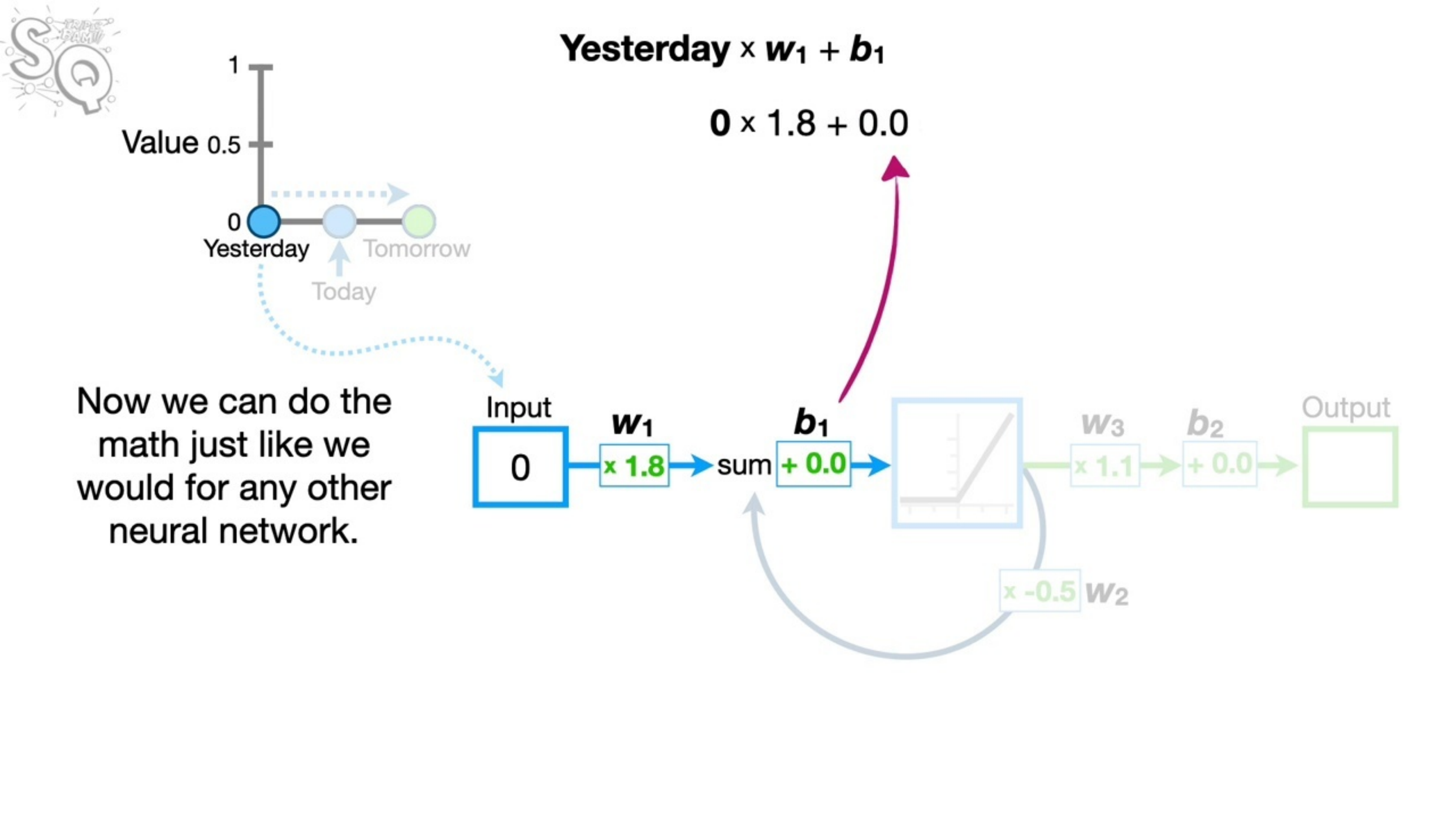
Now we can do the math just like we would for any other neural network.

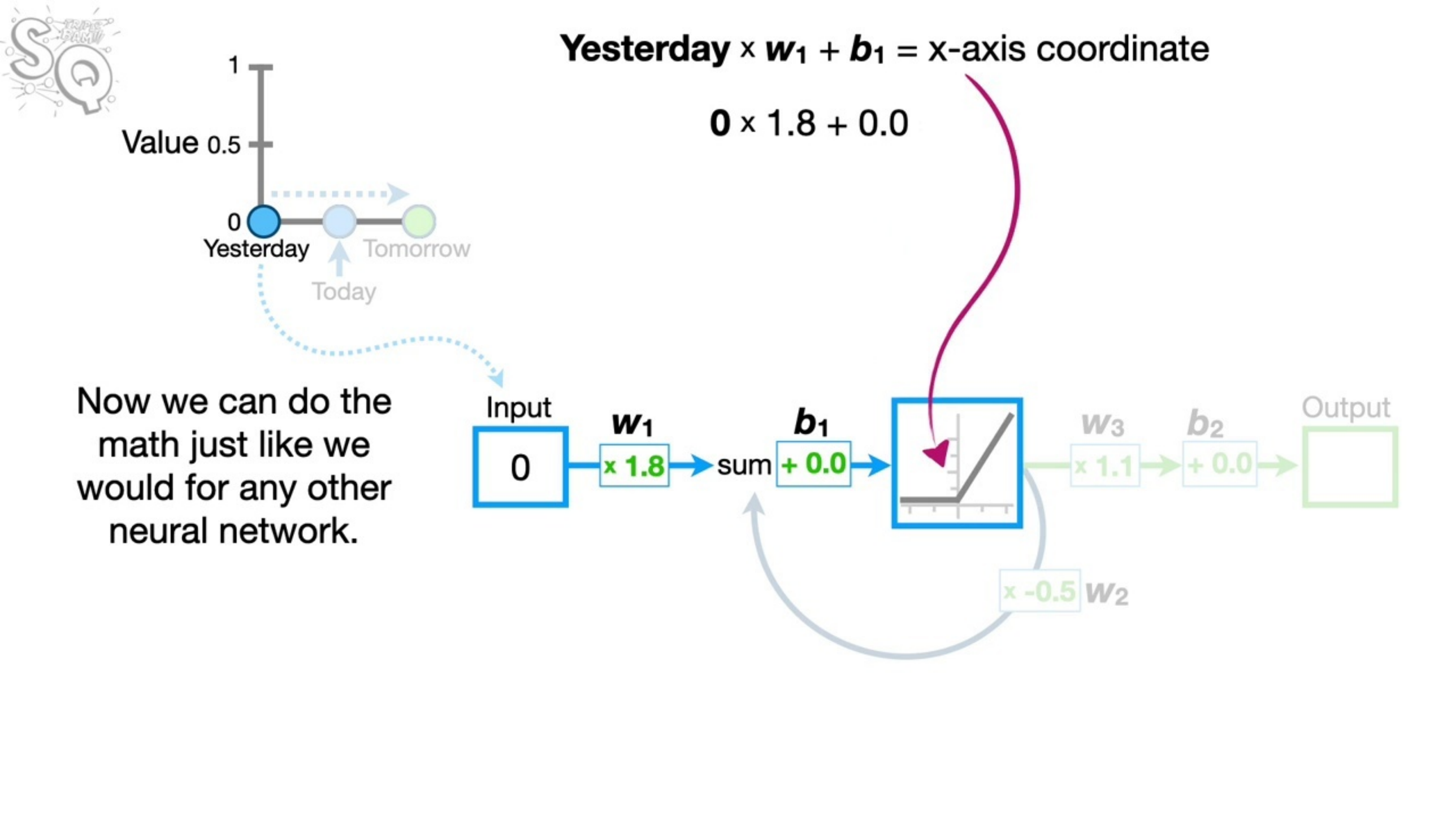


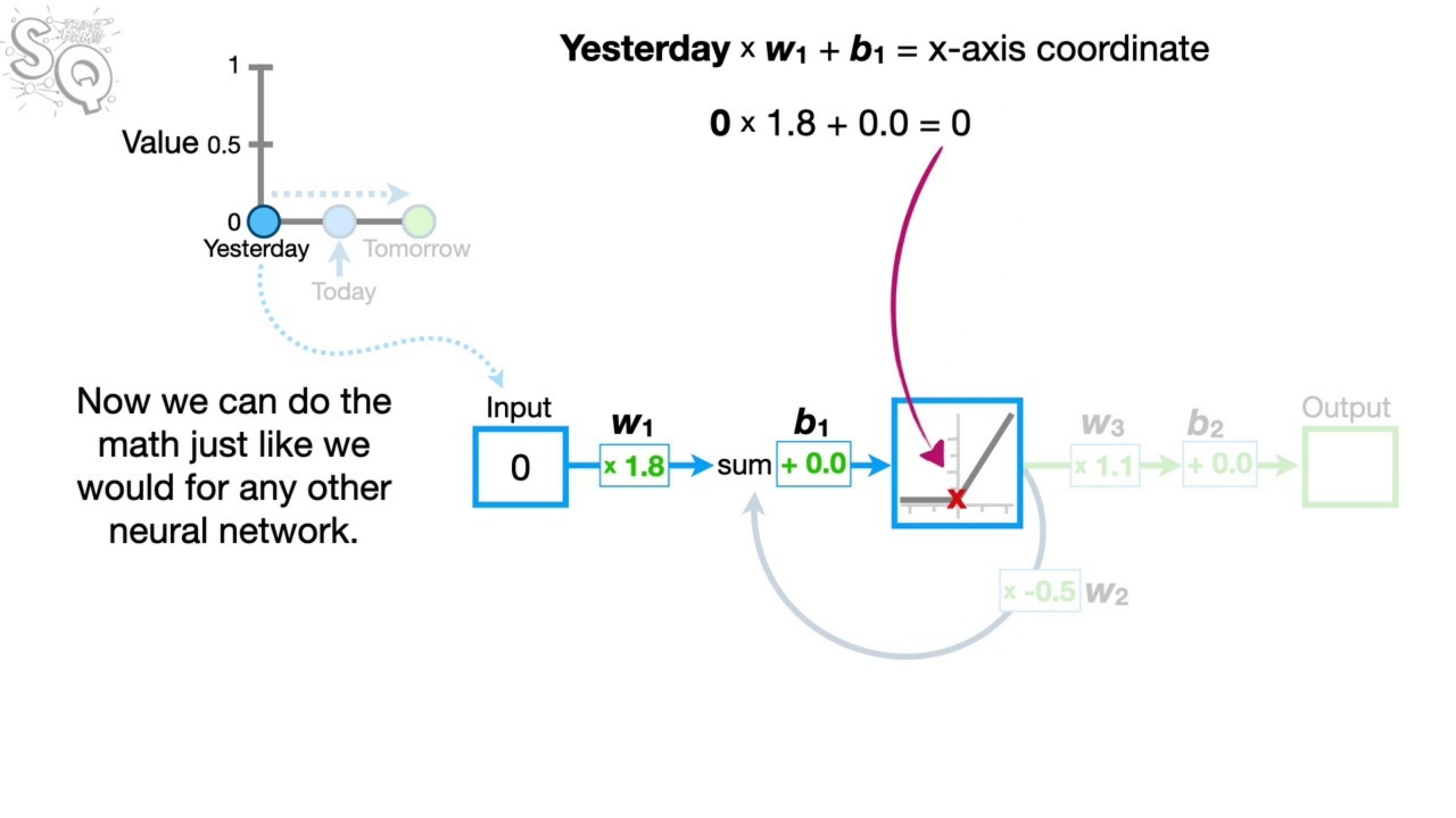

Yesterday x w_1
1
Value 0.5
0
Yesterday
Today
Tomorrow
Now we can do the math just like we would for any other neural network.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2

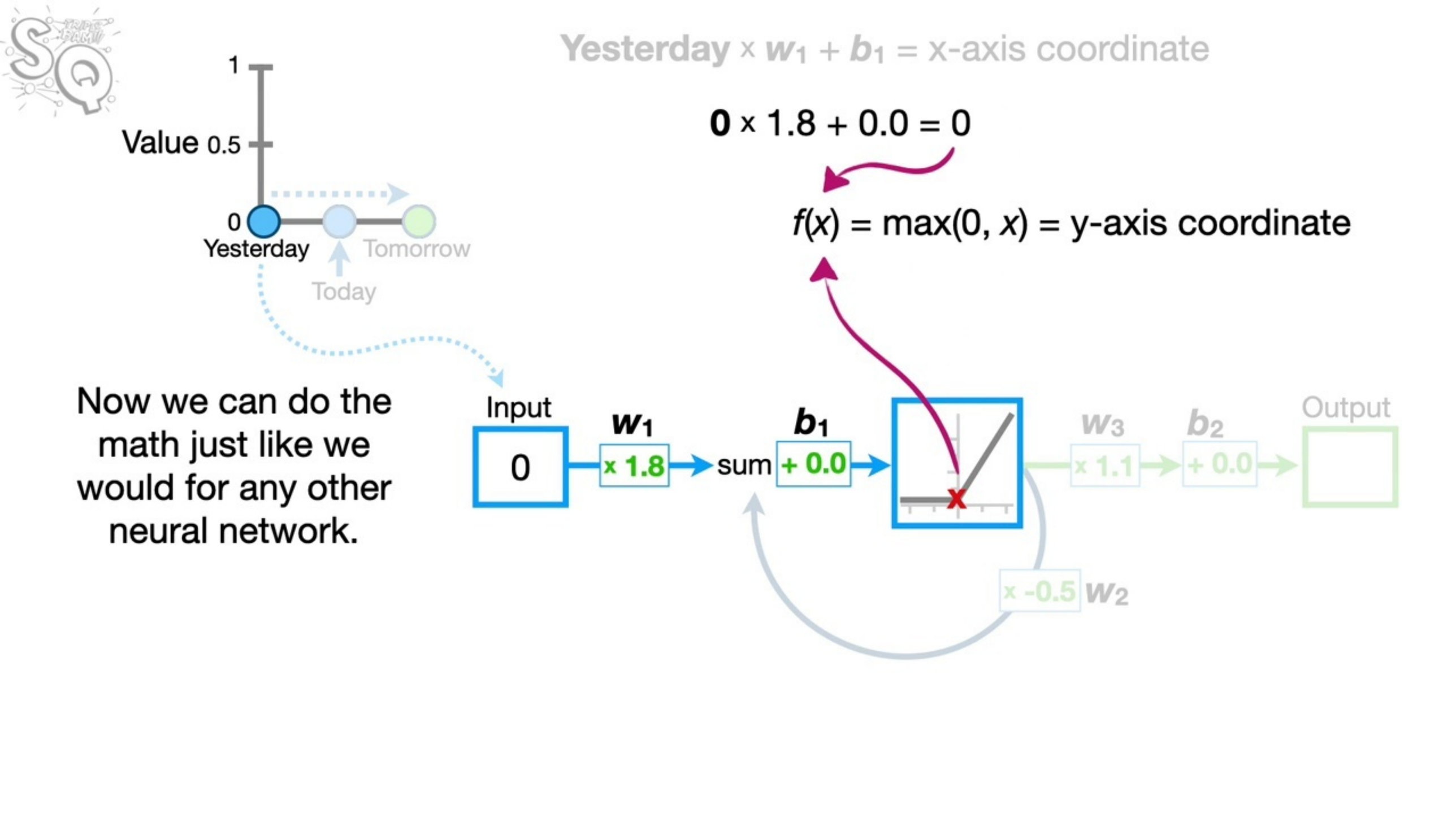

Yesterday × w_1
0 × 1.8
1
Value 0.5
0
Yesterday
Today
Tomorrow
Now we can do the math just like we would for any other neural network.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2

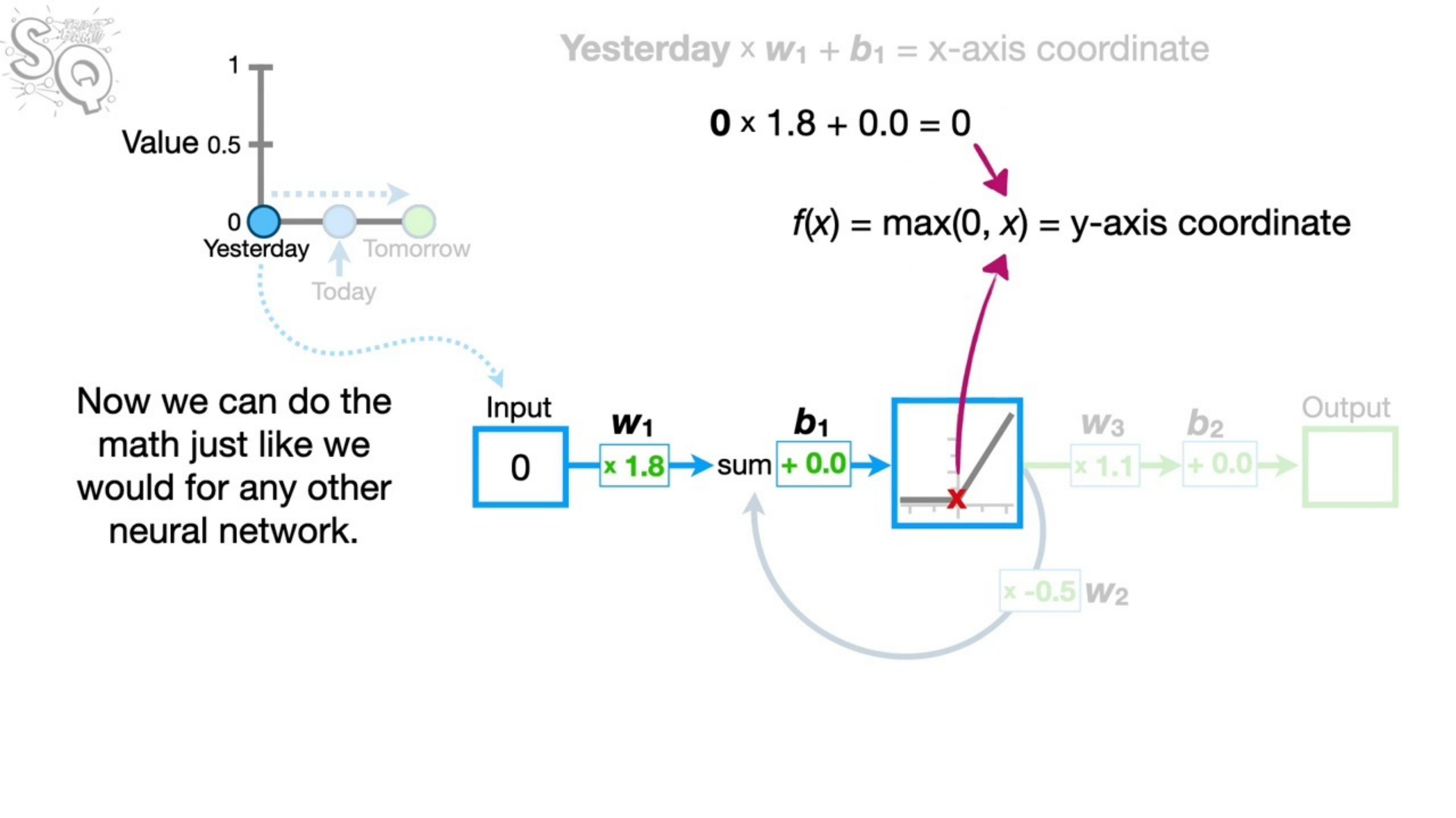

Yesterday × w_1 + b_1
0 × 1.8
1
Value 0.5
0
Yesterday
Today
Tomorrow
Now we can do the math just like we would for any other neural network.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2

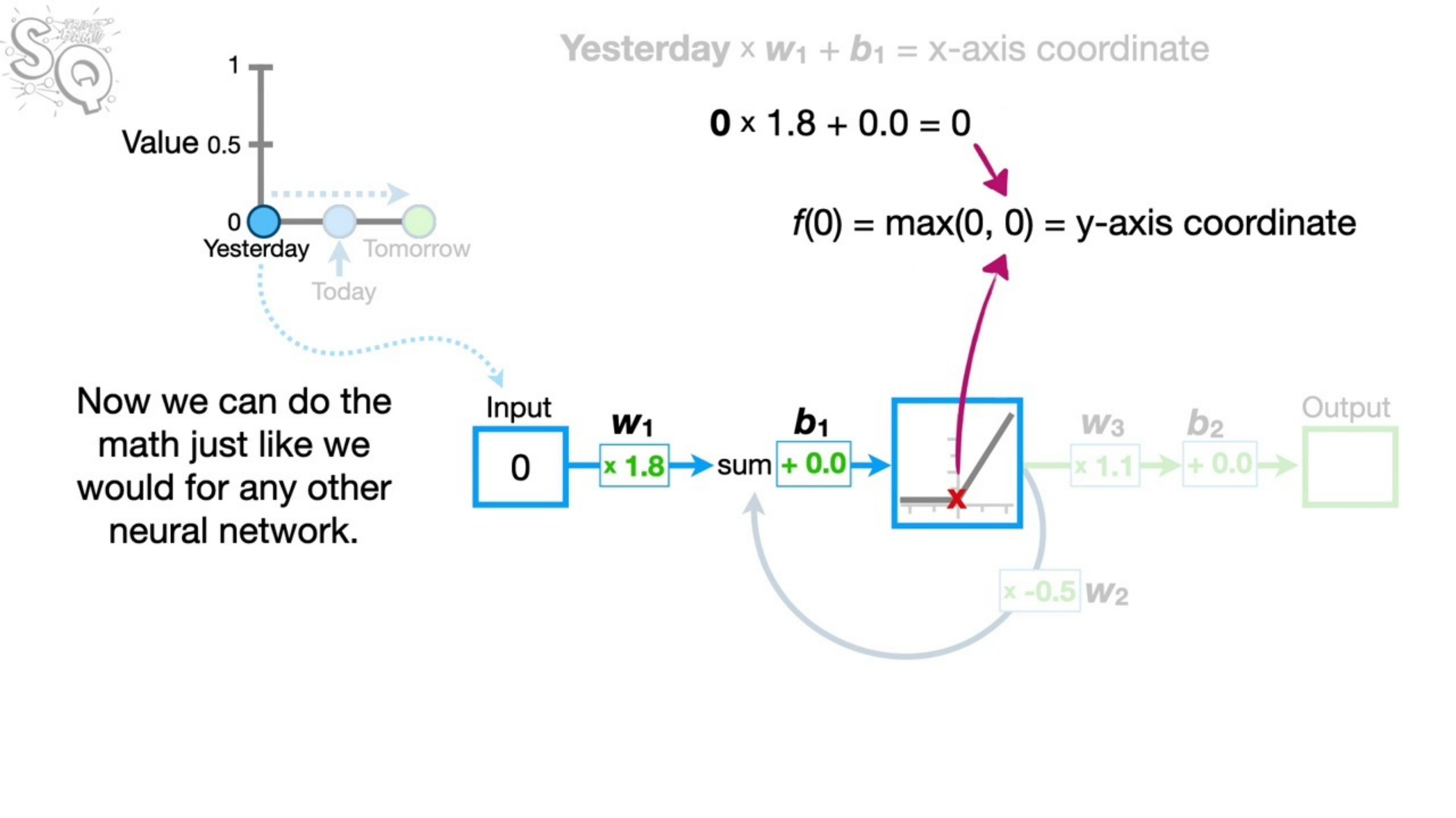

Yesterday × w_1 + b_1
0 × 1.8 + 0.0
1
Value 0.5
0
Yesterday
Today
Tomorrow
Now we can do the math just like we would for any other neural network.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2

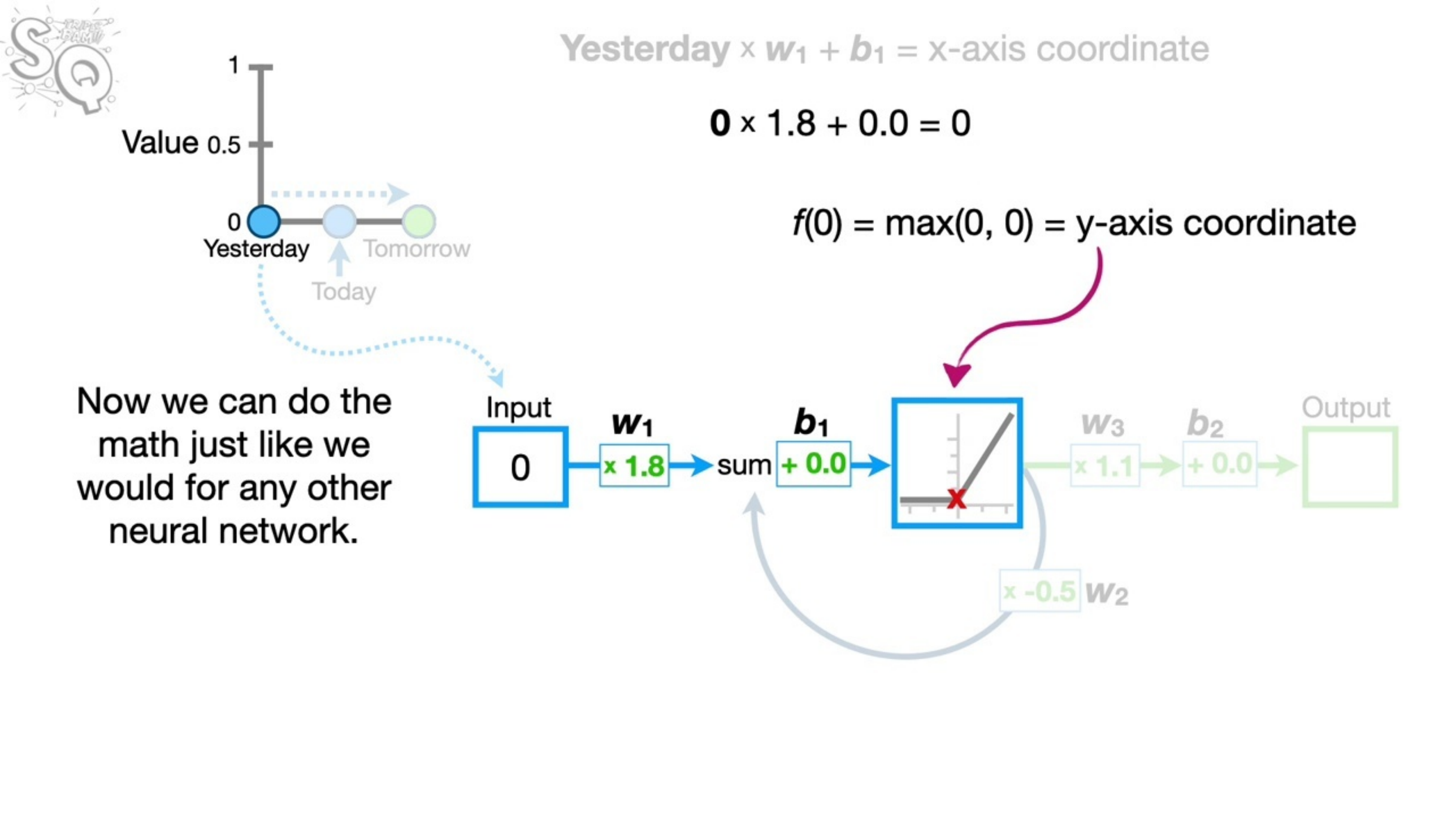

Yesterday × w_1 + b_1 = x-axis coordinate
0 × 1.8 + 0.0
1
Value 0.5
0
Yesterday
Today
Tomorrow
Now we can do the math just like we would for any other neural network.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2

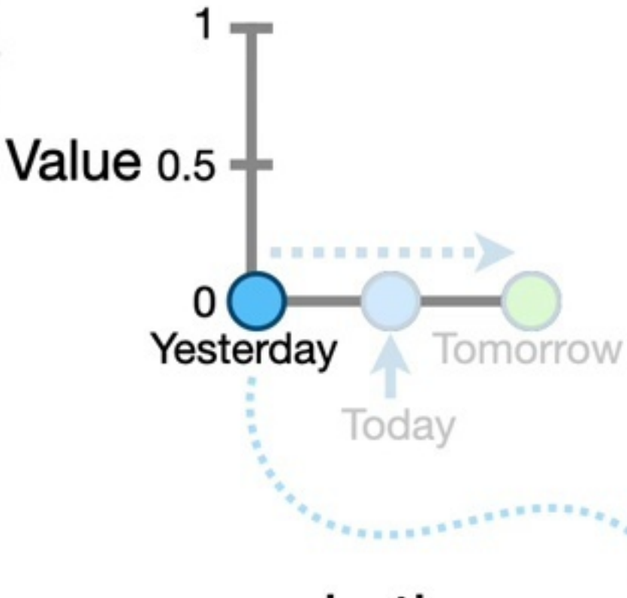

Yesterday × w_1 + b_1 = x-axis coordinate
0 × 1.8 + 0.0 = 0
1
Value 0.5
0
Yesterday
Today
Tomorrow
Now we can do the math just like we would for any other neural network.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2


Yesterday × w_1 + b_1 = x-axis coordinate
1
Value 0.5
0
Yesterday
Today
Tomorrow
0 × 1.8 + 0.0 = 0
f(x) = max(0, x) = y-axis coordinate
Now we can do the math just like we would for any other neural network.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2


Yesterday x w_1 + b_1 = x-axis coordinate
1
Value 0.5
0
Yesterday
Today
Tomorrow
0 x 1.8 + 0.0 = 0
f(x) = max(0, x) = y-axis coordinate
Now we can do the math just like we would for any other neural network.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2


Yesterday x w_1 + b_1 = x-axis coordinate
1
Value 0.5
0
Yesterday
Today
Tomorrow
0 x 1.8 + 0.0 = 0
f(0) = max(0, 0) = y-axis coordinate
Now we can do the math just like we would for any other neural network.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2


Yesterday × w_1 + b_1 = x-axis coordinate
0 × 1.8 + 0.0 = 0
f(0) = max(0, 0) = y-axis coordinate
1
Value 0.5
0
Yesterday
Today
Tomorrow
Now we can do the math just like we would for any other neural network.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2

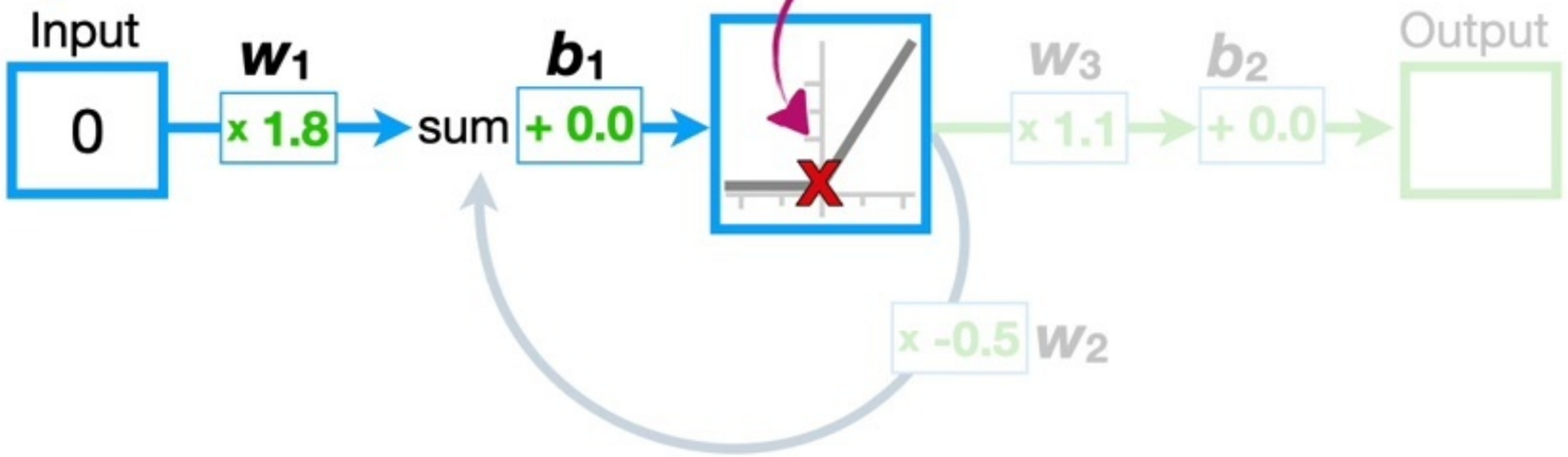


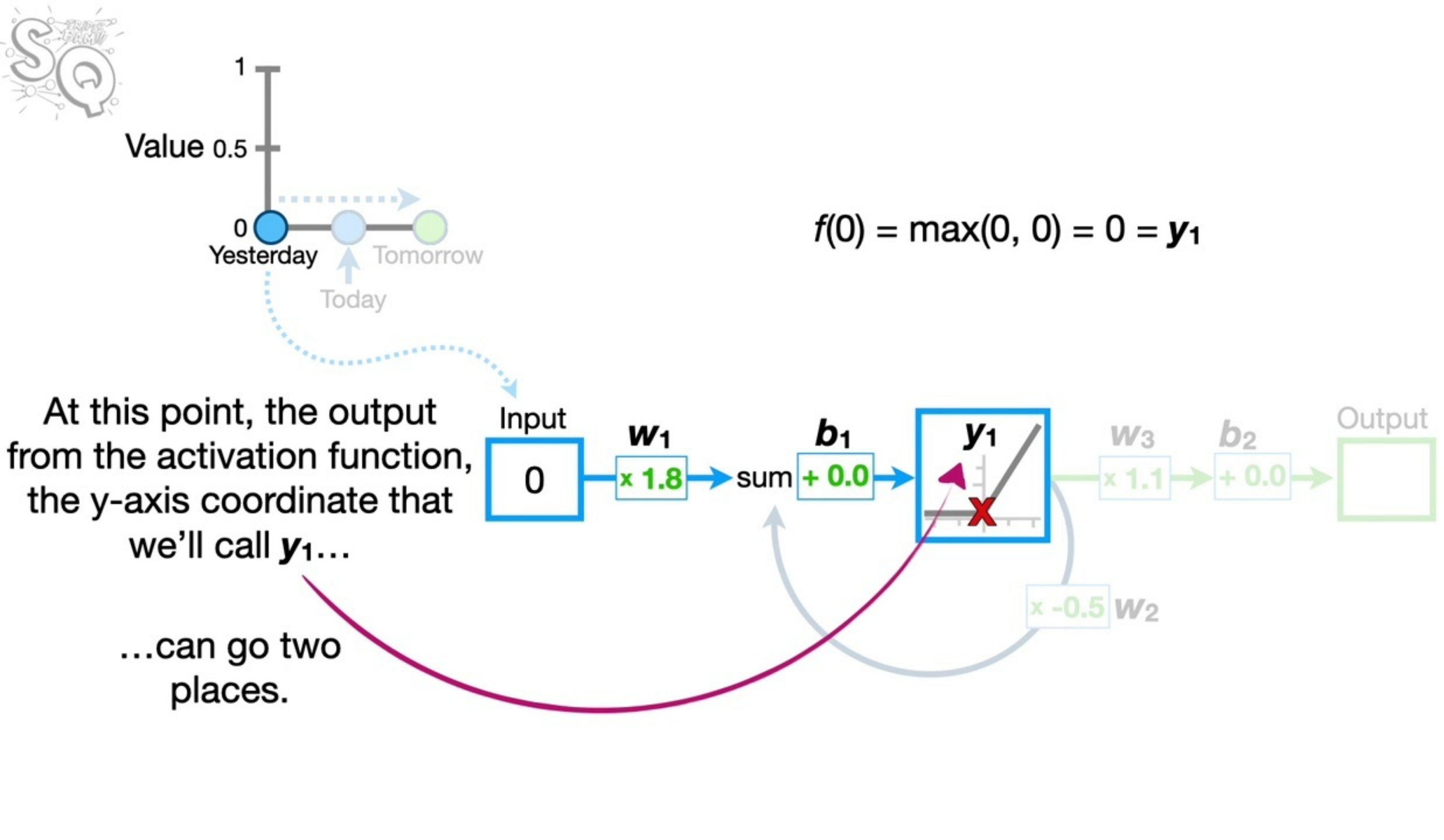
Yesterday × w_1 + b_1 = x-axis coordinate

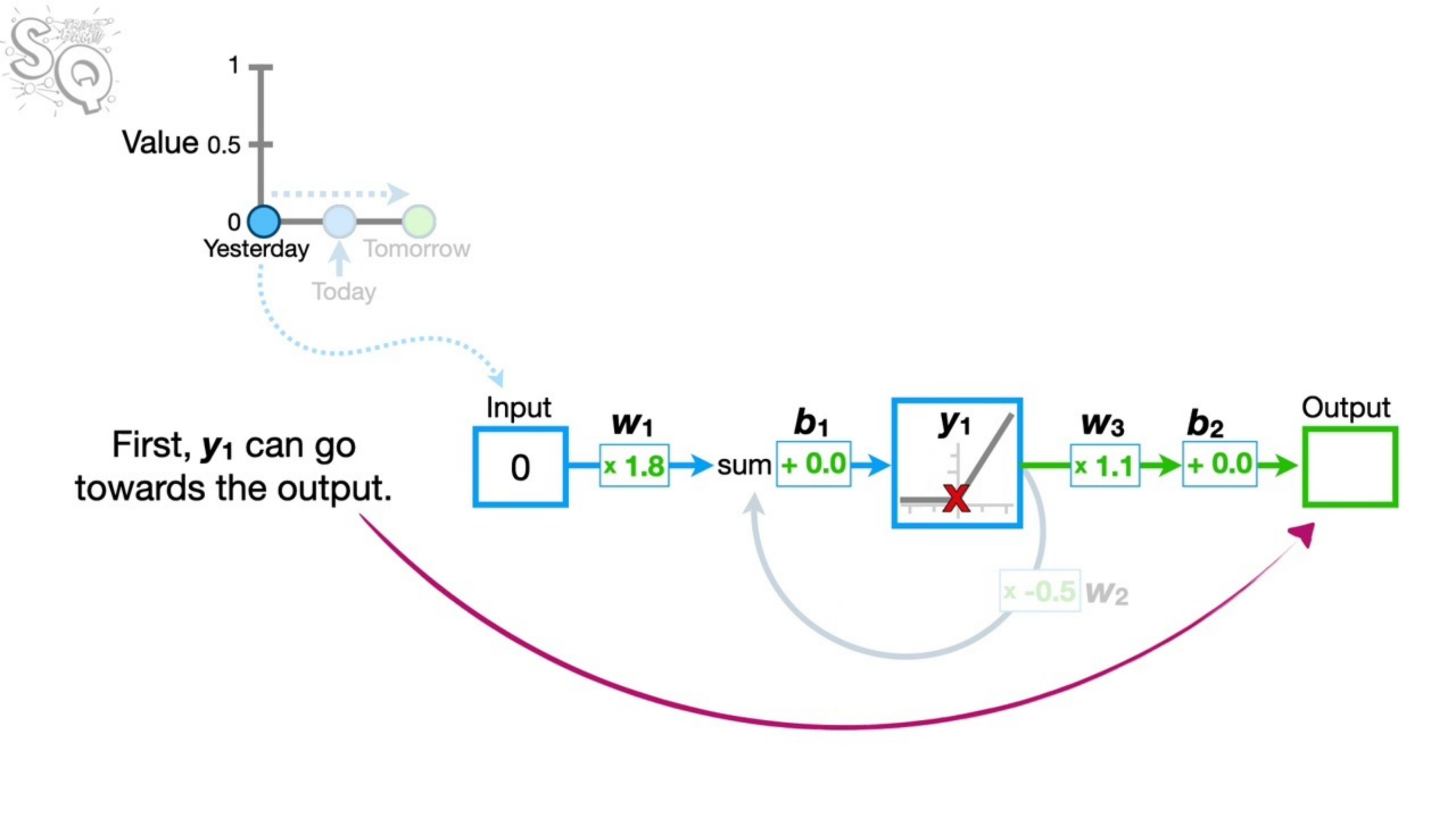
0 × 1.8 + 0.0 = 0

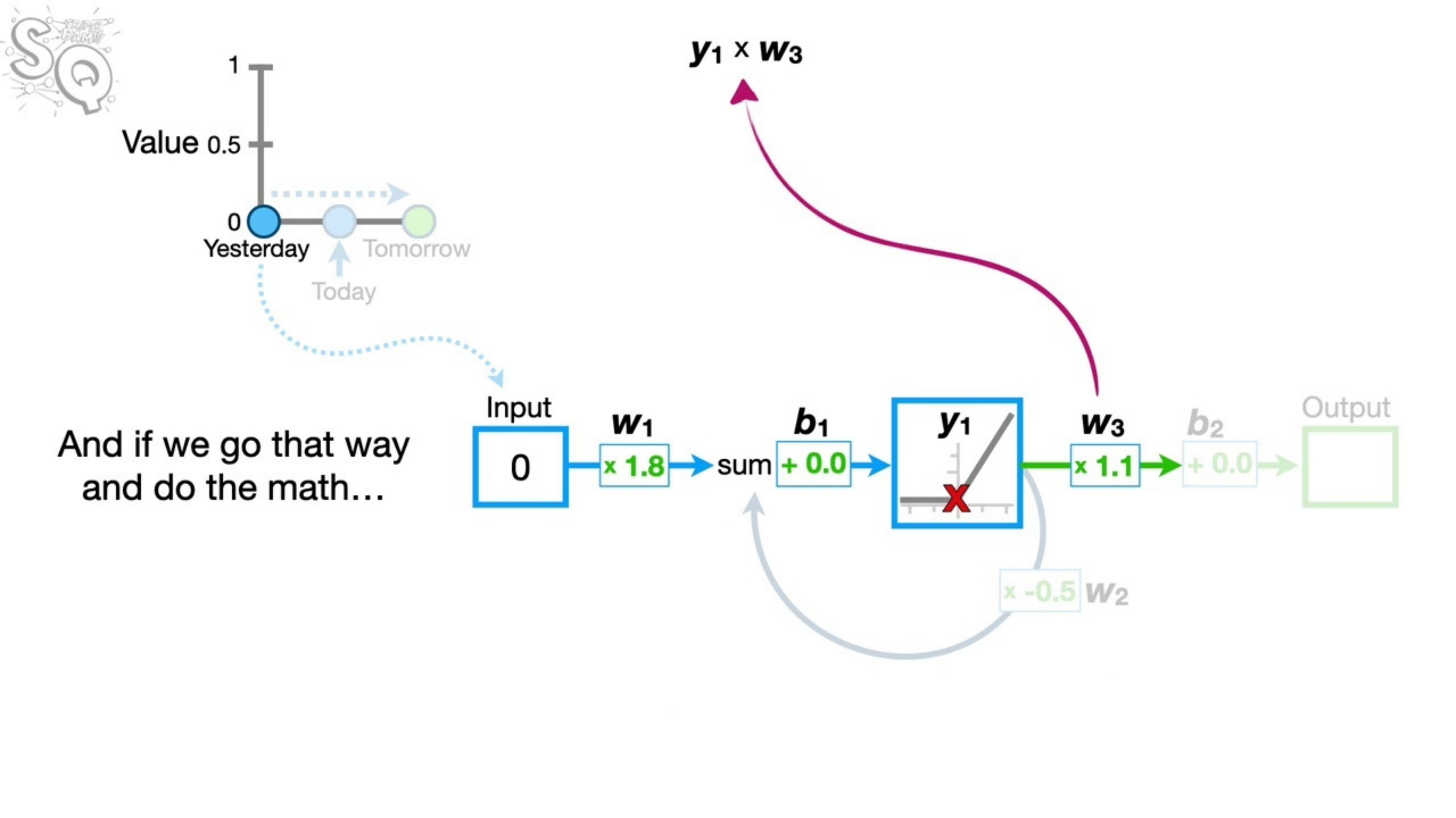
$f(0) = \max(0, 0) = 0$

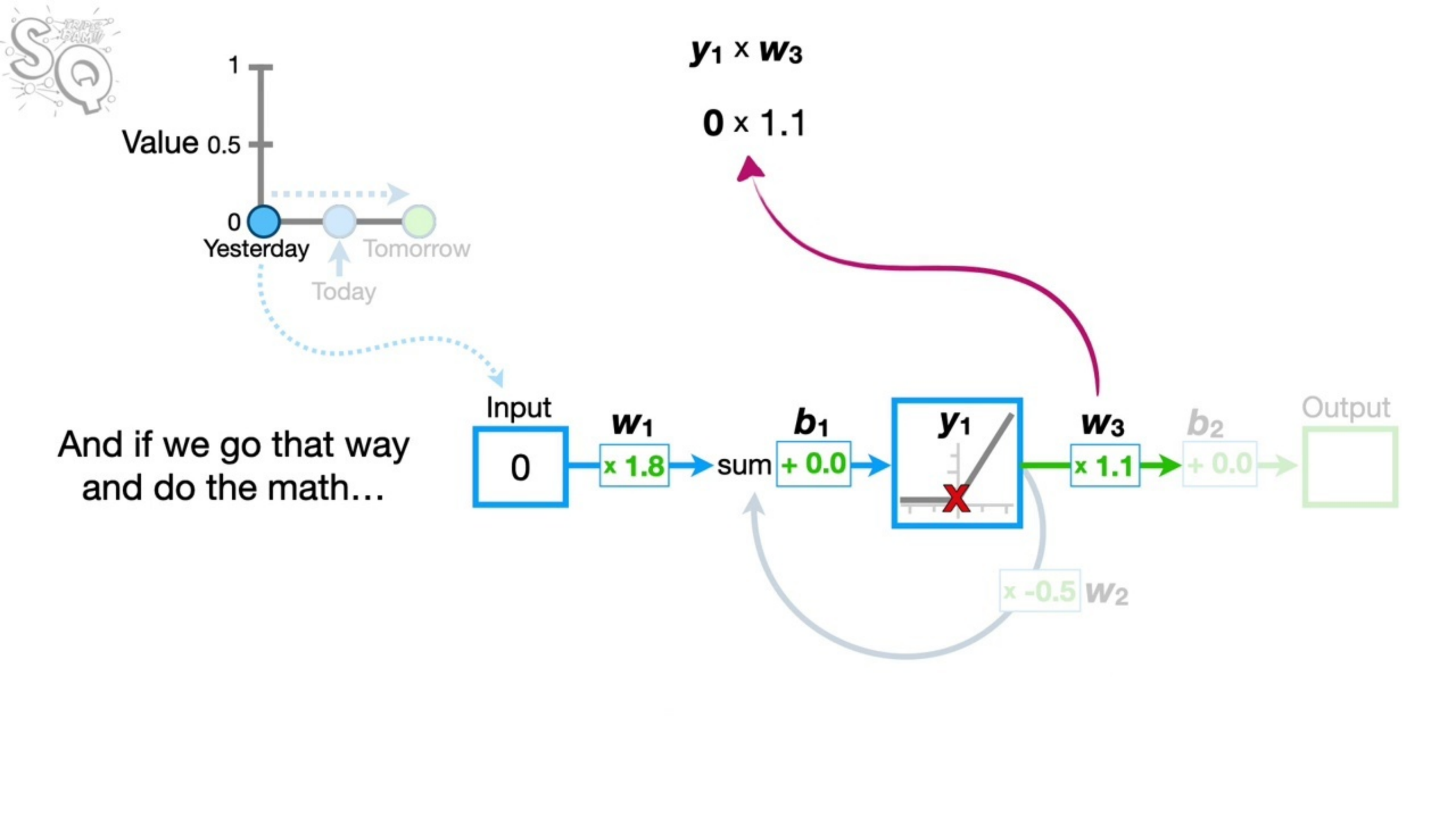
Now we can do the math just like we would for any other neural network.

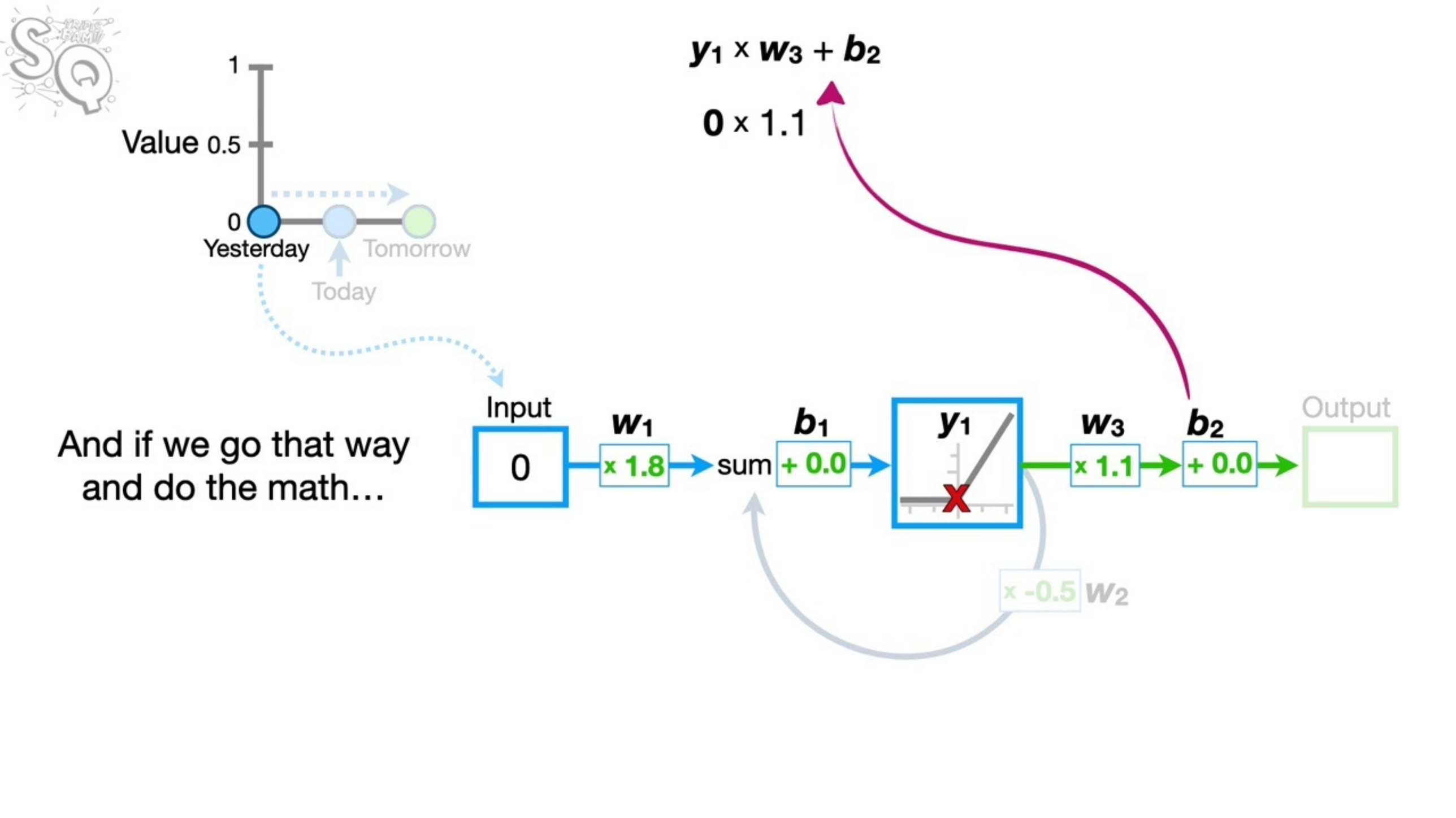


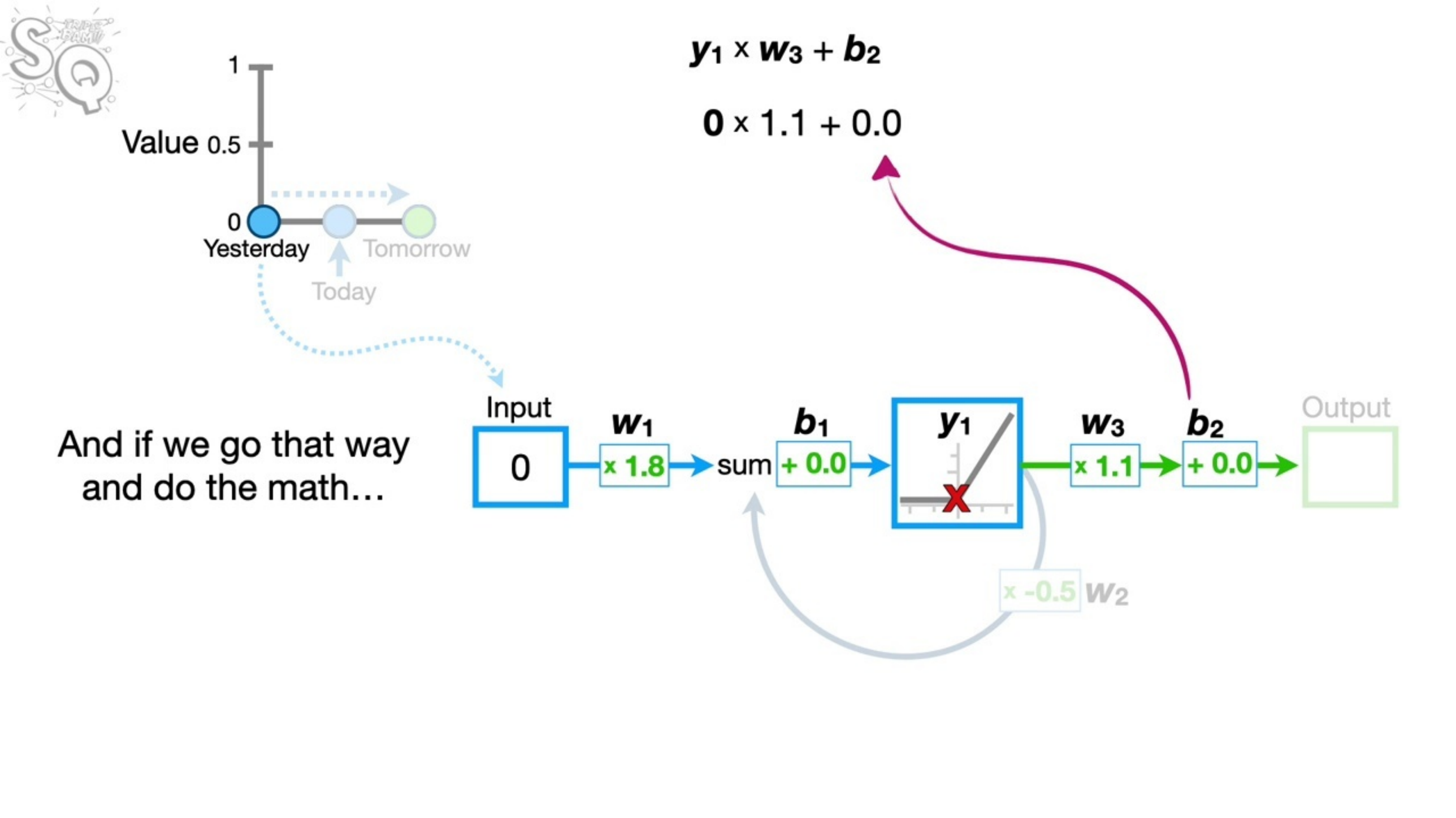

1
Value 0.5
0
Yesterday
Today
Tomorrow
$f(0) = \max(0, 0) = 0 = y_1$
At this point, the output from the activation function, the y-axis coordinate that we'll call y_1…
…can go two places.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2

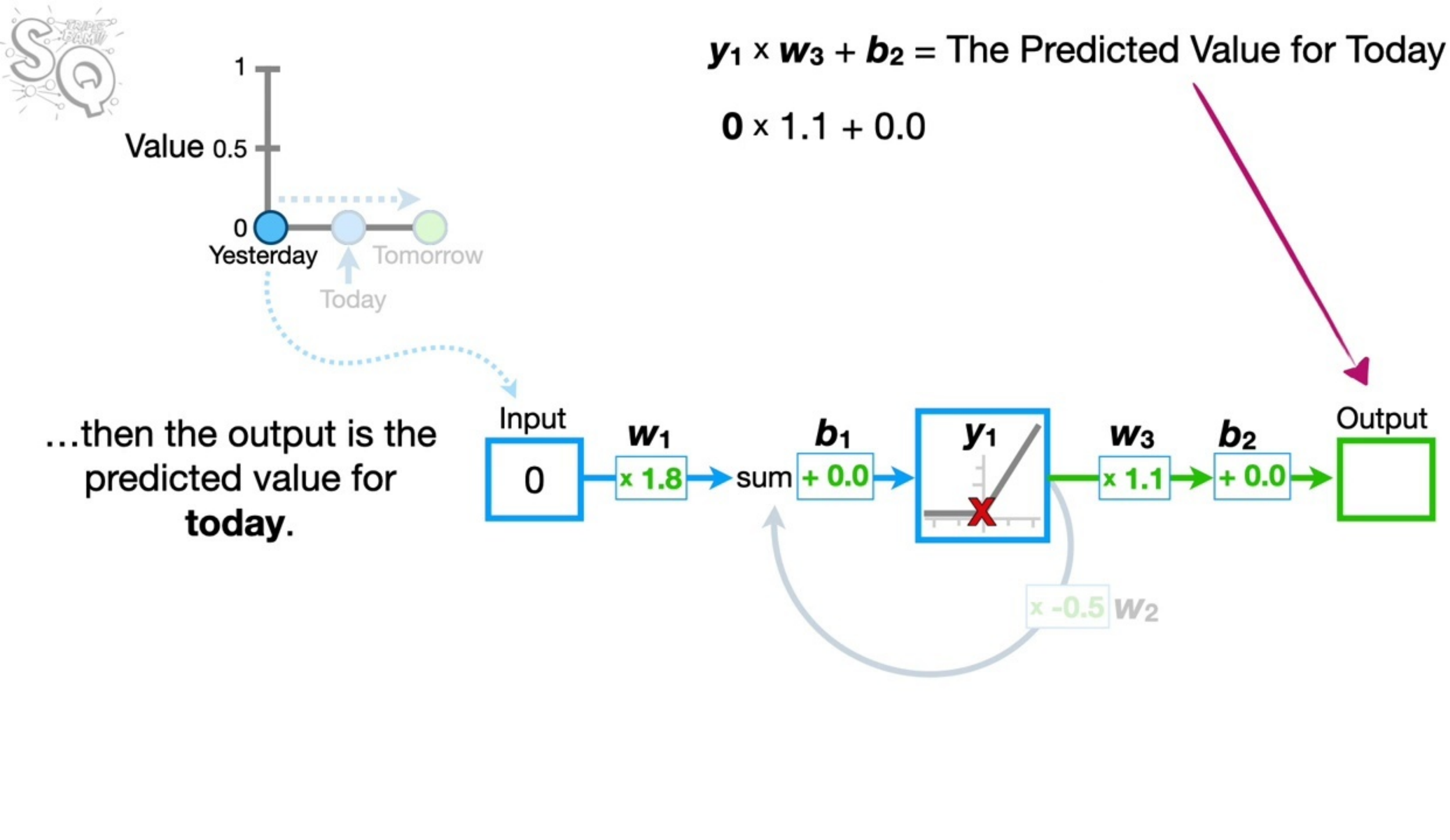

1
Value 0.5
0
Yesterday
Today
Tomorrow
First, y_1 can go towards the output.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5 w_2

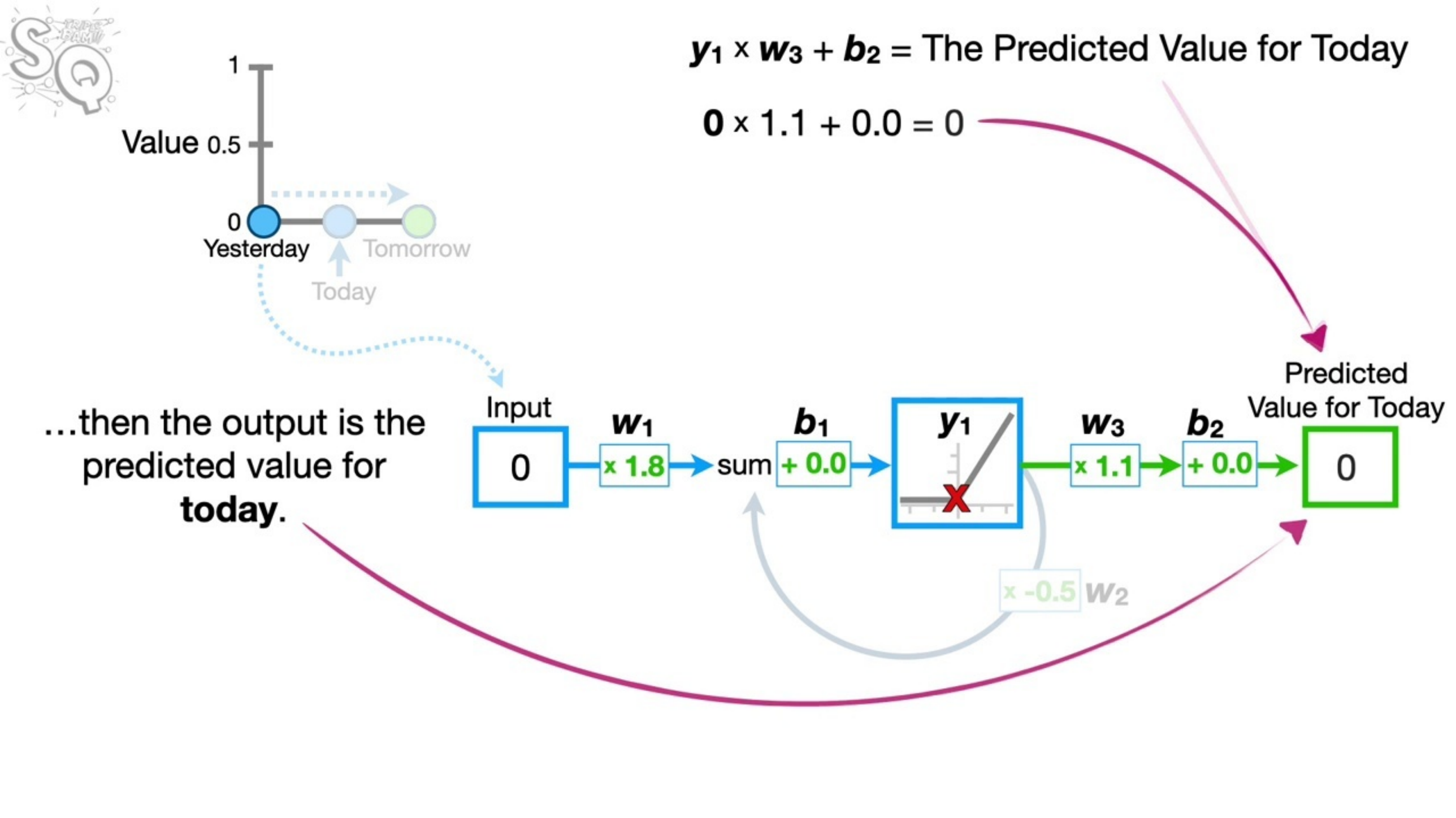

1
Value 0.5
0
Yesterday
Today
Tomorrow
$y_1 \times w_3$
And if we go that way
and do the math…
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2

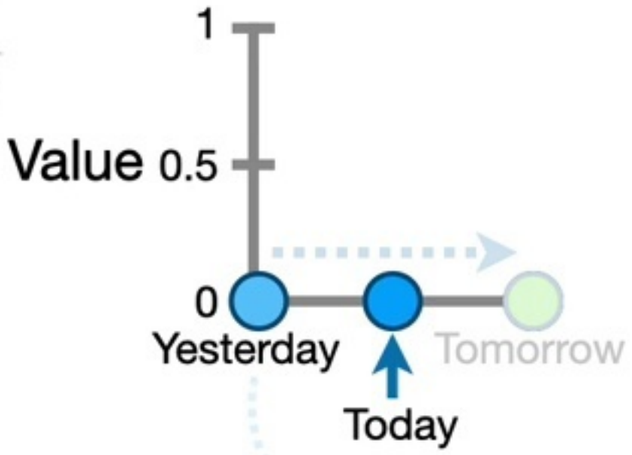

1
Value 0.5
0
Yesterday
Today
Tomorrow
$y_1 \times w_3$
0 x 1.1
And if we go that way
and do the math…
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5 w_2


1
Value 0.5
0
Yesterday
Today
Tomorrow
$y_1 \times w_3 + b_2$
0 x 1.1
And if we go that way
and do the math…
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5 w_2


$y_1 \times w_3 + b_2$
$0 \times 1.1 + 0.0$
1
Value 0.5
0
Yesterday
Today
Tomorrow
And if we go that way and do the math…
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5 w_2


$y_1 \times w_3 + b_2$ = The Predicted Value for Today
0 × 1.1 + 0.0
1
Value 0.5
0
Yesterday
Today
Tomorrow
…then the output is the predicted value for **today**.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5 w_2

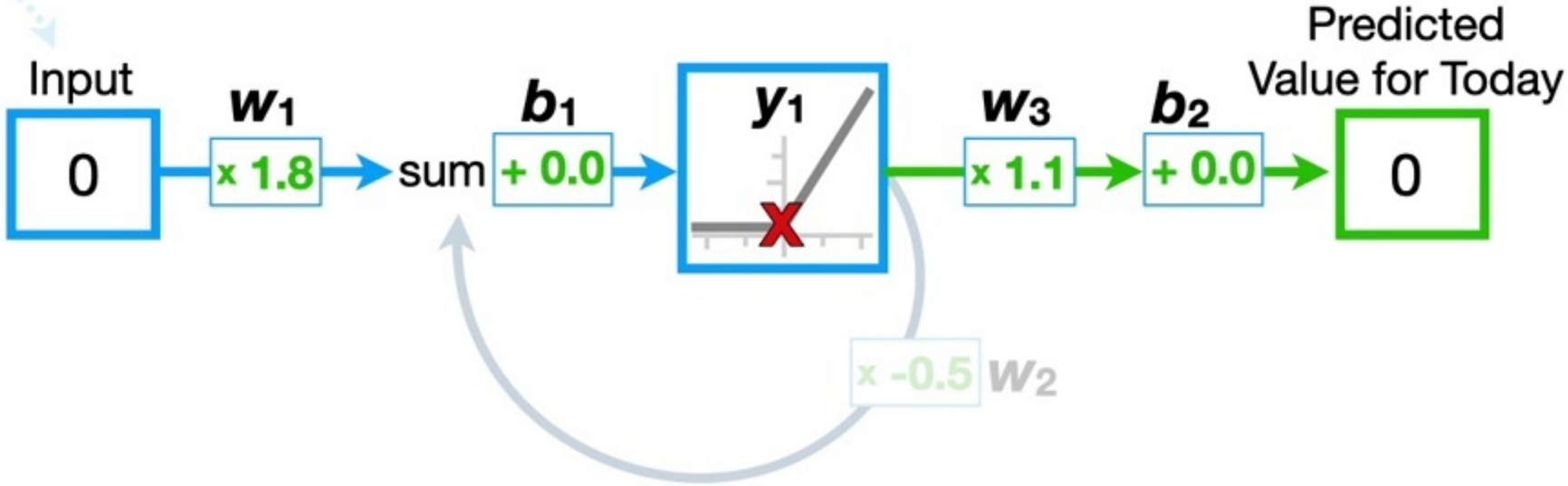

$y_1 \times w_3 + b_2$ = The Predicted Value for Today
0 × 1.1 + 0.0 = 0
1
Value 0.5
0
Yesterday
Today
Tomorrow
…then the output is the predicted value for **today**.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
0
x -0.5 w_2



$y_1 \times w_3 + b_2$ = The Predicted Value for Today

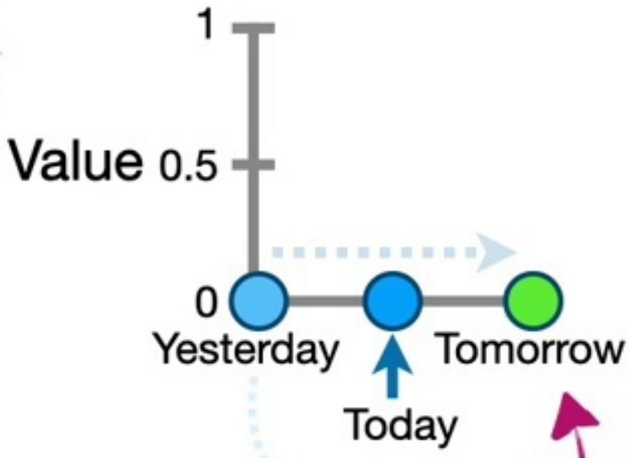
$0 \times 1.1 + 0.0 = 0$

However, we're not interested in the *predicted* value for **today** because we already have the *actual* value for **today**.

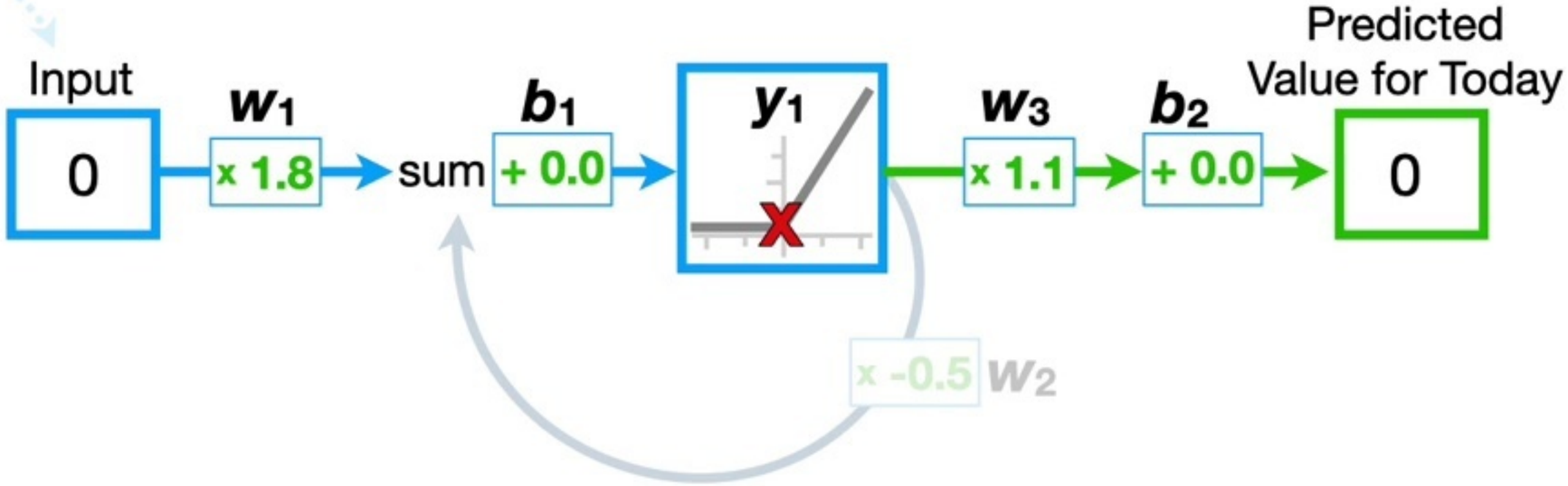


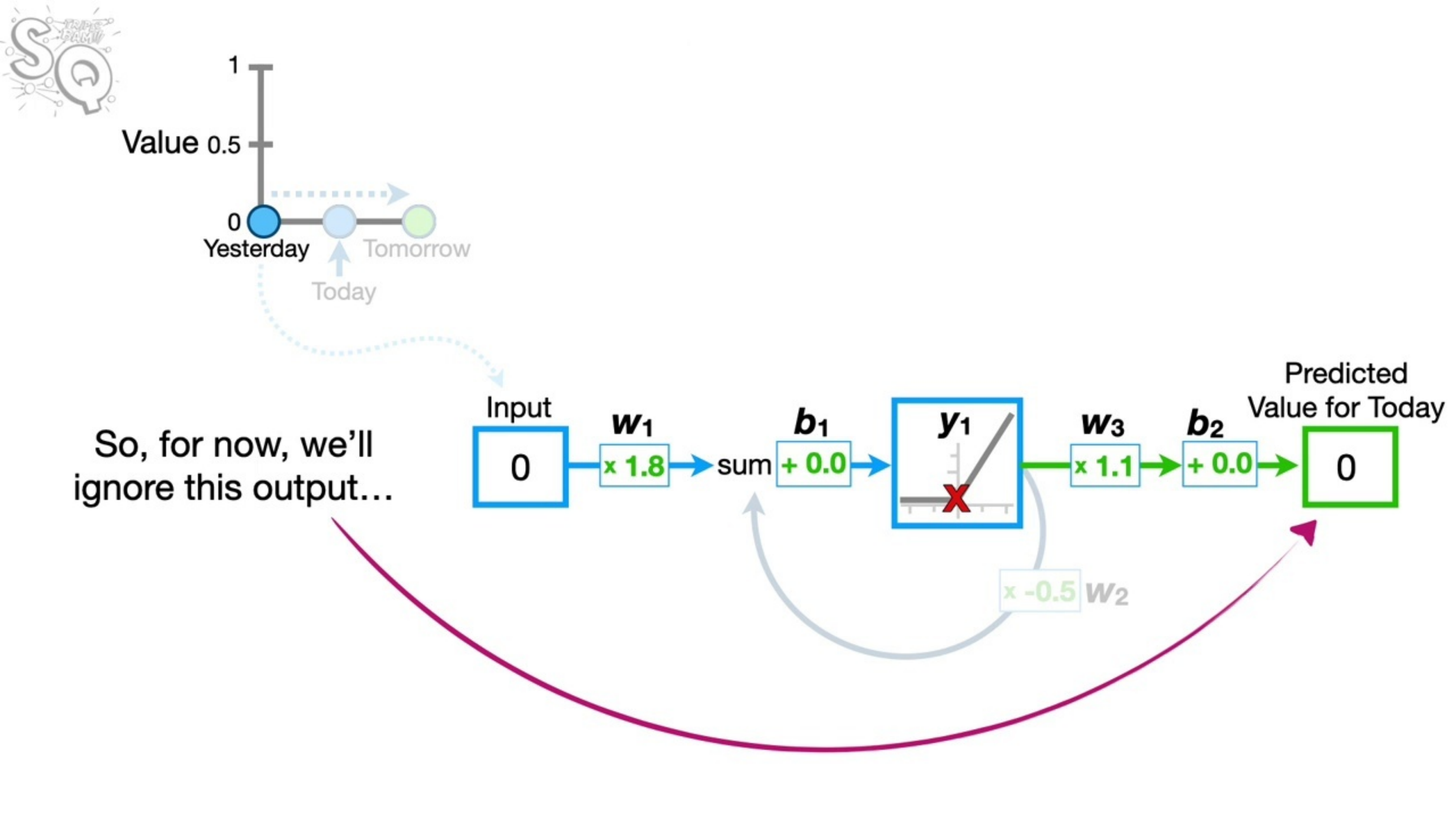
$y_1 \times w_3 + b_2$ = The Predicted Value for Today

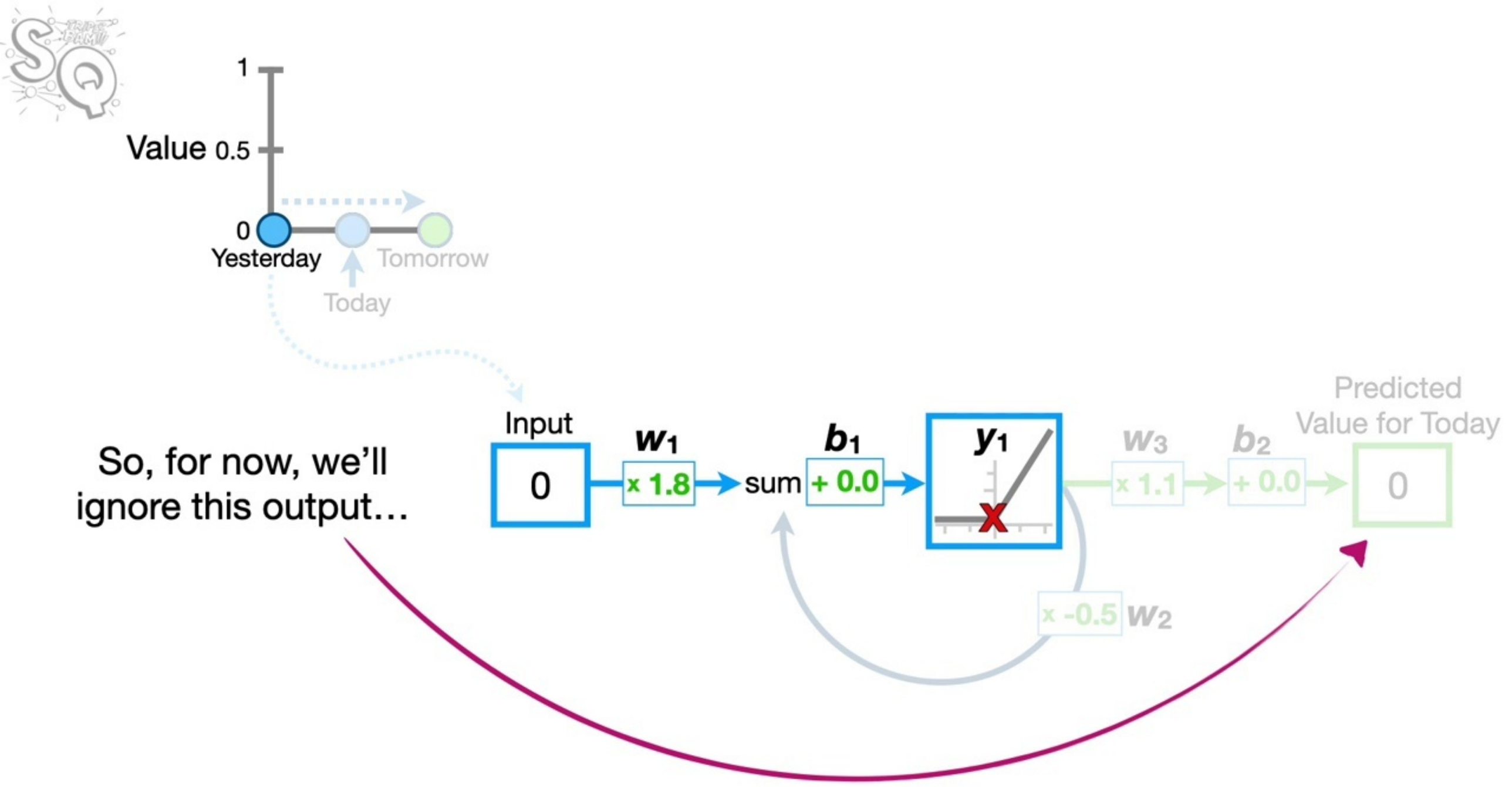
$0 \times 1.1 + 0.0 = 0$

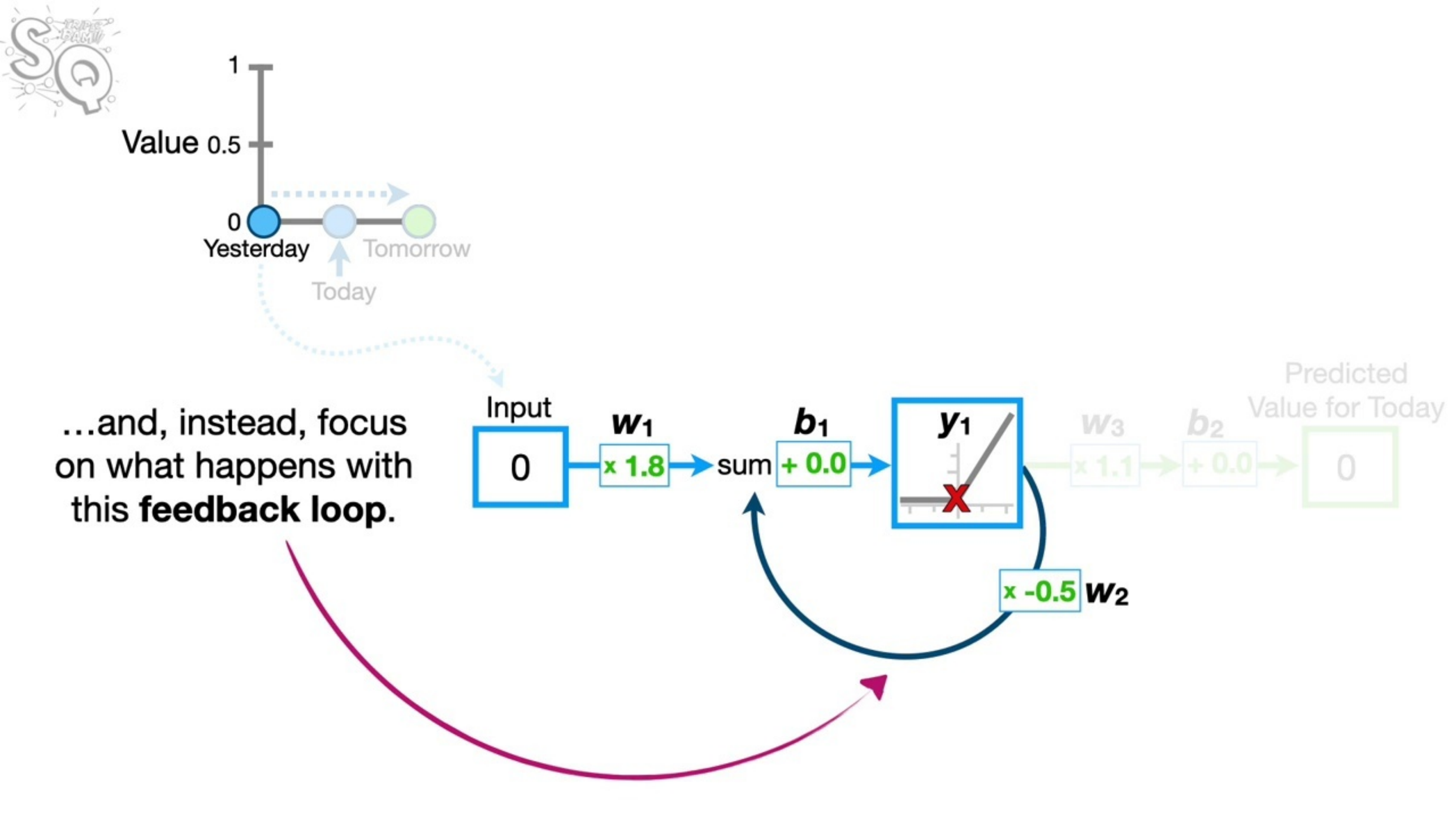


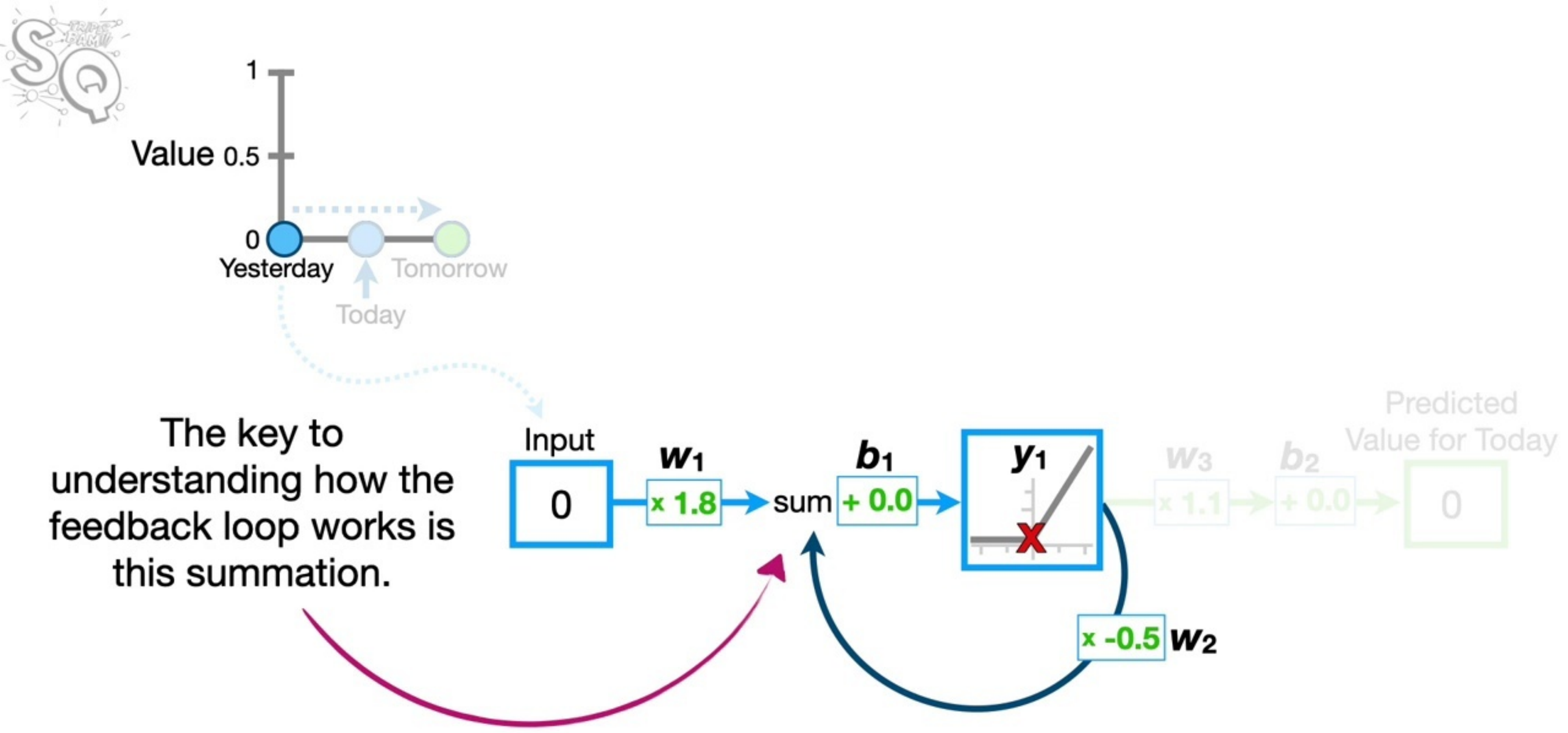
Instead, we want to use both **yesterday** and **today's** value to predict **tomorrow's** value.

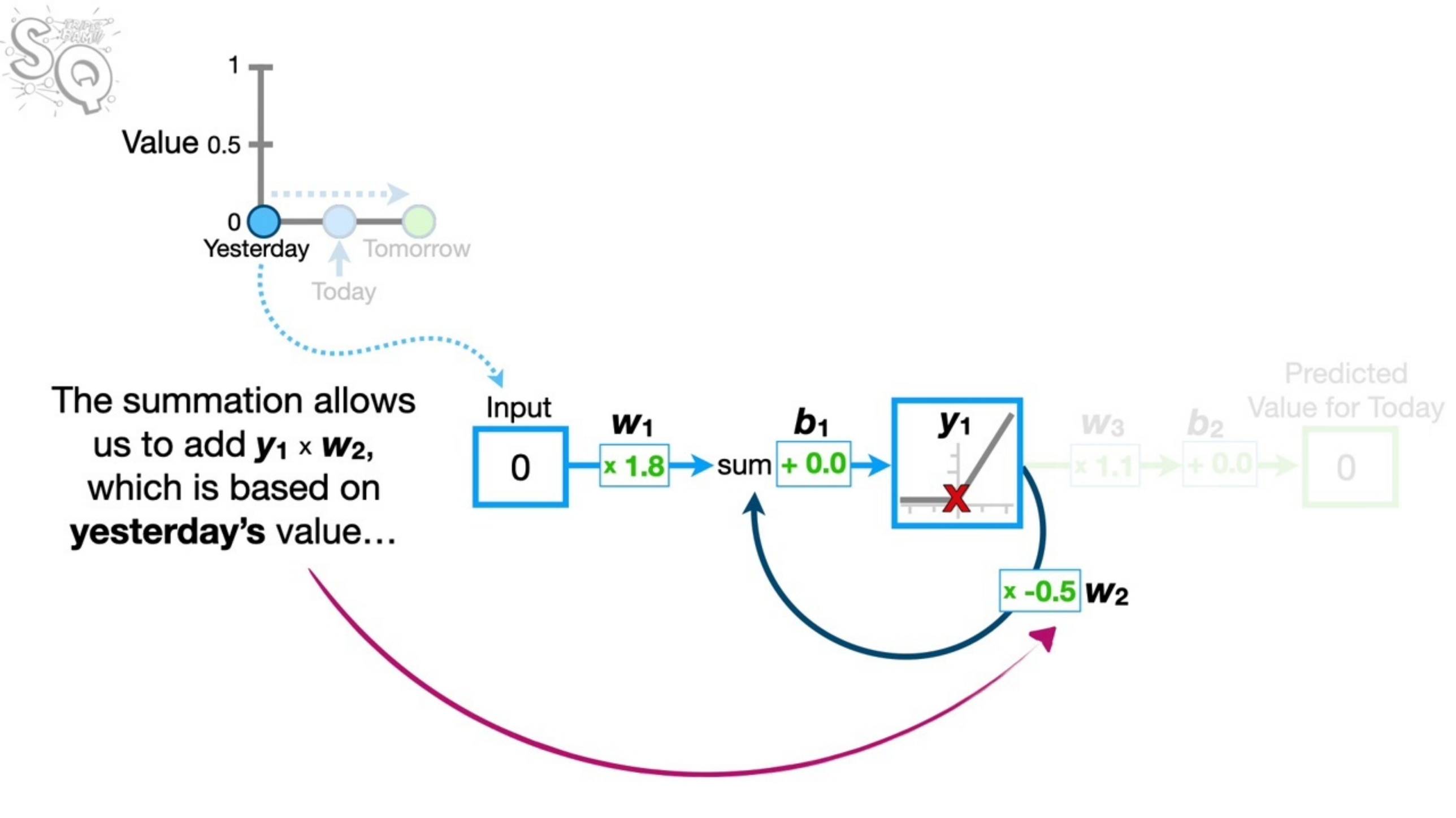


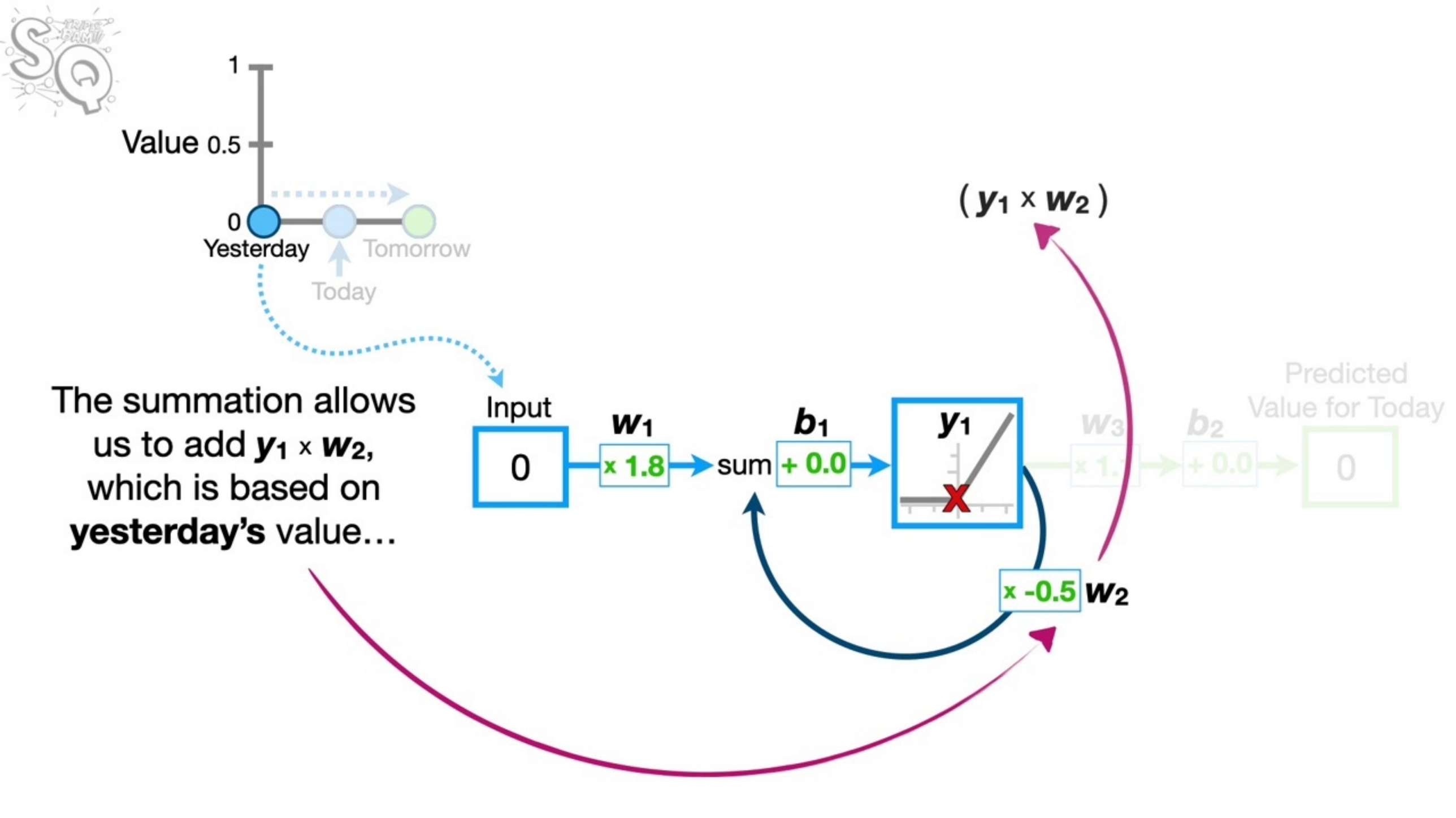

1
Value 0.5
0
Yesterday
Today
Tomorrow
So, for now, we'll ignore this output…
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
0
x -0.5
w_2

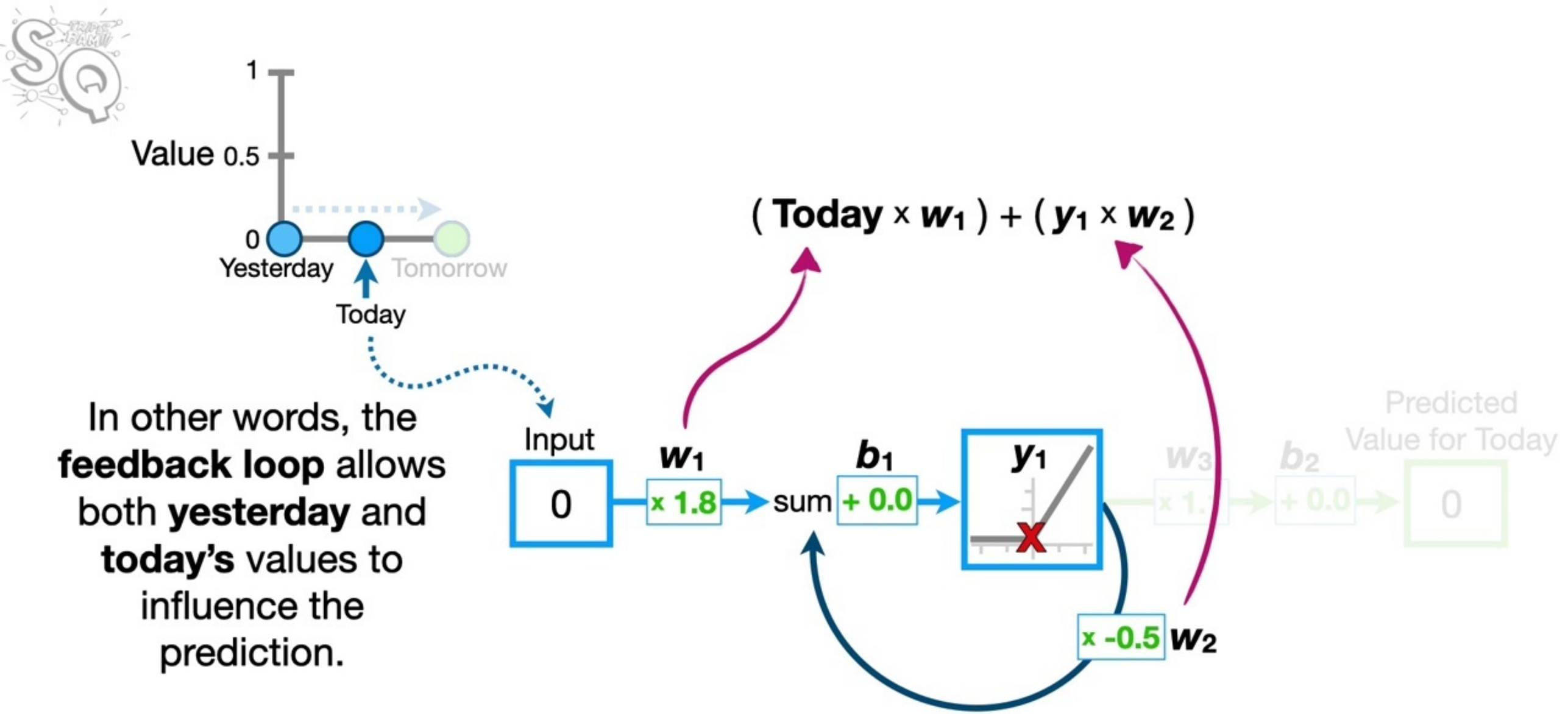

1
Value 0.5
0
Yesterday
Today
Tomorrow
So, for now, we'll ignore this output…
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
0
x -0.5
w_2

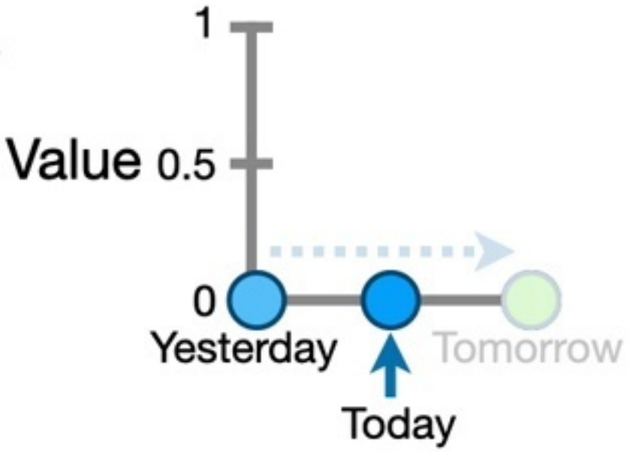

1
Value 0.5
0
Yesterday
Today
Tomorrow
…and, instead, focus on what happens with this **feedback loop**.
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
0
x -0.5
w_2


1
Value 0.5
0
Yesterday
Today
Tomorrow
The key to understanding how the feedback loop works is this summation.
Input
0
w1
x 1.8
sum
b1
+ 0.0
y1
w3
x 1.1
b2
+ 0.0
Predicted Value for Today
0
x -0.5
w2

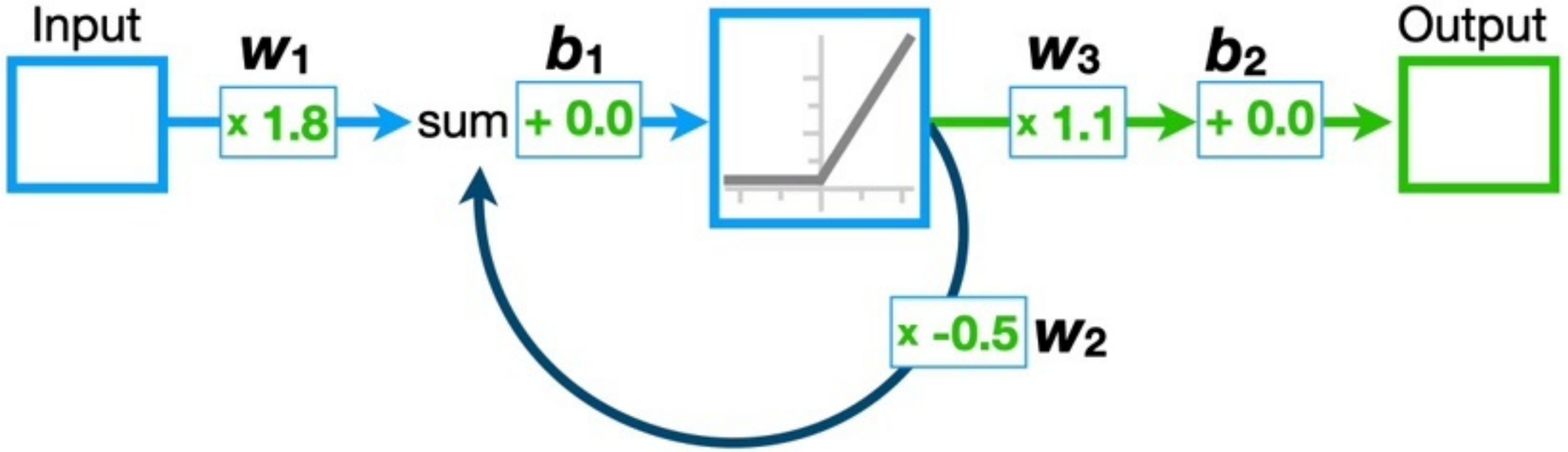

1
Value 0.5
0
Yesterday
Today
Tomorrow
The summation allows us to add $y_1 \times w_2$, which is based on **yesterday's** value…
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
x -0.5
w_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
0


1
Value 0.5
0
Yesterday
Today
Tomorrow
The summation allows us to add $y_1 \times w_2$, which is based on **yesterday's** value…
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
$(y_1 \times w_2)$
x -0.5
w_2
w_3
b_2
+ 0.0
Predicted Value for Today
0

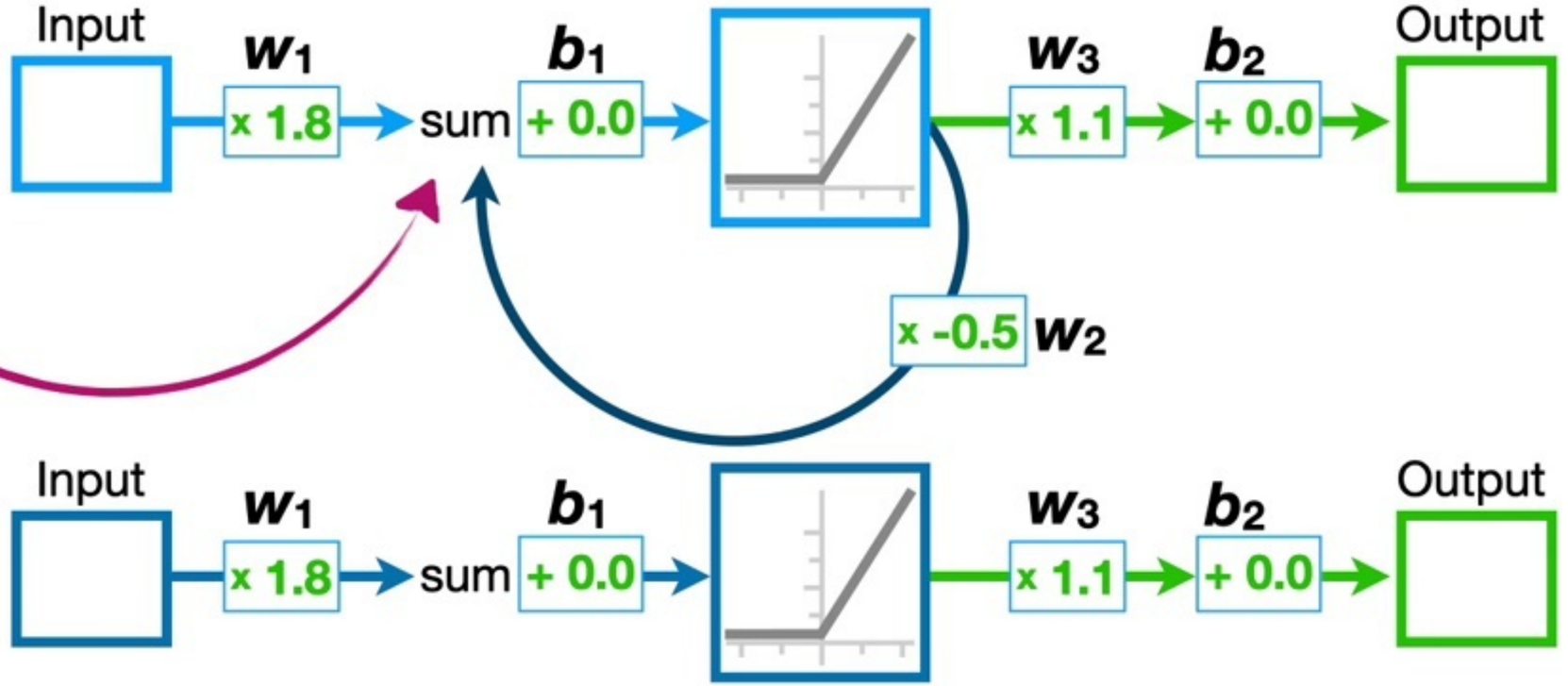

1
Value 0.5
0
Yesterday
Today
Tomorrow
In other words, the feedback loop allows both yesterday and today's values to influence the prediction.
(Today x w_1) + (y_1 x w_2)
Input
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
x -0.5
w_2
w_3
b_2
+ 0.0
Predicted Value for Today
0



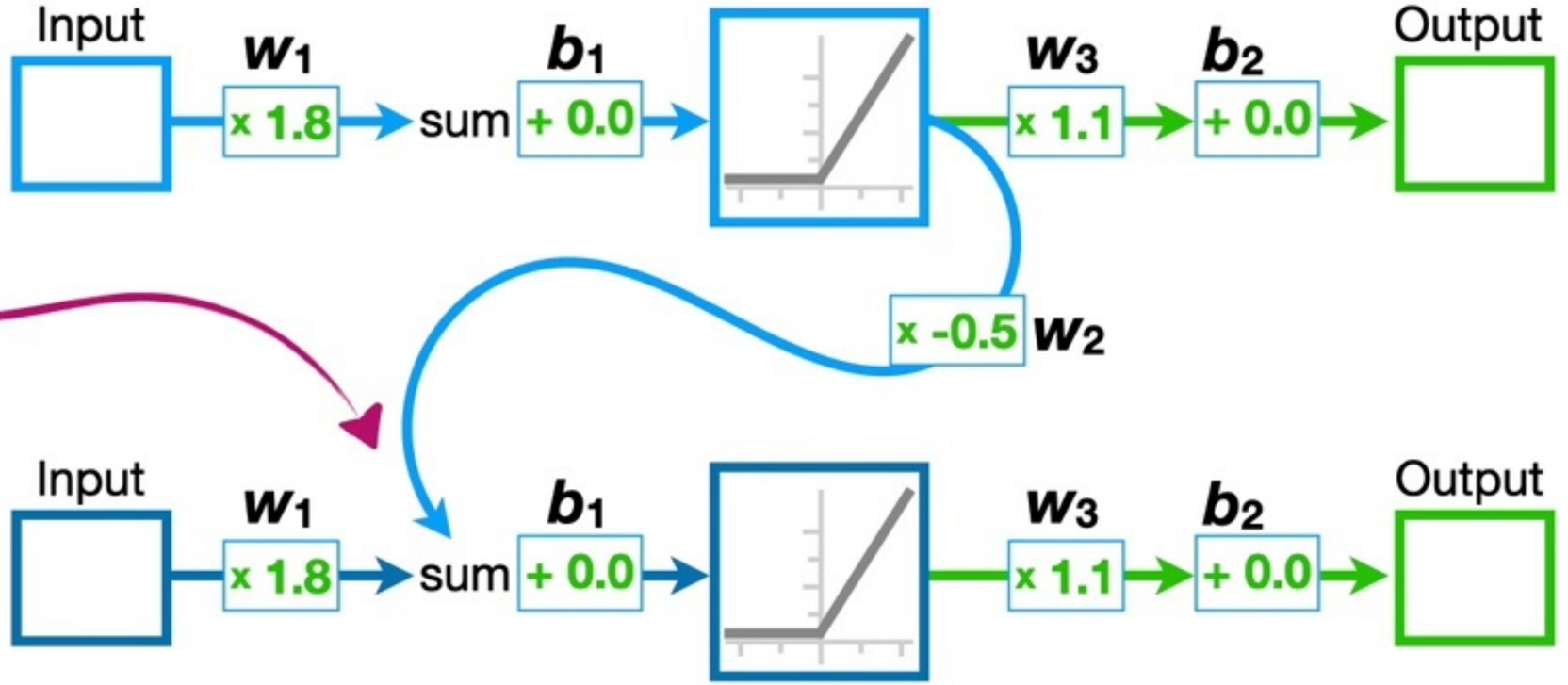
…we can **unroll** the feedback loop by making a copy of the neural network for each input value.



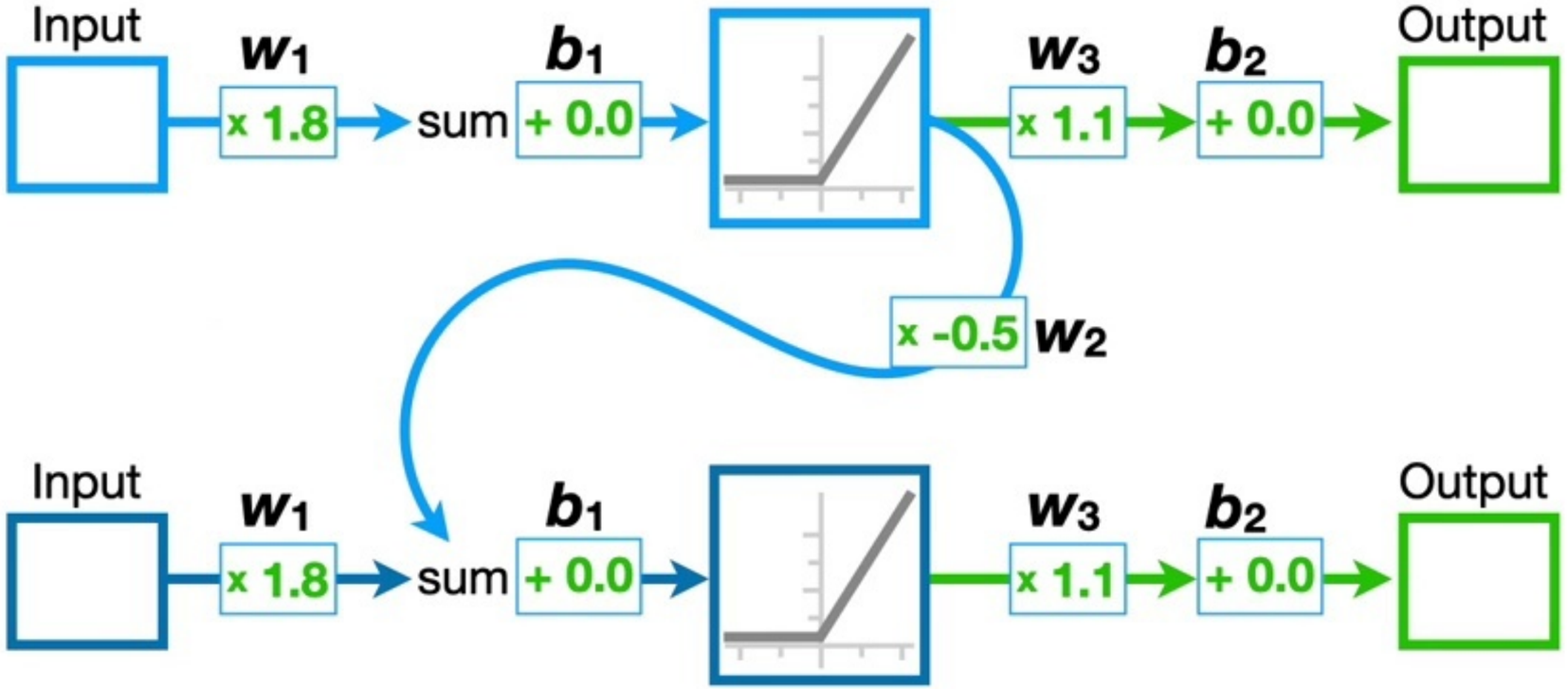
Now, instead of pointing the **feedback loop** to the sum in the first copy…

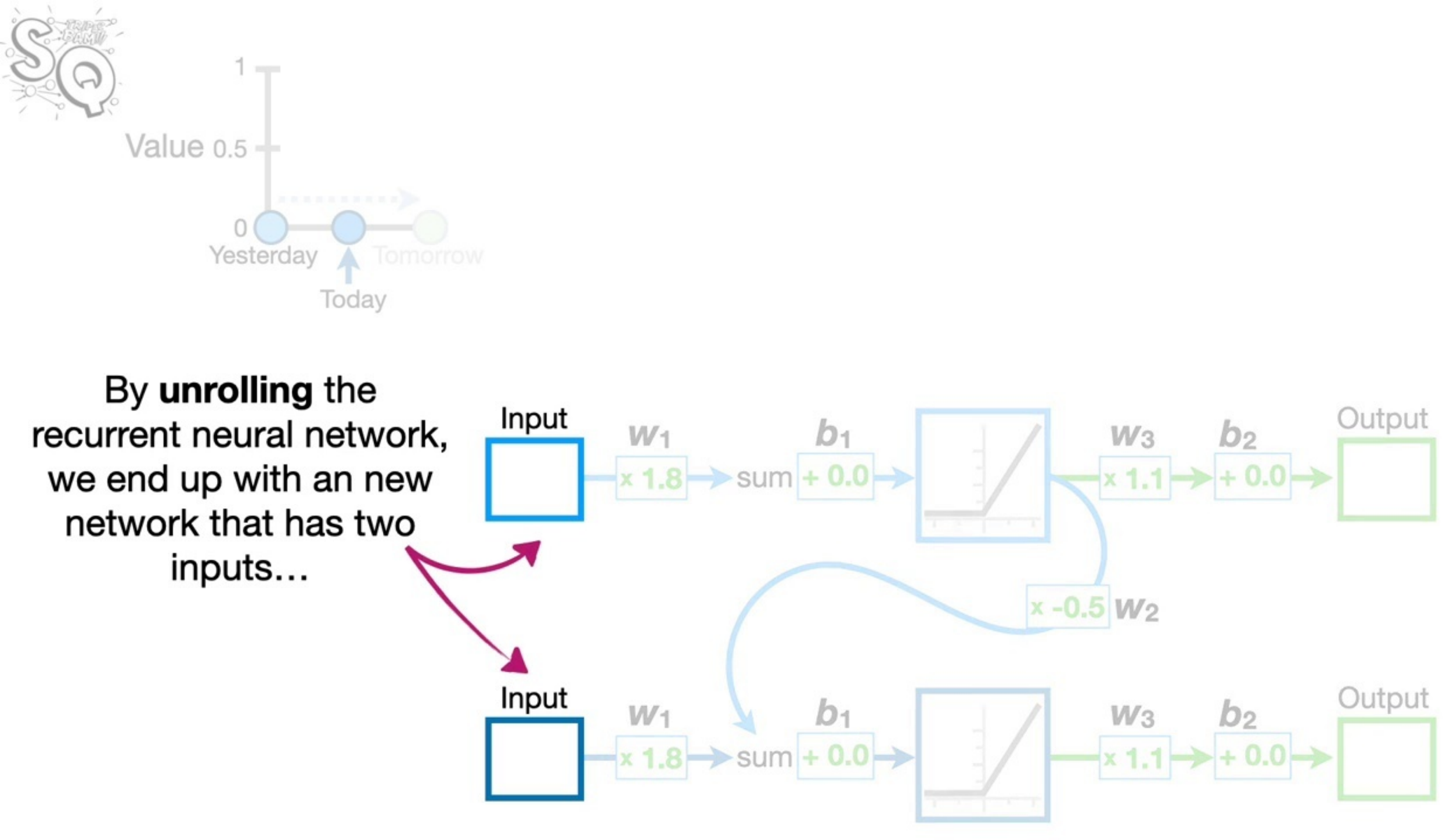


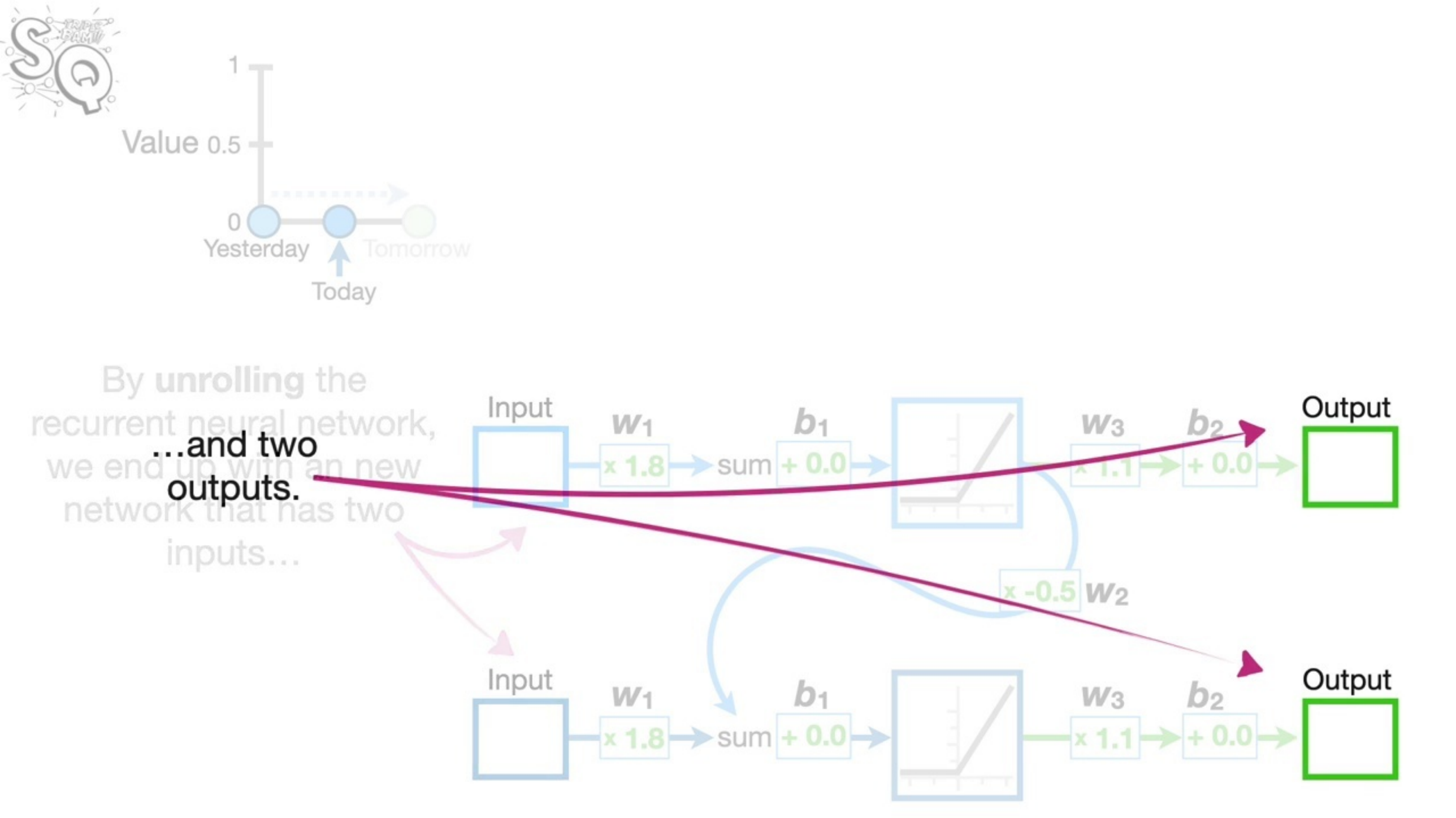
…we can point it to the sum in the second copy.

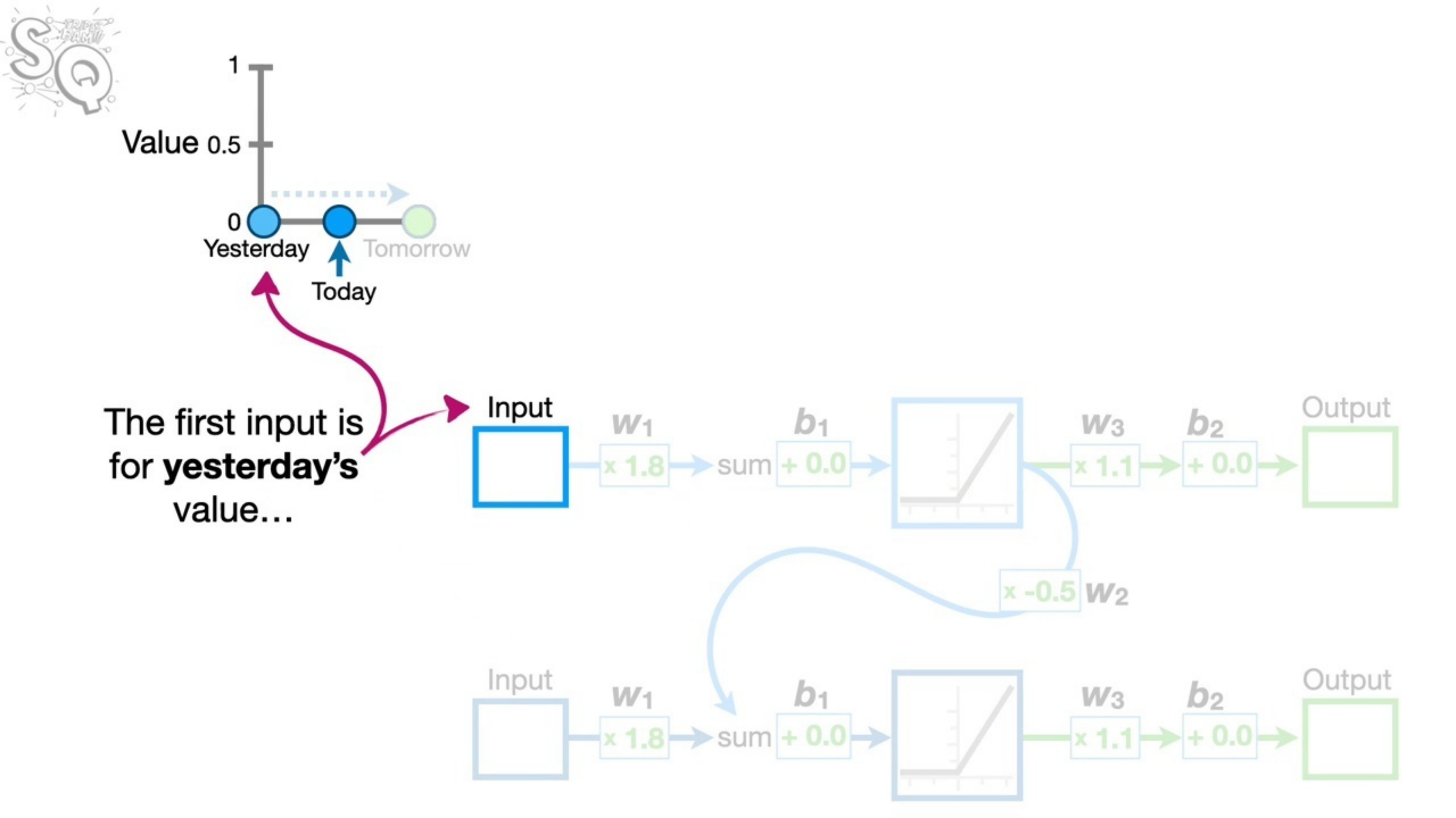


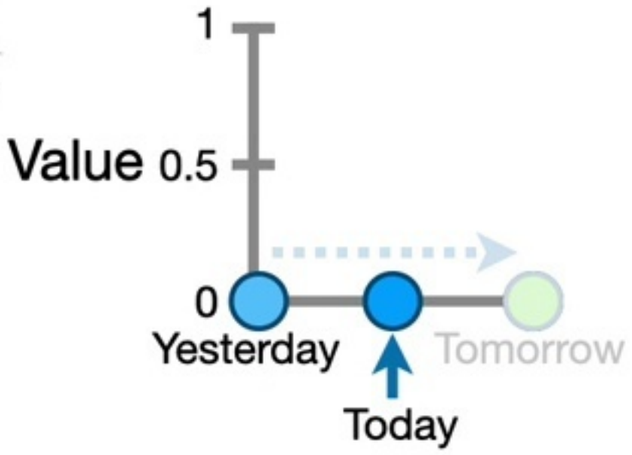
By **unrolling** the recurrent neural network, we end up with an new network that has two inputs…



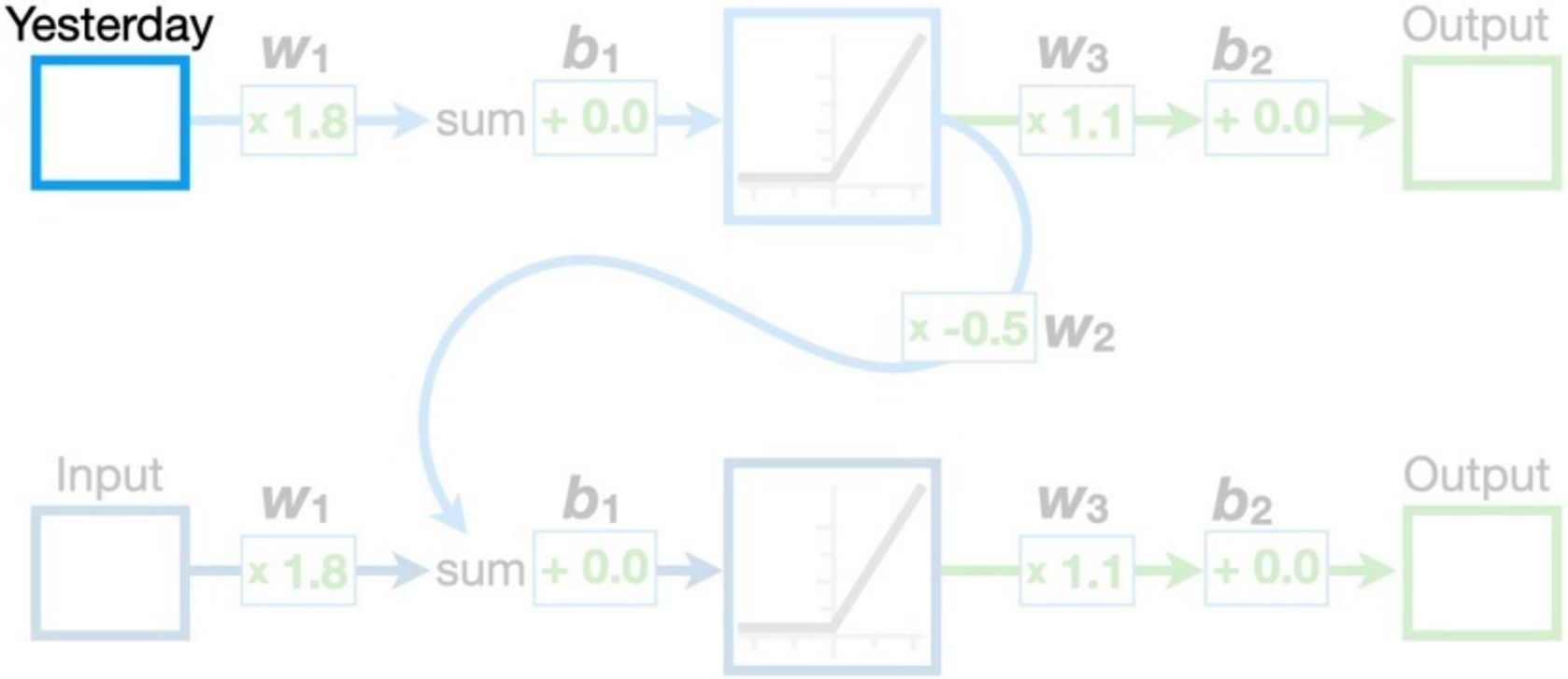

1
Value 0.5
0
Yesterday
Today
Tomorrow
By **unrolling** the recurrent neural network, we end up with an new network that has two inputs…
Input
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2
Input
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output

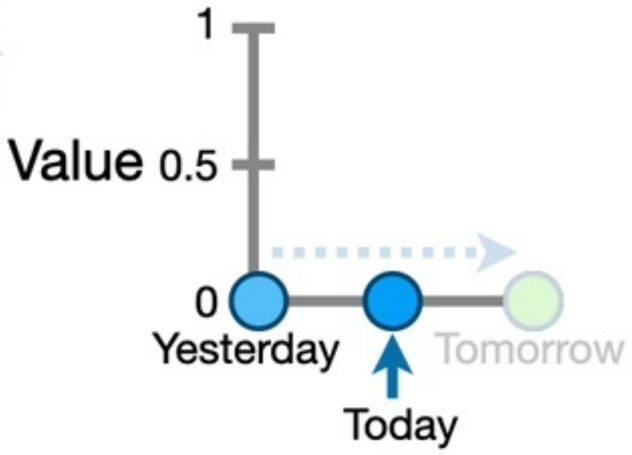

1
Value 0.5
0
Yesterday
Today
Tomorrow
By unrolling the recurrent neural network, we end up with an new network that has two inputs…
…and two outputs.
Input
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2
Input
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output


1
Value 0.5
0
Yesterday
Today
Tomorrow
The first input is for **yesterday's** value…
Input
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output
x -0.5
w_2
Input
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output

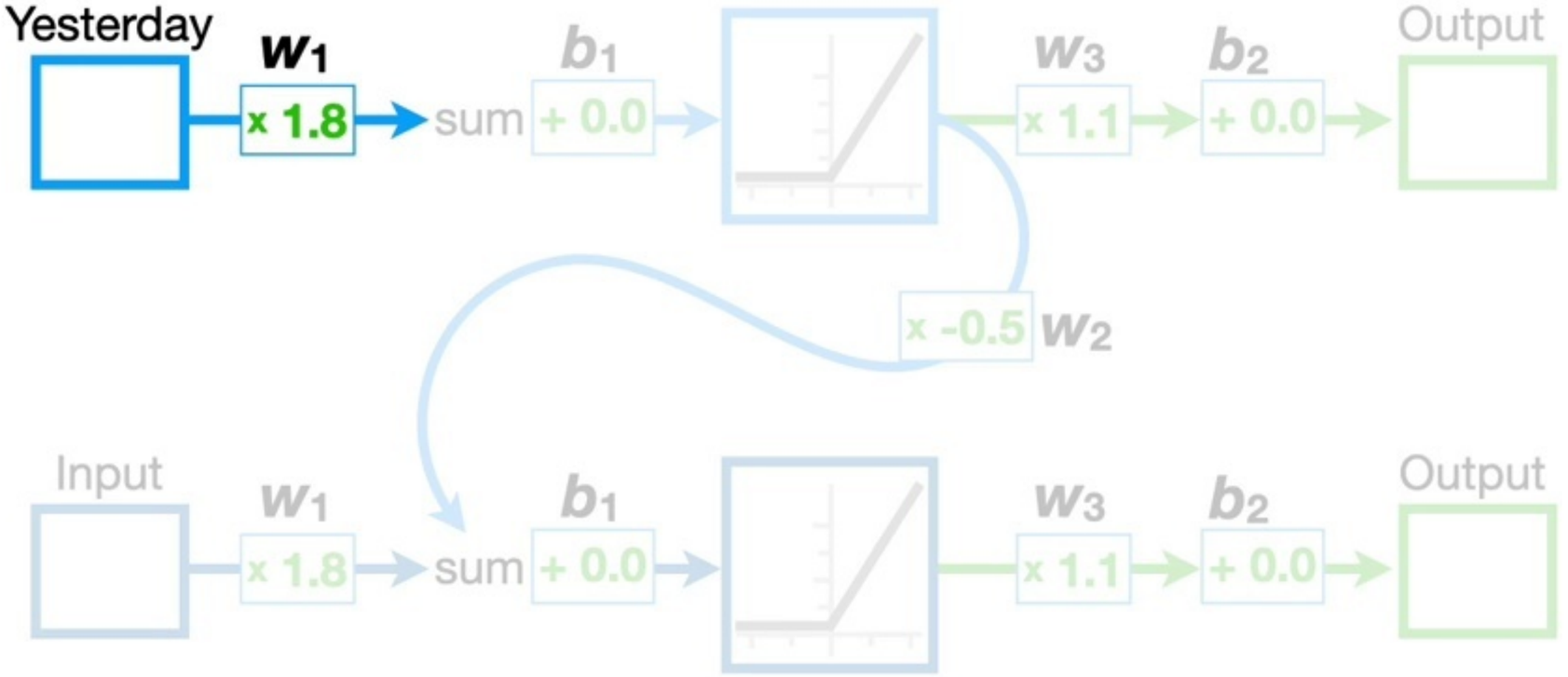


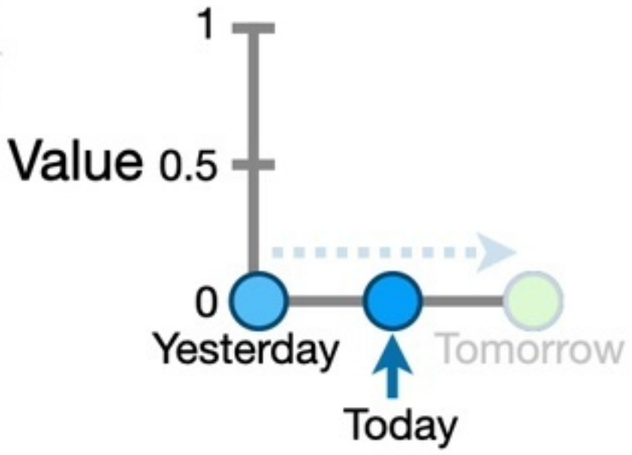
…and if we do the math straight through to the first output like we did earlier…



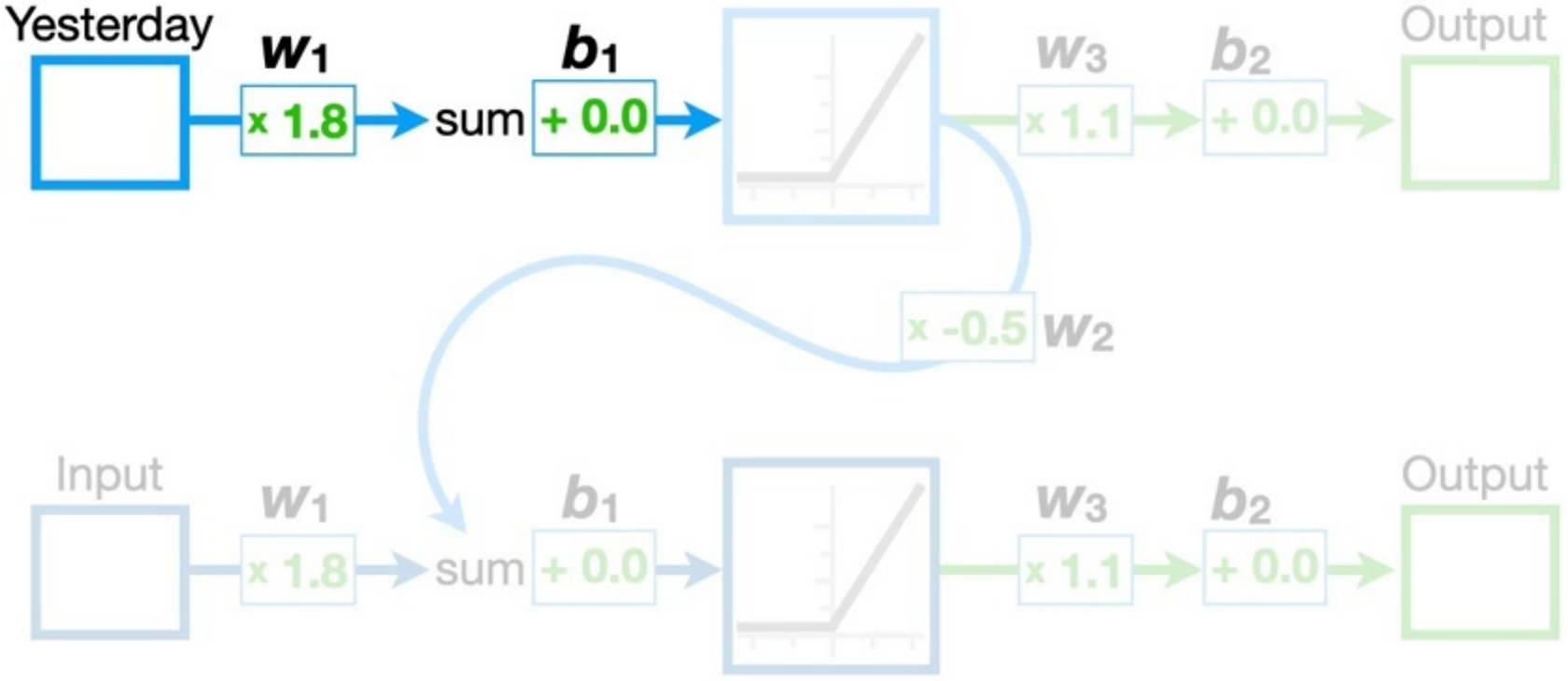


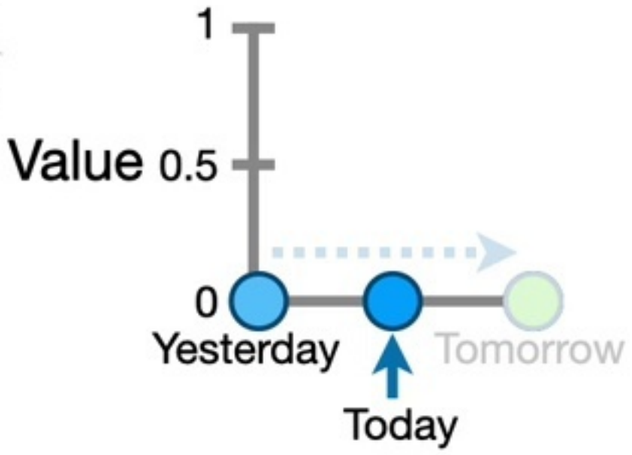
…and if we do the math straight through to the first output like we did earlier…



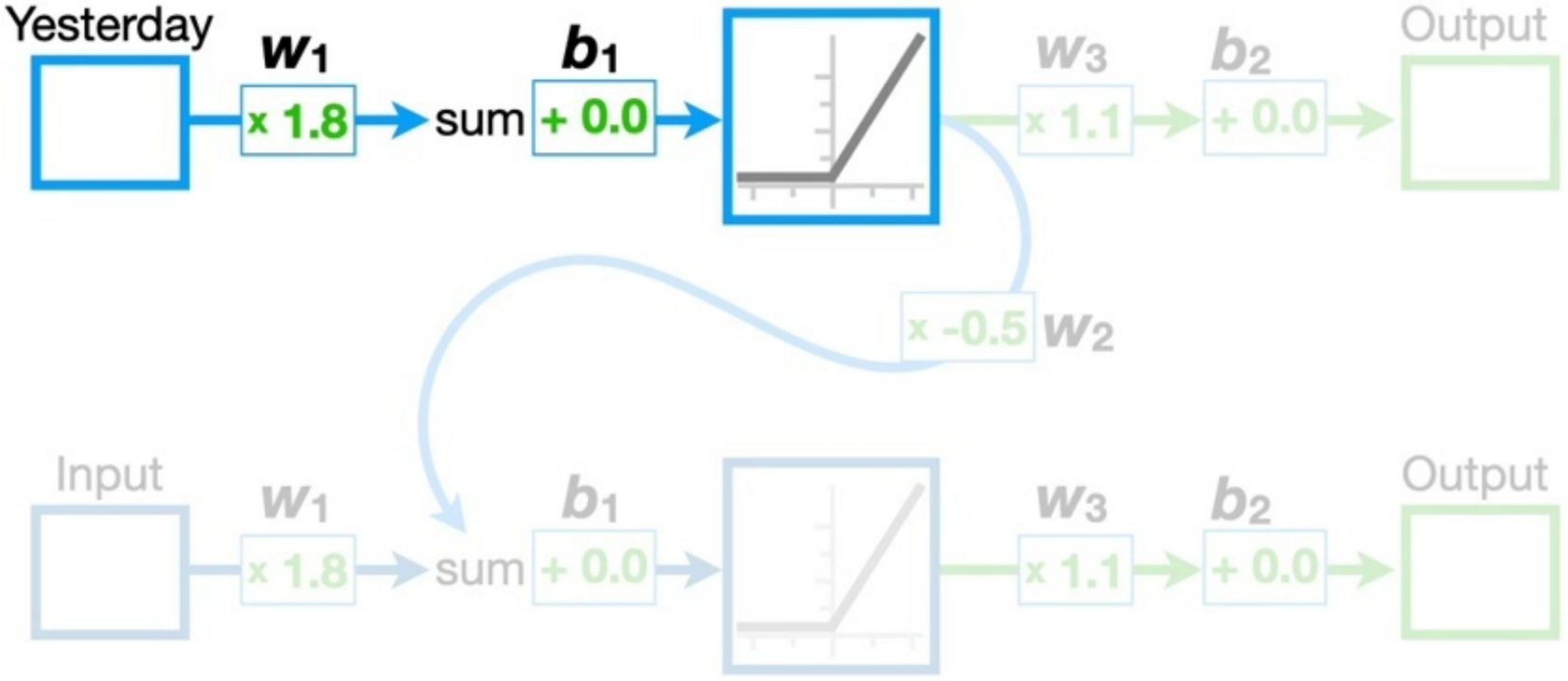


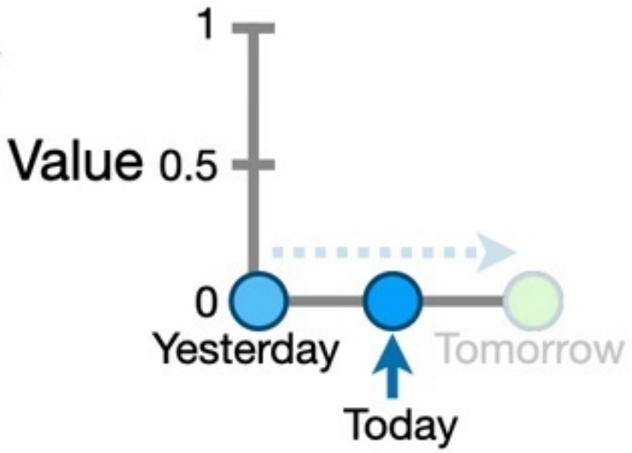
…and if we do the math straight through to the first output like we did earlier…



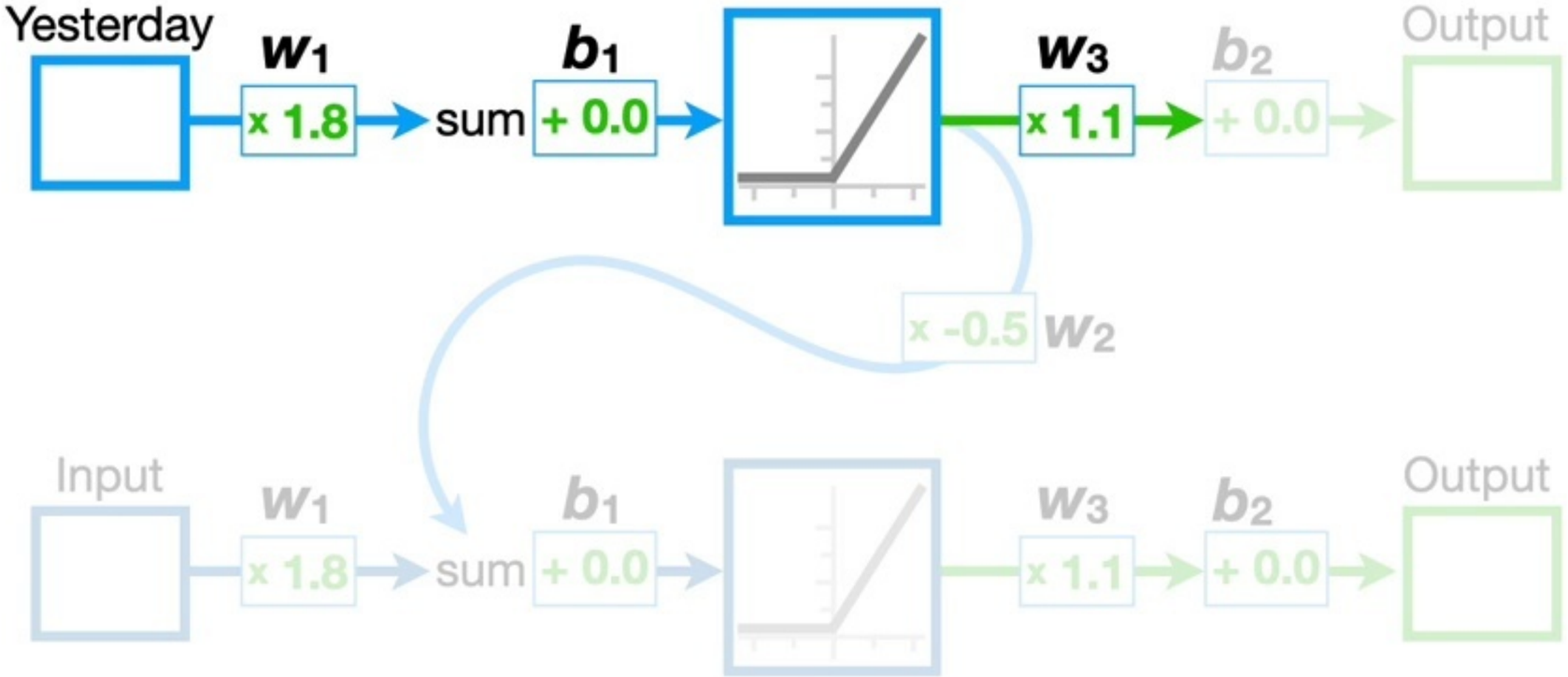


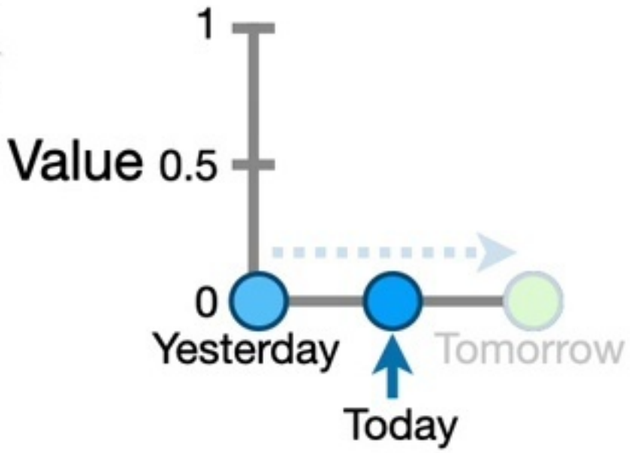
…and if we do the math straight through to the first output like we did earlier…



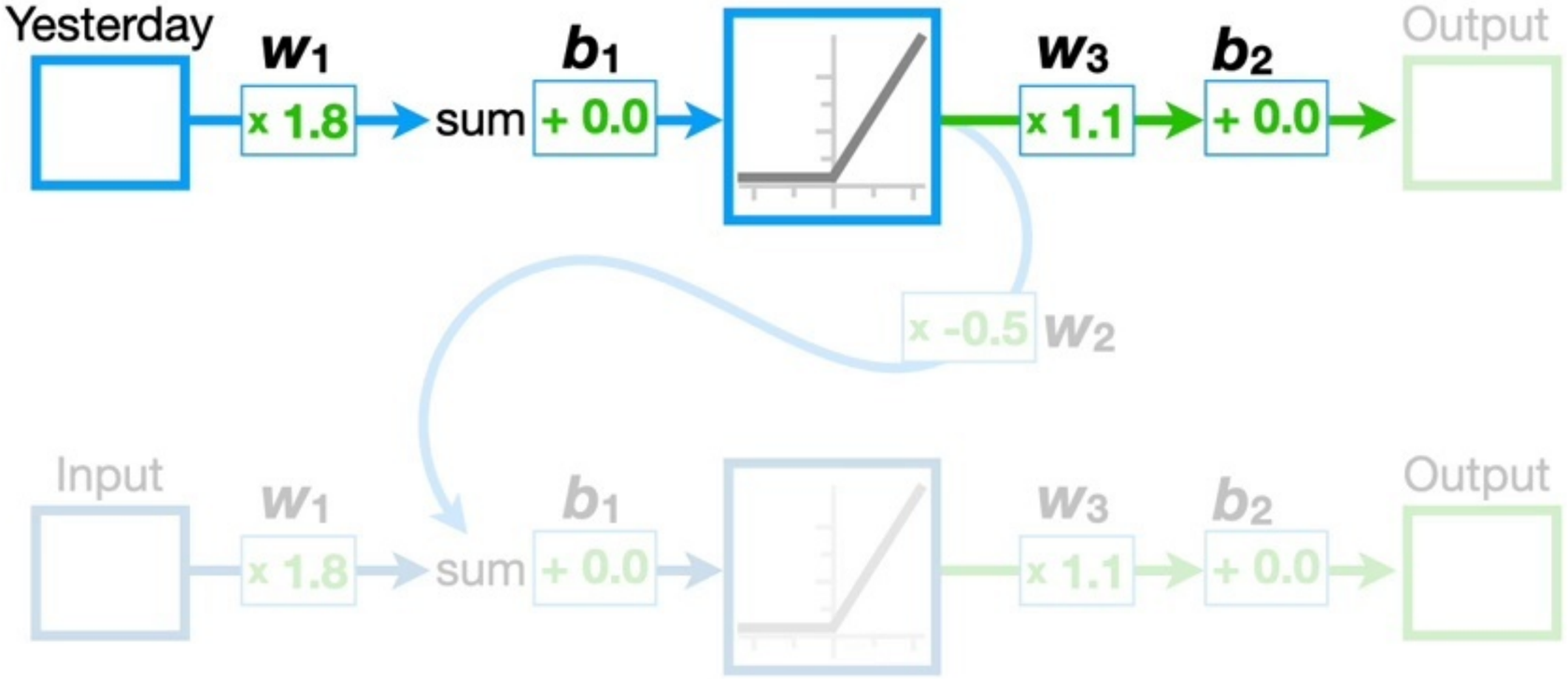


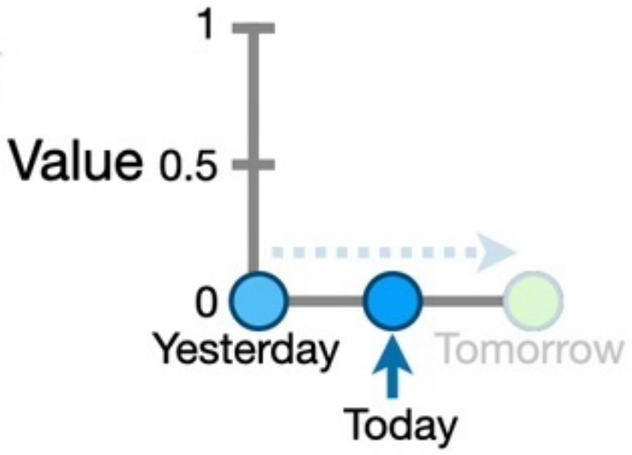
…and if we do the math straight through to the first output like we did earlier…



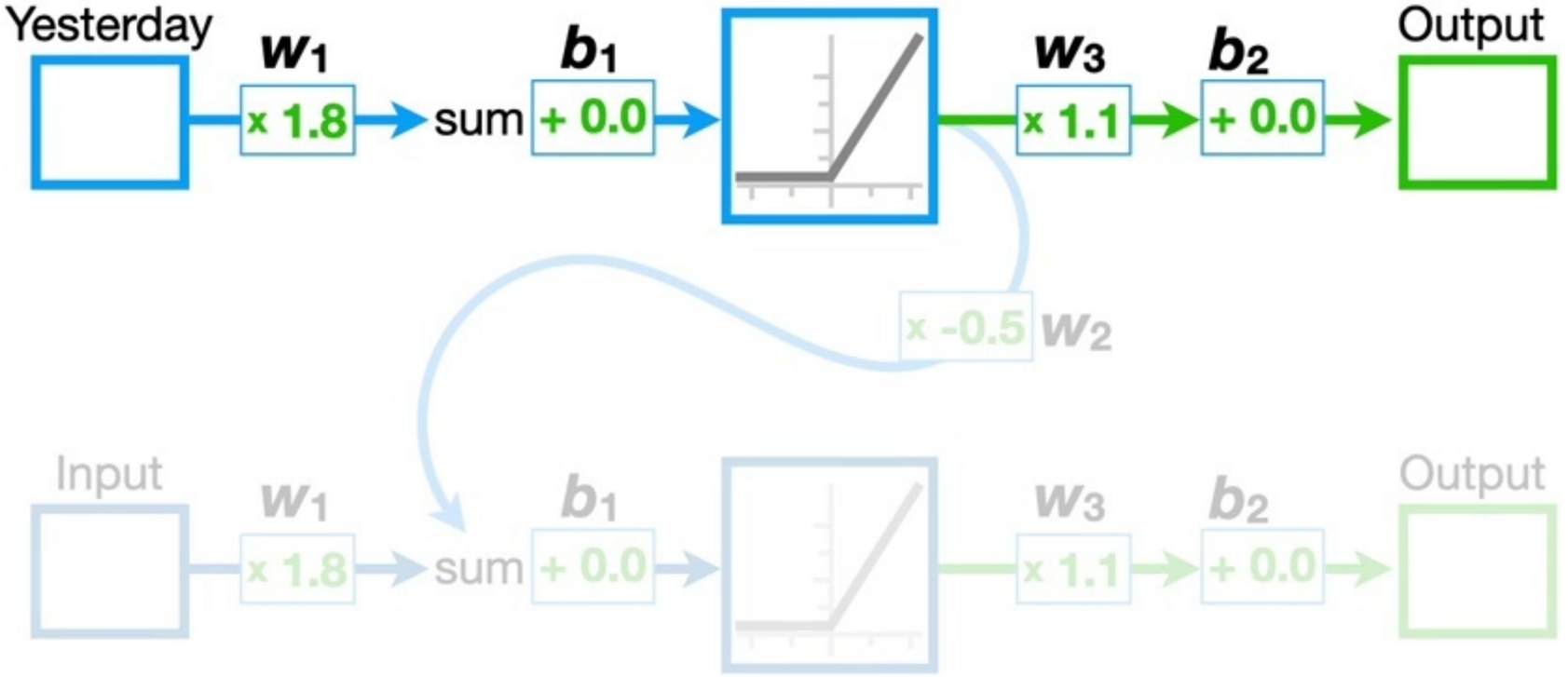


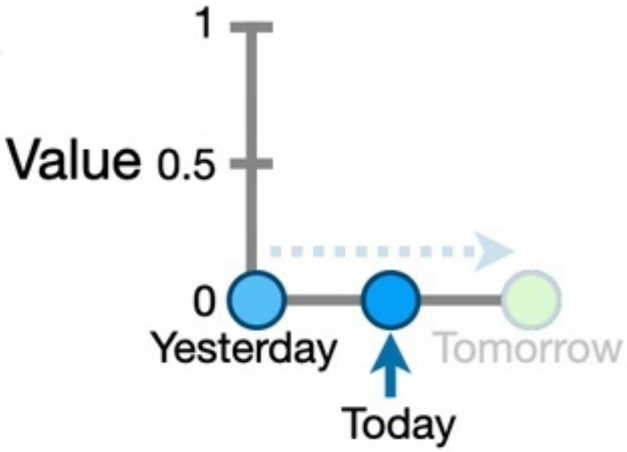
…and if we do the math straight through to the first output like we did earlier…



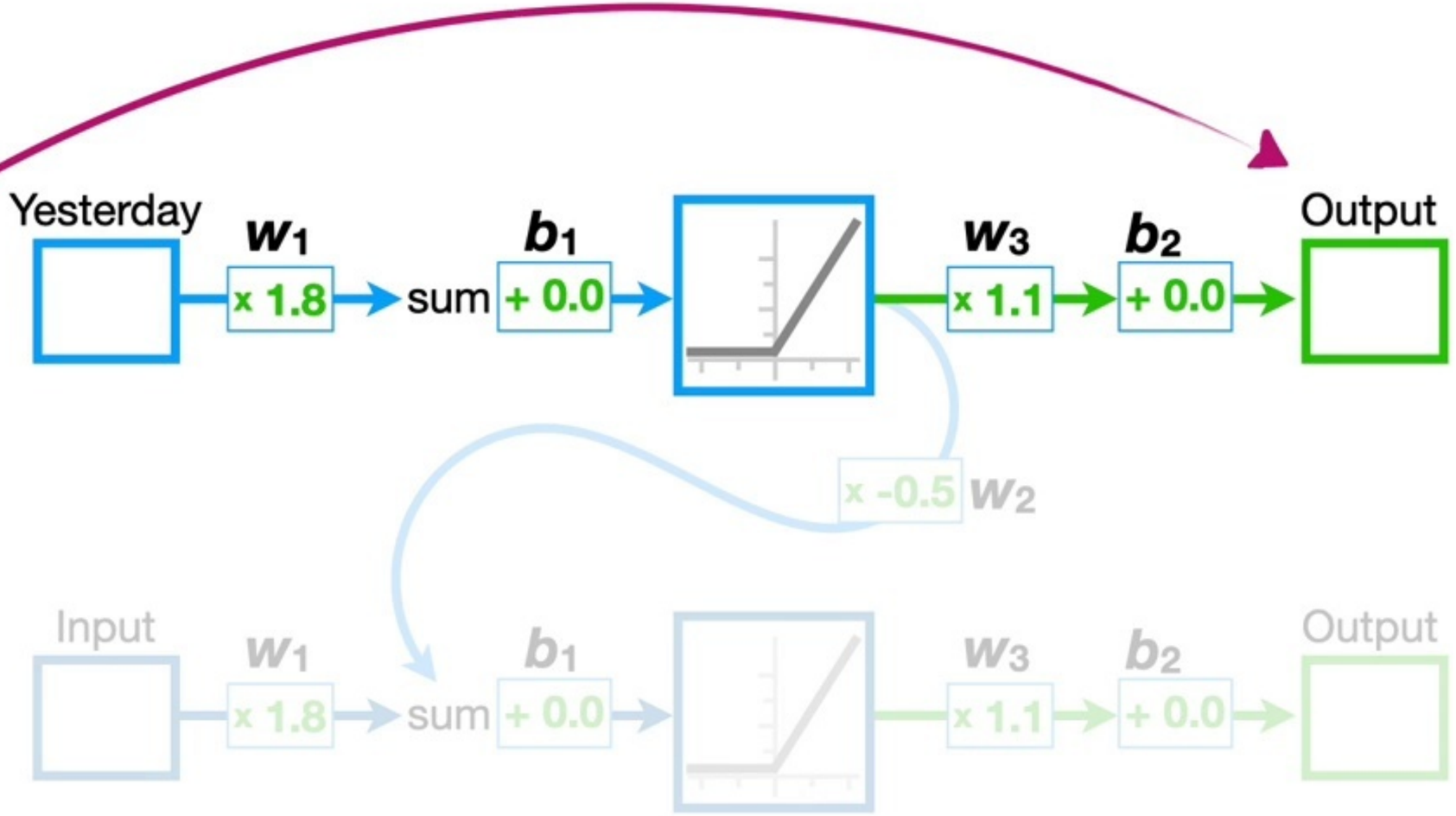


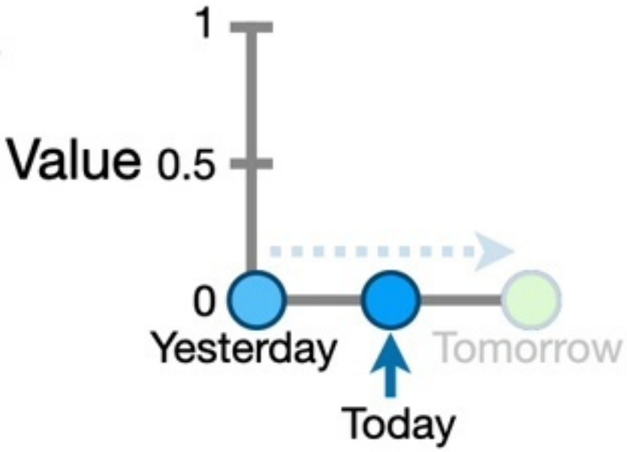
…and if we do the math straight through to the first output like we did earlier…



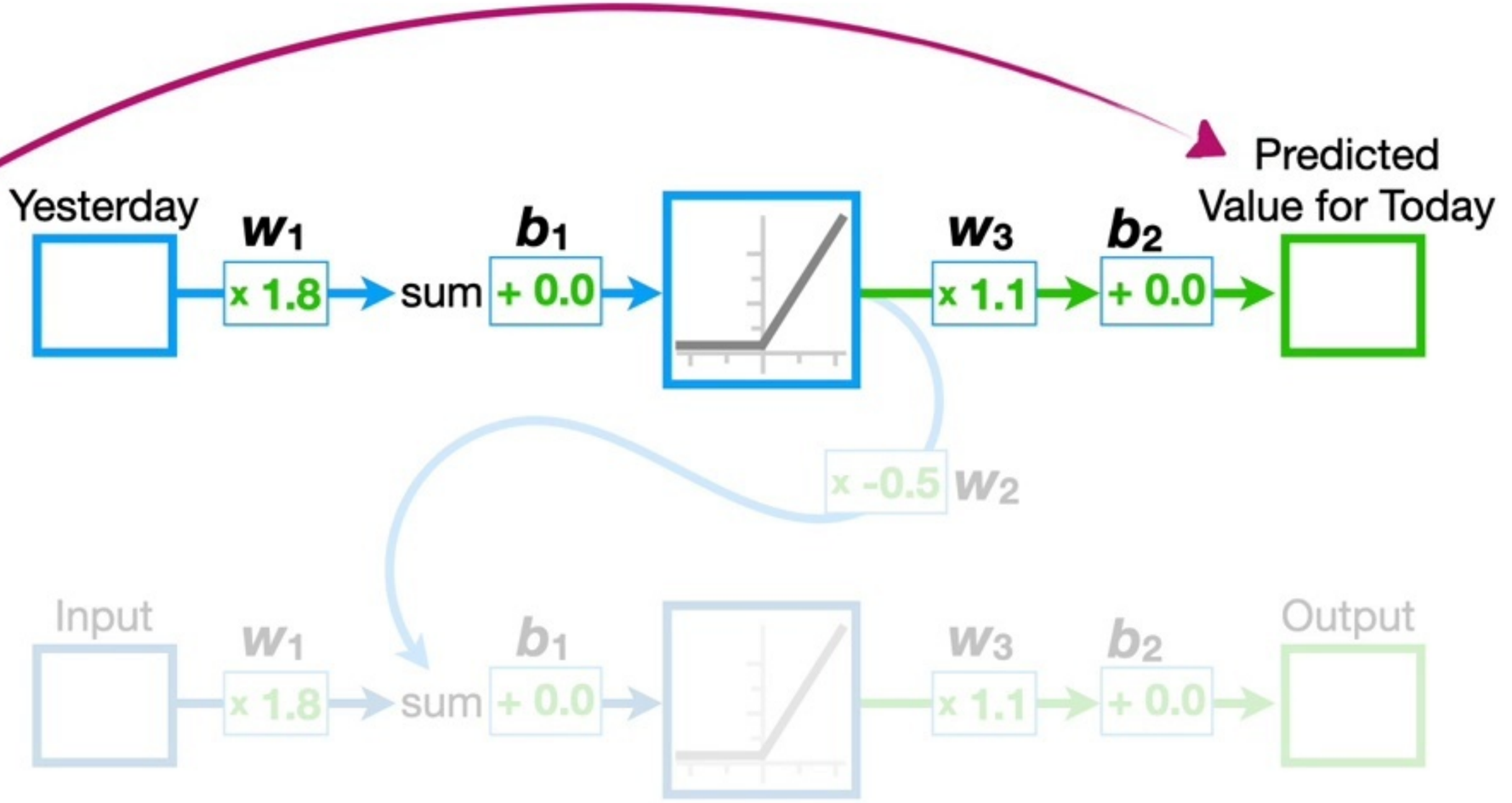


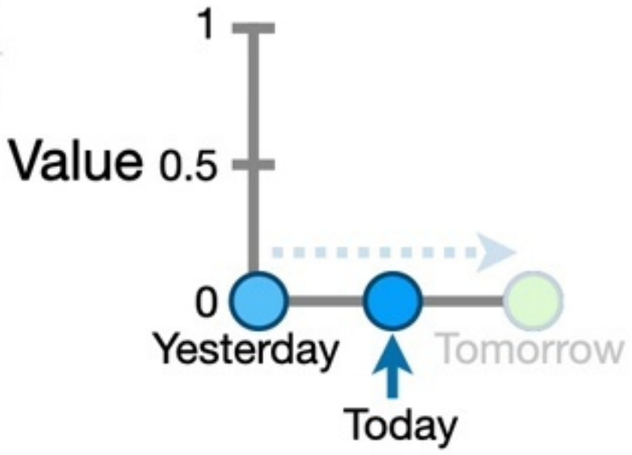
…we get the predicted value for **today**.



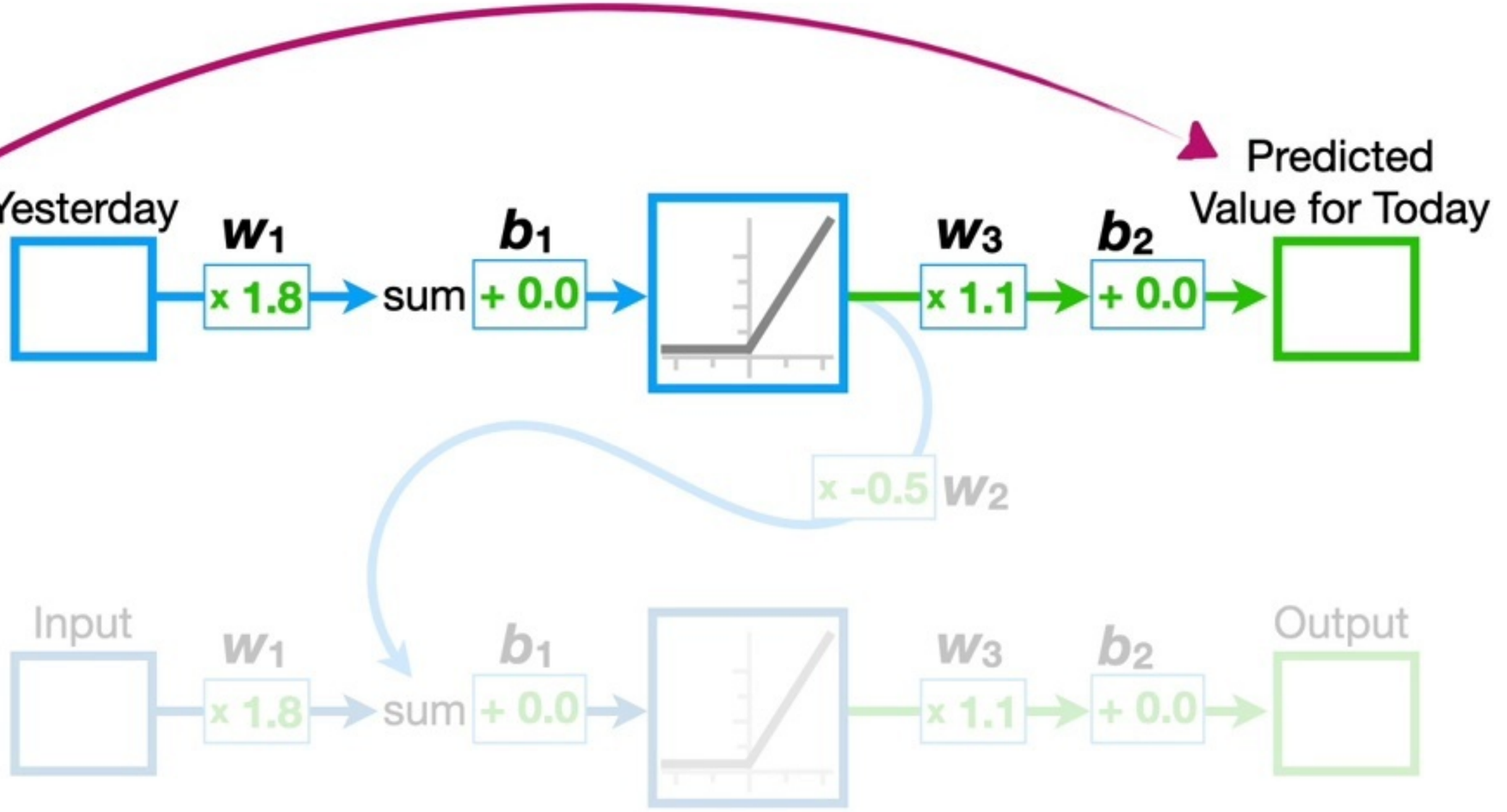


…we get the predicted value for **today**.

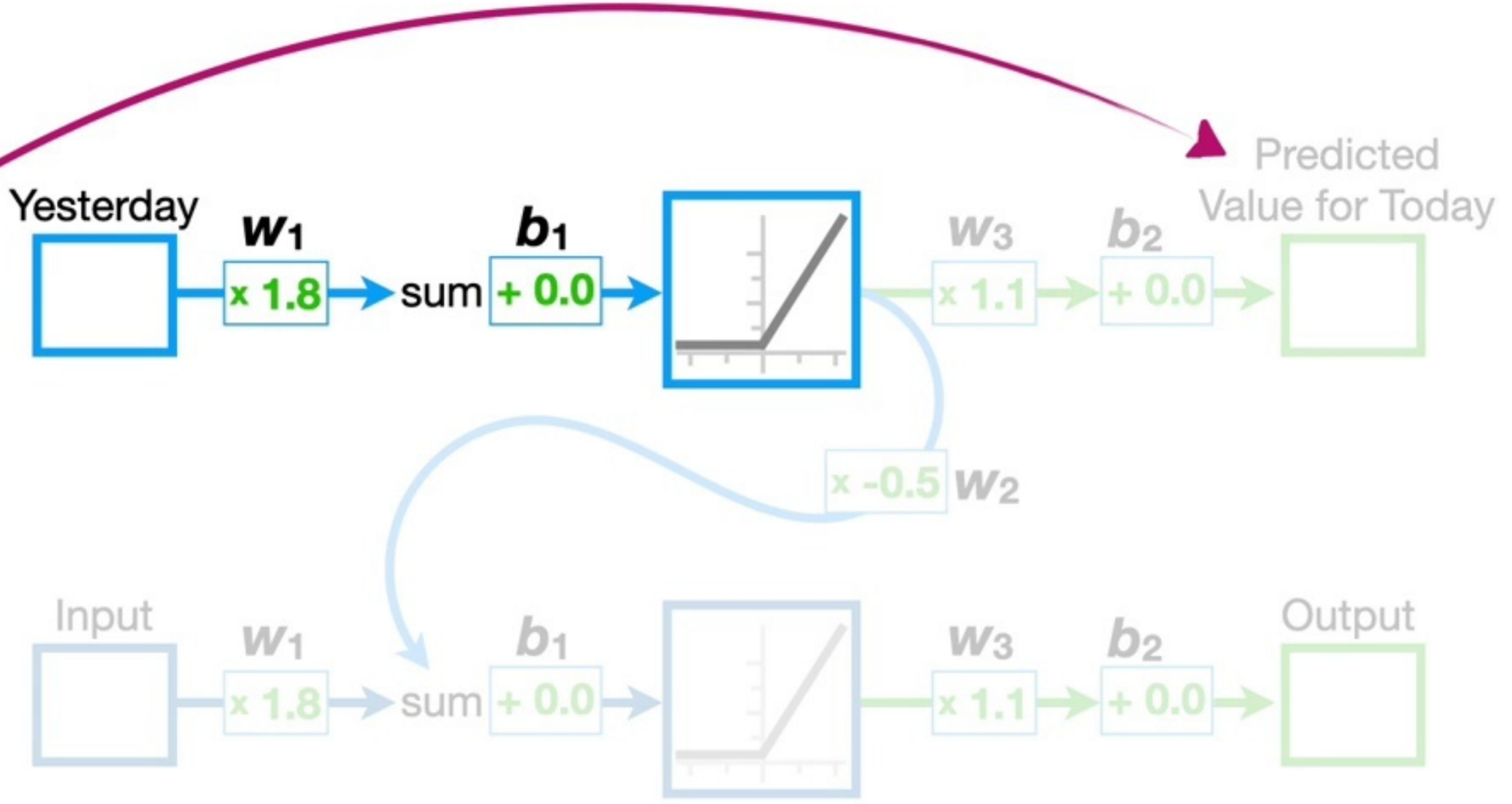


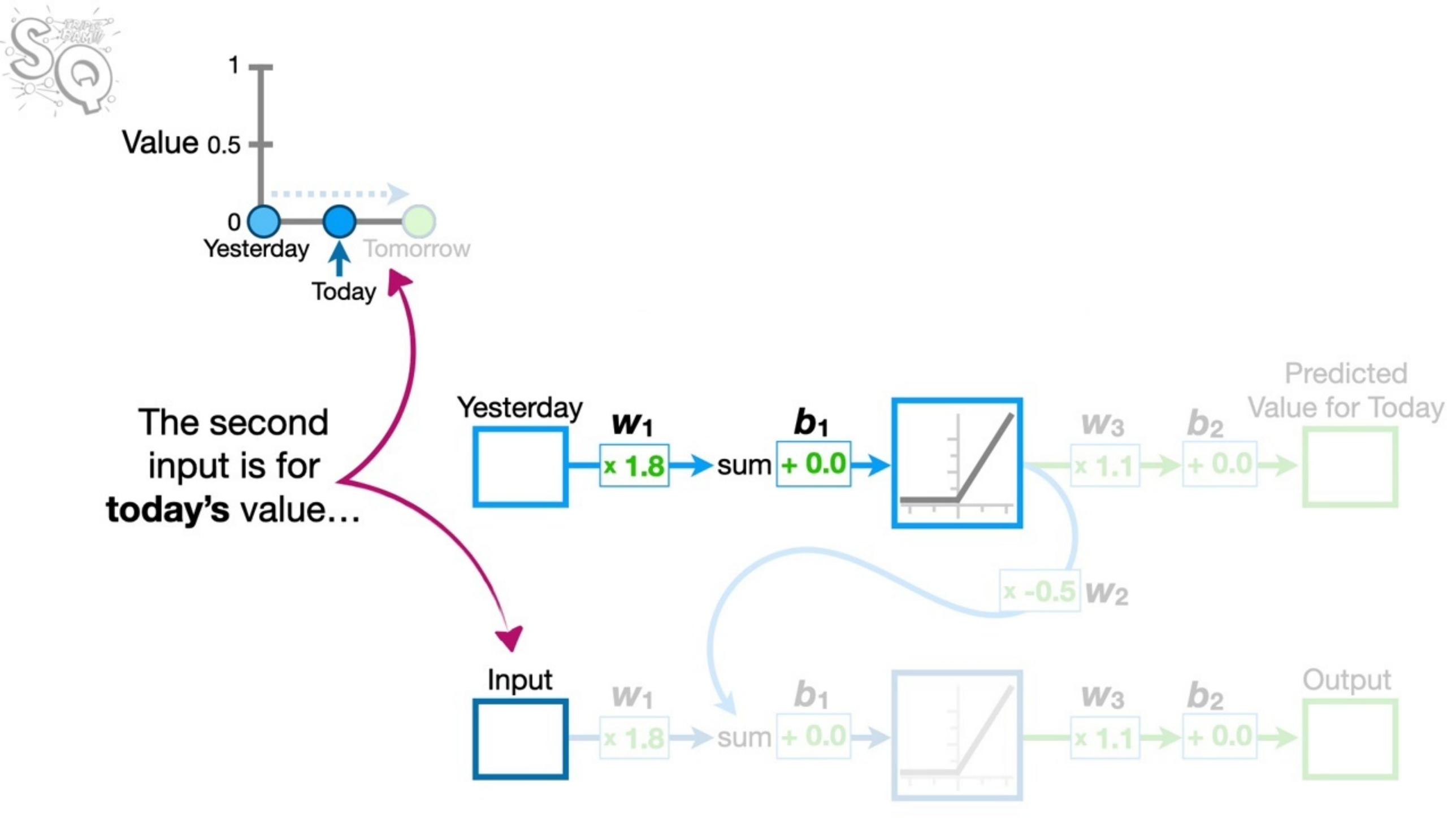


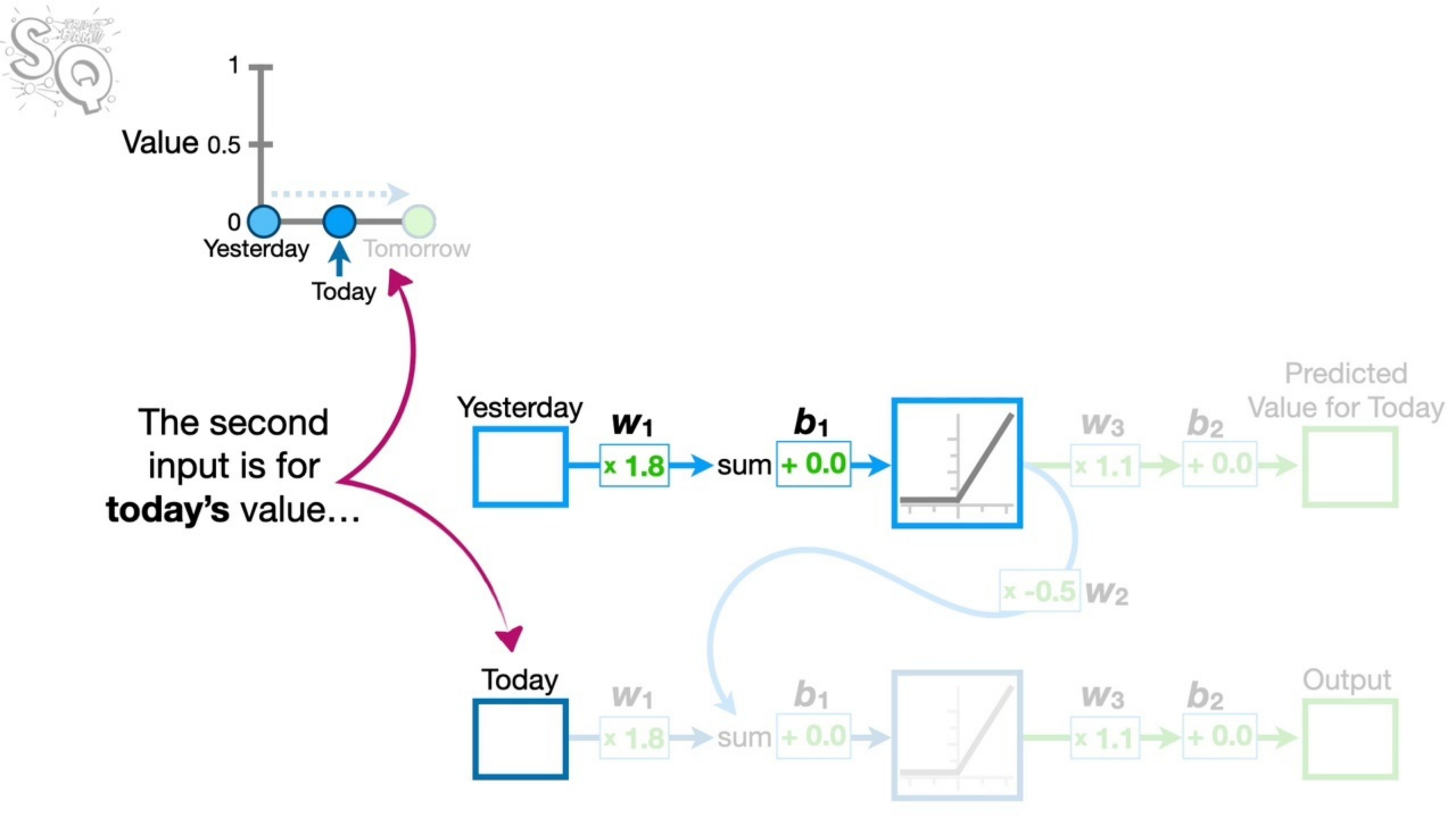
However, as we saw earlier, we can ignore this output.



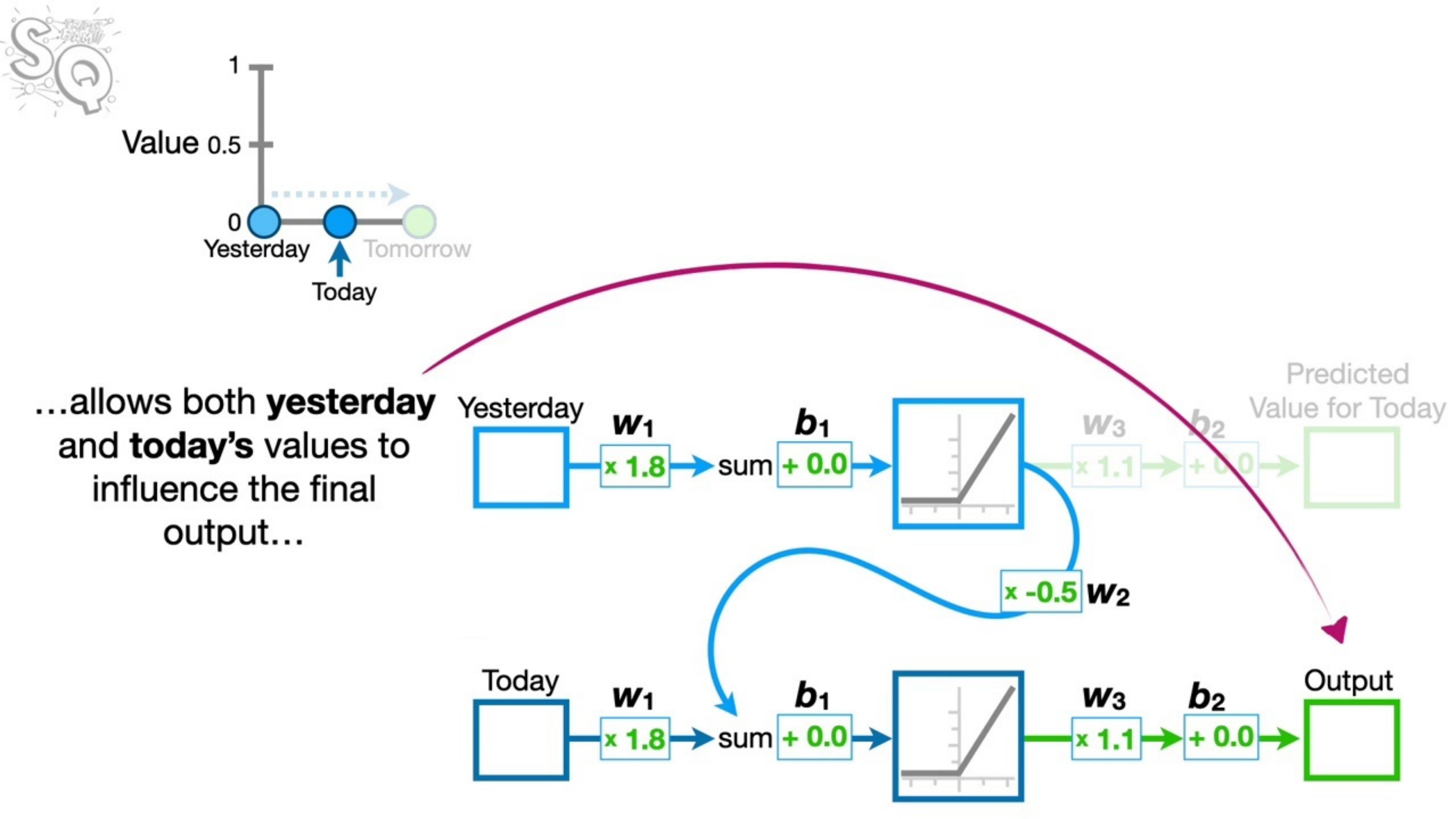
However, as we saw earlier, we can ignore this output.

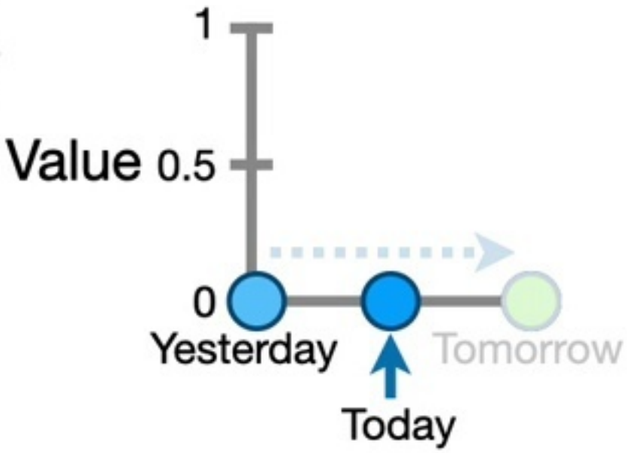



1
Value 0.5
0
Yesterday
Today
Tomorrow
The second input is for **today's** value…
Yesterday
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Input
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output

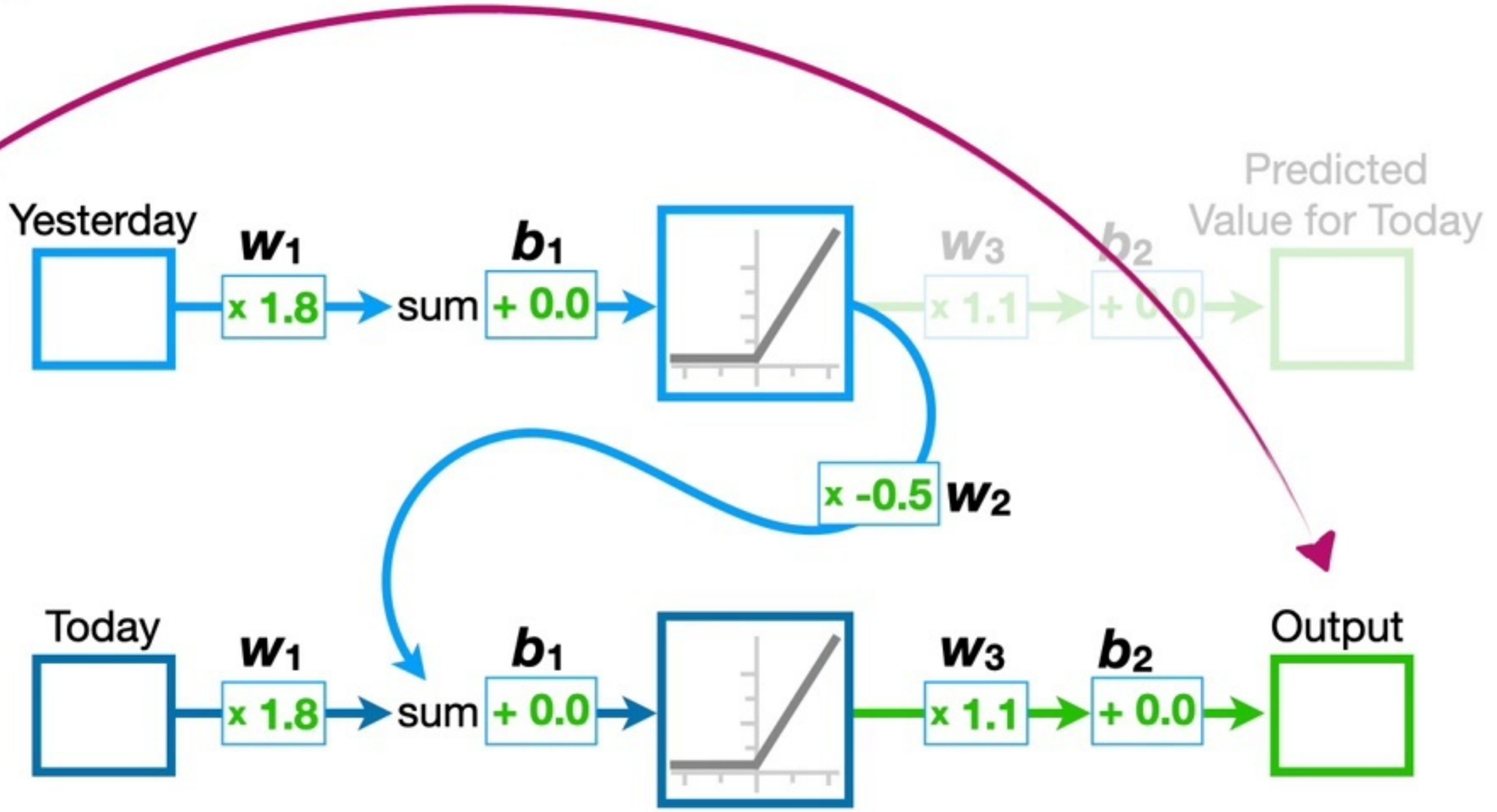

1
Value 0.5
0
Yesterday
Today
Tomorrow
The second input is for **today's** value…
Yesterday
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output

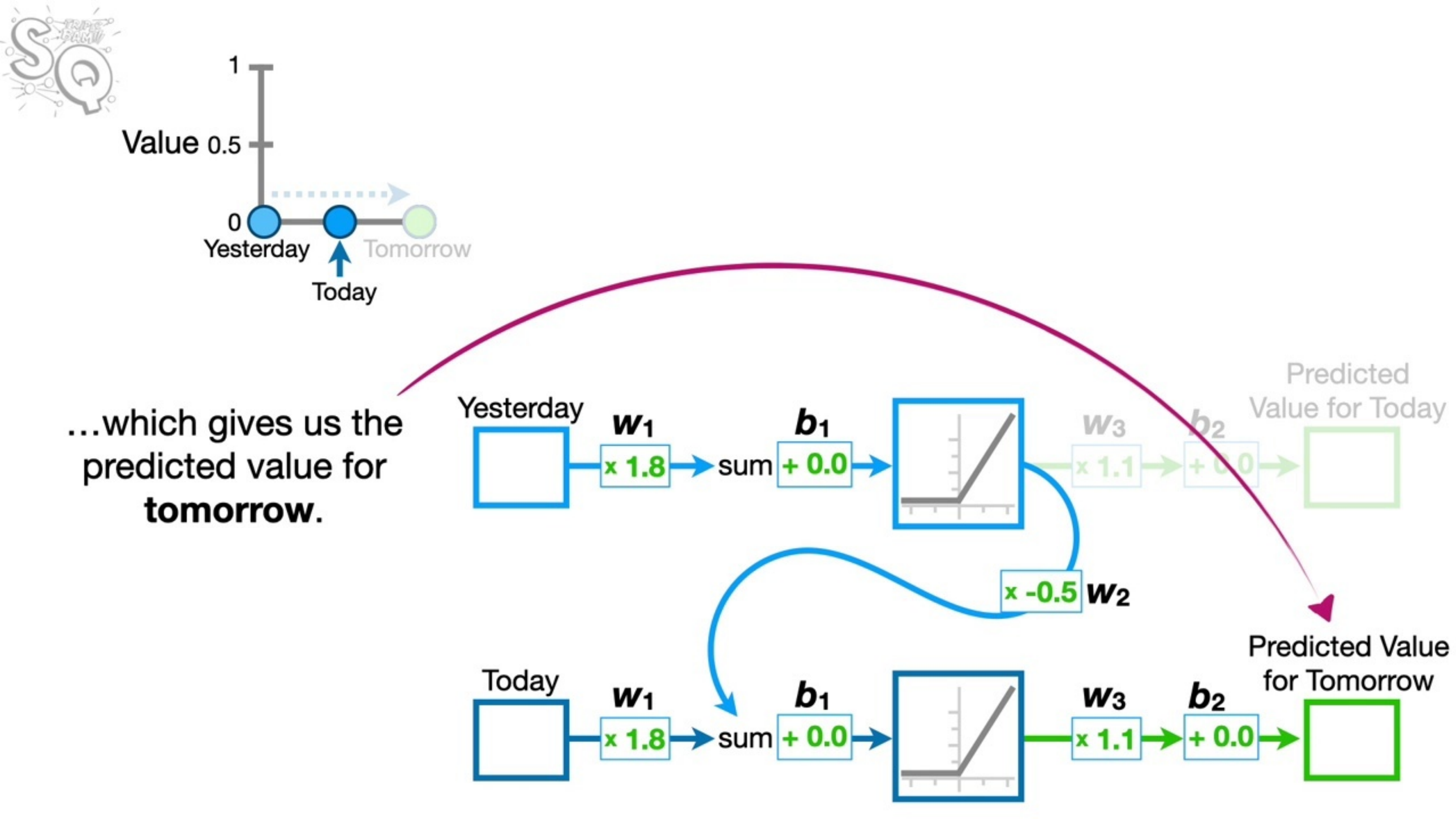
…and the connection between the first activation function and the second summation…

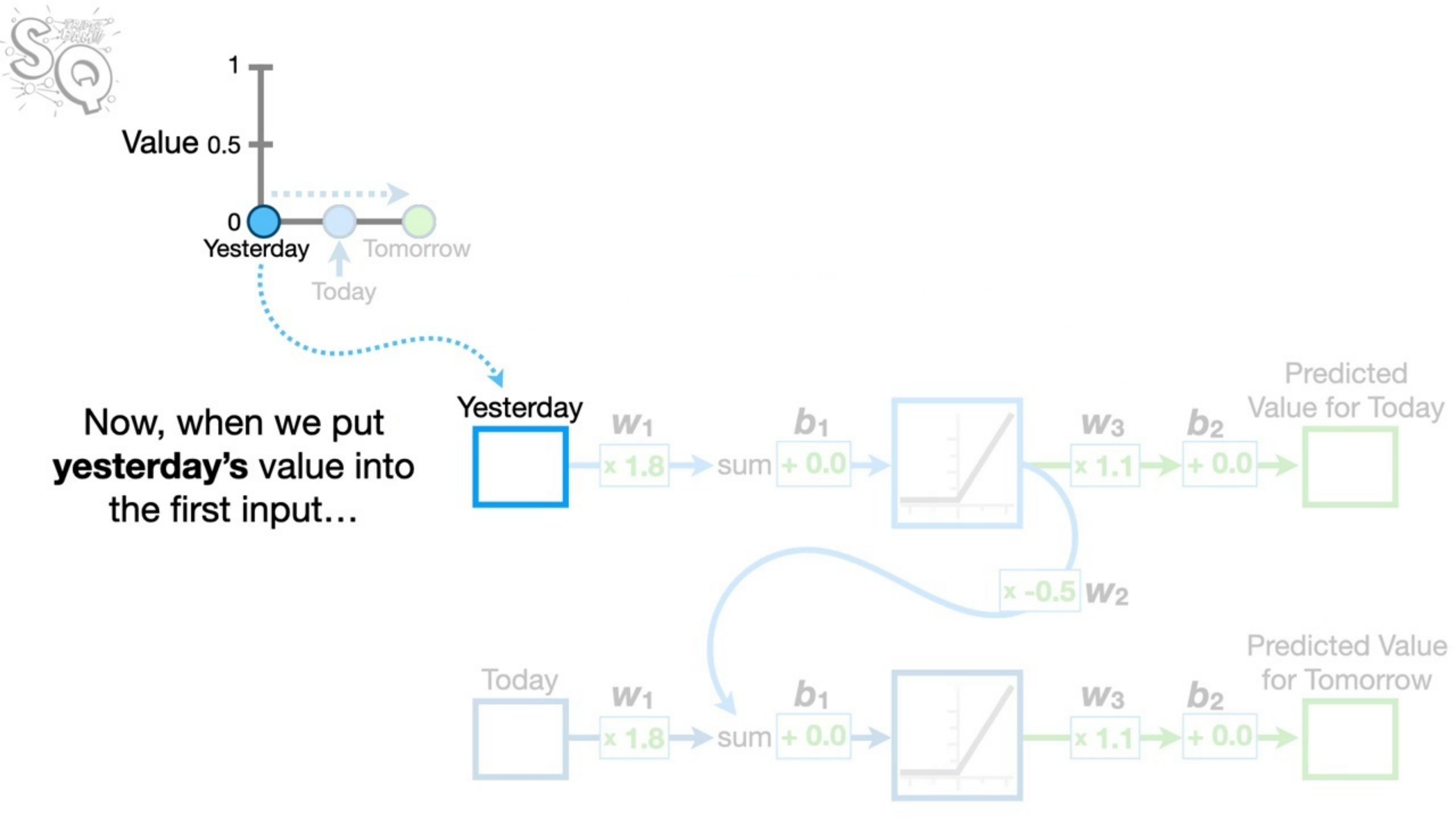

1
Value 0.5
0
Yesterday
Today
Tomorrow
…allows both **yesterday** and **today's** values to influence the final output…
Yesterday
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Output

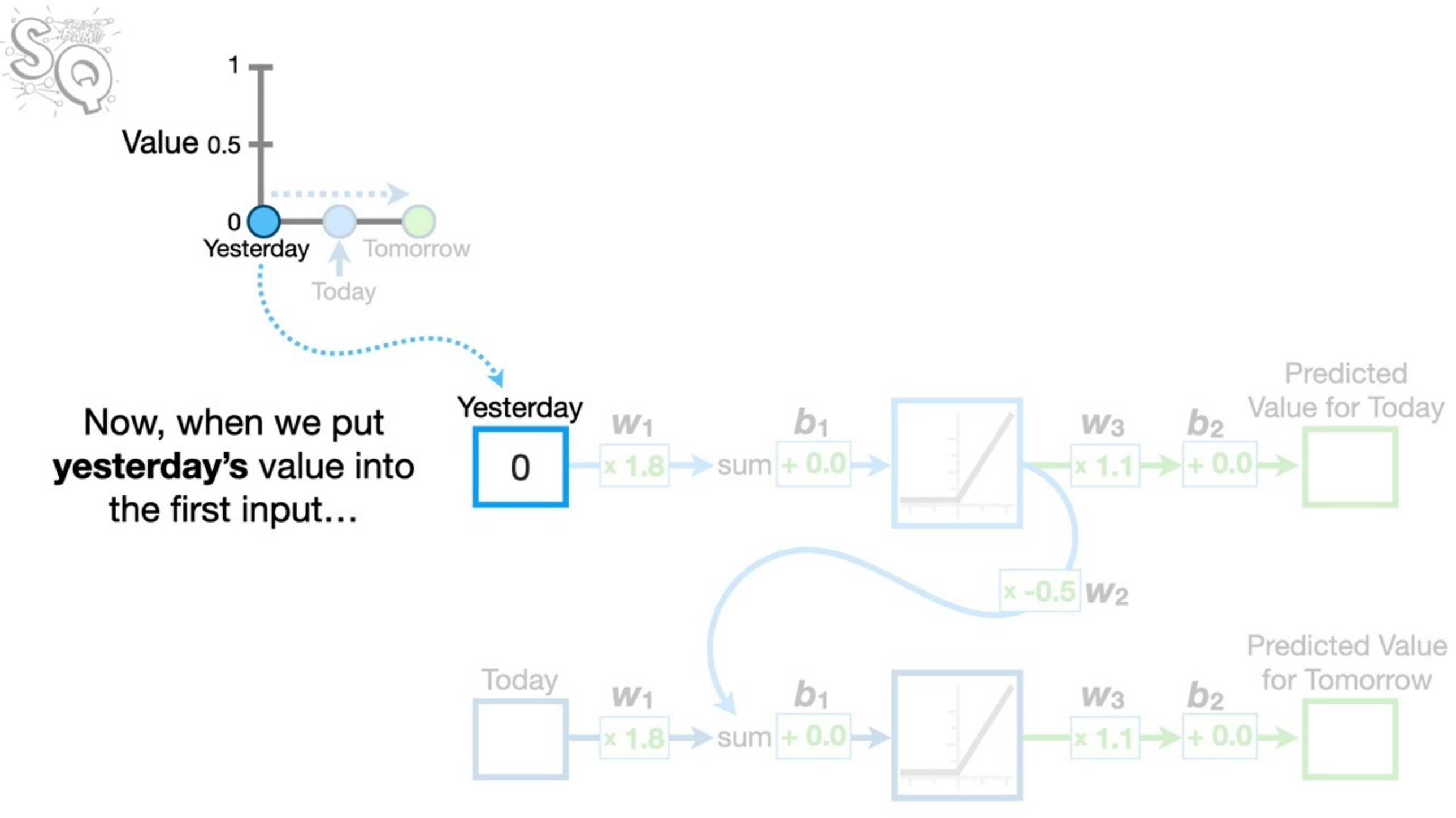


…which gives us the predicted value for **tomorrow**.

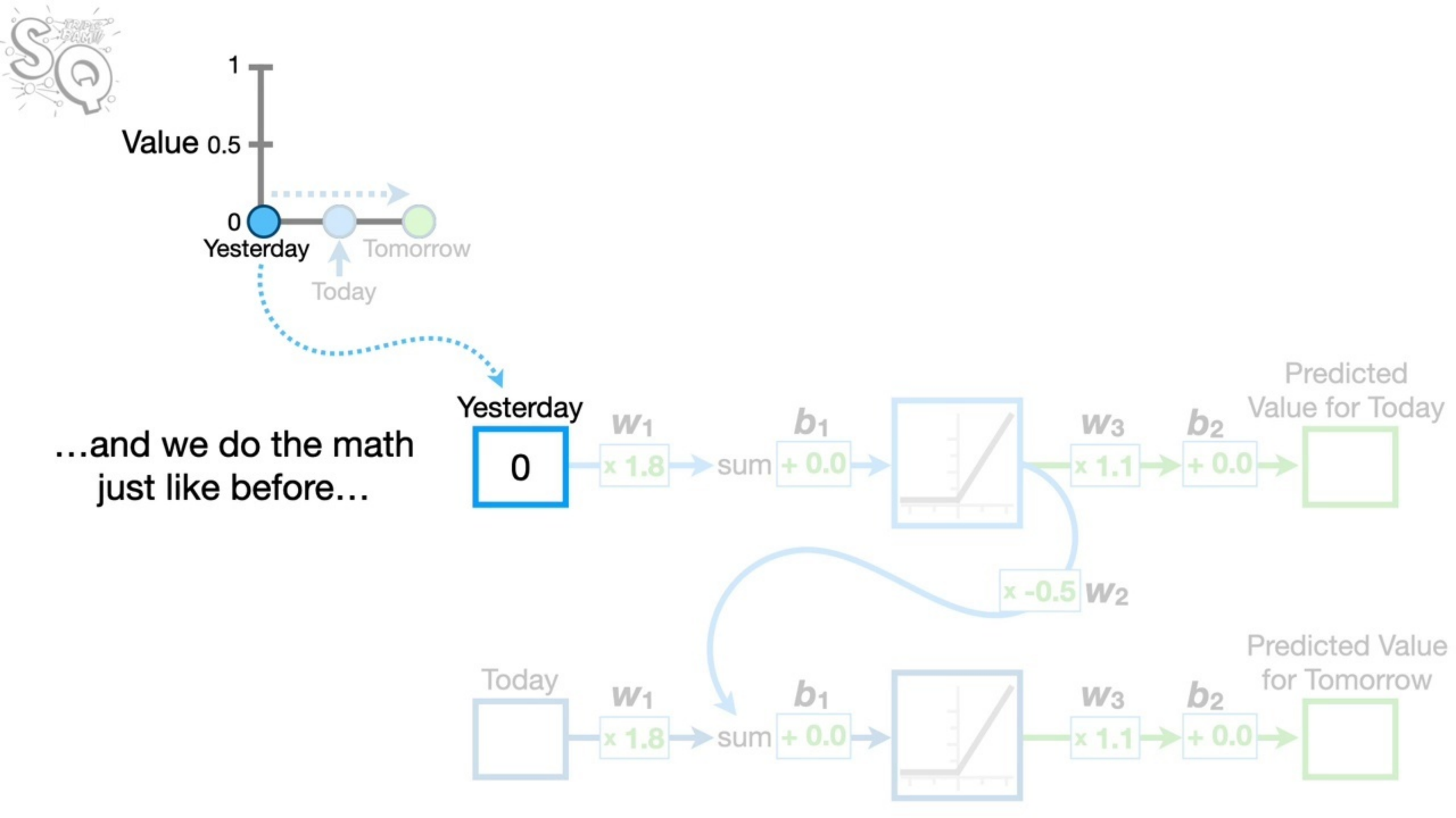


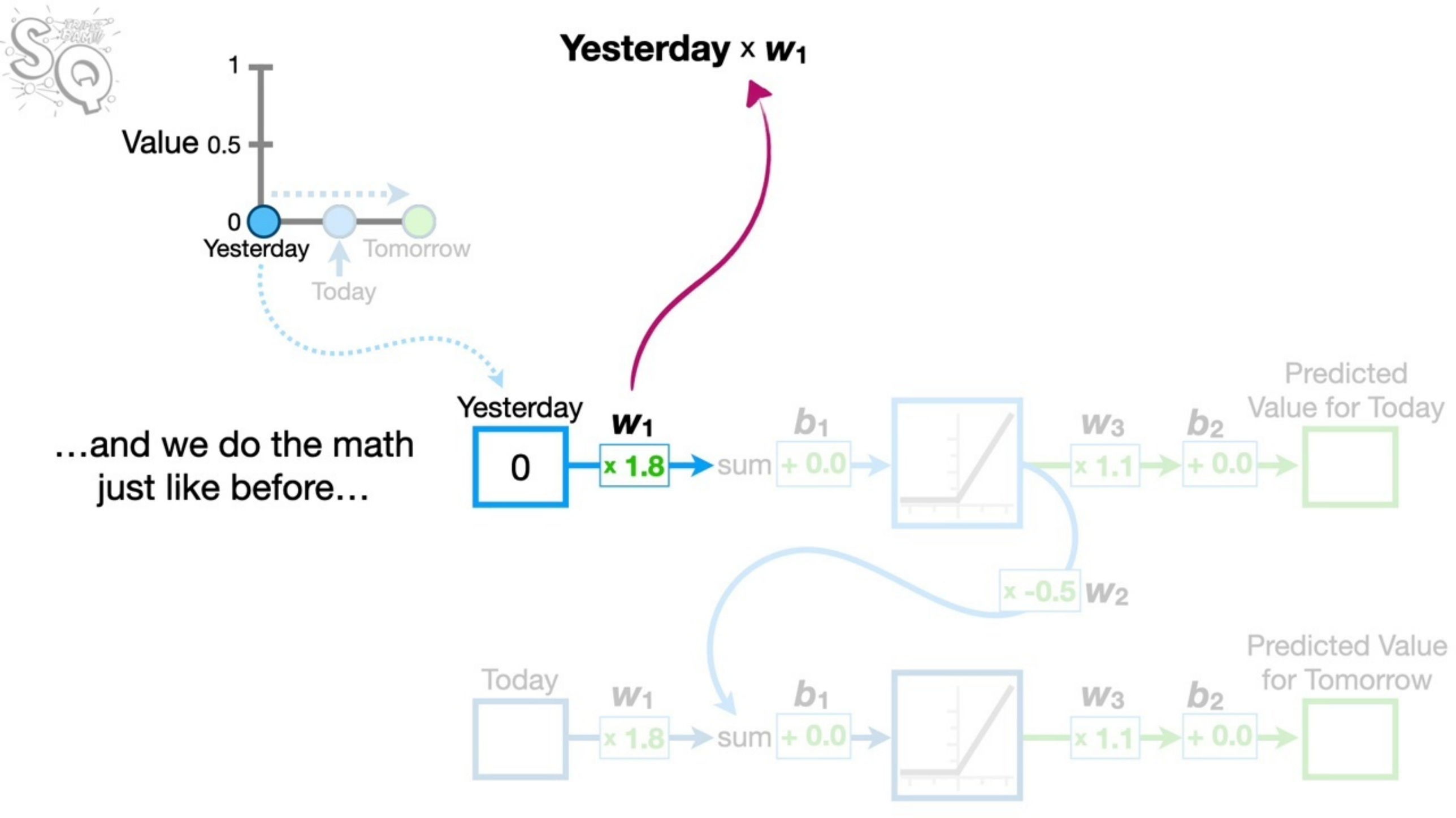

1
Value 0.5
0
Yesterday
Today
Tomorrow
…which gives us the predicted value for **tomorrow**.
Yesterday
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Predicted Value for Tomorrow
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0

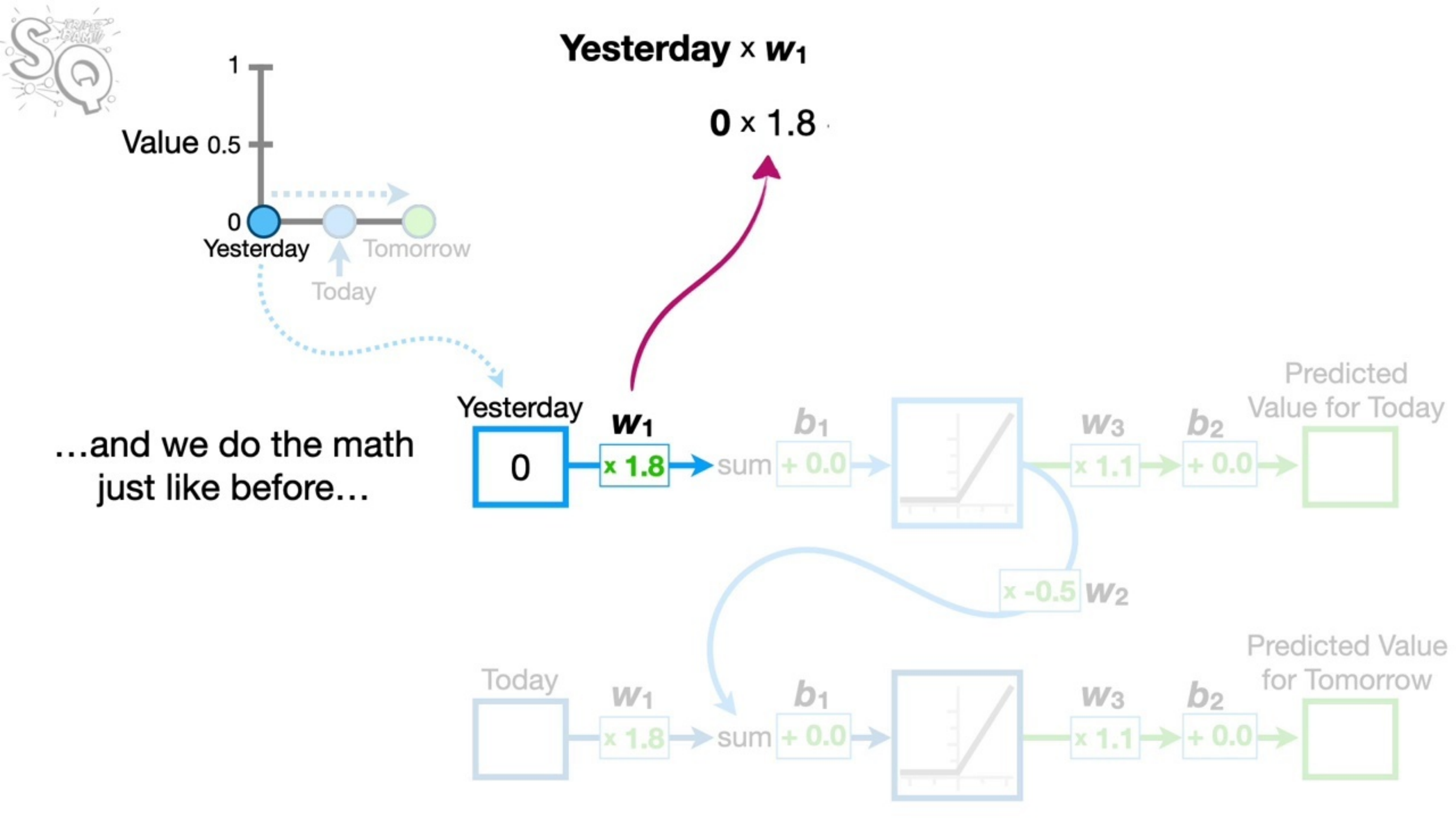

1
Value 0.5
0
Yesterday
Today
Tomorrow
Yesterday
Now, when we put **yesterday's** value into the first input…
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

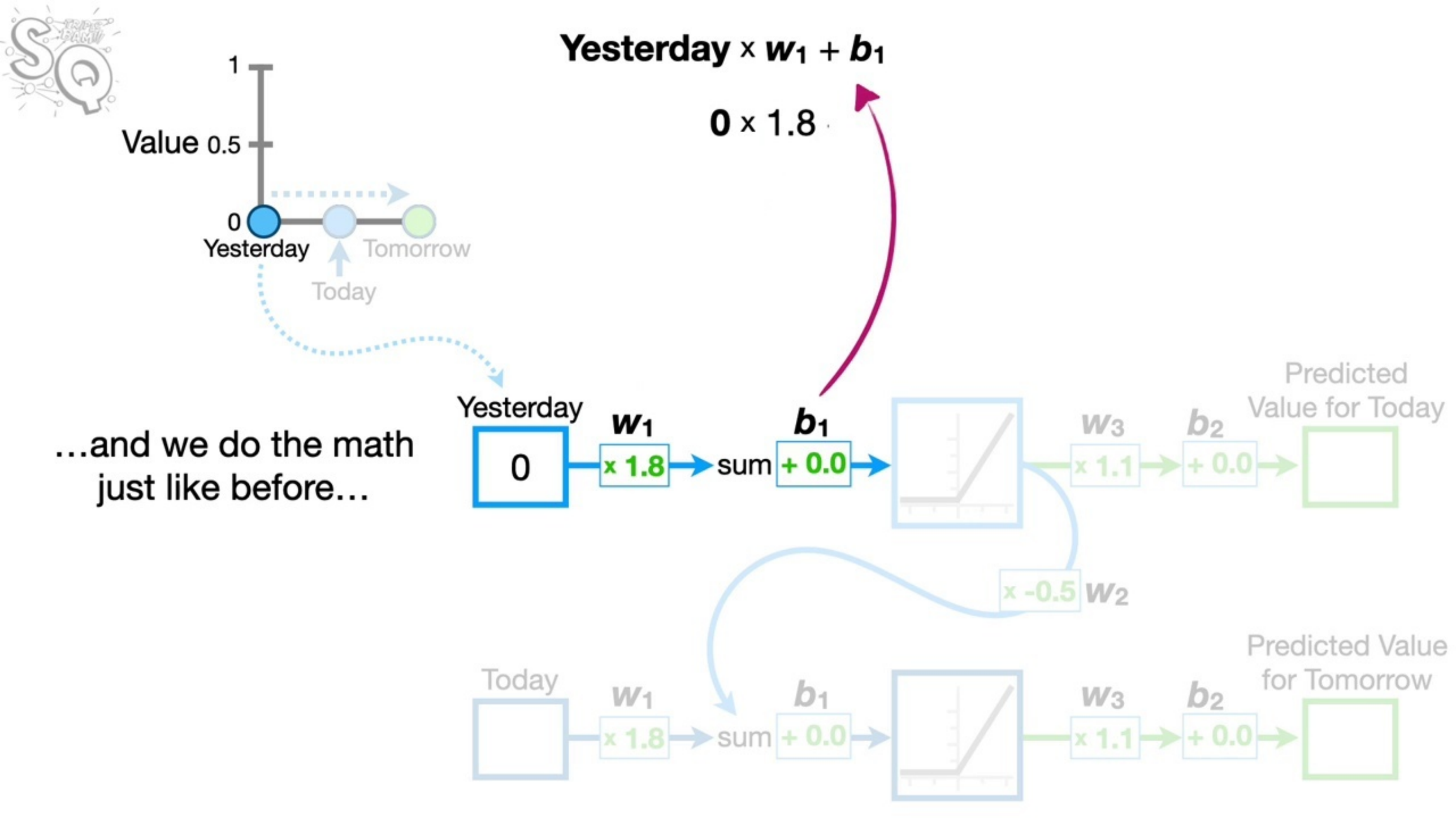


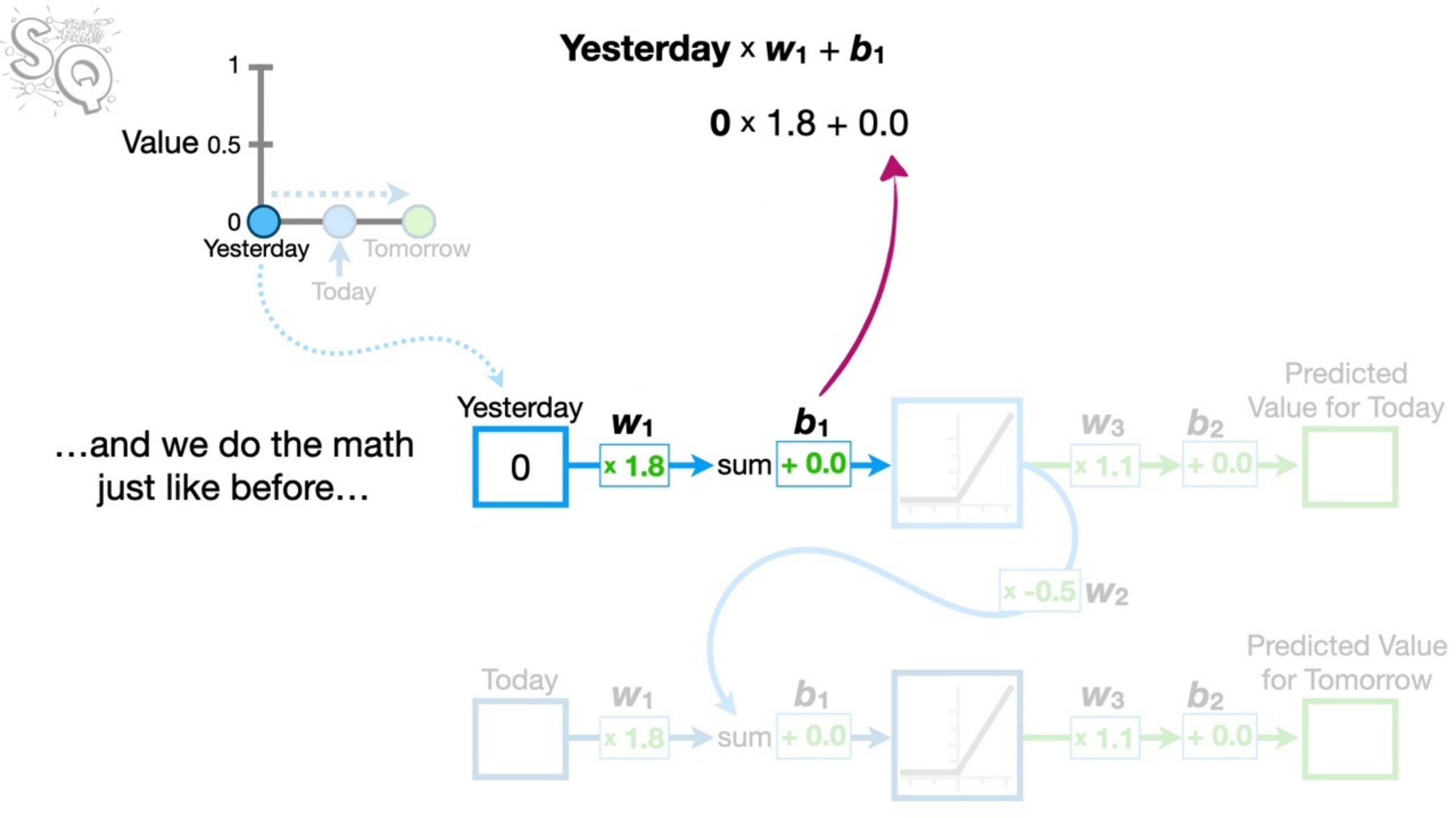
Now, when we put **yesterday's** value into the first input…

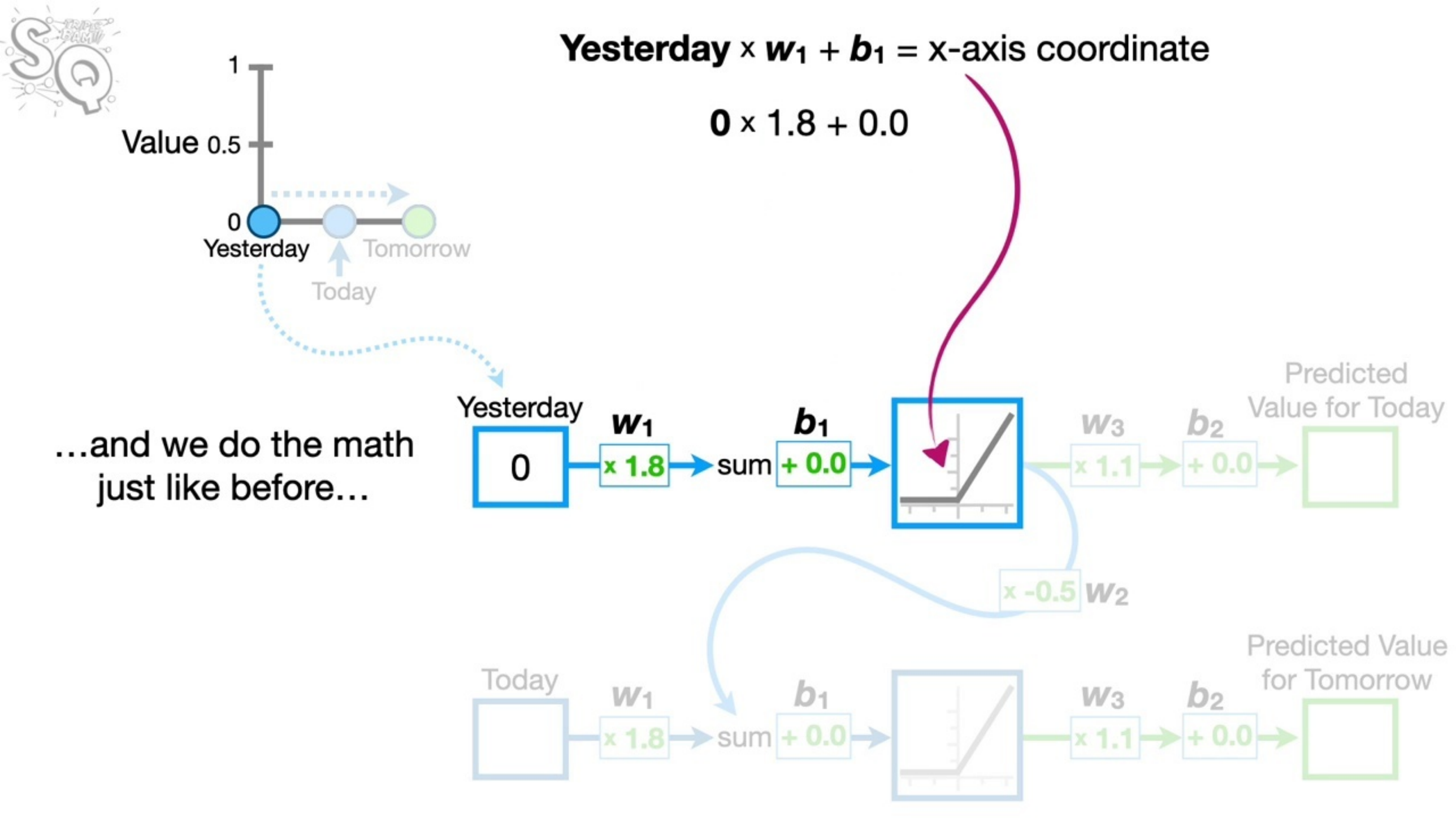

1
Value 0.5
0
Yesterday
Today
Tomorrow
…and we do the math just like before…
Yesterday
0
w_1
x 1.8
b_1
sum
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
b_1
sum
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

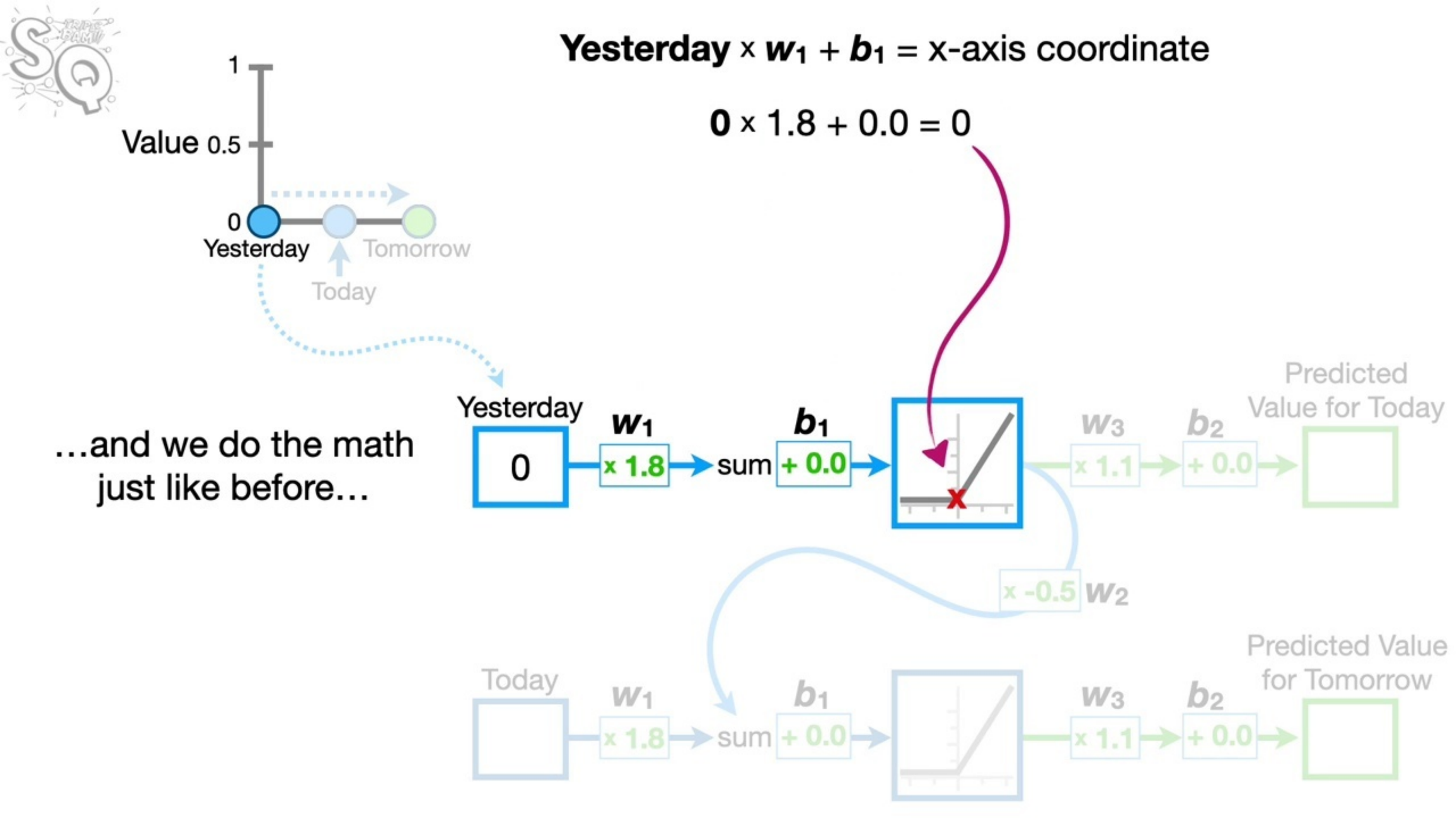

Yesterday × w_1
1
Value 0.5
0
Yesterday
Tomorrow
Today
…and we do the math just like before…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5 w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

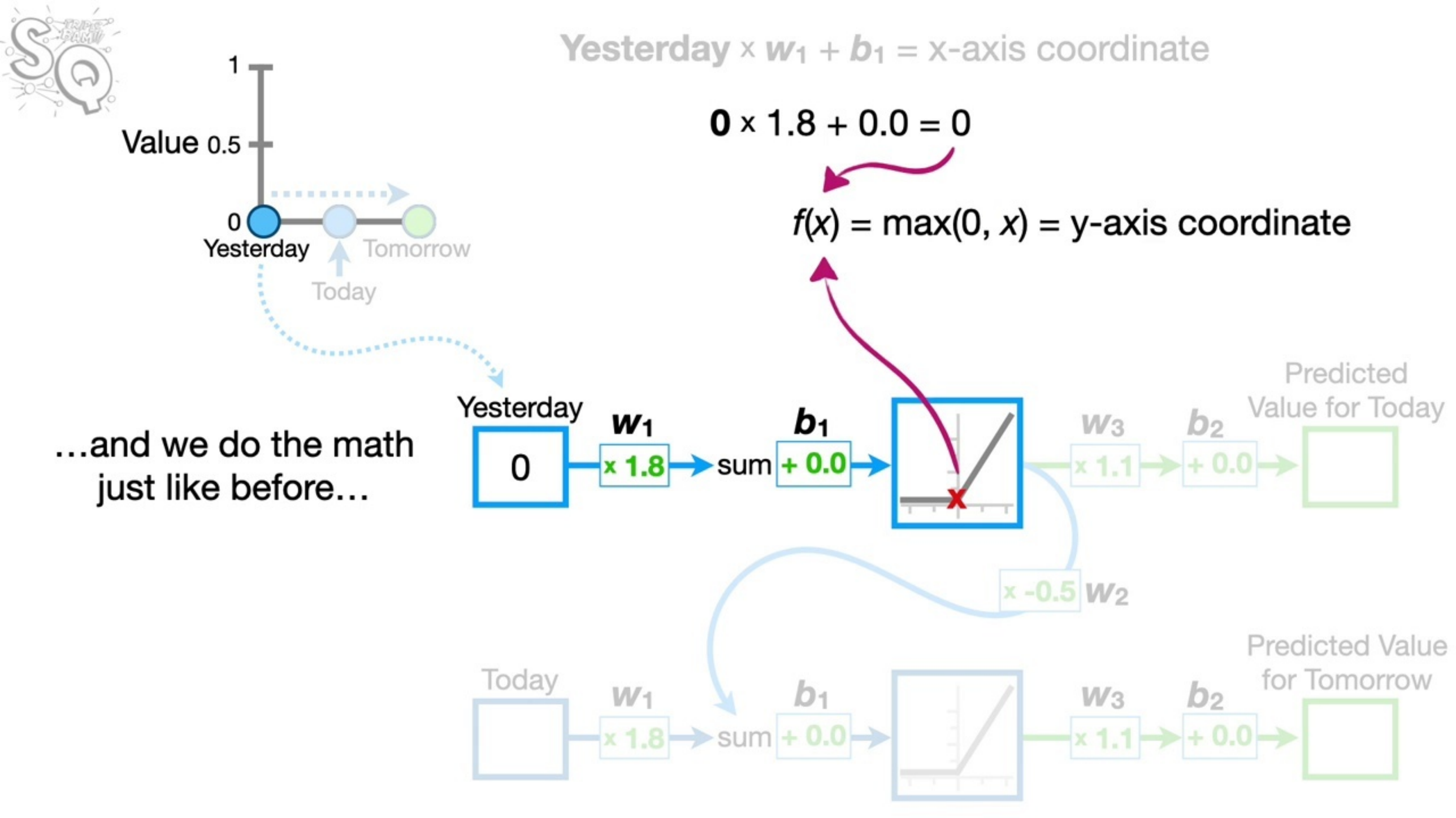

Yesterday × w_1
0 × 1.8
1
Value 0.5
0
Yesterday
Tomorrow
Today
…and we do the math just like before…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

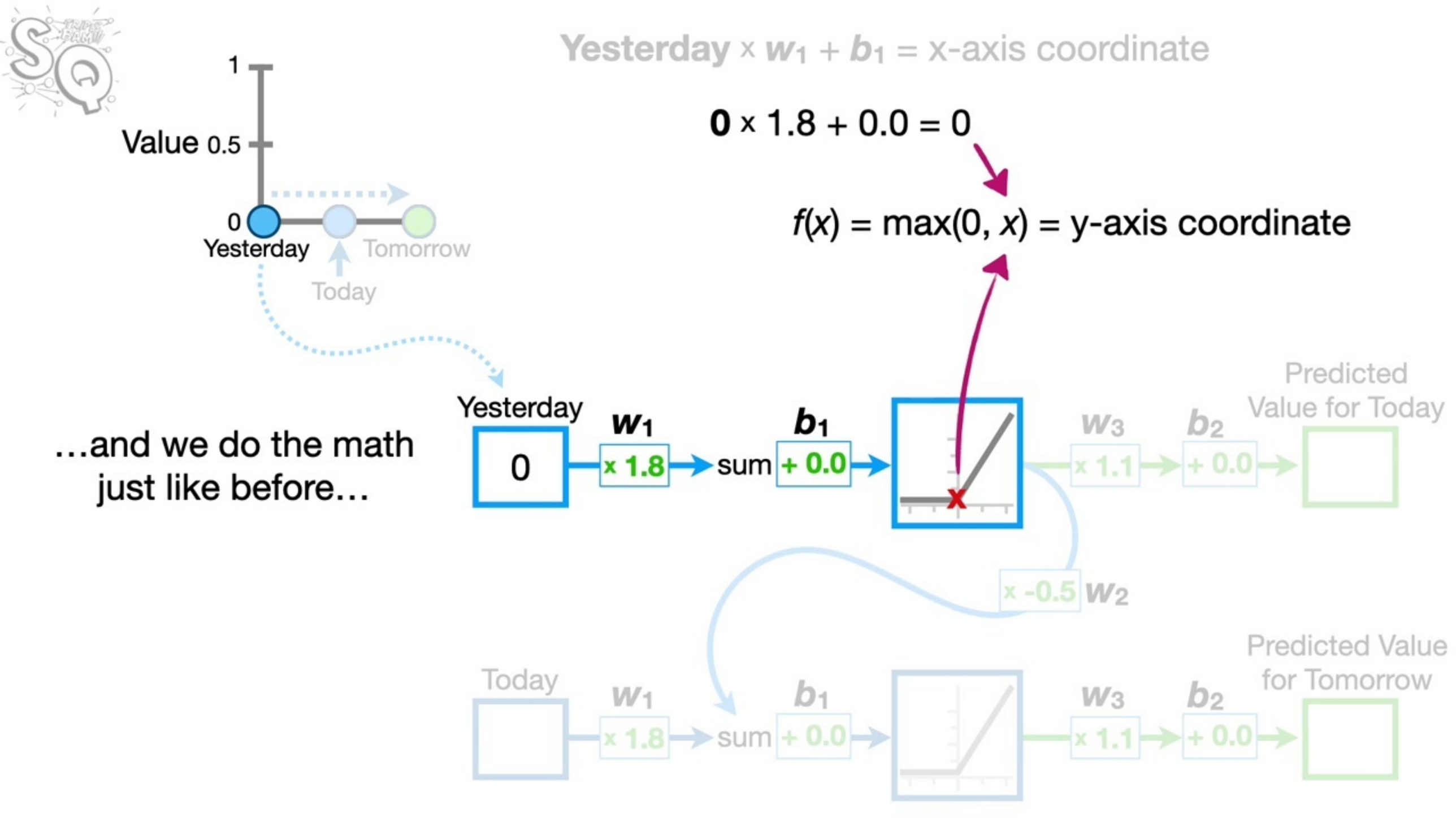

Yesterday × w_1 + b_1
0 × 1.8
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and we do the math just like before…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

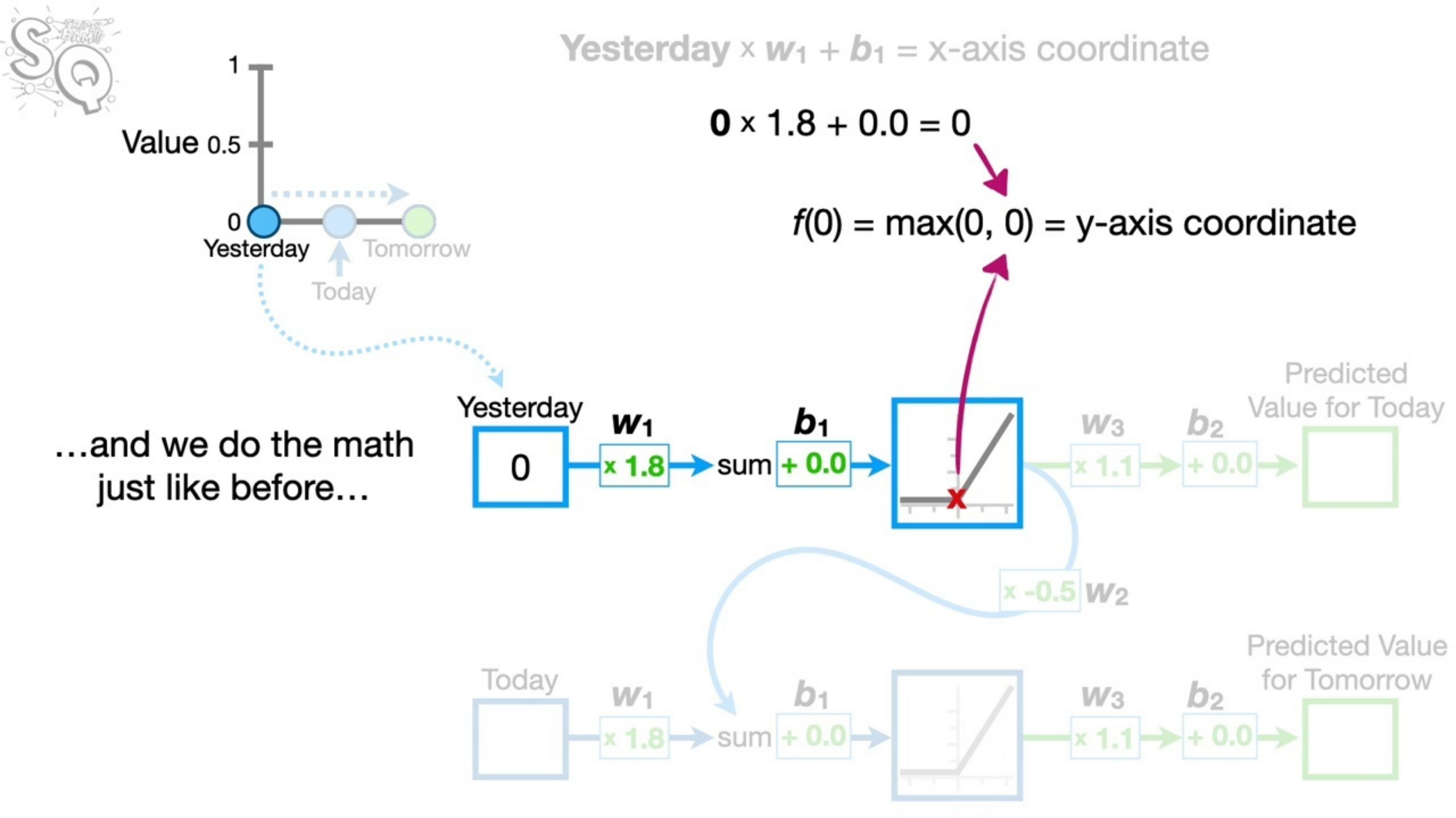

Yesterday × w_1 + b_1
0 × 1.8 + 0.0
1
Value 0.5
0
Yesterday
Tomorrow
Today
…and we do the math just like before…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

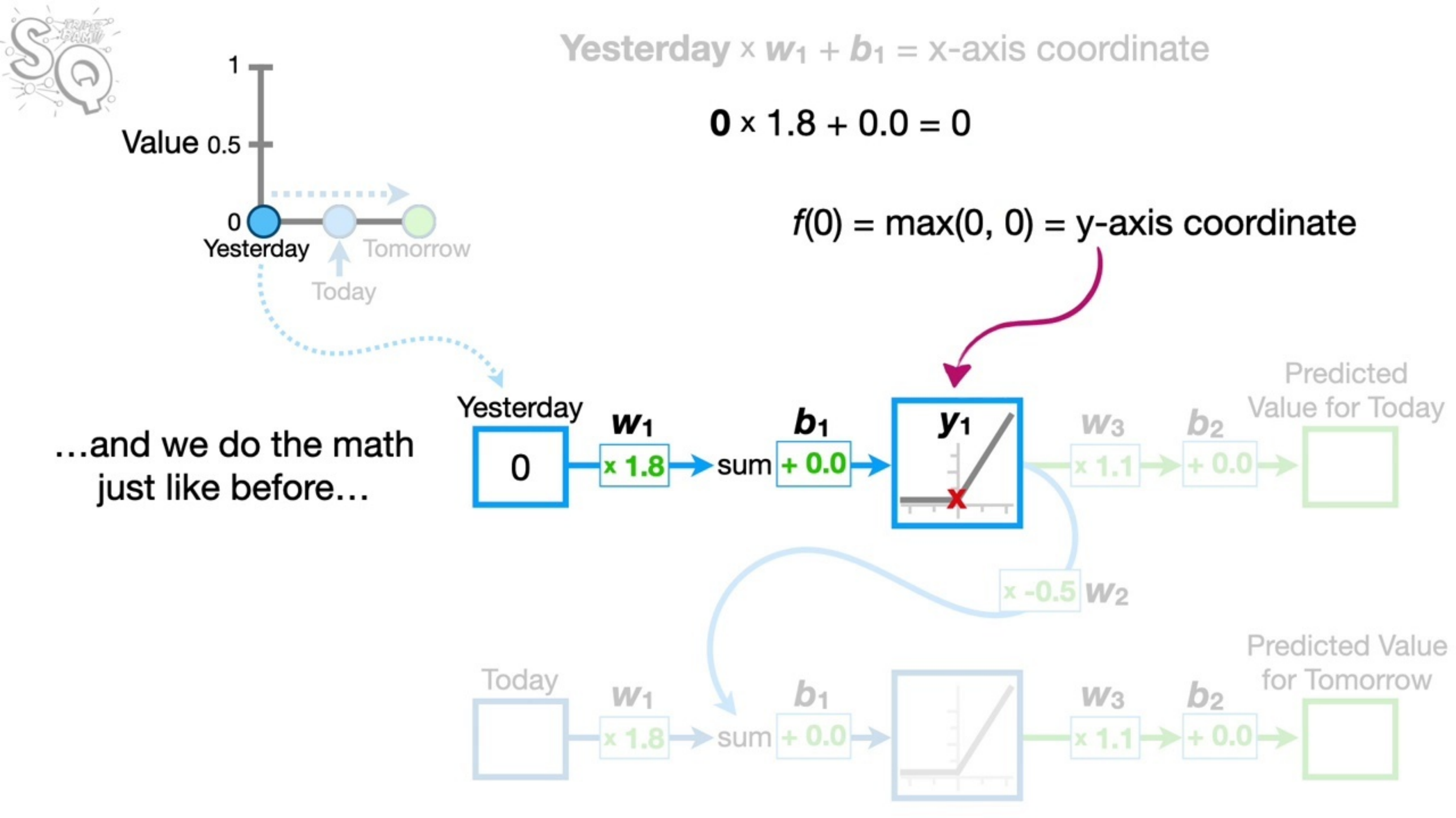

Yesterday × w_1 + b_1 = x-axis coordinate
0 × 1.8 + 0.0
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and we do the math just like before…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

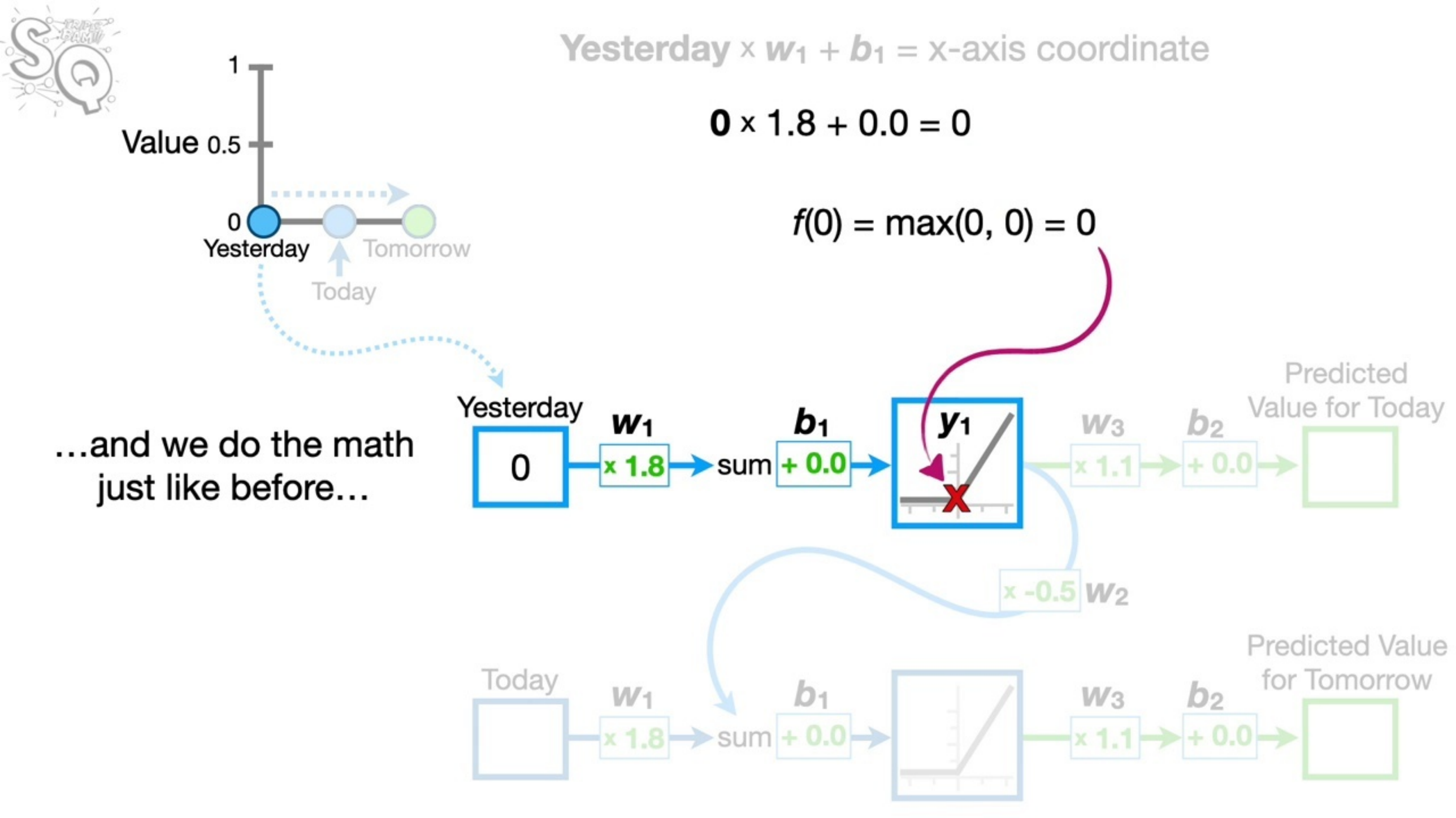

Yesterday × w_1 + b_1 = x-axis coordinate
0 × 1.8 + 0.0 = 0
1
Value 0.5
0
Yesterday
Tomorrow
Today
…and we do the math just like before…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

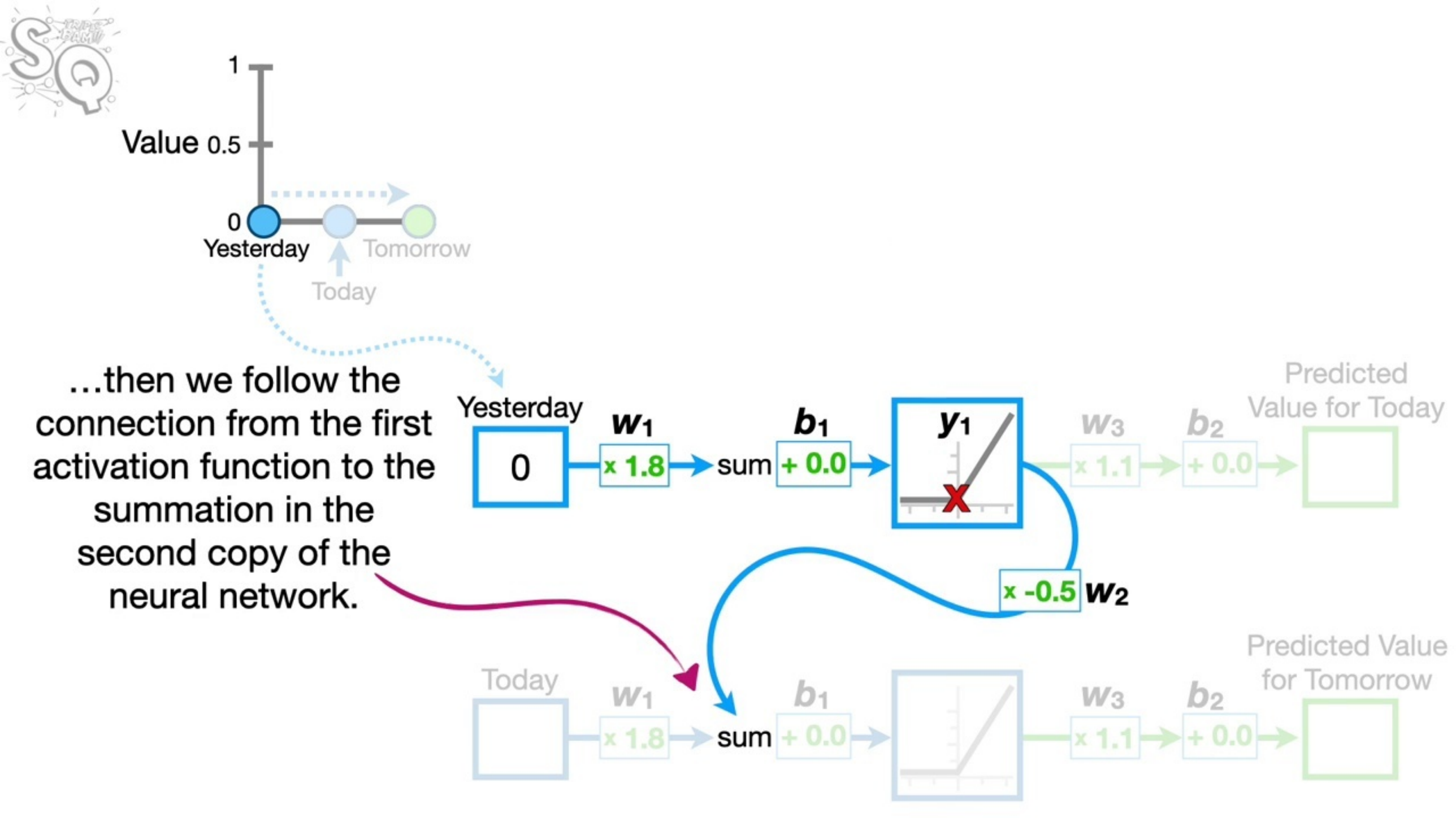

Yesterday × w_1 + b_1 = x-axis coordinate
1
Value 0.5
0
Yesterday
Tomorrow
Today
0 × 1.8 + 0.0 = 0
f(x) = max(0, x) = y-axis coordinate
…and we do the math just like before…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
Predicted Value for Tomorrow

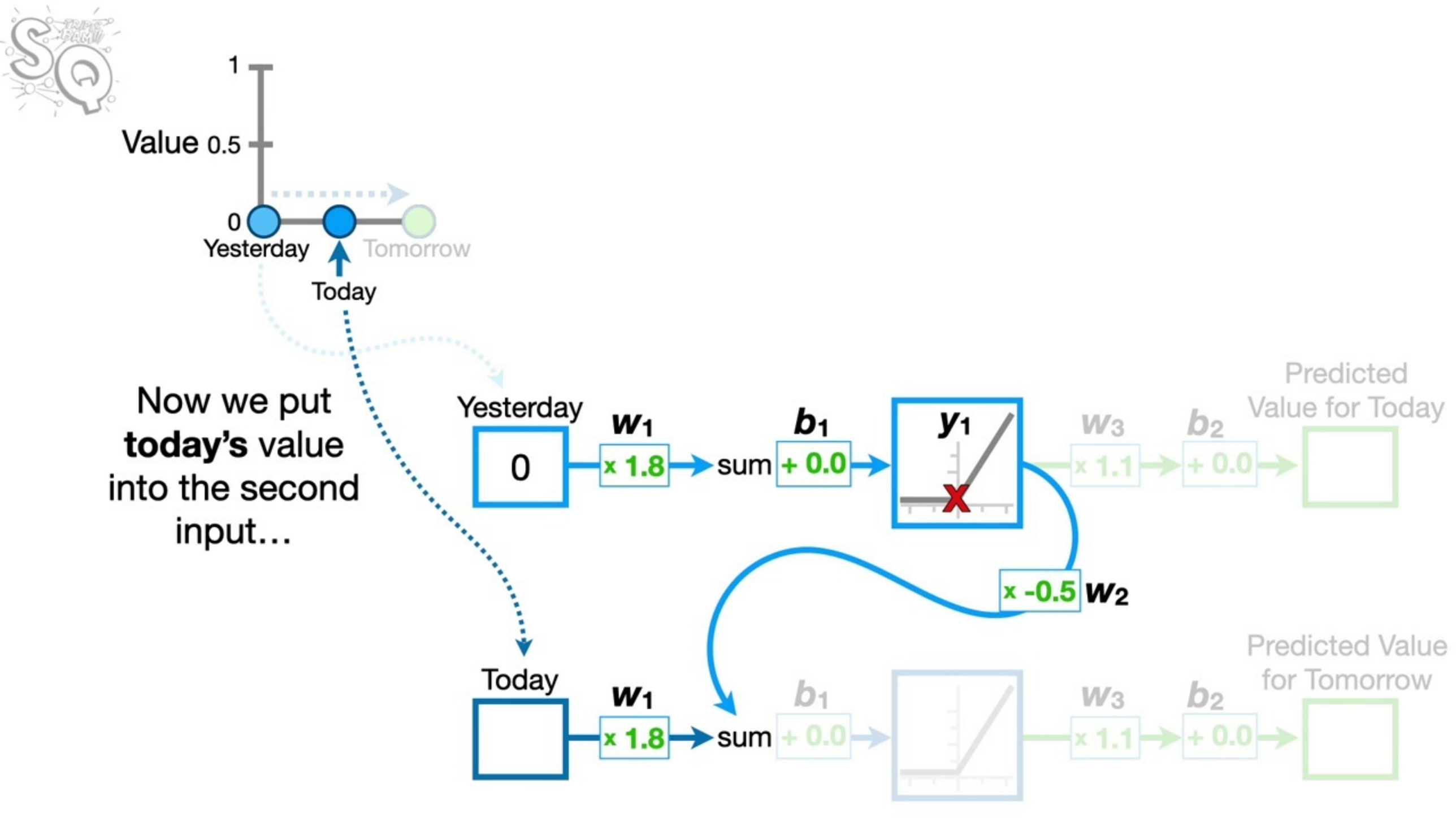

Yesterday × w_1 + b_1 = x-axis coordinate
1
Value 0.5
0
Yesterday
Tomorrow
Today
0 × 1.8 + 0.0 = 0
f(x) = max(0, x) = y-axis coordinate
…and we do the math just like before…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

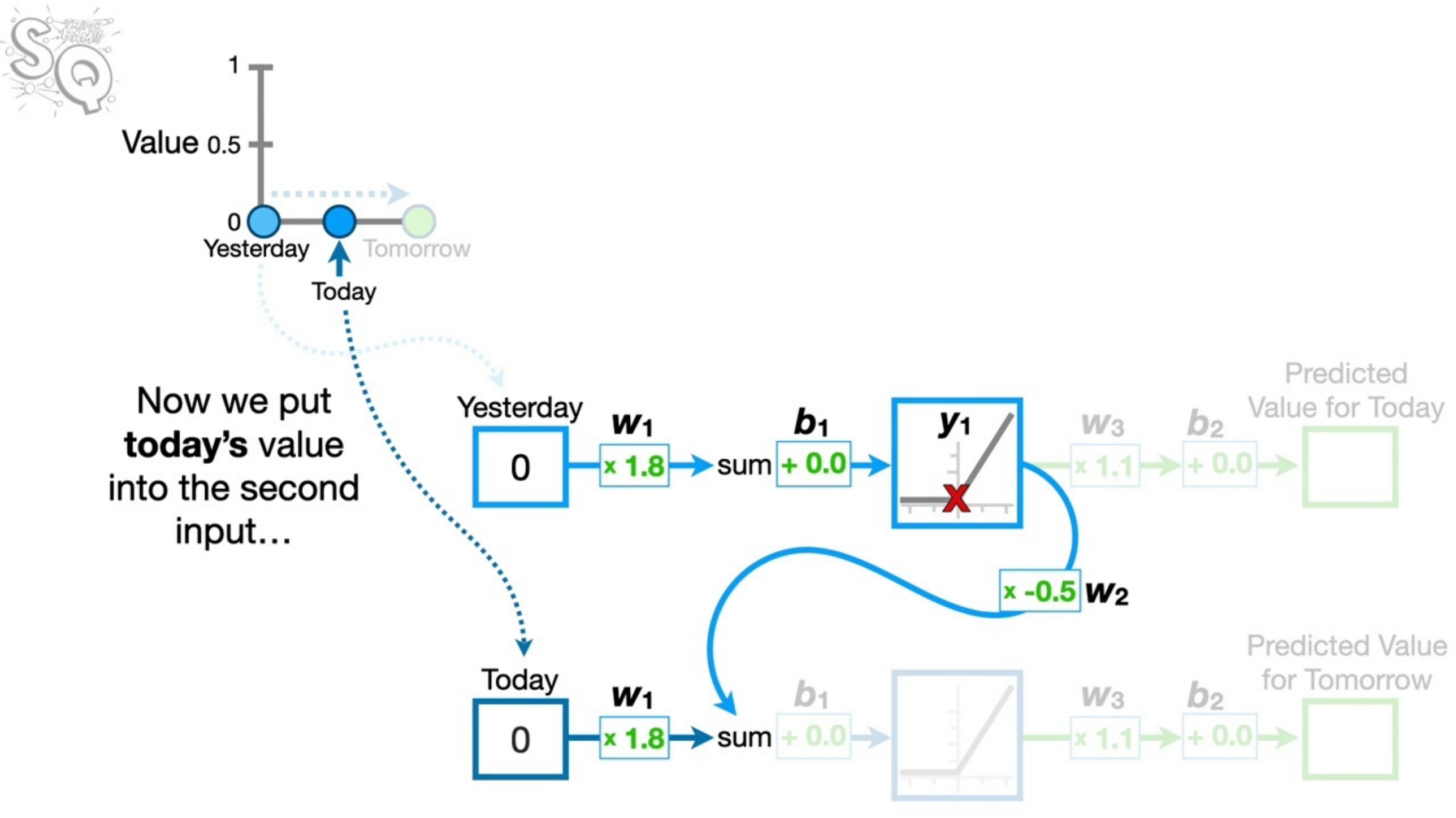

Yesterday × w_1 + b_1 = x-axis coordinate
1
Value 0.5
0
Yesterday
Tomorrow
Today
0 × 1.8 + 0.0 = 0
f(0) = max(0, 0) = y-axis coordinate
…and we do the math just like before…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
Predicted Value for Tomorrow

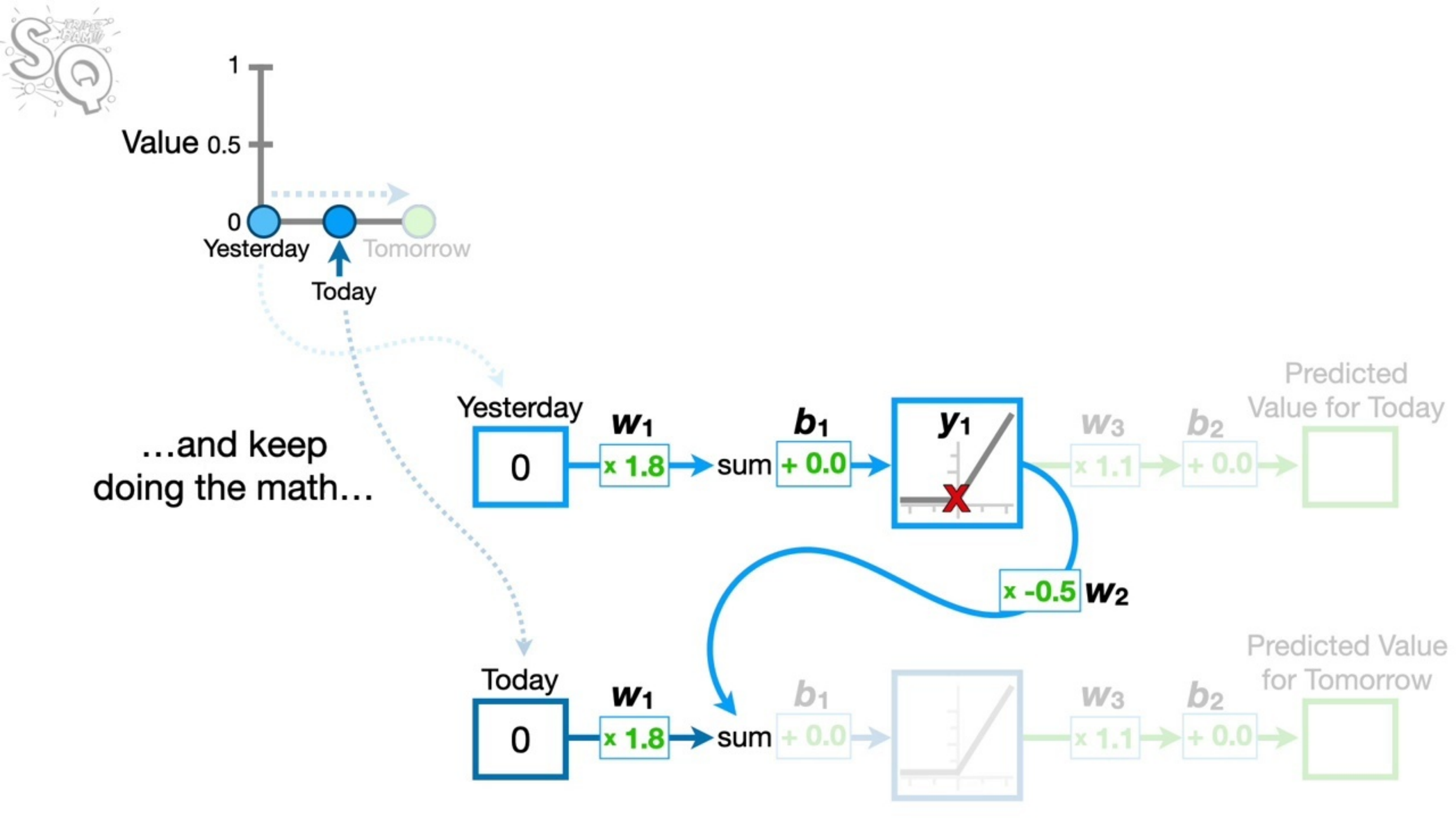

Yesterday × w_1 + b_1 = x-axis coordinate
1
Value 0.5
0
Yesterday
Tomorrow
Today
0 × 1.8 + 0.0 = 0
f(0) = max(0, 0) = y-axis coordinate
…and we do the math just like before…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

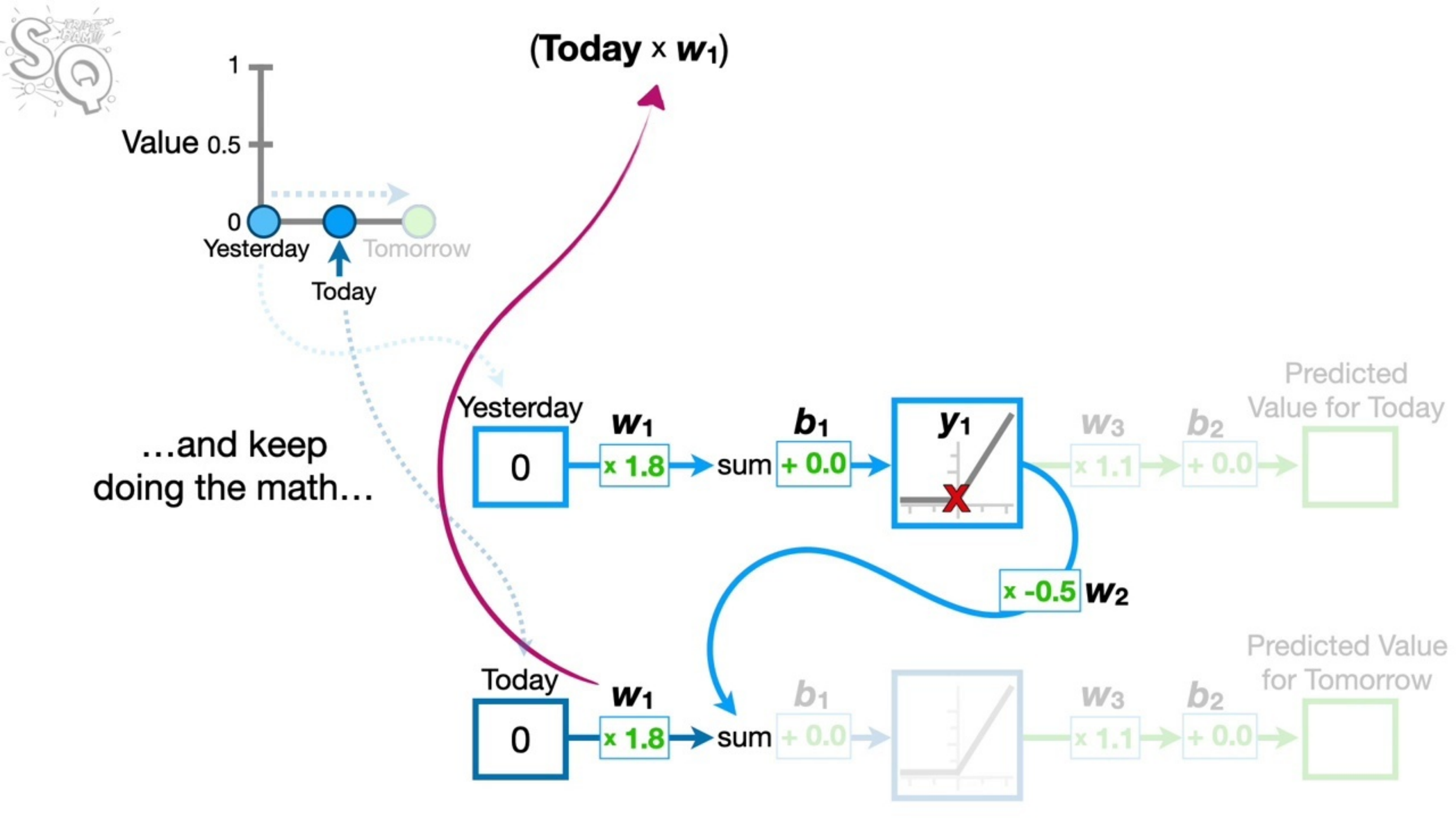

Yesterday × w_1 + b_1 = x-axis coordinate
0 × 1.8 + 0.0 = 0
f(0) = max(0, 0) = 0
1
Value 0.5
0
Yesterday
Tomorrow
Today
…and we do the math just like before…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

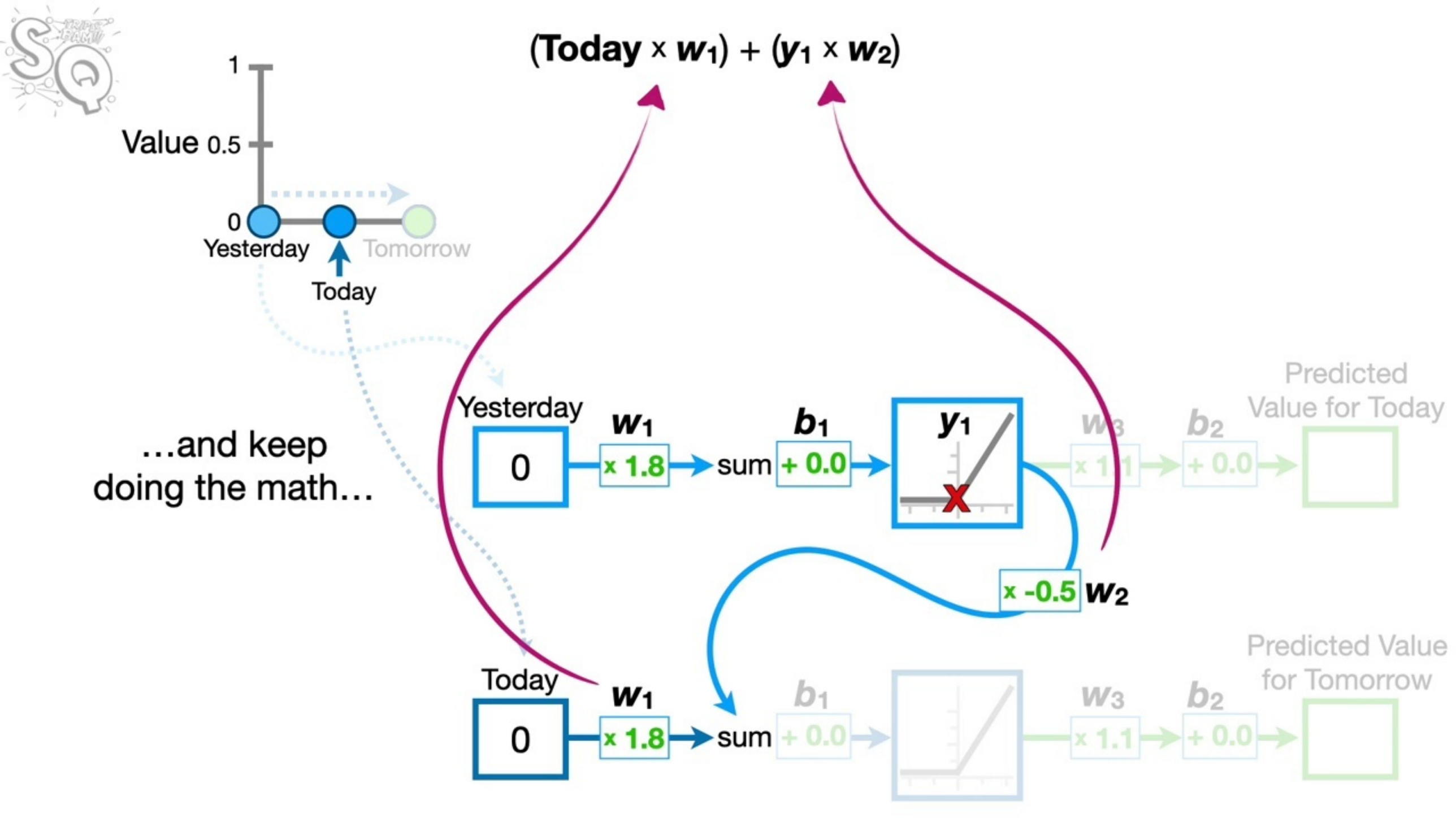

1
Value 0.5
0
Yesterday
Today
Tomorrow
…then we follow the connection from the first activation function to the summation in the second copy of the neural network.
Yesterday
0
w1
x 1.8
sum
b1
+ 0.0
y1
w3
x 1.1
b2
+ 0.0
Predicted Value for Today
x -0.5
w2
Today
w1
x 1.8
sum
b1
+ 0.0
w3
x 1.1
b2
+ 0.0
Predicted Value for Tomorrow

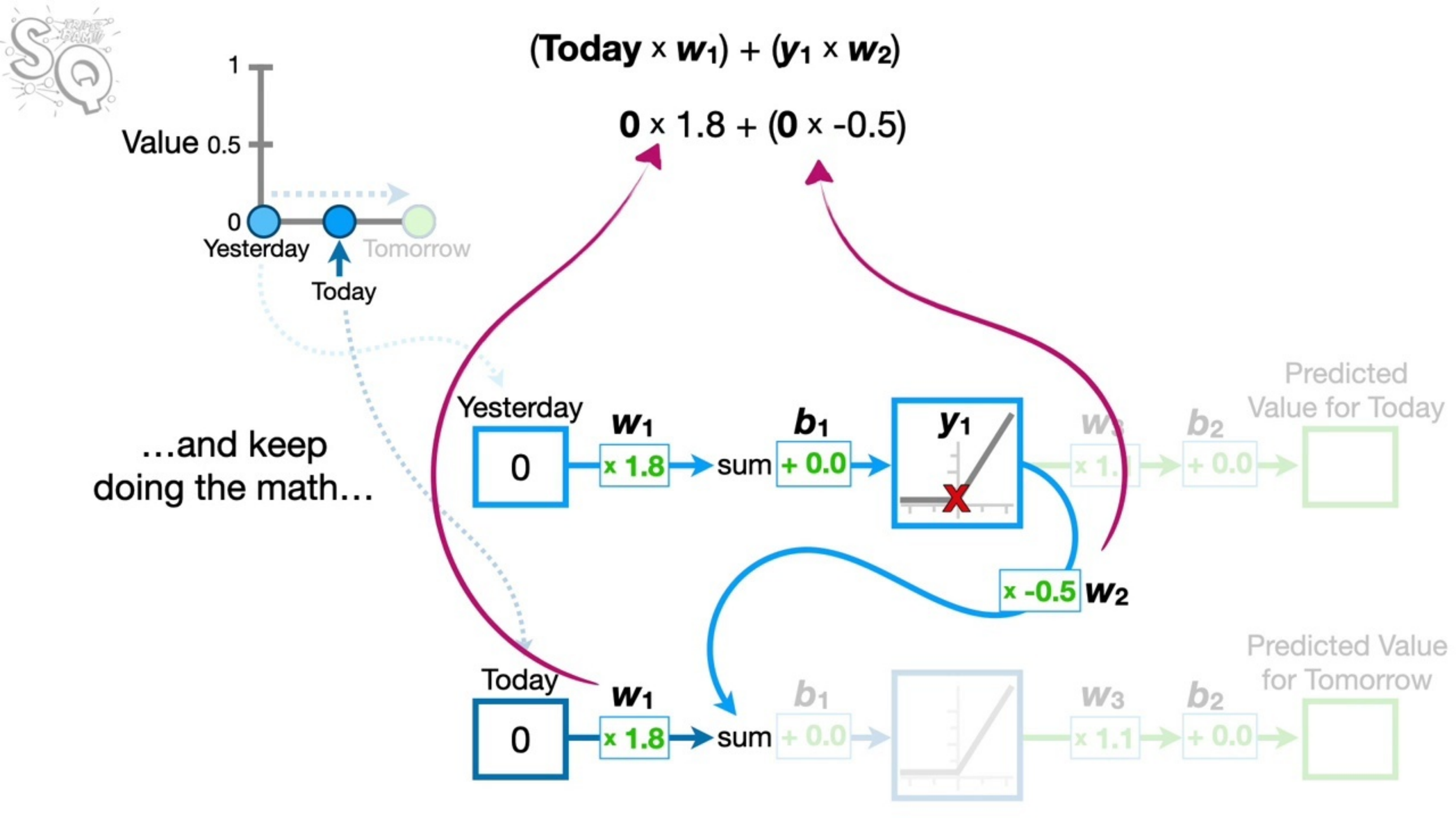

1
Value 0.5
0
Yesterday
Today
Tomorrow
Now we put **today's** value into the second input…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

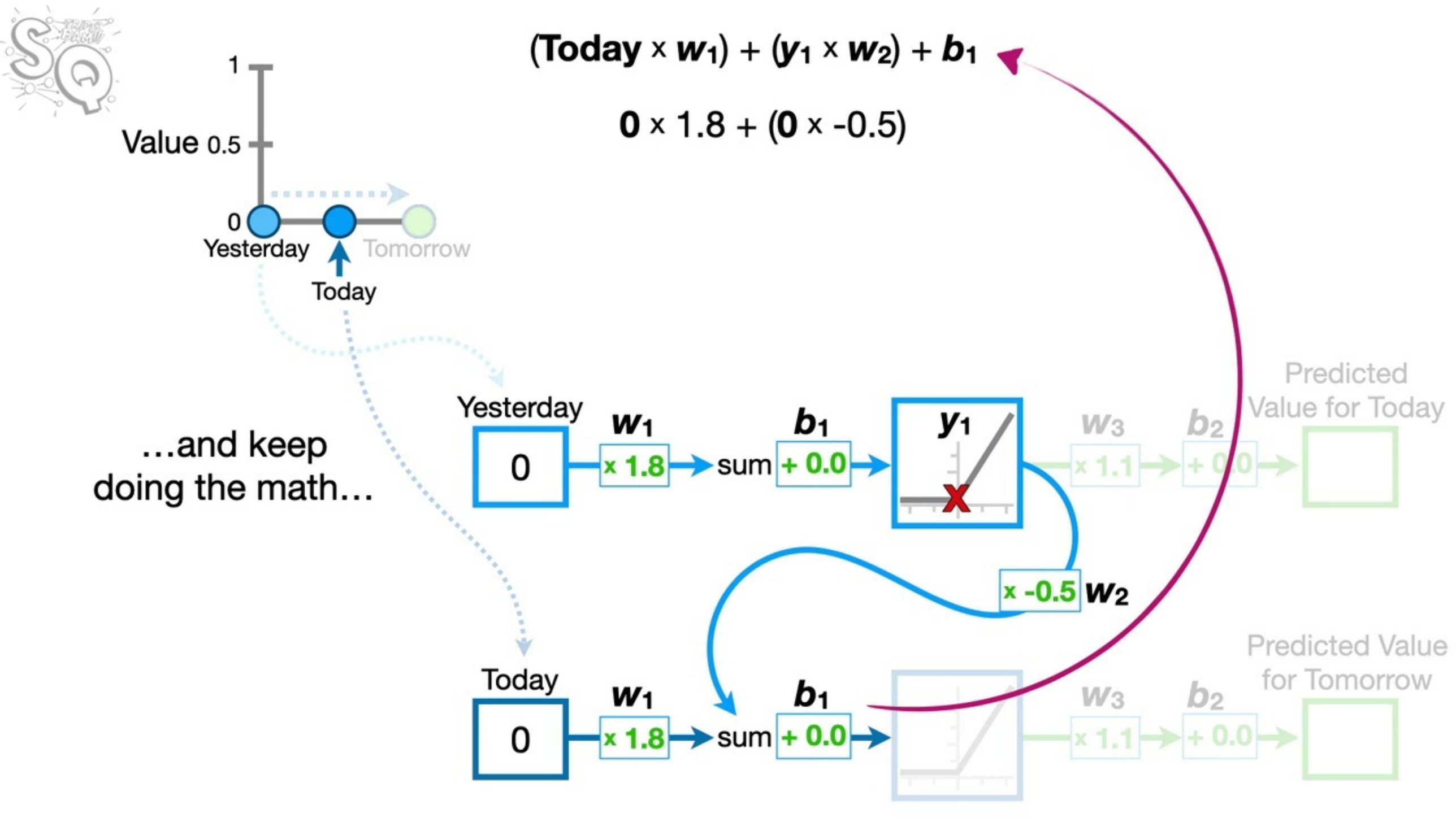

1
Value 0.5
0
Yesterday
Today
Tomorrow
Now we put **today's** value into the second input…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

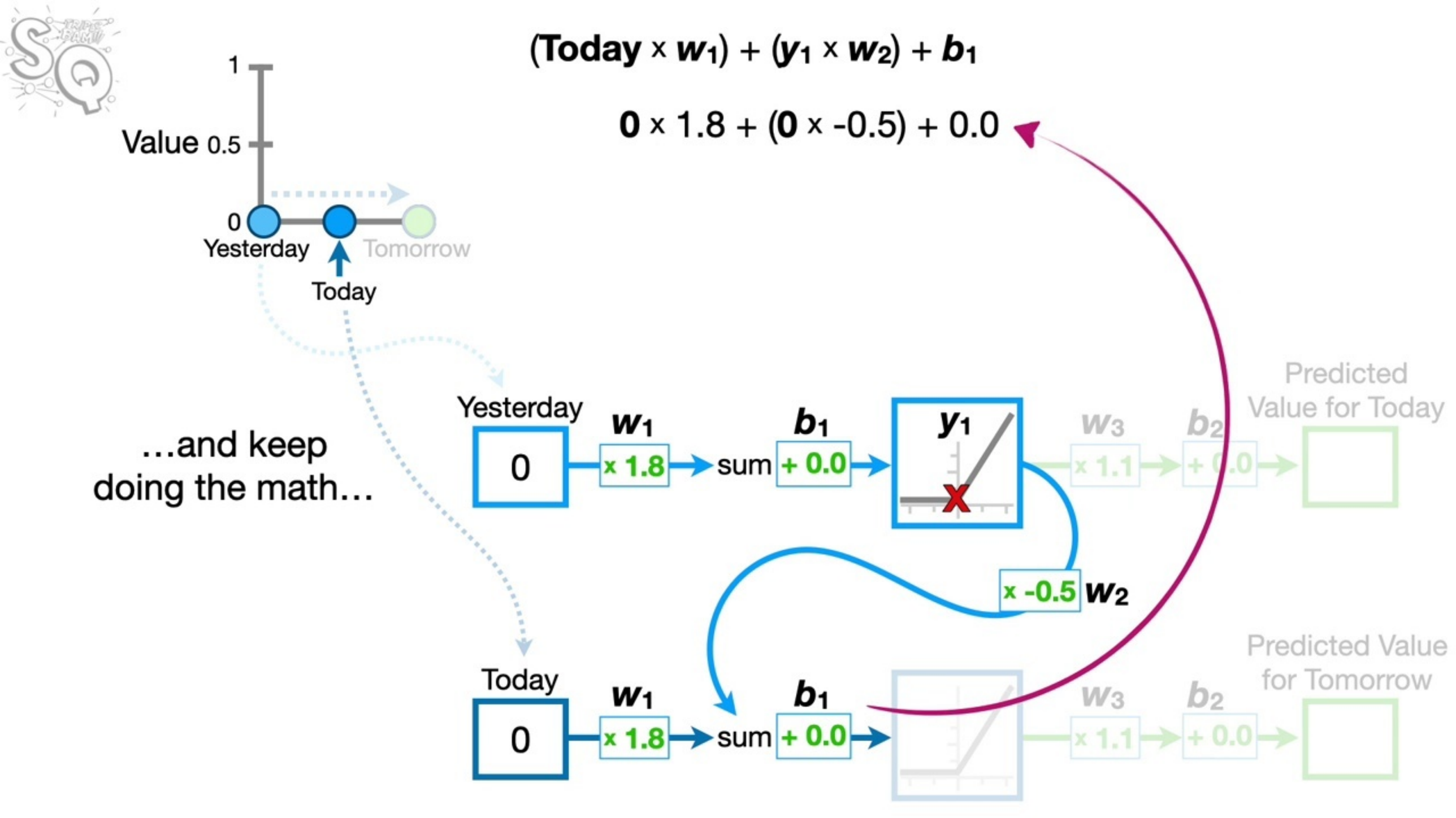

1
Value 0.5
0
Yesterday
Today
Tomorrow
…and keep doing the math…
Yesterday
0
w1
x 1.8
sum
b1
+ 0.0
y1
w3
x 1.1
b2
+ 0.0
Predicted Value for Today
x -0.5
w2
Today
0
w1
x 1.8
sum
b1
+ 0.0
w3
x 1.1
b2
+ 0.0
Predicted Value for Tomorrow

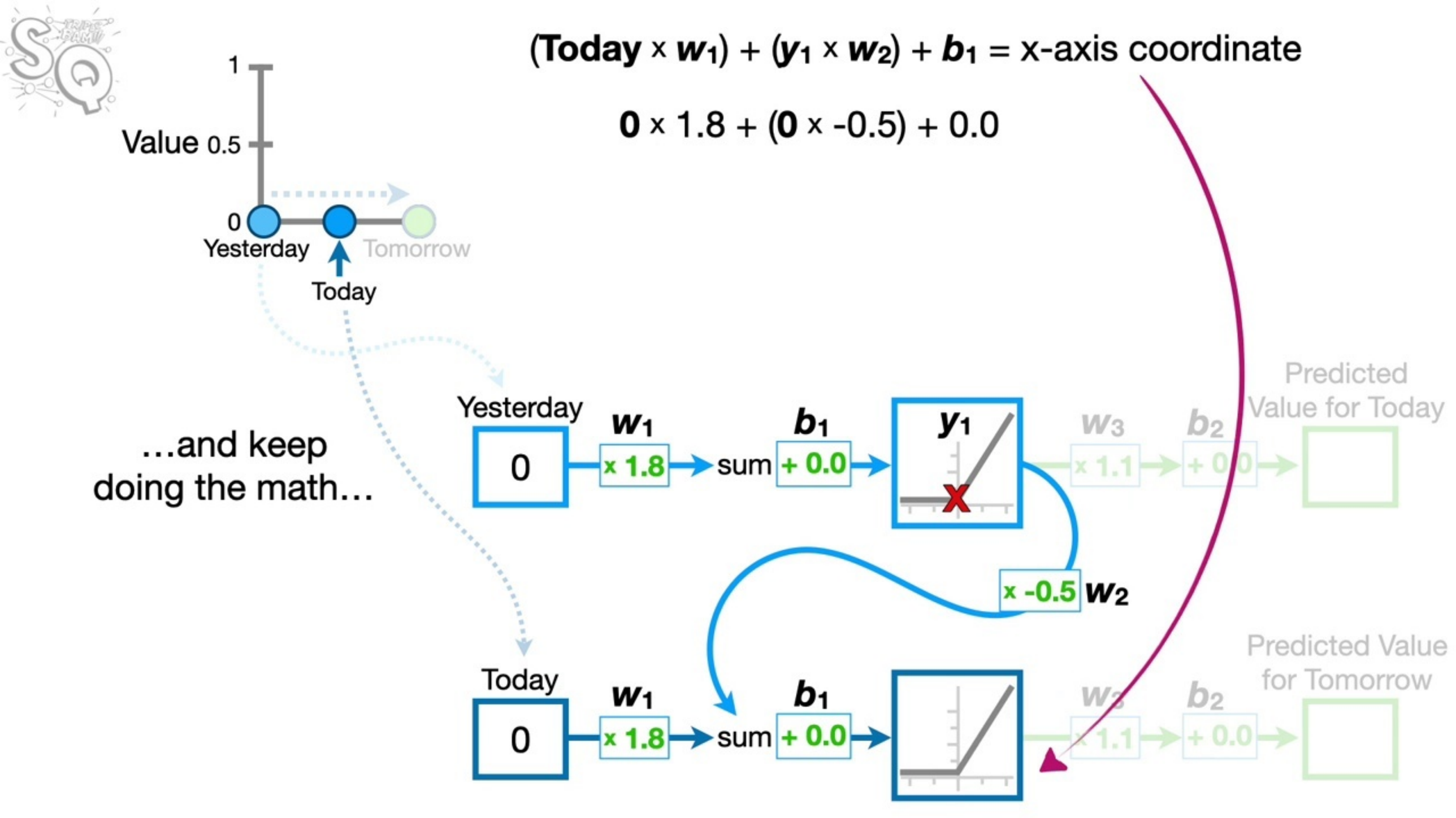

(Today x w_1)
1
Value 0.5
0
Yesterday
Tomorrow
Today
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

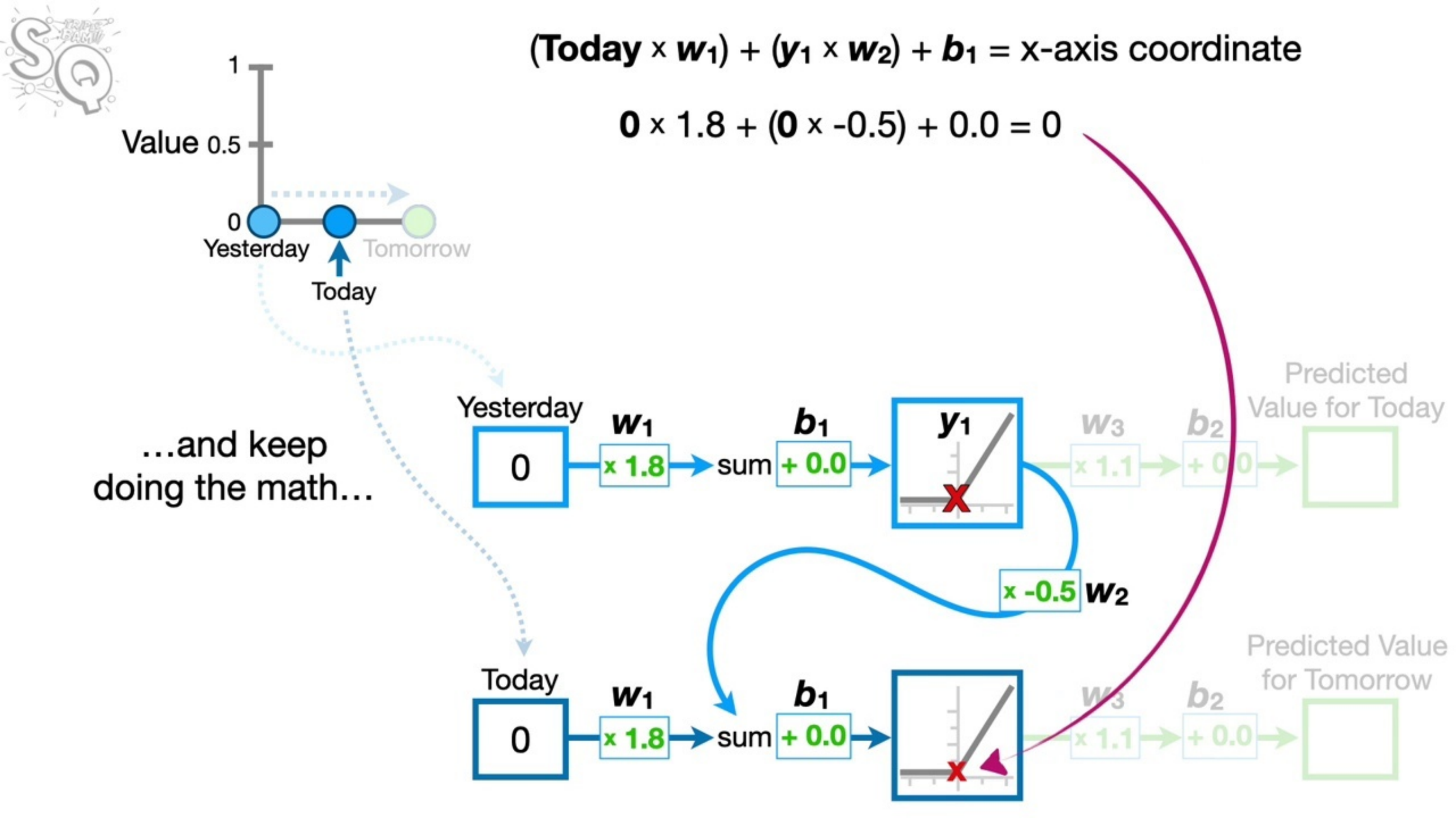

(Today x w_1) + (y_1 x w_2)
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

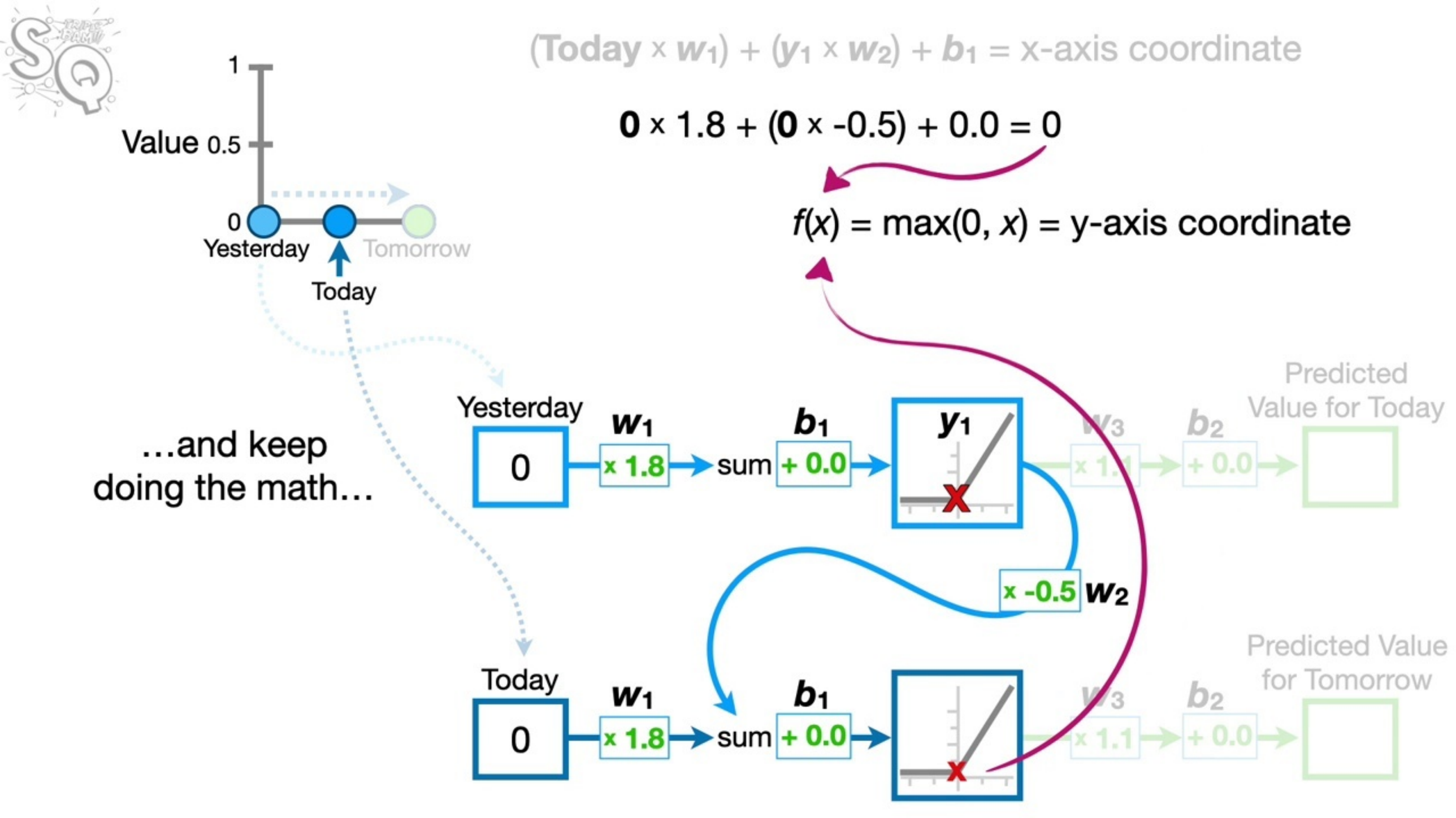

(Today x w_1) + (y_1 x w_2)
0 x 1.8 + (0 x -0.5)
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
x -0.5
w_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

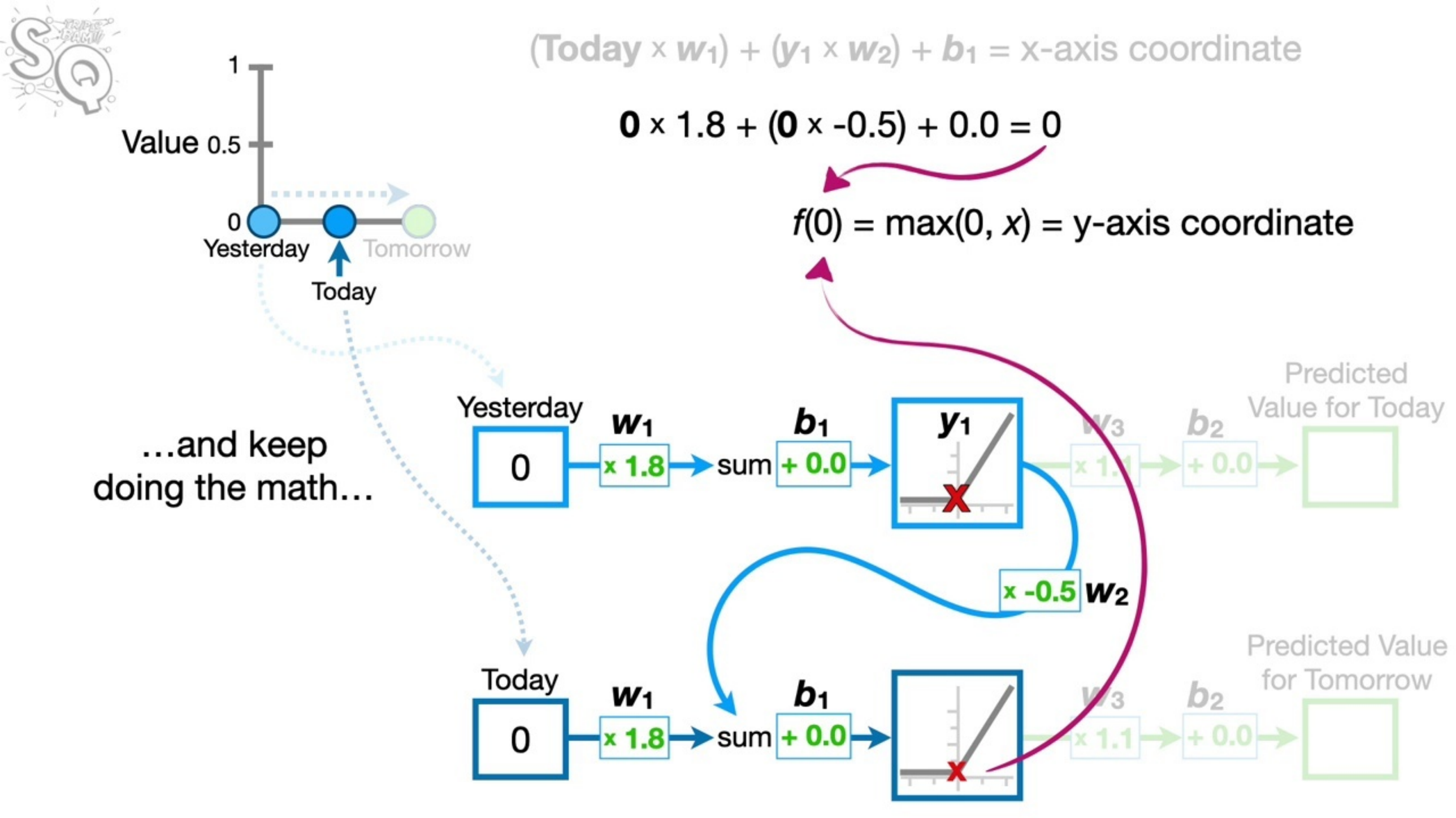

(Today x w_1) + (y_1 x w_2) + b_1
0 x 1.8 + (0 x -0.5)
1
Value 0.5
0
Yesterday
Tomorrow
Today
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

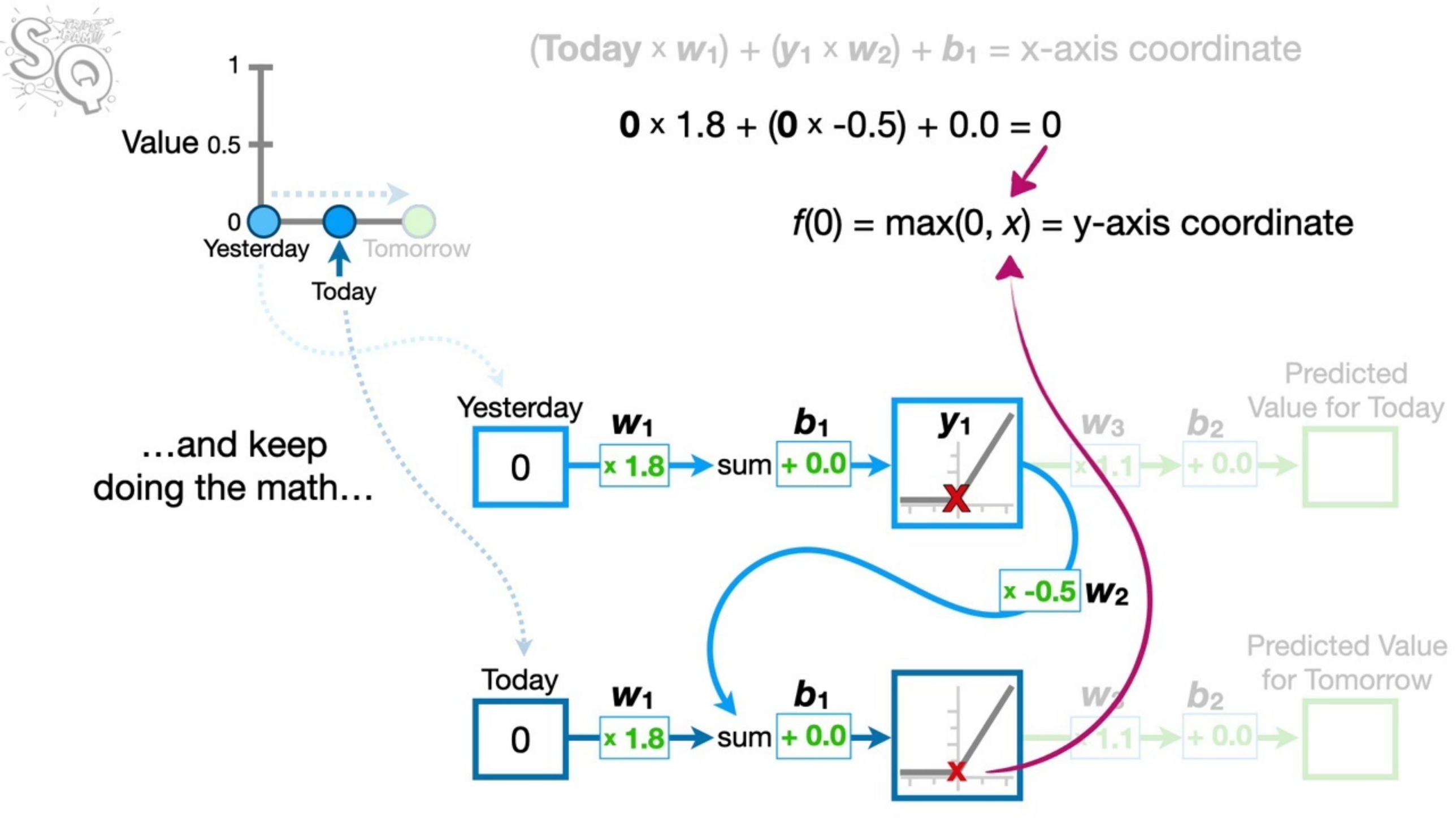

(Today x w_1) + (y_1 x w_2) + b_1
0 x 1.8 + (0 x -0.5) + 0.0
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

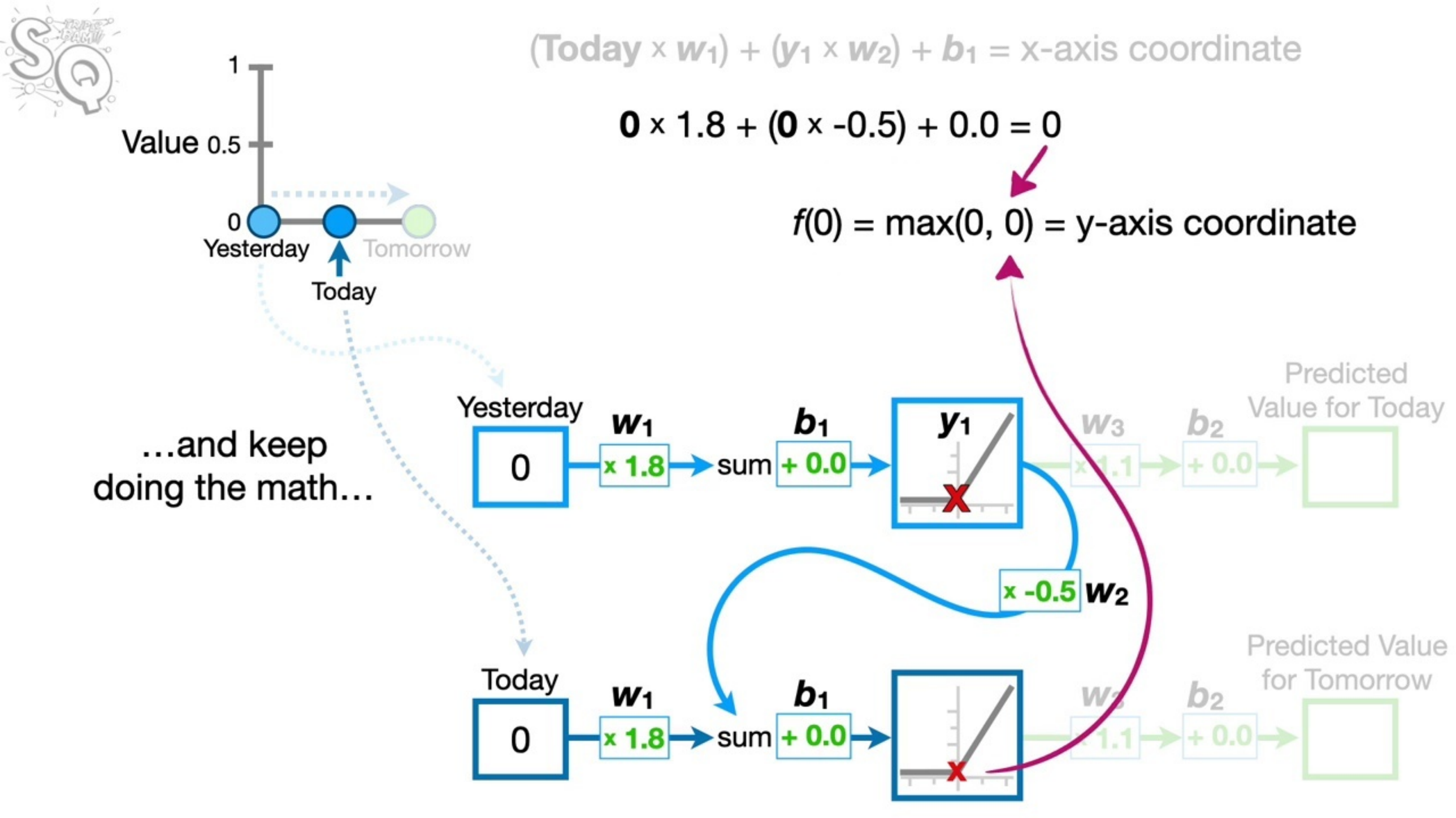

(Today x w_1) + (y_1 x w_2) + b_1 = x-axis coordinate
0 x 1.8 + (0 x -0.5) + 0.0
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

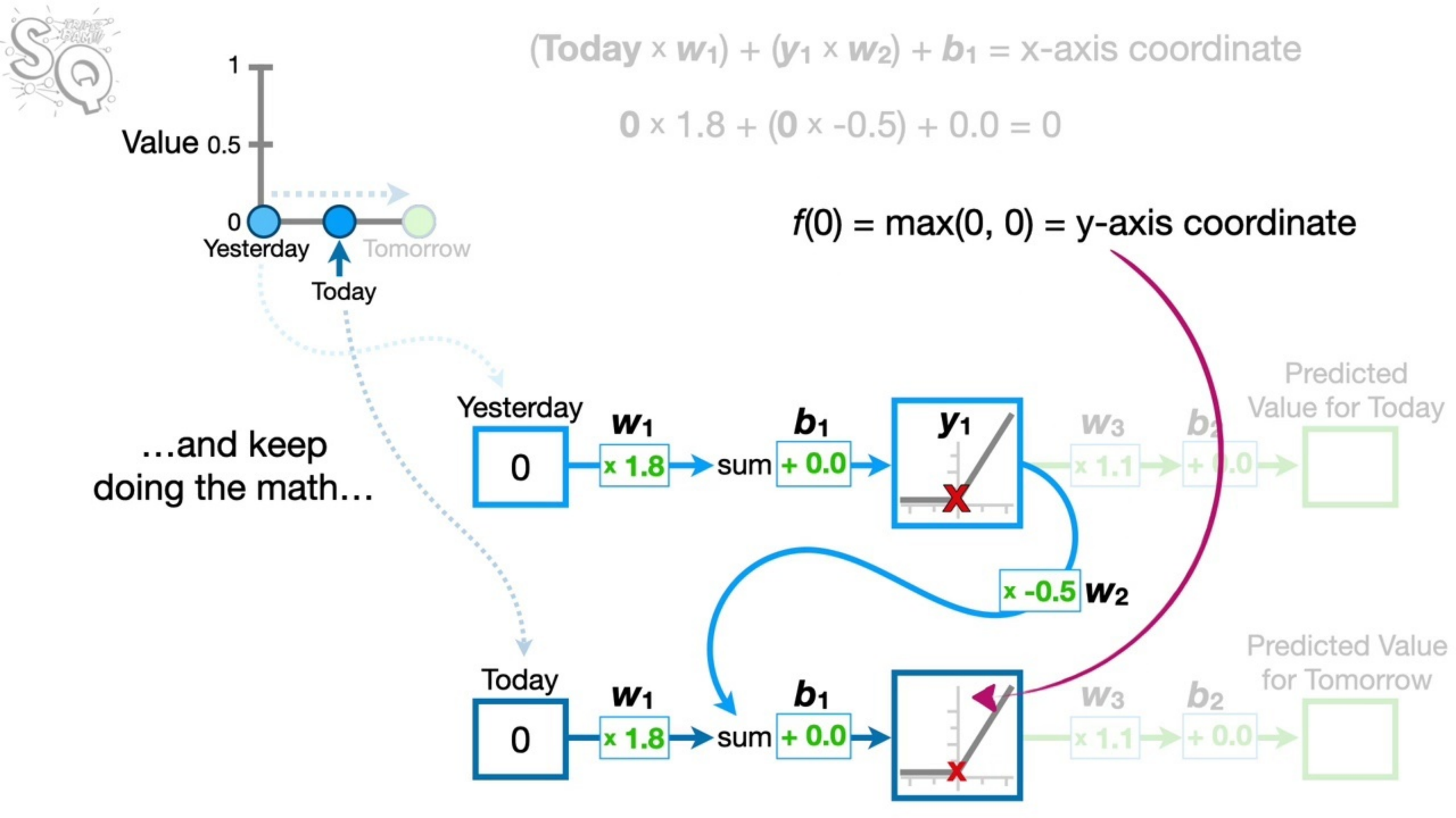

(Today x w_1) + (y_1 x w_2) + b_1 = x-axis coordinate
0 x 1.8 + (0 x -0.5) + 0.0 = 0
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

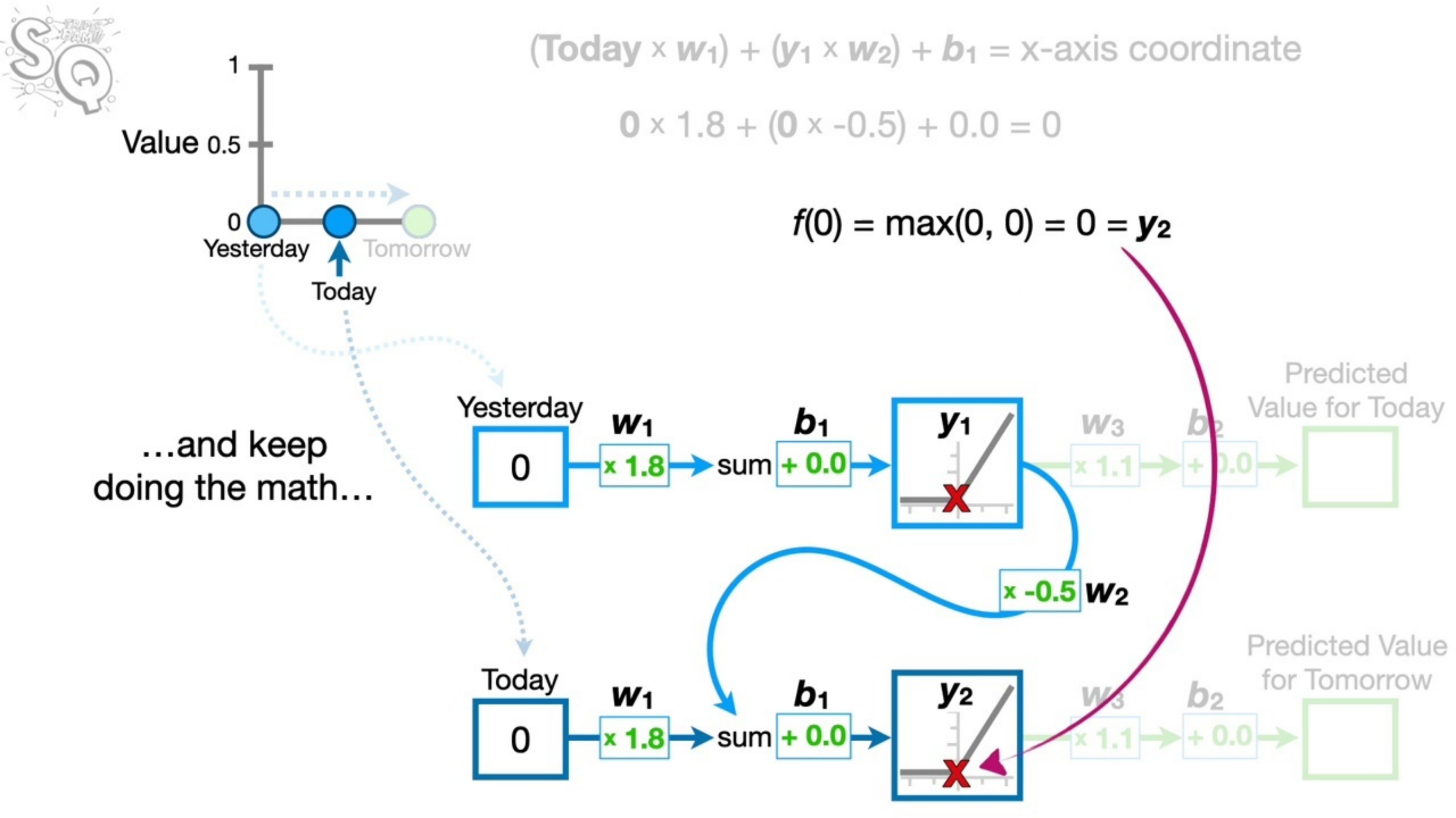

(Today x w_1) + (y_1 x w_2) + b_1 = x-axis coordinate
0 x 1.8 + (0 x -0.5) + 0.0 = 0
f(x) = max(0, x) = y-axis coordinate
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

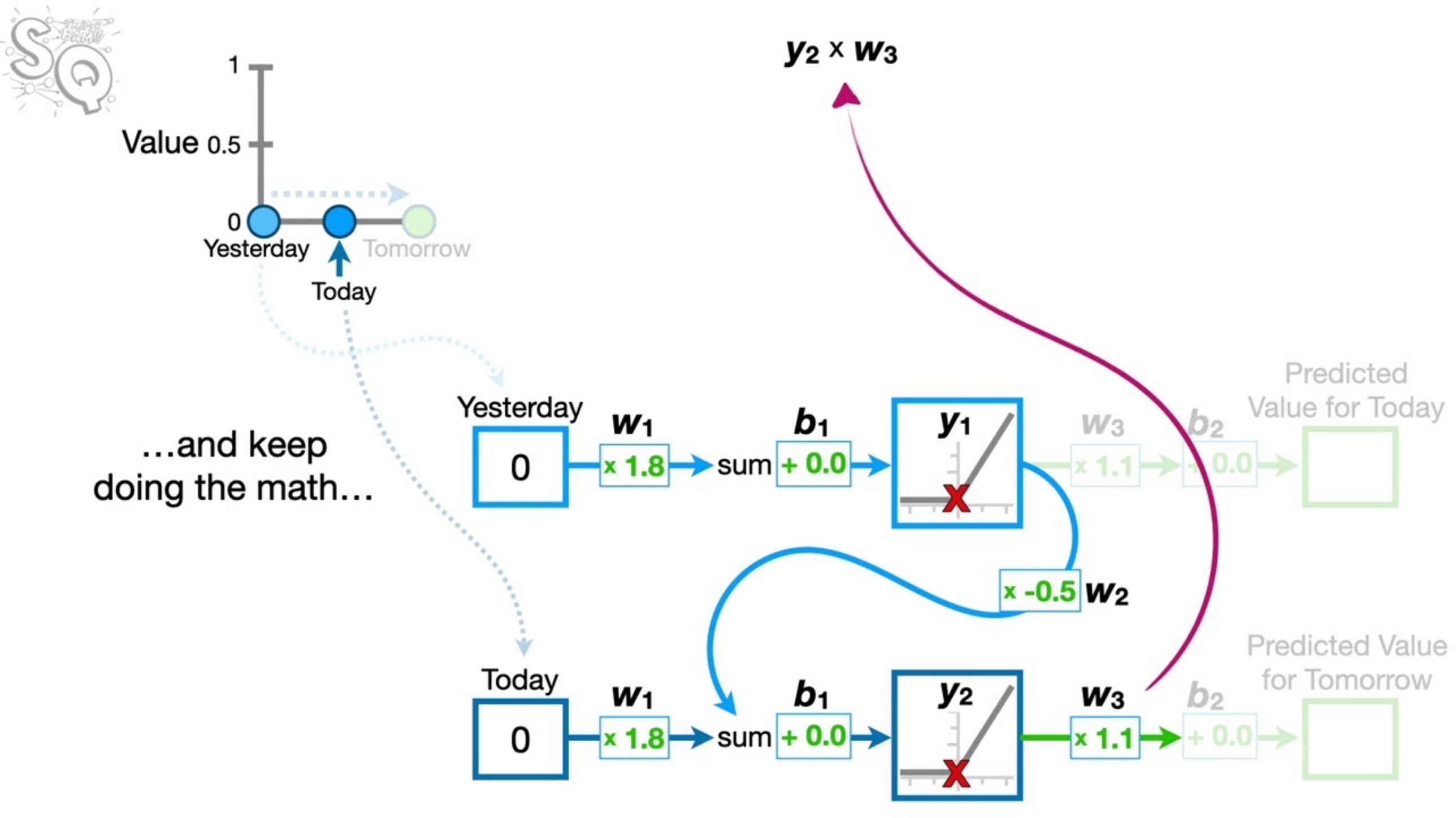

(Today x w_1) + (y_1 x w_2) + b_1 = x-axis coordinate
1
Value 0.5
0
Yesterday
Today
Tomorrow
0 x 1.8 + (0 x -0.5) + 0.0 = 0
$f(0) = \max(0, x)$ = y-axis coordinate
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

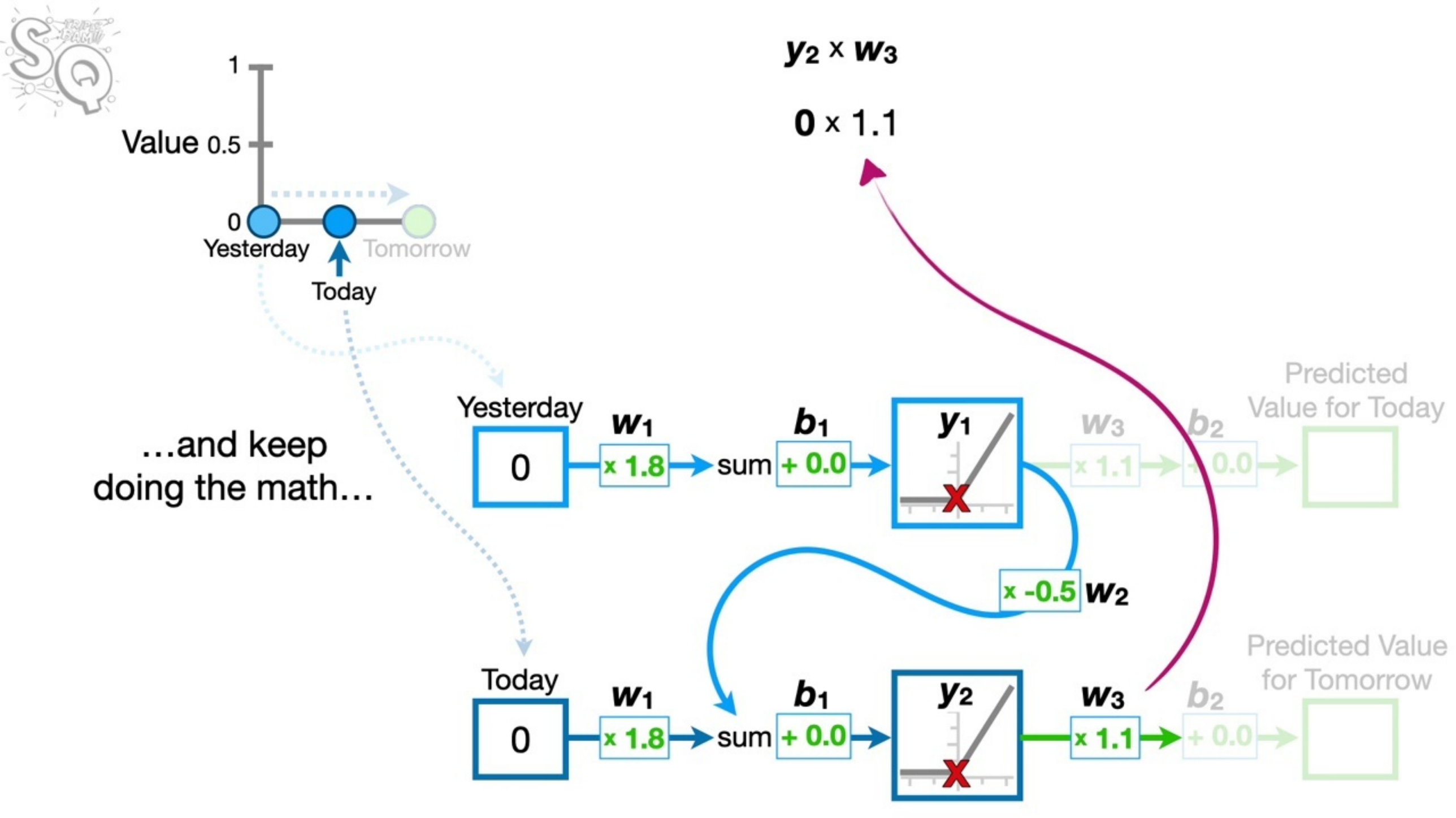

(Today x w_1) + (y_1 x w_2) + b_1 = x-axis coordinate
0 x 1.8 + (0 x -0.5) + 0.0 = 0
f(0) = max(0, x) = y-axis coordinate
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

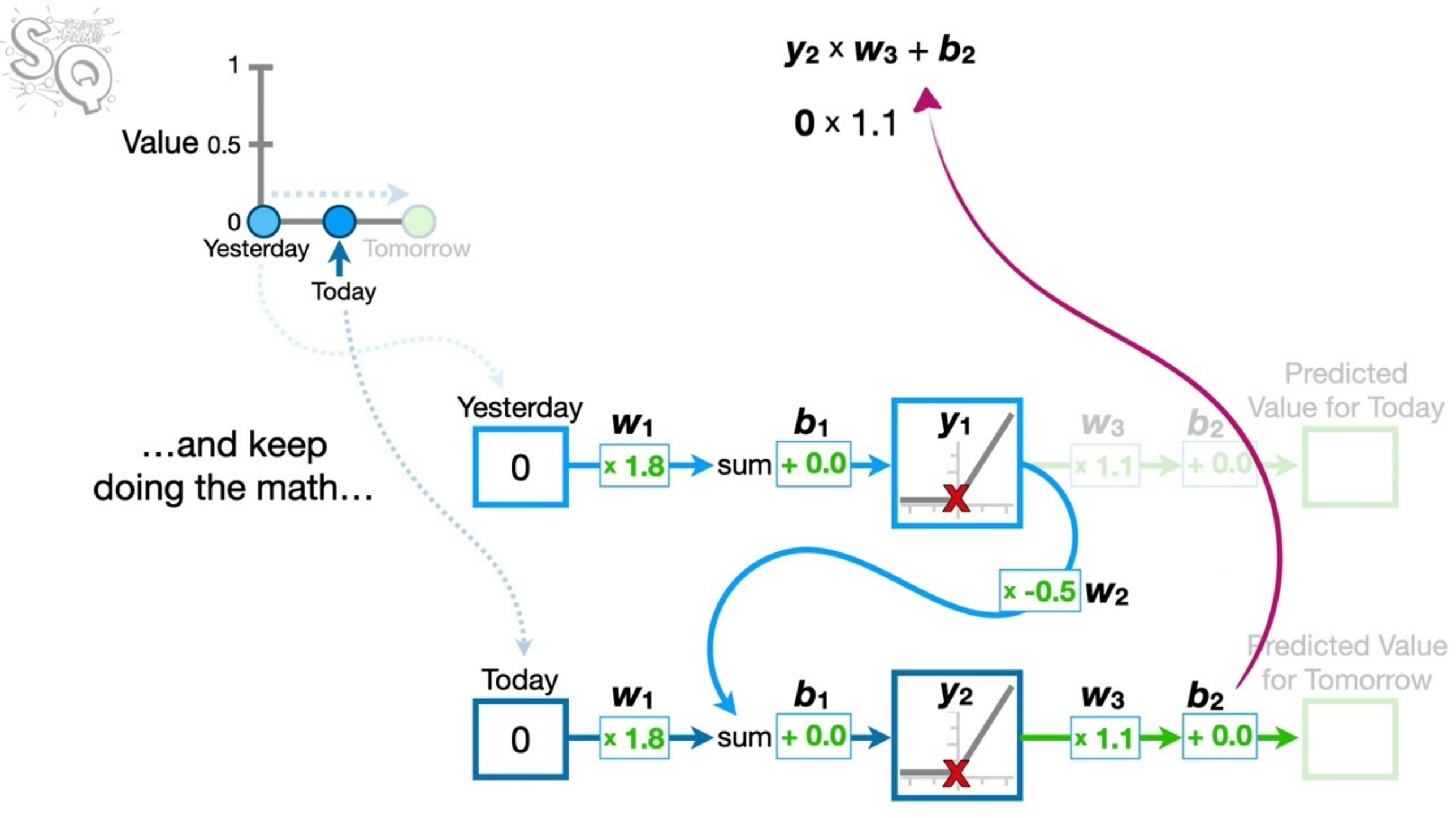

(Today x w_1) + (y_1 x w_2) + b_1 = x-axis coordinate
0 x 1.8 + (0 x -0.5) + 0.0 = 0
f(0) = max(0, 0) = y-axis coordinate
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

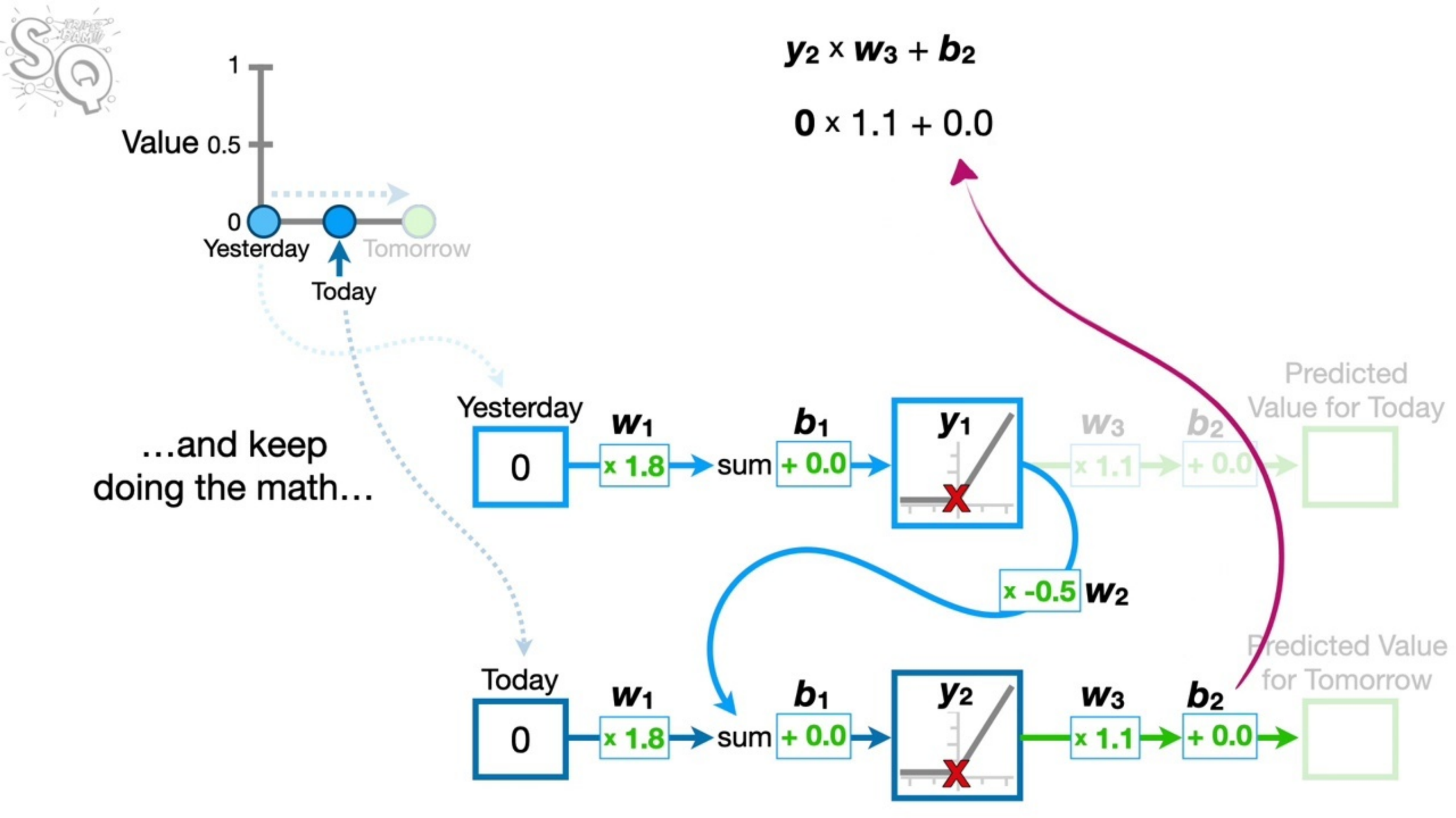

(Today x w_1) + (y_1 x w_2) + b_1 = x-axis coordinate
0 x 1.8 + (0 x -0.5) + 0.0 = 0
1
Value 0.5
0
Yesterday
Today
Tomorrow
f(0) = max(0, 0) = y-axis coordinate
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

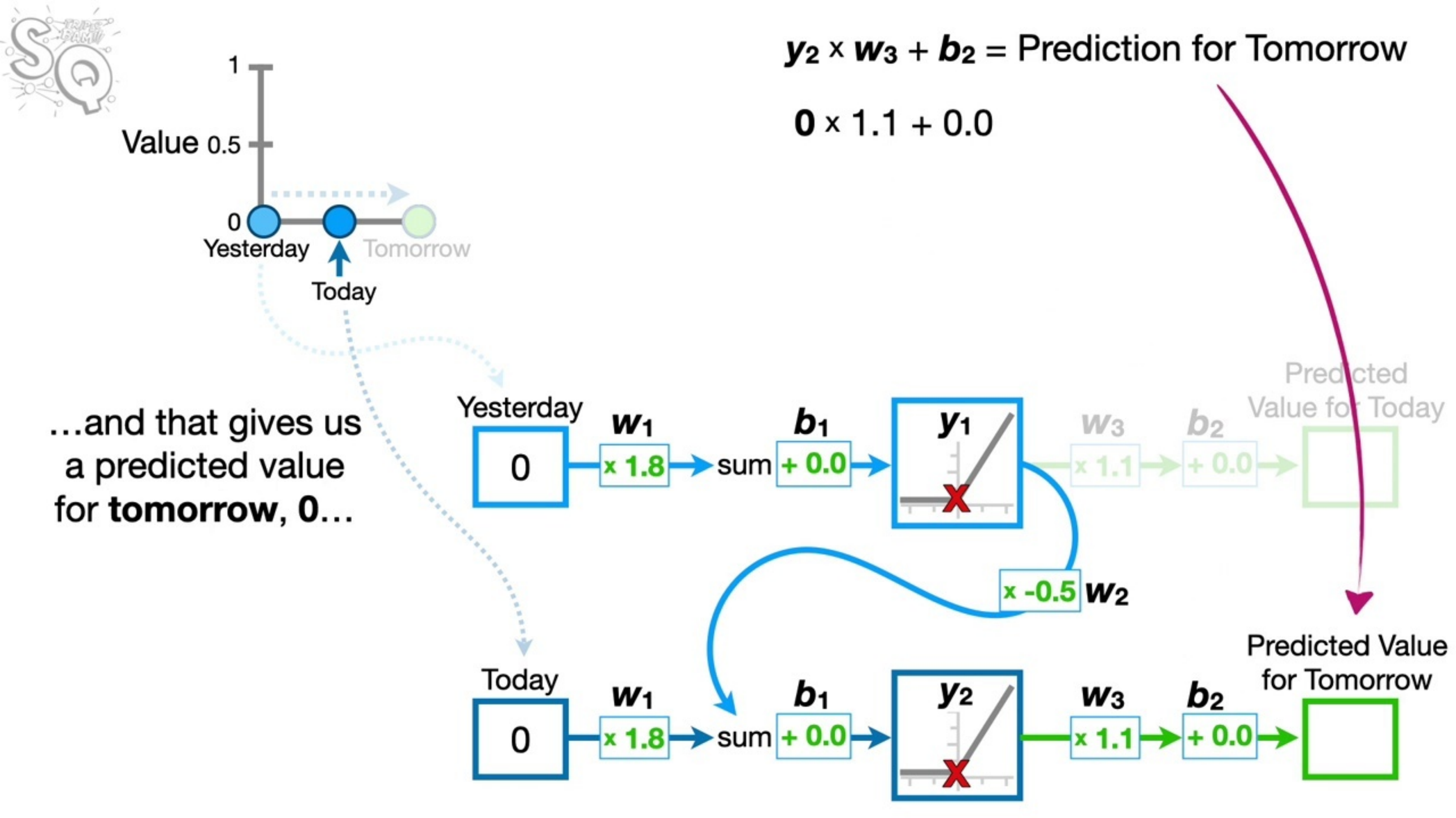

(Today x w_1) + (y_1 x w_2) + b_1 = x-axis coordinate
0 x 1.8 + (0 x -0.5) + 0.0 = 0
1
Value 0.5
0
Yesterday
Today
Tomorrow
$f(0) = \max(0, 0) = 0 = y_2$
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
y_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

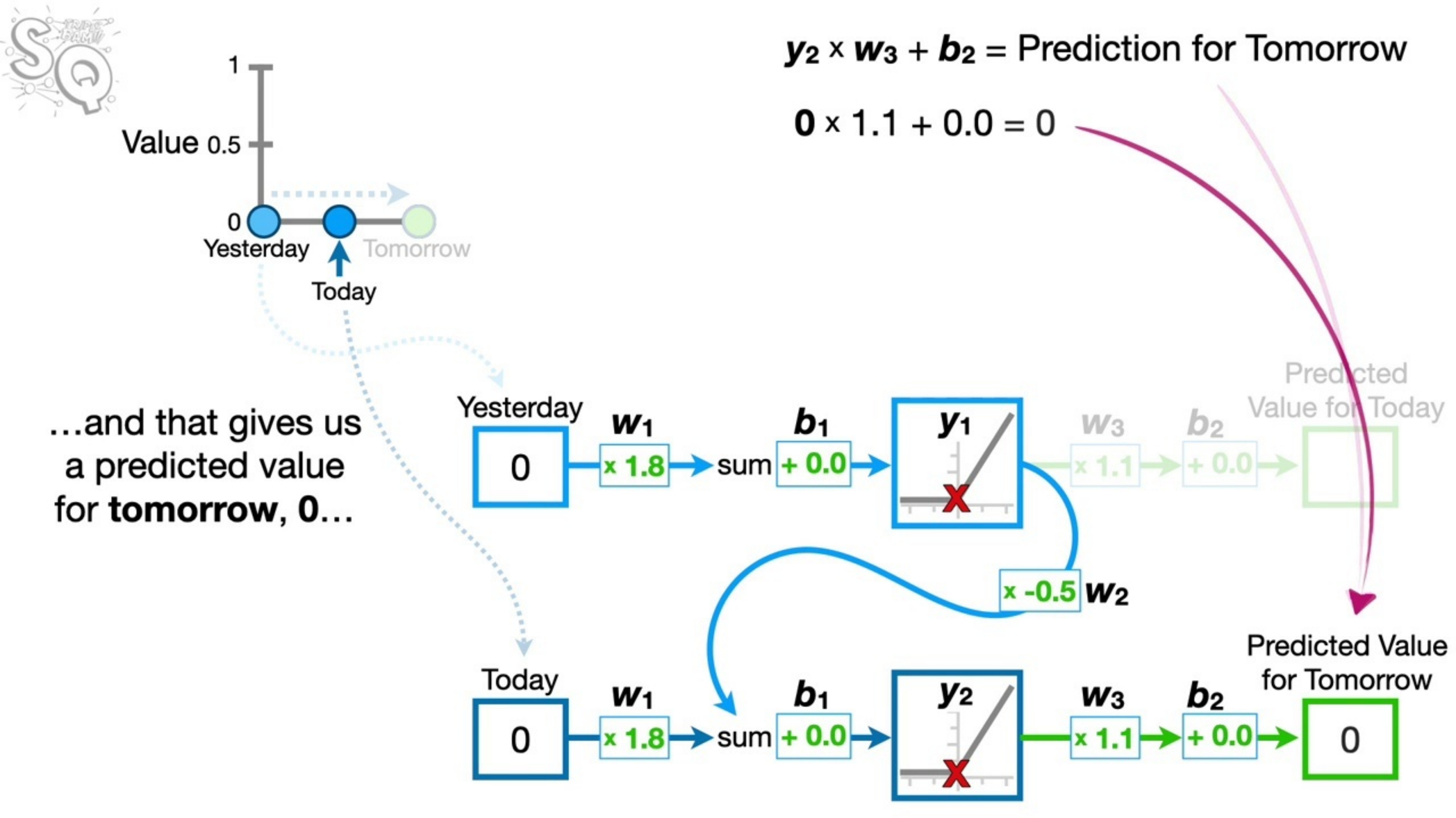

1
Value 0.5
0
Yesterday
Today
Tomorrow
…and keep doing the math…
$y_2 \times w_3$
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
y_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

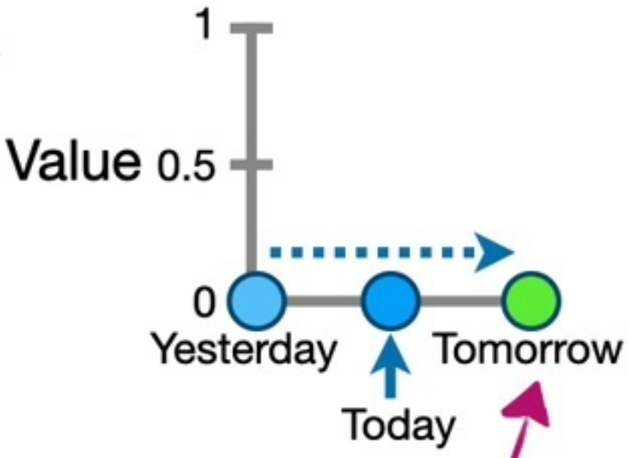

1
Value 0.5
0
Yesterday
Today
Tomorrow
…and keep doing the math…
$y_2 \times w_3$
0 x 1.1
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
y_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow


1
Value 0.5
0
Yesterday
Today
Tomorrow
$y_2 \times w_3 + b_2$
0 x 1.1
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
y_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow


$y_2 \times w_3 + b_2$
$0 \times 1.1 + 0.0$
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and keep doing the math…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
y_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow


$y_2 \times w_3 + b_2$ = Prediction for Tomorrow
0 × 1.1 + 0.0
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and that gives us a predicted value for **tomorrow**, **0**…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
y_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow

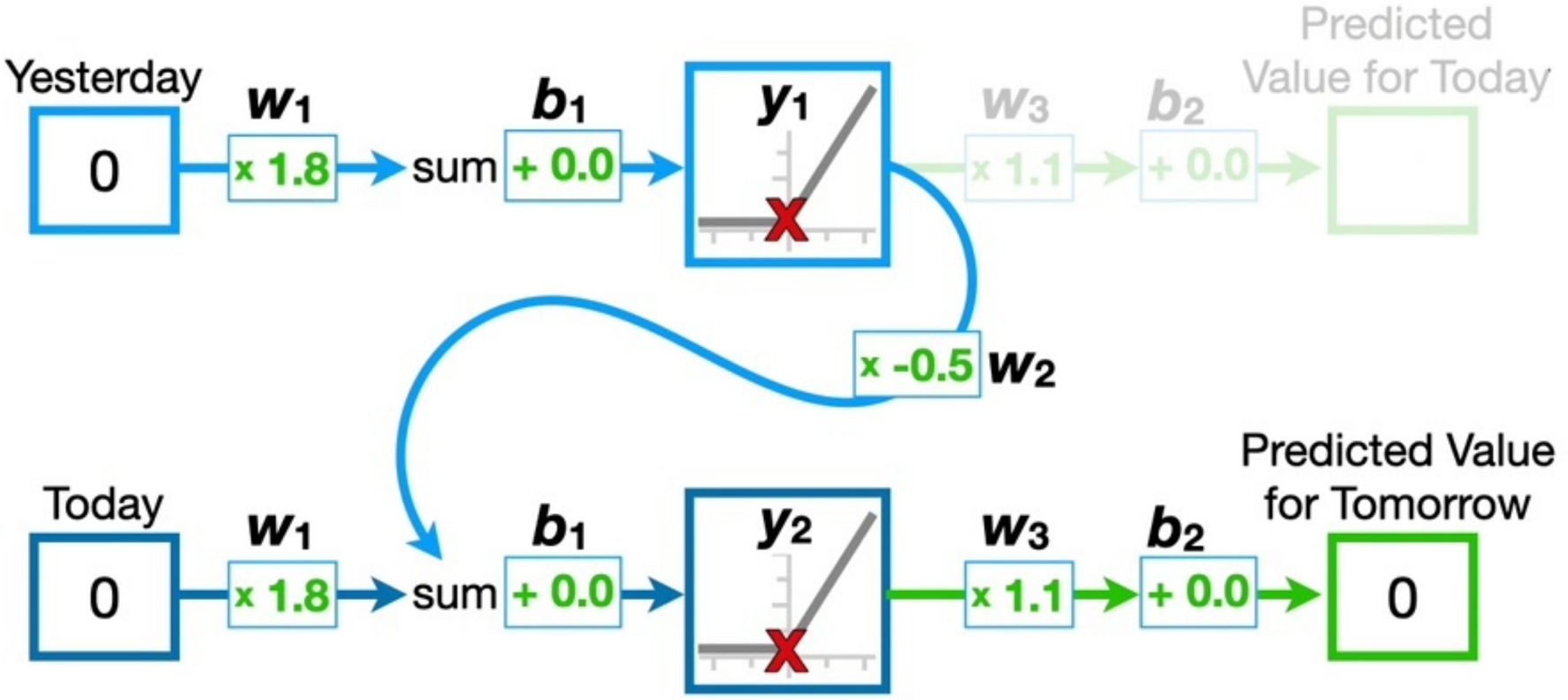

$y_2 \times w_3 + b_2$ = Prediction for Tomorrow
0 × 1.1 + 0.0 = 0
1
Value 0.5
0
Yesterday
Today
Tomorrow
…and that gives us a predicted value for **tomorrow**, **0**…
Yesterday
0
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0
w_1
x 1.8
sum
b_1
+ 0.0
y_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow
0

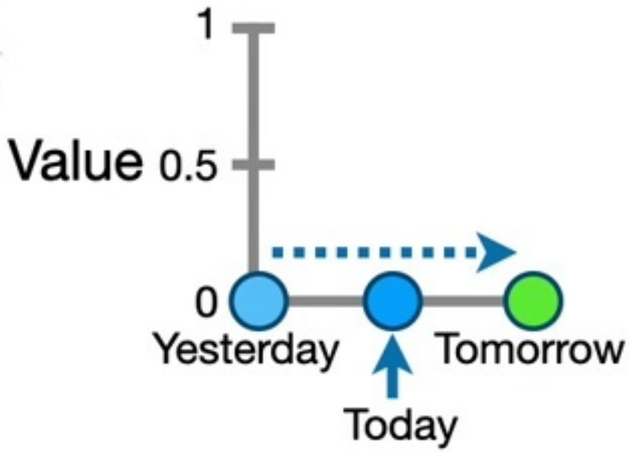


$y_2 \times w_3 + b_2$ = Prediction for Tomorrow

$0 \times 1.1 + 0.0 = 0$

…which is consistent with the original observation.

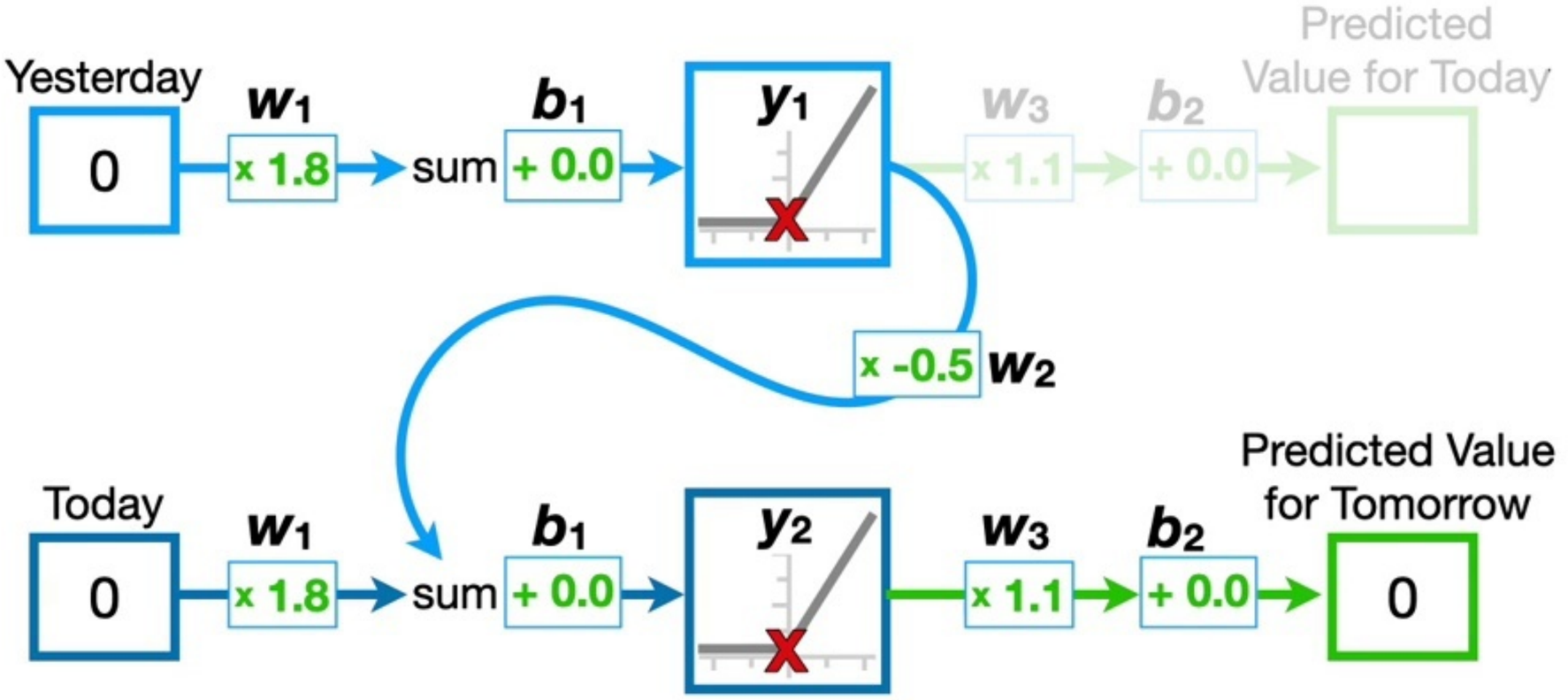


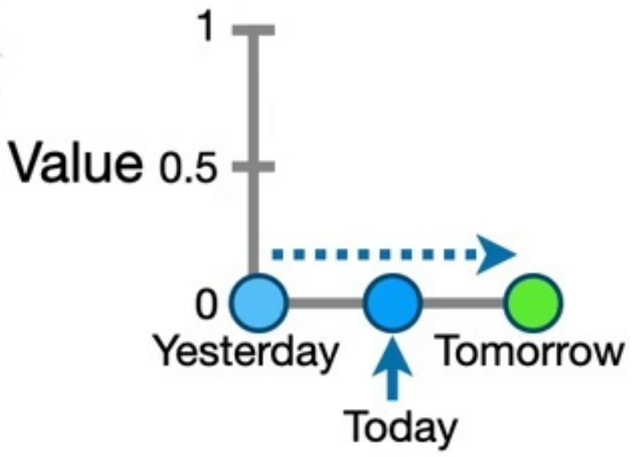


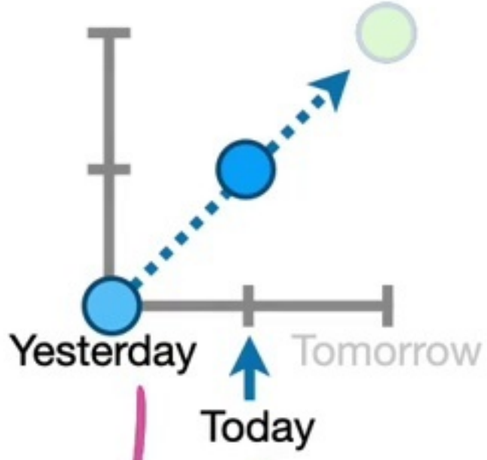
$y_2 \times w_3 + b_2 = \text{Prediction for Tomorrow}$

$0 \times 1.1 + 0.0 = 0$

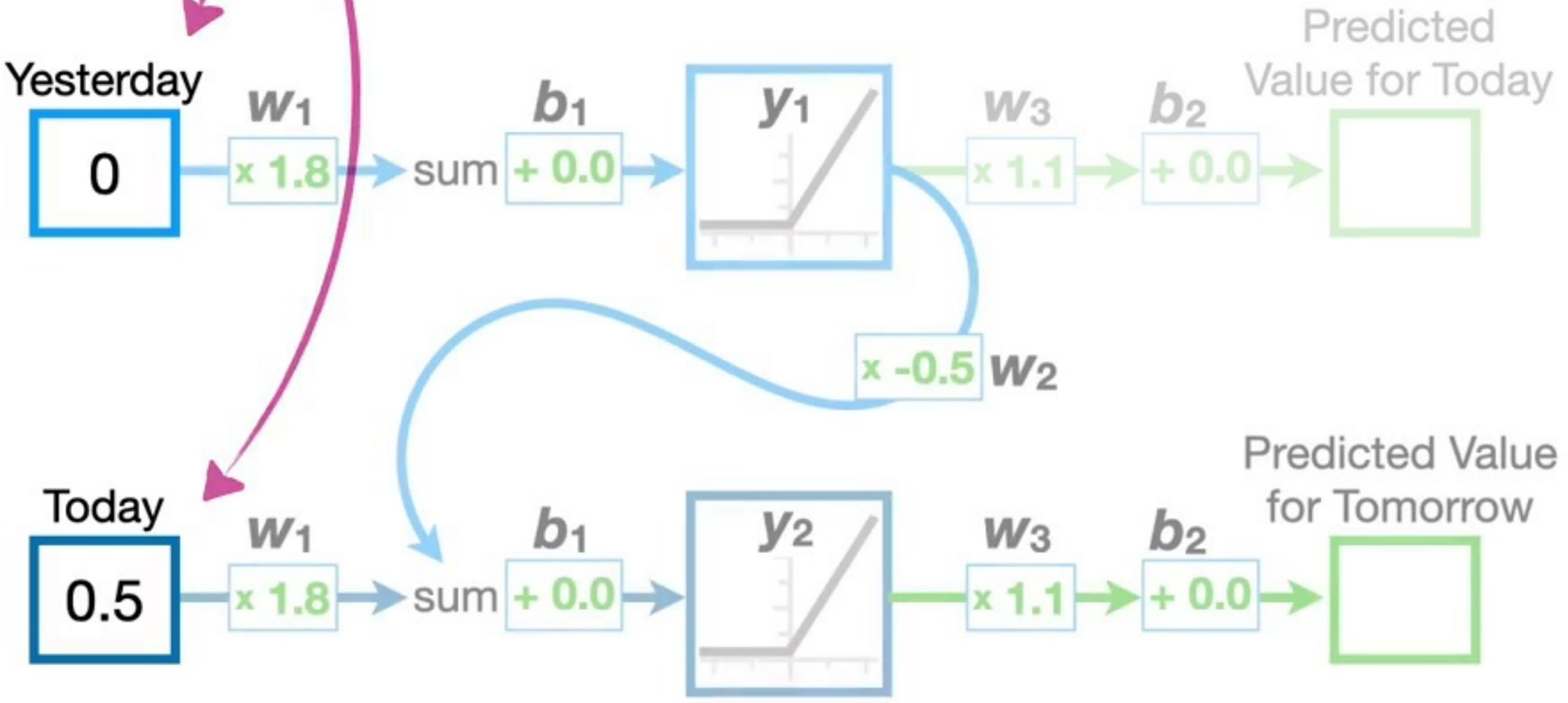
In other words, the recurrent neural network correctly predicted **tomorrow's** value.

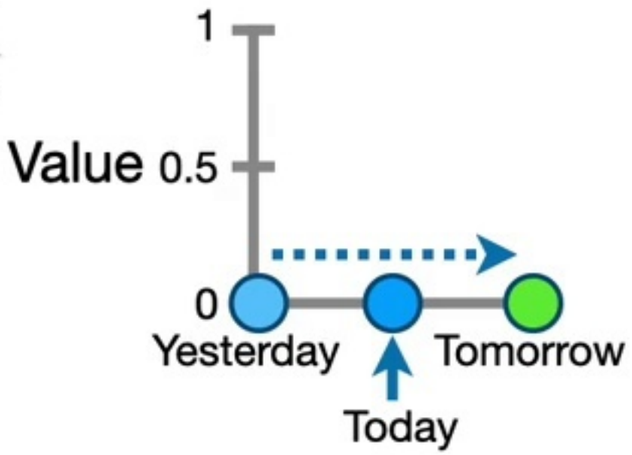


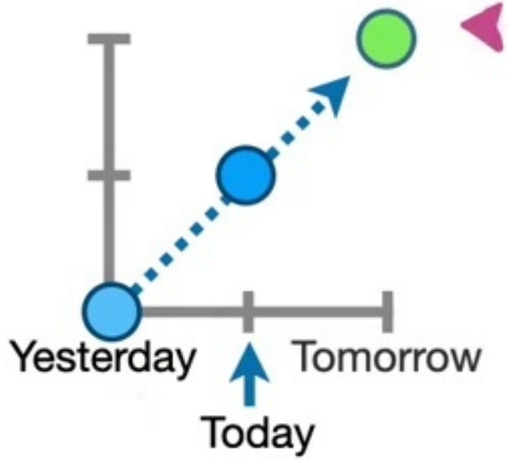


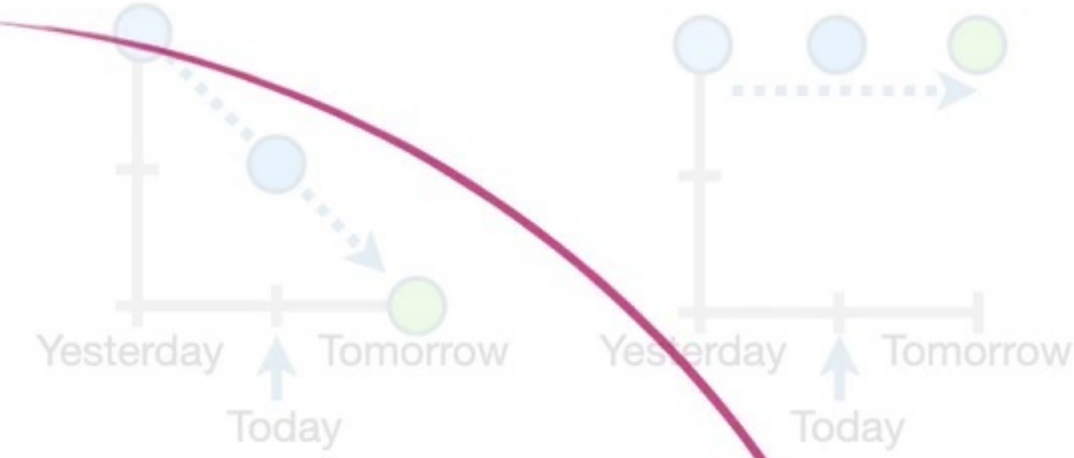


Likewise, when we run **yesterday** and **today's** values for the other scenarios through the recurrent neural network we predict the correct values for **tomorrow**.

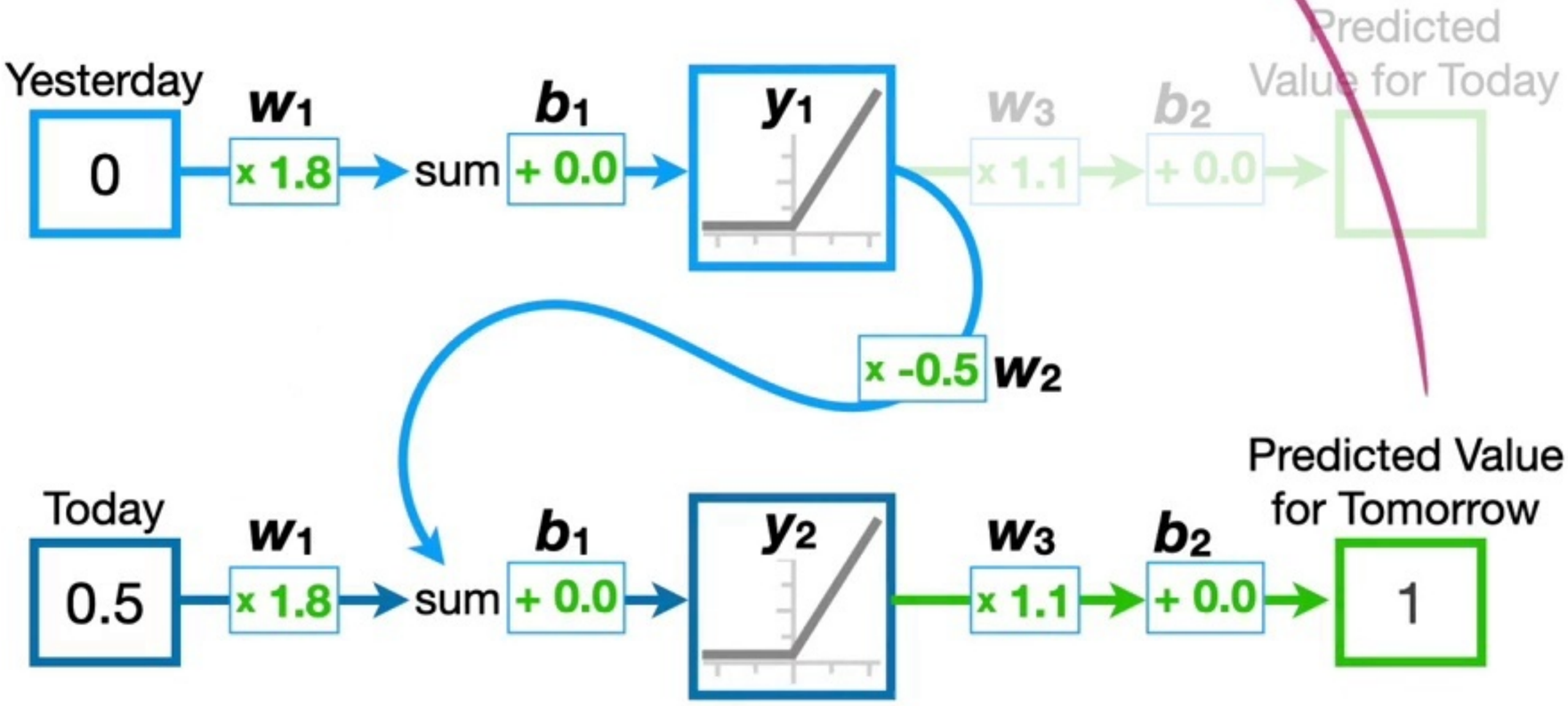


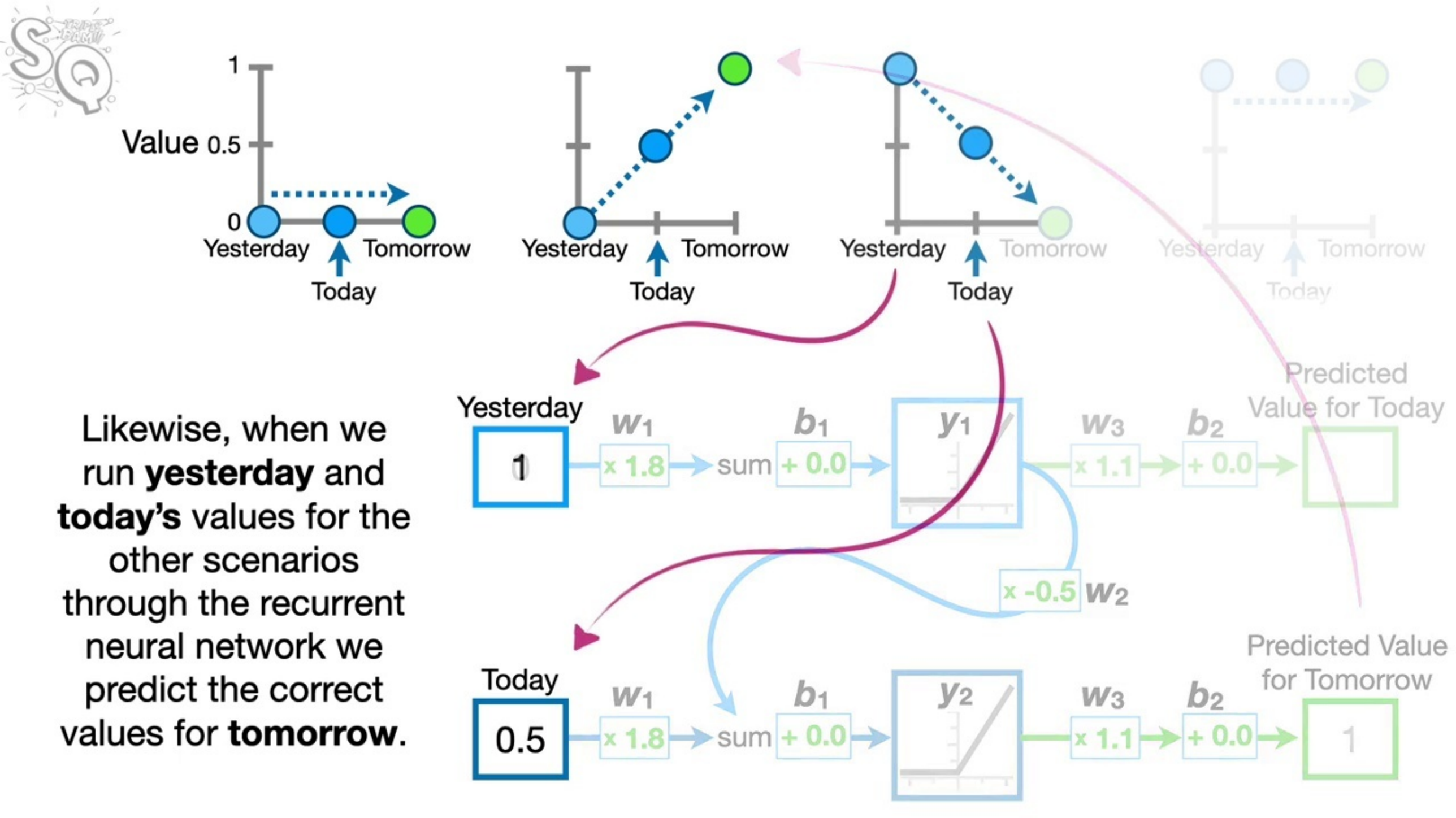




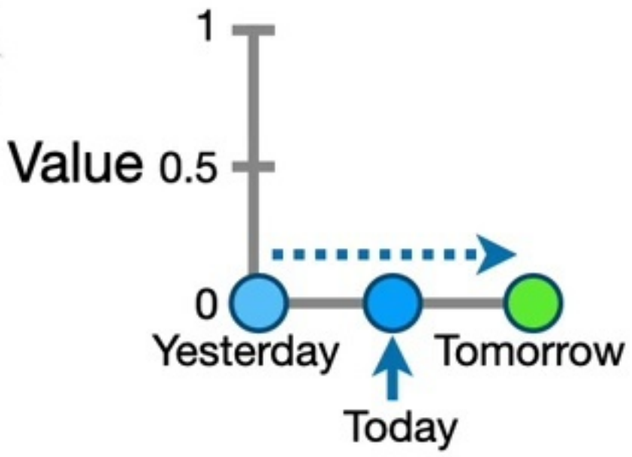


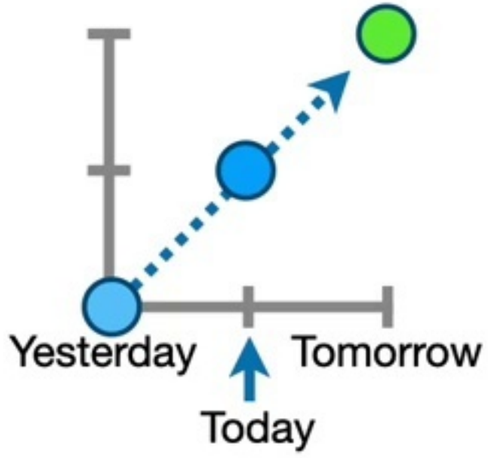
Likewise, when we run **yesterday** and **today's** values for the other scenarios through the recurrent neural network we predict the correct values for **tomorrow**.

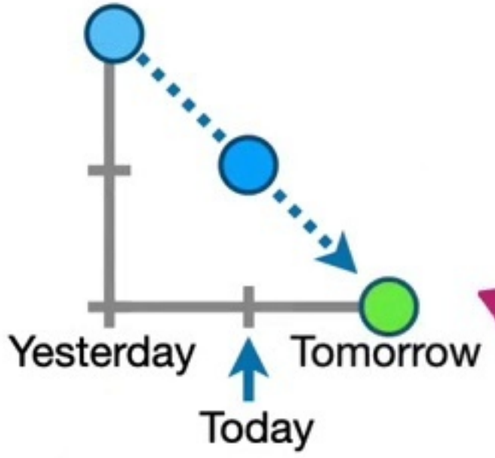




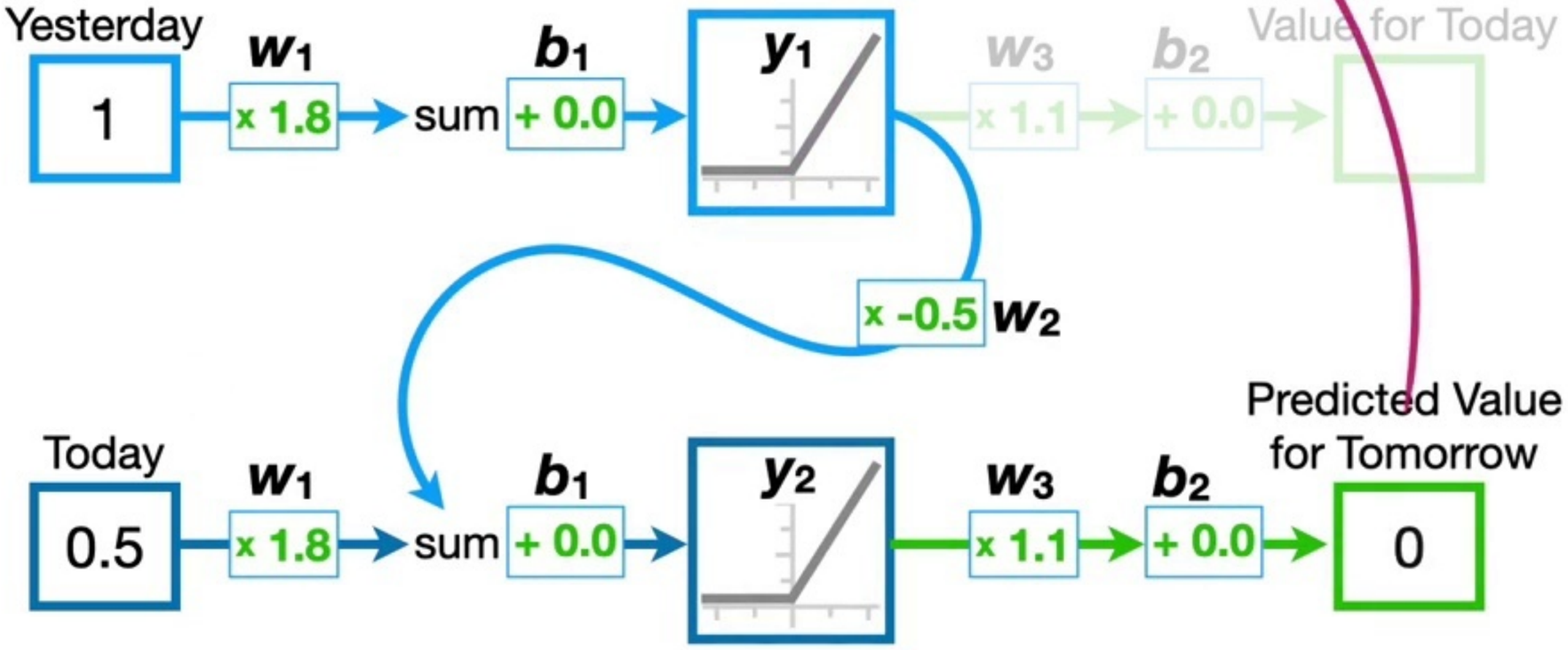
Likewise, when we run **yesterday** and **today's** values for the other scenarios through the recurrent neural network we predict the correct values for **tomorrow**.

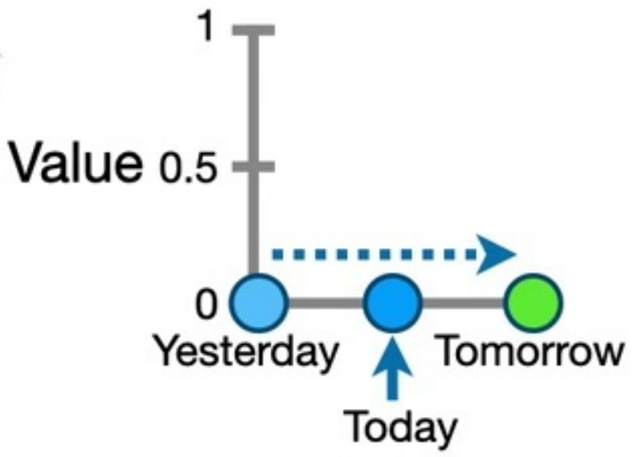


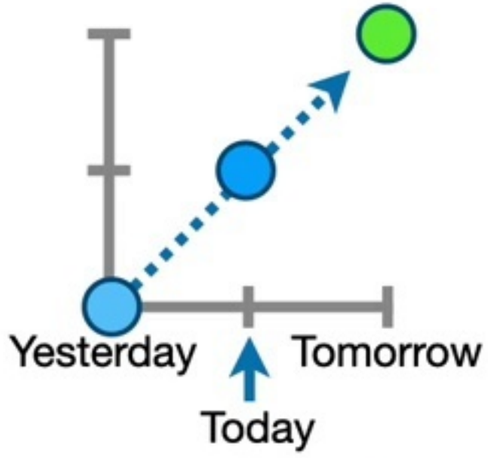


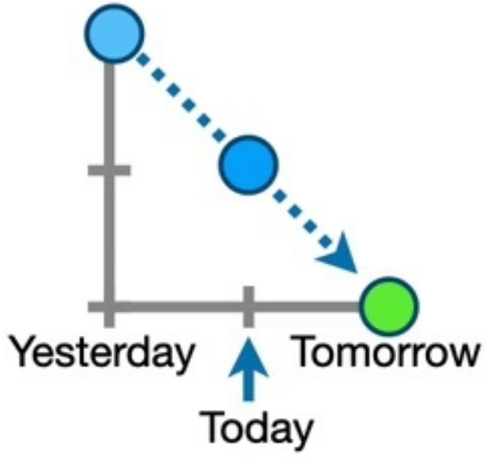


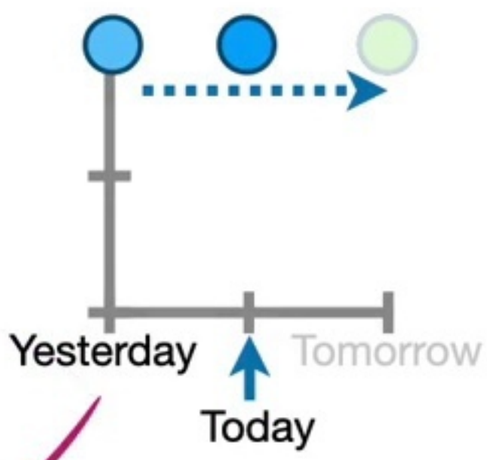
Likewise, when we run **yesterday** and **today's** values for the other scenarios through the recurrent neural network we predict the correct values for **tomorrow**.



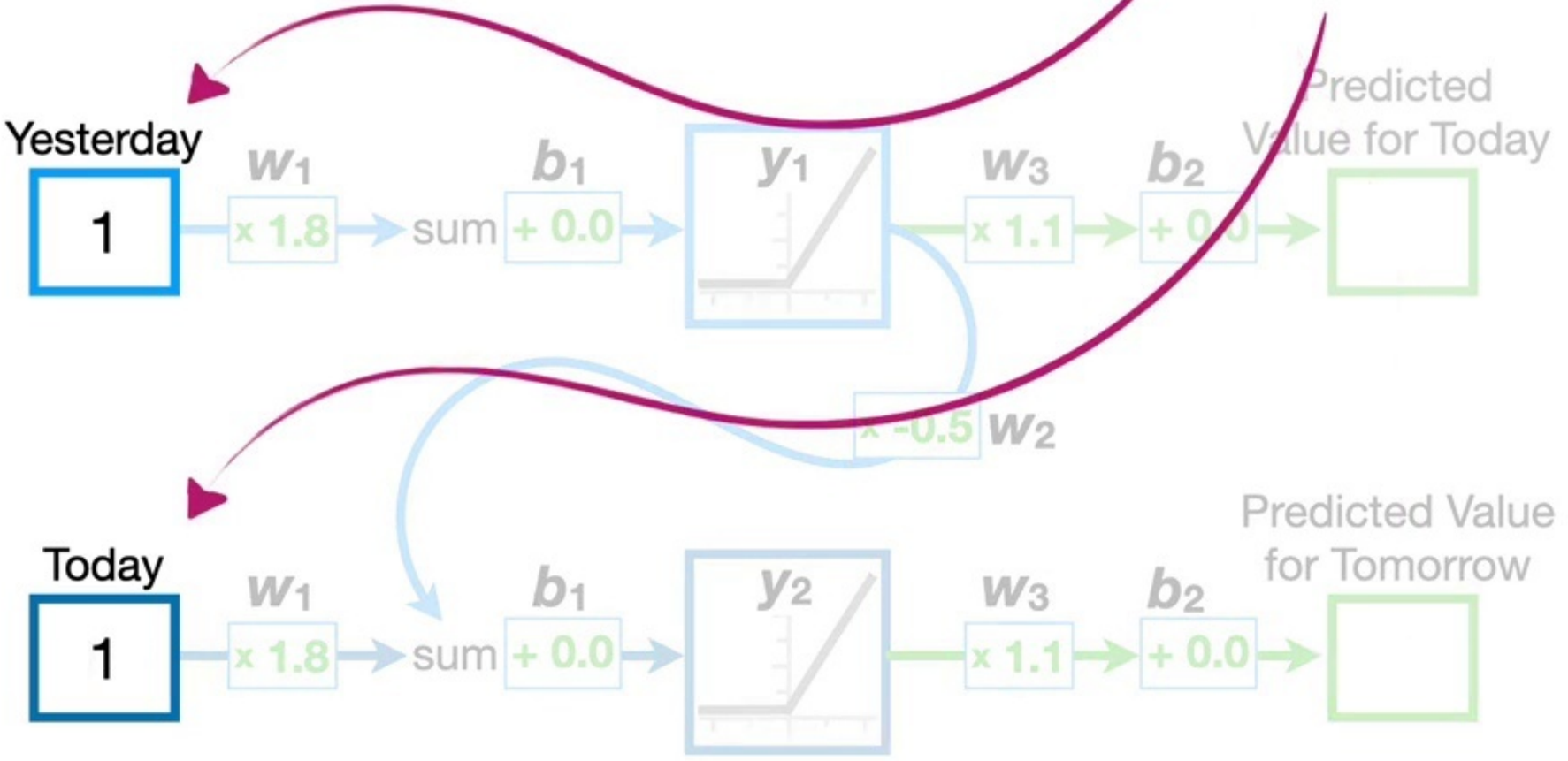


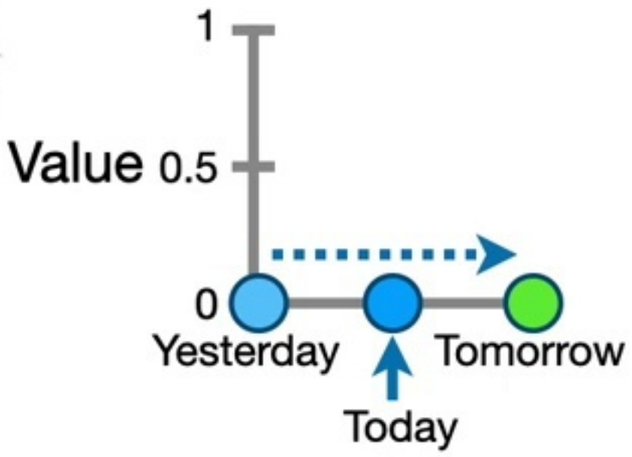


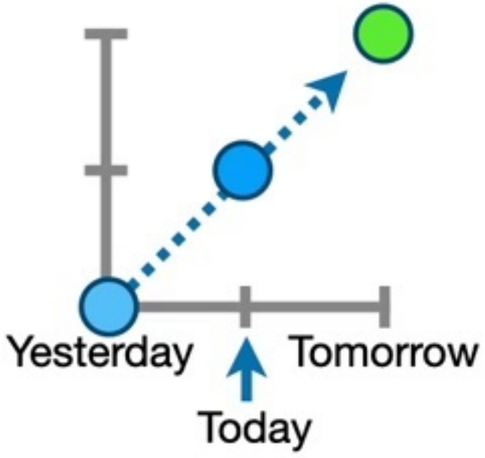


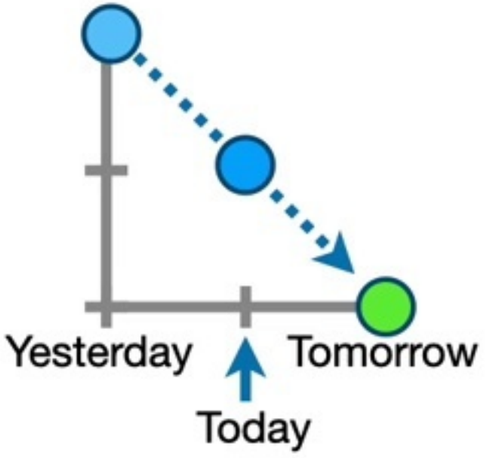


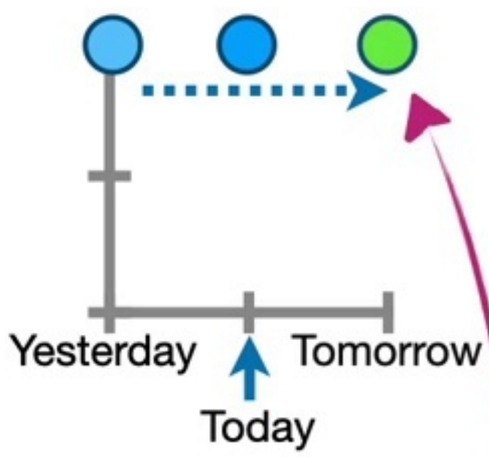
Likewise, when we run **yesterday** and **today's** values for the other scenarios through the recurrent neural network we predict the correct values for **tomorrow**.



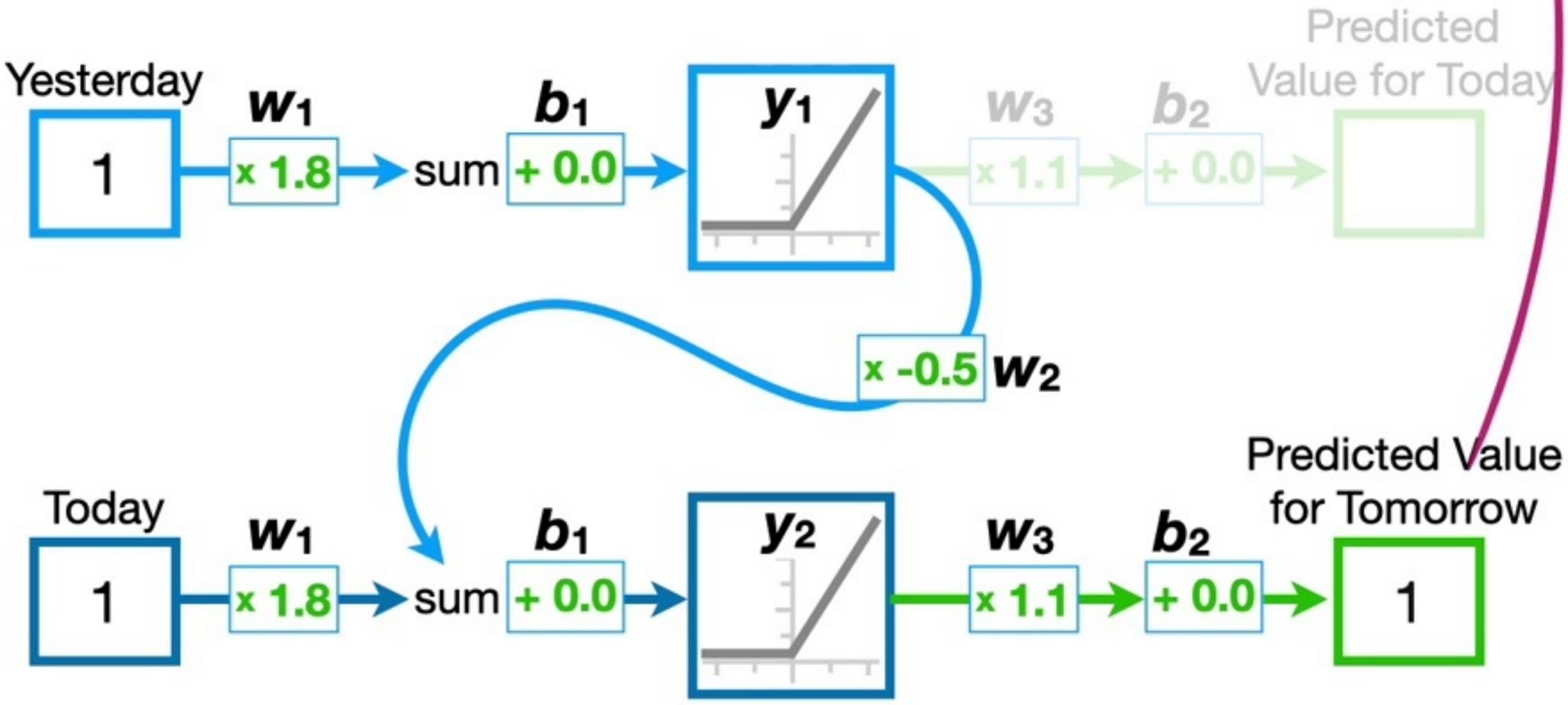


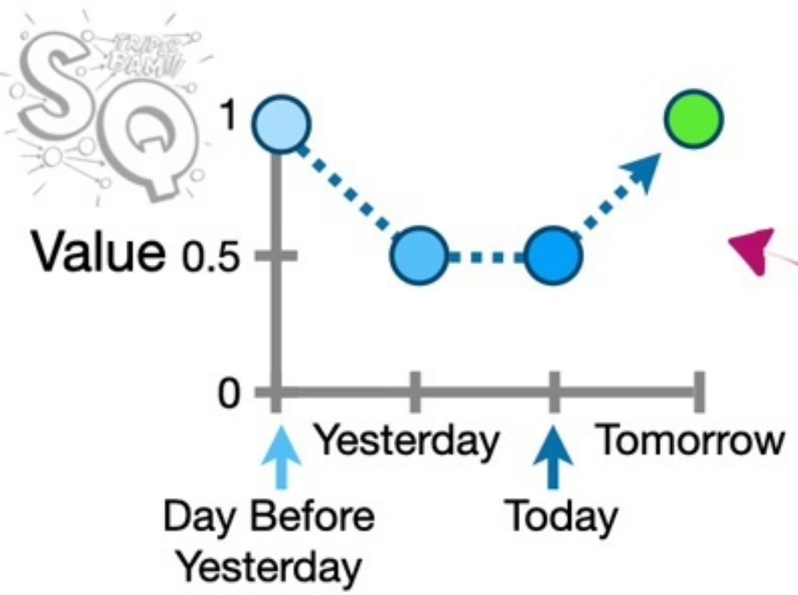




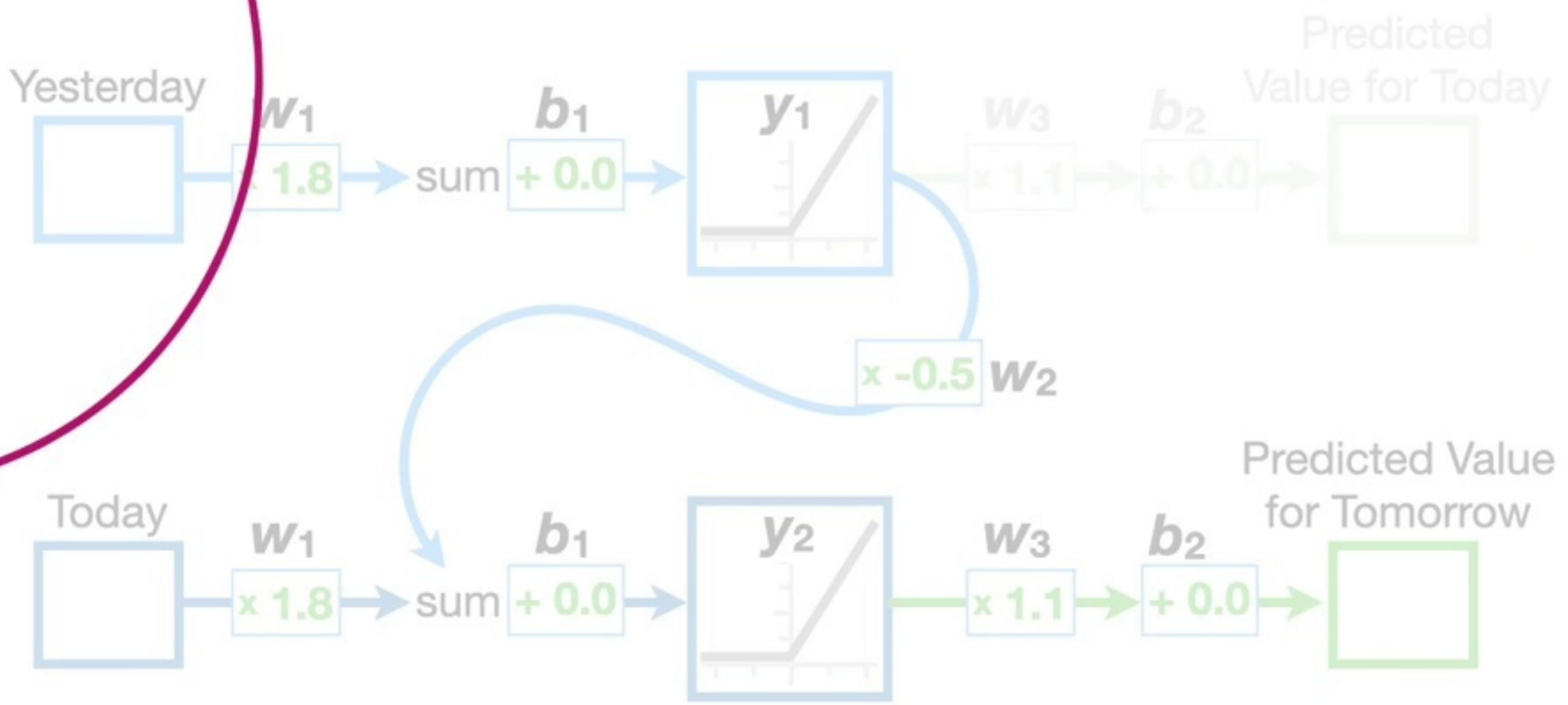


Likewise, when we run **yesterday** and **today's** values for the other scenarios through the recurrent neural network we predict the correct values for **tomorrow**.

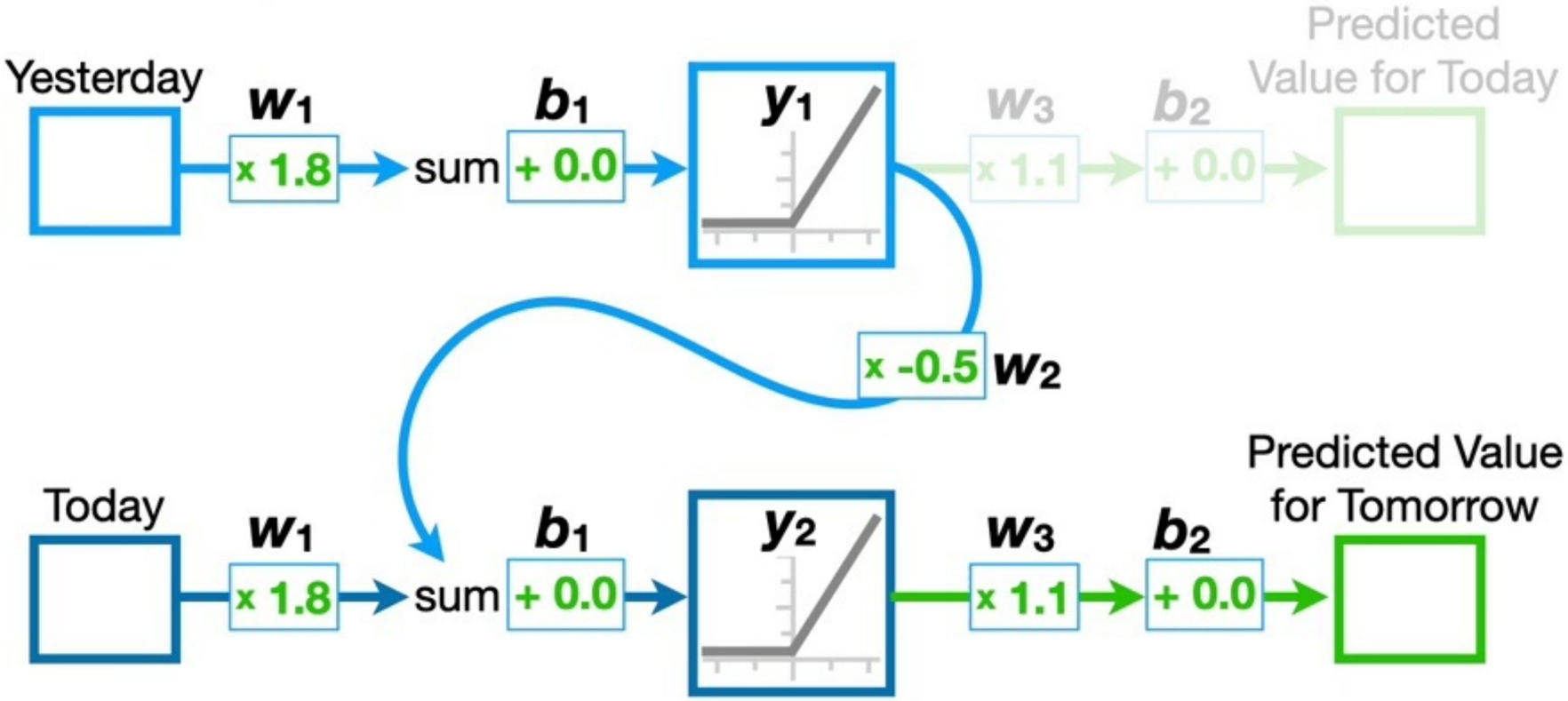




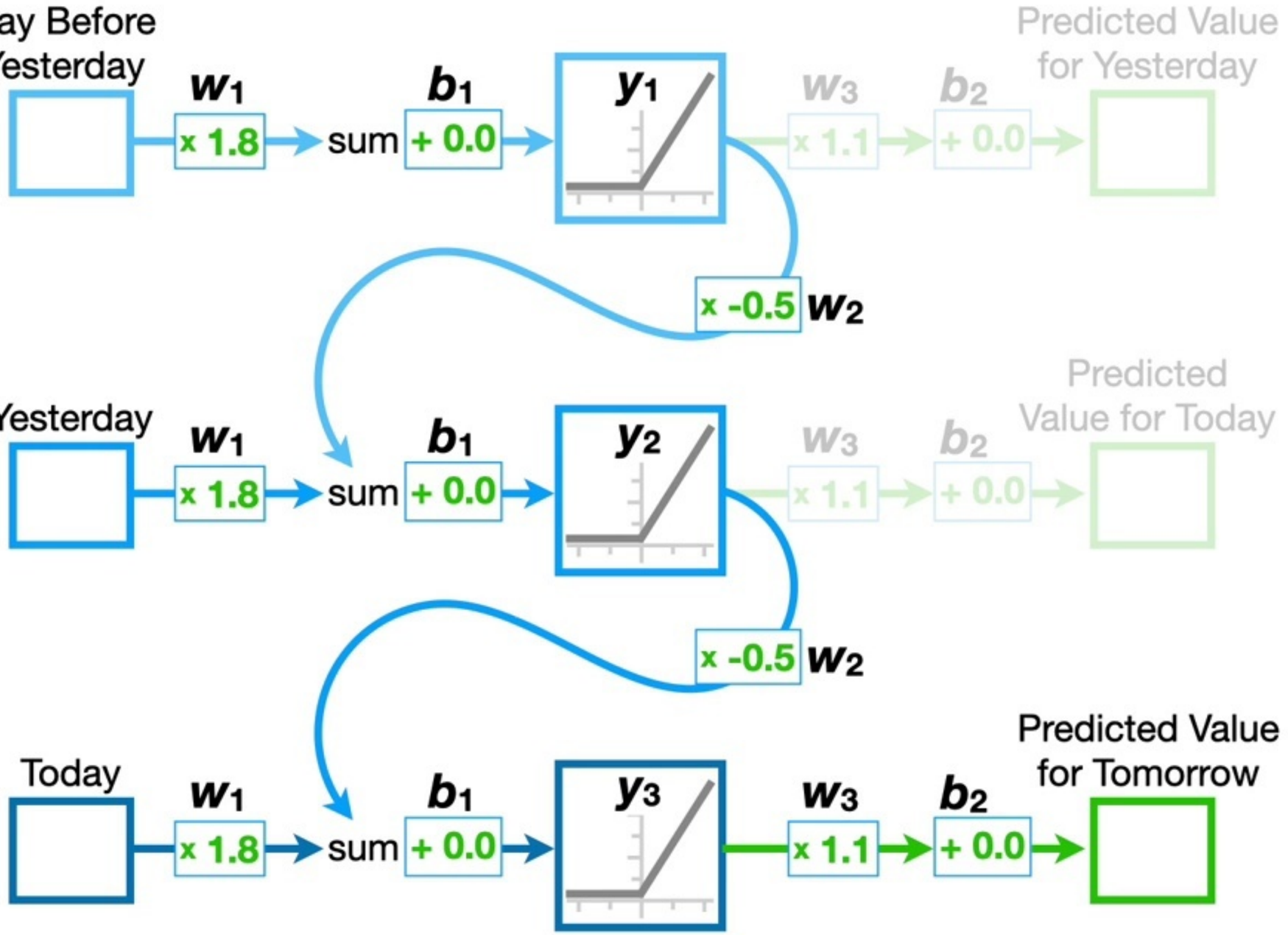
When we want to use **3** days of data to make a prediction about **tomorrow's** price, like this…

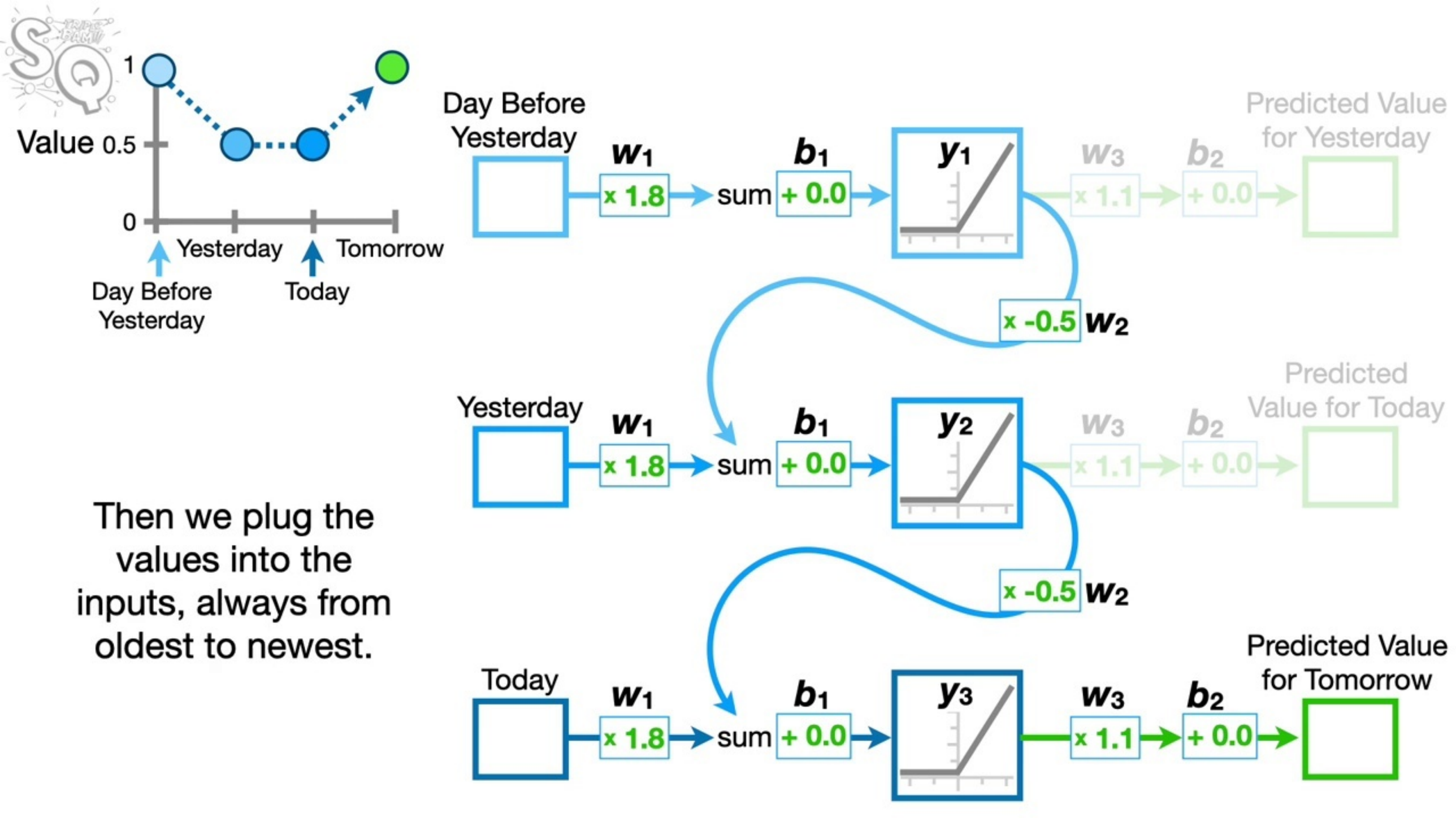


…then we just keep **unrolling** the recurrent neural network until we have an input for each day of data.

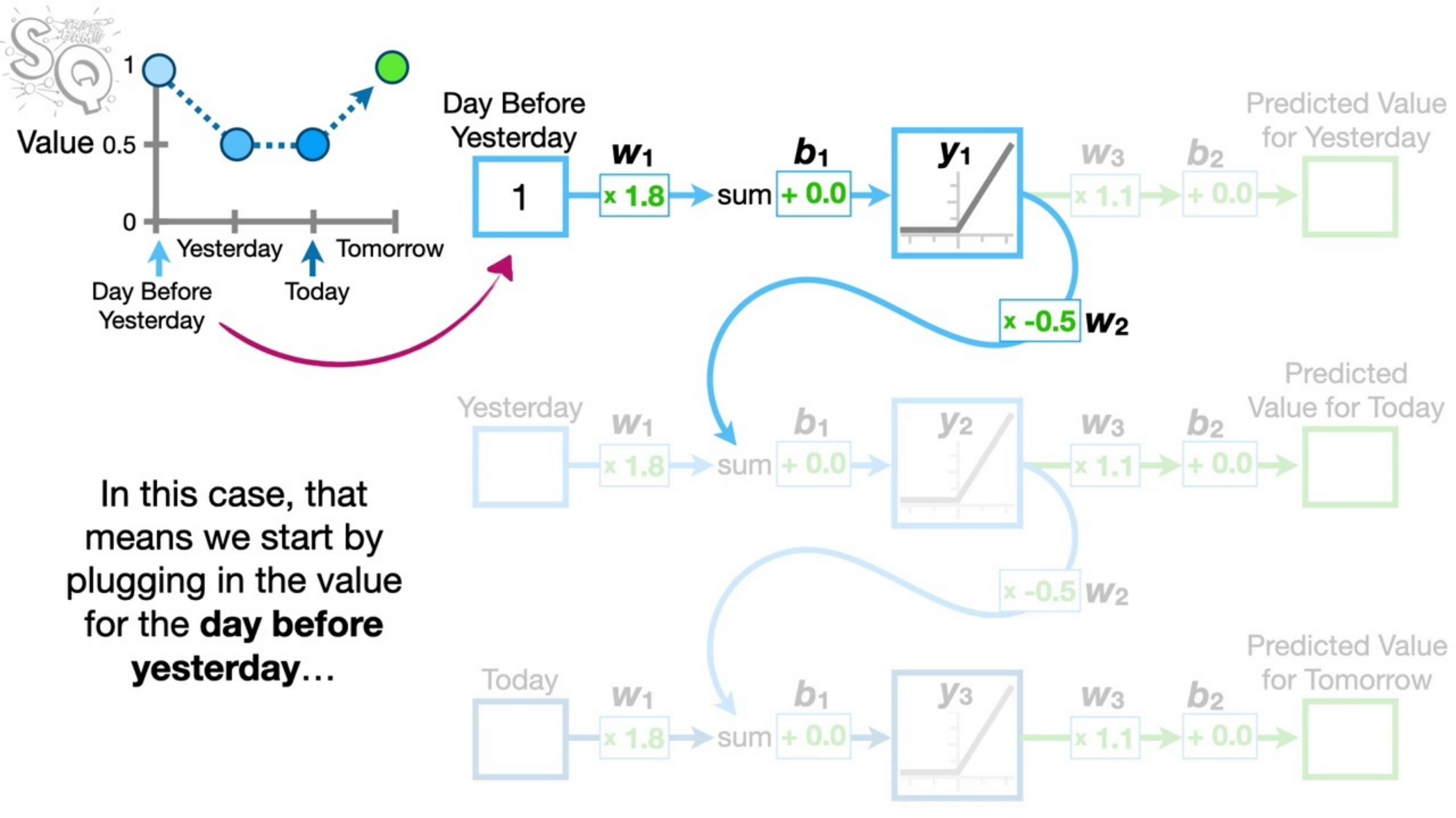


…then we just keep **unrolling** the recurrent neural network until we have an input for each day of data.

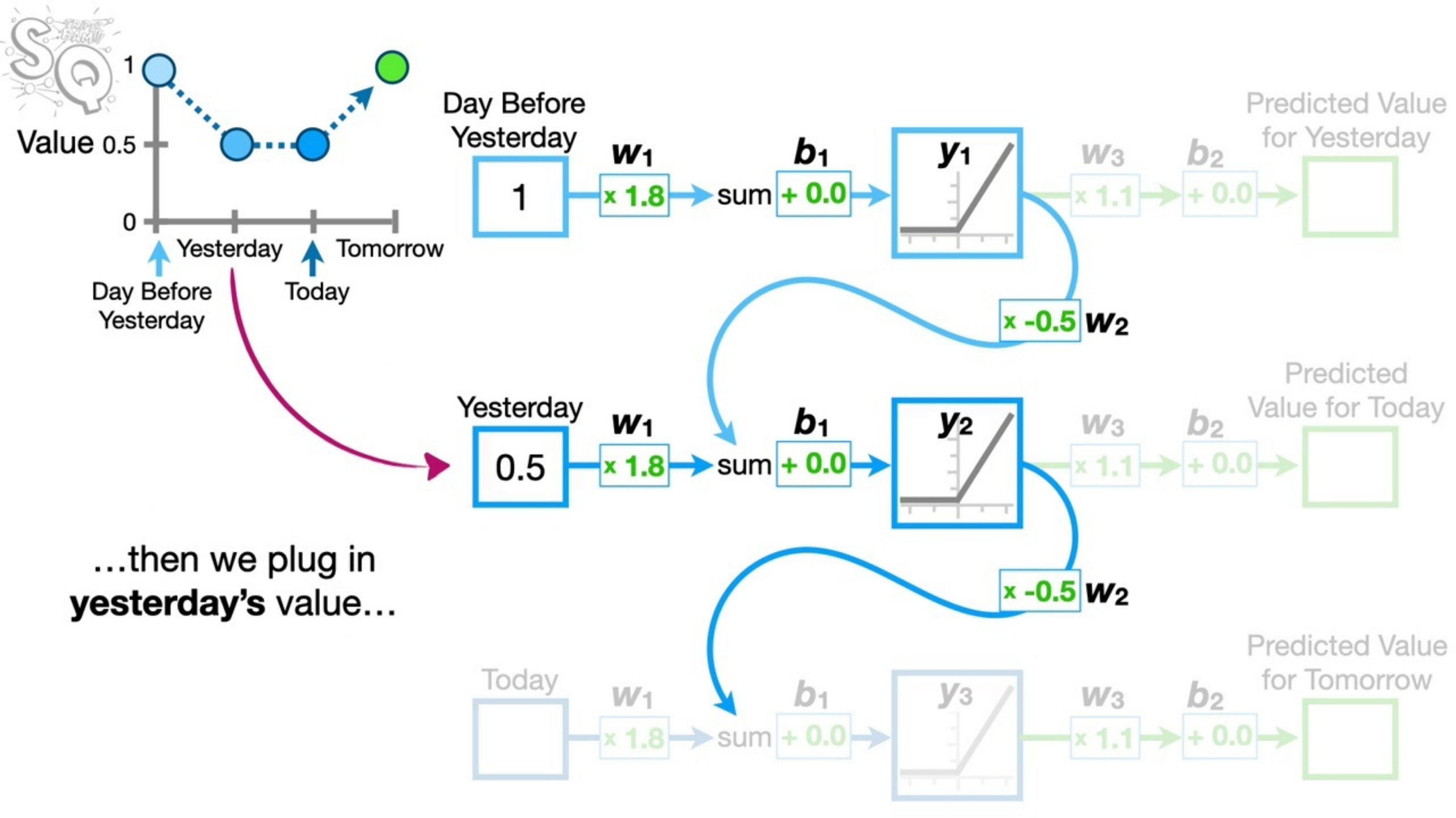


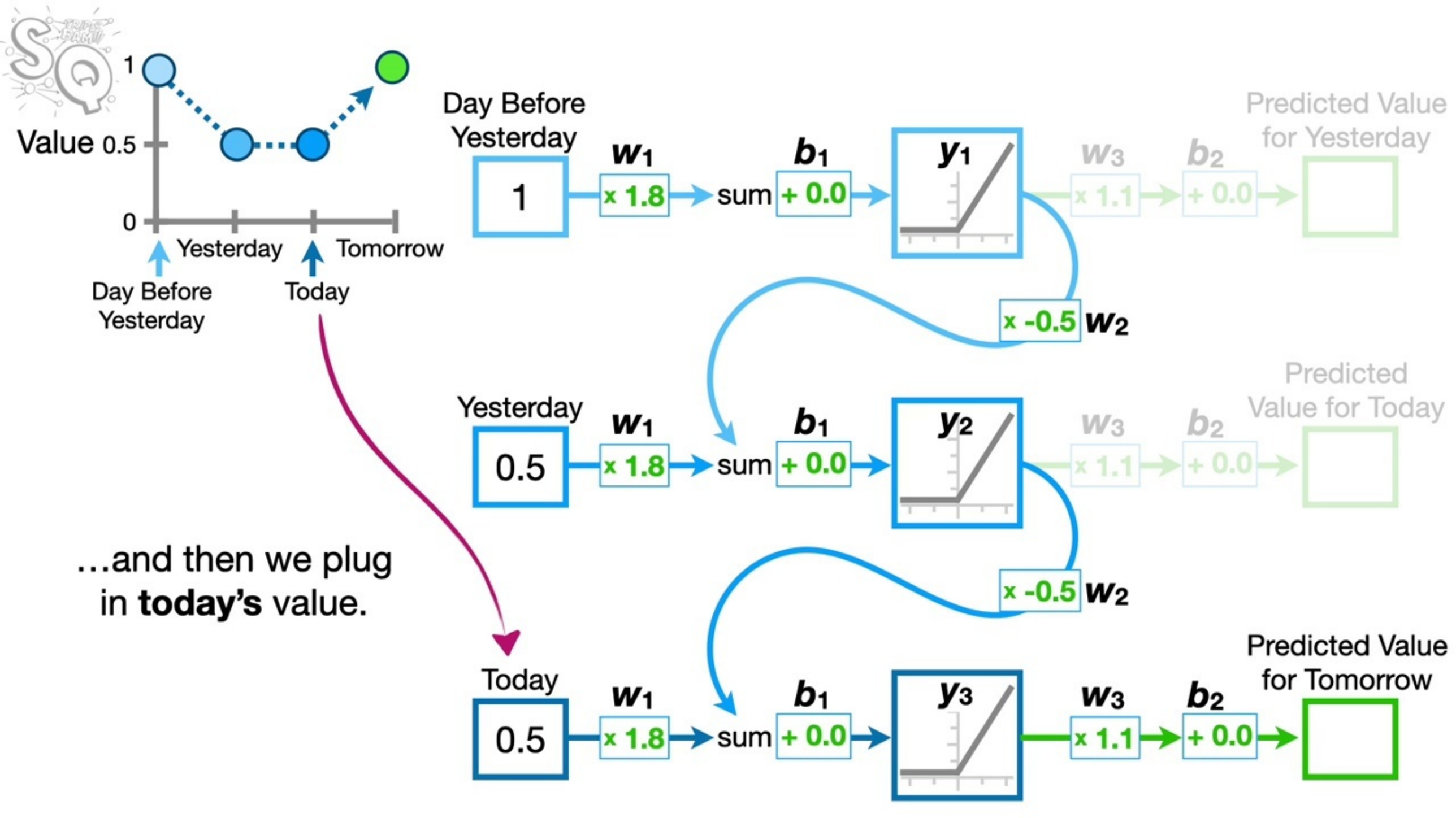


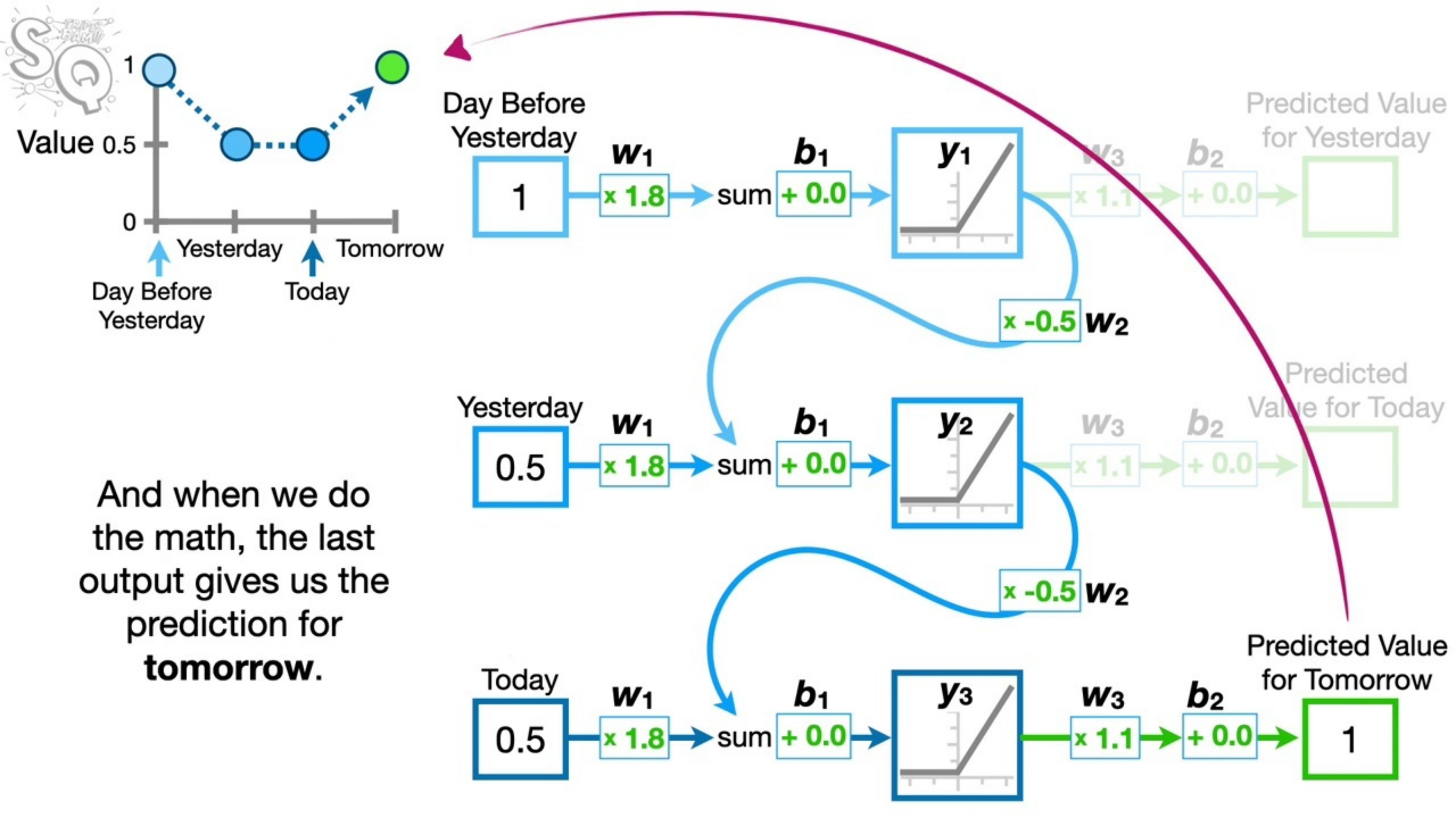
Then we plug the values into the inputs, always from oldest to newest.



In this case, that means we start by plugging in the value for the **day before yesterday**…

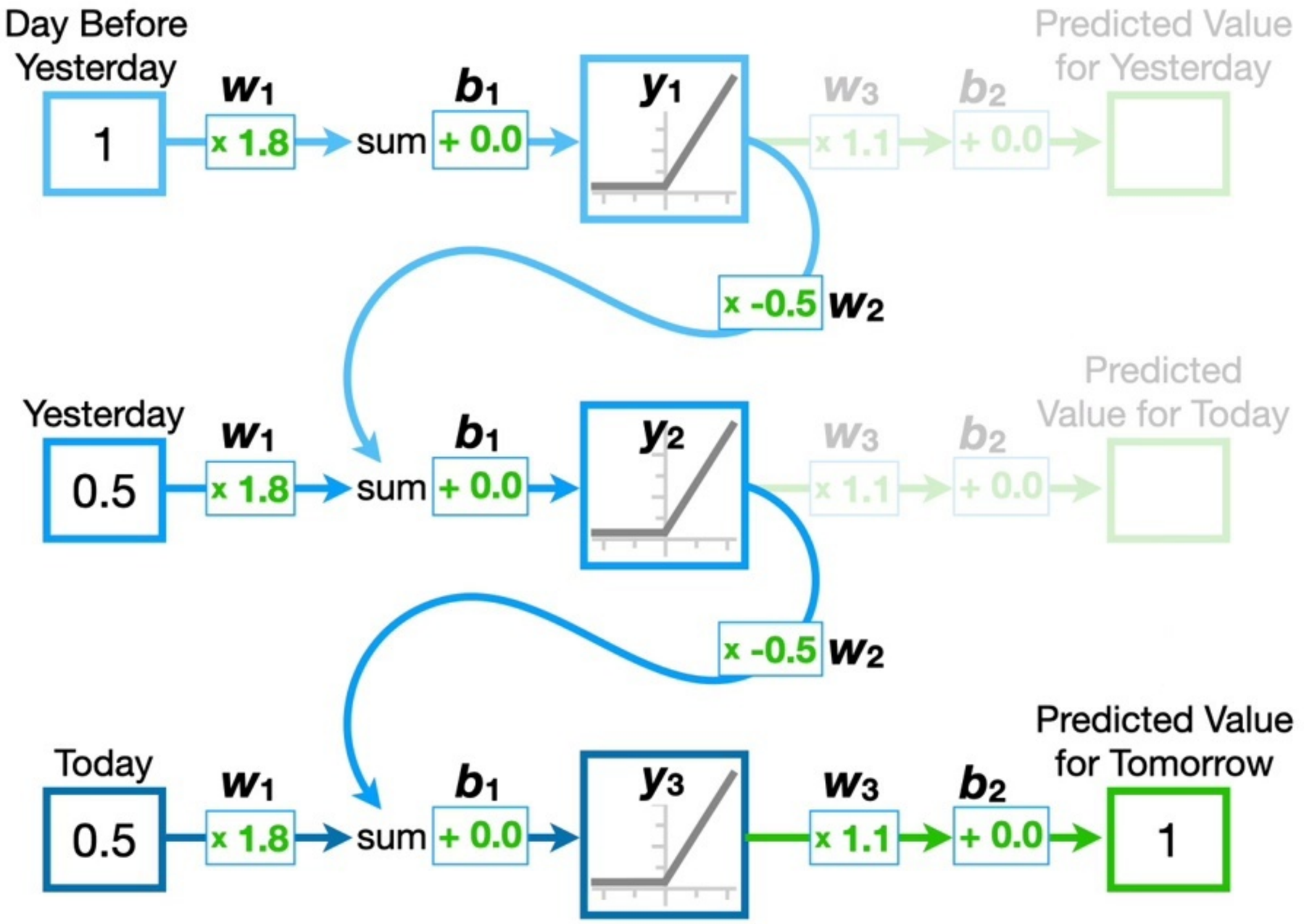

1
Value 0.5
0
Yesterday
Tomorrow
Day Before Yesterday
Today
Day Before Yesterday
1
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Yesterday
x -0.5
w_2
Yesterday
0.5
w_1
x 1.8
sum
b_1
+ 0.0
y_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
…then we plug in **yesterday's** value…
Today
w_1
x 1.8
sum
b_1
+ 0.0
y_3
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow


1
Value 0.5
0
Yesterday
Tomorrow
Day Before Yesterday
Today
Day Before Yesterday
1
w1
x 1.8
sum
b1
+ 0.0
y1
w3
x 1.1
b2
+ 0.0
Predicted Value for Yesterday
x -0.5
w2
Yesterday
0.5
w1
x 1.8
sum
b1
+ 0.0
y2
w3
x 1.1
b2
+ 0.0
Predicted Value for Today
x -0.5
w2
…and then we plug in **today's** value.
Today
0.5
w1
x 1.8
sum
b1
+ 0.0
y3
w3
x 1.1
b2
+ 0.0
Predicted Value for Tomorrow

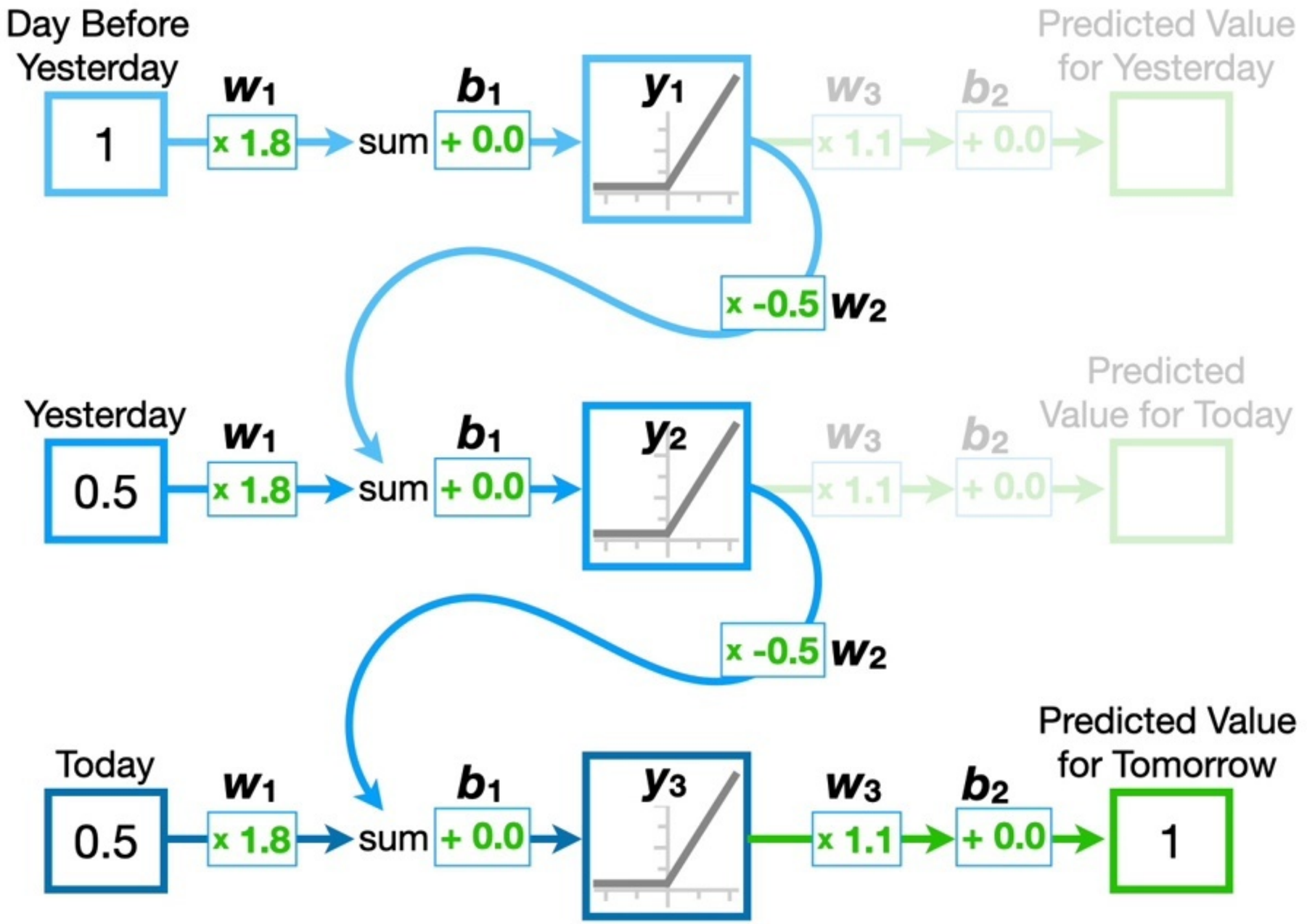


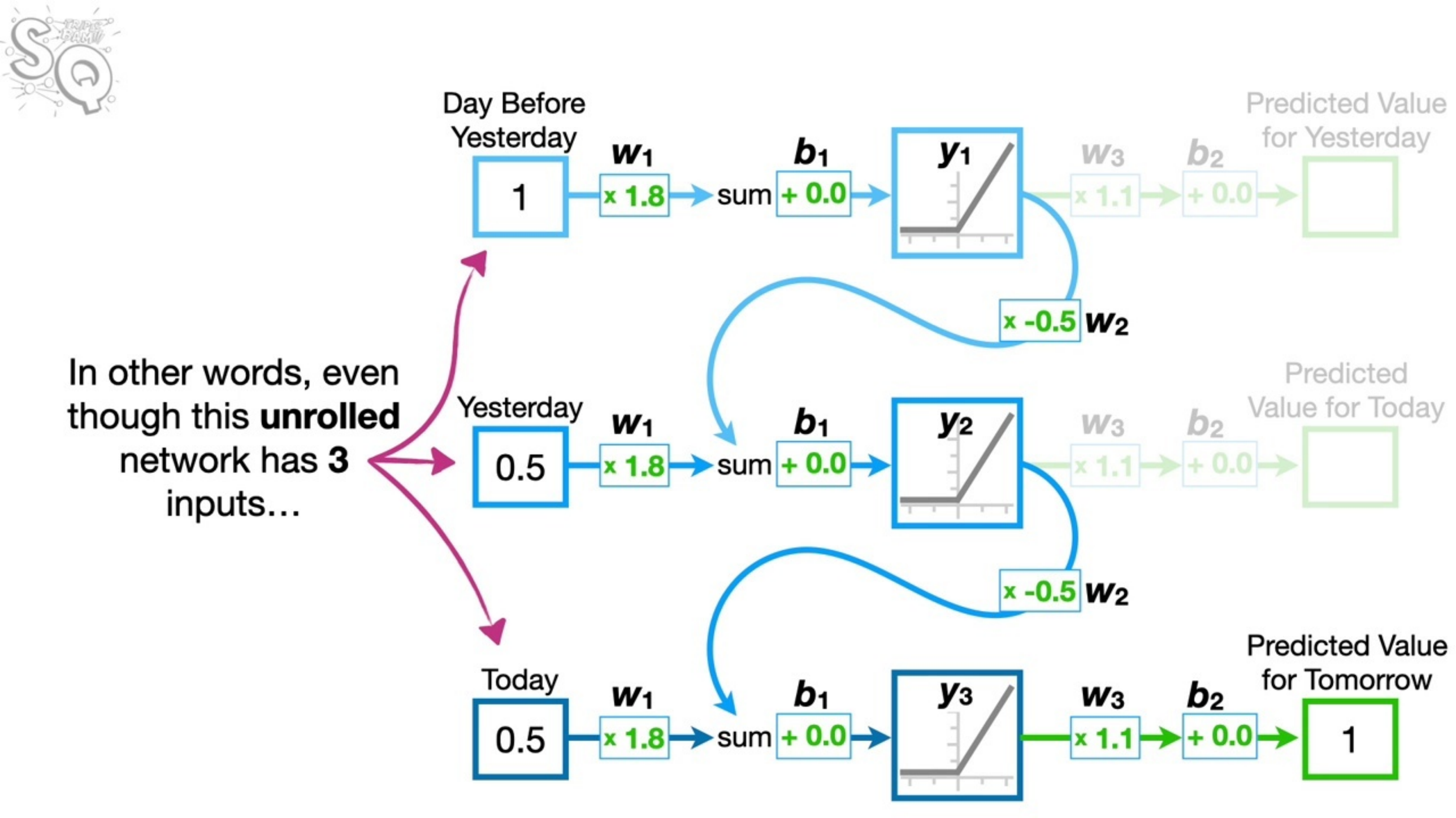
And when we do the math, the last output gives us the prediction for **tomorrow**.

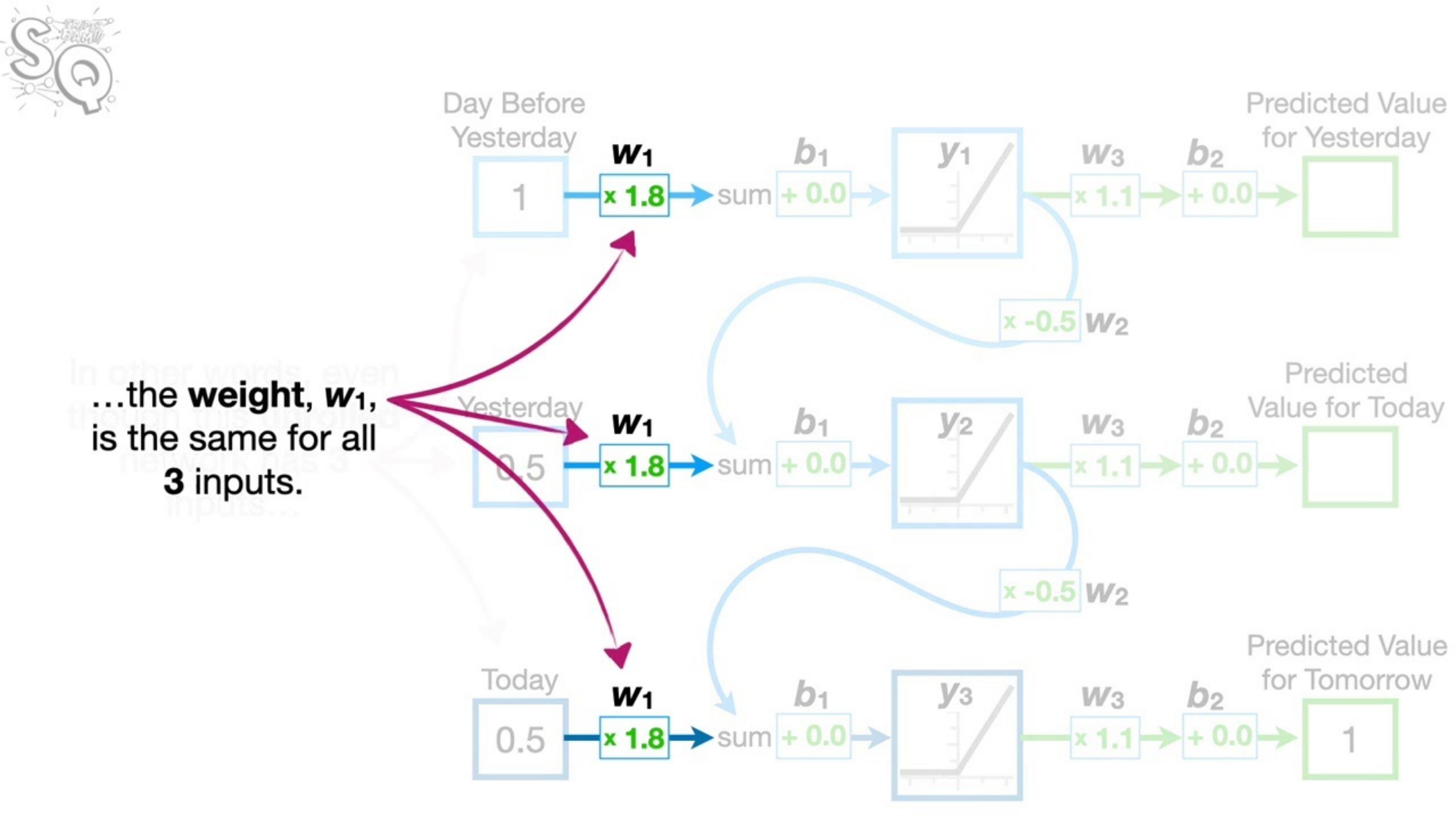
NOTE: Regardless of how many times we **unroll** a recurrent neural network, the **weights** and **biases** are shared across every input.

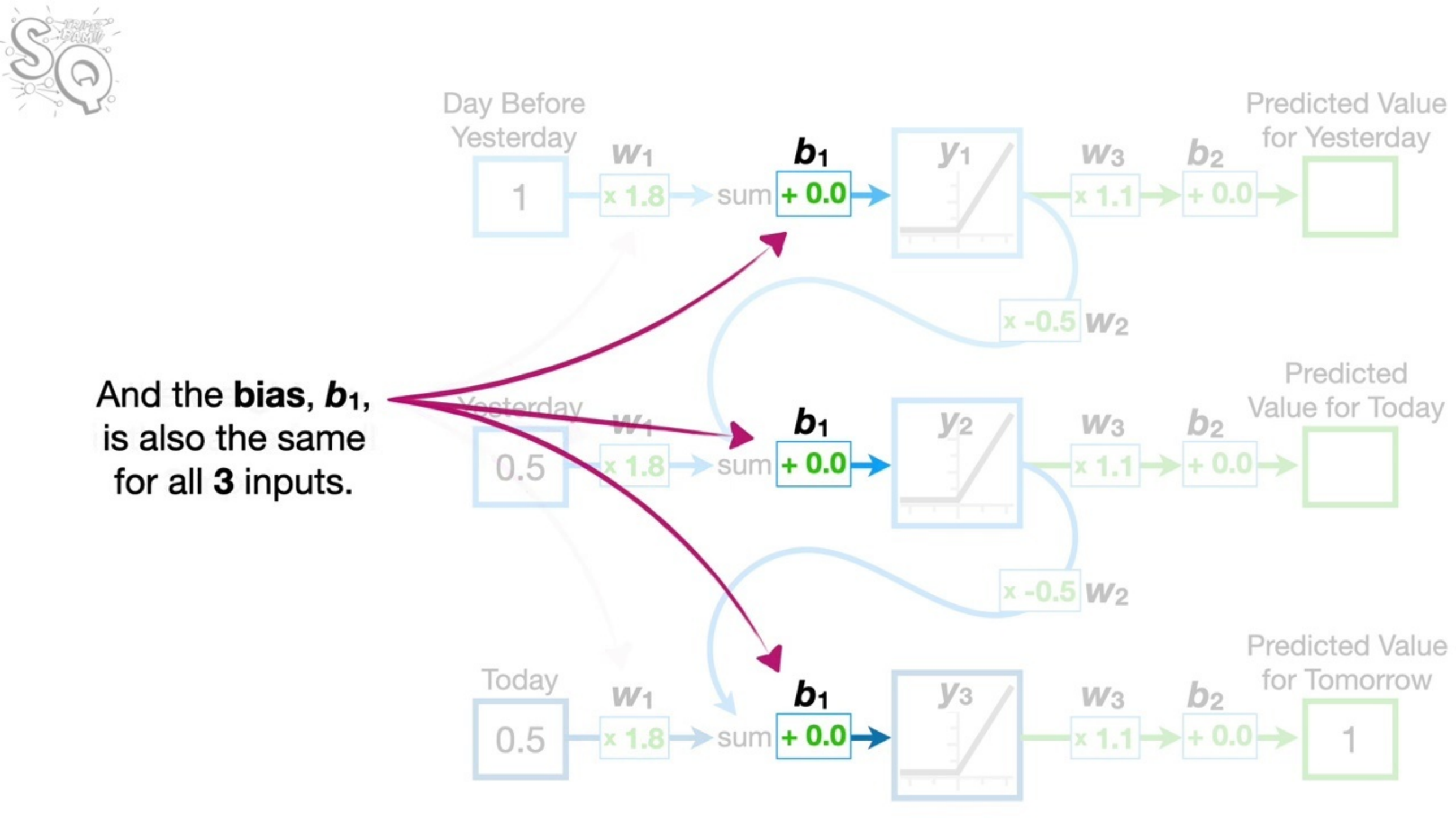


In other words, even though this **unrolled** network has **3** inputs…

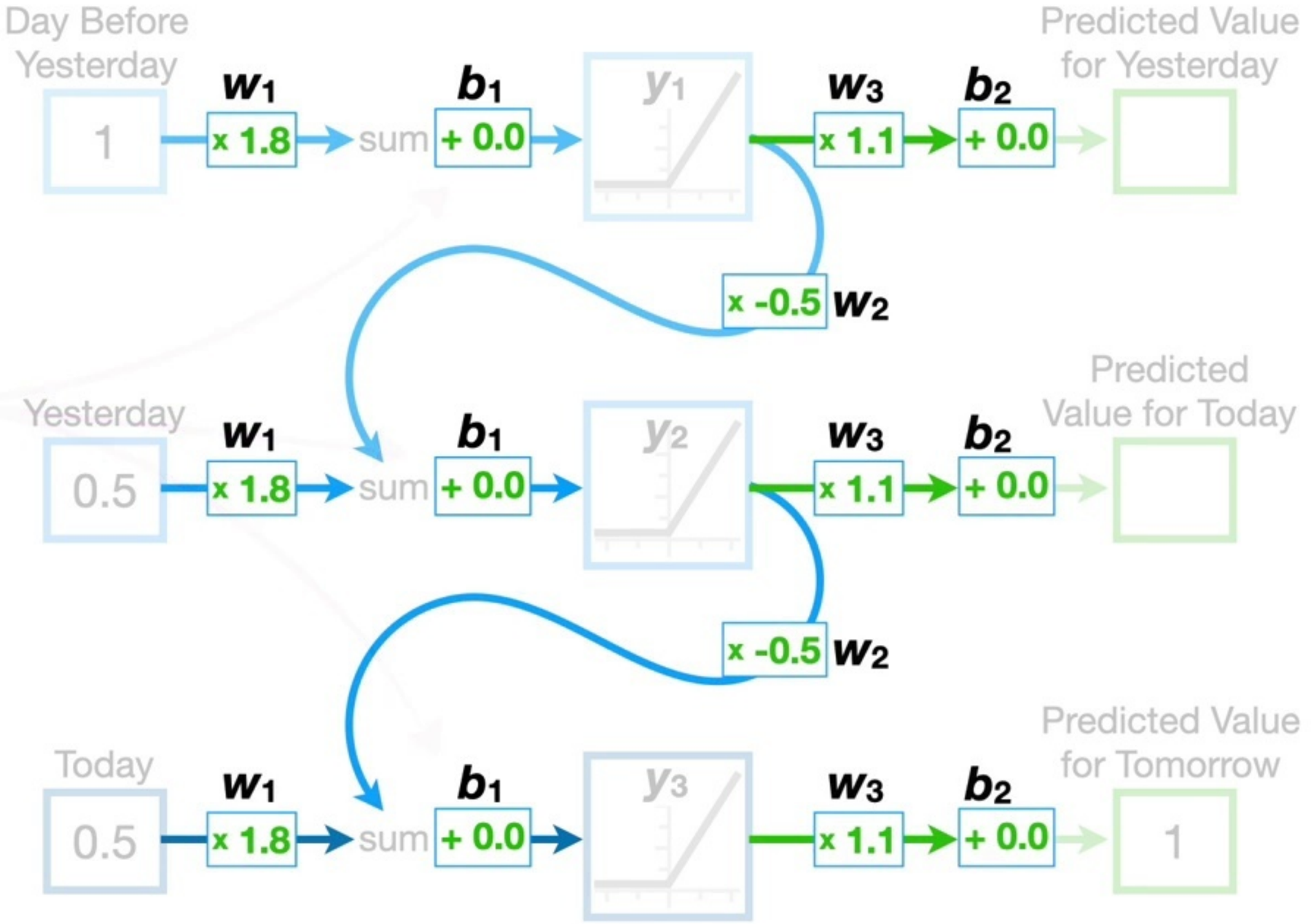



Day Before Yesterday
1
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Yesterday
x -0.5
w_2
In other words, even though this **unrolled** network has **3** inputs…
Yesterday
0.5
w_1
x 1.8
sum
b_1
+ 0.0
y_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0.5
w_1
x 1.8
sum
b_1
+ 0.0
y_3
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow
1

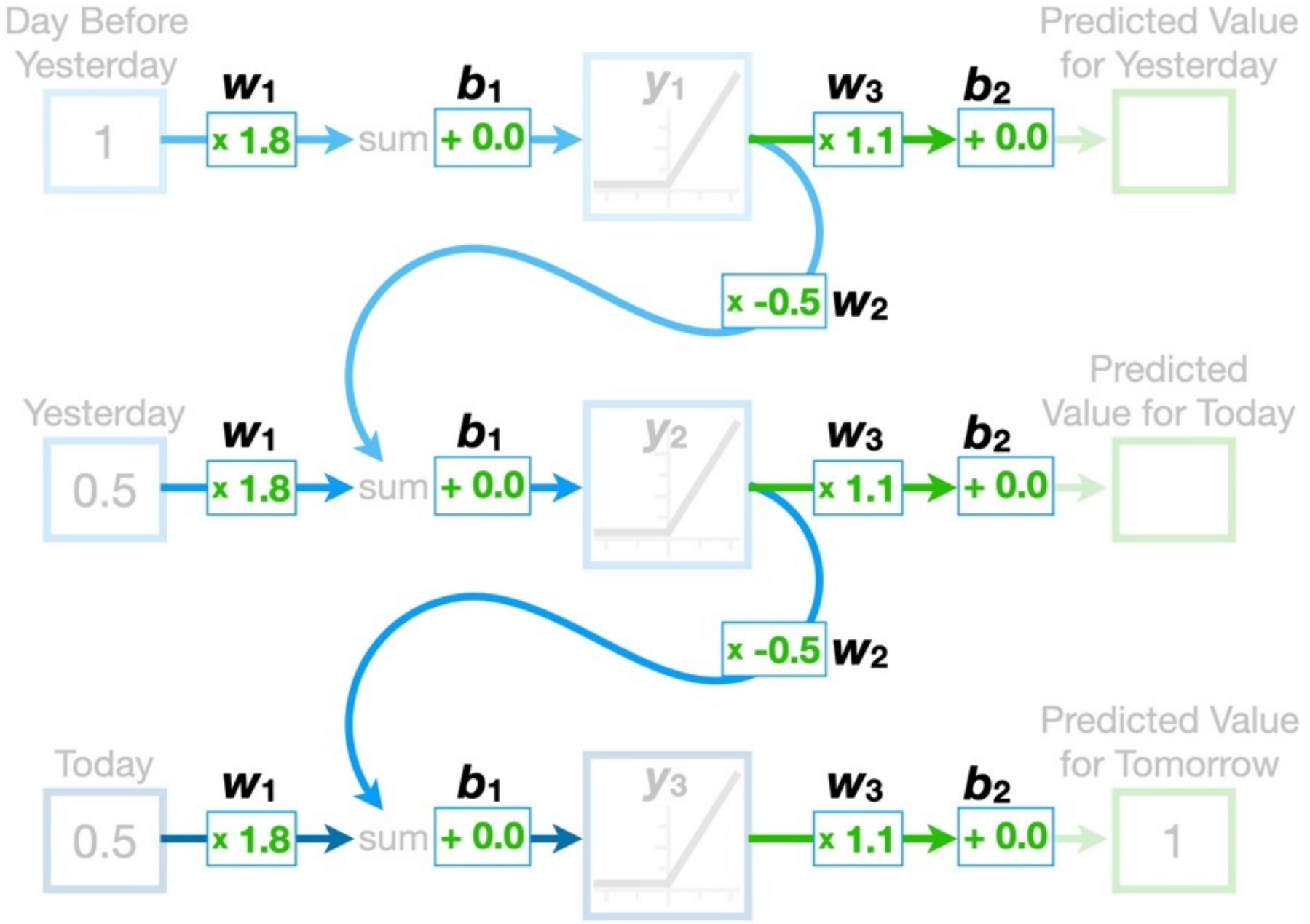

Day Before Yesterday
1
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Yesterday
x -0.5
w_2
…the **weight**, w_1, is the same for all **3** inputs.
Yesterday
0.5
w_1
x 1.8
sum
b_1
+ 0.0
y_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0.5
w_1
x 1.8
sum
b_1
+ 0.0
y_3
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow
1


Day Before Yesterday
1
w_1
x 1.8
sum
b_1
+ 0.0
y_1
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Yesterday
x -0.5
w_2
And the **bias**, b_1, is also the same for all **3** inputs.
Yesterday
0.5
w_1
x 1.8
sum
b_1
+ 0.0
y_2
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Today
x -0.5
w_2
Today
0.5
w_1
x 1.8
sum
b_1
+ 0.0
y_3
w_3
x 1.1
b_2
+ 0.0
Predicted Value for Tomorrow
1

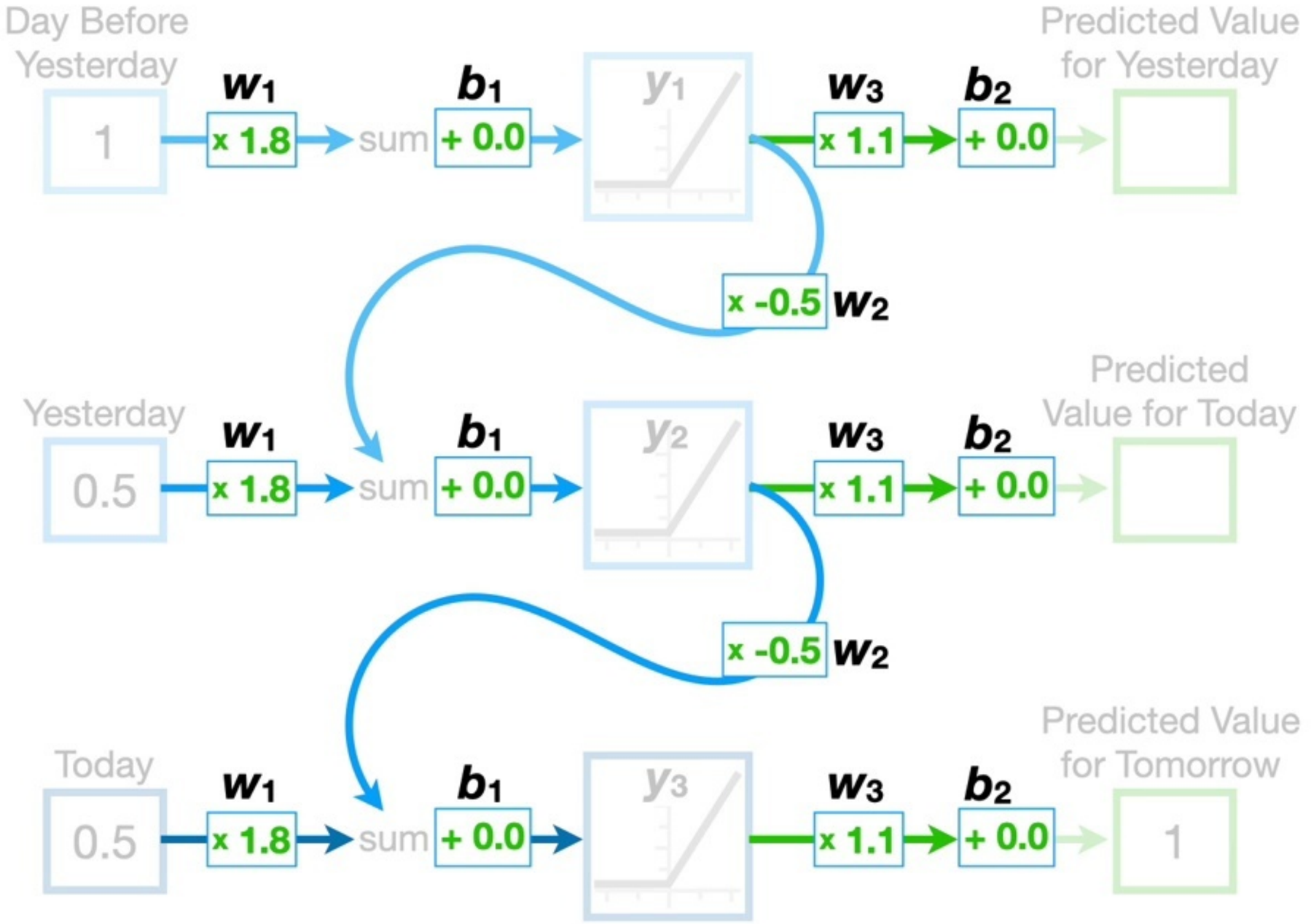
Likewise, all of the other **weights** and **biases** are shared.



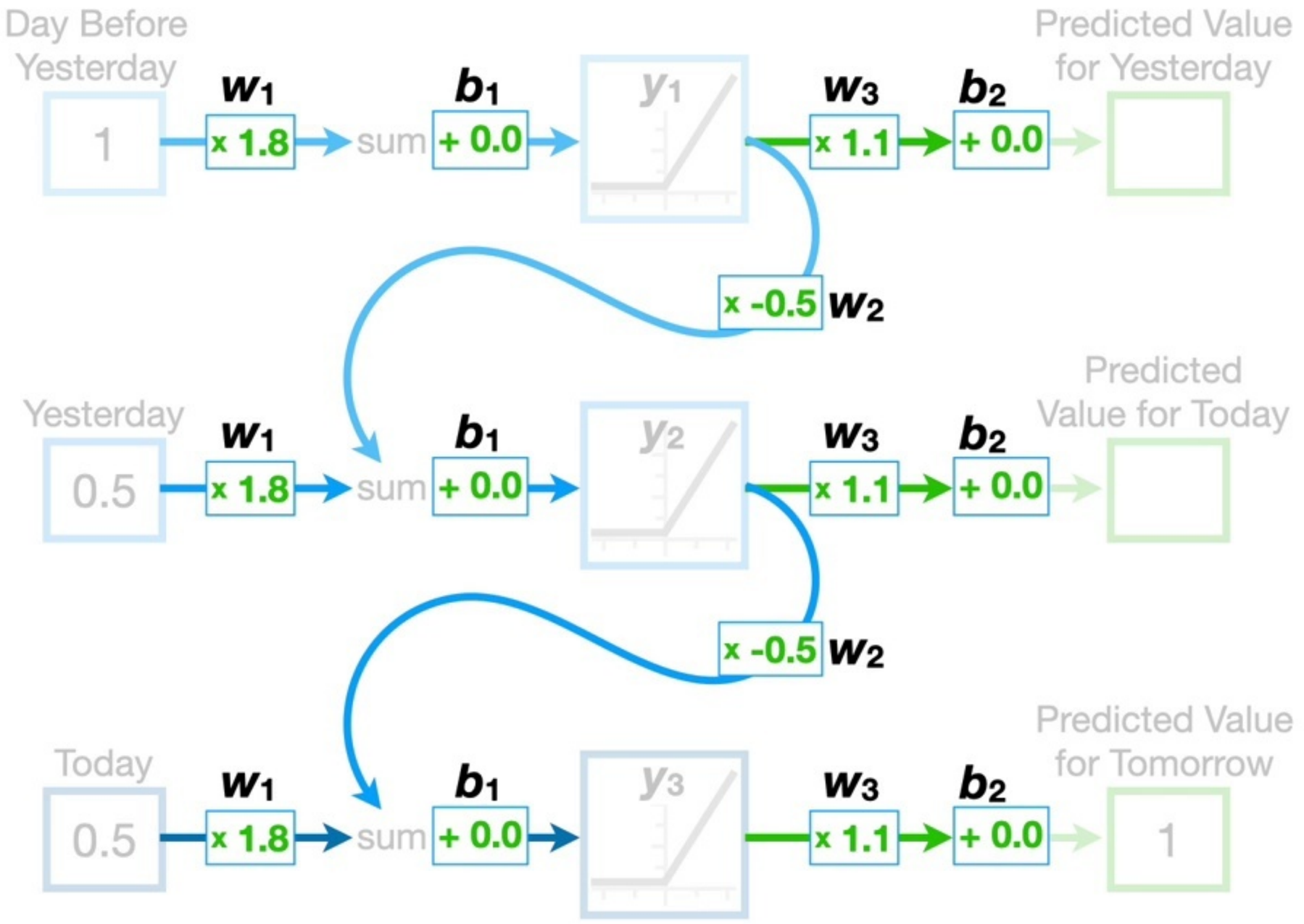
So, no matter how many times we **unroll** a recurrent neural network, we never increase the number of **weights** and **biases** that we have to train.



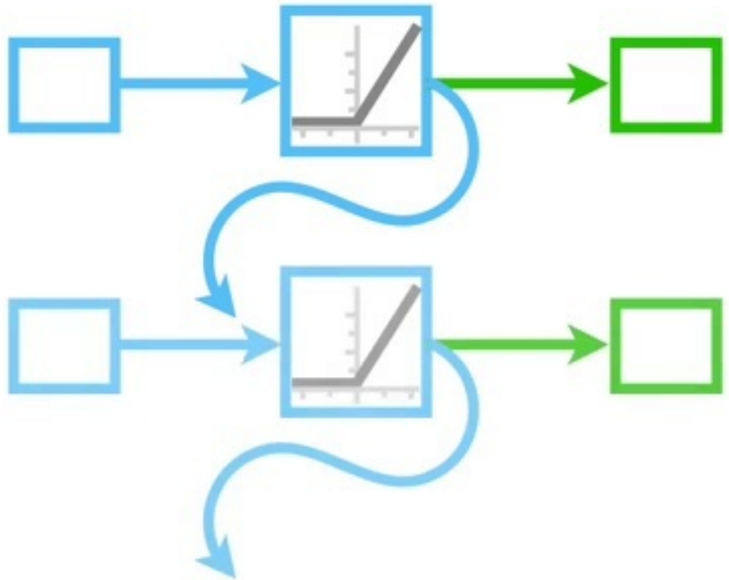
OK, now that we've talked about what makes ***basic*** recurrent neural networks so cool…



…let's briefly talk about why they are not used very often.



One big problem is that the more we **unroll** a recurrent neural network, the harder it is to train.



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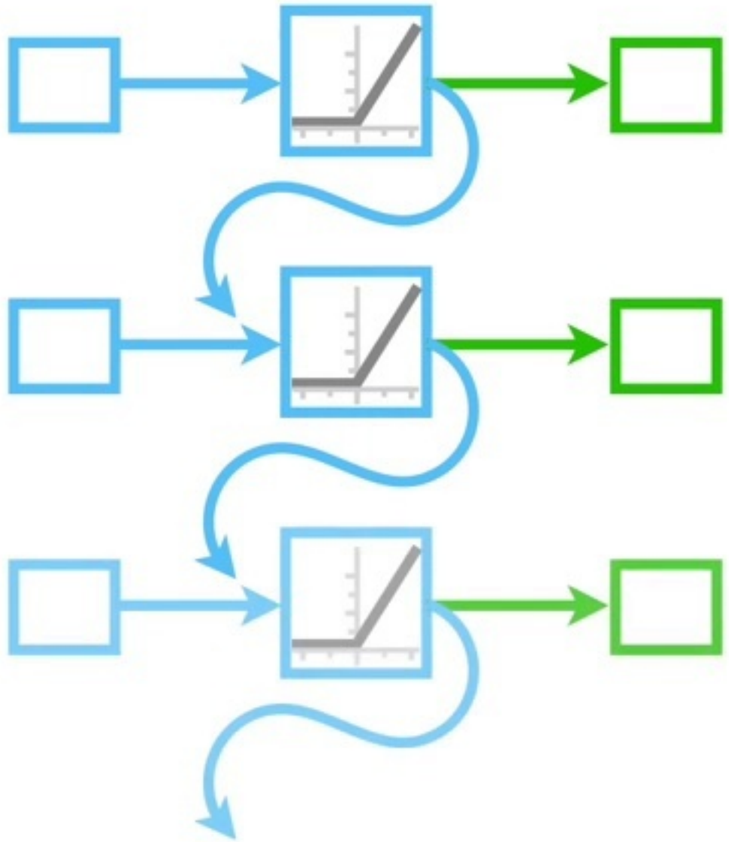

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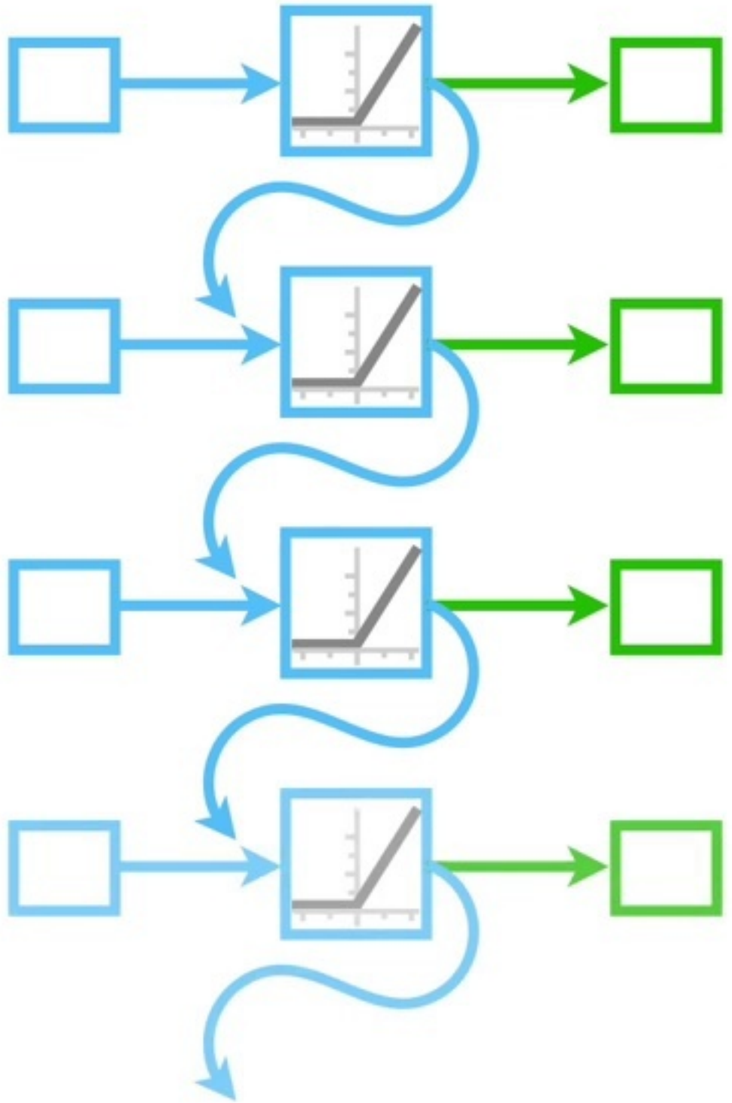
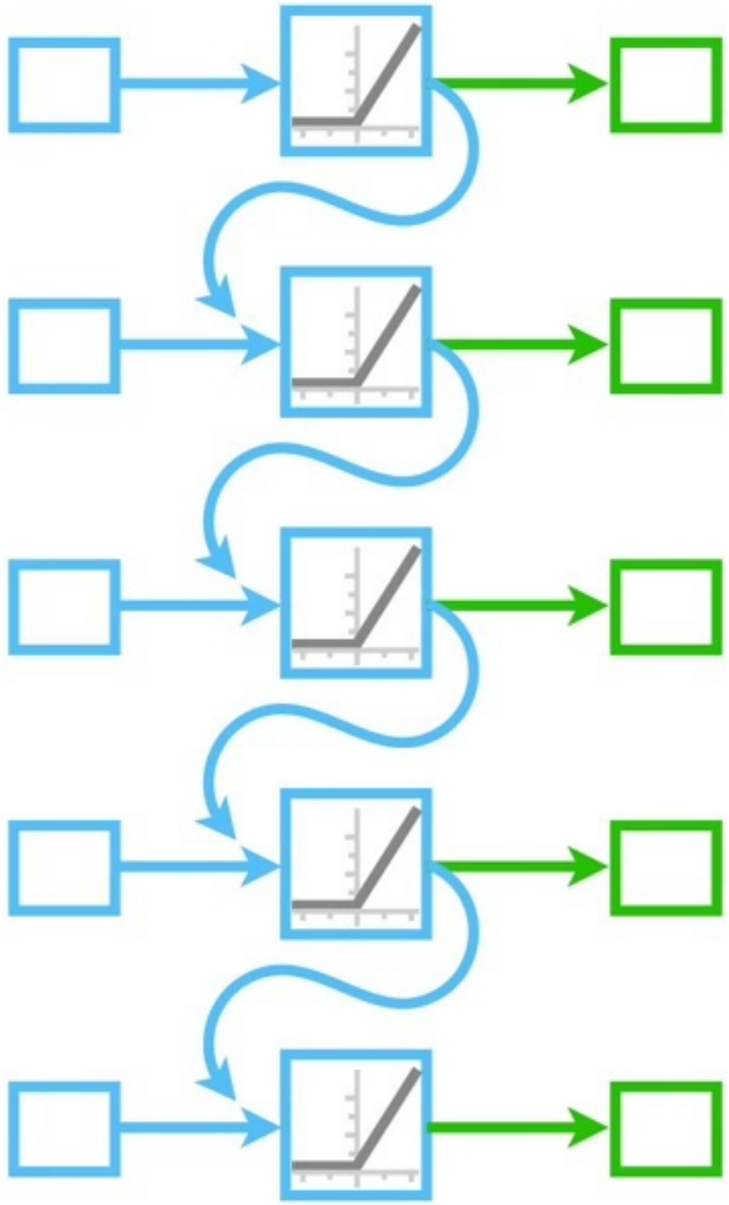
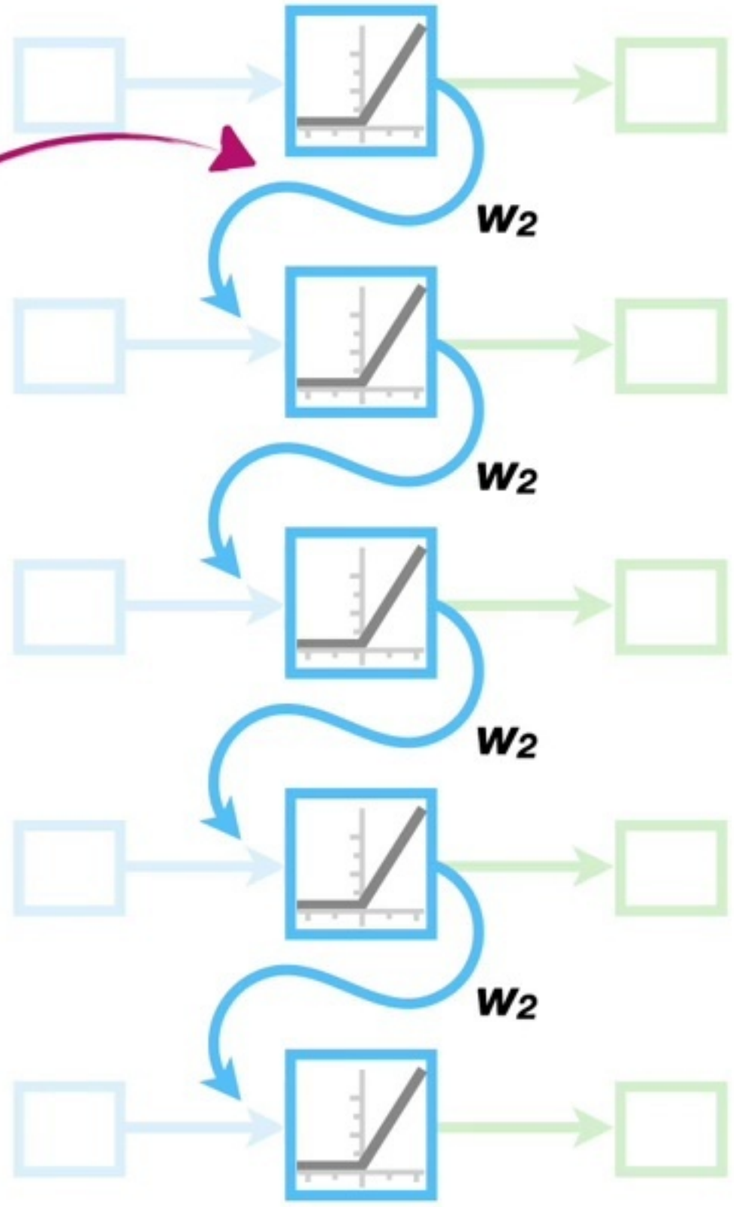


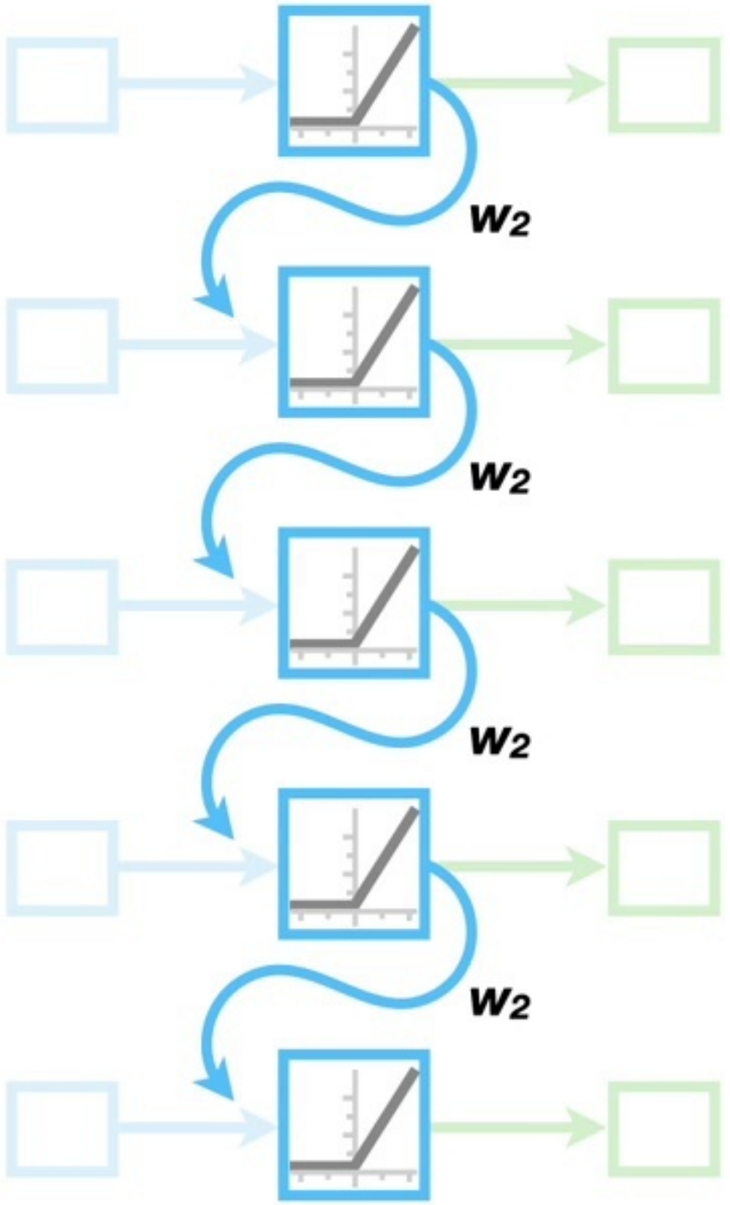
This problem is called **The Vanishing/Exploding Gradient Problem.**



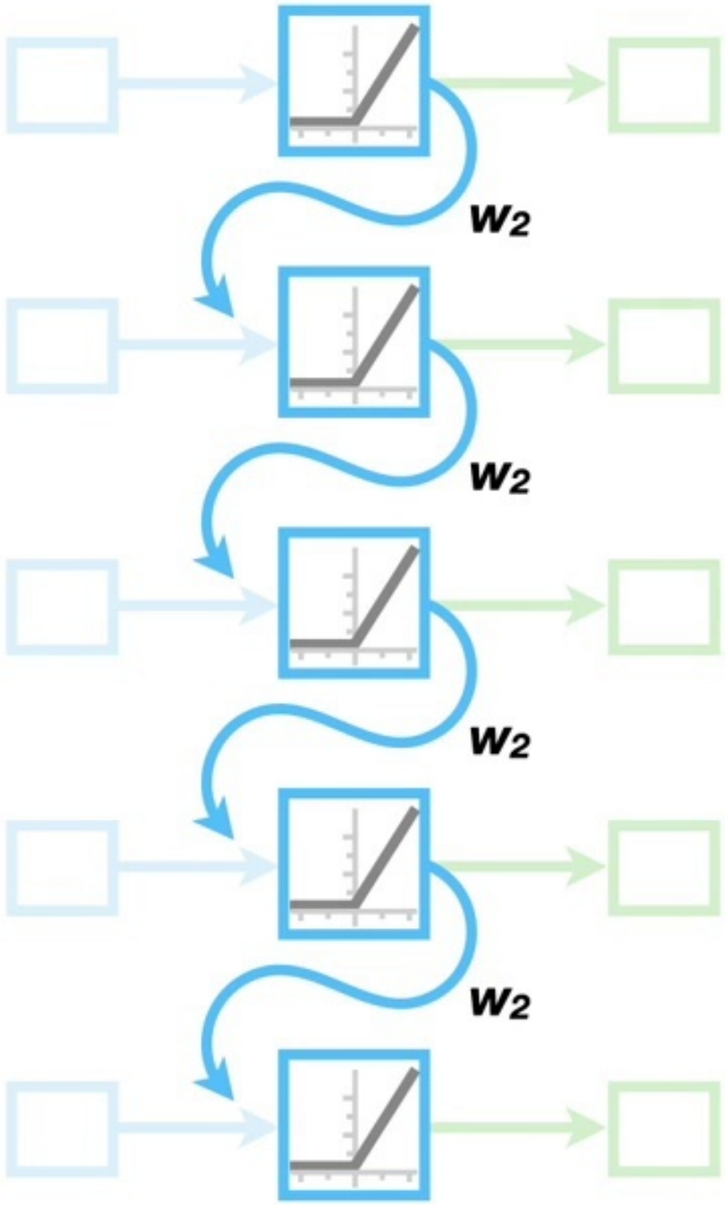
In our example, **The Vanishing/Exploding Gradient** problem has to do with the **weight** along the squiggle that we copy each time we **unroll** the network.



NOTE: To make it easier to understand **The Vanishing/ Exploding Gradient Problem**, we're going to ignore the other **weights** and **biases** in this network and just focus on w_2.



Also, just to remind you, when we optimize neural networks with **Backpropagation**, we first find the derivatives, or **Gradients**, for each parameter.



$$\frac{d\,SSR}{d\,w_1} = \frac{d\,SSR}{d\,Predicted} \times \frac{d\,Predicted}{d\,y_2} \times \frac{d\,y_2}{d\,x_2} \times \frac{d\,x_2}{d\,w_1} + \ldots$$

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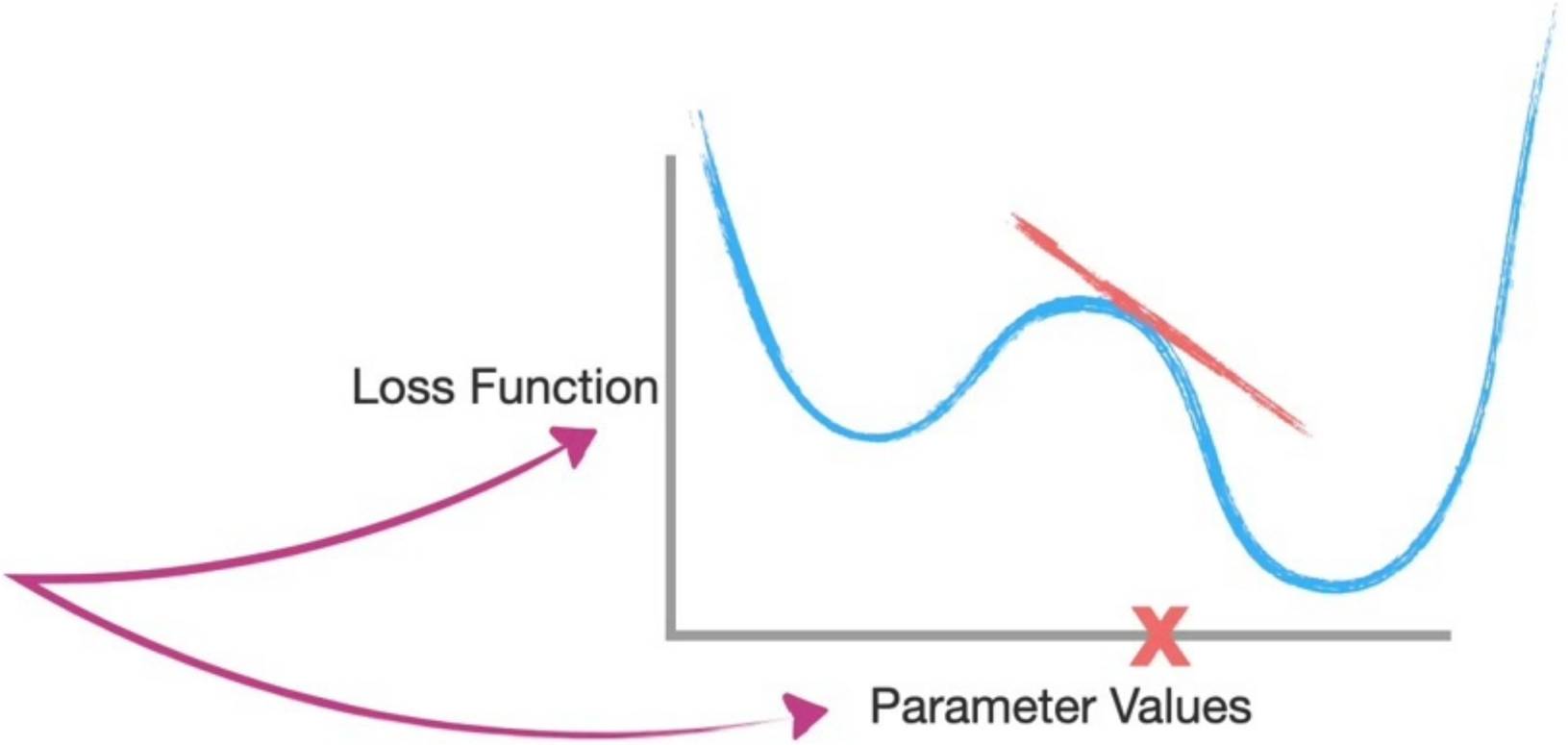

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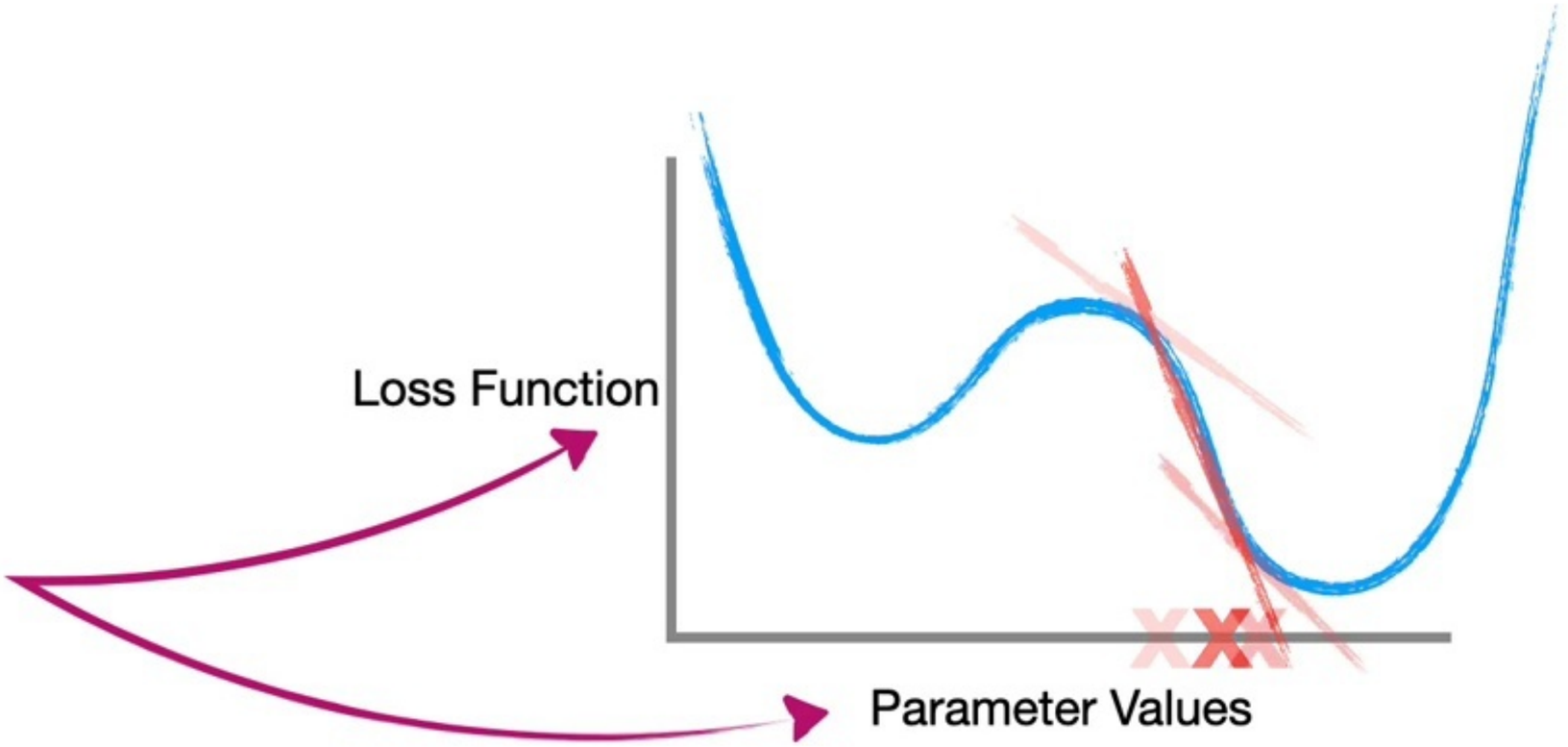

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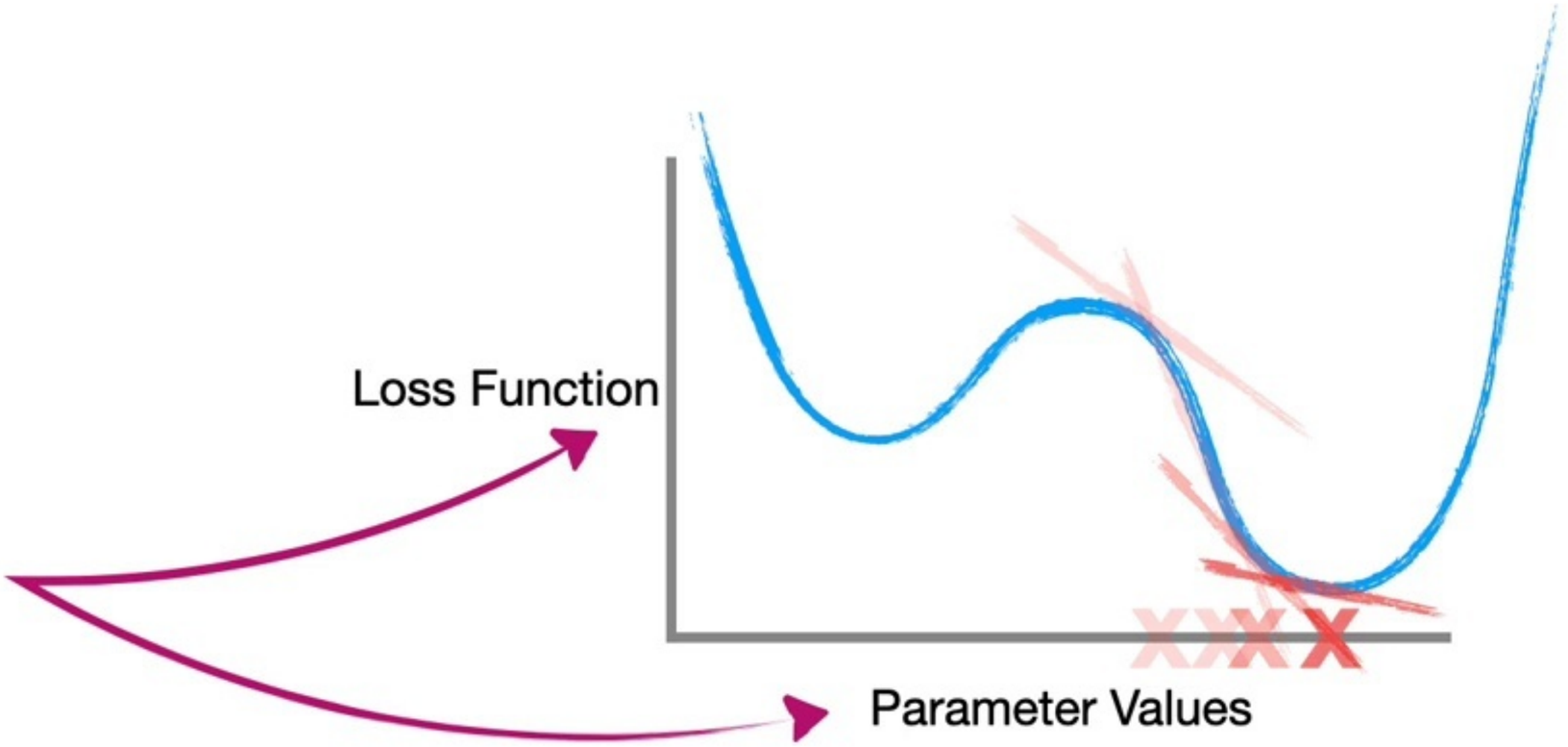

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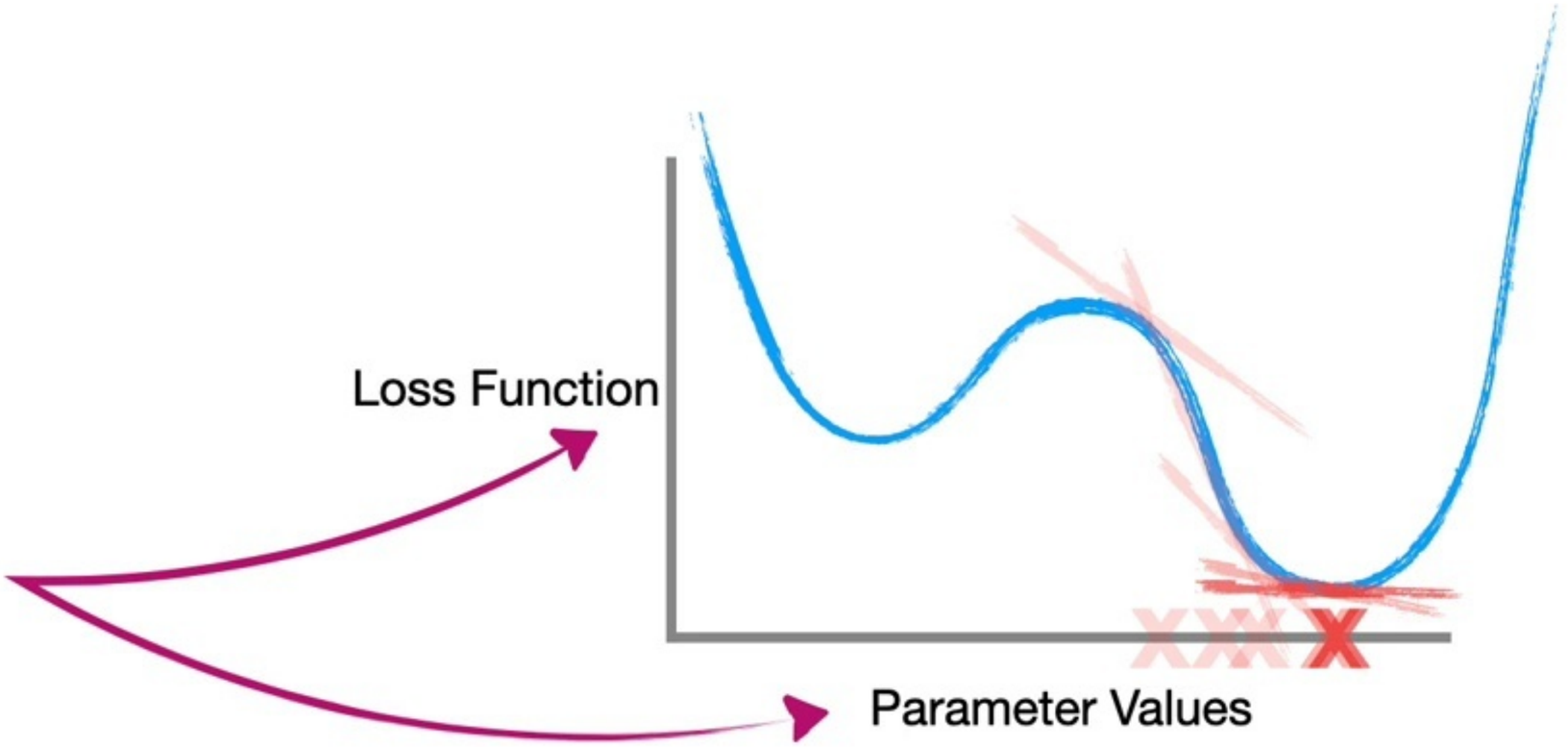
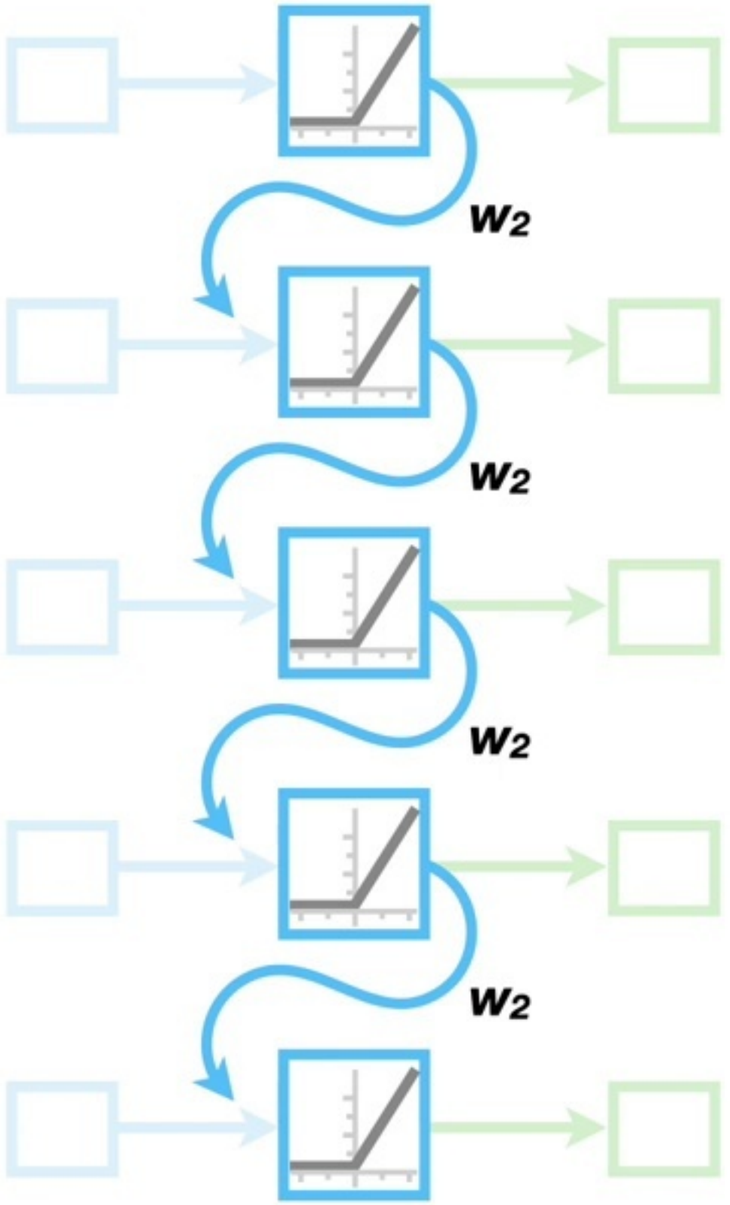
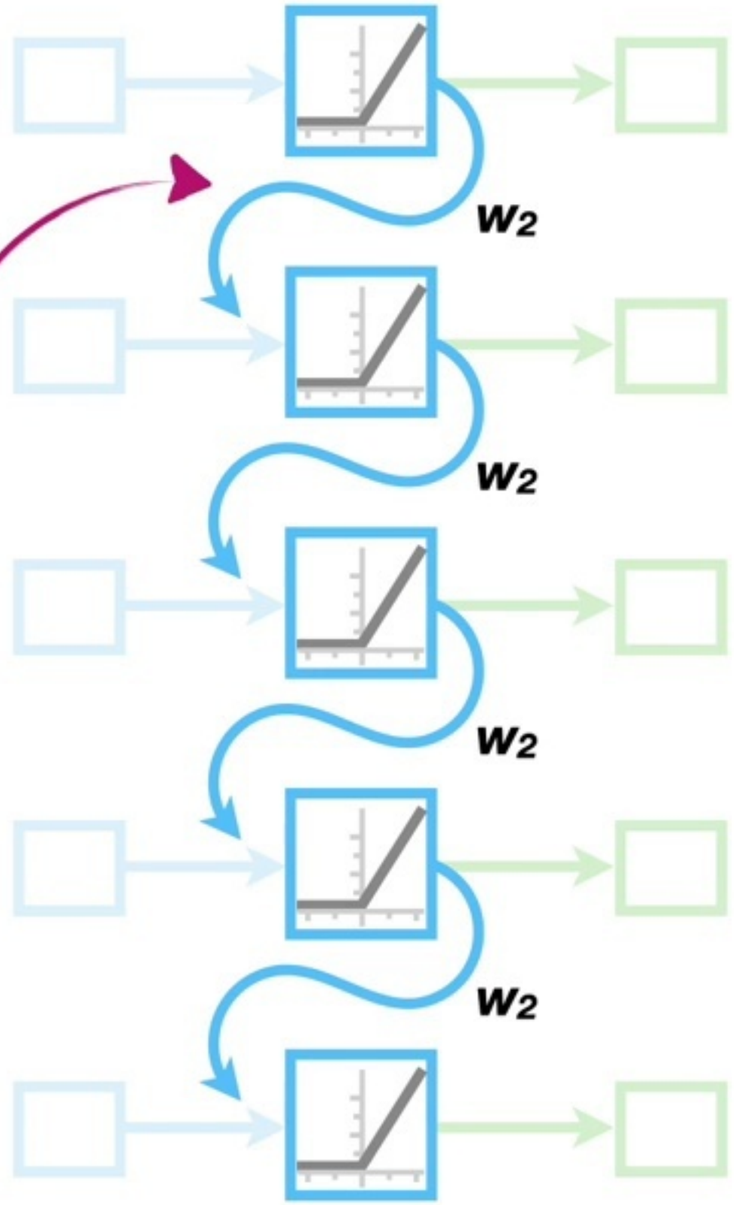


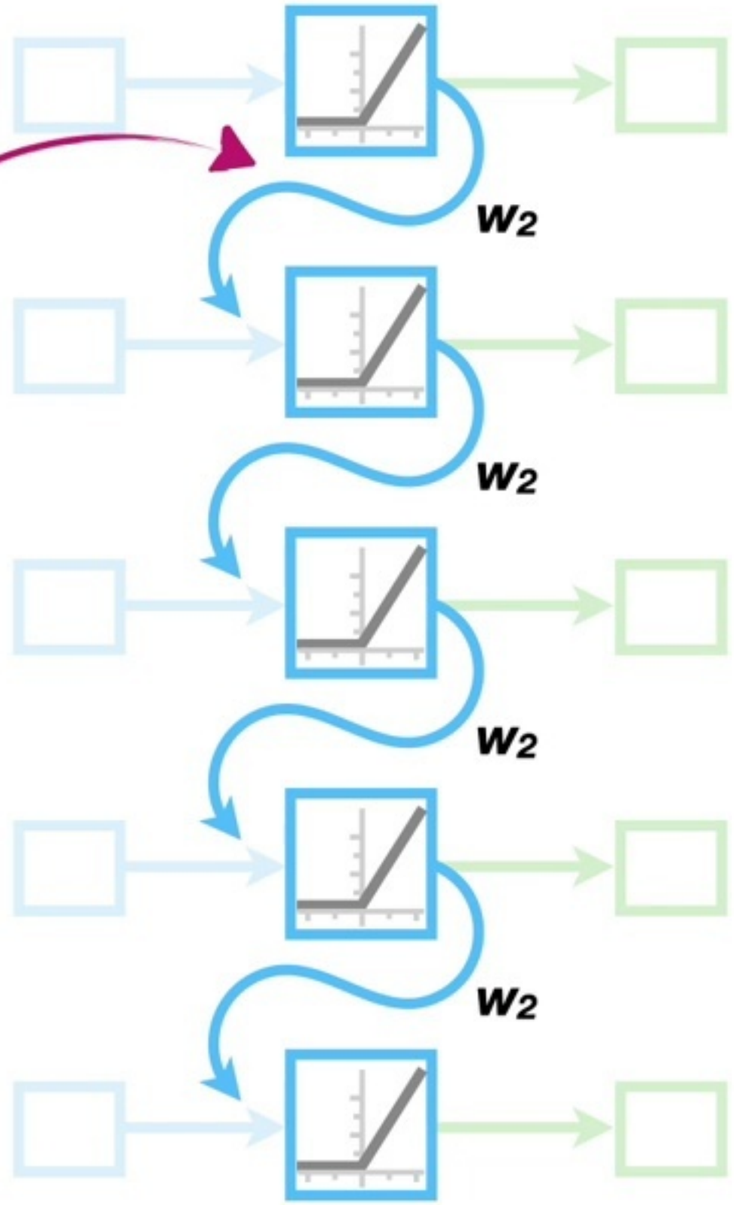
…we’re going to start by showing how a gradient can ***Explode***.



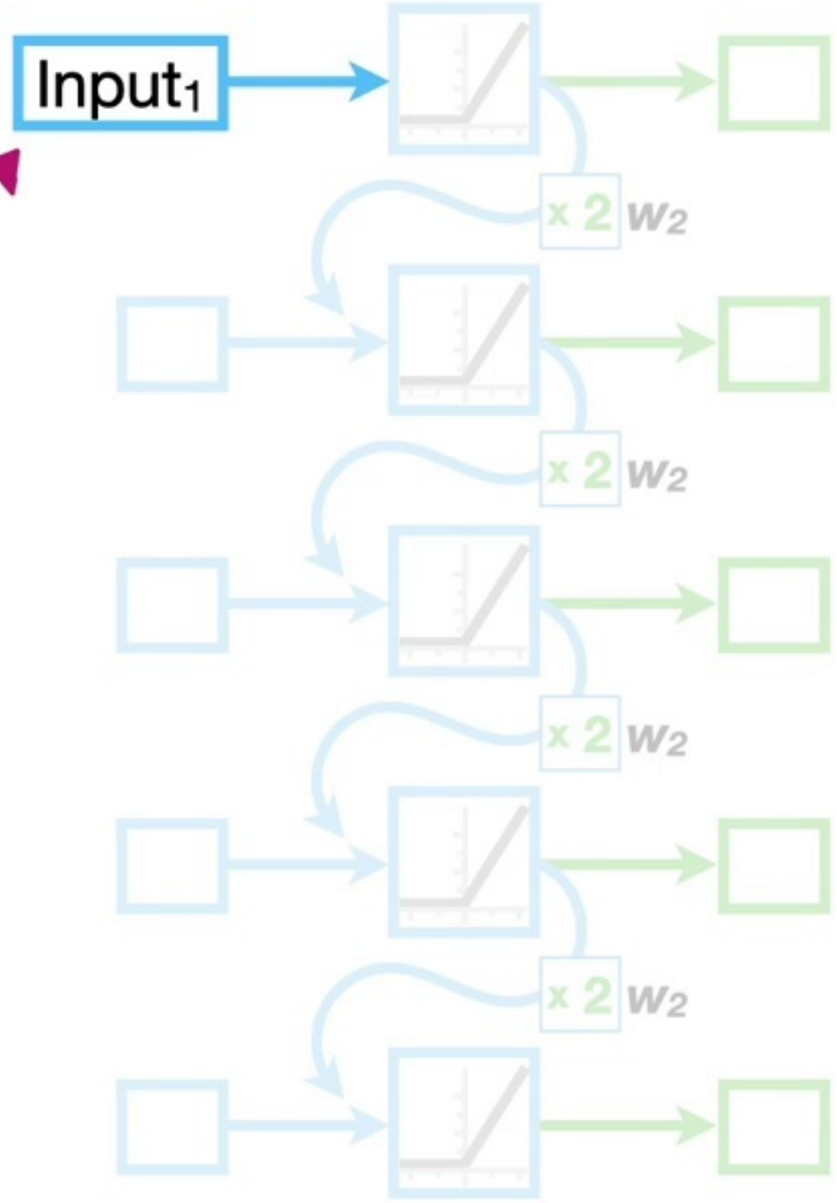
In our example, the gradient will ***explode***, when we set w_2 to any value larger than **1**.

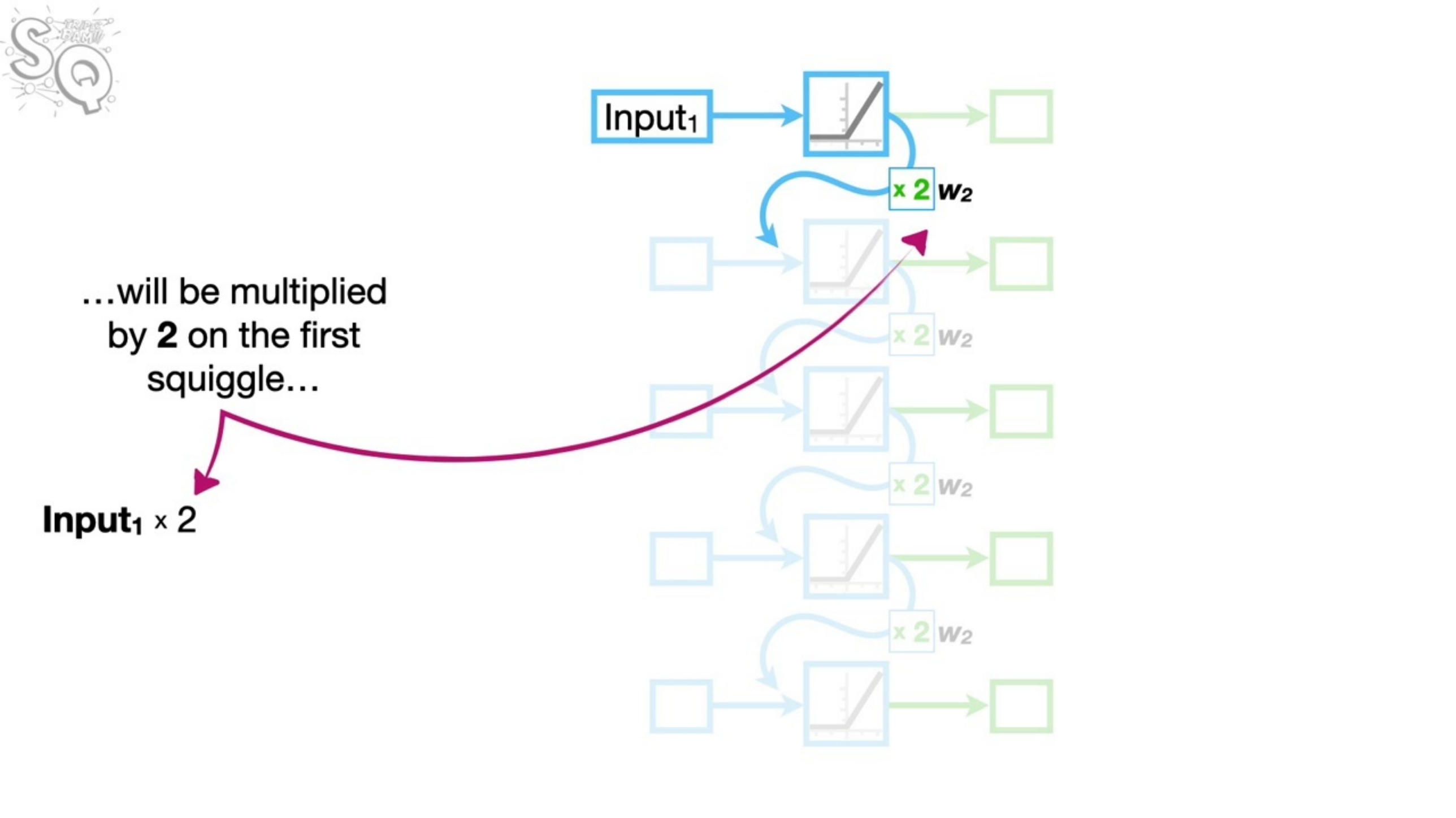


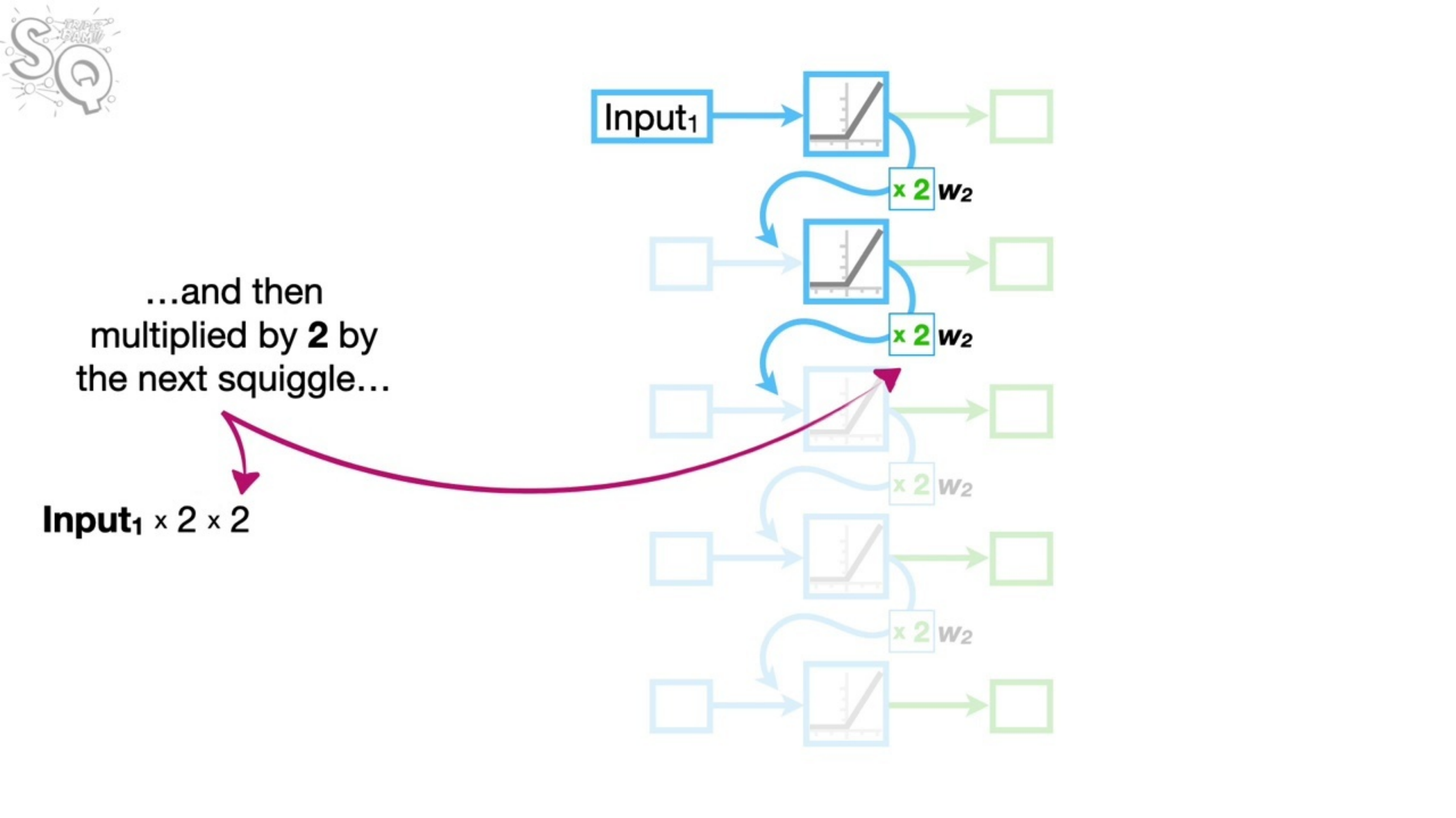
So let's set
$w_2 = 2$.

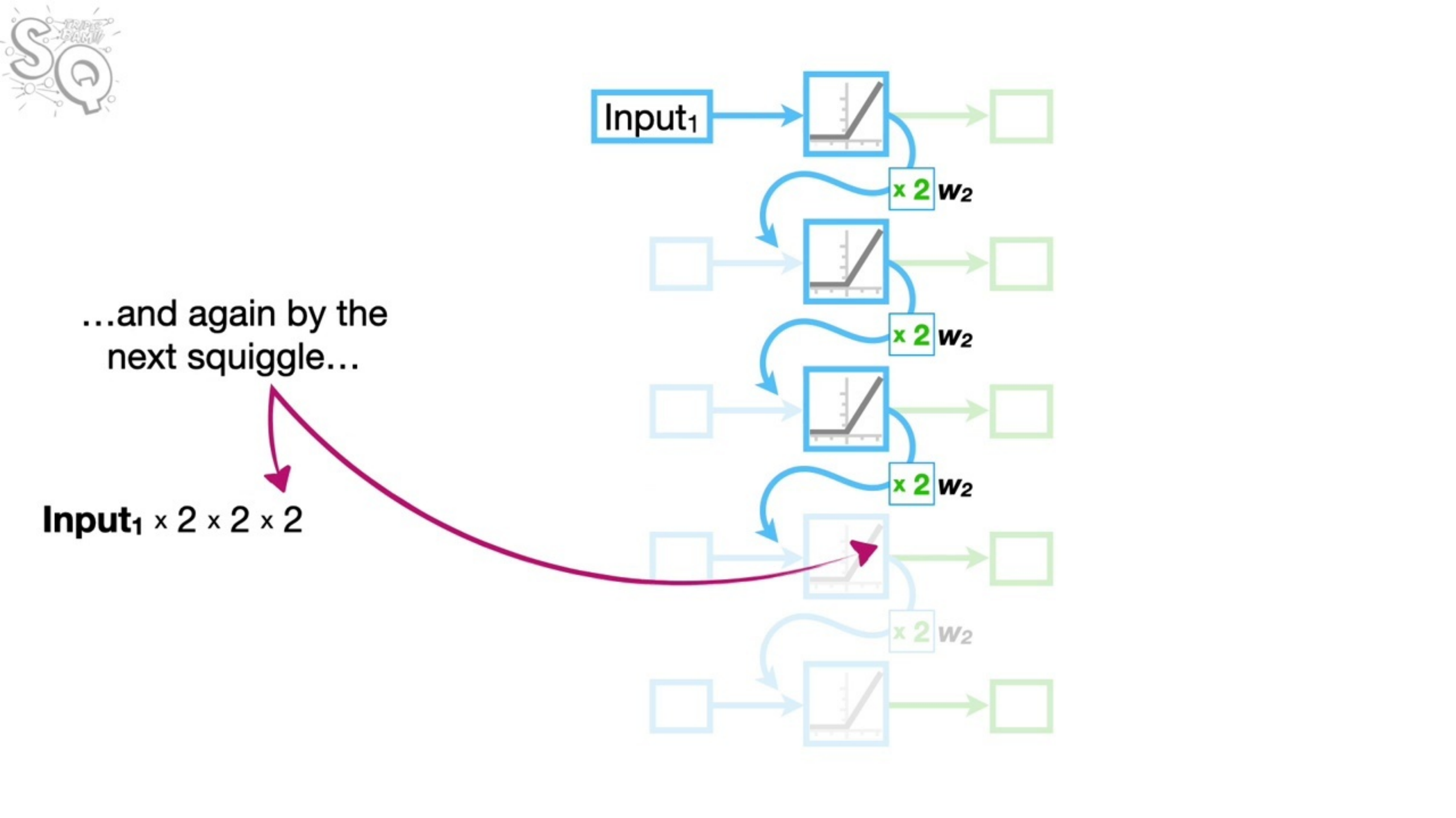


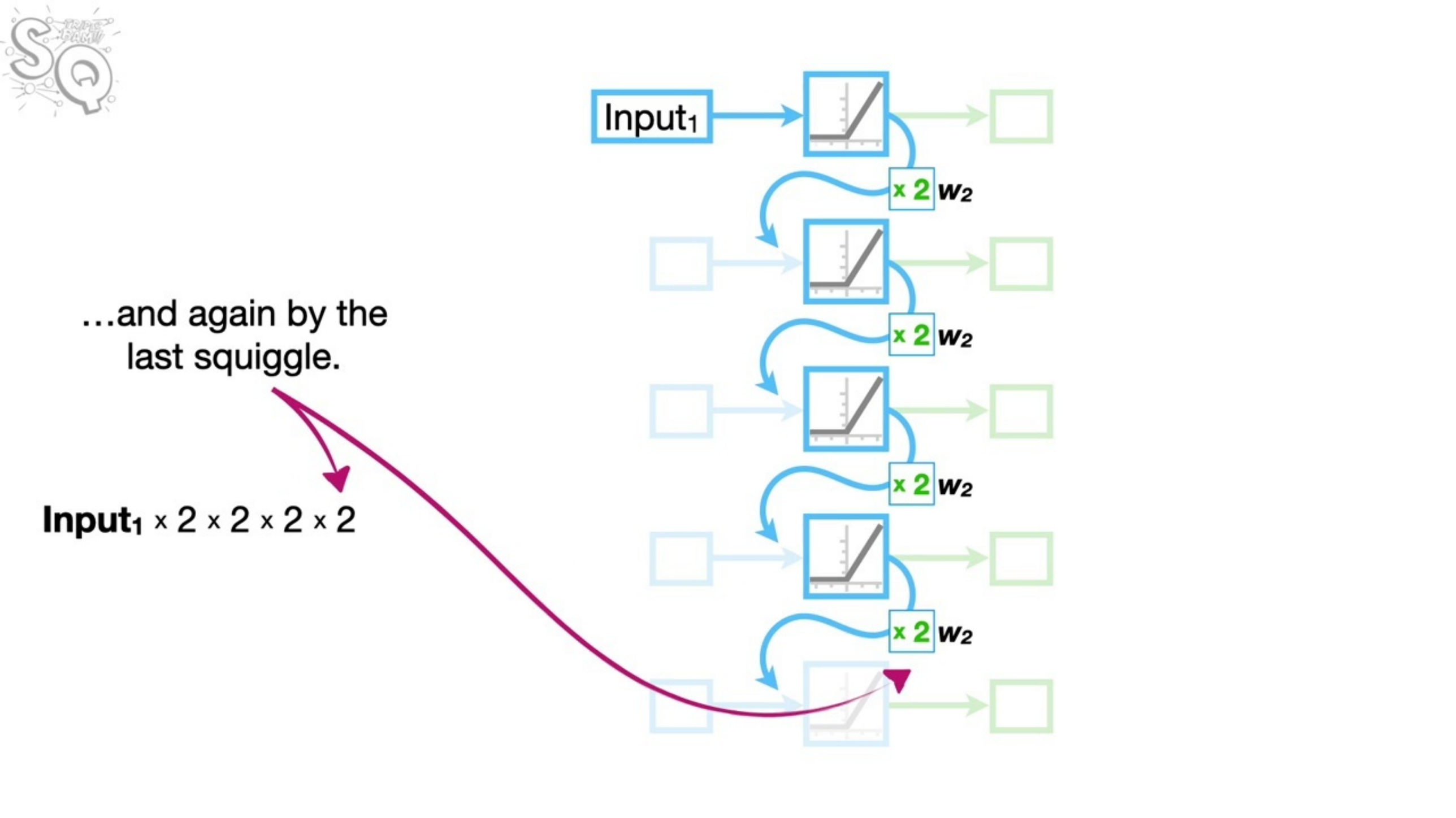
Now, the first input value, **Input$_1$**…




Input1
x 2 w2
x 2 w2
x 2 w2
x 2 w2
…will be multiplied by 2 on the first squiggle…
Input1 x 2

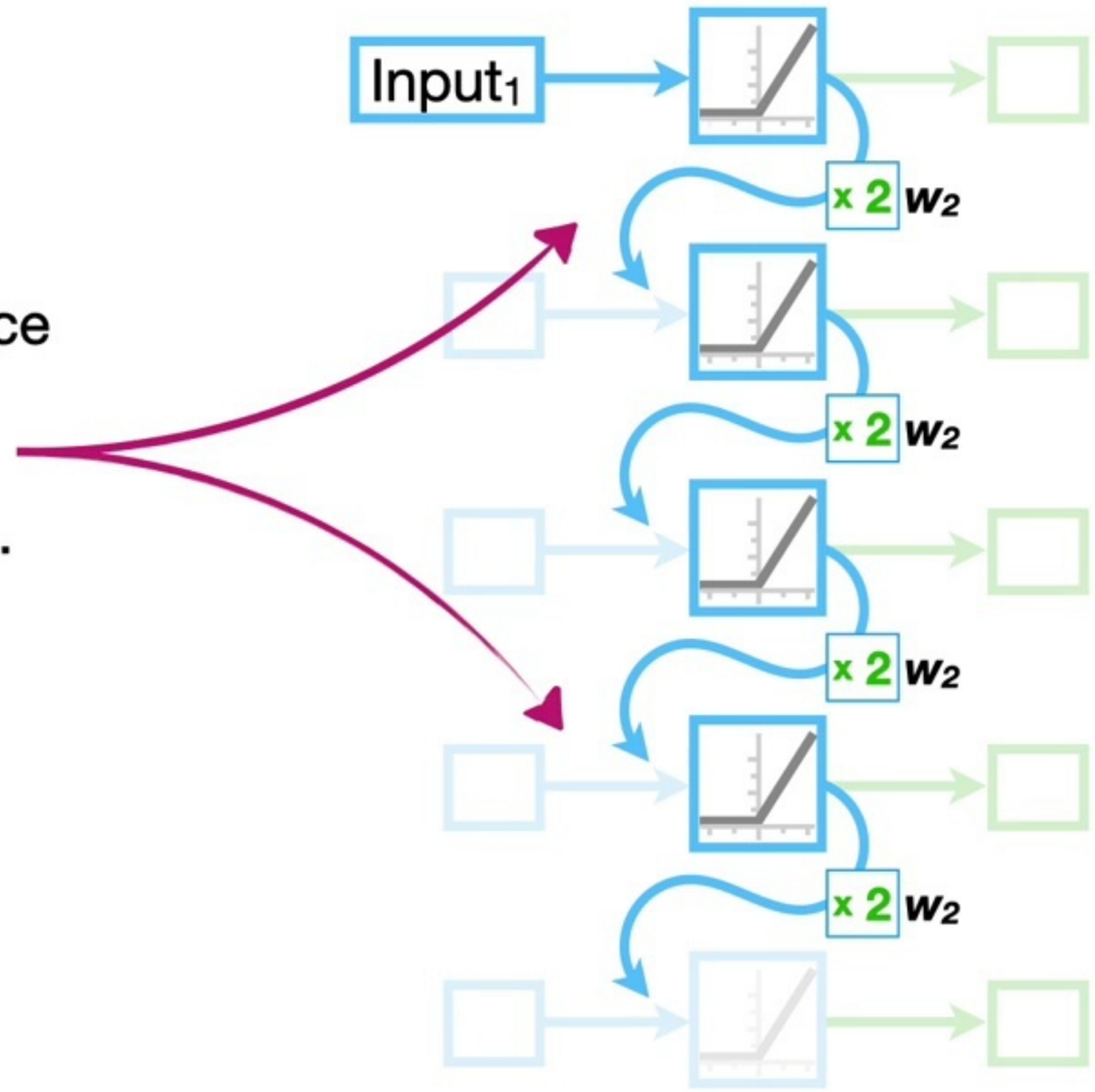

Input1
x 2 w2
x 2 w2
x 2 w2
x 2 w2
…and then
multiplied by 2 by
the next squiggle…
Input1 x 2 x 2


Input1
x 2 w2
x 2 w2
x 2 w2
x 2 w2
…and again by the next squiggle…
Input1 x 2 x 2 x 2


Input1
x 2 w2
x 2 w2
x 2 w2
x 2 w2
…and again by the last squiggle.
Input1 x 2 x 2 x 2 x 2

In other words, since we **unrolled** the recurrent neural network **4** times…

Input$_1$ × 2 × 2 × 2 × 2



…we multiply the input value by w_2, which is **2**, raised to the number of times we **unrolled**, which is **4**.

$$\textbf{Input}_1 \times 2 \times 2 \times 2 \times 2$$

$$= \textbf{Input}_1 \times 2^4$$

$$= \textbf{Input}_1 \times w_2^{\text{Num. Unroll}}$$

And that means the first input value is amplified **16** times before it gets to the final copy of the network.

$$\textbf{Input}_1 \times 2 \times 2 \times 2 \times 2$$

$$= \textbf{Input}_1 \times 2^4$$

$$= \textbf{Input}_1 \times w_2^{\text{Num. Unroll}}$$

Now, if we had **50** sequential days of stock market data, which, to be honest, really isn't that much data…

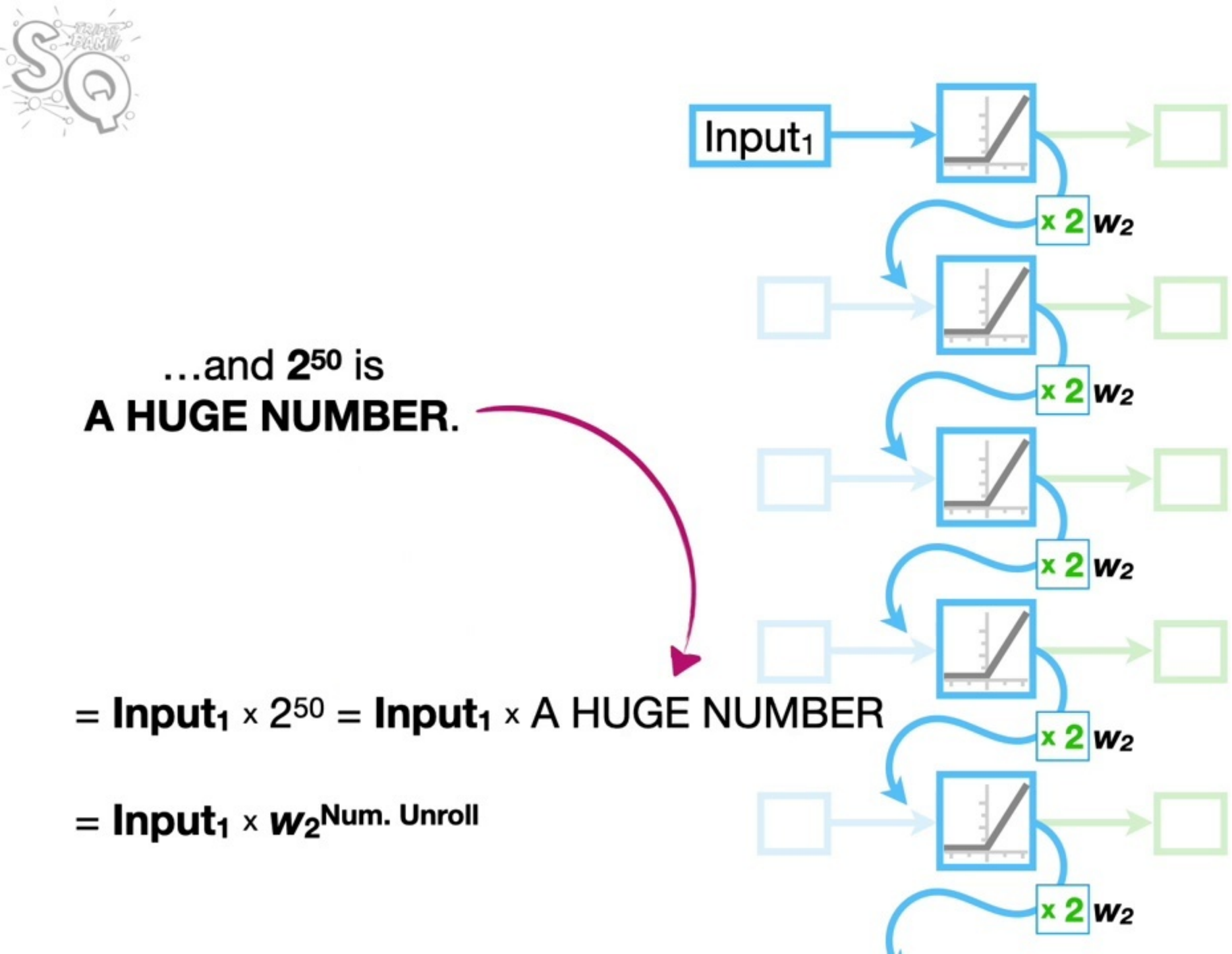
= **Input**$_1$ x 2^{50}

= **Input**$_1$ x $w_2^{\text{Num. Unroll}}$

…then we would **unroll** the network **50** times…

= **Input**$_1$ x 2^{50}

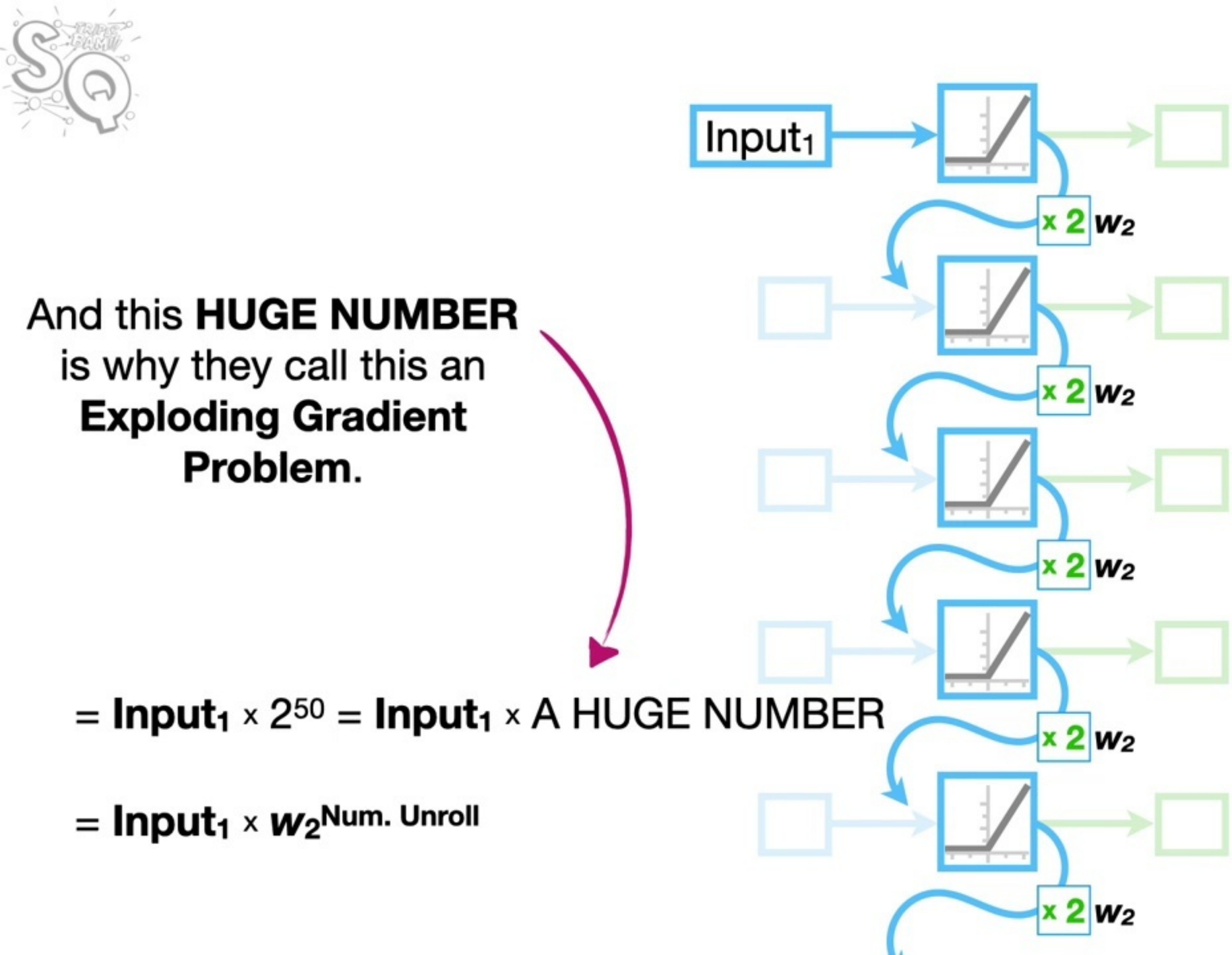
= **Input**$_1$ x $w_2^{\text{Num. Unroll}}$



…and 2^{50} is
A HUGE NUMBER.

$= \textbf{Input}_1 \times 2^{50} = \textbf{Input}_1 \times$ A HUGE NUMBER

$= \textbf{Input}_1 \times w_2^{\text{Num. Unroll}}$



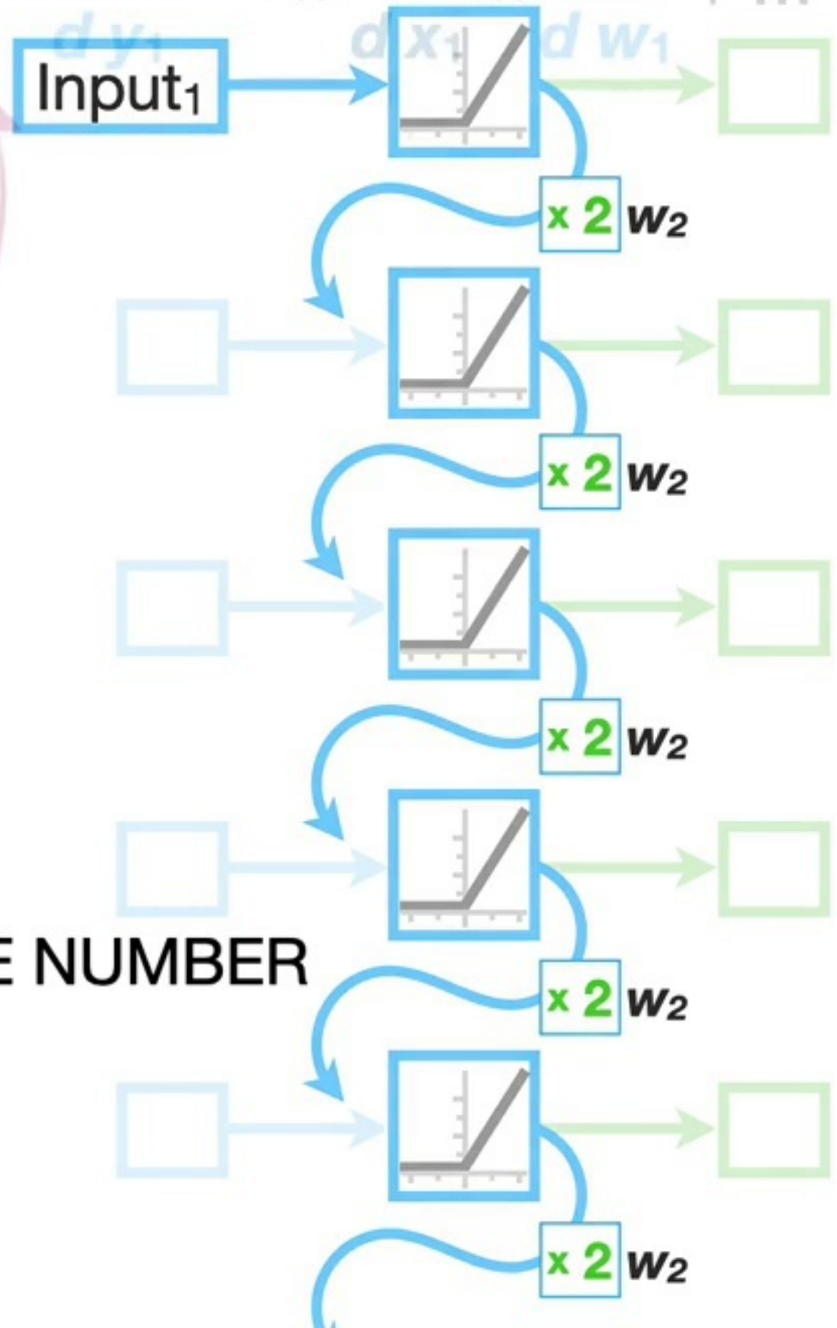
And this **HUGE NUMBER** is why they call this an **Exploding Gradient Problem.**

$= \textbf{Input}_1 \times 2^{50} = \textbf{Input}_1 \times$ A HUGE NUMBER

$= \textbf{Input}_1 \times w_2^{\text{Num. Unroll}}$

$$\frac{d\,SSR}{d\,w_1} = \frac{d\,SSR}{d\,Predicted} \times \frac{d\,Predicted}{d\,y_1} \times \frac{d\,y_1}{d\,x_1} \times \frac{d\,x_1}{d\,w_1} + \ldots$$

If we tried to train this recurrent neural network with backpropagation, this **HUGE NUMBER** would find its way into some of the gradients…



$= \mathbf{Input_1} \times 2^{50} = \mathbf{Input_1} \times$ A HUGE NUMBER

$= \mathbf{Input_1} \times \boldsymbol{w_2}^{\text{Num. Unroll}}$

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$$\frac{d\,x_1}{d\,w_1} = \frac{d}{d\,w_1}\,\text{Input1} \times w_1 \times w_2^{50}\ldots$$

$$= \text{Input}_1 \times 2^{50} = \text{Input}_1 \times \text{A HUGE NUMBER}$$

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$$= \text{Input}_1 \times 2^{50} = \text{Input}_1 \times \text{A HUGE NUMBER}$$

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$$\frac{d\,SSR}{d\,w_1} = \frac{d\,SSR}{d\,Predicted} \times \frac{d\,Predicted}{d\,y_1} \times \frac{d\,y_1}{d\,x_1} \times \frac{d\,x_1}{d\,w_1} + \ldots$$

…and that would make it hard to take small steps to find the optimal **weights** and **biases**.

$$\frac{d\,x_1}{d\,w_1} = \frac{d}{d\,w_1}\,\text{Input1} \times w_1 \times w_2^{50}\ldots$$

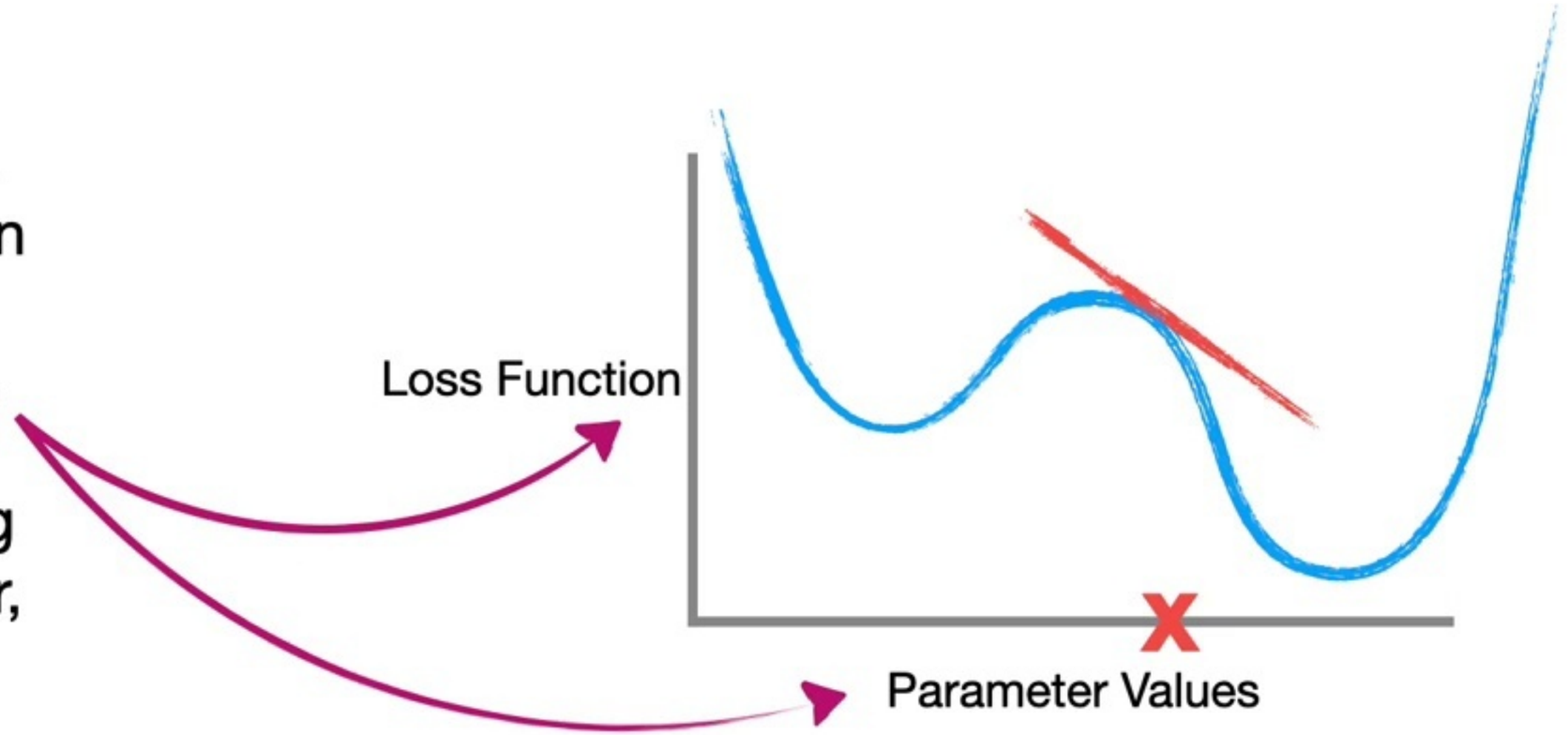
$$= \frac{d}{d\,w_1}\,\text{Input1} \times w_1 \times \text{A HUGE NUMBER}\ldots$$

$= \textbf{Input}_1 \times 2^{50} = \textbf{Input}_1 \times \text{A HUGE NUMBER}$

$= \textbf{Input}_1 \times w_2^{\text{Num. Unroll}}$

However, when the **Gradient** contains **A HUGE NUMBER**, then we'll end up taking relatively large steps.

And instead of finding the optimal parameter, we'll just bounce around a lot.



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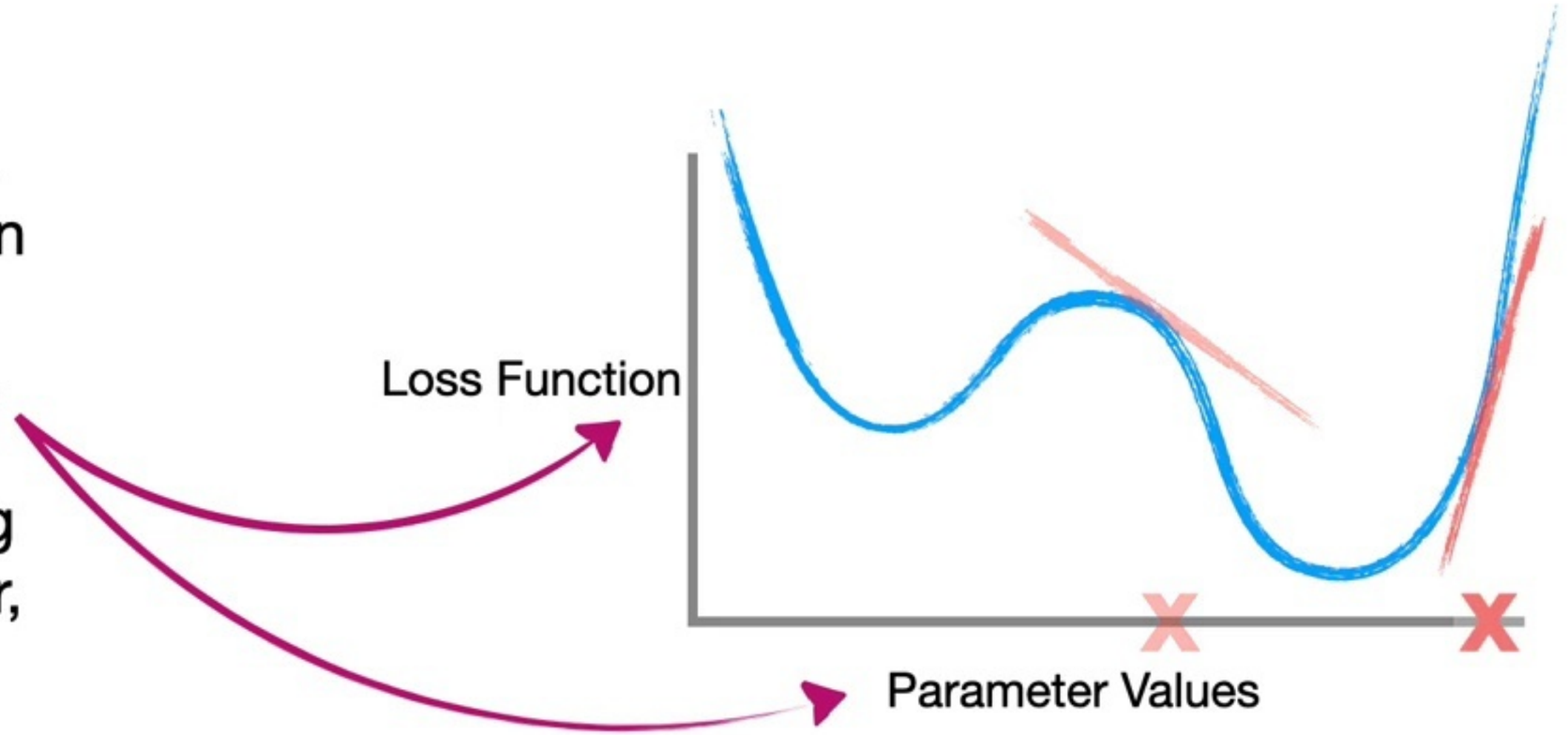

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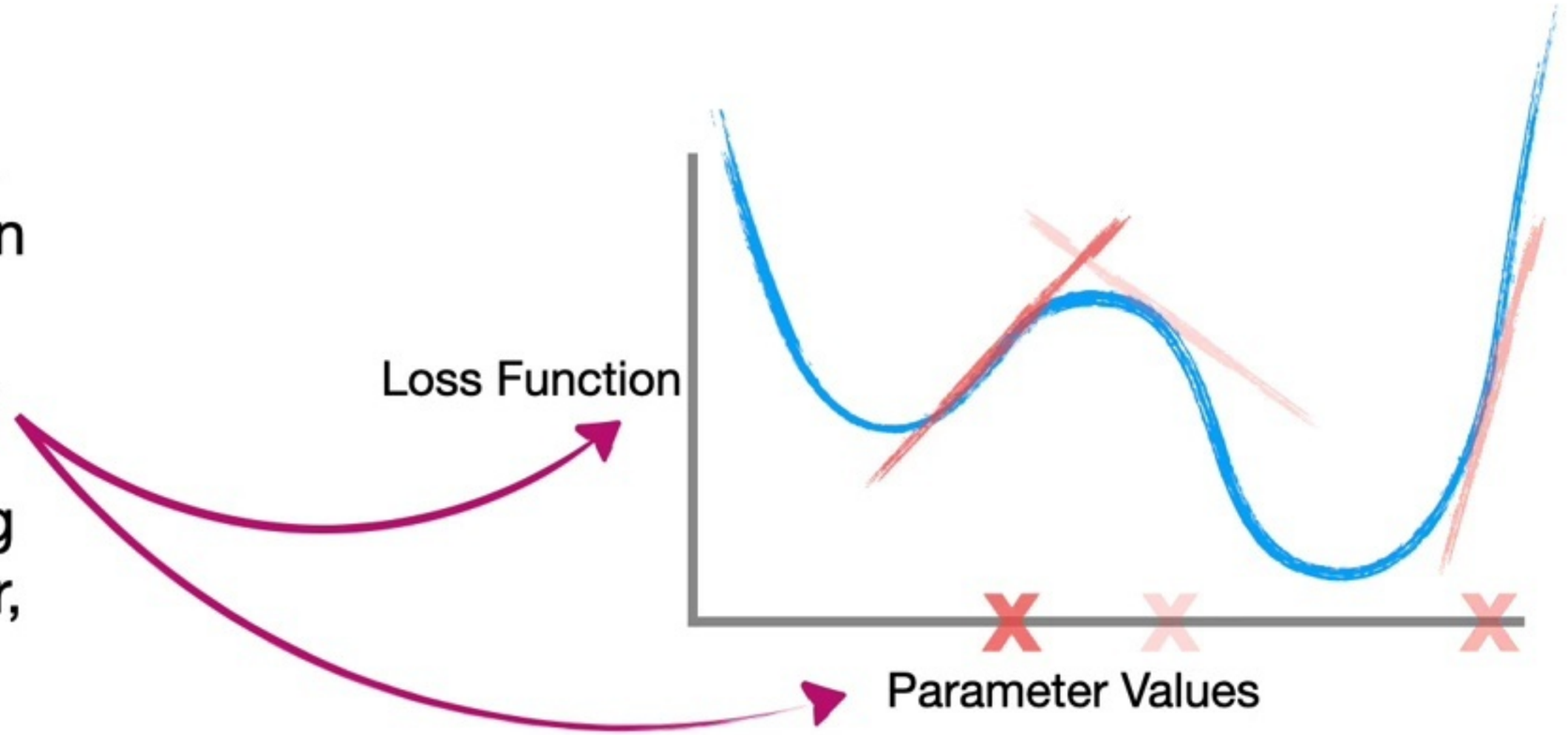

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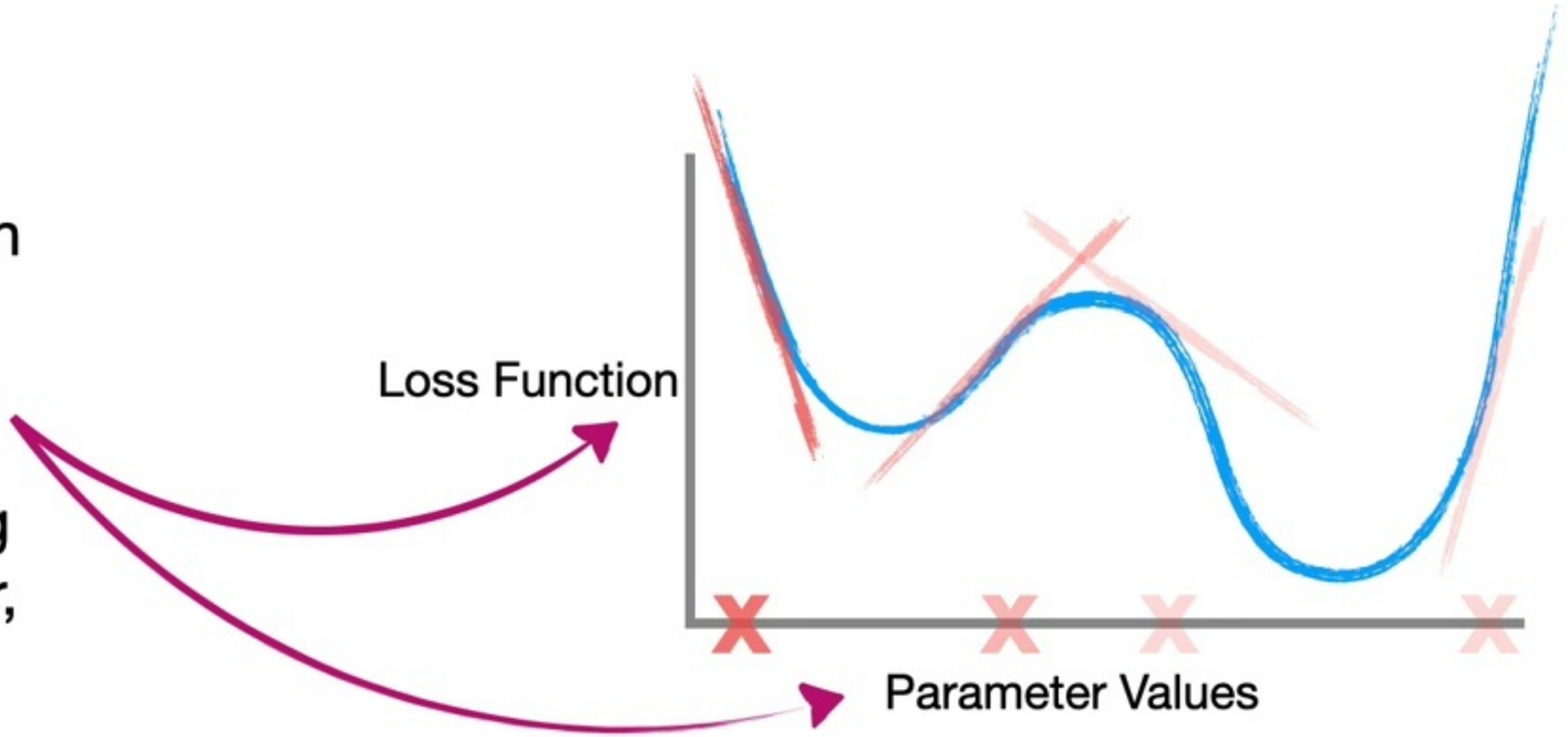

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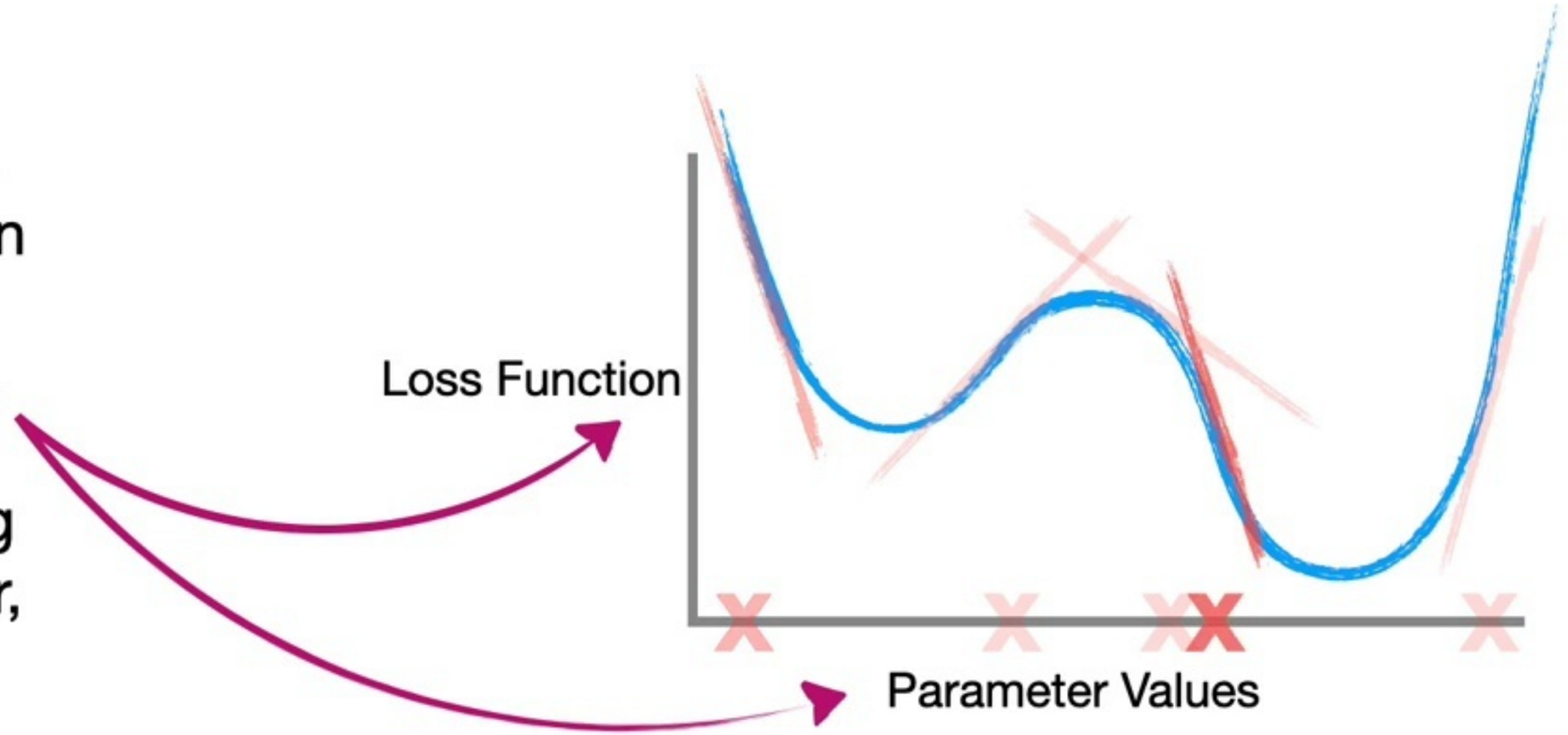

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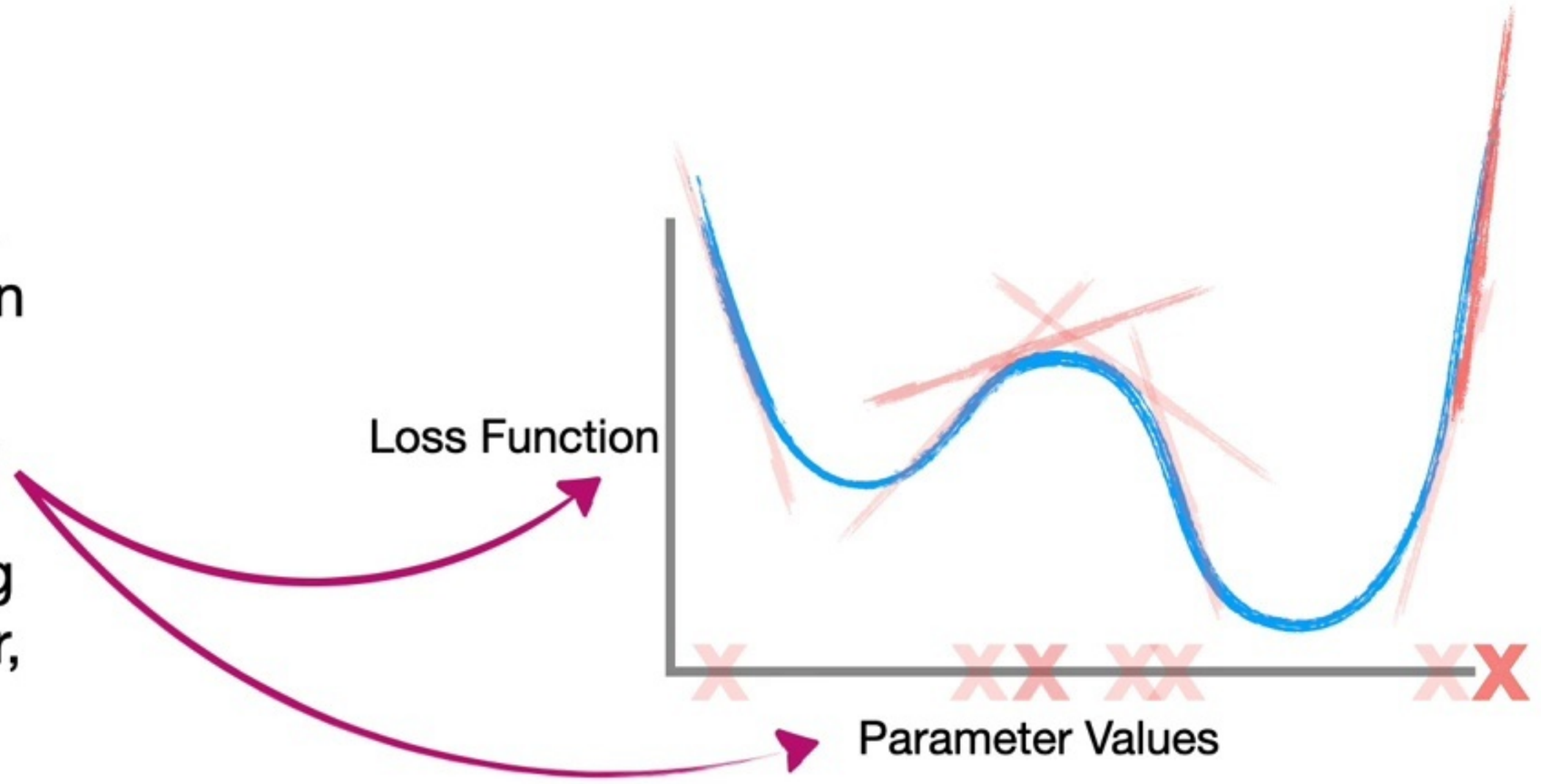

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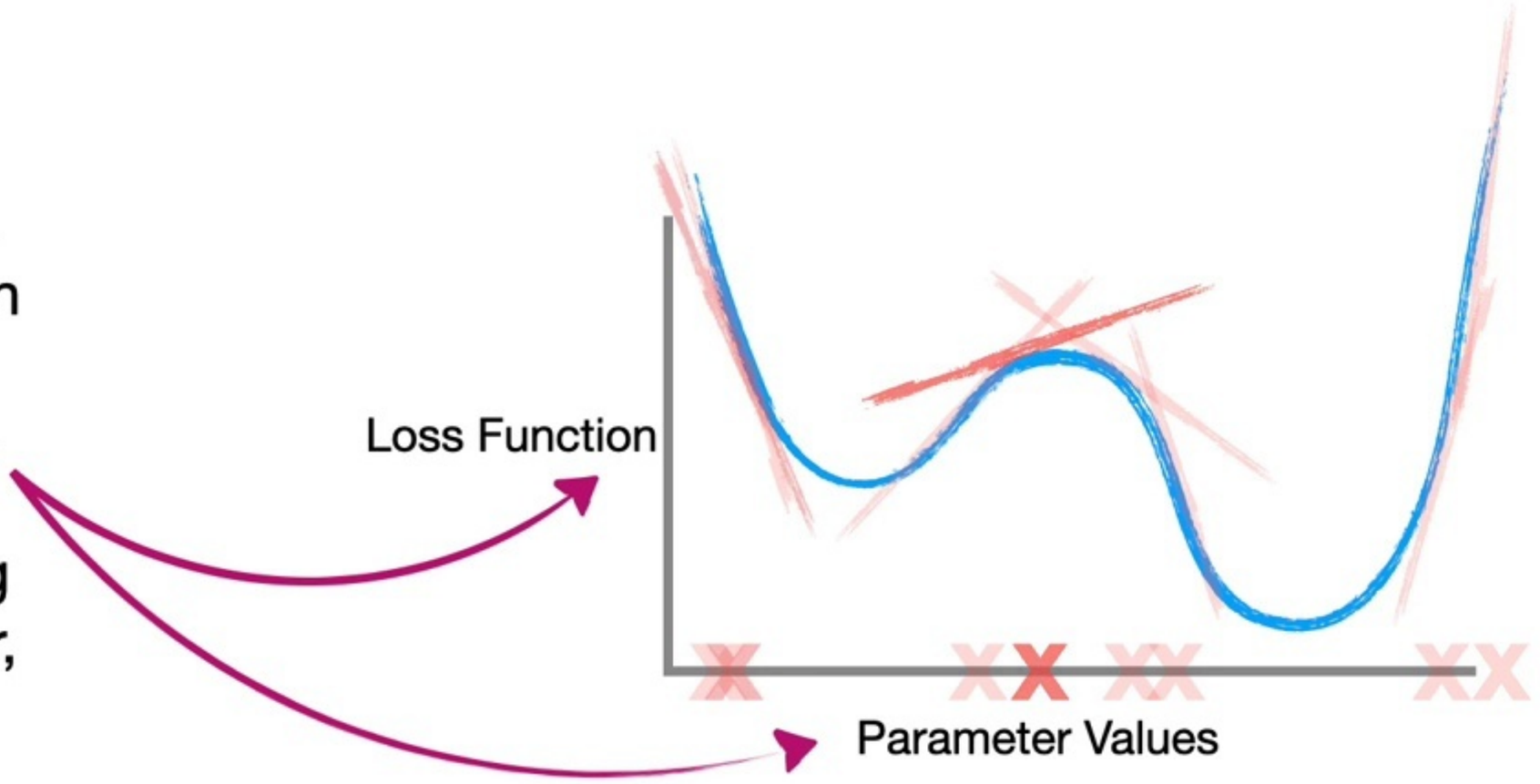
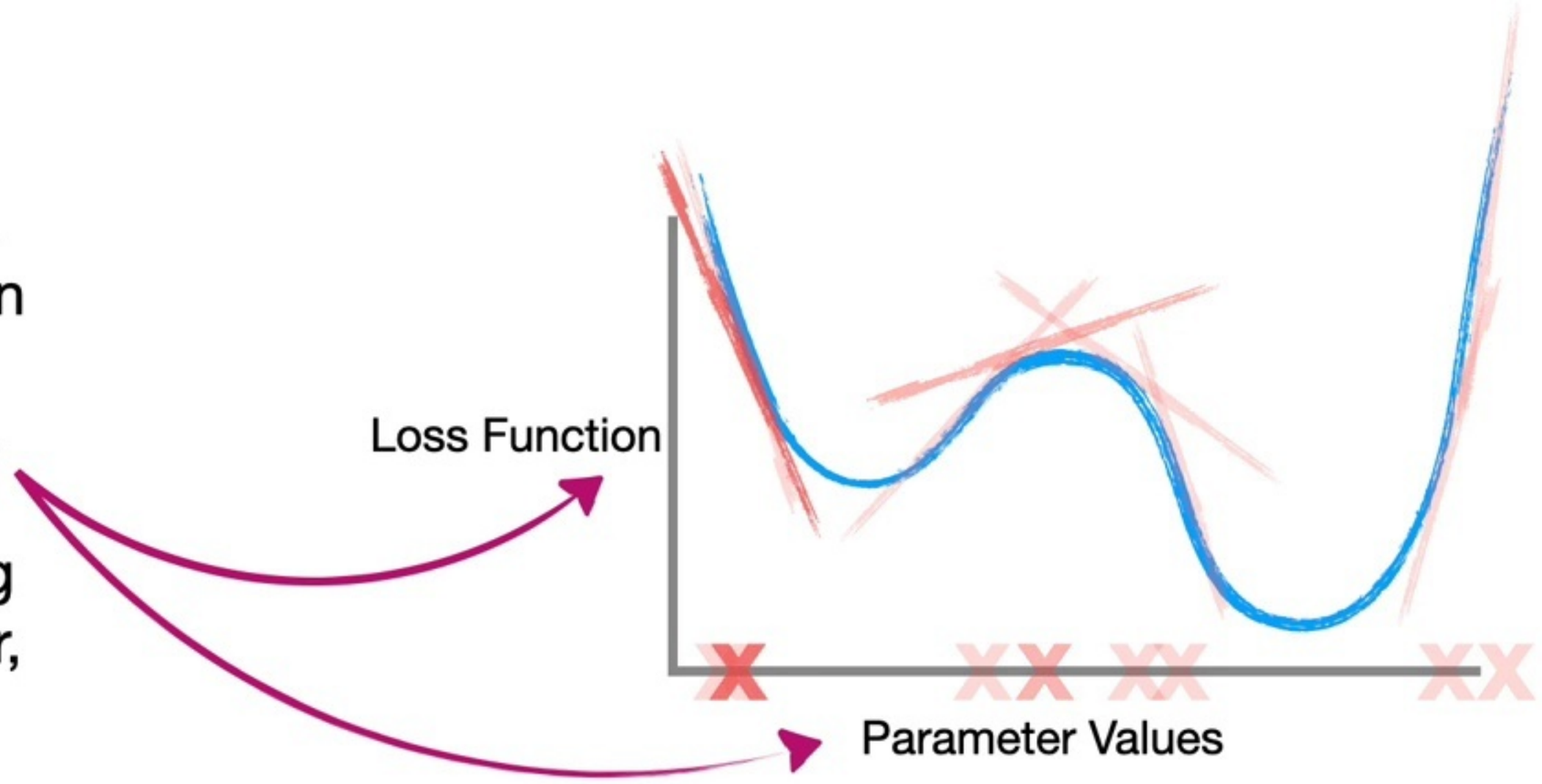
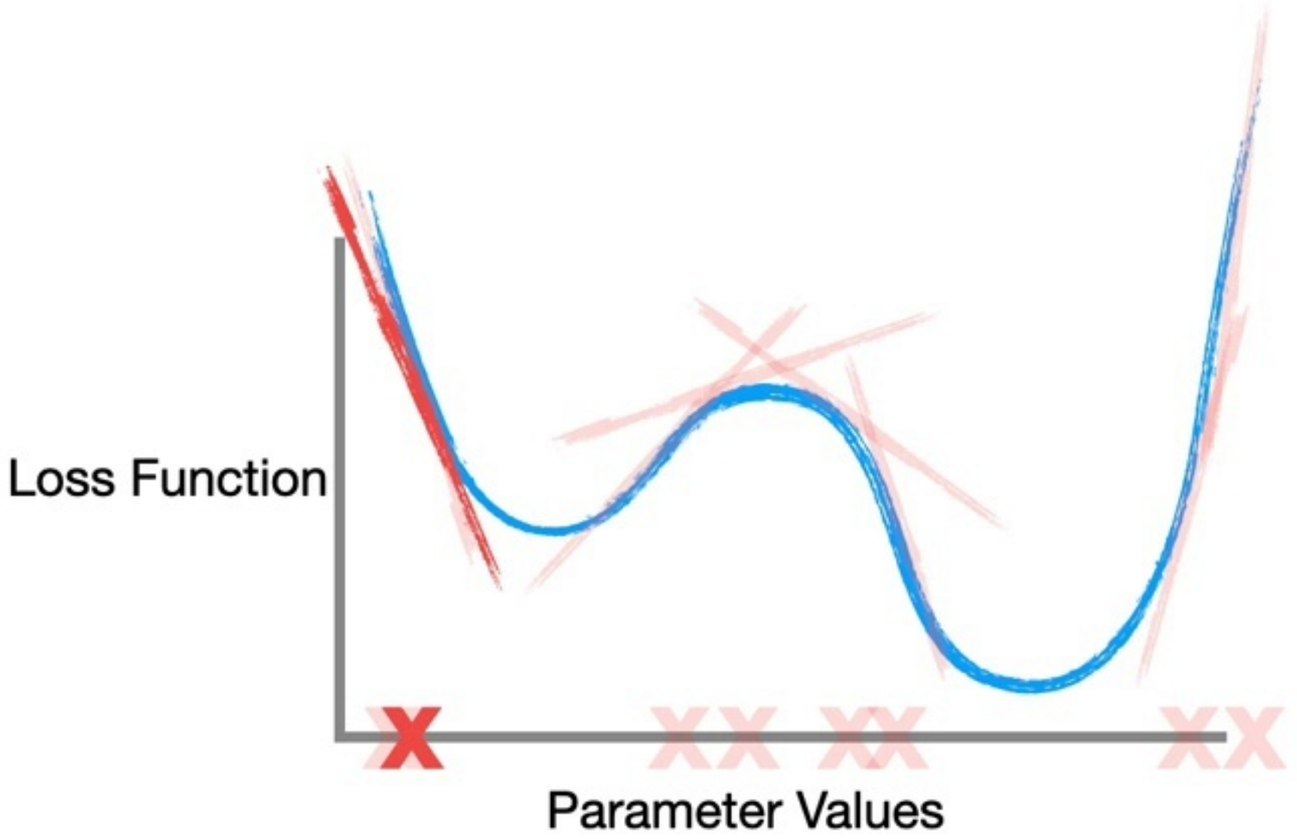


However, when the **Gradient** contains **A HUGE NUMBER**, then we'll end up taking relatively large steps.

And instead of finding the optimal parameter, we'll just bounce around a lot.

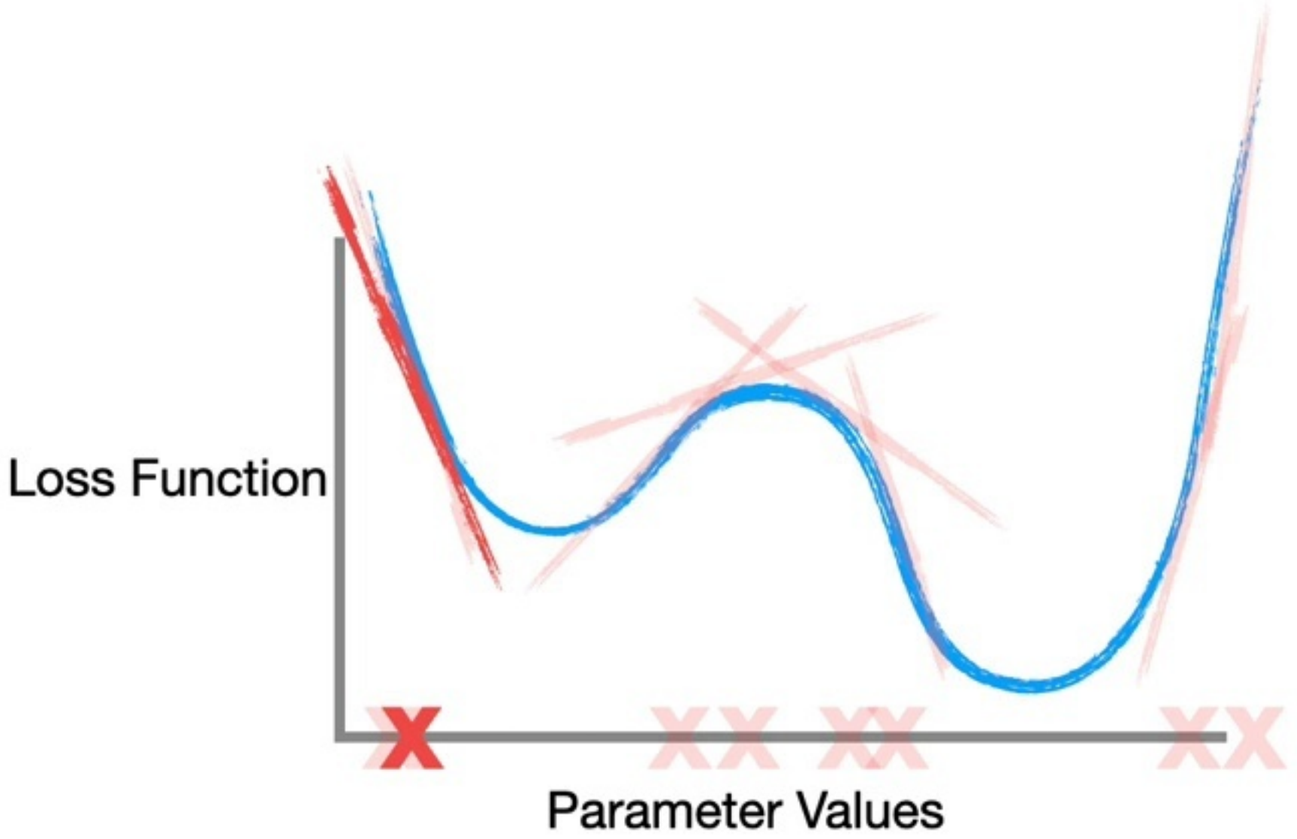


One way to prevent **The Exploding Gradient Problem** would be to limit w_2 to values **< 1**.



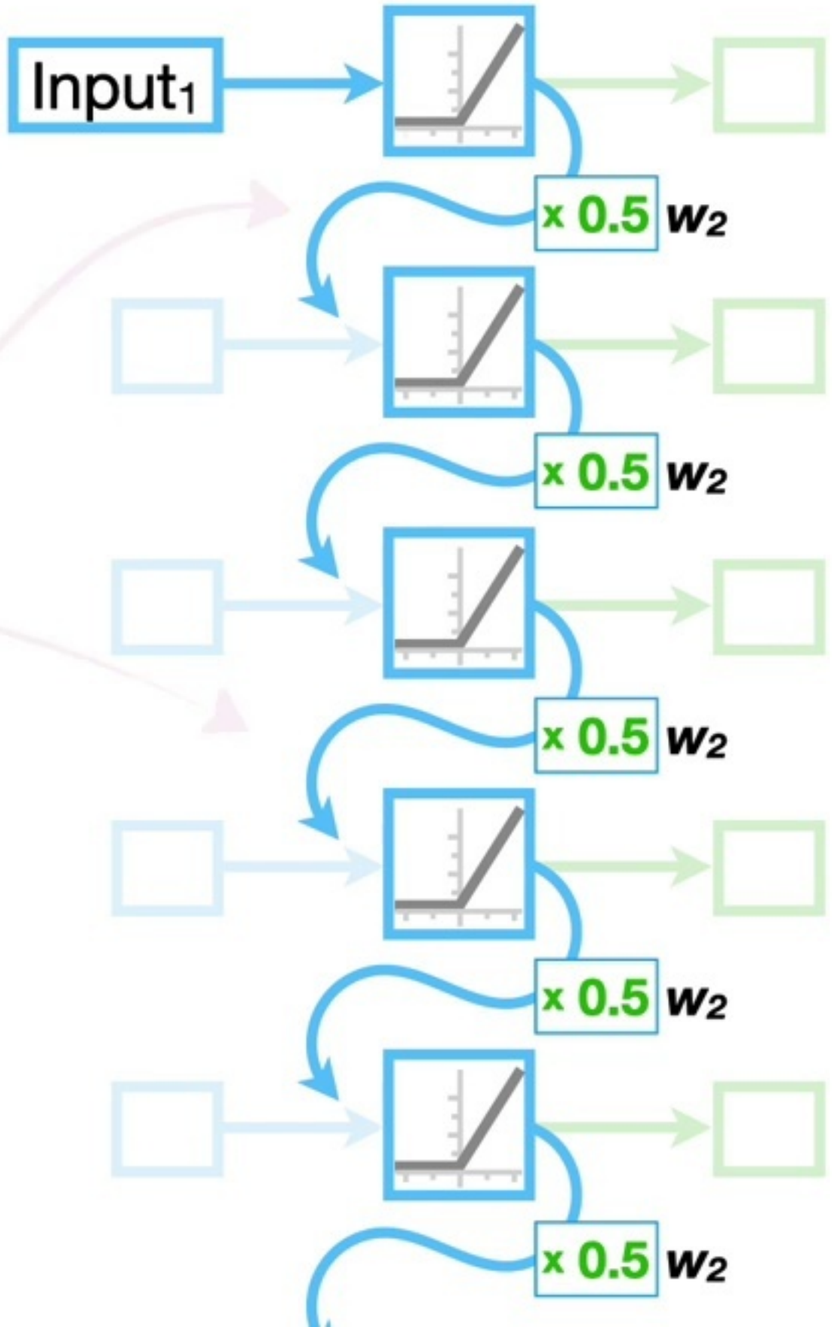
One way to prevent **The Exploding Gradient Problem** would be to limit w_2 to values **< 1**.

However, this results in **The Vanishing Gradient Problem**.



Now, just like before, we multiply the first input by w_2 raised to the number of times we **unroll** the network.

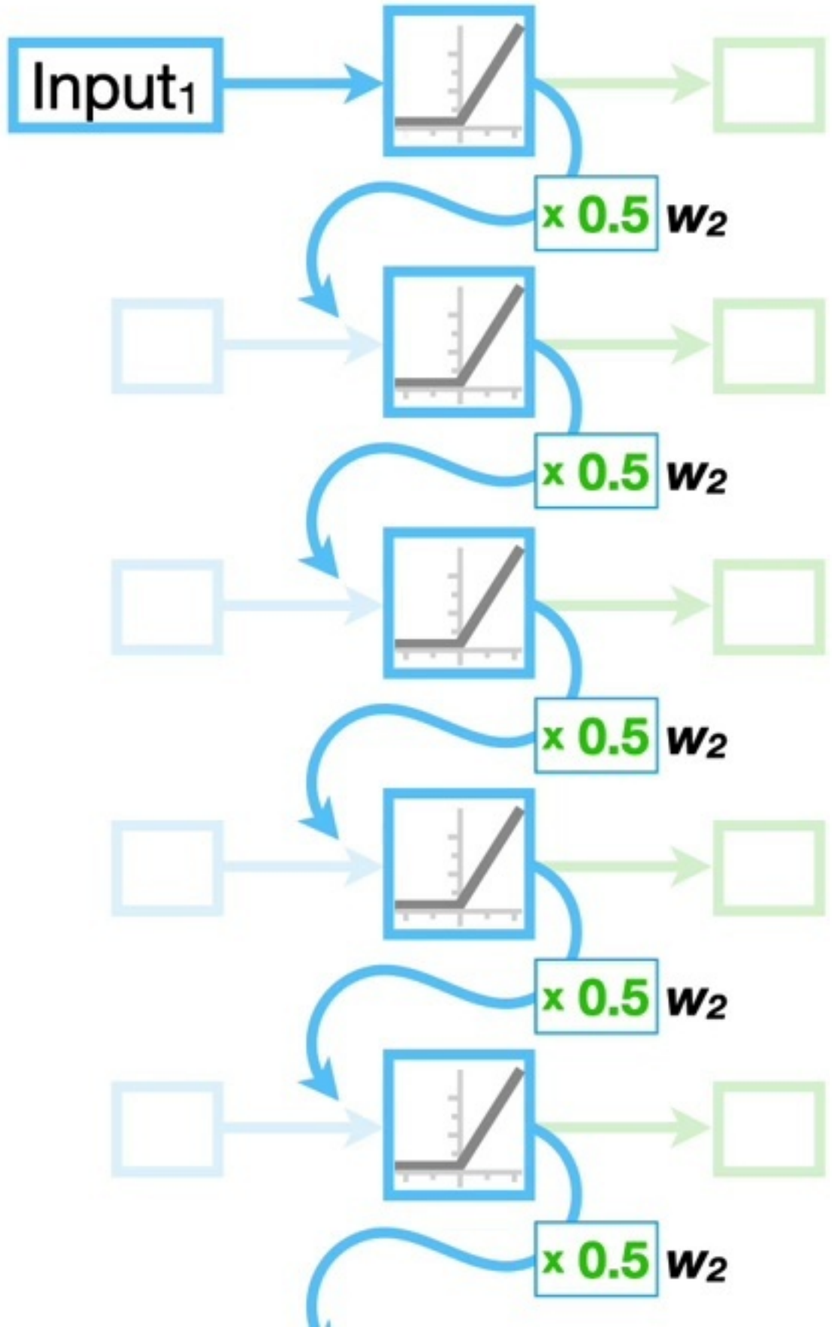
$$\textbf{Input}_1 \times w_2^{\textbf{Num. Unroll}}$$

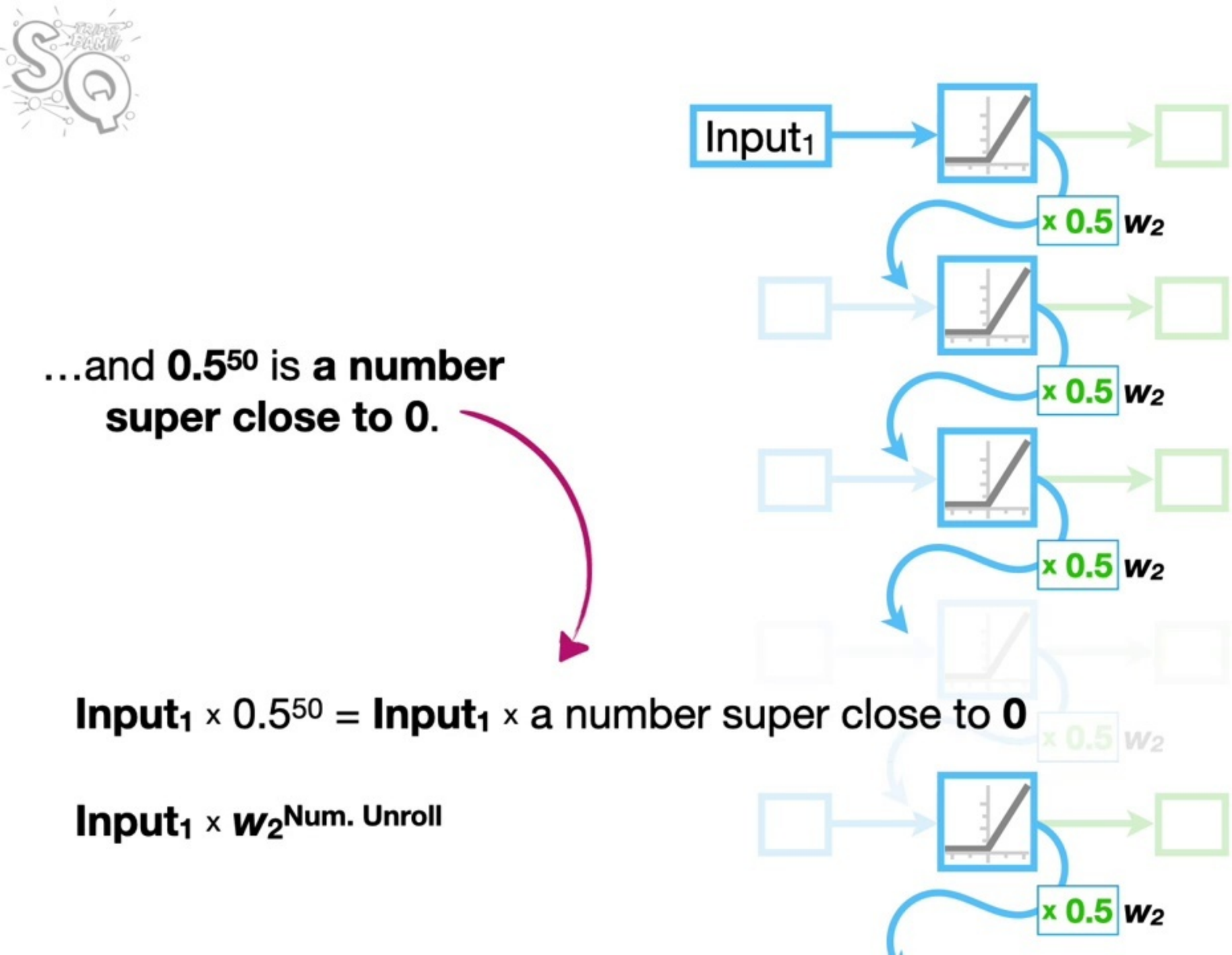


So if we have **50** sequential input values, that means multiplying **Input$_1$** by **0.5^{50}**…

Input$_1$ x 0.5^{50}

Input$_1$ x $w_2^{\text{Num. Unroll}}$

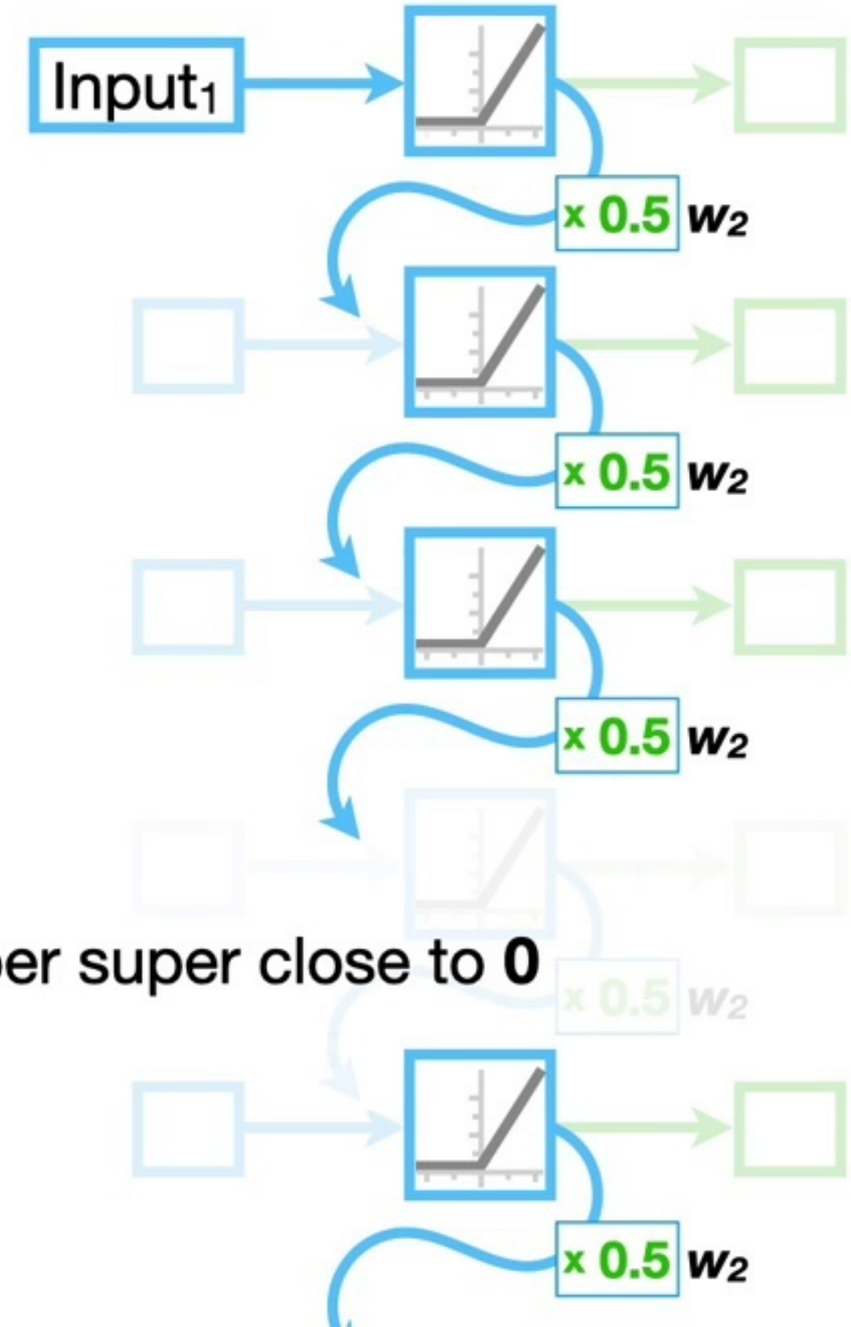




…and **0.5^{50} is a number super close to 0.**

$Input_1 \times 0.5^{50} = Input_1 \times$ a number super close to 0

$Input_1 \times w_2^{\text{Num. Unroll}}$

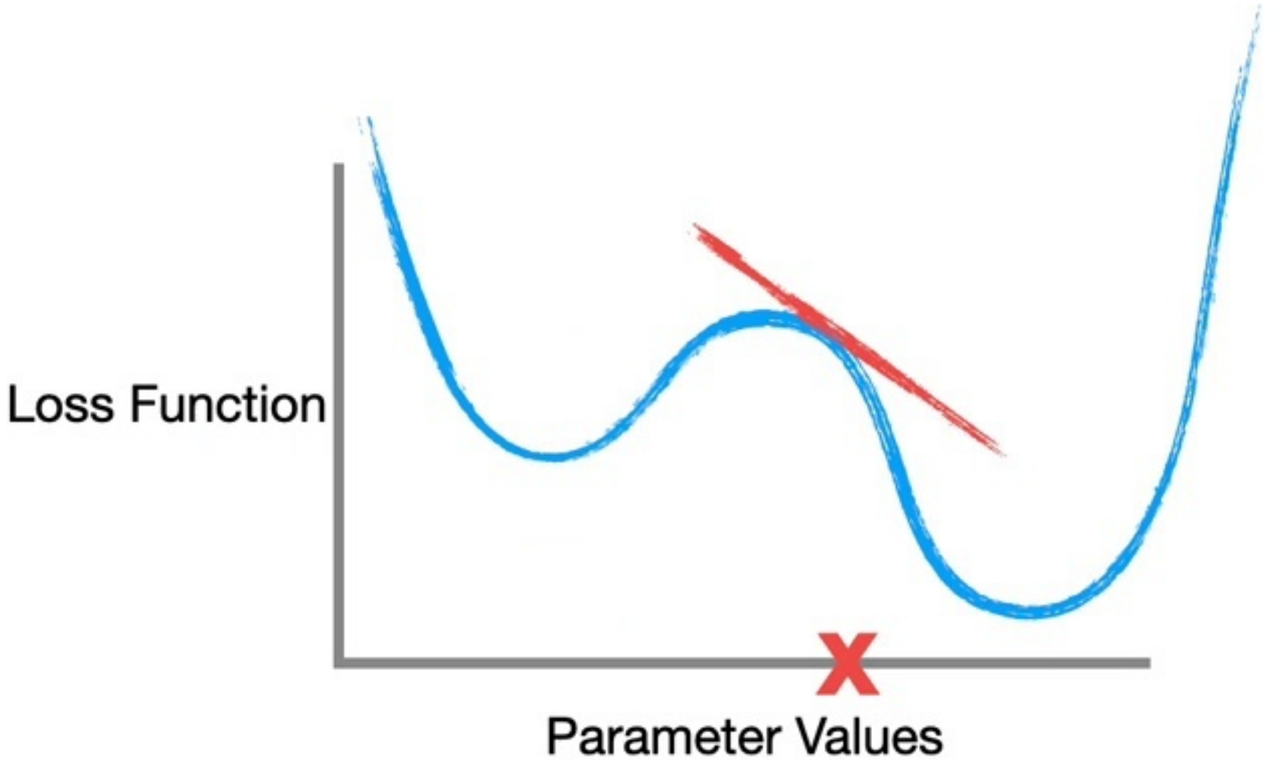


Because this number is **super close to 0**, this is called the **Vanishing Gradient Problem**.

Input$_1$ x 0.5^{50} = **Input$_1$** x a number super close to **0**

Input$_1$ x $w_2^{\text{Num. Unroll}}$

Now, when optimizing a parameter, instead of taking steps that are too large, we end up taking steps that are too small.



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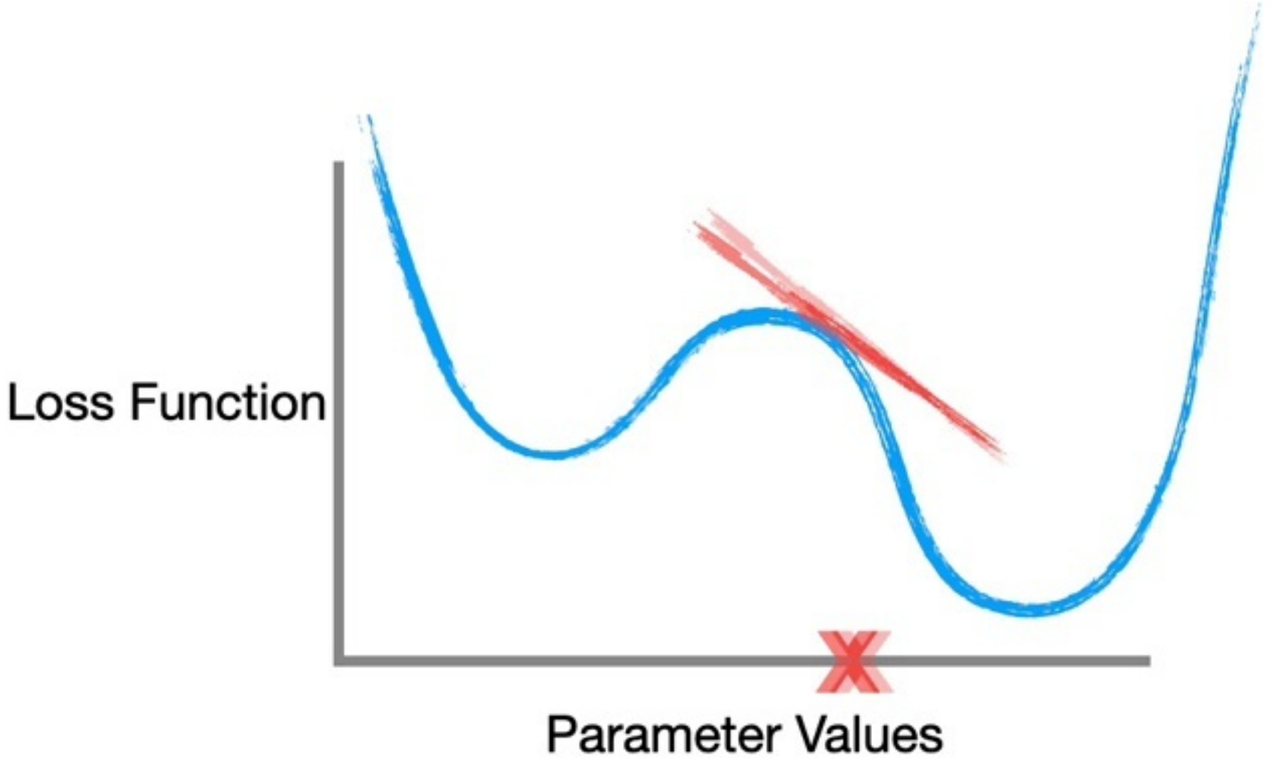

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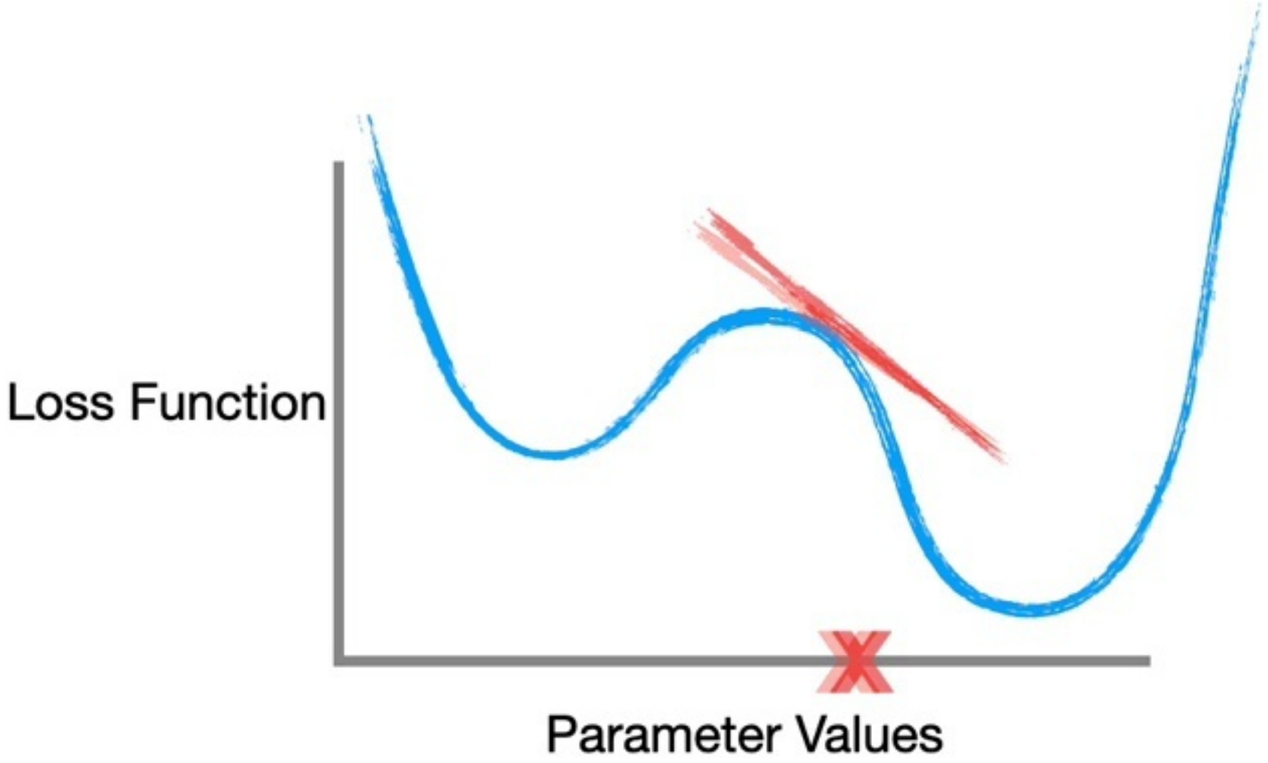

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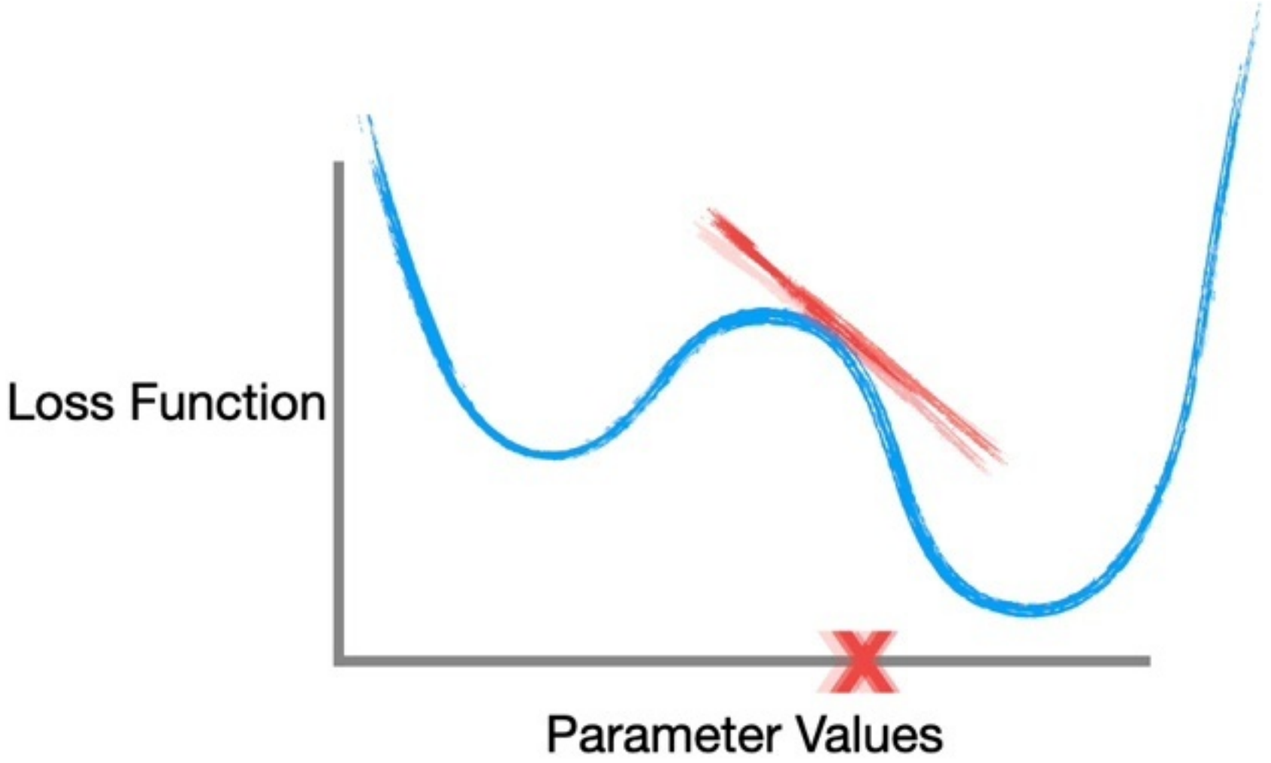

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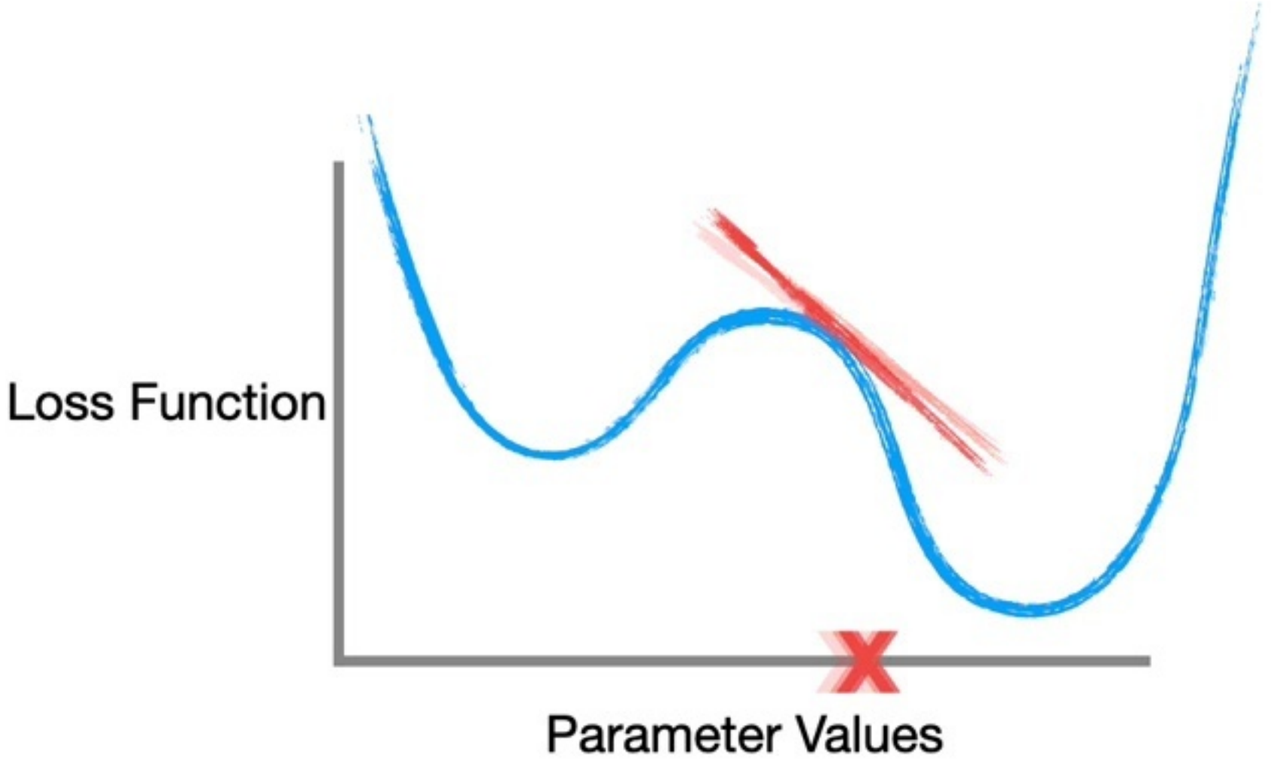

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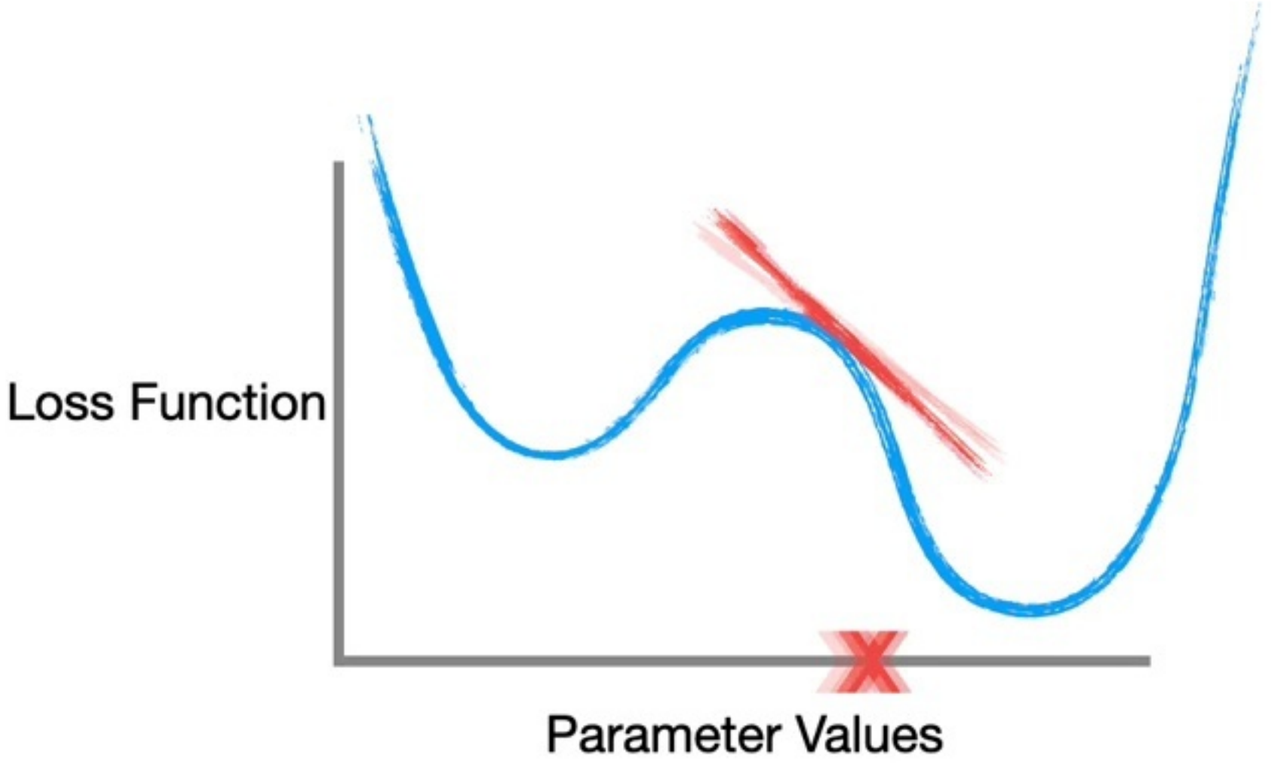

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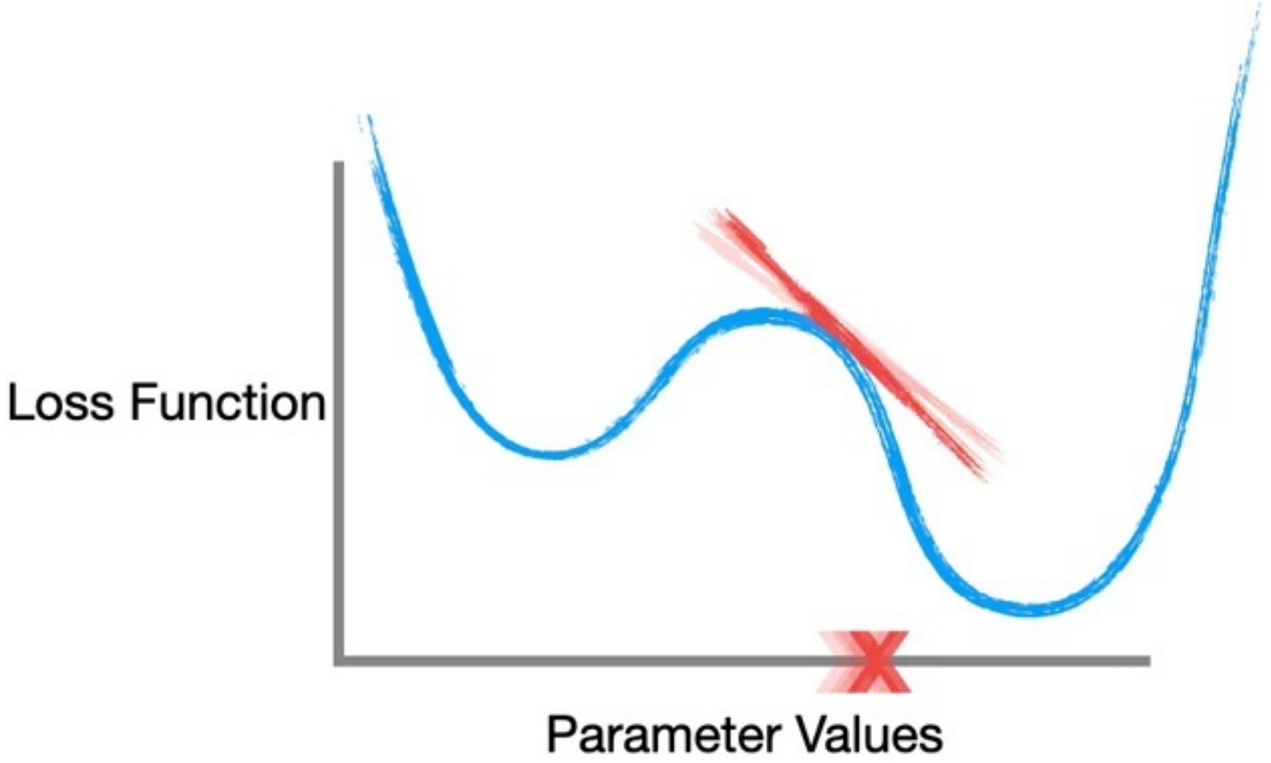

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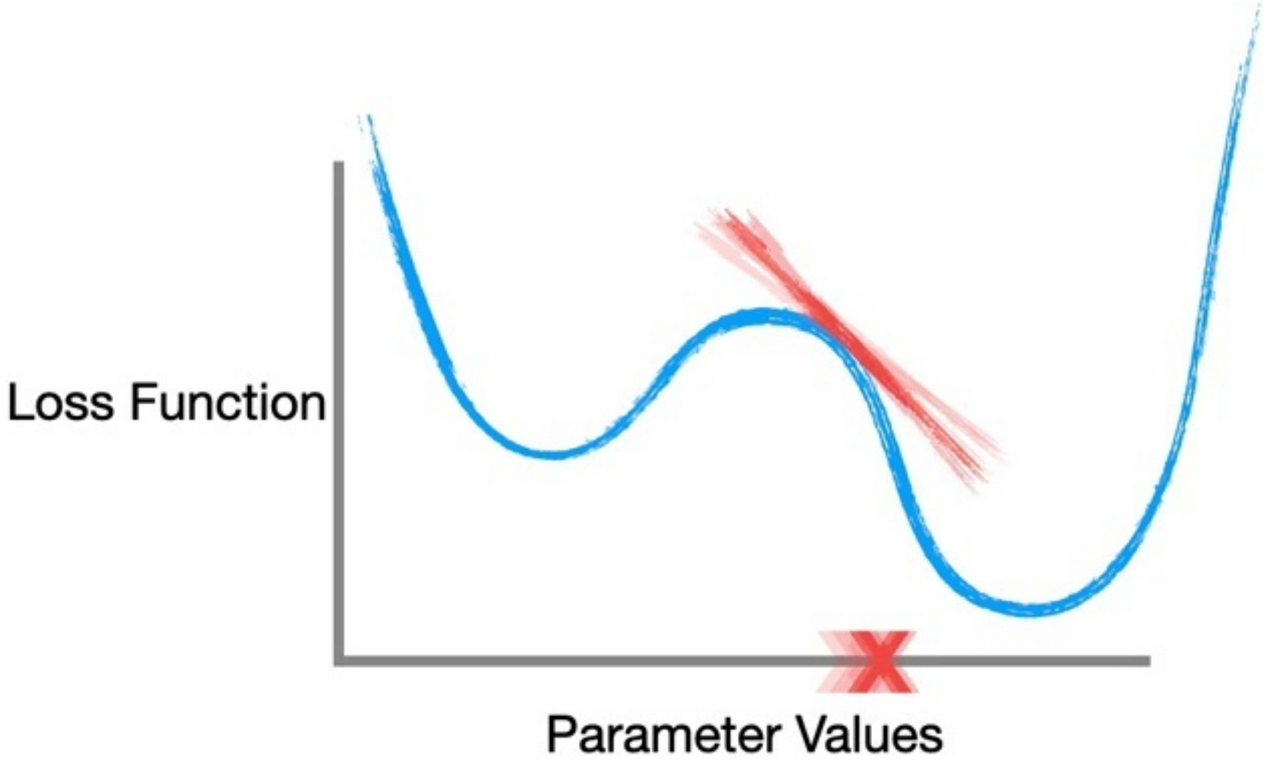

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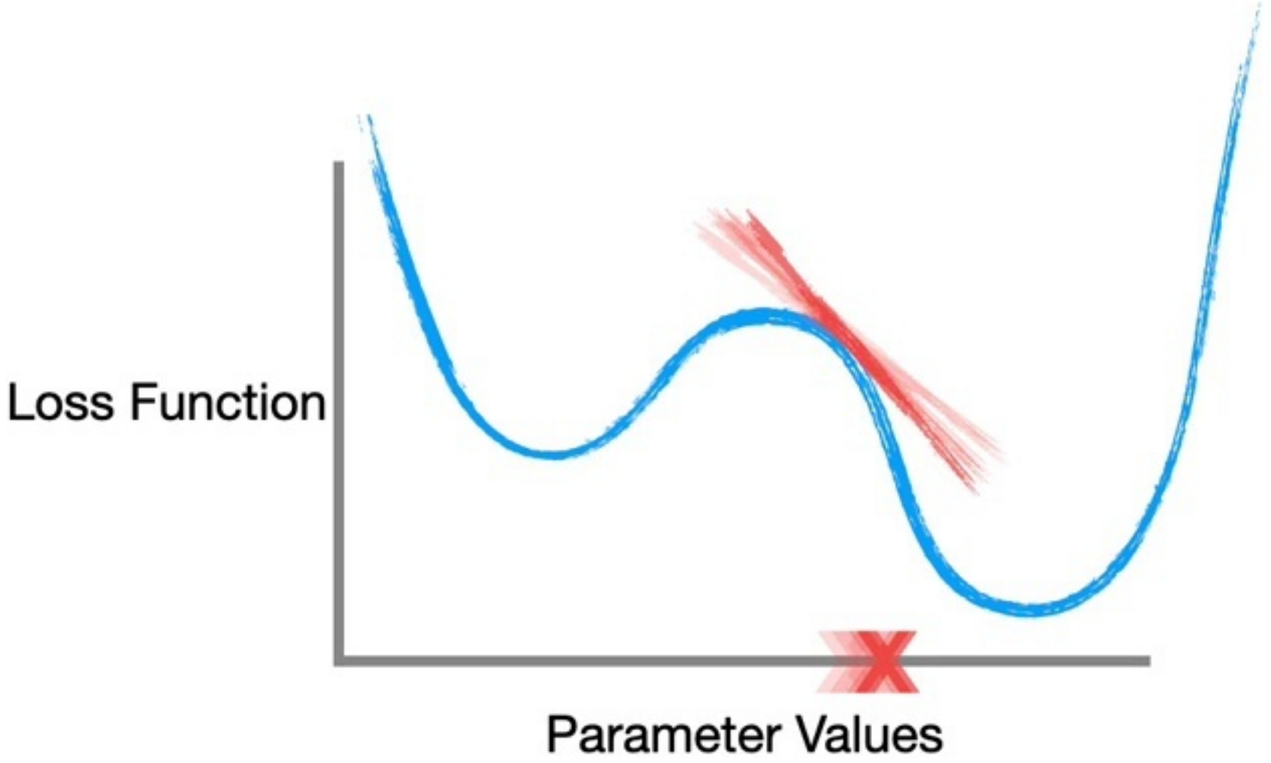

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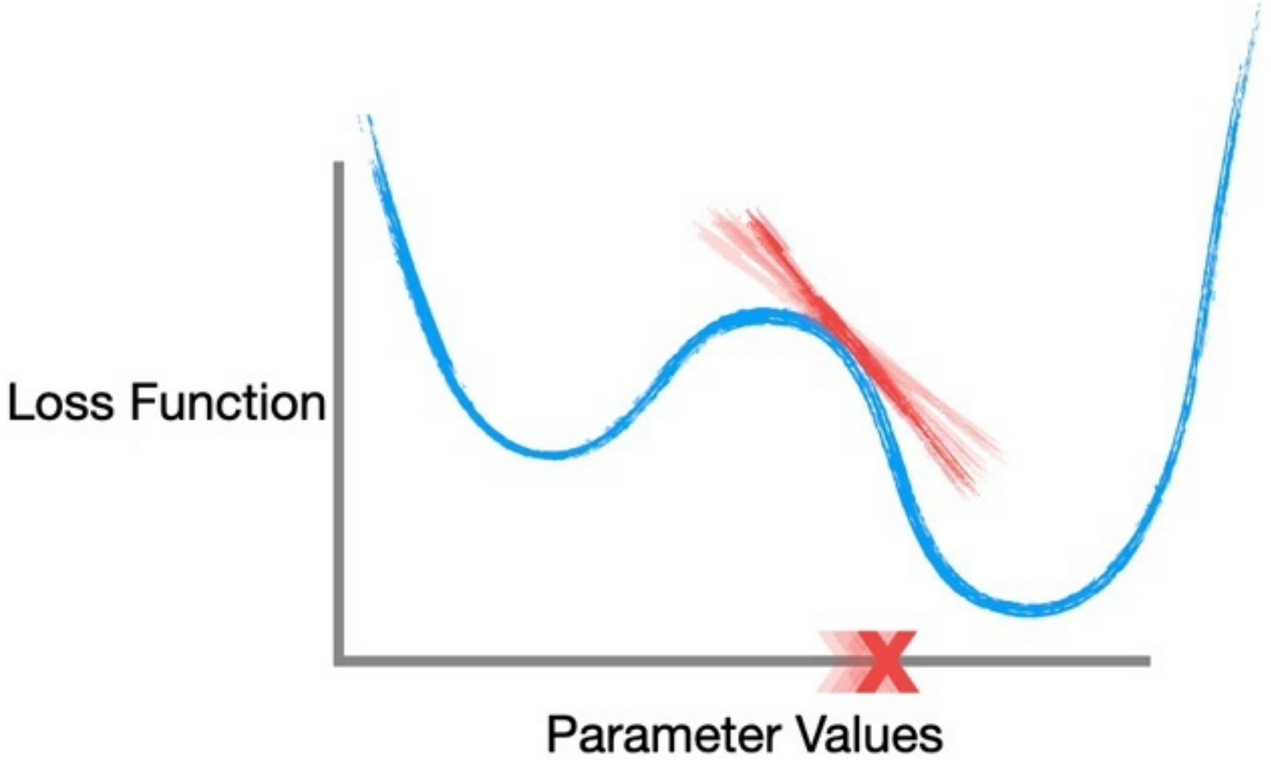

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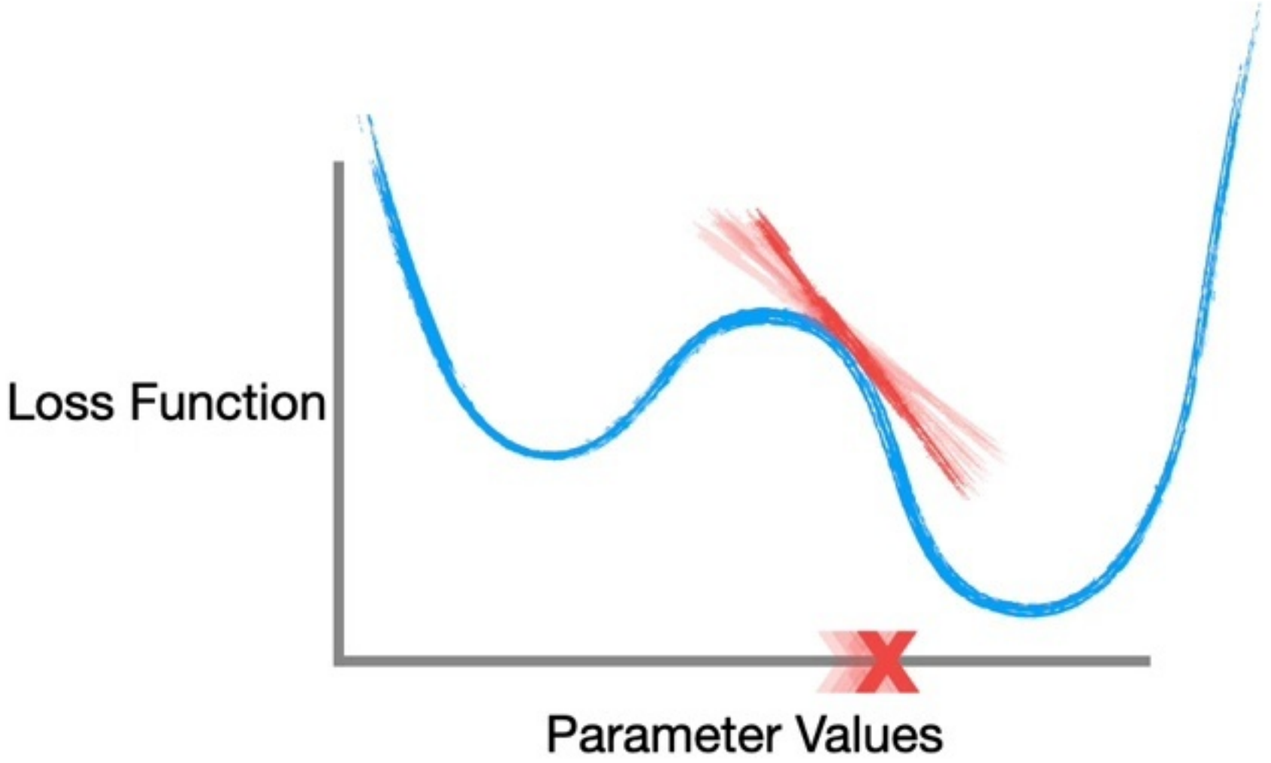

And as a result, we end up hitting the maximum number of steps we are allowed to take before we find the optimal value.