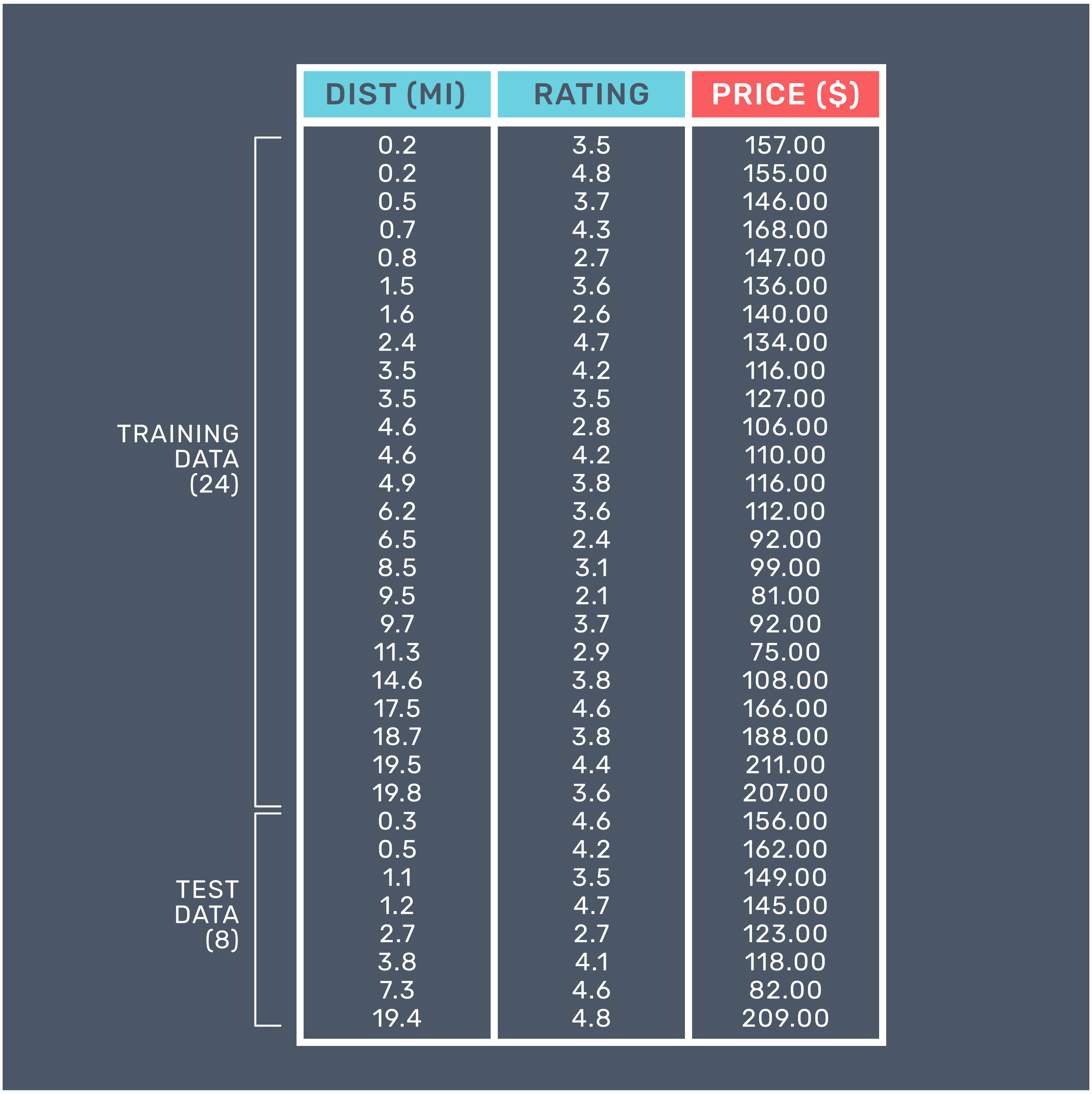


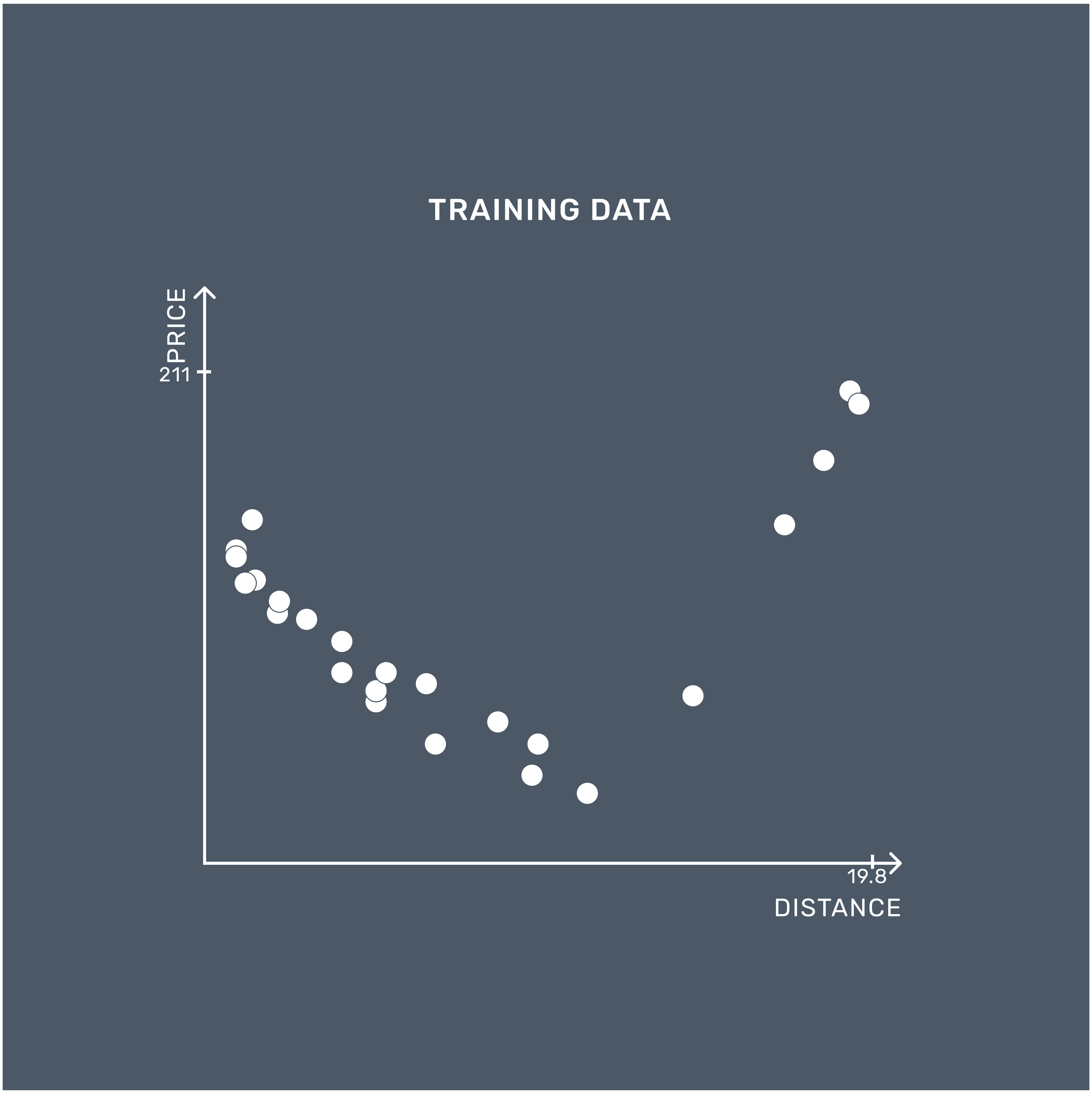
| | DIST (MI) | RATING | PRICE ($) |
|---|---|---|---|
| TRAINING DATA (24) | 0.2 | 3.5 | 157.00 |
| | 0.2 | 4.8 | 155.00 |
| | 0.5 | 3.7 | 146.00 |
| | 0.7 | 4.3 | 168.00 |
| | 0.8 | 2.7 | 147.00 |
| | 1.5 | 3.6 | 136.00 |
| | 1.6 | 2.6 | 140.00 |
| | 2.4 | 4.7 | 134.00 |
| | 3.5 | 4.2 | 116.00 |
| | 3.5 | 3.5 | 127.00 |
| | 4.6 | 2.8 | 106.00 |
| | 4.6 | 4.2 | 110.00 |
| | 4.9 | 3.8 | 116.00 |
| | 6.2 | 3.6 | 112.00 |
| | 6.5 | 2.4 | 92.00 |
| | 8.5 | 3.1 | 99.00 |
| | 9.5 | 2.1 | 81.00 |
| | 9.7 | 3.7 | 92.00 |
| | 11.3 | 2.9 | 75.00 |
| | 14.6 | 3.8 | 108.00 |
| | 17.5 | 4.6 | 166.00 |
| | 18.7 | 3.8 | 188.00 |
| | 19.5 | 4.4 | 211.00 |
| | 19.8 | 3.6 | 207.00 |
| TEST DATA (8) | 0.3 | 4.6 | 156.00 |
| | 0.5 | 4.2 | 162.00 |
| | 1.1 | 3.5 | 149.00 |
| | 1.2 | 4.7 | 145.00 |
| | 2.7 | 2.7 | 123.00 |
| | 3.8 | 4.1 | 118.00 |
| | 7.3 | 4.6 | 82.00 |
| | 19.4 | 4.8 | 209.00 |

## THE DATASET

The difference is this time, we have two features instead of one. Here, we bring back the rating feature that we left out in Chapter 1.

Another difference is the size of the dataset. We had only 12 data points in Chapter 1. For this task, we are adding 20 more, making up a total of 32 data points. We'll use 24 for training and 8 for testing.

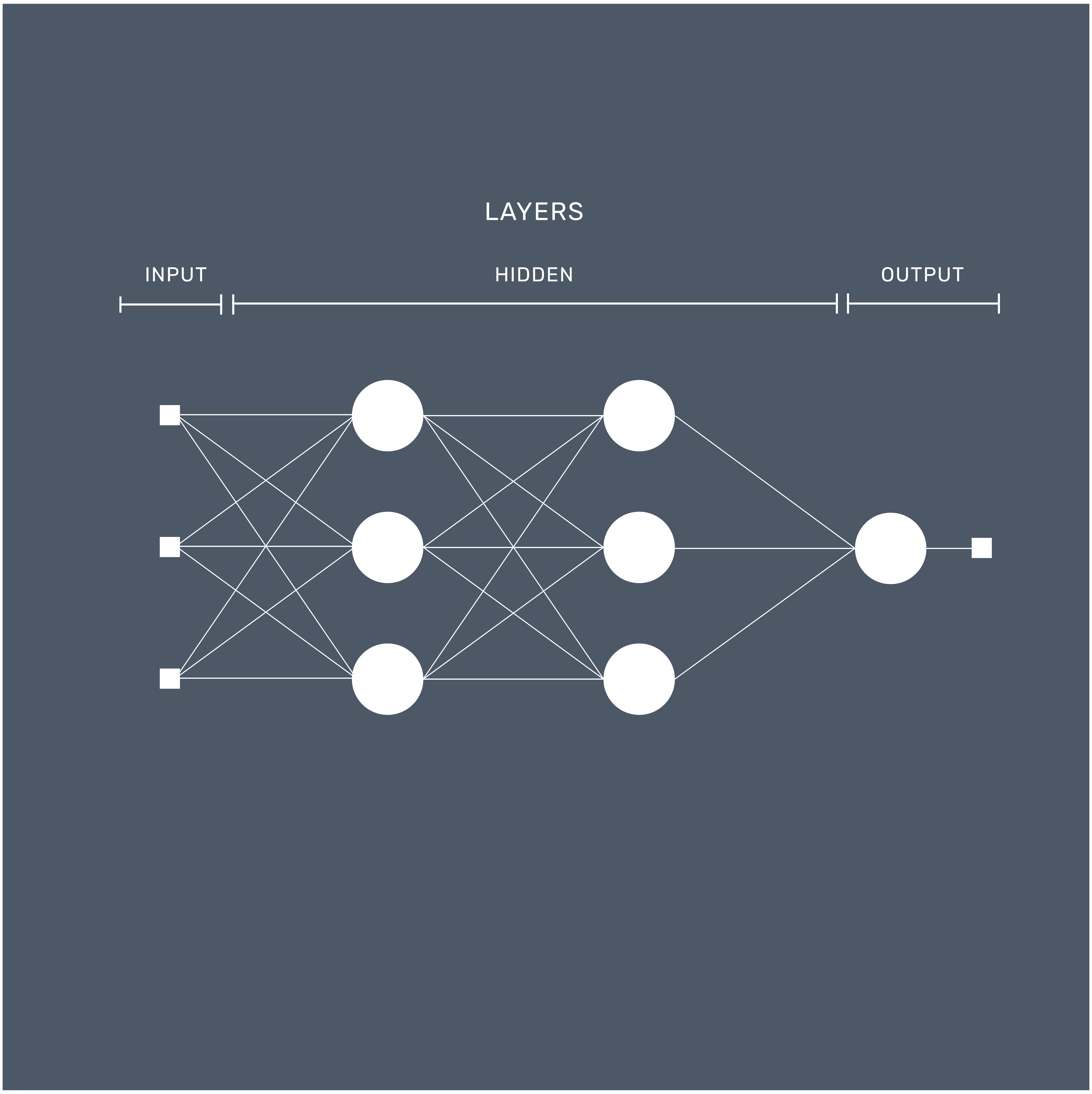
The result is, instead of linear, our task now becomes a *non-linear regression* task. Let's see why this is so.



## THE DATASET

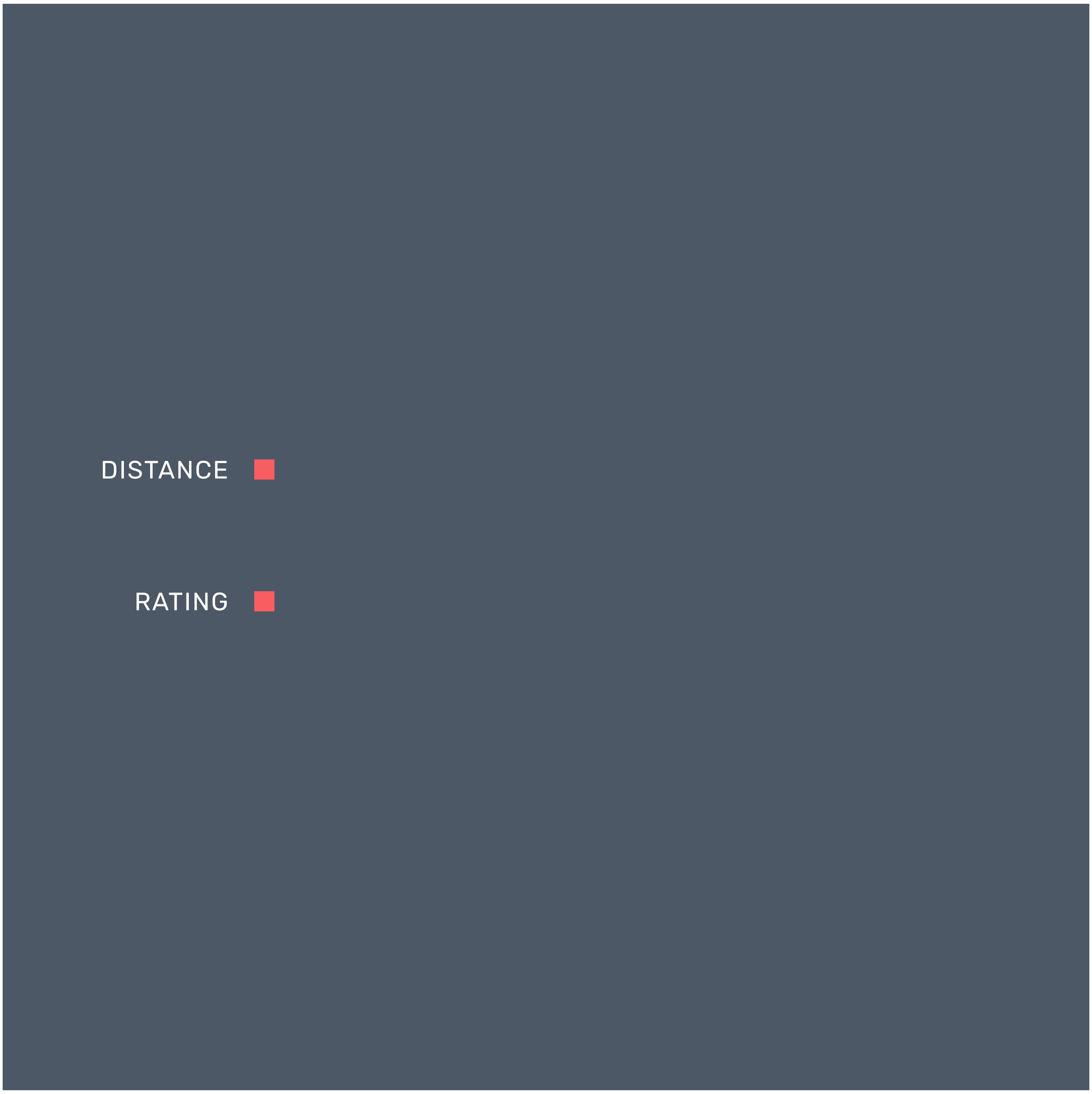
The data points we used in Chapter 1 are on the left side of this curve. As we add more hotels to the dataset, we find that the dynamic changes. In the beginning, the farther we get from the city center, the cheaper the prices become. This is expected because there will be a higher demand for hotels closer to the center. But there is a point in the middle where the room rates get more expensive the further away we get. The reason is that these are the resort-type hotels that charge similar, if not higher, prices.

This dataset no longer has a linear relationship. The distance-price relationship now has a bowl shape, which is *non-linear*. This is what we want our neural network to produce.



## LAYERS

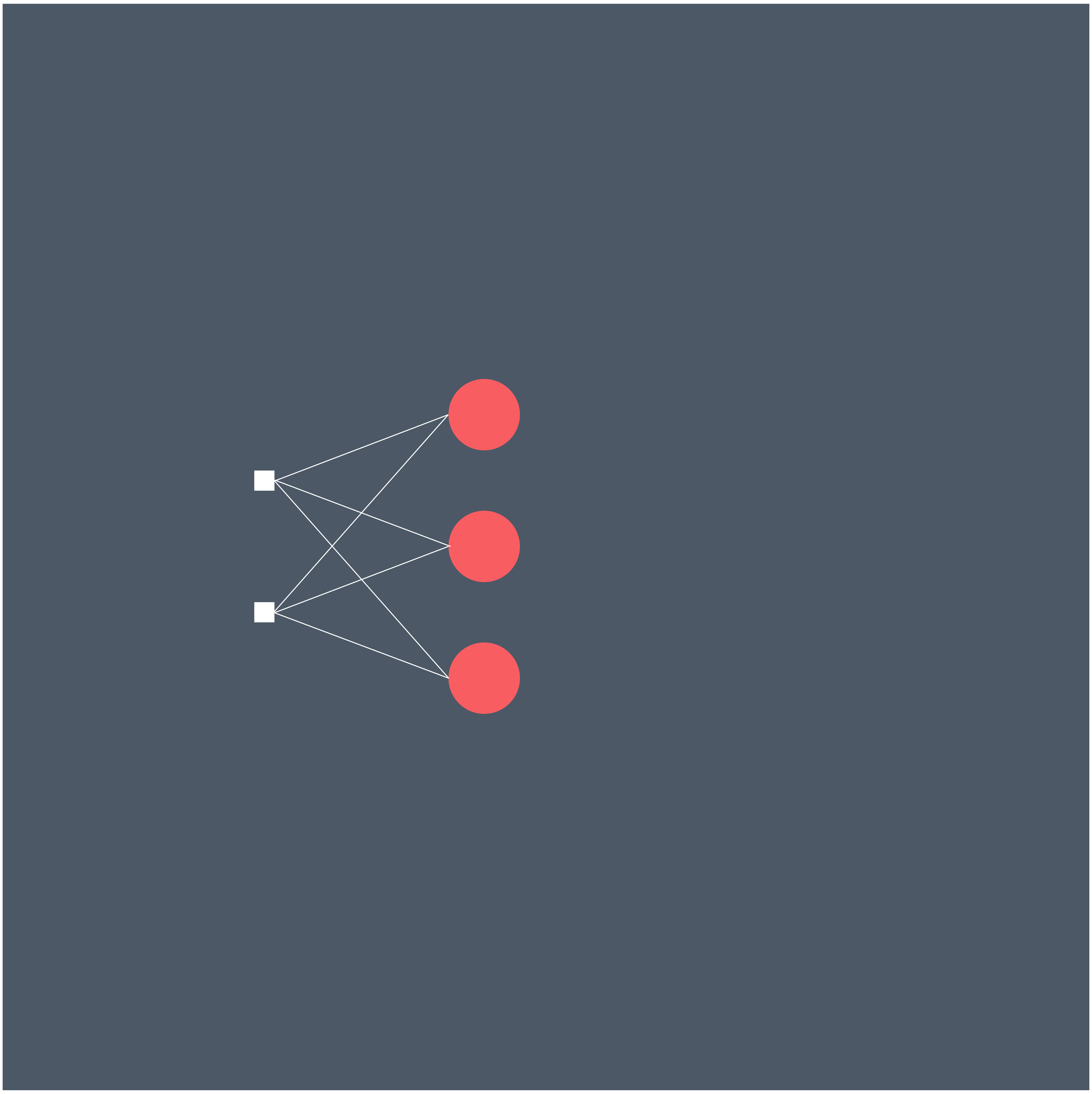
We have seen that a neural network consists of layers. A typical neural network, like the one we are building, has one *input layer* and one *output layer*. Everything in between is called the *hidden layer*.



## INPUT LAYER

Let's get started with the architecture.

The number of inputs is equal to the number of features, which means we'll have two inputs.



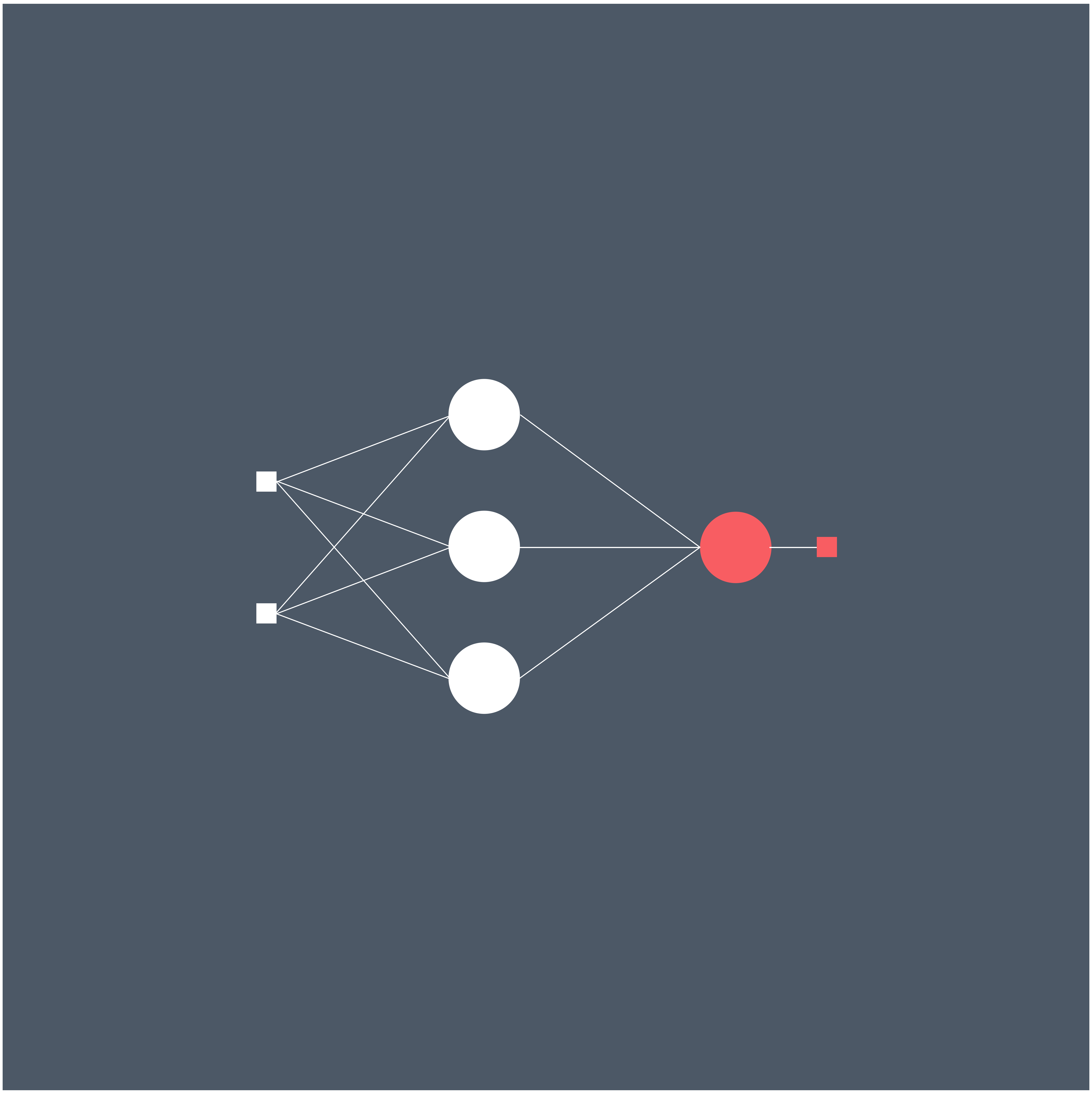
## HIDDEN LAYER

We'll have one hidden layer consisting of three units of neurons.

The choice of the number of layers and units depends on the complexity of the data and the task. In our case, we have a small dataset, so this configuration is sufficient.

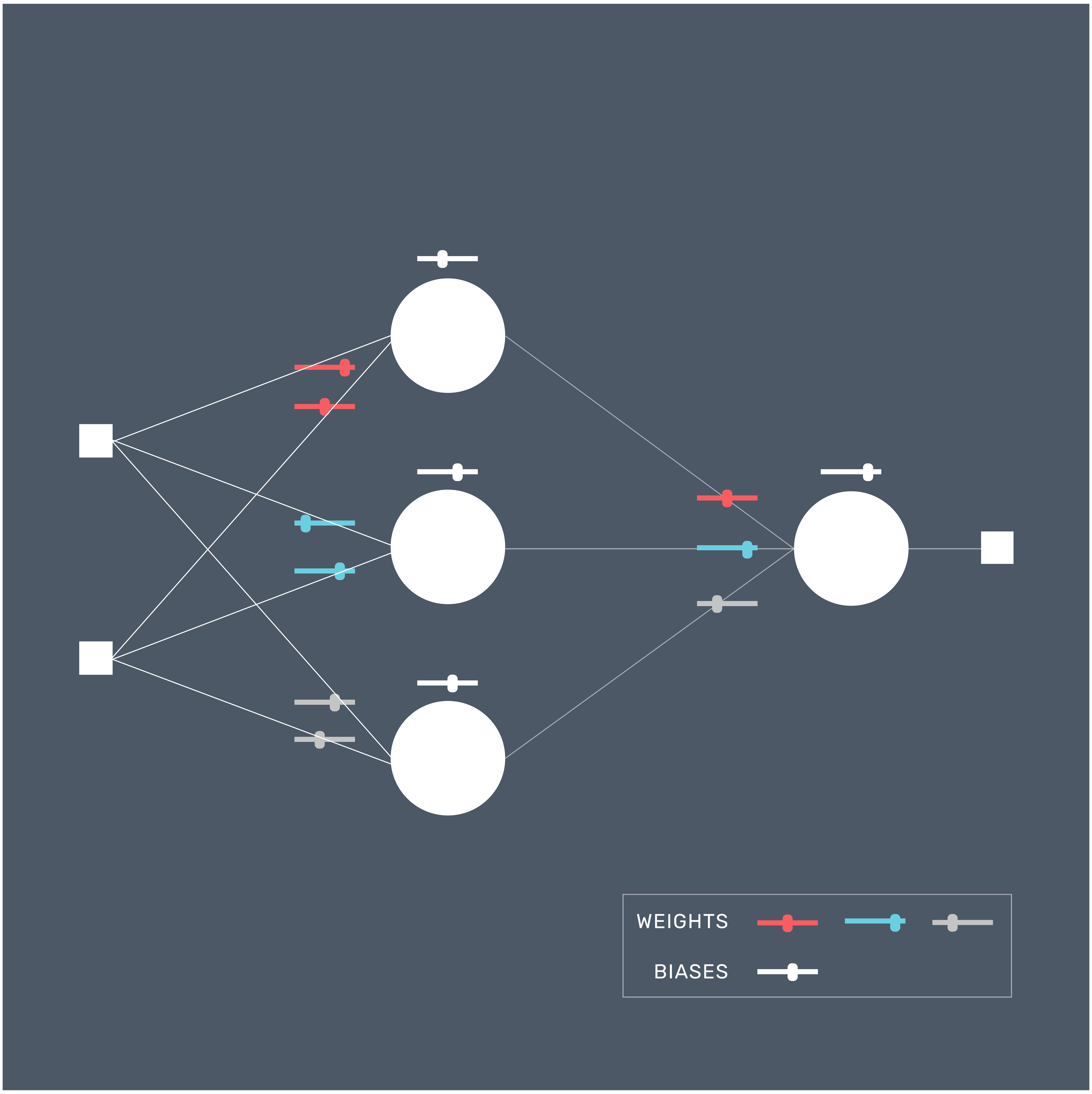
What do hidden layers do? A hidden layer transforms the information it receives from the previous layer into useful forms. Guided by the goal of the task, it looks for patterns and signals and decides which ones are important.

This cascades across the layers and up to the output layer, which will have received a summarized and relevant piece of information to aid its predictions.



## OUTPUT LAYER

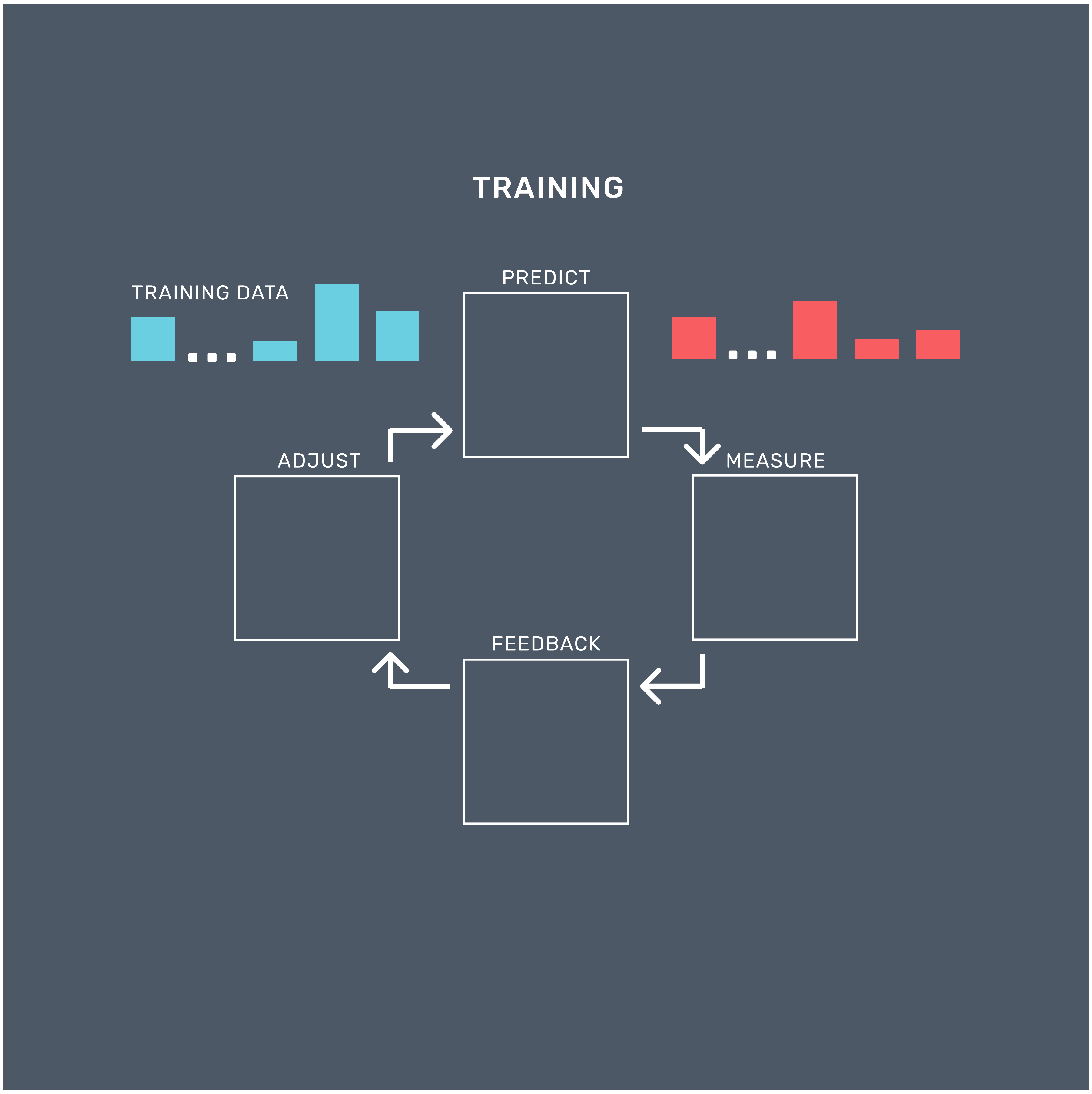
We complete the neural network by adding one unit of neuron in the output layer, whose job is to output the predicted prices.



## WEIGHTS AND BIASES

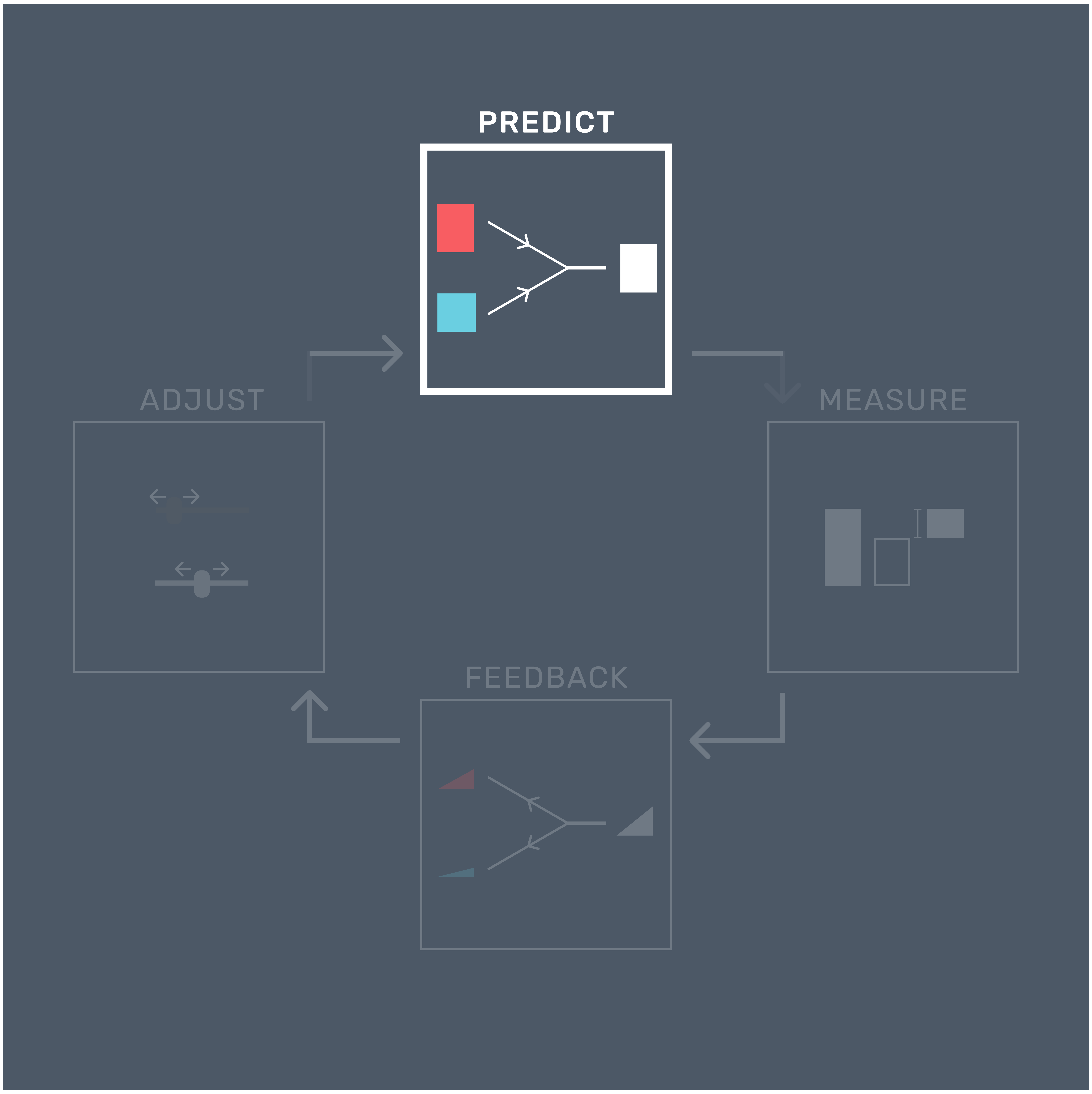
As for the parameters, recall that each neuron has weights equal to the number of its inputs and one bias.

So, in our case, we have a total of nine weights and four biases. And as in Chapter 1, we'll assign initial values for these parameters.



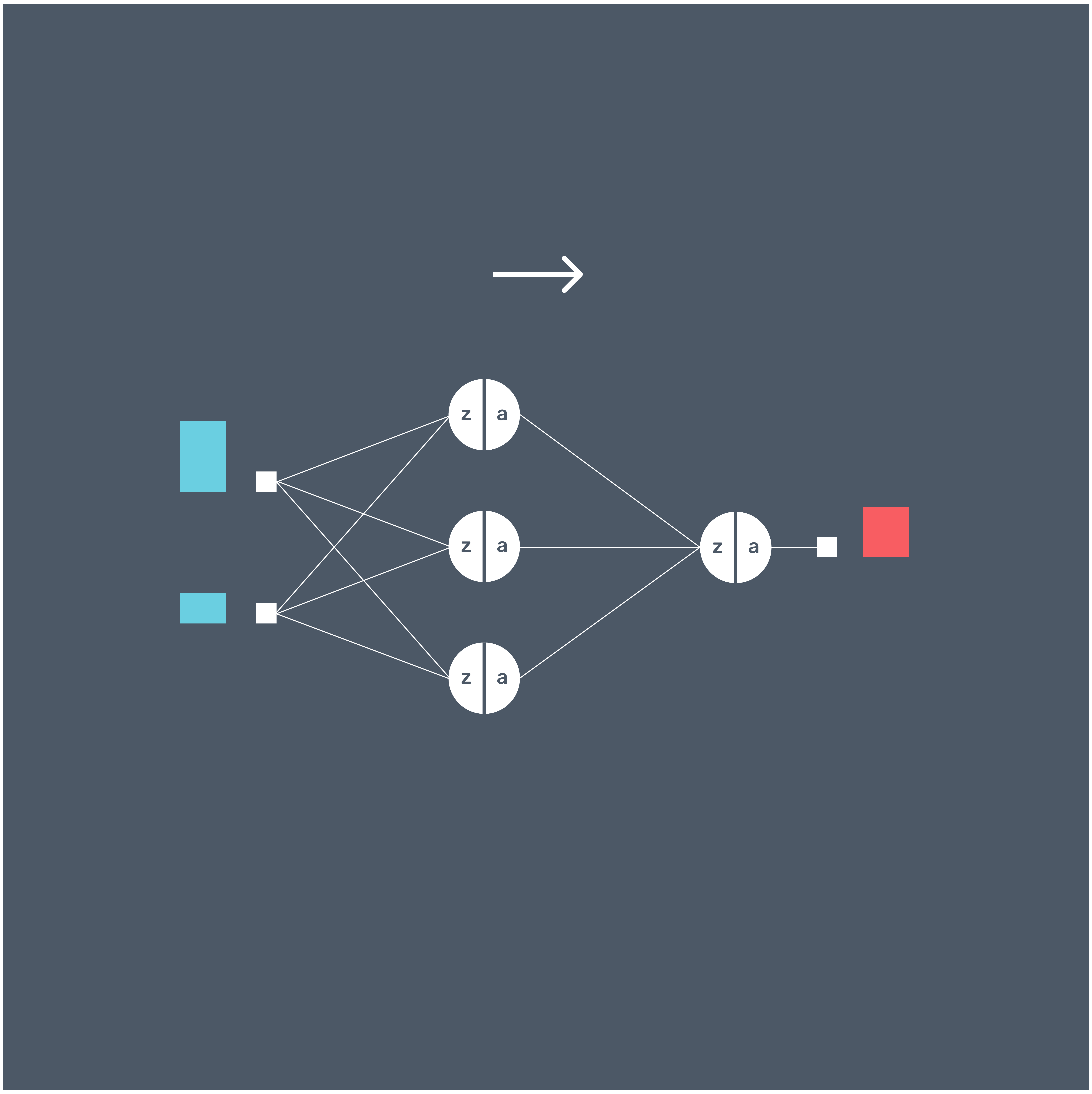
### TRAINING

Now that the data and architecture are in place, it's time to start training. Recall the four-step cycle: *Predict - Measure - Feedback - Adjust.*



## PREDICT

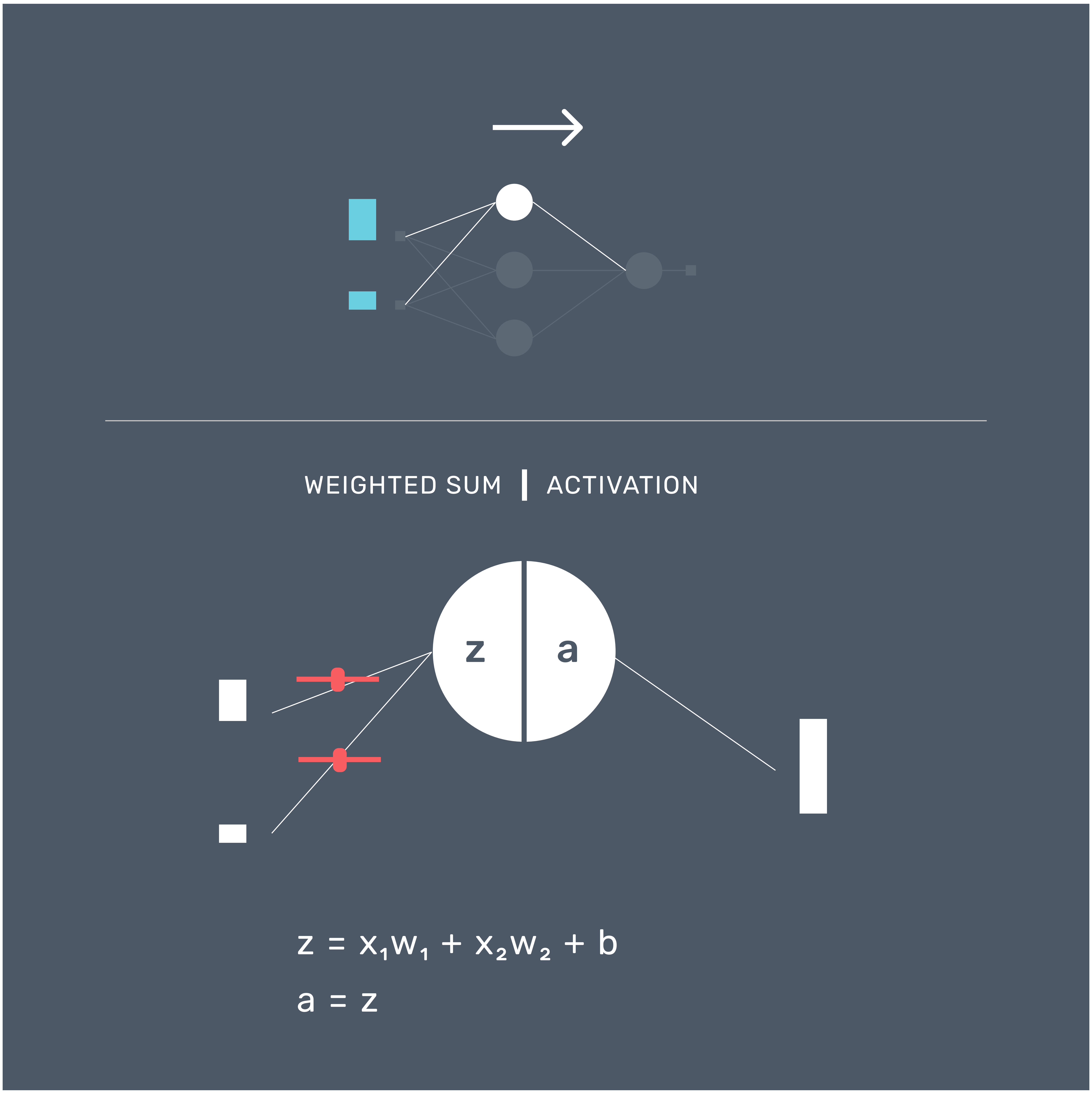
Let’s begin with the first step, *predict*.



## PREDICT

Recall that in this step, each data point is passed through the neural network and prediction is generated on the other side.

Now that we have more neurons, the weighted sum and activation computations will take place at each neuron. Let's look at a couple of examples.

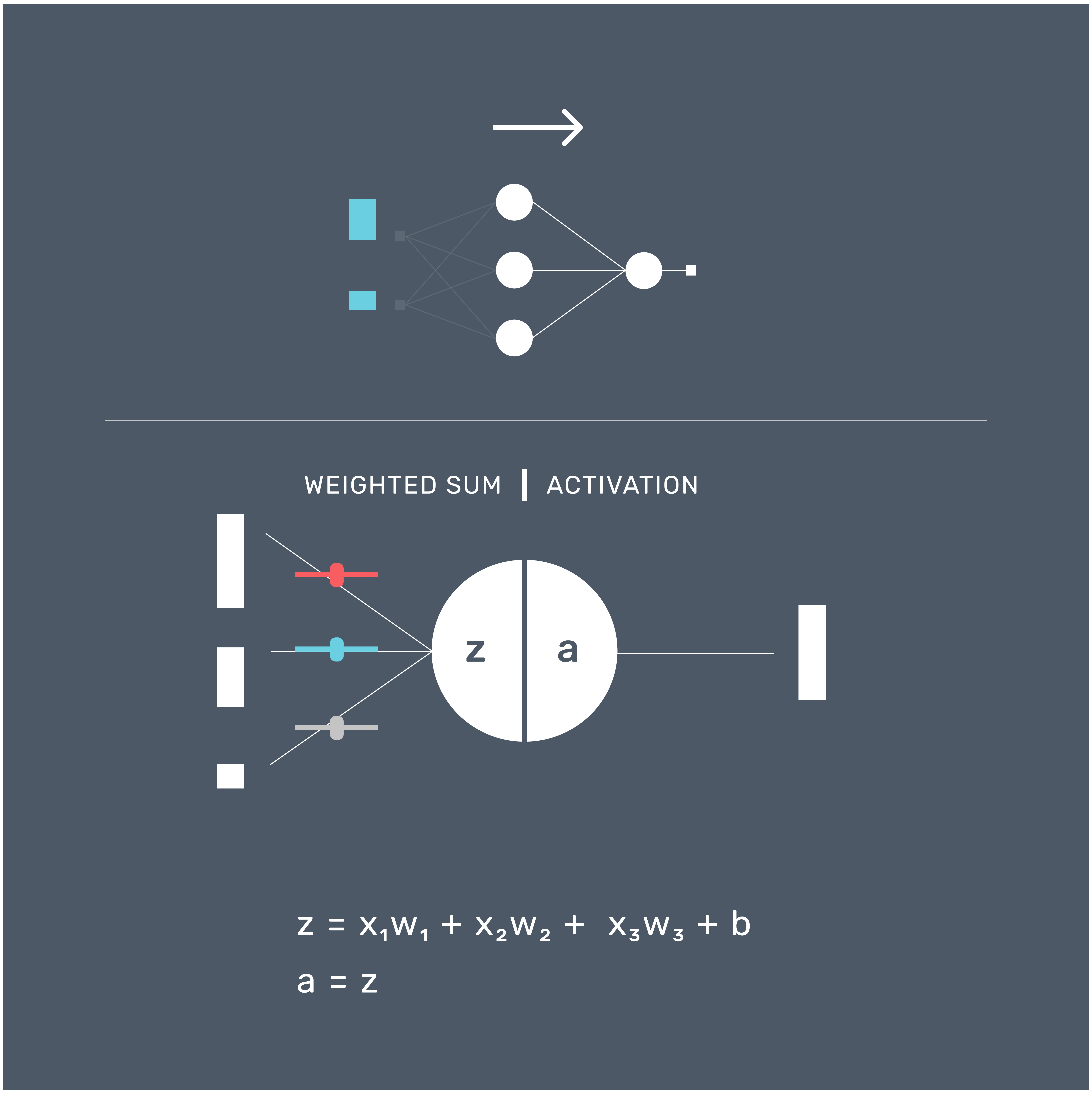


$$z = x_1 w_1 + x_2 w_2 + b$$

$$a = z$$

## EXAMPLE 1

The first example is the first neuron in the hidden layer. It takes the original data's features as inputs, performs the weighted sum, and adds a bias value. Then it goes through a linear activation function, which returns the same output as the input.

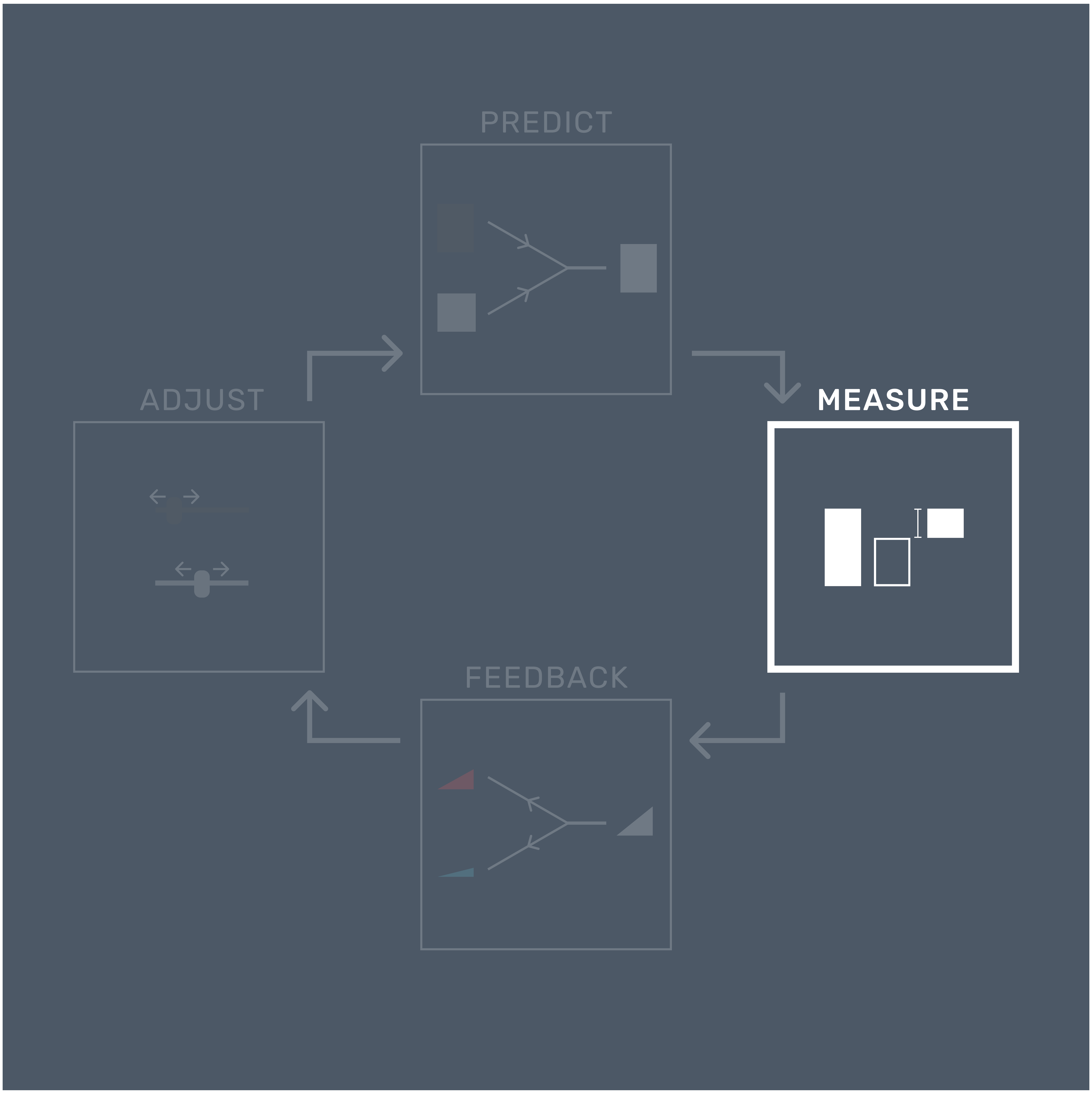


$$z = x_1w_1 + x_2w_2 + x_3w_3 + b$$

$$a = z$$

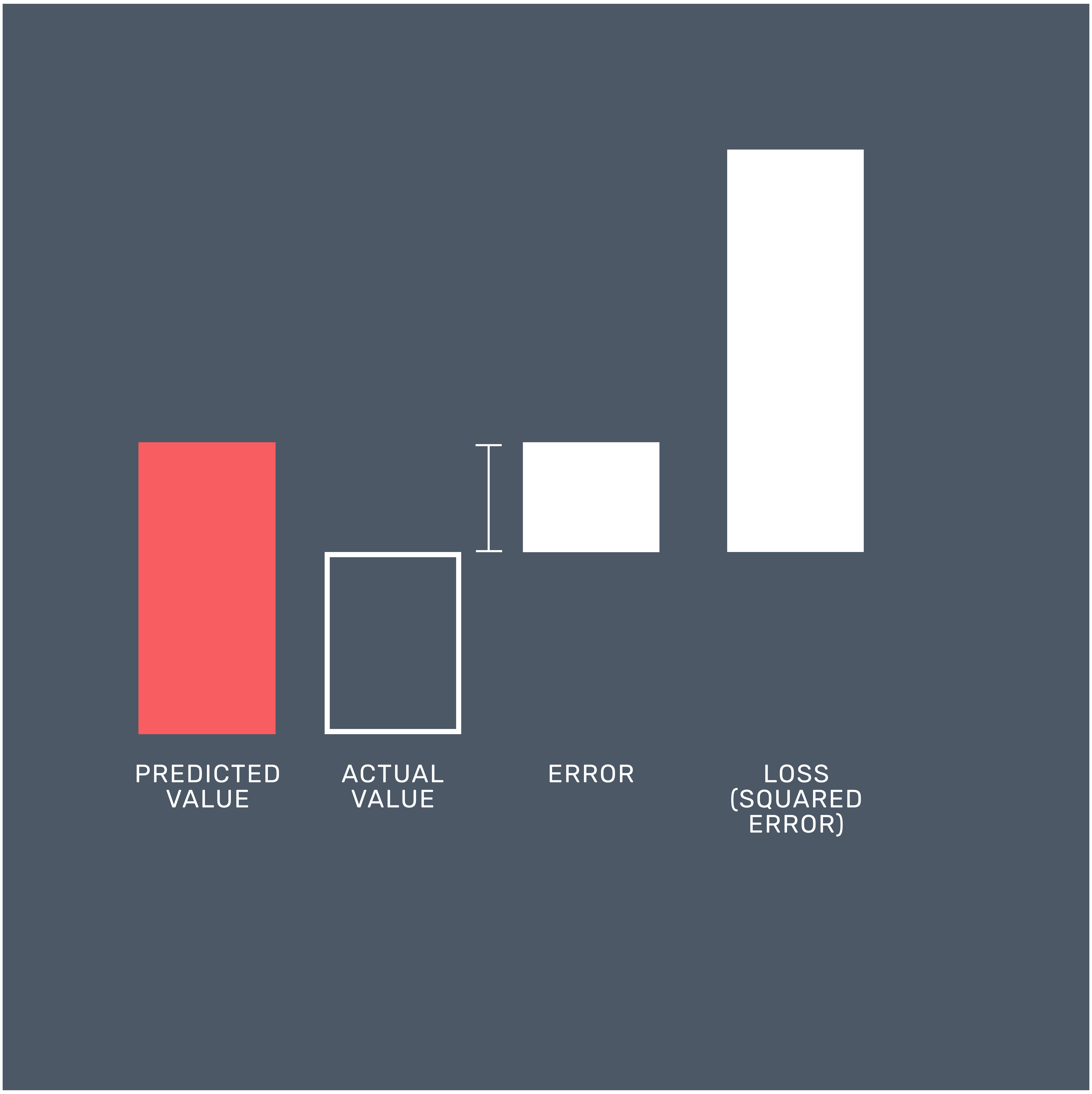
## EXAMPLE 2

The second example is the neuron in the output layer. It takes the three outputs of the previous layer as inputs. As in the first example, it then performs the weighted sum, adds a bias, and performs the linear activation.



## MEASURE

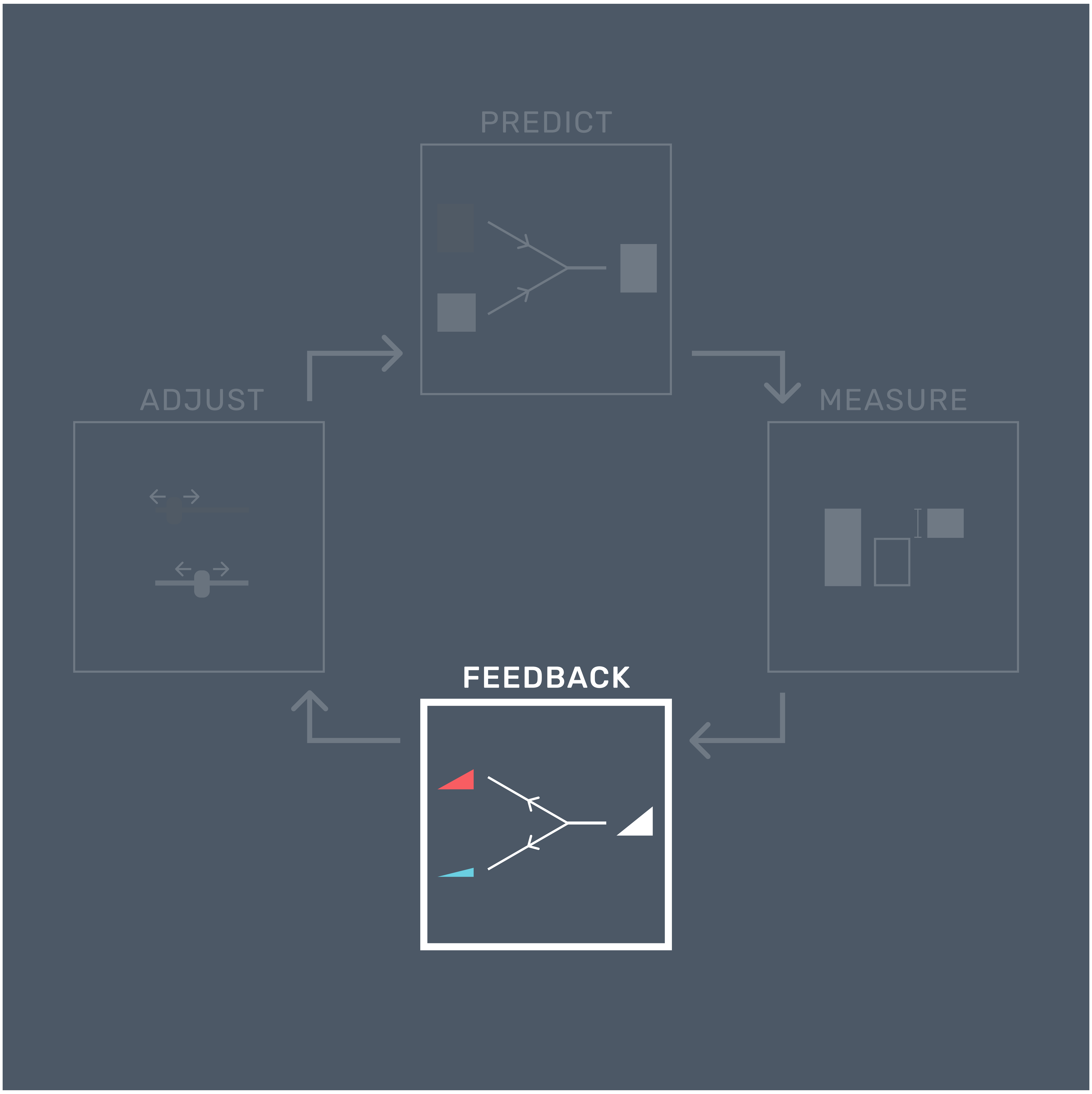
In the second step, *measure*, we quantify the performance of the prediction.



## MEASURE

This is still a regression task, so we can use the same loss function as in Chapter 1—the MSE.

Averaging the squared error over all twenty-four training data points gives us the MSE.

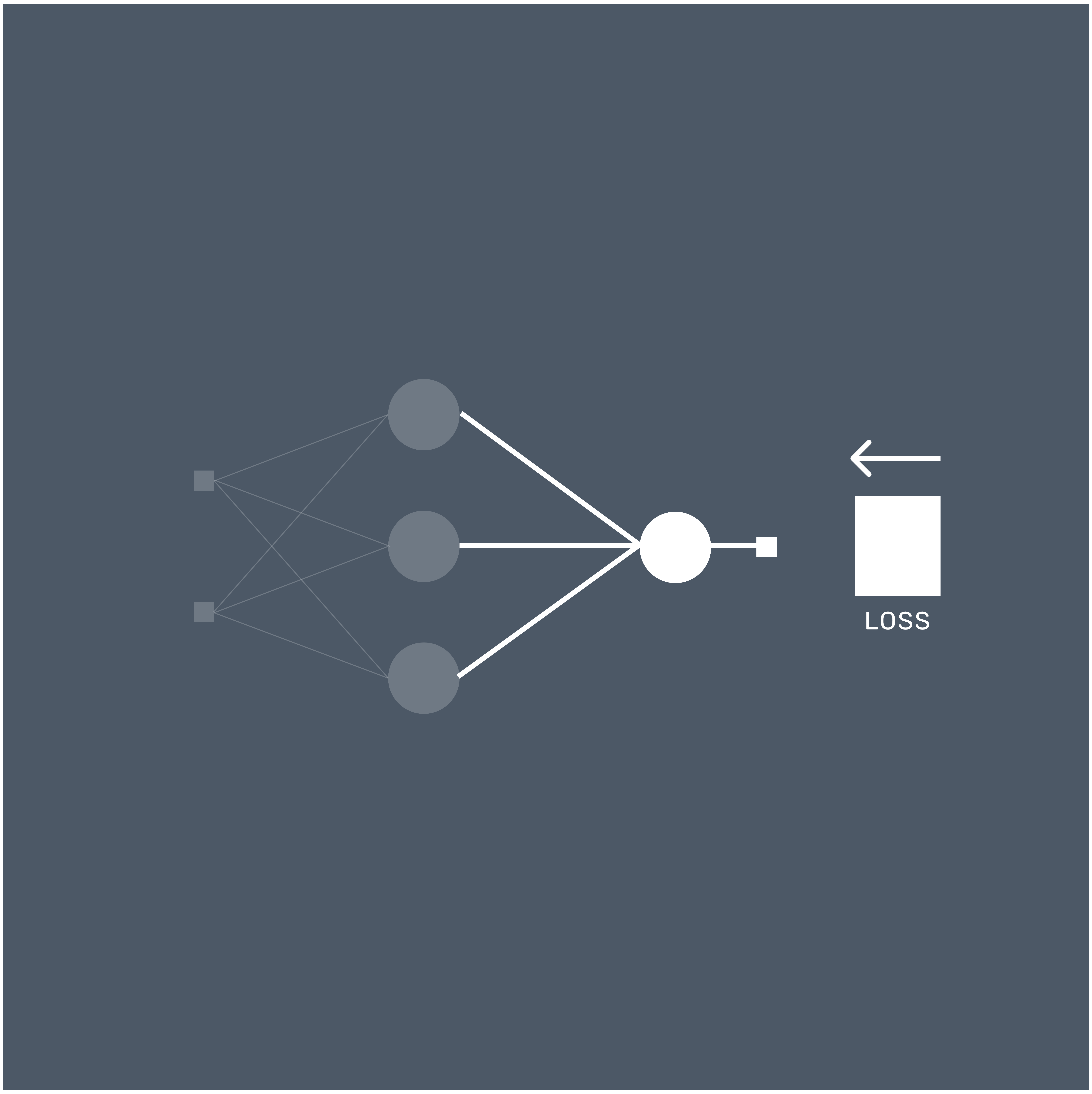


## FEEDBACK

The third step, *feedback*, is where it gets interesting. Here, we'll find a lot more things going on compared to the single-neuron case.

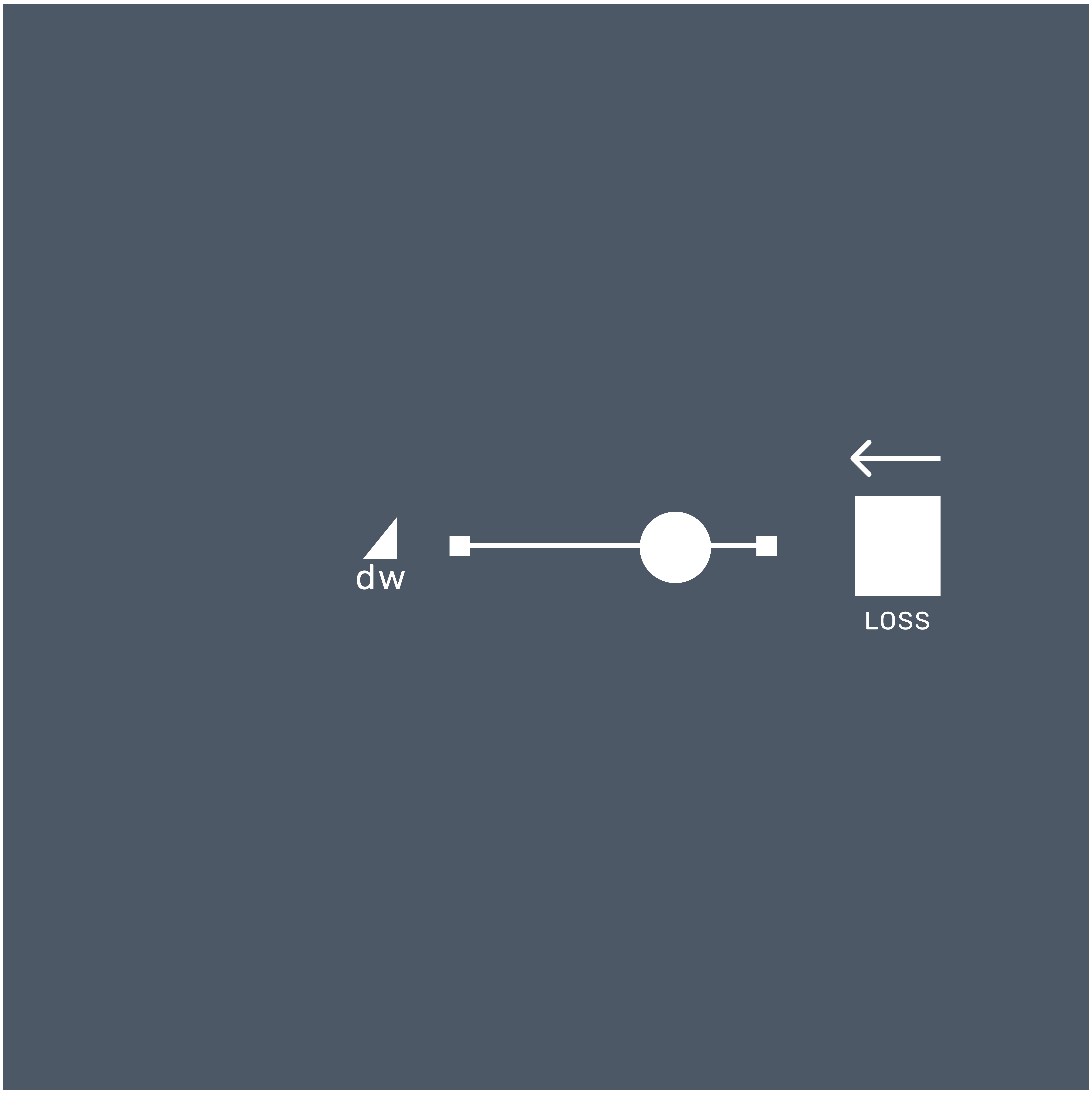
This part of the book will be quite dense. For this, it is helpful to keep in mind the goal of this step, which is to find the parameter gradients so the neural network can adjust its parameters.

Let's dive into it.



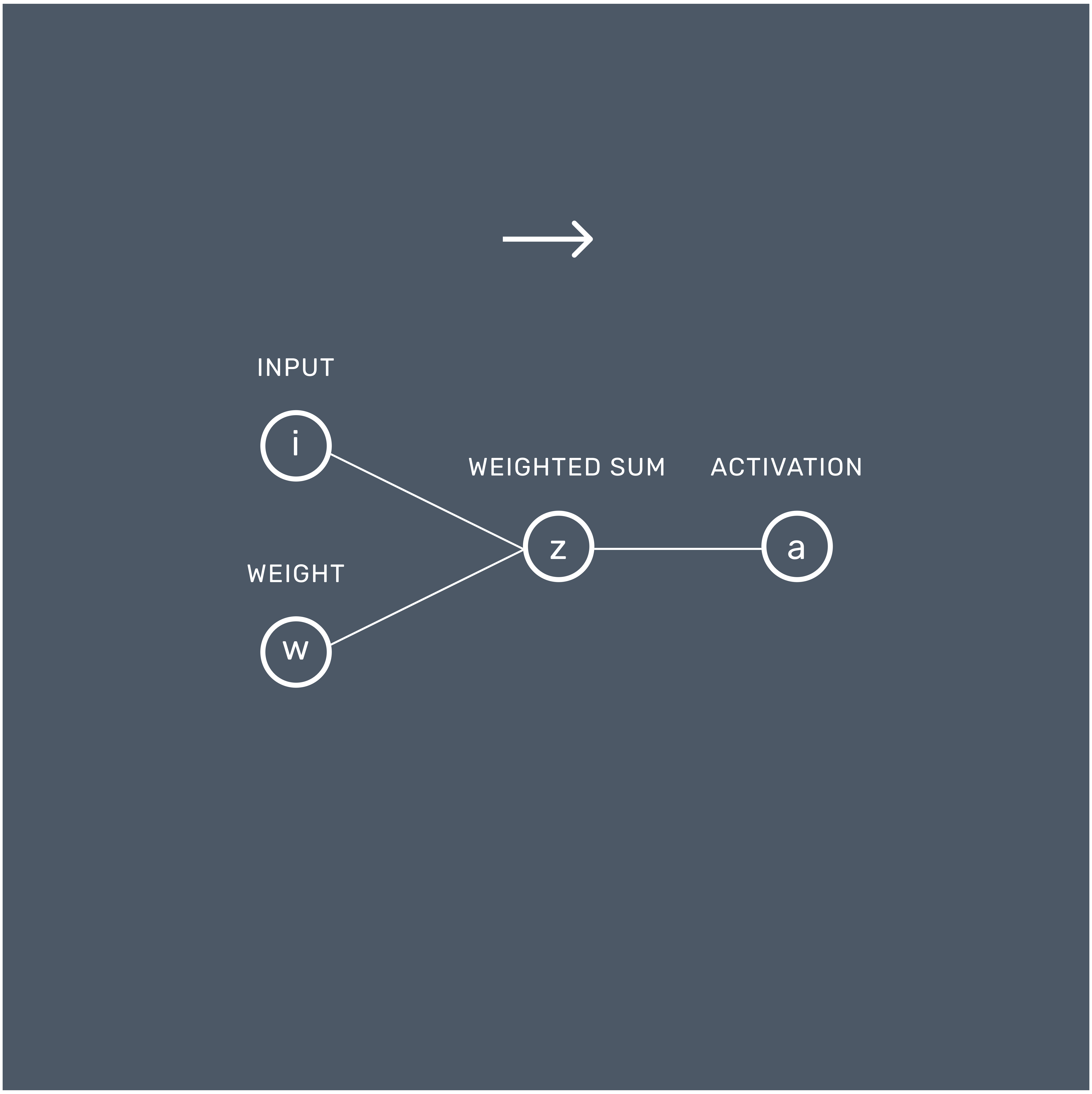
## FEEDBACK

We'll start with the output layer and move backward to the input layer. Again, for simplicity, we'll focus on the weights for now and come back to the biases later.



## SINGLE NEURON

In Chapter 1, with a single-neuron network, we computed the weight gradient based on the loss (MSE). But what really happened under the hood? Let's now see how the loss was fed back to the neural network.

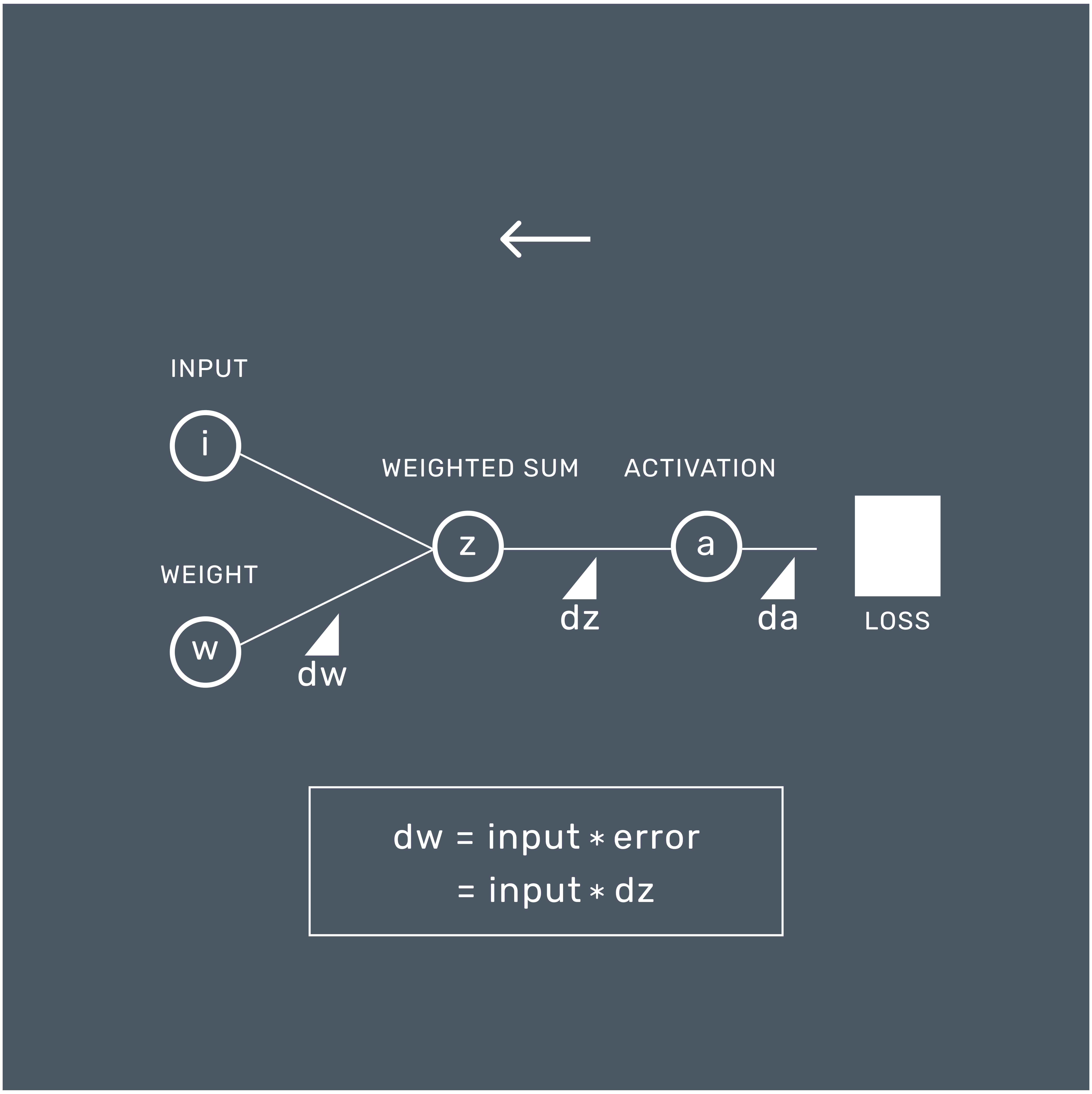


## FORWARD COMPUTATION GRAPH

Keeping to the single-neuron example for now, we can picture the flow of data using a *computation graph*. It provides a way to visualize how information traverses the neural network.

Here we have the forward computation graph, which represents the *predict* step of the training cycle.

Note that the graph you are seeing is a slightly simplified version, sufficient to aid our discussion.

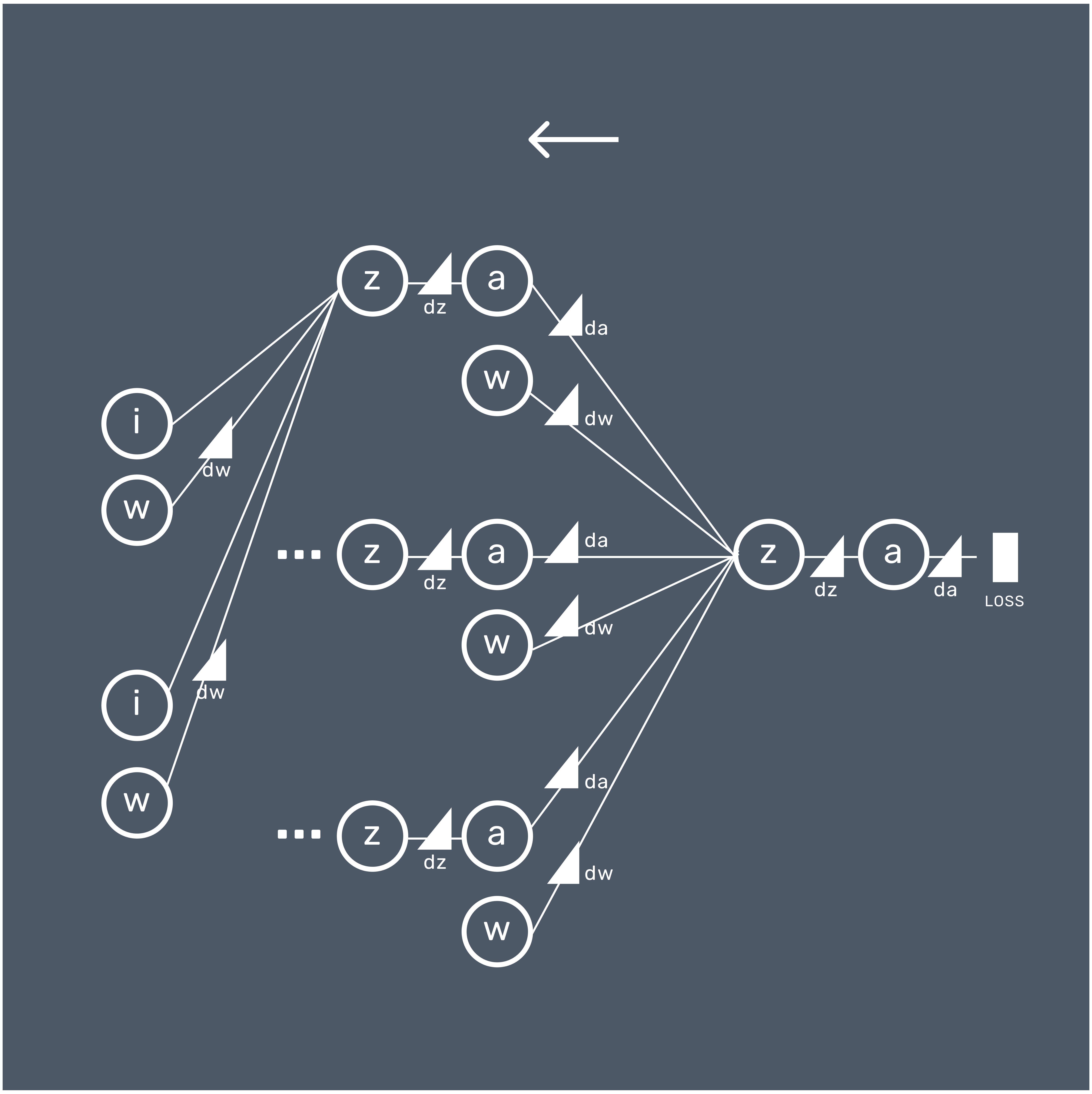


## BACKWARD COMPUTATION GRAPH

Meanwhile, the backward computation graph represents the *feedback* step. Here, we find new terms representing the activation gradient (*da*) and the weighted sum gradient (*dz*). They have been there all along, but for simplicity, were not shown in the earlier examples.

We need these other gradients to arrive at *dw*. The concept is called the *chain rule*. We won't cover the math, but the idea is this: We can compute a particular gradient if we know the gradient adjacent to it. Here, we can compute *da* from the loss value, which means we can compute *dz*, which means we can compute *dw*.

In fact, whenever *error* was mentioned in Chapter 1, it was referring to *dz*, which is the gradient adjacent to *dw*.

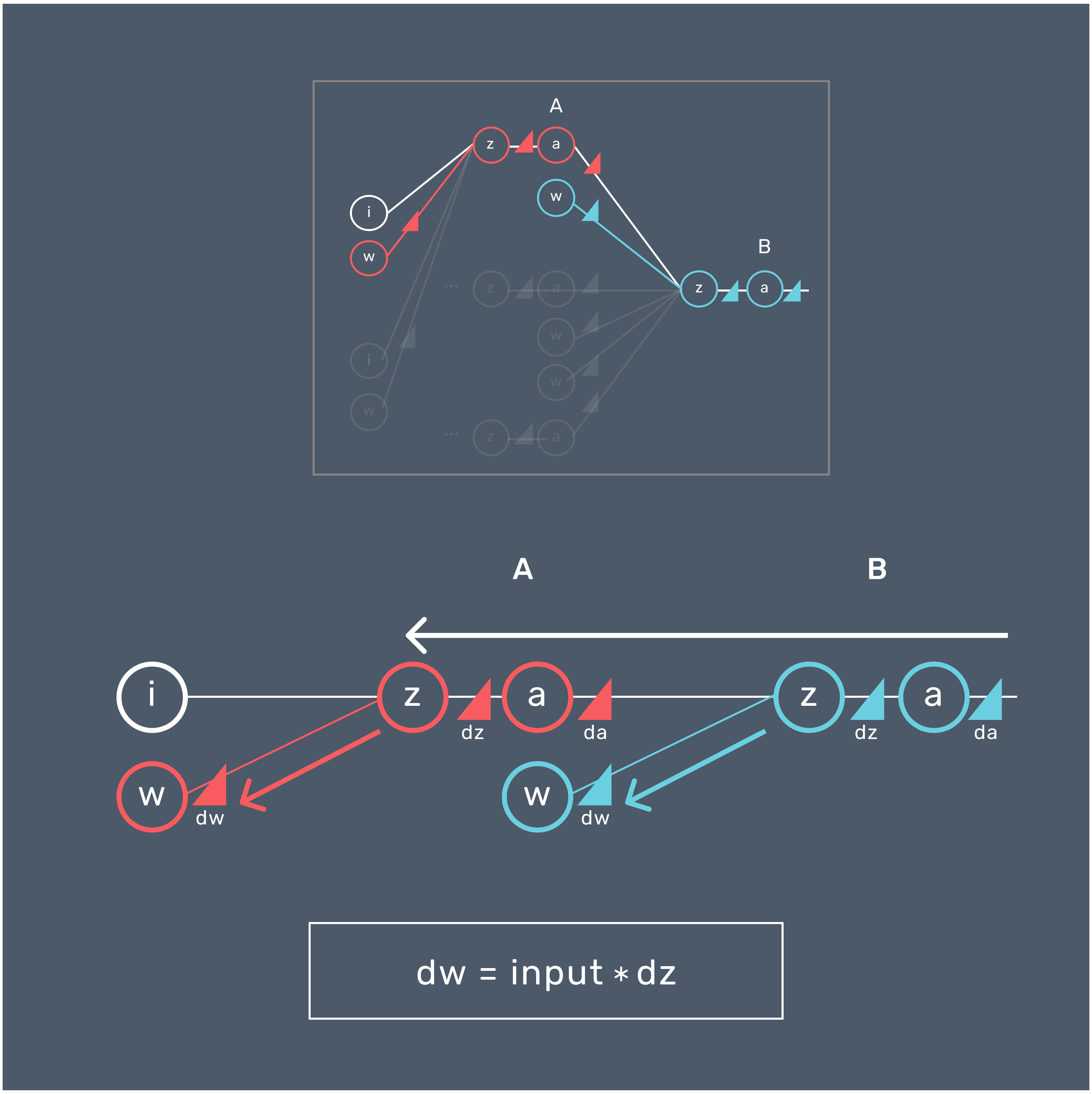


## BACKPROPAGATION

Let's return to this chapter's neural network. The backward computation graph is shown here for all four neurons. Starting from the loss value, information flows back to all neurons so that each weight receives its gradient, *dw*.

In deep learning, this process is called *backpropagation*.

This graph looks pretty complex, so let's pick one example.



$$dw = \text{input} * dz$$

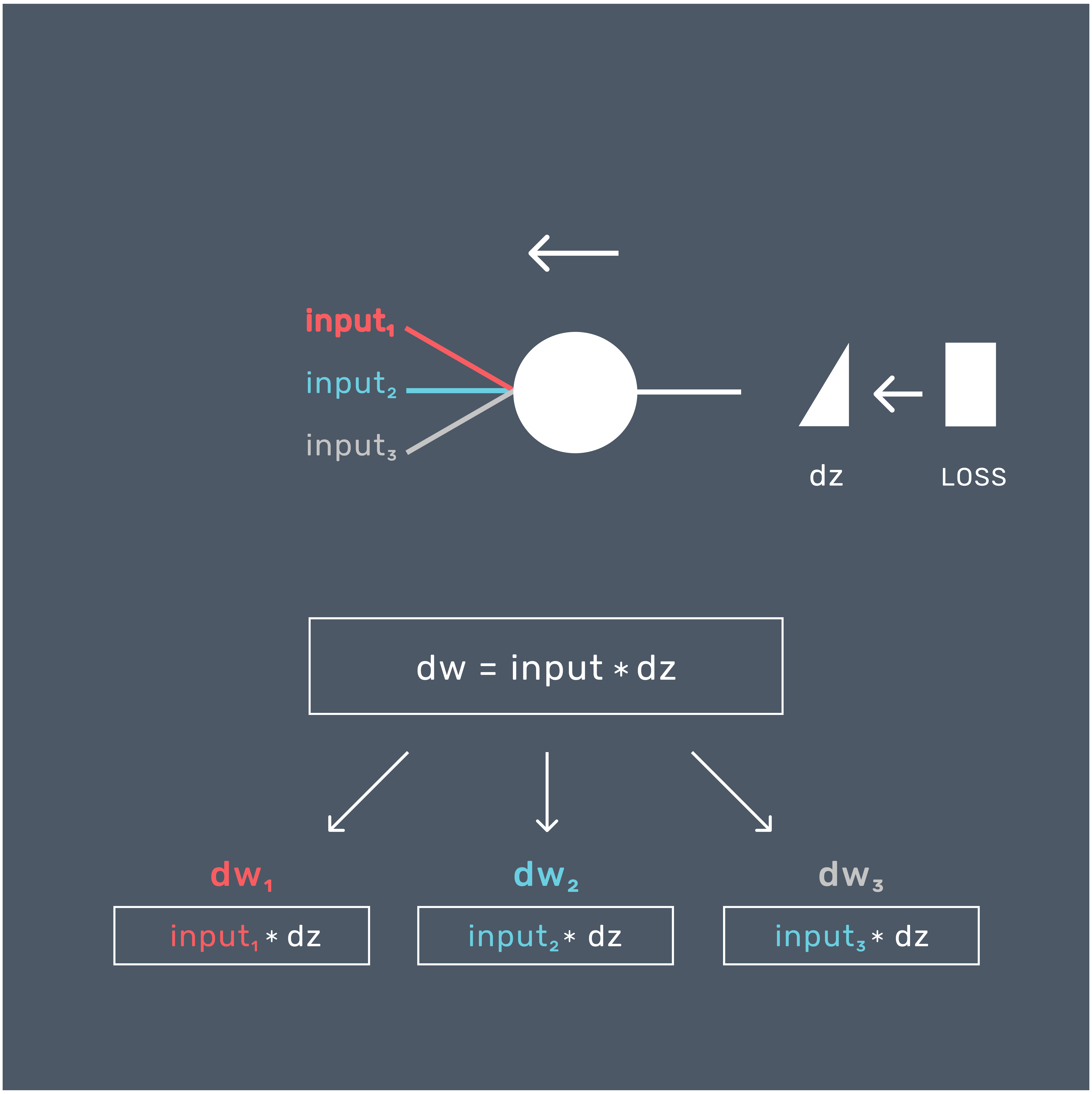
## EXAMPLE

In this example, we'll focus on two weight gradients, red and blue, involving two neurons, A and B.

Tracing the lines along the graph, we obtain the red *dw* by multiplying the input data *i* by neuron A's *dz*.

Meanwhile, we obtain the blue *dw* by multiplying neuron A's output (which becomes neuron B's input) by neuron B's *dz*.

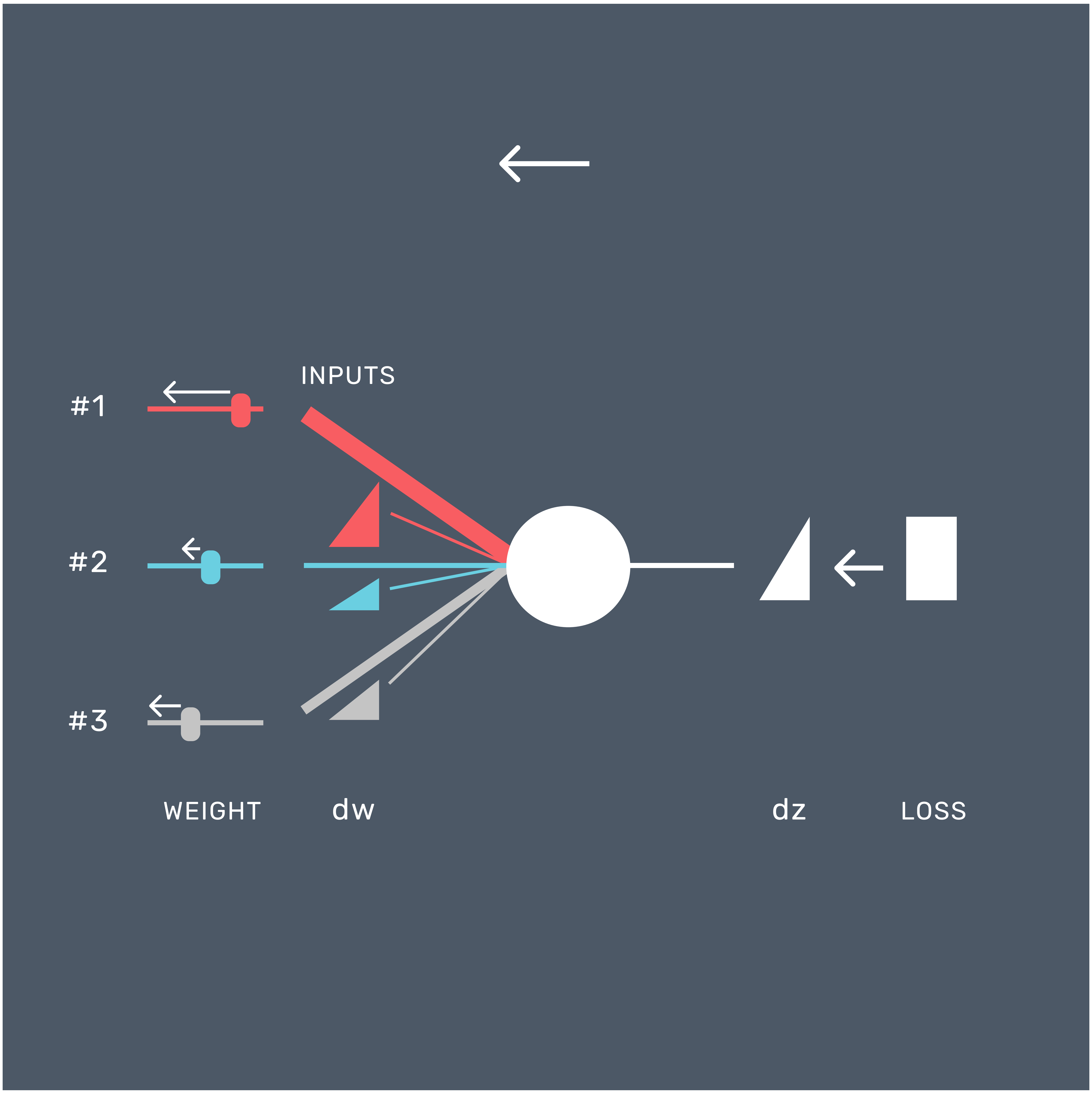
You may be wondering, how did we know the formula for *dw* in the first place, and what about the formulas for *dz* and *da*? Unfortunately, we won't cover them in this book, but if you are curious, do check out other resources to understand the math derivations.



## MAGNITUDE

Let's take a closer look at the magnitude of the weight gradients, starting with the neuron in the output layer.

Inspecting the formula shows that the larger the input, the larger the corresponding weight gradient. But what does this mean?

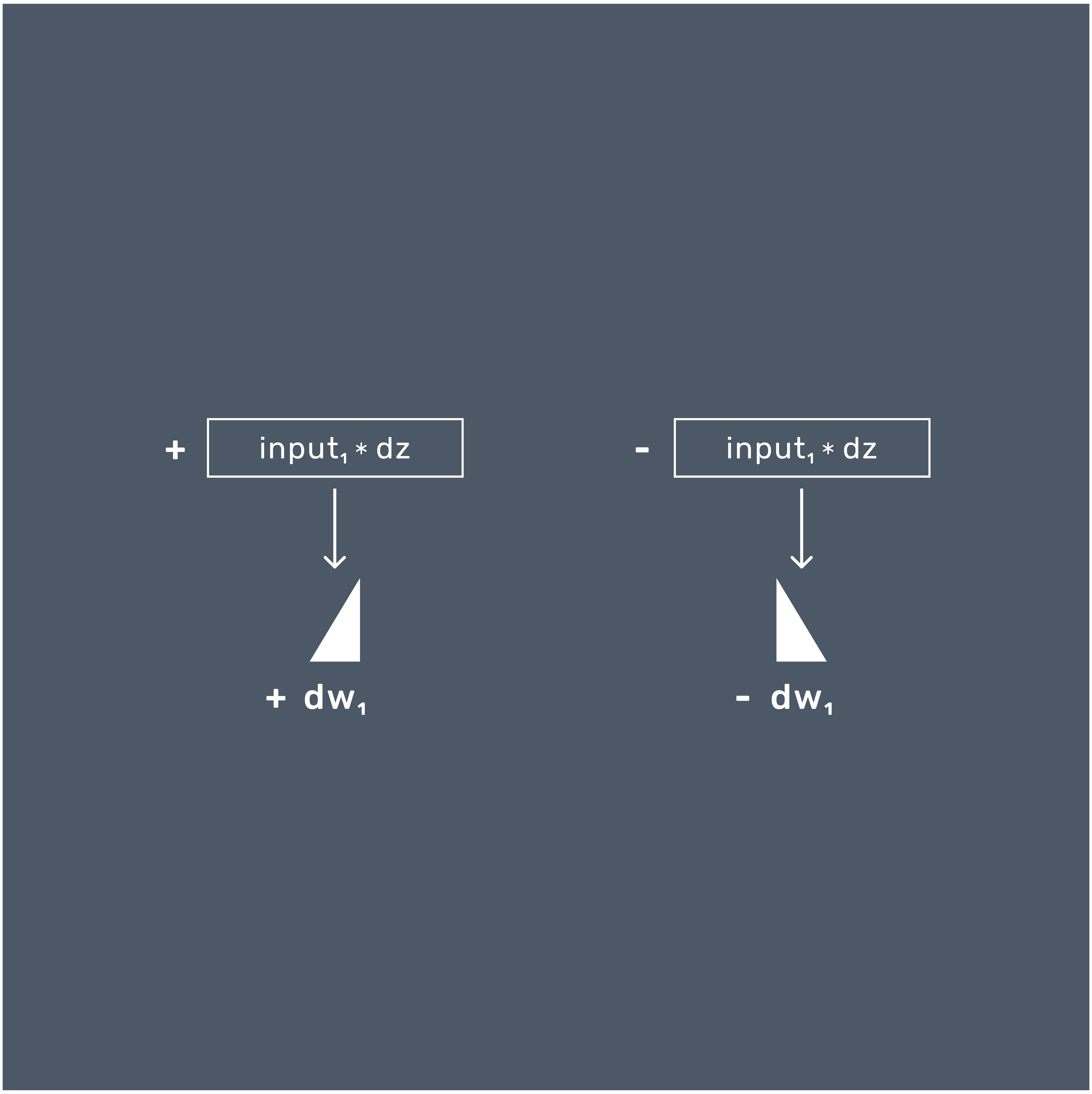


## ERROR CONTRIBUTION

This means that the larger inputs have a greater influence on the output value, and thus on the prediction outcome. Therefore, this formula enables the network to assign the larger weight adjustments to inputs that make the bigger difference.

We can also think of this in terms of error contribution.

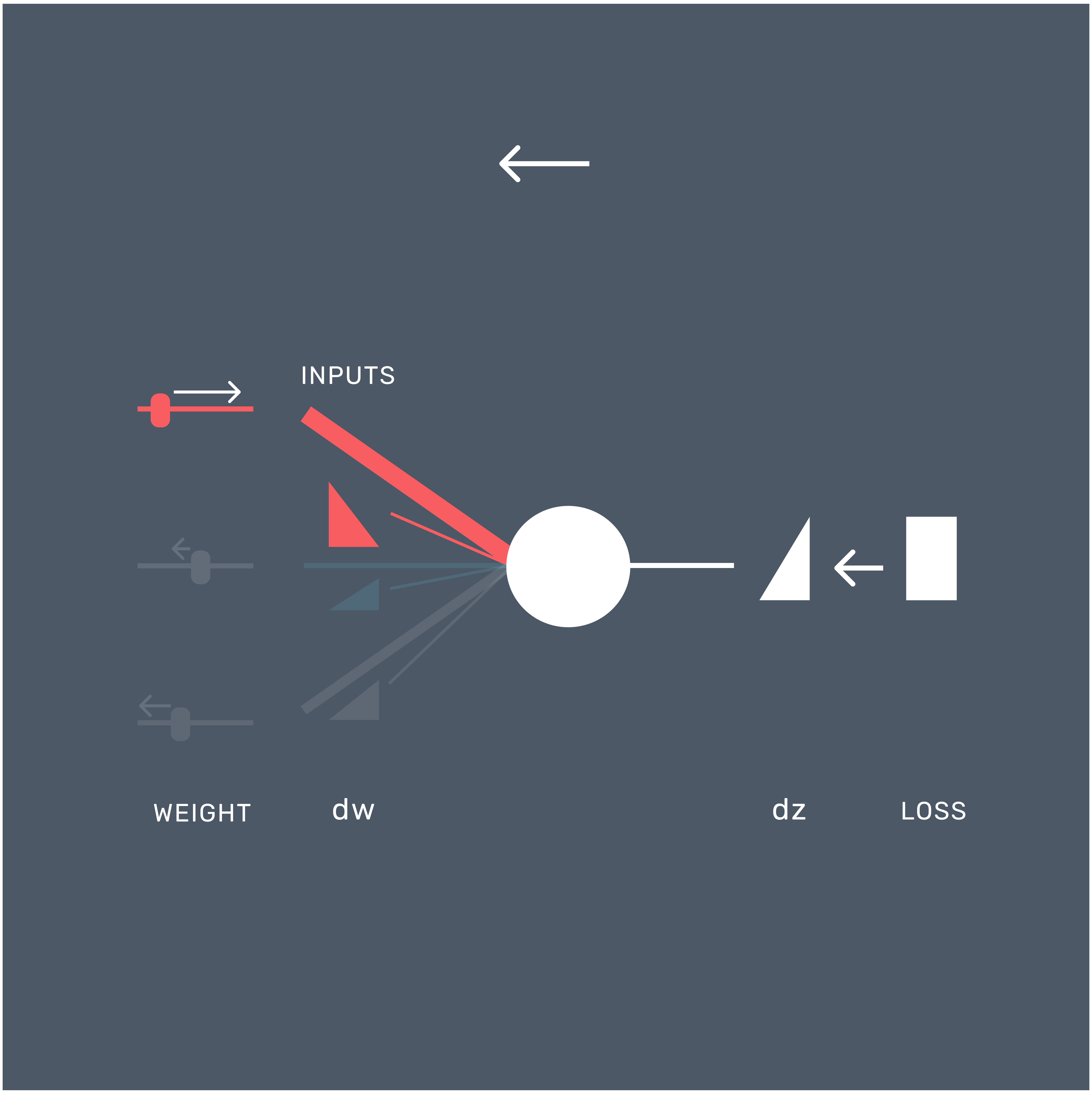
Suppose input #1 is the largest. This tells us that input #1 is the one that contributed the most toward the error. So, we want to tell input #1 to make the biggest weight adjustment, and we do that by giving it the biggest weight gradient.



### DIRECTION

Recall that weight gradients have both magnitude and direction. As the gradients backpropagate, their directions can change too.

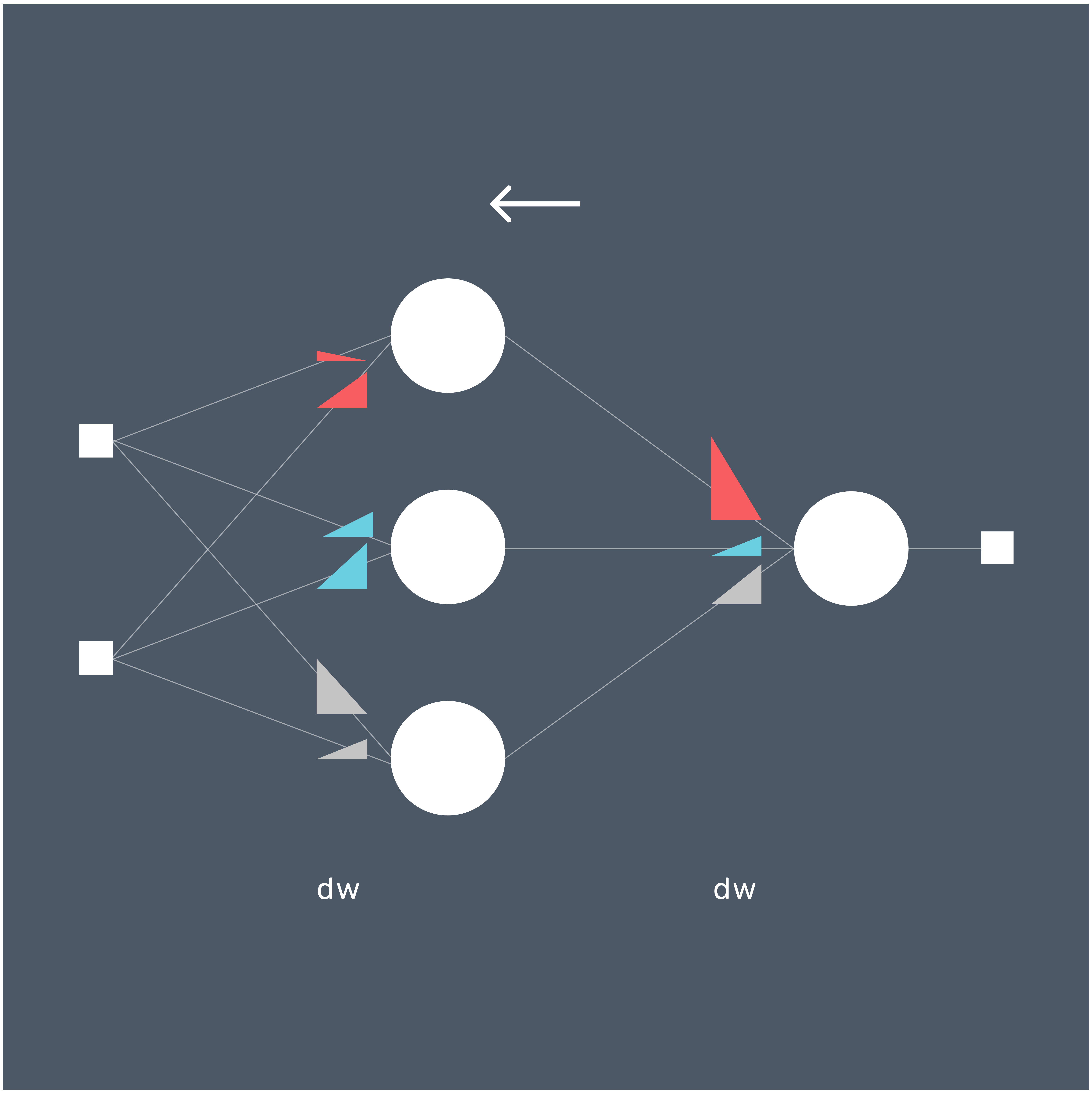
If either the input or *dz* is negative, then the weight gradient will be negative.



## NEGATIVE GRADIENT

A negative weight gradient means that the network will need to increase its weight instead.

If you recall the gradient descent discussion in Chapter 1, a negative value causes the gradient to flip its shape.

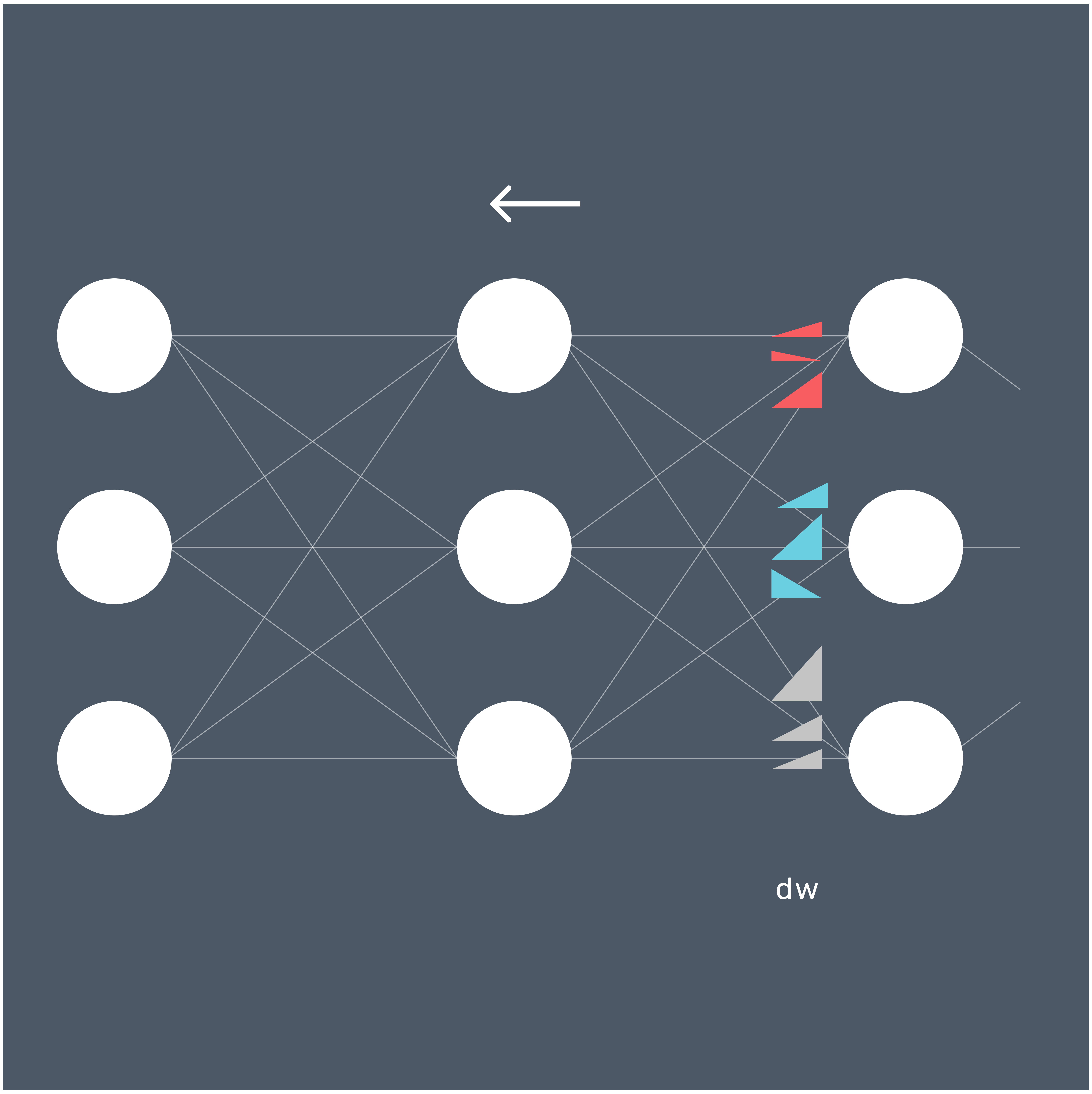


## REPEAT FOR THE WHOLE NETWORK

The same principle applies to the rest of the neural network. Backpropagation continues until all the weights have received their gradients.

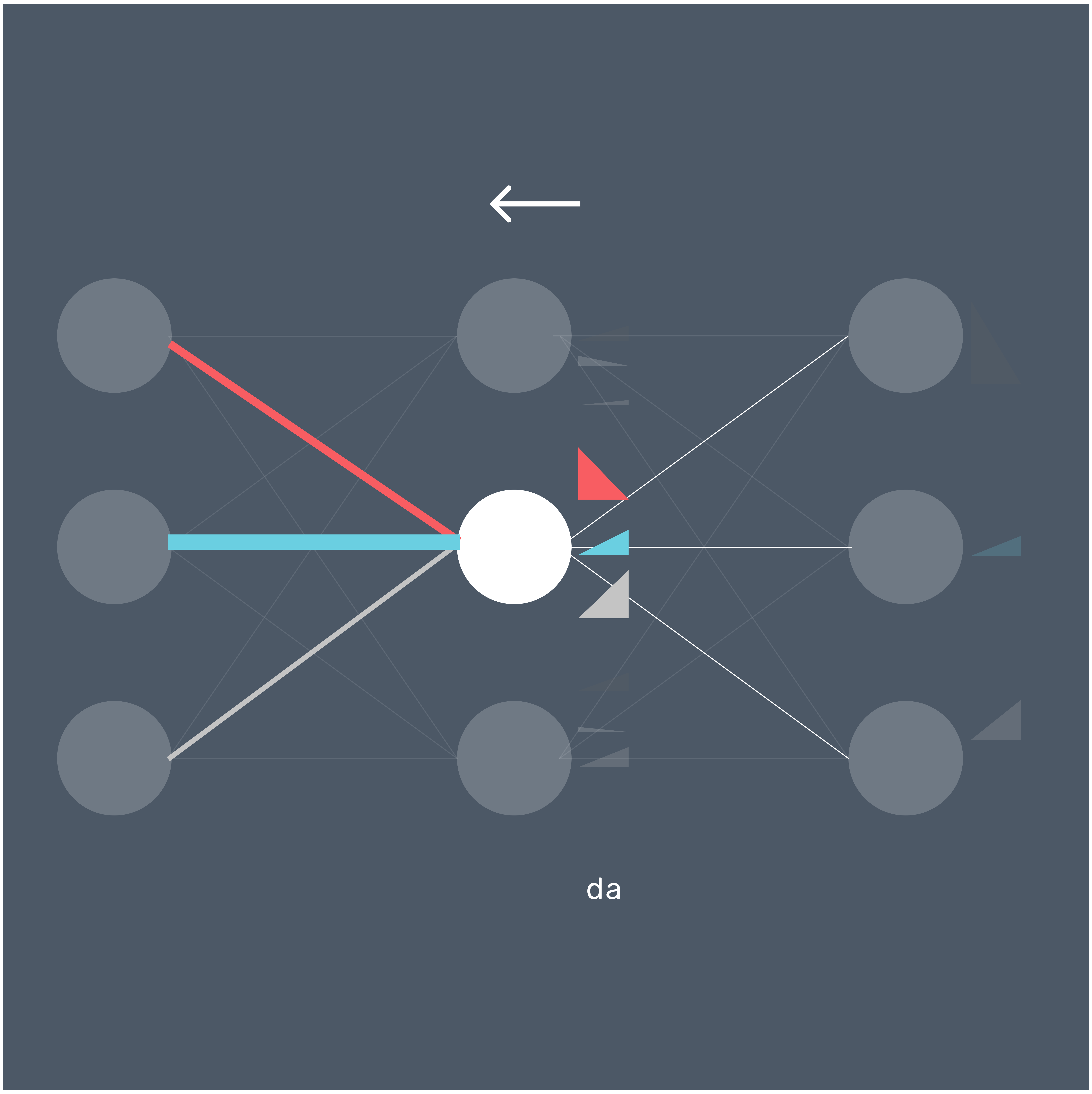
The good news is, in practice, there are well-established deep learning frameworks such as PyTorch and Tensorflow that handle all the tedious computations on our behalf!

Nevertheless, the value of understanding how it all works is immense.



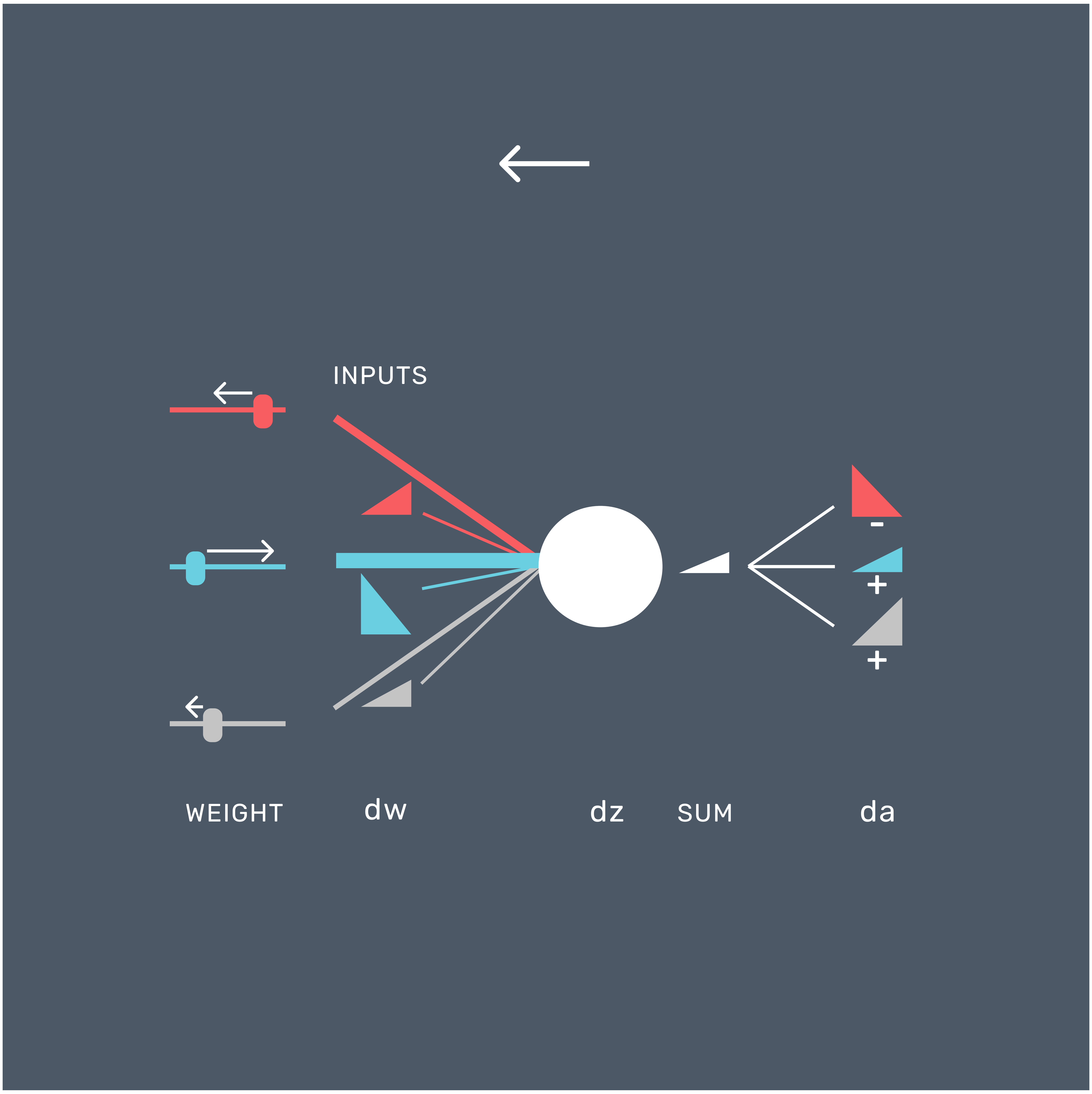
## EXAMPLE WITH A BIGGER NETWORK

Now let’s firm up our understanding of how backpropagation works. Suppose we had a larger network with a few more hidden layers.



## EXAMPLE NEURON

Take this neuron in the middle for example. It has just received the *da* gradients from its outputs. But what does it do with them?

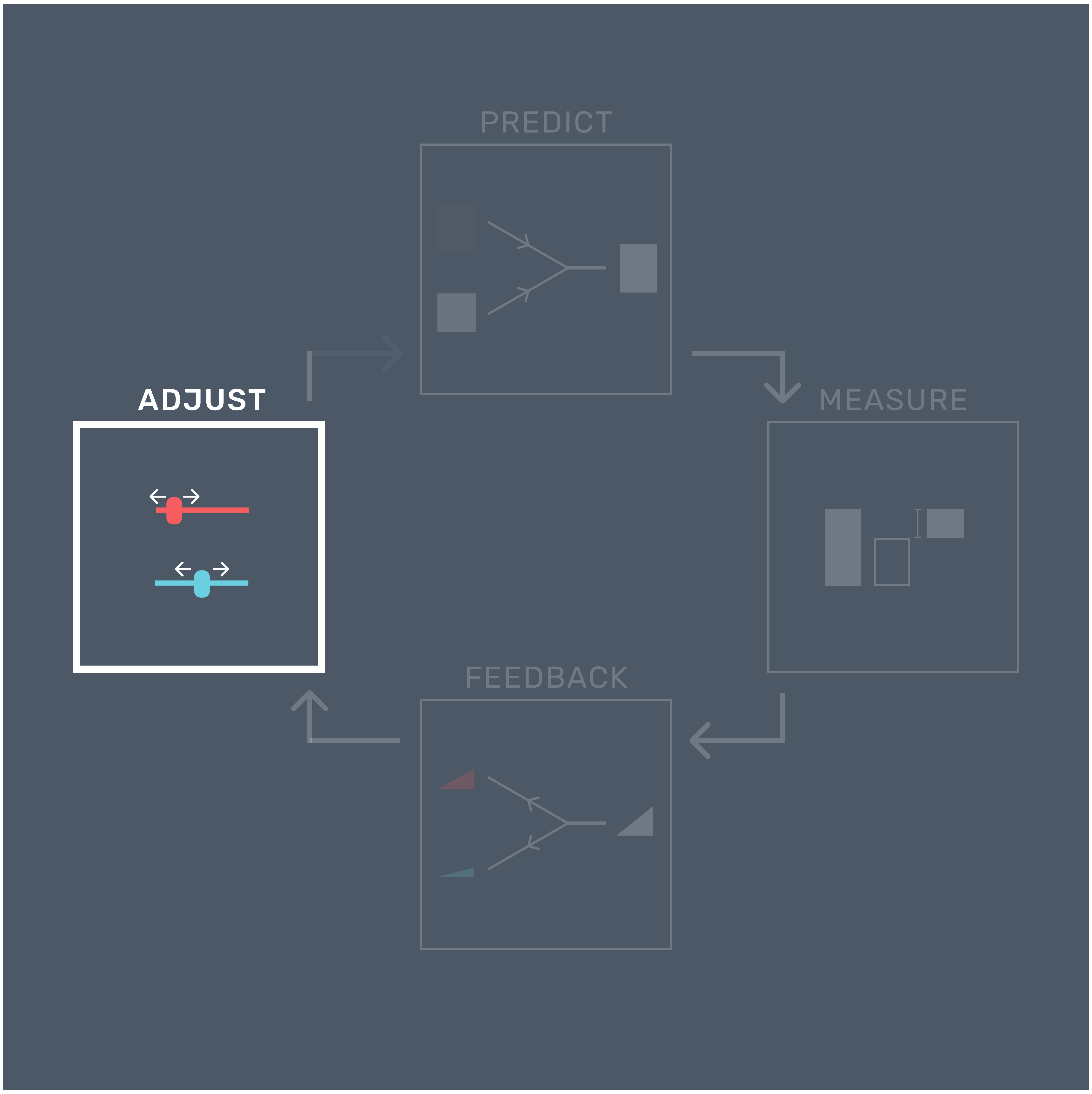


## EXAMPLE NEURON

The first thing it does is to sum up these *da* values. This represents the net gradient coming from the three outputs.

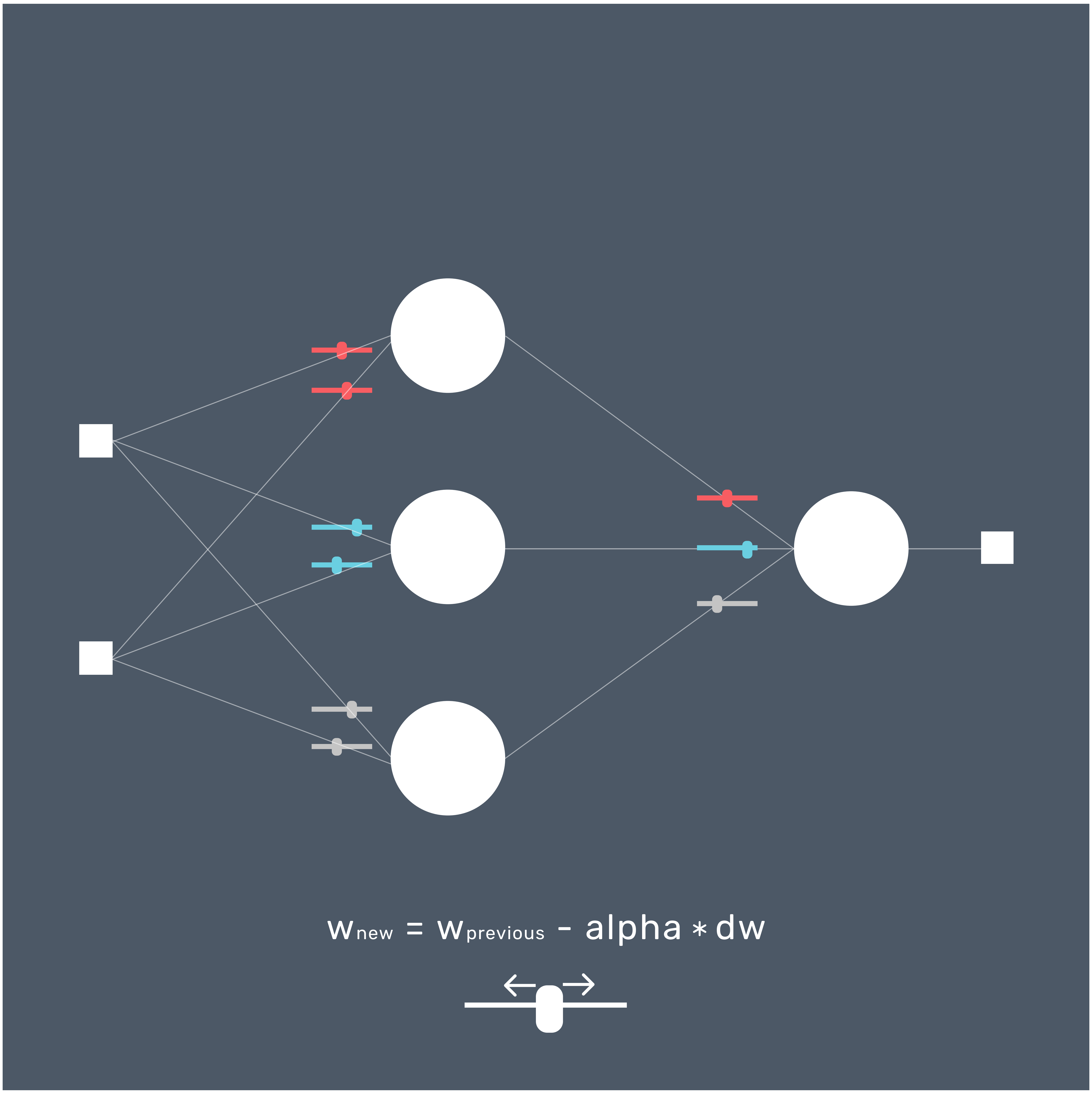
As per the chain rule, *da* gives rise to *dz*.

And then, we get the *dw* for each input by multiplying *dz* by the inputs.



## ADJUST

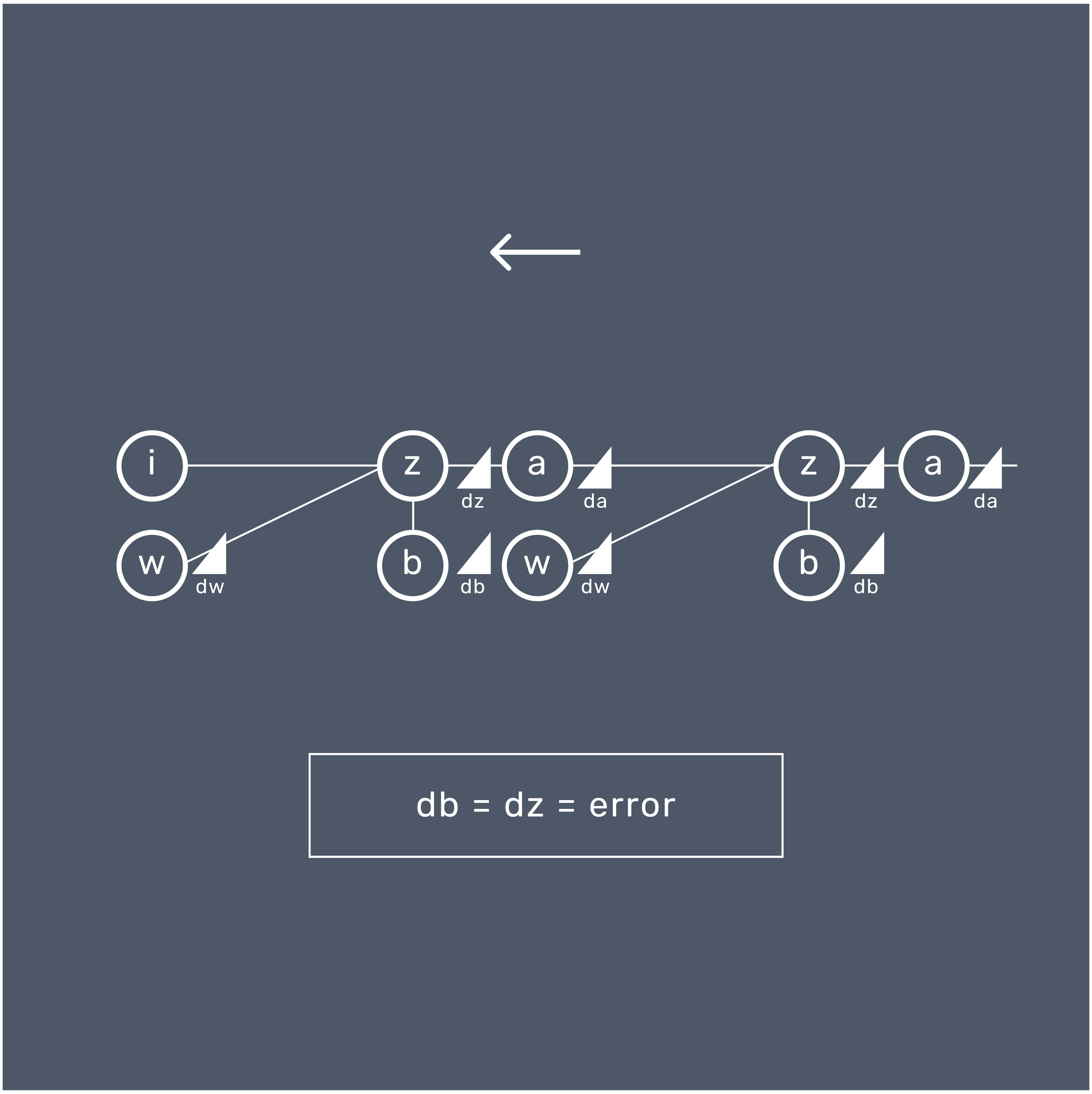
The fourth step, *adjust*, is where we perform the weight adjustments.



$$w_{new} = w_{previous} - alpha * dw$$

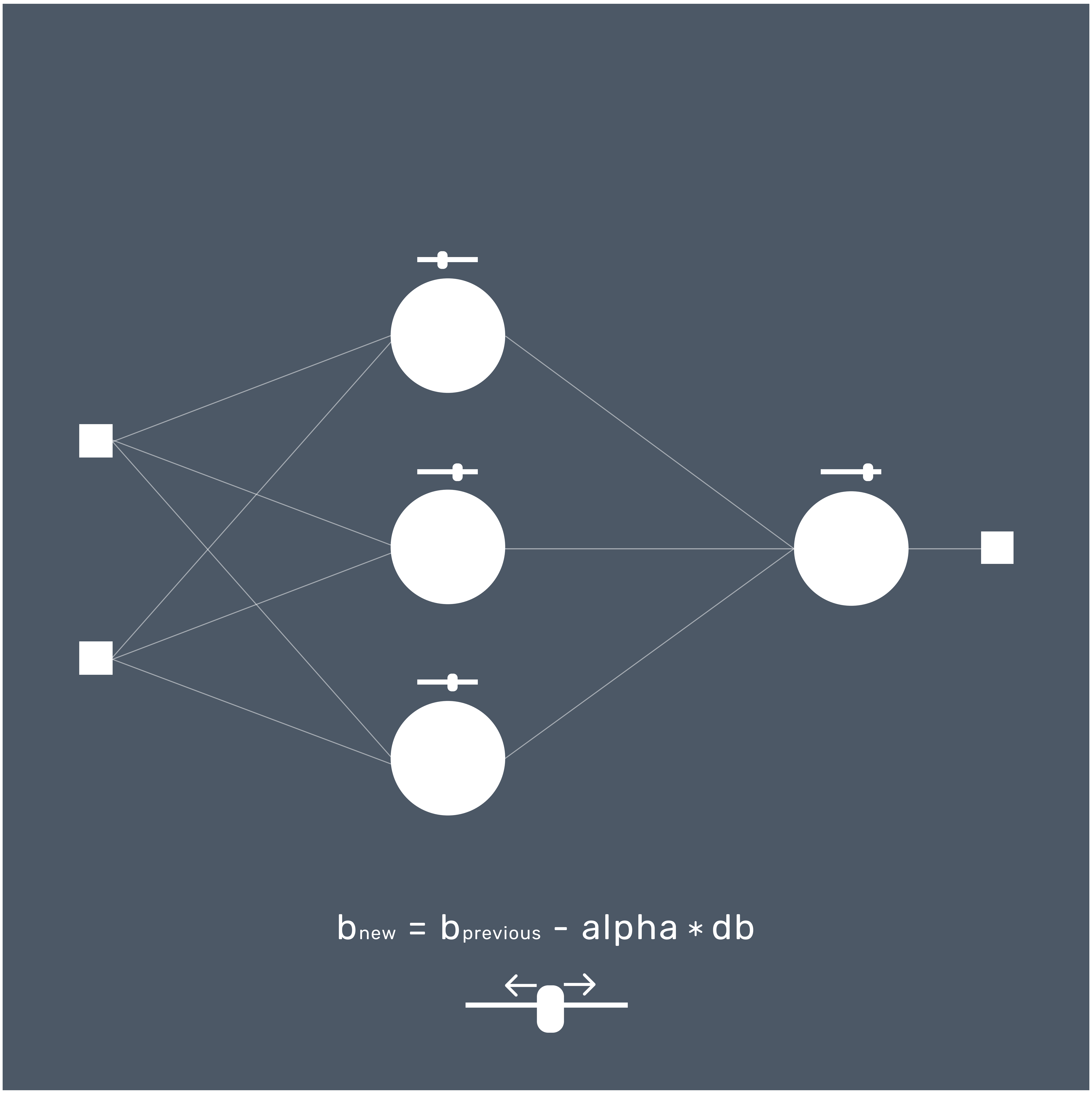
## WEIGHT ADJUSTMENT

As in Chapter 1, we can now adjust the nine weights according to the gradients that they receive.



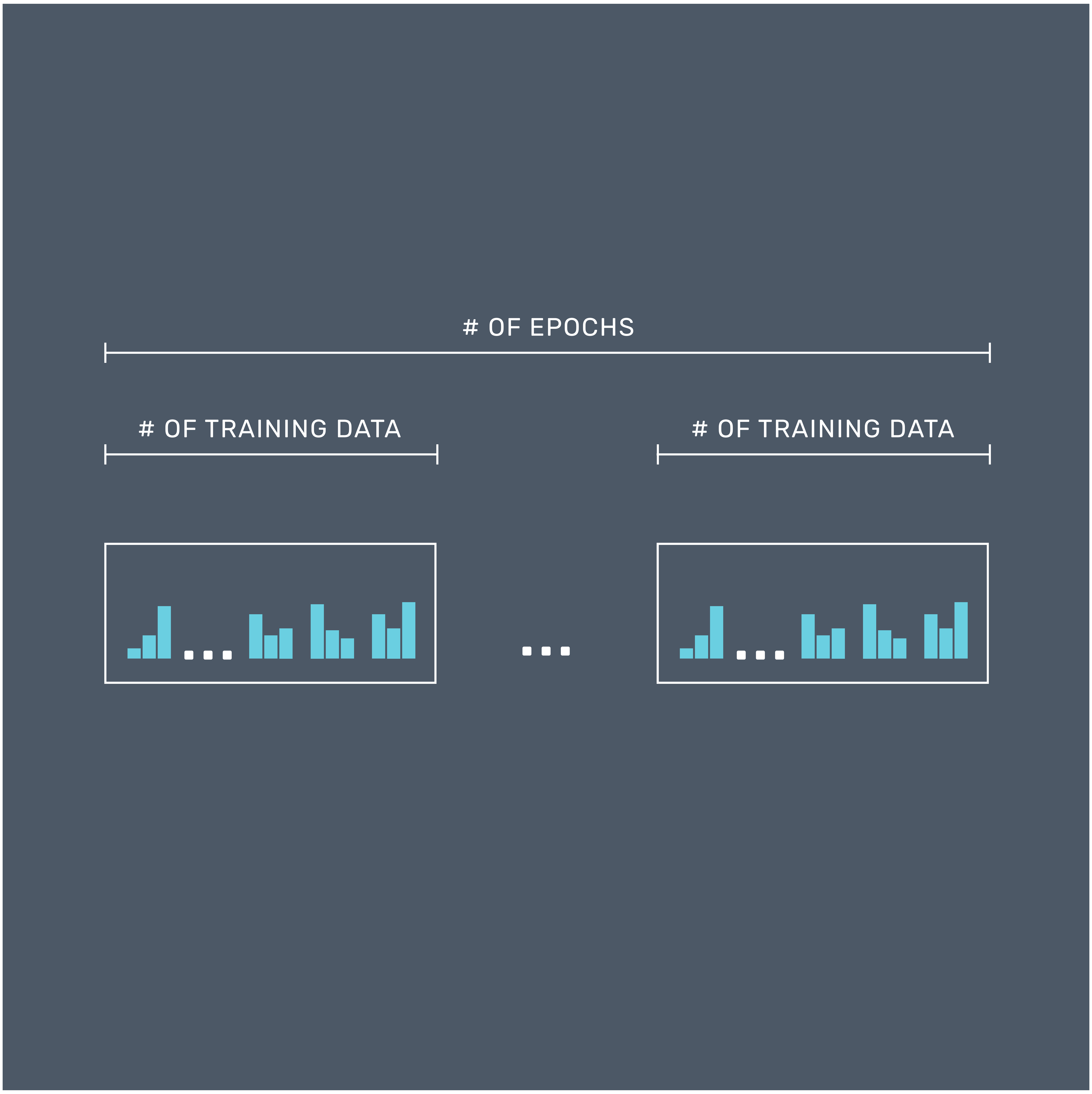
## BIAS

Let’s now bring the bias term back into the picture. As before, the formula for the bias gradient *db* is simply equal to the error, which we now know is given by *dz*.



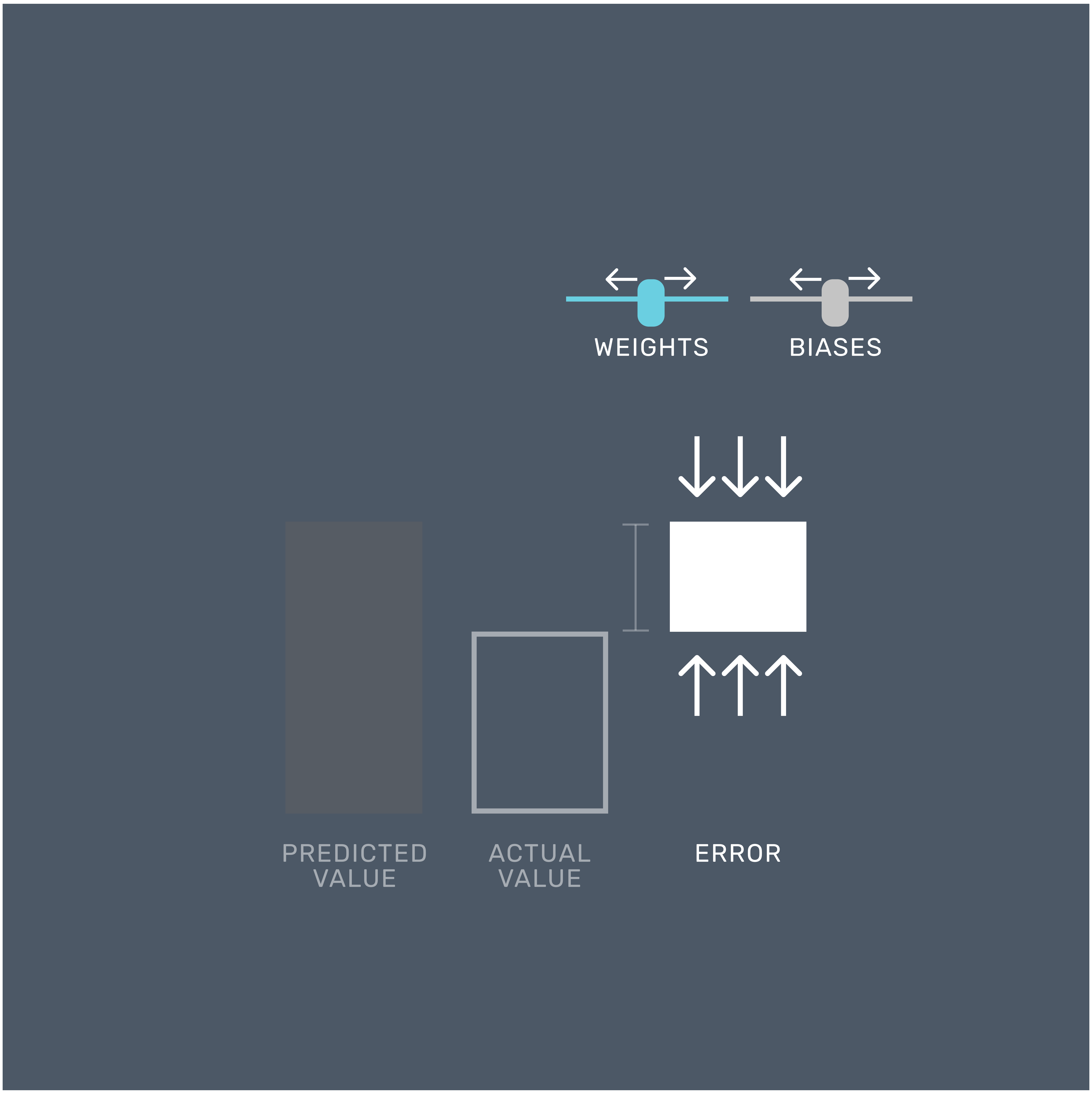
### BIAS ADJUSTMENT

The neural network can now adjust the biases based on their gradients.



## EPOCHS

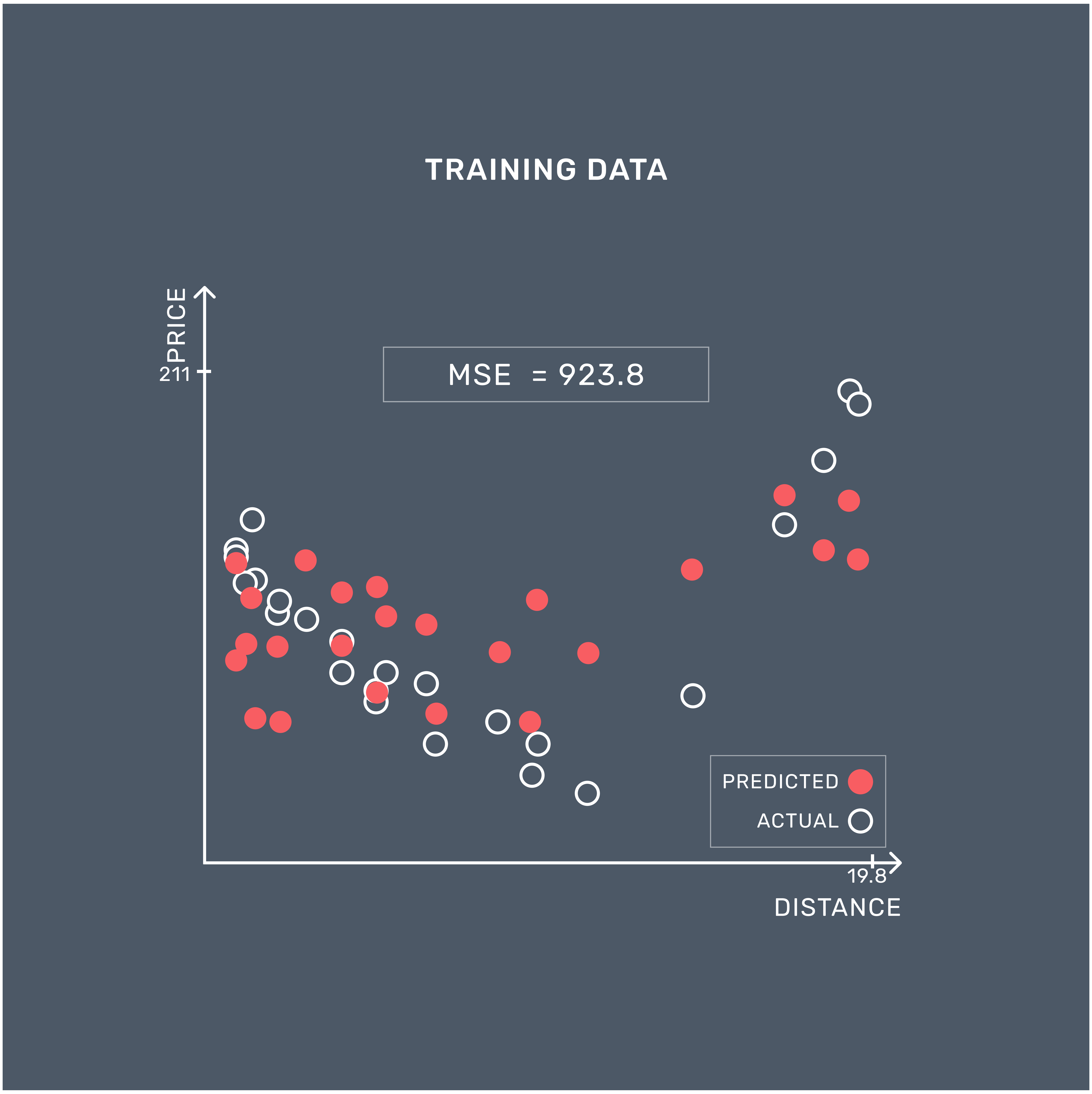
We'll repeat the training cycle for 800 epochs. This task requires more epochs compared to Chapter 1. This is because of the non-linearity, which will take a longer time to learn than a linear case.



## REVISITING OUR GOAL

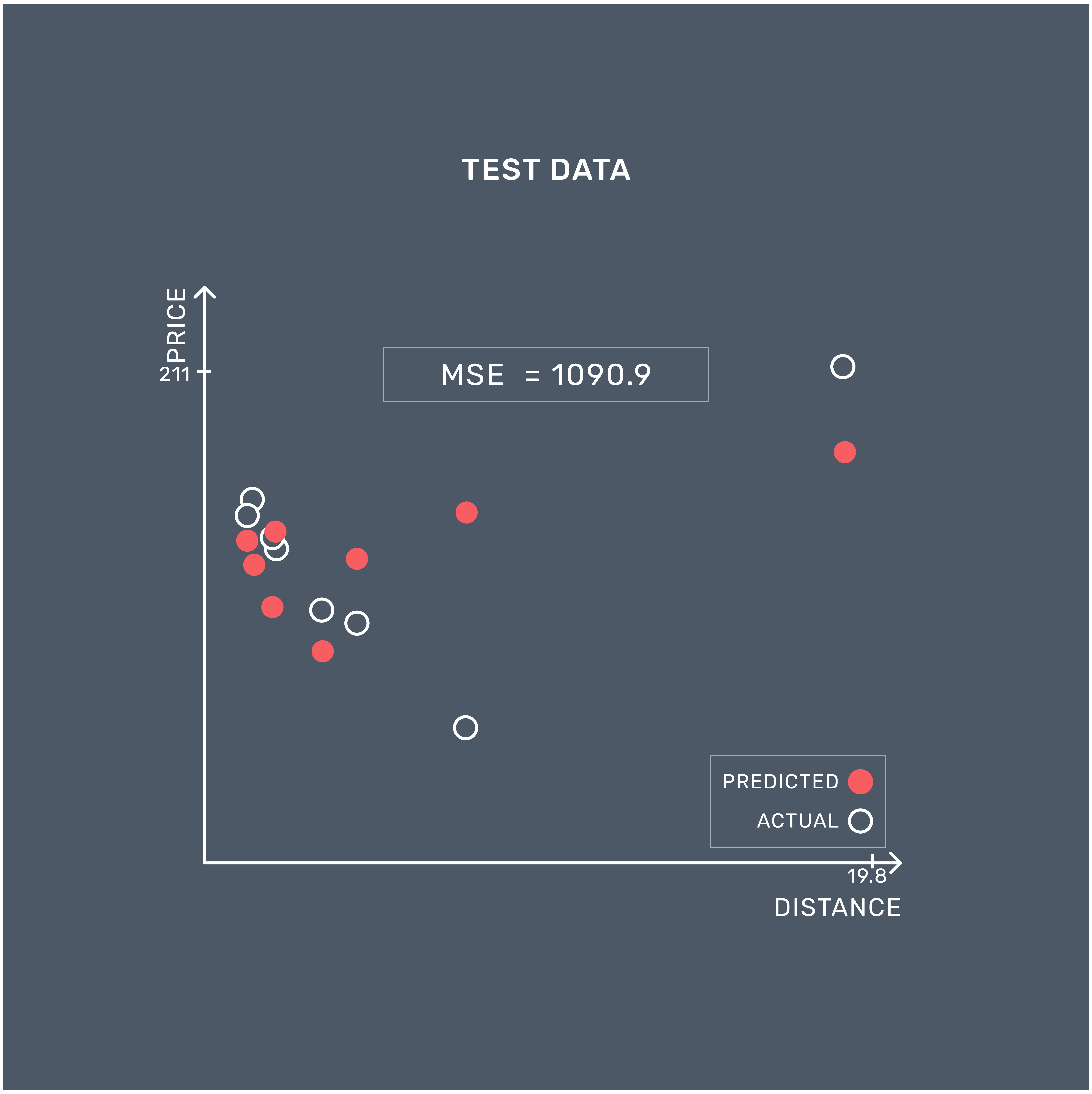
With all the details, it's easy to lose sight of the goal. It's a good time to remind ourselves that all this boils down to finding the optimal weights that give the most accurate predictions.

Now that training is complete, the neural network should have learned enough to produce decent predictions.



## TRAINING PERFORMANCE

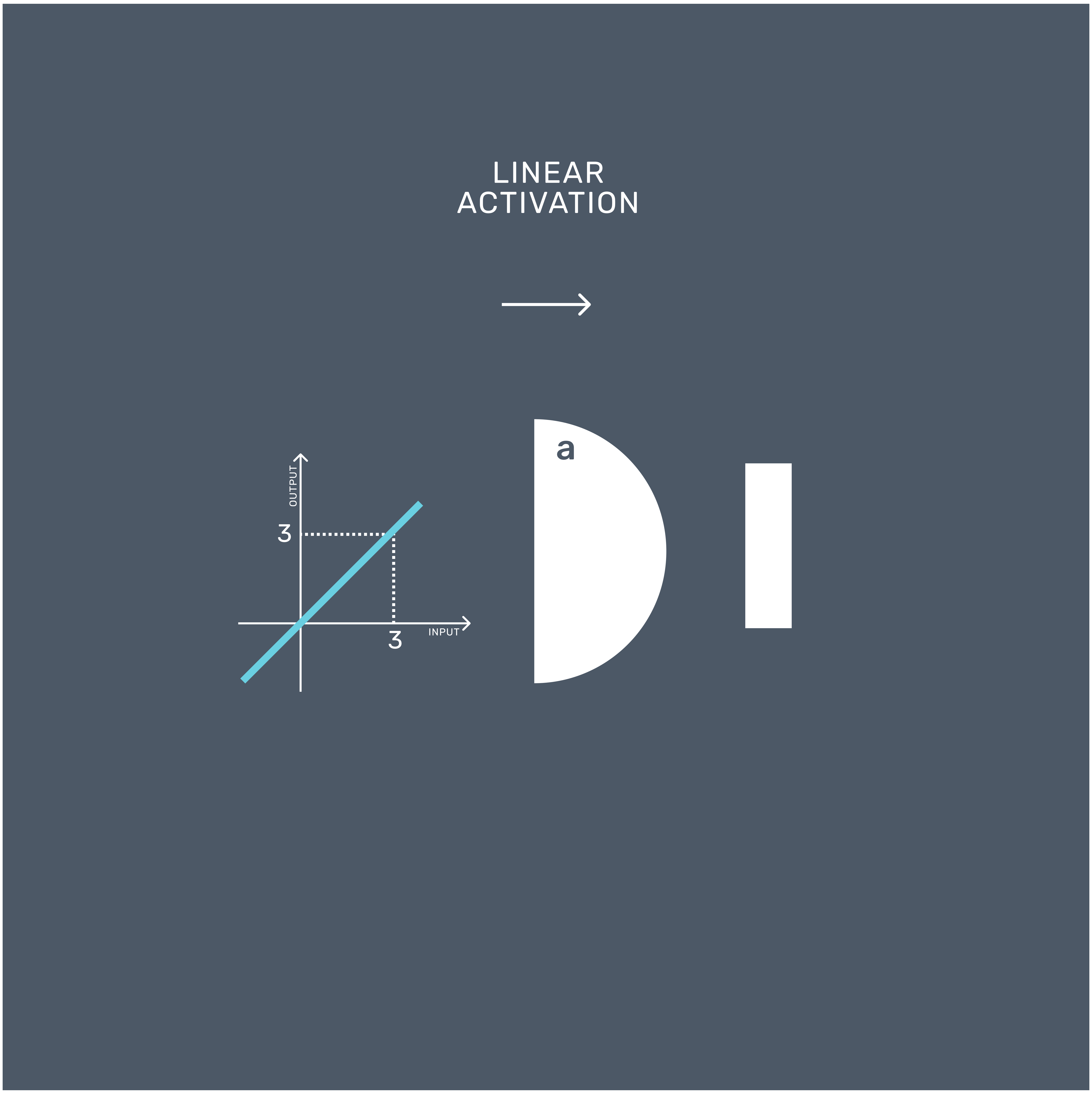
However, this doesn't seem to be the case. The MSE of the training data is very poor. Meanwhile, when plotted, the predictions seem as good as random. It appears that the neural network hasn't learned much!



## TEST PERFORMANCE

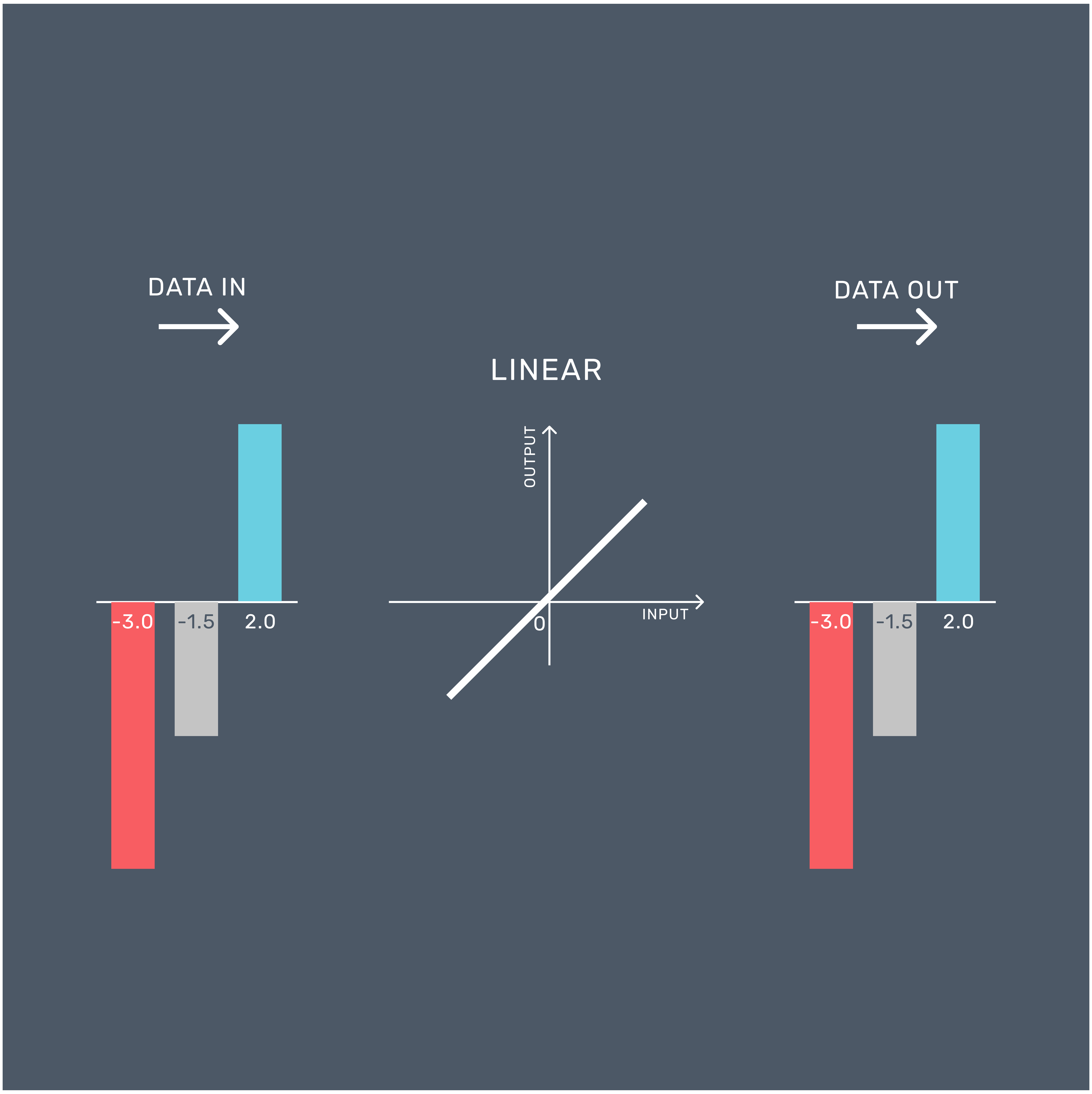
The same is true with the test data. The predictions don't seem anywhere close to the actual values.

So, where did this go wrong?



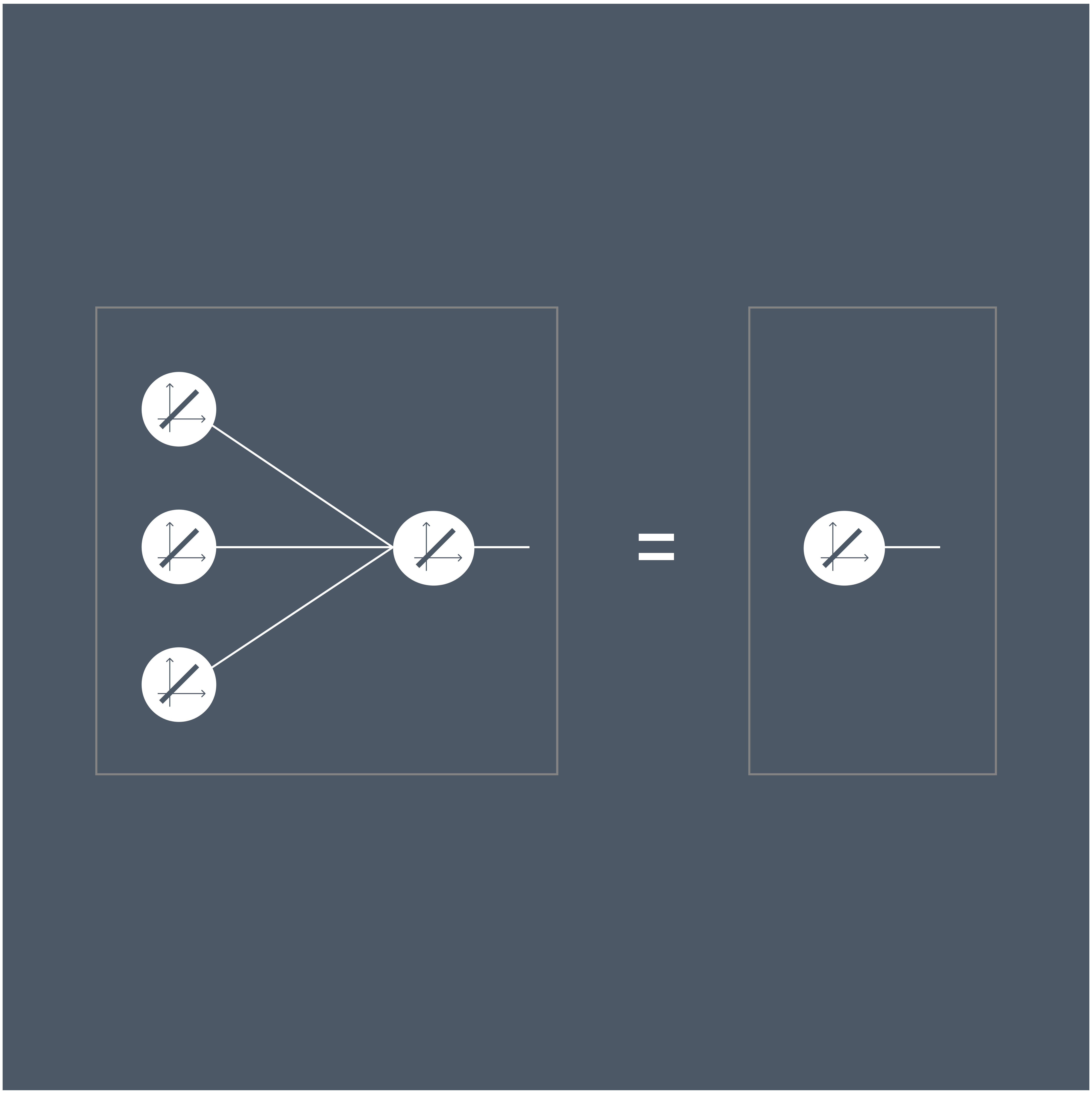
## ACTIVATION FUNCTION

The answer lies in the activation function that we used. All neurons were using linear activation.



## LINEAR ACTIVATION

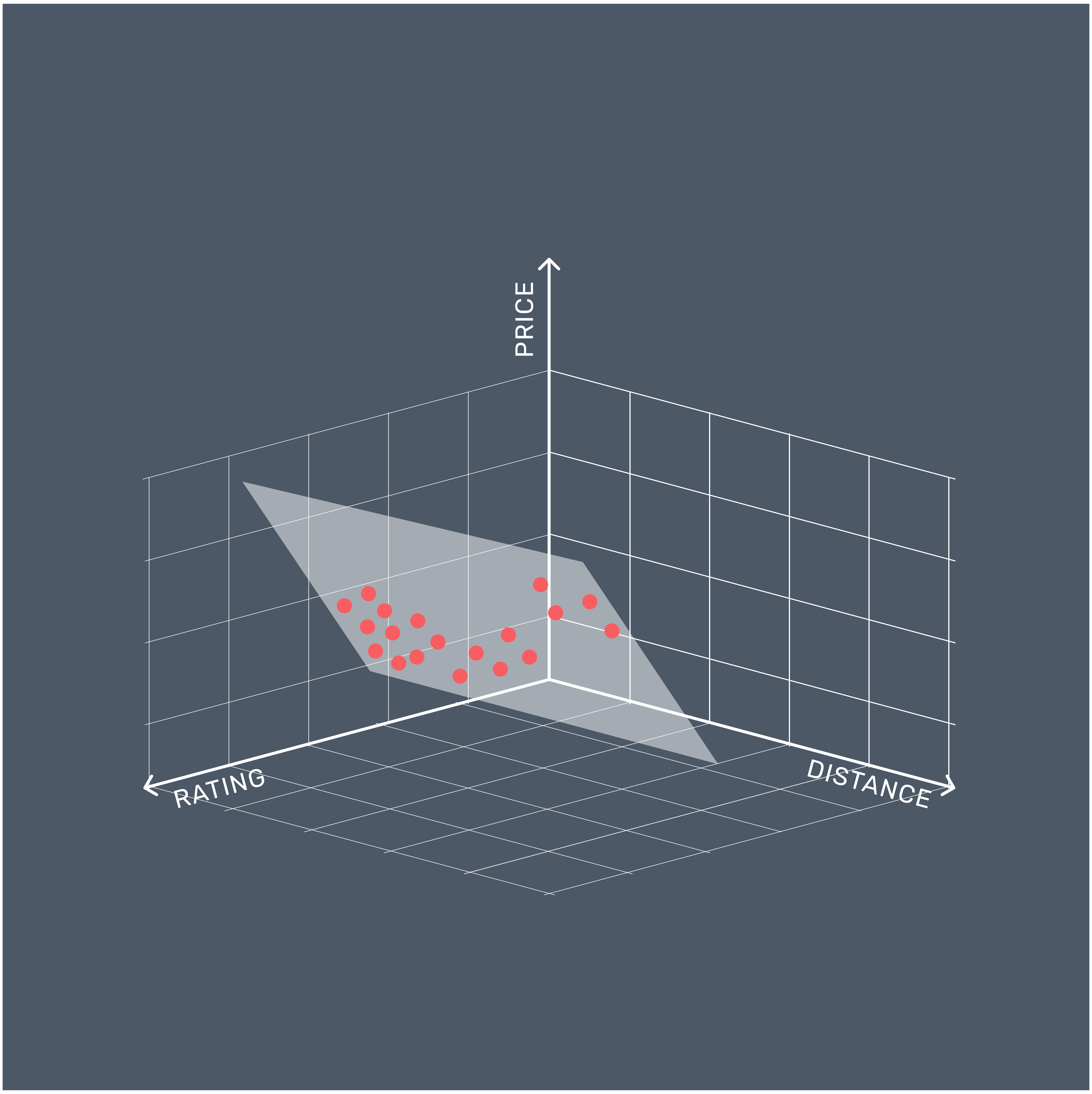
As we've seen, a linear activation function returns exactly the same value of the input it receives.



## LINEARITY

It can be shown mathematically that if all neurons in the hidden layer are using linear activation, they make no difference to the output. It doesn't matter how many neurons there are. It is effectively the same as having no hidden layer, which is equivalent to what we had in Chapter 1.

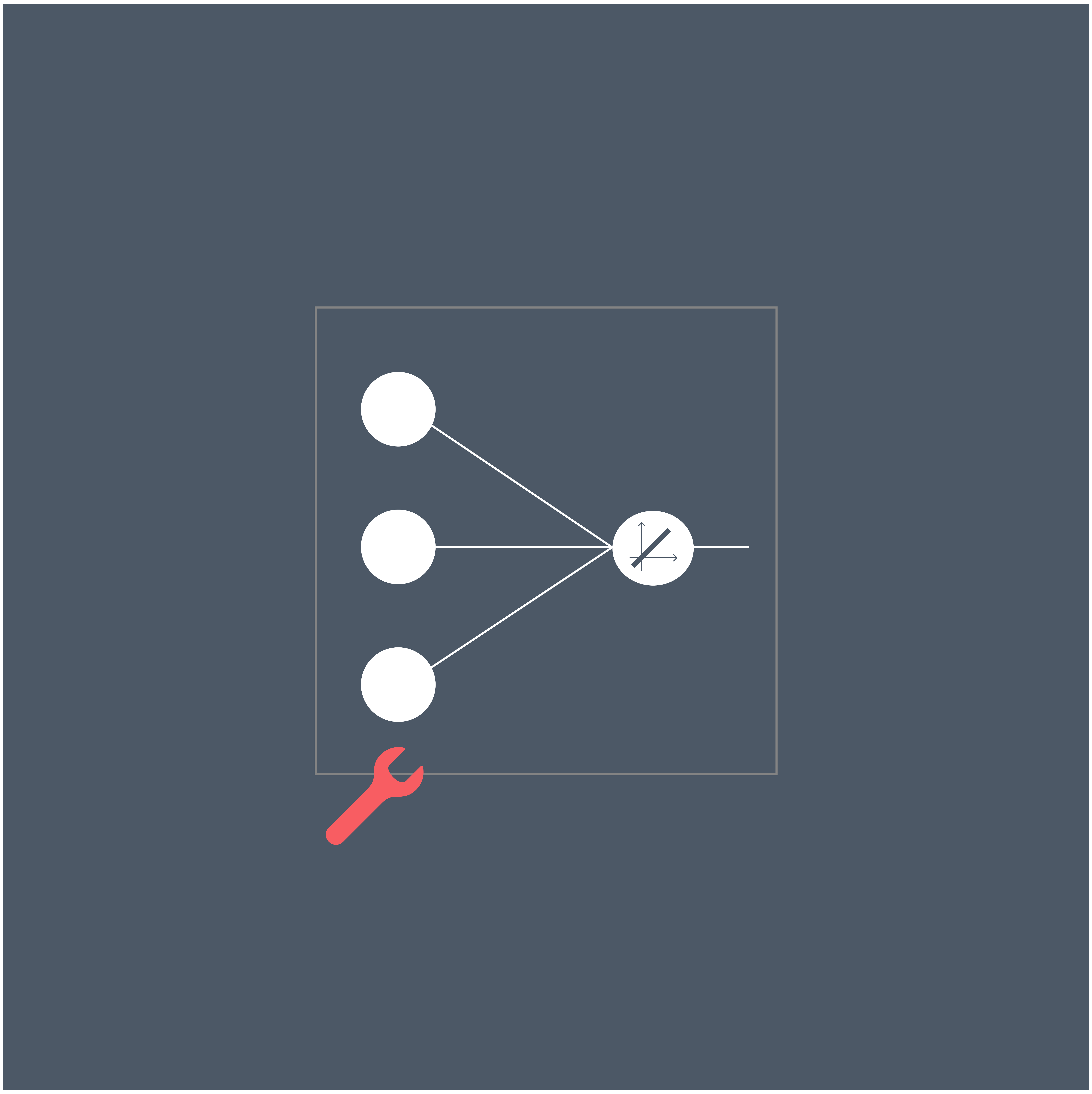
For this reason, our neural network was unable to capture the non-linearities in the data.



### LINEAR PLANE

Returning to our earlier plot of training predictions, it may not appear that the results were linear.

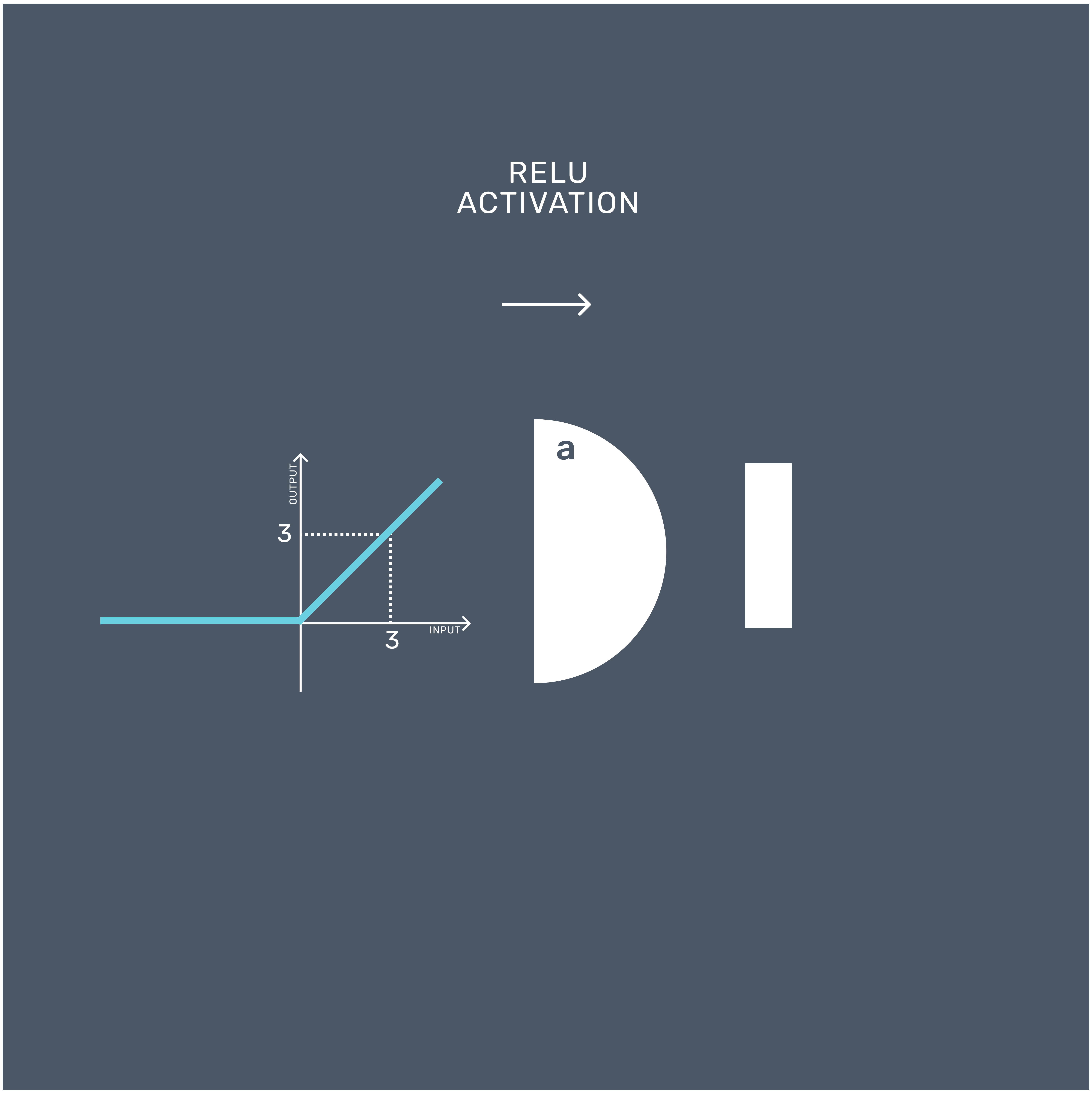
But indeed, they were. If we were to plot the predictions on a 3D chart, we would see them falling on a linear 2D plane.



## NON-LINEARITY

The solution to our problem is to introduce non-linearity in the hidden layers. With non-linearity, having hidden layers now makes a huge difference.

The more layers and neurons the neural network has, the more complex relationships in the data it can capture.

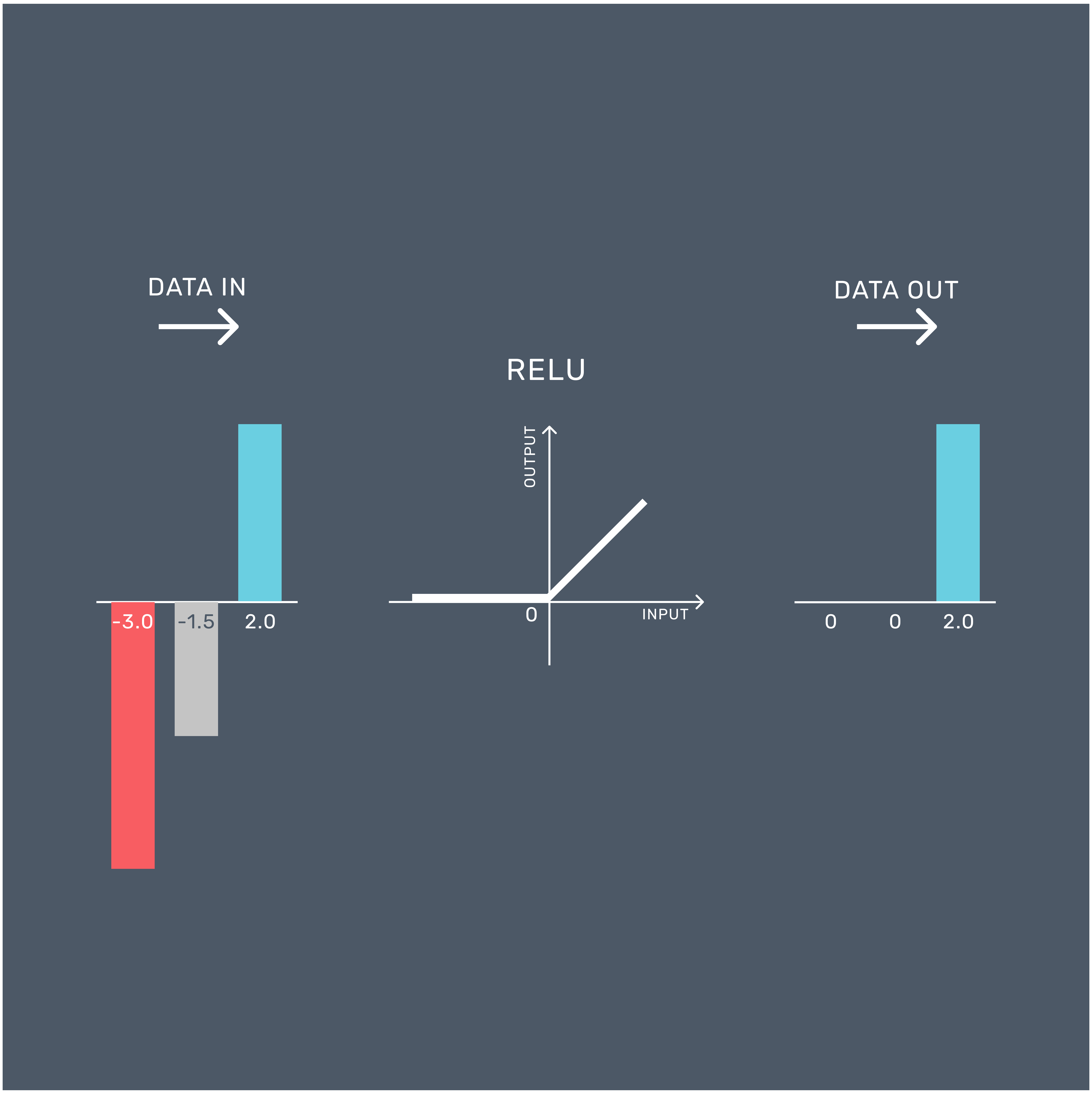


## RELU ACTIVATION FUNCTION

To add the much-needed non-linearity, we turn to an activation function called the *rectified linear unit (ReLU)*. It is an activation function used widely in neural networks today. It's a simple change from the linear function, but it serves its purpose and does its job very well.

For any positive input, the ReLU activation outputs the same value, just like the linear activation.

The difference is for the negative inputs. If the input is negative, the ReLU activation will output zero.

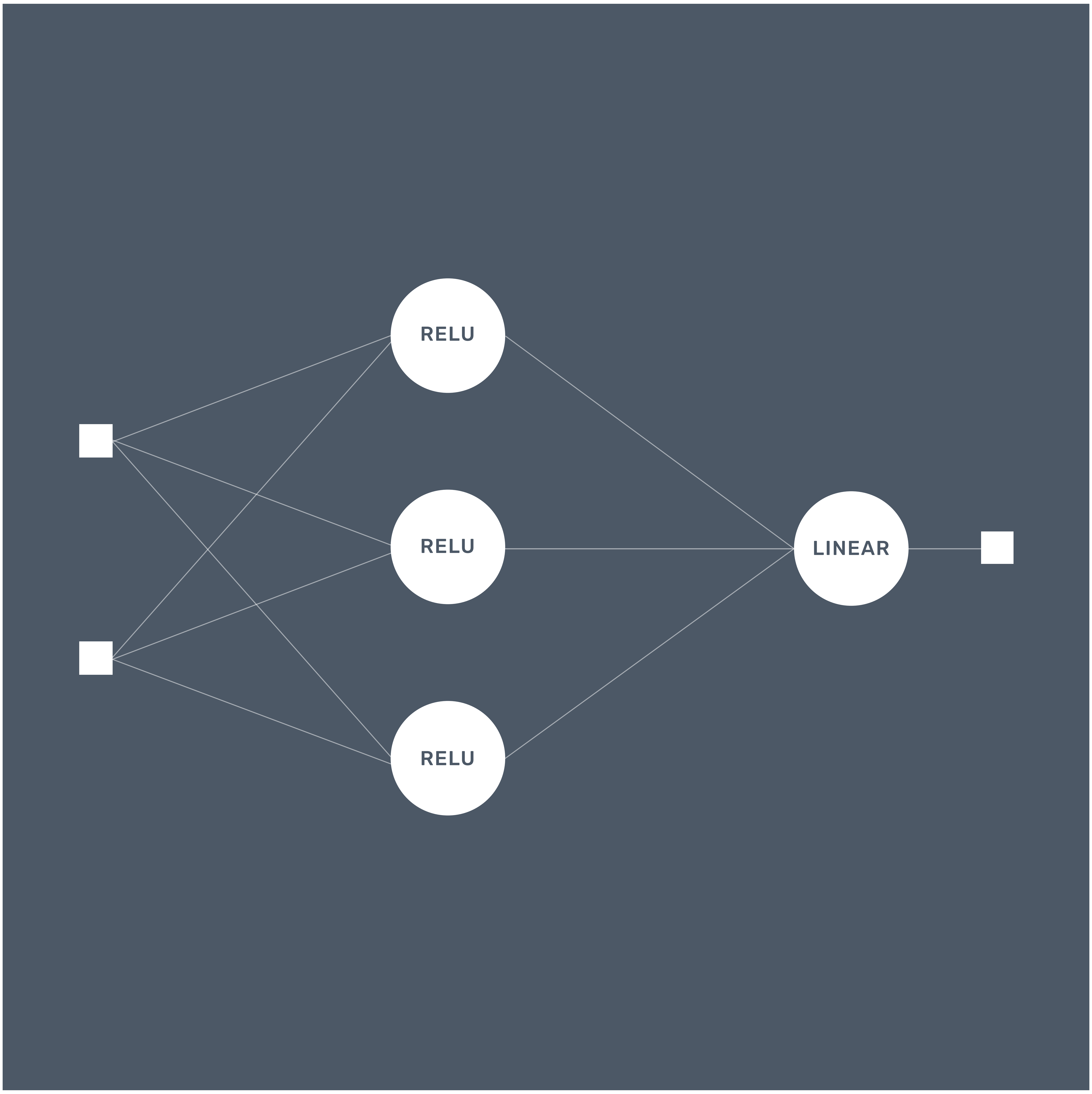


## CHOICE

The ReLU effectively works like a gate - it turns on whenever the input is above zero and turns off otherwise. As simple as it may look, it enables the neuron to have a pretty powerful ability—a choice.

With linear activation, it doesn't matter whether it thinks a piece of information is important or not, it just lets it through.

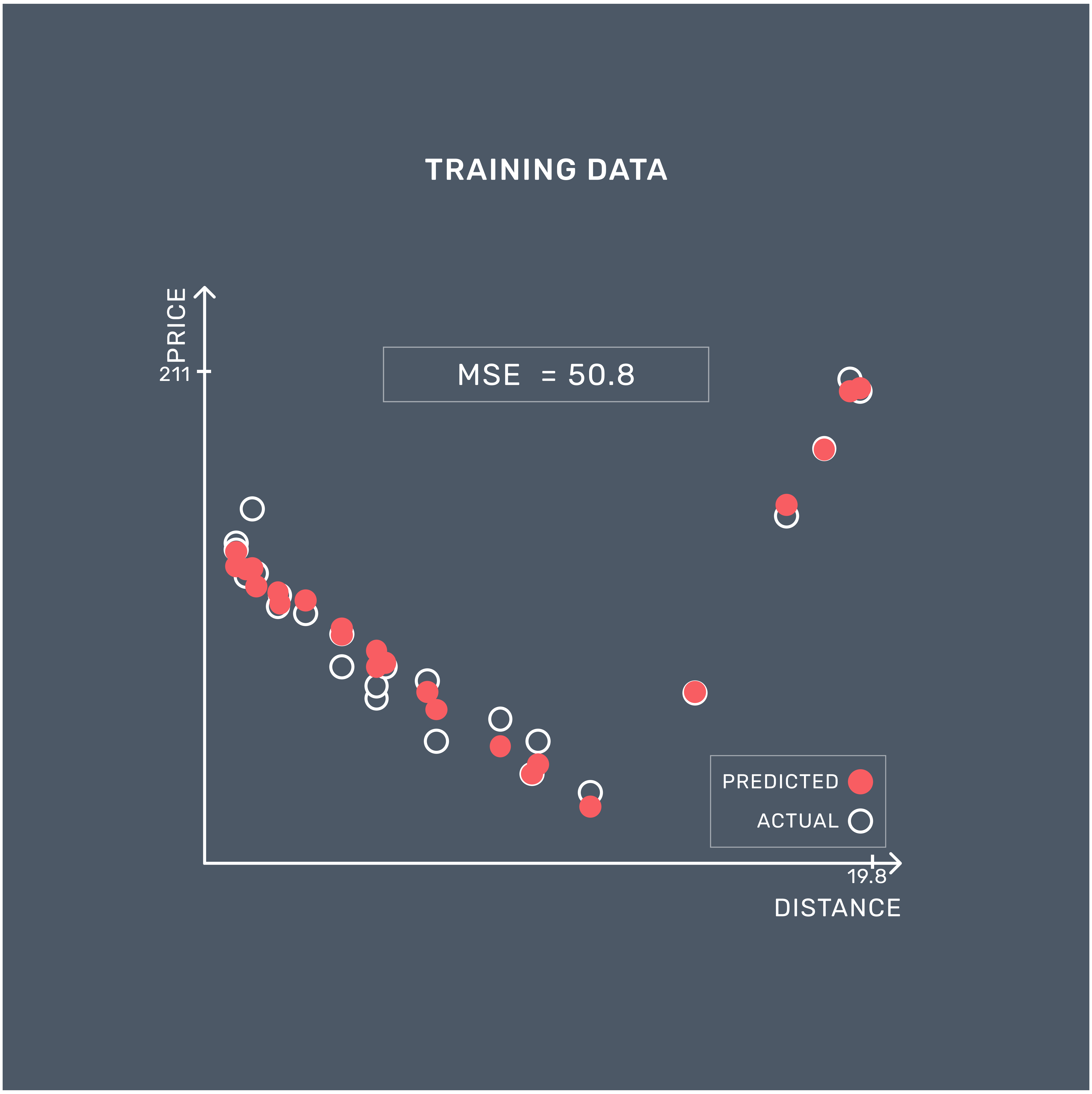
But with ReLU, every neuron can make a difference. It can now choose to only ‘activate’ when the input is positive.



## RECONFIGURE

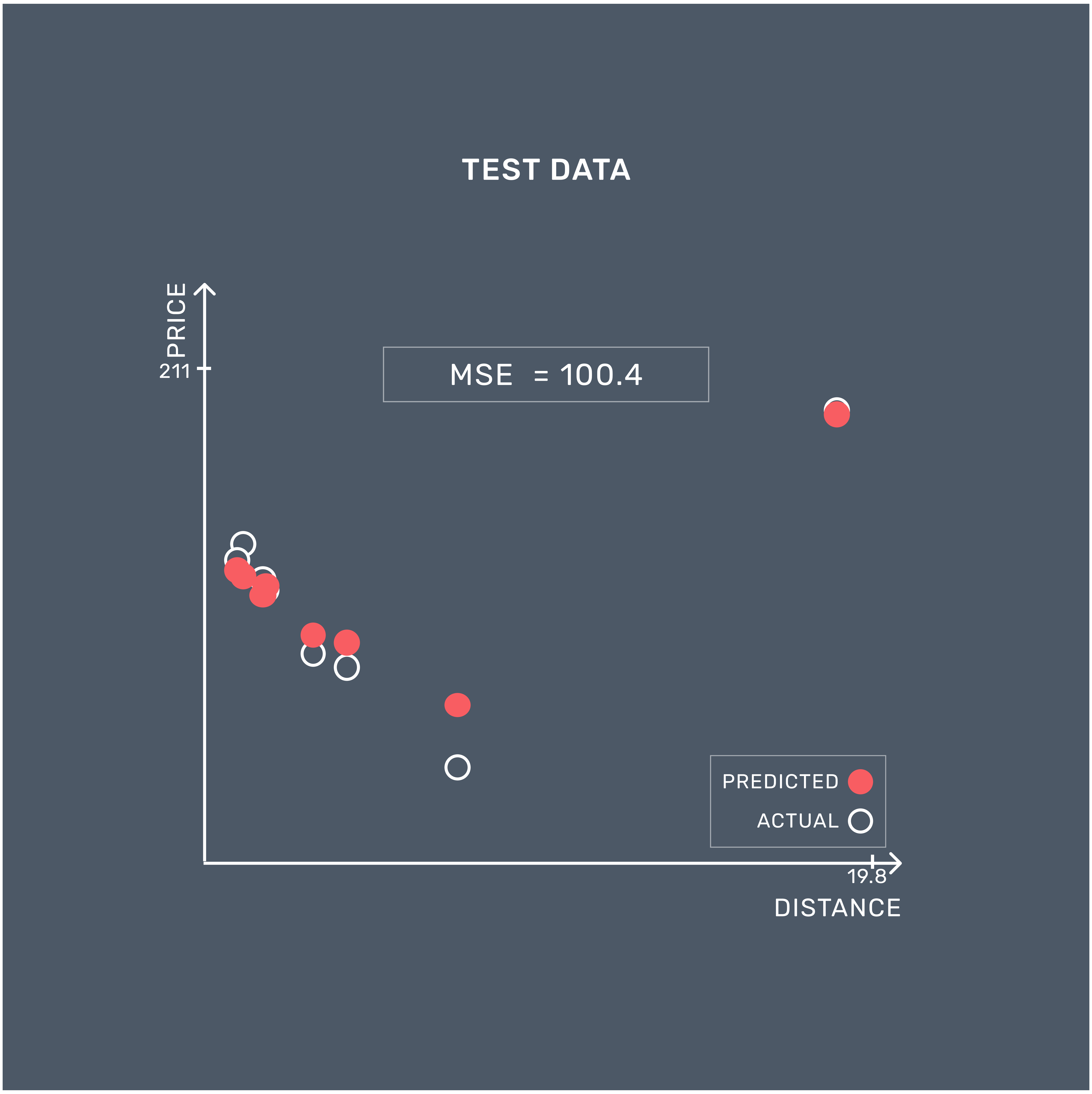
We'll now replace the linear activation functions in the hidden layer with ReLU.

In the output layer, it’s fine to keep the linear activation for this task. In the next chapter, we'll see a task where we do need to change the activation function in the output layer.



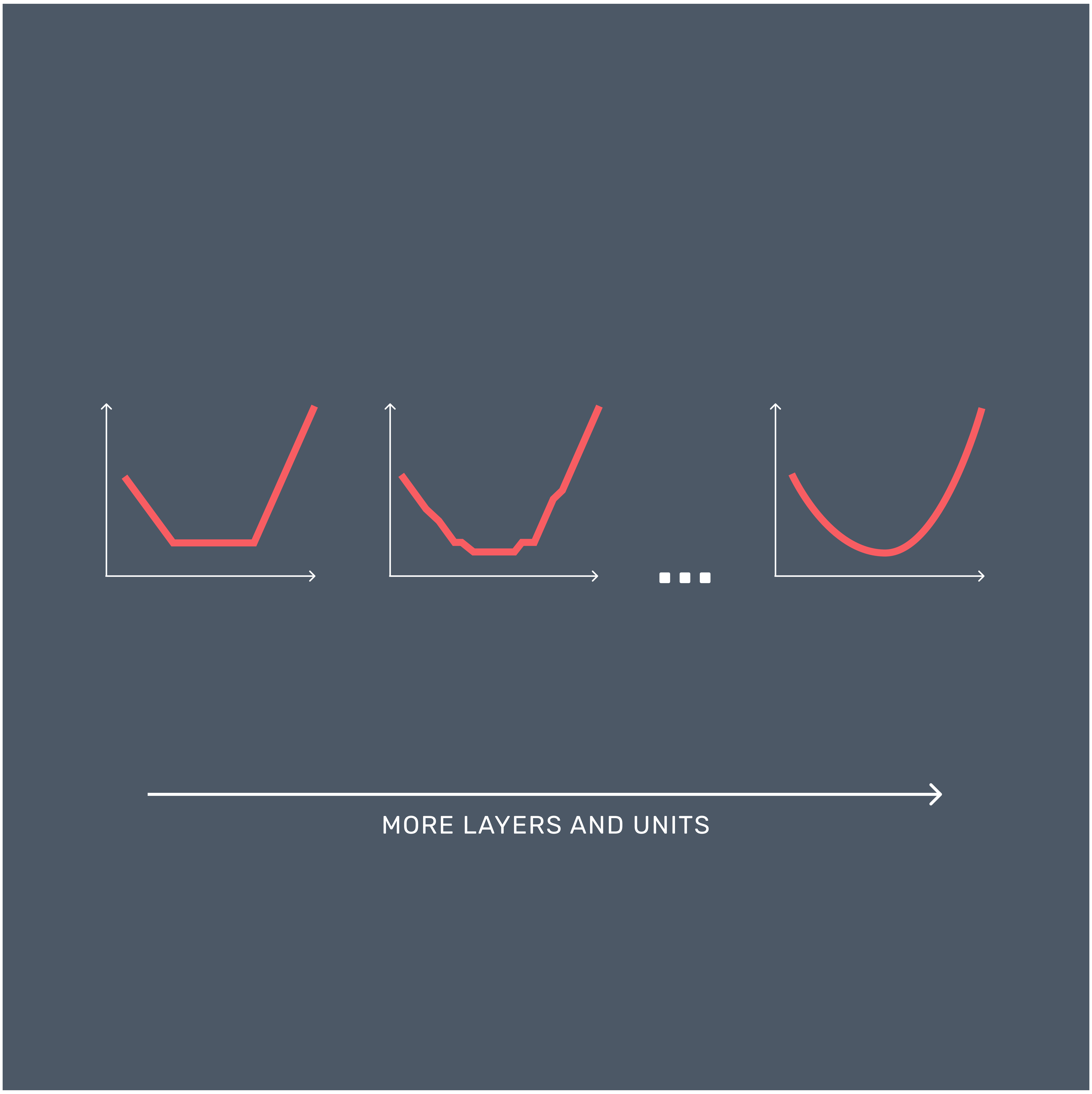
## TRAINING PERFORMANCE

This time, it looks like we are heading in the right direction. The MSE of the training predictions is much better now.



## TEST PERFORMANCE

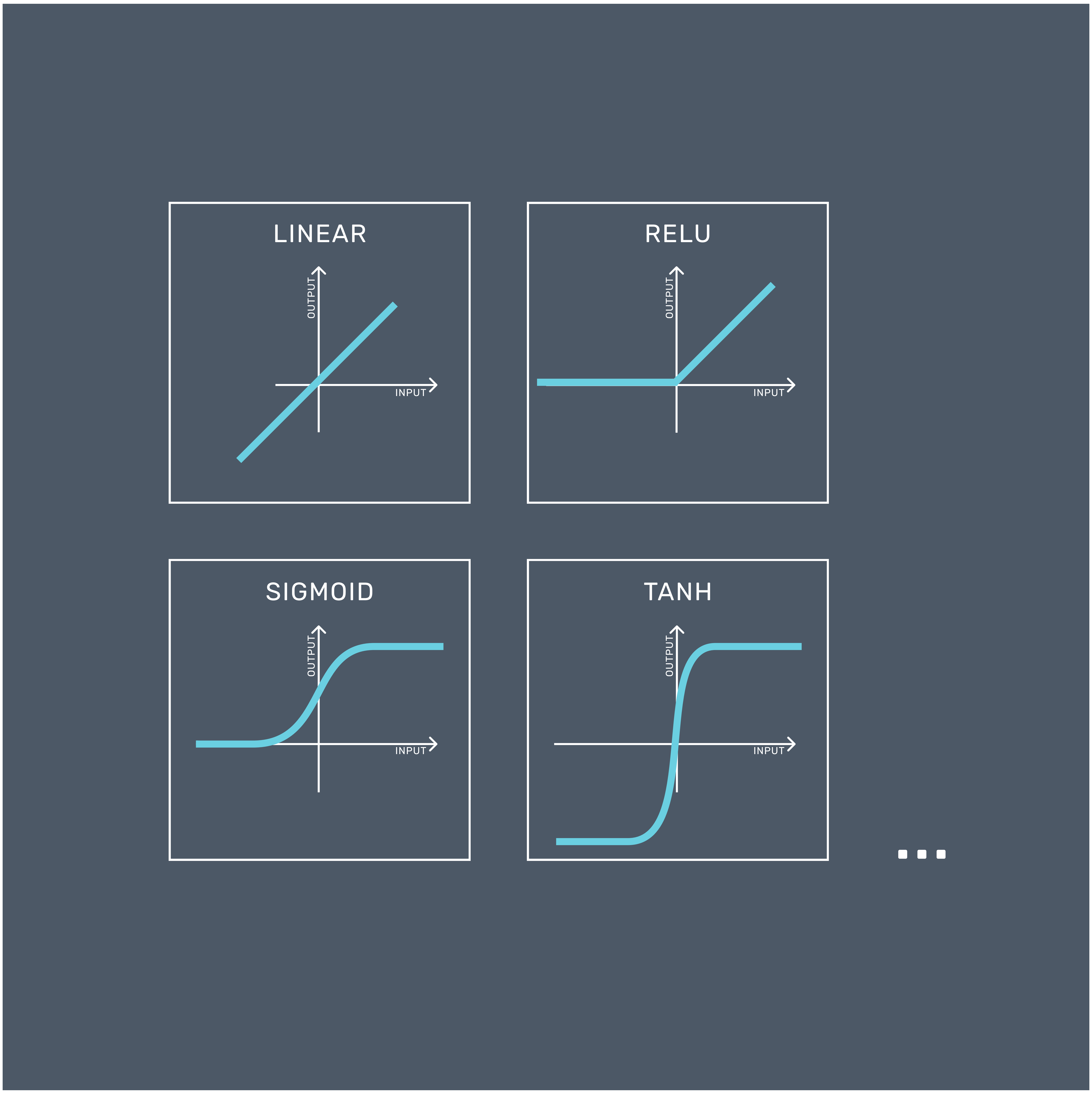
And the MSE of the test predictions is not too bad either. As in Chapter 1, we can bring it closer to the training MSE by having more data points and ensuring that the training and test distributions are similar.



## MORE NEURONS

If we want to, we can further improve the performance by adding more layers and units.

As we add more neurons, the neural network will be able to increase the granularity of its predictions, resulting in a prediction curve that is smoother and more well-defined.

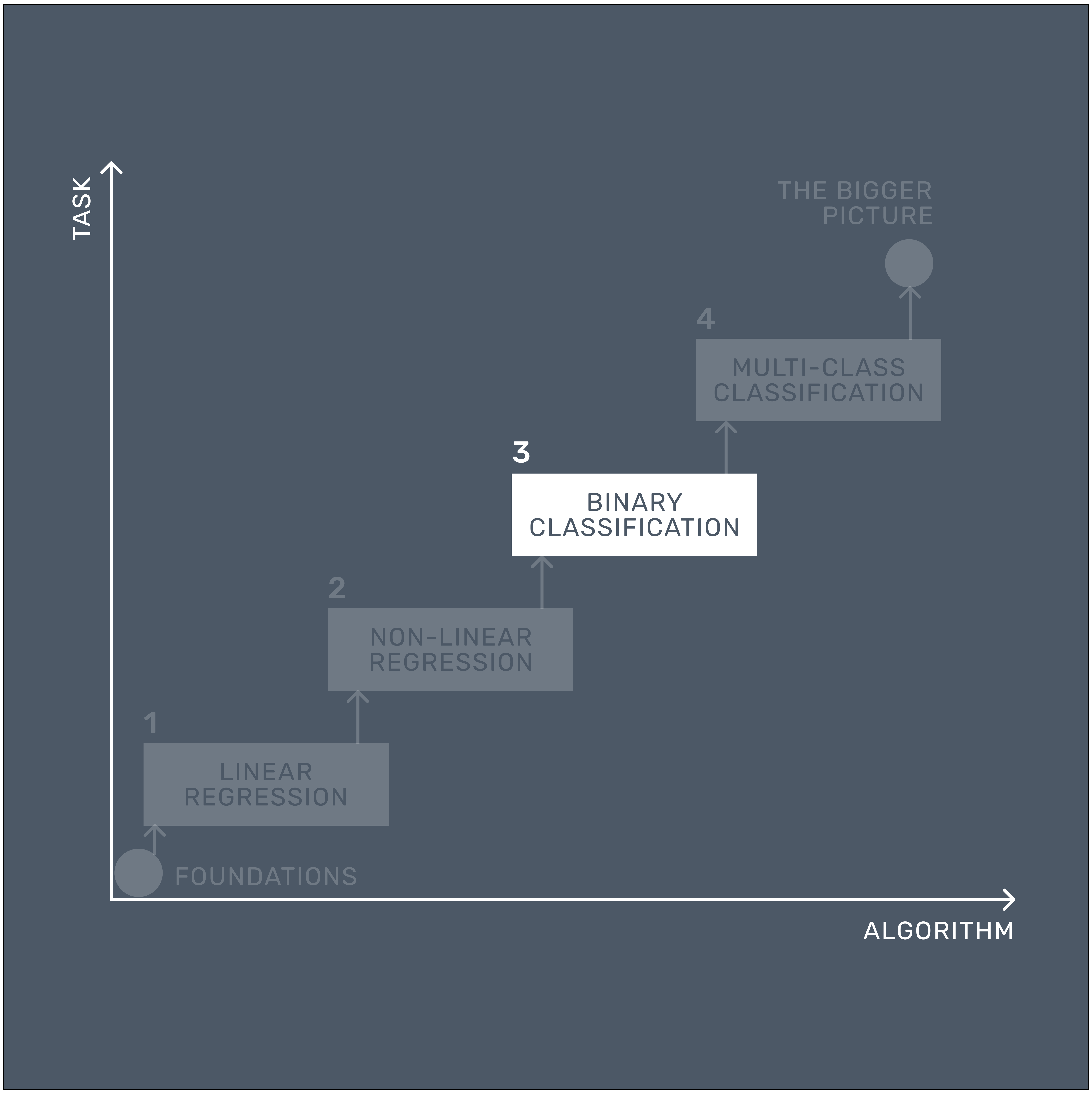


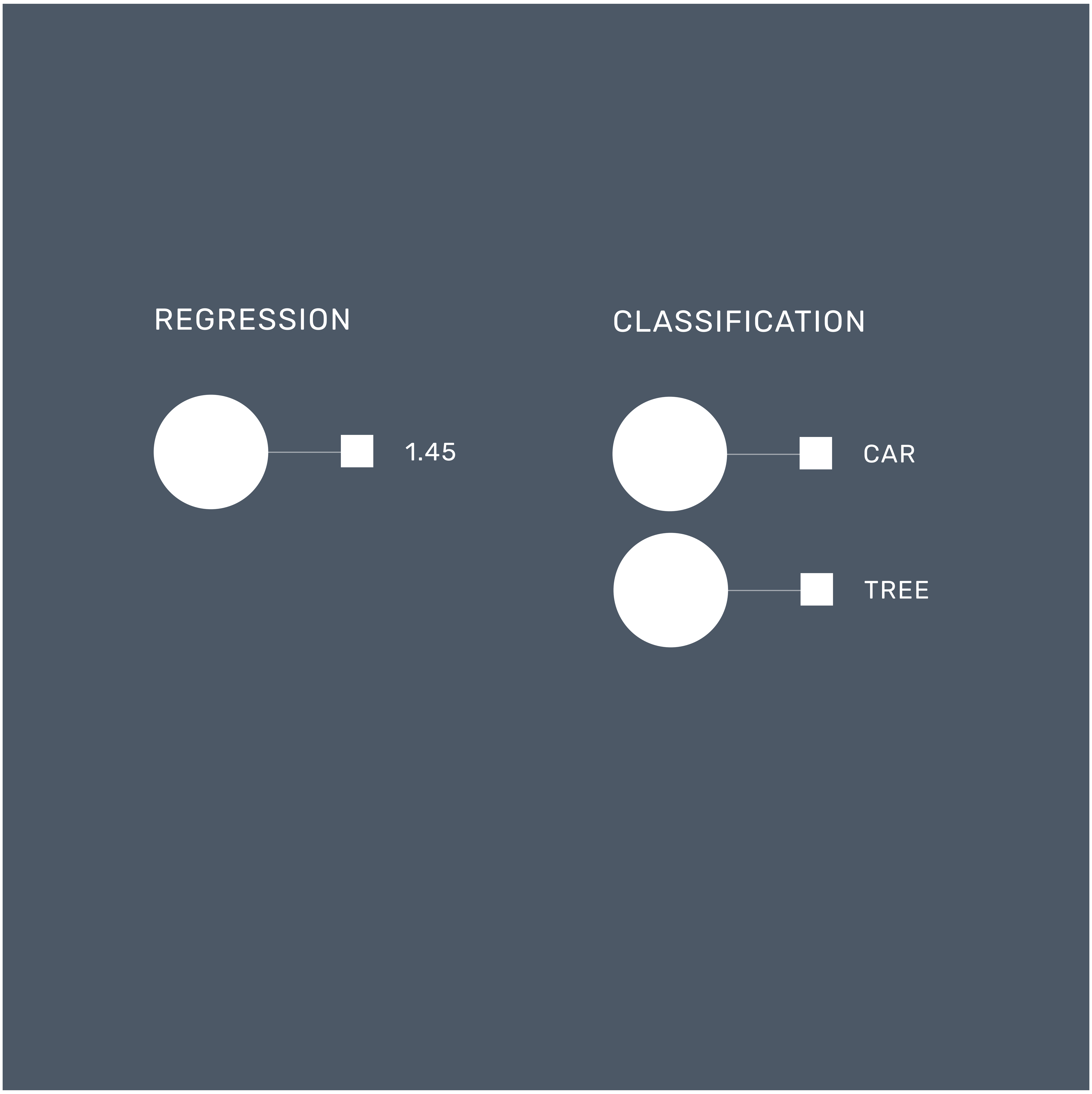
## ACTIVATION FUNCTIONS

There are many other types of activation functions. Some of the more commonly used ones are shown here. Each activation function allows the neural network to exhibit a different kind of quality compared to the others.

We'll look at another type, *sigmoid*, in the next chapter.

# 3 - BINARY CLASSIFICATION

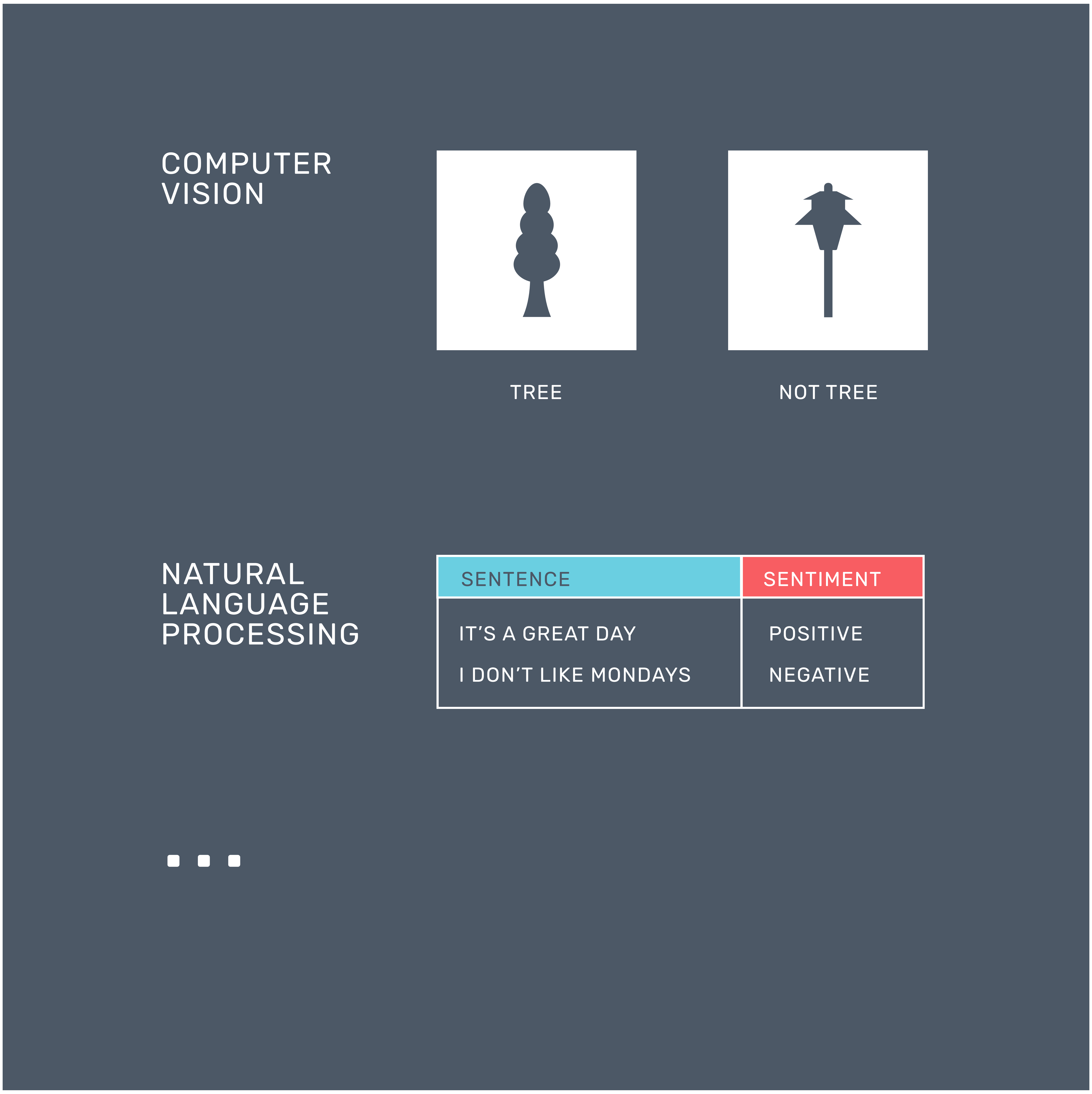




## CLASSIFICATION

We have seen how the neural network performs regression tasks. In this chapter, we'll see how it performs another type of task—*classification*.

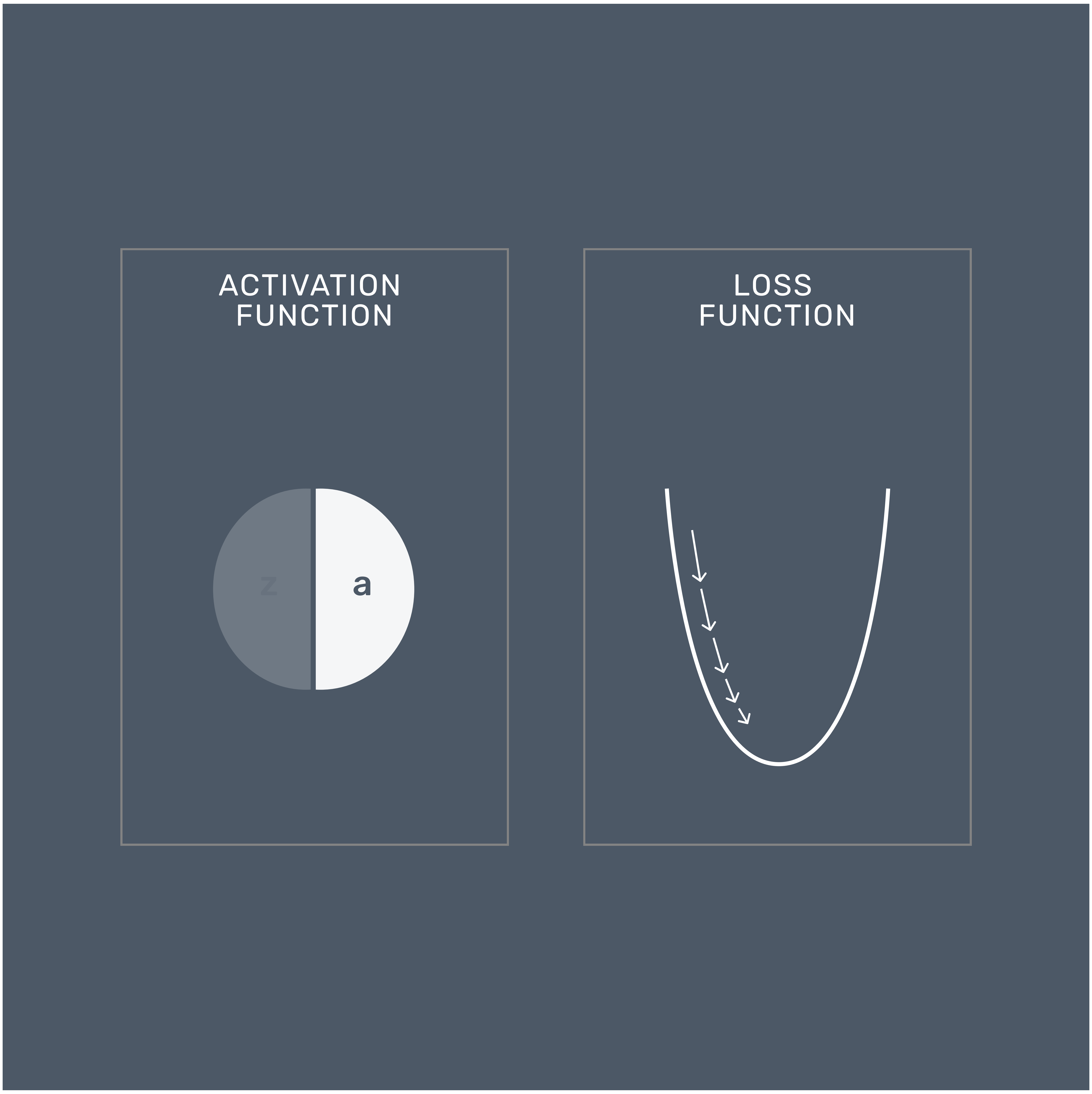
While regression is about predicting continuous values, classification is about predicting groups.



| SENTENCE | SENTIMENT |
|---|---|
| IT'S A GREAT DAY | POSITIVE |
| I DON'T LIKE MONDAYS | NEGATIVE |

## CLASSIFICATION USE CASES

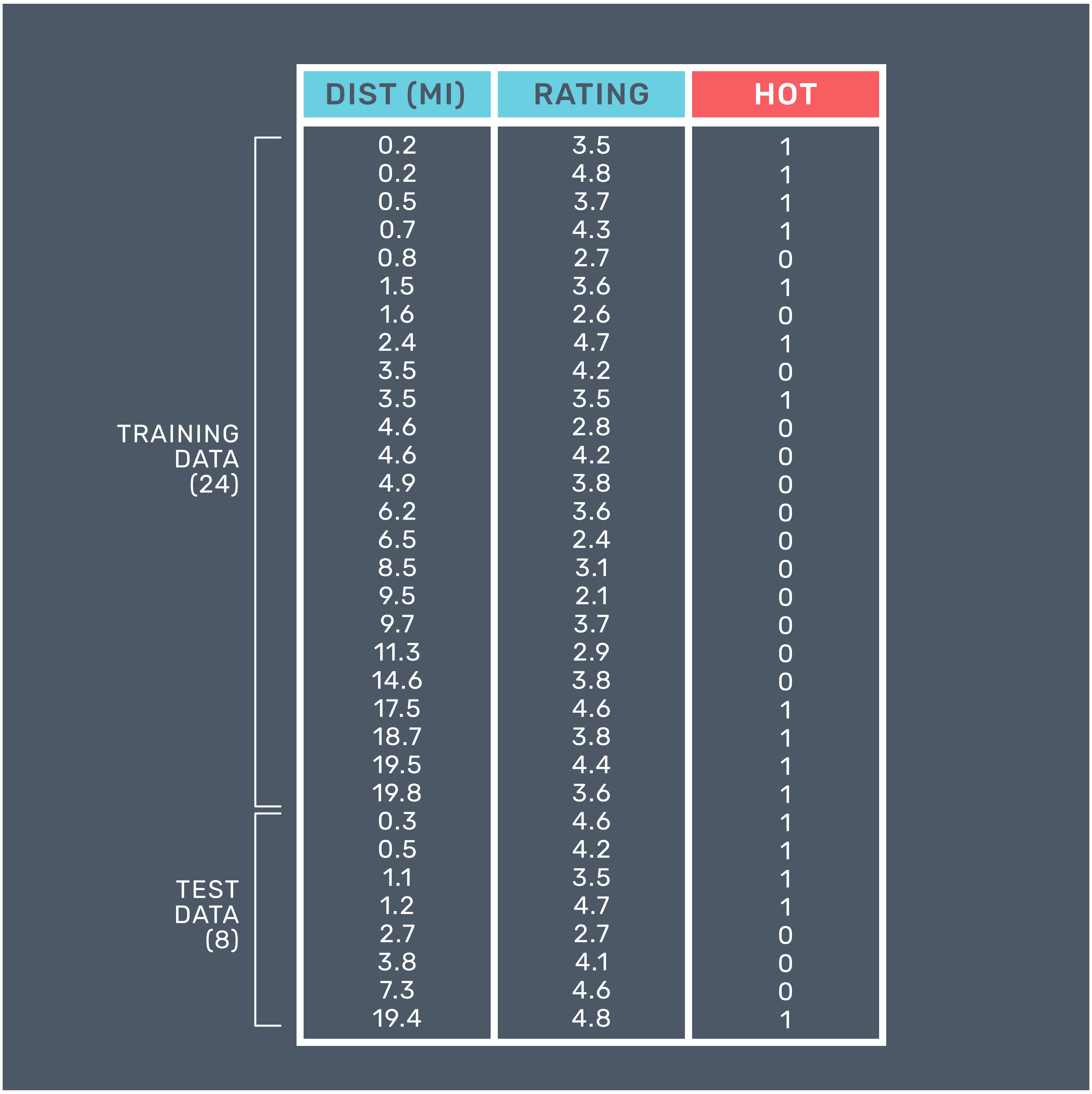
There is an endless list of deep learning use cases in the real world that involve classification. The classic examples are image classification in computer vision and sentiment analysis in natural language processing (NLP).



## CLASSIFICATION VS. REGRESSION

The good news is, as we move from regression to classification, the basic principles of the neural network remain the same.

In fact, there are only two major differences to note. The first is the type of activation function and the second is the type of loss function. We'll learn more about them in this chapter.



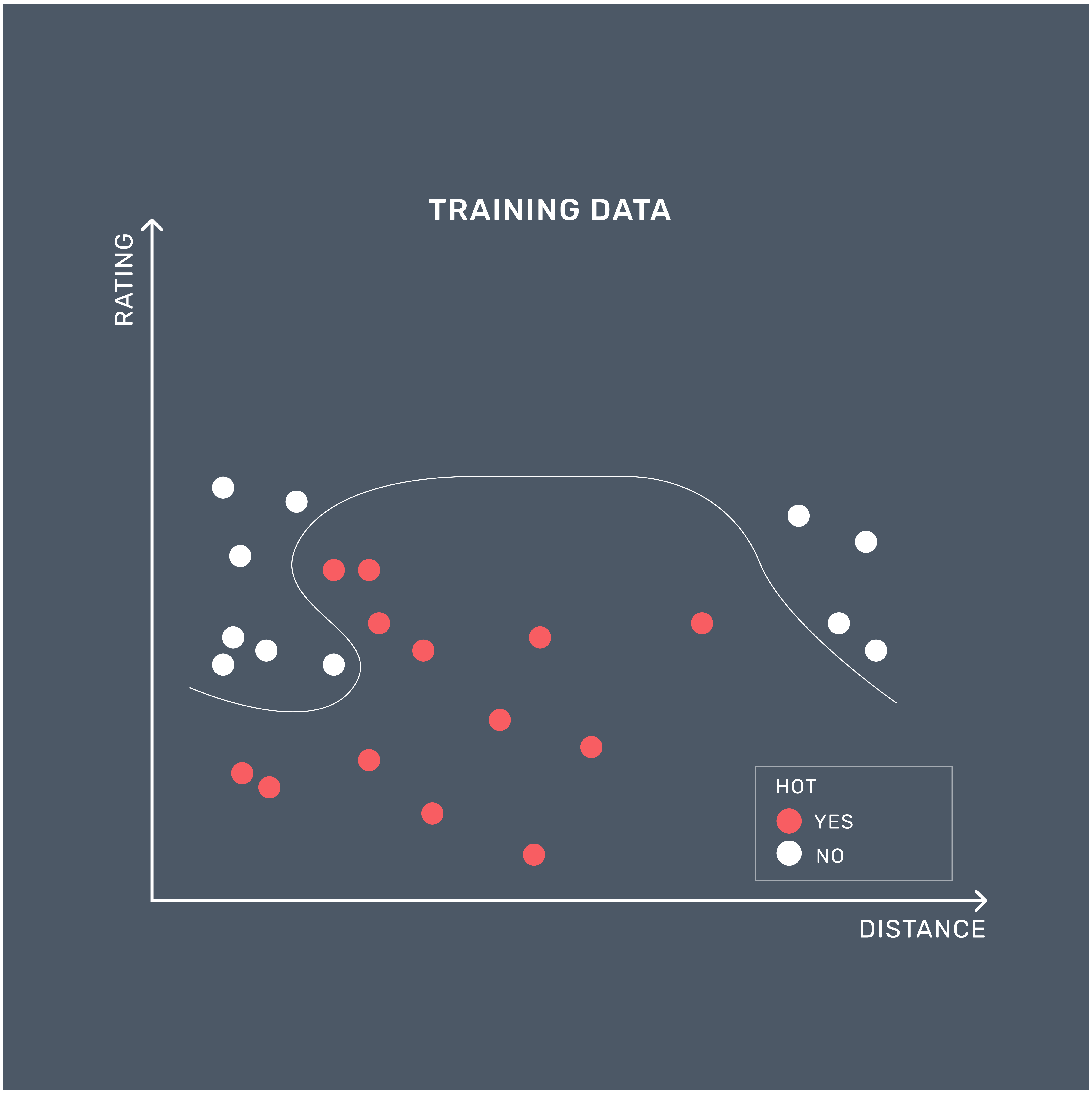
| | DIST (MI) | RATING | HOT |
|---|---|---|---|
| TRAINING DATA (24) | 0.2 | 3.5 | 1 |
| | 0.2 | 4.8 | 1 |
| | 0.5 | 3.7 | 1 |
| | 0.7 | 4.3 | 1 |
| | 0.8 | 2.7 | 0 |
| | 1.5 | 3.6 | 1 |
| | 1.6 | 2.6 | 0 |
| | 2.4 | 4.7 | 1 |
| | 3.5 | 4.2 | 0 |
| | 3.5 | 3.5 | 1 |
| | 4.6 | 2.8 | 0 |
| | 4.6 | 4.2 | 0 |
| | 4.9 | 3.8 | 0 |
| | 6.2 | 3.6 | 0 |
| | 6.5 | 2.4 | 0 |
| | 8.5 | 3.1 | 0 |
| | 9.5 | 2.1 | 0 |
| | 9.7 | 3.7 | 0 |
| | 11.3 | 2.9 | 0 |
| | 14.6 | 3.8 | 0 |
| | 17.5 | 4.6 | 1 |
| | 18.7 | 3.8 | 1 |
| | 19.5 | 4.4 | 1 |
| | 19.8 | 3.6 | 1 |
| TEST DATA (8) | 0.3 | 4.6 | 1 |
| | 0.5 | 4.2 | 1 |
| | 1.1 | 3.5 | 1 |
| | 1.2 | 4.7 | 1 |
| | 2.7 | 2.7 | 0 |
| | 3.8 | 4.1 | 0 |
| | 7.3 | 4.6 | 0 |
| | 19.4 | 4.8 | 1 |

## THE DATASET

We'll use the same dataset as in Chapter 2 with one difference—we have replaced the target with a new one.

Let's suppose that we are tracking the hotels with the highest demand, segregating them from those which are not. This is represented by the new target called *hot* which has two possible values - *yes* and *no*.

The target is no longer a continuous variable but is a *categorical variable* instead. Categorical variables have a known, fixed number of values, or more precisely, *classes*. Unlike continuous variables, these classes do not imply any order (for example, whether one class is better than the other).

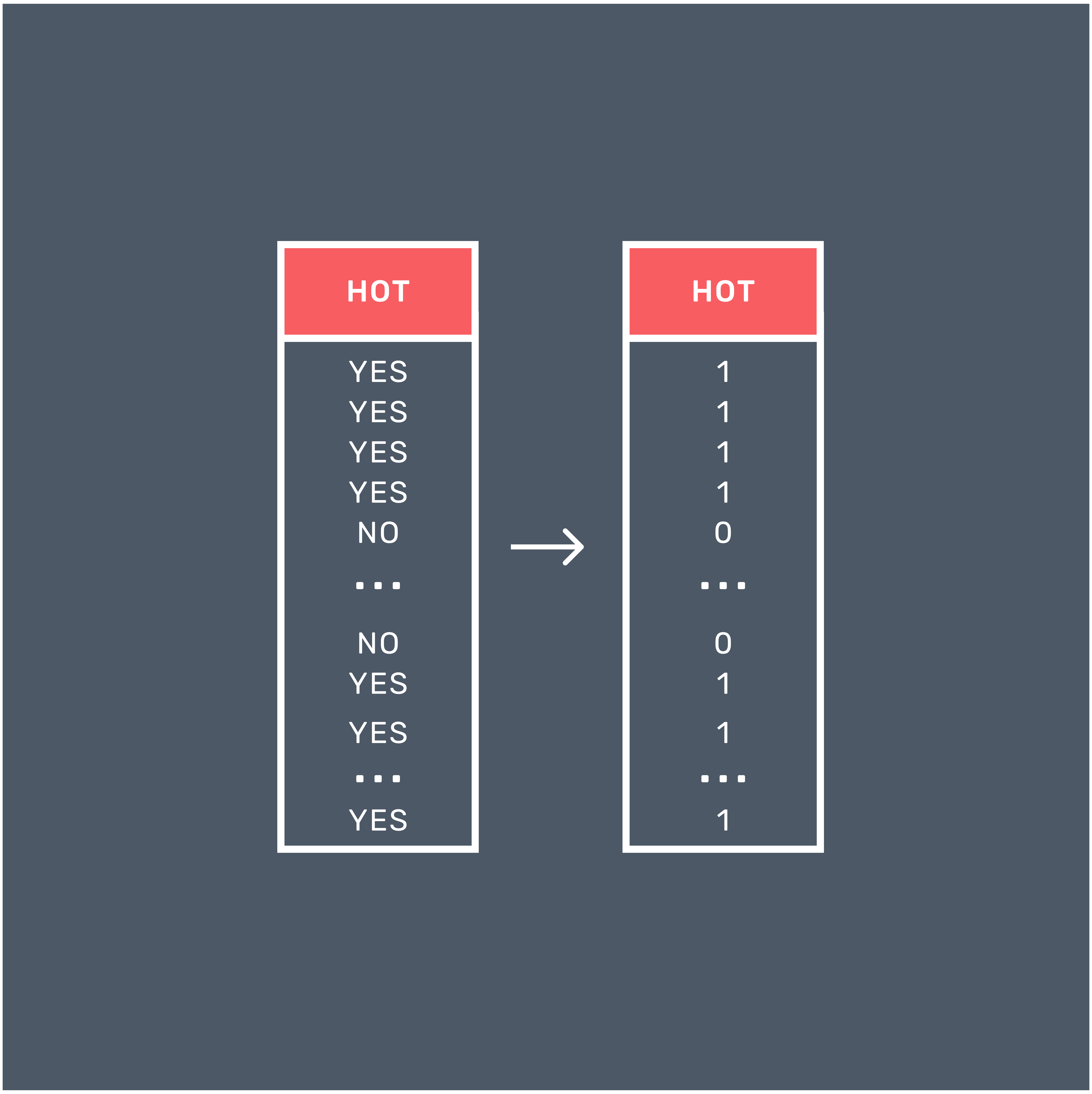


## THE DATASET

Recall that for regression, we wanted to model the line (for a single-feature scenario) or plane (for a two-feature scenario) where the predicted values would fall on.

As for classification, we want to model the classification *boundary* that separates the classes. For classification, it's more common to use the term *label* instead of *target*, so we will use that term from now on.

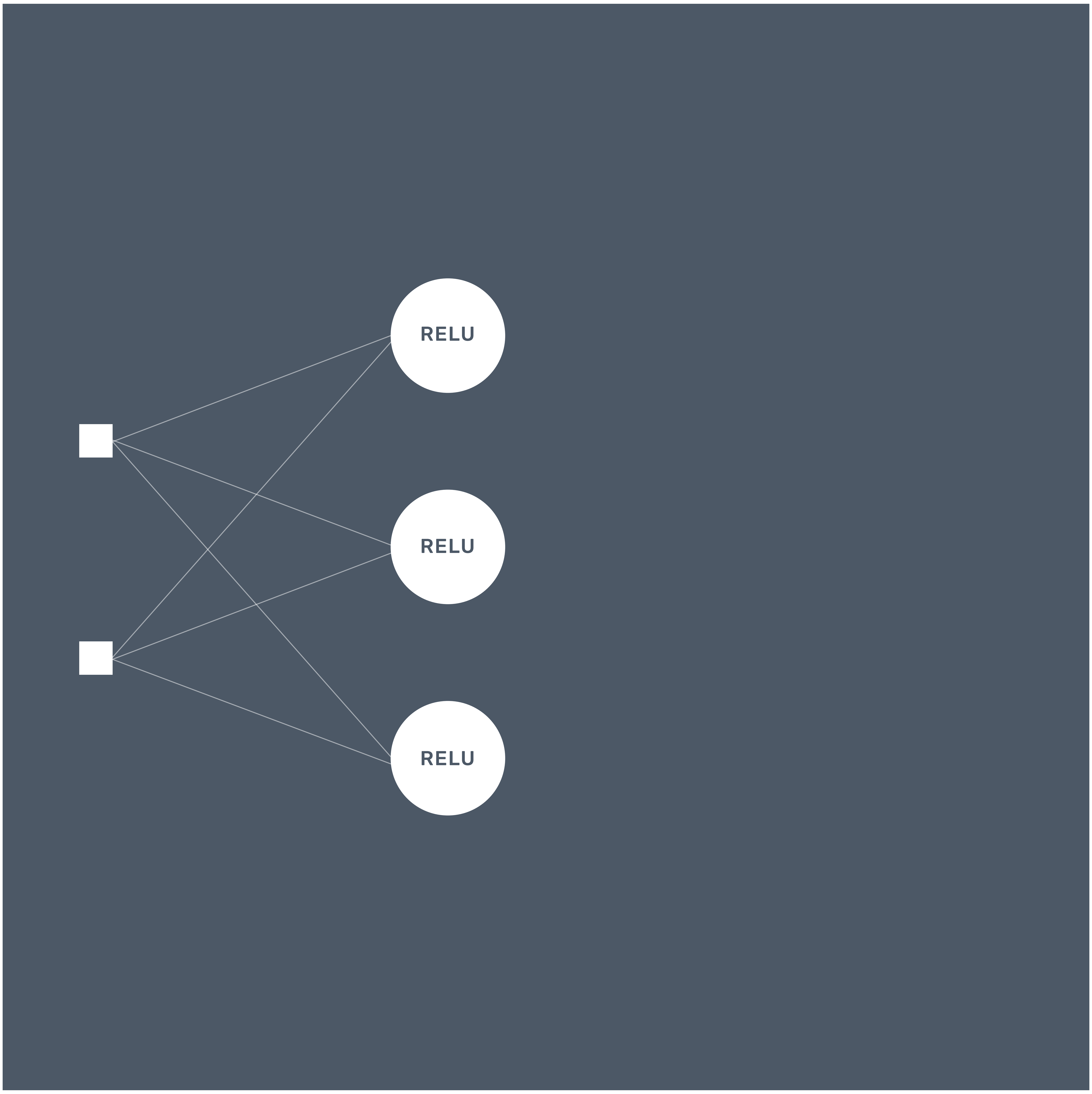
Here is shown the plot of the actual class for each training data point. Also shown is an example of a hand-drawn boundary that separates the two classes. This is what we want our neural network to produce.



## BINARY CLASSIFICATION

Our task is called a *binary classification* task because the outcome will be either one or the other - *yes* or *no*.

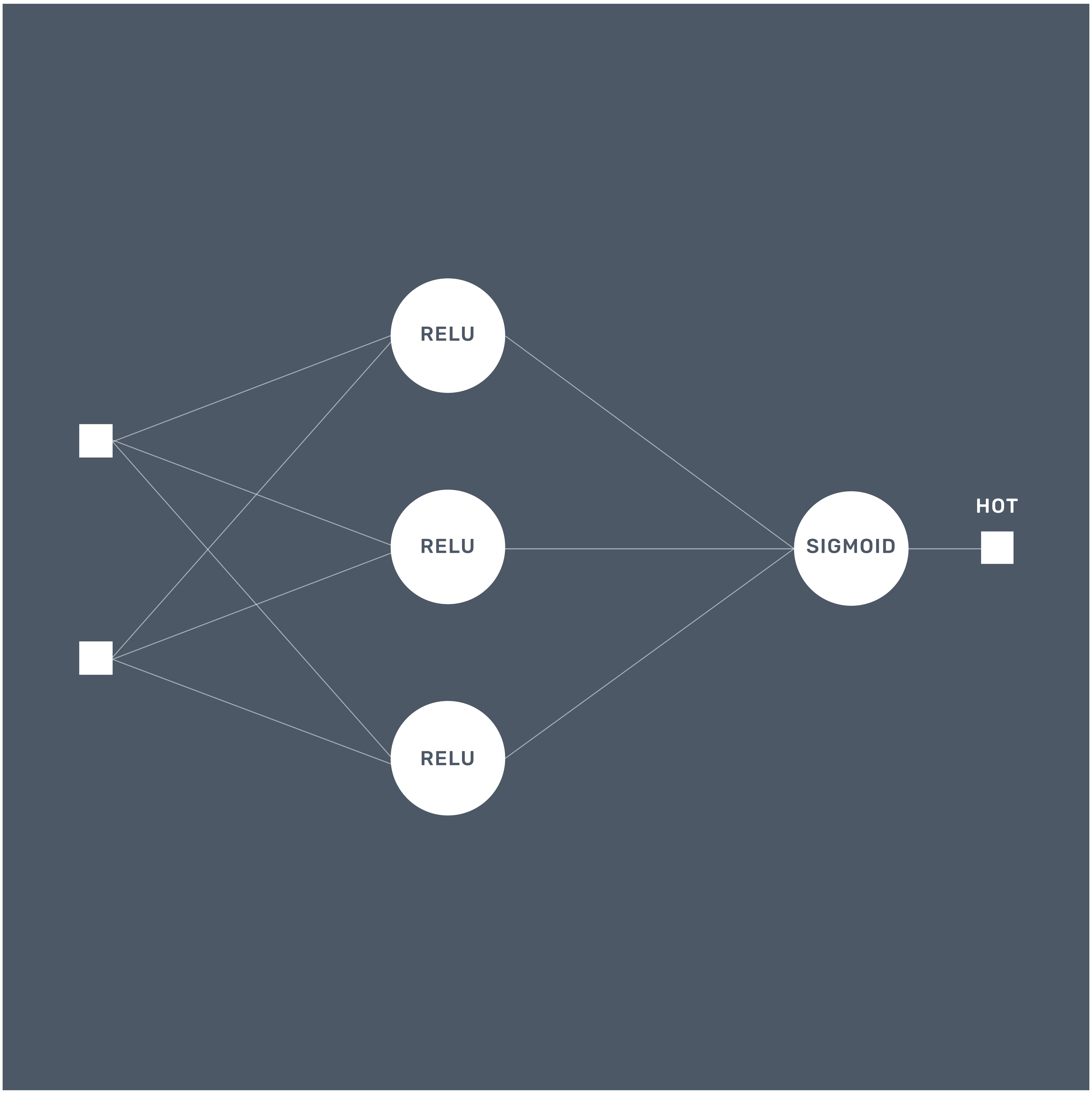
Before we can proceed with training, we need to convert the labels into a numeric format. For this purpose, we'll assign discrete values 1 for *yes* and 0 for *no*.



## INPUT & HIDDEN LAYERS

Let's start building the neural network architecture that we need for this task.

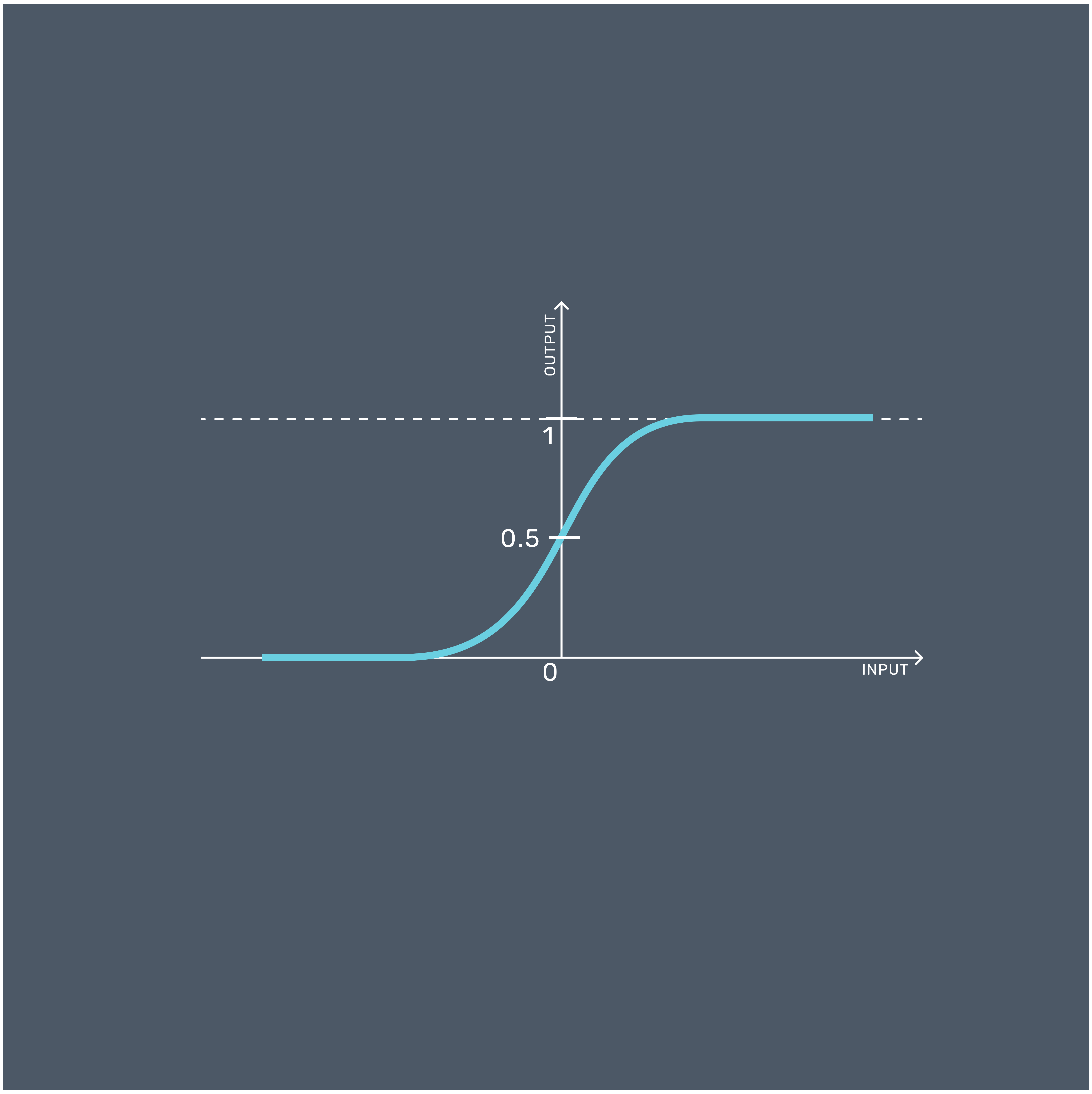
We'll stick with the same number of layers and units as in the previous task. The activation function in the hidden layer also remains unchanged as ReLU.



## OUTPUT LAYER

In fact, the overall architecture remains the same.

The only difference is in the output, where we'll replace the linear activation function with a new one called *sigmoid*. Let's take a look at how it works.

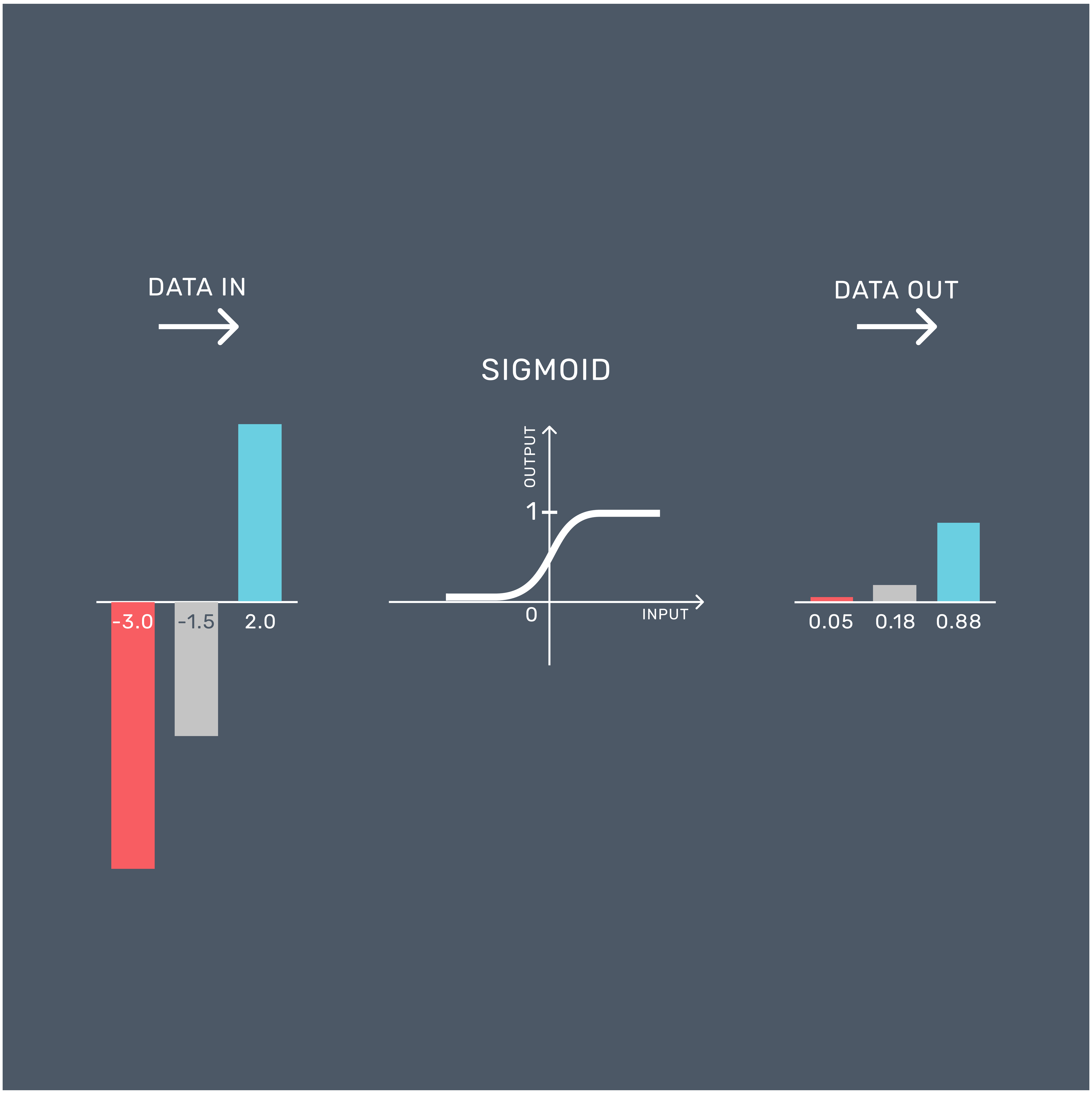


## SIGMOID ACTIVATION FUNCTION

Since the labels are discrete numbers of 0s and 1s, we must set up the neural network so that the predictions return either 0 or 1 and nothing else.

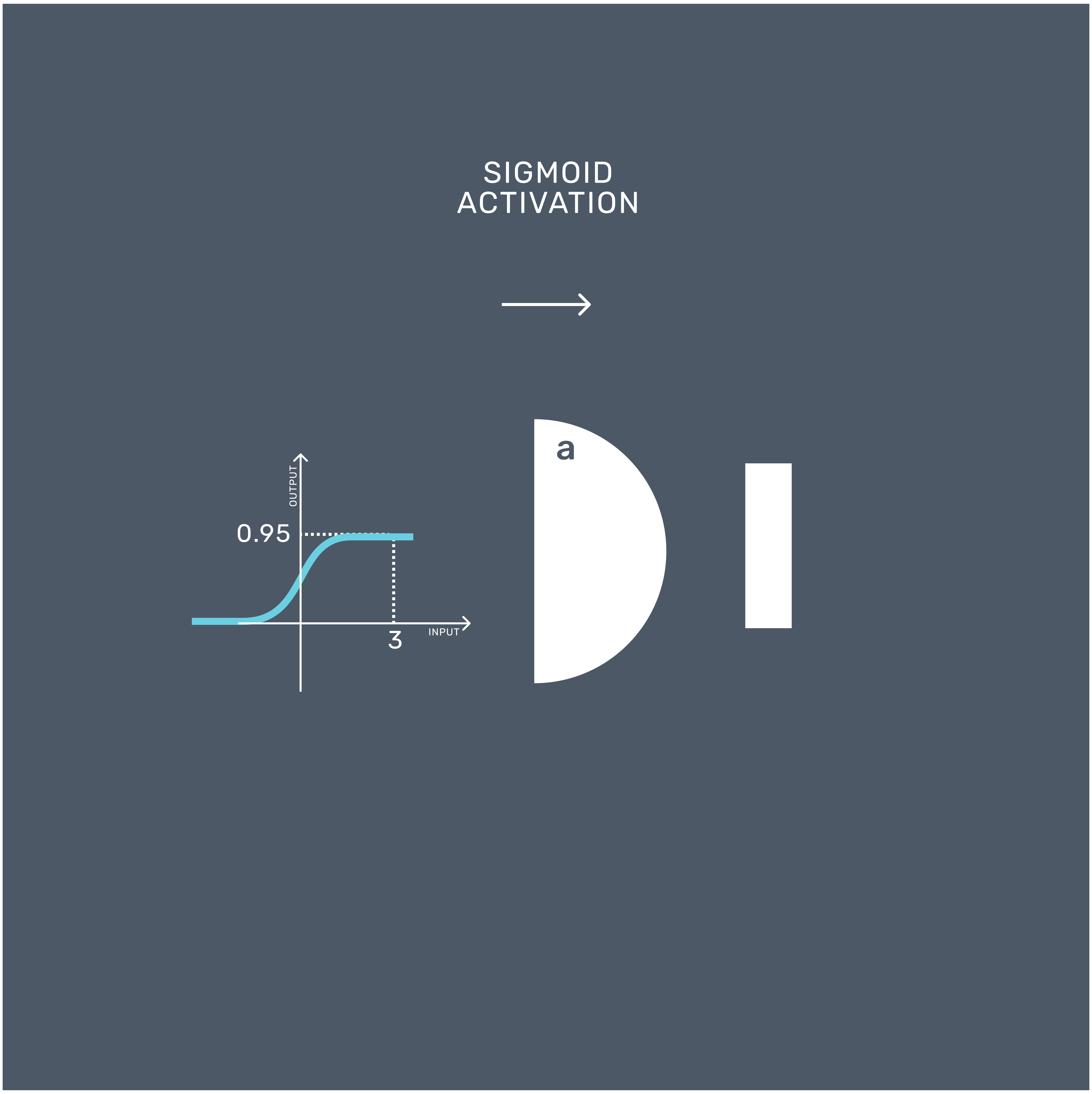
We can't achieve that with the current configuration. This is because the linear activation outputs continuous values instead of discrete.

A sigmoid function solves this problem by squeezing its input into a value between 0 and 1.



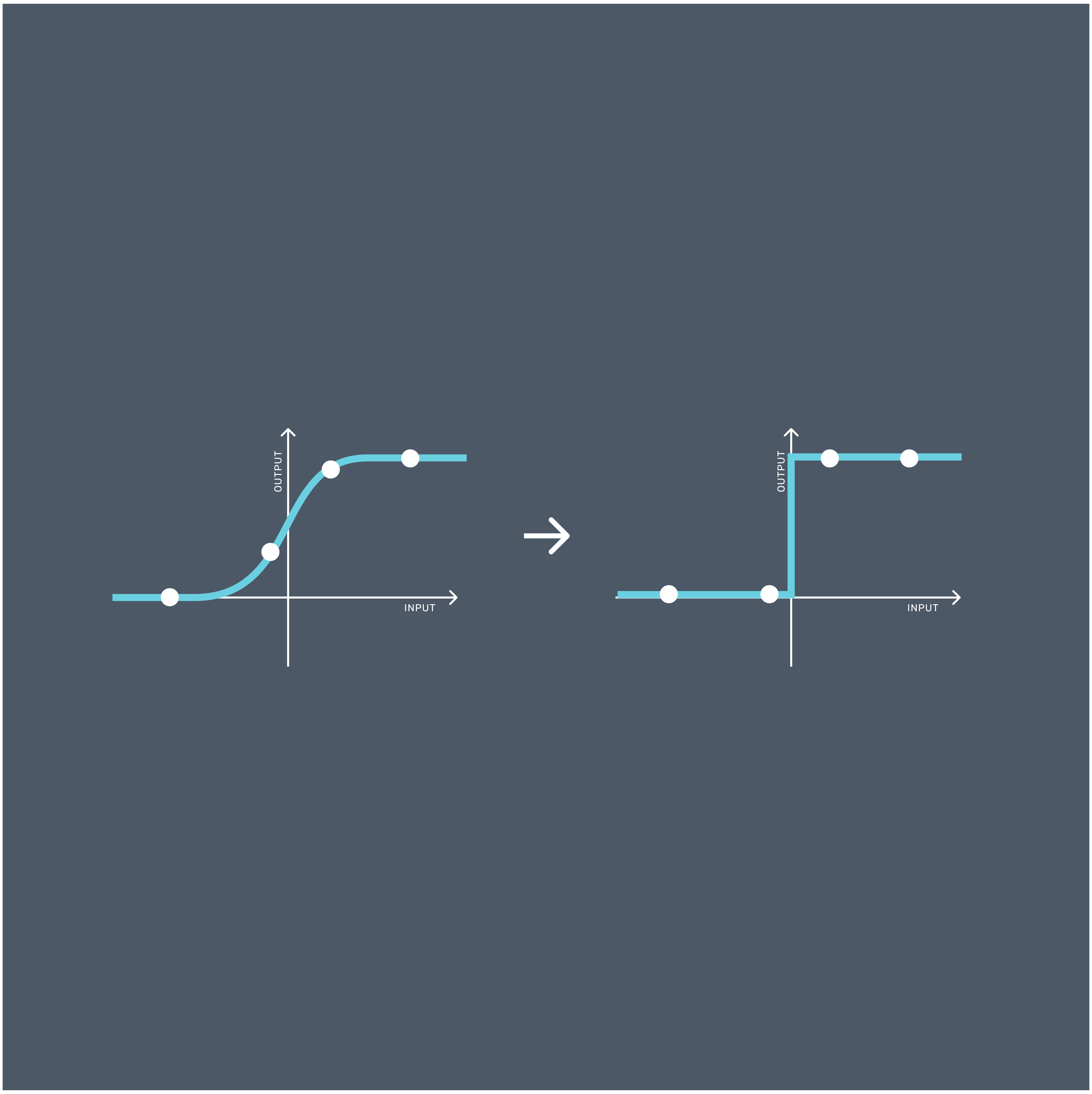
## SIGMOID ACTIVATION FUNCTION

Regardless of how large or small the input is, this function ensures that it is converted into a number between 0 and 1.



## OUTPUT LAYER

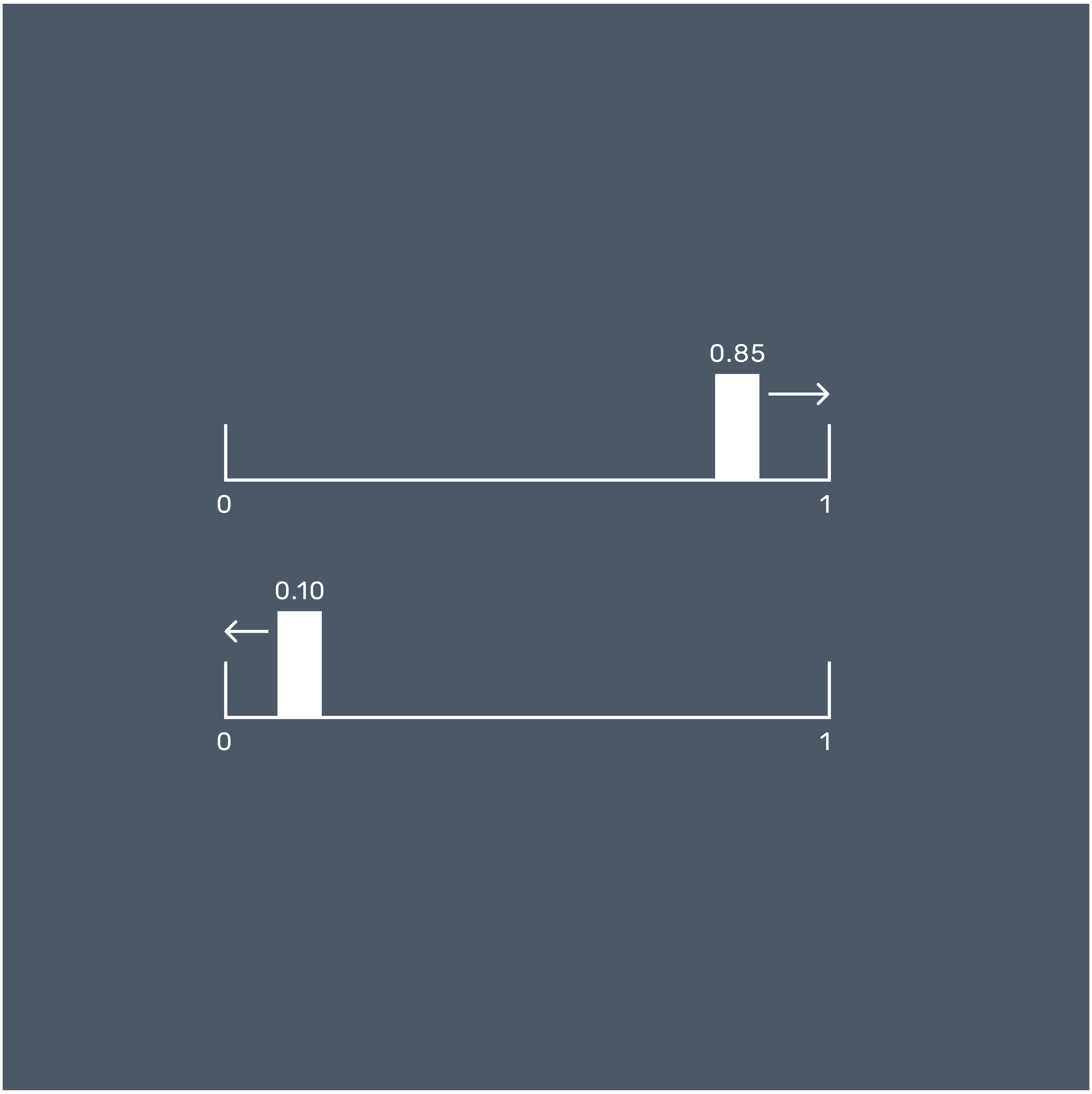
For this reason, we'll use the sigmoid activation function in the output layer.



## DISCRETIZE

This still leaves us with a small problem. We can now convert the output to fall *between* 0 and 1, but what we need is a value of *either* 0 or 1. The output has to be discrete.

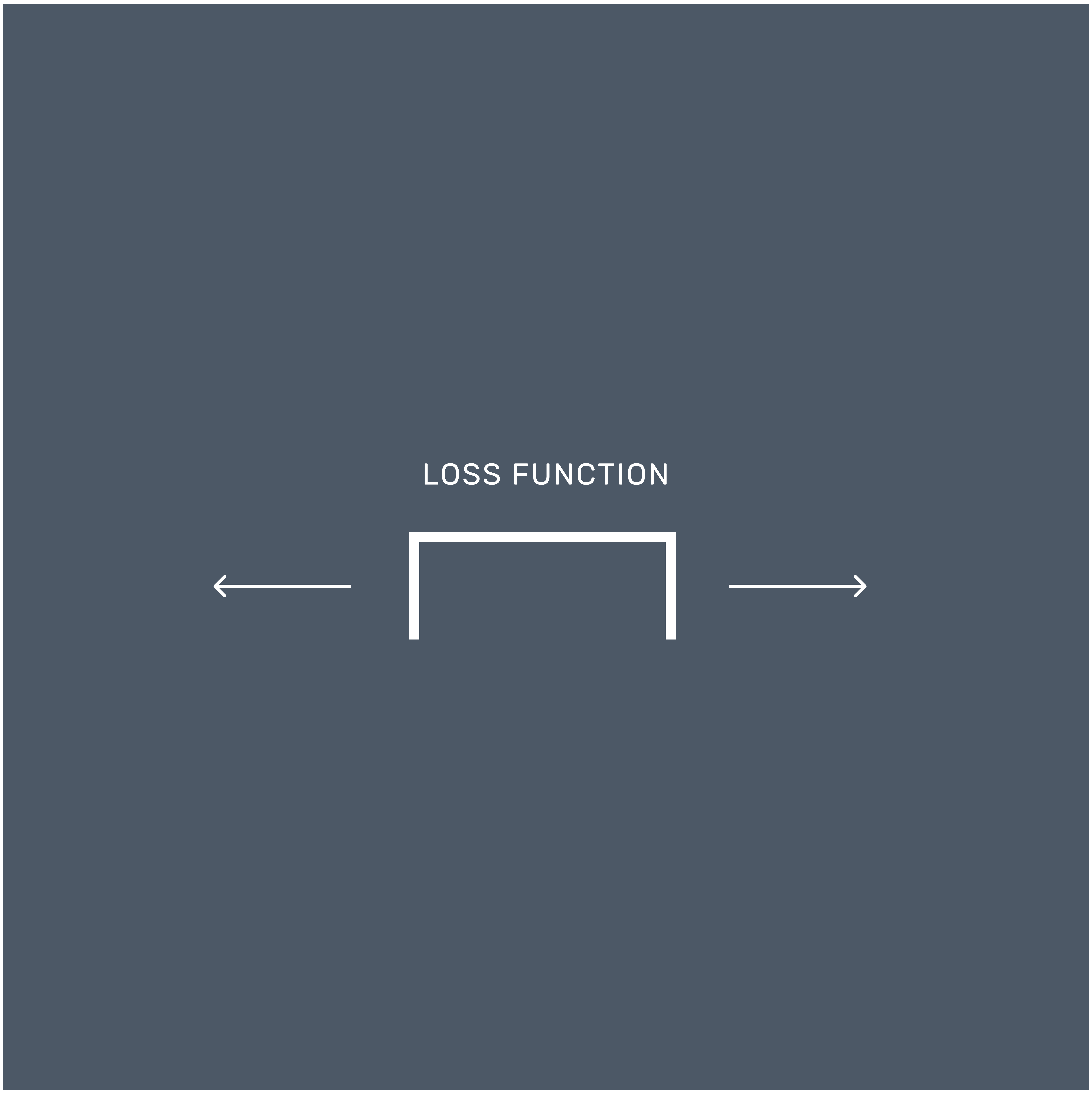
For this, we can add an extra computation step to convert the output to 1 if it's greater than 0.5, and to 0 if it's less than 0.5.



## PROBABILITY

Why does this work? We can think of the output of the sigmoid activation as representing a probability.

For example, if the output is 0.88, the neural network is indicating that the label has a higher probability of being 1. And if the output is 0.12, it has a higher probability of being 0.

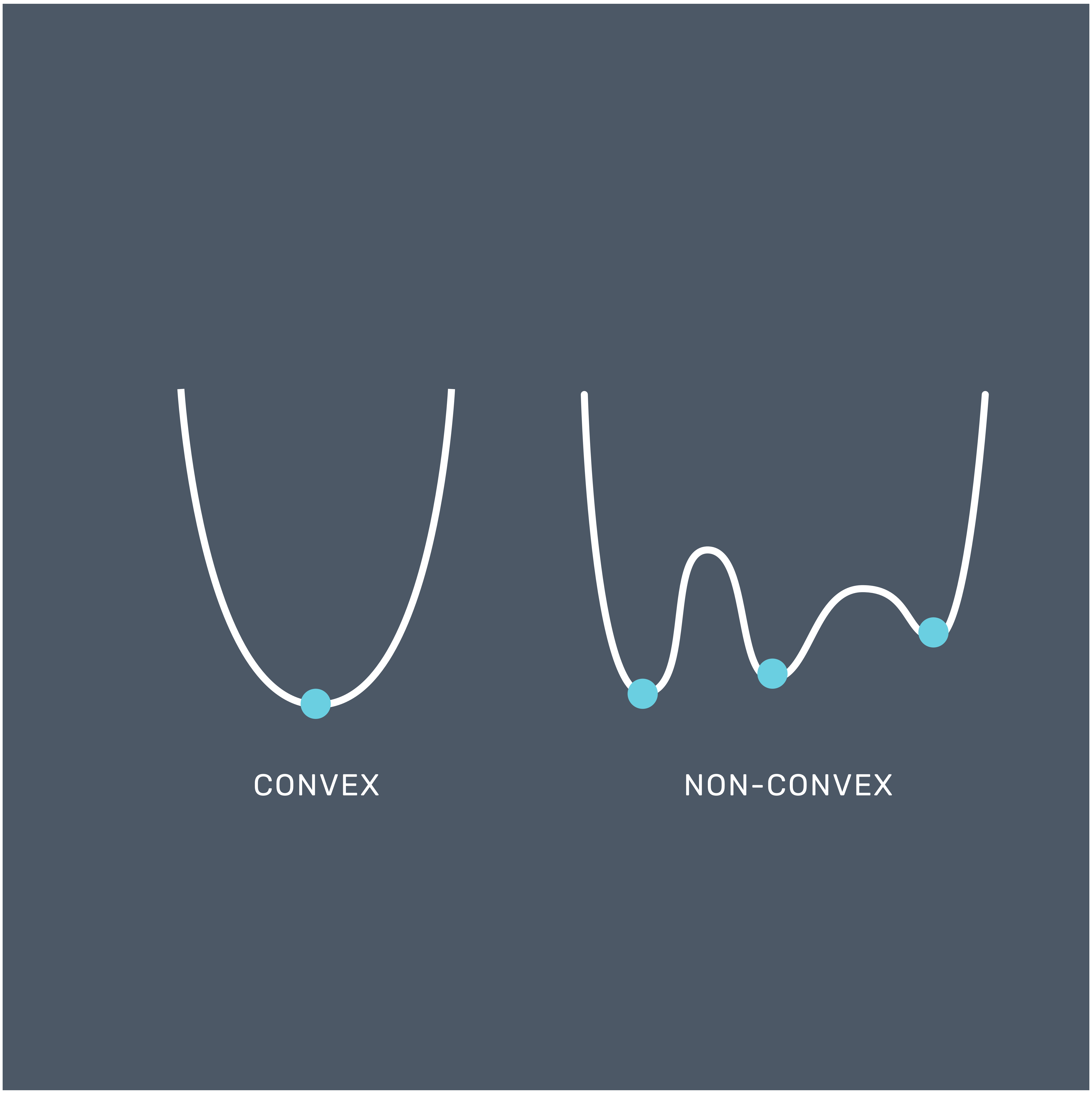


## LOSS FUNCTION

But how can we implement this concept? The answer is the loss function.

Recall that the loss function defines the goal of the neural network, and as a result, dictates how it behaves.

We have covered the first difference between regression and classification—the activation function. Now we'll look at the second one—designing the loss function.

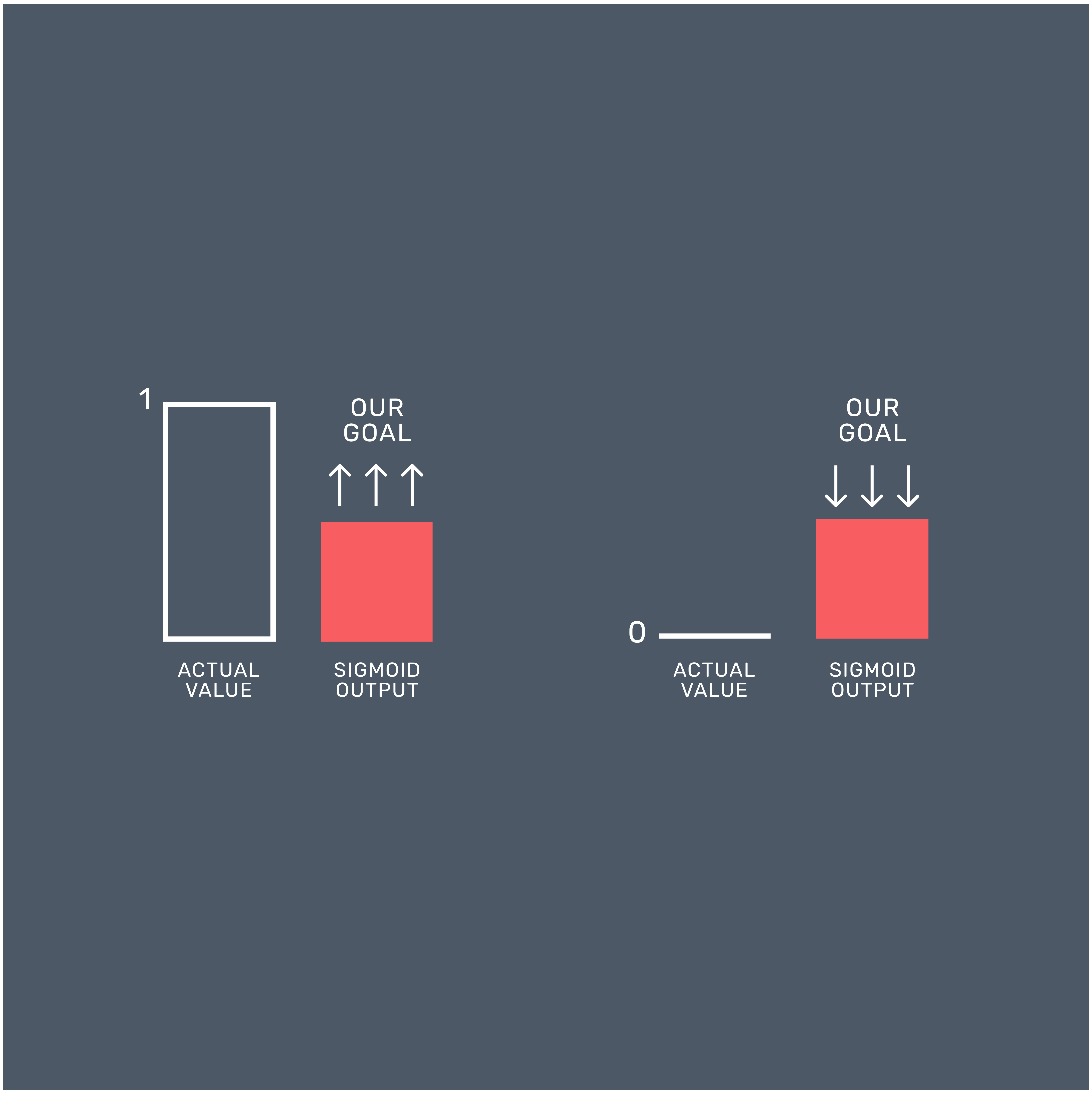


## CONVEX AND NON-CONVEX

For regression, we chose MSE as the loss function because it gives us a desirable property of a single minimum point on the loss curve. We call this a *convex* loss function.

It turns out however (we won't cover the math here) that using an MSE in a binary classification task will result in a *non-convex* loss function. It means that there will be more than one location along the loss curve where a *local* minimum exists, making it difficult for the neural network to find its true, or *global* minimum.

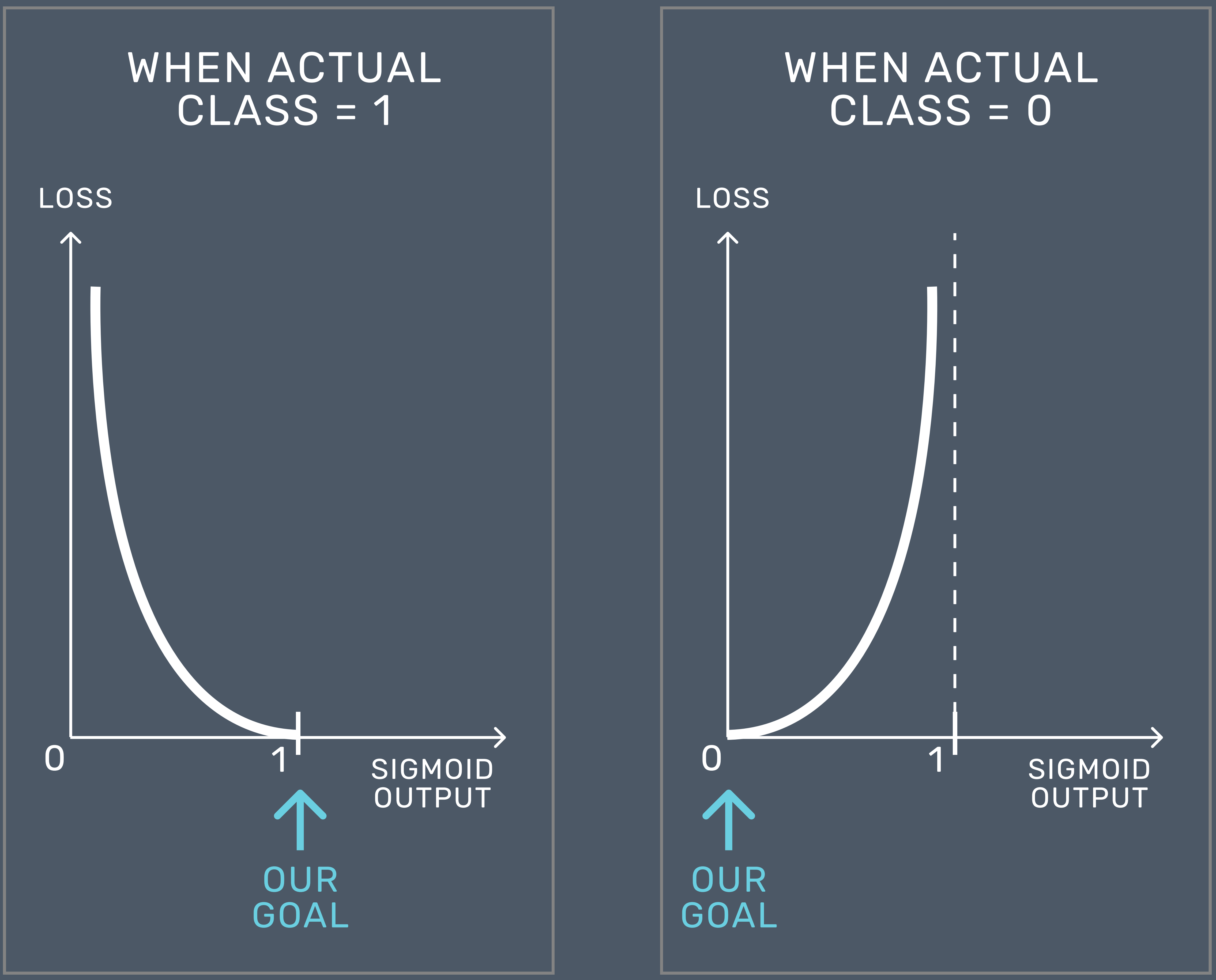
For this reason, we'll need to use a different type of loss function.



## THE GOAL

Our goal is to output a prediction of 1 when the actual value is 1 and a prediction of 0 when the actual value is 0.

That is, to get a prediction of 1, we want the sigmoid's output to be as close to 1 as possible, and vice versa for 0.

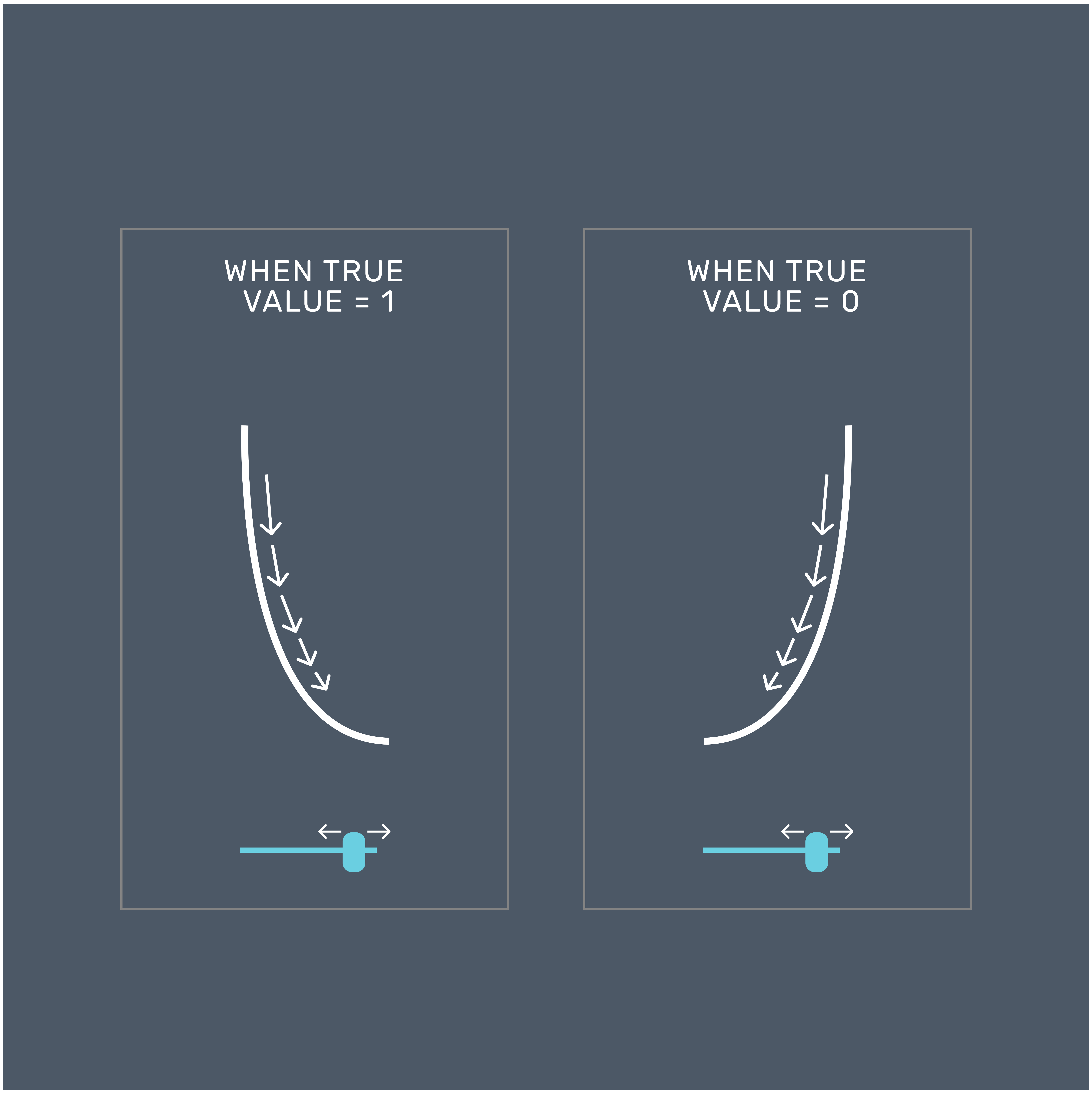


## LOSS FUNCTION

The loss function we'll be using is called the *binary cross entropy*. This function fulfills our need to have a convex loss curve.

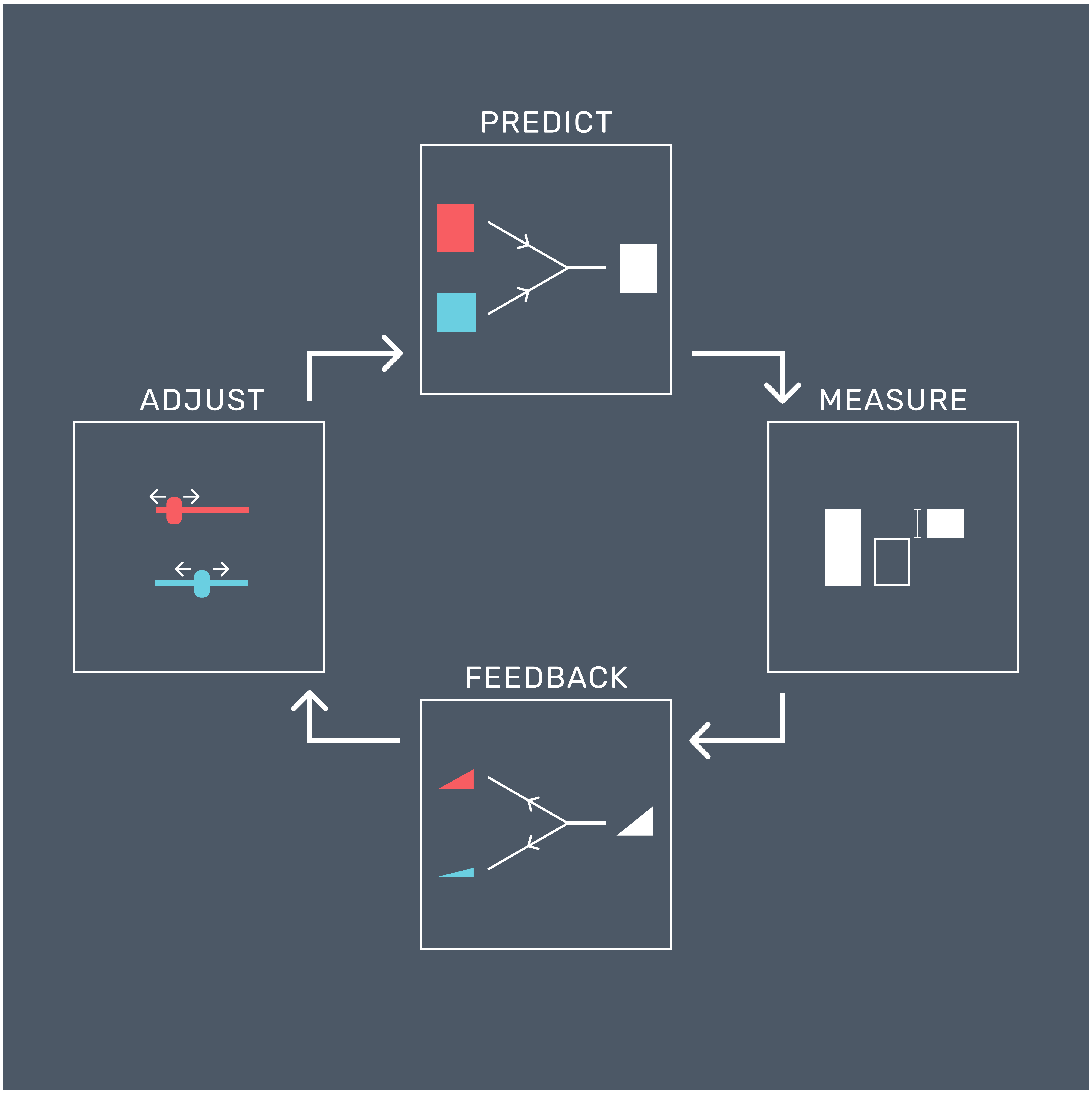
The plots here depicts the shape of this loss function, with each class having its own loss curve.

When the actual class is 1, we want the sigmoid output to be as close to 1 as possible, correspondingly pushing the loss toward its minimum. And when the actual class is 0, we want the sigmoid output to be as close to 0 as possible, pushing the loss toward its minimum.



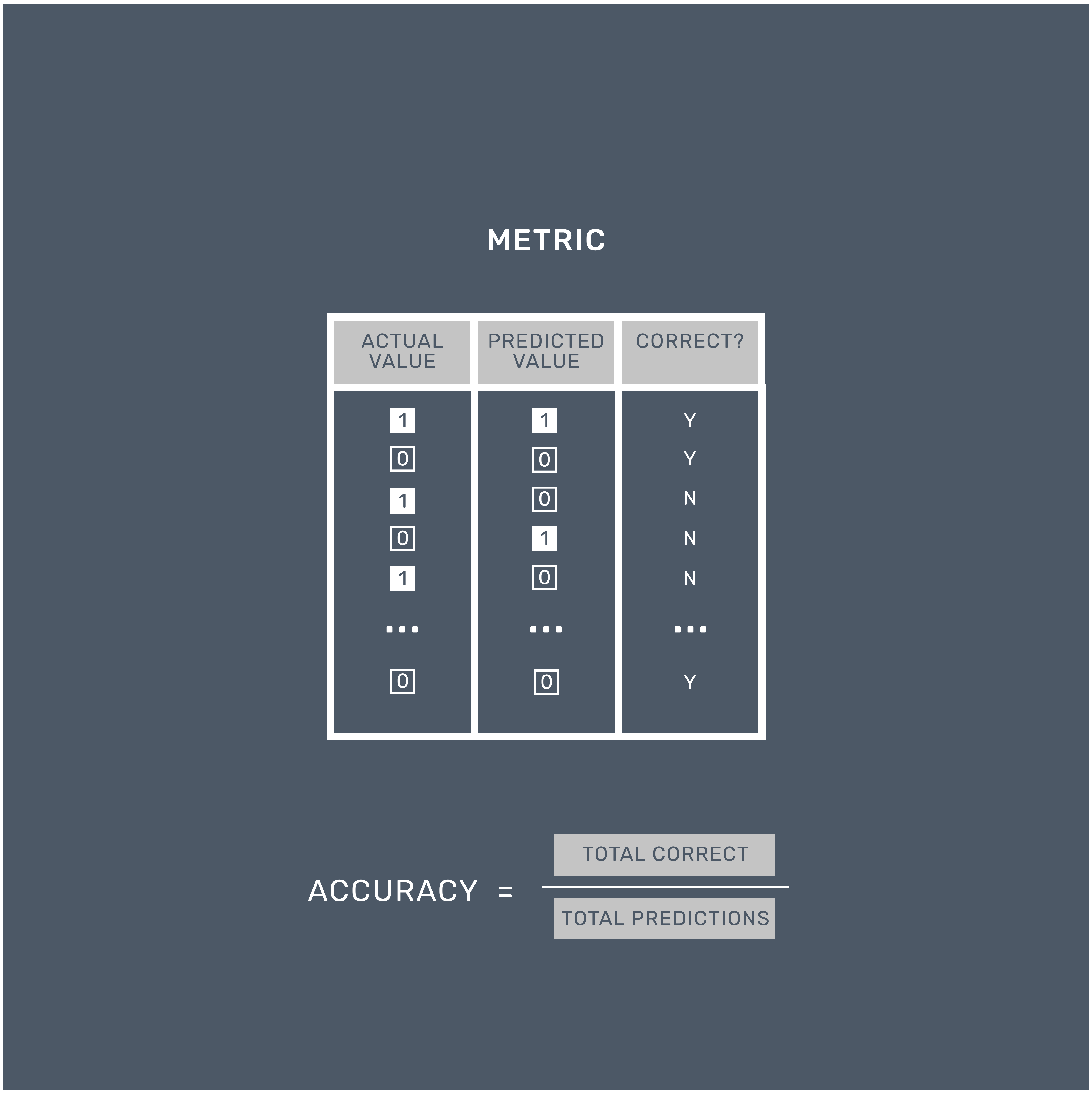
## GRADIENT DESCENT

From here, we can perform the weight updates using the same gradient descent approach as in Chapters 1 and 2.



## TRAINING

We are now in a position to train the neural network. The training cycle follows the same four steps as in the previous chapters.



METRIC

| ACTUAL VALUE | PREDICTED VALUE | CORRECT? |
|---|---|---|
| 1 | 1 | Y |
| 0 | 0 | Y |
| 1 | 0 | N |
| 0 | 1 | N |
| 1 | 0 | N |
| ... | ... | ... |
| 0 | 0 | Y |

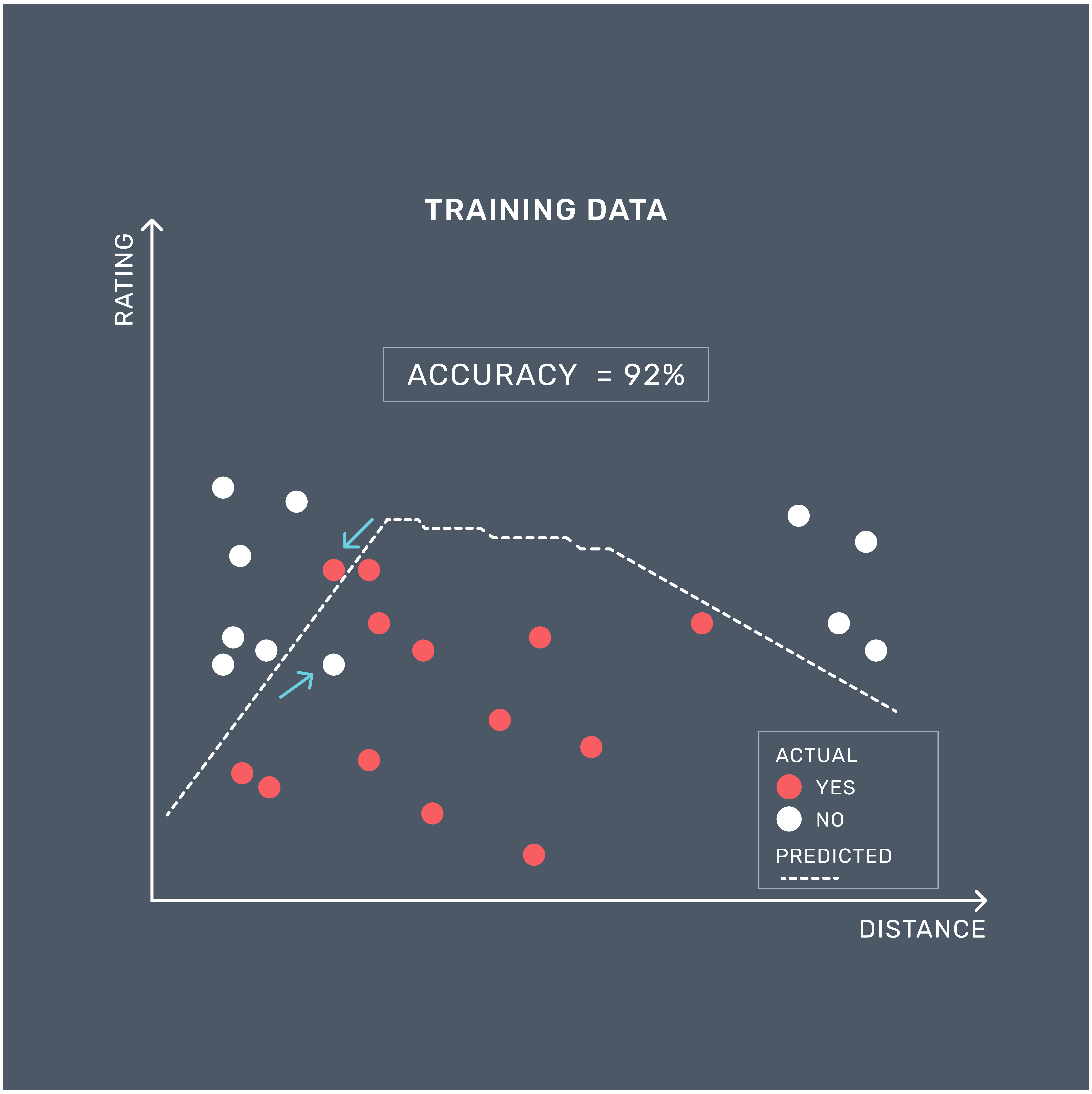
$$\text{ACCURACY} = \frac{\text{TOTAL CORRECT}}{\text{TOTAL PREDICTIONS}}$$

## ACCURACY

There is one last change, which is the metric to measure performance.

In the regression task, we used the MSE both as the cost and the metric.

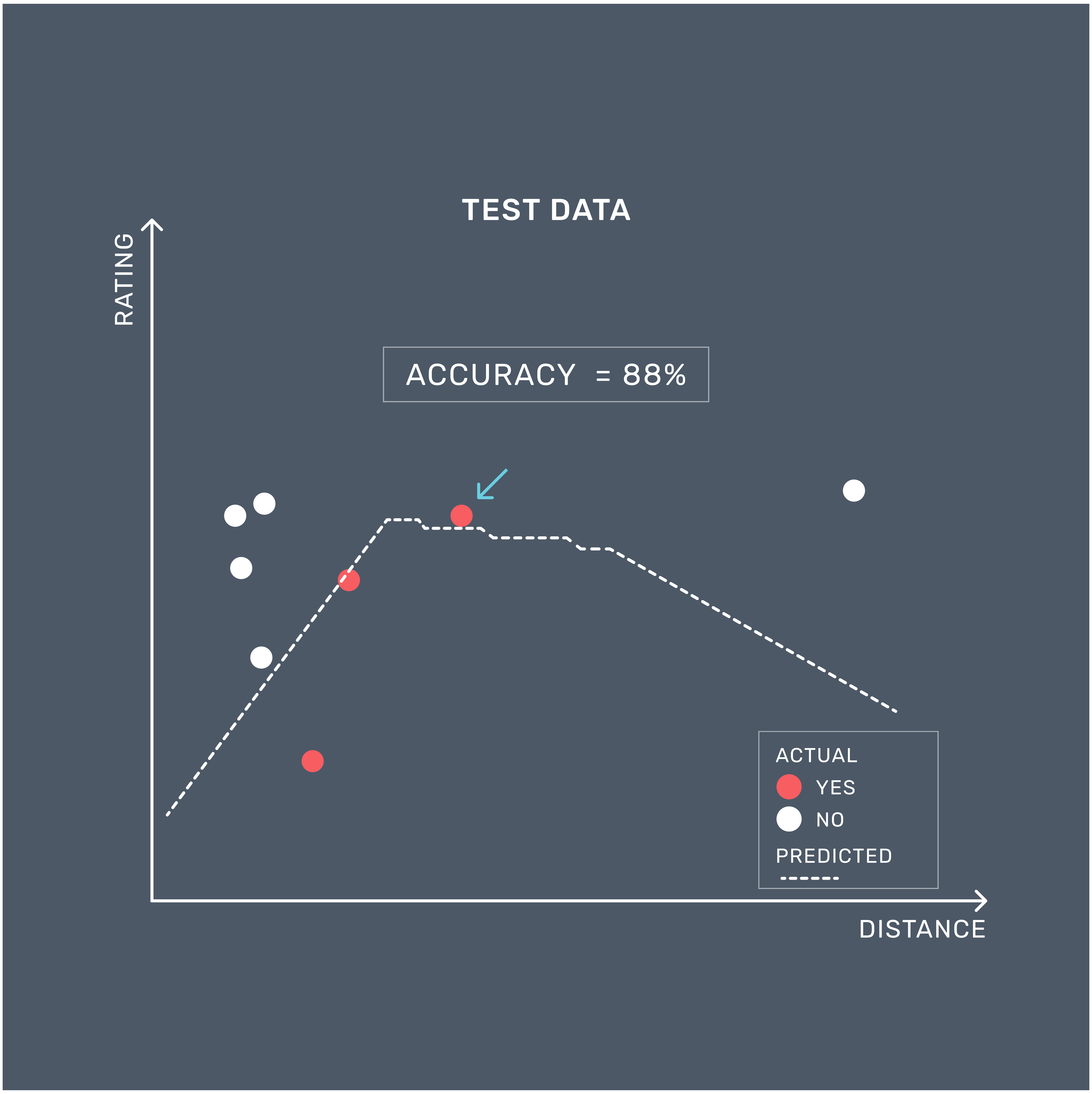
In a classification task, we need to use a different metric to better reflect the performance of the model. We'll use *accuracy*, which gives us the percentage of correct predictions over all predictions.



## TRAINING PERFORMANCE

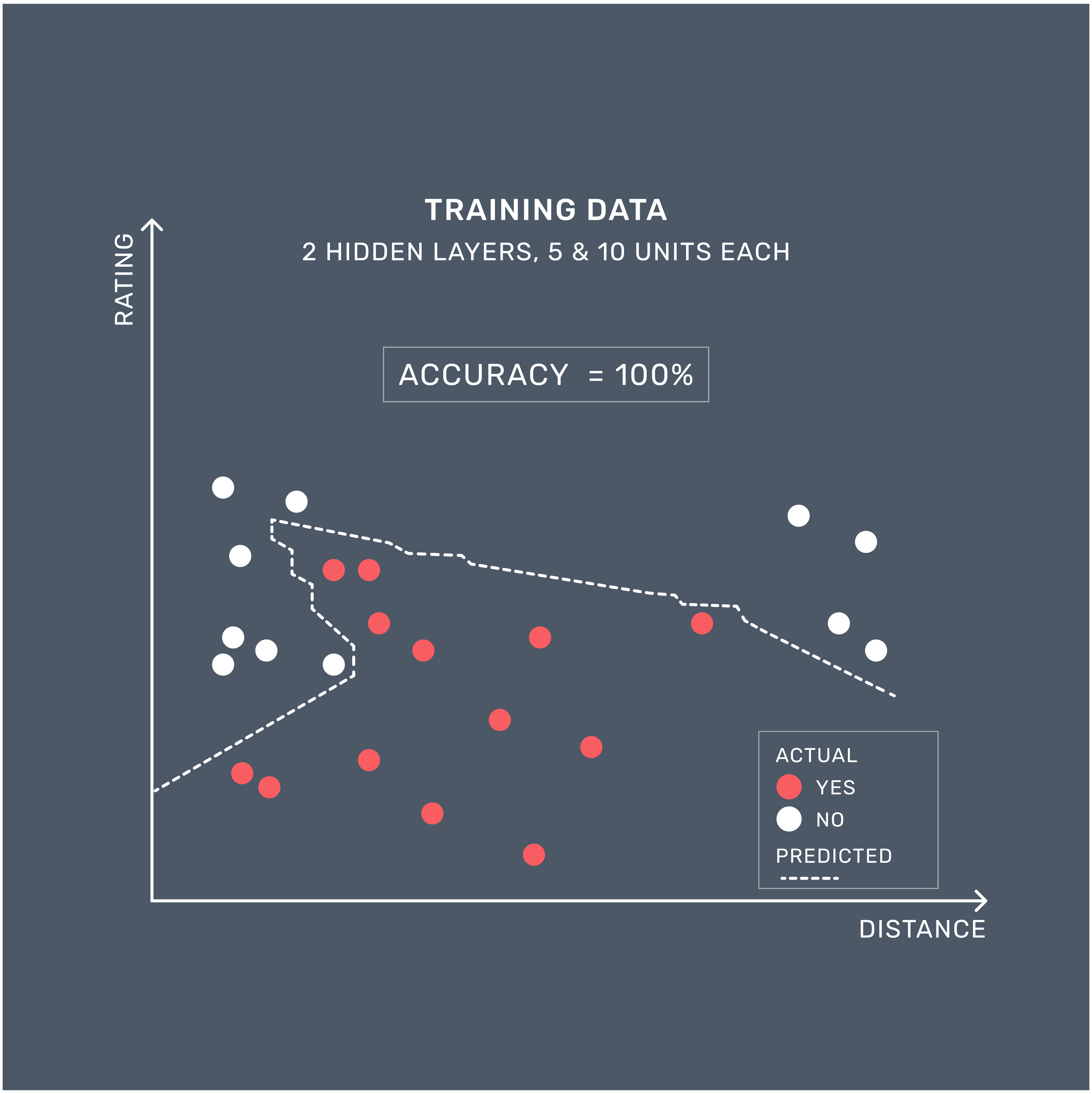
Using the accuracy metric, we can see that the model does pretty well on the training dataset.

The plot also shows the decision boundary of our trained neural network, representing the predictions.



## TEST PERFORMANCE

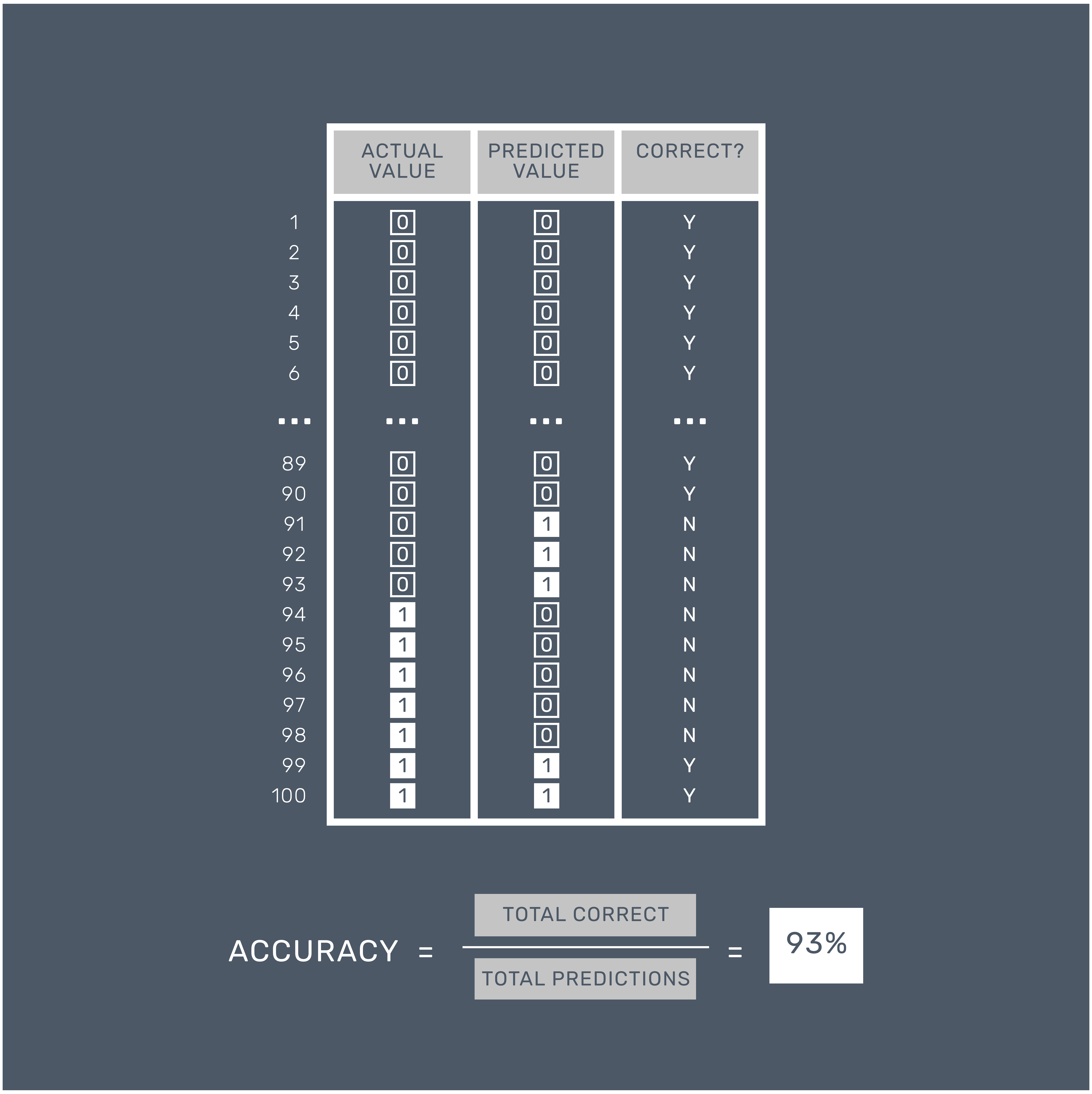
The prediction on the test data also shows a respectable performance, given the limited number of data points.



## A BIGGER NETWORK

As in the regression task, we can further improve the performance by adding more layers and units.

The plot here shows the decision boundary after modifying the neural network to contain two hidden layers with five and ten units of neurons each. The granularity of its predictions increased, resulting in a more well-defined and accurate prediction curve.



| | ACTUAL VALUE | PREDICTED VALUE | CORRECT? |
|---|---|---|---|
| 1 | 0 | 0 | Y |
| 2 | 0 | 0 | Y |
| 3 | 0 | 0 | Y |
| 4 | 0 | 0 | Y |
| 5 | 0 | 0 | Y |
| 6 | 0 | 0 | Y |
| ... | ... | ... | ... |
| 89 | 0 | 0 | Y |
| 90 | 0 | 0 | Y |
| 91 | 0 | 1 | N |
| 92 | 0 | 1 | N |
| 93 | 0 | 1 | N |
| 94 | 1 | 0 | N |
| 95 | 1 | 0 | N |
| 96 | 1 | 0 | N |
| 97 | 1 | 0 | N |
| 98 | 1 | 0 | N |
| 99 | 1 | 1 | Y |
| 100 | 1 | 1 | Y |

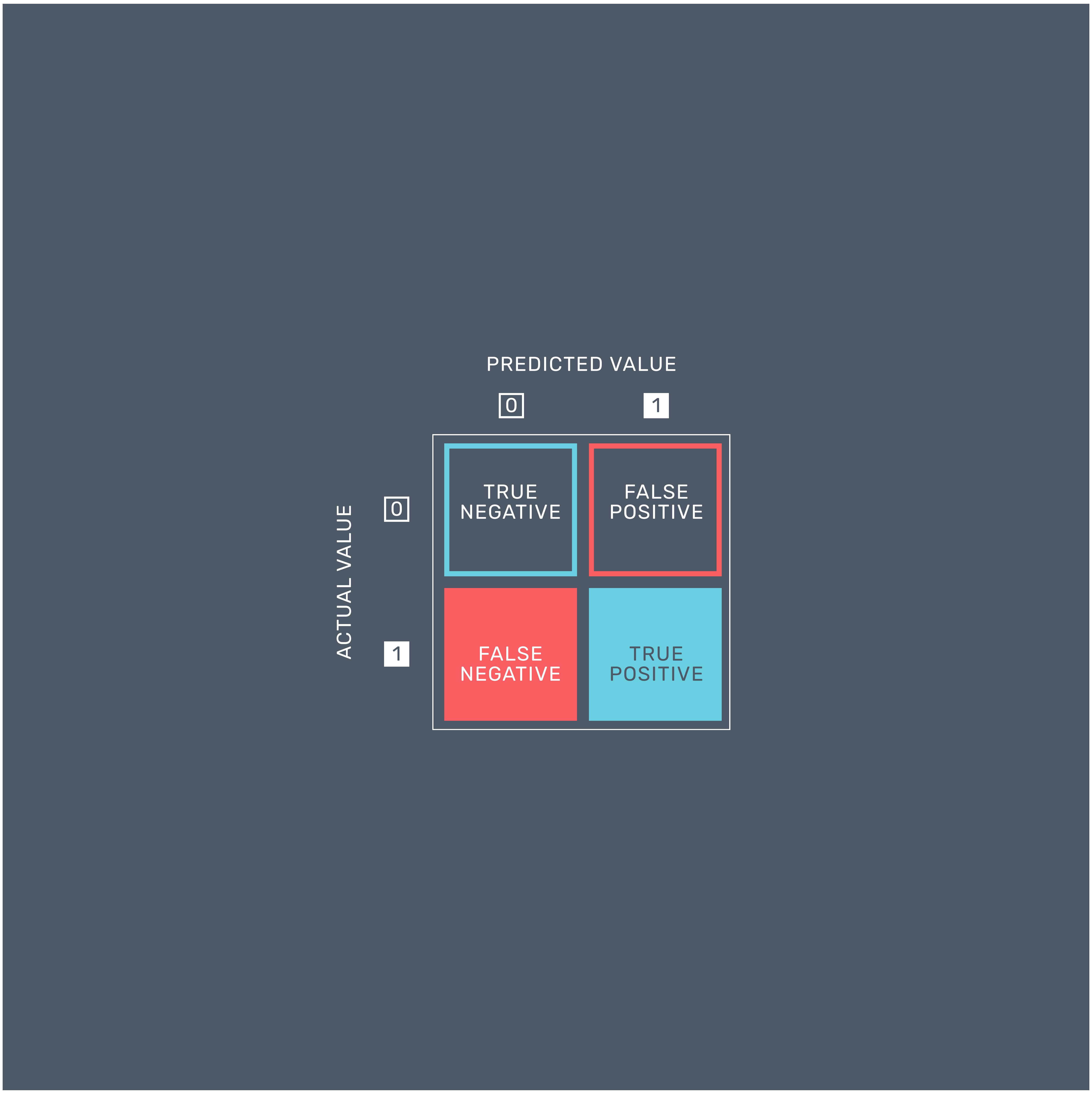
$$\text{ACCURACY} = \frac{\text{TOTAL CORRECT}}{\text{TOTAL PREDICTIONS}} = \boxed{93\%}$$

## WHEN ACCURACY BECOMES INACCURATE

Accuracy is often used as the measure of classification performance because it is simple to compute and is easy to interpret.

However, it can become misleading in some cases. This is especially true when dealing with imbalanced data, which is when certain classes contain way more data points than the rest.

Let's take the example of predicting fraud credit card transactions. Suppose we have a dataset of 100 data points, of which only 7 are fraud cases. If we simply predicted all the outputs to be 0, we would still manage to get an accuracy value of 93%! Clearly something isn't right.

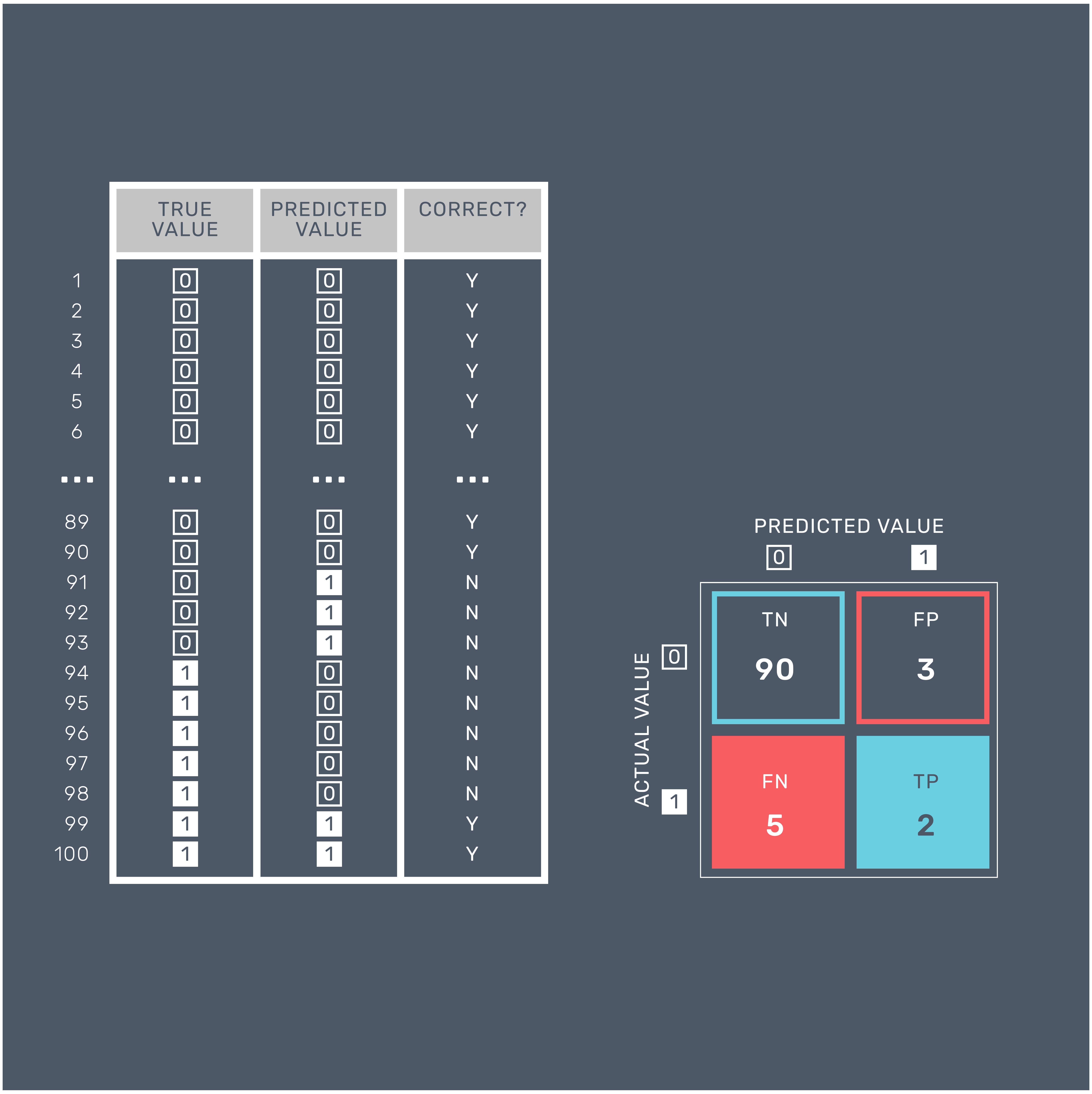


## CONFUSION MATRIX

The *confusion matrix* provides a way to measure performance in a balanced way. It shows the count of predictions falling into one of the following:

- True Negative (TN): when both the actual and predicted values are 0.
- False Positive (FP): when the actual value is 0 but the predicted value is 1.
- False Negative (FN): when the actual value is 1 but the predicted value is 0.
- True Positive (TP): when both the actual and predicted values are 1.

For our example, 0 represents the *not fraud* class while 1 represents the *fraud* class.

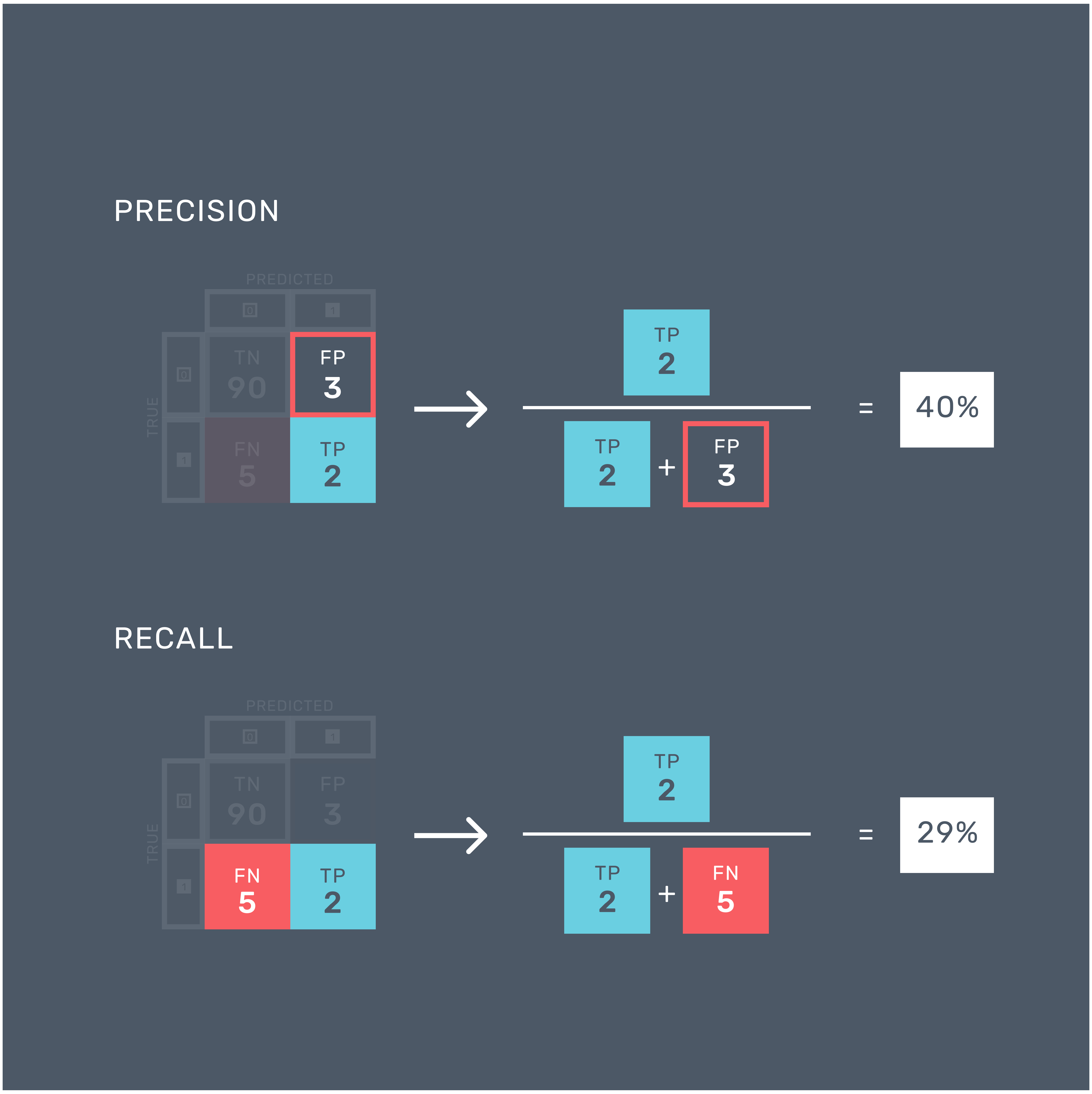


| | TRUE VALUE | PREDICTED VALUE | CORRECT? |
|---|---|---|---|
| 1 | 0 | 0 | Y |
| 2 | 0 | 0 | Y |
| 3 | 0 | 0 | Y |
| 4 | 0 | 0 | Y |
| 5 | 0 | 0 | Y |
| 6 | 0 | 0 | Y |
| ... | ... | ... | ... |
| 89 | 0 | 0 | Y |
| 90 | 0 | 0 | Y |
| 91 | 0 | 1 | N |
| 92 | 0 | 1 | N |
| 93 | 0 | 1 | N |
| 94 | 1 | 0 | N |
| 95 | 1 | 0 | N |
| 96 | 1 | 0 | N |
| 97 | 1 | 0 | N |
| 98 | 1 | 0 | N |
| 99 | 1 | 1 | Y |
| 100 | 1 | 1 | Y |

| | | PREDICTED VALUE | |
|---|---|---|---|
| | | 0 | 1 |
| ACTUAL VALUE | 0 | TN<br>90 | FP<br>3 |
| | 1 | FN<br>5 | TP<br>2 |

## APPLIED TO DATA

Applied to the credit card fraud dataset, we get 90, 3, 5, and 2 respectively for TN, FP, FN, and TP.

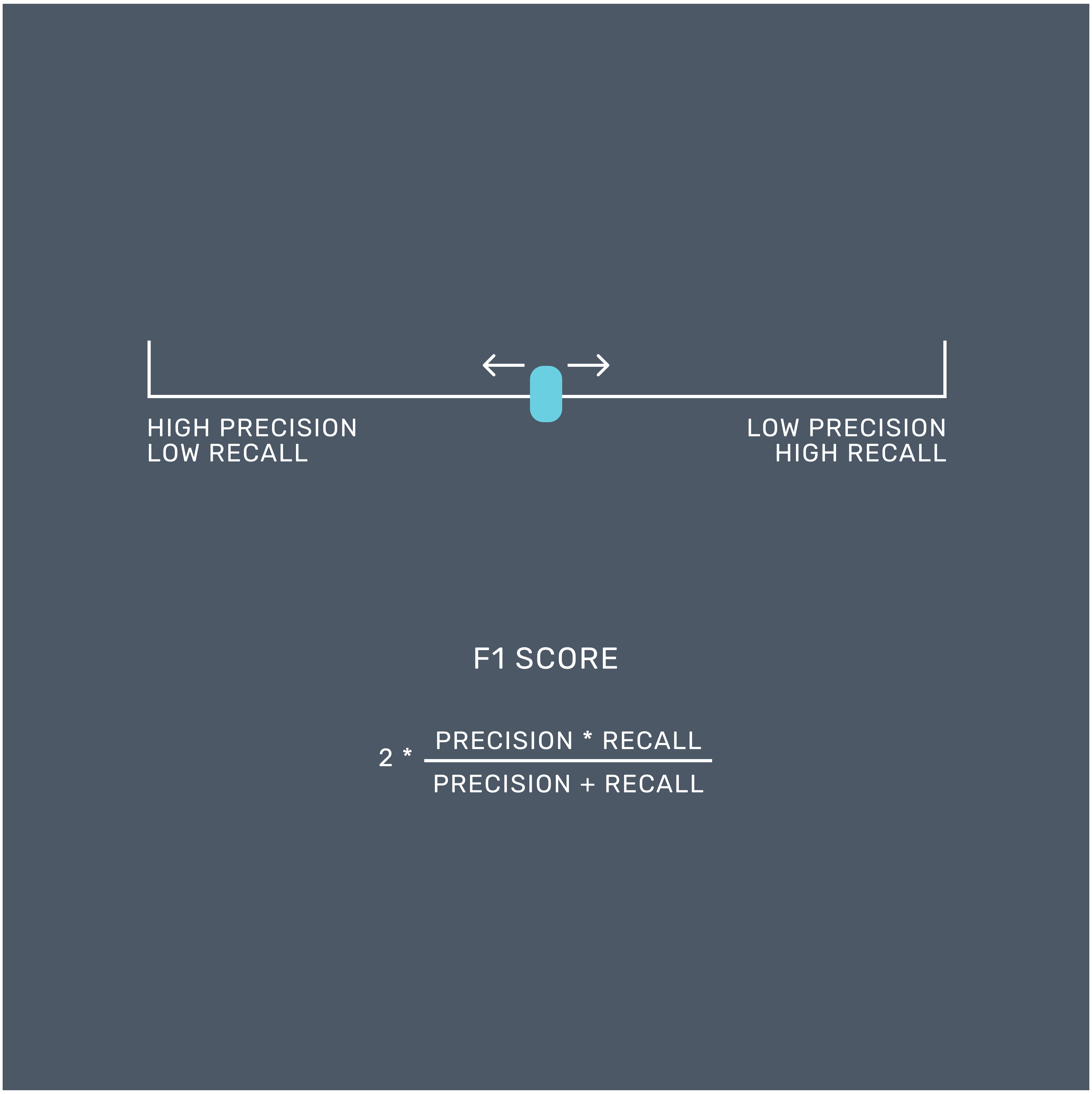


## PRECISION AND RECALL

From here, we can compute two types of metrics: *precision* and *recall*.

The reason for the curiously high accuracy was the dominance of the true negatives, diluting the rest. With precision and recall, we remove the focus on these true negatives and instead give all the attention to the other three categories.

We can see from the precision and recall scores that they offer a more reliable performance indicator than accuracy.



$$2 * \frac{\text{PRECISION * RECALL}}{\text{PRECISION + RECALL}}$$

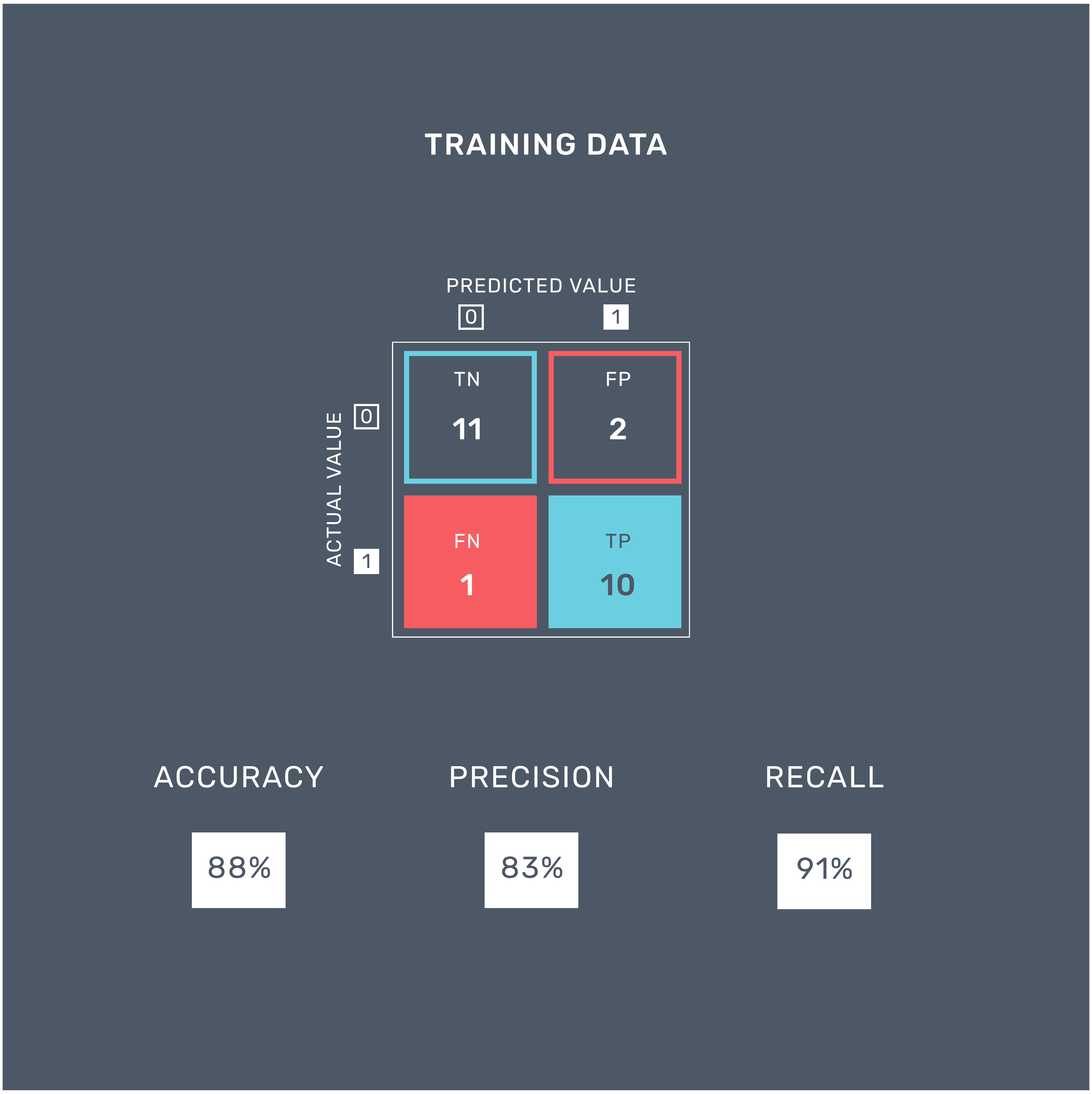
## F1 SCORE

However, we still need to strike a balance between precision and recall.

To illustrate its importance, suppose the model from the credit card fraud prediction achieved high recall and low precision. This would lead to a high number of false positives. This is good for detecting as many fraud cases as possible, but comes at the expense of flagging non-fraud cases as frauds.

Conversely, if the model achieved high precision and low recall, this would result in a high number of false negatives. This is good for correctly classifying the non-fraud cases but will miss out on real fraud cases.

We can address this problem with the *F1 Score*, which provides a balanced emphasis on precision and recall.



TRAINING DATA

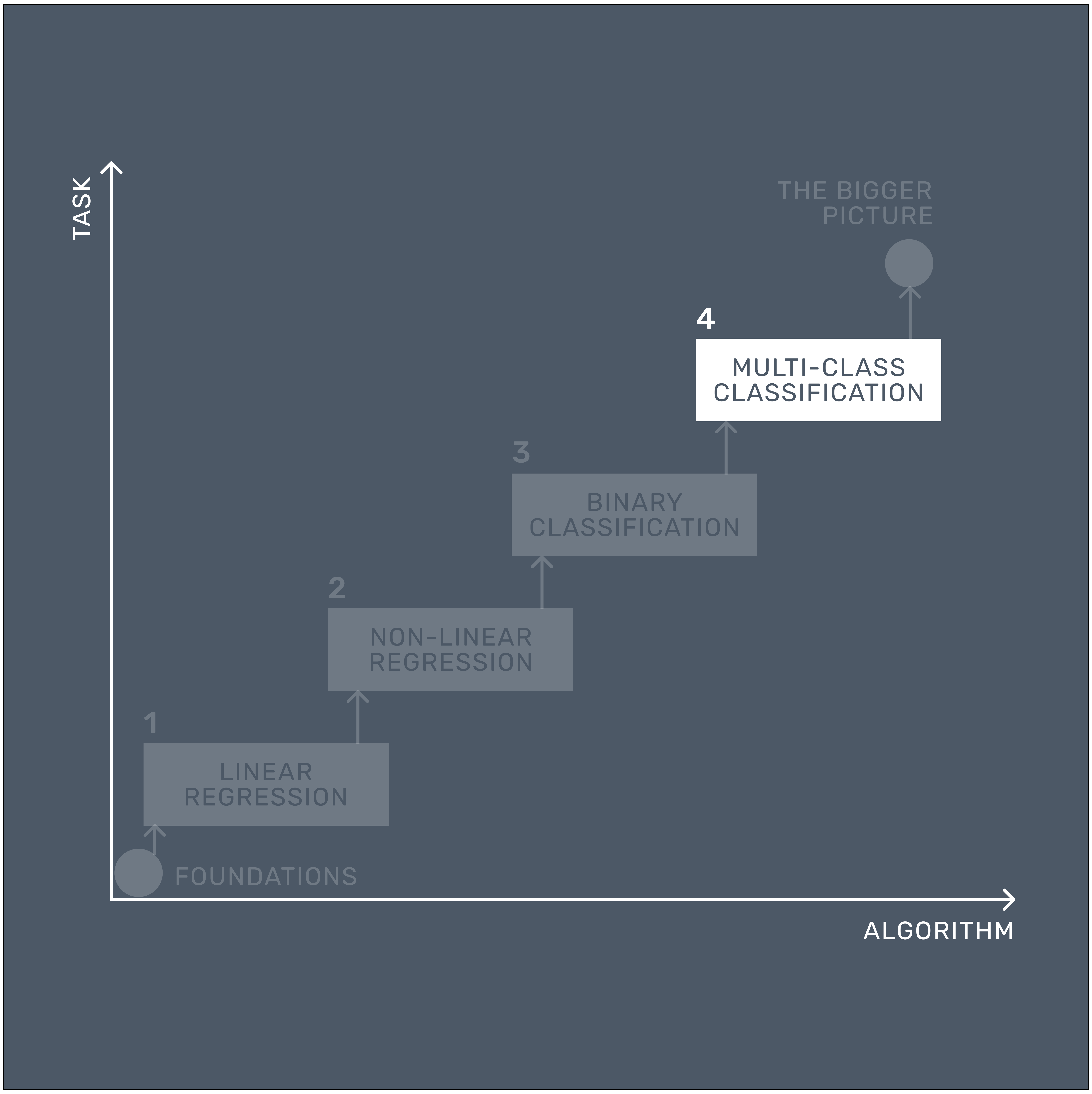
| | | PREDICTED VALUE | |
|---|---|---|---|
| | | 0 | 1 |
| ACTUAL VALUE | 0 | TN<br>11 | FP<br>2 |
| | 1 | FN<br>1 | TP<br>10 |

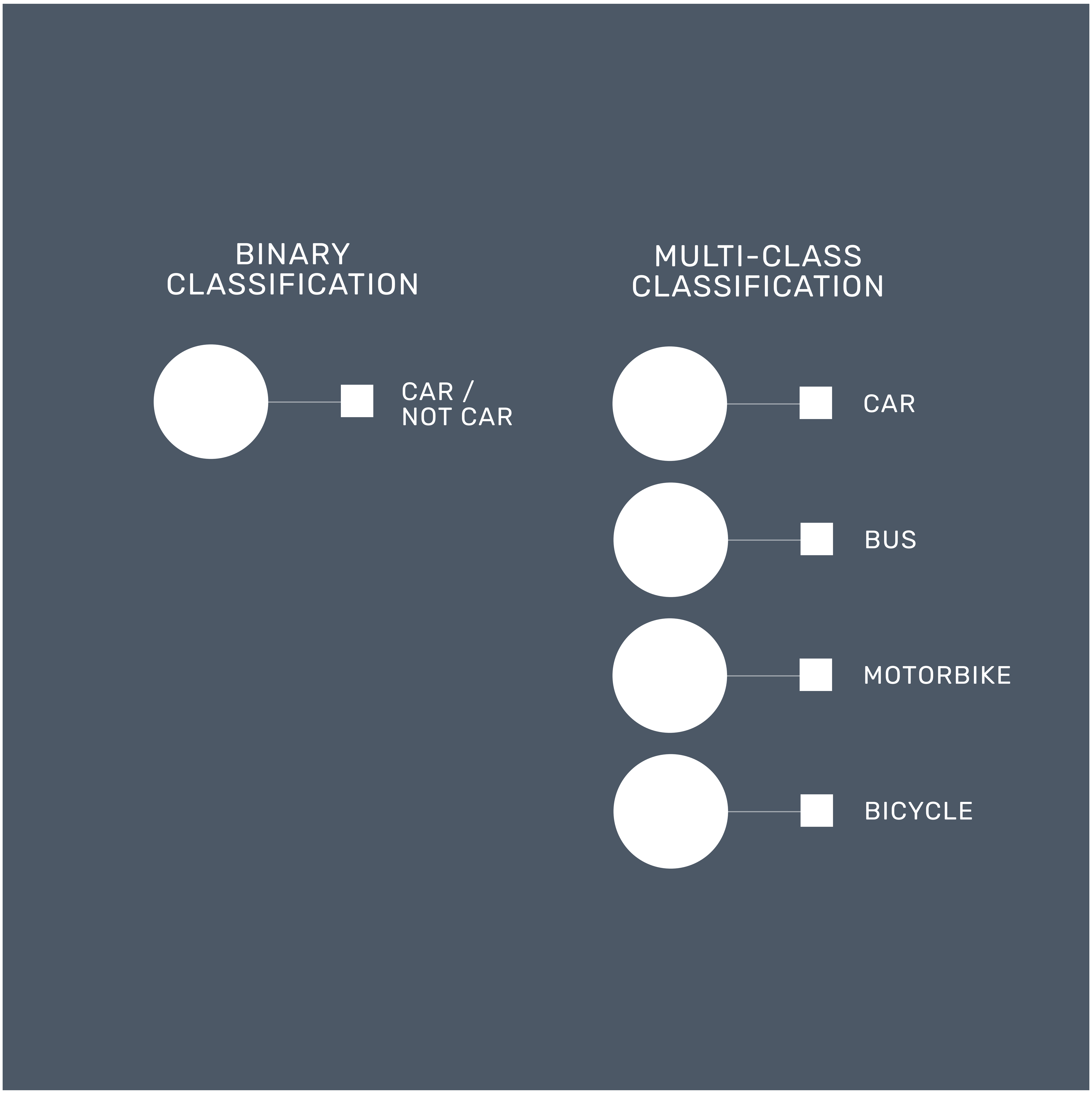
| ACCURACY | PRECISION | RECALL |
|---|---|---|
| 88% | 83% | 91% |

## PERFORMANCE

Going back to our hotels dataset, we get an accuracy score that's comparable with precision and recall, indicating that our dataset is balanced.

# 4 - MULTI-CLASS CLASSIFICATION

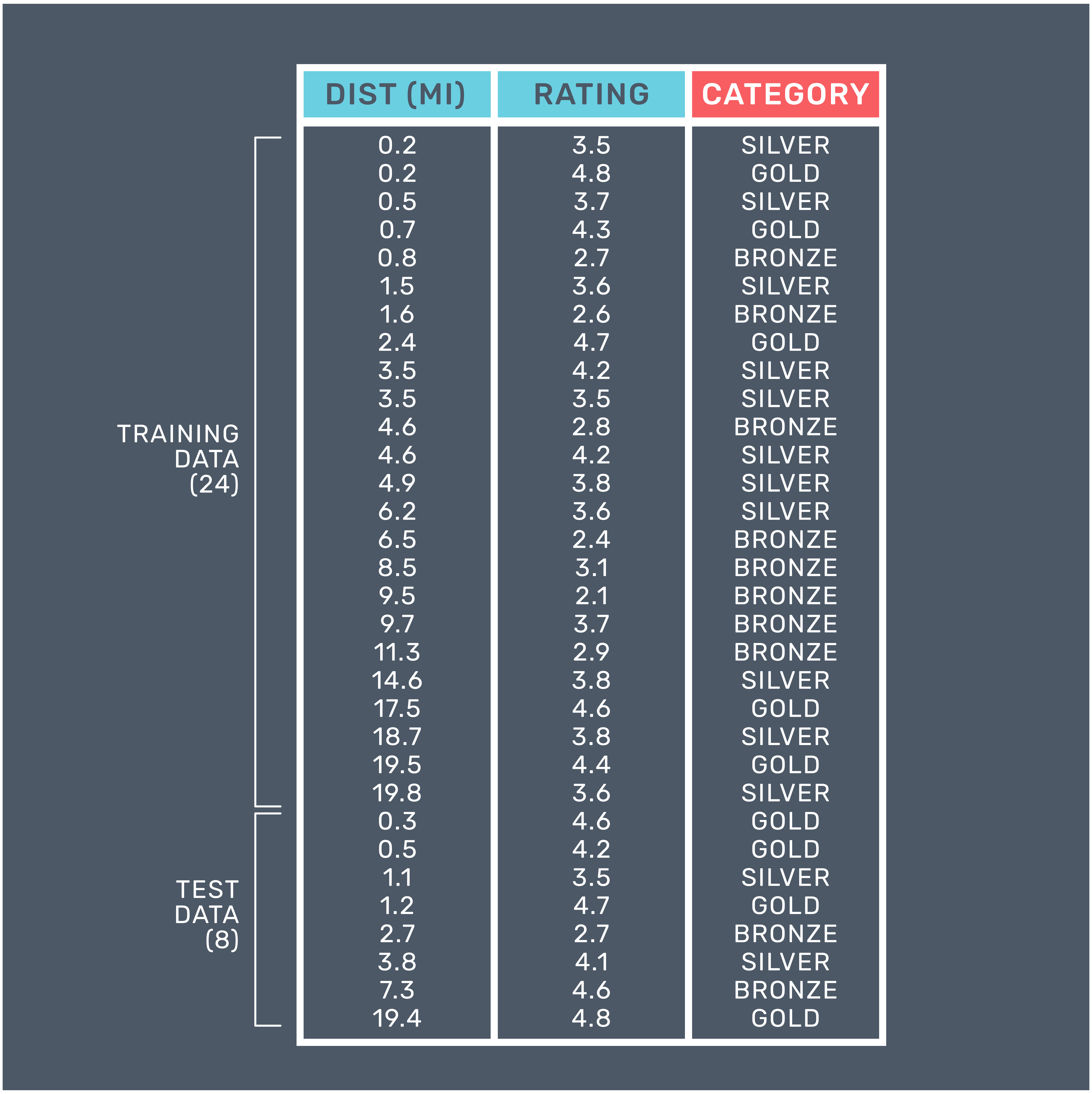




## BINARY VS. MULTI-CLASS CLASSIFICATION

In the last chapter, our task was to predict between two possible classes. But what if we had a label with more than two classes?

Such a task is called *multi-class classification*. To make the neural network work for this type of task, we'll need to modify its architecture slightly. This is what this chapter is about.



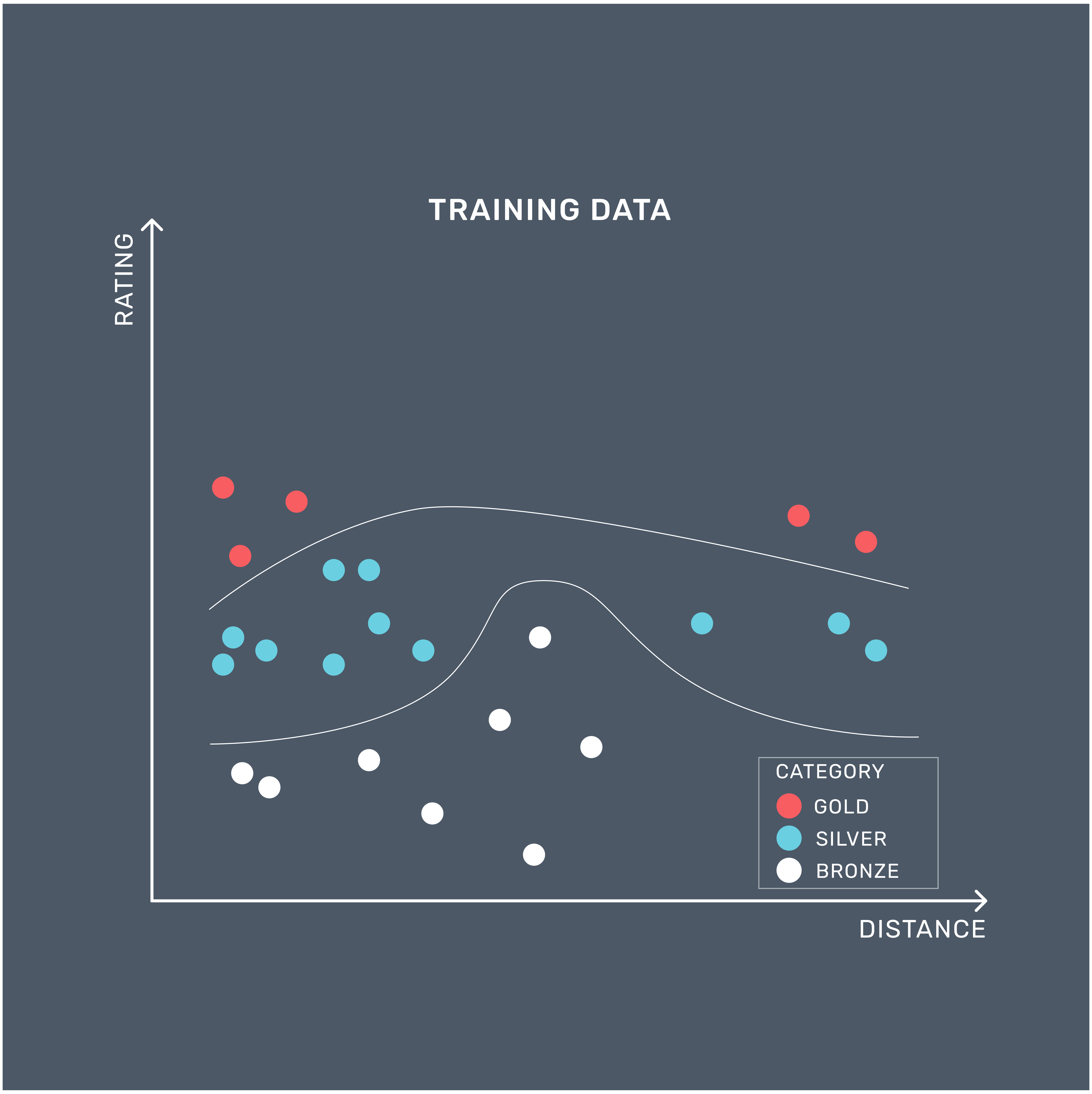
| | DIST (MI) | RATING | CATEGORY |
|---|---|---|---|
| TRAINING DATA (24) | 0.2 | 3.5 | SILVER |
| | 0.2 | 4.8 | GOLD |
| | 0.5 | 3.7 | SILVER |
| | 0.7 | 4.3 | GOLD |
| | 0.8 | 2.7 | BRONZE |
| | 1.5 | 3.6 | SILVER |
| | 1.6 | 2.6 | BRONZE |
| | 2.4 | 4.7 | GOLD |
| | 3.5 | 4.2 | SILVER |
| | 3.5 | 3.5 | SILVER |
| | 4.6 | 2.8 | BRONZE |
| | 4.6 | 4.2 | SILVER |
| | 4.9 | 3.8 | SILVER |
| | 6.2 | 3.6 | SILVER |
| | 6.5 | 2.4 | BRONZE |
| | 8.5 | 3.1 | BRONZE |
| | 9.5 | 2.1 | BRONZE |
| | 9.7 | 3.7 | BRONZE |
| | 11.3 | 2.9 | BRONZE |
| | 14.6 | 3.8 | SILVER |
| | 17.5 | 4.6 | GOLD |
| | 18.7 | 3.8 | SILVER |
| | 19.5 | 4.4 | GOLD |
| | 19.8 | 3.6 | SILVER |
| TEST DATA (8) | 0.3 | 4.6 | GOLD |
| | 0.5 | 4.2 | GOLD |
| | 1.1 | 3.5 | SILVER |
| | 1.2 | 4.7 | GOLD |
| | 2.7 | 2.7 | BRONZE |
| | 3.8 | 4.1 | SILVER |
| | 7.3 | 4.6 | BRONZE |
| | 19.4 | 4.8 | GOLD |

## THE DATASET

We'll use the same dataset as Chapter 3 and again, have a new label called *category*. Suppose there's a certification agency that classifies hotels into three categories—*gold*, *silver*, and *bronze*.

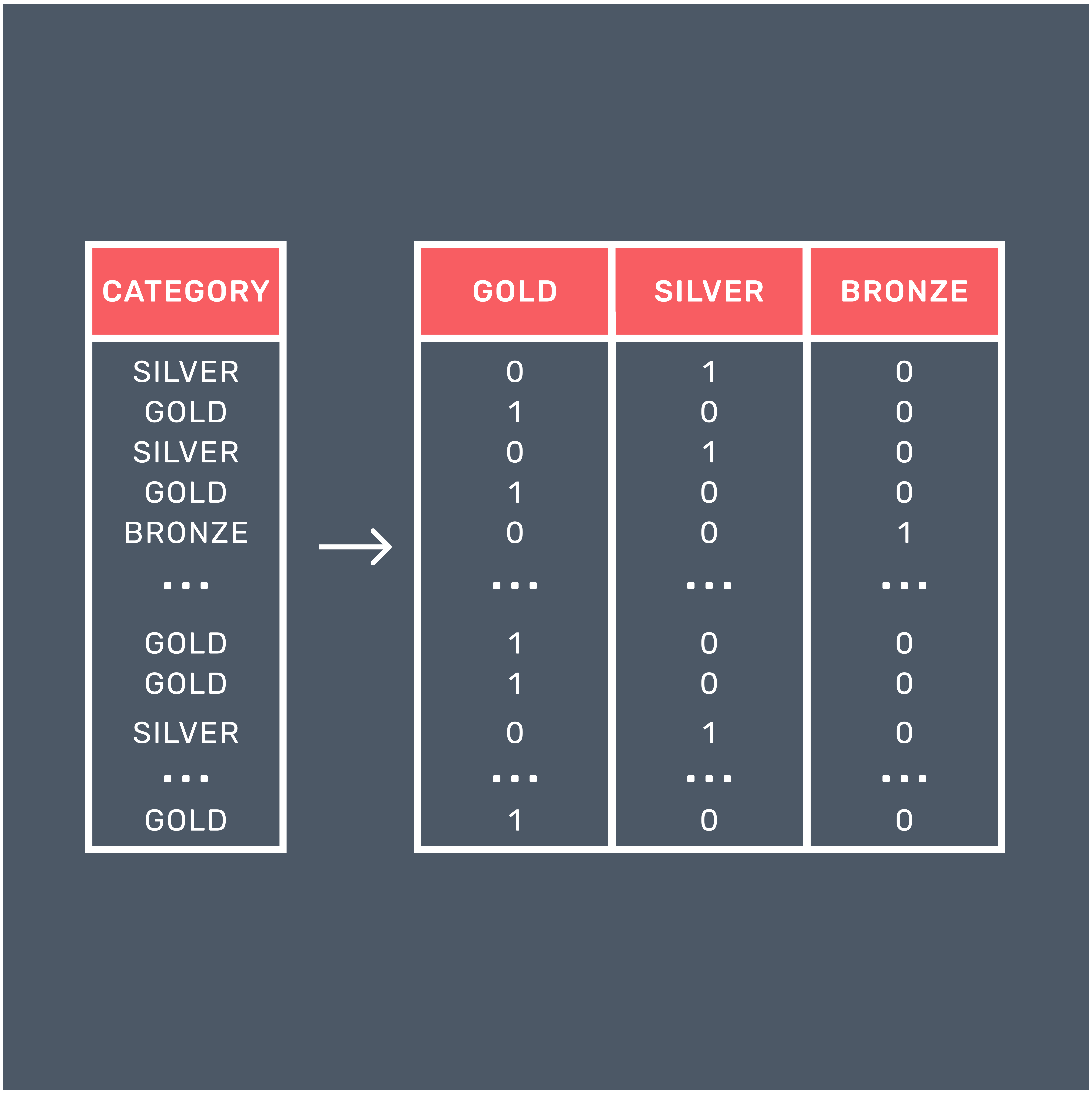
Our goal is to predict the category for a given hotel based on the features.

The label is a categorical variable, which means that order is not implied. Though the class names suggest that some order may exist, we just want to classify them without worrying about which class is better than which.



## THE DATASET

Here is shown the plot of the actual class for each training data point, along with an example of hand-drawn boundaries separating the three classes. This is what we want our neural network to produce.



| CATEGORY |
|---|
| SILVER |
| GOLD |
| SILVER |
| GOLD |
| BRONZE |
| ... |
| GOLD |
| GOLD |
| SILVER |
| ... |
| GOLD |

→

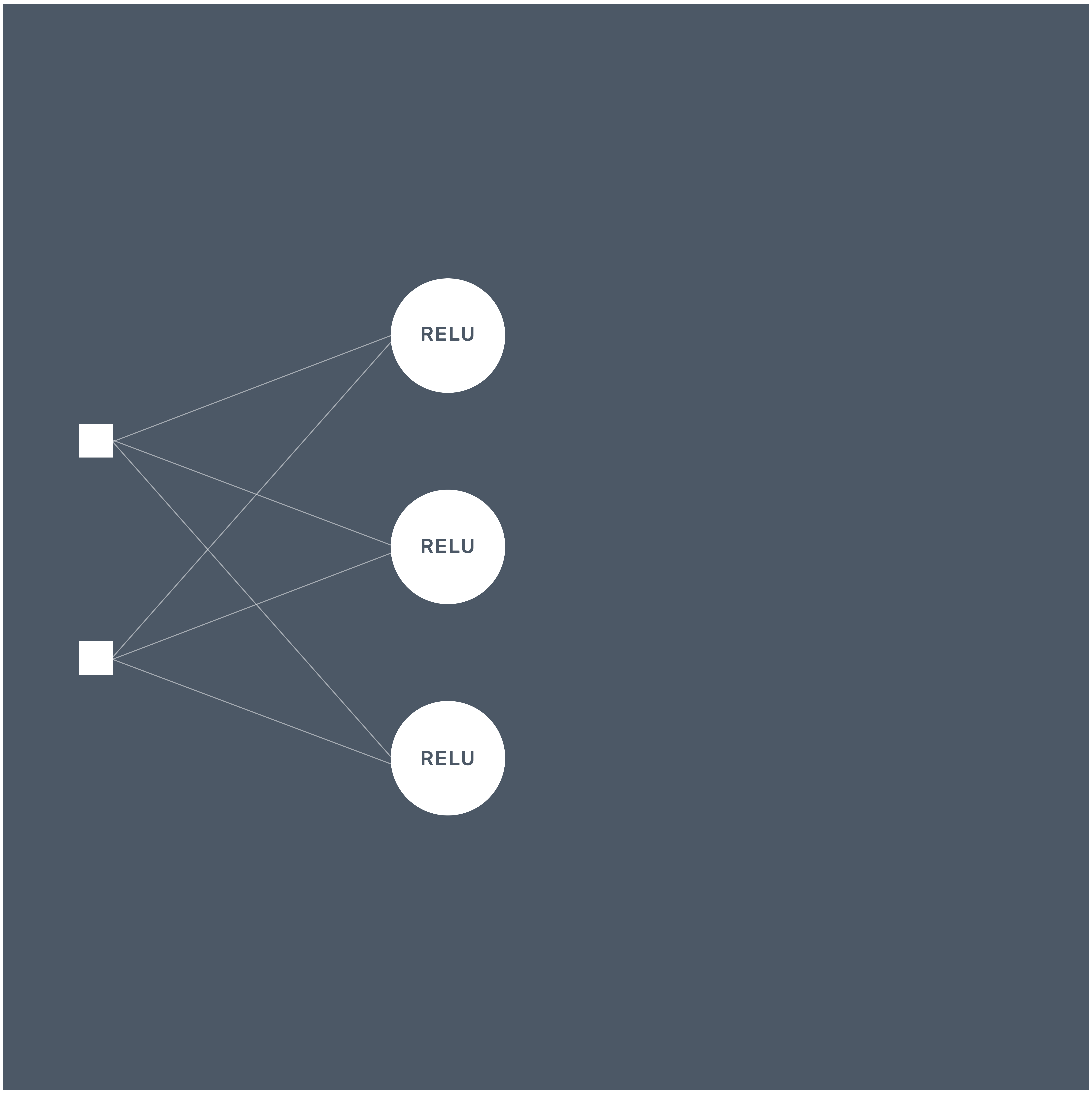
| GOLD | SILVER | BRONZE |
|---|---|---|
| 0 | 1 | 0 |
| 1 | 0 | 0 |
| 0 | 1 | 0 |
| 1 | 0 | 0 |
| 0 | 0 | 1 |
| ... | ... | ... |
| 1 | 0 | 0 |
| 1 | 0 | 0 |
| 0 | 1 | 0 |
| ... | ... | ... |
| 1 | 0 | 0 |

## ONE-HOT ENCODING

First, we need to convert the classes into a numeric format. Since we have more than two classes this time, converting them into 0s and 1s won't work.

We need to use a method called *one-hot encoding*. Here, we create a new column for each class. Then we treat each column as a binary classification output, assigning the value 1 for yes and 0 for no.

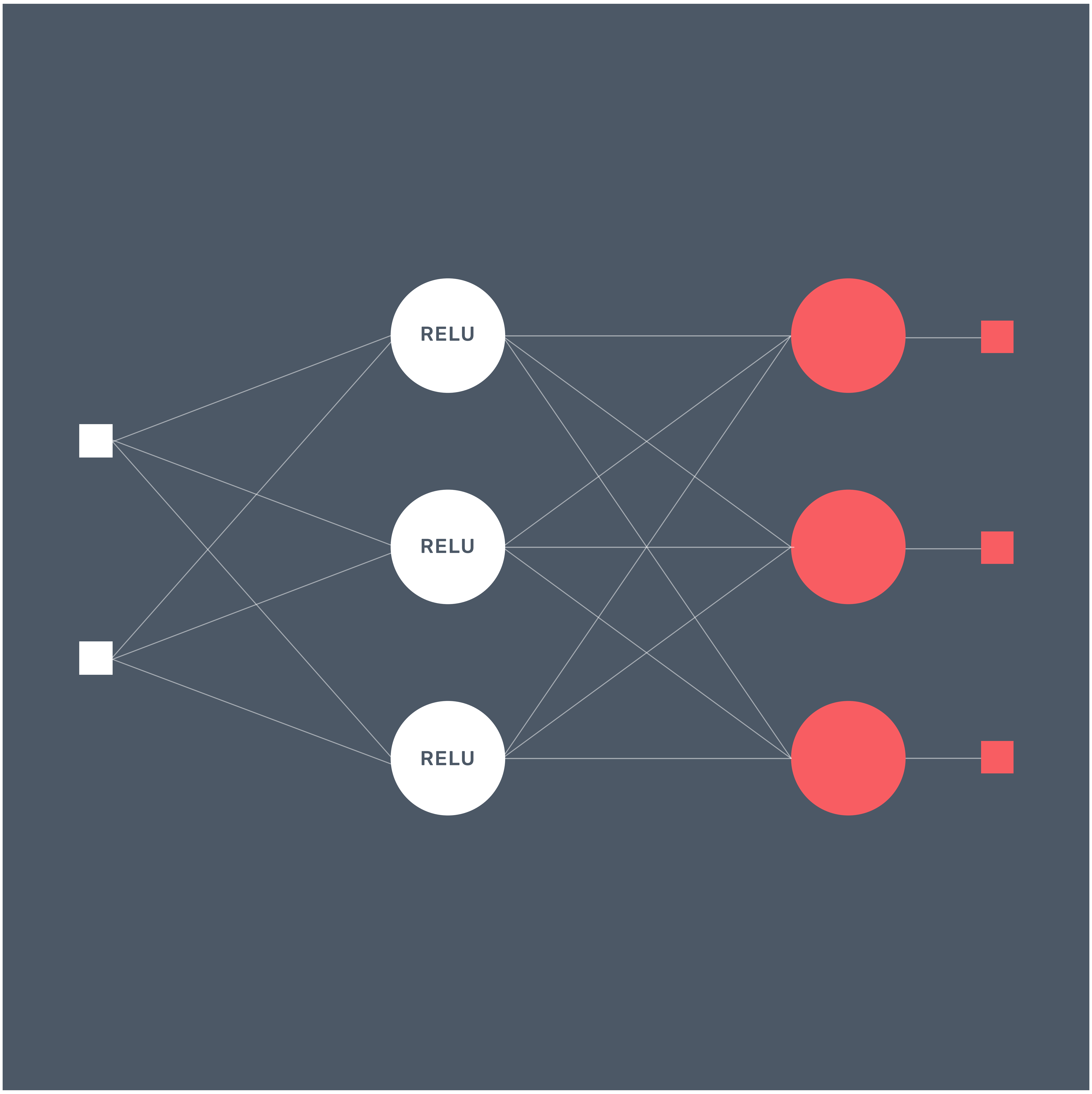
Note that if we also had features of the categorical type, we would apply the same method. Suppose we had a feature called *view* with possible values of *pool*, *garden*, and *none*. This will translate into three one-hot encoded features, one for each class.



## NEURAL NETWORK ARCHITECTURE

We'll start building the neural network with the input layer, where there are no changes from the previous chapter.

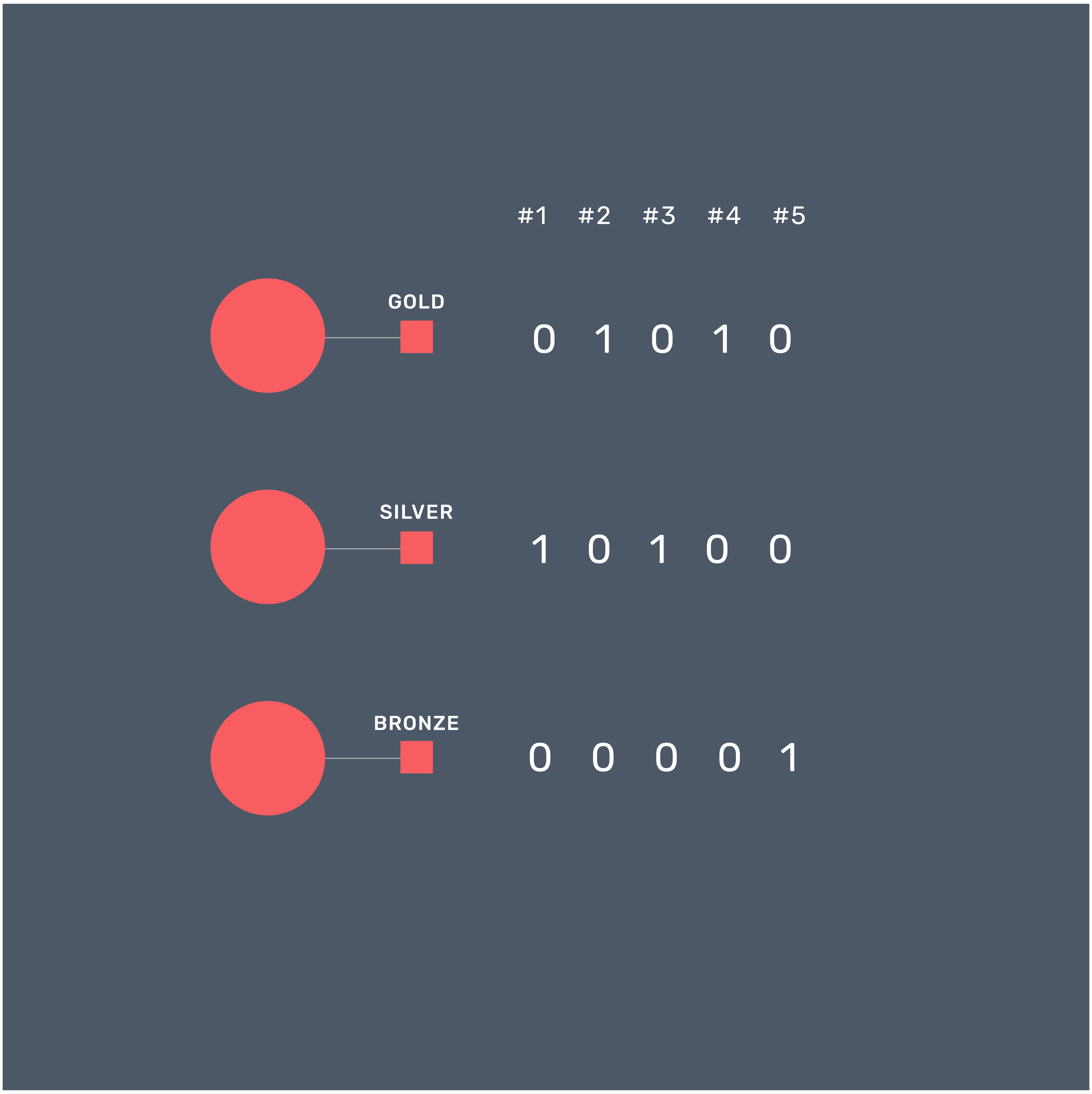
We'll also retain the same number of hidden layers and units, and keep ReLU as the activation function.



## NEURAL NETWORK ARCHITECTURE

As for the output layer, we need to make some changes. A single-neuron output only works for binary classification.

For multi-class classification, we need to have the same number of neurons as classes. Each neuron represents one class, and its output is mapped to the corresponding one-hot encoded column. To understand this, let's look at some examples.

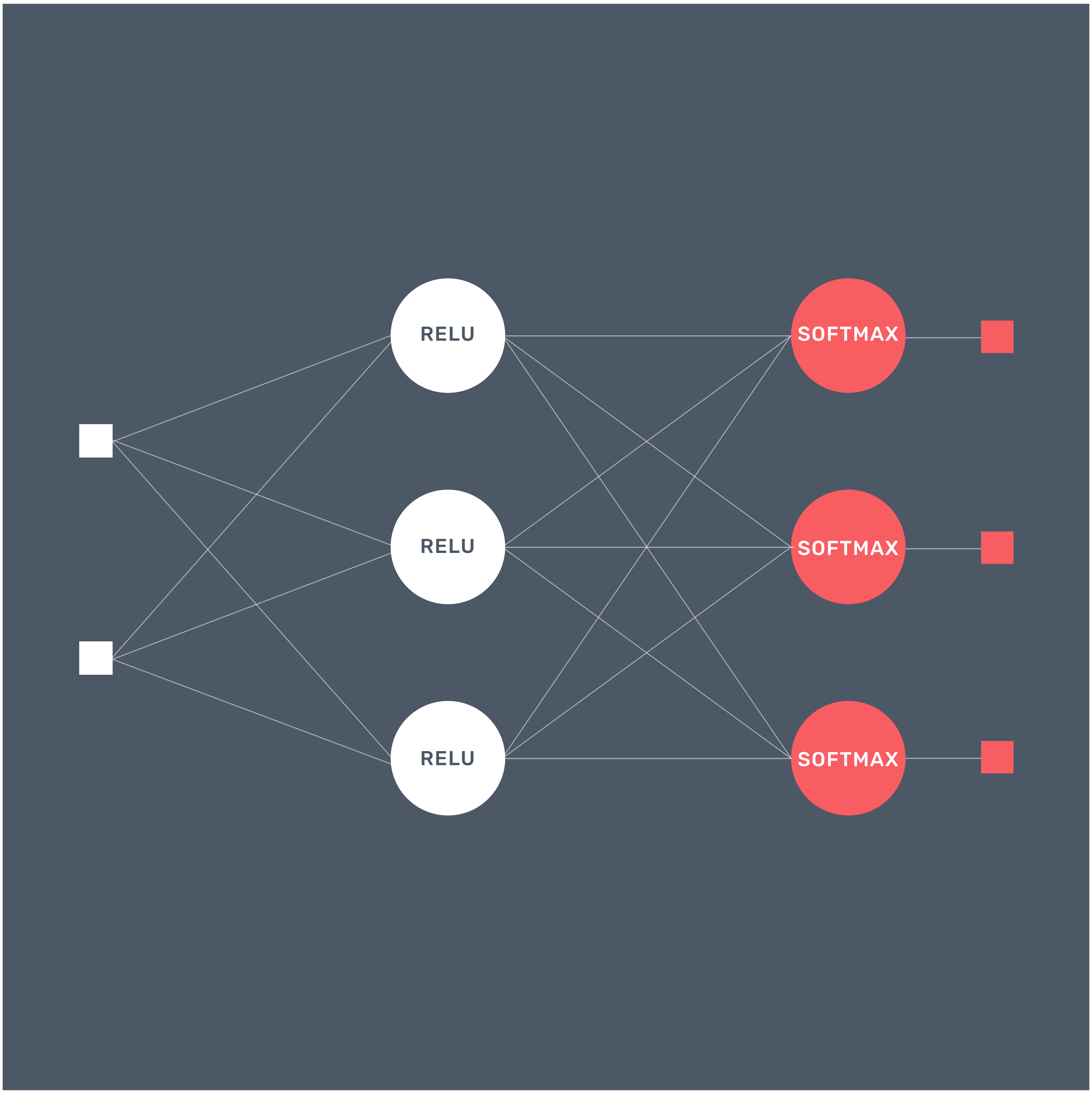


### OUTPUT VALUES

Here we have the labels of the first five data points—silver, gold, silver, gold, and bronze.

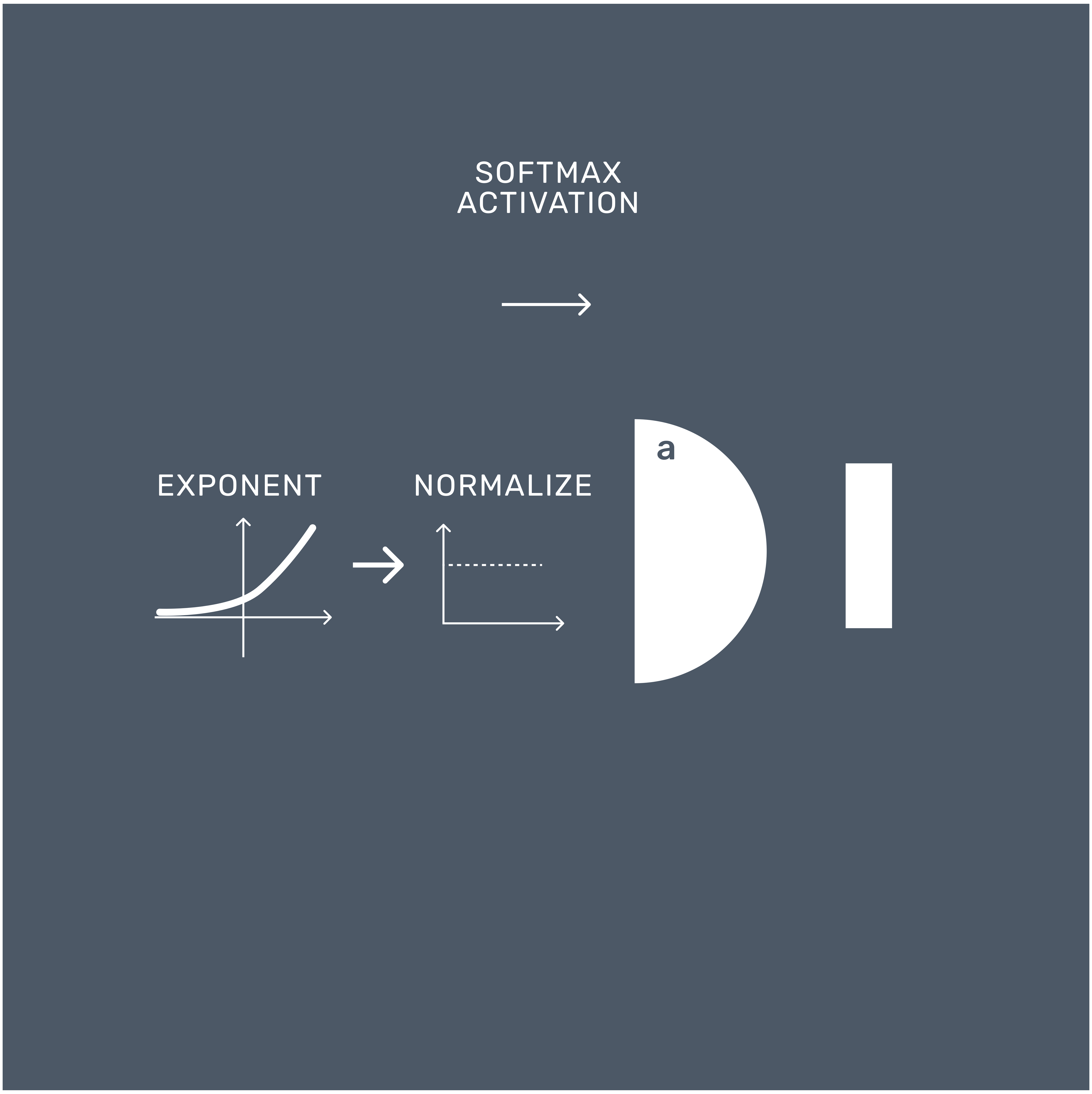
Take the first data point as an example. For the silver class, the neural network should ideally predict 0, 1, and 0 for the first, second, and third neurons.

In short, for each data point, the neuron of the actual class should output 1 while other neurons should output 0.



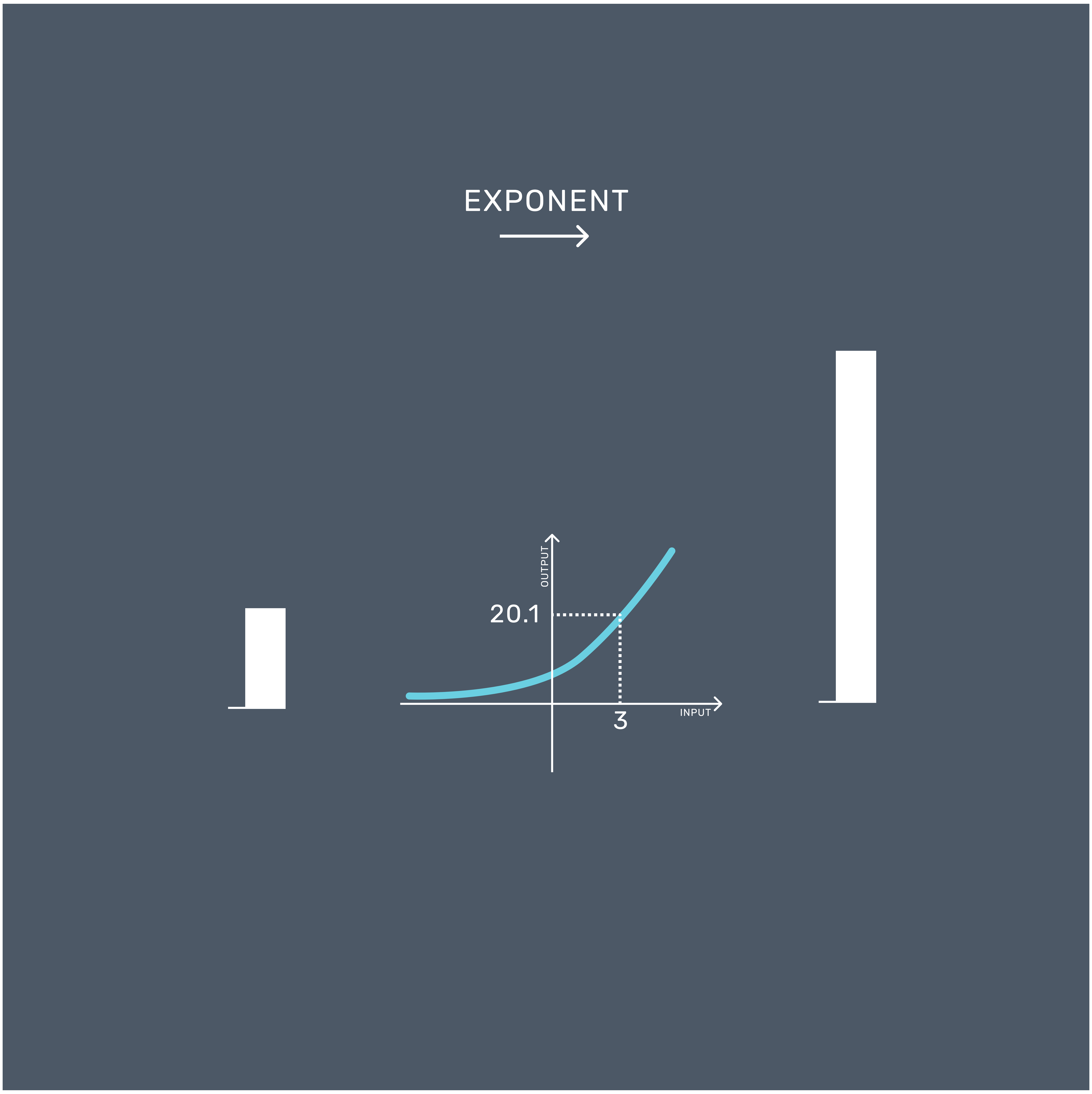
## OUTPUT LAYER ACTIVATION

There is also a change in the activation functions in the output layer. We'll introduce a new function called *softmax*.



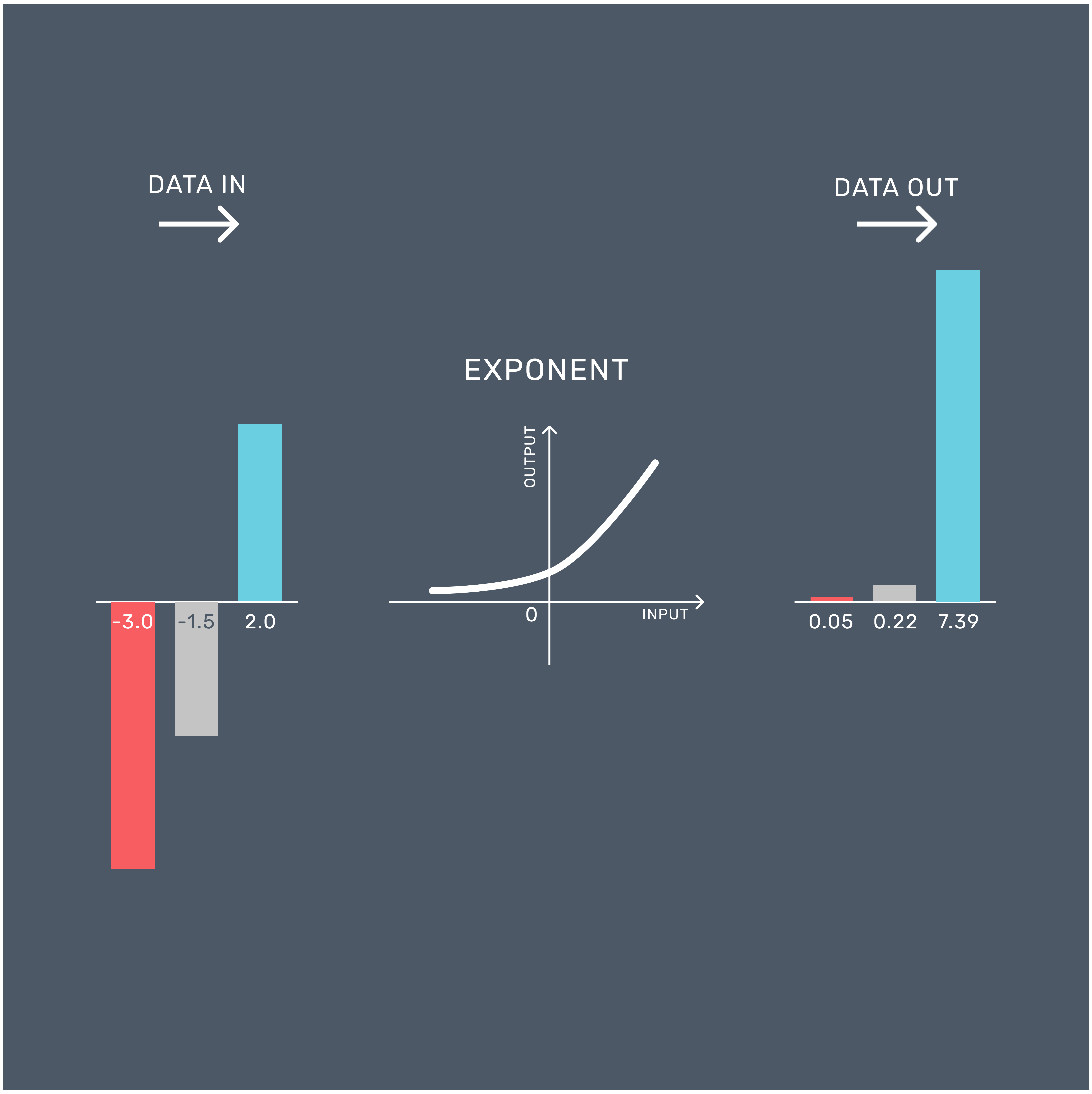
## SOFTMAX ACTIVATION FUNCTION

The softmax activation performs a two-step computation on its input: *exponentiation* and *normalization*.



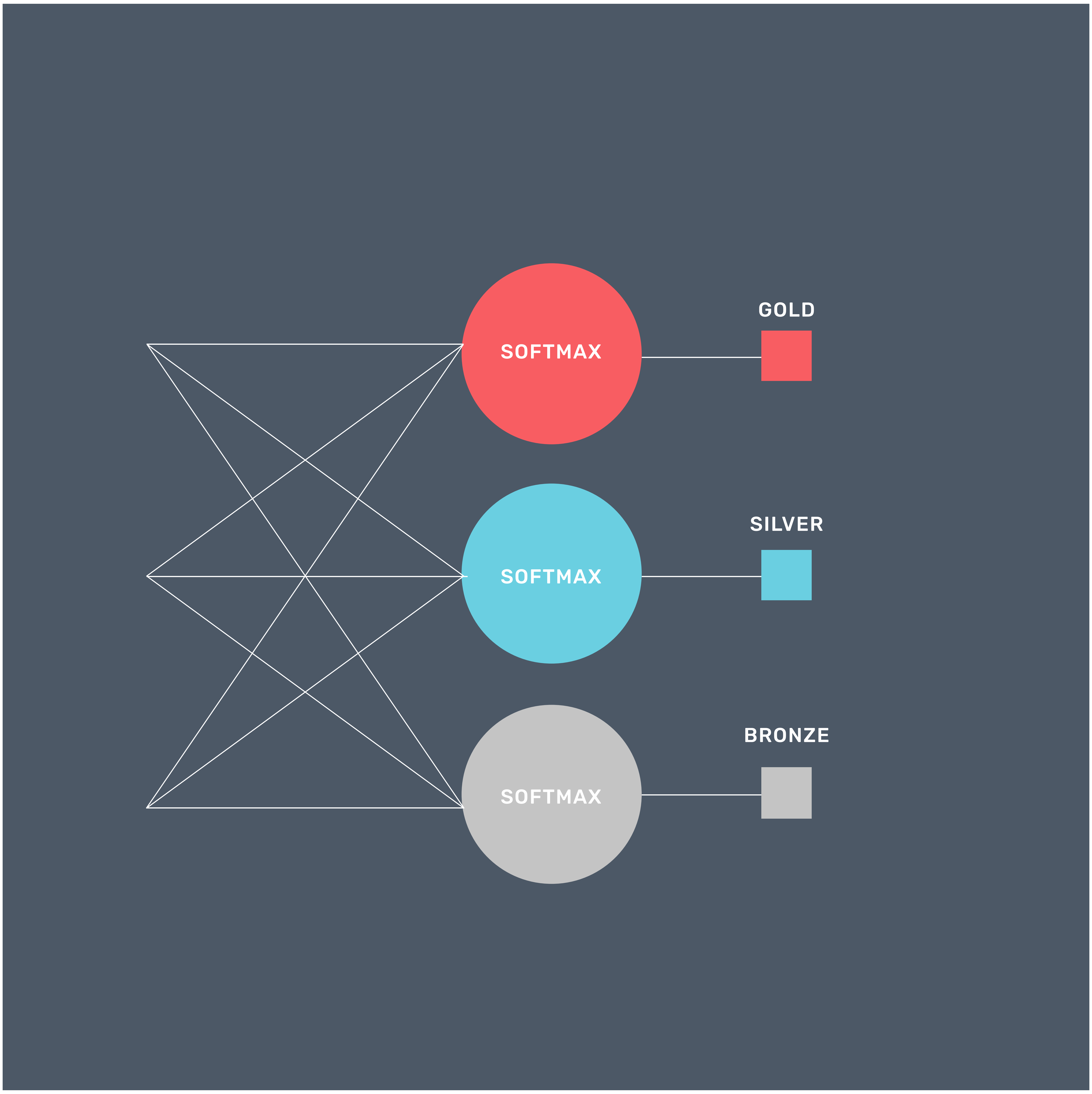
## EXPONENT

In the first step, it turns the input into its exponent.



## EXPONENT

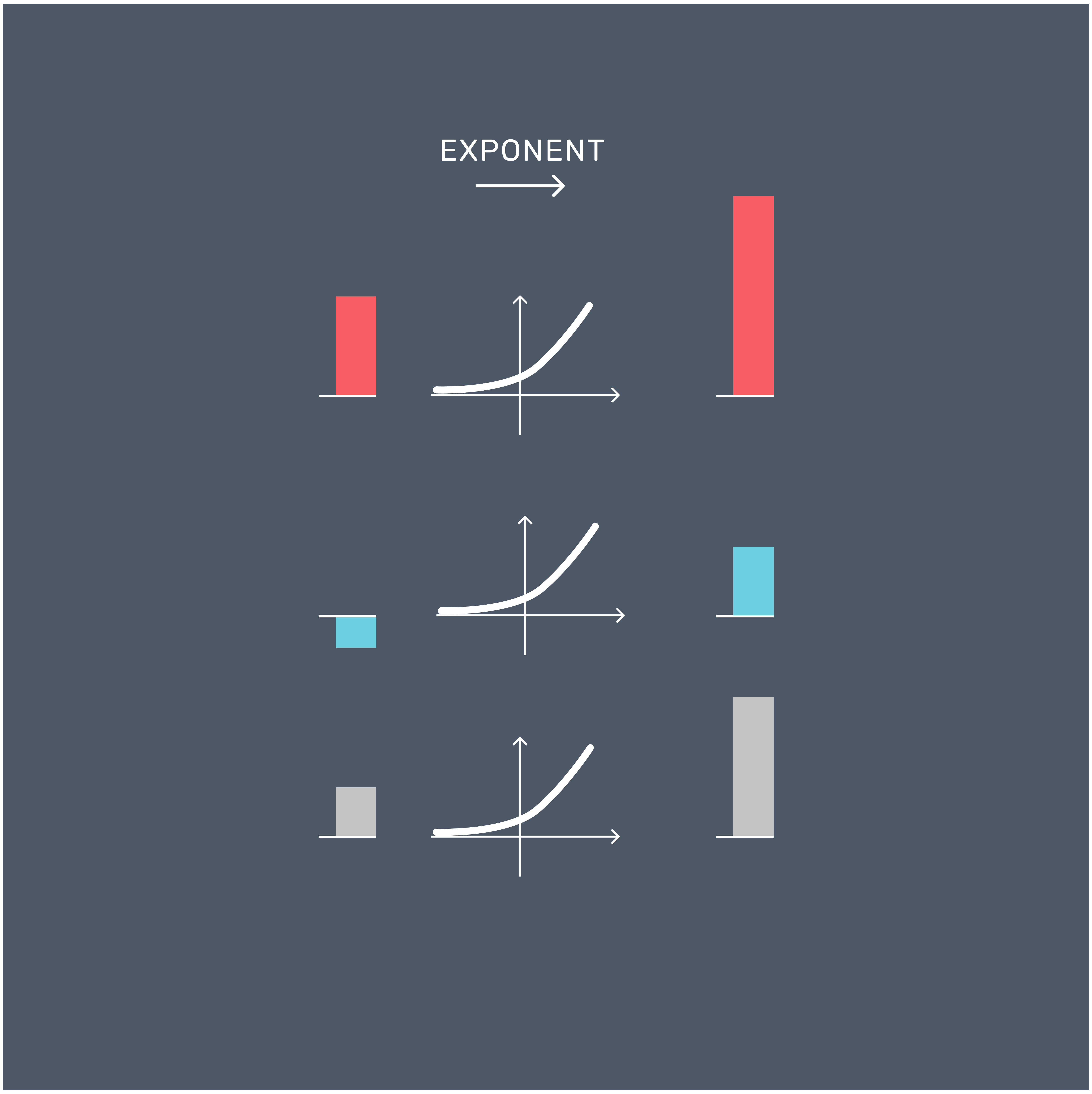
The effect of exponentiation is to transform any number into a positive number. Additionally, it amplifies the large inputs more than the small ones.



## THE FULL LAYER

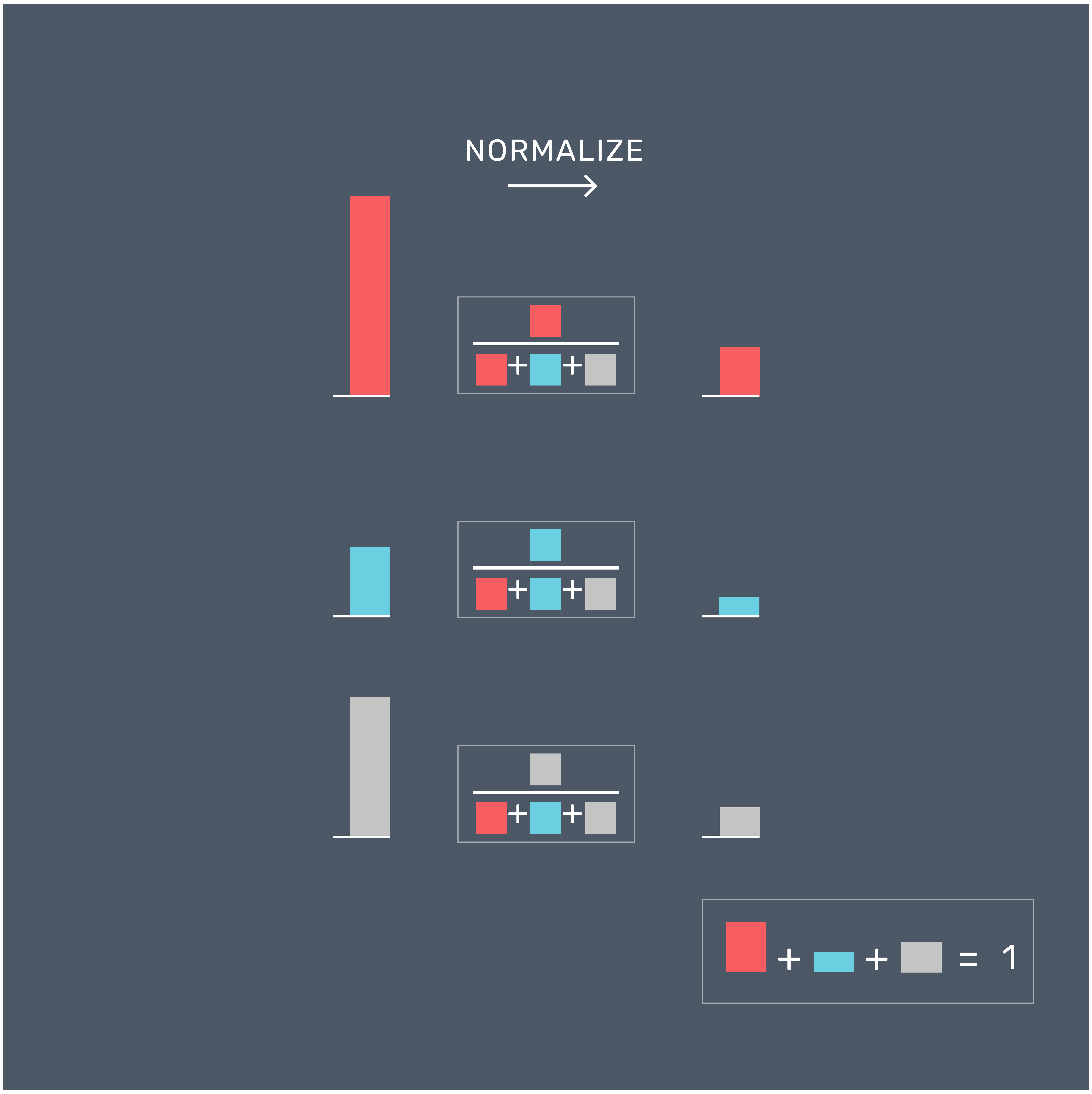
To understand how the second step, normalization, works, we need to look at the layer as a whole.

Here we have the three units of neurons, one for each class.



## EXPONENT

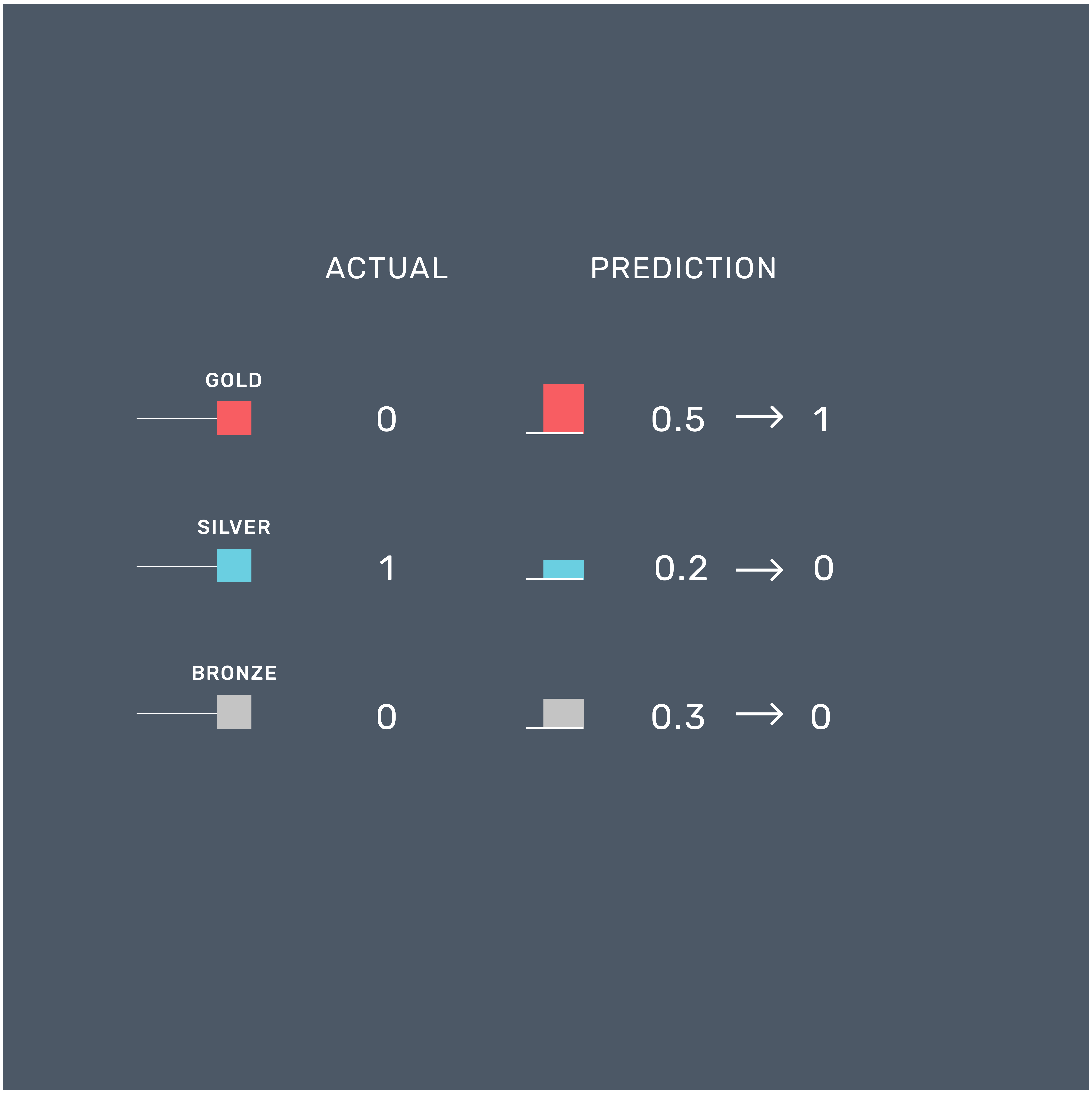
Each neuron performs the exponentiation on its input, which then becomes the input for the normalization step.



## NORMALIZE

In the normalization step, each input is divided by the sum of all inputs. This becomes the output of the neural network.

As a result, the sum of all outputs will always be 1. This is a useful outcome because we can now treat the outputs as probability values, as we did in Chapter 3.

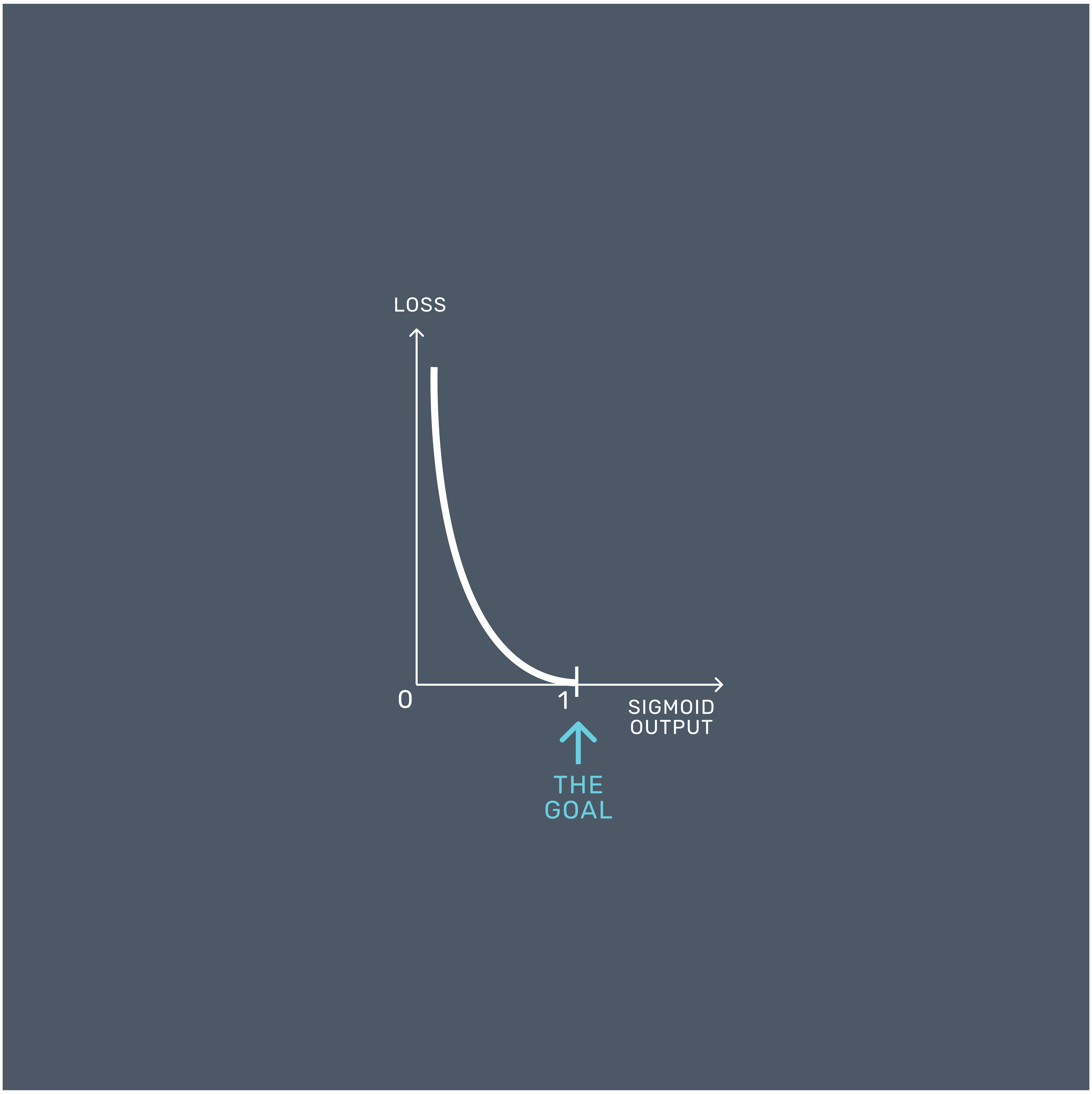


## EXAMPLE PREDICTION

Let's take an example where the actual class is silver. And suppose that each neuron's softmax activation produces 0.5, 0.2, and 0.3.

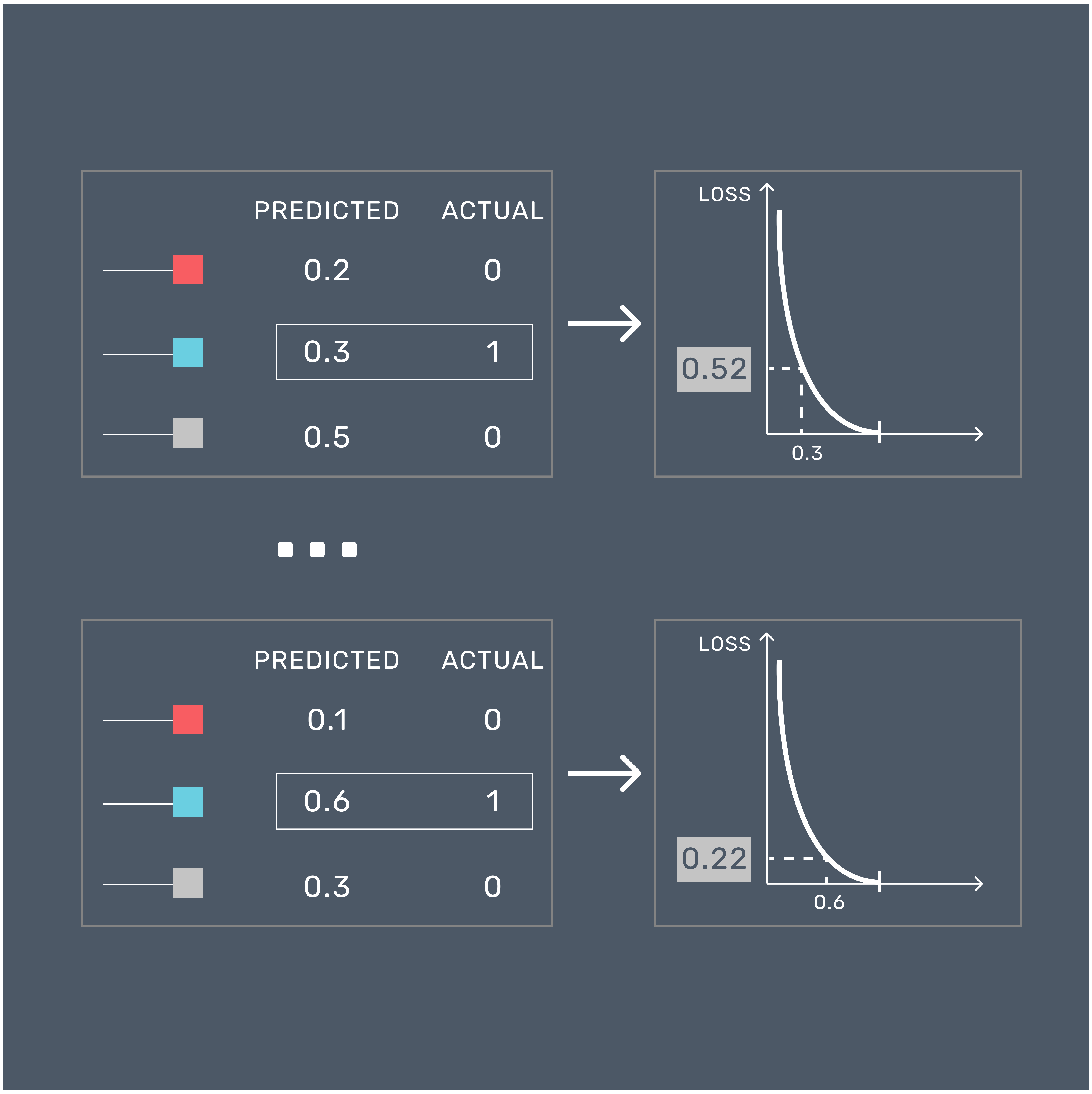
Treating them as probabilities, we assign 1 to the neuron with the largest output and 0 to the other neurons.

In this example, the predicted class does not match the actual class. This brings us to the next discussion - the loss function.



## LOSS FUNCTION

The loss function we'll be using is called *categorical cross entropy.* It is essentially the same as the binary cross entropy loss function we used in Chapter 3, but a generalized version. The categorical cross entropy works for any number of classes, unlike its binary counterpart.

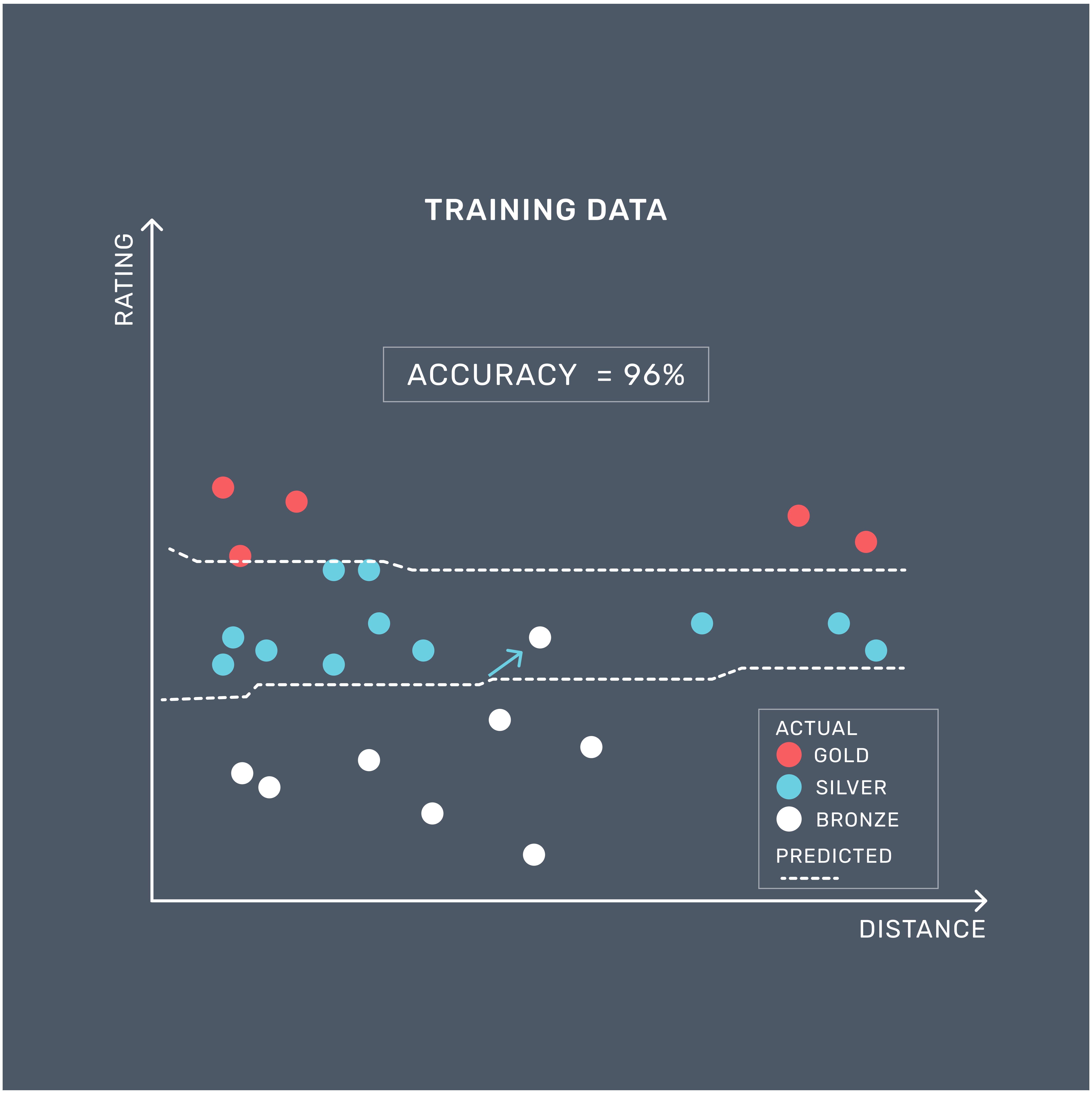


## LOSS FUNCTION EXAMPLE

Let's look at an example. Here, the actual class is silver. So, we want the neural network to output the highest probability at the second neuron.

In one of the earlier training epochs, we can see that the output at the second neuron is 0.3, which isn't very good. This results in a high loss value.

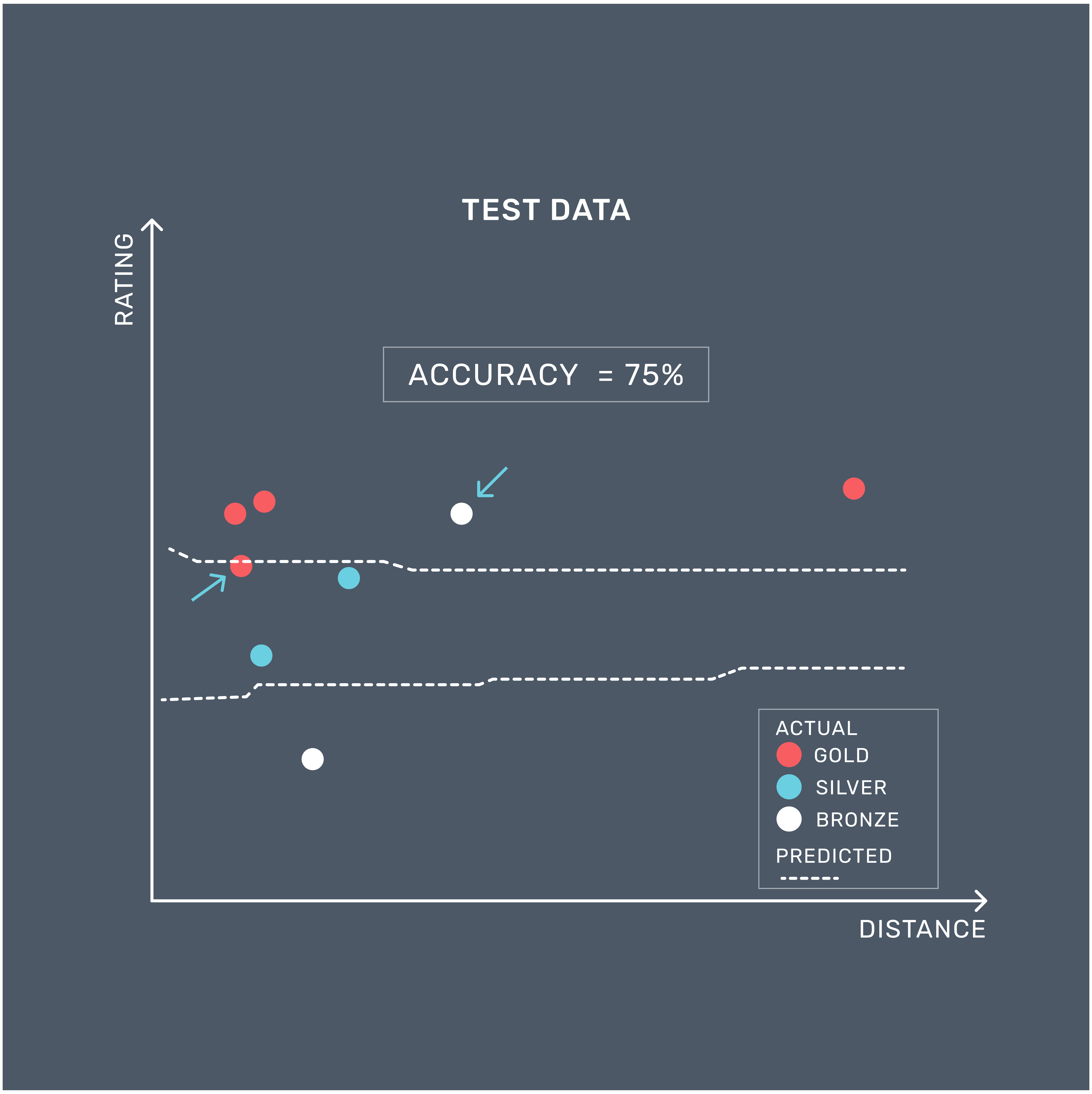
In one of the later epochs, this neuron produces an output of 0.6. This indicates an improvement, which is reflected in the decreasing loss value.



## TRAINING PERFORMANCE

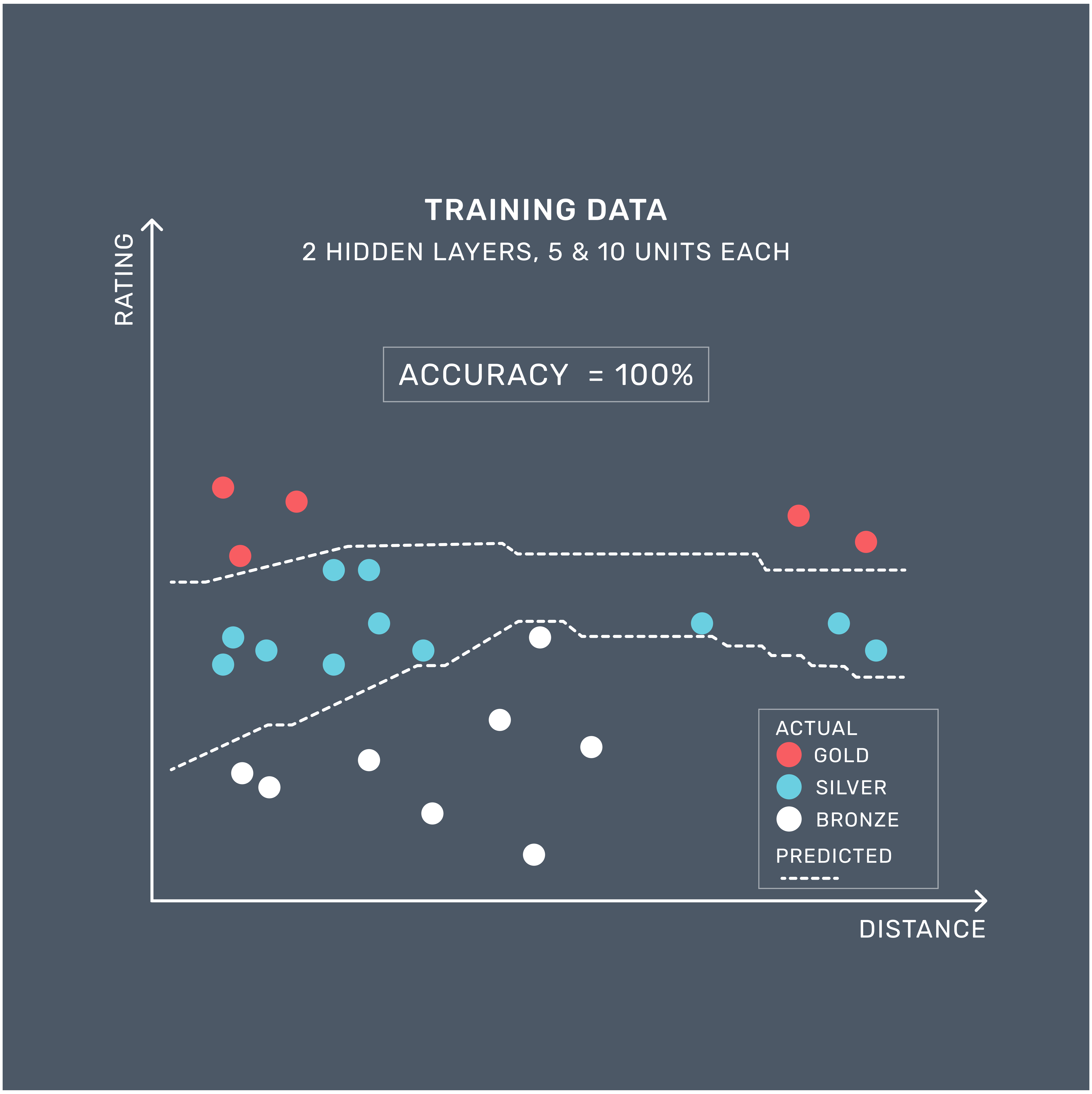
Using the accuracy metric, we can see that the model does pretty well on the training dataset.

The plot also shows the decision boundary of our trained neural network, representing the predictions.



## TEST PERFORMANCE

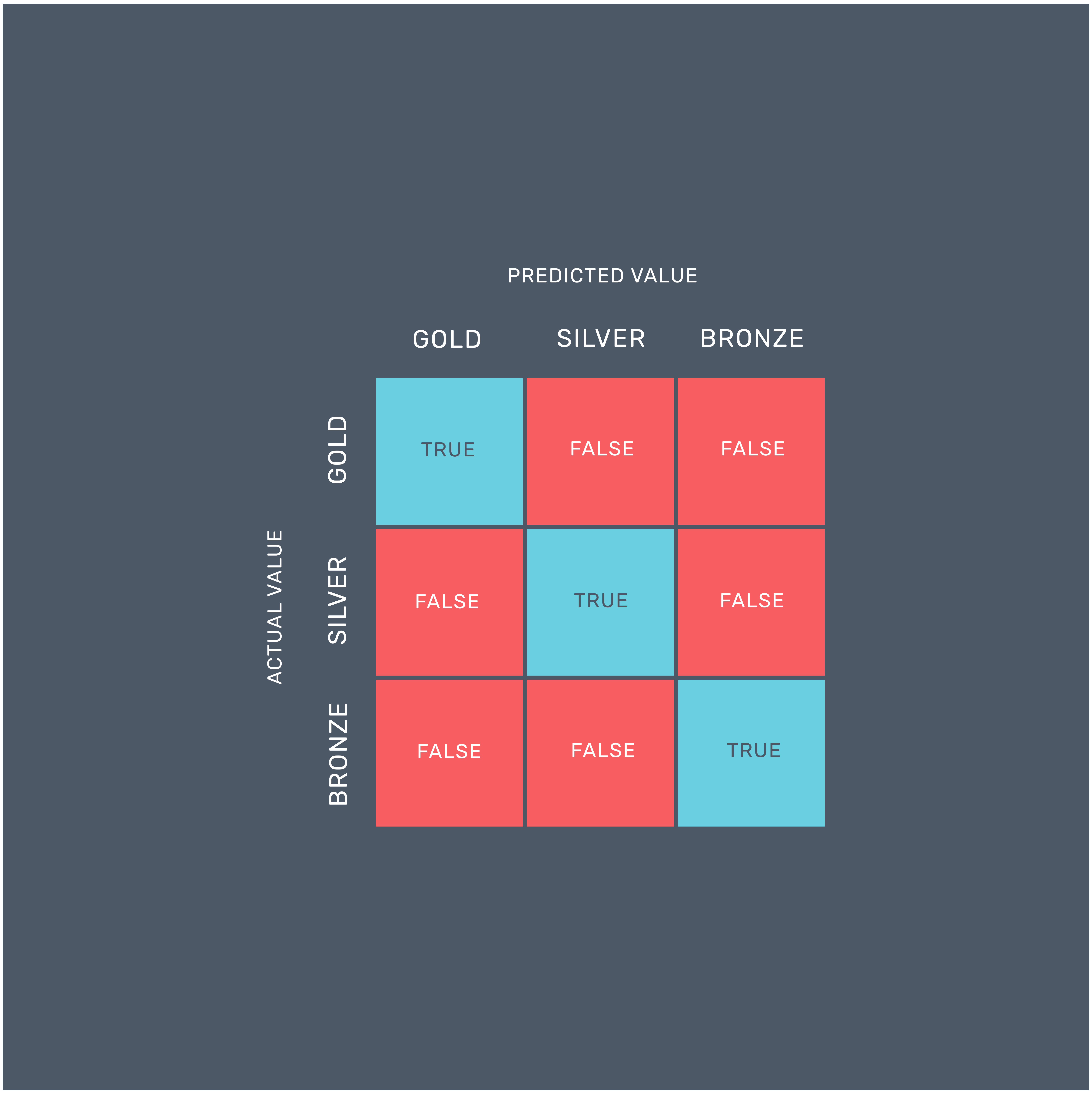
The prediction on the test data also shows a respectable performance, given the limited number of data points.



## A BIGGER NETWORK

As in Chapter 3, we can further improve the performance by adding more layers and units.

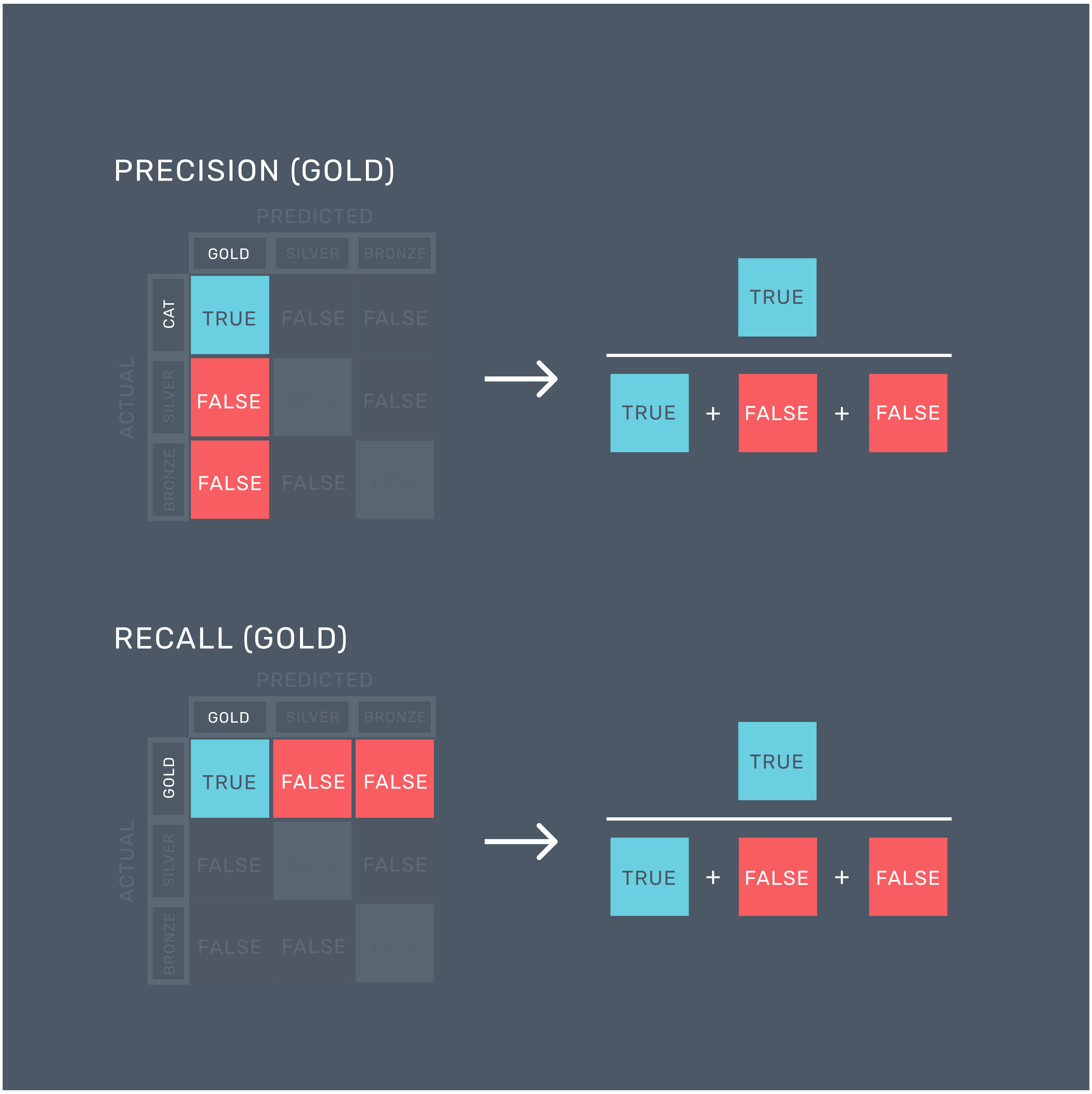
The plot here shows the decision boundaries after modifying the neural network to contain two hidden layers with five and ten units of neurons each. The granularity of its predictions increased, resulting in a more well-defined and accurate prediction curve.



|  |  | PREDICTED VALUE |  |  |
|---|---|---|---|---|
|  |  | GOLD | SILVER | BRONZE |
| ACTUAL VALUE | GOLD | TRUE | FALSE | FALSE |
|  | SILVER | FALSE | TRUE | FALSE |
|  | BRONZE | FALSE | FALSE | TRUE |

## CONFUSION MATRIX

The confusion matrix for this task is now expanded to a 3-by-3 matrix. The diagonal cells account for the correct predictions for each class, while the remaining cells account for the incorrect predictions.



PRECISION (GOLD)

| | | PREDICTED | | |
|---|---|---|---|---|
| | | GOLD | SILVER | BRONZE |
| ACTUAL | CAT | TRUE | FALSE | FALSE |
| | SILVER | FALSE | TRUE | FALSE |
| | BRONZE | FALSE | FALSE | TRUE |

$$\rightarrow \quad \frac{\text{TRUE}}{\text{TRUE} + \text{FALSE} + \text{FALSE}}$$

RECALL (GOLD)

| | | PREDICTED | | |
|---|---|---|---|---|
| | | GOLD | SILVER | BRONZE |
| ACTUAL | GOLD | TRUE | FALSE | FALSE |
| | SILVER | FALSE | TRUE | FALSE |
| | BRONZE | FALSE | FALSE | TRUE |

$$\rightarrow \quad \frac{\text{TRUE}}{\text{TRUE} + \text{FALSE} + \text{FALSE}}$$

## PRECISION AND RECALL

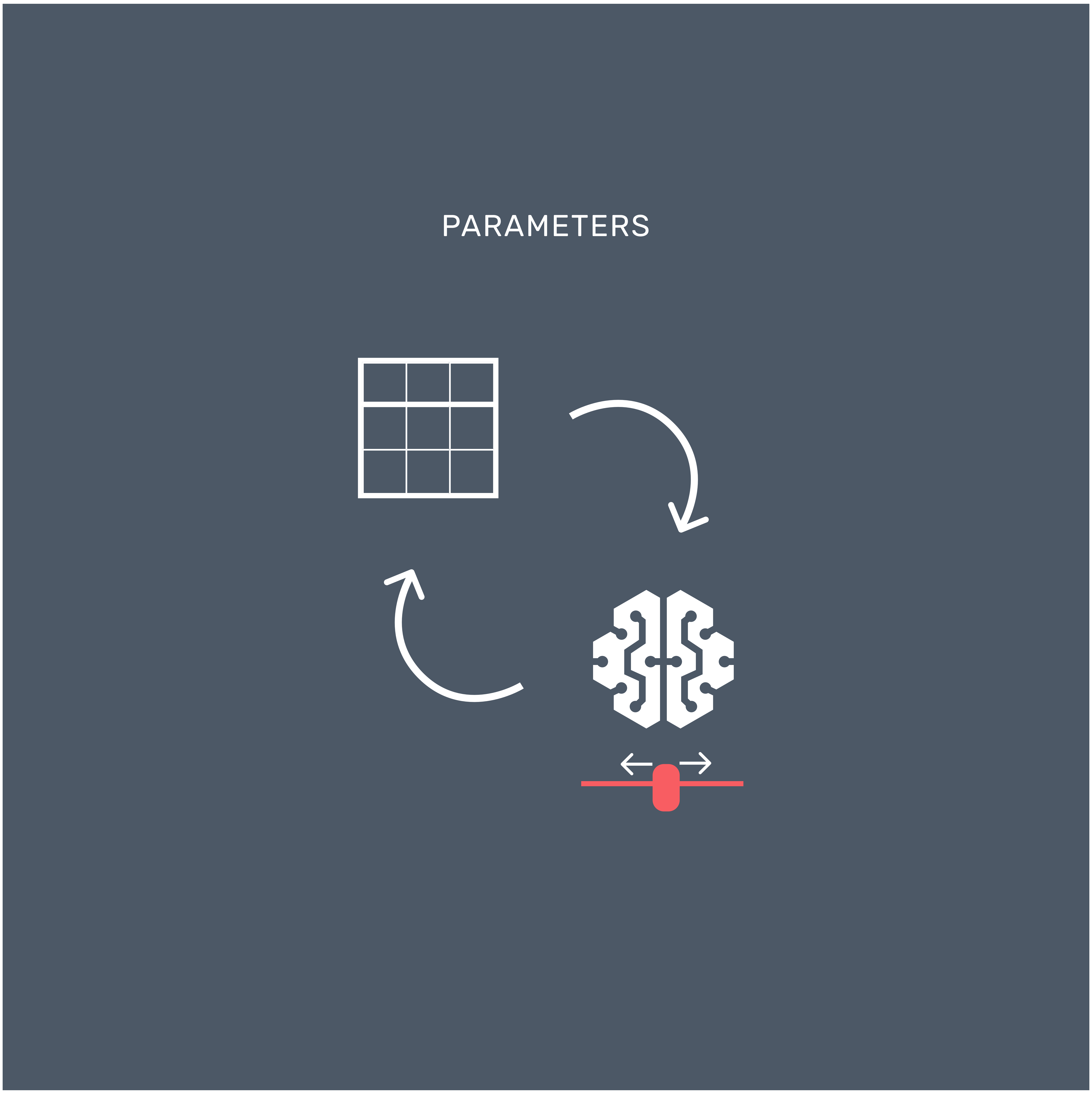
For multi-class classification, each class will have its own set of precision and recall metrics. Here we have an example for the gold class.

## HYPERPARAMETERS

And with that, our fourth and final task is complete.

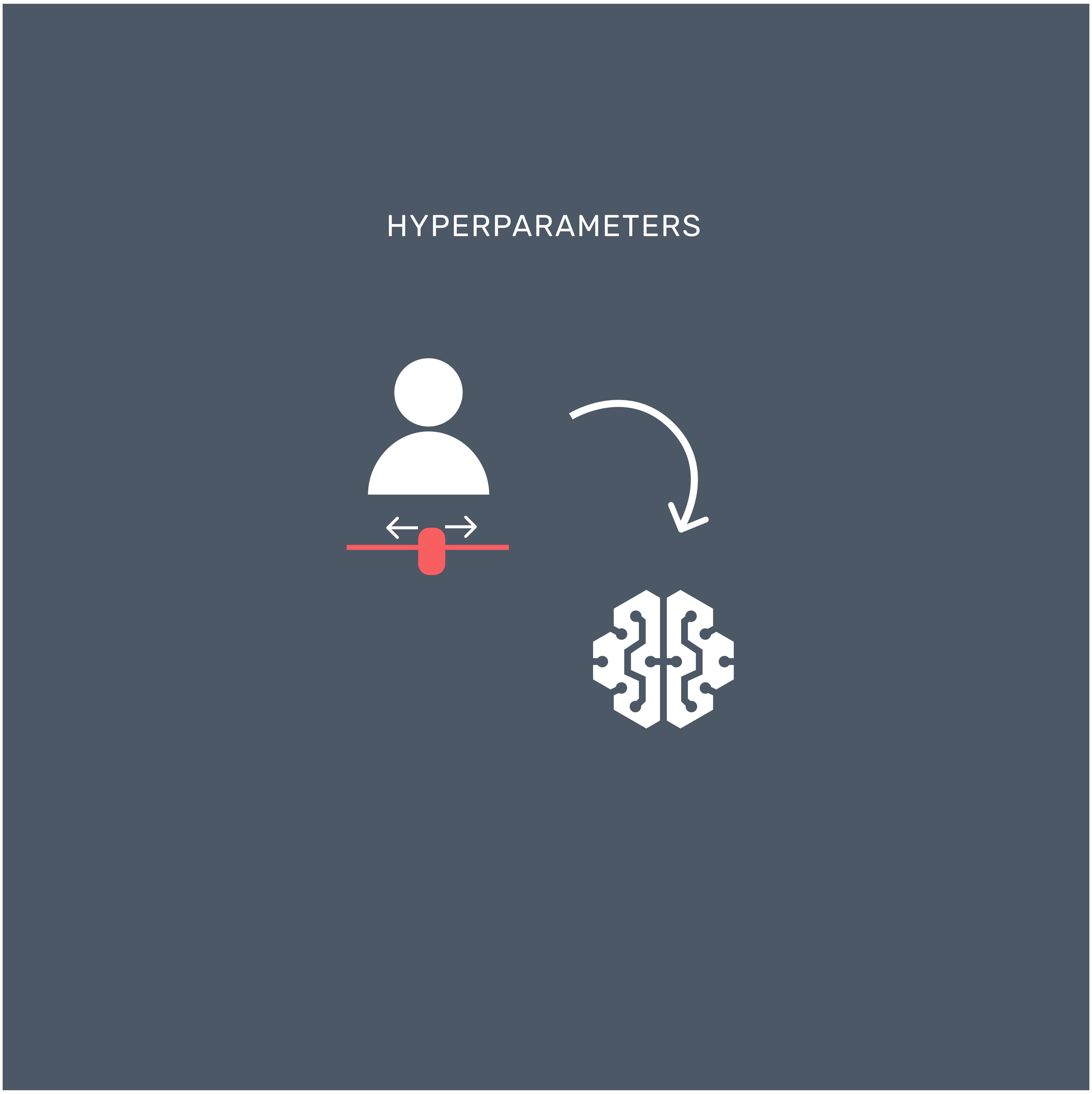
For the remainder of this chapter, we'll look at various ways to improve our prediction results. We can divide them into two groups—*hyperparameters* and *data*.

First, let's look at hyperparameters. You may not have noticed, but we have covered some of them in the four tasks. Now let's take a closer look.



## PARAMETERS

Recall that parameters—weights and biases—are learned by the neural network during training.

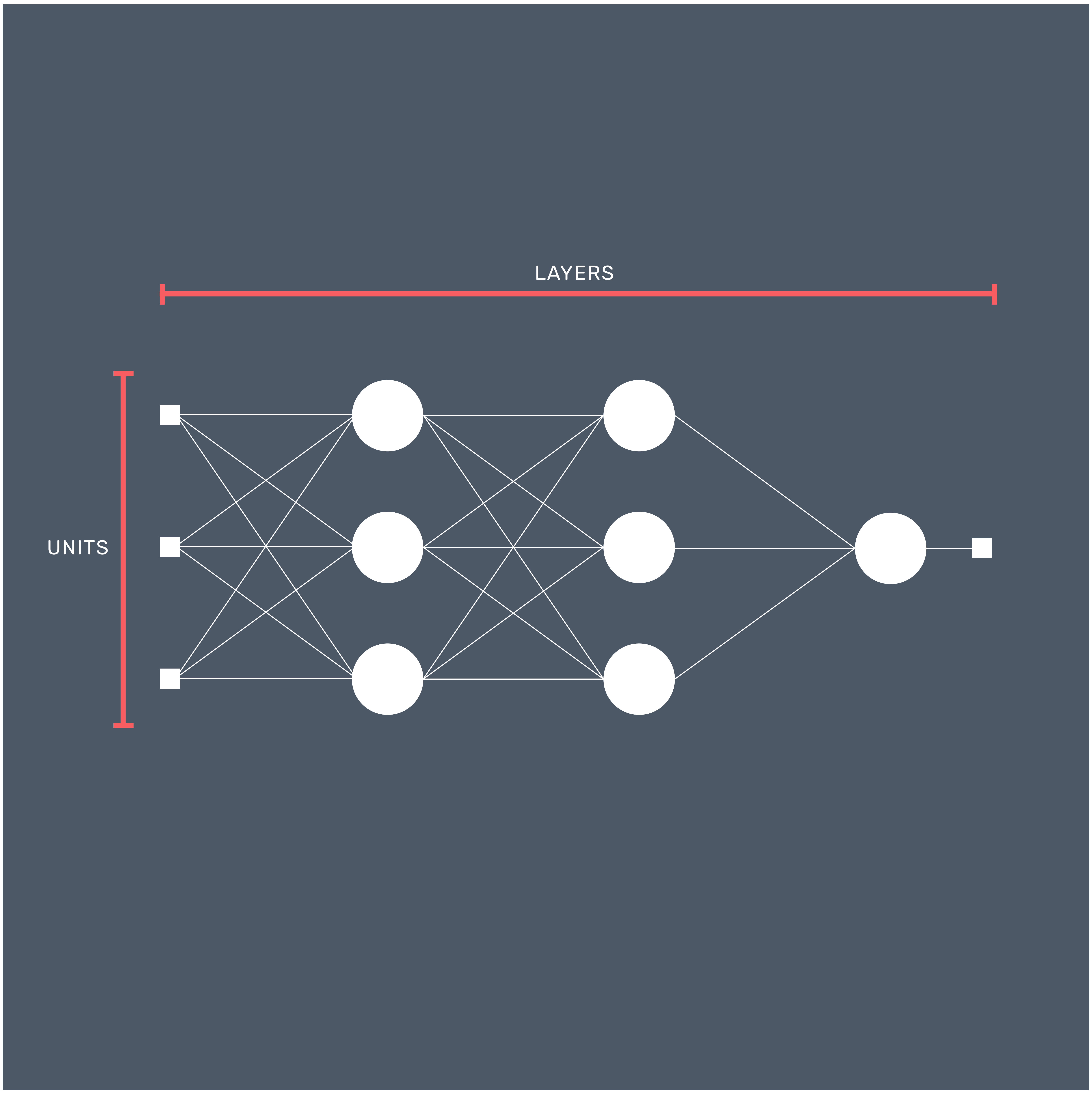


## HYPERPARAMETERS

On the other hand, hyperparameters are parameters that cannot be learned by the neural network. Instead, we need to provide them.

Choosing the right hyperparameters requires experience and is both an art and a science. They are no less important in successfully training a neural network.

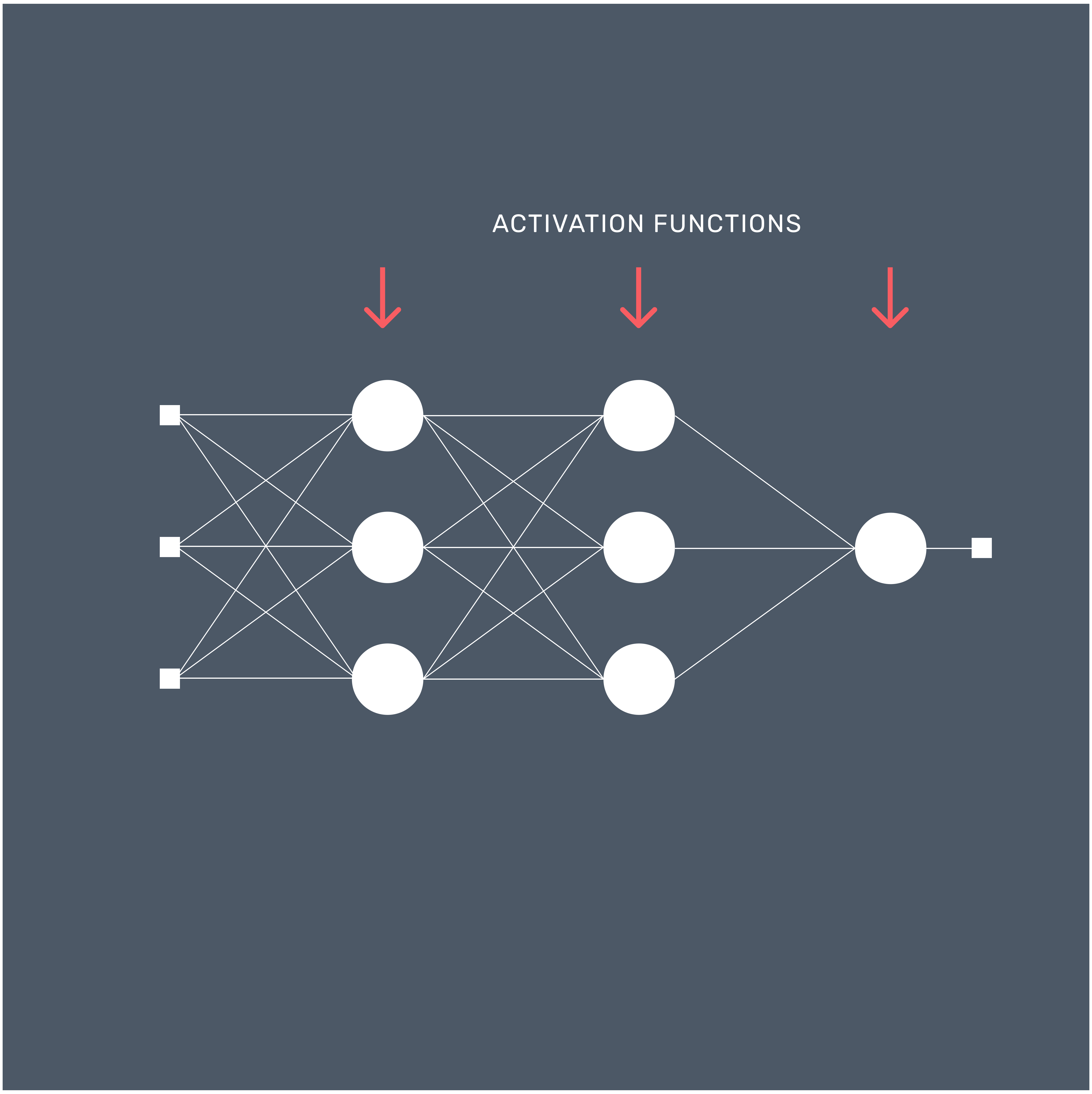
There are many types of hyperparameters, so let’s cover some of the key ones.



## SIZE

This is obvious, but one of the most important hyperparameters is the size of the neural network itself.

We change the size by increasing or decreasing the number of layers and units in each layer. A larger network is capable of handling more complex tasks and data.

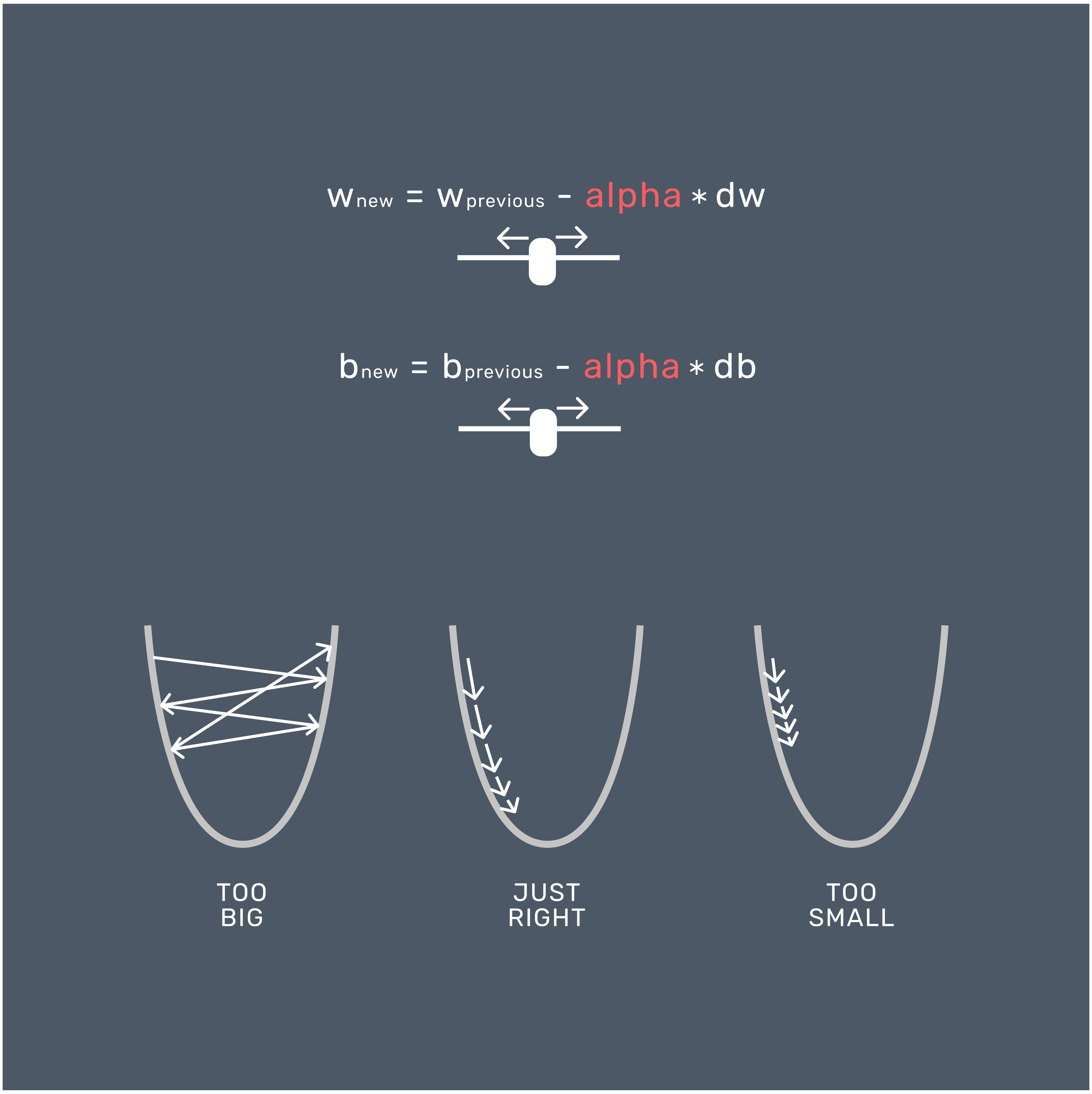


## ACTIVATION FUNCTION

Another hyperparameter is the type of activation function in each neuron.

This depends on the nature of the task, but ReLU is typically used in the hidden layers, or at least is a good option to start with.

As for the output layer, this largely depends on the task, for example, whether it's a regression or classification task.



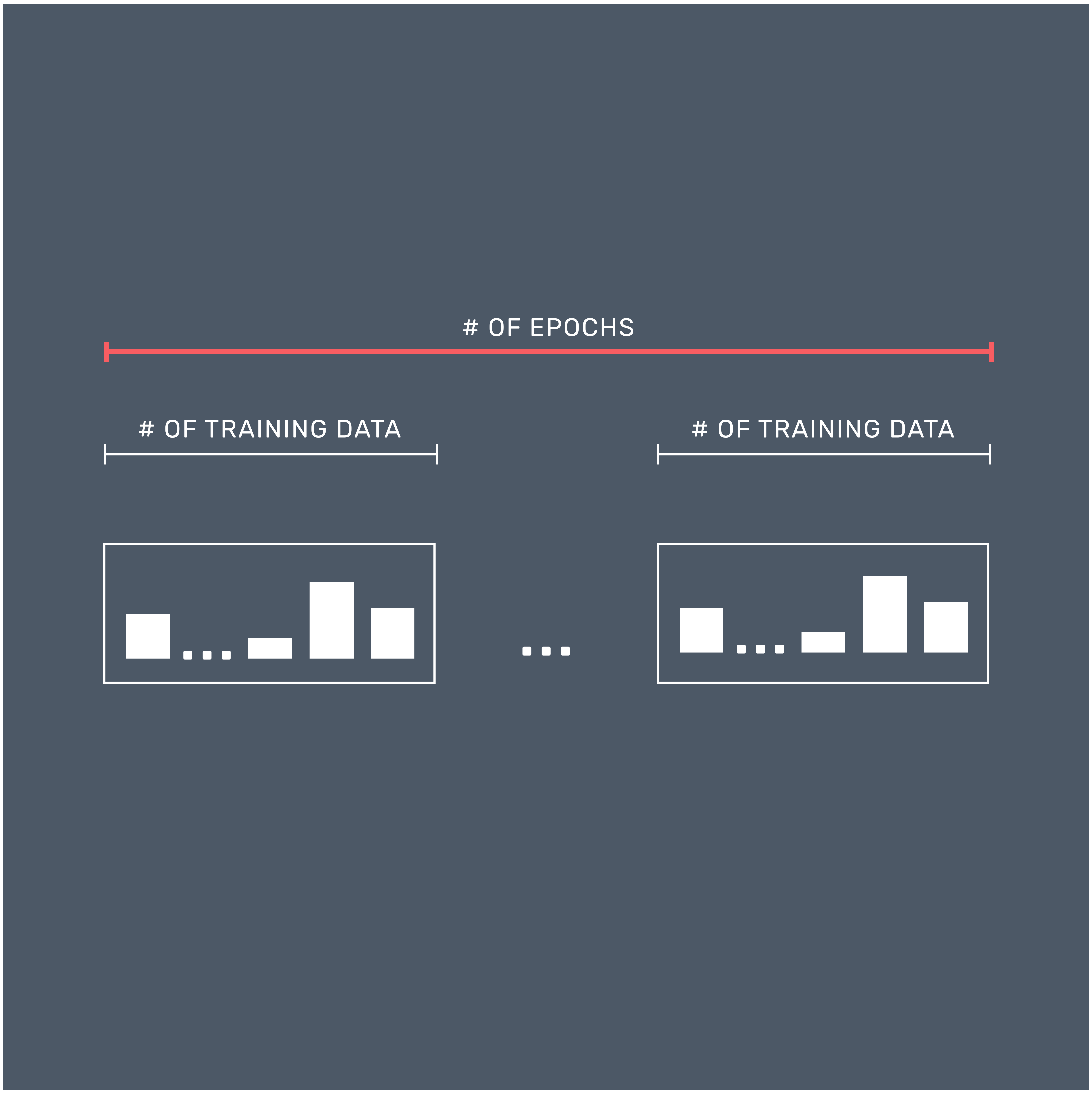
$$w_{new} = w_{previous} - \text{alpha} * dw$$

$$b_{new} = b_{previous} - \text{alpha} * db$$

## LEARNING RATE

In all of our tasks, we have kept to a learning rate (or alpha) of 0.08. This value was chosen simply by trial and error, and there is no reason not to change it in other scenarios.

As discussed earlier, we don't want the learning rate to be too large or too small. Too big and learning will be erratic. Too small and learning will be slow.

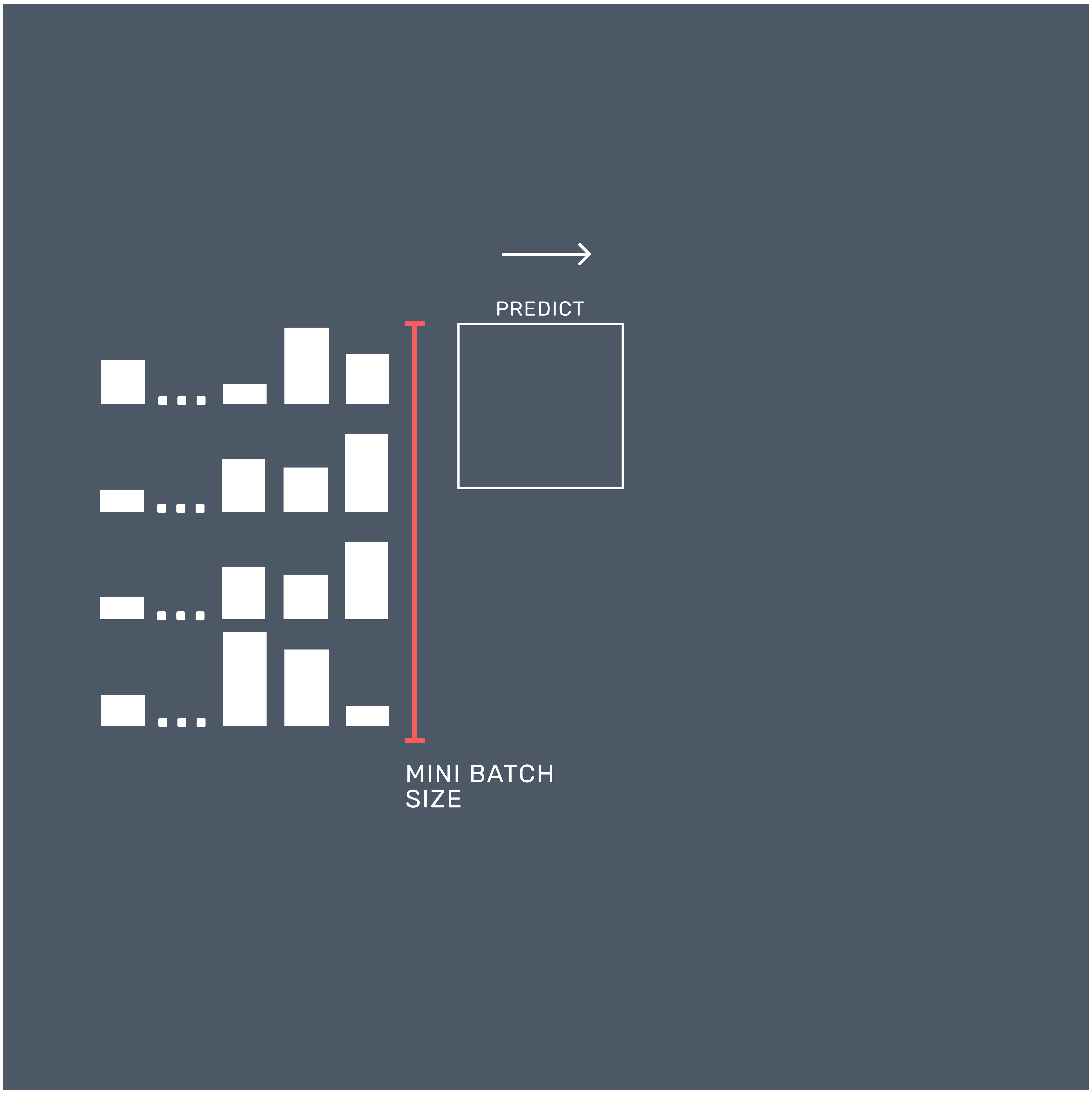


## NUMBER OF EPOCHS

We chose 100 epochs for Chapter 1 and 800 epochs for Chapters 2, 3, and 4 by trial and error.

An alternative approach is to set a very large epoch and configure training to stop automatically once certain performance criteria are met. This is called *early stopping*.

Finding the right epoch for a task is important because too many epochs can lead to the model ‘learning too much', including unwanted noise in the data. On the other hand, too few epochs can lead to the model not capturing enough information from the data.



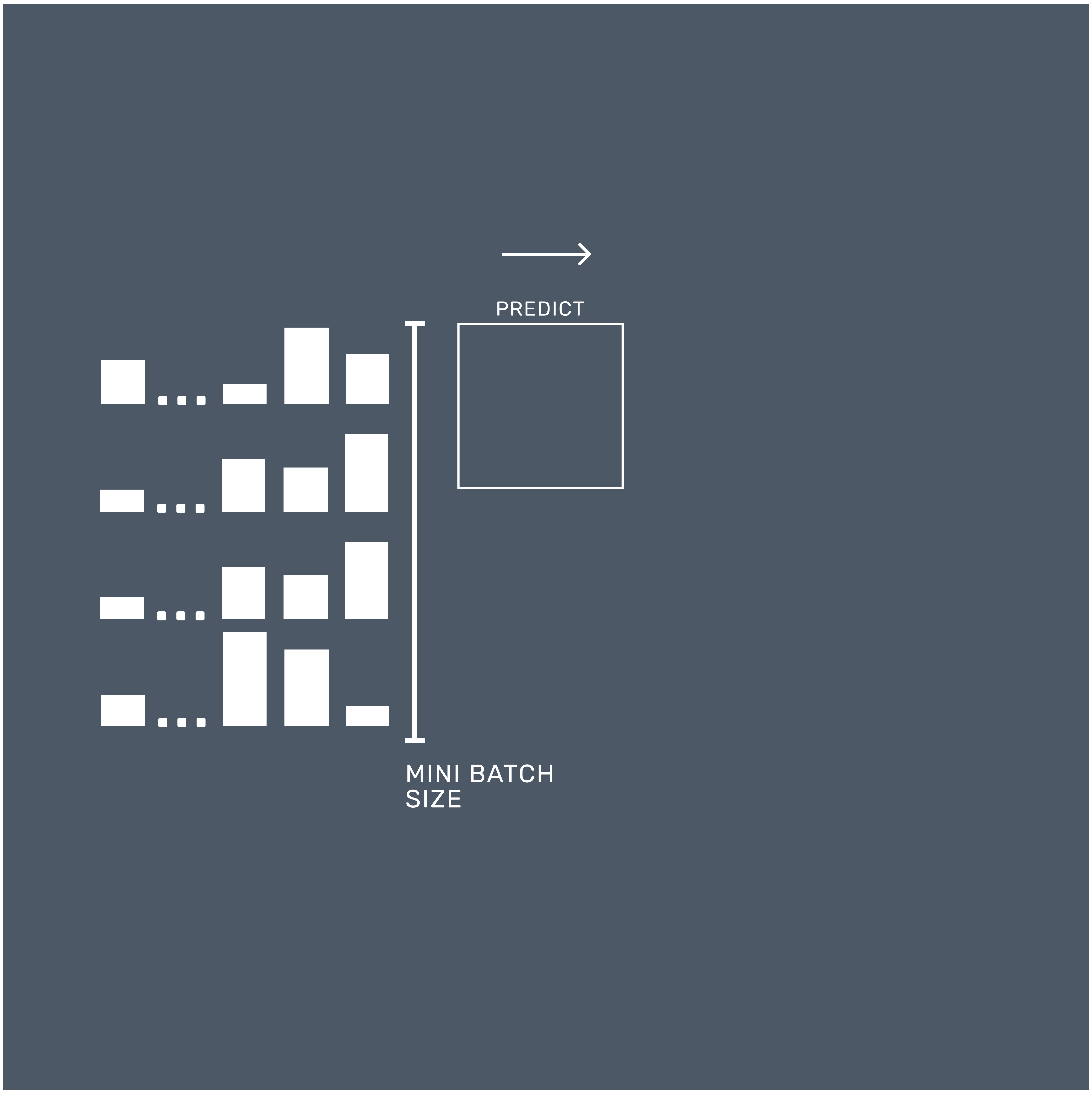
## BATCH SIZE

In our tasks, we had a maximum of twenty-four training data points, which we trained as a full batch. However, in a typical training dataset, the number of data points is so large that we need to split them into mini batches. This hyperparameter is called the *batch size*. In the diagram above, the batch size is four.

This brings us to the other way to improve our prediction results—by working on the data.

## DATA TECHNIQUES

We'll look at a few data techniques that we can use to improve our predictions.

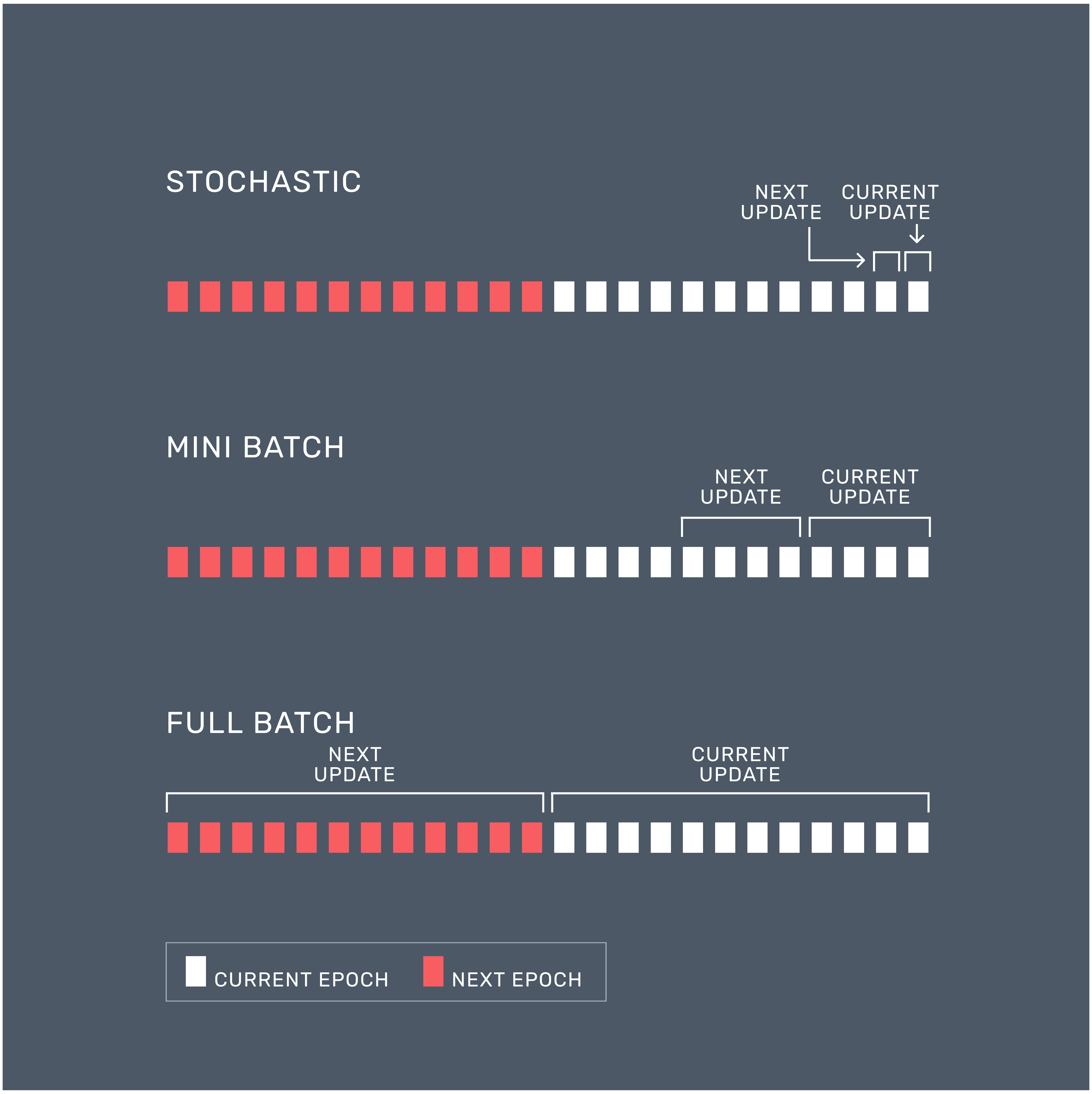


## MINI BATCH

Let’s expand on the concept of mini batches.

We perform mini batching for a number of reasons. One of them is hardware limitation. For a very large dataset, we cannot fit the data points all at once into the computer’s memory. The solution is to split them into mini batches.

Another reason is performance. Let’s see why this is so.

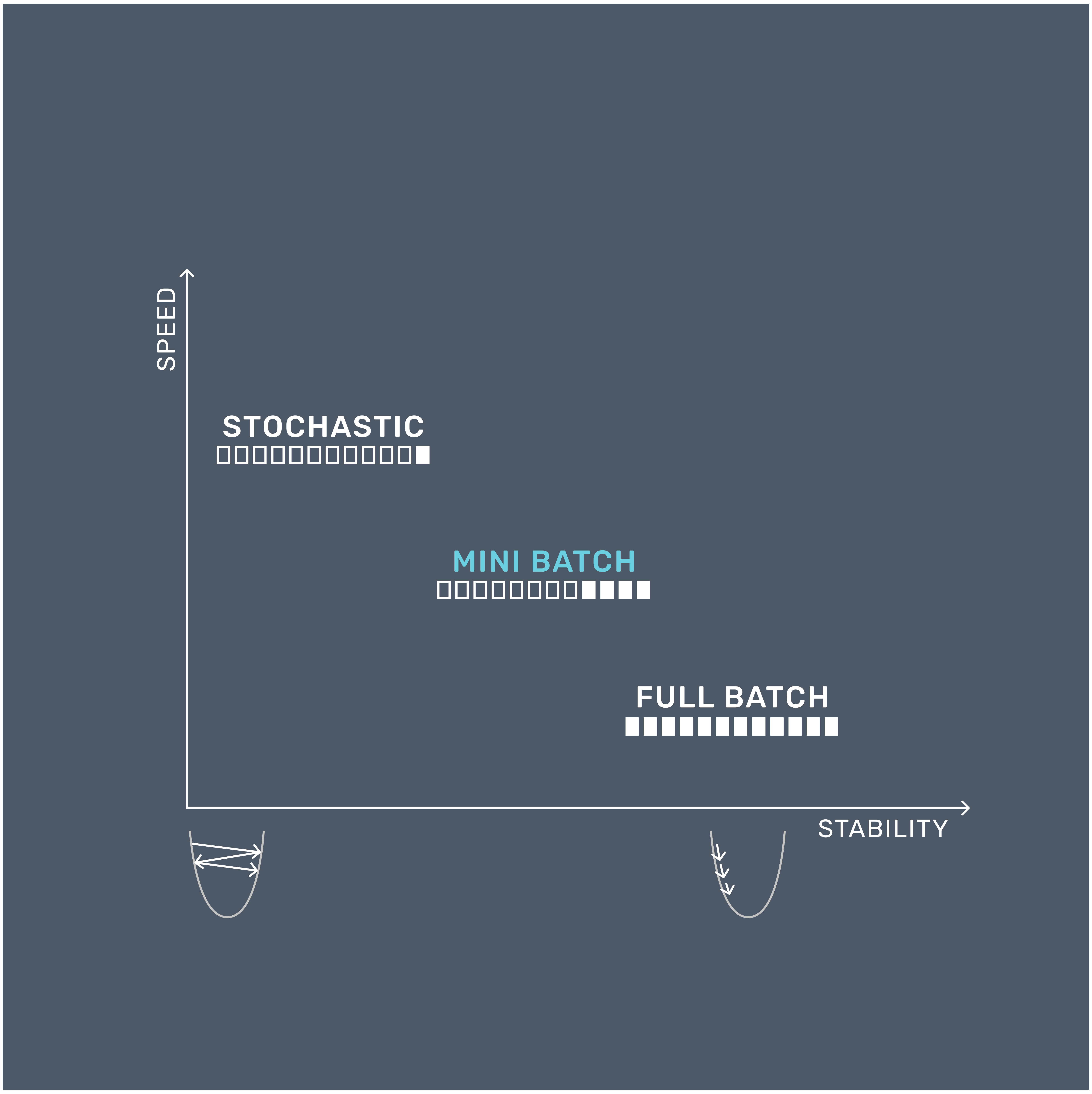


## MINI BATCH

Recall that in the fours tasks, the model performed parameter adjustments after an entire epoch is complete. This is called *full batch gradient descent.*

At the other extreme, the model may also perform updates at every data point. This is called *stochastic gradient descent.*

*Mini batch gradient descent* is somewhere in between. For example, a batch size of four means that the model performs the updates after every four training data points.



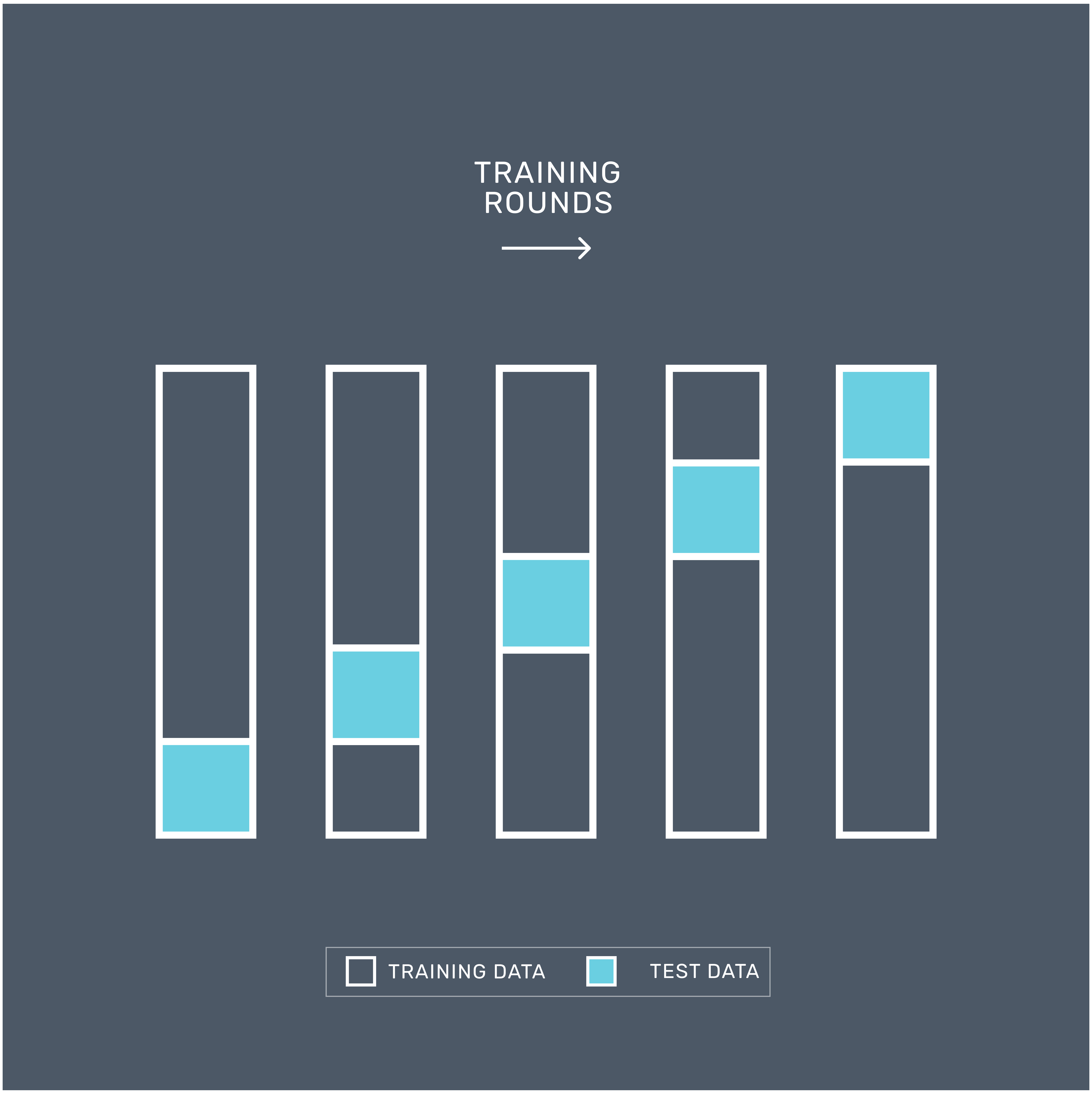
## BALANCE

How do these options affect performance?

Imagine having a huge dataset where each epoch takes a tremendous amount of time to complete. With full batch gradient descent, the time between parameter updates will be too long.

Conversely, stochastic gradient descent brings the advantage of fast feedback loops. However, since each update is based on only one data point, learning becomes erratic and unstable.

The mini batch gradient descent captures the best of both worlds, offering a balance between speed and stability.

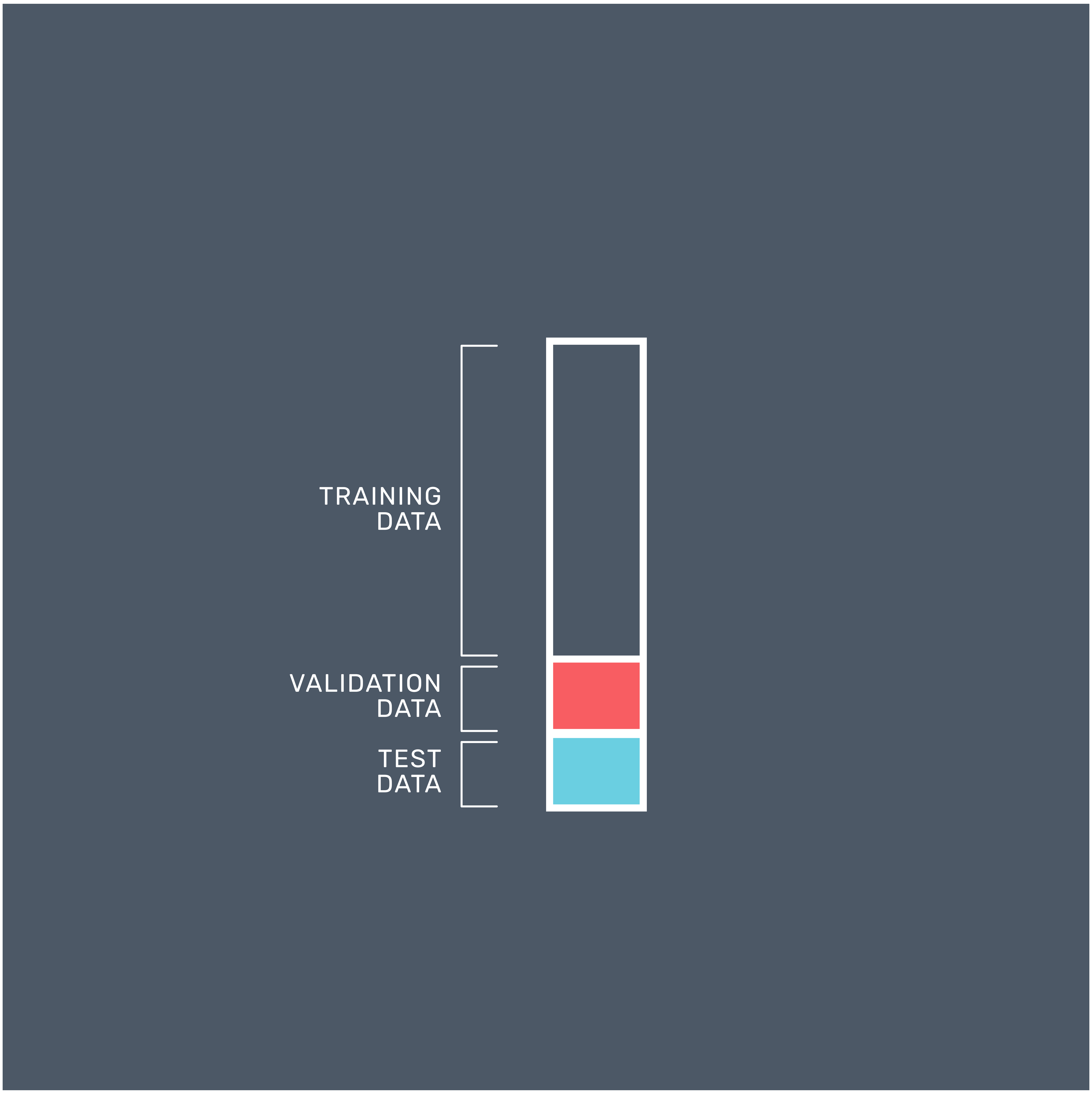


## K-FOLD CROSS VALIDATION

Let's move on to the next technique. Sometimes *overfitting* can occur in training, where the model is too attuned to the training data and performs poorly on new data points. This is especially true when the training dataset is small.

One way to address this is to use *K-fold cross validation.* Here, we cycle through the training-test data split over many training rounds such that by the end, every data point will have been used for training.

The performance metrics are then averaged over the number of rounds.



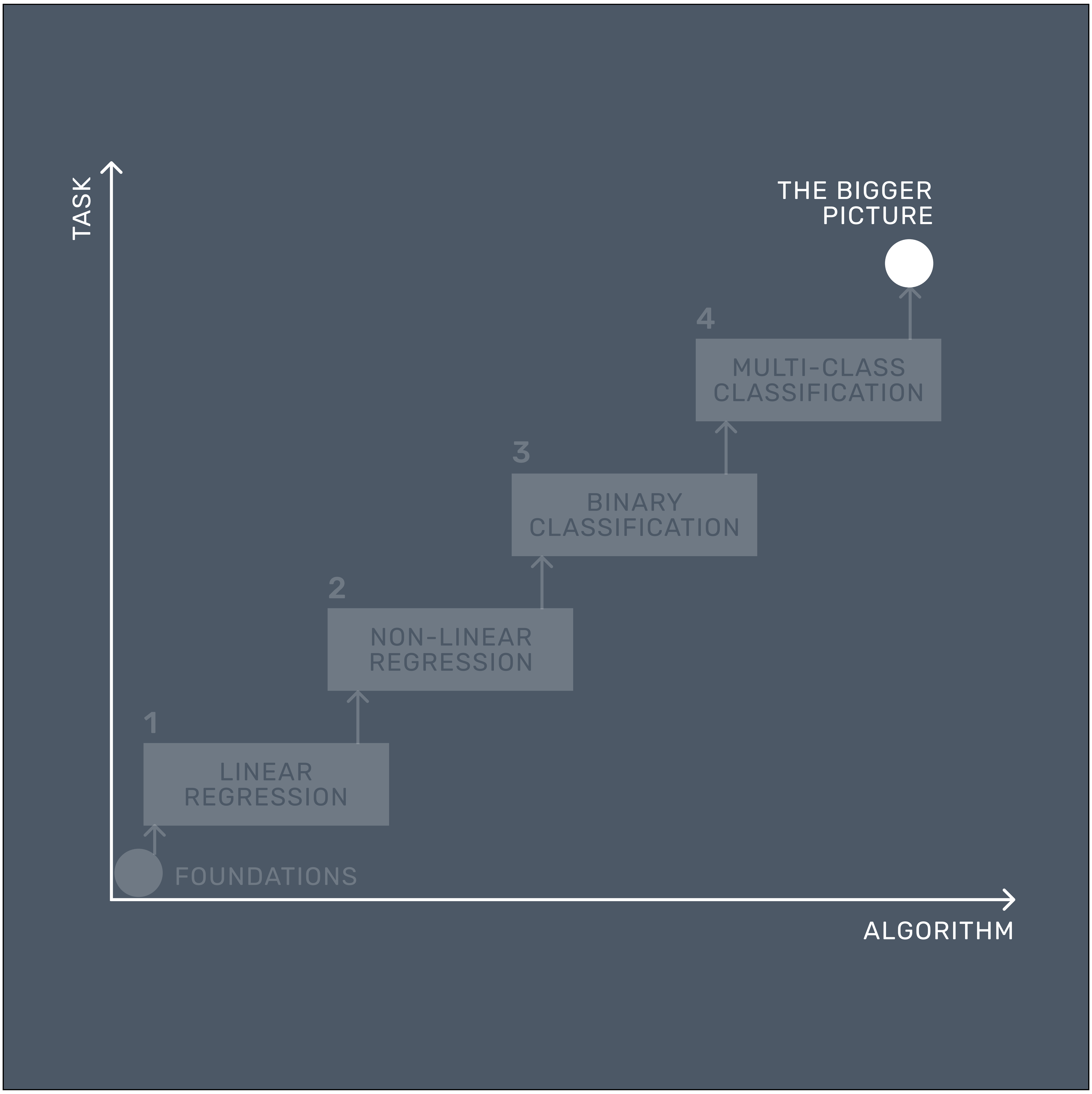
## VALIDATION SET

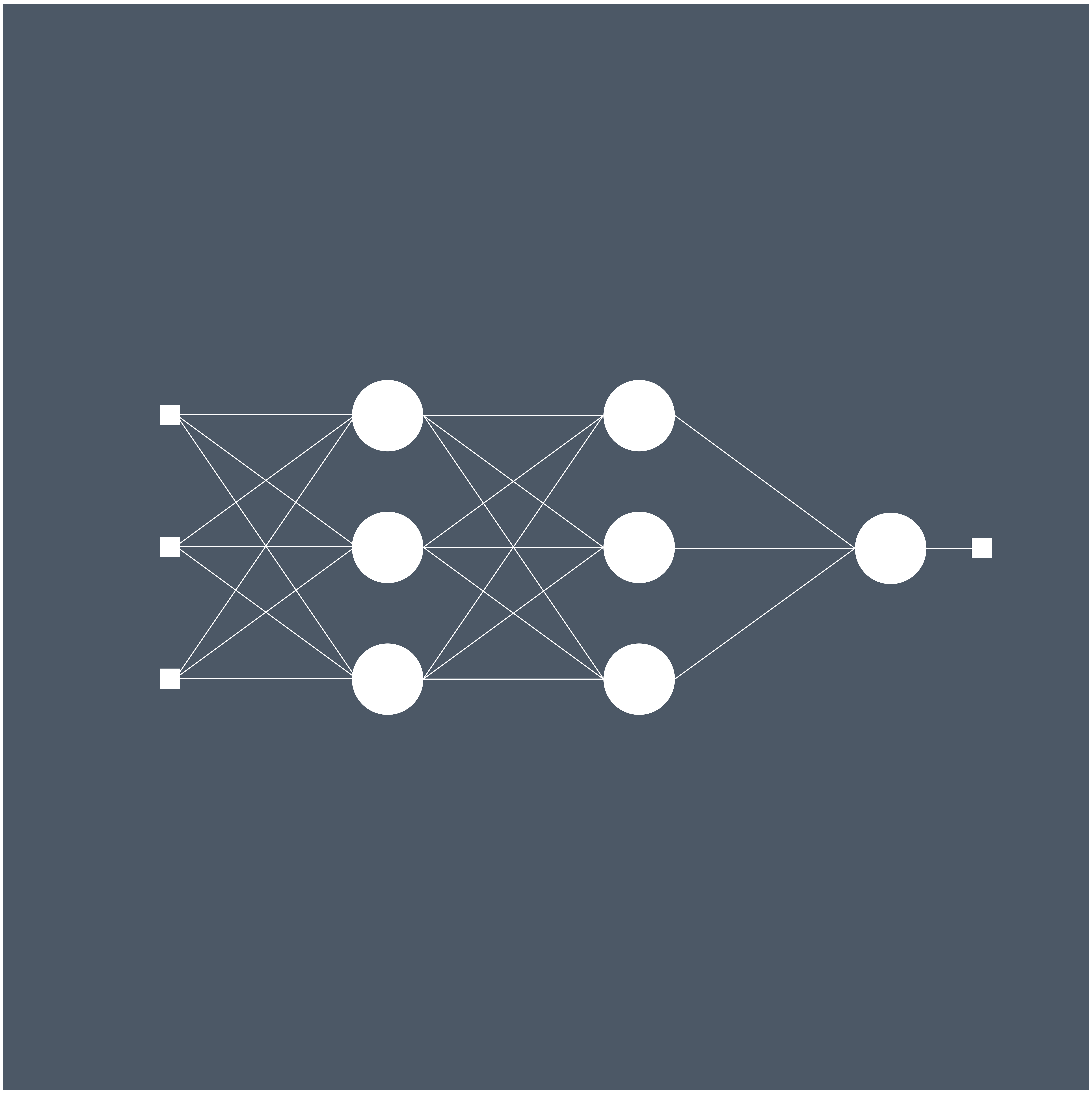
In all our tasks, for simplicity, we have split the dataset into two sets—training and test. However, in practice, it is common to split them into three sets—the other one being the *validation* set.

In this case, the role of the test set as we've been using will be replaced by the validation set.

This means we can set aside the test set until the model is fully ready. This offers a more accurate way to measure performance since these are fresh data points that the model has never seen.

# THE BIGGER PICTURE

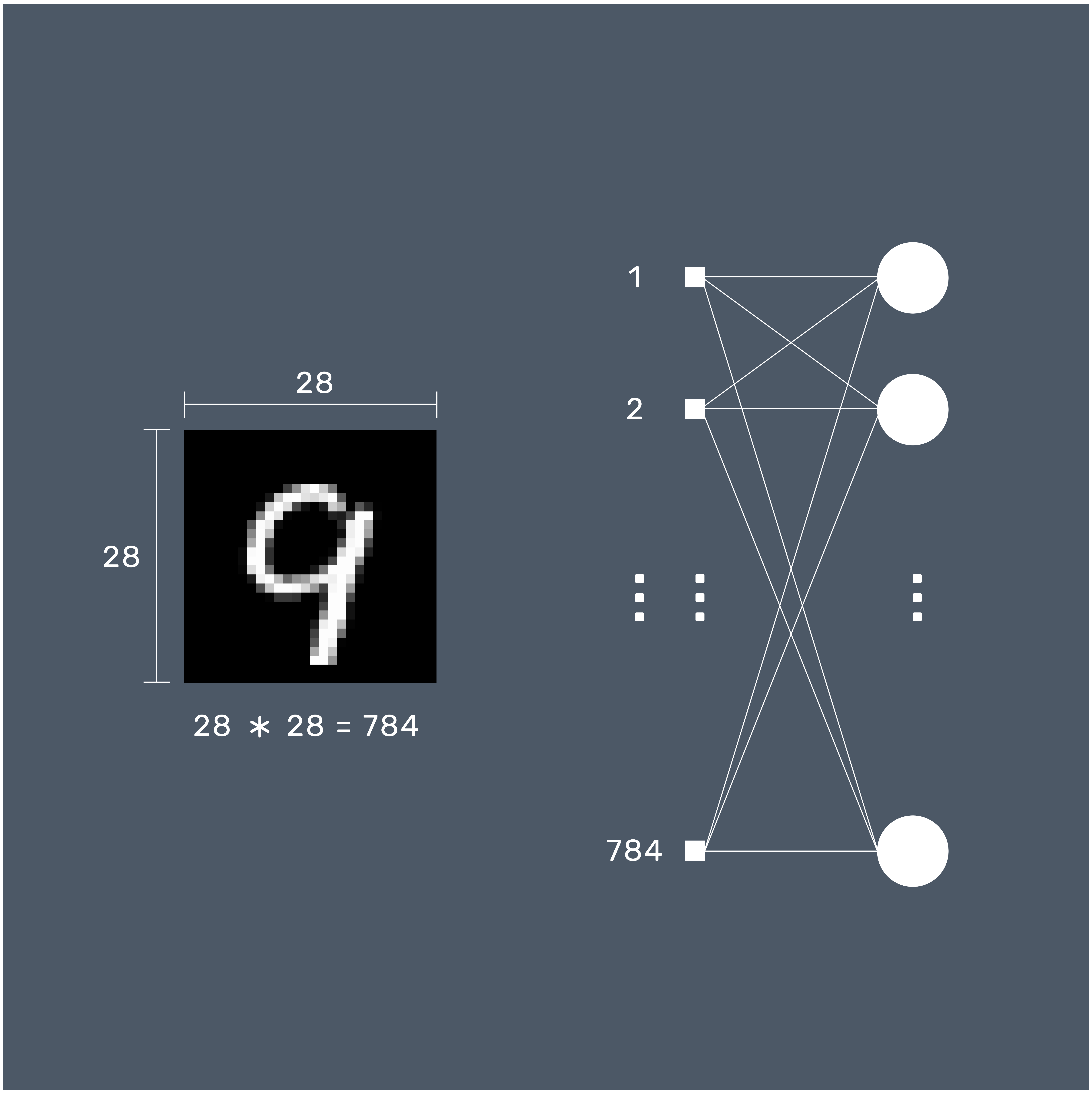




## FEEDFORWARD NEURAL NETWORKS

In this final chapter, we'll take a brief tour of deep learning architectures beyond what's been covered so far.

Let's start with the *feedforward neural network*. This is the quintessential version of neural networks, and it is the version we used in the four tasks. It's called feedforward because information flows through the layers only in the forward direction.

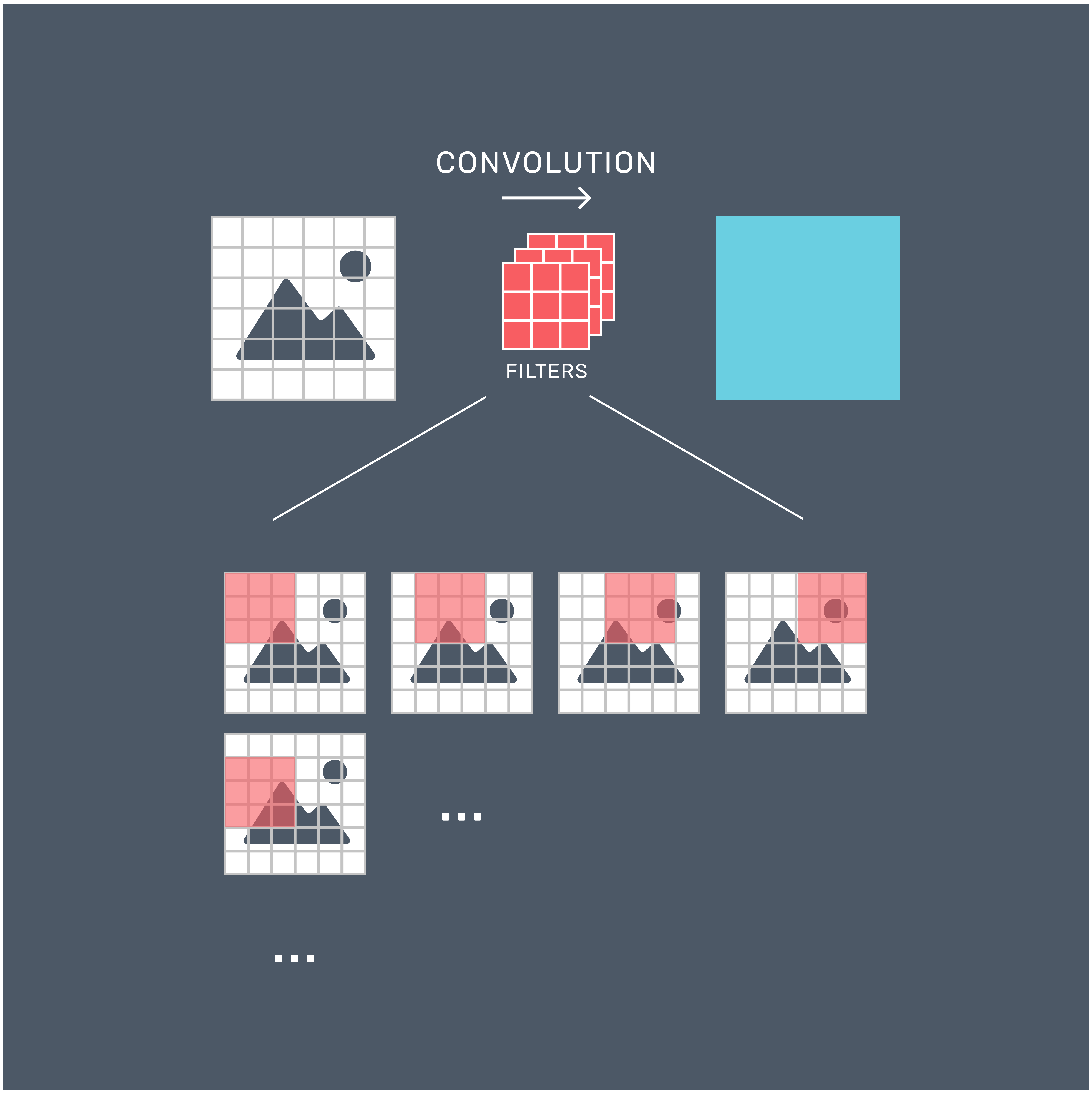


## FEEDFORWARD NEURAL NETWORKS

We had a small network with only two inputs, but we can expand it to be as big as we need it.

Take a look at this *MNIST* dataset. It is an image dataset where each data point contains an image of a handwritten number. This is a multi-class classification task to predict the number based on the image. The features are the individual pixels (28 x 28), while the label is a number between 0 and 9.

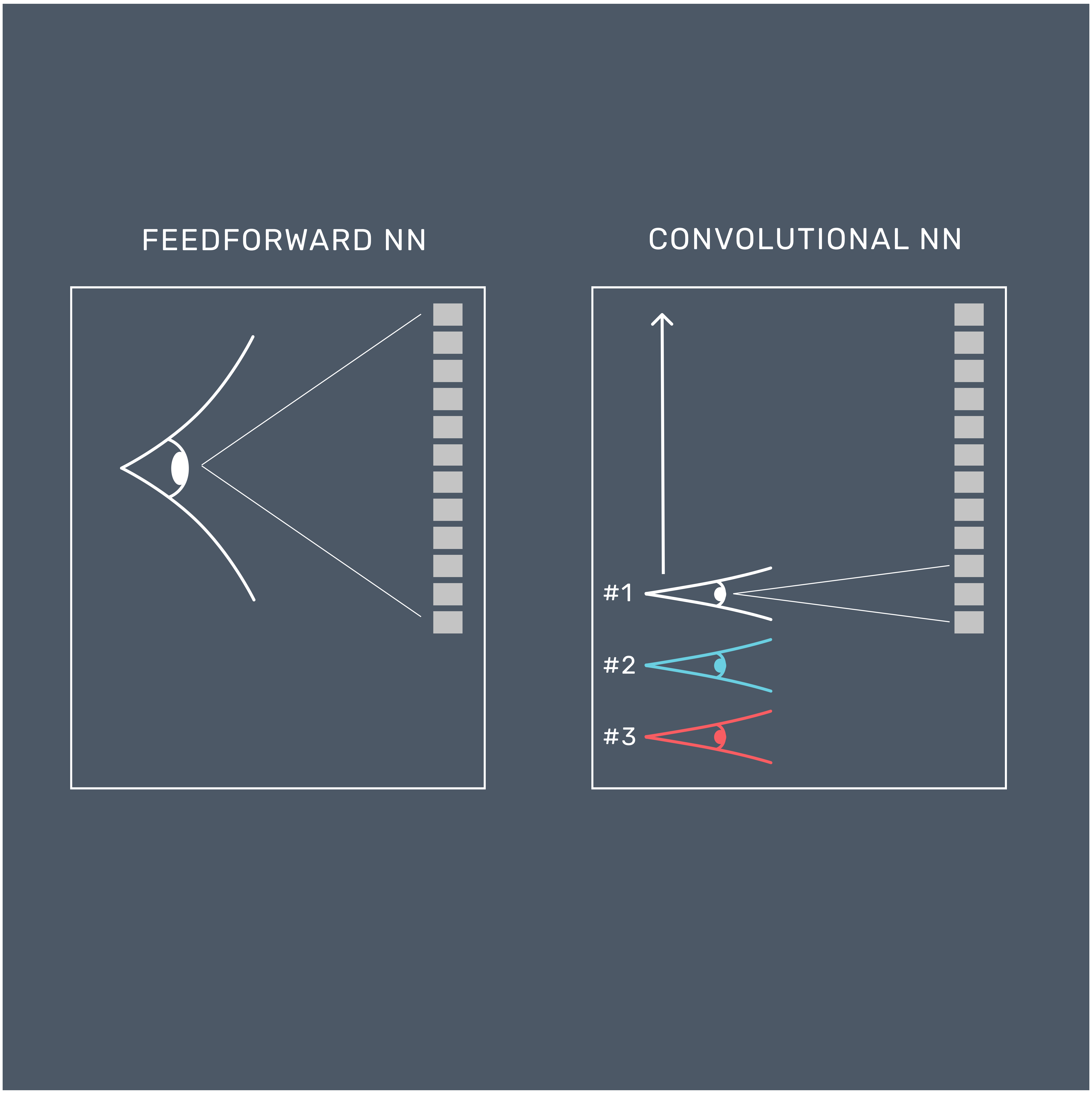
There are 784 features, which means that 784 inputs are going into the first hidden layer. Additionally, such a task will require even more hidden layers with a substantial number of neurons in each.



## CONVOLUTIONAL NEURAL NETWORKS

Now let's look at another type - the *convolutional neural network (CNN)*, typically used for image data.

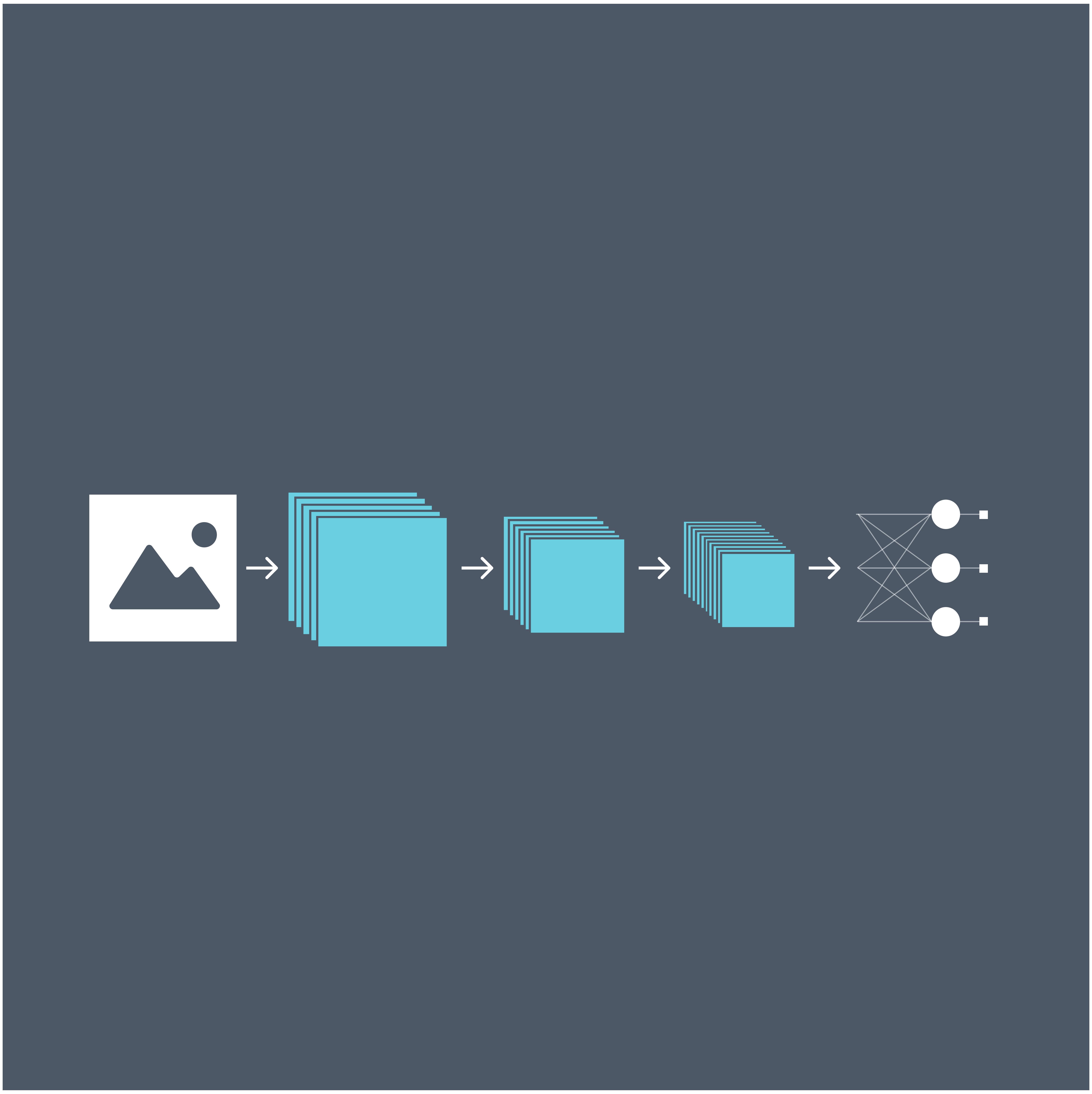
The idea with this architecture is, instead of feeding all inputs to all neurons, we group neurons into smaller sets called *filters*. These filters don't take the inputs all at once. Instead, they scan through the small sections of the inputs sequentially.



## CONVOLUTIONAL NEURAL NETWORKS

The scanning effect makes it perfect for image data. It takes advantage of the fact that in images, a pixel has a stronger relationship with its surrounding pixels than with pixels far away.

These filters learn uniquely at the individual level and synergistically at the collective level.



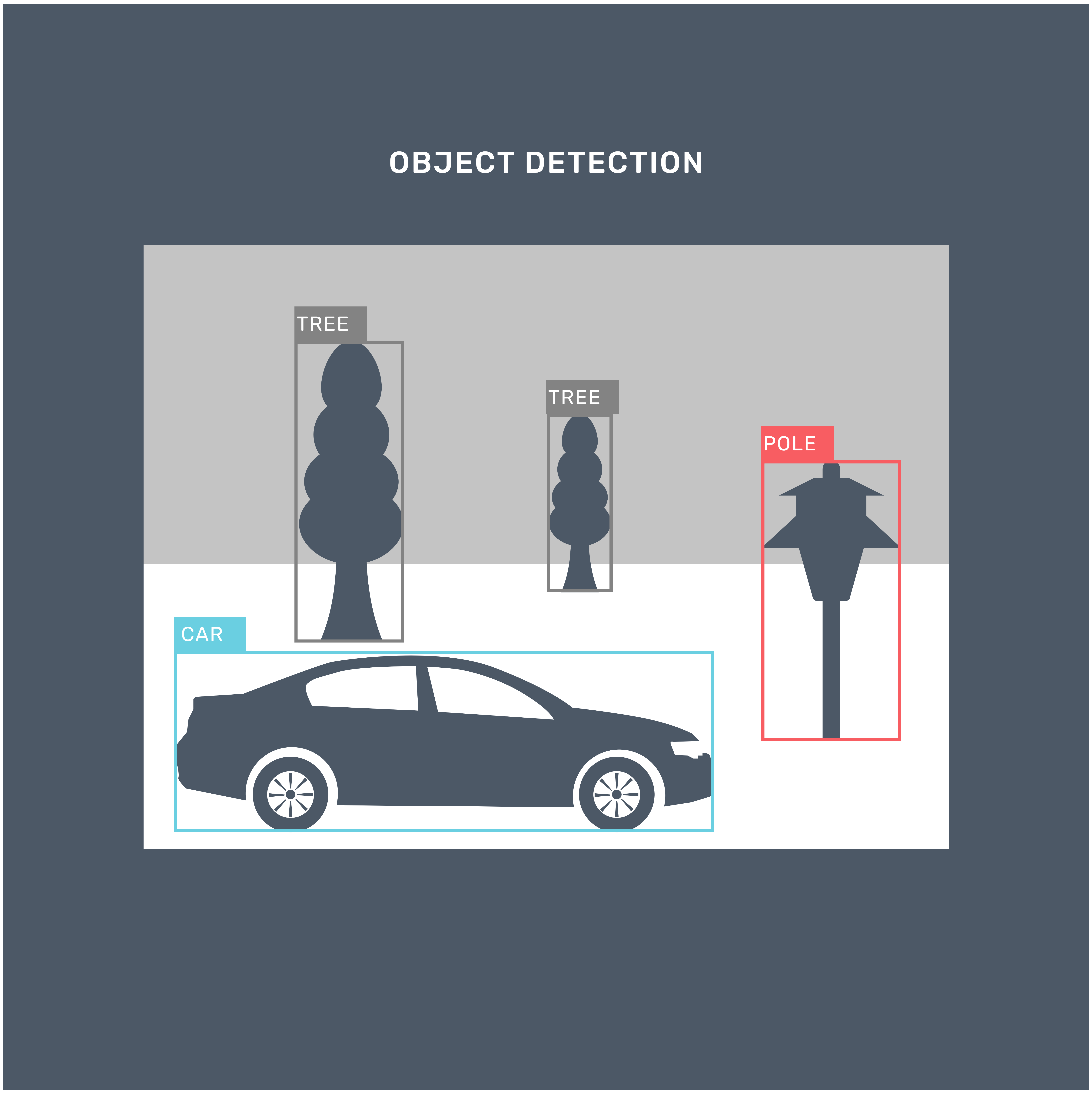
## CONVOLUTIONAL NEURAL NETWORKS

This process is repeated over several layers, and the result is a compressed version of the data. This information is finally fed into a standard layer to produce the prediction.

IMAGE CLASSIFICATION
TREE
NOT TREE

## IMAGE CLASSIFICATION

Let’s look at some use cases of the CNN. The first is *image classification*, where the task is to predict the class of an image. It’s the same type of task as the MNIST example, but with a different architecture.

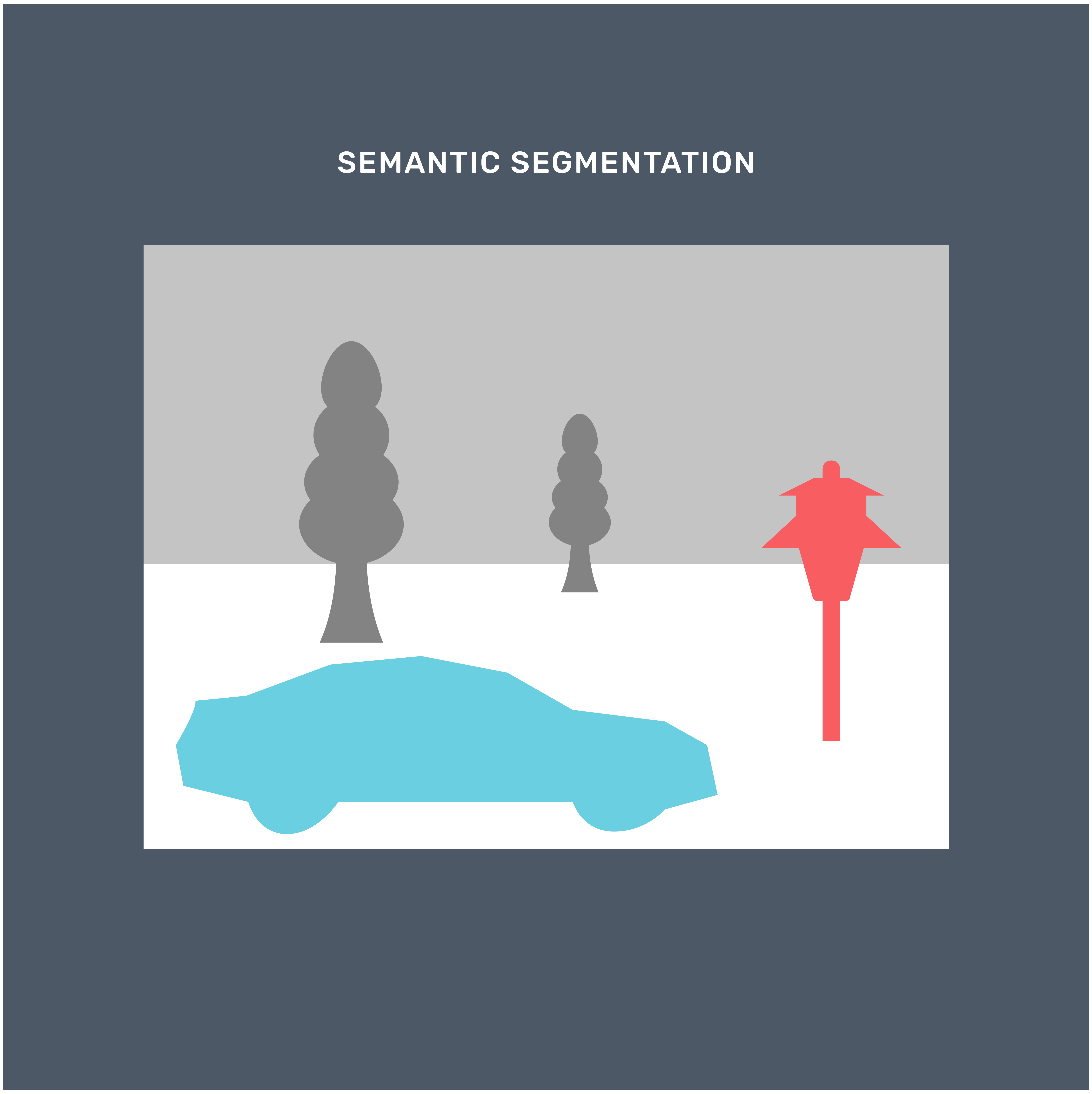


## OBJECT DETECTION

Another use case is *object detection*. It involves both classification and regression.

As for classification, this time each image could contain more than one class. Here is an example where we have four objects belonging to one of three classes.

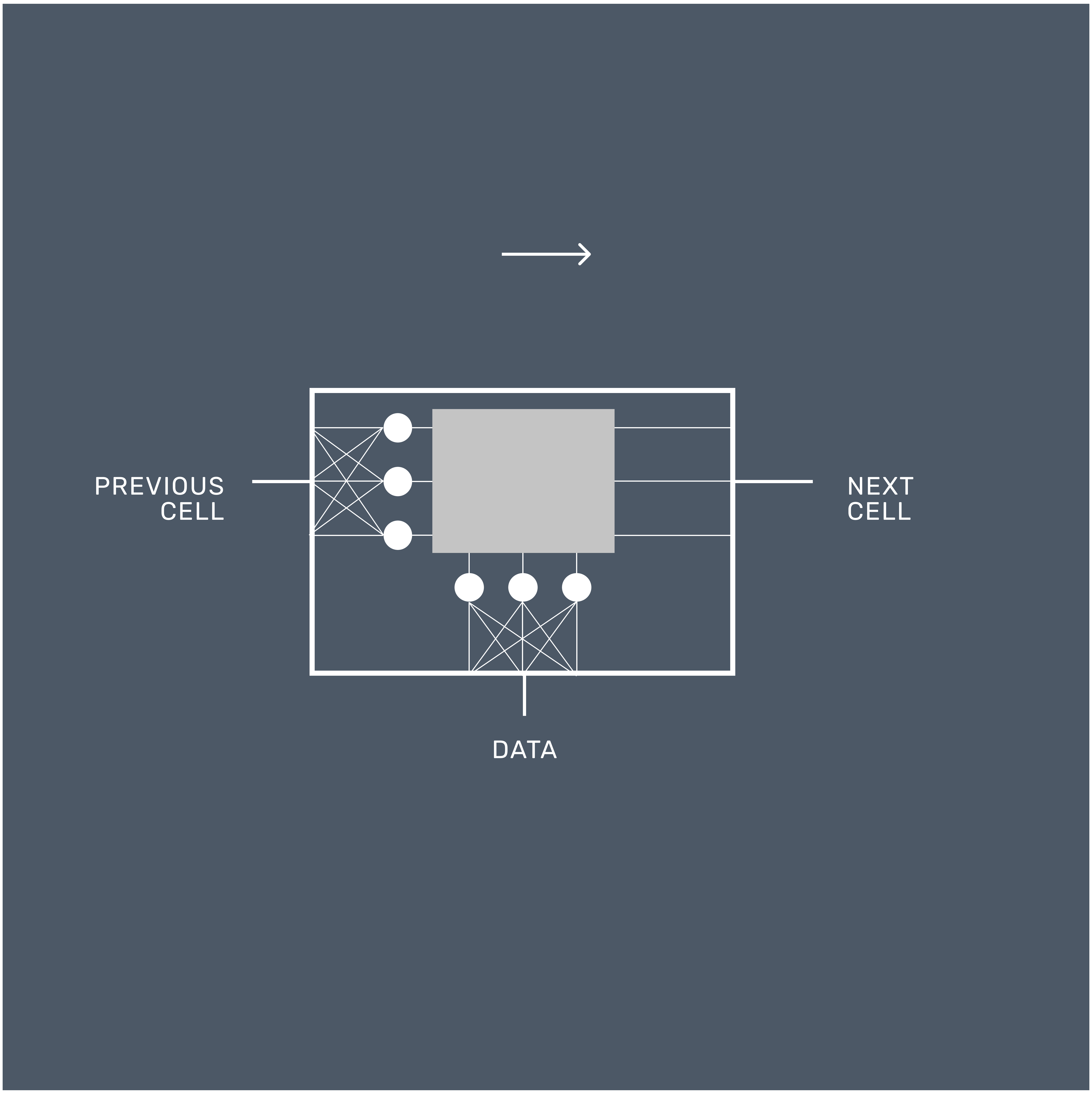
As for regression, the task is to predict the position on the image where these objects are located.



## SEMANTIC SEGMENTATION

Another use case is semantic segmentation. This task is similar to image classification, except that classification is performed at the pixel level instead of at the image level.

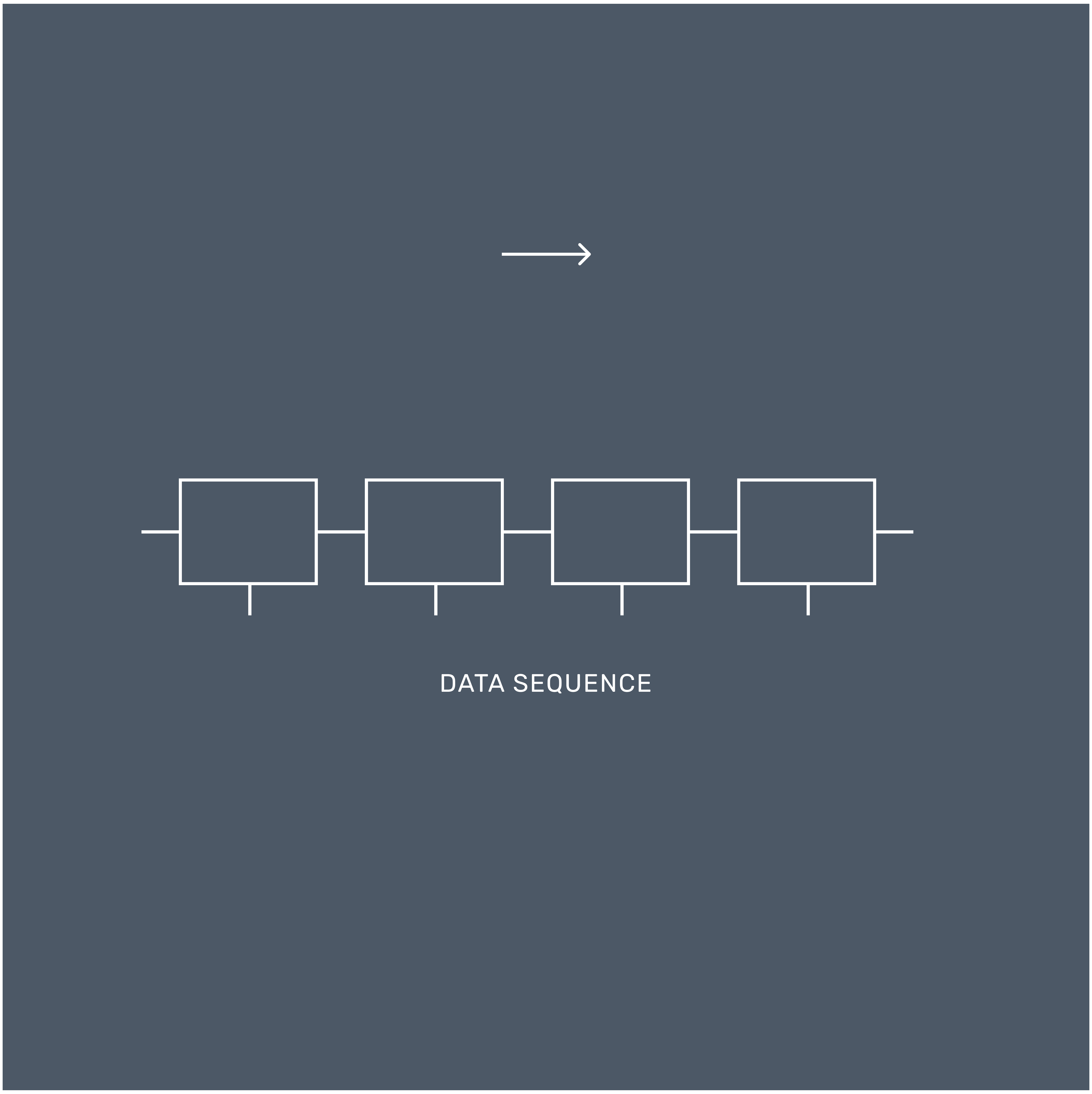
The result is a finer definition of object boundaries on the image.



## RECURRENT NEURAL NETWORKS

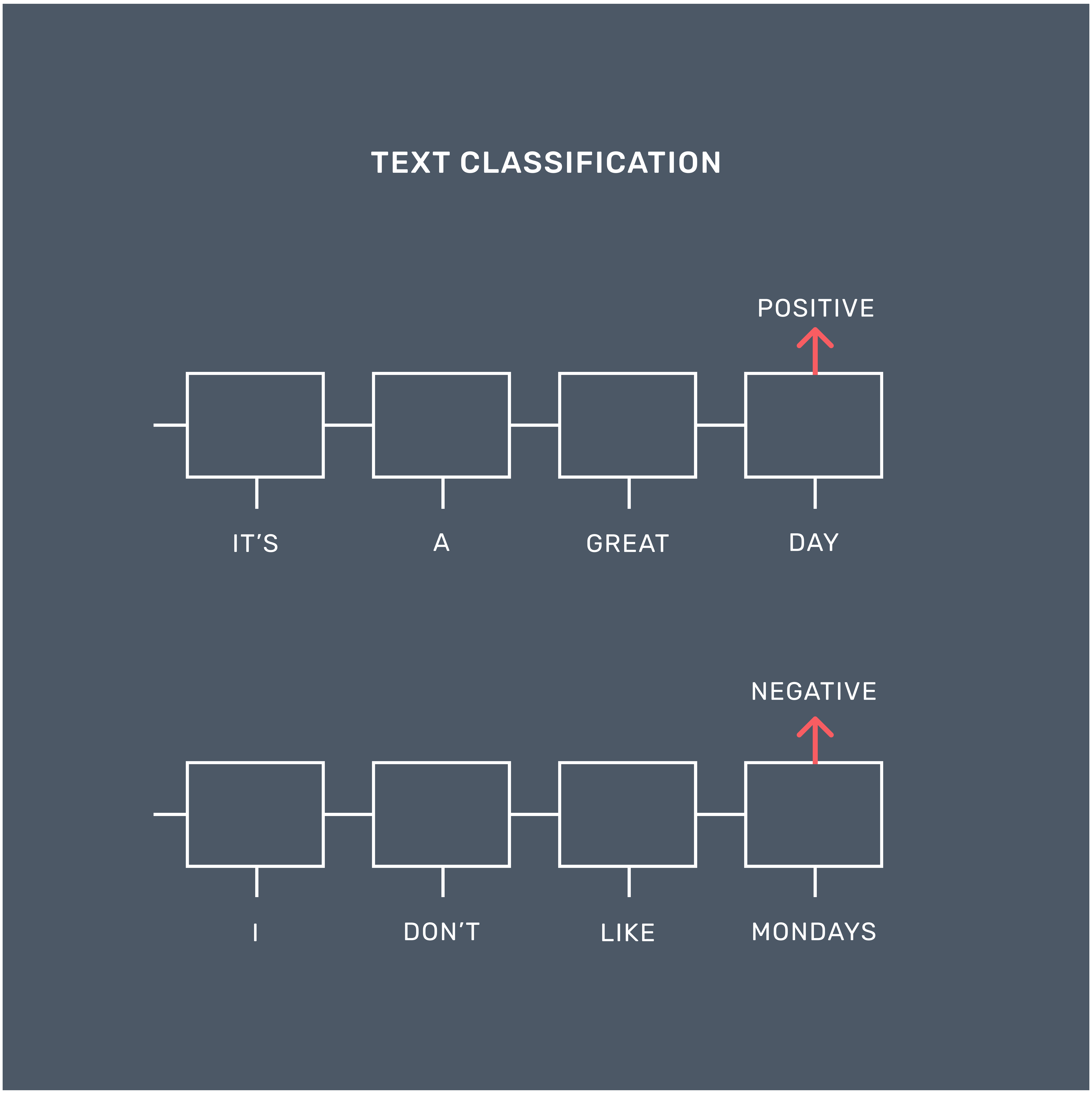
Let's take a look at another architecture - the *recurrent neural network (RNN)*. This architecture is designed to work with data types with a sequence element, such as text, music, and time-series data.

This diagram depicts one building block of the RNN. It has two inputs. The first input is the data from the current step of a sequence, while the other input is the output of the previous step's RNN block.



## RECURRENT NEURAL NETWORKS

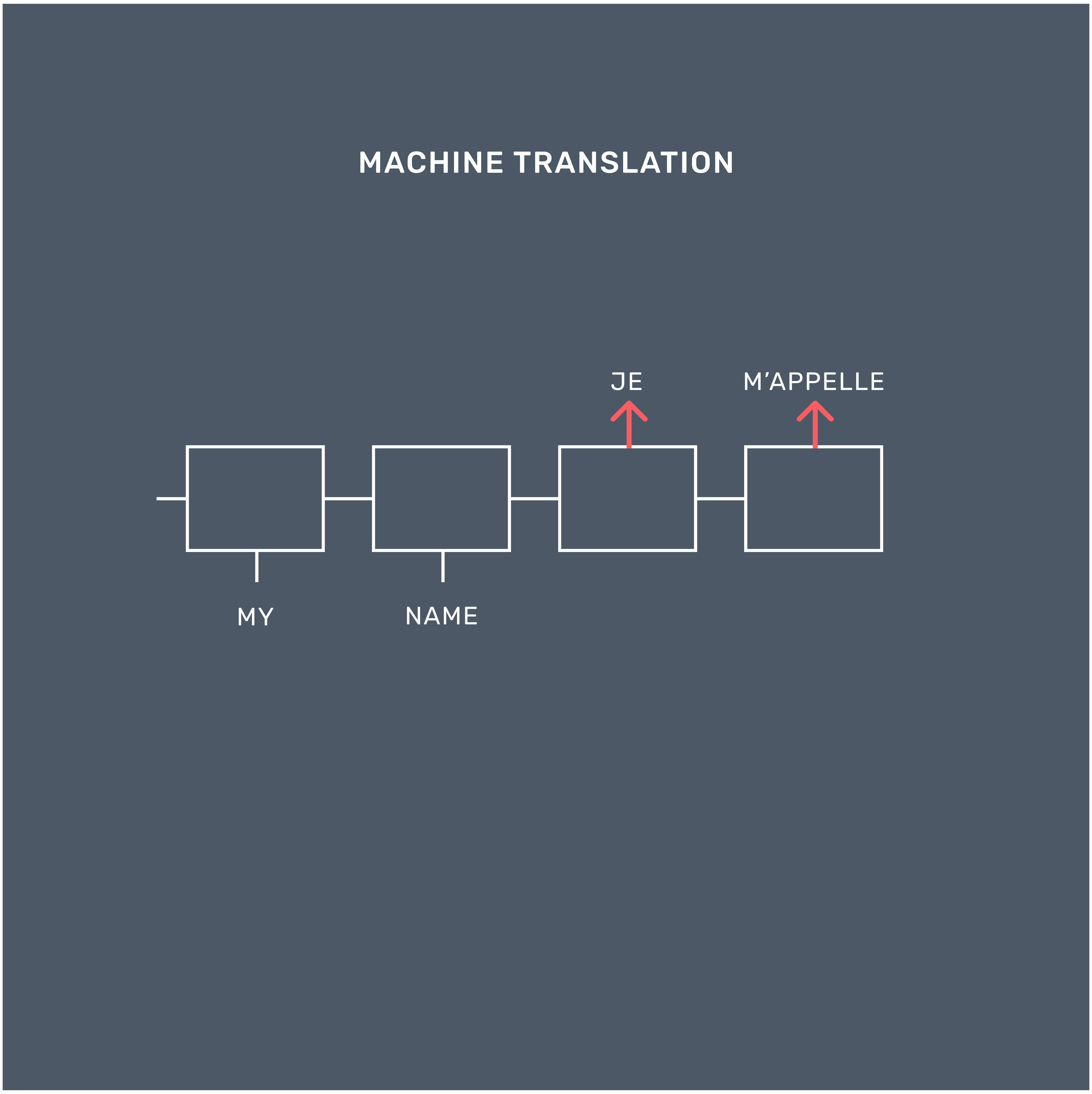
By chaining these blocks together, we can pass information from each step of the sequence to the end of the network.



## TEXT CLASSIFICATION

Let's take a use case - *text classification*. Here we have an example of sentiment analysis, where the task is to predict the sentiment in a sentence.

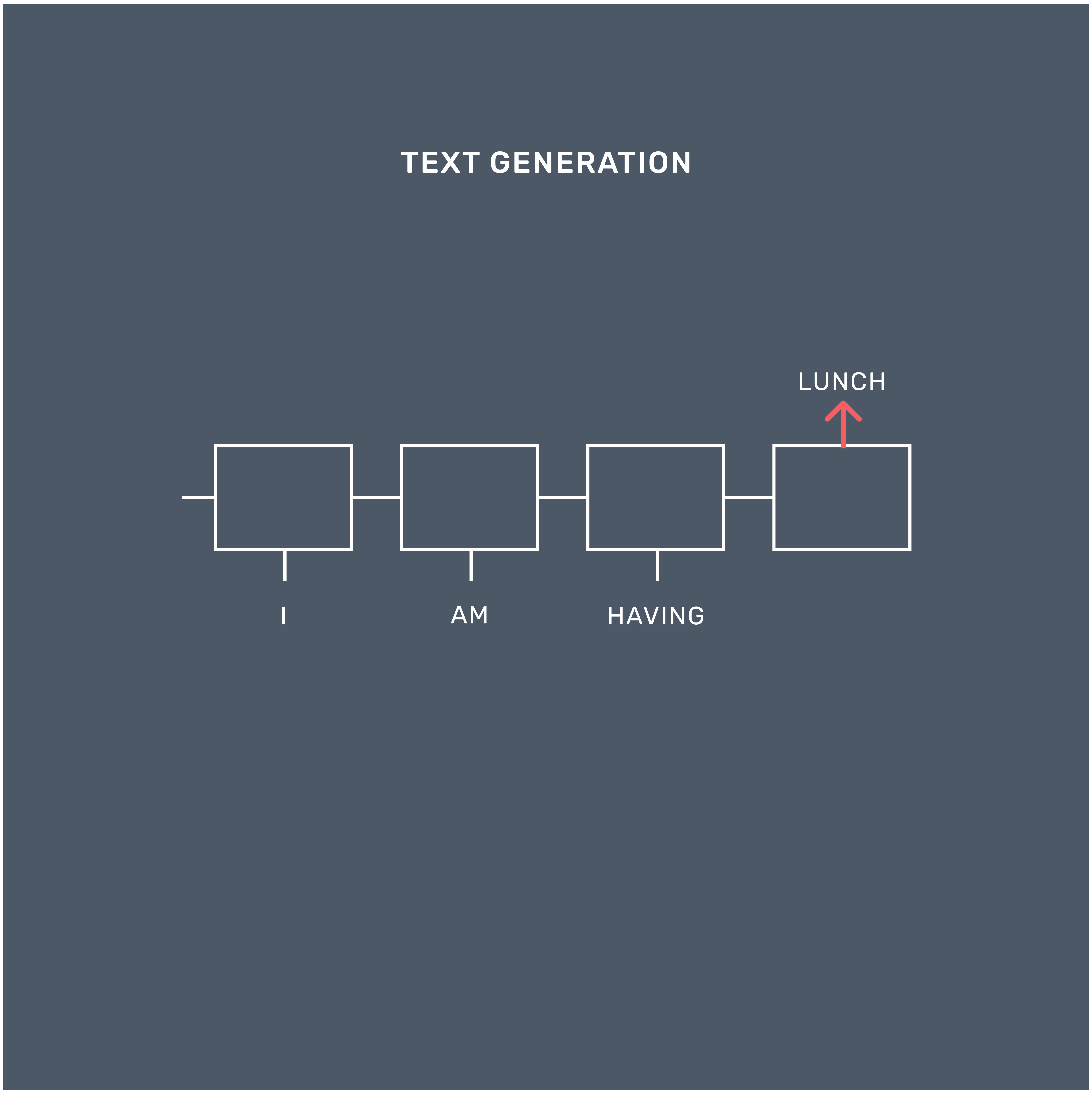
Using an RNN architecture allows us to capture the essence of each word in a sentence, which together forms the meaning of the entire sentence.



## MACHINE TRANSLATION

Another use case is *machine translation*. Here, the RNN generates many outputs instead of one.

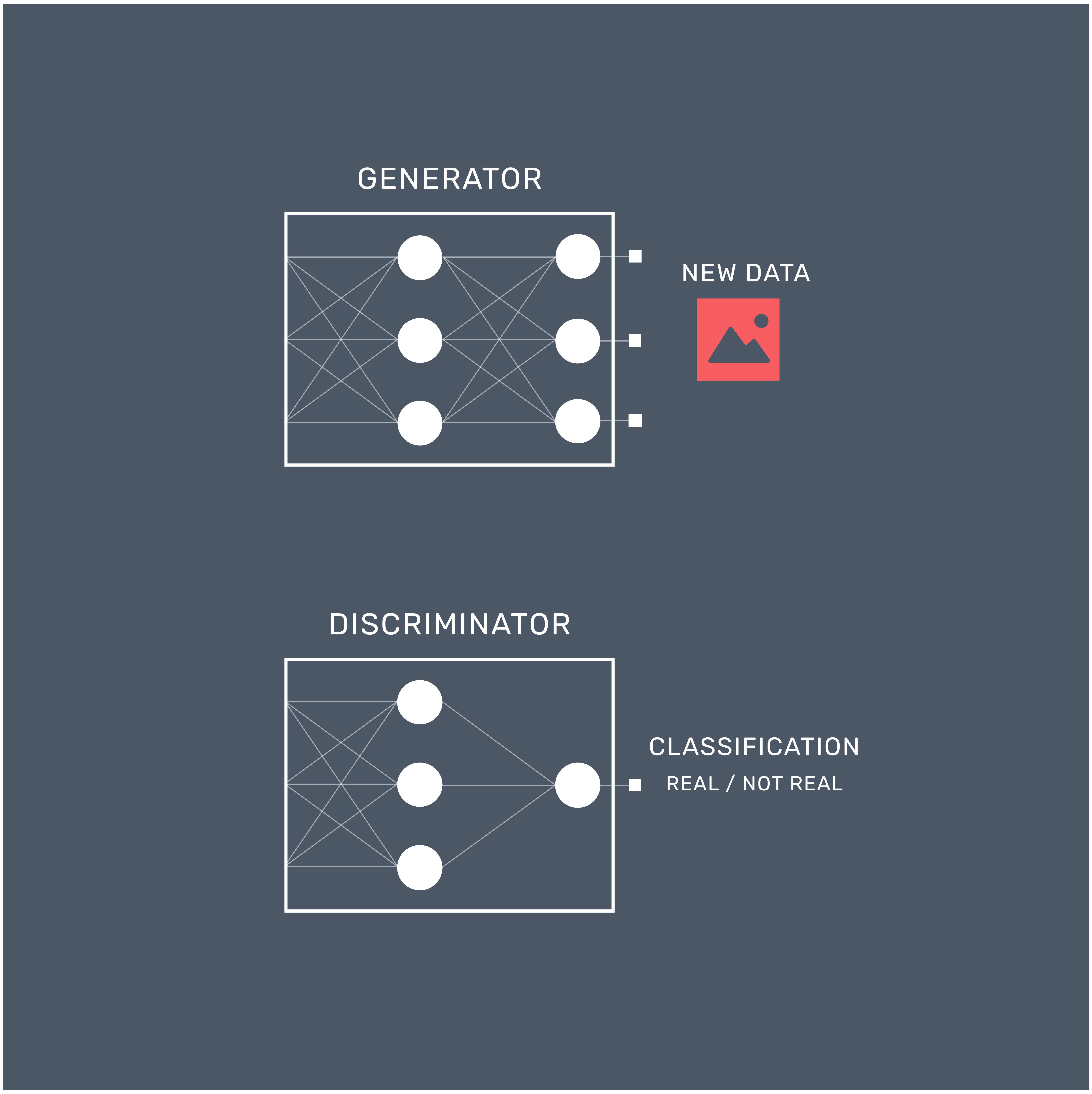
Take a look at this example of a translation of a short phrase from English to French.



## TEXT GENERATION

Another interesting use case is *text generation*. Here, we can train the neural network to predict the next word, given a sequence of words.

We can repeat this for as many words as we want. This means we can train it to generate a complete sentence, an essay, or even an entire book!

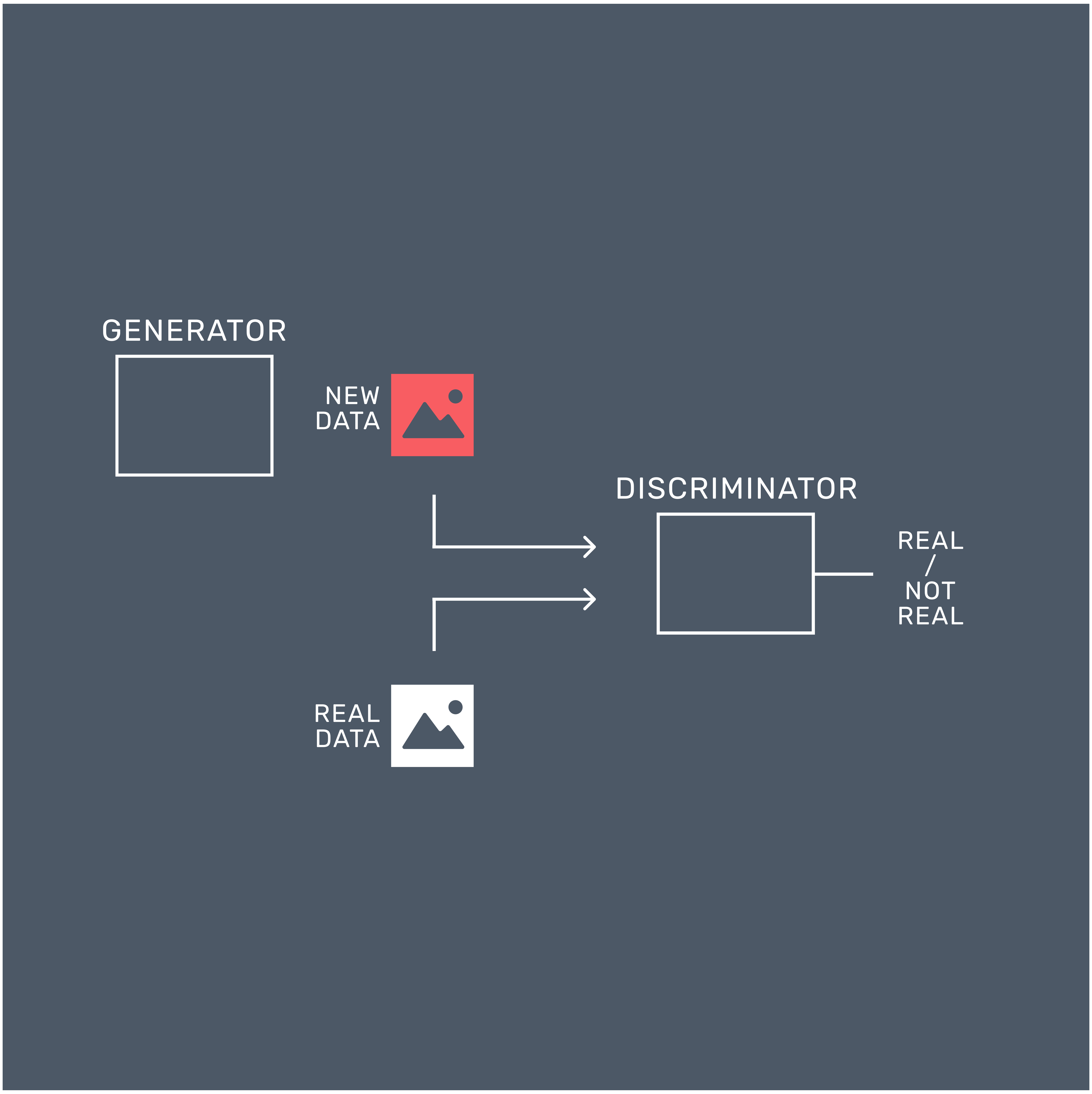


## GENERATIVE ADVERSARIAL NETWORKS

When it comes to generating new outputs, there is another architecture called the *Generative Adversarial Networks (GAN)*.

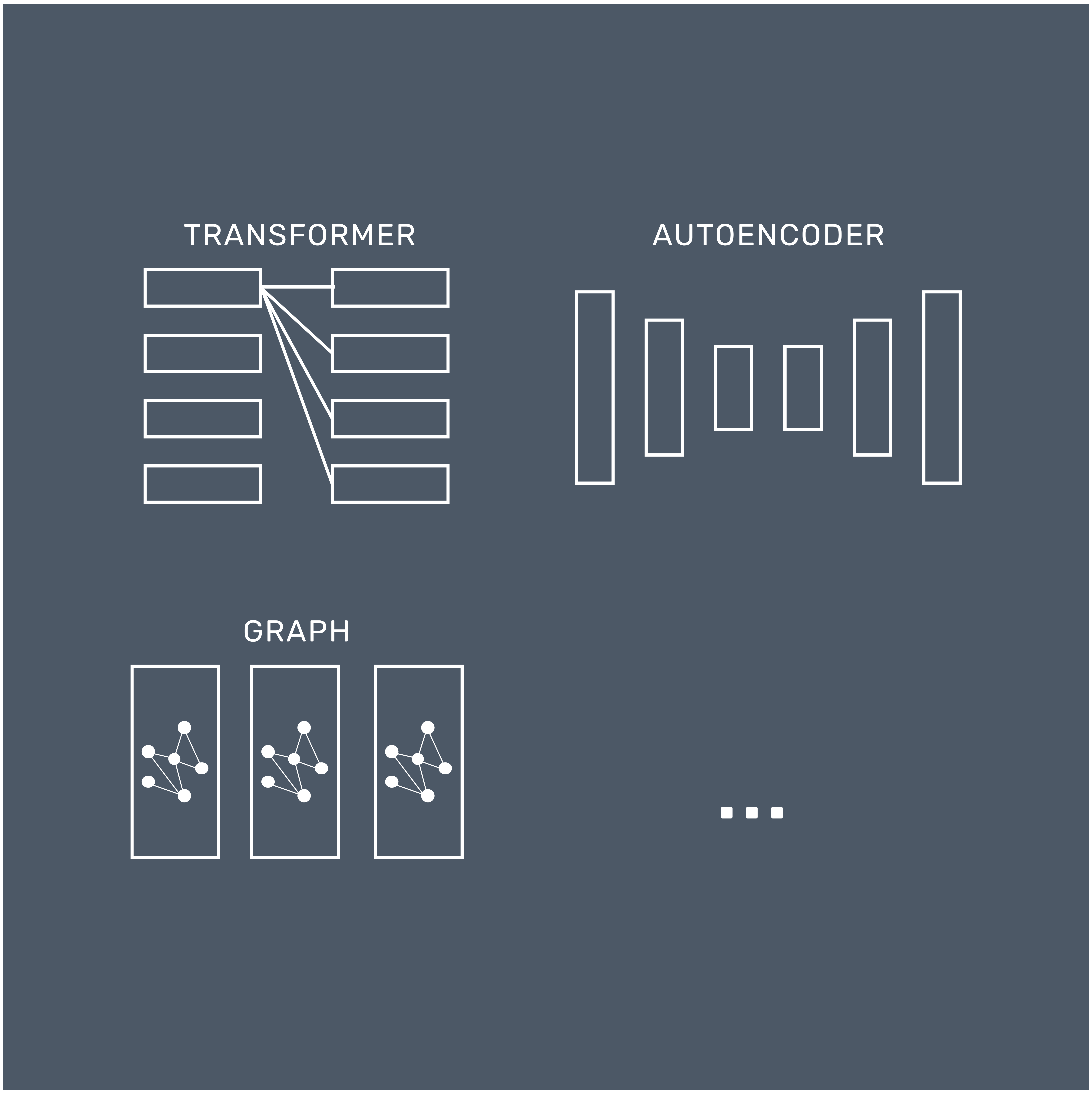
Given a training dataset, the GAN can create new data points that follow the same distribution but yet distinct from the original.

The GAN consists of two competing neural networks, the *generator* and the *discriminator*. The generator's role is to generate new examples that look as real as possible, while the discriminator's role is to determine if they are real.



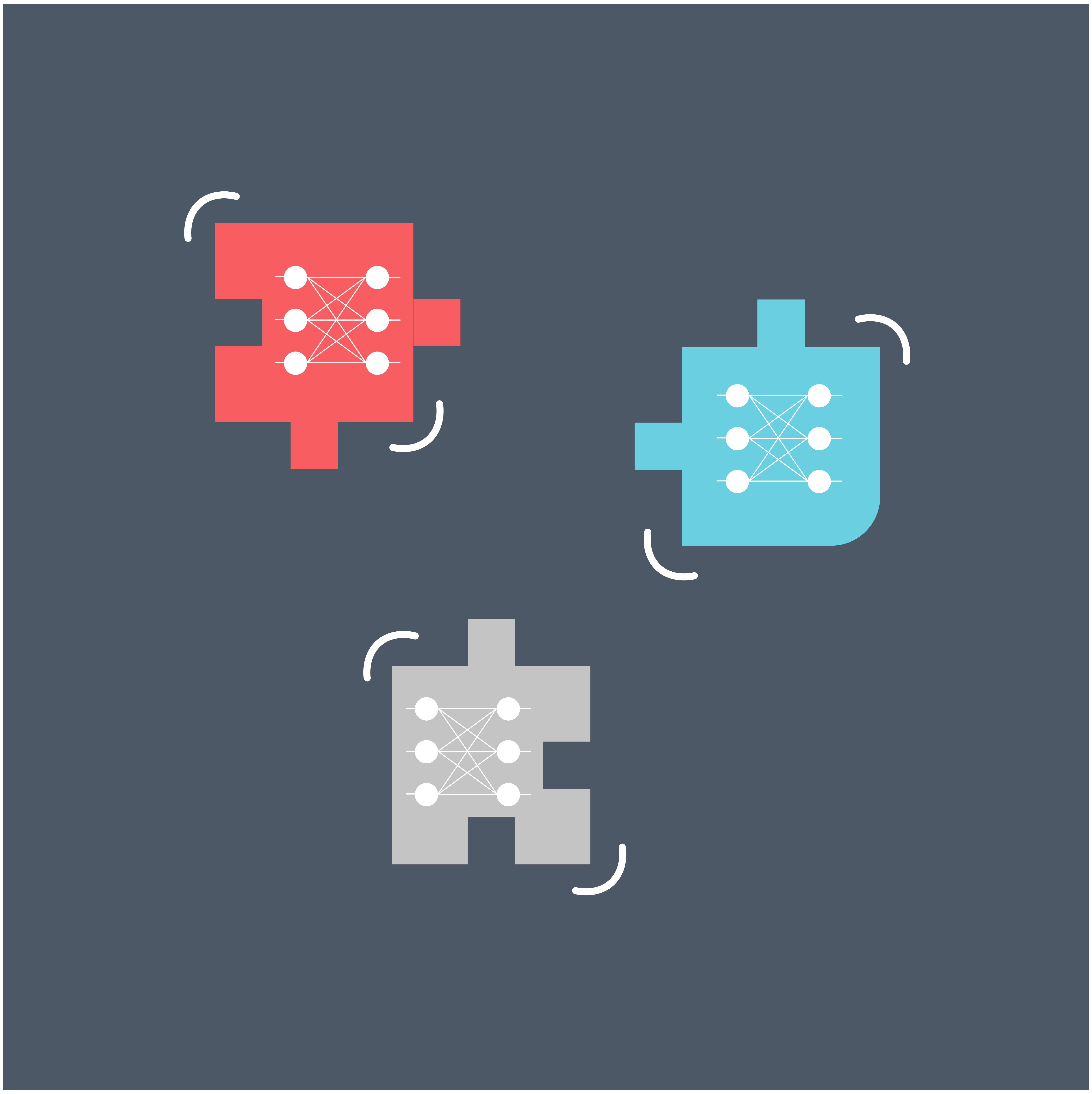
## GENERATIVE ADVERSARIAL NETWORKS

The architecture is designed so that both networks will keep improving after each training round. As more examples are given, the discriminator becomes increasingly good at detecting the real ones. At the same time, the generator's output will become more and more similar to the real ones.



## OTHER ARCHITECTURES

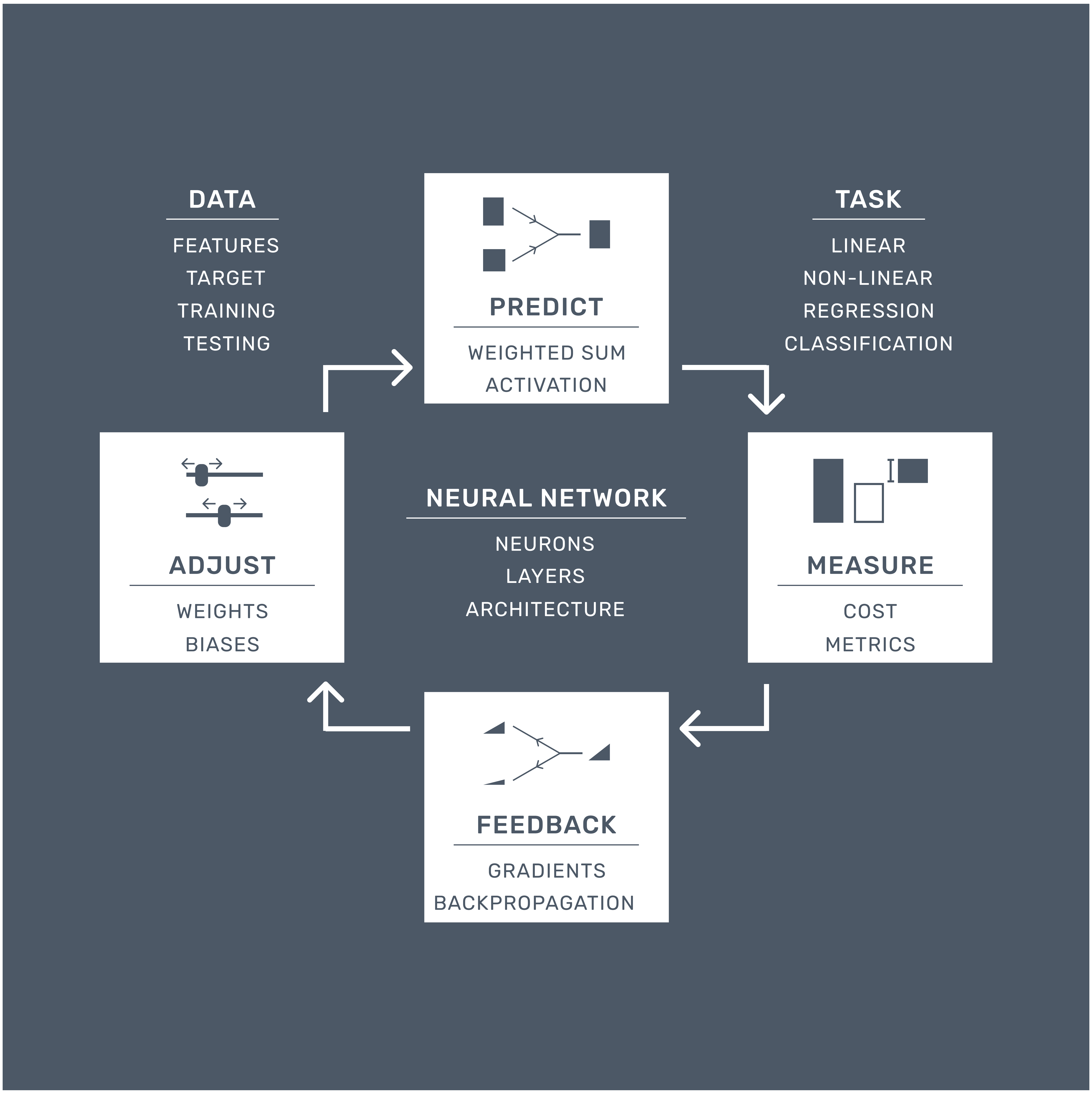
There are many other architectures out there, and new ones continue to emerge. It is an exciting area of research where breakthroughs keep on coming.



## CONCLUSION

Deep learning has immense potential to address some of the world's toughest challenges. Of course, it is not the solution to all problems, but it has proven its versatility and is making an impact in various industries and verticals.

By and large, it is still a relatively new technology. The opportunities are wide open for us to innovate and create solutions that make the world a better place.



## KEY CONCEPTS REVISITED

We have now reached the end of the book. Let's now return to this summary of the key concepts that we have covered. It is a good time to revisit them and review your understanding about deep learning.

## SUGGESTED RESOURCES

If you are ready to go further into your deep learning journey and are looking to get hands-on practice, here are some books that I suggest for you to check out.

- *Grokking Deep Learning* by Andrew W. Trask [Manning Publications]
- *Neural Networks and Deep Learning* by Michael Nielsen [Free Online]
- *Math for Deep Learning* by Ronald T. Kneusel [No Starch Press]
- *Deep Learning with PyTorch* by Eli Stevens, Luca Antiga, and Thomas Viehmann [Manning Publications]
- *Python Machine Learning* by Sebastian Raschka and Vahid Mirjalili [Packt Publishing]
- *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow* by Aurélien Géron [O'Reilly Media]
- *Grokking Machine Learning* by Luis G. Serrano  [Manning Publications]
- *Deep Learning with Python* by François Chollet [Manning Publications]
- *Deep Learning Illustrated* by Jon Krohn, Grant Beyleveld, and Aglaé Bassens [Addison-Wesley Professional]
- *Deep Learning: A Visual Approach* by Andrew Glassner [No Starch Press]
- *Generative Deep Learning* by David Foster [O'Reilly Media]

I just wanted to mention that there are way more resources out there than listed here. You can treat this as a starting point but by no means an exhaustive list of resources.

## THANK YOU

Thank you so much for reading my book! I hope you have enjoyed reading it.

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