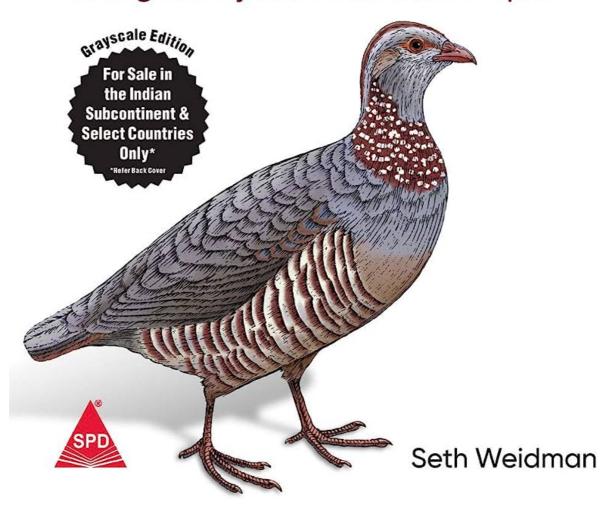


# Deep Learning from Scratch

**Building with Python from First Principles** 



# Prompt : Make me understand "The Chain Rule" in derivatives as a 10 years old

Sure! Let's understand the chain rule using a simpler example. Imagine you have two friends, Alice and Bob, and they both have different ways of doing things. Alice has a special machine that can change numbers, and Bob has another machine that can do different things with numbers. Now, imagine you want to know how fast something is changing when you use both machines together.

Let's say Alice's machine is represented by the function f, and Bob's machine is represented by the function g. When you use both machines in a row, it's like doing one operation after another. So, you want to know how fast something is changing after you use Alice's machine and then Bob's machine.

To figure out how fast things are changing, you need to use the chain rule. The chain rule tells you that to find the combined rate of change, you need to multiply two things: the rate at which Alice's machine changes things, and the rate at which Bob's machine changes things.

In other words, you need to know how fast Alice's machine changes things when you give it the output of Bob's machine, and you also need to know how fast Bob's machine changes things.

Let's say you want to find out how fast the number 5 changes when you use both machines. First, you put the number 5 into Bob's machine, and it gives you the number 3. Then, you take this number 3 and put it into Alice's machine. And let's say Alice's machine multiplies any number by 2. So, when you put the number 3 into Alice's machine, you get 6 as the final result.

Now, to use the chain rule, you need to know how fast Alice's machine changes things when you give it the output of Bob's machine. If you know that Alice's machine always doubles any number, you know that the rate at which it changes things is 2.

Next, you need to know how fast Bob's machine changes things. Let's say Bob's machine subtracts 1 from any number. So, if you put the number 5 into Bob's machine, it changes to 4. This means the rate at which Bob's machine changes things is -1. To find the combined rate of change, you multiply these two rates together: 2 (Alice's rate) times -1 (Bob's rate). So, the combined rate of change is -2. This means that when you use both machines together, the number 5 is changing at a rate of -2. In other words, if

#### Math

Mathematically, the theorem states—in a rather nonintuitive form—that, for a given value **x**,

$$rac{df_{2}}{du}(x)=rac{df_{2}}{du}(f_{1}\left( x
ight) ) imesrac{df_{1}}{du}(x)$$

where *u* is simply a dummy variable representing the input to a function.

#### NOTE

When describing the derivative of a function f with one input and output, we can denote the *function* that represents the derivative of this function as  $\frac{df}{du}$ . We could use a different dummy variable in place of u—it doesn't matter, just as  $f(x) = x^2$  and  $f(y) = y^2$  mean the same thing.

On the other hand, later on we'll deal with functions that take in *multiple* inputs, say, both x and y. Once we get there, it will make sense to write  $\frac{df}{dx}$  and have it mean something different than  $\frac{df}{dy}$ .

This is why in the preceding formula we denote *all* the derivatives with a u on the bottom: both  $f_1$  and  $f_2$  are functions that take in one input and produce one output, and in such cases (of functions with one input and one output) we'll use u in the derivative notation.

## **Diagram**

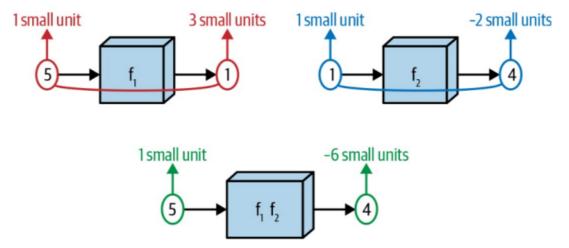


Figure 1-8. An illustration of the chain rule

Intuitively, using the diagram in Figure 1-8, the derivative of the composite function *should* be a sort of product of the derivatives of its constituent functions. Let's say we feed the value 5 into the first function, and let's say further that computing the *derivative* of the first function at u = 5 gives us a value of 3—that is,  $\frac{df_1}{du}(5) = 3$ .

Let's say that we then take the *value* of the function that comes out of the first box—let's suppose it is 1, so that  $f_1(5) = 1$ —and compute the derivative of the second function  $f_2$  at this value: that is,  $\frac{df_2}{du}(1)$ . We find that this value is -2.

If we think about these functions as being literally strung together, then if changing the input to box two by 1 unit yields a change of -2 units in the output of box two, changing the input to box two by 3 units should change the output to box two by  $-2 \times 3 = -6$  units. This is why in the formula for the chain rule, the final result is ultimately a product:  $\frac{df_2}{du}(f_1(x))$  times  $\frac{df_1}{du}(x)$ .

### Code

Let's code this up and show that computing derivatives in this way does in fact yields results that "look correct". We'll use the square function from "Basic functions in Numpy" along with sigmoid, another function that ends up being important in deep learning:

```
In [ ]: from IPython.core.debugger import set_trace
    import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
    import time
    import yfinance as yf
    import warnings
    warnings.filterwarnings('ignore')
    %matplotlib inline
```

```
In [ ]: import numpy as np

def sigmoid(x: np.array) -> np.array:
    '''Apply the sigmoid function to each element in the input ndarray.'''
    return 1/(1 + np.exp(-x))
```

The sigmoid function is commonly used to introduce non-linearity in neural networks and to squash the output values between 0 and 1, making it suitable for tasks such as binary classification or probability estimation.

#### And now we code up the chain rule:

```
In [ ]: def chain_deriv_2(chain,input_range: np.array)->np.array:
            Uses the chain rule to compute the derivative of two nested functions:
            (f2(f1(x)))' = f2'(f1(x)) * f1'(x)
            assert len(chain) == 2, \
            "This function requires 'Chain'objects of length 2"
            assert input_range.ndim == 1, \
            "Function requires a 1-D ndarray as input_range"
            f1 = chain[0]
            f2 = chain[1]
            #df1/dx
            f1_of_x =f1(input_range)
            #df1/du
            df1dx = deriv(f1, input range)
            #df2/du(f1(x))
            df2du = deriv(f2, f1(input_range))
            #Multiplying these quantities together at each point
            return df1dx * df2du
```

```
In [ ]: import matplotlib.pyplot as plt

PLOT_RANGE = np.arange(-3, 3, 0.01)

chain_1 = [square, sigmoid]
    chain_2 = [sigmoid, square]

plot_chain(chain_1, PLOT_RANGE)
    plot_chain_deriv(chain_1, PLOT_RANGE)

plot_chain(chain_2, PLOT_RANGE)
    plot_chain_deriv(chain_2, PLOT_RANGE)
```

```
In [ ]:
```