DATA MINING 2
Gradient Descent

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Contains edited slides from StatQuest

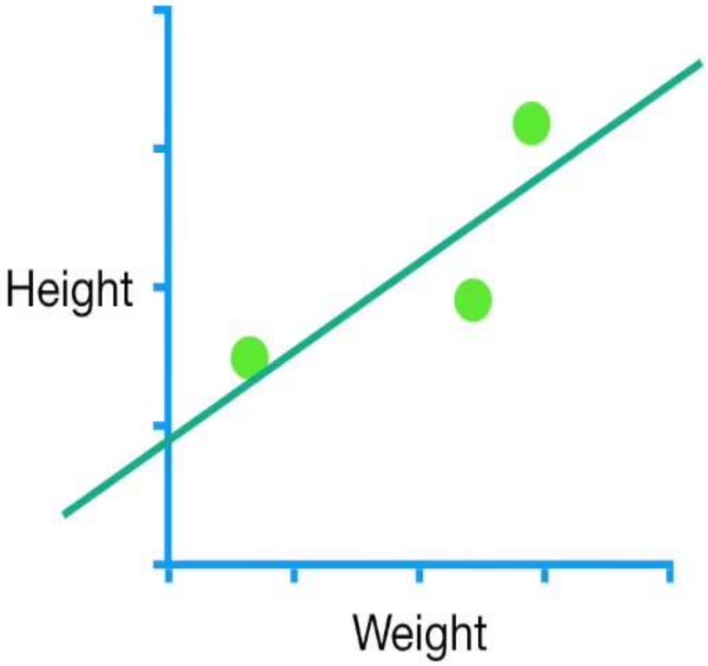
UNIVERSITÀ DI PISA

Gradient Descent

- GD is a very effective and widely usable mathematical technique to find the best parameters in many and various tasks such as
- Linear Regression
- Logistic Regression
- Neural Networks
- …

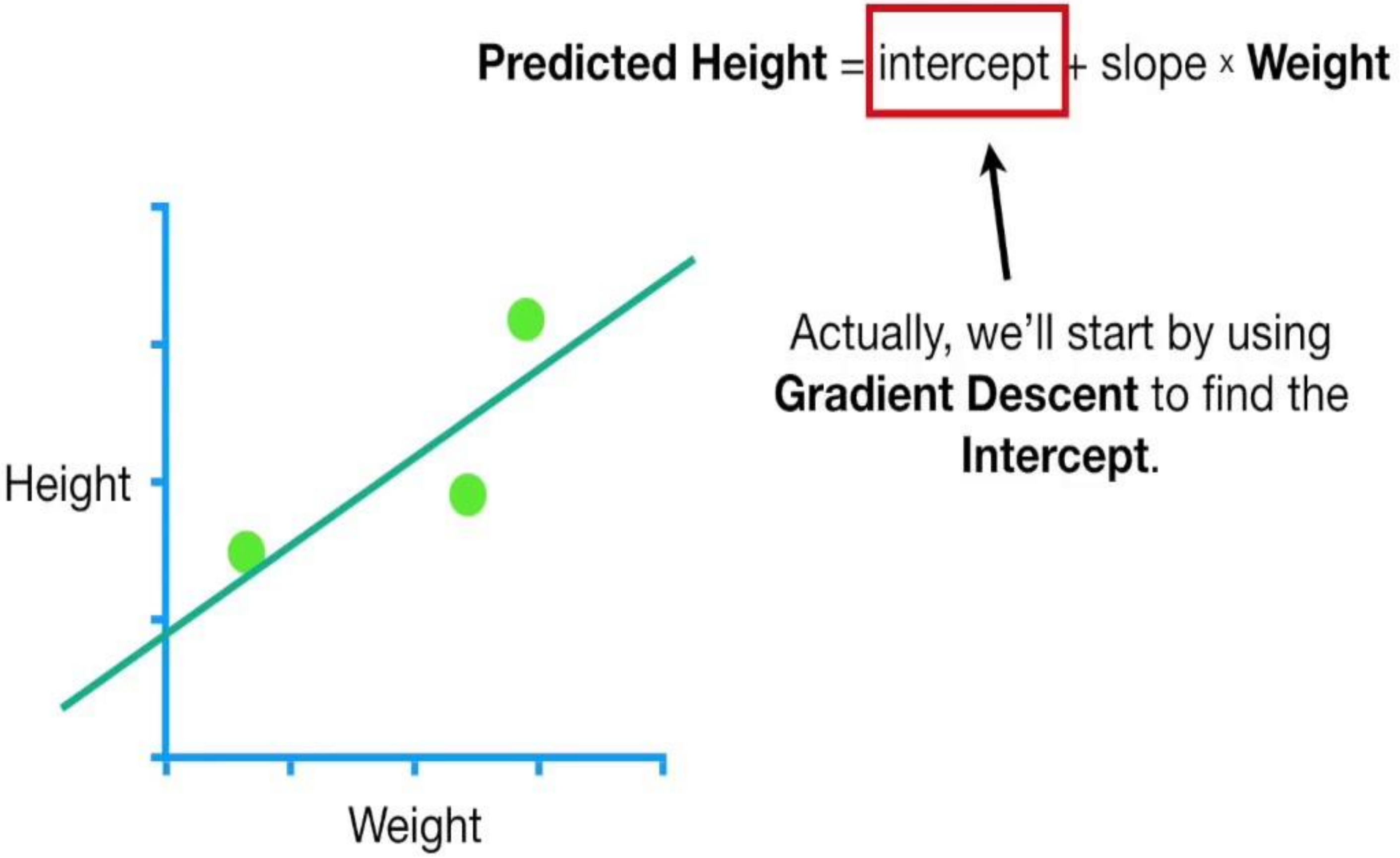
GD for Linear Regression

Predicted Height = intercept + slope × **Weight**



So let's learn how **Gradient Descent** can fit a line to data by finding the optimal values for the **Intercept** and the **Slope**.

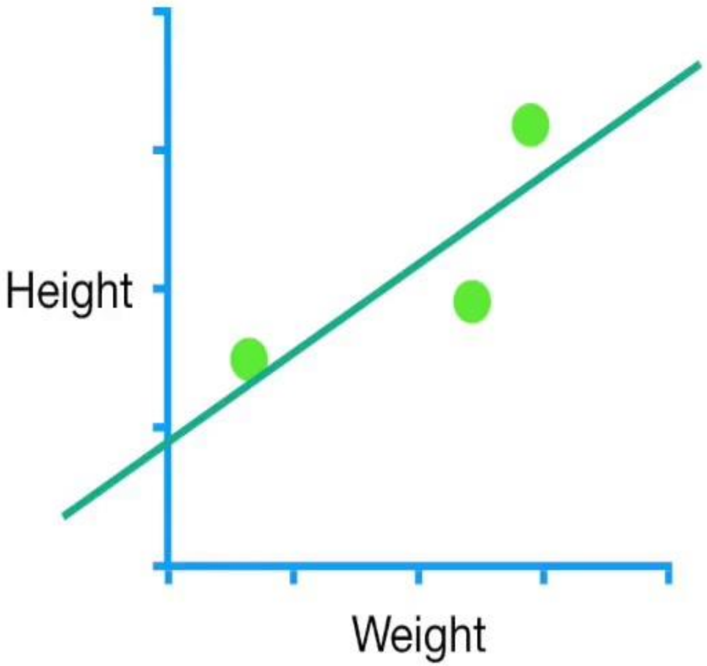
GD to find *b*



Predicted Height = intercept + slope × **Weight**
Actually, we'll start by using **Gradient Descent** to find the **Intercept**.
Height
Weight

GD to find *b*

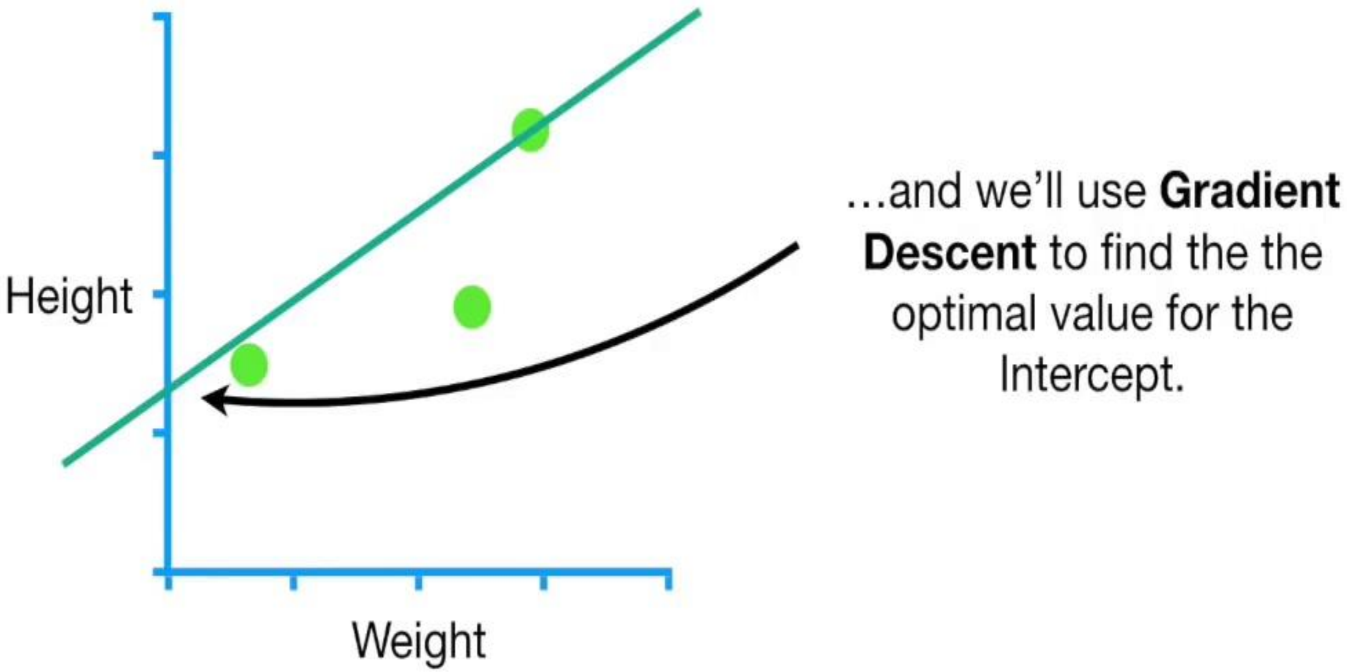
Predicted Height = intercept + slope × **Weight**



So for now, let's just plug in the **Least Squares** estimate for the **Slope**, **0.64**.

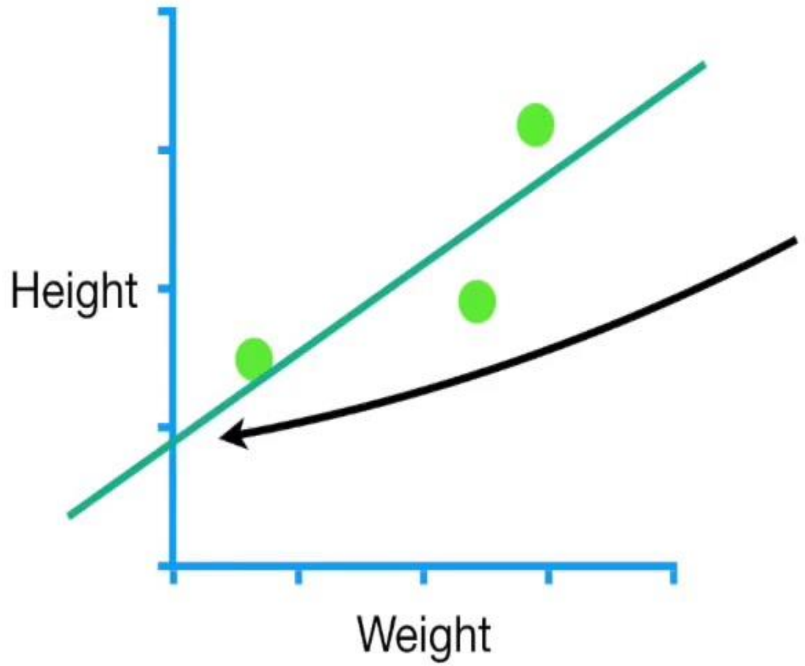
GD to find *b*

Predicted Height = intercept + 0.64 × **Weight**



GD to find *b*

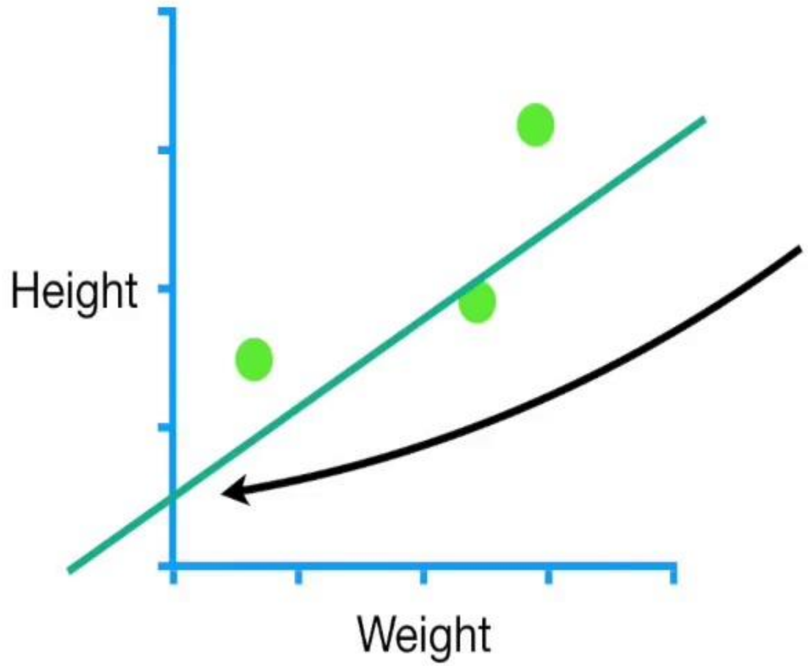
Predicted Height = intercept + 0.64 × **Weight**



...and we'll use **Gradient Descent** to find the the optimal value for the Intercept.

GD to find *b*

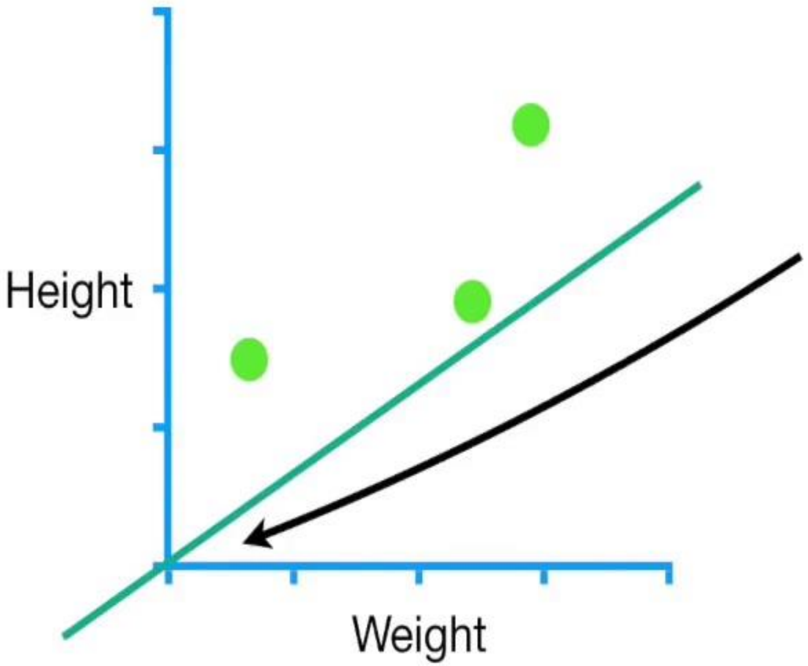
Predicted Height = intercept + 0.64 × **Weight**



...and we'll use **Gradient Descent** to find the the optimal value for the Intercept.

GD to find *b*

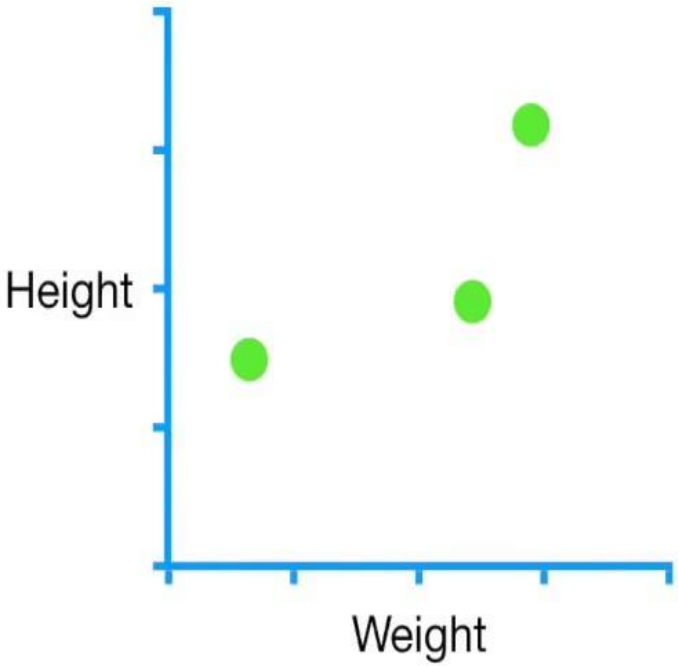
Predicted Height = intercept + 0.64 × **Weight**



...and we'll use **Gradient Descent** to find the the optimal value for the Intercept.

GD to find *b*

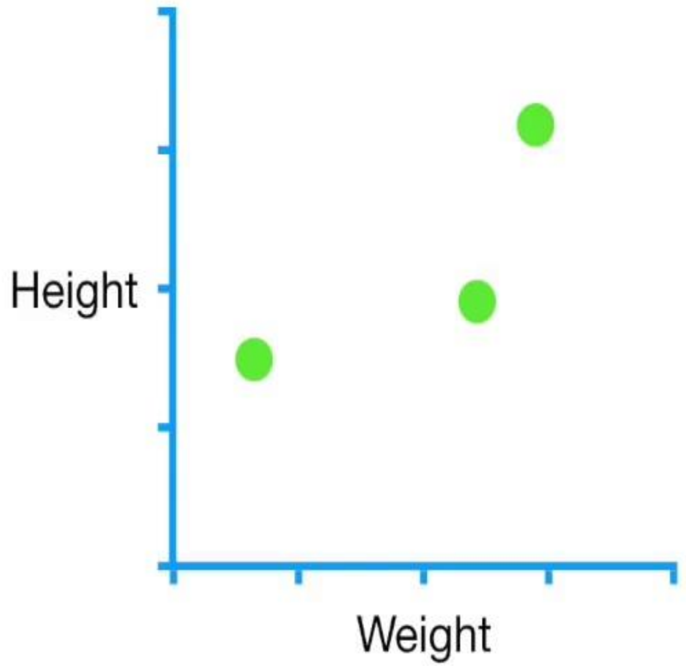
Predicted Height = intercept + 0.64 × **Weight**



The first thing we do is pick a random value for the **Intercept**.

GD to find *b*

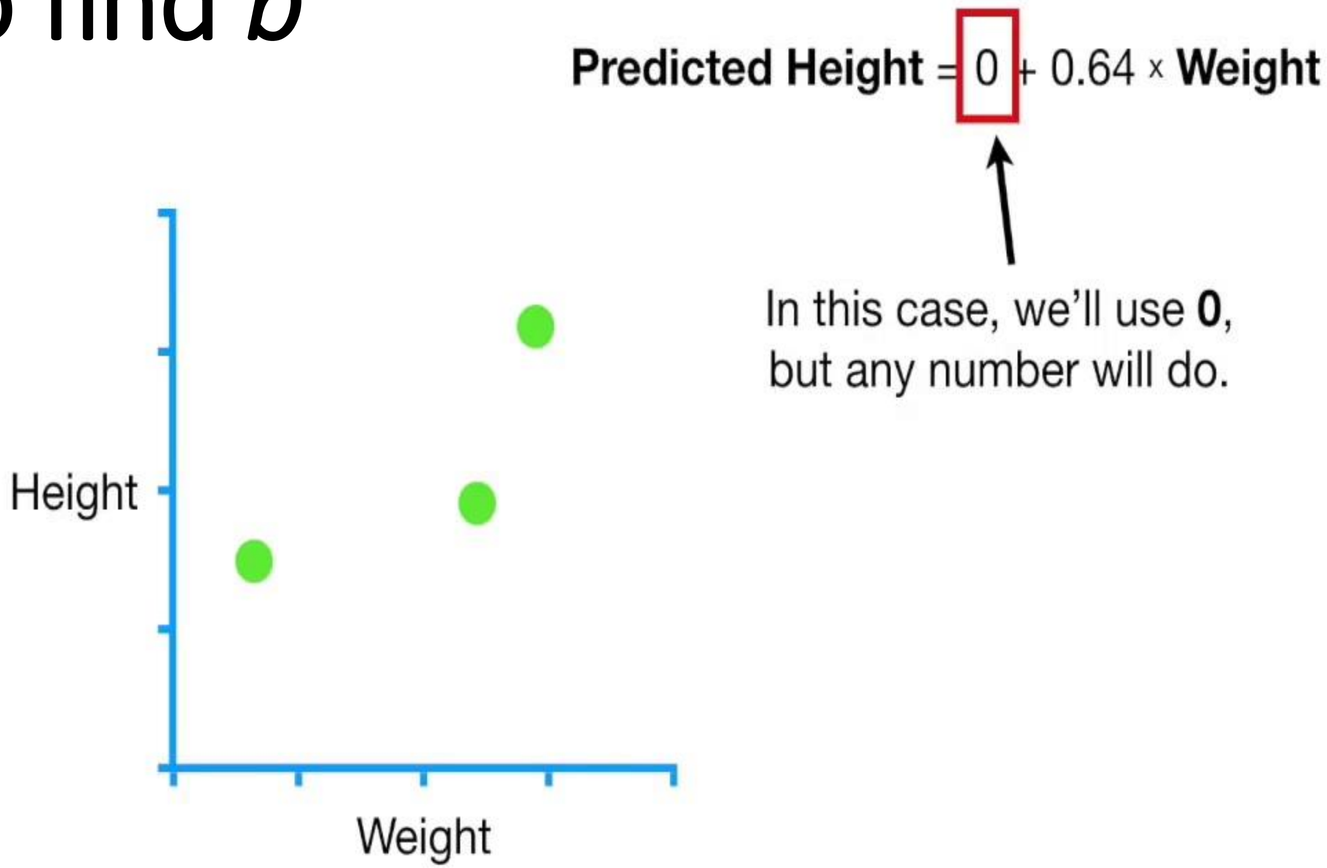
Predicted Height = intercept + 0.64 × **Weight**



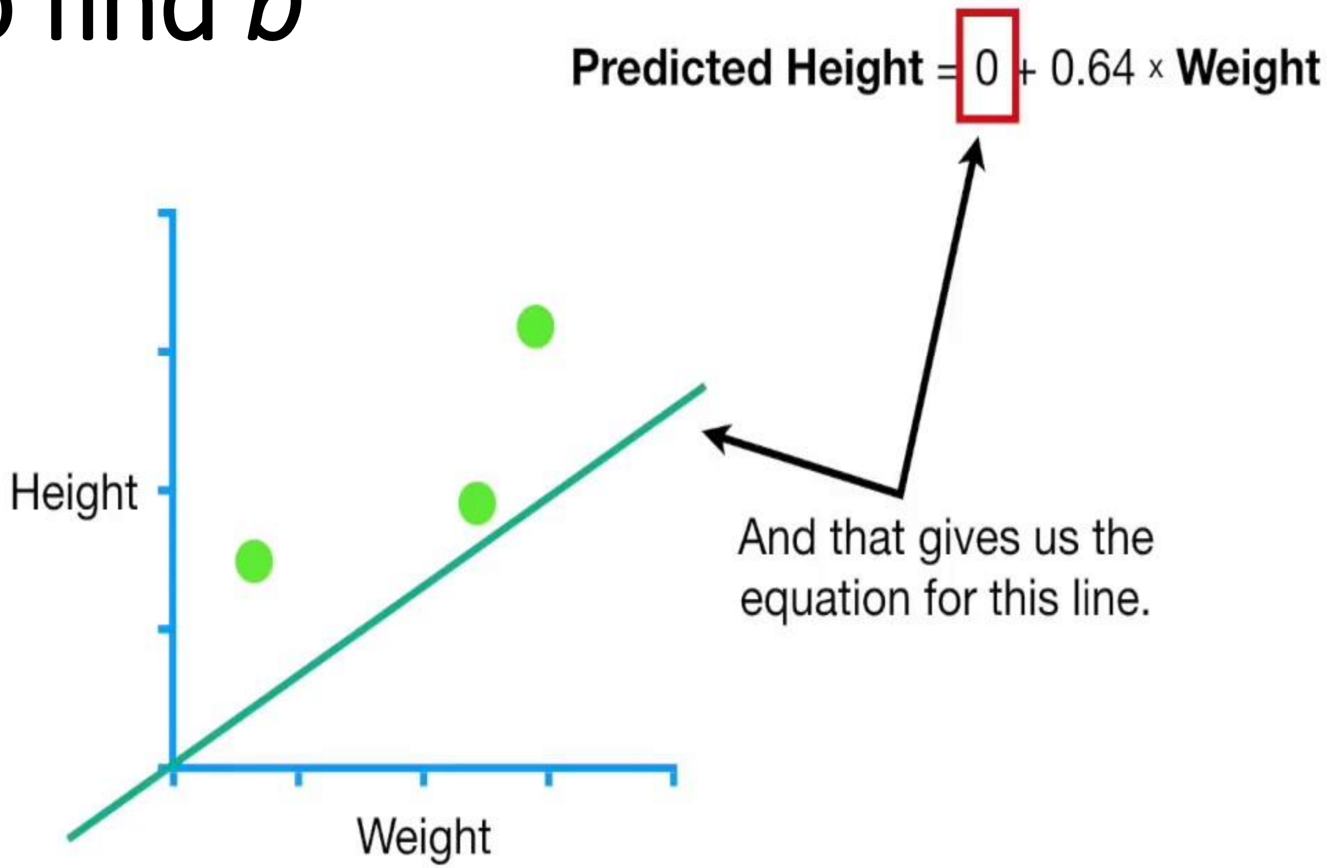
The first thing we do is pick a random value for the **Intercept**.

This is just an initial guess that gives **Gradient Descent** something to improve upon.

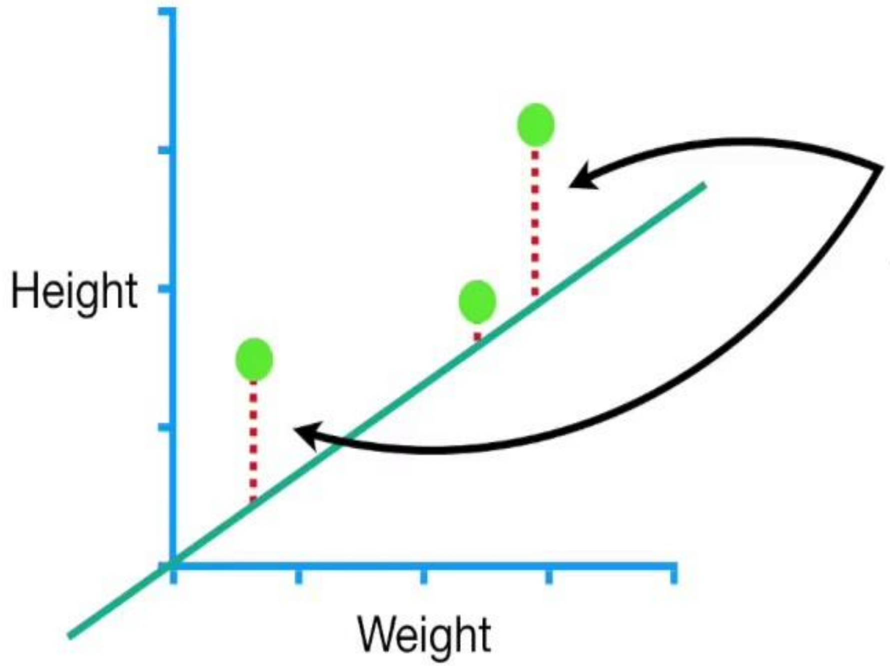
GD to find *b*


Predicted Height = 0 + 0.64 × Weight
In this case, we'll use 0, but any number will do.
Height
Weight

GD to find *b*

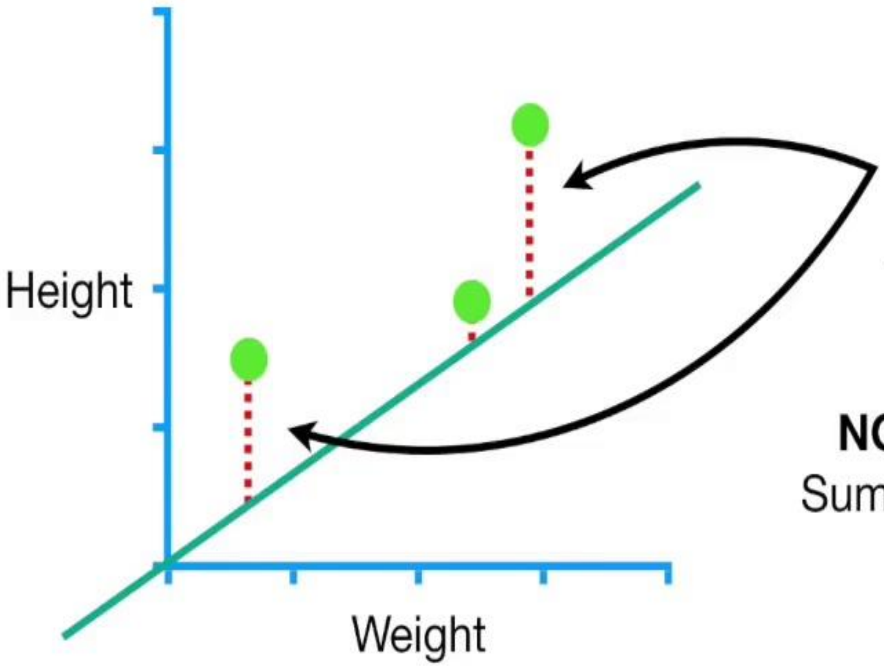

Predicted Height = 0 + 0.64 x Weight
Height
Weight
And that gives us the equation for this line.

GD to find *b*



In this example, we will evaluate how well this line fits the data with the **Sum of the Squared Residuals**.

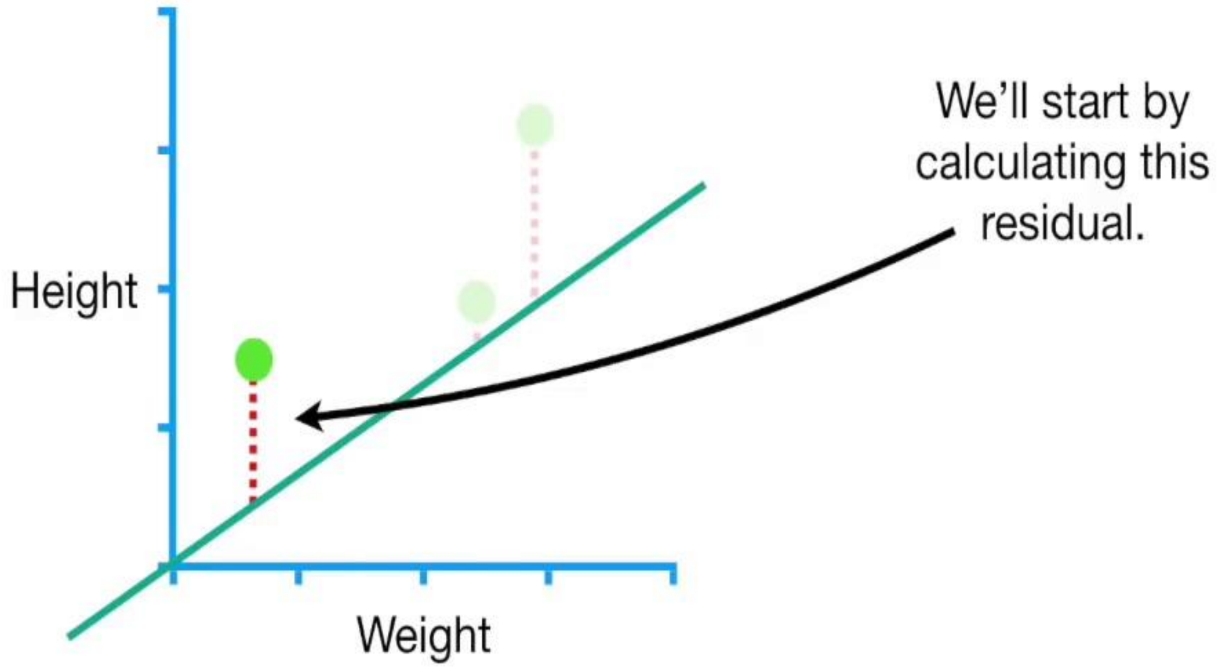
GD to find *b*



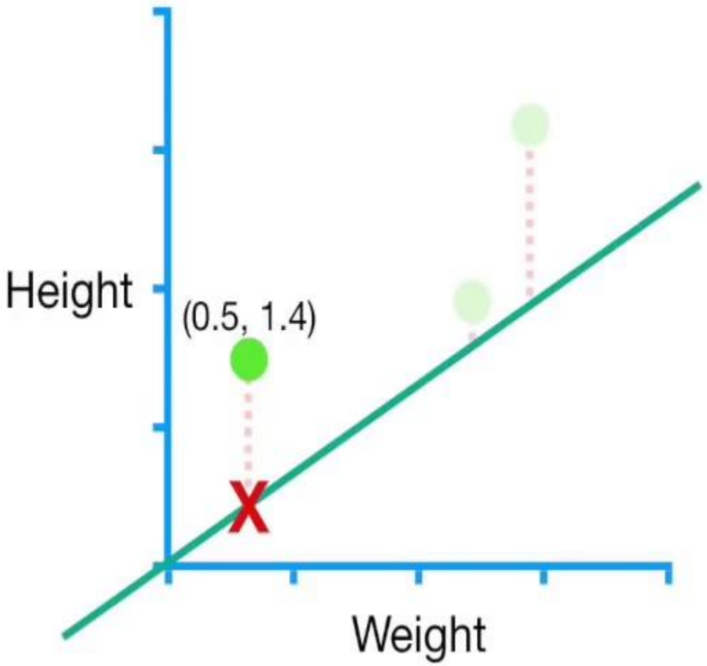
In this example, we will evaluate how well this line fits the data with the **Sum of the Squared Residuals**.

NOTE: In Machine Learning lingo, The Sum of the Squared Residuals is a type of **Loss Function**.

GD to find *b*



GD to find b

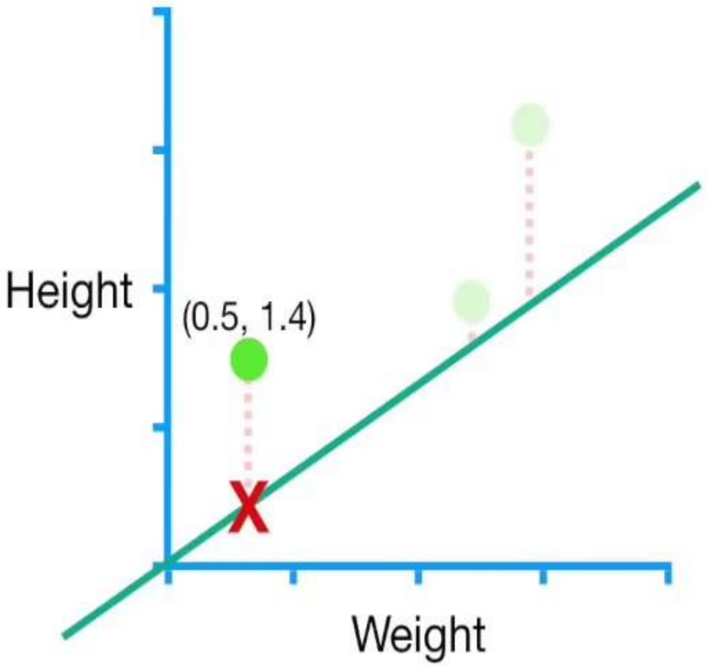


We get the **Predicted Height**, the point on the line…

…by plugging **Weight = 0.5** into the equation for the line…

Predicted Height = 0 + 0.64 × **Weight**

GD to find *b*

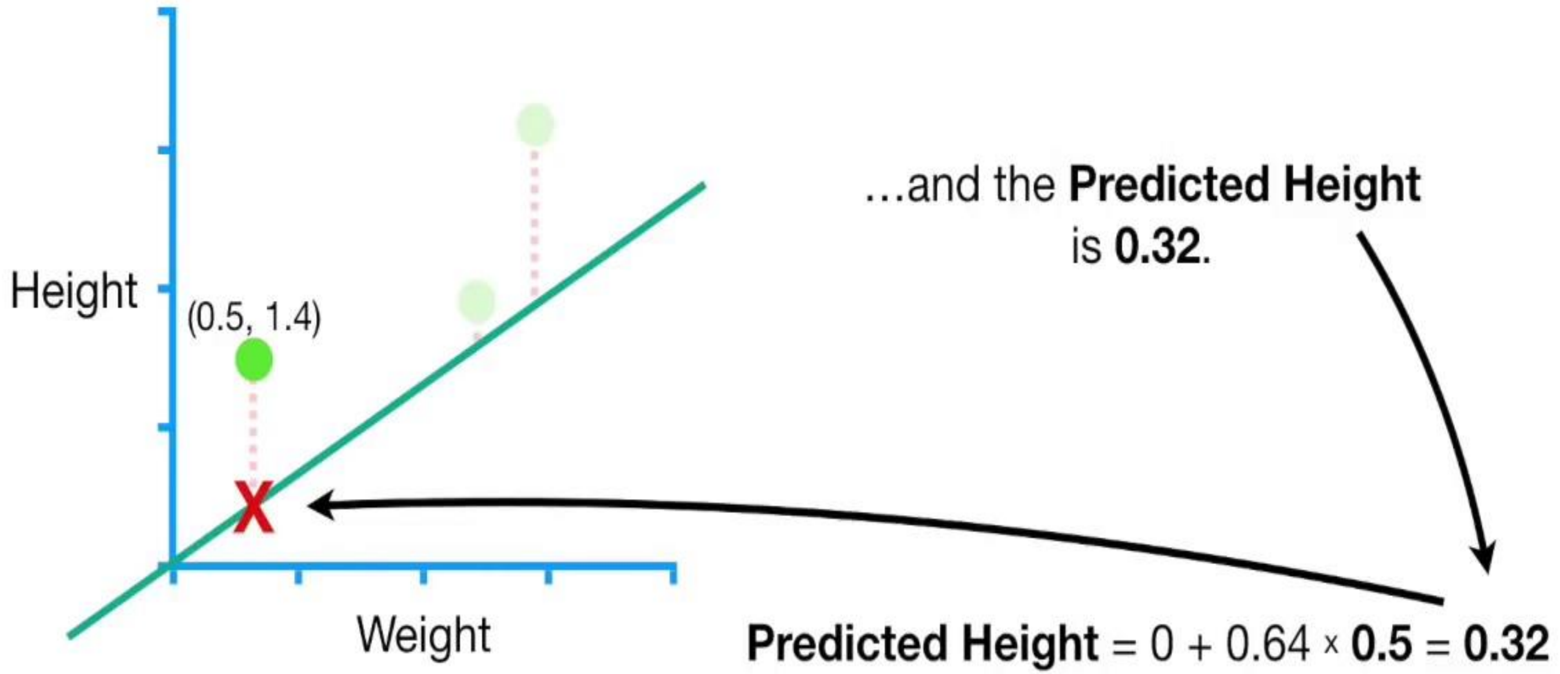


We get the **Predicted Height**, the point on the line…

…by plugging **Weight = 0.5** into the equation for the line…

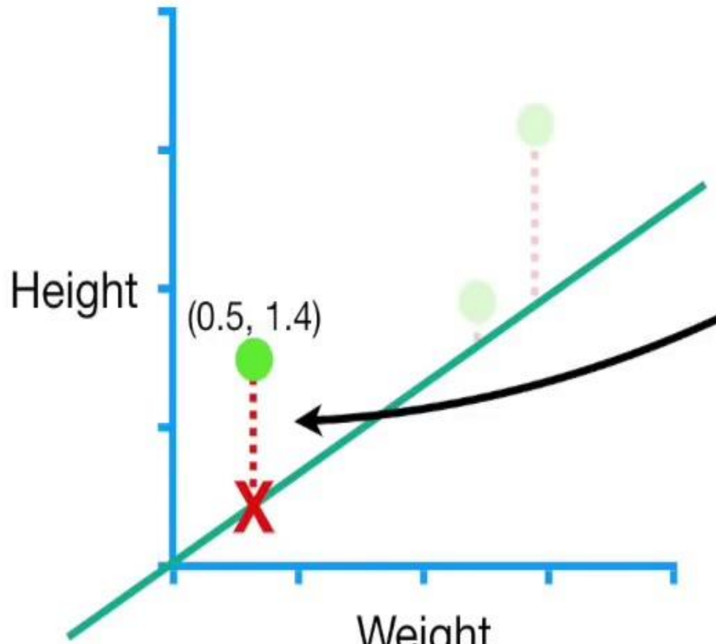
Predicted Height = 0 + 0.64 × **0.5**

GD to find *b*



Height
(0.5, 1.4)
Weight
...and the **Predicted Height** is **0.32**.
Predicted Height = 0 + 0.64 × **0.5** = **0.32**

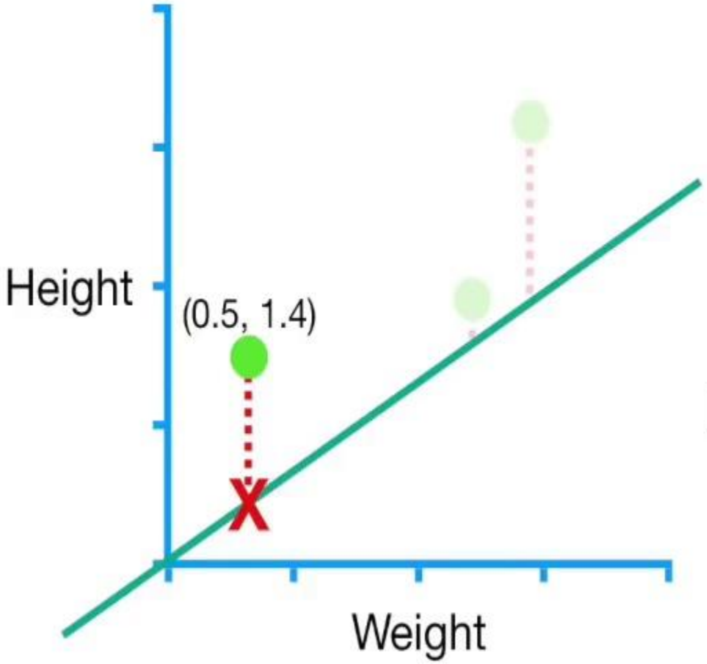
GD to find *b*



The residual is the difference between the **Observed Height**, and the **Predicted Height**…

Predicted Height = 0 + 0.64 × **0.5** = **0.32**

GD to find *b*



The residual is the difference between the **Observed Height**, and the **Predicted Height**…

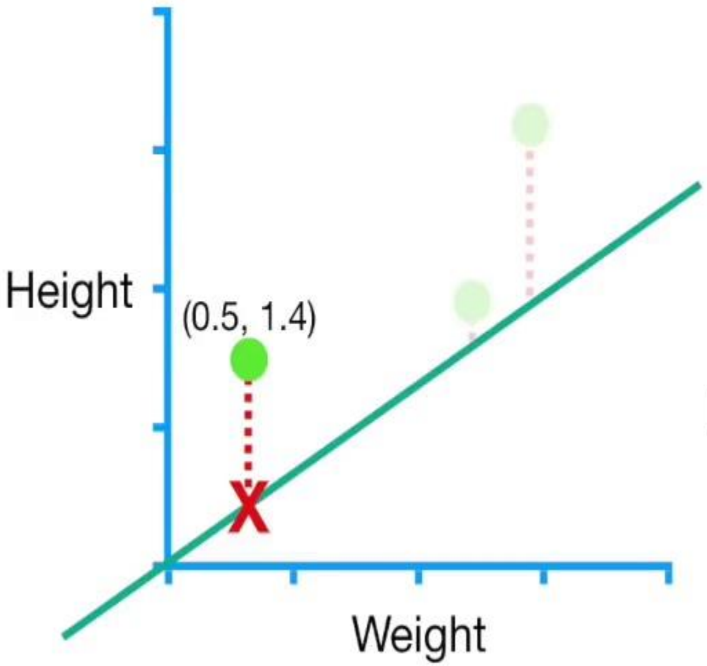
Residual = **Observed Height** - **Predicted Height**

Predicted Height = 0 + 0.64 × **0.5** = **0.32**

GD to find b

Sum of squared residuals =

We'll keep track of the Sum of the Squared Residuals up here.

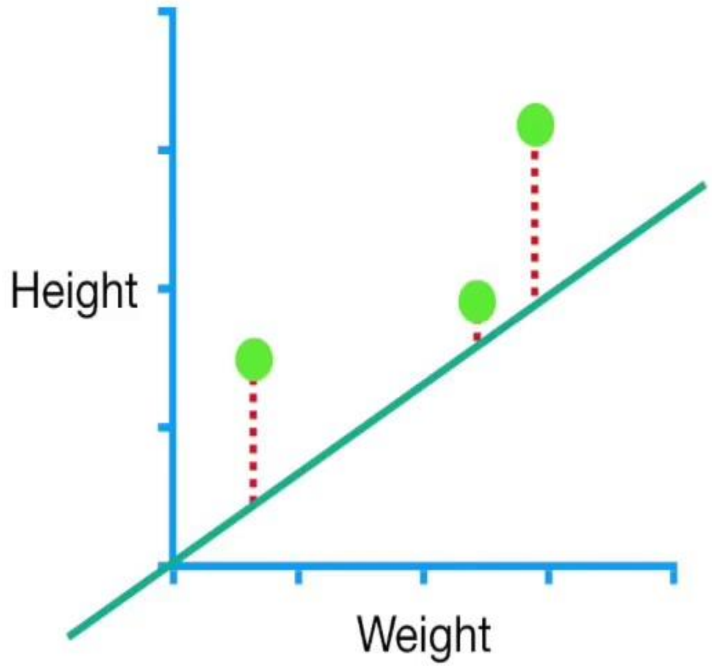


Residual = 1.4 - 0.32 = **1.1**

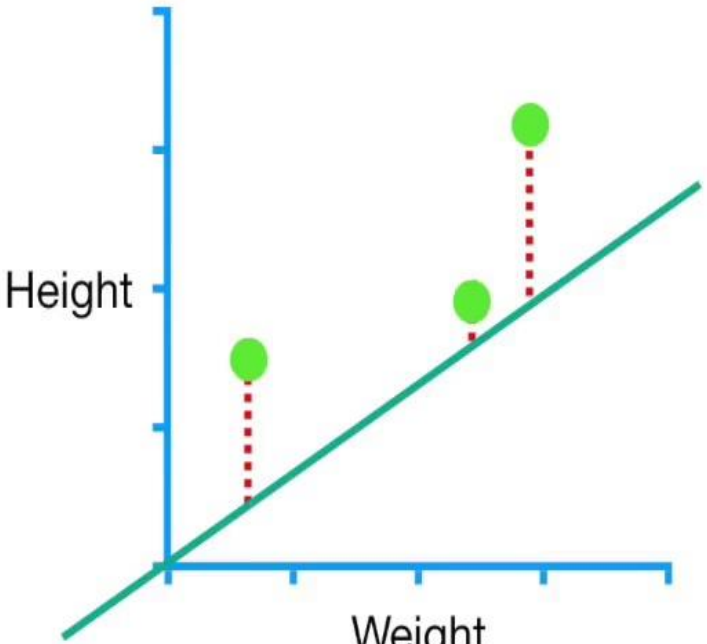
Predicted Height = 0 + 0.64 × **0.5** = **0.32**

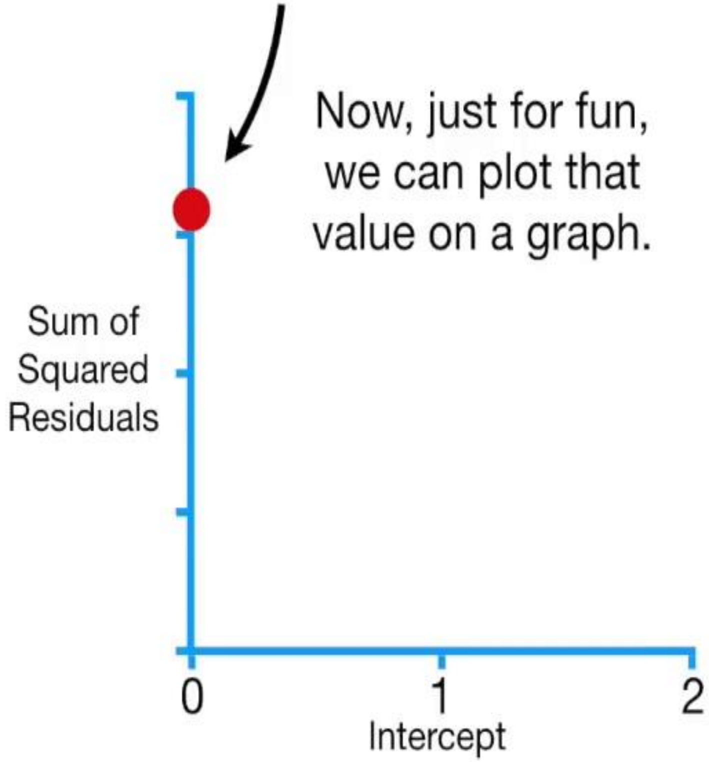
Sum of squared residuals = $1.1^2 + 0.4^2 + 1.3^2 = 3.1$

In the end, **3.1** is the Sum of the Squared Residuals.

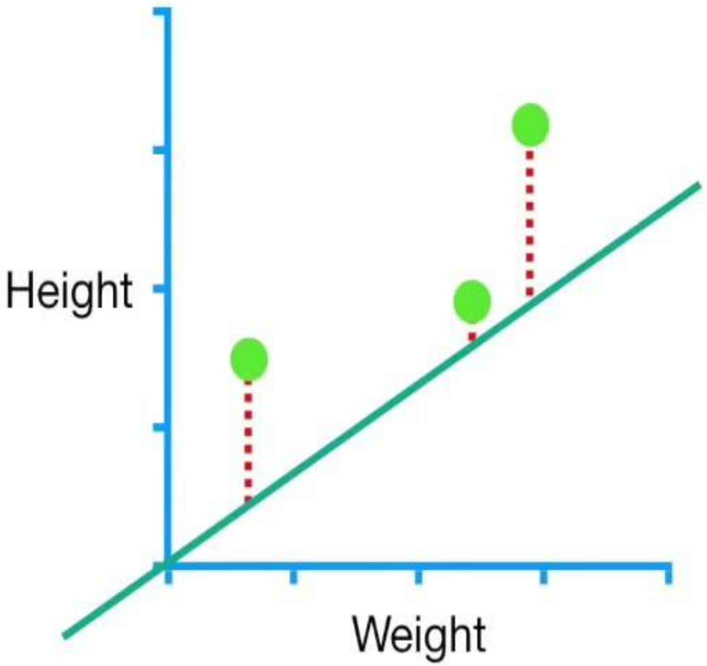


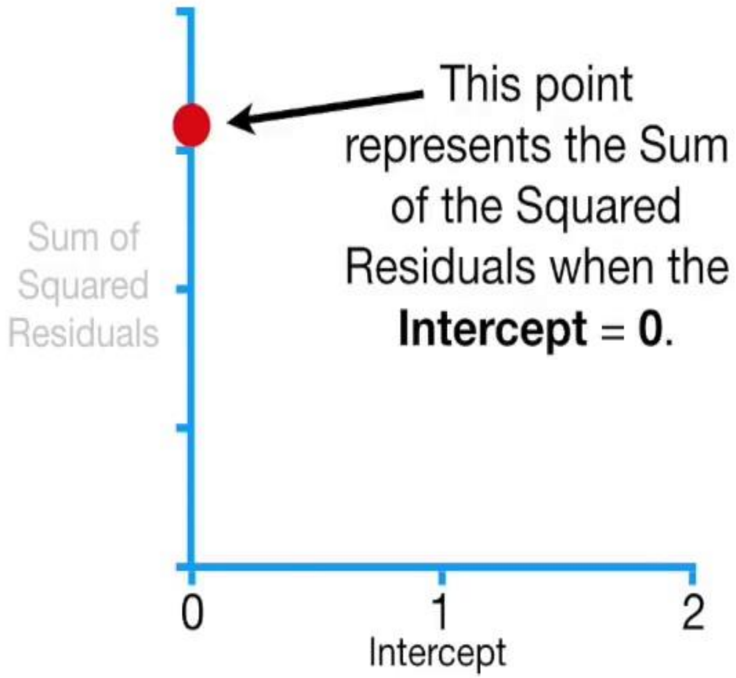
Sum of squared residuals = $1.1^2 + 0.4^2 + 1.3^2 = 3.1$



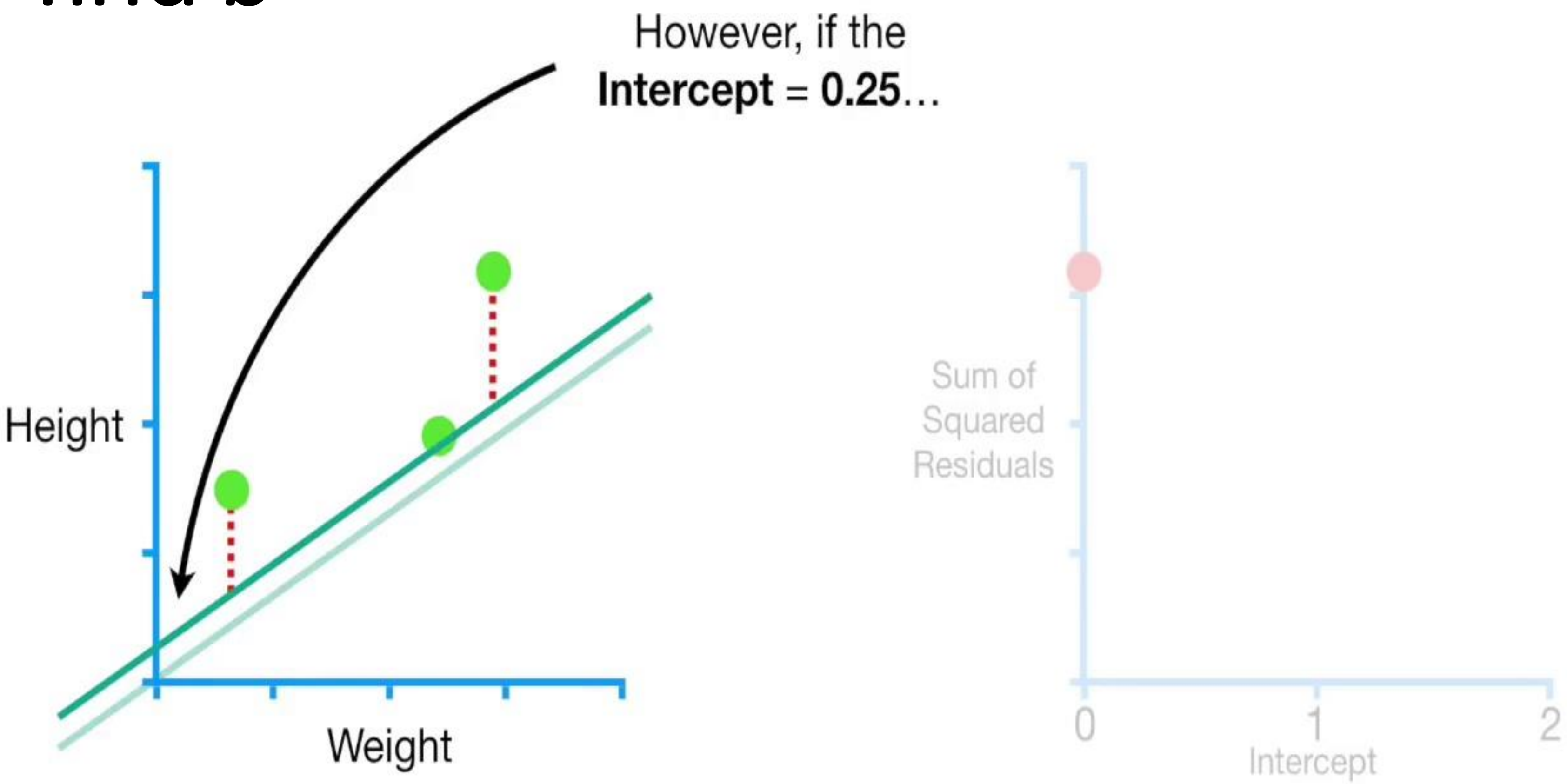


Sum of squared residuals = $1.1^2 + 0.4^2 + 1.3^2 = 3.1$

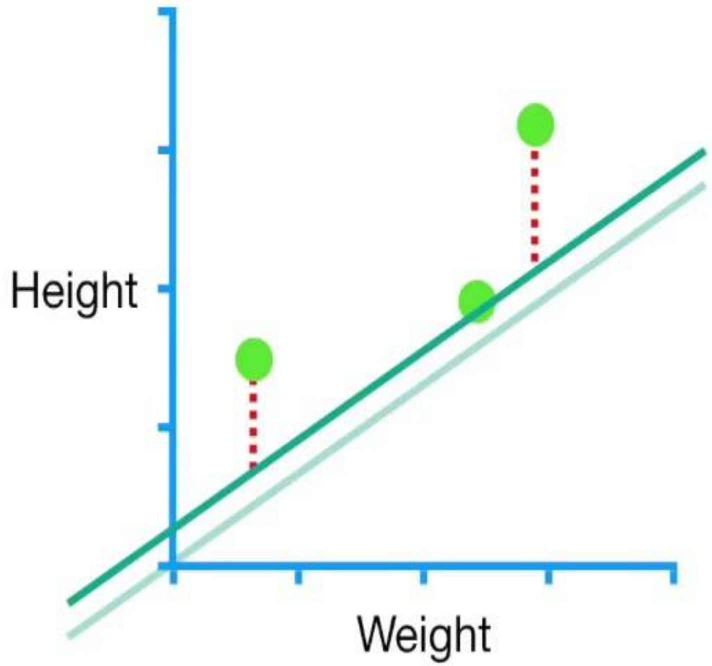


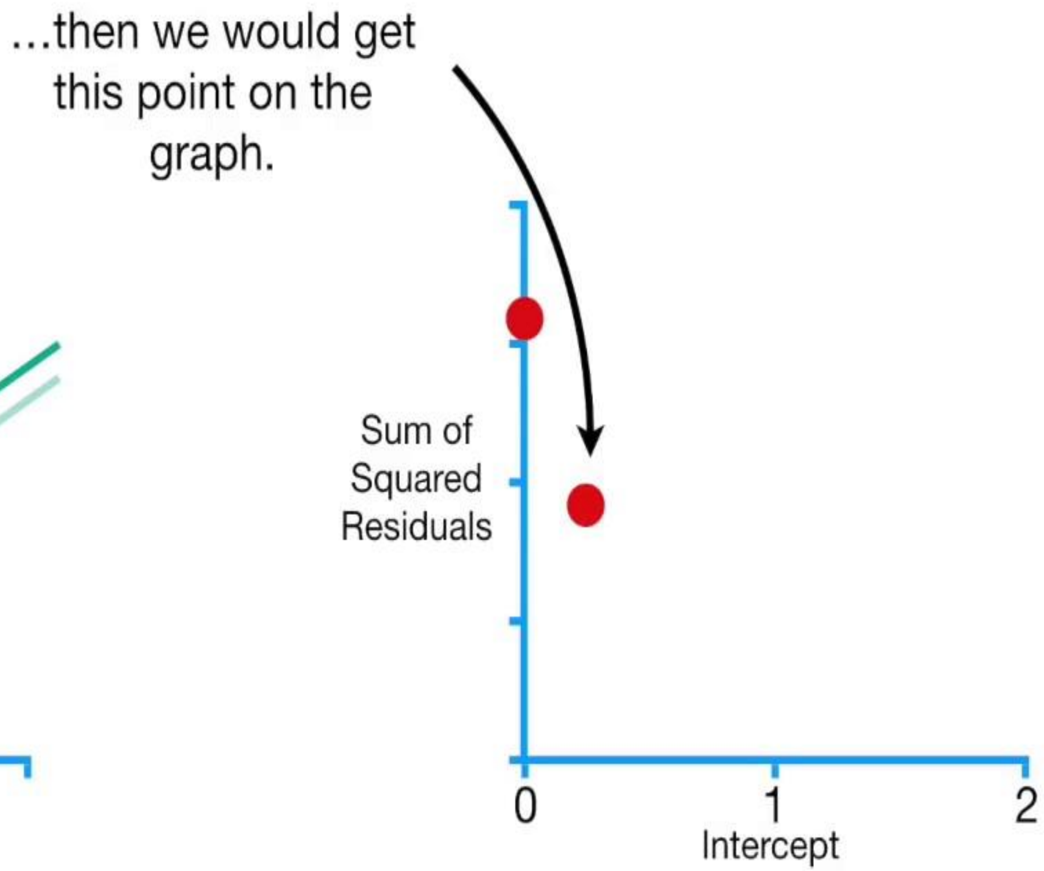


GD to find *b*

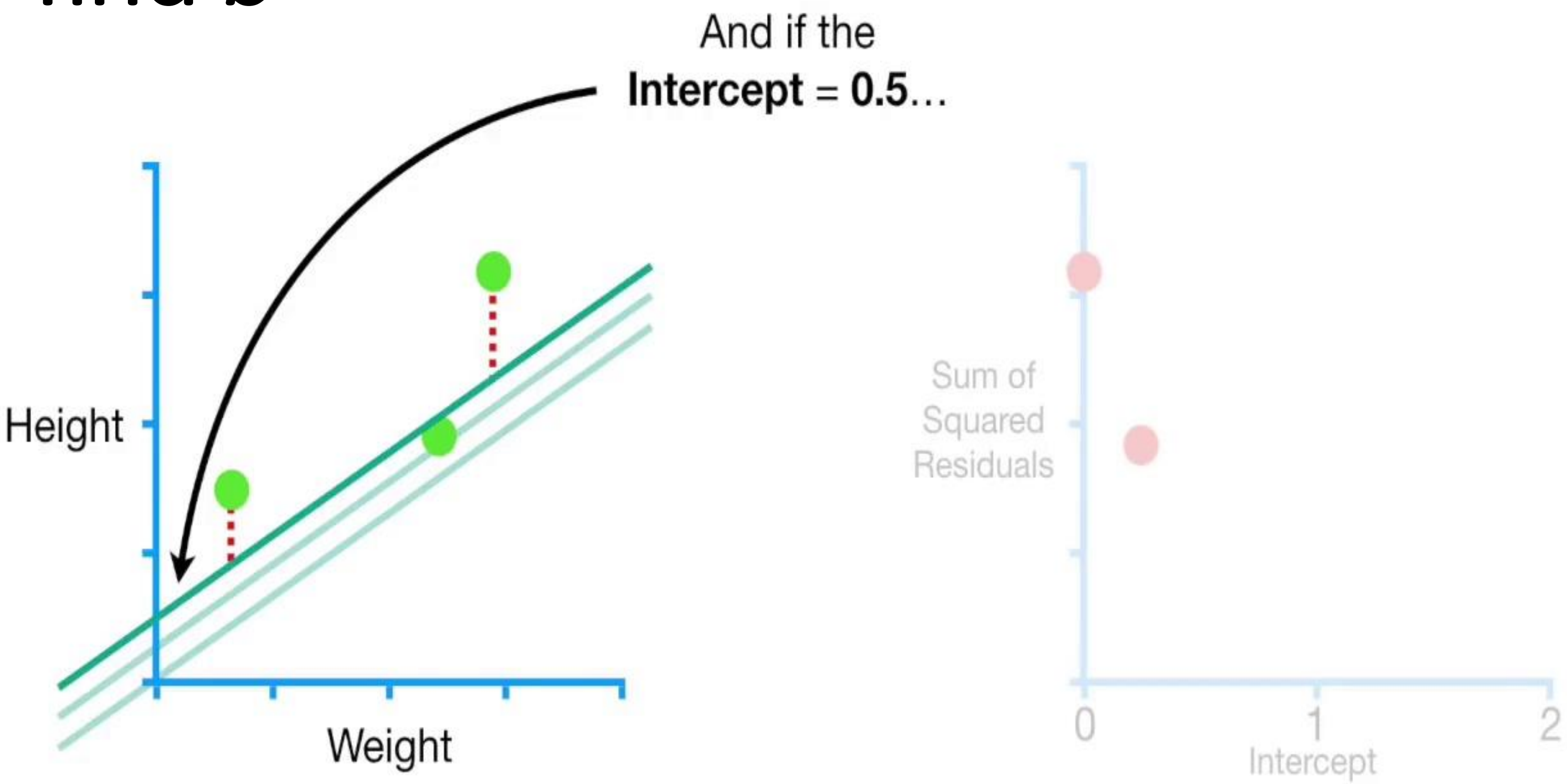

However, if the
Intercept = **0.25**…
Height
Weight
Sum of
Squared
Residuals
0
1
2
Intercept

GD to find *b*

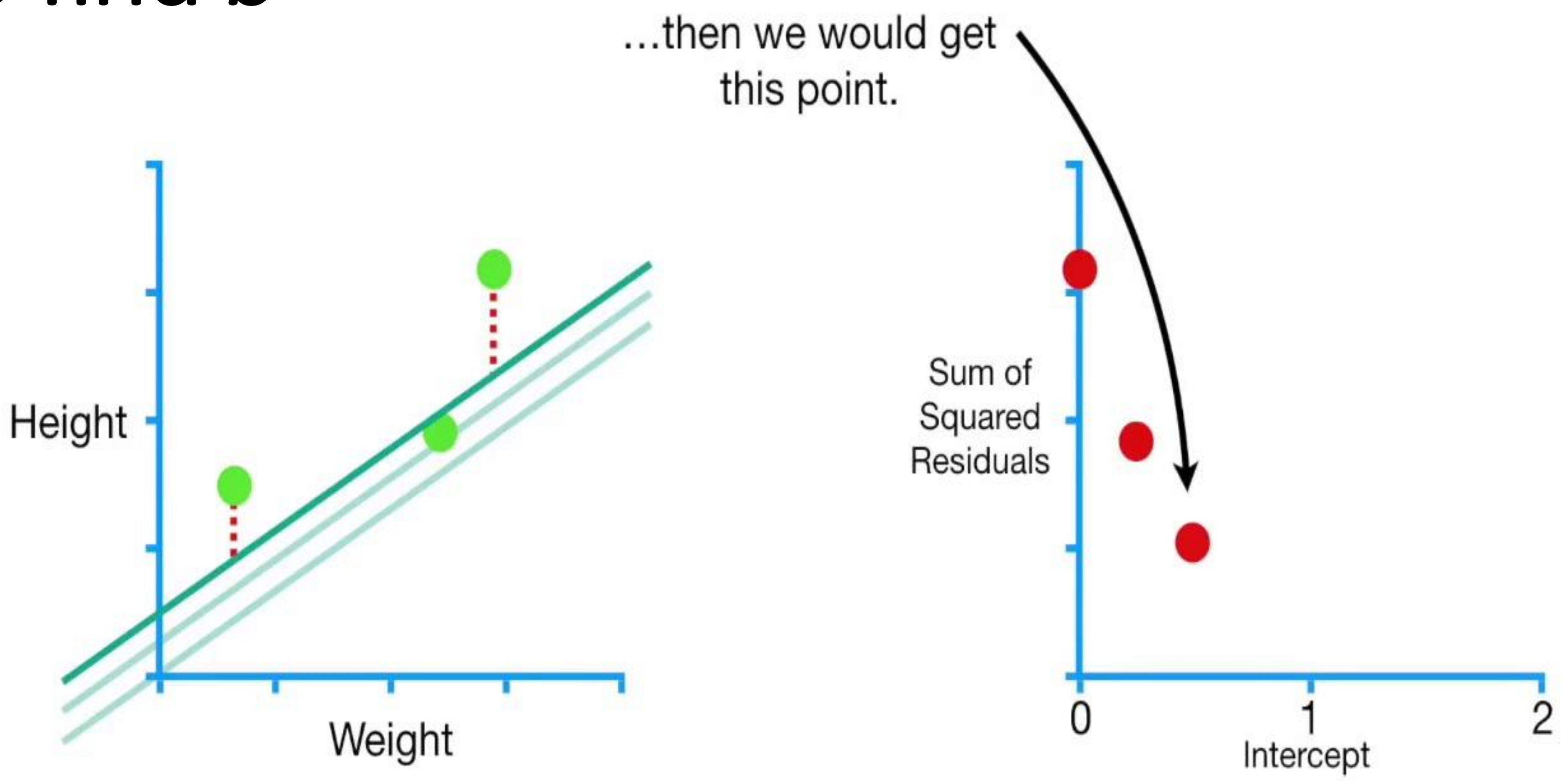

Height
Weight


...then we would get this point on the graph.
Sum of Squared Residuals
0
1
2
Intercept

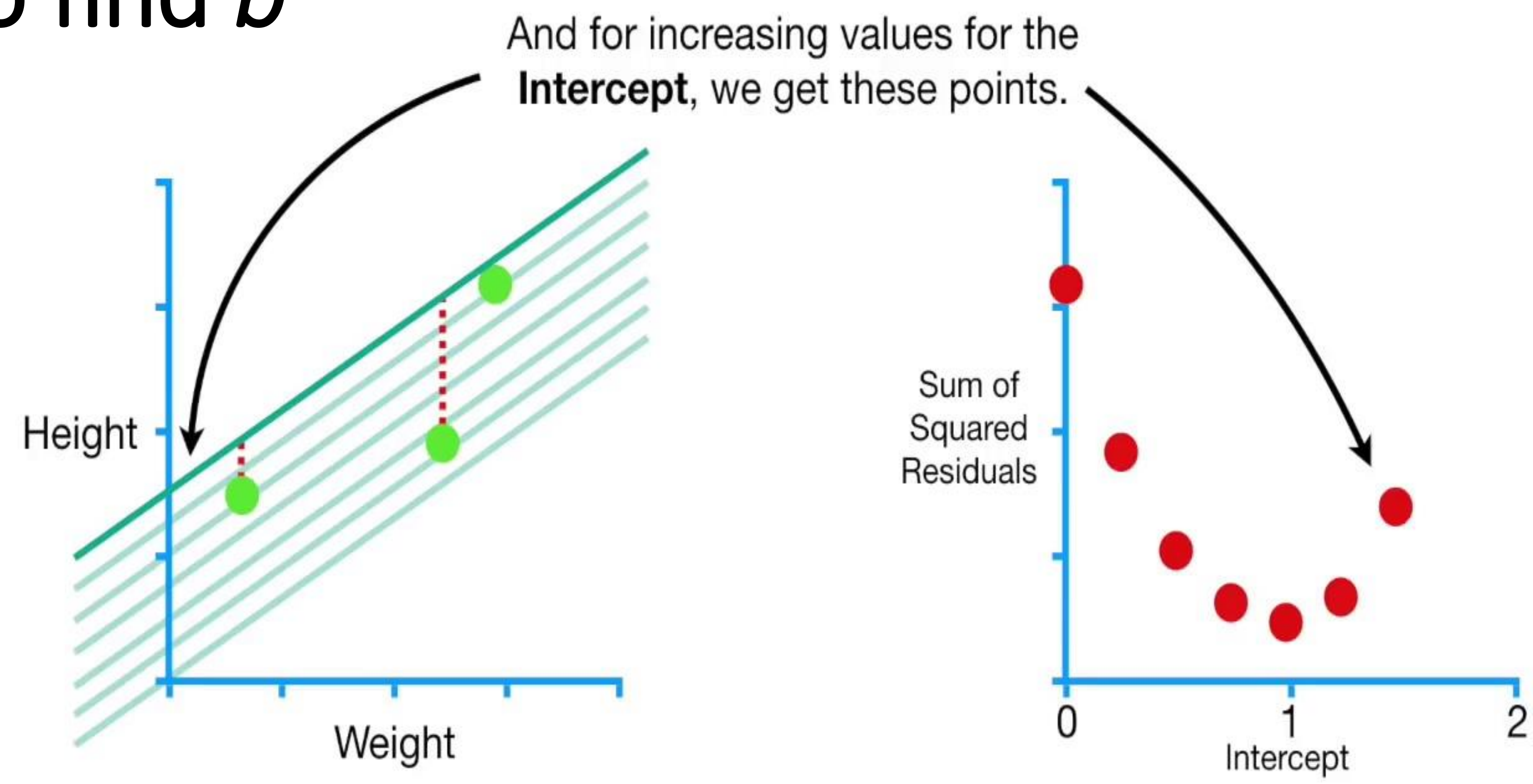
GD to find *b*


And if the
Intercept = 0.5...
Height
Weight
Sum of
Squared
Residuals
0
1
2
Intercept

GD to find *b*

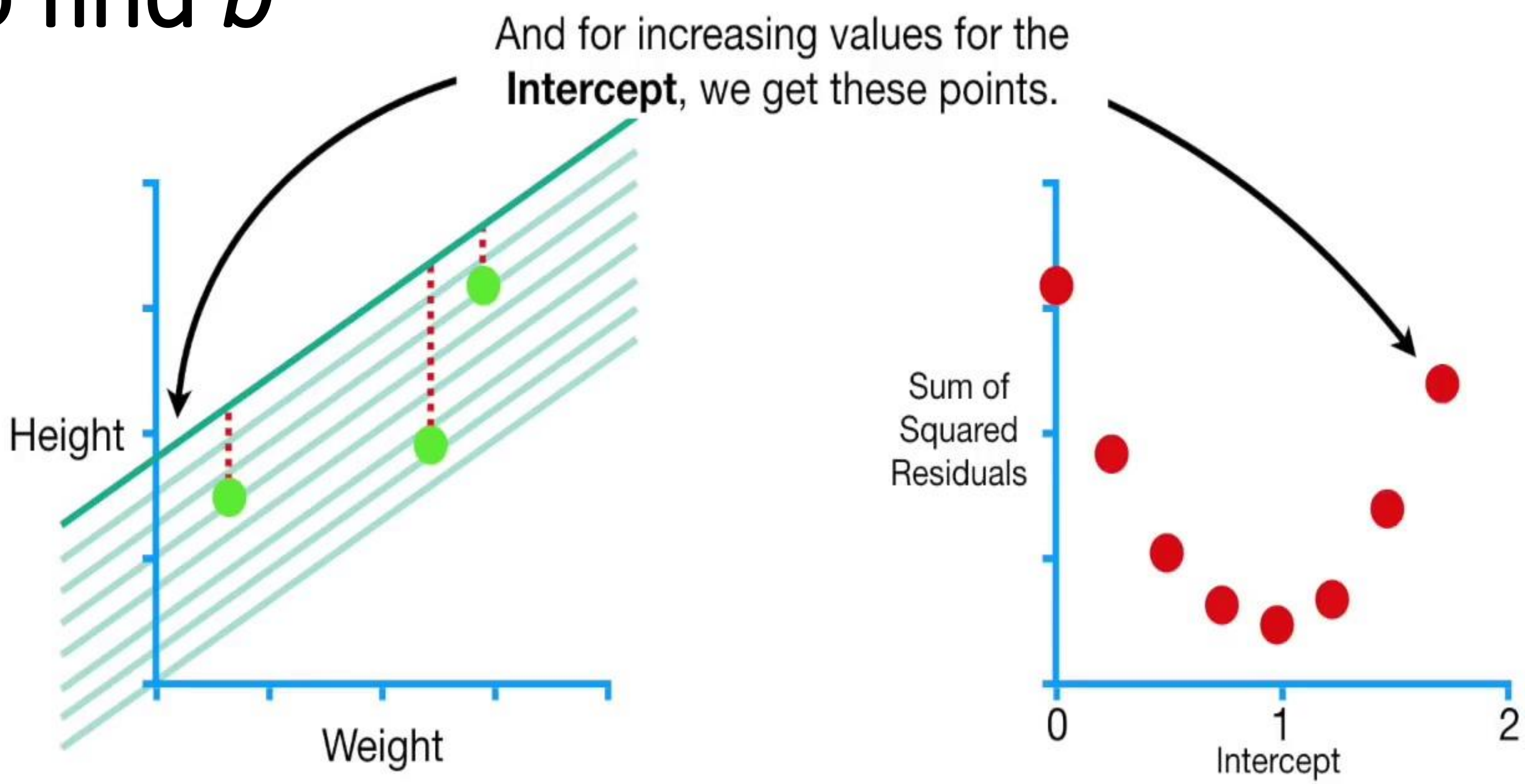

...then we would get
this point.
Height
Weight
Sum of
Squared
Residuals
0
1
2
Intercept

GD to find *b*

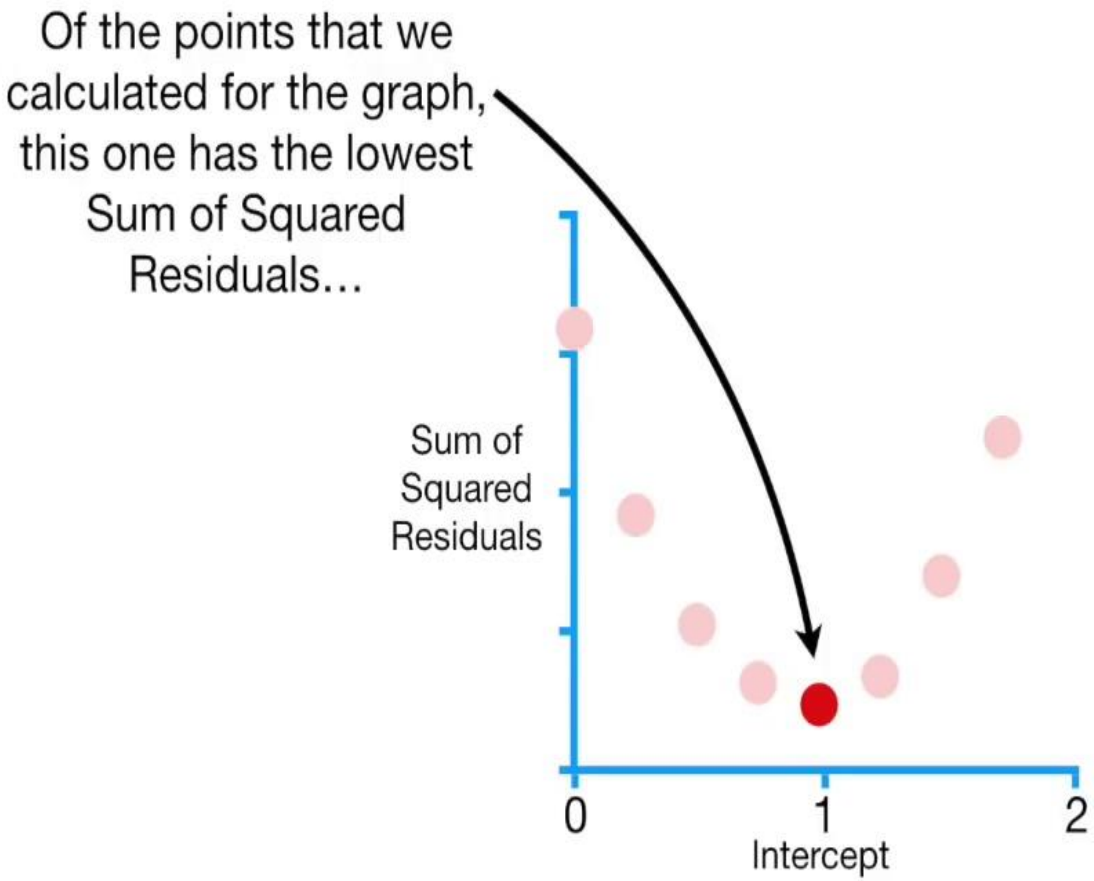


And for increasing values for the **Intercept**, we get these points.
Height
Weight
Sum of Squared Residuals
0
1
2
Intercept

GD to find *b*

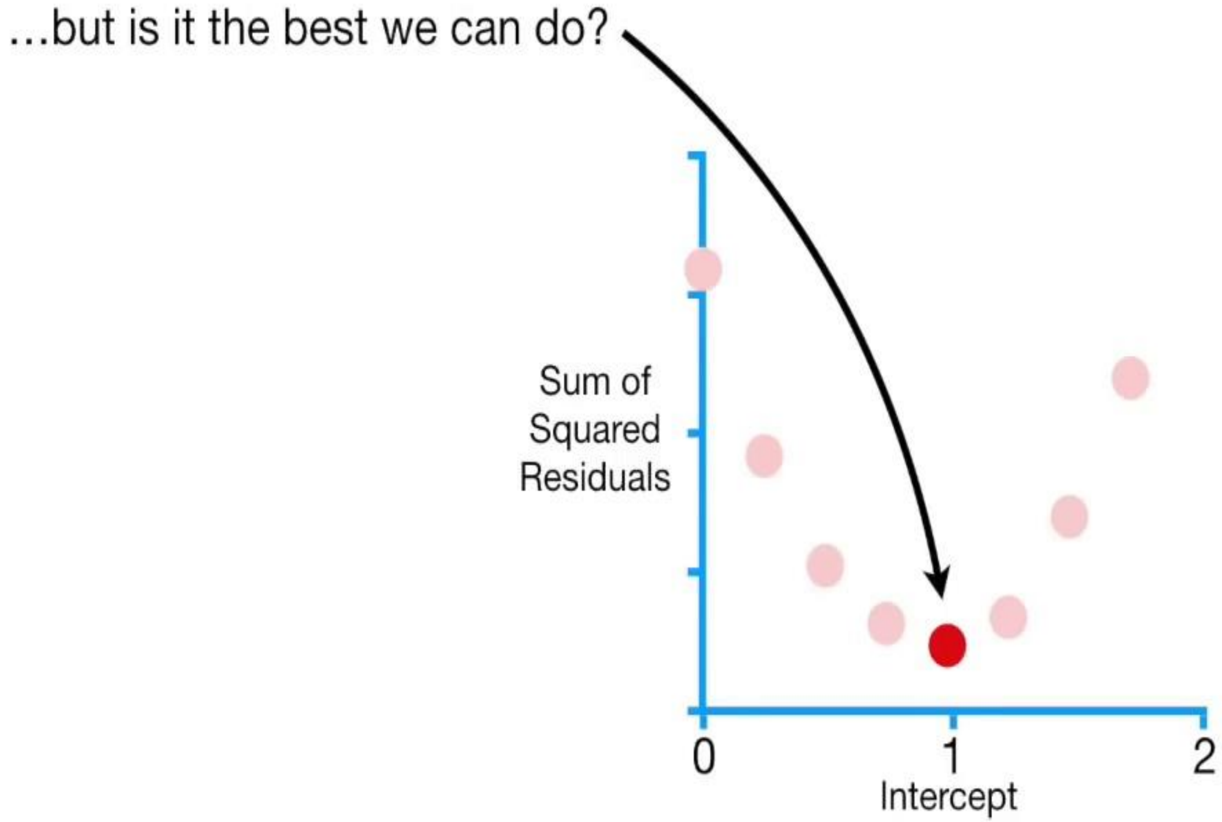

And for increasing values for the
Intercept, we get these points.
Height
Weight
Sum of
Squared
Residuals
0
1
2
Intercept

GD to find *b*

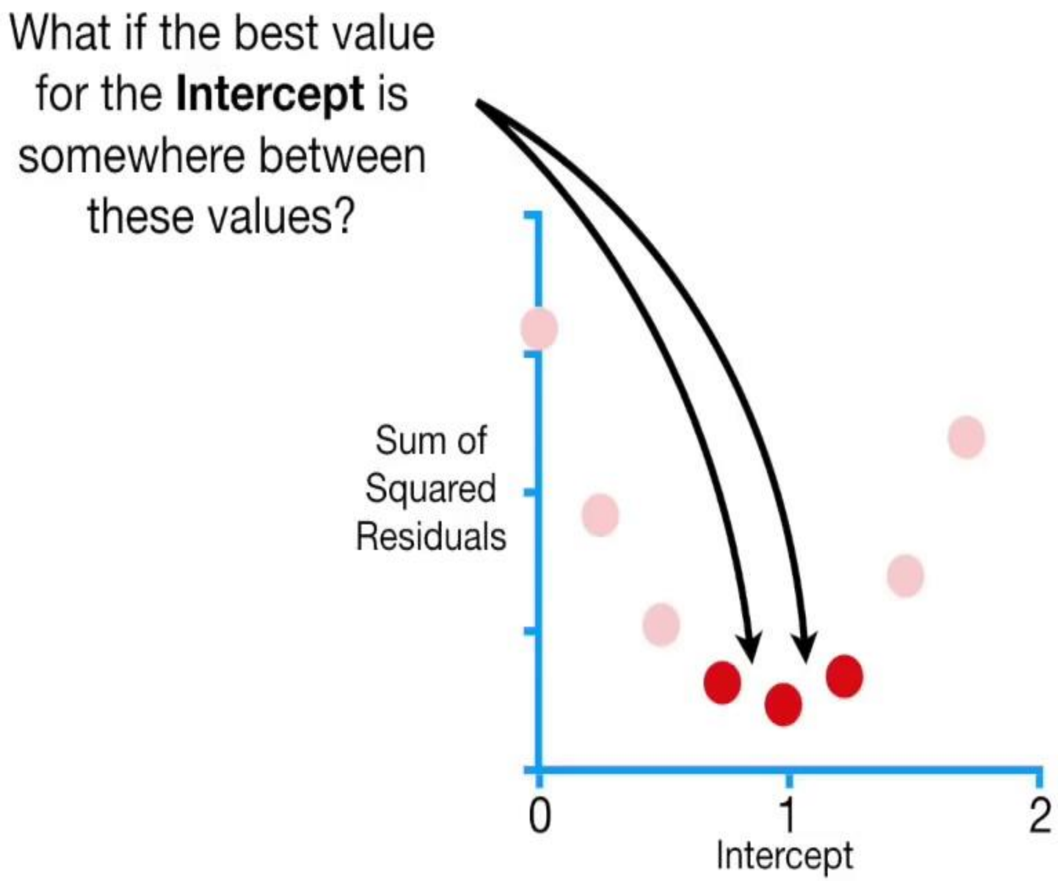


Of the points that we calculated for the graph, this one has the lowest Sum of Squared Residuals...
Sum of Squared Residuals
0
1
2
Intercept

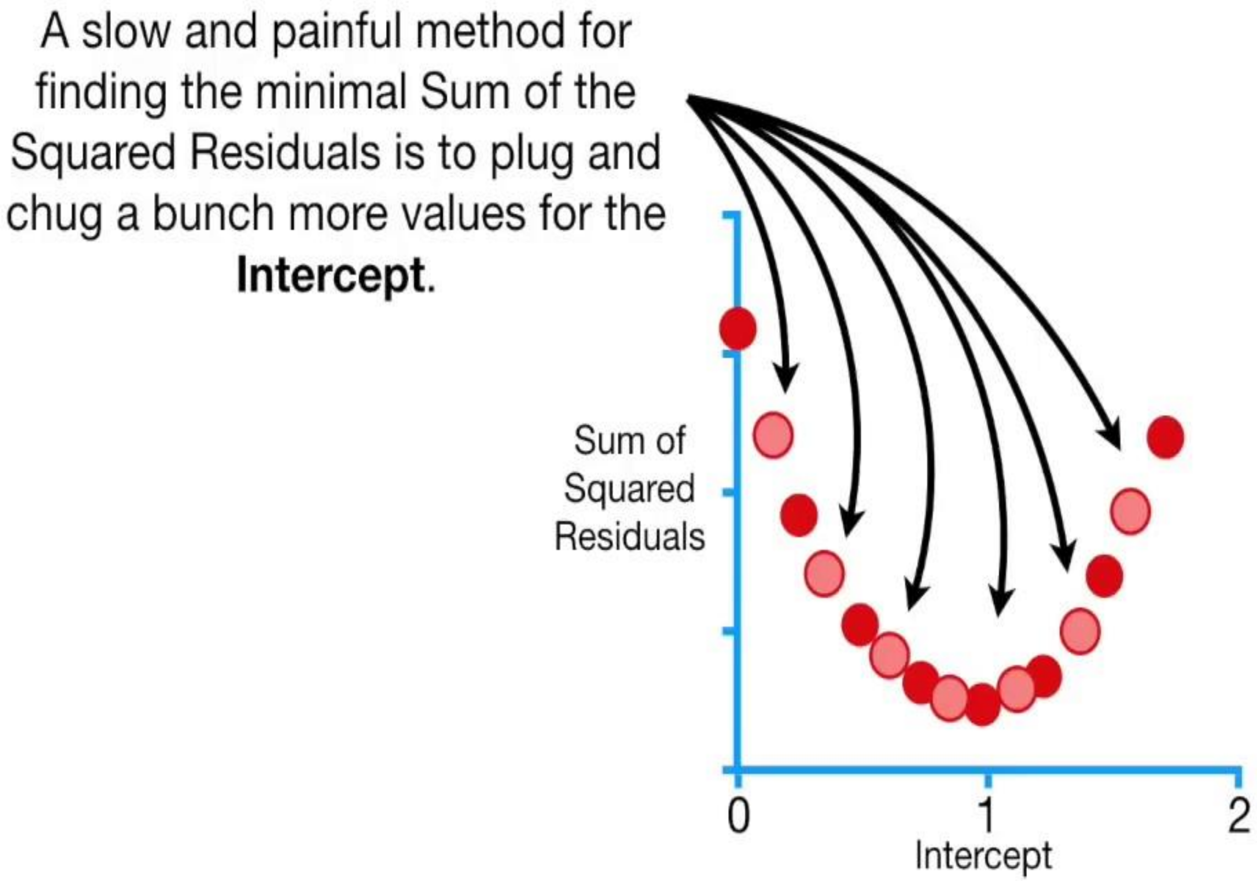
GD to find *b*


...but is it the best we can do?
Sum of
Squared
Residuals
0
1
2
Intercept

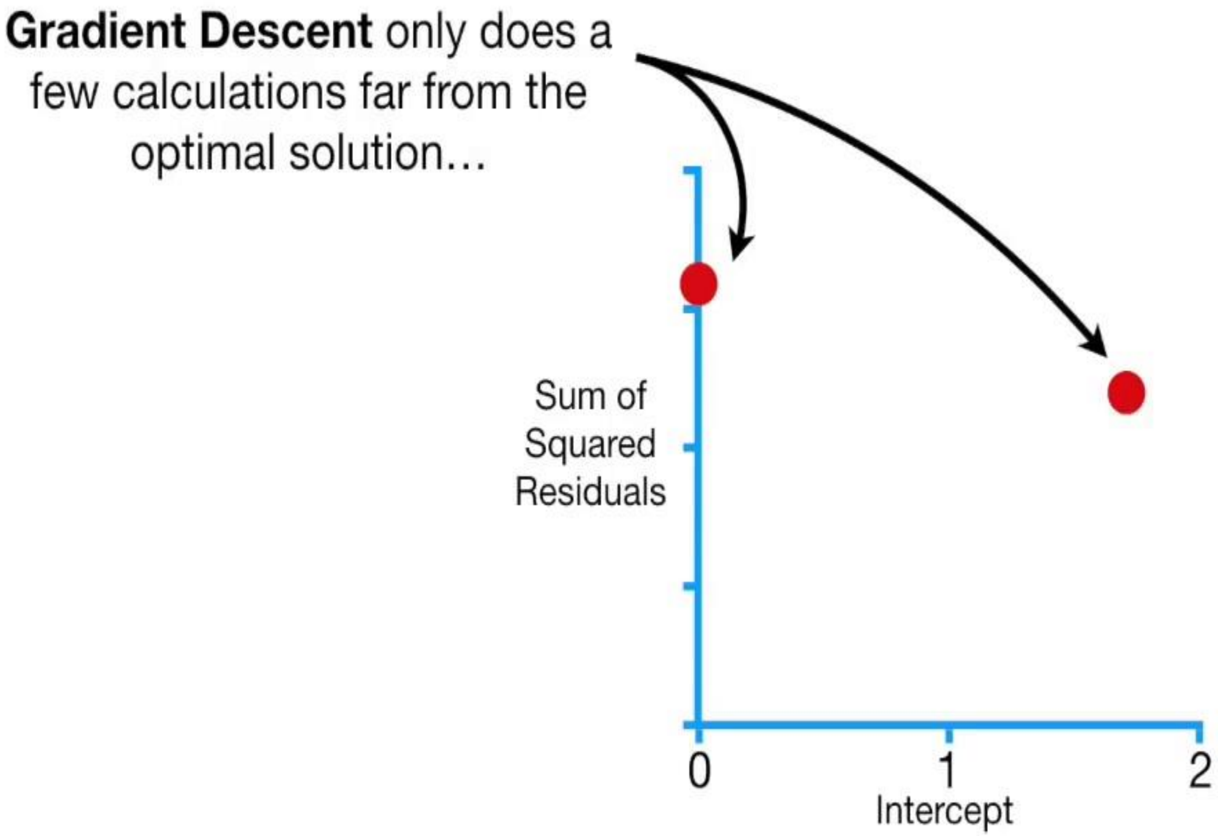
GD to find *b*


What if the best value for the **Intercept** is somewhere between these values?
Sum of Squared Residuals
0
1
2
Intercept

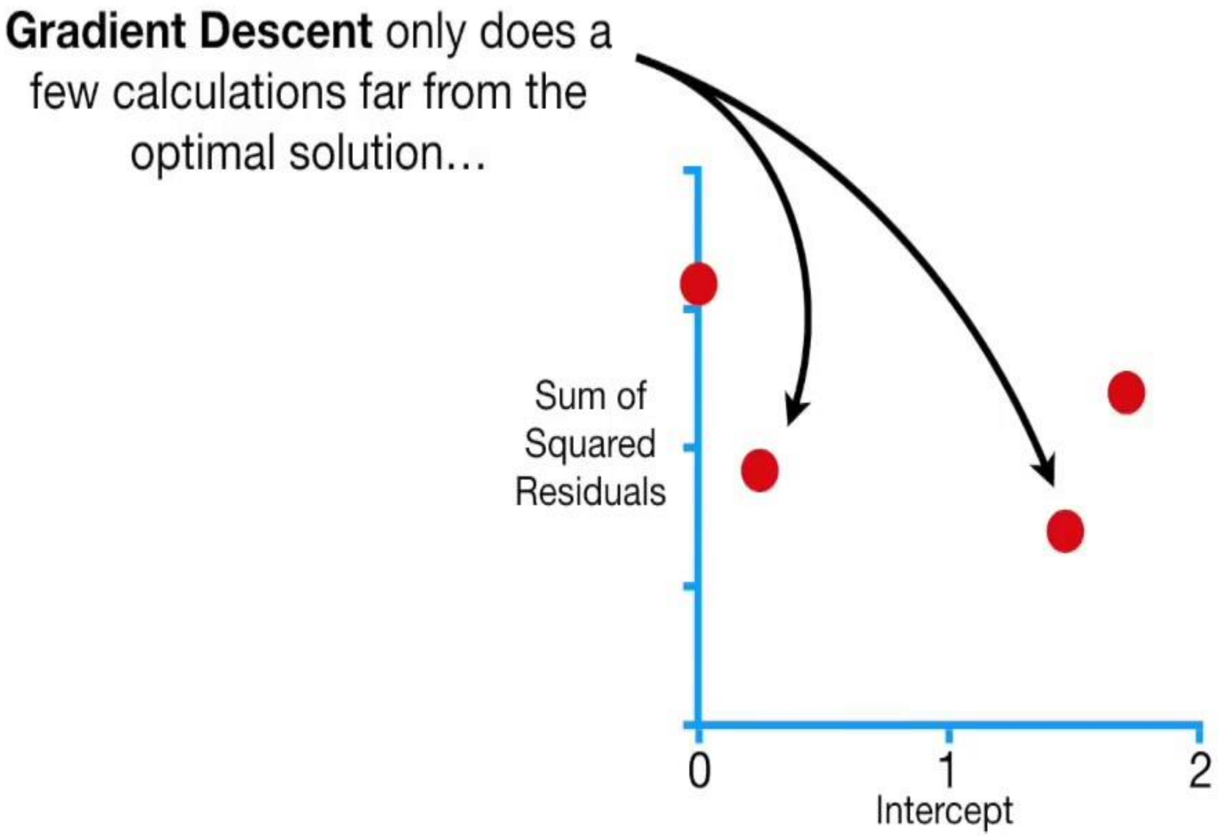
GD to find *b*


A slow and painful method for finding the minimal Sum of the Squared Residuals is to plug and chug a bunch more values for the **Intercept**.
Sum of Squared Residuals
0
1
2
Intercept

GD to find *b*

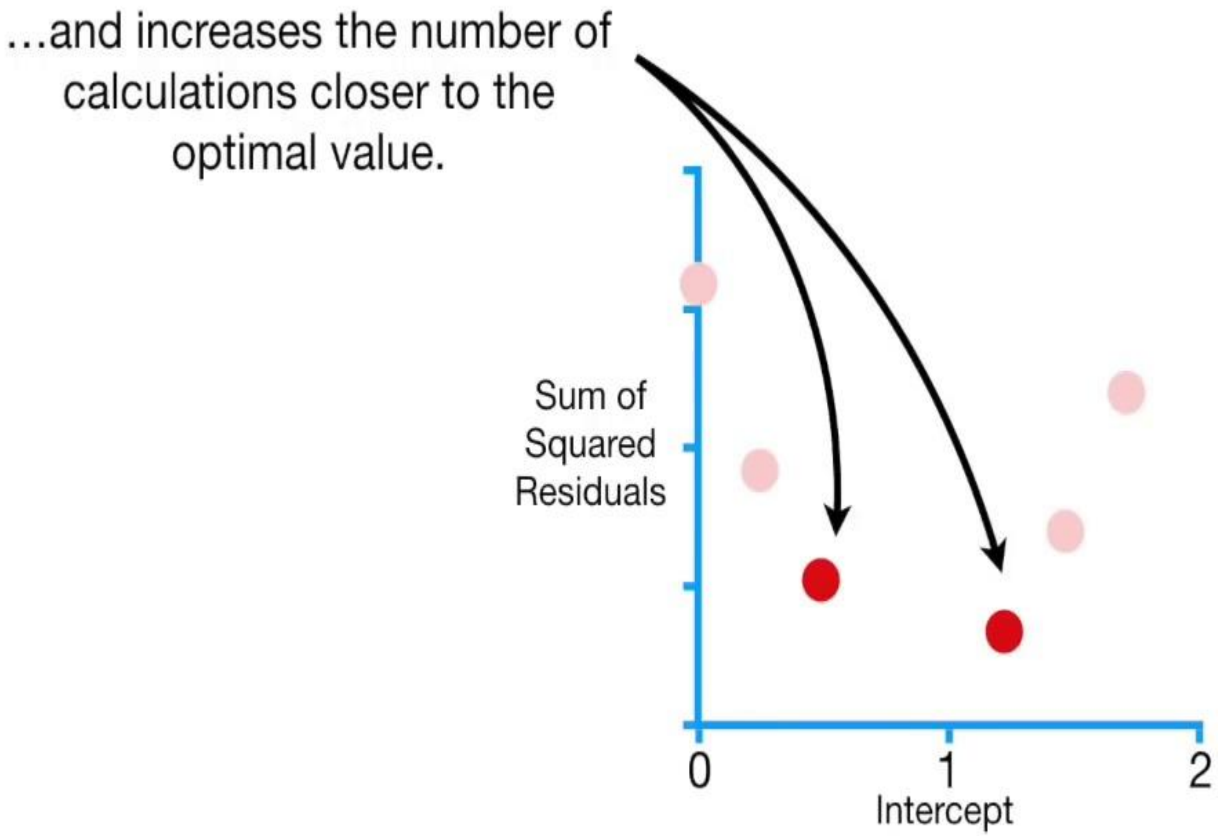

Gradient Descent only does a few calculations far from the optimal solution...
Sum of Squared Residuals
0
1
2
Intercept

GD to find *b*

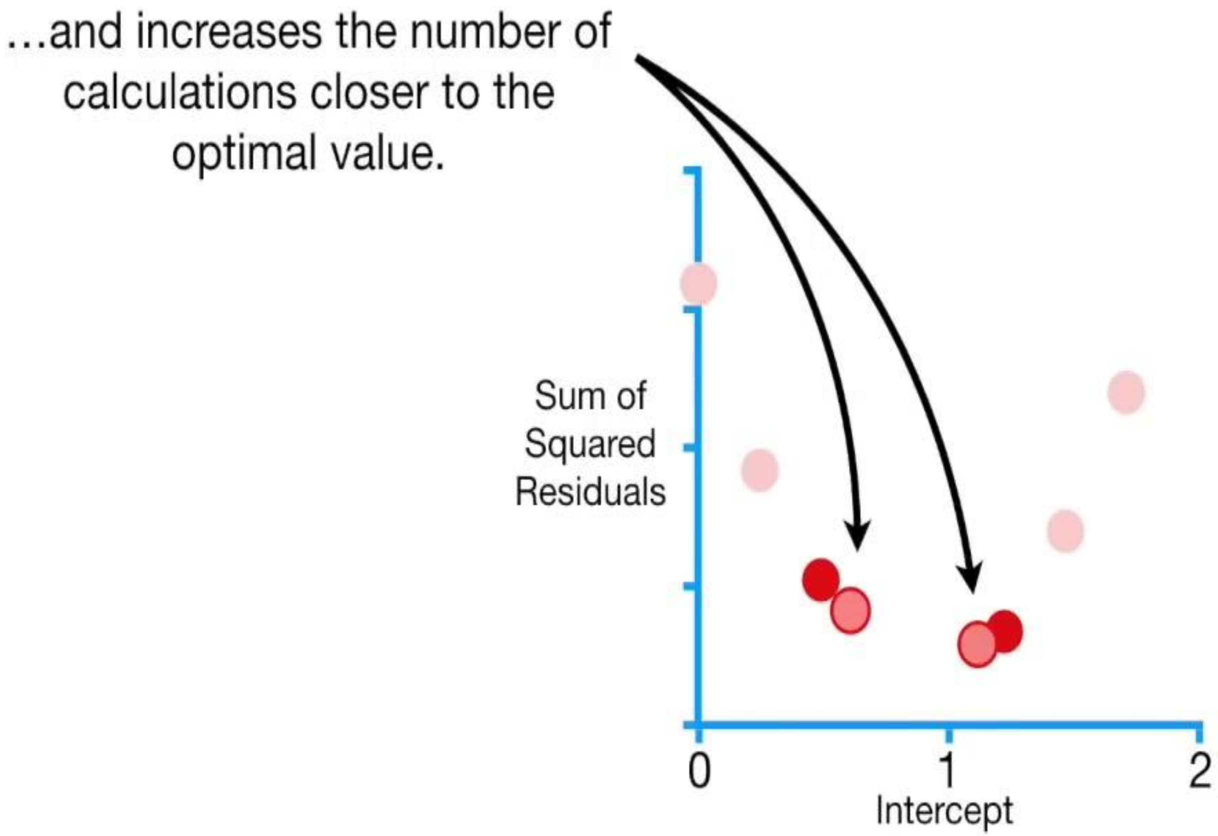


Gradient Descent only does a few calculations far from the optimal solution…
Sum of Squared Residuals
0
1
2
Intercept

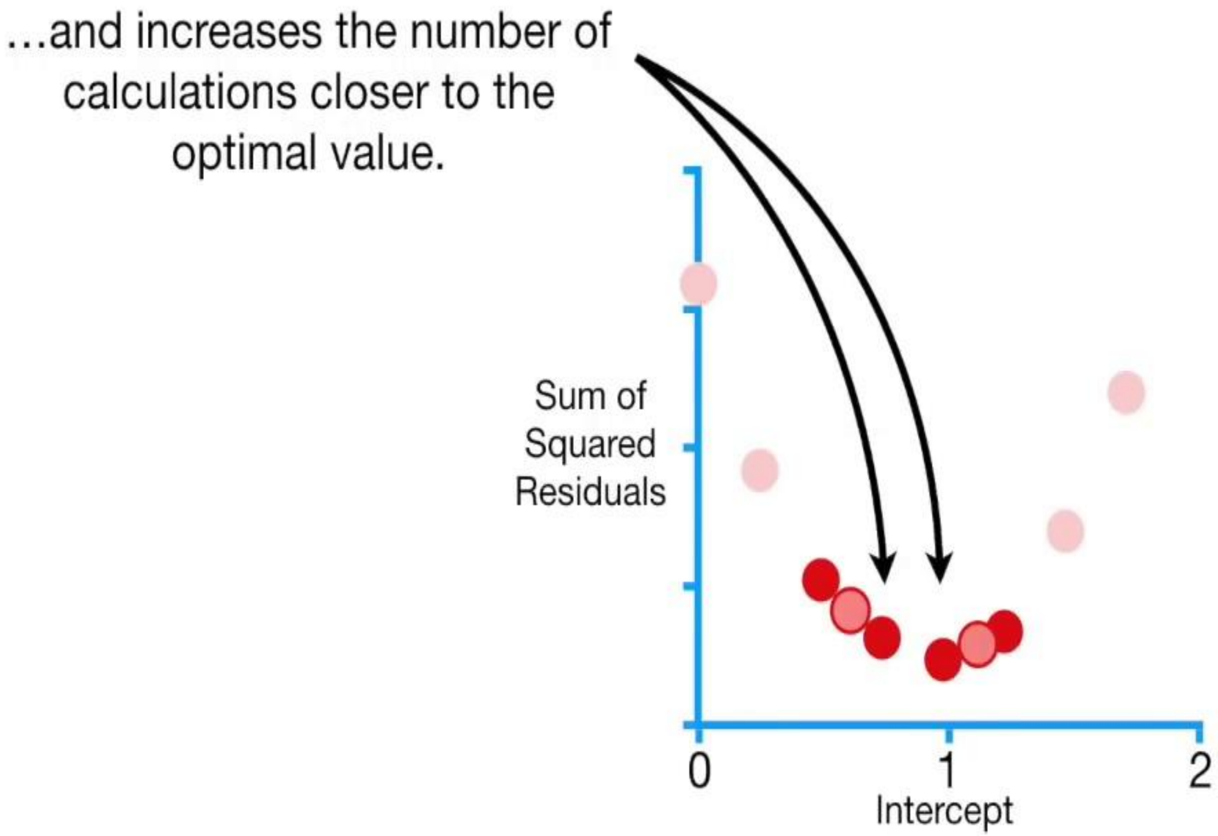
GD to find *b*


...and increases the number of
calculations closer to the
optimal value.
Sum of
Squared
Residuals
0
1
2
Intercept

GD to find *b*

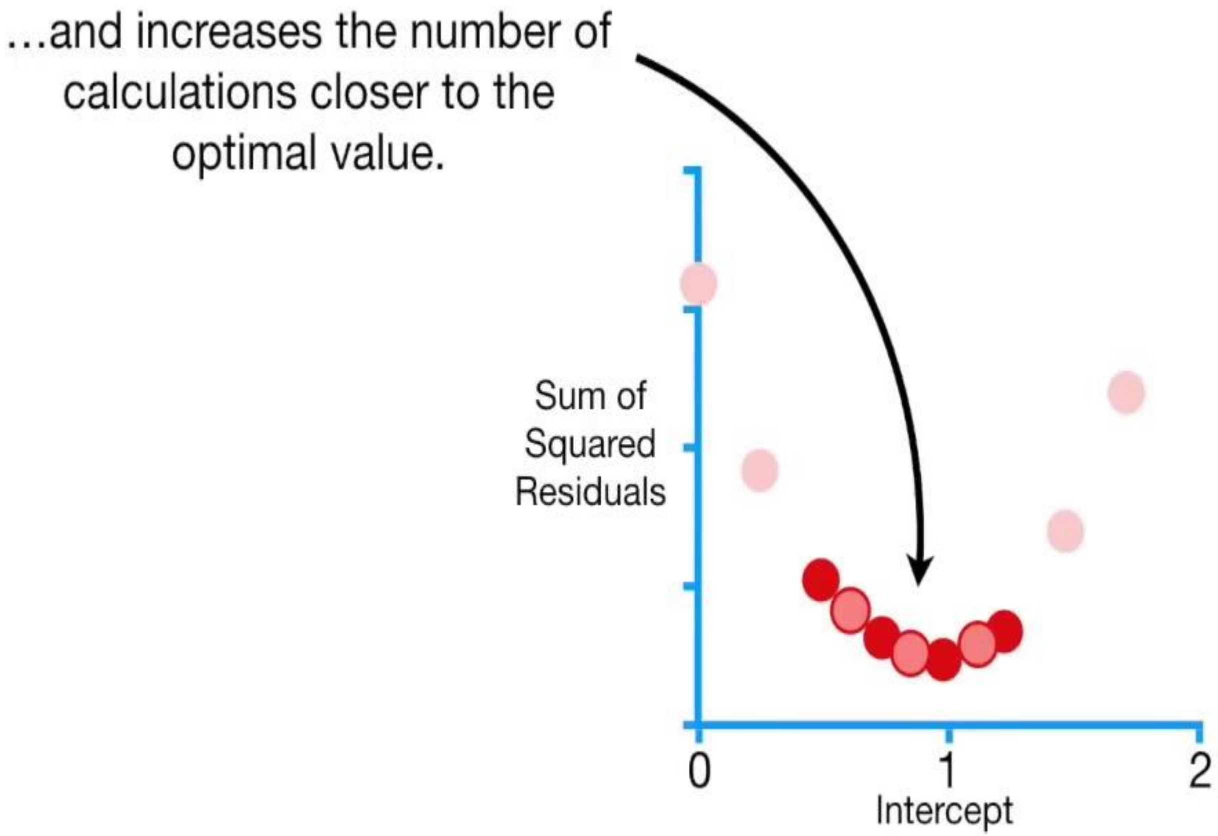

...and increases the number of
calculations closer to the
optimal value.
Sum of
Squared
Residuals
0
1
2
Intercept

GD to find *b*

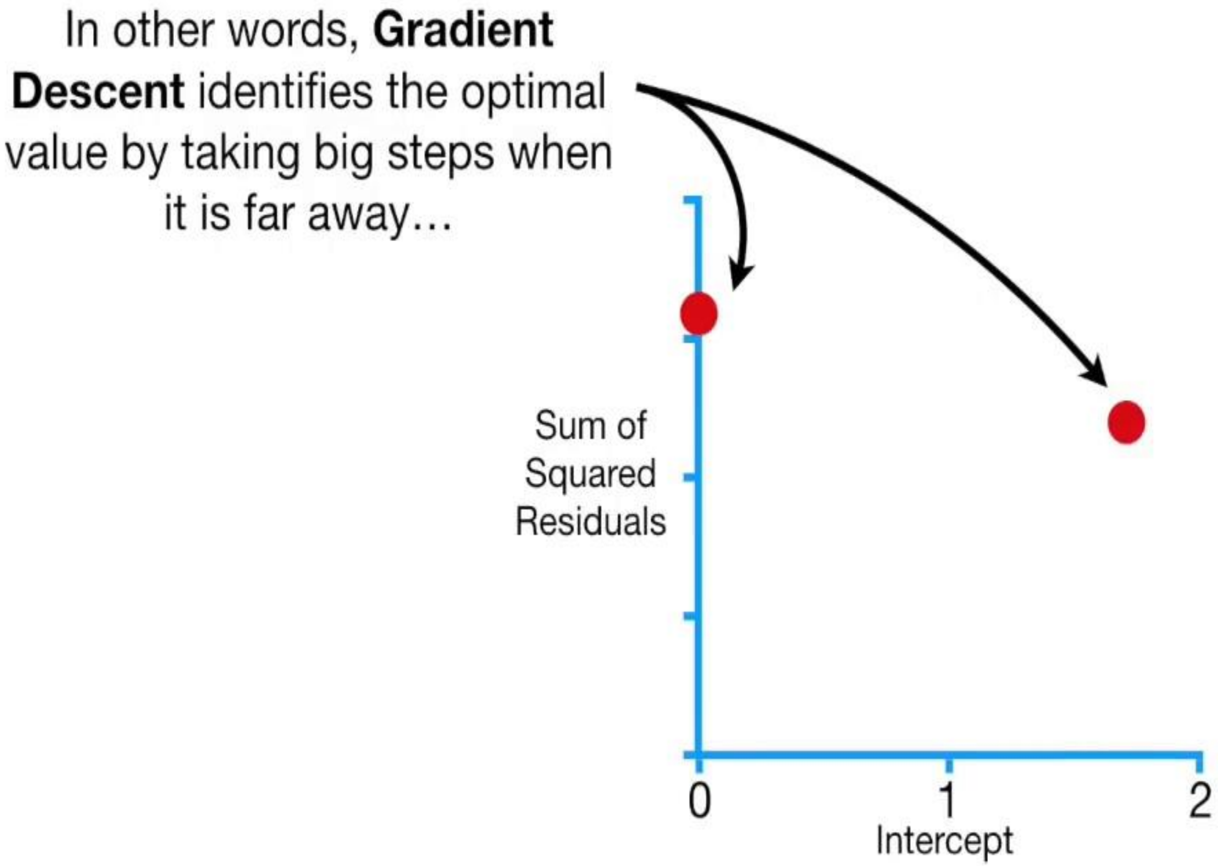


...and increases the number of calculations closer to the optimal value.
Sum of Squared Residuals
0
1
2
Intercept

GD to find *b*

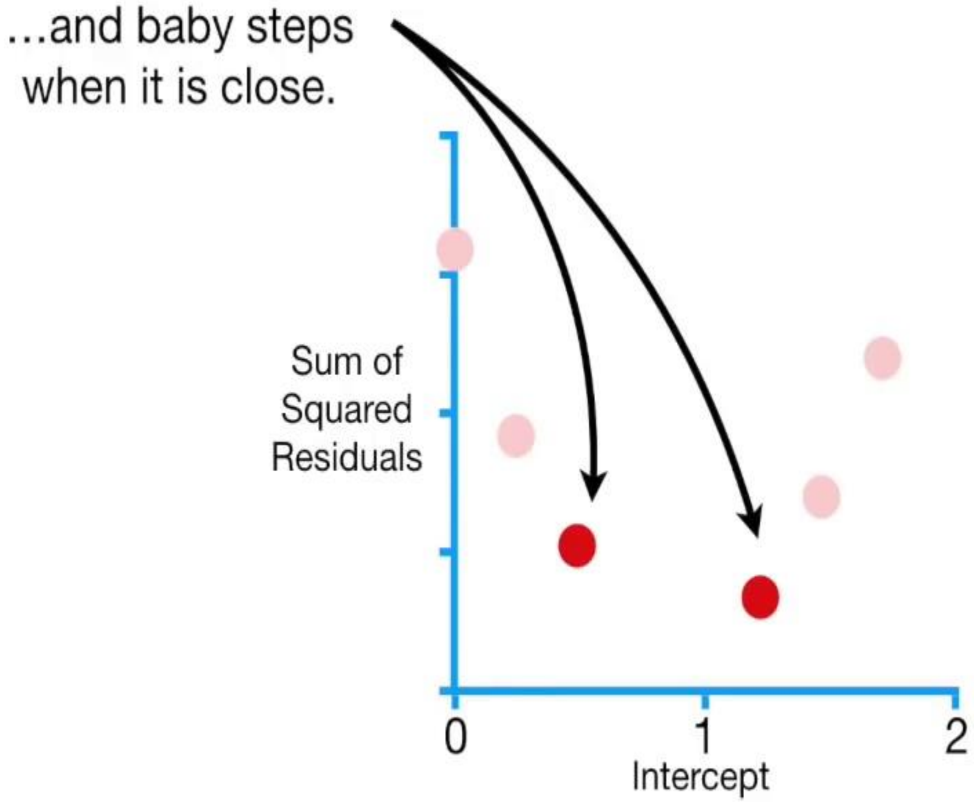

...and increases the number of
calculations closer to the
optimal value.
Sum of
Squared
Residuals
0
1
2
Intercept

GD to find *b*



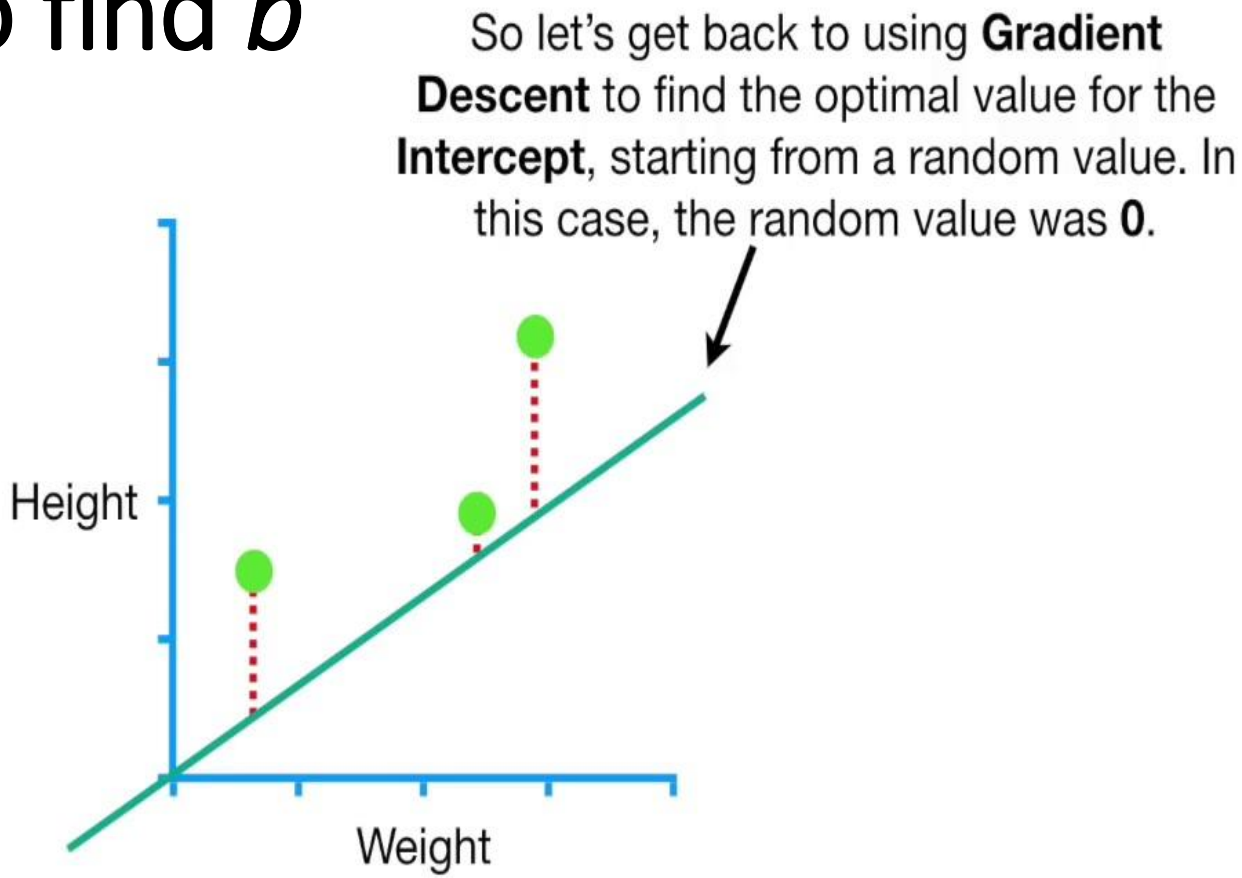
In other words, **Gradient Descent** identifies the optimal value by taking big steps when it is far away…
Sum of Squared Residuals
0
1
2
Intercept

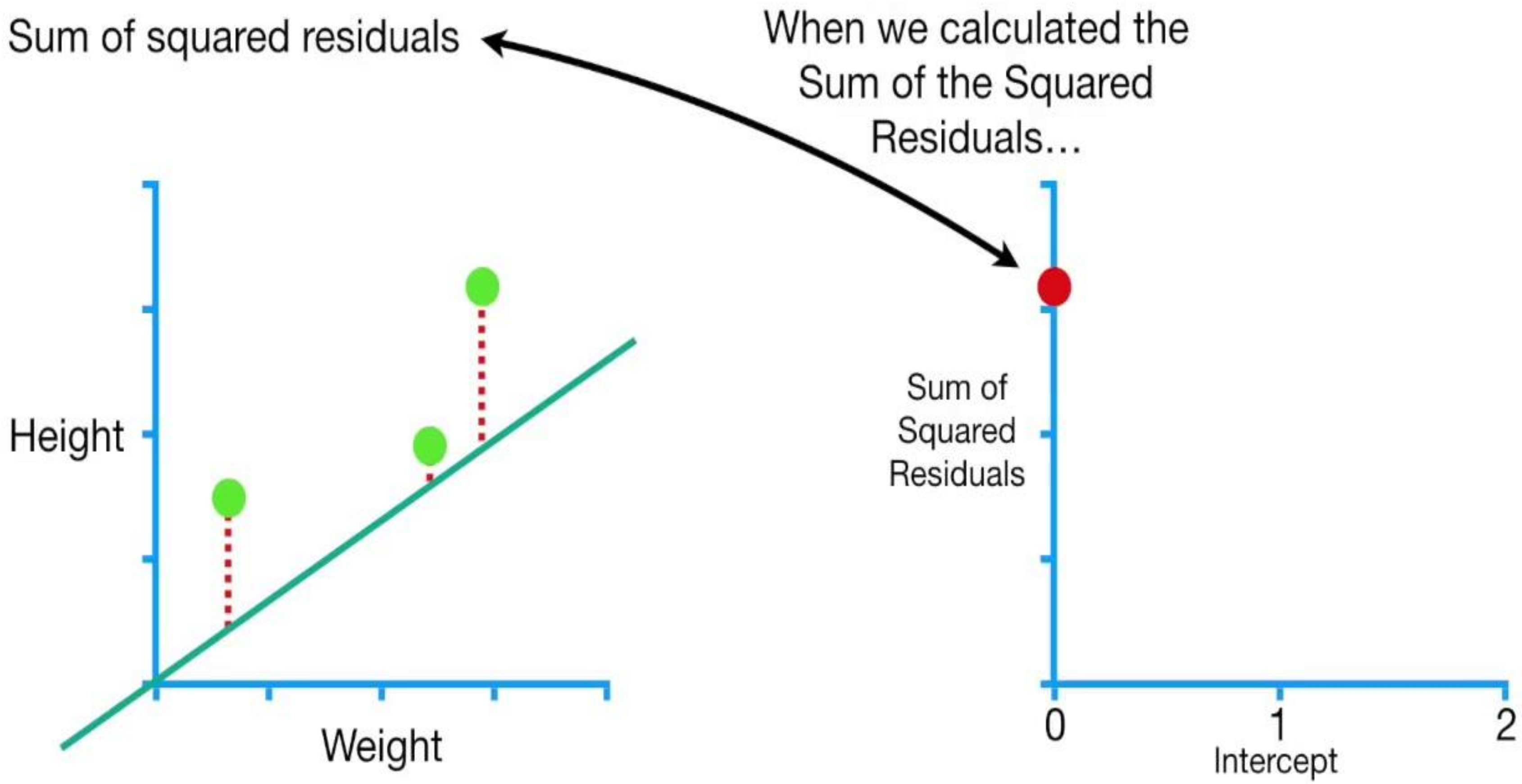
GD to find *b*



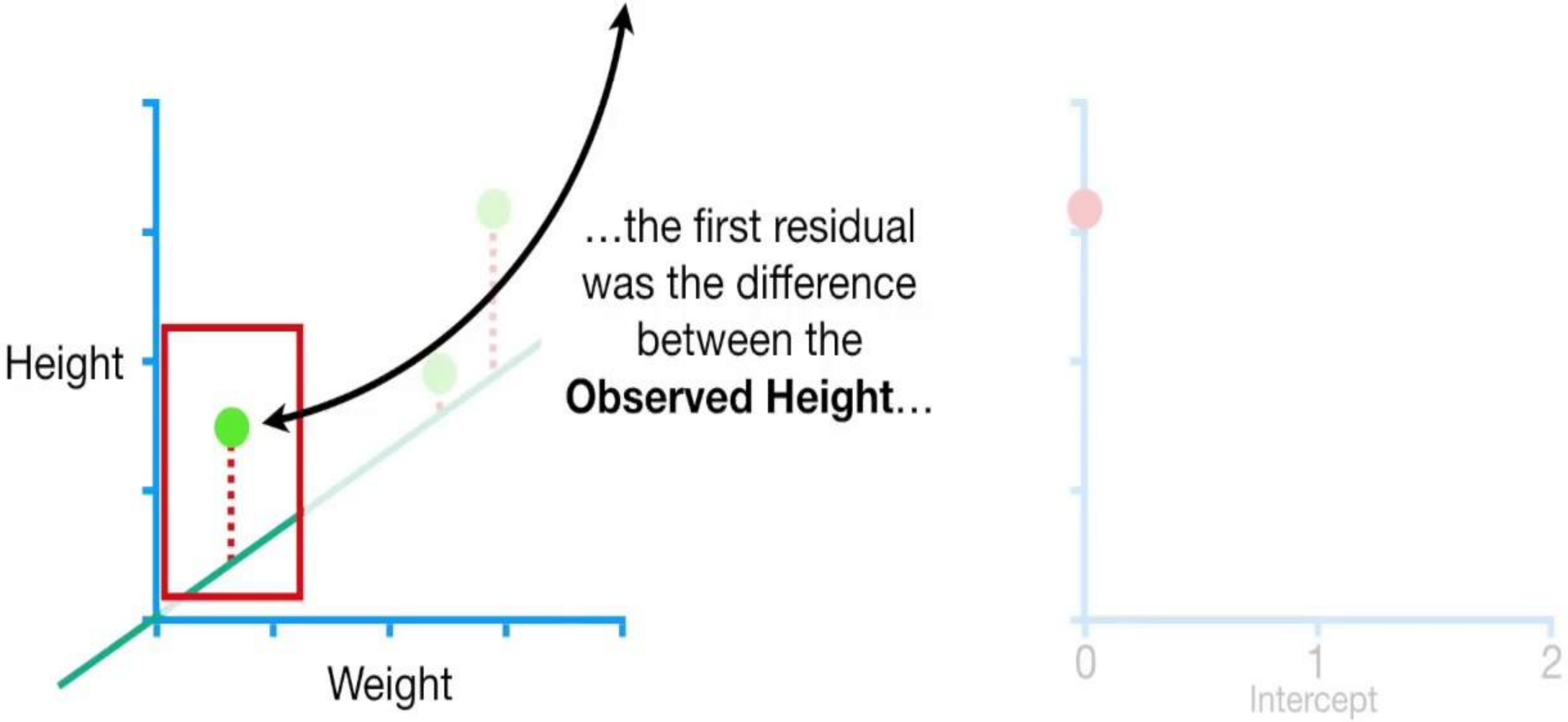
...and baby steps
when it is close.
Sum of
Squared
Residuals
0
1
2
Intercept

GD to find *b*

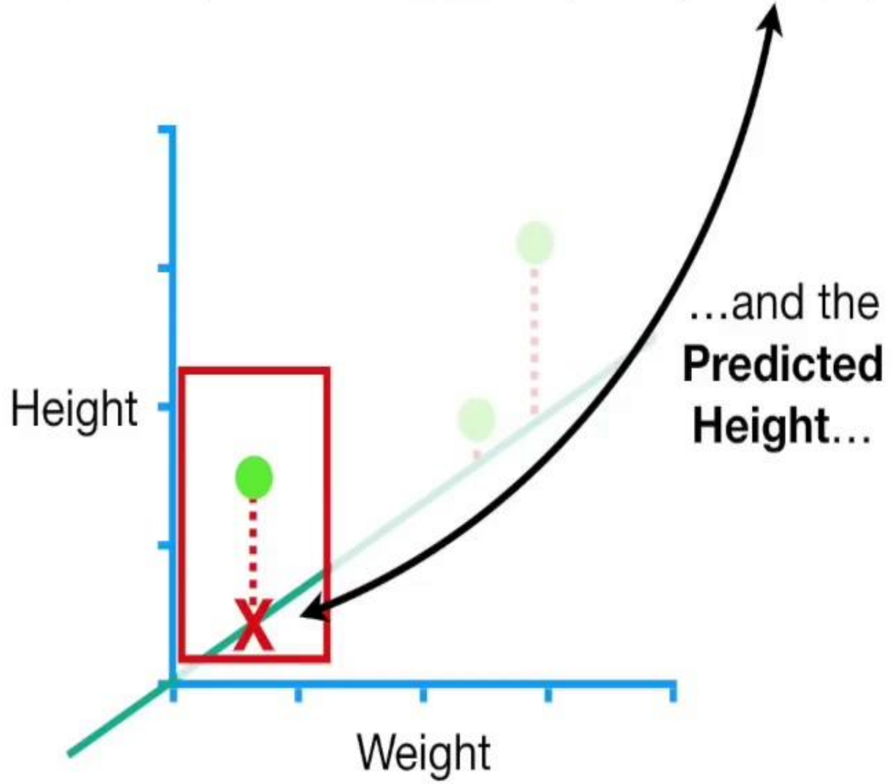

So let's get back to using **Gradient Descent** to find the optimal value for the **Intercept**, starting from a random value. In this case, the random value was **0**.
Height
Weight

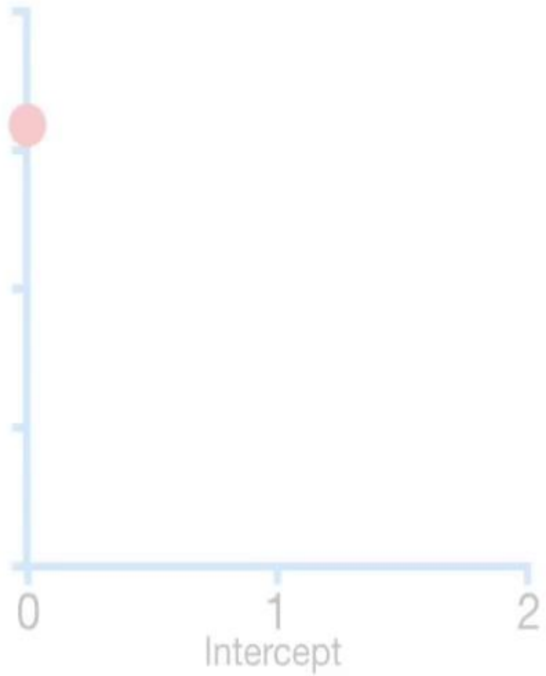

Sum of squared residuals
When we calculated the Sum of the Squared Residuals...
Height
Weight
Sum of Squared Residuals
0
1
2
Intercept

Sum of squared residuals = $(\text{observed} - \text{predicted})^2$

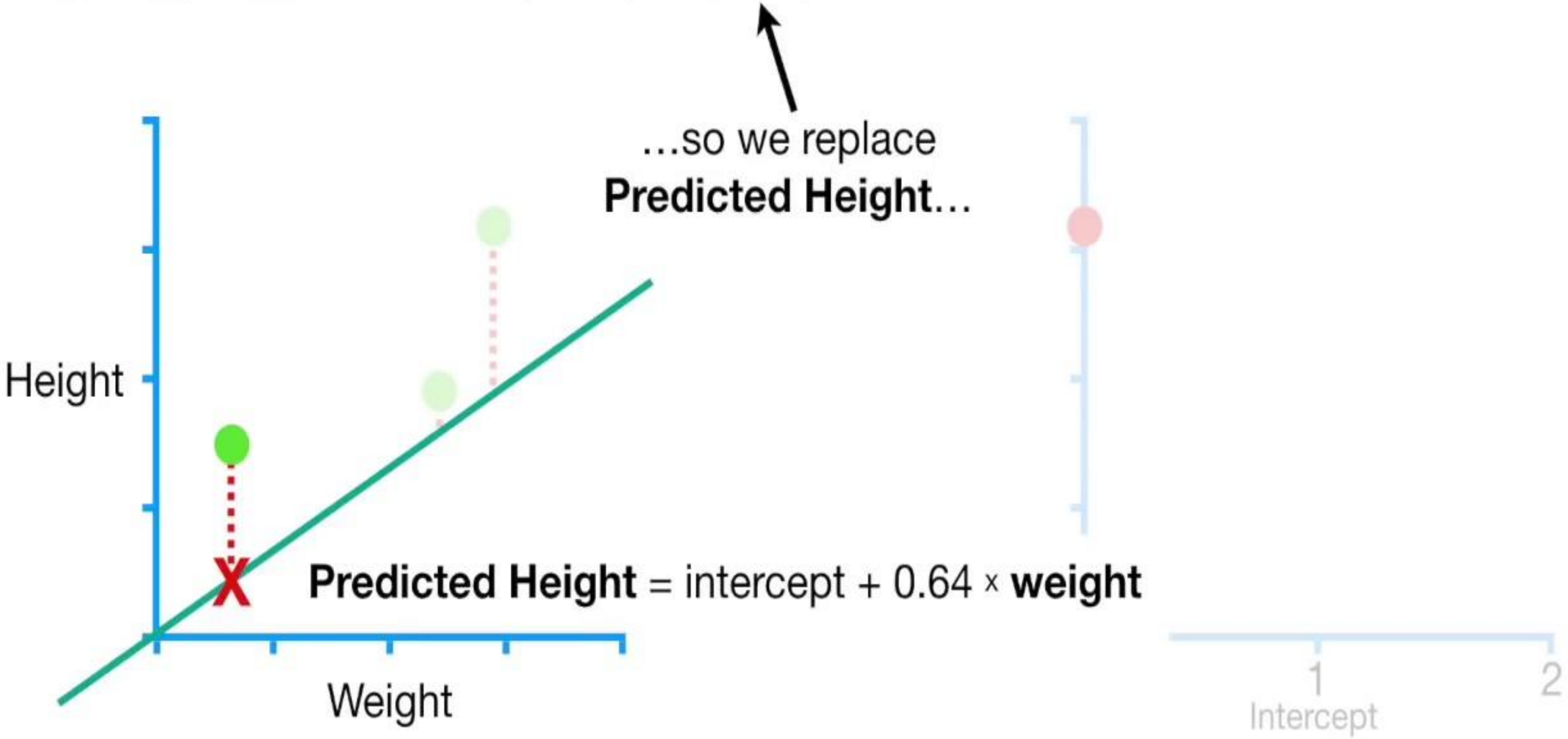


Sum of squared residuals = (**1.4** - predicted)^2



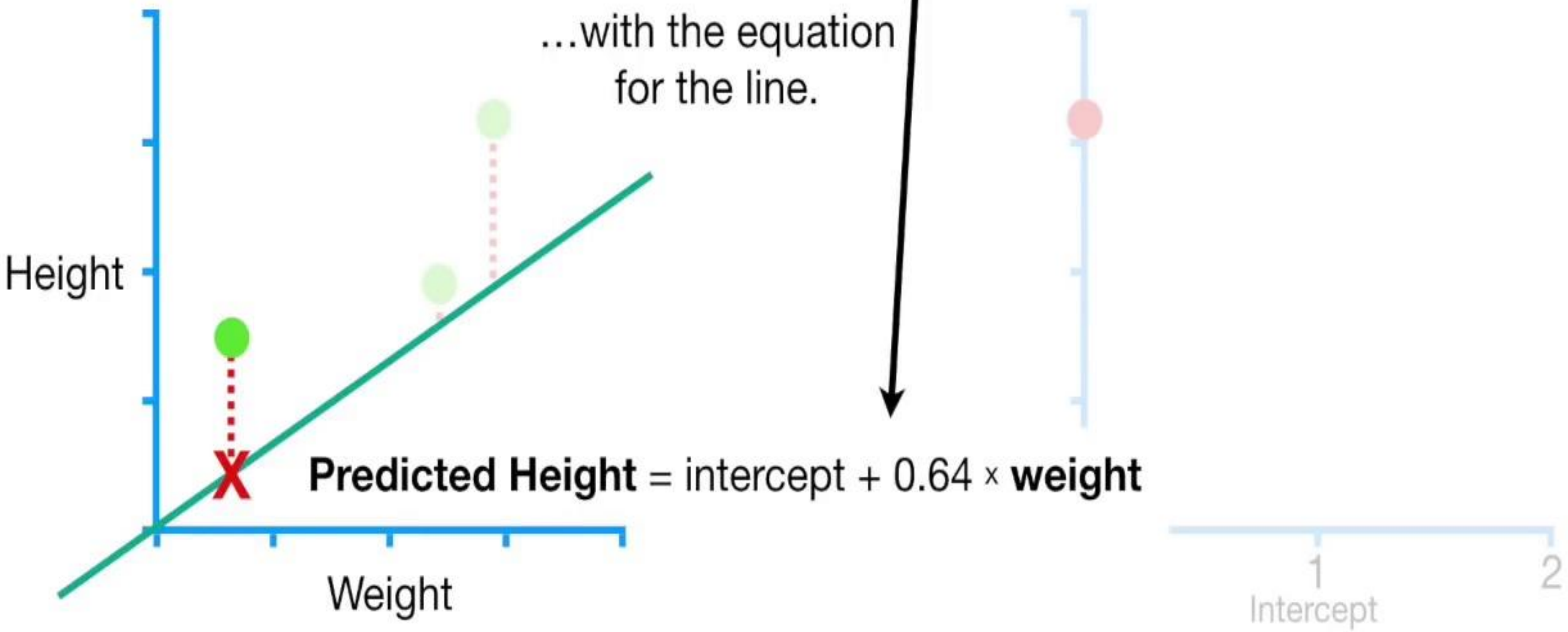


Sum of squared residuals = (**1.4** - predicted)^2



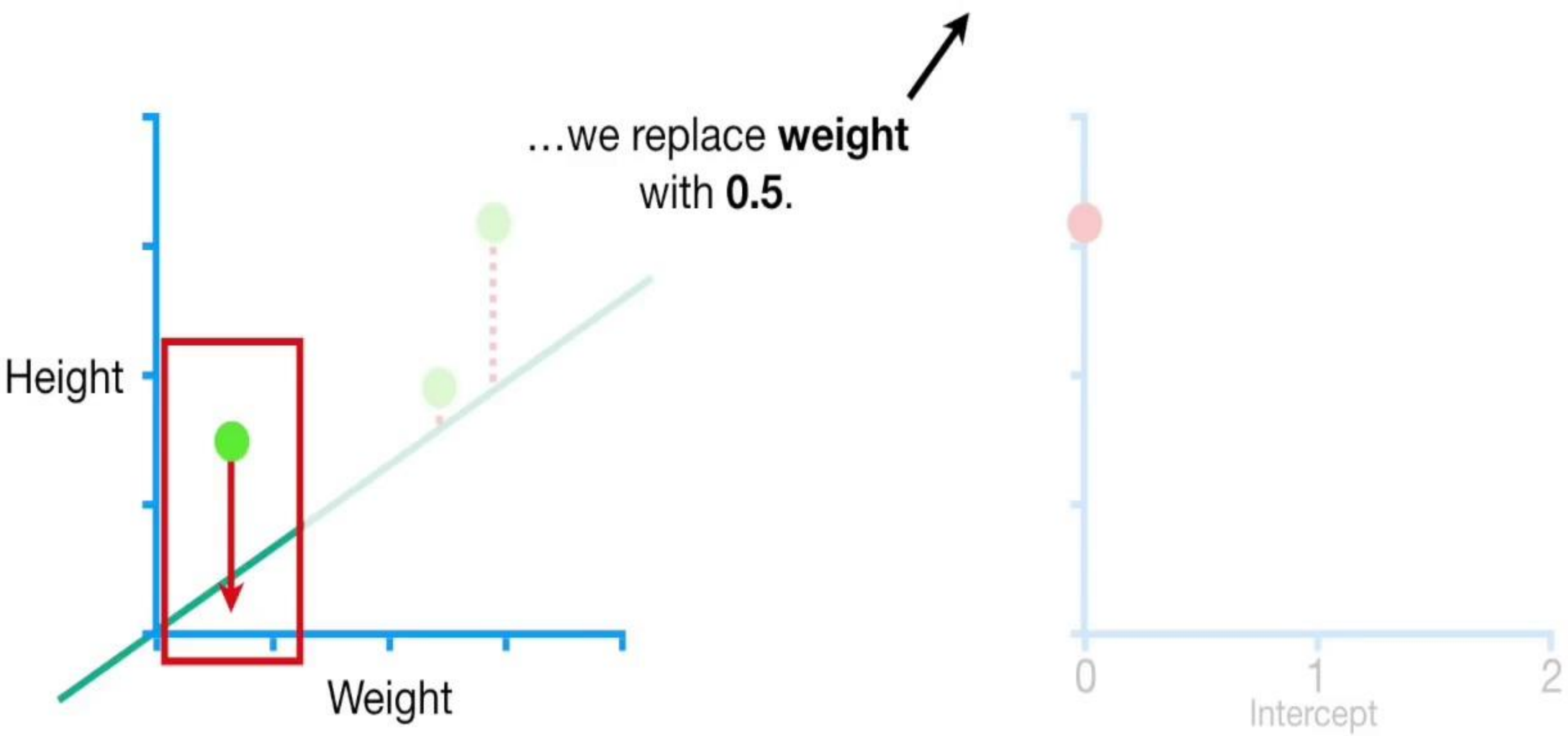
Sum of squared residuals = (**1.4** - (intercept + 0.64 × **weight**))^2

...with the equation for the line.

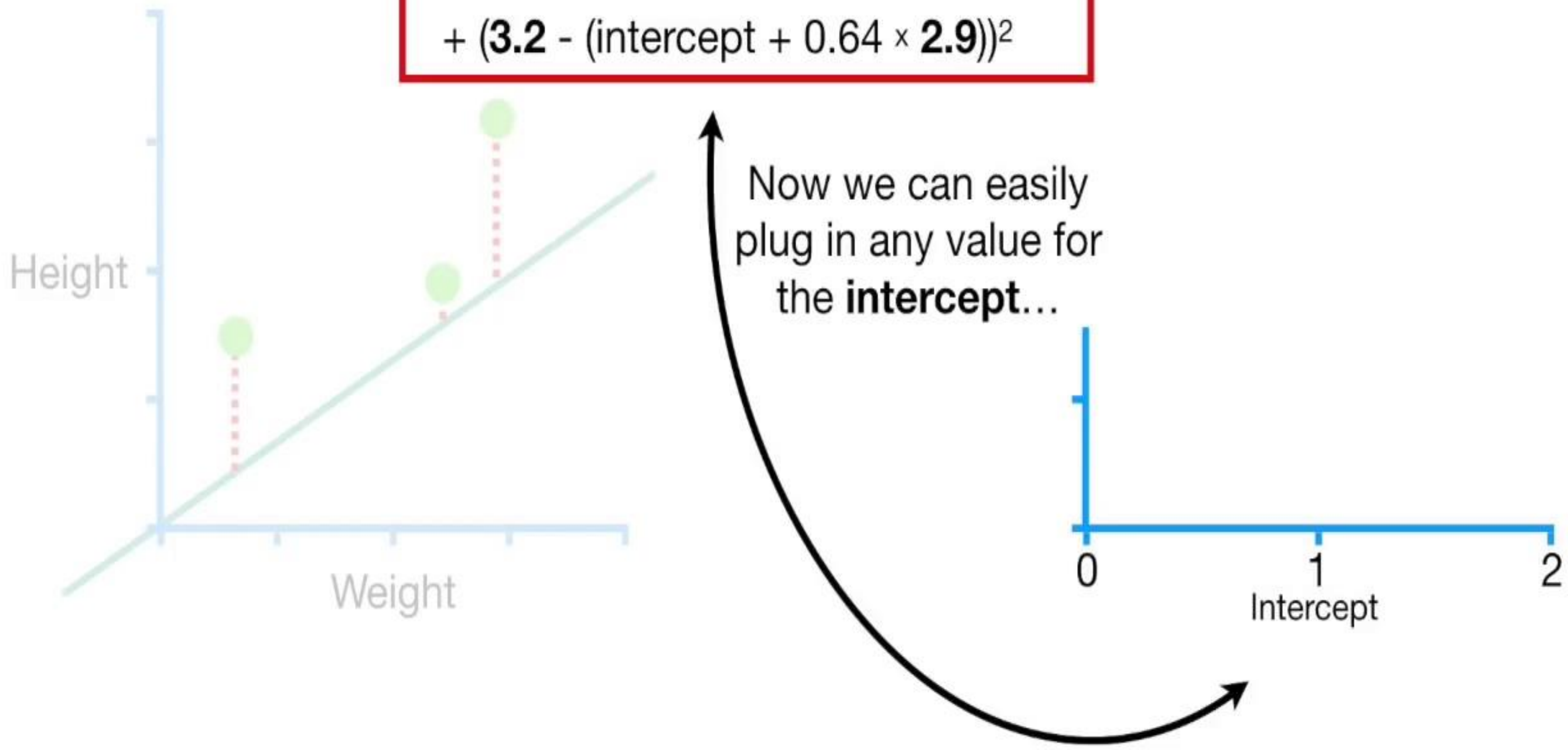


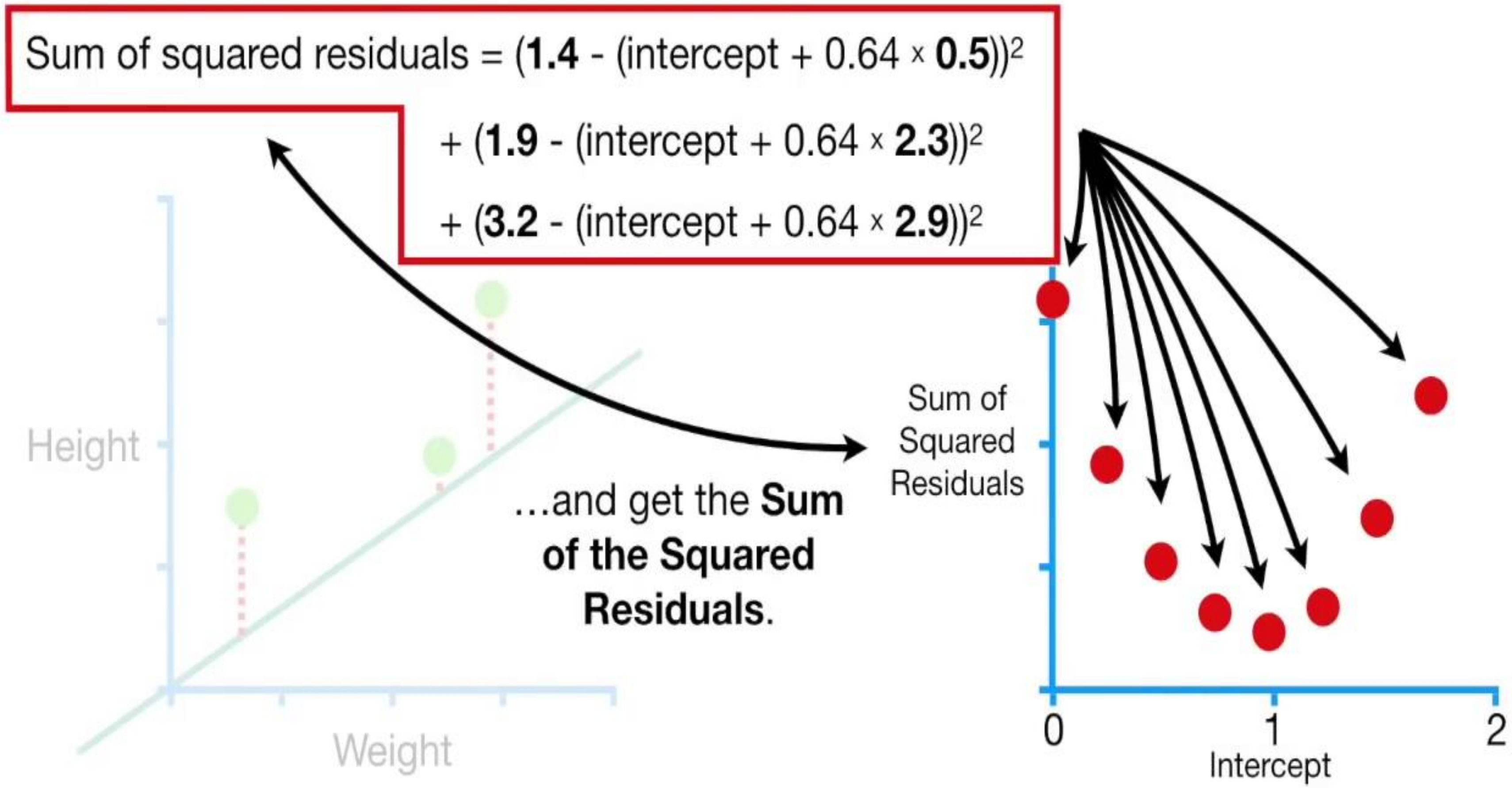
Predicted Height = intercept + 0.64 × **weight**

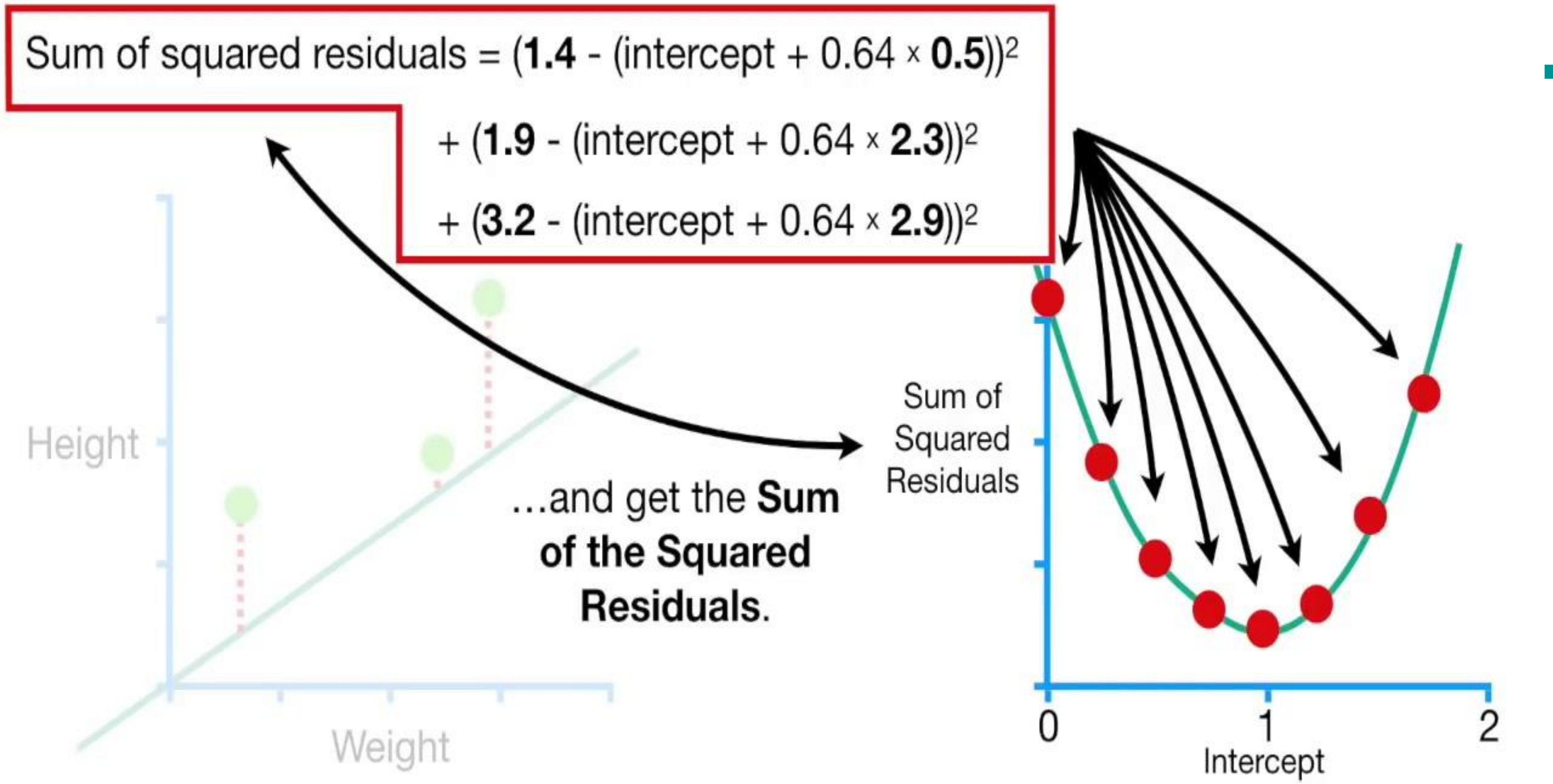
Sum of squared residuals = (**1.4** - (intercept + 0.64 × **0.5**))^2



$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))^2$$
$$+ (\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))^2$$
$$+ (\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))^2$$



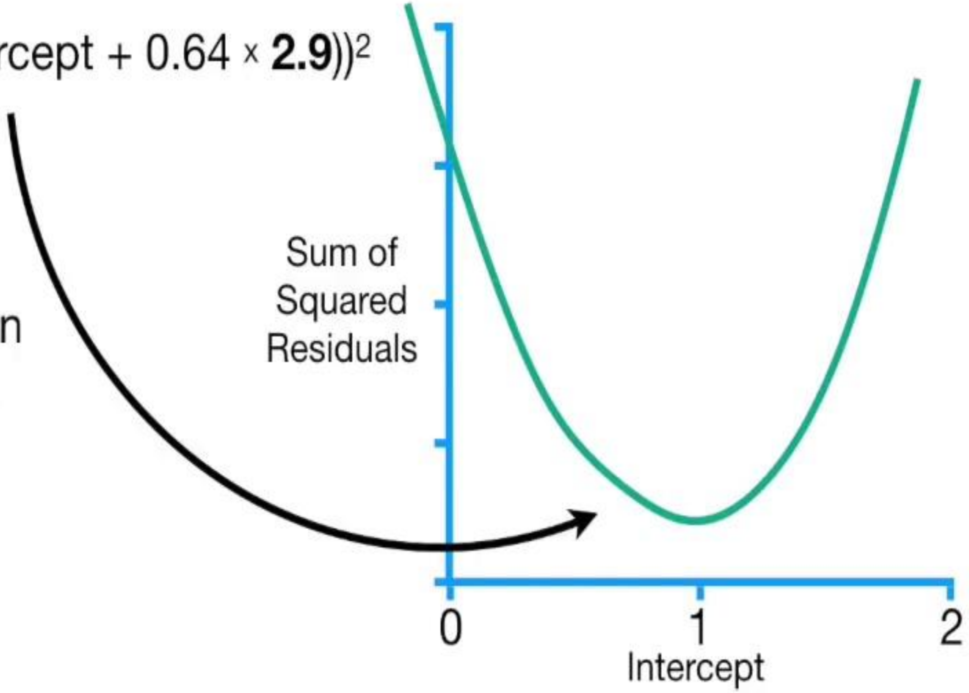

Sum of squared residuals = (1.4 - (intercept + 0.64 x 0.5))2
+ (1.9 - (intercept + 0.64 x 2.3))2
+ (3.2 - (intercept + 0.64 x 2.9))2
Height
Weight
...and get the Sum of the Squared Residuals.
Sum of Squared Residuals
0
1
2
Intercept



Sum of squared residuals = (1.4 - (intercept + 0.64 x 0.5))2
+ (1.9 - (intercept + 0.64 x 2.3))2
+ (3.2 - (intercept + 0.64 x 2.9))2
Height
Weight
...and get the Sum of the Squared Residuals.
Sum of Squared Residuals
0
1
2
Intercept

$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))^2 + (\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))^2 + (\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))^2$$

Thus, we now have an equation for this curve…

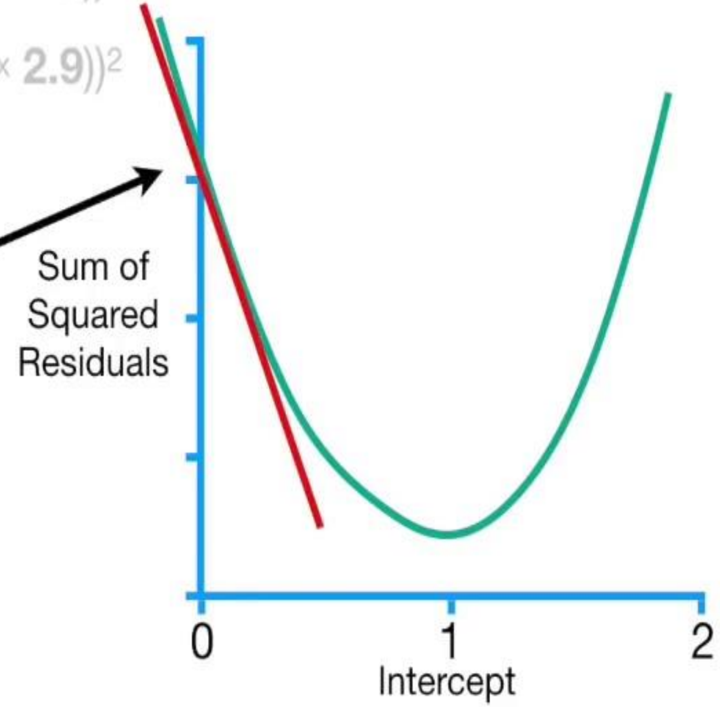


Sum of squared residuals = (**1.4** - (intercept + 0.64 × **0.5**))^2

+ (**1.9** - (intercept + 0.64 × **2.3**))^2

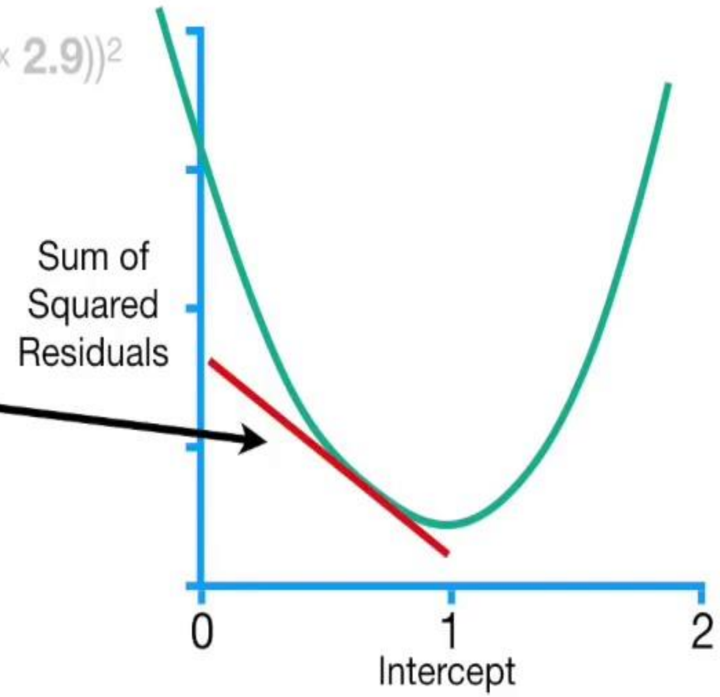
+ (**3.2** - (intercept + 0.64 × **2.9**))^2

…and we can take the derivative of this function and determine the slope at any value for the **Intercept**.



$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))^2 + (\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))^2 + (\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))^2$$

…and we can take the derivative of this function and determine the slope at any value for the **Intercept**.

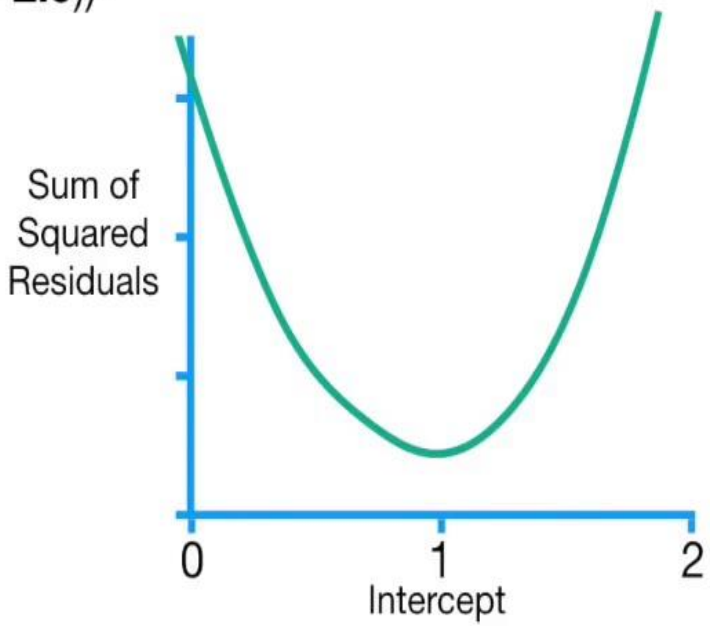


Sum of squared residuals = $(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))^2$

$+ (\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))^2$

$+ (\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))^2$

So let's take the derivative of the Sum of the Squared Residuals with respect to the **Intercept**.



$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))^2$$
$$+ (\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))^2$$
$$+ (\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))^2$$

$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} =$$

$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))^2$$

$$+ (\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))^2$$

$$+ (\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))^2$$

…the derivative of the first part…

$$\frac{d}{d\ intercept} \text{Sum of squared residuals} = \frac{d}{d\ intercept} (\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))^2$$

$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))^2$$
$$+ (\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))^2$$
$$+ (\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))^2$$

…plus the derivative of the second part…

$$\frac{d}{d\,\textit{intercept}} \text{Sum of squared residuals} = \frac{d}{d\,\textit{intercept}} (\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))^2$$
$$+ \frac{d}{d\,\textit{intercept}} (\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))^2$$

$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))^2$$

$$+ (\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))^2$$

$$+ (\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))^2$$

...plus the derivative of the third part.

$$\frac{d}{d\,\textit{intercept}} \text{Sum of squared residuals} = \frac{d}{d\,\textit{intercept}} (\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))^2$$

$$+ \frac{d}{d\,\textit{intercept}} (\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))^2$$

$$+ \frac{d}{d\,\textit{intercept}} (\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))^2$$

$$\frac{d}{d\ intercept}(\mathbf{1.4} - (intercept + 0.64 \times \mathbf{0.5}))^2 = 2(\mathbf{1.4} - (intercept + 0.64 \times \mathbf{0.5})) \times -1$$

$$= -2(\mathbf{1.4} - (intercept + 0.64 \times \mathbf{0.5}))$$

...and this...

...is the derivative of the first part...

$$\frac{d}{d\ intercept} \text{Sum of squared residuals} = \frac{d}{d\ intercept}(\mathbf{1.4} - (intercept + 0.64 \times \mathbf{0.5}))^2$$

$$+ \frac{d}{d\ intercept}(\mathbf{1.9} - (intercept + 0.64 \times \mathbf{2.3}))^2$$

$$+ \frac{d}{d\ intercept}(\mathbf{3.2} - (intercept + 0.64 \times \mathbf{2.9}))^2$$

$$\frac{d}{d\ intercept}(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))^2 = 2(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5})) \times -1$$

$$= -2(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))$$

...so we plug it in.

$$\frac{d}{d\ intercept}\text{Sum of squared residuals} = -2(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))$$

$$+ \frac{d}{d\ intercept}(\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))^2$$

$$+ \frac{d}{d\ intercept}(\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))^2$$

GD to find *b*

Now we need to take the derivative of the next two parts.

$$\frac{d}{d\ intercept} \text{Sum of squared residuals} = -2(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))$$

$$+ \frac{d}{d\ intercept} (\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))^2$$

$$+ \frac{d}{d\ intercept} (\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))^2$$

GD to find *b*

$$\frac{d}{d\ intercept}\text{Sum of squared residuals} = -2(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5})$$

$$+ -2(\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))$$

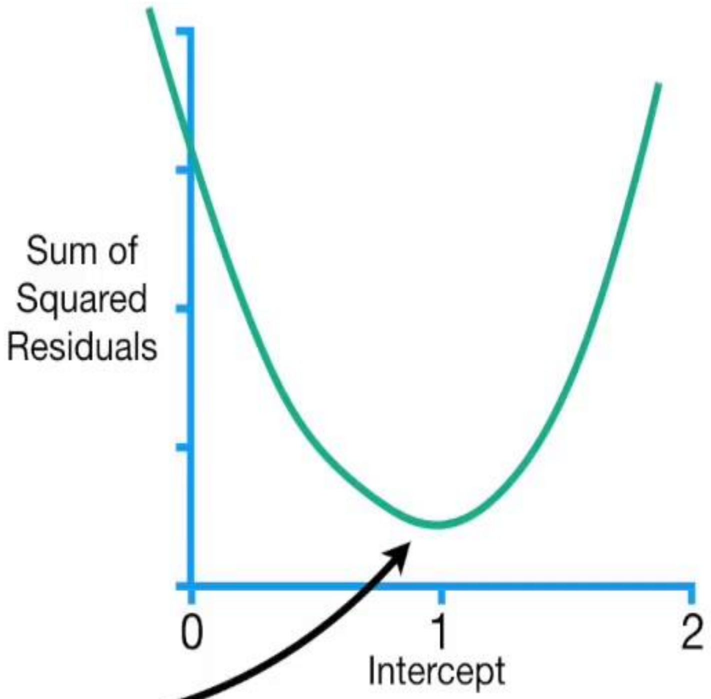
$$+ -2(\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))$$

$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))$$

$$+ -2(\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))$$



Now that we have the derivative, **Gradient Descent** will use it to find where the Sum of Squared Residuals is lowest.

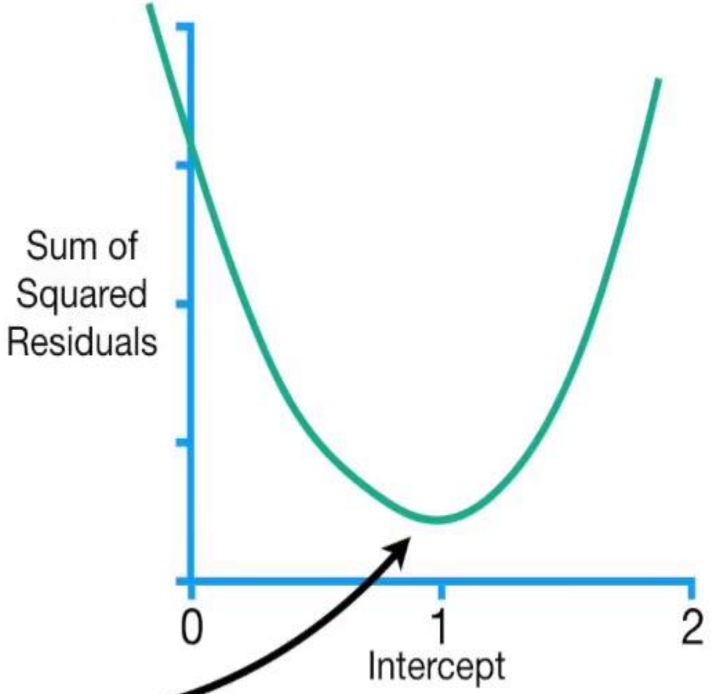
$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))$$

$$+ -2(\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))$$

NOTE: If we were using **Least Squares** to solve for the optimal value for the **Intercept**, we would simply find where the the slope of the curve = **0**.



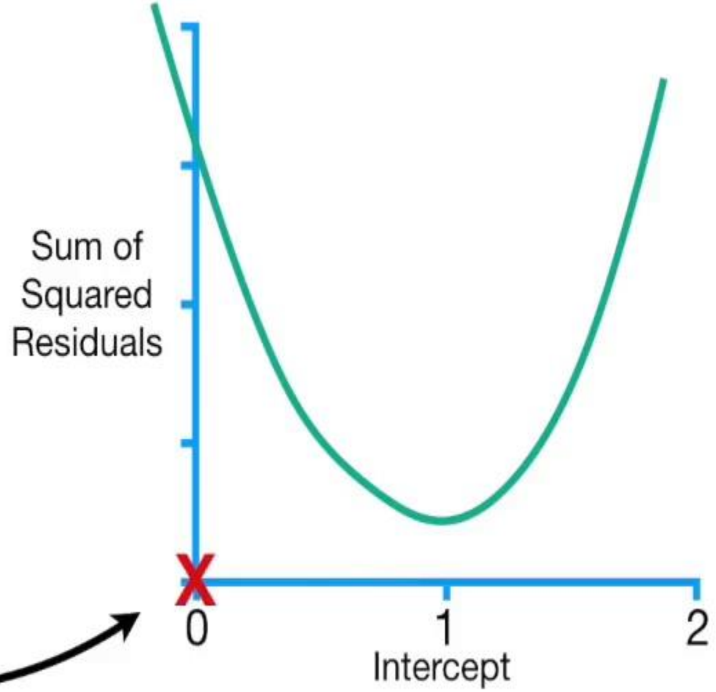
$$\frac{d}{d\ intercept} \text{Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5})$$

$$+ -2(\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))$$

In contrast, **Gradient Descent** finds the minimum value by taking steps from an initial guess until it reaches the best value.

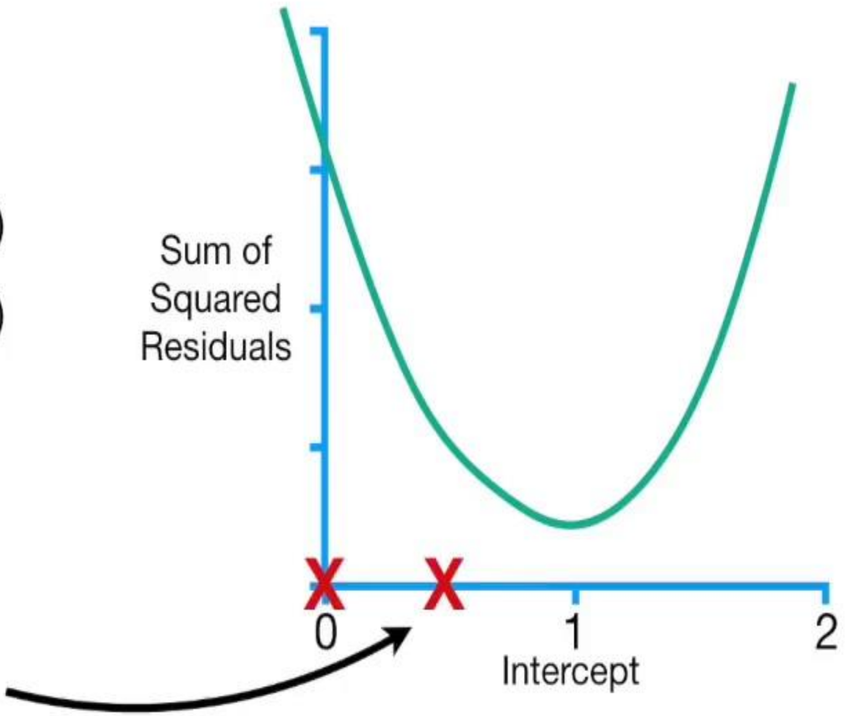


$$\frac{d}{d\ intercept} \text{ Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))$$

$$+ -2(\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))$$



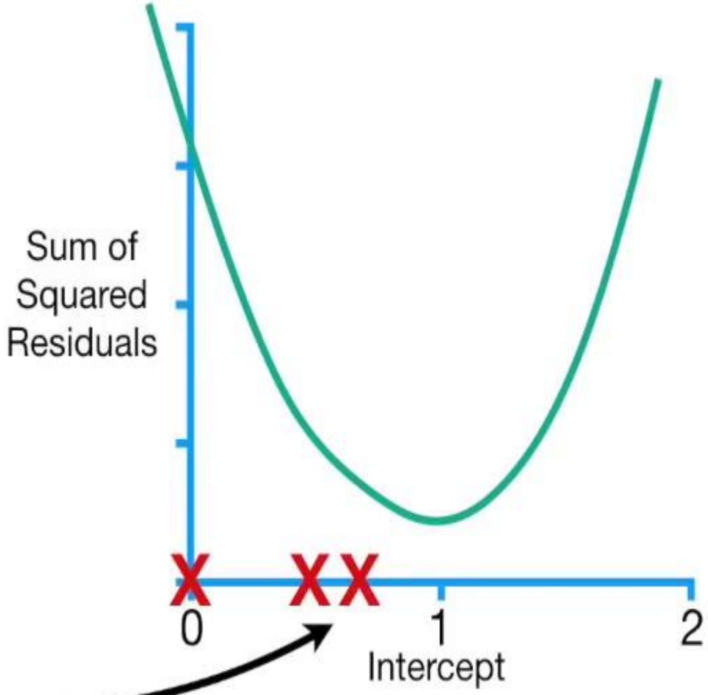
In contrast, **Gradient Descent** finds the minimum value by taking steps from an initial guess until it reaches the best value.

$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))$$

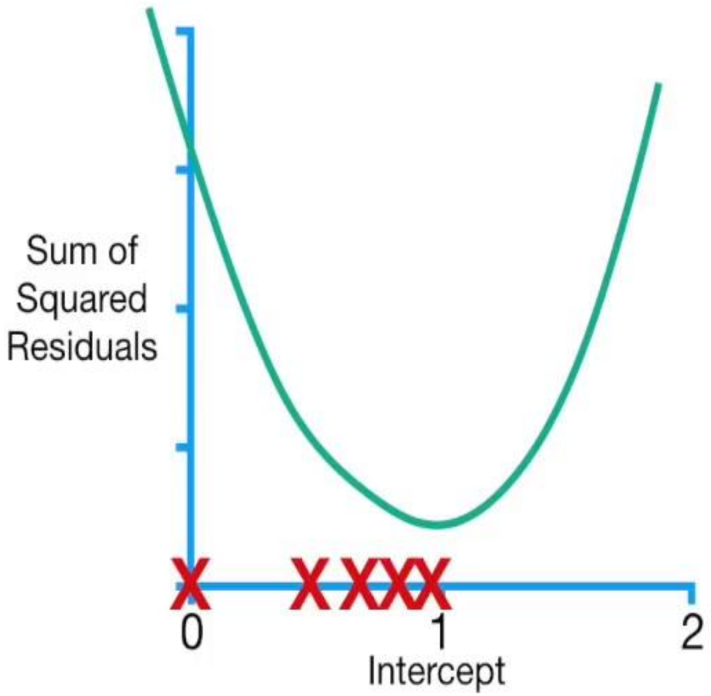
$$+ -2(\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))$$



In contrast, **Gradient Descent** finds the minimum value by taking steps from an initial guess until it reaches the best value.

$$\frac{d}{d\ intercept} \text{ Sum of squared residuals} =$$
$$-2(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))$$
$$+ -2(\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))$$
$$+ -2(\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))$$



This makes **Gradient Descent** very useful when it is not possible to solve for where the derivative = **0**, and this is why **Gradient Descent** can be used in so many different situations.

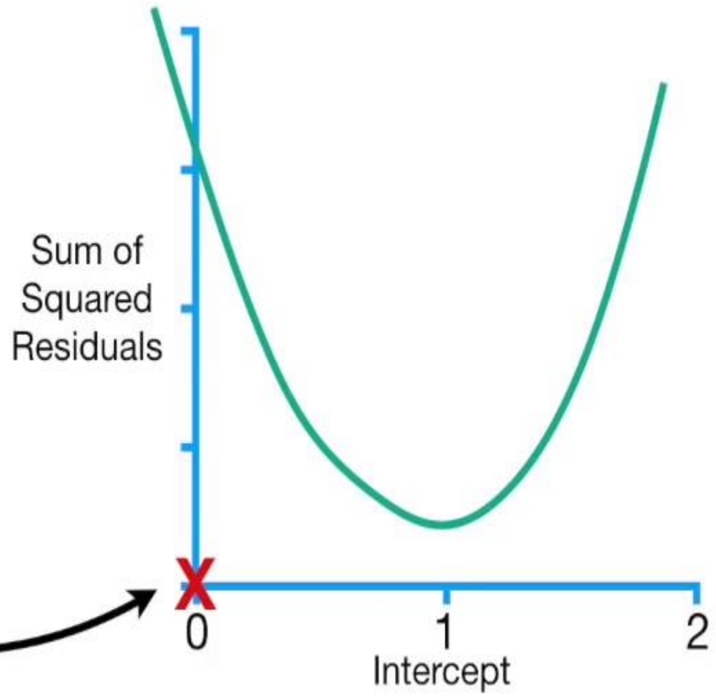
$$\frac{d}{d\ intercept} \text{ Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (\text{intercept} + 0.64 \times \mathbf{0.5}))$$

$$+ -2(\mathbf{1.9} - (\text{intercept} + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (\text{intercept} + 0.64 \times \mathbf{2.9}))$$

Remember, we started by setting the **Intercept** to a random number. In this case, that was **0**.



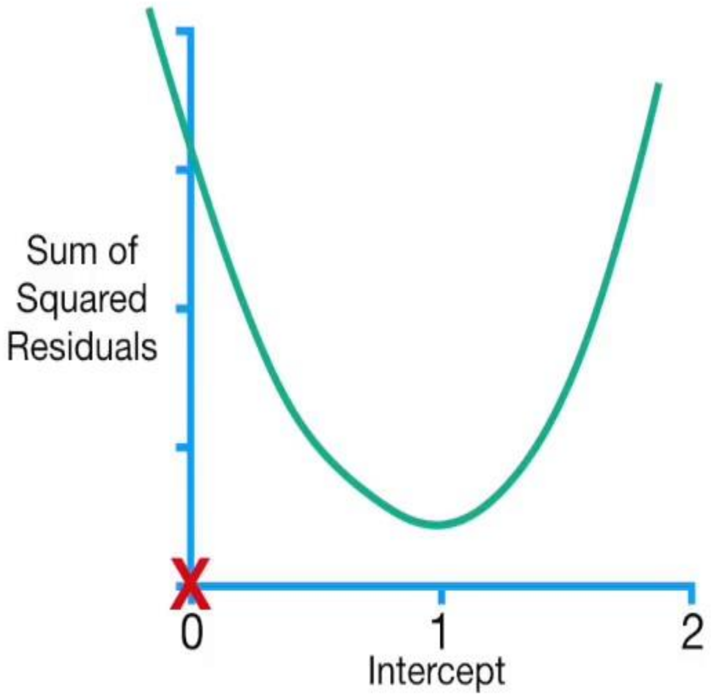
$$\frac{d}{d\ intercept} \text{Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5}))$$

$$+ -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

So we plug **0** into the derivative…



$$\frac{d}{d\ intercept}\text{ Sum of squared residuals} =$$

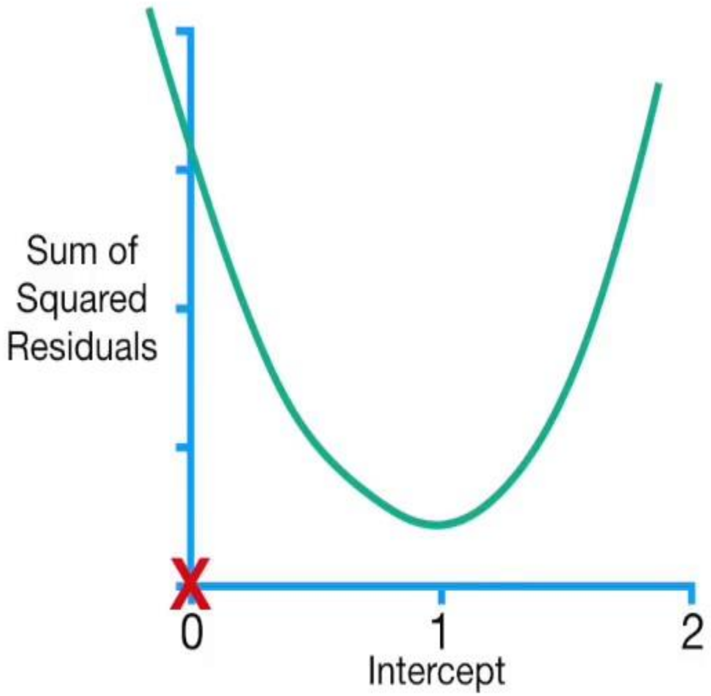
$$-2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5}))$$

$$+ -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

$$= -5.7$$

...and we get **-5.7**.



$$\frac{d}{d\ intercept} \text{ Sum of squared residuals} =$$

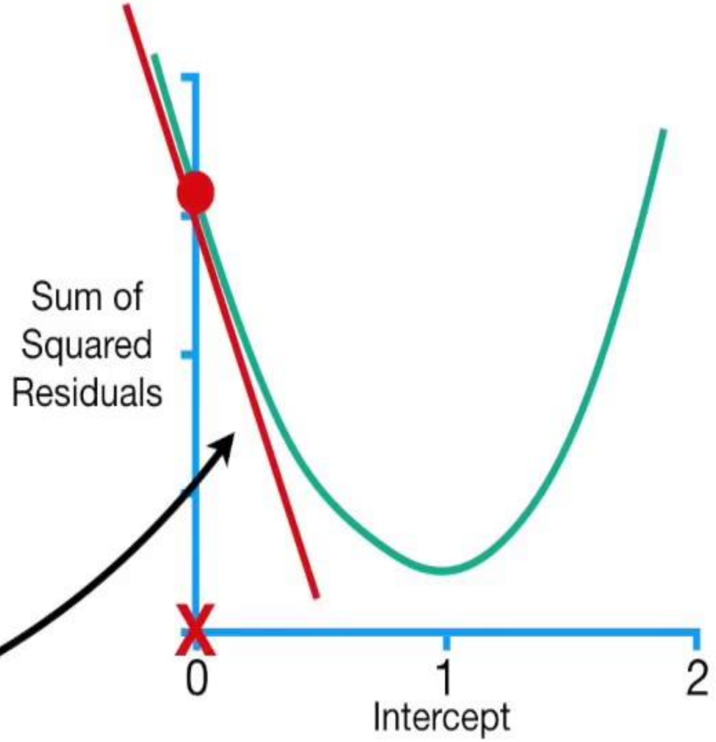
$$-2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5}))$$

$$+ -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

$$= -5.7$$

So when the **Intercept** = **0**,
the slope of the curve = **-5.7**.



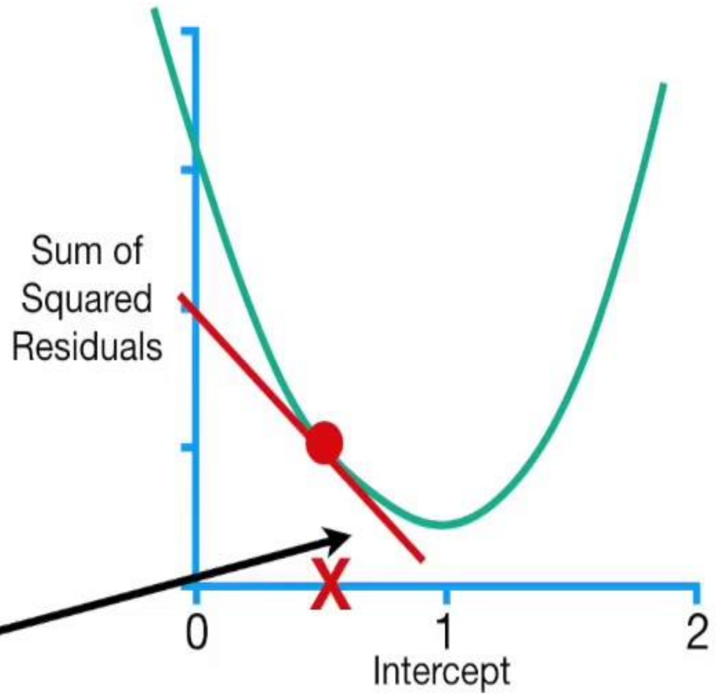
$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5})$$

$$+ -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

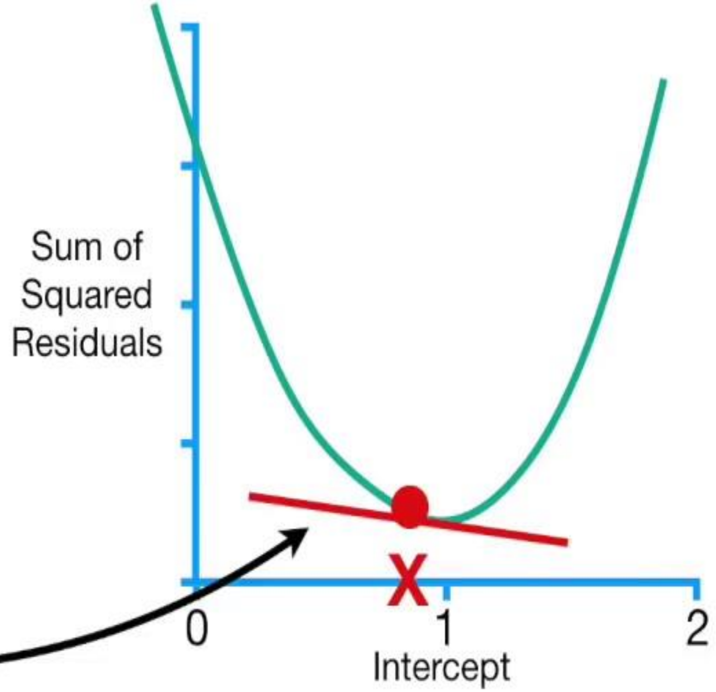
$$= -5.7$$



NOTE: The closer we get to the optimal value for the **Intercept**, the closer the slope of the curve gets to **0**.

$$\frac{d}{d\ intercept}\text{ Sum of squared residuals} = -2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5})) + -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3})) + -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

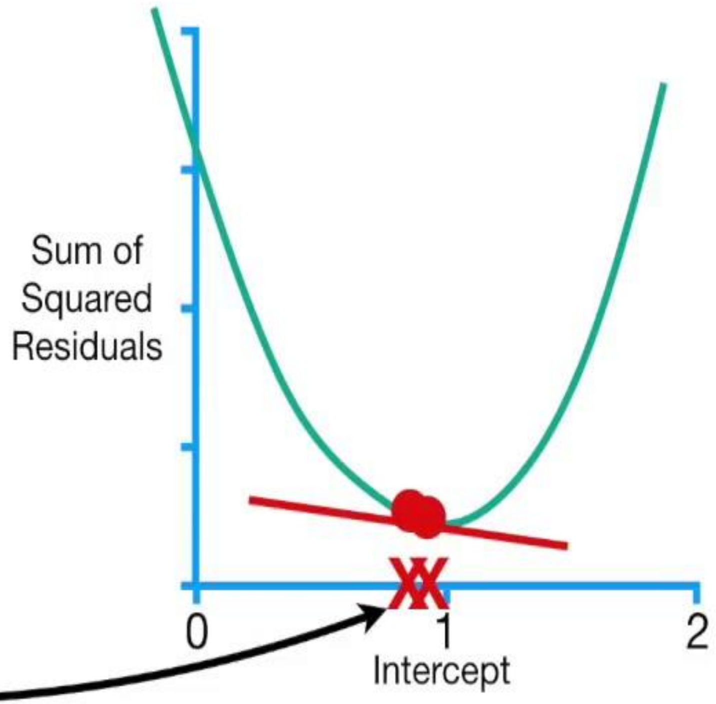
$$= -5.7$$



This means that when the slope of the curve is close to **0**…

$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} = -2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5})) + -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3})) + -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9})) = -5.7$$

…then we should take baby steps, because we are close to the optimal value…



$$\frac{d}{d\ intercept} \text{ Sum of squared residuals} =$$

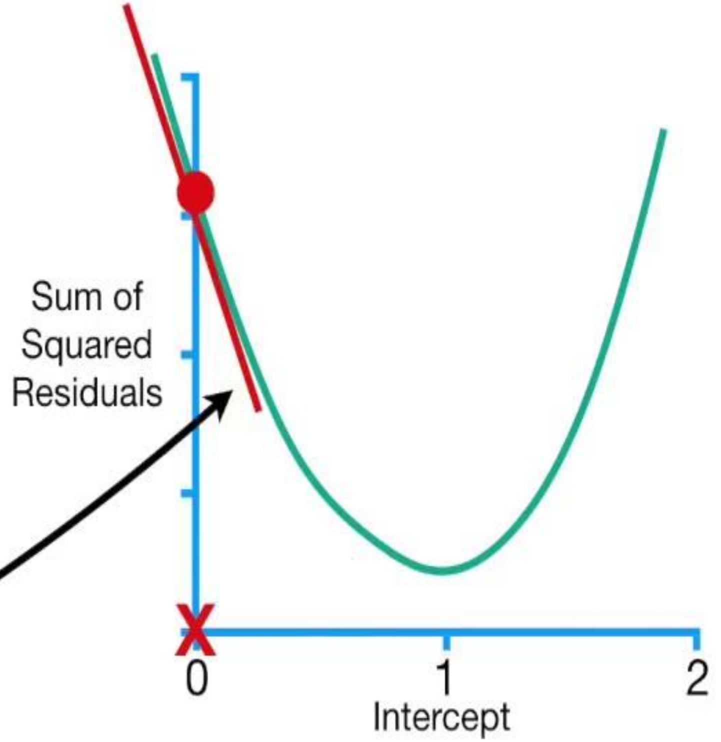
$$-2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5}))$$

$$+ -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

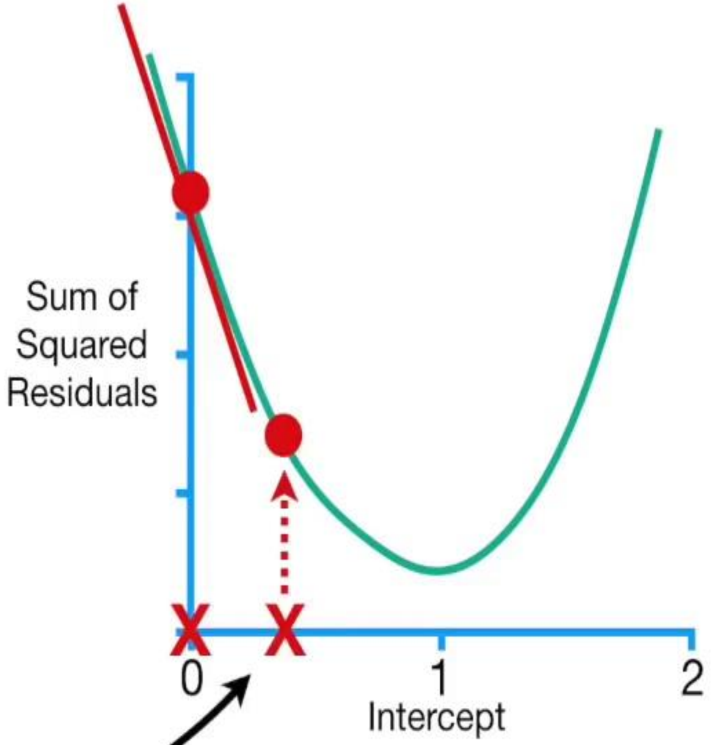
$$= -5.7$$

...and when the slope is far from **0**...



$$\frac{d}{d\ intercept}\text{ Sum of squared residuals} = -2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5})) + -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3})) + -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

$$= -5.7$$



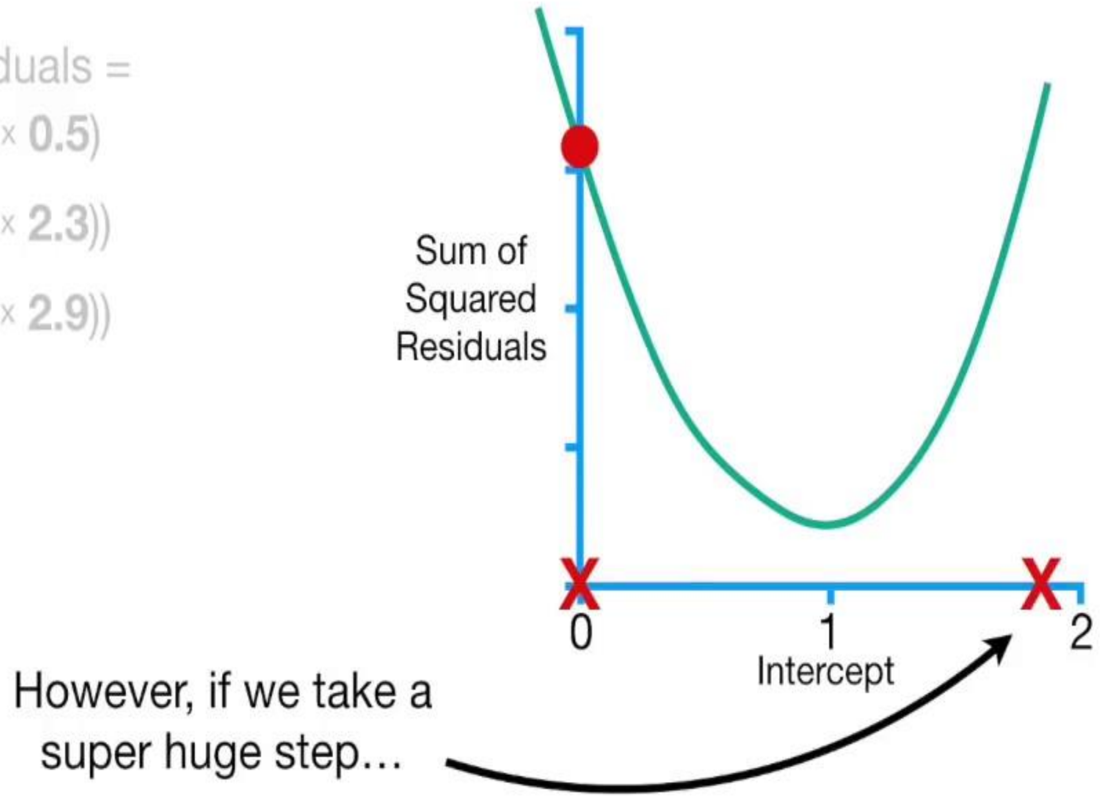
…then we should take big steps, because we are far from the optimal value.

$$\frac{d}{d\ intercept} \text{Sum of squared residuals} = -2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5}))$$

$$+ -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3}))$$

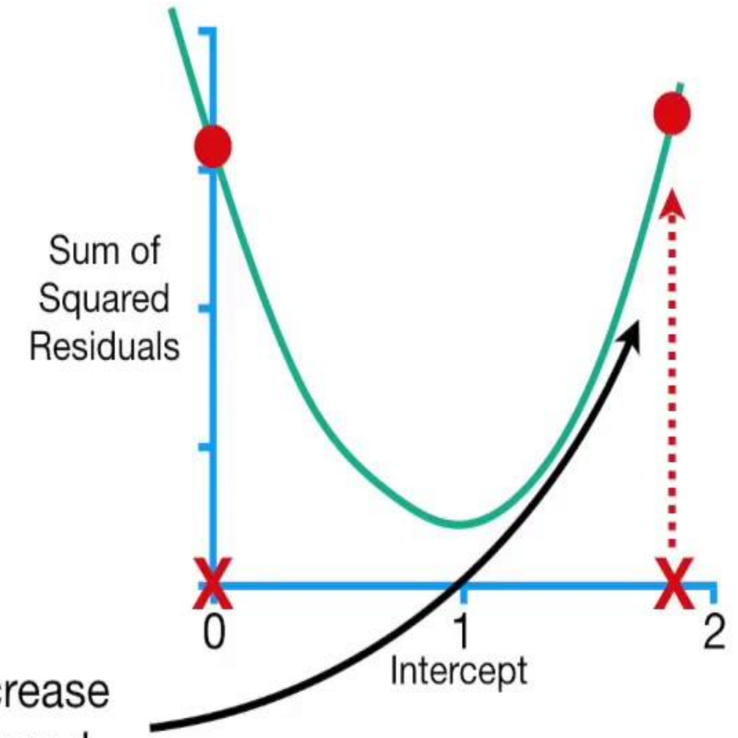
$$+ -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

$$= -5.7$$



$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} = -2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5}) + -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3})) + -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

$$= -5.7$$

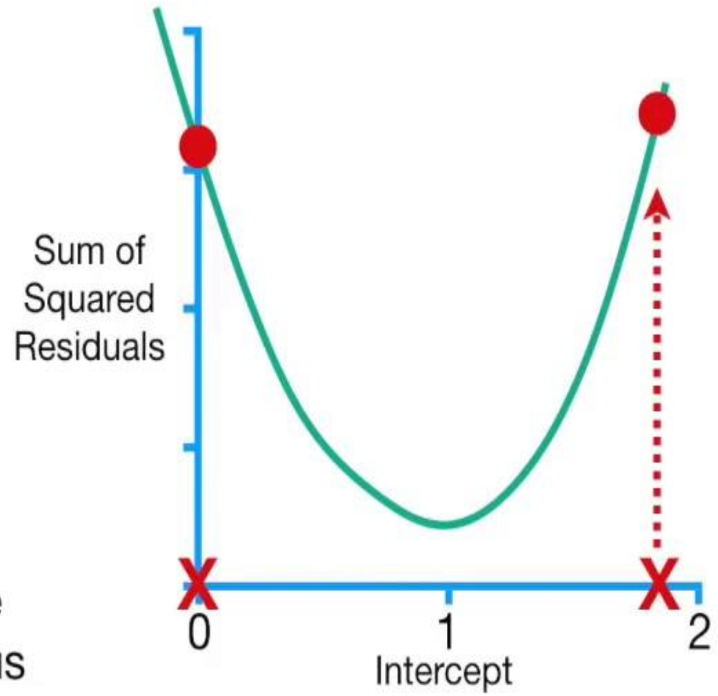


...then we would increase the Sum of the Squared Residuals!

$$\frac{d}{d\ intercept} \text{Sum of squared residuals} = -2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5})) + -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3})) + -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

$$= -5.7$$

So the size of the step should be related to the slope, since it tells us if we should take a baby step or a big step, but we need to make sure the big step is not too big.



$$\frac{d}{d\ intercept} \text{ Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5}))$$

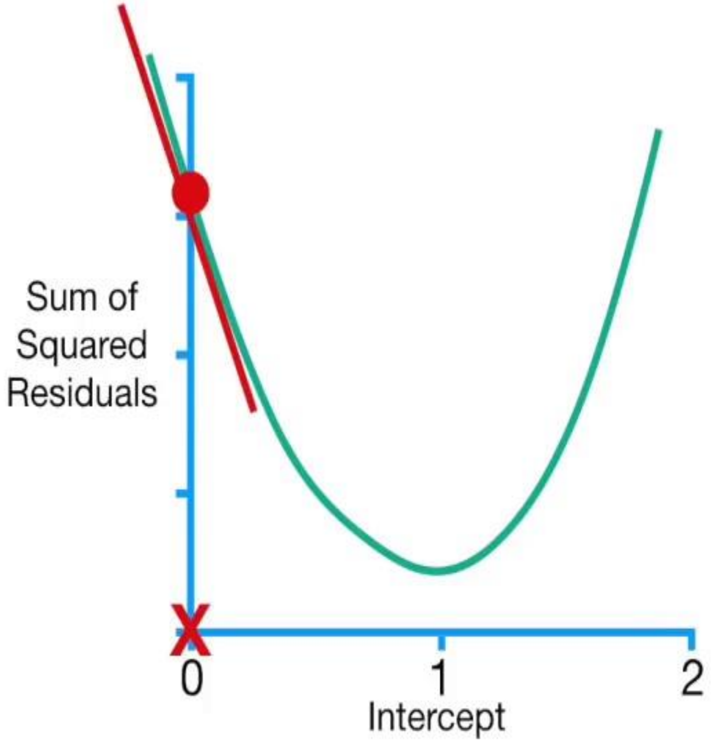
$$+ -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

$$= -5.7$$

Step Size = -5.7

Gradient Descent determines the **Step Size** by multiplying the **slope**…



$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5}))$$

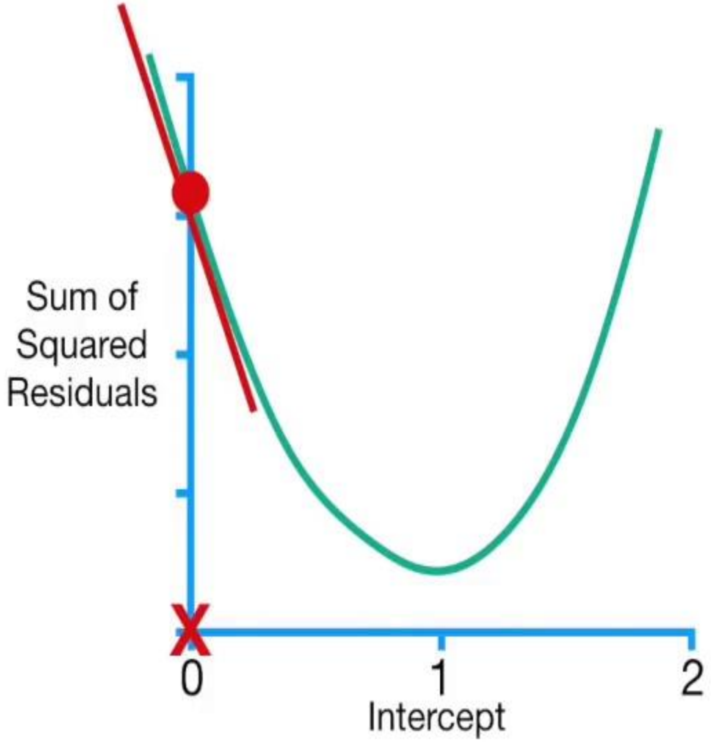
$$+ -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

$$= -5.7$$

Step Size = -5.7 × 0.1

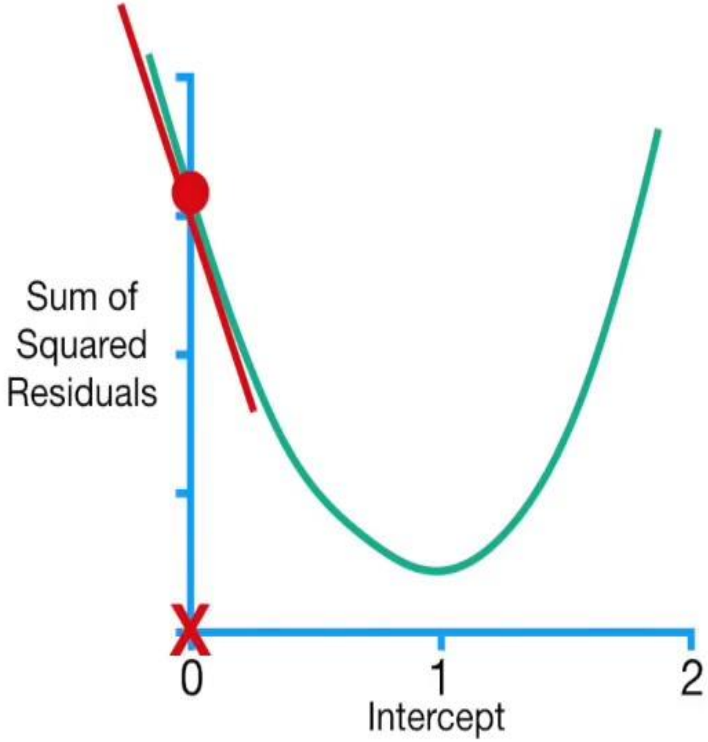
...by a small number called **The Learning Rate**.



$$\frac{d}{d\ intercept} \text{Sum of squared residuals} = -2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5})) + -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3})) + -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9})) = -5.7$$

Step Size = -5.7 × 0.1 = -0.57

When the **Intercept** = **0**, the **Step Size** = **-0.57**.



$$\frac{d}{d\ intercept}\text{ Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5}))$$

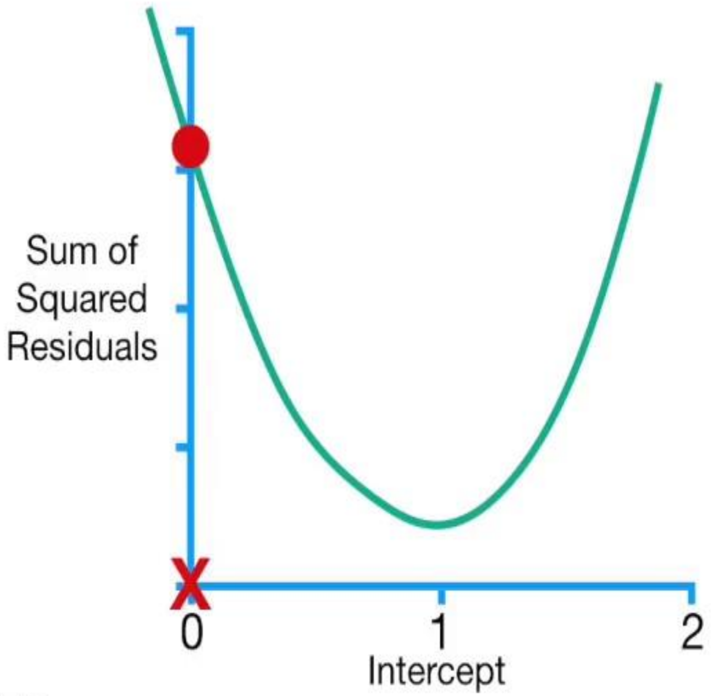
$$+ -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

$$= -5.7$$

Step Size = -5.7 × 0.1 = -0.57

New Intercept = ⟵ With the **Step Size**, we can calculate a **New Intercept**.



$$\frac{d}{d\ intercept}\text{ Sum of squared residuals} =$$

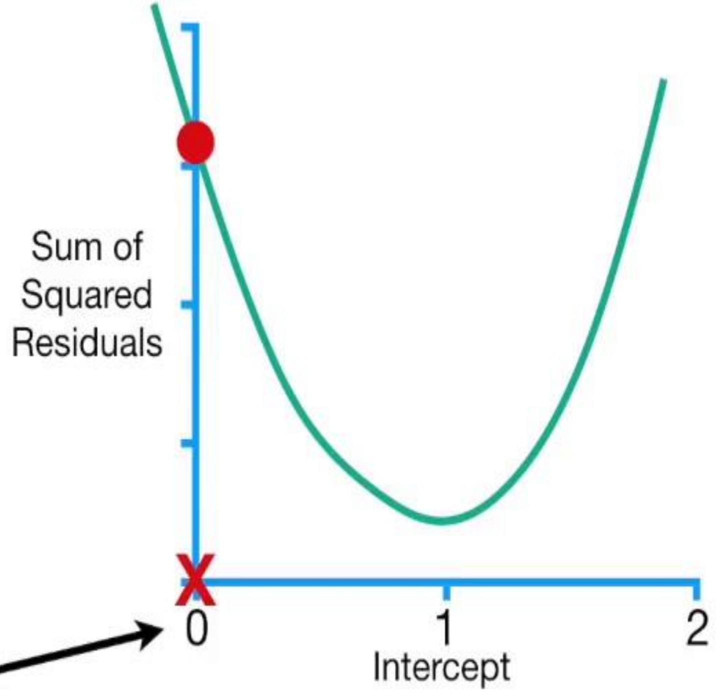
$$-2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5}))$$

$$+ -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9}))$$

$$= -5.7$$

Step Size = -5.7 × 0.1 = -0.57



New Intercept = **Old Intercept** - **Step Size**

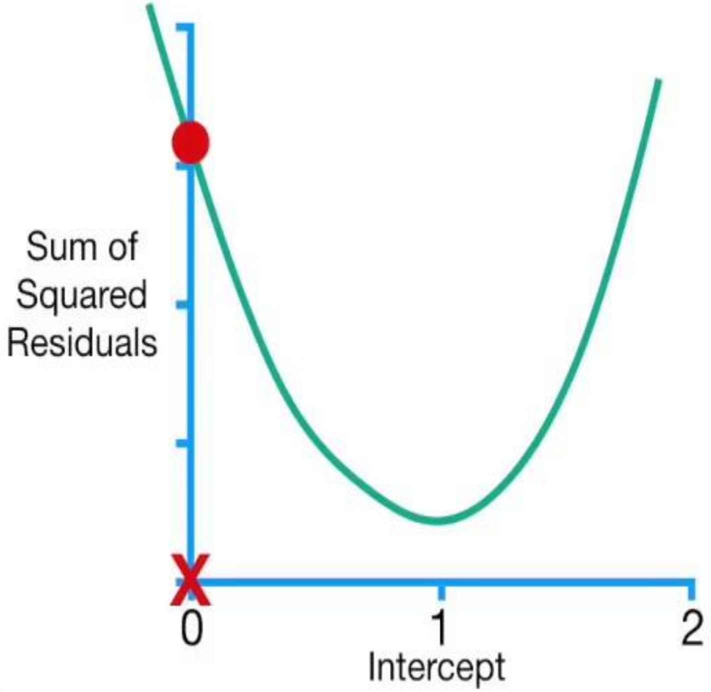
The **New Intercept** is
the **Old Intercept**…

$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} = -2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5})) + -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3})) + -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9})) = -5.7$$

Step Size = -5.7 × 0.1 = -0.57

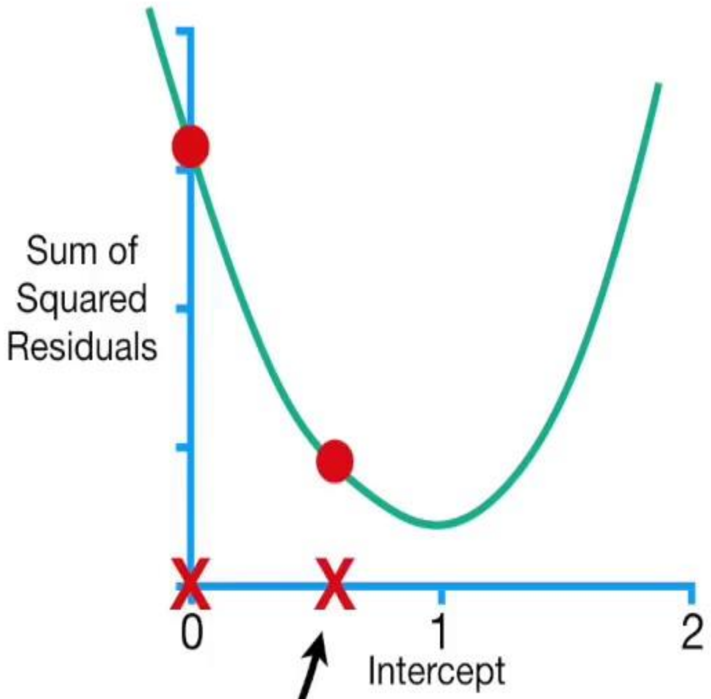
New Intercept = **Old Intercept** - **Step Size**

...minus the **Step Size**.



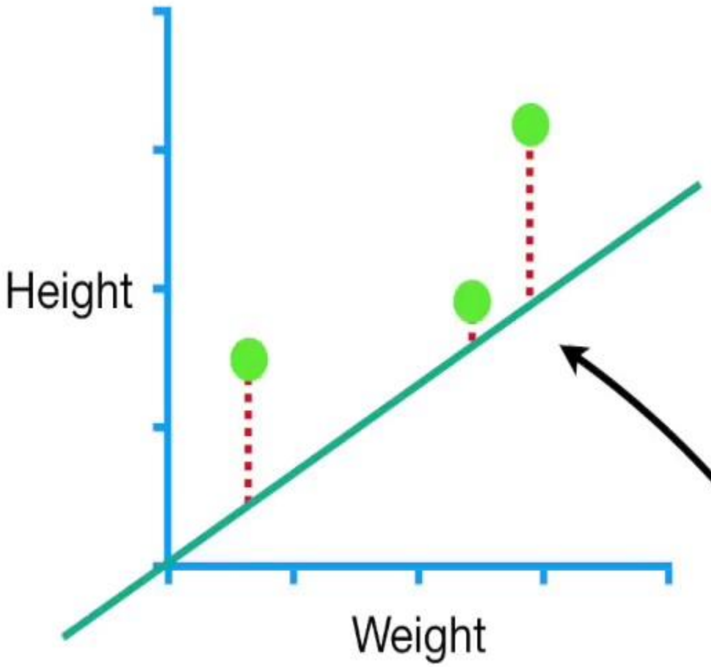
$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} = -2(\mathbf{1.4} - (0 + 0.64 \times \mathbf{0.5})) + -2(\mathbf{1.9} - (0 + 0.64 \times \mathbf{2.3})) + -2(\mathbf{3.2} - (0 + 0.64 \times \mathbf{2.9})) = -5.7$$

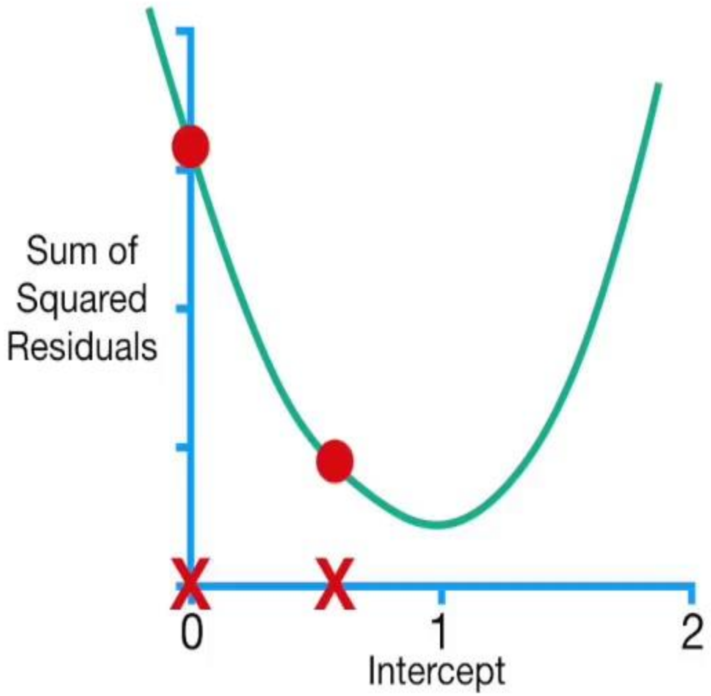
Step Size = -5.7 × 0.1 = -0.57



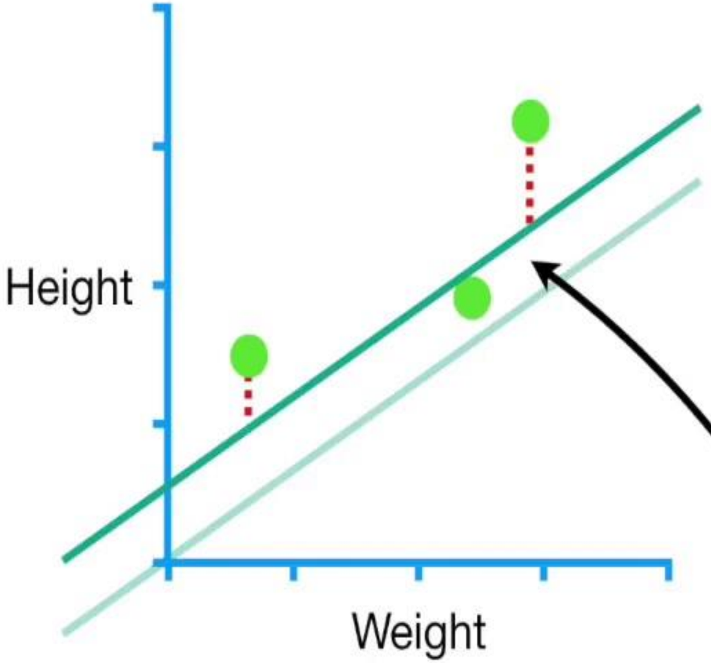
New Intercept = 0 - (-0.57) = **0.57**

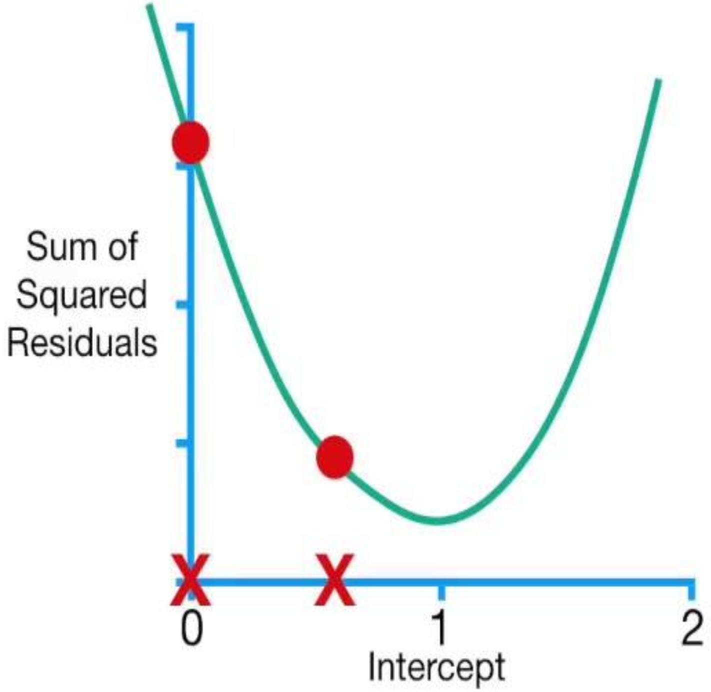
…and the the **New Intercept** = **0.57**.





Going back to the original data and the original line, with the **Intercept** = **0**…



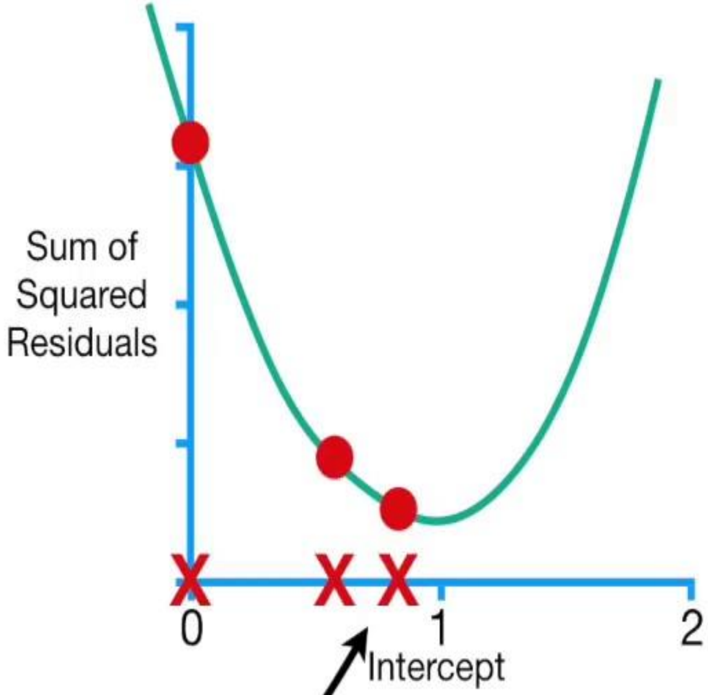


...we can see how much the residuals shrink when the **Intercept** = **0.57**.

$$\frac{d}{d\ intercept} \text{ Sum of squared residuals} = -2(\mathbf{1.4} - (0.57 + 0.64 \times \mathbf{0.5})) + -2(\mathbf{1.9} - (0.57 + 0.64 \times \mathbf{2.3})) + -2(\mathbf{3.2} - (0.57 + 0.64 \times \mathbf{2.9}))$$

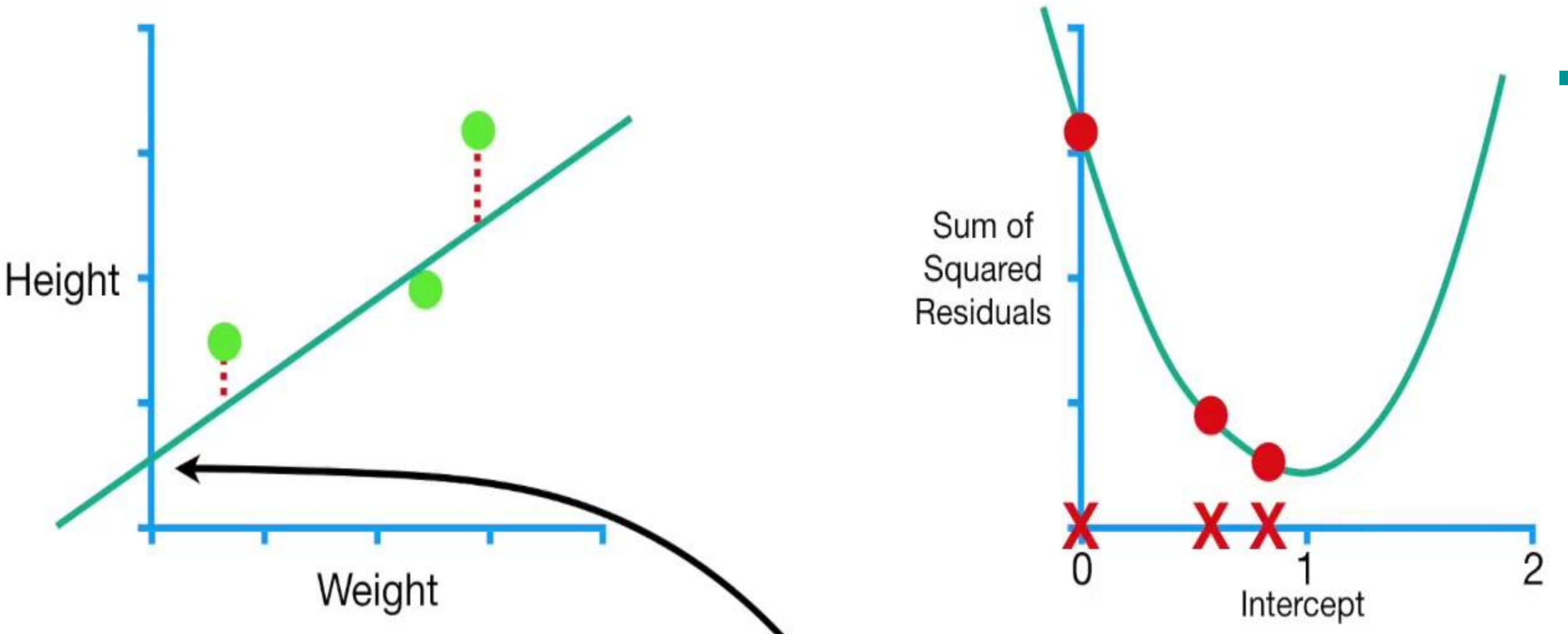
$$= -2.3$$

Step Size = -2.3 × 0.1 = **-0.23**

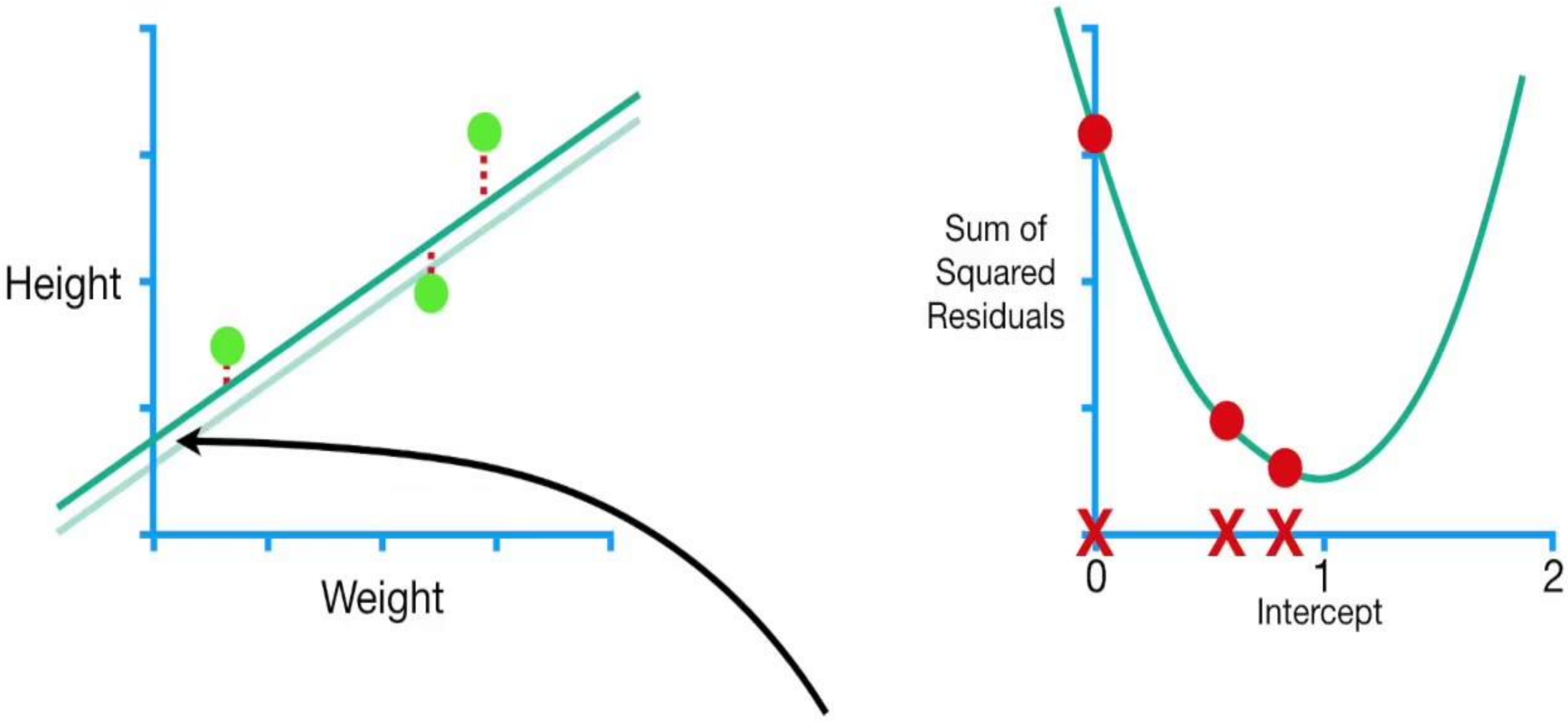


New Intercept = 0.57 - (-0.23) = **0.8**

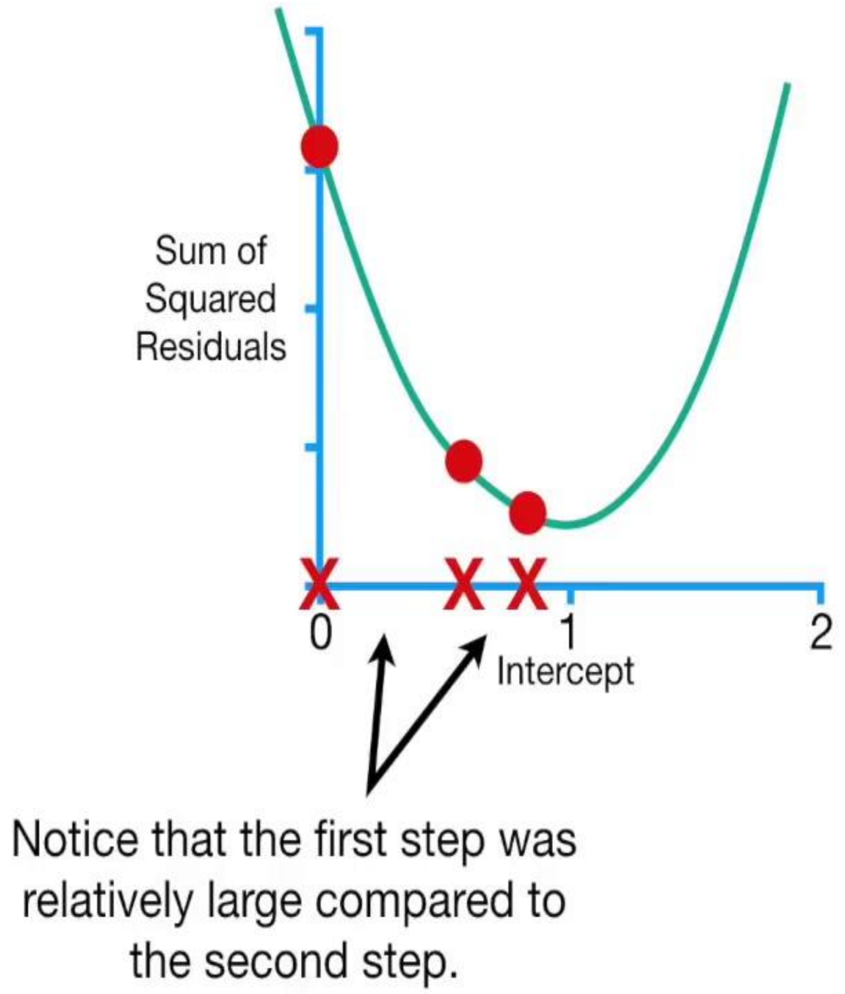
...and the **New Intercept** = **0.8**

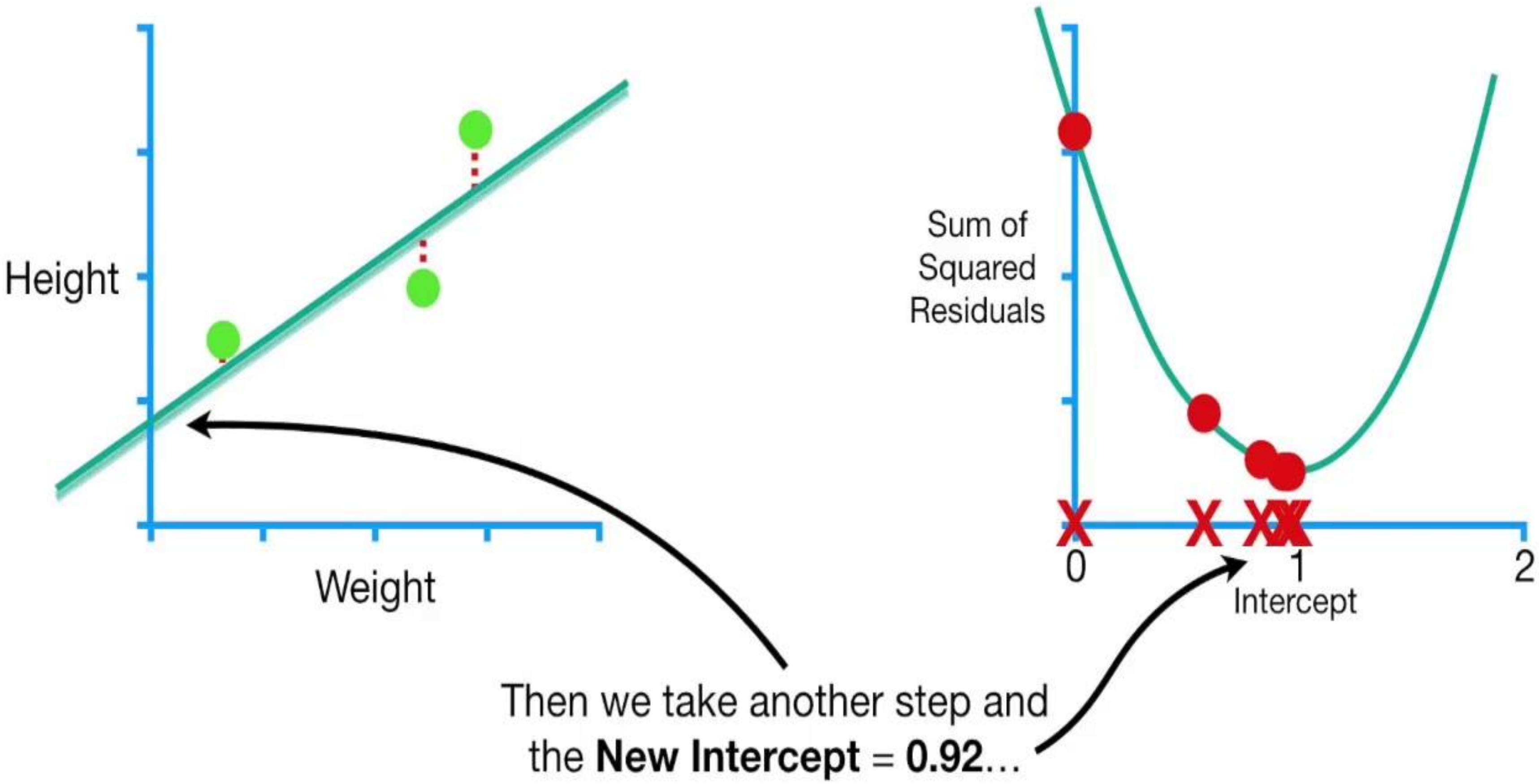


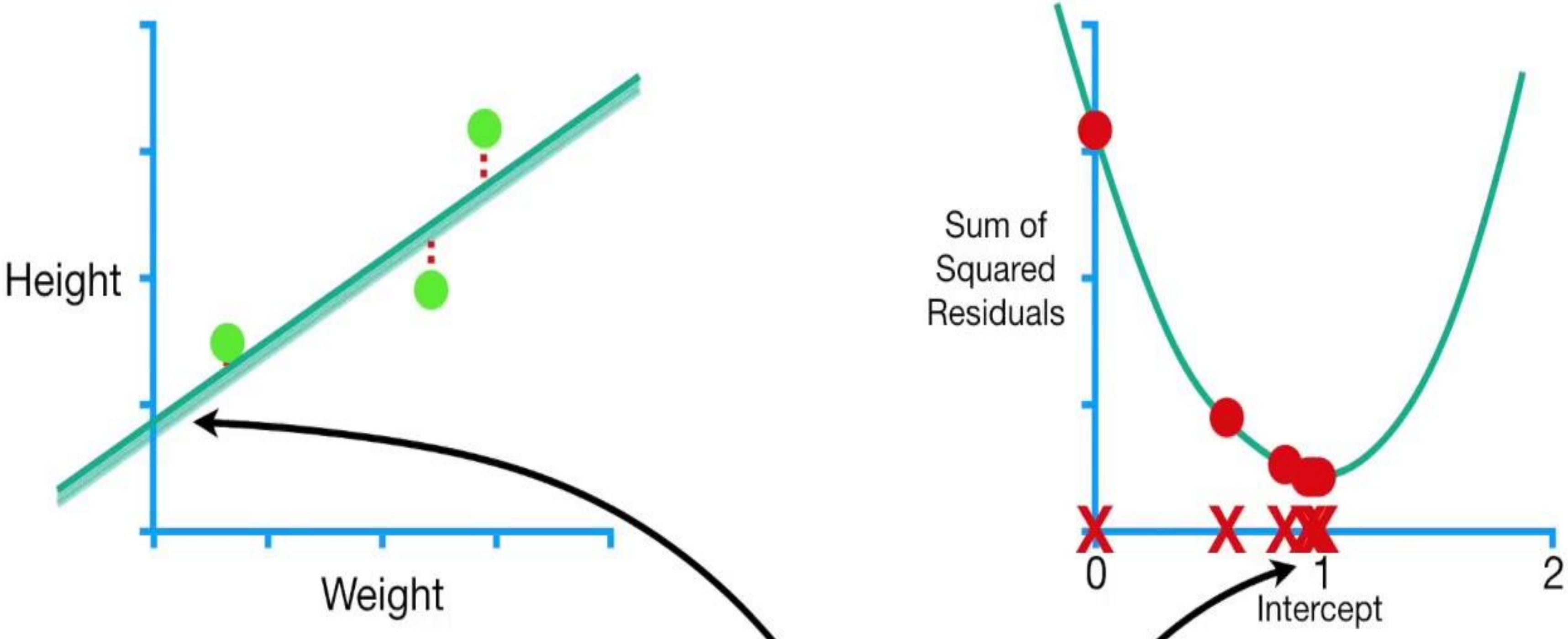
Now we can compare the residuals when the **Intercept** = **0.57**…



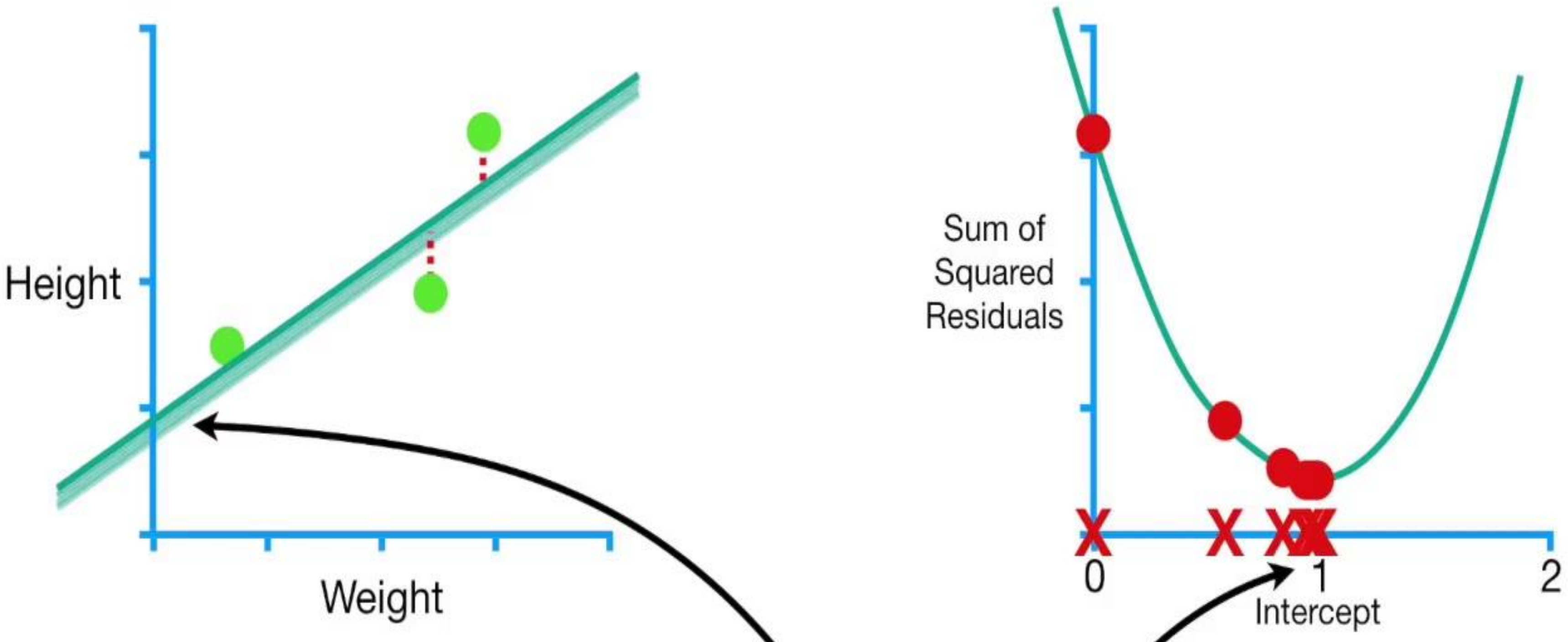
...to when the **Intercept** = **0.8**


Sum of Squared Residuals
0
1
2
Intercept
Notice that the first step was relatively large compared to the second step.


Height
Weight
Sum of Squared Residuals
0
1
2
Intercept
Then we take another step and the New Intercept = 0.92…



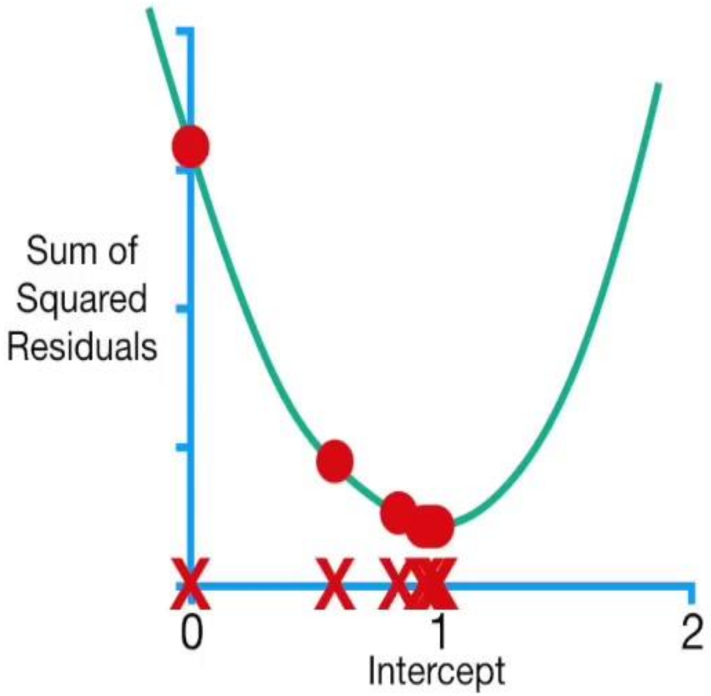
...and then we take another
step and the
New Intercept = **0.94**...



...and then we take another step and the **New Intercept** = **0.95**.

GD to find *b*

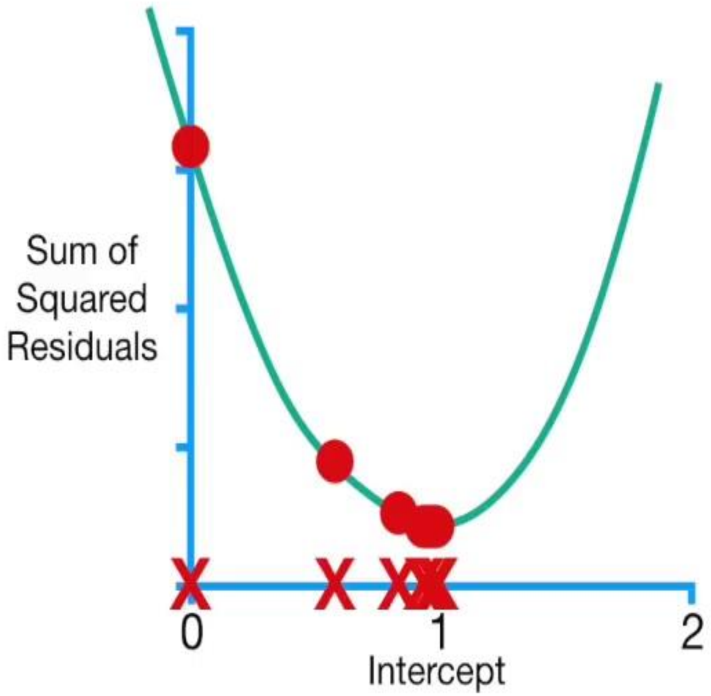
After 6 steps, the **Gradient Descent** estimate for the **Intercept** is **0.95**.



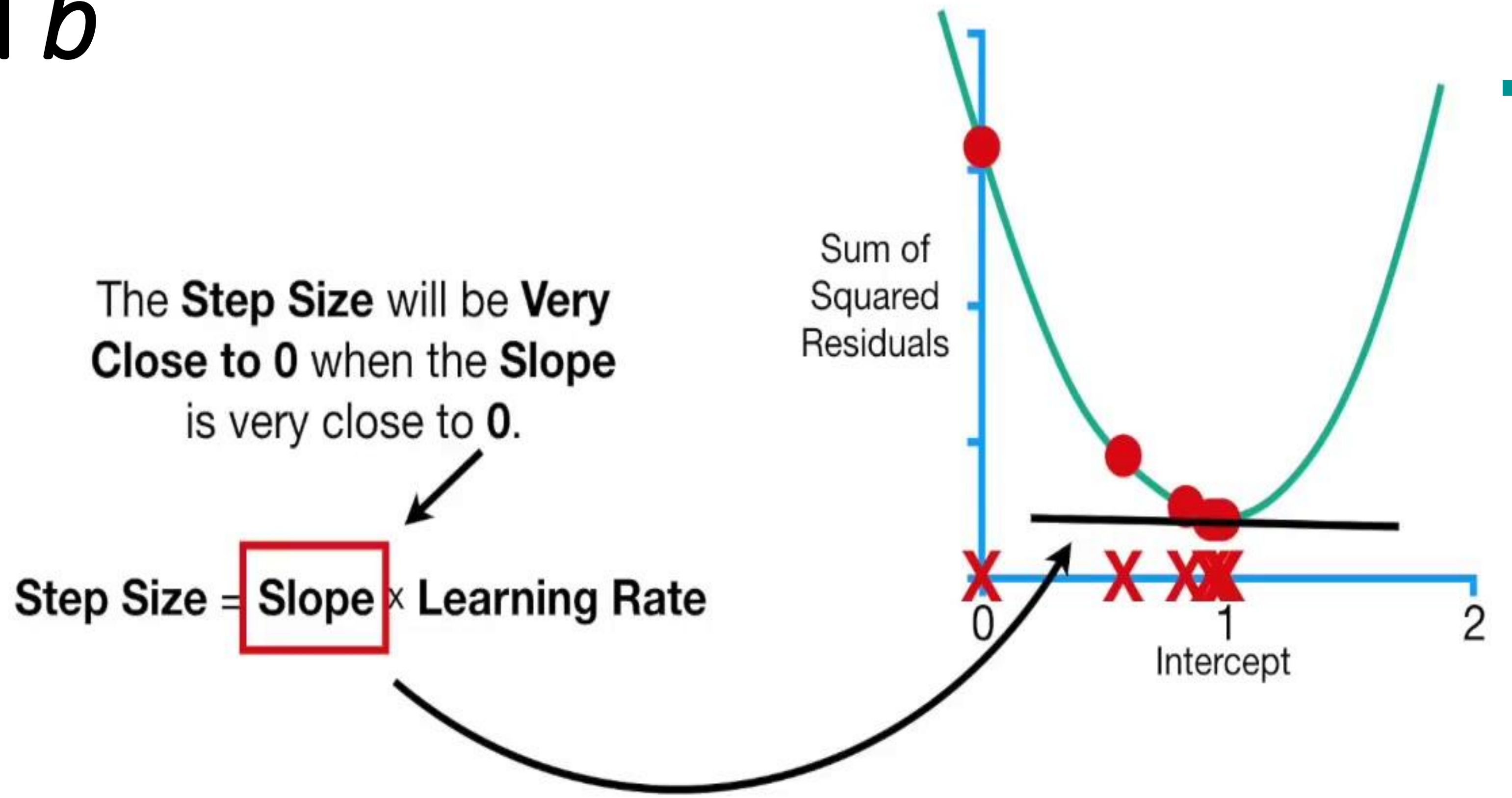
GD to find *b*

Gradient Descent stops when the **Step Size** is **Very Close To 0**.

Step Size = **Slope** × **Learning Rate**



GD to find *b*

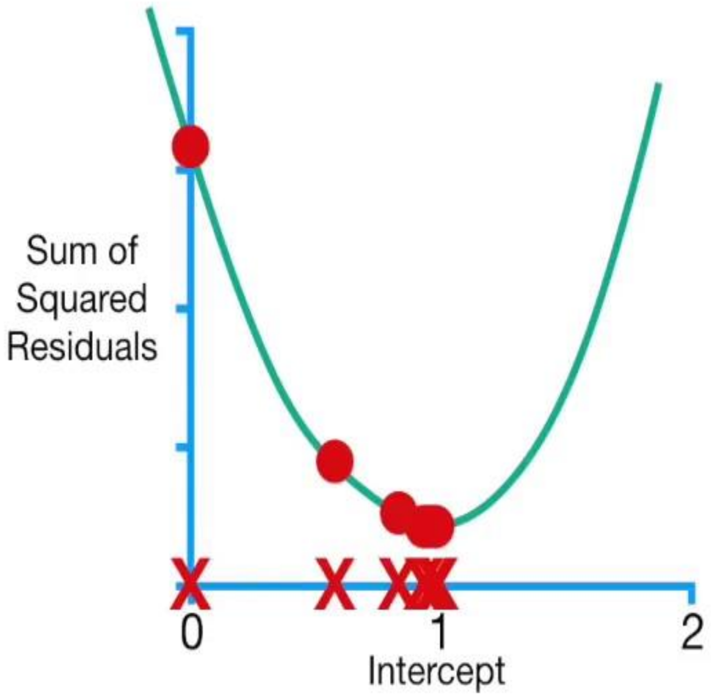


The **Step Size** will be **Very Close to 0** when the **Slope** is very close to **0**.
Step Size = **Slope** × **Learning Rate**
Sum of Squared Residuals
0
1
2
Intercept

GD to find *b*

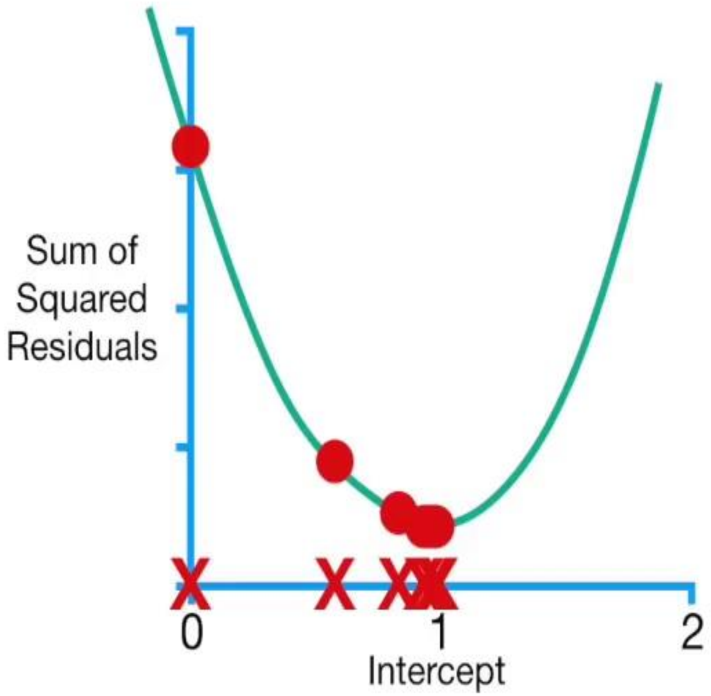
In practice, the
Minimum Step Size = 0.001
or smaller.

Step Size = Slope × Learning Rate



GD to find *b*

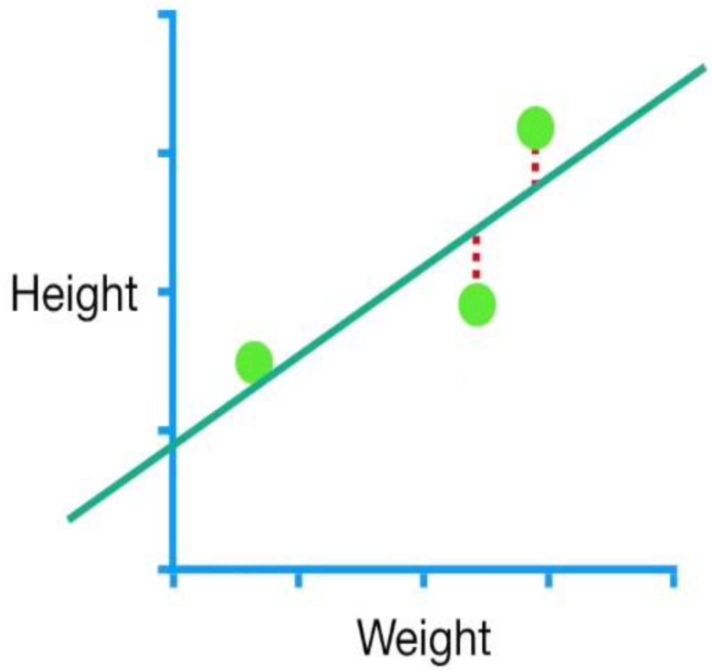
That said, **Gradient Descent** also includes a limit on the number of steps it will take before giving up.



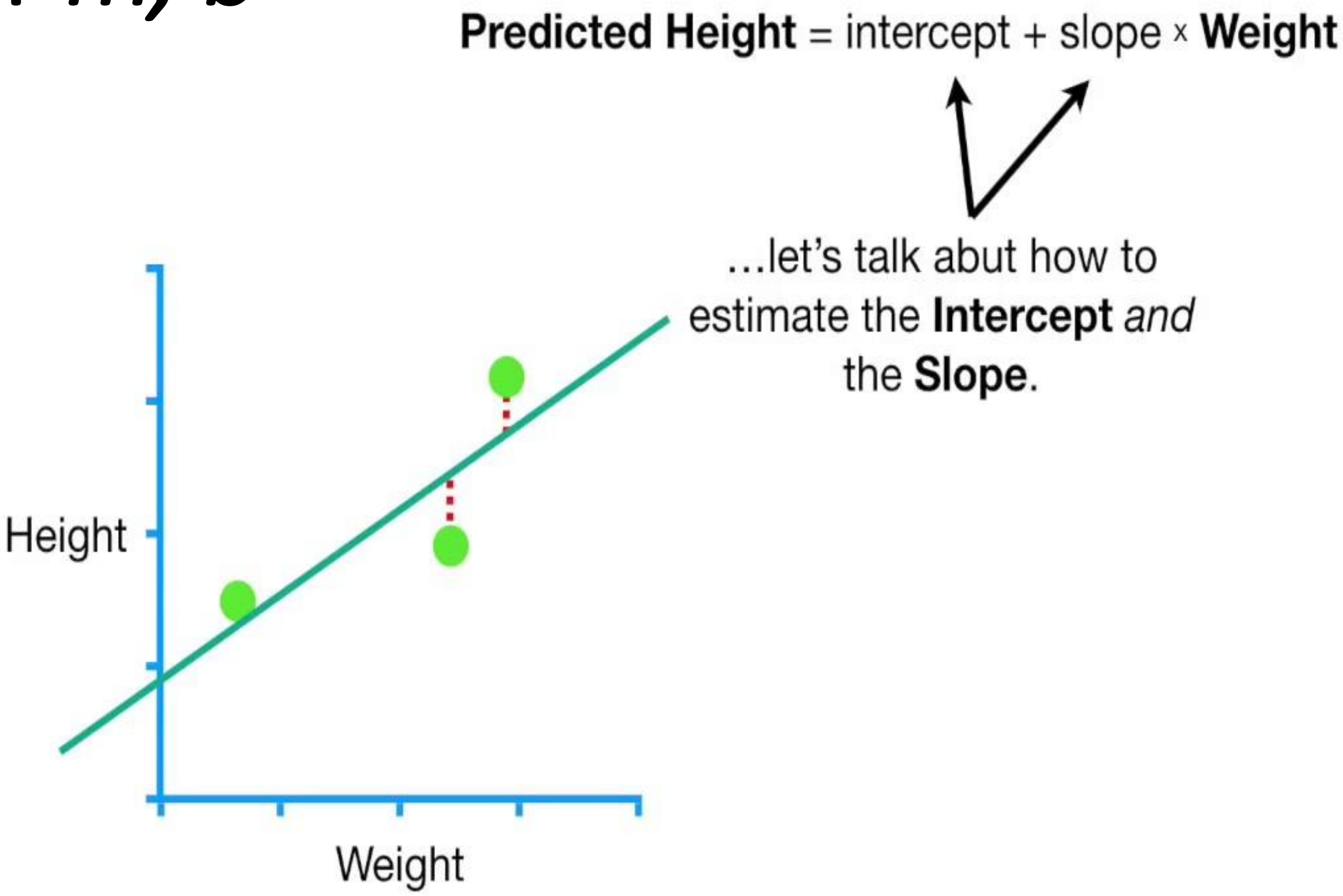
GD for *m, b*

Predicted Height = intercept + 0.64 × **Weight**

Now that we understand how **Gradient Descent** can estimate the **Intercept**…



GD for *m, b*

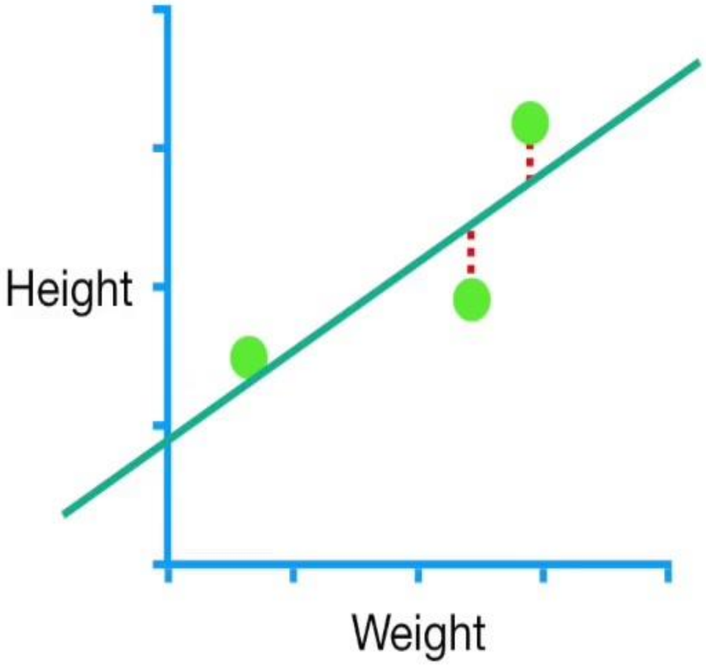


Predicted Height = intercept + slope × Weight
...let's talk abut how to estimate the Intercept and the Slope.
Height
Weight

Sum of squared residuals = $(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$

$+ (\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$

$+ (\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$



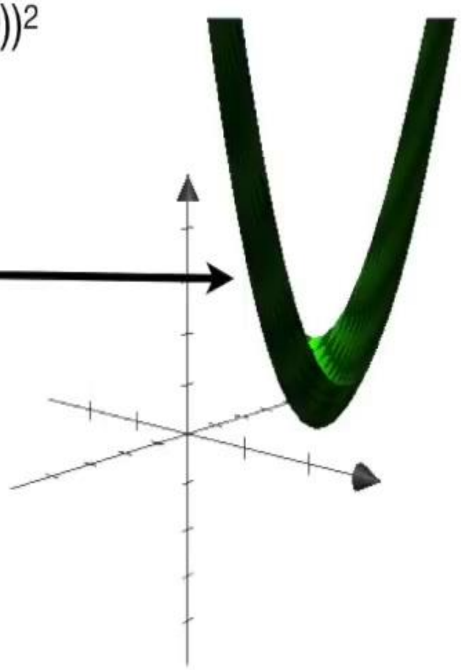
Just like before, we will use the Sum of the Squared Residuals as the **Loss Function**

$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$$

$$+ (\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$$

$$+ (\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$$

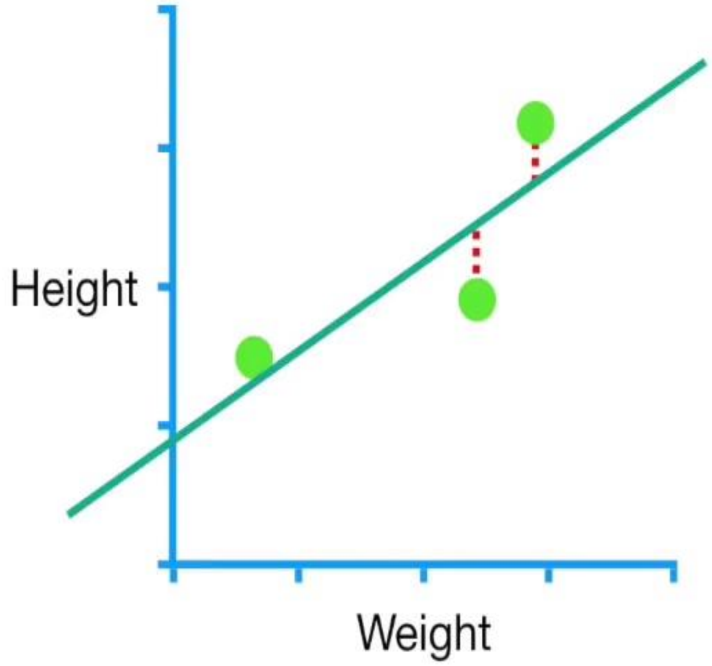
This is a 3-D graph of the **Loss Function** for different values for the **Intercept** and the **Slope**



Sum of squared residuals = (**1.4** - (intercept + slope × **0.5**))^2

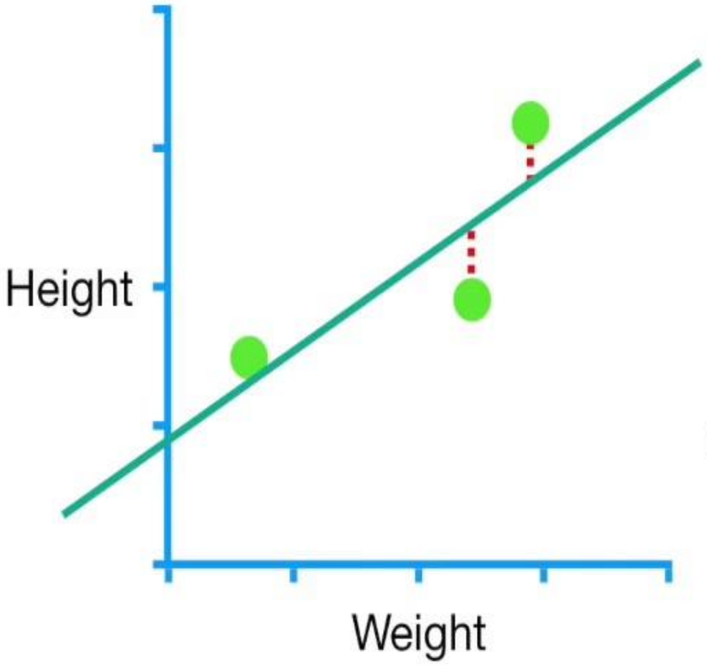
+ (**1.9** - (intercept + slope × **2.3**))^2

+ (**3.2** - (intercept + slope × **2.9**))^2



So, just like before, we need to take the derivative of this function…

$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$$
$$+ (\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$$
$$+ (\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$$



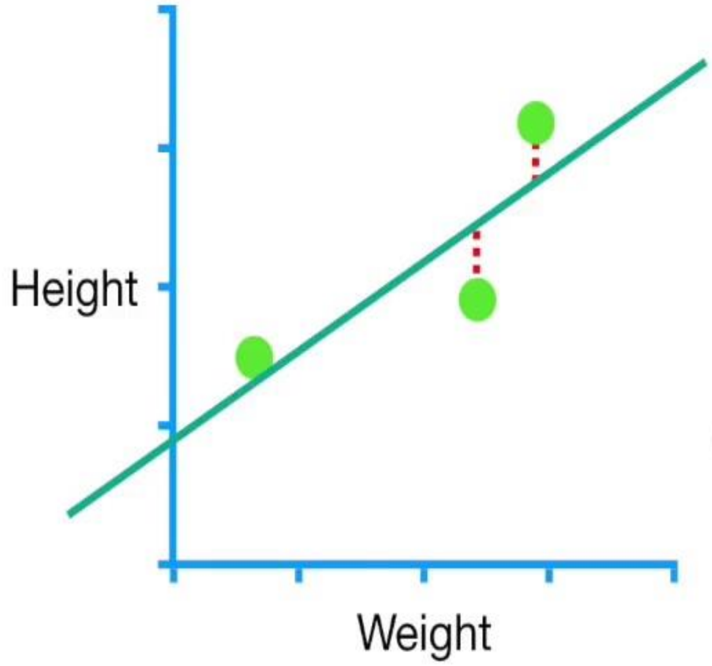
…and just like before, we'll take the derivative with respect to the **Intercept**…

$$\frac{d}{d\ intercept} \text{Sum of squared residuals}$$

Sum of squared residuals = (**1.4** - (intercept + slope × **0.5**))^2

+ (**1.9** - (intercept + slope × **2.3**))^2

+ (**3.2** - (intercept + slope × **2.9**))^2



…but unlike before, we'll also take the derivative with respect to the **Slope**!

$$\frac{d}{d\ intercept} \text{Sum of squared residuals}$$

$$\frac{d}{d\ slope} \text{Sum of squared residuals}$$

Sum of squared residuals = $(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$

$+ (\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$

$+ (\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$

We'll start by taking the derivative with respect to the intercept.

$\frac{d}{d\ intercept}$ Sum of squared residuals =

Sum of squared residuals = $(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$

$+ (\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$

$+ (\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$

Just like before, we take the derivative of each part…

$$\frac{d}{d\ intercept} \text{Sum of squared residuals} = \frac{d}{d\ intercept} (\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$$

$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$$

$$+ (\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$$

$$+ (\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$$

Just like before, we take the derivative of each part…

$$\frac{d}{d\ intercept} \text{Sum of squared residuals} = \frac{d}{d\ intercept} (\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$$

$$+ \frac{d}{d\ intercept} (\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$$

$$+ \frac{d}{d\ intercept} (\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$$

$$\frac{d}{d\ intercept}(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2 = 2(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5})) \times -1$$

$$= -2(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))$$

...and this...

...is the derivative of the first part...

$$\frac{d}{d\ intercept}\text{Sum of squared residuals} = \frac{d}{d\ intercept}(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$$

$$+ \frac{d}{d\ intercept}(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$$

$$+ \frac{d}{d\ intercept}(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$$

GD for *m, b*

Likewise, we replace these terms with their derivatives…

$$\frac{d}{d\ intercept} \text{Sum of squared residuals} = -2(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))$$

$$+ -2(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))$$

$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$$
$$+ (\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$$
$$+ (\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$$

Now let's take the derivative of the Sum of the Squared Residuals with respect to the **Slope**.

$$\frac{d}{d\,slope}\ \text{Sum of squared residuals} =$$

$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$$
$$+ (\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$$
$$+ (\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$$

Just like before, we take the derivative of each part…

$$\frac{d}{d\,slope}\ \text{Sum of squared residuals} = \frac{d}{d\,slope}\ (\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$$

$$\text{Sum of squared residuals} = (\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$$

$$+ (\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$$

$$+ (\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$$

Just like before, we take the derivative of each part…

$$\frac{d}{d\,slope} \text{Sum of squared residuals} = \frac{d}{d\,slope} (\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$$

$$+ \frac{d}{d\,slope} (\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$$

$$+ \frac{d}{d\,slope} (\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$$

$$\frac{d}{d\,slope}(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2 = 2(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5})) \times -\mathbf{0.5}$$

$$= -2 \times \mathbf{0.5}(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))$$

...and this...

...is the derivative of the first part...

$$\frac{d}{d\,slope}\text{Sum of squared residuals} = \frac{d}{d\,slope}(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))^2$$

$$+ \frac{d}{d\,slope}(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))^2$$

$$+ \frac{d}{d\,slope}(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))^2$$

$$\frac{d}{d\,slope}(\mathbf{1.4} - (intercept + slope \times \mathbf{0.5}))^2 = 2(\mathbf{1.4} - (intercept + slope \times \mathbf{0.5})) \times \mathbf{-0.5}$$

$$= -2 \times \mathbf{0.5}(\mathbf{1.4} - (intercept + slope \times \mathbf{0.5}))$$

...so we plug it in.

$$\frac{d}{d\,slope}\text{Sum of squared residuals} = -2 \times \mathbf{0.5}(\mathbf{1.4} - (intercept + slope \times \mathbf{0.5}))$$

$$+ \frac{d}{d\,slope}(\mathbf{1.9} - (intercept + slope \times \mathbf{2.3}))^2$$

$$+ \frac{d}{d\,slope}(\mathbf{3.2} - (intercept + slope \times \mathbf{2.9}))^2$$

Likewise, we replace these terms with their derivatives.

$$\frac{d}{d\,slope} \text{ Sum of squared residuals} = -2 \times \mathbf{0.5}(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))$$

$$+ -2 \times \mathbf{2.3}(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))$$

$$+ -2 \times \mathbf{2.9}(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))$$

$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5})$$

$$+ -2(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))$$

Here's the derivative of the Sum of the Squared Residuals with respect to the **Intercept**...

...and here's the derivative with respect to the **Slope**.

$$\frac{d}{d\ slope}\ \text{Sum of squared residuals} =$$

$$-2 \times \mathbf{0.5}(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))$$

$$+ -2 \times \mathbf{2.9}(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))$$

$$+ -2 \times \mathbf{2.3}(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))$$

$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5})$$

$$+ -2(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))$$

NOTE: When you have two or more derivatives of the same function, they are called a **Gradient**.

$$\frac{d}{d\ slope}\ \text{Sum of squared residuals} =$$

$$-2 \times \mathbf{0.5}(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))$$

$$+ -2 \times \mathbf{2.9}(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))$$

$$+ -2 \times \mathbf{2.3}(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))$$

$$\frac{d}{d\ intercept} \text{Sum of squared residuals} =$$

-2(**1.4** - (intercept + slope × **0.5**)

\+ -2(**1.9** - (intercept + slope × **2.3**))

\+ -2(**3.2** - (intercept + slope × **2.9**))

We will use this **Gradient** to **descend** to lowest point in the **Loss Function**, which, in this case, is the Sum of the Squared Residuals…

…thus, this is why this algorithm is called **Gradient Descent**!

$$\frac{d}{d\ slope} \text{Sum of squared residuals} =$$

-2 × **0.5**(**1.4** - (intercept + slope × **0.5**))

\+ -2 × **2.9**(**3.2** - (intercept + slope × **2.9**))

\+ -2 × **2.3**(**1.9** - (intercept + slope × **2.3**))

$$\frac{d}{d\ intercept}\ \text{Sum of squared residuals} = -2(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5})) + -2(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3})) + -2(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))$$

Just like before, we will start by picking a random number for the **Intercept**. In this case we'll set the **Intercept** = **0**…

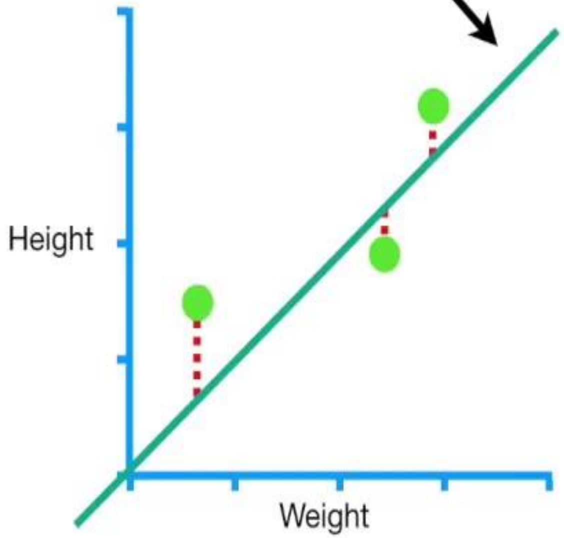
…and we'll pick a random number for the **Slope**. In this case we'll set the **Slope** = **1**.

$$\frac{d}{d\ slope}\ \text{Sum of squared residuals} = -2 \times \mathbf{0.5}(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5})) + -2 \times \mathbf{2.9}(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9})) + -2 \times \mathbf{2.3}(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))$$

$$\frac{d}{d\ intercept} \text{Sum of squared residuals} = -2(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5})) + -2(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3})) + -2(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))$$

$$\frac{d}{d\ slope} \text{Sum of squared residuals} = -2 \times \mathbf{0.5}(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5})) + -2 \times \mathbf{2.9}(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9})) + -2 \times \mathbf{2.3}(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))$$

Thus, this line, with **Intercept** = **0** and **Slope** = **1**, is where we will start.



$$\frac{d}{d\ intercept} \text{ Sum of squared residuals} = -2(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))$$
$$+ -2(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))$$
$$+ -2(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))$$

Now let's plug in **0** for the **Intercept** and **1** for the **Slope**…

$$\frac{d}{d\ slope} \text{ Sum of squared residuals} = -2 \times \mathbf{0.5}(\mathbf{1.4} - (\text{intercept} + \text{slope} \times \mathbf{0.5}))$$
$$+ -2 \times \mathbf{2.9}(\mathbf{3.2} - (\text{intercept} + \text{slope} \times \mathbf{2.9}))$$
$$+ -2 \times \mathbf{2.3}(\mathbf{1.9} - (\text{intercept} + \text{slope} \times \mathbf{2.3}))$$

$$\frac{d}{d\ intercept} \text{ Sum of squared residuals} =$$

$$-2(\mathbf{1.4} - (0 + 1 \times \mathbf{0.5})$$

$$+ -2(\mathbf{1.9} - (0 + 1 \times \mathbf{2.3}))$$

$$+ -2(\mathbf{3.2} - (0 + 1 \times \mathbf{2.9})) \boxed{= \mathbf{-1.6}}$$

...and that gives us two **Slopes**...

$$\frac{d}{d\ slope} \text{ Sum of squared residuals} =$$

$$-2 \times \mathbf{0.5}(\mathbf{1.4} - (0 + 1 \times \mathbf{0.5}))$$

$$+ -2 \times \mathbf{2.9}(\mathbf{3.2} - (0 + 1 \times \mathbf{2.9}))$$

$$+ -2 \times \mathbf{2.3}(\mathbf{1.9} - (0 + 1 \times \mathbf{2.3})) \boxed{= \mathbf{-0.8}}$$

$$\frac{d}{d\ intercept} \text{ Sum of squared residuals} = -2(\mathbf{1.4} - (0 + 1 \times \mathbf{0.5})) + -2(\mathbf{1.9} - (0 + 1 \times \mathbf{2.3})) + -2(\mathbf{3.2} - (0 + 1 \times \mathbf{2.9})) = \mathbf{-1.6}$$

$$\textbf{Step Size}_{\text{Intercept}} = -1.6 \times \textbf{Learning Rate}$$

...now we plug the **Slopes** into the **Step Size** formulas...

$$\frac{d}{d\ slope} \text{ Sum of squared residuals} = -2 \times \mathbf{0.5}(\mathbf{1.4} - (0 + 1 \times \mathbf{0.5})) + -2 \times \mathbf{2.9}(\mathbf{3.2} - (0 + 1 \times \mathbf{2.9})) + -2 \times \mathbf{2.3}(\mathbf{1.9} - (0 + 1 \times \mathbf{2.3})) = \mathbf{-0.8}$$

$$\textbf{Step Size}_{\text{Slope}} = -0.8 \times \textbf{Learning Rate}$$

$$\frac{d}{d\ intercept} \text{Sum of squared residuals} = -2(1.4 - (0 + 1 \times 0.5)) + -2(1.9 - (0 + 1 \times 2.3)) + -2(3.2 - (0 + 1 \times 2.9)) = -1.6$$

$$\text{Step Size}_{\text{Intercept}} = -1.6 \times \textbf{Learning Rate}$$

…and multiply by the **Learning Rate**, which this time we set to **0.01**…

$$\text{Step Size}_{\text{Slope}} = -0.8 \times \textbf{Learning Rate}$$

$$\frac{d}{d\ slope} \text{Sum of squared residuals} = -2 \times 0.5(1.4 - (0 + 1 \times 0.5)) + -2 \times 2.9(3.2 - (0 + 1 \times 2.9)) + -2 \times 2.3(1.9 - (0 + 1 \times 2.3)) = -0.8$$

$$\frac{d}{d\,intercept} \text{ Sum of squared residuals} = -2(\mathbf{1.4} - (0 + 1 \times \mathbf{0.5})) + -2(\mathbf{1.9} - (0 + 1 \times \mathbf{2.3})) + -2(\mathbf{3.2} - (0 + 1 \times \mathbf{2.9})) = \mathbf{-1.6}$$

$$\textbf{Step Size}_{Intercept} = -1.6 \times 0.01 = \mathbf{-0.016}$$

New Intercept = **Old Intercept** - **Step Size**

Now we calculate the **New Intercept** and **New Slope** by plugging in the **Old Intercept** and the **Old Slope**…

$$\frac{d}{d\,slope} \text{ Sum of squared residuals} = -2 \times \mathbf{0.5}(\mathbf{1.4} - (0 + 1 \times \mathbf{0.5})) + -2 \times \mathbf{2.9}(\mathbf{3.2} - (0 + 1 \times \mathbf{2.9})) + -2 \times \mathbf{2.3}(\mathbf{1.9} - (0 + 1 \times \mathbf{2.3})) = \mathbf{-0.8}$$

$$\textbf{Step Size}_{Slope} = -0.8 \times 0.01 = \mathbf{-0.008}$$

New Slope = **Old Slope** - **Step Size**

$$\frac{d}{d\ intercept}\text{ Sum of squared residuals} = -2(\mathbf{1.4} - (0 + 1 \times \mathbf{0.5})) + -2(\mathbf{1.9} - (0 + 1 \times \mathbf{2.3})) + -2(\mathbf{3.2} - (0 + 1 \times \mathbf{2.9})) = \mathbf{-1.6}$$

$$\textbf{Step Size}_{\text{Intercept}} = -1.6 \times 0.01 = \mathbf{-0.016}$$

New Intercept = 0 - (-0.016) = 0.016

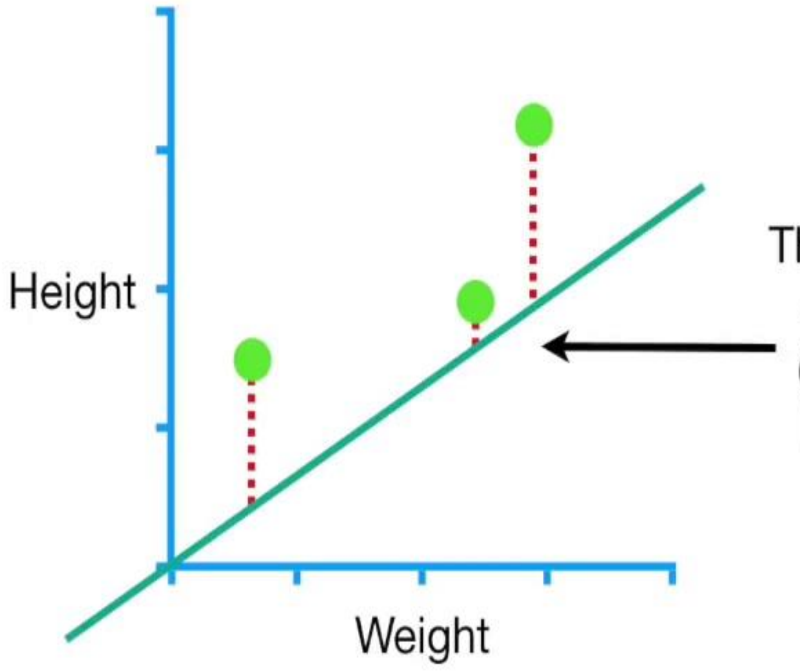
…and we end up with a **New Intercept** and a **New Slope**.

$$\frac{d}{d\ slope}\text{ Sum of squared residuals} = -2 \times \mathbf{0.5}(\mathbf{1.4} - (0 + 1 \times \mathbf{0.5})) + -2 \times \mathbf{2.9}(\mathbf{3.2} - (0 + 1 \times \mathbf{2.9})) + -2 \times \mathbf{2.3}(\mathbf{1.9} - (0 + 1 \times \mathbf{2.3})) = \mathbf{-0.8}$$

$$\textbf{Step Size}_{\text{Slope}} = -0.8 \times 0.01 = \mathbf{-0.008}$$

New Slope = 1 - (-0.008) = 1.008

GD for *m, b*

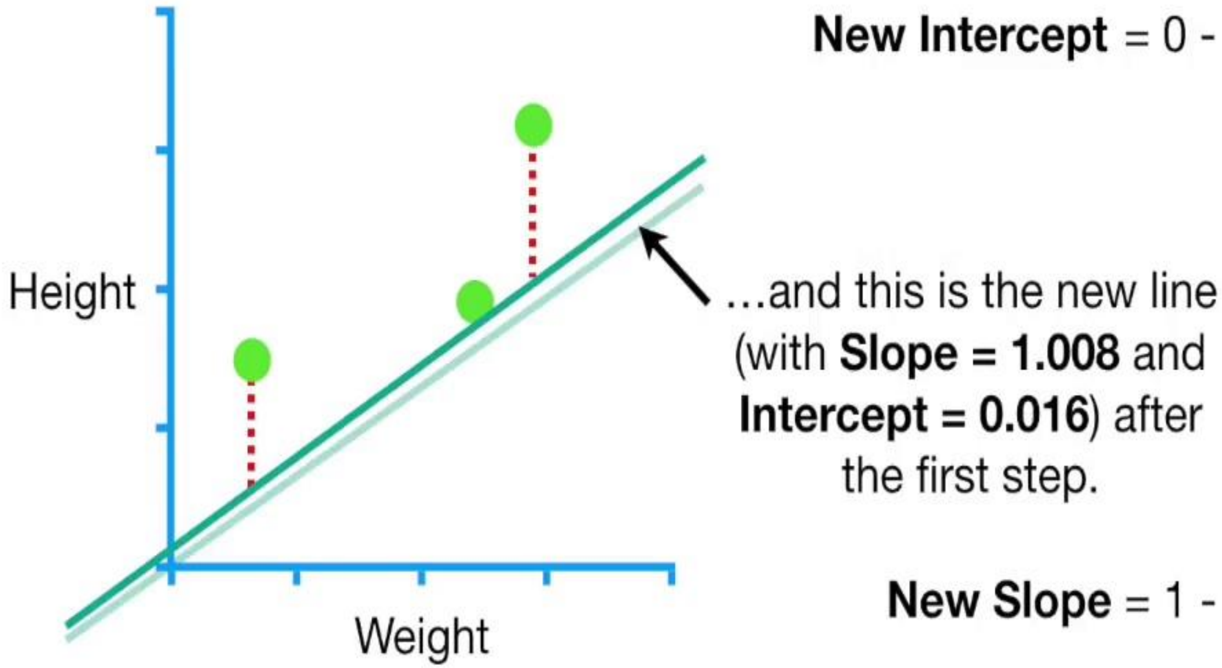


New Intercept = 0 - (-0.016) = 0.016

This is the line we started with… (**Slope = 1** and **Intercept = 0**)

New Slope = 1 - (-0.008) = 1.008

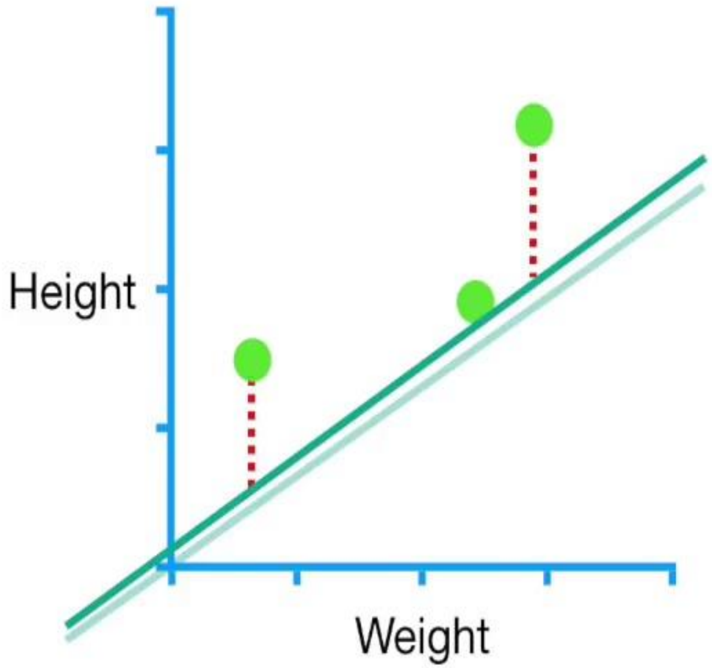
GD for *m, b*



New Intercept = 0 - (-0.016) = 0.016

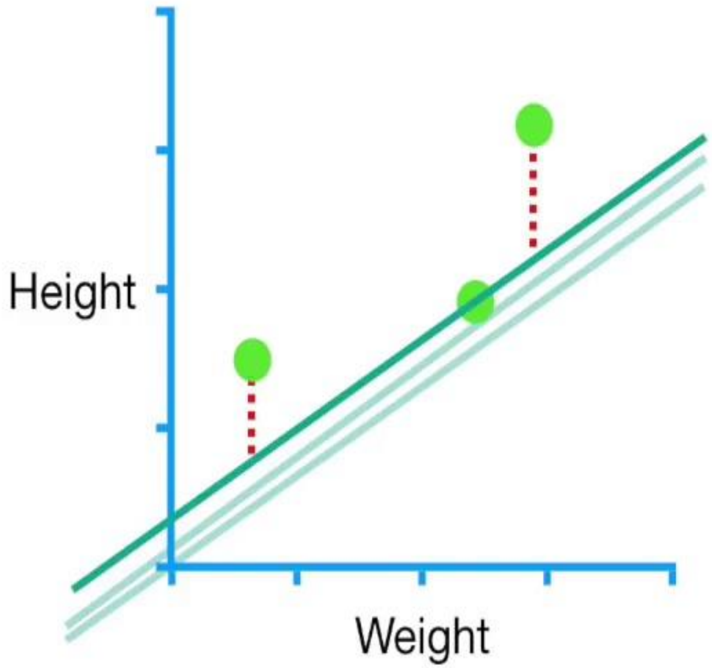
New Slope = 1 - (-0.008) = 1.008

GD for *m, b*



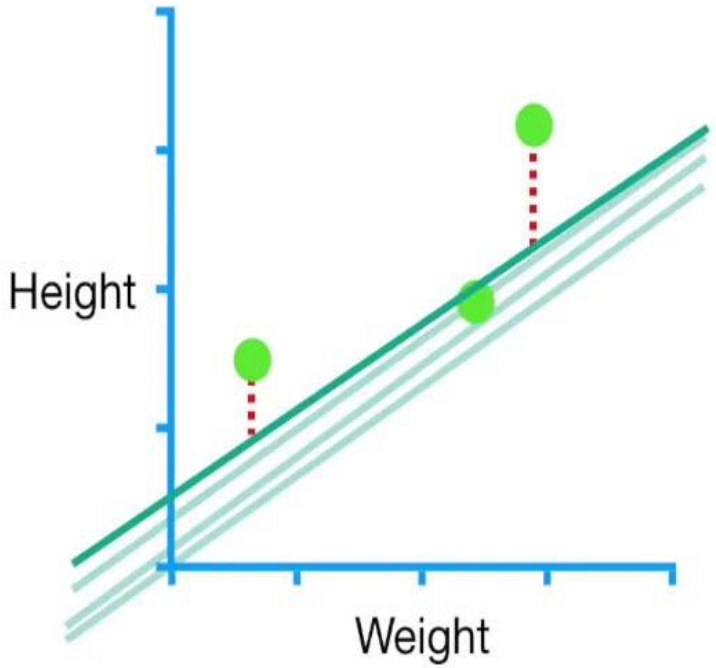
Now we just repeat what we did until all of the **Steps Sizes** are very small or we reach the **Maximum Number of Steps**.

GD for *m, b*



Now we just repeat what we did until all of the **Steps Sizes** are very small or we reach the **Maximum Number of Steps**.

GD for *m, b*



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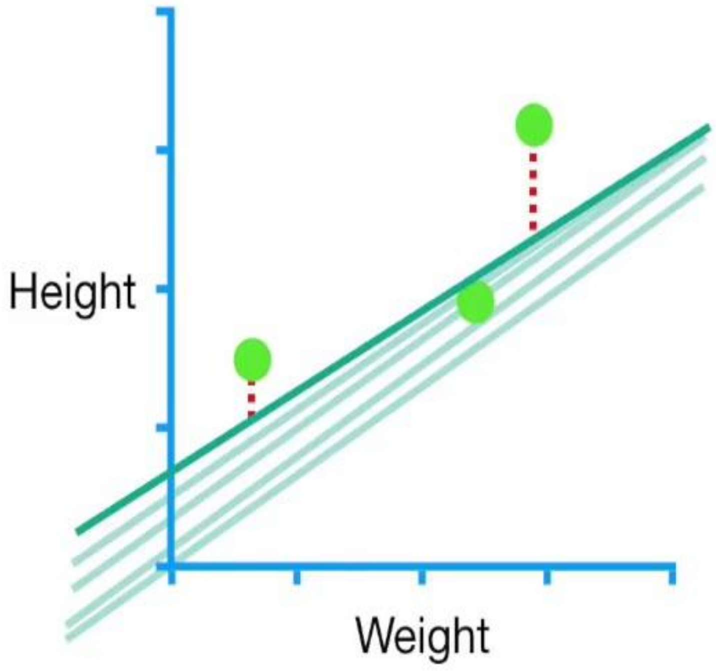
GD for *m, b*



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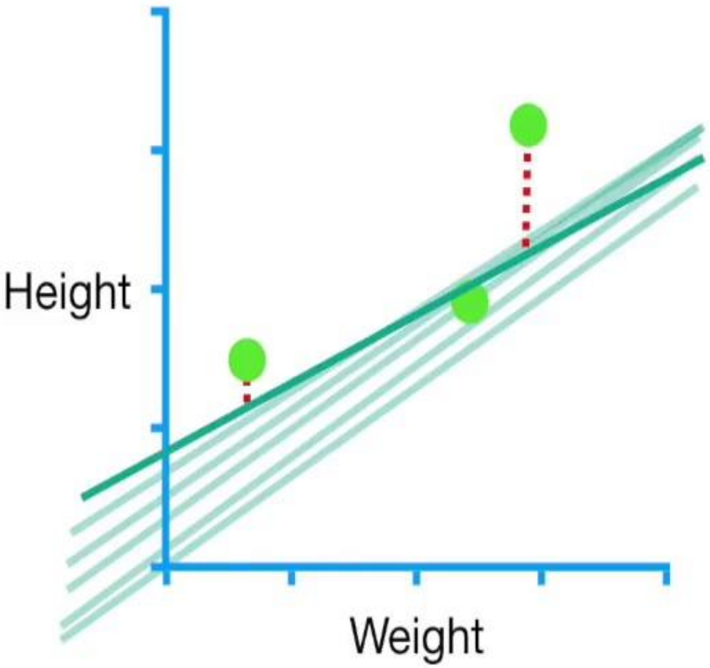
GD for *m, b*



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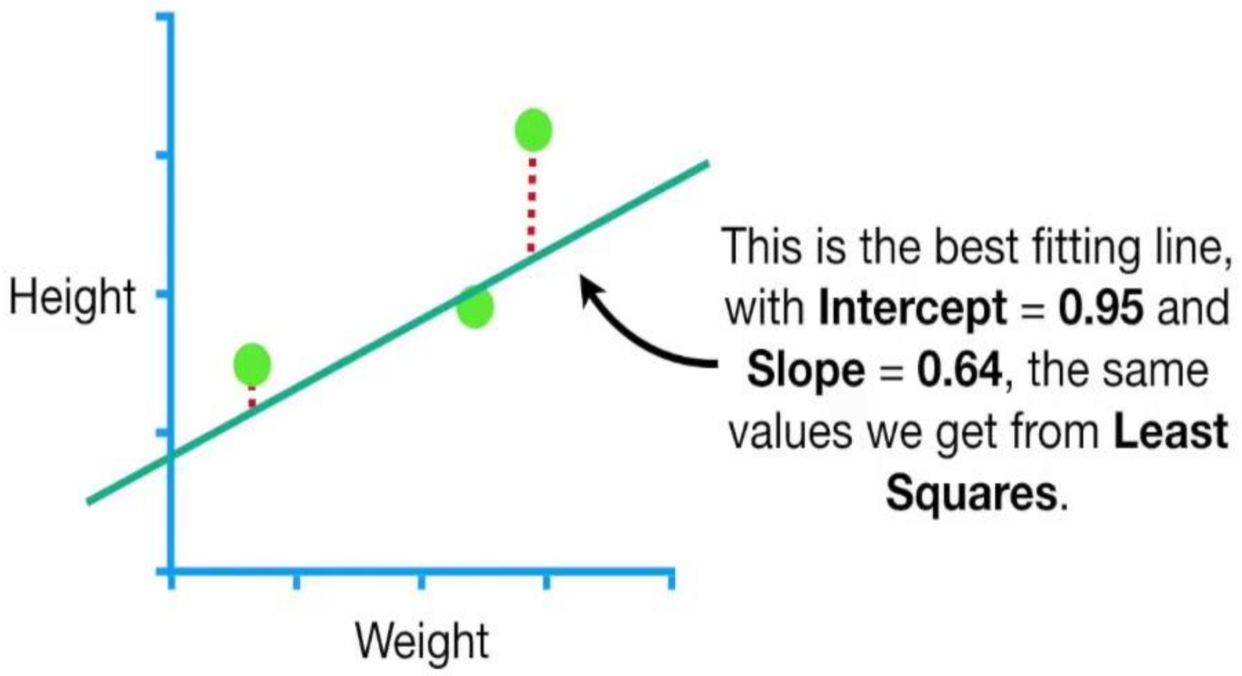
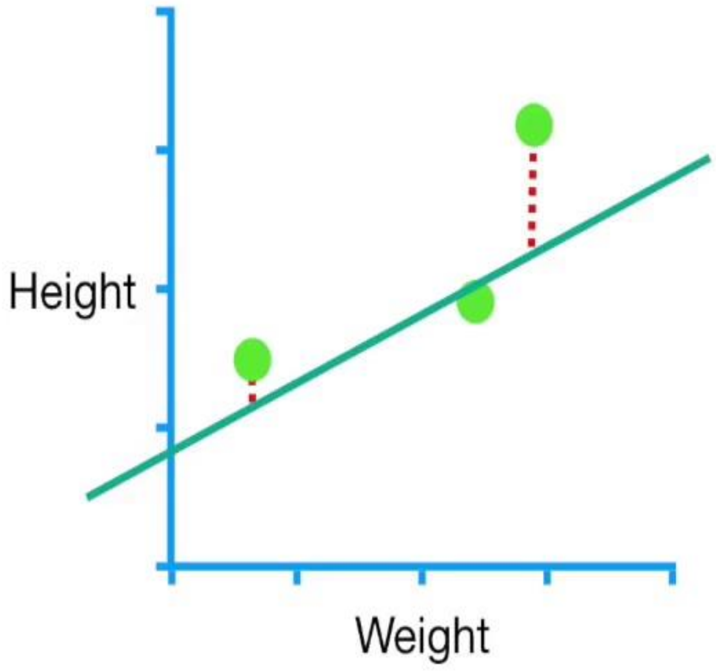
GD for *m, b*

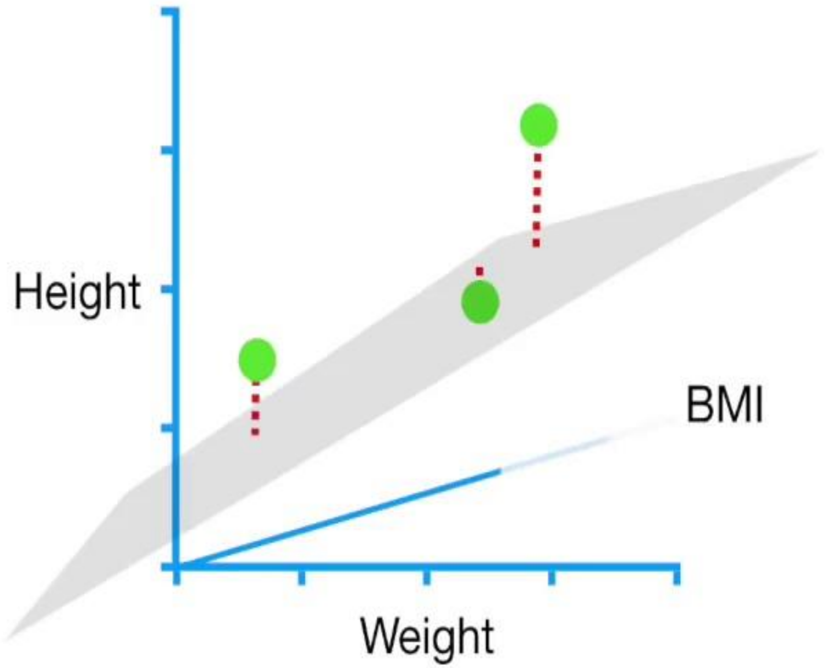

Height
Weight
This is the best fitting line, with Intercept = 0.95 and Slope = 0.64, the same values we get from Least Squares.

GD for *m, b*



We now know how **Gradient Descent** optimizes two parameters, the **Slope** and **Intercept**.

GD for more parameters and variables



If we had more parameters, then we'd just take more derivatives and everything else stays the same.

Gradient Descent Recap

Step 1: Take the derivative of the **Loss Function** for each parameter in it.
In fancy Machine Learning Lingo, take the **Gradient** of the **Loss Function**.

Gradient Descent Recap

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Step 2: Pick random values for the parameters.

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Step 3: Plug the parameter values into the derivatives (ahem, the **Gradient**).

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Step 4: Calculate the Step Sizes: **Step Size** = **Slope** × **Learning Rate**

Gradient Descent Recap

Step 1: Take the derivative of the **Loss Function** for each parameter in it.
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Step 4: Calculate the Step Sizes: **Step Size** = **Slope** x **Learning Rate**

Step 5: Calculate the New Parameters:

New Parameter = **Old Parameter** - **Step Size**

Gradient Descent Recap

Now go back to **Step 3** and repeat until **Step Size** is very small, or you reach the **Maximum Number of Steps**.

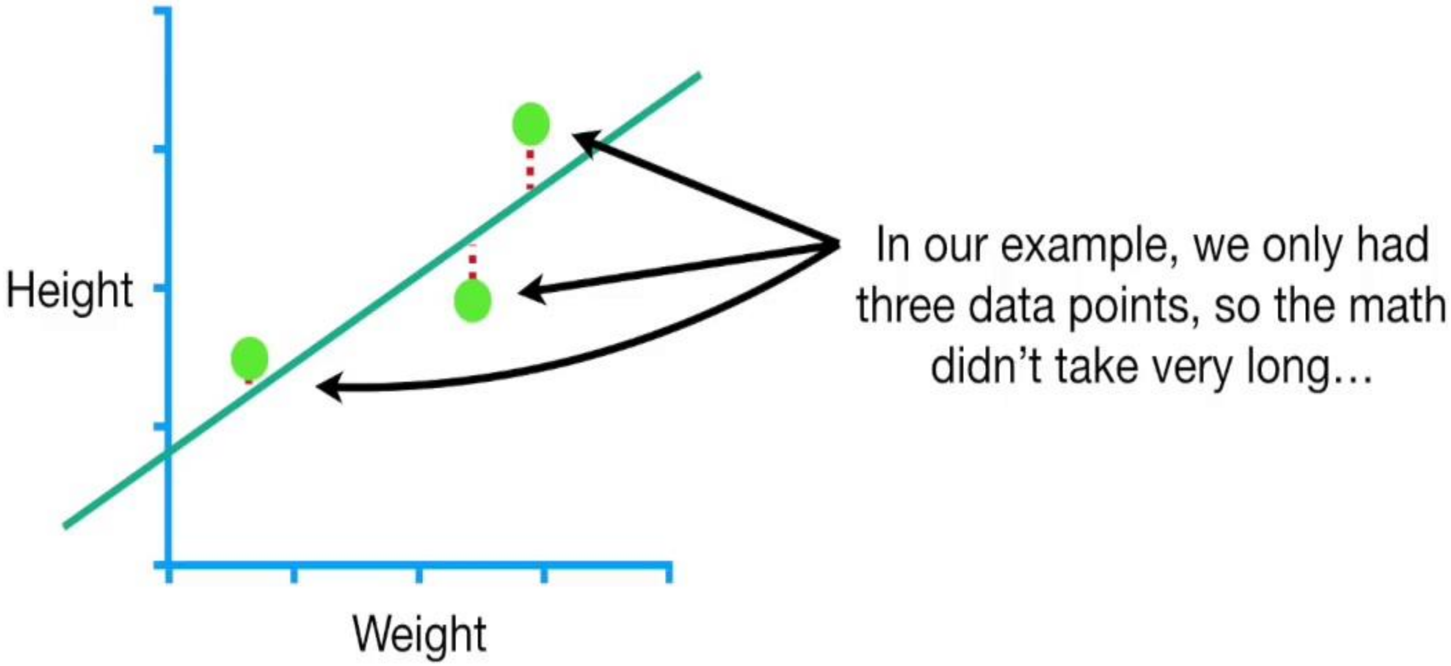
Step 3: Plug the parameter values into the derivatives (ahem, the **Gradient**).

Step 4: Calculate the Step Sizes: **Step Size** = **Slope** × **Learning Rate**

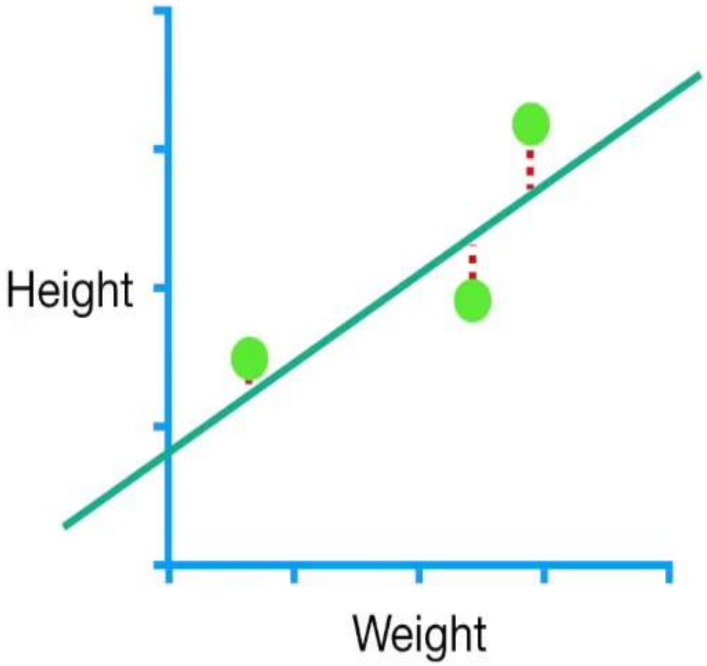
Step 5: Calculate the New Parameters:

New Parameter = **Old Parameter** - **Step Size**

Stochastic Gradient Descent

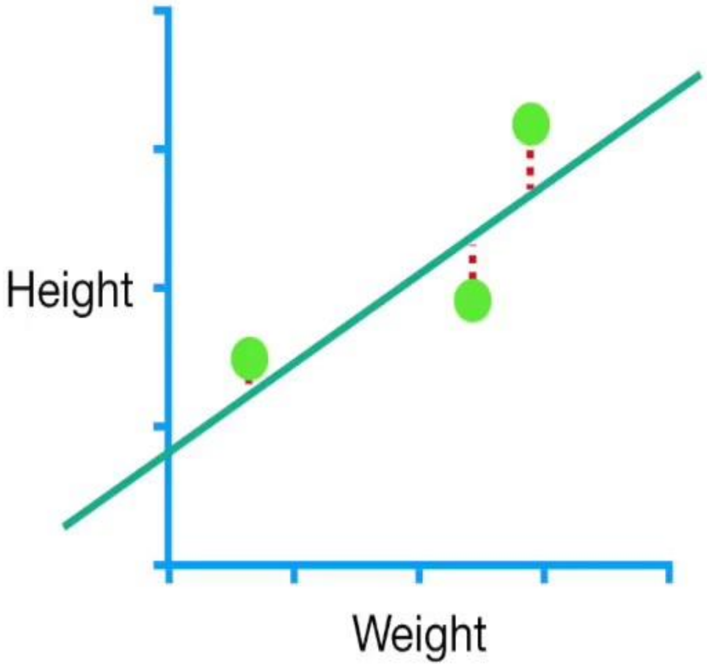


Stochastic Gradient Descent



...but when you have millions of data points, it can take a long time.

Stochastic Gradient Descent



So there is a thing called **Stochastic Gradient Descent** that uses a randomly selected subset of the data at every step rather than the full dataset.

This reduces the time spent calculating the derivatives of the **Loss Function**.

GD Summary

- GD is an optimization algorithm.
- You can use GD to find minimum (or maximum, then it is called Gradient Ascent) of many different functions.
- GD does not really care what is the function that it minimizes, it just does what it was asked for.
- Using GD, you must know how tell if one value of the parameter of interest is "better" than the other.
- You must provide GD some function to minimize/maximize, and GD will deal with finding its optimum value.

References

- Lemaréchal, C. (2012). "Cauchy and the Gradient Method" (PDF). Doc Math Extra: 251–254.
- An overview of gradient descent optimization algorithms “Sebastian Ruder”, https://arxiv.org/abs/1609.04747