

...let's see how the most common
Gradient Boost configuration would
use this **Training Data** to Predict
Weight.

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88
1.6	Green	Female	76
1.5	Blue	Female	56
1.8	Red	Male	73
1.5	Green	Male	77
1.4	Blue	Female	57



Average Weight

71.2

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88
1.6	Green	Female	76
1.5	Blue	Female	56
1.8	Red	Male	73
1.5	Green	Male	77
1.4	Blue	Female	57

The first thing we do is calculate the average **Weight**.

Average Weight

71.2



Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88
1.6	Green	Female	76
1.5	Blue	Female	56
1.8	Red	Male	73
1.5	Green	Male	77
1.4	Blue	Female	57

This is the first attempt at predicting everyone's weight.

Average Weight

71.2

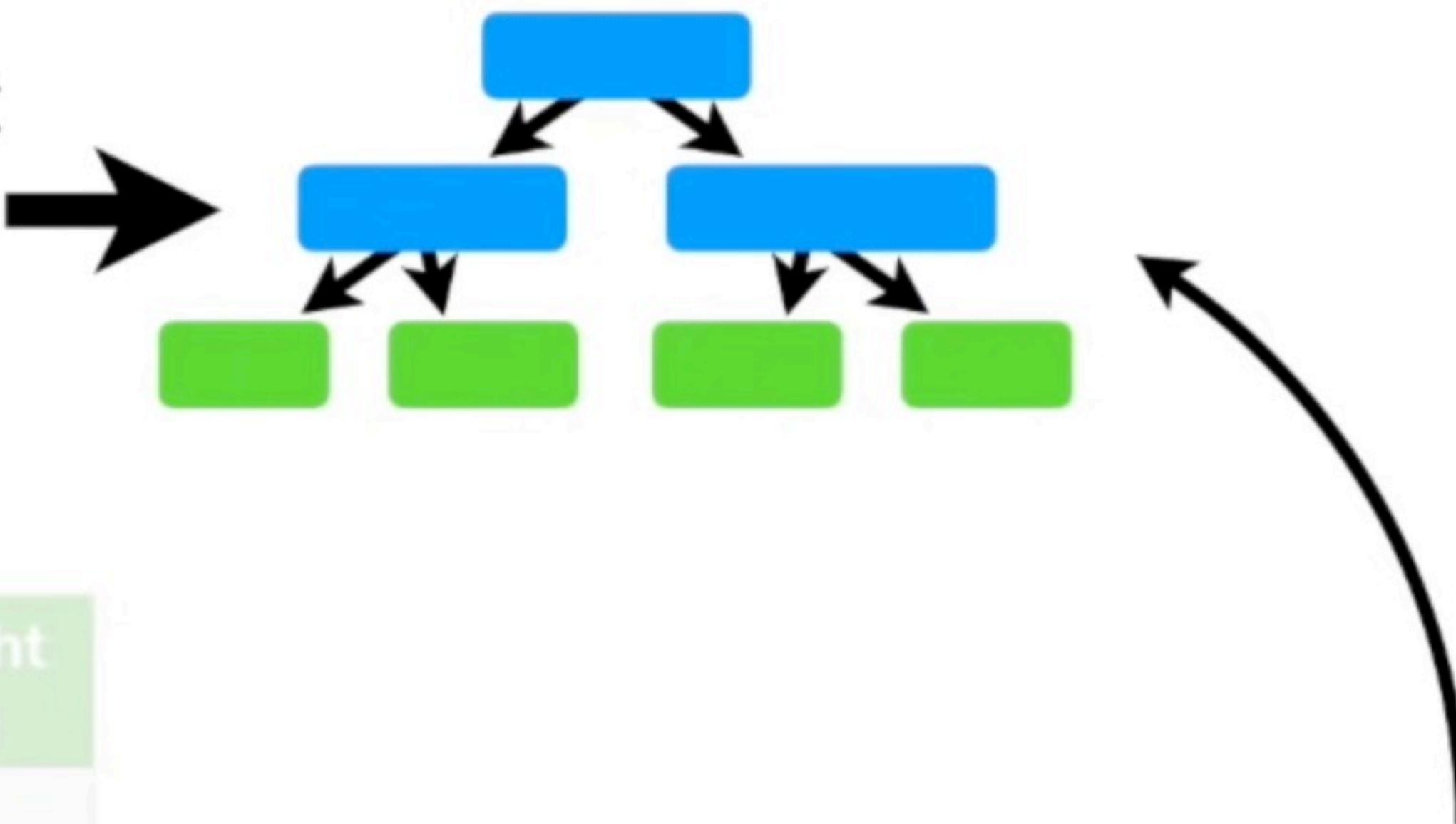


Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88
1.6	Green	Female	76
1.5	Blue	Female	56
1.8	Red	Male	73
1.5	Green	Male	77
1.4	Blue	Female	57

In other words, if we stopped right now, we would predict that everyone **Weighed 71.2 kg.**

Average Weight

71.2

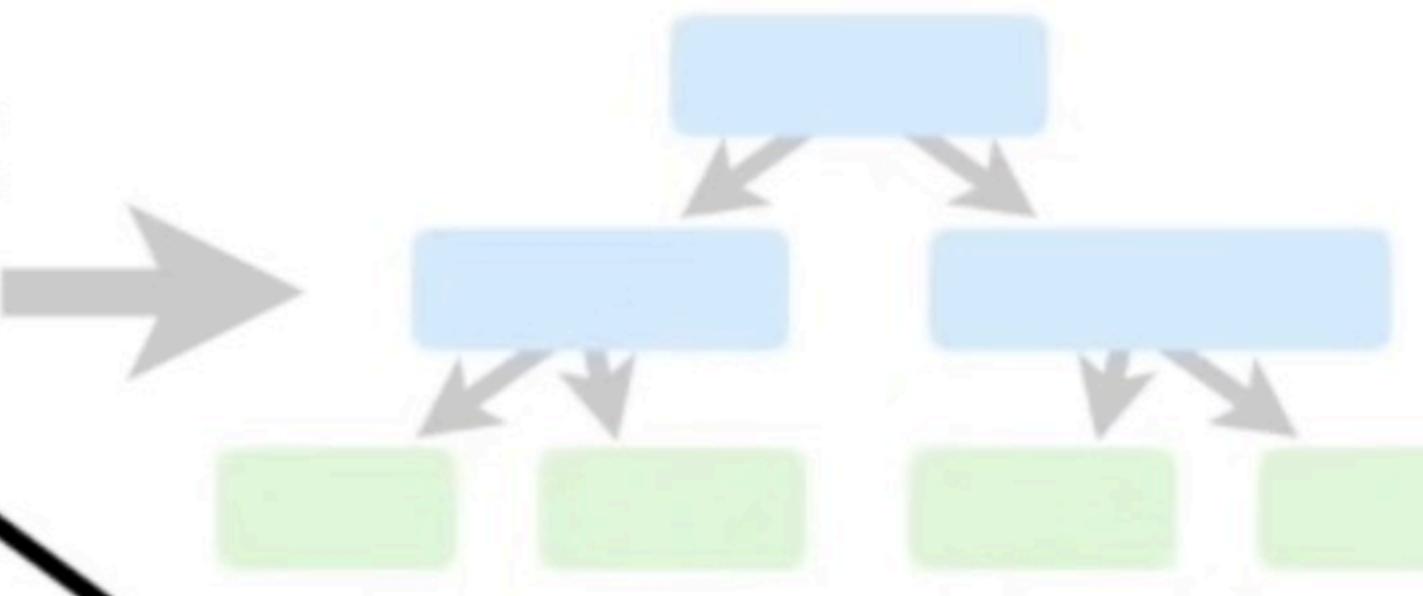


Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88
1.6	Green	Female	76
1.5	Blue	Female	56
1.8	Red	Male	73
1.5	Green	Male	77
1.4	Blue	Female	57

The next thing we do is build a tree based on the errors from the first tree.

Average Weight

71.2



Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88
1.6	Green	Female	76
1.5	Blue	Female	56
1.8	Red	Male	73
1.5	Green	Male	77
1.4	Blue	Female	57

The errors that the previous tree made are the differences between the **Observed Weights** and the **Predicted Weight, 71.2.**

(Observed Weight - Predicted Weight)

Average Weight

71.2

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88
1.6	Green	Female	76
1.5	Blue	Female	56
1.8	Red	Male	73
1.5	Green	Male	77
1.4	Blue	Female	57

So let's start by plugging in **71.2** for the **Predicted Weight...**

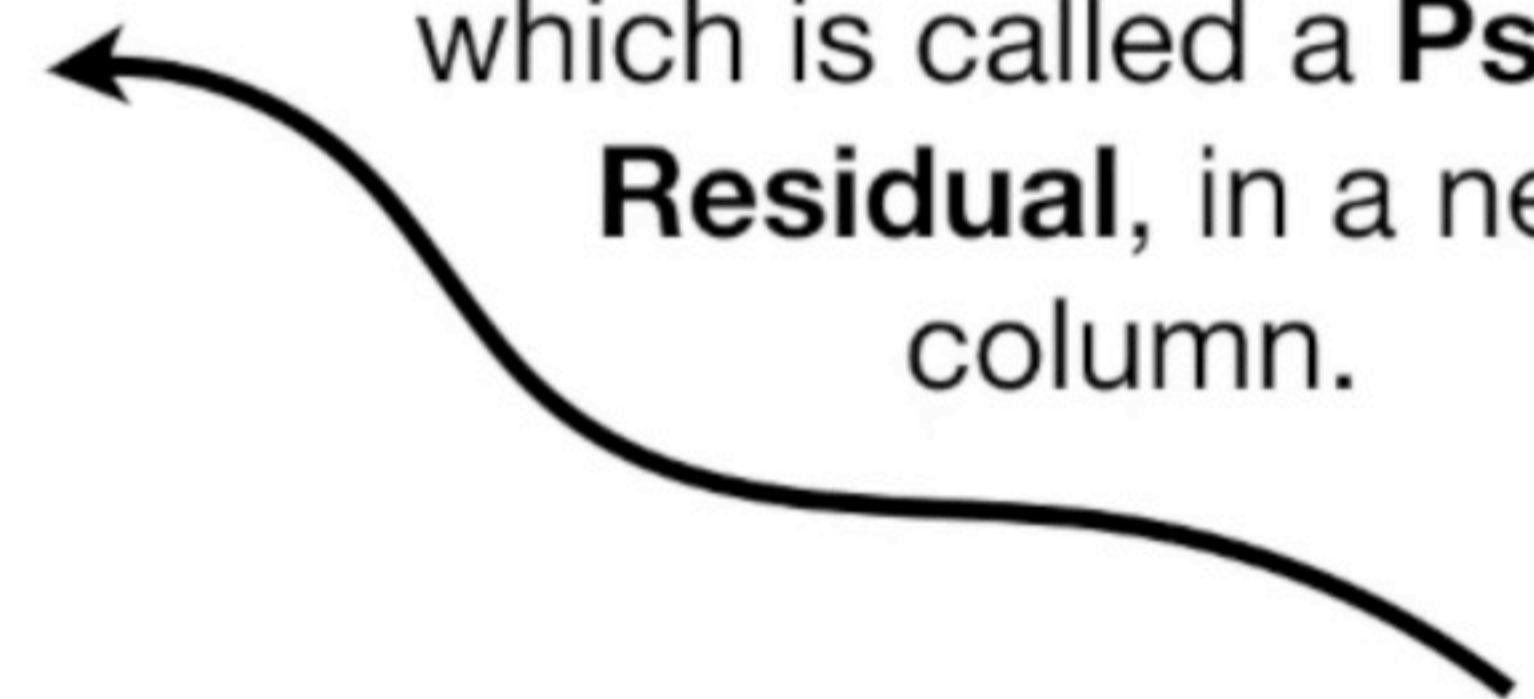
(Observed Weight - 71.2)

Average Weight

71.2

Height (m)	Favorite Color	Gender	Weight (kg)	Residual
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	
1.5	Blue	Female	56	
1.8	Red	Male	73	
1.5	Green	Male	77	
1.4	Blue	Female	57	

...and save the difference,
which is called a **Pseudo
Residual**, in a new
column.



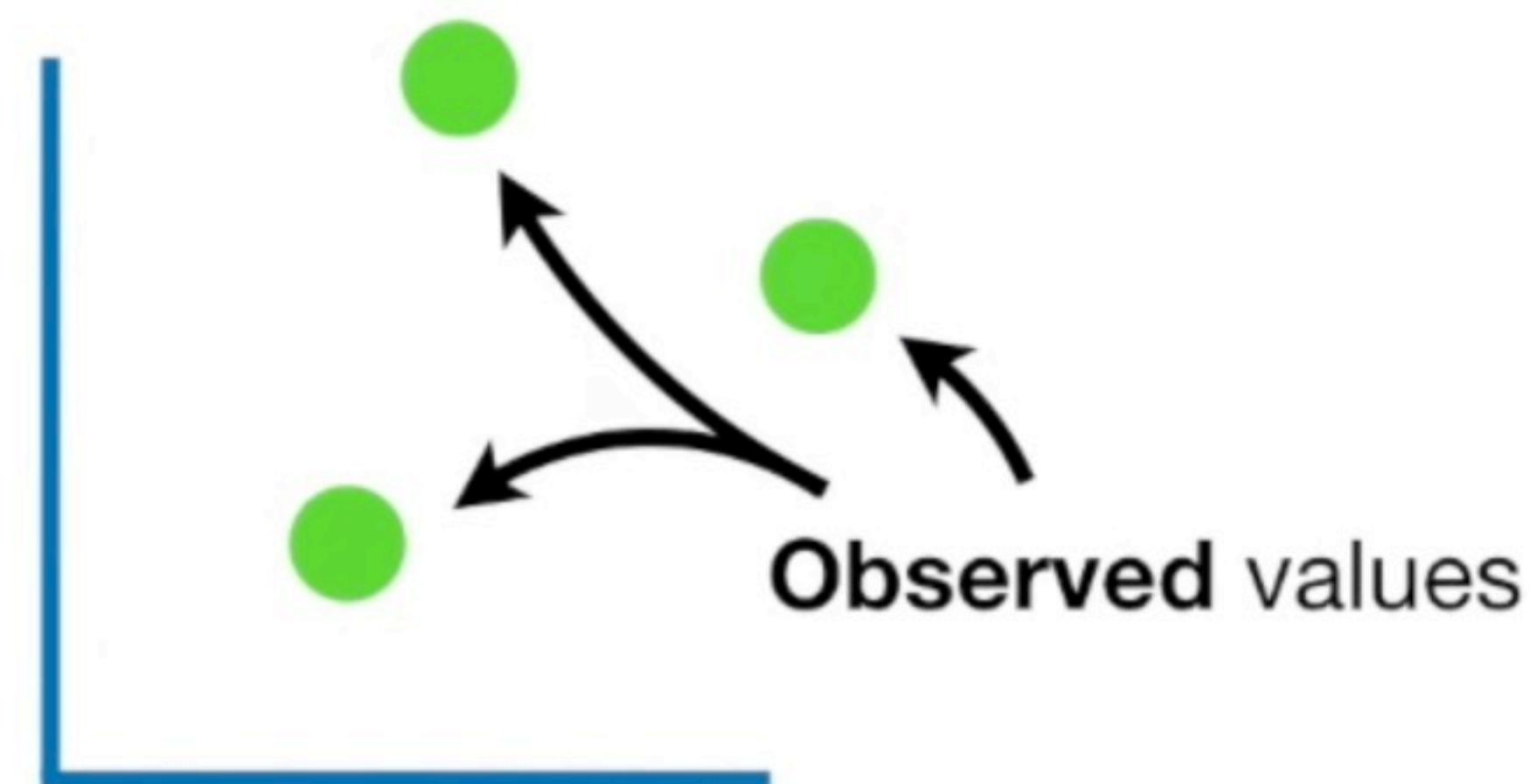
$$(88 - 71.2) = 16.8$$

Average Weight

71.2

NOTE: The term **Pseudo Residual** is based on **Linear Regression**, where the difference between the **Observed** values and the **Predicted** values results in **Residuals**.

Height (m)	Favorite Color	Gender	Weight (kg)	Residual
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	
1.5	Blue	Female	56	
1.8	Red	Male	73	
1.5	Green	Male	77	
1.4	Blue	Female	57	

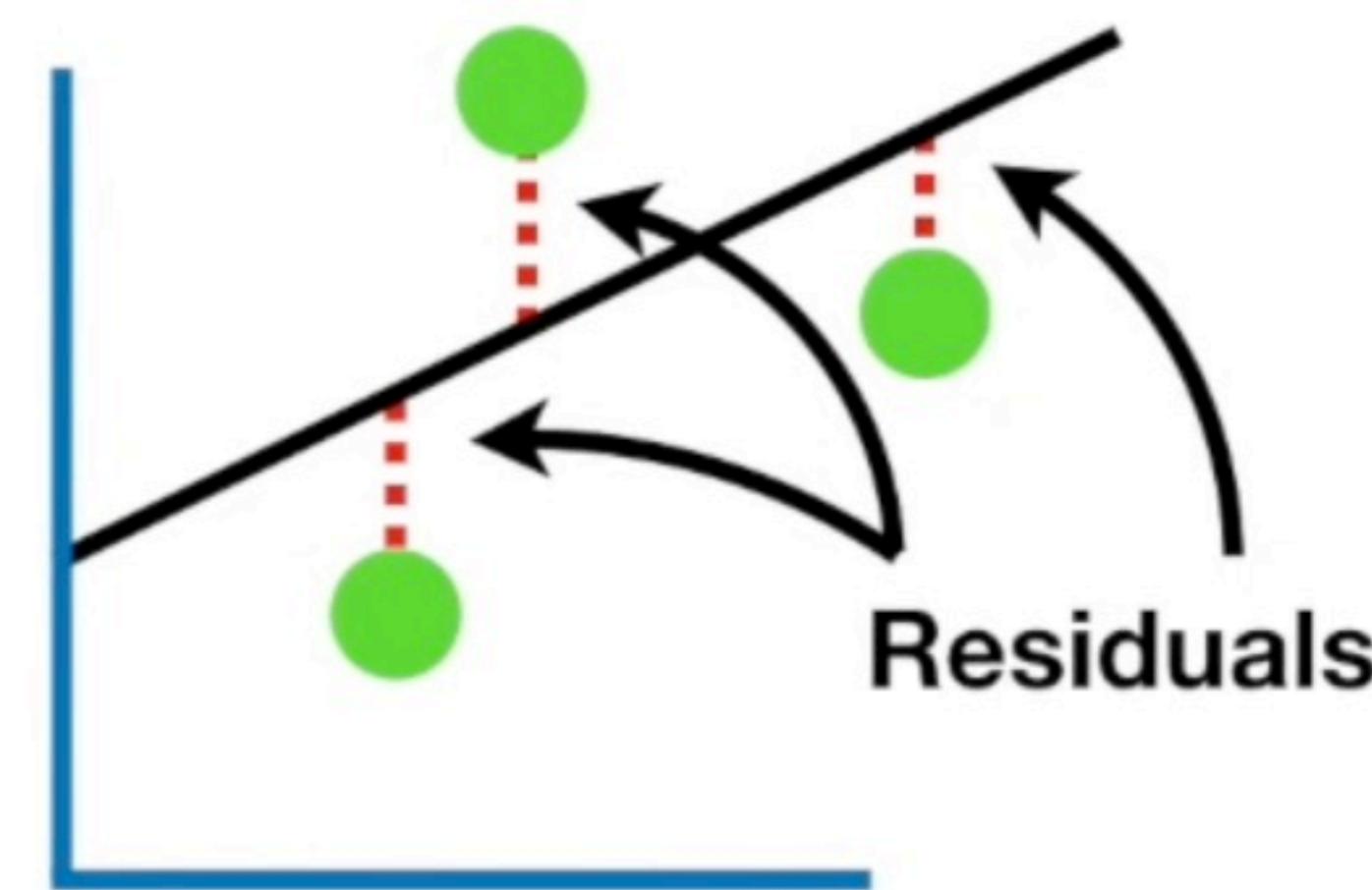


Average Weight

71.2

NOTE: The term **Pseudo Residual** is based on **Linear Regression**, where the difference between the **Observed** values and the **Predicted** values results in **Residuals**.

Height (m)	Favorite Color	Gender	Weight (kg)	Residual
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	
1.5	Blue	Female	56	
1.8	Red	Male	73	
1.5	Green	Male	77	
1.4	Blue	Female	57	



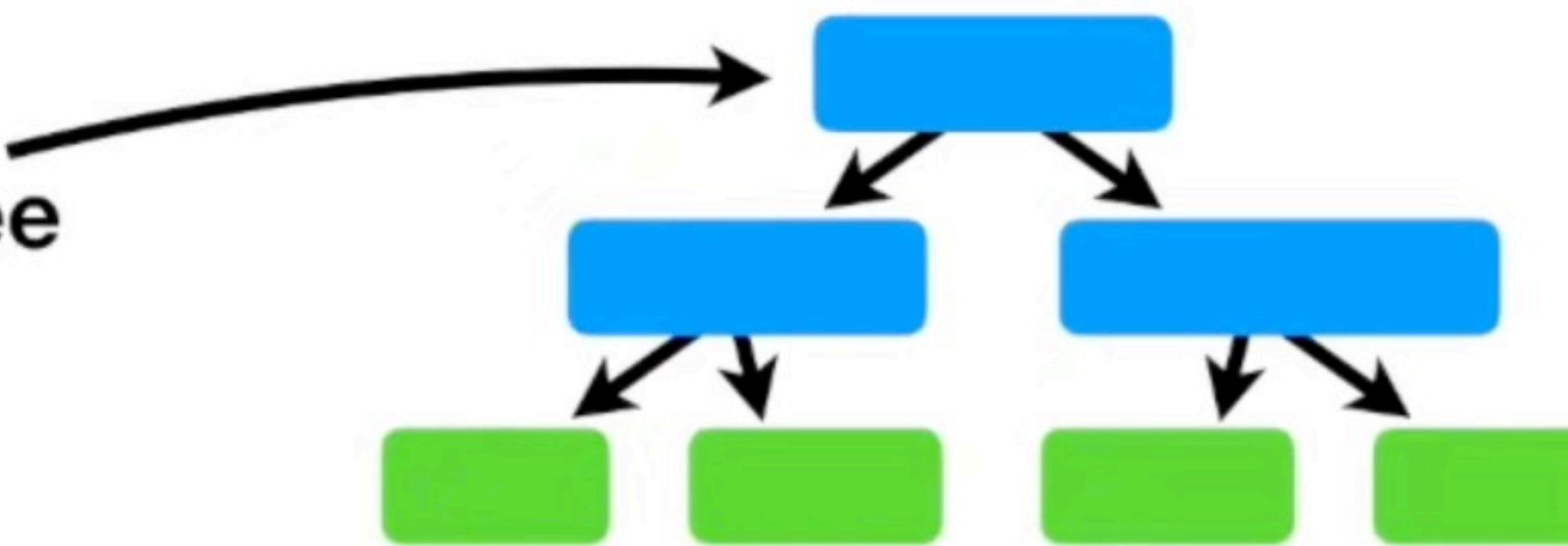
Average Weight

71.2

Height (m)	Favorite Color	Gender	Weight (kg)	Residual
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	
1.5	Blue	Female	56	
1.8	Red	Male	73	
1.5	Green	Male	77	
1.4	Blue	Female	57	

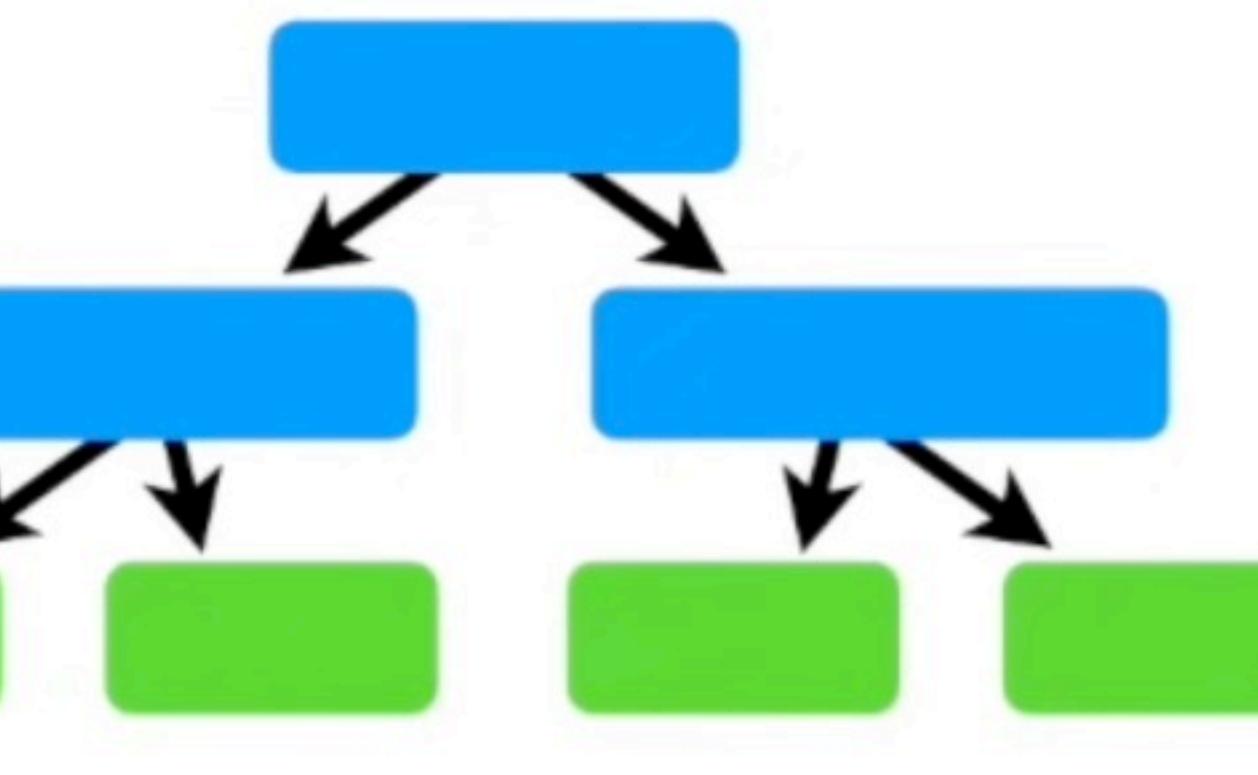
The “**Pseudo**” part of **Pseudo Residual** is a reminder that we are doing **Gradient Boost**, not **Linear Regression**, and is something I’ll talk more about in **Part 2** of this series when we go through the math.

Now we will build a **Tree**

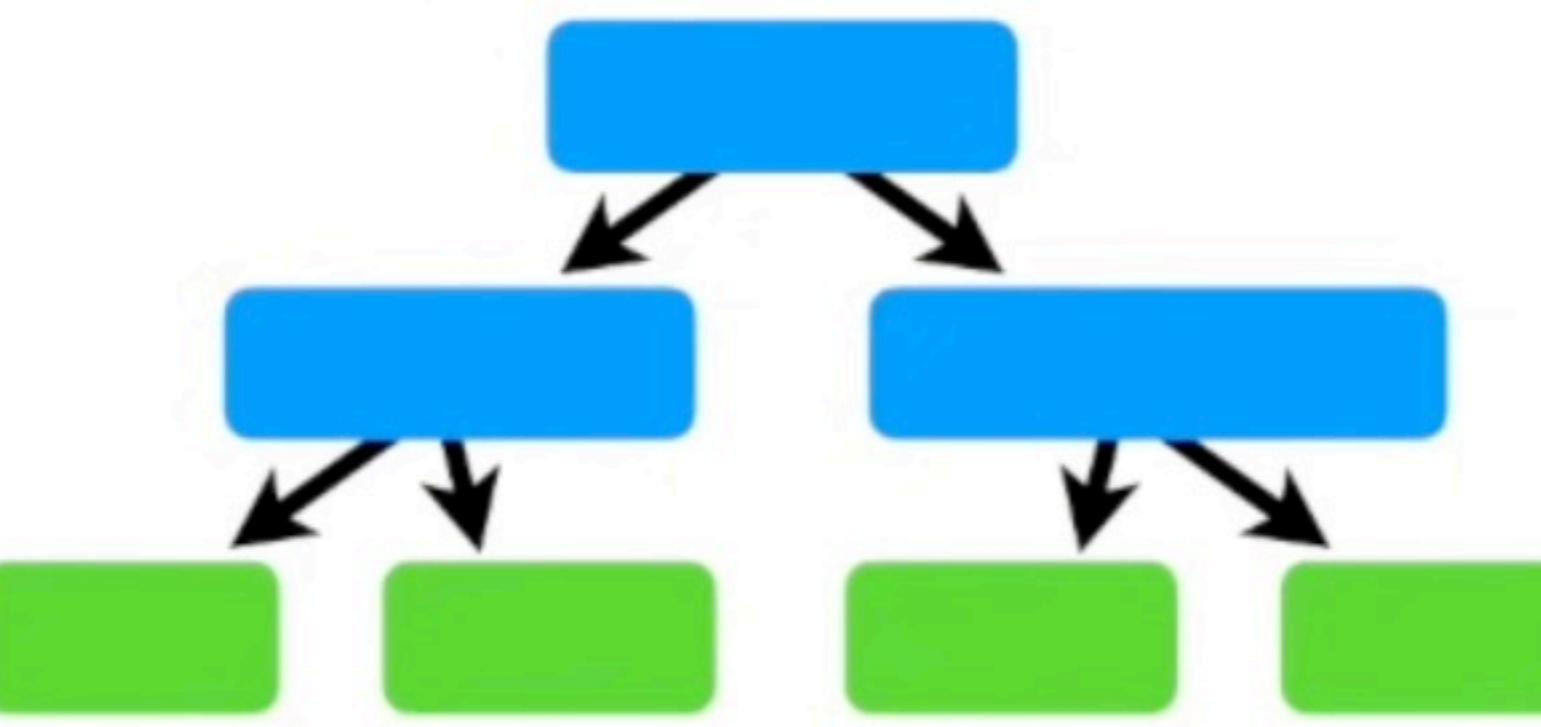


Height (m)	Favorite Color	Gender	Weight (kg)	Residual
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	4.8
1.5	Blue	Female	56	-15.2
1.8	Red	Male	73	1.8
1.5	Green	Male	77	5.8
1.4	Blue	Female	57	-14.2

Now we will build a **Tree**, using
Height, Favorite Color and Gender...



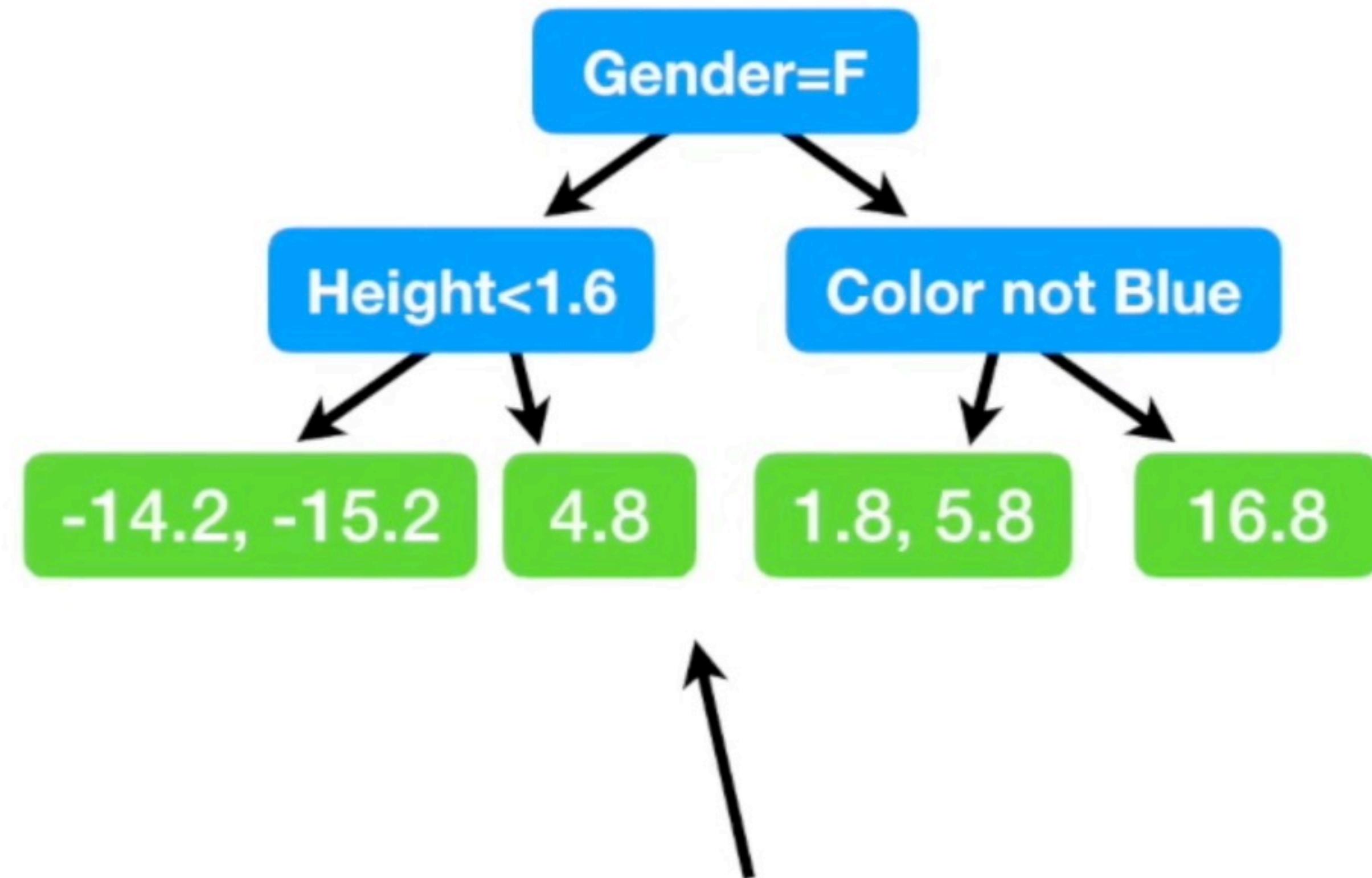
Height (m)	Favorite Color	Gender	Weight (kg)	Residual
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	4.8
1.5	Blue	Female	56	-15.2
1.8	Red	Male	73	1.8
1.5	Green	Male	77	5.8
1.4	Blue	Female	57	-14.2



Height (m)	Favorite Color	Gender	Weight (kg)	Residual
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	4.8
1.5	Blue	Female	56	-15.2
1.8	Red	Male	73	1.8
1.5	Green	Male	77	5.8
1.4	Blue	Female	57	-14.2

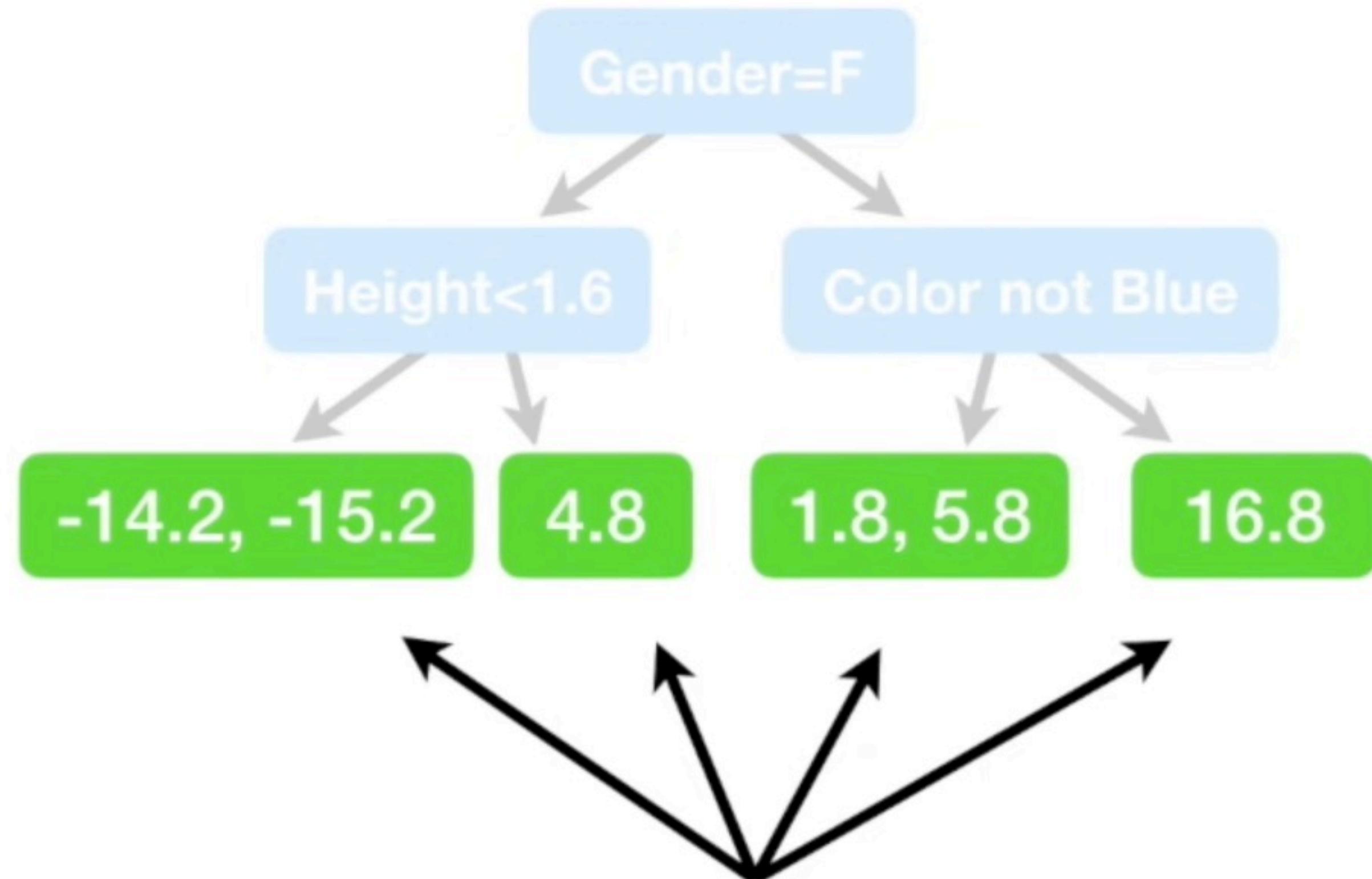
If it seems strange to **Predict** the **Residuals** instead of the original **Weights**, just bear with me and soon all will become clear.

Height (m)	Favorite Color	Gender	Residual
1.6	Blue	Male	16.8
1.6	Green	Female	4.8
1.5	Blue	Female	-15.2
1.8	Red	Male	1.8
1.5	Green	Male	5.8
1.4	Blue	Female	-14.2



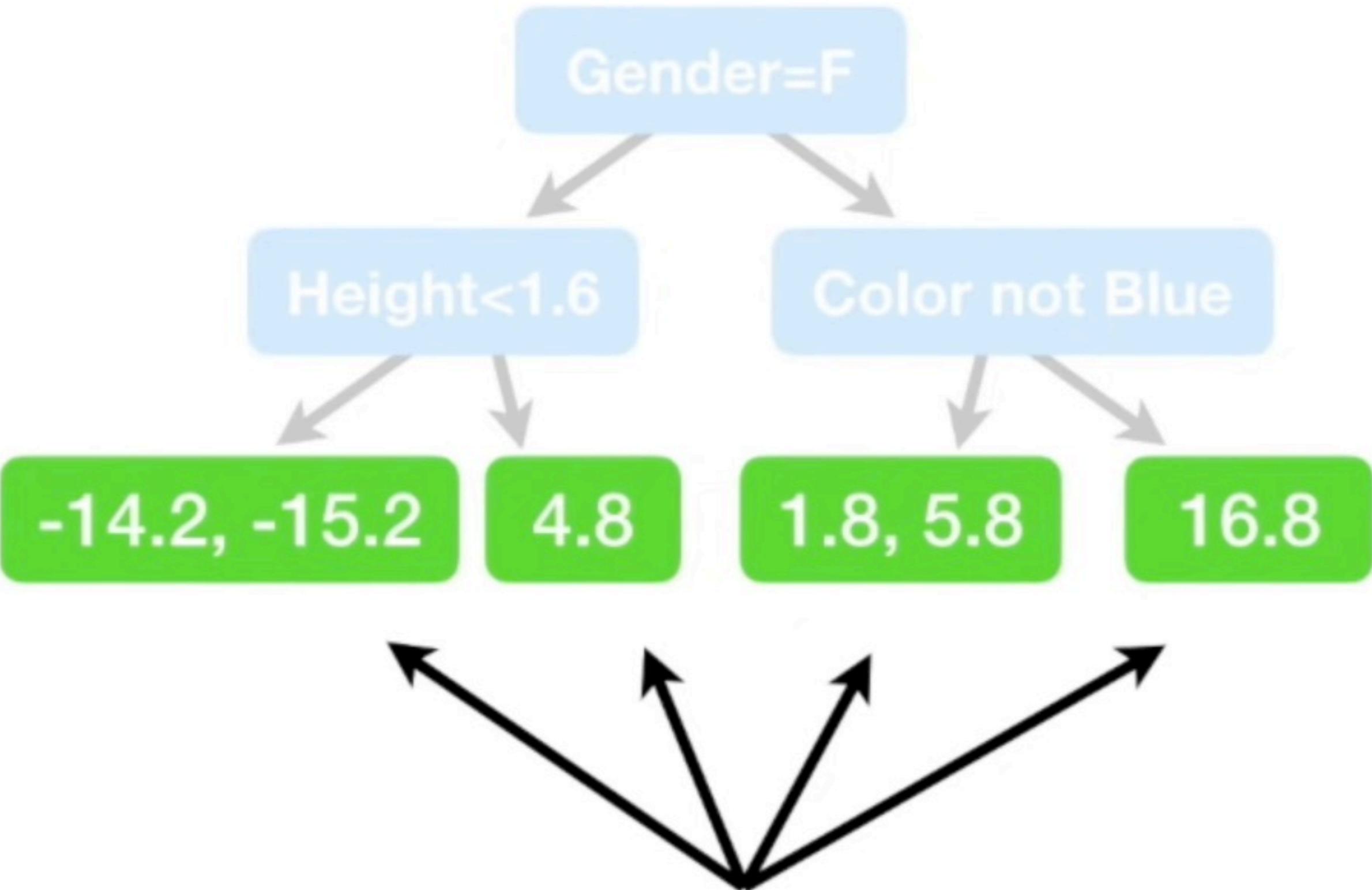
So, setting aside the reason why we are building a tree to **Predict the Residuals** for the time being, here's the tree!

Height (m)	Favorite Color	Gender		Residual
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	4.8
1.5	Blue	Female	56	-15.2
1.8	Red	Male	73	1.8
1.5	Green	Male	77	5.8
1.4	Blue	Female	57	-14.2



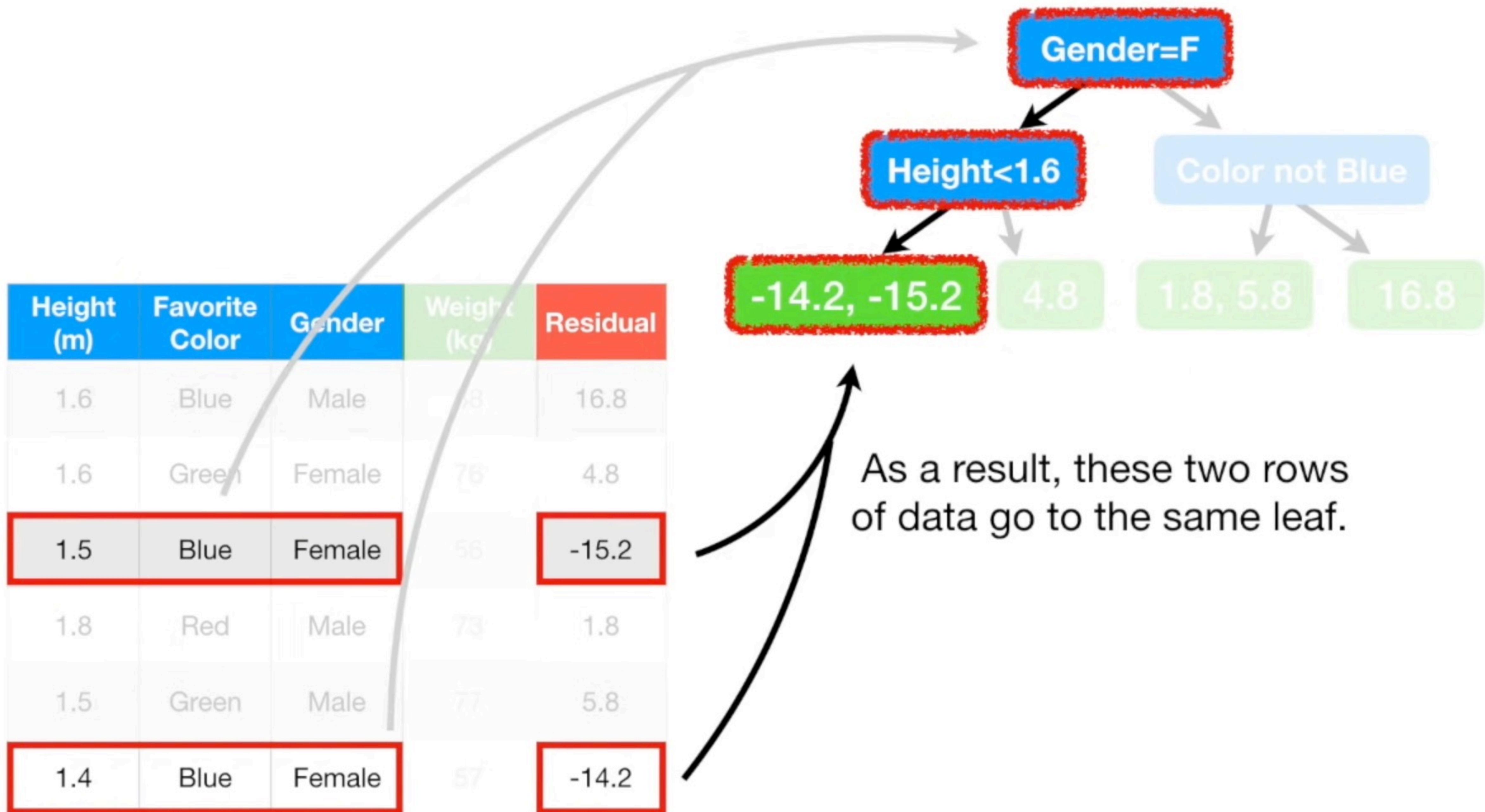
Remember, in this example we are only allowing up to four leaves...

Height (m)	Favorite Color	Gender	Residual
1.6	Blue	Male	16.8
1.6	Green	Female	4.8
1.5	Blue	Female	-15.2
1.8	Red	Male	1.8
1.5	Green	Male	5.8
1.4	Blue	Female	-14.2

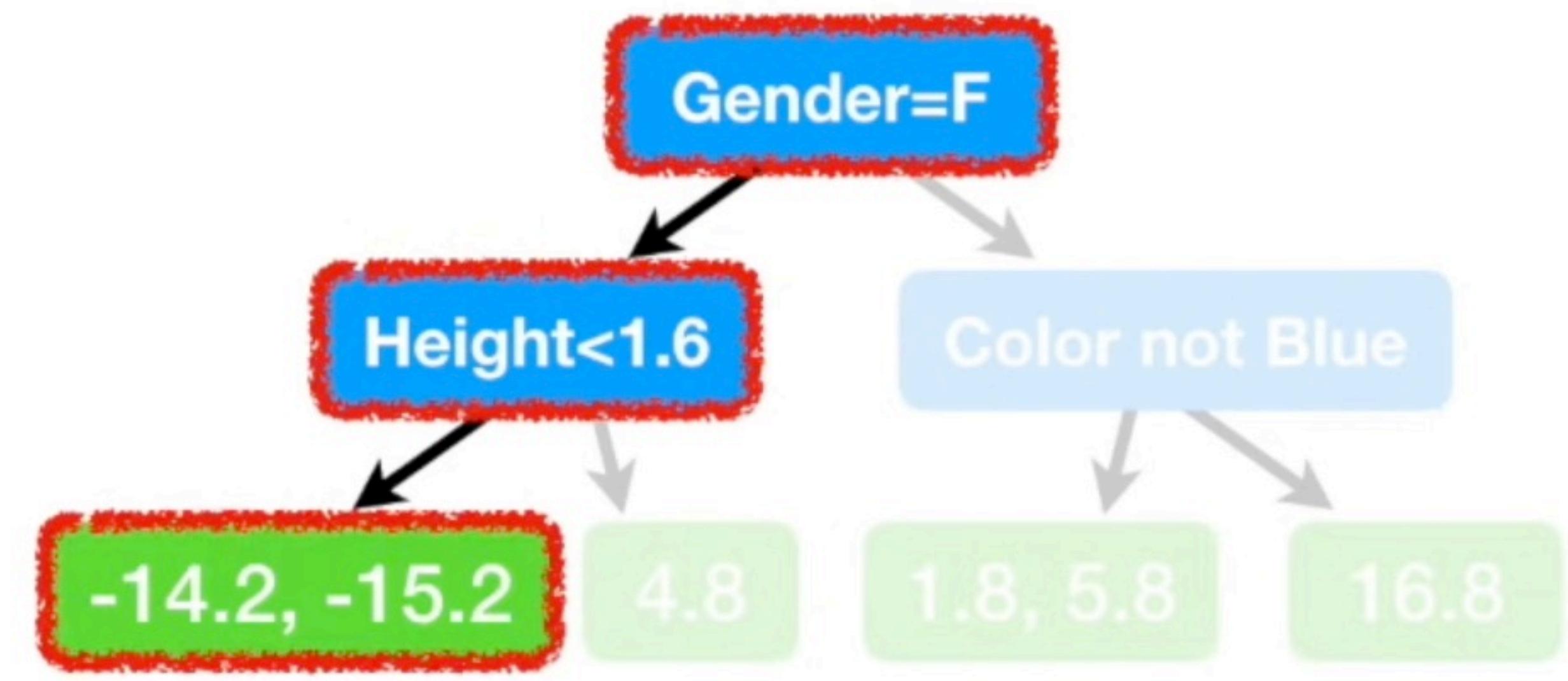


Remember, in this example we are only allowing up to four leaves...

...but when using a larger dataset, it is common to allow anywhere from **8** to **32**.



Height (m)	Favorite Color	Gender	Weight (kg)	Residual
1.6	Blue	Male	56	16.8
1.6	Green	Female	78	4.8
1.5	Blue	Female	56	-15.2
1.8	Red	Male	73	1.8
1.5	Green	Male	77	5.8
1.4	Blue	Female	57	-14.2



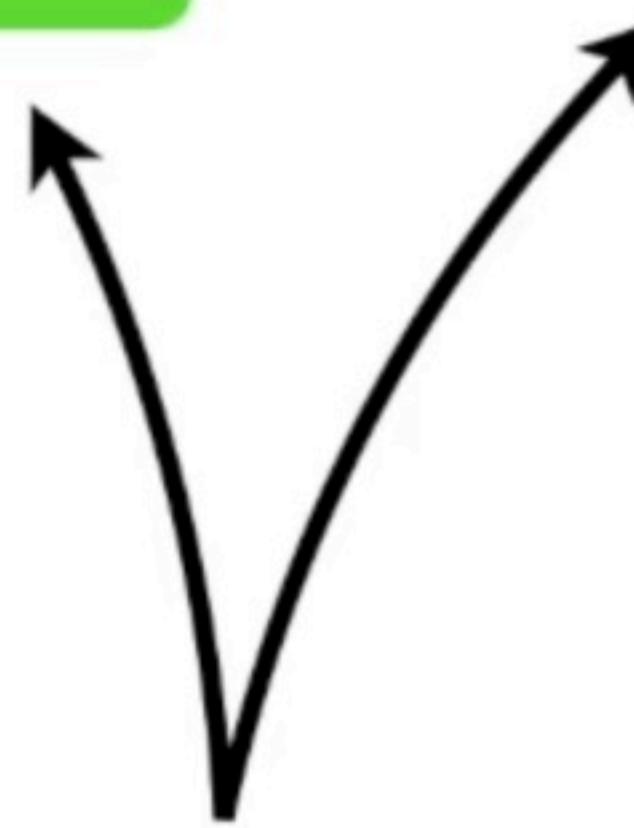
So we replace these residuals with their average.

$$\frac{(-14.2 + -15.2)}{2}$$

Average Weight

71.2

+



Gender=F

Height<1.6

-14.7

Color not Blue

4.8

3.8

16.8

Now we can now combine
the original leaf...

Average Weight

71.2



Gender=F

Height<1.6

Color not Blue

-14.7

4.8

3.8

16.8

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

...to make a new
Prediction of an
individual's **Weight** from
the **Training Data**.

Average Weight

71.2



We start with the initial
Prediction, 71.2...

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

Average Weight

71.2

+

Gender=F

Height<1.6

Color not Blue

-14.7

4.8

3.8

16.8

...then we run the
data down the tree...

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

Average Weight

71.2

+

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

Gender=F

Height<1.6

Color not Blue

-14.7

4.8

3.8

16.8

...and we get 16.8...

Average Weight

71.2

+

Gender=F

Height<1.6

Color not Blue

-14.7

4.8

3.8

16.8

...so the **Predicted Weight** = $71.2 + 16.8 = 88$

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

Average Weight

71.2

+

Gender=F

Color not Blue

16.8

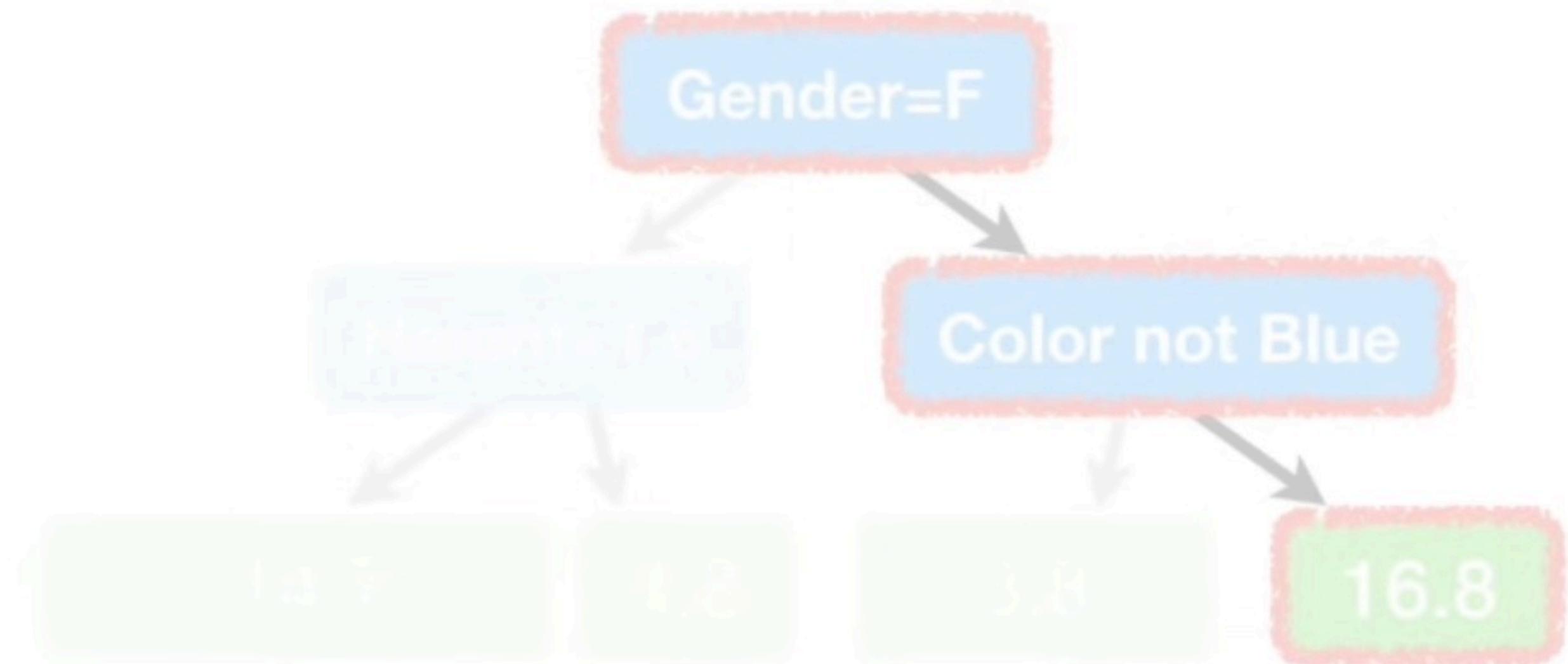
$$\text{Predicted Weight} = 71.2 + 16.8 = 88$$

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

Is this awesome???

Average Weight

71.2



$$\text{Predicted Weight} = 71.2 + 16.8 = 88$$

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

No. The model fits the
Training Data too well.



I like this



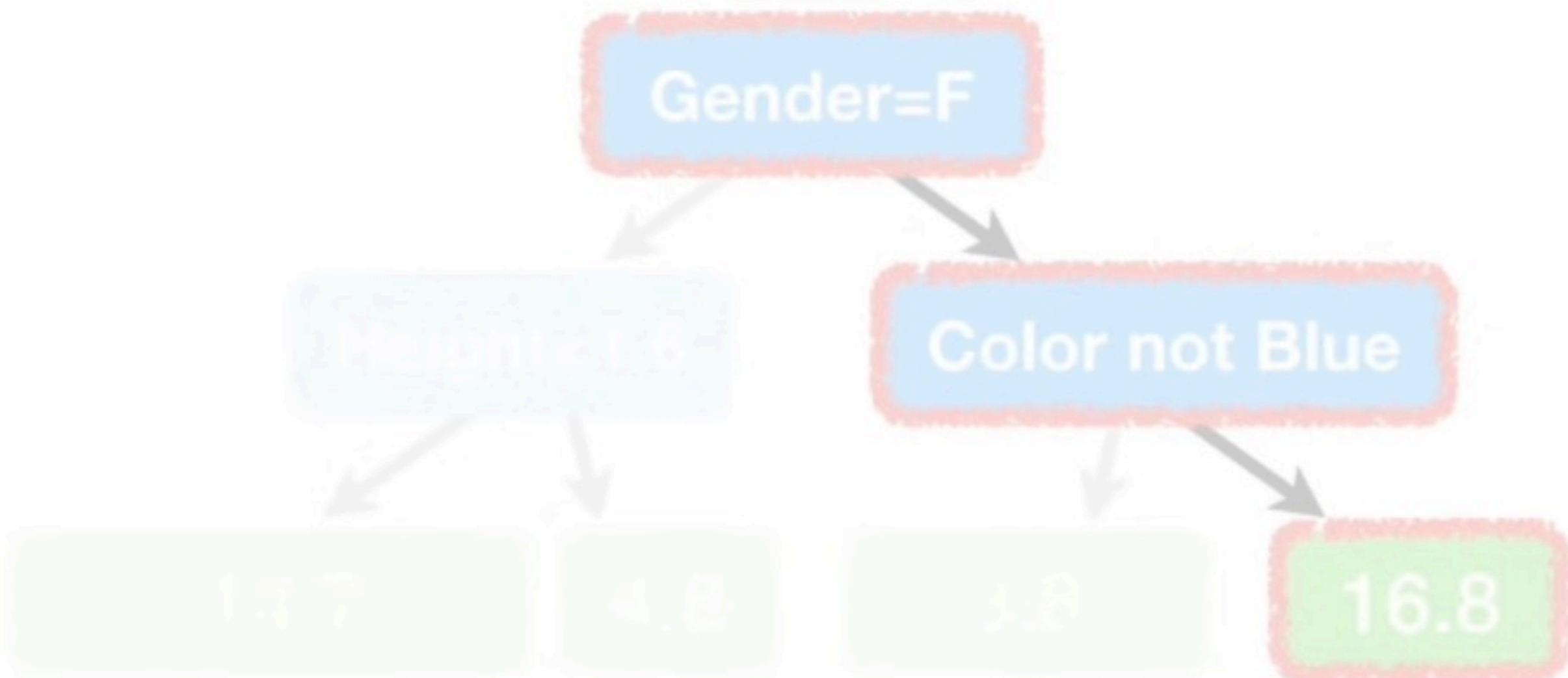
9:03 / 15:51

Building the first tree to predict weight >



Average Weight

71.2



$$\text{Predicted Weight} = 71.2 + 16.8 = 88$$

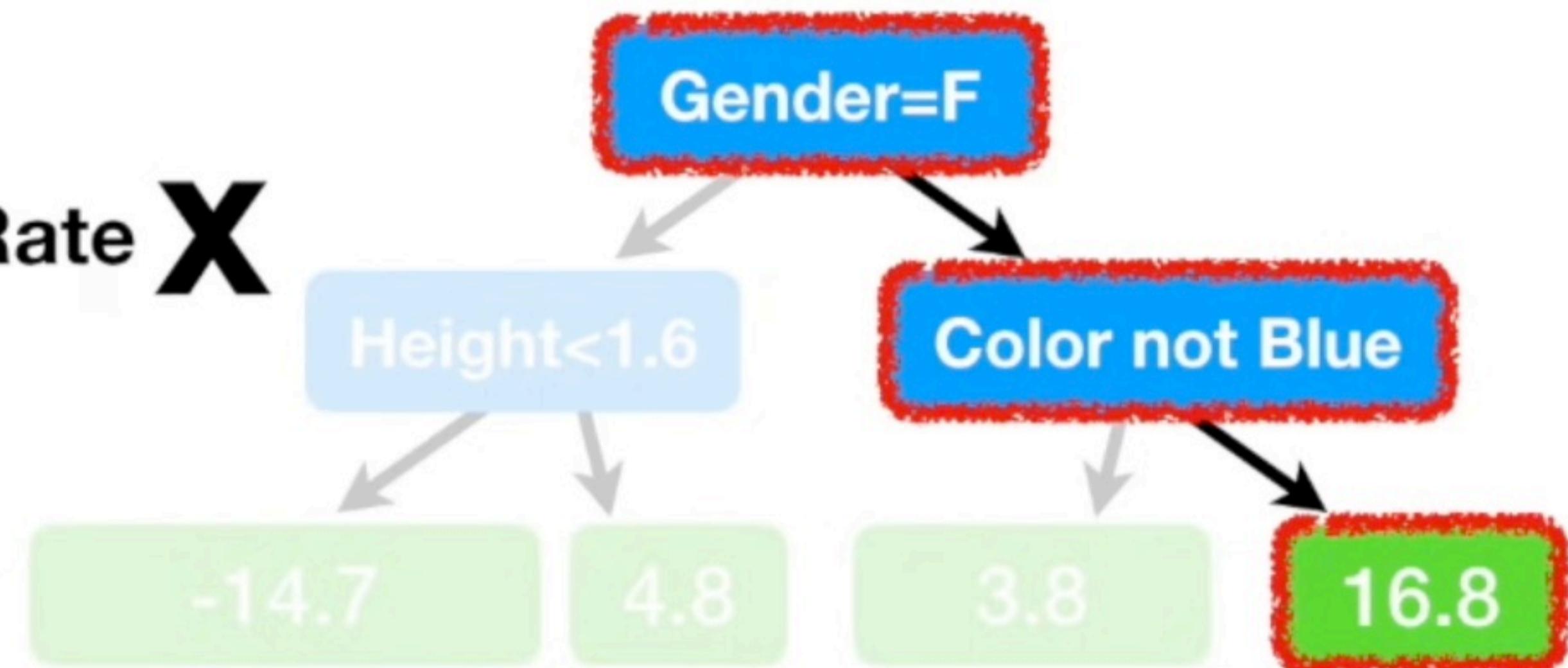
Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

In other words, we have low **Bias**, but probably very high **Variance**.

Average Weight

71.2

+ Learning Rate X



Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

Gradient Boost deals with this problem by using a **Learning Rate** to scale the contribution from the new tree.

The **Learning Rate** is a value between **0** and **1**.

Average Weight

71.2

+

0.1 X

Gender=F

Height<1.6

Color not Blue

-14.7

4.8

3.8

16.8

Now the **Predicted Weight** = $71.2 + (0.1 \times 16.8) = 72.9$

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

Average Weight

71.2

+

0.1

X

Gender=F

Color not Blue

16.8

3.8

3.8

16.8

$$\text{Predicted Weight} = 71.2 + (0.1 \times 16.8) = 72.9$$

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

With the **Learning Rate** set to **0.1**, the new **Prediction** isn't as good as it was before...

Average Weight

71.2

+

0.1

X

Gender=F

Height<1.6

Color not Blue

-14.7

4.8

3.8

16.8

$$\text{Predicted Weight} = 71.2 + (0.1 \times 16.8) = 72.9$$

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

...but it's a little bit better than the **Prediction** made with just the original leaf, which predicted that all samples would weigh **71.2**.

Average Weight

71.2

+

0.1

X



Gender=F

Height<1.6

Color not Blue

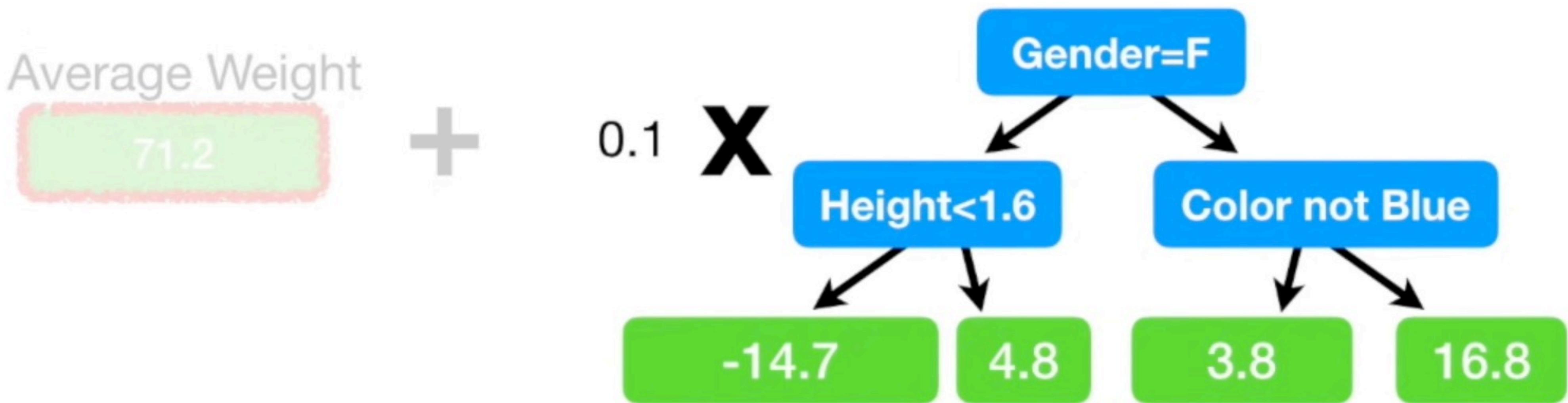
-14.7

4.8

3.8

16.8

In other words, scaling the tree by the **Learning Rate** results in a small step in the right direction.



According to the dude that invented
Gradient Boost, Jerome Friedman,
empirical evidence shows that taking lots of
small steps in the right direction results in
better **Predictions** with a **Testing Dataset**,
i.e. lower **Variance**.

Average Weight

71.2

+

0.1

X

Gender=F

Height<1.6

Color not Blue

-14.7

4.8

3.8

16.8

So let's build another tree so we can take another small step in the right direction.

Average Weight

71.2

+

0.1

X

Gender=F

Height<1.6

Color not Blue

-14.7

4.8

3.8

16.8

Height (m)	Favorite Color	Gender	Weight (kg)	Residual
1.6	Blue	Male	88	
1.6	Green	Female	76	
1.5	Blue	Female	56	
1.8	Red	Male	73	
1.5	Green	Male	77	
1.4	Blue	Female	57	

$$\text{Residual} = (88 - (71.2 + 0.1 \times 16.8))$$

$$= 15.1$$

...and we save that in the column for **Pseudo Residuals**.

Average Weight

71.2

+

0.1

X

Gender=F

Height<1.6

Color not Blue

4.8

3.8

16.8

14.1

Height (m)	Favorite Color	Gender	Weight (kg)	Residual
1.6	Blue	Male	88	15.1
1.6	Green	Female	76	
1.5	Blue	Female	56	
1.8	Red	Male	73	
1.5	Green	Male	77	
1.4	Blue	Female	57	

$$\text{Residual} = (76 - 71.2 + (0.1 \times 4.8))$$

Then we repeat for all of
the other individuals in the
Training Dataset.

Average Weight

71.2

+

0.1

X

Gender=F

Height<1.6

Color not Blue

-14.7

4.8

3.8

16.8

Height (m)	Favorite Color	Gender	Weight (kg)	Residual
1.6	Blue	Male	88	15.1
1.6	Green	Female	76	4.3
1.5	Blue	Female	56	-13.7
1.8	Red	Male	73	1.4
1.5	Green	Male	77	5.4
1.4	Blue	Female	57	-12.7

Small bam.

Average Weight

71.2

+

0.1

X

Gender=F

Height<1.6

Color not Blue

Residual
16.8
4.8
-15.2
1.8
5.8
-14.2

Residual
15.1
4.3
-13.7
1.4
5.4
-12.7

...and these are the **Residuals** after
adding the new tree scaled by the
Learning Rate.

Average Weight

71.2

+

0.1 X

Gender=F

Height<1.6

Color not Blue

Residual

16.8

4.8

-15.2

1.8

5.8

-14.2

Residual

15.1

4.3

-13.7

1.4

5.4

-12.7

-14.7

4.8

3.8

16.8

The new **Residuals** are all
smaller than before, so
we've taken a small step in
the right direction.

Just like before, since multiple samples ended up in these leaves, we just replace the **Residuals** with their averages.

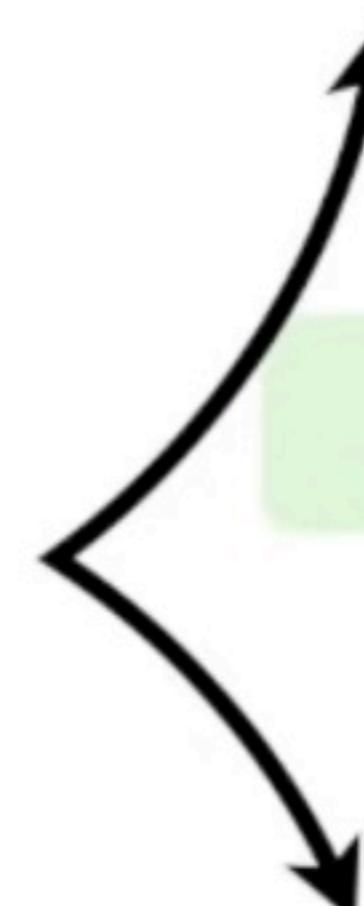


Average Weight

71.2

NOTE: We scale all of the **Trees** by the **Learning Rate**, which we set to **0.1...**

0.1 X



0.1 X



Average Weight

71.2

+ 0.1 X

Gender=F

Height<1.6

-14.7

4.8

3.8

16.8

Now we're ready to make
a new **Prediction** from the
Training Data.



Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

+ 0.1 X

Gender=F

Height<1.6

-13.2

4.3

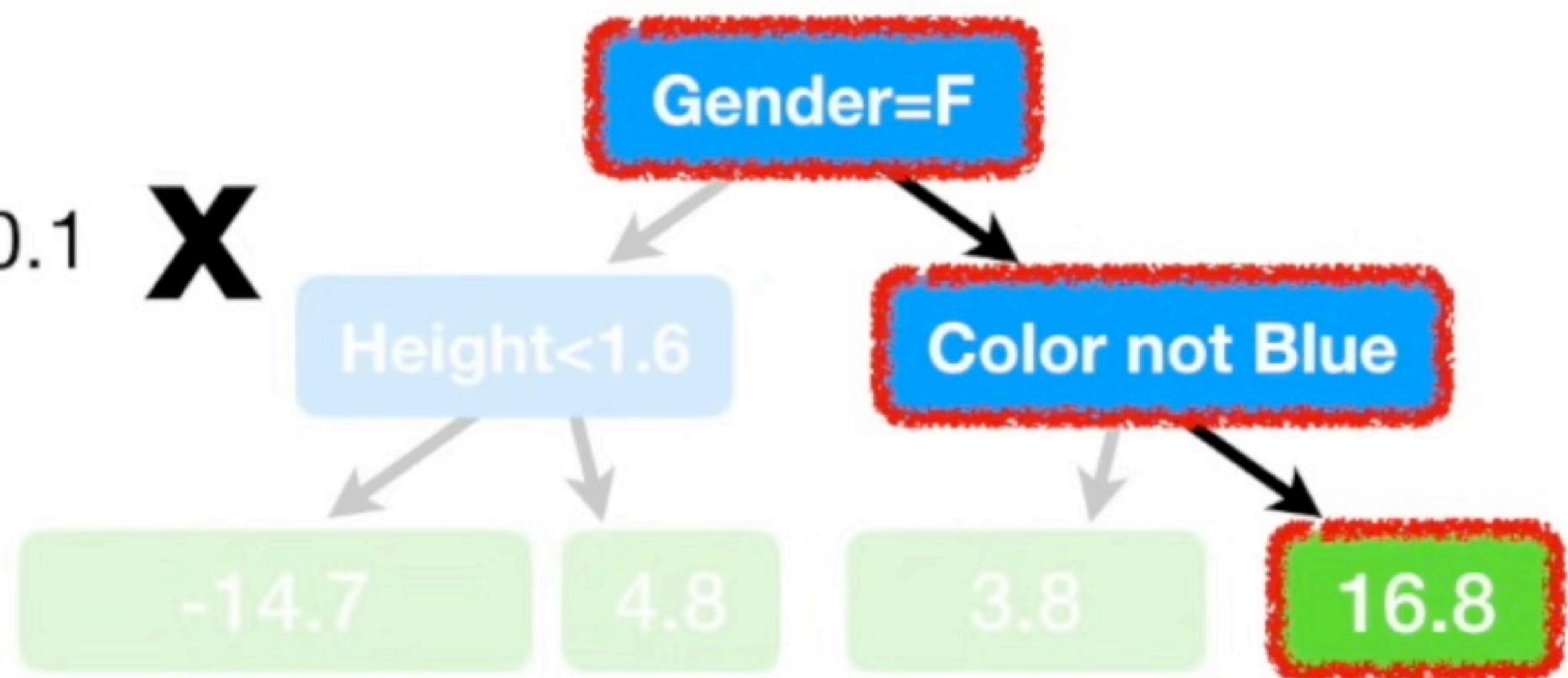
3.4

15.1

Average Weight

71.2

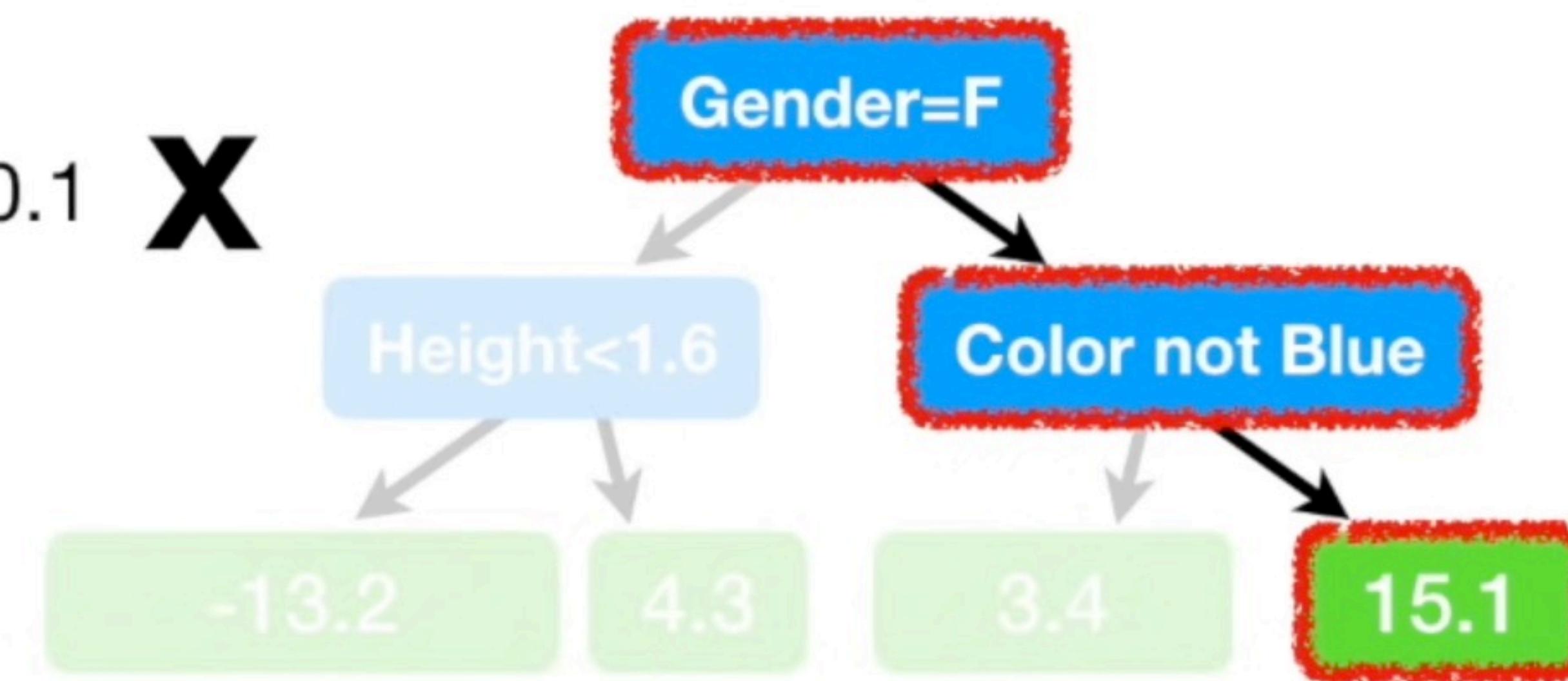
+ 0.1 X



...and the scaled amount
from the second Tree.

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

+ 0.1 X



Average Weight

71.2

+ 0.1 X

Gender=F

Height<1.6

-14.7

4.8

Color not Blue

3.8

16.8

Which is another small step closer to the **Observed Weight**.

$$71.2 + (0.1 \times 16.8) + (0.1 \times 15.1)$$

$$= 74.4$$

Height (m)	Favorite Color	Gender	Weight (kg)
1.6	Blue	Male	88

+ 0.1 X

Gender=F

Height<1.6

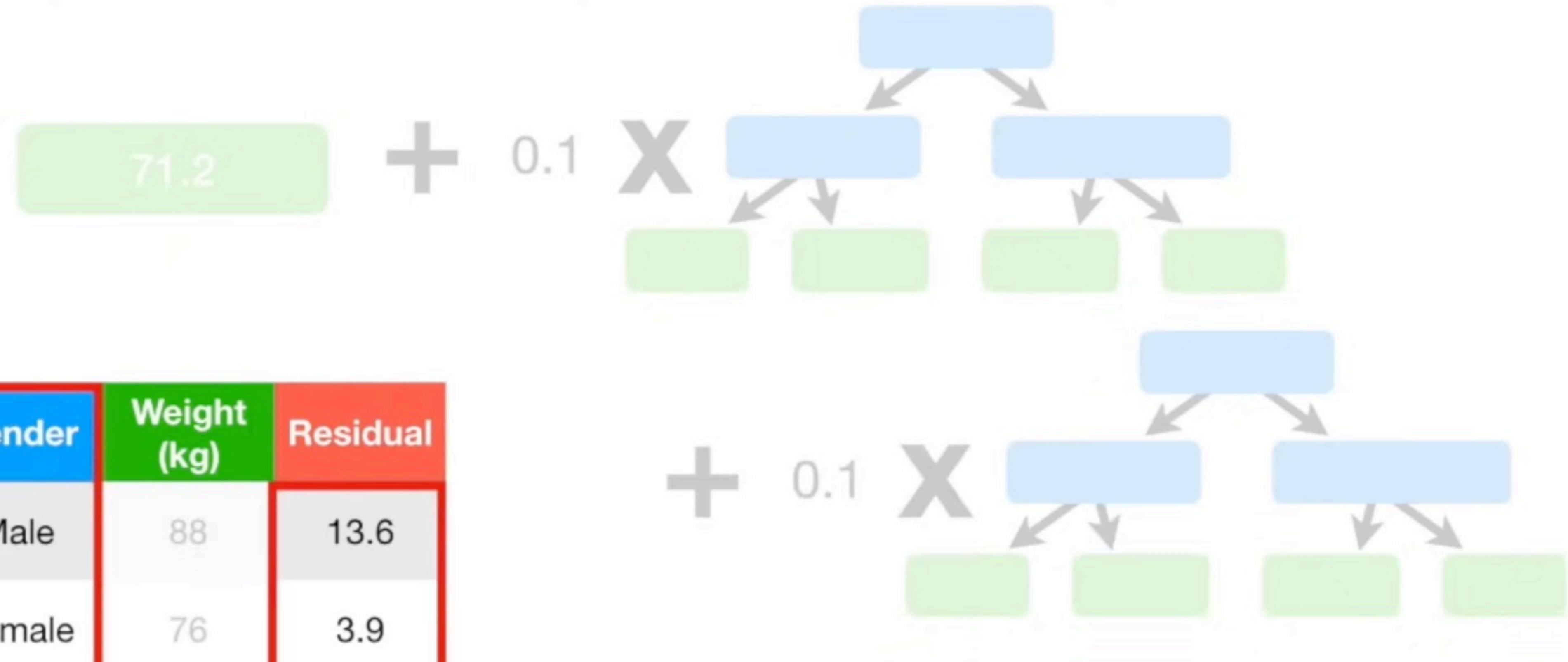
-13.2

4.3

Color not Blue

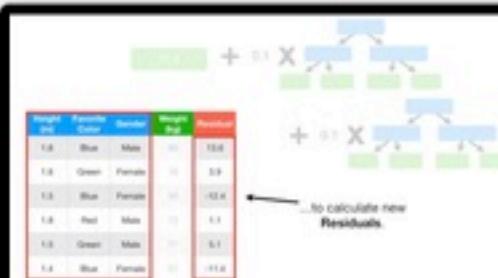
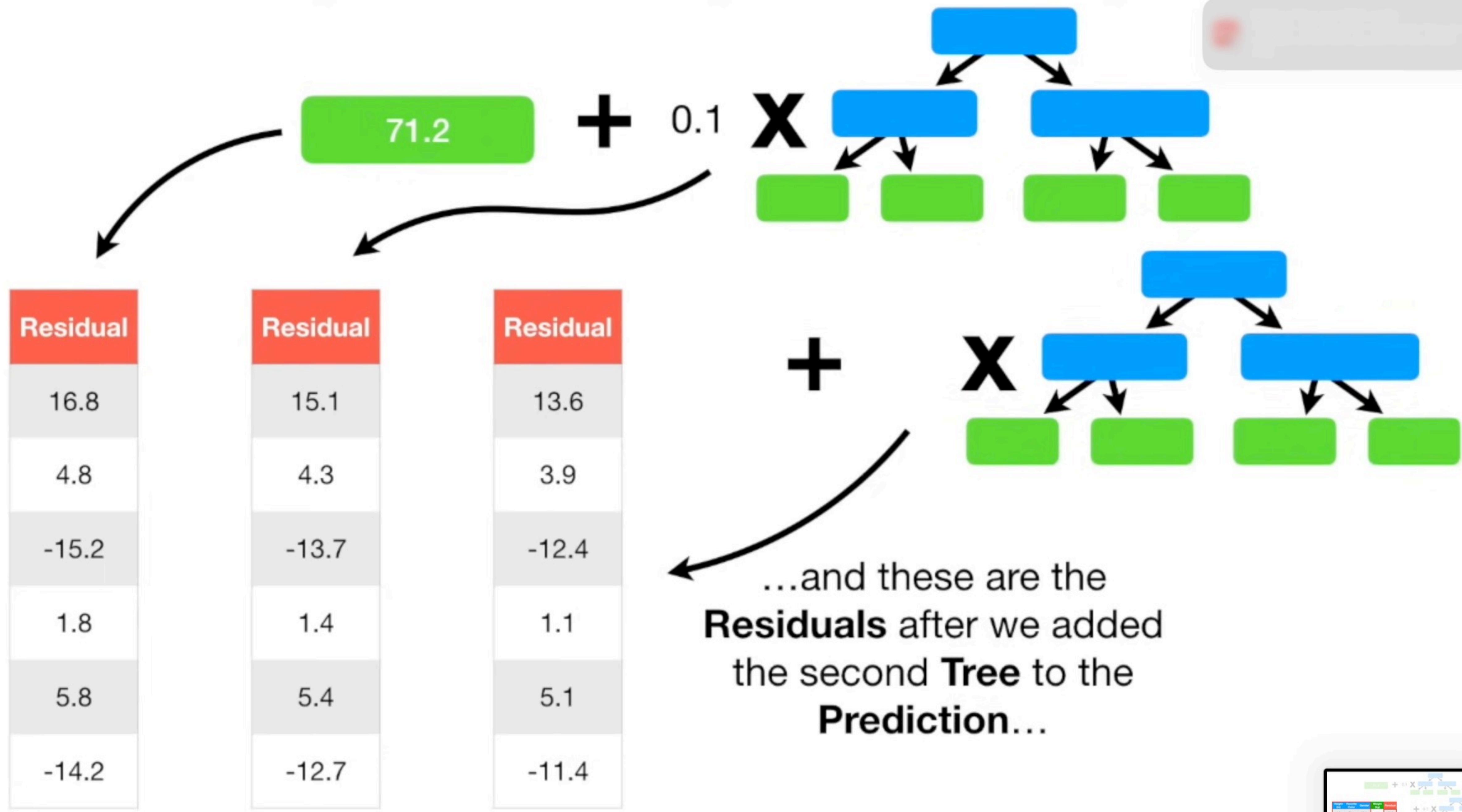
3.4

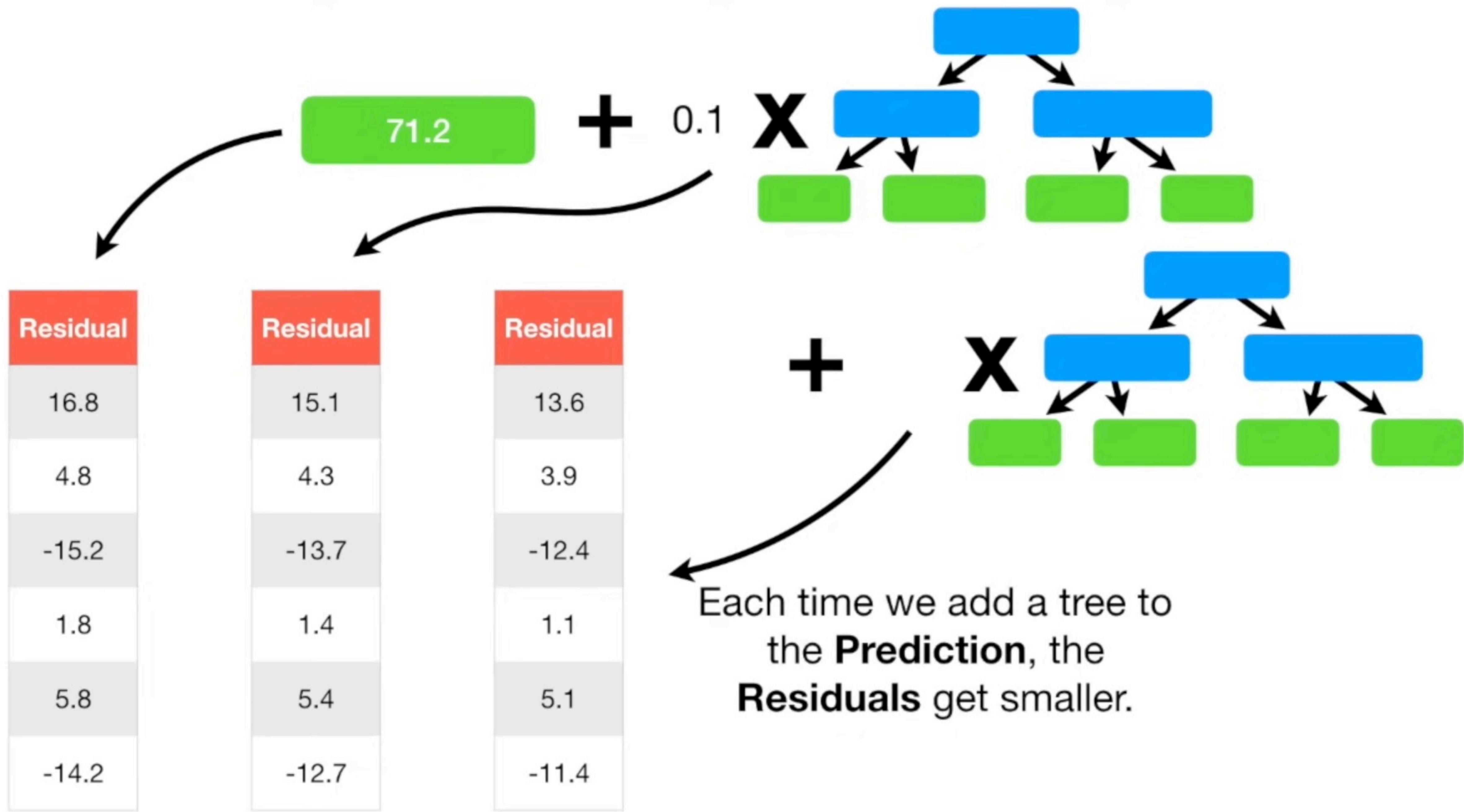
15.1

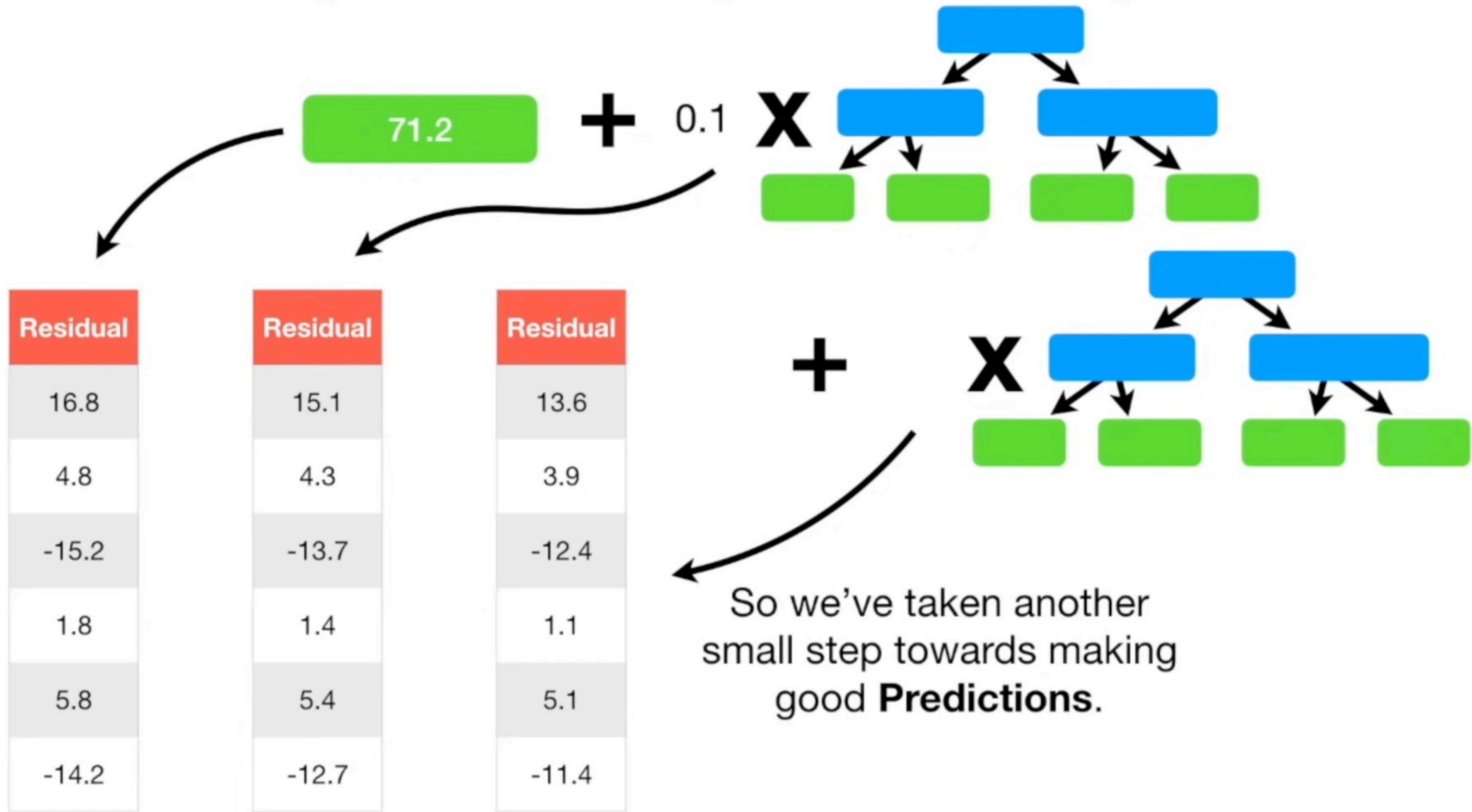


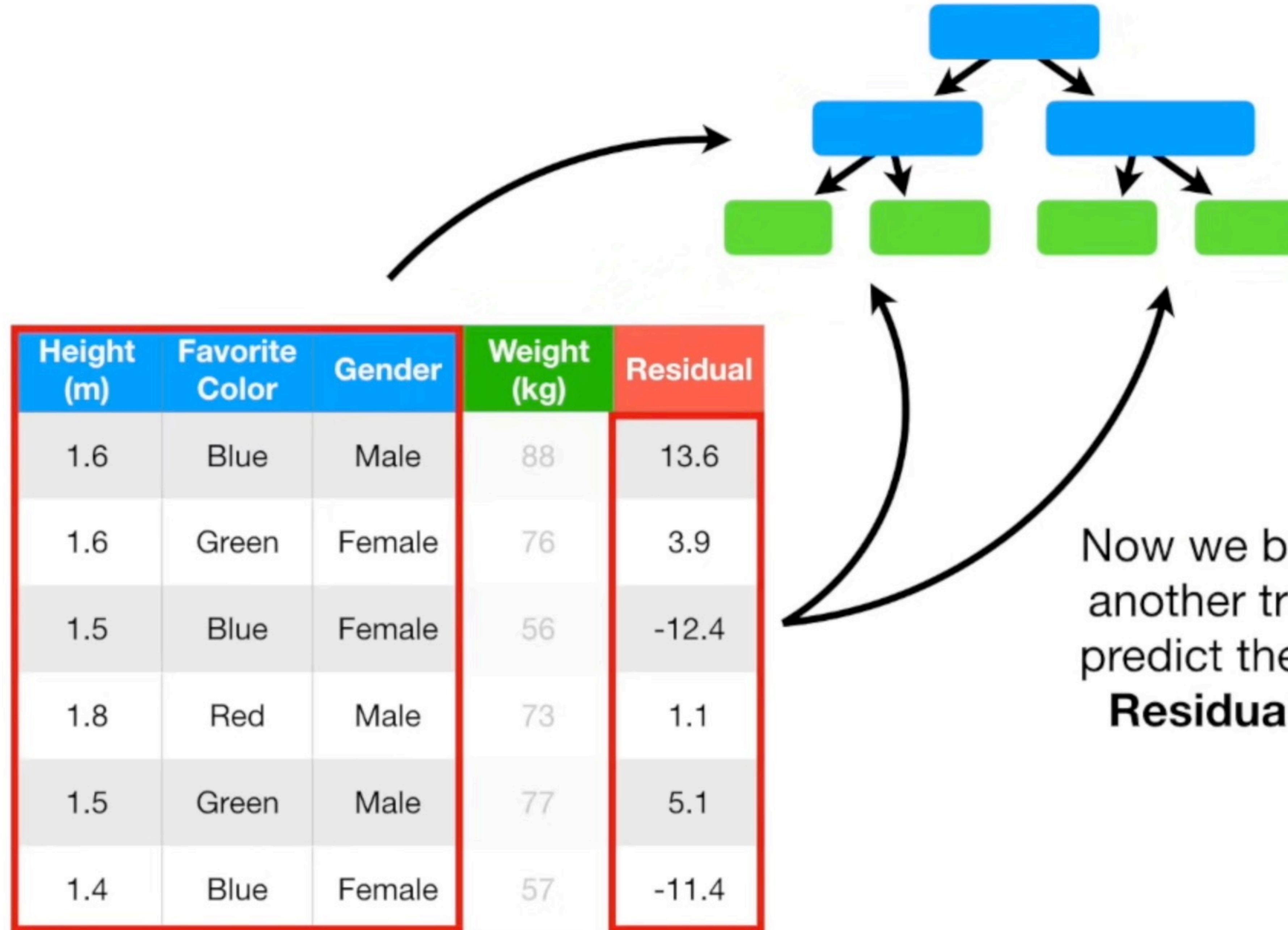
Height (m)	Favorite Color	Gender	Weight (kg)	Residual
1.6	Blue	Male	88	13.6
1.6	Green	Female	76	3.9
1.5	Blue	Female	56	-12.4
1.8	Red	Male	73	1.1
1.5	Green	Male	77	5.1
1.4	Blue	Female	57	-11.4

...to calculate new
Residuals.









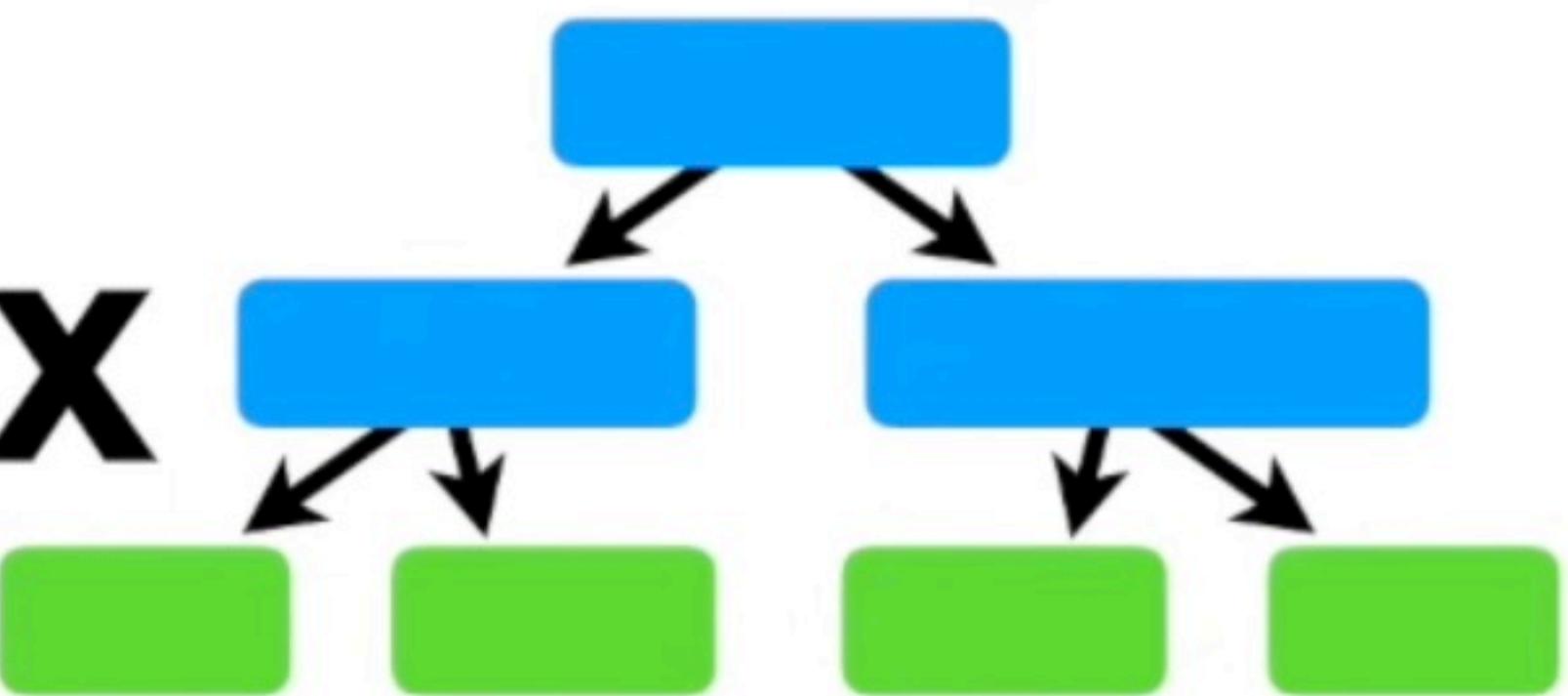
Now we build a
another tree to
predict the new
Residuals...

71.2

+

0.1

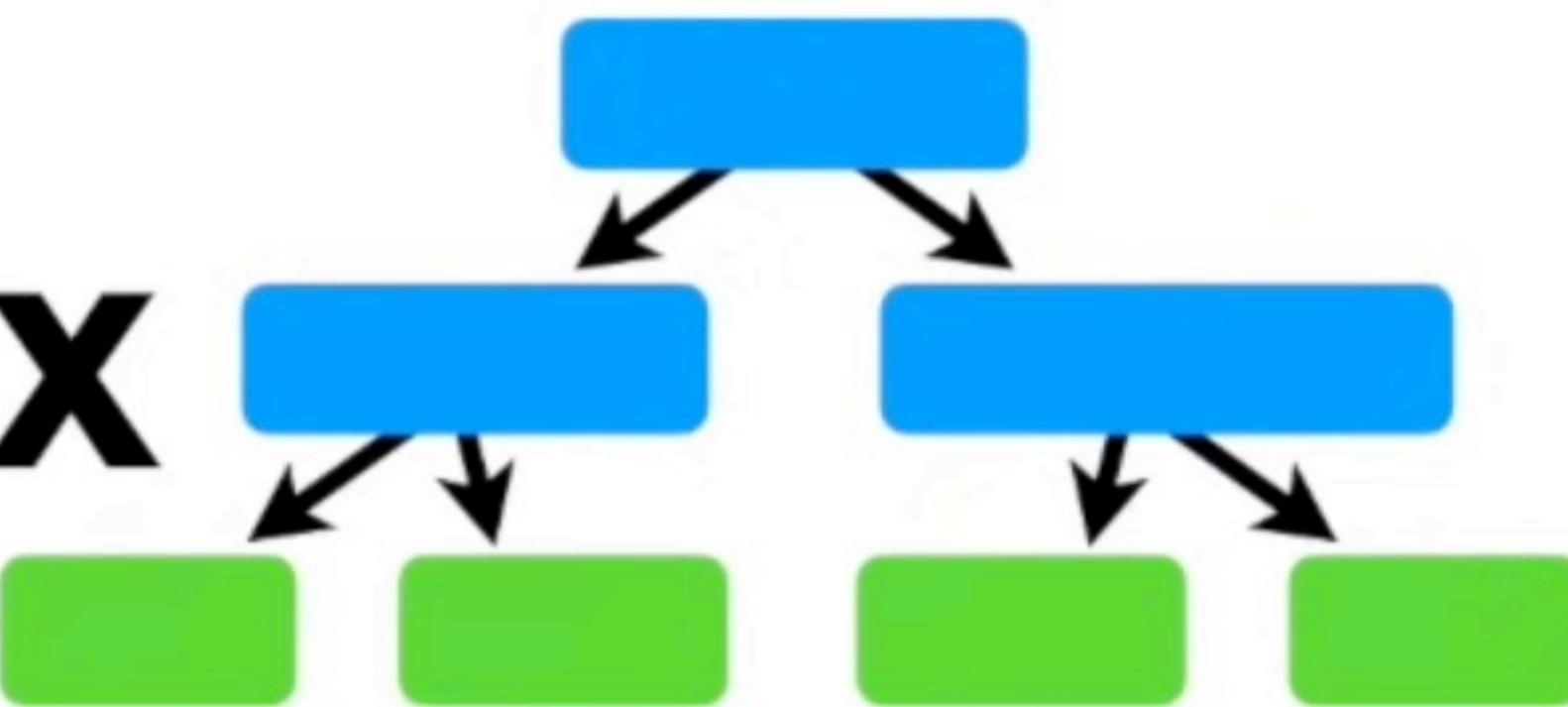
X



+

0.1

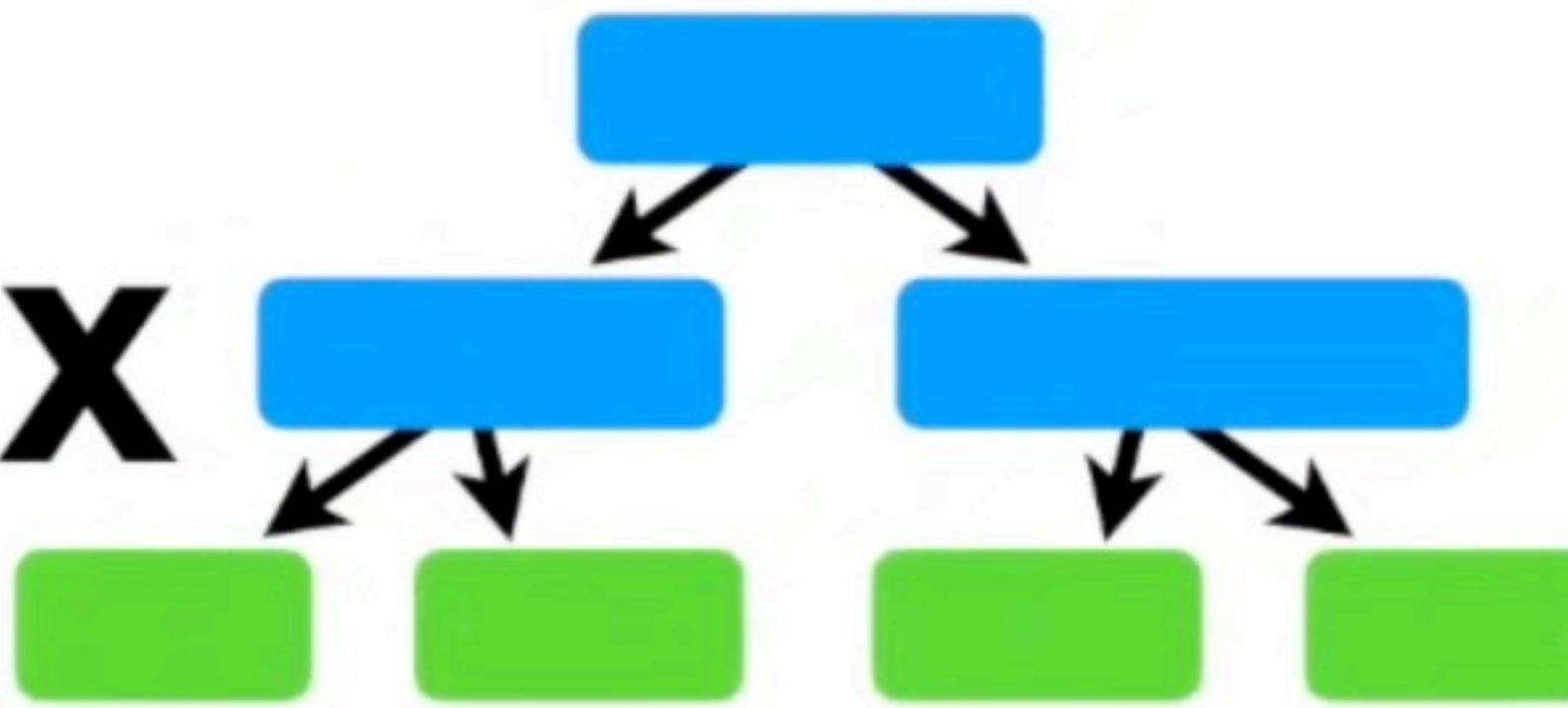
X



+

0.1

X

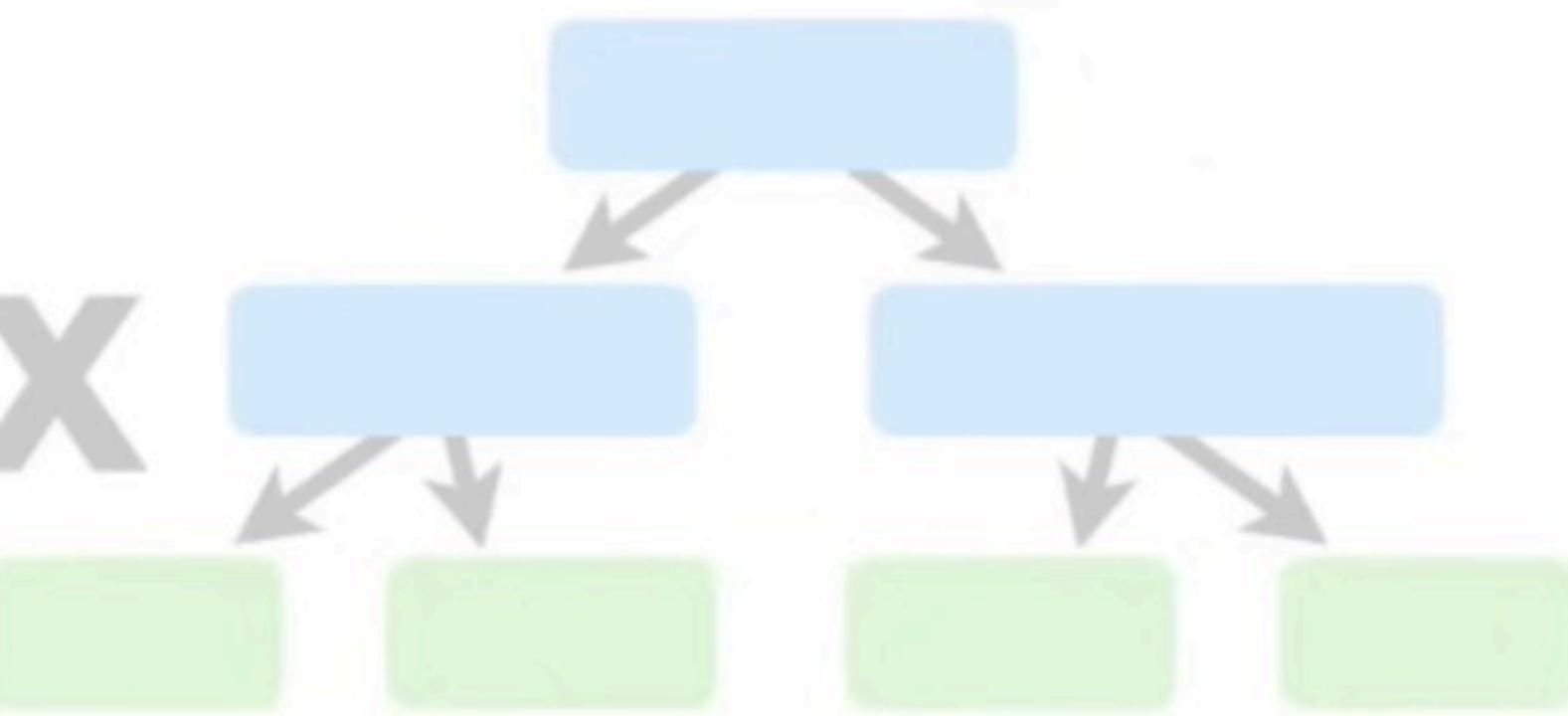


...and we keep making trees until we reach the maximum specified, or adding additional trees does not significantly reduce the size of the **Residuals**.

...etc...etc...etc...

71.2

$+ 0.1 \times$

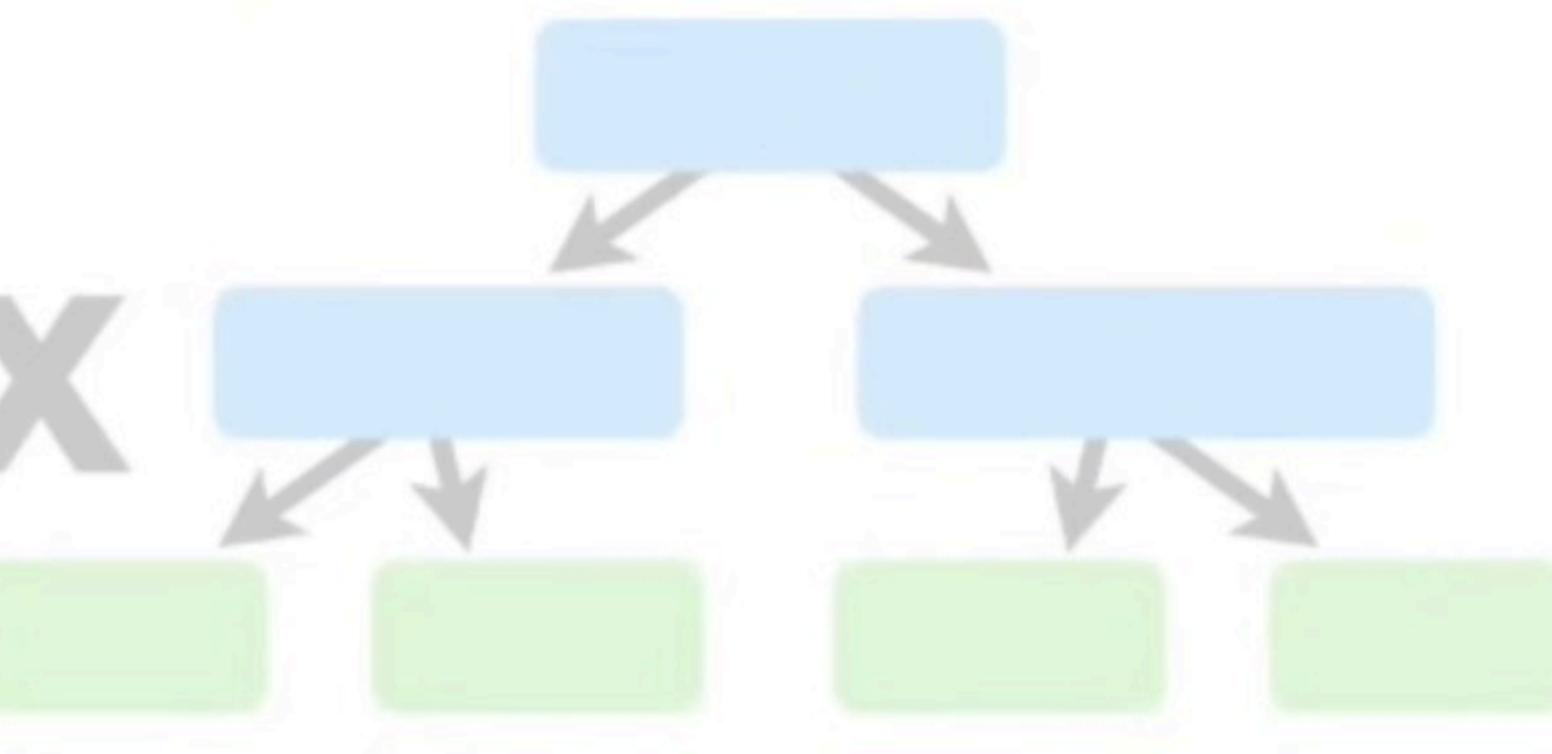


Then, when we get some
new measurements...

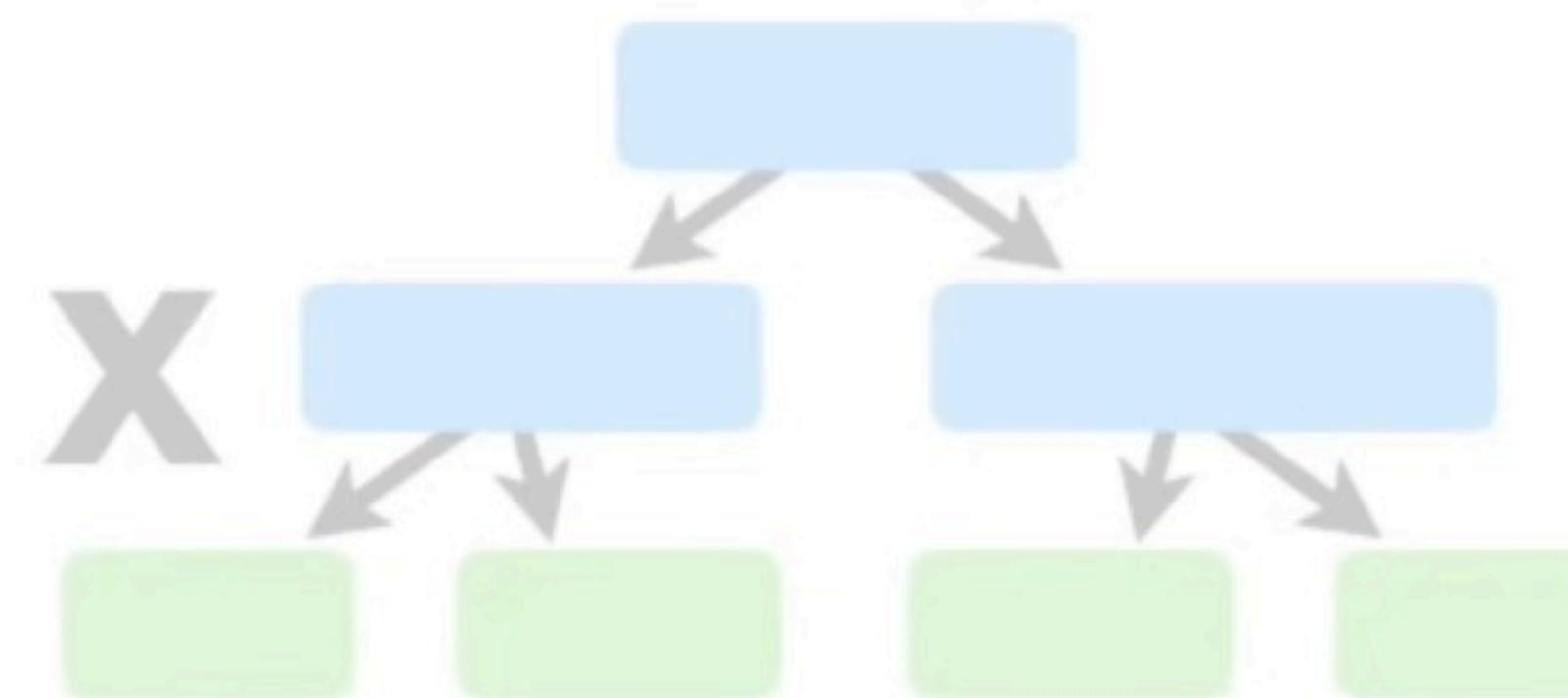


Height (m)	Favorite Color	Gender	Weight (kg)
1.7	Green	Female	???

$+ 0.1 \times$



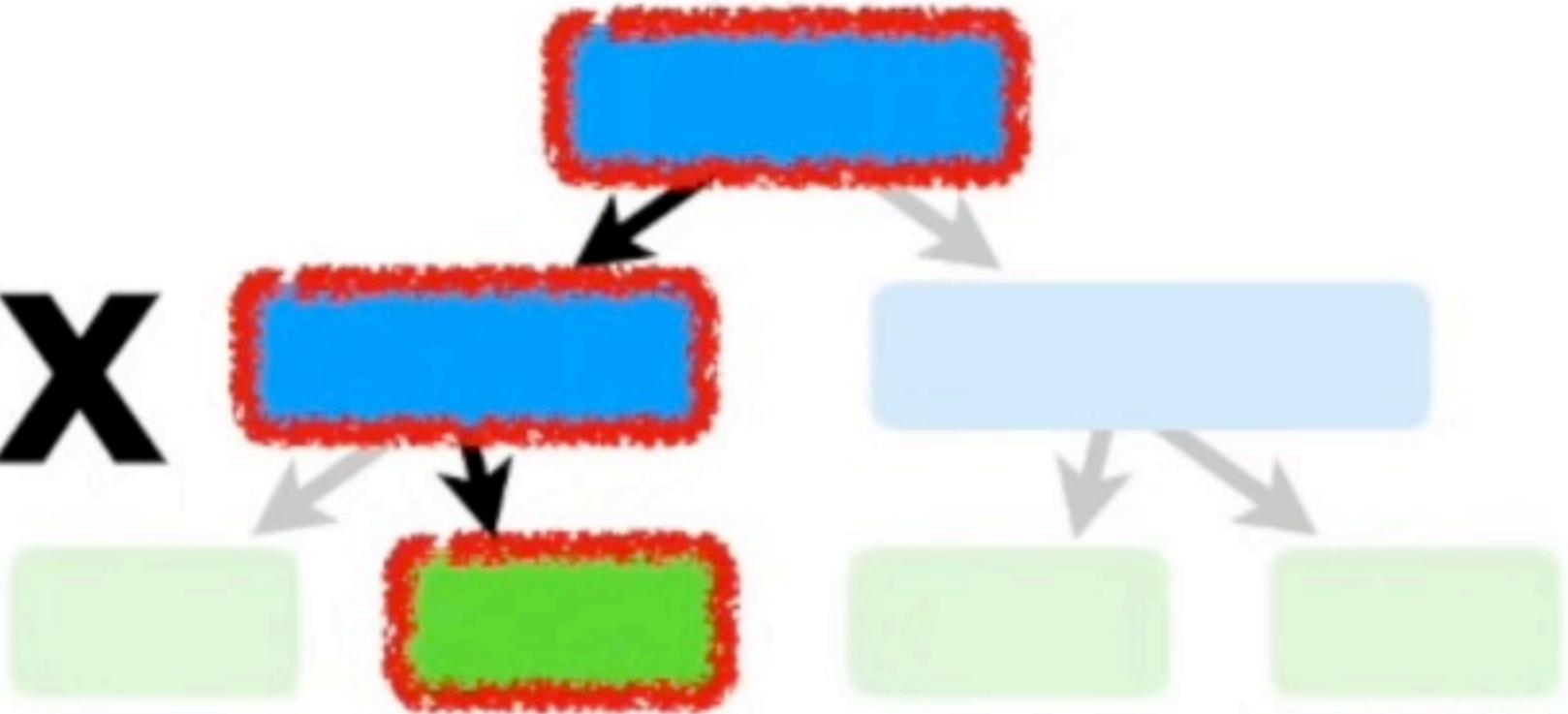
$+ 0.1 \times$



...etc...etc...etc...

71.2

+ 0.1 X

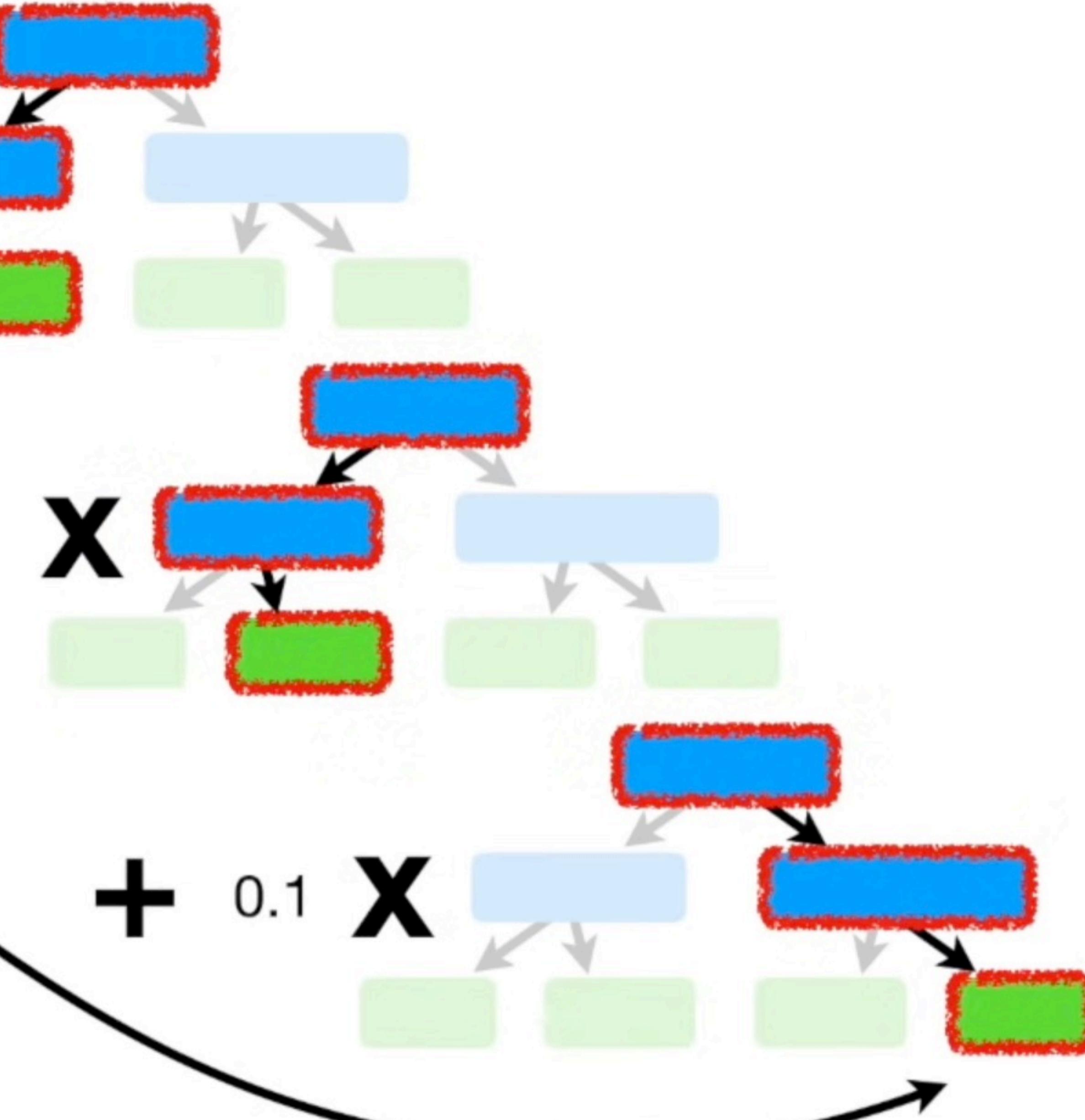


+ 0.1 X

...and the third tree...

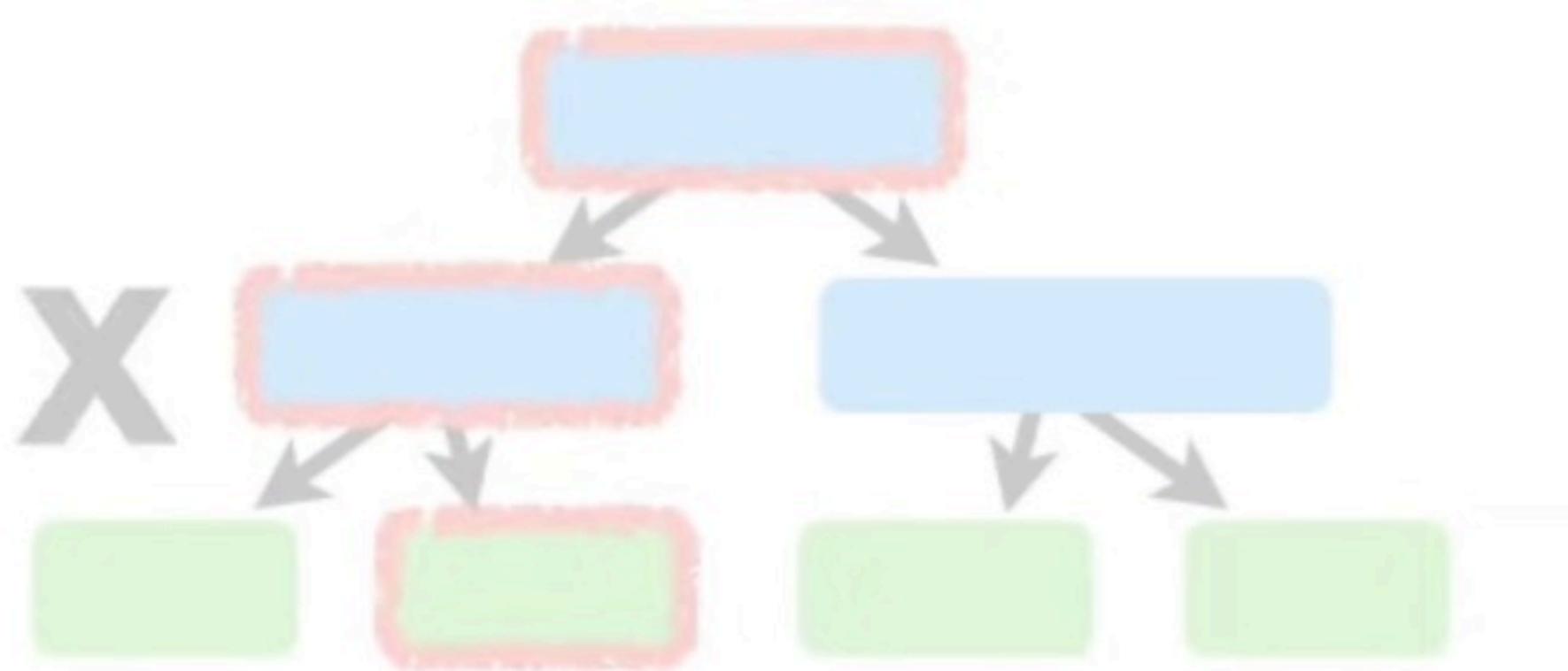
Height (m)	Favorite Color	Gender	Weight (kg)
1.7	Green	Female	???

+ 0.1 X



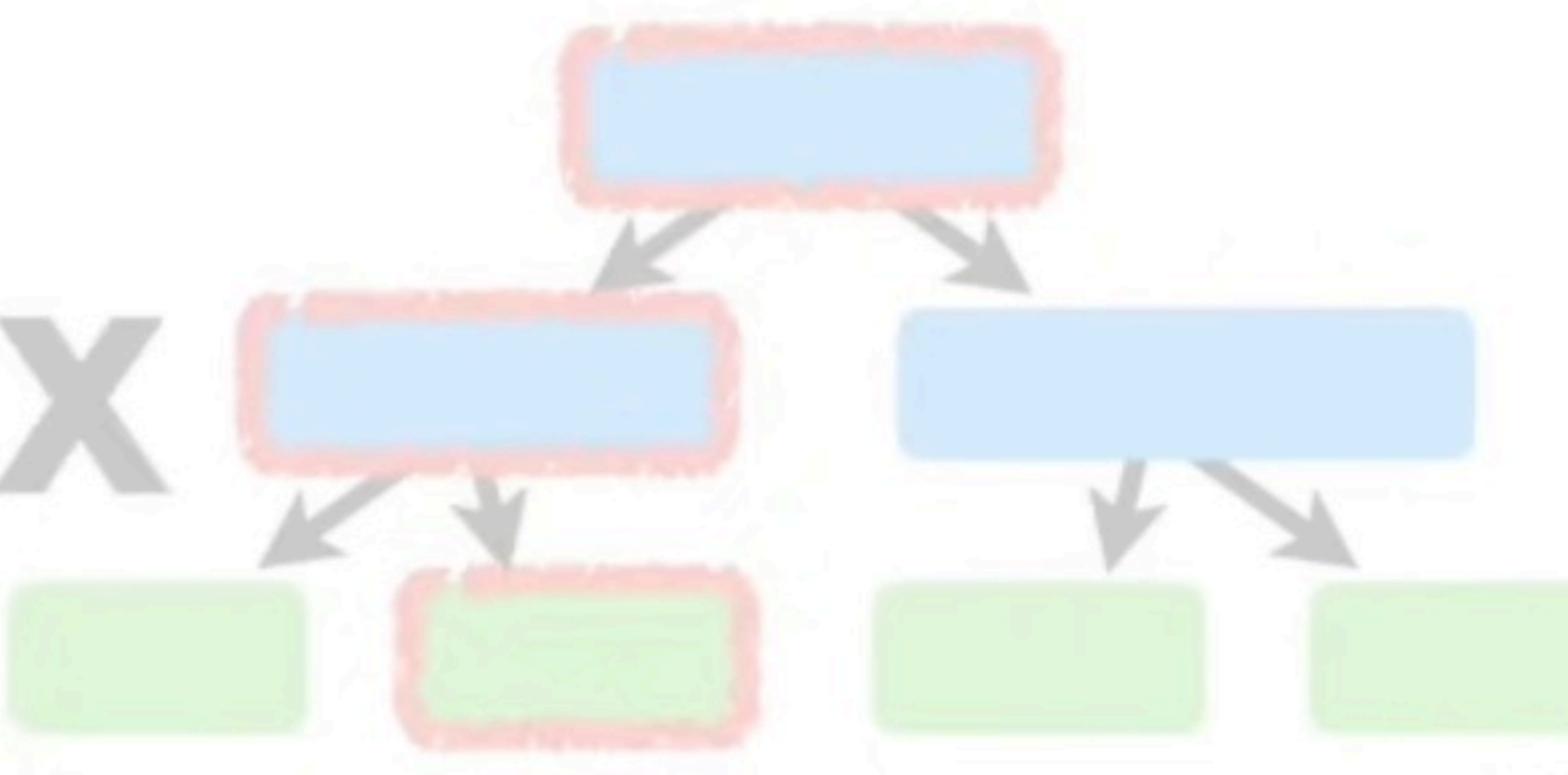
...etc...etc...etc...

+ 0.1 X



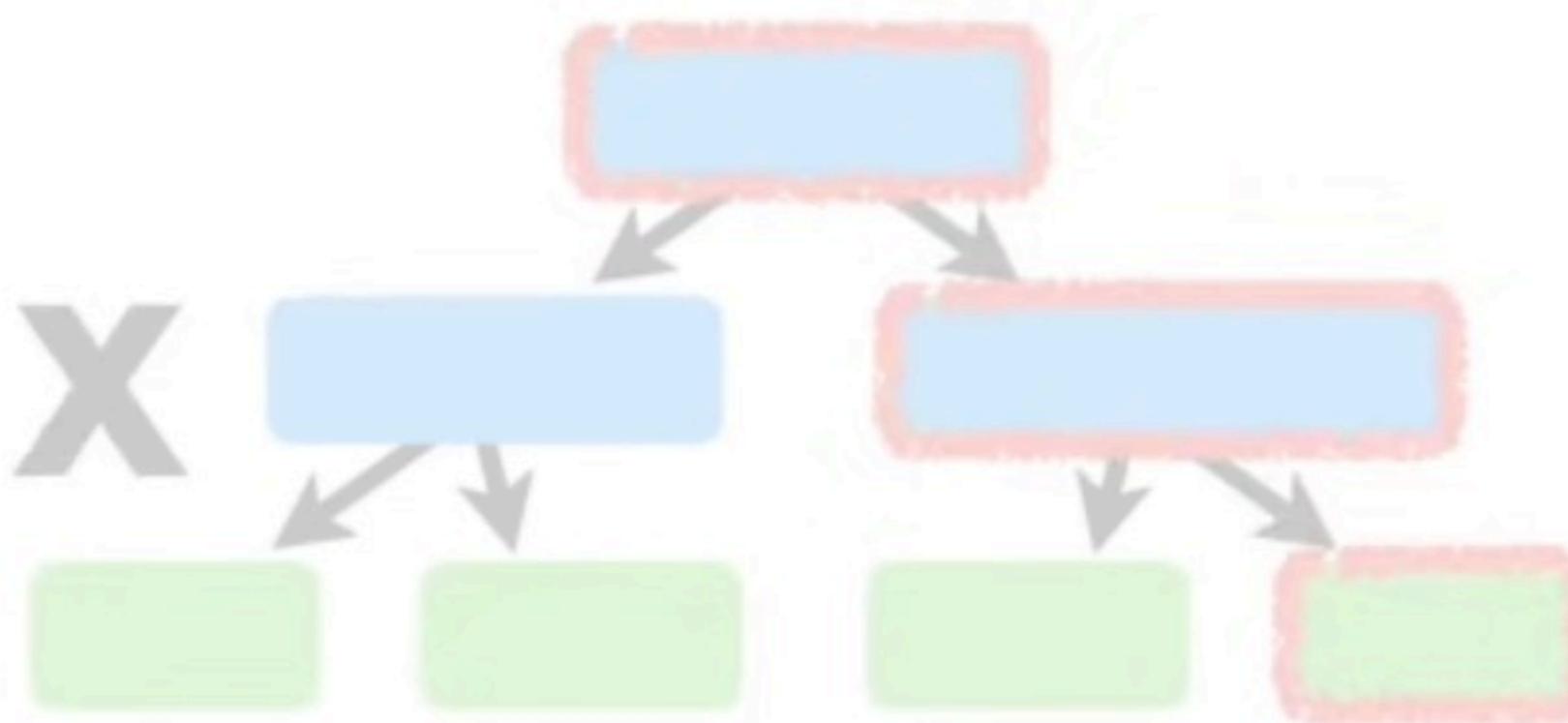
...and once the math is all done, we are left with the **Predicted Weight**.

+ 0.1 X



Height (m)	Favorite Color	Gender	Weight (kg)
1.7	Green	Female	70

+ 0.1 X



...etc...etc...etc...

