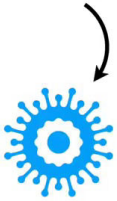
Imagine we developed
a new drug…

Imagine we developed
a new drug…

VS.

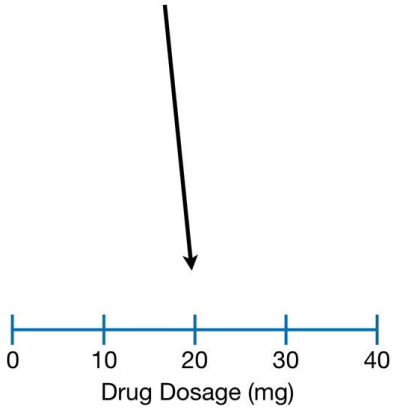
…to cure the
common cold.

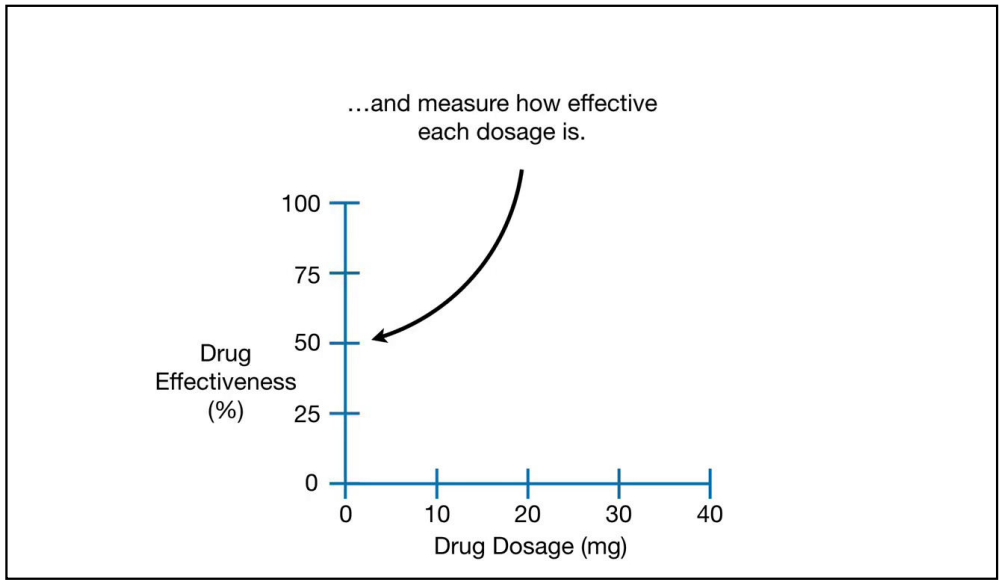


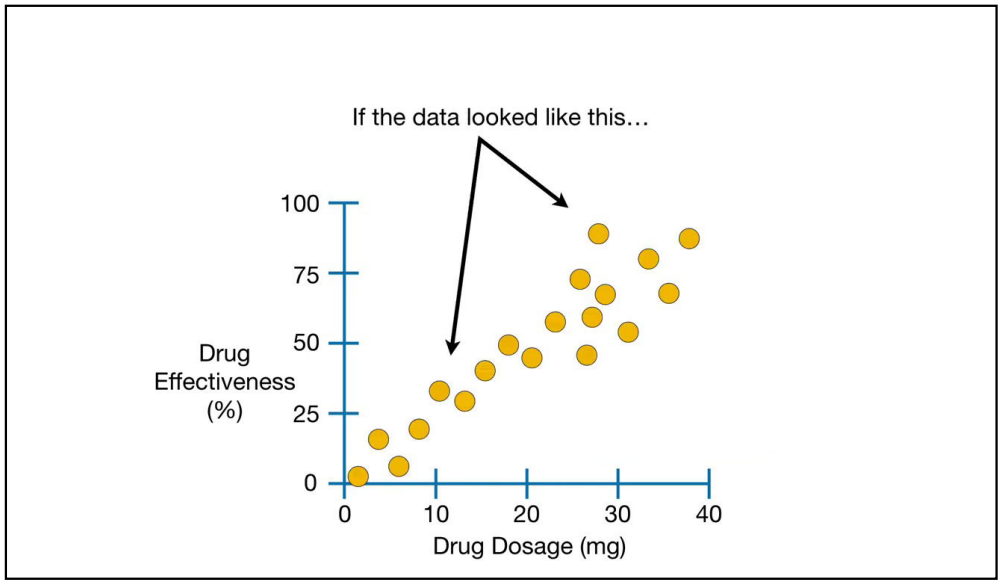
However, we don't know the optimal
dosage to give to patients.

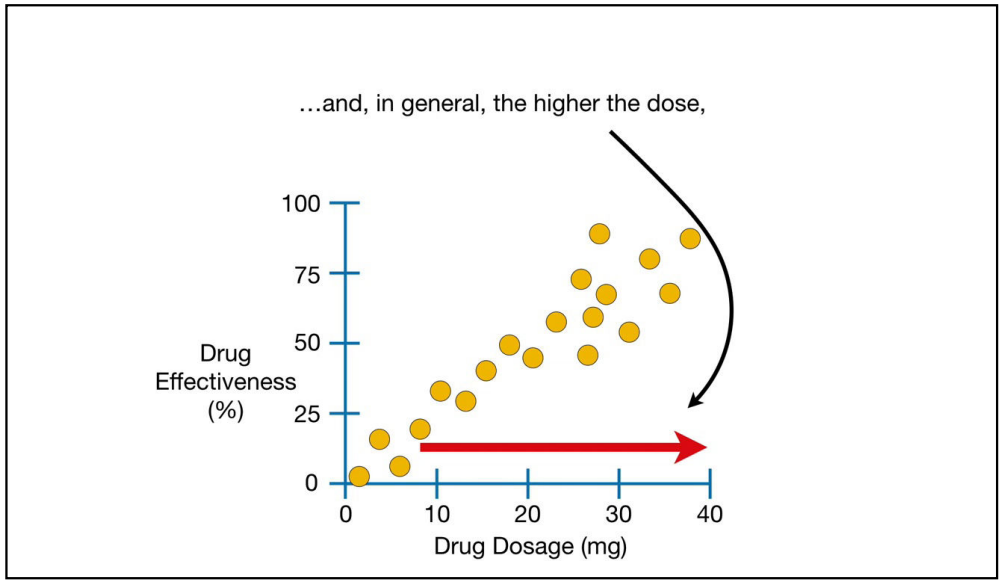
VS.

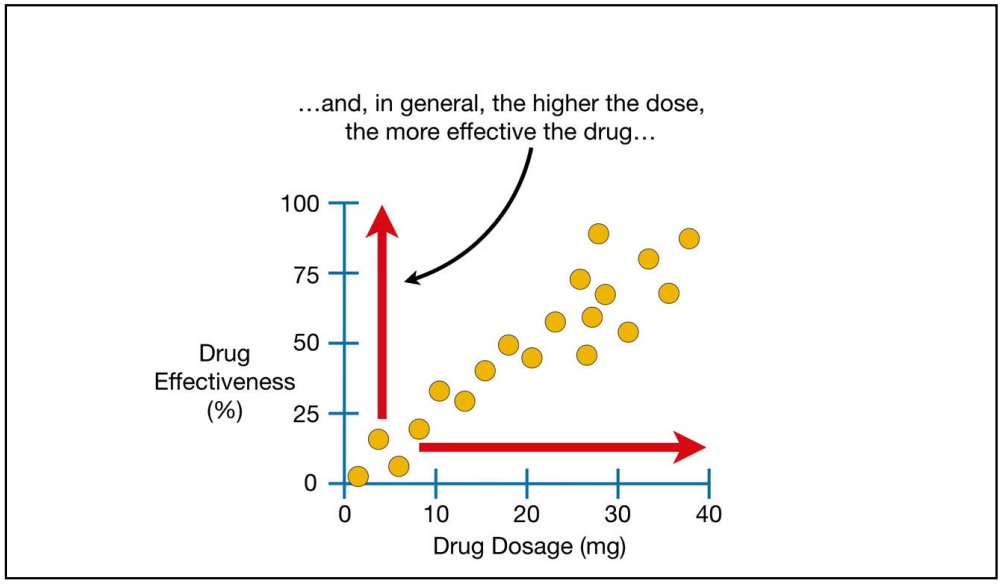
So we do a clinical trial with
different dosages…



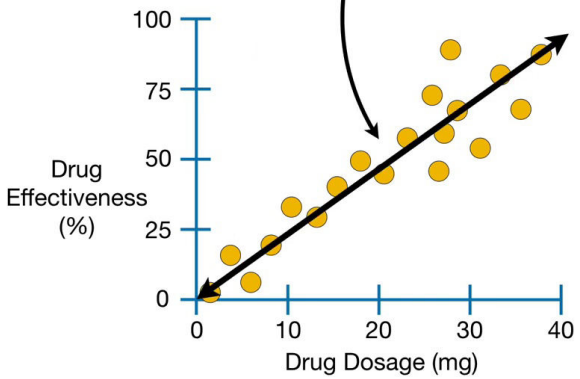

…and measure how effective each dosage is.
100
75
50
25
0
Drug Effectiveness (%)
0
10
20
30
40
Drug Dosage (mg)


If the data looked like this…
100
75
50
25
0
Drug Effectiveness (%)
0
10
20
30
40
Drug Dosage (mg)

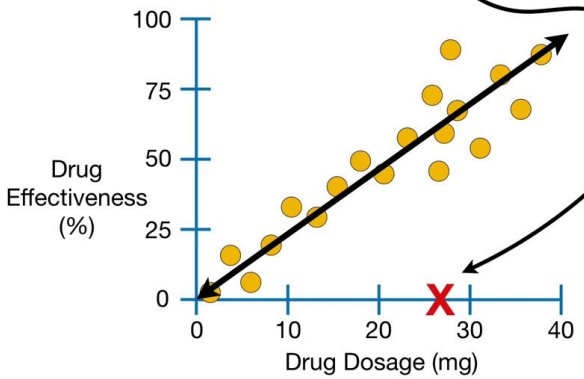

…and, in general, the higher the dose,
100
75
50
25
0
Drug Effectiveness (%)
0
10
20
30
40
Drug Dosage (mg)


…and, in general, the higher the dose, the more effective the drug…
100
75
50
25
0
Drug Effectiveness (%)
0
10
20
30
40
Drug Dosage (mg)

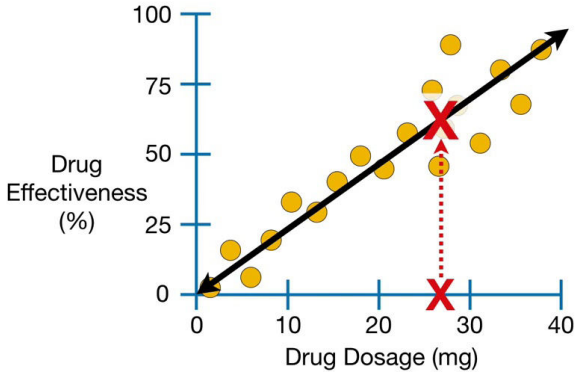
…then we could easily fit a line to the data…



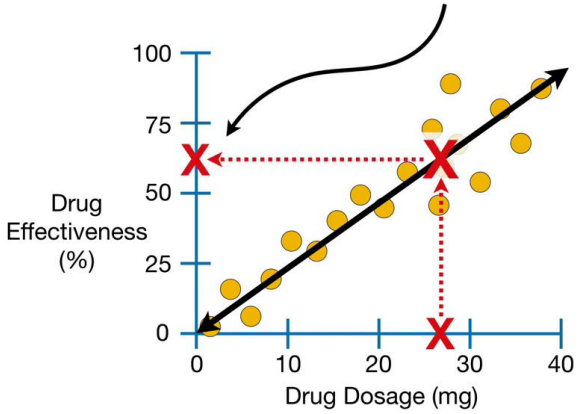
…and if someone told us they were taking a **27 mg Dose**…

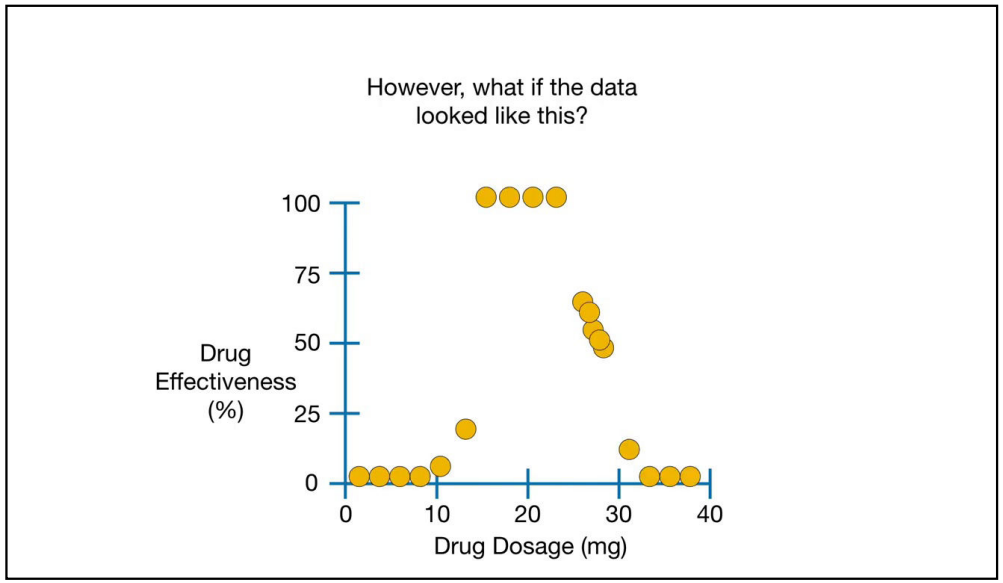


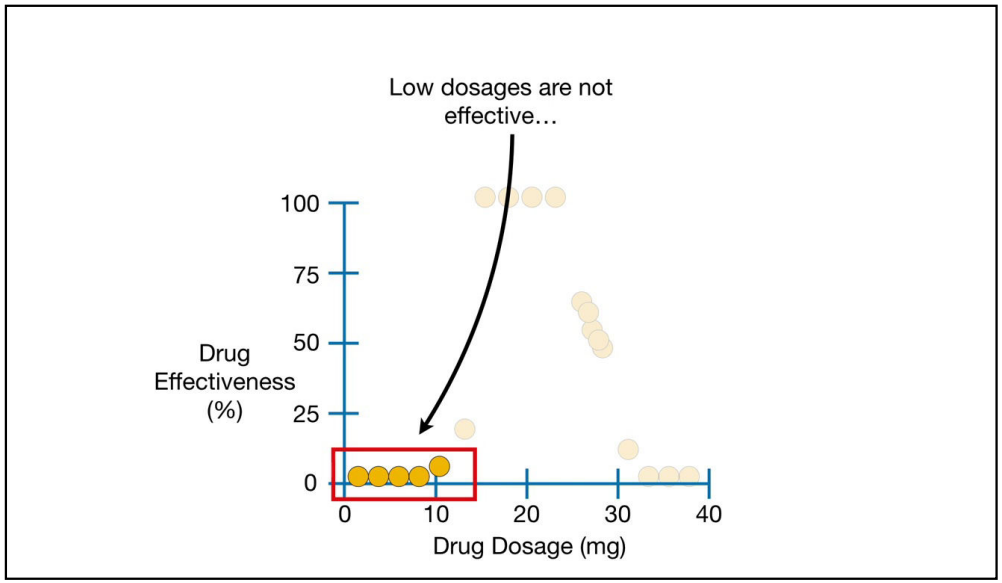
…we could use the line to predict that a **27 mg Dose** should be **62% Effective**.

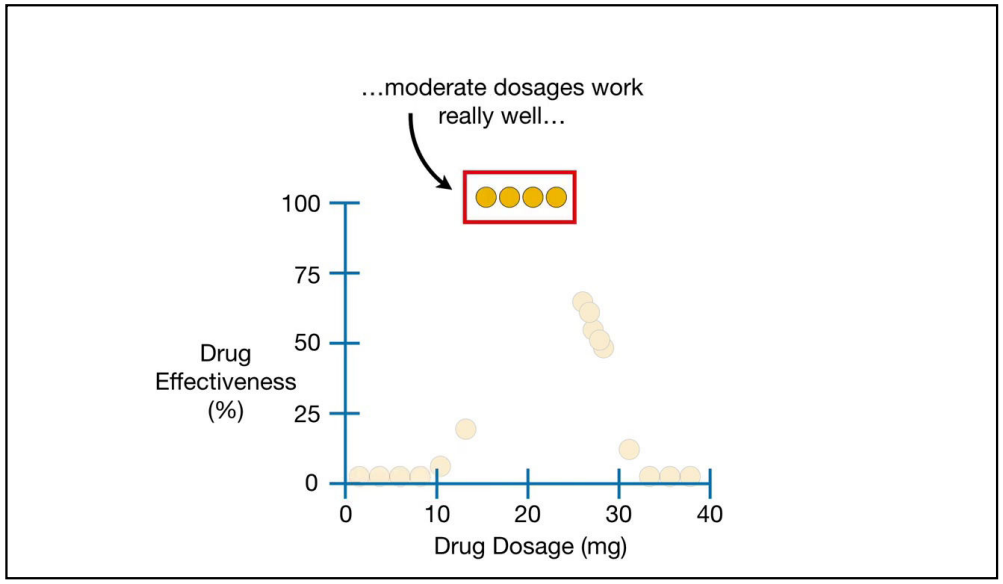


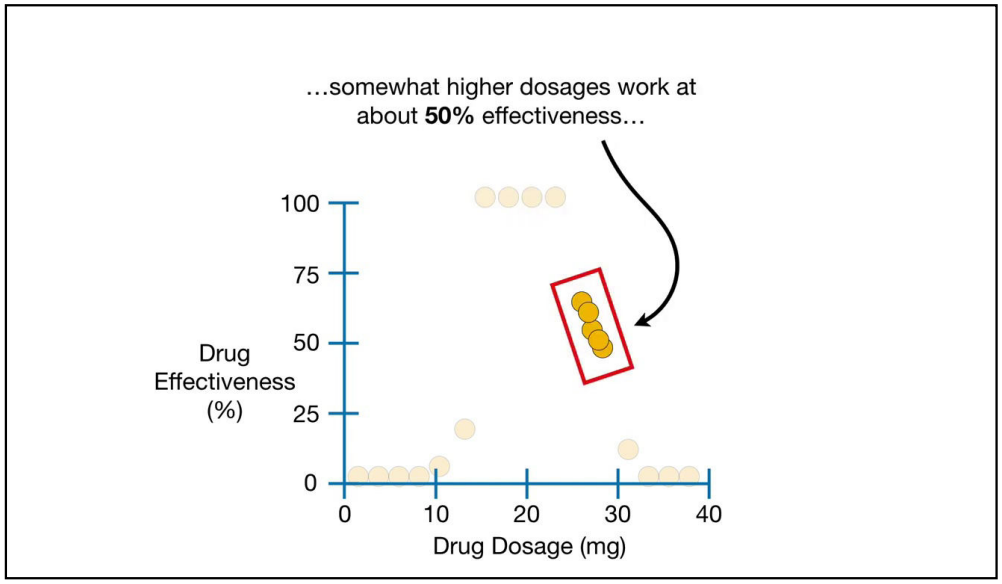
…we could use the line to predict that a **27 mg Dose** should be **62% Effective**.

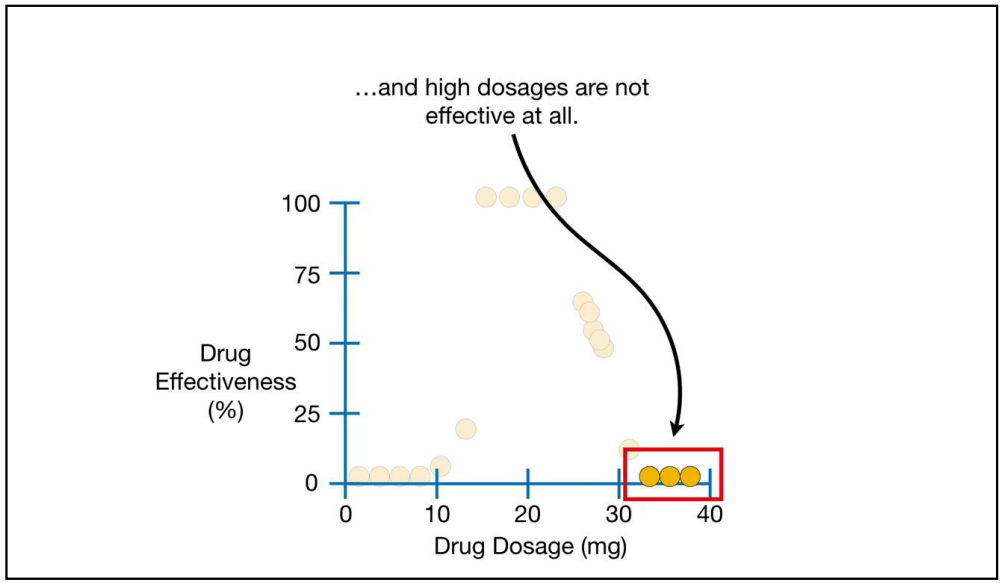


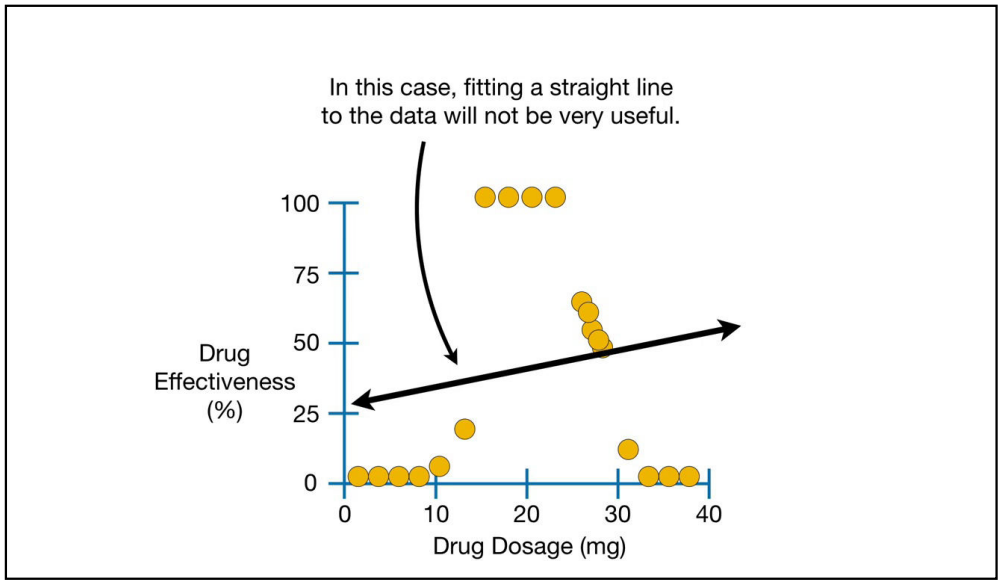

However, what if the data looked like this?
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

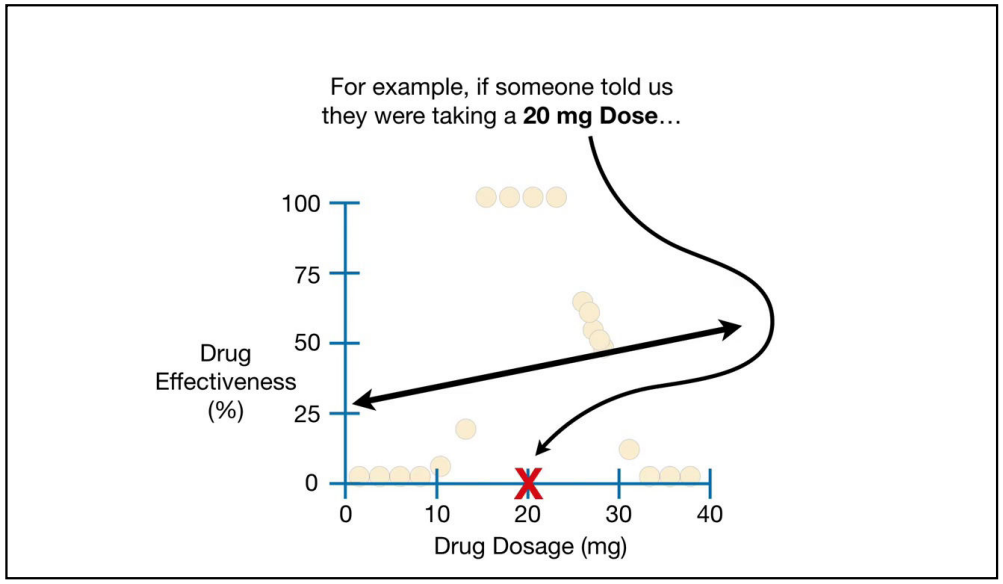

Low dosages are not effective…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

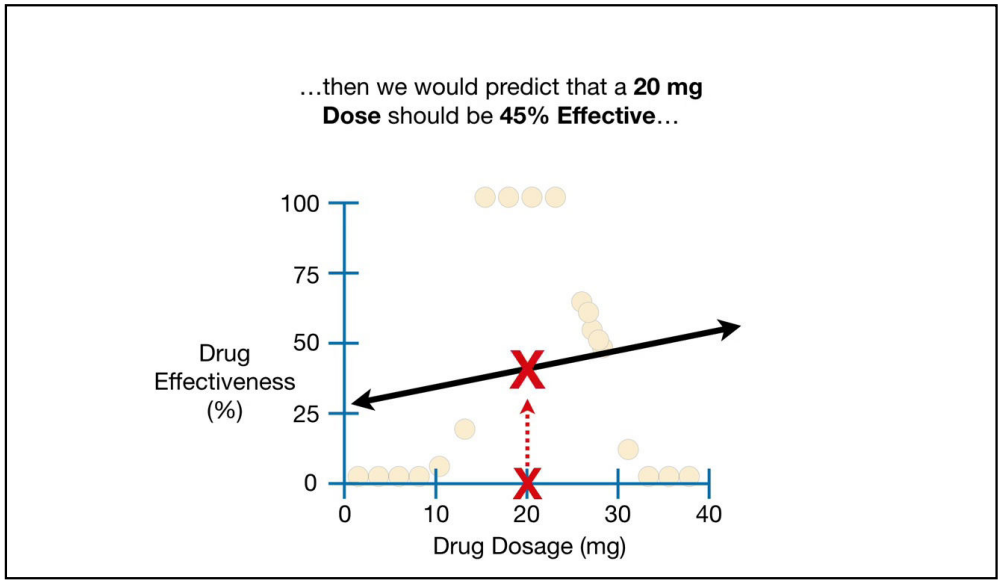

…moderate dosages work really well…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)


…somewhat higher dosages work at about 50% effectiveness…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

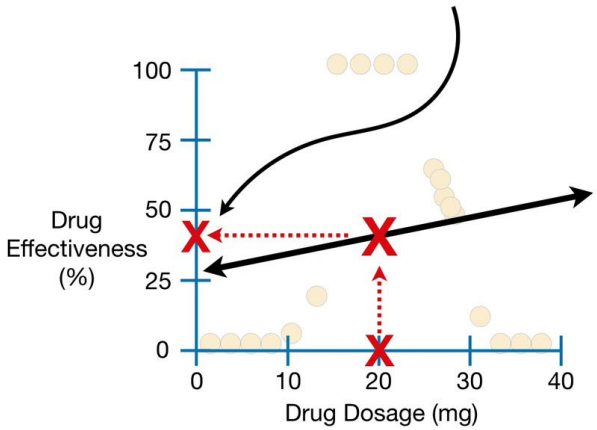

…and high dosages are not
effective at all.
Drug
Effectiveness
(%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)


In this case, fitting a straight line
to the data will not be very useful.
Drug
Effectiveness
(%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

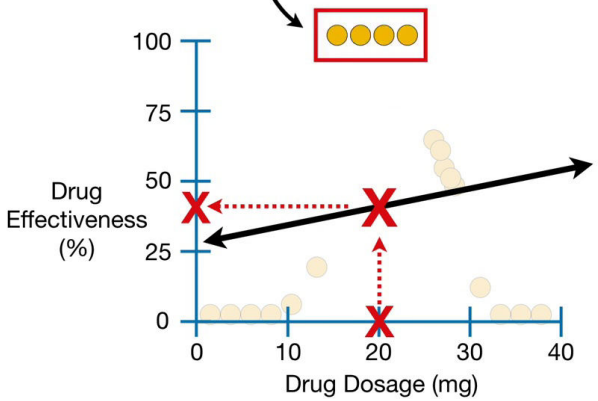

For example, if someone told us
they were taking a **20 mg Dose**…
Drug
Effectiveness
(%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)


…then we would predict that a **20 mg
Dose** should be **45% Effective**…
Drug
Effectiveness
(%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

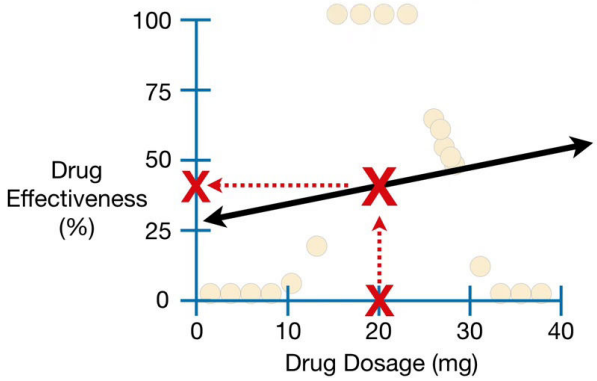
…then we would predict that a **20 mg Dose** should be **45% Effective**…



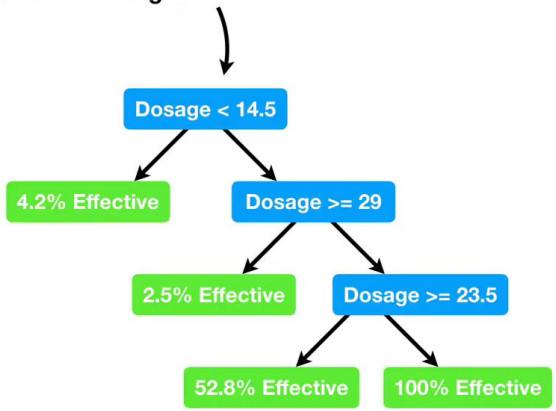
…even though the observed data says that it should be **100% Effective**.



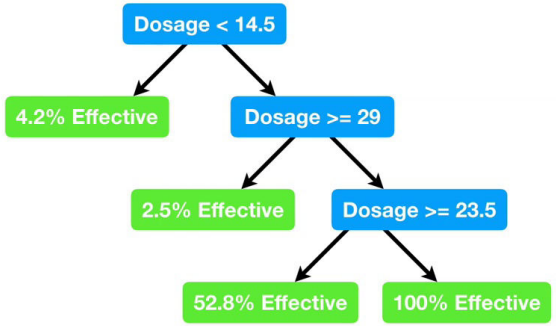
So we need to use something other than a straight line to make predictions.



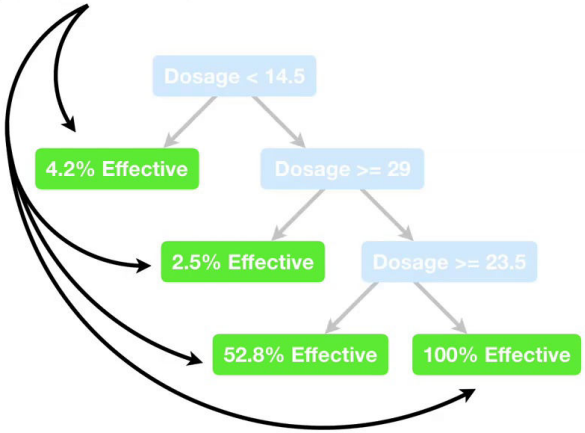
One option is to use a **Regression Tree**.

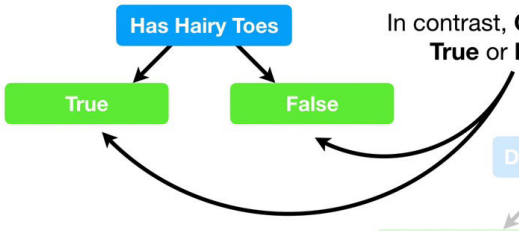


Regression Trees are a type of **Decision Tree.**

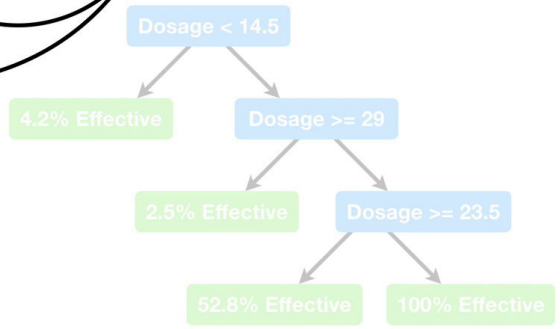


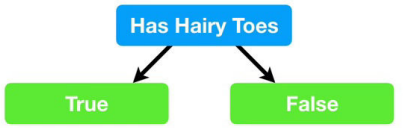
In a **Regression Tree**, each leaf represents a numeric value.



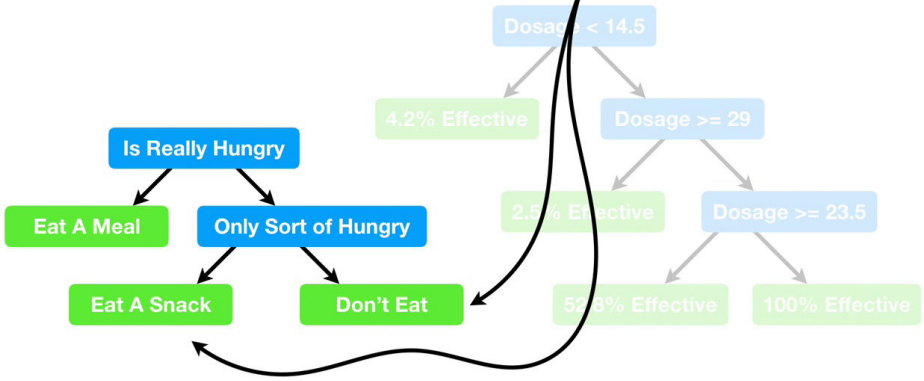


In contrast, **Classification Trees** have **True** or **False** in their leaves…

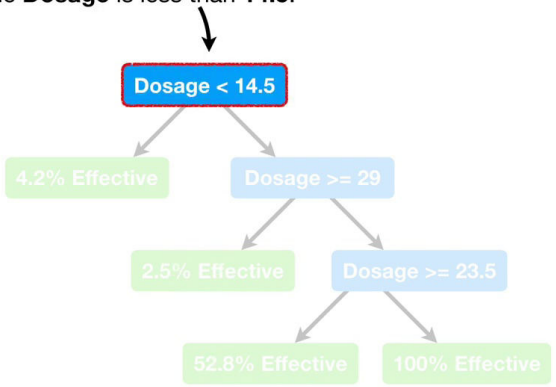




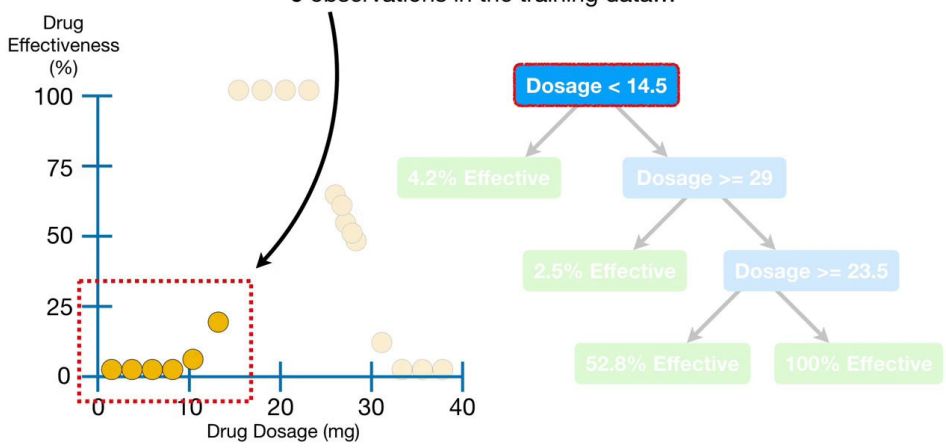
…or some other discrete category.



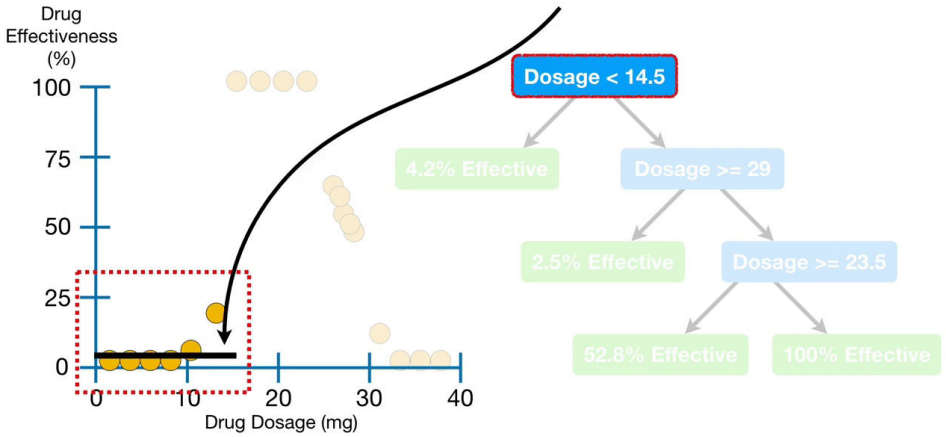
With *this* **Regression Tree**, we start by asking if the **Dosage** is less than **14.5**.



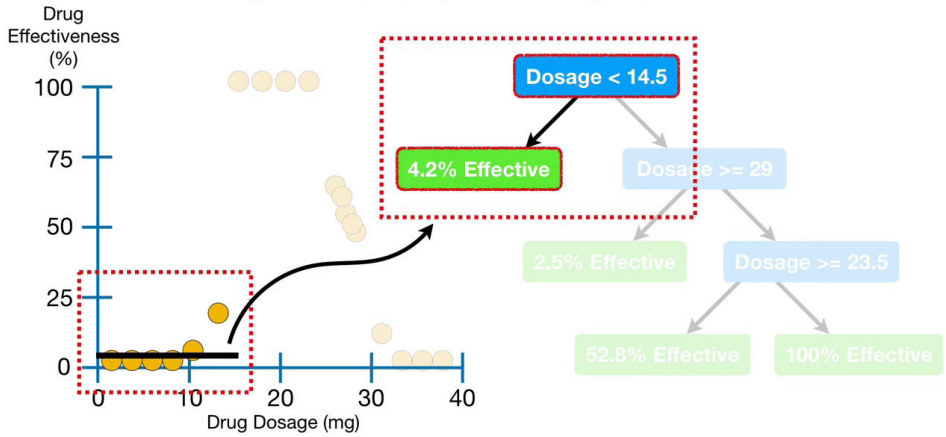
…if so, then we are talking about these **6** observations in the training data…

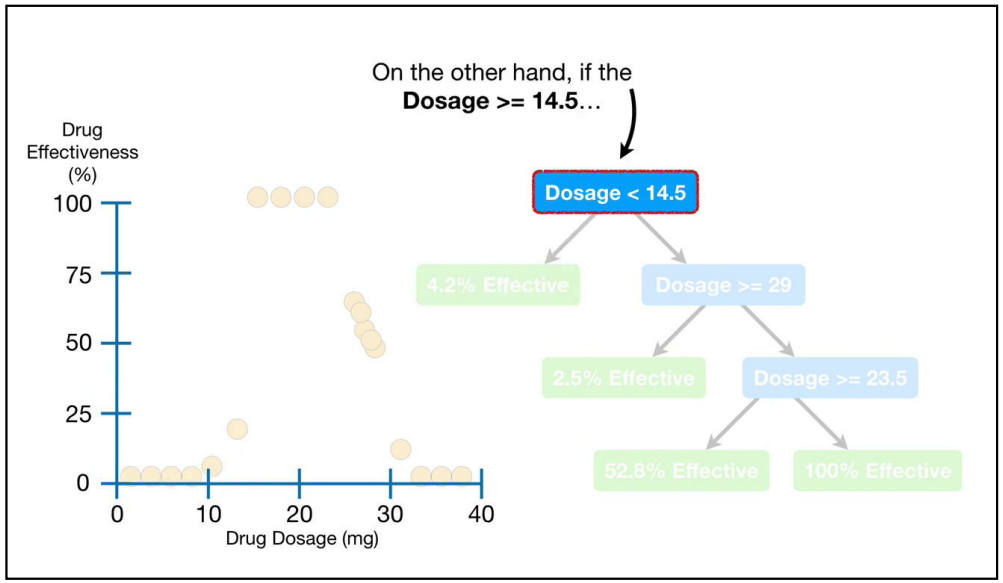


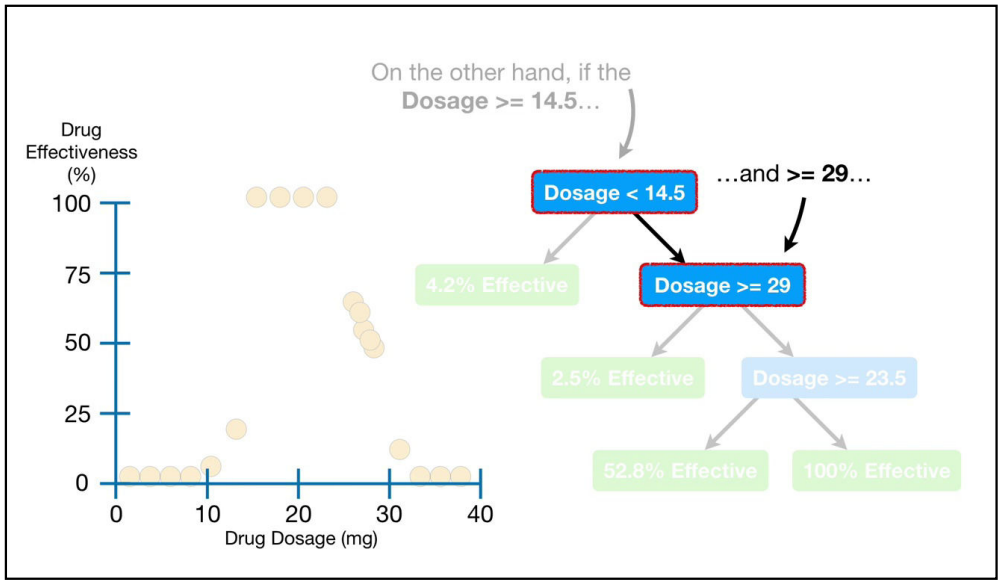
…and the average **Drug Effectiveness** for these **6** observations is **4.2%**…

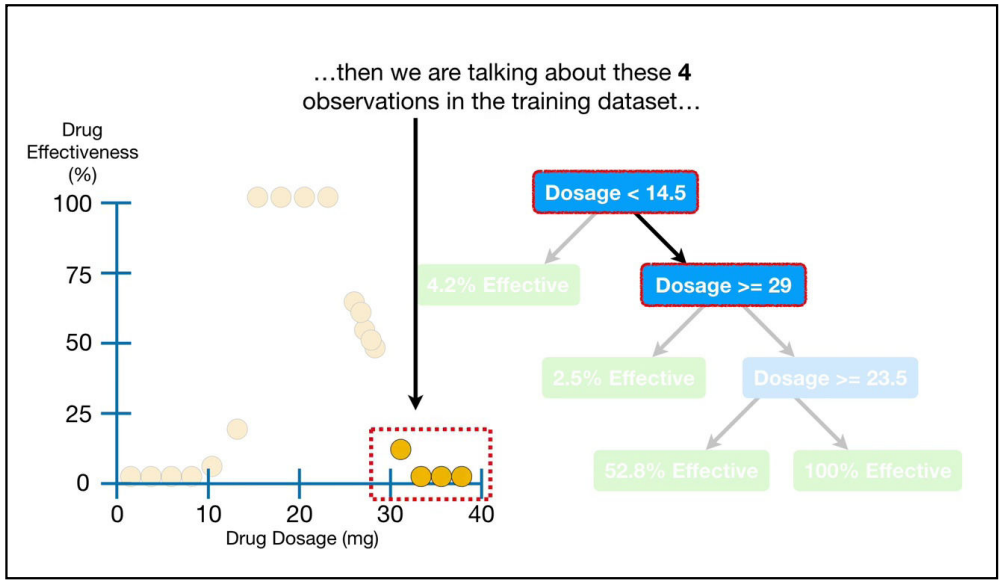


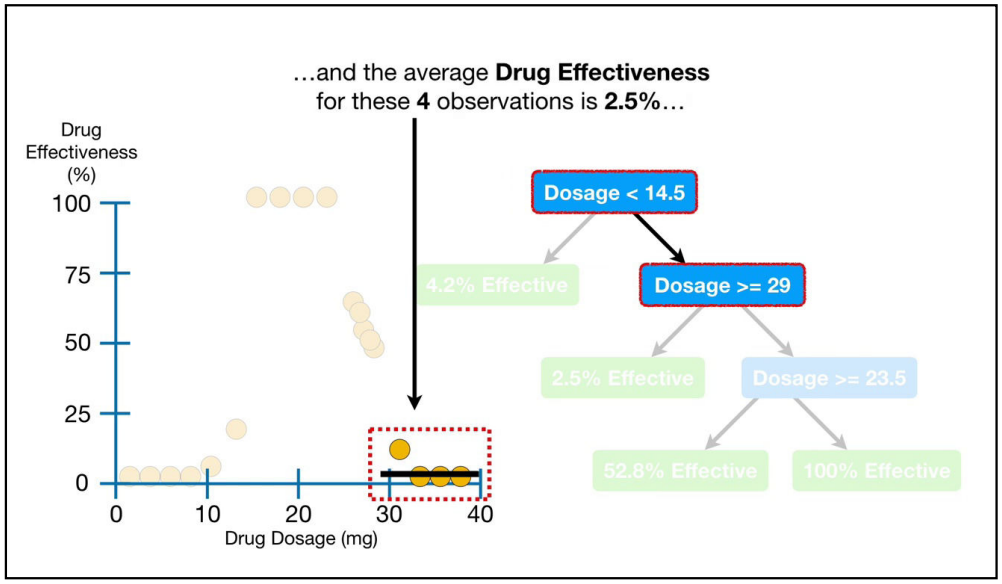
…so the tree uses the average value, **4.2%**, as its prediction for people with **Dosages < 14.5**.

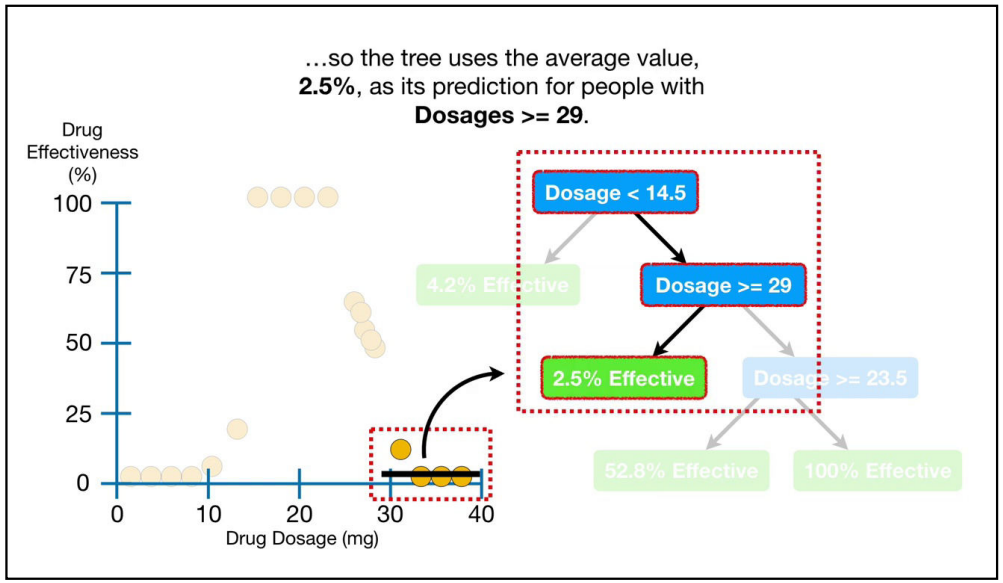


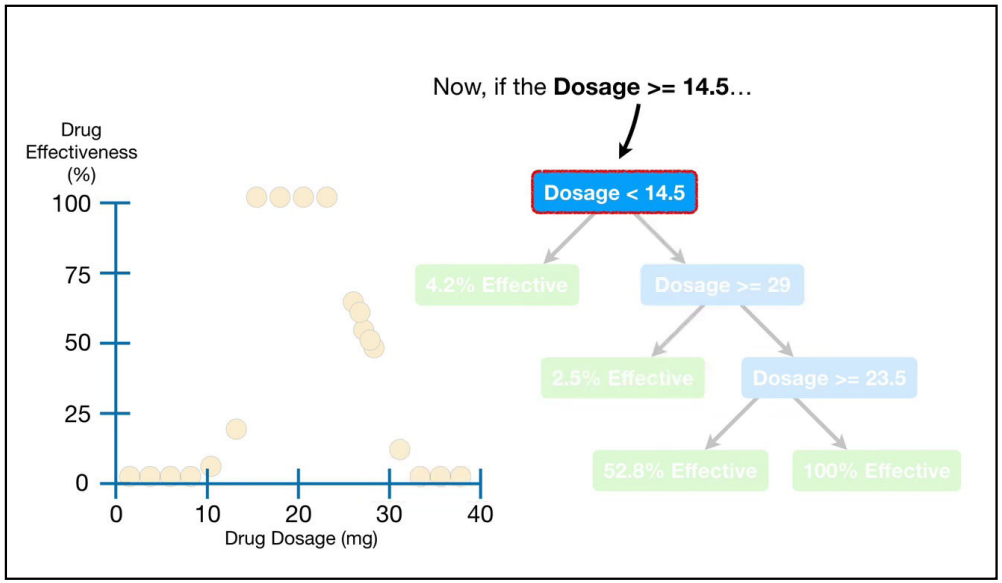

On the other hand, if the
Dosage >= 14.5…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

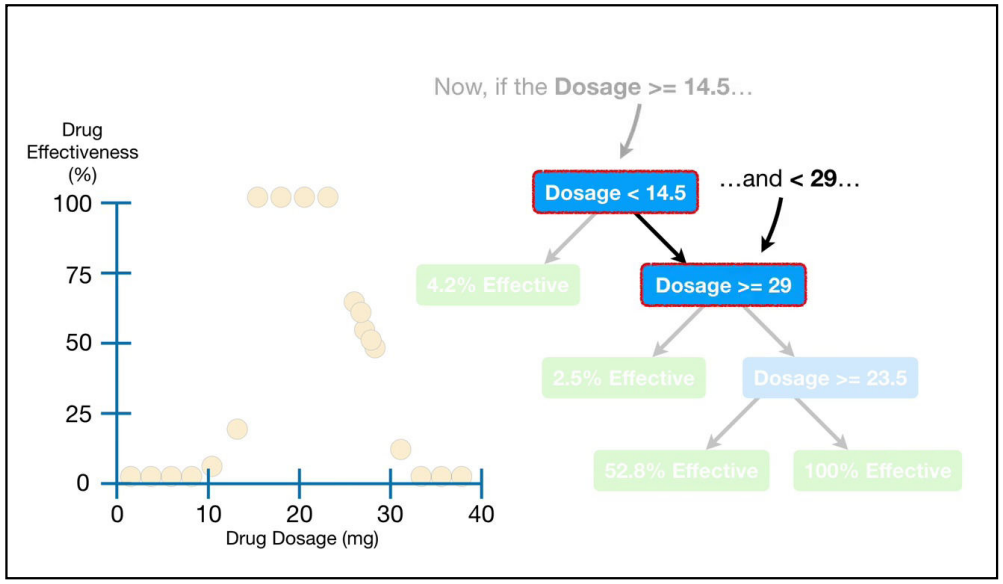

On the other hand, if the
Dosage >= 14.5…
…and >= 29…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

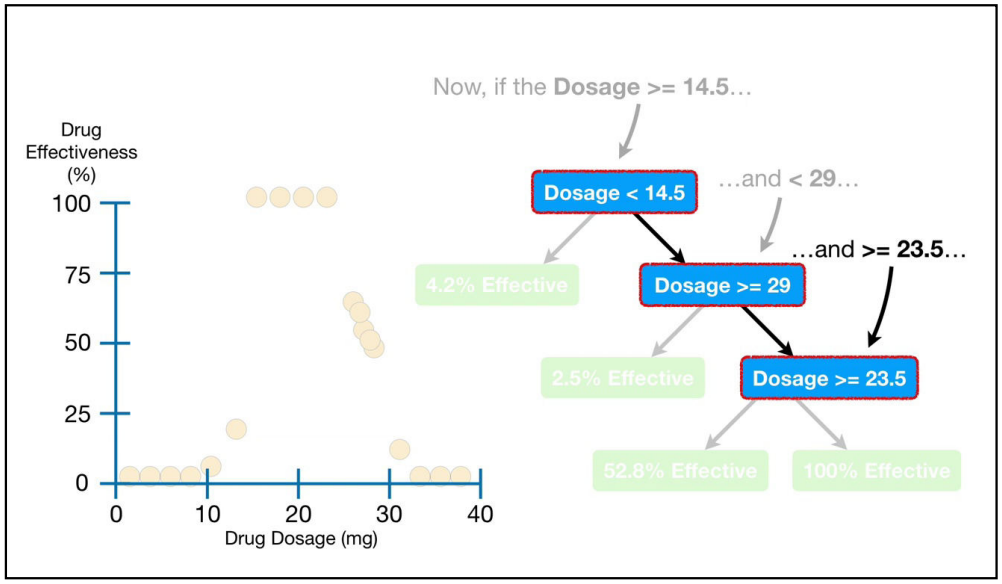

…then we are talking about these 4
observations in the training dataset…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

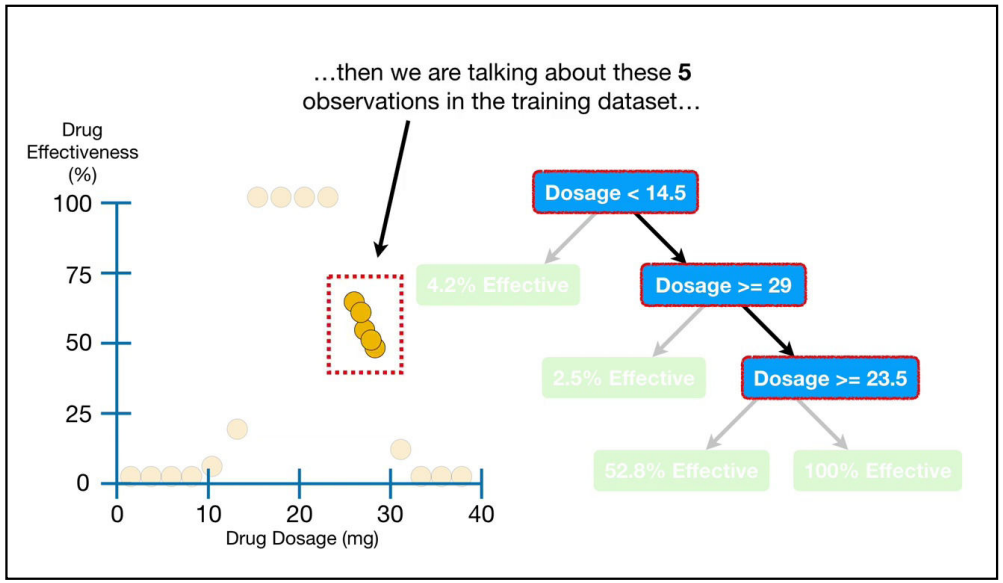

…and the average Drug Effectiveness
for these 4 observations is 2.5%…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

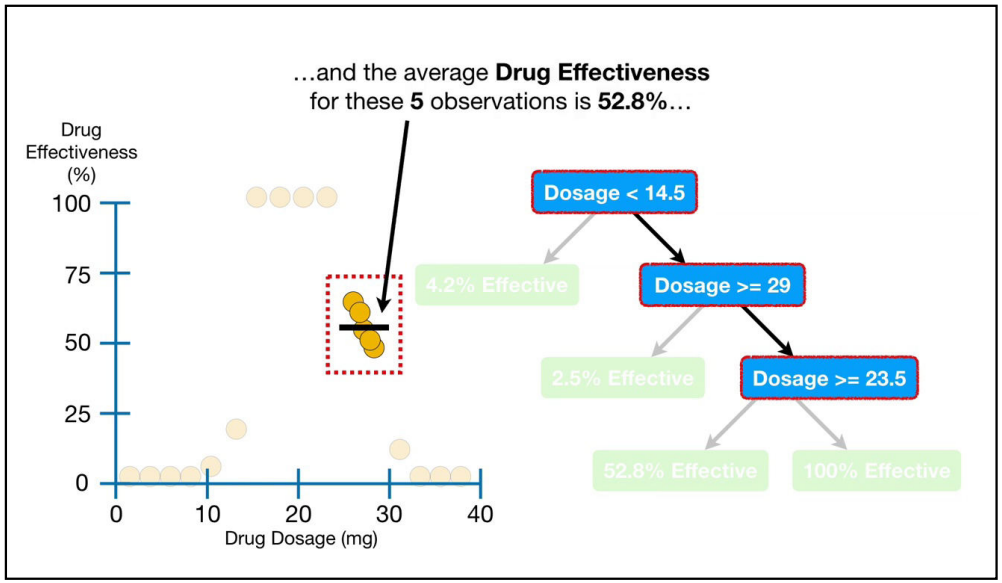

…so the tree uses the average value,
2.5%, as its prediction for people with
Dosages >= 29.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

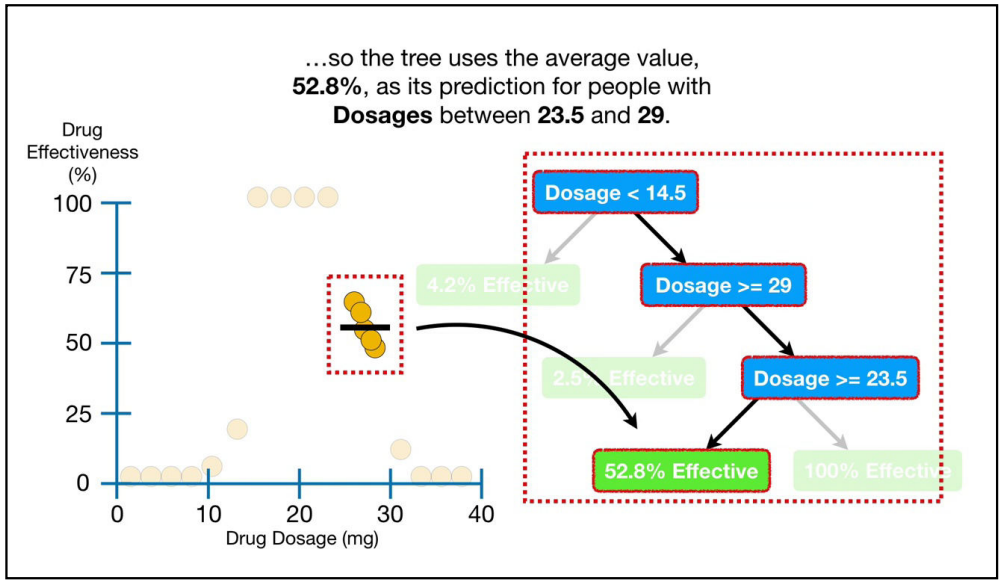

Now, if the Dosage >= 14.5…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

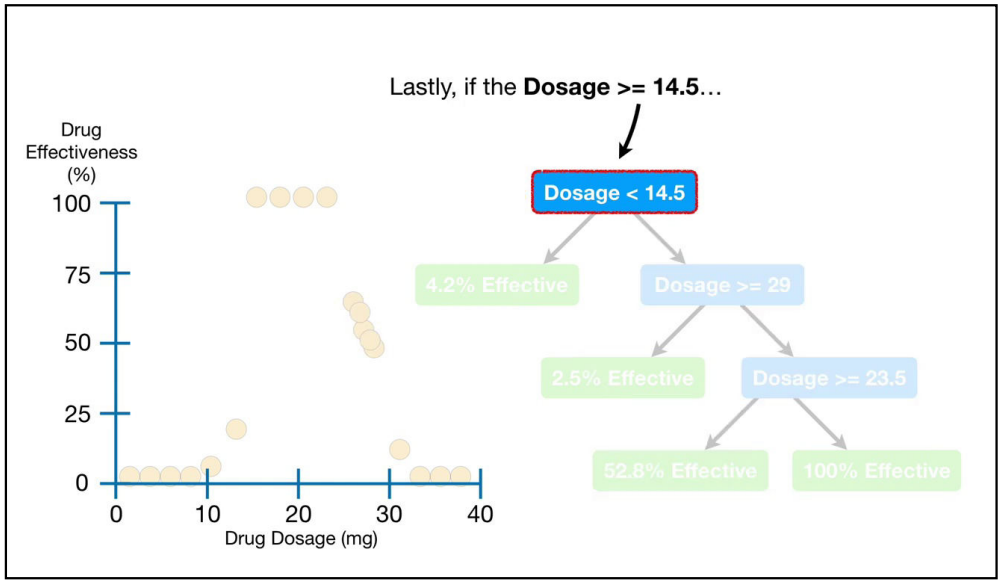

Now, if the Dosage >= 14.5…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
…and < 29…
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

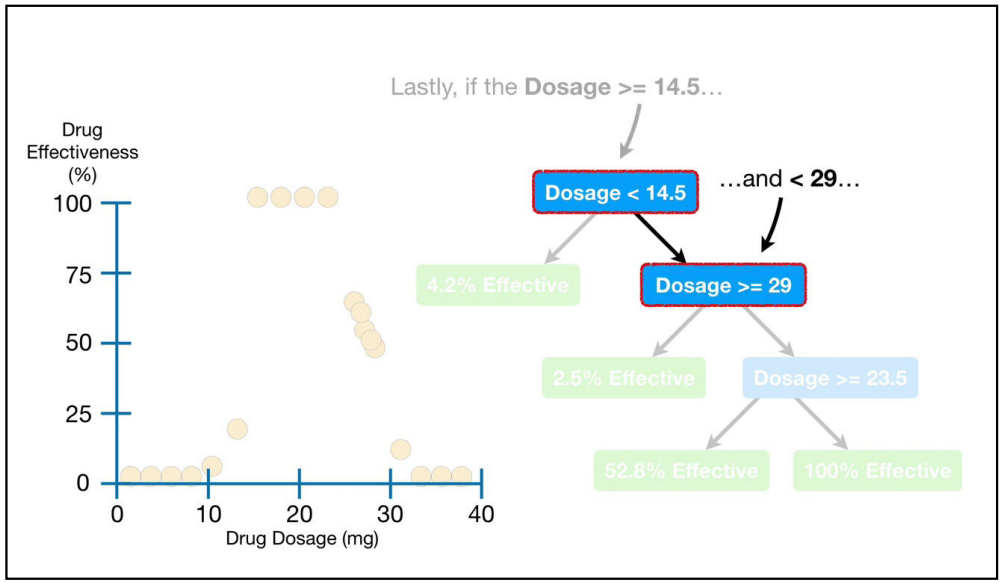

Now, if the Dosage >= 14.5…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
…and < 29…
…and >= 23.5…
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

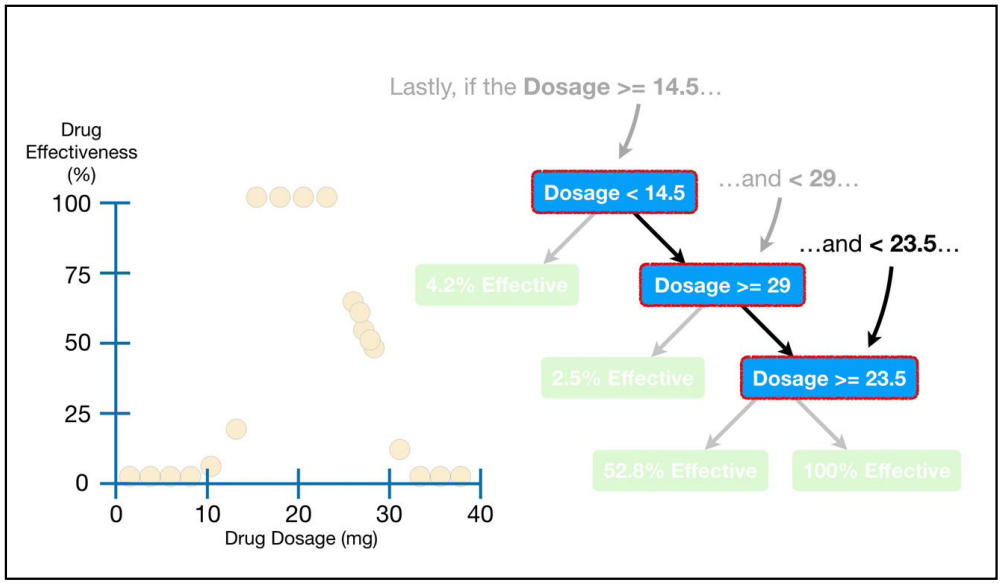

…then we are talking about these **5** observations in the training dataset…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

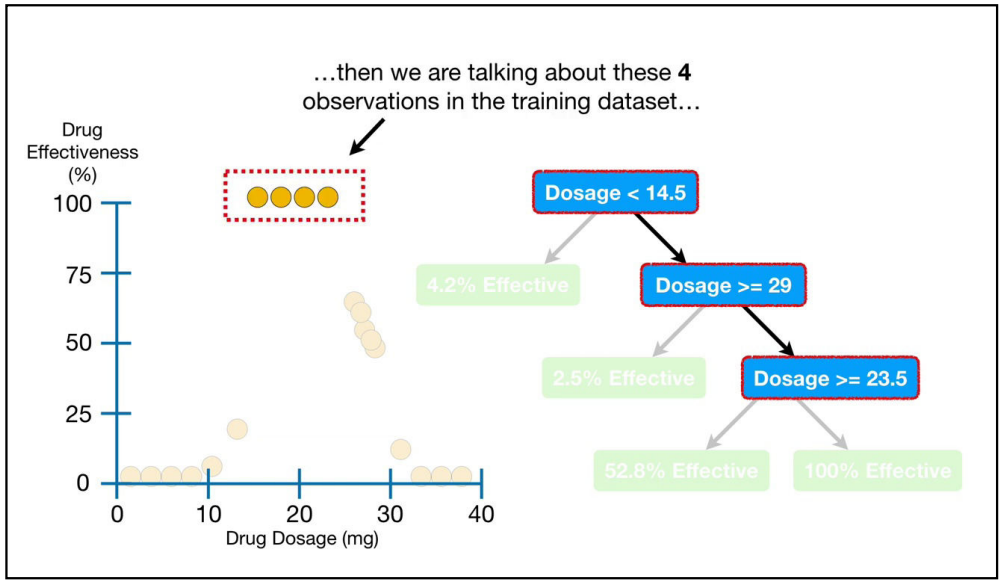

…and the average **Drug Effectiveness** for these **5** observations is **52.8%**…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

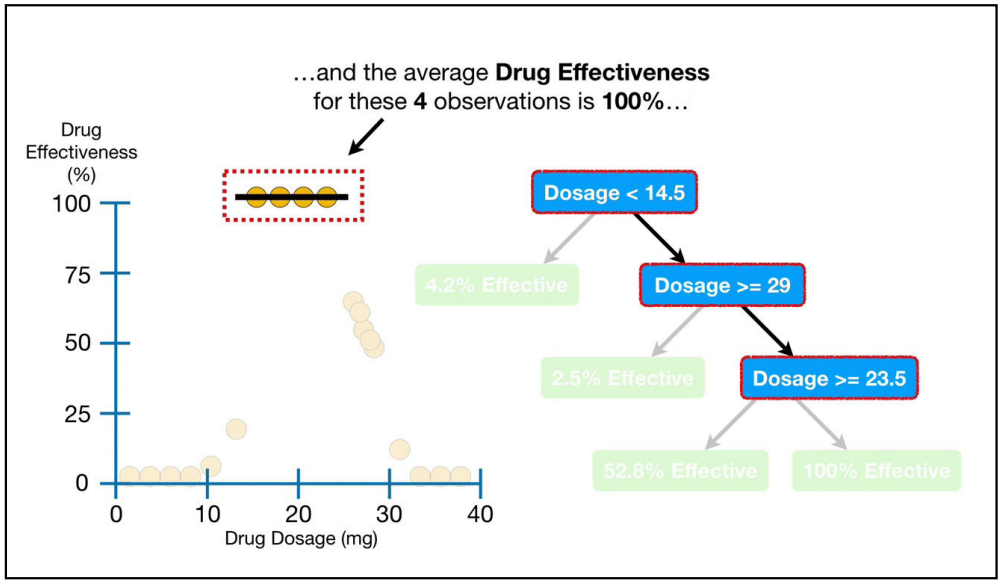

…so the tree uses the average value, **52.8%**, as its prediction for people with **Dosages** between **23.5** and **29**.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage >= 29
Dosage >= 23.5
52.8% Effective

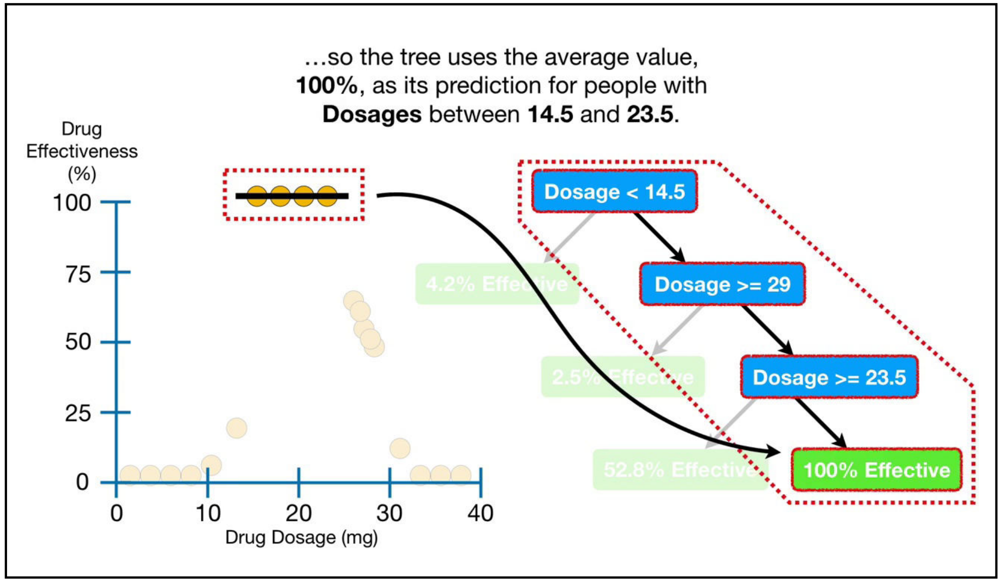

Lastly, if the **Dosage >= 14.5**…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

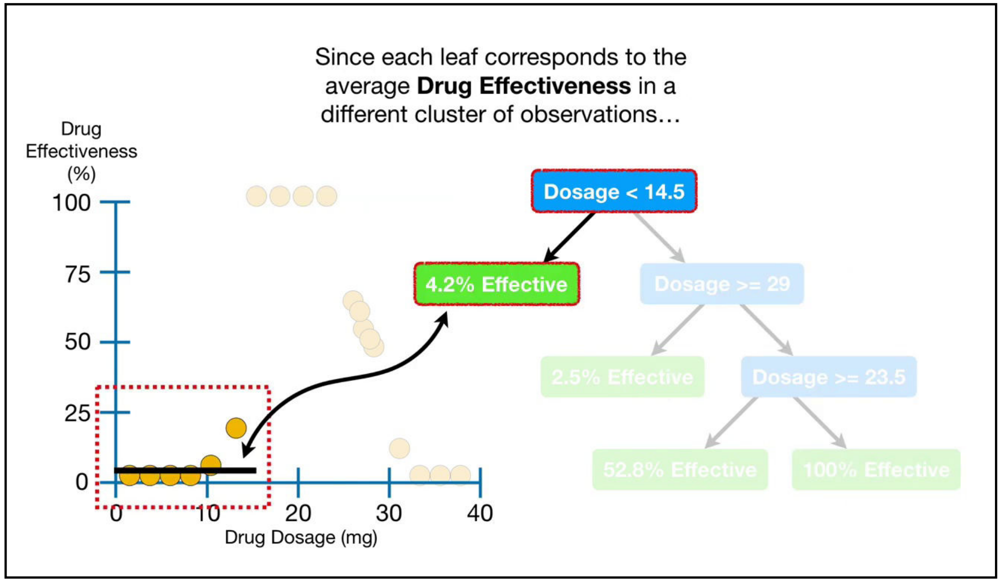

Lastly, if the Dosage >= 14.5…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
…and < 29…
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

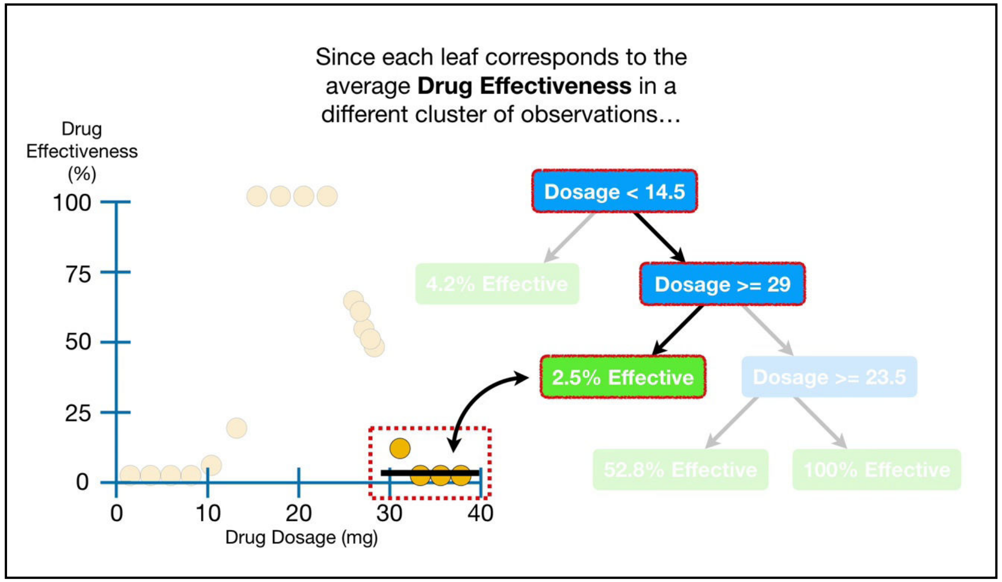

Lastly, if the Dosage >= 14.5…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
…and < 29…
…and < 23.5…
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

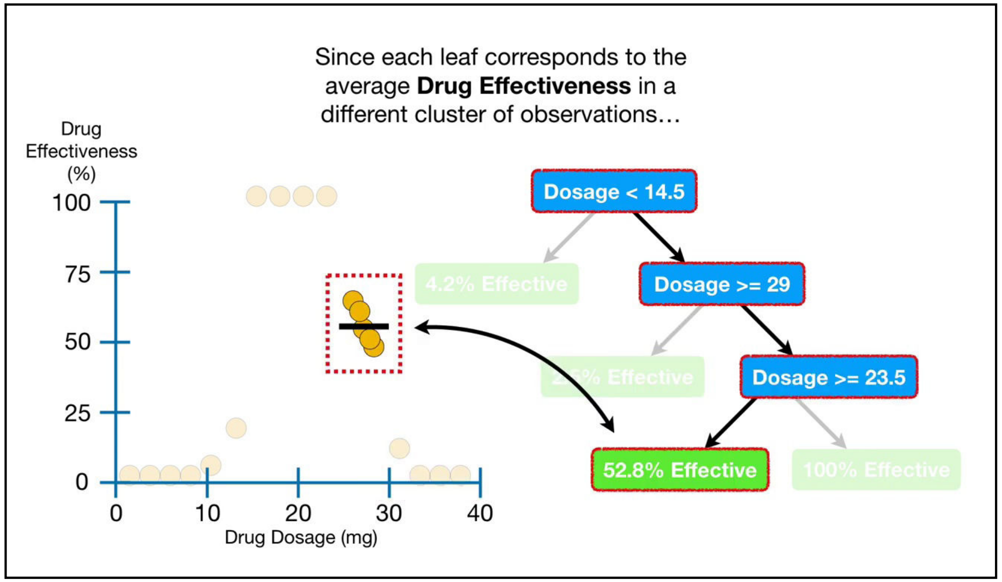

…then we are talking about these 4 observations in the training dataset…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

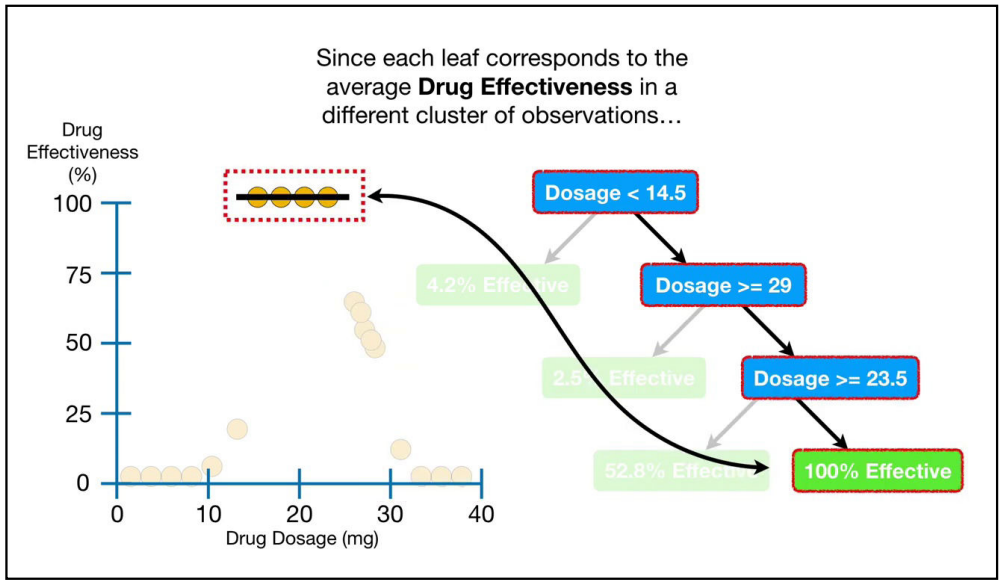

…and the average Drug Effectiveness for these 4 observations is 100%…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

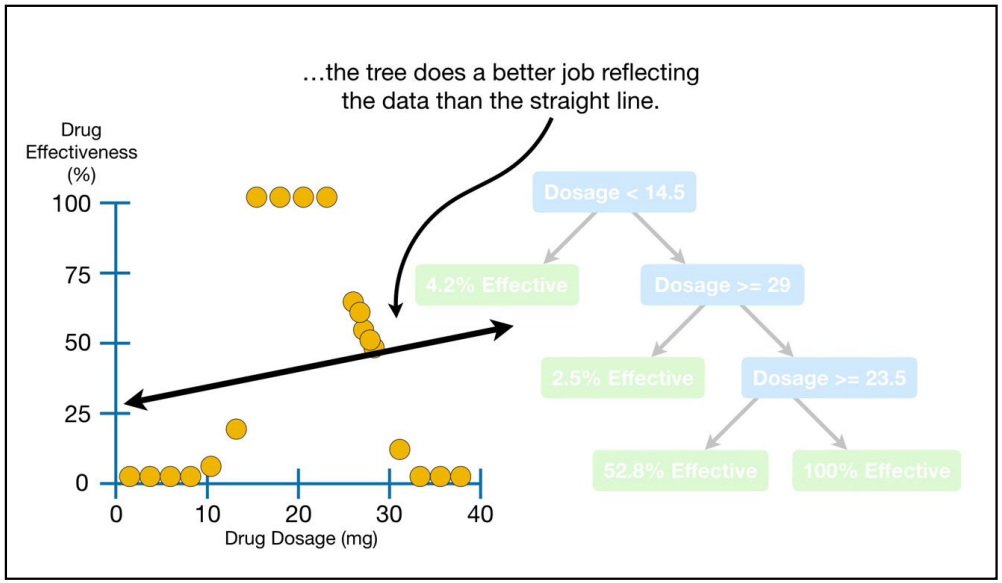

...so the tree uses the average value,
100%, as its prediction for people with
Dosages between 14.5 and 23.5.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

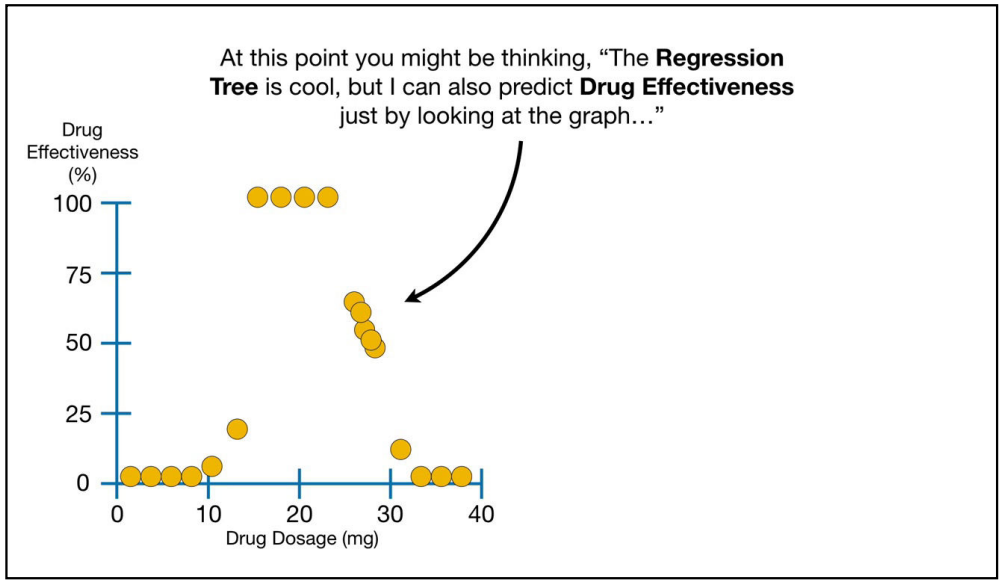

Since each leaf corresponds to the
average Drug Effectiveness in a
different cluster of observations...
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

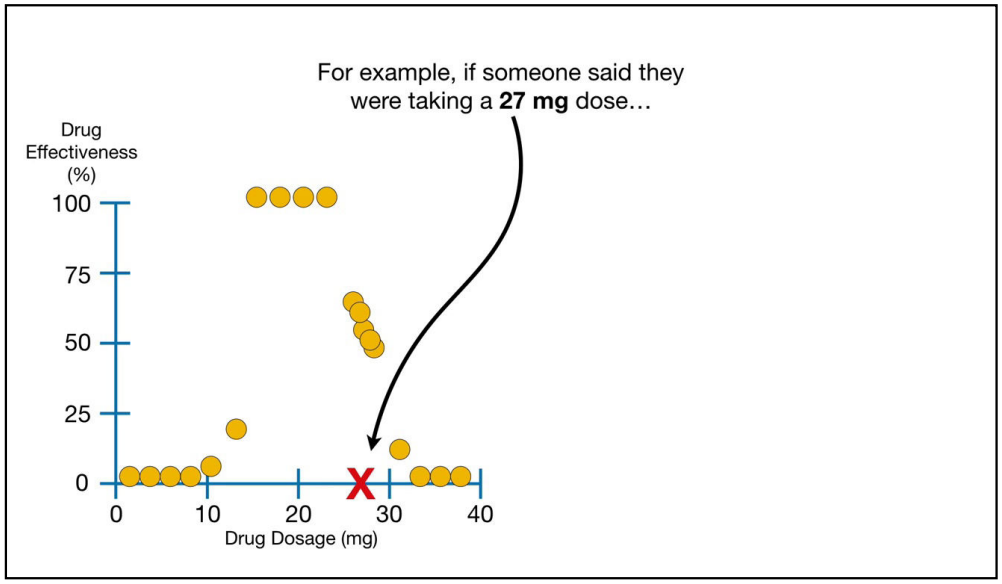

Since each leaf corresponds to the
average Drug Effectiveness in a
different cluster of observations...
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective


Since each leaf corresponds to the
average Drug Effectiveness in a
different cluster of observations...
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
Dosage >= 23.5
52.8% Effective
100% Effective

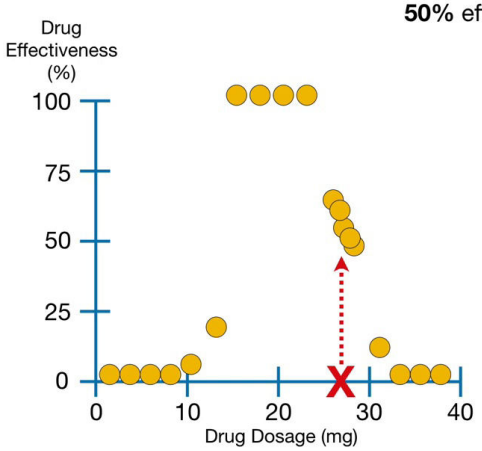

Since each leaf corresponds to the average **Drug Effectiveness** in a different cluster of observations…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective


…the tree does a better job reflecting the data than the straight line.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

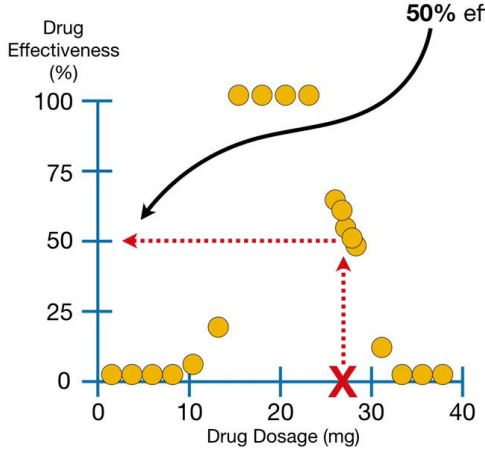

At this point you might be thinking, “The **Regression Tree** is cool, but I can also predict **Drug Effectiveness** just by looking at the graph…”
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)


For example, if someone said they were taking a **27 mg** dose…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
X

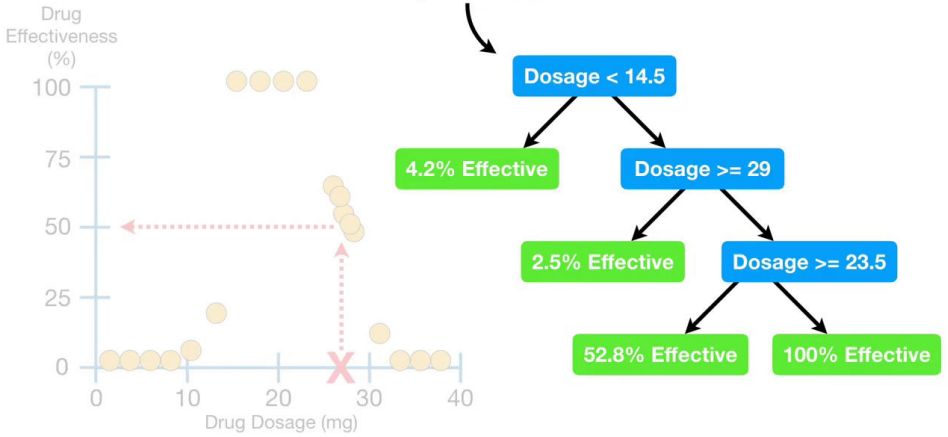
…then, just by looking at the graph,
I can tell that the drug will be about
50% effective.



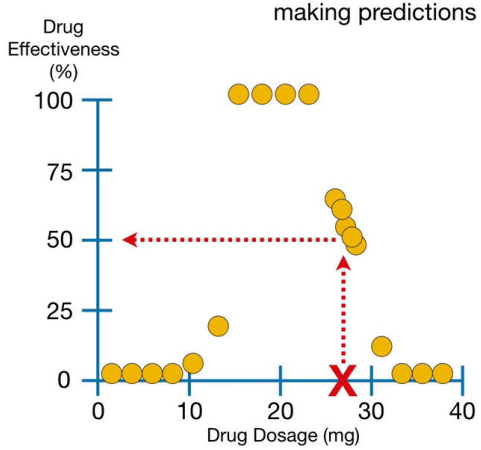
…then, just by looking at the graph,
I can tell that the drug will be about
50% effective.



So why make a big deal about the
Regression Tree?



When the data are super simple and we are only using
one predictor, **Dosage**, to predict **Drug Effectiveness**,
making predictions by eye isn't terrible.

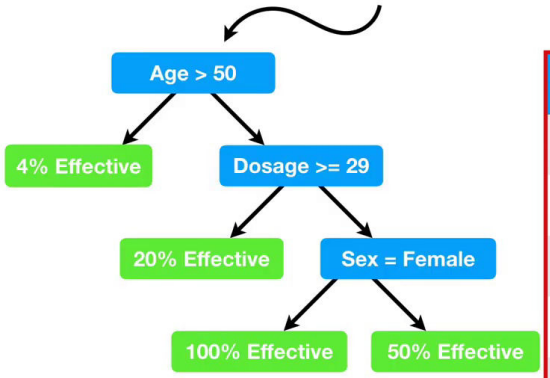


Dosage	Drug Effect.
10	58
20	60
35	57
5	44
etc…	etc…

But when we have **3** or more predictors, like **Dosage**, **Age** and **Sex**, to predict **Drug Effectiveness**, drawing a graph is very difficult, if not impossible.

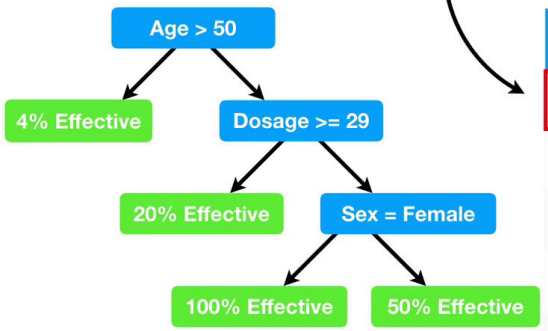
Dosage	Age	Sex	Etc.	Drug Effect.
10	25	Female	…	98
20	73	Male	…	0
35	54	Female	…	100
5	12	Male	…	44
etc…	etc…	etc…	etc…	etc…

In contrast, a **Regression Tree** easily accommodates the additional predictors.



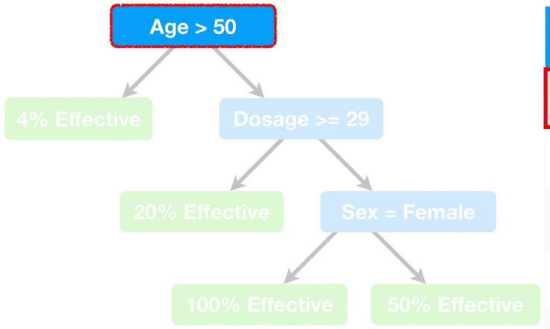
Dosage	Age	Sex	Etc.	Drug Effect.
10	25	Female	…	98
20	73	Male	…	0
35	54	Female	…	100
5	12	Male	…	44
etc…	etc…	etc…	etc…	etc…

For example, if we wanted to predict the **Drug Effectiveness** for this patient…



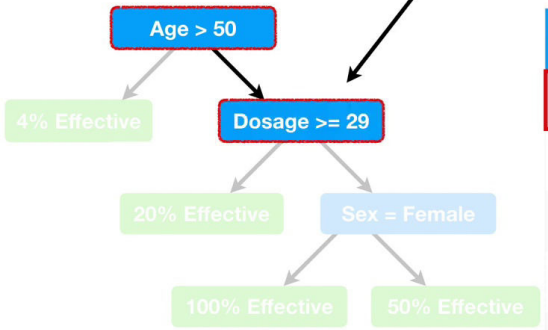
Dosage	Age	Sex	Etc.	Drug Effect.
10	25	Female	…	98
20	73	Male	…	0
35	54	Female	…	100
5	12	Male	…	44
etc…	etc…	etc…	etc…	etc…

…we start by asking if they are older than **50**…



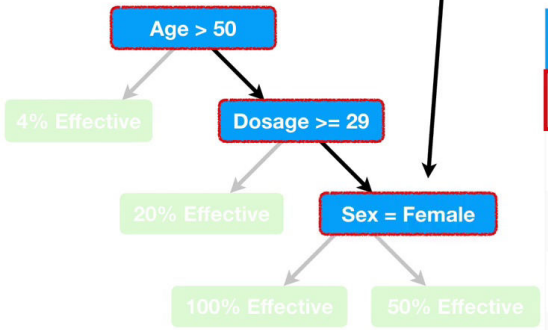
Dosage	Age	Sex	Etc.	Drug Effect.
10	25	Female	…	98
20	73	Male	…	0
35	54	Female	…	100
5	12	Male	…	44
etc…	etc…	etc…	etc…	etc…

…and since they *not* over **50**, we follow the branch on the *right* and ask if their **Dosage >= 29**…



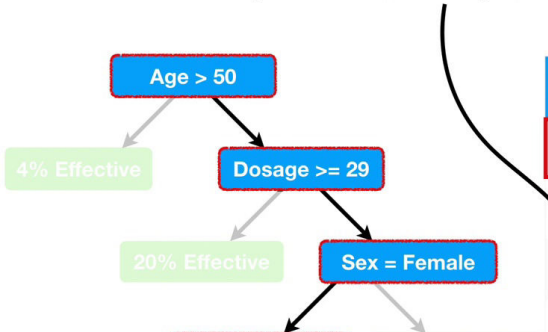
Dosage	Age	Sex	Etc.	Drug Effect.
10	25	Female	…	98
20	73	Male	…	0
35	54	Female	…	100
5	12	Male	…	44
etc…	etc…	etc…	etc…	etc…

…and since their dosage is *not* **>= 29**, we follow the branch on the *right* and ask if they are **Female**…



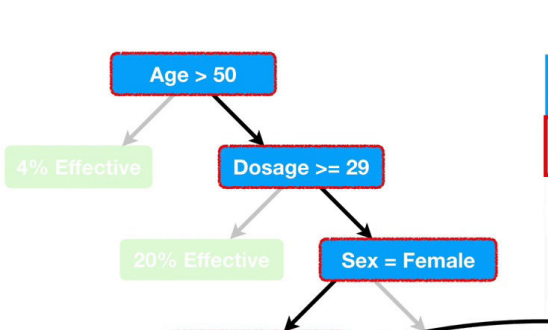
Dosage	Age	Sex	Etc.	Drug Effect.
10	25	Female	…	98
20	73	Male	…	0
35	54	Female	…	100
5	12	Male	…	44
etc…	etc…	etc…	etc…	etc…

…and since they *are* **Female**, we follow the branch on the *left* and predict that the dosage will be **100% Effective**…



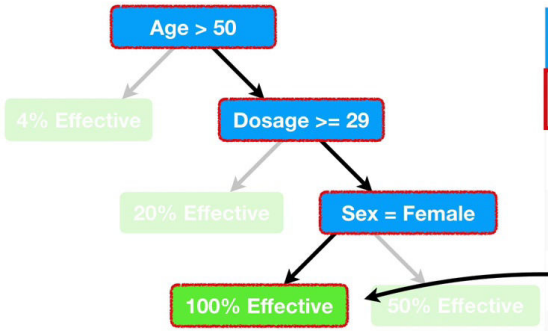
Dosage	Age	Sex	Etc.	Drug Effect.
10	25	Female	…	98
20	73	Male	…	0
35	54	Female	…	100
5	12	Male	…	44
etc…	etc…	etc…	etc…	etc…

…and that's not too far off from the truth, **98%**.



Dosage	Age	Sex	Etc.	Drug Effect.
10	25	Female	…	98
20	73	Male	…	0
35	54	Female	…	100
5	12	Male	…	44
etc…	etc…	etc…	etc…	etc…

OK, now that we know that **Regression Trees** can easily handle complicated data…

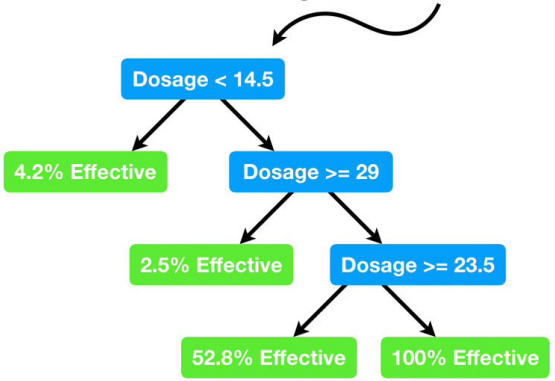


Dosage	Age	Sex	Etc.	Drug Effect.
10	25	Female	…	98
20	73	Male	…	0
35	54	Female	…	100
5	12	Male	…	44
etc…	etc…	etc…	etc…	etc…

…let's go back to the original data, with just one predictor, **Dosage**…

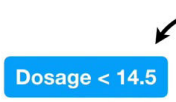
Dosage	Drug Effect.
10	58
20	60
35	57
5	44
etc…	etc…

…and talk about how to build this **Regression Tree** from scratch…



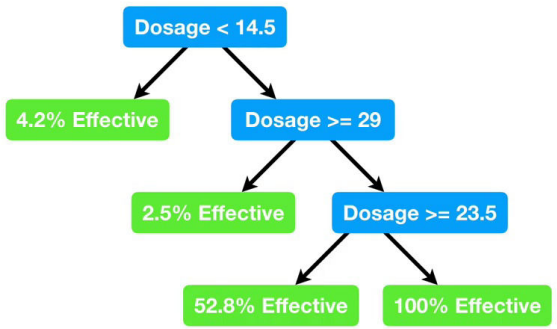
Dosage	Drug Effect.
10	58
20	60
35	57
5	44
etc…	etc…

…and since **Regression Trees** are built from the top down…



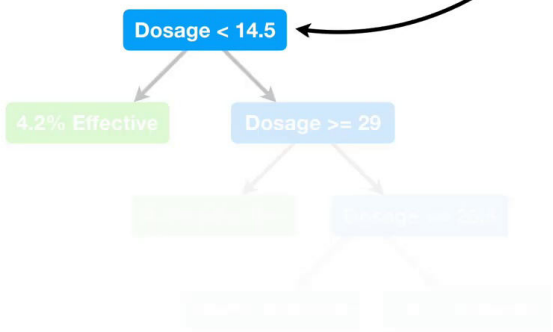
Dosage	Drug Effect.
10	58
20	60
35	57
5	44
etc…	etc…

…and since **Regression Trees** are built from the top down…



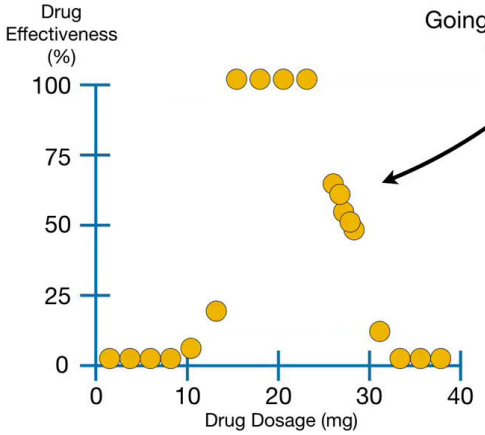
Dosage	Drug Effect.
10	58
20	60
35	57
5	44
etc…	etc…

…the first thing we do is figure out why we start by asking if **Dosage < 14.5**.



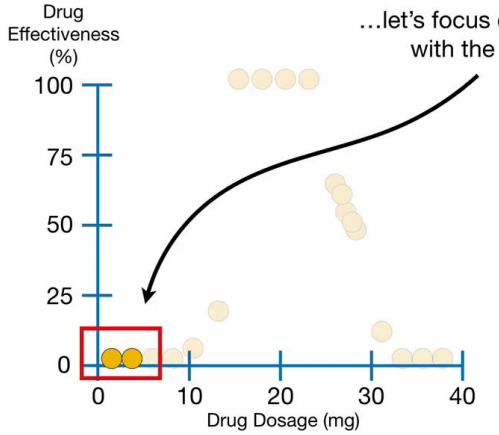
Dosage	Drug Effect.
10	58
20	60
35	57
5	44
etc…	etc…

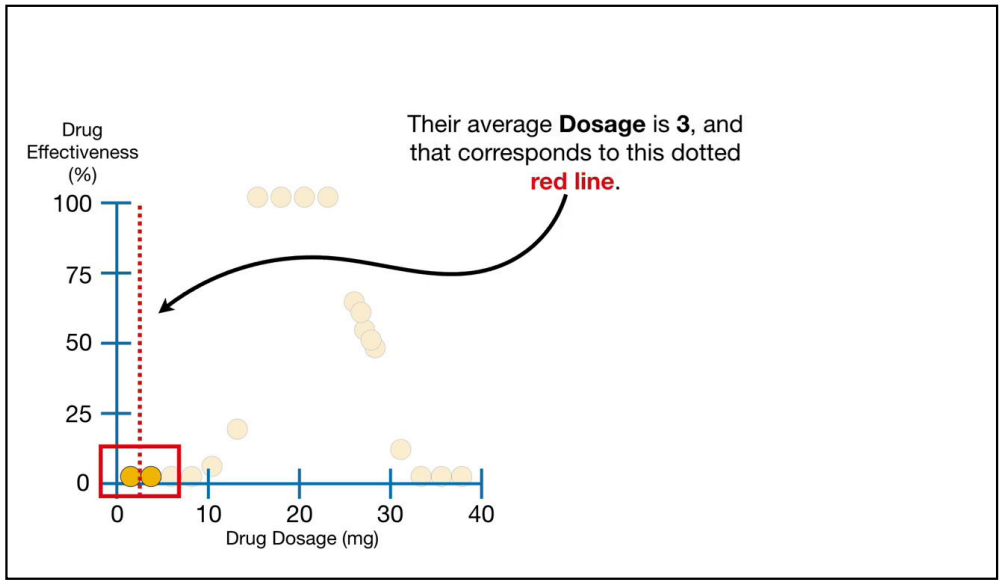
Going back to the graph of the data…

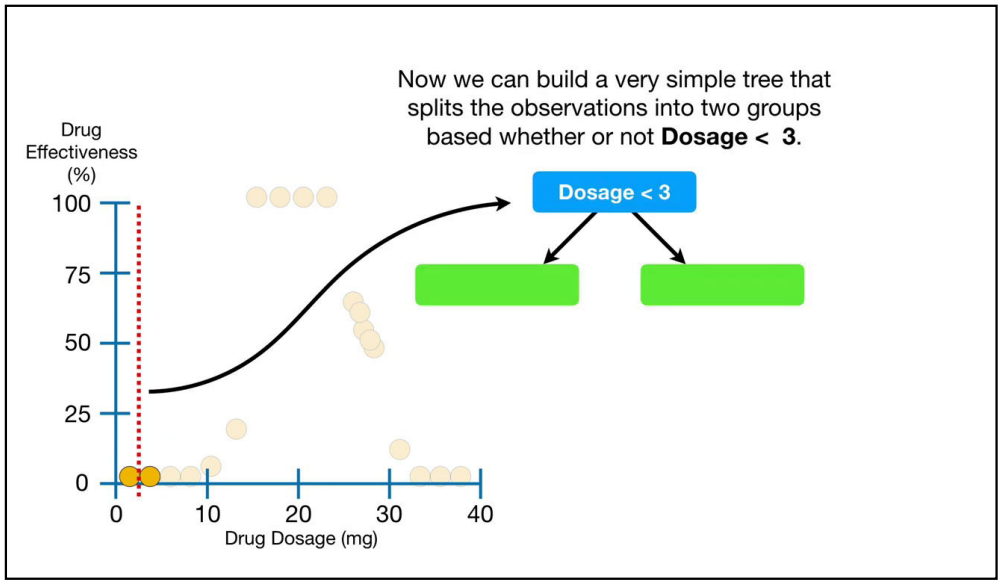


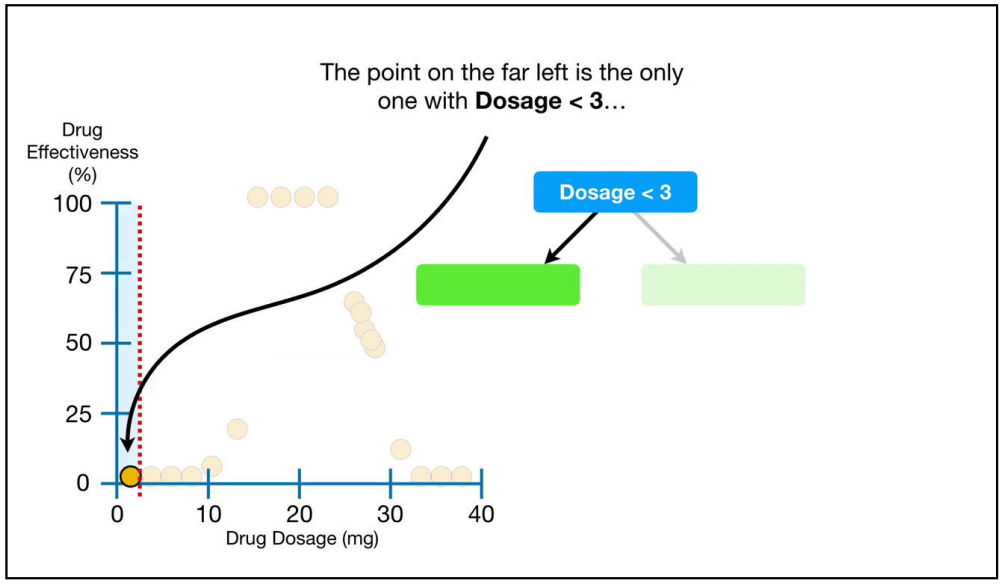
Dosage	Drug Effect.
10	58
20	60
35	57
5	44
etc…	etc…

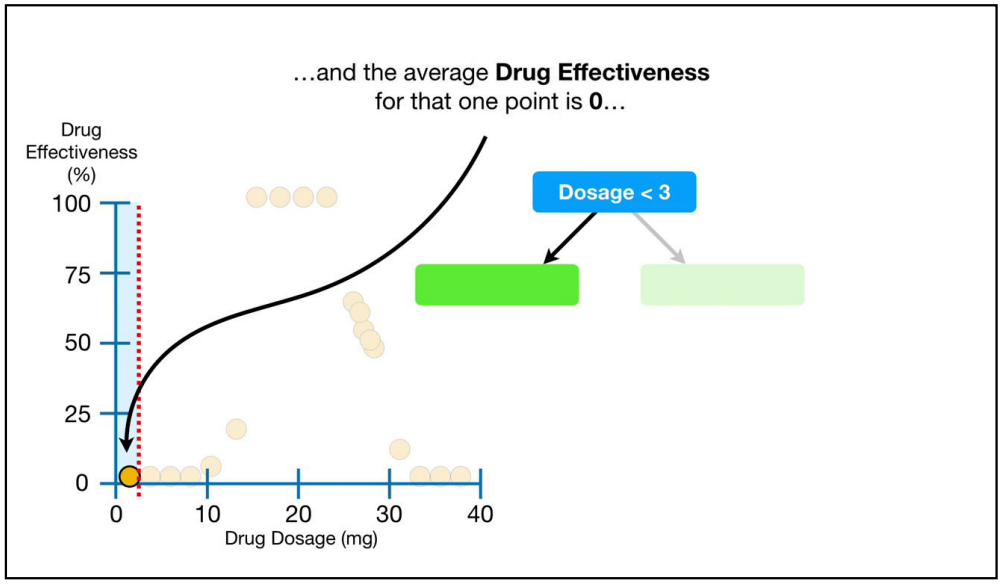
…let's focus on the two observations with the smallest **Dosages**.

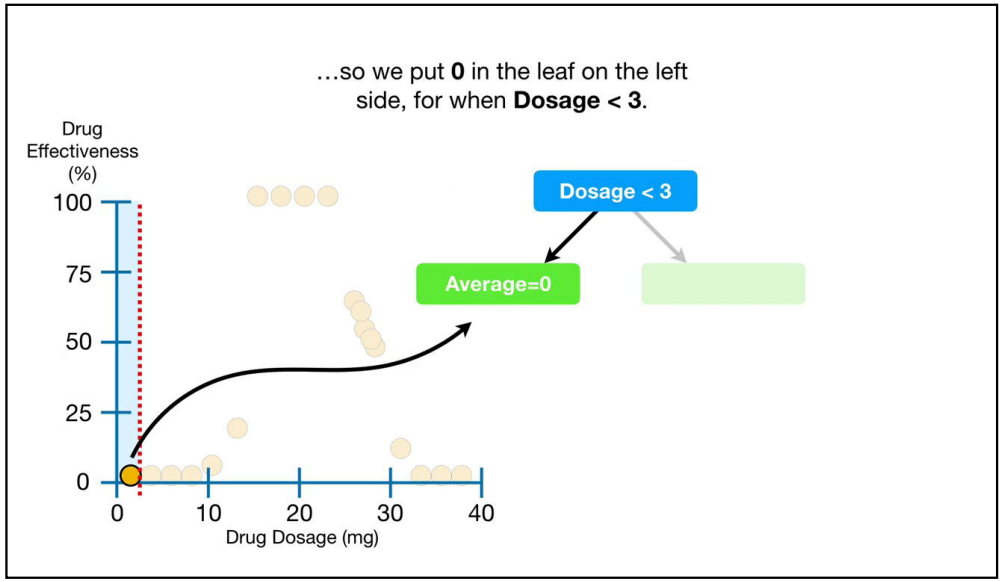


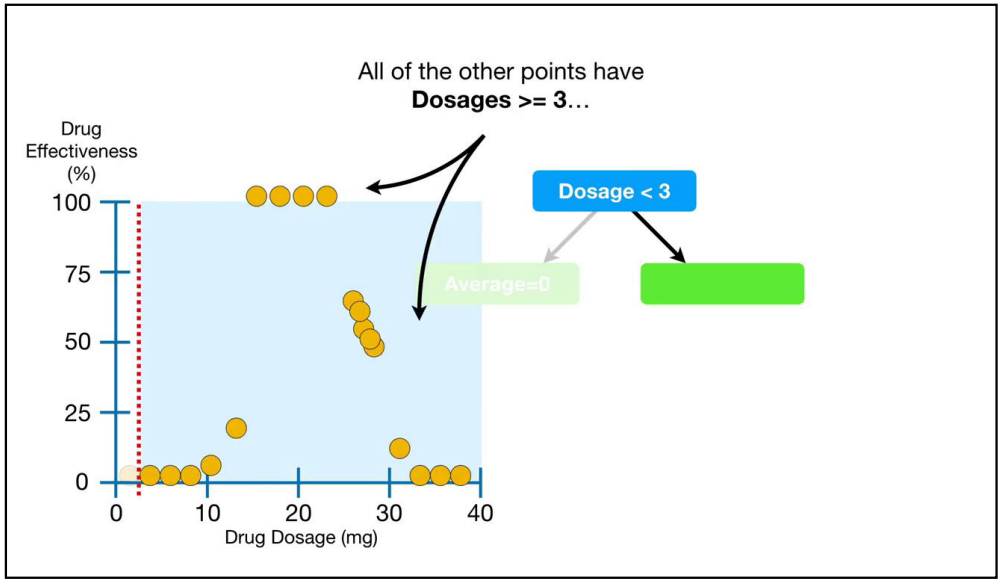

Their average **Dosage** is **3**, and that corresponds to this dotted **red line**.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

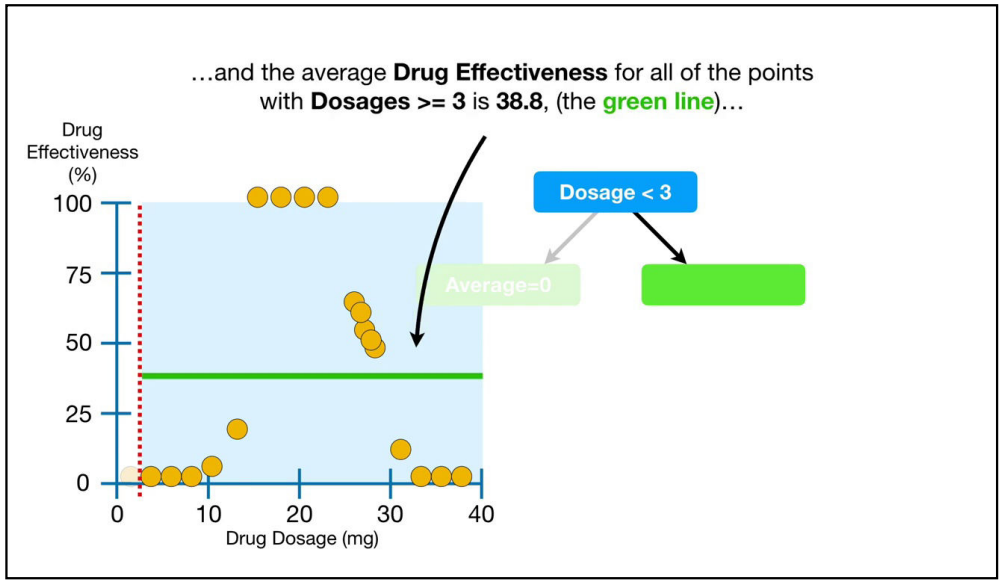

Now we can build a very simple tree that splits the observations into two groups based whether or not **Dosage < 3**.
Drug Effectiveness (%)
Dosage < 3
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

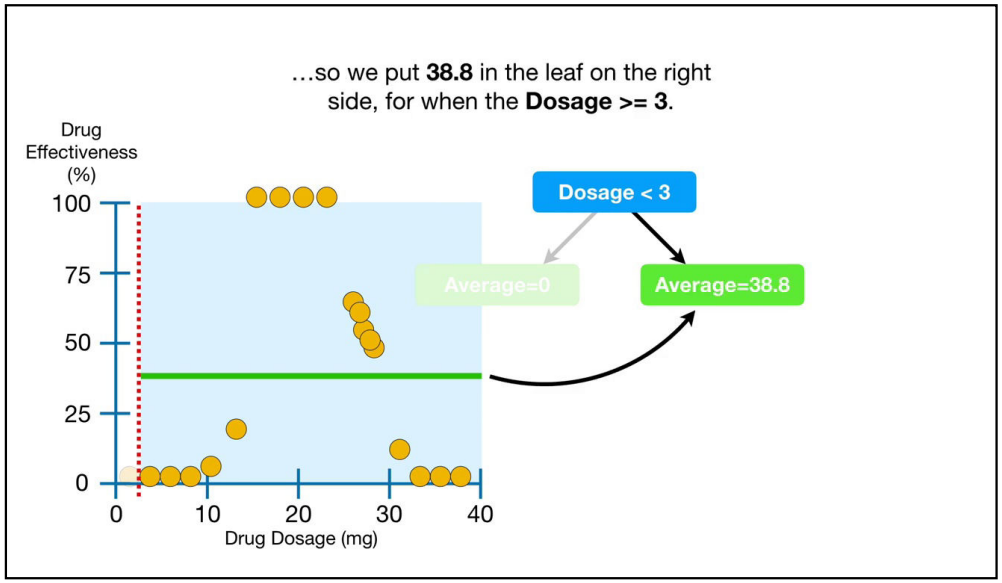

The point on the far left is the only one with **Dosage < 3**…
Drug Effectiveness (%)
Dosage < 3
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

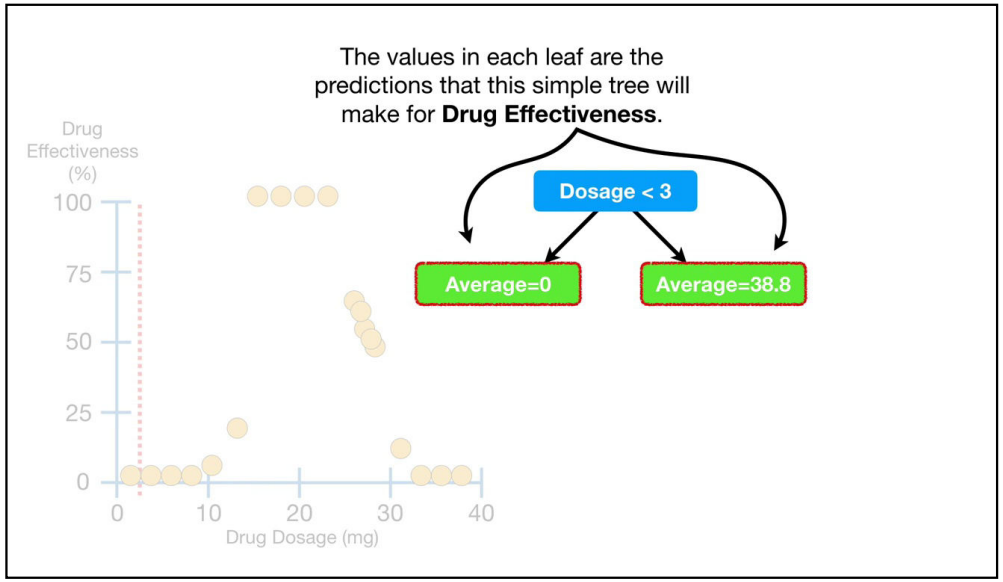

…and the average **Drug Effectiveness** for that one point is **0**…
Drug Effectiveness (%)
Dosage < 3
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

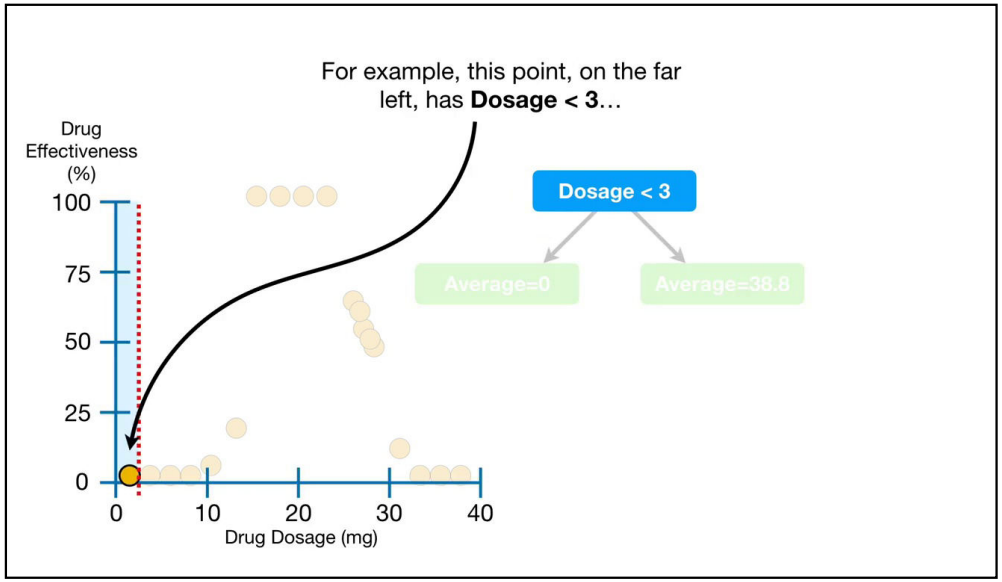

…so we put **0** in the leaf on the left side, for when **Dosage < 3**.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 3
Average=0
0
10
20
30
40
Drug Dosage (mg)

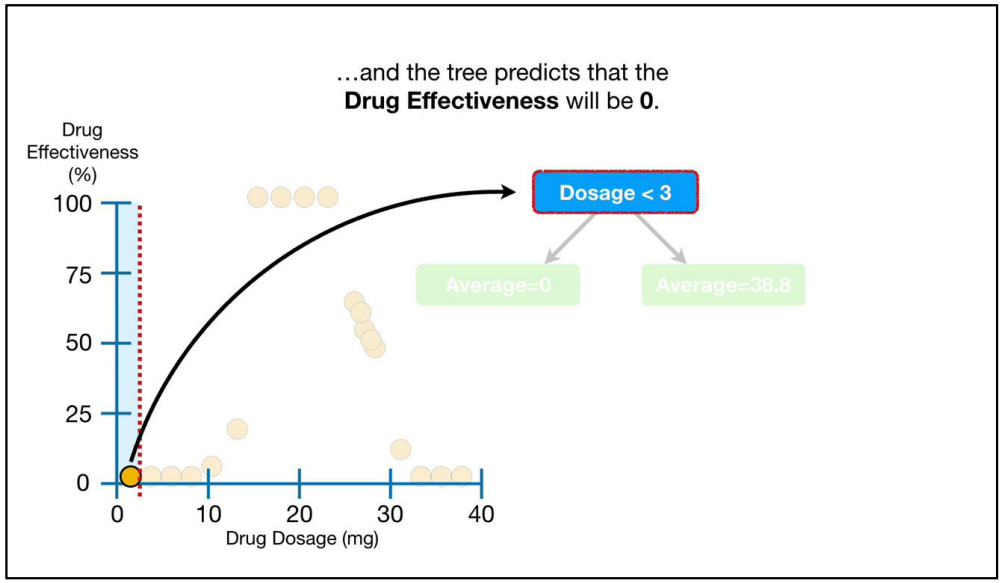

All of the other points have **Dosages >= 3**…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 3
Average=0
0
10
20
30
40
Drug Dosage (mg)

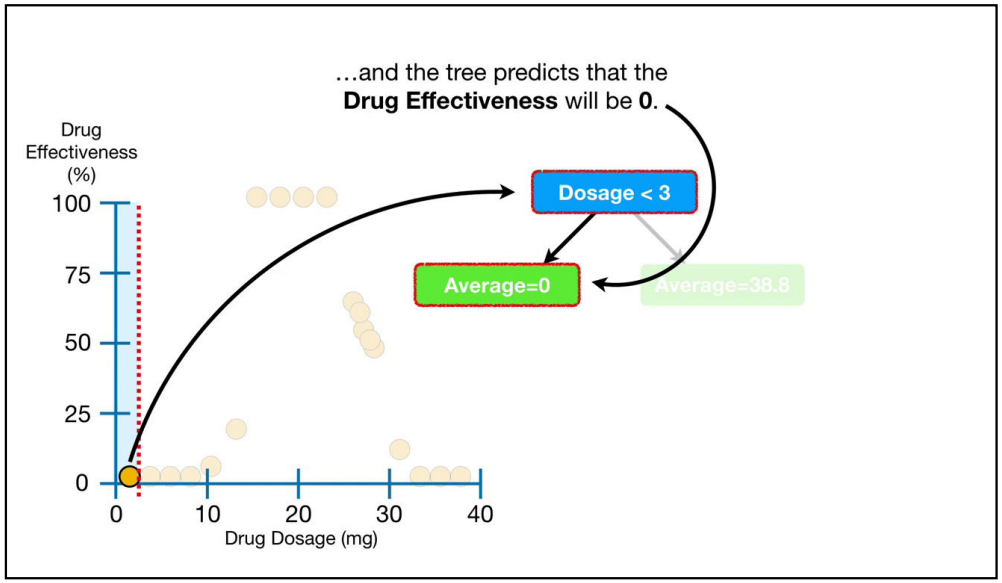

…and the average **Drug Effectiveness** for all of the points with **Dosages >= 3** is **38.8**, (the **green line**)…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 3
Average=0
0
10
20
30
40
Drug Dosage (mg)

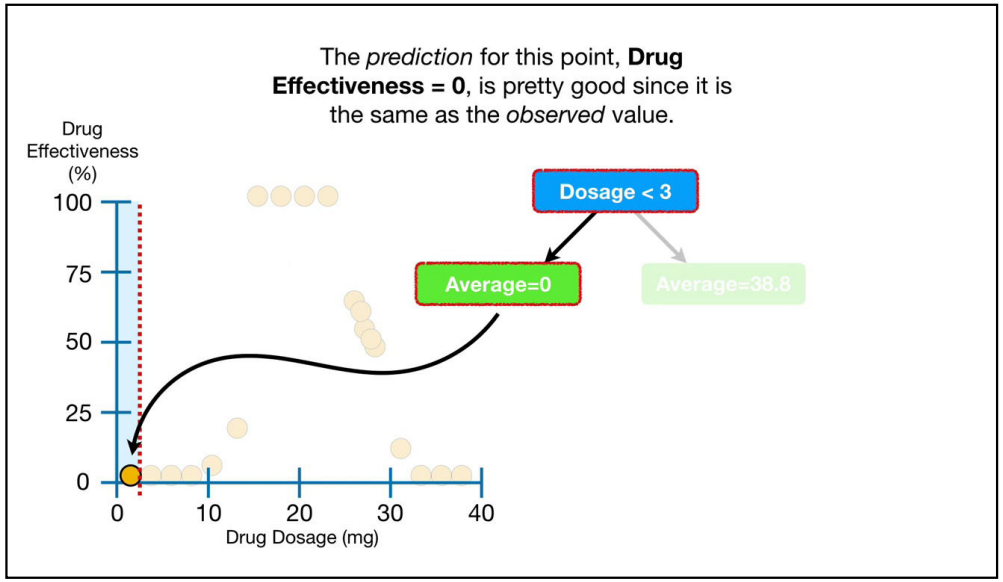

…so we put **38.8** in the leaf on the right side, for when the **Dosage >= 3**.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 3
Average=0
Average=38.8
0
10
20
30
40
Drug Dosage (mg)

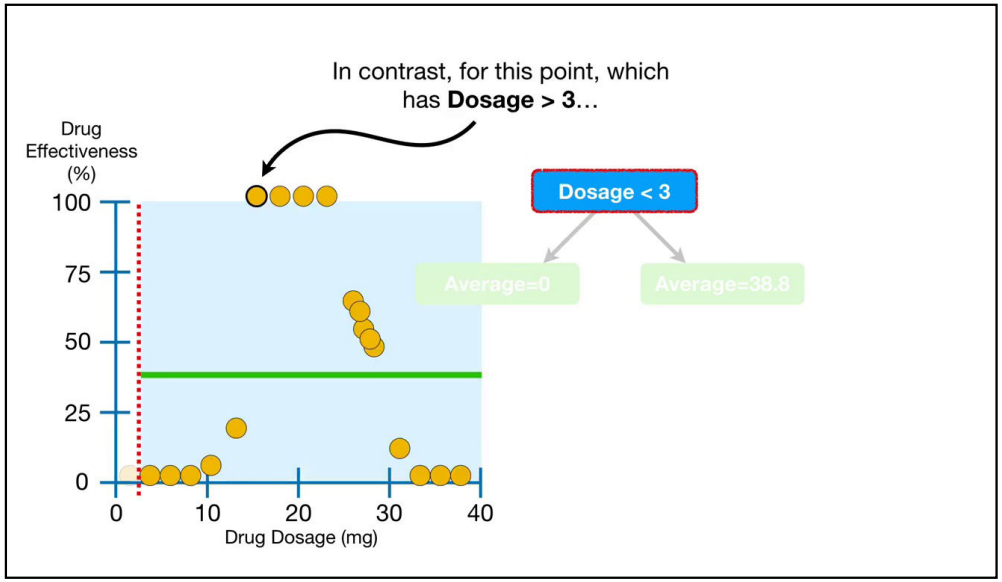

The values in each leaf are the predictions that this simple tree will make for **Drug Effectiveness**.
Dosage < 3
Average=0
Average=38.8
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

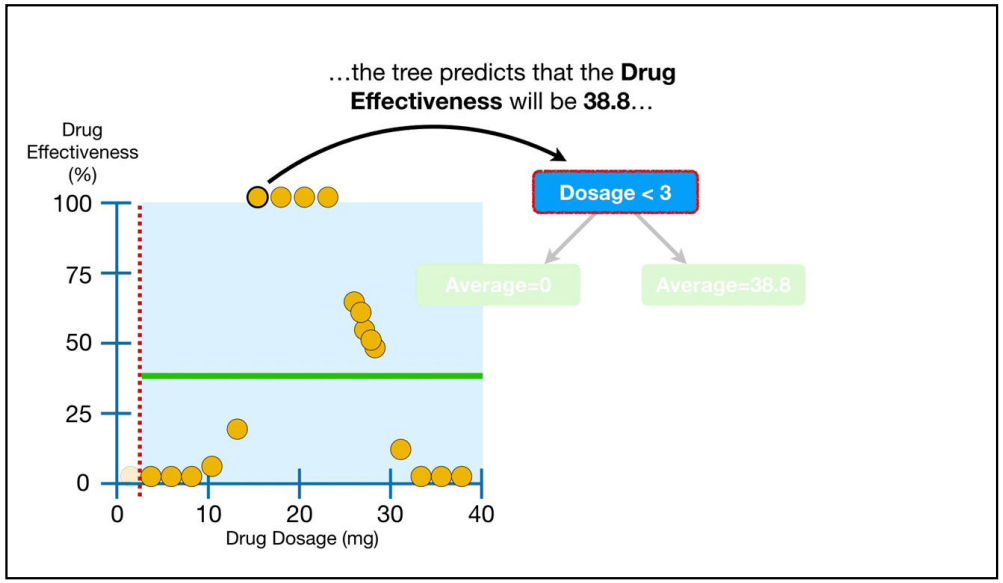

For example, this point, on the far left, has **Dosage < 3**…
Dosage < 3
Average=0
Average=38.8
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

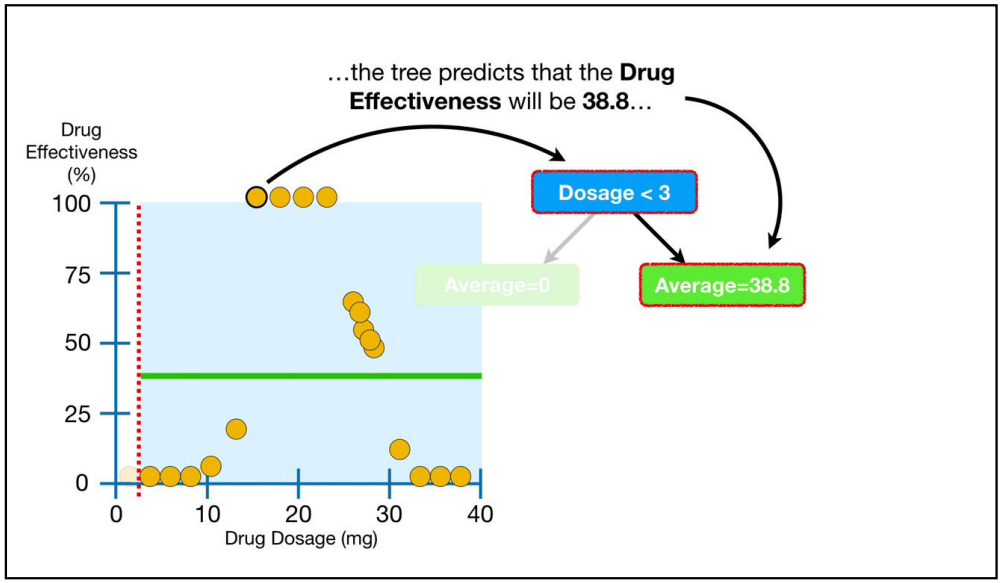

…and the tree predicts that the **Drug Effectiveness** will be **0**.
Dosage < 3
Average=0
Average=38.8
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

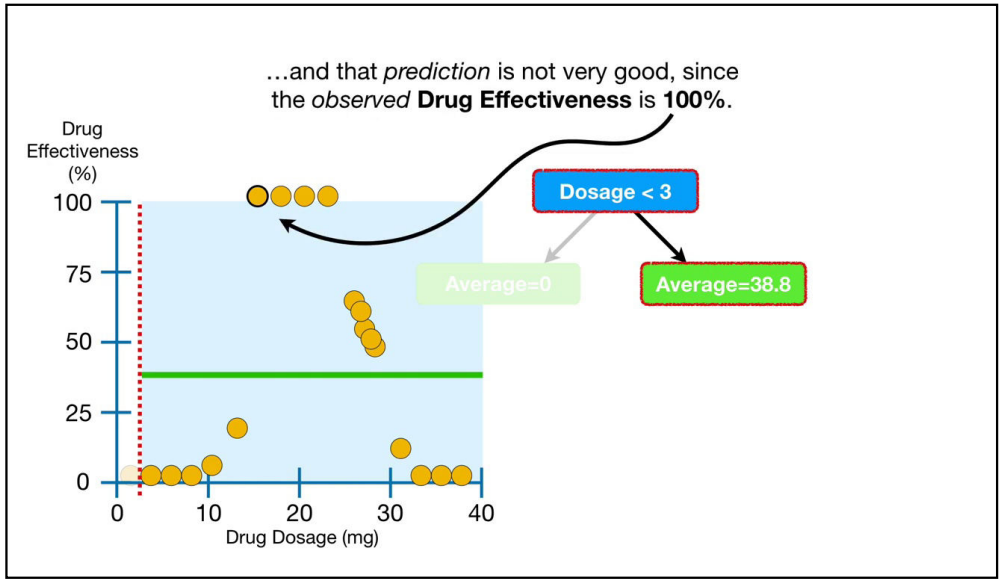

…and the tree predicts that the **Drug Effectiveness** will be **0**.
Dosage < 3
Average=0
Average=38.8
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

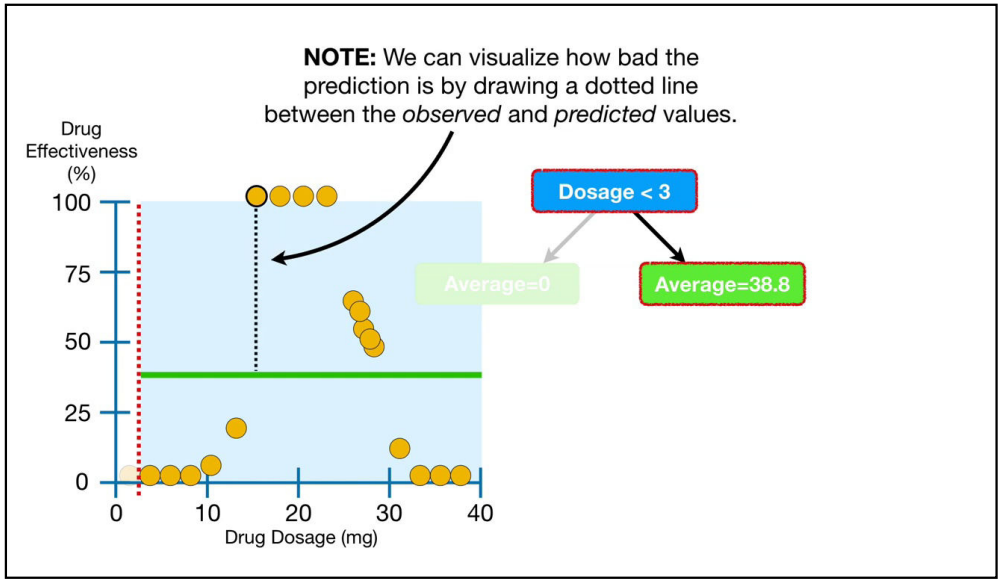

The *prediction* for this point, **Drug Effectiveness = 0**, is pretty good since it is the same as the *observed* value.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8

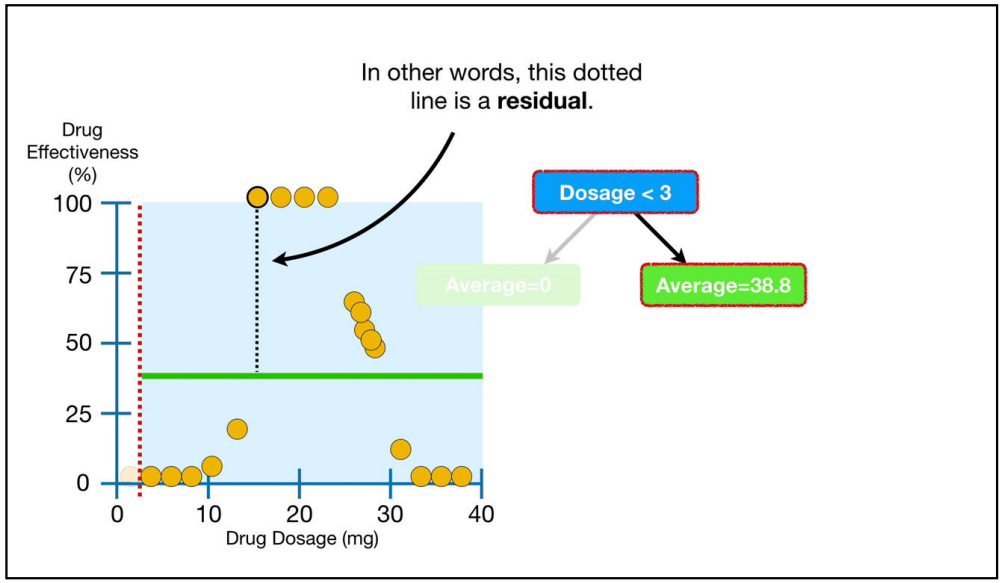

In contrast, for this point, which has **Dosage > 3**…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8

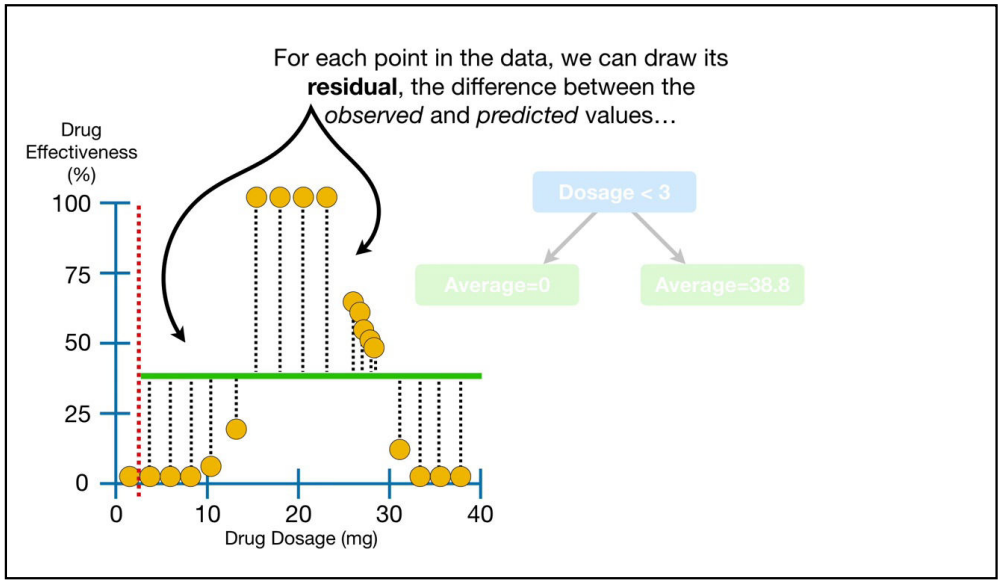

…the tree predicts that the **Drug Effectiveness** will be **38.8**…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8

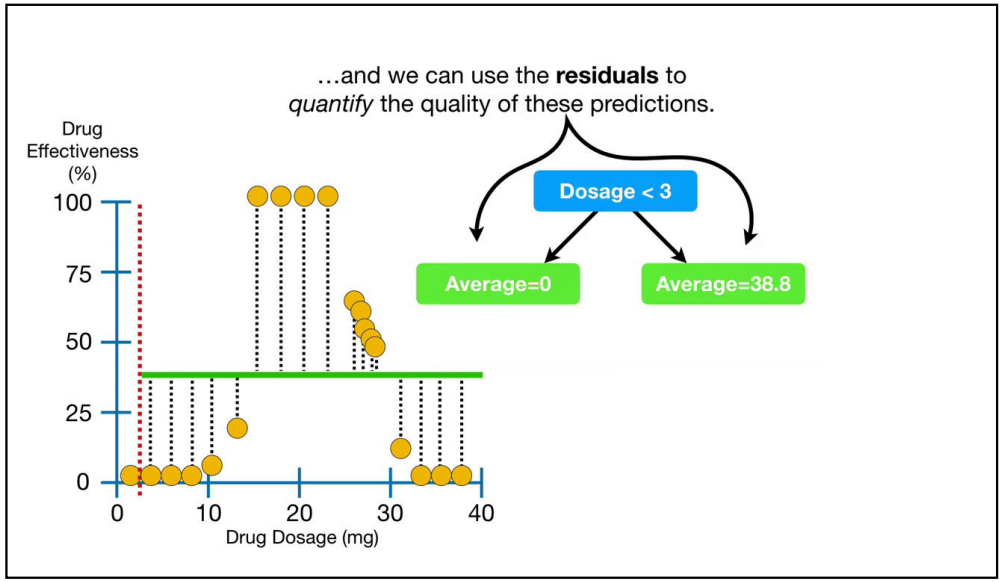

…the tree predicts that the **Drug Effectiveness** will be **38.8**…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8

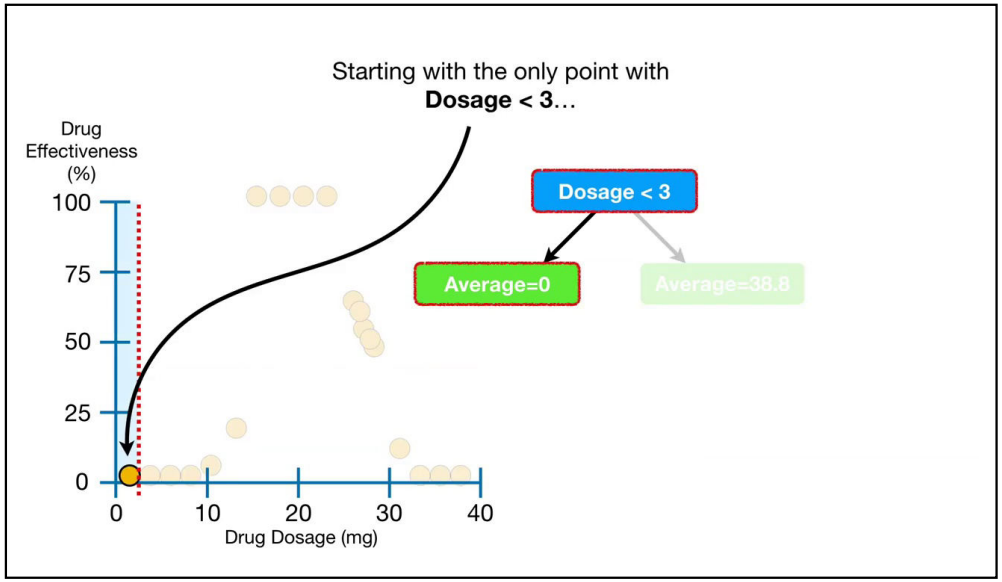

…and that *prediction* is not very good, since the *observed* **Drug Effectiveness** is **100%**.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8

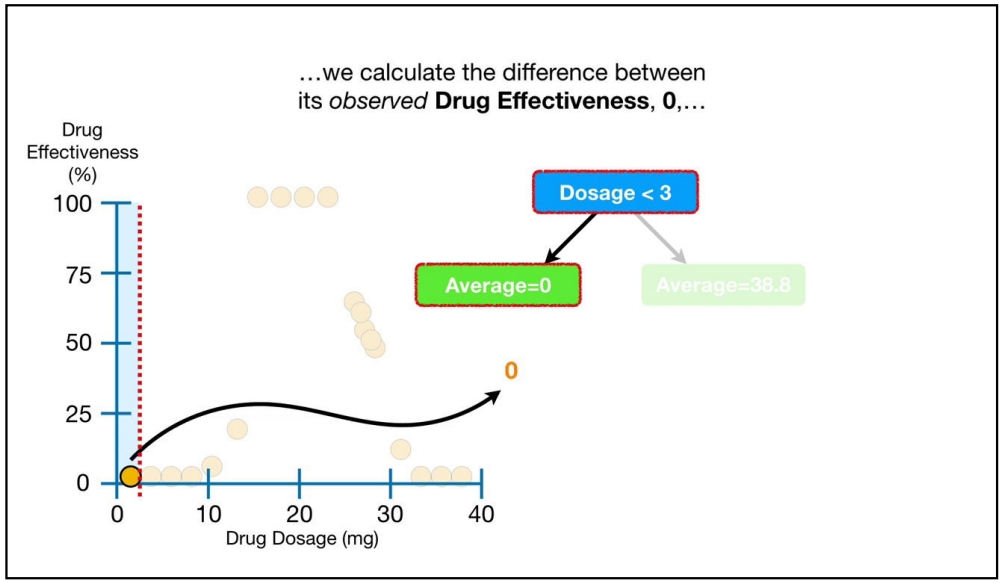

NOTE: We can visualize how bad the prediction is by drawing a dotted line between the *observed* and *predicted* values.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8

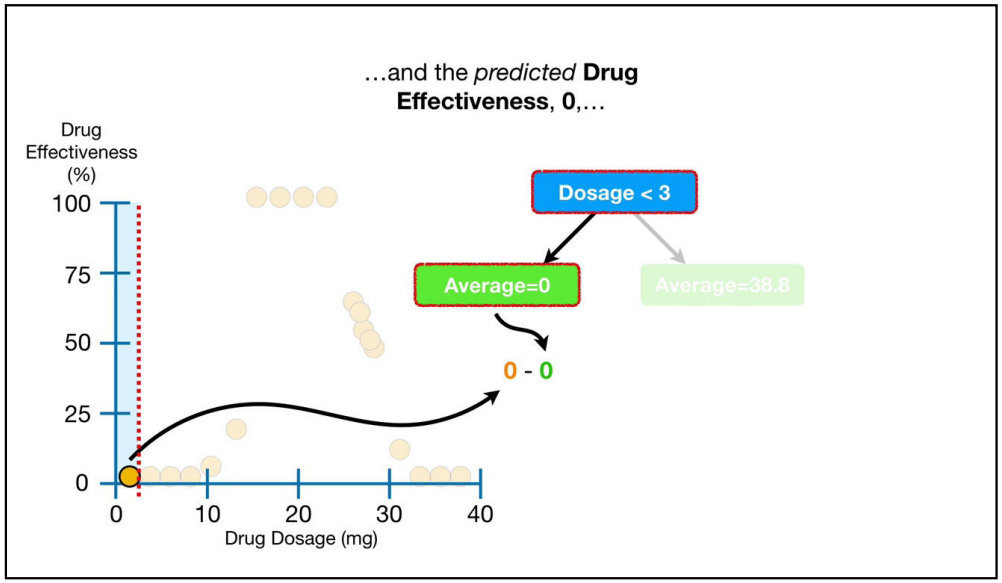

In other words, this dotted line is a **residual**.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8

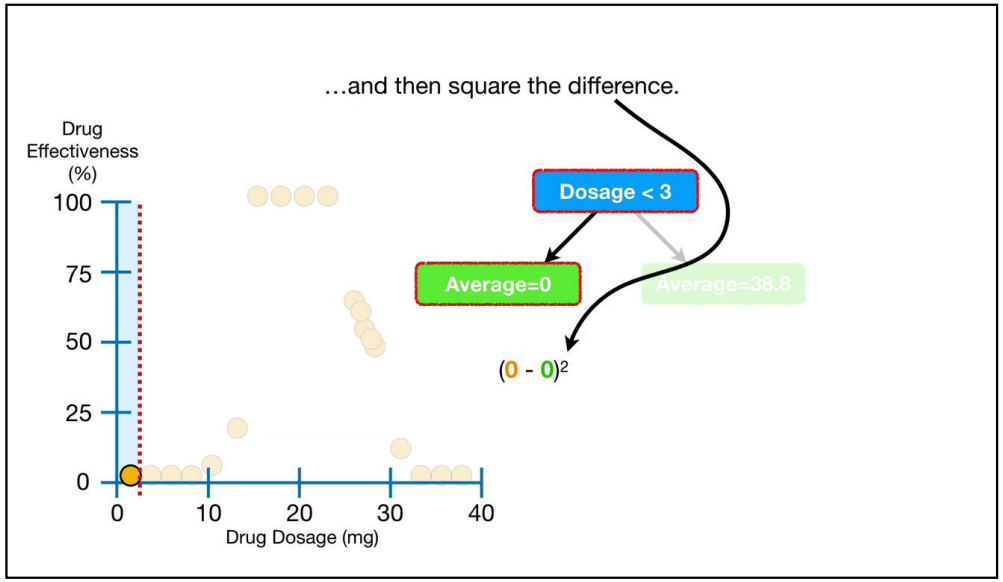

For each point in the data, we can draw its **residual**, the difference between the *observed* and *predicted* values…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8

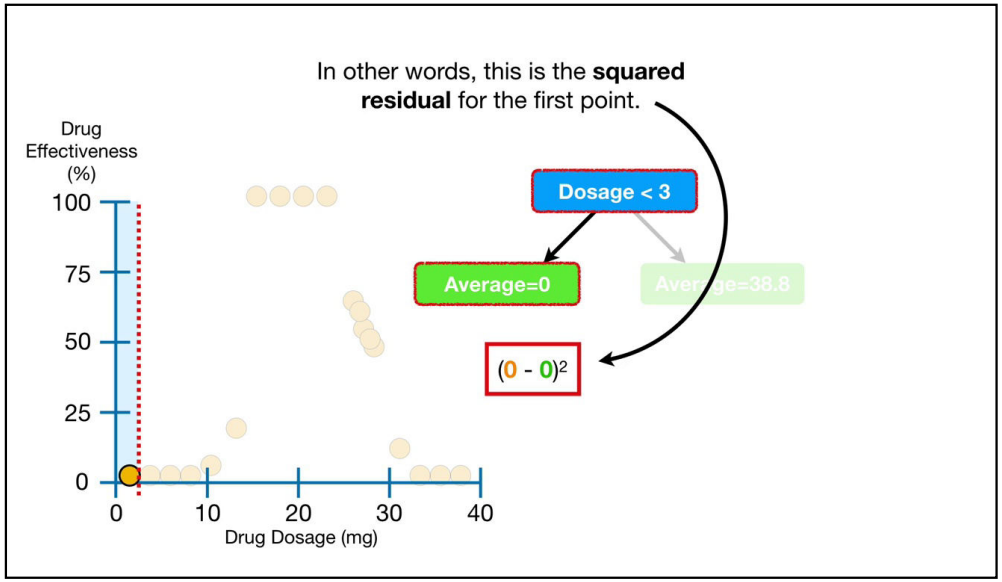

…and we can use the **residuals** to
quantify the quality of these predictions.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8

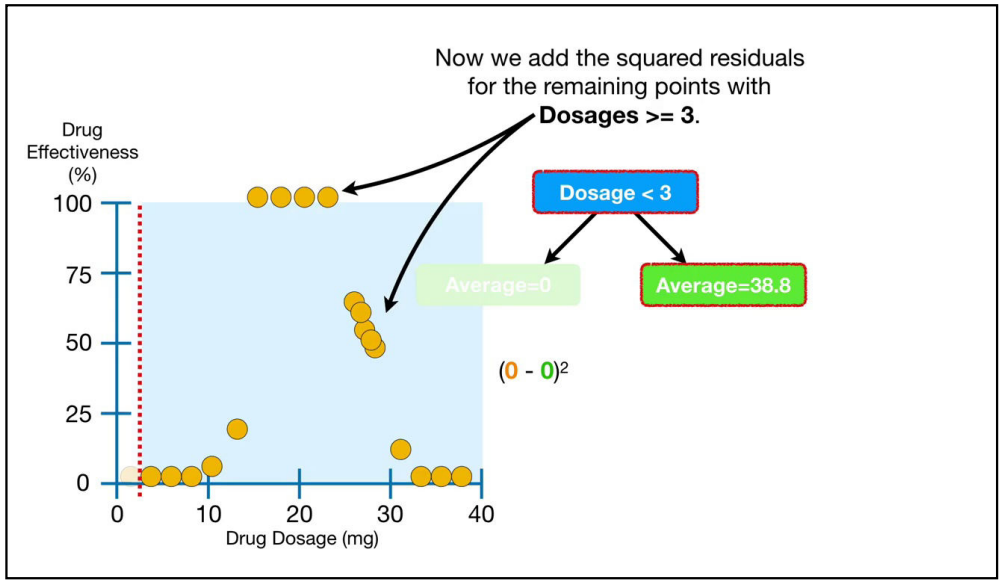

Starting with the only point with
Dosage < 3…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8

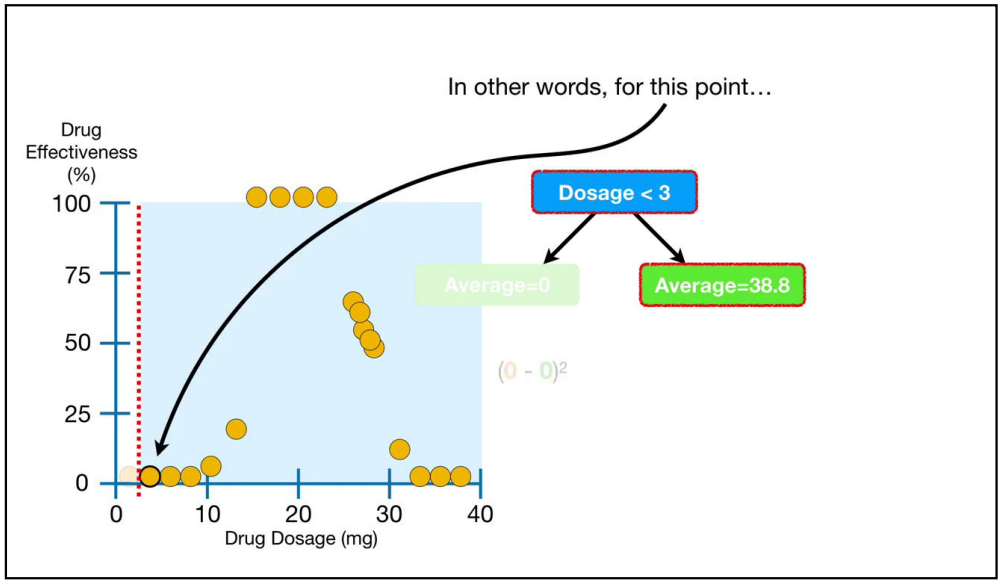

…we calculate the difference between
its *observed* **Drug Effectiveness**, **0**,…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
0

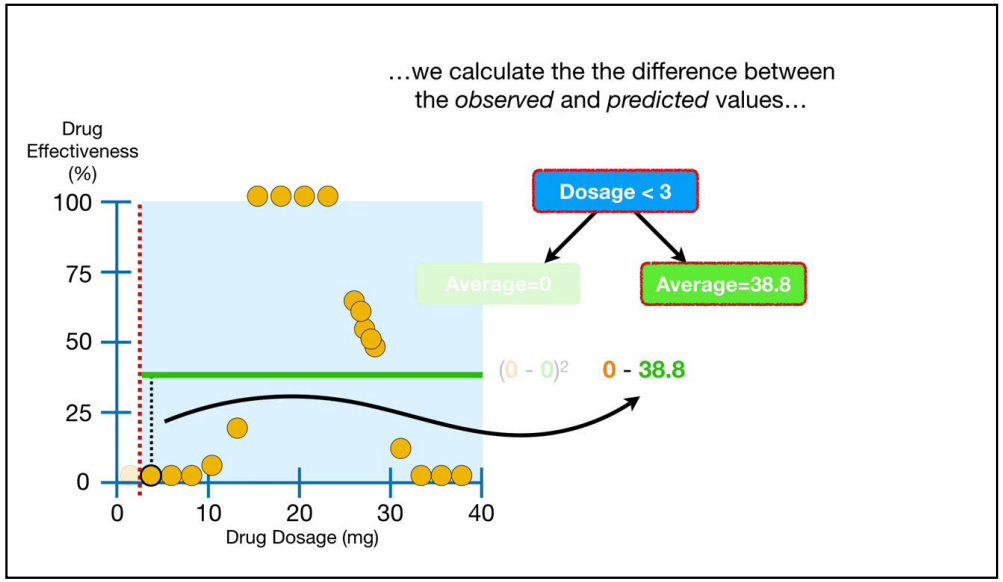

…and the *predicted* **Drug Effectiveness**, **0**,…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
0 - 0

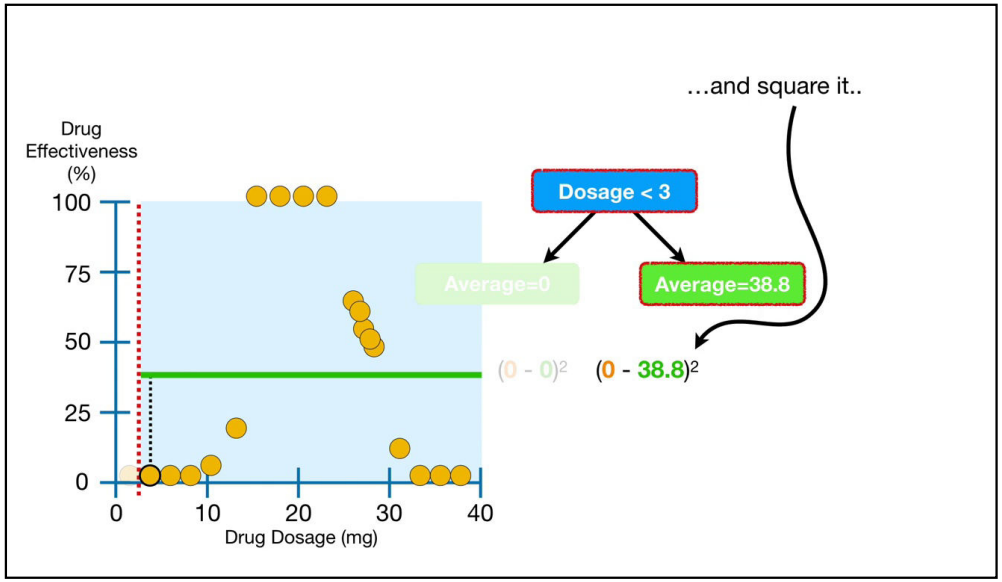

…and then square the difference.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)²

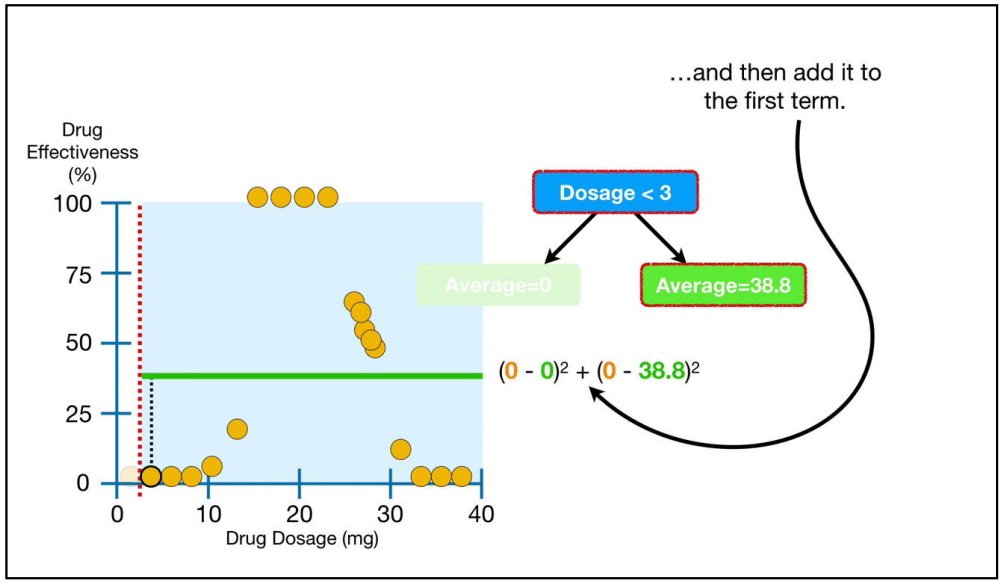

In other words, this is the squared residual for the first point.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
(0 - 0)²

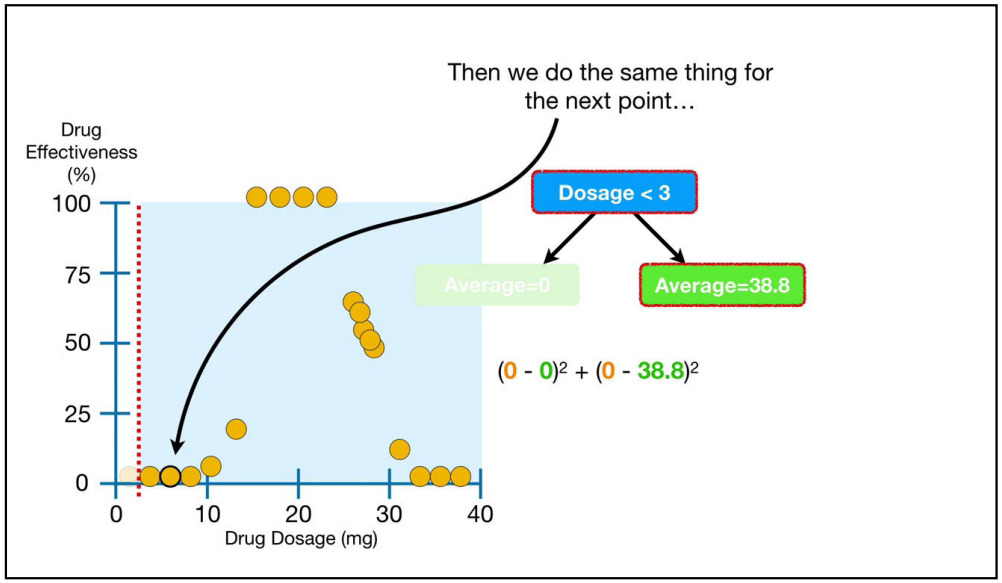

Now we add the squared residuals for the remaining points with Dosages >= 3.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)²

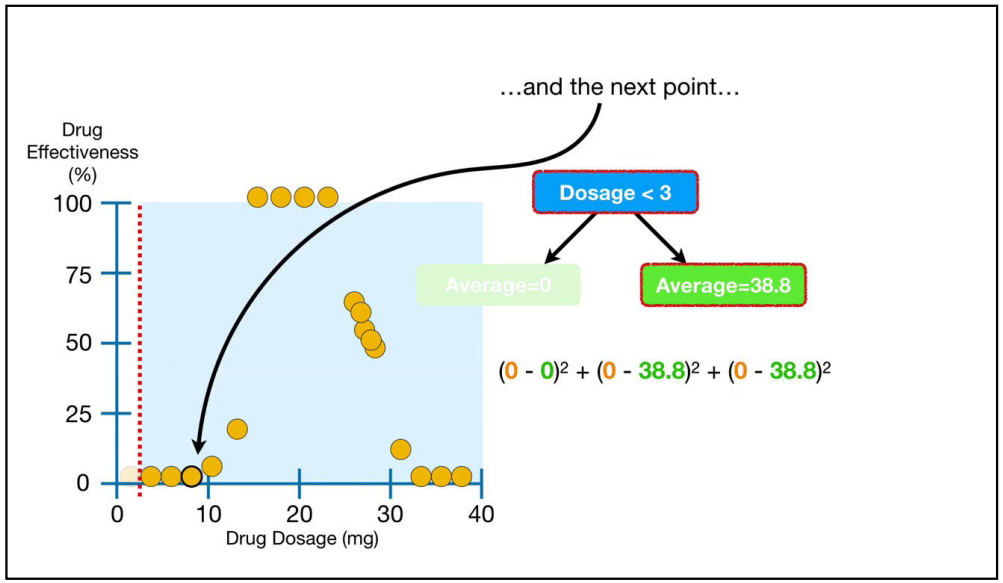

In other words, for this point…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)²

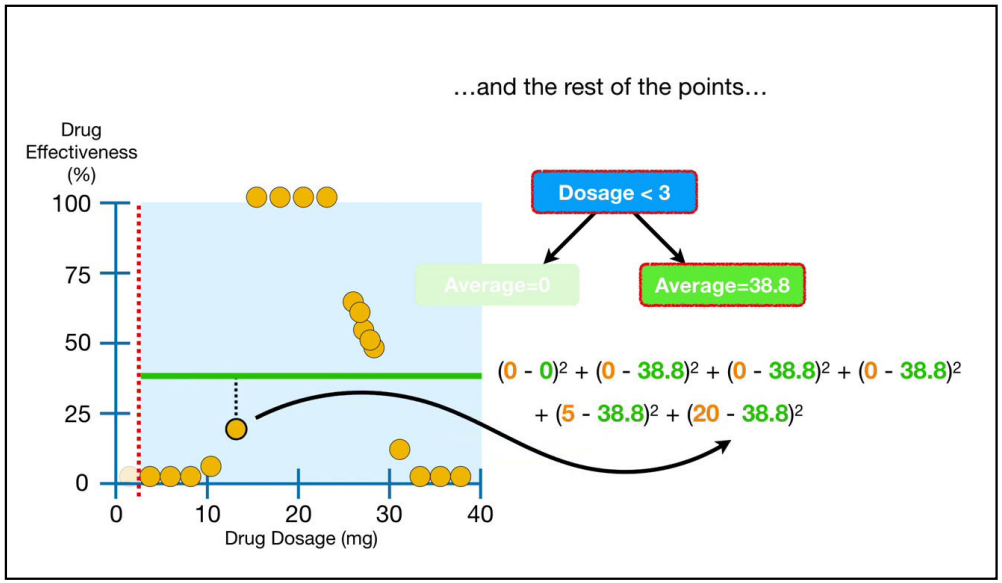

…we calculate the the difference between
the *observed* and *predicted* values…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)²
0 - 38.8

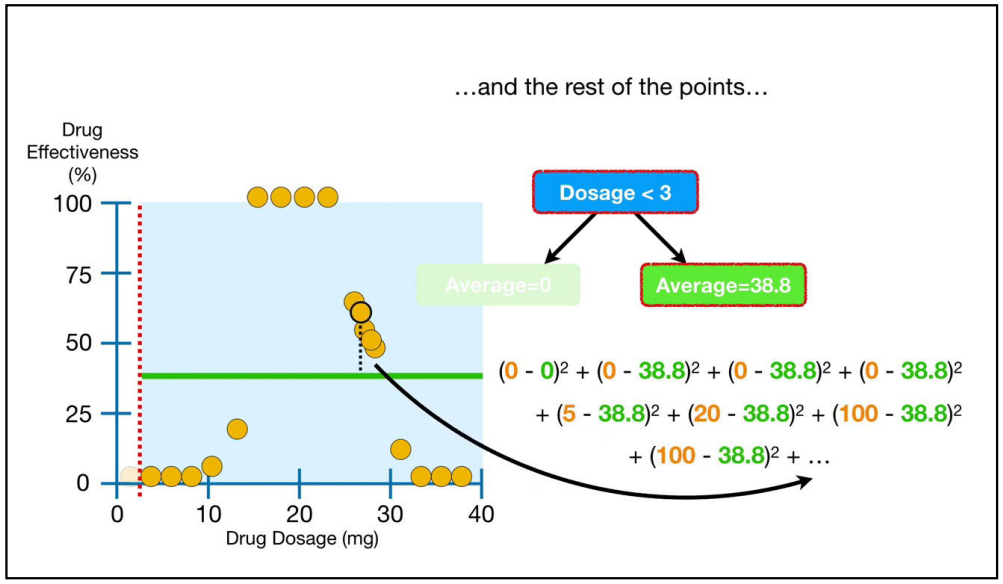

…and square it..
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)²
(0 - 38.8)²

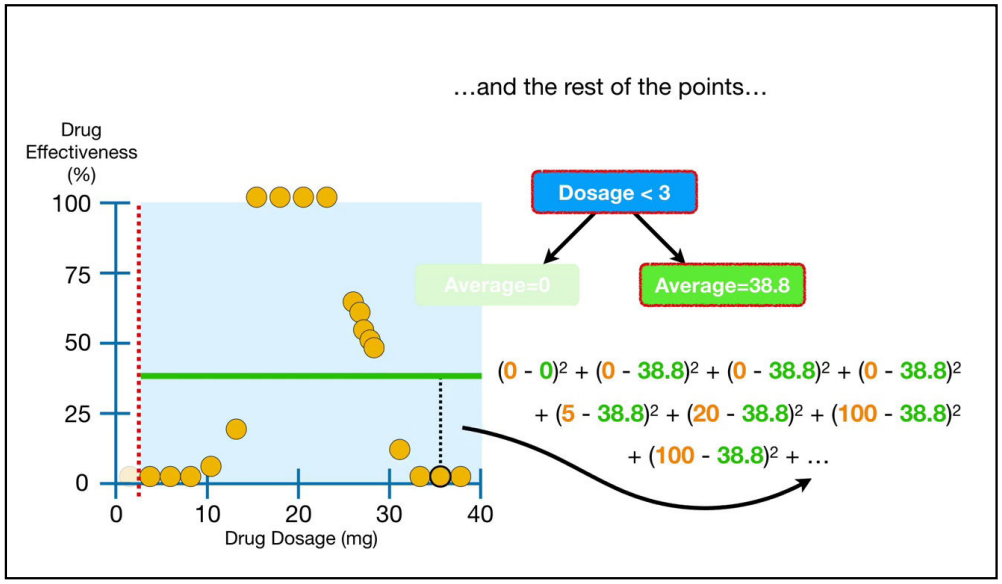

…and then add it to
the first term.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)² + (0 - 38.8)²

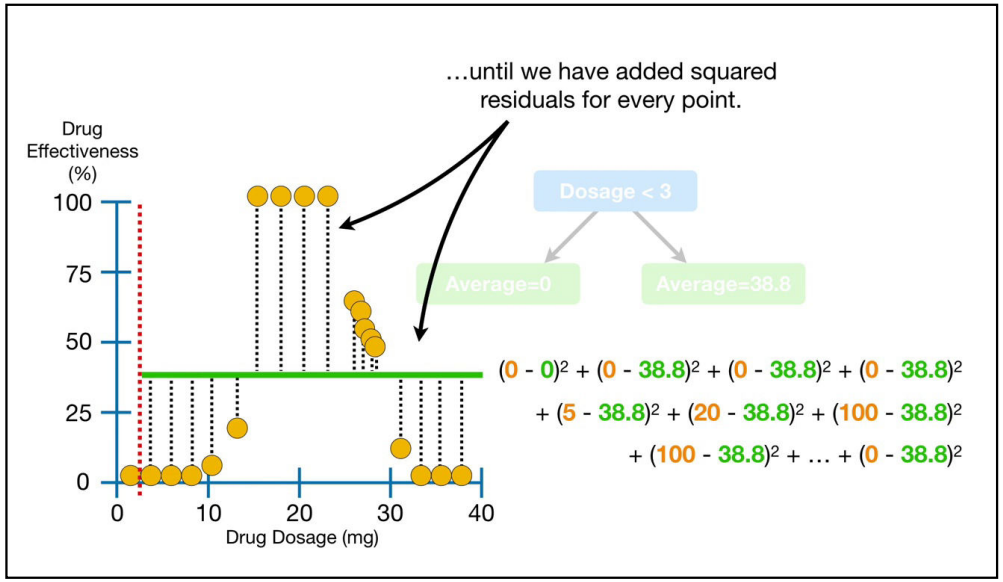

Then we do the same thing for
the next point…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)² + (0 - 38.8)²

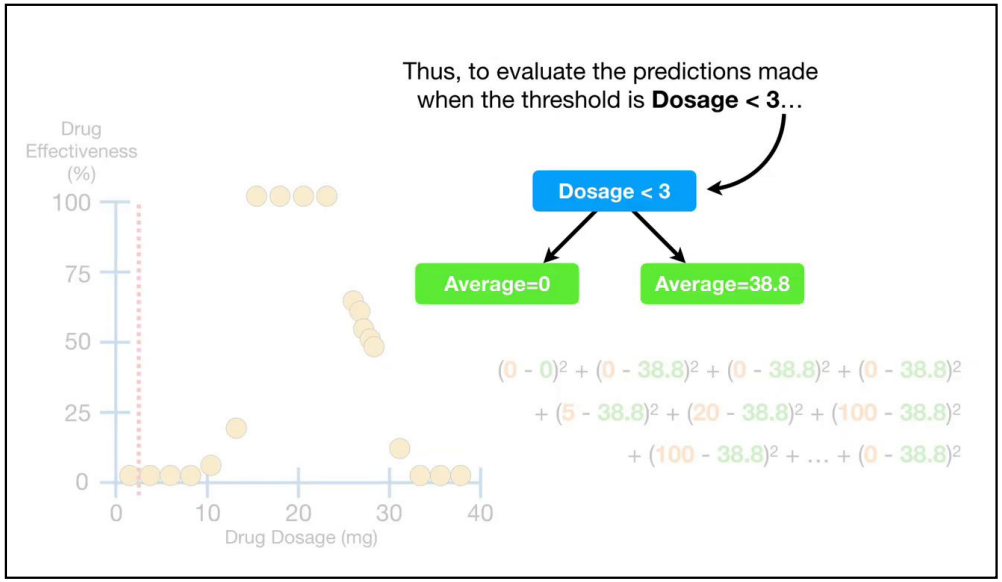

…and the next point…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)² + (0 - 38.8)² + (0 - 38.8)²

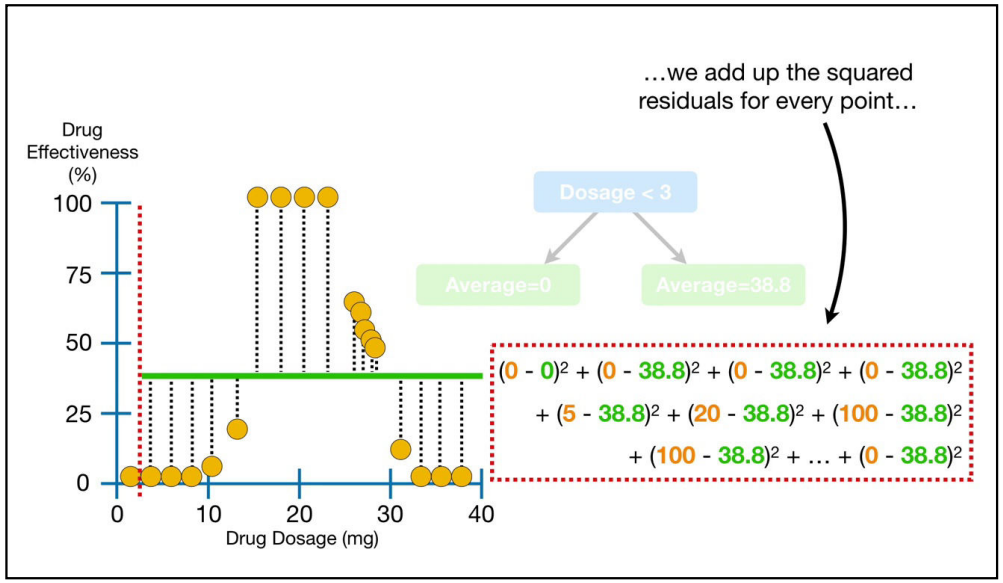

…and the rest of the points…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)² + (0 - 38.8)² + (0 - 38.8)² + (0 - 38.8)²
+ (5 - 38.8)² + (20 - 38.8)²

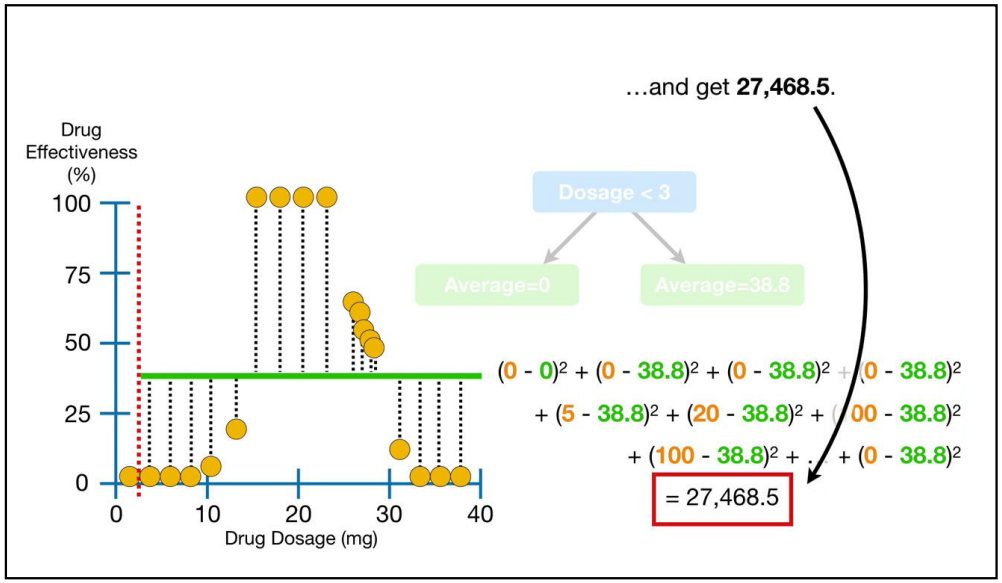

…and the rest of the points…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)² + (0 - 38.8)² + (0 - 38.8)² + (0 - 38.8)²
+ (5 - 38.8)² + (20 - 38.8)² + (100 - 38.8)²
+ (100 - 38.8)² + …

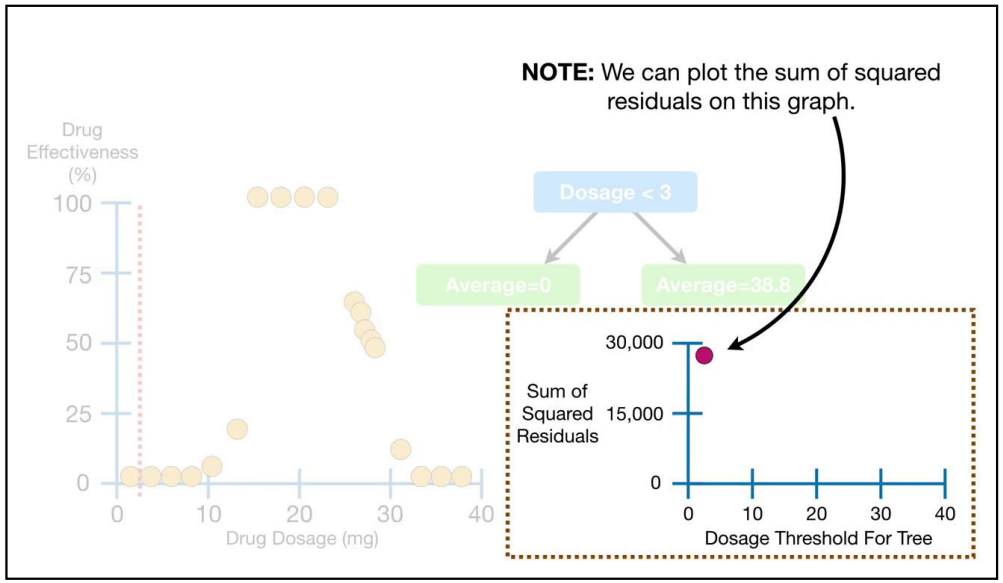

…and the rest of the points…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)² + (0 - 38.8)² + (0 - 38.8)² + (0 - 38.8)²
+ (5 - 38.8)² + (20 - 38.8)² + (100 - 38.8)²
+ (100 - 38.8)² + …

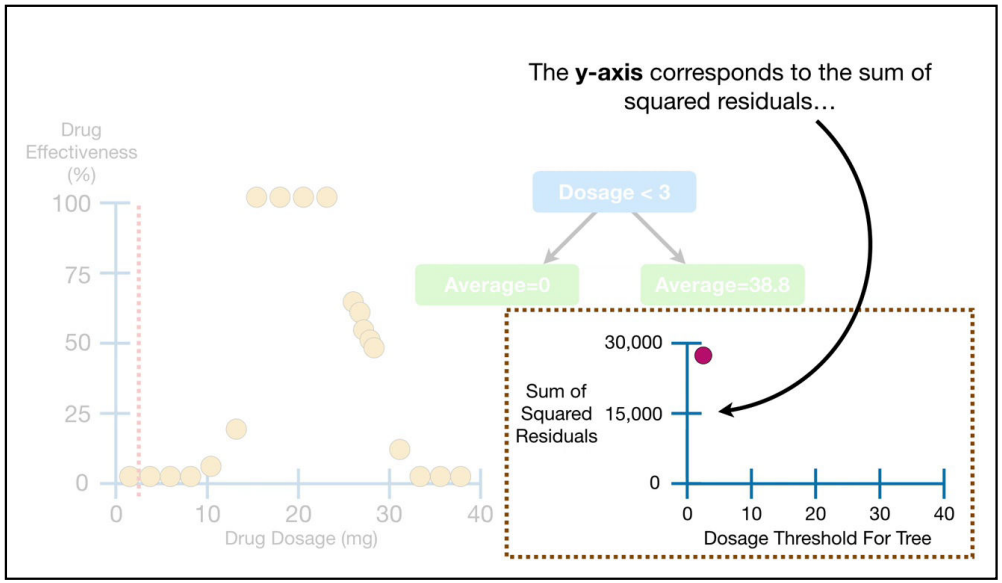

…until we have added squared residuals for every point.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)² + (0 - 38.8)² + (0 - 38.8)² + (0 - 38.8)²
+ (5 - 38.8)² + (20 - 38.8)² + (100 - 38.8)²
+ (100 - 38.8)² + … + (0 - 38.8)²

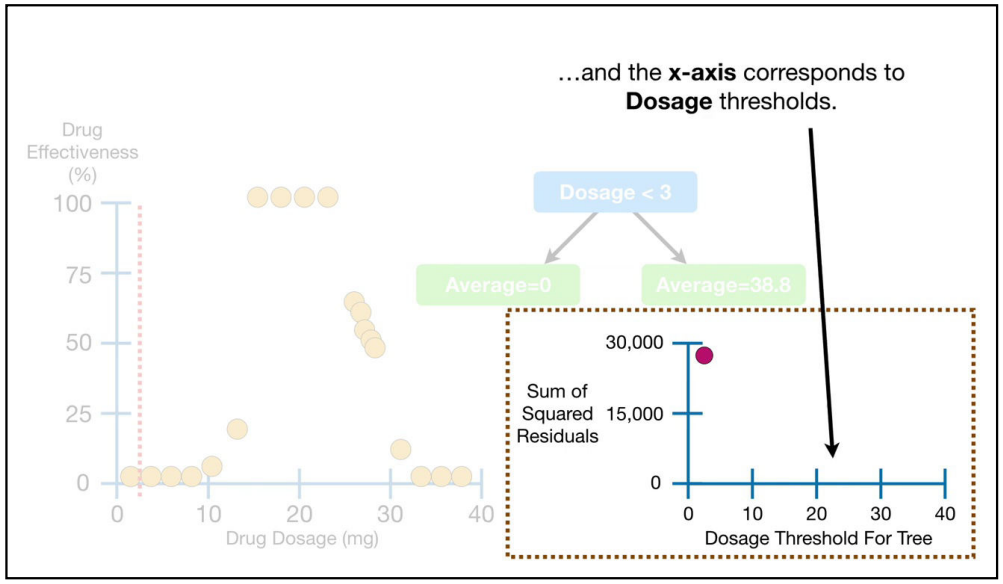

Thus, to evaluate the predictions made when the threshold is Dosage < 3…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)² + (0 - 38.8)² + (0 - 38.8)² + (0 - 38.8)²
+ (5 - 38.8)² + (20 - 38.8)² + (100 - 38.8)²
+ (100 - 38.8)² + … + (0 - 38.8)²

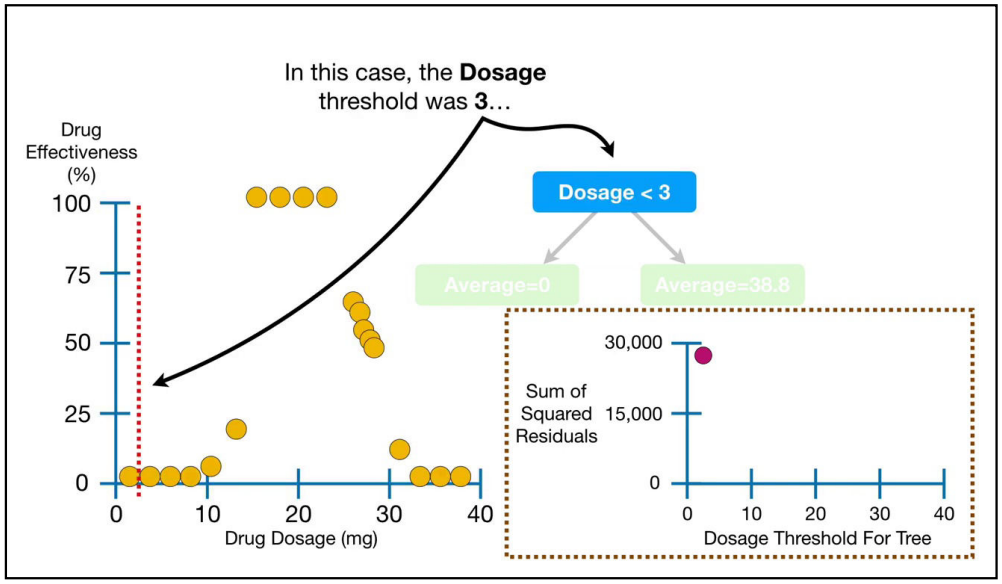

…we add up the squared residuals for every point…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)² + (0 - 38.8)² + (0 - 38.8)² + (0 - 38.8)²
+ (5 - 38.8)² + (20 - 38.8)² + (100 - 38.8)²
+ (100 - 38.8)² + … + (0 - 38.8)²

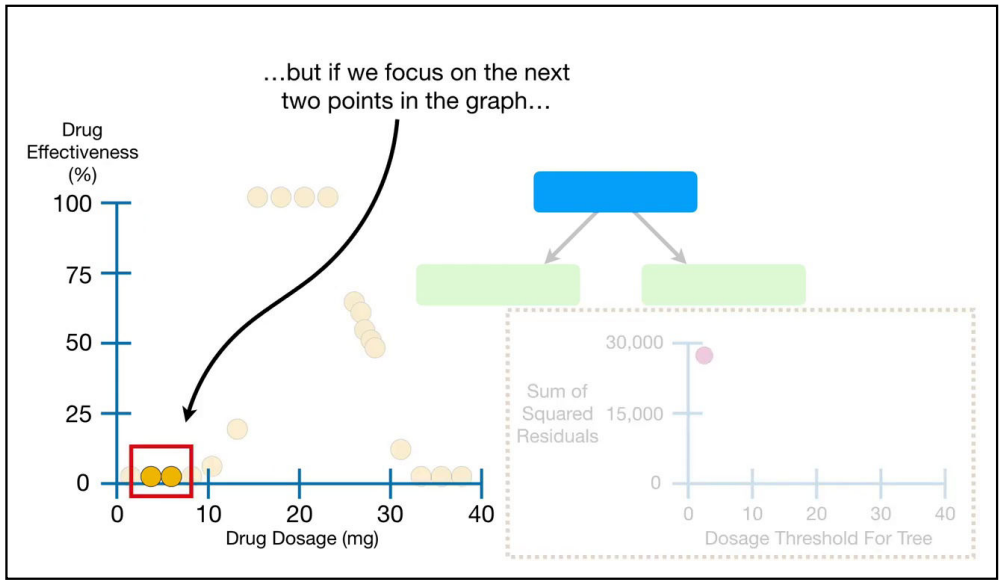

…and get 27,468.5.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
(0 - 0)² + (0 - 38.8)² + (0 - 38.8)² + (0 - 38.8)²
+ (5 - 38.8)² + (20 - 38.8)² + (100 - 38.8)²
+ (100 - 38.8)² + … + (0 - 38.8)²
= 27,468.5

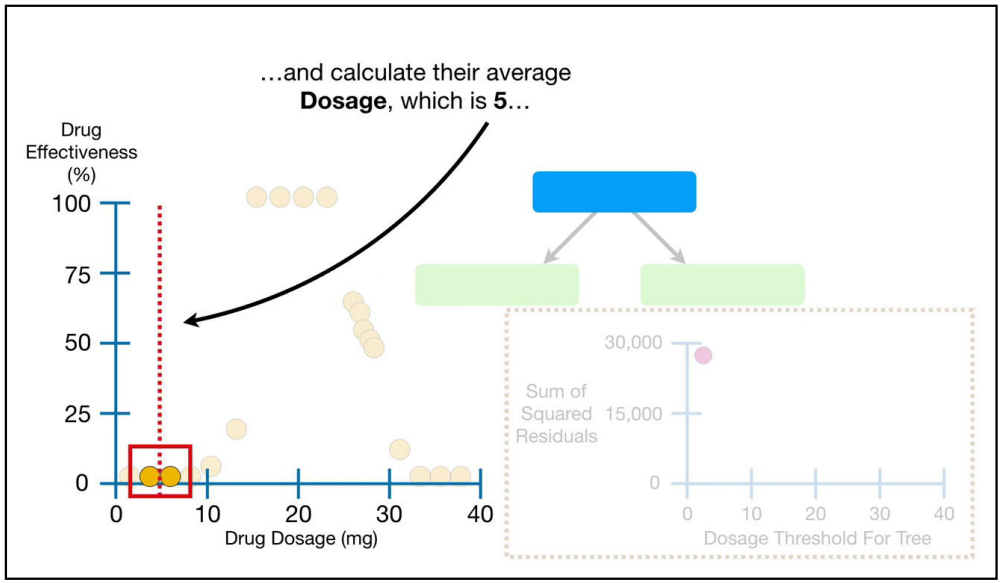

NOTE: We can plot the sum of squared residuals on this graph.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

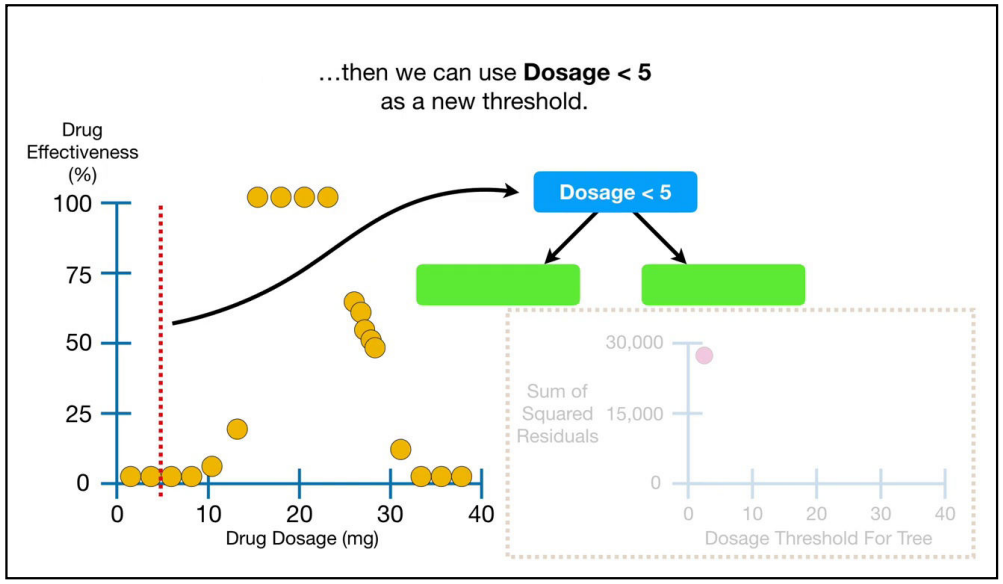

The y-axis corresponds to the sum of squared residuals…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

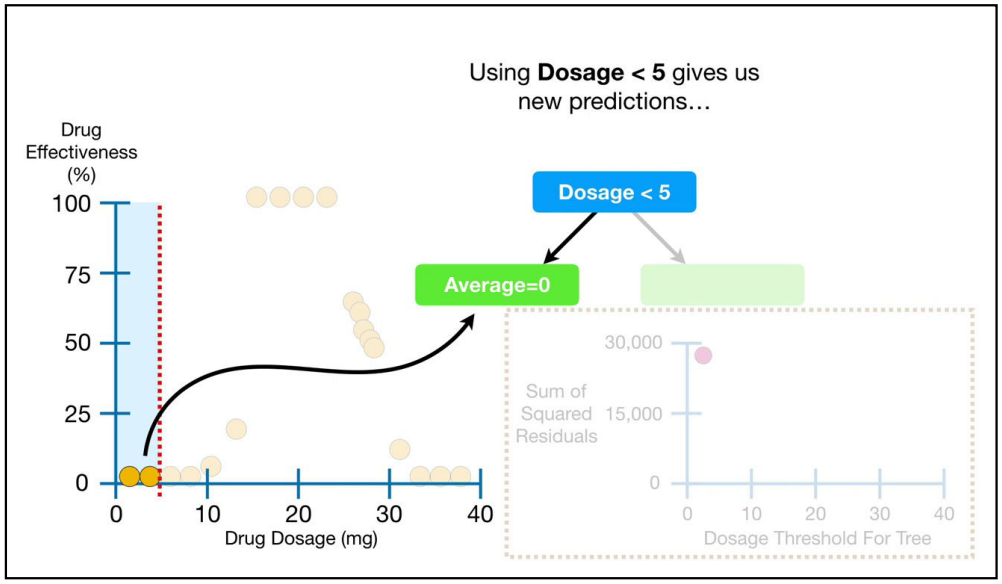

…and the x-axis corresponds to Dosage thresholds.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

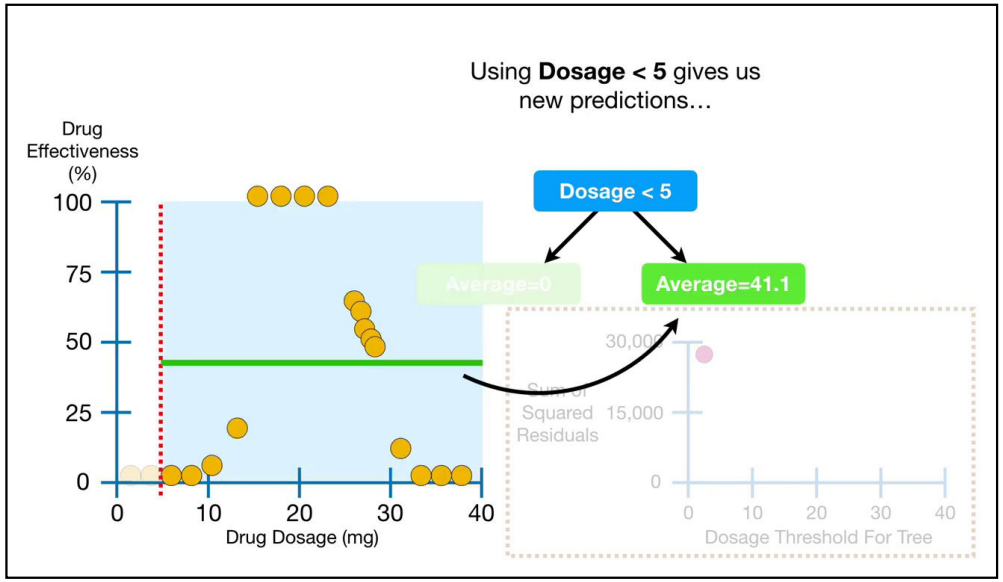

In this case, the Dosage threshold was 3…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 3
Average=0
Average=38.8
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

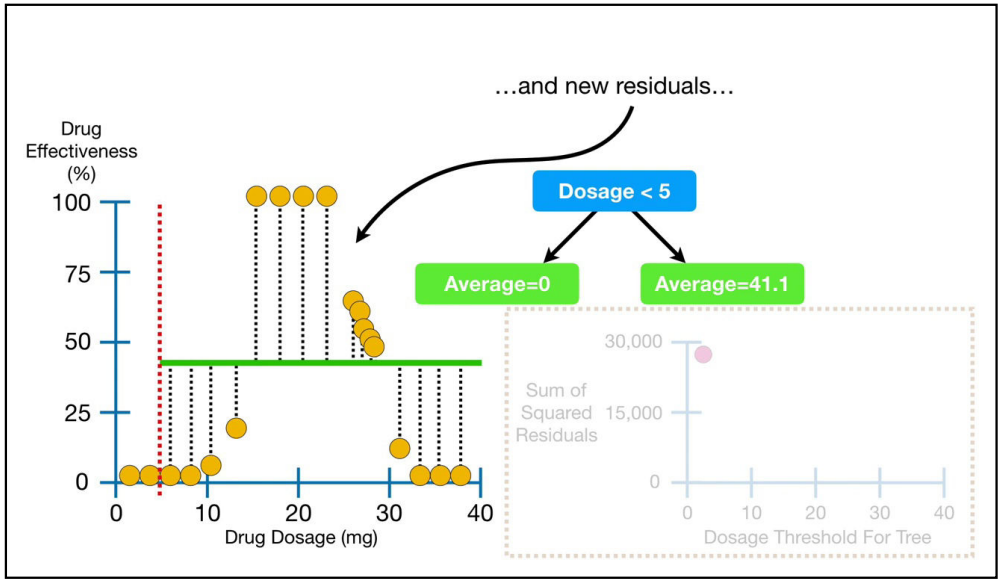

…but if we focus on the next two points in the graph…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

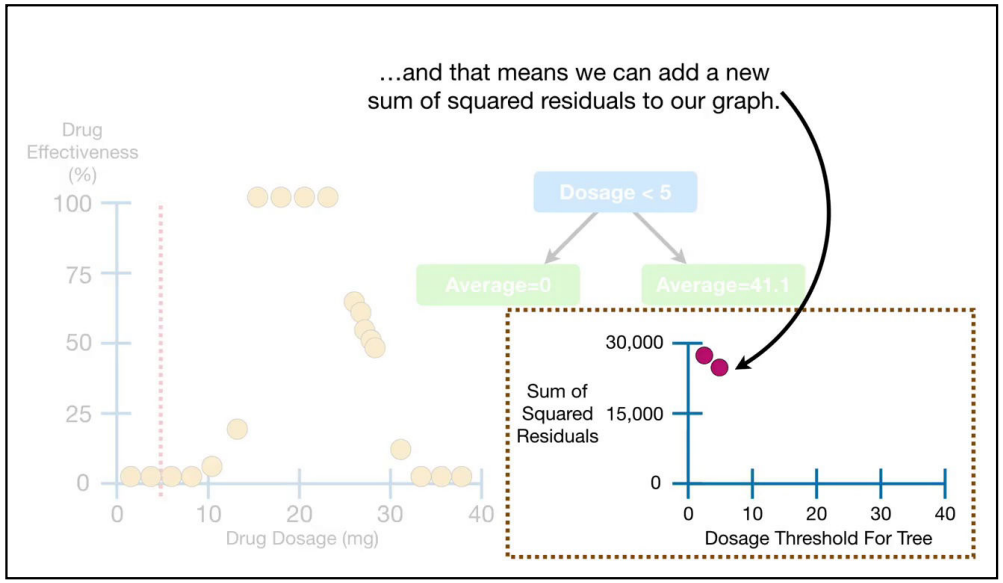

…and calculate their average **Dosage**, which is **5**…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

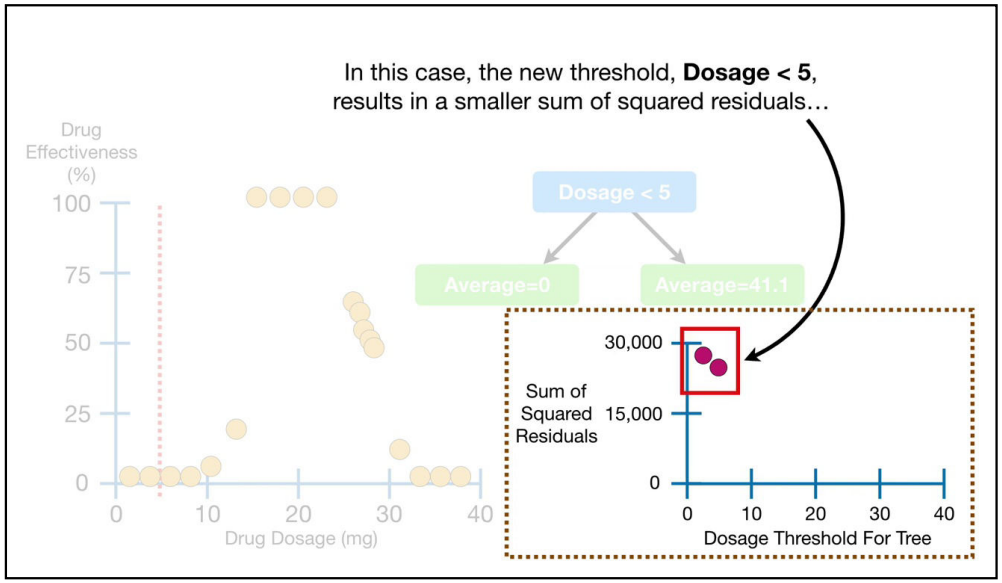

…then we can use **Dosage < 5** as a new threshold.
Drug Effectiveness (%)
Dosage < 5
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

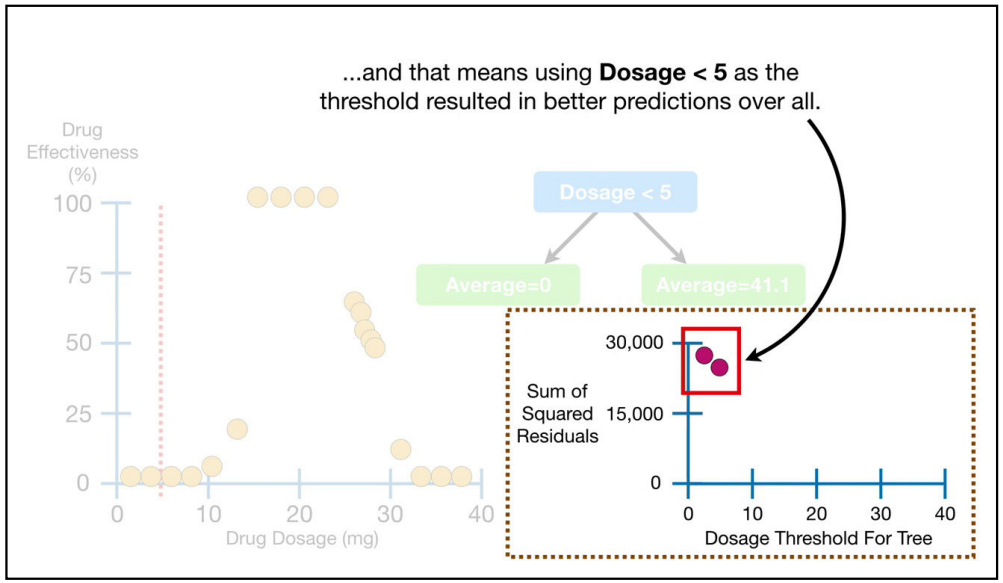

Using **Dosage < 5** gives us new predictions…
Drug Effectiveness (%)
Dosage < 5
Average=0
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

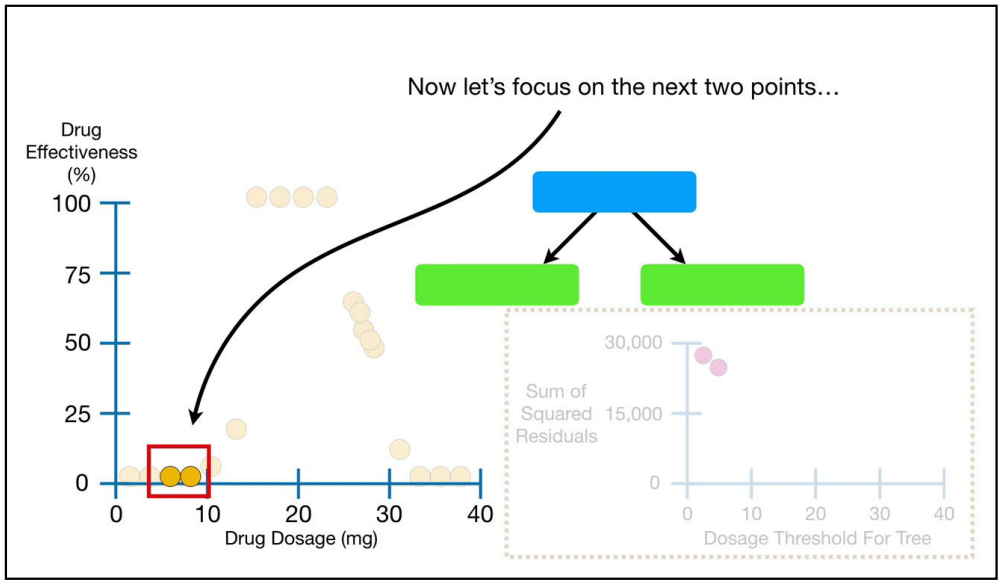

Using **Dosage < 5** gives us new predictions…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 5
Average=0
Average=41.1
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

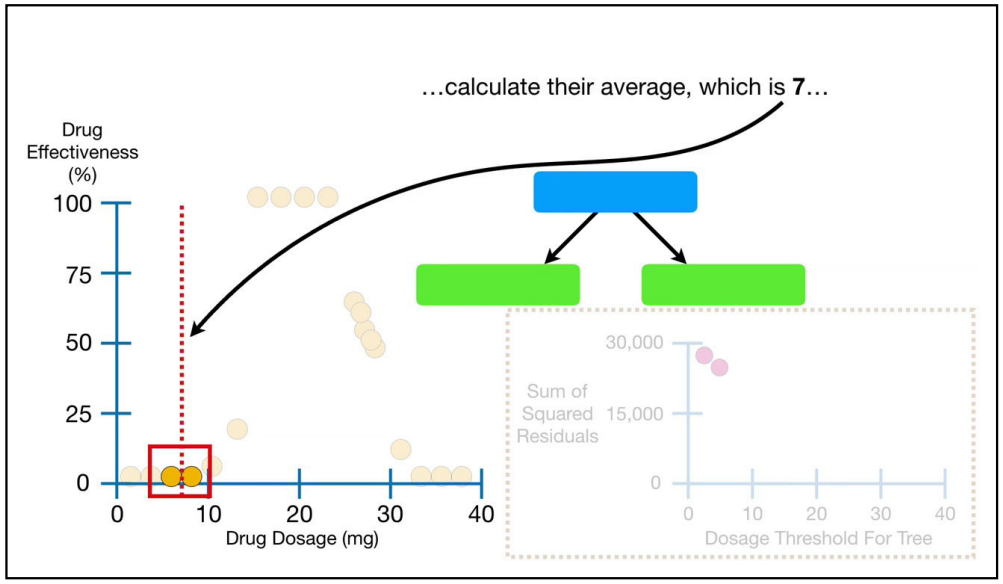

…and new residuals…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 5
Average=0
Average=41.1
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

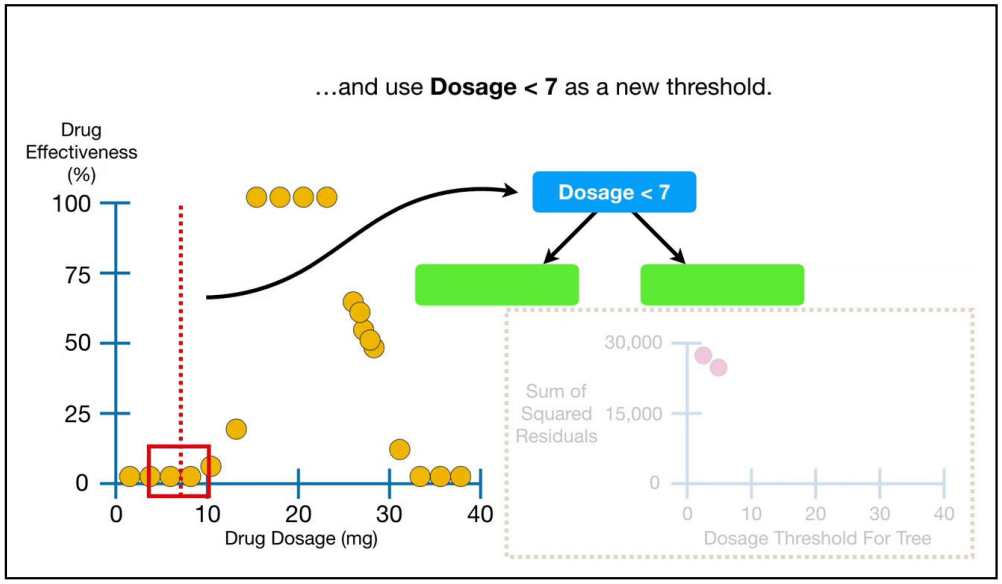

…and that means we can add a new sum of squared residuals to our graph.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 5
Average=0
Average=41.1
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

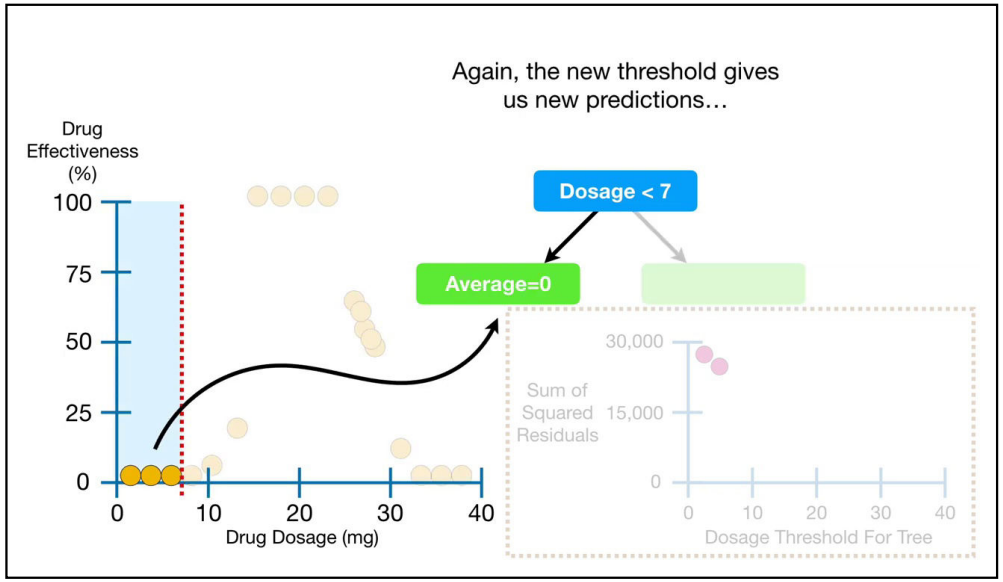

In this case, the new threshold, **Dosage < 5**, results in a smaller sum of squared residuals…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 5
Average=0
Average=41.1
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

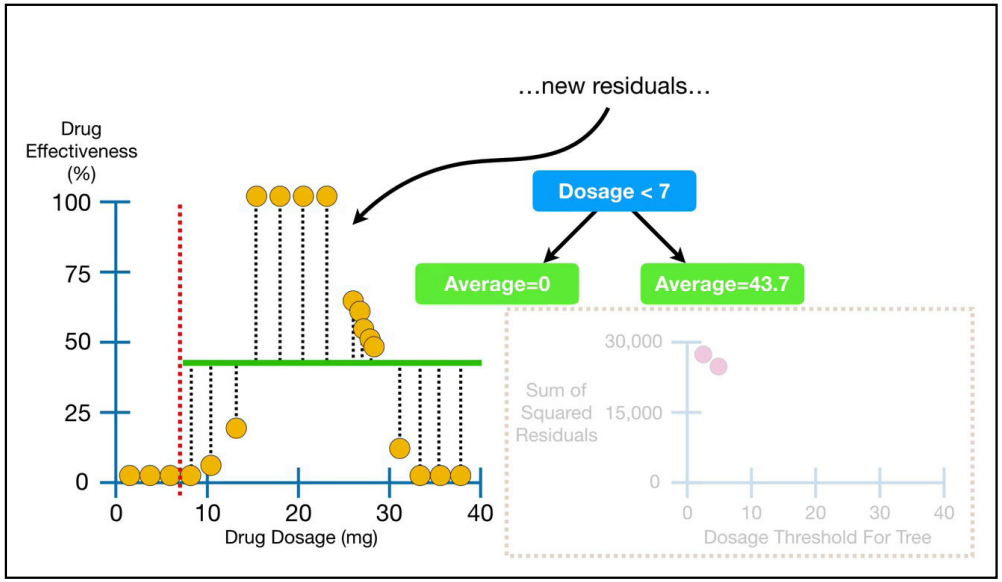

...and that means using **Dosage < 5** as the threshold resulted in better predictions over all.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 5
Average=0
Average=41.1
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

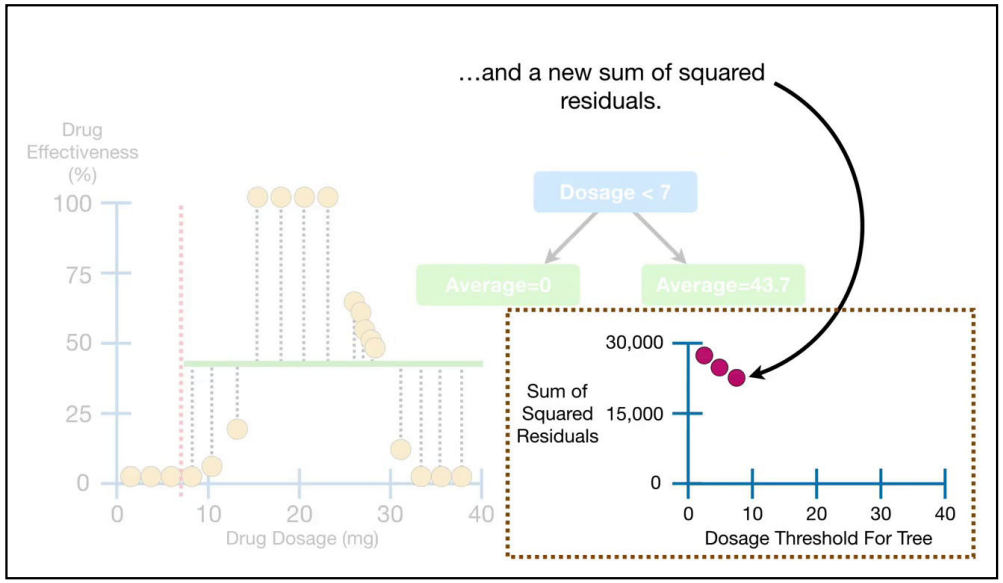

Now let's focus on the next two points...
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

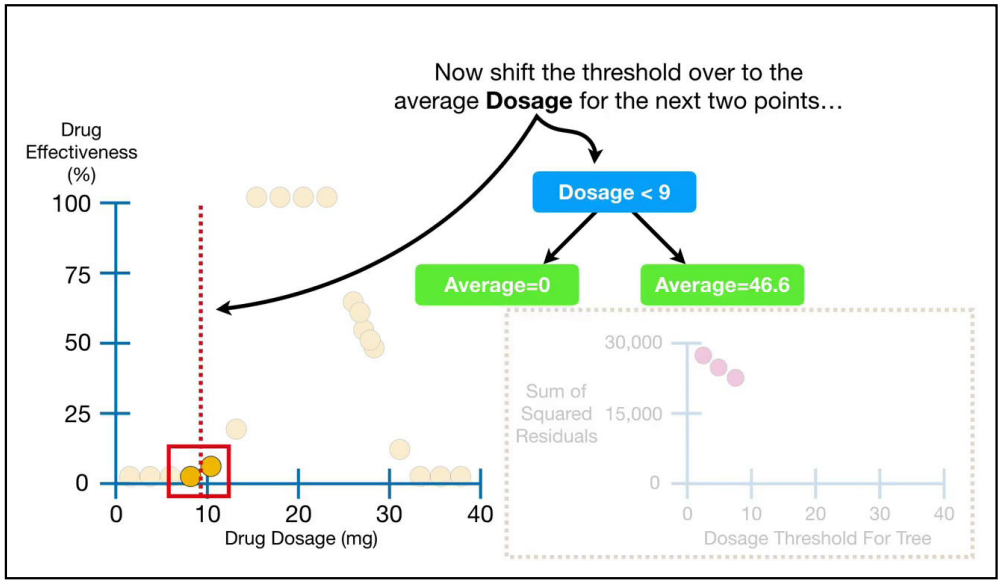

...calculate their average, which is **7**...
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

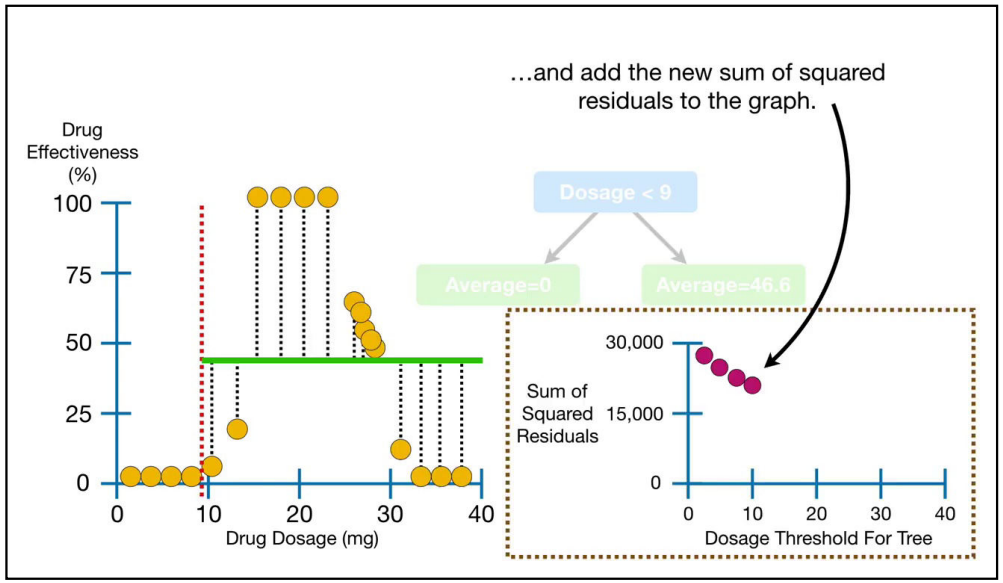

...and use **Dosage < 7** as a new threshold.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 7
0
10
20
30
40
Drug Dosage (mg)
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

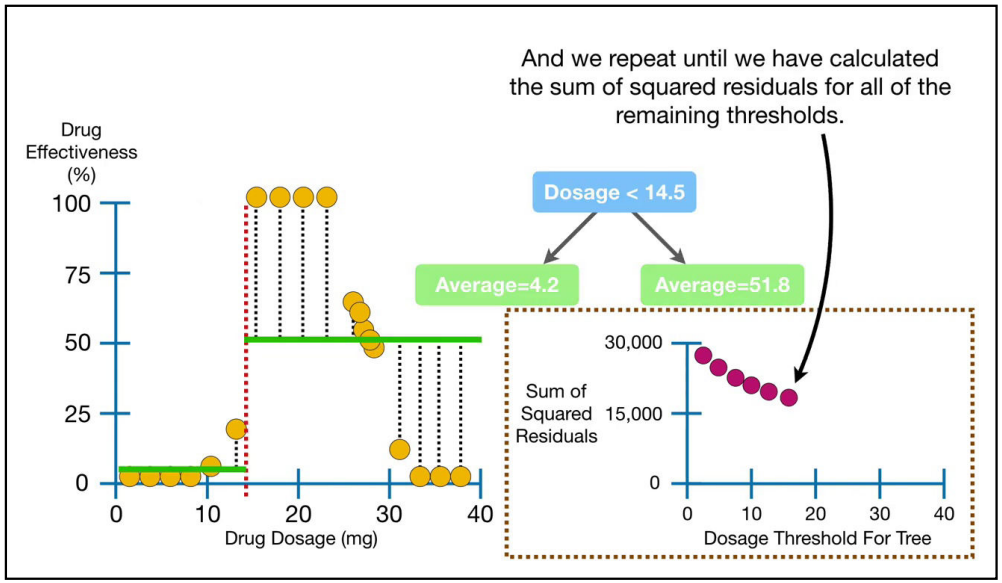

Again, the new threshold gives us new predictions…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 7
Average=0
0
10
20
30
40
Drug Dosage (mg)
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

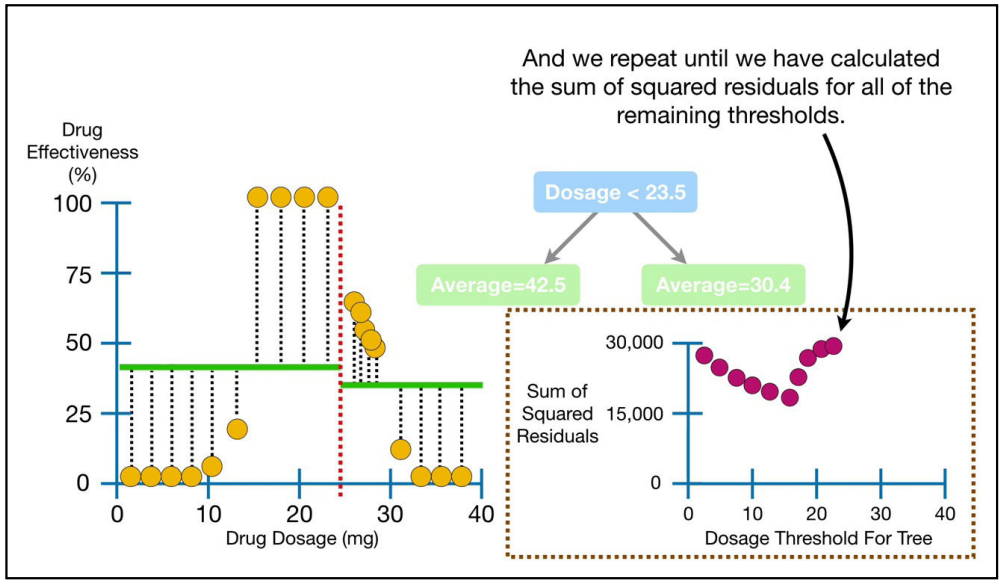

…new residuals…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 7
Average=0
Average=43.7
0
10
20
30
40
Drug Dosage (mg)
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

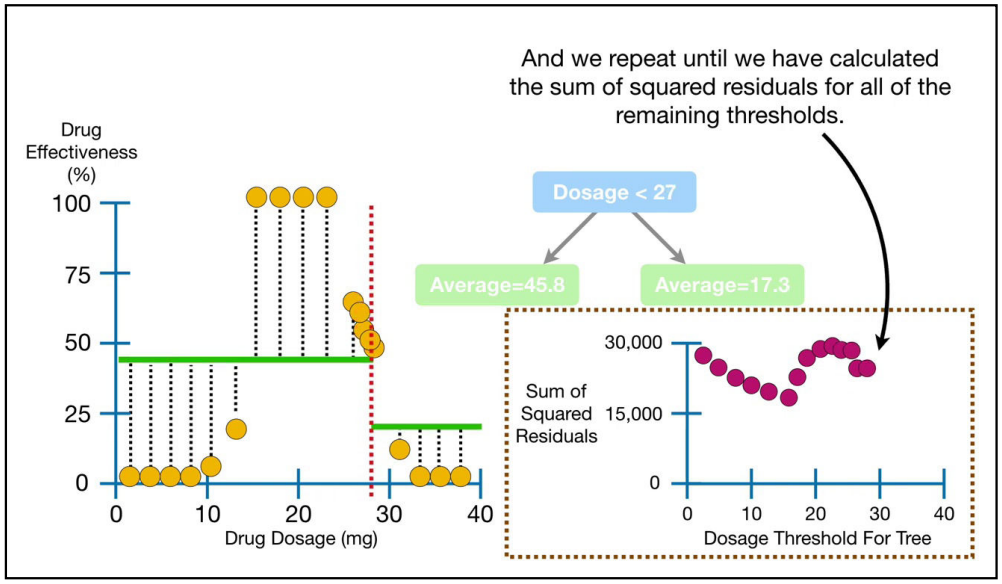

…and a new sum of squared residuals.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 7
Average=0
Average=43.7
0
10
20
30
40
Drug Dosage (mg)
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

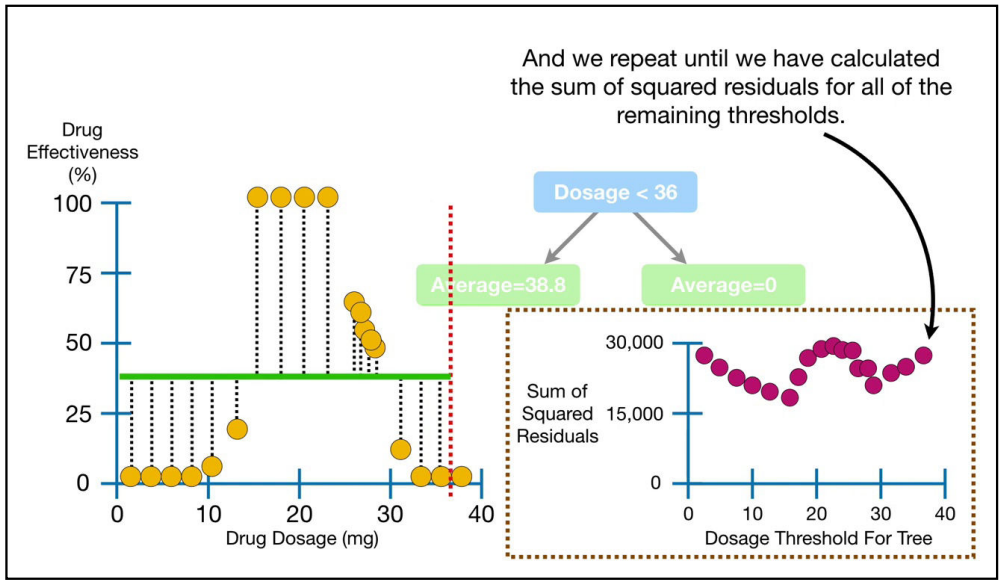

Now shift the threshold over to the average **Dosage** for the next two points…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 9
Average=0
Average=46.6
0
10
20
30
40
Drug Dosage (mg)
30,000
Sum of Squared Residuals
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

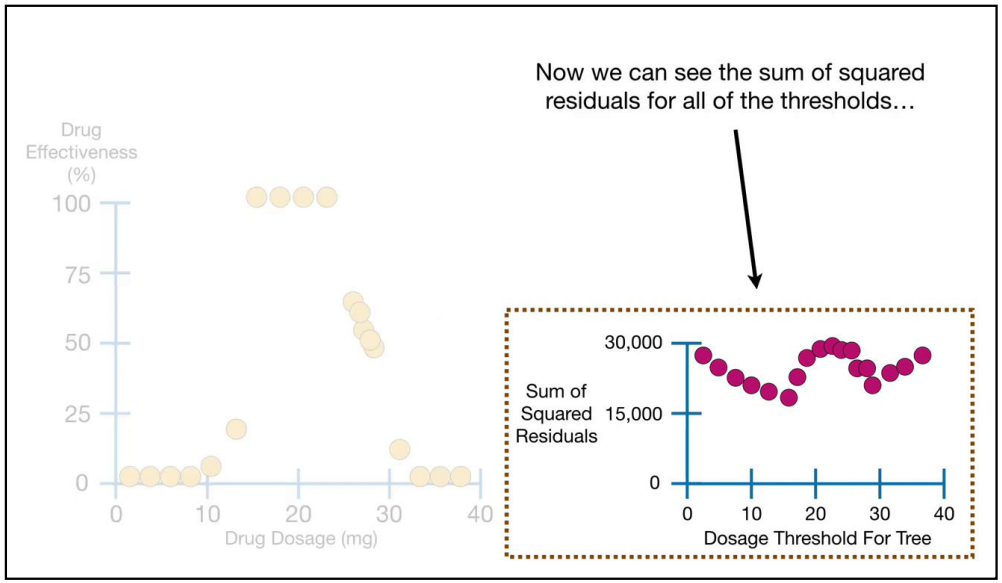

…and add the new sum of squared residuals to the graph.
Drug Effectiveness (%)
Dosage < 9
Average=0
Average=46.6
Sum of Squared Residuals
Drug Dosage (mg)
Dosage Threshold For Tree

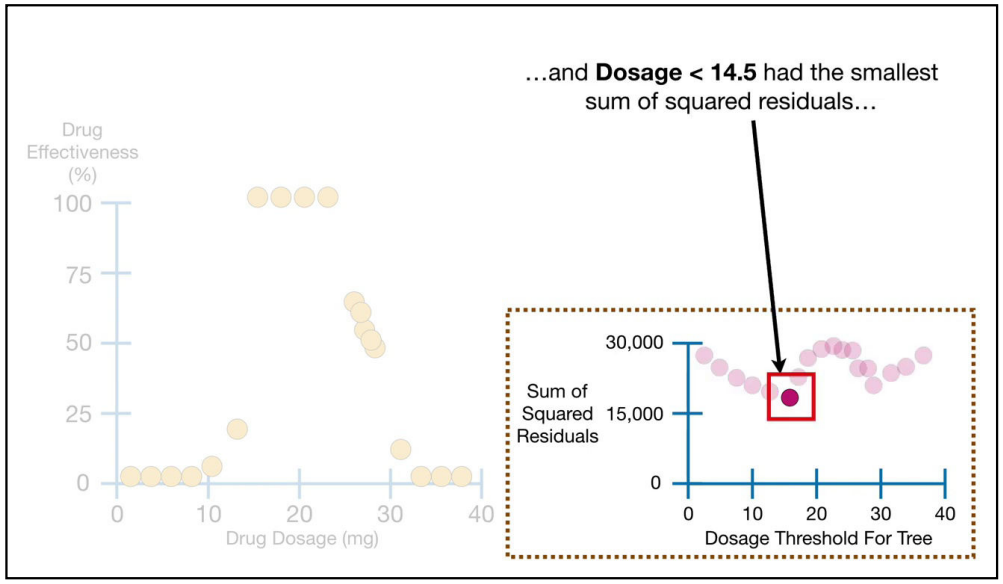

And we repeat until we have calculated the sum of squared residuals for all of the remaining thresholds.
Drug Effectiveness (%)
Dosage < 14.5
Average=4.2
Average=51.8
Sum of Squared Residuals
Drug Dosage (mg)
Dosage Threshold For Tree

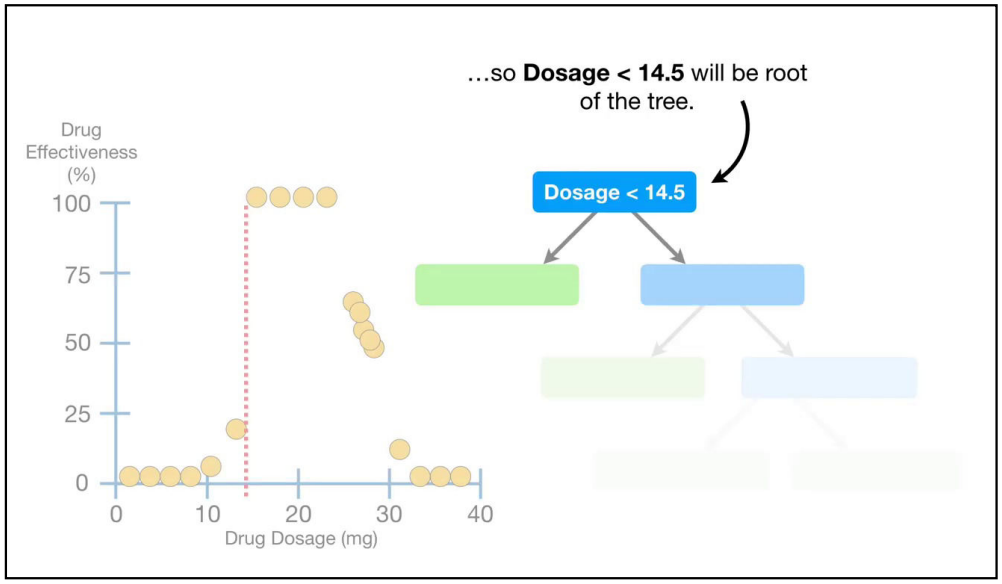

And we repeat until we have calculated the sum of squared residuals for all of the remaining thresholds.
Drug Effectiveness (%)
Dosage < 23.5
Average=42.5
Average=30.4
Sum of Squared Residuals
Drug Dosage (mg)
Dosage Threshold For Tree

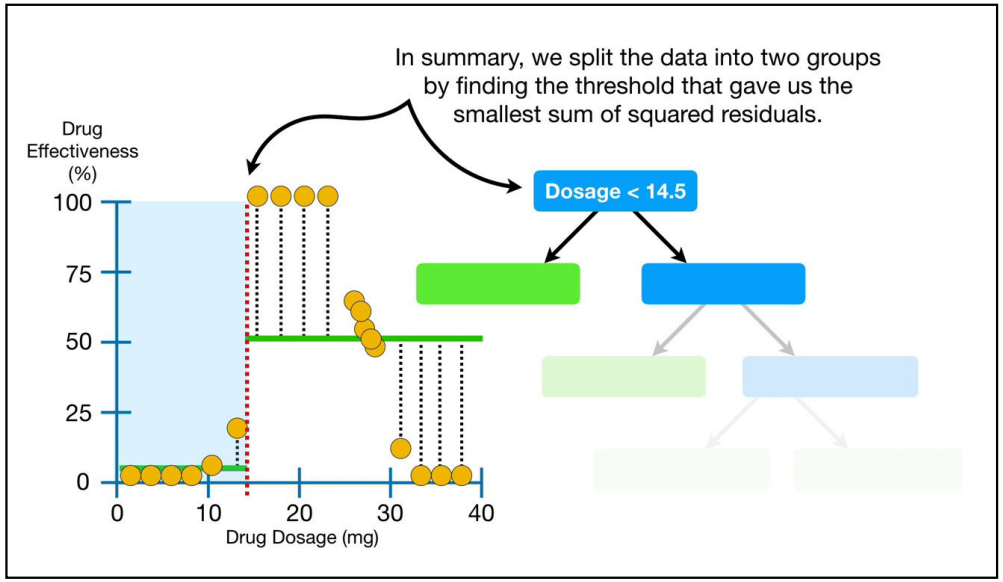

And we repeat until we have calculated the sum of squared residuals for all of the remaining thresholds.
Drug Effectiveness (%)
Dosage < 27
Average=45.8
Average=17.3
Sum of Squared Residuals
Drug Dosage (mg)
Dosage Threshold For Tree

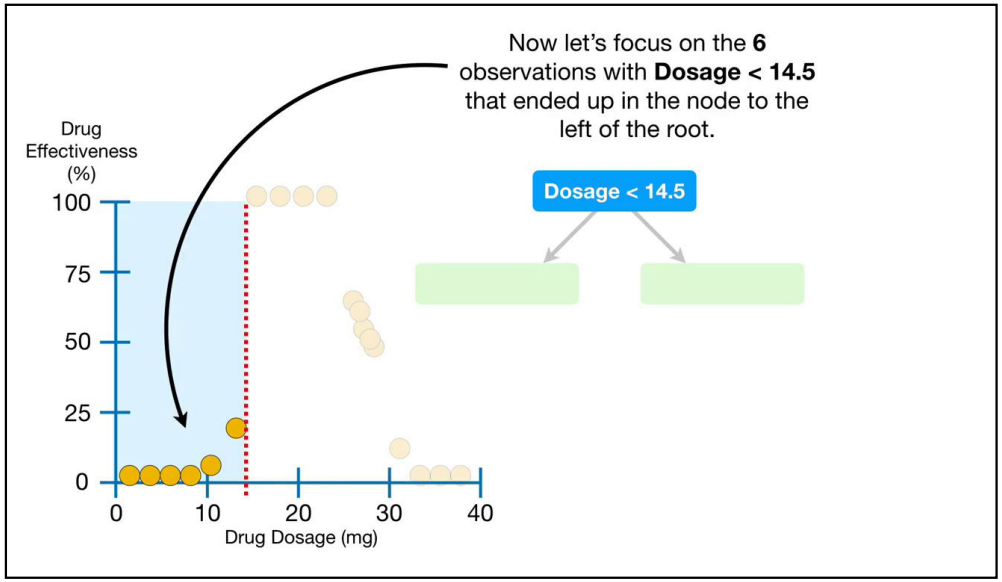

And we repeat until we have calculated the sum of squared residuals for all of the remaining thresholds.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 36
Average=38.8
Average=0
Sum of Squared Residuals
30,000
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

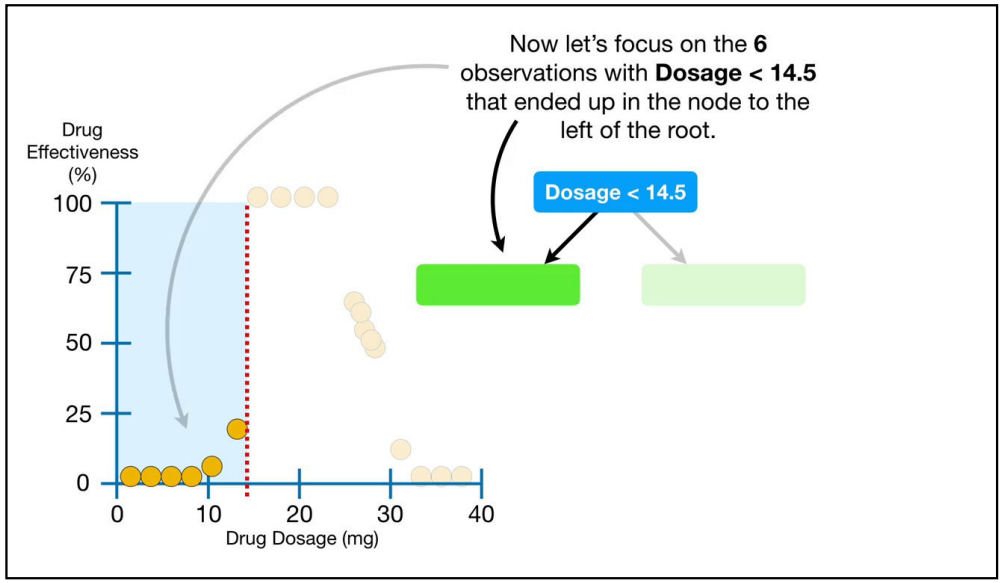

Now we can see the sum of squared residuals for all of the thresholds…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Sum of Squared Residuals
30,000
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

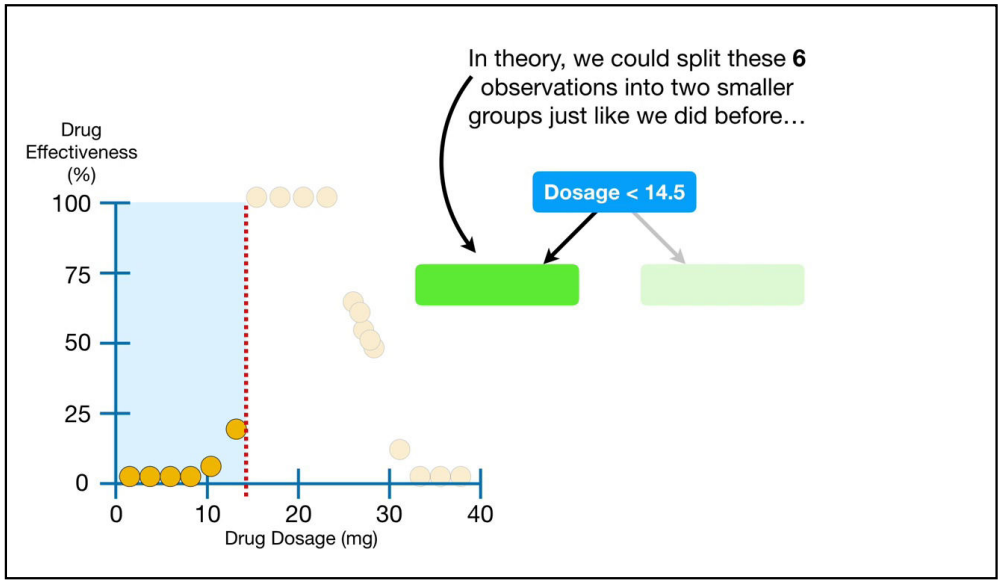

…and **Dosage < 14.5** had the smallest sum of squared residuals…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Sum of Squared Residuals
30,000
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

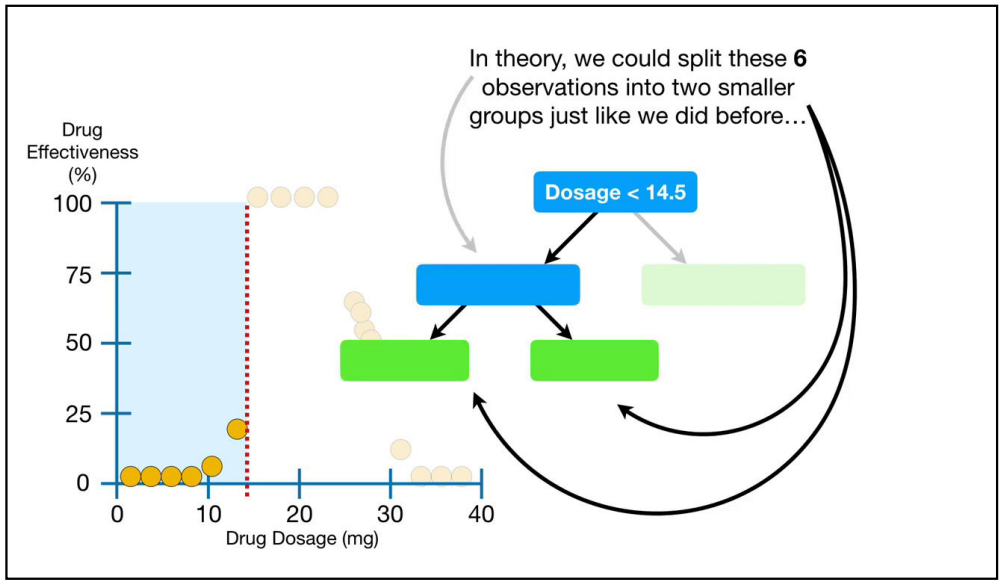

…so **Dosage < 14.5** will be root of the tree.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5

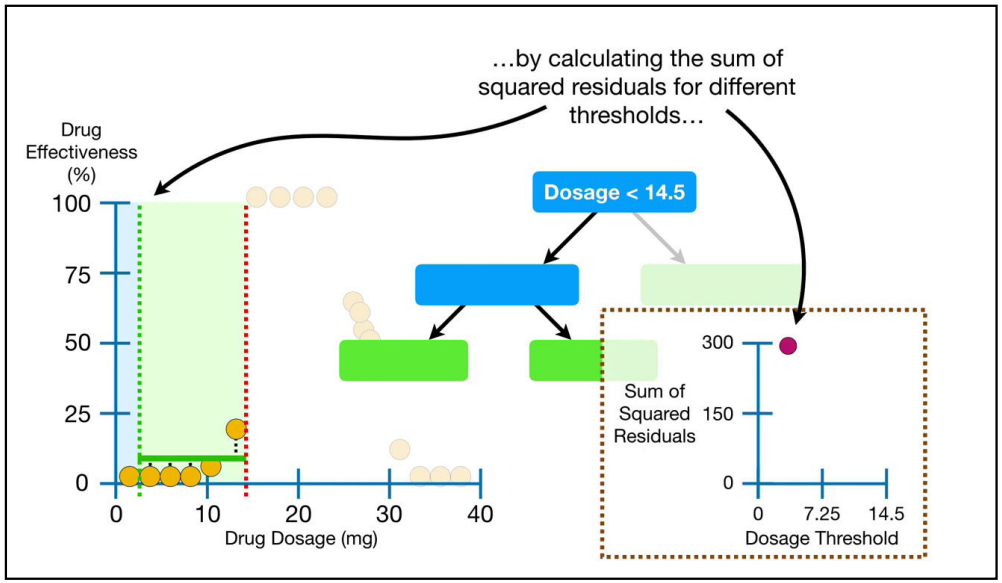

In summary, we split the data into two groups by finding the threshold that gave us the smallest sum of squared residuals.
Drug Effectiveness (%)
Dosage < 14.5
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

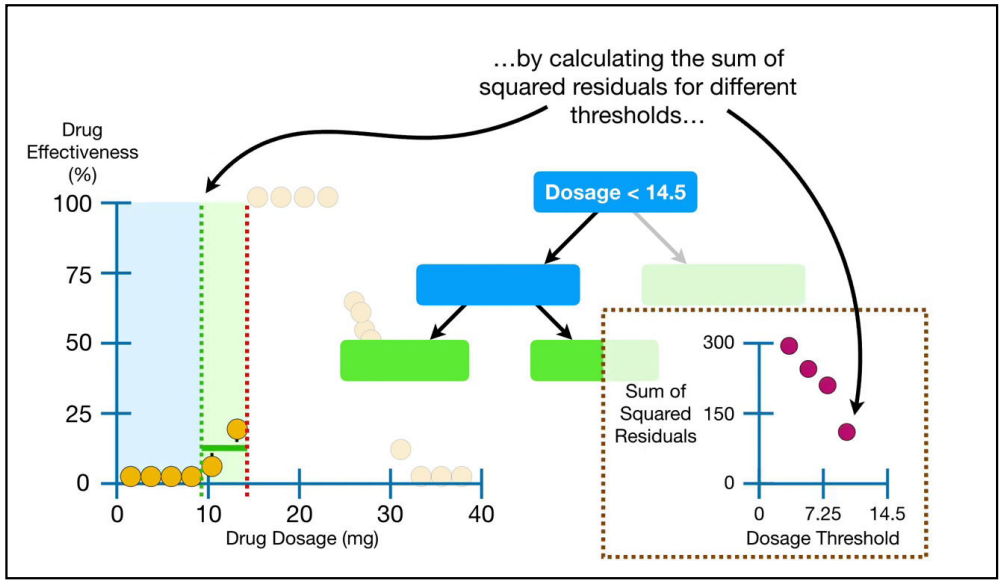

Now let's focus on the **6** observations with **Dosage < 14.5** that ended up in the node to the left of the root.
Drug Effectiveness (%)
Dosage < 14.5
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

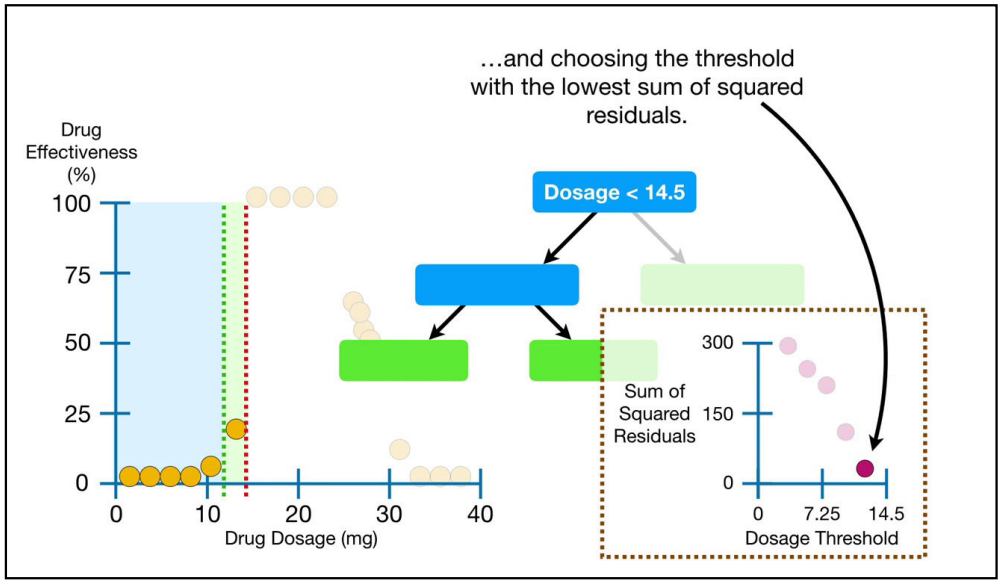

Now let's focus on the **6** observations with **Dosage < 14.5** that ended up in the node to the left of the root.
Drug Effectiveness (%)
Dosage < 14.5
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

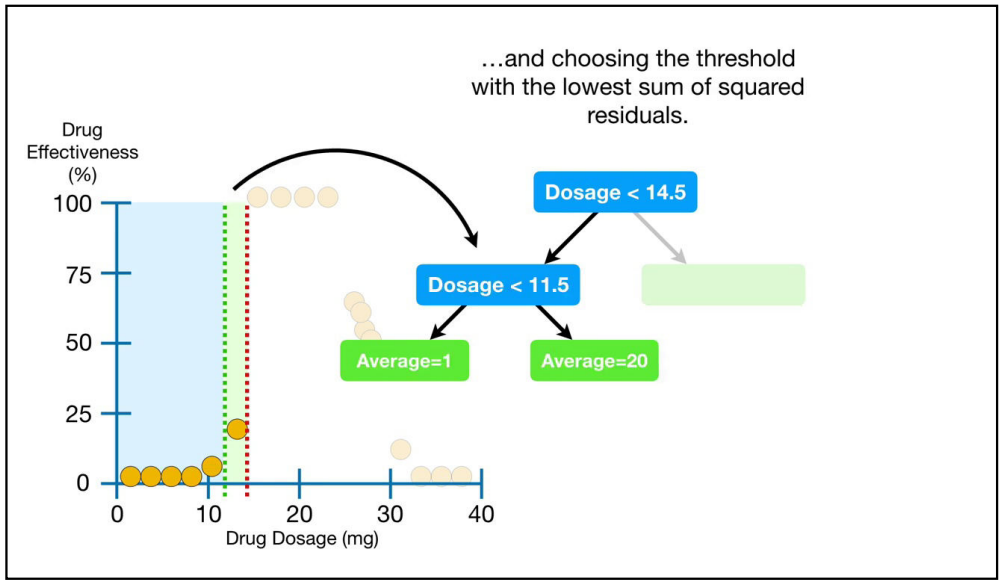

In theory, we could split these **6** observations into two smaller groups just like we did before…
Drug Effectiveness (%)
Dosage < 14.5
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

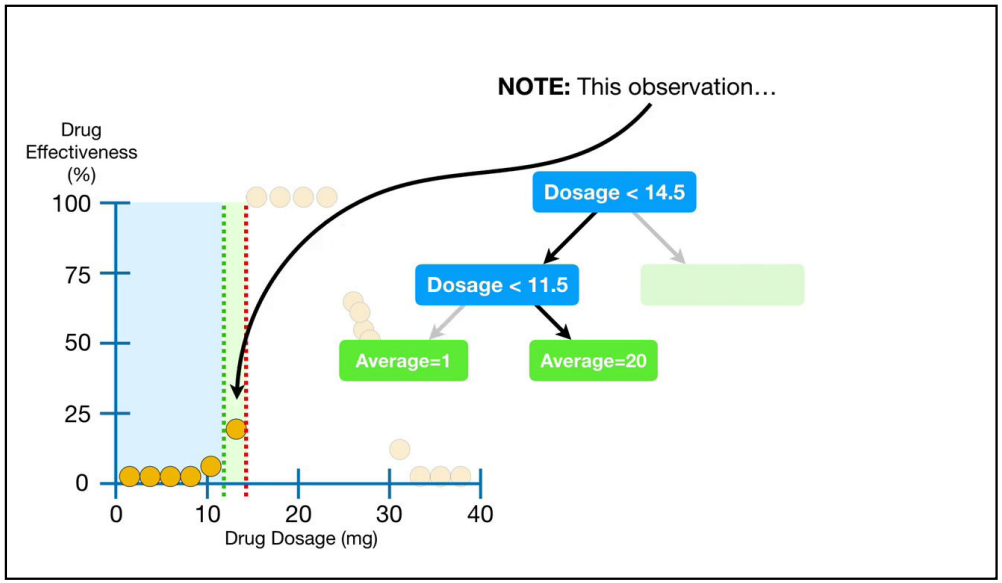

In theory, we could split these **6** observations into two smaller groups just like we did before…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
0
10
20
30
40
Drug Dosage (mg)

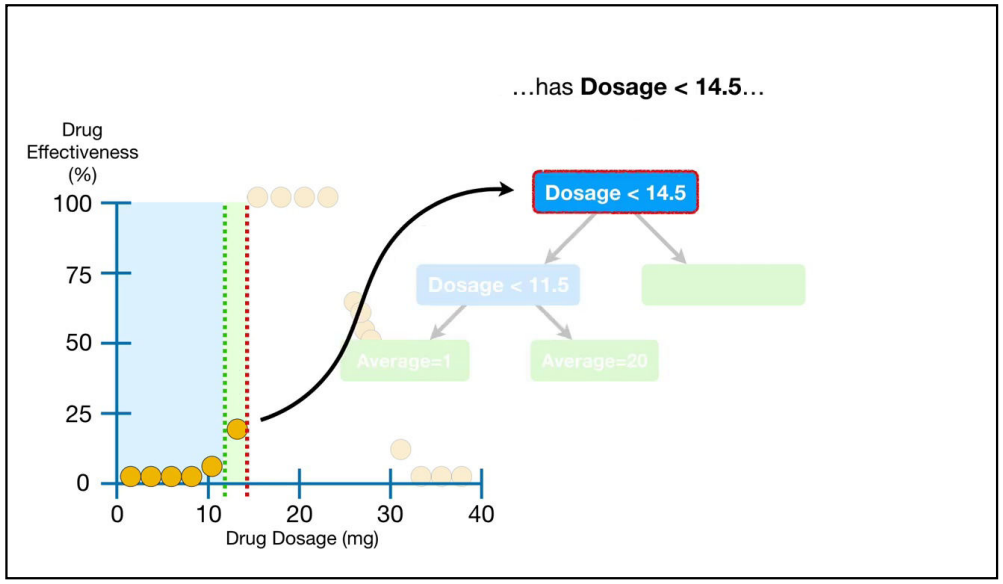

…by calculating the sum of squared residuals for different thresholds…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
0
10
20
30
40
Drug Dosage (mg)
Sum of Squared Residuals
300
150
0
0
7.25
14.5
Dosage Threshold

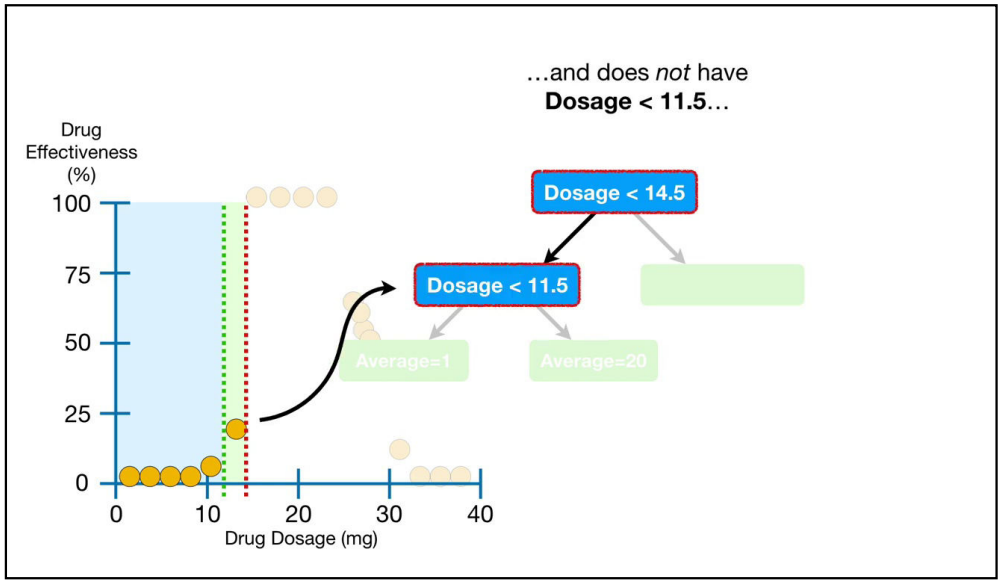

…by calculating the sum of squared residuals for different thresholds…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
0
10
20
30
40
Drug Dosage (mg)
Sum of Squared Residuals
300
150
0
0
7.25
14.5
Dosage Threshold

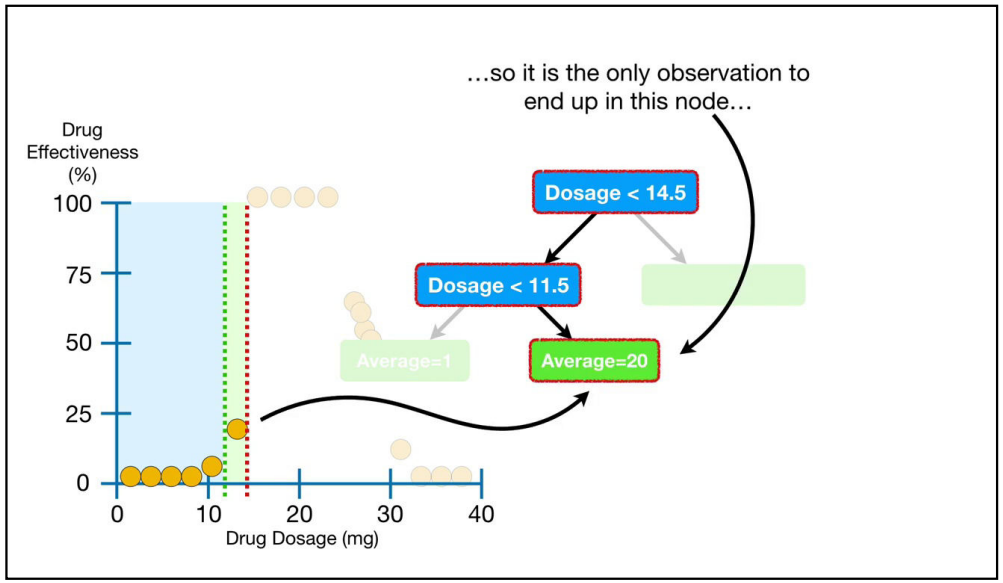

…and choosing the threshold with the lowest sum of squared residuals.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
0
10
20
30
40
Drug Dosage (mg)
Sum of Squared Residuals
300
150
0
0
7.25
14.5
Dosage Threshold

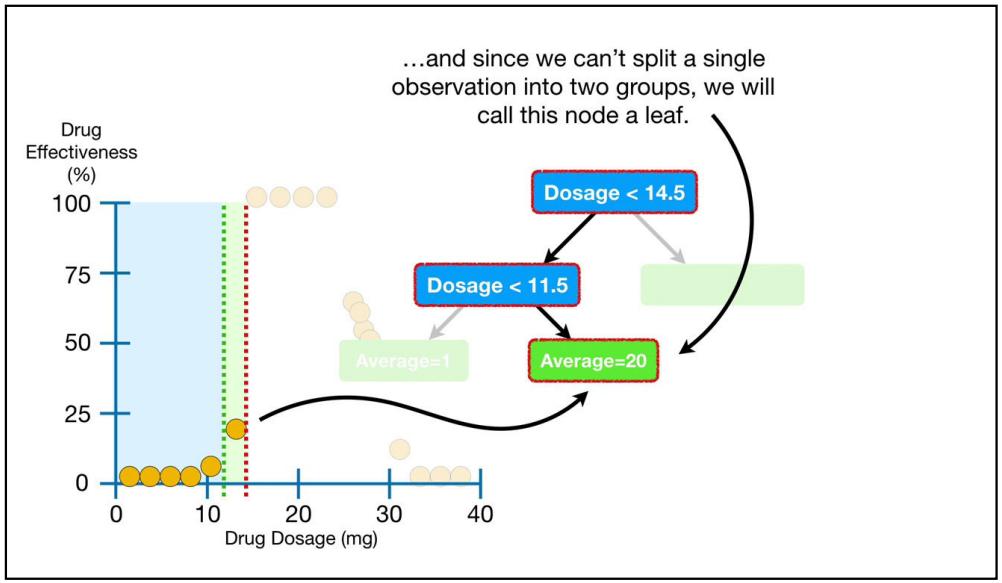

…and choosing the threshold with the lowest sum of squared residuals.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Average=1
Average=20
0
10
20
30
40
Drug Dosage (mg)

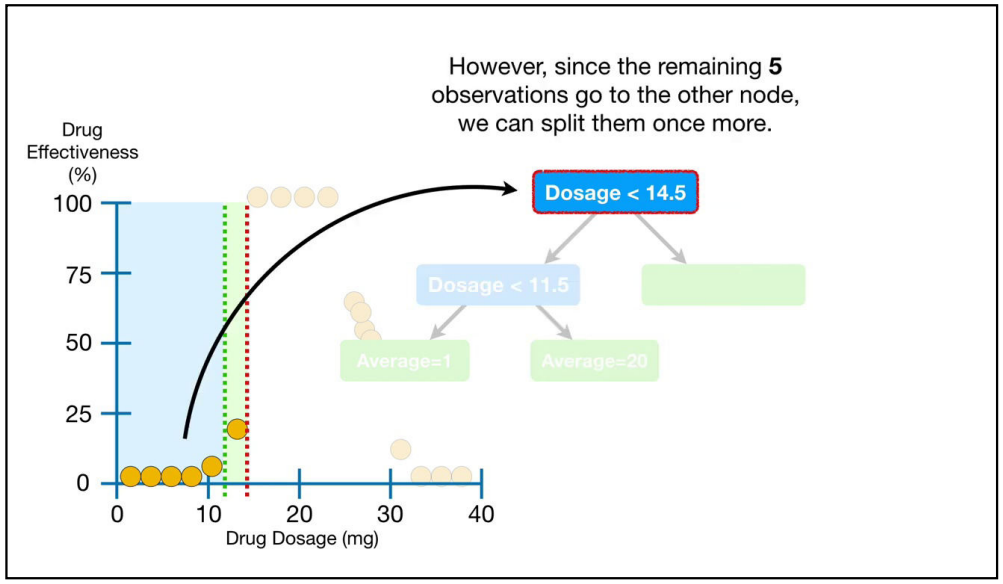

NOTE: This observation…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Average=1
Average=20
0
10
20
30
40
Drug Dosage (mg)

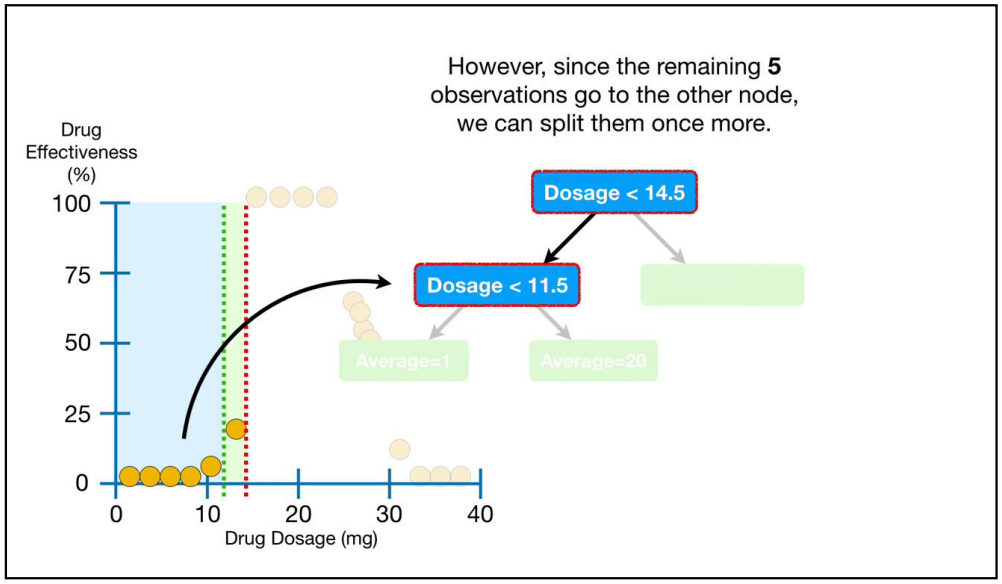

…has Dosage < 14.5…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Average=1
Average=20
0
10
20
30
40
Drug Dosage (mg)

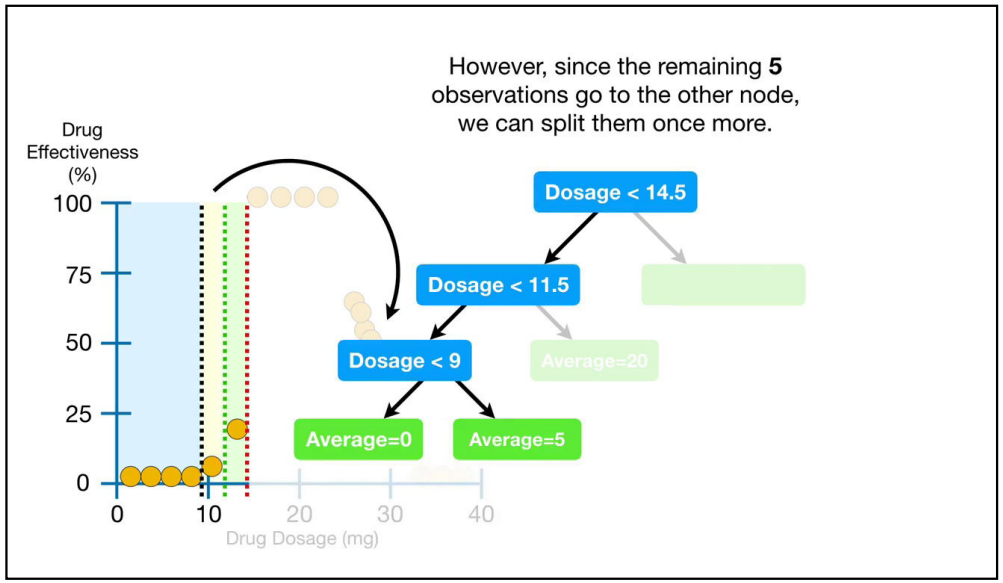

…and does *not* have Dosage < 11.5…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Average=1
Average=20
0
10
20
30
40
Drug Dosage (mg)

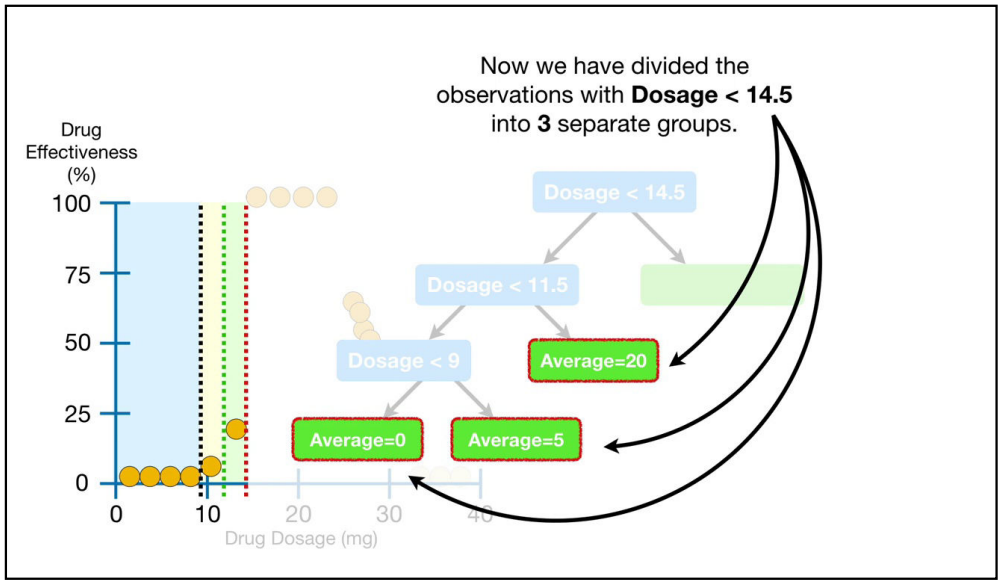

…so it is the only observation to end up in this node…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage < 11.5
Average=1
Average=20

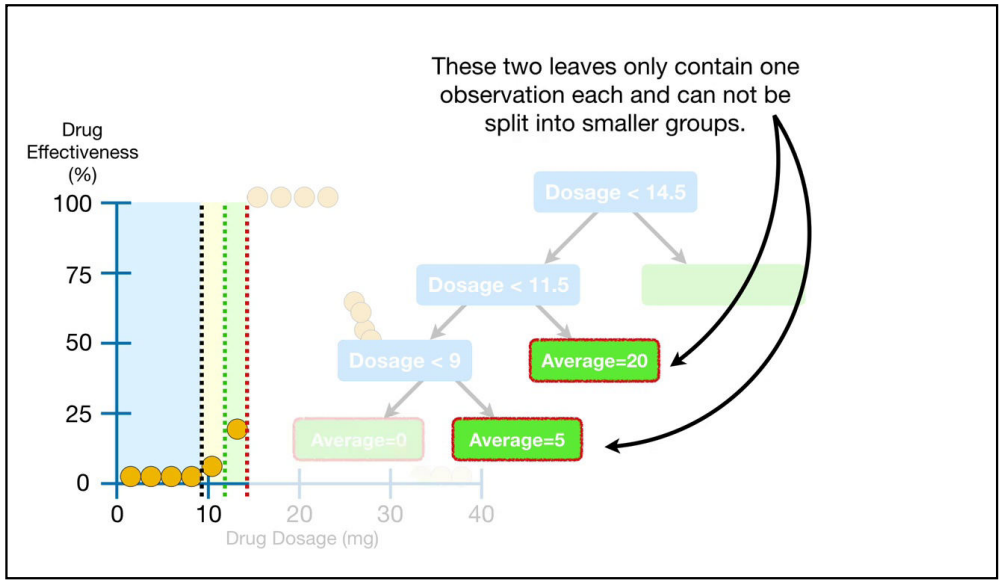

…and since we can't split a single observation into two groups, we will call this node a leaf.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage < 11.5
Average=1
Average=20

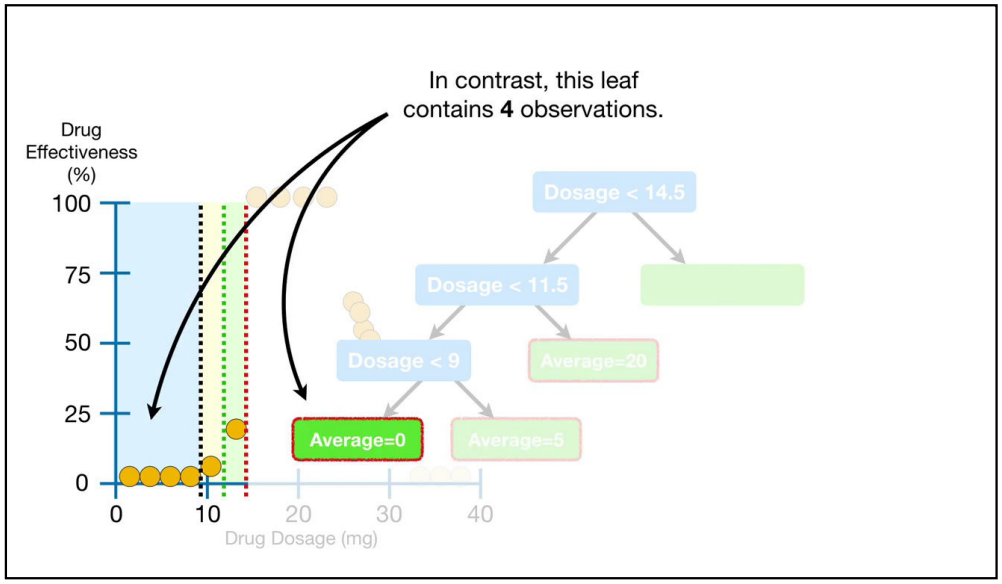

However, since the remaining **5** observations go to the other node, we can split them once more.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage < 11.5
Average=1
Average=20

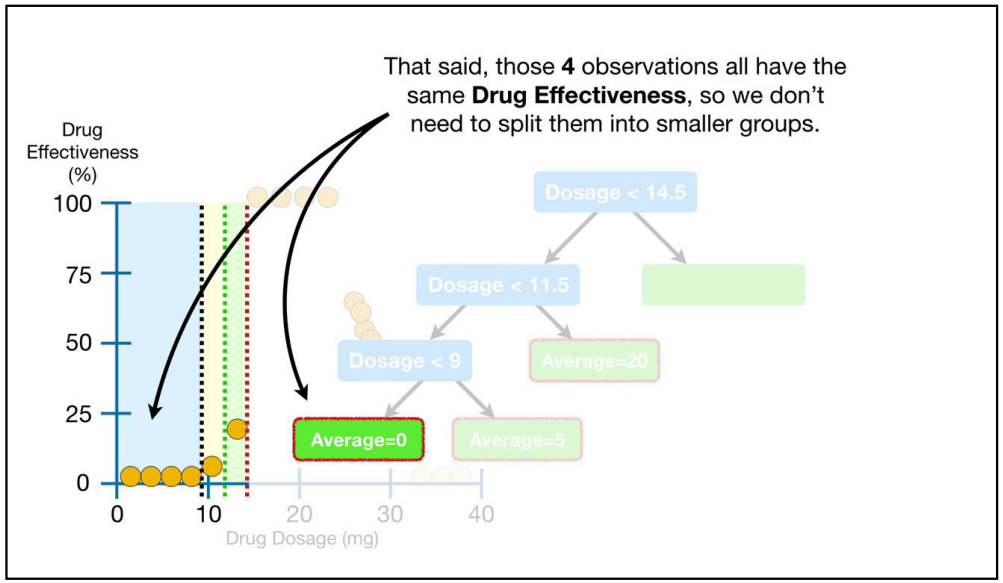

However, since the remaining **5** observations go to the other node, we can split them once more.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage < 11.5
Average=1
Average=20

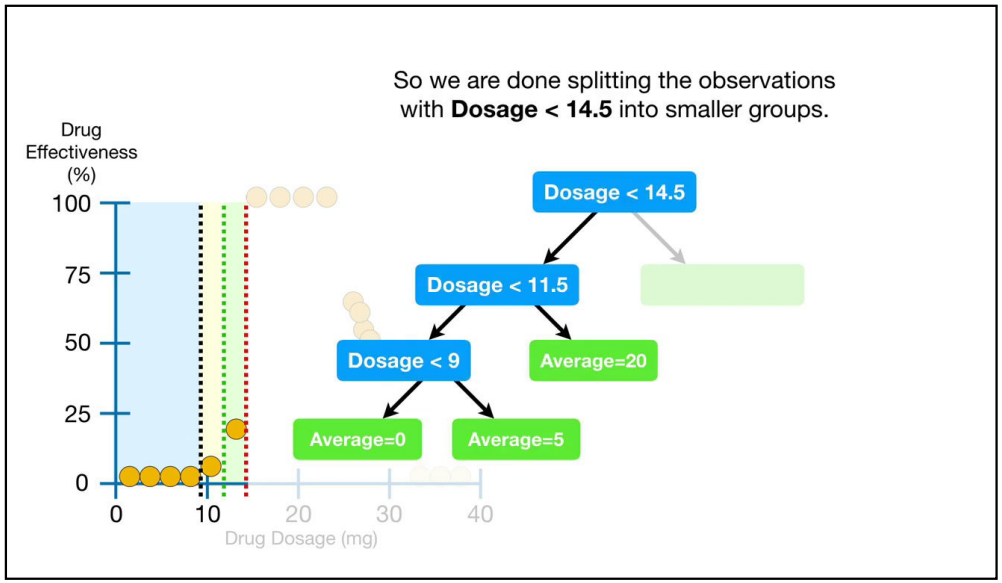

However, since the remaining **5** observations go to the other node, we can split them once more.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5
0
10
20
30
40
Drug Dosage (mg)

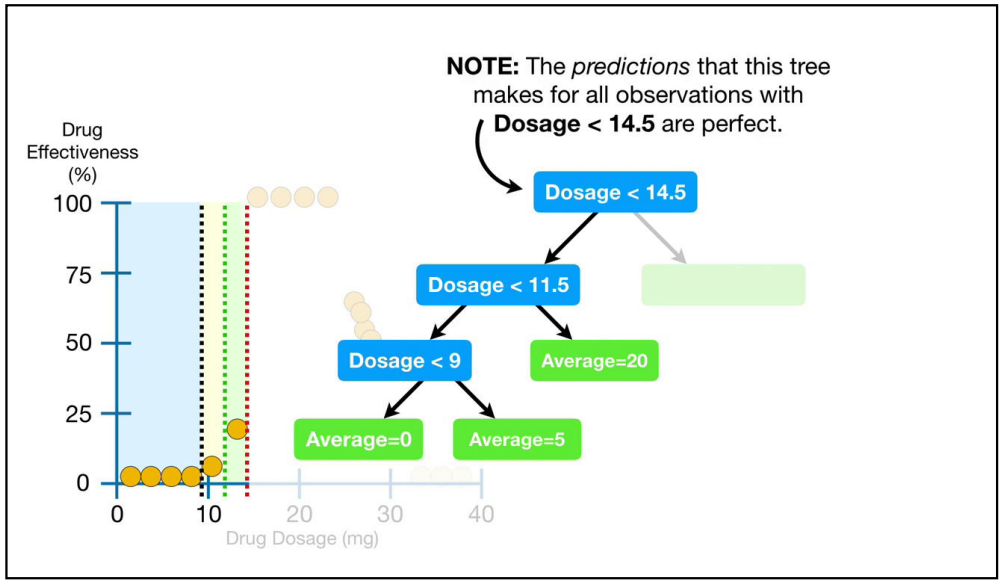

Now we have divided the observations with **Dosage < 14.5** into **3** separate groups.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5
0
10
20
30
Drug Dosage (mg)

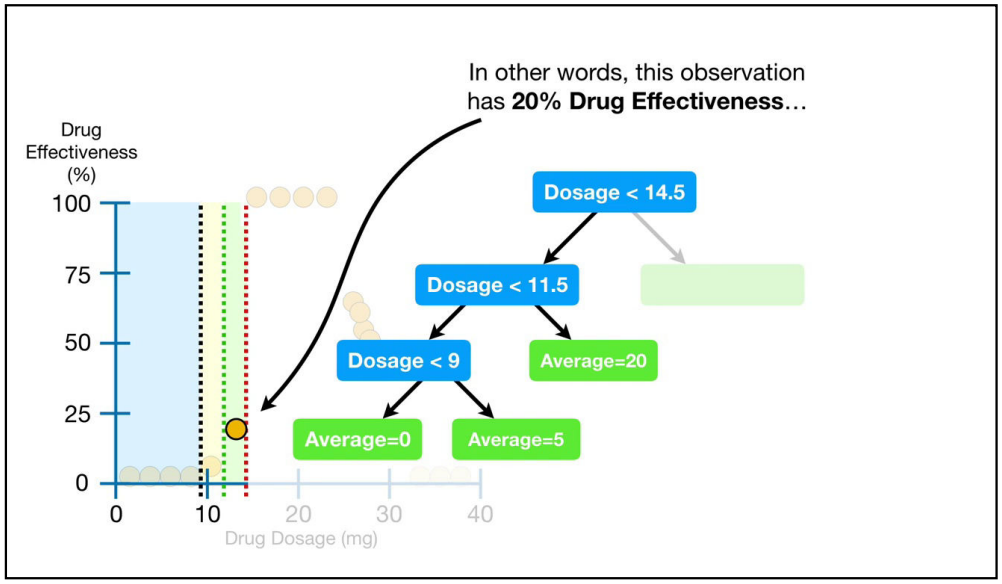

These two leaves only contain one observation each and can not be split into smaller groups.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5
0
10
20
30
40
Drug Dosage (mg)

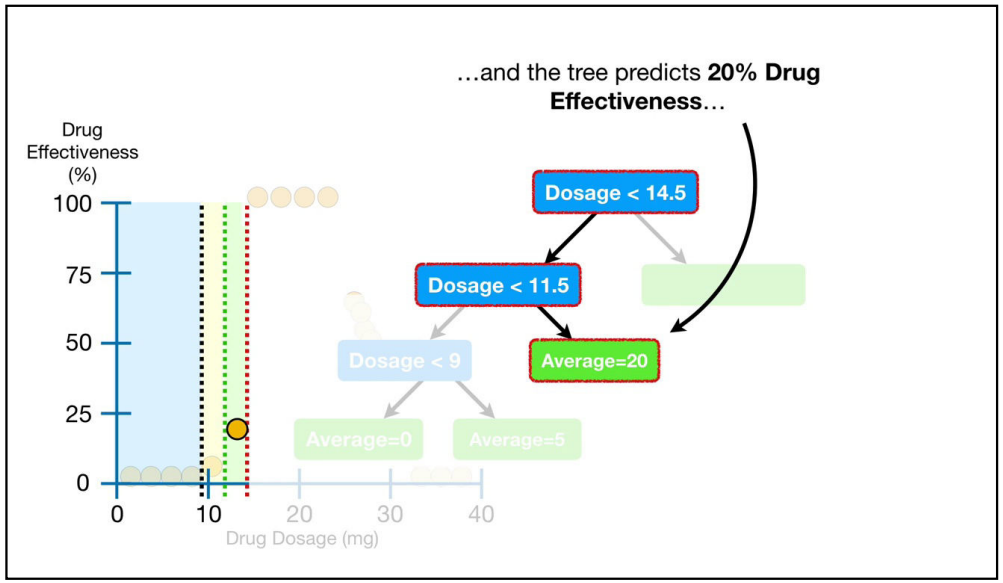

In contrast, this leaf contains **4** observations.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5
0
10
20
30
40
Drug Dosage (mg)

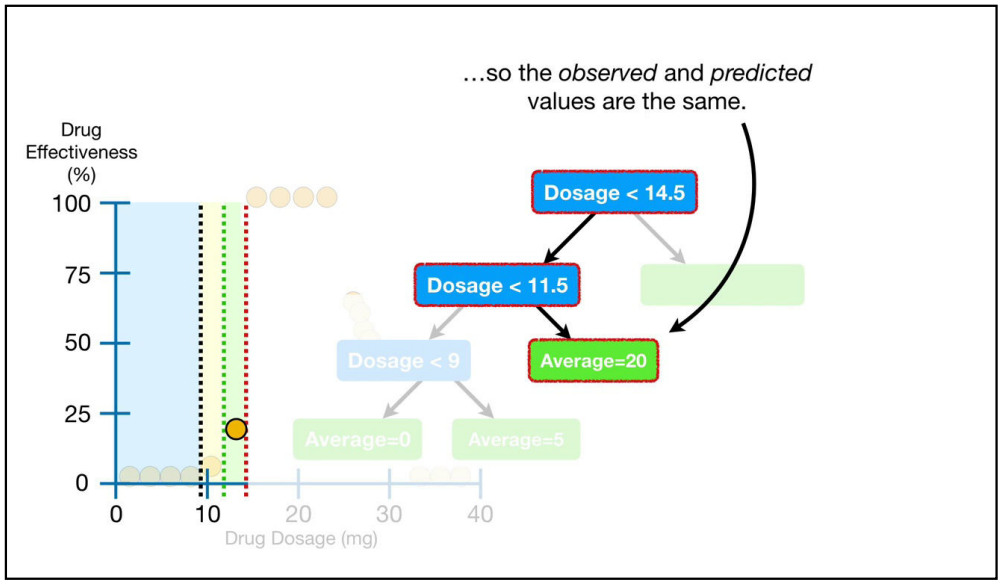

That said, those **4** observations all have the same **Drug Effectiveness**, so we don't need to split them into smaller groups.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5

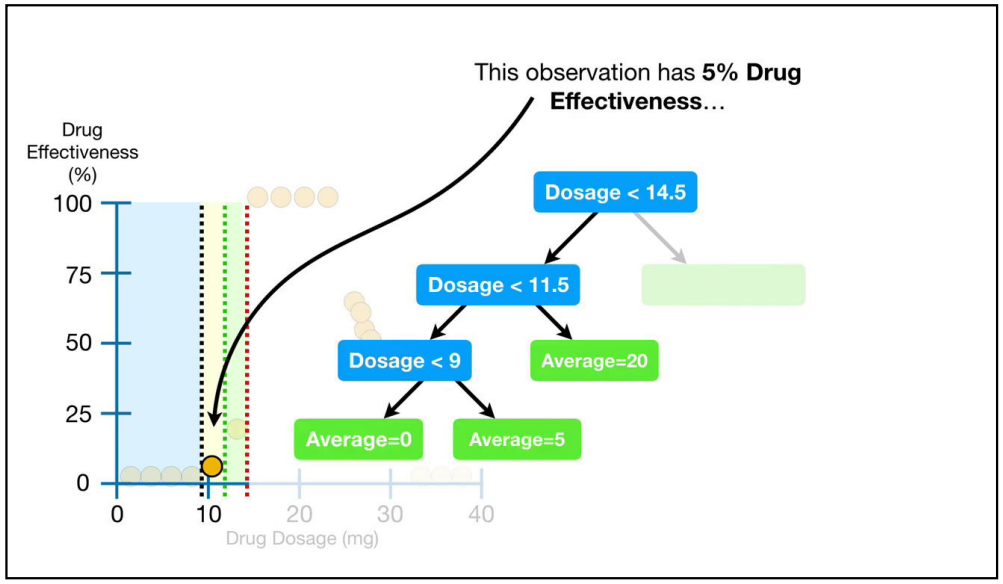

So we are done splitting the observations with **Dosage < 14.5** into smaller groups.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5

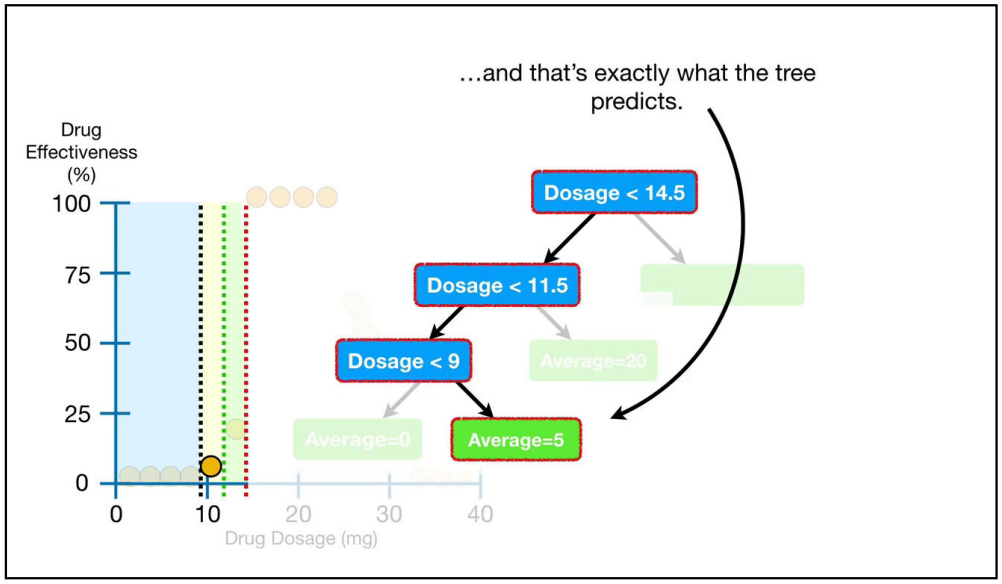

NOTE: The *predictions* that this tree makes for all observations with **Dosage < 14.5** are perfect.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5

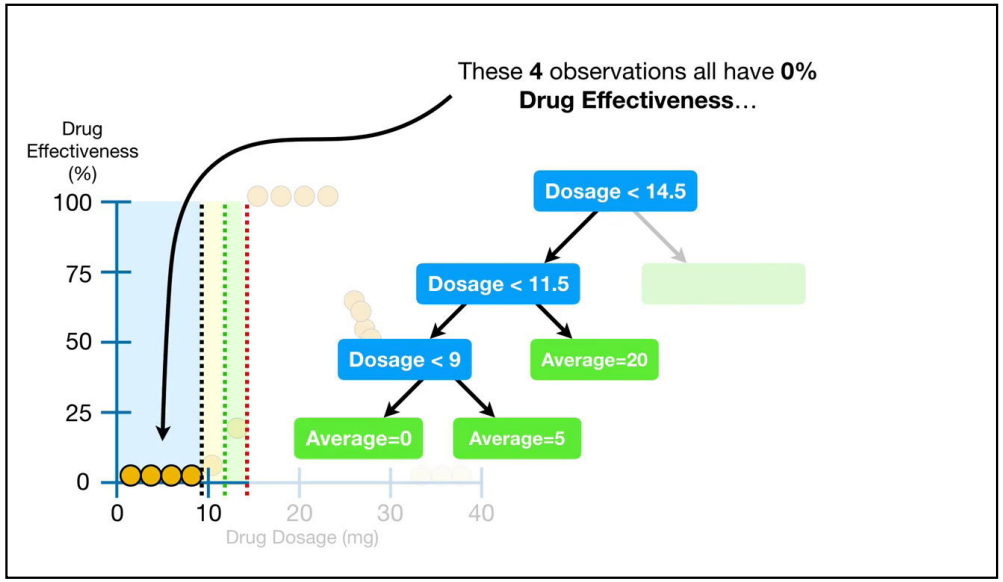

In other words, this observation has **20% Drug Effectiveness**…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5

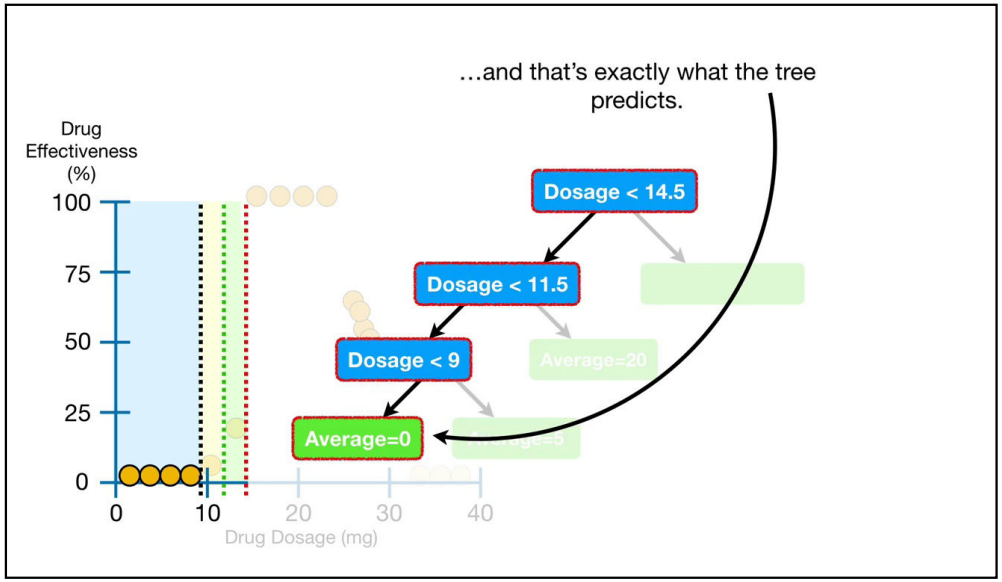

…and the tree predicts **20% Drug Effectiveness**…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5

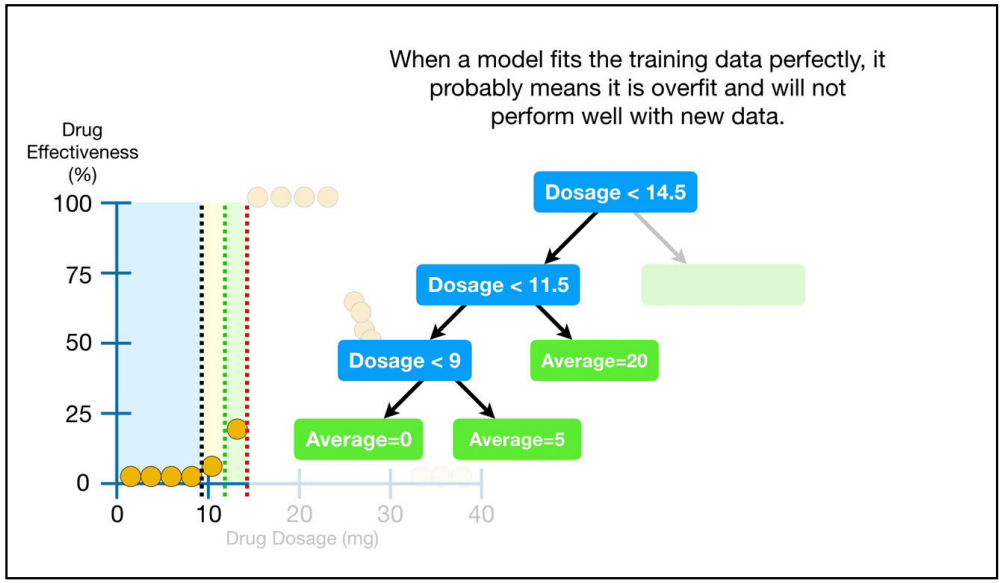

…so the *observed* and *predicted* values are the same.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5

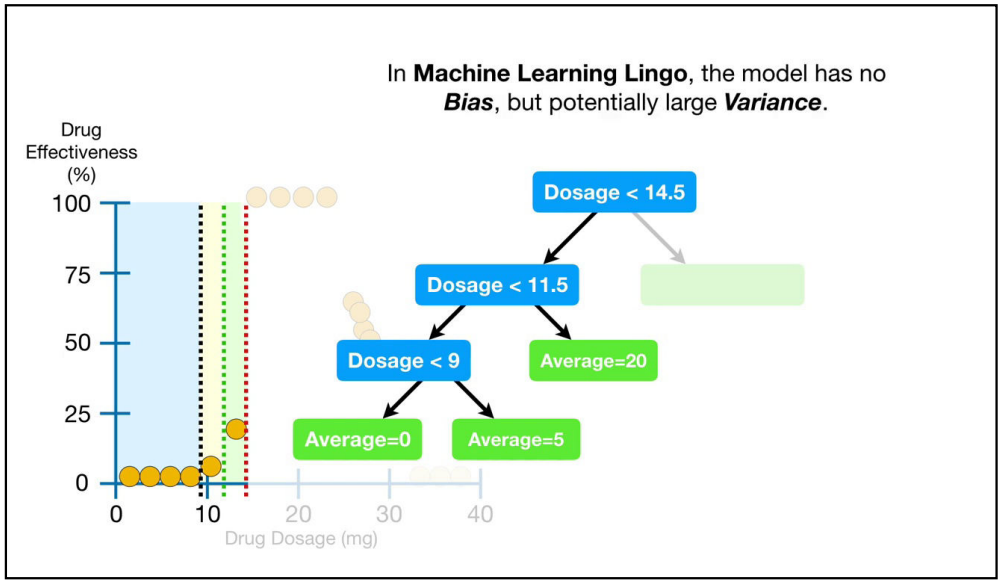

This observation has **5% Drug Effectiveness**…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5


…and that's exactly what the tree predicts.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5

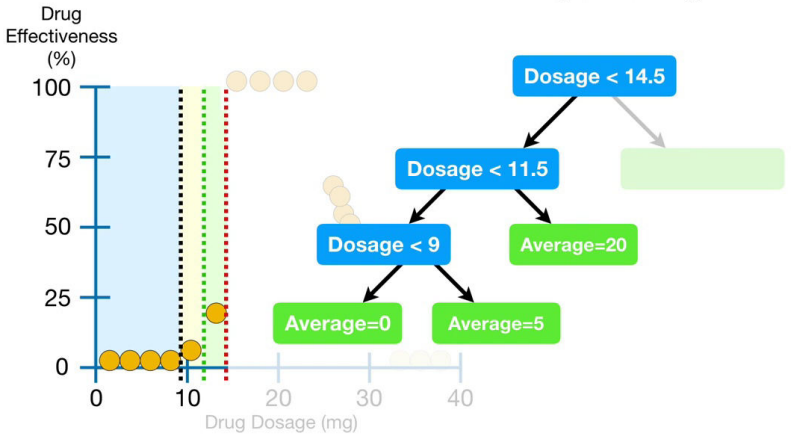

These 4 observations all have 0% Drug Effectiveness…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5
0
10
20
30
40
Drug Dosage (mg)


…and that's exactly what the tree predicts.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
0
10
20
30
40
Drug Dosage (mg)

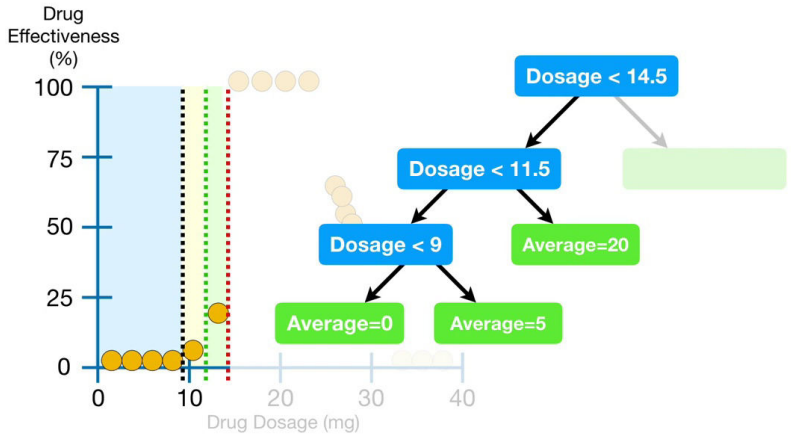

When a model fits the training data perfectly, it probably means it is overfit and will not perform well with new data.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5
0
10
20
30
40
Drug Dosage (mg)


In Machine Learning Lingo, the model has no Bias, but potentially large Variance.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5
0
10
20
30
40
Drug Dosage (mg)

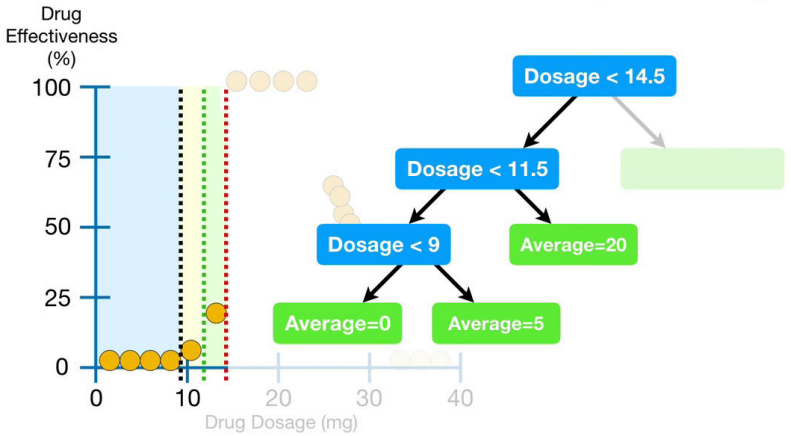
Is there a way to prevent our tree from overfitting the training data?



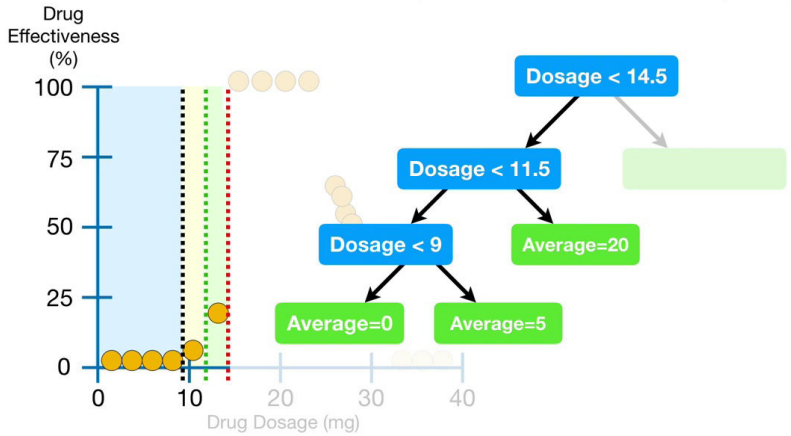
Yes, there are a bunch of techniques.

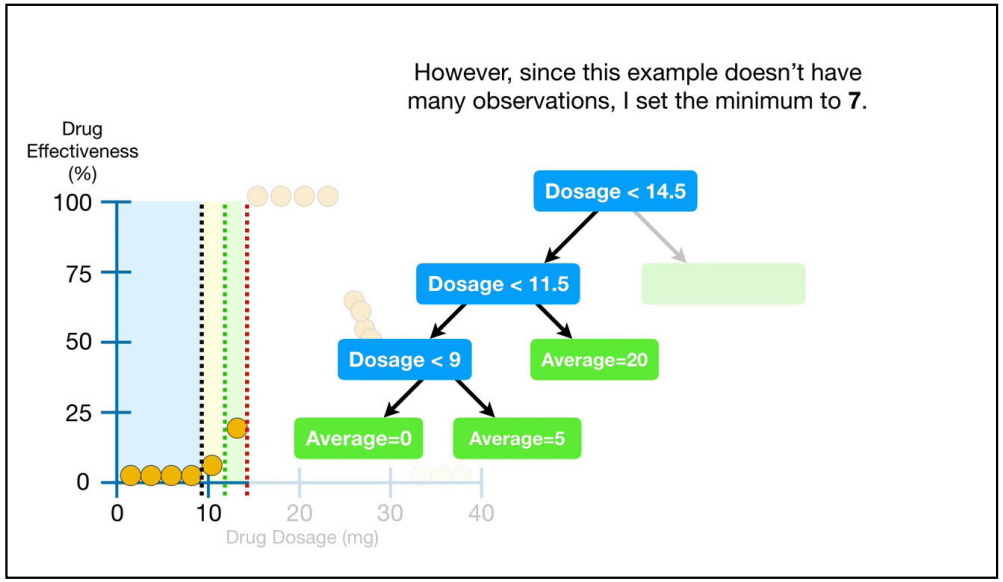


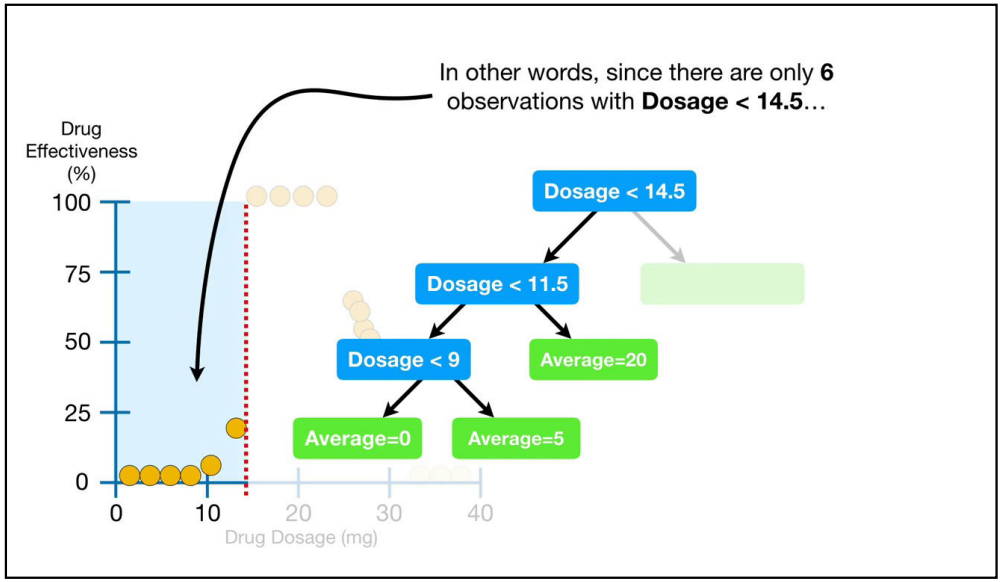
The simplest is to only split observations when there are more than some minimum number.

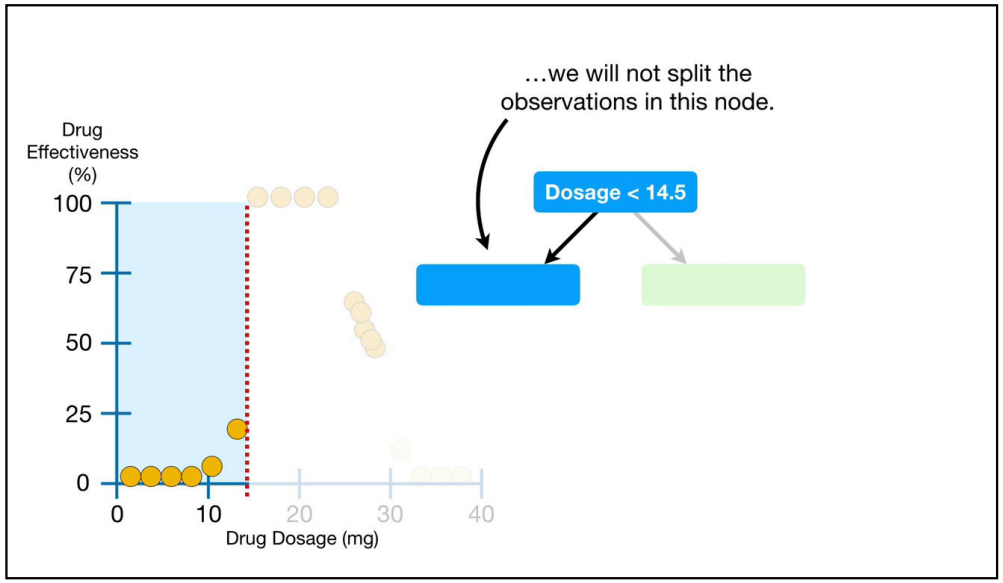


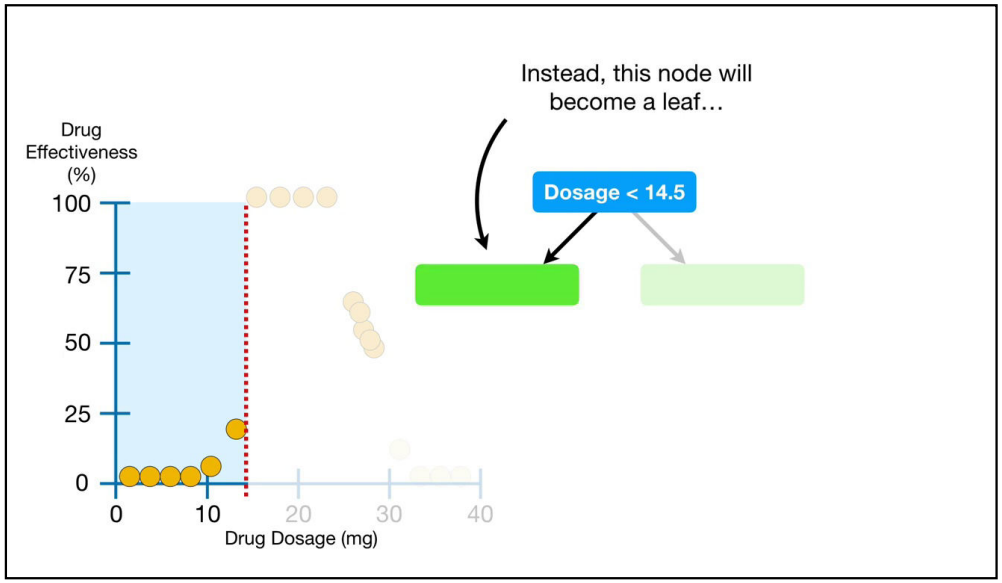
Typically, the minimum number of observations to allow for a split is **20**.

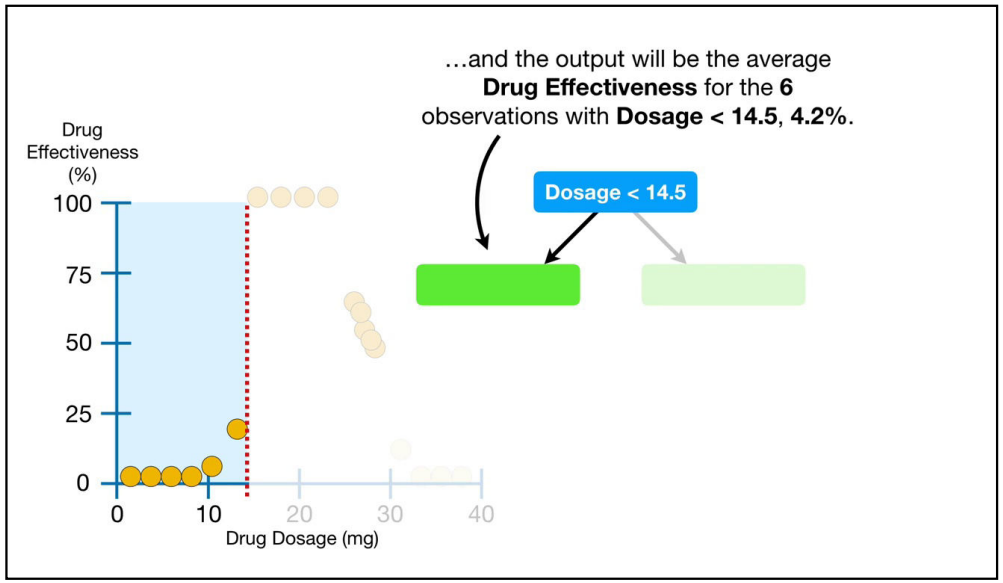


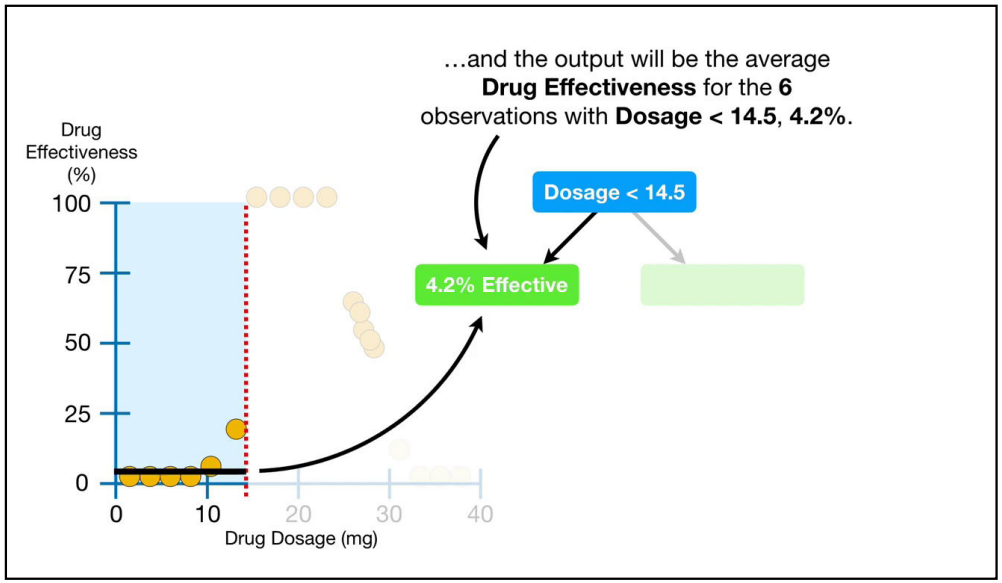

However, since this example doesn't have many observations, I set the minimum to 7.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5
0
10
20
30
40
Drug Dosage (mg)

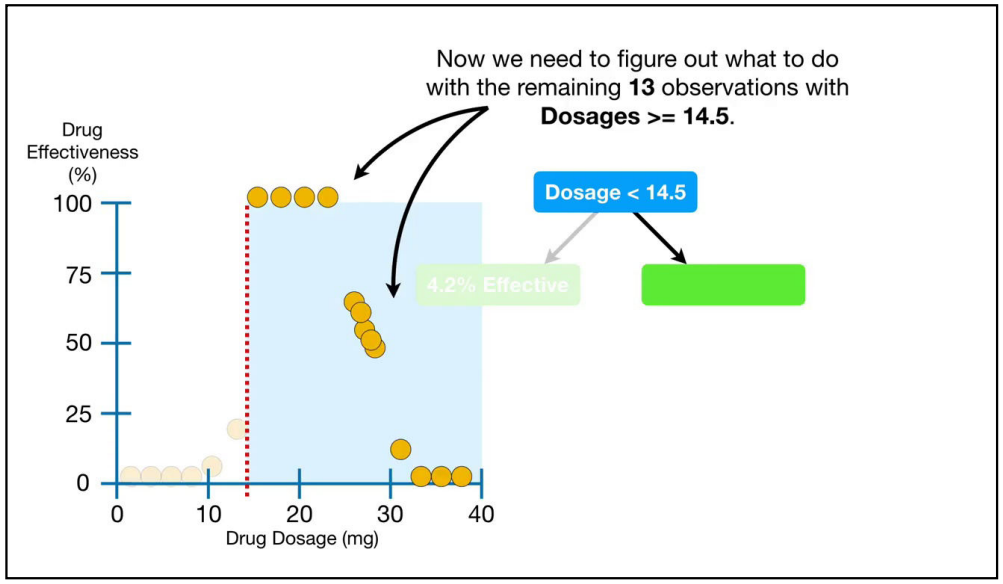

In other words, since there are only 6 observations with Dosage < 14.5…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
Dosage < 11.5
Dosage < 9
Average=20
Average=0
Average=5
0
10
20
30
40
Drug Dosage (mg)

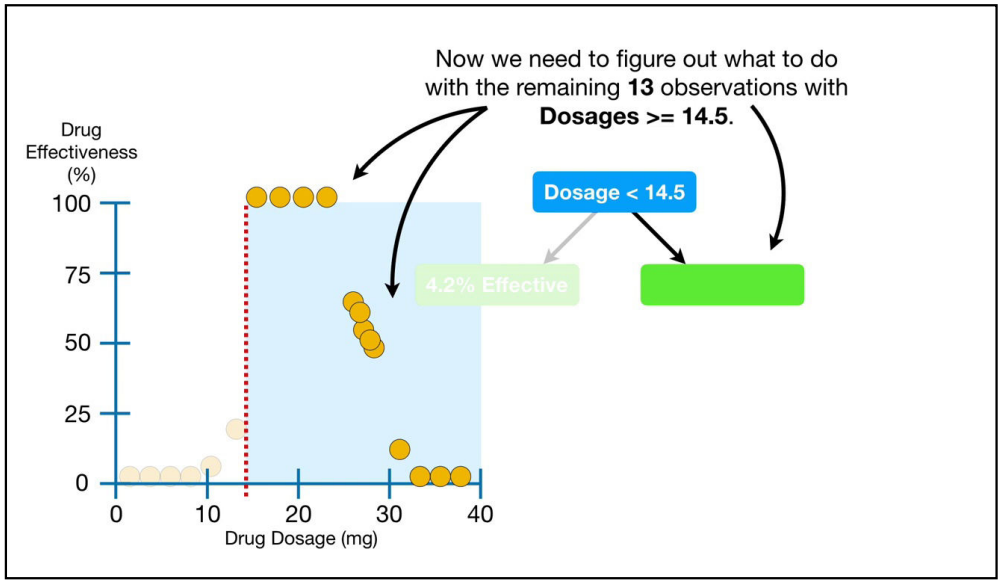

…we will not split the observations in this node.
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
0
10
20
30
40
Drug Dosage (mg)

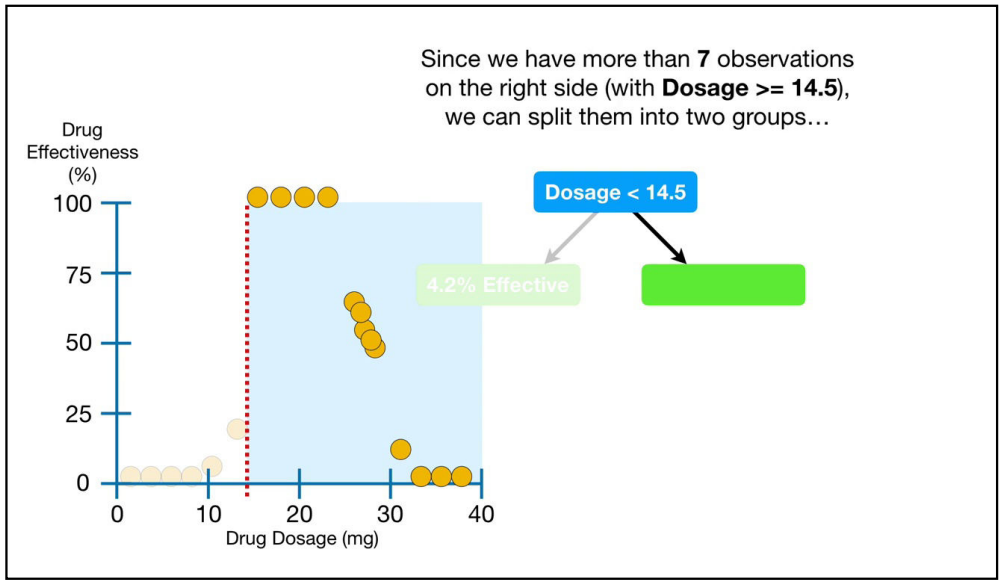

Instead, this node will become a leaf…
Drug Effectiveness (%)
100
75
50
25
0
Dosage < 14.5
0
10
20
30
40
Drug Dosage (mg)

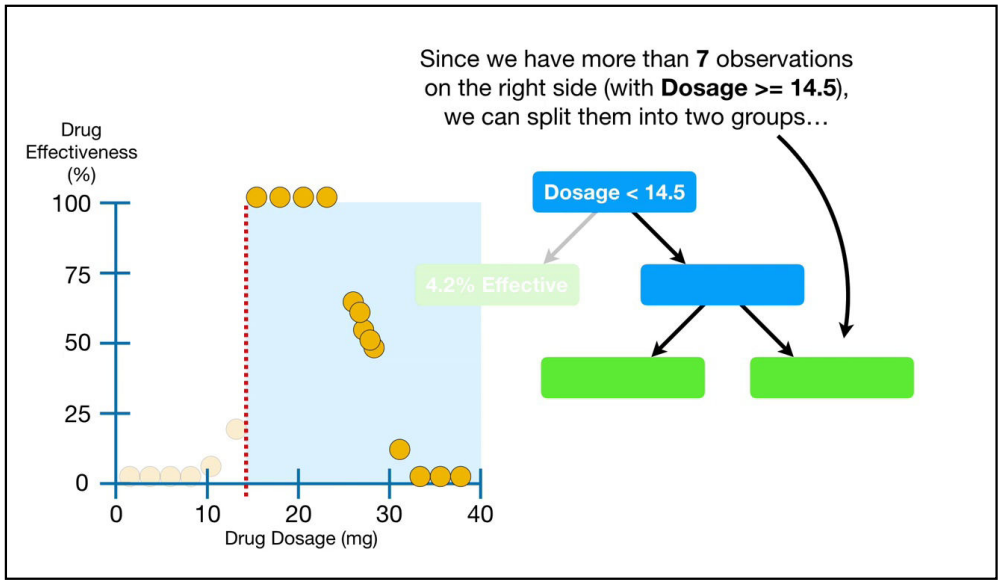

…and the output will be the average
Drug Effectiveness for the **6**
observations with **Dosage < 14.5**, **4.2%**.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5

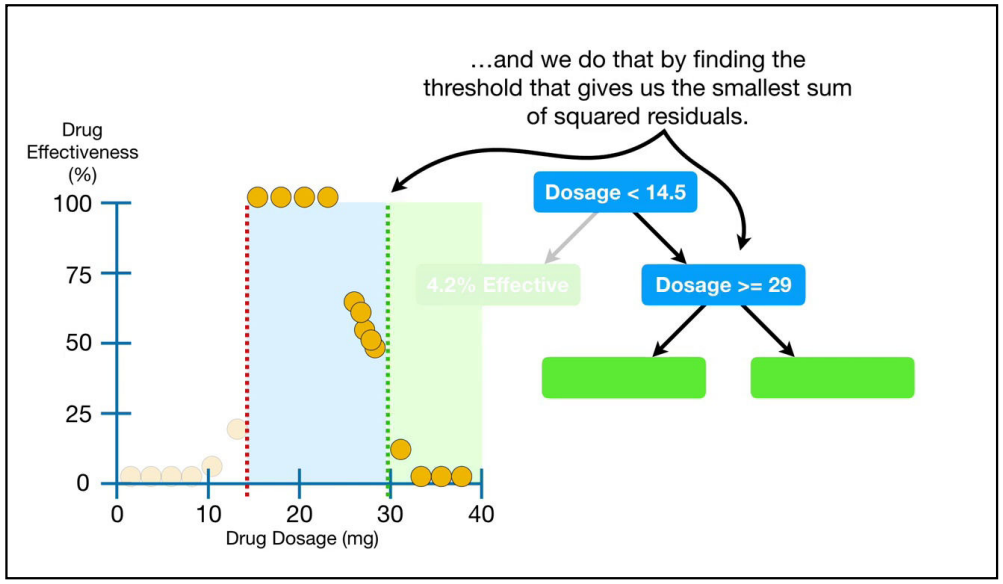

…and the output will be the average
Drug Effectiveness for the **6**
observations with **Dosage < 14.5**, **4.2%**.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective

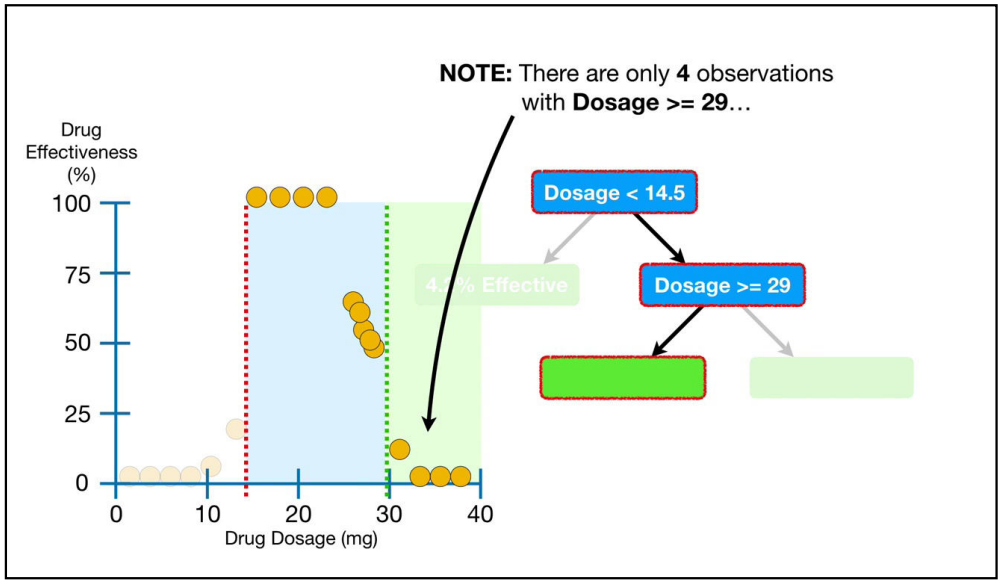

Now we need to figure out what to do
with the remaining **13** observations with
Dosages >= 14.5.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective

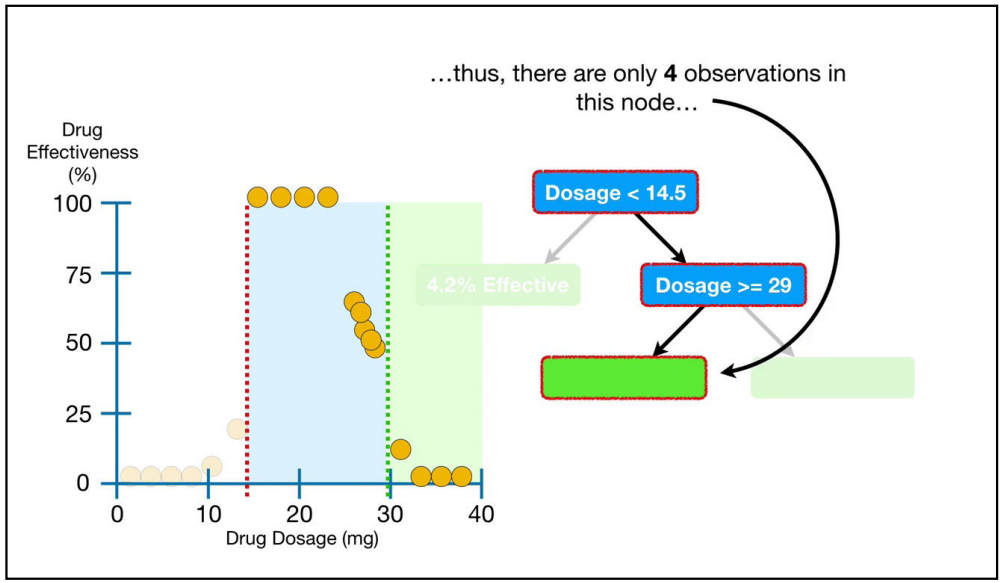

Now we need to figure out what to do
with the remaining **13** observations with
Dosages >= 14.5.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective

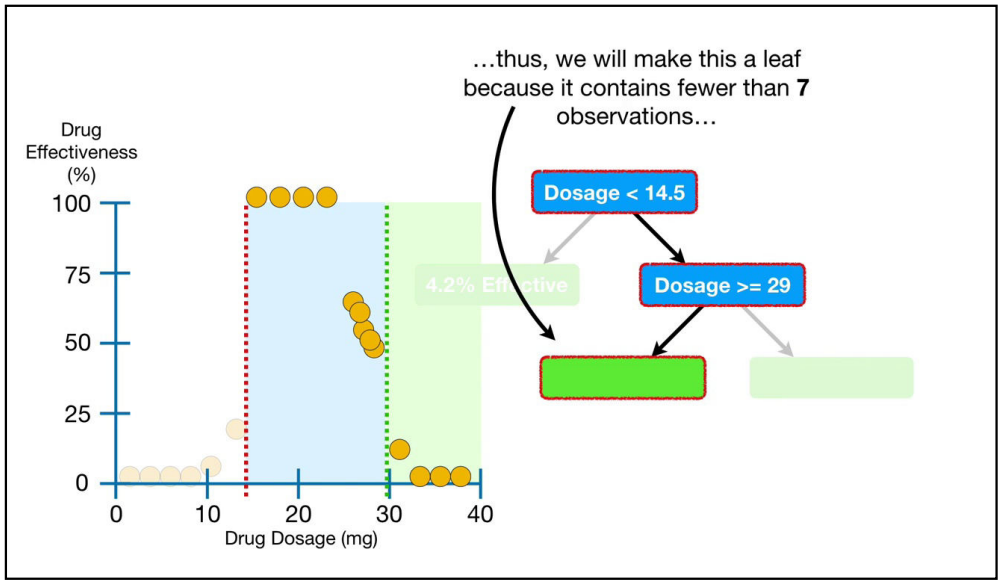

Since we have more than **7** observations on the right side (with **Dosage >= 14.5**), we can split them into two groups…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective

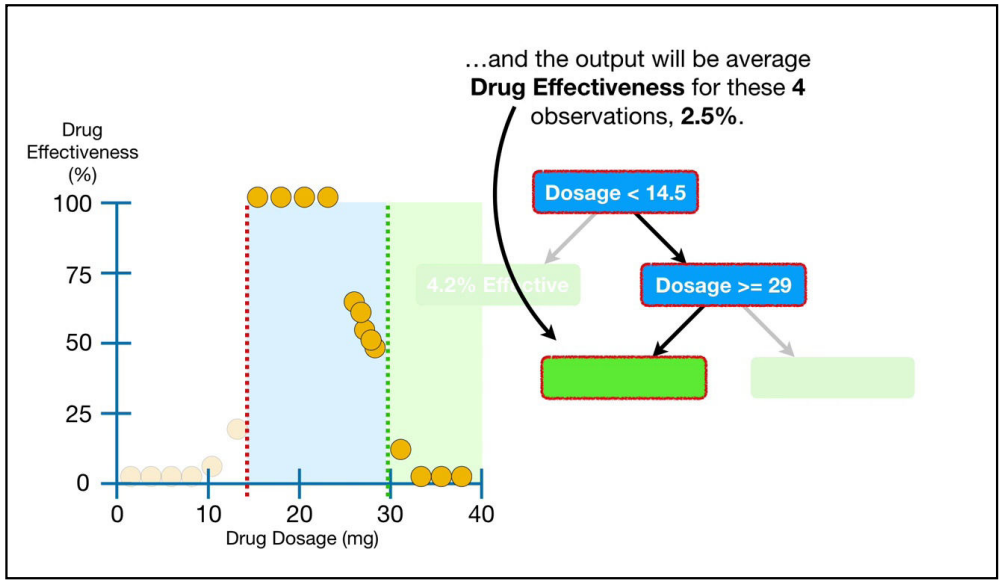

Since we have more than **7** observations on the right side (with **Dosage >= 14.5**), we can split them into two groups…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective

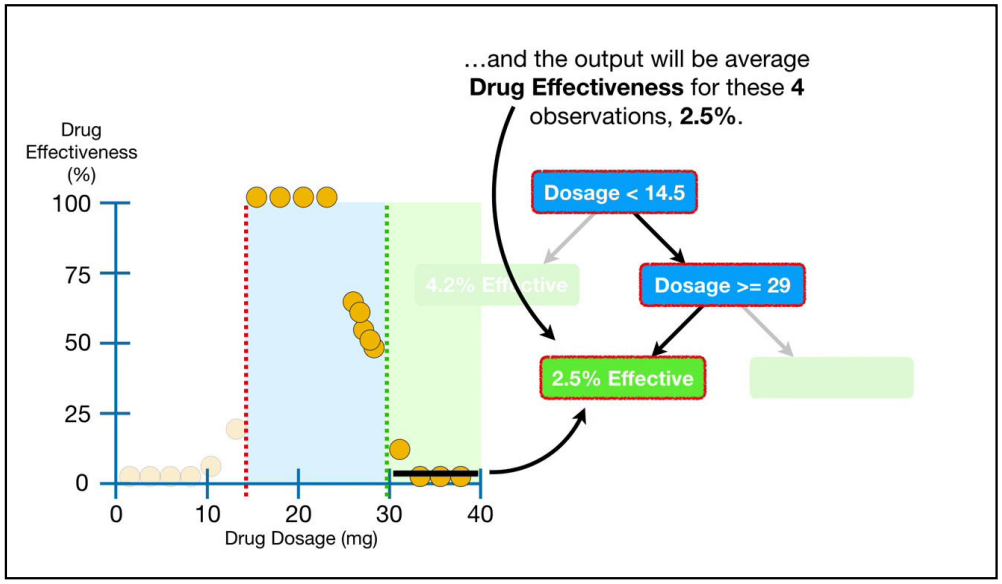

…and we do that by finding the threshold that gives us the smallest sum of squared residuals.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29

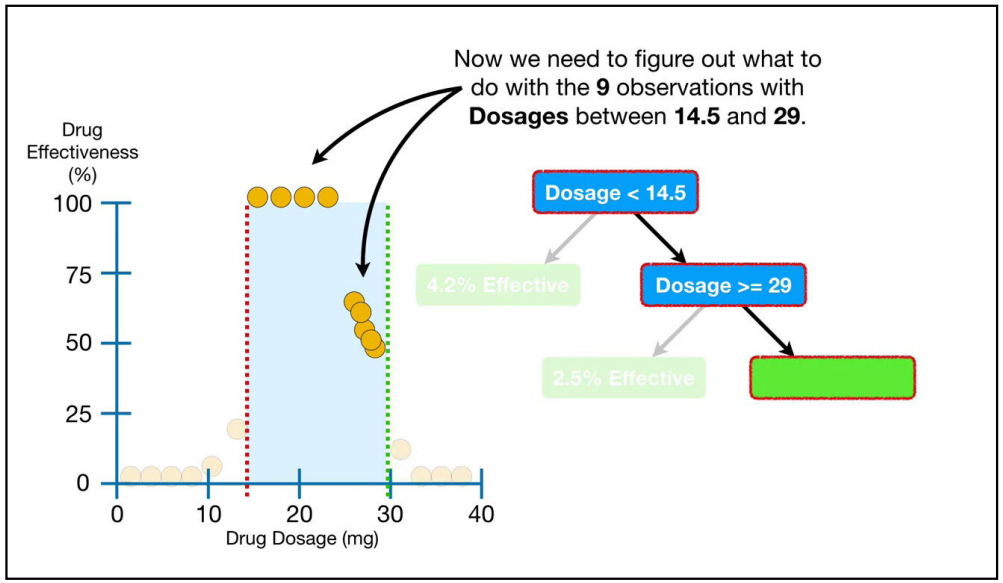

NOTE: There are only **4** observations with **Dosage >= 29**…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage >= 29

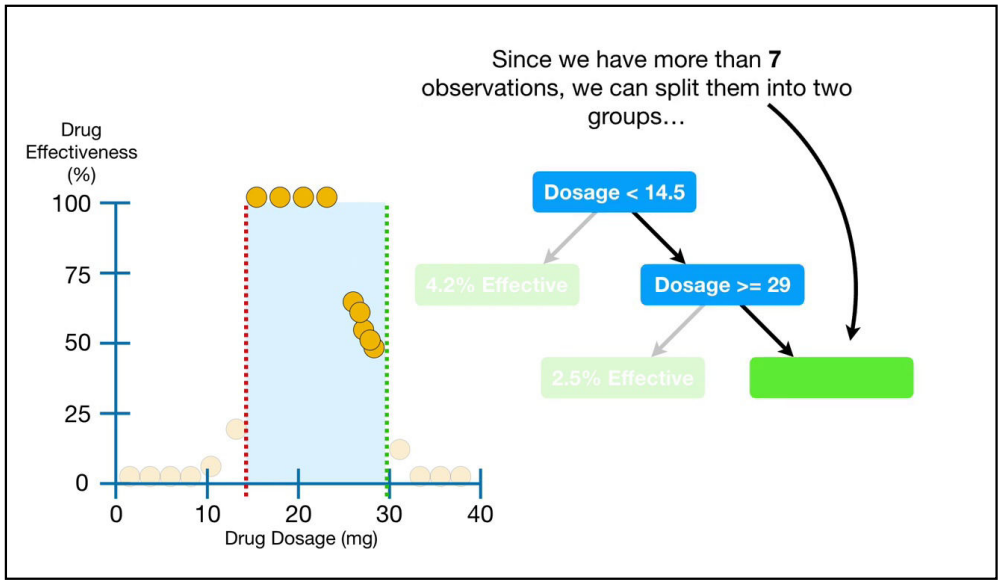

…thus, there are only **4** observations in this node…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
4.2% Effective
Dosage < 14.5
Dosage >= 29

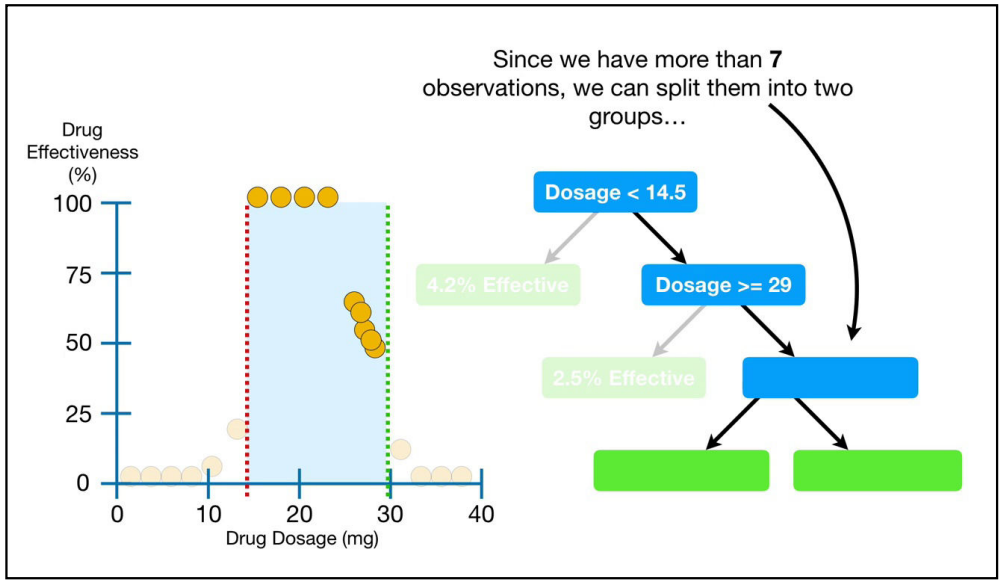

…thus, we will make this a leaf because it contains fewer than **7** observations…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage >= 29

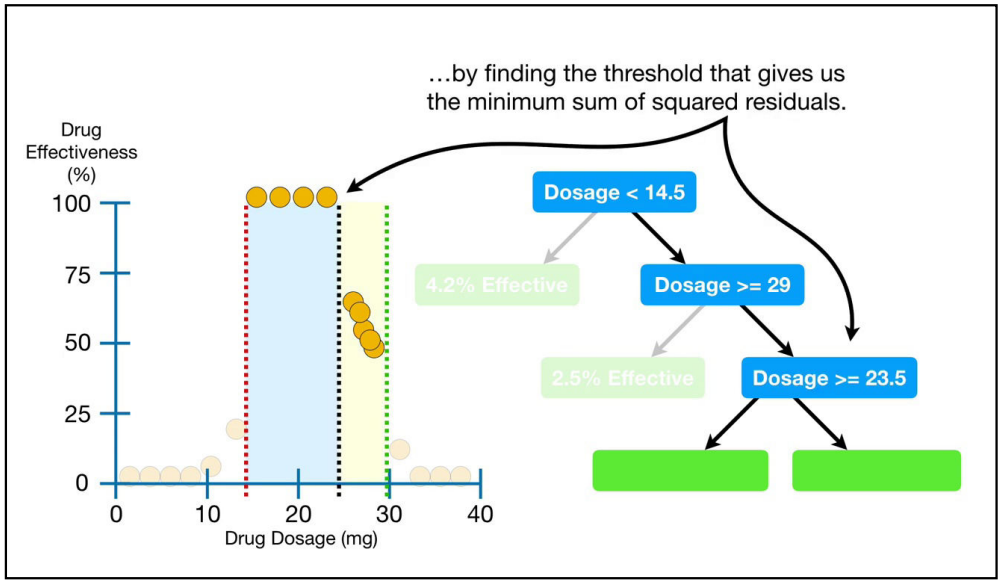

…and the output will be average **Drug Effectiveness** for these **4** observations, **2.5%**.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage >= 29

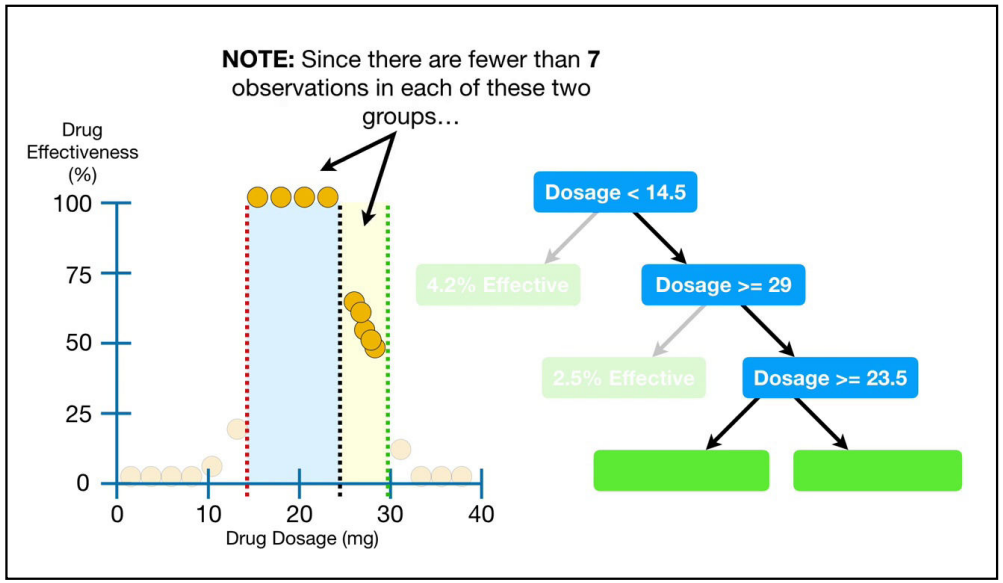

…and the output will be average **Drug Effectiveness** for these **4** observations, **2.5%**.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
Dosage >= 29
2.5% Effective

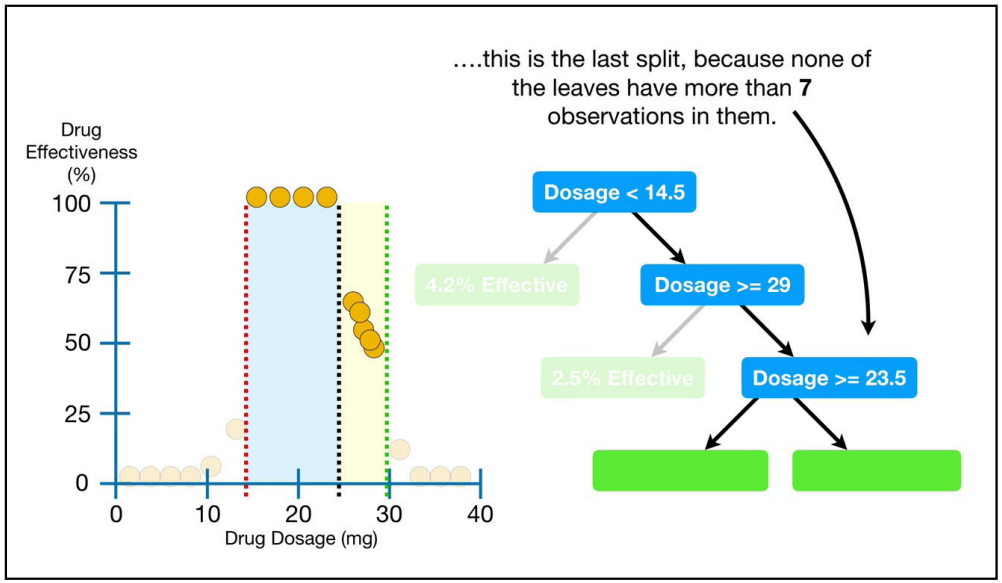

Now we need to figure out what to do with the **9** observations with **Dosages** between **14.5** and **29**.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective

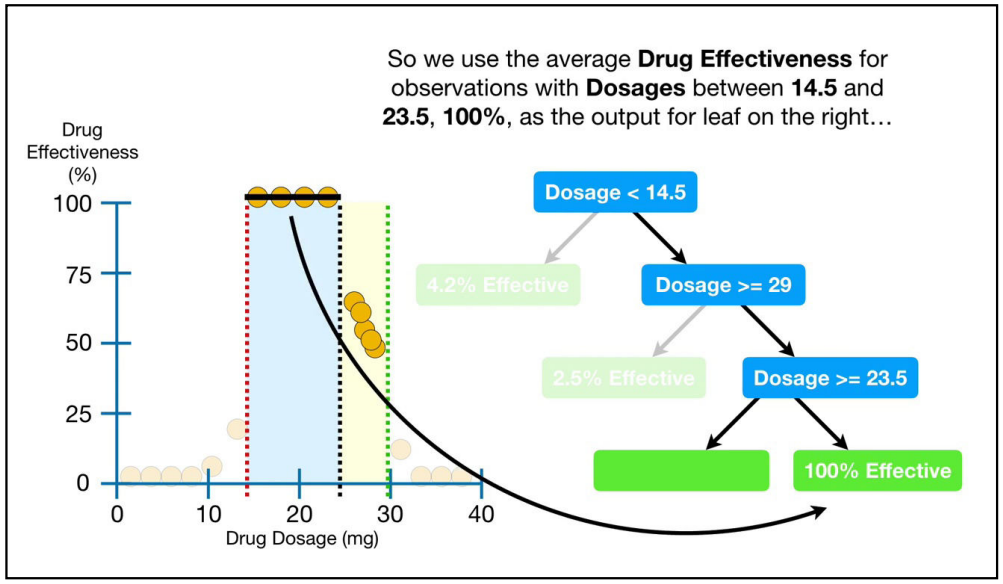

Since we have more than **7** observations, we can split them into two groups…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective

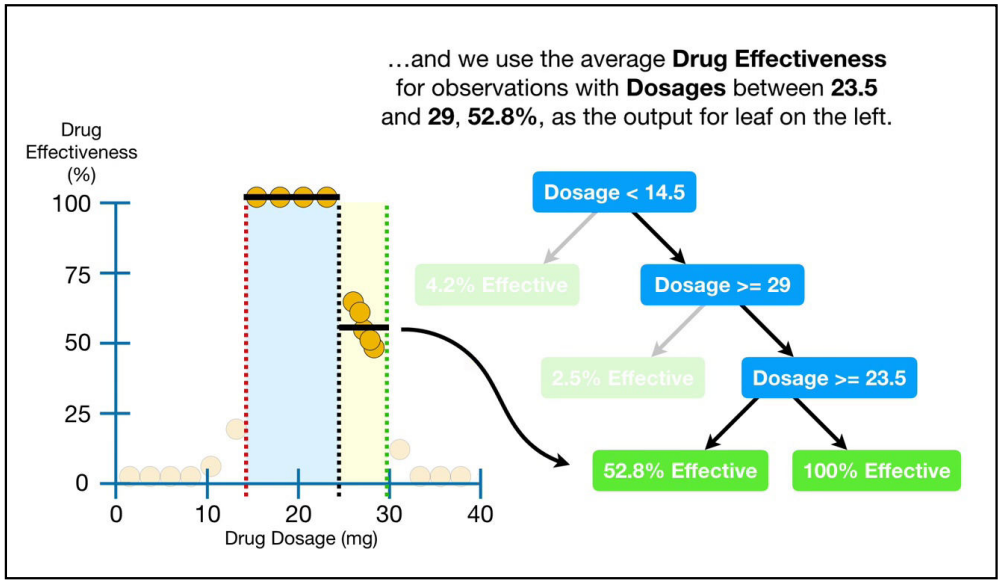

Since we have more than **7** observations, we can split them into two groups…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective


…by finding the threshold that gives us the minimum sum of squared residuals.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5

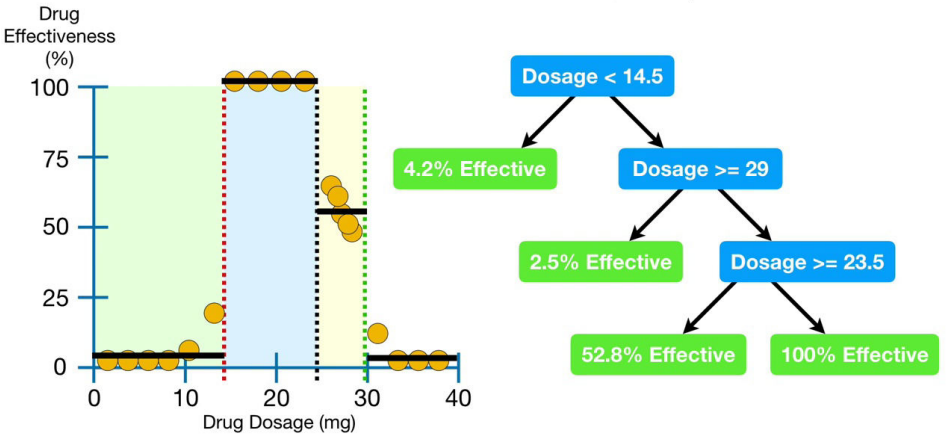

NOTE: Since there are fewer than **7** observations in each of these two groups…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5


….this is the last split, because none of the leaves have more than **7** observations in them.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5

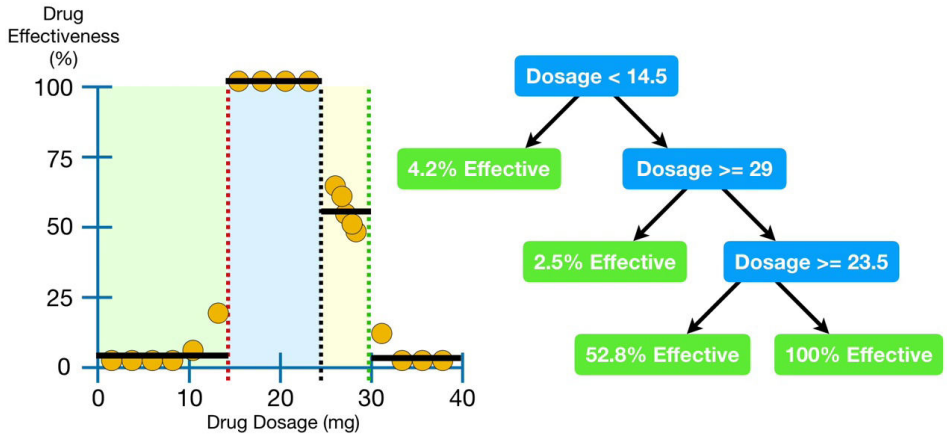

So we use the average **Drug Effectiveness** for observations with **Dosages** between **14.5** and **23.5**, **100%**, as the output for leaf on the right…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
100% Effective


…and we use the average **Drug Effectiveness** for observations with **Dosages** between **23.5** and **29**, **52.8%**, as the output for leaf on the left.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Dosage < 14.5
4.2% Effective
Dosage >= 29
2.5% Effective
Dosage >= 23.5
52.8% Effective
100% Effective

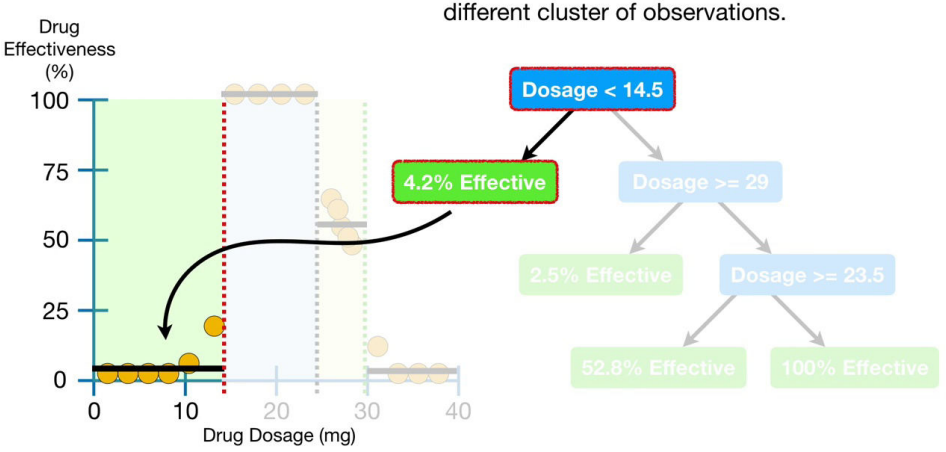
Since no leaf has more than **7** observations in it,…



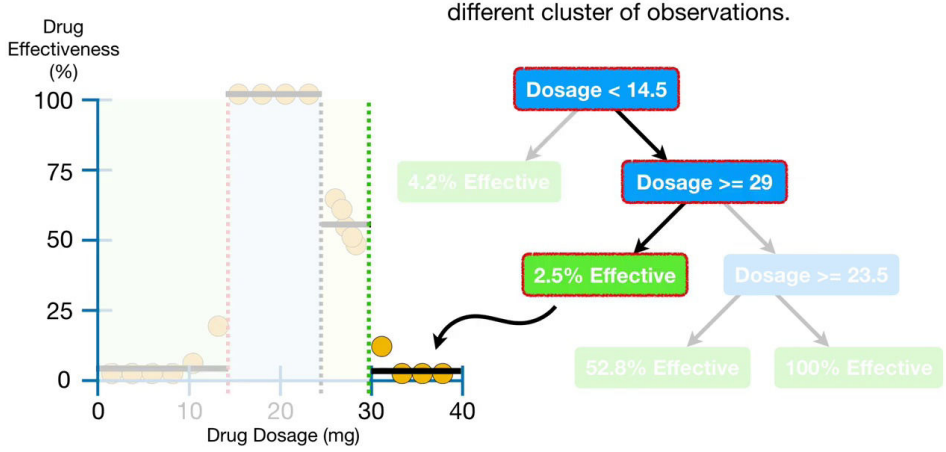
…we're done building the tree…



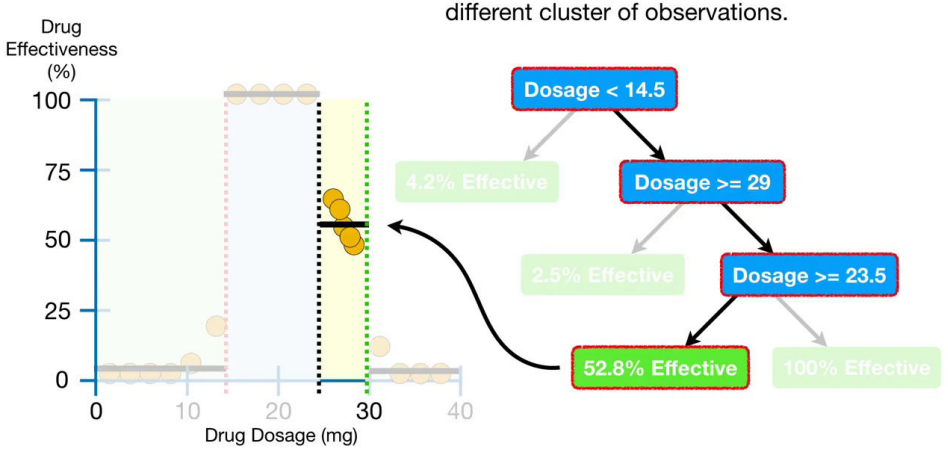
…and each leaf corresponds to the average **Drug Effectiveness** from a different cluster of observations.



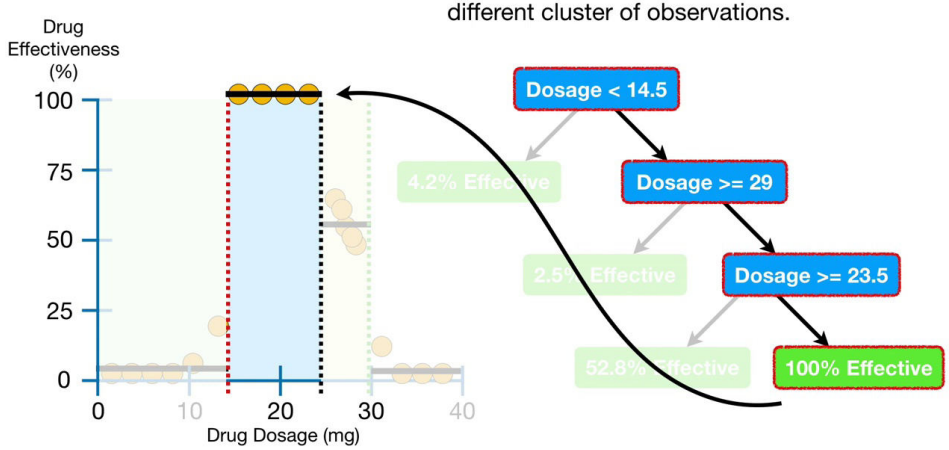
…and each leaf corresponds to the average **Drug Effectiveness** from a different cluster of observations.



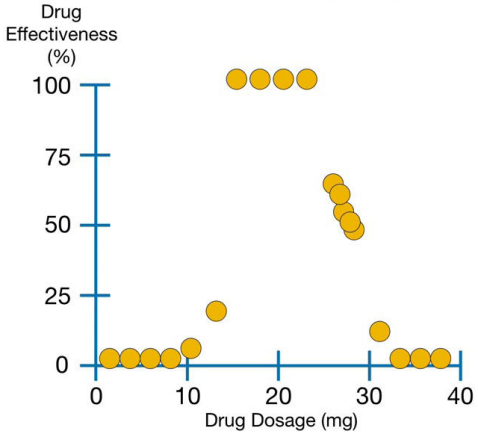
…and each leaf corresponds to the average **Drug Effectiveness** from a different cluster of observations.



…and each leaf corresponds to the average **Drug Effectiveness** from a different cluster of observations.



So far we have built a tree using a single predictor, **Dosage**, to predict **Drug Effectiveness**.



Dosage	Drug Effect.
10	58
20	60
35	57
5	44
etc…	etc…

Now let's talk about how to build a tree to predict **Drug Effectiveness** using a bunch of predictors.

Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

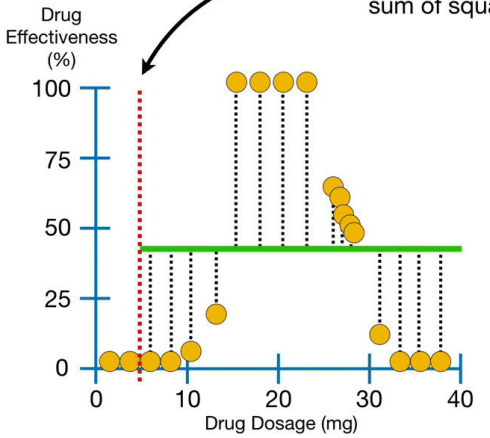
Just like before, we will start by using **Dosage** to predict **Drug Effectiveness**.

Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

Just like before, we will start by using **Dosage** to predict **Drug Effectiveness**.

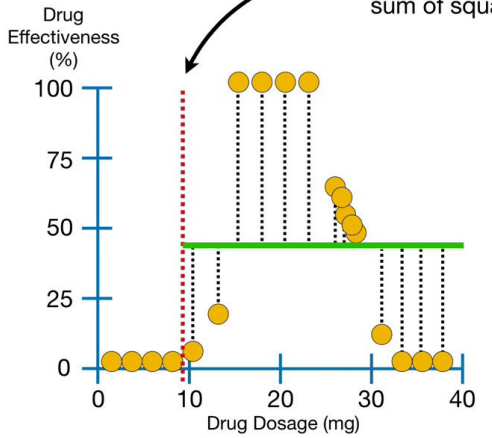
Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

Thus, just like before, we will try different thresholds for **Dosage** and calculate the sum of squared residuals at each step…



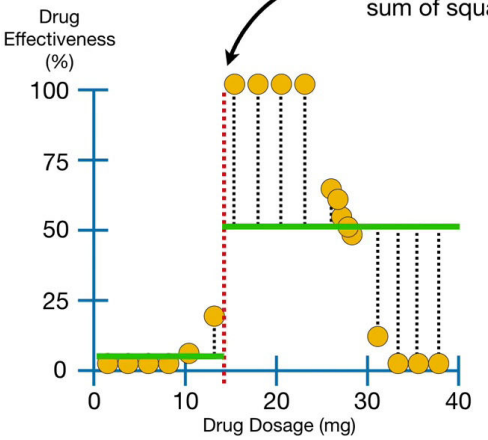
Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

Thus, just like before, we will try different thresholds for **Dosage** and calculate the sum of squared residuals at each step…



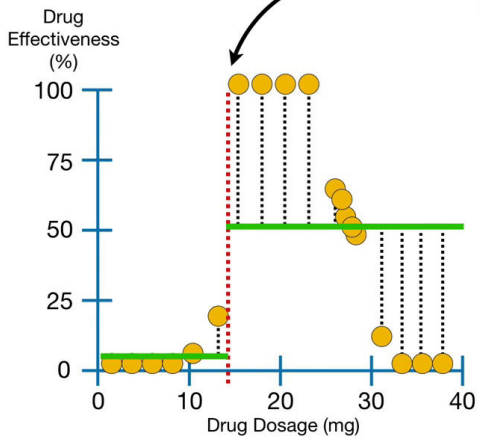
Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

Thus, just like before, we will try different thresholds for **Dosage** and calculate the sum of squared residuals at each step…

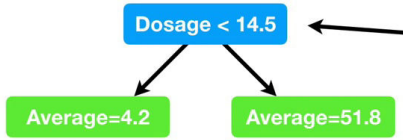


Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

…and pick the threshold that gives us the minimum sum of squared residuals.



Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…



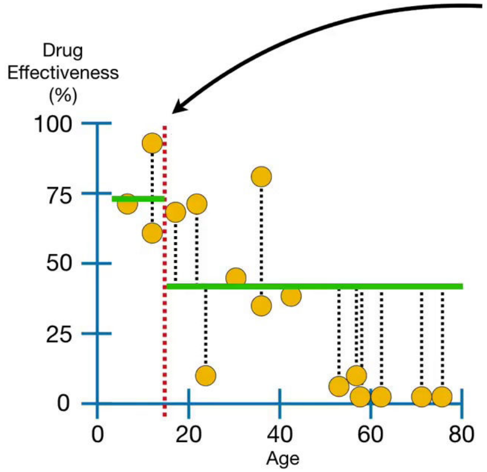
The best threshold becomes a *candidate* for the root.

Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

Now we focus on using **Age** to predict **Drug Effectiveness**.

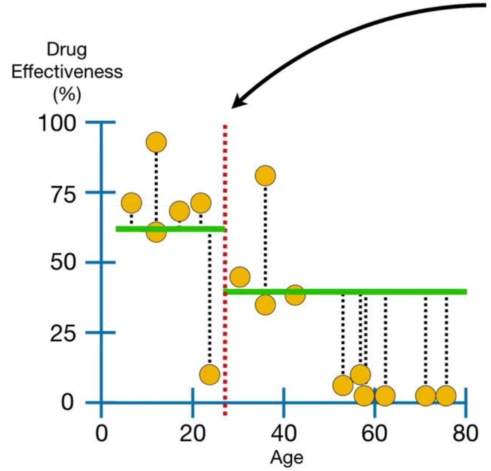
Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

Just like with **Dosage**, we try different thresholds for **Age** and calculate the sum of squared residuals at each step…



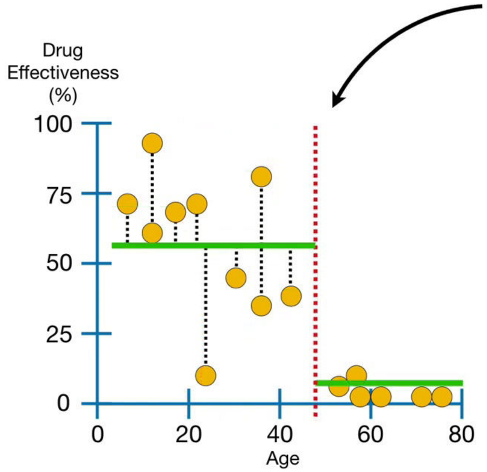
Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

Just like with **Dosage**, we try different thresholds for **Age** and calculate the sum of squared residuals at each step…



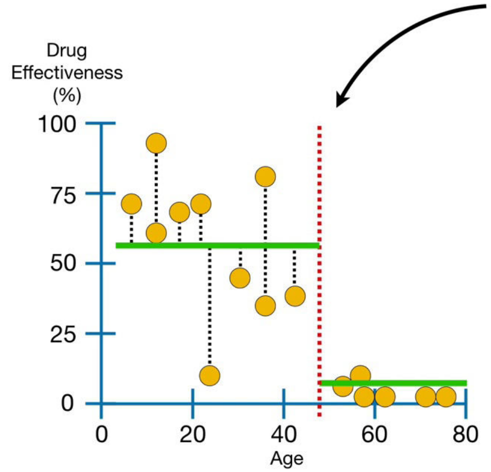
Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

Just like with **Dosage**, we try different thresholds for **Age** and calculate the sum of squared residuals at each step…

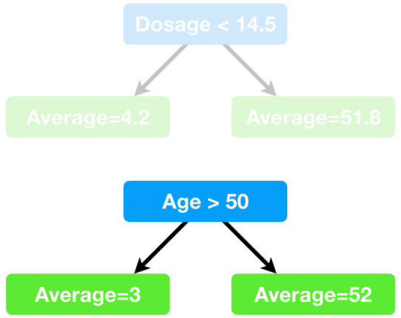


Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

…and pick the one that gives us the minimum sum of squared residuals.



Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…



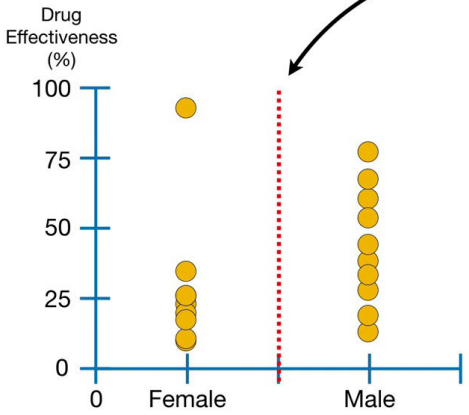
The best threshold becomes another *candidate* for the root.

Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

Now we focus on using **Sex** to predict **Drug Effectiveness**.

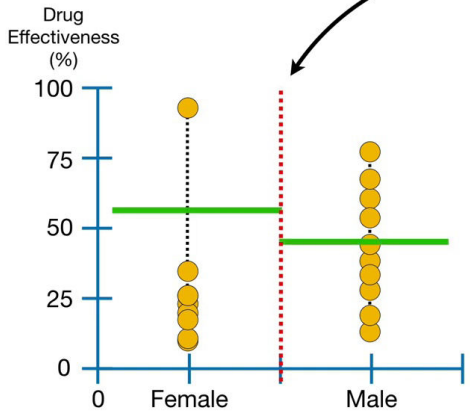
Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

With **Sex**, there is only one threshold to try…

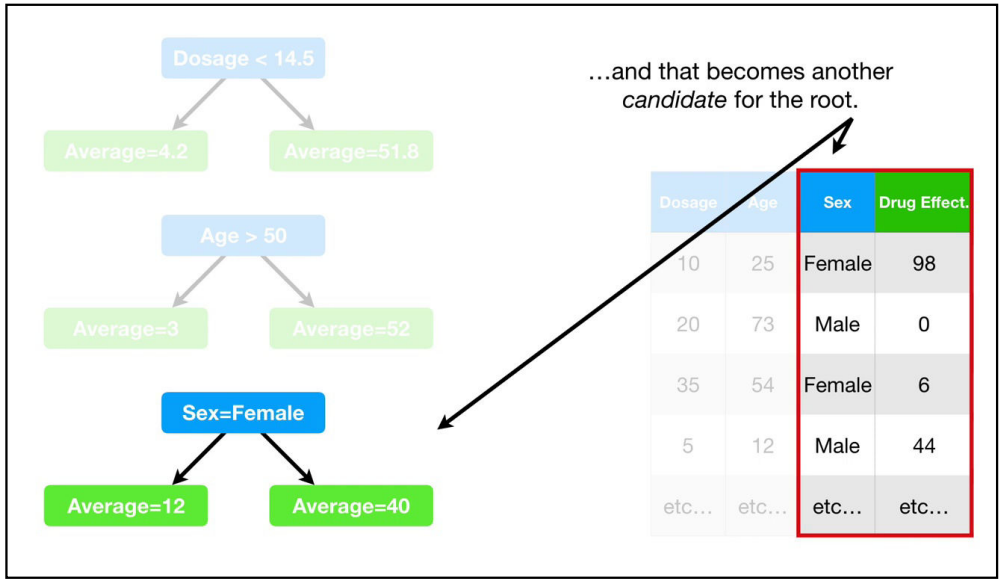


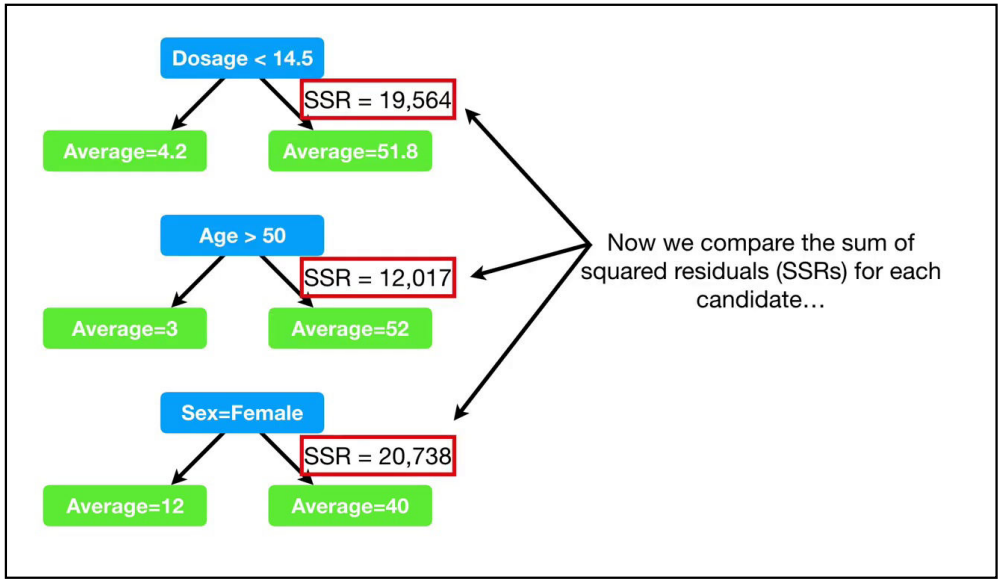
Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

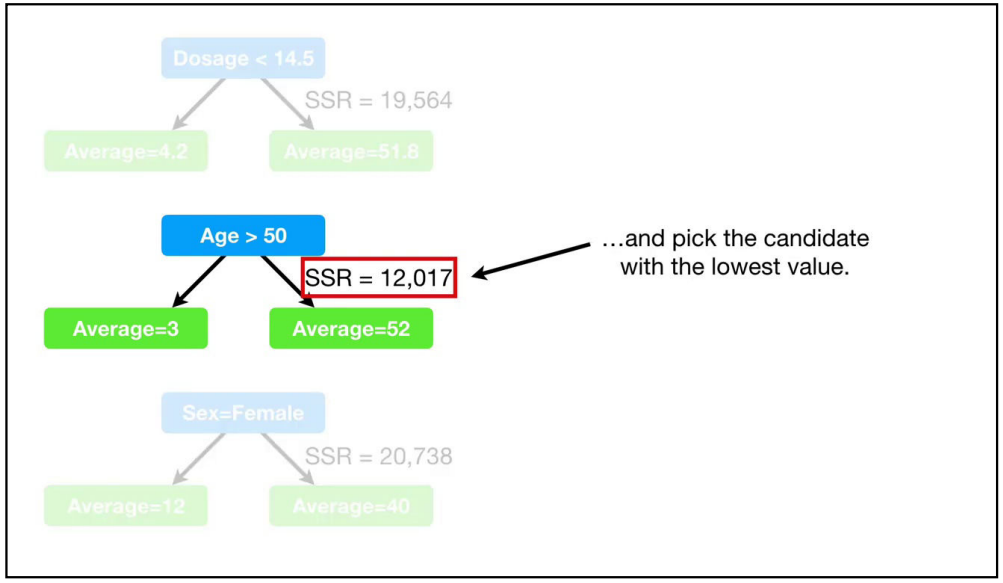
…so we use that threshold to calculate the sum of squared residuals…

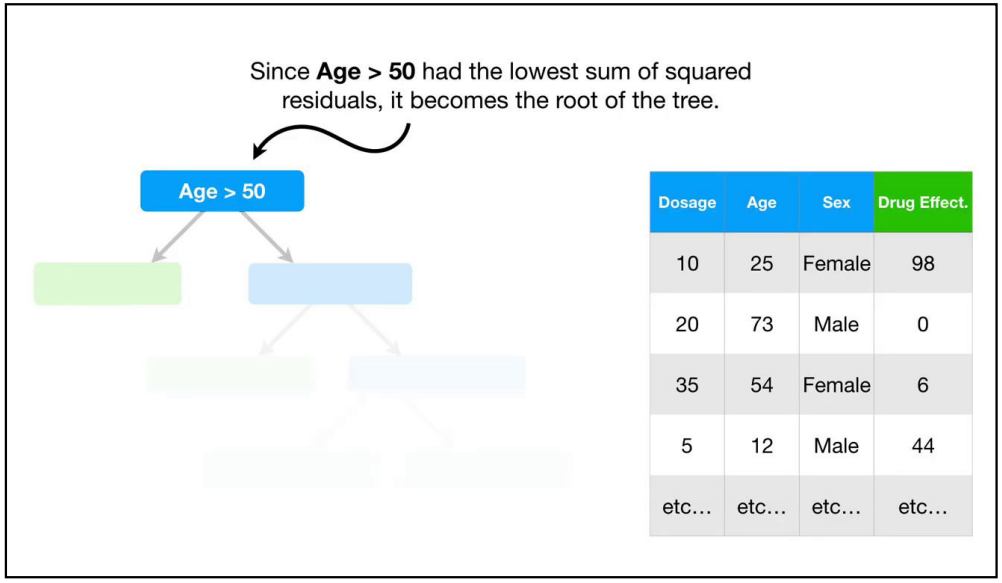


Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

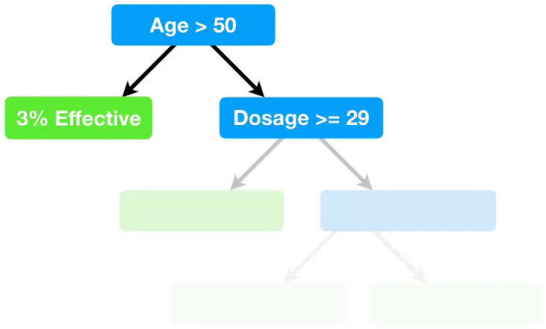

Dosage < 14.5
Average=4.2
Average=51.8
Age > 50
Average=3
Average=52
Sex=Female
Average=12
Average=40
…and that becomes another *candidate* for the root.
Dosage
Age
Sex
Drug Effect.
10
25
Female
98
20
73
Male
0
35
54
Female
6
5
12
Male
44
etc…
etc…
etc…
etc…


Dosage < 14.5
SSR = 19,564
Average=4.2
Average=51.8
Age > 50
SSR = 12,017
Average=3
Average=52
Sex=Female
SSR = 20,738
Average=12
Average=40
Now we compare the sum of squared residuals (SSRs) for each candidate…


Dosage < 14.5
SSR = 19,564
Average=4.2
Average=51.8
Age > 50
SSR = 12,017
Average=3
Average=52
Sex=Female
SSR = 20,738
Average=12
Average=40
…and pick the candidate with the lowest value.

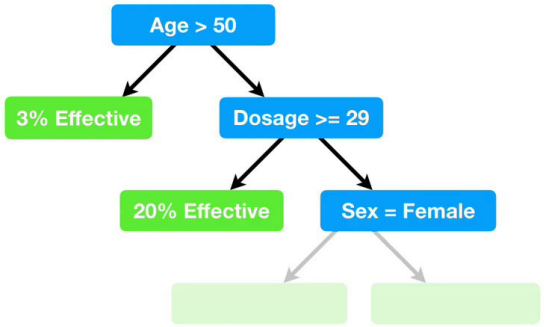

Since **Age > 50** had the lowest sum of squared residuals, it becomes the root of the tree.
Age > 50
Dosage
Age
Sex
Drug Effect.
10
25
Female
98
20
73
Male
0
35
54
Female
6
5
12
Male
44
etc…
etc…
etc…
etc…

Then we grow the tree just like before, except now we compare the lowest sum of squared residuals from each predictor.



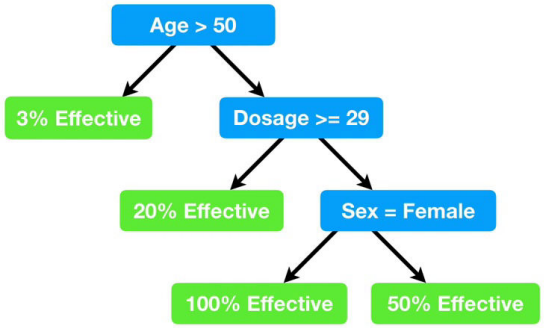
Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

Then we grow the tree just like before, except now we compare the lowest sum of squared residuals from each predictor.



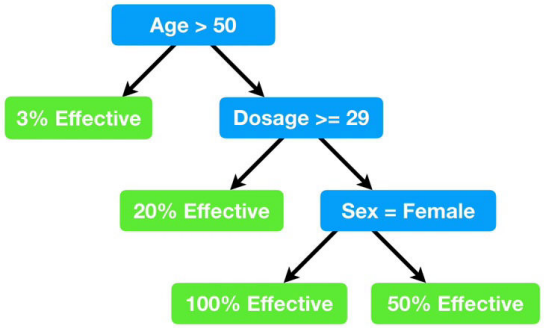
Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

Then we grow the tree just like before, except now we compare the lowest sum of squared residuals from each predictor.



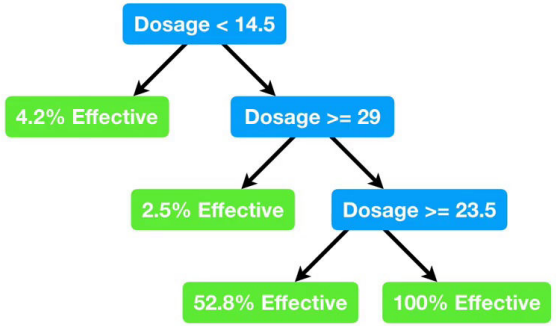
Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

And just like before, when a leaf has less than a minimum number of observations, which is usually **20**, but we are using **7**, we stop trying to divide them.

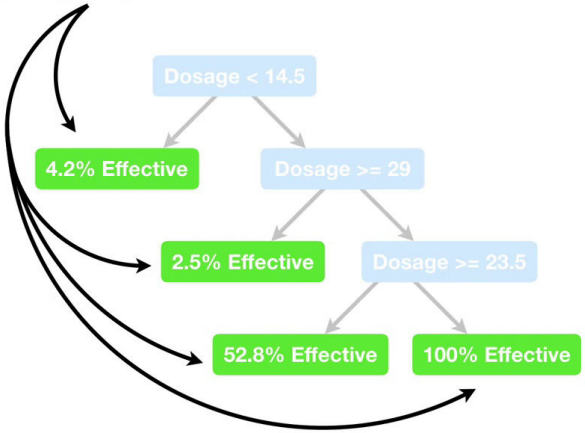


Dosage	Age	Sex	Drug Effect.
10	25	Female	98
20	73	Male	0
35	54	Female	6
5	12	Male	44
etc…	etc…	etc…	etc…

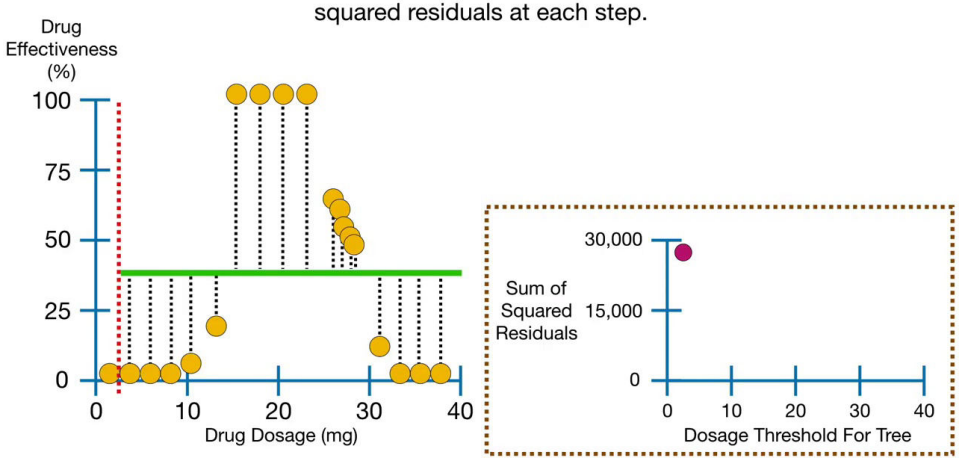
Regression Trees are a type of **Decision Tree.**



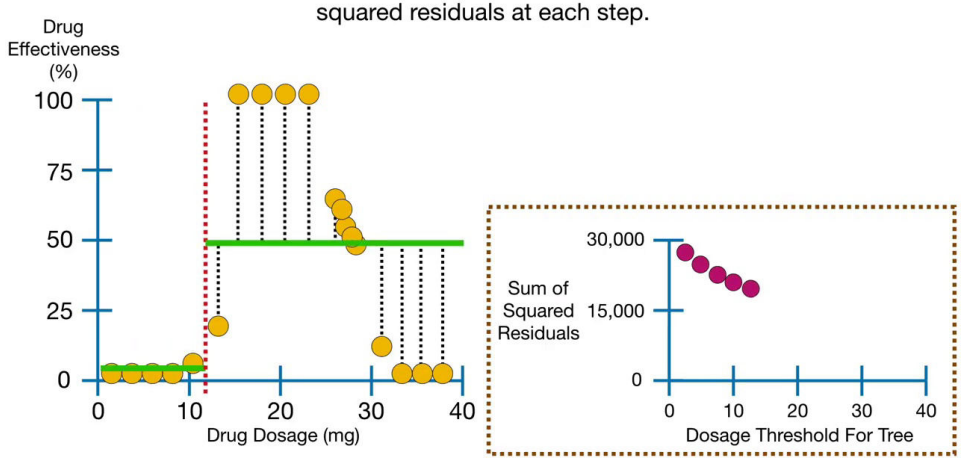
In a **Regression Tree**, each leaf represents a numeric value.

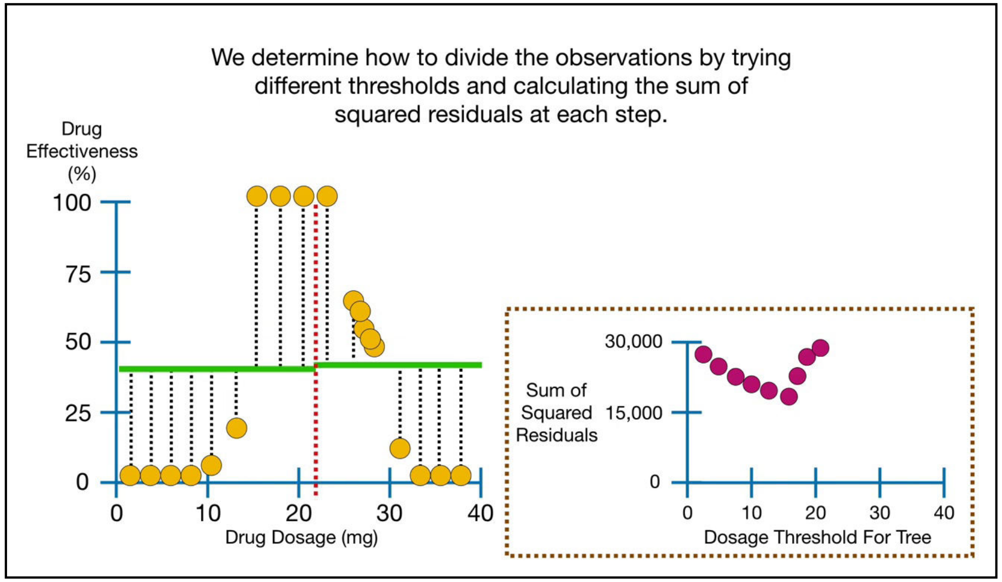


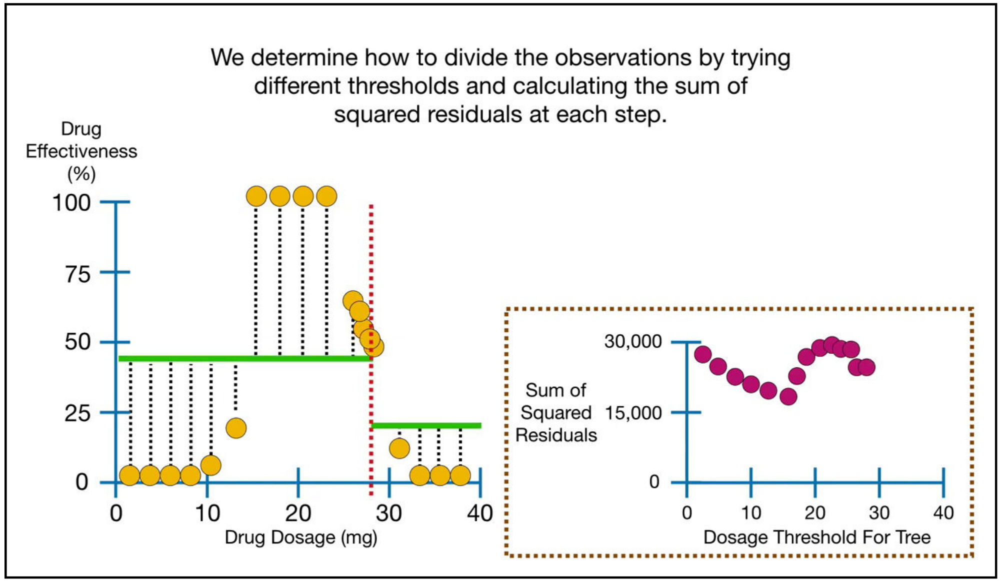
We determine how to divide the observations by trying different thresholds and calculating the sum of squared residuals at each step.

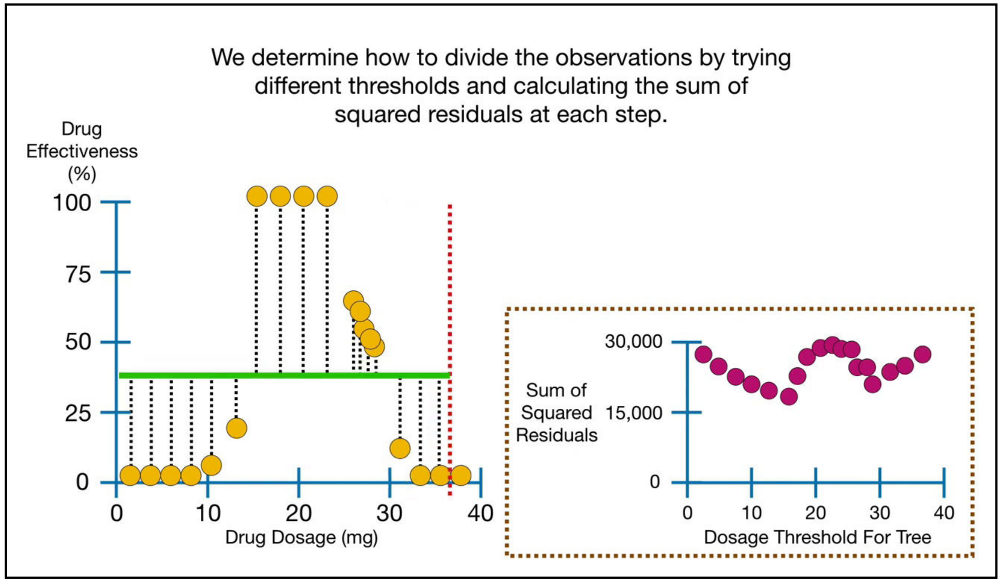


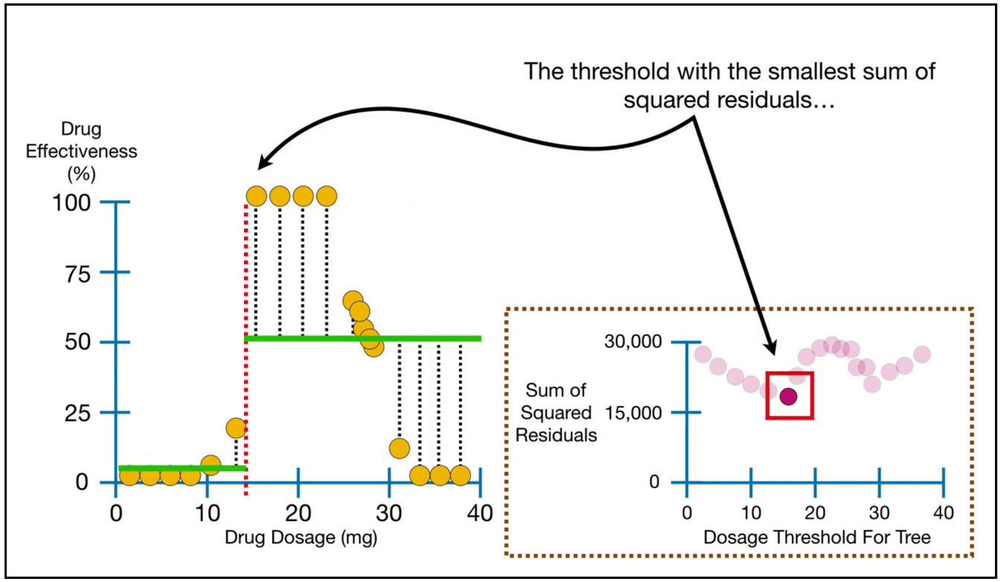
We determine how to divide the observations by trying different thresholds and calculating the sum of squared residuals at each step.

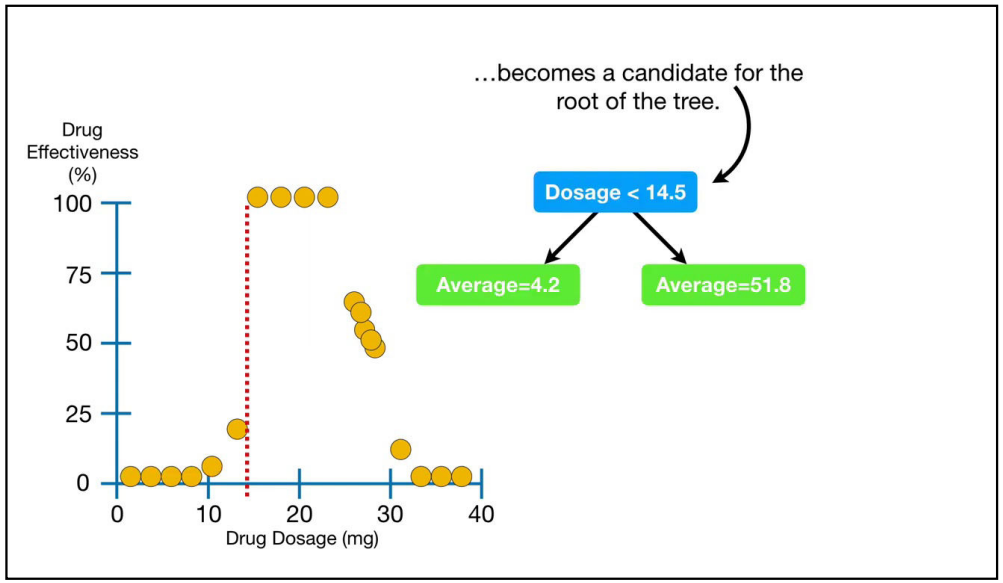


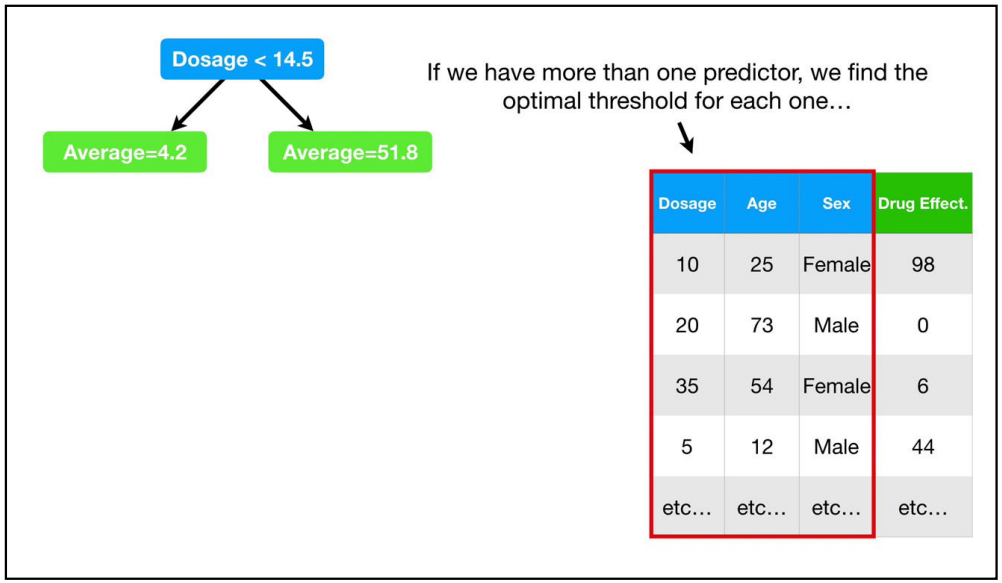

We determine how to divide the observations by trying different thresholds and calculating the sum of squared residuals at each step.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Sum of Squared Residuals
30,000
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

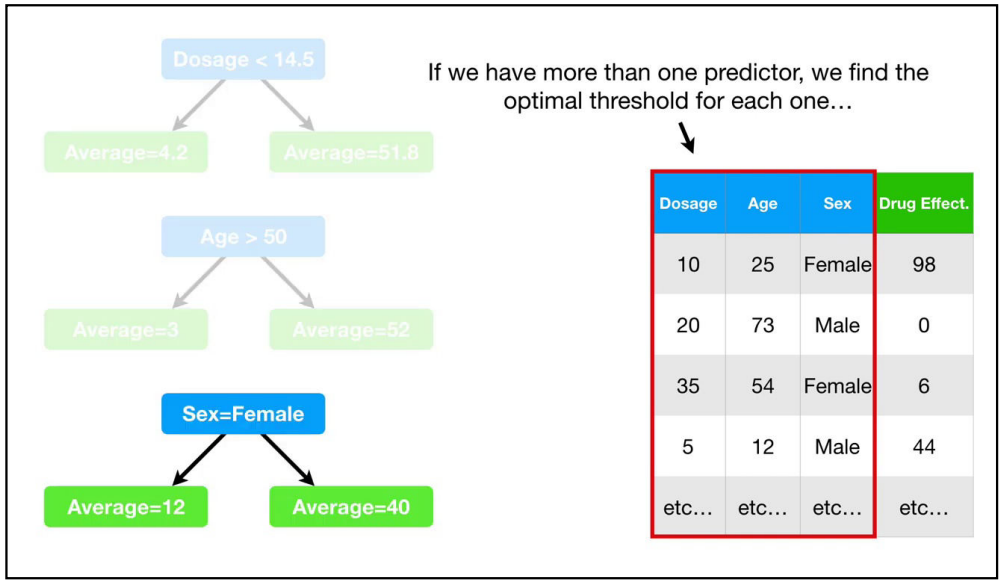

We determine how to divide the observations by trying different thresholds and calculating the sum of squared residuals at each step.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Sum of Squared Residuals
30,000
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

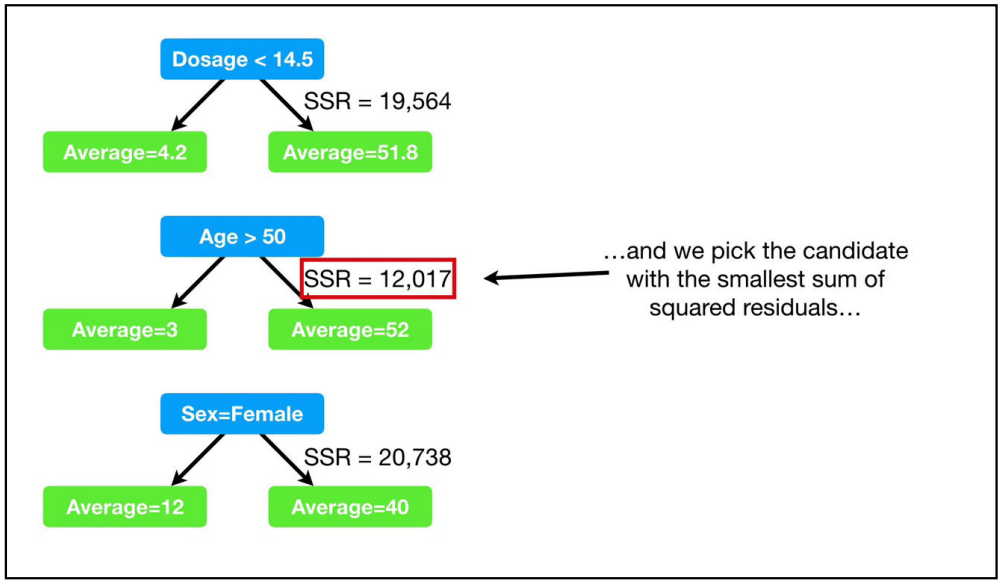

We determine how to divide the observations by trying different thresholds and calculating the sum of squared residuals at each step.
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Sum of Squared Residuals
30,000
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

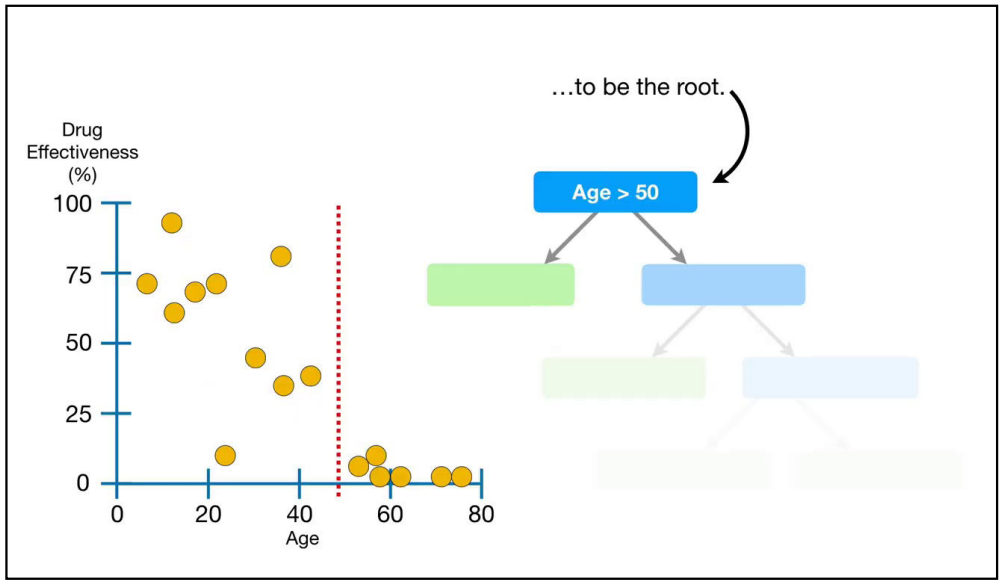

The threshold with the smallest sum of squared residuals…
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)
Sum of Squared Residuals
30,000
15,000
0
0
10
20
30
40
Dosage Threshold For Tree

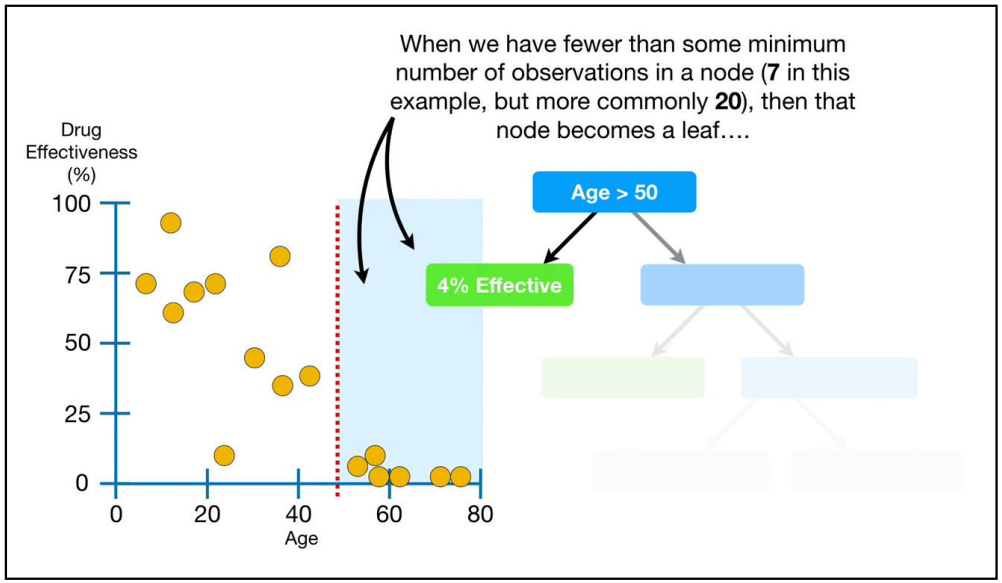

…becomes a candidate for the root of the tree.
Dosage < 14.5
Average=4.2
Average=51.8
Drug Effectiveness (%)
100
75
50
25
0
0
10
20
30
40
Drug Dosage (mg)

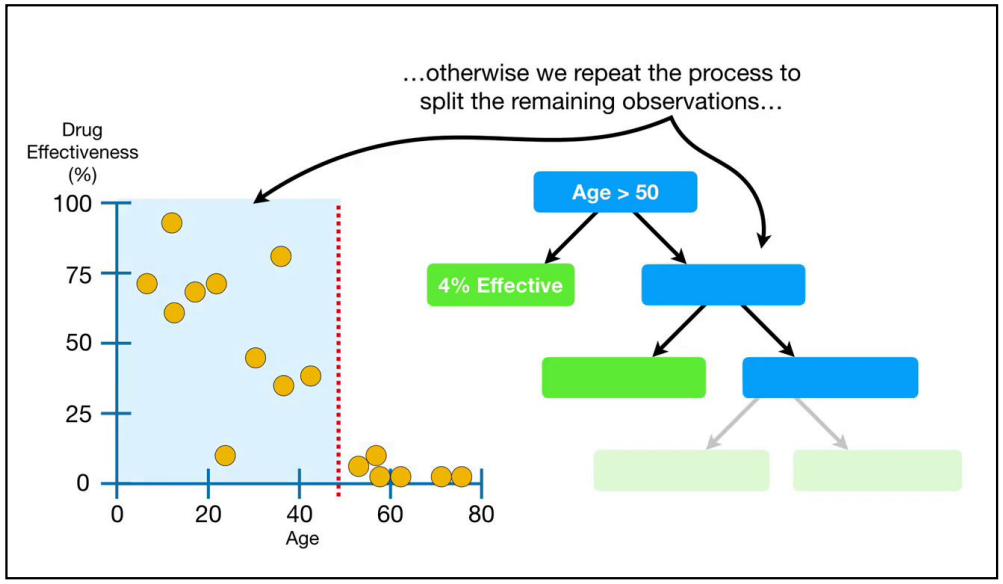

Dosage < 14.5
Average=4.2
Average=51.8
If we have more than one predictor, we find the optimal threshold for each one…
Dosage
Age
Sex
Drug Effect.
10
25
Female
98
20
73
Male
0
35
54
Female
6
5
12
Male
44
etc…
etc…
etc…
etc…

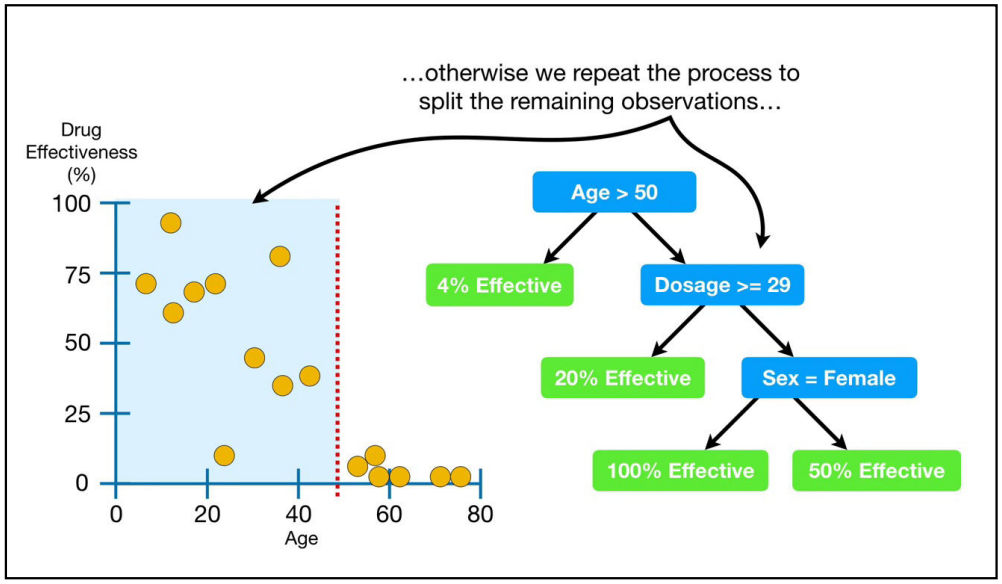

Dosage < 14.5
Average=4.2
Average=51.8
Age > 50
Average=3
Average=52
Sex=Female
Average=12
Average=40
If we have more than one predictor, we find the optimal threshold for each one…
Dosage
Age
Sex
Drug Effect.
10
25
Female
98
20
73
Male
0
35
54
Female
6
5
12
Male
44
etc…
etc…
etc…
etc…


Dosage < 14.5
SSR = 19,564
Average=4.2
Average=51.8
Age > 50
SSR = 12,017
Average=3
Average=52
…and we pick the candidate with the smallest sum of squared residuals…
Sex=Female
SSR = 20,738
Average=12
Average=40

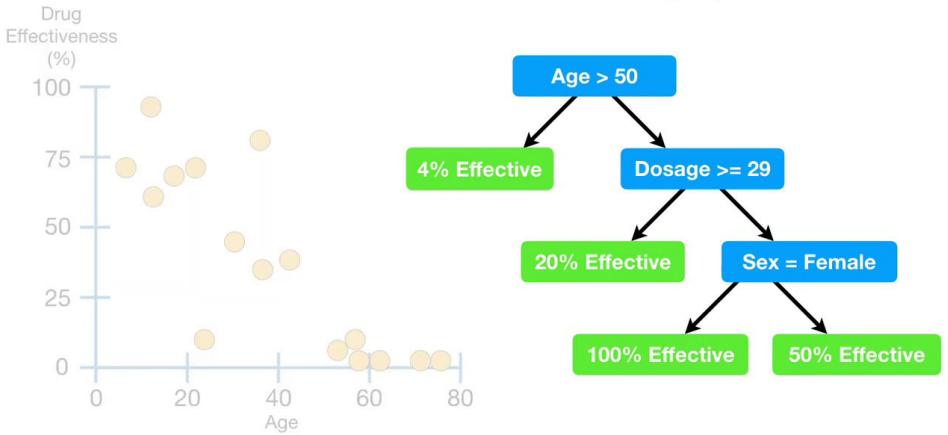

…to be the root.
Drug Effectiveness (%)
100
75
50
25
0
0
20
40
60
80
Age
Age > 50


When we have fewer than some minimum number of observations in a node (7 in this example, but more commonly 20), then that node becomes a leaf….
Drug Effectiveness (%)
100
75
50
25
0
0
20
40
60
80
Age
Age > 50
4% Effective


…otherwise we repeat the process to split the remaining observations…
Drug Effectiveness (%)
100
75
50
25
0
0
20
40
60
80
Age
Age > 50
4% Effective


…otherwise we repeat the process to split the remaining observations…
Drug Effectiveness (%)
100
75
50
25
0
0
20
40
60
80
Age
Age > 50
4% Effective
Dosage >= 29
20% Effective
Sex = Female
100% Effective
50% Effective

…until we can no longer split the observations into smaller groups…



…and then we are done.