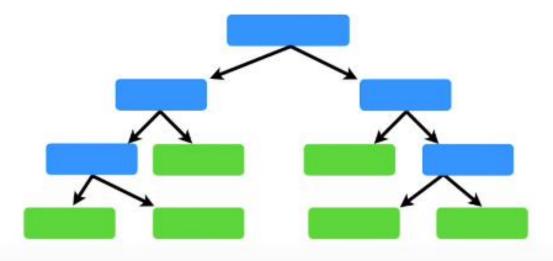
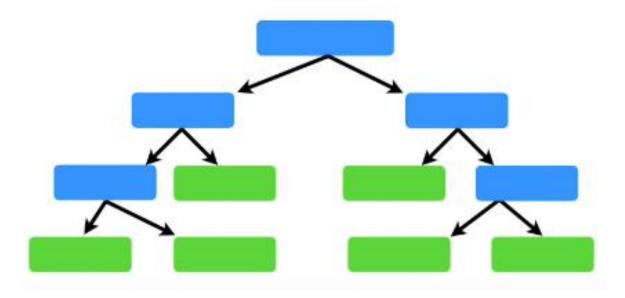
RANDOM FOREST

Decision Trees are easy to build, easy to use and easy to interpret...

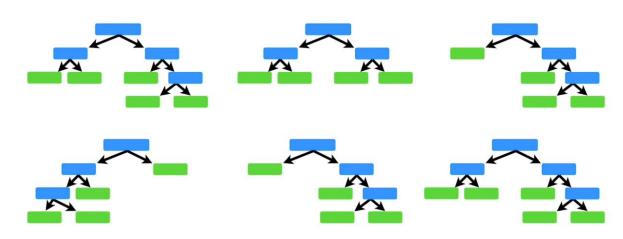


...but in practice they are not that awesome.

In other words, they work great with the data used to create them, but they are not flexible when it comes to classifying new samples.



The good news is that **Random Forests** combine the simplicity of decision trees with flexibility resulting in a vast improvement in accuracy.



1 Create Bootstrap dataset

Original Dataset

Chest Pain	Good Blood Circ.	Blocked Arteries	Weight	Heart Disease
No	No	No	125	No
Yes	Yes	Yes	180	Yes
Yes	Yes	No	210	No
Yes	No	Yes	167	Yes

Bootstrapped Dataset

Chest Blood Circ.	Blocked Arteries	Weight	Heart Disease
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To create a bootstrapped dataset that is the same size as the original, we just randomly select samples from the original dataset.

The important detail is that we're allowed to pick the same sample more than once.

Original Dataset

Chest Pain	Good Blood Circ.	Blocked Arteries	Weight	Heart Disease
No	No	No	125	No
Yes	Yes	Yes	180	Yes
Yes	Yes	No	210	No
Yes	No	Yes	167	Yes

Bootstrapped Dataset

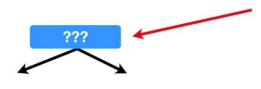
Chest Pain	Good Blood Circ.	Blocked Arteries	Weight	Heart Disease
Yes	Yes	Yes	180	Yes
No	No	No	125	No
Yes	No	Yes	167	Yes
Yes	No	Yes	167	Yes

Step 2: Create a decision tree using the bootstrapped dataset, but only use a random subset of variables (or columns) at each step.

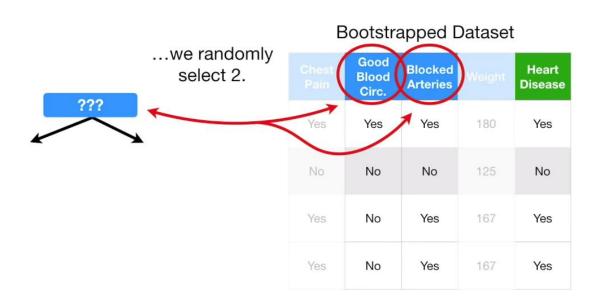
In this example, we will only consider 2 variables (columns) at each step.

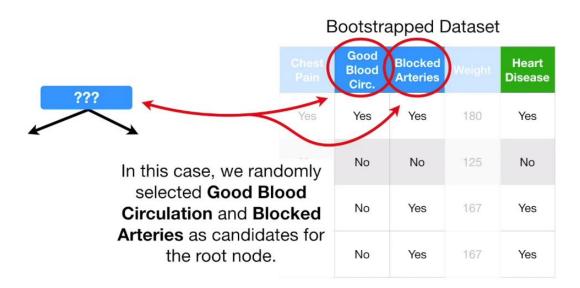
Chest Pain	Good Blood Circ.	Blocked Arteries	Weight	Heart Disease
Yes	Yes	Yes	180	Yes
No	No	No	125	No
Yes	No	Yes	167	Yes
Yes	No	Yes	167	Yes

Thus, instead of considering all 4 variables to figure out how to split the root node...



Chest Pain	Good Blood Circ.	Blocked Arteries	Weight	Heart Disease
Yes	Yes	Yes	180	Yes
No	No	No	125	No
Yes	No	Yes	167	Yes
Yes	No	Yes	167	Yes





Just for the sake of the example, assume that **Good Blood Circulation** did the best job separating the samples.

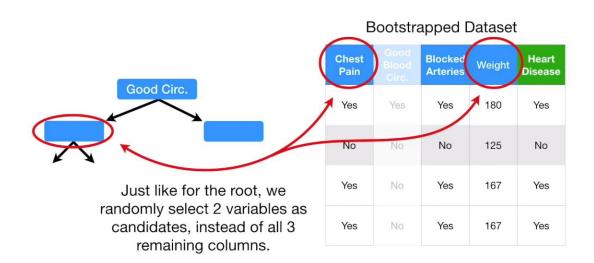


Chest Pain	Good Blood Circ.	Blocked Arteries	Weight	Heart Disease
Yes	Yes	Yes	180	Yes
No	No	No	125	No
Yes	No	Yes	167	Yes
Yes	No	Yes	167	Yes

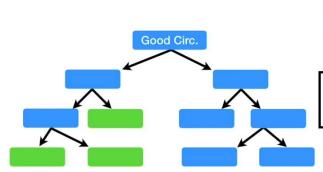
Since we used **Good Blood Circulation**, I'm going to grey it out so that we focus on the remaining variables.

Good Circ.

Chest Pain	Good Blood Circ.	Blocked Arteries	Weight	Heart Disease
Yes	Yes	Yes	180	Yes
No	No	No	125	No
Yes	No	Yes	167	Yes
Yes	No	Yes	167	Yes



Bootstrapped Dataset



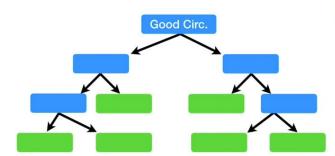
Yes	Yes	Yes	180	Yes

And we just build the tree as usual, but only considering a random subset of variables at each step.

100	110	,00	, , ,	100	
Yes	No	Yes	167	Yes	

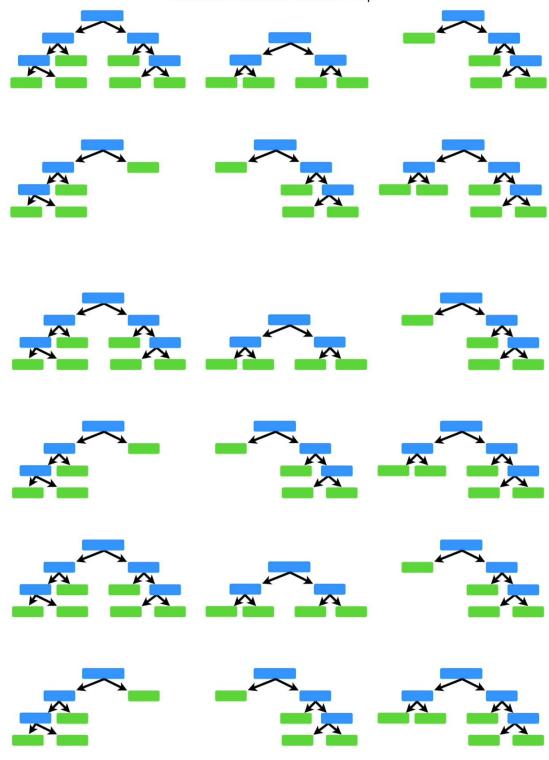
We built a tree...

- 1) Using a bootstrapped dataset
- 2) Only considering a random a subset of variables at each step.

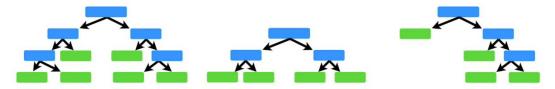


Chest Pain	Good Blood Circ.	Blocked Arteries	Weight	Heart Disease
Yes	Yes	Yes	180	Yes
No	No	No	125	No
Yes	No	Yes	167	Yes
Yes	No	Yes	167	Yes

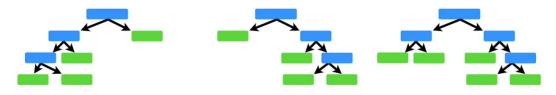
Now go back to Step 1 and repeat: Make a new bootstrapped dataset and build a tree considering a subset of variables at each step.



Using a bootstrapped sample and considering only a subset of the variables at each step results in a wide variety of trees.

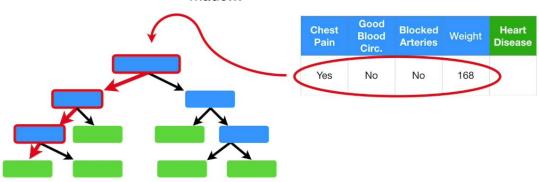


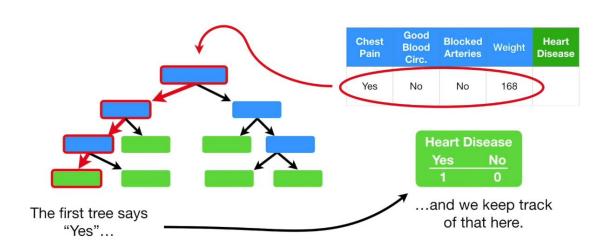
The variety is what makes random forests more effective than individual decision trees.



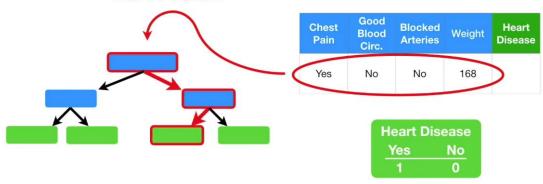
Chest Pain	Good Blood Circ.	Blocked Arteries	Weight	Heart Disease
Yes	No	No	168	\bigcirc

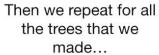
...and now we want to know if they have heart disease or not. So we take the data and run it down the first tree that we made...

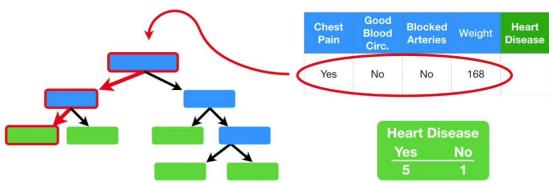




Now we run the data down the second tree that we made...



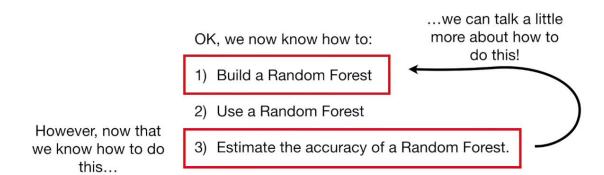


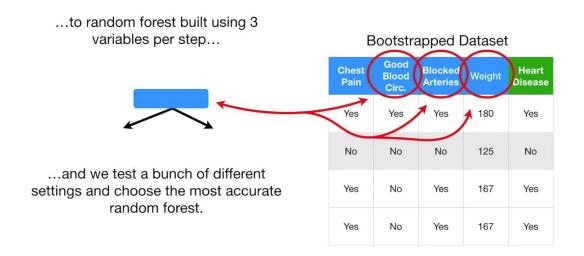


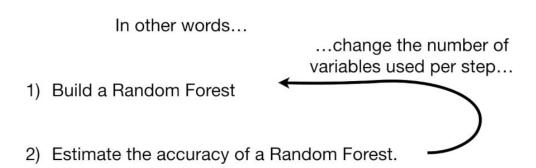
Chest Pain	Good Blood Circ.	Blocked Arteries	Weight	Heart Disease
Yes	No	No	168	YES

In this case, "Yes" received the most votes, so we will conclude that this patient has heart disease.









Do this for a bunch of times and then choose the one that is most accurate. Typically, we start by using the square of the number of variables and then try a a few settings above and below that value.