

# DATA 301:

## Gradient Boosted Trees

(XGBoost, lightGBM)

# Topics

Introduction

Bagging verses Boosting

Example

Benefits

Drawbacks

Packages

Summary

# Introduction

Random forest are a collection of decision trees that are created using a technique called 'bagging'

Which means create a bunch of independent decision trees and average (or majority) vote their results

Boosted decision trees are a collection of decision trees that are created using a technique called 'boosting'

Which means create the trees one at a time, each new tree designed to improve upon previous trees estimates

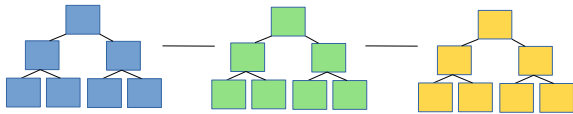
# Bagging verses Boosting

Bagging

# Bagging verses Boosting

## Bagging

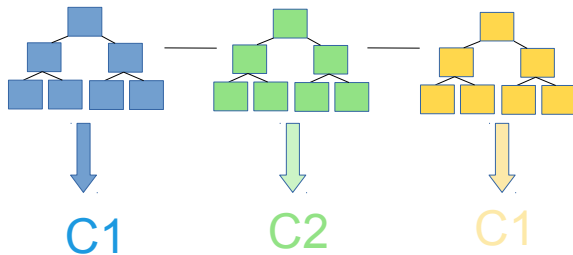
Multiple independent trees



# Bagging verses Boosting

## Bagging

Multiple independent trees



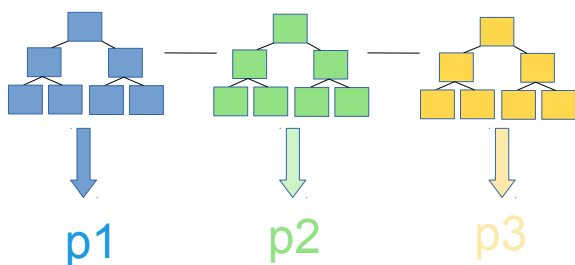
For Classification  
Use majority vote

C1 C2 C1 = C1

# Bagging verses Boosting

## Bagging

Multiple independent trees



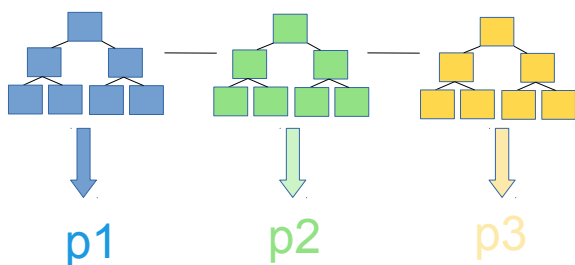
For Regression just Average results

$$(p1 + p2 + p3)/3 = \text{val}$$

# Bagging verses Boosting

## Bagging

Multiple independent trees



For Regression just Average results

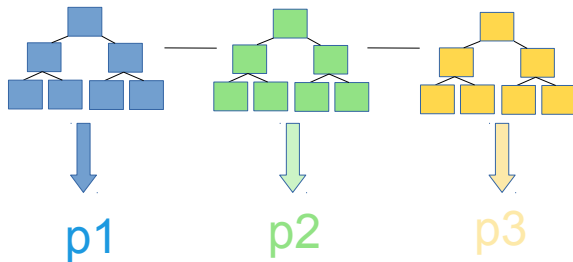
$$(p1 + p2 + p3)/3 = \text{val}$$



# Bagging verses Boosting

## Bagging

Multiple independent trees



For Regression just Average results

$$(p1 + p2 + p3)/3 = \text{val}$$

Build trees in parrallel  
so very fast

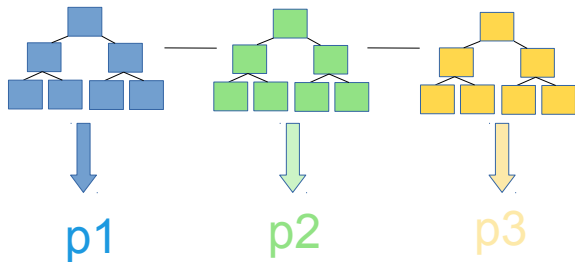
## Boosting

■ Start with average target value

# Bagging versus Boosting

## Bagging

Multiple independent trees



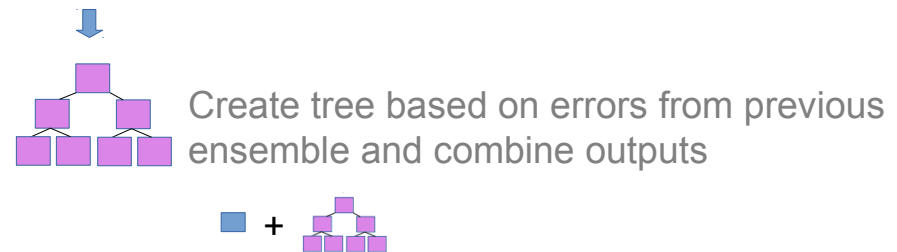
For Regression just Average results

$$(p1 + p2 + p3)/3 = \text{val}$$

Build trees in parallel  
so very fast

## Boosting

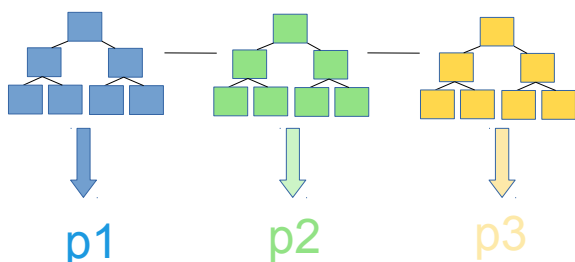
Start with average target value



# Bagging versus Boosting

## Bagging

Multiple independent trees



For Regression just Average results

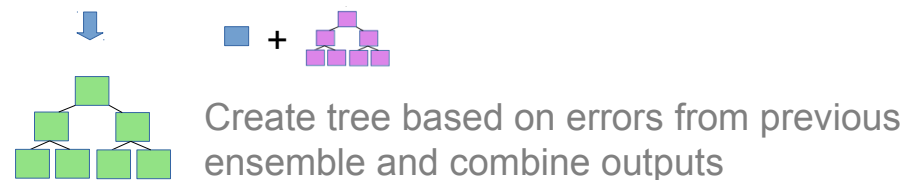
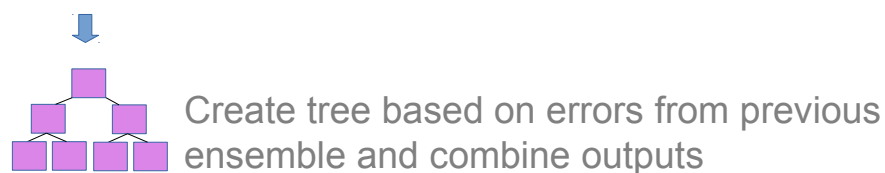
$$(p1 + p2 + p3)/3 = \text{val}$$

Lets stick with regression

Build trees in parrallel  
so very fast

## Boosting

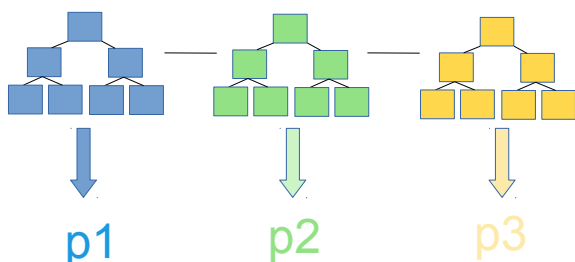
Start with average target value



# Bagging versus Boosting

## Bagging

Multiple independent trees



For Regression just Average results

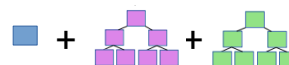
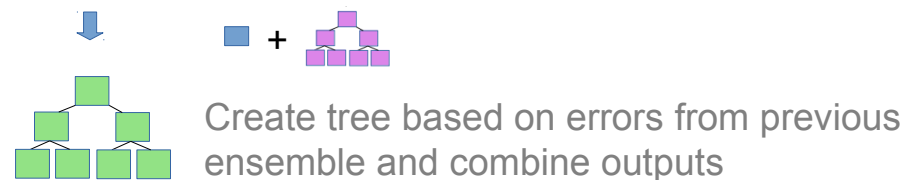
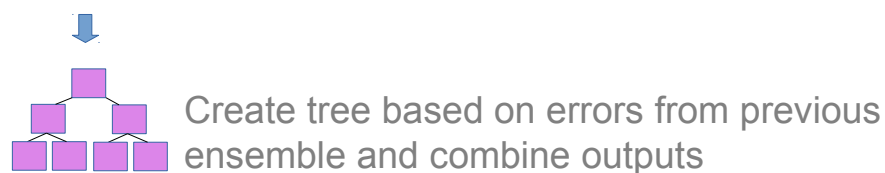
$$(p1 + p2 + p3)/3 = \text{val}$$

Lets stick with regression

Build trees in parrallel  
so very fast

## Boosting

Start with average target value

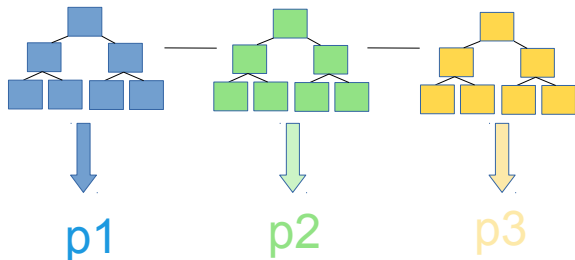


Continue until build number trees requested  
Or additional trees fail to improve prediction

# Bagging versus Boosting

## Bagging

Multiple independent trees



For Regression just Average results

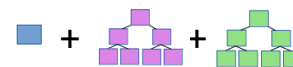
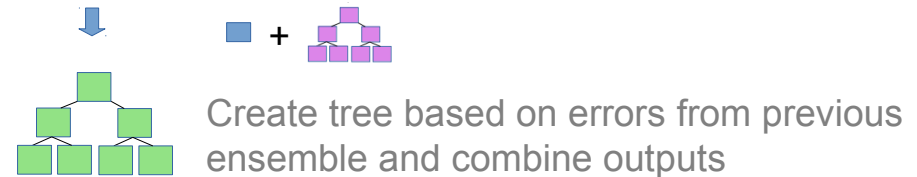
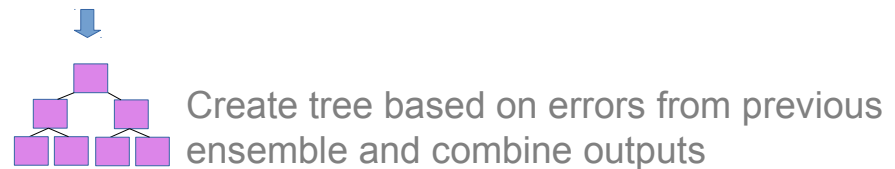
$$(p1 + p2 + p3)/3 = \text{val}$$

Lets stick with regression

Build trees in parrallel  
so very fast

## Boosting

Start with average target value



Continue until build number trees requested  
Or additional trees fail to improve prediction

Build trees sequentially so slow  
But more accurate than Random Forest

# Example

Height	Color	Gender	Weight
1.6	Blue	Male	88
1.6	Green	Female	76
1.5	Blue	Female	56
1.8	Red	Male	73
1.5	Green	Male	77
1.4	Blue	Female	57

Average weight

71.2

Calculate average weight

# Example

Height	Color	Gender	Weight	Residuals
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	
1.5	Blue	Female	56	
1.8	Red	Male	73	
1.5	Green	Male	77	
1.4	Blue	Female	57	

Average weight

71.2

Calculate difference between  
average weight and Weight  
Add as new column Residuals  
(1<sup>st</sup> row  $88 - 71.2 = 16.8$ )

# Example

Height	Color	Gender	Weight	Residuals
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	4.8
1.5	Blue	Female	56	-15.2
1.8	Red	Male	73	1.8
1.5	Green	Male	77	5.8
1.4	Blue	Female	57	-14.2

Average weight

71.2

Calculate difference between  
average weight and Weight  
Add as new column Residuals  
(1<sup>st</sup> row  $88 - 71.2 = 16.8$ )  
Do for All rows



# Example

Height	Color	Gender	Weight	Residuals
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	4.8
1.5	Blue	Female	56	-15.2
1.8	Red	Male	73	1.8
1.5	Green	Male	77	5.8
1.4	Blue	Female	57	-14.2

Average weight

71.2

Now build a tree to predict the Residuals using Height, Color and Gender to predict the residuals. Trees have several tuning Parameters,

max\_depth= how many levels per tree

max\_leaf\_nodes: number terminal leaf nodes

Set max\_leaf\_nodes = 4 for this problem

# Example

Height	Color	Gender	Weight	Residuals
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	4.8
1.5	Blue	Female	56	-15.2
1.8	Red	Male	73	1.8
1.5	Green	Male	77	5.8
1.4	Blue	Female	57	-14.2

Average weight

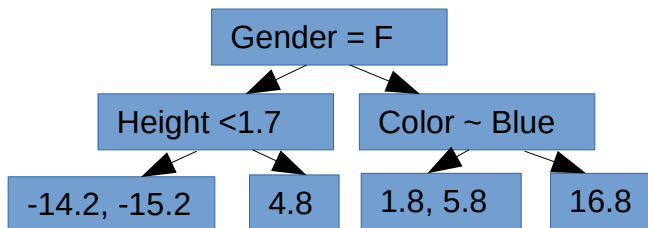
71.2

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# Example

Height	Color	Gender	Weight	Residuals
1.6	Blue	Male	88	16.8
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1.8	Red	Male	73	1.8
1.5	Green	Male	77	5.8
1.4	Blue	Female	57	-14.2

Average weight

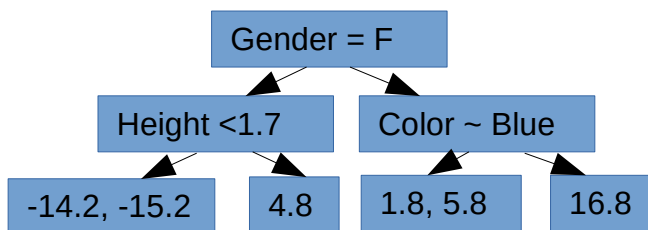
71.2

Now build a tree to predict the Residuals using Height, Color and Gender to predict the residuals. Trees have several tuning Parameters,

max\_depth= how many levels per tree

max\_leaf\_nodes: number terminal leaf nodes

Set max\_leaf\_nodes = 4 for this problem



But can have a max of 4 leaf nodes

# Example

Height	Color	Gender	Weight	Residuals
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	4.8
1.5	Blue	Female	56	-15.2
1.8	Red	Male	73	1.8
1.5	Green	Male	77	5.8
1.4	Blue	Female	57	-14.2

Average weight

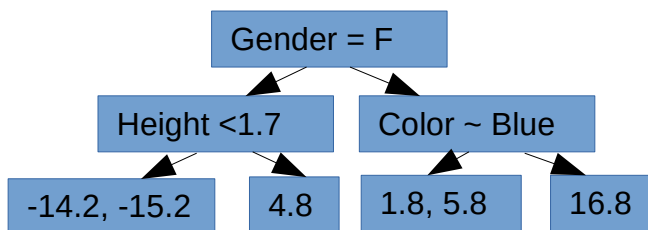
71.2

Now build a tree to predict the Residuals using Height, Color and Gender to predict the residuals. Trees have several tuning Parameters,

max\_depth= how many levels per tree

max\_leaf\_nodes: number terminal leaf nodes

Set max\_leaf\_nodes = 4 for this problem



So average the leaf nodes with more than 2 values

$$(-14.2 + -15.2) / 2 = -14.7$$

$$(1.8 + 5.8) / 2 = 3.8$$

Example from <https://www.youtube.com/watch?v=3CC4N4z3GJc>

# Example

Height	Color	Gender	Weight	Residuals
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	4.8
1.5	Blue	Female	56	-15.2
1.8	Red	Male	73	1.8
1.5	Green	Male	77	5.8
1.4	Blue	Female	57	-14.2

Average weight

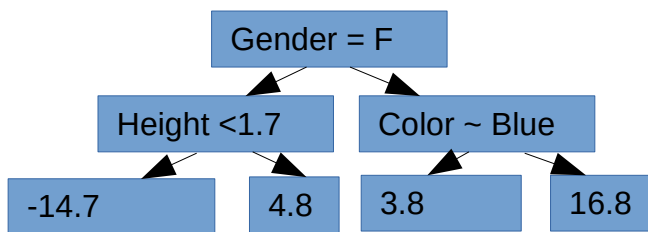
71.2

Now build a tree to predict the Residuals using Height, Color and Gender to predict the residuals. Trees have several tuning Parameters,

max\_depth= how many levels per tree

max\_leaf\_nodes: number terminal leaf nodes

Set max\_leaf\_nodes = 4 for this problem



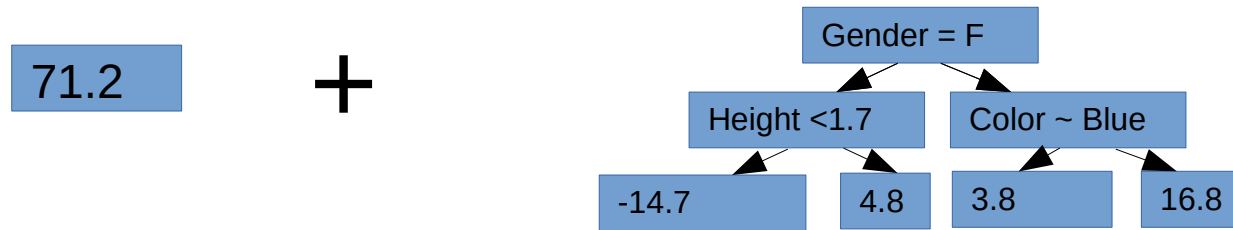
So average the leaf nodes with more than 2 values

$$(-14.2 + -15.2) / 2 = -14.7$$

$$(1.8 + 5.8) / 2 = 3.8$$

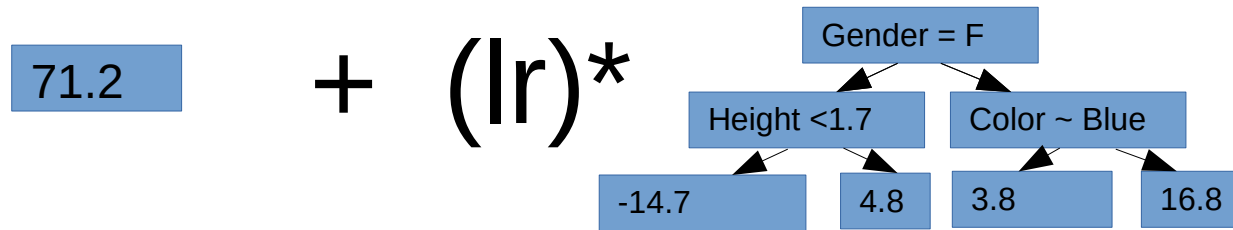
Example from <https://www.youtube.com/watch?v=3CC4N4z3GJc>

# Example



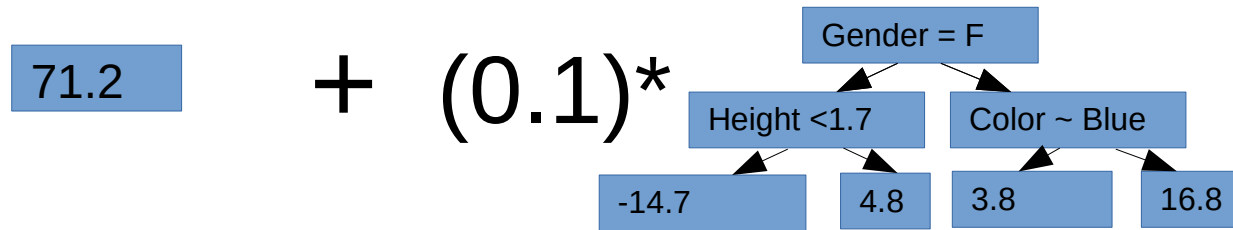
Combine new tree with  
Original leaf and use to  
calculate new residuals

# Example



Use only part of the new trees  
prediction to prevent overfitting by  
Multiplying it's output by learning rate  $< 1$

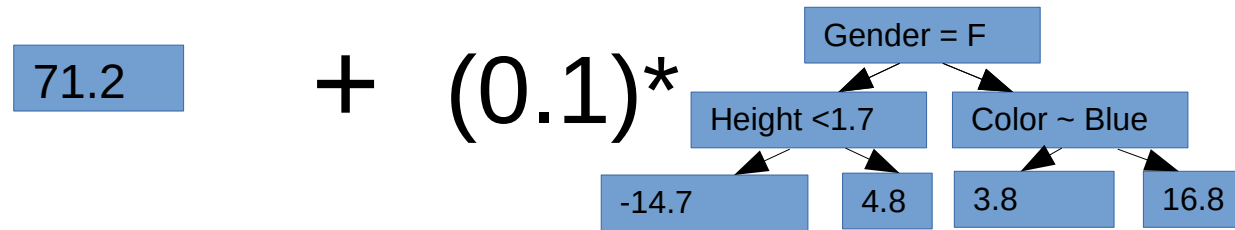
# Example



Use only part of the new trees  
prediction to prevent overfitting by  
Multiplying it's output by learning rate (lr)  
Lr=0.1



# Example

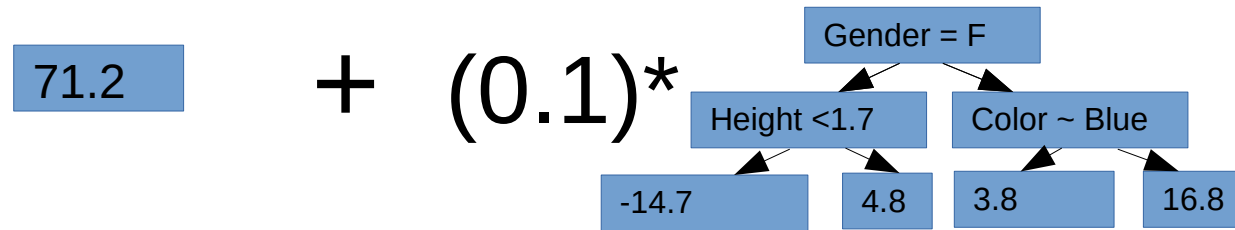


Calculate predicted weight (for row 0)  
 $71.2 + 0.1 * 16.8 = 72.9$

Height	Color	Gender	Weight
1.6	Blue	Male	88
1.6	Green	Female	76
1.5	Blue	Female	56
1.8	Red	Male	73
1.5	Green	Male	77
1.4	Blue	Female	57

Example from <https://www.youtube.com/watch?v=3CC4N4z3GJc>

# Example



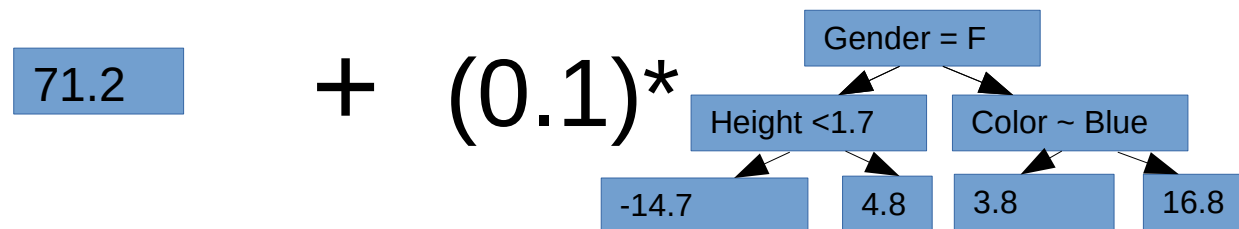
Calculate predicted weight (for row 0)  
 $71.2 + 0.1 * 16.8 = 72.9$

Which is a little better than 71.2

Height	Color	Gender	Weight
1.6	Blue	Male	88
1.6	Green	Female	76
1.5	Blue	Female	56
1.8	Red	Male	73
1.5	Green	Male	77
1.4	Blue	Female	57

Example from <https://www.youtube.com/watch?v=3CC4N4z3GJc>

# Example



Calculate predicted weight (for row 0)  
 $71.2 + 0.1 * 16.8 = 72.9$

Height	Color	Gender	Weight	Residuals
1.6	Blue	Male	88	15.1
1.6	Green	Female	76	
1.5	Blue	Female	56	
1.8	Red	Male	73	
1.5	Green	Male	77	
1.4	Blue	Female	57	

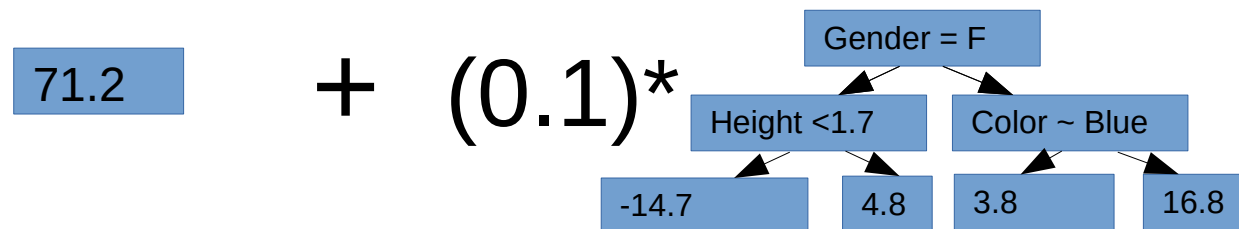
Which is a little better than 71.2

Calculate the new residuals (first row)  
 $88 - 72.9 = 15.1$

We are getting closer to the true weight

Example from <https://www.youtube.com/watch?v=3CC4N4z3GJc>

# Example



Calculate predicted weight (for row 0)  
 $71.2 + 0.1 * 16.8 = 72.9$

Height	Color	Gender	Weight	Residuals
1.6	Blue	Male	88	15.1
1.6	Green	Female	76	4.3
1.5	Blue	Female	56	-13.7
1.8	Red	Male	73	1.4
1.5	Green	Male	77	5.4
1.4	Blue	Female	57	-12.7

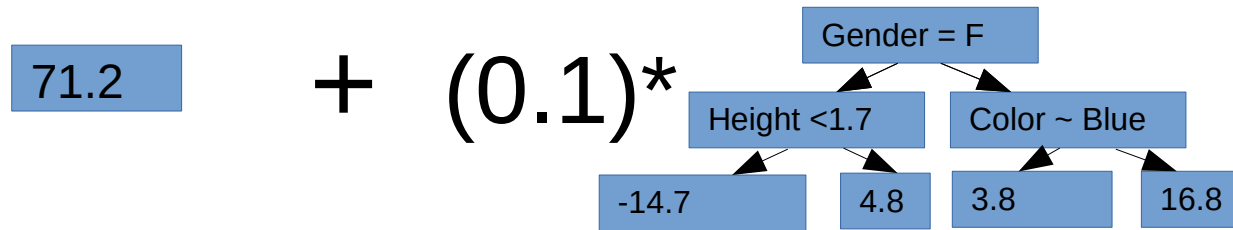
Which is a little better than 71.2

Calculate the new residuals (first row)  
 $88 - 72.9 = 15.1$

Do for all rows

Example from <https://www.youtube.com/watch?v=3CC4N4z3GJc>

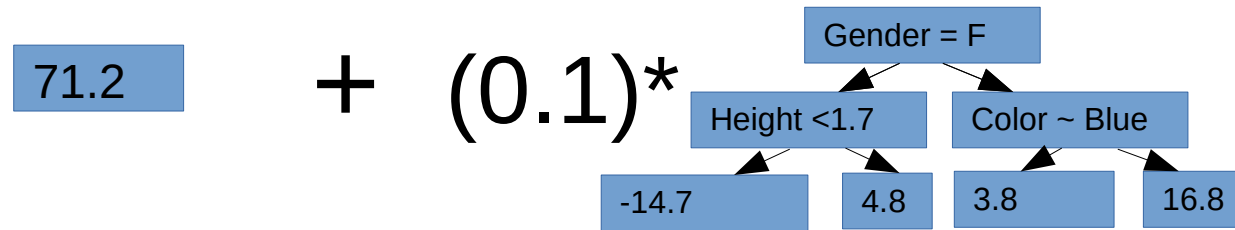
# Example



Original  
residuals

Residuals
16.8
4.8
-15.2
1.8
5.8
-14.2

# Example



Original  
residuals

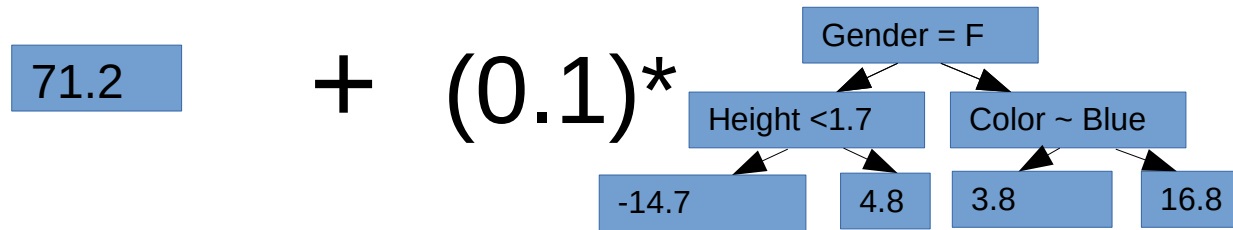
Residuals
16.8
4.8
-15.2
1.8
5.8
-14.2

New  
residuals

Residuals
15.1
4.3
-13.7
1.4
5.4
-12.7

Note that we are reducing the  
Residual size

# Example



Original  
residuals

Residuals
16.8
4.8
-15.2
1.8
5.8
-14.2

New  
residuals

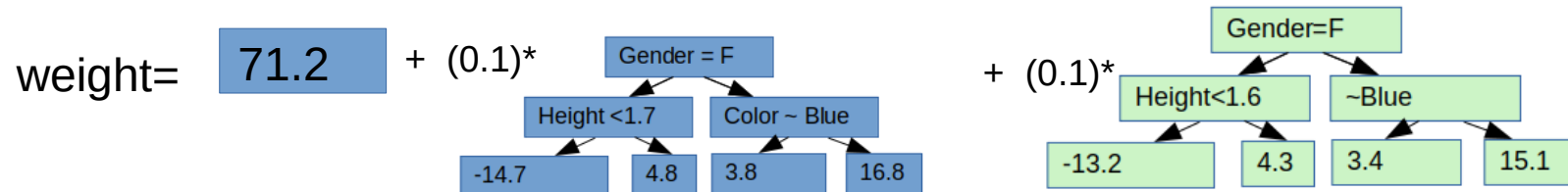
Residuals
15.1
4.3
-13.7
1.4
5.4
-12.7

Note that we are reducing the  
Residual size

Repeat the process of calculating  
Residuals and building trees until  
Either max trees are reached or  
Residuals stop getting better.

# Example

When we have enough trees, we can predict weight





# Example

When we have enough trees, we can predict weight

$$\text{weight} = 71.2 + (0.1) * \left[ \begin{array}{c} \text{Gender} = F \\ \swarrow \quad \searrow \\ \text{Height} < 1.7 \quad \text{Color} \sim \text{Blue} \\ \swarrow \quad \searrow \quad \swarrow \quad \searrow \\ -14.7 \quad 4.8 \quad 3.8 \quad 16.8 \end{array} \right] + (0.1) * \left[ \begin{array}{c} \text{Gender} = F \\ \swarrow \quad \searrow \\ \text{Height} < 1.6 \quad \sim \text{Blue} \\ \swarrow \quad \searrow \quad \swarrow \quad \searrow \\ -13.2 \quad 4.3 \quad 3.4 \quad 15.1 \end{array} \right]$$

Height	Color	Gender	Weight
1.6	Blue	Male	88



$$\begin{aligned} \text{Weight} &= 71.2 + 0.1 * 16.8 + 0.1 * (15.1) \\ &= 74.39 \end{aligned}$$

# Example

When we have enough trees, we can predict weight

$$\text{weight} = 71.2 + (0.1) * \begin{array}{c} \text{Gender} = F \\ \swarrow \quad \searrow \\ \text{Height} < 1.7 \quad \text{Color} \sim \text{Blue} \\ \swarrow \quad \searrow \quad \swarrow \quad \searrow \\ -14.7 \quad 4.8 \quad 3.8 \quad 16.8 \end{array} + (0.1) * \begin{array}{c} \text{Gender} = F \\ \swarrow \quad \searrow \\ \text{Height} < 1.6 \quad \sim \text{Blue} \\ \swarrow \quad \searrow \quad \swarrow \quad \searrow \\ -13.2 \quad 4.3 \quad 3.4 \quad 15.1 \end{array}$$

Height	Color	Gender	Weight
1.6	Blue	Male	88



$$\begin{aligned} \text{Weight} &= 71.2 + 0.1 * 16.8 + 0.1 * (15.1) \\ &= 74.39 \end{aligned}$$

The more trees you have the more accurate it gets (at the risk of overfitting)

Example from <https://www.youtube.com/watch?v=3CC4N4z3GJc>

# Benefits

- Reducing residual approach lets trees push wrong answers in the right direction.
- Each tree tries to improve the overall model by reducing residuals. They work together.
- More accurate than random forest, where each tree makes an independent estimate.

# Drawbacks

- Trees calculated serially. Much slower than Random Forest
- More hyperparameters to tune (learning rate, max\_tree\_depth, max\_number\_leaves etc.)

# Packages

- XGBoost
- lightGBM

# Summary

- Gradient Boosted trees are the preferred tree ensemble given it's increase in accuracy (or F1, or  $R^2$  or whatever performance metric of choice)
- Work with regression and classification
- Not built into scikitlearn
- Harder to tune (more hyperparameters)
- Longer to train