DATA 301: Gradient Boosted Trees (lightGBM, catboost)

Topics

Introduction
Bagging verses Boosting
Example
Boosting Benefits
Boosting 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

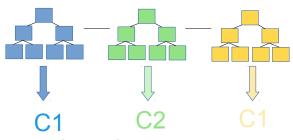
Bagging

Multiple independent trees



Bagging

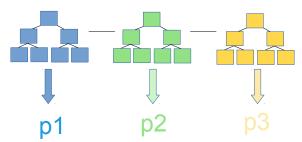
Multiple independent trees



For Classification Use majority vote

Bagging

Multiple independent trees

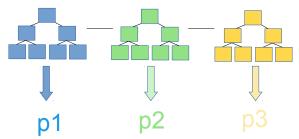


For Regression just Average results

$$(p1 + p2 + p3)/3 = val$$

Bagging

Multiple independent trees



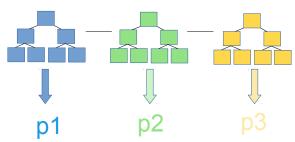
For Regression just Average results

$$(p1 + p2 + p3)/3 = val$$

Build trees in parallel so very fast

Bagging

Multiple independent trees



For Regression just Average results

$$(p1 + p2 + p3)/3 = val$$

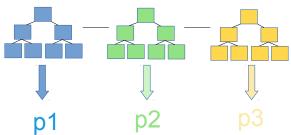
Boosting

Start with average target value

Build trees in parallel so very fast

Bagging

Multiple independent trees

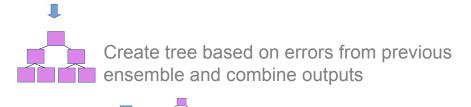


For Regression just Average results

$$(P1 + p2 + p3)/3 = val$$

Boosting

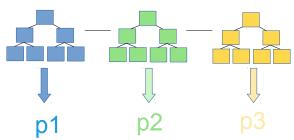
Start with average target value



Build trees in parrallel so very fast

Bagging

Multiple independent trees



For Regression just Average results

$$(P1 + p2 + p3)/3 = val$$

Boosting

Start with average target value



Create tree based on errors from previous ensemble and combine outputs





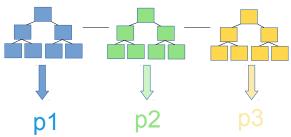


Create tree based on errors from previous ensemble and combine outputs

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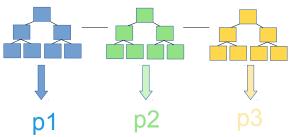


Continue until build number trees requested Or additional trees fail to improve prediction

Build trees in parrallel so very fast

Bagging

Multiple independent trees



For Regression just Average results

$$(P1 + p2 + p3)/3 = val$$

Boosting

Start with average target value



Create tree based on errors from previous ensemble and combine outputs







Create tree based on errors from previous ensemble and combine outputs



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

Build trees in parrallel so very fast

Build trees sequentially so slow.
But more accurate than bagged methods like
Random Forest

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

Average weight

Height	Color	Gender	Weight	Residuals
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	
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71.2 Calculate difference between average weight and Weight Add as new column, Residuals

(1st row 88-71.2=16.8)

Average weight

Height	Color	Gender	Weight	Residuals
1.6	Blue	Male	88	16.8
1.6	Green	Female	76	4.8
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71.2 C

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

Average weight

71.2

Height	Color	Gender	Weight	Residuals
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Now build a tree to predict the Residuals.

Use Height, Color and Gender.Trees have several tuning Parameters,

max_depth= how many levels per tree

max_leaf_nodes: number terminal leaf nodes

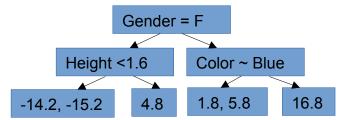
Set max_leaf_nodes = 4 for this problem

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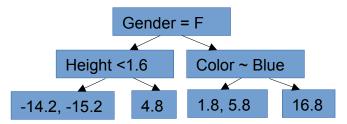


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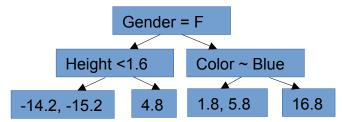
But can have a max of only 4 leaf nodes

Average weight

71.2

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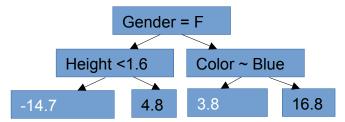
So average the leaf nodes with more than 2 values (-14.2+-15.2)/2=-14.7 (1.8 + 5.8)/2=3.8

Average weight

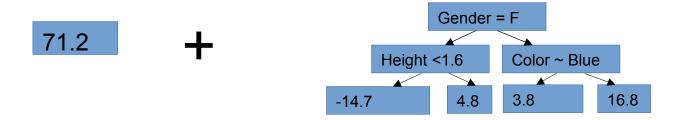
71.2

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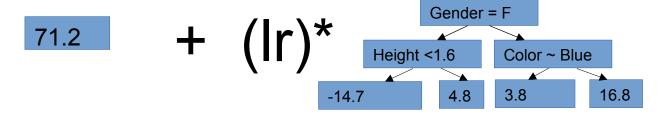
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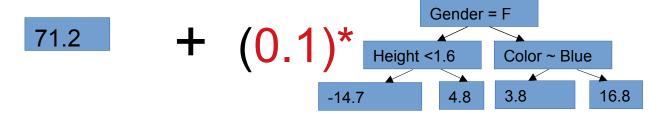
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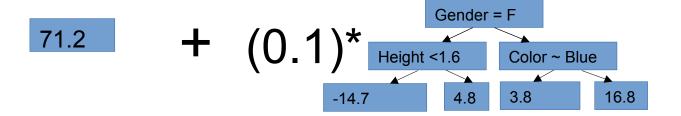
Combine new tree with Original leaf and use to calculate new residuals



Use only part of the new trees prediction to prevent overfitting (low bias, high variance) by Multiplying it's output by learning rate <1

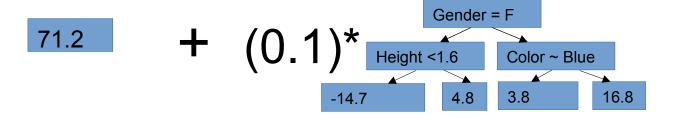


Use only part of the new trees prediction to prevent overfitting (low bias, high variance) by Multiplying it's output by learning rate <1
Lr=0.1



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

Height	Color	Gender	Weight
1.6	Blue	Male	88
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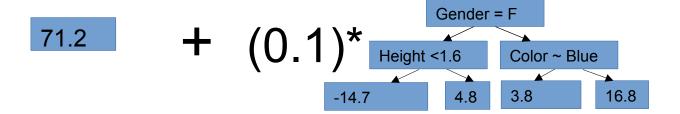
Which is a little better than 71.2 (the original average estimate)

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

Height	Color	Gender	Weight	Residuals	Which is a little better than 71.2
1.6	Blue	Male	88	15.1	
1.6	Green	Female	76		Calculate the new residuals (first row) 88-72.9=15.1
1.5	Blue	Female	56	00-72.9-13.1	00 72.0 10.1
1.8	Red	Male	73		We are getting closer to the true weight
1.5	Green	Male	77		
1.4	Blue	Female	57		

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

Height	Color	Gender	Weight	Residuals	Which is a little better than 71.2
1.6	Blue	Male	88	15.1	
1.6	Green	Female	76	4.3	Calculate the new residuals (first row) 88-72.9=15.1
1.5	Blue	Female	56	-13.7	00 72.0 10.1
1.8	Red	Male	73	1.4	Do for all rows
1.5	Green	Male	77	5.4	
1.4	Blue	Female	57	-12.7	

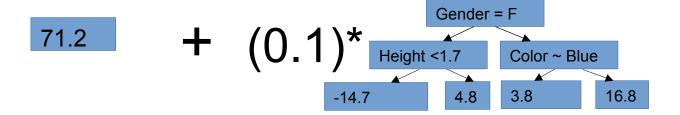


Original residuals							
16.8							
4.8							
-15.2							
1.8							
5.8							
-14.2							

New residuals

Residuals
15.1
4.3
-13.7
1.4
5.4
-12.7

Note that the New Residuals are lower Than the originals. We are reducing the Error as we add more trees.



Original residuals						
16.8						
4.8						
-15.2						
1.8						
5.8						
-14.2						

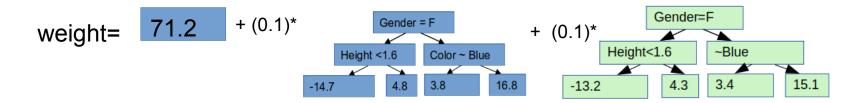
New residuals

Residuals
15.1
4.3
-13.7
1.4
5.4
-12.7

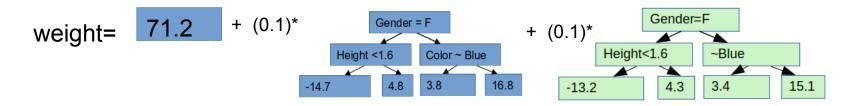
Note that the New Residuals are lower Than the originals. We are reducing the Error as we add more trees.

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

When we have enough trees, we can predict weight

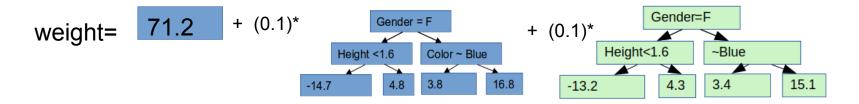


When we have enough trees, we can predict weight



Height	Color	Gender	Weight	Weight= 71.2 + 0.1*16.8 + 0.1*(15.1)
1.6	Blue	Male	88	= 74.39

When we have enough trees, we can predict weight



Height	Color	Gender	Weight	Weight= 71.2 + 0.1*16.8 + 0.1*(15.1)
1.6	Blue	Male	88	= 74.39

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

Benefits

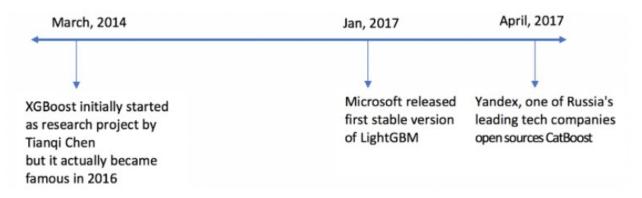
- Reducing residual approach lets trees push wrong answers in the 'right' direction.
- Each tree tries to improve the overall model by reducing residuals. Trees work together.
- More accurate than random forest, where each tree makes an independent estimate.

Drawbacks

- Trees calculated serially. Much slower than Random Forest which is calculated in parallel.
- More hyperparameters to tune (learning rate, max_tree_depth, max_leaf_nodes etc.)

Packages

- LightGBM: by Microsoft, gradient boosted trees
- Catboost: by Yandex, more gradient boosted trees
- Sklearn: GradientBoostingClassifier and GradientBoostingRegressor, not covered here since LightGBM and Catboost are faster, more accurate and support sklearns default model training procedure
- XGBoost: still more gradient boosted trees, not covered here because they take MUCH longer to train than catboost or 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
- Built into scikitlearn
- Harder to tune (more hyperparameters)
- Longer to train