Machine Learning

Part 4: Classical Machine Learning Model

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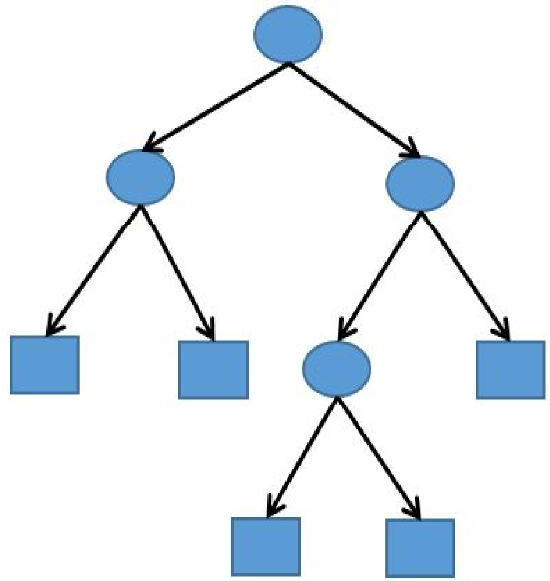


Tree Ensembles

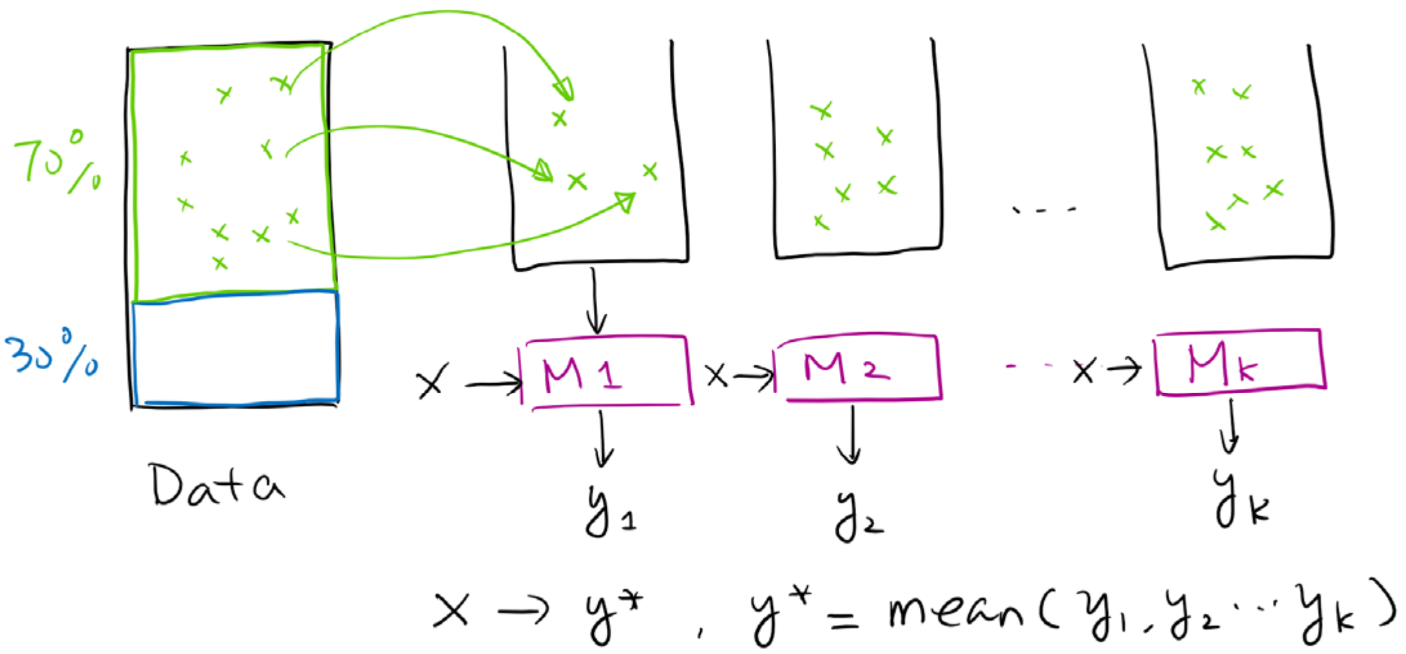
CART

Please Check out the note.

Bagging

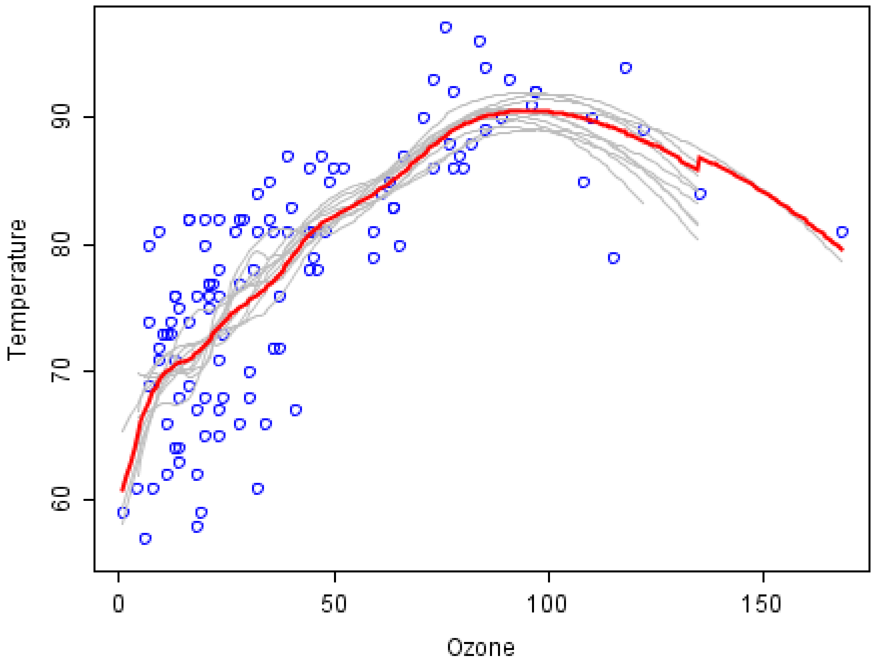
Bagging is the abbreviation of Bootstrap Aggregating.

Bootstrapping is any test or metric that relies on random sampling with replacement.



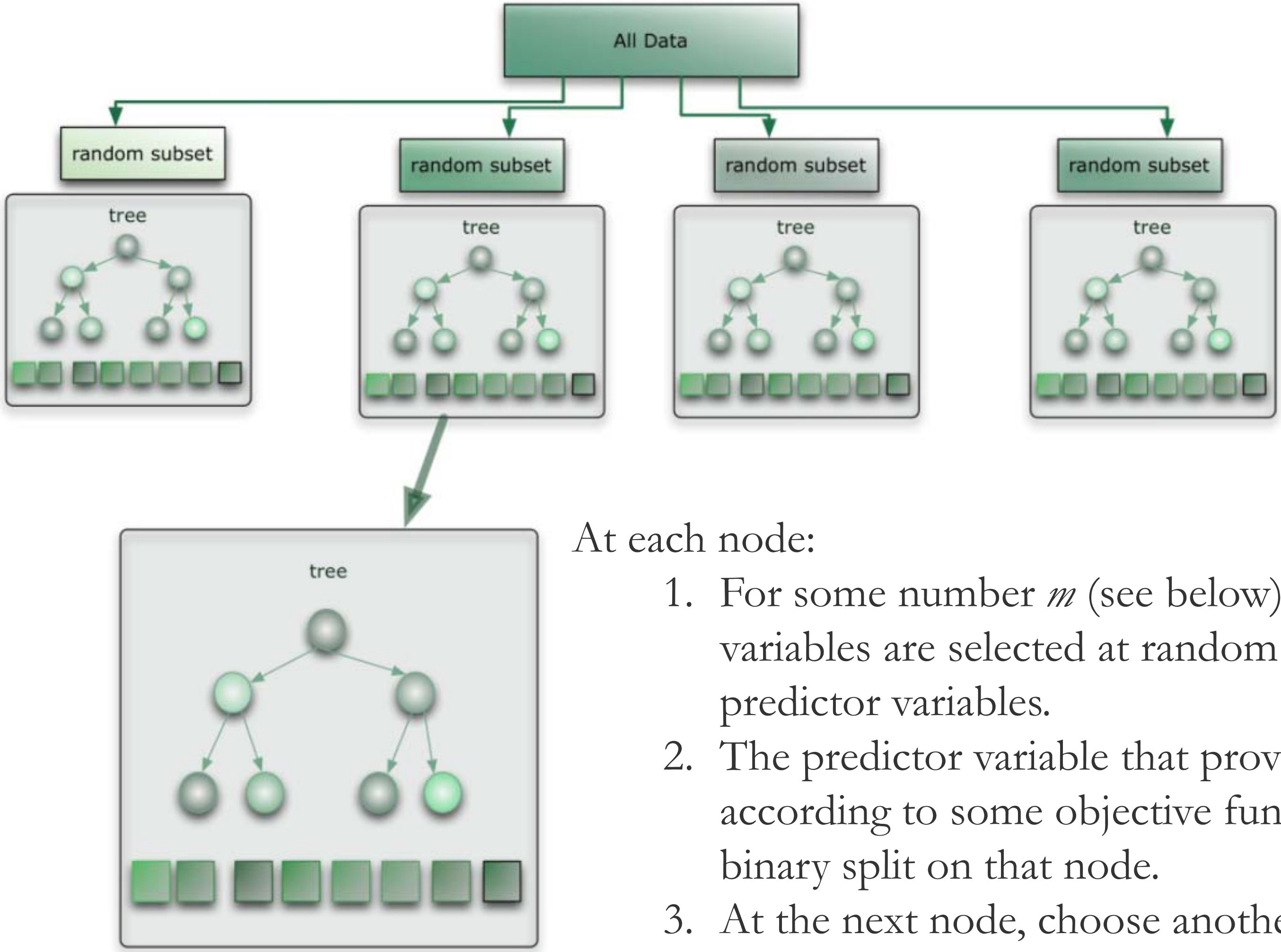
Bagging

proposed by Leo Breiman in 1994 to improve classification by combining classifications of randomly generated training sets.



Given a standard training set D of size *n*, bagging generates *m* new training sets, each of size n′ , by sampling from D uniformly with replacement (bootstrapping). By sampling with replacement, some observations may be repeated in each round. If $n' = n$, then for large *n* the sampled set is expected to have the fraction (1 - 1/e) of original data (≈63.2%)

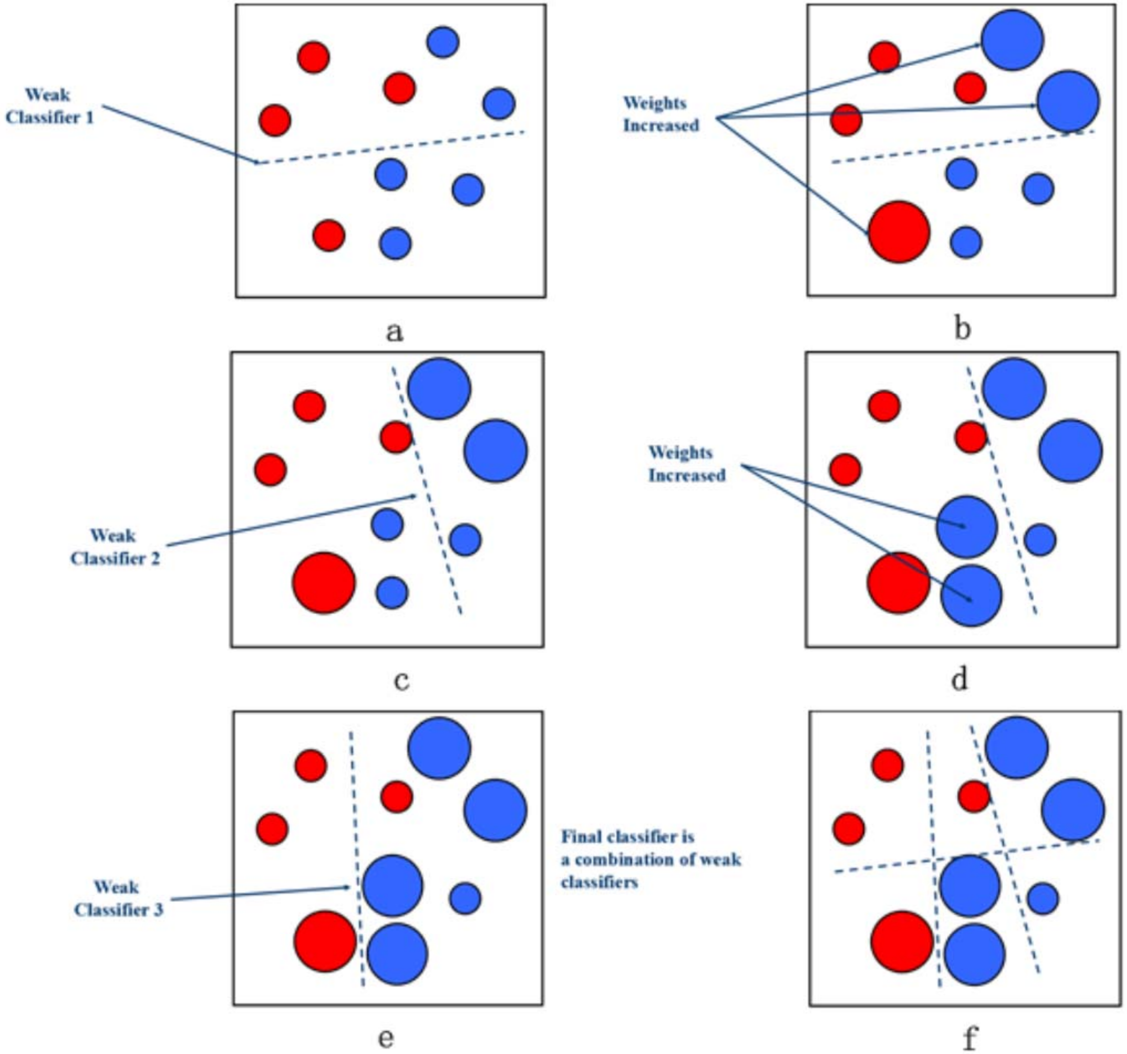
Random Forest



At each node:

1. For some number *m* (see below), *m* predictor variables are selected at random from all the predictor variables.
2. The predictor variable that provides the best split, according to some objective function, is used to do a binary split on that node.
3. At the next node, choose another *m* variables at random from all predictor variables and do the same.

Partition


Weak
Classifier 1
a
Weights
Increased
b
Weak
Classifier 2
c
Weights
Increased
d
Weak
Classifier 3
e
Final classifier is
a combination of weak
classifiers
f

Adaptive Boost

The output of the other learning algorithms ('weak learners') is combined into a weighted sum that represents the final output of the boosted classifier. AdaBoost is adaptive in the sense that subsequent weak learners are tweaked in favor of those instances misclassified by previous classifiers. AdaBoost is sensitive to noisy data and outliers.

- Samples $x_1 \ldots x_n$
- Desired outputs $y_1 \ldots y_n, y \in \{-1, 1\}$
- Initial weights $w_{1,1} \ldots w_{n,1}$ set to $\frac{1}{n}$
- Error function $E(f(x), y, i) = e^{-y_i f(x_i)}$
- Weak learners $h\colon x \rightarrow [-1, 1]$

Information Gain

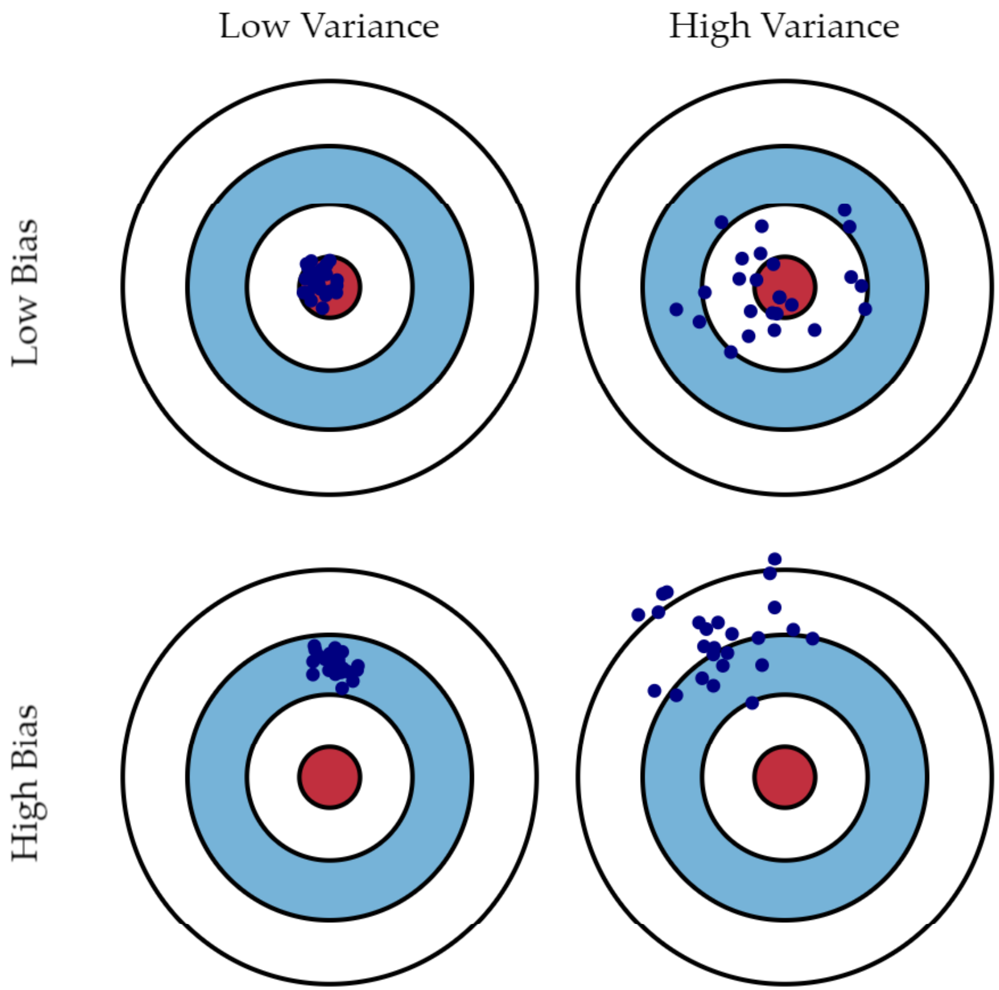
For t in $1 \ldots T$:

- Choose $h_t(x)$:
  - Find weak learner $h_t(x)$ that minimizes ϵ_t,

    the weighted sum error for misclassified points $\epsilon_t = \sum_{\substack{i=1 \\ h_t(x_i) \neq y_i}}^{n} w_{i,t}$
  - Choose $\alpha_t = \frac{1}{2} \ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$
  - Add to ensemble:
    - $F_t(x) = F_{t-1}(x) + \alpha_t h_t(x)$
  - Update weights:
    - $w_{i,t+1} = w_{i,t} e^{-y_i \alpha_t h_t(x_i)}$ for all i
  - Renormalize $w_{i,t+1}$ such that $\sum_i w_{i,t+1} = 1$
  - (Note: It can be shown that $\frac{\sum_{h_{t+1}(x_i)=y_i} w_{i,t+1}}{\sum_{h_{t+1}(x_i)\neq y_i} w_{i,t+1}} = \frac{\sum_{h_t(x_i)=y_i} w_{i,t}}{\sum_{h_t(x_i)\neq y_i} w_{i,t}}$

    at every step, which can simplify the calculation of the new weights.)

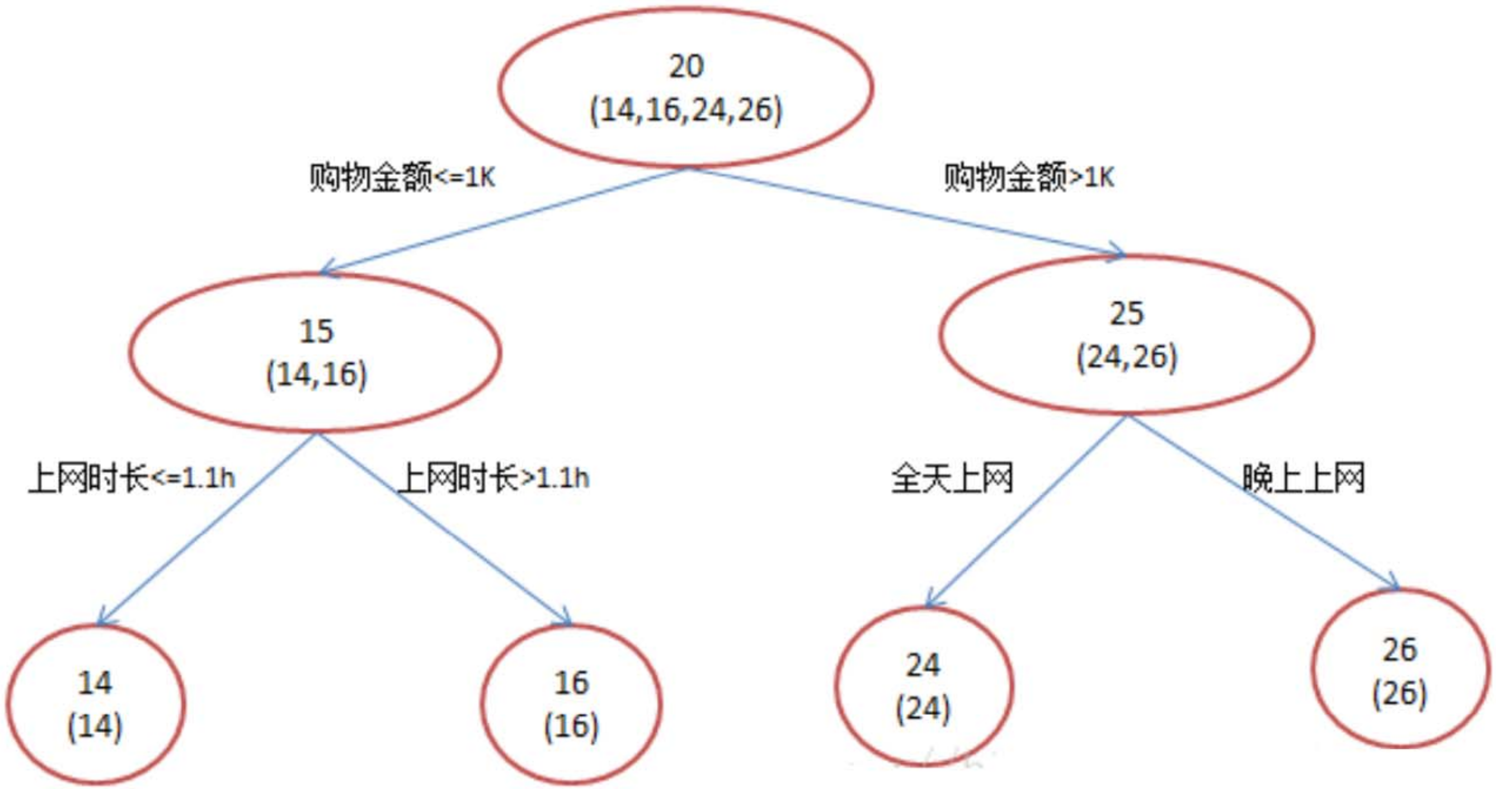
Bias-Variance



GBDT

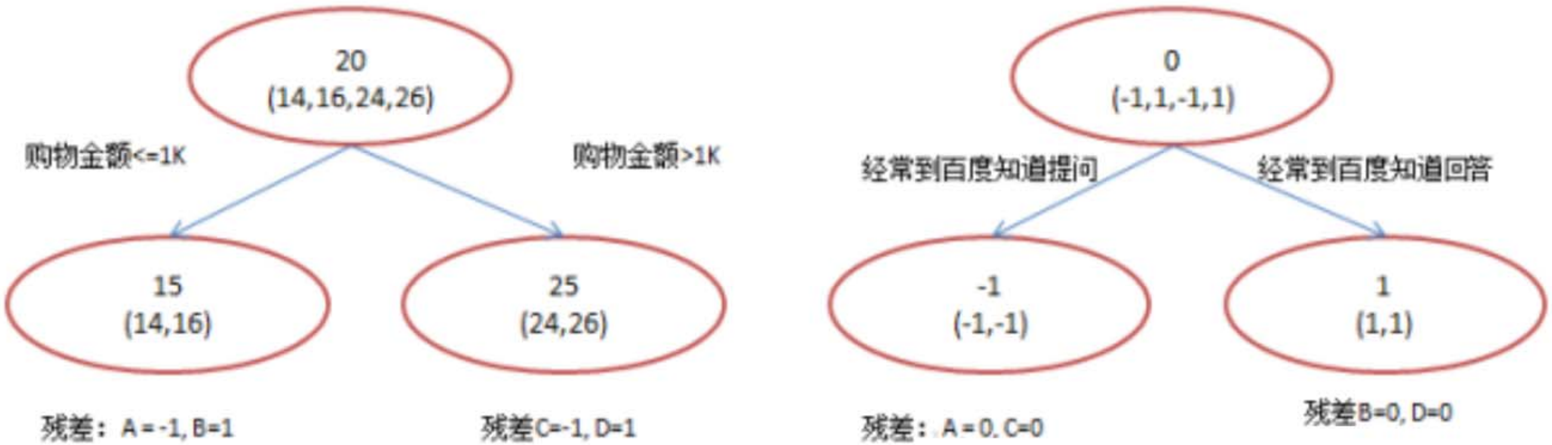
Please Check out the note.

GBDT Example



https://toutiao.io/posts/u52t61/preview

Discretization



XGBoost

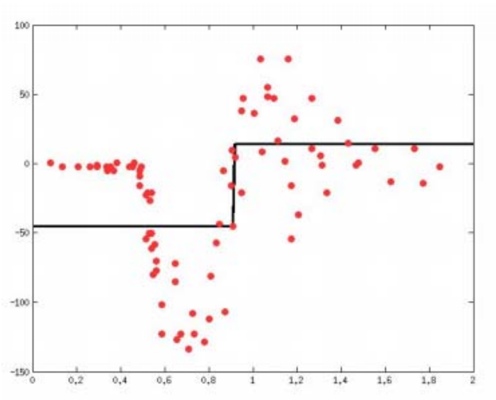
What is XGBoost?

XGBoost stands for e**X**treme **G**radient **B**oosting.

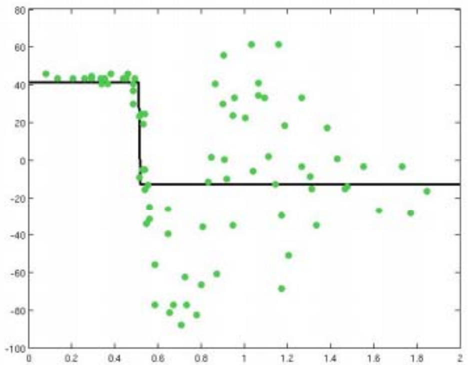
The name xgboost, though, actually refers to the engineering goal to push the limit of computations resources for boosted tree algorithms. Which is the reason why many people use xgboost.

https://homes.cs.washington.edu/~tqchen/2016/03/10/story-and-lessons-behind-the-evolution-of-xgboost.html

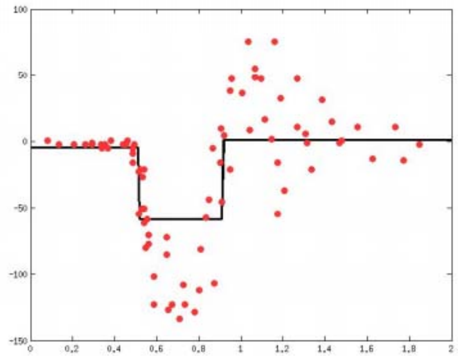
Gradient Boosting



Learn a weak DT predictor

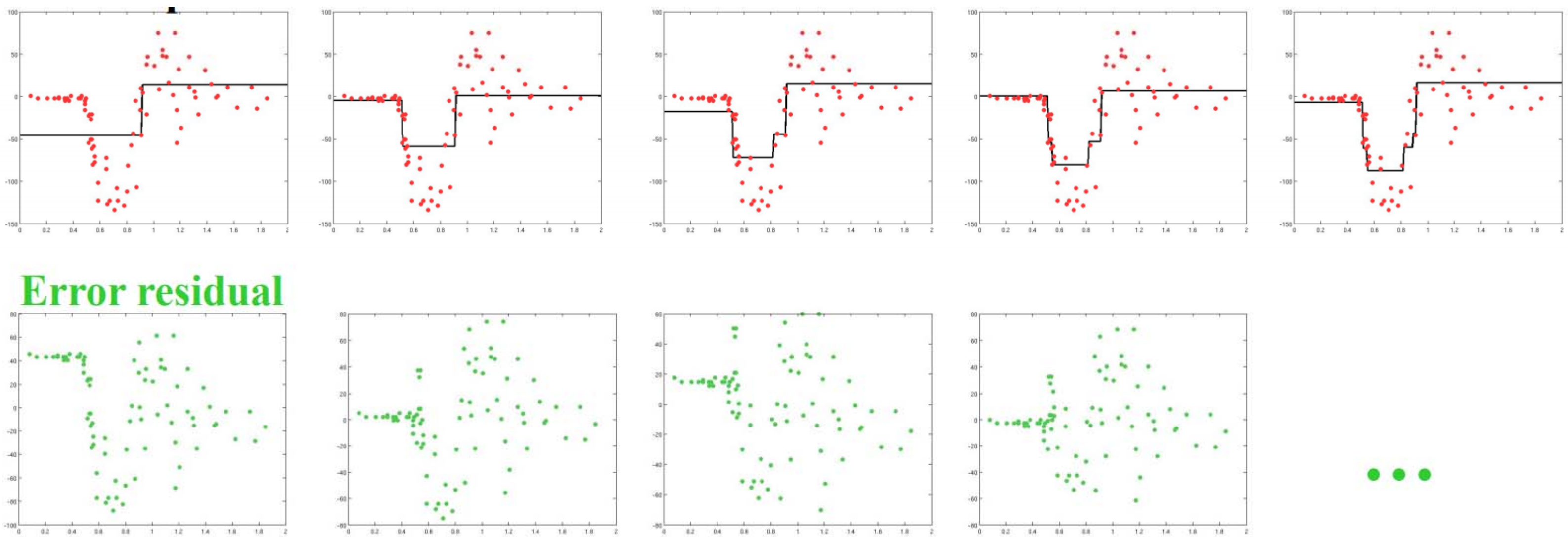


Try to correct its errors (again using a DT)



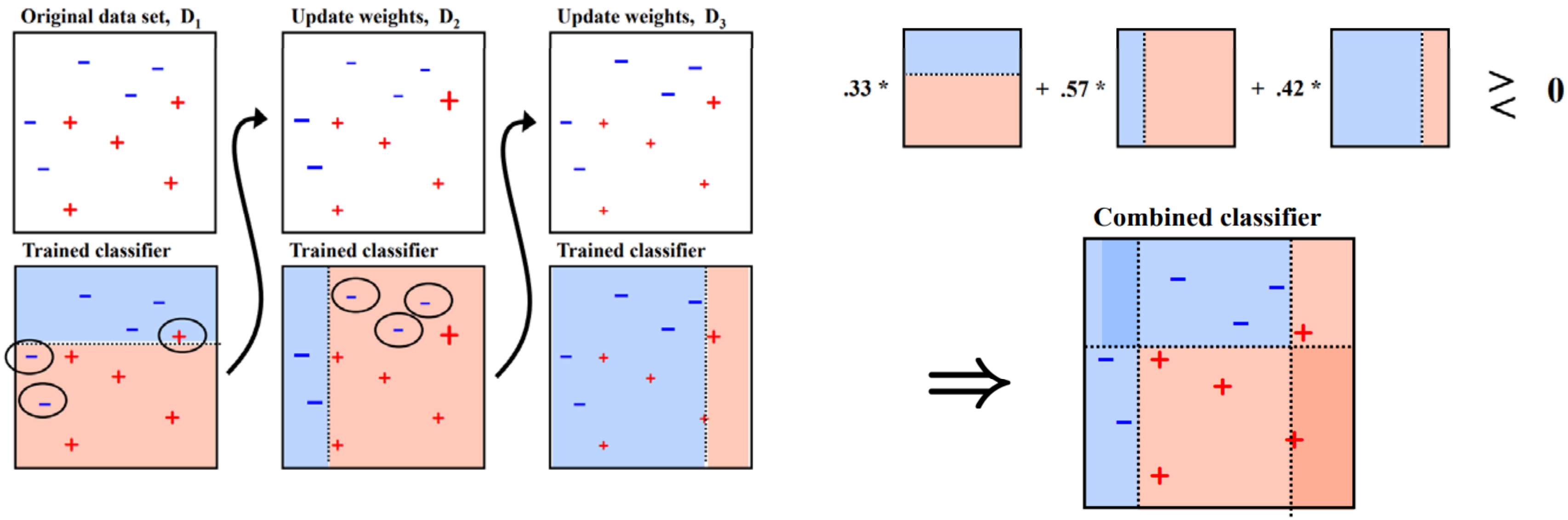
Combining gives a better predictor...

Gradient Boosting



Learn sequence of predicgors to fit the residue
Alexander Ihler: MLDM Class:
https://canvas.eee.uci.edu/courses/3287/assignments/syllabus

Boosting



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