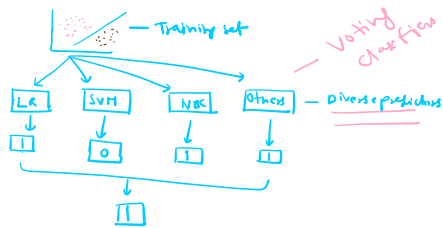


Decision Tree - Different subset of training set

Bagging, Boosting,



$V_{\text{out}} \Rightarrow C = 64\% - 36\%$   
 $m = \text{size of the data}$   
 $n \leq m = \text{LR on } n \text{ sample}$   
 $c \leq C = \text{No. of columns}$

Bagging (Boosting)  
 $(1 - \frac{1}{m})^n$   
 $\sim 36\%$   
 $m = 100$   
 $\Rightarrow n_1 = \frac{64\%}{1} = 64$   
 $\Rightarrow n_2 = \frac{36\%}{1} = 36$   
 $\Rightarrow 100 = m$   
 10 turning into 100  
 DT - 100 - 36

64% - Within the bag  
 36% - 0.08  
 Bagging - 10  
 ① DT - 100 - 64 - 0.08  
 ② DT - 100 - 64 - 0.08  
 ③ 1  
 ④ DT - 100 - 64 - 36

Random Sample  $\Rightarrow$   
 OR 100 - Dimension  
 $\Rightarrow$  50/100  
 $\Rightarrow$  50/100  
 $\Rightarrow$  1  
 $\Rightarrow$  25  $\leq$  5  
 $\Rightarrow$  10  
 $\Rightarrow$  5

Bagging & Boosting  $\Rightarrow$   
 ① Use multiple/different algorithms  
 ② Use same algorithm on random subsets of the training data - bagging  
 Boosting

Random patches & Subspaces  $\Rightarrow$  Max features & bootstrap-features  
 Random Forest  $\Rightarrow$  max-features = "auto"

Extra Trees  $\Rightarrow$  not bootstrapped  $\rightarrow$  random 10 threshold

Gradient Boosting  $\Rightarrow$  Ensemble  $\Rightarrow$  DT + DT + DT + DT + ... + DT

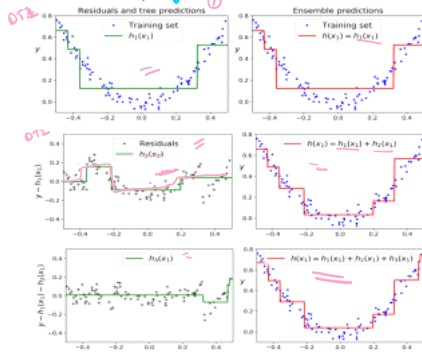


Figure 7.6. In this depiction of Gradient Boosting, the first predictor (top left) is trained normally, then each consecutive predictor (middle left and lower left) is trained on the previous predictor's residuals; the right column shows the resulting ensemble's predictions.

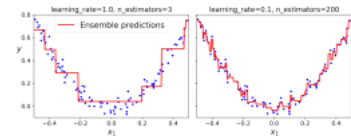
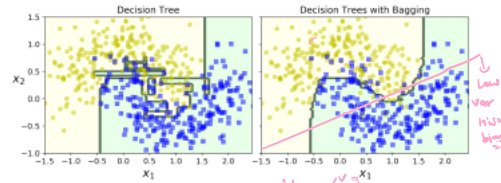


Figure 7.7. GBM ensembles with not enough predictors (left) and too many (right).

X-Boost | Light GBM | Cat Boost Algorithm



bootstrap=False and max\_samples=1.0]

bootstrap\_features to True and/or max\_features

Complexity - fit