

9.2 Bagging

Individual trees suffer from high variance.

Bootstrap aggregation (bagging) reduces variability by averaging many single tree's fits to bootstrapped replicates of the dataset.

For $b=1, \dots, B$

① Generate bootstrap dataset from $\{(x_i, y_i)\}_{i=1}^n$ with replacement, to get $\{(x_i^*, y_i^*)\}_{i=1}^n$.

② Fit tree to $\{(x_i^*, y_i^*)\}$ to get $\hat{f}^b(x)$.

The bagging predictor is

$$\hat{f}(x) = \frac{1}{B} \sum_{b=1}^B \hat{f}^b(x)$$

(like
Random
Forest
for
regression)

Bagged trees tend to perform better on out of sample data.

Notions of variable importance for bagged trees are not as straightforward.

- Track improvement in RSS for each individual feature.

For fixed
feature

For each tree, descend until you hit a split over that feature, compare squared error between not splitting over that feature vs. splitting over that feature.

\bar{y}

x_2

x_1

$\sum (y_i - \bar{y})^2$

\hat{c}_1	\hat{c}_2
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x_2

x_1

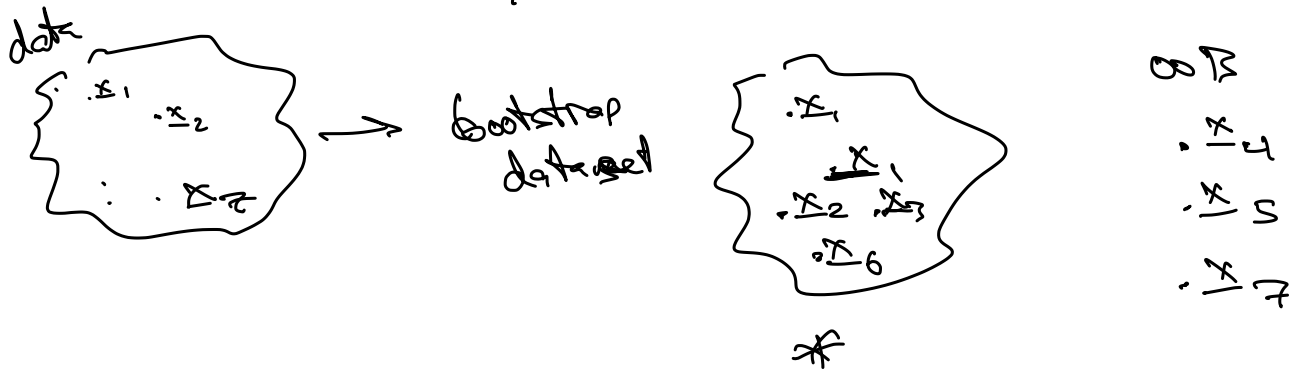
$\left(\sum_{\text{left}} (y_i - \hat{c}_1)^2 + \sum_{\text{right}} (y_i - \hat{c}_2)^2 \right)$

Permutation-based importance

For both bootstrapped dataset, some data points are not sampled, these are the out of bag (OOB) samples.

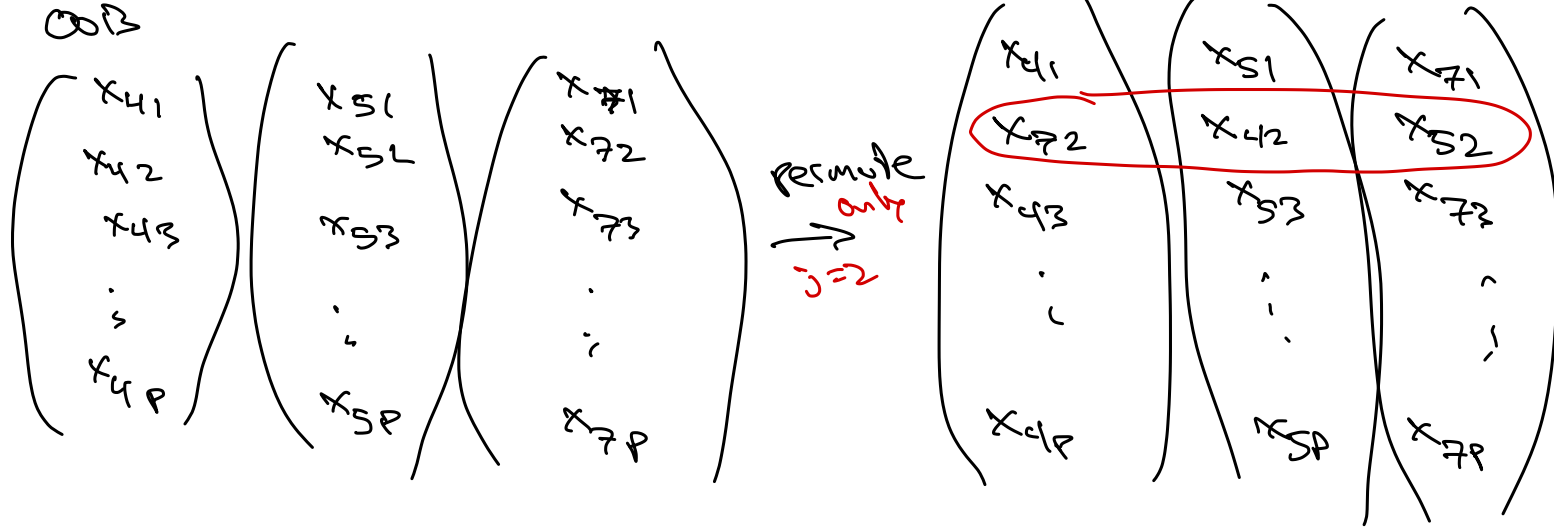
First, predict OOB samples based on fitted model in bag.

Then, fix feature j , permute that feature amongst all OOB samples & re-predict. Do this for all $j=1, \dots, P$ & $b=1, \dots, B$, compare decrease in accuracy over the unperturbed fit.



① fit to $*$, predict $\hat{f}^*(x_4), \dots, \hat{f}^*(x_7)$

② choose a feature $\frac{ex}{j=2}$



$x_{perm 4, 5, 7}$

$\hat{f}^*(x_{4perm}), \dots, \hat{f}^*(x_{7perm})$

