

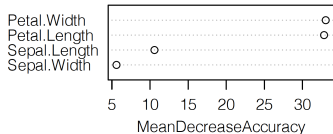
# Introduction to Machine Learning

## Random Forests: Feature Importance



### Learning goals

- Understand that the goal of defining variable importance is to enhance interpretability of the random forest
- Know definition of variable importance based on improvement in split criterion
- Know definition of variable importance based on permutations of OOB observations



## VARIABLE IMPORTANCE

- Single trees are highly interpretable
- Random forests as ensembles of trees lose this feature
- Contributions of the different features to the model are difficult to evaluate
- Way out: variable importance measures
- Basic idea: by how much would the performance of the random forest decrease if a specific feature were removed or rendered useless?



# VARIABLE IMPORTANCE / 2

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Measure based on improvement in split criterion

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**for** features  $x_j, j = 1$  to  $p$  **do**

**for** tree base learners  $\hat{b}^{[m]}, m = 1$  to  $M$  **do**

        Find all nodes  $\mathcal{N}$  in  $\hat{b}^{[m]}$  that use  $x_j$ .

        Compute improvement in splitting criterion achieved by them.

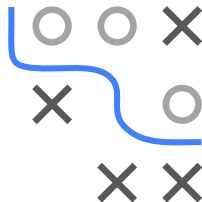
        Add up these improvements.

**end for**

    Add up improvements over all trees to get feature importance of  $x_j$ .

**end for**

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# VARIABLE IMPORTANCE / 3

Tree 1

	$x_1$	$x_p$	$y$	$\hat{y}$
1	2.00	1	1	
2	1.42	0		
3	2.01	1	1	
4	1.55	0	0	
5	1.89	1		
...				
n	1.72		1	0

....

Tree M

	$x_1$	$x_p$	$y$	$\hat{y}$
1	2.00	1	1	
2	1.42	0		
3	2.01	1	1	
4	1.55	0	0	
5	1.89	1		
...				
n	1.72		1	0

Permutation of feature 1

Tree 1

	$x_1$	$x_p$	$y$	$\hat{y}$
1	1.42	1	1	
2	1.89	0		
3	1.55	1	0	
4	1.72	0	0	
5	2.01	1		
...				
n	2.00		1	1

....

Tree M

	$x_1$	$x_p$	$y$	$\hat{y}$
1	1.42	1	1	0
2	1.89	0		
3	1.55	1	0	
4	1.72	0		
5	2.01	1	1	
...				
n	2.00		1	1

In-bag observations  
 Out-of-bag observations

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Measure based on permutations of OOB obs.

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Estimate OOB error  $\widehat{err}_{OOB}$ .

**for** features  $x_j$ ,  $j = 1$  to  $p$  **do**

    Perform permutation  $\psi_j$  on  $x_j$  to distort  
     feature-target relation for  $x_j$ .

**for** distorted observations  $(\mathbf{x}_{\psi_j}^{(i)}, y^{(i)})$ ,  $i = 1$  to  $n$  **do**

        Compute OOB prediction  $\hat{y}_{OOB, \psi_j}^{(i)}$ .

        Compute corresponding loss  $L(y^{(i)}, \hat{y}_{OOB, \psi_j}^{(i)})$ .

**end for**

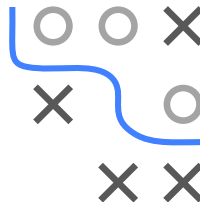
    Estimate importance of  $j$ -th variable

$$\widehat{VI}_j = \widehat{err}_{OOB, \psi_j} - \widehat{err}_{OOB}$$

$$= \frac{1}{n} \sum_{i=1}^n L(y^{(i)}, \hat{y}_{OOB, \psi_j}^{(i)}) - \widehat{err}_{OOB}.$$

**end for**

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# VARIABLE IMPORTANCE / 4

- Measure based on improvement in split criterion:  
MeanDecreaseGini (average total decrease in node impurities, measured by the Gini index)
- Measure based on permutations of OOB observations:  
MeanDecreaseAccuracy (average decrease in accuracy for predictions of OOB observations after permuting the  $j$ -th feature)

