

```
In [1]: %run Latex_macros.ipynb  
        %run beautify_plots.py
```

In [2]: *# My standard magic ! You will see this in almost all my notebooks.*

```
from IPython.core.interactiveshell import InteractiveShell  
InteractiveShell.ast_node_interactivity = "all"
```

```
# Reload all modules imported with %aimport
```

```
%load_ext autoreload
```

```
%autoreload 1
```

```
%matplotlib inline
```

Feature Importance

Given the n features in \mathbf{x} , which are the "most important" ?

The multiple trees in a Random Forest offer several ways to answer this question.

Importance: Decrease in Impurity

Recall that the question that splits the examples corresponding to a node is chosen so as to maximize Information Gain.

One method of measuring the importance of \mathbf{x}_j is the amount of impurity decrease it creates.

- For each feature x_j
 - find each node n in *any* tree in the forest with question (j, v) for *any* v
 - compute the information gain of the split on (j, v)
 - average the information gain across all such nodes

That is, how much does impurity decrease when \mathbf{x}_j is used in a question.

- This is a biased method
 - Recall the universe of possible values of \mathbf{x}_j is V_j
 - Larger $|V_j|$ means \mathbf{x}_j is more likely to appear in a questions
 - e.g., when \mathbf{x}_j is a continuous variable that has been made discrete
 - So \mathbf{x}_j will appear in more questions

Importance: Permutation importance

Let's consider building one tree from bootstrapped sample S .

Create another sample S' , derived from S by *permuting* the values of \mathbf{x}_j .

- maintains the unconditional distribution of \mathbf{x}_j
- breaks the correlation of \mathbf{x}_j with the target and other features

We can now measure the importance of \mathbf{x}_j as

- the change in out of bag accuracy of the tree built from S and S' .

That is, if \mathbf{x}_j is unimportant, then permuting its values should have little effect on accuracy.

Permutation Importance, feature j

\mathbf{X}

\mathbf{x}_1	\mathbf{x}_2	...	\mathbf{x}_j	...	\mathbf{x}_n
$\mathbf{x}_1^{(1)}$	$\mathbf{x}_2^{(1)}$...	$\mathbf{x}_j^{(1)}$...	$\mathbf{x}_n^{(1)}$
$\mathbf{x}_1^{(2)}$	$\mathbf{x}_2^{(2)}$...	$\mathbf{x}_j^{(2)}$...	$\mathbf{x}_n^{(2)}$
\vdots	\vdots		\vdots		\vdots
$\mathbf{x}_1^{(i)}$	$\mathbf{x}_2^{(i)}$...	$\mathbf{x}_j^{(i)}$...	$\mathbf{x}_n^{(i)}$
\vdots	\vdots		\vdots		\vdots
$\mathbf{x}_1^{(n)}$	$\mathbf{x}_2^{(n)}$...	$\mathbf{x}_j^{(n)}$...	$\mathbf{x}_n^{(n)}$



Score

 \mathbf{X}_{Perm}

\mathbf{x}_1	\mathbf{x}_2	...	\mathbf{x}_j	...	\mathbf{x}_n
$\mathbf{x}_1^{(1)}$	$\mathbf{x}_2^{(1)}$...	$\mathbf{x}_j^{(i_1)}$...	$\mathbf{x}_n^{(1)}$
$\mathbf{x}_1^{(2)}$	$\mathbf{x}_2^{(2)}$...	$\mathbf{x}_j^{(i_2)}$...	$\mathbf{x}_n^{(2)}$
\vdots	\vdots		\vdots		\vdots
$\mathbf{x}_1^{(i)}$	$\mathbf{x}_2^{(i)}$...	$\mathbf{x}_j^{(i_i)}$...	$\mathbf{x}_n^{(i)}$
\vdots	\vdots		\vdots		\vdots
$\mathbf{x}_1^{(n)}$	$\mathbf{x}_2^{(n)}$...	$\mathbf{x}_j^{(i_n)}$...	$\mathbf{x}_n^{(n)}$

Score_{Perm}Score – Score_{Perm}

Permutation importance also has issues

- may be biased if \mathbf{x}_j is strongly correlated with another feature $\mathbf{x}_{j'}$

In that case $\mathbf{x}_{j'}$ may compensate for the permuted \mathbf{x}_j , making \mathbf{x}_j seem unimportant.

In [4]: `print("Done")`

Done