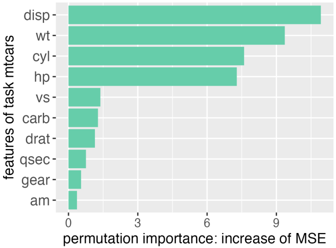
# Introduction to Machine Learning

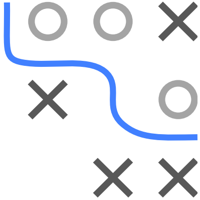
## Random Forest
## Feature Importance




**Learning goals**

- Understand that the goal of feature importance is to enhance interpretability of RF
- Understand FI based on feature permutation
- Understand FI based on improvement in splits

# PERMUTATION FEATURE IMPORTANCE

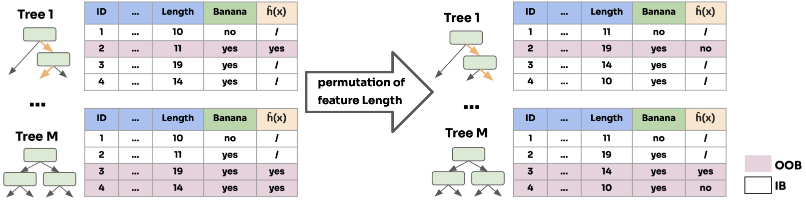


RFs improve accuracy by aggregating multiple decision trees but **lose interpretability** compared to a single tree. **Feature importance** mitigates this problem.

- How much does performance *decrease*, if feature is removed / rendered useless?
- We permute values of considered feature
- Removes association between feature and target, keeps marginal distribution
- Can obtain $\widehat{\mathrm{GE}}$ of RF (without and with permuted features) by predicting OOB data, to **efficiently compute FI during training**
- Avoids not only new models (if feature would be removed) but can already use "OOB test data" during training

| ID | Color | Form | Origin | ~~Length~~ | Banana |
|---|---|---|---|---|---|
| 1 | yellow | round | domestic | ~~10~~ | no |
| 2 | brown | oblong | imported | ~~11~~ | yes |
| 3 | green | oblong | imported | ~~19~~ | yes |
| 4 | yellow | oblong | domestic | ~~14~~ | yes |

# PERMUTATION IMPORTANCE




Tree 1 (before permutation):

| ID | ... | Length | Banana | $\hat{h}(x)$ |
|---|---|---|---|---|
| 1 | ... | 10 | no | / |
| 2 | ... | 11 | yes | yes |
| 3 | ... | 19 | yes | / |
| 4 | ... | 14 | yes | / |

Tree M (before permutation):

| ID | ... | Length | Banana | $\hat{h}(x)$ |
|---|---|---|---|---|
| 1 | ... | 10 | no | / |
| 2 | ... | 11 | yes | / |
| 3 | ... | 19 | yes | yes |
| 4 | ... | 14 | yes | yes |

Tree 1 (after permutation):

| ID | ... | Length | Banana | $\hat{h}(x)$ |
|---|---|---|---|---|
| 1 | ... | 11 | no | / |
| 2 | ... | 19 | yes | no |
| 3 | ... | 14 | yes | / |
| 4 | ... | 10 | yes | / |

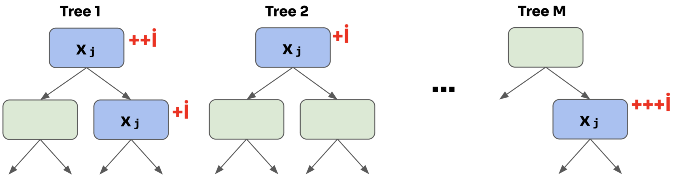
Tree M (after permutation):

| ID | ... | Length | Banana | $\hat{h}(x)$ |
|---|---|---|---|---|
| 1 | ... | 11 | no | / |
| 2 | ... | 19 | yes | / |
| 3 | ... | 14 | yes | yes |
| 4 | ... | 10 | yes | no |

Calculate $\widehat{\mathrm{GE}}_{\mathrm{OOB}}$ using set-based metric $\rho$
**for** features $x_j$, $j = 1 \to p$ **do**
  **for** Some statistical repetitions **do**
    Distort feature-target relation: permute $x_j$ with $\psi_j$
    Compute all $n$ OOB-predictions for permuted feature data, obtain all $\hat{f}^{(i)}_{\mathrm{OOB},\psi_j}$
    Arrange predictions in $\hat{\boldsymbol{F}}_{\mathrm{OOB},\psi_j}$; Compute $\widehat{\mathrm{GE}}_{\mathrm{OOB},j} = \rho(\mathbf{y}, \hat{\boldsymbol{F}}_{\mathrm{OOB},\psi_j})$
    Estimate importance of $j$-th feature: $\widehat{\mathrm{FI}_j} = \widehat{\mathrm{GE}}_{\mathrm{OOB},j} - \widehat{\mathrm{GE}}_{\mathrm{OOB}}$
  **end for**
  Average obtained $\widehat{\mathrm{FI}_j}$ values over reps
**end for**

# IMPURITY IMPORTANCE

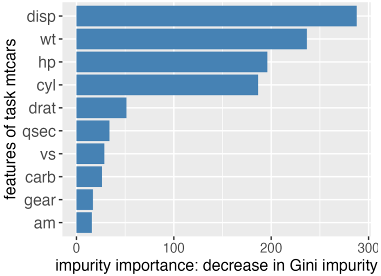
Alternative: Add up all *improvements* in splits where feature $x_j$ is used.

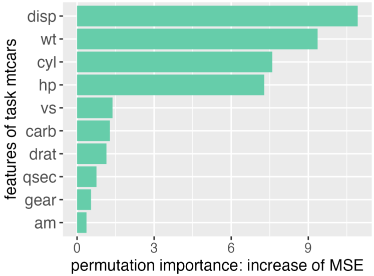



**for** features $x_j$, $j = 1 \to p$ **do**
    **for** all models $\hat{b}^{[m]}$, $m = 1 \to M$ **do**
        Find all splits in $\hat{b}^{[m]}$ on $x_j$
        Extract improvement / risk reduction for these splits
        Sum them up
    **end for**
    Add up improvements over all trees for FI of $x_j$
**end for**

# IN PRACTICE / OUTLOOK

Let's compare both FI variants on `mtcars`:




- Both methods are **biased toward features with more levels** (i.e., continuous or categoricals with many categories) ▸ Strobl et al. 2007
- More advanced versions exist
- PFI and FI have been generalized, see our lecture on IML!