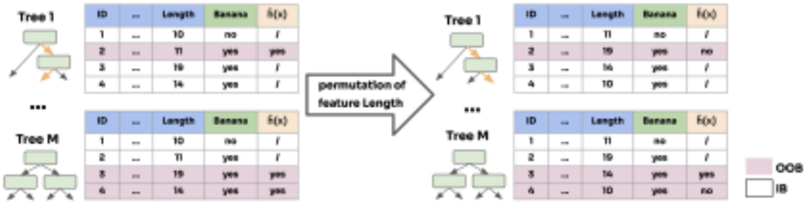
PERMUTATION FEATURE IMPORTANCE

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

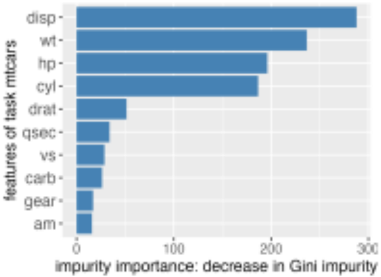
PERMUTATION IMPORTANCE

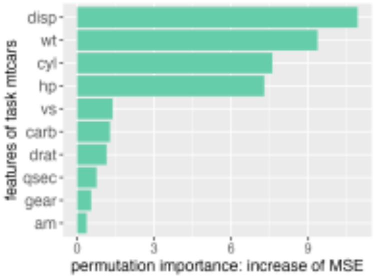


Calculate $\widehat{\mathrm{GE}}_{\mathrm{OOB}}$ using set-based metric ρ
for features x_j, $j = 1 \to p$ **do**
  for Some statistical repetitions **do**
    Distort feature-target relation: permute x_j with ψ_j
    Compute all n OOB-predictions for permuted feature data, obtain all $\hat{f}^{(i)}_{\mathrm{OOB},\psi_j}$
    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

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!