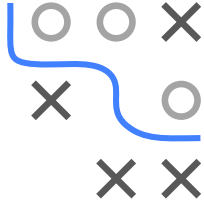
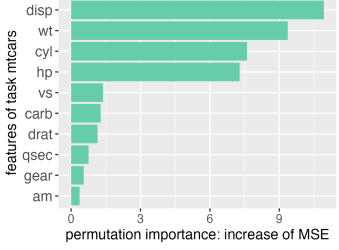
Introduction to Machine Learning



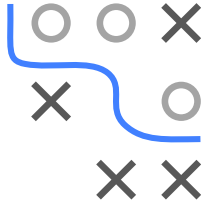
Random Forest
Feature Importance



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

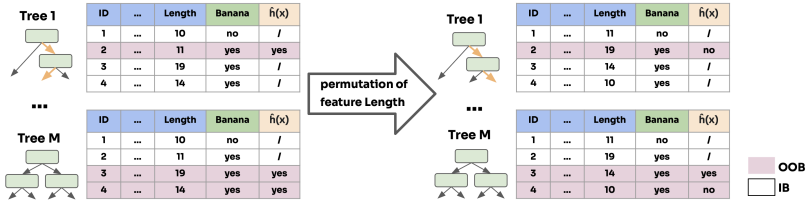


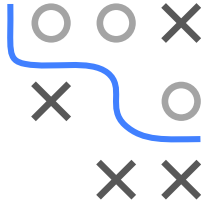
RFs improve accuracy by aggregating multiple decision trees but **lose interpretability** compared to a single tree. **Feature importance** mitigates this problem.

- 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

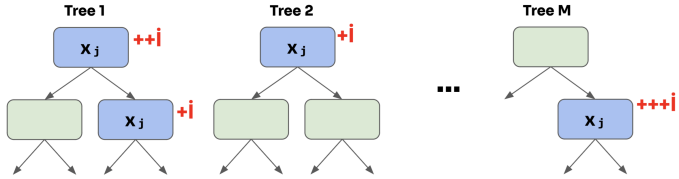


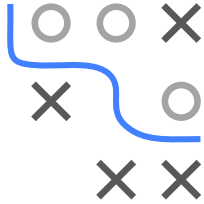


1: Calculate $\widehat{\mathrm{GE}}_{\mathrm{OOB}}$ using set-based metric ρ
2: **for** features x_j, $j = 1 \to p$ **do**
3: **for** Some statistical repetitions **do**
4: Distort feature-target relation: permute x_j with ψ_j
5: Compute all n OOB-predictions for permuted feature data, obtain all $\hat{f}^{(i)}_{\mathrm{OOB},\psi_j}$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

IMPURITY IMPORTANCE

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

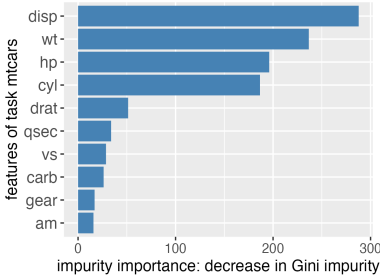


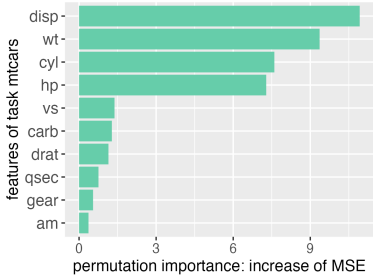


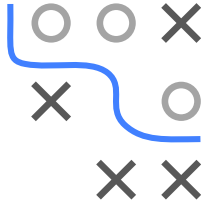
1: **for** features x_j, $j = 1 \to p$ **do**
2: **for** all models $\hat{b}^{[m]}$, $m = 1 \to M$ **do**
3: Find all splits in $\hat{b}^{[m]}$ on x_j
4: Extract improvement / risk reduction for these splits
5: Sum them up
6: **end for**
7: Add up improvements over all trees for FI of x_j
8: **end for**

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!