4.2. Permutation feature importance

Permutation feature importance is a model inspection technique that can be used for any fitted estimator when the data is rectangular. This is especially useful for non-linear or opaque estimators. The permutation feature importance is defined to be the decrease in a model score when a single feature value is randomly shuffled [1]. This procedure breaks the relationship between the feature and the target, thus the drop in the model score is indicative of how much the model depends on the feature. This technique benefits from being model agnostic and can be calculated many times with different permutations of the feature.

The `permutation_importance` function calculates the feature importance of estimators for a given dataset. The `n_repeats` parameter sets the number of times a feature is randomly shuffled and returns a sample of feature importances. Permutation importances can either be computed on the training set or an held-out testing or validation set. Using a held-out set makes it possible to highlight which features contribute the most to the generalization power of the inspected model. Features that are important on the training set but not on the held-out set might cause the model to overfit.

Note that features that are deemed non-important for some model with a low predictive performance could be highly predictive for a model that generalizes better. The conclusions should always be drawn in the context of the specific model under inspection and cannot be automatically generalized to the intrinsic predictive value of the features by them-selves. Therefore it is always important to evaluate the predictive power of a model using a held-out set (or better with cross-validation) prior to computing importances.

4.2.1. Relation to impurity-based importance in trees

Tree based models provides a different measure of feature importances based on the mean decrease in impurity (MDI, the splitting criterion). This gives importance to features that may not be predictive on unseen data. The permutation feature importance avoids this issue, since it can be applied to unseen data. Furthermore, impurity-based feature importance for trees are strongly biased and favor high cardinality features (typically numerical features). Permutation-based feature importances do not exhibit such a bias. Additionally, the permutation feature importance may use an arbitrary metric on the tree's predictions. These two methods of obtaining feature importance are explored in: Permutation Importance vs Random Forest Feature Importance (MDI).

4.2.2. Strongly correlated features

When two features are correlated and one of the features is permuted, the model will still have access to the feature through its correlated feature. This will result in a lower importance for both features, where they might *actually* be important. One way to handle this is to cluster features that are correlated and only keep one feature from each cluster. This use case is explored in: Permutation Importance with Multicollinear or Correlated Features.

Examples:

- Permutation Importance vs Random Forest Feature Importance (MDI)
- Permutation Importance with Multicollinear or Correlated Features

References:

[1] L. Breiman, "Random Forests", Machine Learning, 45(1), 5-32, 2001. https://doi.org/10.1023/A:1010933404324

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