TO DO

- describe how inf trees works with viz
- describe grouped predictors
- compare viz from all three rf variable importances on D3

INFTrees and INFforests Variable Importance

Theory

While conditional variable importance (Strobl et al) conditionally permutes each variable given the structure signified by the model that predicts the response, $Y \sim X_1, ..., X_i, ..., X_p$, our method conditionally permutes each variable given the structure outlined in a new model with the variable of interest as the response, $X_i \sim X_1, ...X_{i-1}, X_{i+1}, ...X_p$. This is not the most straightforward process, as trees partition the sample space, however, in INFTrees these partitions on the variables $X_1, ...X_{i-1}, X_{i+1}, ...X_p$ are treated as psuedo partitions on the variable of interest, X_i. This is accomplished by first partitioning on the sample predictors $X_1, ...X_{i-1}, X_{i+1}, ...X_p$ and then infering the partitions on X_i. As a visualizaiton of this, lets return to the D_3 dataset discussed in chapter 2.

Figure ___: A scatterplot of the first

Grouped Predictors

The theory behind INFtrees combines the permuatation approach to variable importance found in Strobl et al with Breiman et al 1984's notion of grouped predictors.

INFTrees

For a CART, T, representing the model Y $X_1, ..., X_p$ where $Y, X_1, ..., X_p$ are vectors of length n, the INFTrees algorithm proceeds as follows:

Algorithm 1 INFTree, $VI_{inf}(T)$

for each $X_i \in X_1, ..., X_p$ **do**
    Calculate: $\Phi_o = RSS(T, (Y, X_1, ..X_p))$
    Fit the tree T_{X_i}, where $T_{X_i} : X_i \sim X_1, ..., X_{i-1}, X_{i+1}, ...X_p$
    Extract the set P_{X_i} of partitions on X_i from T_{X_i}
    Permute X_i with respect to P_{X_i}
    Find $\Phi^* = RSS(T, (Y, X_1, ..., \bar{X}_i, ...X_p))$
    The difference between these values, $\Phi^* - \Phi_o$, is the variable importance for X_j on T,
end for

This procedure allows the null hypothesis that Y is independent of X_i given the values of $X_1, ...X_{i-1}, X_{i+1}, ...X_p$ to be tested. Therefor, values of VI_{inf} could be compared in a similar manner to the coefficients of linear regression.

INFForests

The algorithm for determining $VI_{inf}(R)$ follows similarly.

Algorithm 2 INFForests, $VI_{inf}(R)$

Fit a random forest, R on the dataset D fitting the model $Y \sim X_1, ..., X_p$.
for each $X_i \in X_1, ..., X_p$ **do**
  for each $t \in R$ **do**
    Calculate: $\Xi_o = \frac{1}{\nu_t} RSS(t, \bar{B}^t)$
    Calculate a tree T_i that predicts $X_i \sim X_1, ..., X_{i-1}, X_{i+1}, ...X_p$ using the subset of the observations used to fit t
    Permute the subset of X_i contained in $\bar{B}_t$ with respect to the set of partions P_{xi} from T_i.
    Now find $\Xi^* = \frac{1}{\nu_t} RSS(t, \bar{B}_t^*)$
    The difference between these values, $\Xi^* - \Xi_o$, is the variable importance for X_i on t
  end for
  Average over all $t \in R$

$$VI_{inf}(X_i, R) = \frac{1}{ntree} \sum^{ntree} \Xi^* - \Xi_o$$

$$VI_{inf}(X_j, R) = \frac{1}{ntree} \sum^{ntree} \frac{1}{\nu_t} RSS(t, \bar{B}_t^*) - \frac{1}{\nu_t} RSS(t, \bar{B}^t)$$

end for

Comparisons and Applications