A Comparison of Different Variable Importance Measures

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Measuring variable importance in random forests





Measuring variable importance in random forests

- Gini importance
 mean Gini gain produced by X_j over all trees
 (can be severely biased due to estimation bias and
 mutiple testing; Strobl et al., 2007)
- permutation importance
 mean decrease in classification accuracy after
 permuting X_j over all trees
 - (unbiased when subsampling is used; Strobl et al., 2007)

over all trees:

The permutation importance

$$VI(\mathbf{x}_j) = \frac{\sum_{t=1}^{ntree} VI^{(t)}(\mathbf{x}_j)}{ntree}$$

The permutation importance

Variable

Variable

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importance in RF

within each tree t $VI^{(t)}(\mathbf{x}_{j}) = \frac{\sum_{i \in \overline{\mathfrak{B}}^{(t)}} I\left(y_{i} = \hat{y}_{i}^{(t)}\right)}{\left|\overline{\mathfrak{B}}^{(t)}\right|} - \frac{\sum_{i \in \overline{\mathfrak{B}}^{(t)}} I\left(y_{i} = \hat{y}_{i,\pi_{j}}^{(t)}\right)}{\left|\overline{\mathfrak{B}}^{(t)}\right|}$ $\hat{y}_{i}^{(t)} = f^{(t)}(\mathbf{x}_{i}) =$ predicted class before permuting $\hat{y}_{i,\pi_i}^{(t)} = f^{(t)}(\mathbf{x}_{i,\pi_j})$ = predicted class after permuting X_j $\mathbf{x}_{i,\pi_j} = (x_{i,1}, \dots, x_{i,j-1}, x_{\pi_j(i),j}, x_{i,j+1}, \dots, x_{i,p})$ Note: $VI^{(t)}(\mathbf{x}_i) = 0$ by definition, if X_i is not in tree t What kind of independence corresponds to this kind of permutation? $n \mid y_n \mid x_{\pi_i(n),j} \mid z_n$ $H_0: X_i \perp Y, Z \text{ or } X_i \perp Y \land X_i \perp Z$ $P(Y, X_i, Z) \stackrel{H_0}{=} P(Y, Z) \cdot P(X_i)$

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What kind of independence corresponds to this kind of permutation?

the original permutation scheme reflects independence of X_j from both Y and the remaining predictor variables Z

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Suggestion: Conditional permutation scheme

obs	Y	X_j	Ζ
1	<i>y</i> 1	$X_{\pi_{j Z=a}(1),j}$	$z_1 = a$
3	<i>y</i> 3	$X_{\pi_j Z=a}(3), j$	$z_3 = a$
27	Y 27	$X_{\pi_{j Z=a}(27),j}$	<i>z</i> ₂₇ = <i>a</i>
6	<i>Y</i> 6	$X_{\pi_{j Z=b}(6),j}$	$z_6 = b$
14	<i>Y</i> 14	$X_{\pi_{j Z=b}(14),j}$	$z_{14} = b$
33	<i>Y</i> 33	$X_{\pi_{j Z=b}(33),j}$	$z_{33} = b$
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 $H_0: X_j \perp Y | Z$

 $P(Y, X_j | Z) \stackrel{H_0}{=} P(Y | Z) \cdot P(X_j | Z)$ or $P(Y | X_j, Z) \stackrel{H_0}{=} P(Y | Z)$ What kind of independence corresponds to this kind of permutation?

the original permutation scheme reflects independence of X_j from both Y and the remaining predictor variables Z

 \Rightarrow a high variable importance can result from violation of

either one!

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Technically use any partition of the feature space for conditioning

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Technically

- use any partition of the feature space for conditioning
- here: use binary partition already learned by tree for each tree
 - determine variables to condition on (via threshold)
 - extract their cutpoints
 - generate partition using cutpoints as bisectors

Strobl et al. (2008)

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Simulation results



Toy example

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Conditional

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variable

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spurious correlation between shoe size and reading skills in school-children



from party 0.9-991

Peptide-binding data



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Other variable importance measures

- partial correlation, standardized beta conditional effect of X_j given <u>all other</u> variables in the model
- "averaging over orderings"
 - ▶ for linear models (relaimpo, Grömping, 2006)
 LMG Lindeman, Merenda, and Gold (1980),
 ≈ "dominance analysis" Azen and Budescu (2003)
 PMVD Feldman (2005)
 - for GLMs (hier.part, Walsh and Nally, 2008)
 "hierarchical partitioning" Chevan and Sutherland (1991)
 - \mathbb{R}^2 decomposition

Desirable (?) properties

- proper decomposition: scores sum up to model R^2
- non-negativity
- exclusion: $\beta_i = 0 \Rightarrow \text{score} = 0$
- *inclusion*: $\beta_i \neq 0 \Rightarrow \text{score} \neq 0$

Grömping (2007)

Other variable importance measures

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Other variable

Other variable

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- ▶ random forest permutation importance ≈ "averaging over trees" unconditional varimp (randomForest, party, Breiman et al., 2006; Hothorn et al., 2008) conditional varimp (party, Hothorn et al., 0089)
- elastic net (elasticnet, caret, Zou and Hastie, 2008; Kuhn, 2008) grouping property: correlated predictors get similar (largest) score

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Desirable (?) properties

- proper decomposition: scores sum up to model R²
 LMG, PMVD
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Grömping (2007)

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Desirable (?) properties

- \blacktriangleright proper decomposition: scores sum up to model R^2 LMG, PMVD
- non-negativity LMG, PMVD, RF varimp (in principle)
- exclusion: $\beta_i = 0 \Rightarrow \text{score} = 0$
- ▶ *inclusion*: $\beta_i \neq 0 \Rightarrow$ score $\neq 0$

Grömping (2007)

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Desirable (?) properties

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- *inclusion*: $\beta_i \neq 0 \Rightarrow$ score $\neq 0$ all

Grömping (2007)

Desirable (?) properties

- proper decomposition: scores sum up to model R^2 LMG, PMVD
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- *inclusion*: $\beta_i \neq 0 \Rightarrow$ score $\neq 0$

Grömping (2007)

Other variable

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Simulation study

dgp: $y_i = \beta_1 \cdot x_{i,1} + \cdots + \beta_{12} \cdot x_{i,12} + \varepsilon_i, \ \varepsilon_i \stackrel{i.i.d.}{\sim} N(0,1)$ $X_1,\ldots,X_{12}\sim N(0,\Sigma)$

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Linear model



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LMG



coefficient in dgp

Linear model

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PMVD



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RF unconditional importance



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RF unconditional importance



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RF unconditional importance





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RF unconditional importance





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RF unconditional importance

RF conditional importance

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RF conditional importance



coefficient in dgp





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RF conditional importance



RF conditional importance





RF conditional importance



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Elastic net

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RF conditional importance



Now wait a second...

what about elastic net's grouping property?

Elastic net





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Elastic net



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Elastic net



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▶ w.r.t. prediction accuracy: importance measures following the *exclusion* principle rule

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▶ w.r.t. prediction accuracy: importance measures following the *exclusion* principle rule standardized betas, PMVD (not quite), RF conditional measures importance (especially with large mtry) and elastic net Summary (tuned!)

Summary

- ▶ w.r.t. prediction accuracy: importance measures following the *exclusion* principle rule standardized betas, PMVD (not quite), RF conditional importance (especially with large mtry) and elastic net (tuned!)
- ▶ RF: not limited to linear model, interactions included, applicable even if p > 30

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Summary

- ▶ w.r.t. prediction accuracy: importance measures following the *exclusion* principle rule standardized betas, PMVD (not quite), RF conditional importance (especially with large mtry) and elastic net (tuned!)
- RF: not limited to linear model, interactions included. applicable even if p > 30
- ▶ if you want elastic net to group: don't tune!?

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