Study on tree-based methods

MATH 6380 project 2

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Outline

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Studying tree based methods...

Why did we choose tree-based methods?

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- Tree-based methods are straight-forward and easy to implement.
- There are yet many improvement methods.
- Studied the method on 2 datasets.

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The dataset

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Goal for this dataset

Do straightforward analysis and compare with Lasso (PJ 1).

What we found

In terms of MSE, simple regression tree(0.11) slightly worse than Lasso(0.06); bagging, random forest and boosting even better(0.04, 0.02).

Visualize the results

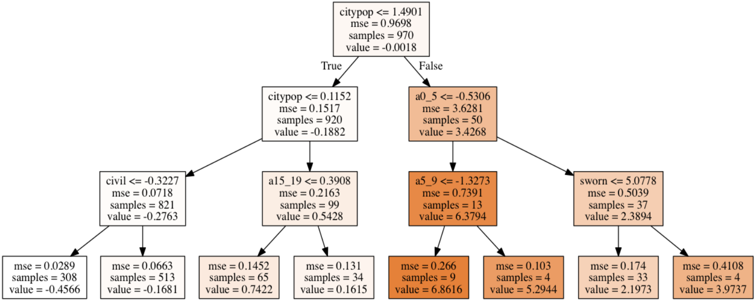

Figure: Regression tree on crime data

Boosting and random forests

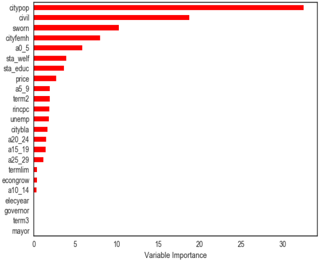

Figure: Importance from boosting

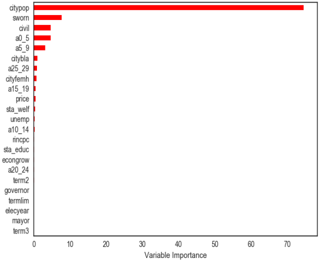

Figure: Importance from random forest

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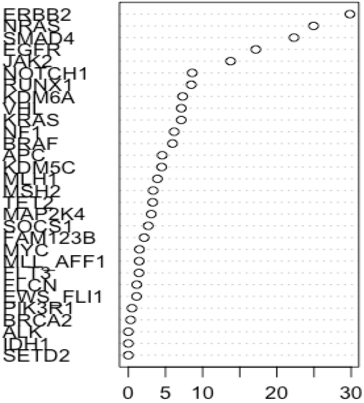
Variable Importance

- The **R randomForest** package optionally produces 2 additional pieces of information. One is called **Variable Importance**, a measure of the importance of the predictor variables.
- It is based upon the mean decrease of accuracy in predictions on the out of bag samples when a given variable is excluded from the model.
- In this project, we define variables/predictors with $\%IncMSE > 0$ as important variables, then select them as our predictors in our final model.

Importanct Variables in BinaryDrug

The necessary calculations are carried out tree by tree as the random forest is constructed. Our experience has been that even though the variable importance measures may vary from run to run, the ranking of the importances is quite stable.



A potential variable selection method?

- We have tried *LASSO* in this dataset. Bad.
- Somebody introduced $p-value$ selection. Kaggle $MSE = 3.08$. Good.
- Can we do better using variable importance?

some V.I related models

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- V.I + **MLR**, Kaggle $MSE = 3.26057$
- V.I + **Random Forest** with using all V.I, Kaggle $MSE = 3.23067$
- So sad. And I don't know why.

However...

- What if we adapt a **Random Forest** with *mtry* slightly > # of V.I ?
- Say in this Kaggle Competition, # of V.I is 25, and we have tried $mtry = 25$ to 30, all giving us MSE lower than 3.10.
- (Maybe) this can be explained from that, using slightly more *mtry* in each iteration can have a higher chance covering all those V.I when building **Random Forest**.

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To conclude our work in PJ2...

1. Tree-based regression algos are suitable for these discrete-input, continous-output datasets.
2. As a metric, **Variable Importance** may not be useful for variable selection process.