Visually Exploring Random Forests

The ggRandomForests package

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UseR! 2014

Random Forests

Statistical Modeling: The Two Cultures

Two goals of statistical models:

- Prediction: Predict the response given future observations
- Information: Explain association of covariates to the response

L. Breiman 2001

Random Forests

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- Ensemble of Classification/Regression Trees

randomForest R Package

- RStudio CRAN logs rank: 61

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- Advantages
  - Predictive Performance (A+)
  - Simple to train/tune
  - Non-parametric/non-linear
  - Built in generalization error estimates

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- Disadvantages
  - Information (F)

randomForest

Generic randomForest algorithm

- Bootstrap Data (B)
  - Training set (b)
  - Hold out set (oob)

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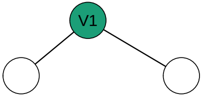

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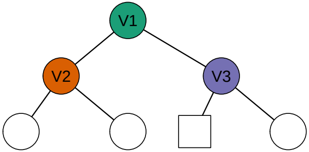

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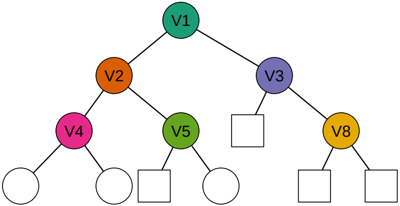

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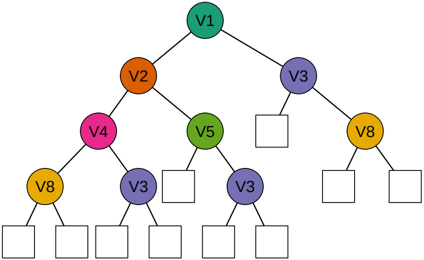

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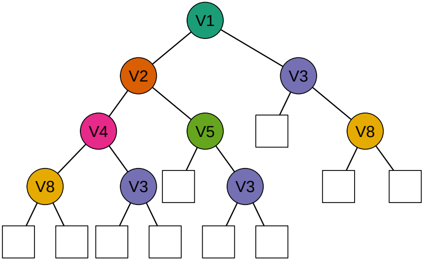
- A Stopping Rule
- Tree Estimates
- Aggregate for Forest Estimates



randomForests for Survival

Ishwaran et al., 2008

randomForestSRC package: A unified treatment for

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  - Parallel Execution (OpenMP)
  - Minimal Depth Variable Selection

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  - Parallel Execution (OpenMP)
  - Minimal Depth Variable Selection
- Disadvantages
  - Some performance optimization remains
  - Graphics. . .

ggRandomForest package

Goal: Simplify graphical representation of randomForests.

In progress:
`https://github.com/ehrlinger/ggRandomForests`

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- Extracts data.frame objects from a randomForest[SRC].
- Create ggplot graphic elements from each data.frame type.

Unified graphics for Survival, Regression and Classification Forests

Example: Heart Surgery Data

Yoon et.al. 2010

Four surgical treatments:

CABG, CABG+MVR, CABG+SVR, Transplant

- 1466 patients (observations n)
- 46 covariates (predictors p)
- randomForest imputation for missing data.
- 2 separate outcomes (response)
  - Hospital Death (binary, events=43)
  - Survival time with censoring (events=444)

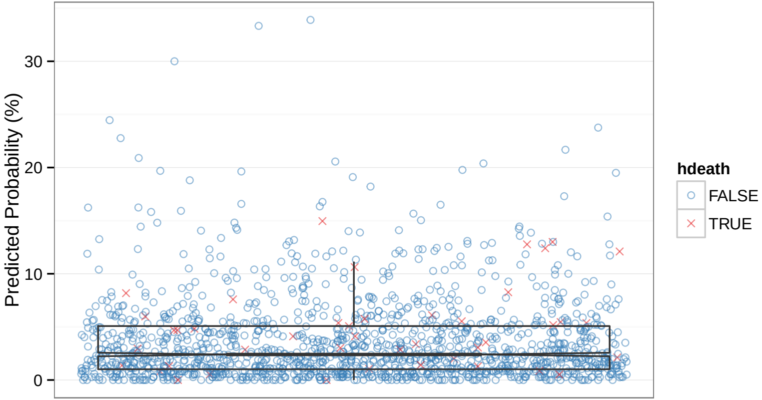
Classification Forests

```
# randomForestSRC classification forest
rf.cls = rfsrc(hdeath~., data=dta.rfc,
               ntree=ntree )

# ggRandomForests default (predicted values)
plot.ggRFsrc(rf.cls)
```

Classification - predicted probability

Hospital Death

```
plot.ggRFsrc(rf.cls)
```

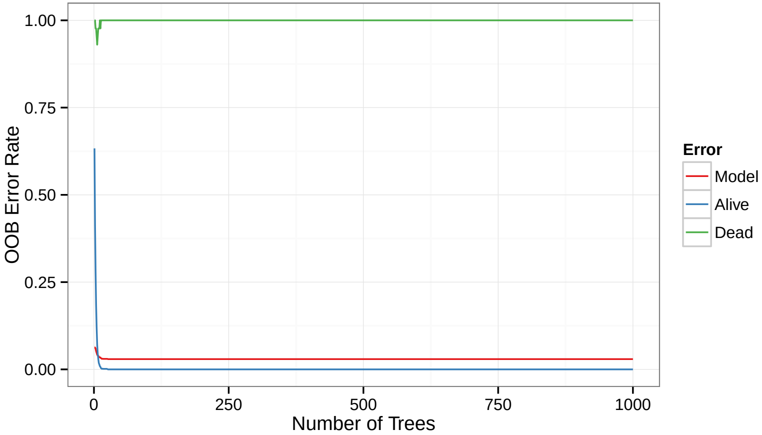


ggError function

```r
# ggRandomForest error convergence rate
gg.err = ggError(rf.cls)
plot(gg.err)

# or...
plot.ggError(rf.cls)
```

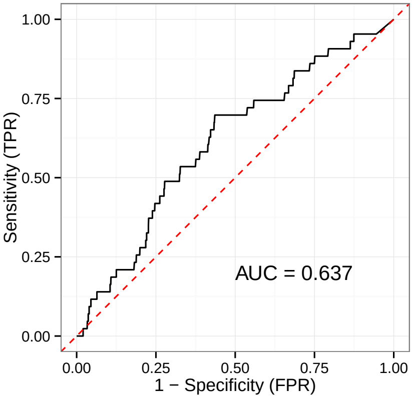
ggError function

```
plot.ggError(rf.cls)
```



ROC curves

```
plot.ggROC(rf.cls)
```



Random Forests for Survival

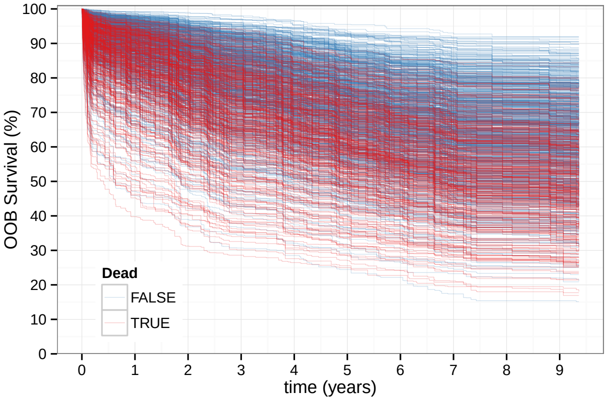
```
# randomForestSRC survival forest
rf.surv = rfsrc(Surv(ivdead,dead)~.,
                data = dta.rfs,
                ntree = ntree)

# ggRandomForests default (predicted survival)
plot.ggRFsrc(rf.surv)
```

Alternatively:

```
# ggRFsrc data object
srvData = ggRFsrc(rf.surv)
plot(srvData)
```

Random Forests for Survival

```
plot.ggRFsrc(rf.surv)
```



ggError Function

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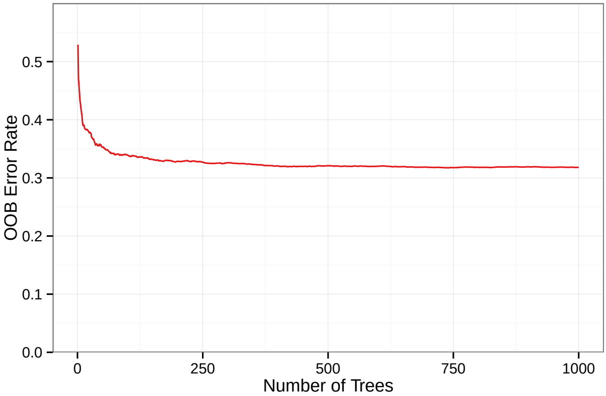
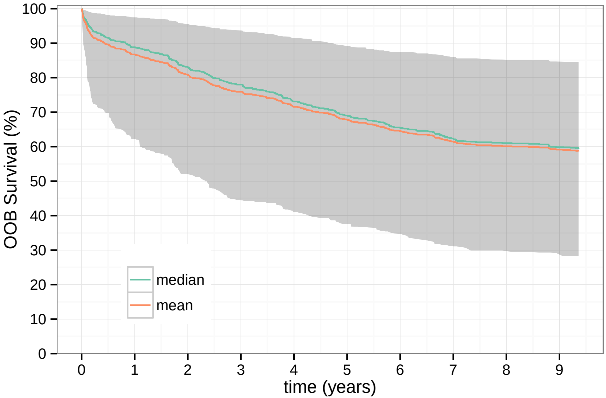


Survival Forests

```
plot.ggRFsrc(rf.surv, se=.95)
```



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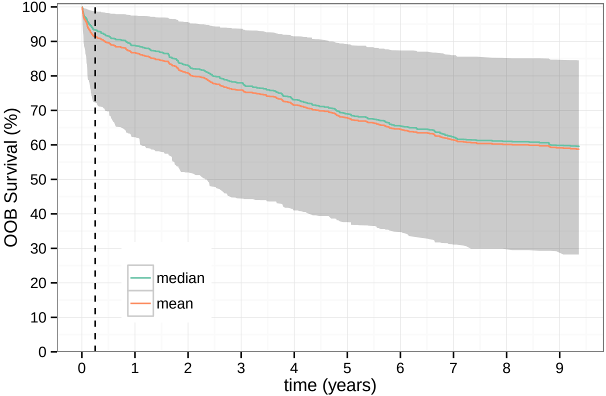

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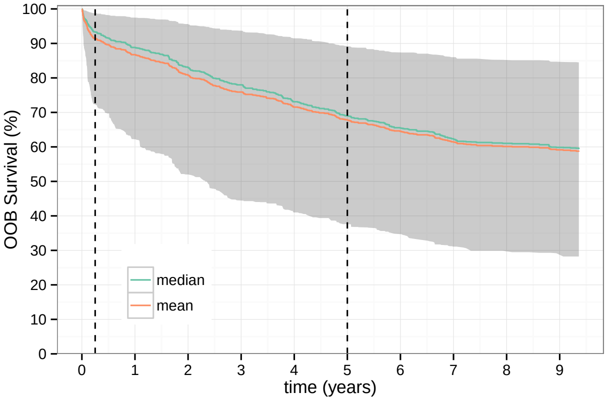
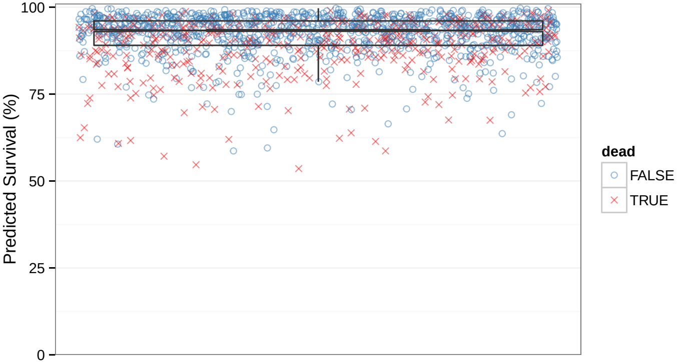
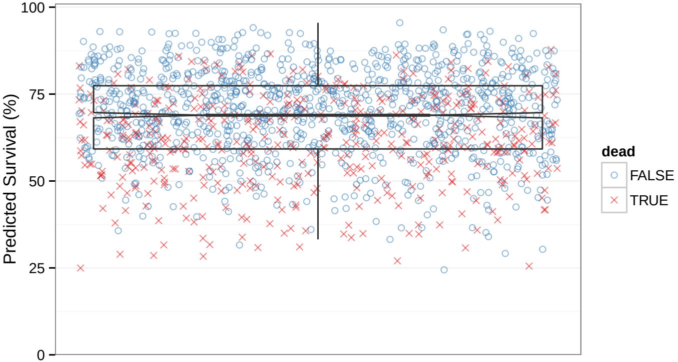


Survival Forests (3 month)



Survival Forests (5 year)



But how do randomForests predict?

We want the good prediction ... and information too!

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  - Variable Importance (VIMP)
  - Minimal Depth

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We want the good prediction . . . and information too!

- Which Variables contribute?
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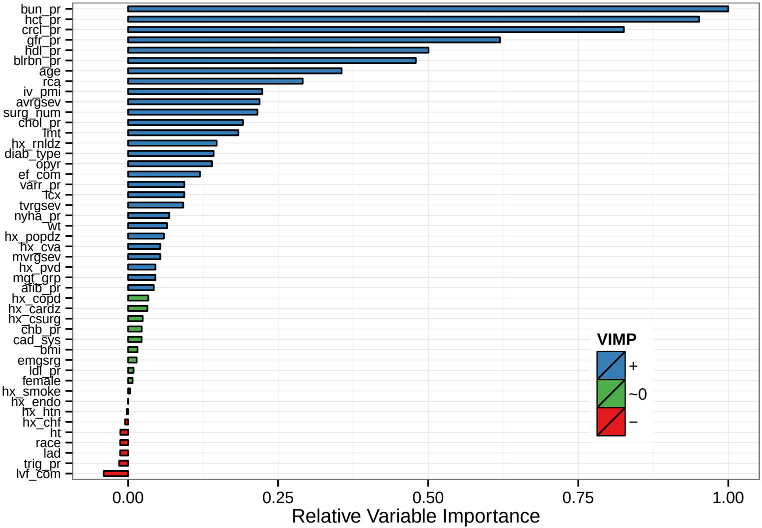
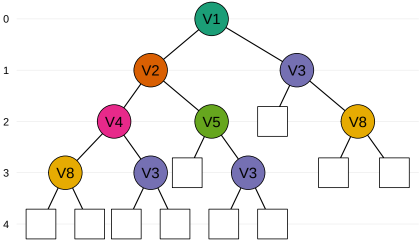
  - Minimal Depth
- How do Variables contribute?
  - Variable Dependence plots
  - Partial Dependence plots

Variable Importance

```
vimp.plt=plot.ggVimp(rf.surv)
```



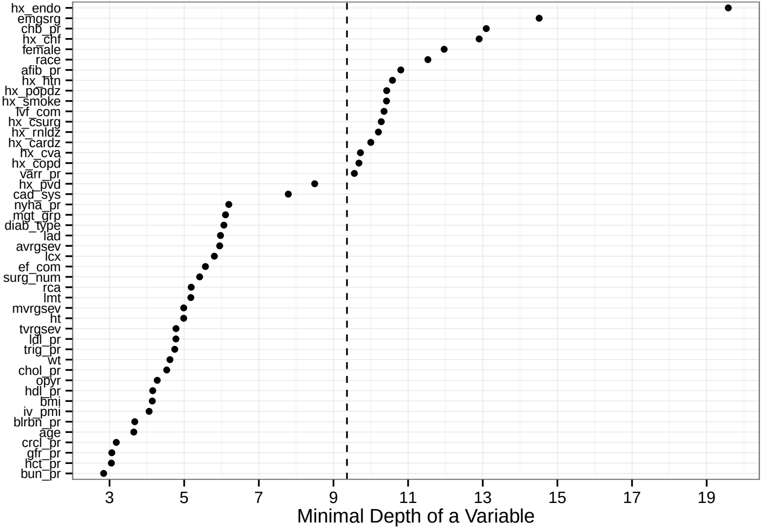
Minimal Depth



- Average (minimal) split distance from the root node (0) over the entire forest
- Measure of how a variable segregates the population

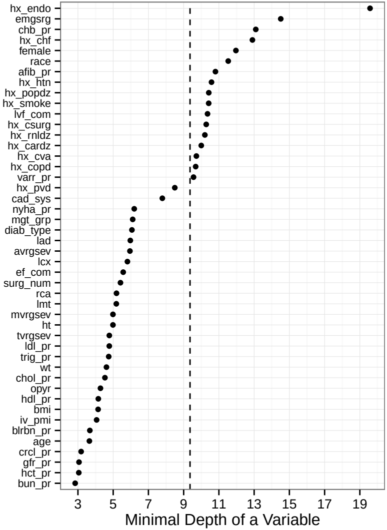
Minimal Depth

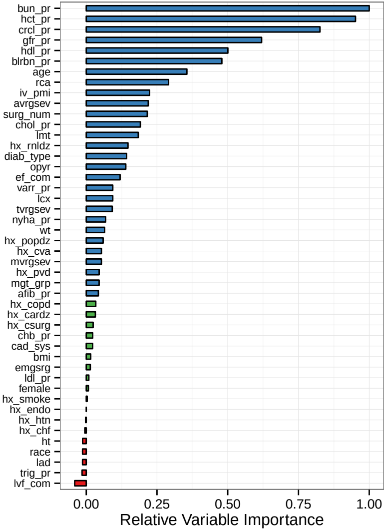
```r
md.plt=plot.ggMinimalDepth(rf.surv)
```



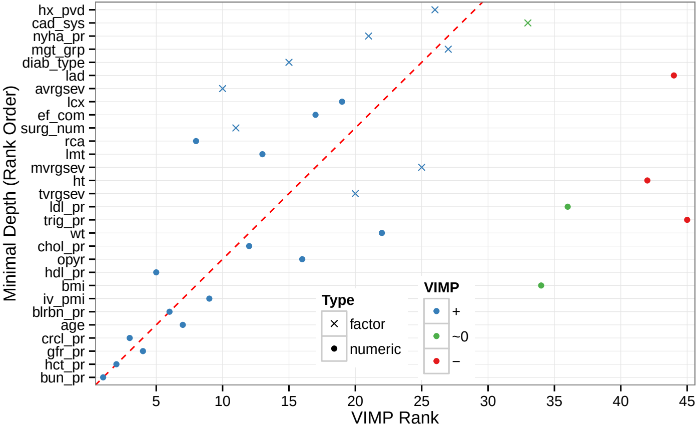
Minimal Depth and VIMP

```
grid.arrange(md.plt, vimp.plt)
```

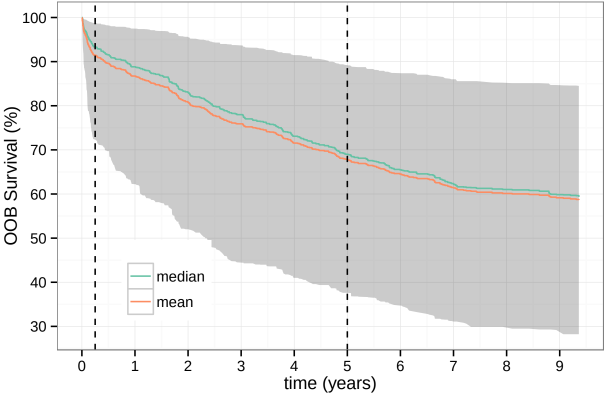




Minimal Depth and VIMP

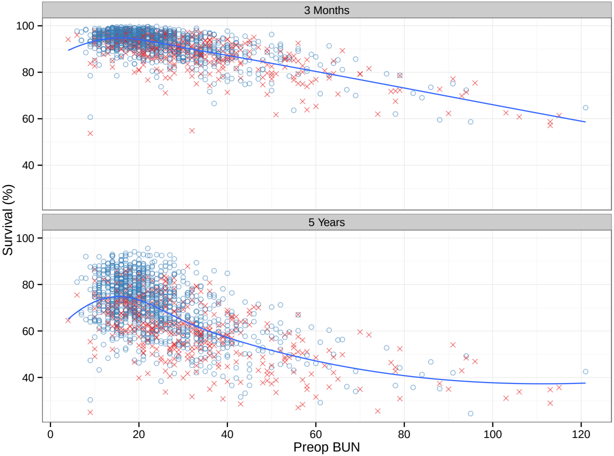


How do variables contribute?



Variable Dependence Plot

```
plot.ggVariable(rf.surv, vars="bun_pr",
                time=c(.25, 5))
```



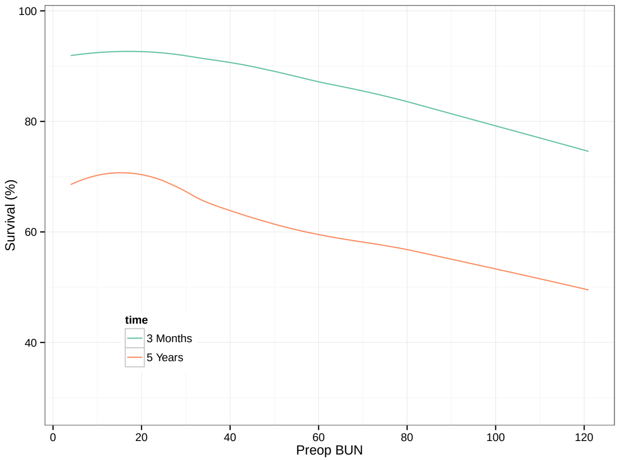
Partial Variable Dependence

```
# randomForestSRC partial plots
rf.part = plot.variable(rf.surv,
                        xvar.names = "bun_pr",
                        partial=TRUE,
                        time=c(.25,5),
                        show.plots = FALSE)

# ggRandomForests plot function
plot.ggPartial(rf.part)
```

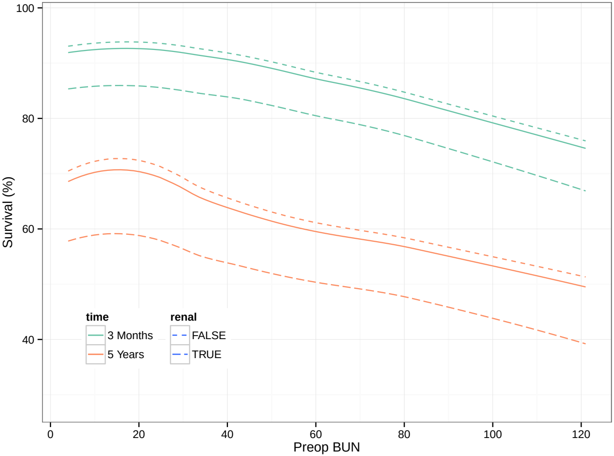
Partial Variable Dependence

```
plot.ggPartial(rf.part,...)
```

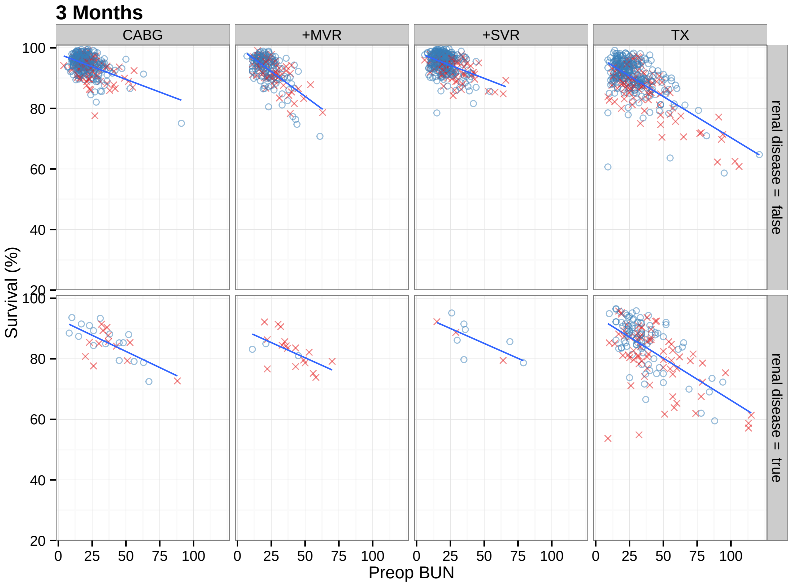


Partial Variable Dependence

```
plot.ggPartial(rf.part ,...)
```



Conditional Plots



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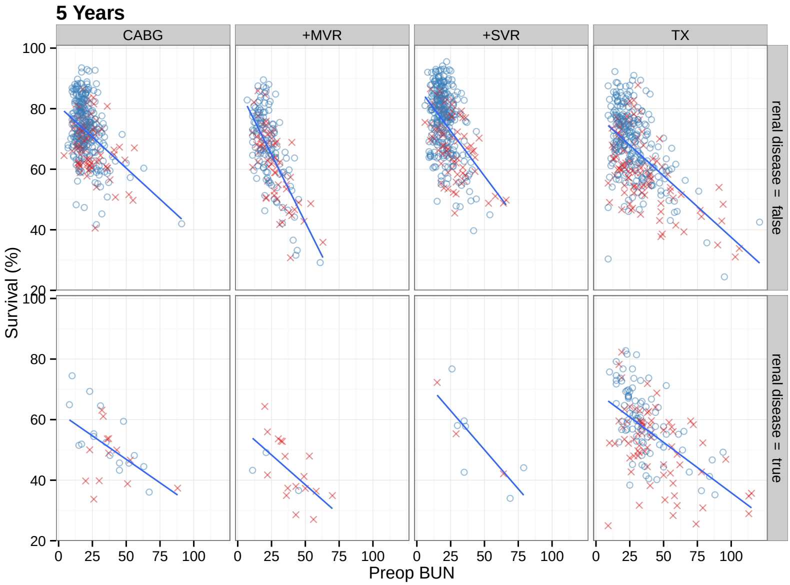
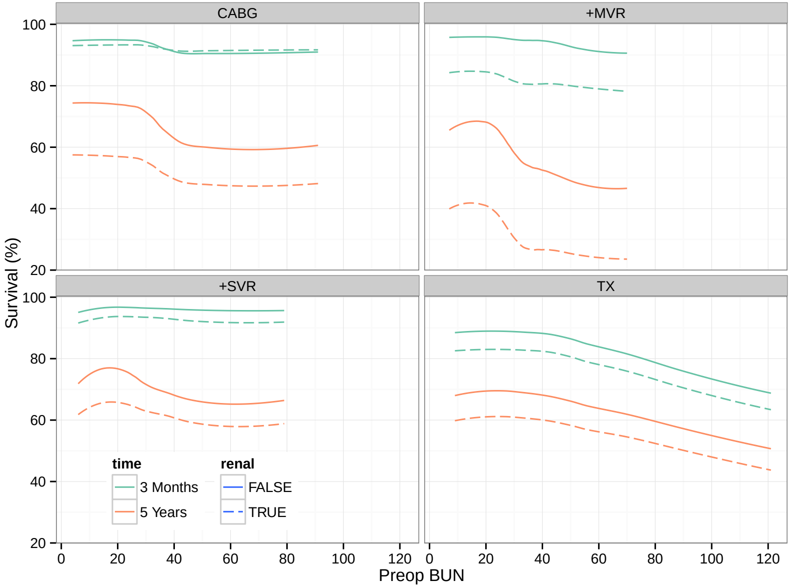


Partial Dependence Coplots



The ggRandomForest Package

For good prediction . . . and information too!

- Which Variables contribute?
  - Variable Importance (VIMP) - mispecification
  - Minimal Depth - segmentation and selection
- How do Variables contribute?
  - Variable Dependence plots - Covariate Trends
  - Partial Dependence plots - Risk Adjusted Trends

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Unified graphics for Survival, Regression and Classification Forests

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References I

- Breiman, L. (2001b). "Statistical Modeling: The Two Cultures". In: *Statistical Science* 16.3, pp. 199–231.
- Breiman, L. (2001a). "Random Forests". In: *Machine Learning* 45.1, pp. 5–32.
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References II

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