

Predictors of Implement and Plan to Implement

Stats Group and BCHC

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Analysis Plan

For each outcome we would like to identify any salient associations among demographic and institutional variables. We will use random forests to both measure how good a prediction can be created and to identify which attributes are important for the prediction. We will give descriptive statistics broken down by the 6 levels of the targets.

Read Data

Data were downloaded from redcap.

```
load("~/Box Sync/bchc/bchc.Rdata")
```

basic summary of retained variables

```
summary(x)
```

```
##          imp          qi3          four          plan          set
## no implem:18  no qi  :17  imp, no qi:17  no plan: 8  UniHosp   :17
## implem      :23  qi team: 6  no imp    :18  plan    :10  CorpHosp   : 7
## NA's        : 3  NA's    :21  NA's      : 9  NA's      :26  Community :14
##                                                     BirtCenter: 2
##                                                     Other      : 1
##                                                     NA's       : 3
##
##   acred      years      nonwhite      role
## TJC :38  Min.    : 4.00  Mode :logical  provider      : 1
## DVN : 3  1st Qu.:20.00  FALSE:38  directcaregiver: 9
## none: 3  Median :28.00  TRUE :6    nursemanager   :17
##                Mean  :27.17  NA's :0    gradstudent    : 2
##                3rd Qu.:36.00                other      :12
##                Max.   :50.00                NA's       : 3
##                NA's    :3
##   climate      culture      orgcapacity      unitcapacity      accreditation
## noeffect:31  noeffect:23  noeffect:28  noeffect:31  noeffect:32
## top4      :13  top4      :21  top4      :16  top4      :13  top4      :12
##
##
##
##
##   management      physician      nursing      patient      documentation
## noeffect:37  noeffect:35  noeffect:37  noeffect:38  noeffect:22
## top4      : 7  top4      : 9  top4      : 7  top4      : 6  top4      :22
```

```
##
##
##
##
##
##      emr      time      accredit      staff      admin
## noeffect:25  noeffect:39  noeffect:31  noeffect:23  noeffect:34
## top4      :19  top4      : 5  top4      :13  top4      :21  top4      :10
##
##
##
##
##      nm      md      champ      student      right
## noeffect:37  noeffect:41  noeffect:30  noeffect:35  noeffect:12
## top4      : 7  top4      : 3  top4      :14  top4      : 9  top4      :32
##
##
##
##
##      individual
## noeffect:15
## top4      :29
##
##
##
##
```

Random Forests

Random forests attempts to build a classifier by creating a large number of decision trees from bootstrapped data randomly selecting potential features. A good attribute of this method is its ability function when there are more predictors than observations. Additionally the method is robust against correlated predictors, missing values. The output contains the out of the box(oob) error rate which is the rate of error for ensemble of trees applied to data not used to train the model. That makes the oob error resistant to overfitting.

Models can be calibrated with weights to place more value on correctly identifying either level of the target. We did not do that here so models are scored based on their overall correct prediction.

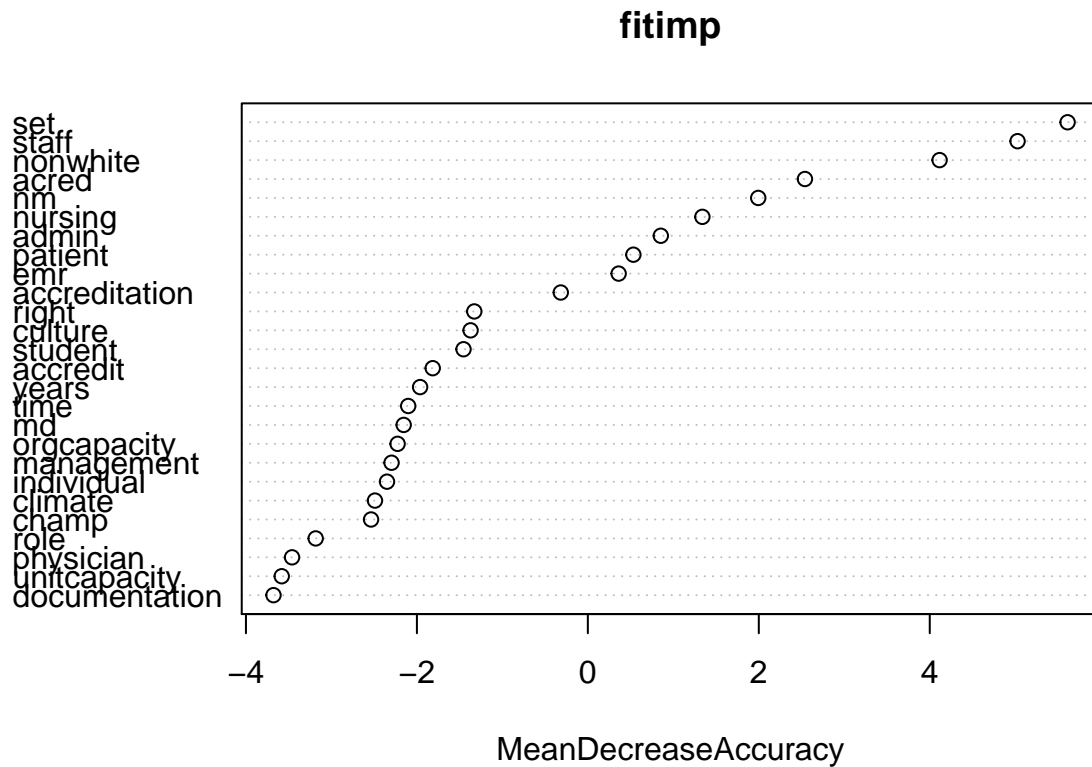
Implementation

```
fitimp <- randomForest(imp ~ ., data= x[,-c(2:4)],ntree=500,na.action='na.omit',importance=T)
fitimp

##
## Call:
## randomForest(formula = imp ~ ., data = x[, -c(2:4)], ntree = 500,      importance = T, na.action = 
##      Type of random forest: classification
##      Number of trees: 500
## No. of variables tried at each split: 5
##
```

```
##          OOB estimate of  error rate: 46.34%
## Confusion matrix:
##          no implem implem class.error
## no implem      6      12  0.6666667
## implem        7      16  0.3043478
```

```
varImpPlot(fitimp,type=1)
```

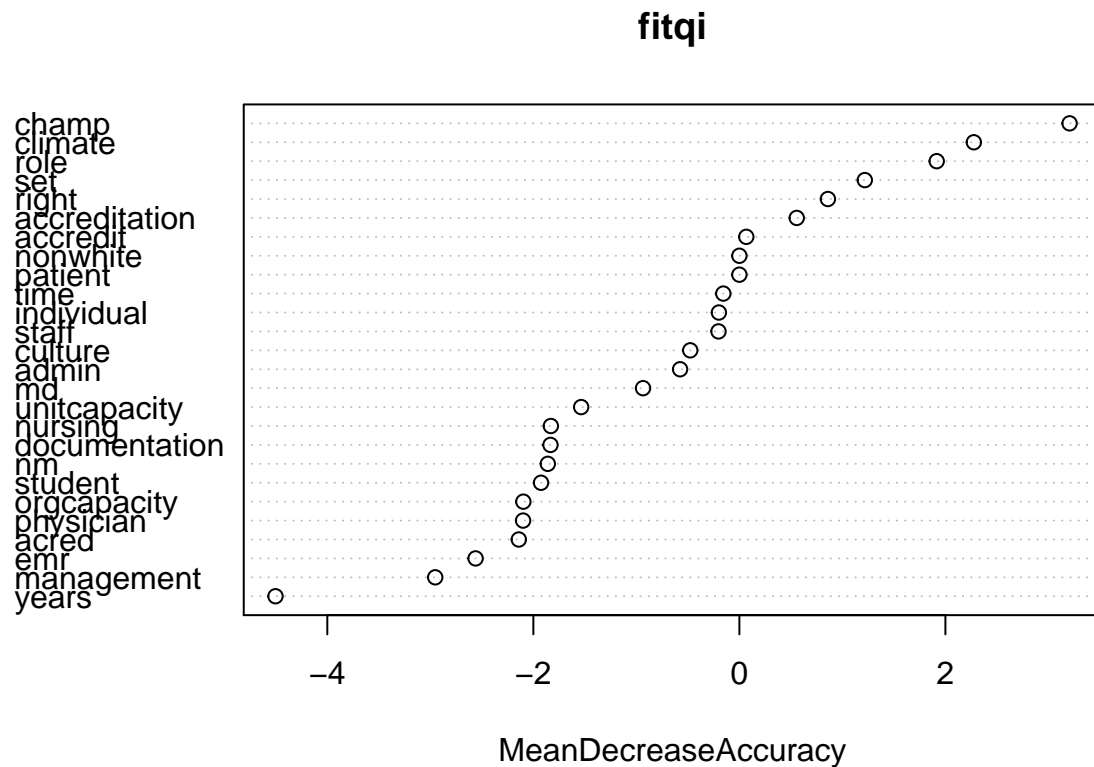


QI

```
fitqi <- randomForest(qi3 ~ ., data= x[,-c(1,3,4)],ntree=500,na.action='na.omit',importance=T)
fitqi
```

```
##
## Call:
## randomForest(formula = qi3 ~ ., data = x[, -c(1, 3, 4)], ntree = 500,      importance = T, na.action
##          Type of random forest: classification
##          Number of trees: 500
## No. of variables tried at each split: 5
##
##          OOB estimate of  error rate: 26.09%
## Confusion matrix:
##          no qi qi team class.error
## no qi      17      0      0
## qi team      6      0      1
```

```
varImpPlot(fitqi,type=1)
```



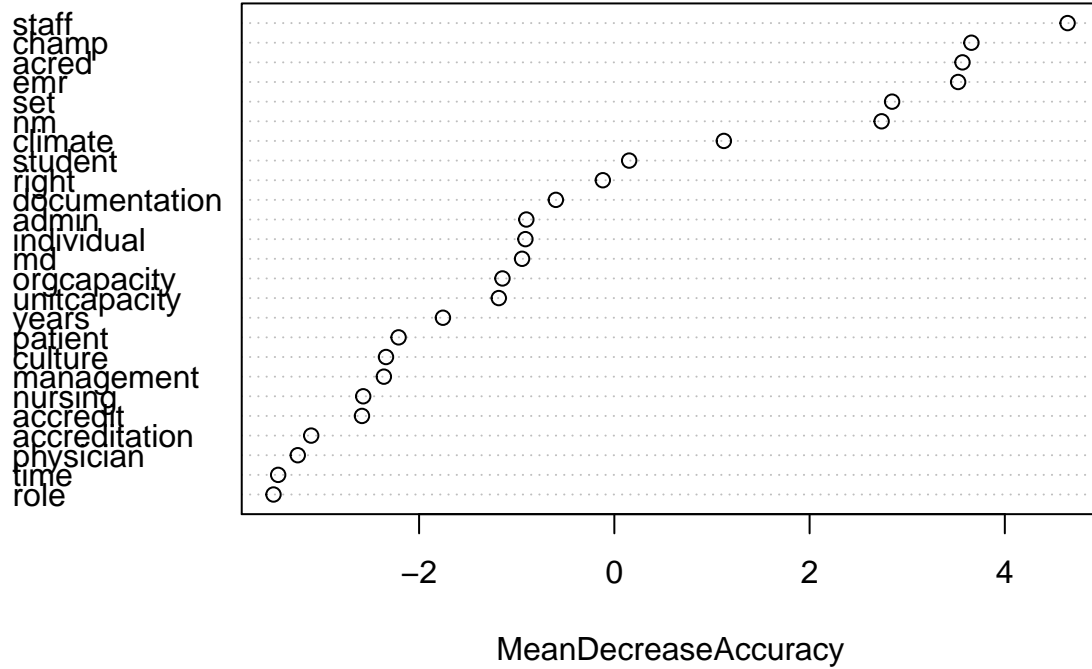
four

```
fit4 <- randomForest(four ~ ., data= x[,-c(1:2,4,8)],ntree=500,na.action='na.omit',importance=T)
fit4

##
## Call:
## randomForest(formula = four ~ ., data = x[, -c(1:2, 4, 8)], ntree = 500,      importance = T, na.ac
##           Type of random forest: classification
##           Number of trees: 500
## No. of variables tried at each split: 5
##
## OOB estimate of  error rate: 51.43%
## Confusion matrix:
##           imp, no qi no imp class.error
## imp, no qi          9      8  0.4705882
## no imp             10      8  0.5555556

varImpPlot(fit4,type=1)
```

fit4



plan

```
fitplan <- randomForest(plan ~ ., data= x[, -c(1:3)], ntree=500, na.action='na.omit', importance=T)
fitplan

##
## Call:
## randomForest(formula = plan ~ ., data = x[, -c(1:3)], ntree = 500,      importance = T, na.action =
##           Type of random forest: classification
##           Number of trees: 500
## No. of variables tried at each split: 5
##
## OOB estimate of  error rate: 44.44%
## Confusion matrix:
##      no plan plan class.error
## no plan      2   6      0.75
## plan         2   8      0.20
varImpPlot(fitplan, type=1)
```

fitplan

