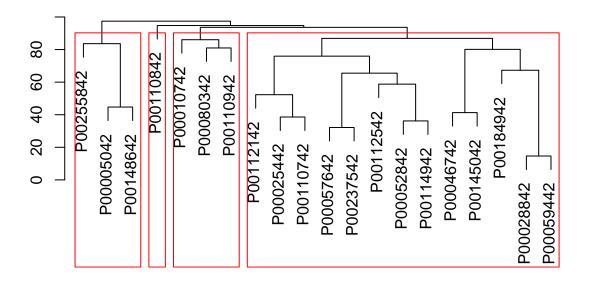
Principle Components



Gradient Boosting

```
library(gbm)

## Warning: package 'gbm' was built under R version 3.4.4

## Loaded gbm 2.1.4

set.seed(11)
gbm_split <- initial_split(data.wide, prop = .7)
gbm_train <- training(gbm_split)
gbm_test <- testing(gbm_split)</pre>
```

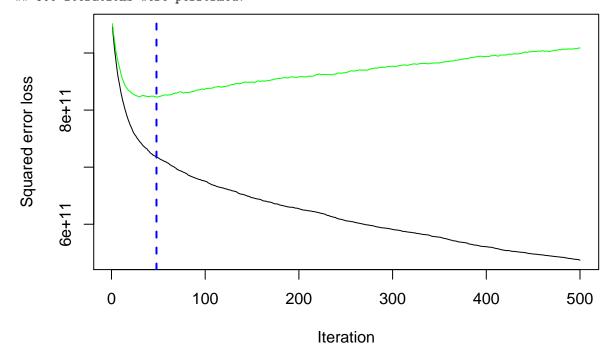
Perform a grid search which iterates over every combination of hyperparameter values and allows us to assess which combination tends to perform well.

```
# create hyperparameter grid
hyper_grid <- expand.grid(</pre>
  shrinkage = c(.01, .05, .1),
  interaction.depth = c(1, 3, 5),
  n.minobsinnode = c(5, 7, 10),
  bag.fraction = c(0.7, .85, 1),
  optimal_trees = 0,
                                     # a place to dump results
  min_RMSE = 0
                                     # a place to dump results
)
# randomize data
random_index <- sample(1:nrow(gbm_train), nrow(gbm_train))</pre>
random_ames_train <- gbm_train[random_index, ]</pre>
# grid search
for( i in 1:nrow(hyper_grid)) {
  # reproducibility
```

```
set.seed(123)
  # train model
  gbm.tune <- gbm(</pre>
    formula = purc.total~gender+age+occupation+city_category+stay_years+marital_status,
    distribution = "gaussian",
    data = random_ames_train,
    n.trees = 5000,
    interaction.depth = hyper_grid$interaction.depth[i],
    shrinkage = hyper_grid$shrinkage[i],
    n.minobsinnode = hyper_grid$n.minobsinnode[i],
    bag.fraction = hyper_grid$bag.fraction[i],
    train.fraction = .75,
    n.cores = NULL, # will use all cores by default
    verbose = FALSE
  # add min training error and trees to grid
  hyper_grid$optimal_trees[i] <- which.min(gbm.tune$valid.error)
  hyper_grid$min_RMSE[i] <- sqrt(min(gbm.tune$valid.error))</pre>
hyper_grid %>%
  dplyr::arrange(min_RMSE) %>%
 head(10)
##
      shrinkage interaction.depth n.minobsinnode bag.fraction optimal_trees
## 1
           0.05
                                 5
                                               10
                                                           0.7
## 2
           0.10
                                 3
                                                7
                                                            1.0
                                                                           33
## 3
           0.10
                                 3
                                               10
                                                            1.0
                                                                           33
## 4
           0.10
                                 3
                                                5
                                                            1.0
                                                                           26
## 5
           0.05
                                 3
                                               10
                                                            1.0
                                                                           70
## 6
           0.05
                                 3
                                                7
                                                            1.0
                                                                           60
## 7
           0.05
                                 3
                                                5
                                                            1.0
                                                                           65
                                                           0.7
## 8
           0.05
                                 5
                                               5
                                                                           58
## 9
           0.01
                                 3
                                                5
                                                            1.0
                                                                          339
                                 3
                                               10
## 10
           0.01
                                                            1.0
                                                                          359
      min_RMSE
##
## 1 823864.6
## 2 823913.3
## 3 823969.5
## 4 824066.3
## 5 824076.9
## 6 824094.2
## 7 824132.1
## 8 824212.1
## 9 824219.1
## 10 824274.3
# train a cross validated model using parameters specified above
gbm.fit.final <- gbm(</pre>
  purc.total~gender+age+occupation+city_category+stay_years+marital_status,
  data=gbm_test,
  distribution = "gaussian",
```

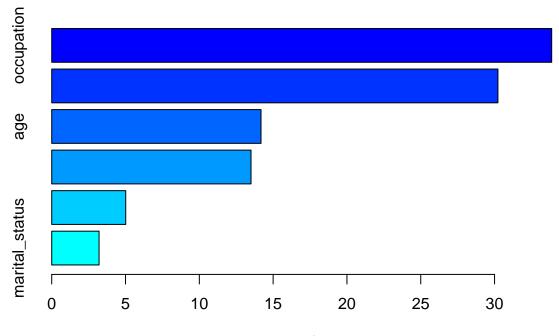
```
n.trees = 500,
interaction.depth = 5, #ensemble a bunch of stumps
shrinkage = 0.05,
cv.folds = 5,
n.minobsinnode = 10,
bag.fraction=0.70,
n.cores = NULL, # will use all cores by default
verbose = FALSE
)
print(gbm.fit.final)
```

```
## gbm(formula = purc.total ~ gender + age + occupation + city_category +
## stay_years + marital_status, distribution = "gaussian", data = gbm_test,
## n.trees = 500, interaction.depth = 5, n.minobsinnode = 10,
## shrinkage = 0.05, bag.fraction = 0.7, cv.folds = 5, verbose = FALSE,
## n.cores = NULL)
## A gradient boosted model with gaussian loss function.
## 500 iterations were performed.
```



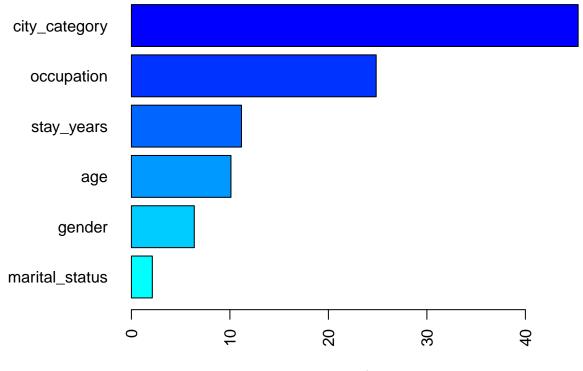
The best cross-validation iteration was 48.
There were 6 predictors of which 6 had non-zero influence.

summary(gbm.fit.final)



Relative influence

```
##
                             var
                                   rel.inf
## occupation
                      occupation 33.869892
## city_category
                   city_category 30.227669
## age
                             age 14.178672
## stay_years
                      stay_years 13.502324
## gender
                          gender 5.014235
## marital_status marital_status 3.207209
par(mar = c(5, 8, 1, 1))
summary(
  gbm.fit.final,
  cBars = 10,
  \#method = relative.influence,
  method=permutation.test.gbm,
  las = 2
```



Relative influence

```
##
                      rel.inf
                var
## 1 city_category 45.356134
        occupation 24.851952
## 2
## 3
         stay_years 11.176619
                age 10.107433
## 4
## 5
             gender 6.383976
## 6 marital_status 2.123887
pred <- predict(gbm.fit.final, n.trees = gbm.fit.final$n.trees, gbm_test)</pre>
# results
caret::RMSE(pred, gbm_test$purc.total)
```

```
## Warning in as.POSIXlt.POSIXct(Sys.time()): unknown timezone 'zone/tz/2018g.
## 1.0/zoneinfo/America/Detroit'
```

[1] 732861.3