Some investigation and debugging of multilevel BART-based BA trees

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Problem: None of the born-again GLMM trees make splits

Possible causes:

- 1) Not enough signal in the data, so it is actually realistic and correct that there are no splits.
- 2) Programming mistakes.
- 3) We are not drawing from the posterior like we think we do.
- 4) Inclusion of random effects messes up born-again approach. Perhaps we should first try an approach without random effects.
- 5) Proposed born-again approach (with draws from BART posterior) does not work.

Example dataset

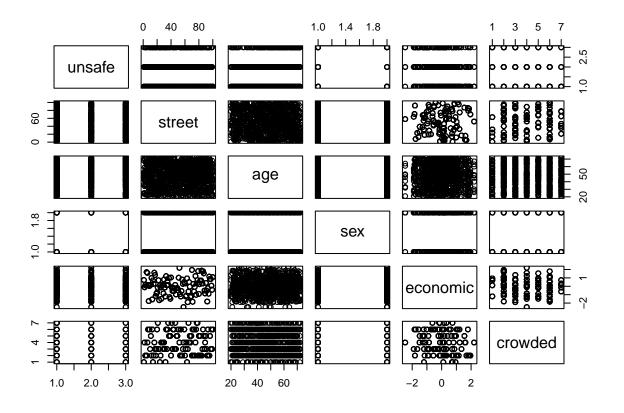
We load the **safety** dataset, fit a standard GLMM tree and multilevel BART ensemble and evaluate predictive accuracy:

```
library("foreign")
safety <- read.spss("Safety.sav", to.data.frame = TRUE)</pre>
## re-encoding from CP1252
## Warning in read.spss("Safety.sav", to.data.frame = TRUE): Undeclared level(s) 2,
## 3, 4, 5, 6 added in variable: crowded
head(safety)
##
     street person age agediv10
                                   sex economic crowded age10c sexc
                                                                             econc
## 1
                 1 52
                            5.2
                                  male 0.7438186
                                                      low 0.4849 -0.52 0.7438186
          1
## 2
          1
                 2
                   20
                            2.0
                                  male 0.7438186
                                                      low -2.7151 -0.52 0.7438186
                 3
                                                      low -0.3151 0.48 0.7438186
## 3
          1
                   44
                            4.4 female 0.7438186
                                  male 0.7438186
                                                      low -0.4151 -0.52 0.7438186
## 4
          1
                 4
                   43
                            4.3
## 5
          1
                 5
                   68
                            6.8
                                  male 0.7438186
                                                      low 2.0849 -0.52 0.7438186
## 6
          1
                 6 50
                            5.0
                                  male 0.7438186
                                                      low 0.2849 -0.52 0.7438186
##
     crowdedc
                 unsafe
## 1
        -2.96 sometimes
## 2
        -2.96
                  never
## 3
        -2.96
                  never
## 4
        -2.96 sometimes
## 5
        -2.96
                  often
## 6
        -2.96
                  never
```

dim(safety) ## [1] 1000 12 #plot(safety)

Response, cluster id and predictor variables are:

```
vars <- c("unsafe", "street", "age", "sex", "economic", "crowded")</pre>
plot(safety[ , vars])
```



```
table(safety$unsafe) ## enough variance present
```

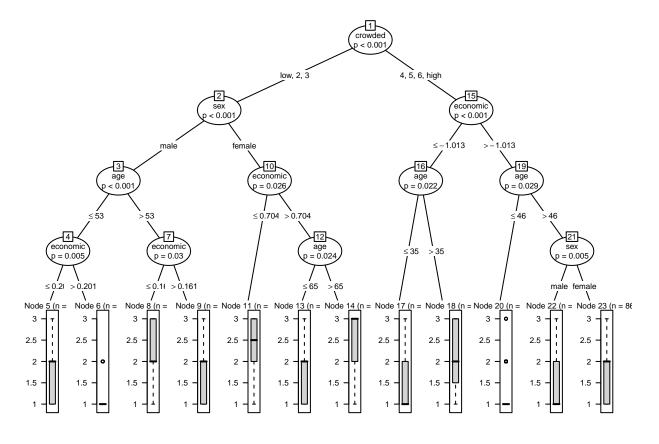
```
##
##
       never sometimes
                             often
##
         505
                    306
                               189
safety$unsafe <- as.numeric(safety$unsafe)</pre>
table(complete.cases(safety[ , vars])) ## only complete cases, nice!
##
## TRUE
## 1000
Select training and test sets:
set.seed(420)
train_ids <- sample.int(n = nrow(safety), size = floor(.75*nrow(safety)),</pre>
                          replace = F)
```

```
safety_train <- safety[train_ids, ]</pre>
safety_test <- safety[-train_ids, ]</pre>
var(safety$unsafe)
## [1] 0.5947387
var(safety_train$unsafe)
## [1] 0.5744566
var(safety_test$unsafe)
```

[1] 0.6573655

Fit mixed-effects tree

```
library("glmertree")
lmmt <- lmertree(unsafe ~ 1 | street | age + sex + economic + crowded,</pre>
                   data = safety_train)
length(lmmt$tree)
## [1] 23
plot(lmmt$tree, gp = gpar(cex = .5))
```



VarCorr(lmmt)

Groups Name Std.Dev.

```
## street (Intercept) 0.10698
## Residual 0.62917
```

The tree has quite some splits. The ICC is large enough for random effects to be of relevance.

```
lmmt_preds <- predict(lmmt, newdata = safety_test)
mean((lmmt_preds - safety_test$unsafe)^2) ## MSE</pre>
```

```
## [1] 0.5561308
```

To check if there is actual signal of relevance in the data, we obtain predictions from the tree only (i.e., random effects assumed 0):

```
lmmt_preds2 <- predict(lmmt, newdata = safety_test, re.form = ~0)
mean((lmmt_preds2 - safety_test$unsafe)^2) ## MSE</pre>
```

```
## [1] 0.5699146
```

The random effects are not that influential. There seems to be at least some signal captured by the tree.

Fit multilevel BART ensemble

```
library("dbarts")
set.seed(420)
mbart <- rbart_vi(unsafe ~ age + sex + economic + crowded,</pre>
                  data = safety_train, group.by = safety_train$street,
                  test = safety_test, group.by.test = safety_test$street,
                  n.trees = 200, keepTrees = TRUE)
#mbart$fit[[4]]$plotTree(199)
head(mbart$fit[[4]]$getTrees(199)) ## fit is a list with 4 elements, correspond to chains?
##
     sample tree
                   n var value
## 1
          1 199 750 -1
## 2
          2 199 750 -1
                             0
## 3
          3 199 750 -1
                             0
## 4
          4 199 750 -1
                             0
## 5
            199 750 -1
                             0
          5
                             0
## 6
            199 750 -1
```

It appears that tree 199 did not implement any splits. Do any trees have splits?

```
splits <- matrix(NA, ncol = 4, nrow = 200)
rownames(splits) <- paste0("tree", 1:200)
colnames(splits) <- paste0("chain", 1:4)
for (j in 1:4) {
  for (i in 1:200) {
    splits[i, j] <- sum(mbart$fit[[j]]$getTrees(i)$var)
  }
}
table(splits)</pre>
```

```
## splits
## -800
## 800
```

No splits seem to be implemented whatsoever. Although I am not entirely sure that having -1 for var means that no split was made.

Obtaining posterior distributions

[1] 0.5091925

Multilevel BART seems to do better than the tree, so born-again approach may improve.

Q: Can we extract random effects covariance matrix from multilevel BART object?

Whatever fitted does, works pretty well. But we do not know what fitted does, nor do we know what predict does.

We check what the different options look like for respondents with y = 1, 2, 3:

[1] 0.730838

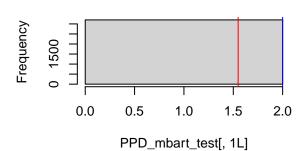
[1] 0.74

[1] 0.7336923

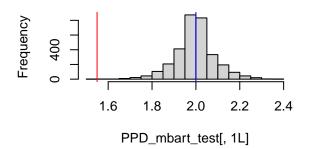
Person 1, ppd

0 1 2 3 4 PPD_mbart_test[, 1L]

Person 1, bart



Person 1; ev



mean((safety_test\$unsafe - apply(PPD_mbart_test, 2, median))^2)

[1] 0.74

[1] 0.7336923

```
hist(PPD_mbart_test[ , 3L], main = "Person 3; ev")
abline(v = bart_preds_test[3], col = "red")
abline(v = safety_test$unsafe[3], col = "blue")
bart_preds_test[3]
```

[1] 1.689202

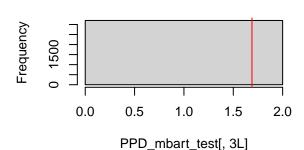
safety_test\$unsafe[3]

[1] 3

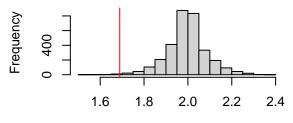
Person 3, ppd

0 1 2 3 4 5 PPD_mbart_test[, 3L]

Person 3, bart



Person 3; ev



PPD_mbart_test[, 3L]

[1] 0.730838

```
## [1] 0.74
```

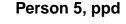
[1] 0.7336923

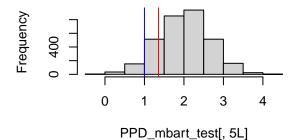
```
hist(PPD_mbart_test[ , 5L], main = "Person 5; ev")
abline(v = bart_preds_test[5], col = "red")
abline(v = safety_test$unsafe[5], col = "blue")
bart_preds_test[5]
```

[1] 1.356232

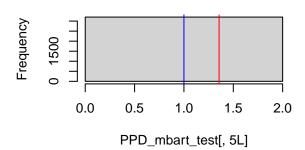
safety_test\$unsafe[5]

[1] 1

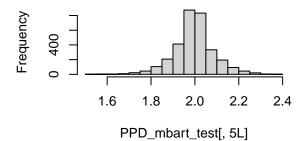




Person 5, bart



Person 5; ev



According to the documentation of rbart_vi, this is the model:

$$y_i \sim N(f(x_i) + \alpha_{g_i}, \sigma^2)$$

 $\alpha_j \sim N(0, \tau^2)$

So, y_i follows normal distribution with mean ("ev") $f(x_i) + \alpha_{g_i}$ and variance σ^2 . I thus suspect that "ev" returns samples from $f(k_i) + \alpha_{g_i}$, "ppd" returns samples from $f(k_i) + \alpha_{g_i}$ as well as samples from the residuals (which have variance σ^2). We don't know what "bart" returns, but it would make sense if it is $f(k_i)$; but counter intuitively this seems to be a constant in the current dataset

PPD has a column for each observation, and a row (why 3200?) for each MCMC sampling iteration?

I have no idea how predictions are generated from the posterior distribution. What I do know is that fitted does not return the median of the PPD returned by predict:

```
par(mfrow = c(1, 2))
cor(bart_preds_test, apply(PPD_mbart_test, 2, median))
## [1] 0.2058868
cor(bart_preds_test, apply(PPD_mbart_test, 2, mean))
## [1] 0.1967401
var(bart_preds_test)
## [1] 0.1547001
dim(PPD_mbart_test)
## [1] 3200 250
dim(safety_test)
## [1] 250 12
PPD_mbart_test2 <- predict(mbart, newdata = safety_test, type = "ppd",
                     group.by = safety_test$street, combineChains = FALSE)
cor(bart_preds_test, apply(PPD_mbart_test2[1, 1:800, 1:250], 2, median))
## [1] 0.2201375
cor(bart_preds_test, apply(PPD_mbart_test2[1, 1:800, 1:250], 2, mean))
## [1] 0.1974335
PPD_mbart_test3 <- predict(mbart, newdata = safety_test, type = "bart",</pre>
                     group.by = safety_test$street, combineChains = TRUE)
cor(bart_preds_test, apply(PPD_mbart_test3, 2, median))
## Warning in cor(bart_preds_test, apply(PPD_mbart_test3, 2, median)): the standard
## deviation is zero
## [1] NA
cor(bart_preds_test, apply(PPD_mbart_test3, 2, mean))
## Warning in cor(bart_preds_test, apply(PPD_mbart_test3, 2, mean)): the standard
## deviation is zero
## [1] NA
PPD_mbart_test4 <- predict(mbart, newdata = safety_test, type = "ev",
                     group.by = safety_test$street, combineChains = TRUE)
cor(bart_preds_test, apply(PPD_mbart_test4, 2, median))
## [1] 0.2058868
```

```
cor(bart_preds_test, apply(PPD_mbart_test4, 2, mean))

## [1] 0.1967401

var(mbart$ranef.mean)

## [1] 0.001225738

var(lmmt$ranef$street)

## (Intercept)

## (Intercept)

## (Intercept) 0.001951822

str(mbart$tau)

## num [1:4, 1:800] 0.0678 0.0956 0.0881 0.1605 0.0696 ...

mbart$fitted
```

NULL

TODO

With the safety data, it appears we obtain an ensemble without any splits? We need a dataset which surely splits. The MHserviceDemo data from package glmertree is one to try.

Born again approach using constant prediction

```
## Groups Name Std.Dev.
## street (Intercept) 0.160279
## Residual 0.026675
```

The BA tree is much bigger than the original tree. The variance of the random effects has remained the same.

We assess predictive accuracy and fidelity to black-box predictions:

```
lmmt_ba_preds <- predict(lmmt_ba, newdata = safety_test)
mean((lmmt_ba_preds - safety_test$unsafe)^2) ## Accuracy MSE

## [1] 0.5117983
mean((lmmt_ba_preds - bart_preds_test)^2) ## Fidelity MSE</pre>
```

```
## [1] 0.001155273
```

VarCorr(lmmt_ba)

Fidelity is very high (BA tree might simply mimic all splits from BART ensemble?), predictive accuracy has improved, though at price of increased complexity.

Born again approach using full PPD

I have no idea how to get the (right) posterior distribution at the moment.

```
PPD_mbart_train <- predict(mbart, newdata = safety_train, type = "ppd",</pre>
                       group.by = safety_train$street, combineChains = TRUE)
dim(PPD_mbart_train)
## [1] 3200 750
## stack rows of PPD
#as.vector(PPD_mbart_train)
#art_gen_dat_large <- cbind(safety_train, )</pre>
#bart_preds_train <- fitted(object = mbart, type = "ppd", sample = "train")</pre>
\#art\_gen\_dat\$unsafe \leftarrow bart\_preds\_train
\#lmmt_ba \leftarrow lmertree(unsafe \sim 1 \mid street \mid age + sex + economic + crowded,
                      data = art\_gen\_dat)
#length(lmmt_ba$tree)
#VarCorr(lmmt_ba)
#lmmt_ba_preds <- predict(lmmt_ba, newdata = safety_test)</pre>
#mean((lmmt_ba_preds - safety_test$unsafe)^2) ## Accuracy MSE
#mean((lmmt_ba_preds - bart_preds_test)^2) ## Fidelity MSE
```