

Survival Ensembles

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1 Illustrations and Applications

This document reproduces the data analyses presented in [Hothorn et al. \(2006\)](#). For a description of the theory behind applications shown here we refer to the original manuscript. The results differ slightly due to technical changes or bug-fixes in **mboost** that have been implemented after the paper was printed.

1.1 Acute myeloid leukemia

Data preprocessing Compute IPC weights, define risk score and set up learning sample:

```
R> AMLw <- IPCweights(Surv(clinical$time, clinical$event))  
R> risk <- rep(0, nrow(clinical))
```

```

R> rlev <- levels(clinical[, "Cytogenetic.group"])
R> risk[clinical[, "Cytogenetic.group"] %in% rlev[c(7,
8, 4)]] <- "low"
R> risk[clinical[, "Cytogenetic.group"] %in% rlev[c(5,
9)]] <- "intermediate"
R> risk[clinical[, "Cytogenetic.group"] %in% rlev[-c(4,
5, 7, 8, 9)]] <- "high"
R> risk <- as.factor(risk)
R> AMLlearn <- cbind(clinical[, c("time", "Sex",
"Age", "LDH", "WBC", "FLT3.aberration.", "MLL.PTD",
"Tx.Group.")], risk = risk, iexpressions[,
colnames(iexpressions) %in% selgenes[["Clone.ID"]]])
R> cc <- complete.cases(AMLlearn)
R> AMLlearn <- AMLlearn[AMLw > 0 & cc, ]
R> AMLw <- AMLw[AMLw > 0 & cc]

```

Model fitting Fit random forest for censored data

```

R> ctrl <- cforest_control(mincriterion = 0.1, mtry = 5,
minsplitt = 5, ntree = 250)
R> AMLrf <- cforest(I(log(time)) ~ ., data = AMLlearn,
control = ctrl, weights = AMLw)

```

and L_2 Boosting for censored data

```

R> AML12b <- glmboost(I(log(time)) ~ ., data = AMLlearn,
weights = AMLw, control = boost_control(mstop = 5000))

```

Compute fitted values

```

R> AML12b <- AML12b[mstop(aic)]
R> cAML <- coef(AML12b)
R> cAML[abs(cAML) > 0]

```

(Intercept)	Age	WBC
0.5642932	0.0059785	-0.0056200
MLL.PTDyes	Tx.Group.AUTO	Tx.Group.Ind
-0.3153912	0.4542954	-2.1216104
`IMAGE:145643`	`IMAGE:345601`	`IMAGE:377560`
0.1062577	0.0043043	0.0275653
`IMAGE:2043415`	`IMAGE:1584563`	`IMAGE:347035`
0.0550938	-0.0025929	-0.0084766
`IMAGE:262695`	`IMAGE:26418`	`IMAGE:950479`
0.0269555	0.0080214	0.0371741
`IMAGE:1534700`	`IMAGE:1472689`	`IMAGE:1526826`
0.0283645	0.0225640	-0.0278373
`IMAGE:786302`	`IMAGE:243614`	`IMAGE:417884`
0.0449326	-0.0566722	-0.0248869
`IMAGE:1592006`	`IMAGE:884333`	`IMAGE:133273`
-0.0355121	0.0128054	0.0257924
`IMAGE:950888`	`IMAGE:809533`	`IMAGE:49389`

```
R> plot(aic <- AIC(AML12b))
```

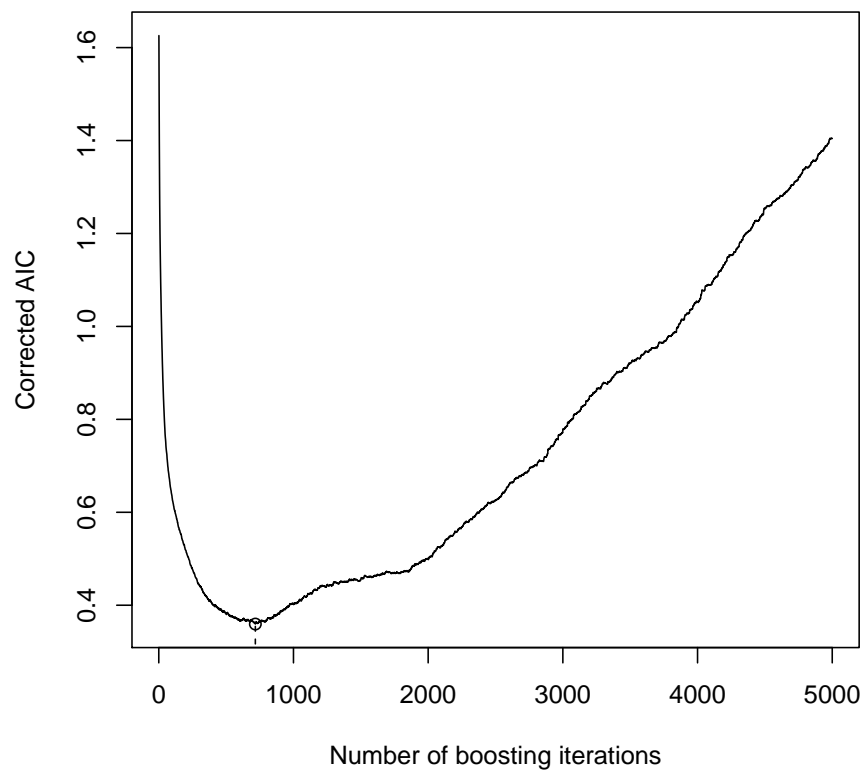


Figure 1: AIC criterion for AML data.

```

0.0348510      -0.0583489      0.1210483
`IMAGE:856174` `IMAGE:435036` `IMAGE:491751`
0.0205370      0.0620215      0.1155506
`IMAGE:782835` `IMAGE:52930` `IMAGE:2545705`
-0.1108508      -0.0245246      -0.0788422
`IMAGE:756405` `IMAGE:129032` `IMAGE:1610168`
0.0085293      -0.1158217      0.0137998
`IMAGE:69002` `IMAGE:2019101` `IMAGE:1456160`
-0.2793326      -0.0966590      -0.1041466
`IMAGE:2566064` `IMAGE:565083` `IMAGE:843028`
0.0154665      0.1875592      0.0698328
`IMAGE:68794` `IMAGE:488505` `IMAGE:291756`
0.0761390      0.2784632      0.0994879
`IMAGE:810801` `IMAGE:1702742` `IMAGE:380462`
0.0465851      -0.0104549      -0.0957299
`IMAGE:154472` `IMAGE:302540` `IMAGE:135221`
-0.1454724      0.0188789      -0.0366827
`IMAGE:1567220`
0.0485058

```

```

R> AMLprf <- predict(AMLrf, newdata = AMLlearn)
R> AMLpb <- predict(AMLl2b, newdata = AMLlearn)

```

1.2 Node-positive breast cancer

Data preprocessing Compute IPC weights and set up learning sample:

```

R> data("GBSG2", package = "ipred")
R> GBSG2w <- IPCweights(Surv(GBSG2$time, GBSG2$cens))
R> GBSG2learn <- cbind(GBSG2[, -which(names(GBSG2) %in%
      c("time", "cens"))], ltime = log(GBSG2$time))
R> n <- nrow(GBSG2learn)

```

Model fitting

```

R> LMmod <- lm(ltime ~ ., data = GBSG2learn, weights = GBSG2w)
R> LMerisk <- sum((GBSG2learn$ltime - predict(LMmod))^2 *
      GBSG2w)/n
R> TRmod <- rpart(ltime ~ ., data = GBSG2learn, weights = GBSG2w)
R> TRerisk <- sum((GBSG2learn$ltime - predict(TRmod))^2 *
      GBSG2w)/n
R> ctrl <- cforest_control(mincriterion = qnorm(0.95),
      mtry = 5, minsplit = 5, ntree = 100)
R> RFmod <- cforest(ltime ~ ., data = GBSG2learn,
      weights = GBSG2w, control = ctrl)
R> L2Bmod <- glmboost(ltime ~ ., data = GBSG2learn,
      weights = GBSG2w, control = boost_control(mstop = 250))
R> L2BHubermod <- glmboost(ltime ~ ., data = GBSG2learn,
      weights = GBSG2w, family = Huber(d = log(2)))

```

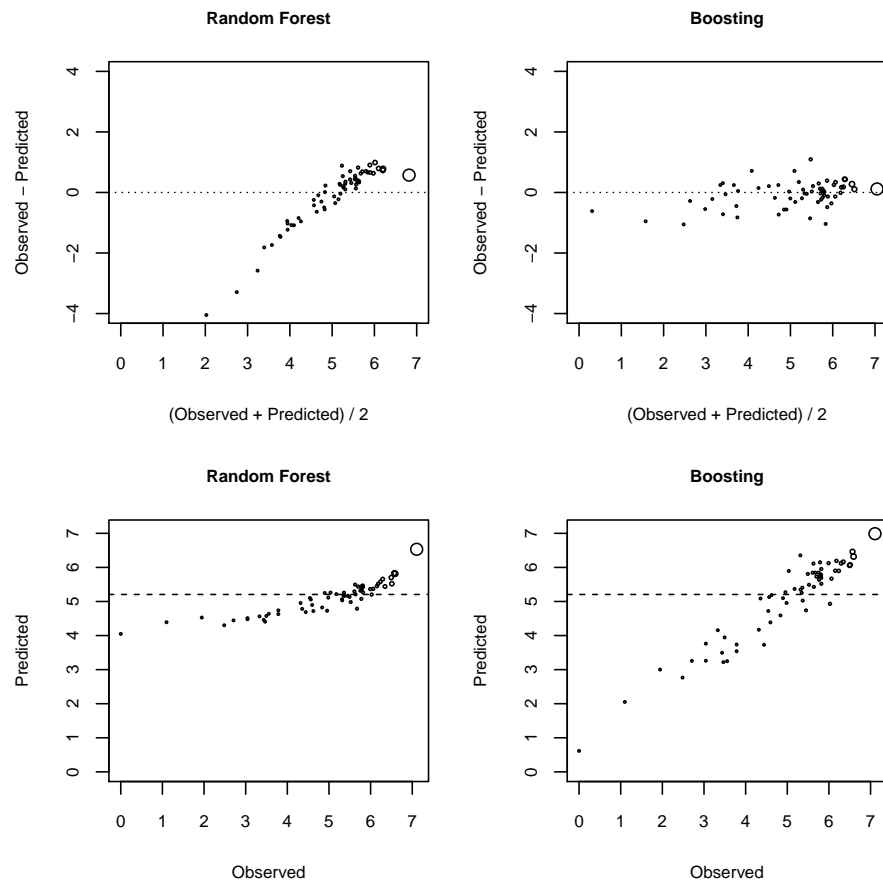


Figure 2: AML data: Reproduction of Figure 1.

```
R> plot(aic <- AIC(L2Bmod))
```

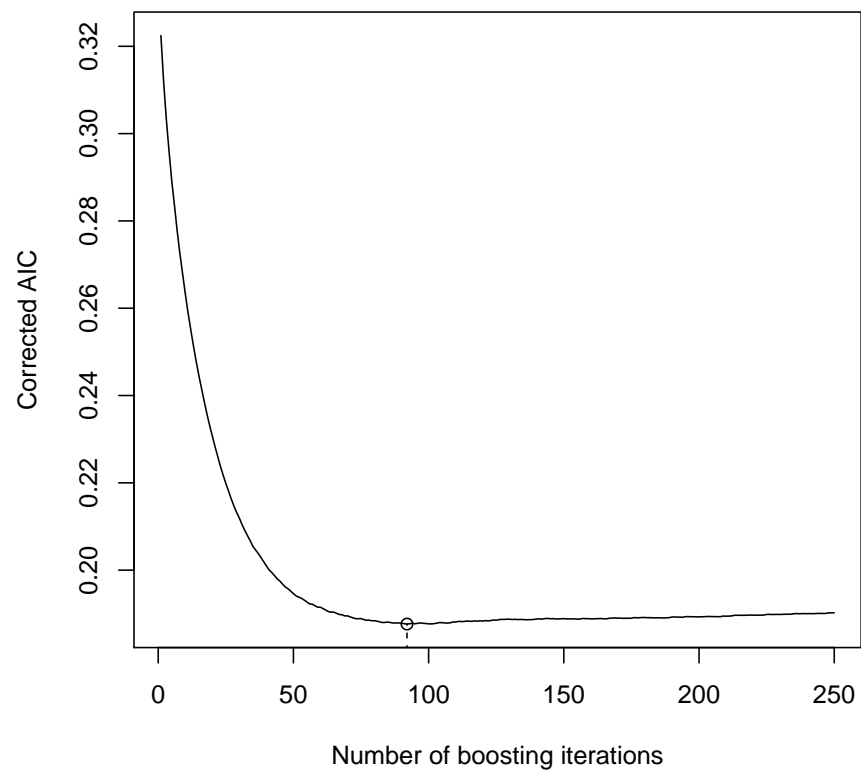


Figure 3: AIC criterion for GBSG2 data.

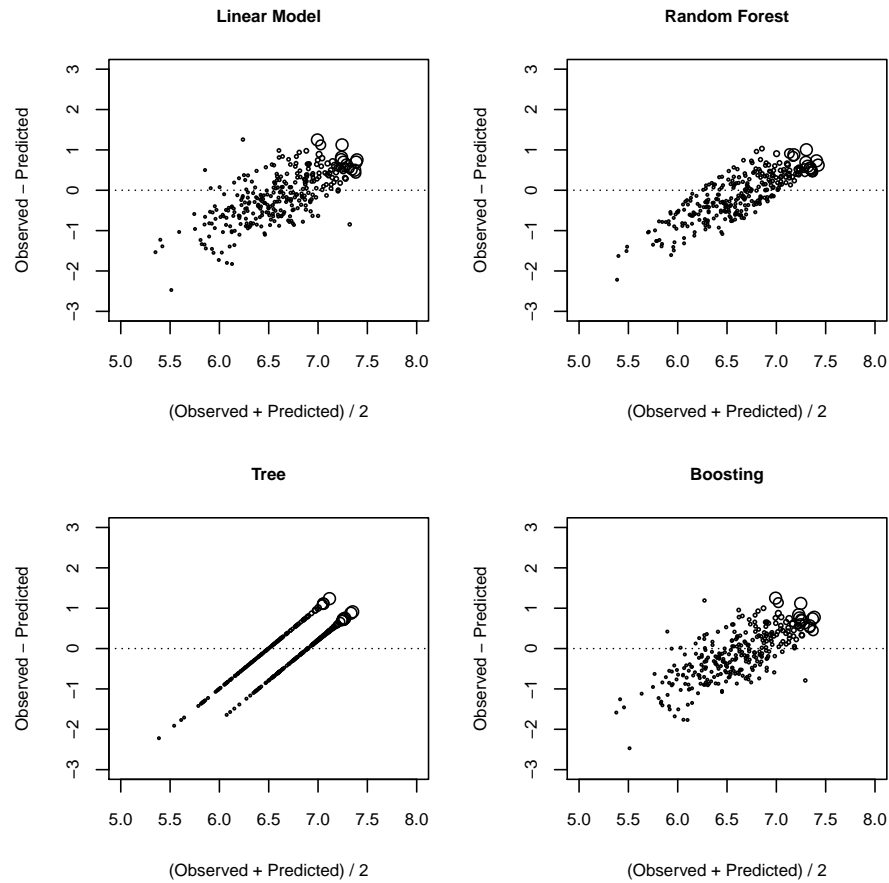


Figure 4: GBSG-2 data: Reproduction of Figure 3.

Compute fitted values:

```
R> GBSG2Hp <- predict(L2BHubermod, newdata = GBSG2learn)
R> L2Berisk <- sum((GBSG2learn$ltime - predict(L2Bmod,
  newdata = GBSG2learn))^2 * GBSG2w)/n
R> RFerisk <- sum((GBSG2learn$ltime - predict(RFmod,
  newdata = GBSG2learn))^2 * GBSG2w)/n
```

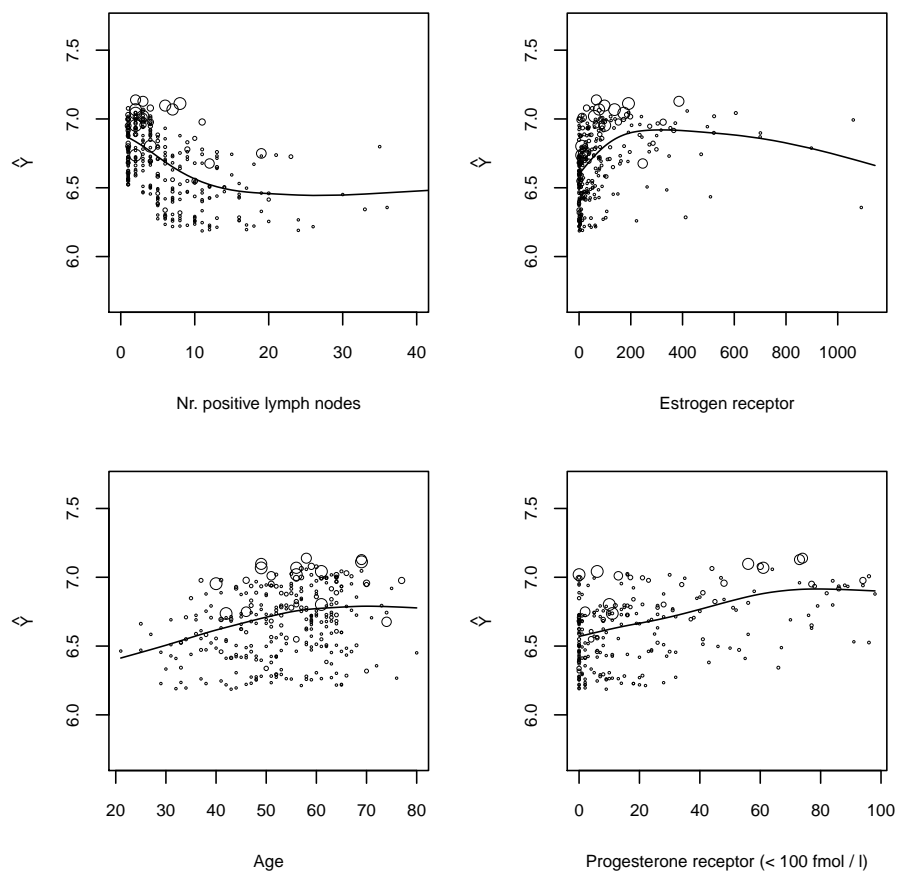


Figure 5: GBSG-2 data: Reproduction of Figure 5.

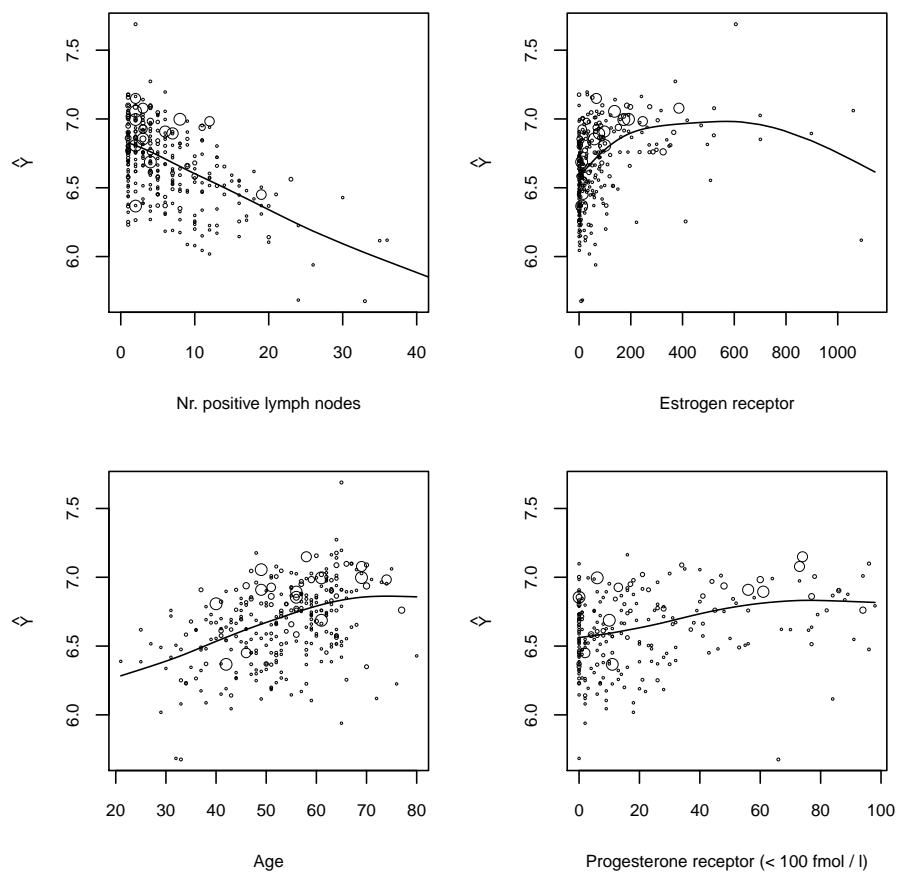


Figure 6: GBSG-2 data: Reproduction of Figure 6.

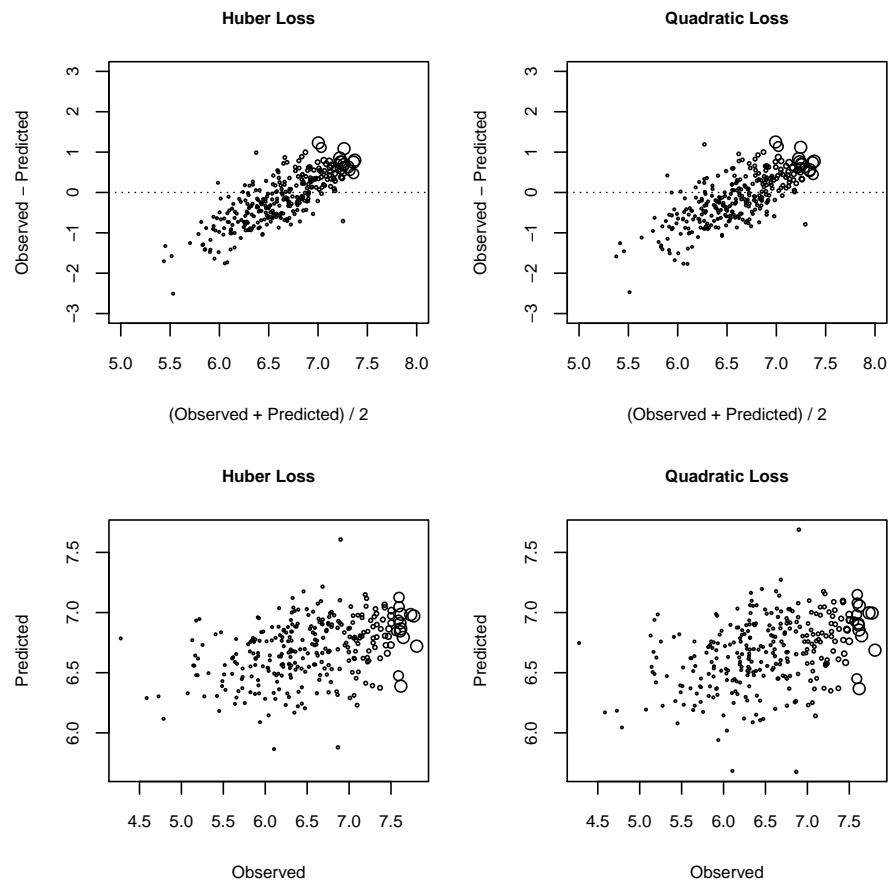


Figure 7: GBSG-2 data: Reproduction of Figure 7.

References

- T.~Hothorn, P.~Bühlmann, S.~Dudoit, A.~Molinaro, and M.~van~der~Laan.
Survival ensembles. *Biostatistics*, 7:355–373, 2006.