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.

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,
        minsplit = 5, ntree = 250)
R> AMLrf <- cforest(I(log(time)) ~ ., data = AMLlearn,
        control = ctrl, weights = AMLw)
```

and L_2Boosting for censored data

```
R> AMLl2b <- glmboost(I(log(time)) ~ ., data = AMLlearn,
        weights = AMLw, control = boost_control(mstop = 5000))
```

Compute fitted values

```
R> AMLl2b <- AMLl2b[mstop(aic)]
R> cAML <- coef(AMLl2b)
R> cAML[abs(cAML) > 0]
```

```
     (Intercept)              Age              WBC
      0.03094981       0.00854937      -0.00364371
      MLL.PTDyes    Tx.Group.AUTO      Tx.Group.IC
     -0.50709786       0.90185340       0.04037578
    Tx.Group.Ind riskintermediate   `IMAGE:145643`
     -1.86134842       0.11825619       0.19788355
 `IMAGE:2542486`   `IMAGE:345601`   `IMAGE:377560`
      0.00442375       0.02935101       0.11000322
  `IMAGE:428782`  `IMAGE:2043415`  `IMAGE:1584563`
      0.01010658       0.05911671      -0.17883619
  `IMAGE:347035`   `IMAGE:262695`   `IMAGE:950479`
     -0.03307600       0.00080156       0.09049309
  `IMAGE:898305`  `IMAGE:1472689`   `IMAGE:150702`
      0.00523016       0.03498572       0.01367553
 `IMAGE:1526826`    `IMAGE:66507`   `IMAGE:786302`
```

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

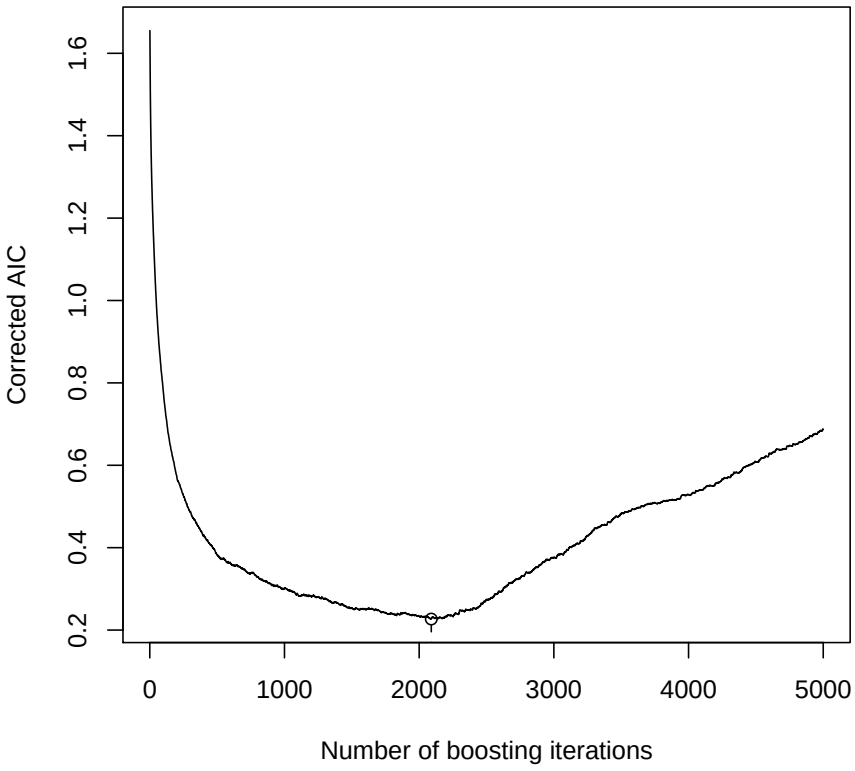

Figure 1: AIC criterion for AML data.

```
    -0.01805326       0.00399127       0.08941300
 `IMAGE:243614`   `IMAGE:417884`   `IMAGE:1592006`
    -0.05776062      -0.04890054      -0.02269622
`IMAGE:1917063`   `IMAGE:884333`    `IMAGE:133273`
    -0.06536720       0.04189990       0.06594787
 `IMAGE:950888`   `IMAGE:809533`     `IMAGE:49389`
     0.02027810      -0.15986981       0.06352703
 `IMAGE:789357`   `IMAGE:142139`   `IMAGE:1558053`
    -0.01252187       0.00089307       0.07795515
 `IMAGE:856174`   `IMAGE:504421`    `IMAGE:435036`
     0.01115234       0.06861766       0.06094620
 `IMAGE:491751`   `IMAGE:782835`     `IMAGE:52930`
     0.04336285      -0.17924185      -0.03503330
`IMAGE:2545705`   `IMAGE:756405`    `IMAGE:502664`
    -0.09886616       0.07713650       0.03620466
 `IMAGE:129032`  `IMAGE:1610168`    `IMAGE:327676`
    -0.31322459       0.01260374      -0.02117310
  `IMAGE:69002`   `IMAGE:121551`  `IMAGE:2019101`
    -0.41671336      -0.08107446      -0.06531175
`IMAGE:1456160`   `IMAGE:430318`  `IMAGE:2566064`
    -0.10208684      -0.07297586       0.06126683
  `IMAGE:74537`  `IMAGE:1606557`    `IMAGE:306812`
     0.04523784       0.14243526       0.03504441
 `IMAGE:565083`   `IMAGE:843028`     `IMAGE:68794`
     0.29555347       0.05619983       0.23722775
 `IMAGE:488505`   `IMAGE:167205`    `IMAGE:291756`
     0.33464829       0.00217136       0.04973319
 `IMAGE:810801`  `IMAGE:1702742`    `IMAGE:380462`
     0.08725523      -0.04428190      -0.13182519
 `IMAGE:154472`   `IMAGE:302540`    `IMAGE:135221`
    -0.24723347       0.17175129      -0.01972168
`IMAGE:1567220`   `IMAGE:594630`
     0.02473376      -0.07396882
```

```
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)
```

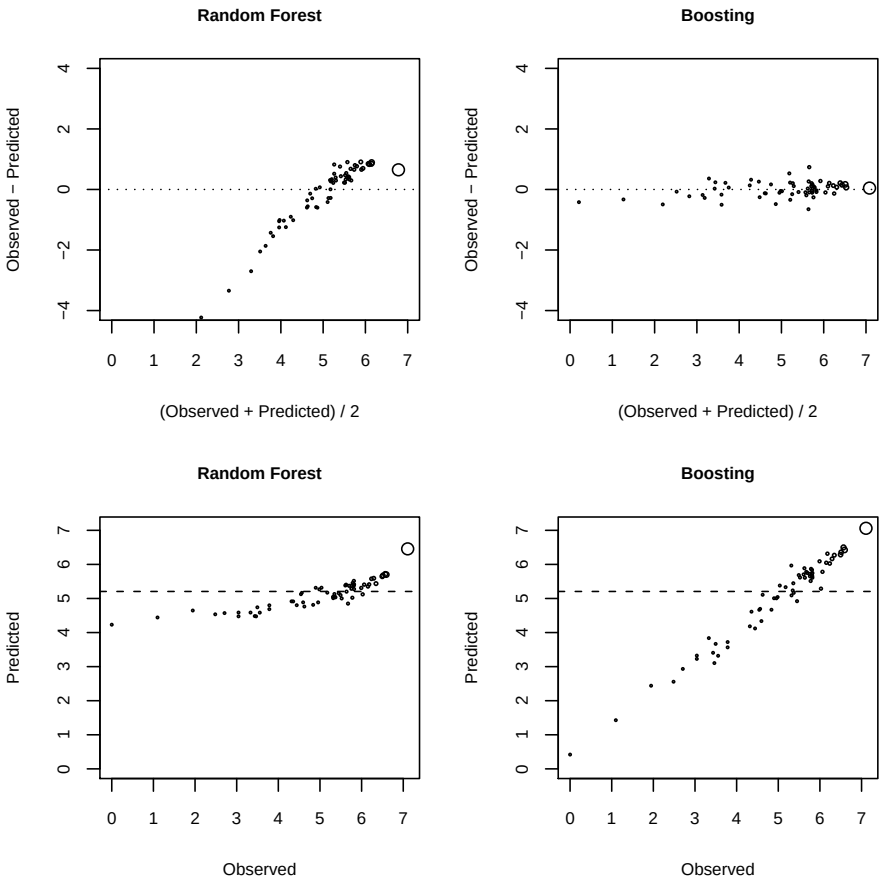

Figure 2: AML data: Reproduction of Figure 1.

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)))
```

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
```

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

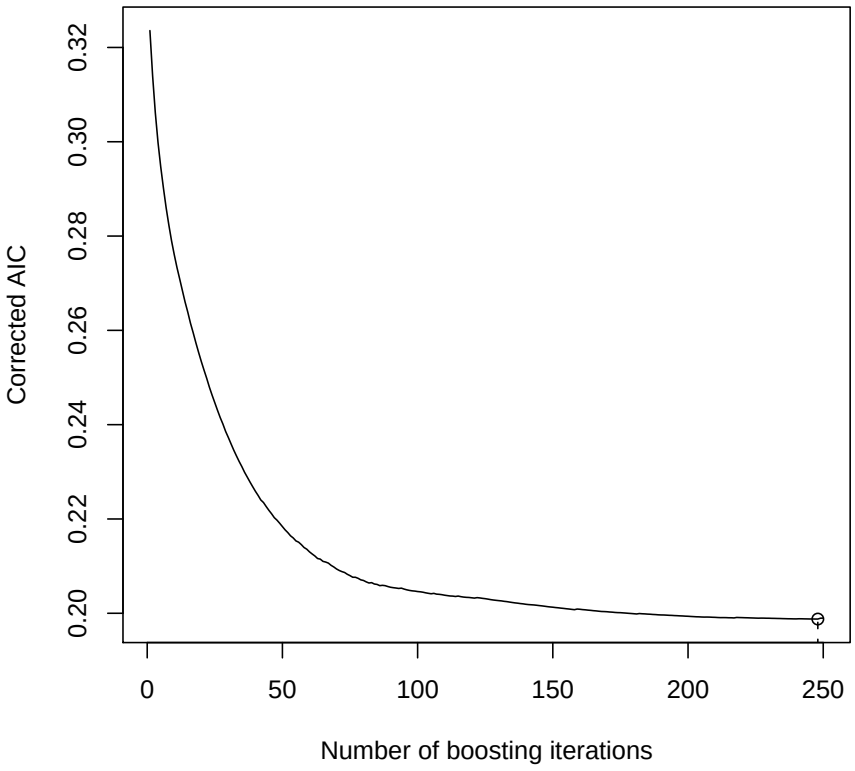

Figure 3: AIC criterion for GBSG2 data.

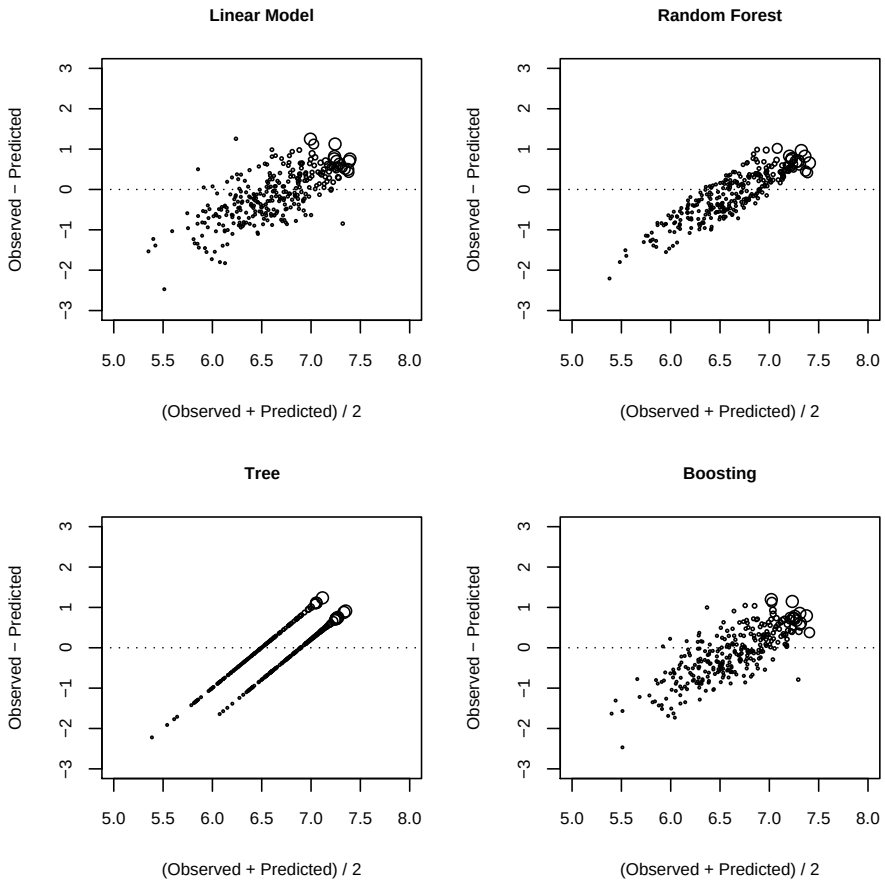

Figure 4: GBSG-2 data: Reproduction of Figure 3.

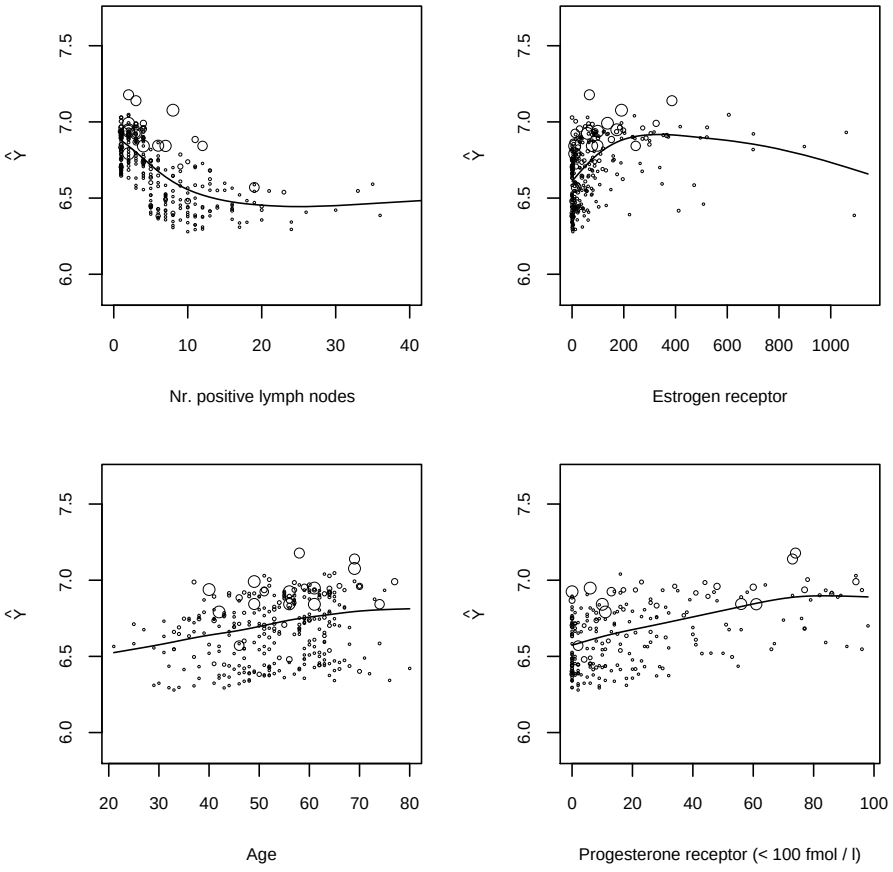

Figure 5: GBSG-2 data: Reproduction of Figure 5.

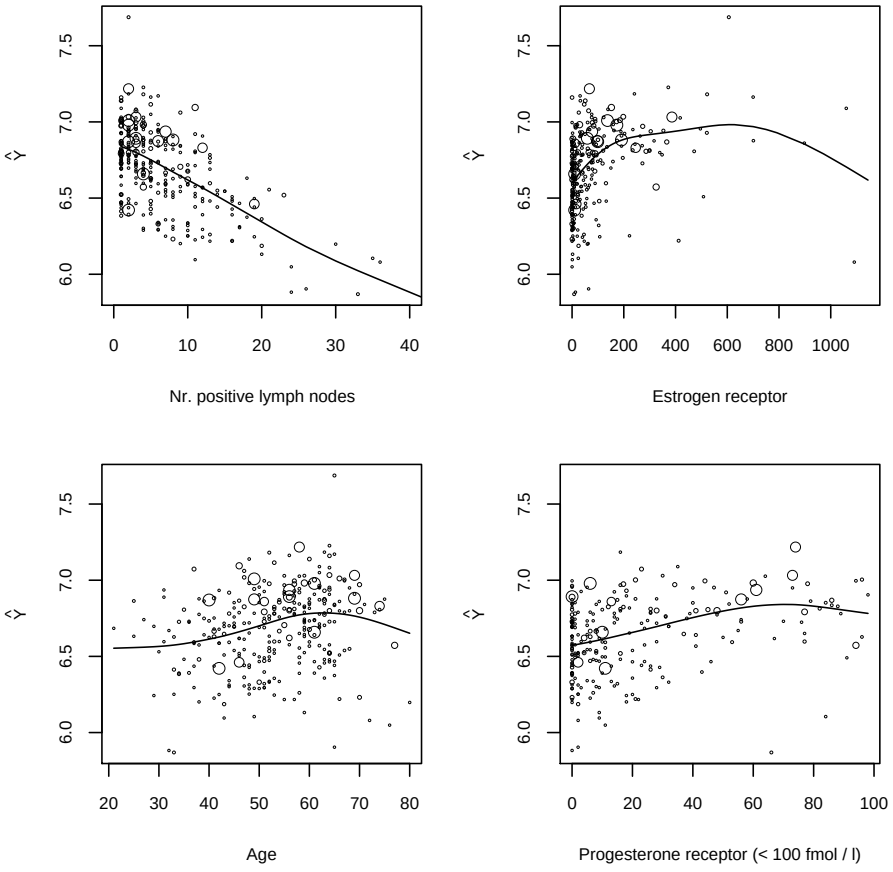

Figure 6: GBSG-2 data: Reproduction of Figure 6.

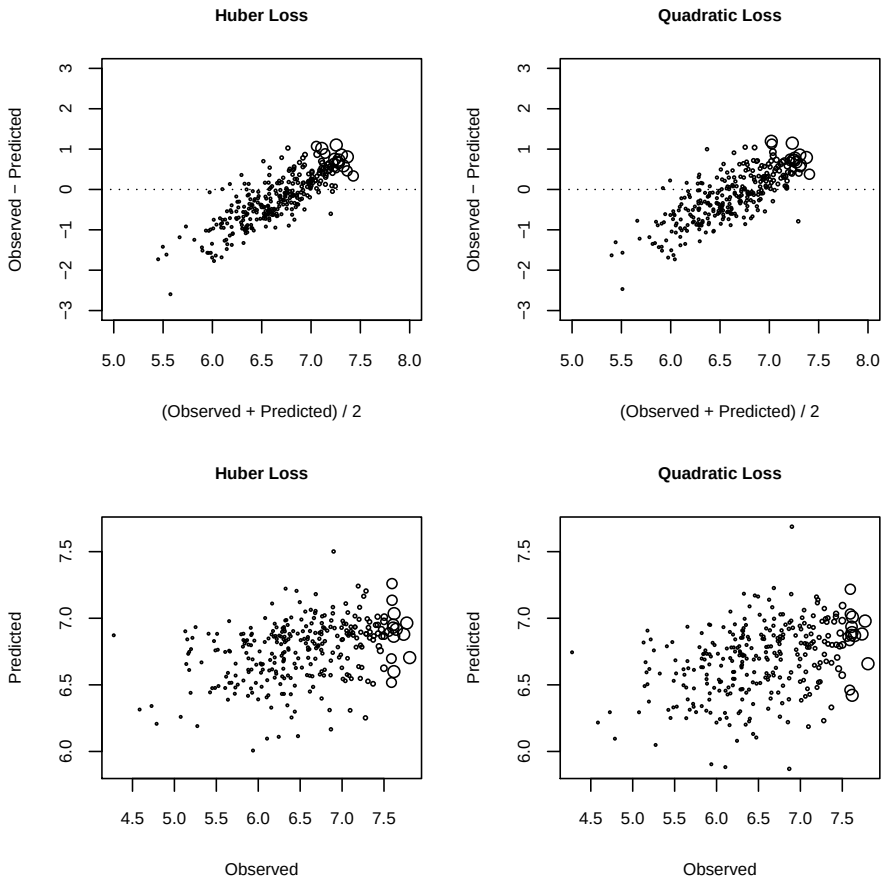

Figure 7: GBSG-2 data: Reproduction of Figure 7.

References

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