Shape my City: Political participation in Lucerne

Survey questions

- Kennen Sie die Möglichkeiten, sich auf städtischer Ebene mit persönlichen Anliegen einzubringen
- Kennen Sie die Möglichkeiten, sich in städtische Projekte einzubringen?
- Kennen Sie die Möglichkeiten, städtische Projekte vorzuschlagen?
- Wie zufrieden sind Sie mit den Möglichkeiten, Ihre persönlichen Anliegen auf städtischer Ebene einzubringen?
- Wie zufrieden sind Sie mit den Möglicheiten sich in städtische Projekte einzubringen?
- Wie zufrieden sind Sie mit den Möglicheiten Projekte vorzuschlagen?

Demographics

- Geschlecht
- Altersgruppe
- Quartier
- Zuzug
- Bildung
- Haushalt
- Kinder_Schule

```
library(dplyr)
library(ggplot2)
library(gtable)
library(tree)
```

Load data

```
# load data
df <- read.csv("./cleaned_data.csv", sep=";", header=TRUE)
```

Prepare data

```
#rename columns
df <- df %>% rename(knw.personal.matters = v_316,
               sat.personal.matters = v_106,
               knw.participate = v_212,
               knw.propose = v_365,
               sat.participate = v_366,
               sat.propose = v_367,
```

```r
                Geschlecht = Sex
                )

# create subset
df.small <- select(df, c("Geschlecht", "Altergruppe","Beziehungstatus","Quartier", "Zuzug", "Bildung",

# have a look at values
df.small %>% count(knw.personal.matters)
df.small %>% count(knw.participate)
df.small %>% count(knw.propose)
df.small %>% count(sat.personal.matters)
df.small %>% count(sat.participate)
df.small %>% count(sat.propose)

df.small %>% count(Geschlecht)
df.small %>% count(Altergruppe)
df.small %>% count(Quartier)
df.small %>% count(Zuzug)
df.small %>% count(Bildung)
df.small %>% count(HH)
df.small %>% count(Kinder_Schule)
df.small %>% count(Erwerb)

# delete all rows without an answer
df.small <-  df.small[rowSums(df.small == -77 | df.small == 0)==0,,]

# convert all columns to factors
df.small <- replace(df.small, TRUE, lapply(df.small, factor))

# level names
Zuzug.levels = c("<2", "2-5", "6-10", "11-15", "16-20", "21-25", ">25")
Bildung.levels = c("Berufslehre", "Gymnasium", "Hochschule", "Andere")
Quartier.levels = c("Innenstadt", "Rechte Seeseite", "Linke Seeseite", "Rechtes Reussufer", "Linkes Reus
Altergruppe.levels = c("0-9", "10-19", "20-29", "30-39", "40-49", "50-65", "65-84", "85+")
HH.levels = c("Einpersonenhaushalt", "Elternteil mit Kind(ern)", "Paar ohne Kinder", "Paar mit Kind(ern
```

Logistic Regression models

For yes/no questions

```r
lm.knw.personal.matters <- glm(knw.personal.matters ~ Geschlecht + Altergruppe + Beziehungstatus + Quart
                               family = "binomial",
                               data = df.small)

summary(lm.knw.personal.matters)
```

```
##
## Call:
## glm(formula = knw.personal.matters ~ Geschlecht + Altergruppe +
##     Beziehungstatus + Quartier + Zuzug + Bildung + HH + Kinder_Schule +
##     Erwerb, family = "binomial", data = df.small)
```

```
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0102  -0.9699  -0.4034   0.9804   2.0843
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)        0.90876    1.24061   0.733  0.46386
## Geschlecht2        0.51376    0.18735   2.742  0.00610 **
## Geschlecht3      -13.76713  882.74345  -0.016  0.98756
## Altergruppe2      -0.38530    1.14295  -0.337  0.73603
## Altergruppe3      -0.22794    1.13062  -0.202  0.84023
## Altergruppe4      -0.09337    1.12801  -0.083  0.93403
## Altergruppe5      -0.27004    1.13693  -0.238  0.81225
## Altergruppe6      -0.46686    1.14923  -0.406  0.68457
## Altergruppe7      -0.58405    1.19600  -0.488  0.62531
## Altergruppe8     -14.21551  882.74424  -0.016  0.98715
## Beziehungstatus2   0.11382    0.26848   0.424  0.67162
## Quartier2         -0.13453    0.29323  -0.459  0.64639
## Quartier3         -0.15382    0.26828  -0.573  0.56640
## Quartier4         -0.27971    0.28715  -0.974  0.33000
## Quartier5         -0.74774    0.32375  -2.310  0.02091 *
## Quartier6         -0.94875    0.51014  -1.860  0.06292 .
## Zuzug2            -0.27088    0.39418  -0.687  0.49197
## Zuzug3            -0.43000    0.42155  -1.020  0.30771
## Zuzug4            -0.86657    0.44615  -1.942  0.05210 .
## Zuzug5            -1.25809    0.47434  -2.652  0.00799 **
## Zuzug6            -1.07209    0.42971  -2.495  0.01260 *
## Zuzug7            -1.68355    0.39581  -4.253 2.11e-05 ***
## Bildung4           0.16950    0.43014   0.394  0.69355
## Bildung7          -0.45277    0.23781  -1.904  0.05692 .
## Bildung8           0.25791    0.35234   0.732  0.46418
## HH2                0.46015    0.43526   1.057  0.29043
## HH3                0.02129    0.31228   0.068  0.94564
## HH4               -0.33615    0.36590  -0.919  0.35826
## HH5                0.02688    0.33711   0.080  0.93644
## Kinder_Schule2     0.52142    0.32813   1.589  0.11204
## Erwerb2           -0.05718    0.23857  -0.240  0.81058
## Erwerb3           -0.16791    0.51440  -0.326  0.74411
## Erwerb4            0.55443    0.47412   1.169  0.24225
## Erwerb5           -0.12117    0.40622  -0.298  0.76549
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 853.90  on 615  degrees of freedom
## Residual deviance: 742.88  on 582  degrees of freedom
## AIC: 810.88
##
## Number of Fisher Scoring iterations: 13
```

Interpretation

```r
# without Interaction
lm.knw.participate <- glm(knw.participate ~ Geschlecht + Altergruppe + Beziehungstatus + Quartier + Zuzu
               family = "binomial",
               data = df.small)

summary(lm.knw.participate)
```

```
##
## Call:
## glm(formula = knw.participate ~ Geschlecht + Altergruppe + Beziehungstatus +
##     Quartier + Zuzug + Bildung + HH + Kinder_Schule + Erwerb,
##     family = "binomial", data = df.small)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.3867  -1.0372   0.6344   0.8842   1.9209
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)         1.72171    1.29466   1.330 0.183567
## Geschlecht2         0.39383    0.19401   2.030 0.042363 *
## Geschlecht3       -14.36244  882.74345  -0.016 0.987019
## Altergruppe2        0.62844    1.15653   0.543 0.586866
## Altergruppe3        0.70986    1.15224   0.616 0.537845
## Altergruppe4        0.77498    1.15430   0.671 0.501975
## Altergruppe5        0.29070    1.16256   0.250 0.802549
## Altergruppe6       -0.15358    1.17375  -0.131 0.895899
## Altergruppe7       -0.14913    1.22182  -0.122 0.902853
## Altergruppe8      -14.35071  882.74427  -0.016 0.987029
## Beziehungstatus2   -0.11116    0.27626  -0.402 0.687419
## Quartier2          -0.36211    0.29564  -1.225 0.220646
## Quartier3          -0.08718    0.27724  -0.314 0.753177
## Quartier4          -0.07696    0.29722  -0.259 0.795688
## Quartier5          -0.33435    0.32574  -1.026 0.304689
## Quartier6          -0.84875    0.49065  -1.730 0.083658 .
## Zuzug2             -0.74880    0.44993  -1.664 0.096061 .
## Zuzug3             -0.68489    0.47993  -1.427 0.153566
## Zuzug4             -0.95689    0.49810  -1.921 0.054722 .
## Zuzug5             -1.29266    0.51619  -2.504 0.012271 *
## Zuzug6             -0.89588    0.47591  -1.882 0.059773 .
## Zuzug7             -1.67776    0.44121  -3.803 0.000143 ***
## Bildung4            0.02162    0.46433   0.047 0.962870
## Bildung7           -0.90144    0.24984  -3.608 0.000309 ***
## Bildung8            0.12090    0.37516   0.322 0.747258
## HH2                 0.18351    0.45148   0.406 0.684394
## HH3                 0.08918    0.32521   0.274 0.783926
## HH4                -0.18850    0.37054  -0.509 0.610946
## HH5                -0.37690    0.35517  -1.061 0.288598
## Kinder_Schule2      0.26296    0.31813   0.827 0.408478
## Erwerb2            -0.32393    0.23962  -1.352 0.176420
## Erwerb3            -0.79391    0.55226  -1.438 0.150555
## Erwerb4             0.31909    0.48129   0.663 0.507341
## Erwerb5            -0.21033    0.43069  -0.488 0.625301
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 824.57  on 615  degrees of freedom
## Residual deviance: 717.27  on 582  degrees of freedom
## AIC: 785.27
##
## Number of Fisher Scoring iterations: 13
```

```
# without Interaction
lm.knw.propose <- glm(knw.propose ~ Geschlecht + Altergruppe + Beziehungstatus + Quartier + Zuzug + Bil
               family = "binomial",
               data = df.small)

summary(lm.knw.propose)
```

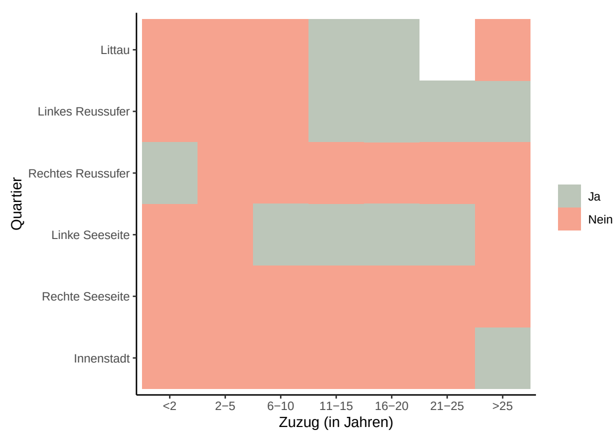
```
##
## Call:
## glm(formula = knw.propose ~ Geschlecht + Altergruppe + Beziehungstatus +
##     Quartier + Zuzug + Bildung + HH + Kinder_Schule + Erwerb,
##     family = "binomial", data = df.small)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.5929  -1.0890   0.5921   0.8424   1.5535
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)          0.31200    1.32205   0.236  0.81344
## Geschlecht2          0.46614    0.20377   2.288  0.02216 *
## Geschlecht3        -14.63702  882.74345  -0.017  0.98677
## Altergruppe2         1.70799    1.15285   1.482  0.13846
## Altergruppe3         2.41918    1.17100   2.066  0.03884 *
## Altergruppe4         2.42688    1.17071   2.073  0.03817 *
## Altergruppe5         2.35277    1.18354   1.988  0.04682 *
## Altergruppe6         1.73770    1.18964   1.461  0.14410
## Altergruppe7         1.67993    1.22430   1.372  0.17001
## Altergruppe8       -13.15883  882.74431  -0.015  0.98811
## Beziehungstatus2  -0.05519    0.29526  -0.187  0.85173
## Quartier2          -0.56741    0.29810  -1.903  0.05698 .
## Quartier3          -0.10693    0.29294  -0.365  0.71510
## Quartier4          -0.39609    0.30048  -1.318  0.18744
## Quartier5          -0.38889    0.33956  -1.145  0.25209
## Quartier6          -0.73392    0.48523  -1.513  0.13040
## Zuzug2             -0.89861    0.52148  -1.723  0.08485 .
## Zuzug3             -0.41429    0.56479  -0.734  0.46324
## Zuzug4             -1.26400    0.55746  -2.267  0.02336 *
## Zuzug5             -1.39758    0.57460  -2.432  0.01500 *
## Zuzug6             -1.20306    0.54265  -2.217  0.02662 *
## Zuzug7             -1.39285    0.50553  -2.755  0.00587 **
## Bildung4           -0.34997    0.47675  -0.734  0.46291
## Bildung7           -0.58123    0.25694  -2.262  0.02369 *
```

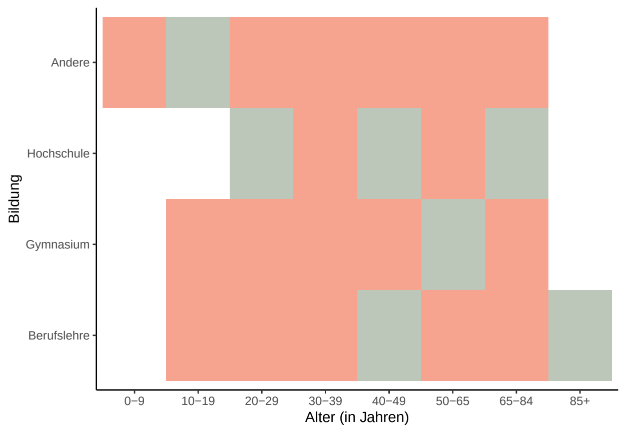
```
## Bildung8            0.03337    0.38287   0.087  0.93055
## HH2                -0.17299    0.45591  -0.379  0.70435
## HH3                -0.03338    0.34092  -0.098  0.92201
## HH4                -0.30411    0.38188  -0.796  0.42583
## HH5                -0.04269    0.38416  -0.111  0.91151
## Kinder_Schule2     -0.03788    0.31737  -0.119  0.90499
## Erwerb2            -0.12638    0.24744  -0.511  0.60951
## Erwerb3             0.12375    0.61682   0.201  0.84099
## Erwerb4             0.30391    0.47496   0.640  0.52226
## Erwerb5             0.57207    0.53438   1.071  0.28438
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 761.19  on 615  degrees of freedom
## Residual deviance: 675.78  on 582  degrees of freedom
## AIC: 743.78
##
## Number of Fisher Scoring iterations: 13
```

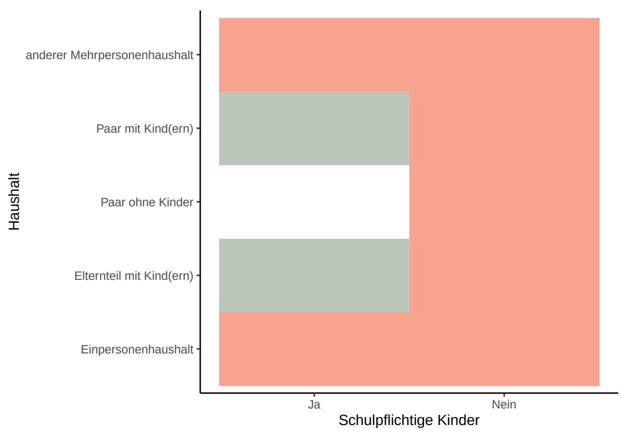
Heatmaps

for yes/no qustions

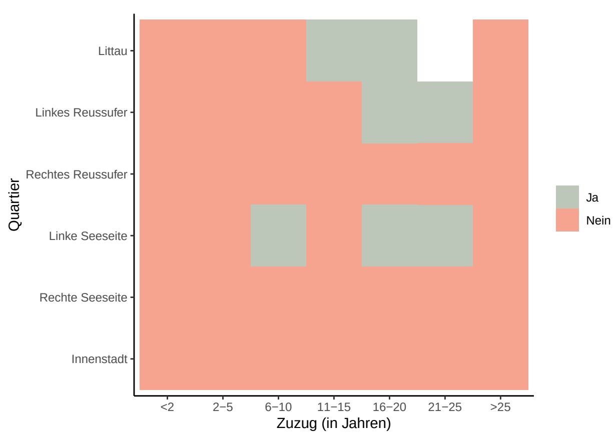
"Kennen Sie Möglichkeiten, um persönliche Anliegen einzubringen?"

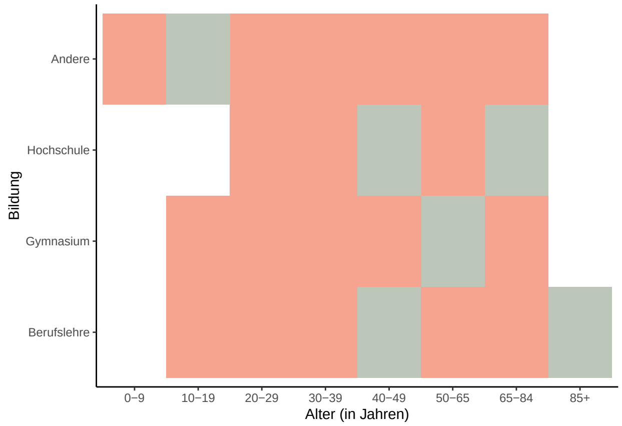


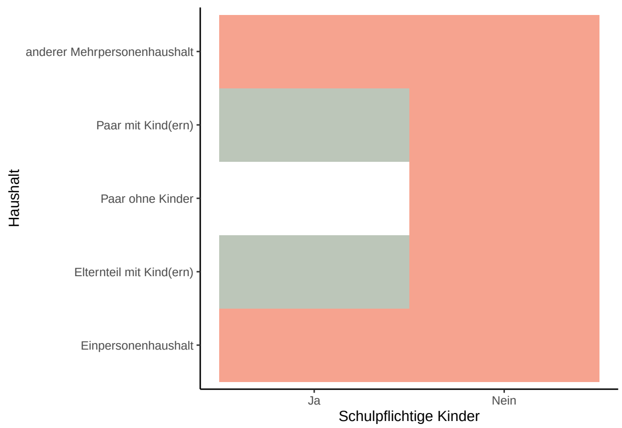




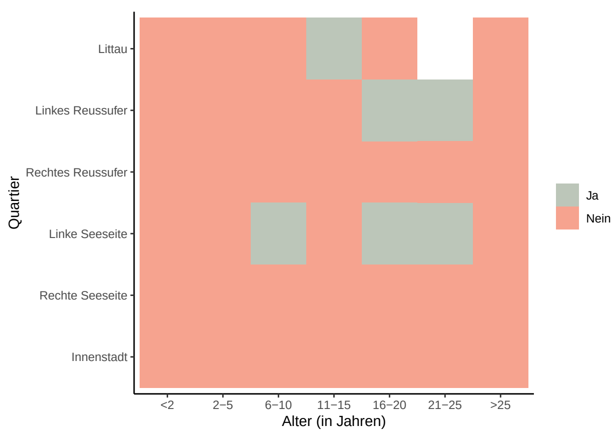
"Kennen Sie Möglichkeiten, sich in städtischen Projekten einzubringen?"

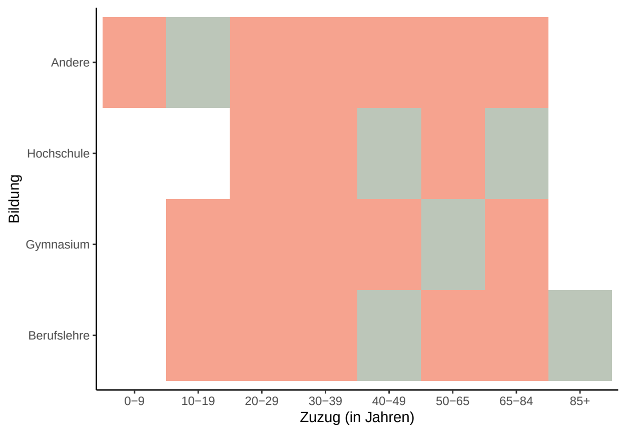


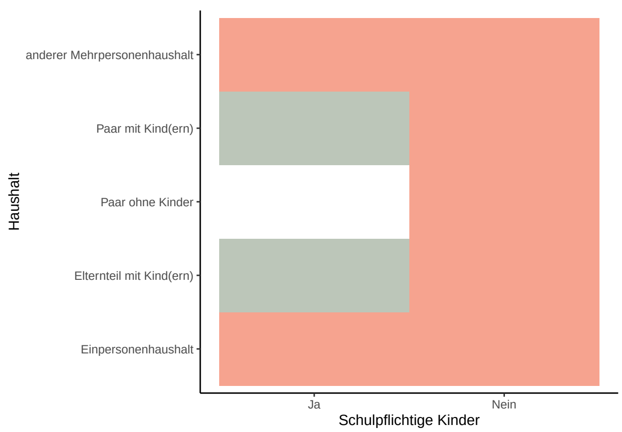




"Kennen Sie Möglichkeiten, städtische Projekte vorzuschlagen?"







Desicion Trees

```
# create train data set
set.seed(73)
ratio <- 0.7
total <- nrow(df.small)

train <- sample(1:total, as.integer(total * ratio))
```

```
table(df.small$knw.personal.matters)
```

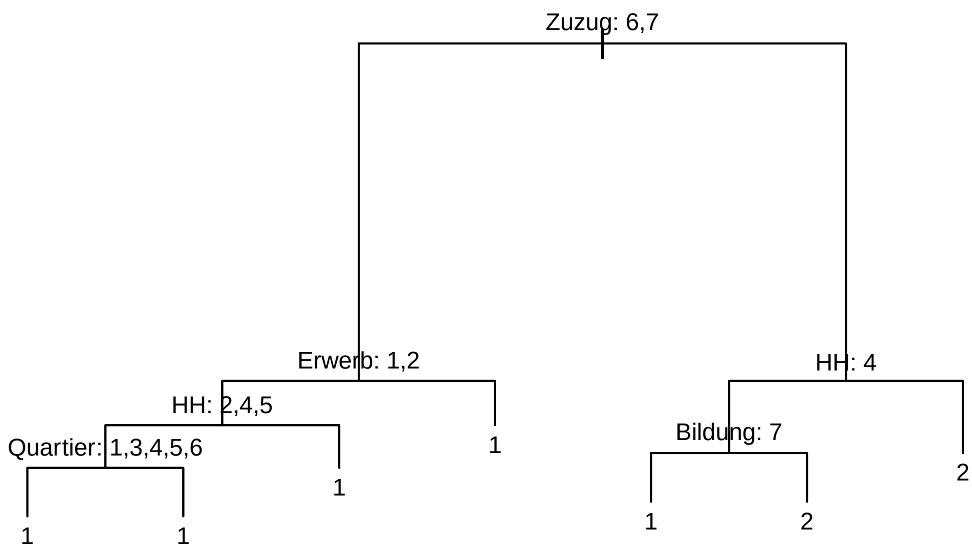
```
##
##   1   2
## 311 305
```

```
set.seed(1234)
tree.classification.316 <- tree(knw.personal.matters ~ Geschlecht + Altergruppe + Beziehungstatus + Qua
                                 data=df.small, subset=train)

summary(tree.classification.316)
```

```
##
## Classification tree:
## tree(formula = knw.personal.matters ~ Geschlecht + Altergruppe +
##     Beziehungstatus + Quartier + Zuzug + Bildung + HH + Kinder_Schule +
##     Erwerb, data = df.small, subset = train)
## Variables actually used in tree construction:
## [1] "Zuzug"    "Erwerb"   "HH"       "Quartier" "Bildung"
## Number of terminal nodes:  7
## Residual mean deviance:  1.209 = 512.8 / 424
## Misclassification error rate: 0.3086 = 133 / 431
```

```
plot(tree.classification.316)
text(tree.classification.316, pretty=1, cex=0.75)
```




```
table(df.small$knw.participate)
```

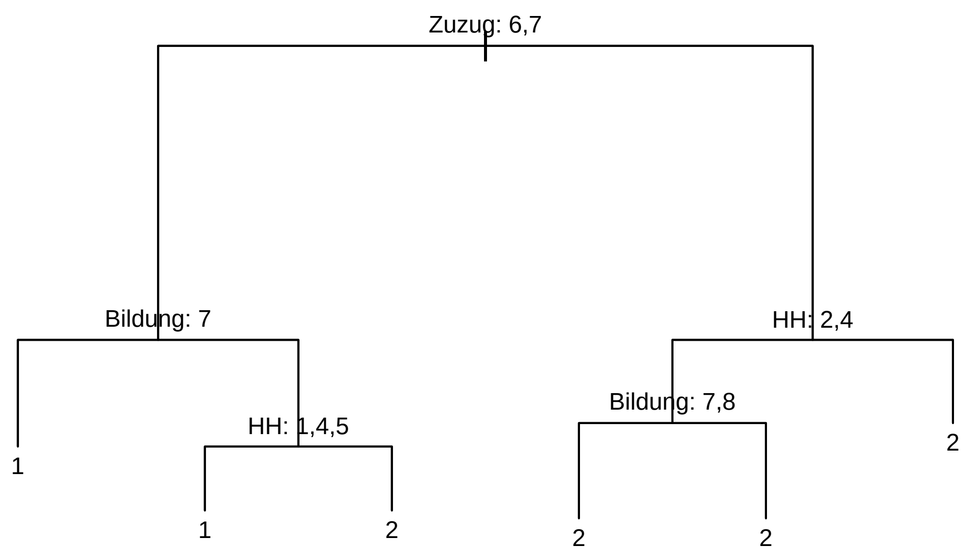
```
##
##   1   2
## 241 375
```

```
set.seed(1234)
tree.classification.212 <- tree(knw.participate ~ Geschlecht + Altergruppe + Beziehungstatus + Quartier
                                 data=df.small, subset=train)

summary(tree.classification.212)
```

```
##
## Classification tree:
## tree(formula = knw.participate ~ Geschlecht + Altergruppe + Beziehungstatus +
##     Quartier + Zuzug + Bildung + HH + Kinder_Schule + Erwerb,
##     data = df.small, subset = train)
## Variables actually used in tree construction:
## [1] "Zuzug"   "Bildung" "HH"
## Number of terminal nodes:  6
## Residual mean deviance:  1.192 = 506.4 / 425
## Misclassification error rate: 0.3063 = 132 / 431
```

```r
plot(tree.classification.212)
text(tree.classification.212, pretty=1, cex=0.75)
```




```r
tree.classification.212.pred <- predict(tree.classification.212, df.small[train,], type="class")

# confusion table to determine classification error on *train data*
(tree.classification.212.pred.ct <- table(tree.classification.212.pred,
                                           df.small[train,]$knw.participate))
```

```
##
## tree.classification.212.pred   1   2
##                            1  82  49
##                            2  83 217
```

```
tree.classification.212.pred.correct <- 0
tree.classification.212.pred.error <- 0
for (i1 in 1:2) {
  for (i2 in 1:2) {
    if (i1 == i2) {
      tree.classification.212.pred.correct <- tree.classification.212.pred.correct +
        tree.classification.212.pred.ct[i1,i2]
    }else{
     tree.classification.212.pred.error <- tree.classification.212.pred.error +
       tree.classification.212.pred.ct[i1,i2]
    }
  }
}
(tree.classification.212.pred.rate <- tree.classification.212.pred.correct/
    sum(tree.classification.212.pred.ct))
```

```
## [1] 0.6937355
```

```
# portion of correctly classified observations 51.3%
(tree.classification.212.pred.error <- 1 - tree.classification.212.pred.rate)
```

```
## [1] 0.3062645
```

```
# train error (pruned): 48.7%

# and on test data --> test error
tree.classification.212.pred.test <- predict(tree.classification.212,
                                             df.small[-train,], type="class")
# confusion table to determine classification error on *test data*
(tree.classification.212.pred.test.ct <- table(tree.classification.212.pred.test,
                                               df.small[-train,]$knw.participate))
```

```
##
## tree.classification.212.pred.test  1  2
##                                  1 33 33
##                                  2 43 76
```

```
tree.classification.212.pred.correct <- 0
tree.classification.212.pred.error <- 0
for (i1 in 1:2) {
  for (i2 in 1:2) {
    if (i1 == i2) {
      tree.classification.212.pred.correct <- tree.classification.212.pred.correct +
        tree.classification.212.pred.test.ct[i1,i2]
    }else{
      tree.classification.212.pred.error <- tree.classification.212.pred.error +
        tree.classification.212.pred.test.ct[i1,i2]
    }
  }
}
(tree.classification.212.pred.rate <- tree.classification.212.pred.correct/
    sum(tree.classification.212.pred.test.ct))
```

```
## [1] 0.5891892
```

```r
# portion of correctly classified observations 53.0%
(tree.classification.212.pred.error <- 1 - tree.classification.212.pred.rate)
```

```
## [1] 0.4108108
```

```r
# test error (pruned): 47.0%
```

Out-of-sample Performance about 60% –> Bad