Game of Thrones - Survival Analysis

Description

- Author: Anthony Jourdan
- Date: 8 April 2020

Objectives

Target of this study is to analyze how much time was spent on screen by characters of GoT before they died (or the show ends). We will try to find most influencing criterions among social indicators, and build a survival model. This model will then be evaluated and checked on a test dataset.

Dataset description

Dataset Information

Dataset downloaded from here

Game of Thrones mortality and survival dataset

Dataset posted on 13.06.2019, 10:25 by Reidar Lystad Benjamin Brown

This dataset includes data from Game of Thrones Seasons 1–8. The dataset comprises two separate datasets and an accompanying data dictionary. The character dataset contains 359 observations (i.e. characters) and 35 variables, including information about sociodemographic, exposures, and mortality. The episode dataset contains 73 observations (i.e. episodes) and 8 variables, including information about episode running time.

In this study we will use only the character dataset.

Character dataset

- Number of observations: 359.
- Outcome: **exp_time_hrs** - On screen time before death = Survival time of character (calculated as the time between first apparition and death)
- Censoring indicator: **dth_flag**
  = 0 if character is not dead by the end of the show, = 1 otherwise
- Explanatory variables:

sex of character:	1. = Male
	2. = Female
religion (at time of death):	1. = Great Stallion
	2. = Lord of Light
	3. = Faith of the Seven
	4. = Old Gods
	5. = Drowned God
	6. = Many Faced God
	7. = Other
	9. = Unknown/Unclear
occupation (at time of death):	1. = Silk collar
	2. = Boiled leather collar
	9. = Unknown/Unclear

social_status:	1. = Highborn
	2. = Lowborn
allegiance_last:	1. = Stark
	2. = Targaryen
	3. = Night's Watch
	4. = Lannister
	5. = Greyjoy
	6. = Bolton
	7. = Frey
	8. = Other
	9. = Unknown/Unclear
allegiance_switched:	1. = No
	2. = Yes

prominence	1. = low <1
continuous variable splitted	2. medium
in 3 groups	3. high >3 (top 30 char.)

Data Preparation

Load needed libraries

```
library(tidyverse)
library(survival)
library(ggfortify)
library(ggplot2)
library(broom)
library(survminer)
library(survivalROC)
```

Import data from csv file and format output:

```
raw_data = read.csv("./GoT_dataset/character_data_S01-S08.csv")
dat_full = raw_data %>%
  select(name,
         exp_time_hrs,
         dth_flag,
         sex, religion,
         occupation, social_status,
         allegiance_last, allegiance_switched,
         prominence) %>%
  mutate(sex = c("Male", "Female")[match(sex, c(1,2))],
         religion = c("Great Stallion",
                  "Lord of Light",
                  "Faith of the Seven",
                  "Old Gods",
                  "Drowned God",
                  "Many Faced God",
                  "Other",
                  "Unknown/Unclear")[match(religion,c(1,2,3,4,5,6,7,9))],
         occupation = c("Silk collar",
                    "Boiled leather collar",
                    "Unknown/Unclear")[match(occupation,c(1,2,9))],
         social_status = c("Highborn", "Lowborn")[match(social_status,c(1,2))],
         allegiance_last = c("Stark",
                         "Targaryen",
                         "Night's Watch",
                         "Lannister",
                         "Greyjoy",
                         "Bolton",
                         "Frey",
                         "Other",
                         "Unknown/Unclear")[match(allegiance_last,c(1,2,3,4,5,6,7,8,9))],
         allegiance_switched = c("No", "Yes")[match(allegiance_switched,c(1,2))],
         prominence = ifelse(prominence>3, "High",
                         ifelse(prominence<1, "Low", "Medium")
                         ))
```

Keep 15% of data for evaluating the final model

```
train_size = 85 / 100 * nrow(dat_full)
idx.dat = sample.int(nrow(dat_full), size = train_size, replace = FALSE)
dat = dat_full[idx.dat,]
dat_test = dat_full[-idx.dat,]
```

Data Exploration

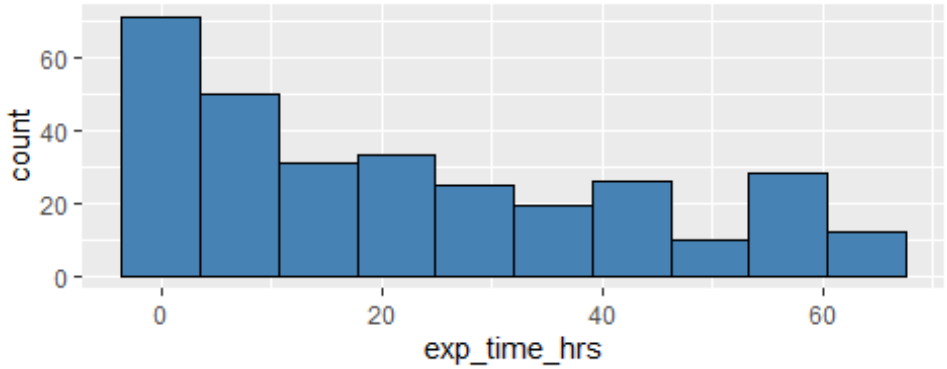
Outcome: Survival duration

Let's have a look at basic statistics about the survival duration.

```
summary(dat$exp_time_hrs)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    4.22   17.96   22.42   38.03   63.99

ggplot(dat,aes(exp_time_hrs)) + geom_histogram(bins = 10, color="black",fill="steelblue")
```



Median screen time for characters is 18 hours and 75% are not able to be on screen more than 38 hours, but it can be because they are dead or because the show has ended (careful with histograms and censored data)

Censoring indicator

Proportion of people dead before the end of the show.

```
prop.table(table(dat$dth_flag))

##         0         1
## 0.4098361 0.5901639
```

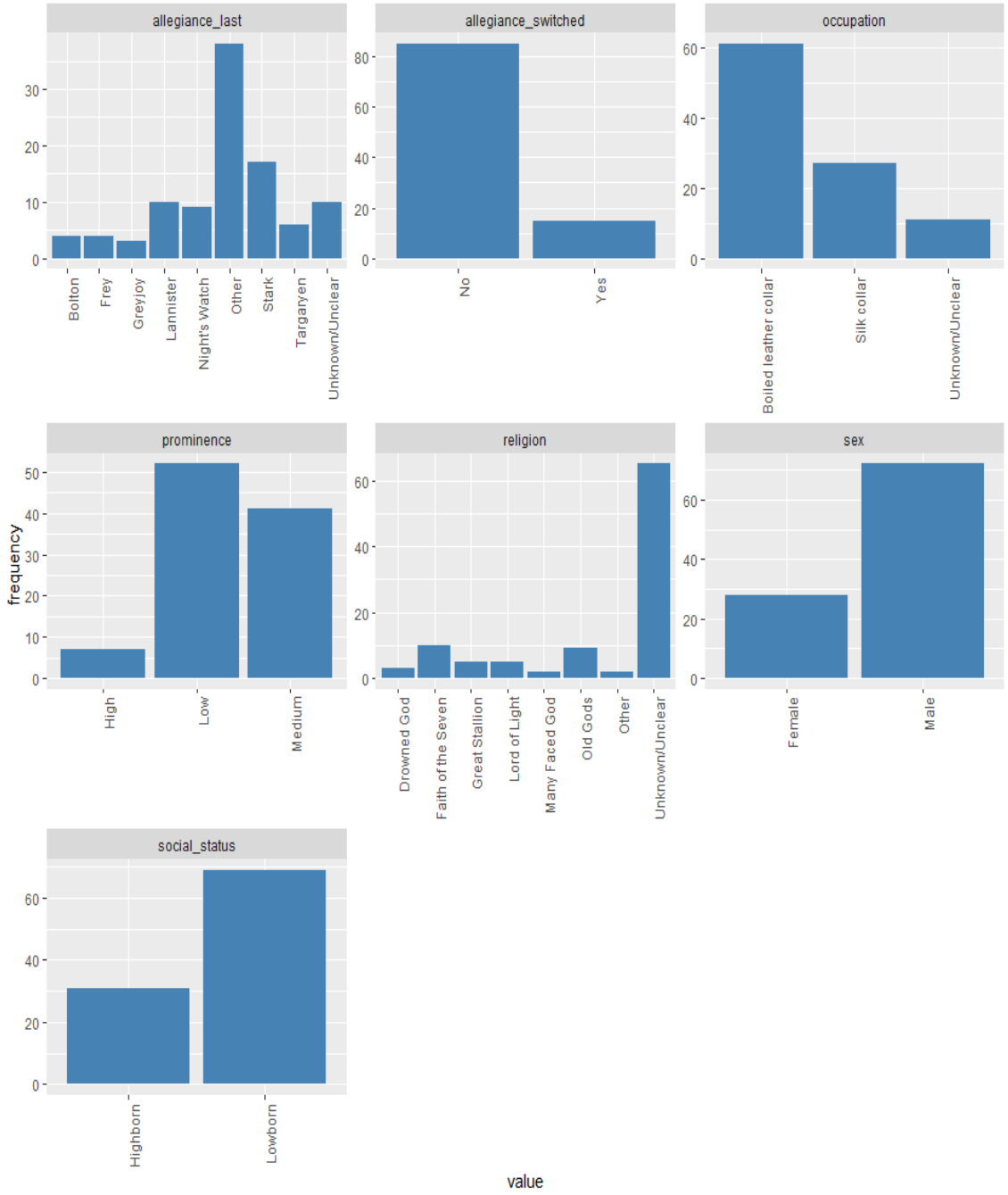
Roughly 40% of data are censored, 60% of the characters in the study are dead before the end of the TV show.

Explanatory variables

Show explanatory variables composition:

```
d_plot = dat %>%
  select(-name,-exp_time_hrs,-dth_flag) %>%
  gather() %>%
  group_by(key) %>%
  count(value) %>%
  mutate(frequency=round(`n`/sum(`n`)*100,0)) %>%
  arrange(desc(key),desc(frequency))

d_plot %>% ggplot(aes(x=value, y=frequency)) +
    facet_wrap(~ key, scales = "free") +
    geom_bar(stat="identity", fill="steelblue") +
    theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



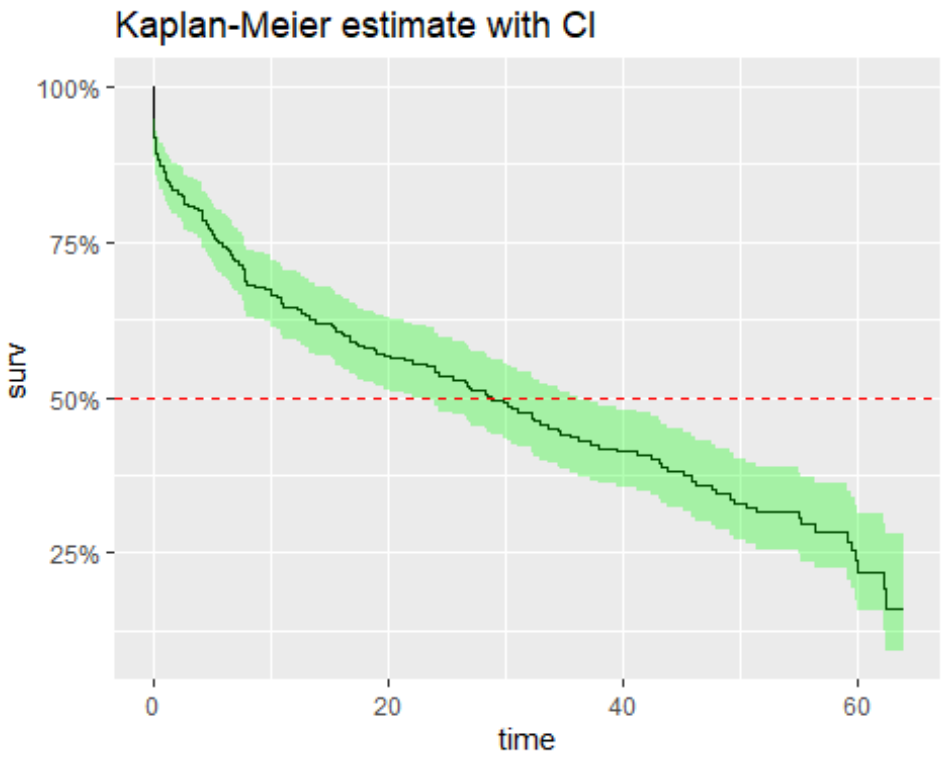
Main things to have in mind during analysis:

- 70% of characters are men, 30% are women.
- 70% are lowborn, 30% are high born, but we should see more survival in highborn (as they are less on the field during wars?)
- Most are boiled leather collar (60%)
- 65% of the population have not known or unclear religion –> Careful to check if meaningful
- Main allegiance is for Stark Family, after the “other” category, no sure to know what is the difference with “unknown/unclear”
- A vast majority of character have not switched allegiance during the show (does it help them to survive?)
- We have a smaller high prominence category, which make sense as it represents top characters of the show, low and medium are quite balanced.

Global survival overview

Kaplan-Meyer estimator

```
fit.KM = survfit(Surv(exp_time_hrs, dth_flag) ~ 1, data = dat)
autoplot(fit.KM,conf.int.fill = "#00FF00", censor=FALSE) +
  geom_hline(yintercept=.5, linetype="dashed", color = "red") +
  ggtitle("Kaplan-Meier estimate with CI")
```



Median Survival Time: 28.8hrs - As a character, you would have 50% of change to appear on screen up to 28.8hrs

```
fit.KM
```

```
## Call: survfit(formula = Surv(exp_time_hrs, dth_flag) ~ 1, data = dat)
##
##       n  events  median 0.95LCL 0.95UCL
##   305.0   180.0    28.8    22.1    36.3
```

Survival vs Explanatory variables

Used functions

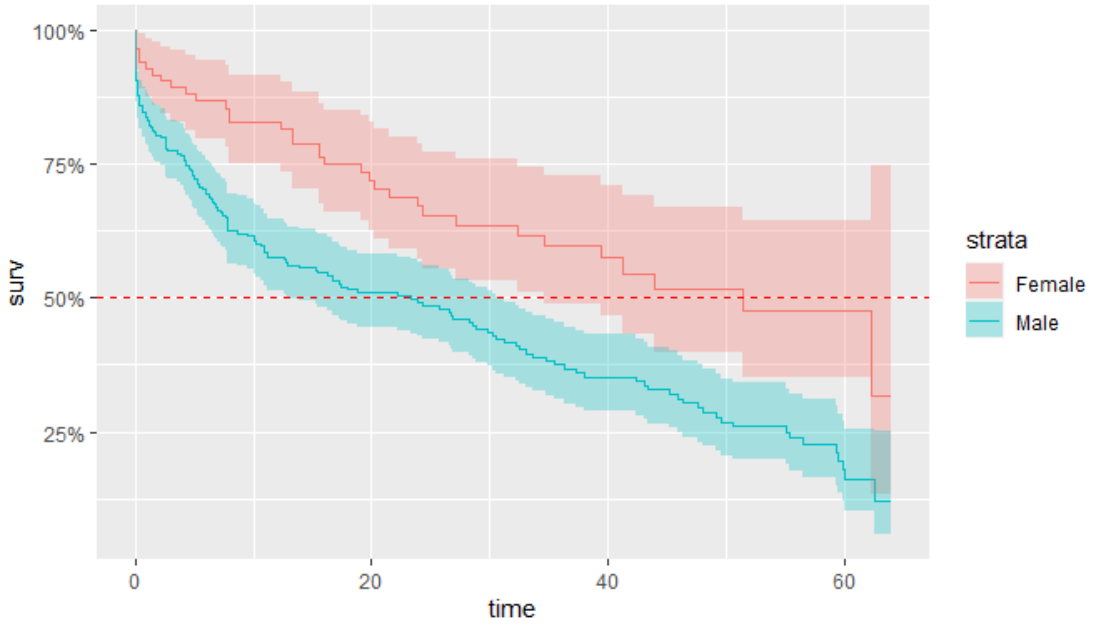
```
# draw the KM survival curve with stratification with a given exlanatory variable
plot_KM <- function(df,col,CI=TRUE){
  fit = survfit(Surv(df$exp_time_hrs, df$dth_flag) ~ df[,col])
  autoplot(fit,conf.int=CI,censor=FALSE) +
    geom_hline(yintercept=.5, linetype="dashed", color = "red")
}

# Print the medians for stratas (+formating)
print_medians <- function(df,col){
  fit = survfit(Surv(df$exp_time_hrs, df$dth_flag) ~ df[,col])
  infos_fit = surv_median(fit) %>%
    mutate(strata=substr(strata,11,100))
  cat("Medians:\n")
  cat(sprintf("%*s %*s %*s\n",25,"Group",15,"Median",20,"Conf.Interval"))
  fit.conf=paste("( ",infos_fit$lower,";",infos_fit$upper," )",sep="")
  cat(sprintf("%*s %*s %*s\n",25,infos_fit$strata,15,infos_fit$median,20,fit.conf))
}

# Print cox regression HR+CI and LRT for stratas (+formating)
print_cox <- function(df,col){
  fit_cox = coxph(Surv(df$exp_time_hrs, df$dth_flag) ~ df[,col])
  x = tidy(fit_cox)
  cox.ref = fit_cox$xlevels[[1]][1]
  cox.term = substr(x$term,10,100)
  cox.hr = round(exp(x$estimate),2)
  cox.hr.conflow = round(exp(x$conf.low),2)
  cox.hr.confhigh = round(exp(x$conf.high),2)
  cat("Cox Regression:\n")
  cat(sprintf("%*s %*s %*s\n",25,"Group",15,"Hazard Ratio",20,"Conf.Interval"))
  cat(sprintf("%*s %*s %*s\n",25,cox.ref,15,"(Reference)",20,"-"))
  cox.conf=paste("( ",cox.hr.conflow,";",cox.hr.confhigh," )",sep="")
  cat(sprintf("%*s %*s %*s\n",25,cox.term,15,cox.hr,20,cox.conf))
  y = glance(fit_cox)
  cox.lrt = ifelse(y$p.value.log<0.01,
                   formatC(y$p.value.log, format = "e", digits = 2),
                   formatC(y$p.value.log, digits = 2))
  cat(paste("\nLikelihood Ratio Test:",cox.lrt))
}
```

- How is gender influencing survival time?

```
plot_KM(dat,"sex")
```




```
print_cox(dat,"sex")
```

```
## Cox Regression:
##                     Group    Hazard Ratio        Conf.Interval
##                    Female     (Reference)                    -
##                      Male            1.97        ( 1.36;2.86 )
##
## Likelihood Ratio Test: 1.45e-04
```

Likelihood ratio test (LRT) pvalue is very small, proving that there is a significant difference between men and women survival time.

Hazard ration is 1.97, meaning that men have almost twice more chances to be killed than women

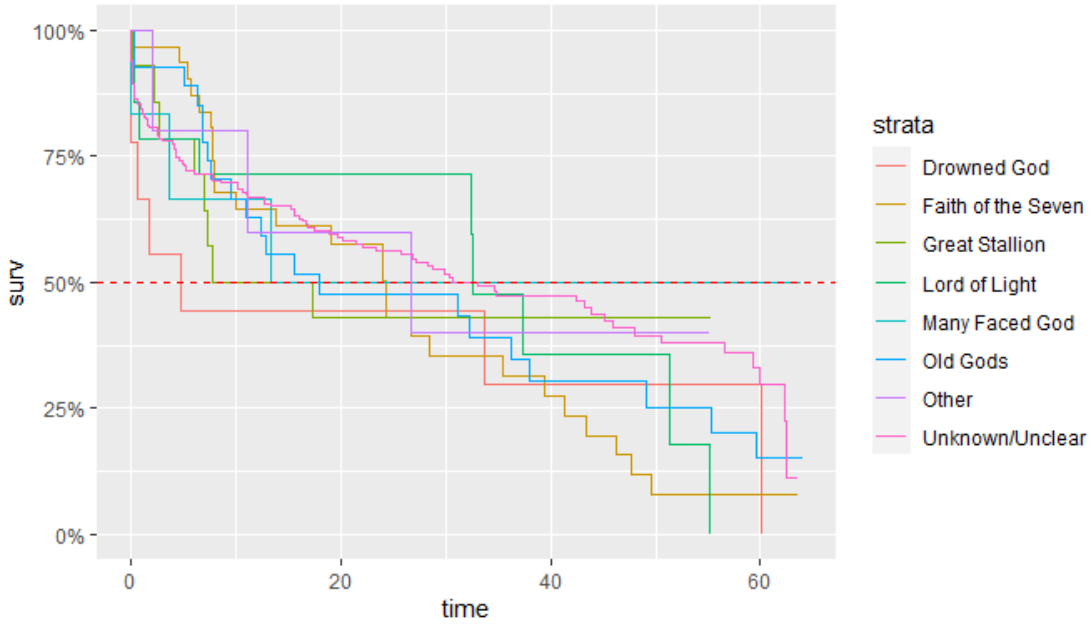
Here is the median survival time for each category:

```
print_medians(dat,"sex")
```

```
## Medians:
##                     Group          Median        Conf.Interval
##                    Female           51.42         ( 34.57;NA )
##                      Male           23.38       ( 12.92;30.6 )
```

- How is religion survival time?

```
plot_KM(dat,"religion",FALSE)
```




```
print_cox(dat,"religion")
```

```
## Cox Regression:
##                       Group    Hazard Ratio        Conf.Interval
##                 Drowned God     (Reference)                    -
##          Faith of the Seven            0.89        ( 0.39;2.06 )
##              Great Stallion            0.71        ( 0.26;1.97 )
##               Lord of Light             0.7        ( 0.26;1.88 )
##              Many Faced God            0.46        ( 0.12;1.77 )
##                    Old Gods            0.74        ( 0.32;1.75 )
##                       Other            0.61        ( 0.16;2.38 )
##             Unknown/Unclear            0.61        ( 0.28;1.31 )
##
## Likelihood Ratio Test: 0.69
```

Cox regression LRT pvalue is quite large and > 5% pointing that there is no significant difference between religions.

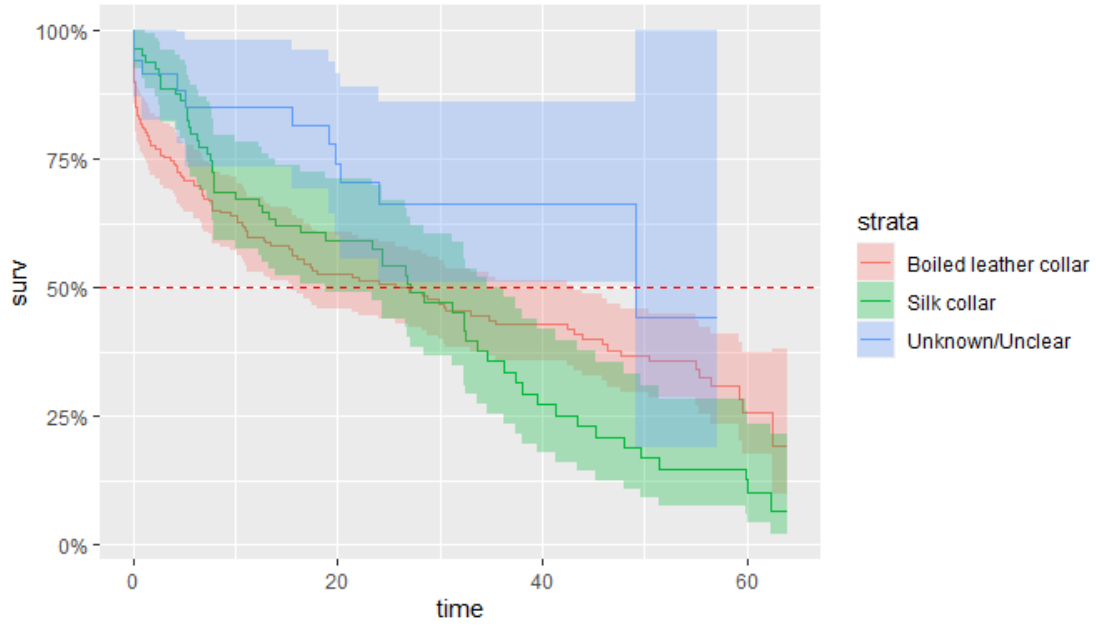
One thing that can be noted from the graph is that the “Drowned God” religion has a median survival time very low… If you were of this religion, you would have only 50% chance stay on screen more than 1.11hrs! (pretty scary)

```
print_medians(dat,"religion")
```

```
## Medians:
##                       Group          Median        Conf.Interval
##                 Drowned God            4.79          ( 0.56;NA )
##          Faith of the Seven           24.34      ( 10.05;41.33 )
##              Great Stallion          12.535           ( 6.9;NA )
##               Lord of Light           32.56         ( 32.36;NA )
##              Many Faced God           13.36          ( 3.59;NA )
##                    Old Gods           17.96      ( 10.96;55.34 )
##                       Other           26.63         ( 11.17;NA )
##             Unknown/Unclear           33.06      ( 23.38;47.99 )
```

- How is occupation influencing?

```
plot_KM(dat,"occupation")
```




```
print_cox(dat,"occupation")
```

```
## Cox Regression:
##                      Group    Hazard Ratio        Conf.Interval
##     Boiled leather collar     (Reference)                    -
##                Silk collar            1.14        ( 0.83;1.57 )
##           Unknown/Unclear            0.49        ( 0.26;0.92 )
##
## Likelihood Ratio Test: 0.019
```

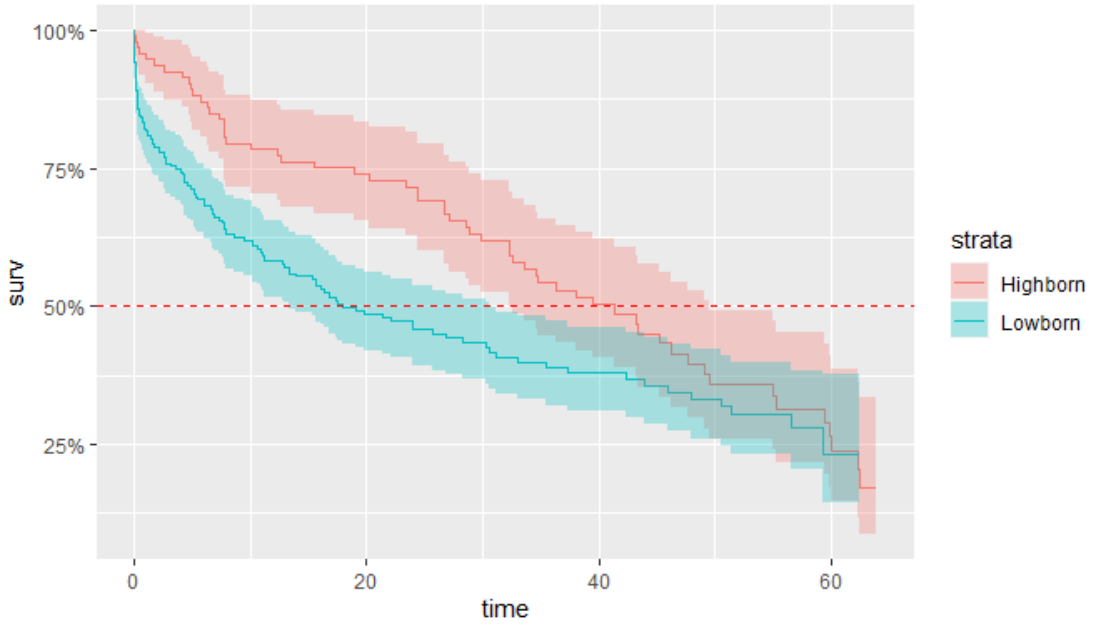
LRT pvalue is < 5%, we can say that at least one group is significantly different from other. It's certainly due to the group 'Unknown/Unclear' which has a hazard ratio close to 0.5, the 2 others are very close (HR ~ 1). this can be also seen on the medians were CI are overlapping.

```
print_medians(dat,"occupation")
```

```
## Medians:
##                      Group          Median        Conf.Interval
##      Boiled leather collar           25.68      ( 15.57;43.17 )
##                 Silk collar           27.12      ( 18.87;34.57 )
##            Unknown/Unclear           49.15         ( 49.15;NA )
```

- Is social status influencing?

```
plot_KM(dat,"social_status")
```




```
print_cox(dat,"social_status")
```

```
## Cox Regression:
##                    Group    Hazard Ratio        Conf.Interval
##                 Highborn     (Reference)                    -
##                  Lowborn            1.49        ( 1.08;2.05 )
##
## Likelihood Ratio Test: 0.012
```

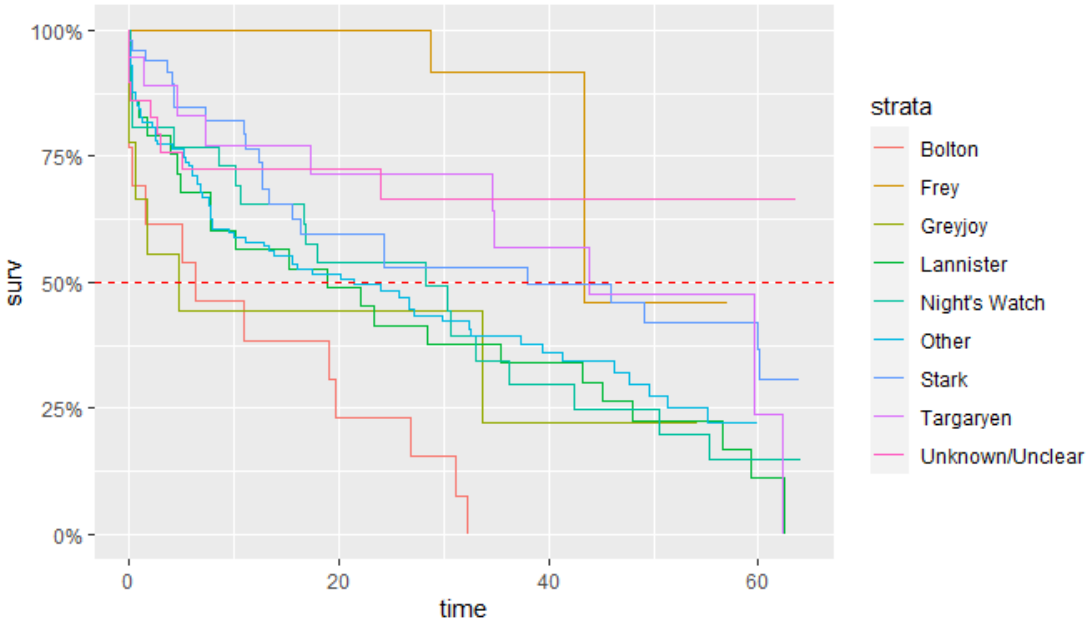
Again, LRT pvalue is <5%, meaning that to be highborn or lowborn is significantly different in terms of survival time in GoT.

```
print_medians(dat,"social_status")
```

```
## Medians:
##                    Group          Median        Conf.Interval
##                 Highborn           41.33      ( 32.36;49.59 )
##                  Lowborn           17.96       ( 13.36;30.6 )
```

– Is the last allegiance made influencing?

```
plot_KM(dat,"allegiance_last",FALSE)
```




```
print_cox(dat,"allegiance_last")
```

```
## Cox Regression:
##                       Group    Hazard Ratio        Conf.Interval
##                      Bolton     (Reference)                    -
##                        Frey            0.06        ( 0.01;0.27 )
##                      Greyjoy           0.58        ( 0.22;1.54 )
##                    Lannister           0.47        ( 0.24;0.93 )
##                Night's Watch           0.41         ( 0.2;0.84 )
##                        Other           0.41        ( 0.23;0.74 )
##                        Stark           0.24        ( 0.12;0.48 )
##                     Targaryen          0.25        ( 0.11;0.58 )
##               Unknown/Unclear          0.18        ( 0.08;0.42 )
##
## Likelihood Ratio Test: 1.02e-05
```

LRT pvalue is < 5%, we can say that at least one group is significantly different from other.

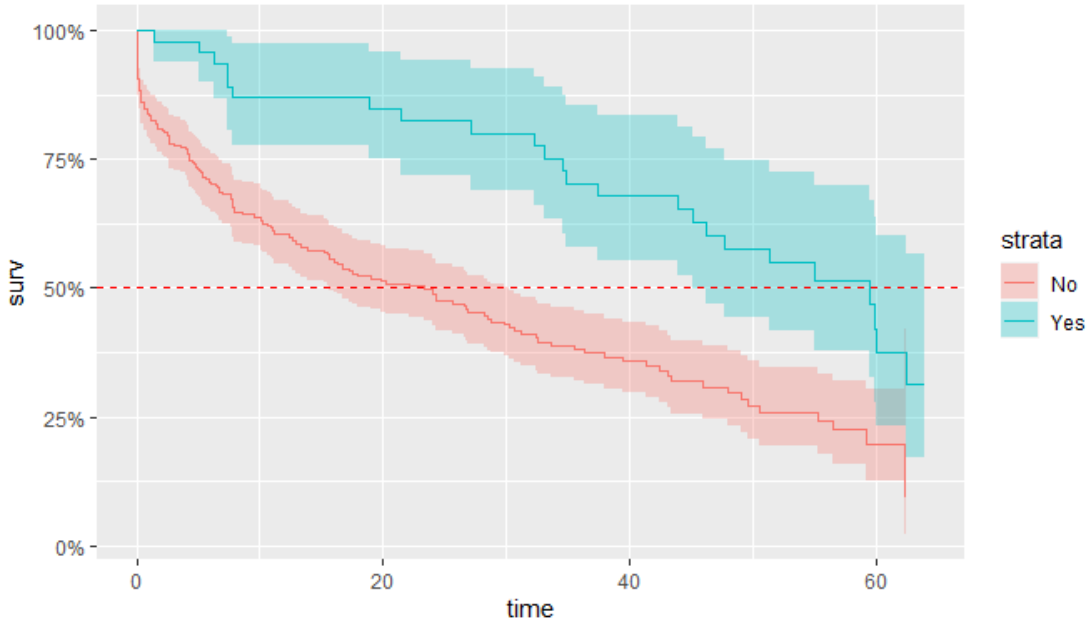
If your allegiance goes to ‘Bolton’, then you have 0% of chance to be present during all the show. But if you follow the ‘Greyjoy’, then your median survival time is only of 1.11hrs…

```
print_medians(dat,"allegiance_last")
```

```
## Medians:
##                       Group          Median        Conf.Interval
##                      Bolton            6.26          ( 0.28;NA )
##                        Frey           43.37         ( 43.37;NA )
##                      Greyjoy           4.79          ( 0.56;NA )
##                    Lannister          18.87       ( 7.75;45.18 )
##                Night's Watch          28.28      ( 10.61;50.52 )
##                        Other          21.45      ( 11.17;37.37 )
##                        Stark          38.03          ( 15.5;NA )
##                     Targaryen         43.92          ( 34.57;NA )
##               Unknown/Unclear            NA             ( NA;NA )
```

– Is the fact to have switched allegiance during the show influencing?

```
plot_KM(dat,"allegiance_switched")
```




```
print_cox(dat,"allegiance_switched")
```

```
## Cox Regression:
##                      Group    Hazard Ratio        Conf.Interval
##                         No     (Reference)                    -
##                        Yes            0.41        ( 0.26;0.64 )
##
## Likelihood Ratio Test: 1.58e-05
```

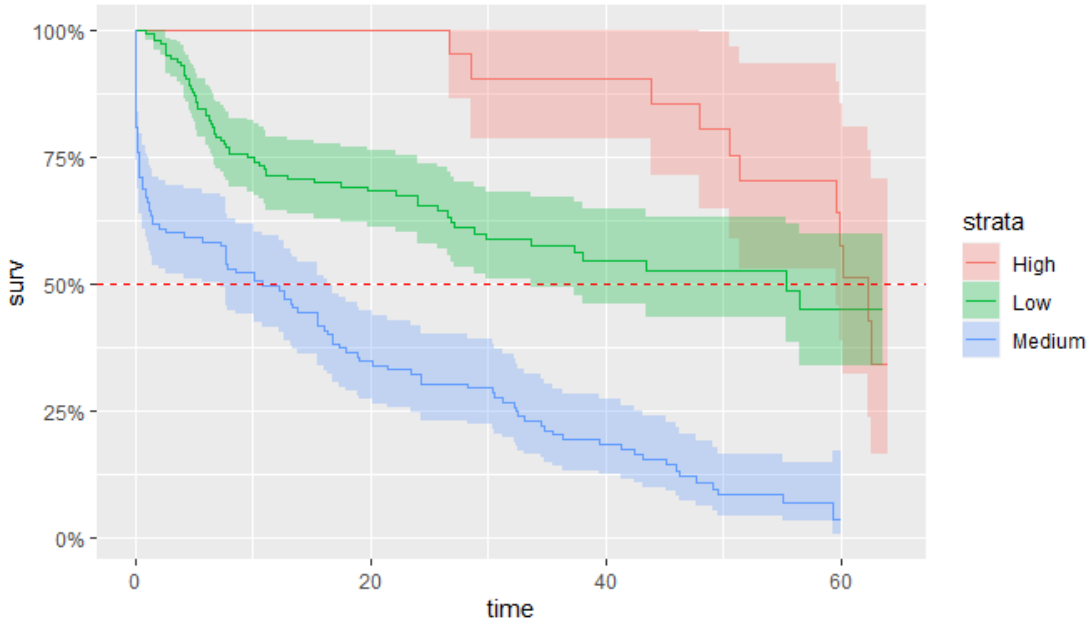
pvalue < 5%, the change in allegiance has a real impact on the characters survival times. it seems, that in GoT, if you want to maximize your chances to survive, you have to not be too strict with your allegiance.

```
print_medians(dat,"allegiance_switched")
```

```
## Medians:
##                      Group          Median        Conf.Interval
##                         No           23.38      ( 15.57;30.32 )
##                        Yes           59.54         ( 45.18;NA )
```

– How is prominence influencing?

```
plot_KM(dat,"prominence")
```




```
print_cox(dat,"prominence")
```

```
## Cox Regression:
##                      Group    Hazard Ratio        Conf.Interval
##                       High     (Reference)                    -
##                        Low            1.94       ( 0.98;3.83 )
##                     Medium            6.28      ( 3.21;12.32 )
##
## Likelihood Ratio Test: 1.08e-16
```

Very significant difference, sounds logic for characters with high prominence (stars of the show), that producers decided not to kill them at the beginning of the show so their survival time is higher than others. It seems more surprising to me, that people with low prominence have a higher survival time than the ones in the middle.

```
print_medians(dat,"prominence")
```

```
## Medians:
##                      Group          Median        Conf.Interval
##                       High           62.35         ( 59.54;NA )
##                        Low           55.34         ( 33.64;NA )
##                     Medium           10.89       ( 7.34;16.32 )
```

Build a model of Survival time in GoT

- Model selection

Let's start with a full model (using all explanatory variables) and run a step-wise model selection based on AIC.

```
dat_model = select(dat,-name)
Model_Full = coxph(Surv(exp_time_hrs,dth_flag)~.,data=dat_model)
MAIC = step(Model_Full)
```

```
## Start:  AIC=1723.26
## Surv(exp_time_hrs, dth_flag) ~ sex + religion + occupation +
##     social_status + allegiance_last + allegiance_switched + prominence
##
##                        Df    AIC
## - religion              7 1716.2
## - allegiance_last       8 1721.9
## - occupation            2 1722.0
## <none>                    1723.3
## - social_status         1 1725.1
## - sex                   1 1727.1
## - allegiance_switched   1 1736.0
## - prominence            2 1780.3
##
## Step:  AIC=1716.24
## Surv(exp_time_hrs, dth_flag) ~ sex + occupation + social_status +
##     allegiance_last + allegiance_switched + prominence
##
##                        Df    AIC
## - occupation            2 1714.8
## <none>                    1716.2
## - social_status         1 1717.2
## - allegiance_last       8 1718.8
## - sex                   1 1720.5
## - allegiance_switched   1 1727.7
## - prominence            2 1771.3
##
## Step:  AIC=1714.76
## Surv(exp_time_hrs, dth_flag) ~ sex + social_status + allegiance_last +
##     allegiance_switched + prominence
##
##                        Df    AIC
## <none>                    1714.8
## - social_status         1 1715.4
## - allegiance_last       8 1719.6
## - sex                   1 1721.2
## - allegiance_switched   1 1727.6
## - prominence            2 1769.1
```

After the step-wise selection, it appears that religion and occupation can be removed from model.

- Model description & explanation

What's the model looks like?

```
summary(MAIC)
```

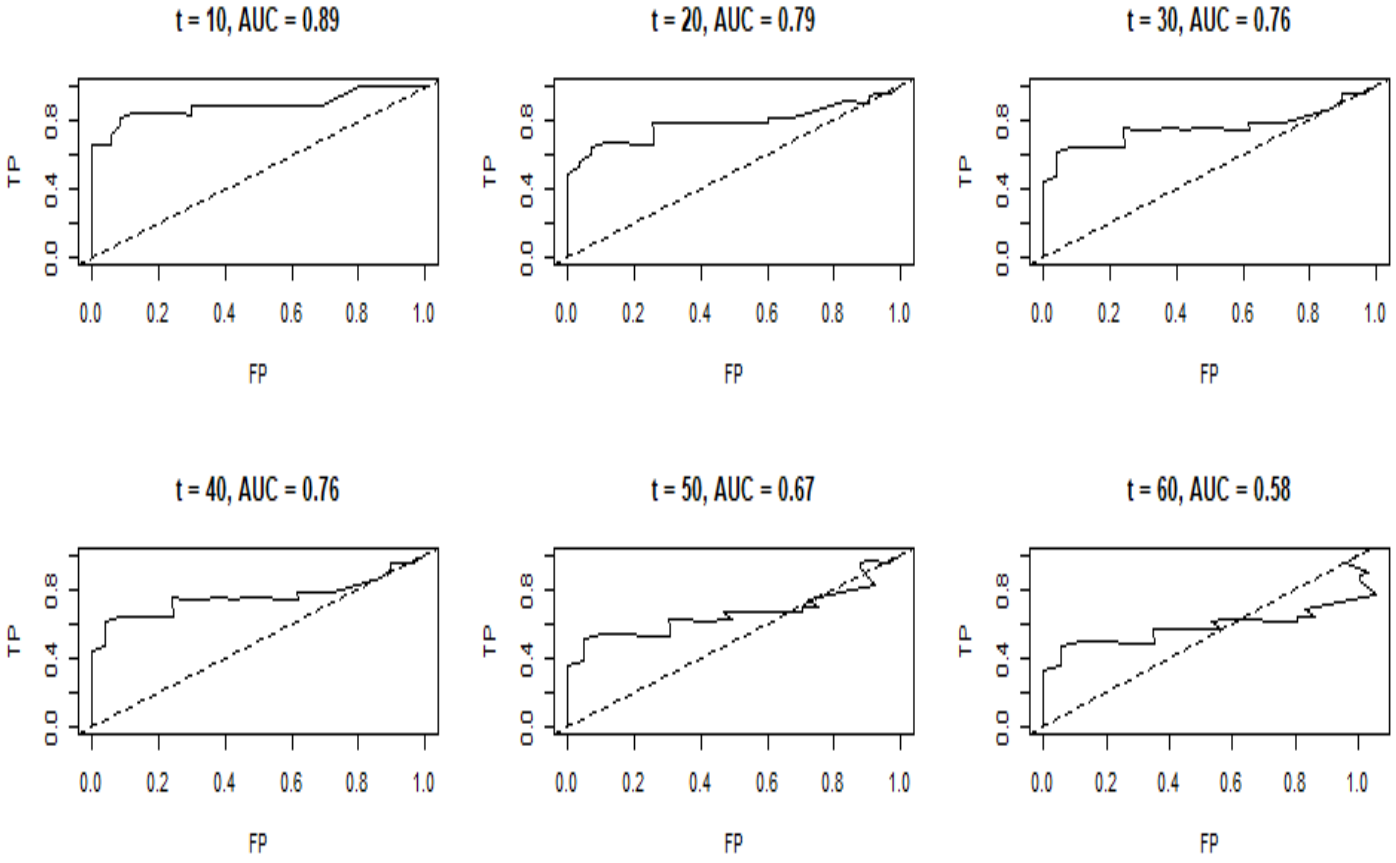
```
## Call:
## coxph(formula = Surv(exp_time_hrs, dth_flag) ~ sex + social_status +
##     allegiance_last + allegiance_switched + prominence, data = dat_model)
##
##   n= 305, number of events= 180
##
##                                    coef exp(coef) se(coef)      z Pr(>|z|)
## sexMale                         0.56158   1.75344  0.20130  2.790 0.005275 **
## social_statusLowborn            0.29359   1.34124  0.18394  1.596 0.110453
## allegiance_lastFrey            -1.54787   0.21270  0.80873 -1.914 0.055625 .
## allegiance_lastGreyjoy          0.11117   1.11758  0.51004  0.218 0.827461
## allegiance_lastLannister       -0.62418   0.53570  0.35607 -1.753 0.079603 .
## allegiance_lastNight's Watch   -0.98427   0.37371  0.36170 -2.721 0.006503 **
## allegiance_lastOther           -0.50191   0.60537  0.31087 -1.615 0.106414
## allegiance_lastStark           -1.06295   0.34544  0.36307 -2.928 0.003415 **
## allegiance_lastTargaryen       -0.70029   0.49644  0.43507 -1.610 0.107482
## allegiance_lastUnknown/Unclear -1.27573   0.27923  0.44821 -2.846 0.004423 **
## allegiance_switchedYes         -0.89655   0.40797  0.24958 -3.592 0.000328 ***
## prominenceLow                  -0.04301   0.95790  0.38290 -0.112 0.910557
## prominenceMedium                1.20346   3.33163  0.36157  3.328 0.000873 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                                exp(coef) exp(-coef) lower .95 upper .95
## sexMale                           1.7534     0.5703   1.18180    2.6016
## social_statusLowborn              1.3412     0.7456   0.93527    1.9234
## allegiance_lastFrey               0.2127     4.7014   0.04359    1.0379
## allegiance_lastGreyjoy            1.1176     0.8948   0.41127    3.0369
## allegiance_lastLannister          0.5357     1.8667   0.26659    1.0765
## allegiance_lastNight's Watch      0.3737     2.6759   0.18393    0.7593
## allegiance_lastOther              0.6054     1.6519   0.32916    1.1134
## allegiance_lastStark              0.3454     2.8949   0.16956    0.7037
## allegiance_lastTargaryen          0.4964     2.0143   0.21161    1.1647
## allegiance_lastUnknown/Unclear    0.2792     3.5813   0.11600    0.6722
## allegiance_switchedYes            0.4080     2.4511   0.25014    0.6654
## prominenceLow                     0.9579     1.0440   0.45227    2.0288
## prominenceMedium                  3.3316     0.3002   1.64017    6.7675
##
## Concordance= 0.75  (se = 0.019 )
## Likelihood ratio test= 124.2  on 13 df,   p=<2e-16
## Wald test            = 112.2  on 13 df,   p=<2e-16
## Score (logrank) test = 129.9  on 13 df,   p=<2e-16
```

Evaluating and checking model

ROC curve charts

Look at the ROC curves on test set:

```
lp = predict(MAIC, newdata = dat_test, type="lp")
ROC_func <- function(t){
  res = survivalROC(Stime = dat_test$exp_time_hrs,
            status = dat_test$dth_flag,
            marker = lp,
            predict.time = t,
            method = "KM")
  with(res, plot(TP ~ FP, type = "l", main = sprintf("t = %.0f, AUC = %.2f", t, AUC)))
  abline(a = 0, b = 1, lty = 2)
  res
}
layout(matrix(1:6, byrow = TRUE, ncol = 3))
res.survivalROC.age.sex <- lapply(1:6 * 10, function(t) {
    ROC_func(t)
})
```



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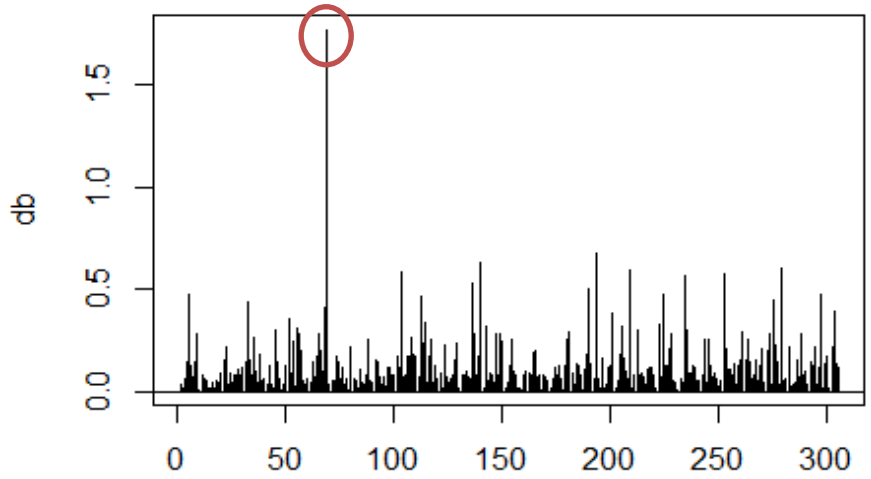
Case deletion residuals:

```
dfbetas = residuals(MAIC, type='dfbetas')
db = sqrt(rowSums(dfbetas^2))
plot(db,type = 'h')
abline(h=0)
```

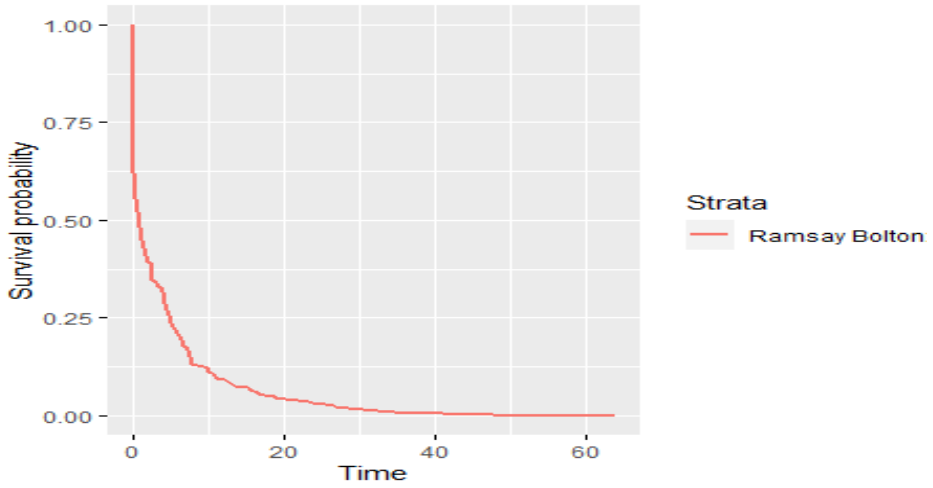


One case seems to have a larger impact on final estimates, let's find who it is:

```
idx=names(db[db>1])
dat[idx,]
```

	name	exp_time_hrs	dth_flag	sex	religion	occupation	social_status	allegiance_last	allegiance_switched	prominence
165	Ramsay Bolton	31.18	1	Male	Old Gods	Silk collar	Lowborn	Bolton	No	Medium

```
dat_new = dat[idx,]
z = list()
for(i in 1:nrow(dat_new)) {
    row <- dat_new[i,]
    p_s = survfit(MAIC,newdata = row)
    z = c(z,list(p_s))
}
names(z)=dat_new$name
ggsurvplot_combine(z, censor = FALSE, ggtheme = theme_gray(), legend="right")
```



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Conclusions

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