Analysis of Employee attrition

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The following code generates descriptive statistics and basic plots, cleans data and performs some hypothesis tests. Finally three Survival Analysis models are applied in order to ascertain the predictors of employee turnover.

The data is real, provided by Edward Babushkin - https://edwvb.blogspot.com/2017/10/employee-turnover-how-to-predict-individual-risks-of-quitting.html?m=1

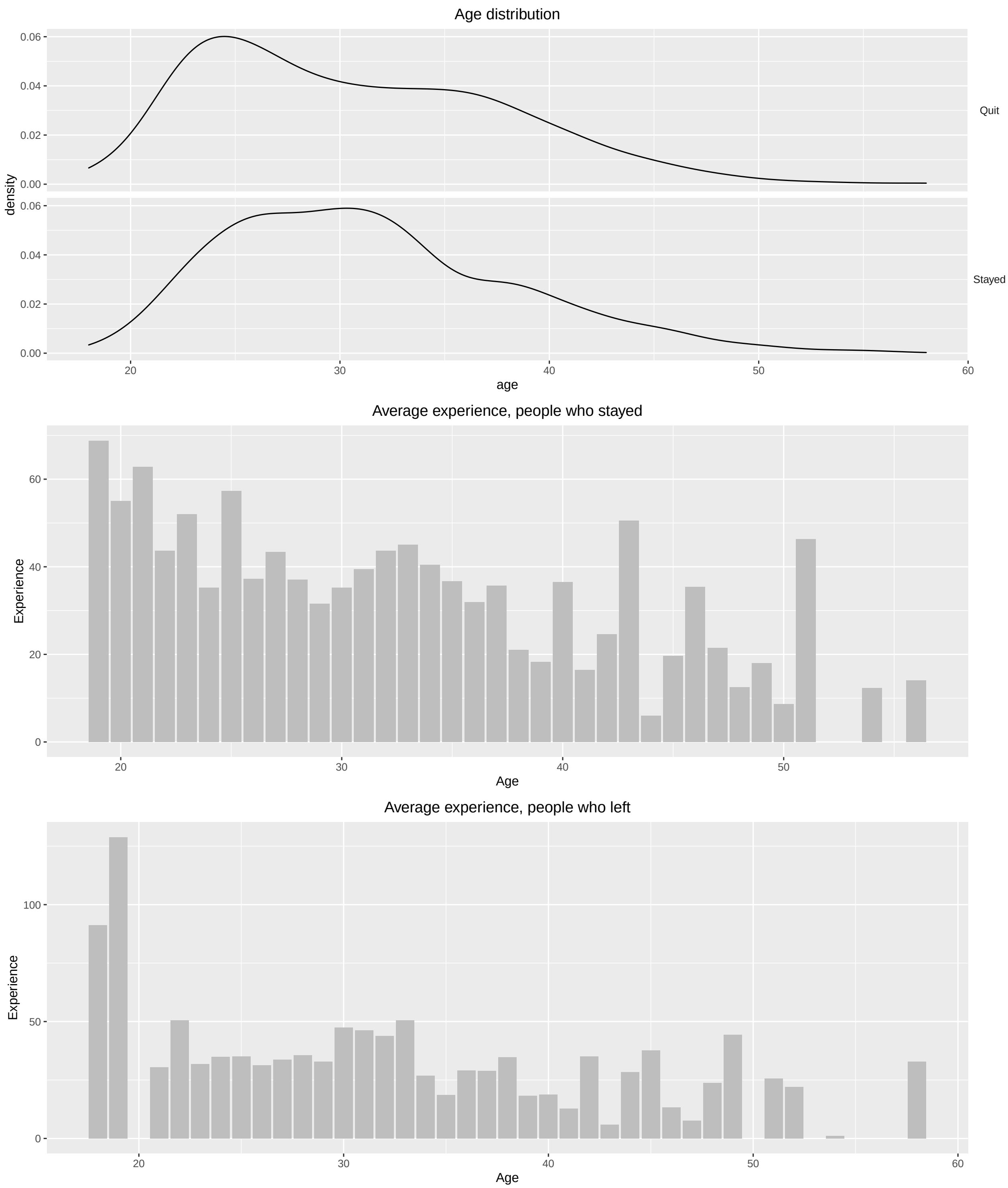
Cleaning

```
##       stag              event       gender       age                 industry
##  Min.   :  0.3942   Quit  :553   m:275   Min.   :18.00   Retail      :280
##  1st Qu.: 11.7125   Stayed:554   f:832   1st Qu.:25.00   manufacture:143
##  Median : 24.4107                        Median :30.00   IT          :122
##  Mean   : 36.6903                        Mean   :31.03   Banks       :111
##  3rd Qu.: 51.4497                        3rd Qu.:36.00   etc         : 92
##  Max.   :179.4497                        Max.   :58.00   Consult     : 73
##                                                          (Other)     :286
##                profession        traffic
##  HR                 :739   youjs      :311
##  IT                 : 74   empjs      :247
##  Sales              : 65   rabrecNErab:206
##  etc                : 37   friends    :115
##  Marketing          : 30   referal    : 94
##  BusinessDevelopment: 27   KA         : 65
##  (Other)            :135   (Other)    : 69

##      coach      head_gender  greywage      way        extraversion
##  no     :667   f:536       white:984   bus :668   Min.   : 1.000
##  yes    :130   m:571       grey :123   car :325   1st Qu.: 4.600
##  my head:310                           foot:114   Median : 5.400
##                                                   Mean   : 5.578
##                                                   3rd Qu.: 7.000
##                                                   Max.   :10.000
##     independ      selfcontrol        anxiety          novator
##  Min.   : 1.00   Min.   : 1.000   Min.   : 1.700   Min.   : 1.000
##  1st Qu.: 4.10   1st Qu.: 4.100   1st Qu.: 4.800   1st Qu.: 4.400
##  Median : 5.50   Median : 5.700   Median : 5.600   Median : 6.000
##  Mean   : 5.47   Mean   : 5.616   Mean   : 5.674   Mean   : 5.878
##  3rd Qu.: 6.90   3rd Qu.: 7.200   3rd Qu.: 7.100   3rd Qu.: 7.500
##  Max.   :10.00   Max.   :10.000   Max.   :10.000   Max.   :10.000
```

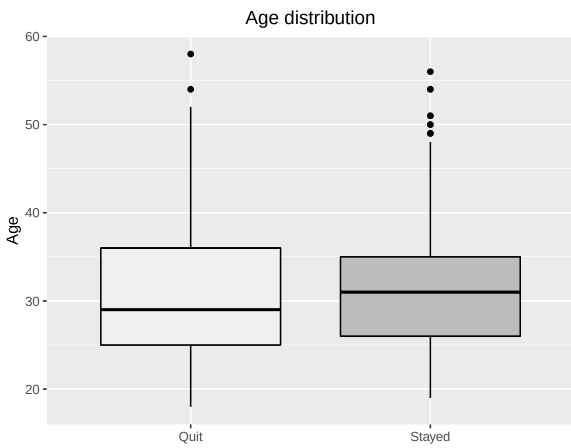
Visualization

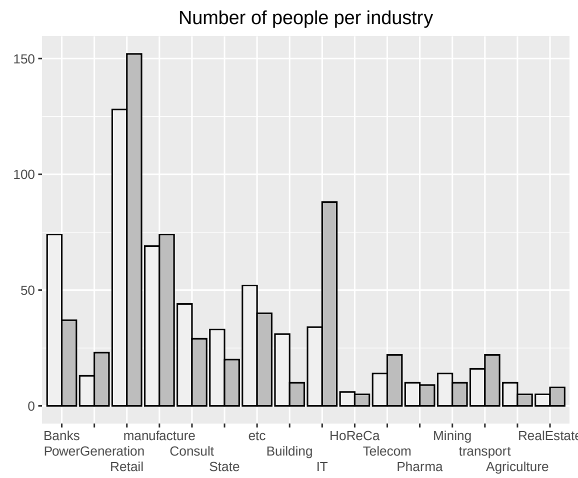
```r
# -

# Age distr
graph1 <- ggplot(data, mapping = aes(x = age)) + geom_density() + facet_grid(event~.) +
  labs(title = "Age distribution") +
  theme(plot.title = element_text(hjust = 0.5), strip.text.y = element_text(angle = 0), strip.backgroun

# experience vs age
graph2.1 <- data[data$event == "Stayed",] %>% group_by(age) %>% summarize(mean(stag)) %>%
  rename(avg_stag = `mean(stag)`) %>%
  ggplot(mapping = aes(x = age, y = avg_stag)) + geom_col(fill = "Grey")  +
  labs(title = "Average experience, people who stayed", x = "Age", y = "Experience") +
  theme(plot.title = element_text(hjust = 0.5))

graph2.2 <- data[data$event == "Quit",] %>% group_by(age) %>% summarize(mean(stag)) %>%
  rename(avg_stag = `mean(stag)`) %>%
  ggplot(mapping = aes(x = age, y = avg_stag)) + geom_col(fill = "Grey")  +
  labs(title = "Average experience, people who left", x = "Age", y = "Experience") +
  theme(plot.title = element_text(hjust = 0.5))

graph3 <- melt(data %>% select(event,(extraversion:novator))) %>%
  ggplot(mapping = aes(x = variable, y = value, fill = event), size = 10) +
  stat_summary(fun = mean, position = "dodge" ,geom = "bar", color = "black") + labs(title = "Big 5 sco
  theme(plot.title = element_text(hjust = 0.5), axis.title.x = element_text(color = "white"), legend.ti
  scale_fill_brewer(palette = "Greys")

graph4 <- data %>% ggplot(mapping = aes(x = age, event)) + geom_boxplot(aes(fill = event), color = "bla
  coord_flip() + labs(title = "Age distribution", x = "Age") +
  theme(plot.title = element_text(hjust = 0.5), axis.title.x = element_blank(), legend.title = element_
  scale_fill_brewer(palette = "Greys")

graph5 <- data %>% ggplot(mapping = aes(x = industry)) +
  geom_bar(aes(fill = event), color = "black", position = "dodge", show.legend = FALSE) +
  theme(plot.title = element_text(hjust = 0.5) ,axis.title.y = element_blank(), legend.title = element_
  labs(title = "Number of people per industry", x = "") + scale_x_discrete(guide = guide_axis(n.dodge =
  scale_fill_brewer(palette = "Greys")

graph6 <- data %>% ggplot(mapping = aes(x = profession)) +
  geom_bar(aes(fill = event), color = "black", position = "dodge", show.legend = FALSE) +
  theme(plot.title = element_text(hjust = 0.5), axis.title.y = element_blank(), legend.title = element_
  labs(title = "Number of people per profession", x = "") + scale_x_discrete(guide = guide_axis(n.dodge
  scale_fill_brewer(palette = "Greys")

graph7 <- data %>% ggplot(mapping = aes(x = way)) +
  geom_bar(aes(fill = event), color = "black", position = "dodge", show.legend = FALSE) +
  theme(plot.title = element_text(hjust = 0.5), axis.title.y = element_blank(), legend.title = element_
  labs(title = "Commute choice", x = "") + scale_fill_brewer(palette = "Greys")

graph8 <- melt(data %>% select(event, age, stag)) %>% ggplot(mapping = aes(x = variable, y = value, fil
  stat_summary(fun = mean, color = "black", position = "dodge", geom = "bar", show.legend = FALSE) + la
  theme(plot.title = element_text(hjust = 0.5), legend.title = element_blank()) +
```

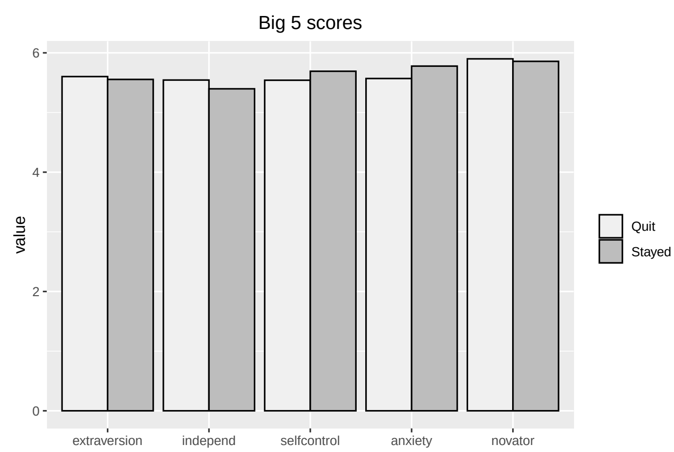
```
  scale_fill_brewer(palette = "Greys")

ggarrange(graph1, graph2.1, graph2.2, nrow = 3, widths = c(2, c(1, 1)))
```

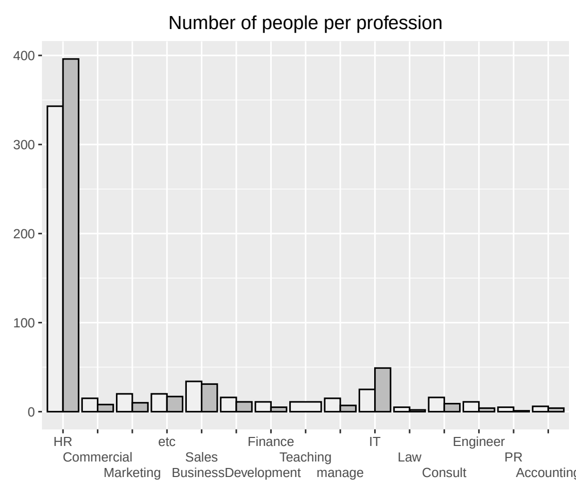


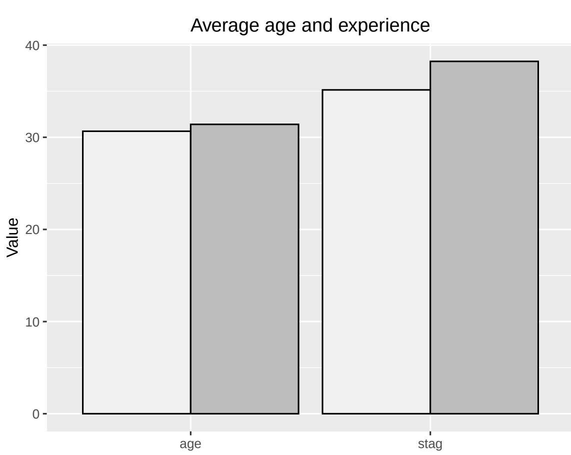

```
ggarrange(graph4 ,graph5, graph3, graph6, graph8, graph7)
```

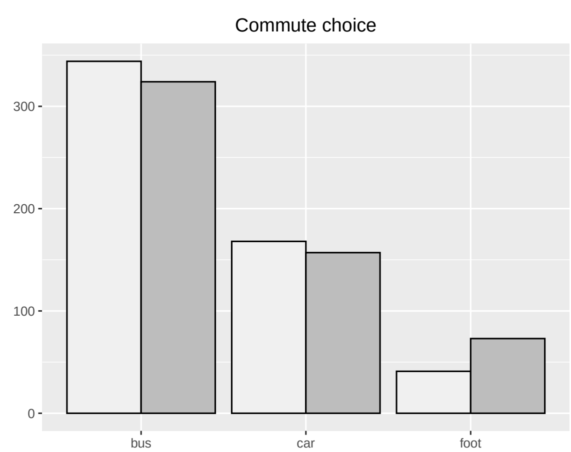












Statistical tests

```
# - STATISTICAL TESTS

# H0: B1 = B2 = B3 = B4 = B5 = 0
```

```r
# H1: B1 != 0 or B2 != 0, or both, or..., or all

big5_event <- data[data$event == "Quit",  names(data) %in% c("independ", "anxiety", "extraversion", "no
big5_no_event <- data[data$event == "Stayed",  names(data ) %in% c("independ", "anxiety", "extraversion
big5.pvalue <- HotellingsT2Test(big5_event, big5_no_event)$p.value

# H0: p = 0.5 (probability of leaving)
# H1: p < 0.5

male_event = dim(data[(data$event == "Quit") & (data$gender == "m"),  "gender"])[1]
len_male_evth = dim(data[data$gender == "m", "gender"])[1]
male.pvalue <- pbinom(male_event, len_male_evth, 0.5) #Cannot reject


female_event = dim(data[(data$event == "Quit") & (data$gender == "f"),  "gender"])[1]
len_female_evth = dim(data[data$gender == "f","gender"])[1]
female.pvalue <- pbinom(female_event, len_female_evth, 0.5) #Cannot reject

head_male_event = dim(data[(data$event == "Quit") & (data$head_gender == "m"),  "head_gender"])[1]
len_head_male_evth = dim(data[data$head_gender == "m","head_gender"])[1]
headmale.pvalue <- pbinom(head_male_event, len_head_male_evth, 0.5) #Cannot reject

head_female_event = dim(data[(data$event == "Quit") & (data$head_gender == "f"),  "head_gender"])[1]
len_head_female_evth = dim(data[data$head_gender == "f","head_gender"])[1]
headfemale.pvalue <- pbinom(head_female_event, len_head_female_evth, 0.5) #Cannot reject

# H0: B1 = 0
# H1: B1 != 0

age_event = data[data$event == "Quit", "age"]
age_no_event = data[data$event == "Stayed", "age"]
age.pvalue <- t.test(age_event, age_no_event)$p.value #Cannot reject

stag_event = data[data$event == "Quit", "stag"]
stag_no_event = data[data$event == "Stayed", "stag"]
stag.pvalue <- t.test(stag_event, stag_no_event)$p.value #Cannot reject


pvalues = c(big5.pvalue, male.pvalue, female.pvalue, headmale.pvalue, headfemale.pvalue, age.pvalue, sta
testnames = c("Hoteling's t-test: Big 5" , "binomial test: males", "binomial test: females", "binomial
significant_at_0.05 = pvalues < 0.05

data.frame(testnames,pvalues, significant_at_0.05)
```

```
##                      testnames    pvalues significant_at_0.05
## 1    Hoteling's t-test: Big 5 0.21493521               FALSE
## 2        binomial test: males 0.35878148               FALSE
## 3      binomial test: females 0.59586499               FALSE
## 4   binomial test: head males 0.82138355               FALSE
## 5 binomial test: head females 0.18219375               FALSE
## 6                t-test: age 0.07625558               FALSE
## 7               t-test: stag 0.13239632               FALSE
```

Survival analysis

Why use survival analysis, instead of logistic methods?

- Logistic methods are classification models, that is, they assume that there are two categories of employees: those who stay and those who leave. This is not only wrong (all employees are expected to leave eventually), but inaccurate even when imposing time thresholds. Let's say we want to predict the likelihood of quitting at a one-year threshold, using a logistic regression. Our results could possibly indicate that there are some super-employees in our firm: they have an incredibly high likelihood to stay for one year. However, our model would fail to ascertain whether or not these super-employees would quit at dramatic rates after 1.5 years, and therefore would not be helpful for many problems. However, if said thresholds were considered of strategic importance (for example, a 3-month threshold), the use of logistic methods could be justified when taking into account the following point.
- Results achieved with a logistic regression indicate that current tenure is the most important predictor of turnover. This is not an actionable insight, since hiring decisions cannot depend on this variable. The only way to surpass this limitation while staying close to the realm of logistic methods would imply the use of a time series model with an auto correlated quitting-likelihood variable, which is roughly equivalent to Survival Analysis. One circumstance in which this requirement can be dodged is a short-term time frame, (i.e 3 months), since the autocorrelation is deemed to be insignificant. In the rest of cases, Survival Analysis gets the most out of the predictive power of tenure.
- Survival analysis allows you to be precise and detect meaningful breakpoints and trends, and readily present them to a non technical audience.
- If you actually want to find breakpoints or changes in slope (splines), you should probably plot the dataset like a distribution of tenure-survival. That would already resemble survival analysis in a graphical way. This is because it is much more intuitive to understand (and model) breakpoints this way.

```
newdat <- read_csv("data/turnover-data-set_utf.csv", show_col_types = FALSE,
                  col_types = "dififfffffffddddd")
newdat <- newdat[!duplicated(newdat) & !apply(is.na(newdat), 1, any),]

train <- newdat[sample(nrow(newdat), nrow(newdat) * 0.7), ]
test <- newdat[setdiff(seq_len(nrow(newdat)), sample(nrow(newdat), nrow(newdat) * 0.7)), ]
```

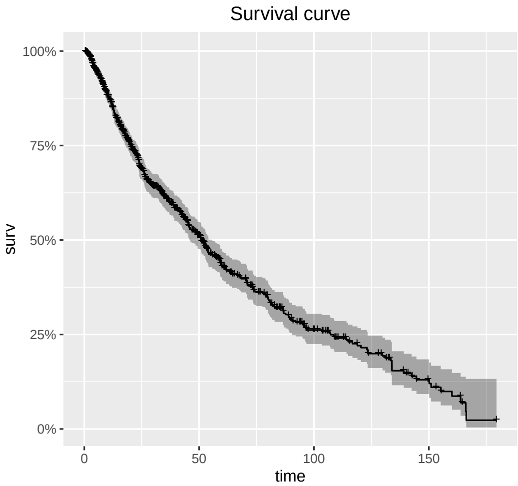
Kaplan-Meier model

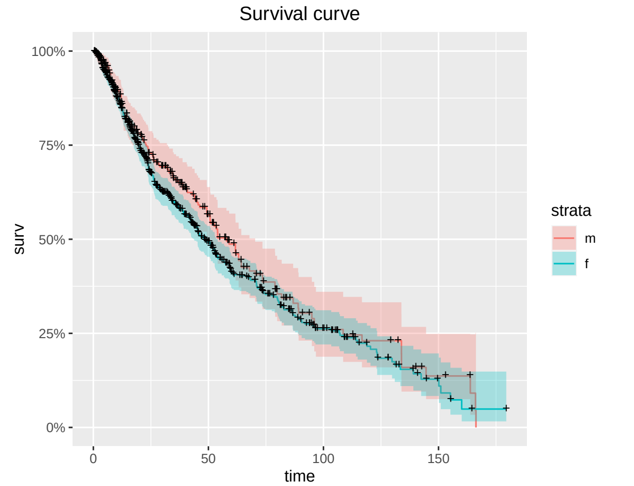
The simplest possible model and our baseline. It takes into account a single independent variable, namely, tenure. However, we can generate many survival curves for every possible realization of another variable. This already provides useful insight.

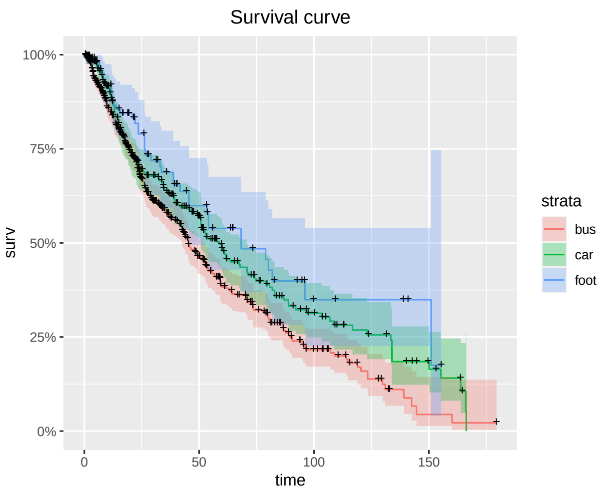
```
objSurv <- with(train, Surv(stag, event))
survfit(objSurv ~ 1)
```

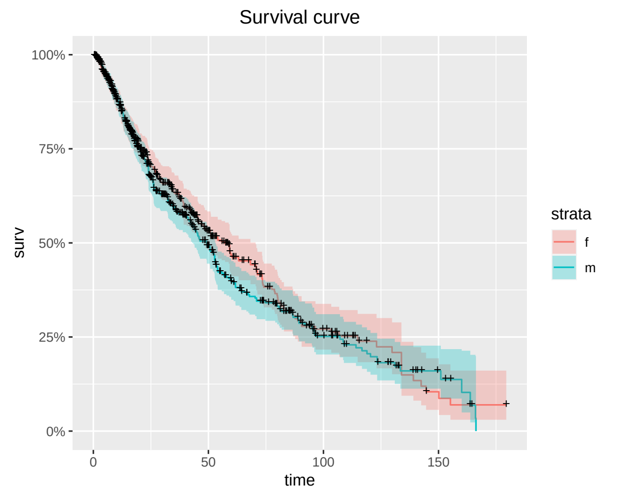
```
## Call: survfit(formula = objSurv ~ 1)
##
##         n events median 0.95LCL 0.95UCL
## [1,] 774    385   50.7    45.3    56.8
```

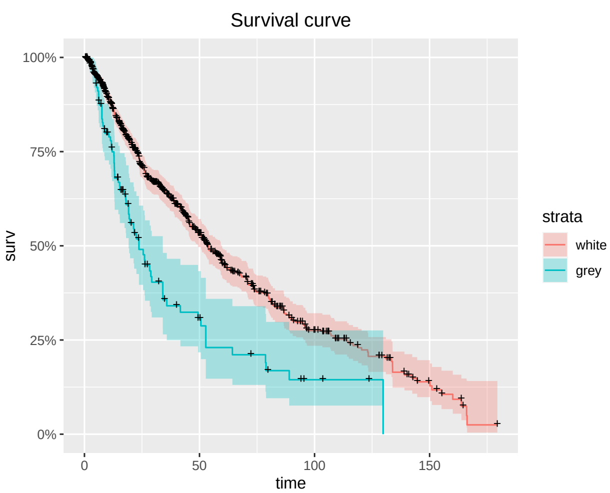
```
survplot1 <- autoplot(survfit(Surv(stag, event) ~ 1, data = newdat)) + labs(title = "Survival curve") +
survplot2 <- autoplot(survfit(Surv(stag, event) ~ gender, data = newdat)) + labs(title = "Survival curve
survplot3 <- autoplot(survfit(Surv(stag, event) ~ way, data = newdat)) + labs(title = "Survival curve")
survplot4 <- autoplot(survfit(Surv(stag, event) ~ head_gender, data = newdat)) + labs(title = "Survival
survplot5 <- autoplot(survfit(Surv(stag, event) ~ greywage, data = newdat)) + labs(title = "Survival cu
survplot6 <- autoplot(survfit(Surv(stag, event) ~ coach, data = newdat)) + labs(title = "Survival curve

ggarrange(survplot1, survplot2, survplot3, survplot4, survplot5, survplot6)
```

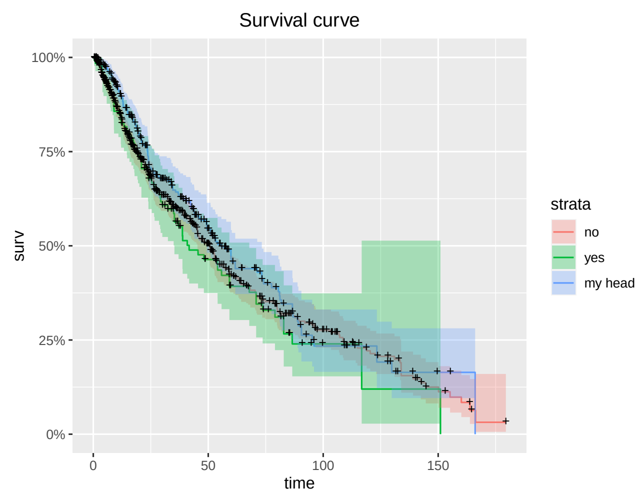




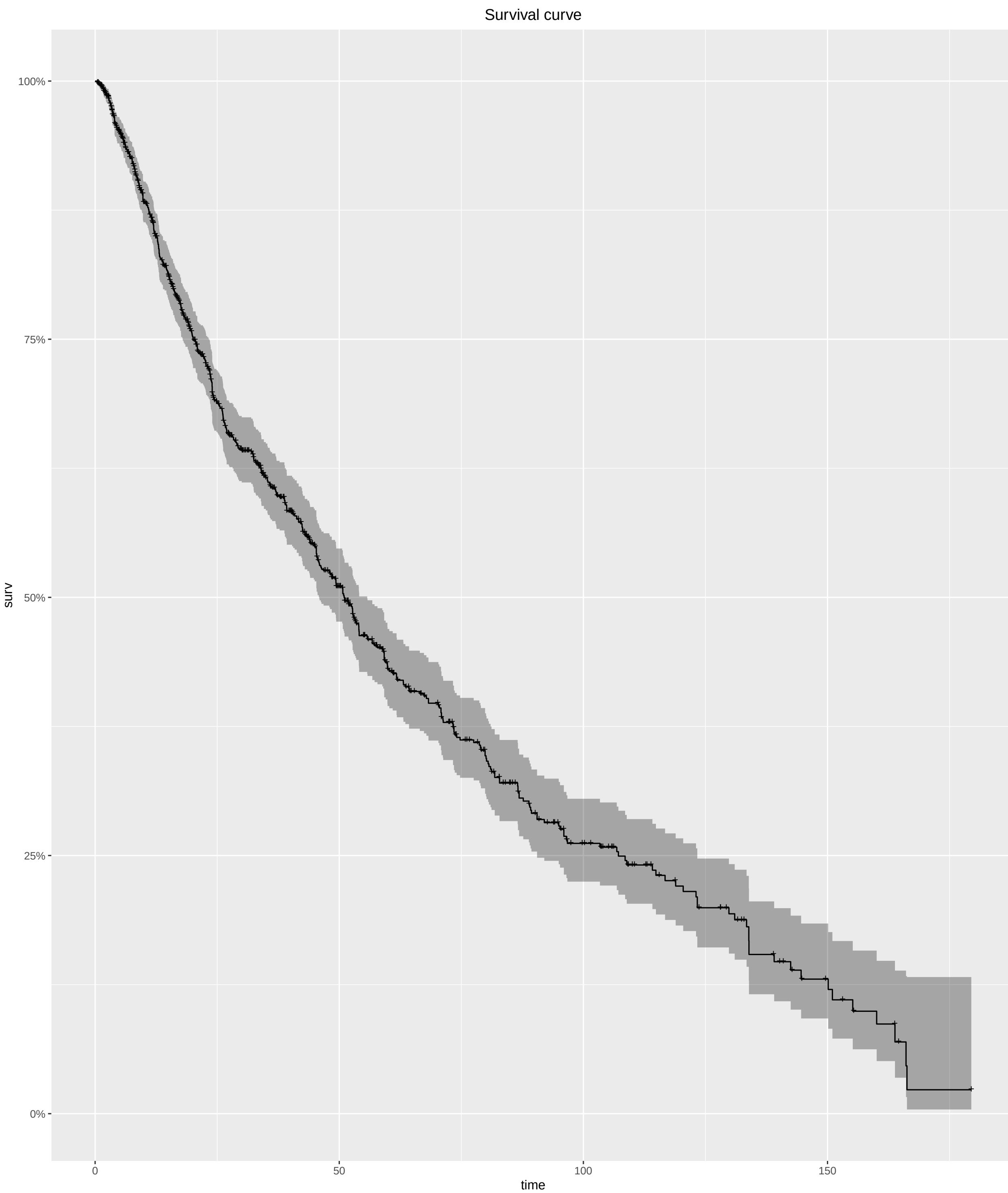









```
survplot7 <- autoplot(survfit(Surv(stag, event) ~ 1 ,data = newdat)) + labs(title = "Survival curve") +

survplot7
```



Cox model

Fitting cox model that accounts for all covariates but assumes them to be stable over time:

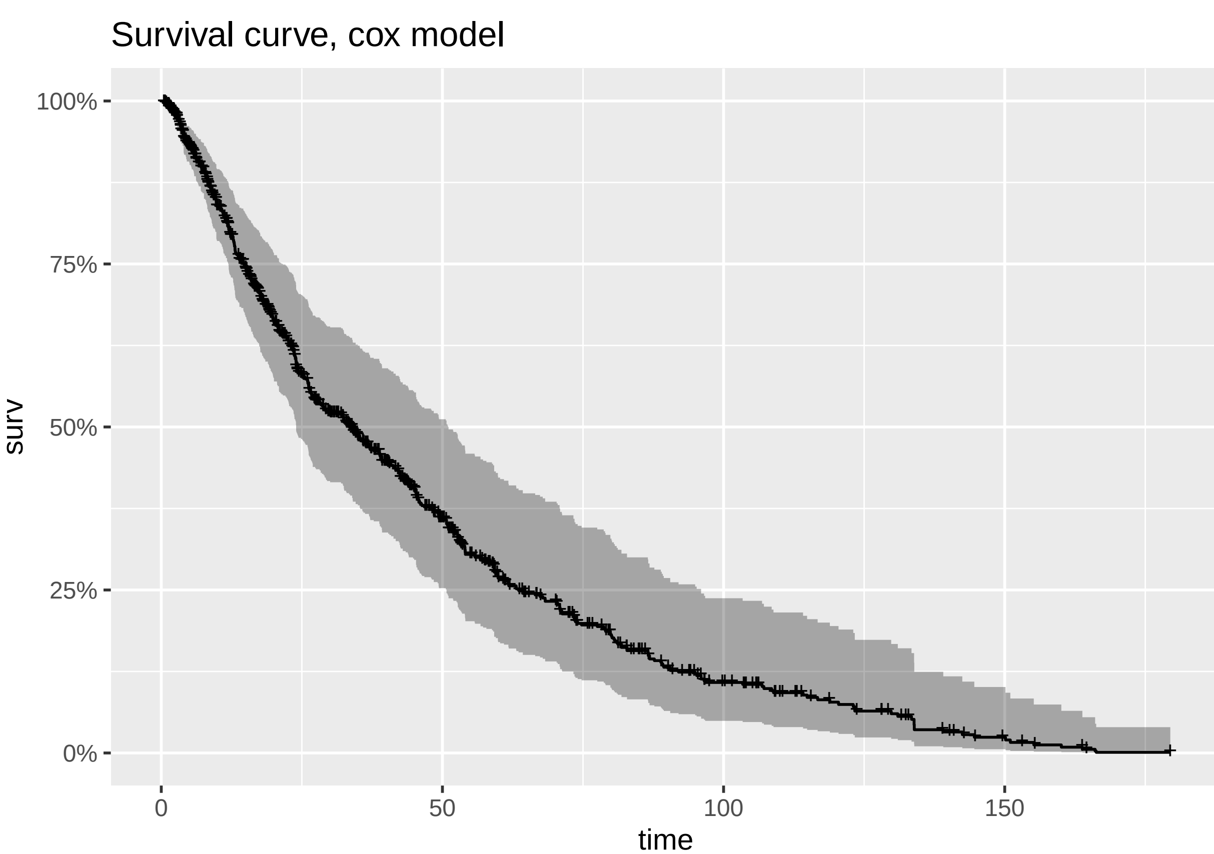
```
cox <- coxph(Surv(stag, event) ~ 1 +  gender + age + industry +
               + greywage + way + extraversion + independ + selfcontrol +
```

```
               anxiety + novator+ coach + head_gender, data = newdat)

summary(cox)
```

```
## Call:
## coxph(formula = Surv(stag, event) ~ 1 + gender + age + industry +
##     +greywage + way + extraversion + independ + selfcontrol +
##     anxiety + novator + coach + head_gender, data = newdat)
##
##   n= 1107, number of events= 553
##
##                               coef exp(coef)  se(coef)      z Pr(>|z|)
## genderf                   0.010213  1.010265  0.111203  0.092 0.926824
## age                       0.023624  1.023905  0.006741  3.505 0.000457 ***
## industryPowerGeneration -0.591848  0.553304  0.306951 -1.928 0.053836 .
## industryRetail          -0.642597  0.525925  0.149685 -4.293 1.76e-05 ***
## industrymanufacture     -0.526270  0.590804  0.173383 -3.035 0.002403 **
## industryConsult         -0.012943  0.987140  0.197223 -0.066 0.947675
## industryState           -0.220205  0.802355  0.215093 -1.024 0.305947
## industryetc             -0.177630  0.837252  0.185944 -0.955 0.339433
## industryBuilding          0.046920  1.048039  0.220251  0.213 0.831302
## industryIT              -0.884081  0.413094  0.211747 -4.175 2.98e-05 ***
## industryHoReCa          -0.341230  0.710895  0.431231 -0.791 0.428773
## industryTelecom         -0.925861  0.396190  0.295136 -3.137 0.001707 **
## industryPharma          -0.555370  0.573860  0.348911 -1.592 0.111446
## industryMining          -0.244900  0.782783  0.298681 -0.820 0.412250
## industrytransport       -0.405938  0.666351  0.279887 -1.450 0.146957
## industryAgriculture       0.527673  1.694984  0.343511  1.536 0.124510
## industryRealEstate      -1.154774  0.315129  0.475330 -2.429 0.015123 *
## greywagegrey              0.624656  1.867602  0.133713  4.672 2.99e-06 ***
## waycar                  -0.211375  0.809470  0.100122 -2.111 0.034757 *
## wayfoot                 -0.464456  0.628477  0.171858 -2.703 0.006881 **
## extraversion              0.030479  1.030948  0.034828  0.875 0.381510
## independ                -0.012817  0.987265  0.035085 -0.365 0.714882
## selfcontrol             -0.036709  0.963957  0.035258 -1.041 0.297812
## anxiety                 -0.032466  0.968055  0.033551 -0.968 0.333219
## novator                   0.009905  1.009954  0.030170  0.328 0.742675
## coachyes                  0.167281  1.182087  0.138525  1.208 0.227206
## coachmy head            -0.001242  0.998759  0.107407 -0.012 0.990773
## head_genderm              0.017668  1.017825  0.094271  0.187 0.851334
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                         exp(coef) exp(-coef) lower .95 upper .95
## genderf                    1.0103     0.9898    0.8124    1.2563
## age                        1.0239     0.9767    1.0105    1.0375
## industryPowerGeneration    0.5533     1.8073    0.3032    1.0098
## industryRetail             0.5259     1.9014    0.3922    0.7052
## industrymanufacture        0.5908     1.6926    0.4206    0.8299
## industryConsult            0.9871     1.0130    0.6707    1.4530
## industryState              0.8024     1.2463    0.5264    1.2231
## industryetc                0.8373     1.1944    0.5815    1.2054
## industryBuilding           1.0480     0.9542    0.6806    1.6138
```

```
## industryIT                0.4131      2.4208     0.2728     0.6256
## industryHoReCa            0.7109      1.4067     0.3053     1.6553
## industryTelecom           0.3962      2.5240     0.2222     0.7065
## industryPharma            0.5739      1.7426     0.2896     1.1371
## industryMining            0.7828      1.2775     0.4359     1.4057
## industrytransport         0.6664      1.5007     0.3850     1.1533
## industryAgriculture       1.6950      0.5900     0.8645     3.3232
## industryRealEstate        0.3151      3.1733     0.1241     0.8000
## greywagegrey              1.8676      0.5354     1.4370     2.4272
## waycar                    0.8095      1.2354     0.6652     0.9850
## wayfoot                   0.6285      1.5911     0.4487     0.8802
## extraversion              1.0309      0.9700     0.9629     1.1038
## independ                  0.9873      1.0129     0.9217     1.0575
## selfcontrol               0.9640      1.0374     0.8996     1.0329
## anxiety                   0.9681      1.0330     0.9064     1.0339
## novator                   1.0100      0.9901     0.9520     1.0715
## coachyes                  1.1821      0.8460     0.9010     1.5508
## coachmy head              0.9988      1.0012     0.8092     1.2328
## head_genderm              1.0178      0.9825     0.8461     1.2244
##
## Concordance= 0.629  (se = 0.014 )
## Likelihood ratio test= 115.3  on 28 df,   p=1e-12
## Wald test            = 120.3  on 28 df,   p=2e-13
## Score (logrank) test = 124.9  on 28 df,   p=3e-14
```

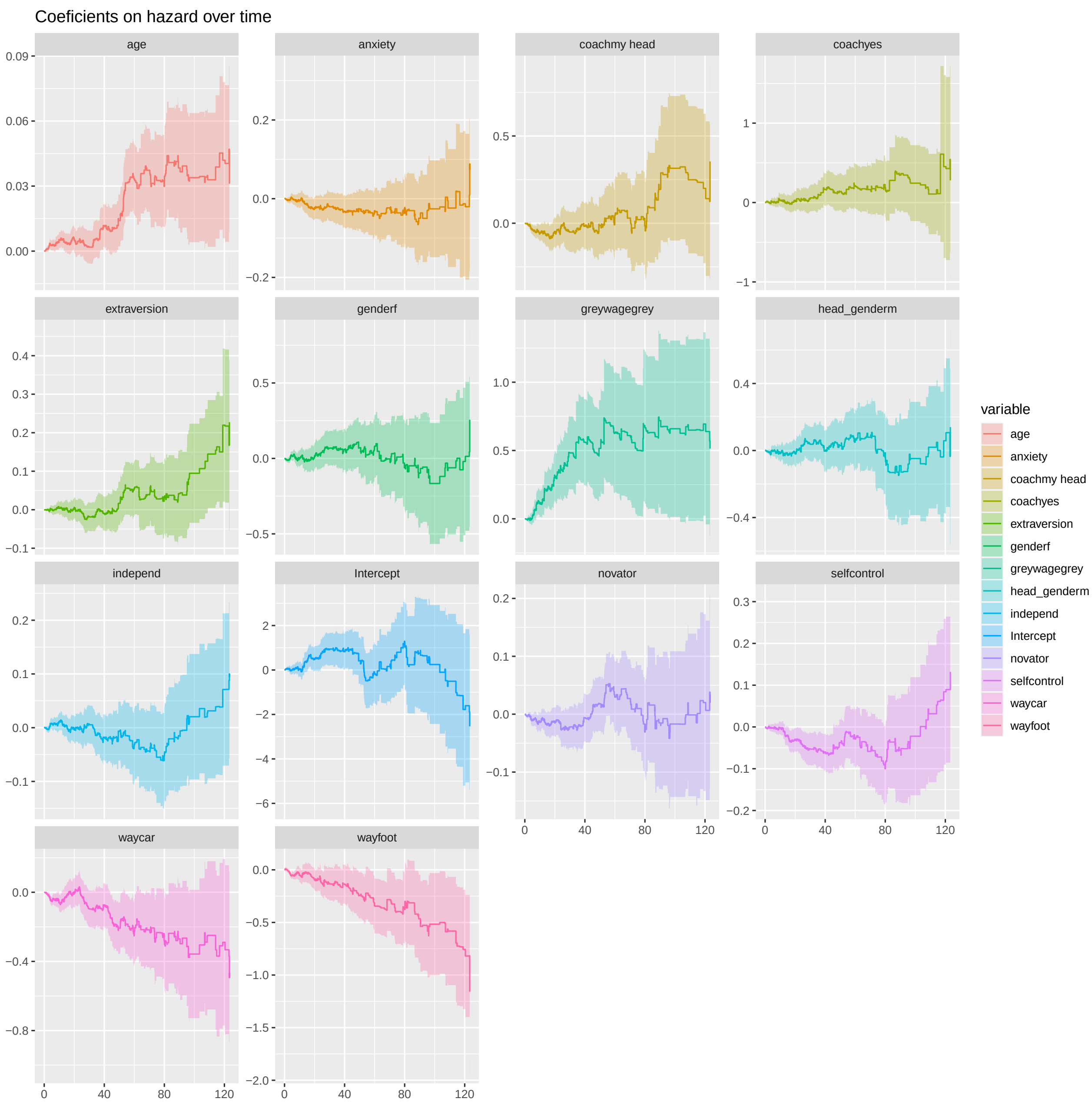
```
autoplot(survfit(cox)) + labs(title = "Survival curve, cox model")
```



Aalen model

This model doesn't assume assume coefficients are stable

```
aa_fit = aareg(Surv(stag, event) ~ 1 +  gender + age +
                  greywage + way + extraversion + independ + selfcontrol +
                  anxiety + novator + coach + head_gender, data = newdat)

autoplot(aa_fit) + labs(title = "Coeficients on hazard over time")
```



Some hazard effects clearly vary over time (a(t) - XB(t)), so the cox implementation should be taken with a grain of salt.
Grey wage is a predictor of quitting, and going to work by foot is a negative predictor of quitting.

Age is a predictor of quitting on longer tenures. Higher conscientiousness is associated to lower turnover in the first years.

Practical recommendation: hire in surroundings, offer help in accommodation.
People with longer tenure and age are at risk. Maybe senior promotion is not encouraged, or salary for more senior roles is not competitive, so people with more experience are more prone to leave when they acquire seniority.
Look for weak signals of conscientiousness when hiring (naturally, one cannot rely on psychometric tests since they are likely to be tricked to favor conscientiousness).

References:

Cox DR. A note on the graphical analysis of survival data. Biometrika. 1979;66:188–190

Kaplan EL, Meier P. Nonparametric estimation from incomplete observations. J Am Stat Assoc. 1958;53:457–481