

Survival Analysis with HGAT group and telomerase status

Run Jin

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This notebook will do the following survival analysis

1. Univariate analysis

- DMG H3K28 vs rest
- ALT vs. non-ALT for all samples
- Telhunt score (separate into categories by 1.07)
- CCA telhunt category

2. Multivariate analysis

- DMG H3K28 vs rest + ALT vs. non-ALT
- DMG H3K28 vs rest + ALT vs. non-ALT + sex + ATRX (mut N/Y)
- DMG H3K28 vs rest + Telhunt score (categorical) + sex + ATRX (mut N/Y)
- DMG H3K28 vs rest + Telhunt score (continuous) + sex + ATRX (mut N/Y)
- DMG H3K28 vs rest + CCA Telhunt category + sex + ATRX (mut N/Y)

Packages and functions Read in set up script.

```
library(survival)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union
```

```
library(ggplot2)
library(ggpubr)
```

Set up directories

```

root_dir <- rprojroot::find_root(rprojroot::has_dir(".git"))
analysis_dir <- file.path(root_dir, "analyses", "survival-analysis")

plots_dir <- file.path(analysis_dir, "plots")
if (!dir.exists(plots_dir)) {
  dir.create(plots_dir)
}

output_dir <- file.path(analysis_dir, "output")
if (!dir.exists(output_dir)) {
  dir.create(plots_dir)
}

```

Read in files

```

# get the meta information
meta <- readr::read_tsv(file.path(root_dir,
                                "analyses/add-histologies/output/ALT PBTA oct 2021 (including all plates)-up
                                # remove existing ones to get newer data
                                dplyr::select(-c("OS_days", "OS_status"))

```

```
## Rows: 900 Columns: 115
```

```

## -- Column specification -----
## Delimiter: "\t"
## chr (56): Kids_First_Biospecimen_ID_DNA, Kids_First_Biospecimen_ID_RNA, Kids...
## dbl (52): TH T/TH N, UBTF Binary, ATRX Reverse Binary, ATRX IHC Binary, ATRX...
## lgl (7): ATRX Stata, cell_line_composition, DAXX_fusion, ...34, NF...39, CC...

##
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.

```

```

# get survival information
survival_v21 <- readr::read_tsv(file.path(root_dir,
                                "analyses/add-histologies/input-v21/pbta-histologies.tsv")) %>%
  dplyr::select("Kids_First_Participant_ID", "OS_days", "OS_status", "PFS_days") %>%
  distinct()

```

```
## Rows: 2840 Columns: 38
```

```

## -- Column specification -----
## Delimiter: "\t"
## chr (33): Kids_First_Biospecimen_ID, sample_id, aliquot_id, Kids_First_Part...
## dbl (5): OS_days, age_last_update_days, normal_fraction, tumor_fraction, tu...

##
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.

```

Organize data

```
# join with meta
meta <- meta %>%
  dplyr::left_join(survival_v21) %>%
  dplyr::distinct(Kids_First_Participant_ID, .keep_all = TRUE)

## Joining, by = "Kids_First_Participant_ID"

# recode for analysis
meta_formatted <- meta %>%
  # recode the categories -
  # DECEASED maps to a survival event status of 1, LIVING maps to a censored observation with value 0
  dplyr::mutate(OS_status_recoded = case_when(
    OS_status == "LIVING" ~ 0,
    OS_status == "DECEASED" ~ 1
  )) %>%
  # retain only ones with OS days
  dplyr::filter(!is.na(OS_days)) %>%
  # calculate the years
  dplyr::mutate(OS_years = OS_days / 365.25) %>%
  dplyr::mutate(PFS_status = if_else(PFS_days < OS_days, 1, 0)) %>%
  # categorize by telhunt scores
  dplyr::mutate(tel_hunt_cat = case_when(
    `TH T/TH N` > 1.07 ~ "High",
    `TH T/TH N` < 1.07 ~ "Low"
  )) %>%
  # categorize by DMG, H3K28 or not
  dplyr::mutate(dmg_h3k28 = case_when(
    grepl("DMG, H3 K28", molecular_subtype) ~ "DMG",
    TRUE ~ "non-DMG"
  )) %>%
  # categorize ATRX
  dplyr::mutate(atrx_mut = case_when(
    !is.na(`ATRX Mutation`) ~ "ATRX_mut",
    TRUE ~ "non_ATRX_mut"
  )) %>%
  # rename telhunt score and CCA
  dplyr::mutate(telhunt_score = `TH T/TH N`)

# define as factor
meta_formatted$dmg_h3k28 <- factor(meta_formatted$dmg_h3k28, levels = c("non-DMG", "DMG"))
meta_formatted$tel_hunt_cat <- factor(meta_formatted$tel_hunt_cat, levels = c("Low", "High"))
meta_formatted$group <- factor(meta_formatted$group, levels = c("non-HGAT", "HGAT"))
meta_formatted$phenotype <- factor(meta_formatted$phenotype, levels = c("non-ALT", "ALT"))

# define as numeric
meta_formatted$telhunt_score <- as.numeric(meta_formatted$telhunt_score)
meta_formatted_hgat <- meta_formatted %>%
  dplyr::filter(group == "HGAT")
```

Log Rank analysis

Generate output for categorical files - only hgg group is used

```
for(ind_var in c("dmg_h3k28", "tel_hunt_cat", "group", "atrx_mut", "phenotype")){
  # define model
  model <- paste0("survival::Surv(time = OS_years, event = OS_status_recoded) ~ ", ind_var)

  # depending on which variables are used, data used will be different
  data_used <- meta_formatted

  # run survival analysis
  fit <- survival::survdif(formula(model),
                           data = data_used)
  # Obtain p value for Chi-Squared stat
  fit$p.value <- pchisq(fit$chisq, df = length(fit$n) - 1, lower = FALSE)

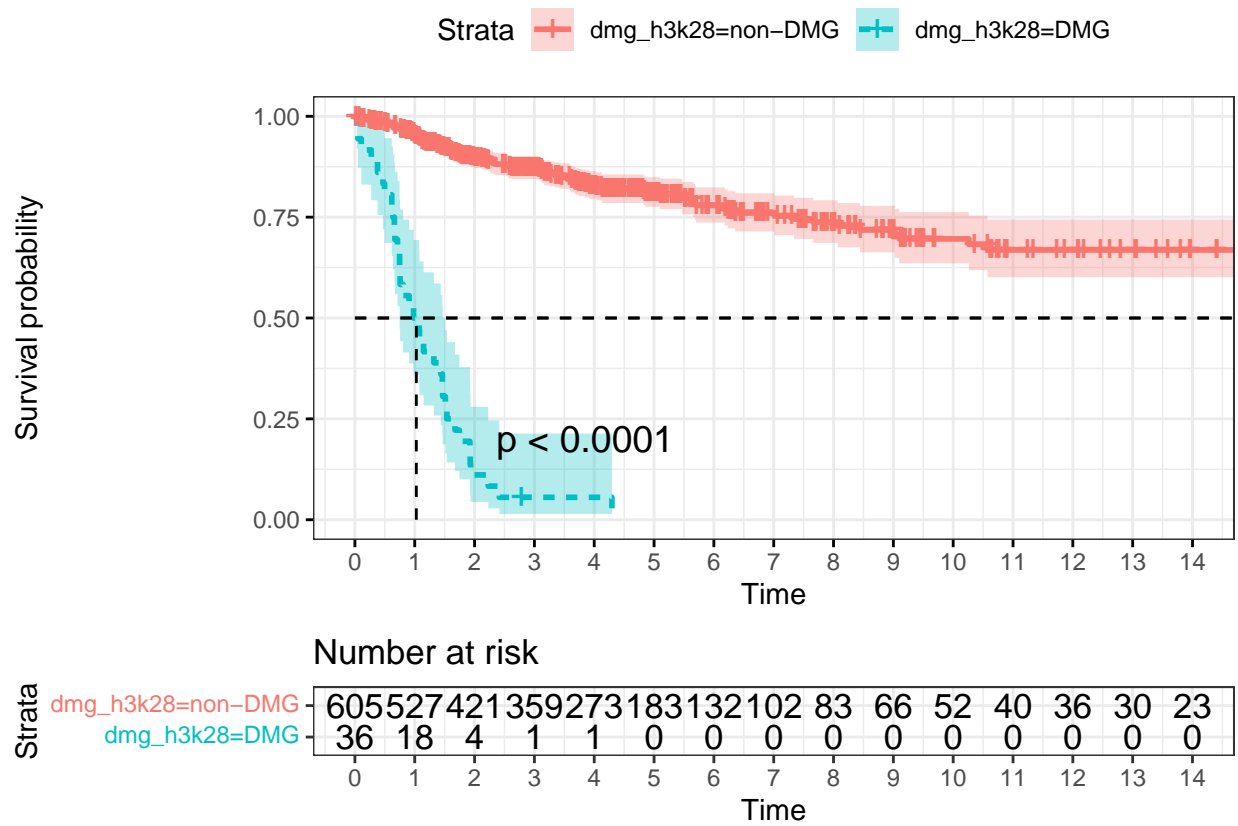
  # save the output
  saveRDS(fit, file.path(output_dir, paste0("log_rank_survival_per_", ind_var, ".RDS")))

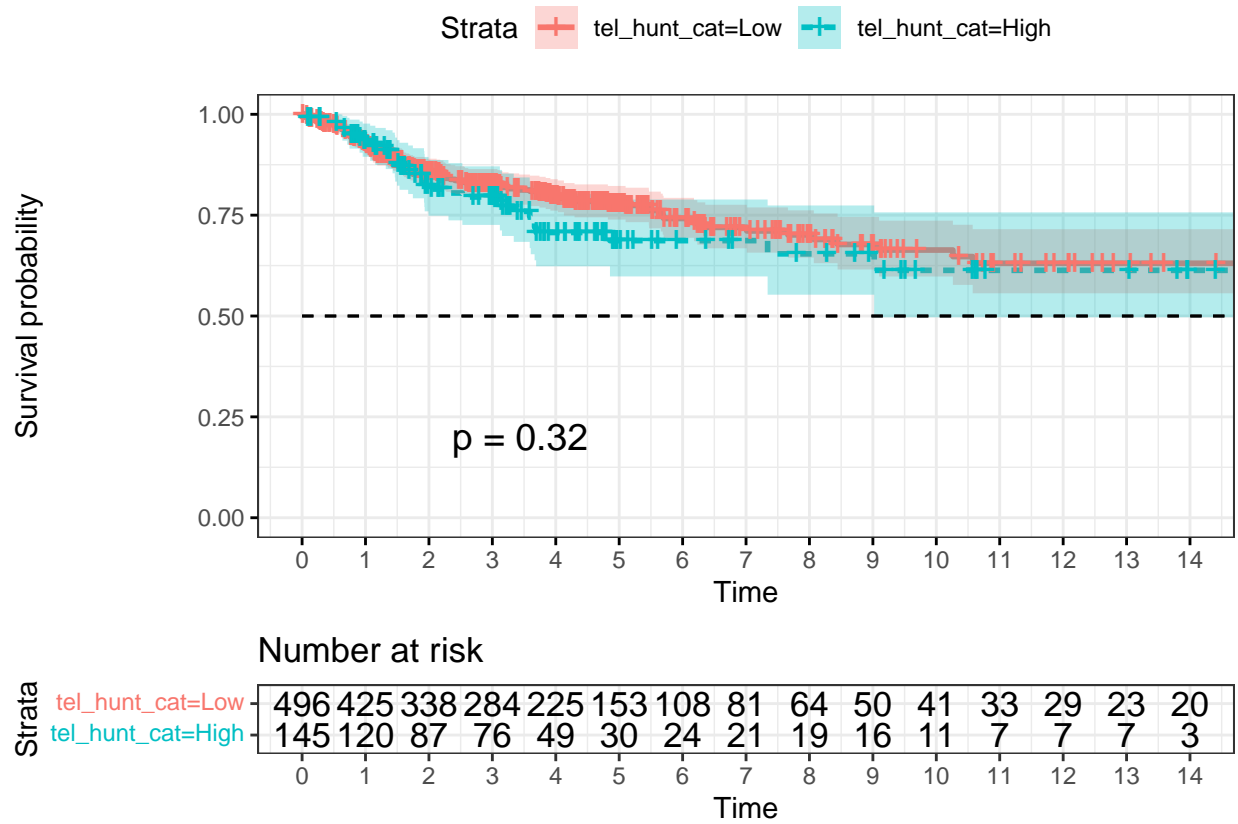
  # generate plots fit
  fit_plot <- survfit(formula(model), data = data_used)

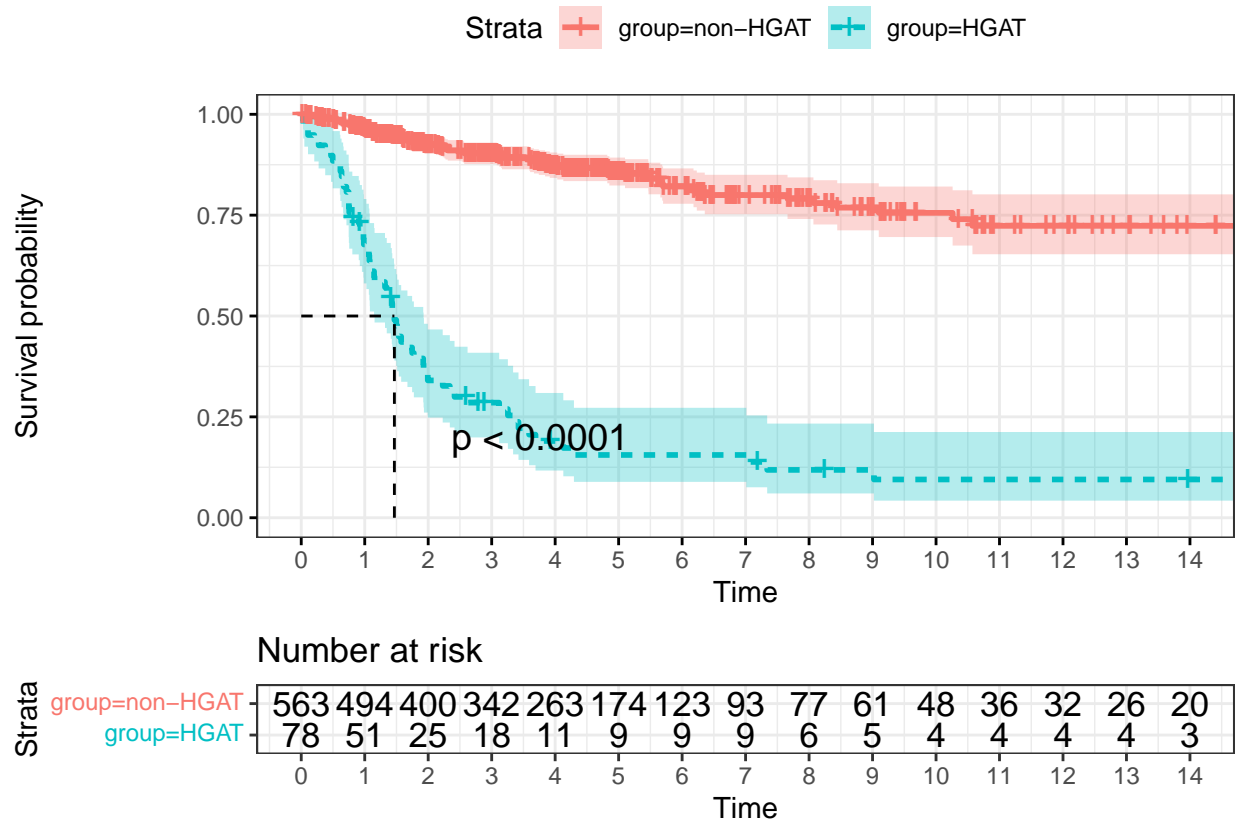
  # output the plot
  plot_logrank <- survminer::ggsurvplot(fit_plot,
                                         data=data_used,
                                         xlim = c(0, 14),
                                         break.time.by = 1,
                                         pval = TRUE,
                                         conf.int = TRUE,
                                         risk.table = TRUE, # Add risk table
                                         linetype = "strata", # Change line type by groups
                                         surv.median.line = "hv", # Specify median survival
                                         ggtheme = theme_bw())

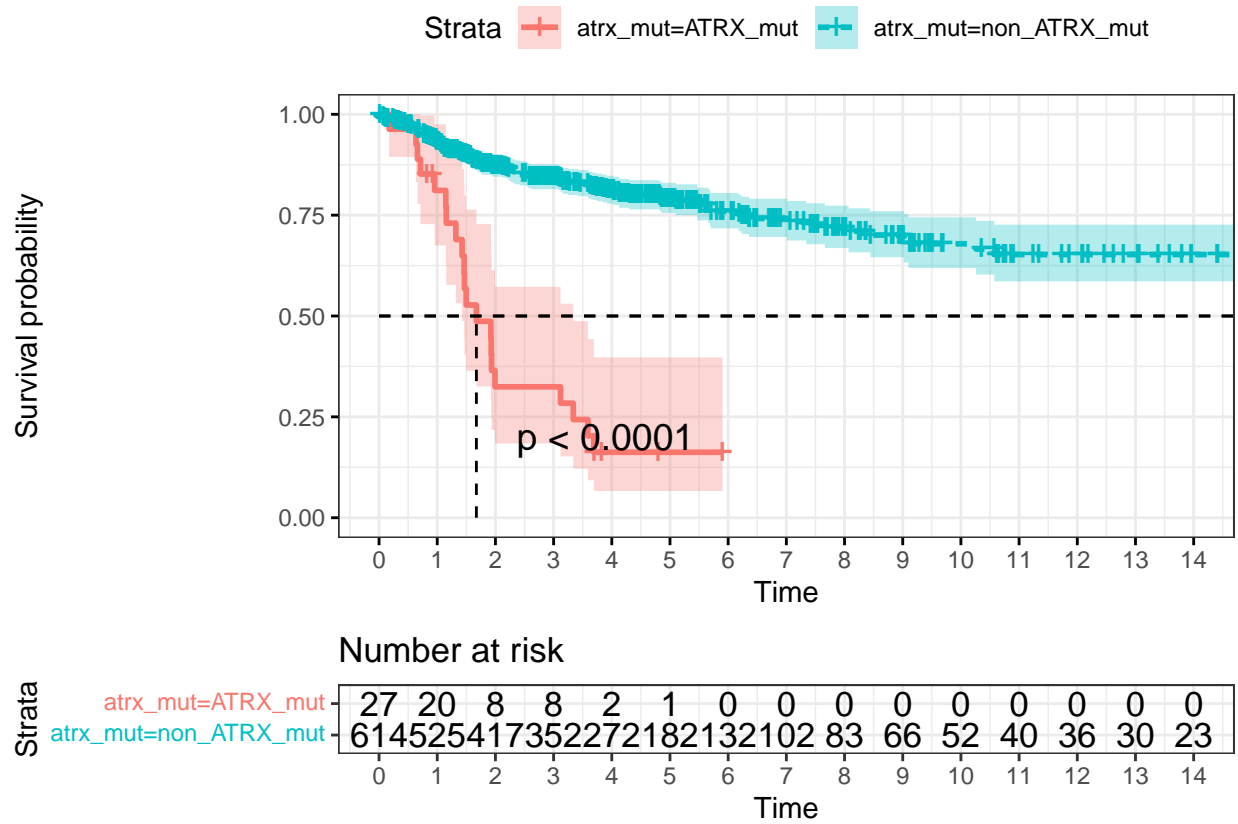
  print(plot_logrank)
  # Make this plot a combined plot
  surv_plot_logrank <- cowplot::plot_grid(plot_logrank[[1]],
                                          plot_logrank[[2]],
                                          nrow = 2,
                                          rel_heights = c(2.5, 1))

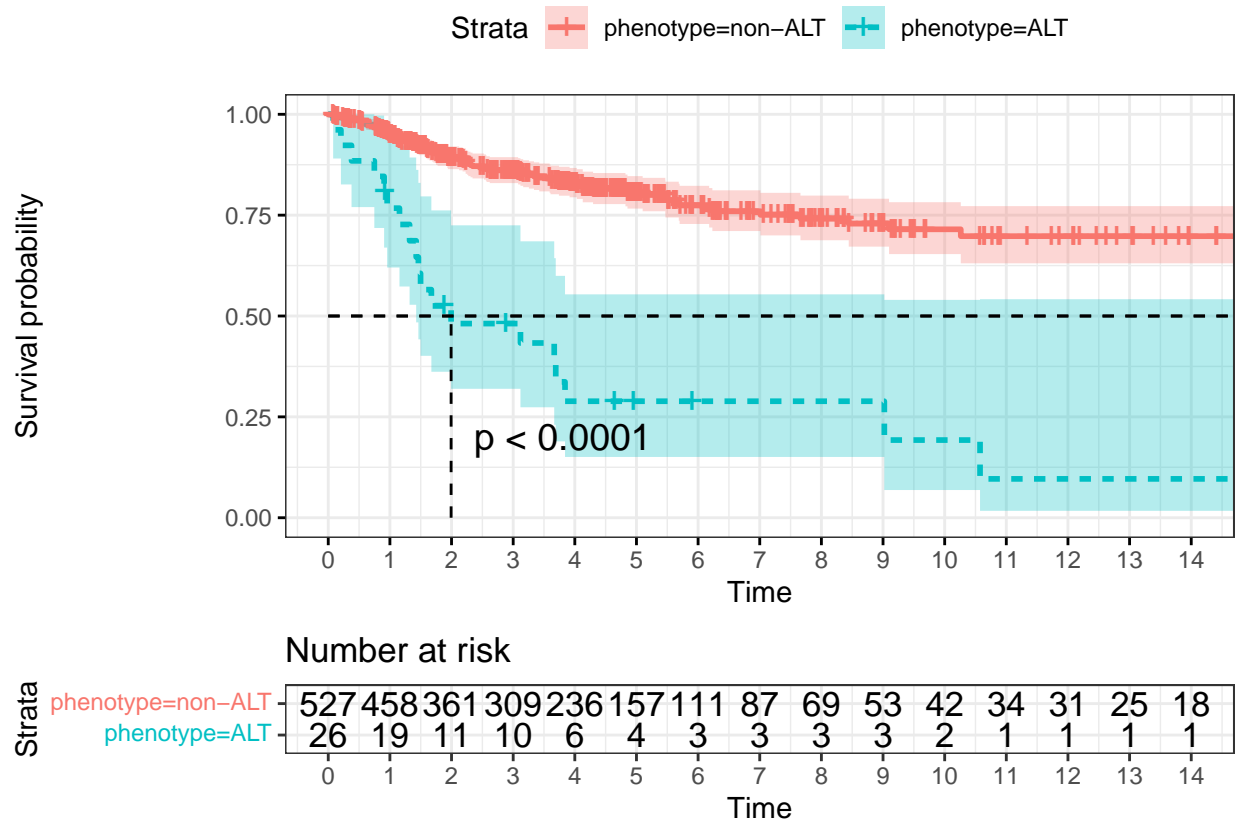
  # Save the plot
  cowplot::save_plot(filename = file.path(plots_dir,
                                          paste0("logrank_survival_by_", ind_var, ".png")),
                     plot = surv_plot_logrank)
}
```











Multivariate analysis

Two comparisons made are `tp53_score + telomerase_score + hgg_group` and `tp53_score + telomerase_score + broad_histology_display`

Multivariate analysis - DMG H3K28 vs rest + ALT vs. non-ALT - DMG H3K28 vs rest + ALT vs. non-ALT + sex + ATRX (mut N/Y) - DMG H3K28 vs rest + Telhunt score (categorical) + sex + ATRX (mut N/Y) - DMG H3K28 vs rest + Telhunt score (continuous) + sex + ATRX (mut N/Y)

```
# define multi-variables that we are using for analyzing survival
list_of_variates <- c("dmg_h3k28+group",
  "dmg_h3k28+group+reported_gender+atrx_mut",
  "dmg_h3k28+group+tel_hunt_cat+reported_gender+atrx_mut",
  "dmg_h3k28+group+telhunt_score+reported_gender+atrx_mut",
  "dmg_h3k28+group+phenotype+reported_gender+atrx_mut"
)

# define model
for (ind_var in list_of_variates){
  model <- paste0("survival::Surv(time = OS_years, event = OS_status_recoded) ~ ", ind_var)

  # depending on which variables are used, data used will be different
  data_used <- meta_formatted

  fit <- survival::coxph(
```

```

    formula(model),
    data = data_used
  )
  # generate output
  table <- broom::tidy(fit)

  # Save the table data in a TSV
  readr::write_tsv(table, file.path(output_dir, paste0("cox_reg_results_per_", ind_var, ".tsv")))

  print(table)

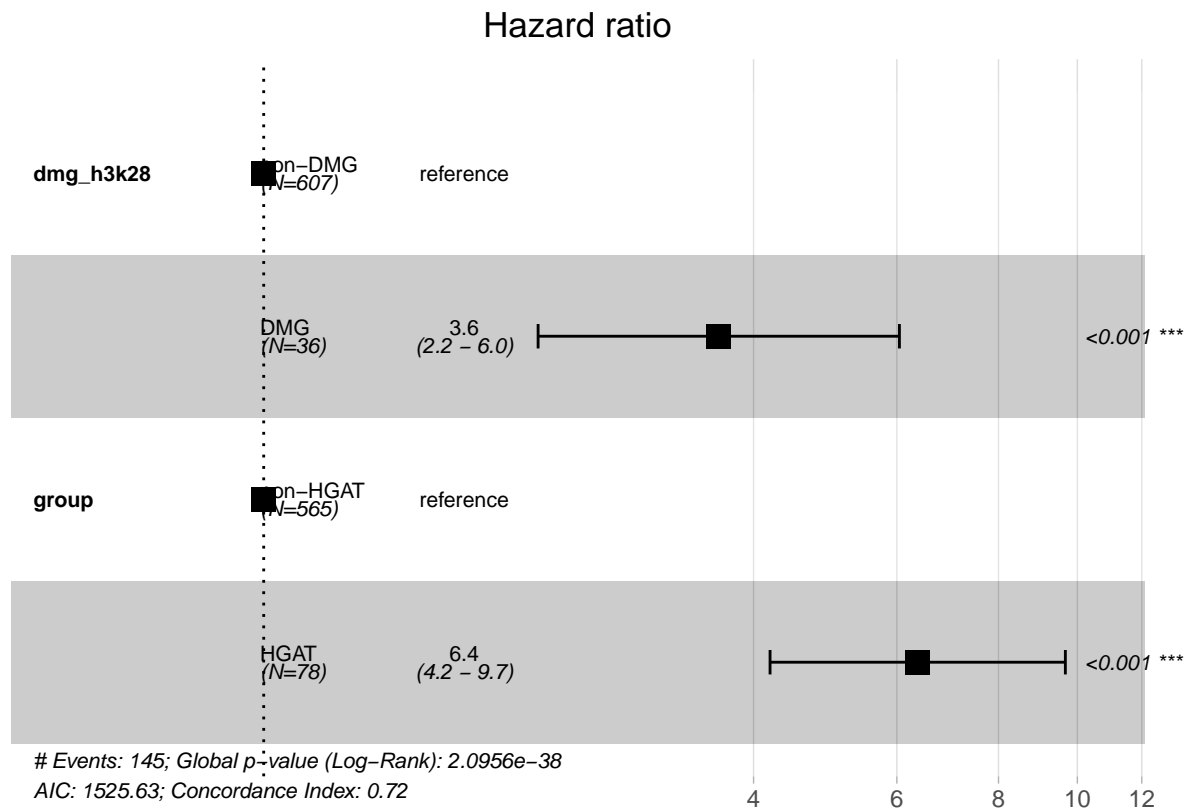
  # printout the plot
  forest_coxph <- survminer::ggforest(fit, data = data_used)
  print(forest_coxph)
}

```

```

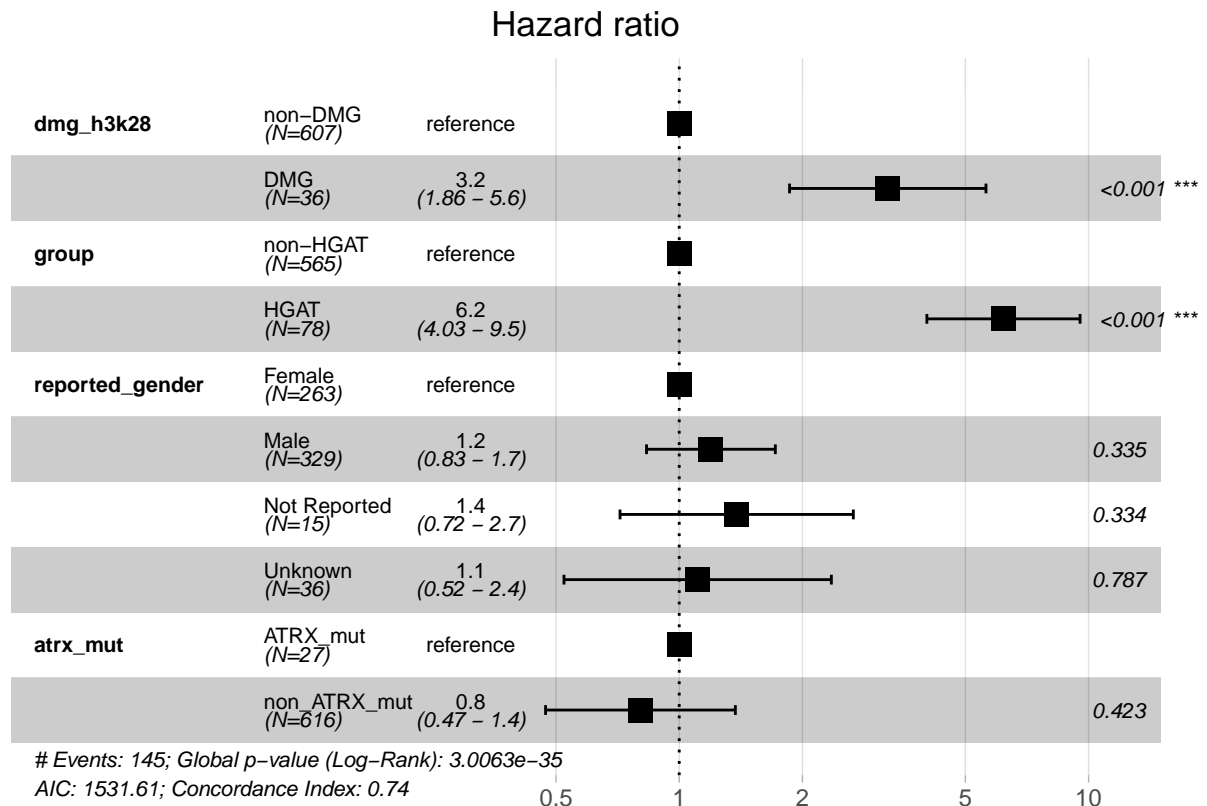
## # A tibble: 2 x 5
##   term      estimate std.error statistic  p.value
##   <chr>      <dbl>    <dbl>    <dbl>    <dbl>
## 1 dmg_h3k28DMG  1.29      0.261     4.94 7.93e- 7
## 2 groupHGAT    1.85      0.213     8.68 3.91e-18

```

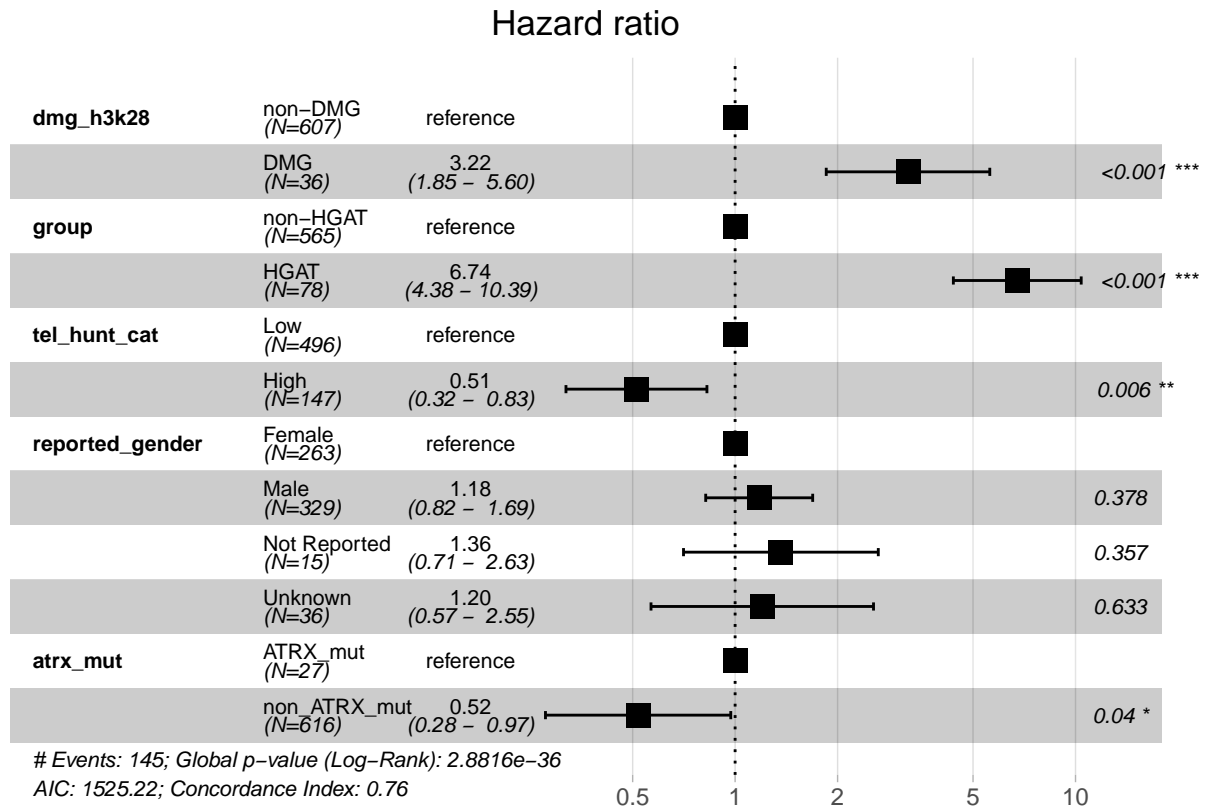


```
## # A tibble: 6 x 5
```

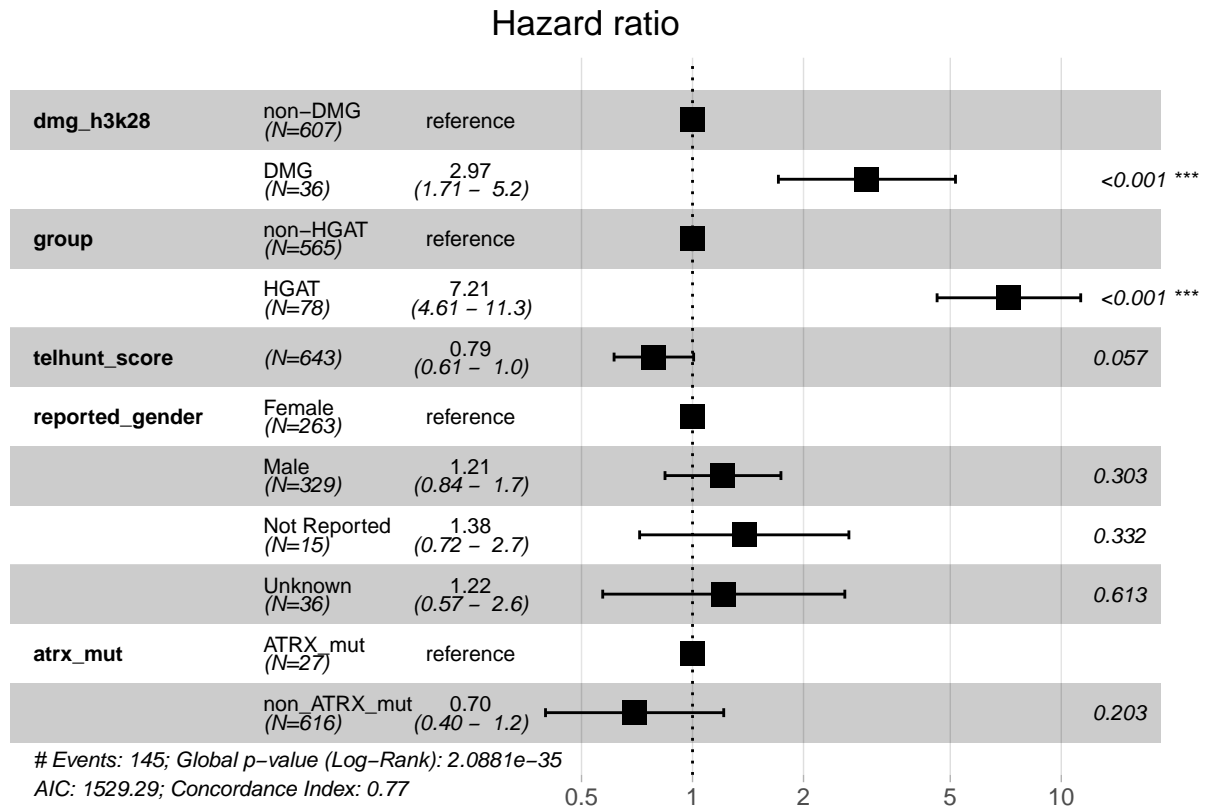
```
## term estimate std.error statistic p.value
## <chr> <dbl> <dbl> <dbl> <dbl>
## 1 dmgh3k28DMG 1.17 0.282 4.16 3.17e- 5
## 2 groupHGAT 1.82 0.220 8.30 1.07e-16
## 3 reported_genderMale 0.178 0.185 0.965 3.35e- 1
## 4 reported_genderNot Reported 0.323 0.335 0.965 3.34e- 1
## 5 reported_genderUnknown 0.104 0.384 0.270 7.87e- 1
## 6 atrx_mutnon_ATRX_mut -0.218 0.272 -0.801 4.23e- 1
```



```
## # A tibble: 7 x 5
## term estimate std.error statistic p.value
## <chr> <dbl> <dbl> <dbl> <dbl>
## 1 dmgh3k28DMG 1.17 0.282 4.14 3.43e- 5
## 2 groupHGAT 1.91 0.221 8.65 5.08e-18
## 3 tel_hunt_catHigh -0.668 0.243 -2.74 6.06e- 3
## 4 reported_genderMale 0.163 0.185 0.882 3.78e- 1
## 5 reported_genderNot Reported 0.310 0.336 0.921 3.57e- 1
## 6 reported_genderUnknown 0.184 0.384 0.478 6.33e- 1
## 7 atrx_mutnon_ATRX_mut -0.656 0.320 -2.05 4.01e- 2
```



```
## # A tibble: 7 x 5
##   term                estimate std.error statistic  p.value
##   <chr>                <dbl>    <dbl>    <dbl>    <dbl>
## 1 dmrg_h3k28DMG        1.09      0.282     3.86 1.13e- 4
## 2 groupHGAT            1.98      0.229     8.64 5.86e-18
## 3 telhunt_score       -0.241    0.127    -1.90 5.68e- 2
## 4 reported_genderMale  0.190    0.185     1.03 3.03e- 1
## 5 reported_genderNot Reported 0.323    0.333     0.969 3.32e- 1
## 6 reported_genderUnknown 0.195    0.386     0.506 6.13e- 1
## 7 atrx_mutnon_ATRX_mut -0.362    0.284    -1.27 2.03e- 1
```



```
## # A tibble: 6 x 5
##   term                estimate std.error statistic  p.value
##   <chr>                <dbl>     <dbl>     <dbl>    <dbl>
## 1 dmrg_h3k28DMG         1.36       0.328      4.15 3.38e- 5
## 2 groupHGAT             1.65       0.262      6.30 3.04e-10
## 3 phenotypeALT          0.452      0.320      1.41 1.58e- 1
## 4 reported_genderMale    0.185      0.201      0.920 3.57e- 1
## 5 reported_genderUnknown 0.159      0.442      0.360 7.19e- 1
## 6 atr_x_mutnon_ATR_X_mut -0.142     0.364     -0.390 6.96e- 1
```

