Simple 3-state Partitioned Survival model in R

The DARTH workgroup

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- Jalal H, Pechlivanoglou P, Krijkamp E, Alarid-Escudero F, Enns E, Hunink MG. An Overview of R in Health Decision Sciences. Med Decis Making. 2017; 37(3): 735-746. https://journals.sagepub.com/doi/abs/10.1177/0272989X16686559
- Krijkamp EM, Alarid-Escudero F, Enns EA, Jalal HJ, Hunink MGM, Pechlivanoglou P. Microsimulation modeling for health decision sciences using R: A tutorial. Med Decis Making. 2018;38(3):400–22. https://journals.sagepub.com/doi/abs/10.1177/0272989X18754513
- Krijkamp EM, Alarid-Escudero F, Enns E, Pechlivanoglou P, Hunink MM, Jalal H. A Multidimensional Array Representation of State-Transition Model Dynamics. BioRxiv 670612 2019.https://www.biorxiv.org/content/10.1101/670612v1

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Change eval to TRUE if you want to knit this document.

01 Load packages

```
if (!require('pacman')) install.packages('pacman'); library(pacman) # use this package to conveniently
# load (install if required) packages from CRAN
p_load("here", "dplyr", "devtools", "gems", "flexsurv", "flexsurvcure", "survminer", "survHE", "ggplot2
# install_github("DARTH-git/darthtools", force = TRUE) # Uncomment if there is a newer version
p_load_gh("DARTH-git/darthtools")
```

02 Load functions

```
# No function needed
```

03 Input model parameters

```
v_names_states <- c("Healthy", "Sick", "Dead") # state names</pre>
c_1
          <- 1 / 12
                                       # cycle length (a month)
          <- 10
                                       # number of years (10 years)
n_t
set.seed(2020)
                                       # set the seed
                                       # number of simulations
n_sim
          <- 100
n_states <- length(v_names_states) # No of states</pre>
times
          <- seq(0, n_t, c_1)</pre>
                                       # the cycles in years
```

Create a transition probability matrix with all transitions indicated and numbered.

Generate data.

```
n_pat <- 550  # cohort size
n_years <- 30  # number of years
generate <- gen_data(n_pat, n_years)  # generates true, censored and OS/PFS data
OS_PFS_data <- generate$OS_PFS_data  # store the OS / PFS structured data
head(OS_PFS_data)</pre>
```

04 Analysis

Showcasing the use of packages survival, flexsurv.

```
fit_KM_OS <- survfit(Surv(time = OS_time, event = OS_status) ~ 1, data = OS_PFS_data)
plot(fit_KM_OS, mark.time = T)
# a prettier way of plotting!!
ggsurvplot(
 fit_KM_OS,
 data = OS_PFS_data,
 size = 1,
                          # change line size
                         # custom color palettes
 palette = c("blue3"),
 conf.int = TRUE,
                           # Add confidence interval
 pval = TRUE,
                          # Add p-value
                         # Add risk table
 risk.table = TRUE,
 risk.table.height = 0.25, # Useful to change when you have multiple groups
 ggtheme = theme_bw(), # Change ggplot2 theme
 xlab = 'Time in years', # Change X-axis label
 title = "Survival curve for Overall Survival (OS)",
 subtitle = "Based on Kaplan-Meier estimates"
```

Cumulative hazards:

```
# plot cumulative hazards
ggsurvplot(
  fit_KM_OS,
  data = OS_PFS_data,
  size = 1,
                               # change line size
 palette = c("blue3"),  # custom color palettes
conf.int = TRUE,  # Add confidence interval
  pval = FALSE,
                                # Add p-value
                          # Add risk table
 risk.table = TRUE,
 risk.table.height = 0.25, # Useful to change when you have multiple groups
 ggtheme = theme_bw(),  # Change ggplot2 theme
xlab = 'Time in years',  # Change X-axis label
  ylab = 'Cumulative hazard',
  title = "Cumulative hazard for Overall Survival (OS)",
  subtitle = "Based on Nelson-Aalen estimates",
  fun = "cumhaz"
```

04.1 Survival Analysis

Fit different parametric survival models and choose the best fitting ones.

We developed a function fit.fun that allows you to fit several parametric survival models at once. The function utilizes functionality from another R package - survHE.

We also developed a function fit.fun.cure that allows you to fit several parametric mixture cure models at once.

Select the best-fitting model for OS and PFS based on goodness-of-fit measures like AIC and BIC.

Superimpose the best-fitting survival curves on the Kaplan-Meier curves.

```
# PFS
fit_KM_PFS <- survfit(Surv(time = PFS_time, event = PFS_status) ~ 1, data = OS_PFS_data)</pre>
# Select the best fitted survivor function based on the smallest AIC
best_PFS <- fit_PFS$model.objects$models[[choose_PFS]]</pre>
# plot KM for PFS
PFS_superimpose <- ggsurvplot(</pre>
 fit_KM_PFS,
  data = OS_PFS_data,
  size = 1,
                              # change line size
                            # custom color palettes
  palette = c("orange2"),
  conf.int = TRUE,
                              # Add confidence interval
  pval = TRUE,
                             # Add p-value
                        # Add risk table
 risk.table = TRUE,
 risk.table.height = 0.25, # Useful to change when you have multiple groups
 ggtheme = theme_bw(),  # Change ggplot2 theme
xlab = 'Time in years',  # Change X-axis label
 title = "Kaplan-Meier survival curve for Progression-Free Survival (PFS)",
  subtitle = paste0("Superimposed by ", choose_PFS, " survival curve")
```

```
# extract the estimated survival probabilities and the confidence intervals
summary_best_PFS <- as.data.frame(summary(best_PFS))</pre>
# superimpose the survival probabilities
PFS_superimpose$plot <- PFS_superimpose$plot +</pre>
  geom_line(aes(x=time, y=est), size=0.55, alpha=0.65, data=summary_best_PFS)
# superimpose the lower bound of the confidence interval
PFS_superimpose$plot <- PFS_superimpose$plot +</pre>
 geom_line(aes(x=time, y=lcl), size=0.55, alpha=0.65, linetype='dashed', data=summary_best_PFS)
# superimpose the upper bound of the confidence interval
PFS_superimpose$plot <- PFS_superimpose$plot +</pre>
  geom_line(aes(x=time, y=ucl), size=0.55, alpha=0.65, linetype='dashed', data=summary_best_PFS)
PFS_superimpose
# OS
# Select the best fitted survivor function based on the smallest AIC
best_OS <- fit_OS$model.objects$models[[choose_OS]]</pre>
# plot KM for OS
OS_superimpose <- ggsurvplot(
 fit_KM_OS,
 data = OS_PFS_data,
 size = 1,
                            # change line size
                           # custom color palettes
 palette = c("blue3"),
  conf.int = TRUE,
                           # Add confidence interval
 pval = TRUE,
                           # Add p-value
 risk.table = TRUE,
                            # Add risk table
 risk.table.height = 0.25, # Useful to change when you have multiple groups
 ggtheme = theme_bw(), # Change ggplot2 theme
 xlab = 'Time in years', # Change X-axis label
 title = "Kaplan-Meier survival curve for Overall Survival (OS)",
  subtitle = paste0("Superimposed by ", choose_OS, " survival curve")
)
# extract the estimated survival probabilities and the confidence intervals
summary_best_OS <- as.data.frame(summary(best_OS))</pre>
# superimpose the survival probabilities
OS_superimpose$plot <- OS_superimpose$plot +
  geom_line(aes(x=time, y=est), size=0.55, alpha=0.65, data=summary_best_OS)
# superimpose the lower bound of the confidence interval
OS_superimpose$plot <- OS_superimpose$plot +
 geom line(aes(x=time, y=lcl), size=0.55, alpha=0.65, linetype='dashed', data=summary best OS)
# superimpose the upper bound of the confidence interval
OS_superimpose$plot <- OS_superimpose$plot +
  geom_line(aes(x=time, y=ucl), size=0.55, alpha=0.65, linetype='dashed', data=summary_best_OS)
OS_superimpose
```

We can plot the hazard ratio of OS vs. PFS using the best-fitting models.

```
df_HR <- boot_hr(surv_model1 = best_PFS, surv_model2 = best_OS, times = times, B = 100)
df_HR %>% filter(time > 1) %>%
    ggplot(aes(x = time, y = med)) +
        geom_ribbon(aes(ymin=lcl, ymax=ucl), colour = NA, fill = "darkgreen", alpha=0.1) +
        geom_line(size = 0.5, color = "darkgreen") +
        scale_x_continuous(breaks = c(1:10)) +
        labs(title = "Hazard ratio of PFS vs. OS",
```

```
subtitle = "Median [2.5%, 97.5%]",
x = "time (years)",
y = "hazard ratio") +
theme_bw()
```

We developed the function surv_prob to extract survival probabilities from a partitioned survival model obtained by partsurv. We also developed the function trans_prob to convert survival probabilities into transition probabilities.

```
surv_prob(best_OS) # extract survival probabilities
trans_prob(surv_prob(best_OS)) # convert survival probabilities to transition probabilities
```

04.2 Partitioned Survival model

```
# construct a partitioned survival model out of the chosen models
m_M_PSM <- partsurv(pfs_survHE = fit_PFS,</pre>
                    os_survHE = fit_OS,
                    choose_PFS = choose_PFS,
                    choose_OS = choose_OS,
                    time = times,
                    v_names_states = v_names_states)
# plot the results of PSM and the true data
plot_trace_PSM(time = times, partsurv.model = m_M_PSM, v_names_states = v_names_states)
# construct a PSA partitioned survival model out of the fitted models
m_M_PSM_PSA <- partsurv(pfs_survHE = fit_PFS,</pre>
                        os_survHE = fit_OS,
                        choose_PFS = choose_PFS,
                        choose_OS = choose_OS,
                        time = times,
                        v_names_states = v_names_states,
                        PA = T, n_{sim} = 1000)
# plot the results of PSM and the trace
plot_trace_PSM(time = times, partsurv.model = m_M_PSM_PSA, PA = T, v_names_states = v_names_states)
```

Other outputs from the partitioned survival model could be explored:

```
# Expected survival
m_M_PSM$pfs.expected.surv
m_M_PSM$os.expected.surv
```