

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

c_l      <- 1 / 12          # cycle length (a month)
n_t      <- 10              # number of years (10 years)
set.seed(2020)              # set the seed
n_sim    <- 100             # number of simulations

n_states <- length(v_names_states) # No of states
times    <- seq(0, n_t, c_l)      # the cycles in years
```

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

```
tmat <- matrix(NA, n_states, n_states, dimnames = list(v_names_states, v_names_states))
tmat["Healthy", "Sick"] <- 1
tmat["Healthy", "Dead"] <- 2
tmat["Sick", "Dead"] <- 3

layout.fig <- c(2,1)
plotmat(t(tmat), t(layout.fig), self.cex = 0.5, curve = 0, arr.pos = 0.76,
        latex = T, arr.type = "curved", relsize = 0.85, box.prop=0.8,
        cex = 0.1, box.cex = 0.7, lwd = 1)
```

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)
```

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
  palette = c("blue3"),    # custom color palettes
  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 = "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
  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
  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.

```
# R package flexsurv allows parametric fitting of curves
fit_weib <- flexsurvreg(Surv(time = OS_time, event = OS_status) ~ 1, data = OS_PFS_data,
  dist = "weibull")
plot(fit_weib)
```

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`.

```
# fit all parametric models to the data and extract the AIC/BIC.
# Select the one with the most appropriate fit
# Repeat for PFS and OS
fit_PFS <- fit.fun(time = "PFS_time", status = "PFS_status", data = OS_PFS_data,
                  extrapolate = TRUE, times = times)
fit_OS  <- fit.fun(time = "OS_time", status = "OS_status", data = OS_PFS_data,
                  extrapolate = TRUE, times = times)
```

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

```
# fit all parametric mixture cure models to the data and extract the AIC/BIC.
# Select the one with the most appropriate fit
# Repeat for PFS and OS
fit_PFS_cure <- fit.fun.cure(time = "PFS_time", status = "PFS_status", data = OS_PFS_data,
                             extrapolate = TRUE, times = times)
fit_OS_cure  <- fit.fun.cure(time = "OS_time", status = "OS_status", data = OS_PFS_data,
                             extrapolate = TRUE, times = times)
```

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

```
# Check AIC of each model to assess goodness-of-fit
GoF_PFS <- data.frame(AIC = c(fit_PFS$AIC, fit_PFS_cure$AIC),
                     BIC = c(fit_PFS$BIC, fit_PFS_cure$BIC))
GoF_OS  <- data.frame(AIC = c(fit_OS$AIC, fit_OS_cure$AIC),
                     BIC = c(fit_OS$BIC, fit_OS_cure$BIC))
choose_PFS <- rownames(GoF_PFS)[which.min(GoF_PFS$AIC)]; choose_PFS
choose_OS  <- rownames(GoF_OS)[which.min(GoF_OS$AIC)]; choose_OS
```

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)
# Select the best fitted survivor function based on the smallest AIC
best_PFS <- fit_PFS$model.objects$models[[choose_PFS]]
# plot KM for PFS
PFS_superimpose <- ggsvplot(
  fit_KM_PFS,
  data = OS_PFS_data,
  size = 1,                # change line size
  palette = c("orange2"),  # custom color palettes
  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 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))
# superimpose the survival probabilities
PFS_superimpose$plot <- PFS_superimpose$plot +
  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 +
  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 +
  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]]
# plot KM for OS
OS_superimpose <- 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 = 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))
# 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,
                   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,
                       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

```