# Appendix: <br> Multilevel competing risk models <br> to evaluate the risk of nosocomial infection <br> - Statistical methods and $R$ code - 

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## Statistical methods

## Model 1: Shared frailty models for event-specific hazard rates - the etiology (rate) model

The classical way to analyse competing risks data is to study event-specific hazard rates. We introduce random effects for each ICU by a shared gamma frailty model [1,2]. Thus, for each event $k$ (NI, death w/o NI, discharge w/o NI ), for the $j$-th patient in the $i$-th ICU, the event-specific hazard rate with a shared frailty term $Z_{i}^{k}$ is defined as

$$
\begin{equation*}
\lambda_{i j}^{k}\left(t \mid Z_{i}^{k}\right)=Z_{i}^{k} \lambda_{0}^{k}(t) \tag{1}
\end{equation*}
$$

The frailty term $Z_{i}^{k}$ is a random effect which varies across ICUs (patients within ICU share the same frailty) and is assumed to be Gamma distributed with shape parameter $1 / \theta_{k}$ and inverse scale parameter $1 / \theta_{k}$, thus $E\left(Z^{k}\right)=1$ and $\operatorname{Var}\left(Z^{k}\right)=\theta_{k}$. Large values of $\theta_{k}$ signify a closer positive relationship between patients within ICU and greater heterogeneity across ICUs. The baseline hazard for event $k$ is labeled as $\lambda_{0}^{k}(t)$.

Observed covariates $X$ are considered in a multiplicative way as follows

$$
\begin{equation*}
\lambda_{i j}^{k}\left(t \mid X_{i j}, Z_{i}^{k}\right)=Z_{i}^{k} \lambda_{0}^{k}(t) \exp \left(\beta^{k} X_{i j}\right) \tag{2}
\end{equation*}
$$

We consider patient-individual as well as ICU-specific covariates.

## Model 2: Shared frailty model for the subdistribution hazard of NI - the prediction (risk) model

For studying the risk (cumulative incidence function) of NI, we use the Fine and Gray model [3] and introduce a shared frailty structure to investigate heterogeneity in a similar way as Katsahian et al [4]. Thus, we set all event times to time until potential censoring for patients who are discharged and died w/o NI [5]. These times are known because of administrative censoring. Then we fit shared frailty models in analogy to formula 1 and 2 to this modified data set.

Table 1: Hypothetical data. ICU ID=identity code for the ICU, patient ID = identity code for the patient, time=time from admission, to=type of event ( $1=$ NI, $2=$ death without NI, $3=$ discharge without NI, $0=$ censored), timepotcens=time from admission to potential censoring, timesubNI=subdistribution time for NI (times of competing events are replaced with timepotcens), lefttruncated data should use the start-stop notation

| ICU ID | patient ID | time | to | timepotcens | timesubNI | covariates |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 1 | 5 | 1 | 45 | 5 | 0 |
| 1 | 2 | 8 | 3 | 65 | 65 | 1 |
| 1 | 3 | 4 | 2 | 73 | 73 | 1 |
| 1 | 4 | 17 | 1 | 123 | 17 | 1 |
| 1 | 5 | 9 | 3 | 47 | 47 | 0 |
| 1 | 6 | 5 | 3 | 79 | 79 | 0 |
| 2 | 7 | 7 | 3 | 76 | 76 | 1 |
| 2 | 8 | 8 | 3 | 65 | 65 | 1 |
| 2 | 9 | 14 | 1 | 123 | 14 | 1 |
| 2 | 10 | 12 | 2 | 54 | 54 | 0 |
| 2 | 11 | 9 | 1 | 76 | 9 | 0 |
| 2 | 12 | 9 | 0 | 89 | 9 | 1 |
| $(\ldots)$ | $(\ldots)$ | $(\ldots)$ | $(\ldots)$ | $(\ldots)$ | $(\ldots)$ | $(\ldots)$ |

## Data analysis

## Software

For all analyses we used the flexible R-package frailtyPack [6].

## R code

```
# load the software
library("frailtypack")
# data should look like in table 1
# note that data$timesubNI<-ifelse(data$status==1,data$time,data$timepotcens)
# run model 1 and formula 1 for nosocomial infection using
# semi-parametric hazard functions with the penalized likelihood estimation
model1_NI<-frailtyPenal(Surv(time,to==1) ~ cluster(ICU_id) ,
    data=data,n.knots=7,kappa1=1000,Frailty=TRUE,cross.validation=TRUE)
# plot baseline hazard
plot(model1_NI)
# plot frailties
plot(model1_NI$frailty.pred)
# print results
```

```
print(model1_NI)
summary(model1_NI)
# perform the same analysis for death without NI by
# replacing Surv(time,to==1) by Surv(time,to==2)
# perform the same analysis for discharge without NI by
# replacing Surv(time,to==1) by Surv(time,to==3)
# Multivariate model
# run model 1 and formula 2 for nosocomial infection using
# semi-parametric hazard functions with the penalized likelihood estimation
model1_NI_multi<-frailtyPenal(Surv(time,to==1) ~ cluster(ICU_id) + covariates ,
    data=data,n.knots=7,kappa1=1000,Frailty=TRUE,cross.validation=TRUE)
# Subdistribution model
# run model 2 for nosocomial infection using
# semi-parametric hazard functions with the penalized likelihood estimation
model2_NI<-frailtyPenal(Surv(timesubNI,to==1) ~ cluster(ICU_id) ,
    data=data,n.knots=7,kappa1=1000,Frailty=TRUE,cross.validation=TRUE)
model2_NI_multi<-frailtyPenal(Surv(timesubNI,to==1) ~ cluster(ICU_id) + covariates,
    data=data,n.knots=7,kappa1=1000,Frailty=TRUE,cross.validation=TRUE)
```


## References

[1] Liquet B, Timsit JF, Rondeau V. Investigating hospital heterogeneity with a multi-state frailty model: application to nosocomial pneumonia disease in intensive care units. BMC Med Res Methodol. 2012;12:79.
[2] Rondeau V, Commenges D, Joly P. Maximum penalized likelihood estimation in a gamma-frailty model. Lifetime Data Anal. 2003 Jun;9(2):139-153.
[3] Fine J, Gray RJ. A proportional hazards model for the subdistribution of a competing risk. J Am Stat Assoc. 1999;94(446):496-509.
[4] Katsahian S, Boudreau C. Estimating and testing for center effects in competing risks. Stat Med. 2011 Jun;30(13):1608-1617.
[5] Beyersmann J, Allignol A, Schumacher M. Competing Risks and Multistate Models with R. Springer, New York; 2011.
[6] Rondeau V, Mazroui Y, Gonzalez JR. frailtypack: An R package for the analysis of correlated survival data with frailty models using penalized likelihood estimation or parametrical estimation. Journal of Statistical Software. 2012;47(4):1-28.

Additional information: boxplots of the frailties as an alternative display of the data published in the main manuscript

Figure 1: Outcome: NB. model 0 - null model, model 1 - with ICU level covariates only, model 2 - with patient level covariates only, model 3 - all covariates


Figure 2: Outcome: death without NB. model 0 - null model, model 1 - with ICU level covariates only, model 2 - with patient level covariates only, model 3 - all covariates


Figure 3: Outcome: discharge without NB. model 0 - null model, model 1 - with ICU level covariates only, model 2 - with patient level covariates only, model 3 - all covariates


Figure 4: Outcome: NB subdistribution. model 0 - null model, model 1 - with ICU level covariates only, model 2 - with patient level covariates only, model 3 - all covariates


