

# A SEMI-MARKOV MODEL FOR INTERVAL-CENSORED DATA

## ANALYSIS OF THE EVOLUTION OF KIDNEY TRANSPLANT RECIPIENTS

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# Introduction

- ▶ Multistate approaches are becoming increasingly used for the analysis of longitudinal data.
- ▶ Semi-Markov models explicitly define distributions of waiting times.
- ▶ In the follow-up of patients, transition times are known to have occurred in some interval.
- ▶ **Objective** : The development of a flexible semi-Markov model which allow for interval censoring.

## Introduction

### Semi-Markov model

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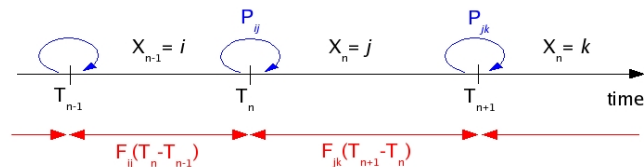
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# Definitions (1)



- ▶  $\rightarrow$  Probability of jumping from the State  $i$  to the State  $j$ .
- ▶  $\longleftrightarrow$  Staying times  $T_{n+1} - T_n \rightsquigarrow F_{ij}(T_{n+1} - T_n)$ .

# Definitions (2)

## Embedded Markov chain

$$P_{ij} = P(X_{n+1} = j | X_n = i)$$

- ▶ If state  $i$  is not persistent then  $P_{ij} \geq 0$  and  $P_{ii} = 0$ .
- ▶ If state  $i$  is persistent then  $P_{ij} = 0$  and  $P_{ii} = 1$ .

# Definitions (2)

## Embedded Markov chain

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## Distribution of waiting times

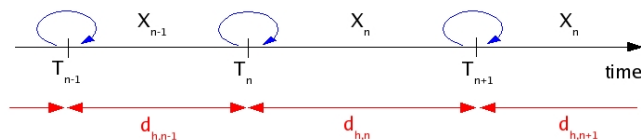
- ▶  $F_{ij}(x) = P(T_{n+1} - T_n \leq x | X_{n+1} = j, X_n = i)$ .
- ▶  $F_{ij}(x) = F^{(ij)}(x, \varphi_{ij})$ .

$$\implies S_{ij}(x), f_{ij}(x) \text{ et } \lambda_{ij}(x)$$

# Loglikelihood (1)

## Contribution of a transition exactly observed $\delta_{h,r}^E$

Let  $d_{h,r} = T_{h,r+1} - T_{h,r}$ , the waiting time in the state  $X_{h,r}$  before jumping to the state  $X_{h,r+1}$ .

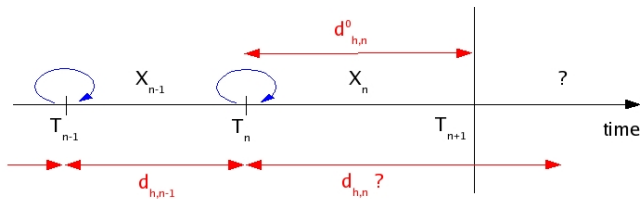


$$\begin{aligned} & \lim_{\Delta d \rightarrow 0^+} \frac{P(d_{h,r} < x < d_{h,r} + \Delta d, X_{h,r+1} = j | X_{h,r} = i)}{\Delta d} \\ = & \lim_{\Delta d \rightarrow 0^+} \frac{P(d_{h,r} < x < d_{h,r} + \Delta d | X_{h,r+1} = j, X_{h,r} = i)}{\Delta d} \\ & \times P(X_{h,r+1} = j | X_{h,r} = i) = P_{ij} f_{ij}(d_{h,r}) \end{aligned}$$

# Loglikelihood (2)

## Contribution of a right-censored transition $\delta_{h,r}^R$

Let  $d_{h,r}^0$  be a value such that if  $d_{h,r} < d_{h,r}^0$  then  $d_{h,r}^0$  is observed and  $d_{h,r}$  is not.



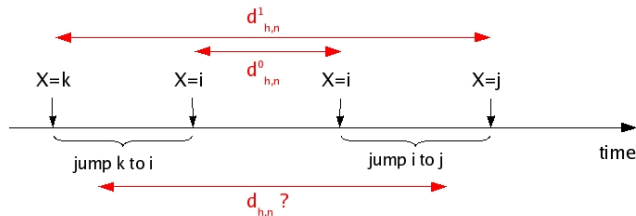
$$\begin{aligned} & P(d_{h,r} > d_{h,r}^0 | X_{h,r} = i) \\ &= \sum_{j \neq i} P(X_{h,r+1} = j | X_{h,r} = i) P(d_{h,r} > d_{h,r}^0 | X_{h,r+1} = j, X_{h,r} = i) \\ &= \sum_{j \neq i} P_{ij} \int_{d_{h,r}^0}^{\infty} f_{ij}(u) du = \sum_{j \neq i} P_{ij} S_{ij}(d_{h,r}^0) \end{aligned}$$



# Loglikelihood (3)

## Contribution of an interval-censored transition $\delta_{h,r}^1$

Let  $d_{h,r}^1$  be a value such that if  $d_{h,r}^1 > d_{h,r}$  then  $d_{h,r}^1$  is observed and  $d_{h,r}$  is not.



$$\begin{aligned} P(d_{h,r}^0 < x < d_{h,r}^1, X_{h,r+1} = j | X_{h,r} = i) \\ &= P(X_{h,r+1} = j | X_{h,r} = i) \int_{d_{h,r}^0}^{d_{h,r}^1} f_{ij}(u) du \\ &= P_{ij} \left( \int_0^{d_{h,r}^1} f_{ij}(u) du - \int_0^{d_{h,r}^0} f_{ij}(u) du \right) \\ &= P_{ij} (F_{ij}(d_{h,r}^1) - F_{ij}(d_{h,r}^0)) = P_{ij} (S_{ij}(d_{h,r}^0) - S_{ij}(d_{h,r}^1)) \end{aligned}$$

# Loglikelihood (4)

## Contribution of an initial observation for the subject $h$

By defining  $z_{h,0j}$ , the vector of covariates associated with the initial state  $j$  for the  $h^{\text{th}}$  subject, the usual multinomial logistic regression can be written as :

$$P(X_{h,1} = j) = \frac{\exp(\gamma_{0j} + \beta_{0j}z_{h,0j})}{\sum_{k=1}^c \exp(\gamma_{0k} + \beta_{0k}z_{h,0k})} \quad \text{for } j = 1, \dots, c$$

with  $\gamma_{0c} = 0$  and  $\beta_{0c} = 0$ , in order to obtain  $\sum_{j=1}^c \pi_{0j} = 1$ .

# Loglikelihood (5)

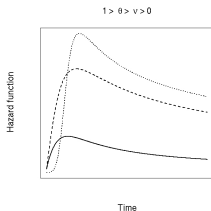
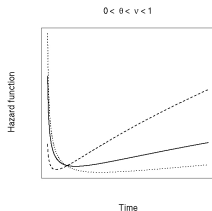
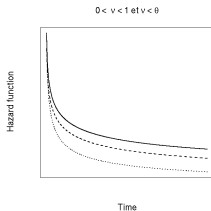
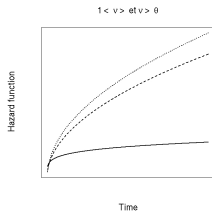
$$\begin{aligned} \ln \mathcal{L} &= \sum_h \left\{ \gamma_{0X_{h,1}} + \beta_{0X_{h,1}} z_{h,0} X_{h,1} - \ln \left( \sum_{i=1}^c \exp(\gamma_{0i} + \beta_{0i} z_{h,0} X_{h,1}) \right) \right\} \\ &+ \sum_{ij} \sum_{X_{h,r}=i, X_{h,r+1}=j} \left\{ \delta_{h,r}^E \left[ \ln P_{ij} + \ln S_{ij}(d_{h,r}) + \ln \lambda_{ij}(d_{h,r}) \right] \right. \\ &+ \left. \delta_{h,r}^I \left[ \ln P_{ij} + \ln (S_{ij}(d_{h,r}^0) - S_{ij}(d_{h,r}^1)) \right] \right\} \\ &+ \sum_i \sum_{X_{h,r}=i} \left\{ \delta_{h,r}^R \left[ \ln \left( \sum_{j \neq i} P_{ij} S_{ij}(d_{h,r}^0) \right) \right] \right\} \end{aligned}$$

where  $\gamma_{0c} = \beta_{0c} = 0$ .

# Modelling assumptions (1)

Generalised Weibull distribution ( $\nu_{ij}, \sigma_{ij}, \theta_{ij} > 0$ )

- ▶ Hazard,  $\lambda_{ij}(x) = \frac{1}{\theta_{ij}} \left(1 + \left(\frac{x}{\sigma_{ij}}\right)^{\nu_{ij}}\right)^{\frac{1}{\theta_{ij}} - 1} \frac{\nu_{ij}}{\sigma_{ij}} \left(\frac{x}{\sigma_{ij}}\right)^{\nu_{ij} - 1}$
- ▶ Survival,  $S_{ij}(x) = \exp\left(1 - \left(1 + \left(\frac{x}{\sigma_{ij}}\right)^{\nu_{ij}}\right)^{\frac{1}{\theta_{ij}}}\right)$



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# Modelling assumptions (2)

## Incorporation of covariates (PH)

- ▶ Proportional Hazard (PH) assumption.

$$S_{ij}(x, \eta_{h,ij}) = S_{0,ij}(x) \exp(\eta_{h,ij})$$

$$\lambda_{ij}(x, \eta_{h,ij}) = \lambda_{0,ij}(x) \exp(\eta_{h,ij})$$

- ▶ Respect of the PH assumption.  
plotting  $\log(-\log(S_{ij}(x)))$  against the survival time  $x$ .

# Kidney transplant recipients (1)

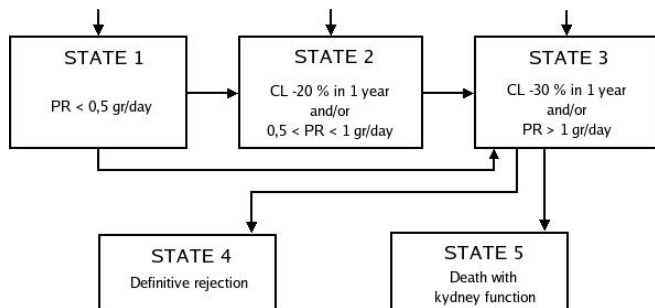
## Data description

- ▶ Prospective study of kidney transplant recipients (DIVAT).
- ▶ 997 patients and 1980 exact or censored transitions.
- ▶ Data were computerized at each checkup visit.
- ▶ 5 explanatory variables have been retained :
  - ▶ gender (men = 1 ; women = 0),
  - ▶ cold ischemia time (1 if  $\geq 16$  hours and 0 otherwise),
  - ▶ year of the transplantation (1 if  $< 1998$  and 0 otherwise),
  - ▶ recipient age at the time of transplantation (1 if  $\geq 55$  years of age and 0 otherwise),
  - ▶ delayed graft function (1 if  $\geq 6$  days and 0 otherwise).

# Kidney transplant recipients (2)

## Multistate structure

- ▶ 3-gravity states with two markers :
  - ▶ Creatinine clearance (CL)
  - ▶ Proteinuria (PR)
- ▶ 2-terminal states : chronic rejection of the kidney and death of the patient.



# Results (1)

## Covariates associated with the initial probabilities

Transition	Covariate	Estim.	SE	p-value
0 → 1	Intercept	2.85	0.19	0.0001
0 → 1	Recipient Gender	-0.39	0.17	0.0226
0 → 1	Delayed graft function	-0.53	0.17	0.0014
0 → 2	Intercept	-0.67	0.44	0.1258
0 → 2	Cold ischemia time	1.13	0.44	0.0092



# Results (2)

## Covariates associated with the intensities of transition

Transition	Covariate	Estim.	SE	RR	p-value
1 → 2	Year of transplant	-0.80	0.12	0.45	0.0001
1 → 3	Recipient Gender	0.29	0.15	1.34	0.0484
1 → 3	Year of transplant	-1.20	0.21	0.30	0.0001
2 → 3	Year of transplant	-0.54	0.12	0.59	0.0001
3 → 5	Recipient age	1.48	0.39	4.41	0.0001

# Results (3)

## Parameters of the waiting times distributions

Transition	$\sigma_{ij}$		$\nu_{ij}$		$\theta_{ij}$	
	Estim.	ET	Estim.	ET	Estim.	ET
1 $\rightarrow$ 2	36.14	31.97	0.53	0.03	0.24	0.09
1 $\rightarrow$ 3	34.11	65.20	0.52	0.05	0.19	0.15
2 $\rightarrow$ 3	33.40	31.34	0.56	0.03	0.30	0.13
3 $\rightarrow$ 4	10.16	1.56	1.49	0.11	.	.
3 $\rightarrow$ 5	18.48	47.62	1.14	0.23	1.46	3.75

# Concluding remarks

## Summary of the results

- ▶ Multinomial logistic regression usefull in order to identify covariates associated with the initial probabilities.
- ▶ Parcimony of the generalized Weibull distribution ( $\cup$  – or  $\cap$  – shape).

# Concluding remarks

## Summary of the results

- ▶ Multinomial logistic regression useful in order to identify covariates associated with the initial probabilities.
- ▶ Parsimony of the generalized Weibull distribution ( $\cup$  – or  $\cap$  – shape).

## Limits of the model and work in progress

- ▶ Delete the transition  $1 \rightarrow 3$ , even if this transition is informative for clinicians.

$$P_{12}P_{23} \int_0^{d_{h,r}} f_{12}(x)f_{23}(d_{h,r} - x)dx$$

- ▶ Estimate the cut-off of the markers in order to determine the best states of gravity.
- ▶ Construction of an hidden semi-Markov model in order to take into account the short-term fluctuation.