Statistical Methods in Cancer Epidemiology using R

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Finnish Cancer Registry

Lecture 9

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Points to be covered

- 1. Relative survival estimators
- 2. Age-standardised relative survival
- 3. Period approach
- 4. Regression modelling of relative survival.
- Packages popEpi and rstpm2.
- ► Functions survtab(), glm(), relpois_ag(), stpm2().

Population-based cancer survival

- Relative (net) survival is the standard measure in population-based cancer survival
- Relative survival summarizes patients' excess mortality, i.e. additional mortality patients have compared with mortality in a relevant reference population.
- Does not rely on cause of death information
 - ► The quality of cause-of-death information varies over time, between types of cancer and between regions and countries.
 - Many cancer registries do not record cause of death.
 - Cause of death is rarely a simple dichotomy.

Excess mortality and relative survival

► Total mortality among patients $\lambda(t)$ is the sum of population mortality $\lambda_{\mathsf{P}}(t)$ and excess mortality $\lambda_{\mathsf{E}}(t)$ due to cancer:

$$\lambda(t) = \lambda_{\mathsf{P}}(t) + \lambda_{\mathsf{E}}(t)$$

▶ Relative survival $S_E(t)$ is the survival function related to the excess mortality:

$$S_{\mathsf{E}}(t) = \exp\left[-\int_0^t \lambda_{\mathsf{E}}(u) \ du\right]$$

- Often interpreted as the survival **probability** in a hypothetical situation where the cancer would be the only possible cause of death with all other causes being eliminated.
- ▶ N.B. Independence of competing risks is required but this assumption cannot be assessed based on the data!

Non-parametric relative survival estimators (hazard-based)

► Ederer II (Ederer and Heise 1958)

$$S_{\mathsf{E},\mathsf{EII}}(t_k) = \exp\left(-\sum_{j=1}^k \Delta_j rac{d_j - d_j^*}{y_j}
ight)$$

- $ightharpoonup \Delta_i = \text{length of follow-up time interval } j$
- $ightharpoonup d_j = \text{number of deaths}$
- $ightharpoonup d_i^* =$ expected number of deaths (same as in SMR estimation)
- $v_i = \text{number person-years}$
- Pohar Perme estimator (Pohar Perme et al. 2012)

$$S_{\mathsf{E},\mathsf{PP}}(t_k) \exp\left(-\sum_{j=1}^k \Delta_j \frac{d_j^w - d_j^{*w}}{y_j^w}\right)$$

▶ d_j^w , d_j^{*w} and y_j^w are based on individual-level observations of d_j , d_j^* and y_j weighted by the patient-specific cumulative expected survival probability (see Seppä et al. 2016).

Properties of the estimators

- Non-standardised Ederer II estimator overestimates relative survival because of informative censoring of old patients with high other-cause mortality
 - use age-standardised Ederer II
- Pohar Perme estimator corrects for this bias by giving larger weights for observations of older patients
- ▶ Both the Pohar Perme and the age-standardised Ederer II estimator are valid for 5-year net survival of cancer patients.

Age-standardised relative survival

- Weighted average of age-specific relative survival estimates $S_{\text{F}}(t) = \sum_{a=1}^{K} w_a S_{\text{F},a}(t)$ where $\sum_{a=1}^{K} w_a = 1$
 - weight w_a is a standard for the proportion of patients in age group a at the beginning of follow-up
- ► E.g. International Cancer Survival Standards
 - ICSS1: elderly (most cancers)
 - ► ICSS2: little age dependence (eg. melanoma, brain, cervix)
 - ► ICSS3: young adults (eg. testis, hodgkin lymphoma); starify 15-44 into narrower groups

Age group (a)	W _{ICSS1}	W _{ICSS2}	W _{ICSS3}
15-44	0.07	0.28	0.60
45-54	0.12	0.17	0.10
55-64	0.23	0.21	0.10
65-74	0.29	0.20	0.10
75+	0.29	0.14	0.10

Ex. Oral cancer data

Relative survival analysis

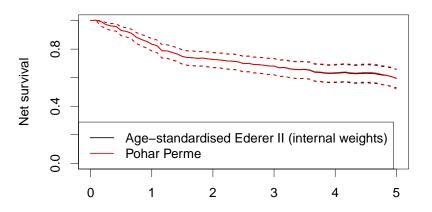
- expected mortality is derived from the mortality rates in the population of Finland
- assume the date on diagnosis would a random date between 1985 and 2005.

```
orca <- read.table(file="oralca2.txt")</pre>
library(Epi)
library(popEpi)
set.seed(23032020)
orca$dg_date <- runif(nrow(orca), min=1985, max=2005)</pre>
orca$sex <- ifelse(orca$sex=="Male",0,1)</pre>
names(orca)[2] <- "dg_age"</pre>
Lex <- Lexis(entry = list(FUT = 0, AGE = dg_age, CAL = dg_date),</pre>
            exit = list(FUT = time),
            data = orca.
            exit.status =
              factor(event, levels = 0:2,
                      labels = c("alive", "canD", "othD")),
            merge = TRUE)
```

Ex. Oral cancer data, Ederer II and Pohar Perme

```
pm <- popmort
names(pm) <- c("sex", "CAL", "AGE", "haz")</pre>
cutpoints <-c(0,55,65,75,Inf)
Lex$agegr <- cut(Lex$dg_age, cutpoints, right=F)</pre>
#Age-standardised Ederer II estimator
surv.EII <- survtab(FUT ~ 1 + adjust(agegr), data = Lex,</pre>
              surv.type = "surv.rel",
              pophaz = pm, weights = "internal",
              breaks = list(FUT = seq(0, 5, 1/12))
#Pohar Perme estimator
surv.PP <- survtab(FUT ~ 1, data = Lex,</pre>
              surv.type = "surv.rel", relsurv.method = "pp",
              pophaz = pm,
              breaks = list(FUT = seq(0, 5, 1/12))
```

Ex. Oral cancer data, Ederer II and Pohar Perme



Time from entry

Ex. Oral cancer data, ICSS weights

Use external weights (ICSS1) in age standardisation:

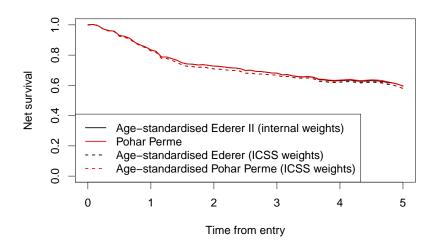
```
ICSS$agegr <- cut(ICSS$age, cutpoints, right = FALSE)
w <- aggregate(ICSS1~agegr, data = ICSS, FUN = sum)
w</pre>
```

```
agegr ICSS1
1 [0,55) 19000
2 [55,65) 23000
3 [65,75) 29000
4 [75,Inf) 29000
```

Ex. Oral cancer data, ICSS weights

Ex. Oral cancer data, internal vs ICSS weights

Ex. Oral cancer data, ICSS weights

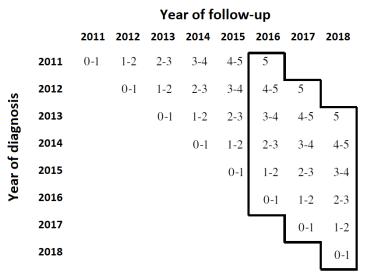


Period approach

- Survival estimates in a cohort of patients tend to be outdated
 - ► 5-year survival estimate requires follow-up data on patients diagnosed ≥ 5 years ago.
- Use period approach (Brenner et al. 2004) to produce maximally updated estimates of patient survival
 - follow-up of patients is restricted to a calendar time window.
 - e.g. patients diagnosed in 2011-2018 and followed-up in 2016-2018.
 - patients diagnosed earlier than 2016 do not contribute to survival estimate before coming to the follow-up window 2016-2018 (late entry).
 - ▶ interpretation: survival in patients, who would have the same follow-up time specific excess mortality rates as those observed in 2016-2018. (A prediction for patients diagnosed in 2016-2018.)

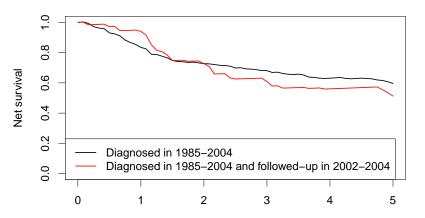
Period approach

Example: 5-year survival based on patients diagnosed in 2011-2018 and followed in calendar time window 2016-2018.



Ex. Oral cancer data, period approach

Ex. Oral cancer data, period approach



Regression models for relative survival

1. Logarithm of excess mortality

$$\log[\lambda_{\mathsf{E}}(t)] = \alpha + \beta X$$

can be modelled by using Poisson regression with a user-specified link function (Dickman et al. 2004).

2. Logarithm of cumulative excess mortality

$$\log[\Lambda_{\mathsf{E}}(t)] = \mathsf{spline}[\log(t) \mid \alpha] + \beta X$$

can be modelled using spline functions for the baseline cumulative excess hazard (rstpm2 package)

Ex. Oral cancer data, piecewise constant excess hazard

Ex. Oral cancer data, piecewise constant excess hazard

Aggregated data

Lex

	agegr	fot	pyrs	${\tt at.risk}$	d.exp	${\tt from0to0}$	fromOto1
1:	[0,55)	0	94.163	100	0.4176292	0	15
2:	[0,55)	1	81.649	85	0.3764739	1	4
3:	[0,55)	2	75.902	80	0.3727492	5	8
4:	[0,55)	3	118.216	67	0.5752607	8	6
5:	[55,65)	0	66.439	71	0.7529778	0	9
6:	[55,65)	1	53.859	62	0.6535970	3	10
7:	[55,65)	2	46.049	49	0.6024387	3	4
8:	[55,65)	3	72.744	42	0.9819390	3	7
9:	[65,75)	0	83.234	89	2.3992428	0	14
10:	[65,75)	1	68.080	75	2.0061784	0	12
11:	[65,75)	2	60.721	63	1.8970814	1	4
12:	[65,75)	3	91.164	58	3.0119818	8	10
13:	[75,Inf)	0	66.487	78	5.8403911	0	26
14:	[75,Inf)	1	42.927	52	3.9569316	0	15
15:	[75,Inf)	2	33.630	37	3.4714270	0	5
16:	[75,Inf)	3	55.426	32	6.5913538	2	10

Ex. Oral cancer data, piecewise constant excess hazard

Proportional hazards between age groups?

```
## fit model using aggregated data
rpm <- relpois_ag(formula = from0to1 ~ fot + agegr,</pre>
                 data = Lex, d.exp = d.exp, offset = log(pyrs))
ci.exp(rpm)
             exp(Est.) 2.5% 97.5%
(Intercept) 0.1299963 0.0845701 0.1998229
fot[1, 2) 0.7921478 0.4951471 1.2672964
fot[2, 3) 0.4500391 0.2392291 0.8466161
fot[3, 5) 0.3974890 0.2250555 0.7020377
agegr[55,65) 1.3009831 0.7600595 2.2268746
agegr[65,75) 1.1746621 0.6841282 2.0169189
agegr[75,Inf) 2.1077956 1.2363790 3.5933985
## non-proportional effect of age (=follow-up time age interaction)
rpm2 <- update(rpm, . ~ fot*agegr)</pre>
anova(rpm, rpm2, test="LRT")$`Pr(>Chi)`[2]
```

Ex. Oral cancer data, spline functions

Mortality from any cause and from cancer, and excess mortality

```
library(rstpm2)
orca$agegr <- cut(orca$dg_age, cutpoints, right=F)</pre>
#mortality from any cause
fit <- stpm2(Surv(time, event%in%c(1,2))~1,
              data=orca, df=3)
#cause (cancer)-specific mortality
fit2 <- stpm2(Surv(time, event%in%c(1))~1,
               data=orca,df=3)
#excess mortality
orca$ex_age <- floor(orca$dg_age+orca$time)</pre>
orca$ex_year <- floor(orca$dg_date+orca$time)</pre>
orca <- merge(orca,pm,</pre>
               by.x=c("sex","ex_age","ex_year"),
               by.y=c("sex","AGE","CAL"))
fit3 <- stpm2(Surv(time, event%in%c(1,2))~1,
               data=orca, df=3,
               bhazard=orca$haz)
```

Ex. Oral cancer data, hazard

Ex. Oral cancer data, hazard

