# **Applications of Uni-List Capture-Recapture Methods in Meta-Analysis**

Dankmar Böhning Southampton Statistical Sciences Research Institute and Mathematical Sciences, University of Southampton, UK



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204 Southampton Statistical Sciences Research Institute (S<sub>3</sub>R)

CBeing a part of SaRI isone of the most significant milestones in my career. The courses. delivered by excellent professionals from the University of Southampton and abroad provided good insights into statistics. I have no doubt that SaRI will continue to grow and enrich with its highly qualified and professional academic staff. It hasbeen a pleasure to be part of this prestigious group. >>

Carla Azevedo SgRIPhD student

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some help may be provided
\* For more information on continued assessment

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#### **Obesity Treatment**

# Risk of completed suicide after bariatric surgery: a systematic review

C. Peterhänsel<sup>1,2</sup>, D. Petroff<sup>3,4</sup>, G. Klinitzke<sup>1,2</sup>, A. Kersting<sup>1</sup> and B. Wagner<sup>1,2</sup>

# **Case-study: Obesity Treatment**

# Risk of completed suicide after bariatric surgery: a systematic review

- bariatric surgery is one of the most effective treatments for morbid obesity, indicating a significant long-term weight loss
- while overall mortality decreases in patients who received bariatric surgery, risk of suicide is still an issue
- Peterhänsel et al. (2013) undertake a meta-analysis on completed suicide after bariatric surgery
- 27 studies are included in the analysis

	Person-years	Weight	# of patients	# of women	# of suicides	Country
Adams	77,602	0.5397	9,949	8,556	21	USA
Marceau	10,388	0.0722	1,423	1,025	6	Canada
Marsk	8,877	0.0617	1,216	0	4	Sweden
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Table 2 List of papers included for the estimate of the suicide rate in decreasing order of person-years

The column entitled 'weight' is the fraction of the total number of person-years and is used in the analysis for comparing the estimated suicide rate for patients after a bariatric operation with the rate for an equivalent general population.



# **Case-study: Obesity Treatment**

Risk of completed suicide after bariatric surgery: a systematic review

- selection bias issue: only studies with completed suicide are included
- Peterhänsel et al. (2013):

The most crucial point in the analysis was the proper treatment of the selection bias because of the method of finding papers.

• hence, suicide rate will be *overestimated* (potentially substantially)

#### conventional meta-analysis

- in a nutshell, the conventional approach for a meta-analytic analysis (Cooper and Hedges 1994, Egger *et al.* 1995, Stangl and Berry 2000, Borenstein *et al.* 2009:311) proceed as follows:
- let  $X_i$  denote the observed count of suicides in study *i* and  $E(X_i) = \mu_i$  its corresponding expected value
- also, let  $P_i$  denote the person-years in study i
- Then, in meta-analysis a summary measure as a weighted average of the study-specific rates on log-scale is used:

$$\sum_{i=1}^n w_i \log(X_i/P_i) / \sum_{i=1}^n w_i$$

where  $w_i$  is a proxy estimate of the inverse variance, here  $w_i = Y_i$  leading to

$$\sum_{i=1}^n Y_i \log(X_i/P_i) / \sum_{i=1}^n Y_i$$

#### conventional meta-analysis

- another approach (Barendregt et al. 2013) works on the rate scale
- an attractive choice for w<sub>i</sub> in

$$\sum_{i=1}^n w_i(X_i/P_i)/\sum_{i=1}^n w_i$$

is

$$w_i = P_i$$

• this is in the Mantel-Haenszel philosophy weighting with the denominator (here the person-years) leading to

$$\hat{\lambda} = \sum_{i=1}^{n} X_i / \sum_{i=1}^{n} P_i$$

as a summary estimate of the overall rate  $\lambda$ 

#### conventional meta-analysis

 a benefit of the Mantel-Haenszel approach here is that the variance of λ̂ is easy to calculate:

$$Var(\hat{\lambda}) = Var(\sum_{i=1}^{n} X_i / \sum_{i=1}^{n} P_i)$$
$$= \sum_{i=1}^{n} \lambda P_i / (\sum_{i=1}^{n} P_i)^2$$

which is estimated as



 using this technique we find an overall rate of 44.51 suicides per 100,000 person years with a 95% CI of 33.60 – 55.42

## problem with the conventional approach

- any of these conventional approaches cope with zero-event studies missing
- hence we need to turn to other ideas

## the idea of capture-recapture

- objective is to determine the size N of an elusive target population
- some mechanism (life trapping, register, surveillance system) identifies a unit repeatingly
- there is a count X informing about the number of identifications of each unit in the target population

#### sample

available: sample

 $X_1, X_2, \dots, X_N$ 

leading to

Table: Frequency distribution of count X of repeated identifications

x	0	1	2	3	4	 population size
$f_{x}$	$f_0$	$f_1$	<i>f</i> <sub>2</sub>	f <sub>3</sub>	<i>f</i> <sub>4</sub>	 N

#### problem

if  $X_i = 0$  unit is not observed leading to a reduced observable sample

 $X_1, X_2, ..., X_n$ 

where - w.l.g. - we assume that

$$X_{n+1} = X_{n+2} = \dots = X_N = 0$$

Table: Frequency distribution of count X of repeated identifications

x	0	1	2	3	4	 observed size
$f_{x}$	-	$f_1$	<i>f</i> <sub>2</sub>	f <sub>3</sub>	<i>f</i> 4	 п

hence

 $f_0 = N - n$  is unknown

#### why does data set fit into the capture-recapture setting?

- target population: *studies* on bariatric surgery with or without completed suicide
- identifying mechanism: online web-search including databases PubMed (PM), Web of Knowledge (WK), PsychInfo (PI), ScienceDirect (SD) and Google Scholar (GS)
- X<sub>i</sub> number of completed suicides in study *i*: can be viewed as the count of repeated identifications for study *i*

## modelling

- · to cope with missing zeros we need to involve modelling
- $p_x = P(X = x)$  for  $x = 0, 1, 2, \cdots$  base model
- for example *Poisson* :

$$p_x = \exp(-\mu)\mu^x/x! = \exp(-\lambda P)(\lambda P)^x/x!$$

 $\lambda$  suicide rate, P person-time,  $\mu = \lambda P$ 

Table: Frequency distribution of count X of repeated identifications

# modelling

- need to incorporate study-specific person-times
- $p_{ix} = P(X_i = x | P_i)$  probab. for x events in study with person-time  $P_i$
- for example *Poisson* :

$$p_{ix} = \exp(-\lambda P_i)(\lambda P_i)^x/x!$$

 $\lambda$  suicide rate,  $P_i$  person-time in study i,  $\mu = \lambda P$ 

• complete data likelihood

$$\prod_{i=1}^{n}\prod_{x=0}^{m}p_{ix}^{f_{ix}}$$

where  $f_{ix}$  is the frequency of studies with person-time  $P_i$  and event count x

• in our case, for given  $P_i$  the frequency  $f_{ix}$  is zero except for one value of x where it is one

## EM philosophy: E-step

 $f_{i0}$  is unknown and needs to be replaced by its expected value: E - step there is a general solution for the E-step:

$$e_{i0} := E(f_{i0}|f_{i1}, \cdots, f_{in}; P_i) = N_i p_{i0}$$

where  $N_i$  is the population size of studies with person-time  $P_i$ it follows that

$$e_{i0} = N_i p_{i0} = (n_i + e_i) p_{i0}$$

where  $n_i = f_{i1} + \cdots + f_{in}$  ( = 1 in our case)

it follows further that

$$e_{i0} = n_i \frac{p_{i0}}{1 - p_{i0}}$$

which *replaces*  $f_{i0}$  in the complete, unobserved likelihood leading to the complete, expected likelihood

## EM philosophy: E-step

note the relationship to the *Horvitz* – *Thompson* estimator:

$$\hat{N}_i = n_i + e_{i0} = n_i + n_i \frac{p_{i0}}{1 - p_{i0}} = \frac{n_i}{1 - p_{i0}}$$

and

$$\hat{N} = \sum_{i=1}^{n} \hat{N}_i = \sum_{i=1}^{n} \frac{n_i}{1 - p_{i0}}$$

in the case study we have that  $n_i = 1$  for  $i = 1, \cdots, n$ 

the E-step provides as by - product the item we are most interested in: the count of studies with no suicides, alternatively, the total number of studies

## EM philosophy: M-step

we need to maximize the complete, expected data likelihood



the solution will *depend* on the model used: in the *Poisson* case the complete data log-likelihood is

$$\sum_{i=1}^{n} \sum_{x=1}^{m} f_{ix} [-\mu_i + x \log \mu_i] - e_{i0} \mu_i$$

with  $\mu_i = \lambda P_i$  which is maximized for

$$\hat{\lambda} = \frac{\sum_{i=1}^{n} \sum_{x=1}^{m} x f_{ix}}{\sum_{i=1}^{n} (\sum_{x=1}^{m} P_{i} f_{ix} + P_{i} e_{i0})}$$

## **EM** philosophy

now, the EM algorithm toggles between E- and M-step until convergence

 $E\text{-step}\longleftrightarrow M\text{-step}$ 

start	rate MH:	0.0004451183	
step:	1 rate:	0.000353999 size:	121.9951
step:	2 rate:	0.000329974 size:	129.6188
step:	3 rate:	0.000321995 size:	132.4051
step:	4 rate:	0.000319157 size:	133.4304
step:	5 rate:	0.000318122 size:	133.8086
step:	14 rate:	0.0003175201 size	: 134.03
step:	15 rate:	0.0003175201 size	: 134.03

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Table 2 List of papers included for the estimate of the suicide rate in decreasing order of person-years

The column entitled 'weight' is the fraction of the total number of person-years and is used in the analysis for comparing the estimated suicide rate for patients after a bariatric operation with the rate for an equivalent general population.

## EM philosophy: full set of covariates

here an illustration in the Poisson case

$$p_{ix} = P(X_i = x | \beta; \mathbf{z}_i) = \exp(-\mu_i)\mu_i^x/x!$$

and

$$\log \mu_i = \beta^T \mathbf{z_i}$$

if there are only person-times

 $\log \mu_i = \log \lambda + \log P_i$ 

# **EM philosophy**

complete data likelihood - with covariates

```
\prod_{i=1}^{n}\prod_{x=0}^{m}p_{ix}^{f_{ix}}
```

where

- $p_{ix} = P(X_i = x | \beta; \mathbf{z_i})$
- $\mathbf{z}_i$  represents the *i*-th covariate combination for  $i = 1, \cdots, n$
- $f_{ix}$  is the frequency of observed counts equal to x for the *i*-th covariate combination
- f<sub>i0</sub> remains unknown

#### E-step

we have

$$e_{i0} = n_i \frac{p_{i0}}{1 - p_{i0}}$$

with  $p_{i0} = P(X_i = 0 | \beta; \mathbf{z_i})$ 

M-step

to maximize

 $\prod_{i=1}^n \prod_{x=1}^m p_{ix}^{f_{ix}} p_{i0}^{e_{i0}}$ 

this is model dependent; in the Poisson case with log-link

 $p_{ix} = P(X_i = x | \beta; \mathbf{z_i}) = \exp(-\mu_i)\mu_i^x / x!,$  with log  $\mu_i = \beta^T \mathbf{z_i}$ 

## M-step for the Poisson case with only person-times

$$p_{ij} = P(X_i = j | \beta; \mathbf{z_i}) = \exp(-\mu_i)\mu_i^j/j!$$

and

$$\mu_i = \exp(\eta + \underbrace{\log P_i}_{\text{log-person-times become offset}})$$

so, here simply

$$\mu_i = \exp(\beta^T \mathbf{z_i}) = \exp(\eta + \log P_i)$$

where  $\eta$  is the log-rate

## alternatives to the EM philosophy

• use the observed, zero-truncated likelihood directly:

$$\prod_{i=1}^{n} \prod_{x=1}^{m} \left( \frac{p_{ix}}{1 - p_{i0}} \right)^{f_{ix}}$$

where  $p_{ix} = P(X_i = x | \beta; \mathbf{z_i})$  as before

- depends on the chosen model (Poisson, geometric, binomial, negative-binomial,...)
- use favorite algorithm such as NR, FS, or GN
- retrieve effect estimate  $\hat{\beta}$

#### population size estimation with Horvitz-Thompson

Horvitz - Thompson estimator

$$\hat{N} = \sum_{i=1}^{N} I_i / w_i$$

where

- *l<sub>i</sub>* is an indicator if the i-th study of the population of target studies is observed
- $w_i = P(I_i = 1) = 1 P(I_i = 0) = 1 p_{i0} = 1 P(X_i = 0 | \hat{\beta}; \mathbf{z_i})$
- under Poisson:  $w_i = 1 \exp(-\mu_i)$  and  $\hat{\mu}_i = \exp(\hat{\beta}^T \mathbf{z}_i)$

so that

$$\hat{N} = \sum_{i=1}^{n} 1/[1 - \exp(\hat{\beta}^{T} \mathbf{z_{i}})]$$

#### study population size estimation

so, in case we have use only person-times as offset

$$\hat{N} = \sum_{i=1}^{n} 1/[1 - \exp(-\exp(\hat{\eta} + \log PT_i))]$$

for the data

$$\hat{N} = \sum_{i=1}^{n} 1/[1 - \exp(\exp(\hat{\eta} + \log PT_i))] = 134$$

total studies with and without completed suicide after bariatric surggery

	Person-years	Weight	# of patients	# of women	# of suicides	Country
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# Table: Linear predictors considered

Linear	Proportion	Country	Interaction	log-person-time
predictor	of women	of origin		as offset
0	No	No	No	No
1	No	No	No	Yes
2	Yes	No	No	Yes
3	No	Yes	No	Yes
4	Yes	Yes	No	Yes
5	Yes	Yes	Yes	Yes

Table: Values of the maximised log-likelihood, number of parameters, and BIC statistic s for models under consideration.

Distribution	LP	Maximised	Number of	BIC
		log-likelihood	parameters	
	5	-22.7	4	58.6
	4	-23.0	3	55.9
Poisson	3	-23.0	2	52.6
	2	-23.4	2	53.4
	1	-23.7	1	50.7
	0	-68.7	1	139.9
	5	-22.7	5	61.9
	4	-23.0	4	59.2
Negative-	3	-23.0	3	55.9
binomial	2	-23.4	3	56.7
	1	-23.7	2	54.0
	0	-38.7	2	84.0

- in principle, we have a population of size N
- for each element *i* we have an indicator *l<sub>i</sub>* telling us if element *i* has been sampled or not

$$t_i = egin{cases} 1, \; ext{if sampled} \ 0, \; ext{otherwise} \end{cases}$$

where *i* = 1, ..., *N* 

- the classical nonparametric bootstrap would then consider random samples with replacement from  $I_1, ..., I_N$
- problem is that we have only observed n out of N
- using the observed sample I<sub>1</sub>,..., I<sub>n</sub> for the bootstrap would underestimate the variability of N
- the idea is to impute N using  $\hat{N}$

Horvitz – Thompson estimator

$$\hat{N} = \sum_{i=1}^{N} I_i / \hat{w}_i$$

where

• 
$$\hat{w}_i = \hat{P}(I_i = 1) = 1 - \hat{P}(I_i = 0)$$

- under Poisson:  $\hat{w}_i = 1 \exp(-\hat{\mu}_i)$  and  $\hat{\mu}_i = \exp(\hat{\beta}^T \mathbf{z}_i)$
- or  $\hat{N} = \sum_{i=1}^{n} 1/[1 \exp(-\exp(\hat{\beta}^T \mathbf{z_i}))]$
- this gives our imputed sample  $I_1, ..., I_n, ..., I_{\hat{N}}$
- note that  $I_{n+1}, ..., I_{\hat{N}}$  are all zero ( $\hat{N}$  needs to be rounded)

finally

- we can consider bootstrap samples  $I_1^*, ... I_{\hat{N}}^*$
- note that there is now variability in the observed sample size *n*
- as all elements in the bootstrap sample with zero counts are truncated, it does not matter that we have *no* covariate information on the truncated counts
- using the zero-truncated bootstrap sample we estimate  $\hat{N}^*$
- this process is repeated B times (B = 25,000 for example)



- median = 133 studies on bariatic surgery with or without completed suicide
- 95% percentile confidence interval: 93 167 (red vertical bars)

- in a similar way a 95% percentile confidence interval for the suicide rate is computed
- 24.84 49.39 per 100,000 person years
- with median rate of 31.86 per 100,000 person years
- for comparison: the unadjusted rate is 44.51 per 100,000 person years

## acknowledgments

- joint work with Layna Dennett and Antony Overstall (University of Southampton)
- a paper version is available at:
- Layna Charlie Dennett, Antony Overstall, Dankmar Böhning (2023): Zero-Truncated Modelling Meta-Analysis for When Studies with No Events Are Systematically Excluded: Estimating Completed Suicide After Bariatric Surgery. https://arxiv.org/abs/2305.01277

## further issues: one-inflation



#### further issues: one-inflation



Figure: The Guardian 30 Dec 2016: "Thousands of drink-drivers offend again"

# drink-driving in Britain

- drink-driving (DD) relates to driving (or attempting to drive) while being above the legal alcohol limit
- according to the Guardian (30/12/16): 219,000 motorist were caught once, 8,068 twice, etc. (see Table below)

Table: Frequency distribution of the count (per person) of DVLA reported drink-driving (DD) in the UK between 2011 and 2015 (figures are based on DR10 endorsements)



Figure: One-inflation distorts the Poisson fit



Figure: One-inflation distorts the Poisson fit

## a synthetic example

- 500 counts sampled from Po(1)
- 500 extra-counts of 1 so that N = 1,000
- $\hat{\lambda} = 0.4091$  and

$$\mathsf{HTE} = \frac{n}{1 - \exp(-\hat{\lambda})} = \frac{824}{1 - \exp(-0.4091)} = 2454$$

Table: one-inflated Poisson data



lambda

- one-inflation leads to  $\hat{\lambda} << \lambda$
- Horvitz-Thompson estimator  $n \frac{1}{1-\exp(-\hat{\lambda})} >> N$
- as  $g(\lambda) = \frac{1}{1 \exp(-\lambda)}$  strictly decreasing

#### two processes

- do not know the size: *zero truncation*
- many counts of ones (singletons): one inflation

this can be modelled as

$$(1-w)I_1(x) + \frac{w}{1-p(0;\theta)}p(x;\theta)$$

The Annals of Applied Statistics 2019, Vol. 13, No. 2, 1198–1211 https://doi.org/10.1214/18-AOAS1232 © Institute of Mathematical Statistics, 2019

#### THE IDENTITY OF THE ZERO-TRUNCATED, ONE-INFLATED LIKELIHOOD AND THE ZERO-ONE-TRUNCATED LIKELIHOOD FOR GENERAL COUNT DENSITIES WITH AN APPLICATION TO DRINK-DRIVING IN BRITAIN

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## GOF in the case study

Table: Frequency distribution for observed and fitted count of completed suicide under zero-truncated Poisson with offset for person-times;  $\chi^2_{(2)} = 1.59$  and p - value = 0.45

count of completed suicide	0	1	2	3	4+
observed frequency $f_{x}$	-	18	3	3	3
fitted frequency $\hat{f}_{x}$	-	18.3	4.5	1.7	2.5



#### how to present fitted frequency for complex model

suppose a model (here for a Poisson with log-link) the has been fitted leading to

 $\hat{\mu}_i = \exp(\hat{\beta}^T \mathbf{z_i})$ 

for unit *i* in the sample, then:

$$\hat{f}_x = \sum_{i=1}^n \exp(-\hat{\mu}_i)\hat{\mu}_i^x/x!$$

Statistical Methods in Medical Research Volume 25, Issue 2, April 2016, Pages 902-916 © The Author(s) 2013, Article Reuse Guidelines https://doi.org/10.1177/0962280212473386



Article

#### The covariate-adjusted frequency plot

Heinz Holling<sup>1</sup>, Walailuck Böhning<sup>1</sup>, Dankmar Böhning<sup>2</sup>, and Anton K Formann<sup>3,†</sup>

### alternative: Bayes

- posterior  $\propto$  likelihood  $\times$  prior
- in our case

$$\pi(\lambda|x_1,\cdots,x_n) \propto \underbrace{\prod_{i} \frac{\exp(-\lambda P_i)}{1-\exp(-\lambda P_i)} (\lambda P_i)^{x_i}}_{ZT-Poisson-likelihood} \times \underbrace{\pi(\lambda)}_{prior}$$

or

$$\pi(\lambda|x_1,\cdots,x_n) = \frac{\prod_i \frac{(\lambda P_i)^{x_i}}{\exp(-\lambda P_i)-1} \times \pi(\lambda)}{\int_{\lambda} \prod_i \frac{(\lambda P_i)^{x_i}}{\exp(-\lambda P_i)-1} \times \pi(\lambda) \ d\lambda}$$

## priors

- non-informative  $\pi(\lambda) = 1$
- 95% CI: 23.14 43.20 per 100,000 person years
- posterior median 31.75 per 100,000 person years
- more interesting are the population sizes
- 95% CI: 103 178 with posterior median of 134 studies



## priors

- non-informative but proper log  $\lambda \sim N(0, 1000^2)$
- 95% CI: 23.47 43.17 per 100,000 person years
- posterior median 31.66 per 100,000 person years
- more interesting the population sizes
- 95% CI: 103 175 with posterior median of 134 studies

•

- for comparison with  $\pi(\lambda) = 1$ :
- 95% CI: 103 178 with posterior median of 134 studies

## priors

- Jeffreys invariance prior  $\pi(\lambda) \propto \sqrt{\text{Fisher information}} = \sqrt{(\sum_i P_i)/\lambda}$
- 95% CI: 104-181 with posterior median of 133 studies
- for comparison with  $\pi(\lambda) = 1$ :
- 95% CI: 103 178 with posterior median of 134 studies





Figure: *left*: Jeffreys invariance prior *right*: non-informative improper prior

#### overview

Table: all methods for estimating the total size of studies in a nutshell

method	median	95% CI
MLE with bootstrap	133	93 - 167
Bayes prior:		
improper non-informative	134	103 - 178
log-normal	134	103 - 175
Jeffreys	133	104 - 181

#### Table: a final point: model (likelihood) assessment is essential

Distribution	LP	BIC	pop size
	5	58.6	125
	4	55.9	119
Poisson	3	52.6	118
	2	53.4	134
	1	50.7	134
	0	139.9	31

#### Table: recall: linear predictors considered

Linear predictor	Proportion of women	Country of origin	Interaction	log-person-time as offset
0	No	No	No	No
1	No	No	No	Yes
2	Yes	No	No	Yes
3	No	Yes	No	Yes
4	Yes	Yes	No	Yes
5	Yes	Yes	Yes	Yes

