



Methodological aspects in the analysis of adverse events in time-to-event data

Regina Stegherr¹, Jan Beyersmann¹, Claudia Schmoor², Michael Luebbert³,
Tim Friede⁴

¹Institute of Statistics, Ulm University;

²Clinical Trials Unit, Faculty of Medicine and Medical Center, University of Freiburg, Freiburg, Germany

³Hematology, Oncology, and Stem-Cell Transplantation, Faculty of Medicine and Medical Center, University of Freiburg, Freiburg, Germany

⁴Department of Medical Statistics, University Medical Center Göttingen, Göttingen, Germany

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regina.stegherr@uni-ulm.de

Background: Safety Analyses

- Safety in terms of adverse events (AEs) is a relevant aspect of risk-benefit assessment of therapies (Unkel et al. 2018)
- Probability of an AE often estimated by **(incidence) proportion**
- But:
 - **Varying follow-up times** and **censoring** present
 - Incidence proportion leads to **underestimation**
- **Incidence density** (incidence rate) (Bender et al. 2016): **constant hazards** assumption (Kraemer, 2009), does not estimate AE probability
- Non-parametric **Kaplan-Meier** estimator of AE probability accounts for censoring
- But:
 - **Competing events** (death, progression,...) present (Allignol et al. 2016)
 - Parametric estimator based on incidence density and non-parametric Kaplan-Meier estimator both lead to **overestimation**
- Non-parametric **Aalen-Johansen** estimator is an unbiased estimator of the AE probability
- Parametric estimator of the AE probability can be constructed from the AE and competing events (CE) hazards under constant hazard assumption

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In this presentation

We aim to

- compare the different estimators quantifying the adverse event probability to the gold standard Aalen-Johansen estimator
- compare different methods for obtaining the variances of the estimators
- compare them not only at the maximal event time but also at two specific quantiles of the observed times as these variances may be large at the end of follow-up
- investigate the relative importance of the following three sources of bias:
 - censoring
 - competing events
 - model misspecifications

to answer the following questions

- (1) Is ignoring competing events worse than misspecifying the model (falsely assuming constant hazards)?
- (2) How appropriate is the use of the incidence proportion to quantify the AE risk?

Estimating the AE probability at follow-up time point τ

Consider the situation of a clinical trial comparing two treatments A and B

- Incidence proportion: $IP_A = \frac{\# \text{ AE in } [0, \tau] \text{ in group A}}{\# \text{ of patients in group A}}$
- Incidence density: $ID_A(\tau) = \frac{\# \text{ AE in } [0, \tau] \text{ in group A}}{\text{patient-time at risk in group A (restricted by } \tau)}$
Probability Transform (1-Kaplan-Meier like): $1 - \exp(-ID_A(\tau) \cdot \tau)$
- 1 - Kaplan-Meier: also censors competing event
- Aalen-Johansen estimator (Gold standard):
$$CIF_A(\tau) = \sum_{u \in (0, \tau]} \prod_{v \in (0, u)} \left(1 - \Delta \hat{\Lambda}_A(v) - \Delta \hat{\Lambda}_B(v) \right) \Delta \hat{\Lambda}_A(u)$$
- Probability transform of incidence density accounting for competing events (Aalen-Johansen like): $\frac{ID_A(\tau)}{ID_A(\tau) + \overline{ID}_A(\tau)} \left(1 - \exp(-\tau \cdot [ID_A(\tau) + \overline{ID}_A(\tau)]) \right)$
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- Probability transform of incidence density accounting for competing events

$$\text{(Aalen-Johansen like): } \frac{ID_A(\tau)}{ID_A(\tau) + \overline{ID}_A(\tau)} \left(1 - \exp(-\tau \cdot [ID_A(\tau) + \overline{ID}_A(\tau)]) \right)$$

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Variances of estimators

Model based variances:

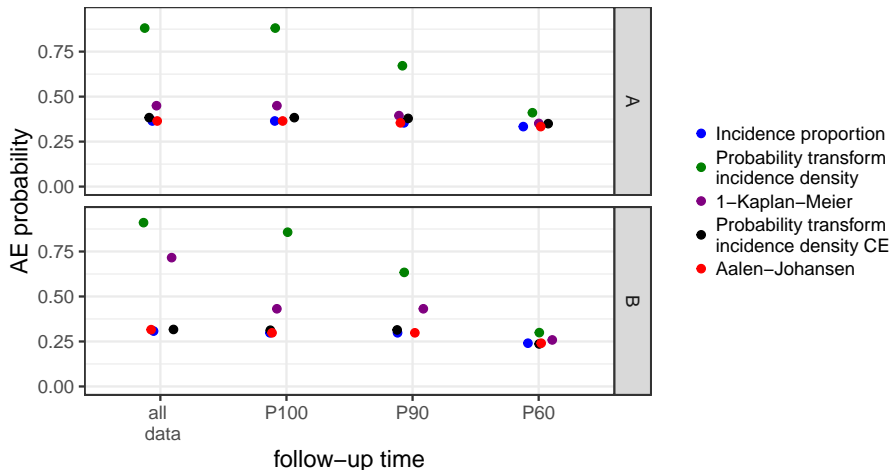
- Incidence proportion: $\hat{s}_A^2 = (\text{IP}_A(\tau) \cdot (1 - \text{IP}_A(\tau))) / n_A$
- Probability transform incidence density: (similar to KM)
 $\hat{s}_A^2 = \tau^2 \cdot \exp(-\tau \cdot \text{ID}_A(\tau))^2 \cdot \widehat{\text{var}}(\text{ID}_A(\tau))$
- 1- Kaplan-Meier: Greenwood variance estimator
- Aalen-Johansen estimator: Greenwood-type variance estimator (Allignol et al. 2010)
- Probability transform incidence density accounting for competing events:
 Using $\widehat{\text{var}}(\text{ID}_A(\tau)) = \frac{\# \text{ AE in } [0, \tau] \text{ in group A}}{(\text{patient-time at risk in group A (restricted by } \tau))^2}$
 and $\widehat{\text{var}}(\overline{\text{ID}}_A(\tau))$ analogous and apply delta-method

Alternative: Use bootstrap to obtain empirical variances as there may be problems for the variances of the parametric estimators (Hjort, 1992)

Varying follow-up times

- Incidence proportion usually only calculated at the end of follow-up (does not account for censoring)
 - Evaluate estimators at end of follow-up (all data) in each group
- To account for different follow-up in groups A and B:
 - Evaluate estimators at $\tau = \min(\tau_A, \tau_B)$ (P100), with τ_A and τ_B largest observed event time in group A and B, respectively
- As estimators (e.g. Kaplan-Meier) at the end of follow-up may have larger variability due to small numbers still at risk (Pocock et al. 2002):
 - Evaluate estimators at earlier time point when more patients are still at risk
 - Evaluate estimators at $\tilde{\tau} = \min(\tilde{\tau}_A, \tilde{\tau}_B)$, with $\tilde{\tau}_A(p)$ and $\tilde{\tau}_B(p)$ defined as event time when $p \cdot 100\%$ of all patients in group A and group B, respectively, are still at risk, e.g., $p = 0.9$ (P90) and $p = 0.6$ (P60)

Example - Oncology trial (hardly any censoring)



- Probability transform incidence density and 1-Kaplan-Meier overestimate
- Incidence proportion, probability transform incidence Density accounting for CE and Aalen-Johansen close

Example - Oncology trial

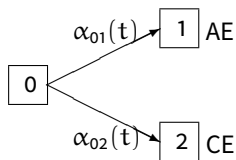
Variances of different estimates at "all data" and P60

FU time	estimator	model based variance A	Bootstrap variance A	model based variance B	Bootstrap variance B
all data	Incidence proportion	0.0024	0.0025	0.0020	0.0019
all data	Probability transform incidence density	0.0018	0.0036	0.0014	0.0034
all data	1-Kaplan-Meier	0.0054	0.0060	0.0419	0.0509
all data	Probability transform incidence density CE	0.0026	0.0026	0.0021	0.0020
all data	Aalen-Johansen	0.0024	0.0025	0.0022	0.0020
P60	Incidence proportion	0.0023	0.0022	0.0018	0.0016
P60	Probability transform incidence density	0.0030	0.0032	0.0025	0.0023
P60	1-Kaplan-Meier	0.0026	0.0024	0.0021	0.0018
P60	Probability transform incidence density CE	0.0024	0.0027	0.0017	0.0017
P60	Aalen-Johansen	0.0023	0.0022	0.0018	0.0016

Simulations

Investigate the effect of

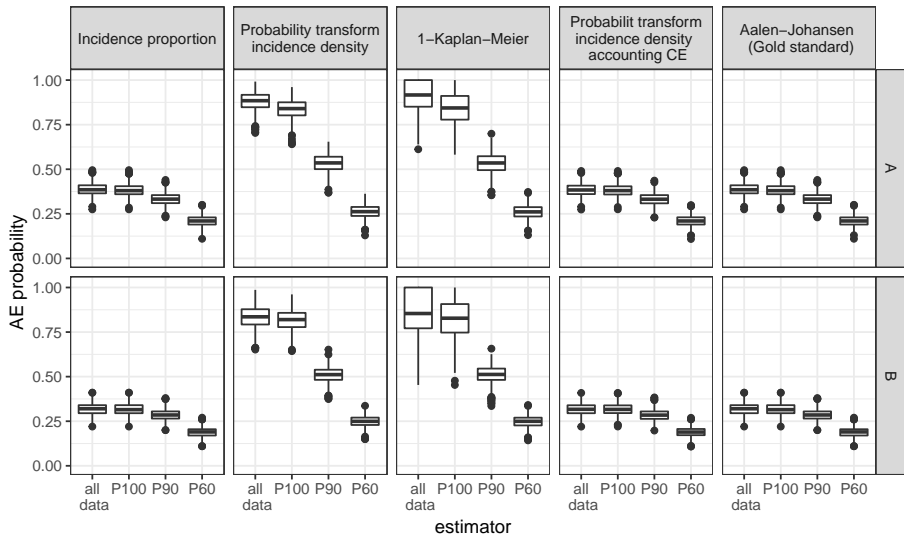
1. constant vs non-constant hazards
2. censoring vs no censoring



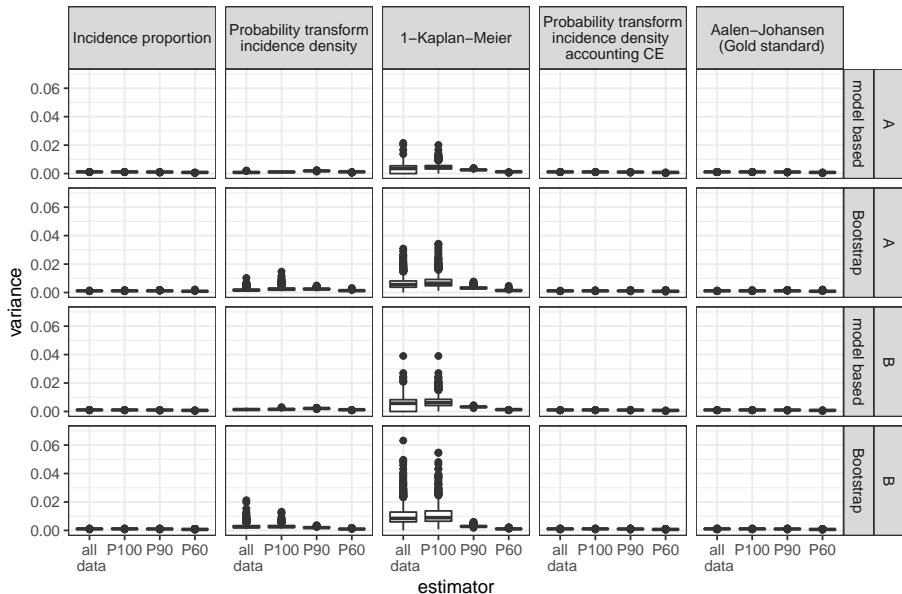
by simulating $N = 1000$ datasets of the following scenarios with parameter chosen similar to the data example

Scenario	$\alpha_{01}^A(t)$	$\alpha_{02}^A(t)$	$\alpha_{01}^B(t)$	$\alpha_{02}^B(t)$	$n_A = n_B$	censoring
(1) constant	0.00265	0.0424	0.00246	0.0530	200	no
(2) constant	0.00265	0.0424	0.00246	0.0530	400	25%
(3) time-dependent	$\frac{1}{2}t$	$\frac{1.8}{t+2}$	$\frac{1}{8}t$	$\frac{1.8}{t+2}$	400	20%

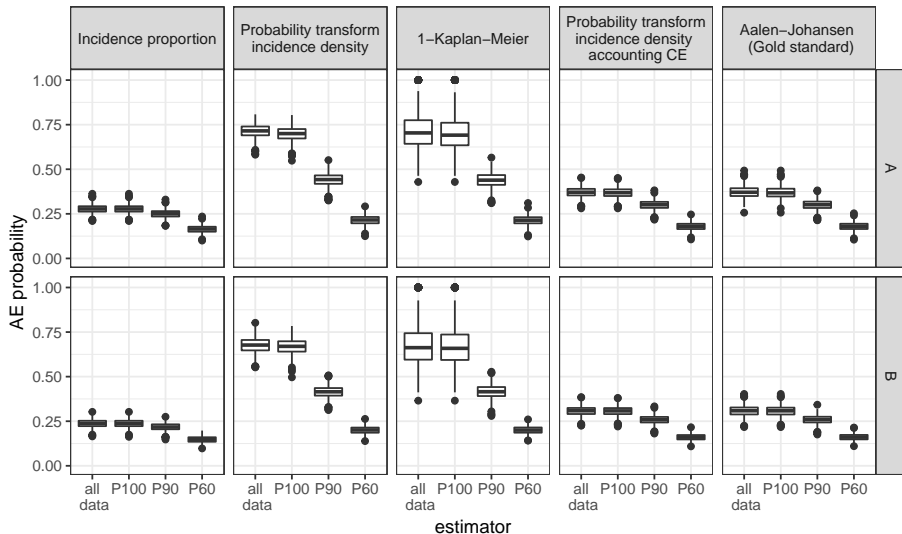
Scenario 1: constant hazards, no censoring



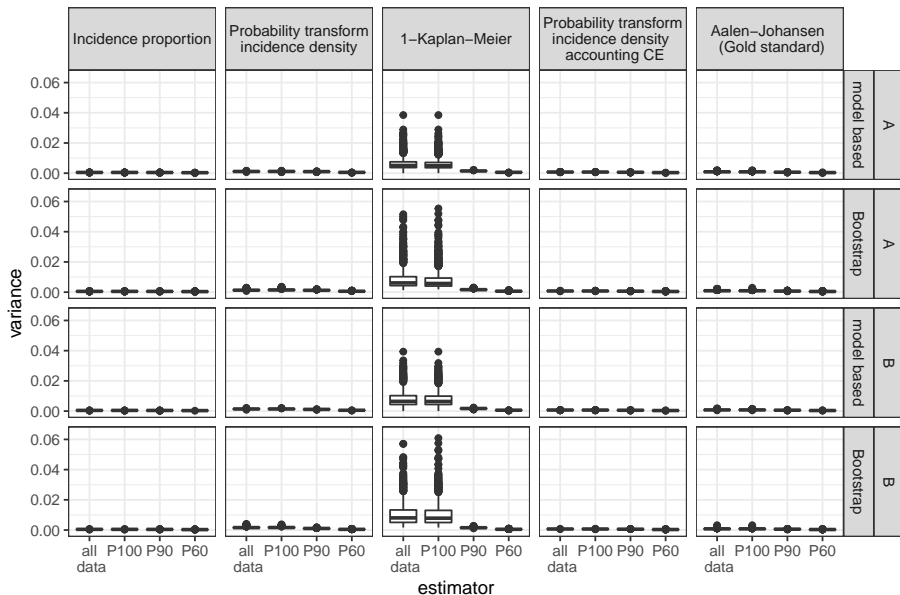
Scenario 1: constant hazards, no censoring



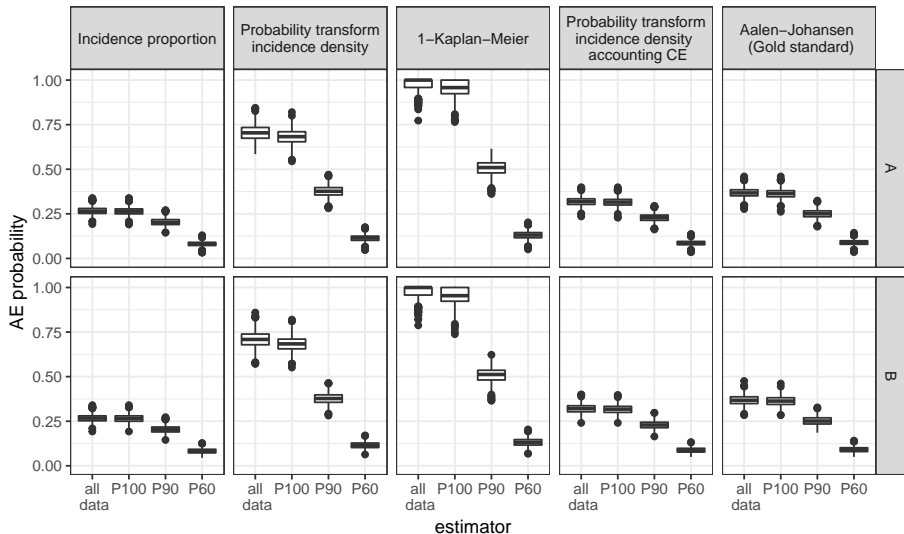
Scenario 2: constant hazards, with censoring



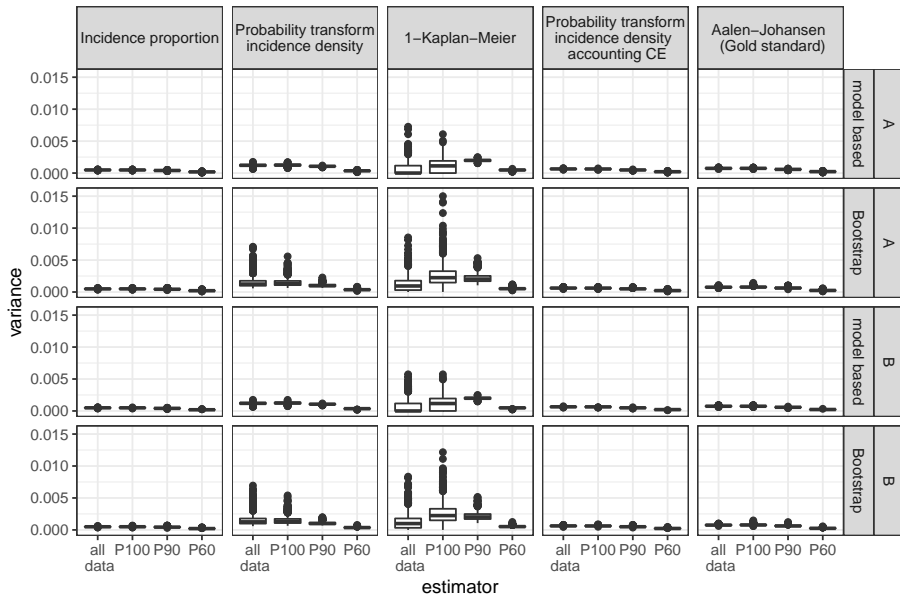
Scenario 2: constant hazards, with censoring



Scenario 3: time-dependent hazards, with censoring



Scenario 3: time-dependent hazards, with censoring



Simulations: Summary

- Probability transform of incidence density and 1-Kaplan-Meier overestimate AE probability (Scenario 1,2,3)
- Incidence proportion underestimates in censored scenarios (Scenario 2,3)
- Here, incidence density accounting for competing events slightly underestimates compared to Aalen-Johansen estimator (Scenario 3)
- Bootstrapped variances of incidence density and 1-Kaplan-Meier with outliers in absence of censoring (Scenario 1)
- Variance of non-parametric estimators comparable to the one of parametric estimators in absence of censoring; With censoring slightly increased variance for non-parametric estimator (Scenario 1,2)

Discussion

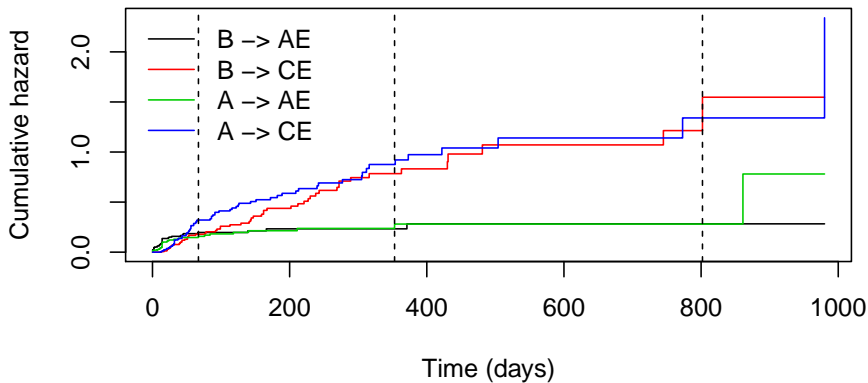
- (1) Ignoring competing events more of a problem than model misspecifications (falsely assuming constant hazards)
- (2) Incidence proportion underestimates in presence of censoring
 - Only small differences in AE probability estimators for evaluation at 60% quantile
 - Ongoing and future analyses: Rare AEs, frequency categories, different constellations of time-varying hazards, group comparisons, estimators of hazard ratio, ...
 - Survival analysis for Adverse events with Varying follow-up times - SAVVY project (academic and pharmaceutical): Aim to improve guidelines on reporting the incidence of adverse events with varying follow-up times - Empirical study including randomized controlled clinical trials from several companies and summarizing the results via meta-analysis

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Back-Up: Example - Oncology trial

Cumulative hazards



Back-Up: Example - Oncology trial

Variances at P100

FU time	estimator	model based variance A	Bootstrap variance A	model based variance B	Bootstrap variance B
P100	Incidence prop	0.0024	0.0025	0.0020	0.0019
P100	Incidence dens	0.0018	0.0041	0.0025	0.0045
P100	1-Kaplan-Meier	0.0054	0.0060	0.0062	0.0067
P100	Incidence dens CE	0.0026	0.0027	0.0022	0.0021
P100	Aalen-Johansen	0.0024	0.0025	0.0020	0.0019

Back-Up

Simulations - Scenario 3 - Hazard plot

black: time-dep (weibull) for AE in A

blue: time-dep (weibull) for AE in B

red: time-dep for CE in both

