

# Statistical Issues in the Analysis of Adverse Events in Time-To-Event Data

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Talk based on

- A. Allignol, J. Beyersmann, C. Schmoor, Statistical Issues in the Analysis of Adverse Events in Time-To-Event Data, *Pharm Stat* 2016 (online)

# Introduction

- The analysis of safety in terms of adverse events (AE) is relevant in almost all clinical trials
- In general, AEs can occur at any point in time during the patients' time under observation
- Often, inadequate methods are used for the analysis. They do not take the time-to-event structure of these data into account  
E.g., one might see more AEs, because treatment successfully prolongs survival

## Aim of this talk

Explain and illustrate basic concepts of the correct analysis of AEs in patients with different/incomplete observation times

# Introduction

- The proportion of adverse events is usually estimated by

$$\frac{\#AE}{n},$$

#AE the number of patients with the interesting AE and n the sample size

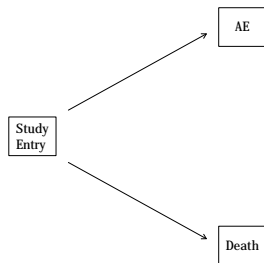
- This is usually the quantity that is reported, irrespective of how complete the data are
- **If** the data are complete, #AE/n is the right estimate for  $P(AE)$

# (Time to) First AE or Death, Whatever Comes First

## No Censoring

### Simplified situation:

- (Time to) first AE or death without prior AE, whatever comes first
- We consider AEs of a certain kind, such that  $\#AE \leq n$
- Complete data, i.e., no censoring
- $\frac{\#AE}{n}$  is the right estimate of  $P(AE)$  if the data are complete
- Introduce time  $t$  (still complete data)



$$\hat{P}(AE \text{ in } [0, t]) = \frac{\#AE \text{ in } [0, t]}{n}$$

# (Time to) First AE or Death, Whatever Comes First

## No Censoring

### Simplified situation:

- Patients may die without experiencing an AE
- Death is a competing event (competing risk) for AE — after death the AE cannot occur anymore
- Probability to experience the composite event (AE or death without prior AE, whatever comes first)

$$\begin{aligned} & \hat{P}(\text{AE} \in [0, t]) + \hat{P}(\text{Death w/o prior AE in } [0, t]) \\ &= \frac{\# \text{ AE or death (whatever comes first) in } [0, t]}{n} \\ &= 1 - \hat{P}(T > t) \end{aligned}$$

T time to first AE or death whatever comes first

# (Time to) First AE or Death, Whatever Comes First

## With Censoring

### Situation with incomplete data (censoring)

- **Numerators unknown:** # AE or death (whatever comes first) in  $[0, t]$
- $\hat{P}(T > t)$  is estimated by the Kaplan-Meier estimator

$$\hat{P}_{KM}(T > t) = \prod_{u < t} \left( 1 - \frac{\# \text{observed composite events at } u}{\# \text{under observation and no event before } u} \right)$$

The Kaplan-Meier estimator is meant to approximate

$$1 - \frac{\# \text{AE or death (whatever comes first) in } [0, t]}{n}$$

- Without censoring, both are equal
- N.B.: 1 - Kaplan-Meier approximates an empirical distribution function. Which approaches 1. I.e.,  $P(T < \infty) = 1$

# (Time to) First AE or Death, Whatever Comes First

## With Censoring

**Question:** How do we estimate  $\hat{P}(\text{AE} \in [0, t])$ ?

### Simple proportions

- Simple proportions should not be used because they are biased, e.g.,

$$\frac{\# \text{observed AEs in } [0, t]}{n}$$

estimates  $P(\text{AE in } [0, t] | T \leq \text{observation time})$ , which is not relevant

# (Time to) First AE or Death, Whatever Comes First

## With Censoring

**Question:** How do we estimate  $\hat{P}(AE \in [0, t])$ ?

### **Kaplan-Meier estimator censoring the competing event**

- Often the Kaplan-Meier estimator is used for estimation of  $P(AE \text{ in } [0, t])$  by treating death without prior AE as censored observation.
- 1 - Kaplan-Meier approximates a distribution function, i.e.,

$$1 - \text{Kaplan-Meier} \rightarrow 1,$$

but  $P(AE) + P(\text{Death w/o prior AE}) \rightarrow 1$

- Thus using Kaplan-Meier to approximate  $P(AE \text{ in } [0, t])$  overestimates



# (Time to) First AE or Death, Whatever Comes First

## With Censoring

**Question:** How do we estimate  $\hat{P}(\text{AE} \in [0, t])$ ?

### **Aalen-Johansen estimator of the cumulative incidence function (CIF)**

- The Aalen-Johansen estimator of CIF for estimating the probability of event is the correct method when competing events are present

# Cumulative Incidence Function

The CIF of AE,  $P(T \leq t, \text{AE})$  is the expected proportion of patients experiencing an AE over the course of time

- $1 - \hat{P}(T > t)$  is the probability to experience the composite event (AE or death w/o prior AE) in  $[0, t]$
- One can show that

$$1 - \hat{P}(T > t) = \sum_u \hat{P}(T > u-) \cdot \frac{\# \text{ AE or death at } u}{\# \text{ under observation just before } u}$$

with  $\hat{P}(T > u-)$  the Kaplan-Meier estimator evaluated just before time  $u$

# Cumulative Incidence Function

The CIF of AE,  $P(T \leq t, \text{AE})$  is the expected proportion of patients experiencing an AE over the course of time

- Aalen-Johansen estimator of the CIF: Same estimator, but counting only AE as event

$$\hat{P}(T \leq t | \text{AE}) = \sum_u \hat{P}(T > u-) \cdot \frac{\text{\# AE at } u}{\text{\# under observation just before } u},$$

- $\hat{P}(T \leq t | \text{AE})$  equals  $\frac{\text{\#AE in } [0, t]}{n}$  in the absence of censoring
- Note that

$$1 - \text{Kaplan-Meier of all events} = \text{CIF AE} + \text{CIF death}$$

# Illustration

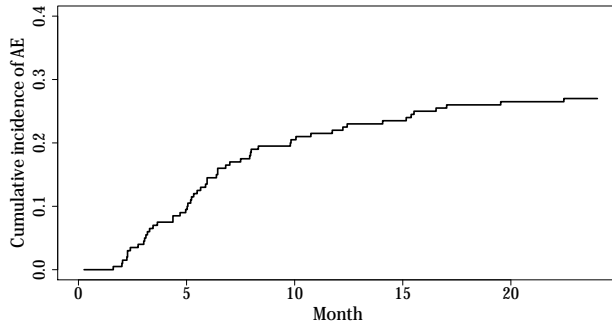
- Data of 200 patients with complete follow-up of 2 years for all patients
- We are interested in a specific type of AE
- Patients can die before the AE occurs
- At the end of the follow-up
  - 54 patients with AE
  - 48 deaths without prior AEwere observed

$$\frac{54}{200} = 0.27$$

# Illustration

Example with complete follow-up of 2 years for all patients (no censoring)

Recall:  $\frac{\#AE}{n} = 0.27$

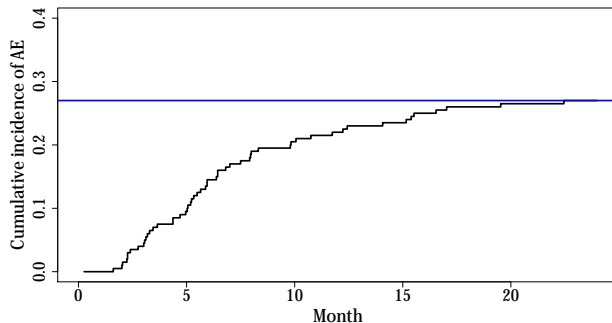


Cumulative incidence of AE is **0.27** at the plateau

# Illustration

Example with complete follow-up of 2 years for all patients (no censoring)

Recall:  $\frac{\#AE}{n} = 0.27$

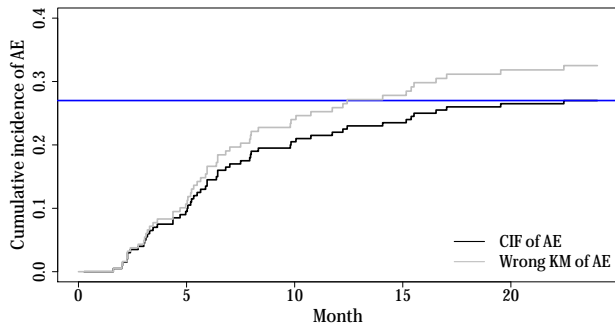


Cumulative incidence of AE is **0.27** at the plateau

## Illustration: Don't use Kaplan-Meier

Example with complete follow-up of 2 years for all patients (no censoring)

Recall:  $\frac{\#AE}{n} = 0.27$

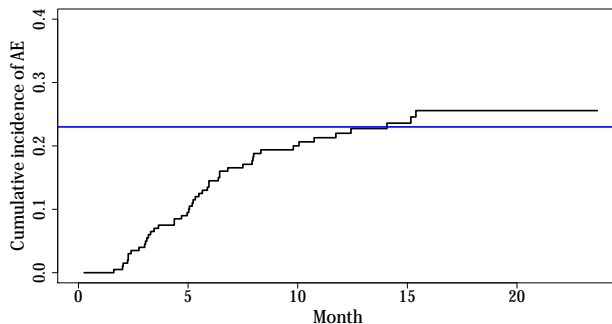


Cumulative incidence of AE is **0.27** at the plateau

# Illustration

## Example with **artificial censoring**

$$\frac{\#AE}{n} = \frac{46}{200} = 0.23; 42 \text{ deaths}$$



Cumulative incidence of AE is **0.26** at the plateau

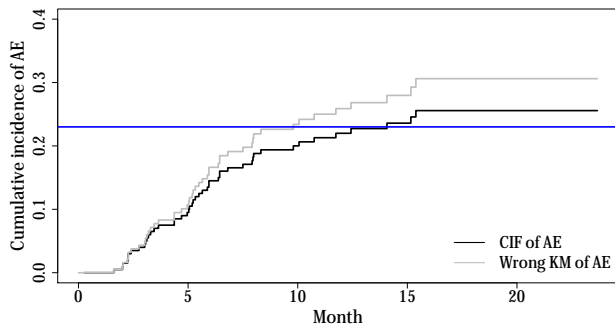
Using simple proportions to estimate  $P(\text{AE in } [0, t])$  leads to underestimation



# Illustration

## Example with **artificial censoring**

$$\frac{\#AE}{n} = \frac{46}{200} = 0.23; 42 \text{ deaths}$$



Cumulative incidence of AE is **0.26** at the plateau

Using the Kaplan-Meier estimator to estimate  $P(\text{AE in } [0, t])$  leads to overestimation

# Everything is Based on Hazards

- The Kaplan-Meier estimator is based on estimates of the hazard  $\alpha(t)dt$

$$\frac{\# \text{ Composite event at } t}{\# \text{ under observation at } t^-},$$

- which decomposes into

$$\frac{\# \text{ AE at } t}{\# \text{ under observation at } t^-} + \frac{\# \text{ Death at } t}{\# \text{ under observation at } t^-}$$

- Motivates the Nelson-Aalen estimator of the cumulative hazard  $\int_0^t \alpha(u)du$ , e.g., of AE

$$\sum_u \frac{\# \text{ AE at } u}{\# \text{ under observation at } u^-}$$

## Censoring by a Competing Event

- Censoring by a competing event is a subtle issue
- I.e., the Nelson-Aalen estimator of the cumulative hazard of AE is

$$\sum_u \frac{\# \text{ AE at } u}{\# \text{ under observation at } u-}$$

Only AE events are “counted”

- One way to do that **in practice** is to censor the competing event, e.g., death
- **However**, we can’t “censor away” when computing probabilities

$$\hat{P}(T \leq t | \text{AE}) = \sum_u \hat{P}(T > u-) \cdot \frac{\# \text{ AE at } u}{\# \text{ under observation just before } u}$$

## Comparison of (Treatment) Groups

- Cox model for composite event,  $\alpha(t|Z) = \alpha_0(t) \exp(\beta Z)$ , when comparing groups  $Z = 0$  and  $Z = 1$
- Cox model for **AE**

$$\alpha_{\text{AE}}(t|Z) = \alpha_{\text{AE};0}(t) \exp(\beta_{\text{AE}}Z)$$

For comparison of (treatment) groups with respect to AE-hazard:

Hazard ratio ( $Z = 1$  vs  $Z = 0$ ) =  $\exp(\beta_{\text{AE}})$

- Counts only AEs  $\rightarrow$  censor death events
  - In perfect analogy to the Nelson-Aalen estimator
- **However** the picture is complete only by looking at all the sides, i.e.,

$$\alpha_{\text{death}}(t|Z) = \alpha_{\text{death};0}(t) \exp(\beta_{\text{death}}Z)$$

For comparison of (treatment) groups with respect to Death-hazard:

Hazard ratio ( $Z = 1$  vs  $Z = 0$ ) =  $\exp(\beta_{\text{death}})$

## The Fine and Gray Model

**Aim:** One model that directly compares (treatment) groups with respect to AE probability instead of the event-specific hazard

- Instead of the event-specific hazard of, e.g., AE

$$\frac{\# \text{ AE at } u}{\# \text{ patients not censored and w/o AE or death at } u-}$$

- Consider the subdistribution hazard

$$\frac{\# \text{ AE at } u}{\# \text{ patients not censored and w/o AE at } u-}$$

- Fine and Gray model  $\Leftrightarrow$  Cox-type model for the subdistribution hazard
- Subdistribution hazard constructed such that

$$1 - \exp\left(\int \text{subdistribution hazard of AE}\right) = \text{CIF of AE}$$

→ Results directly interpretable in terms of the CIF of AE

# Discussion

- While analysing AEs in time to event data, simple proportions should not be used
- AEs are always subject to competing risks, i.e., the occurrence of a certain AE may be precluded by the main outcome of interest or another fatal AE
- Common survival techniques for hazards that censor the competing event are still valid, but incomplete analyses
- The competing event should also be subject to such an analysis
- Incidence rate (density) of AE equivalent to considering  $\alpha_{AE}(t) \equiv \alpha_{AE}$ . Same considerations about the analysis of the competing event apply
- Common survival techniques for probability estimation with Kaplan-Meier that censor the competing event are **not** valid

# Discussion

## Comparison of (Treatment) Groups

- Comparison of event-specific hazards reflects direct effect of treatment on instantaneous (daily) AE risk
  - The competing event should also be subject to such an analysis
- Comparison of the *subdistribution hazards* results in a comparison of (treatment) groups with respect to CIF
  - “Summary” analysis
  - Guidelines for competing risks analysis: Study of **both** event-specific hazards **and** subdistribution hazard of the event of interest (AE)

## Censoring by a competing event is

- **Independent** in the sense that it retains the form of the competing process intensity
- **Informative** as it impacts probabilities





# Incidence Density

## Illustration with artificial censoring

- Incidence density (ID) of AE

$$\frac{\#AE}{\text{Population time at risk}'}$$

equivalent to considering  $\alpha_{AE}(t) \equiv \alpha_{AE}$

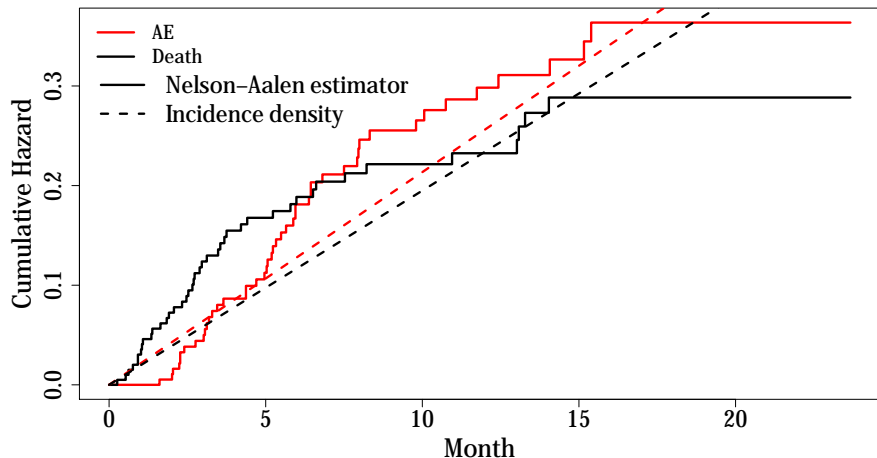
- Not so bad if incidence density of the competing event is also analysed
- E.g., with complete data

$$\frac{\text{ID AE}}{\text{All-cause ID}} = \frac{\#AE/\text{Population time at risk}}{(\#AE + \#Deaths)/\text{Population time at risk}} = \frac{\#AE}{n}$$

assuming constant hazards

# Incidence Density

## Illustration with artificial censoring



# Incidence Density

## Illustration with artificial censoring

