Clinical trial design based on a multistate model that jointly models progression-free and overall survival

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Who

Meller et al. (2019):







Erdmann et al. (2023):







Power gains through exploiting correlations:

Group-sequential designs: over time.

Enrichment designs: over nested subpopulations.

Goal:

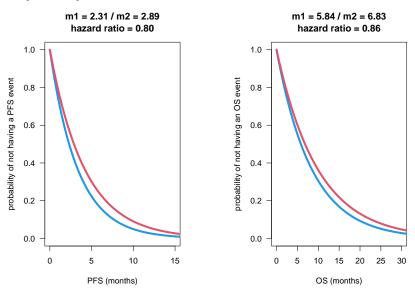
design trial with PFS and OS

Co-primary (win both) or multiple (win ≥ 1)

Typical approach:

- 1) Split significance level
- 2) PFS: exponential, plan GSD
- 3) OS: exponential (or NPH), plan GSD, align OS interim with PFS final

Example: exponential for PFS and OS



Compute necessary #events based on α -split and GSD assumptions.

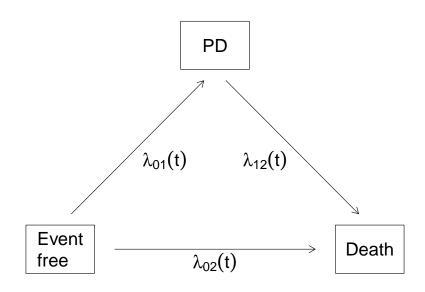
Why is this not necessarily optimal?

- 1) Ignores cor(PFS, OS).
- 2) PFS + OS both involve death ⇒ OS not independent from PFS!
 - 3) OS cannot be PH.

How can we fix that?

PFS and OS are connected through illness-death model.

Canonical extension of survival analysis



Illness-death multistate model for PFS and OS

Transition probabilities to move from state l at time s to state m at time t:

$$P_{lm}(s,t) := P(X(t) = m|X(s) = l, \text{history}).$$

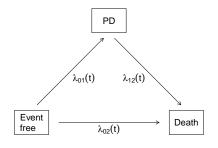
If X(t) non-Markov: P_{11} and P_{12} depend on **PFS time** t_1 .

Estimate P_{lm} 's nonparametrically by Aalen-Johansen estimator.

Illness-death model w/o recovery, P_{lm} as functions of transition intensities, Aalen et al. (2008):

$$\begin{split} P_{00}(s,t) &=& \exp\left(-\int_s^t \lambda_{01}(u) + \lambda_{02}(u) \; \mathrm{d}u\right), \\ P_{11}(s,t;\mathbf{t_1}) &=& \exp\left(-\int_s^t \lambda_{12}(u;\mathbf{t_1}) \; \mathrm{d}u\right), \\ P_{22}(s,t) &=& 1, \\ P_{01}(s,t) &=& \int_s^t P_{00}(s,u_-)\lambda_{01}(u)P_{11}(u,t;u) \; \mathrm{d}u, \\ P_{12}(s,t;\mathbf{t_1}) &=& 1-P_{11}(s,t;\mathbf{t_1}), \\ P_{02}(s,t) &=& 1-\left(P_{00}(s,t) + P_{01}(s,t)\right). \end{split}$$

Illness-death model for PFS and OS



PFS: waiting time in initial state 0, PFS = $\inf\{t : X(t) \neq 0\}$.

$$S_{PFS}(t) = P(PFS > t) = P_{00}(0, t).$$

OS: time until reaching state 2, $OS = \inf\{t : X(t) = 2\}$.

$$S_{OS}(t) = P(OS > t) = P_{00}(0, t) + P_{01}(0, t).$$

(Non-)Proportional hazards

Induced survival functions

Meller et al. (2019):

$$S_{PFS}(t) = P(PFS > t) = P_{00}(0, t),$$

 $S_{OS}(t) = P(OS > t) = S_{PFS}(t) + P_{01}(0, t).$

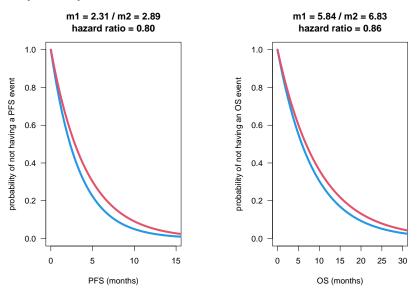
Assume constant transition hazards:

$$\begin{split} S_{PFS}(t) &=& \exp\Bigl(-(\lambda_{01}+\lambda_{02})t\Bigr), \\ S_{OS}(t) &=& \frac{S_{PFS}(t)}{\lambda_{012}}\Bigl(\lambda_{12}-\lambda_{02}-\lambda_{01}\exp(-\lambda_{012}t)\Bigr) \end{split}$$

with abbreviation $\lambda_{012} := \lambda_{12} - \lambda_{01} - \lambda_{02}$.

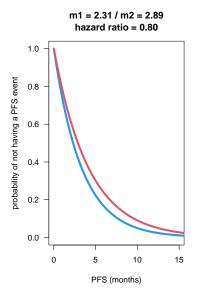
Hazard functions via h(t) = -S'(t)/S(t).

Example: exponential for PFS and OS

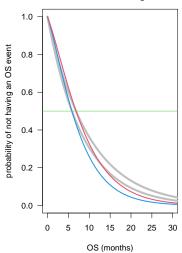


Compute necessary #events based on α -split and GSD assumptions.

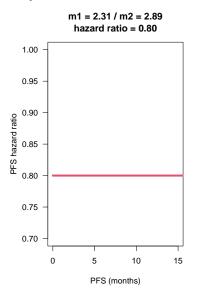
Example: median-matching survival functions induced by IDM



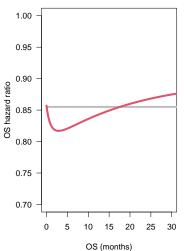
m1 = 5.84 / m2 = 6.83 hazard ratio = 0.86 / average HR = 0.83



Example: hazard ratio as function of time - mind y-axis!



m1 = 5.84 / m2 = 6.83hazard ratio = 0.86 / average HR = 0.83



Proportional hazards for OS

PH for PFS for time-homogeneous transition hazards.

Hazard ratio for OS:

$$h_{OS}(t) = \frac{(\lambda_{12} - \lambda_{02})(\lambda_{01} + \lambda_{02}) - \lambda_{01}\lambda_{12} \exp(-\lambda_{012}t)}{(\lambda_{12} - \lambda_{02}) - \lambda_{01} \exp(-\lambda_{012}t)}.$$

$$\theta_{OS}(t) = h_{OS,A}(t)/h_{OS,B}(t).$$

When is $\theta_{OS}(t)$ independent of t?

- $\lambda_{12} = \lambda_{02}$ in both groups: progression has no impact on death hazard.
- $\lambda_{01} = 0$ in both groups: no progression occurs.
- $\lambda_{012} := \lambda_{12} \lambda_{01} \lambda_{02} = 0$: denominator of h_{OS} equal to 0.

Assumption that we have PH for PFS AND OS unrealistic to hold in real clinical trial.

Clinical trial design via simulation from IDM

Clinical trial planning

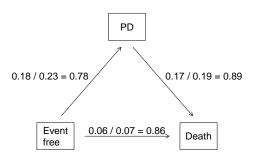
- Type I error: P(reject at least one H_0 irrespective of which are true).
- Power: assume $\geq 1~H_1$ is true:
 - Endpoint-specific: P(reject H_0) for each endpoint separately.
 - At least: P(reject $> 1 H_0$ of PFS and OS).
 - Joint: P(reject both H₀ for PFS and OS).

Clinical trial design

Design feature	Standard approach	Illness-death model
Assumptions to	Control medians and hazard	Transition-specific hazards
make	ratios for PFS and OS	
#quantities	4	6
Cor(PFS, OS)	Not exploited	Explicitly modelled through
		IDM
Proportional	Assumed for OS, although not	NPH properly induced through
hazards	met	IDM
α allocation	Bonferroni	Bonferroni
Number of	Schoenfeld's formula	Tune through simulation
events		
Power	Disjoint per endpoint	Any type of power

Simulation of PFS - OS

Scenario 4



Features:

- Drug effect on all transitions.
- PFS HR = 0.8.
- Average hazard ratio for OS: 0.832.

How to plan a trial?

Co-primary endpoints PFS and OS, one analysis each

Global significance level: 0.05.

Design feature	PFS	os	
Local significance level	0.01	0.04	
Critical value	2.576	2.054	
Hazard ratio	0.80	0.832 (AHR)	
Power	80%	80%	
Events using Schoenfeld	939	992	
Simulate from IDM under H ₀	Empirical type I error: 0.0499		
Joint power of Schoenfeld sample size with	Joint power: 0.708		
these critical values			
Tune number of events to get	939	905	
endpoint-specific power of 80%			
Empirical power per endpoint	0.797	0.801	
Empirical joint power	Joint power: 0.686		

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Before you ask...

...let me make a few comments

NPH for OS: should we use something else than logrank test and hazard ratio?

Hypothesis test and effect quantification independent of MSM.

What is role of the Markov assumption?

- Markov assumption: probability of future transition only depends on (i) state currently occupied and (ii) time t.
- If violated: individual transition hazards random quantities through dependence on history.
- S_{PFS} , S_{OS} : estimation straightforward even if X non-Markov.
- Meller et al. (2019): joint distribution of PFS and OS for non-Markov. Can be leveraged.

...let me make a few comments

Do we always gain power for OS? No!

Power for OS depends on:

- Knowledge of PFS to "predict" OS.
- Induced shape of survival functions. Relative effect can be smaller than, e.g., that of median-matching exponential survival functions.

Interim analysis for OS: see paper.

Does the IDM approach make some "regulatory-incompatible" assumptions?

- In our opinion not at all.
- Need to assume 6 transition-specific hazards. Maybe more uncommon to inform, but conceptually no different from PFS / OS medians.
- Current approach: assumes PH for OS ⇒ we know can't be true!
- + Markov.

Conclusions

Conclusions and outlook

Conclusions:

- Illness-death model for PFS and OS:
 - Properly account for induced hazard ratio as a function of time, $\theta_{OS}(t)$, for OS.
 - Exploit correlation between PFS and OS.
- Sample size for OS might decrease or increase!
- Proper simulation of PFS and OS on patient-level.

Outlook:

- Broadly applicable: surrogacy, interim decisions based on PFS, OS prediction, ...
- Combine subpopulation + illness-death model for PFS OS. Tira trials.
- Extendable to more states, Beyer et al. (2020).

Resources

Resources:

- Meller et al., Meller et al. (2019).
- Paper on arxiv.
- Package simIDM on github and CRAN. Exponential, Weibull, piecewise exponential transition hazards.
- Linkedin post.
- Further MSM resources:
 - Beyer et al. on use of MSMs for early-phase decision-making, Beyer et al. (2020).
 - MS example.
 - Material of BBS seminar "Competing Risks and Multi-State Models".
 - oncomsm: R package by Boehringer colleagues, "Bayesian Multi-State Models for Early Oncology".

Slides can be downloaded on www.kasparrufibach.ch.

Thank you for your attention.

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- Andersen, P. K., Borgan, O., Gill, R. D., and Keiding, N. (1993). Statistical Models Based on Counting Processes. Springer.
- Beyer, U., Dejardin, D., Meller, M., Rufibach, K. and Burger, H. U. (2020). A multistate model for early decision-making in oncology. *Biometrical journal* 62 550–567.
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Backup

Advantages of illness-death model for PFS and OS

Illness-death model:

- Assumptions on X(t) induce properties of transition intensities, (joint) probabilities, survival functions of PFS and OS.
- Estimation of derived quantities straightforward by plugging in estimated intensities.
- Can reflect disease specifics and drug mode-of-action in transition hazards, see also Beyer et al. (2020).

Multistate model formulation

Transition probabilities:

- Full description of multistate model by only assuming existence of intensities
 λ₀₁, λ₀₂ and λ₁₂.
- Formulas, even for non-Markov case: Aalen et al. (2008).

Meller et al. (2019):

- Embed PFS and OS in multistate model framework,
- formulas for P_{lm}'s assuming Weibull transition hazards for time-inhomogeneous Markov and semi-Markov (explicit),
- inference via counting process likelihood,
- $P(PFS \le u, OS \le v)$ for X non-Markov (generic).

Allows derivation of any functional of PFS and OS.

Assumptions for multistate model

Multistate model sufficiently smooth so that following intensities exist:

$$\begin{split} \lambda_{0j}(t) &= \lim_{\Delta t \searrow 0} \frac{P(\text{PFS} \in [t, t + \Delta t), X(\text{PFS}) = j \mid \text{PFS} \ge t)}{\Delta t}, j = 1, 2, \\ \lambda_{12}(t; t_1) &= \lim_{\Delta t \searrow 0} \frac{P(X(t + \Delta t) = 2 \mid X(t -) = 1, \text{PFS} = t_1)}{\Delta t} \\ &= \lim_{\Delta t \searrow 0} \frac{P(\text{OS} - \text{PFS} \in [t - t_1, t - t_1 + \Delta t) \mid \text{OS} \ge t, \text{PFS} = t_1)}{\Delta t} \quad \text{for } \mathbf{t_1} < \mathbf{t}. \end{split}$$

t1: observed PFS time, i.e. time when leaving state 0.

Assumptions for multistate model

X(t) Markov:

- Time-inhomogeneous: intensity of death after progression does not depend on time of progression, $\lambda_{12}(t;t_1) = \lambda_{12}(t)$ for all $t_1 < t$.
- Homogeneous: intensities are time-constant, i.e. Exponential, $\lambda_{ij}(t) = \lambda_{ij}, i, j = 0, 1, 2.$

X(t) non-Markov (= semi-Markov for illness-death model without recovery):

- Intensities depend on state patient is in at s and entire history ≤ s, i.e. all transitions.
- Relevant for $1 \rightarrow 2$ transition only, as $0 \rightarrow 1, 2$ are rooted in initial state 0.

As soon as a quantity depends on $1 \rightarrow 2$ transition we need to be specific about assumption on X(t).

Illness-death multistate model for PFS and OS

Transition probabilities to move from state I at time s to state m at time t:

$$P_{lm}(s,t) := P(X(t) = m|X(s) = l, \text{history}).$$

Illness-death model w/o recovery, P_{lm} as functions of transition intensities, Aalen *et al.* (2008):

$$P_{00}(s,t) = \exp\left(-\int_{s}^{t} \lambda_{01}(u) + \lambda_{02}(u) du\right),$$

$$P_{11}(s,t;\mathbf{t}_{1}) = \exp\left(-\int_{s}^{t} \lambda_{12}(u;t_{1}) du\right),$$

$$P_{22}(s,t) = 1,$$

$$P_{01}(s,t) = \int_{s}^{t} P_{00}(s,u_{-})\lambda_{01}(u)P_{11}(u,t;u) du,$$

$$P_{12}(s,t;\mathbf{t}_{1}) = 1 - P_{11}(s,t;\mathbf{t}_{1}),$$

$$P_{02}(s,t) = 1 - \left(P_{00}(s,t) + P_{01}(s,t)\right).$$

If X(t) non-Markov:

- P_{11} and P_{12} depend on PFS time t_1 .
- Although P_{01} , P_{02} depend on λ_{12} they do not depend on t_1 .

Intuition behind transition probabilities

 $P_{00}(s,t)$, $P_{11}(s,t;t_1)$: exp of cumulative hazards \Rightarrow standard survival functions.

$$P_{01}(s,t) = \int_{s}^{t} P_{00}(s,u_{-})\lambda_{01}(u)P_{11}(u,t;u) du$$
: integral of

- $P_{00}(s, u_{-})\lambda_{01}(u)$: "infinitesimal probabilities" to move from 0 to 1 at time u, $u \in (s, t]$,
- P₁₁(u, t; u): subsequently stay in state 1 until at least time t, with progression happened in u.

Multistate model for PFS and OS

Joint distribution:

$$P(PFS \le u, OS \le v) = P(X(u) \in \{1, 2\}, X(v) = 2)$$

$$= P(X(v) = 2 | X(u) = 1) \cdot P_{01}(0, u) + P_{02}(0, u).$$

X inhomogeneous Markov: $P(X(v) = 2|X(u) = 1) = P_{12}(u, v)$ independent of progression time $t_1 \le u$.

X non-Markov:

- Integrate P₁₂(u, v; t₁) over conditional distribution of all possible progression times t₁ ≤ u.
- Formula tedious (see Meller et al. (2019)) ⇒ simulate in applications.

Simulation of PFS and OS on patient level

In the past when simulating PFS and OS how did you make sure...

- ...PFS ≤ OS for each patient,
- ...PFS = OS possible,
- ...association between PFS and OS transparent.

Simulation of (Markov) MSM:

- Nested series of competing risk experiments.
- MSM trajectors of individual in IDM can generated:
 - 1. Waiting time t_0 in initial state: Generated from CDF $F(t) = 1 P_{00}(0, t)$.
 - 2. State entered at t_0 : binomial experiment which decides with probability $\frac{\lambda_{01}(t_0)}{\lambda_{01}(t_0) + \lambda_{02}(t_0)}$ on State 1. If death \Rightarrow stop,
 - 3. otherwise waiting time t_1 in State 1 is generated from CDF $F(t) = 1 \exp(-\int_{t_0}^{t_0+s} \lambda_{12}(u) du)$.
 - 4. Death will happen at time $t_0 + t_1$.
- Add drop-out (random censoring) and administrative censoring.
- Non-Markov: model λ_{12} as function of entry time t_0 and time since time origin in Step 3 above.
- All implemented in simIDM on github and CRAN.

Doing now what patients need next

R version and packages used to generate these slides:

R version: R version 4.2.3 (2023-03-15 ucrt)

Base packages: stats / graphics / grDevices / utils / datasets / methods / base
Other packages: checkmate / survival / rpact / reporttools / xtable / prodlim / simIDM

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