

Analysis Methods for Non-Proportional Hazards

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Non-Proportional Hazards (NPH): What Does It Mean?

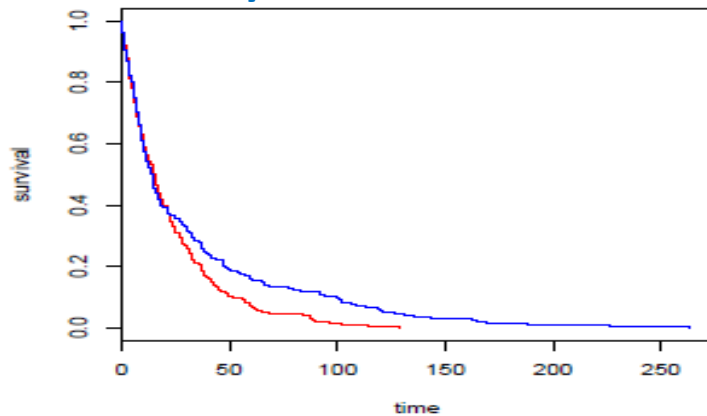
- Most popular methods in randomized clinical trial:
 - **Kaplan-Meier (KM): describe** probability of survival over time
 - **log-rank test (LRT): detect** difference in treatment effect
 - **Cox regression (CR): summarize** the treatment effect
- Log-rank p-value, hazard ratio, and naive median are the standard metrics of reporting
- Are they good summary measures when the treatment effect is not constant over time? : **NPH problem**
 - For example, recent immunotherapy development showed evidence of a delayed effect
- How to cope with NPH problem at design and analysis stages?

Log-rank Test and Cox Regression : Fits to All?

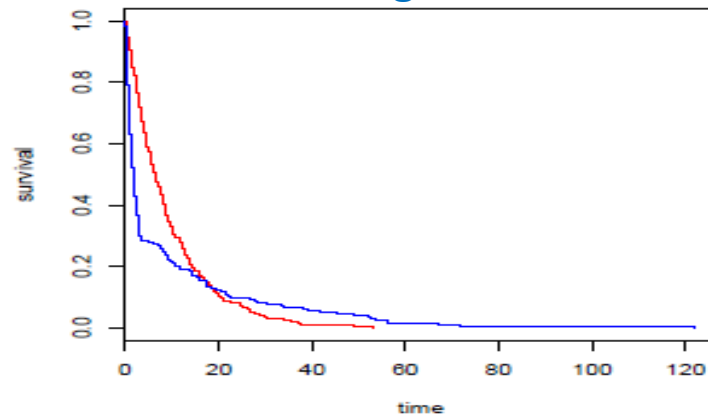
- **LRT** : introduced by Nathan Mantel in 1966
- **CR**: introduced by Sir David R Cox in 1972
- LRT and CR are **closely related**
- LRT is fully nonparametric
 - **most powerful** for proportional hazards (PH)
 - can cause **substantial power loss** if PH assumption does not hold
- Key assumption for CR: **constant** effect over time
 - treatment effect summarized by hazard ratio (HR)
 - problematic if PH assumption violates

Different Types of NPH

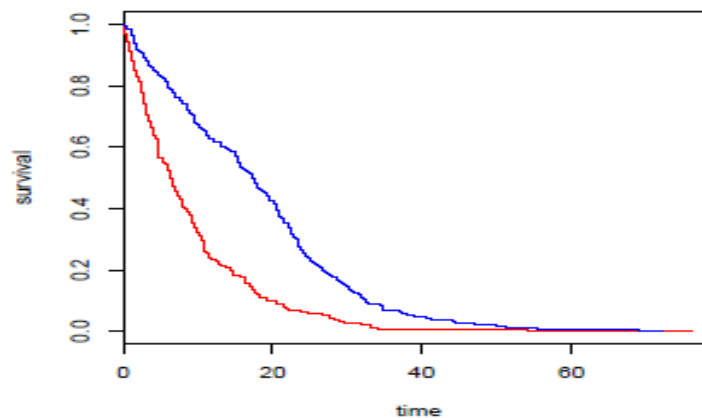
Delayed Treatment Effect



Crossing Hazard



Diminishing Treatment Effect



- Uncertainty related to the type of NPH when trial starts

Analysis and Design Trial with NPH: Key Challenges

- NPH has been discussed extensively in literature
 - alternative methods for hypothesis testing and estimation
- However, application in real life is still rare
- **Main challenge:** NPH type cannot be pre-identified
 - treatment effect profile is unknown at design stage
- **Key questions** for today's forum : in presence of NPH
 - how to plan primary analysis appropriately?
 - How to design a trial?
 - how to efficiently communicate the results with non-statisticians?

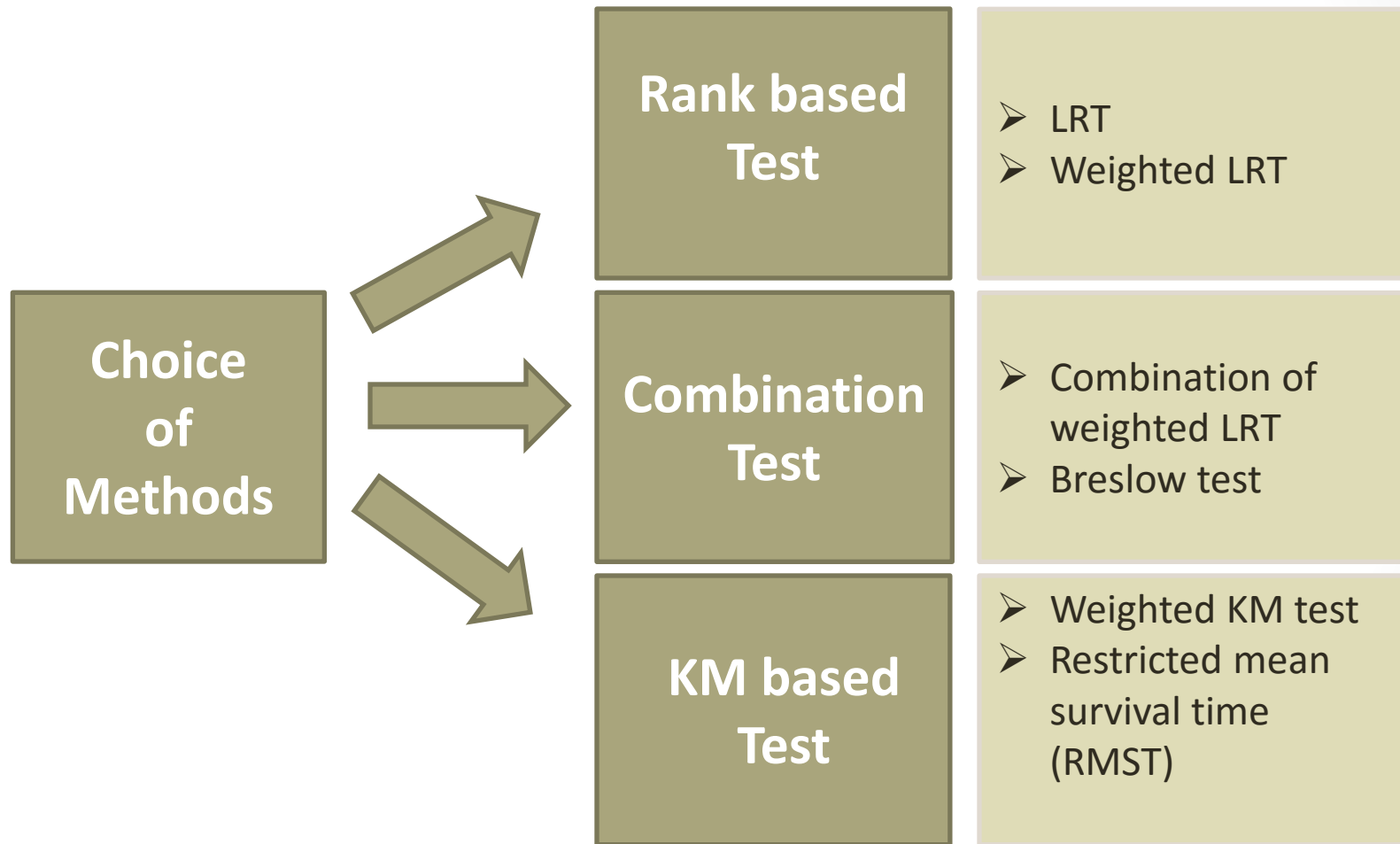
Choice of Primary Analysis in Confirmatory Trials

- Regarding **primary analysis ICH E9** states

*For each clinical trial contributing to a marketing application, all important details of its design and conduct and the principal features of its **proposed statistical analysis should be clearly specified in a protocol written before the trial begins**. The extent to which the procedures in the protocol are followed and the **primary analysis is planned a priori will contribute to the degree of confidence in the final results and conclusions of the trial**.*

- Specifying primary analysis when NPH is expected: **need robust statistical method** to handle
 - possibility of different types of NPH
 - possibility of different specifications (e.g. lag time for treatment effect)

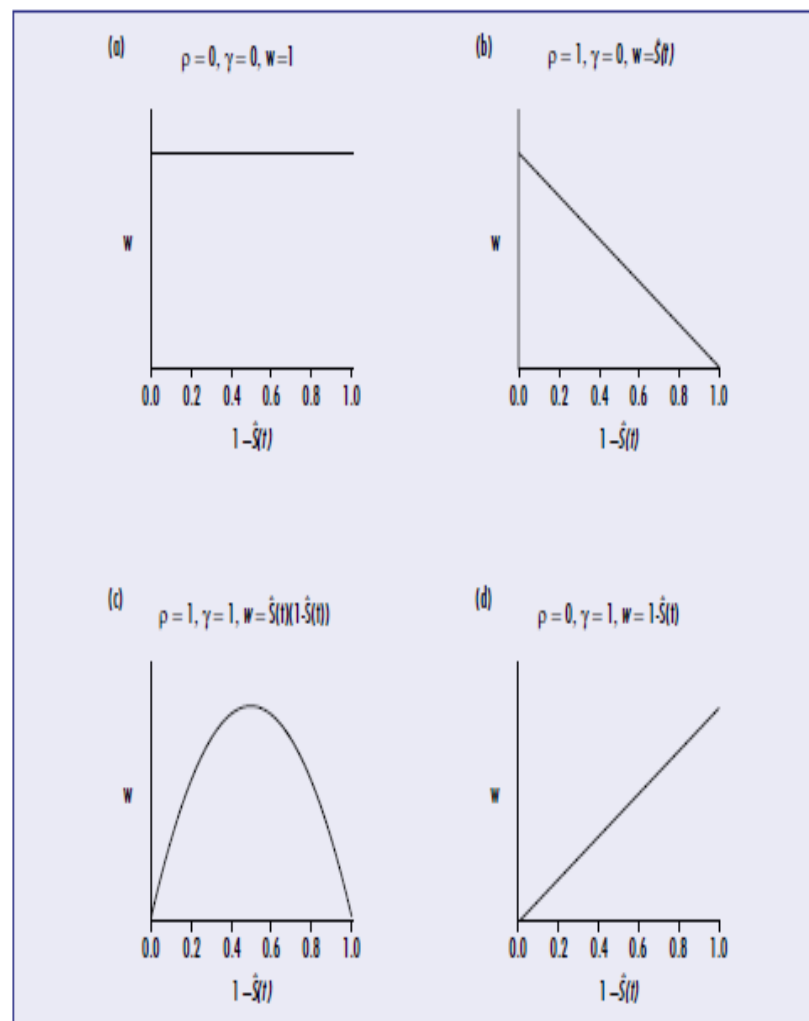
Choice of Primary Analysis



Weighted Log-rank Test

- Fleming and Harrington proposed a class of weighted log-rank test (FH) based on the $G^{\rho,\gamma}$ family
- Assign weight to events

$$W_n(t) = (S_n(t))^{\rho}(1 - S_n(t))^{\gamma}$$
- Values of ρ and γ implies
 - $\rho > 0, \gamma = 0$: early difference
 - $\rho = 0, \gamma > 0$: late difference
 - $\rho > 0, \gamma > 0$: mid difference
 - $\rho = 0, \gamma = 0$: log-rank test



Combination Test

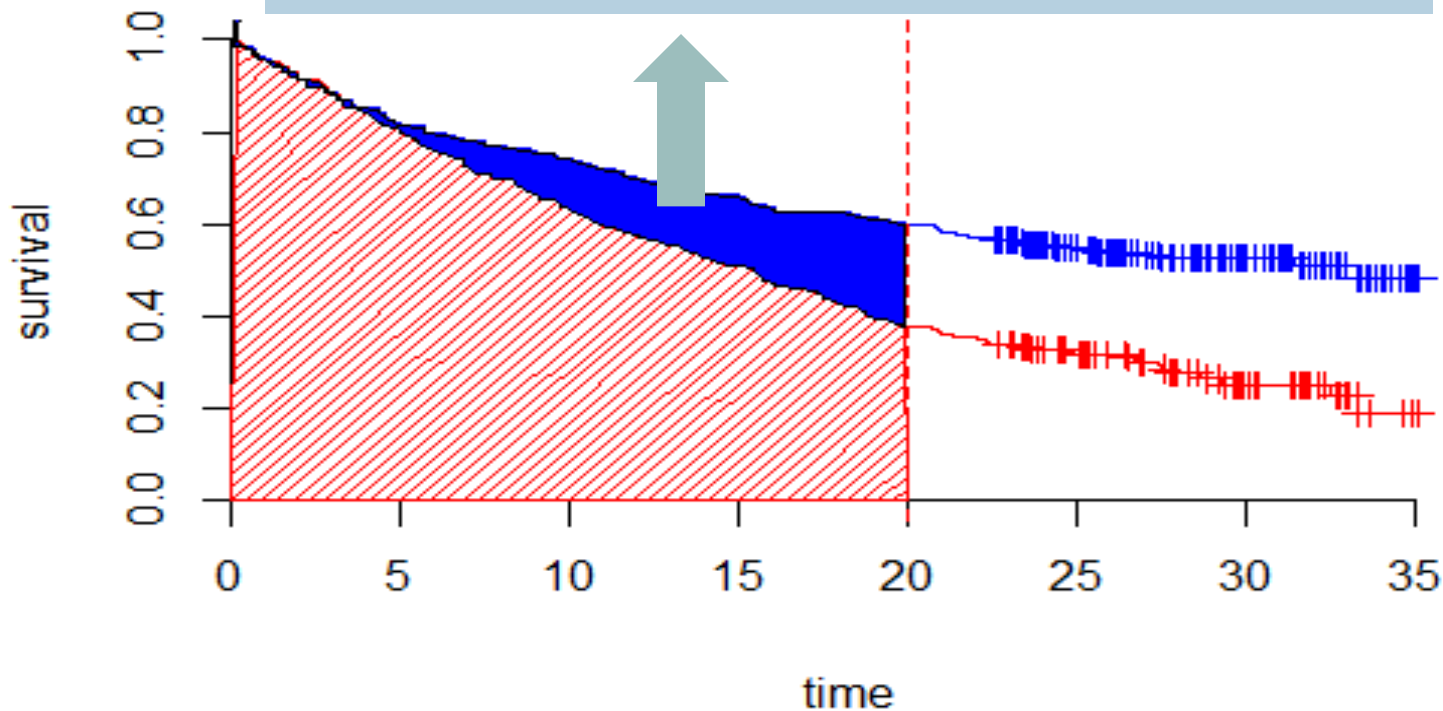
- Major difficulty for FH LRT:
 - specification of ρ and γ parameter: mis-specification may imply a loss of power
- Possible alternative : **Combination test**
 - handles simultaneously a range of NPH types
 - choose the appropriate weight in “adaptive” fashion
- Similar concepts are explored by
 - **Yang and Prentice 2010**: *Adaptively Weighted log-rank Test*
 - Garès et. al. 2017: maximal statistics over $FH(0, \gamma)$
 - **Karrison 2016**: *Versatile tests*

Combination of FH Log-rank Test (Max-Combo)

- We have considered two combinations
 - combination of $G^{0,0}$ and $G^{0,1}$: **Combo 1**
 - combination of $G^{0,0}$, $G^{0,1}$, $G^{1,1}$, $G^{1,0}$: **Combo 2**
- **Max-Combo test** : largest of the absolute value of the test statistics
- “*Adaptive*” procedure involving selection of best test statistics: **requires multiplicity correction**
 - Bonferroni-Holmes adjustment (conservative)
 - adjustment using the joint asymptotic distribution of the FH log-rank test statistics (**recommended**)
- Can be pre-specified easily at protocol stage : **satisfies ICH E9 condition**

Kaplan-Meier Based Tests

- Treatment effect (Difference scale) at month 20
- **KM based test** are based on the difference/ratio between two KM curves



Kaplan-Meier Based Tests

- **Weighted Kaplan-Meier test: (Pepe and Fleming, 1989, 1991)**
 - weighted difference of area under KM curves up to a **specified cut-off**
 - weights are based on KM estimate of censoring
 - need to specify **the cut-off**: can be affected by censoring
- **Restricted mean survival time (RMST) (Uno *et al* 2014)**
 - area under the KM plot prior to specific time-point: can be easily interpreted as “life expectance”
 - treatment effect: difference or ratio of RMST
 - need to specify **the cut-off**: can be affected by censoring

Other Methods

- **Piecewise log-rank test (Xu. *et al* 2016)**
 - piecewise weighted log-rank test within specified time intervals
 - optimal when weights for earlier events are zero
 - *power/type-I error greatly affected if intervals are incorrectly specified*
- **Other combination tests :**
 - **Breslow et. al. 1984:** combination of log-rank test and test of acceleration
 - **Logan 2008:** combination of log-rank test and milestone survival, it suffers similar problem as other KM based tests
- In the next talk the simulation study results will be presented

Reporting Treatment Effect

- When NPH is present: HR depends on time
 - HR or average HR as a single number is less useful
 - *what statistics to be reported to quantify treatment effect?*
 - *how to appropriately pre-specify to meet ICH E9?*
- A **sequential approach (Royston and Parmar 2010)**
 - **First step:** perform Max-combo test to conclude about the “Null” hypothesis (no treatment effect)
 - **Second step:** regardless of results in step 1, gather evidence of NPH, possible options
 - Grambsch–Therneau test for PH
 - other graphic diagnostics for confirming PH
 - **Third step:** choose treatment effect summary based on step 2- *treatment effect estimate beyond test statistics*

Choice of Treatment Effect Summary

- If PH assumption is reasonable
 - **HR from Cox regression (CR)** and corresponding 95% confidence interval (CI)
 - secondary analysis: average HR from weighted CR and 95% confidence interval (weight chosen by Max-combo)
- If there is evidence of NPH, the possible metrics
 - **ordinary/average HR** with 95% CI (Max-combo estimate)
 - **difference in RMST at t^*** : gain in *life expectancy* at clinically relevant time point t^* (pre-specified)
 - **difference in milestone survival at t^*** : gain in chance of survival at clinically relevant time point t^* (pre-specified)
 - secondary analysis: piecewise HR with 95% CI
- In **session III**, case studies will elaborate this approach

Conclusion

- NPH team looked into different possible methodologies
- Max-combo looks a promising approach
 - allows possibility for different NPH type
 - provides robustness under model mis-specification
- In presence of NPH a single measure is less useful
 - a sequential approach can be useful
- Team has included all the procedures in a R package
“**nphsim**” : freely available from *github*
- In next talks, the team members will present simulation results and case studies

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Back-up

Max-Combo Test

Let, $Z_1 = \mathbf{G}^{0,0}$, $Z_2 = \mathbf{G}^{0,1}$, $Z_3 = \mathbf{G}^{1,1}$, and $Z_4 = \mathbf{G}^{1,0}$

Max-Combo Test : $\mathbf{Z}_{\max} = \max(|Z_1|, |Z_2|, |Z_3|, |Z_4|)$

Under \mathbf{H}_0 , $(Z_1, Z_2, Z_3, Z_4) \sim N_4(\mathbf{0}, \mathbf{\Sigma})$ (Karrison et. al 2016)

$\mathbf{\Sigma} = (\sigma_{ij})_{4 \times 4}$; $\sigma_{ij} = \text{cov}(\mathbf{G}^{a,b}, \mathbf{G}^{c,d}) = V(\mathbf{G}^{a+c/2, b+d/2})$: $a, b, c, d = 0 \text{ or } 1$

The p-value for \mathbf{Z}_{\max} can be derived by integrating under the multi-variate normal density

Average Hazard Ratio

- Average hazard ratio (AHR) represents the “average effect” of treatment over the course of the trial
- Associated estimator of Max-Combo test: AHR using weighted cox regression (WCR)
- Choosing weight (ρ, γ) that provides maximal test statistics
 - variance: robust estimate proposed by Lin and Wei 1989
 - point estimate and 95% confidence interval
 - multiplicity adjusted confidence interval using null distribution of Max-Combo
- However, the WCR under non-proportional hazards lack intuitive simplicity