

IDENTIFYING SUBGROUPS OF TREATMENT RESPONDERS A meta-analytic approach

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 - PI Martin Underwood (Warwick)
- "Blostatistische Methoden zur effizienten Evaluation von Individualisierten Therapien (BIMIT)"
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small populations research

- Work package C: Tim Friede, Marius Placzek, Rolang Gera (Göttingen); Heinz Schmidli (Novartis)
- "Innovative methodology for small populations research (InSPiRe)"
 - funded by EC under FP7
 - Work package 4: Tim Friede, Steffen Unkel, Christian Röver (Göttingen); Beat Neuenschwander, Simon Wandel (Novartis); Norbert Benda (BfArM); ...



OUTLINE

- Motivation: Personalised medicine
- Identifying subgroups in a single trial
- Extension to several trials: Meta-analytic framework
- Clinical development plans: Integration of subgroup identification and confirmation
- Concluding remarks



PERSONALISED MEDICINE

- Efficacy, safety and consequently benefit-risk might vary across patient population
- Personalised medicine
 - Stratification of patient populations
 - Drive towards targeted treatments
- Enrichment of clinical study populations (Temple, 2010)
 - "to identify a population of patients in whom a drug effect, if present, is more likely to be demonstrable"
- Identification of subgroups of patients responding particularly well to a particular treatment



STRATIFIED MEDICINE: EXAMPLES OF TARGETED THERAPIES

Table I. Oncology products approved in the USA for selected populations.		
Compound	Target	Indication
Crizotinib (Xalkori®)	ALK	ALK-rearranged non-small cell lung cancer
Vemurafenib (Zelboraf®)	BRAF	BRAF mutant advanced melanoma
Trametinib (Mekinist®)	MEK	BRAF mutant advanced melanoma
Trastuzumab (Herceptin®)	Her 2	Her 2 expressing breast cancer
Lapatinib (Tykerb®)	Her 2	Her 2 expressing metastatic gastric cancer
Rituximab (Rituxan®)	CD20	CD20(+) B-cell lymphomas
Cetuximab (Erbitux®)	EGFR	KRASwt, EGFR(+) metastatic colorectal cancer
Panitumumab (Vectibix®)	EGFR	KRASwt, EGFR(+) metastatic colorectal cancer

Table I from Mehta et al. (2014) Stat Med

STRATIFIED MEDICINE:

- SOME PROJECTS WE ARE INVOLVED IN
- Better treatments (in terms of benefit-risk ratio) through stratification of populations
- Clinical collaborations



für Bildung und Forschung

- Individualize MS (KKNMS, BMBF)
- Low back pain repository (Warwick, NIHR)



- Stratification of ICD populations
 - EU-Trig-Treat





- Methodological research
 - **Designs for clinical research**: biomarker-driven designs, adaptive subgroup selection Bundesministerium



IMPROVING OUTCOMES FROM THE TREATMENT OF LOW BACK PAIN

- NIHR funded project lead by Martin Underwood (Warwick, UK)
- Project aim
 - "... to improve the clinical and cost-effectiveness of low back pain treatment by providing patients, their clinical advisors, and health service purchasers with better information about which participants are most likely to benefit from which treatment choices."

- Individual patient data of 19 randomised controlled trials
- Total of 9,328 patients



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MODERATORS OF TREATMENT EFFECT

- Baseline variables affecting treatment effect; sometimes also referred to as "predictive" factors (not to be confused with prognostic factors)
- Technically interaction effects between baseline variable and treatment effect
- ▶ For instance, analysis of covariance (ANCOVA) with treatment, baseline covariables and treatment-by-baseline covariable interactions
- More sophisticated: Fractional polynomials (Royston & Sauerbrei, 2004)



SUBGROUP IDENTIFICATION

- For an overview refer to recent systematic literature review by Ondra et al. (2015) on methods for subgroup identification and confirmation in clinical trials
- Exploratory subgroup identification
 - attracted a lot of attention over the past years
 - several methods proposed
- Here we describe one we adopted when working on the back pain repository ...



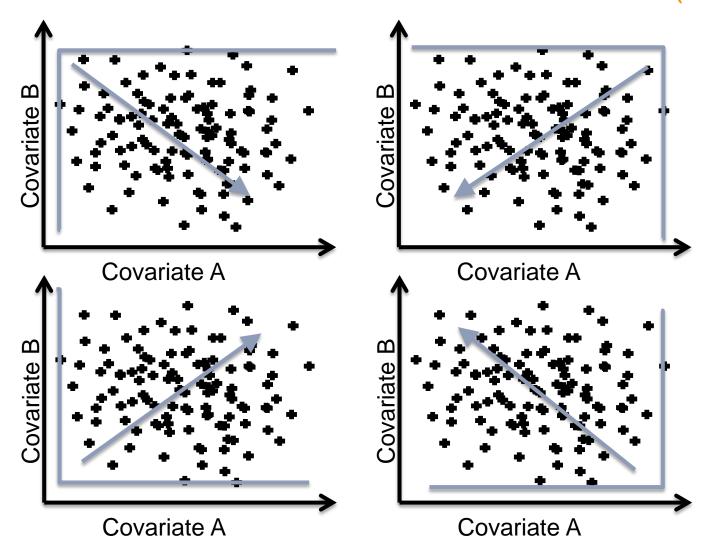
ADAPTIVE REFINEMENT BY DIRECTED PEELING (ARDP) ALGORITHM

- Proposed by LeBlanc et al. (2005) to identify risk groups (prognostic factors)
- Risk groups defined by (half open) "boxes" resulting in simple rules
- Here modified to identify subgroups responding particularly well to treatment (predictive factors)

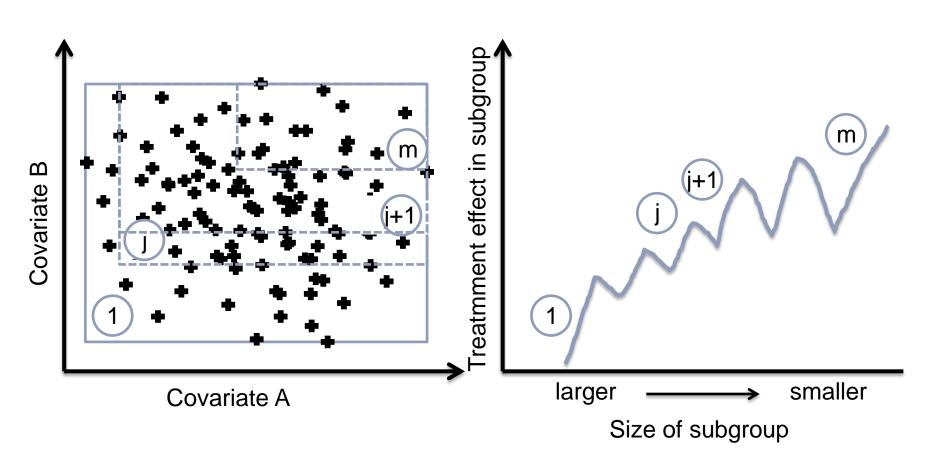
SUB-GROUP IDENTIFICATION: UNIVERSITÄTSMEDIZIN : UMG GÖTTINGEN : UMG ADAPTIVE REFINEMENT BY DIRECTED PEELING

- 1. Investigating interactions of covariates with treatment determines covariates to be included and direction of peeling
- 2. Start with a "subgroup" B^0 that includes all observations.
- 3. For each variable we **peel a certain number of observations off** resulting in subgroups B_i^m , j = 1, ..., p.
- 4. For each subgroup B_j^m calculate the **treatment-by-subgroup** interaction and select the B_j^m which gives the largest improvement on the interaction effect in comparison to the previous iteration. The selected subgroup is then called B^{m+1} .
- 5. Estimate the treatment effects for the outcome of interest for subgroup B^{m+1} .
- 6. Repeat steps 3 to 5 until the size of the remaining region is not smaller than *r*.











- Algorithm can be applied to various kinds of endpoints
 - Continuous: Gaussian linear models
 - Binary: logistic regression
 - Time-to-event: Cox proportional hazard models
- No distributional assumption regarding the covariates required, but they should be ordinal with sufficient number of possible outcomes
- ▶ If covariable not ordinal, then order could be imposed: order the categories by the regression coefficients estimated in Step 1 of the algorithm (LeBlanc et al., 2005).



- ▶ "Experience with simulated data with low signal shows that there can be substantial estimation bias due to peeling if there are a moderate number of predictors (p>5)." (LeBlanc et al., 2005)
- ▶ LeBlanc et al. (2005) suggested resampling methods to reduce selection bias and for inference
- K-fold crossvalidation to reduce bias in estimation
- Permutation test to test whether the prognostic subgroups are associated with outcome



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MODERATORS OF TREATMENT EFFECT

- Modelling between-study heterogeneity
- Hierarchical (mixed-effects) model
 - Fixed effects: treatment, covariables, treatment-by-covariable interactions
 - Random effects: trial and trial-by-treatment interaction (as in random effects meta-analysis)
 - Example with continuous outcome in SAS

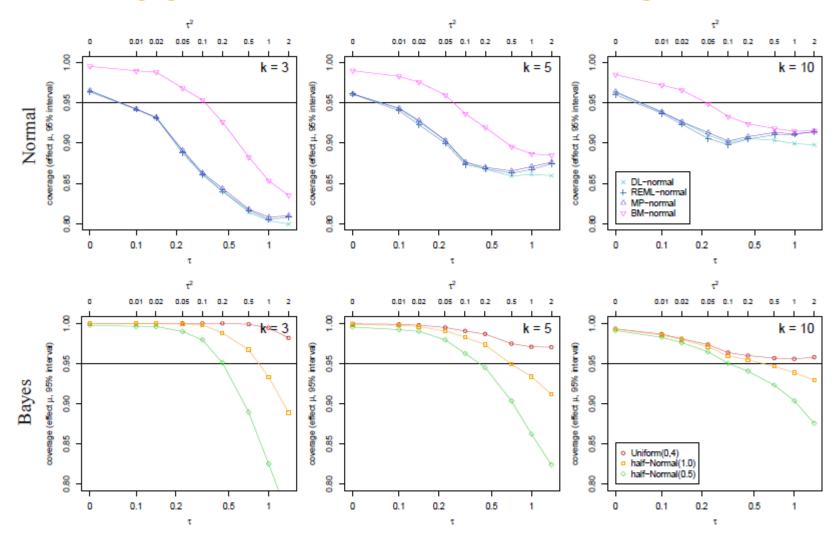
```
1  proc mixed data=&data;
2    class &trt &trials;
3    model &outcome = &trt &var &trt*&var / s ddfm=satterth;
4    random intercept &trt / subject=&trials;
5    repeated / group=&trials;
6    run;
```



- Extension to multiple trials by including terms for between-trial heterogeneity in the model
- Random effects meta-analyses of interaction effects
 - Two-step procedure: interaction effects estimated from individual trials are combined in random-effects metaanalyses
 - One-step procedure: hierarchical model

ESTIMATION OF BETWEEN-TRIAL HETEROGENEITY WITH FEW TRIALS





Friede et al. (2015)



META-ANALYSIS WITH FEW SMALL STUDIES

If you want to learn more about this ...

Evidence Synthesis and the Use of Co-Data (CEN Invited Session)

Invited session

Wednesday, 17 June 2015

09:00 - 10:30

Room: U6-A10

Session chair: Held, Leonhard; Friede, Tim

Röver, Christian: Meta-analysis of few small studies in small populations and rare diseases
Author list: Röver, Christian; Neuenschwander, Beat; Wandel, Simon; Friede, Tim

The between-study heterogeneity plays a central role in random-effects meta-analysis. Especially when the analysis is based on few studies, which is a common problem not only for rare diseases, external a-priori information on heterogeneity may be helpful. In case of little information, the use of plausible weakly informative priors is recommended. Computational simplifications (using the bmeta R package) helped to speed up computations for Bayesian standard random-effects meta-analysis to explore the frequentist properties of Bayesian estimators for different priors. We investigated a range of scenarios (heterogeneities, numbers of studies), to compare bias, MSE and coverage of the Bayesian and classical estimators. The different approaches are illustrated using an application in pediatric transplantation.

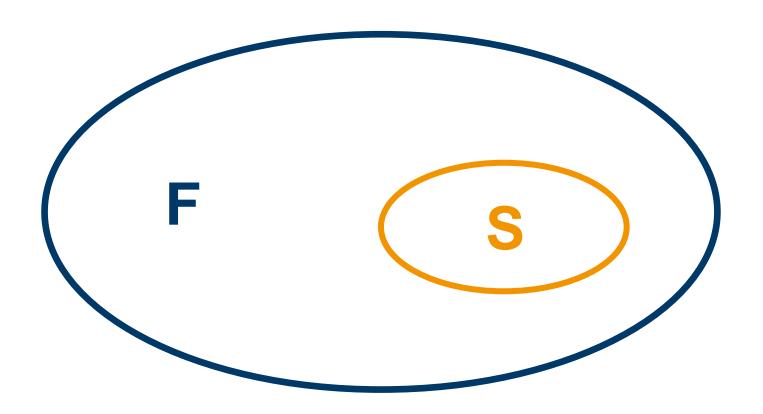


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STRATIFIED MEDICINE



Full population

Sub-population



CLINICAL DEVELOPMENT PROGRAMME INCLUDING AN ADAPTIVE ENRICHMENT DESIGN

- Biomarker-defined subgroup identified in exploratory study
- Subgroup to be confirmed by independent data
- Confirmation of treatment effect in selected population



ADAPTIVE ENRICHMENT DESIGN

- Stage 1: Recruit patients from full population (F)
- Interim analysis: make the decisions on ...
 - whether trial is stopped for futility
 - ▶ if trial is continued, decide whether recruitment is from full population (F) or subpopulation (S) (enrichment)
 - testing strategy in final analysis
- Final analysis: test for an effect in F and/ or S



ADAPTIVE ENRICHMENT DESIGN

If you want to learn more about this topic ...

Adaptive Clinical Trials with Subpopulation Selection

Invited session

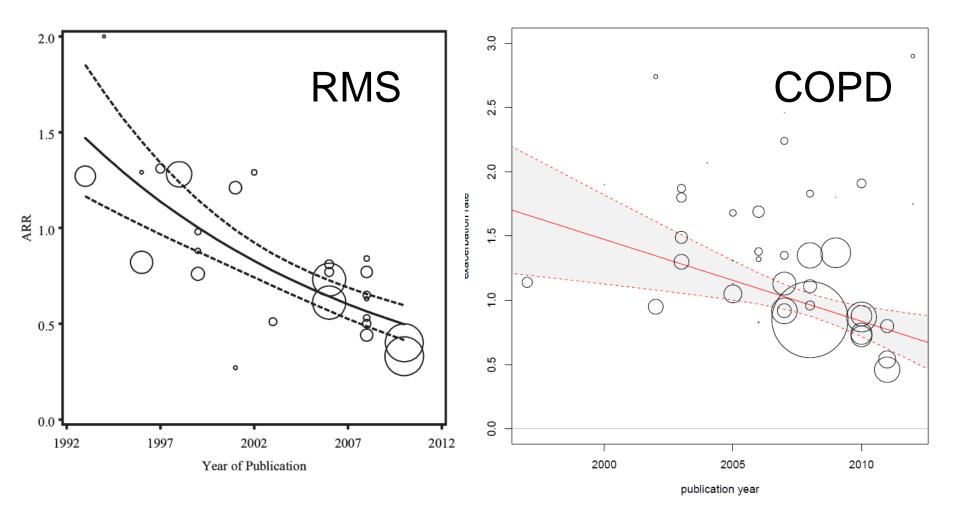
Thursday, 18 June 2015

14:00 - 15:30

Room: Aula Martini

Session chair: Heinzmann, Dominik; Rufibach, Kaspar

UNCERTAINTY IN PLANNING TRIALS: UNIVERSITÄTSMEDIZIN : UMG Trends in Placebo Event rates in Chronic Conditions



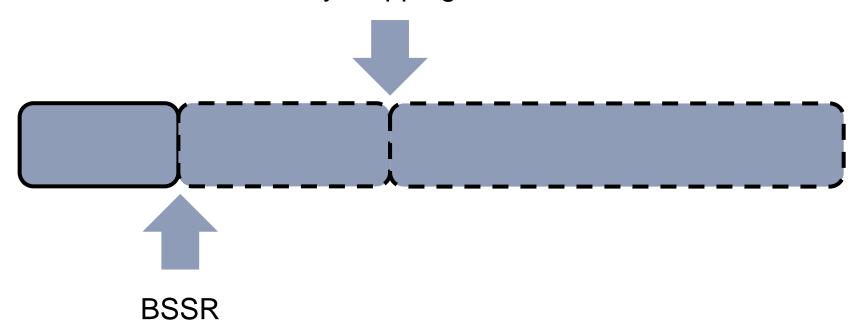
Nicholas et al. (2011) MSJ

Röver et al. (2015)



BLINDED SAMPLE SIZE REESTIMATION (BSSR) IN ADAPTIVE ENRICHMENT DESIGNS

Enrichment decision / Futility stopping



- Early IA for blinded sample size reestimation
- Later IA for enrichment decision / futility stopping (unblinding)



OUTLINE

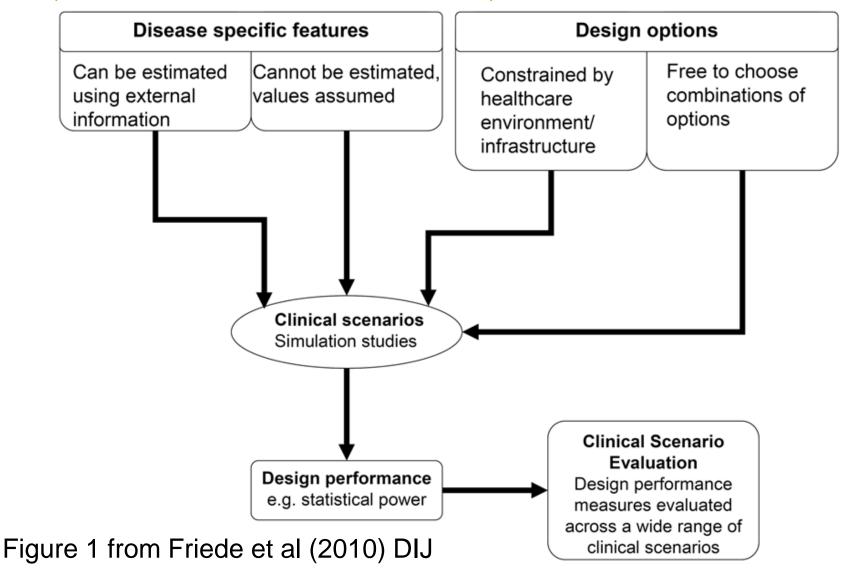
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Clinical Scenario Evaluation (CSE) UNIVERSITÄTSMEDIZIN LUMG



Framework for the Assessment of Competing Strategies

(Benda et al, 2010; Friede et al, 2010)



CONCLUDING REMARKS



- Subgroup identification based on Adaptive Refinement by Directed Peeling (ARDP)
 - Facilitates decision making on subgroup selection balancing size of subgroup with size of treatment effect
- Subgroup identification from multiple trials
 - Some level of between-trial heterogeneity expected and should be reflected in statistical model
 - Estimation difficult if only a small number of studies included in the analysis
- Gain in power by adaptive enrichment design compared to separate studies / fixed design can be substantial
- Assessment of complex development plans usually requires extensive simulations