Bayesian methods for borrowing historical information: The power prior for the linear regression model

Akalu Banbeta[1,2], Emmanuel Lesaffre[3], and Joost van Rosmalen[4]

[1]I-Biostat, UHasselt, Hasselt, Belgium

[2]Department of Statistics, Jimma University, Jimma, Ethiopia

[3]I-Biostat, KU Leuven, Leuven, Belgium

[4]Department of Biostatistics, Erasmus University Medical Center, Rotterdam, The Netherlands

Related publications:
- Banbeta et al et al, Stat in Med 38 (7), 1147-1169 (2019)
- Neuenschwander et al, Clinic Trials 7, 5-18 (2010)

Introduction

- Including control data from similar previous clinical trials (historical data) may improve power and may reduce the necessary study size.
- In practice, there are unanticipated differences of patients' characteristics (covariates) across trials, which can lead to a biased estimates of the treatment effect, unless the effects of the covariates are adjusted for.

Bayesian approaches

- **Modified power prior (MPP)** : estimate the relative weight of the historical controls based on difference with current controls
  - assumes independent power parameter ("**MPP Ind**") and
  - the power parameter have a hierarchical structure ("**DMPP**").
- **Meta-analytic-predictive (MAP) prior**: assume exchangeability of parameters across all studies
- **Pooled data**: pooling of historical and randomized controls
- **Current data:** ignoring historical controls

Simulation design and settings

Aim of the study: Comparison of methods for their performance.

Data generation:

- 3 historical control studies with 100 subjects per arm in each trial. *For* the i^{th} subject in the k^{th} trial the response will be

$$y_{ik} \sim N(\mu_{ik}^{*}, \sigma^{2})$$

$$\mu_{ik}^{*} = b_{ok} + b_{1k}x_{1k} + b_{2k}x_{2k} + b_{3k}x_{3k},$$

x_1 for the treatment type
x_2 for a categorical covariate
x_3 for a continuous covariate

Scenarios:

Scenario 1: intercept (b_{ok}) varies between studies

Scenario 2: covariate coefficients $(b_{2k}$ and $b_{3k})$ vary across studies

Scenario 3: covariate distribution $(x_{2k}$ and $x_{3k})$ vary cross studies

Analysis: With and without covariate adjustment

UHASSELT KNOWLEDGE IN ACTION

Results and Conclusions

		Scenario 1				Scenario 2		Scenario3	
		Unadj		Adj		Unadj	Adj	Unadj	Adj
Outcome	Method	Hom	Het	Hom	Het	Het	Het	Het	Het
Type I error	Current Data	0.061	0.062	0.065	0.051	0.045	0.056	0.060	0.060
	Pooled Data	0.055	0.309	0.054	0.389	0.373	0.432	0.151	0.050
	MAP	0.055	0.058	0.045	0.051	0.045	0.036	0.065	0.043
	MPP Ind	0.050	0.111	0.042	0.130	0.105	0.047	0.066	0.042
	DMPP	0.051	0.103	0.042	0.125	0.079	0.045	0.072	0.041
Power	Current Data	0.537	0.555	0.710	0.711	0.443	0.717	0.527	0.688
	Pooled Data	0.702	0.618	0.861	0.716	0.513	0.594	0.904	0.855
	MAP	0.598	0.554	0.769	0.717	0.397	0.524	0.543	0.757
	MPP Ind	0.643	0.592	0.818	0.730	0.468	0.695	0.655	0.817
	DMPP	0.650	0.582	0.823	0.732	0.463	0.715	0.687	0.821
Calibrated Power	Current Data	0.510	0.520	0.676	0.708	0.466	0.715	0.491	0.656
	Pooled Data	0.654	0.255	0.852	0.371	0.188	0.267	0.768	0.855
	MAP	0.575	0.529	0.784	0.716	0.412	0.593	0.505	0.775
	MPP Ind	0.644	0.431	0.829	0.571	0.396	0.706	0.607	0.833
	DMPP	0.649	0.437	0.834	0.598	0.395	0.733	0.639	0.835

Abbreviations: Adj, Adjusted; DMPP, dependent modified power prior; Het, heterogeneous; Hom, homogeneous; MAP, meta-analytic predictive; MPP, modified power prior; Unadj, Unadjusted.

- For homogeneous data the Dependent MPP methods have higher power than its competitors
- For variation across studies in the intercept of model, the MPP methods yielded slightly increased type I error rates, whereas the MAP approach maintained the nominal 5% type I error rate.
- The MPP approach could handle variations of data due to the covariate coefficients and covariate distributions across studies and thereby gives better results than the MAP.