

Incorporating published univariable associations in diagnostic and prognostic modeling

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Clinical Prediction Modeling

Aim

- provide a **probability** of **outcome** presence (diagnosis) or occurrence (prognosis) in an **individual**

Typical Approach

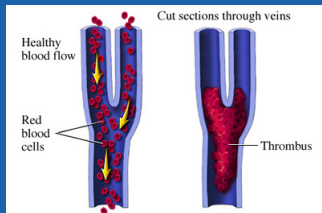
- 1 Collection of Individual Patient Data (IPD)
- 2 Data Analysis (descriptives, missing values, ...)
- 3 Investigation of potential predictors
- 4 (Logistic) Regression Modeling
- 5 Evaluation of generalizability: validation studies



Practical Example

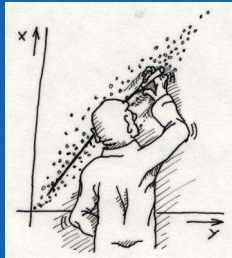
Diagnosis of Deep Vein Thrombosis

- Derivation dataset (IPD) of 1,295 patients
- Predictors: gender, oral contraceptive use, presence of malignancy, recent surgery, absence of leg trauma, vein distension, calf difference, D-dimer test
- Logistic Regression Modeling
- Validation dataset of 1,756 patients
 - Discrimination: 0.86 (AUC)
 - Calibration: 1.12 (Calibration slope)



Improving Generalization

- Increase Sample Size
 - Individual Participant Data
 - Individual Study Centers
- Amplify Sample Spectrum
 - Domain
 - Heterogeneity
- Apply Robust Estimation
 - Penalization & Shrinkage
 - Model Updating
 - Including External Knowledge



The Adaptation Method

- Introduced by Steyerberg/Greenland
- Re-estimates a multivariable coefficient
- Incorporates univariable coefficients from literature (e.g. log odds ratios for binary outcomes)

$$\begin{aligned}\beta_{m|L} &= \beta_{u|L} + (\beta_{m|I} - \beta_{u|I}) \\ \text{var}(\beta_{m|L}) &= \text{var}(\beta_{u|L}) + \text{var}(\beta_{m|I}) - \text{var}(\beta_{u|I})\end{aligned}$$



The Improved Adaptation Method

- Unbiased variance component

$$\text{var}(\beta_{m|L}) = \text{var}(\beta_{u|L}) + \text{var}(\beta_{m|I}) + \text{var}(\beta_{u|I}) - 2\text{cov}(\beta_{m|I}, \beta_{u|I})$$

- Distributional

$$\beta_{u|L} \sim \mathcal{N}(\mu_{u|L}, \sigma_{u|L}^2), \beta_{m|I} \sim \mathcal{N}(\mu_{m|I}, \sigma_{m|I}^2), \beta_{u|I} \sim \mathcal{N}(\mu_{u|I}, \sigma_{u|I}^2)$$

- Robust Estimation

$$\mu_{m|I} \sim \text{Cauchy}(0, 2.5), \mu_{u|I} \sim \text{Cauchy}(0, 2.5)$$



Performance study

Simulation study

- Reference model with 2 predictors for generating data with $x_1, x_2 \sim \mathcal{N}(0, 1)$ and $r(x_1, x_2) = 0$
- Individual Patient Data ($n_{\text{IPD}} = 100 \rightarrow 1000$)
- 4 heterogeneous literature studies ($n_j = 500$)

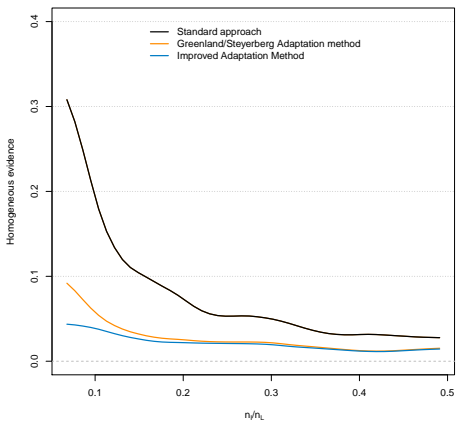
Case study: Diagnosis of Deep Vein Thrombosis

- IPD: Multivariable dataset ($n = 1,295$)
- LIT: 7 unadjusted odds ratios (biomarker D-dimer)
- Update D-dimer coefficient in multivariable prediction model
- External validation of updated prediction model ($n = 1,756$)

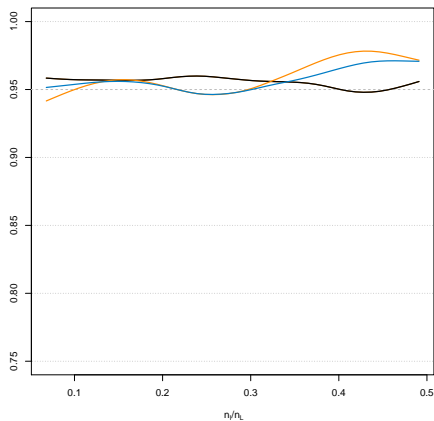


Simulation Study: homogeneous literature evidence

Mean Squared Error

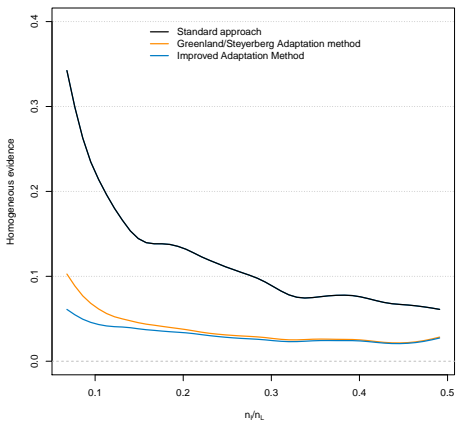


95% CI coverage

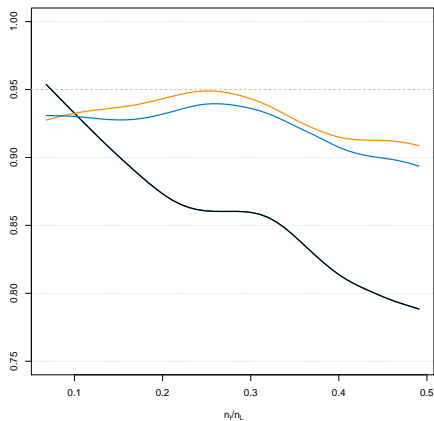


Simulation Study: heterogeneous literature evidence

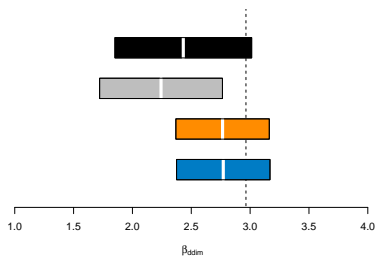
Mean Squared Error



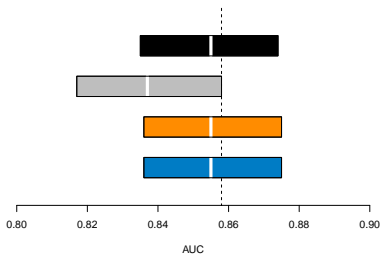
95% CI coverage



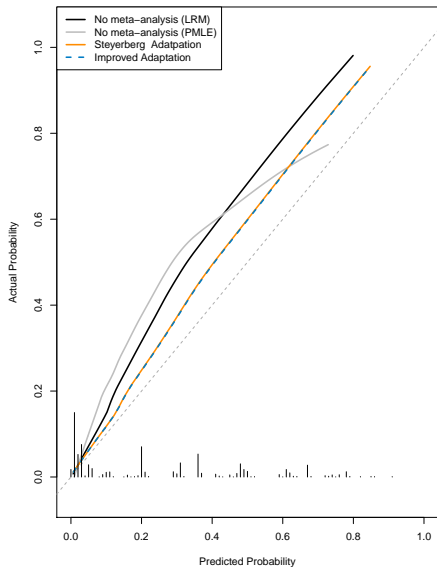
D-dimer Coefficient Bias and Coverage



Model Discrimination



Model Calibration



Discussion

- Strengths
 - Aggregation usually improves estimation
 - Abundance of external knowledge
 - Straightforward implementation of approaches
 - Explicit aggregated models (no black boxes)
- Weaknesses
 - Heterogeneity of external knowledge
 - Performance gain not always very large
 - Additional efforts required during derivation phase
- Ongoing research
 - incorporation of previously published prediction models with similar and different predictors

