

# Recent developments in measurement error modelling

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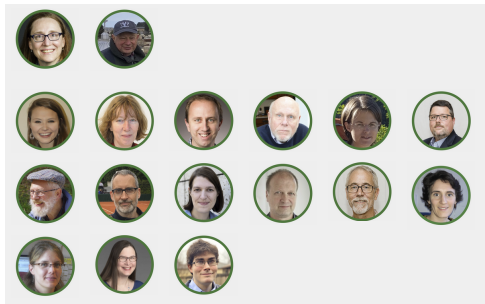
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# The topic Group TG4

## Members

Victor Kipnis, Pamela Shaw (chairs)

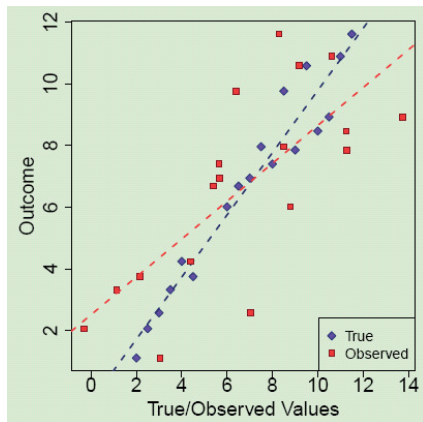
Jonathan Bartlett, Hendriek Boshuizen, Raymond Carroll, Veronika Deffner, Kevin Dodd, Laurence Freedman, Paul Gustafson, Ruth Keogh, Helmut Küchenhoff, Douglas Midthune, Cécile Proust-Lima, Anne Thiebaut, Janet Tooze, Michael Wallace



<http://www.stratostg4.statistik.uni-muenchen.de/Home.html>

# Why should we care about measurement errors ?

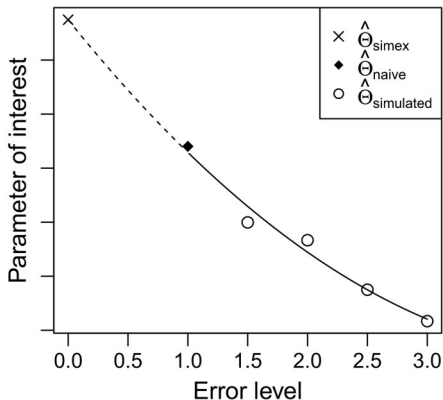
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# How should we deal with measurement errors ?

## The answer: Statistical modelling

- Model relationship between bias and amount of measurement error : SIMEX



# Likelihood/Bayes and Regression calibration

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- General model including the measurement process

$$\text{Main model} \quad [Y | X, Z, \beta]$$

$$\text{Error model} \quad [X^* | X, Z, \eta]$$

$$\text{Exposure model} \quad [X | Z, \lambda]$$

Use Maximum Likelihood or Bayes

- Measurement model: **Regression calibration**
  - 1 Find a model for  $E(X|X^*, Z)$  by validation data or replication
  - 2 Replace the unobserved  $X$  by estimate  $E(X|X^*, Z)$  in the main model
  - 3 Adjust variance estimates by bootstrap or asymptotic methods

# Overview Articles

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- Keogh R, Shaw P, Gustafson P, Carroll R, Deffner V, Dodd K, Küchenhoff H, Tooze J, Wallace M, Kipnis V, Freedman L (2020). *STRATOS guidance document on measurement error and misclassification of variables in observational epidemiology: Part 1 basic theory, validation studies and simple methods of adjustment*. Statistics in Medicine.
- Shaw P, Gustafson P, Carroll R, Deffner V, Keogh R, Tooze J, Kipnis V, Wallace M, Küchenhoff H, Freedman L (2020). *STRATOS guidance document on measurement error and misclassification of variables in observational epidemiology: Part 2 sample size, more complex methods of adjustment and advanced topics*. Statistics in Medicine.
- Wallace M (2020). *Analysis in an imperfect world*. Significance.

# Berkson error

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Observations  $X^*$  with Berkson error are less variable than the true value  $X$

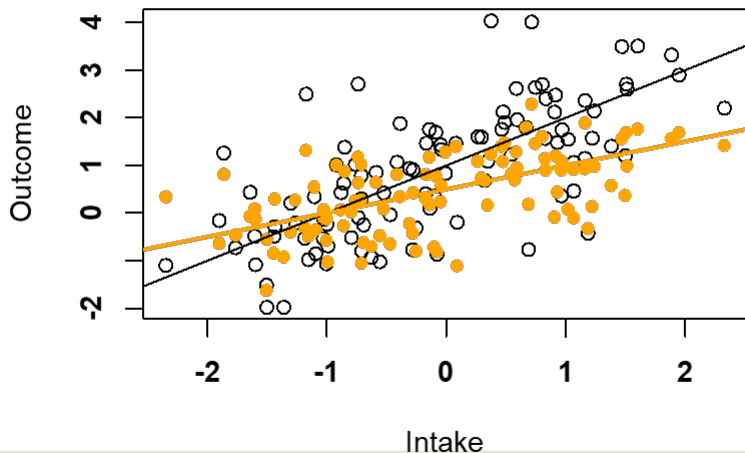
$$X = X^* + \text{error}$$

Examples:

- A predicted value  $X^*$  from a regression equation has less variability than the original outcome, due to unexplained variance
- (unbiased) prediction with machine learning methods
- Regression calibration, since one uses a prediction equation for  $X$ .

# Impact on Berkson error in outcome Variable Y

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# Predicted values in epidemiology

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- There is increasing use of prediction and calibration equations in medicine
- Naïve analyses with predicted outcomes are subject to multiple biases
- Distributional summaries are biased, quantiles appear less extreme
- Regressions reliant on predicted outcomes will have biased coefficients
- Regressions reliant on predicted exposures need SE adjustment
- Awareness of the effects of Berkson error and methods to adjust for it need more attention

# Regression calibration

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Boe LA, Shaw PA et al. (2023) *Issues in Implementing Regression Calibration Analyses*. Am J Epidemiol.

- 1 To avoid bias, the calibration equation should include all confounders included in the outcome model.
- 2 a validation study should be conducted internally.
- 3 The validation study should be large enough
- 4 Same functional form of the exposure in main model and calibration model outcome model.
- 5 When regression calibration is used, SEs must be adjusted to account for the uncertainty in the estimation of the calibration equation.
- 6 When a calibration model covariate mediates the exposure-outcome relationship, special methods should be used.

# Time-varying exposures prone to measurement error in survival analyses.

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Work in progress by Cécile Proust-Lima, Viviane Philipps, Veronika Deffner, Hendrieke Boshuizen, Laurence Freedman, Anne Thiébaud

- Association between a time-varying exposure and a time to event:
- Measures of an underlying continuous-time process are measured with error and/or measured at sparse and irregular times

Methods:

- Last Value Carried Forward (LOCF)
- Regression calibration
- multiple imputation
- Joint modelling

# Results

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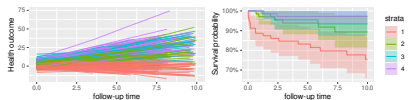
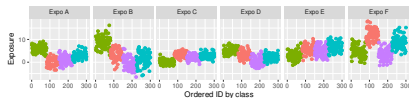
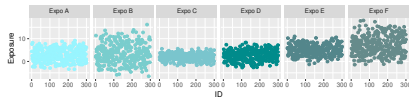
- LOCF may give strong biased estimates
- Approximations with Two-stage methods are valid if they account for early truncation by the event: using data available after the event if external (Regression Calibration) incorporating information on the event (Multiple Imputation)
- Joined model works very well (expected as the generation model)  
Results obtained under correct specification!
- Variance estimation with RC and MI using Rubins rule

# Methods for handling misclassification in variables which are an outcome of latent class analyses

Proust-Lima C, Saulnier T, Philipps V, et al. (2023) *Describing complex disease progression using joint latent class models for multivariate longitudinal markers and clinical endpoints*. *Statistics in Medicine*.

## Latent class Strategy

- 1 Estimate a latent class model on the exposure data:
- 2 Create a classification by assigning each subject to a fitted class:
- 3 Use this assignment in subsequent analyses



# Main results

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Latent class analysis:

- easy and graphical interpretation but inherent error of classification generally ignored
- induces incorrect interpretations especially when classes are not well separated

Methods:

- two effective methods of correction: conditional regression or two-stage
- may apply to any type of data
- require specific computation of the variance (bootstrap or analytical)
- rely on the assumptions of the model used Software: Mplus and Latent Gold (correction, conditional) R package lcmm (conditional, two-stage)

# Machine learning and Measurement error

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Guenther F, Brandl C, Winkler TW, et al. (2020) *Chances and challenges of machine learning-based disease classification in genetic association studies illustrated on age-related macular degeneration* Genetic Epidemiology.

Gustafson, P. (2021) Invited Commentary: Quantitative Bias Analysis Can See the Forest for the Trees Comment. AMERICAN JOURNAL OF EPIDEMIOLOGY

- machine learning algorithms estimate amount of misclassification and Measurement error
- integration in epidemiologic models via SIMEX, ML and Bayes possible
- methods for assessing measurement error (label noise in Machine learning literature) effects and correction methods are a current issue of research.