How to Stop Ignoring Automated Classification Errors

Differential Measurement Error & Intercoder Reliability in Measurement Error Models

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Addressing Misclassification Errors in Text-as-Data Approaches

- Automated text classifiers (ACs) based on Supervised Machine Learning (SML) gain traction (Baden et al., 2022; Hase et al., 2022; Jünger et al., 2022)

- *Misclassification errors* cause bias in downstream regression analyses

- Existing approaches to correct this bias include:

    - Regression Calibration (Fong & Tyler, 2021)
    - Multiple Imputation (Blackwell et al., 2012)
    - Pseudo-Likelihood based on Confusion Matrix (Zhang, 2021)
    - Maximum Likelihood Models – we provide a tailored implementation (Carroll et al., 2006)

Key Questions

1

RQ1: Which error correction methods do scholars employ for SML-based text classification?

2

RQ2: Which error correction methods *should* scholars employ for SML-based text classification?

Misclassification is a largely ignored threat

1

Identification of SML-based text-as-data studies (*N* = 49) via existing reviews
(Baden et al., 2022; Hase et al., 2022; Jünger et al., 2022; Song et al., 2021)

- Of empirical applications, 41.9% create covariates & 29% outcome variables via SML-based ACs
- **Only 16.1%** of studies mention misclassification errors, only **single study** employs correction method

Using Validation Data to Correct Estimates

2

We desire a method that will:

- provide consistent estimates
- generalize to studies where an AC measures a covariate or outcome
- handle bias and differential error[1]

We use monte-carlo simulations to test proposed methods.

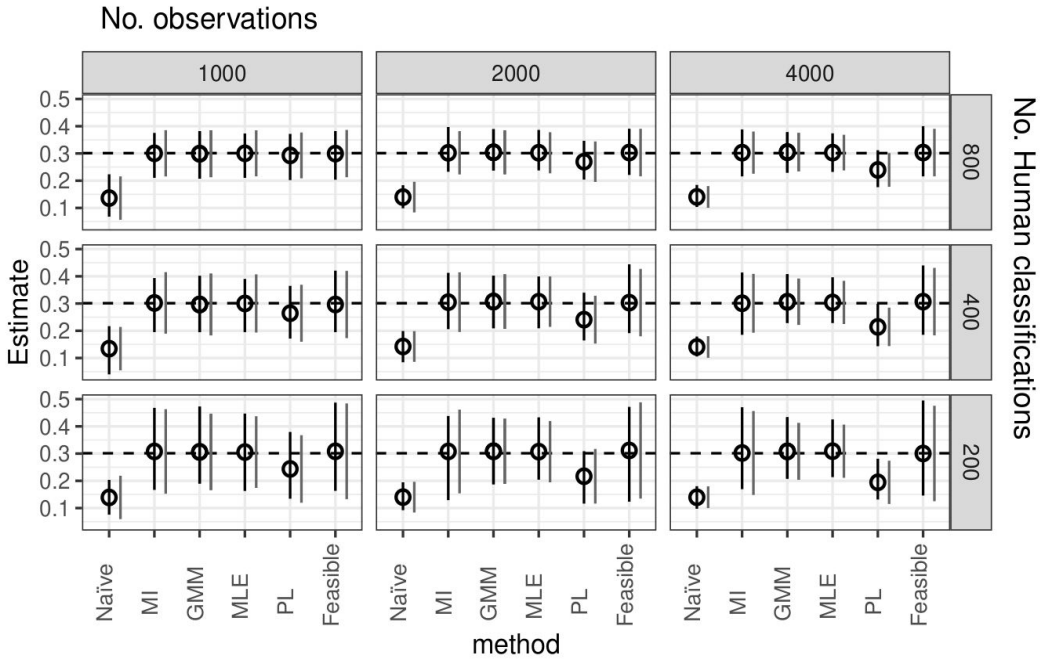
[1] Differential error is when misclassifications directly depend on the outcome.

Results: Nondifferential error

Our *likelihood modeling* approach and *GMM calibration* (Fong and Taylor) is consistent and efficient when error is nondifferential error.

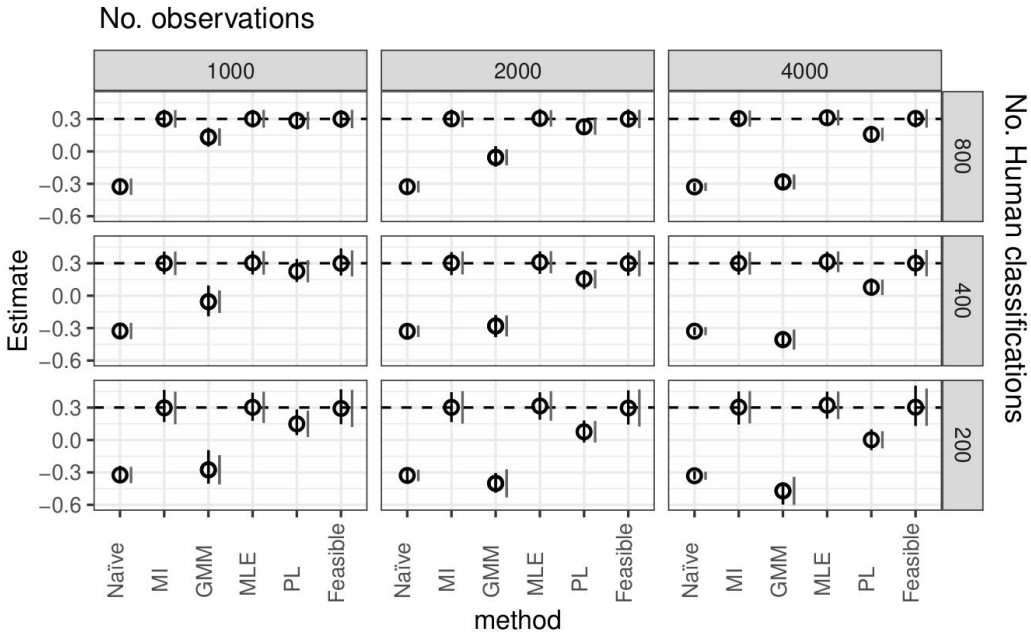
Notably, Zhang 2021's *pseudo-likelihood method* (PL) is inconsistent.

Multiple imputation is consistent, but inefficient.



Results: Differential error

Only our *likelihood modeling* approach and *multiple imputation* are consistent when measurement error is differential.

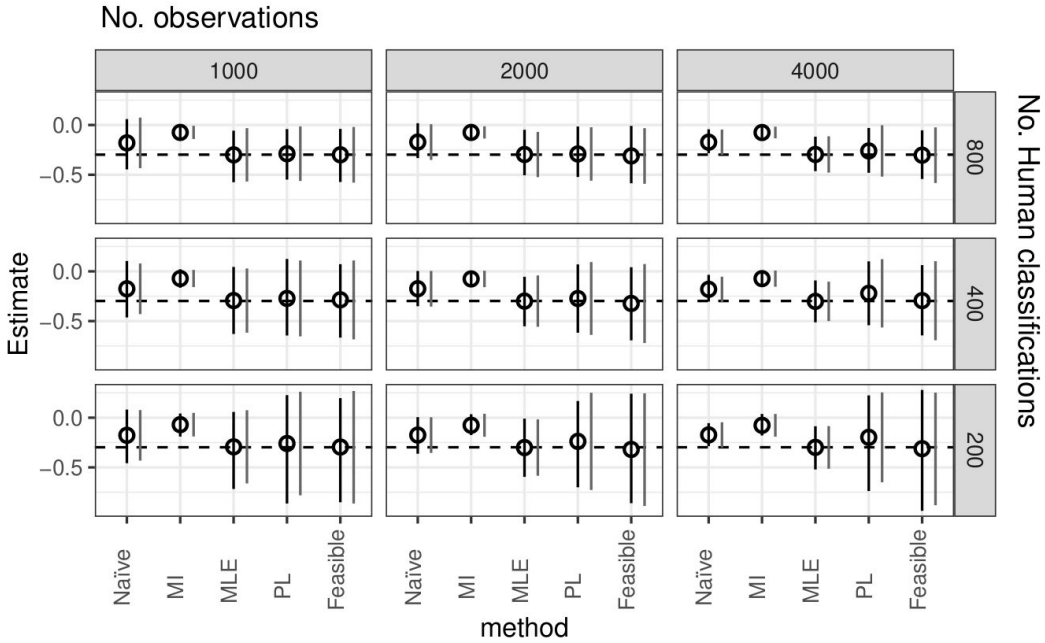


Results: (unbiased) Error in the outcome

Our *likelihood modeling* method is consistent and efficient when classification errors are in the outcome.

Multiple imputation is inconsistent.

Zhang 2021's *pseudo-likelihood model* is consistent, but inefficient.



Conclusion

(1) *"Validate, validate, validate" - yeah, but how?*
   (a) Prediction / accuracy metrics are not enough. They don't capture differential measurement errors or determine how measurement error affects inference.
   (b) Validation data can diagnose differential error.
   (c) Human coders make mistakes, use at least 2.

(2) *Validation data can be used to correct for (differential) measurement errors*

(3) *Report the "naïve", "feasible", and appropriate corrected estimates.*

Thank you!

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