Misclassification in Automated Content Analysis Causes Bias in Regression:

Can We Fix It? Yes We Can!

Nathan TeBlunthuis (nathante@umich.edu)[1]
Valerie Hase [3]
Chung-Hong Chan [4]

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Northwestern University [2]
LMU Munich[3]
GESIS[4]

Introduction

I'm an *computational social scientist* doing interdisciplinary research about how people organize to produce *public goods* and do *collective action* online and how technology can support them.

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Our paper

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[Submitted on 12 Jul 2023]

Misclassification in Automated Content Analysis Causes Bias in Regression. Can We Fix It? Yes We Can!

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Automated classifiers (ACs), often built via supervised machine learning (SML), can categorize large, statistically powerful samples of data ranging from text to images and video, and have become widely popular measurement devices in communication science and related fields. Despite this popularity, even highly accurate classifiers make errors that cause misclassification bias and misleading results in downstream analyses-unless such analyses account for these errors. As we show in a systematic literature review of SML applications, communication scholars largely ignore misclassification bias. In principle, existing statistical methods can use "gold standard" validation data, such as that created by human annotators, to correct misclassification bias and produce consistent estimates. We introduce and test such methods, including a new method we design and implement in the R package misclassificationmodels, via Monte Carlo simulations designed to reveal each method's limitations, which we also release. Based on our results, we recommend our new error correction method as it is versatile and efficient. In sum, automated classifiers, even those below common accuracy standards or making systematic misclassifications, can be useful for measurement with careful study design and appropriate error correction methods.

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Current best practice is transparency (e.g., precision; recall; F1 scores).

We can do better!
Our statistical methodology can use validation data to correct misclassification bias.

I'm going to show the only method that works well for random and non-random errors in dependent and independent variables.

What's wrong?

We want to estimate $Y \sim X\beta_X + Z\beta_Z$, but we use $W = \begin{cases} X & \text{if classifier is right} \\ \neg X & \text{if classifier is wrong} \end{cases}$.

In general, $\beta_W \neq \beta_X$.

Real Data Example

Civil comments: Dataset of 448,000 comments annotated for *toxicity* and *identity disclosure*, additional info on *likes*.

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We test logistic regression models with *toxicity* predicted or annotated.

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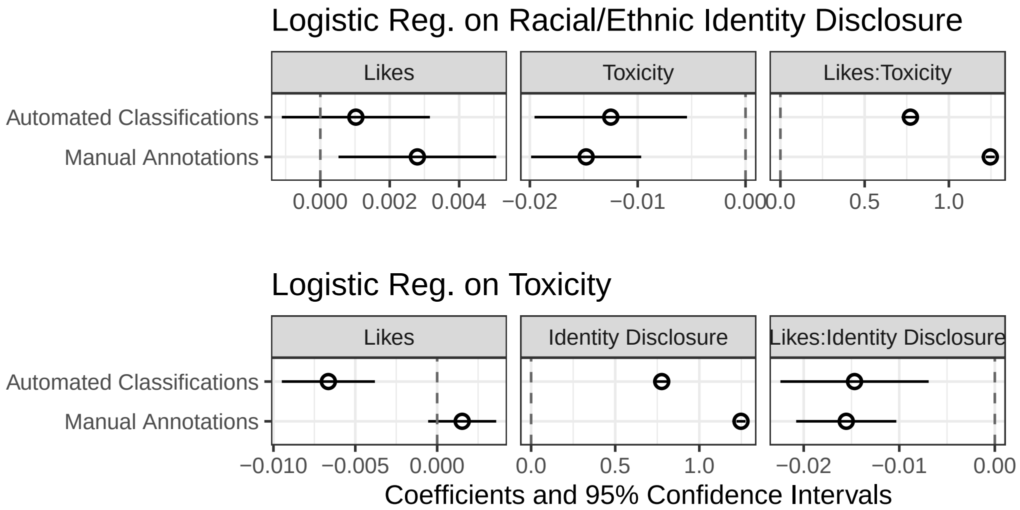

Transparency about Misclassification is Not Enough!


CAN WE
FIX IT?

Fixing it with `misclassificationmodels`: (IV Case)

The civil comments dataset has 488,000 observations! What if we can only afford 10,000?

```
fixed <- glm_fixit(race_disclosed ~ toxicity_coded || toxicity_pred * likes
                   data = perspective.data,
                   data2 = validation.data,
                   proxy_formula = toxicity_pred~toxicity_coded
                                                  *race_disclosed,
                   proxy_family = binomial(),
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                   truth_family = binomial())
```

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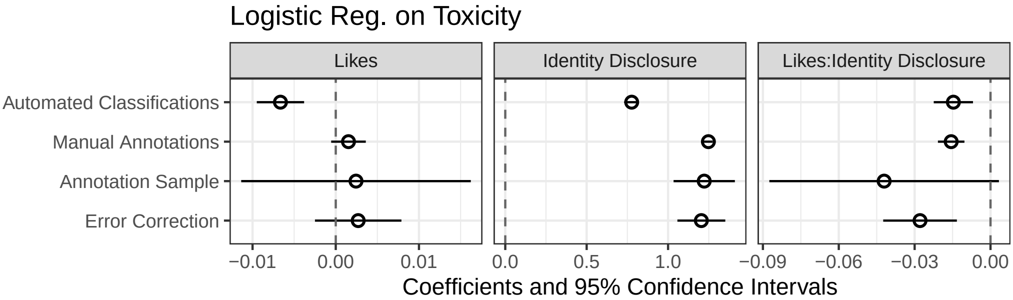

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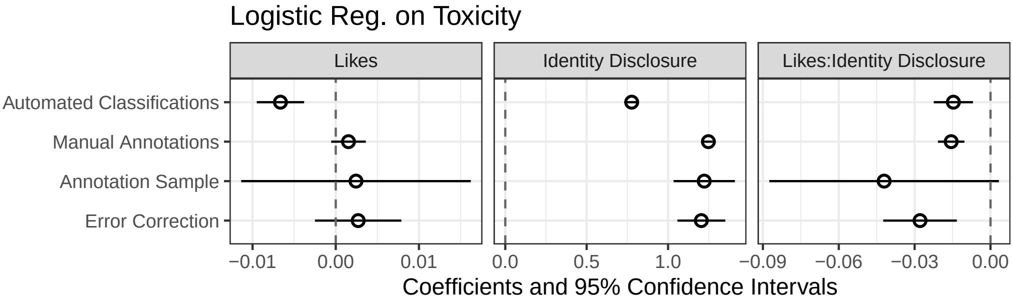

How does it work?

Notation

Y Dependent variable (dv) aka Outcome.

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X The variable measured via an AC.

Maximum Likelihood Adjustment for Misclassification

Our proposed approach implements a framework drawn from biostats.*

[*Carroll et al., *Measurement Error in Nonlinear Models*]

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This requires specifying 2-3 models:

Main model: Outcome Y given X, Z (e.g., $Y = B_0 + B_1 X + B_2 Z + \varepsilon$).
Proxy Model: Automatic classifications W given X, Y, Z.
Truth Model: Annotations X (only needed in the IV case).

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"Integrate out" missing annotations. g Jointly fit the product of the three models via maximum likelihood (MLE). If the models are valid, statistical theory promises *consistent* estimates.

More info on why this works on backup slides.

[*Carroll et al., *Measurement Error in Nonlinear Models*]

Methods from Prior Work in Social Science

Regression Calibration via Generalized Method of Moments (GMM)*

Use *manual annotations* to calibrate predictions; IV only.

Multiple Imputation (MI)†

Use predictions to impute *manual annotations*; IV or DV.

Pseudo-likelihood (PL)‡

Use *precision and recall* to model misclassification; IV or DV.

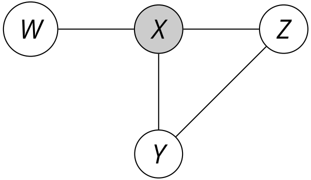
---

*(Fong and Tyler, "Machine Learning Predictions as Regression Covariates")

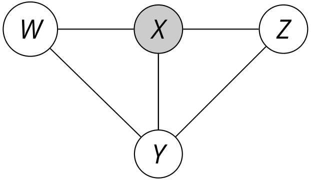
†(Blackwell, Honaker, and King, "A Unified Approach to Measurement Error and Missing Data")

‡(Zhang, *How Using Machine Learning Classification as a Variable in Regression Leads to Attenuation Bias and What to Do About It*)

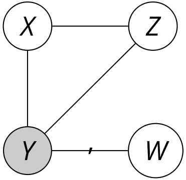
Types of Misclassification Bias



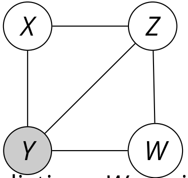
(a) When classifications *W* are independent of *Y* given *X*, a model using *W* has *non-differential error*.



(b) When classifications *W* depend on *Y* given *X*, we have *differential error*.



(c) An unbiased classifier measuring the outcome makes *nonsystematic* errors.



(d) When predictions *W* are independent of *Z* given *Y*, misclassification is *systematic*.

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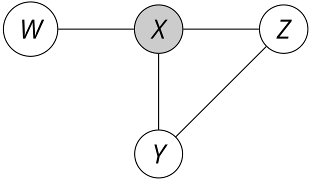

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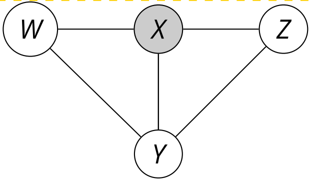

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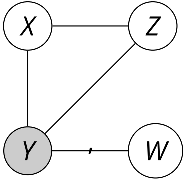

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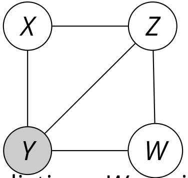

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Evaluating Methods to Correct Misclassification Bias

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We want a method that provides:

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- Accurate uncertainty quantification.
- Whether an AC measures X or Y.
- When misclassification is *differential* or *systematic*.

Monte-carlo simulation

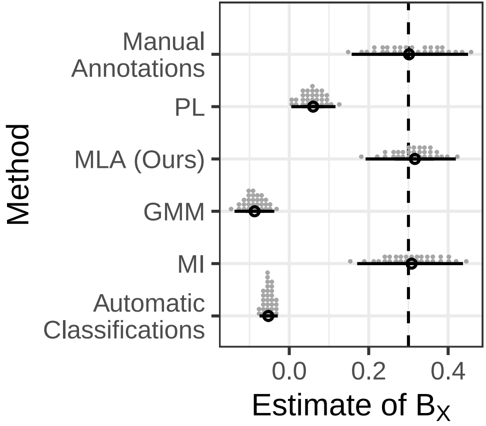
Low-medium accuracy classifier ($\sim$ 73% accuracy).

Relatively large effect sizes.

Reletively large dataset ($N = 10,000$)

Decent sample of validation data (200 labels).

Results: IV Case



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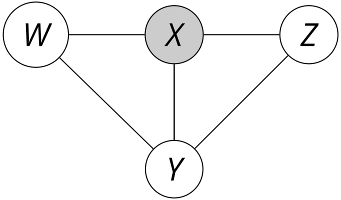

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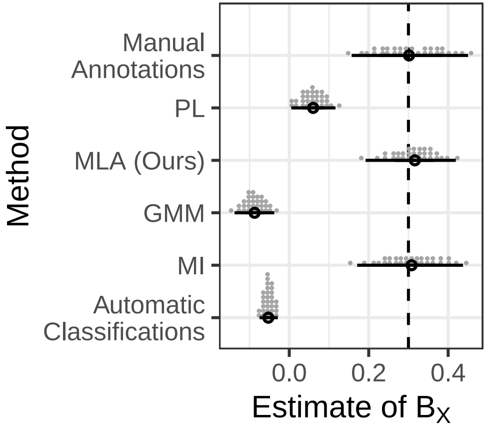

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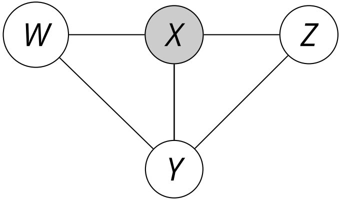

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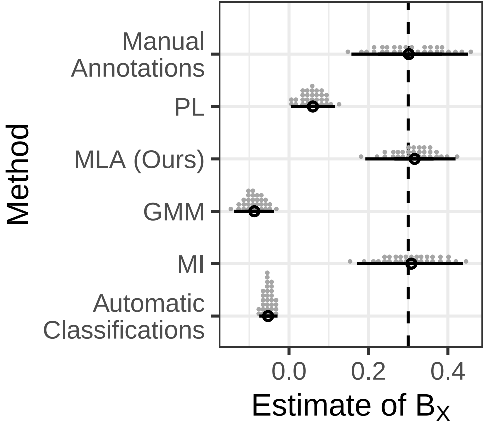

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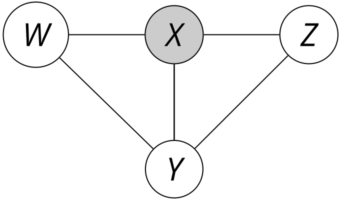

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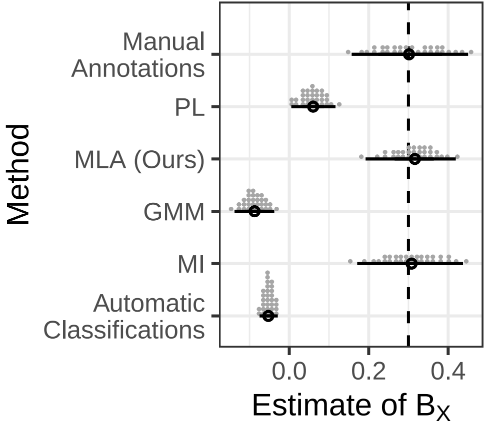

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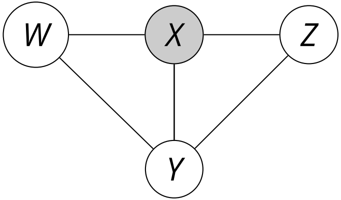
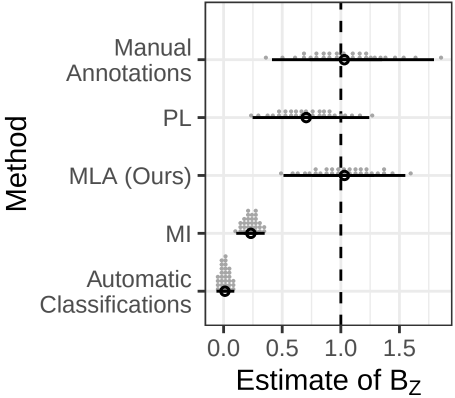
MLA (ours) is more efficient!



Results: DV Case



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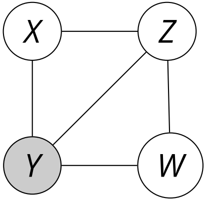

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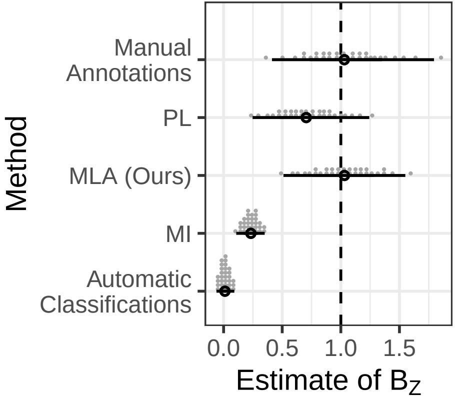

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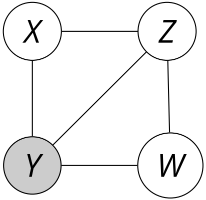

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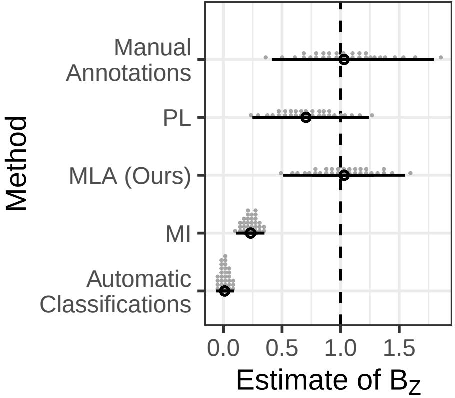

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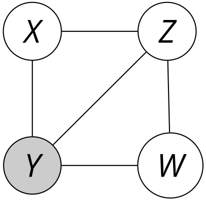

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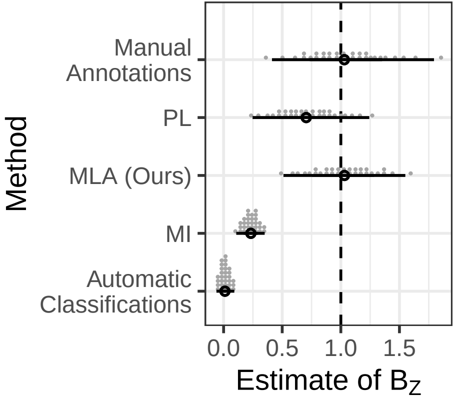

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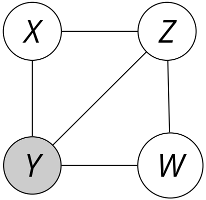
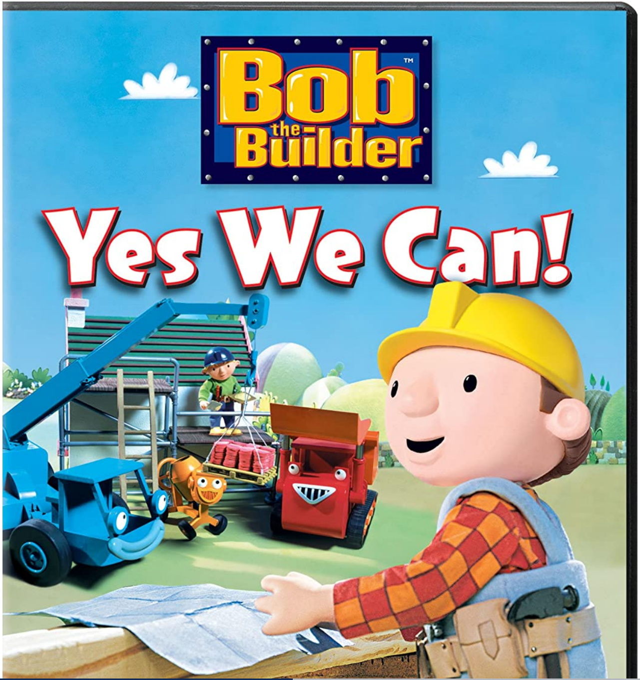
MLA (ours) is the only consistent method.




Bob the Builder
Yes We Can!

Limitations

MLA requires a correct model for W. This is possible when SML features are fully observed.

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MLA requires a correct model for W. This is possible when SML features are fully observed.

All correction methods assume error-free ground truth, but human annotators also make errors. Future work can try to account for both sources of error. *

*see Bachl and Scharkow, "Correcting Measurement Error in Content Analysis"

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https://teblunthuis.cc

Read our paper:

Backup Slides

MLA Derivation: IV Case

Following Carroll et al., *Measurement Error in Nonlinear Models*. Maximizing the joint likelihood given Y and W $L(Theta|Y, W)$ suffices to adjust for misclassification error. We only observe X sometimes, but we can integrate it out when missing.

$$
\begin{aligned}
P(Y, W) &= \sum_x P(Y, W, X = x) && (1)\\
&= \sum_x P(Y|W, X = x)P(W, X = x) && (2)\\
&= \sum_x P(Y, X = x)P(W|Y, X = x) && (3)\\
&= \sum_x P(Y|X = x)P(W|Y, X = x)P(X = x) && (4)
\end{aligned}
$$

MLA Specification: IV Case

Consider the regression model $Y = B_0 + B_1 X + B_2 Z + \varepsilon$ and automated classifications W of the independent variable X. We can assume that the probability of W follows a logistic regression model of Y, X, and Z and that the probability of X follows a logistic regression model of Z. In this case, the likelihood model below is sufficient to consistently estimate the parameters: $\Theta = \{\Theta_Y, \Theta_W, \Theta_X\} = \{\{B_0, B_1, B_2\}, \{\alpha_0, \alpha_1, \alpha_2, \alpha_3\}, \{\gamma_0, \gamma_1\}\}$.

$$\mathcal{L}(\Theta; y, w) = \prod_{i=0}^{N} \sum_{x} f_{\Theta_Y}(y_i | x_i, z_i; \Theta_Y) p_{\Theta_W}(w_i | x_i, y_i, z_i; \Theta_W) p_{\Theta_X}(x_i | Z_i; \Theta_X) \quad (5)$$

$$f_{\Theta_Y}(y_i | x_i, z_i; \Theta_Y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{(y_i - (B_0 + B_1 x_i + B_2 z_i))^2}{\sigma})^2} \quad (6)$$

$$p_{Theta_W}(w_i | x_i, y_i, z_i; \Theta_W) = \frac{1}{1 + e^{-(\alpha_0 + \alpha_1 y_i + \alpha_2 x_i + \alpha_3 z_i)}} \quad (7)$$

$$p_{Theta_X}(x_i | z_i; \Theta_X) = \frac{1}{1 + e^{-(\gamma_0 + \gamma_1 z_i)}} \quad (8)$$

MLA Derivation: DV Case

As with the IV case, maximizing $\mathcal{L}(\Theta|Y, W)$, the joint likelihood of the parameters Θ given the outcome Y and automated classifications W measuring the dependent variable Y (Carroll et al., *Measurement Error in Nonlinear Models*). We just need to integrate out the missing Y.

$$P(Y, W) = \sum_{y} P(Y = y, W) \tag{9}$$

$$= \sum_{y} P(Y)P(W|Y) \tag{10}$$

MLA Specification: DV Case

If we assume that the probability of Y follows a logistic regression model of X and Z and allow W to be biased and to directly depend on X and Z, then maximizing the following likelihood is sufficient to consistently estimate the parameters $\Theta = \{\Theta_Y, \Theta_W\} = \{\{B_0, B_1, B_2\}, \{\alpha_0, \alpha_1, \alpha_2, \alpha_3\}\}$.

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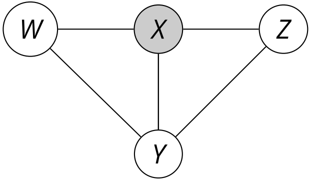
$$p_{\Theta_Y}(y_i | x_i, z_i; \Theta_Y) = \frac{1}{1 + e^{-(B_0 + B_1 x_i + B_2 z_i)}} \tag{12}$$

$$p_{\Theta_W}(w_i | y_i, x_i; Z_i, \Theta_W) = \frac{1}{1 + e^{-(\alpha_0 + \alpha_1 y_i + \alpha_2 x_i + \alpha_3 z_i)}} \tag{13}$$

Simulation Study: IV Case



Y and Z are normally distributed.

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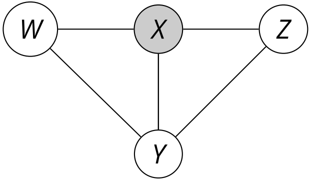

Y and Z are normally distributed.
X is binary with $P(X) = 0.5$, observed 200 times, missing at random (MAR), correlated with Z ($\rho = 0.24$).

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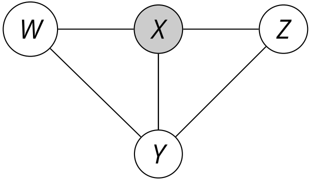

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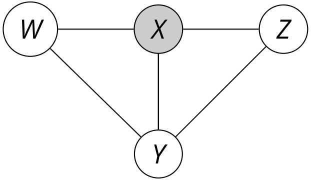

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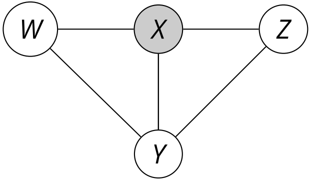
W is a classifier predicting X with $\sim 0.73\%$ accuracy.
W's errors correlate with Y ($\rho = -0.17$).

Simulation Study: IV Case



Y and Z are normally distributed.
X is binary with $P(X) = 0.5$, observed 200 times, missing at random (MAR), correlated with Z ($\rho = 0.24$).
W is a classifier predicting X with $\sim 0.73\%$ accuracy.
W's errors correlate with Y ($\rho = -0.17$).
10,000 observations; repeat simulations 500 times.

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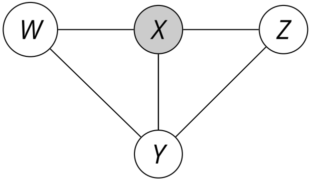

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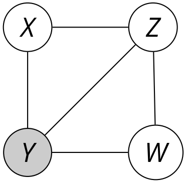
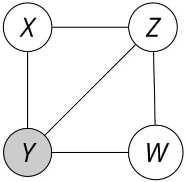
Methods tested: *GMM*, *MI*, *PL*, *MLA*, no correction (*Naïve*), annotated data only (*Feasible*).

Simulation Study: DV Case



Like the IV case only:
W is a classifier predicting *Y* with $\sim 0.73\%$ accuracy, errors correlate with *Z* ($\rho = 0.2$).

Simulation Study: DV Case



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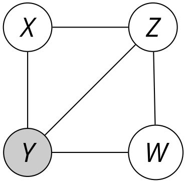

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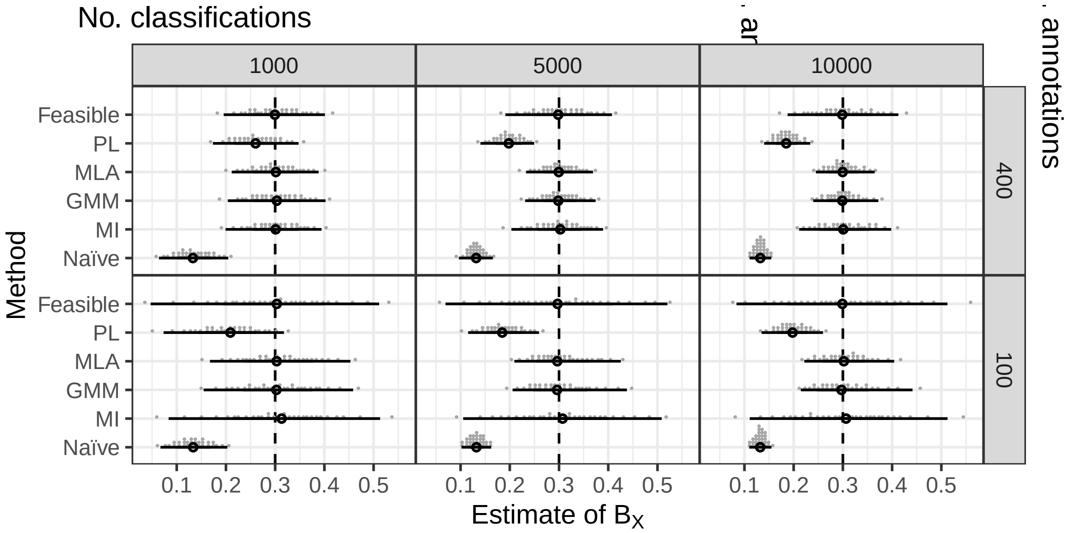
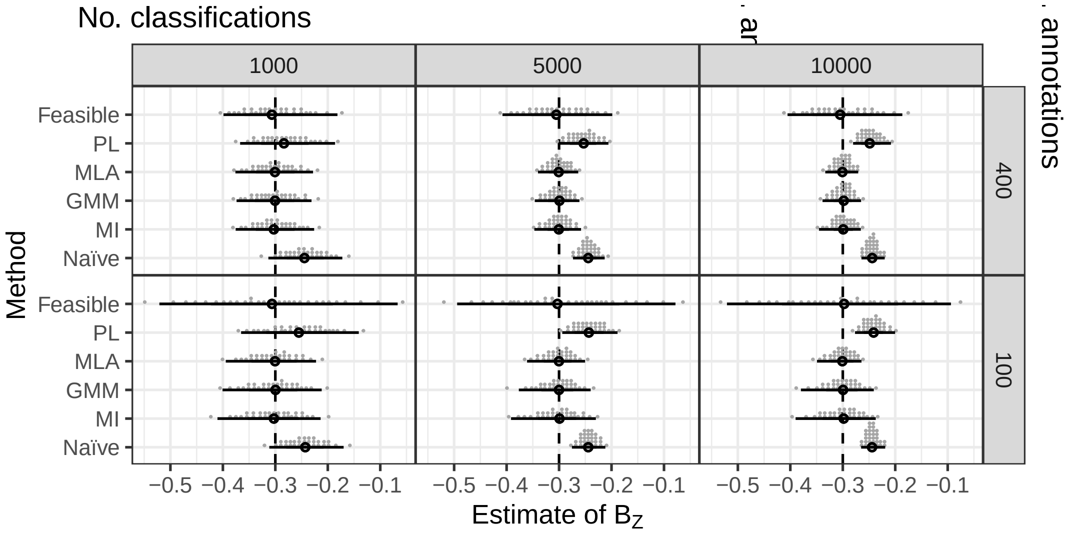
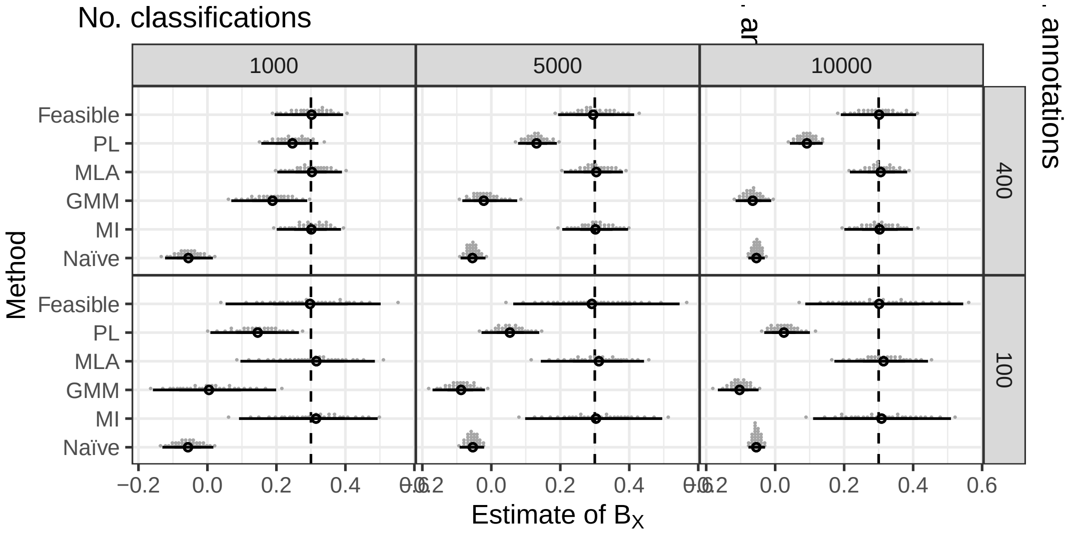
Simulation Results: Non-differential Error



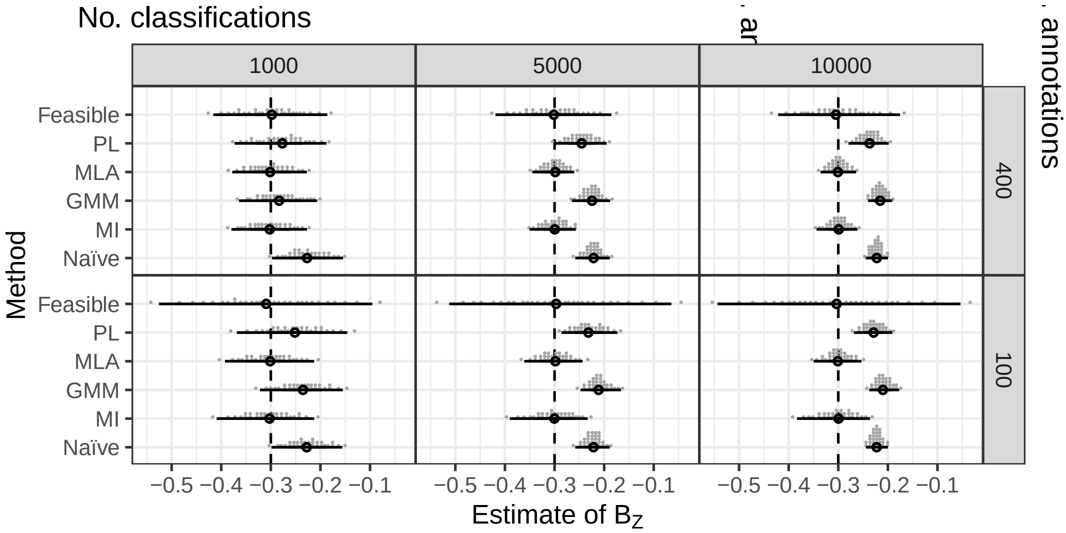
Simulation Results: Non-differential Error (Z)



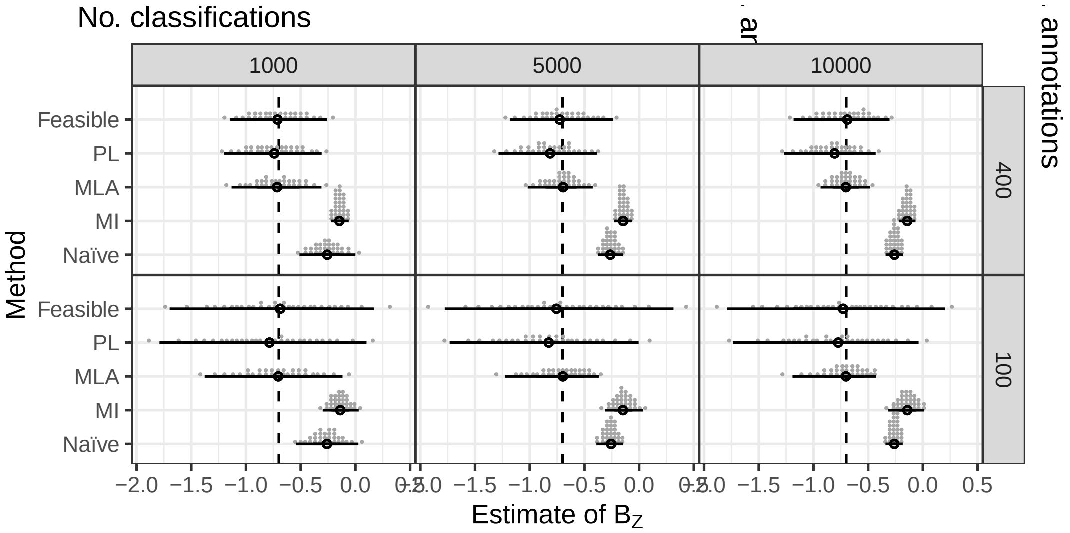
Simulation Results: Differential Error



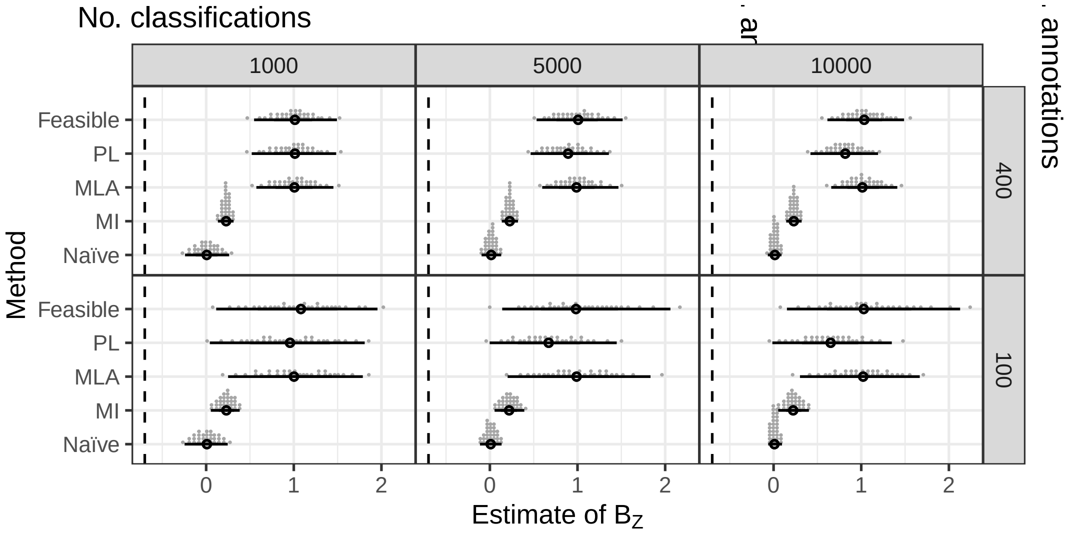
Simulation Results: Differential Error (Z)



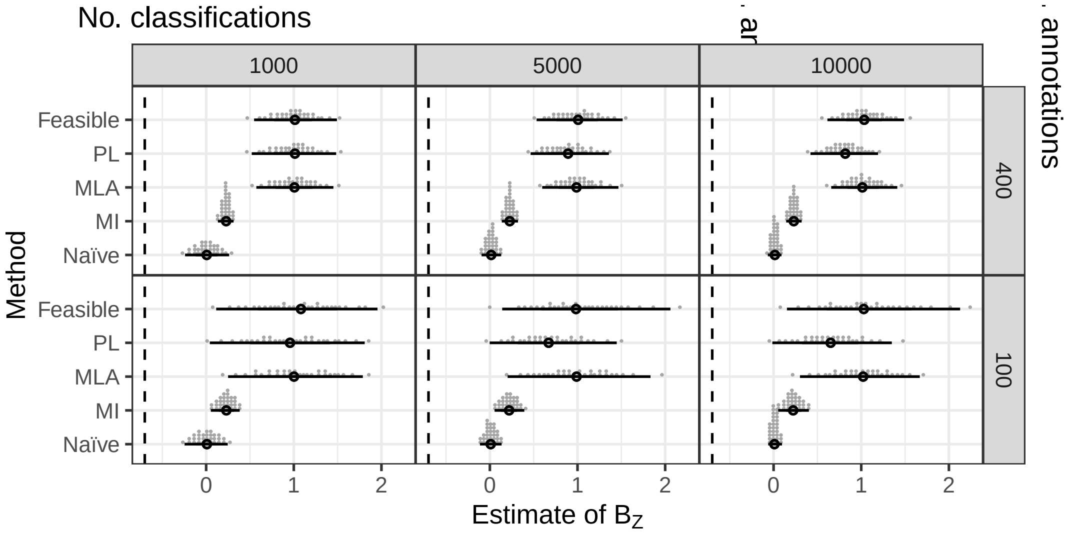
Simulation Results: Nonsystematic Misclassification



Simulation Results: Nonsystematic Misclassification (X)



Simulation Results: Systematic Misclassification



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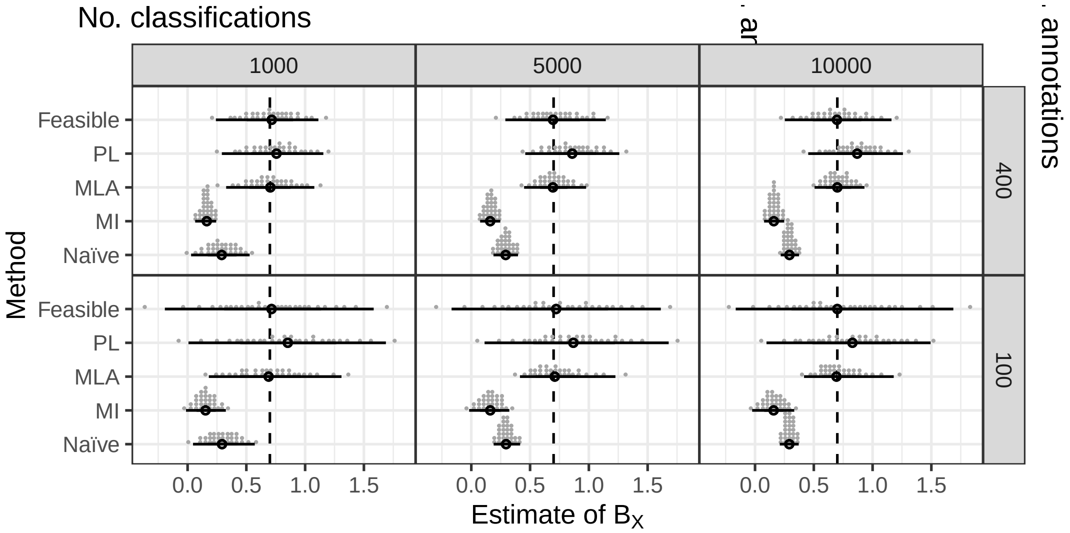


Fixing it with `misclassificationmodels`

```
kable(nrow(research.data))
```

x
4900

```
kable(research.data[1:5,],align='c')
```

y	z	w
-0.16	0	1
-0.33	1	1
0.59	1	0
-0.05	0	0
-0.12	1	1

Fixing it with `misclassificationmodels`

```r
kable(nrow(validation.data))
```

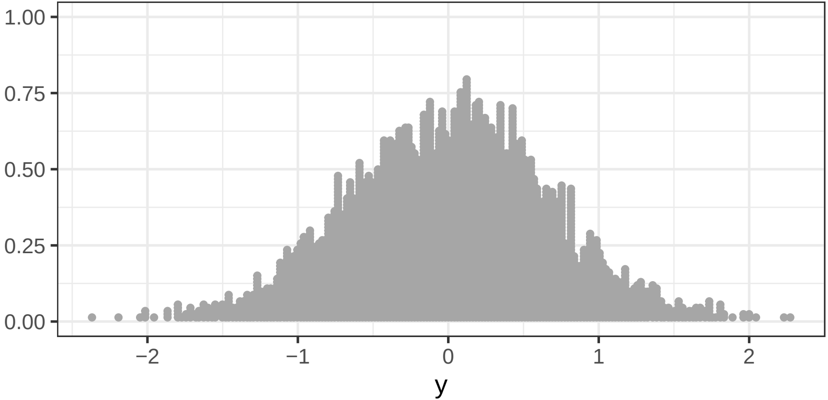
x
100

```r
kable(validation.data[1:5,],align='c')
```

x	y	z	w
0	0.54	0	0
0	-0.51	0	1
1	-0.27	1	1
1	-0.36	1	1
1	0.13	0	1

Fixing it with `misclassificationmodels`

```r
library(ggdist)
ggplot(research.data, aes(x=y)) + geom_dots(binwidth=unit(0.01,"npc"),
                                            overflow='compress')
```



Fixing it with `misclassificationmodels` (Normal data)

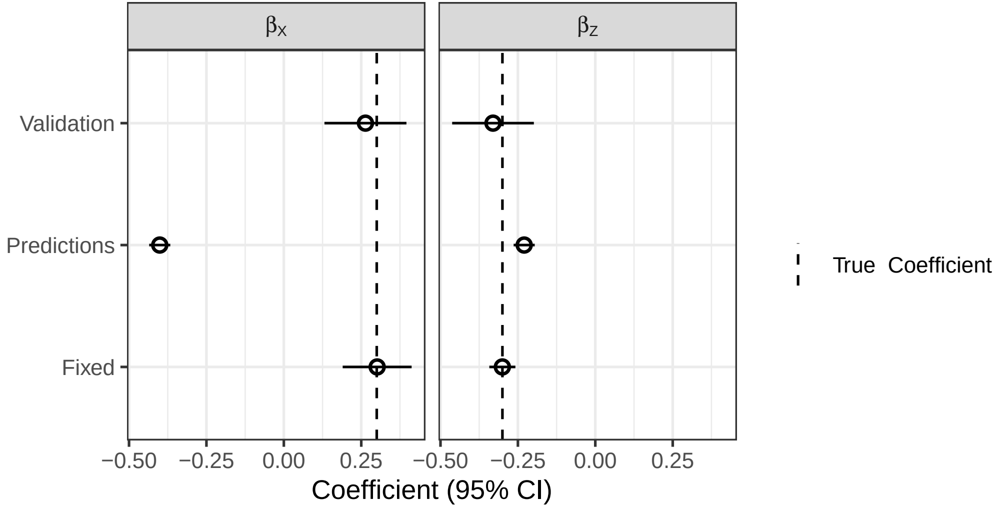
```r
tab <- table(w = validation.data[["w"]], x = validation.data[["x"]])
conmat <- caret::confusionMatrix(tab,mode = "everything",positive = "1")
kable(conmat[["byClass"]][c("Precision",
                            "Recall",
                            "F1",
                            "Sensitivity",
                            "Specificity")])
```

	x
Precision	0.60
Recall	0.56
F1	0.58
Sensitivity	0.56
Specificity	0.57

Fixing it with `misclassificationmodels` (Normal data)

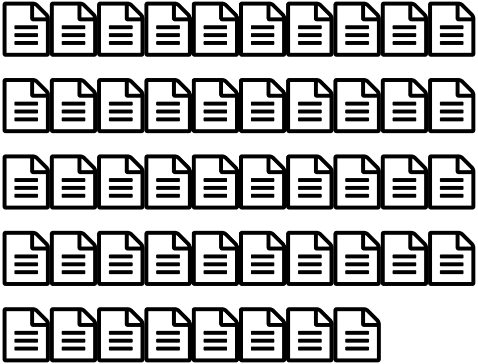
```
validation <- lm(y~x+z,data=validation.data)

predictions <- lm(y~w+z,data=research.data)

fixed <- glm_fixit(formula = y ~ x || w + z,
                   data = research.data,
                   data2 = validation.data,
                   proxy_formula = w ~ x*y*z,
                   proxy_family = binomial(),
                   truth_formula = x ~ z,
                   truth_family = binomial())
```

Fixing it with `misclassificationmodels` (Normal data)



Systematic Literature Review

Systematic Literature Review



SML-based text-as-data studies (N=48) identified in prior reviews.*

[* Baden et al., “Three Gaps in Computational Text Analysis Methods for Social Sciences”
Hase, Mahl, and Schäfer, “Der „Computational Turn“”
Jünger, Geise, and Hännelt, “Unboxing Computational Social Media Research From a Datahermeneutical Perspective: How Do Scholars Address the Tension Between Automation and Interpretation?”

Song et al., “In Validations We Trust?”]

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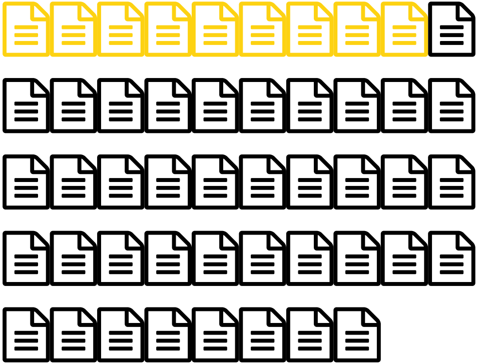

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9 mention misclassification as a threat to validity.

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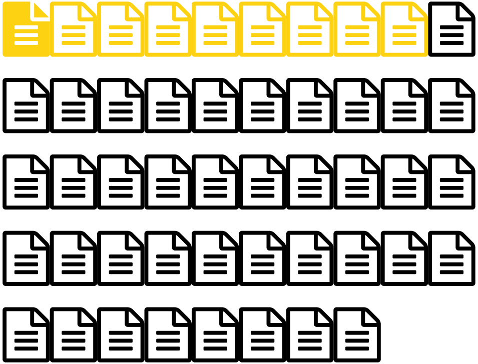

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Misclassification is a largely ignored threat.