A benchmark dataset for detecting frames in multi-topical news content: Online Appendix

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Regression coefficients of the Bayesian model

Table 1

# Fixed Effects

Parameter	Median	89% CI	pd	Rhat	ESS
(Intercept)	0.47	(0.39, 0.55)	100%	1.003	1482.00
method_typeSemisupervised	-0.11	(-0.20, -9.51e-03)	95.70%	1.002	1334.00
method_typeAutomatic	-0.15	(-0.24, -0.06)	98.90%	1.003	1270.00

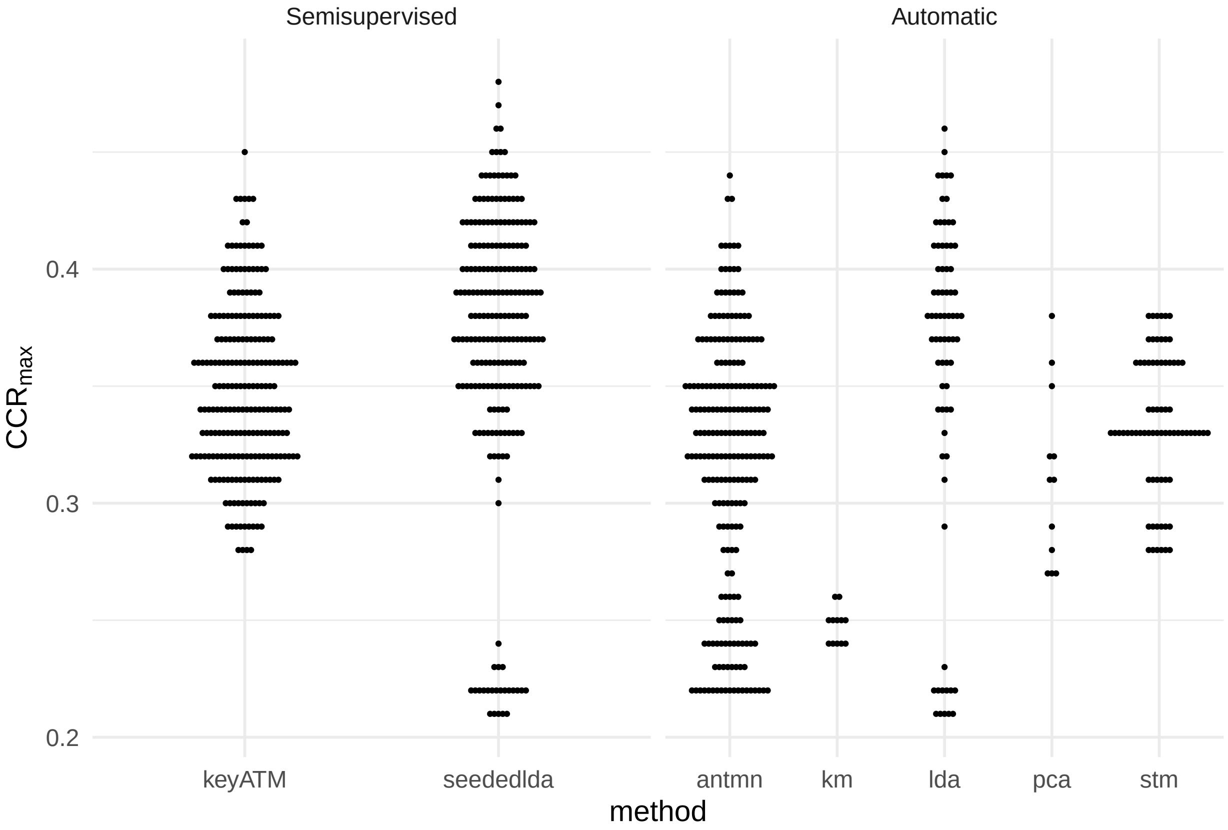
Table 2

# Sigma

Parameter	Median	89% CI	pd	Rhat	ESS
sigma	0.05	(0.05, 0.05)	100%	1.000	3519.00

$R^2 = 0.1828662$

Visualization of the variance



Comparing confidence level of correct and incorrect expert coding

We modeled the correctness of expert coding ("F1" is equal to the ground truth) and confidence level ("F2"), while adjusting for individual differences between the two experts using Bayesian multilevel logistic regression analysis. The following is the robust conditional effect plot. There is no evidence to suggest that there is a trend. Therefore, experts can either confidently give correct and incorrect coding.

Simulation of increasing sample size

In this analysis, we simulated the possible outcome of increasing the sample size on the multiverse analysis.

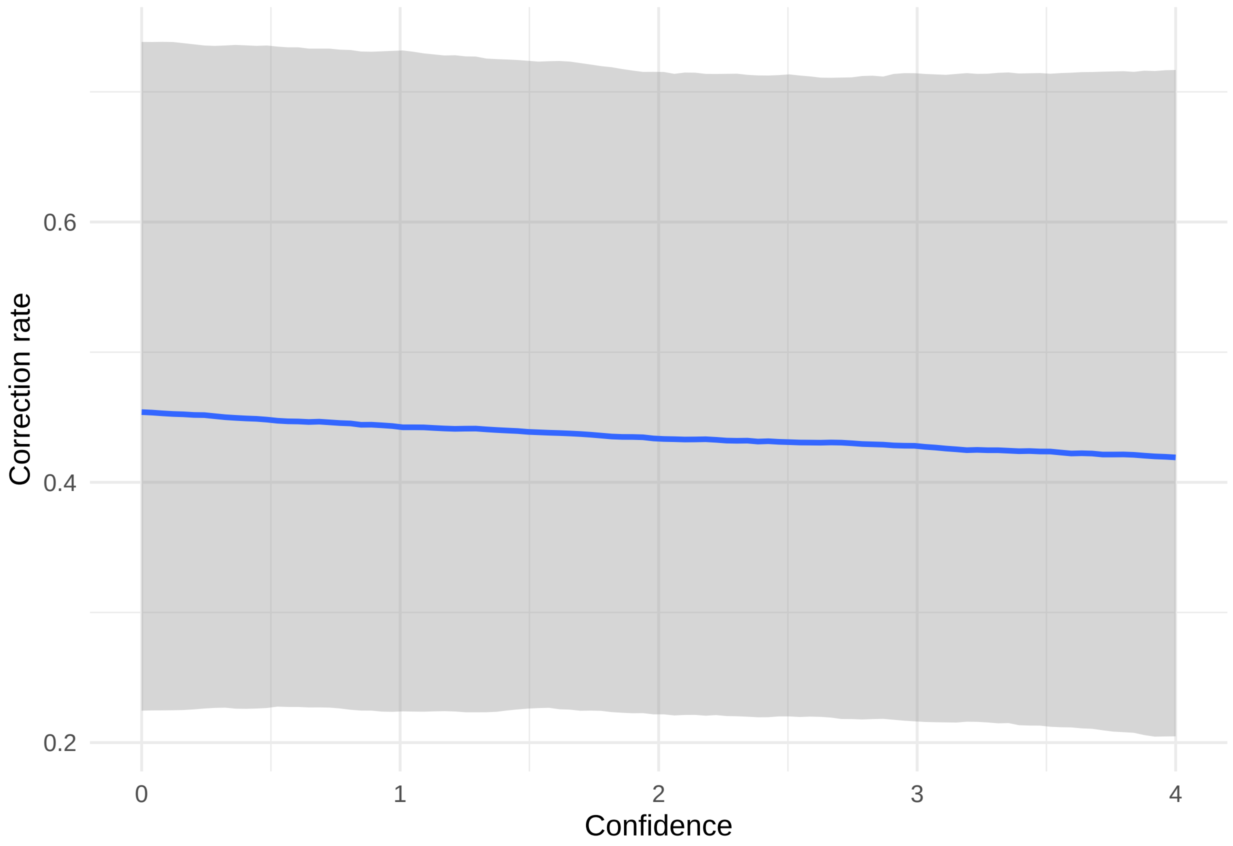


Figure 1. Robust conditional effects from the Bayesian model on the relationship between correction rate of expert coding and confidence at 89% credibility

From our 100 articles, we created further synthetic articles following the principle of bootstrapping. We synthesized more articles based on the following algorithm:

1. Randomly select one article
2. Tokenize this article into its n sentences
3. From these n sentences, randomly draw n sentences from these sentences with replacement. Therefore, one sentence can appear more than once.
4. Concatenate these randomly drawn n sentences into a synthetic article, assign this article with the same topic and frame as the original article

We repeat the above process for 500, 1000, and 2000 times to generate 3 different corpora. This approach is compatible with the bag-of-words representation used in all unsupervised and semi-supervised methods because the word order is not considered. Also in step 3, topical and frame clues have the same natural chance of being selected. To put this simulation in another perspective, it simulates whether frames, rather than topics, are more likely to be picked up by these unsupervised and semi-supervised methods when the sample size increases.

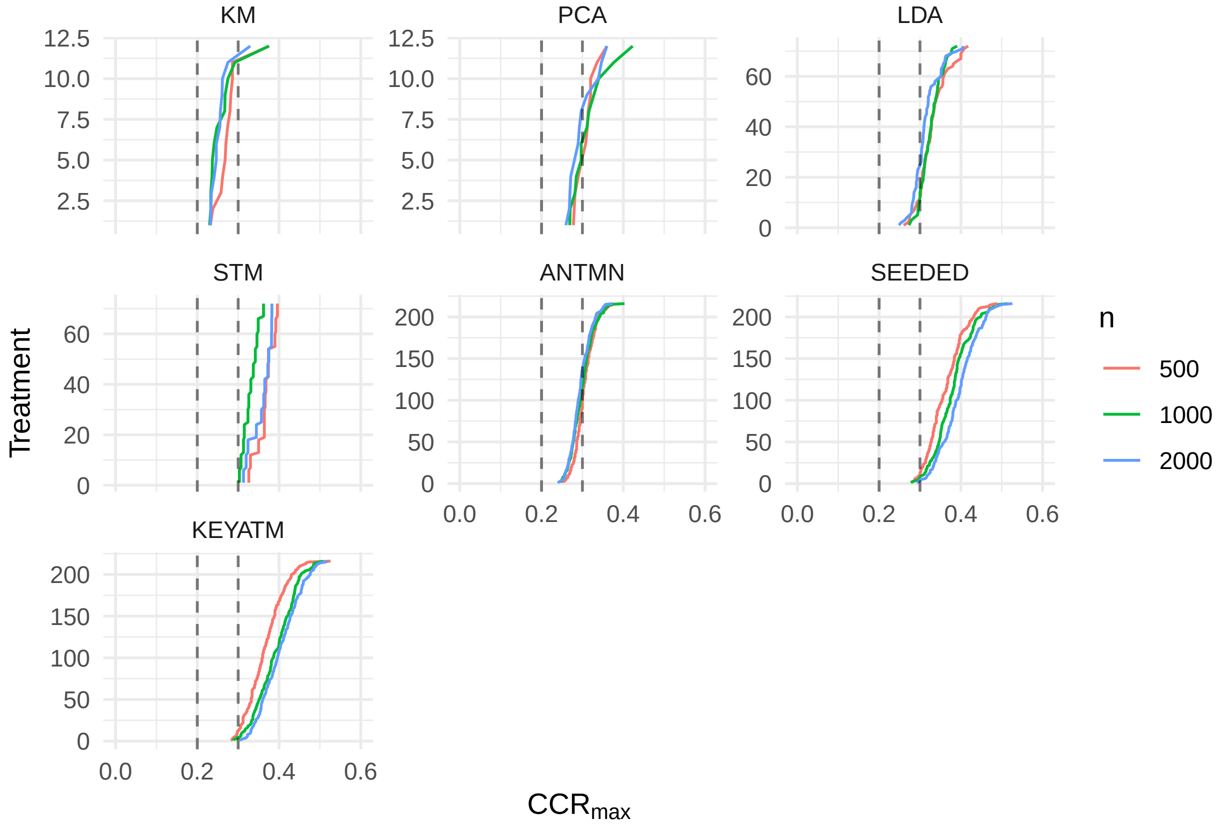


Figure 2. Multiverse analyses with different sample sizes: 500, 1000, 2000

The above figure shows the sorted CCR_{max} like the visualization of multiverse in the main text. All confidence intervals have been stripped for clarity as we are only interested in the point estimate. The treatments are the same as the main analysis and they are not displayed in the y-axes.

From this simulation, it is extremely unlikely that increasing the sample size would increase the CCR_{max} for all unsupervised methods. Instead, all methods, except KM and STM, perform more like the de-facto null (0.3) with the increasing sample size. Therefore, these methods appear to be more keen to pick up **topics**, rather than frames, when sample size increases: the sorted performance curve rescinding towards the null value with the highest sample size. For the two semi-supervised methods, increasing the sample size appears to provide better resistance against the rescinding.

We also performed the same Bayesian analysis using the simulated data. By increasing the sample size, it appears that both H1 and H2 would become more significant, instead of the other way around.

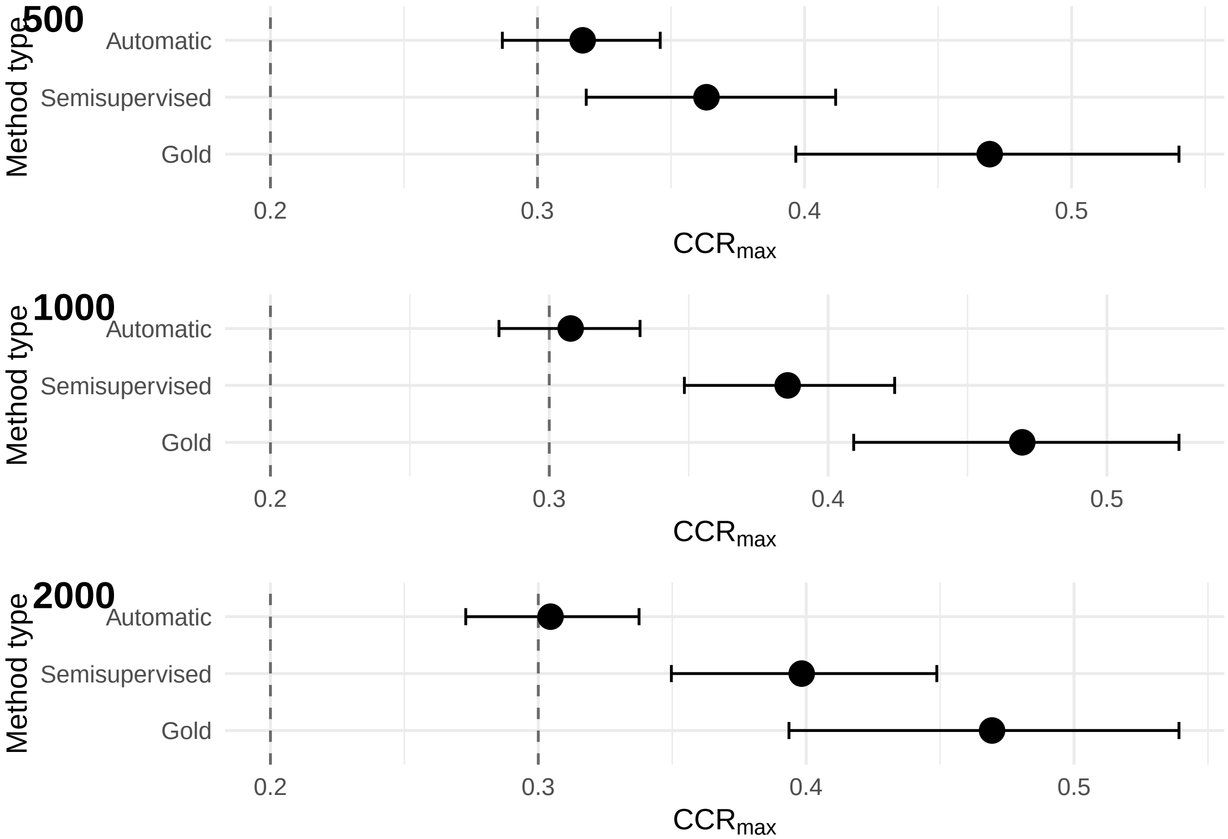


Figure 3. Robust conditional effects from the Bayesian model of the "gold standard", semi-supervised and automatic methods at 89% credibility with different simulated sample sizes