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Response presentation on “Sensitivity Analysis for Causal Mediation through Text: an Application to Political Polarization”

Outline

1. Feedback
2. Main contributions
3. Sensibility of Data
4. Key assumptions check
5. Mediator robustness
6. Improvements

Feedback

Presentation style

- Motivation
- Slide structure
- Support material (Graphs, Tables...)

Feedback

Analysis of the paper

- Amount of information
- Explanation of key theories
- Interpretation of results
- Future research

Main contributions

1. Introduce a **sensitivity analysis for mediation** when the information on the mediator is observed for only one group in an experiment.

- No text data for the control group
- Because no meaningful relationship is identified, the mediation sensitivity procedure is not needed.
- Other contributions: marketing applications, power analysis

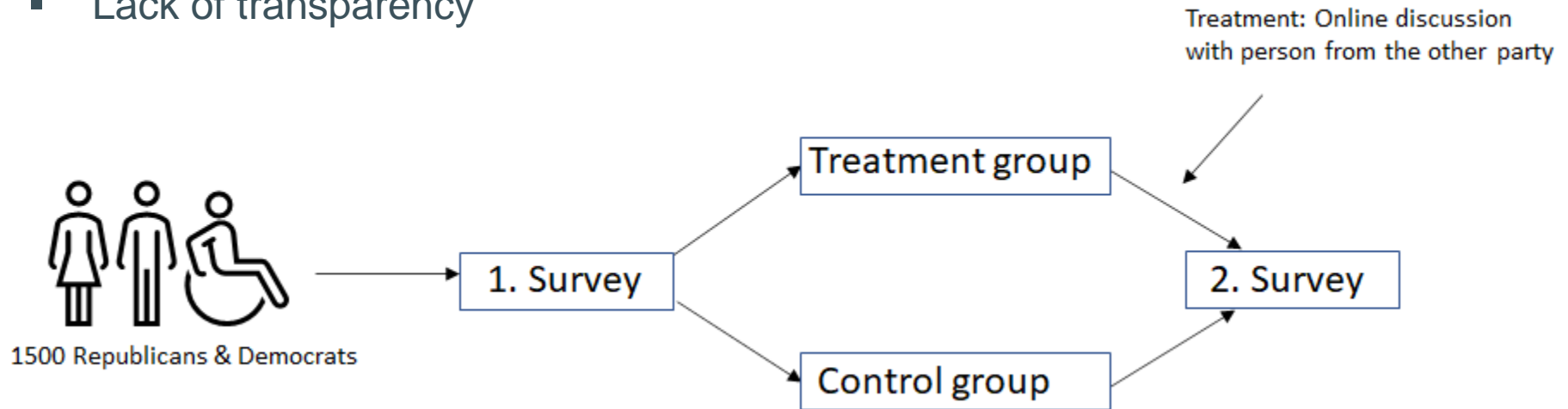
Main contributions

2. Demonstrate the difficulty of **using unsupervised text models** for performing a causal analysis

- Problem: These unsupervised text models do not perform well and need domain knowledge
- Reason: Small size of the data

Sensibility of Data

- Lack of transparency

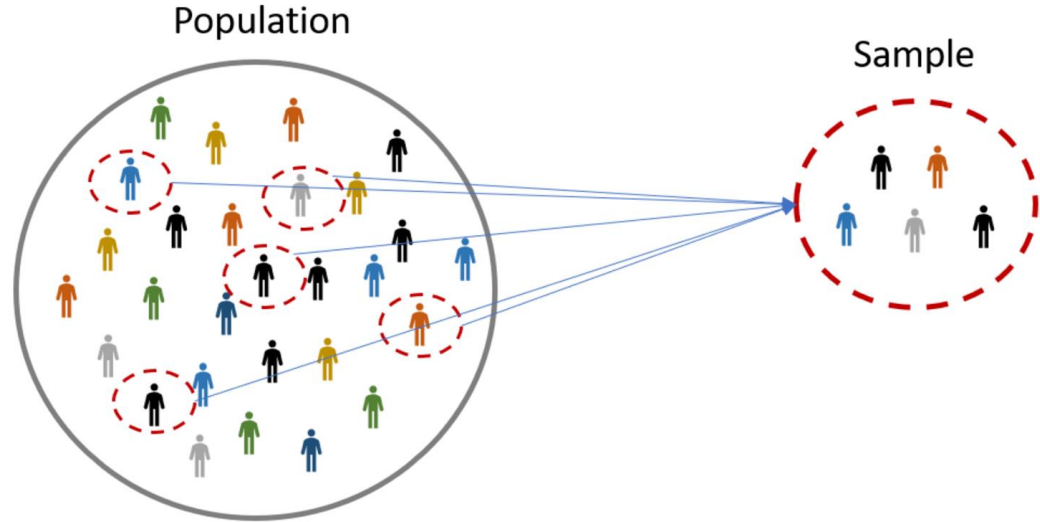


Sensibility of Data

- Problems with survey data:
 1. Response bias (Paulhus 1991)
 2. Experimenter bias (Innes and Fraser 1971)
 3. Attrition bias (Nunan et al. 2018)

Sensibility of Data

- Small sample size



Sensibility of Data

- Data Preprocessing
 - Making all words lower case
 - Removing standard stop-words
 - Dropping words that appear in fewer than 1% documents

Possible extensions:

- Stemming (e.g. running → run)
- Lemmatization (e.g. ran → run)
- Text normalization (e.g. btw → by the way)

Key Assumptions Check

1. Stable Unit Treatment Value Assumption (SUTVA)

- 1) The potential outcomes for any unit do not vary with the treatments assigned to other units.
- 2) For each unit, there are no different forms or versions of each treatment level, which lead to different potential outcomes.

Key Assumptions Check

2. Conditional independence or unconfoundedness

- Treatment is assigned independent of the potential outcome

$$Y_i(0), Y_i(1) \perp\!\!\!\perp T_i | X_i$$

Additional assumptions regarding cross-world quantities $M_i(1)$ and $Y_i(0, M_i(1))$:

- Conditional independence of the treatment
- Conditional independence of the mediators

Key Assumptions Check

3. Positivity

- Ensures that every observation has a strictly positive chance of being in the treatment group or control group

For all i , $0 < \Pr(T_i = 1 | X=x) < 1$

- Positivity is testable

Key Assumptions Check

- A randomized experiment guarantees that conditional independence and positivity hold
 - But given the existing data from the experiment, the authors cannot rely on the randomization to identify causal effects
- Solution: Rely on prior work that identifies politeness or civility as a key feature in producing persuasive text
 - But politeness is probably not a good mediator

Key Assumptions Check

4. Additional assumption

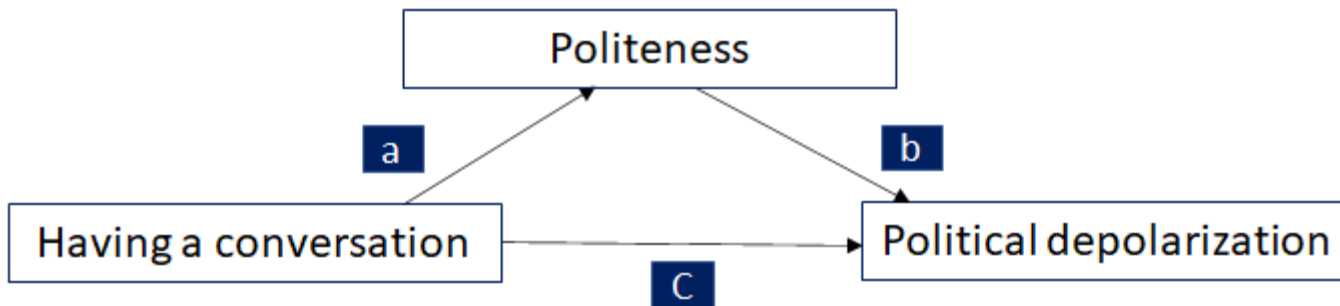
- $p(Y|M)$ is the same for $T = 1$ and $T = 0$
- This assumption becomes testable only by changing the underlying research questions.

Key Assumptions Check

5. Summary measures of the text might need some changes in assumptions

- This requires replacing the existing assumptions with ones that include the summarization procedure.

Mediator robustness



- a and b: Indirect effect of treatment on outcome through the mediator
- c: Direct treatment-outcome effect

Mediator robustness

- Politeness as a weak mediator

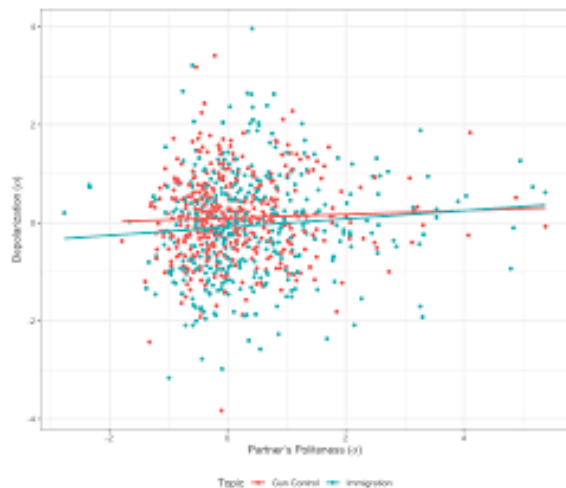


Figure 1: Depolarization and partner politeness (Tierney and Volfovsky 2021)

	All	Dem	Rep
	(1)	(2)	(3)
Politeness	0.069* (0.035)	0.119* (0.046)	0.002 (0.052)
Constant	0.160 (0.215)	0.565 (0.288)	-0.294 (0.312)
Observations	819	408	411

Table 1: Results from regressing depolarization on partner politeness and demographic control variables (Tierney and Volfovsky 2021)

Mediator robustness

- Formalize language as constitutive variable (Keith et al. 2021)

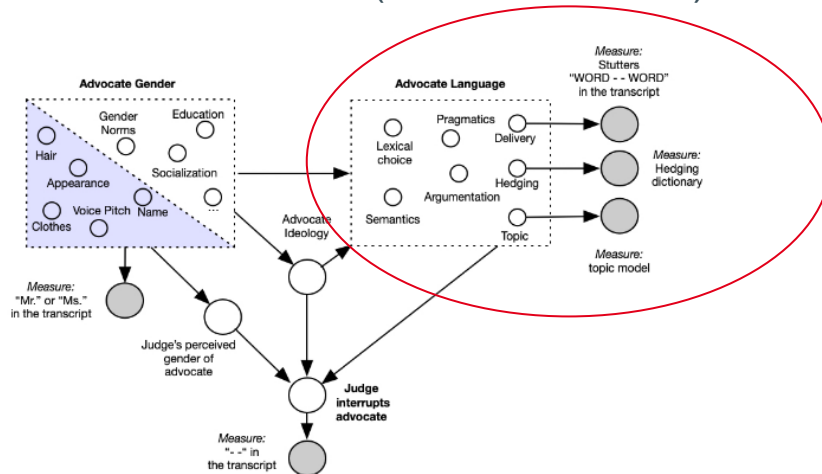


Figure 2: Constitutive causal diagram for gendered interruption in U.S. Supreme Court oral arguments

Mediator robustness

Further problems:

- Violation of ignorability of the mediator (Imai et al. 2010)
- Dependence between social group perception and language perception (Keith et al. 2021)

Improvements

- Summary statistics for data
- Larger dataset or adjust research question
- Extend the data pre-processing
- Other mediators

References

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- Trang Quynh Nguyen, Elizabeth B. Sarker, Ian Schmid, Noah Greifer, Elizabeth L. Ogburn, Ina M. Koning, and Elizabeth A. Stuart. 2021. Clarifying causal mediation analysis: From simple to more robust strategies for estimation of marginal natural (in)direct effects.
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- Imai, Kosuke, Luke Keele, and Dustin Tingley. "A general approach to causal mediation analysis." Psychological methods 15.4 (2010): 309.