Exploratory and Confirmatory Causal Inference for High Dimensional Interventions

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(Drawing from joint work with Christian Fong, Molly Roberts, and Brandon Stewart)

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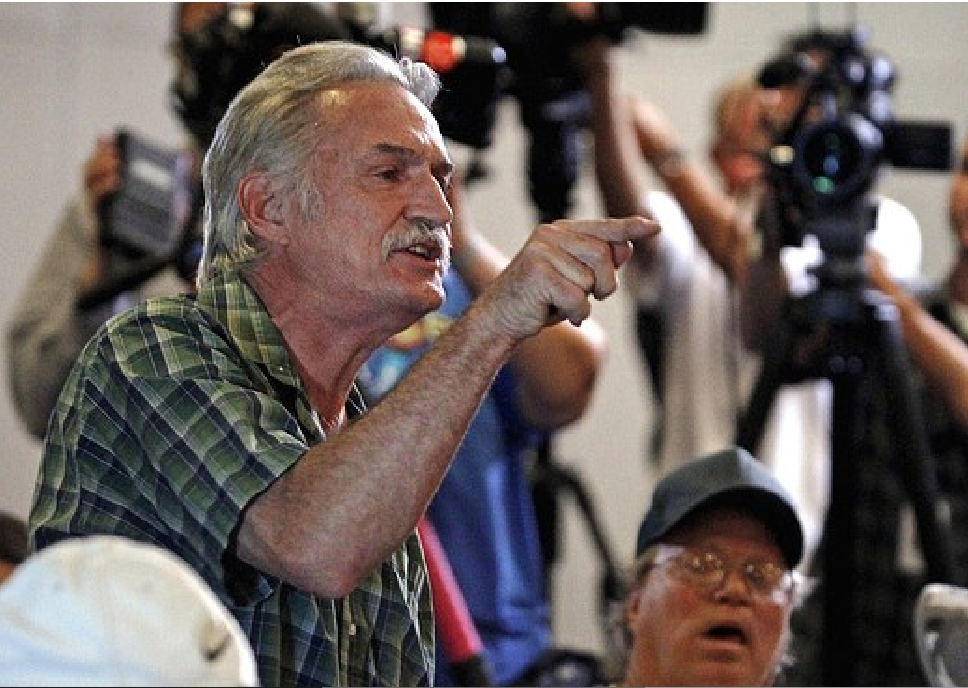
Causal Inference with Text Treatments

- How does X affect Y?

- How does X affect Y?
- X is often high-dimensional $\rightsquigarrow$ encoded in natural language


‘Brutal Anti-Cruz Attack Ad
Just 30 Seconds Of Candidate’s Photo
Displayed Without Any Text, Voiceover, Music’
The Onion




RESIST
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RESIST
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USA
Shelby Hall
Engineering and Computing Sciences


DANGER
RUN
WITH
HAND

Causal effect of text?

(Discover) Causal effect of text?

Candidate Backgrounds: Running Example for Paper

How do voters evaluate candidates?

- Candidates have policy positions and partisan affiliation
- Also have lives before elected office

What biographical facts affect voter evaluations?

Survey Experiment

Current Approaches: Text-Based Survey Experiments

Document 1: He earned his Juris Doctor in 1997 from Yale Law School, where he operated free legal clinics for low-income residents of New Haven, Connecticut.

Document 2: He served in South Vietnam from 1970 to 1971 during the Vietnam War in the Army Rangers' 75th Ranger Regiment, attached to the 173rd Airborne Brigade. He participated in 24 helicopter assaults...

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Observe difference in evaluations of biographies $\rightsquigarrow$ Difficult to generalize underlying features (treatments) that drive response

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Condition 1:

[] majored in economics and political science at Miami University in Oxford, Ohio, where he became interested in the writings of Friedrich Hayek, Ludwig von Mises, and Milton Friedman...

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Design isolates the feature of the text (treatment) that drives the response $\rightsquigarrow$ What if you don't know interesting features (treatments) of text?

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Automatically discover treatments

$+$

Estimate marginal effects

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Assumptions 1-4 are sufficient to identify the $AMCE_k$ for arbitrary k.

Discovering Treatments and Estimating Marginal Effects

Discovery of Treatments from Text Corpora

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    b) Ensure we avoid “p-hacking" (false discovery)

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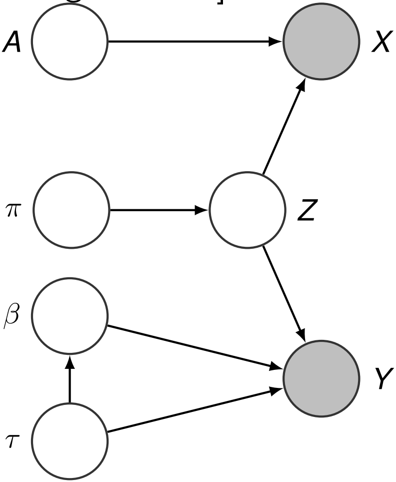
Treatments on simplex imply marginalization impossible $\rightsquigarrow$ increase in one category implies decrease in other category

The Supervised Indian Buffet Process (sIBP, distinct [though related] to Quadrianto et al 2013)



Text and response depend on latent treatments

- Treatment assignment

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z_{i,k} &\sim \text{Bernoulli}(\pi_k) \\
\pi_k &\sim \prod_{m=1}^{k} \eta_m \\
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- Document Creation:

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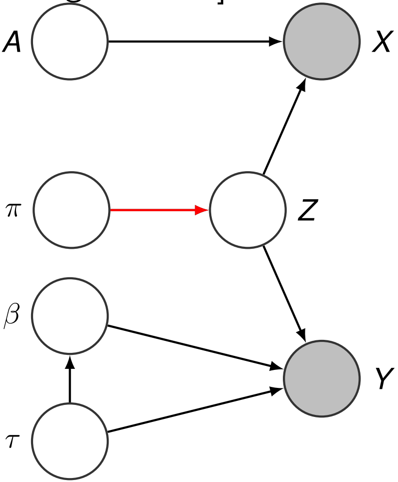

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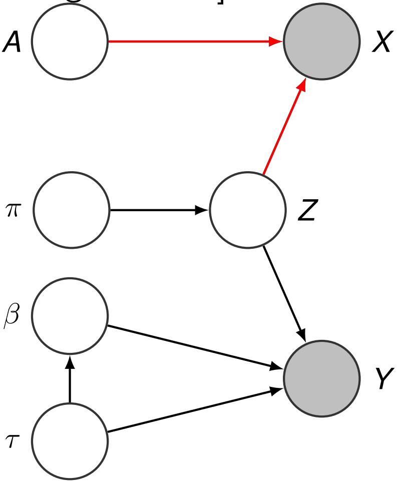

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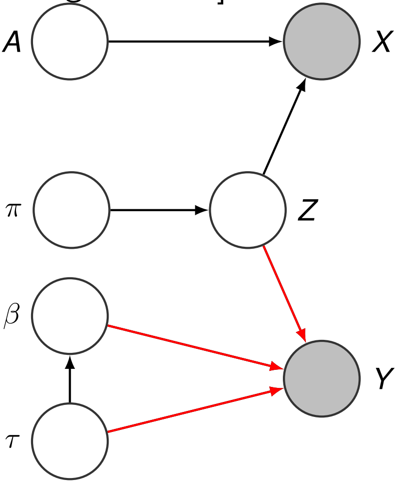

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    b) Estimate effect of treatments with regression, with a bootstrap procedure to estimate uncertainty

Candidate Biographies on Wikipedia: Setup

Barbara Mikulski $\rightsquigarrow$ Barbara Schumacher

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neighborhood of East Baltimore, the eldest of the
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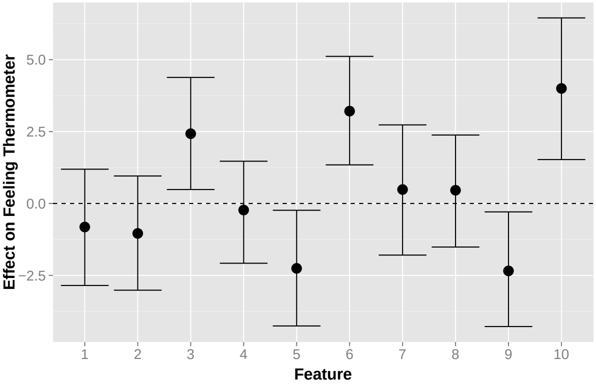
2,651 training, 2,652 test

Candiate Biographies on Wikipedia: Results

Treatment	Keywords
3	director, university, received, president, phd, policy
5	elected, house, democratic, seat
6	united_states, military, combat, rank
9	law, school_law, law_school, juris_doctor, student
10	war, enlisted, united_states, assigned, army



Consumer Financial Protection Bureau: Timely Response?

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- Consumers log complaint about financial products

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"The service representative was harsh and not listening to my questions. Attempting to collect on a debt I thought was in a grace period ...They were aggressive and unwilling to hear it."

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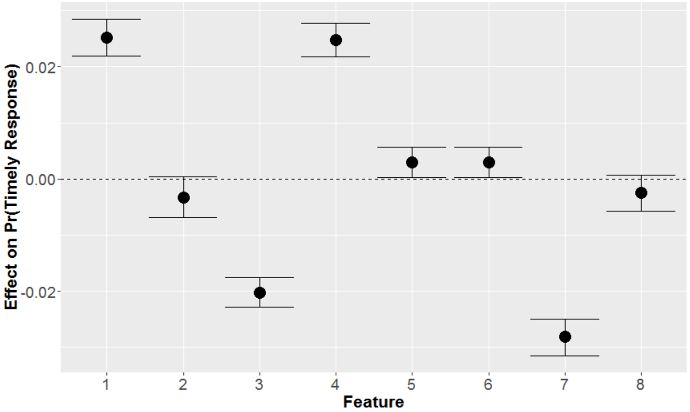
Treatment	Keywords
1	payment, card, debt , xxx , payment , loan
3	amount, call, account, time, pay, modification
4	interest, branch, number, xxxx_xxxx, told, house
7	month, credit_card, collection, received, called, loan_modificat



Conclusions and Future Directions

- Empirical Test of assumptions (sufficiency); Clarification of risks (Analyst SUTVA, Causal Effects with LDA)
- New treatment discovery methods
- Application to non-text settings (images, voting records)
- Text as Treatment ; Text as Outcome (STM, Roberts et al); Text as Outcome and Treatment