Causal Inference with Latent Variables

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- Causal Inference With Text-Based Treatments

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Apply framework to infer public reaction to Trump tweets

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- Increasing interest in using text-based measures for causal inference

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- Concerns about credibility
- Concerns about extrapolation
- Concerns about attribution, interpretation, and equilibrium (Bueno de Mesquita and Tyson, 2019)

What features of Trump's rhetoric cause a reaction? $\rightsquigarrow$ Our framework will blend A/B Tests with more traditional vignette experiments

Donald J. Trump
@realDonaldTrump

Following

Little Adam Schiff, who is desperate to run for higher office, is one of the biggest liars and leakers in Washington, right up there with Comey, Warner, Brennan and Clapper! Adam leaves closed committee hearings to illegally leak confidential information. Must be stopped!

4:39 AM - 5 Feb 2018

31,930 Retweets **99,706** Likes

48K 32K 100K

Tweet 1:

Why would Kim Jong-un insult me by calling me “old," when I would NEVER call him “short and fat?" Oh well, I try so hard to be his friend-and maybe someday that will happen!

Tweet 2:

Steve Bannon will be a tough and smart new voice at @BreitbartNews...maybe even better than ever before. Fake News needs the competition!

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

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Effect will be dependent on "background" text

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Negotiations on DACA have begun. Republicans want to make a deal and Democrats say they want to make a deal. Wouldn't it be great if we could finally, after so many years, solve the DACA puzzle. This will be our last chance, there will never be another opportunity! March 5th.

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Latent Representation (Codebook) $\rightsquigarrow$ true whether hand coded, supervised, or unsupervised

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Many ways for different words to deliver same latent treatment

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May change more than the theoretical treatment of interest

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In addition to usual credibility concerns

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Specify a pre-analysis plan?

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Specify a pre-analysis plan? It could:

- Define codebook/latent treatments
- Procedure for determining vignettes
- Procedure for minimizing (estimating) background text influence
- Limit credibility concerns

Pre-Analysis Plan (PAP)

Prior to analysis: declare plan

1) Declare all hypotheses
2) Specify all coding rules
3) Declare all statistical procedures
4) Commit to reporting all results

Output: Algorithm that takes new data and produces results

After analysis: report in line with declaration

1) Report all hypotheses
2) Report all results

This is a useful framework! $\rightsquigarrow$ But what actually happens?

Grimmer, Lal, and Renshon (In Progress)

Plans $\rightsquigarrow$ Papers

Papers $\rightsquigarrow$ Plans

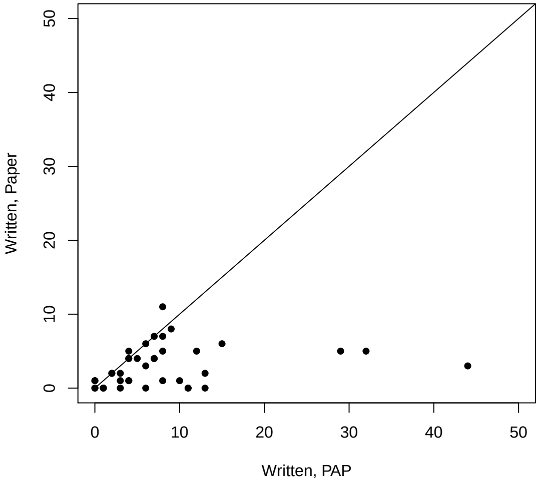
Analyzing Pre-Analysis Plans

Evidence in Governance And Politics: EGAP

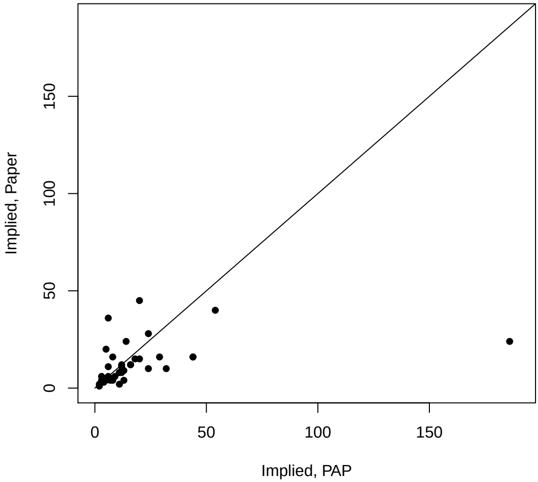
`http://egap.org/design-registrations`

- Pre-registration data:
    - Meta-data: Title, link, Year, Authors
    - Content: # Written Hypotheses, # Statistical Hypotheses
- Paper data:
    - Meta data: Journal, title, link
    - Content: # Written Hypotheses, # Statistical Hypotheses, # References to PAP

Comparing Written Hypotheses in PAP and Papers



Comparing Hypotheses Implied from Statistics



Paper$\rightsquigarrow$ PAP

- 31: Top journal articles in PS (APSR / AJPS / JOP / PA / QJPS) and Economics (AER / QJE / AEJs / JPubE / JDevE) mention PAPs
- 26/31 : claimed to have used preanalysis plans
- 12/26: linked to the PAP (11/26 of these worked; 1 article linked to a pdf now defunct personal website)
- Average number of mentions of PAPs is 2.7, modal article mentions the preanalysis plan in the text and footnote.

How to Think About PAPs and Credibility?

Experiments in a sequence $\rightsquigarrow$ market incentives for replication

Train/Test Split

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- Gaming the splits?

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- Explicit discovery phase in research

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2) Method for discovering features (treatments)
3) Method for estimating marginal effect for discovered features (treatments)

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Conjoint With Discovered Treatments (or) Discover Features that Drive Response in A/B Test

Identifying the AMCE

- An individual sees a text ($\boldsymbol{X}_i$: text seen by i)
- Function (assume known for now): text $\rightsquigarrow$ treatments in text ($\boldsymbol{Z}_i \equiv g(\boldsymbol{X}_i)$)

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Proposition 1

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

Applying Framework to Vignette Experiments

Standard vignette experiment

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Standard vignette experiment $\rightsquigarrow$ one vignette per latent treatment

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Fong and Grimmer (2019): Many vignettes per treatment enable sensitivity analysis

Discovering Treatments and Estimating Marginal Effects

Discovery of Treatments from Text Corpora

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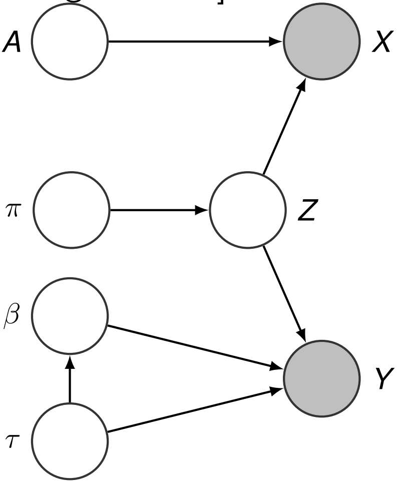
Focus on instances where specific g of interest is discovered $\rightsquigarrow$ Biased, inconsistent estimator unless discovery unrelated to effect

Discovery method for a g

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



Text and response depend on latent treatments

- Treatment assignment

$$z_{i,k} \sim \text{Bernoulli}(\pi_k)$$
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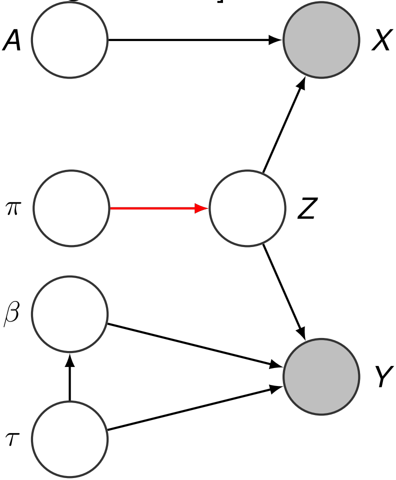

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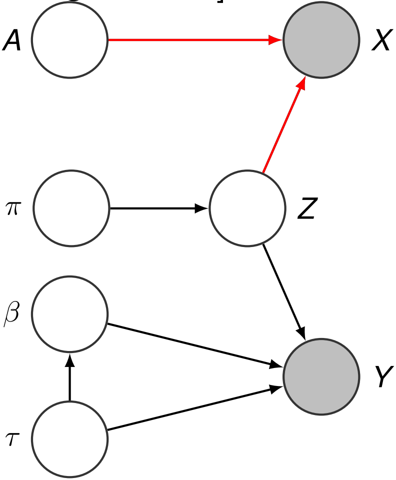

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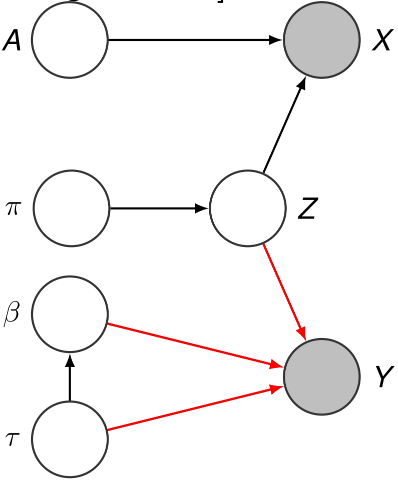

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Trump Tweets

`YouGov`: survey response to trump tweets

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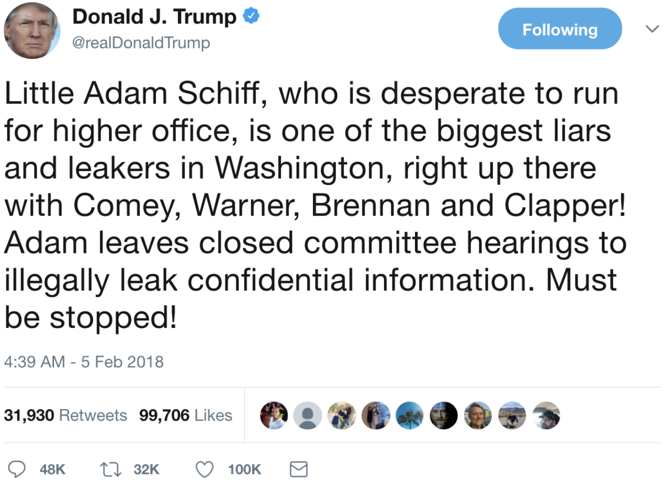
YouGov: survey response to trump tweets


Donald J. Trump
@realDonaldTrump
Following

Little Adam Schiff, who is desperate to run for higher office, is one of the biggest liars and leakers in Washington, right up there with Comey, Warner, Brennan and Clapper! Adam leaves closed committee hearings to illegally leak confidential information. Must be stopped!

4:39 AM - 5 Feb 2018

31,930 Retweets 99,706 Likes

48K 32K 100K

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- Survey Equal # Republicans, Democrats, Independents: read Trump tweet + evaluate (`Great, Good, OK, Bad, Terrible`)

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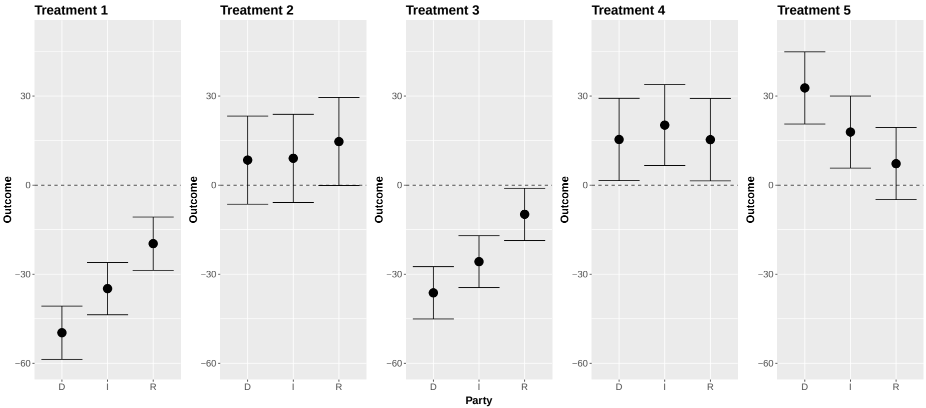
Treatment 1	Treatment 2	Treatment 3	Treatment 4	Treatment 5
fake	cuts	obamacare	flotus	prime
news	strange	senators	behalf	minister
media	tax	repeal	anthem	korea
cnn	luther	healthcare	melania	north
election	stock	replace	nfl	stock
story	market	republican	flag	market
nbc	alabama	vote	prayers	china
stories	reform	republicans	bless	executive
hillary	record	senate	ready	prayers
clinton	high	north	players	order


Treatment 1
Treatment 2
Treatment 3
Treatment 4
Treatment 5
Outcome
30
0
−30
−60
D
I
R
Party

Sensitivity Analysis: analogous to residual plot in linear regression

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R Package: `textEffect`

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