Text as Data

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Discovery and Measurement

What is the research process? (Grimmer, Roberts, and Stewart 2017)

1) Discovery: a hypothesis or view of the world
2) Measurement according to some organization
3) Causal Inference: effect of some intervention

Text as data methods assist at each stage of research process

Causal Inference

A Causal Inference Refresher

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- Fundamental problem of causal inference observe only one $\boldsymbol{Y}_i(\boldsymbol{T}_i)$

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$$\text{ATE} = E[Y(1) - Y(0)]$$

  - Estimate with:

$$\widehat{\text{ATE}} = E[Y(1)|T = 1] - E[Y(0)|T = 0]$$

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$$\widehat{\text{ATE}} = \frac{\sum_{i=1}^{N} I(T_i = 1) Y_i}{\sum_{i=1}^{N} I(T_i = 1)} - \frac{\sum_{i=1}^{N} I(T_i = 0) Y_i}{\sum_{i=1}^{N} I(T_i = 0)}$$

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Question: how do we accurately estimate quantities like ATE?

Our Plan for the Day

- Experimental design
- Conditional average treatment effects
- Methods for estimating heterogeneous treatment effects

An Example Experiment

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Rep. Harold “Hal" Rogers (KY-05) announced today that Kentucky is slated to receive $962,500 to protect critical infrastructure- power plants, chemical facilities, stadiums, and other high-risk assets, through the U.S. Department of Homeland Security’s buffer zone protection program

An Example Experiment

A federal grant will help keep the Brainerd Lakes Airport operating in winter weather. Today, Congressman Jim Oberstar announced that the Federal Aviation Administration (FAA) will award $528,873 to the Brainerd airport. The funding will be used to purchase new snow removal and deicing equipment.

An Example Experiment

Congresswoman Darlene Hooley (OR-5) and Congressmen Earl Blumenauer (OR-3), David Wu (OR-1) and Greg Walden (OR-2) joined together today in announcing $375,000 in federal funding for the Oregon Partnership to combat methamphetamine abuse in Oregon.

An Example Experiment

What information in credit claiming messages affect evaluations?

Rewarding Actions and Type of Expenditure, Not Money

Experiment: vary the recipient of money and the action reported in credit claiming statement (and many other features)

Rewarding Actions and Type of Expenditure, Not Money

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Treatments: type

1) Planned Parenthood
2) Parks
3) Gun Range
4) Fire Department
5) Police
6) Roads

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Experiment: vary the recipient of money and the action reported in credit claiming statement (and many other features)
Treatments: type, stage

1) Will request
2) Requested
3) Secured

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1) \$50 Thousand
2) \$20 Million

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Treatments: type, stage, money, collaboration

1) Alone
2) w/ Senate Democrat
3) w/ Senate Republican

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Treatments: type, stage, money, collaboration, partisanship

1) Democrat
2) Republican

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Treatments: type, stage, money, collaboration, partisanship
Control Condition:

Advertising press release

Rewarding Actions and Type of Expenditure, Not Money

Example Treatment:
Headline: Representative [blackbox] secured $50 Thousand to purchase safety equipment for local firefighters
Body: Representative [blackbox] (Democrat) and Senator [blackbox], a Democrat, secured $50 Thousand to purchase safety equipment for local firefighters.
Rep. [blackbox] said "This money will help our brave firefighters stay safe as they protect our businesses and homes"

Rewarding Actions and Type of Expenditure, Not Money

Example Treatment:
Headline: Representative [blackbox] will request $20 million for medical equipment at the local Planned Parenthood.
Body: Representative [blackbox] (Democrat), will request $20 million for medical equipment at the local Planned Parenthood.
Rep. [blackbox] said "This money would help provide state of the art care for women in our community."

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Mechanics$\rightsquigarrow$ Mechanical Turk sample (Findings are replicated in representative samples, using real representatives/senators)

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\text{MCATE}_{\mathsf{T}_j = k, \mathbf{x}} &= \text{E}[Y(\mathsf{T}_j = k)|\mathbf{x}] - \text{E}[Y(0)|\mathbf{x}] \\
\widehat{\text{MCATE}_{\mathsf{T}_j}}_{= k, \mathbf{x}} &= \frac{\sum_{i=1}^{N} Y_i I(\mathsf{T}_j = k, \mathbf{x}_i = \mathbf{x})}{\sum_{i=1}^{N} I(\mathsf{T}_j = k, \mathbf{x}_i = \mathbf{x})} - \frac{\sum_{i=1}^{N} Y_i I(\mathsf{T}_i = 0, \mathbf{x}_i = \mathbf{x})}{\sum_{i=1}^{N} I(\mathsf{T}_i = 0, \mathbf{x}_i = \mathbf{x})}
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  - LASSO, Find It (Imai and Ratkovic, 2013) $\rightsquigarrow$ sparsity

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  - LASSO, Find It (Imai and Ratkovic, 2013)$\rightsquigarrow$ sparsity
  - Ridge, KRLS (Hainmueller and Hazlett, 2013)$\rightsquigarrow$ flexible surface, dense

Rewarding Actions and Type of Expenditure, Not Money

$$\text{MCATE}_{\text{T}_j = k, \mathbf{x}} = \text{E}[Y(\text{T}_j = k)|\text{x}] - \text{E}[Y(0)|\text{x}]$$

$$\widehat{\text{MCATE}}_{\text{T}_j = k, \mathbf{x}} = \frac{\sum_{i=1}^{N} Y_i I(\text{T}_j = k, \text{x}_i = \text{x})}{\sum_{i=1}^{N} I(\text{T}_j = k, \text{x}_i = \text{x})} - \frac{\sum_{i=1}^{N} Y_i I(\text{T}_i = 0, \text{x}_i = \text{x})}{\sum_{i=1}^{N} I(\text{T}_i = 0, \text{x}_i = \text{x})}$$

- Curse of Dimensionality: highly variable estimates, (sometimes) empty strata
- Separate systematic differences from noise $\rightsquigarrow$ data and assumptions Heterogeneous treatment effect methods
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Create ensemble: weighting methods by (unique) out of sample predictive performance

Weighted Ensemble to Measure Credit Claiming Rate

- Suppose we have M ($m = 1, \ldots, M$) models.

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  - Result $\widehat{\pi}_m$ for each method

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  - (Alternatively) Estimate weights from mixture model (EBMA) (Raftery et al 2005; Montgomery, Hollenback, Ward 2012)$\leadsto$ EM, Gibbs, Variational Approximation

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- Generate effects of interest (perhaps weighting to other population) $\mathbf{x}_{\text{new}}$

Returning to Example Experiment

Recall: experiment to assess effects of credit claiming on approval $\rightsquigarrow$ 1,074 participants (MTurk)

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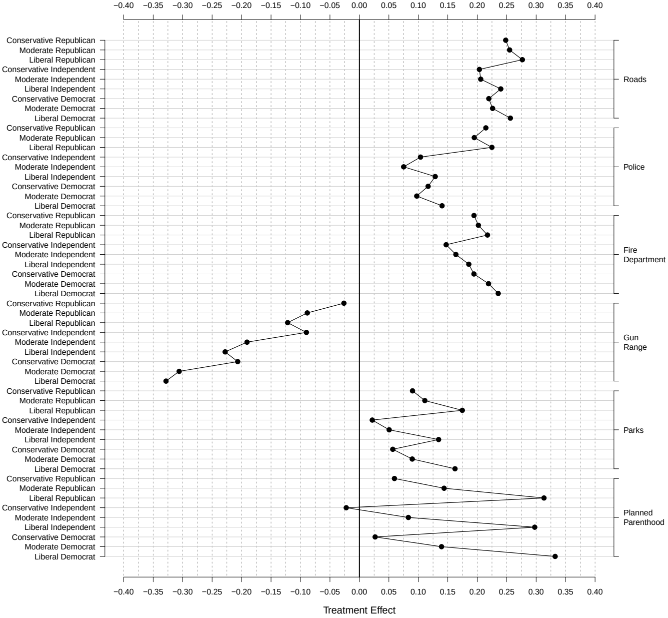
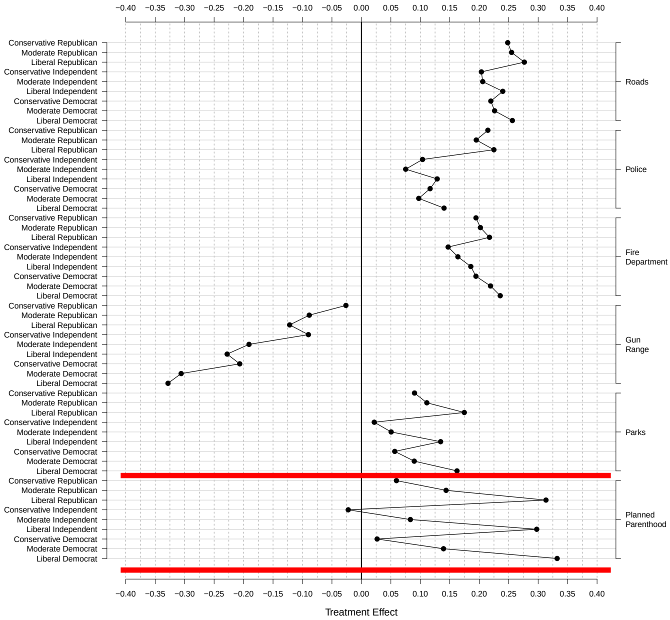
3) Find it (0.14)


Conservative Republican
Moderate Republican
Liberal Republican
Conservative Independent
Moderate Independent
Liberal Independent
Conservative Democrat
Moderate Democrat
Liberal Democrat
Roads
Police
Fire Department
Gun Range
Parks
Planned Parenthood
−0.40 −0.35 −0.30 −0.25 −0.20 −0.15 −0.10 −0.05 0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40
Treatment Effect



−0.40 −0.35 −0.30 −0.25 −0.20 −0.15 −0.10 −0.05 0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40
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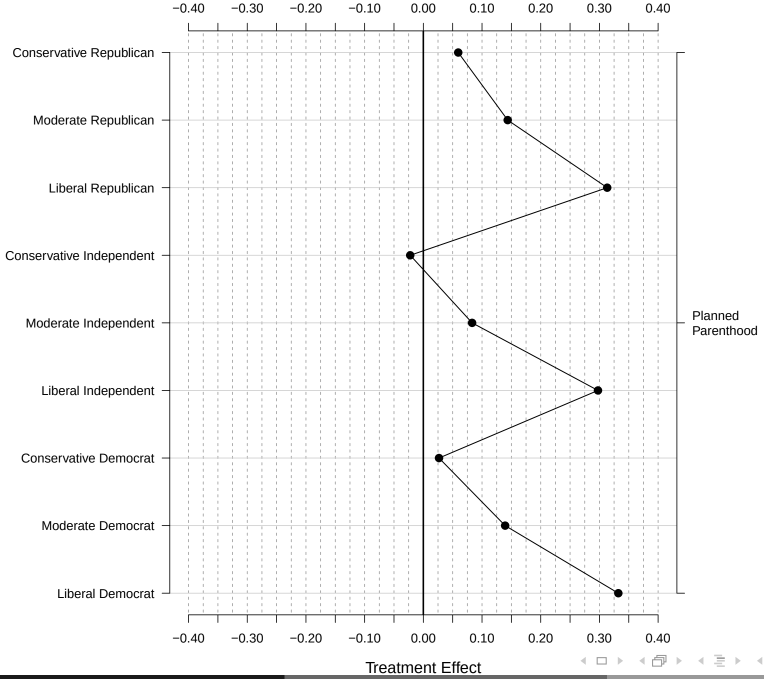
−0.40 −0.30 −0.20 −0.10 0.00 0.10 0.20 0.30 0.40
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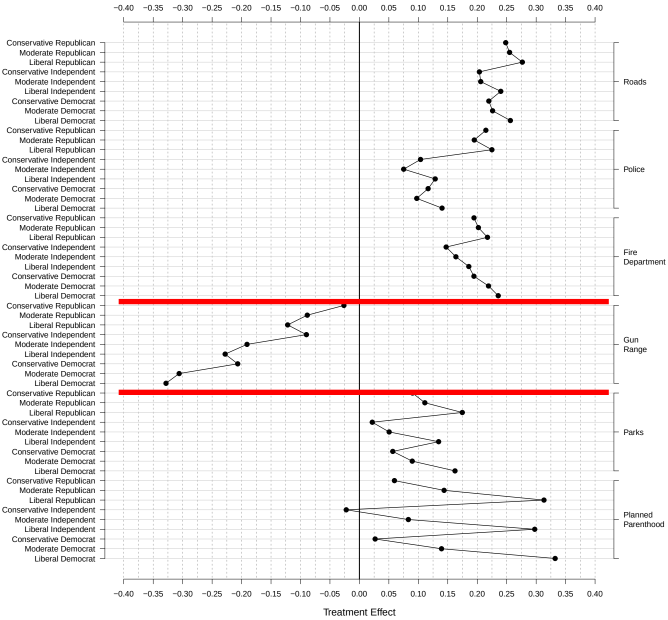

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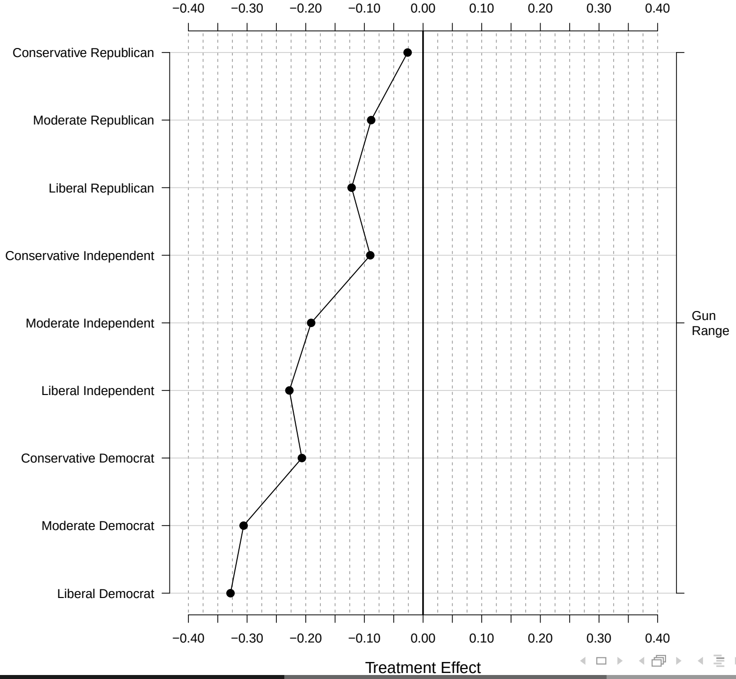
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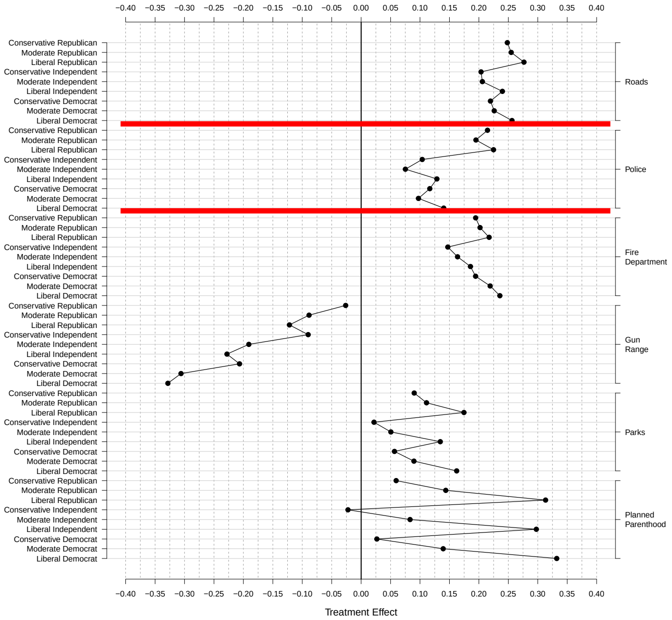

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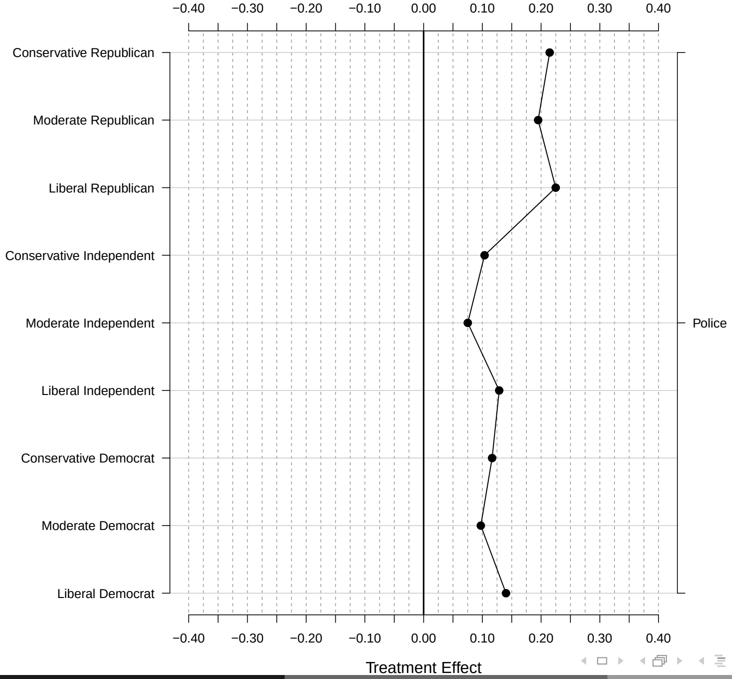
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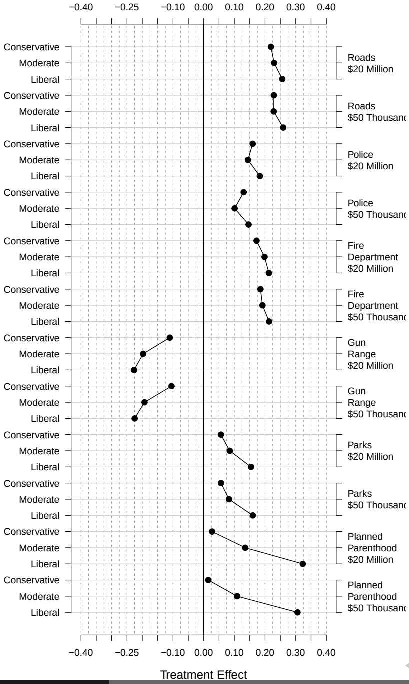

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Gun
Range
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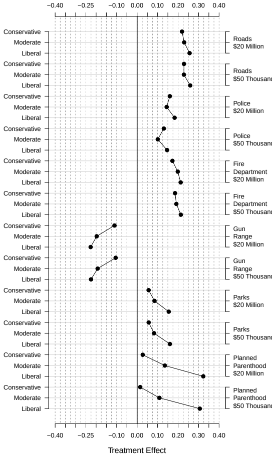

$\rightsquigarrow$ Constituents evaluate expenditures using qualitative information, rather than numerical facts

Estimating Heterogeneous Treatment Effects and the Effects of Heterogeneous Treatments

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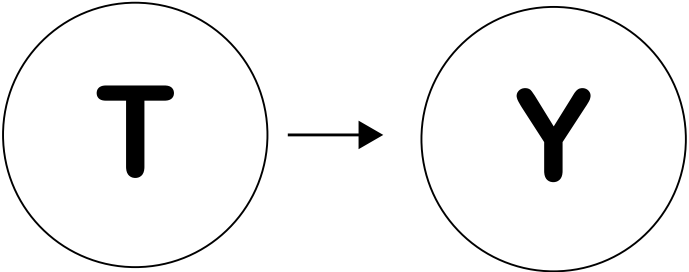
The Causal Inference Problem

- Two roles: text as outcome and text as treatment



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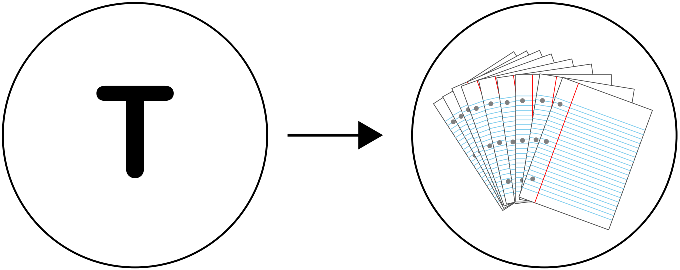

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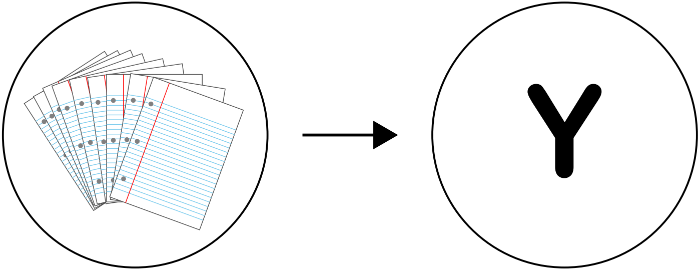

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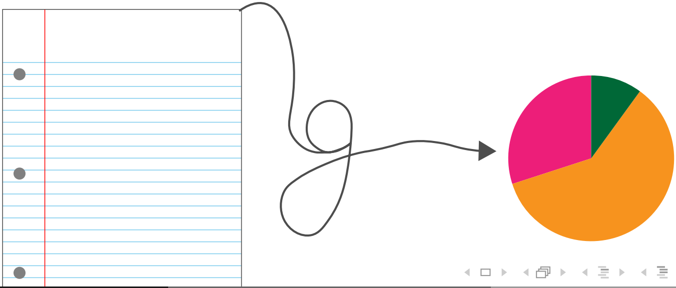

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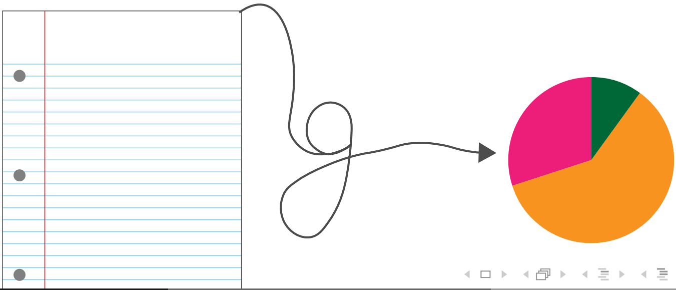

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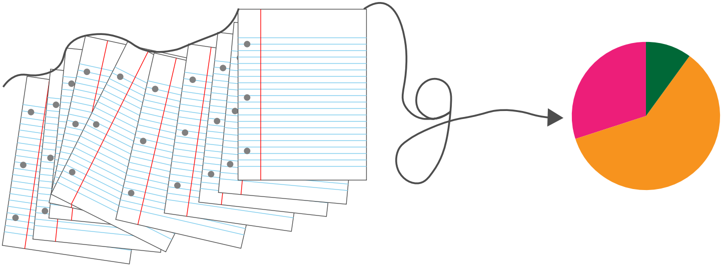

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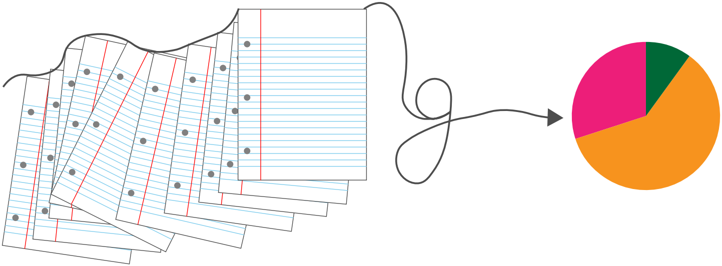

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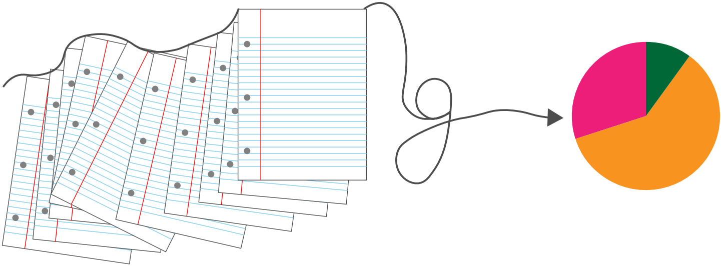

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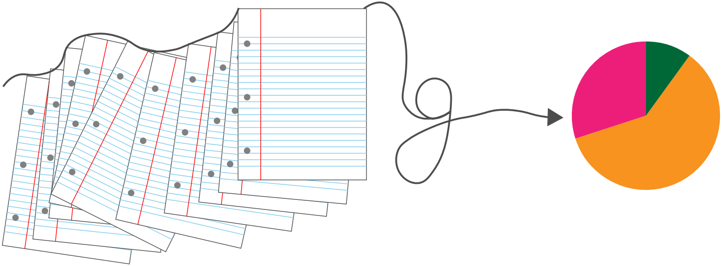
- Text as treatment: always requires an exclusion restriction



What's a social scientist to do?

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Two Solutions:

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A) Pre-Analysis Plan:

What's a social scientist to do?

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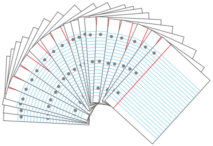

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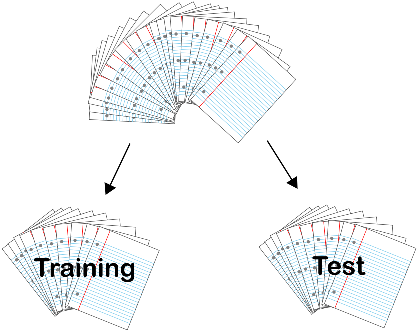

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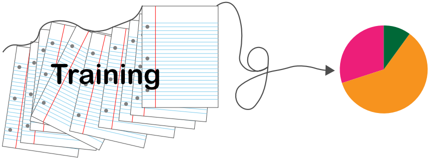

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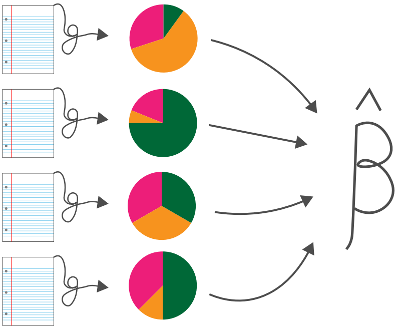

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Train-Test allows for discovery while avoiding possibilities of overfitting and PCILV

Two Running Examples: Treatment and Outcome

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Text as Outcome

How do presidents going public affect news coverage? (Franco, Grimmer, and Lim 2019)

What features of Trump's rhetoric cause a reaction?

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!

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

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Randomly assign 1, 1′ and assess response $\rightsquigarrow$ are we interested in effect of one word?

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

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

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Proposition 1

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

Discovering Treatments and Estimating Marginal Effects

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Cannot compare categories from $\boldsymbol{T}_1$ and $\boldsymbol{T}_2 \rightsquigarrow$ properties of estimator (bias, consistency) not defined!

Discovery method for a g

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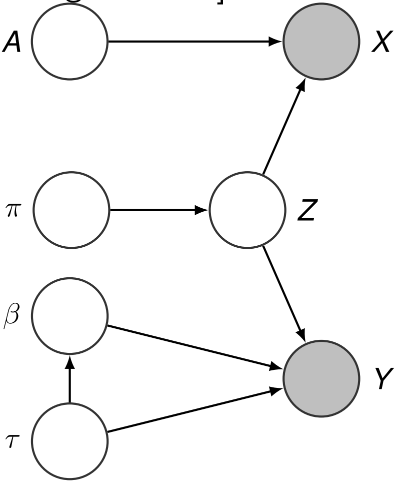

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- Treatment assignment

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- Document Creation:

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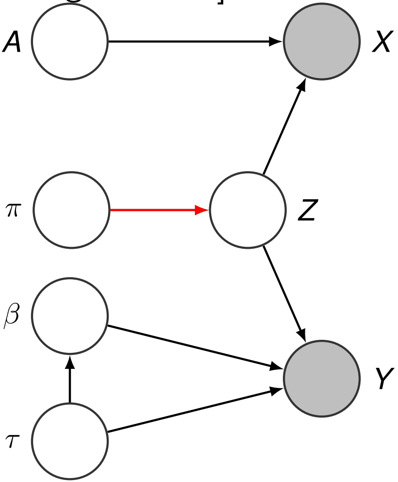

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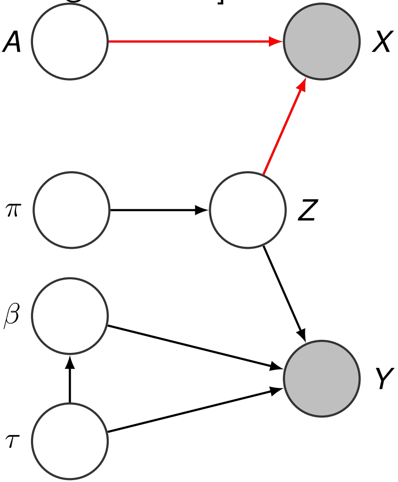

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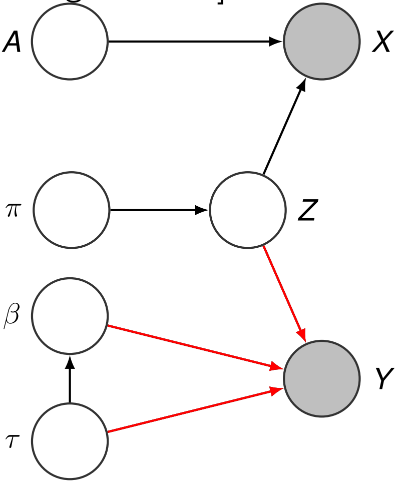

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`YouGov`: survey response to trump tweets

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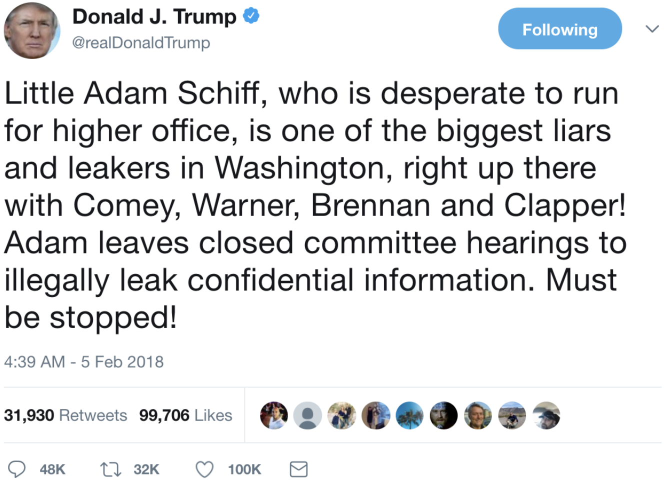

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- Train (66%), Test (33%), Clustered by tweet

Trump Tweets

`YouGov`: survey response to trump tweets

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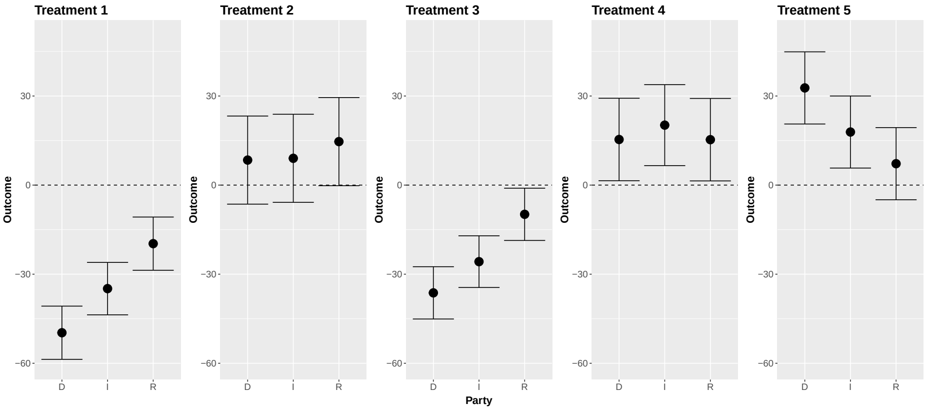
Treatment 1	Treatment 2	Treatment 3	Treatment 4	Treatment 5
fake	cuts	obamacare	flotus	prime
news	strange	senators	behalf	minister
media	tax	repeal	anthem	korea
cnn	luther	healthcare	melania	north
election	stock	replace	nfl	stock
story	market	republican	flag	market
nbc	alabama	vote	prayers	china
stories	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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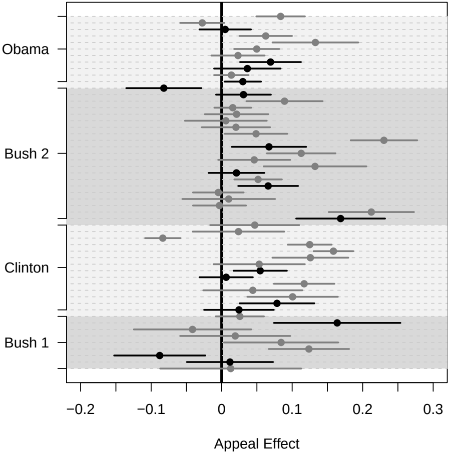
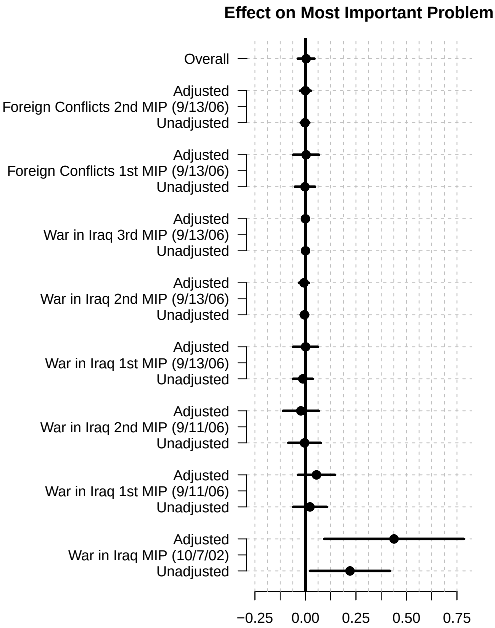
R Package: `textEffect`

Text as Outcome

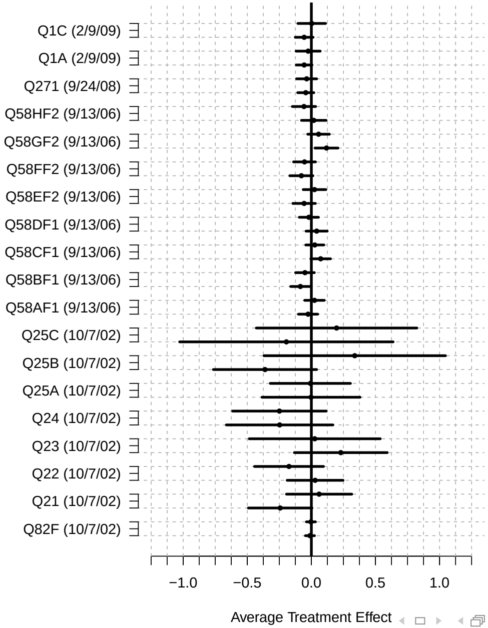
How do presidents "going public" affect public opinion?



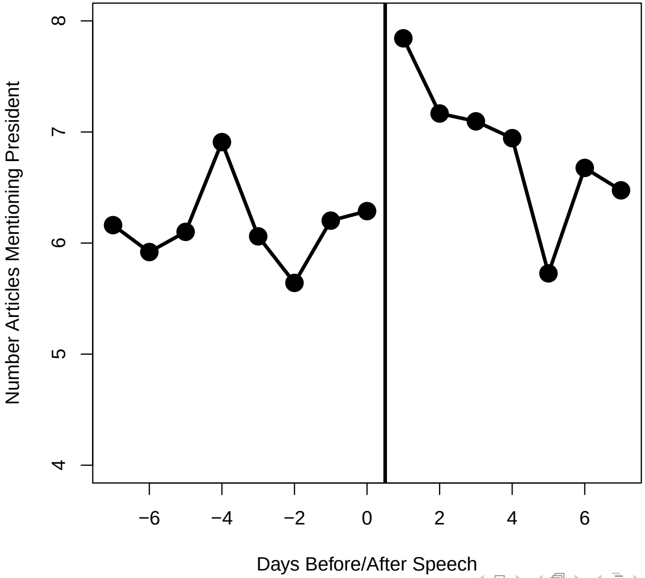
Obama
Bush 2
Clinton
Bush 1
−0.2
−0.1
0
0.1
0.2
0.3
Appeal Effect


Effect on Most Important Problem
Overall
Adjusted
Foreign Conflicts 2nd MIP (9/13/06)
Unadjusted
Adjusted
Foreign Conflicts 1st MIP (9/13/06)
Unadjusted
Adjusted
War in Iraq 3rd MIP (9/13/06)
Unadjusted
Adjusted
War in Iraq 2nd MIP (9/13/06)
Unadjusted
Adjusted
War in Iraq 1st MIP (9/13/06)
Unadjusted
Adjusted
War in Iraq 2nd MIP (9/11/06)
Unadjusted
Adjusted
War in Iraq 1st MIP (9/11/06)
Unadjusted
Adjusted
War in Iraq MIP (10/7/02)
Unadjusted
−0.25
0.00
0.25
0.50
0.75

Effect on Responses Related to Topic of Speech



How do presidents "going public" affect the media agenda?



Number Articles Mentioning President
Days Before/After Speech
4
5
6
7
8
−6
−4
−2
0
2
4
6

1) (Assume) random assignment of treatments (use an interrupted time series design)

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$$\text{ATE}_k \;=\; \text{E}[g(\boldsymbol{Y}(1))_k - g(\boldsymbol{Y}(0))_k]$$

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A President's effect on newspaper agenda

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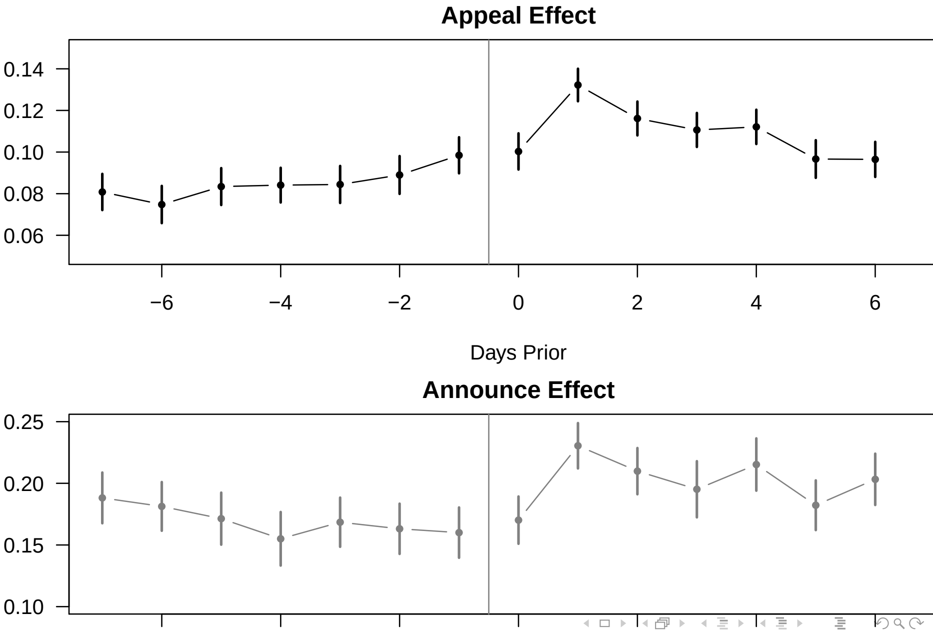
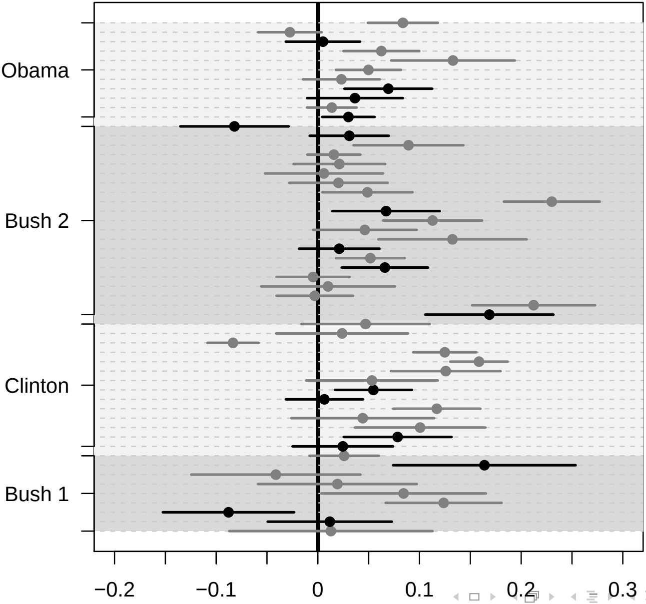
- Effect estimate: interrupted time series design on topic prevalence (compare share immediately before to share day after)


Appeal Effect
0.14
0.12
0.10
0.08
0.06
−6
−4
−2
0
2
4
6
Days Prior
Announce Effect
0.25
0.20
0.15
0.10


Obama
Bush 2
Clinton
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−0.2
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- Text as Treatment , Text as Outcome , Text as Confounder, Text as Treatment and Outcome