# Text as Data

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# Discovery and Measurement

What is the research process? (Grimmer, Roberts, and Stewart 2019)

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

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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)

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Treatments: type

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

# 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)

Treatments: type, stage

1) Will request
2) Requested
3) Secured

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Experiment: vary the recipient of money and the action reported in credit claiming statement (and many other features)
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1) $50 Thousand
2) $20 Million

# 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)
Treatments: type, stage, money, collaboration

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

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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"

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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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  - LASSO, Find It (Imai and Ratkovic, 2013)$\rightsquigarrow$ sparsity

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- Curse of Dimensionality: highly variable estimates, (sometimes) empty strata
- Separate systematic differences from noise $\rightsquigarrow$ data and assumptions
  Heterogeneous treatment effect methods
  - LASSO, Find It (Imai and Ratkovic, 2013) $\rightsquigarrow$ sparsity
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Create ensemble: weighting methods by (unique) out of sample predictive performance

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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)$\rightsquigarrow$ EM, Gibbs, Variational Approximation

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

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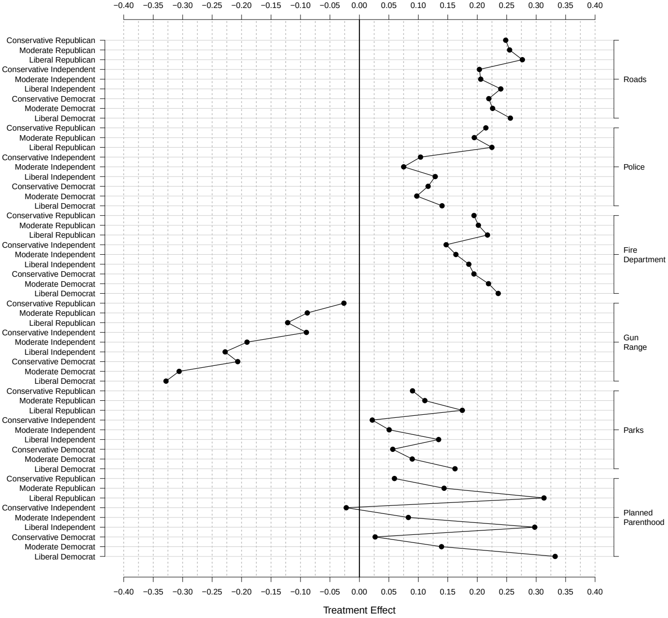

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Conservative Republican
Moderate Republican
Liberal Republican
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Roads
Police
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Gun Range
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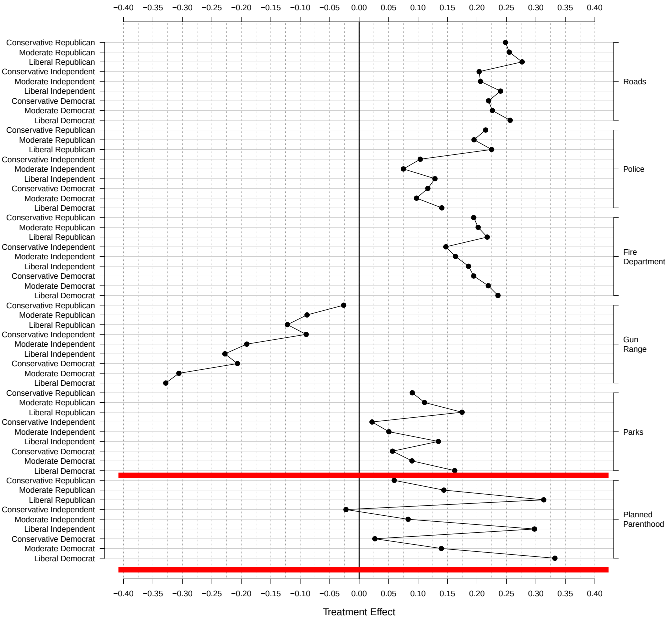
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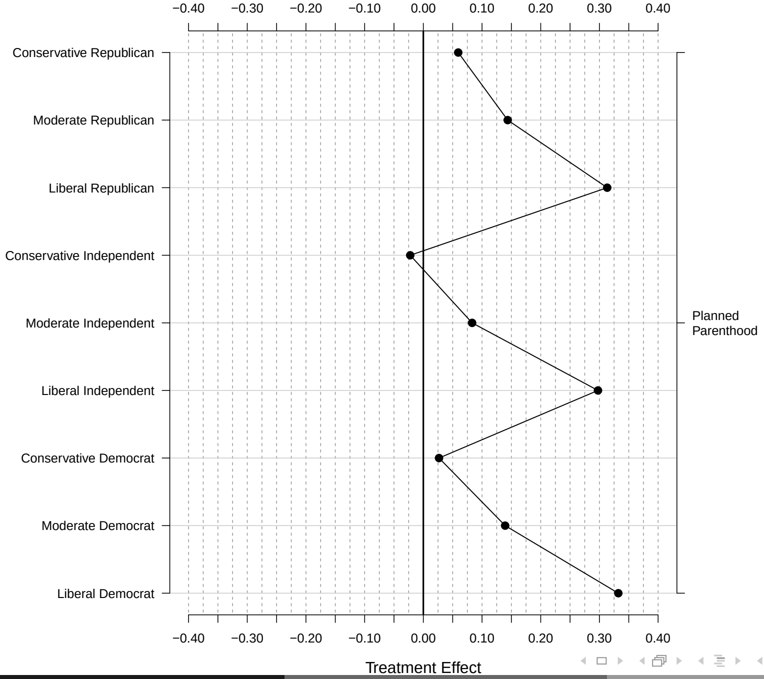
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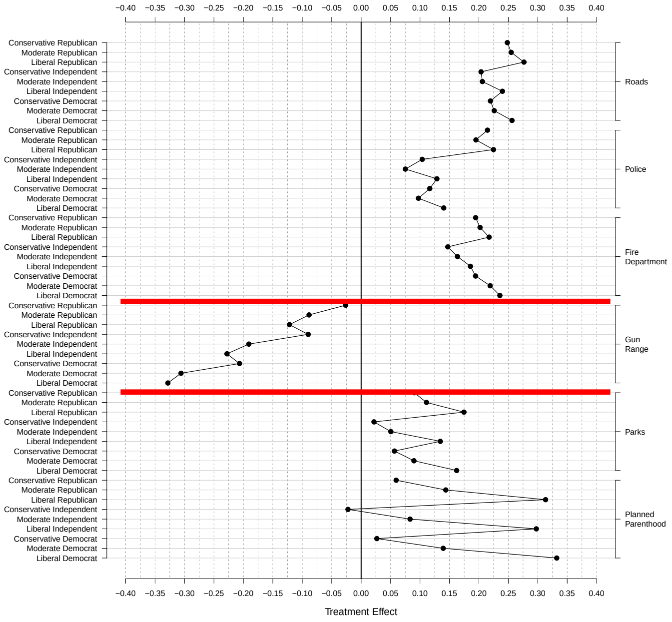
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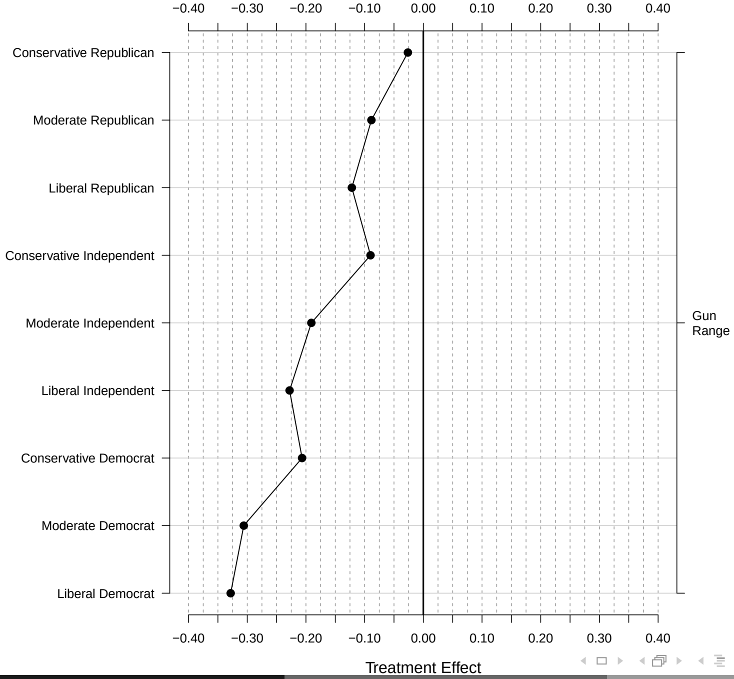

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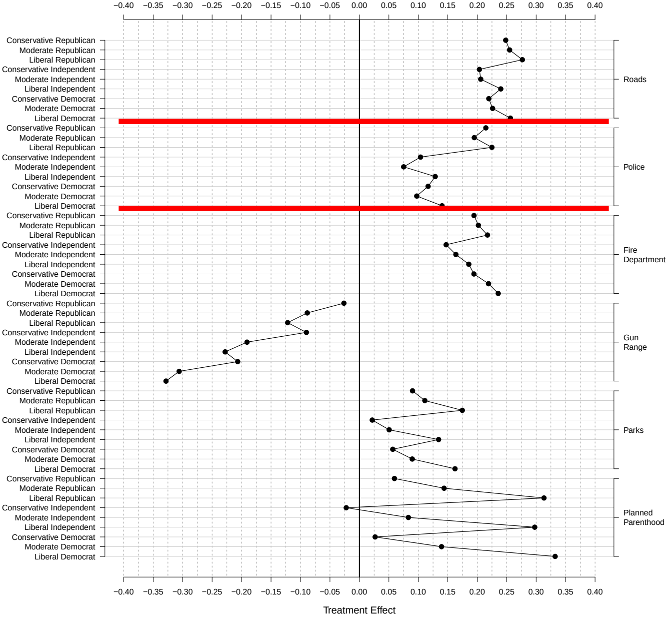

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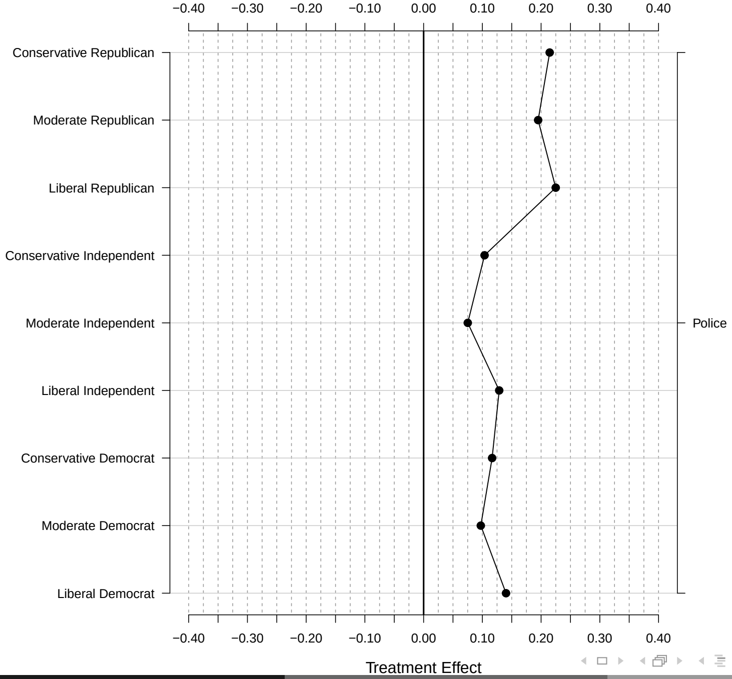
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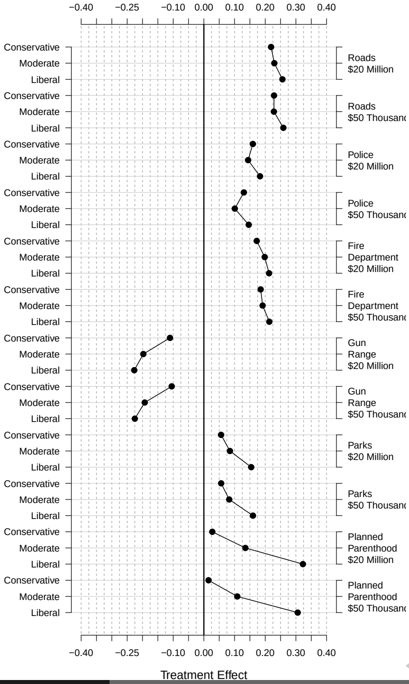
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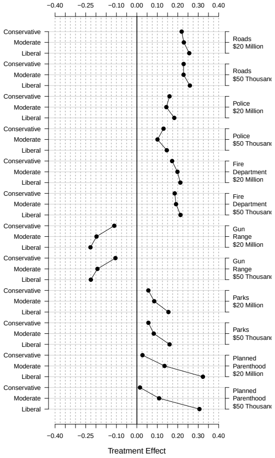


$\rightsquigarrow$ Constituents evaluate expenditures using qualitative information, rather than numerical facts

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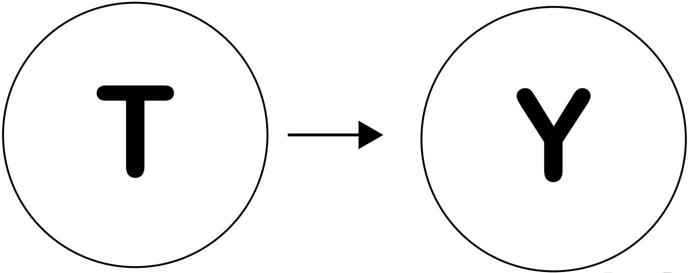

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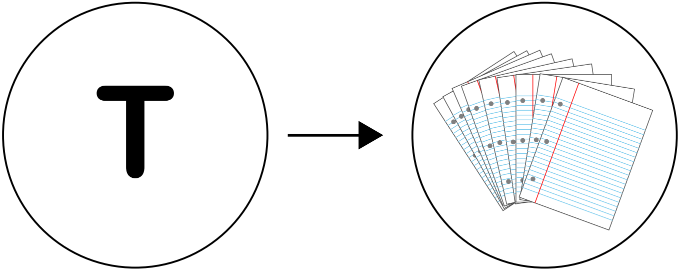

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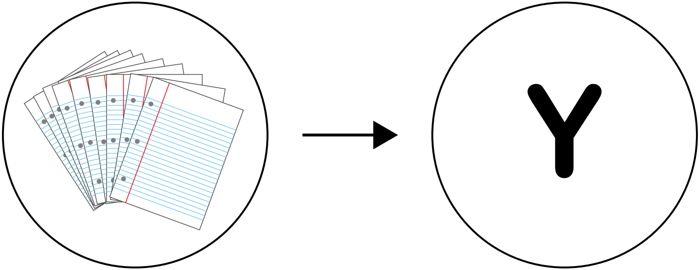

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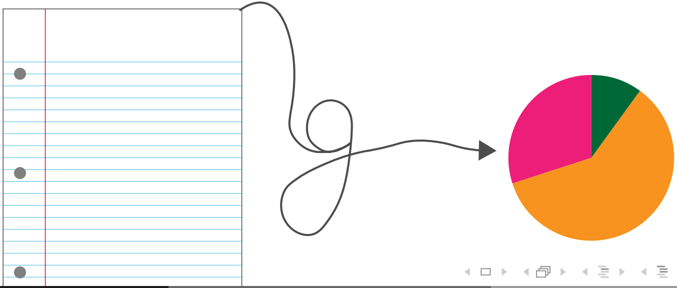

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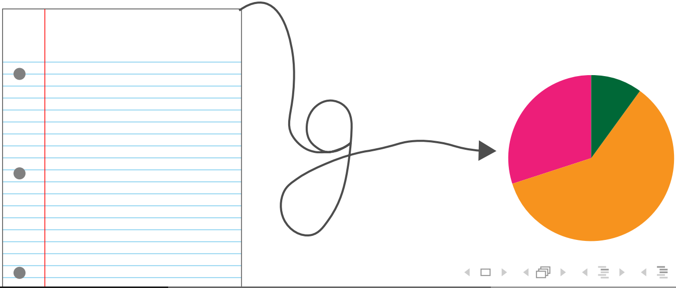

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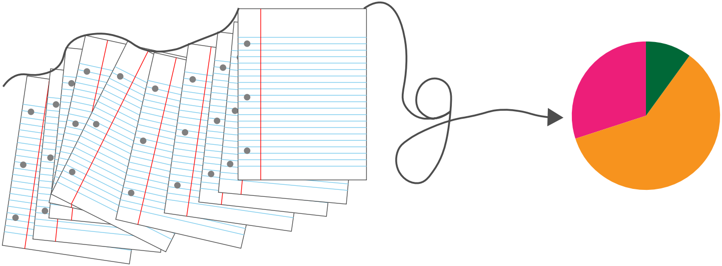

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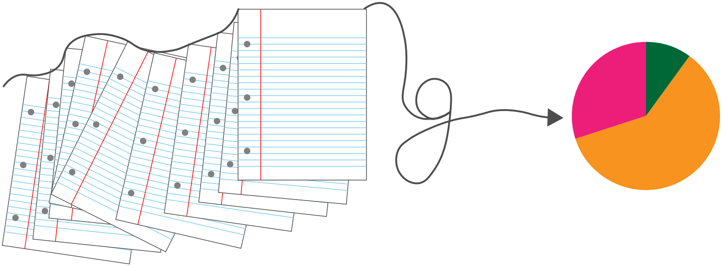

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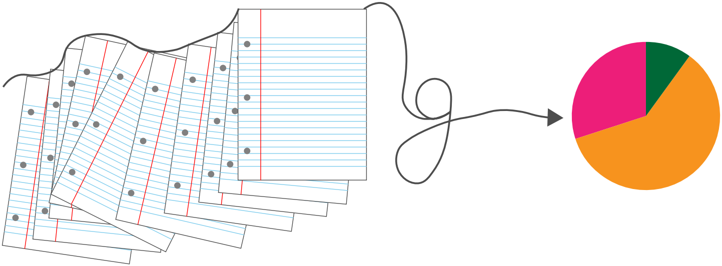
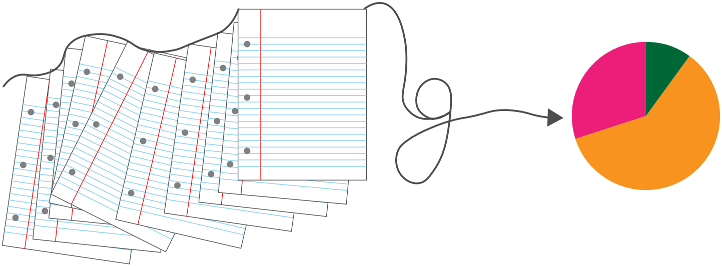


# The Causal Inference Problem

- Two roles: text as outcome and text as treatment
- Any text analysis requires mapping from high to low dimensions
- Need to look at the data to create a good maps
- Subtle problem: Fundamental Problem of Causal Inference with Latent Variables (PCILV)
  - $\rightarrow$ use same observations to discover pattern and infer causal effects
  - $\rightarrow$ causes key properties of estimators (bias, consistency) to be undefined
- Text as treatment: always requires an exclusion restriction



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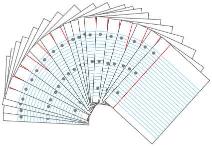

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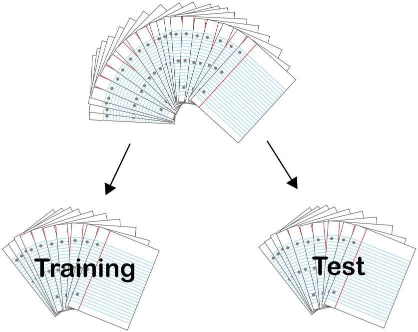

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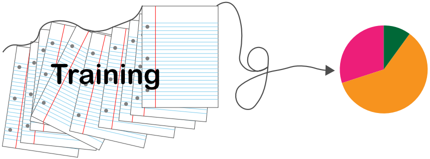

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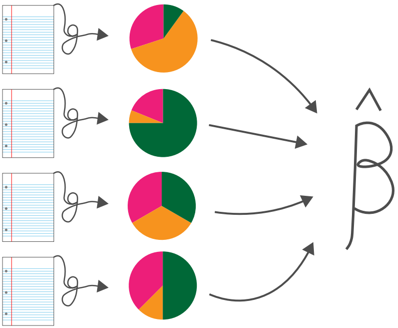

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Train-Test allows for discovery while avoiding possibilities of overfitting and PCILV

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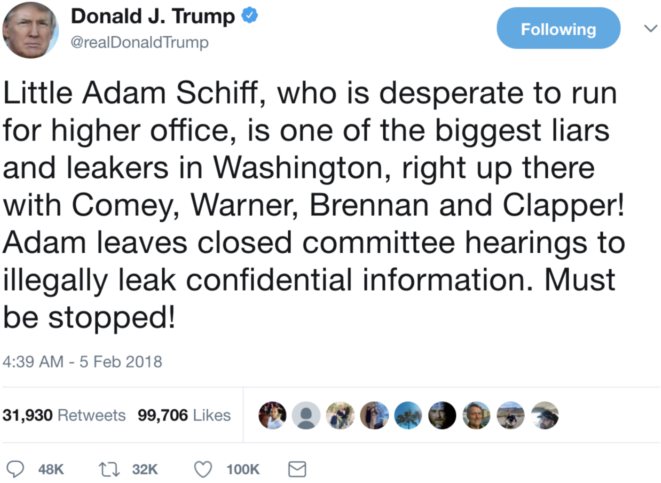
Text as Outcome

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!

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:

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

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Tweet $1'$:

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Randomly assign $1, 1^{'}$ and assess response $\rightsquigarrow$ are we interested in effect of one word?

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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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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 $\text{AMCE}_k$ for arbitrary $k$.*

# Discovering Treatments and Estimating Marginal Effects

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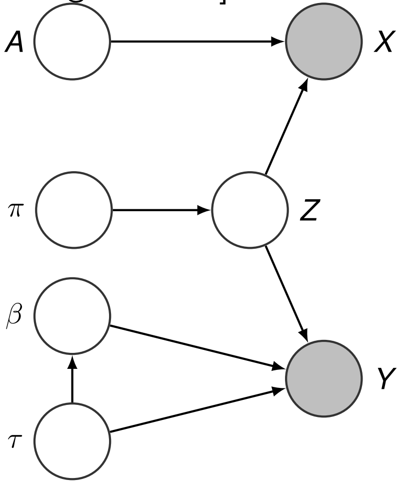
Cannot compare categories from $\boldsymbol{T}_1$ and $\boldsymbol{T}_2 \rightsquigarrow$ properties of estimator (bias, consistency) not defined!

# Discovery method for a $g$

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




Text and response depend on latent treatments

- Treatment assignment

$$
\begin{aligned}
z_{i,k} &\sim \text{Bernoulli}(\pi_k) \\
\pi_k &\sim \prod_{m=1}^{k} \eta_m \\
\eta_m &\sim \text{Beta}(\alpha, 1)
\end{aligned}
$$

- Document Creation:

$$
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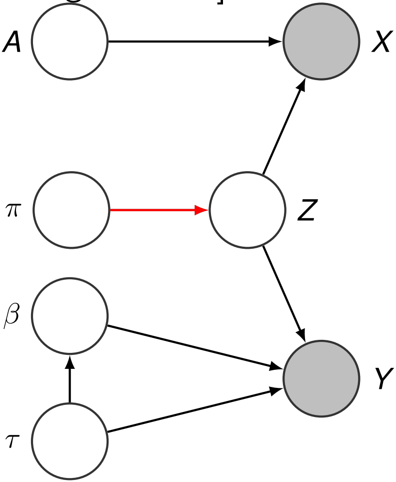


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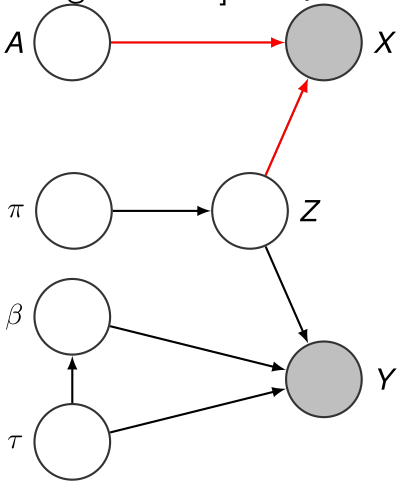


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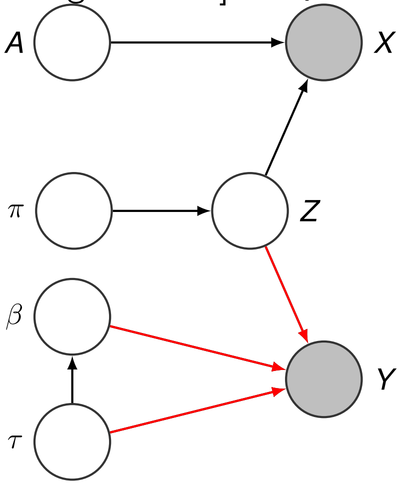


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# Trump Tweets

`YouGov`: survey response to trump tweets

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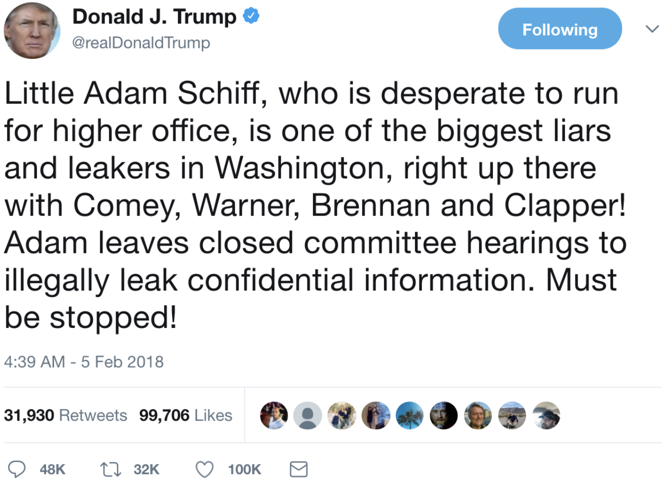

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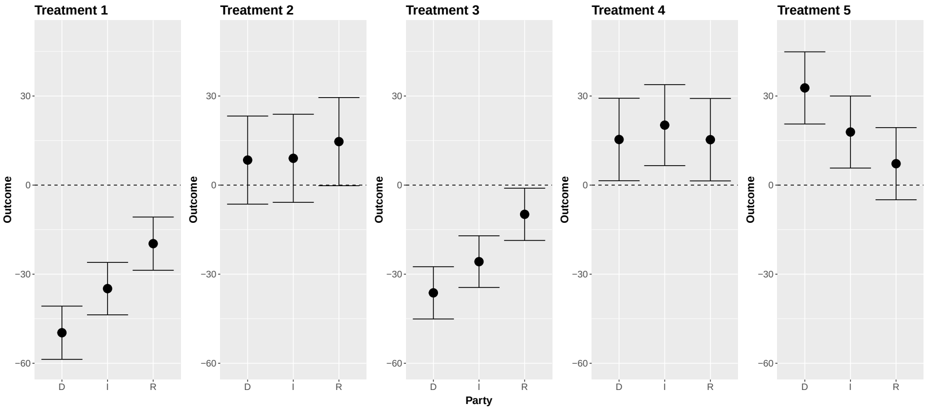
| Treatment 1 | Treatment 2 | Treatment 3 | Treatment 4 | Treatment 5 |
|---|---|---|---|---|
| fake | cuts | obamacare | flotus | prime |
| news | strange | senators | behalf | minister |
| media | tax | repeal | anthem | korea |
| cnn | luther | healthcare | melania | north |
| election | stock | replace | 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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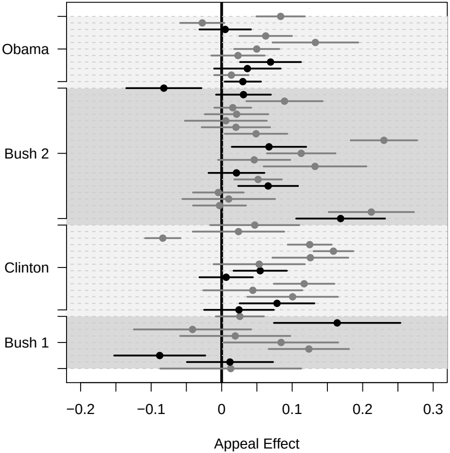
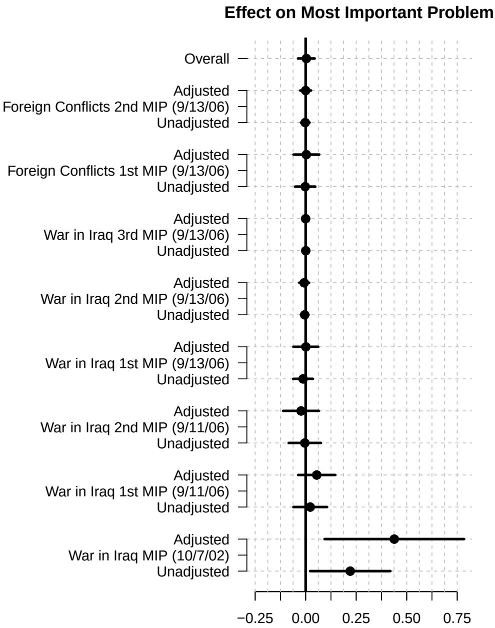
R Package: `textEffect`

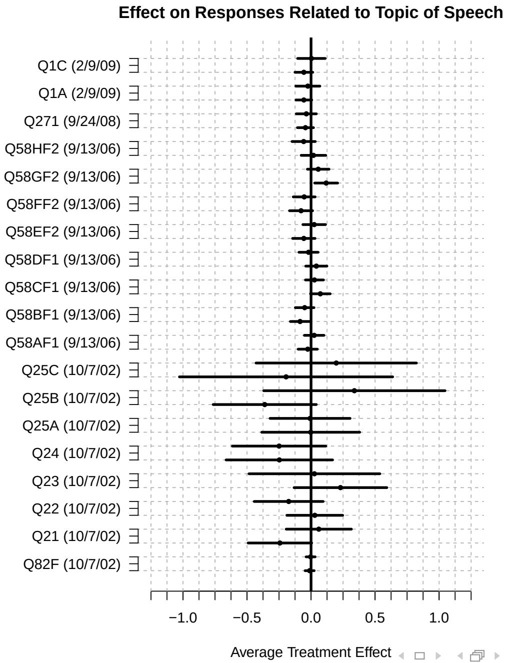
# Text as Outcome

# How do presidents "going public" affect public opinion?

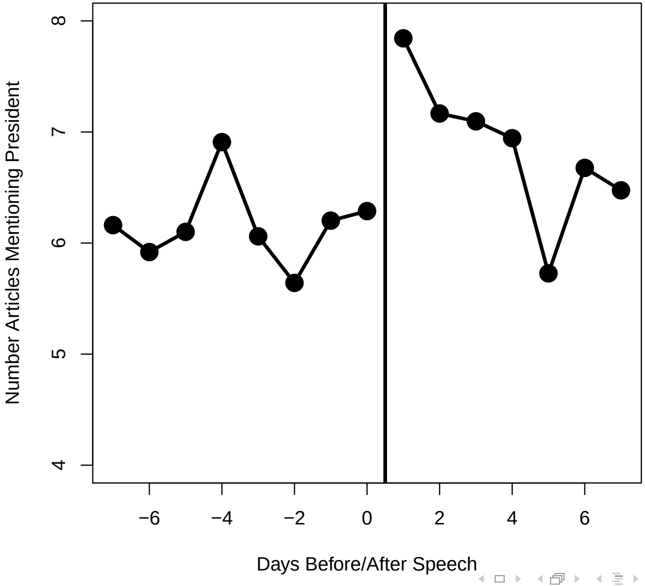


Obama
Bush 2
Clinton
Bush 1
−0.2
−0.1
0
0.1
0.2
0.3
Appeal Effect


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
Q1C (2/9/09)
Q1A (2/9/09)
Q271 (9/24/08)
Q58HF2 (9/13/06)
Q58GF2 (9/13/06)
Q58FF2 (9/13/06)
Q58EF2 (9/13/06)
Q58DF1 (9/13/06)
Q58CF1 (9/13/06)
Q58BF1 (9/13/06)
Q58AF1 (9/13/06)
Q25C (10/7/02)
Q25B (10/7/02)
Q25A (10/7/02)
Q24 (10/7/02)
Q23 (10/7/02)
Q22 (10/7/02)
Q21 (10/7/02)
Q82F (10/7/02)
−1.0
−0.5
0.0
0.5
1.0
Average Treatment Effect

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


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

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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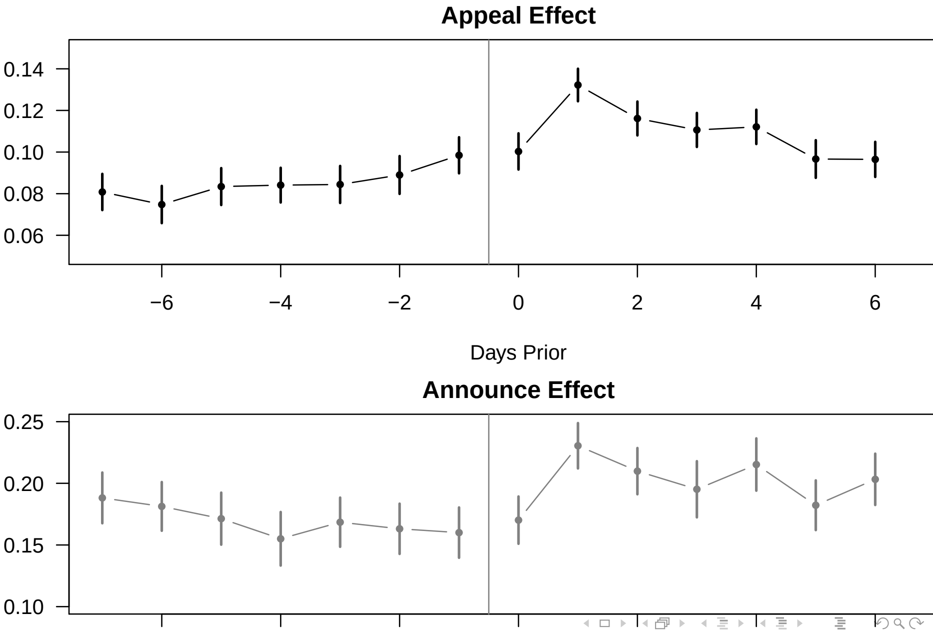
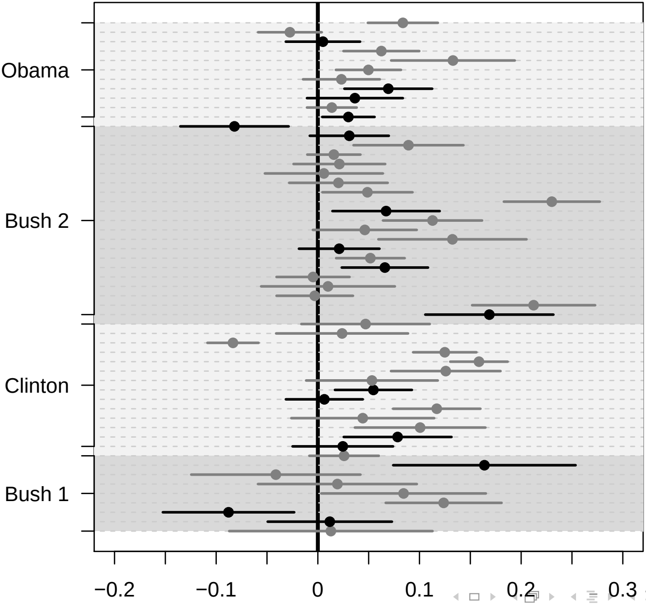
- Train: 10%, Test 90%
- Effect estimate: interrupted time series design on topic prevalence (compare share immediately before to share day after)


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
Bush 1
−0.2
−0.1
0
0.1
0.2
0.3

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