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

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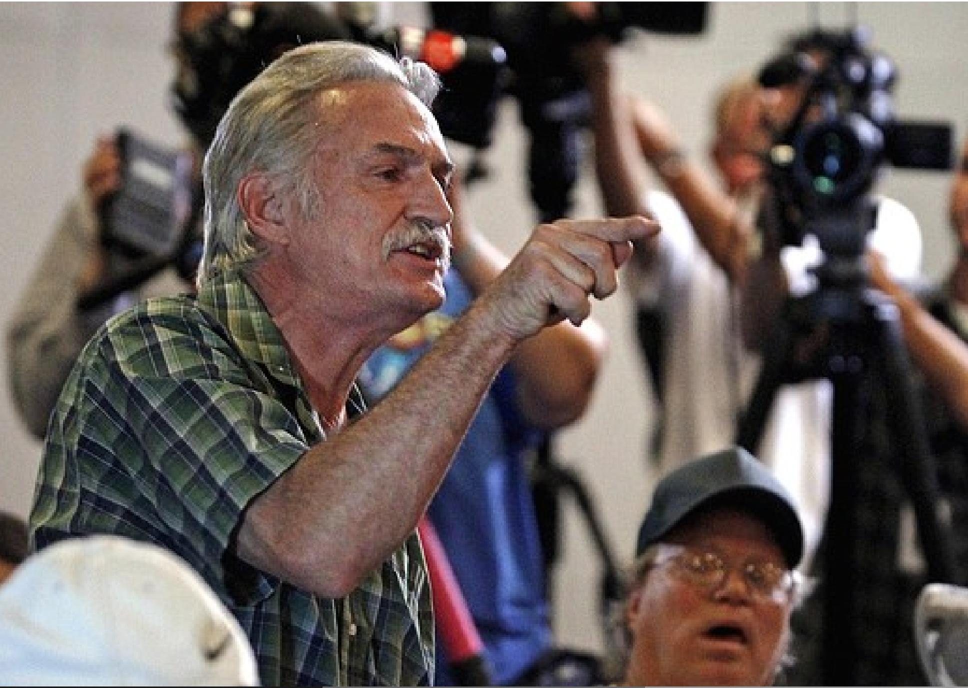
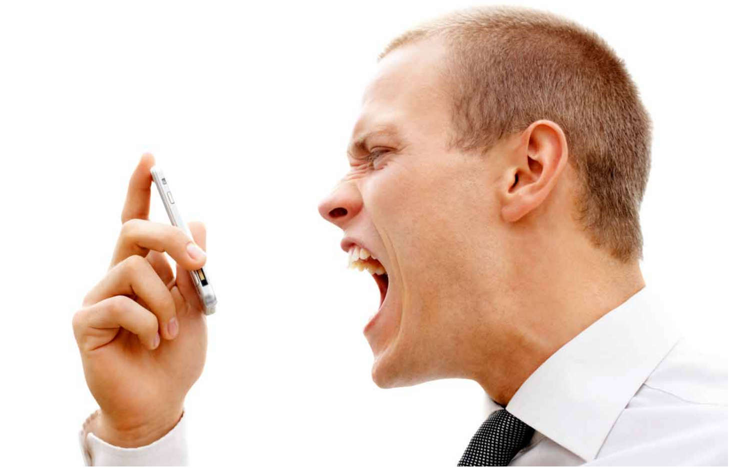
Discovery and Estimation




RESIST
RESIST
RESIST


USA
Shelby Hall
Engineering and Computing Sciences


DANGER
RUN
WITH

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Causal Inference in Text

Text as Intervention & Text as Response

1) Causal inference: latent representation of texts (g function to find latent features)
2) Discovery of features + Estimating effects$\rightsquigarrow$ train/test split

Which consumer complaints lead to a timely response?

Complaint A:
“I have been cheated by Wells Fargo! They were to set me up on an interest free payment plan, and I trusted them to do that. However, they set me up on a payment plan that took me way beyond the interest free date...Wells Fargo really sucks! I will avoid doing business with them in the future."

Complaint B:
“My name is XXXX XXXX. I am a Wells Fargo account holder. Wells Fargo illegally withdrew money from my account without notice or explanation"

Complaint A:
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Complaint B:
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Random assign A/B and assess response $\rightsquigarrow$ what about the complaint makes it better?

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Complaint A$'$:
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Random assign A, A' and assess response $\rightsquigarrow$ are we interested in effect of one word?

Complaint A (Treatment 1):
"I have been cheated by Wells Fargo! They were to set me up on an interest free payment plan, and I trusted them to do that. However, they set me up on a payment plan that took me way beyond the interest free date...Wells Fargo really sucks! I will avoid doing business with them in the future."

Complaint $A^{'}$ (Treatment 0):
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Latent Representation $\rightsquigarrow$ true whether hand coded, supervised, or unsupervised

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- Explicit discovery phase in experiment

Automatically discover treatments

$+$

Estimate marginal effects

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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

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- An individual sees a text ($\boldsymbol{X}_i$: text seen by i)
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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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    b) Ensure we avoid "p-hacking" (false discovery)

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2) Classification Stability $\rightsquigarrow$ same text leads to same label (retrained)

Train/Test split ensures both hold.

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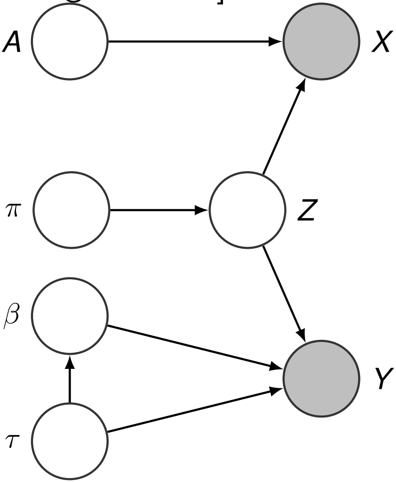
Treatments on simplex imply marginalization impossible $\rightsquigarrow$ increase in one category implies decrease in other category

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 \\
\eta_m &\sim \text{Beta}\left(\alpha, 1\right)
\end{aligned}
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- Document Creation:

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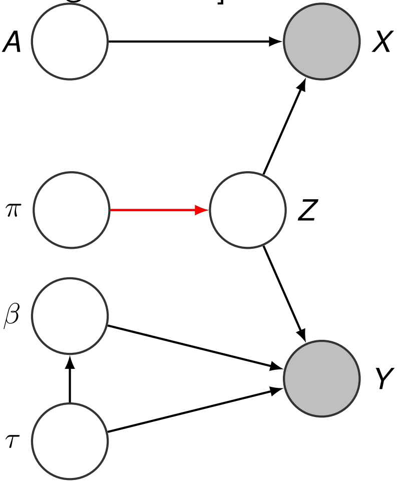

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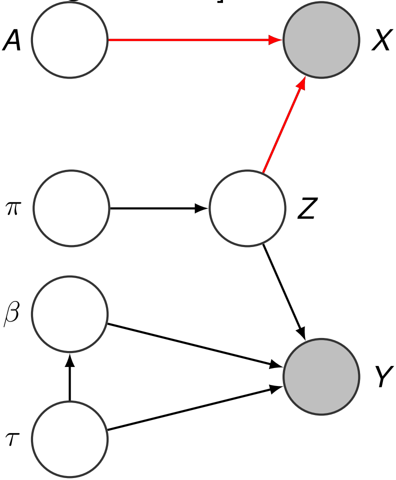

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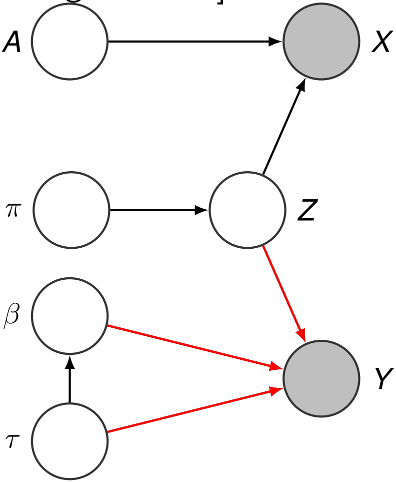

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\boldsymbol{\beta}|\tau &\sim \text{MVN}(\mathbf{0}, \tau^{-1} I_K) \\
\tau &\sim \text{Gamma}(a, b)
\end{aligned}
$$

Discovery of Treatments from Text Corpora

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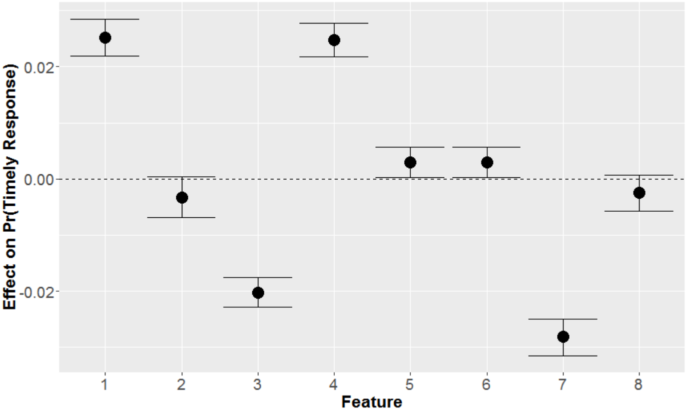
Treatment	Keywords
1	payment, card, debt , xxx , payment , loan
3	amount, call, account, time, pay, modification
4	interest, branch, number, xxxx_xxxx, told, house
7	month, credit_card, collection, received, called, loan_modificat



Candidate Biographies on Wikipedia: Setup

Barbara Mikulski $\rightsquigarrow$ Barbara Schumacher

`Schumacher was born and raised in the Highlandtown neighborhood of East Baltimore, the eldest of the three daughters of Christine Eleanor (nee Kutz) and William Schumacher. Her parents were both of Polish descent; her immigrant great-grandparents had owned a bakery in Baltimore. During her high school years at the Institute of Notre Dame, she worked in her parents' grocery store...`

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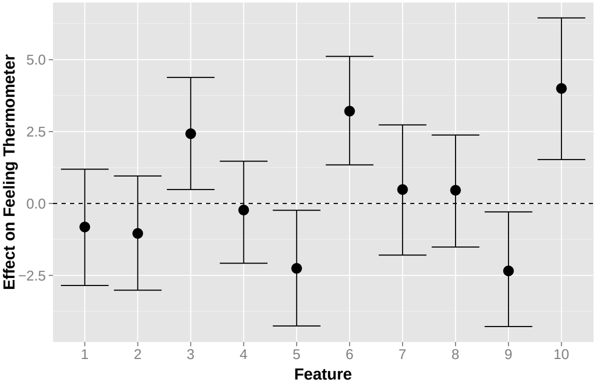
2,651 training, 2,652 test

Candiate Biographies on Wikipedia: Results

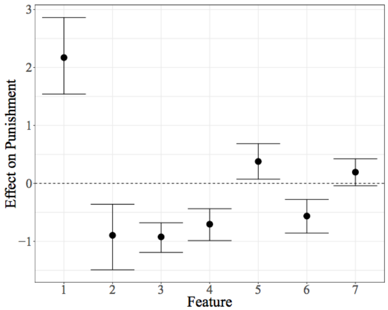
Treatment	Keywords
3	director, university, received, president, phd, policy
5	elected, house, democratic, seat
6	united_states, military, combat, rank
9	law, school_law, law_school, juris_doctor, student
10	war, enlisted, united_states, assigned, army



Two Examples from Jane Esberg (2017)

1.1 Spain Political Prisoner Trials

Text data: Random sample of 1,800 (out of 3,900) Spanish Tribunal of Public Order criminal summaries (1964-1975).
Outcome: Trial decision (punishment in years).



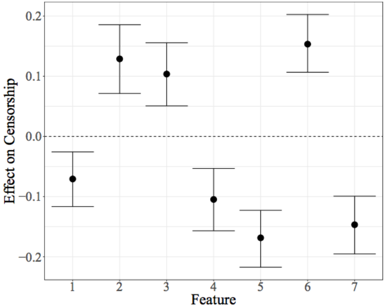
Feature			
1	2	3	4
crime	delinquent	drunk	accusation
adult	francoist	boss	disorder
responsible	youth	disturbance	pretend
author	policy	alcohol	financial
legal	subversive	yelling	traffic
5	6	7	
communist	gun	illicit	
party	possession	licence	
propaganda	pistol	revolver	
organization	fire	milimeter	
violence	munition	belonging	

Figure 1: *Trial summary features and effect on punishment in Spain*

Two Examples from Jane Esberg (2017)

1.2 Chile Movie Censorship

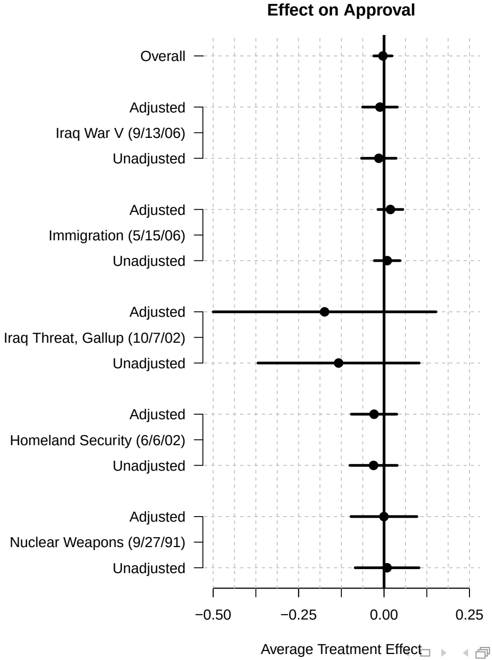
Text data: IMDb keywords for the 6,000 movies reviewed under Chile's dictatorship.
Outcome: Whether a film was banned (0/1).



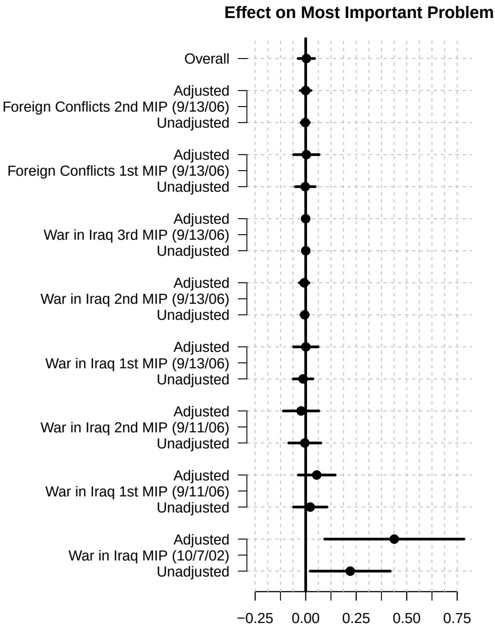
Feature			
1	2	3	4
singing	lust	death	rifle
photograph	cleavage	blood	cowboy
drinking	nudity	cruelty	gunfighter
relationship	erotic	corpse	saloon
tears	mini skirt	knife	battle
5	6	7	
hero	voyeur	tough guy	
showdown	undressing	quick draw	
fistfight	peeping tom	explosion	
martial arts	scantily clad	warrior	
ambush	nudity	lone	

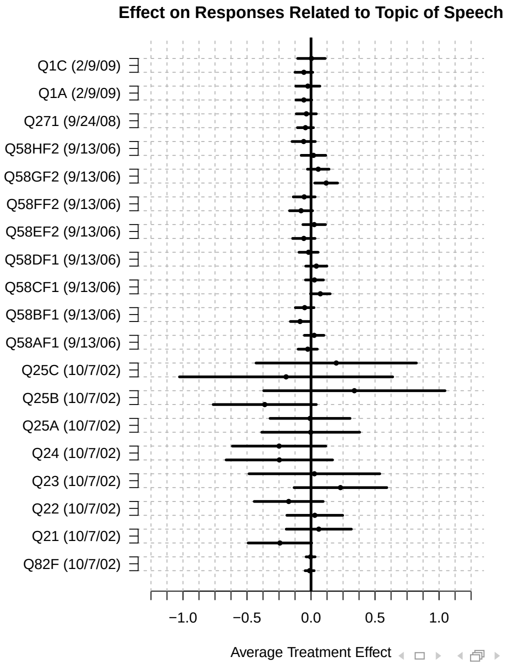
Figure 2: *Movie features and effect on censorship in Chile*

How do presidents "going public" affect public opinion?

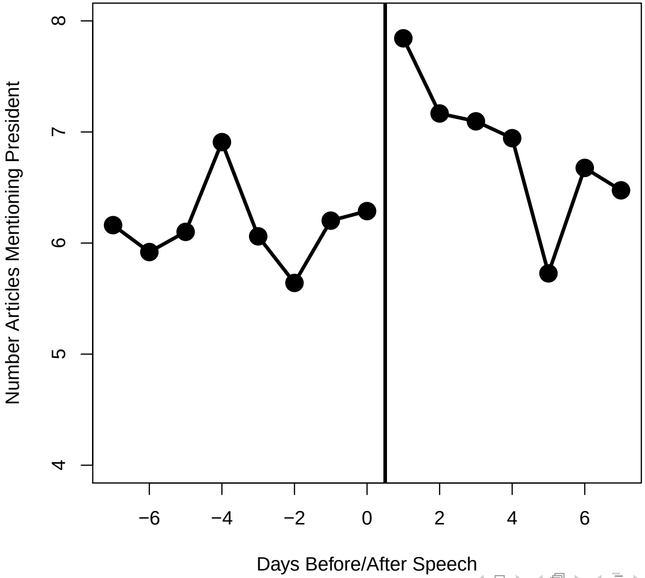


Effect on Approval
Overall
Adjusted
Iraq War V (9/13/06)
Unadjusted
Adjusted
Immigration (5/15/06)
Unadjusted
Adjusted
Iraq Threat, Gallup (10/7/02)
Unadjusted
Adjusted
Homeland Security (6/6/02)
Unadjusted
Adjusted
Nuclear Weapons (9/27/91)
Unadjusted
−0.50
−0.25
0.00
0.25
Average Treatment Effect


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 ~~public opinion~~ 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

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2) Obtain text based response $\boldsymbol{Y}_i(T_i)$

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Function g now uncovers latent features of response: map from text to small number of categories

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

Discovering (Estimating) Dependent Variable

- Numerous options to discover: (hand coding, supervised models, unsupervised models, mixture)

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Train/Test Split

1) (Assume) random assignment of treatments

2) Obtain text based response $\boldsymbol{Y}_i(T_i)$

1) (Assume) random assignment of treatments
2) Obtain text based response $\boldsymbol{Y}_i(T_i)$
3) Randomly split response and text into train/test split

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A President's effect on newspaper agenda

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- Response: newspaper articles mentioning `president` in 10 highest circulation papers, two-week window around speech

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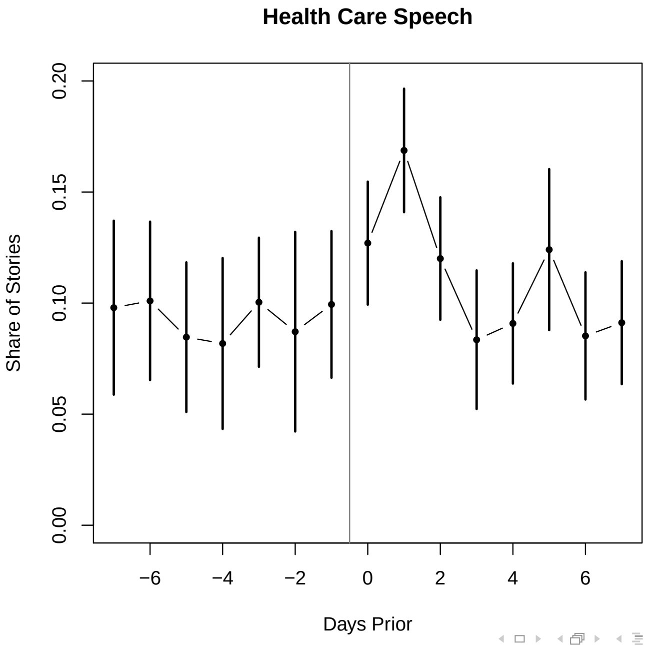
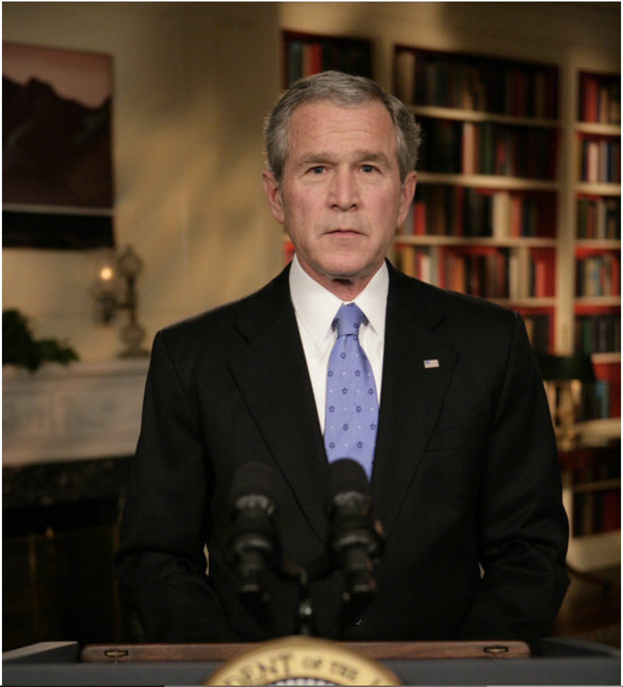
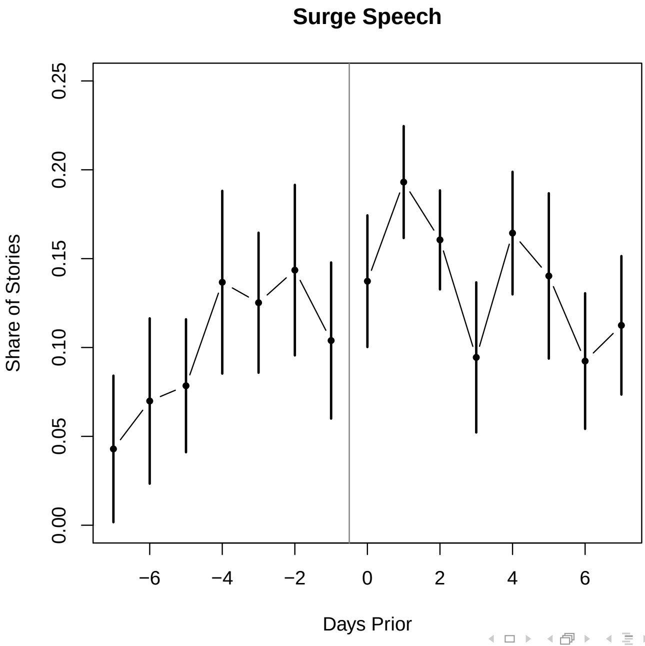
A President's effect on newspaper agenda

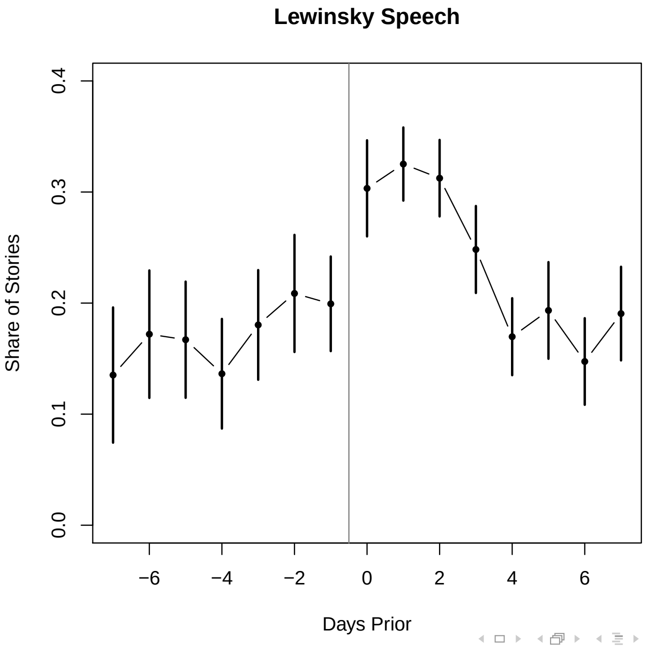
- Response: newspaper articles mentioning `president` in 10 highest circulation papers, two-week window around speech
- Treatment: Number of days before/after speech article was published
- 159,217 articles
- Train: 10%, Test 90%
- Effect estimate: interrupted time series design on topic prevalence (compare share immediately before to share immediately after)

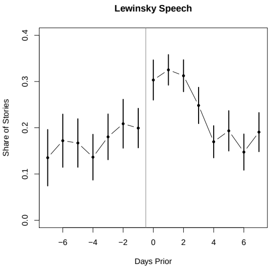

gettyimages
Pool
90534940


Health Care Speech
Share of Stories
0.00
0.05
0.10
0.15
0.20
−6
−4
−2
0
2
4
6
Days Prior




Surge Speech
Share of Stories
0.00
0.05
0.10
0.15
0.20
0.25
−6
−4
−2
0
2
4
6
Days Prior


Lewinsky Speech
Share of Stories
0.0
0.1
0.2
0.3
0.4
−6
−4
−2
0
2
4
6
Days Prior



Across speeches $\rightsquigarrow$ consistent effect on agenda

Immigration Application

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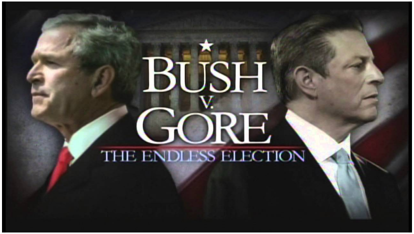

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"A 28-year-old single man, a citizen of another country, was convicted of illegally entering the United States. Prior to this offense, he had served two previous prison sentences each more than a year. One of these previous sentences was for a violent crime and he had been deported back to his home country."

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"A 28-year-old single man, a citizen of another country, was convicted of illegally entering the United States. Prior to this offense, he had never been imprisoned before."

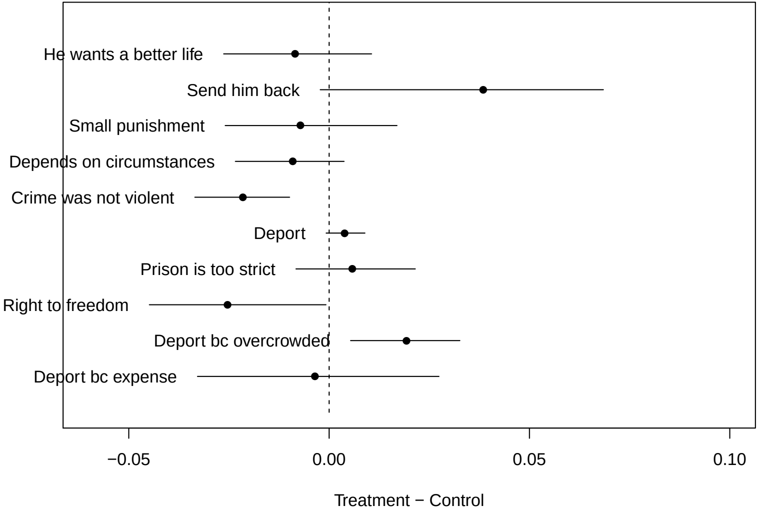
Immigration Experiment Results

Label	Highest Probability Words
He wants a better life	didnt, want, pay, better, life, probabl, isnt
Send him back	back, countri, send, home, well, charg
Small punishment	offens, reason, like, chanc, first, can, citizen
Depends on circum.	come, depend, doesnt, free, feel, law
Crime was not violent	crime, commit, violent, immigr, wasnt, look
Deport	deport, that, give, counti, peopl, look, guilti
Prison is too strict	enter, anyth, right, live, realli, illeg, anybodi
Right to freedom	just, tri, get, hes, came, freedom, put
Deport bc overcrowded	sent, prison, think, alreadi, anoth, done
Deport bc expense	dont, think, know, time, need, serv, crimin

Immigration Experiment Results

Label	Representative Document
He wants a better life	we're the land of opportunity everybody wants a better life
Send him back	send him back to his country
Small punishment	"it was his first offense, didn't hurt anybody, maybe a fine though, probation or something. that's nice serious like murder or robbery"
Depends on circumstances	it depends on reaason why he is coming into state if he was coming to beter himself its ok if he has a record he should be disbarred or deported
Crime was not violent	because he didnt commit a crime that was effecting someone else's individual liberties
Deport	he should be deported
Prison is too strict	because he didnt do anything except illegally enter
Right to freedom	Because he's just trying to get his freedom. Maybe he's trying to away from a tough situation/that country- maybe it's not good for him.
Deport bc overcrowded	he should be sent to prison in another country our prisons are over crowded already
Deport bc expense	because i think he shold be deported-p-i don't think he should be supported in our prison system and i don't think he should be allowed to immigrate here

Immigration Experiment Results



Conclusions and Future Directions

- Sequential (inductive) approach to social science: build theory with successive experiments
- Testing assumptions and new causal quantities of interest
- General Framework: Application to non-text settings (images, voting records)
- Text as Treatment , Text as Outcome , Text as Outcome and Treatment