Text as Data

Justin Grimmer

Associate Professor
Department of Political Science
Stanford University

December 2nd, 2014

Poster Session

Thursday. Set up begins at 9am, take down (promptly!) at 11am
Please email me a copy of your poster
Please attend!!!

Causal Inference and Text

1) Task
   i) Assess the effect of a text
      - Advertisement
      - Argument
   ii) Assess a text based response
      - Open ended responses (Roberts et al, 2014)
      - Politicians + rhetoric
   iii) Condition on text for selection on observable
      - Popularity of Clerics, given prior rhetoric (Nielsen, 2014)
2) Objective Function
   - Depends on Setting
3) Optimization:
   - Depends on Setting
4) Validation
   - Assumptions $\rightsquigarrow$ proofs for identification
   - Simulations $\rightsquigarrow$ strain identification assumptions, observe behavior
   - Sensitivity analysis $\rightsquigarrow$ examine sensitivity of analysis to assumptions

Many Open Questions!

A Causal Inference Refresher

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.
- Each unit receives treatment $\boldsymbol{T}_i$ (potentially vector valued)

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.
- Each unit receives treatment $\boldsymbol{T}_i$ (potentially vector valued)
- Suppose we have (potentially vector valued) response $\boldsymbol{Y}_i(\boldsymbol{T}_i)$

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.
- Each unit receives treatment $\boldsymbol{T}_i$ (potentially vector valued)
- Suppose we have (potentially vector valued) response $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
    - Unit i's response to treatment $\boldsymbol{T}_i$

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.
- Each unit receives treatment $\boldsymbol{T}_i$ (potentially vector valued)
- Suppose we have (potentially vector valued) response $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
    - Unit i's response to treatment $\boldsymbol{T}_i$
    - Function: maps from treatments to responses

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.
- Each unit receives treatment $\boldsymbol{T}_i$ (potentially vector valued)
- Suppose we have (potentially vector valued) response $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
    - Unit i's response to treatment $\boldsymbol{T}_i$
    - Function: maps from treatments to responses
- Fundamental problem of causal inference observe only one $\boldsymbol{Y}_i(\boldsymbol{T}_i)$

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.
- Each unit receives treatment $\boldsymbol{T}_i$ (potentially vector valued)
- Suppose we have (potentially vector valued) response $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
  - Unit i's response to treatment $\boldsymbol{T}_i$
  - Function: maps from treatments to responses
- Fundamental problem of causal inference observe only one $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
- Quantity of interest:

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.
- Each unit receives treatment $\boldsymbol{T}_i$ (potentially vector valued)
- Suppose we have (potentially vector valued) response $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
  - Unit i's response to treatment $\boldsymbol{T}_i$
  - Function: maps from treatments to responses
- Fundamental problem of causal inference observe only one $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
- Quantity of interest:
  - Simplest (yet very powerful) case$\rightsquigarrow$ $T_i \in \{0,1\}$, $Y_i(T_i) \in \{0,1\}$

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.
- Each unit receives treatment $\boldsymbol{T}_i$ (potentially vector valued)
- Suppose we have (potentially vector valued) response $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
    - Unit i's response to treatment $\boldsymbol{T}_i$
    - Function: maps from treatments to responses
- Fundamental problem of causal inference observe only one $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
- Quantity of interest:
    - Simplest (yet very powerful) case$\rightsquigarrow$ $T_i \in \{0, 1\}$, $Y_i(T_i) \in \{0, 1\}$

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

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.
- Each unit receives treatment $\boldsymbol{T}_i$ (potentially vector valued)
- Suppose we have (potentially vector valued) response $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
  - Unit i's response to treatment $\boldsymbol{T}_i$
  - Function: maps from treatments to responses
- Fundamental problem of causal inference observe only one $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
- Quantity of interest:
  - Simplest (yet very powerful) case$\rightsquigarrow$ $T_i \in \{0, 1\}$, $Y_i(T_i) \in \{0, 1\}$

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

  - Estimate with:

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.
- Each unit receives treatment $\boldsymbol{T}_i$ (potentially vector valued)
- Suppose we have (potentially vector valued) response $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
  - Unit i's response to treatment $\boldsymbol{T}_i$
  - Function: maps from treatments to responses
- Fundamental problem of causal inference observe only one $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
- Quantity of interest:
  - Simplest (yet very powerful) case$\rightsquigarrow$ $T_i \in \{0, 1\}$, $Y_i(T_i) \in \{0, 1\}$

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

  - Estimate with:

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

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.
- Each unit receives treatment $\boldsymbol{T}_i$ (potentially vector valued)
- Suppose we have (potentially vector valued) response $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
  - Unit i's response to treatment $\boldsymbol{T}_i$
  - Function: maps from treatments to responses
- Fundamental problem of causal inference observe only one $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
- Quantity of interest:
  - Simplest (yet very powerful) case$\rightsquigarrow$ $T_i \in \{0, 1\}$, $Y_i(T_i) \in \{0, 1\}$

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

  - Estimate with:

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

A Causal Inference Refresher

- Suppose we have N units, $i = 1, \ldots, N$.
- Each unit receives treatment $\boldsymbol{T}_i$ (potentially vector valued)
- Suppose we have (potentially vector valued) response $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
  - Unit i's response to treatment $\boldsymbol{T}_i$
  - Function: maps from treatments to responses
- Fundamental problem of causal inference observe only one $\boldsymbol{Y}_i(\boldsymbol{T}_i)$
- Quantity of interest:
  - Simplest (yet very powerful) case$\rightsquigarrow$ $T_i \in \{0, 1\}$, $Y_i(T_i) \in \{0, 1\}$

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

  - Estimate with:

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

Question: how do we accurately estimate quantities like ATE?

Our Plan for the Day

- Experimental research design
  1) Many potential treatments $\rightsquigarrow$ text based treatments
  2) Text based responses
- Observational research design
  3) Condition on prior texts

An Example Experiment

An Example Experiment

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

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

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

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

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, partisanship

1) Democrat
2) Republican

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, 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."

Rewarding Actions and Type of Expenditure, Not Money

214 other conditions

Rewarding Actions and Type of Expenditure, Not Money

214 other conditions

Dependent variable: Approve of representative

Rewarding Actions and Type of Expenditure, Not Money

214 other conditions
Dependent variable: Approve of representative

Goal $\rightsquigarrow$ measure effect of credit claiming content on approval ratings

Rewarding Actions and Type of Expenditure, Not Money

214 other conditions
Dependent variable: Approve of representative

Goal $\rightsquigarrow$ measure effect of credit claiming content on approval ratings
Mechanics $\rightsquigarrow$ Mechanical Turk sample (Findings are replicated in representative samples, using real representatives/senators)

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$
- $Y_i(\mathbf{T}_i)$: participant i's Approval decision under treatment $\mathbf{T}_i$

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$
- $Y_i(\mathbf{T}_i)$: participant i's Approval decision under treatment $\mathbf{T}_i$
- Quantities of Interest

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$
- $Y_i(\mathbf{T}_i)$: participant i's Approval decision under treatment $\mathbf{T}_i$
- Quantities of Interest
- Effect of particular component of message:

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$
- $Y_i(\mathbf{T}_i)$: participant i's Approval decision under treatment $\mathbf{T}_i$
- Quantities of Interest
- Effect of particular component of message:
    - $\mathrm{T}_{\text{stage}} = \text{Secured}$

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$
- $Y_i(\mathbf{T}_i)$: participant i's Approval decision under treatment $\mathbf{T}_i$
- Quantities of Interest
- Effect of particular component of message:
  - $\mathrm{T}_{\text{stage}} = \text{Secured}$
  - $\mathrm{T}_{\text{stage}} = \text{Requested}$

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$
- $Y_i(\mathbf{T}_i)$: participant i's Approval decision under treatment $\mathbf{T}_i$
- Quantities of Interest
- Effect of particular component of message:
  - $\mathrm{T}_{\text{stage}} =$ Secured
  - $\mathrm{T}_{\text{stage}} =$ Requested
  - $\mathrm{T}_{\text{stage}} =$ Will Request

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$
- $Y_i(\mathbf{T}_i)$: participant i's Approval decision under treatment $\mathbf{T}_i$
- Quantities of Interest
- Effect of particular component of message:
  - $\mathrm{T}_{\text{stage}} =$ Secured
  - $\mathrm{T}_{\text{stage}} =$ Requested
  - $\mathrm{T}_{\text{stage}} =$ Will Request
  - $\mathrm{T}_j = k$

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$
- $Y_i(\mathbf{T}_i)$: participant i's Approval decision under treatment $\mathbf{T}_i$
- Quantities of Interest
- Marginal Average Treatment Effect ($\text{MATE}_{\mathrm{T}_j = k}$)

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$
- $Y_i(\mathbf{T}_i)$: participant i's Approval decision under treatment $\mathbf{T}_i$
- Quantities of Interest
- Marginal Average Treatment Effect ($\text{MATE}_{\mathrm{T}_j=k}$)

$$\text{MATE}_{\mathrm{T}_j=k} \quad = \quad \int \mathrm{E}[Y(\mathrm{T}_j = k, \mathbf{T}_{-j}) - Y(0)]\mathrm{dF}_{\mathbf{T}_{-j}|\mathrm{T}_j=k}$$

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$
- $Y_i(\mathbf{T}_i)$: participant i's Approval decision under treatment $\mathbf{T}_i$
- Quantities of Interest
- Marginal Average Treatment Effect ($\text{MATE}_{\mathrm{T}_j=k}$)

$$\begin{aligned}
\text{MATE}_{\mathrm{T}_j=k} &= \int \mathrm{E}[Y(\mathrm{T}_j = k, \mathbf{T}_{-j}) - Y(0)]\mathrm{dF}_{\mathbf{T}_{-j}|\mathrm{T}_j=k} \\
\text{MATE}_{\mathrm{T}_j=k} &= \mathrm{E}[Y(\mathrm{T}_j = k) - Y(0)]
\end{aligned}$$

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$
- $Y_i(\mathbf{T}_i)$: participant i's Approval decision under treatment $\mathbf{T}_i$
- Quantities of Interest
- Marginal Average Treatment Effect ($\text{MATE}_{\mathrm{T}_j = k}$)

$$\text{MATE}_{\mathrm{T}_j = k} = \mathrm{E}[Y(\mathrm{T}_j = k)|\mathrm{T}_j = k] - \mathrm{E}[Y(0)|\mathrm{T} = 0]$$

Rewarding Actions and Type of Expenditure, Not Money

- Participant i ($i = 1, \ldots, N$), has treatment assignment $\mathbf{T}_i$
- If $\mathrm{T}_i = 0$ for control condition
- $\mathbf{T}_i = (\mathrm{T}_{i,\text{type}}, \mathrm{T}_{i,\text{stage}}, \mathrm{T}_{i,\text{money}}, \mathrm{T}_{i,\text{collab.}}, \mathrm{T}_{i,\text{part.}})$
- $Y_i(\mathbf{T}_i)$: participant i's Approval decision under treatment $\mathbf{T}_i$
- Quantities of Interest
- Marginal Average Treatment Effect ($\text{MATE}_{\mathrm{T}_j=k}$)

$$\begin{aligned}
\text{MATE}_{\mathrm{T}_j=k} &= \mathrm{E}[Y(\mathrm{T}_j = k)|\mathrm{T}_j = k] - \mathrm{E}[Y(0)|\mathrm{T} = 0] \\
\widehat{\text{MATE}}_{\mathrm{T}_j=k} &= \frac{\sum_{i=1}^N Y_i I(\mathrm{T}_{ij} = k)}{\sum_{i=1}^N I(\mathrm{T}_{ij} = k)} - \frac{\sum_{i=1}^N Y_i I(\mathrm{T}_i = 0)}{\sum_{i=1}^N I(\mathrm{T}_i = 0)}
\end{aligned}$$

Rewarding Actions and Type of Expenditure, Not Money

- Response may be conditional on respondent characteristics **x**

Rewarding Actions and Type of Expenditure, Not Money

- Response may be conditional on respondent characteristics $\mathbf{x}$
- For example $\mathbf{x} =$ (Conservative, Republican)

Rewarding Actions and Type of Expenditure, Not Money

- Response may be conditional on respondent characteristics $\mathbf{x}$
- For example $\mathbf{x} =$ (Conservative, Republican)
- Marginal Conditional Average Treatment Effect ($\text{MCATE}_{\text{T}_j = k, \mathbf{x}}$)

Rewarding Actions and Type of Expenditure, Not Money

- Response may be conditional on respondent characteristics $\mathbf{x}$
- For example $\mathbf{x} =$ (Conservative, Republican)
- Marginal Conditional Average Treatment Effect ($\text{MCATE}_{\text{T}_j=k,\mathbf{x}}$)

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

Rewarding Actions and Type of Expenditure, Not Money

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

Rewarding Actions and Type of Expenditure, Not Money

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

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

Rewarding Actions and Type of Expenditure, Not Money

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

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

- Curse of Dimensionality: highly variable estimates, (sometimes) empty strata

Rewarding Actions and Type of Expenditure, Not Money

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

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

- Curse of Dimensionality: highly variable estimates, (sometimes) empty strata
- Separate systematic differences from noise $\rightsquigarrow$ data and assumptions

Rewarding Actions and Type of Expenditure, Not Money

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

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

- Curse of Dimensionality: highly variable estimates, (sometimes) empty strata
- Separate systematic differences from noise $\rightsquigarrow$ data and assumptions Heterogeneous treatment effect methods

Rewarding Actions and Type of Expenditure, Not Money

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

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

- 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

Rewarding Actions and Type of Expenditure, Not Money

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

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

- 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
  - Ridge, KRLS (Hainmueller and Hazlett, 2013)$\rightsquigarrow$ flexible surface, dense

Rewarding Actions and Type of Expenditure, Not Money

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

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

- 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
  - Ridge, KRLS (Hainmueller and Hazlett, 2013) $\rightsquigarrow$ flexible surface, dense
  - Model m to estimate some function $g_m(\text{T}_j = k, \boldsymbol{x})$

Rewarding Actions and Type of Expenditure, Not Money

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

- 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
  - Ridge, KRLS (Hainmueller and Hazlett, 2013) $\rightsquigarrow$ flexible surface, dense
  - Model m to estimate some function $g_m(\text{T}_j = k, \boldsymbol{x})$
- Perform well: $g_m(\text{T}_j = k, \boldsymbol{x})$ accurately estimates response surface $(\text{E}[Y(\text{T}_j = k)|\mathbf{x}])$

Rewarding Actions and Type of Expenditure, Not Money

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

- 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
    - Ridge, KRLS (Hainmueller and Hazlett, 2013)$\rightsquigarrow$ flexible surface, dense
    - Model m to estimate some function $g_m(\text{T}_j = k, \boldsymbol{x})$
- Perform well: $g_m(\text{T}_j = k, \boldsymbol{x})$ accurately estimates response surface ($\text{E}[Y(\text{T}_j = k)|\mathbf{x}]$)
- Perform well: accurate out of sample prediction and classification (van der Laan et al 2007, Raftery et al 2005)

Rewarding Actions and Type of Expenditure, Not Money

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

- 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
  - Ridge, KRLS (Hainmueller and Hazlett, 2013) $\rightsquigarrow$ flexible surface, dense
  - Model m to estimate some function $g_m(\text{T}_j = k, \boldsymbol{x})$
- Perform well: $g_m(\text{T}_j = k, \boldsymbol{x})$ accurately estimates response surface $(\text{E}[Y(\text{T}_j = k)|\mathbf{x}])$
- Perform well: accurate out of sample prediction and classification (van der Laan et al 2007, Raftery et al 2005)

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.

Weighted Ensemble to Measure Credit Claiming Rate

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

$$\widehat{\text{MCATE}}_{\text{T}_j=k,\mathbf{x}} = \sum_{m=1}^{M} \widehat{\pi}_m(\widehat{g}_m(\text{T}_j = k, \mathbf{x}) - \widehat{g}_m(0, \mathbf{x}))$$

Weighted Ensemble to Measure Credit Claiming Rate

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

$$\widehat{\text{MCATE}}_{\text{T}_j = k, \mathbf{x}} = \sum_{m=1}^{M} \widehat{\pi}_m (\widehat{g}_m(\text{T}_j = k, \mathbf{x}) - \widehat{g}_m(0, \mathbf{x}))$$

Weighted Ensemble to Measure Credit Claiming Rate

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

$$\widehat{\text{MCATE}}_{\text{T}_j = k, \mathbf{x}} = \sum_{m=1}^{M} \widehat{\pi}_m (\widehat{g}_m(\text{T}_j = k, \mathbf{x}) - \widehat{g}_m(0, \mathbf{x}))$$

Weighted Ensemble to Measure Credit Claiming Rate

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

$$\widehat{\text{MCATE}}_{\text{T}_j = k, \mathbf{x}} = \sum_{m=1}^{M} \widehat{\pi}_m (\widehat{g}_m(\text{T}_j = k, \mathbf{x}) - \widehat{g}_m(0, \mathbf{x}))$$

- Estimate weights $(\widehat{\pi}_m)$

Weighted Ensemble to Measure Credit Claiming Rate

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

$$\widehat{\text{MCATE}}_{\text{T}_j = k, \mathbf{x}} = \sum_{m=1}^{M} \widehat{\pi}_m (\widehat{g}_m(\text{T}_j = k, \mathbf{x}) - \widehat{g}_m(0, \mathbf{x}))$$

- Estimate weights ($\widehat{\pi}_m$)
    - 10-fold cross validation: generate M out of sample predictions for each observation

Weighted Ensemble to Measure Credit Claiming Rate

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

$$\widehat{\text{MCATE}}_{\mathsf{T}_j = k, \mathbf{x}} = \sum_{m=1}^{M} \widehat{\pi}_m (\widehat{g}_m(\mathsf{T}_j = k, \mathbf{x}) - \widehat{g}_m(0, \mathbf{x}))$$

- Estimate weights ($\widehat{\pi}_m$)
    - 10-fold cross validation: generate M out of sample predictions for each observation
      $\widehat{\mathbf{Y}}_i = (\widehat{Y}_{i1}, \widehat{Y}_{i2}, \ldots, \widehat{Y}_{iM})$

Weighted Ensemble to Measure Credit Claiming Rate

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

$$\widehat{\text{MCATE}}_{\text{T}_j = k, \mathbf{x}} = \sum_{m=1}^{M} \widehat{\pi}_m(\widehat{g}_m(\text{T}_j = k, \mathbf{x}) - \widehat{g}_m(0, \mathbf{x}))$$

- Estimate weights $(\widehat{\pi}_m)$
  - 10-fold cross validation: generate M out of sample predictions for each observation $\widehat{\mathbf{Y}}_i = (\widehat{Y}_{i1}, \widehat{Y}_{i2}, \ldots, \widehat{Y}_{iM})$
  - Estimate weights with constrained regression:

Weighted Ensemble to Measure Credit Claiming Rate

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

$$\widehat{\text{MCATE}}_{\text{T}_j = k, \mathbf{x}} = \sum_{m=1}^{M} \widehat{\pi}_m (\widehat{g}_m(\text{T}_j = k, \mathbf{x}) - \widehat{g}_m(0, \mathbf{x}))$$

- Estimate weights ($\widehat{\pi}_m$)
  - 10-fold cross validation: generate M out of sample predictions for each observation
    $\widehat{\mathbf{Y}}_i = (\widehat{Y}_{i1}, \widehat{Y}_{i2}, \ldots, \widehat{Y}_{iM})$
  - Estimate weights with constrained regression:

$$Y_i = \sum_{m=1}^{M} \pi_m \hat{Y}_{im} + \epsilon_i$$

Weighted Ensemble to Measure Credit Claiming Rate

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

$$\widehat{\text{MCATE}}_{\text{T}_j = k, \mathbf{x}} = \sum_{m=1}^{M} \widehat{\pi}_m (\widehat{g}_m(\text{T}_j = k, \mathbf{x}) - \widehat{g}_m(0, \mathbf{x}))$$

- Estimate weights ($\widehat{\pi}_m$)
  - 10-fold cross validation: generate M out of sample predictions for each observation
    $\widehat{\mathbf{Y}}_i = (\widehat{Y}_{i1}, \widehat{Y}_{i2}, \ldots, \widehat{Y}_{iM})$
  - Estimate weights with constrained regression:

$$Y_i = \sum_{m=1}^{M} \pi_m \hat{Y}_{im} + \epsilon_i$$

where we impose constraints: $\pi_m \geq 0$ and $\sum_{m=1}^{M} \pi_m = 1$.

Weighted Ensemble to Measure Credit Claiming Rate

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

$$\widehat{\text{MCATE}}_{\text{T}_j = k, \mathbf{x}} = \sum_{m=1}^{M} \widehat{\pi}_m(\widehat{g}_m(\text{T}_j = k, \mathbf{x}) - \widehat{g}_m(0, \mathbf{x}))$$

- Estimate weights $(\widehat{\pi}_m)$
  - 10-fold cross validation: generate M out of sample predictions for each observation
    $\widehat{\mathbf{Y}}_i = (\widehat{Y}_{i1}, \widehat{Y}_{i2}, \ldots, \widehat{Y}_{iM})$
  - Estimate weights with constrained regression:

$$Y_i = \sum_{m=1}^{M} \pi_m \hat{Y}_{im} + \epsilon_i$$

    where we impose constraints: $\pi_m \geq 0$ and $\sum_{m=1}^{M} \pi_m = 1$.
  - Result $\widehat{\pi}_m$ for each method

Weighted Ensemble to Measure Credit Claiming Rate

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

$$\widehat{\text{MCATE}}_{\text{T}_j = k, \mathbf{x}} = \sum_{m=1}^{M} \widehat{\pi}_m (\widehat{g}_m(\text{T}_j = k, \mathbf{x}) - \widehat{g}_m(0, \mathbf{x}))$$

- Estimate weights $(\widehat{\pi}_m)$
  - 10-fold cross validation: generate M out of sample predictions for each observation
    $\widehat{\mathbf{Y}}_i = (\widehat{Y}_{i1}, \widehat{Y}_{i2}, \ldots, \widehat{Y}_{iM})$
  - (Alternatively) Estimate weights from mixture model (EBMA) (Raftery et al 2005; Montgomery, Hollenback, Ward 2012)$\rightsquigarrow$ EM, Gibbs, Variational Approximation

Weighted Ensemble to Measure Credit Claiming Rate

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

$$\widehat{\text{MCATE}}_{\text{T}_j = k, \mathbf{x}} \;=\; \sum_{m=1}^{M} \widehat{\pi}_m(\widehat{g}_m(\text{T}_j = k, \mathbf{x}) - \widehat{g}_m(0, \mathbf{x}))$$

- Estimate weights $(\widehat{\pi}_m)$
- Estimate $\widehat{g}_m(\text{T}_j = k, \mathbf{x}) \rightsquigarrow$ Apply all M models to entire data set

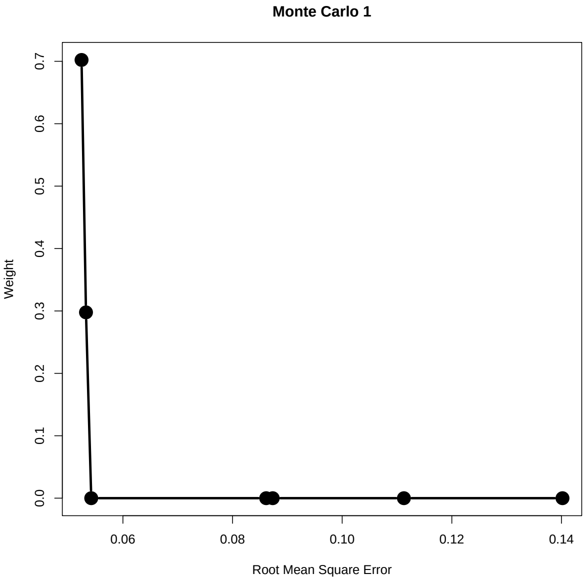
Weighted Ensemble to Measure Credit Claiming Rate

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

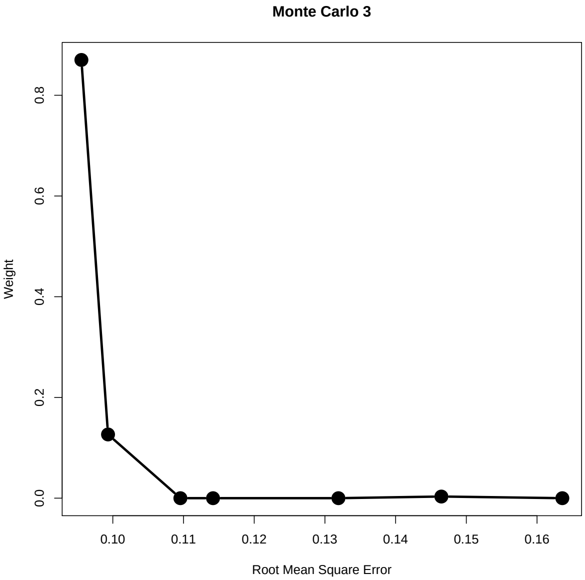
$$\widehat{\text{MCATE}}_{\text{T}_j = k, \mathbf{x}_{\text{new}}} = \sum_{m=1}^{M} \widehat{\pi}_m(\widehat{g}_m(\text{T}_j = k, \mathbf{x}_{\text{new}}) - \widehat{g}_m(0, \mathbf{x}_{\text{new}}))$$

- Estimate weights ($\widehat{\pi}_m$)
- Estimate $\widehat{g}_m(\text{T}_j = k, \mathbf{x})$ $\rightsquigarrow$ Apply all M models to entire data set
- Generate effects of interest (perhaps weighting to other population) $\mathbf{x}_{\text{new}}$

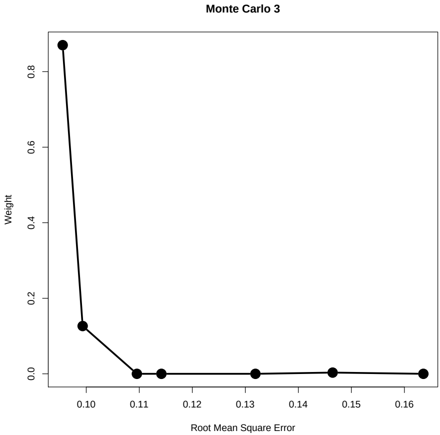
Monte Carlo Evidence



Monte Carlo Evidence



Monte Carlo Evidence



Ensembles outperform constituent methods $\rightsquigarrow$ ensembles place weight on better performing method

Returning to Example Experiment

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

Returning to Example Experiment

Recall: experiment to assess effects of credit claiming on approval $\rightsquigarrow$ 1,074 participants (MTurk)
Apply ensemble method (7 constituent methods, 10 fold cross validation), including treatments and Partisanship and Ideology.

Returning to Example Experiment

Recall: experiment to assess effects of credit claiming on approval $\rightsquigarrow$
1,074 participants (MTurk)
Apply ensemble method (7 constituent methods, 10 fold cross validation), including treatments and Partisanship and Ideology.
Positive weight on three methods:

Returning to Example Experiment

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

Apply ensemble method (7 constituent methods, 10 fold cross validation), including treatments and Partisanship and Ideology.

Positive weight on three methods:

1) LASSO (0.62)

Returning to Example Experiment

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

Apply ensemble method (7 constituent methods, 10 fold cross validation), including treatments and Partisanship and Ideology.

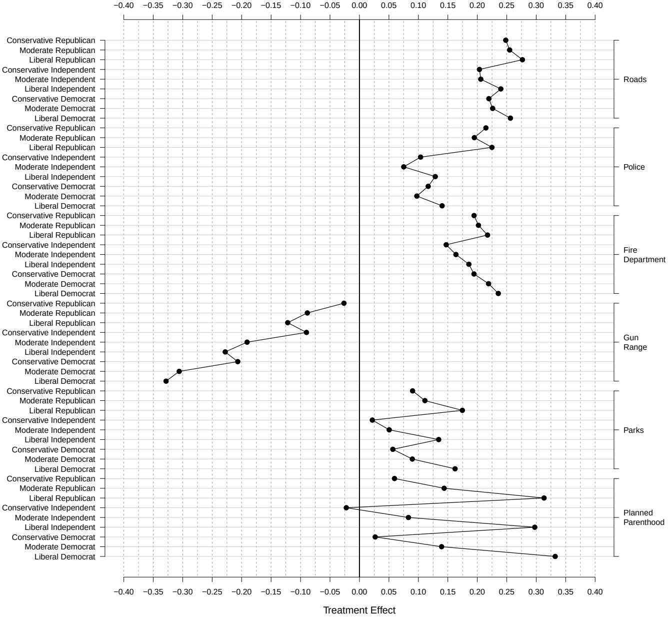
Positive weight on three methods:

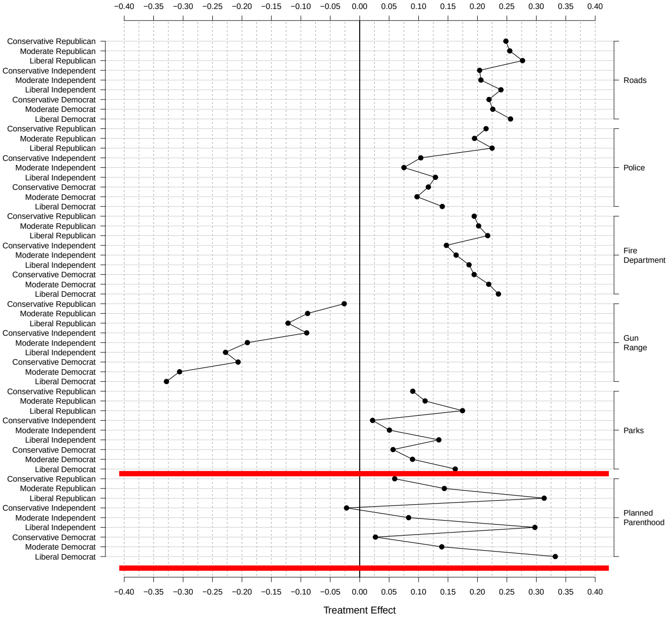
1) LASSO (0.62)
2) KRLS (0.24)

Returning to Example Experiment

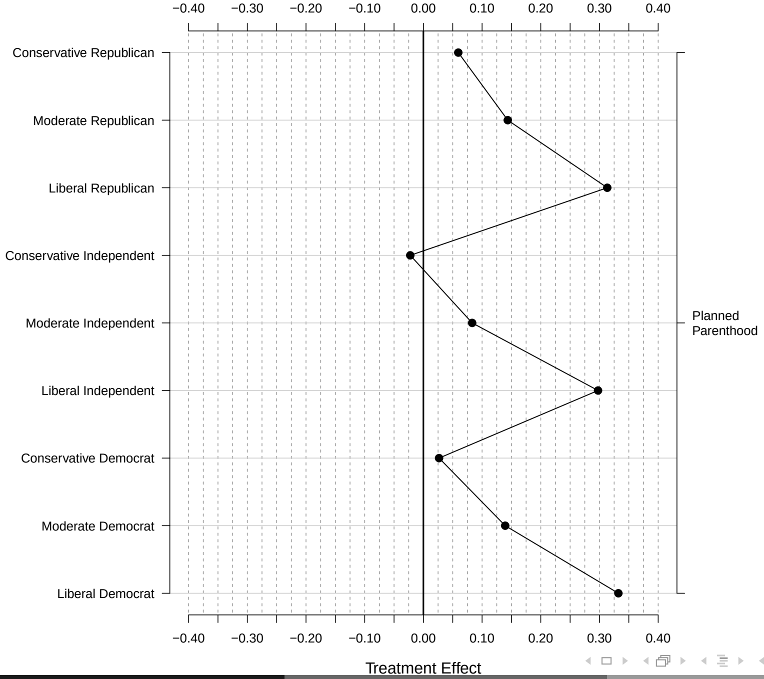
Recall: experiment to assess effects of credit claiming on approval $\rightsquigarrow$ 1,074 participants (MTurk)
Apply ensemble method (7 constituent methods, 10 fold cross validation), including treatments and Partisanship and Ideology.
Positive weight on three methods:

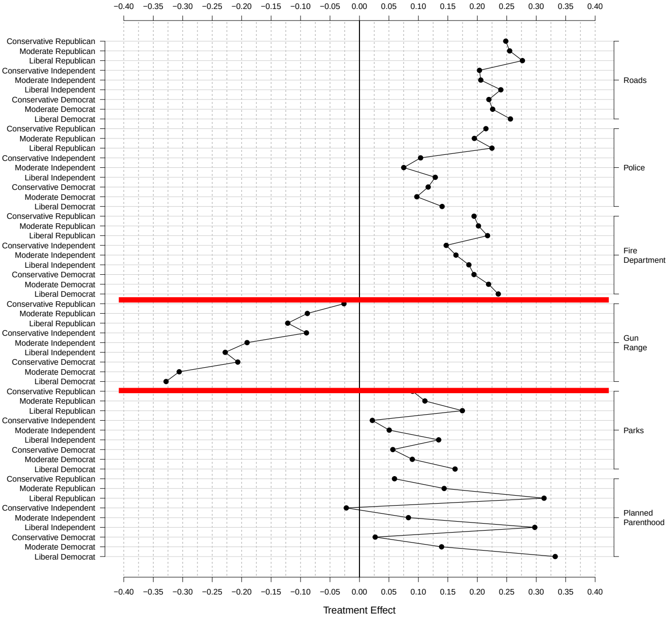
1) LASSO (0.62)
2) KRLS (0.24)
3) Find it (0.14)


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

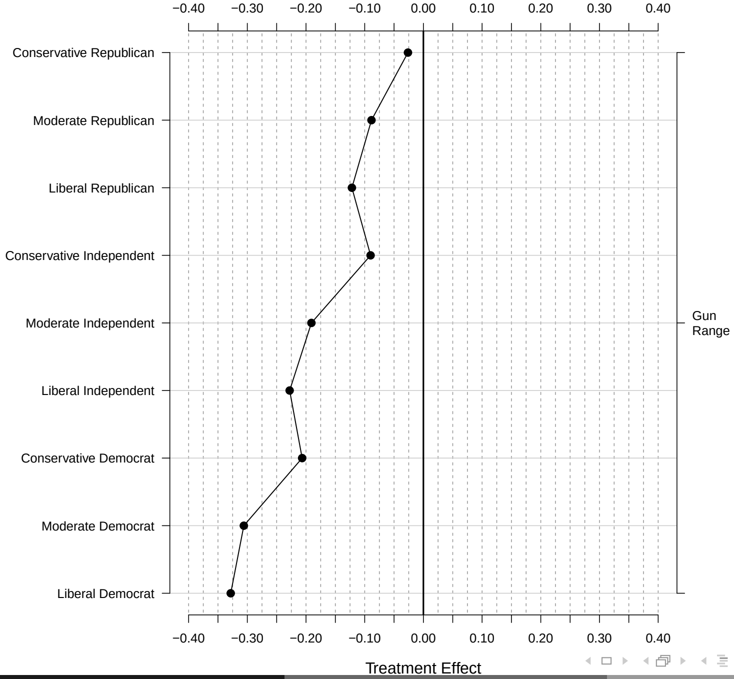


−0.40 −0.35 −0.30 −0.25 −0.20 −0.15 −0.10 −0.05 0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40
Conservative Republican
Moderate Republican
Liberal Republican
Conservative Independent
Moderate Independent
Liberal Independent
Conservative Democrat
Moderate Democrat
Liberal Democrat
Roads
Police
Fire Department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

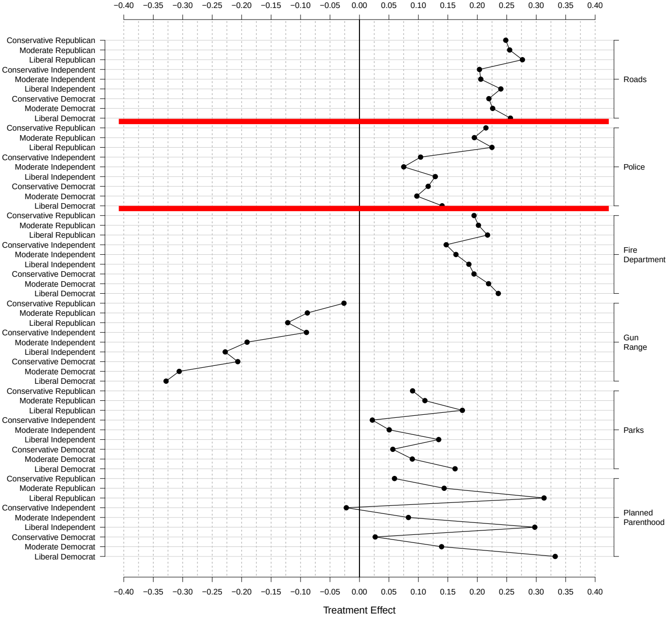

−0.40 −0.30 −0.20 −0.10 0.00 0.10 0.20 0.30 0.40
Conservative Republican
Moderate Republican
Liberal Republican
Conservative Independent
Moderate Independent
Liberal Independent
Conservative Democrat
Moderate Democrat
Liberal Democrat
Planned Parenthood
Treatment Effect



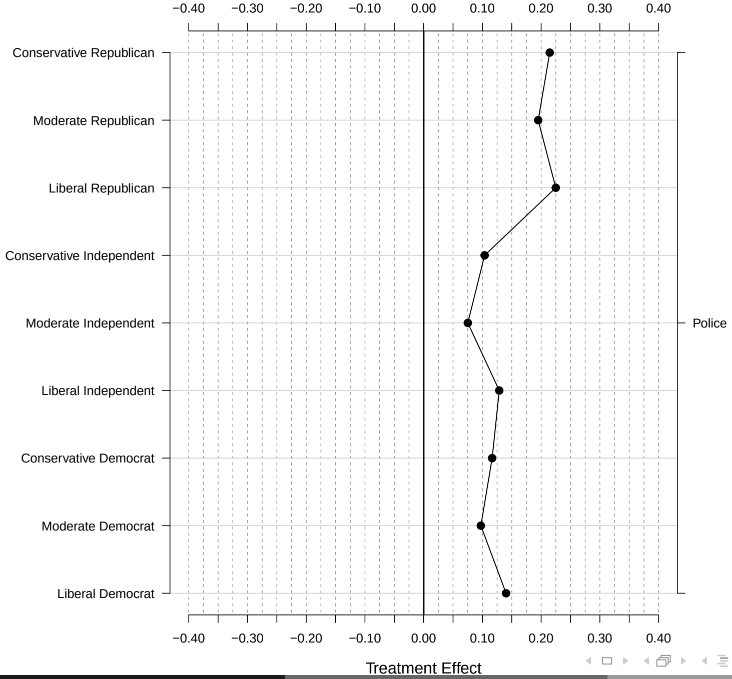
−0.40 −0.35 −0.30 −0.25 −0.20 −0.15 −0.10 −0.05 0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40
Conservative Republican
Moderate Republican
Liberal Republican
Conservative Independent
Moderate Independent
Liberal Independent
Conservative Democrat
Moderate Democrat
Liberal Democrat
Roads
Police
Fire Department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

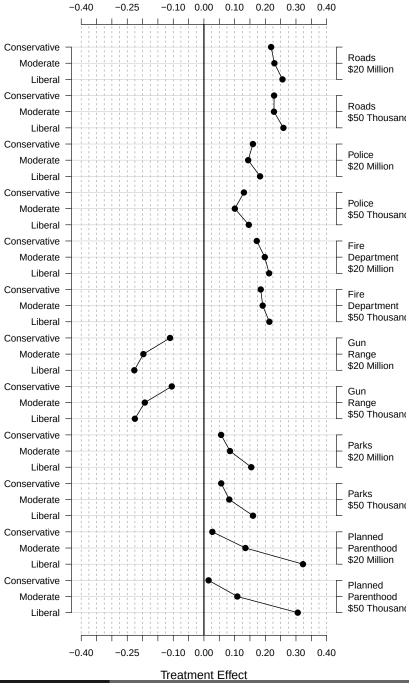


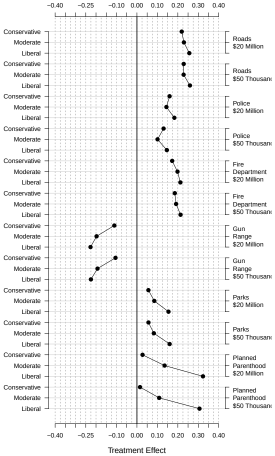
−0.40
−0.30
−0.20
−0.10
0.00
0.10
0.20
0.30
0.40
Conservative Republican
Moderate Republican
Liberal Republican
Conservative Independent
Moderate Independent
Liberal Independent
Conservative Democrat
Moderate Democrat
Liberal Democrat
Gun Range
Treatment Effect



Treatment Effect
Roads
Police
Fire Department
Gun Range
Parks
Planned Parenthood
Conservative Republican
Moderate Republican
Liberal Republican
Conservative Independent
Moderate Independent
Liberal Independent
Conservative Democrat
Moderate Democrat
Liberal Democrat
−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


−0.40
−0.30
−0.20
−0.10
0.00
0.10
0.20
0.30
0.40
Conservative Republican
Moderate Republican
Liberal Republican
Conservative Independent
Moderate Independent
Liberal Independent
Conservative Democrat
Moderate Democrat
Liberal Democrat
Police
Treatment Effect


-0.40 -0.25 -0.10 0.00 0.10 0.20 0.30 0.40
Conservative
Moderate
Liberal
Roads
$20 Million
Roads
$50 Thousand
Police
$20 Million
Police
$50 Thousand
Fire
Department
$20 Million
Fire
Department
$50 Thousand
Gun
Range
$20 Million
Gun
Range
$50 Thousand
Parks
$20 Million
Parks
$50 Thousand
Planned
Parenthood
$20 Million
Planned
Parenthood
$50 Thousand
Treatment Effect



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

Estimating Heterogeneous Treatment Effects and the Effects of Heterogeneous Treatments

Issues with experimental design

Estimating Heterogeneous Treatment Effects and the Effects of Heterogeneous Treatments

Issues with experimental design

- Treatments are conditional on what else is included: averaging other quantities $\neq$ to excluding other quantities

Estimating Heterogeneous Treatment Effects and the Effects of Heterogeneous Treatments

Issues with experimental design

- Treatments are conditional on what else is included: averaging other quantities $\neq$ to excluding other quantities
- Potential for fishing is massive $\rightsquigarrow$ pre analysis plan

Estimating Heterogeneous Treatment Effects and the Effects of Heterogeneous Treatments

Issues with experimental design

- Treatments are conditional on what else is included: averaging other quantities $\neq$ to excluding other quantities
- Potential for fishing is massive$\rightsquigarrow$ pre analysis plan
- Assumption about the way information delivered:

Estimating Heterogeneous Treatment Effects and the Effects of Heterogeneous Treatments

Issues with experimental design

- Treatments are conditional on what else is included: averaging other quantities $\neq$ to excluding other quantities
- Potential for fishing is massive$\rightsquigarrow$ pre analysis plan
- Assumption about the way information delivered:
    1) We know salient dimensions

Estimating Heterogeneous Treatment Effects and the Effects of Heterogeneous Treatments

Issues with experimental design

- Treatments are conditional on what else is included: averaging other quantities $\neq$ to excluding other quantities
- Potential for fishing is massive $\rightsquigarrow$ pre analysis plan
- Assumption about the way information delivered:
  1) We know salient dimensions
  2) We're constructing effects that correspond with effects in reality

The Causal Effect of Texts?

The Causal Effect of Texts?

More general framework.

The Causal Effect of Texts?

More general framework.
Suppose we have text j, $j = 1, 2, \ldots, J$, $\boldsymbol{T}_j$.

The Causal Effect of Texts?

More general framework.
Suppose we have text j, $j = 1, 2, \ldots, J$, $\boldsymbol{T}_j$.
Potential outcome is: $Y_i(\boldsymbol{T}_j)$

The Causal Effect of Texts?

More general framework.
Suppose we have text j, $j = 1, 2, \ldots, J$, $\boldsymbol{T}_j$.
Potential outcome is: $Y_i(\boldsymbol{T}_j)$
Question: how do we encode the information in $\boldsymbol{T}_j$ to find effects?

Text as the Response

Text as the Response

Suppose we have some dichotomous treatment $T_i \in \{0, 1\}$.

Text as the Response

Suppose we have some dichotomous treatment $T_i \in \{0, 1\}$.
Outcome: some text based response $\boldsymbol{Y}_i(T_i)$:

Text as the Response

Suppose we have some dichotomous treatment $T_i \in \{0, 1\}$.
Outcome: some text based response $\boldsymbol{Y}_i(T_i)$:

- Treatment:
- Potential outcome:

Text as the Response

Suppose we have some dichotomous treatment $T_i \in \{0, 1\}$.
Outcome: some text based response $\boldsymbol{Y}_i(T_i)$:

- Treatment: marginal legislators
- Potential outcome: press releases

Text as the Response

Suppose we have some dichotomous treatment $T_i \in \{0, 1\}$.
Outcome: some text based response $\boldsymbol{Y}_i(T_i)$:

- Treatment: marginal legislators, issue frame
- Potential outcome: press releases, open ended survey response

Text as the Response

Suppose we have some dichotomous treatment $T_i \in \{0, 1\}$.
Outcome: some text based response $\boldsymbol{Y}_i(T_i)$:

- Treatment: marginal legislators, issue frame, negative emotion words
- Potential outcome: press releases, open ended survey response, subsequent Facebook posts

Text as the Response $\rightsquigarrow$ Assumed Categories

Set of predetermined categories:

Text as the Response $\rightsquigarrow$ Assumed Categories

Set of predetermined categories: $\{C_1, C_2, \ldots, C_K\}$

Text as the Response$\rightsquigarrow$ Assumed Categories

Set of predetermined categories: $\{C_1, C_2, \ldots, C_K\}$

- Classify the texts$\rightsquigarrow$ hand coding or supervised learning

Text as the Response $\rightsquigarrow$ Assumed Categories

Set of predetermined categories: $\{C_1, C_2, \ldots, C_K\}$

- Classify the texts $\rightsquigarrow$ hand coding or supervised learning
    - Each document now an indicator vector $\boldsymbol{L}_i$

Text as the Response$\rightsquigarrow$ Assumed Categories

Set of predetermined categories: $\{C_1, C_2, \ldots, C_K\}$

- Classify the texts$\rightsquigarrow$ hand coding or supervised learning
    - Each document now an indicator vector $\boldsymbol{L}_i$
- Straightforward estimator

Text as the Response $\rightsquigarrow$ Assumed Categories

Set of predetermined categories: $\{C_1, C_2, \ldots, C_K\}$

- Classify the texts $\rightsquigarrow$ hand coding or supervised learning
  - Each document now an indicator vector $\boldsymbol{L}_i$
- Straightforward estimator

$$\text{ATE}_k = \frac{\sum_{i=1}^{N} I(L_{ik} = 1, T_i = 1)}{\sum_{i=1}^{N} I(T_i = 1)} - \frac{\sum_{i=1}^{N} I(L_{ik} = 1, T_i = 0)}{\sum_{i=1}^{N} I(T_i = 0)}$$

Text as the Response $\rightsquigarrow$ Assumed Categories

Set of predetermined categories: $\{C_1, C_2, \ldots, C_K\}$

- Classify the texts $\rightsquigarrow$ hand coding or supervised learning
  - Each document now an indicator vector $\boldsymbol{L}_i$
- Straightforward estimator

$$\text{ATE}_k = \frac{\sum_{i=1}^{N} I(L_{ik} = 1, T_i = 1)}{\sum_{i=1}^{N} I(T_i = 1)} - \frac{\sum_{i=1}^{N} I(L_{ik} = 1, T_i = 0)}{\sum_{i=1}^{N} I(T_i = 0)}$$

- Additional (or usual?) concern: measurement error

Text as the Response$\rightsquigarrow$ Unsupervised Categories

Structural Topic Models

Text as the Response$\rightsquigarrow$ Unsupervised Categories

Structural Topic Models $\rightsquigarrow$ suppressing priors

Text as the Response $\rightsquigarrow$ Unsupervised Categories

Structural Topic Models $\rightsquigarrow$ suppressing priors

$$\boldsymbol{\pi}_i \sim \text{Logistic Normal}(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{T}_i, \boldsymbol{\Sigma})$$

Text as the Response $\rightsquigarrow$ Unsupervised Categories

Structural Topic Models $\rightsquigarrow$ suppressing priors

$$\begin{aligned}
\boldsymbol{\pi}_i &\sim \text{Logistic Normal}(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{T}_i, \boldsymbol{\Sigma}) \\
\boldsymbol{\tau}_{im} &\sim \text{Multinomial}(1, \boldsymbol{\pi}_i)
\end{aligned}$$

Text as the Response ⇝ Unsupervised Categories

Structural Topic Models ⇝ suppressing priors

$$
\begin{aligned}
\boldsymbol{\pi}_i &\sim \text{Logistic Normal}(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{T}_i, \boldsymbol{\Sigma}) \\
\boldsymbol{\tau}_{im} &\sim \text{Multinomial}(1, \boldsymbol{\pi}_i) \\
x_{im}|\tau_{imk} = 1 &\sim \text{Multinomial}(\boldsymbol{\theta}_k)
\end{aligned}
$$

Text as the Response $\rightsquigarrow$ Unsupervised Categories

Structural Topic Models $\rightsquigarrow$ suppressing priors

$$
\begin{aligned}
\boldsymbol{\pi}_i &\sim \text{Logistic Normal}(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{T}_i, \boldsymbol{\Sigma}) \\
\boldsymbol{\tau}_{im} &\sim \text{Multinomial}(1, \boldsymbol{\pi}_i) \\
x_{im} | \tau_{imk} = 1 &\sim \text{Multinomial}(\boldsymbol{\theta}_k) \\
\theta_{kj} &\propto \exp\left(\gamma_j + \gamma_{jk1} T_i\right)
\end{aligned}
$$

Text as the Response $\rightsquigarrow$ Unsupervised Categories

Structural Topic Models $\rightsquigarrow$ suppressing priors

$$
\begin{aligned}
\boldsymbol{\pi}_i &\sim \text{Logistic Normal}(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{T}_i, \boldsymbol{\Sigma}) \\
\boldsymbol{\tau}_{im} &\sim \text{Multinomial}(1, \boldsymbol{\pi}_i) \\
x_{im}|\tau_{imk} = 1 &\sim \text{Multinomial}(\boldsymbol{\theta}_k) \\
\theta_{kj} &\propto \exp\left(\gamma_j + \gamma_{jk1} T_i\right)
\end{aligned}
$$

- Quantity 1: Topic prevalence

Text as the Response $\rightsquigarrow$ Unsupervised Categories

Structural Topic Models $\rightsquigarrow$ suppressing priors

$$
\begin{aligned}
\boldsymbol{\pi}_i &\sim \text{Logistic Normal}(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{T}_i, \boldsymbol{\Sigma}) \\
\boldsymbol{\tau}_{im} &\sim \text{Multinomial}(1, \boldsymbol{\pi}_i) \\
x_{im} | \tau_{imk} = 1 &\sim \text{Multinomial}(\boldsymbol{\theta}_k) \\
\theta_{kj} &\propto \exp\left(\gamma_j + \gamma_{jk1} T_i\right)
\end{aligned}
$$

- Quantity 1: Topic prevalence
    - $\boldsymbol{\beta}_1 = (\beta_{11}, \beta_{12}, \ldots, \beta_{1K})$

Text as the Response $\rightsquigarrow$ Unsupervised Categories

Structural Topic Models $\rightsquigarrow$ suppressing priors

$$
\begin{aligned}
\boldsymbol{\pi}_i &\sim \text{Logistic Normal}(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{T}_i, \boldsymbol{\Sigma}) \\
\boldsymbol{\tau}_{im} &\sim \text{Multinomial}(1, \boldsymbol{\pi}_i) \\
x_{im}|\tau_{imk} = 1 &\sim \text{Multinomial}(\boldsymbol{\theta}_k) \\
\theta_{kj} &\propto \exp\left(\gamma_j + \gamma_{jk1} T_i\right)
\end{aligned}
$$

- Quantity 1: Topic prevalence
  - $\boldsymbol{\beta}_1 = (\beta_{11}, \beta_{12}, \ldots, \beta_{1K})$
  - β_{1k} = change in attention to topic k for treated units in logistic-normal space

Text as the Response $\rightsquigarrow$ Unsupervised Categories

Structural Topic Models $\rightsquigarrow$ suppressing priors

$$
\begin{aligned}
\boldsymbol{\pi}_i &\sim \text{Logistic Normal}(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{T}_i, \boldsymbol{\Sigma}) \\
\boldsymbol{\tau}_{im} &\sim \text{Multinomial}(1, \boldsymbol{\pi}_i) \\
x_{im} | \tau_{imk} = 1 &\sim \text{Multinomial}(\boldsymbol{\theta}_k) \\
\theta_{kj} &\propto \exp\left(\gamma_j + \gamma_{jk1} T_i\right)
\end{aligned}
$$

- Quantity 1: Topic prevalence
  - $\boldsymbol{\beta}_1 = (\beta_{11}, \beta_{12}, \ldots, \beta_{1K})$
  - β_{1k} = change in attention to topic k for treated units in logistic-normal space
- Quantity 2: Topic Content

Text as the Response $\rightsquigarrow$ Unsupervised Categories

Structural Topic Models $\rightsquigarrow$ suppressing priors

$$
\begin{aligned}
\boldsymbol{\pi}_i &\sim \text{Logistic Normal}(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{T}_i, \boldsymbol{\Sigma}) \\
\boldsymbol{\tau}_{im} &\sim \text{Multinomial}(1, \boldsymbol{\pi}_i) \\
x_{im}|\tau_{imk} = 1 &\sim \text{Multinomial}(\boldsymbol{\theta}_k) \\
\theta_{kj} &\propto \exp\left(\gamma_j + \gamma_{jk1} T_i\right)
\end{aligned}
$$

- Quantity 1: Topic prevalence
  - $\boldsymbol{\beta}_1 = (\beta_{11}, \beta_{12}, \ldots, \beta_{1K})$
  - β_{1k} = change in attention to topic k for treated units in logistic-normal space
- Quantity 2: Topic Content
  - γ_{jk1} = change in prevalence of word j for topic k for treated units

Text as the Response $\rightsquigarrow$ Unsupervised Categories

Structural Topic Models $\rightsquigarrow$ suppressing priors

$$
\begin{aligned}
\boldsymbol{\pi}_i &\sim \text{Logistic Normal}(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{T}_i, \boldsymbol{\Sigma}) \\
\boldsymbol{\tau}_{im} &\sim \text{Multinomial}(1, \boldsymbol{\pi}_i) \\
x_{im} | \tau_{imk} = 1 &\sim \text{Multinomial}(\boldsymbol{\theta}_k) \\
\theta_{kj} &\propto \exp\left(\gamma_j + \gamma_{jk1} T_i\right)
\end{aligned}
$$

- Quantity 1: Topic prevalence
  - $\boldsymbol{\beta}_1 = (\beta_{11}, \beta_{12}, \ldots, \beta_{1K})$
  - β_{1k} = change in attention to topic k for treated units in logistic-normal space
- Quantity 2: Topic Content
  - γ_{jk1} = change in prevalence of word j for topic k for treated units

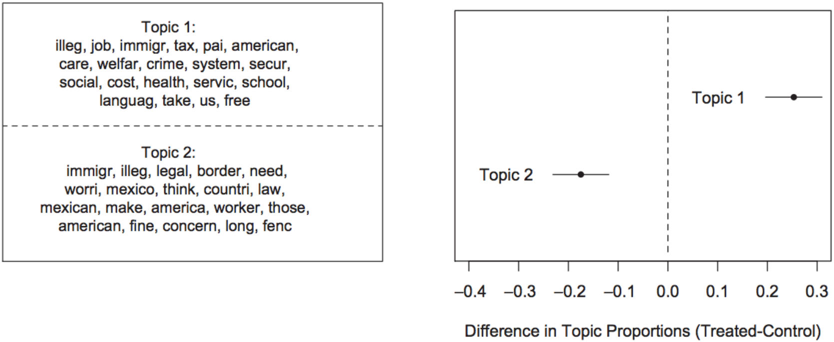
Parameters (mapped back to appropriate space) are used for effect estimates

Topic Prevalence

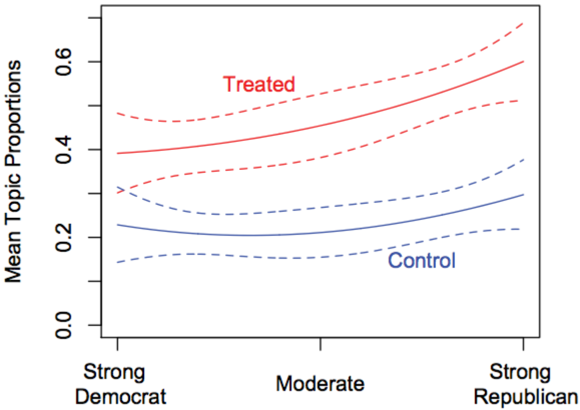
Gadarian and Albertson:

1) Treatment: worry about immigration
2) Control (treatment 2): think about immigration
3) Response: open ended survey prompt about immigration

Topic Prevalence



Topic Prevalence



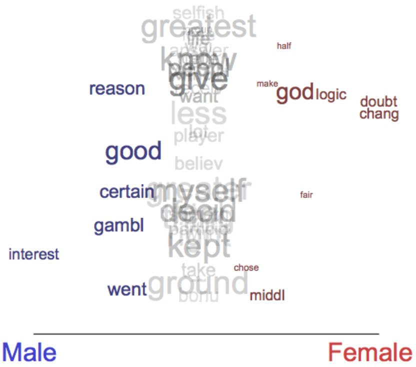
Topic Content

Rand, Greene and Nowak: one-shot public goods game

1) Treatment: encourage to think intuitively
2) Control (treatment 2): encourage to think strategically
3) Response: open ended response on strategy
4) Different in topic content by gender

Topic Content

FIGURE 15 Intuitive Topic Allowing for Different Vocabularies Based on Gender



Estimating the Effect of Treatment with Text Response

What do you when treatment affects the categories (not just attention to categories)?

Estimating the Effect of Treatment with Text Response

What do you when treatment affects the categories (not just attention to categories)?

1) What are the quantities of interest?

Estimating the Effect of Treatment with Text Response

What do you when treatment affects the categories (not just attention to categories)?

1) What are the quantities of interest?
   - They are a function of the treated quantities

Estimating the Effect of Treatment with Text Response

What do you when treatment affects the categories (not just attention to categories)?

1) What are the quantities of interest?
   - They are a function of the treated quantities $\rightsquigarrow$ categories depend on treatment

Estimating the Effect of Treatment with Text Response

What do you when treatment affects the categories (not just attention to categories)?

1) What are the quantities of interest?
   - They are a function of the treated quantities $\rightsquigarrow$ categories depend on treatment
2) What are the conditions for accurate estimation? (identification)

Estimating the Effect of Treatment with Text Response

What do you when treatment affects the categories (not just attention to categories)?

1) What are the quantities of interest?
   - They are a function of the treated quantities$\rightsquigarrow$ categories depend on treatment
2) What are the conditions for accurate estimation? (identification)
   - Take an expectation to compute bias, but categories change with each treatment arrangement

Text as Data: Going Forward

Text as Data: Going Forward

- What we've done

Text as Data: Going Forward

- What we've done
  - Text preprocessing $\rightsquigarrow$ variable recipe

Text as Data: Going Forward

- What we've done
  - Text preprocessing $\rightsquigarrow$ variable recipe
  - Text tasks

Text as Data: Going Forward

- What we've done
    - Text preprocessing $\rightsquigarrow$ variable recipe
    - Text tasks
        - Separating words $\rightsquigarrow$ Fightin' words

Text as Data: Going Forward

- What we've done
  - Text preprocessing $\rightsquigarrow$ variable recipe
  - Text tasks
    - Separating words $\rightsquigarrow$ Fightin' words
    - Embedding $\rightsquigarrow$ principal components

Text as Data: Going Forward

- What we've done
  - Text preprocessing$\rightsquigarrow$ variable recipe
  - Text tasks
    - Separating words$\rightsquigarrow$ Fightin' words
    - Embedding$\rightsquigarrow$ principal components
    - Unsupervised methods$\rightsquigarrow$ clustering, topic models

Text as Data: Going Forward

- What we've done
  - Text preprocessing$\rightsquigarrow$ variable recipe
  - Text tasks
    - Separating words$\rightsquigarrow$ Fightin' words
    - Embedding$\rightsquigarrow$ principal components
    - Unsupervised methods$\rightsquigarrow$ clustering, topic models
    - Supervised methods $\rightsquigarrow$ LASSO, Ridge

Text as Data: Going Forward

- What we've done
  - Text preprocessing$\rightsquigarrow$ variable recipe
  - Text tasks
    - Separating words$\rightsquigarrow$ Fightin' words
    - Embedding$\rightsquigarrow$ principal components
    - Unsupervised methods$\rightsquigarrow$ clustering, topic models
    - Supervised methods $\rightsquigarrow$ LASSO, Ridge
    - Ideology

Text as Data: Going Forward

- What we've done
  - Text preprocessing$\rightsquigarrow$ variable recipe
  - Text tasks
    - Separating words$\rightsquigarrow$ Fightin' words
    - Embedding$\rightsquigarrow$ principal components
    - Unsupervised methods$\rightsquigarrow$ clustering, topic models
    - Supervised methods $\rightsquigarrow$ LASSO, Ridge
    - Ideology
- A lot left to do:

Text as Data: Going Forward

- What we've done
  - Text preprocessing $\rightsquigarrow$ variable recipe
  - Text tasks
    - Separating words $\rightsquigarrow$ Fightin' words
    - Embedding $\rightsquigarrow$ principal components
    - Unsupervised methods $\rightsquigarrow$ clustering, topic models
    - Supervised methods $\rightsquigarrow$ LASSO, Ridge
    - Ideology
- A lot left to do:
  - Text preprocessing

Text as Data: Going Forward

- What we've done
  - Text preprocessing $\rightsquigarrow$ variable recipe
  - Text tasks
    - Separating words $\rightsquigarrow$ Fightin' words
    - Embedding $\rightsquigarrow$ principal components
    - Unsupervised methods $\rightsquigarrow$ clustering, topic models
    - Supervised methods $\rightsquigarrow$ LASSO, Ridge
    - Ideology
- A lot left to do:
  - Text preprocessing
    - Natural language processing techniques

Text as Data: Going Forward

- What we've done
  - Text preprocessing $\rightsquigarrow$ variable recipe
  - Text tasks
    - Separating words $\rightsquigarrow$ Fightin' words
    - Embedding $\rightsquigarrow$ principal components
    - Unsupervised methods $\rightsquigarrow$ clustering, topic models
    - Supervised methods $\rightsquigarrow$ LASSO, Ridge
    - Ideology
- A lot left to do:
  - Text preprocessing
    - Natural language processing techniques
    - Bringing along other information $\rightsquigarrow$ synonyms, previous sentences, etc

Text as Data: Going Forward

- What we've done
  - Text preprocessing $\rightsquigarrow$ variable recipe
  - Text tasks
    - Separating words $\rightsquigarrow$ Fightin' words
    - Embedding $\rightsquigarrow$ principal components
    - Unsupervised methods $\rightsquigarrow$ clustering, topic models
    - Supervised methods $\rightsquigarrow$ LASSO, Ridge
    - Ideology
- A lot left to do:
  - Text preprocessing
    - Natural language processing techniques
    - Bringing along other information $\rightsquigarrow$ synonyms, previous sentences, etc
  - Machine learning $\rightsquigarrow$ scratched the surface

Text as Data: Going Forward

- What we've done
  - Text preprocessing$\rightsquigarrow$ variable recipe
  - Text tasks
    - Separating words$\rightsquigarrow$ Fightin' words
    - Embedding$\rightsquigarrow$ principal components
    - Unsupervised methods$\rightsquigarrow$ clustering, topic models
    - Supervised methods $\rightsquigarrow$ LASSO, Ridge
    - Ideology
- A lot left to do:
  - Text preprocessing
    - Natural language processing techniques
    - Bringing along other information$\rightsquigarrow$ synonyms, previous sentences, etc
  - Machine learning$\rightsquigarrow$ scratched the surface
    - Classification methods

Text as Data: Going Forward

- What we've done
  - Text preprocessing $\leadsto$ variable recipe
  - Text tasks
    - Separating words $\leadsto$ Fightin' words
    - Embedding $\leadsto$ principal components
    - Unsupervised methods $\leadsto$ clustering, topic models
    - Supervised methods $\leadsto$ LASSO, Ridge
    - Ideology
- A lot left to do:
  - Text preprocessing
    - Natural language processing techniques
    - Bringing along other information $\leadsto$ synonyms, previous sentences, etc
  - Machine learning $\leadsto$ scratched the surface
    - Classification methods
    - Unsupervised methods

Text as Data: Going Forward

- What we've done
  - Text preprocessing $\rightsquigarrow$ variable recipe
  - Text tasks
    - Separating words $\rightsquigarrow$ Fightin' words
    - Embedding $\rightsquigarrow$ principal components
    - Unsupervised methods $\rightsquigarrow$ clustering, topic models
    - Supervised methods $\rightsquigarrow$ LASSO, Ridge
    - Ideology
- A lot left to do:
  - Text preprocessing
    - Natural language processing techniques
    - Bringing along other information $\rightsquigarrow$ synonyms, previous sentences, etc
  - Machine learning $\rightsquigarrow$ scratched the surface
    - Classification methods
    - Unsupervised methods
    - Deep learning

Text as Data: Going Forward

- What we've done
  - Text preprocessing $\rightsquigarrow$ variable recipe
  - Text tasks
    - Separating words $\rightsquigarrow$ Fightin' words
    - Embedding $\rightsquigarrow$ principal components
    - Unsupervised methods $\rightsquigarrow$ clustering, topic models
    - Supervised methods $\rightsquigarrow$ LASSO, Ridge
    - Ideology
- A lot left to do:
  - Text preprocessing
    - Natural language processing techniques
    - Bringing along other information $\rightsquigarrow$ synonyms, previous sentences, etc
  - Machine learning $\rightsquigarrow$ scratched the surface
    - Classification methods
    - Unsupervised methods
    - Deep learning

Course theme: think what is the social scientific purpose of the task?