Text as Data

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Department of Political Science
Stanford University

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Final Project

Poster Session: 12/4

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- Make posters in LaTeX or related software for asthetics

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  - Avoid: Long/breezy lit reviews that merely list previous scholarship

Supervised Learning: Ensemble Learning

1) Task

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Heuristic (upon which we'll improve):

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$$\begin{aligned} \Pr(\text{Correct Guess}|\text{Votes}) &= \Pr(3 \text{ correct}) + \Pr(2 \text{ correct}) \\ &= 0.75^3 + 3 \times (0.75^2 \times 0.25) \end{aligned}$$

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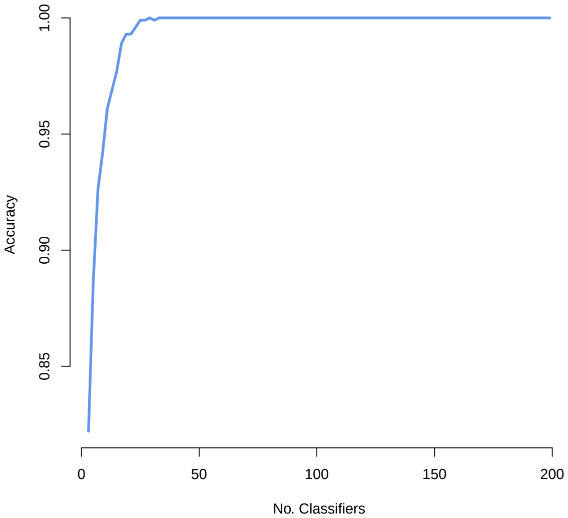
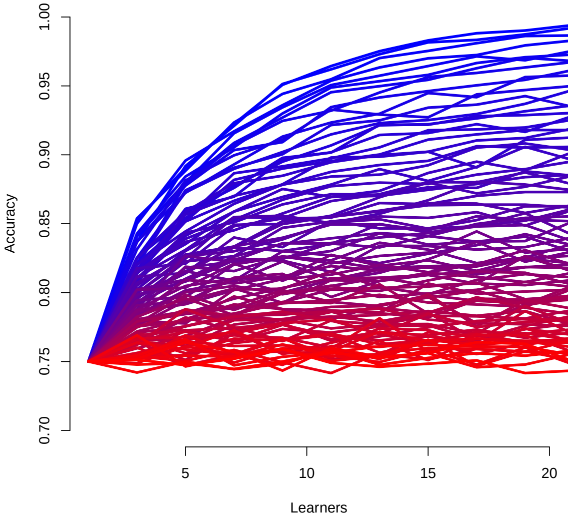


Ensemble Learning: Intuition

Diverse and Accurate matter.



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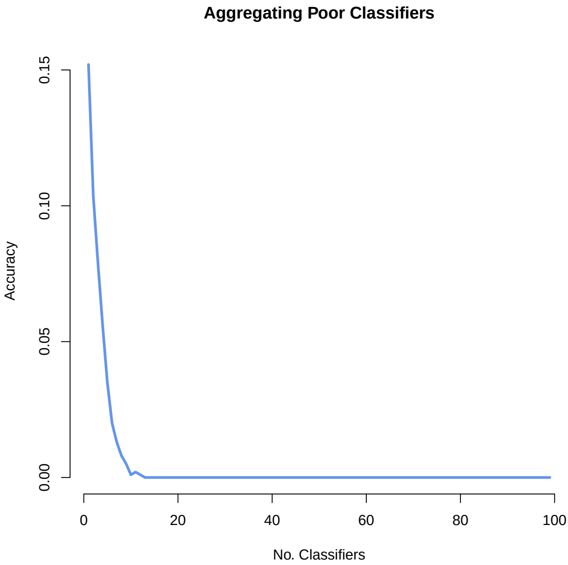

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$$\lim_{M\to\infty} P(\bar{B} > 0.5) = 1$$

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&= \underbrace{\rho\sigma^2}_{\text{Resolve with independence}} + \underbrace{\frac{1-\rho}{M}\sigma^2}_{\text{Resolve with }\uparrow\text{classifiers}}
\end{aligned}
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- Strong Correlation between classifiers

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Curse of dimensionality(!!!)

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Curse of dimensionality(!!!)

Approximate with regions $\rightsquigarrow$ search for splits of data to approximate stratification

Classification and Regression Trees (CART): Objective function

Labels $\boldsymbol{Y}_i$ and documents $\boldsymbol{x}_i$

$$
\begin{aligned}
E[Y|\boldsymbol{x}_i] &= \widehat{f}(\boldsymbol{x}_i) \\
&= \sum_{p=1}^{P} c_p I(\boldsymbol{x}_i \in R_p)
\end{aligned}
$$

where:

- R_p describes a region $\rightsquigarrow$ node
- c_p describes values of Y_i for document in R_p

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Suppose we want to minimize sum of squared residuals with each node

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Determining an optimal partition $\rightsquigarrow$ NP-Hard.

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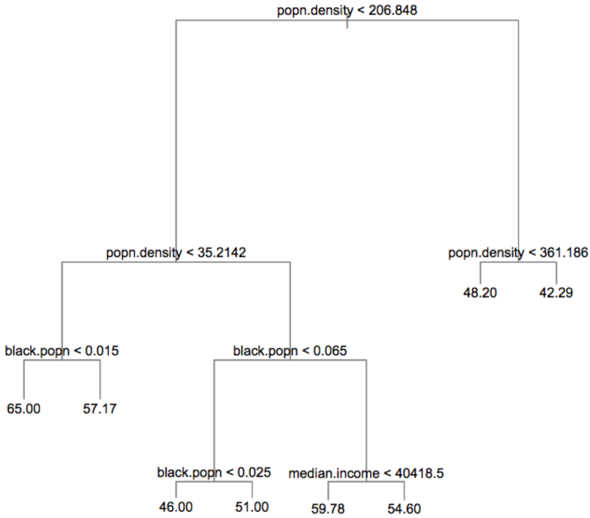
$$(j^*, s^*) = \arg\min_{j,s} \left[\underbrace{\min_{c_1} \sum_{i=1}^{N} I(x_{ij} < s)(Y_i - c_1)^2}_{\text{“cost” group 1}} + \underbrace{\min_{c_2} \sum_{i=1}^{N} I(x_{ij} > s)(Y_i - c_2)^2}_{\text{“cost” group 2}} \right]$$

Classification and Regression Trees (CART): Algorithm

- Start in Node
- Partition according to Greedy algorithm
- Continue until some stopping rule: number of observations per node

CART Picture (Spirling 2008)



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- Random forest $\rightsquigarrow$ introduce additional sampling to induce independence $\rightsquigarrow$ Only split on subset of variables

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- With many poor predictors$\rightsquigarrow$ the p selected may be meaningless

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Weighted ensemble: weights determined by (unique) out of sample predictive performance

Committee Methods:
Fit many methods, average with equal weights

- Voting (classification)
- Averaging (predictions)

Problem: many poor methods may overwhelm high quality fit (remember earlier figures)
Solution: learn weights via cross validation

Weighted Ensemble to Classify Documents

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

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(Classify if above threshold)

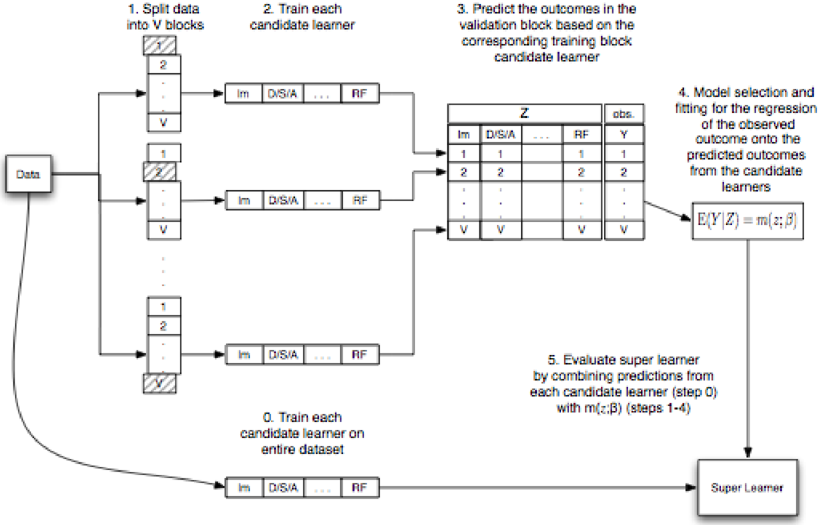

Figure 1: Flow Diagram for Super Learner

Why Super Learn?

van der Laan et al (2007) prove:

- Asymptotically: super learners will perform as well the best candidates for data
- Oracle: performs like the best possible method among candidate methods
  - Asymptotically outperforms constituent methods
  - Performs as well as optimal combinations of those methods

Practical questions:

- Final regression:
  - Logistic
  - Linear
  - Could super learn again!
- How Many Folds?
  - van der Laan et al's proofs rely on growing folds with N (but slowly)
  - Use 10-fold cross validation for simulations

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Estimate: $Y_i \in \{\text{Credit}, \text{Not Credit}\}$

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- LASSO 0
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- Random Forest 61%
- A Support Vector Machine16%
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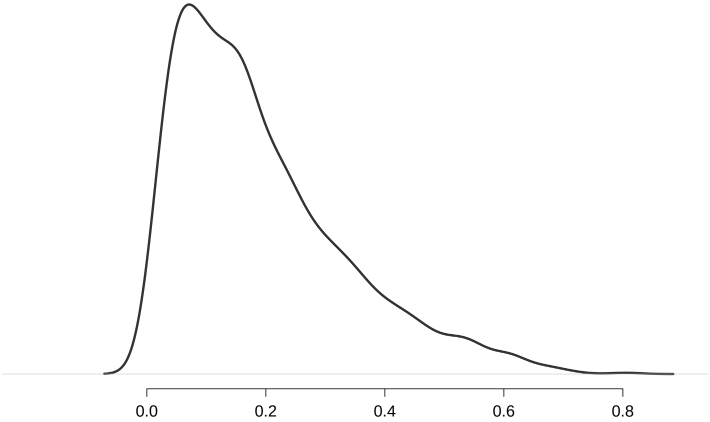
Strategic Credit Claiming to Build a Personal Vote



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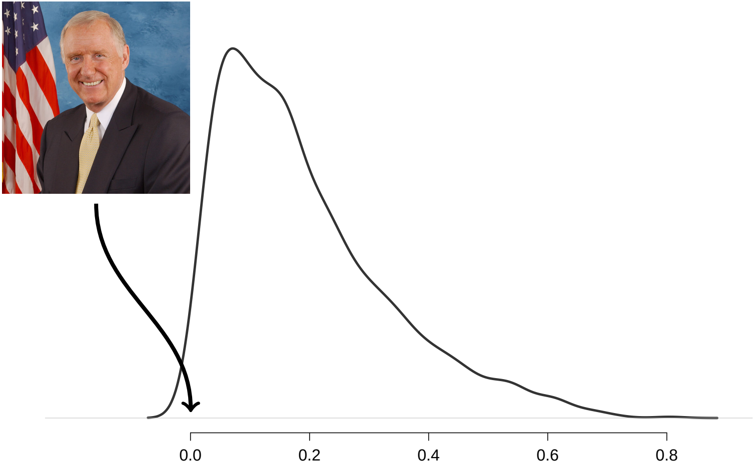
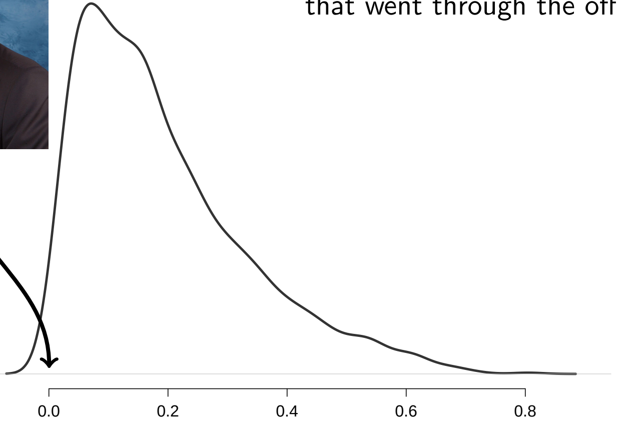


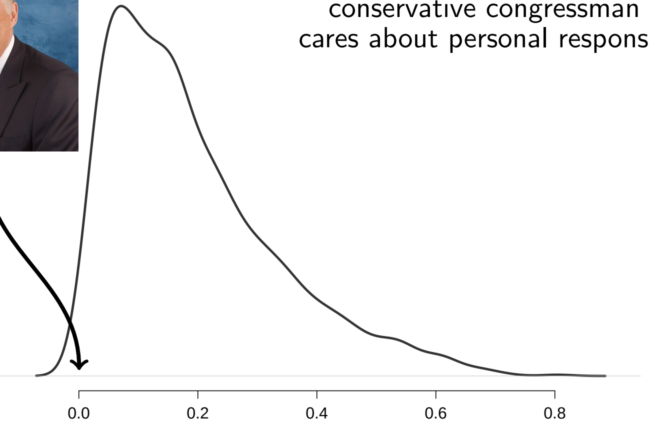
Strategic Credit Claiming to Build a Personal Vote

John McGroff: "voted for every spending bill " that went through the office"



Strategic Credit Claiming to Build a Personal Vote

John McGroff: “Not the actions of a fiscally ”
conservative congressman who
cares about personal responsibility”



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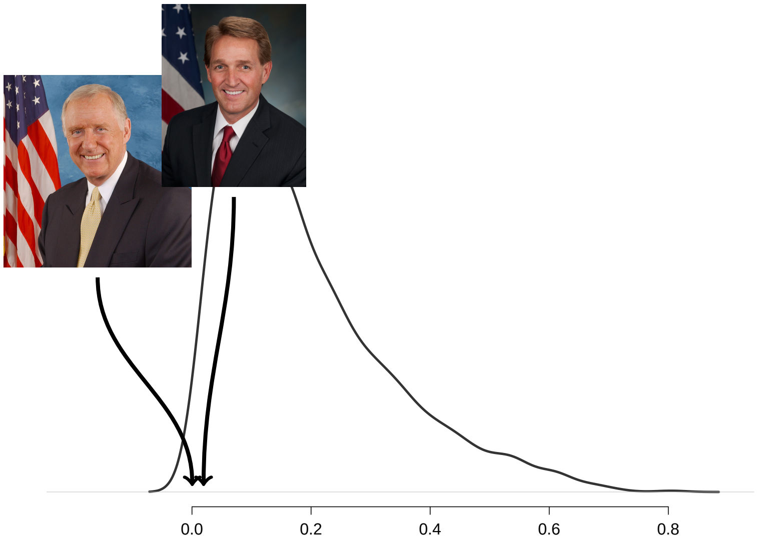

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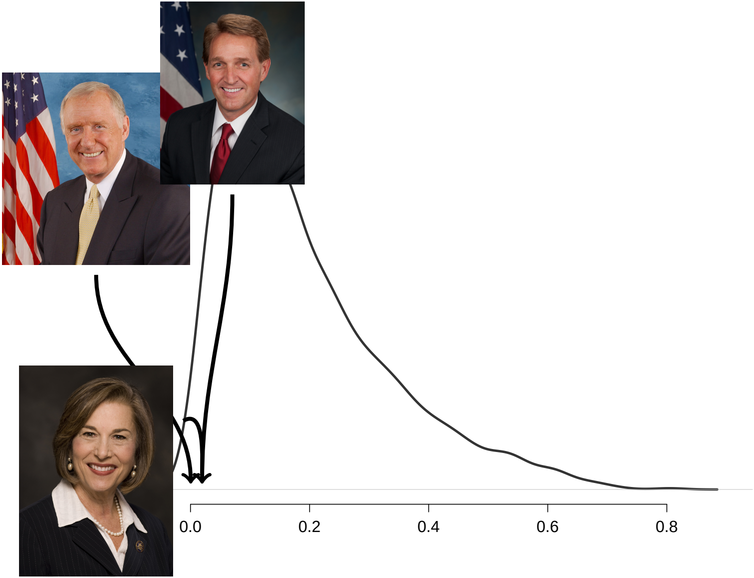

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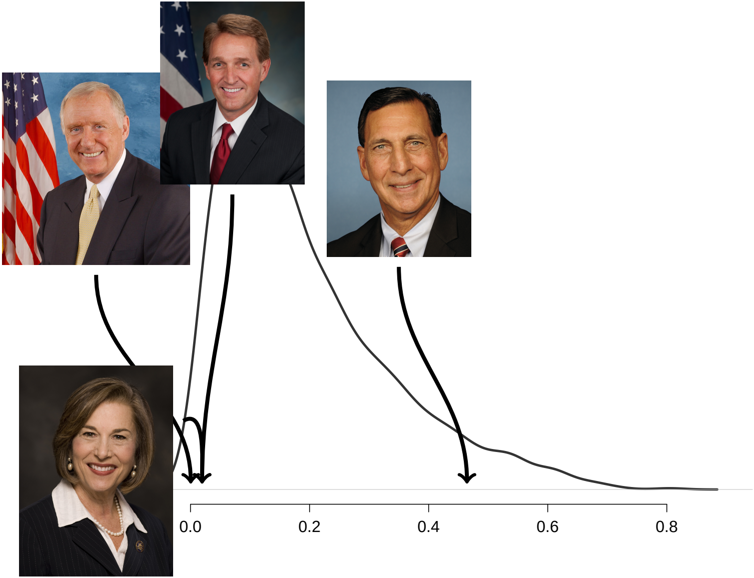

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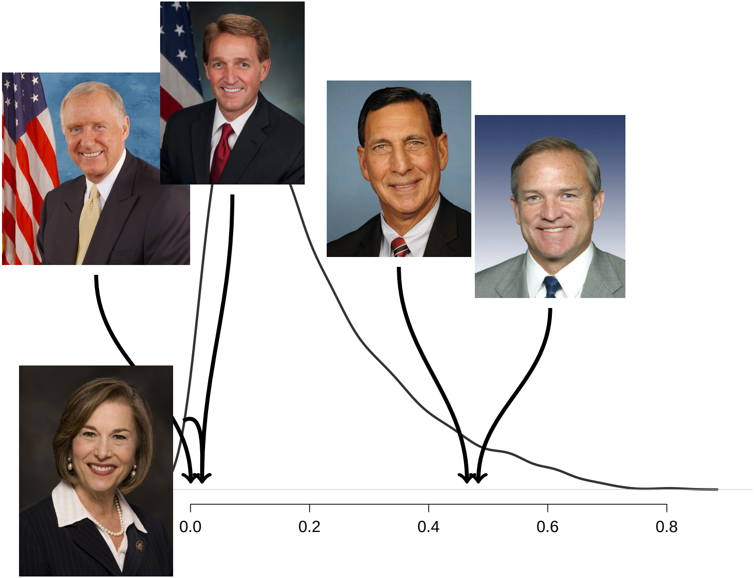

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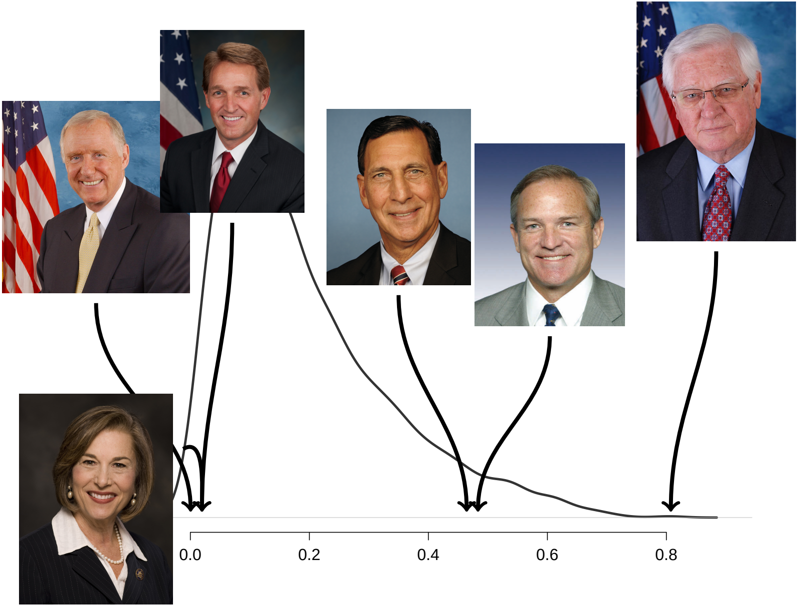
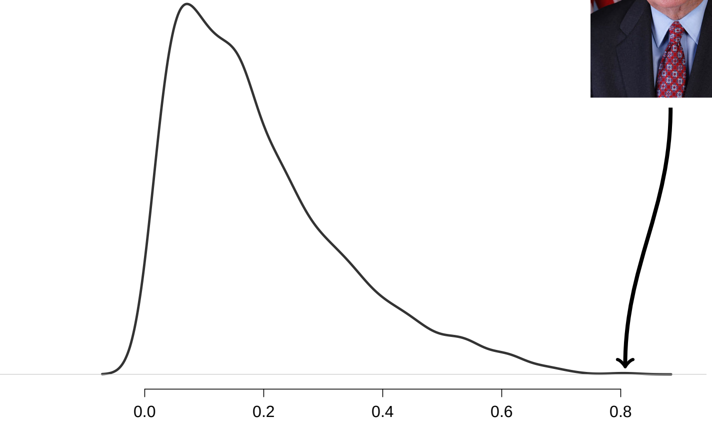


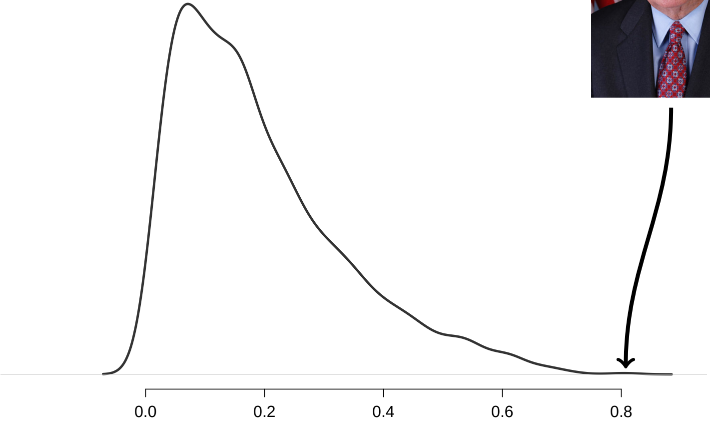
Strategic Credit Claiming to Build a Personal Vote

“We just can’t afford luxuries like ideology”



Strategic Credit Claiming to Build a Personal Vote

Lexington Herald-Leader: Prince of Pork



Other Reasons to Ensemble (Dietterich 2000)

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- With little data, many algorithms offer similar performance

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Ensembles Beyond Text Data

Machine Learning $\leftrightarrow$ Causal Inference

An Example Experiment

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

An Example Experiment

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

An Example Experiment

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

An Example Experiment

What information in credit claiming messages affect evaluations?

Rewarding Actions and Type of Expenditure, Not Money

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

Rewarding Actions and Type of Expenditure, Not Money

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

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Dependent variable: Approve of representative

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

Rewarding Actions and Type of Expenditure, Not Money

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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)

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

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- Effect of particular component of message:
  - $\text{T}_{\text{stage}} = \text{Secured}$
  - $\text{T}_{\text{stage}} = \text{Requested}$

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  - $\mathrm{T}_j = k$

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

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\text{MATE}_{\mathrm{T}_j=k} &= \mathrm{E}[Y(\mathrm{T}_j = k) - Y(0)]
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- Response may be conditional on respondent characteristics $\mathbf{x}$

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

Rewarding Actions and Type of Expenditure, Not Money

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

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

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  Heterogeneous treatment effect methods
  - LASSO, Find It (Imai and Ratkovic, 2013)$\rightsquigarrow$ sparsity

Rewarding Actions and Type of Expenditure, Not Money

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

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  - 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

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

- Curse of Dimensionality: highly variable estimates, (sometimes) empty strata
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Create ensemble: weighting methods by (unique) out of sample predictive performance

Weighted Ensemble to Measure Credit Claiming Rate

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

Weighted Ensemble to Measure Credit Claiming Rate

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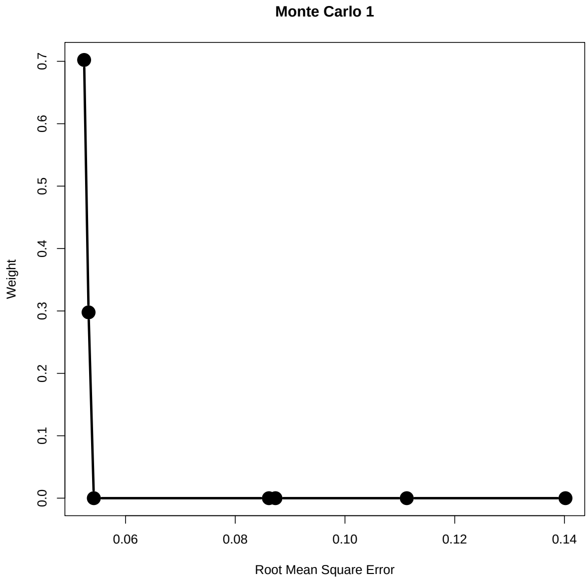
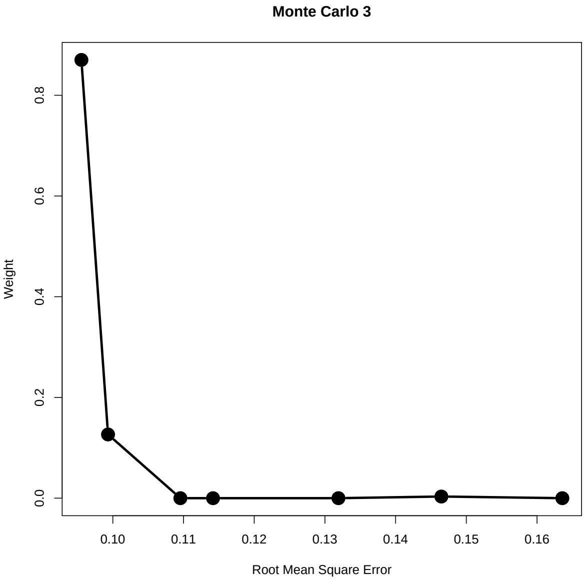
- Estimate weights ($\widehat{\pi}_m$)
- Estimate $\widehat{g}_m(\text{T}_j = k, \mathbf{x})$ $\rightsquigarrow$ Apply all M models to entire data set
- Generate effects of interest (perhaps weighting to other population) $\mathbf{x}_{\text{new}}$

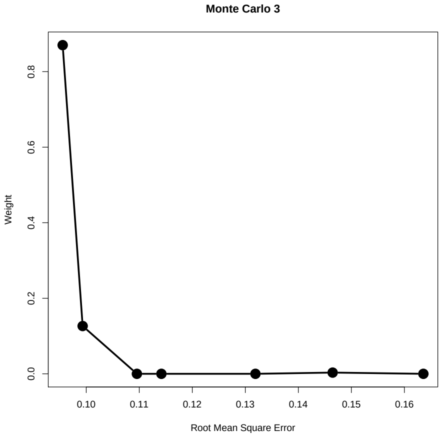
Monte Carlo Evidence



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)

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2) KRLS (0.24)

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Positive weight on three methods:

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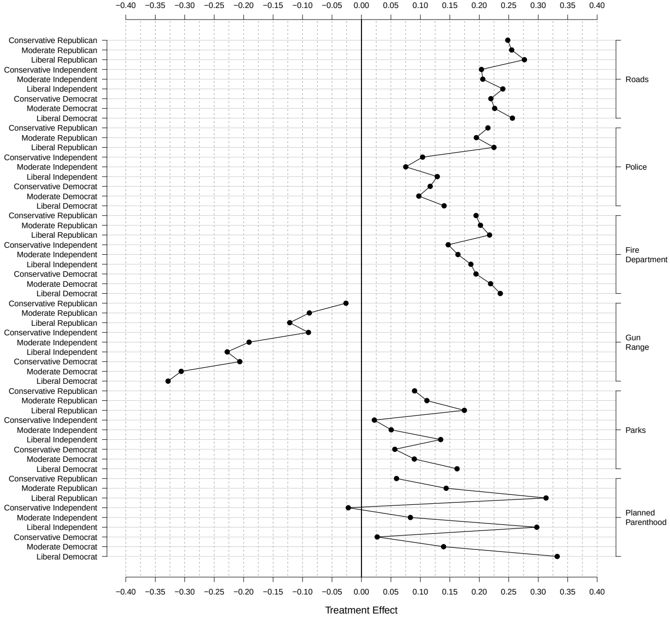
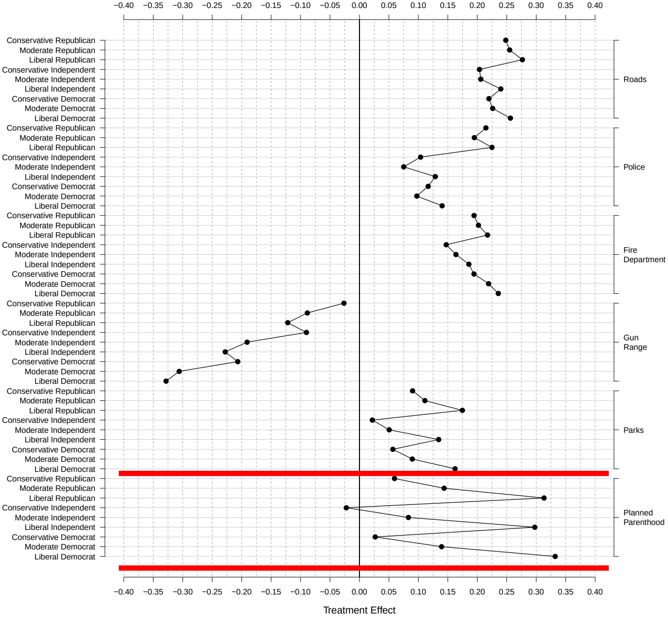
2) KRLS (0.24)
3) Find it (0.14)



−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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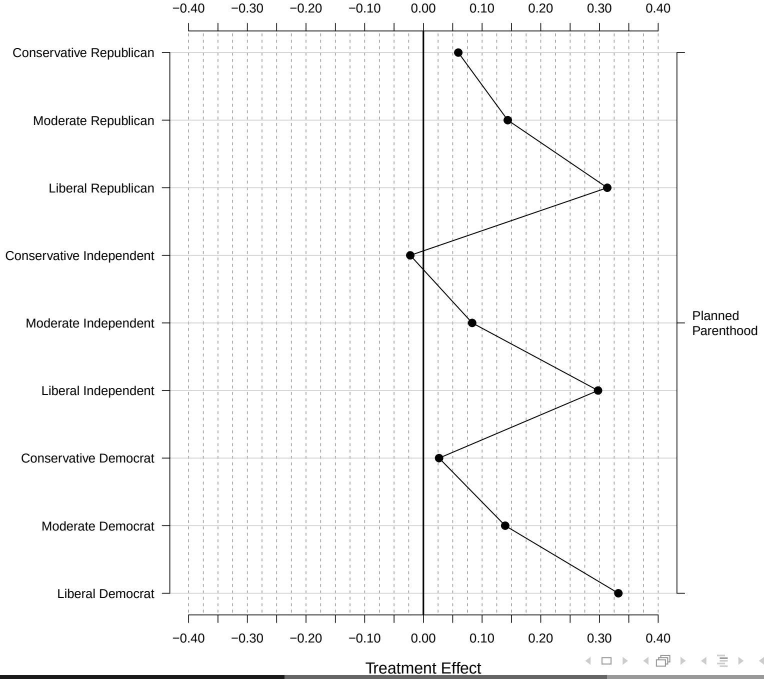

−0.40 −0.30 −0.20 −0.10 0.00 0.10 0.20 0.30 0.40
Conservative Republican
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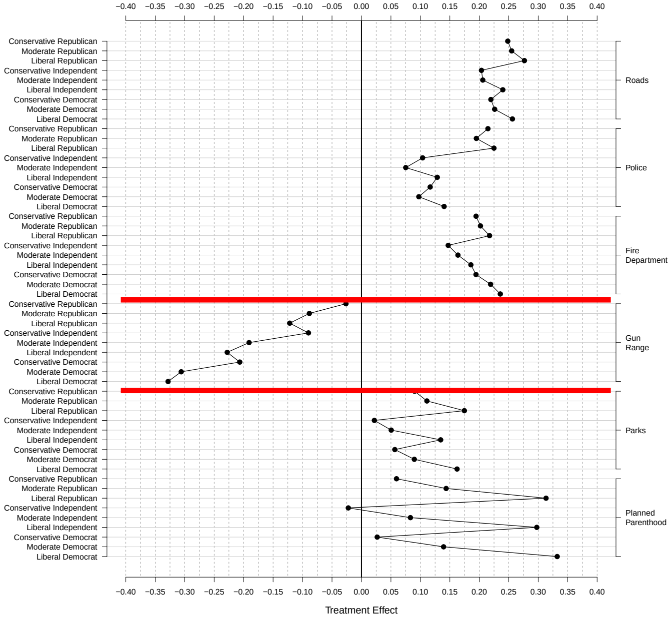

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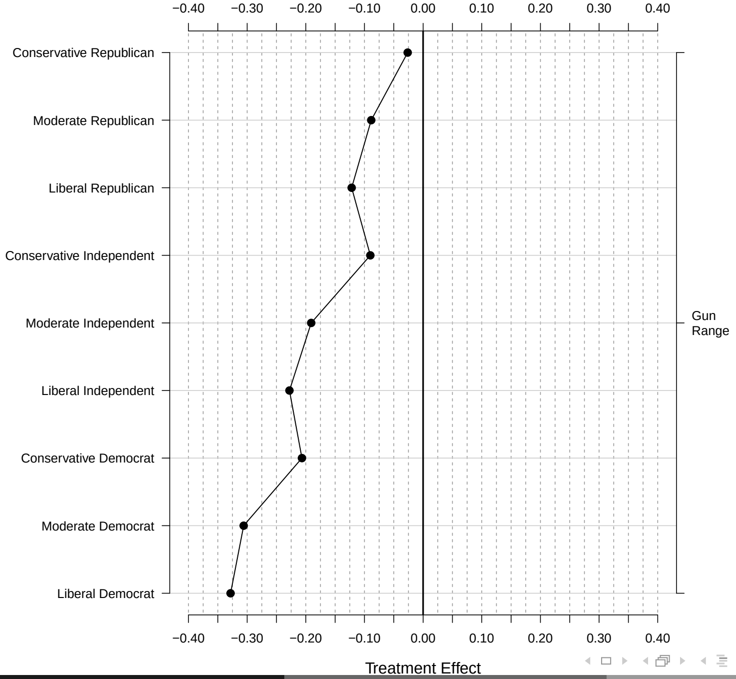

−0.40
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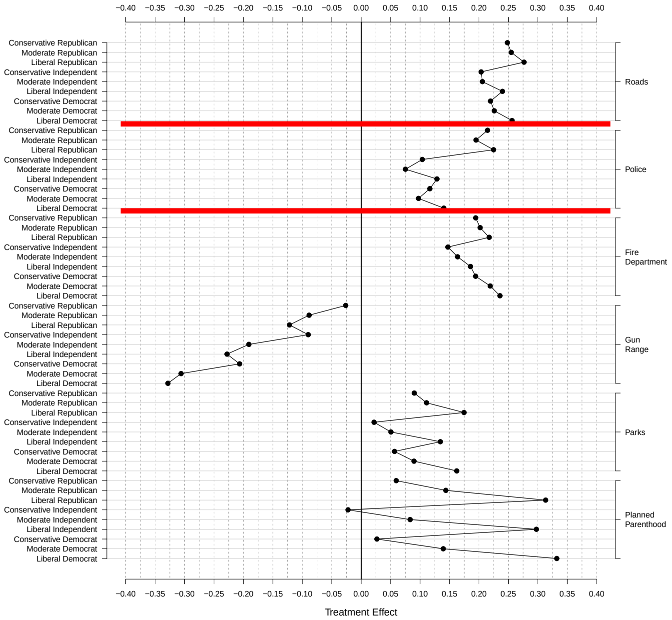
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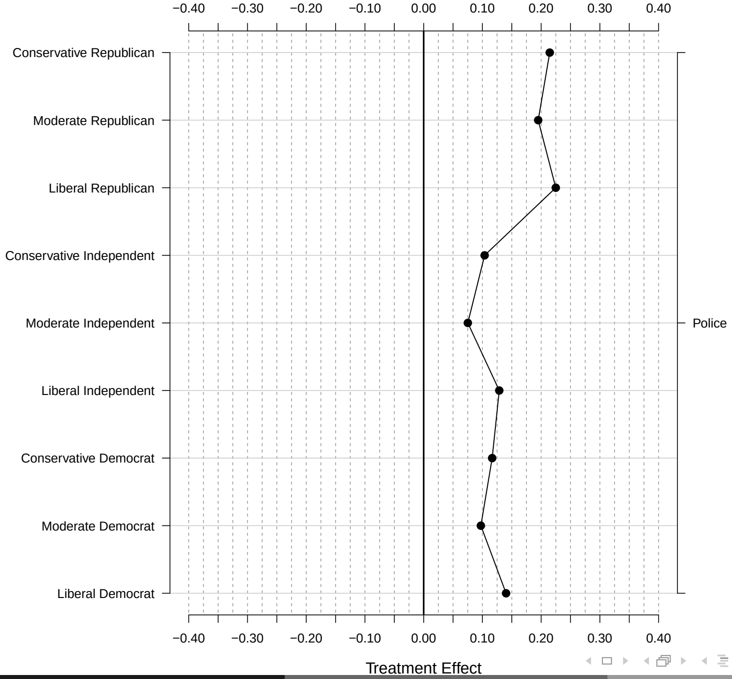

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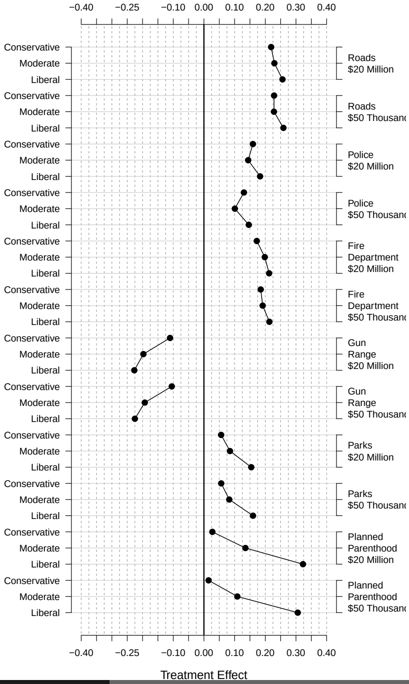

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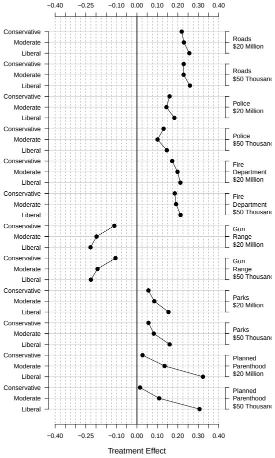

$\rightsquigarrow$ Constituents evaluate expenditures using qualitative information, rather than numerical facts

Ensembles to Estimate Heterogeneous Effects

Ensembles: prediction, classification, estimation of heterogeneous effects

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R package $\rightsquigarrow$ implement methods, create synthetic observations, visualize results

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  2) Accurate

Ensembles $\rightsquigarrow$ leverage many contributions to build better estimates.