Probing the Causal Effects of Exposure to News

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Slides: https://bit.ly/2CCHXJL

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The debate

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Cosmides and Tooby (1996), Gigerenzer (2011), many economics textbooks

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Goals:

1. Compare quality of learning in a neutral vs. political context
2. Quantify the credibility penalty from true information by testing a model of stereotypical reasoning

Simple example: Hair color

What is $Pr(Red\ hair|Irish)$?

		dark	*light*	*red*
Group	Irish			
	Rest of the world			

What is $Pr(Red\ hair|Irish)$?

Only 10%.

		dark	*light*	*red*
Group	Irish	50%	40%	10%
	Rest of the world	85%	14%	1%

What is $Pr(Red\ hair|Irish)$?

Group		*dark*	*light*	*red*
	Irish	50%	40%	10%
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- $Pr(Redhair)$ may be easier to guess than $Pr(Red\ hair|Irish)$. So **giving data to people might worsen accuracy of beliefs**.
- $Pr(Dark\ hair|Irish) = 5 \times Pr(Red\ hair|Irish)$
- Ranking or types the same for both groups
- Ease of recall

Learning threat

$Pr(Red\ hair|Irish)$ is mistakenly over-estimated. Why?

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Representativeness

$$t_G^* = \underset{t\in\{dark,light,red\}}{\arg\max} \frac{Pr(t|G)}{Pr(t|\neg G)}$$

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Representativeness

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The representative color is red: $t_{IRISH}^* = 10 > \frac{40\%}{14\%} > \frac{50\%}{85\%}$.

Similar problems

- G = African-American; T = {poor, middle-income, rich}
- G = Democrat; T = {socialist,...}
- G = Republican; T = {alt-right,...}

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- The median African-American household is not poor
  but poverty is more prevalent among African-Americans
- The average Democrat is not a socialist
  but you are more likely to meet a socialist at a gathering of Democrats than at a meet-up of centrists of Republicans

Proposed context

G = CNN, Fox News

T = {negative news coverage, neutral/positive news coverage}

It is true that negative stories about the Trump administration are more common on CNN than on Fox. However:

- Stories on CNN are not consistently negative
- If $\Pr(\mathrm{N}|\mathrm{CNN})$ is overestimated, then all negative content, $\Pr(\cdot|N)$ may be mistakenly classified as "left-wing" or "liberal".

Theory

- 2 types of news sources
- Each source is equally likely
- Two types of articles are produced: neutral and negative
- α % of stories from the left-wing source are neutral
- β % of stories from the right-wing source are neutral
- Assume $\beta > \alpha$
- Then regardless of whether $\alpha > 1/2$, the representative story type for left-wing publications will be *negative*
- Learning (about source type) will be distorted (Bordalo, Coffman, Gennaioli and Shleifer, 2016)

	Neutral stories	Negative stories
Left-wing news source	αN_l	$(1-\alpha)N_l$
Right-wing news source	βN_r	$(1-\beta)N_r$

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Assuming equal priors:

$$Pr(LW|N) = \frac{1-\alpha}{(1-\alpha)+(1-\beta)}$$

A biased learner believes

$$Pr(N|LW)^{biased} = Pr(N|LW) \times \frac{h(R(N, LW))}{\sum_t Pr(t|LW)h_t(R(t, LW))}$$

$h(.)$ captures how representitve type t is in category G.

Let $h_t = \delta^{r(t)}$ where $r(t)$ is the ranking of the tone based on the representativeness.

The *exemplar* tone of a left-wing publication is negative:

$$t^*_{LW} = argmax_{t \in \{pos,neg\}} \frac{Pr(t|LW)}{Pr(t|RW)} = \frac{1-\alpha}{1-\beta} > \frac{\alpha}{\beta}$$

Let $Pr(N|LW) = \pi_{N,LW}$. Because "negative" is the representative category for a left-wing news-source, the agent will believe

$$Pr(LW|N)^{biased} = \frac{\pi^{biased}_{N,LW} \times Pr(LW)}{\pi^{biased}_{N,LW} \times Pr(LW) + \pi^{biased}_{N,RW} \times Pr(RW)}$$

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$$Pr(LW|N)^{biased} = \frac{\pi^{biased}_{N,LW} \times Pr(LW)}{\pi^{biased}_{N,LW} \times Pr(LW) + \pi^{biased}_{N,RW} \times Pr(RW)}$$

$$= \frac{(1-\alpha) \times \frac{\delta}{(1-\alpha)\delta + \alpha\delta^2} \times \frac{1}{2}}{[\pi^{biased}_{N,LW} + \pi^{biased}_{N,RW}] \times \frac{1}{2}} > Pr(LW|N)$$

Prediction: When a news story is negative, subjects will overestimate the probability that the news story came from a left-wing source

Hypotheses

1. People make quick judgments about the ideology of the source when they notice the tone of the coverage
2. Mislearning (low-quality updating) will be more likely after infromation about the media landscape is provided
3. Assignment to information about the extent of negative press coverage will 1) weaken the belief that the media makes the public well-informed; 2) increase perceptions of negativity bias; 3) increase perceptions of excessive hostility of the media

Experiment: Control group

	Red signal	Blue signal
Event A	0.44	0.56
Event B	0.85	0.15

Experiment: Control group

Possible framing as a sports contest

	Red signal	Blue signal
Jets will win	0.44	0.56
Comets will win	0.85	0.15

Treatment: Show the (true) distribution of stories about the Trump administration

	Positive / neutral stories	Negative stories
CNN	44%	56%
Fox News	85%	15%

True probabilities are predictions

	Bayesian posterior	BSCG model predicts Pr(G|t) will be…
Pr(CNN|Negative)	78.9%	**Over-estimated**
Pr(CNN|Positive or Neutral)	34.1%	**Under-estimated**
Pr(Fox|Positive or Neutral)	65.9%	**Over-estimated**
Pr(Fox|Negative)	21.1%	**Under-estimated**

Learning (Outcome I)

Control group

"After observing a red signal from the robot, what is the probability that Jets will win?"

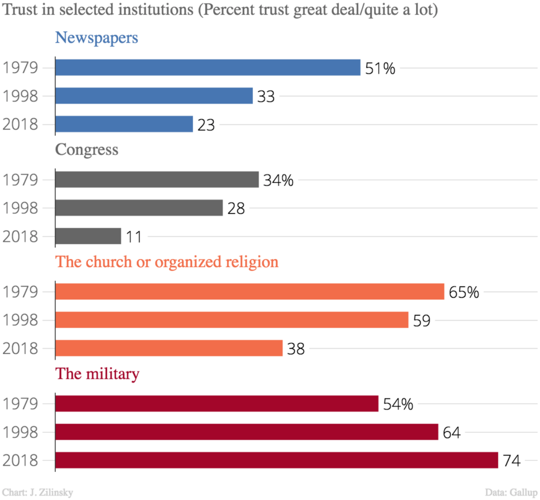
Treatment group

"What is the probability that the positive/neutral story was aired on CNN?"

Elicit views of media bias (Outcome II)

After exposure to information about the differences in the degree of negative coverage of the Trump administration, participants will be asked to answer:

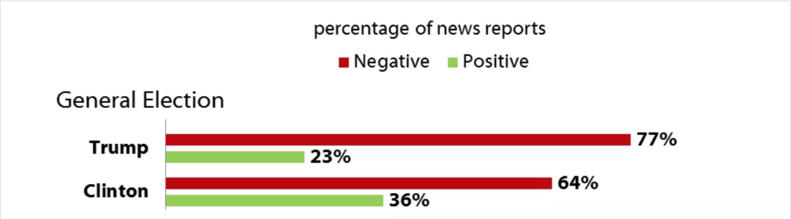
- "Are most journalists helping readers to have a more accurate understanding our world?" (0-100 sliding scale)
- "Are most journalists creating a biased view of the world by reporting too many negative stories of scandal, crime, and similar subjects?" (0-100 sliding scale)
- "Do you believe there is too much hostility among journalists against a particular politician or against a specific political party?" (0-100 sliding scale)


Trust in selected institutions (Percent trust great deal/quite a lot)
Newspapers
1979
51%
1998
33
2018
23
Congress
1979
34%
1998
28
2018
11
The church or organized religion
1979
65%
1998
59
2018
38
The military
1979
54%
1998
64
2018
74
Chart: J. Zilinsky
Data: Gallup

Specific problem: low media credibility

Tone of the coverage

Shorenstein Center (Harvard)



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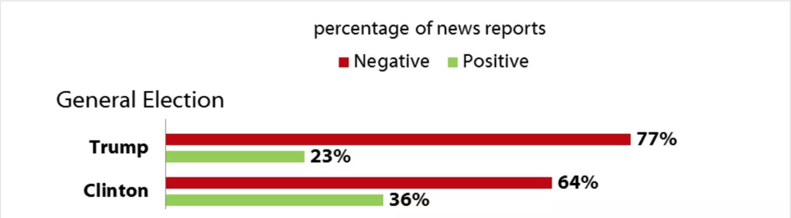


Pew Research Center

Coverage of Trump admin:

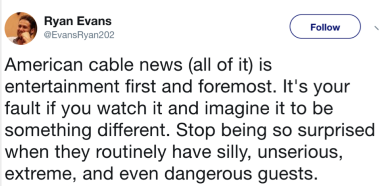
- CNN: 6% positive; 56% negative
- Fox News: 30% positive; 15% negative

https://shorensteincenter.org/news-coverage-2016-general-election/ http://www.journalism.org/2017/10/02/trump-first-100-days-appendix-a-a-deeper-look-at-the-outlet-with-the-most-stories-in-each-outlet-group/

Motivation

"The nation's watchdog has lost much of its bite and won't regain it until the public perceives it as an impartial broker, applying the same reporting standards to both parties." (Byron York, Washington Examiner)

"Whether or not the world really is getting worse, the nature of news will make us think that it is" (Pinker, 2018)



(Publisher or Texas NatSec Review)

Motivation, ctd.

- Munger, Luca, Nagler & Tucker (2018): “no evidence that assignment to read clickbait headlines drives affective polarization, information retention or trust in media”
- Blom (2018): “the level of believability of news headlines about illegal immigration was for a large part the result of an interaction of perceptions about news source trust and news content expectancy”

- There is a view that we need to make citizens read more hard news. Attention received online suggests entertainment is the preferred type of content (Followers of NYT, at around 42 million, are dwarfed by Katy Perry's 107 million)
- But if news makes people cynical or more partisan, then posterior beliefs will be even less consistent with rational expectations

Recap

- **Control group:** Abstract (non-political) learning problem
- **Treatment group:** True information about the media landscape

OUTCOMES:

1. Quality of learning across treatments
2. Media credibility (with/without true data about the extent of negativity)