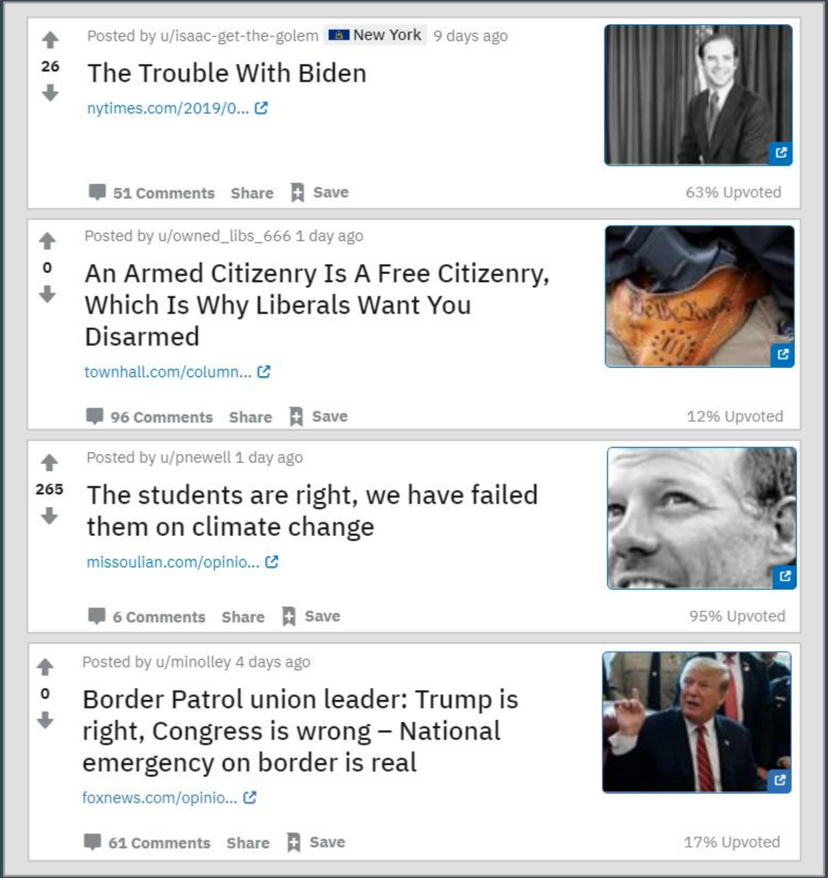
Perceptions of Labeling Opinion and News Article Titles in reddit News Feeds

UC Berkeley W241 Spring, 2019
Craig Fujii / Tako Hisada / Cameron Kennedy

reddit News Feed contains News <u>and</u> Opinion Articles

- Reddit is *"a massive collection of forums, where people can share news and content or comment on other people's posts."*
  Will Nicol - Digital Trends

- Issue where news and opinions articles are commingled:
  Misperception of opinion articles as news



Research Question

Does adding a label preceding the article title within a reddit news feed change the readers' perception of the article's political tone and/or factualness?

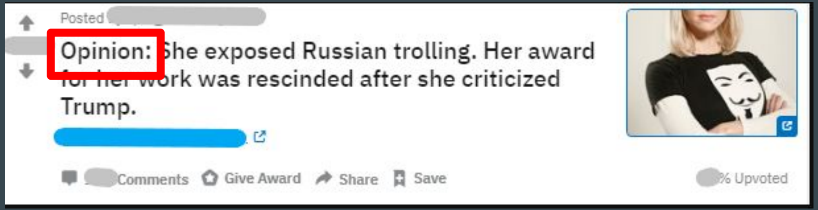
Hypothesis

Labeling opinion articles will change the readers' perception of the article's political tone and/or factualness

Treatment

Take an news feed article

Add an identifying label preceding the title



"News:" label for news articles

"Opinion:" label for opinion articles

Outcome Measurements

Political Tone

Very Liberal	Liberal	Slightly Liberal	Politically Neutral (Moderate)	Slightly Conservative	Conservative	Very Conservative
○	○	○	○	○	○	○
High	Medium	Low	Neutral	Low	Medium	High

Tone converted to political intensity on 4 point scale: neutral to high

Factualness

Mostly factual	Somewhat factual	Somewhat opinionated	Mostly opinionated
○	○	○	○

Factorial Design

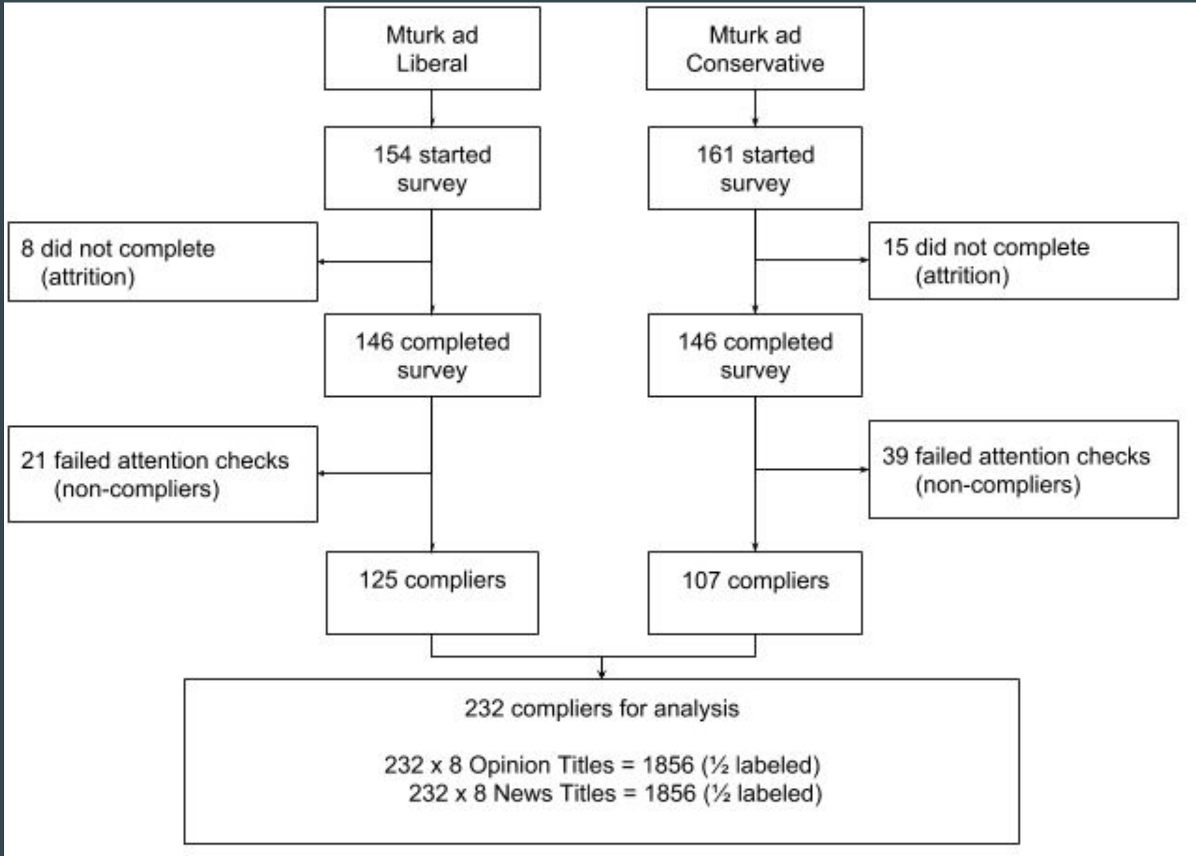
- 8 political topics
- 2 article types [opinion (O) / news (N)]
- 2 treatment groups
  - Control
  - Treatment: Labeled (_Lab)
- Requires four groupings to mix
- Randomization at 3 levels
  - Group level : I, II, III, IV
  - Flight level: Colors grouping
  - Article-Titles within flights
- Between subject comparisons at topic and article type level
  - Red Control
  - Blue Treatment

Randomization

	4 Groups (I,II, III, IV) with four flights per Group			
Group Details				
I	X1-A	X2-BR	X3-B	X4-AR
	1_N	5_O_Lab	5_N	1_O_Lab
	2_N	6_O_Lab	6_N	2_O_Lab
	3_O	7_N	7_O_Lab	3_N_Lab
	4_O	8_N	8_O_Lab	4_N_Lab
II	X1-AR	X2-A	X3-BR	X4-B
	1_O	1_N_Lab	5_O	5_N_Lab
	2_O	2_N_Lab	6_O	6_N_Lab
	3_N	3_O	7_N_Lab	7_O_Lab
	4_N	4_O	8_N_Lab	8_O_Lab
III	X1-B	X2-AR	X3-A	X4-BR
	5_N	1_O_Lab	1_N	5_O_Lab
	6_N	2_O_Lab	2_N	6_O_Lab
	7_O	3_N	3_O_Lab	7_N_Lab
	8_O	4_N	4_O_Lab	8_N_Lab
IV	X1-BR	X2-B	X3-AR	X4-A
	5_O	5_N_Lab	1_O	1_N_Lab
	6_O	6_N_Lab	2_O	2_N_Lab
	7_N	7_O	3_N_Lab	3_O_Lab
	8_N	8_O	4_N_Lab	4_O_Lab

Study Administration

- Survey: Qualtrics
- Recruitment: Amazon Mturk
- Blocked on political affiliation
  - Liberal
  - Conservative
- Survey Distribution:
  - Four time slots
  - Over three days



**Keeping respondents who failed attention checks had a minor dilutive effect on results but did not change conclusions.*

Covariates

Demographics

n	232
Reg to vote	225 (97%)
Female	111 (48%)
Age	
20-29 years	33 (14%)
30-39 years	90 (39%)
40-49 years	42 (18%)
50-59 years	35 (15%)
60-69 years	26 (11%)
>= 70 years	6 (3%)
Race	
White	129 (83%)
Asian	22 (9%)
Black	12 (5%)
Other	6 (2%)
Education	
Less than high school	0 (0%)
High school graduate	22 (9%)
Some college	44 (19%)
2 year degree	34 (15%)
4 year degree	102 (44%)
Master's degree	19 (8%)
PhD / Doctorate	11 (5%)

Political information

Political View	
Extremely Liberal	32 (14%)
Liberal	67 (29%)
Slightly Liberal	26(11%)
Moderate, middle of road	16 (7%)
Slightly Conservative	33 (14%)
Conservative	38(16%)
Extremely Conservative	20 (8%)
Political Party	
Democrat	109 (47%)
Republican	78 (34%)
Independent	41 (18%)
Libertarian	4 (2%)
Political Interest	
Very interested	109 (47%)
Somewhat interested	109 (47%)
Not very interested	13 (6%)
Not at all interested	1 (<1%)

Social Media

Reddit Use	
5+ times per day	35 (15%)
2 - 4 times per day	41 (18%)
Roughly once a day	15 (6%)
A few times a week	38 (16%)
Roughly once a week	24 (10%)
Less than once a week	48 (21%)
Never	31 (13%)
Social Media Use	
5+ times per day	76 (33%)
2 - 4 times per day	82(35%)
Roughly once a day	31 (13%)
A few times a week	25 (11%)
Roughly once a week	11 (5%)
Less than once a week	5 (2%)
Never	2 (1%)

Ordinal Data Requires Proportional Odds Logistic Regression

How do we handle regression with ordinal data?

- Problem: Ordinal data implies nonlinear "distance" between categories
- Solution: Proportional Odds Logistic Regression (`polr` function in `MASS` library)
- High-Level Process:
    - Uses "cutpoints" between categories
    - Calculates odds ratio per cutpoint: $\texttt{Odds Ratio=}\dfrac{\texttt{P(category below cutpoint)}}{\texttt{P(category above cutpoint)}}$
    - Transforms to log odds
    - Fits regression in this log odds space between treatment and control categories
- Outputs:
    - Treatment effect: Detects category shifts (but not very interpretable; units: log odds)
    - Significance test: Standard error and t-value
- See example in Appendix

Results

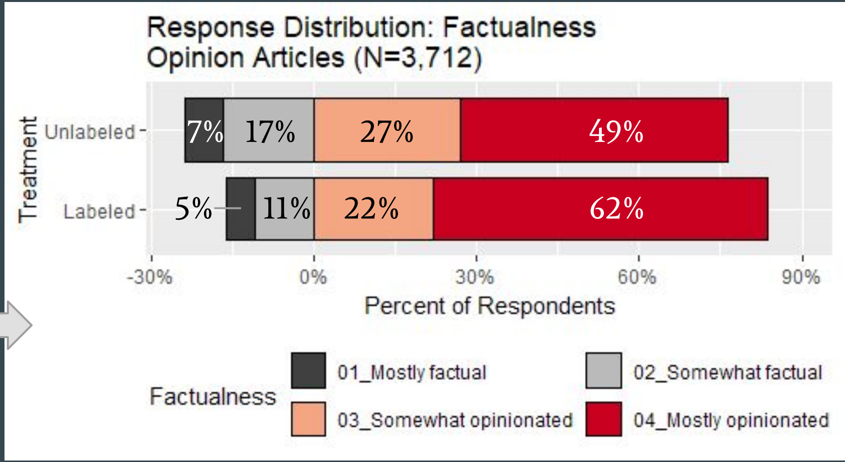
Research Question*: Does labeling articles change perception political intensity or factualness?

Statistical Significance

	Outcome: Intensity	Outcome: Factualness
News Articles	❌ $p = 0.474$	❌ $p = 0.982$
Opinion Articles	❌ $p = 0.893$	✔ $p = 6.28\times10^{-8}$

p-values represent models with treatment and effect only (no covariates)

Effect Size: Opinion Article Factualness



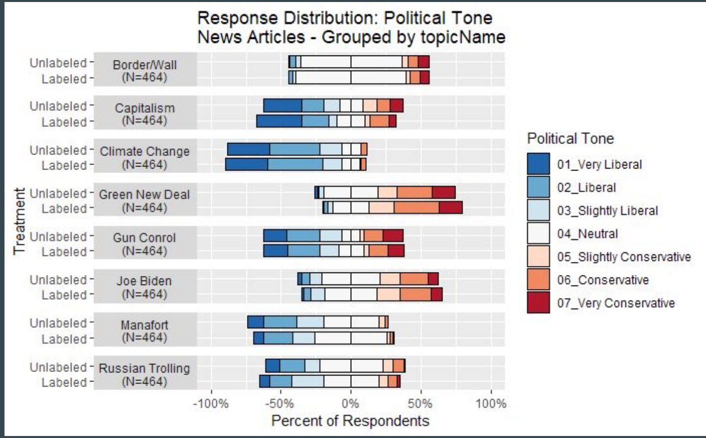
*Abridged version

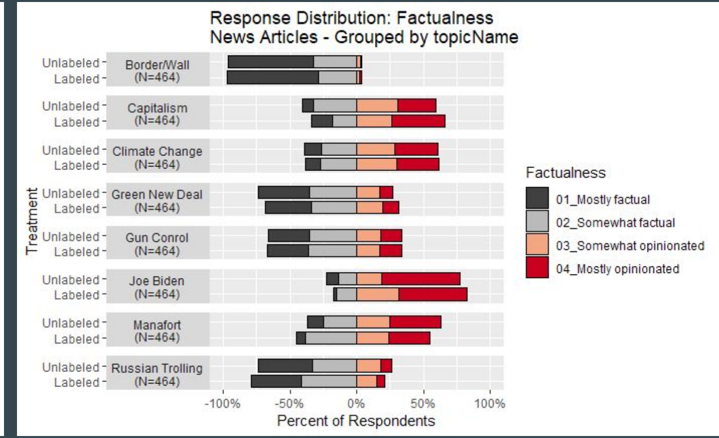
Which topics contribute to our effect? Which don't?

Political Tone

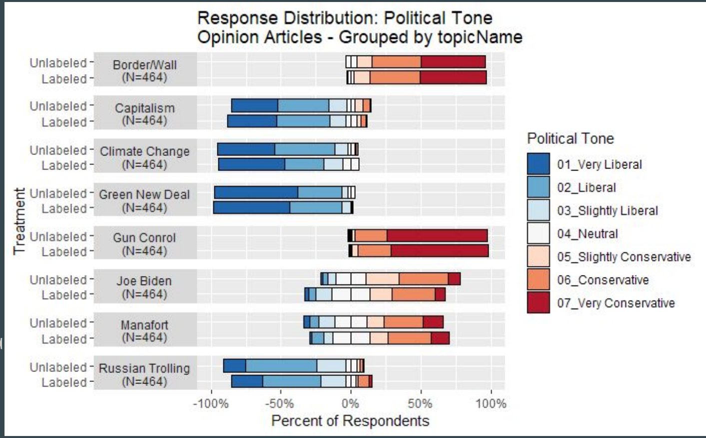
Factualness

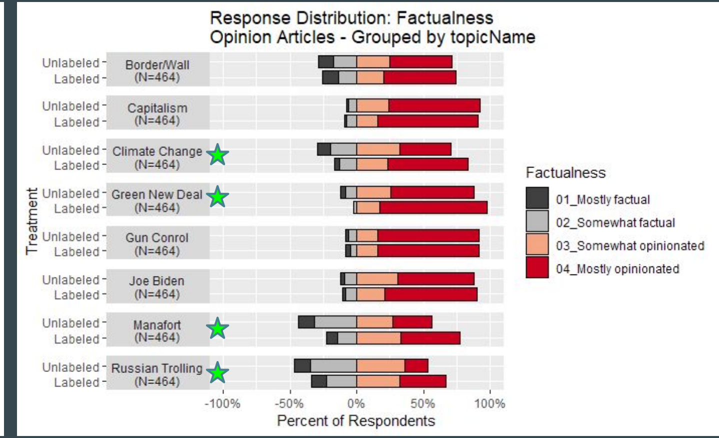
News Articles





Opinion Articles





★ = *Statistical significance at p=0.05 threshold*

Model

Summary of Models:

Measure: Factualness

Subset: Opinion Articles

1. Treatment only (no covariates)
2. Treatment + Article Clarity, Article Tone, and Subject Political Views
3. Treatment + Article Topic
4. Treatment + Several Covariates

Notes:

- *Positive coefficients indicate shift toward more opinionated responses, and negative toward more factual responses*
- *Baseline covariates (result relative to categories not shown):*
  - *Article Clarity: "Ambiguous"*
  - *Article Tone: "Conservative"*
  - *topicName: "Border / Wall"*

Consistent treatment effect

Difference in article clarity, but neither article tone nor subject political view

Differences among most topics

Table 1:

	Dependent variable:			
	fact			
	(1)	(2)	(3)	(4)
treat1	0.490***	0.526***	0.530***	0.513***
	(0.090)	(0.092)	(0.093)	(0.094)
ArticleClarityclear		1.293***		1.318***
		(0.102)		(0.103)
ArticleToneLiberal		−0.053		−0.055
		(0.091)		(0.092)
MturkPolViewLiberal		0.047		0.027
		(0.092)		(0.102)
topicNameCapitalism			1.069***	
			(0.193)	
topicNameClimate Change			0.054	
			(0.178)	
topicNameGreen New Deal			1.047***	
			(0.192)	
topicNameGun Control			1.258***	
			(0.200)	
topicNameJoe Biden			0.695***	
			(0.184)	
topicNameManafort			−0.481***	
			(0.175)	
topicNameRussian Trolling			−0.820***	
			(0.173)	
Data Subset	Opinion	Opinion	Opinion	Opinion
Fixed Interest in Politics	No	No	No	Yes
Fixed Surveyed Political Party	No	No	No	Yes
Fixed Gender	No	No	No	Yes
Fixed Age	No	No	No	Yes
Fixed Income	No	No	No	Yes
Fixed Reddit Usage	No	No	No	Yes
Fixed Social Media Usage	No	No	No	Yes
Observations	1,856	1,856	1,856	1,856

Note: *p<0.1; **p<0.05; ***p<0.01

Conclusions

Labeling shifts perception in factualness of opinion articles

No significant differences in political intensity or in news articles

Next Steps

Potential Next Steps: Clear case to extend this work (for team with more $)

- Beyond Mechanical Turk
- Between subjects, not within
- With numerous article choices
- Probably just for opinion articles, not news labeling (but keep news as a control)
- Both within and beyond reddit

Ideal for reddit and other news aggregators, who would likely also want to measure additional outcomes such as profitability, total viewership, new viewership, etc.

Questions

Including additional covariates did not shrink our standard errors. Why?

Appendix

- ROXO Grammar
- Proportional Odds Logistic Regression Example

ROXO

Randomize the order of the colors of the following 4 groups and the order within groups:

- $N\ R_G\ R_F\ [R_A(\_O)(\_O)(\_O)(\_O)]\ [R_A(\_O)(\_O)(XO)(XO)]\ [R_A(XO)(XO)(\_O)(\_O)]\ [R_A(XO)(XO)(XO)(XO)]$
- Legend:
  - R = Randomization (G=Group Level, F=Flight Level, A=Article Level)
  - N = Non-equivalent groups
  - _ = Control
  - X = Treatment
  - O = Observation

Proportional Odds Logistic Regression Example

Hypothesis:

These dice are loaded!

Blue Box = Log Odds Transformed Space
Regression Happens Here!

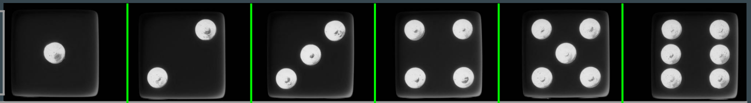
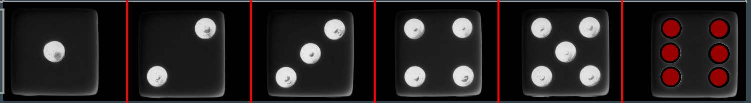
Simulation Output: 20,000 Rolls

```
Call: polr(formula = factor(Roll) ~ Treat,
data = dt, Hess = T)

Coefficients:
       Value  Std. Error  t value
Treat  0.2581    0.02491   10.36

Intercepts:
                  Value    Std. Error  t value
01_One|02_Two     -1.5487   0.0226    -68.5679
02_Two|03_Three   -0.6459   0.0193    -33.5413
03_Three|04_Four   0.0247   0.0186      1.3271
04_Four|05_Five    0.6733   0.0192     35.1351
05_Five|06_Six     1.4656   0.0216     67.8674
```

Control (Fair Dice)

Fair Dice						
Actual Probability	17%	17%	17%	17%	17%	17%
Actual Odds of Lower Roll	1:5 (0.2)	1:2 (0.5)	1:1 (1)	2:1 (2)	5:1 (5)	
Log Odds (model fit)	-1.55	-0.65	0.02	0.67	1.47	
Treatment Effect (subtracted)	0.26	0.26	0.26	0.26	0.26	
Log Odds (model fit)	-1.81	-0.91	-0.24	0.41	1.21	
Actual Odds of Lower Roll	1:5.7 (0.18)	1:2.3 (0.43)	1:1.2 (0.82)	1.5:1 (1.5)	3:1 (3)	
Actual Probability	15%	15%	15%	15%	15%	25%
Loaded Dice						

Treatment (Loaded Dice)