Speaking Truth to Twitter

Team 3

Hertie School of Governance

May 12, 2016

Outline

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Main Changes

- We only focussed on Trump, not Clinton
- Our sample was drawn from unconnected accounts which had recently liked a Trump tweet (4420)
- We randomly assigned 1000 accounts to our treatment group and 3420 to our control group

Implementation

- We created 5 similar Twitter accounts (**@twi_truth, @truth_to_twitt, @truthToTwitt, @SpeakingTw, @facts_for_twitt**) - see figure 1
- We regularly created Twitter Apps for each account. Robots used these to automatically tweet the treatment groups
- We sent nearly 7000 tweets over 19 days (see table 1)
- Our server automatically monitored our observation group, recording 1,475,347 tweets and 170,516 likes

Implementation

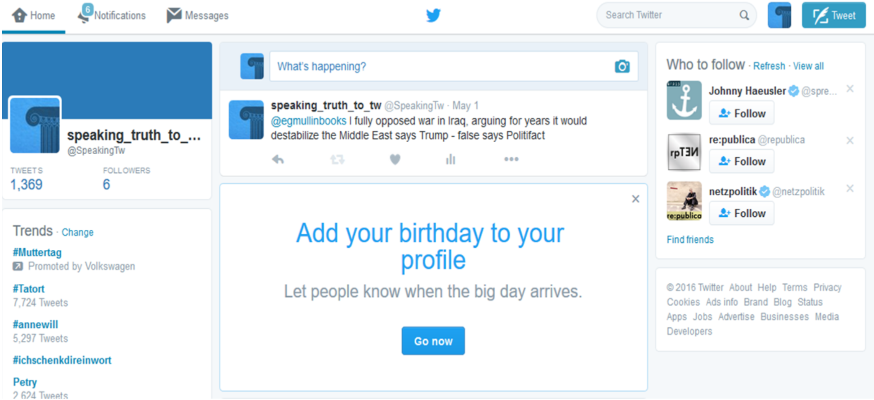

Figure 1 : Example Twitter profile

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Implementation

Tweet number	Text	Truth	Start date
1	@LostinMemphis Trump says most wire transfers to Mexico from undocumented immigrants-half true says award-winning website Politifact	0	2016-04-14
2	@LostinMemphis Trump says his deficit to Clinton much smaller than Reagan's against Carter-false says award-winning website Politifact	-2	2016-04-20
3	@LostinMemphis Trump says Ted Cruz is mathematically out of winning the race - mostly true says politifact	1	2016-04-22
4	@LostinMemphis Trump says PA lost 35%, and Harrisburg 40%, of manufacturing jobs since 2001 - Mostly true says politifact	1	2016-04-25
5	@LostinMemphis Trump says football coach Rex Ryan won championships in NY twice - false says Politifact. He never did	-2	2016-04-27
6	@LostinMemphis Trump says ISIS makes millions of dollars a week by selling Libyan oil - false says Politifact	-2	2016-04-29
7	@LostinMemphis Trump says he fully opposed war in Iraq arguing for years it would destabilize the Middle East - false says Politifact	-2	2016-04-30

Table 1 : Example tweets

Implementation

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We received

- 164 retweets
- 369 likes
- 417 replies

Responses

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Responses

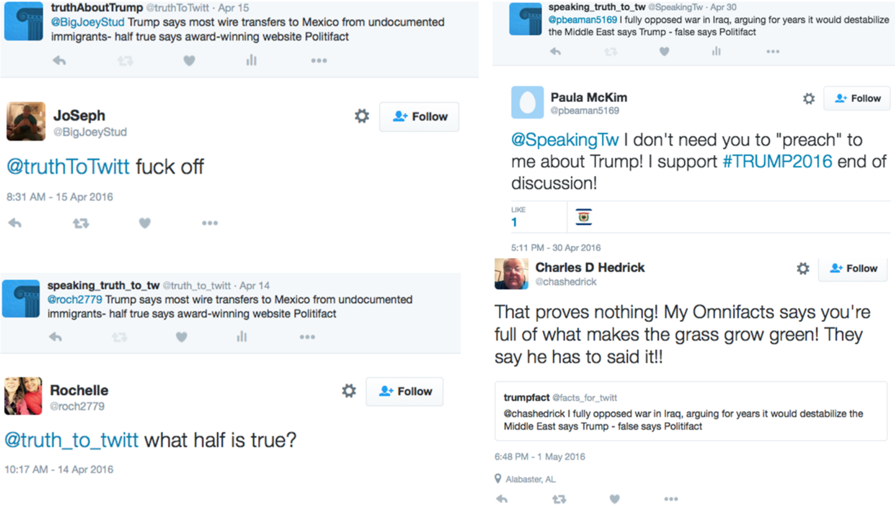

Figure 2 : Some interesting comments

Outline

Descriptive Statistics

Descriptive statistics before the treatment period are similar in treatment and control groups

Variable	Mean		Median		SEM	
	Control	Tweetment	Control	Tweetment	Control	Tweetment
Avg tweet "Trump"	2.46	2.41	1.00	0.86	0.08	0.13
Avg likes	0.57	0.56	0.14	0.14	0.02	0.03
Avg #MAGA	0.26	0.19	0.00	0.00	0.01	0.02
Avg mentions	1.43	1.41	0.57	0.57	0.05	0.09
Avg retweets	0.59	0.59	0.00	0.00	0.03	0.06
Followers	120.81	113.38	55.00	51.0	3.06	5.50
Following	210.94	201.82	93.50	91.00	5.90	11.06

Table 2 : Descriptive statistics before the treatment period

Descriptive Statistics

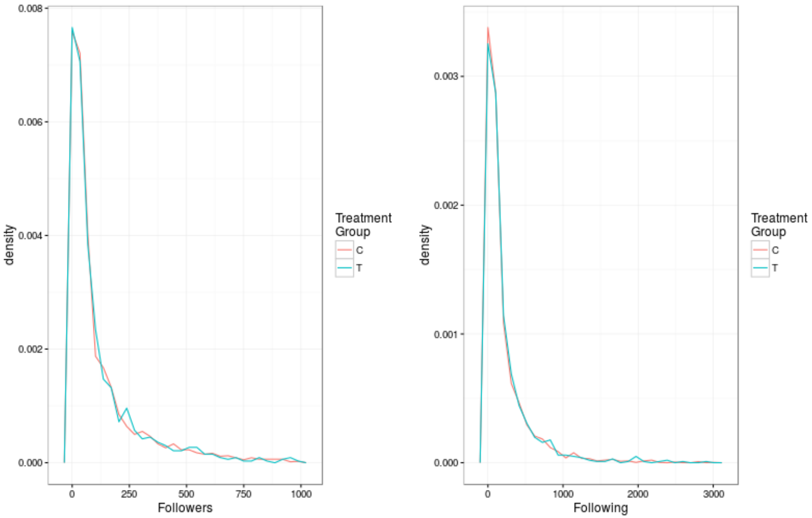

Figure 3 : Probability density plots of treatment and control group follower and following count

Outline

Results: Data and Dependent Variables

From the like and tweet data we collected, we used the following as dependent variables (all per user per day) - tweet data excludes replies to our tweets

- number of likes of tweets by Donald Trump
- number of retweets of tweets by Donald Trump
- number of tweets using the hashtag "#MakeAmericaGreatAgain"
- number of tweets including the key word "Trump"

Results: Difference in Means

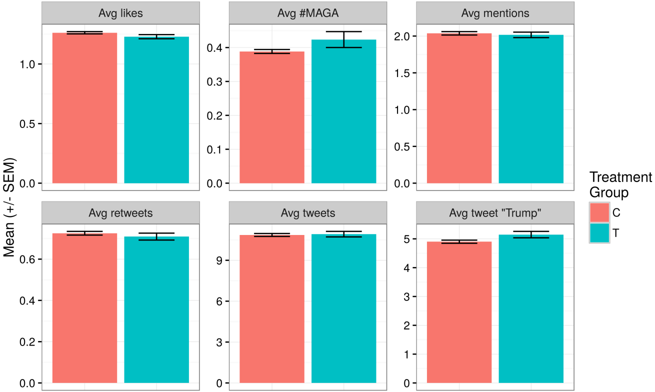

Figure 4 : Per user per day means of each dependent variable in treatment and control groups during the treatment period

Results: Difference in Means

variable	control mean	treatment mean	p-value
Avg likes	1.26	1.23	0.09 *
Avg tweets	10.86	10.92	0.79
Avg retweets	0.73	0.71	0.39
Avg mentions	2.04	2.02	0.63
Avg #MAGA	0.39	0.42	0.15
Avg tweet "Trump"	4.90	5.15	0.05 **

Table 3 : A t-test on the difference in means between treatment and control groups

Results: Differences over time

Likes

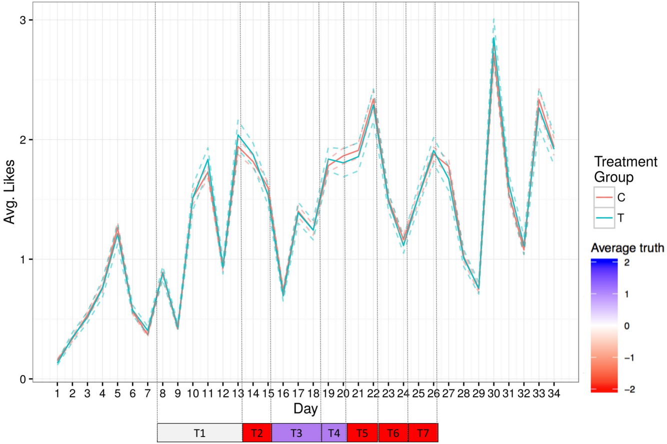

Figure 5 : Likes over time

Results: Differences over time

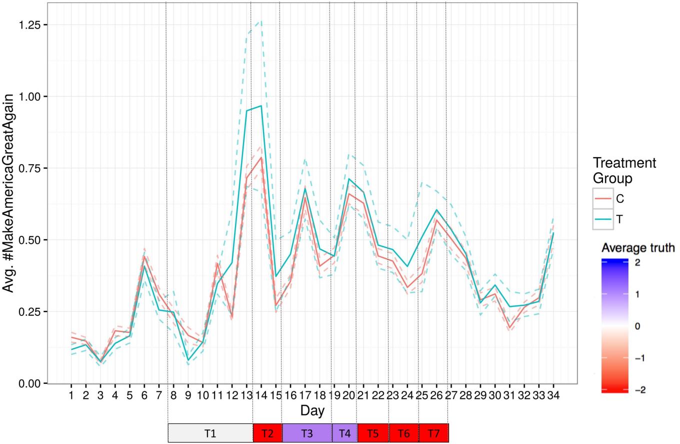

Figure 6 : #MakeAmericaGreatAgain over time

Results: Fixed Effects Model

Table 4 : Individual tweet dummies

	Dependent variable:					
	y					
	likes	tweets	retweets	mentions	MAGA	keywords
	(1)	(2)	(3)	(4)	(5)	(6)
temptweet1	0.001	0.098	−0.010	−0.069	0.055	0.091
	(0.081)	(0.512)	(0.078)	(0.127)	(0.094)	(0.284)
temptweet2	0.133	−0.048	0.020	−0.015	0.144	0.241
	(0.130)	(0.971)	(0.083)	(0.172)	(0.190)	(0.530)
temptweet3	−0.065	0.797	−0.024	0.044	0.034	0.735
	(0.076)	(1.081)	(0.058)	(0.181)	(0.082)	(0.571)
temptweet4	−0.085	0.126	−0.072	−0.102	−0.012	0.182
	(0.104)	(1.239)	(0.083)	(0.254)	(0.074)	(0.716)
temptweet5	−0.128	−0.315	−0.042	−0.096	0.028	0.139
	(0.106)	(1.192)	(0.084)	(0.204)	(0.067)	(0.634)
temptweet6	−0.040	−1.940	−0.023	−0.120	0.009	−0.325
	(0.105)	(1.638)	(0.081)	(0.252)	(0.087)	(0.921)
temptweet7	−0.020	−0.705	0.005	−0.077	0.064	0.046
	(0.081)	(1.038)	(0.068)	(0.164)	(0.118)	(0.585)
F-Test (-tive Tweets)	2.378	1.238	0.172	0.249	3.406	0.293
Pr(>F) (-tive Tweets)	0.05	0.292	0.953	0.91	0.009	0.883
Observations	150,246	150,246	150,246	150,246	150,246	150,246
R^2	0.0001	0.00005	0.00002	0.00001	0.0001	0.0001
Adjusted R^2	0.0001	0.00005	0.00002	0.00001	0.0001	0.0001
F Statistic (df = 7; 150205)	1.851*	1.025	0.343	0.292	2.412**	1.204

Results: Fixed Effects Model

Table 5 : Tweet truth dummies

	Dependent variable:					
	y					
	likes	tweets	retweets	mentions	MAGA	keywords
	(1)	(2)	(3)	(4)	(5)	(6)
posdummy	−0.027	0.192	−0.038	−0.050	−0.005	0.268
	(0.057)	(0.945)	(0.053)	(0.157)	(0.034)	(0.501)
negdummy	−0.009	−0.552	0.021	−0.015	0.073	−0.103
	(0.031)	(0.409)	(0.029)	(0.080)	(0.086)	(0.231)
neutdummy	0.052	0.331	0.014	0.003	0.016	0.111
	(0.055)	(0.519)	(0.058)	(0.109)	(0.035)	(0.274)
F-Test (-tive Tweets)	2.378	1.238	0.172	0.249	3.406	0.293
Pr(>F) (-tive Tweets)	0.05	0.292	0.953	0.91	0.009	0.883
Observations	150,246	150,246	150,246	150,246	150,246	150,246
R^2	0.00004	0.00003	0.00002	0.00001	0.0001	0.00002
Adjusted R^2	0.00004	0.00002	0.00002	0.00001	0.0001	0.00002
F Statistic (df = 3; 145791)	1.909	1.234	1.115	0.277	3.269**	1.193
Note:						*p<0.1; **p<0.05; ***p<0.01

Outline

Interpretation of results

Two different hypotheses:

1. rational updaters
2. motivated reasoners

Results are unclear:

- Some changes in engagement with Trump are observable
- Different variables react in different directions
- Hard to attribute effects to individual tweets or to truth levels of tweets

Conclusion

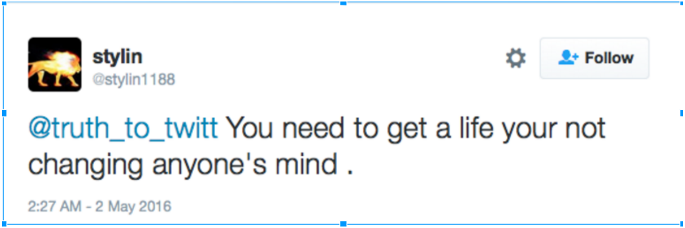

Figure 7 : Your not changing any minds

Limitations

- The results only apply to a limited population of active twitter users who tweet about Trump
- Attrition: 10 individuals asked to drop out
- We “only” measure an ITT effect:
- Bias from manipulation of the twitter feed
- Uncertainty about the time when the tweets were seen