Appealing to the Base or to the Moveable Middle? Incumbents' Partisan Messaging Before the 2016 U.S. Congressional Elections

Libby Hemphill[1] (@libbyh) and Matthew A. Shapiro[2]
[1] University of Michigan
[2] Illinois Institute of Technology

Main takeaway

Democrats and Republicans differed in their partisanship:

- Democrats decreased their partisanship, following the "median voter" playbook
- Republicans remained consistent in their messaging, using Twitter to activate and reinforce their base

Background

- Median Voter Theorem (Downs 1957)
- Activation and reinforcement (Lazarsfeld, Berelson, and Gaudet 1948)
- Direct (Mitchell, Gottfried, Barthel, & Shearer, 2016) and indirect (Shapiro and Hemphill 2017) political audiences on Twitter
- Measuring polarization through tweets (Hemphill, Culotta, and Heston 2016)

Hypotheses

1. As the election nears, politicians will exhibit **lower** polarization scores.
2. As the election nears, politicians will exhibit **higher** polarization scores.
3. Majority party incumbents will exhibit **lower** polarization scores than minority party incumbents.
4. Candidates in close races will exhibit **lower** polarization scores.

Why both higher and lower?

1. **Median voter theorem**: reduce partisanship to attract the moveable middle
2. **Activate and Reinforce**: increase partisanship to get base to the polls
3. **Low Congressional approval + unpopular presidential candidate**: reduce partisanship to appear less extreme
4. **Close race**: reduce partisanship to reduce effect of party affiliation

#Polar Scores for Measuring Partisanship on Twitter

1. Collect tweets
2. Identify “framing” or “positioning” hashtags
3. Create binary hashtag vectors for each MOC
4. Run through feature selection algorithms, where hashtags are features
5. Assign signed scores to tags: #Polar-Hashtag
6. Sum signed tag scores: #Polar-User

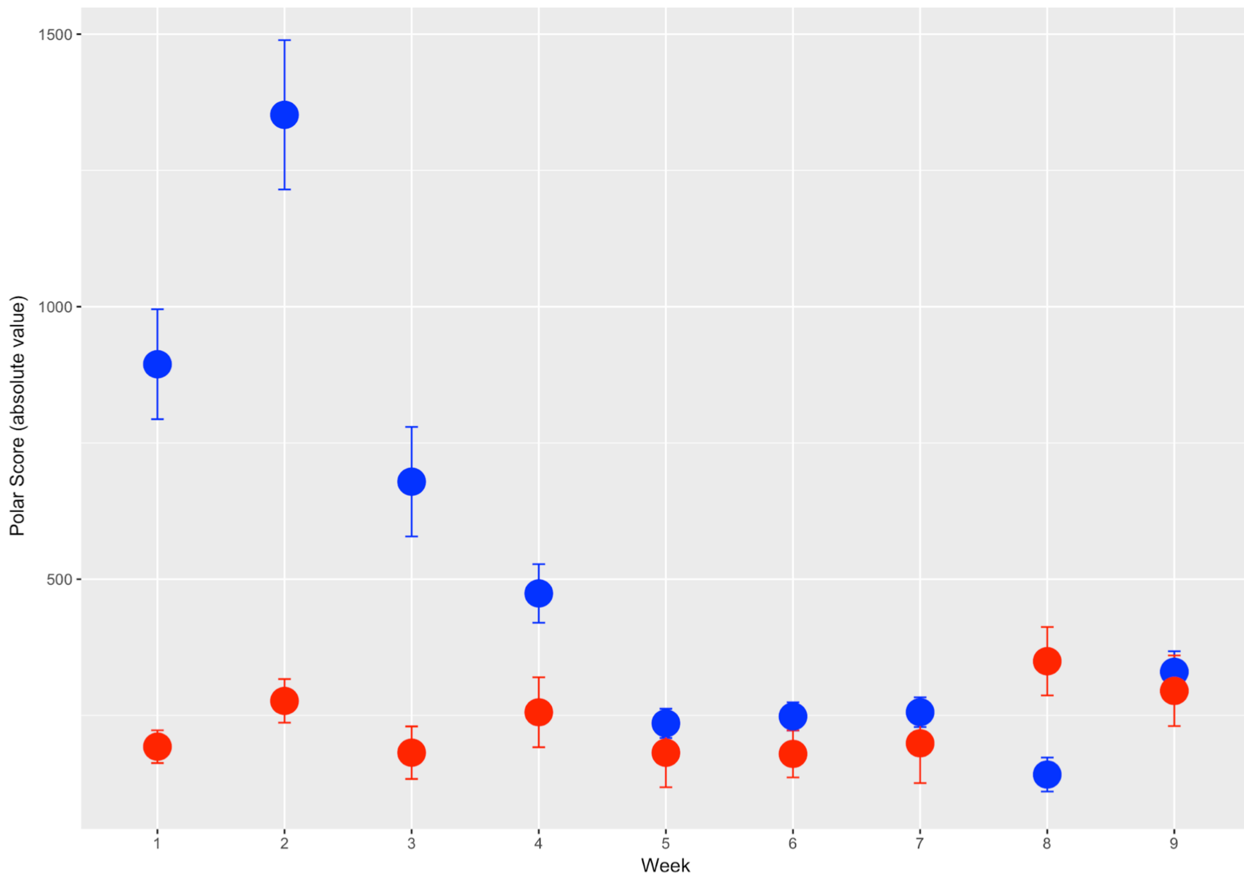
Methods

1. Collect tweets from incumbents (**25,483** tweets from **458** accounts)
2. Calculate #polar scores for each week from Labor Day to Election Day
3. Predict #polar scores using individual, party, time, and race measures

Measures

Variable	Type	Operationalization
abs	outcome	Absolute value of the average partisanship of the member of Congress's Twitter feed for week
handle	predictor	Twitter handle associated with the member of Congress's account
party	predictor	1 = Republican; 0 = Democratic
week	predictor	Number of the week (1 = week beginning Labor Day)
margin of victory	predictor	Ratio of votes separating the winner and the runner-up to sum of votes both candidates received

#Polar scores over time



	Overall Model	Republicans	Democrats
Fixed Effects			
Week	**-117.29***** (9.32)	2.82 (4.40)	**-110.01***** (12.99)
Party (Republican)	**-878.60***** (95.63)		
Week * Party	**125.10***** (12.56)		
Random Effects			
Handle	324614	148321	487028
Handle, week	779051	154608	1640135
Model Fit			
AIC	49875	25868	23113

	Week alone	Including race margin
Fixed Effects		
Week	**-47.44***** (6.91)	**-117.27***** (9.318)
Party (Republican)		**-874.07***** (96.155)
Margin		0.653 (1.170)
Week * Party		**125.077***** (12.563)
Model Fit		
AIC	49962	49877

Results

Hypothesis	Result
Median Voter: Lower scores	Supported
IPP: Higher scores	Not supported
Unpopular Congress, presidential candidate: Lower scores	Supported
Close race: Lower scores	Not supported

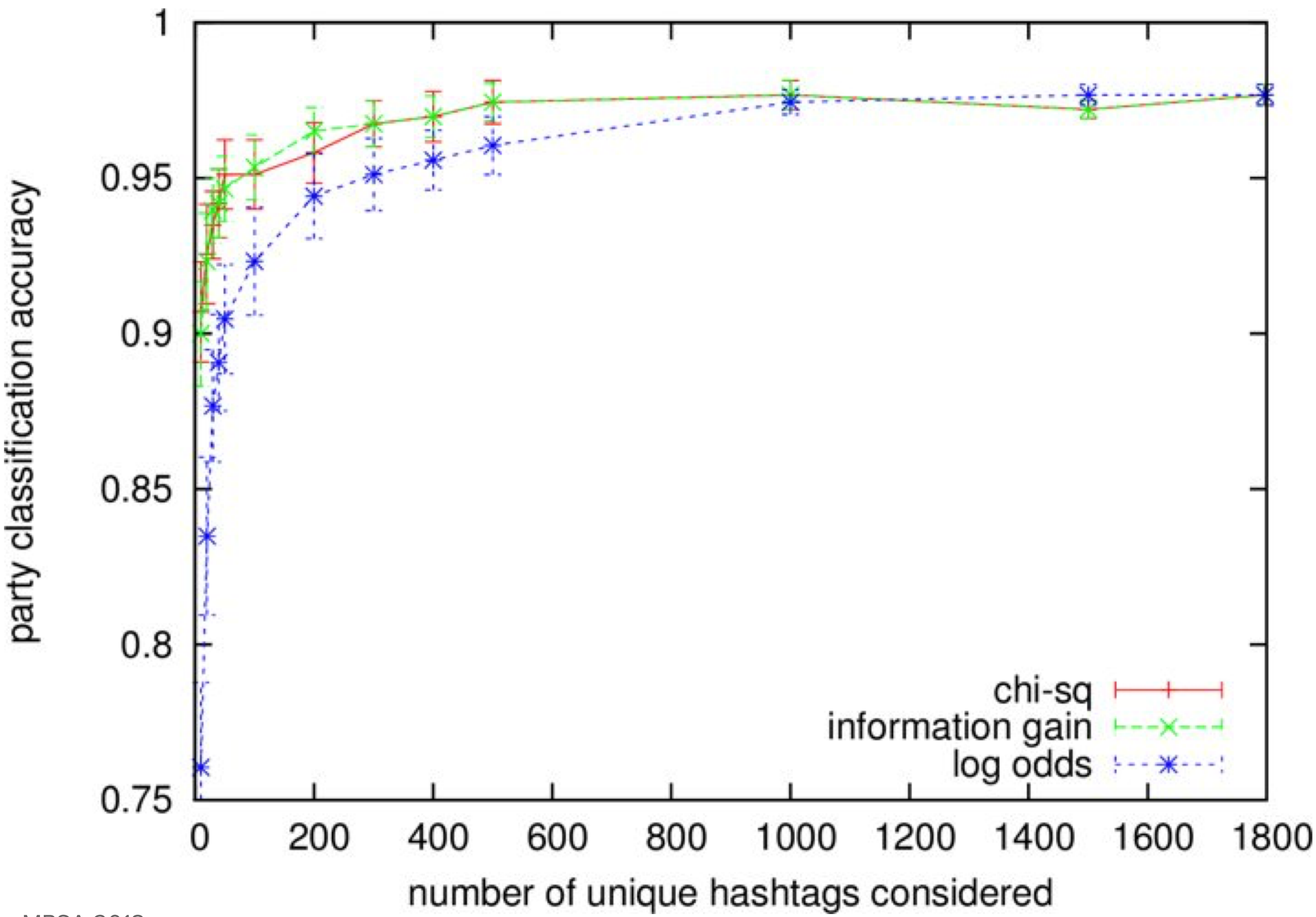
Takeaways

- Republicans and Democrats employed different strategies.
  - Republicans - stake a moderate claim and stay there (mostly)
  - Democrats - message in line with Congressional action, move to the middle right before the election
- Trump didn't make 2016 unique, at least not on this measure.
- Future work: challengers and campaign accounts

Supplemental Slides

Evaluating #Polar Scores Algorithms

- Split D into k equal-sized sets $D_1 \ldots D_k$
- For each set
  - Construct $D_{train} = D \backslash D_k$; $D_{test} = D_k$
  - Rank features in D_{train} according to F
  - Retain the top m features
  - Fit a classifier on D_{train} using only the selected m features
  - Predict the class assignments for the held-out observations in D_{test}


party classification accuracy
1
0.95
0.9
0.85
0.8
0.75
0
200
400
600
800
1000
1200
1400
1600
1800
number of unique hashtags considered
chi-sq
information gain
log odds