Social Networks 36 (2014) 177–184

Contents lists available at ScienceDirect

Social Networks

journal homepage: www.elsevier.com/locate/socnet

A method for computing political preference among Twitter followers

Jennifer Golbeck[a,*], Derek Hansen[b]

[a] Human-Computer Interaction Lab, College of Information Studies, University of Maryland, College Park, MD, United States
[b] Information Technology, Brigham Young University, Provo, UT, United States

ARTICLE INFO

Keywords:
Twitter
Politics
Liberal
Conservative
News
Journalism

ABSTRACT

There is great interest in understanding media bias and political information seeking preferences. As many media outlets create online personas, we seek to automatically estimate the political preferences of their audience, rather than examining the bias of the media source. In this paper, we present a novel method for computing the political preferences of an organization's Twitter followers. We present an application of this technique to estimate the political preferences of the audiences of U.S. media outlets, government agencies, and interest groups and think tanks. We also discuss how these results may be used and extended.

1. Introduction and related work

As government agencies, media outlets, and other organizations establish online presences in social media, understanding the characteristics of their audiences is an important task. It has implications for how information is presented in social environments where personalization is often expected. Furthermore, it can provide valuable information to marketers, policy analysts, and social science researchers.

Fortunately, users of these social media services leave a public trail of their activities, and that behavior can be used to infer information about their preferences. In this paper, we present a technique for estimating audience preferences in a given domain on the microblogging service Twitter. We use U.S. politics as our domain and motivating example. We present a method for computing the political preference of an audience by analyzing their "following" behavior and illustrate this approach with media outlets, government, and interest groups and think tanks. This method was first outlined in our previous work (removed for anonymity), and we extend the method and analysis here.

Although our study is about the political preferences of audiences—not media bias, or the biases of other organizations—it is worth briefly discussing the extensive research on analyzing media bias as it is strongly correlated with audience preferences. A subset of this work uses automated methods to infer liberal/conservative bias of news stories and outlets. These automated methods do not depend on subjective measurements of bias, although the specific techniques used to infer bias can be problematic and are highly contested.

For example, one approach is to compute a media bias score based on citations in news stories. News outlets that cite "think tanks" which are also cited by Representatives with a known liberal bias are assumed to be more liberal (Groseclose and Milyo, 2005). Another approach is to compare keywords and phrases used by Representatives of known political persuasions with those used in news articles; news outlets that use terms like "death tax" and "illegal immigration" are more likely to be conservative (Gentzkow and Shapiro, 2010). A final approach assigns a liberal/conservative score to web documents based on the number of times they are co-cited with other web documents that have a known political bias (Efron, 2004).

In contrast to these approaches, we estimate the political preferences of news outlet audiences, not the news outlet content itself. Our strategy is similar to Groseclose and Milyo (2005) in that we use Representatives' liberal/conservative ratings as a starting point for our scoring. However, we use Twitter Follow relationships rather than article citations. Using Follow relationships avoids a key concern with Groseclose and Milyo (2005)—that results rely too much on the nuances of journalist and Representative citation practices. Our approach does not require a researcher to read stories and find citations (as in Groseclose and Milyo, 2005), or access to large corpuses of news stories and congressional speeches. Instead, it relies instead on freely available and open access data from Twitter.

2. Method and sampling

We compute the political preference of an audience by using sites like Twitter that embed users' information-seeking choices into social media ties. Our examples and applications are in the political domain, but the technique is generalizable when the right

* Corresponding author. Tel.: +1 3014057185.
E-mail addresses: jgolbeck@umd.edu (J. Golbeck), dlhansen@byu.edu (D. Hansen).

0378-8733/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.socnet.2013.07.004

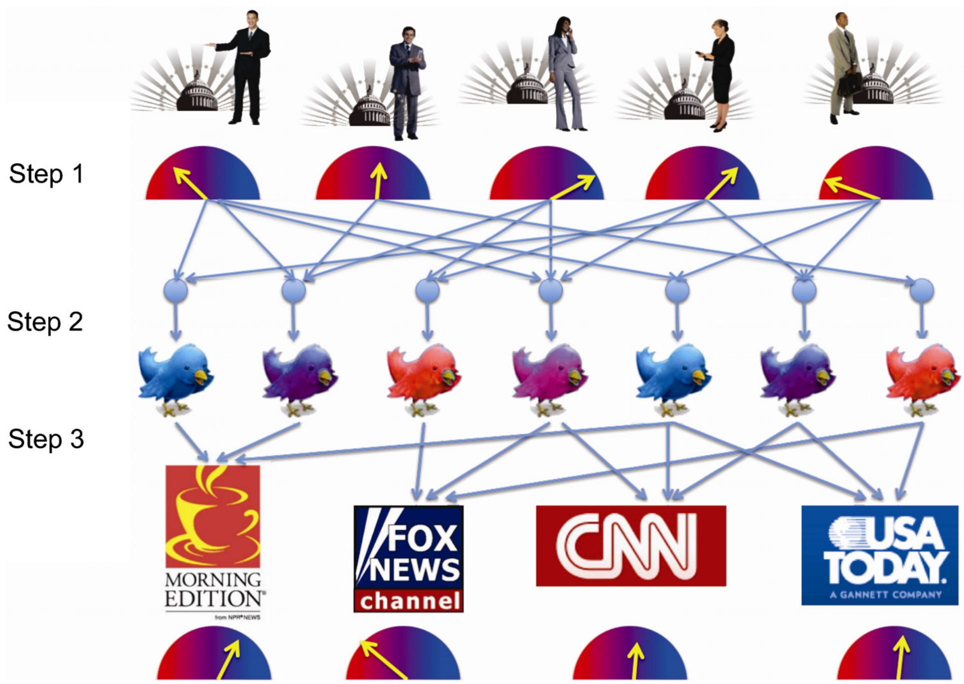

Fig. 1. An illustration of our process for scoring users and organizations.

background information is available. Fig. 1 illustrates our approach, which comprises the following steps.

Step 1: Apply known scores to a seed group. (In our case, these are Representatives using Twitter.) We then need a source for liberal/conservative ratings of Representatives. Two sources were available to us:

- The first set was obtained from Americans for Democratic Action (ADA), who puts out an annual report that considers the voting record of members of Congress (ADA, 2009). ADA defines a key set of votes that indicate liberal and conservative positions, and uses the Representative's voting record to assign each a score. The most liberal score is a 1.0, and the most conservative is 0.0. This is a widely accepted measure of political position. We apply the 2009 ADA ratings to our main dataset of 111th Congress members.
- In addition, we used DW-nominate scores (Clinton, 2004). The DW-Nominate scores have two dimensions, and the first most closely represents traditional liberal/conservative positions. These scores range from −1 to +1, with lower values representing more liberal positions and higher values representing conservative positions. These values could be used in place of ADA scores anywhere in our analysis, and we test them in the next section where we validate our method.

Step 2: Map the scores of the seed group onto their followers to create P-Scores. We collect the list of followers for each member of Congress on Twitter (i.e., Congress Followers). An inferred political preference score (*P-Score*) for each Congress Follower is computed as the simple average of the liberal/conservative scores for all Representatives he or she follows. Our approach relies on the assumption that people's political preferences will, on average, reflect those of the Representatives they follow. Prior literature on "selective exposure" to political information suggests this assumption is reasonable since people seek after information from those with similar political views (Frey, 1986; Garret, 2009). We verify this assumption through surveys and quantitative measures, discussed below in the next section on "Validating Follower Scores".

Step 3: Map the inferred scores of the seed group followers (Congress Followers) onto the target of the investigation. In this case, that includes the Twitter accounts of media outlets, government agencies, and interest groups and think tanks. A simple approach is to assign the average of the liberal/conservative scores of all Congress Followers who also follow the target media outlet. However, this approach raises a problem: Twitter users may not represent the overall population well. Therefore, we use a sampling method to more closely approximate the distribution of liberal and conservative tendencies as described below.

The main dataset we used was collected during the 111th Congress. Although Democrats outnumbered Republicans in Congress at the time, Republicans significantly outnumbered Democrats on Twitter (127 to 103). Furthermore, Republican Twitter users tended to have disproportionately more followers than Democrats. Even excluding John McCain, who had over 1.7 million followers as a result of the 2008 Presidential election (more than 30 times the next most-followed member of Congress, and nearly twice the total number of followers of all other Representatives), the total number of Republican followers was 581,997, compared to 291,050 for Democrats. (We duly note that some of these users likely follow both Republicans and Democrats.)

Without any adjustment, news outlet audiences would appear more conservative than they would if Twitter users' politics mirrored those of the more general U.S. population.

Since Republicans are overrepresented on Twitter when compared to their representation on Congress, we sampled members of congress to more closely match the roughly equal ratio of Republicans and Democrats in the general population. John McCain was excluded as an outlier, because the followers gained during his 2008 Presidential run makes him a particularly abnormal and overly influential data point.

Representatives were broken into groups by the number of followers they had: *over 10,000; 1000–5000; 500–1000; 100–500; 10–100*. Within each group, we randomly selected equal numbers of Republican and Democratic representatives until we had the maximum number for the least represented group. For example, if there were 20 Republicans and 15 Democrats in a group, our sample would include all 15 Democrats as well as 15 randomly selected Republicans from the same group. We chose equal numbers from each party, since the two parties have roughly the same number of members in Congress. For each selected Representative, we randomly selected the number of followers equal to the minimum number for the group in which he or she was a member (e.g., for a Representative from the "1000–5000" group, we selected 1000 random followers). Both independents and all their followers were included in all samples.

To compute the final media audience P-Scores, we used a 10-fold validation. We drew 10 samples using this technique, computed the P-Score for each media audience using each sample, and averaged the followers' scores across samples. Each sample included 160 congresspeople[1] and an average of 171,905 followers. Note that while we actually selected 200,820 followers, plus the 10,679 followers of the two independents, there was overlap in these selections. For example, a follower of John Culberson may also be a follower of Mark Warner. Thus, while we selected two followers, they were the same person. Thus, after deduplication, the total number of followers in our samples was significantly lower than the total number of followers initially selected.

3. Validating follower scores

Our process depends on the assumption that the Representatives a user follows represent that user's political beliefs. We tested this assumption in two ways.

3.1. Assumption Test #1: quantitative validation

We conducted an experiment during the 2012 U.S. Presidential election. Our goal was to examine a user's tweets to determine which candidate he or she supported, and then correlate that with the user's P-Score.

We collected a list of all users who follow at least one member of Congress and assigned scores to those users. Scores were calculated using the method described above with both the ADA dataset and DW-Nominate scores as a base. We then randomly sorted the list of users, and on Election Day collected tweets for as many users as possible. This was limited by Twitter's query rate limits, and whether or not users' profiles were public. We collected a total of 91,372 tweets from 60,171 users posted on Election Day.

All of an individual's tweets were collected into a single "document" representing that user. We filtered the user list to contain only people who used common hashtags, phrases, or calls to support for the candidates. After a first pass over the data, we selected the following terms as filters, and coded only users who had one of the following phrases in their tweets.

- obama2012
- obamabiden2012
- vote4obama
- voteobama
- "vote obama"
- "vote for obama"
- romney2012
- romneyryan2012
- voteromney
- vote4romney
- "vote romney"
- "vote for romney"

Note that we did not conclude which candidate a user supported based on these keywords; many users negated these phrases (e.g., "don't vote for romney"). Rather, this list gave us a subset of users who were clearly expressing a political stance on the election in their tweets. This gave us a list of 4399 users.

[1] 2 independents, and the following number of Democrats and Republicans from the following groups: 1 with 10–99 followers, 4 with 100–499 followers, 10 with 500–999 followers, 49 with 1000–4999 followers, 9 with 5000–9999 followers, and 6 with over 10,000 followers.

3.2. Assumption Test #2: qualitative validation

Two coders reviewed the tweets, marking each user as a supporter of Obama, Romney, or neither (if the tweets did not clearly support a candidate). Because the positions were very clear, the coders disagreed on only 50 users, giving a Cohen's Kappa measure of inter-coder reliability of .983. The results were: 565 users with no clear candidate preference in their tweets, 1972 Romney supporters, and 1812 Obama supporters.

Fig. 2 shows the distribution of scores for Obama and Romney supporters using the ADA baseline (a) and the DW-Nominate baseline (b). Both charts show the scores for the population who did not indicate support for one candidate or another (this was the vast majority of our user base).

The ADA-based scores are more polarized. This is consistent with the initial distribution of the ADA ratings for members of congress. In both distributions, there is a clear separation between Obama and Romney supporters. In the ADA-based data (a), where higher values indicate more liberal positions, most Romney supporters have extremely low values, while Obama supporters have high values. With the DW-Nominate-based scores, the distribution is less dramatic, but consistent. In this data, lower scores indicate liberal positions. This part of the range is dominated by Obama supporters, while Romney supporters dominate the higher values.

The average value for each group is also conspicuously different. Using ADA-based scores, Obama supporters' average P-Score was 0.806, while Romney supporters scored 0.174 on average. With DW-Nominate-based scores, Obama supporters averaged −0.208, while Romney supporters had an average score of 0.370 (these values scale to 0.604 and 0.315 respectively when converted into the 0–1 scale of ADA). The differences between Obama and Romney supporters were significantly different in both cases for $p < 0.0001$ (Student's t-test).

These results strongly indicate that our method for calculating P-Scores for individuals based on their following behavior yields an accurate estimate of their true political leanings.

Another important insight of this analysis is the relationship between ADA and DW-Nominate scores for users. Recall that higher values are liberal in ADA scores but conservative in DW-Nominate scores. The correlation between these values over our sampled users is −0.927: a nearly perfect negative linear relationship. Thus, even though the basis for the scores varies, they produce remarkably similar values for individuals in our dataset. Since the two datasets produce basically interchangeable P-Scores in our method, we use ADA data in the rest of our analysis, since we had more complete and timely ADA data for the 111th Congress.

One potential limitation of our work is the possibility that users who follow Representatives on Twitter may not be representative of the overall U.S. population. This is likely the case, given that those who actively decide to follow a Representative are probably more politically aware and active; such characteristics are often accompanied by more extreme political tendencies (Converse, 1964; Miller and Merrill Shanks, 1996). If this is true, our estimated audience political preference scores for media outlets will rely on the Twitter follow behavior of "politically savvy users", rather than the general population. This is not necessarily problematic, although it does affect the meaning of the P-Scores. In our political example with the bi-modal distribution, the *Avg. P-Score* for any given media outlet is roughly equivalent to the ratio of "political savvy" liberals and conservatives that follow that news outlet.

4. Media audiences' political preference

Our first application of this method was to estimate the political preferences of audiences of the same popular media outlets

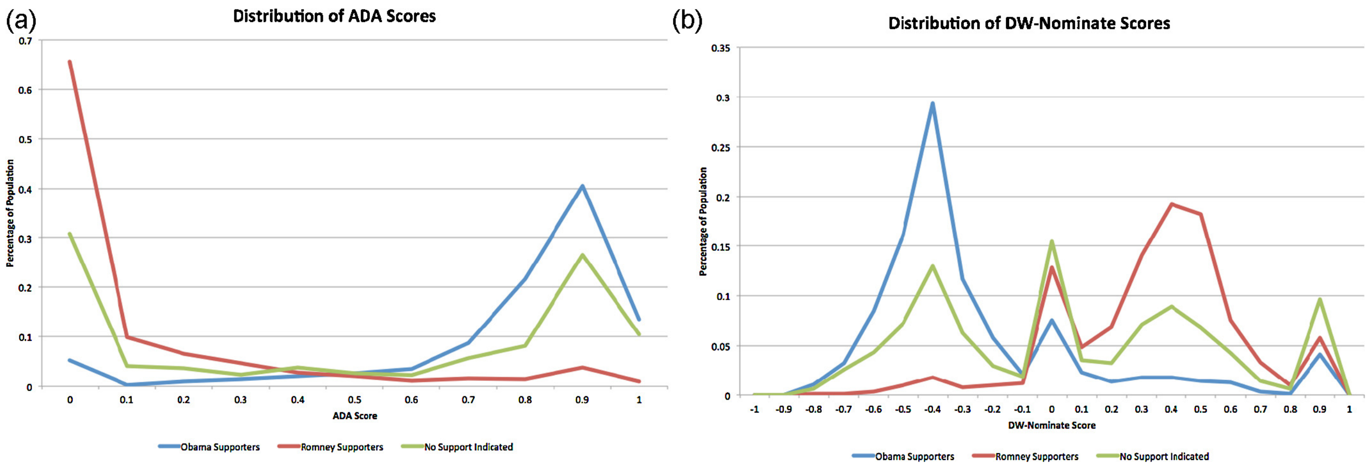

Fig. 2. Distribution of P-Scores calculated with ADA (a) and DW-Nominate (b) values for Obama and Romney supporters.

evaluated in Groseclose and Milyo (2005), through their ADA-based P-Scores. Table 1 shows the average of the audience's scores, along with the percentage of each outlet's followers who were considered when computing the value (i.e., the percentage of the outlet's followers who also followed a Representative).

Note that for each outlet, the average number of followers we used is a relatively small percentage of their total number of followers. This is because we can only compute scores based on the media outlet's followers who also have P-scores. P-scores require the user to follow a member of congress. Since there are relatively few followers of congress, especially compared to media outlets with millions of followers, the overlap in followers will be small. While our sampling further reduced the group of users considered, the increase in the number of users with no sampling only increased the percentage of followers by an average of 8%. For the larger media outlets, the increase was often less than 1%. Thus, sampling had a relatively small effect on the number of followers considered, but improved the representativeness of the followers (Fig. 3).

For traditionally conservative outlets (Lewis and Poole, 2004), such as Fox News (DellaVigna and Kaplan, 2007), we found audiences with correspondingly conservative P-Scores: Fox News (0.256), the Drudge Report (0.265), and the Washington Times (0.290). There are no outlets with audiences that have P-Scores that are liberal to the same extent that these are conservative; however, some liberal preference is visible in the audiences of outlets like the New York Times (0.604) (considered to be liberal leaning (Lewis and Poole, 2004; Munson and Resnick, 2010)) and NPR's Morning Edition (0.659).

The vast majority of these media outlets' audiences—15 out of 20—fall between the moderate scores of 0.4 and 0.6. Half are even closer to the midpoint, falling within 0.05 of the perfect moderate (0.5). This suggests that most media outlets audiences have roughly equal numbers of liberal and conservative Congress Followers (after sampling users in a ratio that matches the general population).

Our findings of audience preference are similar to the estimates of political orientation of media outlets found in Efron (2004), which used co-citation of hyperlinks to infer political orientation of web documents and their associated news outlets. Although the scales differ, like Efron (2004), we found that the Wall Street Journal and The New York Times equally deviated from the middle in opposite directions (conservative and liberal, respectively). This similarity may come from the fact that Efron (2004) relies partially

Table 1
The average audience P-Scores for the twenty popular media outlets studied in Groseclose and Milyo (2005). Averages are computed over 10 randomly drawn samples using the sampling method described earlier. Results are sorted from most conservative to most liberal. Note that without sampling as discussed above, scores are lower for all outlets.

Media outlet	Twitter user ID	Total followers	Average % of followers	Average score	Average score without sampling
Fox News	foxnews	266,121	7.33	0.256	0.194
The Drudge Report	Drudge_Report	102,981	20.52	0.265	0.204
Washington Times	washtimes	13,545	33.75	0.290	0.274
Wall Street Journal	WSJ	392,332	5.75	0.409	0.337
US News & World Report	usnews	7836	28.60	0.490	0.466
The L.A. Times	latimes	72,296	9.91	0.506	0.451
USA Today	USATODAY	63,714	9.90	0.513	0.459
Good Morning America	gma	1,698,875	0.72	0.518	0.412
The News Hour	NewsHour	54,787	12.79	0.521	0.415
CBS News	CBSNews	1,578,599	0.94	0.531	0.431
Newsweek	Newsweek	1,256,536	1.25	0.537	0.441
Washington Post	washingtonpost	154,400	9.51	0.542	0.436
The Today Show	todayshow	629,088	1.89	0.549	0.447
The Early Show	theearlyshow	12,628	11.16	0.552	0.512
Time Magazine	TIME	2,134,411	0.99	0.569	0.470
ABC World News	abcworldnews	12,973	14.93	0.570	0.522
CNN Breaking News	Cnnbrk	3,314,716	1.40	0.578	0.488
NBC Nightly News	nbcnightlynews	27,137	16.85	0.580	0.537
The New York Times	nytimes	2,553,291	1.40	0.604	0.518
Morning Edition (NPR)	MorningEdition	6146	17.22	0.659	0.624

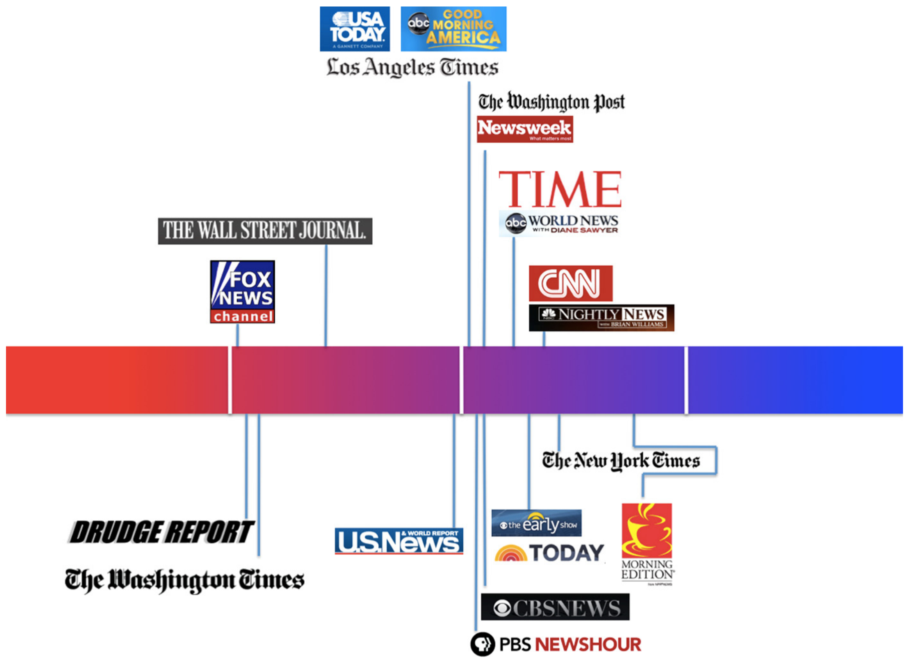

Fig. 3. The scores for audiences of major media outlets, ranging from most conservative (red) to liberal (blue). White lines indicate scores of 0.25, 0.5, and 0.75. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

on news outlet audiences by using website linking behavior. Our method provides a more direct estimate of audience political preferences by focusing on follower relationships.

It is important to note that these scores do *not* imply that the outlets themselves present news in a way that reflects their audience's political preferences.

5. Beyond media: interest groups, think tanks, and government agencies

While the political preferences of media outlets originally inspired this study, our technique is applicable to any organization. To illustrate this, we used the method to compute the political preferences of Twitter audiences for a number of Twitter accounts of the U.S. Federal Government, as well as some U.S. think tanks.

We found interesting results in both cases. Among Federal Government Twitter accounts, shown in Table 2, most audiences scored within 0.1 of the moderate mid-point of 0.5. Of the 193 accounts we considered, 149 audiences (77.2%) fell within this range. This suggests that users from across the political spectrum follow these accounts, since they are non-partisan and usually politically neutral.

Fig. 4 illustrates the distribution for three accounts in this middle range: the Department of Defense (DoD), CDC Flu, and NASA Headquarters Photo stream (NASAHQPhoto). All follow a similar pattern: relatively even distribution across the range, with spikes at the high and low end, mirroring the spikes seen overall in our population.

Looking at the far liberal and conservative end of the audiences for U.S. agency accounts, we find some interesting geographic explanations. Among the ten accounts with a score of 0.4 or less, six are Alaskan National Park Service accounts (BeringLandNPS, NoatakNPS, AlaskaCenters, YukonCharleyNPS, LakeClarkNPS, GatesArcticNPS). Alaska is a strongly Republican state, having voted for every Republican Presidential candidate since participating in its first election in 1960, with the sole exception of Lyndon Johnson's landslide victory over Barry Goldwater in 1964. The high percentage of Republicans (typically the party of conservatives) would explain why the followers for these sites emerge as more conservative: Alaskan National parks are of interest to people in Alaska, and, since they tend to be more conservative, so is the Twitter following base.

This effect with the national parks is also present on the liberal end of the spectrum. Five parks (Lowell_NPS, DCParksEastNPS, AlaKahakaiNPS, KalokoNPS, HaleakalaNPS) are found in the range of P-Scores over 0.6, and they are found in the Northeast, D.C., and Hawaii, all traditionally Democratic and more liberal areas.

Issues certainly play a part in the audiences of these accounts. Among the 36 Twitter accounts with scores of 0.6 or higher, eleven of them belong to the Environmental Protection Agency (EPAregion3, EPAowow, EPAnews, EPAgov, EPAespanol, Greenversations, EPAiaplus, EPAregion9, EPAresearch, lisapjackson, EPAnewengland). This is not surprising since environmentalism is a traditionally liberal issue in the U.S.

With interest groups and think tanks, we also found consistency with the audience score and the positions held by the organization (Table 3). Unlike the average P-Scores of government agencies' audiences (which clustered around a moderate 0.5), the average

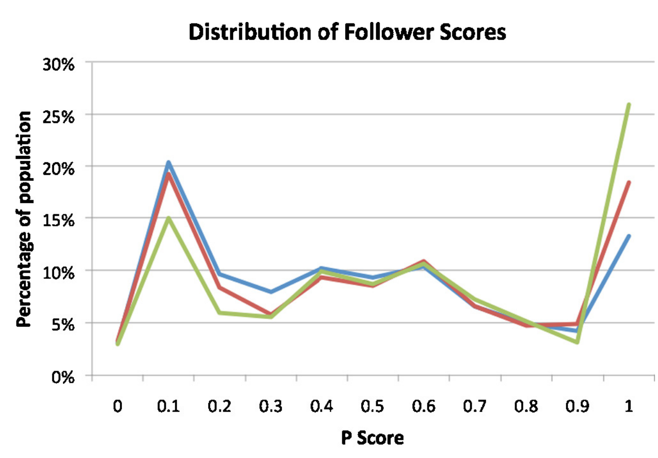

Fig. 4. Distribution of follower P-Scores for three U.S. agency Twitter accounts.

Table 2
The average audience P-Scores for many U.S. Federal Government Twitter accounts. Averages are computed over 10 randomly drawn samples using the sampling method described above. Results are sorted from most conservative to most liberal.

Name	Agency	Avg. P-Score
US CS Hong Kong	CSHongKong	0.336
Commercial Service	CSGermany	0.341
Lake Clark NP & P	LakeClarkNPS	0.365
Yukon-Charley Rivers	YukonCharleyNPS	0.369
Alaska Centers	AlaskaCenters	0.377
Costa Dillon	indianadunesnl	0.388
Noatak NP	NoatakNPS	0.392
BeringLandBridgeNP	BeringLandNPS	0.392
U.S. Commerce Dept.	Sell2Belgium	0.399
Gates Of The Arctic	GatesArcticNPS	0.400
Alaska NPS	AlaskaNPS	0.401
Cape Krusenstern NM	CKrusensternNPS	0.402
US GSA Region 9	US_GSAR9	0.415
Katmai NP	KatmaiNPS	0.416
Kobuk Valley NP	KobukValleyNPS	0.416
BH National Forest	BlackHillsNF	0.420
Bridger Teton NF	BridgerTetonNF	0.423
ChesapeakeOhio Canal	COcanalNPS	0.430
FEMA LRO	FEMALRO	0.435
Safe Healthy Workers	NIOSH	0.440
GrandTeton Natl Park	GrandTetonNPS	0.443
DoD	DeptofDefense	0.450
Industry Relations	gsapbsIRD	0.451
Lake Mead NRA	LakeMeadNRA	0.454
GSA RBA	GSARBA	0.454
IWACenter	GSAIWAC	0.464
Glacier Bay NP	GlacierBayNPS	0.467
femaregion7	femaregion7	0.470
CasaGrandeRuinsNPS	CasaGrandeNPS	0.470
U.S.GSA, Region 2	US_GSAR2	0.470
Lassen NF	USFSLassen	0.472
Klondike Nat'l Park	KlondikeAKNPS	0.473
Zion National Park	ZionNPS	0.476
Hiawatha NF	HiawathaNF	0.477
Denali National Park	DenaliNPS	0.477
NASAHurricane	NASAHurricane	0.477
Yellowstone NP	YellowstoneNPS	0.480
USForestService	USForestService	0.481
Lake Mead Nat'l Area	LakeMeadNPS	0.481
Shawnee	ShawneeNF	0.481
Fort Necessity NB	FtNecessityNPS	0.482
GlacierNationalPark	glaciernps	0.483
EPA Region6	EPAregion6	0.484
girlshealth.gov	girlshealth	0.484
femaregion9	femaregion9	0.485
USFS-Modoc	ModocNF	0.487
Colonial Nat'l Park	ColonialParkNPS	0.491
Mental Health NIMH	NIMHgov	0.491
Los Padres NF	LosPadresNF	0.492
Coconino Natl Forest	CoconinoNF	0.493
NNSA	NNSANews	0.498
GSA	usgsa	0.499
NPS SER EMERGENCY	NPSEMR_SEast	0.501
CDC Flu	CDCFlu	0.505
NIOSH Mining	OMSHR	0.506
Lake Tahoe USFS	LakeTahoeUSFS	0.508
NASA JPL	NASAJPL	0.508
North Umpqua Fire	NorthUmpquaFire	0.509
SaguaroNationalPark	SaguaroNPS	0.509
FCIC Pueblo	pueblo81009	0.510
HFQLG	usfs_hfqlg	0.511
U.S. FDA	FDArecalls	0.512
NASA Kennedy/KSC	NASAKennedy	0.512
ProtectiveTechnology	NPPTL	0.514
NIH for Health	NIHforHealth	0.516
Forest Service, R5	usfs_r5	0.517
National Forests, FL	NFinFlorida	0.517
PharmaSat	PharmaSat	0.517
Spirit and Oppy	MarsRovers	0.519
Pu'ukohola Heiau NHS	PuukoholaNPS	0.519
FDA/CDRH Industry	FDAcdrhIndustry	0.519
FDA Food Recalls	foodrecalls	0.519
GSA ITS	GSA_ITS	0.520
Statue of Liberty	StatueLibrtyNPS	0.521
Sequoia & Kings Park	SequoiaKingsNPS	0.522
FEMA	fema	0.522
Plumas NF	USFSPlumas	0.524
OPAffairs	opa1	0.524
NPS Southeast Fire	SouthEastNPS	0.525
GSA OSBU	GSAOSBU	0.526
US EPA NCER	EPAncer	0.526
USFS Tahoe NF	Tahoe_NF	0.526
Lassen Volcanic NP	LassenNPS	0.526
Homestead NM	HomesteadNM	0.527
CDC_eHealth	CDC_eHealth	0.529
Alcatraz Island	AlcatrazIsland	0.529
FDA Drug Information	FDA_Drug_Info	0.529
Thomas Stone NHS	ThomasStoneNHS	0.531
Breathe Better	BreatheBetter	0.532
Gulf Island	GulfIslandNPS	0.533
U.S. HSF Committee	NASA_HSF	0.534
CMSGov	CMSGov	0.536
insurekidsnow.gov	IKNGov	0.539
Argonne National Lab	argonne	0.540
U.S. EPA NCEA	EPAncea	0.540
NanoSailD	NanoSailD	0.540
NASA Ames ERC	NASA_Ames_ERC	0.542
Bev Godwin	BevUSA	0.544
NOAA Nautical Charts	nauticalcharts	0.544
Johnson Space Center	NASA_Johnson	0.544
Golden Gate NRA	GoldenGateNPS	0.545
USFS_Pike&San Isabel	PSICC_NF	0.546
NIH NHLBI	nih_nhlbi	0.546
GW Birthplace NM	NPSGEWA	0.549
Biscayne NP	BiscayneNPS	0.550
NASA HQ PHOTO	nasahqphoto	0.551
ED_Partners	edpartners	0.551
Katie Armstrong	KatieEArmstrong	0.552
HHSGov	HHSGov	0.552
CDC BioSense	CDC_BioSense	0.552
CDC's Act Early	CDCActEarly	0.553
NASA Nebula	NASAnebula	0.556
womenshealth.gov	womenshealth	0.557
NIGMS	NIGMS	0.558
Sanctuaries (NOAA)	sanctuaries	0.559
LLNL	Livermore_Lab	0.560
Lister Hill Center	NLM_LHC	0.561
Umpqua Nat'l Forest	UmpquaNF	0.562
NASA SDO	NASA_SDO	0.563
Assateague Island NS	AssateagueNPS	0.563
NCRR	ncrr_nih_gov	0.564
Forest Service, ARP	usfsarp	0.565
Hoover Historic Site	HooverNPS	0.566
femaregion1	femaregion1	0.569
NASA en español	NASA_ES	0.575
USDA Forest Service	forestservice	0.576
Gateway NRA-NPS Area	GatewayNPS	0.576
FDAWomen	FDAWomen	0.577
Shenandoah Natl Park	ShenandoahNPS	0.580
Forest Service, R9	usfs_r9	0.580
Harpers Ferry Park	HarpersFerryNPS	0.581
CDC Hepatitis	cdchep	0.581
FlorissantFossilBeds	FlorissantNPS	0.582
USGS Energy Program	usgsenergy	0.583
NCI Media Relations	NCIMedia	0.583
Communications	NCCAM	0.584
NPS Volunteers	NPSVIPNetwork	0.585
Timucuan Preserve	TimucuanNPS	0.585
NIH_for_Funding NIH	NIHforFunding	0.585
NationalParkService	NatlParkService	0.586
Everglades Natl Park	EvergladesNPS	0.587
NIH Human Resources	NIHforJobs	0.587
NLM SIS	NLM_SIS	0.587
US Dept. of Labor	USDOL	0.587
NIH WALS	NIHWALS	0.588
USFS Rocky Mountains	USFSRockyMtns	0.588
NOAA	usnoaagov	0.590
US Dept of Interior	Interior	0.592
US EPA Web	EPAweb	0.592
Wyndeth Davis	NPSEducation	0.593
Natl Diabetes Ed	NDEP	0.594

Table 2 (*Continued*)

Name	Agency	Avg. P-Score
NIH Library	nihlib	0.594
NIAID News	NIAIDNews	0.597
NOAA CIO	NOAACIO	0.597
NOAA, Ocean Explorer	oceanexplorer	0.597
EPA TribalCompliance	usepaTribalComp	0.599
GSA/FAS	FAS_Outreach	0.599
Big Cypress NPres	bicynpres	0.600
Lowell NHP	Lowell_NPS	0.600
US EPA Mid-Atlantic	EPAregion3	0.601
US Dept of Education	usedgov	0.602
EPA - owow	EPAowow	0.605
National Cancer Inst	theNCI	0.605
US EPA News	EPAnews	0.610
CDC NPIN	CDCNPIN	0.610
NCBI_PubMed	ncbi_pubmed	0.611
NOAA Teacher at Sea	TeacherAtSea	0.611
myncbi	myncbi	0.616
Yosemite Science	YosemiteScience	0.621
U.S. EPA	EPAgov	0.622
CDC.gov	CDCgov	0.623
NIH SciEd	NIHSciEd	0.624
NOAA Exhibits	NOAAExhibits	0.624
Ray LaHood	RayLaHood	0.627
National Capital NPS	DCParksEastNPS	0.627
Earth Observatory	NASA_EO	0.628
Lina Younes, EPA	EPAespanol	0.632
Ala Kahakai	AlaKahakaiNPS	0.640
Greenversations	Greenversations	0.640
EPA Indoor airPLUS	EPAiaplus	0.640
HUD News	HUDNews	0.641
EPAregion9	EPAregion9	0.641
BerkeleyLab	BerkeleyLab	0.644
TransportStats	TransportStats	0.648
US EPA Research	EPAresearch	0.659
Hilda L. Solis	HildaSolisDOL	0.661
Massie Ritsch	ED_Outreach	0.663
OPM News	USOPM	0.668
Department of Energy	ENERGY	0.675
KalokoHonokohauNHP	KalokoNPS	0.682
Lisa P. Jackson, EPA	lisapjackson	0.686
Haleakala NP	HaleakalaNPS	0.696
EPA New England	EPAnewengland	0.751

Table 3
The average audience P-Scores for a sample of US think tank Twitter accounts. Averages are computed over 10 randomly drawn samples using the sampling method described above. Results are sorted from most conservative to most liberal.

Name	Think tank	Avg. P-Score
The ACU	ACUConservative	0.128
ATR	taxreformer	0.136
Right to Life	nrlc	0.145
Natl Taxpayers Union	NTU	0.152
NRA News	NRANews	0.163
Heritage Foundation	Heritage	0.166
Christian Coalition	ccoalition	0.177
CAGW	GovWaste	0.184
Manhattan Institute	ManhattanInst	0.191
Hoover Institution	HooverInst	0.194
AEI	AEIonline	0.209
Cato Institute	CatoInstitute	0.211
HudsonInstitute	HudsonInstitute	0.288
Peterson Institute	PIIE_com	0.465
PETA	peta	0.470
CSIS Americas	CSISAmericas	0.486
RAND Corporation	RANDCorporation	0.488
FAS	FAScientists	0.509
IISS News	IISS_org	0.509
Official AARP Tweets	AARP	0.526
CFR	CFR_org	0.526
Stimson Center	StimsonCenter	0.542
WWF	WWF	0.558
CTJ	taxjustice	0.577
Brookings FP	BrookingsFP	0.582
AmnestyInternational	amnesty	0.598
ACLU National	ACLU	0.617
Consumer Federation	ConsumerFed	0.626
CommonCause	CommonCause	0.632
PFAW	peoplefor	0.637
privacy140	privacy140	0.643
Economic Policy Inst	EconomicPolicy	0.649
Center on Budget	CenterOnBudget	0.653
Urban Institute	urbaninstitute	0.660
The NAACP	NAACP	0.678
Sierra Club	Sierra_Club	0.689
EDF	EnvDefenseFund	0.698
NARAL	NARAL	0.728
National NOW	NationalNOW	0.740

scores for interest groups and think tanks tend to be skewed toward the very conservative and the moderate-liberal (see Fig. 5).

The scores of the audiences correlate well with the perspective of the think tank. For example, among the most conservative audiences are the American Conservative Union, American Tax Reformer, the National Right to Life Committee, the National Taxpayers' Union, the National Rifle Association, the Heritage Foundation, and the Christian Coalition—all self-professed conservative organizations or advocates for traditionally conservative positions. There are no groups on the liberal end of the spectrum with scores as liberal as these are conservative, but among the most liberal in audience are the Sierra Club and the Environmental Defense Fund (both environmental groups, mirroring the results we saw among government Twitter accounts), NARAL (a pro-choice group), and the National Organization for Women.

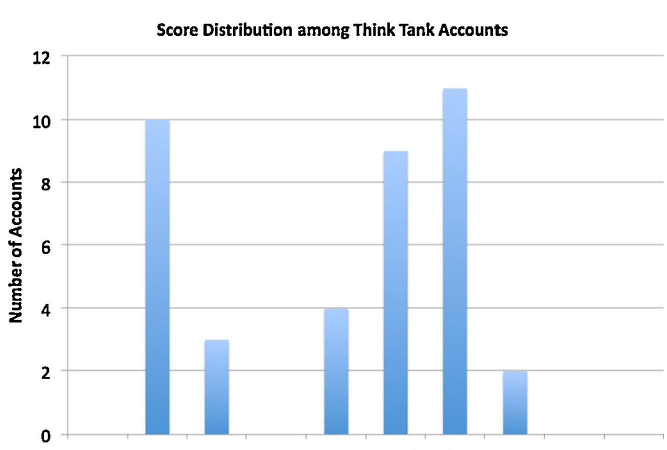

Fig. 5. Distribution of average P-Scores among think tank Twitter accounts.

6. Discussion

There are a number of implications and areas for future work that follow from these results. Many users expect personalized web-based content. Some personalization comes from the structure of the services themselves (e.g., who users choose to follow on Twitter affects which tweets they see). However, there are many opportunities to further personalize and enhance the way information is presented.

Understanding the political preference of an audience can be important for presenting tailored information (including or excluding information to the user's tastes) and personalizing the user's experience. For example, an audience's political preference can be used as input into recommender systems. In collaborative filtering systems, items are recommended by finding people with tastes similar to the user and recommending things those people like. In this context, by knowing a user's political preferences, one could find media outlets that have audiences who share a similar preference, mimicking the basic idea behind collaborative filtering.

Tweets (or information provided on other social media sites) can be highlighted, filtered out, or sorted, based on the similarity of their audiences' political preferences the user's. Alternatively, our method could be used to help recommend tweets commonly read by people on both sides of the political spectrum, reducing homophily (Mondo Times, 2013). Finally, marketers and analysts can use our method to measure their Twitter reach within different political markets to see if they are reaching their intended audience.

Outside of personalization, this technique may have applications for studying media bias in social media. While we have set out to estimate audience political preference, not media bias, previous work has shown that news consumers have a significant preference for like-minded media outlets (Frey, 1986; Garret, 2009) and use new social media tools to actively seek out those with similar views. This implies that people may choose a media outlet because its presentation of the news reflects their own political beliefs, and thus the preference of an audience may generally reflect the bias of the outlet. While we do not have evidence to support this connection, predicting media bias based on audience preferences is an area for future research.

Finally, while we have used political preference and U.S.-based media outlets as our example case, we believe this technique is applicable in other domains. For example, a similar analysis could be done using the Green Scores (which rate how environmentally responsible companies are). These could be used to create an environmental score for Twitter followers of organizations, politicians, and other Twitter accounts. Additionally, our technique could be applied to better understand the political landscape in other countries, assuming that a seed score was available and Twitter was significantly used. This could be important to intelligence analysts, marketers, and researchers trying to understand where different news organizations.

Another natural extension of this work would be to look at the P-score distributions of users of different hashtags or keywords. Instead of looking at the distribution of P-scores for all followers of, say, CNN, one could look at the distribution of P-scores for all Twitter accounts who have Tweeted the hashtag #opengov, #healthreform, #gun, #immigration, or #latino. Tracking changes in P-score averages over time may provide useful to political analysts and marketers seeking to understand the connotations of certain words. The relative simplicity of the method we propose to calculate makes it possible for creators of social media monitoring platforms (e.g., Radian6) to report P-scores and average P-scores for searches and users.

7. Conclusion

In this paper, we presented a technique for estimating the political preferences of Twitter account followers. Using the political domain as our motivating example, we presented a method that uses the follower connections in the Twitter network to propagate liberal/conservative scores from Congresspeople to Congress Followers, and then to audiences of media outlets. Our results show that our method accurately estimates a user's political preference, and that the estimates of media outlets' audiences reflect the liberal/conservative leanings of the media outlets as presented in prior literature. We illustrated how our technique can be generalized by applying it to understanding the audiences of government agencies, interest groups, and think tanks.

The results have potential applications for motivating new interface personalization techniques, improving social media monitoring platforms, understanding media bias, and detecting other types of audience preferences in different domains or locations. There is much future work to be done in this space, and we hope this initial work serves as motivation to pursue those issues.

Acknowledgements

Thanks to members of the University of Maryland's Human Computer Interaction Lab (HCIL) for their helpful comments on an earlier draft.

References

Americans for Democratic Action. Annual Voting Records, 2009. Available at http://www.adaction.org/

Clinton, J., Jackman, S., Rivers, D., 2004. The statistical analysis of roll call data. American Political Science Review 98 (2), 355–370.

Converse, P.E., 1964. The nature of belief systems in mass publics. In: Apter, D. (Ed.), Ideology and Discontent. The Free Press, New York.

DellaVigna, S., Kaplan, E., 2007. The Fox News effect: media bias and voting. Quarterly Journal of Economics 122 (3), 1187–1234.

Efron, M., 2004. The liberal media and right-wing conspiracies: using cocitation information to estimate political orientation in web documents. In: Proceedings of CIKM'04, Washington, DC, November 2004. ACM Press, pp. 390–398.

Frey, D., 1986. Recent research on selective exposure to information. Advances in Experimental Social Psychology, vol. 19. Elsevier, Amsterdam.

Garret, K., 2009. Politically motivated reinforcement seeking: reframing the selective exposure debate. Journal of Communications 59 (December (4)), 676–699.

Gentzkow, M., Shapiro, J., 2010. What drives media slant? Evidence from US daily newspapers. Econometrica 78 (1), 35–71.

Groseclose, T., Milyo, J., 2005. A measure of media bias. The Quarterly Journal of Economics 120 (4), 1191–1237.

Lewis, J.B., Poole, K.T., 2004. Measuring bias and uncertainty in ideal point estimates via the parametric bootstrap. Political Analysis 12, 105–127.

Miller, W.E., Merrill Shanks, J., 1996. The New American Voter, Cambridge, MA.

Mondo Times, 2013. The worldwide news media directory. Available at http://www.mondotimes.com

Munson, S.A., Resnick, P., 2010. Presenting diverse political opinions: how and how much. In: Proceedings of CHI'10, Atlanta, GA, April 2010. ACM Press, pp. 1457–1466.