Partisan Associations of Twitter Users Based on Their Self-descriptions and Word Embeddings*

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Abstract

We use word embeddings (specifically word2vec and doc2vec) to generate partisan associations from the descriptions (biographies) of a group of Twitter users who reported an election incident during the 2016 U.S. general election. A partisan association is the cosine similarity between a description's document vector and a vector that defines a partisan subspace. Partisan subspaces might be associated with individual word vectors, but we define them using differences and averages of word vectors. Our methods include three key innovations: we use document embeddings to study characteristics of Twitter users; we use a loss function keyed to our analytical goals to select hyperparameters for the doc2vec algorithm; we use a sampling idea to generate partisan association scores that are stable. We validate the partisan associations using other Twitter activities such as partisan retweets, favorites ("likes"), hashtag usage and following. We show how to take into account hostile usages of the partisan keywords that are the basis for the partisan associations. We show that the word and document embedding space derived from Twitter users' descriptions is portable to another contemporaneous social media domain (Reddit): in particular we predict the subreddit the user is commenting on using the embedding space produced from the Twitter descriptions. While we do not discuss how partisan associations may change over time, we show that descriptions change over time in ways that are plausible given users' partisan association scores.

1 Introduction

One of the principal problems facing political research that uses Twitter data is the lack of measures of Twitter users' attributes that social scientists often care about, including users' partisanship. Some have proposed methods that draw on other online behavior such as following or retweeting elite targets to get at partisan or ideological notions (e.g. Barbera 2015, 2016; Barbera, Casas, Nagler, Egan, Bonneau, Jost and Tucker 2019), but such methods have trouble with users who do not engage in those behaviors. While users may or may not follow or retweet informatively, most users do describe themselves in what Twitter calls "descriptions"[1] (sometimes described as biographies). Using word embeddings (e.g. Mikolov, Chen, Corrado and Dean 2013; Rheault and Cochrane 2019), we use Twitter descriptions from the last five weeks of the 2016 general election in the United States to compute what we call the "presidential campaign partisan associations" of individual Twitter users. The self-created descriptions mostly do not include explicitly political terms, but descriptions that do not include such terms often include terms that are associated with presidential campaigns or parties. Partisan associations differentiate Twitter users who describe themselves like "Republicans" or like "MAGA" from those who describe themselves like "Democrats" or like "Hillary."

Informally, the idea of our word embeddings method is to learn the non-partisan words that are in the contextual neighborhood of explicitly partisan words. Even if someone does not explicitly use partisan words, they may describe themselves with words that descriptions that feature explicit partisan expressions tend to contain. Our method computes partisan associations for many more users than do methods that attempt to assess similar notions using other kinds of online behavior.

This idea resonates with a line of research that studies the association between partisan sentiments and seemingly non-partisan activities, hobbies, and interests. Cultural objects and personal traits are increasingly associated with political actors or parties—when presented with

[1]Twitter describes the user description as "The user-defined UTF-8 string describing their account." See `https://developer.twitter.com/en/docs/tweets/data-dictionary/overview/user-object.html`.

an image of an individual in a given setting or list of personality traits, individuals frequently assume that the pictured or described individual is a member of a certain party (Goggin, Henderson and Theodoridis 2019; Haieshutter-Rice, Neuner and Soroka 2019; Hetherington and Weiler 2018). While people may or may not describe themselves in explicitly political terms on social media, they may describe hobbies, fandoms or traits that are associated with partisan sentiments. Learning the associations between non-partisan terms and partisan terms allows us to compute partisan associations of users who do not use explicitly partisan terms to describe themselves. Such associations are likely to be especially salient during the Fall of a presidential election, which is the time period we examine.

We implement this idea using word embeddings. There have been many recent works on word embeddings in political science (see, e.g. Monroe and Goist 2018; Rheault and Cochrane 2019). One major advantage word embeddings have over bag-of-words methods is that they take into account word ordering. The key assumption of word embeddings methods is the distributional theory, which contends that the contextual information of a word alone can give a viable representation of a word. This idea can find its roots in the works of Zellig Harris, John Firth, and Ludwig Wittgenstein (Gavagai 2015). Word embeddings methods map individual words—and, depending on the method also map phrases, documents, and covariates—to vectors of real numbers: the vectors are the embeddings. The vectors exist in a vector space. The vectors of similar words are closer to one another in vector space, while dissimilar words' vectors are farther separated in vector space.

Word vectors preserve a large degree of meaning between words. Some evidence for this is that linear algebra arithmetic—such as addition and subtraction—works approximately among the vectors. A famous example, using Google News headlines, is the king is to man as queen is to woman analogy (Mikolov, Chen, Corrado and Dean 2013). That is, using word vectors, and denoting *vec* as the word vector for a specific word,

$$vec(\text{king}) - vec(\text{man}) + vec(\text{woman}) \approx vec(\text{queen})\,.$$

Another famous example involves country capitals (Mikolov, Sutskever, Chen, Corrado and Dean 2013):

$$vec(\text{Paris}) - vec(\text{France}) + vec(\text{Poland}) \approx vec(\text{Warsaw})\,.$$

Word vectors are useful for expressing how words are related to one another.

In particular, we use doc2vec (Le and Mikolov 2014), a neural network-based word embeddings method. The method maps both words and documents to vectors in the same vector space, making documents and words comparable. Our documents are the Twitter descriptions (biographies), each of which we assume characterizes the user who supplied it. The embeddings are the input coefficients of the (single) hidden layer in a neural network (Mikolov, Chen, Corrado and Dean 2013; Mikolov, Sutskever, Chen, Corrado and Dean 2013).

To compute the partisan association of users, we first obtain document and word embeddings using doc2vec (using skip-gram with negative sampling paired with distributed bag-of-words) across all user self-provided descriptions in a database of Twitter users. Next, we choose a set of partisan keywords relevant to the time period of the Twitter users of interest. For example, because our Twitter users' descriptions come from the 2016 U.S. general election period, we choose keywords such as "Trump" and "Clinton" as well as "Republican" and "Democrat." The keywords might be considered separately or pooled. Separate treatment may be appropriate when we want to recognize and explore tensions that existed in the presidential election within parties concerning their presidential candidates. For instance, prominent Republicans famously declared "never Trump," so perhaps keywords like "Trump" and "MAGA" should not be pooled with "Republican."

Such distinctions are one aspect of why we describe the associations we derive using the expression "presidential campaign partisan associations." The other aspect of that full description has to do with the special nature of the campaign period and of the 2016 campaign period. We show some evidence that the partisan sentiments captured by the embeddings persist over time and that the associations we derive using Twitter descriptions carry over to contemporaneous posts in other social media (in particular Reddit), but we do not examine whether the associations themselves vary over time. Almost certainly they do vary, at least in detail. In 2012 or even in 2014 "MAGA" was not a thing, and "Republican" probably had different associations in 2004 than it did in 2016.

Thinking about pooled associations, two kinds of considerations arise. Using the linearity property of word embeddings, we can focus on what words have in common or on how words differ. While it is natural to think in terms of opposing keywords—e.g., "Republican" versus "Democrat"—it is important to recognize what the keywords represent that is similar among them. We will use five Republican keywords and five Democratic keywords. The average of all ten keywords' embeddings we call "usage" because it reflects how much descriptions use words that associate them with both parties and both major party candidates as opposed to not being associated with the parties or candidates. Differences between pairs of facially similar keywords—like the difference between *vec*(Republican) and *vec*(Democrat)—reflect degrees of association with one side or the other with the common usage component removed. Even descriptions that are only slightly associated with partisan usage overall might be associated more with one side than the other. If we want to ignore the differences between parties and candidates or campaigns we can also take the average difference between the Republican keywords' embeddings and the Democratic keywords' embeddings to create an omnibus "partisan association subspace" (Bolukbasi, Chang, Zou, Saligrama and Kalai 2016; Gentzkow, Shapiro and Taddy 2017).

In each case we take the cosine similarity between the document embeddings of each user's description and embeddings or vector averages or differences to produce partisan association scores. The cosine similarity produces a number between -1 and 1. When the cosine similarity is with an embeddings difference that subtracts Democratic embeddings from Republican embeddings, similarity values closer to -1 indicate descriptions that are closer to Democratic keywords, while numbers closer to 1 indicate descriptions that are closer to Republican keywords.

We attribute the resulting associations to the users that have the descriptions.

After reviewing related work, we describe the method of generating partisan association scores, which includes descriptions of three key innovations: using document embeddings to study characteristics of users; using a loss function keyed to our analytical goals to select hyperparameters for the doc2vec algorithm; using a sampling idea to generate partisan association scores that are stable. We apply the method to a group of Twitter users who reported an election incident during the 2016 U.S. general election. We validate the partisan associations using other Twitter activities such as partisan retweets, favorites ("likes"), hashtag usage and following. We show that this technique can be augmented to take into account hostile usages of the partisan keywords of interest. We show that the word and document embedding space derived from Twitter users' descriptions is portable to another contemporaneous social media domain (Reddit). Specifically, we show that we can predict the subreddit the user is commenting on using the word and document embedding space produced by users on Twitter. While we do not discuss how partisan associations may change over time, we show that descriptions change over time in ways that are plausible given users' association scores. Lastly, we discuss the implications of the partisan association score and how we believe that the partisan association score is similar to, but not equivalent to, measures of party identification known elsewhere in the political science literature.

2 Background Literature: Estimating Partisan Associations of Non-Elite Political Actors

A literature that gained traction in the past decade is estimating the ideal points of not only elite political actors (legislators, executives, judges, etc.) but also of non-elite political actors. Bonica (2013) created Campaign Finance Scores (CFScores), which uses an item-response theory (IRT) model to estimate both the ideal points of donors and politicians (Bonica 2013). The choice that the non-elite political actors are making is dividing up a pot of money among politicians; how they divide up that pot reflects their ideology. This allows him to estimate both the ideal points of people donating money (the non-political actors) and the ideal points of politicians (who they receive money from). A major and immediately apparent drawback of his approach is that it relies on the public donor database kept by the FEC, which only publicly discloses donations that were more at or more than \$200. According to a Pew Research Center of report, however, they found that most Americans donate less than \$100 to political campaigns: among those who donated, 55% reported donating less than \$100 (Hughes 2017). Thus, the CFScores are not measuring the ideology of ordinary Americans, but rather, those wealthy enough and/or are politically conscious (and active) enough to feel compelled to donate at least \$200 to a campaign.

Barbera (2015) develops a technique that measures ideology of both elite and non-elite political actors on Twitter. Assuming social networks are homophilic, Barbera (2015) develops a "Bayesian Spatial Following" model that considers ideology as a latent variable, whose value can be inferred by examining which elite political actors and partisan entities, such as Sean Hannity or Rachel Maddow, the user follows. The idea is that the more Republican (or Democratic) politicians an individual follows, the more Republican (or Democratic) the user leans. More specifically, he argues that the decision for a non-political actor to follow a political actor is based on the function of the squared Euclidean distance in the latent ideological dimension between user i and j: $-\gamma||\theta_i - \phi_j||^2$, where $\theta_i \in \mathbb{R}$ is the ideal point of user i and $\phi_j \in \mathbb{R}$ is the ideal point of user j, and γ is a normalizing constant (Barbera 2015). He finds that, using this model, that he can predict up to 90% of users' political contributions correctly based on their ideal point estimations.

There are a few drawbacks with his approach. First, it does not use any of the text information in the user's descriptions or their tweets; he only utilizes the user's descriptions to the extent that some explicitly describe their own political positions in order to validate his ideal point estimations from the user's network. Second, his assumption that users follow users based on the IRT model he develops is slightly incompatible with the rise of algorithmic feeds that Twitter employs. Users can potentially never see their tweets of politicians they no longer agree with on their personalized newsfeed. Third, Barbera's method requires extended calls to the Twitter API, which is particularly cumbersome if the analyst only has access to the free Twitter API and the users of interest follow tens of thousands of users. The method described in this paper only requires the user's description. Fourth, Barbera's method is difficult to update, particularly with changing political environments. As shown in the 2016 election, particularly on the Republican side, many new alt-right Twitter users gained a large following. This would require a re-estimation of the entire model in order to estimate their ideal points and to re-estimate the ideal points of other political actors and partisan entities. It is unclear if pre-existing political actors and partisan entities should remain in the list because users may continue to follow them, or if they should be removed because they may be considered irrelevant in the current political environment. Lastly, his technique requires the Twitter user to follow 8 or more elite political actors or partisan accounts in order to have an ideal point estimated; many Twitter users do not meet this requirement.[2]

Temporao, Kerckhove, van der Linden, Dufresne and Hendrickx (2018)'s text-based approach parses the lexicon of political elites using the Wordfish algorithm; users are then scaled by comparing the words they use on Twitter with the words political elites use on Twitter (Temporao et al. 2018). They assume that the social media content generated by political elites have a more "ideological focus relative to the general user base of a given platform," which means that if a user users language similar to that of a particular political elite, it may tap into the partisan association of the user. With social media's prominence in the last elections, much of the discourse on social media is often created by non-elite political actors themselves rather than created by the political elite. For example, many memes surrounding Donald Trump and Hillary Clinton were created by their respective supporters in 2016, and were often used in tweets and user descriptions. The candidates themselves, however, rarely engaged with these memes. Thus, Temporao et al.'s method seems to miss a rich aspect of the text they are examining: the textual elements that are generated and spread through users participating in the political process on a social media platform.

[2]See Section 6.

3 Partisan Associations from Word Embeddings

A word embedding method takes words from a given text and maps them into a real vector space, where each word maps to a single vector of real numbers in this vector space (e.g. Mikolov, Chen, Corrado and Dean 2013; Pennington, Socher and Manning 2014). The number of dimensions of this vector space is set by the analyst. The value of a word's vector takes into account the surrounding words, so rather than treating words individually, this approach contextualizes words; this has often been considered an advancement over bag-of-words methods. The idea that the meaning of words emerges from the linguistic contexts it inhabits across documents and spoken language is referred to as the distributional hypothesis (Gavagai 2015). This approach to NLP has dominated statistics and computer science since the development of word2vec in 2013 (Mikolov, Chen, Corrado and Dean 2013), and has even been applied to non-NLP problems, such as networks and genomics.

As mentioned before, word embeddings are useful because, although the method for generating the word embeddings may not be linear, it generates embeddings that are related to each other in linear ways. We call this the *analogy property* of word embeddings, because it is able to solve analogies through basic linear algebra arithmetic. Because of the linear analogy solving properties, word embeddings can also be directly compared using cosine similarity to see how similar or dissimilar words (or documents) are, because words with similar meanings are placed closer in word embedding space than words with dissimilar meanings.

3.1 Word Embedding Methods

3.1.1 Word2vec

This paper focuses on neural network-based embeddings. In particular, we focus on doc2vec (Le and Mikolov 2014), a variant of word2vec (Mikolov, Chen, Corrado and Dean 2013). The basis of `word2vec` is a shallow three-layer neural network (a single hidden layer, input layer, and output layer) that is trained on a *fake* task.[3] We use the skip-gram definition of the classification task, in which the model uses the current word to predict the surrounding context words. The input coefficients of the hidden layer are the word embeddings.

The skip-gram model uses the current word to predict the surrounding context words. Given a sequence of training words $w_1, ..., w_T$ and with T being the number of words in the sequence, the objective of the skip-gram model is to maximize the average log probability

$$L = \frac{1}{T} \sum_{t=1}^{T} \sum_{\substack{-c \le j \le c \\ j \ne 0}} \log p(w_{t+j} | w_t) \tag{1}$$

where c is the size of the training context (Mikolov, Sutskever, Chen, Corrado and Dean 2013). The larger the value of c is, the more training examples it takes on and can lead to higher accuracy at the cost of training time.

To calculate the conditional probability in (1), we use the softmax function,

$$p(w_t | w_{t-1}, ..., w_{t-n+1}) = \frac{\exp(h^T v'_{w_t})}{\sum_{w_i \in W} \exp(h^T v'_{w_i})}, \tag{2}$$

where w_t is the current word, h is the output vector of the penultimate network layer, v'_w is the output embedding of word w, and W is the collection of all words.[4] In the skip-gram formulation the probability is

$$p(w_O | w_I) = \frac{\exp\left(v'^T_{w_O} v_{w_I}\right)}{\sum_{w=1}^{W} \exp\left(v'^T_w v_{w_I}\right)}, \tag{3}$$

where v_w and v'_w are the "input" and "output" vector representations of w (Mikolov, Sutskever, Chen, Corrado and Dean 2013), and W is the number of words in the vocabulary. More informally, v_{w_I} is the word2vec word embedding and v'_{w_O} is the output layer.[5]

[3]For an introduction to neural networks, see Hastie, Tibshirani and Friedman (2009, chapter 11).

[4]Notice that the form of $h^T v'_{w_t}$ in (2) means that word embeddings are rotationally invariant: premultiplying h and v'_{w_t} by an orthonormal matrix P leaves the inner product unchanged. Such rotations also do not affect the cosine similarities we will use.

[5]In the notation of Mikolov, Sutskever, Chen, Corrado and Dean (2013), the current word is W_I and the surrounding

As a computational matter (3) is intractable, because the cost of computing $\nabla \log p(w_O|w_I)$ (needed for optimization) is proportional to the number of words in the corpus, which can be very large. Negative sampling makes this approach tractable. Mikolov, Sutskever, Chen, Corrado and Dean (2013) define negative sampling by the objective function

$$\log \sigma\left(v_{w_O}^{\prime T} v_{w_I}\right) + \sum_{i=1}^{k} \mathbb{E}_{w_i \sim P_n(w)} \left[\log \sigma(-v_{w_i}^{T} v_{w_I})\right]$$

where $\sigma(x) = 1/(1 + \exp(-x))$ and $P_n(w)$ is a noise distribution; that is, this is a distribution of words that do *not* belong in the context of the target word, w_I. This function replaces every $\log P(w_O|w_I)$ term in the skip-gram objective function. The remarkable property of negative sampling is that it requires k only in the range of 5–20; for small training datasets k can be as small as 2–5. This dramatically speeds up computational times compared to calculating $\nabla \log(p(w_O|w_I))$ directly.[6]

Mikolov, Sutskever, Chen, Corrado and Dean (2013) also propose subsampling frequent words. The logic is that words that occur very often—such as “in,” “the” and “a”—do not provide much information, while rarer words, such as “France” and “Paris” provide much more useful information. They address this issue by discarding words from the training set with probability $P(w_i) = 1 - \sqrt{t/f(w_i)}$, where $f(w_i)$ is the frequency of the word w_i and t is a chosen threshold.[7]

These sampling-based changes greatly improve the computational feasibility of word2vec. In Section 3.2.5 we address the samplings’ implications for reliability. The state-of-the-art word2vec implementation is arguably in Python’s `gensim` package (Řehůřek and Sojka 2010). For all the improvements made to word2vec, word2vec is still largely based on the above model.

words are W_O.

[6]The noise distribution $P_n(w)$ is a hyperparameter, but Mikolov, Sutskever, Chen, Corrado and Dean (2013) find that the unigram distribution $U(w)$ raised to a power of 3/4 (that is, $U(w)^{3/4}/Z$) outperforms most distributions, but they do not directly report results of their findings.

[7]Mikolov, Sutskever, Chen, Corrado and Dean (2013) set the default value $t = 10^{-5}$.

3.1.2 Doc2vec

Doc2vec (Le and Mikolov 2014) extends word2vec by creating a paragraph, or document, embedding in the same vector space as the word embeddings. This paragraph can be thought of as another word. The document vector is trained in the same way as the word embeddings, through stochastic gradient descent where the gradient is obtained by backpropogation.

We use the variant of doc2vec called the Distributed Bag of Words version of Paragraph Vector (PV-DBOW). This approach is analogous to the skip-gram approach in word2vec. Rather than trying to predict a target word using the context plus paragraph ID, this approach simply uses the paragraph vector to try to predict the words that exist within that paragraph. It does not require that the words be in any particular order, which is where the bag-of-words part of its name comes from. PV-DBOW does not create word embeddings, but PV-DBOW can be combined with skip-gram in order to create word embeddings even under PV-DBOW.

3.2 Computing Partisan Associations of Twitter Users

We exploit two key components of word embeddings to compute partisan associations of Twitter users: the ability for word embeddings to encode its typical contextual neighborhood and the linearity properties of word embeddings. This section fully describes the methods used to compute partisan associations of Twitter users using the users' self-provided biographies (their Twitter descriptions) using doc2vec.

The major steps are: first, select partisan keywords; second, choose the hyperparameters of the doc2vec algorithm, which we do guided by a loss function that is keyed to our analytical interests; third, create what we call the partisan subspaces; fourth, obtain partisan association scores using the partisan subspaces; fifth, apply a method motivated by sampling ideas to stabilize the scores. We describe these steps in the context of the 2016 U.S. general election, where our data (in the applications section) comes from.

3.2.1 Selecting Partisan Keywords

We choose keywords to reflect our interests and our ideas about what distinctions were important for the 2016 presidential campaign. We focus on the major party candidates and their campaign slogans, as well as the major party names. We use five Republican keywords and five Democratic keywords, matched pairwise by type. Four of the keywords are candidate names: "Trump," "Clinton," "Donald" and "Hillary." Two are the candidates' Twitter handles: "realdonaldtrump" and "hillaryclinton." Two are the campaigns' slogans: "MAGA" and "StrongerTogether." Two are the party names: "Republican" and "Democrat." While other words might also serve as explicitly partisan keywords, we think these words suffice to represent important partisan aspects of the presidential campaign period.[8]

We do not include words that express only disapproval or contempt for candidates or parties. For example we exclude "NeverTrump" as a possible keyword. We envision that use of the keywords relates to positive or at least neutral sentiments toward the referent entity. Section 5 describes how we dealt with people using the keywords in a hostile manner.

3.2.2 Hyperparameter Selection

Although there are multiple ways of selecting hyperparameters for word embedding methods, we select hyperparameters based on an application-specific loss function. Spirling and Rodriguez (2019) discuss hyperparameter selection when no specific goal is specified for the analysis.

Over the specifications listed in Table 1.[9] we chose hyperparameters to minimize loss defined using a set of models for the number of times each user retweeted or favorited ("liked") Tweets from a set of partisan accounts. For each specification, we use averages of ten sample replicates (see Section 3.2.5). The count model is a zero-inflated negative binomial regression model

[8]We also explored the usefulness of other keywords such as "left," "liberal," "progressive," "moderate," "centrist," "right," "conservative," "traditionalist," "libertarian," "socialist," "fascist," "nationalist" and "populist." We also checked the performance of facially nonpartisan words such as "cat," "dog, " "pasta," "hell," "sofa," "couch," "hammock," "seat" and "bench." All of the latter words except "pasta" showed significant signs of being associated with one or the other of the major parties.

[9]An exhaustive search over a grid including all possible combinations of hyperparameters was infeasible.

(Jackman 2017; Zeileis, Kleiber and Jackman 2008). The loss function measures whether the coefficients in the count part of the model have the correct (opposite) signs and how strongly a test rejects the hypothesis that the coefficients are equal.

*** Table 1 about here ***

We use two definitions for the set of partisan Twitter accounts. First are accounts that are partisan because of the way they are retweeted by members of the U.S. House and Senate: included is any account retweeted more than 90 percent disproportionally by one party's members in the U.S. House or Senate and by at least 50 members of one party.[10] We refer to these as Democratic or Republican accounts. Second are accounts listed as influential partisan or ideological accounts by three sources (Joyce 2016*a*,*b*; Faris, Roberts, Etling, Bourassa, Zuckerman and Benkler 2017).[11] We refer to these as right or left accounts. The two sets overlap.

We use cosine similarities for the ten keywords to specify linear predictors for the means in the count and zero-inflation parts of the zero-inflated negative binomial model. Using $\mathcal{J}$ = {(`trump`, `clinton`), (`donald`, `hillary`), (`republican`, `democrat`), (`realdonaldtrump`, `hillaryclinton`), (`maga`, `strongertogether`)} to denote a set of paired keywords, for paired keywords $j = (k_{1j}, k_{2j}) \in \mathcal{J}$ the linear predictors μ_C for the count part of the model and μ_Z for the zero-inflation part of the model are

$$\mu_{Cji} = a_{0j} + a_{1j}k_{1ji} + a_{2j}k_{2ji} \tag{4a}$$

$$\mu_{Zji} = b_{0j} + b_{1j}k_{j1i} + b_{2j}k_{2ji} + b_{3j}\log(m_i + 1)\,, \tag{4b}$$

where m_i is the number of retweets in the timeline of user i. We expect $\text{sign}(a_{1j}) \neq \text{sign}(a_{2j})$ with $\text{sign}(a_{1j}) > 0$ for counts of retweets or favorites of Republican accounts and $\text{sign}(a_{1j}) < 0$ for Democratic accounts.

[10] If m_D and m_R are the counts of retweets of an account by Democratic or Republican members of Congress in the members' timelines, the account must satisfy $m_D/(m_D + m_R) > .9$ or $m_R/(m_D + m_R) > .9$ and $m_D > 50$ or $m_R > 50$. 320 Democratic accounts and 328 Republican accounts satisfy these criteria. See Section 4.1 for the timelines' source.

[11] We use 78 right accounts and 55 left accounts.

To measure how well estimated coefficients match these expectations, we define a loss function that uses the indicator function $\mathcal{I}\left(\text{sign}(\hat{a}_{1j}) = \text{sign}(\hat{a}_{2j})\right)$ and the chi square statistic $\chi\left(\text{H0: } a_{1j} = a_{2j}\right)$ for the test of the hypothesis that $a_{1j} = a_{2j}$:[12]

$$\mathcal{L} = \sum_{j \in \mathcal{J}} \left(5\mathcal{I}\left(\text{sign}(\hat{a}_{1j}) = \text{sign}(\hat{a}_{2j})\right) - \frac{\chi\left(\text{H0: } a_{1j} = a_{2j}\right)}{\sqrt{n_j}} \right), \tag{5}$$

where n_j is the number of observations for pair j.

3.2.3 Obtaining the Partisan Subspaces

To obtain the partisan subspace, we take advantage of the analogy property of word embeddings. In the example of gender given by Bolukbasi et al. (2016), notice the assertion that

$$\mathit{vec}(\text{she}) - \mathit{vec}(\text{he}) + \mathit{vec}(\text{man}) \approx \mathit{vec}(\text{woman})$$

Simple rearrangement yields $\mathit{vec}(\text{she}) - \mathit{vec}(\text{he}) \approx \mathit{vec}(\text{woman}) - \mathit{vec}(\text{man})$. Thus the direction given by $\mathit{vec}(\text{she}) - \mathit{vec}(\text{he})$ captures approximately the same concept as the direction given by $\mathit{vec}(\text{woman}) - \mathit{vec}(\text{man})$. The vector differences define what Bolukbasi et al. (2016) calls the gender subspace. Given the varying usages of gendered words like "she," "woman," "her," etc., they suggest combining the difference vectors by finding principal components of this subspace. Kozlowski, Taddy and Evans (2018) suggests a simpler approach: simply average the difference vectors.

We take this idea to obtain partisan subspaces. We use the plural *subspaces* because we propose using multiple partisan subspaces. This is unlike Bolukbasi et al. (2016) or Kozlowski, Taddy and Evans (2018), who create a *single* gender subspace. Combining the various difference vectors, using either averages or principal components analysis, may seem to make sense at first glance. Combining the subspaces is based on the assumption that because there is approximate equivalence between the difference vectors we can simply combine them in some dimension

[12]When $\hat{a}_{1j}$ and $\hat{a}_{2j}$ have different signs the signs are always as expected, so we use equality as the test condition.

reduction fashion to capture an overall direction like "gender" in the word embedding space. However neither Bolukbasi et al. (2016) nor Kozlowski, Taddy and Evans (2018) actually show that this approximate equivalence is actually true. It is not clear if approximately equivalent means the the difference vectors should nearly have a cosine similarity of 1, or if a cosine similarity of 0.5 will suffice. As we show in Section 4.3, such analogies hardly hold up among partisan keywords.

As defined in Section 4.3, we use various partisan subspaces. For example, using terms from the 2016 U.S. general election, there is a substantive difference between usages of the words "Trump" and "Republican." Many Republicans did not support Trump's presidential bid, and many of Trump's supporters, likewise, did not identify as Republicans. Thus while both $vec(\text{Trump}) - vec(\text{Clinton})$ and $vec(\text{Republican}) - vec(\text{Democrat})$ may represent versions of the partisan subspace, they point to two distinct and interesting versions.

3.2.4 Computing the Partisan Association Score

Obtaining the partisan association scores for the various subspaces is straightforward. Because of the linearity property of word embedding spaces, we can directly compare document and word embeddings using the cosine similarity measure.[13] Cosine similarity takes a value between -1 and 1: -1 indicates that the vectors are directly opposite; 1 indicates that the vectors are exactly aligned; 0 indicates the vectors are orthogonal to each other.

The partisan association score is defined as, for description document embedding D_i for user i and P (the difference vector that defines the partisan subspace),

$$\text{Partisan Association Score} = \frac{D_i \cdot P}{||D_i||||P||} \tag{1}$$

P is, in turn, each of the differences discussed in the previous subsection and defined in Section 4.3. By in each case subtracting the Democratic embedding from the Republican embedding,

[13] The cosine similarity measure is defined as, for vectors A and B of the same dimension, $\cos(A, B) = A \cdot B/||A||||B||$. Cosine similarity does not take length of the vectors into account. There is debate in the word embedding literature about what the length of the word and document embeddings mean [e.g.][]SchakelWilson.

negative numbers represent more Democratic descriptions while positive numbers represent more Republican descriptions.

3.2.5 Obtaining Stable Partisan Association Scores: Multiple Replicates of Doc2vec

As detailed in sections 3.1.1 and 3.1.2, there are many sampling aspects of doc2vec that help the algorithm produce good embeddings that preserve meanings in a reasonable time frame. Negative sampling and subsampling not only help speed up fitting the embeddings, but produce even better embeddings than the algorithm would produce if it did not use negative sampling and subsampling. Also stochastic gradient descent involves sampling. Such sampling implies there is sampling variation across replicates: successive independent executions produce different embeddings, differences that reflect more than mere rotational differences.[14] Parallelization introduces additional variability: even fixing the seed, one cannot obtain the exact same embeddings using the same hyperparameters because of ordering jitter from operating system thread scheduling. The instabilities due to parallelization and stochastic gradient descent are minimal, but the sampling-induced variations are more substantial.

We adopt a sampling solution to the sampling variations. In general, the average of several means from independent samples from the same population has smaller variability than any one of the separate sample means. We view the cosine similarities as such sample means, hence we use the average of the similarities computed using several replicates. To be more precise, word embeddings are numbers that result from approximating a function that maps words into numbers. The word embedding algorithms use various sampling steps to make it feasible to approximate the function. For N users and K keywords, cosine similarities computed using the word embeddings are $N \times K$ functions of the sample estimates. We generate a number of realizations of the cosine similarities for each keyword then average them to get average cosine similarities for the keyword.

The averages are more reliable than similarities computed using single replicates. For instance, the correlations between pairs of replicates using the ten keywords `trump`, `clinton`,

[14] See note 4.

`donald`, `hillary`, `republican`, `democrat`, `realdonaldtrump`, `hillaryclinton`, `maga` and `strongertogether` are .96, .93, .95, .95, .95, .94, .94, .94, .95 and .92, but the correlations between pairs of averages of ten replicates are .99, .99, .99, .99, .99. .99, .98, .99, .99 and .98. The correlations between pairs of averages of fifteen replicates are all .99 or greater. We use averages of ten replicates.

4 Application

4.1 Primary Twitter Data

The description data we use were collected by Mebane, Wu, Woods, Klaver, Pineda and Miller (2018). Mebane, Pineda, Woods, Klaver, Wu and Miller (2017) and Mebane et al. (2018) detail motivations for collecting the data and the procedures used. Briefly, during October 1–November 8, 2016, Mebane et al. (2017) used Twitter APIs with keywords[15] to collect slightly more than six million original Tweets (excluding retweets) from which, using supervised text classification methods, Mebane et al. (2017) recovered 315,180 Tweets that apparently reported one or more election "incidents" (Mebane et al. 2018). 215,230 distinct users posted the Tweets classified as apparent incidents. Of these, 194,336 users had nonempty descriptions,[16] which are the descriptions we use to compute embeddings. The longest description string contains 395 characters, and the median nonempty string length is 96 characters.

We also use these 215,230 users' timelines and favorites ("likes"). Timelines were collected during January 24–February 3, 2018, and favorites were collected during May 14–July 26, 2018.[17] Timelines could be obtained for 196,276 users, each timeline containing between one and 3,399

[15] See Mebane et al. (2017) for these keywords.

[16] Each user's description is the `user$description` string included in the Tweet JSON object for the earliest apparent incident Tweet (during Oct 1–Nov 8) from that user.

[17] To get timelines and favorites we used Twython's (McGrath 2016) `get_user_timeline` and `get_favorites` methods. Twitter limits the number of Tweets that can be obtained using these methods to "up to 3,200 of a user's most recent Tweets" (Twitter 2018). Sometimes we obtained a few more Tweets than that limit. We use a PostgreSQL (Stonebraker and Rowe 1986) database to organize data.

Tweets. Overall the timelines contain 527,961,969 Tweets, of which 177,802,950 are retweets.[18] Favorites could be collected for 185,531 users, and the favorites contain 318,871,273 Tweets. The first Tweet in most timelines and favorites sets is from well before October 1, 2016, and the last Tweet in most is from well after November 8, 2016: Figure 1 displays the time ranges covered by the timelines and favorites for each user. While the last times for all Tweets in timelines predominantly occur after late 2016, the retweets have last times that are more broadly distributed since late 2009. The distribution of last times for favorites resembles that for the retweets.

*** Figure 1 about here ***

In addition to the set of initial descriptions from during Oct 1–Nov 8, 2016, from Tweets that matched keywords used with the APIs and were sent by an incident-Tweeting user we also have descriptions from all original Tweets during the same time period and from all Tweets during Nov 9–Dec 31, 2016. We also have all descriptions obtained while downloading users' timelines during Jan 24–Feb 3, 2018. For the 2016 descriptions the timestamp matches the time of the Tweet the description was part of. For the 2018 descriptions the description is what the user had at download time, and timestamps match the time of download. In all we have 647,572 unique (per user) description strings.

On May 10, 2018, we obtained timelines for all members of the House and Senate who on May 7 were listed at the Twitter accounts for "HouseGOP," "HouseDemocrats" or "SenateDems." Using a collection we did during February 18–March 5, 2018, of up to 10,000 of the Twitter "friends" of each of the 215,230 users—a "friend" is another user the user follows—we counted how many members of the House and Senate the users followed in those "friend" sets.

4.2 Hyperparameter Selection

Table 2 shows loss function values for the hyperparameter specifications.[19] Specification 29 has the smallest loss when the losses for all four sets of counts are summed, and that specification has

[18] 192,063 users have at least one retweet in their timeline.

[19] Loss values for specifications 44 and 45 are not shown because they are same as those for specification 29.

the smallest loss when only retweets are considered. Specification 36 has the smallest loss when only favorites are considered (specification 29 has the second or third smallest loss for favorites). For our embeddings we choose specification 29: the default hyperparameters but with 75 instead of 300 dimensions.

*** Table 2 about here ***

4.3 Partisan Subspaces and Analogies

We develop four different partisan subspaces. We consider various subspaces because, as we show, they reflect different types of partisan associations that exist during the presidential campaign period. For example during the 2016 election, many Republicans did not support Trump, and many Democrats also did not support Clinton. The partisan subspace generated using $vec(\text{Trump}) - vec(\text{Clinton})$ is substantively different from the partisan subspace generated using $vec(\text{Democrat}) - vec(\text{Republican})$. The subspaces are:

1. Names Subspace: $\dfrac{[vec(\text{Trump}) + vec(\text{Donald})]}{2} - \dfrac{[vec(\text{Clinton}) + vec(\text{Hillary})]}{2}$
2. Parties Subspace: $vec(\text{Republican}) - vec(\text{Democrat})$
3. Slogans Subspace: $vec(\text{MAGA}) - vec(\text{StrongerTogether})$
4. Handles Subspace: $vec(\text{realdonaldtrump}) - vec(\text{hillaryclinton})$

We use the analogy property of word embeddings to support using these partisan subspaces. Although Mikolov, Chen, Corrado and Dean (2013) assert the analogy property is a core aspect of word embeddings, it is not a given that every analogy works out as expected. We can directly analyze this by looking at the words closest to specific vectors. For example, if we take the vector $vec(\text{Trump}) - vec(\text{Donald}) + vec(\text{Clinton})$, we might expect the closest vector to be $vec(\text{Hillary})$. This section examines how well such analogies hold up and why these analogies support our decision to use separate subspaces rather than combining all subspaces into a single partisan subspace, as the literature (such as Bolukbasi et al. (2016) and Kozlowski, Taddy and Evans (2018)) has previously done.

To analyze how well the subspaces perform, we use the subspaces and add a Democratic keyword. The expected result should be the Republican keyword corresponding to the Democratic keyword added onto the subspace. For example, if we have $vec(\text{Republican}) - vec(\text{Democrat}) + vec(\text{Clinton})$ we might expect the closest word vector to be $vec(\text{Trump})$.

Table 3 lists the linear algebra arithmetic we calculated. Each line starts with one of the above partisan subspaces, and adds a Democratic keyword. We list the closest word vector to the resultant vector and the cosine similarity between the closest word vector and the resultant vector. We also list the expected closest word and its cosine similarity. What we mean by "closest word vector" is the word vector with the highest cosine similarity to the resulting vector. Calculations were done using the `most_similar` function in the `gensim` package. We note if the expected word vector is not one of the top 10 closest word vectors.

*** Table 3 about here ***

We see that, overall, the subspaces perform as expected. Although it did not always return the expected word, the closest word vector was usually a Republican-associated word. The subspace that performed the worst was the Party subspace. We can see that several Democratic keywords were the closest word vectors to the resultant vectors when it was based on the Party subspace. Thus the Party subspace seems to be capturing a different aspect of partisan expression than the other partisan subspaces. Besides the Party subspace performing poorly, we see the Names subspace performs better when using the two names rather than using the names individually.[20] This may come from the fact that the "natural pairing" of "Trump" with "Clinton" and "Donald" with "Hillary" may not actually be the best pairing: "Trump" might be better paired with "Hillary" than with "Clinton."

[20]"ImWithYou" was a hashtag used by Trump supporters, used as a response to the Democratic candidate hashtag "ImWithHer."

We can further explore the poor performance of the Partisan Party subpsace by running a different set of analogies. We can, instead of using the partisan subspaces, add together the "natural pairings" that exists: Clinton-Trump, Donald-Hillary, Republican-Democrat, realdonaldtrump-hillaryclinton, and MAGA-StrongerTogether. We then subtract out, one-by-one, one of the other keywords. As an example we would calculate
vec(Trump) + *vec*(Clinton) − *vec*(Donald) and see what word vector was closest to this resulting vector. Here we would expect the closest word vector to be *vec*(Hillary). See Table 4 for the results of this analysis.

*** Table 4 about here ***

In Table 4 we see that the closest words when adding together the words "Democrat" and "Republican" and subtracting out one of the other keywords are words like "committee," "county," "party," and so on. Thus these seem to be more formal indications of partisan associations to one of the major parties rather than indicating support for one of the major candidates in the 2016 election. This analysis reinforces the idea that the different partisan subspaces capture different aspects of partisan association.

Because the partisan subspaces seem to be capturing different aspects of partisan association, we eschew generating an overall partisan association score using an averaged partisan subspace in which the five Democratic vectors are subtracted from the five Republican vectors.

4.4 Partisan Associations

We show the distribution of scores for the four partisan subspaces along with a score computed using the average of the ten keywords' vectors. We refer to the latter score as `usage`, in that it captures the extent to which users' tend to use partisan language regardless of directional focus. `usage` is based on the average of all ten keyword vectors while `party`, `names`, `handles` and `slogans` are based on paired vector differences.[21]

[21] `party` is based on *vec*(Republican) − *vec*(Democrat); `names` is based on *vec*(Donald) + *vec*(Trump) − *vec*(Hillary) − *vec*(Clinton); `handles` is based on *vec*(realdonaldtrump) − *vec*(hillaryclinton); and `slogans` is based on *vec*(maga) −

The average vector that is the basis for `usage` captures what the keyword vectors have in common, so `usage` tends to be uncorrelated with the four difference-based associations. Table 5 reports Pearson product-moment correlations between the ten keywords' scores and the scores for the average and difference scores. The keywords' scores are all positively correlated with one another, although the strength of the correlations varies. `usage` is strongly and positively correlated with all ten keyword scores, and the four difference scores are almost always positively correlated with Republican keywords and negatively correlated with Democratic keywords. A small but positive correlation between `handles` and `clinton` is the exception. `usage` is positively but only weakly correlated with the difference scores, and the difference scores are all positively correlated with one another.

*** Table 5 about here ***

Correlations do not tell the whole story about the joint distribution of the scores. The pairwise distributions are not exactly elliptical. Scatterplots of `usage` against the four difference scores in Figure 2 all exhibit greater variation in the difference score for high values of `usage` than for low values. Such variation when `usage` is high is largest for `slogans` and second largest for `names`. People who do not much use partisan language, according to `usage`, can be discriminated in their similarity to Republican as opposed to Democratic language, but the diversity among the set of low `usage` people is smaller. In Figure 3, which shows scatterplots of pairs of the difference scores, the extra dispersion is evident is the noticeable variability in the tails of the plotted points. Relationships between pairs of difference scores are moderate or strong: the smallest correlation is .48, between `party` and `handles`, and the biggest is .72, between `handles` and `slogans`.

*** Figures 2 and 3 about here ***

vec(strongertogether).

4.5 Partisan Associations and Retweets, Favorites and Hashtags

We use zero-inflated negative binomial regression models (Jackman 2017; Zeileis, Kleiber and Jackman 2008) to check how the partisan association scores are conditionally associated with use of partisan retweets, favorites (or "likes") and hashtags. The question is whether partisan associations relate as expected to the frequency with which such partisan actions occur. The more that happens, the more we view partisan associations as measures of partisan engagement and sentiment.

Outcome variables for the regression models are the counts of the number of partisan retweets, favorites or hashtags that occur in each user's timeline. We have the two definitions from Section 3.2.2 for partisan retweets and favorites: "Democratic" versus "Republican"; and "left" versus "right" retweets or favorites. To identify "left" or "right" hashtags we selected from hashtags used by a sample of users who had the words "left" or "right" in their descriptions.[22]

We expect users that have more Republican (or Donald or Trump or realdonaltrump or maga) than Democrat (or Hillary or Clinton or hillaryclinton or strongertogether) associations to more frequently retweet and favorite Republican and right than Democratic and left targets, and likewise more often to use right than left hashtags. This basic directional intuition is subject to two caveats. One is that, as users often write in Tweets in our data, "retweets are not endorsements": that users are retweeting, favoriting or using a target does not mean they have or mean to express positive sentiments toward that target. This caveat raises interpretational

[22]Sampling 160 users each from the 6249 users who used the word "left" in their descriptions and from the 6652 users who used the word "right," we used information from their names, descriptions and timelines (e.g., URLs) to label each user Left, Right or Other. There were 118 Left users and 163 Right users. We then identified all the hashtags in the Left and Right users' timelines and obtained the frequency with which each was used. To represent the left and right hashtags, we selected from hashtags that were used by both Left and Right users but used much more frequently by one group than by the other. The left hashtags are (in lower case) "arpx," "smartnews," "stoprush," "goptaxscam," "medicareforall," "trumpcare," "impeachtrump," "trumprussia," "lgbtq," "theresistance," "trumpshutdown," "aca," "gunsense," "resistance," "imwithher," "demsinphilly," "womensmarch2018," "dreamers," "shitholepresident," "resist," "gopshutdown," "taxscambill," "removenunes," "singlepayer," "notmypresident," "feelthebern," "lgbt," and the right hashtags are "pjnet," "trumpadmin," "ccot," "qanon," "schumershutdown," "tucker," "iranprotests," "prolife," "buildthewall," "boycottnfl," "lockherup," "presidenttrump," "americafirst," "tcot," "draintheswamp," "releasethememo," "deepstate," "fisamemo," "teaparty," "liberals," "trumptrain," "makeamericagreatagain," "winning," "ldsconf," "trump2016," "maga," "fisa," "hannity," "fakenews," "benghazi," "fakenewsawards," "democrats," "foxnews," "isis," "neverhillary," "taxreform."

concerns that we address in Section 5.

The other caveat is that in addition to possible directional motivations users may have varying tendencies to retweet, favorite or use hashtags at all. This consideration enhances the motivation to use the zero-inflated specification, in that the zero-inflation part of the model can detect users who do not much engage in such behaviors, let alone with respect to partisan targets. It is easy to observe that the distributions of retweet, favorite and hashtag counts have excessive zeros compared to any conventional count distribution (Figure 4). The zero-inflation parts of the models include counts of the total retweets, favorites or hashtags in each user's timeline to try to adjust for relevant variations in general behavior.

*** Figure 4 about here ***

The model specification varies slightly from the specifications used in Section 3.2.2. Now instead of using paired keywords the regressors are cosine similarities to averages or differences of embeddings: `usage` and a member of $\mathcal{D} = \{\texttt{party}, \texttt{names}, \texttt{handles}, \texttt{slogans}\}$. For $d \in \mathcal{D}$, the linear predictors μ_C and μ_Z for the count and zero-inflation parts of the model are

$$\mu_{Cdi} = a_{0d} + a_{1d}d_i + a_{2d}\,\texttt{usage}_i \tag{6a}$$

$$\mu_{Zdi} = b_{0d} + b_{1d}d_i + b_{2d}\,\texttt{usage}_i + b_{3d}\log(t_i + 1) + b_{4d}\log(m_i + 1)\,, \tag{6b}$$

where t_i is the number of Tweets (`statuses`) and m_i is the number of either retweets, favorites or hashtags in the timeline of user i. We expect $\text{sign}(a_{1d}) > 0$ for Republican targets and $\text{sign}(a_{1d}) < 0$ for Democratic targets: e.g., a more Republican-versus-Democratic association, which correspond to positive values of `party`, should tend to mean greater production of Republican retweets, favorites and hashtags and less production of Democratic ones. It is also reasonable to expect that those who associate more with partisan language, regardless of direction, should participate more in the kinds of partisan discourse that retweets, favorites and hashtags represent, so for all types of targets we also expect $\text{sign}(a_{2d}) > 0$. It may also happen that there is a directional component to the tendency to produce any rather than no partisan retweets, favorites or hashtags, in which case we should see $\text{sign}(b_{1d}) < 0$ for Republican targets and $\text{sign}(b_{1d}) > 0$ for Democratic targets.

As Figure 5 shows, expectations for the coefficients in the count part of the model are always confirmed: $\text{sign}(\hat{a}_{1d}) > 0$ for Republican and right targets, $\text{sign}(\hat{a}_{1d}) < 0$ for Democratic and left targets (Figure 5(a)), and $\text{sign}(\hat{a}_{2d}) > 0$ for all types of targets (Figure 5(b)).[23] The zero-inflation part of the models partly matches expectations. Figure 5(c) shows that coefficients for Democratic and left retweets and favorites satisfy $\text{sign}(\hat{b}_{1d}) > 0$, and those for Republican retweets and favorites and right retweets satisfy $\text{sign}(\hat{b}_{1d}) < 0$, but coefficients for only three of four left hashtags, two of four right hashtags and one of four right favorites satisfy the expectations. While we have no expectations for the coefficients of `usage` in the zero-inflation part of the models, Figure 5(d) shows that $\hat{b}_{2d}$ is more positive for Democratic and left targets than for Republican and right targets: higher association with partisan language goes with more use of Republican targets and less of Democratic ones.

*** Figure 5 and Tables 6, 7, 8, 9, 10, 11, 12, 13, 14 and 15 about here ***

4.6 Partisan Association Score and Other Terms

We examine the distribution of the various partisan association scores of words that were *not* used to compute the partisan association subspace in order to see if the scores are placed as expected. We look at three specific terms: "ImWithHer", a popular hashtag used by supporters of Hillary Clinton, "MakeAmericaGreatAgain", a popular hashtag used by supporters of Donald Trump, and "NeverTrump", a hashtag used by both Democrats and Republicans that did not support Donald Trump's candidacy.

We graph the distributions of the partisan association scores for users who used one of the three terms not used to compute the partisan association scores in Figure 6.

*** Figure 6 about here ***

[23] Tables 6, 7, 8, 9, 10, 11, 12, 13, 14 and 15 report full details about the estimations.

The distributions of the partisan association scores, relative to various partisan subspaces, makes sense for each term. The distribution of the scores for users who used the term "ImWithHer" tend to be left of the users who used the term "MakeAmericaGreatAgain." The most interesting observation is the distribution of users who used the term "NeverTrump" in their profile, which included both Democratic and Republican users. These are the users who may have not explicitly affiliate themselves with a campaign, such as Republicans who did not want to vote for Trump. Thus their center placement makes sense—the left of the scale represents users who are associated the Democratic campaign, the right are users who associate themselves with the Republican campaign, and the center represents users who have not clearly associated themselves with a campaign (only demonstrated a repudiation of a campaign). We see that this pattern holds across the partisan association scores based on the parties subspace, names subspace, handles subspace and slogans subspace.

5 Hostile Usages of Keywords

Not everyone uses keywords with affirmation—e.g., not everyone uses the word "Trump" to express support for Donald Trump. During the 2016 election many Twitter users expressed contempt toward one (or both) of the main candidates. Many descriptions that contain one or more of the ten keywords express hostility toward the referent, and probably many of the partisan associations for descriptions that do not include a keyword do as well. In a sample of descriptions that contain a keyword or a related word, 18.5 percent contain a hostile expression: 9.5 percent hostile toward a Republican word, 7.6 percent hostile toward a Democratic target and nine percent hostile towards referents from both parties.[24]

Inspired by Gong, Bhat and Viswanath (2016), we develop a classifier[25] that differentiates

[24]We labeled as hostile or not a sample of 500 descriptions from the 4,276 descriptions that contain one or more of the ten keywords, and another sample of 500 from the remaining 3,776 descriptions plus 1,912 descriptions that contains one or more of the words "pence," "kaine," "conservative," "traditionalist," "liberal," "progressive," "dem," "rep," "left," "right," "moderate," "middle" and "independent." Two descriptions in the sample have identical texts.

[25]For classification purposes a keyword is used if it stands alone or is adjacent to a special character. For example, "#Trump" counts as a use of the keyword "Trump," but "TrumpTrain" does not. Including keywords adjacent to

between hostile and not-hostile usages of the keywords.[26] We label keywords as used in a hostile manner or not, then classify unlabeled keywords. The labeled or classified keywords are used to compute embeddings.

5.1 Design of the Support Vector Machine Classifier

Using a training set of 1,000 user descriptions that used at least one keyword[27], we associate each keyword contained in a description with the description. If a description contains more than one keyword, we separate the description into multiple observations. For example, if the description states, "I support Donald Trump," we separate this description into two observations: one for"Donald," and one for "Trump." We create a "tall" dataset in this fashion to accommodate instances where a person may simultaneously use one keyword in a not-hostile fashion while using another in a hostile manner. Creating such a "tall" dataset we get 1,271 observations in the training set, each labeled as a not-hostile usage of a keyword or a hostile usage of the keyword.

The main innovation of our approach is in the creation of features beyond simple text features we used in the classification process. These features are

1. `Both`: whether the user used both a Democratic and Republican keyword in their biography
2. `Republican Word Count`: how many Republican keywords the user used
3. `Democratic Word Count`: how many Democratic keywords the user used
4. `Dummy Variables for the Keywords`: indicator variables for each of the 10 keywords which is 1 for the keyword currently being classified as hostile or not-hostile, and 0 for the other keywords

special characters produces 5,918 descriptions that have keywords. Excluding such (except # and @) produces 4,276.

[26]Newer embeddings methods take into account varying contexts to define multiple embeddings for specific words (for example, mapping "bank" in "bank of the river" to an embedding that is different from "bank" in "depositing money at the bank"), such as BERT (Devlin, Chang, Lee and Toutanova 2018), and further research is needed to understand how to adapt these methods to our particular task.

[27]See note 24.

5. `Dummy Variables for All Keywords`: indicator variables for each of the 10 keywords which is 1 for any keyword used in the profile and 0 for keywords not used

6. `Partisan Affiliation Score`: overall partisan affiliation score generated, using the average of the five Democratic keywords subtracted from the average of the five Republican keywords, when not taking into account hostile or not-hostile usages of keywords

7. `Partisan Affiliation Score, Partisan Keywords Removed`: the overall partisan affiliation score generated, using the average of the five Democratic keywords subtracted from the average of the five Republican keywords, when we take the cosine similarity between the average partisan subspace and the inferred document vector of the user description when all partisan keywords are removed from the user description

In line with the literature, we use a Gaussian kernel support vector machine classifier. We split the labeled dataset into a training set and a holdout set; to fit the hyperparameters, we use tenfold crossvalidation on the training set. We then use the SVM classifier on the holdout set. Precision, recall and F-measure assessments of classification performance, shown in Table 16, match or exceed the state of the art as found in Gong, Bhat and Viswanath (2016).

*** Table 16 about here ***

5.2 Classifying and Embedding

We classify keywords then use the classified keywords to compute hostility-aware embeddings. We apply the hostility classification process of Section 5.1 to descriptions that contain keywords but were not labeled as hostile or not-hostile. Of the 7,500 usages of partisan keywords, 1,376 instances are predicted to be hostile—approximately 18.3% of the instances of keywords. 748 of the 1,376 instances are hostile usages of Republican partisan keywords (9.97%), while 628 of the 1,376 instances are hostile usages of Democratic partisan keywords (8.37%). These percentages match the proportions in the training set. To make not-hostile and hostile usages of keywords lexically distinct, we append "_hostile" to the end of keywords that are labeled or classified hostile (e.g., "clinton_hostile"). We then produce a document and word embedding space as described in Section 3.2, except now not-hostile and hostile usages of the keywords are mapped onto distinct vectors.

We calculate Names, Party, Handles, and Slogans subspaces using, respectively, only the not-hostile variants and only the hostile variants of the partisan keywords, and calculate their respective partisan association scores.[28] In the remainder of the paper we refer to the original partisan associations based on not differentiating between hostile and not-hostile usages as agnostic partisan associations.

Not-hostile partisan associations relate to one another much as agnostic associations do, but hostile partisan associations exhibit distinctive patterns. Table 17 shows correlations among the not-hostile and hostile partisan associations. Correlations among not-hostile associations resemble those reported for agnostic associations in Table 5. All but one of the correlations among hostile partisan associations are negative, and most are small. The exception is intriguing: those closer to "realdonaldtrump_hostile" than to "hillaryclinton_hostile" tend to be more similar to "Democrat_hostile" than to "Republican_hostile" ($r = -.40$). Correlations between not-hostile and hostile associations are as likely negative as positive and generally small. The correlations between not-hostile and hostile `usage` ($r = .67$) and between not-hostile `handles` and hostile `usage` ($r = .19$) are exceptionally large: users whose description is closer to "realdonaldtrump" than to "hillaryclinton" tend to be closer to more hostile usages averaging over all of the ten keywords. All the not-hostile partisan association differences are negatively correlated with their hostile counterparts: so those closer to "Republican" than to "Democrat" tend to be more similar to "Democrat_hostile" than to "Republican_hostile" ($r = -.099$), etc. The scatterplots in Figure 7 emphasize that these negative correlations are small.

*** Table 17 and Figure 7 about here ***

Such negative correlations between corresponding associations appear even more strongly

[28]No usages of "strongertogether" are labeled hostile, so a hostile Slogans subspace cannot be computed.

when agnostic partisan associations are related to hostile associations (Table 18). The respective agnostic versus hostile correlations are: `names`, $r = -.25$; `party`, $r = -.16$; and `handles`, $r = -.16$. Table 18 shows that correlations between corresponding agnostic and not-hostile partisan associations range from $r = .95$ to $= .98$.

*** Table 18 about here ***

6 Following Members of Congress

While our count of how many members of Congress each user follows based our "friends" data collection[29] is not a perfect measure of such following, the counts suggest how many more users our partisan association method covers than methods that rely on following activity. Barbera et al. (2019, 6) require "supporters" of a party to follow three or more members of Congress from that party and no members of the other party, along with other requirements. In our "friends" sets we find that 26,938 users follow three or more Republican Congressmen or Senators and 45,656 follow three or more Democrats, and 9,584 follow three or more Republicans and no Democrats while 22,847 follow three or more Democrats and no Republicans.

We use zero-inflated negative binomial regression models to check how the partisan association scores are conditionally associated with following members of Congress. Table 19 shows models using each of the differences `party`, `names`, `handles` or `slogans` along with `usage` as regressors in the count model linear predictor, and those variables plus a function of the number of Tweets (`statuses`) are used in the linear predictor for the zero-inflation model. The `statuses` variable is omitted from the models for Republican member following because it triggers covariance matrix singularity problems in those zero-inflation models. The partisan associations used for the models of Table 19 are the agnostic associations. Table 20 shows models that use the partisan associations computed using the hostile forms of the keywords.

*** Tables 19 and 20 about here ***

[29]See Section 4.1.

Our expectations for the zero-inflated regression models concern only coefficients in the count models. We expect that the agnostic difference partisan associations should have positive coefficients in the count models for following Republican members and negative coefficients in count models for following Democratic members. Such coefficients mark straightforward party-aligned behavior. Agnostic `usage` should have positive coefficients in the count models for both parties: higher `usage` means more similarity to standard partisan language and so likely more involvement with federal elected officials. The difference partisan associations based on hostile keyword usages should have signs opposite those observed for the agnostic associations. Hostile `usage` we expect to have positive coefficients in the count models for both parties.

With one exception, expectations for the coefficients in the count models are fulfilled. The exception occurs in Table 20: the sign of the coefficient of `names_hostile` in the model for following Republican members is positive. As a user's decription is more similar to `donald_hostile` + `trump_hostile` than to `hillary_hostile` + `clinton_hostile`, the user tends to follow more Republican members of Congress. The simplest explanation is that this pattern relects the activities of Never Trump Republican sympathizers, but of course we can't be sure of that.[30]

Barbera et al. (2019) use voter registration data to help validate their party supporters measure. We lack such data, but we borrow support for the partisan associations from their validations. The partisan associations conditionally associate with the number of members of Congress a user follows, and the conditional associations are plausible—the one unexpected coefficient value turns out to be plausible as well. More evidence, we think, for partisan associations measuring partisan engagement and sentiment, and for partisan associations being diverse.

[30] There is no hostile difference for `slogans`, because no user used "StrongerTogether" in a hostile manner. See 28.

7 Portability of the Twitter Embedding Space

To investigate the extent to which the embeddings found for the Twitter descriptions apply to other domains, we turn to the social media site Reddit. Our goal is to check whether agnostic word embeddings learned from the Twitter descriptions appropriately discriminate among texts produced during the same time period on another social media platform.

Like Twitter, Reddit is one of the most popular sites on the internet and research shows that Reddit users frequently consume news on the site, including election-related news (Mitchell, Holcomb, Barthel and Stocking 2017). To find representative content supporting both candidates, we turn to the most prominent subreddits dedicated to supporting the 2016 major party presidential candidates: r/The_Donald and r/hillaryclinton. These subreddits were selected based on news articles analyzing discussion of the respective candidates on Reddit (see Martin 2017; Mitchell et al. 2017; Kaiser 2018). Between October 1 and November 8, 2016, these subreddits contain respectively 2,316,307 and 316,057 comments.[31] Both r/The_Donald and r/hillaryclinton are extreme in containing expressions of support for the respective candidates, abetted by moderation (see e.g. Sommer 2019).

We include as well a subreddit that on its face appears not to be related to the 2016 presidential contest nor even to politics in general. We assess lack of relatedness in terms of overlap in users. We use a subreddit that has minimal similarity in terms of users but also has a substantial number of comments.[32] The subreddit r/pcmasterrace—devoted to general discussion of PC gaming—has

[31] We obtained Reddit data from Google BigQuery (2019) using SQL queries like `SELECT * FROM ‘fh-bigquery.reddit_comments.2016_10‘ WHERE lower(subreddit) = 'hillaryclinton'` and SELECT * FROM ‘fh-bigquery.reddit_comments.2016_11‘ WHERE subreddit = 'The_Donald' . We use the subbreddit comments from October and November 2016 that satisfy `created_utc<1478624401`, which are comments posted before 2016-11-08 12:00:01 EST.

[32] We use the Subreddit Similarity Calculator (Martin 2016*b*) to sort subreddits by similarity in terms of users to r/The_Donald and r/hillaryclinton. Similarities are based on a pointwise mutual information (PPMI) matrix calculated based on the number of shared users between 2000 representative subreddits and the remaining subreddits. Similarities are cosine distances in the PPMI matrix (Martin 2016*a*, 10–11). We use similarities calculated relative to the sum of the PPMI vectors for r/The_Donald and r/hillaryclinton (i.e., relative to vec_{users}(r/The_Donald) + vec_{users}(r/hillaryclinton)). The smallest similarity is 0.01916262 for r/gonewild (192,585 comments during Oct 1–Nov 8), while the subreddit with the smallest similarity (0.05327619) and at least 300,000 comments is r/pokemon (421,981 comments). r/pcmasterrace has the smallest similarity (0.07793557) among subreddits with at least 500,000 comments. The smallest similarity (0.09632784) among subreddits with at least 1,000,000 comments is r/leagueoflegends (1,115,685 comments).

the least measured user similarity to vec_{users}(r/The_Donald) + vec_{users}(r/hillaryclinton) among subreddits that have at least 500,000 comments during October 1-November 8, 2016. During that period r/pcmasterrace has 560,240 comments. We use it because it is intermediate in number of comments between r/The_Donald and r/hillaryclinton. Considering user similarities to r/The_Donald and r/hillaryclinton separately, r/pcmasterrace is about the 8,000$^{\text{th}}$ most similar subreddit to r/The_Donald and about the 33,000$^{\text{th}}$ most similar to r/hillaryclinton (Martin 2016*a*).

Using multinomial regression models, we estimate how the comments in the three subreddits are conditionally associated with which subreddit contains the comments. Comments are made in response to "posts," and the number of comments per post varies. We catenate all the comments for each post together. The 3,192,604 separate comments become 246,638 catenated comments. Comments for each post are catenated in chronological order. The number of separate comments in each catenation ranges from 70,264 posts that have one comment to one post that has 18,690 comments. In terms of characters, the shortest catenated comment has one character and the longest has 1,928,309 characters. Each catenated comment is treated as a document, and for each document we predict vectors using the Twitter-trained embeddings models. Partisan scores are computed using cosine similarities with the ten keywords' embeddings from the Twitter data, with the cosine similarities being averaged over the ten replicates. Because some catenated comments contain no usable characters, we obtain 245,915 partisan score observations for each keyword.

The comments are associated with subreddits in expected ways. Table 21 shows four multinomial logit regressions of the three subreddit identifiers on averages and differences of partisan scores for the catenated comments. r/pcmasterrace is the reference category. Each regression includes the `usage` average and one of the differences `party`, `names`, `handles` or `slogans`. Coefficients for `usage` are always positive, so comments that are more similar to the ten partisan keywords are marginally more likely to be in r/The_Donald or r/hillaryclinton than in r/pcmasterrace—and more likely to be in r/hillaryclinton than in r/The_Donald (the former's `usage` coefficients are more positive). For the difference variables the coefficients are always more positive for r/The_Donald than for r/hillaryclinton, so more Republican-Trump-maga than

Democrat-Clinton-strongertogether similarities tend to be associated with r/The_Donald rather than with r/hillaryclinton. The `slogans` difference marks the largest distinction.

*** Table 21 about here ***

Word embeddings learned from the corpus of Twitter descriptions induce reasonable document embeddings for the contemporaneous corpus drawn from Reddit. While the Twitter corpus is curated to come from users who made factual observations about the election process, no such limitations are imposed on the participants in the subreddits. The partisan features of the language at that time that we discover from Twitter seem to be portable.

8 Changing Descriptions

While we do not address whether the partisan associations or the underlying embeddings vary over time, we can observe temporal changes in contents of users' descriptions[33] While changes in descriptions may coincide with changes in the embeddings or in the cosine similarities, identifying such changes in the ways words in the corpus are associated with one another raises issues that go beyond the scope of what we can do here (see Kutuzov, Øvrelid, Szymanski and Velldal (2018) and Rodman (N.d.) for current work being done on this issue).

First we focus on the changing frequencies of the ten keywords in the descriptions. We find that during the election period descriptions for our users' probably contain more explicit uses of the keywords than our counts based on their initial descriptions may suggest. And we find that by just over a year after the election the relative frequencies of the keywords had changed.

The first two columns of Table 22 report the percentage of descriptions that contain each keyword in the initial set of descriptions ("election") and in the set of descriptions seen in Tweets after the election through December 31, 2016 ("post-election"). All the keywords are more frequent in the "post-election" data. It is best not to view the "post-election" distribution as reflecting only the situation after the election. While our data collection approach means that we

[33]For description data details see Section 4.1.

see the referent users' descriptions only on November 9, 2016, or later, it is most likely that many of the descriptions were changed earlier than that. The novel "post-election" descriptions are not all consequences of the election's outcome. Many of them changed during the last part of the campaign, even while early voting was occurring or on election day.

*** Table 22 about here ***

The column of Table 22 headed "up to Dec 31" combines the information from the first two time periods in the way that is most informative for the comparison to the data from 2018. If a user does not have a new description during November 9-December 31, 2016, then the initial description from before November 9 is retained, otherwise the first description from during November 9-December 31, 2016 is used. Not all the percentages in the "up to Dec 31" column are greater than those in the "election" column, and all the changes are slight: all the Democratic keywords occur a bit less frequently, as do "republican" and "realdonaldtrump." Keywords "trump," "donald" and "maga" occur a bit more frequently.

By early 2018 the keywords' distribution changes considerably. The frequency of "maga" more than doubles, from .873 percent to 2.071 percent. Use of keyword "realdonaldtrump" increases by about thirty percent (from .078 to .102) and "trump" increases by about twenty-five percent (from 2.175 to 2.730), increases that are almost matched by the twenty percent increase in use of "democrat" (from .846 to 1.017). The remaining keywords are less frequent by early 2018.

Next we observe that the agnostic partisan associations computed using users' initial keywords are conditionally associated with their subsequent actions to change descriptions. We use multinomial regresions where the outcome variable indicates the presence of a novel description for each user in each time period. Table 23 shows that, comparing "election" to "post-election," `usage` is positively associated with having a novel description in the "post-election" data. Given `usage`, `party` and `names` are negatively associated while `handles` and `maga` are positively associated. Comparing either "election" or "uptoDec31" to "early 2018," `usage` is slightly and negatively associated with having a novel description in the "early 2018" data when `party` or `names` are included as covariates but not otherwise. Given `usage`, `names`, `handles` and `slogans` are negatively associated with novel “early 2018” descriptions while `party` is weakly positively associated. Those more similar to “Hillary,” “Clinton,” “hillaryclinton” and “strongertogether” are more likely to change descriptions by early 2018 than are those who are more similar to “Donald,” ’Trump,” “realdonaldtrump” and “maga.” Those more similar to “Democrat” are less likely to make changes than are those who are more similar to “Republican.”

*** Table 23 about here ***

Altogether the changes in descriptions point to a tendency by early 2018 for users to boost mentions of Trump and his campaign slogan, and to boost mentions of the Democratic party, while mentions of Republicans and of Clinton and her campaign diminish. Late during the campaign (after October 1, 2016) everyone whose description used partisan language was more likely to change descriptions than were those whose description did not, and those changes tended to involve more explicit mentions of the major parties, their candidates and those candidates’ campaigns.

9 Discussion

Presidential campaign partisan associations computed from Twitter users’ descriptions behave in many ways as we should expect measures of partisan engagement and sentiment to behave. They predict actions with respect to retweets, favorites, hashtags and following: engagement—users whose descriptions are more similar to partisan keywords regardless of direction (`usage`) tend to use more partisan targets whether the items are Republican (or “right”) or Democratic (or “left”); sentiment—but those whose descriptions are more similar to Donald (or Trump or realdonaldtrump or maga or Republican) than to Hillary (or Clinton or hillaryclinton or strongertogether or Democrat) marginally use more Republican (or “right”) items and fewer Democratic (or “left”) items, and similarly in the opposite directions. The partisan associations have the distributions we expect when these are assessed relative to terms that have clear partisan implications that we do not use as keywords: the distributions for those who use the NeverTrump hashtag are intermediate between the distributions for those who use ImWithHer or MakeAmericaGreatAgain. When applied to a corpus of contemporaneous comments from Reddit, the embeddings learned from the Twitter description data imply partisan associations for the Reddit data that correctly associate with the subreddits r/The_Donald, r/hillaryclinton and r/pcmasterrace.

Almost twenty percent of descriptions that use a keyword contain an expression that is hostile toward the target. Nonetheless for many purposes ignoring the difference between hostile and not-hostile expressions should cause no problems. The not-hostile partisan associations computed when hostile expressions are explicitly labeled are so highly correlated with the agnostic partisan associations—correlations are .95, .97 or .98—that in practice the distinction between them should make no difference. That does not mean that associations defined relative to hostile usages of the ten keywords are not useful. In models of the number of members of Congress users follow, the associations derived from hostile usages behave as expected with one exception—and that one exception is reasonable in light of Never Trump Republicans.

Is it surprising that robust partisan patterns derive from users' Twitter descriptions, few of which include any of the ten keywords and all of which are short (median length 96 characters)? The length of the strings is immaterial. We note that the classic question used to measure party identification (Campbell, Converse, Miller and Stokes 1960) uses fewer than 30 words, even counting the follow up questions. While Twitter descriptions are not responses to survey questions, users generally craft them to try to characterize themselves efficiently. During the presidential election period, the contest between the candidates and parties is widely salient. Indeed, as we observe, after October 1, 2016, and before December 31, 2016, many users change their description to include one or more of the ten keywords. Also the Twitter users whose descriptions we use to compute partisan associations are users who apparently reported a personal experience with the election process, so at least in this sense these are politically engaged people. It's not really surprising that such people during that time express their partisanship when describing themselves, even if perhaps unwittingly.

Partisan associations do not measure party identification (Campbell et al. 1960), although they clearly relate to a less specific notion of partisanship. Party identification is a combination of psychological attachment and habit, and it is considered to be part of a politically engaged individual's identity that can manifest itself in beliefs and behaviors (Campbell et al. 1960). We have not studied possible dynamics of partisan associations (cf. Green, Palmquist and Shickler 2002), and we have no evidence regarding psychological aspects. Even without considering psychology, at least two aspects of partisan associations distinguish them from party identification. First, partisan associations are several: one of the associations we call `party`, but that name relates to the two keywords used to derive it and not to any evidence that it connects more strongly than the other associations do to anything like party identification; the other associations directly connect to the candidates and campaigns, hence facially they relate strongly to "short term forces" such as Campbell et al. (1960) sought to distinguish from party identification. The second consideration that distinguishes partisan associations from party identification is that the partisan associations do not involve any notion of being an Independent: having a value of `party` near zero is not the same thing (cf. Klar and Krupnikov 2016). Perhaps an Independent notion could be developed using cosine similarity to the word "independent," but we have not pursued that.

Even though we use word and document embeddings motivated by the distributional theory, we do not know whether partisan associations are aligned with other identities (cf. Mason 2018). Our findings regarding hostile usages of keywords exhibit negative correlations that match findings regarding negative feelings about political parties with which one does not identify (Abramowitz and Webster 2018). We show that higher `usage` is related to more involvement with partisan retweets, favorites, hashtags, following and subreddits, and the directional associations are generally related to such involvements as one would expect. But we lack evidence whether the associations are related to campaign involvement beyond social media (cf. Huddy, Mason and Aarøe 2015).

We cannot say whether the partisan associations persist beyond the late presidential period precisely as we observe them, but we do know that the sentiments and engagements they entail are durable. The retweets, favorites and hashtags we show relate plausibly to the partisan associations span years before and after the 2016 fall election period. The partisan associations relate plausibly to the pattern of changes we observe in the descriptions by a year after the election.

We use word embedding methods to compute partisan associations of Twitter users, even for users who do not explicitly label their partisan association. To reiterate, the informal idea is to learn the associations between partisan words and non-partisan words such that we can compute the partisan associations of Twitter users who have a self-provided user biography, even if they do not use any partisan words explicitly. To calculate the partisan association for each subspace, we obtain document and word vectors using the doc2vec algorithm, and we construct subspaces by taking the difference between Republican words' vectors and corresponding Democratic words' vectors, such as $vec(\text{Trump}) - vec(\text{Clinton})$. Then we take the cosine similarity between the document vector of the user's description and the subspace of interest. Averages of vectors can also define subspaces. Key contributions that facilitate this straightforward approach to calculating partisan associations include: the use of a loss function to choose hyperparameters for the doc2vec algorithm in a principled, application-specific manner; a direct sampling approach to reduce instability in estimates of the vectors, based on averaging partisan association scores across multiple doc2vec replications.

We apply this method to data from the 2016 general election. developing five subspaces of interest: names, party, handles, slogans and usage. Using the analogies properties of word embedding methods, we find that it is more appropriate to use the four difference subspaces separately rather than averaging all Republican keywords and averaging all Democratic keywords and then taking the difference, as the word embeddings literature has traditionally done with other concepts. The partisan association scores of users who use partisan words that we do not use to compute the partisan association scores are distributed as expected: individuals who use words such as ImWithHer tend to have scores that are more negative (indicating higher Democratic association), while users who use words such as MakeAmericaGreatAgain tend to have scores that are more positive. The various partisan associations are conditionally associated in plausible ways with other forms of partisan Twitter behavior—retweets, favorites (or "likes"), hashtag usages and following. The way partisan associations relate to retweets, favorites, hashtag usages and to changes we observe in users' descriptions suggests the sentiments and engagements that prompt the associations persist over a time much longer than the brief period of weeks during which the description data were gathered. We do not investigate possible dynamics in embeddings or associations.

We also take into account the possibility of users using any of the keywords in a hostile manner (e.g., "I do not like Donald Trump."). We develop an SVM classifier that classifies usages of the keywords as hostile or non-hostile. We develop a set of features that are based on the idea of studying the "shift" in the partisan association scores: that is, what the partisan association score would be for the full profile, and what the partisan association score would be for the profile if it did not have any partisan keywords. The idea is that a major shift in the partisan association score when the partisan keywords are removed may indicate an inconsistent usage of the keywords. In future work, we will develop this classification process into an independent method that political scientists may find helpful when working with Twitter data where it may not be clear if users are engaging in the political process in an affirmative manner or a hostile manner. We find that not-hostile partisan associations that take into account the not-hostile/hostile distinction are highly correlated with agnostic partisan associations that ignore the distinction.

The Twitter following behavior we study in relation to partisan associations is how users follow members of Congress. We find the expected behavior: using agnostic word embeddings, we find that users with more positive partisan associations on any of the four difference scales tend to follow more Republican members of Congress, while users with more negative partisan association scores on any of the four scales tend to follow more Democrats. Using partisan associations derived from hostile usages of keywords, we again mostly see following behavior that is expected—the one exception reinforces the diversity of partisan associations, keying on the distinction between parties by names and the candidates by their names.

We show that the word and document embedding space derived from Twitter users' descriptions is portable to Reddit, another contemporaneous social media domain. In particular we predict the subreddit to which comments belong using the embedding space derived from the Twitter descriptions.

As literary theorist Mikhail Bakhtin argued, words uttered are shaped both by the world the speaker lives in and the audience of the speaker. Usually Twitter users do not use words randomly, but use specific words to describe the world they live in and what they feel is most important to convey to the readers of their profiles. Especially they do this when describing themselves. Because of this purposeful intent we can successfully use word embedding methods to compute partisan associations for users based on their self-descriptions, and the partisan associations have many properties we would like to see in measures of partisan engagement and sentiment.

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Table 1: Hyperparameter Specifications Assessed

label	hyperparameter description
defaults	n=300, window=10, min_count=8, dbow, alpha=.03, remove stopwords, stemming, remove punctuation, remove numbers, remove single words, workers=20
spec 11	n = 150
spec 12	changing window size from 10 to 5
spec 13	changing window size from 10 to 15
spec 14	changing minimum count from 8 to 3
spec 15	changing minimum count from 8 to 13
spec 16	changing distributed bag-of-words (dbow) to distributed memory (dm)
spec 17	changing alpha=0.03 to alpha=0.08
spec 18	not removing stopwords
spec 19	not stemming words
spec 20	not removing punctuation
spec 21	not removing numbers
spec 22	not removing single words
spec 23	not removing stopwords, not stemming words
spec 24	not removing stopwords, not stemming words, not removing single words
spec 25	no preprocessing
spec 26	no punctuation but removing hashtags and @ signs on keywords
spec 27	no preprocessing at all (except lowercasing) but removing hashtags and @ signs on keywords
spec 28	no preprocessing at all, including no lowercasing, but removing hashtags and @ signs on keywords (and lowercased keywords)
spec 29	n = 75
spec 30	n = 500
spec 31	not removing stopwords and n = 150
spec 32	not stemming words and n = 150
spec 33	not removing stopwords and not stemming words and n = 150
spec 34	n=50
spec 35	n=37
spec 36	n=25
spec 37	n = 75, changing minimum count from 8 to 3
spec 38	n = 75, changing minimum count from 8 to 13
spec 39	n = 75, changing minimum count from 8 to 3, not removing single words
spec 40	n = 75, changing minimum count from 8 to 13, not removing single words
spec 41	changing minimum count from 8 to 3, not removing single words
spec 42	changing minimum count from 8 to 13, not removing single words
spec 44	n = 75, 8 workers instead of 20
spec 45	n = 75, 1 worker (8 specified seeds) instead of 20

Note: each specification includes the default hyperparameter settings except for the noted changed details. “spec 1” is the defaults. There were no specifications designated spec 2–10.

Table 2: Hyperparameter Loss Function Values

	Democrat Republican			left right		
label	retweet	favorite	sum	retweet	favorite	sum
defaults	−77.3	−65.6	−142.8	−87.5	−78.3	−165.8
spec 11	−90.3	−76.8	−167.1	−102.2	−91.8	−194.0
spec 12	−75.9	−62.7	−138.6	−83.2	−75.0	−158.2
spec 13	−75.1	−63.2	−138.4	−84.5	−75.0	−159.4
spec 14	−77.4	−66.5	−143.9	−88.1	−79.5	−167.6
spec 15	−79.0	−67.3	−146.4	−89.3	−80.9	−170.1
spec 16	11.0	7.3	18.2	0.6	5.3	5.9
spec 17	−38.7	−34.4	−73.1	−46.0	−44.1	−90.1
spec 18	−74.7	−60.6	−135.3	−81.8	−72.9	−154.7
spec 19	−74.3	−61.4	−135.7	−83.5	−74.3	−157.8
spec 20	−60.1	−51.2	−111.3	−70.4	−60.4	−130.8
spec 21	−69.9	−59.5	−129.4	−80.3	−70.9	−151.1
spec 22	−75.4	−63.9	−139.3	−86.9	−75.3	−162.2
spec 23	−67.2	−56.1	−123.3	−77.1	−68.4	−145.5
spec 24	−71.7	−59.1	−130.8	−79.9	−73.1	−153.0
spec 25	−59.5	−52.2	−111.7	−67.7	−64.2	−131.9
spec 26	−66.3	−57.7	−123.9	−79.0	−67.7	−146.7
spec 27	−58.9	−51.3	−110.2	−67.0	−63.1	−130.1
spec 28	−62.2	−52.9	−115.1	−72.4	−65.9	−138.3
spec 29	−95.1	−80.9	−176.0	−107.4	−99.0	−206.4
spec 30	−64.3	−55.4	−119.7	−74.7	−65.4	−140.1
spec 31	−89.9	−75.1	−164.9	−100.9	−90.9	−191.8
spec 32	−83.3	−70.2	−153.5	−95.0	−86.2	−181.2
spec 33	−82.3	−69.5	−151.8	−93.5	−85.0	−178.5
spec 34	−91.8	−80.0	−171.8	−105.6	−97.3	−202.9
spec 35	−91.9	−81.5	−173.3	−105.9	−98.9	−204.8
spec 36	−89.5	−83.2	−172.7	−101.2	−100.7	−201.9
spec 37	−91.6	−78.1	−169.7	−105.3	−94.5	−199.8
spec 38	−91.6	−76.7	−168.3	−104.2	−94.0	−198.2
spec 39	−70.8	−61.6	−132.4	−84.6	−71.8	−156.4
spec 40	−93.6	−80.0	−173.6	−108.6	−97.3	−205.9
spec 41	−93.3	−79.1	−172.4	−105.9	−95.6	−201.5
spec 42	−68.4	−60.0	−128.4	−80.5	−69.3	−149.8

Table 3: Analogies

Analogy Arithmetic	Closest Word Vector		Cosine Similarity	
	Actual	Expected	Actual	Expected
Trump - Clinton + Hillary	MAGA	Donald	0.815	0.777
Trump - Clinton + Democrat	Republican	Republican	0.694	0.694
Trump - Clinton + hillaryclinton	TrumpTrain	RealDonaldTrump	0.629	0.609
Trump - Clinton + StrongerTogether	ImWithYou	MAGA	0.647	0.624
Donald - Hillary + Clinton	Trump	Trump	0.757	0.757
Donald - Hillary + Democrat	Republican	Republican	0.742	0.742
Donald - Hillary + hillaryclinton	realdonaldtrump	realdonaldtrump	0.606	0.606
Donald - Hillary + StrongerTogether	Trump	MAGA	0.693	—
Republican - Democrat + Clinton	Donald	Trump	0.677	0.653
Republican - Democrat + Hillary	Clinton	Donald	0.745	0.731
Republican - Democrat + hillaryclinton	thedemocrat	realdonaldtrump	0.640	0.544
Republican - Democrat + StrongerTogether	NeverTrump	MAGA	0.659	—
realdonaldtrump - hillaryclinton + Clinton	Trump	Trump	0.724	0.724
realdonaldtrump - hillaryclinton + Hillary	Trump	Donald	0.779	0.735
realdonaldtrump - hillaryclinton + Democrat	Republican	Republican	0.658	0.658
realdonaldtrump - hillaryclinton + StrongerTogether	TrumpPence	MAGA	0.698	0.672
MAGA - StrongerTogether + Clinton	TrumpPence	Trump	0.718	0.718
MAGA - StrongerTogether + Hillary	TrumpPence	Donald	0.797	0.714
MAGA - StrongerTogether + Democrat	conservative	Republican	0.749	0.691
MAGA - StrongerTogether + hillaryclinton	TrumpPence	realdonaldtrump	0.711	0.654
(Trump + Donald - Clinton - Hillary)/2 + Democrat	Republican	Republican	0.754	0.754
(Trump + Donald - Clinton - Hillary)/2 + hillaryclinton	realdonaldtrump	realdonaldtrump	0.644	0.644
(Trump + Donald - Clinton - Hillary)/2 + StrongerTogether	ImWithYou	MAGA	0.658	0.614

Note: [a] Not one of the top 10 closest words.

Table 4: Analogies

Analogy Arithmetic	Closest Word Vector	Cosine Similarity
Trump + Clinton - Donald	Hillary	0.806
Trump + Clinton - Republican	Hillary	0.723
Trump + Clinton - realdonaldtrump	Hillary	0.766
Trump + Clinton - MAGA	Hillary	0.798
Trump + Clinton - Hillary	Donald	0.783
Trump + Clinton - Democrat	Donald	0.711
Trump + Clinton - hillaryclinton	Donald	0.710
Trump + Clinton - StrongerTogether	Donald	0.770
Donald + Hillary - Trump	Clinton	0.790
Donald + Hillary - Republican	Clinton	0.716
Donald + Hillary - realdonaldtrump	Clinton	0.771
Donald + Hillary - MAGA	Clinton	0.770
Donald + Hillary - Clinton	Trump	0.801
Donald + Hillary - Democrat	Trump	0.744
Donald + Hillary - hillaryclinton	Trump	0.808
Donald + Hillary - StrongerTogether	Trump	0.746
Republican + Democrat - Trump	committee	0.608
Republican + Democrat - Donald	committee	0.609
Republican + Democrat - realdonaldtrump	county	0.569
Republican + Democrat - MAGA	committee	0.577
Republican + Democrat - Clinton	party	0.555
Republican + Democrat - Hillary	party	0.574
Republican + Democrat - hillaryclinton	conservative	0.596
Republican + Democrat - StrongerTogether	GOP	0.611
realdonaldtrump + hillaryclinton - Trump	campaign	0.636
realdonaldtrump + hillaryclinton - Donald	StrongerTogether	0.659
realdonaldtrump + hillaryclinton - Republican	Hillary	0.572
realdonaldtrump + hillaryclinton - MAGA	campaign	0.644
realdonaldtrump + hillaryclinton - Clinton	TimKaine	0.538
realdonaldtrump + hillaryclinton - Hillary	TheDemocrat	0.538
realdonaldtrump + hillaryclinton - Democrat	POTUS	0.558
realdonaldtrump + hillaryclinton - StrongerTogether	Donald	0.672
MAGA + StrongerTogether - Trump	ImWithHer	0.743
MAGA + StrongerTogether - Donald	ImWithHer	0.671
MAGA + StrongerTogether - Republican	ImWithHer	0.593
MAGA + StrongerTogether - realdonaldtrump	ImWithHer	0.719
MAGA + StrongerTogether - Clinton	TrumpPence	0.663
MAGA + StrongerTogether - Hillary	TrumpPence	0.671
MAGA + StrongerTogether - Democrat	TrumpPence	0.690
MAGA + StrongerTogether - hillaryclinton	TrumpPence	0.795

Table 5: Correlations Between Cosine Similarities

	clntn	donld	hilry	repub	democ	redtr	hilcl	maga	strgr
trump	.74	.91	.76	.63	.47	.84	.45	.91	.52
clinton	1.00	.74	.92	.57	.61	.65	.66	.61	.67
donald		1.00	.72	.60	.43	.82	.44	.77	.44
hillary			1.00	.58	.66	.66	.74	.66	.79
republican				1.00	.80	.56	.45	.63	.42
democrat					1.00	.39	.58	.41	.63
realdonaldtrump						1.00	.50	.81	.48
hillaryclinton							1.00	.38	.79
maga								1.00	.47
strongertogether									1.00

	usage	names	party	handles	slogans
trump	.89	.35	.28	.41	.44
clinton	.88	−.28	−.024	.016	−.013
donald	.85	.39	.29	.40	.37
hillary	.92	−.29	−.10	−.050	−.065
republican	.77	.092	.36	.13	.24
democrat	.73	−.25	−.28	−.18	−.17
realdonaldtrump	.82	.31	.29	.53	.38
hillaryclinton	.73	−.35	−.19	−.47	−.35
maga	.82	.36	.36	.45	.57
strongertogether	.75	−.35	−.30	−.29	−.45

	usage	names	party	handles	slogans
usage	1.00	.0077	.091	.13	.13
names		1.00	.53	.65	.69
party			1.00	.48	.64
handles				1.00	.72
slogans					1.00

Note: product-moment correlations between cosine similarities with keyword word embedding vectors and with vector averages and differences. $n = 194,336$.

Table 6: Left Retweet Counts Regressed on Partisan Associations

	Count Models			
	(1)	(2)	(3)	(4)
(Intercept)	2.24 (.0094)	2.34 (.0097)	2.29 (.0096)	2.28 (.0095)
party	−2.99 (.046)			
usage	1.25 (.042)			
names		−2.38 (.047)		
usage		1.04 (.043)		
handles			−1.92 (.046)	
usage			1.33 (.042)	
slogans				−2.62 (.046)
usage				1.17 (.042)
log(θ)	−1.1 (.0054)	−1.11 (.0054)	−1.13 (.0054)	−1.1 (.0054)
	Zero-inflation Models			
	(1)	(2)	(3)	(4)
(Intercept)	4.95 (.070)	4.52 (.069)	4.75 (.070)	4.75 (.069)
party	3.91 (.13)			
usage	1.84 (.12)			
names		3.96 (.13)		
usage		2.30 (.12)		
handles			2.42 (.13)	
usage			1.89 (.12)	
slogans				3.92 (.13)
usage				1.82 (.12)
log(1 + retweet_counts)	−1.26 (.012)	−1.25 (.012)	−1.27 (.012)	−1.25 (.012)
log(1 + statuses_counts)	.0722 (.0076)	.0958 (.0076)	.0917 (.0077)	.0905 (.0076)
log likelihood	−4.648e+05	−4.657e+05	−4.667e+05	−4.654e+05

Note: zero-inflated negative binomial regression of counts of retweets of “left” accounts on cosine similarity coefficients derived from doc2vec scores for users’ `description` strings. Table reports coefficient estimates (standard errors in parentheses). $n = 194,336$.

Table 7: Right Retweet Counts Regressed on Partisan Associations

	Count Models			
	(1)	(2)	(3)	(4)
(Intercept)	1.91 (.015)	1.78 (.015)	1.89 (.015)	1.92 (.015)
party	4.30 (.072)			
usage	4.81 (.061)			
names		5.28 (.071)		
usage		4.78 (.060)		
handles			5.35 (.071)	
usage			4.1 (.063)	
slogans				6.27 (.067)
usage				3.8 (.061)
log(θ)	−1.97 (.0062)	−1.94 (.0062)	−1.94 (.0062)	−1.91 (.0062)
	Zero-inflation Models			
	(1)	(2)	(3)	(4)
(Intercept)	5.71 (.087)	5.85 (.086)	5.83 (.086)	5.89 (.086)
party	−1.16 (.15)			
usage	−3.45 (.13)			
names		−.536 (.14)		
usage		−3.70 (.13)		
handles			−1.54 (.14)	
usage			−3.54 (.14)	
slogans				−2.65 (.14)
usage				−3.38 (.13)
log(1 + retweet_counts)	−1.04 (.011)	−1.03 (.011)	−1.04 (.011)	−1.05 (.011)
log(1 + statuses_counts)	−.00918 (.0092)	−.0213 (.0091)	−.0111 (.0091)	−.0135 (.0091)
log likelihood	−3.68e+05	−3.671e+05	−3.668e+05	−3.65e+05

Note: zero-inflated negative binomial regression of counts of retweets of "left" accounts on cosine similarity coefficients derived from doc2vec scores for users' `description` strings. Table reports coefficient estimates (standard errors in parentheses). $n = 194,336$.

Table 8: Democratic Retweet Counts Regressed on Partisan Associations

	Count Models			
	(1)	(2)	(3)	(4)
(Intercept)	3.07 (.0097)	3.18 (.010)	3.12 (.0098)	3.11 (.0098)
party	−3.32 (.048)			
usage	1.41 (.043)			
names		−2.44 (.049)		
usage		1.22 (.045)		
handles			−1.80 (.048)	
usage			1.54 (.043)	
slogans				−2.64 (.049)
usage				1.38 (.044)
log(θ)	−1.28 (.0044)	−1.29 (.0044)	−1.31 (.0044)	−1.28 (.0044)
	Zero-inflation Models			
	(1)	(2)	(3)	(4)
(Intercept)	4.03 (.075)	3.51 (.075)	3.77 (.076)	3.74 (.073)
party	4.90 (.15)			
usage	2.03 (.14)			
names		4.65 (.15)		
usage		2.65 (.14)		
handles			3.49 (.16)	
usage			2.14 (.14)	
slogans				5.01 (.15)
usage				2.17 (.14)
log(1 + retweet_counts)	−1.26 (.012)	−1.25 (.012)	−1.26 (.012)	−1.25 (.012)
log(1 + statuses_counts)	.0947 (.0084)	.119 (.0084)	.109 (.0085)	.112 (.0083)
log likelihood	−5.796e+05	−5.809e+05	−5.819e+05	−5.806e+05

Note: zero-inflated negative binomial regression of counts of retweets of “left” accounts on cosine similarity coefficients derived from doc2vec scores for users’ `description` strings. Table reports coefficient estimates (standard errors in parentheses). $n = 194,336$.

Table 9: Republican Retweet Counts Regressed on Partisan Associations

	Count Models			
	(1)	(2)	(3)	(4)
(Intercept)	1.52 (.014)	1.44 (.014)	1.52 (.014)	1.55 (.014)
party	4.11 (.066)			
usage	4.27 (.056)			
names		4.23 (.065)		
usage		4.33 (.055)		
handles			4.10 (.063)	
usage			3.91 (.058)	
slogans				5.05 (.061)
usage				3.60 (.056)
$\log(\theta)$	−1.81 (.0061)	−1.80 (.0061)	−1.81 (.0061)	−1.77 (.0061)
	Zero-inflation Models			
	(1)	(2)	(3)	(4)
(Intercept)	5.40 (.09)	5.55 (.090)	5.49 (.090)	5.57 (.090)
party	−1.26 (.16)			
usage	−3.25 (.14)			
names		−.349 (.15)		
usage		−3.55 (.14)		
handles			−.511 (.15)	
usage			−3.52 (.15)	
slogans				−2.43 (.15)
usage				−3.19 (.14)
log(1 + retweet_counts)	−1.12 (.012)	−1.1 (.012)	−1.11 (.012)	−1.13 (.012)
log(1 + statuses_counts)	.0572 (.0096)	.0407 (.0095)	.0495 (.0095)	.0491 (.0095)
log likelihood	−3.56e+05	−3.559e+05	−3.559e+05	−3.542e+05

Note: zero-inflated negative binomial regression of counts of retweets of “left” accounts on cosine similarity coefficients derived from doc2vec scores for users’ `description` strings. Table reports coefficient estimates (standard errors in parentheses). $n = 194,336$.

Table 10: Democratic Favorite Counts Regressed on Partisan Associations

	Count Models			
	(1)	(2)	(3)	(4)
(Intercept)	2.98 (.010)	3.10 (.011)	3.04 (.010)	3.03 (.010)
party	−3.23 (.051)			
usage	.616 (.046)			
names		−2.51 (.051)		
usage		.376 (.047)		
handles			−2.03 (.050)	
usage			.720 (.046)	
slogans				−2.70 (.051)
usage				.569 (.046)
log(θ)	−1.57 (.0040)	−1.58 (.0040)	−1.59 (.0040)	−1.58 (.0040)
	Zero-inflation Models			
	(1)	(2)	(3)	(4)
(Intercept)	1.03 (.092)	.676 (.094)	.854 (.092)	.848 (.092)
party	3.82 (.20)			
usage	1.48 (.19)			
names		3.32 (.20)		
usage		1.88 (.20)		
handles			2.75 (.20)	
usage			1.55 (.19)	
slogans				3.60 (.20)
usage				1.60 (.19)
log(1 + favorites_counts)	−1.07 (.014)	−1.06 (.014)	−1.06 (.014)	−1.05 (.014)
log(1 + statuses_counts)	.250 (.011)	.271 (.011)	.261 (.011)	.261 (.011)
log likelihood	−5.876e+05	−5.886e+05	−5.89e+05	−5.883e+05

Note: zero-inflated negative binomial regression of counts of retweets of "left" accounts on cosine similarity coefficients derived from doc2vec scores for users' `description` strings. Table reports coefficient estimates (standard errors in parentheses). $n = 194,336$.

Table 11: Republican Favorite Counts Regressed on Partisan Associations

	Count Models			
	(1)	(2)	(3)	(4)
(Intercept)	1.59 (.015)	1.46 (.015)	1.56 (.016)	1.60 (.015)
party	4.27 (.078)			
usage	4.21 (.066)			
names		4.87 (.077)		
usage		4.25 (.065)		
handles			4.81 (.076)	
usage			3.68 (.068)	
slogans				5.76 (.074)
usage				3.40 (.067)
log(θ)	−2.42 (.0050)	−2.41 (.0051)	−2.41 (.0050)	−2.39 (.0051)
	Zero-inflation Models			
	(1)	(2)	(3)	(4)
(Intercept)	1.73 (.14)	1.94 (.14)	1.88 (.14)	1.89 (.14)
party	−1.77 (.29)			
usage	−3.32 (.27)			
names		−.352 (.28)		
usage		−3.78 (.27)		
handles			−1.31 (.28)	
usage			−3.62 (.28)	
slogans				−3.00 (.27)
usage				−3.38 (.27)
log(1 + favorites_counts)	−1.00 (.018)	−.992 (.017)	−1.01 (.018)	−1.00 (.017)
log(1 + statuses_counts)	.229 (.016)	.212 (.016)	.221 (.016)	.22 (.016)
log likelihood	−3.518e+05	−3.514e+05	−3.514e+05	−3.502e+05

Note: zero-inflated negative binomial regression of counts of retweets of “left” accounts on cosine similarity coefficients derived from doc2vec scores for users’ `description` strings. Table reports coefficient estimates (standard errors in parentheses). $n = 194,336$.

Table 12: Left Favorite Counts Regressed on Partisan Associations

	Count Models			
	(1)	(2)	(3)	(4)
(Intercept)	3.65 (.0096)	3.76 (.0099)	3.70 (.0097)	3.69 (.0097)
party	−3.12 (.047)			
usage	.487 (.042)			
names		−2.53 (.047)		
usage		.235 (.043)		
handles			−2.04 (.047)	
usage			.58 (.042)	
slogans				−2.64 (.047)
usage				.437 (.043)
log(θ)	−1.46 (.0035)	−1.47 (.0035)	−1.48 (.0035)	−1.47 (.0035)
	Zero-inflation Models			
	(1)	(2)	(3)	(4)
(Intercept)	1.26 (.092)	1.01 (.093)	1.12 (.092)	1.16 (.092)
party	3.05 (.20)			
usage	.501 (.19)			
names		2.51 (.20)		
usage		.778 (.20)		
handles			2.10 (.20)	
usage			.583 (.19)	
slogans				2.40 (.20)
usage				.510 (.19)
log(1 + favorites_counts)	−1.15 (.014)	−1.15 (.014)	−1.14 (.014)	−1.15 (.014)
log(1 + statuses_counts)	.22 (.011)	.236 (.011)	.228 (.011)	.229 (.011)
log likelihood	−7.134e+05	−7.142e+05	−7.147e+05	−7.141e+05

Note: zero-inflated negative binomial regression of counts of retweets of “left” accounts on cosine similarity coefficients derived from doc2vec scores for users’ `description` strings. Table reports coefficient estimates (standard errors in parentheses). $n = 194,336$.

Table 13: Right Favorite Counts Regressed on Partisan Associations

	Count Models			
	(1)	(2)	(3)	(4)
(Intercept)	2.28 (.012)	2.19 (.011)	2.27 (.012)	2.30 (.011)
party	3.56 (.057)			
usage	3.66 (.050)			
names		3.63 (.056)		
usage		3.77 (.049)		
handles			3.54 (.055)	
usage			3.35 (.051)	
slogans				4.56 (.053)
usage				3.07 (.050)
log(θ)	−1.86 (.0040)	−1.86 (.0040)	−1.86 (.0040)	−1.84 (.0040)
	Zero-inflation Models			
	(1)	(2)	(3)	(4)
(Intercept)	1.86 (.11)	1.91 (.11)	1.92 (.11)	1.96 (.11)
party	.105 (.24)			
usage	−1.88 (.22)			
names		1.01 (.23)		
usage		−1.98 (.22)		
handles			.258 (.23)	
usage			−2.05 (.22)	
slogans				−1.19 (.23)
usage				−1.95 (.22)
log(1 + favorites_counts)	−1.09 (.015)	−1.08 (.015)	−1.09 (.015)	−1.09 (.015)
log(1 + statuses_counts)	.187 (.013)	.178 (.013)	.182 (.013)	.183 (.013)
log likelihood	−5.207e+05	−5.205e+05	−5.206e+05	−5.189e+05

Note: zero-inflated negative binomial regression of counts of retweets of "left" accounts on cosine similarity coefficients derived from doc2vec scores for users' `description` strings. Table reports coefficient estimates (standard errors in parentheses). $n = 194,336$.

Table 14: Left Hashtag Counts Regressed on Partisan Associations

	Count Models			
	(1)	(2)	(3)	(4)
(Intercept)	1.87 (.01)	1.98 (.01)	1.93 (.010)	1.92 (.010)
party	−3.33 (.049)			
usage	2.68 (.043)			
names		−2.34 (.049)		
usage		2.50 (.044)		
handles			−1.63 (.048)	
usage			2.80 (.044)	
slogans				−2.36 (.047)
usage				2.67 (.044)
log(θ)	−1.39 (.0049)	−1.42 (.0048)	−1.43 (.0048)	−1.41 (.0049)
	Zero-inflation Models			
	(1)	(2)	(3)	(4)
(Intercept)	5.20 (.08)	4.91 (.08)	4.94 (.081)	4.98 (.080)
party	2.54 (.14)			
usage	−1.26 (.12)			
names		1.22 (.13)		
usage		−1.04 (.12)		
handles			−.112 (.14)	
usage			−1.02 (.12)	
slogans				.671 (.13)
usage				−1.15 (.12)
log(1 + hashtags_counts)	−1.27 (.0085)	−1.27 (.0085)	−1.27 (.0085)	−1.27 (.0085)
log(1 + statuses_counts)	−.0141 (.0075)	.00836 (.0076)	.00634 (.0076)	.00516 (.0076)
log likelihood	−4.547e+05	−4.562e+05	−4.569e+05	−4.561e+05

Note: zero-inflated negative binomial regression of counts of retweets of “left” accounts on cosine similarity coefficients derived from doc2vec scores for users’ `description` strings. Table reports coefficient estimates (standard errors in parentheses). $n = 194,336$.

Table 15: Right Hashtag Counts Regressed on Partisan Associations

	Count Models			
	(1)	(2)	(3)	(4)
(Intercept)	1.48 (.012)	1.34 (.011)	1.41 (.011)	1.45 (.011)
party	3.63 (.055)			
usage	5.19 (.049)			
names		4.36 (.055)		
usage		5.29 (.048)		
handles			4.95 (.054)	
usage			4.66 (.050)	
slogans				5.20 (.05)
usage				4.55 (.048)
log(θ)	−1.62 (.0052)	−1.61 (.0052)	−1.59 (.0052)	−1.57 (.0052)
	Zero-inflation Models			
	(1)	(2)	(3)	(4)
(Intercept)	4.65 (.082	4.75 (.081)	4.74 (.081)	4.77 (.081)
party	1.75 (.13)			
usage	−1.72 (.11)			
names		.476 (.13)		
usage		−1.65 (.11)		
handles			−.202 (.13)	
usage			−1.67 (.12)	
slogans				−.684 (.12)
usage				−1.6 (.11)
log(1 + hashtags_counts)	−1.21 (.0081)	−1.21 (.0081)	−1.21 (.0081)	−1.21 (.0081)
log(1 + statuses_counts)	.0697 (.0078)	.0553 (.0077)	.0617 (.0077)	.0573 (.0076)
log likelihood	−4.147e+05	−4.138e+05	−4.127e+05	−4.116e+05

Note: zero-inflated negative binomial regression of counts of retweets of "left" accounts on cosine similarity coefficients derived from doc2vec scores for users' `description` strings. Table reports coefficient estimates (standard errors in parentheses). $n = 194,336$.

Table 16: Confusion Matrix for Hostile Usages Classifier

	Precision	Recall	F1 Score	Support
Not Hostile Usage	0.90	0.92	0.91	254
Hostile Usage	0.66	0.62	0.63	65
Macro Average	0.78	0.77	0.77	319

Table 17: Correlations Between Not-hostile and Hostile Partisan Associations

	not hostile				hostile			
	usage	names	party	handles	usage	names	party	handles
usage: not hostile	1.00	.075	.17	.10	.67	.10	−.072	−.064
names: not hostile		1.00	.58	.69	.17	−.080	.062	−.16
party: not hostile			1.00	.52	.087	.0032	−.099	−.020
handles: not hostile				1.00	.19	−.078	.0098	−.058
usage: hostile					1.00	−.029	−.12	−.039
names: hostile						1.00	.019	−.083
party: hostile							1.00	−.40
handles: hostile								1.00

Note: product-moment correlations between partisan associations computed using hostility-labeled keywords. $n = 194,336$.

Table 18: Correlations Between Agnostic and Hostility-labeled Partisan Associations

	not hostile[b]					hostile[b]			
	usage	names	party	handles	slogans	usage	names	party	handles
usage[a]	.98	.10	.15	.11	.11	.75	.12	−.062	−.066
names[a]	.010	.95	.57	.66	.69	.015	−.25	.12	−.14
party[a]	.096	.57	.97	.50	.66	.12	.0055	−.16	.014
handles[a]	.11	.68	.50	.98	.71	.22	−.11	.061	−.16
slogans[a]	.12	.75	.67	.73	.98	.15	.059	−.0096	−.16

Note: product-moment correlations between partisan associations computed without hostility labeling and partisan associations computed using hostility-labeled keywords. $n = 194,336$.
[a] partisan associations computed without labeling keywords for hostile usage. [b] partisan associations computed with keywords labeled for hostile usage.

Table 19: Congress Following Counts Regressed on Partisan Associations

(a) Republican Members of Congress Followed

	Count Models							
	(1)		(2)		(3)		(4)	
	est	SE	est	SE	est	SE	est	SE
(Intercept)	−.0567	.026	−.112	.025	−.0909	.025	−.00317	.026
diff[a]	1.53	.075	.478	.071	.672	.069	1.18	.068
usage	3.14	.074	3.372	.074	3.24	.075	3.08	.073
log(θ)	−2.13	.018	−2.16	.018	−2.16	.017	−2.08	.019
	Zero-inflation Models							
	(1)		(2)		(3)		(4)	
	est	SE	est	SE	est	SE	est	SE
(Intercept)	−.915	.081	−1.01	.087	−.960	.082	−.767	.072
diff[a]	.0404	.23	.727	.24	1.21	.23	−1.49	.16
usage	−4.14	.23	−4.38	.26	−4.73	.28	−3.36	.19
log likelihood	−2.266e+05		−2.268e+05		−2.268e+05		−2.265e+05	

(b) Democratic Members of Congress Followed

	Count Models							
	(1)		(2)		(3)		(4)	
	est	SE	est	SE	est	SE	est	SE
(Intercept)	.686	.011	.773	.011	.71	.011	.699	.011
diff[a]	−2.25	.057	−2.25	.056	−1.78	.056	−2.21	.056
usage	2.31	.049	2.06	.050	2.28	.049	2.25	.050
log(θ)	−1.49	.009	−1.50	.0093	−1.55	.0092	−1.51	.0093
	Zero-inflation Models							
	(1)		(2)		(3)		(4)	
	est	SE	est	SE	est	SE	est	SE
(Intercept)	−1.93	.12	−2.40	.13	−1.93	.15	−2.09	.14
diff[a]	7.67	.19	6.89	.18	6.58	.21	6.56	.18
usage	3.43	.14	3.77	.15	3.24	.16	3.14	.15
log(1 + statuses_counts)	−.088	.013	−.0556	.014	−.128	.018	−.077	.016
log likelihood	−3.353e+05		−3.355e+05		−3.363e+05		−3.356e+05	

Note: zero-inflated negative binomial regression of counts of members of Congress each user follows. Table reports coefficient estimates (standard errors in parentheses). $n = 194,336$.
[a] partisan association difference variable: (1) `party`; (2) `names`; (3) `handles`; (4) `slogans`. Partisan associations do not distinguish hostile keyword usages. Estimates using hostility-aware partisan associations are similar: coefficients for `usage` are slightly more positive with not-hostile partisan associations.

Table 20: Congress Following Counts Regressed on Hostile Partisan Associations

(a) Republican Members of Congress Followed

	Count Models					
	(1)		(2)		(3)	
	est	SE	est	SE	est	SE
(Intercept)	.0601	.018	.0782	.017	.0233	.014
diff[a]	−.371	.089	1.39	.095	−.367	.090
usage	3.05	.090	3.22	.088	3.20	.085
$\log(\theta)$	−2.35	.0097	−2.33	.011	−2.37	.0072
	Zero-inflation Models					
	(1)		(2)		(3)	
	est	SE	est	SE	est	SE
(Intercept)	−3.11	.28	−3.90	.41	−6.78	1.6
diff[a]	7.37	1.2	−8.94	1.3	17.0	5.5
usage	−5.65	1.2	−.216	.83	2.19	2.2
log likelihood	−2.281e+05		−2.279e+05		−2.281e+05	

(b) Democratic Members of Congress Followed

	Count Models					
	(1)		(2)		(3)	
	est	SE	est	SE	est	SE
(Intercept)	.853	.010	.873	.010	.856	.010
diff[a]	.879	.062	1.03	.062	.261	.060
usage	1.59	.064	1.51	.064	1.48	.064
$\log(\theta)$	−1.73	.0053	−1.72	.0053	−1.73	.0053
	Zero-inflation Models					
	(1)		(2)		(3)	
	est	SE	est	SE	est	SE
(Intercept)	1.52	.25	1.52	.25	1.57	.25
diff[a]	.794	.77	.34	.70	.0845	.68
usage	5.37	.73	5.27	.71	5.04	.71
log(1 + statuses_counts)	−.817	.038	−.814	.038	−.817	.038
log likelihood	−3.384e+05		−3.383e+05		−3.385e+05	

Note: zero-inflated negative binomial regression of counts of members of Congress each user follows. Table reports coefficient estimates (standard errors in parentheses). $n = 194,336$.
[a] partisan association difference variable: (1) `party`; (2) `names`; (3) `handles`. Partisan associations are based on hostile keyword usages.

Table 21: Regressions of Subreddit Identifier on Catenated Comments

	r/The_Donald		r/hillaryclinton	
regressor	Coef	SE	Coef	SE
Intercept	−.416	.019	−4.36	.039
usage	7.46	.059	10.5	.097
party	−1.78	.09	−7.87	.16

	r/The_Donald		r/hillaryclinton	
regressor	Coef	SE	Coef	SE
Intercept	.200	.021	−3.64	.040
usage	7.32	.060	9.75	.096
names	−8.41	.087	−9.87	.14

	r/The_Donald		r/hillaryclinton	
subreddit	Coef	SE	Coef	SE
Intercept	−.351	.020	−4.09	.039
usage	7.58	.059	10.9	.098
handles	−1.81	.081	−7.70	.14

	r/The_Donald		r/hillaryclinton	
subreddit	Coef	SE	Coef	SE
r/The_Donald	−.345	.019	−4.32	.040
r/The_Donald	7.71	.059	11.3	.099
r/The_Donald	−3.24	.087	−12.3	.15

Note: multinomial logit regression of subreddit membership on catanated comment vector averages and differences. r/pcmasterrace is the reference category. Observations by subreddit: r/The_Donald, 207,512; r/hillaryclinton, 11,612; r/pcmasterrace, 26,791.

Table 22: Keyword Frequencies in Novel Descriptions During Each Period

keyword keyword	election	post- election	up to Dec 31	early 2018
trump	2.167	3.813	2.175	2.730
clinton	.428	.560	.359	.231
donald	.253	.472	.288	.272
hillary	.887	1.180	.719	.280
republican	.404	.487	.399	.385
democrat	.865	1.114	.846	1.017
realdonaldtrump	.080	.132	.078	.102
hillaryclinton	.149	.207	.135	.119
maga	.797	1.380	.873	2.071
strongertogether	.098	.138	.083	.051

Note: percentages of initial novel descriptions in each period that contain each keyword string. Number of initial novel descriptions by period: election, 214,458; post-election, 96,055; up to Dec 31, 215,164; early 2018, 143,537.

Table 23: Regressions of Novel Description Occurrence on Partisan Associations

	(1) election vs post-election		(2) election vs early 2018		(3) up to Dec 31 vs early 2018	
regressor	est	SE	est	SE	est	SE
Intercept	−.919	.0081	−.337	.0069	−.340	.0069
usage	.564	.035	−.0722	.031	−.0712	.031
party	−.197	.039	.0704	.034	.0656	.034

	election vs post-election		election vs early 2018		up to Dec 31 vs early 2018	
regressor	est	SE	est	SE	est	SE
Intercept	−.908	.0081	−.329	.0070	−.332	.0070
usage	.551	.035	−.0643	.031	−.0638	.031
names	−.419	.039	−.476	.034	−.478	.034

	election vs post-election		election vs early 2018		up to Dec 31 vs early 2018	
regressor	est	SE	est	SE	est	SE
Intercept	−.916	.0081	−.338	.0069	−.341	.0069
usage	.534	.035	−.0327	.031	−.0319	.031
handles	.109	.038	−.299	.033	−.301	.033

	election vs post-election		election vs early 2018		up to Dec 31 vs early 2018	
regressor	est	SE	est	SE	est	SE
Intercept	−.915	.0081	−.342	.0069	−.345	.0069
usage	.534	.035	−.0307	.031	−.0300	.031
slogans	.104	.038	−.313	.033	−.315	.033

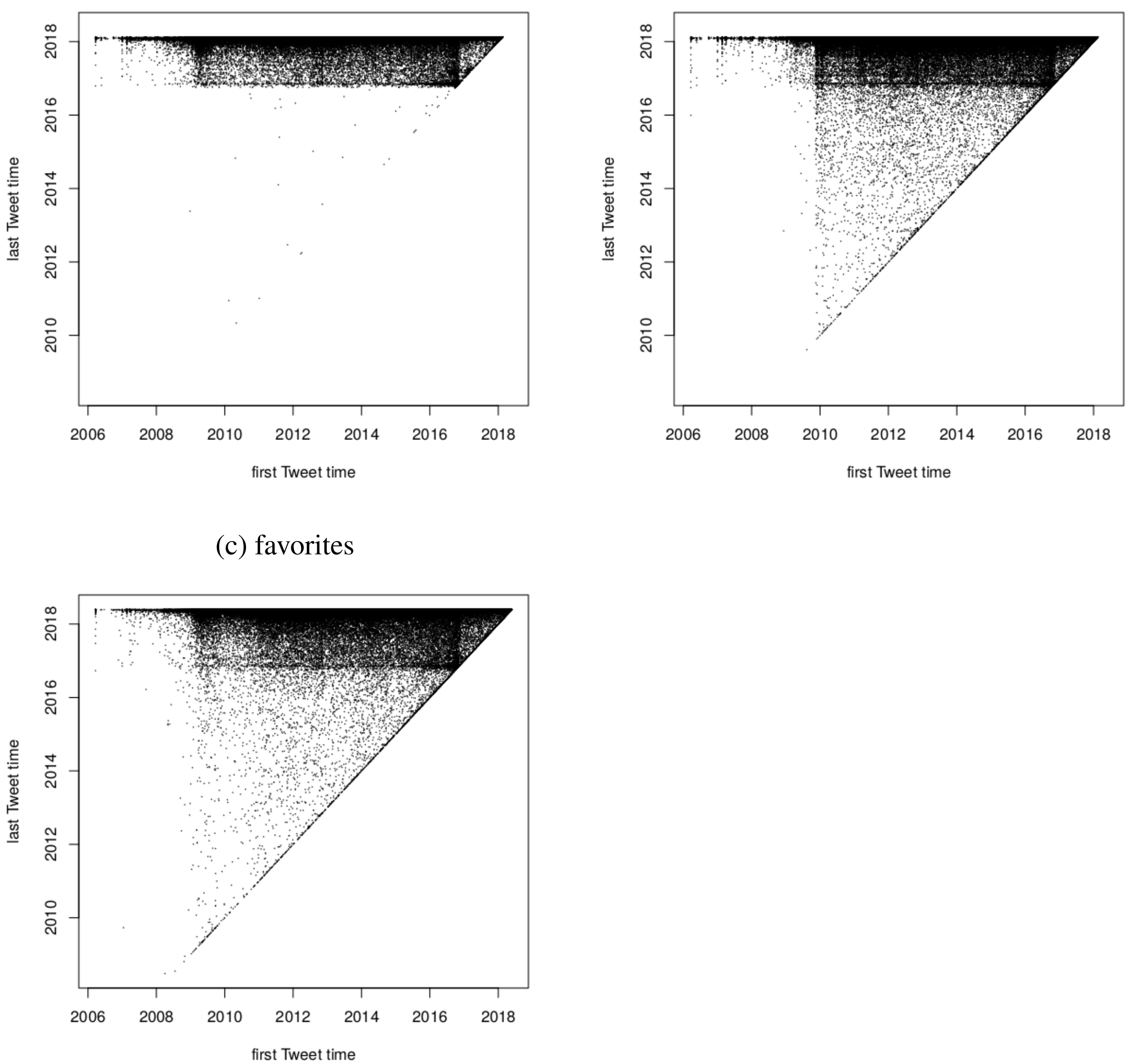
Note: three multinomial logit regressions of the presence of a novel description during each time period. The first period listed in each column heading is the reference category for the referent two-category model.

Figure 1: Timelines and Favorites First and Last Tweet Times

(a) timelines

(b) retweets in timelines

(c) favorites

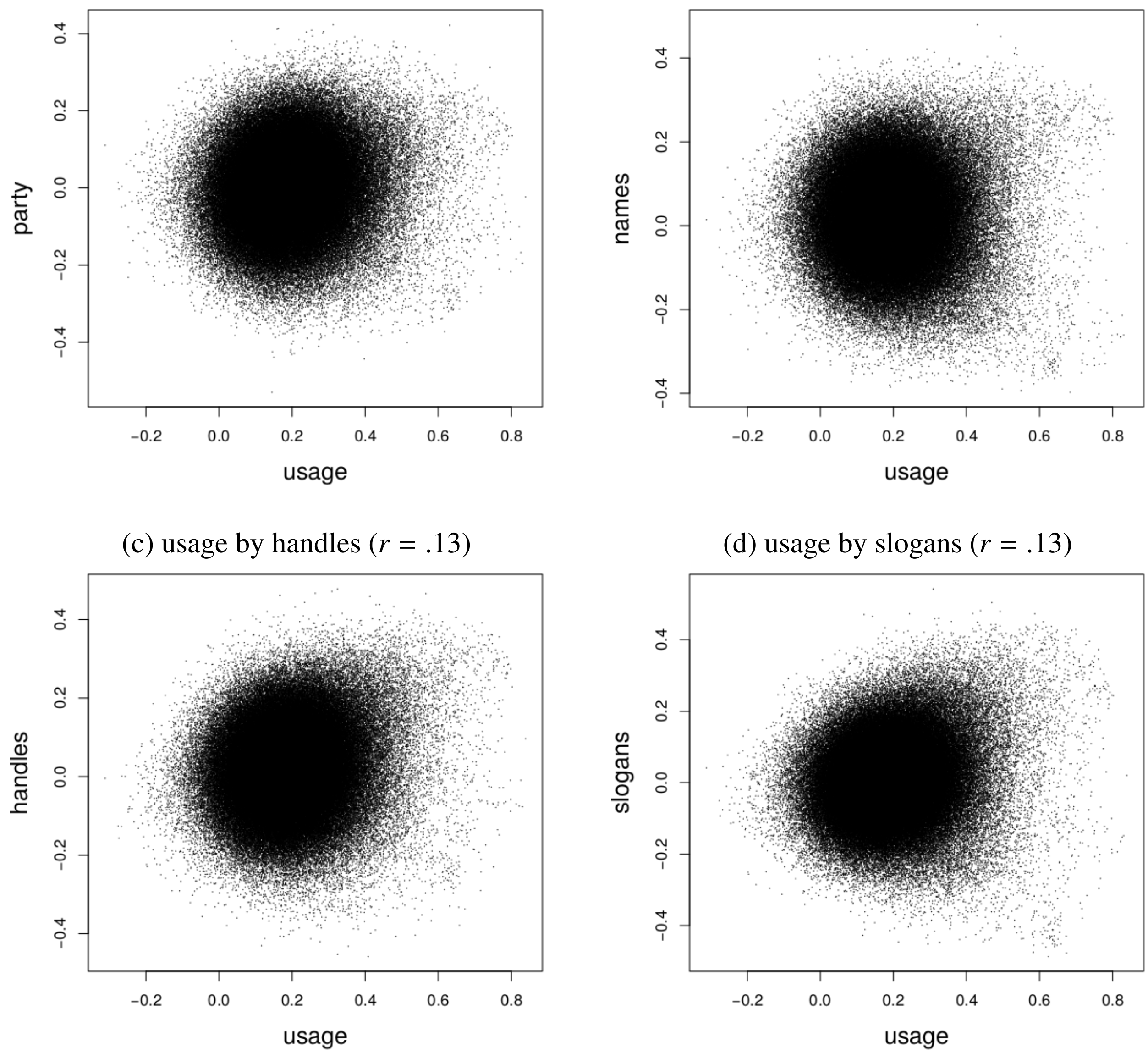


Note: for each user the the earliest Tweet's time in the retrieved timeline or set of favorites is shown on the x-axis, and the y-axis shows the latest Tweet's time.

Figure 2: Cosine Similarities for Word Embedding Vector Combinations

(a) usage by party (r = .091)

(b) usage by names (r = .0077)

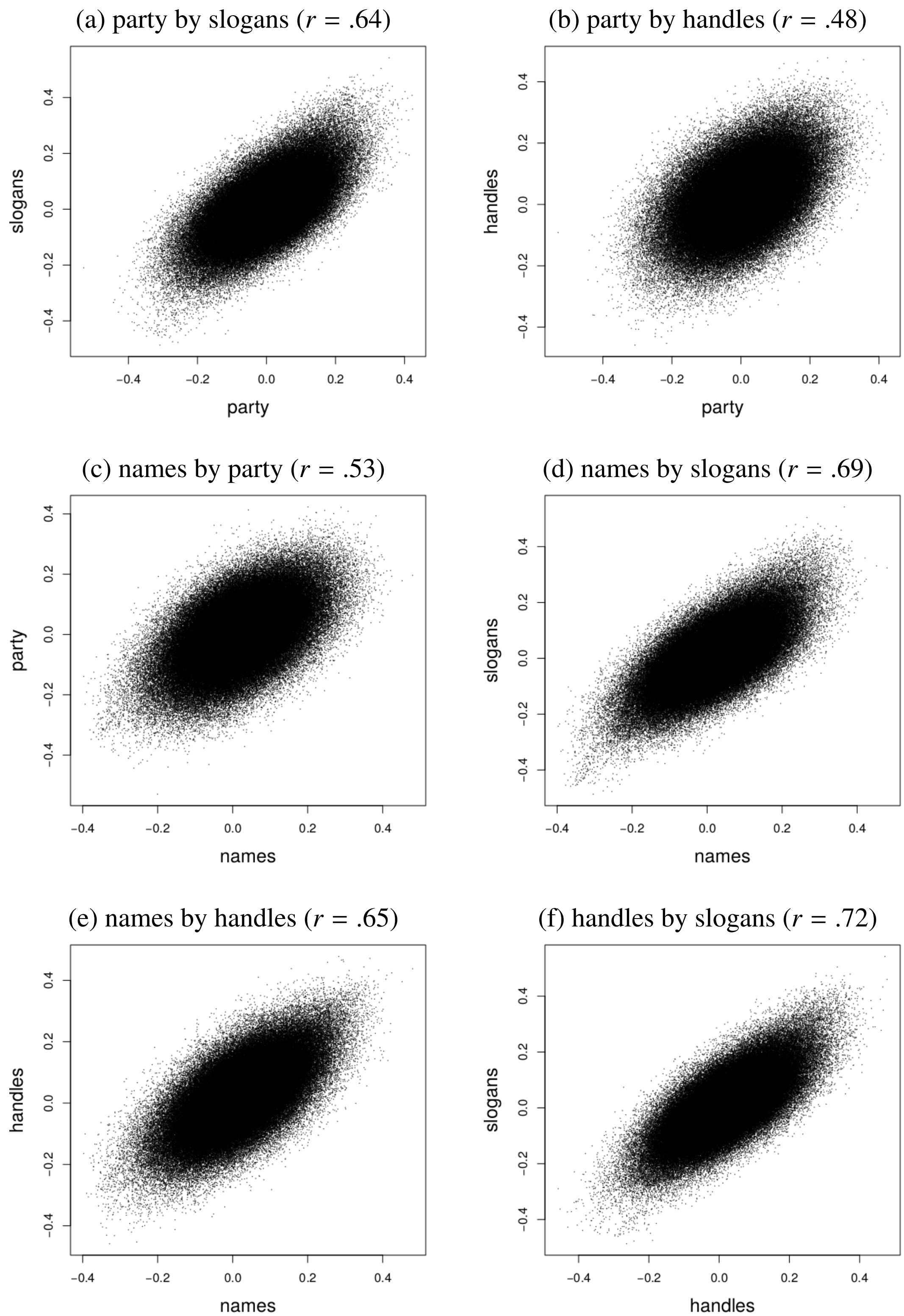


(c) usage by handles (r = .13)

(d) usage by slogans (r = .13)

Note: Scatterplots of partisan association average (`usage`) and difference (`party`, `names`, `handles`, `slogans`) scores. $n = 194,336$. r is the product-moment correlation.

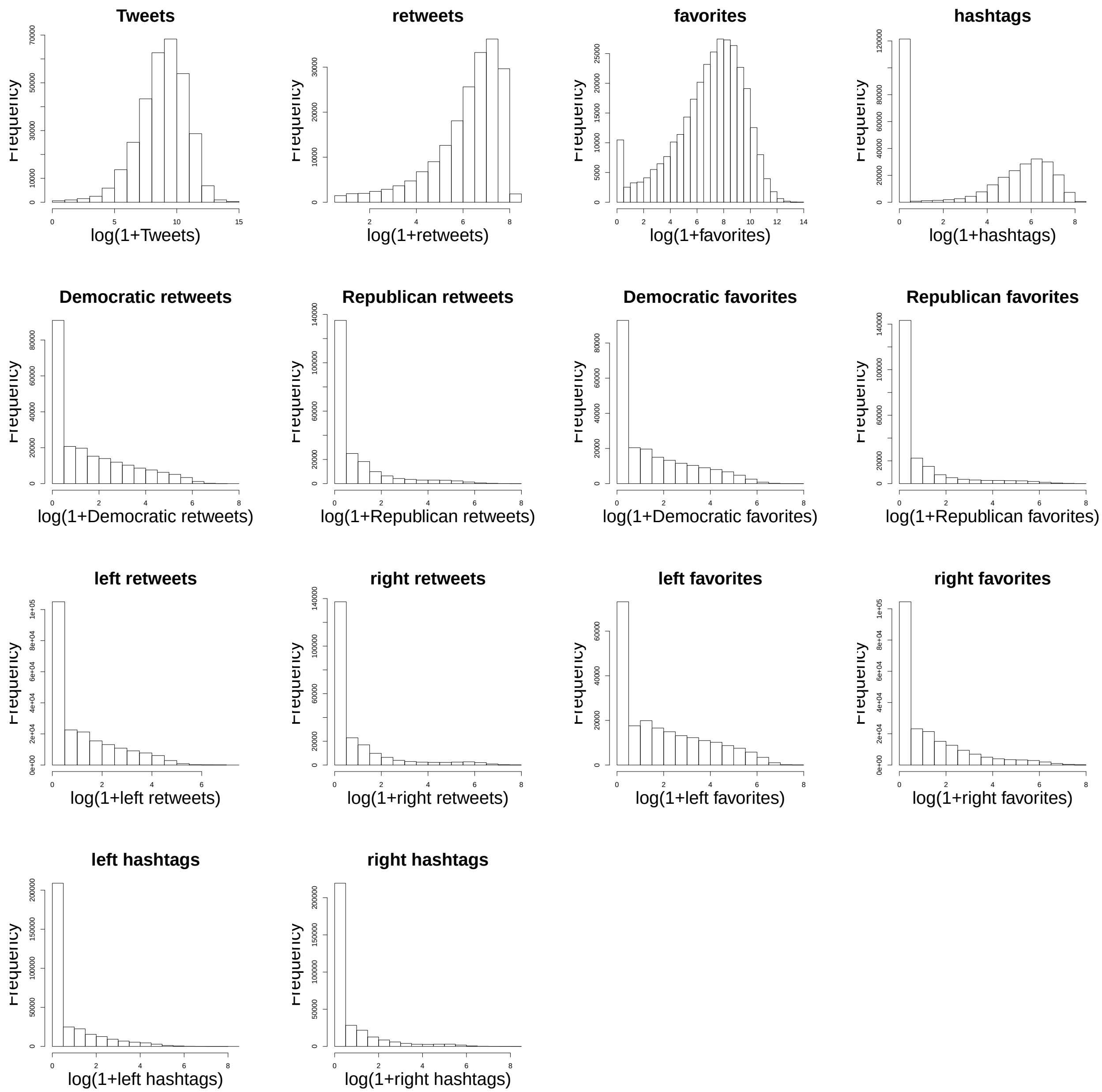
Figure 3: Cosine Similarities for Word Embedding Vector Combinations



(a) party by slogans (r = .64)
(b) party by handles (r = .48)
(c) names by party (r = .53)
(d) names by slogans (r = .69)
(e) names by handles (r = .65)
(f) handles by slogans (r = .72)

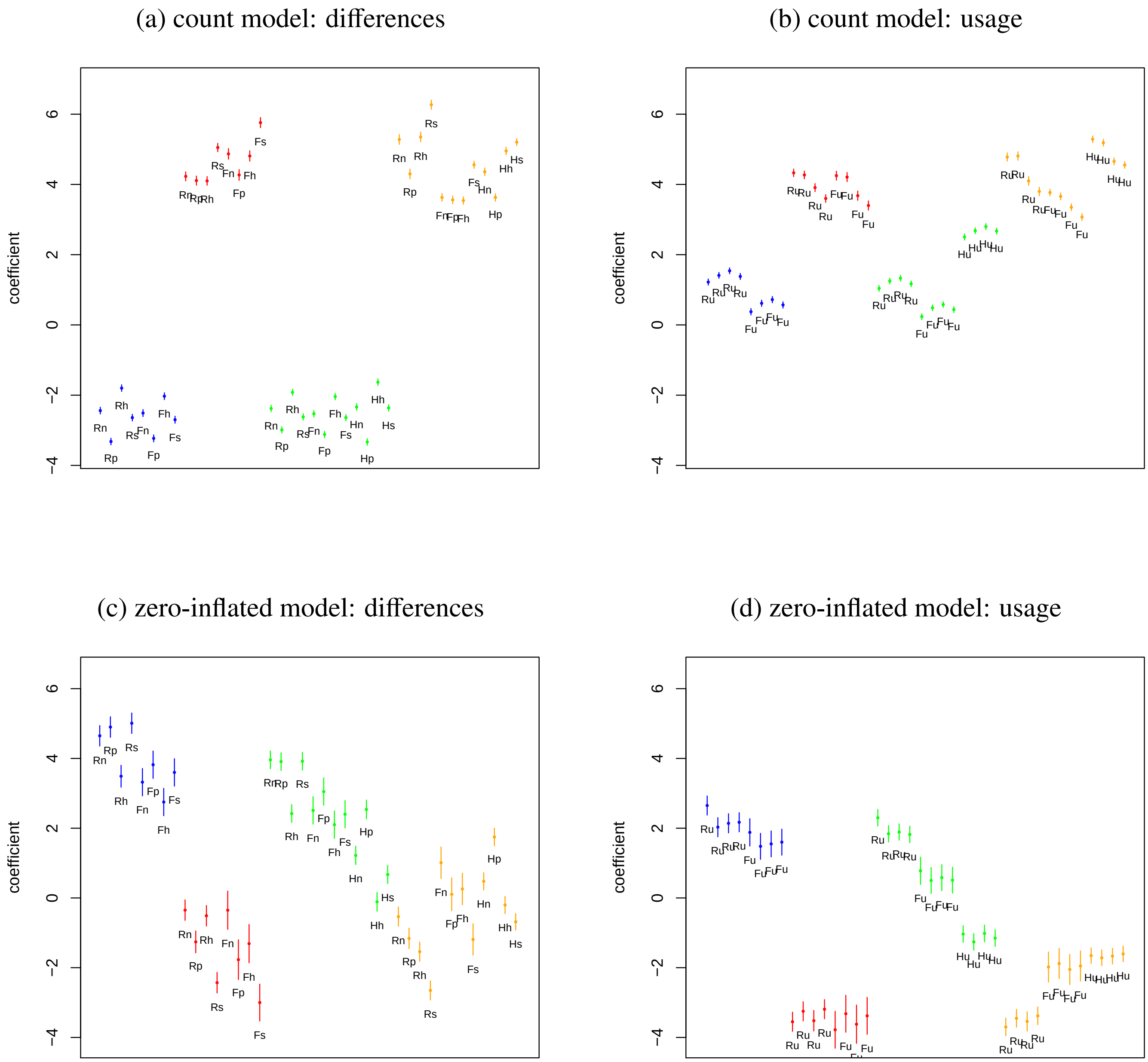
Note: Scatterplots of partisan association difference (`party`, `names`, `handles`, `slogans`) scores. $n = 194,336$. r is the product-moment correlation.

Figure 4: Distributions of Retweet, Favorite and Hashtag Counts



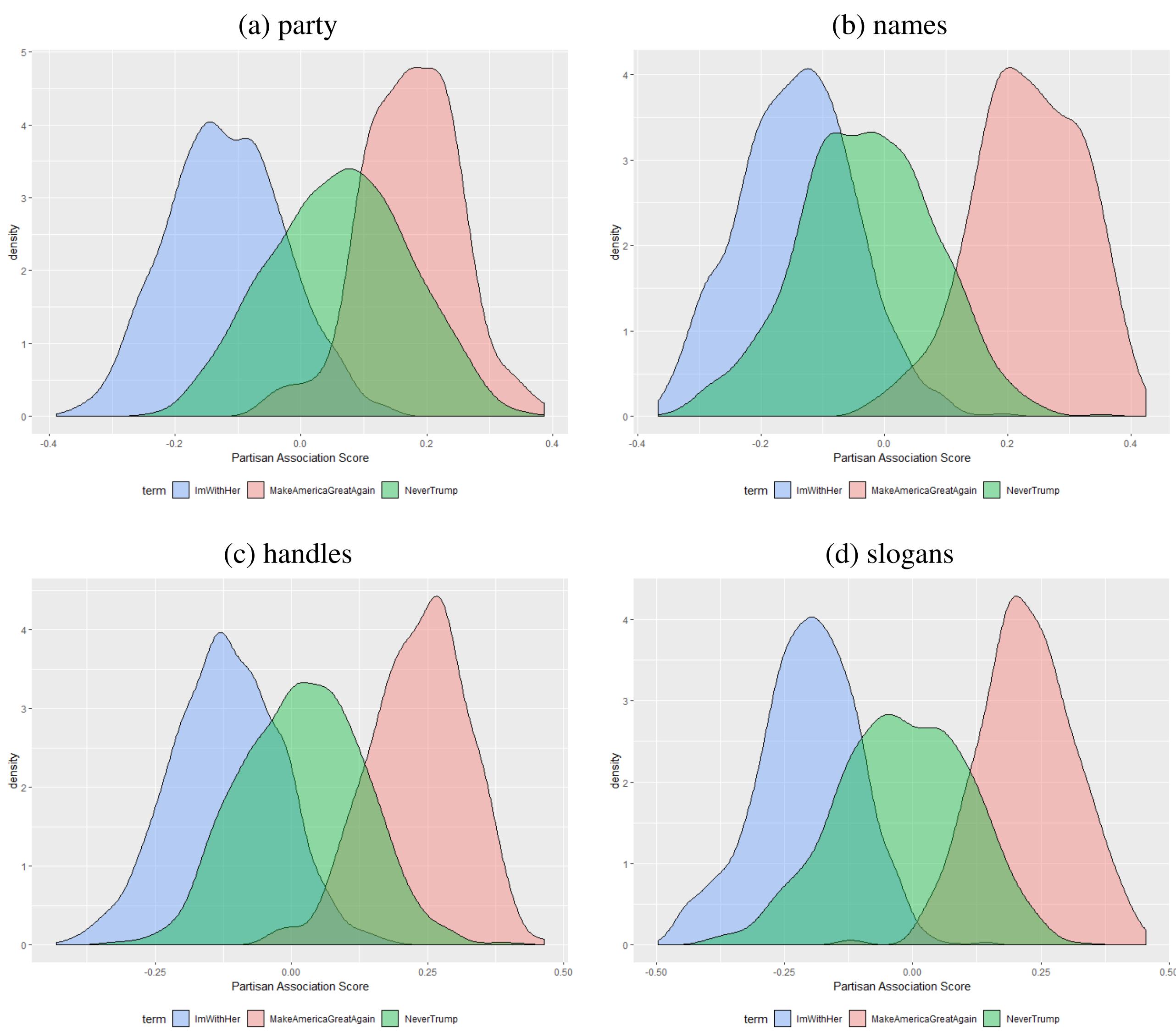
Note: histograms of log counts of Tweets (`statuses`), retweets, favorites or hastags in users' timelines.

Figure 5: Coefficients from Regressions of Retweets, Likes and Hashtags on Partisan Associations



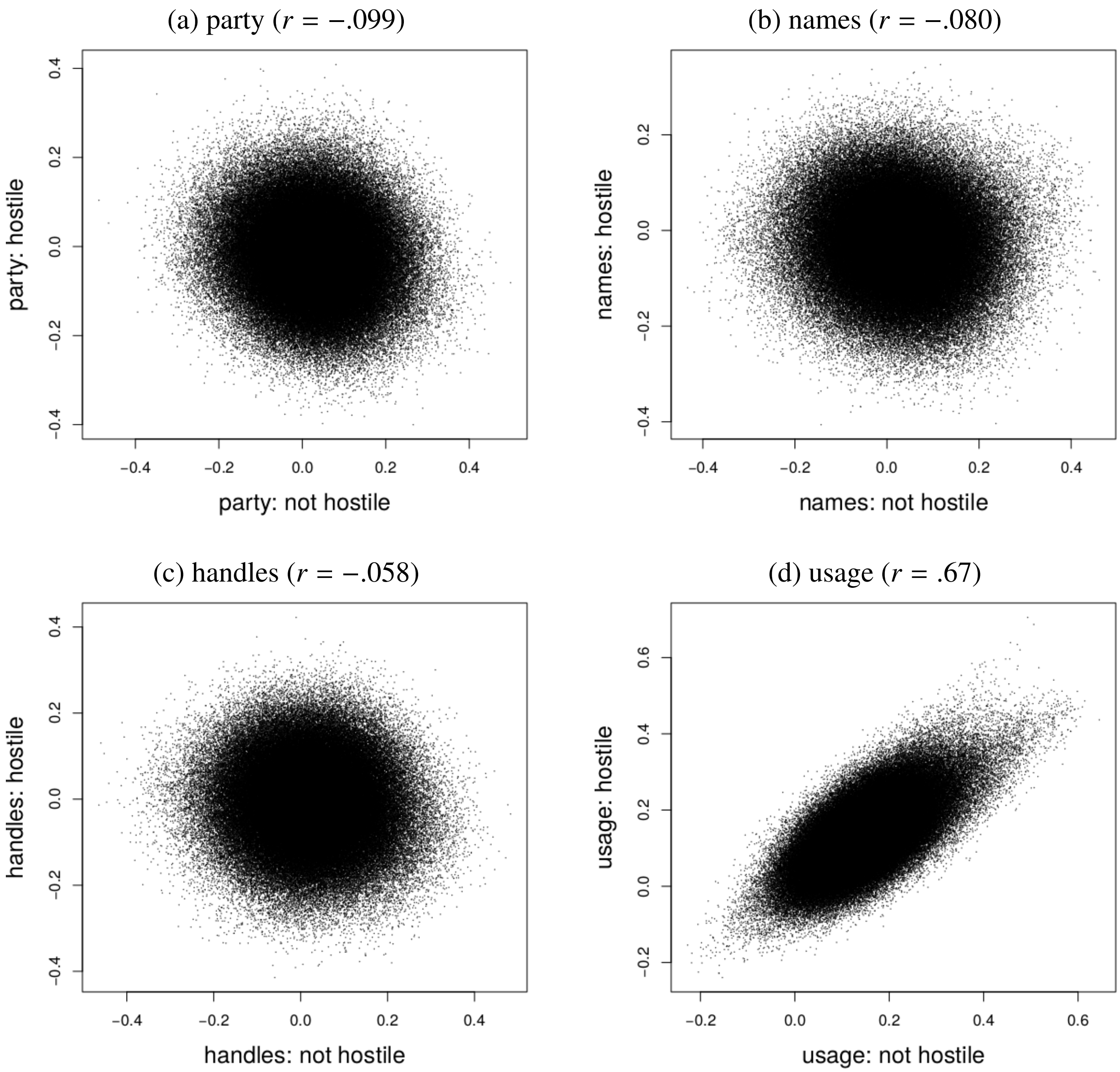
Note: coefficients with 95% confidence intervals from zero-inflated negative binomial count models using partisan association regressors (also Tweet counts and retweets, likes or hashtags counts variables in the zero-inflated models).
Color legend: blue, Democratic; red, Republican; green, left; orange, right.
Letter legend: R, retweet; F, favorite (like); H, hashtag; p, party; n, names; h, handles; s, slogans; u, usage.

Figure 6: Distribution of the Names Partisan Association Scores of users who used given out-of-sample words



Note: distributions of partisan association scores for users whose descriptions include "ImWithHer"," "NeverTrump" or "MakeAmericaGreatAgain."

Figure 7: Not-hostile by Hostile Word Embedding Vector Combinations



Note: Scatterplots of not-hostile versus hostile partisan association average (`usage`) and difference (`party`, `names`, `handles`) scores. $n = 194,336$. r is the product-moment correlation.