Unsupervised User Stance Detection on Twitter
Kareem Darwish$^1$, Peter Stefanov$^2$, Michal J. Aupetit$^1$, Preslav Nakov$^1$

$^1$ Qatar Computing Research Institute
Hamad bin Khalifa University
Doha, Qatar
$^2$ Faculty of Mathematics and Informatics,
Sofia University “St. Kliment Ohridski”,
Sofia, Bulgaria

kdarwish@qf.org.qa, p.stefanov@hotmail.com, maupetit@qf.org.qa, pnakov@qf.org.qa

Abstract
We present a highly effective unsupervised method for detecting the stance of Twitter users with respect to controversial topics. In particular, we use dimensionality reduction to project users onto a low-dimensional space, followed by clustering, which allows us to find core users that are representative of the different stances. Our method has three major advantages over current state-of-the-art methods, which are based on supervised or semi-supervised classification. First, we do not require any prior labeling of users: instead, we create clusters, which are much easier to label manually afterwards, e.g., in a matter of seconds or minutes instead of hours. Second, there is no need for domain- or topic-level knowledge either to specify the relevant stances (labels) or to conduct the actual labeling. Third, our method is robust in the face of data skewness, e.g., when some users or some stances have greater representation in the data. We experiment with different combinations of user similarity features, dataset sizes, dimensionality reduction methods, and clustering algorithms to ascertain the most effective and most computationally efficient combinations across three different datasets (in English and Turkish). Our best combination in terms of effectiveness and efficiency uses retweeted accounts as features, UMAP for dimensionality reduction, and Mean Shift for clustering, and yields a small number of high-quality user clusters, typically just 2–3, with more than 98% purity. Moreover, our method is robust to variations in the parameter values and also with respect to random initialization.

Introduction
Stance detection involves the identification of a position or stance of a user with respect to a topic or towards an entity and has broad applications in studying public opinion, political campaigning, and marketing. Stance detection is particularly interesting in the realm of social media, which offers the opportunity to identify the stance of very large numbers of users, potentially millions, on different issues. Most recent work on stance detection has focused on supervised or semi-supervised classification. In either case, some form of initial manual labeling of tens or hundred of users is performed, followed by user-level supervised classification or label propagation based on the user accounts and the tweets that they retweet and/or the hashtags that they use (Magdy et al. 2016; Penacchiotti and Popescu 2011a; Wong et al. 2013).

Retweets and hashtag use can enable such classification as they capture homophily and social influence (DellaPosta, Shi, and Macy 2015; Magdy et al. 2016), both of which are phenomena that are readily apparent in social media. With homophily, similarly minded users are inclined to create social networks, and members of such networks exert social influence on one another, leading to more homogeneity within the groups. Thus, members of homophilous groups tend to share similar stances on various topics (Garimella 2017). Moreover, the stances of users are generally stable, particularly over short time spans, e.g., over days or weeks. All this facilitates both supervised classification and semi-supervised approaches such as label propagation. Yet, there are several drawbacks of existing methods, which need labeled examples to start with: (i) manual labeling of users requires topic expertise to properly identify the underlying stances; (ii) manual labeling also takes substantial amount of time, e.g., 1–2 hours or more for 50–100 users; and (iii) the distribution of stances in a sample of users to be labeled, e.g., the most active n users or n random users, might be skewed, which could adversely affect classification performance, and fixing this might require non-trivial parameter tweaking or manual data balancing.

Here we aim at performing stance detection in a completely unsupervised manner, thus overcoming the aforementioned shortcomings of supervised and semi-supervised methods. Specifically, we automatically detect homogeneous clusters, each containing a few hundred users or more, and then we let human analysts label each of these clusters based on the common characteristics of the users therein such as the most representative retweeted accounts or hashtags. The resulting user groups can be used directly; they can also serve to train supervised classifiers or as seeds for semi-supervised methods such as label propagation.

Our method works as follows (see also Figure 1): given a set of tweets on a particular topic, we project a sample of active users onto a two-dimensional space based on their similarity, and then we use peak detection/clustering to find core groups of similar users. Using dimensionality reduction has several desirable effects. First, in a lower dimensional space, good projection methods bring similar users closer together while pushing dissimilar users further apart. User visualization in two dimensions also allows an observer to ascertain how separable users with different stances are.
Dimensionality reduction further facilitates downstream clustering, which is typically less effective and less efficient in high-dimensional spaces. Using our method, there is no need to manually specify the different stances a priori. Instead, these are discovered as part of clustering, and can be easily labeled in a matter or minutes at the cluster level, e.g., based on the most salient retweeted or hashtags for a cluster. Also, our method overcomes the problem of class imbalance and the need for expertise about the topic.

In our experiments, we compare different variants of our general stance detection framework. In particular, we experiment with three different dimensionality reduction techniques, namely Fruchterman-Reingold force-directed (FD) graph drawing algorithm (Fruchterman and Reingold 1991), t-Distributed Stochastic Neighbor Embeddings, or t-SNE, (Maaten and Hinton 2008), and Uniform Manifold Approximation and Projection (UMAP) algorithm (McInnes and Healy 2018). For clustering, we compare DBSCAN and Mean Shift, both of which can capture arbitrarily shaped clusters. We also experiment with different features such as Retweeted Tweets and accounts as the basis for computing the similarity between users. The successful combinations entail the use of FD or UMAP for dimensionality reduction, Mean Shift for peak detection, and retweeted accounts to compute user similarity. We also explore the limitations of our proposed method in terms of sensitivity to tuning parameter values and the required minimum number of tweets and users. Figure 1 summarizes our experiments.

We experiment with 15 tweet datasets in different languages and covering various topics, and we show that we are able to produce a small number of user groups (2-3 groups) composed of hundreds of users on average with purity in excess of 98% based on benchmark datasets with truth labels.

The main contributions of this paper are as follows:

1. We introduce a robust stance detection framework for automatically clustering core groups of users without manual intervention, which supports manual bulk labelling of all users in each cluster at once, and is based on dimensionality reduction followed by clustering.

2. We overcome key shortcomings of existing supervised and semi-supervised classification methods, namely the need for topic-informed manual labeling and the presence of potential skews and class imbalance in the data.

3. We show that dimensionality reduction techniques such as FD and UMAP, followed by Mean Shift clustering, can identify core groups of users with purity in excess of 98% according to labeled benchmark data, while being reasonably immune to changes in parameter values.

4. We explore the robustness to many parameters such as tweet set size, kinds of features used to compute similarity, and minimum number of users, among others, to ascertain the minimum requirements for effective stance detection.

5. We further study the computational efficiency of different effective combinations of features, user sample size, dimensionality reduction, and clustering.

Figure 1: Overview of our stance detection pipeline, the options studied in this paper, and the benefits they offer.

| Studied options | Benefits of our approach |
|-----------------|--------------------------|
| Tweets          | Best accuracy (>98% purity) |
| Features        | Slowest comp. time (~2 min) |
| User subset     | 500/1000/5000 |

**Stance Classification:** There is a lot of recent interest in stance detection involving the determination of a person’s position on an issue including the deduction of political preferences (Barberá 2015; Barberá and Rivero 2014) Borge-Holthoefer et al. 2015; Cohen and Ruths 2013; Colleoni, Rozza, and Arvidsson 2014; Conover et al. 2011b; Fowler et al. 2011; Himelboim, McCreery, and Smith 2013; Magdy et al. 2016; Magdy, Darwish, and Weber 2016; Makazhanov, Rafiei, and Waqar 2014; Weber, Garimella, and Batayneh 2013). Using network interaction features, specifically retweeted accounts, was shown to yield better results compared to using content features (Magdy et al. 2016).

**Effective Features:** Several studies have looked at features that may help reveal the stance of users. This includes textual features such as the text of the tweets and hashtags, network interactions such as retweeted accounts and mentions as well as follow relationships, and profile information such as user description, name, and location (Borge-Holthoefer et al. 2015; Magdy et al. 2016; Magdy, Darwish, and Weber 2016; Weber, Garimella, and Batayneh 2013). Using network interaction features, specifically retweeted accounts, was shown to yield better results compared to using content features (Magdy et al. 2016).

**User Classification:** Most studies focused on supervised or semi-supervised methods, which require an initial seed set of labeled users. Label propagation was used to automatically tag users based on the accounts they follow (Barberá 2015) and retweets (Borge-Holthoefer et al. 2015; Weber, Garimella, and Batayneh 2013). Although it has very high precision (often above 95%), it has three drawbacks: (i) it tends to label users who are more extreme in their views, (ii) careful manipulation of thresholds may be required, particularly when the initial tagged user set is imbalanced, and (iii) post checks are needed. Some of these issues can be observed in the “Datasets” section, where two of our test sets were constructed using label propagation.

Supervised classification was used to assign stance labels where classifiers were trained using a variety of features such as tweet text, hashtags, user profile information, retweeted accounts or mentioned accounts (Magdy et al. 2016; Magdy, Darwish, and Weber 2016; Pennacchiotti and Popescu 2011a).
Dimensionality Reduction and Clustering: Beyond the selection of relevant features for stance detection, another challenge for clustering approaches is the number of features. Indeed, an expert may be willing to use as many meaningful input features as possible, expecting the machine to detect automatically the relevant ones for the task at hand. This high-dimensional space is subject to the curse of dimensionality (Verleysen and others 2003). For instance the search space for a solution increases exponentially with dimensionality, is more likely to hide data patterns that could exist in lower dimension subspaces, and increases the computation time and the memory needed for clustering. Also it has been shown that as dimensions increase, the distance from any point to the nearest data point approaches the distance to the furthest data point (Beyer et al. 1999). This is problematic for clustering techniques, which typically assume short within-cluster and large between-cluster distances. We conducted side experiments that involved clustering directly without projecting into a lower dimensional space and all of them failed to produce meaningful clusters. As most clustering techniques are very efficient in low-dimensional spaces, we opted to first reduce the dimensionality and to apply clustering afterwards.

Another issue comes from the need of human experts to ascertain the validity of the clustering result beyond standard clustering statistics. For instance, an expert may want to verify that users belong to the core of separable groups such that they are good representatives of the groups and good candidate seeds for possible subsequent classification.

Such classification can label users with precision typically ranging between 70% and 90%. Rao et al. (Rao et al. 2010) used socio-linguistic features that include types of utterances, e.g., emoticons and abbreviations, and word n-gram features to distinguish between Republicans and Democrats with more than 80% accuracy. Pennacchiotti and Popescu (Pennacchiotti and Popescu 2011a) extended the work of Rao et al. (Rao et al. 2010) by introducing features based on profile information (screen name, profile description, followers, etc.), tweeting behavior, socio-linguistic features, network interactions, and sentiment. It has been shown that users tend to form so-called “echo chambers” where they engage with like-minded users (Himelboim, McCreery, and Smith 2013; Magdy et al. 2016), and they also show persistent beliefs over time and tend to maintain their echo chambers, which reveal significant social influence (Borge-Holthoefer et al. 2013; Magdy et al. 2016; Pennacchiotti and Popescu 2011b). Duan et al. (2012) used so-called “collective classification” techniques to jointly label the interconnected network of users using both their attributes and their relationships. Since there are implicit links between users on Twitter (e.g., they retweet the same accounts or use the same hashtags), collective classification is relevant here. Darwish et al. (2017) extended this idea by employing a so-called user similarity space of lower dimension to improve supervised stance classification. There was a related SemEval-2016 (Mohammad et al. 2016) shared task on stance detection, but it was at the tweet level rather than at the user level.

Visualization has come as a natural way to support the experts using Dimensionality Reduction (DR) techniques also called Multi-Dimensional Projection (MDP) in that field (Nonato and Aupetit 2018). The Force Directed graph drawing technique (Fruchterman and Reingold 1991), the t-distributed Stochastic Neighbor Embedding (t-SNE) (Maaten and Hinton 2008) and the recent Uniform Manifold Approximation and Projection technique (UMAP) (McInnes and Healy 2018), have been widely used as DR techniques for reducing the dimensionality and for transforming high-dimensional data into a two-dimensional scatter plot representations while preserving data similarity and supporting visualization.

Regarding the clustering techniques to be used in the low-dimensional space, we can select them based on their lower computational complexity, their ability to find groups with various shapes, and their low number of parameters to be tuned. Moreover, we are interested in detecting the core clusters likely to generate strong stances, rather than noisy sparse clusters with low influence. DBSCAN (Ester et al. 1996) and Mean Shift (Comaniciu and Meer 2002) are two well-known clustering techniques, which satisfy these constraints, and enable the discovery of core clusters and high-density peaks, respectively, with low computational complexity and few arbitrary parameters to be tuned.

In this work, we explore combinations of (i) relevant input features, namely retweeted tweets, retweeted accounts, and hashtags, (ii) dimensionality reduction of these input spaces into two dimensions using FD, t-SNE and UMAP, and (iii) clustering thereof using DBSCAN and Mean Shift, to determine the most efficient pipeline for finding stance clusters (see Figure 1).

Finding Stance Clusters

Feature Selection: Given a tweet dataset that has been pre-filtered using topical words, we take the n most “engaged” users who have posted a minimum number of tweets in the dataset. Given this sample of users, we compute the cosine similarity between each pair of users. Cosine similarity can be computed based on a variety of features including (re)tweeting identical tweets (T), which is what is used in label propagation, the hashtags that users use (H), or the accounts they retweet (R). The dimensions of the feature spaces are the number of unique tweets, the number of unique hashtags, and the number of unique retweeted accounts for T, R, and H, respectively. We computed cosine similarity using these features as well as all of them combined (TRH). To construct a user’s feature vector using retweeted accounts for example, the elements in the vector would correspond to the number of times the user retweeted each of the retweeted accounts in our dataset normalized by the number of times the user has retweeted any account. For example, if a user has retweeted three accounts with frequencies 5, 100, and 895, the corresponding feature values would be 5/1,000, 100/1,000, and 895/1,000, where 1,000 is the sum of the frequencies.
**Dimensionality Reduction:** We experimented with three different dimensionality reduction techniques, namely:

- **FD** [Fruchterman and Reingold 1991]: The algorithm attempts to minimize the energy in the representation of the network as a 2-dimensional node-link diagram, analogous to a physical system, where edges are springs and nodes bear repulsive charges, such that similar nodes are pulled closer together and dissimilar nodes are pushed further apart. In our work, we used the implementation in the NetworkX toolkit.

- **t-SNE** [Maaten and Hinton 2008]: The cosine similarity matrix between each pair of users is calculated and used to estimate the probability for a user to be the neighbor of another one in the high dimensional space — the farther apart they are in terms of cosine similarity, the lower the probability that they are neighbors. A set of points representing the users is located in the 2-dimensional space and the same probabilistic matrix is computed based on the relative Euclidean distances in that projection space. The position of the points is updated progressively to minimize the Kullback-Leibler divergence between these two probability distributions. We used scikit-learn implementation of t-SNE.

- **UMAP** (McInnes and Healy 2018): UMAP is similar to t-SNE, but it assumes that the data points are uniformly distributed on a Riemannian connected manifold with a locally constant metric. A fuzzy topological structure encoded as a weighted K-Nearest Neighbor graph of the data points is used to model that manifold and its uniform metric. The same structure is built in the projection space across the points representing the data, and their position is updated to minimize the divergence between these two structures. UMAP is significantly more computationally efficient than t-SNE and tends to emphasize the cluster structure in the projection. We used Leland McInnes’s implementation.

**Clustering:** After projecting the users into a two-dimensional space (such as the successful plot A in Figure 2 and the less successful plot in Figure 3), we normalized the coordinates of the points to be between $-1$ and $1$ in both the $x$ and $y$ axis, and we proceeded to identify cluster cores using the following two clustering methods (see plot B in Figure 2):

- **DBSCAN**, a density-based clustering algorithm that attempts to identify clusters based on preset density [Ester et al. 1996]. It has the advantage of being able to identify clusters of any shape. However, it requires the tuning of two parameters related to clustering density, namely: $\epsilon$, which specifies how close nodes need to be to be considered “reachable” neighbors, and $m$, which is the minimum number of nodes required to form a core set. Points that are not in the core set nor reachable by any other points are outliers that are not considered as part of the final clusters. We used the scikit-learn implementation of DBSCAN.

- **Mean Shift**, attempts to find peaks of highest density based on a kernel smoothing function [Comaniciu and Meer 2002], typically using a Gaussian kernel. With a kernel at each point, each point is iteratively shifted to the mean (barycenter) of all the points weighted by its kernel. All points thus converge to the local maximum of the density nearby them. The kernel’s bandwidth parameter determines the number of peaks detected by Mean Shift and all points converging to the same peak are grouped into the same cluster. The bandwidth can be estimated automatically using cross-validation in a probabilistic setting. Orphan peaks where only a few points converge are assumed to be outliers and hence are not clustered. Again, we used the scikit-learn implementation of the algorithm.

Finally, we consider the users within each final cluster as having identical stances. As we show later, we are able to find the most salient retweeted accounts and hashtags for each user cluster by computing a variant of the valence score for each [Conover et al. 2011]. Such can help in easily assigning labels to user clusters.

**Datasets**

We used the datasets in three different languages for testing:

1. **Kavanaugh dataset (English):** We collected tweets pertaining to the nomination of Judge Kavanaugh to the US Supreme Court in two different time intervals, namely September 28-30, 2018, which were the three days following the congressional hearing concerning the sexual assault allegation against Kavanaugh, and October 6-9, 2018, which included the day the Senate voted to confirm Kavanaugh and the following three days. We collected tweets using the Twarc toolkit where we used both the search and the filtering interfaces to find tweets containing any of the following keywords: Kavanaugh, Ford, Supreme, judiciary, Blasey, Grassley, Hatch, Graham, Cornyn, Lee, Cruz, Sasse, Flake, Crapo, Tillis, Kennedy, Feinstein, Leahy, Durbin, Whitehouse, Klobuchar, Coons, Blumenthal, Hirono, Booker, and Harris. These keywords include the judge’s name, his main accuser, and the names of the members of the Senate’s Judiciary Committee. In the process, we collected 23 million tweets, which were authored by 687,194 users. Initially, we manually labeled the 50 users who posted the highest number of tweets in our dataset. It turned out that 35 of them supported the Kavanaugh’s nomination (labeled as pro) and 15 opposed it (labeled as anti). Next, we used label propagation to automatically label users based on their retweet behavior [Darwish et al. 2017] [Kutlu, Darwish, and Elsayed 2018] [Magdy et al. 2016]. The intuition behind this method is that users who retweet a tweet on the target topic are likely to share the same stance as the one expressed in the tweet being retweeted. Given that many of the tweets in our collection were actually retweets or duplicates of other tweets, we labeled users who retweeted 15 or more tweets that were authored or retweeted by the pro group or 6 or more times by anti group and no retweets from the other side as pro or anti, respectively.

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[https://networkx.github.io/](https://networkx.github.io/)  
[https://umap-learn.readthedocs.io/en/latest/](https://umap-learn.readthedocs.io/en/latest/)  
[https://github.com/edsu/twarc](https://github.com/edsu/twarc)
Figure 2: Successful setup: Plot (A) shows how user vectors get embedded by UMAP in 2 dimensions; Plot (B) shows how Mean Shift clusters them; Plot (C) users’ truth labels

Figure 3: Unsuccessful setup: User vectors projected by t-SNE (default parameters); colors show users’ truth labels

We chose to increase the minimum number for the pro group as they were over-represented in the initial manually labeled set. We performed only one label propagation iteration, labeling 48,854 users of which 20,098 were pro and 28,756 were anti. Since we do not have gold labels to compare against, we opted to spot-check the results. Thus, we randomly selected 50 automatically labeled accounts (21 pro and 29 anti), and we manually labeled them. All automatic labels matched the manual labels. As observed, label propagation may require some tuning to work properly, and checks are needed to ensure efficacy.

2. Trump dataset (English): We collected 4,152,381 tweets (from 1,129,459 users) about Trump and the 2018 midterm elections from Twitter over a period of three days (Oct. 25-27, 2018), using the following keywords: Trump, Republican, Republicans, Democrat, Democrats, Democratic, midterm, elections, POTUS (President of the US), SCOTUS (Supreme Court of the US), and candidate. We were interested in users’ stance towardsTrump specifically. To label users with their stance, we made one simplifying assumption, namely that the supporter of a particular party would be supporting the candidate supported by their party. Thus, we labeled users who use “AKParti” (Erdoğan’s party) in their Twitter user name or screen name as pro. Similarly, we labeled users with other parties with candidates (“CHP”, “HDP”, or “IYI”) in their names as anti. Further, users who used pro-Erdoğan hashtags (#devam (meaning “continue”) or #RTE (“Recip Tayib Erdoğan”)) or the anti-Erdoğan hashtag #tamam (“enough”) in their profile description as pro or anti, respectively. In doing so, we were able to automatically tag 2,683 unique users of which 1,836 are pro and 848 are anti. We performed label propagation once where we labeled users who retweeted ten or more tweets that were authored or retweeted by either the pro or the anti groups with no tweets from the other side. This resulted in 233,971 labeled users of which 112,003 were pro and 121,968 were anti. We manually labeled 50 randomly automatically labeled accounts, and manual labeling agreed with automatic labels for 49 of them.

We tried label propagation, but it increased the number of labeled users by 12% only; thus, we dropped it. To check automatic labeling, we randomly labeled 50 users, and for 49 of them the manual labels matched the automatic ones.

3. Erdoğan dataset (Turkish): We collected 19,856,692 tweets (authored by 3,184,659 users) about Erdoğan and the June 24, 2018 Turkish elections that cover the period from June 16-23, 2018 (inclusive). We used many election related terms including political party names, names of popular politicians, and election-related hashtags. We were interested in users’ stance towards Erdoğan specifically. To label users with their stance, we made one simplifying assumption, namely that the supporter of a particular party would be supporting the candidate supported by their party. Thus, we labeled users who use “AKParti” (Erdoğan’s party) in their Twitter user name or screen name as pro. Similarly, we labeled users with other parties with candidates (“CHP”, “HDP”, or “IYI”) in their names as anti. Further, users who used pro-Erdoğan hashtags (#devam (meaning “continue”) or #RTE (“Recip Tayib Erdoğan”)) or the anti-Erdoğan hashtag #tamam (“enough”) in their profile description as pro or anti, respectively. In doing so, we were able to automatically tag 2,683 unique users of which 1,836 are pro and 848 are anti. We performed label propagation once where we labeled users who retweeted ten or more tweets that were authored or retweeted by either the pro or the anti groups with no tweets from the other side. This resulted in 233,971 labeled users of which 112,003 were pro and 121,968 were anti. We manually labeled 50 randomly automatically labeled accounts, and manual labeling agreed with automatic labels for 49 of them.

Experimental Setup
Finding the best configuration(s)

Setup: We randomly sampled tweets from each of our datasets to create 4 sets, with each set containing 5 different sampled subsets of sizes 50k, 100k, 250k, and 1M. We varied the size of the subsets to ascertain the effect of the number of tweets on the quality of clustering. For every subset size (e.g. 50k), we ran 72 experiments on the 15 tweet subsets (5 from every dataset) where we varied the following:
Table 1: Results of combinations that meet success criteria. The table lists average purity, averager number of clusters, the average number of users who were automatically tagged, and the average proportion of users who were tagged (Recall) across the 15 tweet subsets.

| Set | No of User | Feature(s) | Dim-Reduce | Peak Detect | Avg. Purity | Avg. # of Clusters | Avg. Cluster Size | Avg. Recall |
|-----|------------|------------|------------|-------------|-------------|-------------------|------------------|-------------|
| 100k | 500 | R | FD | Mean Shift | 90.1 | 2.0 | 100.9 | 20.2 |
|     | R | UMAP | Mean Shift | 86.6 | 2.5 | 125.4 | 25.1 |
|     | TRH | UMAP | Mean Shift | 85.5 | 2.0 | 145.9 | 29.2 |
|     | 1,000 | R | UMAP | Mean Shift | 90.5 | 2.9 | 196.1 | 19.6 |
|     | TRH | UMAP | Mean Shift | 88.3 | 2.3 | 305.8 | 30.6 |
| 250k | 500 | R | FD | Mean Shift | 98.7 | 2.5 | 171.3 | 34.3 |
|     | R | UMAP | Mean Shift | 98.5 | 2.1 | 179.9 | 36.0 |
|     | TRH | UMAP | Mean Shift | 94.4 | 2.3 | 165.3 | 33.1 |
|     | 1,000 | R | UMAP | Mean Shift | 98.8 | 2.4 | 1,264.3 | 25.3 |
|     | TRH | UMAP | Mean Shift | 98.6 | 2.7 | 1,322.2 | 26.4 |
|     | 5,000 | R | FD | Mean Shift | 99.1 | 2.9 | 196.1 | 19.6 |
|     | R | t-SNE | Mean Shift | 94.9 | 2.1 | 165.1 | 33.0 |
|     | R | UMAP | Mean Shift | 97.5 | 2.6 | 179.8 | 36.0 |
|     | T | UMAP | Mean Shift | 98.0 | 2.0 | 162.3 | 32.5 |
|     | TRH | t-SNE | Mean Shift | 91.7 | 2.3 | 171.3 | 34.3 |
|     | TRH | UMAP | Mean Shift | 98.9 | 2.3 | 186.5 | 37.3 |
| 1M | 500 | R | FD | Mean Shift | 99.0 | 2.6 | 180.4 | 36.1 |
|     | R | t-SNE | Mean Shift | 94.6 | 2.1 | 165.1 | 33.0 |
|     | R | UMAP | Mean Shift | 97.5 | 2.6 | 179.8 | 36.0 |
|     | T | UMAP | Mean Shift | 98.0 | 2.0 | 162.3 | 32.5 |
|     | TRH | t-SNE | Mean Shift | 91.7 | 2.3 | 171.3 | 34.3 |
|     | TRH | UMAP | Mean Shift | 98.9 | 2.3 | 186.5 | 37.3 |
|     | 1,000 | R | FD | Mean Shift | 99.4 | 2.1 | 366.7 | 36.7 |
|     | R | t-SNE | Mean Shift | 94.6 | 2.0 | 309.9 | 31.0 |
|     | R | UMAP | Mean Shift | 94.6 | 2.2 | 403.4 | 40.3 |
|     | T | t-SNE | Mean Shift | 92.7 | 2.0 | 396.5 | 36.9 |
|     | T | UMAP | Mean Shift | 98.6 | 2.0 | 349.8 | 35.0 |
|     | TRH | FD | Mean Shift | 95.7 | 2.1 | 326.3 | 32.6 |
|     | TRH | t-SNE | Mean Shift | 96.0 | 2.1 | 348.1 | 34.8 |
|     | TRH | UMAP | DBSCAN | 81.7 | 2.0 | 415.1 | 41.5 |
|     | TRH | UMAP | Mean Shift | 98.7 | 2.7 | 366.8 | 36.7 |
|     | 5,000 | R | FD | Mean Shift | 99.6 | 2.3 | 1,971.5 | 39.4 |
|     | R | UMAP | Mean Shift | 99.3 | 2.5 | 1,965.2 | 39.3 |
|     | T | t-SNE | Mean Shift | 97.8 | 2.0 | 1,795.0 | 35.9 |
|     | T | UMAP | Mean Shift | 99.2 | 2.1 | 1,869.3 | 37.4 |
|     | TRH | FD | Mean Shift | 99.1 | 2.0 | 1,838.8 | 36.8 |
|     | TRH | UMAP | DBSCAN | 93.2 | 2.2 | 2,180.6 | 43.6 |
|     | TRH | UMAP | Mean Shift | 99.4 | 2.3 | 1,980.7 | 39.6 |

Table 1: Results of combinations that meet success criteria. The table lists average purity, averager number of clusters, the average number of users who were automatically tagged, and the average proportion of users who were tagged (Recall) across the 15 tweet subsets.

- The dimensionality reduction technique: FD, t-SNE, or UMAP. Note that FD does not require any parameter tuning. We used the default parameters for t-SNE and UMAP, with the following changes: for t-SNE, we used perplexity=30.0 and early_exaggeration=12.0, while for UMAP, we used n_neighbors=15 and min_distance=0.1.
- The peak detection/clustering algorithm: DBSCAN or Mean Shift. The used the default parameters for DBSCAN, namely $\epsilon (=0.5)$ and $m (=5)$. For Mean Shift, the bandwidth parameter was estimated automatically.
- The number of top users to cluster: 500, 1,000, or 5,000. Clustering a smaller number of users requires less computation. We only considered users with a minimum of 5 interactions (e.g. 5 retweeted tweets).
- The features used to compute the cosine similarity, namely Retweets (R), Hashtags (H), full Tweeets (T), or all of them (TRH).

Results: We considered a configuration effective if it yielded at least two clusters with an average purity of at least 80% across all clusters and where labels are assigned to at least 10% of the users that were available for clustering.

Table 1 lists all results for experimental configurations that meet our success criteria. A few observations can be readily gleaned from the results, namely:

- Increasing the number of tweets generally led to better results and more configurations start meeting our criteria. No setup involving 50k subsets met our criteria. Purity increased between 8.3-11.9% on identical setups when moving from 100k to 250k, while the improvement in purity was mixed when using the 1M tweet subsets compared to using 250k.
- All setups meeting our criteria when using the 100k and 250k subsets involved using retweets as a feature (R or TRH), FD or UMAP for dimensionality reduction, and Mean Shift for peak detection. Other configurations met our criteria only when using subsets of size 1M.
As mentioned earlier, reducing the size of the tweet sets and the number of users we cluster would lead to greater computational efficiency. Thus, based on the results, we focus on the setup with 250k tweets, 1,000 users, and using R to compute similarity. For UMAP, it is followed by n_neighbors (default=15) and Mean Shift is followed by bin_seeding (True or False). Only the numbers with std=0.0 over multiple runs show std values after them.

- The use of retweets (R) to compute similarity achieved the highest purity when using 1M tweets, 5,000 users, FD, and Mean Shift with purity of 99.6%. Note that this setup is quite computationally expensive.

- The use of hashtags (H) alone to compute similarity failed to meet our criteria under all setups.

### Experiment 2: refining in search of robustness

Thus far, we used the default parameters for all dimensionality reduction and peak detection algorithms. Thus, we conducted two extra sets of experiments on the 250k dataset, using retweets (R) as features, and the 1,000 most active users. In the first, we wanted to ascertain the robustness of our most successful techniques to changes in parameters and to initialization. In the second, we wanted to determine whether we can get other setups to work by tuning their parameters.

**Testing the sensitivity of successful setups:** Our successful setups involved using FD or UMAP or dimensionality reduction and Mean Shift for peak detection. FD does not have any tunable parameters aside from the dimensions of the lower dimensional space, which we set to 2, and the number of iterations, which is by default set to 50. Beyond specifying the output dimension fixed to 2 in our setting, we varied the values of number of neighbors (n_neighbors) in UMAP to equal 5, 10, 15, 20, and 50, where 15 was the default. Mean Shift has one main tunable parameter, namely the bandwidth, which is automatically estimated. As for the rest, we have the option to use bin seeding or not and whether to cluster all points or not. Bin seeding involves dividing the space into buckets that correspond in size to the bandwidth to bin the points therein to increase the efficiency of the algorithm. We experimented with using bin seeding or not, and we chose not to cluster all points by ignoring orphan points. Lastly, since FD and UMAP are not deterministic and may be affected by random initialization, we repeatedly ran all FD+Mean Shift and UMAP+Mean Shift setups 5 times to assess the stability of the results. Ideally, we should get very similar values for purity, the same number of clusters, and very similar number of clustered users. Table[2] reports the results when varying the parameters for UMAP and Mean Shift. We can see that variations in the parameters had very little effect on purity, cluster count, and cluster sizes. Further, running the setups 5 times each led to identical results. Concerning timing information, using binning (bin_seeding=True) led to significant drop in run time. Also, increasing the number of neighbors generally increases run time. Lastly, UMAP+Mean Shift was significantly faster than FD+Mean Shift.

**Tuning unsuccessful setups:** Our unsuccessful setups involved the use of t-SNE for dimensionality reduction and/or DBSCAN for peak detection. We wanted to see if their failure was due to improper parameter tuning. And if so, how sensitive are they to parameter tuning. t-SNE has two main parameters, namely perplexity, which is related to the size of the neighborhood, and early exaggeration, which dictates how far apart the clusters would be placed. DBSCAN has two main parameters, namely minimum neighborhood size and epsilon (\(\epsilon\)), which is the minimum distance between points in a neighborhood. Due to the relatively large number of points that we are clustering, \(\epsilon\) is the important parameter to tune, and we experimented with \(\epsilon\) equal to 0.50 (default), 0.10, and 0.05. Table[3] reports on the results of parameter tuning. As can be seen, no combination of t-SNE or FD with DBSCAN met our minimum criteria (purity \(\geq 0.8\), no. of clusters \(\geq 2\)). t-SNE worked with Mean Shift when perplexity (\(\rho\)) was lowered from 30 (default) to 5. Also, t-SNE turned out to be insensitive to its early_exaggeration (ee) hyperparameter. UMAP worked with DBSCAN when \(\epsilon\) was set to 0.1. Higher values of \(\epsilon\) yielded low purity and too few clusters, and while lower values of \(\epsilon\) led to high purity, it also led to too many clusters. Thus, DBSCAN is more sensitive to parameter selection than it would be desirable. Further, when we ran the UMAP+DBSCAN setup multiple times, the results varied considerably from one run to another. This is also highly undesirable.

| Dim-Reduce | Peak-Detect | Avg. Purity | Avg. # of Clusters | Avg. Cluster Size | Avg. Run Time |
|------------|-------------|-------------|--------------------|-------------------|---------------|
| FD+Mean Shift | - | bin=False | 99.0 | 2.2 | 356.8 | 226 |
| | - | bin=True | 99.2 | 2.1 | 356.0 | 191 |
| UMAP+Mean Shift | neighbors=15 | bin=False | 98.6 | 2.0 | 354.3 | 148 |
| | neighbors=15 | bin=True | 98.4 | 2.0 | 348.9 | 78 |
| | neighbors=50 | bin=True | 98.6 | 2.0 | 353.2 | 129 |
| | neighbors=20 | bin=True | 98.4 | 2.0 | 348.7 | 159 |
| | neighbors=50 | bin=True | 98.4 | 2.0 | 353.7 | 159 |

Table 2: Sensitivity of FD+Mean Shift and UMAP+Mean Shift to parameter variations and random initialization.
where $tf$ is the frequency of the element in either cluster $A$ or not in cluster $A$ ($\neg A$) and total is the sum of all $tf$s for either the A or $\neg A$. We only considered terms that yielded a valence score $V(e) \geq 0.8$. Next we computed the score of each element as its frequency in cluster $A$ multiplied by its valence score as $score(e) = tf(e)_A \cdot V(e)$. Table 4 shows the top 5 retweeted accounts and top 5 hashtags for 250k sampled sets for all three datasets. As the entries and their descriptions in the table show, the salient retweeted accounts and hashtags clearly illustrate the stance of the users in these clusters, and hence can be readily used to assign labels to clusters. For example, the top retweeted accounts and hashtags for the two main clusters for the Kavanaugh and Trump datasets clearly indicate right and left-leaning clusters. A similar picture is seen for the Erdogan dataset clusters.

**Conclusion**

We presented an effective unsupervised method for identifying clusters of Twitter users having similar stances on controversial topics. Our method uses dimensionality reduction coupled with peak detection/clustering. Our method overcomes key shortcomings of existing stance detection methods, which rely on supervised or semi-supervised classification, such as: the need for manual labeling of users, which requires both topic expertise and time; and sensitivity to skew in the distribution of classes in the manually labeled set. For dimensionality reduction, we experimented with three different methods, namely Fruchterman-Reingold force-directed algorithm, t-SNE, and UMAP. Dimensionality reduction has several desirable effects such as bringing together similar items while pushing dissimilar items further apart in a lower dimensional space, visualizing data in 2 dimensions to enable an observer to ascertain how separable users stances are, and enabling the effective use of downstream clustering. For clustering, we experimented with DBSCAN and Mean Shift, both of which are suited for identifying clusters of arbitrary shapes and are able to identify cluster cores while ignoring outliers. We conducted a large set of experiments using different features to compute similarity between users on datasets of different sizes with varying topics and languages that were independently labeled with a combination of manual and automatic technique. Our most accurate setups use retweeted accounts as features, either the Fruchterman-Reingold force-directed algorithm or UMAP for dimensionality reduction, and Mean Shift for clustering, with the UMAP being significantly faster than Fruchterman-Reingold force-directed algorithm. These setups are able to identify groups of users corresponding to the predominant stances on controversial topics with more than 98% purity based on our benchmark data. We are able to achieve these results by working with the most active 500 or 1,000 users in tweet sets containing 250k tweets. We also show the robustness of our best setups to variations in algorithm parameters and to random initialization. In future work, we want to use our stance detection technique to profile popularly retweeted Twitter users, cited websites, and shared media by ascertaining their valence scores across a variety of polarizing topics.

| Dim-Reduce | Peak-Detect | Avg. Purity | Avg. # of Clusters | Avg. Cluster Size | Run Time (s) |
|------------|-------------|-------------|--------------------|------------------|-------------|
| t-SNE+Mean Shift (bin_seeding=True) | - | 69.7 | 1.6 | 256.0 | 290 |
| - | 69.5 | 1.6 | 260.6 | 286 |
| - | 69.6 | 1.8 | 266.6 | 301 |
| UMAP (n_neighbors=15)+DBSCAN | - | 98.0 | 2.0 | 358.0 | 190 |
| - | 98.2 | 2.0 | 359.1 | 193 |
| - | 98.4 | 2.0 | 360.0 | 192 |

Table 3: Sensitivity of t-SNE and DBSCAN to changes in parameters and to random initialization. Experiments on 250k datasets, most engaged 1,000 users, and using R to compute similarity. For t-SNE, we experimented with perplexity ($\rho$) equal to 5 or 30 (default) and early exaggeration equal to 8, 12 (default) and 50. For DBSCAN, we varied epsilon between 0.05 and 0.50 (default). Only the numbers with stdev $>0.0$ over multiple runs show stdev values after them. Entries meeting our success criteria are bolded.

| Dim-Reduce | Peak-Detect | Avg. Purity | Avg. # of Clusters | Avg. Cluster Size | Run Time (s) |
|------------|-------------|-------------|--------------------|------------------|-------------|
| t-SNE+DBSCAN | - | 59.5 | 1 | 409.9 | 195 |
| - | 59.5 | 1 | 409.9 | 195 |
| - | 59.5 | 1 | 409.7 | 201 |
| - | 59.2 | 1 | 397.9 | 184 |
| - | 59.3 | 1 | 397.3 | 193 |
| - | 59.2 | 1 | 397.6 | 195 |
| - | 59.2 | 1 | 410.0 | 135 |
| - | 59.5 | 1 | 410.0 | 135 |
| - | 59.5 | 1 | 410.0 | 135 |
| - | 59.5 | 1 | 410.0 | 135 |
| UMAP (n_neighbors=15)+DBSCAN | - | 98.9 | 16.8 | 341.1 | 78 |
| - | 192 |
| - | 192 |
| - | 192 |

Based on these experiments, it seems that using FD or UMAP for dimensionality reduction in combination with Mean Shift yields the best results with the highest stability. Lastly, the execution time of Mean Shift and DBSCAN are comparable, and UMAP is significantly faster than FD.

**Labeling Clusters:** We wanted to elucidate the cluster outputs by identifying the most salient retweeted accounts and hashtags in each of the clusters. Retweeted accounts and hashtags can help tag the resulting clusters. To compute a salience score for each element (retweeted account or hashtag), we initially computed a modified version of the so-called valence score (Conover et al. 2011) that accommodates for having more than two clusters. The valence score for an element $e$ in cluster $A$ is computed as follows:

$$V(e) = 2 \cdot \frac{tf_A}{total_A} - 1$$

$$score(e) = tf(e)_A \cdot V(e)$$
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### Kavanaugh Dataset

| RT | Description | Score | RT | Description | Score |
|----|-------------|-------|----|-------------|-------|
| @kylegriffin1 | Producer. MSNBC’s @TheLastWord. | 55.0 | @mitchellvii | (pro-Trump) Host of YourVoice America (right leaning media) | 52.5 |
| @krassenstein | Outspoken critic of Donald Trump - Editor at http://HillReporter.com | 34.0 | @FoxNews | | 48.0 |
| @Lawrence | thelastword.msnbc.com | 29.0 | @realDonaldTrump | 45th President of the United States | 48.0 |
| @KamalaHarris | (Dem) U.S. Senator for California. | 29.0 | @Thomas1774Paine | TruePundit.com | 47.0 |
| @MichaelAvenatti | (anti-Trump) Attorney, Advocate, Fighter for Good. | 26.0 | @dbongino | Host of Dan Bongino Podcast. Own the libs. | 44.5 |

| Hashtag | Description | Score | Hashtag | Description | Score |
|---------|-------------|-------|---------|-------------|-------|
| StopKavanaugh | | 5.0 | ConfirmKavanaugh | | 19.0 |
| SNL | Saturday Night Live (ran a skit mocking Kavanaugh) | 4.0 | winning | pro-Trump | 12.0 |
| P2 | progressives on social media | 3.0 | Qanon | alleged insider/conspiracy theorist (pro-Trump) | 11.0 |
| DevilsTriangle | sexual/drinking game | 3.0 | WalkAway | walk away from liberalism/Dem party | 9.0 |
| MSNBC | left-leaning media | 3.0 | KavanaughConfirmation | | 8.0 |

### Trump Dataset

| RT | Description | Score | RT | Description | Score |
|----|-------------|-------|----|-------------|-------|
| @TeaPainUSA | Faithful Foot Soldier of the Resistance | 98.5 | @realDonaldTrump | 45th President of the United States | 95.4 |
| @PalmerReport | Palmer Report: Followed by Obama. Blocked by Donald Trump Jr | 69.8 | @DonaldTrumpJr | EVP of Development & Acquisitions | 72.4 |
| @kylegriffin1 | Producer. MSNBC’s @TheLastWord. | 66.5 | @mitchellvii | (pro-Trump) Host of YourVoice America | 47.9 |
| @maddow | rachel.msnbc.com | 39.5 | @ScottPresler | spent 2 years to defeat Hillary. I’m voting for Trump | 33.0 |
| @tribelaw | (anti-Trump Harvard faculty) | 32.0 | @JackPosobiec | OANN Host. Christian. Conservative. | 32.5 |

| Hashtag | Description | Score | Hashtag | Description | Score |
|---------|-------------|-------|---------|-------------|-------|
| VoteBlue | Vote Dem | 12 | Fakenews | | 18.5 |
| VoteBlueToSaveAmerica | Vote Dem | 11 | Democrats | | 15.5 |
| AMJoy | program on MSNBC | 5 | LDdPoll | Lou Dobbs (Fox news) poll | 12.0 |
| TakeIBack | Democratic slogan | 4 | msm | main stream media | 11.0 |
| Hitler | controversy over the term "nationalist" | 3 | FakeBombGate | claiming bombing is fake | 11.0 |

### Erdoğan Dataset

| RT | Description | Score | RT | Description | Score |
|----|-------------|-------|----|-------------|-------|
| @vekilince | (Muhammem Inci – presidential candidate) | 149.6 | @06melihgokcek | (Ibrahim Melih Gokcek – ex. Governor of Ankara) | 64.9 |
| @cumhuriyetgzt | (Cumhuriyet newspaper) | 104.0 | @GizliArxivTR | (anti-FETÖ/PKK account) | 54.0 |
| @gazetesozcu | (Sozcu newspaper) | 82.5 | @UstAkiOyunlari | (Pro- Erdoğan conspiracy theorist) | 49.7 |
| @kacacakturolunet | (popular anti- Erdoğan account) | 80.0 | @medyasadami | (Freelance journalist) | 42.0 |
| @tgmecelesi | (Mehmet Ali Celebi – leading CHP member) | 65.8 | @Malargir_Rohu | | 37.0 |

| Hashtag | Description | Score | Hashtag | Description | Score |
|---------|-------------|-------|---------|-------------|-------|
| tanam | enough (anti- Erdoğan) | 49.0 | VakitTurkiyeVakti | AKP slogan It is Turkey time | 42.7 |
| MuharremInce | Muharrem Ince – presidential candidate | 43.5 | iyiKurdoanVar | Great that Erdoğan is around | 20.0 |
| demirtaş | Selahattin Demirtaş – presidential candidate | 12.0 | tatanka | Inci’s book of poetry | 19.0 |
| KişçərəqloğluNəSoyli | what did Kişçərəqloğlu (CHP party leader) say | 11.0 | HazırzTurkiye | Turkey: We’re Ready (AKP slogan) | 17.7 |
| mersin | place for Inci rally | 11.0 | katiHDPKK | Killer PKK (Kurdish group) | 17.0 |

Table 4: Salient retweeted accounts (top 5) and hashtags (top 5) for 2 largest clusters for 250k sampled subsets from the Kavanaugh, Trump, and Erdoğan datasets to qualitatively show the efficacy of our method. When describing Twitter accounts, we tried to use the text in the account descriptions as much as possible, with our words put between brackets.