Abstract—This paper presents twAwler, a lightweight twitter crawler that targets language-specific communities of users. twAwler takes advantage of multiple endpoints of the twitter API to explore user relations and quickly recognize users belonging to the targeted set. It performs a complete crawl for all users, discovering many standard user relations, including the retweet graph, mention graph, reply graph, quote graph, follow graph, etc. twAwler respects all twitter policies and rate limits, while able to monitor large communities of active users.

twAwler was used between August 2016 and March 2018 to generate an extensive dataset of close to all Greek-speaking twitter accounts (about 330 thousand) and their tweets and relations. In total, the crawler has gathered 750 million tweets of which 424 million are in Greek; 750 million follow relations; information about 300 thousand lists, their members (119 million member relations) and subscribers (27 thousand subscription relations); 705 thousand trending topics; information on 52 million users in total of which 292 thousand have been since suspended, 141 thousand have deleted their account, and 3.5 million users in total of which 292 thousand have been since suspended, 141 thousand have deleted their account, and 3.5 million are protected and cannot be crawled. twAwler mines the collected tweets for the retweet, quote, reply, and mention graphs, which, in addition to the follow relation crawled, offer vast opportunities for analysis and further research.

I. INTRODUCTION

Social media content offers many opportunities for research in numerous fields and disciplines, including machine learning, natural language processing, epidemiology, sociology, economics, etc. Data mining social media is, however, increasingly difficult, due to technical and policy constraints.

Specifically, twitter has been used in multiple studies and analyses due to its more open and public content. Twitter restricts the reuse and publication of data crawled using its public API to only sharing anonymized information (user and tweet IDs), and moreover restricts the number of queries made to its API to a limited rate. This limitation may be overcome by combining multiple users’ rate limits and aggregating multiple crawls, but (i) this may be considered sharing non-anonymized information by twitter, or (ii) it may require access to expensive resources such as several cloud VMs or a cluster, for a prolonged period of time.

This paper presents twAwler, an open-source[^1] cost-effective, lightweight twitter crawler that can explore, discover and target users related to a specific topic or using a given language. The crawler takes advantage of multiple twitter API endpoints, maximizing the total crawled information while respecting all limits and policies. Moreover, it requires a single users' credentials and can run on a single machine over large periods of time, tolerating reboots and downtime without issue. twAwler aims to be complete, i.e., does not crawl a sample of the user content but instead all of the traffic of the users belonging to the crawled community. The crawler can analyze tweets and generate a multitude of relations and information, including the follow, retweet, mention, reply, quote, and favorite graphs, temporal patterns, topic and word frequencies, etc. The author has used the crawler for a period of 20 months to discover and track a set of all Greek-speaking twitter accounts, using a low-cost machine, the author’s desktop PC. twAwler can perform similarly well for even larger twitter communities, especially when targeting language-specific parts of the twitter graph.

II. TWITTER CRAWLER

twAwler is a custom crawler for twitter data that discovers and monitors Greek-speaking twitter users, monitors all their publicly accessible content. The crawler stores this information and is able to extract multiple relations, including the follow graph, the mention, reply and retweet and quote graphs, the favorite graphs, etc. These relations are timestamped, enabling further analysis using dynamic graph techniques. twAwler maintains a set of tracked users, a set of users that have been marked as greek-speaking, a set of stop-users that are definitely not greek-speaking and the sets of dead, suspended, and protected users. twAwler is structured as a set of small tools and the scripts using them to perform on-demand or continuous crawls.

A. Tweet Crawler

twAwler uses the twitter /statuses/user_timeline API endpoint to crawl the tweets of tracked users. To crawl the selected users’ tweets, twAwler downloads all the user tweets that it can using the request twitter API, up to the 3200 tweets that twitter allows, or until it reaches the last tweet seen when the user was crawled previously. To save on the number of rate limited requests, twAwler prioritizes crawling of users that have a high probability of having tweeted a lot since last crawled. To do that, it computes the average tweets per day for every user and uses two processes of tweet crawling: On the one hand, the crawler sorts all users based on the time since they were last crawled. To do that, it computes the average tweets per day for every user and uses two processes of tweet crawling: On the one hand, the crawler sorts all users based on their expected tweets since they were last crawled and crawls users with a high number of expected tweets. On the other hand, the crawler sorts all users based on the time since they were last crawled and crawls users not visited in a long time. This way, twAwler minimizes the probability of lost tweets, and also make the best use of the available requests per minute that twitter allows. Note that twitter throttles the number of API requests per 15 minutes, that only the last 3200 tweets can be

[^1]: The software will be released under Apache License before this publication is in print. twAwler is about 11KLoC of Python.
requested, and that a maximum of 200 tweets can be returned per request. A simple back-of-the-envelope calculation shows that by delaying crawling to keep the average number of tweets per user crawled close to 1000 since the last visit, we consume half the number of requests per tweet compared to an average of 100 tweets since the last visit.

In addition to the standard twitter user timeline crawling, twit regulatory also looks for tweets from tracked users that are retweets, reply to, or quote other tweets, and use the /statuses/lookup endpoint to ask specifically for information regarding these tweets and their authors. This way, the crawler will eventually discover all interactions of the tracked users and crawl them for analysis of the whole “thread”.

To discover new users in the targeted community, we seed the tracked set of users by performing a search for common greek stopwords on the /statuses/filter twitter streaming API. There is no need to run the filter continuously, as it is only used to seed the tracked users, since the crawler is user-centric and aims for a full crawl of the involved users. In addition to seeding based on stopwords, the crawler adds new users by tracking any retweets in Greek from currently tracked users. Specifically, if the crawler discovers 10 tweets in Greek by an unknown user that have been retweeted by tracked users, then it also starts tracking the new user as there is a high probability they are also Greek-speaking. Moreover, a daily pass discovers tracked users with more than 500 tweets, of which less than 2 per cent are in Greek, and stops tracking them, adding them to the set of users where the crawl stops, as they were found to not be greek-speakers.

B. Follow Graph Crawler

The public twitter API offers four ways of crawling user follow relations, namely using the friends/ids and friends/list API endpoints for crawling the IDs or fully populated user structs of the user’s friends, and followers/ids and followers/list to crawl followers respectively. As rate limits are set separately for each endpoint, twit regulatory crawls all users’ friends and followers using four crawler processes, marking each crawled user to not be crawled again for the following 30 days. This limit is currently arbitrary, as the follow relation does not change often or oscillate, and could be set to a much lower time window while still remaining within the rate limits for a community of this size. Note that two of the four endpoints twit regulatory uses to crawl the follow graph produce detailed user information, whereas the other two produce solely user IDs. These are easily separated and stored as the follow graph and a table of users, where some IDs may not yet be populated with all user information. twit regulatory periodically runs a separate processes to populate missing user information, using the /users/show/:id endpoint, and also utilize the tweet crawler to save the user information for any user for whom it finds it missing or out-of-date. Note that this will generate multiple entries of the user information per user, allowing an analysis to monitor the evolution of the user’s profile, bio, language, etc. over time. Currently, twit regulatory is configured to use a time window of two weeks for crawling user information, and do not store the new information if it only differs in the number of tweets from the user profile last seen.

C. List Crawler

Twitter lists have been used to mine user-curated information in previous research. As they aggregate the opinion, or classification, of users into groups by other users, they amount to valuable crowdsourced information that can be mined to infer common interests, relations, etc. The twitter API offers 4 ways to crawl lists; namely, lists/subscriptions returns information regarding the lists to which a user subscribes, lists/memberships returns information regarding the lists of which a user is a member, lists/members returns the users that are members of a list, and lists/ownerships returns lists curated by the given user. As these have different rate limits, twit regulatory uses four separate crawler processes that crawl lists and users in a round-robin fashion and populate or update the list membership relations.

D. Favorites Crawler

Twitter allows users to signal interest in a tweet by marking it as “favorite” (or “like”). The twitter API offers one way to get a user’s favorites, favorites/list, returning “likes” ordered by date of “liked” tweet. This is one of the most limiting constraints, as any “likes” on tweets older than the newest “like” seen will be lost. To avoid that as much as possible, twit regulatory does not stop after observing previously seen “likes” as with tweets, but continues crawling until having seen more than 190 previously known “likes”. The probability of missing user “likes” remains, but as users often “like” tweets that they observe in the top of their timeline, missing old “likes” happens less often. The twitter web client allows viewing a user’s “likes” in the order they were done, not the order they were tweeted; manually observing the “likes” of five very active users over a period of two days showed a small percentage of missed “likes”. twit regulatory could scrape the web page for these, but does not, as to remain very clearly within the limitations of the twitter API agreement. Note that the rate limiting for favorite crawling is an order of magnitude less than the tweet API limits, resulting in only a sample of the favoriting graph compared to the near-full coverage for the other information.

E. Crawler Storage

twit regulatory currently uses a MongoDB installation to store crawled data. The MongoDB contains the following collections, used to store the crawled data as well as metadata used by the crawler.

The users collection contains user objects as returned by the Twitter API. There may be multiple entries per single user, as discussed above. Each entry is annotated with the insertion date. To avoid sorting and aggregation when scanning for the latest entry for a given user, the data includes an additional field called screen name lower that contains the screen name in lowercase. This field is unique when it exists, and in aggregate helps depict the currently existing users as last seen by the crawler.

The tweets collection contains tweet objects as returned by the Twitter API. Each tweet is unique. As there may be
missing or truncated tweets in the data store, \texttt{twAwler} uses additional curation processes that filter out truncated tweets and use the \texttt{/statuses/lookup} API to properly populate them with the non-truncated version. The author has used this tool to also properly ingest textual dumps of tweets generated by early versions of the crawler, and handle the switch of the tweet length limit from 140 to 280 characters seamlessly.

The \texttt{trends} collection contains trend objects as returned by the \texttt{trends/place} Twitter API for Greece, timestamped and crawled every 15 minutes. The rate limit for trends is never reached, as Greek-speaking accounts tend to have a very large geographical correlation with Greece, and there is currently no need to crawl trending topics for multiple locations.

The \texttt{shorturl} collection contains key-value pairs of shortened URLs and their corresponding target URL, as resolved by \texttt{shorturl}. To populate this collection, \texttt{twAwler} uses both the expanded URL provided for each shortened URL by twitter within each tweet, and also uses a set of crawler processes that interact with URL shortener services or directly with the web, to resolve shortened URLs.

The \texttt{follow} collection stores directed, timestamped follow edges as generated by the follow graph crawler. This amounts to a dynamic graph that approximates the follow relations between tracked users and their friends and followers, i.e., it is a superset of the follow relation between tracked users, and includes their friends and followers regardless of whether their tweets are being tracked.

The \texttt{greeks} collection contains IDs (key) and screen names (not necessarily up-to-date) of users that have been classified as Greek-speaking. \texttt{twAwler} is parametric as to the criterion; the reported deployment is configured to classify users as Greek speakers and track when they satisfy any of the following conditions:

- Users with more than 100 tweets, of which at least 20% are in Greek.
- Users with more than 500 tweets, of which at least 10% are in Greek and their username and bio are in a set of common Greek names or written in the Greek alphabet.

Clearly, the Greek language having a unique alphabet aids significantly in recognizing Greek speakers. However, that is not central to \texttt{twAwler}, as Twitter’s language recognition is very precise in several languages that use the Latin alphabet. Conversely, \texttt{twAwler} marks users as non-Greek speakers and stops the crawler from following them and discovering new users through them, when it has crawled more than 500 of their tweets, of which less than 1% are in Greek. The author has found that these conditions succeed in classifying most users into either Greek-speaking or not, leaving only a small number of inconclusive users. \texttt{twAwler} applies an additional constraint to these, where if more than 30% of a user’s followers and friends have already been classified as Greek-speaking, the inconclusive user is marked as Greek-speaking.

The \texttt{suspended} collection contains IDs and screen names of users that have been observed to be suspended by twitter. Screen names may not necessarily be up-to-date, as the account may have changed its screen name between the time it was last crawled and when it was suspended.
| Feature Name                      | Description                                                                 |
|----------------------------------|-----------------------------------------------------------------------------|
| id                               | The twitter User ID.                                                        |
| screen_name                      | The user’s screen name.                                                    |
| screen_name_len                  | The length of the user’s screen name.                                      |
| screen_name_upper                | The user’s name.                                                           |
| screen_name_lower                | The user’s screen name.                                                    |
| screen_name_digit                | The number of digits in the screen name.                                   |
| screen_name_alpha                | The first letter of the user’s screen name.                                |
| name_len                         | The length of the user’s name.                                             |
| name_upper                       | The user’s name.                                                           |
| name_lower                       | The user’s name.                                                           |
| name_digit                       | The number of digits in the user’s name.                                   |
| name_greek                       | The number of greek letters in the user’s name.                            |
| name                               | The user’s name.                                                           |
| created_at                       | The date the user first joined twitter.                                    |
| tweet_count                      | The total number of tweets created by the user.                            |
| favourites_count                 | The number of users that follow this user.                                 |
| followers_count                  | The number of users that mention this user.                                |
| friends_count                    | The number of users that have retweeted this user.                         |
| fr_to_ratio                      | The ratio of friends to followers.                                         |
| location                         | The user’s location as reported by the user.                               |
| has_location                     | True if the user’s location is inferred from the user’s profile.          |
| time_zone                        | The user’s time zone as reported by the user.                              |
| lang                             | The user’s language as reported by the user.                               |
| protected                        | True if this account was suspended.                                        |
| user_url                         | The URL field of the user’s profile.                                       |
| bio_words                        | The number of all-uppercase words in the user’s bio.                       |
| bio_upper_words                  | The number of uppercase words in the user’s bio.                          |
| bio_lower_words                  | The number of lowercase words in the user’s bio.                          |
| bio_punctuation_chars            | The number of non-ASCII punctuation characters in the user’s bio.          |
| bio_digit_chars                  | The number of digits in the user’s bio.                                    |
| bio_alpha_chars                  | The number of greek letters in the user’s bio.                            |
| bio_upper_chars                  | The number of uppercase letters in the user’s bio.                        |
| bio_lower_chars                  | The number of lowercase letters in the user’s bio.                        |
| bio_greek_chars                  | The number of greek letters in the user’s bio.                            |
| bio_total_chars                  | The total number of greek letters in the user’s bio.                       |
| seen_total_chars                 | The number of users that mention this user.                                |
| seen_greek_total                 | The number of users that have mentioned a user in greek letters.           |
| all_intervals                    | A histogram of time-between-tweets mentions.                              |
| seen_top_tweets                  | The number of users that mention this user.                                |
| top_tweets_pct                   | The percentage of tweets that mention this user.                           |
| top_intervals                    | A histogram of time-between-tweets mentions.                              |
| mention indegree                 | The number of users that have mentioned this user.                         |
| mention outdegree                | The number of users that have retweeted this user.                         |
| mention avg_weight               | The average number of mentions per user.                                   |
| mention avg_inweight             | The average number of mentions per user at least once.                    |
| mention out_weight               | The average number of mentions per user at least once.                    |
| mention out_in_ratio             | The numbers of mentions per user at least once.                           |
| mention_pct                      | The mention count.                                                         |
| most_mentioned_users             | A list of the users that have mentioned this user.                         |
| most_mentioned_by                | The number of users that have most mentioned this user.                   |
| retweet indegree                 | The number of retweets by this user.                                       |
| retweet outdegree                | The percentage of tweets that mention this user.                           |
| retweet avg_weight               | The average number of retweets by this user.                              |
| retweet avg_inweight             | The average number of retweets by this user at least once.                |
| retweet out_weight               | The percentage of tweets that mention this user at least once.             |
| retweet out_in_ratio             | The percentage of tweets that mention this user at least once.             |
| retweet pcnt                     | The percentage of tweets that mention this user.                           |
| most_retweeted_users             | The number of users that have at least one tweet from this user.           |
| most_retweeted_by                | The number of users that have at least one tweet from this user.           |
| rt_intervals                     | A histogram of time-between-retweets by this user.                         |
| reply_indgree                    | The number of replies sent by this user.                                   |
| reply_outdegree                  | The percentage of tweets that were not retweets or replies.                |
| reply_avg_weight                 | The average number of replies sent by this user.                          |
| reply_avg_inweight               | The average number of replies sent by this user at least once.             |
| reply out_weight                 | The percentage of tweets that were not retweets or replies.                |
| reply out_weight_in_ratio        | The percentage of tweets that were not retweets or replies.                |
| replies_pcnt                     | The percentage of tweets that were not retweets or replies.                |
| most_replied_to                  | The number of tweets that were not retweets or replies.                    |
| most_replied_by                  | The percentage of tweets that were not retweets or replies.                |
| reply_intervals                  | A histogram of time-between-replies by this user.                          |
| seen_replied_to                  | The number of tweets that were not retweets or replies.                    |
| most_engaging_tweet              | The percentage of tweets that were not retweets or replies.                |
| plain_tweets                     | A histogram of time-between-replies by this user.                          |
| most_used_sources                | The number of tweets that were not retweets or replies.                    |
| time_between                     | The total number of retweets sent by this user.                            |
| time_between_top                 | The total number of retweets sent by this user.                            |
| time_between_rt                  | The total number of retweets sent by this user.                            |
| time_between_replies             | A histogram of time-between-replies by this user.                          |
| max_daily_interval               | The number of tweets sent by this user per day.                           |
| last_tweeted_at                  | The number of tweets sent by this user per hour of day.                    |
| life_time                        | The number of tweets sent by this user per week.                          |
| tweets_per_hour_of_day           | The number of tweets sent by this user per active day.                     |
| tweets_per_weekday               | The number of tweets sent by this user per active day.                     |
| tweets_per_active_day            | The number of tweets sent by this user per active day.                     |
| tweets_per_day                   | The number of tweets sent by this user per active day.                     |
| last_month                       | The number of tweets sent by this user per day.                           |
| fr_scanned_at                    | The number of tweets sent by this user per day.                           |
| seen_fr                          | The percentage of tweets sent by this user per day.                        |
| gr_fr                            | The percentage of tweets sent by this user per day.                        |
| gr_fr_pcnt                       | The percentage of tweets sent by this user per day.                        |
| fr_pcnt                          | The percentage of tweets sent by this user per day.                        |
| fr_seen                          | The percentage of tweets sent by this user per day.                        |
| fr_replied_to                    | The percentage of tweets sent by this user per day.                        |
| gr_replied_to                    | The percentage of tweets sent by this user per day.                        |
| gr_replied_pcnt                  | The percentage of tweets sent by this user per day.                        |
| fr_replied_pcnt                  | The percentage of tweets sent by this user per day.                        |
| gr_replied_pcnt                  | The percentage of tweets sent by this user per day.                        |
| fr_replied_pcnt                  | The percentage of tweets sent by this user per day.                        |

Fig. 2: List of features per user (1/2)
Table 3: List of features per user (2/2)

| Feature | Description |
|---------|-------------|
| `fr_to_pct` | Percentage of followers currently tracked. |
| `fr_to_jaccard` | Jaccard similarity between the friend and follower sets. |
| `fr_and_to` | Size of the intersection of the friend and follower sets, i.e., all reciprocal follow edges. |
| `fr_or_to` | Size of the union of the friend and follower sets, i.e., all follows in the follow graph. |
| `gr_fr_to` | Number of all friends and followers marked as Greek-speaking. |
| `gr_fr_to_pct` | Percent of Greek-speaking neighbors (friends and followers). |
| `greek` | True if this user was inferred to be Greek or Greek-speaking. |
| `total_words` | Total number of words in all seen tweets. |
| `min_wptw` | Minimum number of words per seen tweet. |
| `avg_wptw` | Average number of words per seen tweet. |
| `med_wptw` | Median number of words per seen tweet. |
| `std_wptw` | Standard deviation of the number of words per tweet. |
| `unique_words` | Number of unique words that this user has used in seen tweets. |
| `lex_freq` | Lexical frequency (the ratio of unique words over total words) over all seen tweets. |
| `total_bigrams` | Number of bigrams constructed from seen tweets. |
| `unique_bigrams` | Number of unique bigrams in seen tweets. |
| `bigram_lex_freq` | Lexical frequency (the ratio of unique bigrams over total bigrams) over all seen tweets. |
| `articles` | Number of times this user was seen using an article (article list mined from Greek Wiktionary). |
| `pronouns` | Number of times this user was seen using a pronoun (pronoun list mined from Greek Wiktionary). |
| `expletives` | Number of times this user was seen using an expletive (expletive list mined from Greek Wiktionary). |
| `locations` | Number of times this user was seen using the name of a place (location list mined from Greek Wiktionary). |
| `emotions` | Number of times this user was seen using an emotion. |
| `emojis` | Number of times this user was seen using an emoji. |
| `all_tokens` | All tokens of text seen in this user’s tweets (words, hashtags, mentions, emoticons, etc.). |
| `all_caps_words` | Number of words seen to be in all-capital letters, excluding words of length 1. |
| `all_caps_words_pct` | Percentage of words seen to be in all-capital letters excluding words of length 1. |
| `all_caps_tweets` | Number of tweets seen to be in all-capital letters. |
| `all_caps_tweets_pct` | Percentage of tweets seen to be in all-capital letters. |
| `all_nocaps_words` | Number of words seen to have no capital letters. |
| `all_nocaps_words_pct` | Percentage of words seen to have no capital letters. |
| `punctuation_chars` | Number of characters that are punctuation in this user’s seen tweets. |
| `punctuation_pct` | Percent of characters that are punctuation in this user’s seen tweets. |
| `total_chars` | Total number of characters in seen tweets. |
| `digit_chars` | Total number of digits in seen tweets. |
| `digit_pct` | Percentage of characters in seen tweets that were digits. |
| `alpha_chars` | Total number of letters in this user’s seen tweets. |
| `alpha_pct` | Percentage of letters in seen tweets. |
| `upper_chars` | Total number of uppercase letters in seen tweets. |
| `upper_pct` | Percentage of uppercase letters in seen tweets. |
| `lower_chars` | Percentage of lowercase letters in this user’s seen tweets. |
| `lower_pct` | Percentage of characters in seen tweets that were lowercase letters. |
| `greek_chars` | Total number of Greek letters in this user’s seen tweets. |
| `greek_pct` | Percentage of characters in seen tweets that were Greek letters. |
| `total_hashtags` | Total number of hashtags this user’s tweets [3]. |
| `hashtags_per_tw` | Minimum, maximum, average, median, and standard deviation of hashtags per tweet [1], [2]. |
| `uniq_hashtags` | Number of unique hashtags seen in tweets written by this user. |
| `total_rt_hashtags` | Total number of hashtags in tweets retweeted by this user. |
| `uniq_rt_hashtags` | Number of unique hashtags seen in tweets retweeted by this user. |
| `most_common_words` | List of most common words (excluding stop-words) used by this user, and their counts. |
| `most_common_bigrams` | List of most common bigrams (excluding stop-words) used by this user, and their counts. |
| `most_common_hashtags` | List of most common hashtags used by this user, and their counts. |
| `most_common_urls` | List of most common domain names in URLs found in this user’s tweets, and their counts. |
| `most_common_rt_urls` | List of most common domain names in URLs found tweets retweeted by this user, and their counts. |
| `seen_urls` | Total number of URLs in all tweets [3]. |
| `urls_per_tw` | Minimum, maximum, average, median, and standard deviation of URLs per tweet [1], [2]. |
| `avg_edit_distance` | Average edit distance between every posted URL and profile name [3]. |
| `daily_sentiment` | Average positive and negative sentiment per tweet mentioning each sentiment, per day, as time-series [3]. |
| `entity_overlap` | A graph of entities. Node weights are counts of tweets mentioning each entity, edge weights are counts of tweets mentioning both entities. |
| `senti_entites` | List of average positive and negative sentiment scores for all seen tweets mentioning an entity, per entity. |
| `favoriters` | Number of users seen to have liked a tweet by this user. |
| `favorited` | Number of users whose any tweet this user has liked. |
| `most_favoriters` | A list of users that have liked this user’s tweets the most, and the number of likes per user. |
| `most_favorited` | A struct of two numbers: Percentages of self references that are done using the male and female gender of the word. |
| `number_of_languages` | Number of languages used by this user [3]. |
| `tweets_per_language` | Number of tweets for the five languages most used. |
| `vector_timestamp` | The UTC timestamp of this vector (this is used by the crawler engine for caching user vectors). |

Fig. 3: List of features per user (2/2)

Fig. 4: Graphs mined from data
of users. \texttt{Awler} includes a web-based dashboard, depicted in Figure 1 to assist with analysis of crawled tweets. The dashboard depicts a selection of the mined features, including time series of a user’s sentiment per day, sentiment per entity, as well as neighbor nodes for multiple relations.

IV. DATA PROCESSING AND GRAPH EXTRACTION

To assist with social network analytics applications, \texttt{Awler} performs additional post-processing of the harvested data to generate a set of graphs. In addition to the Follow Graph, stored as a dynamic graph of timestamped edges, \texttt{Awler} also scans tweets to generate a set of graphs among users, namely the Retweet Graph, Mention Graph, Reply Graph, Quote Graph; all are directed and weighted, where each edge’s weight is the number of observed interactions of the corresponding type, from the source user to the target user. Moreover, \texttt{Awler} mines the list and list membership data crawled to generate the List Similarity Graph; it is an undirected graph where an edge between two users amounts to membership of the same list, and an edge’s weight is the number of lists that include both users. Finally, using the crawled favorites per user \texttt{Awler} extracts the user-to-user Favorite Graph.

Figure 4 shows the size of the mined graphs in vertices and edges, their size on disk, as well as whether they are directed or weighted. Figures 5, 6, and 7 presents the in-degree, out-degree, and undirected degree for the interaction graphs. The list similarity graph is not included, as it could not be easily analyzed by \texttt{Awler} using a single machine. Note that the directionality of the graphs follows action, which in the case of retweets is not the direction information flows. That is, an edge in the Follow Graph points from the follower to the followee, an edge in the Retweet Graph points from the retweeter to the tweeter, an edge in the Mention Graph points from the mentioner to the mentioned, an edge in the Reply Graph points from the replier to the replied-to, an edge in the Quote Graph points from the quoter to the quoted, and an edge in the Favorite Graph points from the favoriter to the favorited.

To evaluate the coverage \texttt{Awler} achieves for the crawled users, Figure 8 compares the distribution of tweets per user as reported by Twitter in the user information returned for each user, with the total count of tweets crawled and saved by \texttt{Awler}. Even though \texttt{Awler} worked for a brief duration compared to the active period of most users, it was able to discover and crawl a very large percentage of the tweets of even the most prolific users. Part of this is possible for active users because \texttt{Awler} follows retweets, replies, and quotes to the past and discovers very old tweets that are not otherwise reachable using the standard API.

As a simple use case for \texttt{Awler}’s usability, Figure 9 shows a simple computation of the maximum lengths for all threads of replies found starting with tweets by users marked as Greek-speaking. The distribution is extremely skewed, with 86% consisting of a tweet and a single reply and 6.3% consisting of two replies, while the single longest thread has length 2185.
V. RELATED WORK

There is a lot of related research focusing on the twitter social network; this section presents representative samples of such work and discusses how TwitterEcho compares or advances the state of the art.

TwitterEcho [7] is a Twitter crawler focused on discovering and crawling small communities. The authors design a targeted crawler and use it to recognize and track Portuguese accounts. TwitterEcho also prioritizes account crawling by ordering users according to their activity patterns, opting to crawl active users more frequently. TwitterEcho is a distributed system requiring multiple clients to crawl and aggregating the results into a single server. TwitterEcho can also be used in this fashion for large communities, but we found that for communities having on the order of 100,000 to 200,000 active users like the Greek-speaking twitter users, one computer suffices. TwitterEcho collected more than 14 million tweets from 100,000 users within 11 months. TwitterEcho manages to use many more available endpoints from the twitter REST API, crawling, in addition to tweets and user information, the follow graph, the favorites of all tracked users, as well as list ownership, subscription, and membership information.

TwitterEcho uses the fact that the Greek alphabet suffices to recognize the language, while TwitterEcho resorts to a more complex language classifier to separate Portuguese from Brazilian.

There is a very large body of literature on feature extraction from twitter content, most of which uses the features to perform classification. TwitterAwler is currently able to efficiently extract a very large subset of all the features mentioned in the following papers. Sakaki et al. [8] augment gender classification with image processing, classifying images as one of cartoon/illustration, famous person, food, goods, memo/leaflet, outdoor/nature, person, pet, screenshot/capture, and other. They use a "bot detection" criterion of whether a user has less than 150 tweets made using a mobile or web client. Liu and Ruths [9] use first name, as reported by the user, for gender inference. We expect that this feature is highly language-dependent, and will perform even better in the Greek language, where names, nouns, etc., are gendered.

Zhang et al. [10] use content and interaction features to construct a model for classifying twitter users into age groups. Uddin et al. [11] use a wide set of features extracted from user information to classify users into six categories: personal users, professional users, business users, spam bots, news feed bots, and viral marketing bots. Hu et al. [11] correlate twitter and linkedin data to classify users into the categories: marketing, administrator, start-up, editor, software engineer, public relations, office clerk, or designer. The authors perform sentiment analysis and present sentiment results on the Pearson scale for each class. Pennacchiotti and Popescu present two versions of the same work [11, 12] in which they use features in four classes to classify users, namely user profile, user tweeting behavior, linguistic content of user messages, and user social network features; and employ a set of hand crafted regular expressions to mine ethnicity and gender.

DARPA has organized a competition on bot detection [6]. All teams used an array of features, where the winning team managed to create visualizations that assisted in rapidly recognizing bots. The competition report describes multiple machine-learning techniques used to cluster users and find bot outliers, detect bot-to-bot similarities, etc.

The study of user activity over time has been studied in previous work, showing that extraction of timeseries data from content may offer valuable insights into user behavior. TwitterAwler mines several timeseries from user activity, including daily sentiment per entity or in total, idle time intervals, etc., facilitating further experimentation in that direction. Paraskevopoulos et al. [13] use the time series of twitter activity to correlate users without location information, with already geotagged users. Ferraz et al. [4] study interaction time intervals in twitter activities and create a theoretical model that closely explains and reproduces observations. They use their model to discover outliers and detect bots. Bild et al. [14] focus on the Retweet Graph and reason about the effects of sampling on a set of metrics such as the distributions of tweets per user, tweet rates, and inter-event time intervals. They find that the Retweet Graph is small-world and scale-free similarly to the follow graph, but with stronger clustering.

Twitter lists have been used as crowdsourced similarity metrics in the past, interpreting the fact that twitter users independently classify other users into their own lists. TwitterAwler extracts and processes list membership information and enables multiple similar use cases to be explored. Kim et al. [15] use twitter lists to recognize representative words for all of the list traffic and associate these words with list members. They also mine keywords from the list names as representative for the list members, even if these words are not used by the members. Wu et al. [16] use Twitter lists to recognize elite from ordinary users and study the usage patterns and content posted in each class. They use twitter lists to recognize elite users via their list-similarity with exemplar accounts. Culotta and Cutler [17] present a method for computing brand perception as a set of metrics of similarity to Entities. They mine entity definitions using twitter lists to identify characteristic accounts, and use Jaccard similarity on follower sets to compute a distance metric from chosen entities.

Often it is useful to analyze content in a non-user-centric
way, to observe propagation patterns or orchestrated behavior, as is the case in bot detection work. Although `tw`Awler performs user-centric crawling and aggregation of data, it includes tools to extract subsets of the reply, quote, mention, and retweet graphs conditional on time intervals or specific content, that allow detailed monitoring of information propagation as used in related work. Ratkiewicz et al. [18] search for astroturfing, or orchestrated campaigns appearing to be grass-roots movements in order to influence opinion. They use hashtags, mentions, URLs and the entire text of every tweet as "memes" and look into propagation patterns in diffusion networks. They use a set of features per meme to classify memes, and assign six GPOMS sentiment dimensions [19]—calm, alert, sure, vital, kind, happy. Tsur and Rappoport [20] analyze use of hashtags in tweets and create a model that predicts the popularity of hashtags based on features like length, capitalization, abbreviations, and number of keystrokes required to type. Anderson et al. [21] study user similarity metrics to predict evaluations and election results. They capture both content similarity and similarity of user interactions, and find that relative social status affects how similarity influences user opinions.

Previous work has focused on greek-speaking twitter users, although at a much smaller scale, and focusing on tweets related to specific events, containing specific keywords or hashtags, etc. In comparison, `tw`Awler targets users instead of tweets, allowing researchers to study specific events in the proper context of existing user relations and interactions. Antonakaki et al. [5] present an analysis of the Greek 2015 referendum and parliamentary elections. They use a stemmer for word matching, and a lexicon-based sentiment analysis to assign sentiment to LDA topics. They produced an accurate prediction of the ballot results by counting number of tweets and tweet sentiment per topic, and assigning topics to outcomes. `tw`Awler uses the same sentiment dictionary, kindly provided by the authors, to extract sentiment features per user and per entity. Theocharis et al. [22] analyze twitter content related to social movements and classify tweets into categories according to their intent. They find a small part of tweets are related to actions and organization, with most being reports about the events and conversations.

VI. CONCLUSIONS

`tw`Awler is a lightweight, user-centric crawler that targets twitter communities based on language. It satisfies twitter crawler constraints and does not require using multiple crawling accounts. Furthermore, it includes post-processing primitives that facilitate data analysis especially with respect to mining relationship graphs, as well as extraction of data in a quasi-anonymized (user id-only) form that can be shared or published without violating twitter’s terms of use. `tw`Awler can assist SNA researchers in gathering data from twitter without violation of its terms. It also facilitates the quick testing of hypotheses or quick replication of previous work by including a wide set of primitives and common computations, out-of-the-box. Although `tw`Awler aims to be lightweight and can be easily deployed on a single machine, further analysis of the data may, however, require more resources.

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