ArCOV-19: The First Arabic COVID-19 Twitter Dataset with Propagation Networks

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Abstract

In this paper, we present ArCOV-19, an Arabic COVID-19 Twitter dataset that covers the period from 27th of January till 31st of March 2020. ArCOV-19 is the first publicly-available Arabic Twitter dataset covering COVID-19 pandemic that includes around 748k popular tweets (according to Twitter search criterion) alongside the propagation networks of the most-popular subset of them. The propagation networks include both retweets and conversational threads (i.e., threads of replies). ArCOV-19 is designed to enable research under several domains including natural language processing, information retrieval, and social computing, among others. Preliminary analysis shows that ArCOV-19 captures rising discussions associated with the first reported cases of the disease as they appeared in the Arab world. In addition to the source tweets and the propagation networks, we also release the search queries and the language-independent crawler used to collect the tweets to encourage the curation of similar datasets.

Keywords: Coronavirus pandemic, popular tweets, spread analysis, misinformation, conversational threads, retweets, social analytics.

1. Introduction

Twitter streams hundreds of millions of tweets daily. In addition to being a medium for the spread and consumption of news, it has been shown to capture the dynamics of real-world events including the spread of diseases such as the seasonal influenza (Kagashe et al., 2017) or more severe epidemics like Zika (Vijaykumar et al., 2018), Ebola (Roy et al., 2020), and H1N1 (McNeil et al., 2016). Moreover, collective conversations on Twitter about an event can have a great influence on the event’s outcomes, e.g., US 2016 presidential elections (Grover et al., 2019). Analyzing tweets about an event, as it evolves, offers a great opportunity to understanding its structure and characteristics, informing decisions based on its development, and anticipating its outcomes as represented in Twitter and, more importantly, in the real world.

Since the first reported case of Novel Coronavirus (COVID-19) in China, in November 2019, the COVID-19 topic has drawn the interest of many Arab users over Twitter. Their interest, reflected in the Arabic content on the platform, has reached a peak after two months when the first case was reported in the United Arab Emirates late in January 2020. This ongoing pandemic has, unsurprisingly, spiked discussions on Twitter covering a wide range of topics such as general information about the disease, preventive measures, procedures and newly-enforced decisions by governments, up-to-date statistics of the spread in the world, and even the change in our daily habits and work styles.

In this work, we aim to facilitate future research on social media during this complex and historical period of our history by curating an Arabic dataset (ArCOV-19) that exclusively covers tweets about COVID-19. We limit the dataset to Arabic since it is one of the most dominant languages in Twitter [Alshaabi et al., 2020a], yet still under-studied in general. ArCOV-19 is the first Arabic Twitter dataset designed to capture popular tweets (according to Twitter search criterion) discussing COVID-19 starting from January 27th till the end of March 2020, constituting about 748k tweets, alongside the propagation networks of the most-popular subset of them. To our knowledge, there is no publicly-available Arabic Twitter dataset for COVID-19 that includes the propagation network of a good subset of its tweets. Some existing efforts have already started to curate COVID-19 datasets including Arabic tweets, but Arabic is severely under-represented (e.g., (Chen et al., 2020; Singh et al., 2020)) or represented by a random sample that is not specifically focused on COVID-19 (e.g., (Alshaabi et al., 2020b)), or the dataset is limited in the period it covers and does not include the propagation networks (e.g., (Alqurashi et al., 2020)). Furthermore, ArCOV-19 includes only popular tweets as we hypothesize that such tweets are more likely to be influential.

The contribution of this paper is three-fold:

- We release ArCOV-19, the first Arabic Twitter dataset about COVID-19 that comprises 748k popular tweets per Twitter search criterion. In addition to the tweets, ArCOV-19 includes propagation networks of a subset of 65k tweets, search queries, and documented implementation of our language-independent tweets crawler.
- We present a preliminary analysis on ArCOV-19, which reveals insights from the dataset concerning temporal, geographical, and topical aspects.

The dataset will be continuously augmented with new tweets over the coming few months.

https://gitlab.com/bigirqu/ArCOV-19
We suggest several use cases to enable research on Arabic tweets in different research areas including, but not limited to, emergency management, misinformation detection, and social analytics.

The reminder of the paper is organized as follows. We present the crawling process followed to acquire **ArCOV-19** in Section 2. We then thoroughly discuss the preliminary analysis that we conducted on the dataset in Section 3. We suggest some use cases to enable research on Arabic tweets in Section 4. We finally conclude in Section 5.

2. Data Collection

**ArCOV-19** includes two major components: the source tweets (i.e., tweets collected via Twitter search API every day) and the propagation networks (i.e., retweets and conversational threads of a subset of the source tweets). In this section, we present how we collected each in Sections 2.1 and 2.2 respectively, and summarize the released data in Section 2.3.

2.1 Tweets Collection

To collect the source tweets, we implemented a popularity-based tweet crawler.[⁶] The crawler takes a set of manually-crafted queries, comprising a target topic, as input. At the end of each day, the crawler issues a search request for each of those queries via Twitter search API[⁵] to get the top popular tweets as defined by Twitter API[¹] on that day. Queries can be keywords (e.g., “Corona”), phrases (e.g., “the killing virus”), or hashtags (e.g., “#the_new_coronavirus”). Twitter returns a maximum of 3,200 tweets per query. We customized the search requests to return only Arabic tweets[⁶] and to exclude all retweets to avoid having copies of the same popular tweet. Additionally, duplicate tweets (returned by different queries) are removed in each day. Finally, tweets are sorted chronologically. We started collecting our data since the 27th of January 2020 using a set of queries that we manually-updated based on our daily tracking of trending keywords and hashtags. The full list of queries used in each day is released alongside our dataset. We denote all collected tweets as **source tweets**.

Due to technical reasons, we missed collecting tweets for a few days. Due to Twitter search API restriction that limits the search results to the past 7 days, we missed the old tweets. To overcome that, we used GetOldTweets3[¹¹] python library to download the search results using the same trending keywords and hashtags we selected around those days.

2.2 Propagation Networks Collection

In addition to the source tweets, we also collected the **propagation networks** (i.e., retweets and conversational threads) of the top 1000 most popular tweets each day. To our knowledge, this is the first Arabic tweet dataset to include such propagation networks. Before getting the most popular tweets on any day, we started from source tweets collected in that day and applied a quality qualification pipeline. We first excluded tweets containing any inappropriate word (using a list of inappropriate words we constructed). Next, tweets with more than two URLs or four hashtags, or shorter than four tokens (all are potentially spam) were dropped. Additionally, duplicate tweets that have exact textual content are also dropped to avoid redundancy; only the most popular of them (according to our scoring criterion below) is kept. Qualified tweets are then scored by popularity defined by the sum of the tweet’s retweet and favorite counts. We finally sort the qualified tweets by their scores and select the most popular 1,000 tweets. We denote the set of all such tweets over all days as the **top subset**.

For those 1,000 tweets per day, we then collected all retweets and conversational threads (i.e., direct and indirect replies). We collected the retweets using Pickaw[⁶] a platform for organizing contests on social media, and the replies[⁶] using PHEME (Zubiaga et al., 2016) Twitter conversation collection script.[⁹]

2.3 Data Release

In summary, we release the following resources as **ArCOV-19** dataset, taking into consideration Twitter content redistribution policy.[¹²]

- **Source Tweets**: tweet IDs of the tweets crawled in each day.
- **Search Queries**: the list of search queries, including keywords, phrases, and hashtags, used in each period to collect our source tweets.
- **Top Subset**: tweet IDs of the top 1,000 most popular tweets for each day.
- **Propagation Networks**: the propagation networks for the top subset which include for each tweet in the top subset:
  - **Retweets**: tweet IDs of the full retweet set.
  - **Conversational Threads**: tweet IDs of the full reply thread (including direct and indirect replies).

Along with the dataset, we provide, in our repository, some pointers to publicly-available crawlers that users can easily use to crawl the tweets given their IDs.

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⁵https://developer.twitter.com/en/docs/tweets/search/api-reference/get-search-tweets
⁶We are not aware of the criterion used by Twitter to retrieve the top tweets, but we believe it is based on a mix of likes, retweets, impressions, etc.
⁷https://github.com/azubiaga/pheme-twitter-conversation-collection
⁸https://developer.twitter.com/en/developer-terms/agreement-and-policy
⁹https://github.com/azubiaga/pheme-twitter-conversation-collection
¹⁰https://github.com/Mottl/GetOldTweets3
¹¹https://github.com/bigirqu/ArCOV-19/
3. ArCOV-19 in Numbers

In this section, we present a statistical summary and conduct a preliminary analysis on ArCOV-19 to shed some light on its major characteristics.

3.1 Tweets and Users Distribution

Table 1 presents an overall summary of the tweets and users statistics in ArCOV-19. It indicates that the total number of source tweets in the dataset is about 748k posted by about 249k unique users. We note that 14.7% of the tweets were posted by verified users (who constitute only 1.42% of the unique users). This is a relatively large percentage, showing that a good portion of the source tweets are indeed popular. The average numbers of followers, friends, and statuses of users are also relatively large, showing that users observed in ArCOV-19 are also popular (and possibly more influential). The table also indicates that 21.3% of the tweets include URLs. We anticipate that this is due to the extensive spreading of news (linked from tweets) during this period. The numbers of tweets that are geotagged and geolocated are also indicated in the table; however, we defer the discussion of such types of tweets to Section 3.3.

Figure 1 illustrates the distribution of tweets over time in ArCOV-19. It is clearly non-uniform. Moreover, the volume of tweets hugely increases when the virus started to spread in several countries in the Arab world. The figure also shows the distribution of the tweets posted by verified users vs. unverified users, showing a similar pattern.

Figure 2 presents the top 25 tweeting users in ArCOV-19. We notice that several of them are news sources, and 20 are verified Twitter accounts. This is again consistent with our crawling criteria focusing only on popular tweets.

Table 1: Tweets and users statistics of ArCOV-19.

| Tweets Statistics                  |   |
|-----------------------------------|---|
| Source Tweets                     | 747,599 |
| Geotagged                         | 486 (0.07%) |
| Geolocated                        | 20,031 (2.68%) |
| Posted by verified users          | 110,141 (14.7%) |
| Include URL                       | 159,239 (21.3%) |
| Top Subset                        | 65,000 (8.69%) |

| Users Statistics                  |   |
|-----------------------------------|---|
| Unique                            | 248,513 |
| Verified                          | 3,537 (1.42%) |
| Average followers count           | 8,334 |
| Average friends count             | 1,274 |
| Average statuses count            | 11,201 |

3.2 Tweets Content & Topics

It is important to demonstrate that the tweets in ArCOV-19 constitute a good representative sample of the Arabic tweets posted during the target period on COVID-19, and that they cover the prevalent topics discussed over Twitter during that period. To help examine this hypothesis, we analyzed the textual content of the tweets; in particular, we identified the most-frequent words, hashtags, and Arab country names in the entire dataset, then tracked their frequency over time. Figure 3 shows the time series (over days) of the three types of keywords.12

The 10 most-frequent words shown in Figure 3(a) indicate two different types of words: those that are directly related to COVID-19 (e.g., “health”) and those that are not but related to prayers and supplications (e.g., “Allah/God”). It is interesting to see the word “Allah” is very frequent early on when the news about the virus started to spread (probably over discussions around whether the pandemic is a punishment from God or not, we believe), then declines over time only to become frequent again when the virus started to widely spread in the Arab world.

Figure 3(b) demonstrates how “#China” hashtag was the most trending one from 27 of January until 20 of February, as COVID-19 was prevalent only in China and still not widely spread (at that time) in other

12 When identifying the most frequent words and hashtags, we excluded the ones we used in our search queries since they are expected to be very frequent by definition.
Figure 3: Time series of the frequency (in percentage of tweets) of top general keywords, hashtags, and Arab country words over the period of ArCOV-19. The time of first reported cases in Arab countries is also indicated and aligned with the time series.
countries. We can see how it started to be less trending as the number of cases started to decline in China by that date. On the other hand, when COVID-19 started to spread in the Arab world, other hashtags started to become viral. Furthermore, Figure 3(b) shows that frequency spikes of “#Iran”, “#Lebanon”, and “#Kuwait” exactly match the confirmation dates of first reported cases in Iran, Lebanon and Kuwait respectively.

To further analyze trending topics, Figure 3 features the timeline of the first reported cases in the Arab countries and aligns them with the time series throughout the figure. Aligning the timeline with the series in Figure 3(c) reveals a significant match between the frequency peaks of several country names and the corresponding dates of first reported cases in those countries, most notably in UAE, Egypt, Lebanon, Kuwait, Oman, Bahrain, Algeria, and Libya. Figure 3 also demonstrates the power of ArCOV-19 in capturing further controversial and trending topics. Table 2 shows a timeline covering dates of specific topics of discussion trending on social media around times of peaks in tweeting frequency in Figure 3(c).

| Country | Date  | Topic                                                                 | Related News                                                                 |
|---------|-------|----------------------------------------------------------------------|--------------------------------------------------------------------------------|
| UAE     | Feb 19| Yemeni Foreign Affairs Minister thanks UAE for evacuating Yemeni students from China | [http://tiny.cc/7iptaz](http://tiny.cc/7iptaz) |
| Iraq    | Feb 20| Iraq announces closure of borders with Iran                           | [http://tiny.cc/yrtuz](http://tiny.cc/yrtuz) |
| Egypt   | Mar 2  | Egyptian health minister announces a visit to China                   | [http://tiny.cc/iqtaz](http://tiny.cc/iqtaz) |
| Kuwait  | Mar 3  | Kuwait bans travels with Egypt including entry of Egyptian residents  | [http://tiny.cc/iqtaz](http://tiny.cc/iqtaz) |
| KSA     | Mar 4-5| Closure of The Grand Mosque in Mecca                                  | [http://tiny.cc/iqtaz](http://tiny.cc/iqtaz) |

Table 2: Examples of trending topics in social media matched by spikes in tweeting frequency in ArCOV-19

We further explore the topics discussed in ArCOV-19 by considering the domains of URLs shared in the tweets. We focused on the top tweets subset of ArCOV-19 (constructed as detailed in Section 2.2) and identified the URLs posted in those tweets. We then expanded them (since Twitter URLs are shortened) and dropped URLs of images and videos to focus only on URLs referring to external sources. We extracted 17,308 URLs from 759 unique domains. The URLs from the China “Global Television Network” (cgtn.com) are commonly shared as well, which can be explained by the fact that COVID-19 started in and heavily affected China.

3.3 Geographic Distribution of Tweets

Although Twitter provides automatic geo-reference functionally, few users (solely around 1-3% (Murdock, 2011; Jurgens et al., 2015) opt to enable it due to privacy and safety reasons. Alternatively, to have an insight about the geographical distribution and diversity of the tweets in our dataset, we examined the place and coordinates attributes of the Tweet object.

We note that the place attribute is an optional attribute that allows the user to select a location from a list provided by Twitter (therefore, the location might not necessarily show the actual location from where the tweet is posted), whereas the coordinates attribute represents the geographic location of the Tweet as reported by the user or client application.

Table 1 shows that ArCOV-19 has 20,031 geolocated tweets (i.e., having values in the place attribute) and 486 geotagged tweets (i.e., having values in the coordinates attribute). Those tweets were posted by 9,543 and 82 unique users respectively. The geolocated tweets constitute about 2.68% of the total source tweets, which is slightly higher than what is reported in previous studies on disaster datasets (Anderson et al., 2019). We anticipate that this is due to the criteria we followed to collect the tweets, which relies on Twitter’s popularity criteria.

Focusing our attention on the geolocated tweets, Figures 5 and 6 depict the overall and daily distributions (respectively) of those tweets over Arab and other countries. The geolocated tweets were indeed posted by users from 81 countries from around the globe. We
found that 91% of them were posted from the Arab world. The largest contribution of the geolocated content (about 35.3%) comes from Saudi Arabia; this is somewhat expected as Saudi users represent the highest number of active Twitter users in the Arab world. Surprisingly, Kuwait comes second with 12.6% of the geolocated content. We believe the rationale is that it was among the first countries that reported the cases in the Middle East. Since then, Kuwait started a series of strict precautions such as a wide lock-down in many vital facilities until the government had imposed a nationwide curfew. We think, after the curfew, the people become more active on Twitter as a platform to break news and discuss developments of the virus.

Additionally, we used related phrases and hashtags to “Kuwait”, “Lebanon”, and “UAE” among the tracking keywords in the period between 22 of February and 13 of March which demonstrates the reason behind their high percentages during that period, as shown in Figure 6. Furthermore, it is not surprising to see the countries that have a few or no cases have the smallest portions of contribution to the content. Others have small audience userbases on Twitter (e.g., Tunisia).

3.4 Propagation Networks

As discussed earlier, we collected the propagation networks of the top subset. Overall, the collected number of retweets is 2,697,951 for the entire subset, and the collected number of replies is 301,535 for only 22 days of the time period. Both are released in ArCOV-19. At the time of collecting the retweets, we were not able to get the retweets of some of the tweets either because they were deleted or they were posted from private accounts. For those collected successfully, Figure 7 illustrates the distribution of retweets per day using boxplots. It shows that the average (and median) number of retweets follows a similar pattern to what was shown in Figure 4 (notice that the Y-axis here is in log scale). We also notice that a good number of tweets got more than 100 retweets; some of them got even larger numbers reaching about 10k retweets or more, showing highly propagated content.

Figure 6: Distribution of geolocated tweets per day.

Figure 7: Distribution of retweets per day for the top subset.

Crawling is still going on for the rest of the days and the repository will be updated accordingly.

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1. https://www.statista.com/statistics/242606/number-of-active-twitter-users-in-selected-countries/
4. Enabling Research

With the spread of Novel Coronavirus in several Arab countries and the subsequent procedural measures taken by the local governments, it continued to dominate discussions over social media (and Twitter in particular) to the time of this writing.

To enable research on different tasks on Arabic Tweets, we make ArCOV-19 publicly-available for the research community. ArCOV-19 is composed of the popular tweets, according to Twitter popularity criteria. Therefore, we envision that it contains the tweets that had received the maximum social interactions (e.g., impressions) which implies they are useful tweets to analyze as they got the most attention of the community. We further provide propagation networks of daily highly popular subset (the top 1,000 most popular) to ensure the quality of tweets. This sample is drawn after filtering out potential low-quality tweets (e.g., spam) and content duplicates.

This careful design and architecture of ArCOV-19 makes it suitable for diverse natural language processing, information retrieval, and computational social science research tasks including, but not limited to, emergency management, misinformation detection, and social analytics, as we discuss below. We anticipate ArCOV-19 to support these tasks on the popular Arabic tweets that we assume have the most effect on shaping public opinion and understanding.

4.1 Emergency Management

As COVID-19 is an international pandemic, national and international health organizations need to analyze the effects of the outbreak. We envision ArCOV-19 to support several tasks such as filtering informative content, summarization, eyewitness identification, geolocation, and studying information (and situational awareness) propagation. The popular tweets provide key insights into different aspects that are of interest to many users. For example, recovered users write about the symptoms of the virus they experienced, infected users search for possible medications, and non-infected people look for protective measures. Other types of information of interest include reports (tolls of cases, deaths, recovered), development of precautions (e.g., quarantine, lockdown, curfew, etc.), among others.

4.2 Misinformation Detection

With the sheer amount of information shared about COVID-19, many rumors are disseminated and getting high attention from the community, which causes a fast propagation of misinformation. This hinders the efforts of the health and governmental organizations on fighting the pandemic as such rumors spread panic and may lead to undesirable consequences (e.g., increase of cases and mortality rate, or lack of supplies due to hoarding). ArCOV-19 supports studying information/claims propagation, claims check-worthiness detection and verification tasks on the most popular tweets. Furthermore, the retweet networks and conversational threads available in ArCOV-19 provide a valuable resource for early detection of fake news and identification of malicious rumor spreading accounts.

4.3 Social Analytics

In addition to sharing reports and awareness, people tend to express their emotions during the outbreak (e.g., big change of lifestyle, social distancing, losing their beloved ones, distance learning, etc.). Therefore, analyzing the sentiment of the tweets to understand the effects of the outbreak on people is of interest to many stakeholders.

Additionally, lots of discussions focused on the causes of Novel Coronavirus and its rapid spread, which can be studied to understand the stance of users toward different aspects of the situation such as claims, and the consequences of the spread. For example, the catastrophic situation caused by the rapid spread of the virus made hospitals go beyond their capacity, which forced doctors to deal with agonizing life-death decisions triggering heated discussions on such issue.

Moreover, in some countries, people are demanding to return resident labors back to their countries to reduce the spread of the virus and limit the country’s resources to only citizens. This stance sparked controversial discussion on social media on the legal, humanitarian, and ethical aspects of these demands. This requires analytical tools to detect hate speech and, generally, offensive language.

5. Conclusion

In this paper, we presented ArCOV-19, the first Arabic Twitter dataset about the Novel Coronavirus (COVID-19) that includes popular tweets and propagation networks, focusing on popular discussions on Twitter. We release all source tweets, top subset, search queries, and the propagation networks. Preliminary analysis showed that ArCOV-19 captured spikes in tweeting frequency for country-specific tweets that are consistent with the first reported cases of COVID-19 in several Arab countries. We also found dominance of news agencies among top tweeting users and among most shared URLs. ArCOV-19 enables research under many domains including natural language processing, information retrieval, and social computing. We plan to continue collecting tweets for the foreseeable future and the dataset will be continuously updated with newly collected tweets and propagation networks.

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