ArCOV19-Rumors: Arabic COVID-19 Twitter Dataset for Misinformation Detection

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ABSTRACT
In this paper we introduce ArCOV19-Rumors, an Arabic COVID-19 Twitter dataset for misinformation detection composed of tweets containing claims from 27th January till the end of April 2020. We collected 138 verified claims, mostly from popular fact-checking websites, and identified 9.4K relevant tweets to those claims. We then manually-annotated the tweets by veracity to support research on misinformation detection, which is one of the major problems faced during a pandemic. We aim to support two classes of misinformation detection problems over Twitter: verifying free-text claims (called claim-level verification) and verifying claims expressed in tweets (called tweet-level verification). Our dataset covers, in addition to health, claims related to other topical categories that were influenced by COVID-19, namely, social, politics, sports, entertainment, and religious.

KEYWORDS
Coronavirus pandemic, fact checking, rumors, claim verification, conversational threads, retweets, spread analysis

1 INTRODUCTION
In addition to being a medium for the spread and consumption of news, Twitter has been shown to capture the dynamics of real-world events including the spread of diseases such as the seasonal influenza [18] or more severe epidemics like Ebola [27]. Since the first reported case of the 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. With the great importance and spread of COVID-19 information, misinformation and fake news have infected the Twitter stream. An early study quantifying COVID-19 medical misinformation on Twitter found that 25% of collected tweets contained misinformation [20]. During COVID-19 pandemic, we observed that misinformation stretched beyond spreading fake and potentially-harmful medical information, to information that can have adverse negative political effects (example: “In light of the unresponsiveness of Yemeni government to requests of evacuation from Yemeni students in Wuhan, Sultan of Oman orders their evacuation.”) and economical effects too (example: “Kuwaitis boycott AlMarai Saudi dairy company after reports on Coronavirus infected employees.”). Combating the spread of such claims and verifying them becomes essential during this sensitive time.

In this work, we aim to facilitate research on misinformation detection on social media during this complex and historical period of our time by introducing an annotated Arabic dataset, ArCOV19-Rumors, that covers tweets spreading COVID-19 related claims. ArCOV19-Rumors extends ArCOV-19 [16], which is the first Arabic COVID-19 Twitter dataset with propagation networks, by a set of 138 COVID-19 verified claims and 9.4K corresponding relevant tweets that were manually-annotated to support both claim-level and tweet-level verification tasks. Claim-level verification is defined as follows: given a short free-text claim (in 1 or 2 sentences) and its corresponding relevant tweets, predict whether the claim is true or false. Tweet-level verification is defined as follows: given a tweet containing a claim, detect whether it is true or false.

To our knowledge, no other Arabic dataset is made available to support both claim-level and tweet-level verification tasks in Twitter given the propagation networks of the tweets in general and on COVID-19 in particular. Some related Twitter datasets were recently released by Elhadad et al. [11] and Rayson [26]. However, neither has the propagation networks of the annotated tweets, and they both support solely the tweet verification task. Elhadad et al. [11] annotated the tweets as true or misleading, however, they were automatically annotated by their trained models, and the performance of these models was not presented by the authors. Rayson [26] released an Arabic misinformation dataset but it only covers COVID-19 health-oriented tweets labeled as true, false, or unrelated. Differently, our dataset covers in addition to health, other types of claims that were influenced by COVID-19, namely, social, politics, sports, entertainment, and religious.

The contribution of this paper is two-fold:

- We construct and release\(^1\) the first Arabic dataset for misinformation detection over Twitter, covering both claim and tweet verification tasks. It contains 138 COVID-19 verified claims that scale to 9.4K labeled relevant tweets along with their propagation networks.
- We suggest and motivate several research tasks that can be addressed using our labeled subset for misinformation detection.

The remainder of the paper is organized as follows. We present studies related to COVID-19 misinformation analysis and datasets in Section 2. The construction of ArCOV19-Rumors is presented in Section 3. Several use cases supported by our dataset are discussed in Section 4. We detail the released components of the dataset in Section 5, and conclude in Section 6.

\(^1\)https://github.com/bigirqu/ArCOV-19
2 RELATED WORK
Misinformation in social media is a continuously growing problem. It is even more severe in times of tension such as the COVID-19 crisis. The negative effects and spread of misinformation about COVID-19 triggered efforts to understand this phenomenon. Many studies analyzed misinformation spreading in Twitter related to COVID-19 [6, 14, 20, 29, 30]. Singh et al. [30] analyzed the spread of five health misinformation over time. Shahi et al. [29] analyzed false and partially false tweets that have been previously fact-checked by a fact-checking platform. Kouzy et al. [20] focused only on health misinformation and analyzed tweets negating health information by trusted sources (e.g., WHO). Cui et al. [7] and Hossain et al. [17] published an English dataset for claim verification, and tweet verification respectively, while Dharawat et al. [9] released a Twitter dataset for health risk assessment of COVID-19-related English tweets.

Similar to existing studies, we extended our raw Arabic COVID-19 Twitter dataset, ArCOV-19 [16], to include manually-annotated tweets to support both claim and tweet verification. ArCOV19-Rumors is the first Arabic COVID-19 dataset that has the propagation networks (i.e., retweets and conversational threads) of the annotated tweets. To our knowledge, there is no work that released a large manually-annotated Arabic dataset for misinformation detection on COVID-19 at both claim and tweet levels. The closest work to ours is that done by Elhadad et al. [11] and Rayson [26]. However, neither have the propagation networks of the annotated tweets, and they both support solely the tweet verification task.

Claim detection and verification are widely studied problems in general. Several non-COVID-19 datasets exist for claim detection [21, 23, 31] and verification [8, 15, 24, 31], however, they either support English language [8, 15, 23, 24, 31] or Chinese language [23, 24]. There are few initiatives targeting Arabic online content, but they support claim detection (i.e., rumor or non-rumor) [1, 2], tweet verification without propagation networks [11, 26], or tweet credibility [10]. Another notable work is a shared task by CLEF CheckThat!Lab for claim verification [3, 4, 13]. To the best of our knowledge, this is the first Arabic dataset that supports both claim and tweet verification on social media using the propagation networks.

3 METHODOLOGY
We extended ArCOV-19 [16], an Arabic Twitter dataset about COVID-19 that comprises over 1M tweets. We labeled a subset of ArCOV-19 tweets to support research on misinformation detection, which is one of the major problems faced during a pandemic. We aim to support two classes of misinformation detection problems (with variants) over Twitter: verifying free-text claims (called claim-level verification) and verifying claims expressed in tweets (called tweet-level verification), covering two common use cases. To that end, we need to collect COVID-19 verified claims, then, for each claim, we need to find, in ArCOV-19, corresponding relevant tweets, and finally, among the relevant tweets, identify those that are either expressing the claim or negating it (to easily propagate the veracity of the claims to them). In this section, we show how we implemented that pipeline (Sections 3.1-5). In Section 4, we motivate and discuss a list of research tasks supported by that labeled data.
Moreover, we discarded the claims that are not very specific, i.e., too general (e.g., "Many Arab countries took security measures against those who refuse to quarantine"). We eventually kept 95 false claims and 43 true claims, a total of 138 claims. Those claims have a total of 9,414 relevant tweets. The final set of claims is diverse and claims fall under different categories, as the misinformation propagating in Twitter during COVID-19 pandemic was not restricted to health. In fact, only 45 of them were health-related. The rest are distributed over social (38), political (22), religious (18), entertainment (9), and sports (6) topical categories.

3.4 Annotating Relevant Tweets

After collecting relevant tweets for each claim, we need to identify those that are expressing or negating the claim, so that we can propagate the label of the claim to them. For each claim, one of the authors of this paper labelled all of its relevant tweets by one of three categories:

- “Expressing same claim” if the main (focused) claim in the tweet is restating, expressing, or rephrasing the target claim. This tweet then receives the same veracity of the target claim; thus it inherits its exact label (whether true or false).
- “Negating the claim” if the main (focused) claim in the tweet is negating or denying the target claim. The veracity of this tweet is then the opposite of the veracity of the target claim, i.e., it is labeled as true if the target claim is false, and vice-versa.
- “Other” if the tweet cannot be labelled as one of the two earlier cases, e.g., expressing opinion or giving advice regarding the claim.

Figure 1 illustrates three example relevant tweets of a false claim translated as “The Chinese President visits one of the mosques in China and asks Muslims to pray to God to alleviate the pandemic”, which is literally stated in the tweet shown in Figure 1(a), thus it is false. On the contrary, the tweet illustrated in Figure 1(c) is denying the claim, and thus is true. It is translated as "What is being circulated about the Chinese President, apologizing to Muslims and visits the mosques and asking them to pray because of the spread of the Corona virus, is totally incorrect. The video is old and dated back to 2016. Source: the Chinese news agency CCTV”. Finally, the tweet illustrated in Figure 1(b) is labelled as “other” due to expressing multiple claims. It is translated as "China bans eating all wild animals and their trade due to Corona Virus. The Chinese President visits a mosque in China and asks the scholars to pray to alleviate the pandemic”.

It is worth mentioning that expressing or negating the claim can be over an external link in the tweet, stated in an image, or said in a video, rather than in the text of the tweet. This was considered while annotating tweets. Providing such tweets in ArCOV19-Rumors allows the development of multi-modal systems, that can use signals in text, images, or videos, to make verification decisions.

3.5 Collecting Propagation Networks

We also collected the propagation networks (i.e., retweets and conversational threads) for each relevant tweet. The propagation networks for tweets that contain misinformation are essential to study its spreading behaviour and can constitute evidential signals for verification. Figure 2 shows some replies to the false tweet presented in Figure 1(a). We notice that some replies have a clear stance against the claim. Moreover, one presents evidence that the tweet is false. In addition to the replies, exploiting profiles of propagators can play a significant role in verifying the tweet [22].

Figure 2: Evidence from replies (with translation) against the false tweet in Fig. 1(a).

4 IMMEDIATE USE CASES

Table 1 presents a statistical summary of the labeled tweets in ArCOV19-Rumors. We define two subsets of tweets. The first is denoted as Claims Subset, which includes all relevant tweets of the claims (labeled as true, false, or other). This is of high interest since all tweets relevant to a specific claim can be used in verifying it. The other is denoted as Tweet Verification Subset, which only includes the relevant tweets that are either expressing or denying
We notice that the distribution of true detection worked on claim-level. A plethora of studies addressed this problem [5, 19, 22, 24], and a Table 1: Statistics of Claims in ArCOV19-Rumors (RPs=Replies, RTs=Retweets).

|                       | Claims Subset | Tweet Vf. Subset |
|-----------------------|---------------|------------------|
| **Total tweets**      | 9,414         | 3,584            |
| False Tweets          | 1,753 (18.6%) | 1,753 (48.9%)    |
| True Tweets           | 1,831 (19.4%) | 1,831 (51.1%)    |
| Other Tweets          | 5,830 (61.9%) | 0                |
| Average tweets / claim| 68            | 26               |
| Tweets with RPs       | 3,161 (33.6%) | 1,222 (34.1%)    |
| Tweets with RTs       | 3,810 (40.5%) | 1,629 (45.5%)    |
| Tweets with RPs & RTs | 2,006 (21.3%) | 772 (21.5%)      |
| Average RPs / tweet   | 33            | 31               |
| Average RTs per / tweet| 16           | 19               |

The original claims, excluding the ones labeled as other. This is also of high interest since each of those tweets is subject to verification. The table indicates that, out of 9.4k labelled relevant tweets, 3.6k of them are either true or false (constituting the tweet verification subset); each is considered a separate tweet-level verification query. We notice that the distribution of true vs. false tweets is balanced, making it a good resource for training verification systems. We also notice that a good portion of both subsets have replies and replies, indicating potentially-useful propagation networks. Accordingly and based on the two subsets, our labeled data can support three different misinformation detection tasks.

### 4.1 Claim-level Verification

This task is defined as follows: given a claim and all corresponding relevant tweets (with their propagation networks), detect the veracity of the claim, i.e., whether the claim is true or false. Many studies worked on claim-level detection, i.e., whether the claim is a rumor or non-rumor [2, 23, 25], and a couple of datasets were released for claim detection but they are either English Twitter datasets [23, 31] or Chinese Weibo datasets [23]. There are some initiatives to support Arabic claim verification but given useful Web pages [13].

### 4.2 Tweet-level Verification

This task is defined as follows: given a tweet (with its propagation networks), detect its veracity, i.e., whether the tweet is true or false. A plethora of studies addressed this problem [5, 19, 22, 24], and a couple of datasets were released to support the task; however they are either English Twitter datasets [8, 15, 24] or Chinese Weibo datasets [24]. Addressing this task in Arabic has never been studied. Existing studies for Arabic tweet verification mainly rely on the tweet content [12, 26], or, additionally, the potentially-relevant Web pages. [3, 4].

There are two other variants of this task that are also supported by ArCOV19-Rumors. The first variant makes also available (to the verification system) the tweets that are relevant to its target claim but were posted earlier (with their propagation networks). To our knowledge, there is no study that addressed this problem. This is an interesting problem for several reasons. First, with the lack of any propagation networks for a target tweet, a verification system can still exploit the networks of the earlier relevant tweets. Second, as time is really critical to debunk fake claims as soon as they are posted, exploiting relevant tweets posted earlier allows verifying the tweet as soon as it is posted, not waiting for its propagation networks. Third, even if the target tweet has propagation networks, relevant tweets might provide more evidence, hence improve the verification accuracy.

The second variant, denoted as Early Tweet Verification, just puts a time limit (or a deadline) on the verification by considering only the tweets and propagation networks that were posted before the target tweet.

### 4.3 Tweet Retrieval

This task is defined as follows: given a tweet that expresses a claim (i.e., a tweet in the tweet verification subset), find all tweets that are expressing the same claim. To our knowledge, this task is understudied; an exception is the work done by Shaar et al. [28] and the task proposed by Barrón-Cedeño et al. [3] in CLEF CheckThat! 2020 lab; however, they focus more on claims than tweets and they release English-only datasets to support this task. Solving this problem helps in applications like finding previously-verified tweets, or clustering tweets expressing the same claim, to avoid re-verification. Another variant of this task aims at finding tweets that are relevant to the claim expressed in the target tweet, i.e., not necessarily expressing it, but just relevant to it. This can be useful in verifying the claim as we discussed earlier.

### 5 DATA RELEASE

In summary, we release the following resources as ArCOV19-Rumors dataset, taking into consideration Twitter content redistribution policy.\(^8\)

- **Verified Claims**: 138 verified claims, each labeled as true or false.
- **Claims Subset**: tweet IDs of the tweets relevant to the verified claims, each labeled as true, false, or other.
- **Propagation Networks of the Claims Subsets**: which includes for each tweet in the claim 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.

### 6 CONCLUSION

In this paper, we presented ArCOV19-Rumors, the first Arabic Twitter dataset that supports both claim-level and tweet-level verification tasks given the propagation networks. We released 138 verified claims associated with 9.4K relevant tweets. Our dataset covers, in addition to health, other types of claims that were influenced by COVID-19 namely, social, politics, sports, entertainment, and religious. The limitation pertaining to our work is that each tweet has been annotated by only one annotator. We plan to mitigate that by recruiting more annotators to attain better quality.

\(^8\)https://developer.twitter.com/en/developer-terms/agreement-and-policy
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