Article:
Singh, I., Bontcheva, K. and Scarton, C. (Submitted: 2021) The false COVID-19 narratives that keep being debunked : a spatiotemporal analysis. arXiv. (Submitted)

The False COVID-19 Narratives That Keep Being Debunked: A Spatiotemporal Analysis

Iknoor Singh, Kalina Bontcheva, and Carolina Scarton
The University of Sheffield, United Kingdom
{i.singh, k.bontcheva, c.scarton}@sheffield.ac.uk

Abstract

The onset of the COVID-19 pandemic led to a global infodemic that has brought unprecedented challenges for citizens, media, and fact-checkers worldwide. To address this challenge, over a hundred fact-checking initiatives worldwide have been monitoring the information space in their countries and publishing regular debunks of viral false COVID-19 narratives. This study examines the database of the CoronaVirusFacts Alliance, which contains 10,381 debunks related to COVID-19 published in multiple languages by different fact-checking organisations. Our spatiotemporal analysis reveals that similar or nearly duplicate false COVID-19 narratives have been spreading in multiple modalities and on various social media platforms in different countries, sometimes as much as several months after the first debunk of that narrative has been published by an IFCN fact-checker. We also find that misinformation involving general medical advice has spread across multiple countries and hence has the highest proportion of false COVID-19 narratives that keep being debunked. Furthermore, as manual fact-checking is an onerous task in itself, therefore the need to repeatedly debunk the same narrative in different countries is leading, over time, to a significant waste of fact-checker resources. To this end, we propose the idea of including a multilingual debunk search tool in the fact-checking pipeline, in addition to recommending strongly that social media platforms need to adopt the same technology at scale, so as to make the best use of scarce fact-checker resources.

Research questions

- Does the database of COVID-19 related debunks published by the International Fact-checking Network (IFCN) in 2020 contain duplicate debunks of the same false narrative? In the case of duplicate debunks, what is the temporal gap between them, i.e. can the same false narrative resurface again significantly later and spread unhindered by the platforms's moderation algorithms in a different language or country?
- What are the spatiotemporal characteristics of recurrent narratives and how do these differ in terms of country, social media platform and modality of content?
- What type of mis/disinformation is the most prevalent and has been debunked by multiple fact-checkers across different countries?
- Can the incorporation of a multilingual debunk search tool within the fact-checking pipeline help with detecting cases of already debunked claims in other languages?

Summary of Main Findings

- The CoronaVirusFacts Alliance comprises over a hundred independent fact-checking organisations, members of the International Fact-Checking Network (IFCN). In 2020 they published a total of 10,381 debunks of false claims related to COVID-19. We use this dataset to find all the fact-checked articles debunking similar or duplicate claims. For this, each claim is compared with all other debunked claims to find the semantically similar claims that have been debunked by multiple fact-checking organisations. Additionally, we analyse and produce visualisations of the spatiotemporal characteristics of duplicate claims and their transition between countries, social media platforms and modalities of content.

- Our study finds a considerable number of duplicate debunks of the same false narratives, out of which most of them appeared in Indian fact-checking websites. Furthermore, misinformation involving general medical advice is most prevalent as it is disseminated across multiple countries and has been debunked multiple times. Finally, our findings reveal that Facebook users contribute to most of the mis/disinformation as same false narratives keep on appearing on it, incognizant of the fact that the fact-check articles for those narratives have already been published in the past in same or in a language different from what the user understands.
- The real-world implication of this study is to bring attention to researchers and journalists towards the problem of multiple fact-checked articles debunking similar claims and thereby proposing the task of multilingual debunk search in the fact-checking pipeline to check if the claim made in one language has already been debunked in another language. Moreover, as the current fact-checking is a laborious manual endeavour, therefore the ability to search debunked claims in a cross-lingual setting will help prevent waste of resources in debunking same claims repeatedly.

Argument & Implications

The COVID-19 pandemic has not only created a global health emergency but has also given rise to interminable infodemic and disinfodemic (Posetti & Bontcheva, 2020) in different parts of the world. In 2020, almost everyone witnessed or was exposed to various kinds of false claims related to coronavirus origin, transmission, medical treatments and many others[1]. Moreover, myriad studies (Limaye et al., 2020; Tasnim et al., 2020) have shown that most of these claims originate on various social media platforms which makes them questionable to their authenticity as there is no method in place to quickly check the credibility of the content as well as the source. The unverified claims often fall into the category of misinformation in which the person spreading the claim is unaware of its falsity. Furthermore, it also involves disinformation where false information is spread intentionally to deceive (Bontcheva et al., 2020). Either of them has the potential to instigate the general public into unethical actions and cause considerable harm. An article by BBC[2] states that around 800 people lost their lives because of misinformation related to coronavirus in just the first three months of 2020. In India, an exodus of a large number of migrants[3] due to fake news caused a national disturbance during the lockdown period.

The research (Vosoughi et al., 2018) has shown that news containing false information disseminates nearly 10 times faster than that of legitimate news. In this case, misleading narratives, for instance once concerning public health are not only detrimental but can also have serious consequences[4]. While the numbers of fact-checking initiatives have grown substantially over the years, still due to limited resources, these are unable to mitigate the impact of dis/mis-information in its inceptive hours (Nakov, 2020). This line of reasoning is also consistent with research (McGlynn et al., 2020) demonstrating the delay between misinformation and debunking tweets paved the way for misinformation to spread on social media

[1] https://www.poynter.org/ifcn-covid-19-misinformation/
[2] https://www.bbc.com/news/world-53755067
[3] https://tinyurl.com/1oa7jcys
[4] https://www.bbc.com/news/world-asia-india-54068007

platforms. Efficiently alleviating COVID-19 mis/disinformation begins with being aware of previously fact-checked claims (Shaar et al., 2020). A report by FullFact[5] shows that there have been cases where similar claims disseminated in different countries at different times and have been debunked by multiple fact-checking organisations, given the debunk for that claim already existed before. While some may argue that these duplicate debunks were generally published on days that lie in proximity of the publication date of the first debunk, our analysis finds that such duplicates differ by weeks and perhaps even by months from its first appearance. These duplicate debunks usually arise when the same claims are shared recurrently on various social media platforms in different countries at different times. Although, the reason behind why people keep on repeating debunked claims is still an open question and not very much explored but few instances show that well-known people such as politicians[6] are known to aggravate this problem by repeating false statements again and again. Another possible reason, which we also extensively explore in this paper is that the debunk made in one language might not be available in another language which could prevent the spreader from being aware about the existence of its debunk.

In this study, we uncover numerous cases where identical false narratives were spreading at different times and whose country, social media platform and modality of content also differed. These are referred to as duplicate claims which propagate either from the original factually inaccurate information, or in the form of new content containing much of the original claim. Besides this, duplicate claims also give rise to duplicate debunks from multiple fact-checking organisations in different languages. We find all such duplicate debunks in the IFCN database and our approach did not require human labeling (Ref. Methods). We further investigate the spatiotemporal characteristics of the fact-checked articles of the same false narratives. We also tried to decipher the reason behind the recurrent spread of debunked dis/mis-information in different countries at different times if it's already been debunked in the first place. For example, claims about the consumption of alkaline rich food for eliminating coronavirus was first debunked in Europe but the claim was here to stay as it was again debunked by fact-checking organisations present in Asian , South American and North American countries (Finding 3). The analysis presented below also demonstrates various common themes in COVID-19 misinformation that have emerged across many countries. For this, we classify the claims into various COVID-19 misinformation categories (Song et al., 2020) to see what type of misinformation spreads the most and has been debunked multiple times. General medical advice is perhaps the most consistent topic related to COVID-19. We will examine some of the common themes in this category at greater length later.

There has been a growing interest in fake news analysis (Singh et al., 2020; Zhou & Zafarani, 2020) and the development of automated fact checking systems (Barrón-Cedeno et al., 2020; Thorne & Vlachos, 2018). In order to diminish the spread of dis/mis-information, the first corrective strategy should be to look for fact-checked articles that have already debunked similar narratives in the past. Previous study (Reis et al., 2020) on the WhatsApp public groups in India and Brazil found a significant portion of misinformation in the form of images shared on the groups even after it gets fact-checked. Another study (Barrón-Cedeno et al., 2020; Shaar et al., 2020) where researchers have worked on detecting previously fact checked claims. However, they only worked on English debunks but in this paper, we shed light on fact-checking articles written in multiple languages debunking the same narratives and thereby demonstrating the need for multilingual debunk search in the fact-checking pipeline. The main implication of this work is to draw attention towards the presence of duplicate fact-checking articles debunking alike claims in multiple languages. Despite the importance of the task of searching previously debunked claims in a multilingual setting, it has largely been ignored by the research community. Also, from the fact checkers perspective, before spending hours doing the research and debunking the claim, it's worth

[5] https://www.societyofeditors.org/soe_news/full-fact-report-tracks-fake-covid-19-news-across-five-countries/
[6] https://www.aljazeera.com/news/2020/12/2/trump-releases-video-repeating-debunked-election-fraud-claims

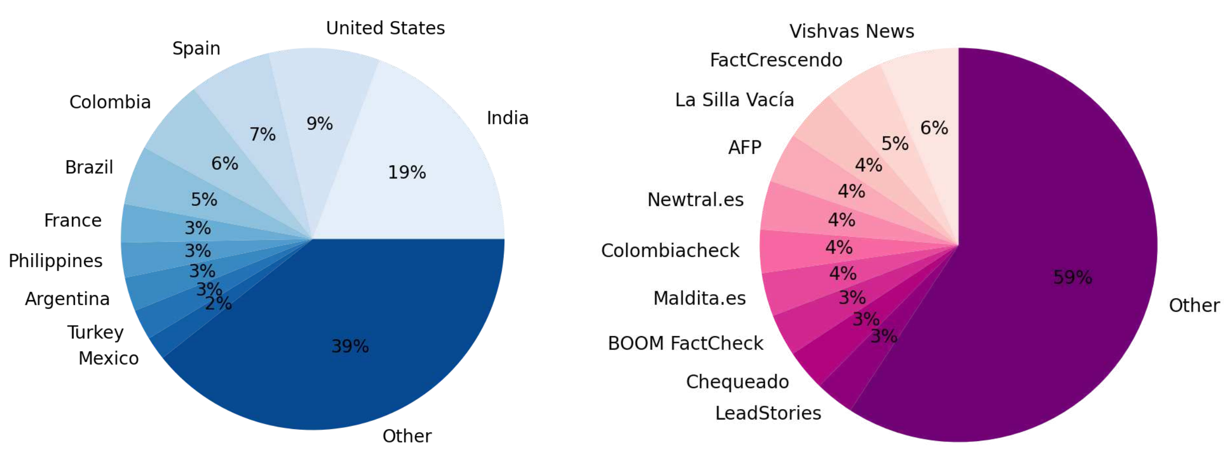
checking if it has already been debunked before to prevent waste of resources, during which other burgeoning numbers of unsubstantiated claims can be fact-checked.

Findings

Finding 1: COVID-19 debunks in the International Fact-Checking Network (IFCN) database contains a significant number of fact-checking articles debunking the same narratives that originate in different countries at different times.

We collect a total of 10,381 debunks out of which we find 1070 debunked claims that already had a debunk about a similar claim from a different fact-checking organisation in the past. This accounts for nearly 10.3% of all the debunks in the IFCN database. Throughout this paper, we refer to these 1070 debunked claims as **query claim debunks** and their duplicate counterparts as **duplicate claim debunks**. In other words, for each query claim debunk we have N (>=1) duplicate claim debunks debunking claims similar to the query claim and these duplicate claim debunks come from different fact-checking organisations written in distinct languages. Please refer to the Appendix for cluster plot visualisation.

Figure 1 a) is the pie chart distribution of the top 10 countries of query claim debunks i.e. top countries where claims already debunked were spreading. The graph shows that India and the United States had the largest number of recurring false narratives and these got debunked multiple times which led to waste in fact-checkers efforts. It depicts that these countries, particularly India with a total proportion of 19% are most vulnerable to even the misinformation which has already been debunked in the past, which also suggests a lack of awareness among the people about the prior fact-checked information. Figure 1 b) illustrates the top 10 fact-checking organisations which are debunking claims for which debunks already exist. The results are very much coherent with Figure 1 a), where Vishvas News which is an Indian fact-checking website publishes a large number of debunks about previously fact-checked claims.



a) b)

Figure 1. a) Pie chart distribution for top 10 countries where the claims already debunked were spreading. b) Pie chart distribution for top 10 fact-checking organisations that published fact-checked articles about the claims that were debunked in the past.

The difference in days between the publication date of query claim debunks and the duplicate claim debunks is illustrated in Figure 2. The histogram plot shows the weekly count with the value of bin set at an interval of 7 days. For example, the first bar shows that there are 884 cases where the difference between the debunk date of query claim and debunk date of duplicate claim is one week or less. Similarly, the second bar shows that there are nearly 300 cases where there is a fortnight difference and so on and so forth. This is worrisome and the subsequent findings help us answer the reason for the existence of such duplicate claim debunks.

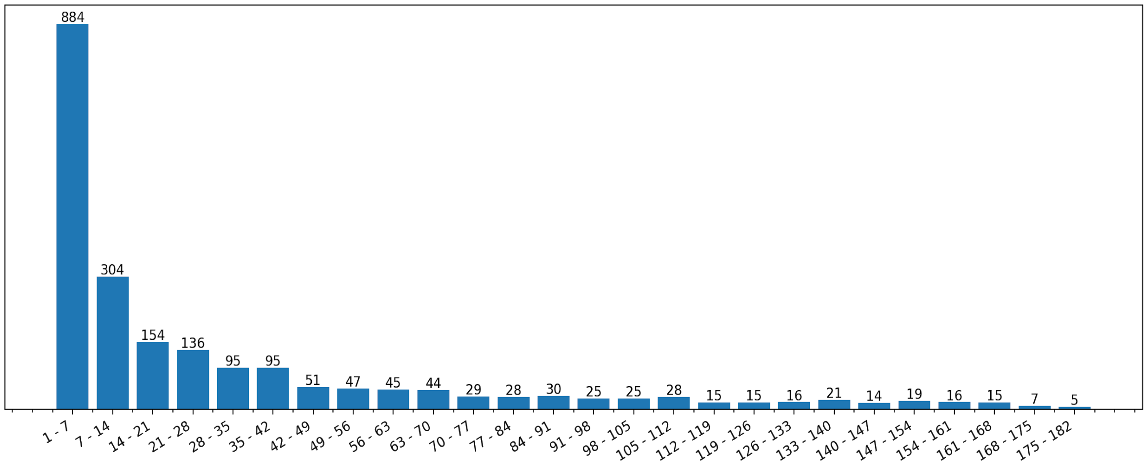
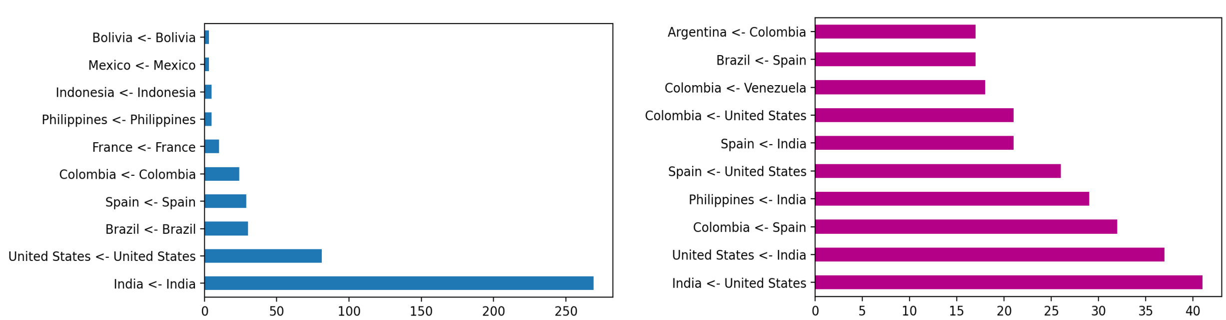


Figure 2. Histogram plot for days difference between query claim debunks and duplicate claim debunks. (Bin set at an interval of 1 week)

Finding 2: Spatiotemporal characteristics of duplicate claims and their transition between countries, social media platforms and modalities of content.

The spatiotemporal characteristics of query claim debunk and the duplicate claim debunk can be used to tell how the information flows or changes between different debunks. In Figure 3, pie charts illustrate the movement of similar claims between different countries. For simplicity, we only consider the top 10 country pairs where Figure 3 a) shows count of cases where both the countries are the same and Figure 3 b) shows cases where both countries are different. For example, "India <- United States" in Figure 3 b) tells that there are around 50 cases where the country of query claim is India and the country of duplicate claim is the United States. As the date of publication of duplicate claim debunk is before the publication date of the query claim debunk (Finding 1) therefore, the sign "<-" between the countries depicts the flow of dis/mis-information between different country pairs.

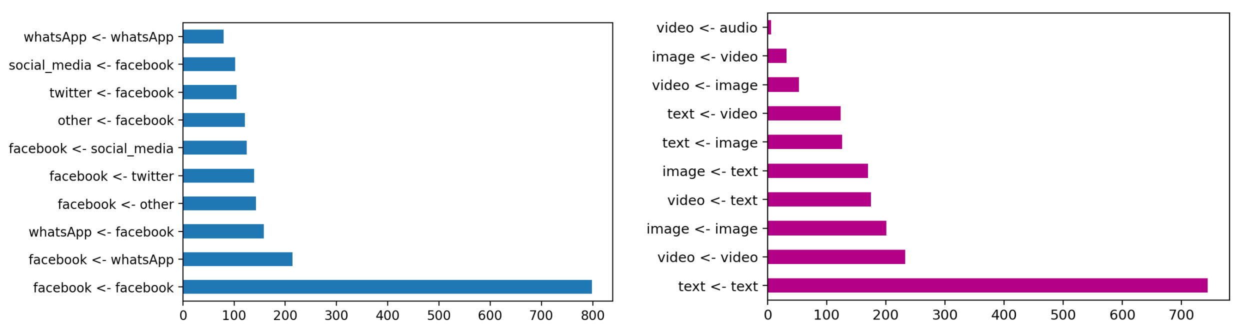


a)

b)

Figure 3. The transition of duplicate claims between different country pairs. a) Shows top 10 counts of cases where both the countries are same and b) Shows top 10 cases where both countries are different

Figure 4 a) demonstrates the transition in social media platforms between the query claim website and the duplicate claim website. In other words, it gives insights into the movement of duplicate claims from one website to another. The graph suggests that for similar claims, the spread between Facebook itself is the highest with around 800 cases, followed by WhatsApp to Facebook which has little more than 200 occurrences. This is particularly concerning as Facebook, which is increasingly being used as a primary source of news (Bridgman et al., 2020), allows the wild spread of content whose falsity has already been fact-checked before. Although, these social media platforms have made efforts[7] to mitigate the spread of false narratives but it's still prevalent as shown in this study and which also corroborates previous research (Burel et al., 2020). Furthermore, people use different modalities of content such as text, image, video etc. to spread factually inaccurate claims. Figure 4 b) shows the modality of content used by query claim and the duplicate claim. It seems the modality for text, video and image remains consistent but there are also considerable cases where there is transition between the modalities of content which claim same things.



a) b)

Figure 4 a) Transition in social media platforms between the query claim website and the duplicate claim website. b) Transition between modality of content used by query claim and the duplicate claim

Figure 5 shows the difference in the language used on the fact-checking articles for both the query claim debunk and the duplicate claim debunk for the top 10 language pairs. Here also, the first symbol is ISO-39 language code of the query claim debunk and the second one is the language used on duplicate claim debunk articles. For monolingual pairs, it's strange to see so many duplicate claim debunks for which debunks already exist in the same language. There are also a significant number of bilingual pairs which means that there is a need for cross-lingual search before debunking a new claim as discussed later in Finding 4.

[7] https://www.washingtonpost.com/technology/2020/11/09/facebook-twitter-election-misinformation-labels/

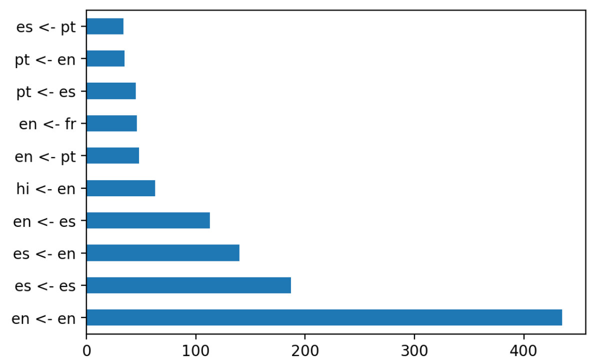
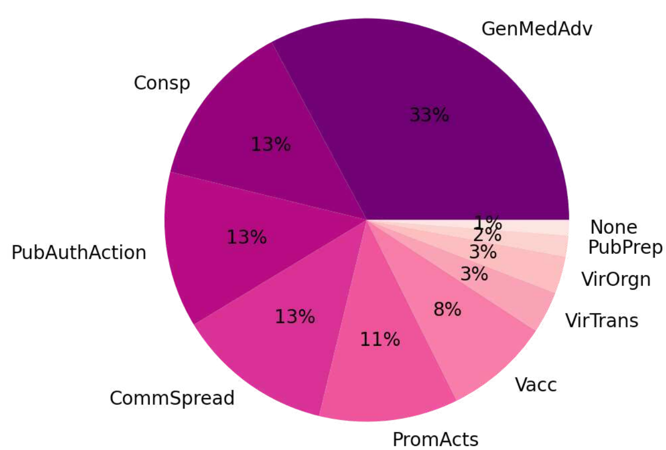


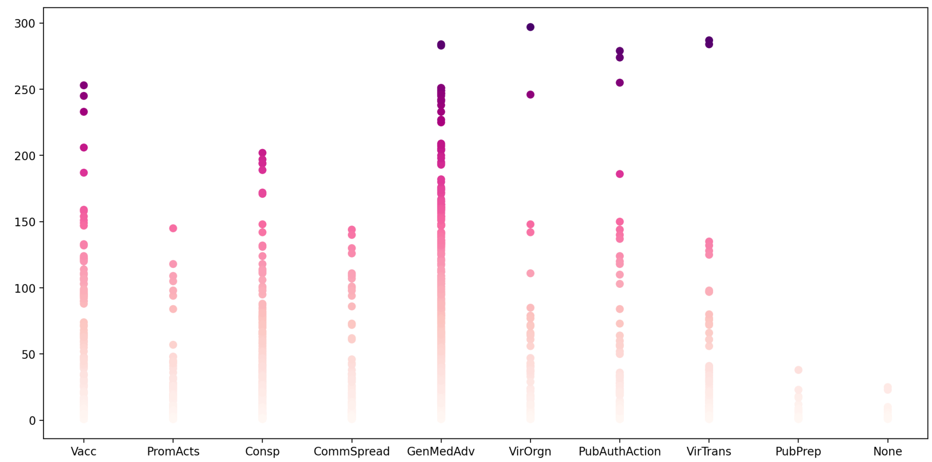
Figure 5. Top 10 count of cases showing the difference in the language used on the fact-checking articles for both the query claim debunk and the duplicate claim debunk

Finding 3: COVID-19 misinformation involving general medical advice got spread across multiple countries and hence has the highest proportion of duplicate claim debunks in our dataset.

To facilitate fact-checkers in quick debunking, researchers (Brennen et al., 2020) have been working on annotating COVID-19 dis/mis-information into different categories such as medical advice, virus origin etc. We annotate the claims using CANTM (Song et al., 2020) to see what kind of claims spreads the most and has the highest number of duplicate claim debunks. Figure 6 a) depicts the pie plot of the categories of claims for which multiple debunks exists. Misleading medical advice (GenMedAdv) is perhaps the most consistent topic of misinformation with the highest proportion of 33%, followed by the conspiracy (Consp), public authority action (PubAuthAction) and community spread (CommSpread) based false claims at 13% each of all of the cases. Figure 6 b) is a scatter plot demonstrating the difference in days between query claim and duplicate claim debunk for different categories of claims. We observe that claims on general medical advice are most densely spread, which means that there exist a lot of cases where the date of publication of duplicate claim debunks differs by many days. Followed by this, claims about vaccine and conspiracy theories are also densely spread as compared to others which are denser on the lower end depicting that the difference in days between the publication date of query claim and duplicate claim debunk is not much.



a)



b)

Figure 6 a) Pieplot for categories of claims. b) Difference in days between query claim debunk and duplicate claim debunks for different categories of claims. The COVID-19 misinformation categories are (i) PubAuthAction (public authority), CommSpread (community spread and impact), GenMedAdv (medical advice, self-treatments, and virus effects), PromActs (prominent actors), Consp (conspiracies), VirTrans (virus transmission), VirOrgn (virus origin and properties), PubPrep (public reaction), Vacc (vaccines, medical treatments, and tests) and None (other).

We further inspect claims that are most widely spread and whose debunks are published at different times of the year. Figure 7 shows a sample of 10 such false narratives about fallacious medical advice which include cures, remedies and prevention methods specific to COVID-19. We find that the debunks are spread across the complete year and these are published in different languages. Subsequently, Figure 8 illustrates the timeline of the appearance of debunks for claims about the consumption of an alkaline-rich diet to eliminate the coronavirus. From our dataset, it appears that the claim was first debunked in Spain in March 2020 and after a month a similar claim was debunked in Indonesia and the United States but it was still here to stay. It is surprising and yet worrisome that the same claim was again debunked in Turkey and Brazil in September and December respectively. One thing that might have led to this unknowing spread of previously debunked claims is the language of the fact-checked article as they all differ as shown in Figure 8 (ISO-39 language code enclosed in brackets after the name of fact-check organisation). We then investigated the language and modality of the claims and find that the claims written in one language are intentionally transformed to other languages and varied modalities (eg. text to image) before it gets propagated to other countries. The social media platforms used to spread the claim in different countries also change over time. Figure 8 shows that the same claim got shared on Facebook, WhatsApp and Twitter.

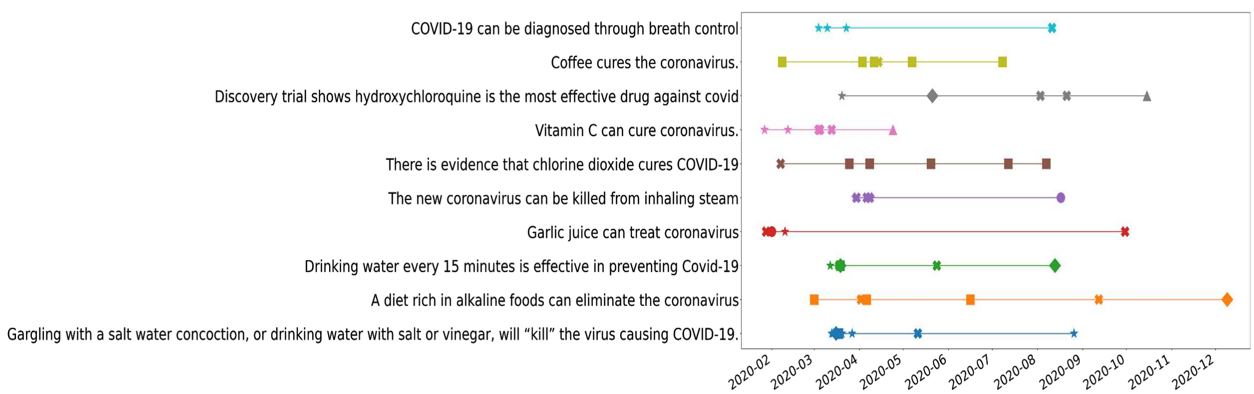


Figure 7. Timeline for a sample of 10 claims about fallacious medical advice. Here the language of debunk article is denoted by different symbols like English : ★ ; Spanish : ■ ; Hindi : ● ; Portuguese : ◆ ; French : ▲; Other : ✖ ;

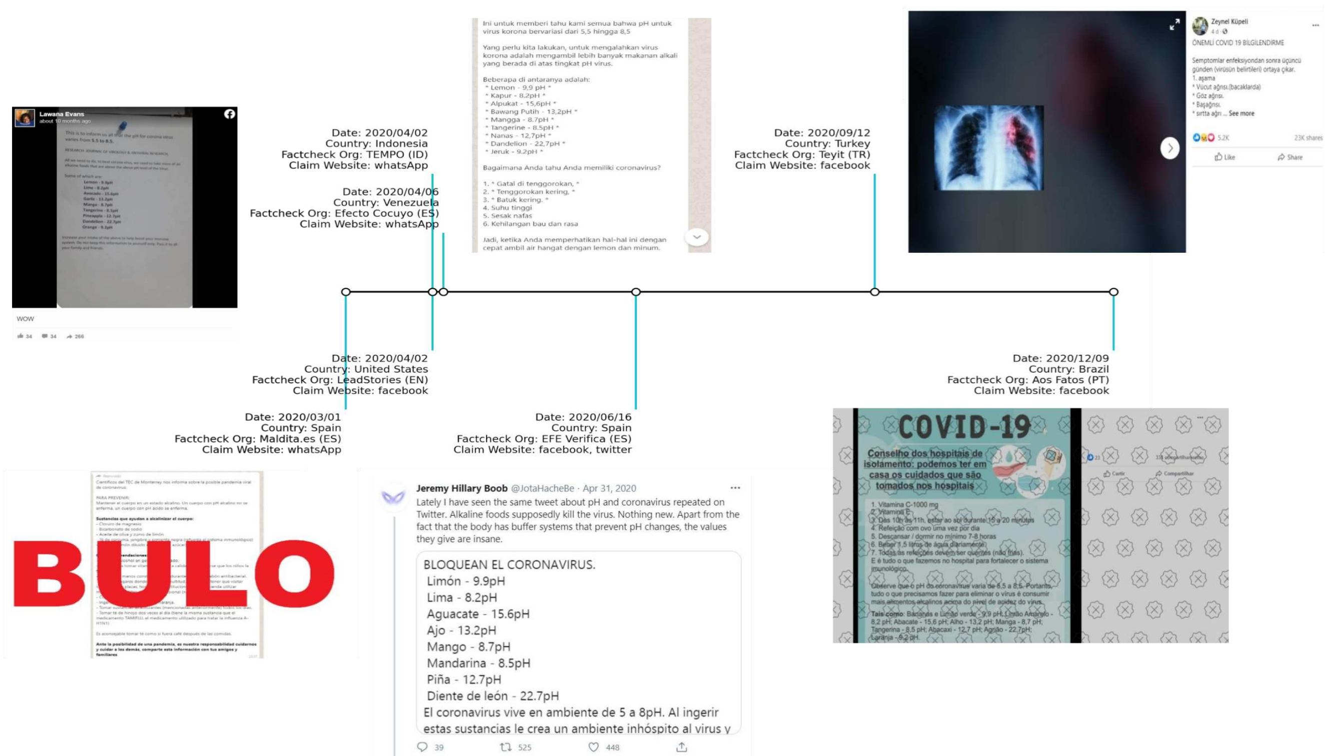


Figure 8. A detailed timeline of claim: “A diet rich in alkaline foods can eliminate the coronavirus”. All the images show the same claims being spread on different social media websites in different languages and varied modalities (top left and bottom right are the images shared on Facebook; top right and bottom centre are the images accompanied by some text shared on Facebook and Twitter respectively; top centre and bottom left show text shared on WhatsApp)

Figure 9 demonstrates the conspiracy theories which were debunked many times. The belief that Covid-19 is linked to 5G technology was common across many countries despite having already been debunked before. Besides this, there were also many falsely attributed claims and conspiracies involving Bill Gates. For example, Figure 10 shows the timeline of the debunks about claims that alleged a statement from Bill Gates that the vaccine against COVID-19 can change human DNA. All the debunks appear in multiple languages at different times over the time span of five months from June to October 2020.

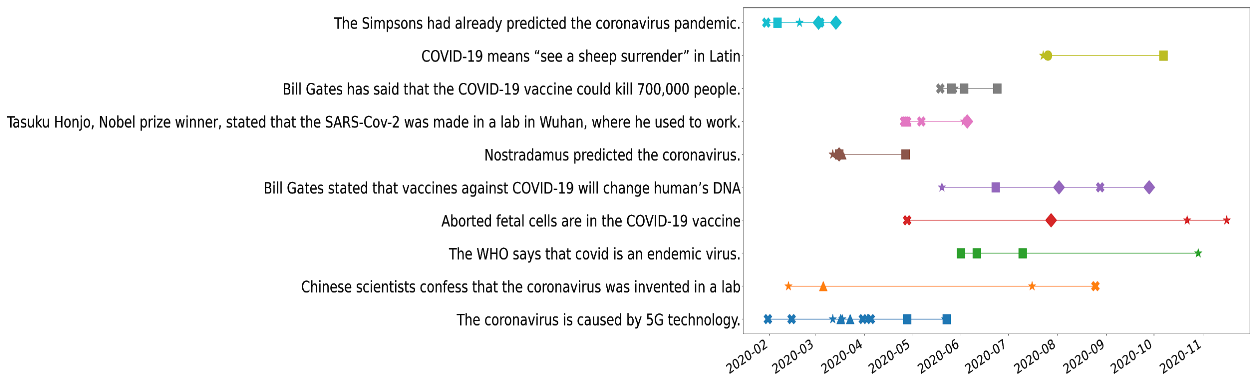


Figure 9. Timeline for a sample of 10 claims about fallacious medical advice. Here the language of debunk article is denoted by different symbols like English : ★ ; Spanish : ■ ; Hindi : ● ; Portuguese : ◆ ; French : ▲; Other : ✖ ;

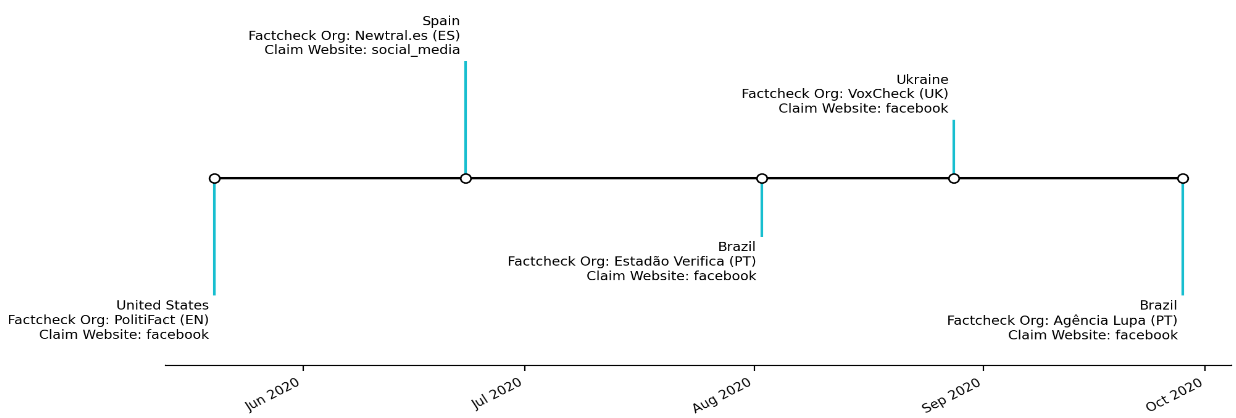


Figure 10. Detailed timeline of claim: "Bill Gates stated that vaccines against COVID-19 will change human's DNA"

Finding 4: The IFCN database majorly comprises of cases where there is not even a single duplicate claim debunk which is of the same language as the debunk of query claim, which necessitates the inclusion of multilingual debunk search in the fact-checking pipeline.

As stated previously, we find 1070 debunks about the claims that already had debunks published by an IFCN fact-checker. Out of these 1070 cases, there are a total of 627 cases for which we don't even have a single duplicate claim debunk which is of the same language as that of the query claim debunk. Alternatively, this shows that if a person from some country is willing to search for fact-check articles about the claim that has already been debunked in a language different from what the person understands, then he/she might not be able to do so due to the language barrier. Although one can make efforts to search through the content in multiple languages, it's usually not done because it's inefficient and it's probably the reason claims spread, incognizant of the fact that they have already been debunked in the past. This necessitates the inclusion of multilingual debunk search in the initial stages of the fact-checking pipeline.

Before we actually indulge in checking the factuality of the claim, it's really important to look if that claim or its substitute has already been debunked by some fact-checking organisation in their regional language. There has been some previous work (Shaar et al., 2020), where researchers have proposed the addition of a verified claim retrieval step in the automated fact-checking pipeline. Our analysis shows that this needs to be a multilingual retrieval step where we should consider a complete pool of debunked claims from all over the world irrespective of the language used in the fact-checked article. As manual fact-checking is time-consuming, it's paramount to avoid this double effort on debunking narratives that have already been fact-checked. Therefore, the ability to search previously debunked claims in multiple languages is beneficial to fact-checkers. On the other hand, it is indeed impossible to fact-check every claim but at least the social media platforms can take an initiative to warn users (Kaiser et al., 2020) before they share content that contains previously debunked claims. Over the years, several fact-checking organisations have emerged which have accumulated a large corpus of fact-checked articles (Augenstein et al., 2019; Shahi & Nandini, 2020) debunking various claims in different languages. This data can effectively be utilised to quickly debunk the repeated false narratives that keep on appearing on various social media platforms and thereby limiting its spread and potential harm that it may cause.

Methods

In order to answer the research questions mentioned above, we need to get the dataset of debunks related to COVID-19. The CoronaVirusFacts Alliance led by International Fact-checking Network (IFCN) consists of more than 100 fact-checking organisations based in 70 countries and covering around 40 languages. All IFCN signatories follow certain principles about good practices while debunking. We use their IFCN Poynter website[8] to collect all claims that have been fact-checked in 2020 (Song et al., 2020). We crawl a total of 10,381 claims related to COVID-19 with their associated debunks. For the purpose of this study, following fields were extracted from the html tags of each debunked claim on their website. Except for the fields provided by Poynter website[9], we also add some additional fields as stated below,

"Claim": Original debunked claim statement from the IFCN Poynter website.
"Country": List of countries where the claim has spread.
"Factcheck Organisation": Name of the fact-checking organisation that has debunked the claim.
"Debunk Link": Link to the fact-checked article debunking the claim (may or may not be in English)
"Debunk Language": Language used in the fact-checked article using langdetect[10]
"Debunk Date": Date of publication of the fact-checked article using htmldate[11]
"Social media website" : List of the websites where claims appeared.
"Modality of content" : Modality of claim using JAPE rule (Cunningham et al., 1999)

[8] https://www.poynter.org/ifcn-covid-19-misinformation/
[9] https://www.poynter.org/wp-content/uploads/2020/05/CORONAVIRUS-FACTS-RFP-Data-Description.pdf
[10] https://pypi.org/project/langdetect/
[11] https://pypi.org/project/htmldate/

In order to find all the duplicate claim debunks, we used the claim field of the debunks collected above to find all the semantically similar claims that were debunked by multiple fact-checkers. We formulate this as a retrieval problem where for each claim we did semantic search on all other debunked claims present in the dataset. We refer to them as **query claim debunks** and all the retrieved duplicate counterparts as **duplicate claim debunks**. For retrieval, we first replace all the words by which the COVID-19 is referred to in the claims (eg. sars-cov2, covid19, 2019-ncov, covid, covid-19) with a single representation i.e. “coronavirus”. After this, we use a multistage approach (Singh et al., 2021) where initial lexical retrieval is done using BM25 Okapi algorithm followed by neural retrieval stage using state-of-the-art text similarity model (Liu et al., 2019; Nogueira & Cho, 2019) to find all the semantically similar claims with their associated debunk article. We set a strict threshold of 0.8 on the relevance score so that we get strong reliable data for the purpose of this study. In addition to this, there were two retrieval constraints: 1) The fact checking organisation of the query claim debunk is different from the fact checking organisation of the retrieved duplicate claim debunk. 2) The date of publication of the duplicate claim debunk is before the date of publication of the query claim. These constraints ensure that we do not get duplicate cases and only the ones which have the debunks from different fact-checking organisations published in the past. As per the IFCN Poynter data description[12], the countries mentioned on the claim page of Poynter are the countries where the falsehood was spreading, therefore we infer that the claims which have been debunked at different times are the claims that have been spreading in distinct countries at different times.

Query Claim Debunk			**Duplicate Claim Debunk**		
Claim	**Debunk Org**	**Date**	**Claim**	**Debunk Org**	**Date**
Vitamin C can cure coronavirus.	Détecteur de rumeurs	2020/04/24	Vitamin C can cure COVID-19.	JTBC news	2020/03/04
			Vitamin C is a miracle cure for the novel coronavirus.	Källkritikbyrån	2020/03/05
			Vitamin C prevents coronavirus.	TjekDet.dk	2020/03/04
			Vitamin C will protect you from the coronavirus.	AFP	2020/03/13
			Consuming large doses of Vitamin C can stop the spread of coronavirus.	Vishvas News	2020/03/04
			Vitamin C can “stop” the new coronavirus.	FactCheck.org	2020/02/12
			The coronavirus can be slowed or stopped with the “immediate widespread use of high doses of vitamin C.”	PolitiFact	2020/01/27
Aborted fetal cells are in the COVID-19 vaccine	Science Feedback	2020/11/16	Vaccines, including the one for COVID-19, include aborted fetal tissues.	VoxCheck	2020/04/28
			Aborted babies used to develop COVID-19 vaccine	AAP FactCheck	2020/10/22
			CoronaVac uses cells from aborted fetuses.	Aos Fatos	2020/07/28

Table 1. Some examples of query claim debunk and their duplicate claim debunks. Note 1) Fact-checking organisation of the query claim debunk and duplicate claim debunks is different. 2) Date of publication of the duplicate claim debunk is before the date of publication of the query claim.

[12] https://www.poynter.org/wp-content/uploads/2020/05/CORONAVIRUS-FACTS-RFP-Data-Description.pdf

We find a total of 1069 debunks (10.3% of all debunks) which already had a debunk about a similar claim in the past. For each of these 1069 query claim debunks, we've N (>=1) duplicate fact-checked articles debunking claims similar to the query claim and these duplicate claim debunks come from different fact-checking organisations written in distinct languages. For some of our analysis, we converted this from a one-to-many relationship into one-to-one relation. Two random examples from the dataset are shown in Table 1.

Our work should be seen in light of the following limitations: i) Dataset used in our analysis should be considered as a weakly labelled dataset as it lacks manual annotations. Although, as mentioned above, we used state-of-the-art semantic similarity models and the threshold was also kept high so as to get only the relevant duplicate claim debunks. ii) For all the fact-checking articles debunking the same narratives, we did not consider any change in rulings made by fact-checkers over the time period. In other words, we assume that if the claim is first declared false by some fact-checking organisation then it remains false irrespective of the time or the place of debunking of a similar claim. This is something we plan to investigate in detail in our future work. iii) Finally, we presume that the reason behind the spread of debunked claim is that the spreader is unaware of the previously fact-checked article about the same false narrative that spread in the past. The sole aim of this research is to bring attention to the general public and the fact-checkers towards the presence of duplicate claim debunks, and thereby suggesting ways to mitigate the spread of debunked claims so that we are better able to deal with infodemic that may happen in future.

Bibliography

Augenstein, I., Lioma, C., Wang, D., Lima, L. C., Hansen, C., Hansen, C., & Simonsen, J. G. (2019). MultiFC: A Real-World Multi-Domain Dataset for Evidence-Based Fact Checking of Claims. Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP),

Barrón-Cedeno, A., Elsayed, T., Nakov, P., Da San Martino, G., Hasanain, M., Suwaileh, R., Haouari, F., Babulkov, N., Hamdan, B., & Nikolov, A. (2020). Overview of CheckThat! 2020: Automatic identification and verification of claims in social media. International Conference of the Cross-Language Evaluation Forum for European Languages,

Bontcheva, K., Posetti, J., Teyssou, D., Meyer, T., Gregory, S., Hanot, C., & Maynard, D. (2020). Balancing Act: Countering Digital Disinformation while respecting Freedom of Expression. *UNESCO*.

Brennen, J. S., Simon, F., Howard, P. N., & Nielsen, R. K. (2020). Types, sources, and claims of COVID-19 misinformation. *Reuters Institute*, *7*, 3-1.

Bridgman, A., Merkley, E., Loewen, P. J., Owen, T., Ruths, D., Teichmann, L., & Zhilin, O. (2020). The causes and consequences of COVID-19 misperceptions: Understanding the role of news and social media. *Harvard Kennedy School Misinformation Review*, *1*(3).

Burel, G., Farrell, T., Mensio, M., Khare, P., & Alani, H. (2020). Co-spread of Misinformation and Fact-Checking Content During the Covid-19 Pandemic. International Conference on Social Informatics,

Cunningham, H., Maynard, D., & Tablan, V. (1999). Jape: a java annotation patterns engine.

Kaiser, B., Wei, J., Lucherini, E., Lee, K., Matias, J. N., & Mayer, J. (2020). Adapting Security Warnings to Counter Online Disinformation. *Supporting materials. URL: https://osf. io/qf8e5*.

Limaye, R. J., Sauer, M., Ali, J., Bernstein, J., Wahl, B., Barnhill, A., & Labrique, A. (2020). Building trust while influencing online COVID-19 content in the social media world. *The Lancet Digital Health*, *2*(6), e277-e278.

Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., & Stoyanov, V. (2019). Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

McGlynn, J., Baryshevtsev, M., & Dayton, Z. A. (2020). Misinformation more likely to use non-specific authority references: Twitter analysis of two COVID-19 myths. *Harvard Kennedy School Misinformation Review*, *1*(3).

Nakov, P. (2020). Can We Spot the" Fake News" Before It Was Even Written? *arXiv preprint arXiv:2008.04374*.

Nogueira, R., & Cho, K. (2019). Passage Re-ranking with BERT. *arXiv preprint arXiv:1901.04085*.

Posetti, J., & Bontcheva, K. (2020). Disinfodemic: dissecting responses to COVID-19 disinformation. *UNESCO*.

Reis, J. C., Melo, P., Garimella, K., & Benevenuto, F. (2020). Can WhatsApp benefit from debunked fact-checked stories to reduce misinformation? *Harvard Kennedy School Misinformation Review*.

Shaar, S., Babulkov, N., Da San Martino, G., & Nakov, P. (2020). That is a Known Lie: Detecting Previously Fact-Checked Claims. Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics,

Shahi, G. K., & Nandini, D. (2020). FakeCovid--A Multilingual Cross-domain Fact Check News Dataset for COVID-19. *arXiv preprint arXiv:2006.11343*.

Singh, I., Deepak, P., & Anoop, K. (2020). On the Coherence of Fake News Articles. Joint European Conference on Machine Learning and Knowledge Discovery in Databases,

Singh, I., Scarton, C., & Bontcheva, K. (2021). Multistage BiCross Encoder: Team GATE Entry for MLIA Multilingual Semantic Search Task 2. *arXiv preprint arXiv:2101.03013*.

Song, X., Petrak, J., Jiang, Y., Singh, I., Maynard, D., & Bontcheva, K. (2021). Classification aware neural topic model for COVID-19 disinformation categorisation. Plos one, 16(2), e0247086.

Tasnim, S., Hossain, M. M., & Mazumder, H. (2020). Impact of rumors and misinformation on COVID-19 in social media. *Journal of preventive medicine and public health*, *53*(3), 171-174.

Thorne, J., & Vlachos, A. (2018). Automated fact checking: Task formulations, methods and future directions. *arXiv preprint arXiv:1806.07687*.

Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, *359*(6380), 1146-1151.

Zhou, X., & Zafarani, R. (2020). A survey of fake news: Fundamental theories, detection methods, and opportunities. *ACM Computing Surveys (CSUR)*, *53*(5), 1-40.

Funding

This work was partially funded by the WeVerify and SoBigData++ projects (EUH2020, grant agreements: 825297 and 871042).

Competing interests

The authors have no competing interests.

Ethics

This work does not involve any human subjects. The International Fact-Checking Network (IFCN) debunks are publicly available.

Data Availability

The International Fact-Checking Network (IFCN) debunks used in this paper are publicly available at https://www.poynter.org/ifcn-covid-19-misinformation/ and the code to scrape the debunks is available at https://github.com/iknoorjobs/IFCN-scraper

Appendix: Gephi Plot

Out of 10,381 debunks in the IFCN database, we find 1070 debunked claims that already had a debunk about the same false narrative from a different fact-checking organisation in the past. We clustered together all such duplicate claim debunks which have more than three debunks that fact-check similar claims and produced a GRAPHML-file so as to visualise the clusters using java-based network analysis applications such as Gephi[13] (Figure 11). The Fruchterman-Reingold force-directed graph drawing algorithm is used to visualise the network in a compact circle with coloured cluster separation based on the modularity class. Here, a node represents a debunk from the fact-checking organisation and the colour represents the cluster of all duplicate claim debunks. The claim statement for each cluster is mentioned as shown in Figure 11.

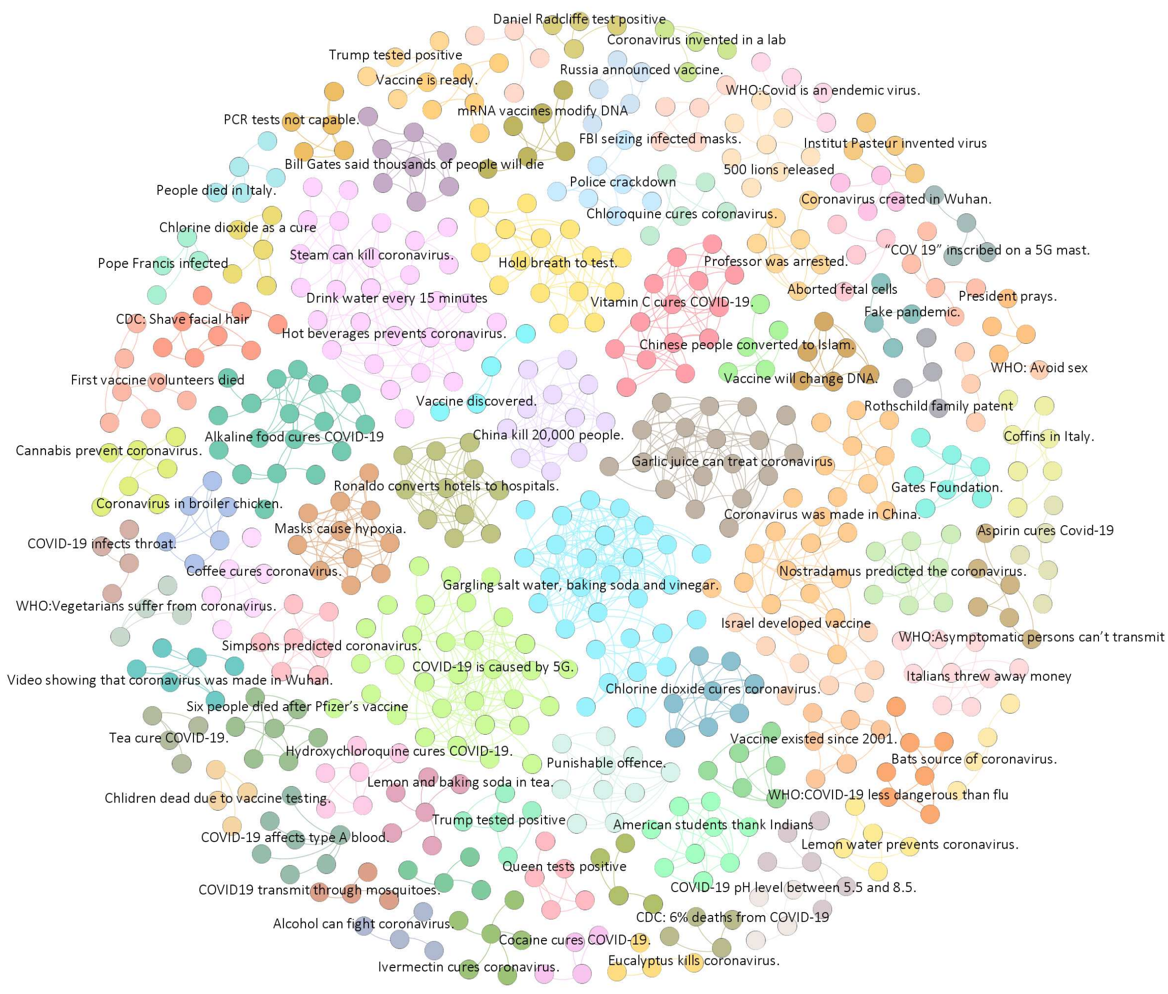


Figure 11. Cluster visualisation for duplicate claim debunks.

[13] https://gephi.org/