Automatically applying a credibility appraisal tool to track vaccination-related communications shared on social media

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ABSTRACT

Background: Tools used to appraise the credibility of health information are time-consuming to apply and require context-specific expertise, limiting their use for quickly identifying and mitigating the spread of misinformation as it emerges. Our aim was to estimate the proportion of vaccination-related posts on Twitter are likely to be misinformation, and how unevenly exposure to misinformation was distributed among Twitter users.

Methods: Sampling from 144,878 vaccination-related web pages shared on Twitter between January 2017 and March 2018, we used a seven-point checklist adapted from two validated tools to appraise the credibility of a small subset of 474. These were used to train several classifiers (random forest, support vector machines, and a recurrent neural network with transfer learning), using the text from a web page to predict whether the information satisfies each of the seven criteria.

Results: Applying the best performing classifier to the 144,878 web pages, we found that 14.4% of relevant posts to text-based communications were linked to webpages of low credibility and made up 9.2% of all potential vaccination-related exposures. However, the 100 most popular links to misinformation were potentially seen by between 2 million and 80 million Twitter users, and for a substantial sub-population of Twitter users engaging with vaccination-related information, links to misinformation appear to dominate the vaccination-related information to which they were exposed.

Conclusions: We proposed a new method for automatically appraising the credibility of webpages based on a combination of validated checklist tools. The results suggest that an automatic credibility appraisal tool can be used to find populations at higher risk of exposure to misinformation or applied proactively to add friction to the sharing of low credibility vaccination information.

KEYWORDS

Health misinformation; Credibility appraisal; Machine learning; Social media

1 INTRODUCTION

1.1 Detection and tracking of misinformation

The spread of misinformation—which we define here to include information that is not a fair representation of available evidence or communicates that evidence poorly—has become an increasingly discussed and studied topic in sociopolitical domains [1]. Early studies of misinformation spread used simulation and simplified models of social networks and progressed through to the use of social media data from Twitter, Facebook, and Tumblr [2–6]. In a recent example, Vosoughi et al. [7] found that false news appears to spread further, faster, and more broadly than other news. Social media observatories may be a useful way to put tools for detection to use in ongoing surveillance [8].

Previous studies have used machine learning approaches to make a binary distinction between misinformation (including disinformation in the form of fake news) and other information presented in news and social media. While most train classifiers using the text extracted from social media posts and web pages, some have also used information about social connections [9–13].

Health-related misinformation can be especially pernicious. People are increasingly influenced by online sources of health information; not only by searching online for symptoms and interventions as needed but also because ongoing exposure to health information in news and social media can shape their attitudes and behaviours. Health information is also complex—it is an example of an application domain where distinguishing between true and false, fake and real, may not have enough nuance to help us understand other characteristics such as persuasiveness and applicability that might influence attitudes and behaviours. To translate research on the...
Most studies examining the prevalence and spread of misinformation have observed only on what users post rather than what they might have seen. A departure from this includes work on human papillomavirus (HPV) vaccination, which used Twitter to examine associations between exposure to certain topics and population-level differences in HPV vaccine coverage in the United States [14], and associations between exposure to negative tweets and later expression of negative opinions in individuals [15]. In the sociopolitical context, a recent analysis monitored how often a panel of United States voters were exposed to or shared false political stories [16]. The ability to measure how people engage and share misinformation on social media may help us better target and monitor the impact of communication interventions in naturalistic settings [17].

1.2 Appraising information credibility
A range of tools have been developed to assess the quality and credibility of online health information. Most were designed as checklists to be used by experts to assess the quality, credibility, and transparency of what they are reading. The DISCERN tool was designed as a general purpose tool for evaluating the quality of health information [18], with an emphasis on web pages that patients might use to support the decisions they make about their health. The Quality Index for health-related Media Reports (QIMR) tool is a more recent addition and differs in that it was designed to be used to evaluate the quality of communications about new biomedical research [19].

Common elements of the tools that are used by experts to assess the quality and credibility of health research reporting and patient information online include: the veracity of the included information; transparency about sources of evidence; disclosure of advertising; simplicity and readability of the language; and use of balanced language that does not distort or sensationalise [20]. What most of the tools have in common is that applying them can be time-consuming and often requires specific training or expertise. Organisations like HealthNewsReview.org (which ended in 2018) use experts to evaluate new health-related communications as they appear in the news media. Given the rate at which new information is made available and the resources needed to appraise them, there is currently no way to keep up with new health-related stories as soon as they appear. While the challenge of information volume versus quality was first discussed two decades ago [21], it remains a key challenge in public health.

1.3 Research objectives
Our aim was to characterise the sharing and potential reach of vaccination-related communications shared on Twitter, relative to its credibility. Because it would not have been feasible to assess the credibility of all web pages manually, we also developed and evaluated machine learning classifiers to automatically estimate the credibility of the relevant web pages we found.

2 METHODS
To estimate the credibility of vaccine-related communications at scale, we collected text from vaccination-related web pages by monitoring links from tweets that mentioned vaccine-related keywords. We sampled web pages and manually appraised the credibility by applying a checklist-based appraisal tool that we developed, and used those data to train classifiers to predict which of the checklist criteria were satisfied in unseen web pages, producing a single score for each web page. Applying these classifiers to all web pages in our collection, we examined patterns of sharing relative to credibility scores.

2.1 Datasets
We collected vaccine-related tweets between 17 January 2017 and 14 March 2018 using Twitter Search Application Programming Interface (API), using a set of pre-defined search terms (including "vaccin*", "immunis*", "vax*", "antivax*"). For each tweet labelled as the English language by Twitter, we stored the text of the tweet and the related tweet metadata including time-stamp and user profile information. Each time we encountered a new user posting a tweet about vaccines or vaccination for the first time in the study period, we additionally collected the lists of users they followed and their followers. This information on social connections was used to construct the social network of users for our analysis. At the end of the data collection period, we collected information for 6,591,566 tweets (including retweets) from 1,860,662 unique users.

To construct a reliable dataset for training, we over-sampled from articles that we expected to have higher credibility using the bibliographic database PubMed1 and Altmetric,2 which tracks links from web pages to articles with DOIs. We used PubMed to search for relevant articles (using search terms "vaccine" or "immunisation" in the title or abstract, expanded to include synonyms automatically by PubMed), which returned 306,886 articles. We then used the set of PubMed IDs with Altmetric to identify a set of URLs that are known to specifically reference vaccine-related journal articles. This allowed us to: (a) exclude URLs on Twitter that linked directly to research articles (our credibility checklist was not designed to assess these); and (b) to deliberately over-sample from webpages that had explicit links to research when constructing our training dataset (because we expected these to meet more of the credibility criteria).

From the set of 6.59 million tweets (including retweets), we extracted 1.27 million unique links to web pages that included news, blogs, videos, and social media posts. We used a Google library3 to detect and remove all non-English web pages. After excluding web pages that included fewer than 300 words in contiguous blocks, we finally included 144,878 web pages in our analysis. Other web pages included links to pages displaying videos and images (e.g. YouTube, Facebook, Instagram), and pages that were not amenable to text extraction for other reasons.

The credibility appraisal tool was developed by three investigators with expertise in public health, public health informatics, science communication, and journalism. To develop a tool that

1https://www.ncbi.nlm.nih.gov/pubmed
2https://www.altmetric.com
3https://code.google.com/p/language-detection/
We then summarised the information as a credibility score for the articles to measure inter-rater reliability, and it was found to be moderate when tested on the three categories (Fleiss’ kappa 0.46; 95% CI 0.41 – 0.52; \( p < 0.001 \)). Inter-rater reliability was near-perfect when the aim was to separate low credibility web pages from all others (Fleiss’ kappa 0.89; 95% CI 0.82 – 0.97; \( p < 0.001 \)).

Figure 1: The proportion of web pages that met the individual criteria in the 474 web pages used to train the classifiers (cri: criterion).

Table 1: The parameters and corresponding values for the initialisation of the language model and classifier

| Parameters          | Value                  |
|---------------------|------------------------|
| weight decay        | 1e-4                   |
| BPTT                | 60                     |
| Batch size          | 52                     |
| Drop outs           | [0.25, 0.1, 0.2, 0.02, 0.15] |
| Embedding size      | 400                    |
| Number of layers    | 3 (language model), 5 (classifier) |
| Optimiser           | Adam [24]              |
| \( \beta_1, \beta_2 \) | 0.8, 0.99              |

The three investigators then applied the credibility appraisal tool to an additional 474 vaccine-related web pages. For each web page, investigators navigated to the website, read the article, and decided whether it satisfied each of the seven criteria. This process produced a set of values (0 or 1) for each each criterion and for each web page. We then summarised the information as a credibility score, defined by the number of criteria that were satisfied, and grouped web pages by credibility score into low (from 0 to 2 criteria satisfied), medium (from 3 to 4 criteria satisfied), and high (from 5 to 7 criteria satisfied). Across the 474 expert-labelled examples (see Section 2.1), the proportion of the web pages that were judged to have satisfied each of the seven credibility criteria varied substantially (Figure 1).

The investigators independently undertook duplicate appraisals of a subset of the articles to measure inter-rater reliability, and it was found to be moderate when tested on the three categories (Fleiss’ kappa 0.46; 95% CI 0.41 – 0.52; \( p < 0.001 \)). Inter-rater reliability was near-perfect when the aim was to separate low credibility web pages from all others (Fleiss’ kappa 0.89; 95% CI 0.82 – 0.97; \( p < 0.001 \)).
For the SVM and RF based classifiers, we performed additional pre-processing to remove stop-words and low-frequency words. After pre-processing, there were 60,660 unique words used across the entire corpus; these were used as features for training and testing RF and SVM classifiers. Each document was represented as a set of feature vectors, where features were defined by term frequency, inverse document frequency (TF-IDF) weights. TF-IDF represents the importance of a word to a document in a corpus, which increases proportionally to the number of times it appears in the document but is offset by the frequency of the word in the corpus, ensuring the similarity between documents be more influenced by discriminative words with relatively low frequencies in the corpus. The best parameters for SVM and RF are found using grid search functionality of scikit-learn library and are given in Table 2.

Table 2: The parameters used for SVM and RF classifiers, all other parameters are kept as default.

| Parameters | Value |
|------------|-------|
| C (SVM)    | 100   |
| gamma (SVM)| 1     |
| kernel (SVM)| linear |
| norm (SVM) | 1     |
| use-idf (SVM)| True |
| max-df (SVM)| 1.0   |
| ngram-range (SVM)| (1, 1) |
| n-estimators (RF)| 10    |
| criterion (RF)| gini  |
| min-impurity-split (RF)| 1e-7 |

Using the expert-labelled data we trained 21 classifiers (one per criterion for each of the RF, SVM and DL-based classifiers) and evaluated the performance of the classifiers in 10-fold cross-validation tests, reporting the average $F_1$-score and accuracy for all three classifiers.

2.3 Sharing and potential exposure estimation

Following the development of a reliable tool for automatically estimating the credibility of vaccine-related communications at scale, we aimed to characterise the patterns of spread relative to credibility. In particular, we were interested in examining where and how often low-credibility information is shared on Twitter. Recall that many previous related studies examining cascades and spread of misinformation have selected stories or hashtags externally judged for veracity, while our approach estimates the credibility of the text on any web page shared at least once in a tweet with relevant keywords. As a consequence, our approach produces a cross-sectional view of information sources shared in relation to the relatively broad topic of vaccines and vaccination.

For each web page that met our study inclusion criteria, we estimated its credibility score. We then aggregated the total number of tweets posted during the study period that included a link to the web page, including tweets and retweets. We then estimated the potential exposure by summing the total number of followers for all tweets and retweets. Note that this represents the maximum possible audience and we did not capture the union of individual users who may have been followers of at least one of the users posting the tweet as has been done in previous studies [14].

To examine how users posting links to low-credibility web pages might be concentrated within or across sub-populations, we also estimated a per-user measure of credibility, which is defined by the list of credibility scores for any user sharing links to one or more web pages. We used these lists in conjunction with information about followers to construct a follower network, which allowed us to identify sub-populations in which low credibility information was shared more often.

3 RESULTS

The RF classifiers produced the highest performance overall, and in most cases predicted whether or not the text on a vaccine-related web page satisfied each of the credibility criteria with over 90% accuracy (Table 3). The SVM-based classifier produced the highest $F_1$-scores for two of the most unbalanced criteria. Further experiments are needed to determine whether the DL-based classifier could outperform the baseline methods if more expert-labelled data are made available. The results show that it is feasible to estimate credibility appraisal for web pages about vaccination without any additional human input, suggesting the performance—although variable—is high enough to warrant their use in surveillance.

We then applied the best-performing classifiers for each of the seven criteria on the documents extracted from the set of 144,878 vaccine-related web pages, producing an estimated credibility score for every page. Fewer unique web pages with low credibility scores were shared on Twitter relative to those with medium or high credibility scores (Figure 3). Measured by the number of times a link was posted on Twitter (including retweets), low credibility
Table 3: Performance of the classifiers (average $F_1$ Score and accuracy in 10-fold cross validation)

|                | DL          |            | SVM          |            | RF          |            |
|----------------|-------------|------------|-------------|------------|-------------|------------|
|                | $F_1$ Score | Accuracy   | $F_1$ Score | Accuracy   | $F_1$ Score | Accuracy   |
| Criterion 1    | 0.851 ±0.005 | 0.740 ±0.008 | 0.903 ±0.052 | 0.842 ±0.045 | 0.950 ±0.015 | 0.924 ±0.019 |
| Criterion 2    | 0.000 ±0.000 | 0.638 ±0.003 | 0.802 ±0.044 | 0.828 ±0.018 | 0.915 ±0.005 | 0.943 ±0.006 |
| Criterion 3    | 0.000 ±0.000 | 0.865 ±0.009 | 0.761 ±0.038 | 0.917 ±0.011 | 0.745 ±0.088 | 0.944 ±0.018 |
| Criterion 4    | 0.882 ±0.001 | 0.789 ±0.002 | 0.903 ±0.042 | 0.833 ±0.068 | 0.959 ±0.017 | 0.936 ±0.022 |
| Criterion 5    | 0.551 ±0.249 | 0.486 ±0.051 | 0.787 ±0.034 | 0.721 ±0.051 | 0.921 ±0.022 | 0.920 ±0.020 |
| Criterion 6    | 0.867 ±0.002 | 0.765 ±0.004 | 0.912 ±0.006 | 0.852 ±0.010 | 0.964 ±0.002 | 0.943 ±0.004 |
| Criterion 7    | 0.000 ±0.000 | 0.840 ±0.008 | 0.801 ±0.029 | 0.924 ±0.006 | 0.764 ±0.057 | 0.936 ±0.004 |

webpages made up 14.4% of posts, compared to 21.1% of posts linked to high credibility webpages.

When we examined the total number of potential exposures by counting followers, we found that the distribution of total potential exposures per web page were roughly equivalent (illustrated by the slope of the three distributions in Figure 4). This indicates that although there were fewer total unique low credibility web pages shared on Twitter during the period, the individual web pages were likely to have been seen by a similar number of Twitter users. Measured by the total proportion of exposures to links to relevant webpages, 9.2% of total exposures were to low credibility webpages, and 24.4% of total exposures were to high credibility webpages. Despite making up a smaller proportion of overall exposures, some of the low credibility web pages were influential; the top 100 by exposure may have been seen by between 2 million and 80 million, and more than 200 had at least 1 million potential exposures.

Low credibility communications were more heavily concentrated among certain groups of users sharing vaccination-related web pages on Twitter. This is evident in a visualization of the follower network for the set of 98,663 Twitter users who posted at least 2 links to web pages included in the study (Figure 5). The network shows heterogeneity in the sharing of links to low credibility communications, suggesting that there are likely to be communities of social media users for whom the majority of what they see and read about vaccination is of low credibility.

4 DISCUSSION

We found that it is feasible to produce machine learning classifiers to estimate the credibility of vaccination-related web pages using a relatively small set of training data. Applying the classifier to text-based vaccination-related web pages shared on Twitter between January 2017 and March 2018, we found that fewer low credibility web pages were shared overall, though some had a potential reach of tens of millions of Twitter users; and that certain sub-populations were much more likely to share and be exposed to low credibility information.

This research adds to what is known about the detection and spread of misinformation on social media. Where much of the prior research has aimed to label articles of social media posts by veracity [9, 10, 12, 13], we instead chose to label information using a
credibility appraisal tool adapted from previously validated instruments [18, 19]. Our approach was therefore more general (the use of reliable evidence was one of 7 criteria), and we did this specifically because vaccine information is sometimes true and misleading, or false but applicable and persuasive. In other related work, Mitra et al. [25] examined the linguistic features in social media posts that influence perceptions of credibility. While we did not examine the linguistic features of the tweets that included links to low credibility information, it would be interesting to connect these ideas to better understand whether they influence user behaviour—making users more likely to engage with a tweet by URL access, replying, and sharing. Our work is not directly comparable to previous studies that have examined how information and misinformation spread through social media [5, 6, 8, 11]. We examined a single broad topic that may not generalise, labelled information according to a broader set of criteria than the veracity of the information, and measured total potential exposures rather than cascades of tweets and retweets. Rather than sampling from a set of known examples of fake and real news, we sampled from across the spectrum of relevant articles shared on Twitter. Structuring the experiments in this way, we found no clear difference in the distribution of total potential exposures between low credibility web pages and others.

We found that specific sub-populations of Twitter users appear to be more often exposed to low credibility information about vaccines.
We developed and tested machine learning methods to support where exposure to low credibility vaccine-related information is shared online, showing that it is feasible. This allowed us to scale our analysis of vaccine-related information shared via posts on Twitter to cover a sample of 144,878 web pages linked from a set of 6.59 million vaccine-related tweets posted between January 2017 and March 2018. We found that although low credibility information was shared less often overall, there are certain sub-populations where exposure to low credibility vaccine-related information is disproportionately high. These results suggest two new ways to address the challenge of misinformation through the automatic credibility appraisal tool. Using the tool to enable surveillance at scale may help us identify at-risk communities and better target resources in health promotion. Embedding the tool in interventions can support improvements in health literacy by flagging and explaining low credibility information for consumers as they engage with the information online.

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