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The current state of fake news: challenges and opportunities

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Abstract

The authenticity of Information has become a longstanding issue affecting businesses and society, both for printed and digital media. On social networks, the reach and effects of information spread occur at such a fast pace and so amplified that distorted, inaccurate or false information acquires a tremendous potential to cause real world impacts, within minutes, for millions of users. Recently, several public concerns about this problem and some approaches to mitigate the problem were expressed. In this paper, we discuss the problem by presenting the proposals into categories: content based, source based and diffusion based. We describe two opposite approaches and propose an algorithmic solution that synthesizes the main concerns. We conclude the paper by raising awareness about concerns and opportunities for businesses that are currently on the quest to help automatically detecting fake news by providing web services, but who will most certainly, on the long term, profit from their massive usage.

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Keywords: Fake news detection; Social Media; Computer Science challenges

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1. Introduction

In the news industry, in particular, but also in society at large, fake news detection has become a central discussion topic, as the need to permanently assess the veracity of digital content has been raised by the constant spread of false news / information. Information veracity is a long-term issue affecting society both for printed and digital media. The sensationalism of not-so-accurate eye catching and intriguing headlines aimed at retaining the attention of audiences to sell information has persisted all throughout the history of all kinds of information broadcast. On social networking websites, the reach and effects of information spread are however significantly amplified and occur at such a fast pace, that distorted, inaccurate or false information acquires a tremendous potential to cause real impacts, within minutes, for millions of users.

Societal issues are being raised about the individuals' ability to tell apart what is fake and what is authentic, while surfing and actively engaging in information overloaded networks. As reported by Anderson [1], youngsters are known to be tech-savvy when compared to their parents, but when it comes to the ability to tell if a news piece is fake or not, they seem as confused as the rest of the society and 44% have confirmed it in a research conducted by Common Sense Media. The same research also indicates that 31% of kids aged 10 to 18 have shared online at least one news story that they later found out was inaccurate or fake. This situation raises a whole new dimension of concerns related to digital literacy that go beyond the mere ability to access and manage technology.

Together with societal challenges, there is a dramatic and inconspicuous situation happening in the media landscape, the public sphere and journalism industry that requires debate and examination, pointing out two main aspects [2]. The first one relies on the fact that news publishers have lost control over the distribution of news, which are presented to Internet users by obscure and unpredictable algorithms. Also, news market newcomers (such as BuzzFeed, Vox and Fusion) have built their presence by embracing these technologies, undermining the long-term positions occupied by more traditional news publishers. The second aspect relies on the increasing power that social media companies, such as Google, Apple, Facebook and Amazon, have gained in controlling who publishes what to whom, and how the publications are monetized.

In the above context, establishing the reliability of online information is a daunting but critical current challenge [3], demanding the attention, regulation and active monitoring of digital content spread by the major parties involved in sustaining how the information is presented and shared among people over the Internet, including search engines and social networking platforms. The fake news subject has become so prevalent that the Commons Culture, Media and Sport Committee is currently investigating concerns about the public being swayed by propaganda and untruths [4]. The curation of high-quality journalism is also at stake, since an increasing proportion of the adults are getting their news from social media and fictional stories are presented in such way that it can be very difficult to tell them apart from what is authentic.

As stated be Conroy [3, 5], fake news detection is defined as the prediction of the chances of a particular news article (news report, editorial, expose, etc.) to be intentionally deceiving. In this paper, we discuss the fake news problem in, the current technical concerns related, among other, to the lack to robustness of automated detection systems, and discuss opportunities that, accordingly, emerge.

2. A review of some relevant cases

Distorted news and "alternate facts" were not a problem in society two years ago, despite the long-term deep changes in the news market [1]. The social concern about these kinds of news has been rather deeply accelerated by the term "fake news", coined by the US elected President, Donald Trump, conveying its origins in the political arena. For example, among other fake news that emerged during the Trump campaign one of the most popular ones consisted on the Pope Francis reported endorsement of Donald Trump for president of the US. The news piece was advanced by the website "Ending The Fed", managed by a Romanian youngster. BBC [4, 6] also refers to the advancement of particular (often extreme) political causes as one of the main sources of fake news, defining them as false information deliberately circulated by those who have scant regard for the truth and act under the motivation of fostering political causes or obtaining revenue out of the online traffic.

In this domain, Facebook has faced an increasing criticism over its role in the 2016 US presidential election because it allowed the propagation of fake news disguised as news stories coming from unchecked websites. This spreading of false information during the election cycle was so severe that Facebook was labelled as "dust cloud of nonsense." [7] The fact is that the presidential election year has shown how the lines have blurred between facts and speculation, with people profiting off the spread of fake news. There were more than 100 news sites that made up pro-Trump content traced to Macedonia, according to a BuzzFeed News investigation [8].

A subversive industry of fake news has been arising as an independent business opportunity in the news market, as is the case of Media Vibes SNC, a Belgium company who owns more than 180 URLs devoted to creating and spreading fake news on the web and on social networks (such as 24aktuelles.com. or react365.com). The company is also responsible for the creation of the user-generated fake news concept, by providing Internet users with an application to develop their own fake news and to spread them on their social networks. The main idea behind the business is supported by the "do-it-yourself media", and fake news can consist of jokes, provocations, sarcasm, etc., that are written by ordinary people (c.f. react365.com).

Another fake news model also worth of mention is the one based on the publication of news pieces in websites with URLs very similar to some of the most popular and well reputed news stations, such as ABC. For instance, the official URL of the station's website is abcnews.go.com and this type of fake news are available at the URL abcnews.com.co. Among his top fake stories that had huge success in 2016 are some of the most known political fake news pieces: "Obama Signs Executive Order Banning The Pledge Of Allegiance In Schools Nationwide", "Donald Trump Protester Speaks Out: «I Was Paid $3,500 To Protest Trump's Rally»" and "Obama Signs Executive Order Declaring Investigation Into Election Results; Revote Planned For Dec. 19th".

Among the main purposes of such fake news business models it's possible to highlight the interest on generating interactions on the social networks, generate web traffic to the fake news pages and earn profit through advertising or to damage someone's image and reputation.

3. Fighting back fake news

In this panorama, Facebook has publicly stated that fake news consists of such a small percentage of what is shared on its network and that it couldn't have had a significant impact (in the US election, for instance). However, at the same time, the social network has also officially insisted that ferreting out the truthful news from the fake ones is a difficult technical problem. This situation is the concrete motivation of our research question: how hard of a problem is it for an algorithm to determine truthful news from what it is not true?

Recently, a communications professor at the Merrimack College in Massachusetts, stated that she faced a similar problem with her students, who cited from sources that are not credible. As an attempt to circumvent this problem, she created a list of fake, misleading or satirical websites [9] as a reference guide for her students. However, as this list (a compilation of URLs together with some remarks and distributed under a Creative Commons license) is basically one and a single opinion of someone about some sites, it has been under severe critics, besides being a very basic approach to the problem solution. Another situation, reported by Paul Mihailidis, who teaches media literacy at Emerson College in Boston, refers to how Facebook users don't stop to critique or judge information before sharing it. Social media users appear to have lost the notion of deep reading by adopting a posture of deep monitoring and, when they see a catchy headline the default is to share [7].

Circumstances as the above mentioned are part of a wider context that has been increasingly demanding attention, regulation and active monitoring: how digital content is spread by the major parties involved in sustaining how the information is presented and shared among people over the internet, including search engines and social networking platforms. The fake news subject has become so prevalent that the Commons Culture, Media and Sport Committee is currently investigating concerns about the public being swayed by propaganda and untruths [4]. The curation of high-quality journalism is also at stake, since an increasing proportion of the adults are getting their news from social media and fictional stories are presented in such way that it can be very difficult to tell them apart from what is authentic.

Recently, reporters of The Guardian [10] informed on a parliamentary inquiry into fake news to consider legislation on how social media platforms handle complaints procedures and to force them to take responsibility for the content (advertisement) they put on pages, in the same way an editor is responsible for the press adds that they print on their newspaper. The newspaper states that Facebook is the principal paid-for tool for political communication and that it has a breach in its own community policy by failing to act on complaints flagged by a BBC reporter. On an interview with Damian Collins, chair of the UK's culture, media and sport (CMS) committee, Damian admitted that society might even reach a point in which democracy is compromised by the high level of virality of fake news [10].

3.1. The general approaches

These concerns were also voiced by the inventor of the world wide web, Sir Tim Berners-Lee, who has set out a five-year strategy, in an open letter, where he unveils a plan to tackle data abuse and fake news, while admitting that the solutions will not be simple [11]. Nevertheless, in early 2017, Wendling [6] reported on a considerable number of worldwide entities, organizations and initiatives aimed at stopping the spread of fake news. These include:

a) **Human intervention** to verify information veracity: with reference to the International Fact Checking Network (IFCN) that allows American and German Facebook users to flag deliberately false articles. Fake news are also being flagged by fact checkers from media organizations such as the Washington Post and Snopes.com. The same methodology is being applied by the French newspaper Le Monde, and its fact-checking unit called "Les Decodeurs" (The Decoders), who have developed a web extension called Decodex.
b) **Using algorithms** to fight algorithms: since algorithms are part of what spreads the fake news (popular content) they can also be part of the solution, by identifying fake content and validating the information sources. These, however, despite the several attempts that have been emerging, still lack the necessary robustness to perform a reliable verification of which information is false or not. We divide these methods into: (1) algorithms that are based on the content; (2) algorithms that are based on the diffusion dynamics of the message, and; (3) hybrid algorithms, which are based on a weighted sum, or a group of features feeding a learning algorithm.

4. Algorithmic fake news detection

In the beginning of the decade the research community started to devote their efforts to the problem of "misleading" information, then to "rumor" detection, or misinformation, and recently to the detection and prevention of fake news.

To predict the veracity of rumors, Soroush et al. identified a set of three features that characterize the information spread: linguistic style used to express rumors, characteristics of people involved in propagating information, and network propagation dynamics. Their model (which was generated using Hidden Markov Models) was allegedly capable to correctly predict the veracity of 75% of the rumors faster than any other public source, including journalists and law enforcement officials [13].

Another approach, taken by Castillo et al. [14] analyzed microblog postings related to "trending" topics, and classified them as credible or not credible, based on 63 features they extracted from their content and 5 features related to propagation dynamics. Then, they used machine learning techniques to create an automatic credibility assessing method [15]. It is curious to note that the same authors, one year before (2010) stated that they found that false information is more likely to be questioned by users than reliable accounts of an event. However, in 2010 a system designed to detect astroturfing campaigns on Twitter (Ratkiewicz et al.) was proposed [15].

It has been widely noticed that, in a network, rumors gradually acquire more credibility as more and more network neighbors acquire them. After some time, a threshold is crossed and the rumor is believed to be true within a community. An interesting framework (the Hoaxy™) has been developed to crosscheck claims against fact-checks [16].

However, a serious obstacle in the modeling of information propagation in the real world as well as in the blogosphere is the fact that the structure of the underlying social network is often unknown. When explicit information on the social network is not available, the strength of the social links is hardly known and their importance cannot be deemed uniform across the network [17]. Heuristic methods are being developed to face this issue, by proposing an algorithm that can efficiently approximate linkage information based on the times at which specific URLs appear in a network of news sites [18].

In the remaining of this section with overview two methods that are opposed. While the first one was created by junior motivated researchers with an approach based on content; the second, is continuously being developed at the time of writing this article, by Facebook and by using a double hybrid model which encompasses human classification with machine learning, content with dynamics of propagation.

4.1. The FiB system

During a ‘hackathon’ at Princeton University, four college students created in 36 hours a browser extension to detect fake news. They named their project “FiB: Stop living a lie”. The system checks the personal news feed and labels each post according to the system’s checked authenticity (verified or non-verified). Basically, the algorithm [7] works based on the following process:

1. For the text as post content, it is used as a search query on Google/Bing. The retrieved searches with high confidence are then summarized and shown to the user.
2. For links, it considers the website's reputation, also querying it against malware and phishing websites databases.
3. For pictures like Twitter snapshots, it first converts the image to text; then it uses the usernames mentioned in the tweet, to get all tweets of these users, and check if current tweet was ever posted by any of the users.

The browser plug-in then adds a little tag in the top-right corner that says whether the story is verified, or not (as illustrated in Fig 1).

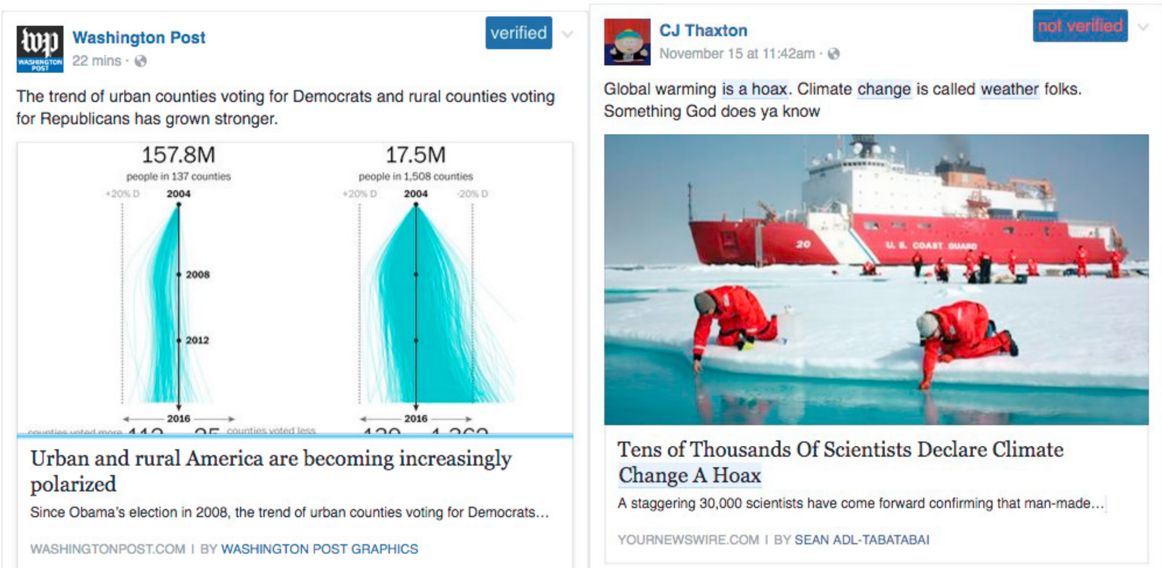

Fig. 1. Verified post (left) and not-verified post (right).

The FiB system can be used in two ways: as a checker for content consumption and for content creation (posting).

Content-consumption: the chrome-extension goes through the Facebook feed in real time as the user is browsing through his/her feed and verifies the authenticity of posts. These posts can be status updates, images or links. The backend AI checks the facts within these posts and verifies them using image recognition, keyword extraction, and source verification and a twitter search to verify if a screenshot of a twitter update posted is authentic. The posts then are visually tagged on the top right corner in accordance with their trust score. If a post is found to be fake, the AI tries to find the corresponding truth and shows it to the user.

Content-creation: Each time a user posts/shares content, the system uses a created “chat bot” to determine if the new post contains any unverified information. If this is the case, the user is notified and can choose to either take it down or to keep it.

From the pure technical perspective, the students created a chrome-extension using Javascript, together with web scraping techniques to extract links, posts, and images, which are then sent to an AI module for analysis. The AI is a collection of API web services (natural language processing, image recognition, etc) that collectively work to produce a single trust factor. The APIs include Microsoft's cognitive services such as image analysis, text analysis, Bing web search, Twitter's search API and Google's Safe Browsing API. The backend was entirely written in Python.

Altogether, this very interesting effort taken by students, particularly in only 36 hours, the system is prone to many problems: free access to web services is certainly the first of them. It is not reasonable to admit that the owners of those services will make them freely available at this scale. Therefore, the system will not work, and will not scale. Nevertheless, the general ideas are interesting and should be further developed.

4.2. The Facebook Fake News Task Team and their approach

In November 2016 it was reported [19, 20] that Facebook had formed an unofficial task force working on the problem of fake news. Through their official channels, Facebook promised to reprioritize fake news on its pages, saying one of their news feed values is "authentic communication" and that it's acting to prevent posts that are "misleading, sensational or spammy". Pages that have been posting fake news have been studied by Facebook's experts and are now expected to be seen less frequently in news feeds, was then reported.

Apart from the buzz and sensationalism, we picked the objective sentences that might lead us to the actual method being used [19] to prevent fake news. We gathered the following four:

- "We categorized pages to identify whether or not they were posting spam or trying to game the Feed by doing things, like asking for likes, comments or shares"
- "We then used posts from these pages to train a model that continuously identifies whether posts from other pages are likely to be authentic"
- "For example, if page posts are often being hidden by people reading them, that's a signal that it might not be authentic".
- "If a post is likely to be authentic (…) your relationship to the person who shared [it] will also be taken into consideration along with the number of likes, shares and comments".

Therefore, Facebook uses, on a first instance, a human classification to identify the purpose of the post, eventually to conclude that it was spamming, or cheating the Facebook Feed. Then, it uses some sort of a machine learning algorithm using the classified posts. As a remark, we notice that there isn't a clear similarity between a post that is not spam, nor a cheating-post, and a fake news. Nevertheless, assuming that there is, the third sentence is still confusing because from the best of our experience, fake news tends to spread, and to spread fast. We must say that at the time of writing this paper Facebook changed the share button of posts, only allowing public posts to be shared. Finally, it is very interesting to see that Facebook uses the "social graph" to obtain intelligence about the spreading of fake news.

5. Exposing the algorithmic core challenges

It seems clear that a judgement on the value of information should not be performed exclusively by machines, in the case they are given total control to decide which information is displayed to who, when and in through which channel. Freedom of speech must be protected at all cost, and that includes taking into consideration distinct types of publications, which may be humoristic, sarcastic or just conveying simple opinions on something, even if they are only based on personal beliefs.

However, one important concept emerges from all these issues: the "fact". Of course, in many situations it is not possible to actually identify if some part of information is a fact, or not. Nevertheless, a fact, in its most simple conception, is composed of something that has happened at some time, somewhere, eventually with/to someone. Taking an abstraction form in terms of entities, we would say that a "fact" should answer the following questions: what? where? when? From this perspective, we do realize that this conjecture leaves many facts out (e.g., "one plus one is two", which is a left-out fact).

However, it still captures the essence of the journalistic criteria to detect information to report on [21]; and that makes a difference because many posts on social media follow the general idea of reporting on something, such as the statements: "A beautiful day"; "I hate this movie"; "Someone does not have a clue of what he's saying". We may, however, try to extract facts and, whenever fact is detected, we may try check it, the difference would be to do it automatically instead of manually [22]. Nevertheless, the essence of the matter is the evaluation between the evidence about a claim and its eventual rebuttal.

5.1. A synthetic high-level algorithm to check facts

Two of the most important core principles of journalism reside on the need to validate facts and to ensure that sources are reliable. The trivial ways to accomplish this in the journalistic arena consist mainly in cross-checking facts with other sources and the source's own reputation, though other variables may also be useful to this balance, such as authority and time-to-press. However, the first two are, generally, the most prolific. In social media, the circumstances are fairly similar: there is the need to confirm the facts and to track record on the trustfulness of the sources.

In order to confirm facts, as we previously defined, we need to follow the high-level algorithm, such as the one presented in Listing 1:

Listing 1. Fact-checking algorithm.

```
1.  candidateTopics:: {List of sources that contain messages about these topics}
2.  text  = retrieveMessageText(source, postId)
3.  Who   = extract(People + Institutions + Organizations, text)
4.  Where = extract(Places + Regions, text)
5.  When  = extract(PeriodsOfTime, text)
6.  Topic = TopicDetection(text)
7.  Fact  ← combine(Topic, Who, Where, When)
8.  Foreach x in candidateTopics
9.     If x.Topic == Fact.Topic Then
10.           result = CrossCheck(x,Fact)
11.           if result == True Then return Validated
12.           else return notValidated
```

Although the algorithm is very high-level, it is useful to uncover the fragilities associated with the process. Let us assume, for the sake of simplicity that in (1) we are collecting all the posts that matter and that these can be efficiently indexed. We don't lose generality by making these assumptions. Step (2) is totally feasible it is just a matter of using the related APIs or scrappers or RSS feeds. Now, although steps (3), (4) and (5) can be achieved with a high level of accuracy using available libraries like those provided by the IBM Watson infrastructure or by StanfordNLP (or by many other), we might always argue that the accuracy is still not perfect. However, there are several promising undergoing researches on using ensemble of entity classifiers with voting mechanisms which get higher results than each of them alone. Topic detection (step 6) has had a boost recently by the use LDA and its performance surpasses human classification (in the agreement of several people on the topic) in some cases [23]. Step 7 also doesn't pose any problem. The iteration on social media posts (8), and the comparison between topics (9) are also perfectly feasible. However, for step 10 we need heuristics. Basically, we are trying to compare two tuples at a time. Each tuple is composed of 4 components, although one of these is already checked (the topic).

The simplest comparison if to check is every component of one tuple matches the correspondent component of the other tuple. However, in many cases this might fail because of the possibility to use different expressions for the same entity. Therefore, we also need a "normalization module for entities". Traditionally, this procedure is achieved by the combination of lemmatization and stemming. Nevertheless, many entities can be left-out. For example, temporal expressions: "tomorrow", "yesterday", "a couple of days ago" may all refer to the same day and in this case lemmatization and stemming can do nothing about it. The same can happen for different ways of referring to someone or someplace, to give just an example.

Now, assuming we can create such a module, the next step would be to create a protocol for equivalence when the components are not equal. This may also happen if one of the components' is missing. For example, we might have the 'who' and the 'where' components but not the 'when' (or any other permutation). However, recent work has been undertaken to compare news media posts with legacy media news. The authors claim that the results for Twitter and Facebook are above 90% accuracy detecting the same meme.

To synthesize, the main weaknesses exposed by the algorithm are:

1. The lack of capacity to be aware of all posts to cross check
2. The NLP libraries used to recognize entities
3. The capacity to compare facts and deduce if they match each other, or not

5.2. Reputation of the sources

In order to track and maintain a history record on a source that can be used for crosschecking, the source must be assigned a score value. That value should dynamically change according to periodic evaluations performed by the system or by a third party centralized, trustful, server system. If this score drops below some pre-defined threshold the source is considered as untrusting, otherwise it can be considered as trustful.

The "history" of a source can be stored into a single value by using alpha-fading statistics [24], a memoryless model which uses all previous data to approximate a α-weighted window.

5.3. Synthesis

Some of the recent approaches to fake news detection, though meritorious, still use a very naïf method that consists of checking if the referred site is in a black list. Therefore, these methods are not: 1) equipped with cross-checking, 2) don't use a history on the reputation of sources, and quite often 3) don't even use a dynamic reputation. We can also distinguish between systems that are based on the accuracy of the content-checking as opposed to systems which take into account the reputation of the sources, or systems that use the dynamics of the spreading meme to detect if the information is credible or not.

6. Conclusions

The quest for a system to prevent the creation of fake news collides with many democratic values like freedom of speech. However, it is possible to identify elements in news pieces (or social media posts) which can be objective, namely the "facts", which can help to address the situation. We believe that, currently, the necessary settings and resources to attack this problem are available: we have the technology in form of algorithms (text mining, machine learning, etc), the hardware to cope with big data, access to big data for training the algorithms. We also have the context and momentum to do it because the problem is well installed in the public conscience, and we have the willpower from the major players.

Still, there are some battles along this war. For example, the battle for the most used AI framework, or which company has more/best data, or which has the best infrastructure to deal with these problems.

Two decades back, IBM Deep Blue – a chess-playing computer – defeated chess master Garry Kasparov in 6 matches. At the time, IBM used an immense amount of secrecy during interviews about their machine. Recently, the panorama has quite changed: last year, Microsoft won a competition whose goal was to develop an image recognition system. Microsoft team explained that they used a trained neural net comprised of more than 200 layers. It is interesting to notice that suddenly all the major companies like Amazon, IBM, Google, Facebook, Twitter, Baidu, Yahoo, and Microsoft have made their code open source and available to anyone. For instance, Google has provided the use of part of its proprietary Deep Learning TensorFlow AI for free to its commercial customers. We can roughly say that during 2016 all the major deep learning libraries became open source and freely available.

This trend to develop and to highly capacitate systems based on open source resources and cloud services, which may be freely available, or available at a small price, hands over the service-providers with an escalating huge power: the power to choose their machine learning algorithms, their pre-trained data and, ultimately, a control over the intelligence that is built on the service provided by their systems. Therefore, the key to one problem is usually the lead to another one, however, this immense availability from major key players might be the necessary basis for fighting the proliferation of fake news.

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