Detecting Misinformation on WhatsApp without Breaking Encryption

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Abstract
The popularity of smartphone messaging apps like WhatsApp are revolutionizing how many users communicate and interact with the internet. Characteristics such as the immediacy of messages directly delivered to the user’s phone and secure communication through end-to-end encryption have made this tool unique but also allowed it to be extensively abused to create and spread misinformation. Due to the private encrypted nature of the messages it is hard to track the dissemination of misinformation at scale. In this work, we propose an approach for WhatsApp to counter misinformation that does not rely on content moderation. The idea is based on on-device checking, where WhatsApp can detect when a user shares multimedia content which have been previously labeled as misinformation by fact-checkers, without violating the privacy of the users. We evaluate the potential of this strategy for combating misinformation using data collected from both fact-checking agencies and WhatsApp during recent elections in Brazil and India. Our results show that our approach has the potential to detect a considerable amount of images containing misinformation, reducing 40.7% and 82.2% of their shares in Brazil and India, respectively.

Introduction
Social media platforms have dramatically changed how people to consume and share news. An individual user can reach as many readers as other traditional media nowadays (Allcott and Gentzkow 2017). Also, social communication around news is becoming more private as messaging apps continue to grow around the world. With over 1.5 billion users, WhatsApp plays an important role in this conjecture as it has become a primary network for discussing and sharing news in countries like Brazil and India where smartphones’ use for news access is already much higher than other devices, including desktop computers and tablets (Newman et al. 2019).

Amid this massive flow of information with more than 55 billion messages a day, of which 4.5 billion are images[1], a large amount of misinformation is posted on this network without any moderation. Several works have already shown how misinformation has negatively affected the democratic discussion in some countries (Moreno, Garrison, and Bhat 2017) [Resende et al. 2019] and even lead to violent lynchings (Arun 2019).

Unlike social platforms such as Twitter and Facebook, which can enforce moderation, the end-to-end encrypted (E2EE) structure of WhatsApp creates a very different scenario where this is not possible. Only the users involved in the conversation have access to the content shared, shielding abusive content from being removed. The key challenge is to fight misinformation in WhatsApp keeping it as a secure communication channel based on end-to-end encryption.

In this work we propose a moderation methodology in which WhatsApp can automatically detect when a user shares images and videos which have previously been labeled as misinformation, similar to how Facebook would flag content for fake news[2] without violating the privacy of the user and compromising the E2EE within the messaging service. The solution is based on having hashes of previously fact-checked content on the device of the user, which can be quickly checked before the content is encrypted. We evaluate the potential of this strategy of combating misinformation using data collected from both fact-checking agencies and WhatsApp during recent elections in Brazil and India. Our results show that our approach has the potential to detect a considerable amount of images containing misinformation, reducing 40.7% and 82.2% of their shares in Brazil and India, respectively.

Background and Motivation
The emergence of E2EE based communication on WhatsApp has provided a new channel to smartphone users, which is seen as significantly more private and secure than other social media platforms like Facebook (Simon et al. 2016). WhatsApp’s E2EE is an important element that ensures user privacy and security, mainly during critical and crisis events. Malka et. al. (Malka, Ariel, and Avidar 2015) demonstrate this importance of WhatsApp in the lives of its users during the wartime in Israel. They show the multi-functional role of the messaging app, functioning as a mass

[1]https://blog.whatsapp.com/10000631/Connectinganuser-users-all-days
[2]https://www.theguardian.com/technology/2017/mar/22/facebook-fact-checking-tool-fake-news
as well as an interpersonal communication channel. Facebook, WhatsApp’s parent company has tried to implement this model across other Facebook properties like Messenger, which has lead WhatsApp and encryption to become the subject of public, media, and political discourse, with some governments arguing that WhatsApp needs to provide legal backdoors for security and law enforcement purposes or enable tracing the source of problematic messages.

WhatsApp since any attempt to look at the content would cause of E2EE, moderating content is a challenging task on WhatsApp since any attempt to look at the content would compromise the security of the communication.

In this paper, we show that there is a simple way to find harmful messages without violating user privacy or creating a threatening surveillance backdoor. Automatic classification through machine learning, users reporting messages and repositories of popular content are means to stop misinformation that are compatible with E2EE, as pointed by recent reports (Gupta and Taneja 2018; Mayer 2019).

Our proposed solution was designed with three main considerations: (i) It should be easy to implement, by allowing WhatsApp to port our solution to their existing infrastructure without much changes; (ii) it must be flexible, be able to detect as much misinformation as possible, at scale, and adapt to the ever-changing trends in misinformation creation; and, (iii) it must not compromise the end-to-end encryption services that WhatsApp provides. Based on these considerations, we propose our solution, that cover parts of the spectrum, basing on two key ingredients:

1. A database of previously fact-checked content: Since Facebook already has partnerships with several fact-checking agencies around the world, such a database is not hard to obtain. Moreover, Facebook also collects media items reported as problematic images (misinformation, hateful, etc) through its internal review processes.

2. Algorithms for hashing and matching similar media content: A hashing algorithm provides a signature to represent an image or video. Given the exact same content, the hashing algorithm produces the same hash. Multiple types of hash functions exist to achieve this goal. In this work, we are primarily interested in two types of hash functions: a. Cryptographic hash, b. Perceptual hash. A cryptographic hash is a one way hash function based on techniques like MD5 or SHA, and produces a string hash given an image. However, even changing a single pixel in the image changes the hash completely. Hence cryptographic hashes can be used to only detect exact matches. On the other hand, perceptual hashing takes care of the drawbacks of a cryptographic hash and produces a hash that can be used to compare similar images. Even if the image is slightly rotated, cropped or has text added, a good perceptual hashing technique can produce a hash that is similar to the original image. There are multiple algorithms to produce perceptual hashes such as Facebook PDQ Hashing, pHash, Microsoft PhotoDNA etc. Perceptual hashing is already widely used today for detecting known harmful content (Farid 2018) and authentication of images (Swaminathan, Yinian Mao, and Min Wu 2006).

Architecture

An overview of the proposed architecture is shown in Figure[1] can be explained in the following steps: (i) WhatsApp maintains a set of hashes of images which have been previously fact-checked, either from publicly available sources or through internal review processes. (ii) These hashes are shipped with the WhatsApp app, storing it on a user’s phone. This step can be periodically updated based on images that Facebook’s moderators have been fact-checking on Facebook, which is much more openly accessible. This set could be condensed and efficiently stored using existing probabilistic data structures like Bloom Filters (Song et al. 2005). (iii) Once a user intends to send an image, WhatsApp checks whether it already exists in the hashed set on the user’s device. If so, a warning confirmation is displayed, asking if the user really wants to share this content. (iv) The message is encrypted and transferred through the usual E2EE methods. (v) When the recipient user receives the message, WhatsApp decrypts the image on the phone, obtains a perceptual hash and also checks it on hashed set on the receiver’s end. (vi) If it already exists, the content is flagged, and a warning is shown to the user indicating that the image could be potential misinformation. Also, providing information about where the image was fact-checked; and in addition, also prevent the image from being forwarded further.

This architecture requires changes in WhatsApp, as it introduces a new component containing hashes stored on the phone and also checking images. It provides high flexibility and the ability to detect near similar images, hence increasing the coverage and effectiveness in countering misinformation. This architecture also fully abides by the current

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[1] https://www.nytimes.com/2019/10/03/us/politics/barr-whatsapp-facebook-encryption.html

[2] https://www.reuters.com/article/us-india-whatsapp-government/india-government-meets-with-whatsapp-over-tracing-of-fake-news-source-idUSKBN1O606GO

[3] https://github.com/facebook/ThreatExchange/tree/master/hashing/tmk

[4] https://www.phash.org

[5] https://www.microsoft.com/en-us/photodna
E2EE pipeline WhatsApp has, where WhatsApp does not have access to any content information. All the matching and intervention is done on the device without the need for any aggregate metadata in the message. Facebook could optionally keep statistics of how many times a match occurred to establish the prevalence and virality of different types of misinformation and to collect stats about users who repeatedly send such content. Note that similar designs have been proposed recently in informing policy decisions in light of governments requesting a backdoor in the encryption (Gupta and Taneja 2018; Mayer 2019).

It is important to mention that while WhatsApp messages are secure in transit, the endpoint devices, such as smartphones and computers, do not offer security. In this sense, our architecture adds new components to the client, adding also more potential for security breaches.

We say that our solution is practical, and deployable because it is an industry-standard to detect unlawful behavior in social media platforms (Fand 2018). For example, WhatsApp scans all unencrypted information on its network such as user/group profile photos, and group metadata for unlawful content such as child pornography, drugs, etc. If flagged, these are manually verified (Constine 2018) and the abusing accounts are banned. Our proposal extends the same methodology to the user’s device in order to enable private detection.

The method works to prevent coordinated disinformation campaigns that are particularly important during elections and other high profile national events but also stops basic misinformation, where a lack of awareness leads to spreading. For instance, while manually labeling the fact-checked misinformation images, we observed that roughly 15% of the images in our data were related to false health information. These are forwarded mostly with the assumption that they might help someone in case they are true. In some cases (e.g. the child kidnapping rumors (Arun 2019)), such benign forwarding of misinformation lead to violence and killing.

Datasets

In order to evaluate the practical potential of the proposed architecture, we need a large dataset from WhatsApp containing misinformation and a large dataset from fact-checkers identifying which content is fake. In this section, we explain how we gathered (i) a dataset from public WhatsApp groups discussing politics from Brazil and India, and (ii) a dataset of fact-checked misinformation images from publicly available fact-checking websites.

WhatsApp Data. To gather the data explored in this work we use available tools (Garimella and Tyson 2018) to get access to messages posted on public WhatsApp groups. We

Table 1: WhatsApp collection.

|        | #Users | #Groups | Unique Images | Total Images | Time Span       |
|--------|--------|---------|---------------|--------------|-----------------|
| Brazil | 17,465 | 414     | 4,524         | 34,109       | 2018/08 - 2018/11 |
| India  | 63,500 | 4,250   | 509k          | 810k         | 2019/02 - 2019/06 |

selected over 400 and 4,200 groups from Brazil and India, respectively, dedicated to political discussions. The period of data collection for both countries includes the respective national elections in these countries. Public groups have been shown to be well used in both countries (Newman et al. 2019; Lokniti 2018) and contain a large amount of misinformation (Resende et al. 2019; Melo et al. 2019a). For this work, we choose to filter only messages containing images. The dataset used in this work is publicly available (Reis et al. 2020) and can be found in the following link: http://doi.org/10.5281/zenodo.3779157. The dataset overview and the total number of users, groups and distinct images are described in Table 1. Note that the volume of content for India is ten times bigger than Brazil.

Fact-checked Images. To collect a set of misinformation that already spread we obtained images that were fact-checked in the past by fact-checking agencies for each country. First, we crawl all images which were fact-checked from popular fact-checking websites from Brazil and India. For each of these images, we also obtained the date when they were fact-checked. Second, we used Google reverse image search to check whether one of the main fact-checking domains was returned when searching for an image in our database. If so, we parsed the fact-checking page and automatically labeled the image as fake or true depending on how the image was tagged on the fact-checking page (Resende et al. 2019). In total, we collected over 100k fact-checked images from Brazil and about 20k images from India.

Next, we used a state-of-the-art perceptual hashing based image matching technique, PDQ hashing, to look for occurrences of the fact-checked images in our public groups data. The PDQ hashing algorithm is an improvement over the commonly used pHash (Zauner 2010) and produces a 256 bit hash using a discrete cosine transformation algorithm. PDQ is used by Facebook to detect similar content is the best known state-of-the-art approach for clustering together similar images. The hashing algorithm can detect near similar images, even if they were cropped differently or they have small amounts of text overlaid on them.

Finally, not all images which are fact-checked contain misinformation. To make sure our dataset was accurately built, we manually verified each image that appears in both the fact-checking websites and in the WhatsApp data.

As shown in Table 2, our final dataset of images previously

https://www.whatsapp.com/security/Whatsapp-Security-Whitepaper.pdf
https://www.nytimes.com/2018/10/19/technology/whatsapp-brazil-presidential-election.html
https://www.theguardian.com/world/2019/apr/21/social-media-shut-down-in-sri-lanka-in-bid-to-stem-misinformation
https://www.buzzfeednews.com/article/pranavdixit/whatsapp-destroyed-village-lynchings-rainpada-india
https://www.whatsapp.com/security/Media-Shut-Down in Sri Lanka in Bid to Stem Misinformation
https://www.theguardian.com/world/2019/apr/21/social-media-shut-down-in-sri-lanka-in-bid-to-stem-misinformation
https://www.nytimes.com/2018/10/19/technology/whatsapp-brazil-presidential-election.html
https://www.factly.in/fakenewscounter/check4spam.com
https://github.com/facebook/ThreatExchange/blob/master/ThreatExchange/threat-exchange/threat-exchange/threat-exchange/pdq-hashing.h
https://www.aosfatos.org
https://g1.globo.com/e-ou-nao-e/
https://veja.abril.com.br/blog/me-engana-que-eu-posto/
https://piaui.folha.uol.com.br/lupa/ and www.boatos.org
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https://piaui.folha.uol.com.br/lupa/ and www.boatos.org
https://www.e-farsas.com
fact-checked contains 135 images from Brazil and 205 images from India, which were shown to contain misinformation. It is important to highlight that many checking agencies do not post the actual image that has been disseminated. Often only altered versions of the image are posted and other versions of the false story are omitted to avoid contributing to the spreading of misinformation. This leads to us to have a small number of matches compared to the total number of fact-checked images we obtained, but that is sufficient to properly investigate the feasibility of the proposed architecture. Direct contact with the fact-checking agencies, like Facebook already does, could increase the size of the fact-checked set much more. Note that even though the set of fact-checked images was small, the fact that these images have been fact-checked means that they were popular and spread widely.

Table 2 shows a summary of the fact-checked images and their activity in our dataset. While similar perceptual hashes are able to identify more than a hundred images in both countries, using just exactly the same hash to find misinformation, only 5.1% of checked images on Brazil were retrieved and 40% of Indian images.

### Potential Prevention of Misinformation

In this section, we evaluate the potential prevention of misinformation in case our architecture was implemented, and the spreading of these images were totally blocked immediately after the fact-checking happens. For this, we computed the timestamp of all the fact-checked images and the occurrence of these images in our WhatsApp data. This way, we are able to measure how many posts were done for each misinformation image before and after the first fact check of this image.

Figure 2 shows the cumulative distribution function (CDF) of the number of shares done before and after the checking of the misinformation images. We can observe in both countries that for the most broadly shared images there are as many posts before as after the checking date. Moreover, for India, there are more shares after checking than before and there are even images with up to 1,000 shares after fact-checking while the maximum shares before do not exceed 100.

Summing all shares, we find that 40.7% of the misinformation image shares in Brazil and 82.2% of the shares in India could have been avoided by flagging the image and preventing it from being forwarded after being fact-checked.

This number drops to 71.7% if we remove the outlier image with the maximum number of shares, as it was shared over 1000 times.

In this work, we propose a practical solution that WhatsApp could implement to prevent misinformation from spreading while ensuring user’s privacy. The solution is based on having a set of already fact-checked image hashes on the user’s device and matching these images with the content being shared. We would expect that by the time fact checking organizations receive and fact check a piece of content, most of its spread would be done, thus defeating the purpose of fact checking. However, as our results show, in part because of the closed nature of the platform, and the lack of a central authority to stop the spread, there are images that keep spreading even long after being fact checked. Looking at the actual sharing of these images in our data, we show that over 40% of the spreading of the misinformation detected in Brazil and 82% in India could have been prevented by implementing these measures in the public groups we monitor.

Apart from presenting a simple, practical and deployable solution to the problem, our paper presents a counter-voice to strong claims by governments to allow back doors in the encryption for law and order purposes. Finally, our approach is also in line with WhatsApp’s efforts to limit forwarding. As showed in recent studies (Melo et al. 2019b), this approach can impose delays in the content dissemination, which represent an extra time for fact-checking and more effectiveness for our approach.

### Limitations

Labeling and implementing forwarding restrictions on already known fake images can only help to a certain degree. Our proposal has a few limitations: (i) Does labeling actually make a difference? Firstly, careful considerations must be taken in order to prevent backfire effect (Nyhan and Reifler 2010, Levin 2017); (ii) Our dataset from WhatsApp is not representative, since it comes from public groups which are a small fraction of all groups. However, this is the largest available sample of WhatsApp data to test such an architecture. (iii) The amount of misinformation that could be prevented could be an overestimate because these fact-checked images are already popular. Even though our approach does not remove all misinformation, it can help remove popular, viral misinformation that has already been fact-checked. Given that only a small amount of...
content gets viral on WhatsApp (Melo et al. 2019b), such efforts are helpful to prevent lethal mis/disinformation campaigns and rumors.

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