H2020-ICT-2018-2 /ICT-28-2018-CSA
SOMA: Social Observatory for Disinformation and Social Media Analysis

Assessing Methods to Analyze Spread of Misinformation in Digital Media

D2.4: Distributed scalable information cascade analysis

Project Reference No	SOMA [825469]
Deliverable	D2.4: Distributed scalable information cascade analysis
Work package	WP2: Methods and Analysis for disinformation modeling
Type	Report
Dissemination Level	Public
Date	30/04/2021
Status	Final
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Document Revision History

Version	Date	Modifications Introduced	
		Modification Reason	Modified by
v0.1	22.04.2021	Consolidation of first draft	DATALAB, Aarhus University
v0.2	23.04.2021	Review	LUISS Datalab, LUISS University
v0.3	29.04.2021	Proofread	DATALAB, Aarhus University
v1.0	30.04.2021	Final version	DATALAB, Aarhus University

Executive Summary

The spread of misinformation in digital media poses a serious threat to society with potentially life-threatening and democracy-altering consequences in the cases of respectively health or political misinformation for example. The report discusses methods used to examine the spread of misinformation, covering methods such as cascade analysis, network analysis and diffusion analysis. For this purpose, a literature review is conducted that leads to the identification of 29 relevant articles focusing on the spread of misinformation. The search result was analyzed focusing on which methods and platforms were used and which topic was analyzed. The outcome of this analysis shows that most studies focus on a single platform, rely on data from a small set of platforms, do not use cascade analyses or network analysis but look at diffusion in a more general way and cover a specific range of topics - with health being the most frequently occurring topic when a specific topic is mentioned. The discussion showed that if several platforms are used, network or cascade analysis is not the method chosen and Facebook is only used in studies that look at the diffusion of misinformation or that develop or improve algorithms for analyses. Furthermore, identified studies lack a discussion of how the used methods and chosen approaches can be generalized or used in different contexts such as a different platform or a different topic. As they also use different approaches, the identification of best practices is difficult.

In in-depth investigations, we look at the approach and method used by the highly cited study of Vosoughi et al. (2018) and conduct first assessments of how their approach can be used in different contexts such as a different type of misinformation and for other platforms than Twitter. Our investigations face several challenges such as disinformation detection related to COVID-19 misinformation and limited access to adequate information to Facebook, Instagram or Reddit using CrowdTangle. That is, even though additional steps are necessary to finally assess transferability, our investigations indicate that transferability of Vosoughi et al.'s (2018) approach is limited.

We identified two main aspects that need improvement for a better understanding of how misinformation spreads in digital media. One being adequate access to diverse platforms, allowing for analyses such as cascade analysis or network analysis. Especially Facebook lacks such access. Secondly more research is needed that applies approaches and methods to different contexts instead of focusing on one specific context. If studies focus on one specific context, context sensitivity should be discussed to a greater extent. Both will help to establish and identify context sensitive factors for the analyses of the spread of misinformation and for developing best practices.

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API: Application Program Interface

URL: Uniform Resource Locator

1. Introduction

In this report, we discuss practices for analyzing the spread of misinformation at scale with a focus on cascade analysis and cross-platform studies. The spread of misinformation presents a serious danger and challenge for society and democratic processes. It can elicit negative emotions and lead to harmful criminal activities online (Almaliki, 2019). Also in relation to the COVID-19 pandemic, which started in 2020, misinformation poses a threat for the health of the population, e.g. regarding vaccination or use of false cures. The impact of misinformation tends to happen in a short time frame after the first publishing and spikes can be observed in times of conflict, war or political events (Burel et al., 2020). Misinformation is conceptually discussed in many studies and the term “misinformation” is contrasted to the term “disinformation” and the term “fake news” (Bechmann, A. & O’Loughlin, B., 2020; Buning, 2018; Farkas & Schou, 2019; Kalsnes, 2018; Tandoc et al., 2018; Wardle, C. & Derakhshan, H., 2017), with differences for example regarding intention behind the spread. Buning (2018) defines disinformation as “false, inaccurate, or misleading information designed, presented and promoted to intentionally cause public harm or for profit”. We use the terms misinformation, disinformation and related terms interchangeably hereupon. As intention, however, is rarely examined in studies analyzing or discussing the spread of misinformation and as not all false information is shared intentionally, we do not restrict the focus of this report to intentionally spread misinformation.

In order to analyze and stop the spread of misinformation in social media, various methods are used. One of the more complex methods is the analysis of information cascades (e.g. Vosoughi et al., 2018). Sharma et al. (2020) define a cascade “as a time-ordered sequence of user responses/ engagements that a piece of information (content) receives, when it is circulated on a social network. It can be labeled as a true or fake news cascade, in accordance with the veracity of the content” (p. 3). Besides the analysis of cascades, studies also look at networks in which misinformation spreads (e.g. Chen et al., 2018) or simply analyze temporal patterns and dynamics of the spread of misinformation (e.g. Allcott et al., 2019). We conduct a literature review in order to identify the methods used and discuss them. In a later section, we will in detail discuss the study from Vosoughi et al. (2018) as one of the highly cited studies applying cascade analysis and examine to what extent a similar approach can be applied to other types of misinformation and other platforms than Twitter. We finally discuss limitations and further steps related to the analysis of the spread of misinformation.

1.1 Purpose and Scope

In this report we will identify and discuss methods such as information cascade analysis for the mapping of disinformation in social media. It is based on the following activities:

▪ an overview of existing methods based on a literature review

▪ a discussion of the identified studies with a focus on transferability to several platforms

▪ an in depth investigation of a highly cited study (Vosoughi et al., 2018) that applies cascade analysis on Twitter with a focus on transferability to other platforms and topics

▪ an outline of potential solutions and needed actions for such solutions for identified limitations and challenges.

1.2 Structure of the report

The report will start with a short summary of methods that are taken into consideration regarding the spread of misinformation. It then continues with a description of the literature review and presents its results. In the following section methods used in the identified studies will be discussed. Subsequent to this section we will discuss one of the studies - the one of Vosoughi et al. (2018) - in more detail and conduct two inquiries on the basis of this study one focusing on another topic and another one on different platforms. The identified challenges and limitations are discussed in the final section that also outlines actions needed to counter these limitations and challenges.

2 Information cascade analysis and the spread of misinformation

The spread of misinformation can be analyzed using information cascade analysis. Information cascade analysis is applicable for the spread of information and of misinformation and refers to analysis of “trajectories and structures of information diffusion” and also addresses “the adopters/ participants in information spreading” (Zhou et al., 2020, p.111:2). Some of the models used were adopted from epidemiological studies (Babcock, Cox, et al., 2019; Kopp et al., 2018). In information cascades nodes are activated if a user engages with the propagated content. Sharma et al. (2020) describe that “the diffusion process starts with an initial set of seed nodes assumed to be activated at the first timestep” (Sharma et al., 2020, p.3). In the next time steps, a previously activated node attempts to activate inactive neighbors and succeeds with a specific probability. Once a node is activated it stays activated in the diffusion process (Sharma et al., 2020). Sharma et al. (2020) summarize findings from several studies that identify features of cascades for discriminating between false and true content. They also address which features of misinformation cascades affect predictive power and “features with high predictive power include - fraction of information flow from low to high-degree nodes which is higher for fake contents, multiple periodic spikes that are particular to fake contents, and greater depth to breadth ratio in the diffusion trees of fake cascades” (p. 3). Vosoughi et al. (2018) describe rumor cascades as originating from a user asserting something in a tweet that can include text, photos or links. Other users then retweet the assertion. Each rumor can be diffused through one or several cascades for which the diffusion process can be defined as “an unbroken, retweet chain with a common, singular origin” (p. 1146). Cascades differ in size with the smallest being a cascade in which the original tweet is not retweetet. Each rumor, fake story, misinformation or claim has as many cascades as the number of times it was independently tweeted by a user. Figure 1 illustrates a Twitter cascade as it is analyzed by Vosoughi et al. (2018), with Twitter users as nodes.

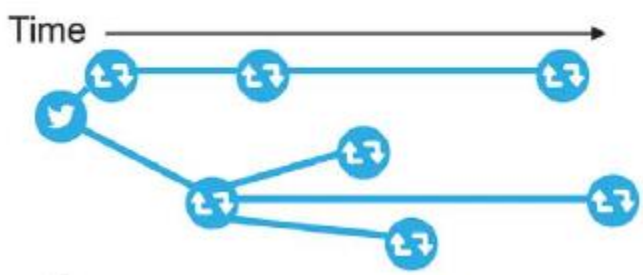

Figure 1 Illustration of a Twitter cascade by Vosoughi et al. (2018, p.1147)

Regarding the spread of misinformation, however, cascade analysis is not the only method used and if it is applied, the focus of application can differ. We will shortly describe some of the main areas of application and other methods to analyze the spread of misinformation.

Prediction - One area of application for cascade analysis refers to the prediction of information cascades. Here Zhou et al. (2020) provide a good overview of methods available. The prediction of information cascades is used in different contexts for example to predict the number of likes of videos or photos or to predict how popular a tweet or hashtag gets (cp. Zhou et al., 2020).

Influencers - Another focus of information cascades analysis refers to the identification of influencers. Budak et al. (2011), for example, aim at identifying the influential people that need to be identified in order to counter a misinformation campaign and refer to this problem as “eventual influence limitation problem” and propose an algorithm they call “predictive hill climbing approach” to solve this problem. A related question is “how many and which users should be targeted in order to have maximum spread”, which is relevant for marketing or advertising (Taxidou & Fischer, 2013, p.1418). Cha et al. (2010) differentiate between different types of influencers based on the interactions on Twitter - namely according to the number of followers, number of retweets and number of mentions. Besides that, influencers can also be differentiated in the extent and time of their influence.

Network - Another dimension consists of network analysis, where the focus is on the networks in which misinformation spreads. Lee et al. (2019), for example, look at networks related to vaccine misinformation on Twitter and find two large communities in the center of the network - namely a pro- and an anti-vaccine camp. Safarnejad et al. (2020) look at different aspects of networks, which are:

- network reach: e.g. number of unique users in the network
- network influence: equals network size and takes into account if one user is retweeted more than once
- diameter: “shortest distance between the 2 most distant vertices in the network” (p. S341)
- density: “measured proportion of potential relationships that actually existed in the network” (p. S341)
- modularity: likelihood that network is divided into potential clusters
- Wiener index: “sum of the shortest paths between all pairs of vertices” (p. S341)
- structural virality: “average distance between all pairs of vertices in the network” (p. S341)
- top out-degree centrality: influence of a single vertex related to the generation of retweets (p. S341) and
- top betweenness centrality: importance of the vertex for the connectivity of the network) (p.S341).

They find differences in almost all of these aspects between health-related misinformation and real information on Twitter. Network analysis can also be used to identify influencers (e.g. Dubois & Gaffney, 2014; Xu et al., 2014).

Diffusion - Besides looking at the diffusion of misinformation in networks and analyzing misinformation cascades, studies also analyze diffusion of misinformation in general (e.g. Nsoesie et al., 2020). That is, the extent to which misinformation spreads and/ or the temporal dynamic of the spread. Indicators that are analyzed are for example the scale of retweets, their range and structural virality, the number of comments or likes (e.g. Chen et al., 2018). Furthermore, an aim can be to identify mechanisms of information diffusion, that is, how users share information or how specific events influence the diffusion (cp. Taxidou & Fischer, 2013).

Time and structure - Information cascades and disinformation spread can be analyzed temporally or structurally (e.g. Sharma et al., 2020). The structural approach refers to the analysis of effects of typical characteristics of social networks. In the temporal approach social media activities are considered as a stream (Taxidou & Fischer, 2013).

The analysis of the spread of misinformation depends in contrast to the examination of the spread of information on the identification and definition of misinformation. That is, misinformation detection is a precondition for cascade analysis and the analysis of spread. All studies examining the spread of misinformation therefore face challenges identified in report D2.3 “Detecting mis- and disinformation in digital media” (Walter et al., 2020).

2.1 Review of existing methods for information cascade analysis

In order to review methods used for information cascade analysis we conducted a systematic literature review. We conducted a search at the Royal Danish Library, which includes 10.113 collections such as Scopus and Web of Science and therefore enables an exhaustive literature search. Even though information cascade analysis can in principle be used for analyzing the spread of misinformation as well, we focus on methods used for analyzing the spread of misinformation. On the one hand studies such as Vosoughi et al. (2018) demonstrate differences in the extent and velocity of spread of true and false information (also see Chin et al., 2020), on the other hand analysis of misinformation pose additional challenges such as misinformation detection that might have an impact on chosen methods. Amoruso et al. (2020), for example, mention that veracity impacts the weight used in analyses. Furthermore, they report that source identification is more complicated regarding false information than for true information. Differences in the spread of misinformation between false and true information can be used in return for identifying misinformation (Babcock, Cox, et al., 2019) For the search we used an extended keyword list related to disinformation and its spread on digital media. The exact search was as followed: The title contains “misinformation” or “disinformation” or “false information” or “fake news” or “false news” AND “spread” or “diffusion” or “distribution” or “circulation” or “dissemination” or “dispersion” AND any fields included “examination” or “analysis” or “method” or “cascade” AND “social media” or “Twitter” or “Facebook” or “digital” or “internet” or “online”. The search was restricted to English publications only but otherwise without additional filters and was conducted in February 2021. Due to the large numbers of words used to describe the spread of misinformation and the development of related methods, the literature review probably does not capture all articles published to the topic. However, it should provide a good overview about the focus and topics of research conducted. The search results contained 200 publications, which were assessed regarding their actual relevance for the topic itself. After the first screening based on title and abstract, 35 articles with a likely high relevance remained. These articles were finally evaluated by taking the theory, method and result section into consideration as well. After this evaluation, six additional publications were not considered as relevant as they do not analyze the spread of disinformation or misinformation or contribute to such analyses. For the remaining 29 publications (a list can be found in the Appendix) we look at publication year to evaluate research dynamics, used databases to evaluate the extent of cross platform analysis, topic of misinformation studied in the publications as indicator for exhaustiveness of misinformation analysis and methodological focus of the publications.

The categorization based on the publication year - see figure 2 - demonstrates that most articles have been published in the most recent years, showing that the analysis of misinformation spread gained attention in the last years and was not as present before 2018.

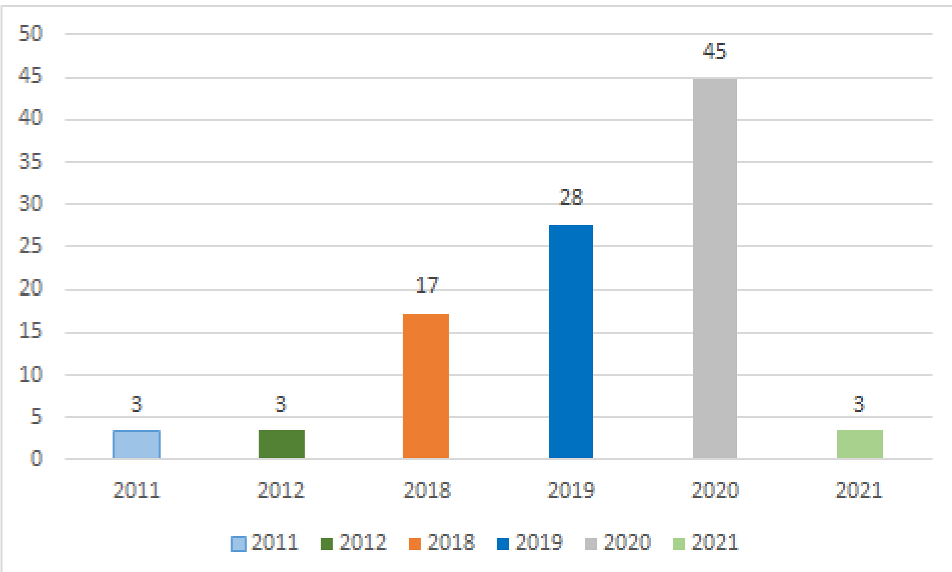

Figure 2 Publications by publication year (percentage)

We also analyzed which database or social media platform was used in the publications as a source for misinformation- see figure 3. The largest percentage of studies uses Twitter data (41%). There are also some that use more than one database - combinations we observed are for example: Twitter & Facebook; Twitter & Facebook & other websites; Weibo & WeChat & other websites and Twitter & Weibo. Only a few studies rely solely on Facebook, Google (mostly search or trend), Weibo, other social media platforms or develop an algorithm without mentioning a specific dataset (titled none). Social media platforms that were used in the studies are: Facebook, Twitter, Weibo, WeChat and YouTube.

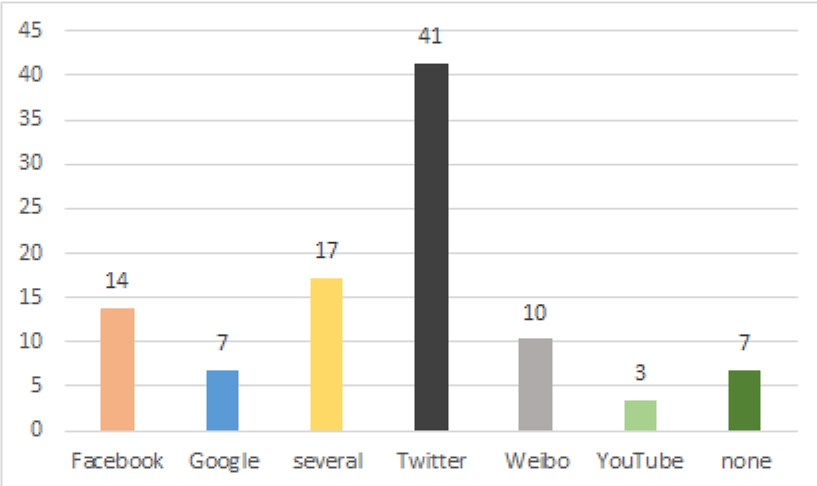

Figure 3 Publications by used platforms (percentage)

Regarding the misinformation topic focused in the articles, we see that the range of topics is limited - see figure 4. Around 38% of the articles do not mention a specific topic or examine misinformation in general. However, also a large percentage (28%) focuses on health-related misinformation, followed by studies that focus on political misinformation (17%). Some studies focus on misinformation related to nature (e.g. genetically modified plants), science or racism.

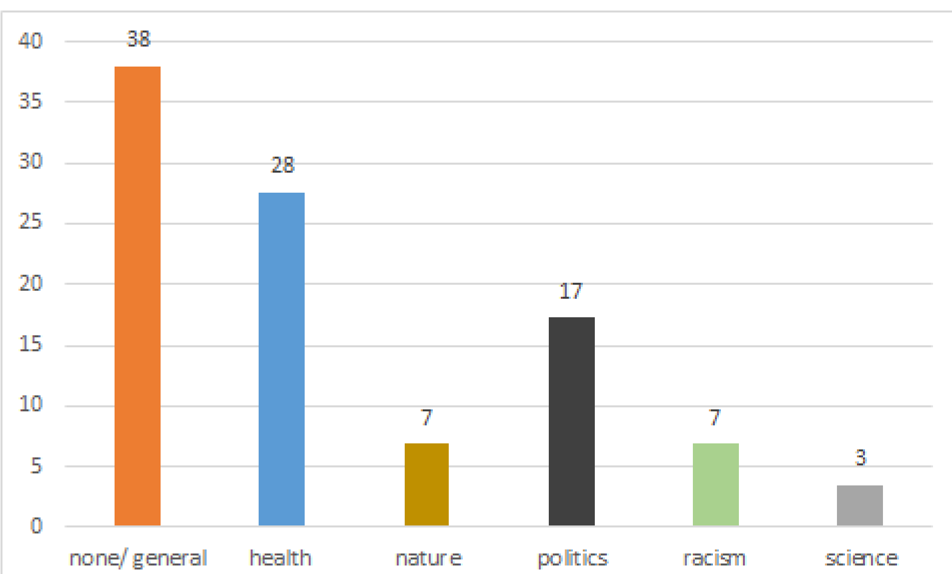

Figure 4 Topics focused on in the publications (percentage)

Related to misinformation topics and used databases is also the methodological focus of the publications. A large percentage of publications (45%) examines the spread or diffusion of misinformation without using cascade or network analysis - see figure 5. The remaining articles focus on the development of algorithms that can be used for analyzing or stopping the spread of misinformation or use network analysis in order to examine the spread of misinformation. From the studies developing algorithms or analyzing networks (16 studies), eight use the term "cascade" to describe their analysis.

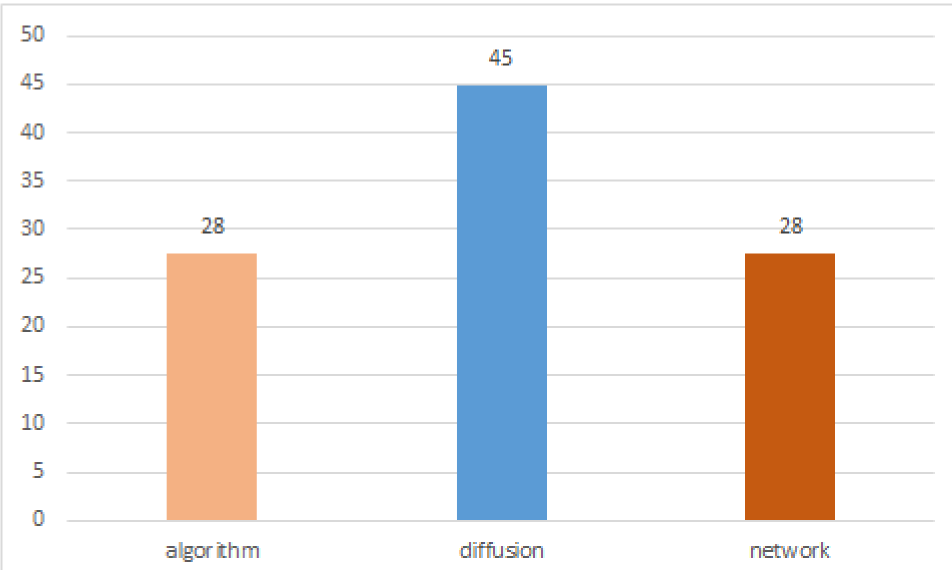

Figure 5 Focus of the publications (percentage)

Next we will shortly focus on relations between the different categories we have identified. On the one hand, even though misinformation about the COVID-19 pandemic was an issue in some publications, there is no clear relation between publication year and health as the main misinformation topic. That is, we observe neither for the 2020 published studies a stronger focus on health nor a specific focus on COVID-19 for the studies with a focus on health-related misinformation. On the other hand, we see a tendency that studies, who apply network analysis use mainly Twitter or Weibo as databases but not Facebook. Besides some studies with focus on algorithm development, Facebook is mainly a database for studies addressing the spread of misinformation.

Furthermore, the publications address a broad range of aspects of misinformation spread such as how to limit the spread (e.g. Amoruso et al., 2020), analyses of how specific misinformation spreads (e.g. Budak, 2019; Burel et al., 2020) or the development of tools for increasing awareness regarding misinformation (Lee et al., 2019).

3 Discussion of used methods

3.1 Cross-platform analysis

In the next section, we will discuss the results from the literature review and potential implications. We will focus on the problem of cross-platform analyses of the spread of misinformation. Dynamics of information sharing likely depend on the social media platform with differences for example between Twitter and Facebook (Budak, 2019). As the literature review revealed, most studies focus on one platform. We will discuss the studies addressing more than one platform in more detail next.

Allcott et al. (2019) use BuzzSumo to get information about engagement with Facebook and Twitter for news sites and fake news sites and examine how engagement changes over time from 2015 to 2018. They find that interaction with misinformation remains high but declined on both examined platforms but more so on Facebook than on Twitter. However, they do not look at information cascades and their analyses are restricted to overall engagement with Facebook and do not look at likes and comments separately for example. Thus, the direct comparison with Twitter is also limited. Also, the study from Baptista & Gradim (2020) that examines disinformation on Facebook related to the Portuguese election in 2019, relies on information provided by BuzzSumo. They find that fake news pages and pages of newspapers differ in the amount of reactions and comments with the first having less but also with the restriction that fake news pages have less publications than news pages. However, they observe more shares for fake news pages.

Amoruso et al. (2020) develop an algorithm for identifying sources of misinformation and for limiting misinformation by identifying the minimum number of entities that are able to identify and block false information. For the validation of their approach, they use different databases from Konect, including YouTube, Facebook, Twitter and other databases. However, more information about their databases is difficult to obtain. Their study also focuses on the development of the algorithms and not on an understanding of disinformation cascades or spread of misinformation on the different platforms. A similar study is conducted from Nguyen et al. (2012), who also focus on the limitation of dissemination of misinformation in social networks and suggest an algorithm-based approach and verify their solution among others in Facebook networks.

Dharshanram et al. (2019) use BuzzFeed for information about engagement on Facebook, Twitter and Youtube for misinformation pages in Tamil language and find more misinformation on YouTube than on the other networks, but their study only addresses the extent of spread for a few pages and not networks or temporal dynamics.

Guo (2020) examines fake news in China, which are identified based on their online presence in Weibo, WeChat and online news articles but do not focus on the spread on social media but on online spread in general.

Thus, none of the studies that use more than one database, use these databases to analyze information cascades but rather they focus on methodological improvements or solely on engagement with and spread of misinformation within these databases.

Studies that solely focus on Facebook analyze the spread of misinformation without looking at cascades. Beletsky et al. (2020) use the CrowdTangle access to Facebook and look at extent of spread for identified misinformation. Or they use Facebook data in order to develop algorithms or methodological approaches and do not focus on examining the spread (e.g. Budak et al., 2011; Chu et al., 2021; Nguyen et al., 2012).

Hence, the studies we identified in the literature review, do not use Facebook for cascade analysis to examine misinformation cascades but rely on other datasets such as YouTube (e.g. Galeano et al., 2020) or Twitter (e.g. Gerts et al., 2020; Lee et al., 2019).

This leads to the conclusion that some platforms provide better access to data and information for more complex analysis such as cascade analysis, than others. In a later section, we shortly exemplify this for Twitter and Facebook based on an own investigation into the option to conduct cross-platform cascade analysis. Facebook provides access to information about engagement with specified content such as URLs or keywords via CrowdTangle. CrowdTangle provides a platform to get information about the public content of Facebook, Instagram and Reddit. There exists one version that is an extension for Chrome and an API solution. The Chrome extension also provides information about Twitter. However, information provided by the Chrome extension cannot be extracted automatically. The API access to the platform:

- does not allow information about Twitter usage
- allows for tracking links and keywords to access information about Facebook, Instagram and Reddit content associated with the chosen keywords or links
- full access is restricted and needs registration and admission.

Based on the design of CrowdTangle, however, it seems that information necessary for conducting cascade analysis is not provided. We will in subsequent sections further look into the possibilities provided by CrowdTangle for the analysis of the spread of misinformation. Twitter launched early access to a new API, providing access after registration and application, to all Twitter conversations so far for researchers. It also provides additional changes that aim at facilitating application and access to Twitter data[1]. The Twitter API provides access to posts

[1] https://developer.twitter.com/en/docs/twitter-api/early-access provides information about the changes (accessed April 14th 2021)

and engagement with tweets and users and thereby enables the analyses of the spread of misinformation more extensively than Facebook.

3.2 Generalizability of methods

Another aspect that needs to be addressed is generalizability of methods and results. The spread of disinformation probably depends on several factors.

Babcock et al. (2019), for example, show that spread of misinformation depends on the indicator used for the analyses with differences between posts, quotes and replies (referring to Twitter data). Another study by Babcock, Beskow, et al. (2019) shows that the kind of misinformation - they differentiate between fake attacks, satire attacks, fake scenes and alt-right related to the Black Panther movie - influences how it spreads. Furthermore, characteristics of the disinformation might affect to what extent it spreads for example as sources and target communities differ (Babcock, Cox, et al., 2019). Also, the type of misinformation can affect its spread. Chen et al. (2018) show for example with Weibo data differences between prevention and treatment related misinformation for gynecologic cancer.

The findings of these studies have at least two implications. On the one hand, they show that the spread of misinformation depends on factors such as type of misinformation or analyzed indicators and therefore results might not easily be transferred to another context. The identified studies in the literature review in general lack a discussion of to what extent the used methods and findings are context sensitive, that is to what extent they can be transferred to other databases, other types of misinformation, other time frames and so on.

On the other hand, as the studies included in the literature review differ largely in scope and focus, the identification of best practices for the analysis of the spread of misinformation or regarding cascade analysis is hindered as comparability is hindered. This leads to the conclusion that studies should describe used methods as concrete as possible to make findings replicable and transferable to other contexts in order to assess transferability and generalizability of findings.

4 A case study for analyzing the spread of misinformation

In this section, we discuss the study from Vosoughi et al. (2018) that was part of the literature review and is cited with a high frequency[2] and by far more often than the other studies in the literature review that apply cascade analysis or network analysis to study the spread of misinformation. We therefore use this study as a case study for further analyses. After a short review of the study, we test in a second step how the model they developed can be applied to datasets across different platforms. Vosoughi et al. (2018) apply a method to Twitter data from 2006 to 2017 and their data includes approximately 126,000 rumor cascades. These rumors are based on investigations from six fact checking organizations. Vosoughi et al. (2018) take the title, body and rating (categorized in true, false and mixed) of each fact-check or rumor into consideration and then automatically collect the cascades associated with each rumor on Twitter. Regarding the cascades, they analyze depth, size, maximum breadth (minimum number of users of a cascade at any depth) and structural virality. In their study they compare diffusion patterns of true and false rumors and find that false information spreads significantly faster, farther, deeper and more broadly than true information. They also look at users contributing to the spread of false information and these users have significantly less followers and follow fewer people, are less active, are verified less often and are Twitter users for a shorter period. A potential explanation Vosoughi et al. (2018) find is that false rumors were more novel than true rumors. Furthermore, they also look at emotions associated with the rumors with sentiment analysis.

Next, we will assess how the approach of Vosoughi et al. (2018) on the one hand can be adjusted to COVID-19 related misinformation - that is a different topic - and on the other hand to different platforms.

4.1 Misinformation identification related to COVID-19

As Vosoughi et al. (2018) have done, we also take information fact-checked by fact checking organizations as a starting point for the identification of misinformation. A preliminary study Charquero Ballester, M. et al. (2021) focus on emotions associated with COVID-19 related misinformation and identify the misinformation based on entries indexed in the Google Fact Check Explorer in March 2020. Even though this study does not focus on information cascades, it gives insights to what extent a similar approach to the one from Vosoughi et al. (2018) can be used to identify misinformation related to COVID-19. The Google Fact Check Explorer indexes debunked stories from several fact checking organizations and is therefore a broader database

[2] 2916 citations according to Google Scholar (April 4th, 2021)

than the one used by Vosoughi et al. (2018). Charquero Ballester, M. et al. (2021) analyze 226 debunked stories published in English and extract keywords from the story titles that are then used as classifiers to identify associated misinformation in Twitter data. For the classifiers, they use a primary keyword that is selected by two independent annotators with the aim to select the most important word or bigram from each title. The overlap between the annotators was high with the same keywords chosen for 89% of the stories. In cases of disagreement, the final primary keyword was selected in discussions. In addition to the primary keyword, a keyword list based on the most meaningful words of the titles is chosen to be used in a second filtering step. The Twitter data comes from 76 hashtags related to COVID-19. The Twitter data is filtered to English only and to March 2020. Retweets are deleted. The Twitter sample includes 17,463,220 tweets. The primary keyword is used to filter these tweets to tweets potentially discussing misinformation. The keyword list is then used to further filter the data. The inclusion of the primary keyword was a requirement for further consideration as well as at least one additional word from the keyword list. This filter process results in a reduced dataset, which comprises 690,006 tweets. Charquero Ballester, M. et al. (2021) analyze a subset of these tweets manually in order to finally identify misinformation related to the debunked stories from the Google Fact Check Explorer. 2,097 tweets are manually checked and only around 29% of these tweets really refers to misinformation. An extrapolation to the starting sample leads to the conclusion that only a very small number of tweets are associated with misinformation. Related to the analyses of information cascades, this study demonstrates that one obstacle is the minimum amount of misinformation spread on Twitter related to COVID-19 - at least in the observed time span. Thus, the approach from Vosoughi et al. (2018) probably is only to a limited extent applicable to shorter time periods - Charquero Ballester, M. et al. (2021) focus on one month, whereas Vosoughi et al. (2018) look at a time period of eleven years - and might not be transferable to non-political topics. As the keyword approach was associated with manual coding, it is rather time consuming and cannot be used to identify misinformation in real time. For an investigation of a cross-platform application, we focus on a URL based approach instead that will be described in the following section.

4.2 Misinformation spread on several platforms

In a next step, we started investigating whether the approach of Vosoughi et al. (2018) can also be applied to other platforms than Twitter. Here we also use the Google Fact Check Explorer to generate a database for the identification of misinformation. We use all COVID-19 related indexed stories from March and April 2020 and manually extract URLs to the original claim that was debunked. Thus, instead of a keyword approach based on titles of debunked stories, we aim at using URLs to identify communication related to misinformation. We aim at using CrowdTangle to get communication from Facebook and Instagram. We use the API to get

Facebook and Instagram content for the extracted misinformation URLs. In the process we faced several challenges. First of all, the extraction of URLs for debunked stories is limited as many stories URLs that can be used in the CrowdTangle API cannot be extracted as the original URLs are outdated, out of service or archived. For the original 340 indexed stories from March and April 2020 we can extract URLs for only 251. A precondition for indexing fact checks in the Google Fact Check Explorer is the application of ClaimReview by an authorized fact checking organization. ClaimReview standardizes the entries and also includes the URLs to the fact-checked story. It also provides the option to include the URLs to the original claim, however, with our access to the API of the Google Fact Check Explorer, it was not possible to extract this information automatically in cases in which it was provided. It needs to be assessed further whether the manually extracted URLs are biased towards specific stories e.g. regarding fact-checking organization or publishing date. First analyses, however, do not reveal systematic biases. Second, the remaining URLs were used as input in the CrowdTangle API (CrowdTangle API | CrowdTangle Help Center) and searched for Facebook content from February to April 2020 (using a tool developed by the Center for Humanities Computing at Aarhus University: GitHub - centre-for-humanities-computing/crowdtangle-api-scraper[3]). We can only extract information for 179 of the 251 extracted URLs. However, with only a very limited output. Only for 46 of the URLs, we found related Facebook content (with only 12 of these having at least 100 interactions). The story providing the most results is associated with 975 Facebook interactions. We find even less content for Instagram. This finding is somewhat surprising, as many fact checking organizations collaborate with Facebook to identify stories for fact-checking. That is, fact-checked stories should be associated with Facebook interaction at least to some extent. A potential explanation for our finding is that CrowdTangle only gives access to public content on Facebook and Instagram. Public content, however, is only a small part of all conversation and interaction happening on Facebook or Instagram. Thus, using the CrowdTangle API might result in missing the main interaction about misinformation as well. The CrowdTangle API also does not reveal much information about who reacts to whom and interacts with whom and this information would be necessary to conduct information cascade analysis. This is probably also one of the reasons why the studies we identified in the literature review do not use Facebook data to analyze disinformation cascades or network analyses but focus on the spread of misinformation.

Both of our investigations are only first assessments of the spread of COVID-19 related misinformation and the spread of misinformation on other platforms than Twitter. Both investigations need additional steps in order to more definitively assess the transferability of Vosoughi et al.'s (2018) approach or for the development of alternative approaches. In order to conduct cascade analysis regarding COVID-19 misinformation on Twitter, additional analyses

[3] Last access: 04/26/2021

are necessary. So far, we have not taken retweets into account for example, which would be necessary to analyze cascades. As we also do not find much misinformation on Twitter in the observed time span and with the focus on COVID-19 misinformation, we might need to extend the time frame and broaden out the topic. We also need additional analyses for the further assessment of the potential to use CrowdTangle as access to Facebook, Instagram and Reddit to examine the spread of misinformation. So far, we have concluded that cascade analysis is not possible with the access provided. However, it needs to be further assessed what is possible instead. Furthermore, both of our investigations as well as the study from Vosoughi et al. (2018) rely on work done by fact checking organizations. However, this approach to misinformation detection and identification is limited as fact-checked misinformation probably is not representative for misinformation in social networks and beyond in general and is no solution for revealing misinformation in real time as fact-checking leads to a time lack between the occurrence and detection (see Bruns, A. & Keller, T., 2020). Alternative methods for misinformation detection, as they also have been discussed in D2.3 "Detecting mis- and disinformation in digital media" (Walter et al., 2020), might also need to be taken into consideration.

5 Actions needed

The conducted literature review revealed on the one hand that not many studies apply cascades analysis for the examination of misinformation, and even if they do, they do not do it across different platforms. Furthermore, the largest percentage of studies relies on Twitter data and examines the spread of misinformation without using cascade analysis or with the aim to improve algorithms for analyses. Additional shortcomings that we identified are that studies rarely assess or discuss to what extent their approaches and methods can be applied to different contexts than the examined one. They also rarely use the same approach so an identification of best practices is hindered. The discussion of used methods and our investigations show that the analysis of the spread of misinformation is context specific with influences of type of misinformation, platform and time examined for example.

In order to develop best practices, studies that do examine the spread of misinformation should discuss to what extent their approach is context specific. But more importantly, we need more studies that apply the used methods to different contexts in order to identify factors that are not context sensitive and in order to understand how context affects analysis and findings.

For studies that compare platforms better access to platforms needs to be established, which is the case especially for Facebook. While Twitter already recently launched an API that allows access to all Twitter conversation so far for researchers, CrowdTangle as an access option to Facebook, Instagram and Reddit only allows access to public conversation and this to a limited extent.

6 Conclusion

In this report, we examine which methods are used in studies that examine the spread of misinformation. For this purpose, we conducted a literature review, which in the end led to 29 identified studies. The literature review and the discussion of the identified studies revealed that most studies only look at one platform for the examination of the spread of misinformation. Furthermore, if they look at more than one, they do not apply information cascade analysis or network analysis but look at the spread of misinformation or develop/improve algorithms for such analyses. The studies only look at a limited range of topics and use a limited set of platforms, from which Twitter is the most used one. Facebook is not used for the analysis of information cascades or information networks. We conclude that this is probably the case due to the limited access options provided by Facebook to information needed for such analyses.

Furthermore, we conclude that studies rarely address to what extent the used methods and approaches can be applied to different contexts and they tend to examine different topics and contexts, which hinders the assessment to what extent the used methods and approaches are generalizable.

In in-depth investigations we assess in first steps to what extent the approach of the highly cited study from Vosoughi et al. (2018) can be adapted for different contexts such as different types of misinformation and different platforms. The investigations lead to the preliminary conclusion, that this is only to a limited extent possible. On the one hand, misinformation detection seems to be more difficult in shorter time periods and with a different thematic focus as misinformation can be detected only to a limited extent. Besides the problem of misinformation detection, we face on the other hand the problem of access to information in additional databases to conduct similar analysis as Vosoughi et al. (2018). We conclude that additional analyses are necessary to finally assess the transferability of Vosoughi et al.'s (2018) approach.

In general, we propose to foster adequate access to information from platforms such as Facebook, Reddit and Instagram and for this purpose, what is especially needed is information about who shares content from whom (retweet information). Studies that look at the spread of misinformation and misinformation cascades should to a greater extent address transferability and context sensitivity. In addition, more studies are needed that apply methods to several contexts in order to better understand transferability and to establish best practices.

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8 Appendix

List of relevant articles after the literature review

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