Human and Algorithmic Contributions to Misinformation Online - Identifying the Culprit*

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Abstract. In times of massive fake news campaigns in social media, one may ask who is to blame for the spread of misinformation online. Are humans, in their limited capacity for rational self-reflection or responsible information use, guilty because they are the ones falling for the misinformation? Or are algorithms that provide the basis for filter bubble phenomena the cause of the rise of misinformation in particular in the political public discourse? In this paper, we look at both perspectives and see how both sides contribute to the problem of misinformation and how underlying metrics shape the problem.

Keywords: Misinformation · Recommender Systems · Cognitive Biases · Opinion Formation.
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1 Introduction

The spread of misinformation in the public sphere is not new to humankind. It has not arisen with the digital age, but has always been present. Emperor Augustus has been found to manipulate his life's work [34] for the archives. And so have other tyrants and dictators throughout history. Still, the effect digitization has had on misinformation seems to change the game drastically.

As early as 1996, Floridi [20] was the first to mention the challenges addressing misinformation in conjunction with the technologies that were to appear in the near future. He warned that with an increase in personalization misinformation online would take novel paths.

For him misinformation would suffer from one of the following: lack of *objectivity*, as in the case of propaganda, lack of *completeness*, as in a case of damnatio memoriae, or lack of *pluralism*, as in the case of censorship.

He writes: "Things may easily become more problematic in the future, for reasons connected to two variables—the number of provusers and the physical integration of the various mass media into a unique digital instrument[. . .]" [20].

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Not only did Floridi correctly foresee the problems personalization on a large scale would bring, but he also recognized the need to arrange the increasing amount of information for end users.

One class of algorithms, so called recommender systems [60] try to achieve this by selecting items that are relevant for the individual user. Relevance is derived from the users' previous decisions. What did they like? What did they buy? Where did they spend time?

In 2011, Pariser published his book the filter bubble [54] explaining how such algorithms take part in designing the web differently for each user. Every user is only exposed to content that matches their preferences, their interests, and their political opinion. The Internet, which used to be praised for allowing free access to information for all, has become an accomplice in mass deception, or more specifically in mass-self deception. However, the existence of filter bubbles or echo chambers has been doubted or moved to the societal fringes of hyperpartisanship [53].

The success of social media in recent years has brought about another drastic change. Initially, intended to improve social interaction and to connect friends across the world, Facebook has become the entry point to the Internet for large parts of the population. It has also become the source of political information for many users. Further, since everyone is now a publisher with a potential 1 Bn people reach in social media, algorithms are required to sort through the large amount of published items to allow users to cope with information overload.

This is also the case for “fake news”, i.e., political propaganda in the disguise of news items [59]. Fake news are subject to the same recommendation algorithms as regular content and are thus often recommended on the basis of other users' interaction with them. The filter bubble dramatically increases the reach of fake news [65], as a positive interaction with such news posts triggers the exposure of this item to other users who are also likely to interact with it positively.

Social media—thus the misinformation on social media—has shown to have an influence on election outcomes in the 2017 elections in Great Britain and the USA [1]. However, it is unclear how large the impact of algorithms were, or whether the sole possibility to spread information (or misinformation) may have contributed to election outcomes opposing what election polls had predicted.

A challenge in predicting real-world outcomes in a digitally connected world lies in the complexity of the underlying interactions. Users' opinions are assumed to be influenced by media exposure and users' choices then influence the algorithms underlying social media. Small effects on either sides (the micro level) can yield drastically different outcome on the whole setting (the macro level) [12]. So, how can we disentangle this mishmash and determine ways to reduce the spread of misinformation?

2 Opinions, Information, and Misinformation

To reduce the spread of misinformation, we must understand what misinformation is, how it is related to information, and how it relates to opinion. For all terms, different definitions exist in different disciplines. Here, we will focus on the following definitions.

What are opinions? **Opinions** are beliefs or convictions of people that contain a sentiment towards an opinion object [27]. Opinions are subjective, thus they are neither correct nor incorrect. When such judgments are held privately they are often referred to as attitudes [51]; only when known to the public are they referred to as opinion. One must ensure to disentangle the concept of public opinion and opinions: the first refers to opinions held by groups of people, while the latter are held by individuals. It is important to note that opinions are not necessary factual or positivistic, but that may solely be normative. Opinions may be based on factual knowledge (i.e. beliefs), but do not have to be.

Information are descriptions of positivistic nature. They describe things as they are. Information is different from facts or data, as it is contextualized and provides references for understanding its meaning. Information often has an author providing these additions to data and facts. Abstract "[i]nformation is seen as an objective commodity defined by the dependency relations between distinct events". [17]. In the realm of online information, information is often considered to be the factual part of an article, a news post, a blog post, or any other form of media.

Misinformation is information that is considered to be counter-factual. This means it contradicts other information that is available. Typically misinformation is referred to as information that is counter-factual, but it is so by mere misinterpretation of data, lack of facts, or knowledge. Authors of misinformation have no ill intent.

Disinformation on other hand is objectively counter-factual information designed in spite of differing data or facts [59]. Disinformation is fabricated and designed to convey counter-factual information. Authors of disinformation have the intent to affect opinions by exposing readers to counter-factual information. Often information is embedded in context that is highly arousal to trigger sharing reactions in recipients. From the reception point of view misinformation is hard—if not impossible—to distinguish from disinformation when facts and data are missing. Thus, disinformation is considered to be a subset of misinformation.

It is important to note that the spread of information and opinion formation processes are closely related. On the one hand opinions are often justified by and based on (mis-)information. On the other hand opinion is then used to filter what information to process [35] and to look for [36].

3 Humans as a Culprit in Spreading Misinformation

We first look at how, social media and media in general affects human opinion formation. To understand the specificities of social media we look at the interaction of how human behavior and human decision making affect the spread of misinformation in social media. We then look at how users use social media, before we address the underlying cognitive biases that partially put the blame in the spread of misinformation on humans.

3.1 Opinion Formation and Media Effects

Understanding how people arrive at their opinions has been studied scientifically since the early to mid 20th century. Early research focused in particular on how individuals shape the opinions of others. So called *opinion leaders* are people that have a high interest in a topic and are consulted by their peers [61]. Efforts were invested to understand how to identify opinion leaders and to understand what personality traits play a role in how someone becomes an opinion leader [11]. Interestingly, opinion leadership is not solely personality dependent, but may change with different domains and topics of interest [49].

When looking at how media affects opinion formation several media effects theories have been proposed. *Agenda setting theory* [47] assumes that the media affects the content of the public discourse by providing a gateway function to curated information. According to the theory, media does not directly influence opinion formation in voting for example. But, by setting the agenda to a topic that is relevant for the election, media can indirectly affect opinion formation with regard to elections.

Cultivation theory [25] goes a little further assuming that the consumption of mass media products has a significant influence on the socialization of human beings, providing reference frames for norms, habits, and fears in a socially constructed reality. It particularly addresses television as a mass media outlet, but mapping it to social media, and in particular filter bubbles in social media, raises critical concerns about the spread of misinformation in social media. People exposed to fake news encultivate perceptions in accordance with said fake news and may become a victim of their own pseudo-realities.

In light of the spiral of silence theory [50], such pseudo-realities become even more worrying. According to the theory, minorities refrain from speaking their opinion to prevent possible backlash and repression. This again decreases the exposure of this particular opinion, increasing fear in others to voice their opinion as well. As a consequence, only majority opinions are heard in the public sphere.

Such effects have been witnessed in social media as well [23], indicating that users might refrain from voicing their opinion online, if they feel to be part of the minority regarding their opinion. Together with filter-bubble pseudo-realities, it becomes hard to determine, whose opinions actually are majorities, whose majorities were created by algorithms, and for whom?

3.2 Use of Social Media

Not every human being is an active social media user. In fact, most people are mostly passive readers online. However, when studying users of Facebook, it shows that people who score highly on the openness scale of the big five personality model are more avid users in particular [2]. This means that people who are more likely to believe new information are more frequently active on social media. Further, they also tend to interact more in social media, increasing the amount of data used by the underlying recommender system.

On one hand, it was shown that active social media use has positive effects on political participation [16]. Users are more interested in politics and interact more frequently with political content online. However, interest is not awareness and interest does not necessarily increase knowledge about politics [72]. For this, factual knowledge must be tested directly.

On the other hand, Lee et al. [41] showed that more active social media usage leads to higher network heterogeneity. This means that more active users have more diverse online friends. This supposedly combats political polarization, although it is unclear how this is achieved.

More active usage also provides more data to the social media provider. This type of information can in theory be used to manipulate the user in elections. Kosinski et al. [40] were able to predict very delicate private information from the seemingly inconspicuous usage data—facebook likes. The researchers were able to accurately predict political orientation, sexual orientation, and substance abuse from a set of likes all publicly shared on facebook. This brings the threat of hacking elections by personal profiling [29]. By providing personalized election commercials or even matching fake news, voting behavior can be manipulated shortly before elections.

Others studies investigated, whether a malevolent agent was even required to shift opinions towards a polarized state. They found that social network structure alone can cause emergent polarization [43] and that differences between users can be generated from first principles in simulation with no prior direction [45].

A particular problem with the spread of misinformation in social media are the negative effects of polarization [18]. By separating users with extreme opinions into subgroups (into their own echo chambers), norm violations in echo chambers are more likely to occur due the perception of anonymity online [33]. These types of incivility can trigger cascades of norm violation [46], as only few individuals deescalate in such cases.

3.3 Cognitive Biases

Some of these problems occur, because human beings have “irrational” thought processes—cognitive biases. Strictly speaking, these thought processes are, from an evolutionary standpoint, well adapted to the tribal life of a great ape. They are only irrational from a modern world perspective with science to show their irrationality. There is nothing inherently bad with cognitive biases. We all have them. The problem is that disinformation often leverages these bias to ensure users share the disinformation.

A strong bias that humans have is the outgroup homogeneity [55] bias. This makes us believe that “the others”, be them political enemies, foreigners, or opposing team members, are all alike. People perceive variability in groups smaller for “them” and perceive variability larger in “us”. This bias is an open invitation for the spread of disinformation that addresses or discredits single individuals in outgroups to discredit the whole group. Targeted recipients find confirmatory evidence in such disinformation for their previously held believes. Such tactics were seen in the refugee crisis in 2015.

Similarly, we tend to follow stereotypic judgments [30] in our decision making. Assuming foreigners to be the culprit in a crime and mentally letting the "nice guy from the neighborhood" of the hook more readily. Partially, this occurs because of the ostrich effect [37], where people ignore relevant information that opposes held believes. Unwanted facts are simply ignored.

The *availability heuristic* [63] affects our decision making process in an interesting way. If we are unaware of a fact, we look for proxy knowledge to use instead. If for example, we are asked how many refugees were involved in crime accusations, we typically do not know the number. We still come up with an estimate, by trying to recall how many references are available from remembering. The more examples come to mind, the higher the estimate. Sadly, not all of these references must refer to facts. They could easily refer to political commercials or fake news posts. This manipulates decision making extensively. The mere-exposure effect accounts for the viability of anti-immigrant misinformation campaigns on social media. The user does not have to believe the misinformation, he just needs to vaguely remember to be affected.

If you as a reader feel, that knowing about biases will help you, I must disappoint you. Even knowing about biases does not reduce susceptibility to these biases, even though you will think differently—as suggested by the blind spot bias [57]. Most biases are innate and are not easily overruled by conscious thought. Babies, for example, are more likely to detect spiders in images, even if there are none [42]. This spider detection bias and our other biases helped with our survival in an uncertain world. In all cases it is safer to believe the rustle in the woods is a bear than just the wind, even though in most cases the wind is to blame. This fact endows us with the agenticity bias [26], making us believe that things that happen must have had a causing agent. This is part of many conspiracy theories, where often an influential agent (e.g., the government) is assumed to prevent the truth from revealing itself [9].

4 Algorithms as a Culprit in Spreading Misinformation

Even though we have seen that humans are partially responsible for the spread of fake news, some of the effects only become explainable when the matching algorithmic counterpart is understood. Here, we do not focus on social bots, although some research showed that social bots could play a role in election outcomes [4]. Instead, we focus on well-meaning algorithms only, which are designed to help the user to cope with the information overload—recommender systems.

4.1 Recommender Systems

Recommender systems were initially designed to help people cope with the large amounts of emails sent by email lists everyday. Tapestry [28]—the first recommender system—was used to let users decide which mails were relevant, which were not, and to then provide recommendation as to whether an email was actually interesting to the user.

This was achieved by so-called collaborative filtering [71], where the decisions of other users were used to measure an average predicted rating of each individual item. This approach was quickly extended to other domains, such as shopping, tourism [21], scholarly education [7], and web search [62].

Different algorithmic approaches were used (e.g., content-based filtering, collaborative filtering, matrix factorization), but the most promising approaches are so-called hybrid recommender systems [8], merging different techniques. More recent approaches, even use social media relationships to improve recommendations [68]. But what does improve actually mean?

4.2 Recommendation Metrics

Typically, recommender systems are evaluated using accuracy metrics. That means that a system's predictions are evaluated against the real user ratings. Assuming the recommender believes you are going to rate a movie with 5 stars, it will be 100% accurate, when you actually do rate it with 5 stars. This metric is easy to understand and seems reasonable, yet it is not very helpful in many aspects.

During the 2009 ACM RecSys conference, Netflix announced a prize of 1 Mio USD for the team that would perform best at recommending movies to viewers. Interestingly, the winning team did so by being able to accurately predict movies that users were *not* interested in. A high accuracy does not make a good recommendation. Good accuracy is not enough [48].

As additional metrics Ge et al. [22] suggested coverage and serendipity. This means that all items should get recommended at least once (i.e., coverage) and that items that are recommended should be novel to the user (i.e., serendipity). Users do want to have diversity in their recommendations, at least when it comes to movies, products, and music recommendations [15]. If this metrics are applied to misinformation, further new misinformation and all misinformation will be shown to at least some users.

In light of misinformation on social media, this also means that the underlying metric of the recommendation system must be known to understand how misinformation is spread in social media. Assuming that social media providers benefit from continued use, any metric that includes dwelling-time or increased involvement by interacting with the content, is a suitable candidate. The problem is that this also captures increased interaction that is caused by highly emotional arousal [3]. Content that angers the reader—such as misinformation—will increase engagement. This engagement is picked up as signal by the recommendation engine.

4.3 User Experience in Recommender Systems

Current research [39] focuses more on the full user experience of recommender systems [10]. Understanding the perceptions that users have about a recommender system is crucial to their user experience [58]. Trending topics in this field are explainability (i.e., showing the user how a recommendation was generated), interactive recommendation, and privacy. This addresses the fact that users have different needs with regard to recommender systems [38].

However, the effects that continued recommendation has on opinion formation still needs further investigation. It is known that some recommender system algorithms increase the exposure of individual items and cause Matthew effects (the more you have, the more you get) [19]. Understanding how to analyze such effect in real recommender systems with real users is still very hard, as it requires to understand both human and algorithmic behaviors and outcomes.

4.4 Interactive Recommender Systems

Interaction has been proposed as a means to improve the quality of recommendations for users. Interaction may come as an interactive visualization that allows for both transparency and controllability of influencing factors [69]. A large number of recommender systems have adapted this approach, which was successful in many different domains [31]. User satisfaction with recommendation increases when interaction is added to the equation [32]. A problem with misinformation in mind is that user exploration is driven by user expectations and user misconceptions as well. The *garden of forking path bias* [24] states that users that interact with visualizations, e.g., become unaware of all those paths not taken for exploration, thus overvaluing the individual items found. Naturally, this increases satisfaction, but it also increases the risk for the spread of misinformation. It allows users to follow their own confirmation bias into the path of self-deception.

4.5 Novel Approaches to Recommender Systems

Very recent approaches have been suggested to include other factors in recommendation. As one concept **trust-based** recommendation [52] incorporates explicit trust-relationships with other users, whose recommendations were successful previously. However, this does not level out the danger of confirmation bias.

Risk-aware recommender systems [5] do not only look at user and item data for their recommendation, but incorporate a model of risk that each recommendation has for the user and the population. In theory, this could be used to reduce the exposure of misinformation to susceptible individuals, however the risk must be modeled explicitly to work properly. Novel scenarios and novel threats are either unevaluated or always considered high risk scenarios.

Value-aware recommender systems [56] go a step further and attach ethical values to items and consider the ethical values for all recommendations. This should in theory lead to value-aware recommendation and ensure higher quality recommendations. Similarly, to risk-aware recommender systems, a value model must be supplied. And it is not clear who determines what is valuable and how much so?

5 Discussion

As we have seen both human and algorithm play a role in the spread of misinformation. Even more so, both parties play a role in each others "mistakes". The recommender system follows a metric, which makes it susceptible to the users confirmation biases. The more a user is interested in a single topic of misinformation, the more the recommender system will provide such misinformation. Even worse, as the most active users are most susceptible to misinformation, such content gets most ratings and thus is most likely to get recommended.

The problem here lies in the chosen *metric*. Most recommender systems are used in some kind of commercial product, which is designed to make money. Amazon recommends products that it believes the customer would buy. Facebook recommends posts that it believes will keep the user on the website to consume more commercials. The metric, which is determined by business rules, impacts the type of content predominantly recommended to users. For misinformation this will be content that is emotionally charged and polarizing. Such content causes a visceral reaction and manipulates users towards interacting with content. Fake News are more readily shared when emotionally charged with emotions like fear, anger, or disgust [70].

From a game theory perspective, the game is rigged against truthful information. It simply is a stable strategy to recommend misinformation, when users prefer such items [67]. This is not to say that users rationally prefer misinformation, but they act in accordance with preferring it.

Troubling is also that discussions about Fake News and "traditional media" have instilled a deep distrust in journalism in teens who rely on facebook and blogs for political information [44]. Confirmation bias and antagonization abound when teenagers discuss politics on social media. Yet, it still requires real life deliberative interaction to find compromise and common ground in political discourse [66].

Approaches in trying to limit these mistakes such as value-aware recommender system suffer from one key problem. Who defines the value model? Who defines what is misinformation and what is not? Who defines what fair exposure of opinions would be like? Should all opinions get the same share of exposure? Should majority opinions get majority exposure? The question of how we want public discourse to be shaped is one of the pressing issues for the digital age.

One approach to address these questions, is through simulation and modelling. Luckily, one part of the equation lends itself readily for simulation—algorithms. First frameworks are being built to simulate the outcome of recommendation in the news domain [6]. Most recommendation engines are readily available as open source and can easily be integrated in a simulation setting. The far harder part to understand is the human side of the equation [14]. Agent-based modelling has been used to understand opinion dynamics, identity formation, and the spread of information [13, 64] since the early 2000s. However, further research is needed to understand the interplay of algorithms and humans in unified complex system.

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