Crucial challenges in large-scale black box analyses

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Abstract. To hold software service and platform providers accountable, it is necessary to create trustworthy, quantified evidence of problematic algorithmic decisions, e.g., by large-scale black box analyses. In this article, we summarize typical and general challenges that arise when such studies are conducted. Those challenges were encountered in multiple black box analyses we conducted, among others in a recent study to quantify, whether Google searches result in search results and ads for unproven stem cell therapies when patients research their disease and possible therapies online. We characterize the challenges by the approach to the black box analysis, and summarize some of the lessons we learned and solutions, that will generalize well to all kinds of large-scale black box analyses. While the studies we base this article on where one-time studies with an explorative character, we conclude the article with some challenges and open questions that need to be solved to hold software service and platform providers accountable with the help of permanent, large-scale black box analyses.

The final authenticated version is available online at https://doi.org/10.1007/978-3-030-78818-6_13.

Keywords: algorithmic accountability · black box analysis · socio-technical systems · challenges · learnings

1 Introduction

When triggered by keywords, search engines recommend lists of resources and information to users, which help them to navigate the vastness of the world wide web. They enable websites to be found, content creators to be heard, and commercial actors like advertisers to conduct business. Thus, providers of search engines and ad exchanges like Google take up a central position in the socio-technical system [21,32] of web search and search engine marketing. Since this socio-technical system is comprised of multiple actors and technical components, it has proven difficult to assign clear responsibilities for problematic search results or ads. For example, political ads can be erroneous and targeted to deceive voters [6], search engine results can reinforce racism [25], or ads with deceiving medical advice can be distributed to users with a severe illness [28]. Some of these actions are illegal, others are only ethically questionable. Some of them fall in the clear responsibility of the ad designer, e.g., factual correctness, others more on the side of the technical system, like the targeting of tainted political ads or the targeted distribution of medical ads with dubious content, which are difficult to assign.

Missing regulation in assigning responsibility is one problem, another obstacle is that these cases are often discussed on anecdotal evidence instead of clear cut data. For example, in the course of the Brexit, the journalist Carole Cadwalladr noticed that many people in her hometown voted leave because they saw targeted political ads on facebook [6]. However, ads on facebook that a user was seeing cannot be retrieved after the fact, resulting in no quantifiable evidence.

To enable an analysis of who gets to see what, there are in principle two solutions: getting insight into the algorithmic systems and all processes around it or, if that is not attainable, a so-called *black box analysis*, which observes and analyzes patterns in the input and output of such a system without insight into its inner workings.

Black box analyses can be used to audit the decisions of an algorithmic system and to detect problematic patterns in them. This is a first and necessary, but not sufficient, step to hold the providers of an algorithmic system accountable. Accountability in general can be defined as "a relationship between an actor and a forum, in which the actor has an obligation to explain and to justify his or her conduct, the forum can pose questions and pass judgement, and the actor may face consequences"[4, p.442]. Following Bovens' definition, Wieringa defined algorithmic accountability as follows: Instead of explaining and justifying its own conduct, algorithmic accountability now focuses on the behavior of the algorithm or the algorithmic system in question, which has to be justified and explained by the person or company who puts it in use. Accordingly, this framework requires (1) an actor (individual, collective or organizational) who explains the behavior of the algorithm to (2) a forum which then challenges this account. The (3) relationship between the two is shaped by disclosure and discussion of (4) the account and its criteria, and ultimately (5) the consequences imposed by the forum [31]. If the actor is held accountable for the results of proprietary algorithms, the latter usually remain undisclosed or obfuscated by design as they constitute trade secrets whose disclosure would allow *gaming* the system [18]. Thus, without any real insight into the algorithmic system and without any hard facts, any demand regarding algorithmic accountability is a toothless tiger and must fail: If the forum has no means to challenge the account of the actor, the actor can in essence not be held accountable.

So far, there have been only a handful of successful attempts to scrutinise the services these platforms provide with such black box analyses, e.g. [7,1,23]. Most of these were sparked by a concrete evidence or tangible suspicion which determined the subsequent process of analysis. Why are there not more black box analyses on this important topic, if they are the necessary basis for a public discourse?

In this paper, we want to discuss the design process and the challenges that arise when conducting a large-scale black box analysis, mainly based on a recent study we conducted in 2019/20.

The study arose from the work of Anna Couturier at the University of Edinburgh and EuroStemCell in the area of public information, patient decision-making, and stem cell research. Her work's focus on the development of patient and researcher co-development of resources on stem cell treatments pointed to a larger question of how information about medical treatments moves through digital spaces. In particular, she investigated the impact of search engines as primary means for patient-led information gathering on their conditions and diseases and subsequent decision making. Feedback from patient advocates from the Parkinson's Disease and Multiple Sclerosis community noted that patients anecdotally noted that their search queries around their conditions often returned advertisements from private clinics offering unproven treatments [4]. This led to an initial study of advertisements of unproven stem cell treatments within the United Kingdom [13]. These initial investigations, however, were unable to address the largest actor within this network of knowledge dissemination; Google Search itself. This blind spot led Anna Couturier to reach out to us to conduct a black box analysis on how often these ads appear and whether they seem to be targeted to patients rather than a healthy control group. In our "2019 Eurostemcell Data Donation Project" we were able to collect evidence that patients do actually see more of these ads [28], despite a new policy by Google to ban stem cell therapy ads [3]. In section 2 the concept of black box analysis and its limitations are presented. In the following section, the above mentioned Eurostemcell Data Donation with its design and results are showcased. Section 4 derives general challenges in conducting a black box analysis, based on the different experiences that were made. In section 5 the basis for the demand for a long term watchdog analyses to ensure algorithmic accountability is lain out and finally section 6 gives a short summary.

2 Black box analysis

The concept of black box analysis can be seen as a descendant of reverse engineering. Diakopoulos defines *Reverse Engineering* as "the process of articulating the specifications of a system through a rigorous examination drawing on domain knowledge, observation, and deduction to unearth a model of how that system works" [10]. It allows the analysis of an opaque system (the black box) by observation of in- and outputs and deduction of the inner mechanics that

[4] These initial impressions were collected during the Wellcome Trust Seed project-funded workshop "Patienthood and Participation in the Digital Era: findings and future directions" hosted by the Usher Institute at the University of Edinburgh in August 2018. (Erikainen et al. [14])

transforms the former into the latter. It can be best achieved if next to the observation of the behavior of the machine it is possible to also generate or manipulate the input, to draw specific conclusions about the relationship between input and output [2]. The central questions for this approach are *What is the analysis process?*, *Which properties can be uncovered, which remain disclosed?* or *What methods should be used?* [2].

An analysis of the relationship between input and output of search engines can only be achieved by a black box analysis, as long as it is not done within the companies themselves. Search engines are based on a composition of multiple algorithms which establish a relationship between input and output and are thus amenable to such an analysis.

2.1 Limits of a black box analysis

Of course, not all kind of questions can be answered by such an analysis [30]: A problem is that search engines, like most other algorithmic systems embedded in a complex socio-technical system, are not a stable research subject:

1. The constant evolution of their code in a constantly improving software development process.
2. User experience is in most cases not the same for all users: It might be altered in A/B tests and shaped by personalization [16,20,5].
3. The complexity of the socio-technical system in which they are embedded. Complexity emerges from the algorithmic system's embedding in a heterogeneous assemblage of various types of social and technical entities that all feedback into the system [30]. Furthermore, algorithms in socio-technical systems are ontogenic, performative and contingent in nature [22]. This means, examining a stable representation of this sort of system is almost impossible due to their "contextual, contingent unfolding across situation, time and space" [22, p.21].
4. Finally, inspection itself can affect the examination [2].

Despite the above limits of a black box analysis, it is still a useful tool: To assess social consequences of an algorithm's deployment, absolute knowledge about its workings may not always be necessary [9]. A "critical understanding of the mechanisms and operational logic" [5, p. 86] is sufficient, as long as it considers those conditions that are required to understand a phenomenon [19].

If that can be achieved, the results of a black box analysis can constitute a meaningful algorithmic accountability relationship in the sense of Wieringa [31] between those, who can access its results (as the forum) and the algorithm provider (as the actor who is held accountable).

However, designing and conducting a reliable black box analysis of search results and ad distributions proves to be challenging as we will report in the next section on the example of our 2019 Eurostemcell Data Donation Project (EDD) and other black box analyses conducted in the last years.

3 A Case Study: Eurostemcell Data Donation

This study was a joint venture between EuroStemCell, the Algorithm Accountability Lab at the TU Kaiserslautern and University of Edinburgh. The main goal was to examine, whether Google was exposing users with a severe illness searching for stem cell treatments to advertisements of unproven and possibly dangerous medical therapies as discussed in the introduction. These ”on the ground” observations led to the joint venture of a black box analysis study and subsequent analysis of search engine results and ads to assess the influence of questionable advertising in the realm of digital health digital marketing on search engines. As the study was induced by such an observation of a probably troublesome phenomenon, it was obvious what exactly had to be measured: the number of search results and ads that patients and non-patients get on (proven or unproven) stem cell therapies. Armed with that, we went into the study design.

3.1 Study design and results

Based on an earlier large-scale black box analysis of Google's search results in the context of the German federal election 2017[23], we used a conceptualised process of a black box analysis by Krafft, Hauer & Zweig [24], shown in Fig. 1. It consists of five phases: The set-up of the accounts which collects the data (1), the data collection phase at the participants' and at the server side (2), the data cleaning phase (3), analysis (4) and finally, the presentation and interpretation of the data (5). For the scope of this article, only the design decisions for phases 1 and 2 are of interest.

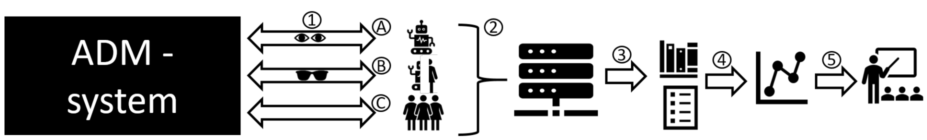

Fig. 1. Conceptualised, technical phases of a black box analysis according to [24].

Design decisions in Phase 1: In the design of the study, the first phase requires the choice of an analysis strategy, namely whether the data is collected based on bot accounts (which is called a *scraping audit*) (1a), on bot accounts simulating humans (1b) or real peoples' user accounts, which is called a *crowdsourced audit* or *data donation* (1c) following [29]. We chose to use both, the first and third approach.

By choosing the crowdsourced approach, patients can contribute to scientific progress and be invited to take an active stand in enacting their autonomy, express solidarity and benefit from indirect reciprocity [27]. For the analysis, we recruited voluntary participants through patient advocacy groups to donate their data. A second group consisted of users without any of the diseases we were looking at, recruited by newsletters and social media. We further added bot accounts with no search history to ensure a baseline, against which we could compare our findings to understand whether patients would get more ads than user accounts without any known health information.

Design decisions for phase 2: The scraping audit was enabled by a browser plugin. It is important to note that we would rather use a way to integrate the data collection into the mobile Google app - however, this would be technically challenging and possibly illegal at the time being. In any case, the plugin automates the search queries and data collection, i.e., once it is installed and runs, the users did not have to do anything. It thus provided a scalable, platform independent and accessible solution that required minimal interaction from the user during the donation. For more than 4 months, the plugins of our participants searched 6 times per day for keywords related to stem cells or specific diseases as long as the browser was running. The plugin scraped the search engine result pages delivered by Google to extract search results and ads.

Our investigation of the crawled data showed that despite an official ban of stem cell therapy related ads by Google at the beginning of the study [17], the captured search results still included ads offering unproven stem cell therapy treatments [28]. On top of that, participants that self-identified as affected, received more advertisement than the control.

4 Challenges in conducting a black box analysis

In the last years, we have conducted black box analyses with respect to search engine results [23], dynamic pricing, filtering of news items on Facebook [24], an analysis of the autoplay function on YouTube, the study we report on here, and, in ongoing work, the collection of ads from Facebook accounts. We always encounter the same kind of severe challenges, based on the choice of how we collect the data in the first phase: a crowd-sourced approach or a bot-based approach.

4.1 Challenges in a crowd-sourced approach

As our study question was whether patients got search results and ads for (unproven) stem cell therapies, we needed to involve real patients in the study. This also entailed that we needed a control group of real people not suffering from the diseases under study.

Problems with participant engagement and enrollment In general, participant enrollment is the more cumbersome, the more technical proficiency it requires. This is particularly salient in the case of our study as the conditions faced by our targeted study groups may, in fact, contribute to difficulties in on-boarding. For example, patients with Parkinson's Disease are on average over the age of 65 years old at first diagnosis [26]. This may lead to challenges with enrollment due to a age demographic unfamiliarity with the technology necessary to take part. In our final study iteration, we were pleased to enroll around 100 patients participants. This number is comparatively large for a socio-anthropological medical study. However, for a large scale statistical analysis of the results, this number is comparatively small.

It would be easiest, if participants could grant scientific study teams a restricted access to their account on the given platform [24]. For example, if they were able to go to their Google account, enroll to the study, and search results and ads would be automatically collected and sent to the conductor of the study. However, at the time being, there is no way to access specific information of social media accounts even if users give their full consent, neither for platforms such as the various Google services, Facebook, or Twitter. Facebook actually offered the Facebook Graph API that granted targeted access to users' accounts if they gave their permission - however, following the Cambridge Analytica Scandal, they restricted this access so much that black box analyses targeting specific aspects like ad distribution or specific messages in the timeline are not possible anymore from outside of Facebook.

Diversity of hardware and software environments Enrolling real persons also entails being confronted with a multitude of devices, operating systems, browsers (that come in different versions), and other software running on the device and interfering with the data collection. In our black box analysis regarding the election in 2017, multiple participants were not able to install the plugin, or it would not send any data, or it would hinder the normal usage of their browsers, e.g., by excessive consumption of computing power. In the running study, we were not able to figure out whether any of this was caused, e.g., by their ad blocking software. Another small problem arose from the different settings of the participant's Google user account, e.g., the setting of the preferred language or the preferred number of search results displayed on one page.

Problems scraping websites The only technology left to collect data that real people see in their search results, was the browser plugin. It is basically a scraper, which is very susceptible to any changes of how the result page in the browser is structured. For example, in our black box analysis study concerning the German election in 2017, Google's layout for their result page changed midway. This resulted in empty data columns in our data collection for some days until we noticed the problem. In our study on dynamic pricing, we learned that web shops are actively fighting against price scraping by changing the structural design of their page regularly, which makes any attempt to investigate personal pricing based on scraping very difficult.

We learned on the one hand that it is absolutely necessary to check the collected data regularly and on the other hand to make any updating procedure of the data collecting software as smooth as possible. Participants are very likely to drop out of the study, if they have to re-install or manually update the data collecting application, as we learned in our black box analysis study in 2017 where one of our plugins had a severe bug: We could not update it remotely and thus a re-installation was necessary. Here we encountered the double-edged challenge of ensuring privacy. In order to maintain the privacy of the data donors, we did not collect contact information, but rather relied on the donor themselves to install and run the donation plugin. We did not even have an email list or other communication channel to make our participants aware of the problem.

Problems caused by dynamic internet content Another general problem in the data collection is the dynamic nature of the content advertised in ads or search results: very often, we collected links from ads that at the time of the analysis were already invalid. We learned that it might have been better to crawl these links at collection time and to save the respective pages for future analysis. However, with A/B-testing being abundant, where part of the users following a link get version A of some website and others get version B (or C, D,...) of it [11], it would be necessary to follow the link from within the plugin. That is, the participant's browser would not only open the Google webpage but also any other webpage advertised or displayed on the results' page. This entails problems of safety and data privacy that are difficult to solve plus it might be illegal w.r.t. general terms and conditions of Google's search engine service.

Almost no manipulation of input possible While the crowd-sourced approach has the huge advantage to collect data that users would see, it is almost impossible to change the "input to the search engine" in any meaningful way, to better understand the real behavior of the system. The "input" to the search engine in a personalised account is not only given by the keywords, time of day the search is conducted, the IP-address of the machine used to conduct the search, and so on, but also by the personal history of searches, of web usage in general, induced properties of the human user imputed by the software (like age, income, gender, etc.). None of this can be easily changed such that a wanted user profile can be consistently achieved. It was this restriction that prompted us to adopt the dual approach of virtual bot-based data gathering. However, the bot-based approach came with its own challenges.

4.2 Challenges in a bot-based approach

Our study was conducted in four countries, where we rented a set of so-called *virtual private servers* to run searches from IP addresses located in the same country.

Problems with bot detections An unfortunate drawback of bot-based approaches is that they are routinely identified by most popular online platforms and then blocked. While these measures are necessary to detect malicious bot attacks, it hinders the mainly benign and public interest-driven scientific investigations. This would include any regular black box analyses by NGOs or the government established to hold software or platform providers accountable.

Problems with regionalisation A small problem that we encountered is the localisation of services by IP-addresses and other indicators of the place from where a service is approached: when using virtual private servers, the IP addresses are not as distributed over the country as if persons would use the service. Moreover, the IP address might be assigned with an industrial area rather than a residential area, resulting in different search result.

Problems with fake account generation In our study, we were lucky that search engine results can be a) obtained without logging into some account and b) analysed rather easily via an HTML-scraping approach. A bot-based approach is nearly impossible if it is necessary to set up fake accounts and/or to

use an app by the software provider. We have discussed some of the problems we encountered when setting up fake accounts with Facebook in Krafft, Hauer & Zweig [24].
However, some of the challenges we identified above can be mitigated by conducting a pre-study.

4.3 Arguments for including a pre-study

Next to profane bugs in the plugin software, a pre-study of reduced length and number of participants can, e.g., help to estimate the size of the effect that is to be studied, thereby indicating the number of participants needed to run reliable statistical analyses. It helps to discover problems with the technical setup that occur very often, giving room for a technical improvement of the user experience. It might also detect problems with quickly changing website layouts, e.g., when website owners use that tactic to hinder scraping as discussed above.

It will also help to reveal at least some of the weaknesses of the study design and to mitigate unanticipated problems: For example, in the study concerning the election of 2017 [23], we were not aware of the fact that searches on Google could result in Google+ pages to be displayed. Google+ was the attempt of Google to create a social network platform and it allowed to build up contacts and to post and comment on URLs. When a person was searched on Google, who was in the contact list, all their contact data would be shown on the result page, in a special area reserved for that information. Similarly, if a key word was searched for, that was associated with any content on the user's Google+-account, that could also become part of the search results. We did not scrape this reserved area of the result page which could possibly contain personal data of contacts of our participants. However, we did scrape the search engine results and thus needed to make sure to delete all results from the Google+-accounts because otherwise these could have been used to deanonymise our participants. Since we did not have time for a pre-study, we were confronted with this problem in the full study which created some problems in the data collection.

We also discovered only in the analysis of the fully collected data, that most probably, the preferred language setting of our participants in their Google account, produced some of the anomalies that we encountered [23]. However, because we were not aware of this additional "input" to the search engine, we did not collect this information and thus, cannot be sure about its effect.

5 From experimental studies to establishing accountability with the help of large-scale black box analyses

As discussed in the introduction, accountability for problematic algorithmic results can only be established if there is a *forum* questioning the conduct of the actor, i.e., the provider of the algorithm-based service. Without reliable, large-scale, quantified evidence and only based on anecdotal evidence or hunches, this has proven to be difficult in the last decades. We conclude that at least for those questions that concern, e.g. fundamental rights of citizens or the protection of vulnerable persons like the patients in our study, an experimental study like ours is not sufficient. It is necessary to implement a permanent large-scale black box analysis based on a sufficiently sized and representative sample of users. In contrast to the phenomenon-induced study we presented here, which searched for evidence to back up anecdotal evidence, we call this the *watchdog approach*: it refers to (institutionalised) continuous scrutiny over an algorithm.

Study design for watchdog analyses To implement a watchdog as part of the forum to hold a software or platform provider accountable [31], the study design needs to be focused on the goal to enable the watchdog's role in the forum. The evidence created by the black box analysis needs to be clear and strong to challenge the actors and to hold them accountable. However, given the state of affairs, especially the lacking access to the necessary data to actually conduct these studies, the above stated technical challenges weaken the collected evidence, or make it impossible to collect it.

Solution to technical challenges It is thus also necessary to overcome the technical challenges that cannot be solved on the side of the watchdog. While the analysis of search engine results including presented ads is technically relatively straight forward, other important analyses can simply not be conducted with state of the art access to platform data. For example, we failed to analyse from a news provider's perspective which of his followers saw what portion of his news [24]. We failed despite the fact that we had **full access** to the Facebook account of the news provider because it did not contain the data we needed. We also failed to set up fake accounts to retrieve the data in another way. This is a problem as German's media structure strives for diversity of news and information. Thus, any subsequent filtering of news outside of the media outlet diminishing that diversity needs to be analyzable and contestable to comply with the rules. Multiple policy consulting committees in Germany and the EU commission have acknowledged the need for the access to relevant data from algorithmic service providers, e.g., the data ethics commission, the Enquete Commission on artificial intelligence, and the EU commission.

6 Summary

In this paper we showed that there are a number of technical challenges that hinder large scale black box analysis of digital platforms. Our group found it an important reminder that the final output of these algorithms was not simply search results, but the potential of an individual impacted by life-altering disease to be exposed to at-best economically exploitative practices and at-worst potentially risky, unproven medical treatments. Some of the challenges discussed in this paper can be mitigated by a careful study design including a pre-study. However, the resources for this and for a large-scale analysis that includes high numbers of patients, should not be underestimated. Next to the technical challenges that can be mitigated there are mayor technical obstacles that can only be resolves together with platform providers. To enable accountability, where it is necessary, a watchdog approach cannot be realized without solving these problems. The study we conducted show that this is a societal problem that cannot be ignored any longer. We see that political bodies like the Deutsche Bundestag [12], the Data Ethics Commission [8] and the European Parliament [15] are currently searching for solutions.

Acknowledgment

The presented project EDD has been partially funded by the EU stem cell public engagement project, EuroStemCell[5] and by a generous grant from the University of Edinburgh School of Social and Political Science. The research was supported by the project GOAL "Governance of and by algorithms" (Funding code 01IS19020) which is funded by the German Federal Ministry of Education and Research.

Publication

The final authenticated version is available online at https://doi.org/10.1007/978-3-030-78818-6_13.

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